Modelling Viewpoints in User Generated Content

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The candidate confirms that the work submitted is his/her own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

DESPOTAKIS, D., DIMITROVA, V., LAU, L. & THAKKER, D. 2013. Semantic Aggregation and Zooming of User Viewpoints in Social Media Content. In: CARBERRY, S., WEIBELZAHL, S., MICARELLI, A. & SEMERARO, G. (eds.) User Modeling, Adaptation, and Personalization. Springer Berlin Heidelberg.

Co-authored with my supervisors, this work relates to Chapters 3,6 and 7.

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Co-authored with my supervisors and project partners from i-maginary srl Milan, Italy, this work relates to Chapters 4,5 and 7. The simulator software, data content and evolution input were provided by i-maginary srl Milan, Italy.

DIMITROVA, V., STEINER, C. M., DESPOTAKIS, D., BRNA, P., ASCOLESE, A., PANNESE, L. & ALBERT, D. To Appear. Semantic Social Sensing for Improving Simulation Environments for Learning. European Conference on Technology Enahanced Learning (ECTEL), 2013.

Co-authored with my main supervisor and project partners, this work relates to Chapter 4. Most of the work was done by others. My work contributed one aspect of the study.

DESPOTAKIS, D., THAKKER, D., DIMITROVA, V. & LAU, L. 2012. Diversity of user viewpoints on social signals: a study with YouTube content. International Workshop on Augmented User Modeling (AUM) in UMAP. Montreal, Canada.

Co-authored with my supervisors, this work relates to Chapters 4 and 7 and partially to Chapter 5.

AMMARI, A., DIMITROVA, V. & DESPOTAKIS, D. 2012. Identifying Relevant YouTube Comments to Derive Socially Augmented User Models: A Semantically Enriched Machine Learning Approach. Advances in User Modeling. In: ARDISSONO, L. & KUFLIK, T. (eds.). Springer Berlin / Heidelberg.

Co-authored with my main supervisor and project colleague, this work relates to Chapter 4. My work contributed partially to the solution described in the paper.

DESPOTAKIS, D. 2011. Multi-perspective Context Modelling to Augment Adaptation in Simulated Learning Environments. *In:* KONSTAN, J., CONEJO, R., MARZO, J. & OLIVER, N. (eds.) *User Modeling, Adaption and Personalization.* Springer Berlin / Heidelberg.

This work presented preliminaries related to Chapter 3 and 5.

DESPOTAKIS, D., LAU, L. & DIMITROVA, V. 2011. A Semantic Approach to Extract Individual Viewpoints from User Comments on an Activity. International Workshop on Augmented User Modeling (AUM) in UMAP. Girona, Spain.

Co-authored with my supervisors, this work presented preliminaries related to Chapters 4, 6 and 7.

AMMARI, A., DIMITROVA, V. & DESPOTAKIS, D. 2011. Semantically Enriched Machine Learning Approach to Filter YouTube Comments for Socially Augmented User Models. Workshop on Augmenting User Models with Real World Experiences (AUM), UMAP. Girona, Spain.

Co-authored with my main supervisor and project colleague, this work relates to Chapter 4. My work contributed partially to the solution described in the paper.

DESPOTAKIS, D. 2010. Capturing Multi-Perspective Knowledge of Job Activities for Training. 5th European Conference on Technology Enhanced Learning (ECTEL), Doctoral Consortium. Barcelona, Spain.

This work presented preliminary ideas at the early stages of my PhD.

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Abstract

The Web 2.0 infrastructure allowed for a tremendous technological growth in the ways that information is distributed and exchanged among individuals. Web sites transformed to hosts of an abundance of user generated content in various domains comprising thereafter social media platforms. This evolution heralded the beginning of a new era for user modelling. Several types of applications have gained benefit from harvesting social media content for either populating or enriching user models by identifying, extracting and analysing digital user traces aiming at improving system responses for adaptation and personalisation.

However, different user experiences and backgrounds determine different user viewpoints, and it is evident that the next generation of user modelling approaches should cater for viewpoints diversity. This can enable better understanding of the users' conceptualisations, their exposure to diverse interpretations overcoming thus the 'filter bubble' effect and enriching their perspective. How can we represent user viewpoints? How can we capture user-viewpoints from user generated content? How can we enable intelligent analysis of user viewpoints to explore diversity?

This research complements notable efforts for viewpoints modelling by addressing three main challenges: (i) enable better understanding of users by capturing the semantics of user viewpoints; (ii) formally represent user viewpoints by capturing the viewpoint focus, and identify the projection of user models on the domain of interest; and, (iii) enable exploration of diversity by providing intelligent methods for analysis and comparison of viewpoints. The proposed approach is wrapped within a framework for representing, capturing and analysing user viewpoint semantics, called ViewS. ViewS defines a semantic augmentation pipeline for processing textual user generated content. The semantic output is then used as input together with the annotating ontologies in a component for capturing viewpoint focus which exploits Formal Concept Analysis. The viewpoint focus model is used then to analyse and compare user viewpoints and explore diversity.

ViewS has been deployed and evaluated for user viewpoints on social signals in interpersonal communication, including emotion and body language, where diverse interpretations can be obtained by different individuals and groups.

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Introduction

1.1 Motivation

A tremendous technological growth has been enabled by the Web 2.0 infrastructure in the ways that information is distributed and exchanged among individuals. Web sites are being transformed to host an abundance of user generated content in various domains. These are collectively known as social media platforms [1].

Twitter[1] accounts for over 500 million users according to the latest 2013 statistics. Over 55 million tweets (short text messages) are generated by users each day[2]. YouTube[3] has 800 million visitors per month, while 100 million people take a social action (e.g. like and sharing videos, commenting on videos) every week[4]. This volume of user generated content concerns a variety of domains (e.g. entertainment, news, work and education), captures real life events and reactions at the time, and can be organised for example with hashtags in Twitter messages and video categories/tags in YouTube.

The plethora of user generated content offers a great potential for real world exploitation by processing with computational methods. Real world can be matched with the virtual world : *people* in the real world are effectively *users* in the virtual world of Social Web. Therefore user's behaviour reflects people's behaviour in a variety of contexts including trends [2], politics [3], social dynamics [4] and business [5].

In line with this trend, recent movement in the user modelling and personalisation community taps into the wisdom of the crowd by: profiling users on the Social Web for adaptation [6, 7], utilising folksonomies for information retrieval [8, 9], archiving social media content for future use [10] and mining the content for collective intelligence [11, 12]. This potential,

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[1] https://twitter.com/

[2] SHIFT DIGITAL : www.shiftdigitalmedia.com

[3] http://www.youtube.com/

[4] YouTube Statistics: http://www.youtube.com/yt/press/statistics.html

however, induces a great challenge when grasped; and requires one to explore and embrace the *diversity* in user generated content.

New expectation has emerged from the next generation of personalisation techniques, as the emphasis shifts from *similarity* to approaches that exploit *diversity*. There are growing arguments that people need to be exposed to information that would challenge or broaden their world view [13]. As stated recently at major personalisation forums [14, 15], effective personalisation should provide more serendipitous experiences, capturing and exploiting diversity in a creative way. The emphasis on diversity is also supported by research in social science. It is recognised that an exposure to, and inclusion of, diverse opinions can lead to more divergent and out of the box thinking. This in turn can improve individual and group problem solving and decision-making [16, 17]. Therefore, the notion of diversity in user generated content needs to be captured and analysed.

As stated in the latest User Modelling Adaptation and Personalisation research forum by Geert-Jan Houben in his keynote [18]: "*there is no one truth*" in the Social Web. To illustrate the potential diverse range of 'truth', consider watching on a social platform a video of a car journey which ended up in a crash on the motorway caused by fog and dangerous driving. Different viewers may comment on different aspects of the car journey they watch, e.g. the car, driver, location, weather or other participants. Some viewers may also tell short personal stories on the specific aspects they experienced from other similar car journeys. Such variety of comments provides a source for different viewpoints, hence diversity, on the activity 'car journey'.

In order to explore diversity, this thesis sets forth that we have to consider *user viewpoints*. Modelling viewpoints enables a deeper *understanding of the user within the domain in its specific instances.*

1.2 Research Questions

The previous example illustrates possible diversity in user comments and their perceptions even on the same item, based on the users' experiences or opinions. In order to deal with diversity in user generated content, computational approaches are needed for modelling viewpoints. In this thesis, a **viewpoint** is defined as

> *"the focus and the collection of relevant statements embedded in a piece of user generated content"*.

The viewpoint *focus* denotes the aspects and characteristics mentioned in the statements made by the user as an outlook of a domain, e.g. a car journey.

The research aims at resolving the key challenges for user viewpoints modelling and seeks answers to the following research questions (RQ):

RQ1. Representation: *How can we represent user viewpoints*?
Conventional user modelling data structures are able to describe a user model with more tangible parameters such as preferences, locations and so on, typically for personalisation-driven applications. For viewpoints modelling, it demands a more flexible, extendable and qualitative representation which can evolve with the growing contextual information for more intelligent analysis. This representation should be able to map between the user's conceptualisation of a domain and the domain model itself.

RQ2. Capturing: *How can we capture the essential characteristics of user viewpoints?*
Numerical methods (e.g. data mining) require large volumes of content as input to derive characteristics statistically. These methods are known to be insufficient for qualitative explanations. Semantic Web technologies have showed promising potential for understanding user contributions and improve personalisation. However, in order to extract viewpoints, more intelligent methods are needed in order to extend the knowledge about the users even when there is only a small amount of content, as well as the users' focus.

RQ3. Analysis: *How can we analyse and compare user viewpoints?*
This new dimension of user modelling, qualitative viewpoints modelling, demands novel intelligent analytical methods which include reasoning, querying and comparison of viewpoint models to explore diversity.

1.3 Scope for Contributions

The above research questions are addressed by this thesis with a framework for modelling viewpoints in user generated content –ViewS (which stands for **View**point **S**emantics). The work contributes in two main research streams:

Semantic Web – For capturing viewpoint semantics, ViewS defines a semantic augmentation component. This requires a novel way to integrate existing tools and technologies to semantically annotate and enrich user generated textual content. A synthesis of linguistic and semantic resources is needed to process text and attach ontological concepts to relevant terms.

User Modelling and Analytics – For representing user viewpoints, ViewS provides a formal definition and a computational framework based on Formal Concept Analysis. For analysing user viewpoints, ViewS lists the characteristics which can be used to describe the user viewpoint based on the formal model and defines comparison operations between viewpoint models. A means for visual comparison of viewpoints is also needed.

1.4 Structure of the Thesis

In Chapter 2, related work is discussed and limitations of the current state-of-the-art methods and technologies are identified. It concludes with the need for intelligent methods to project the user viewpoint model within the domain of interest in order to be able to explore diversity.

In Chapter 3, the ViewS framework is outlined which aims at resolving the aforementioned research questions. The domain for experimentation in this research, non-verbal interpersonal communication, is also presented. This domain is chosen as diverse interpretations can result based on different user experiences and backgrounds.

Chapter 4 explains the first component of ViewS, Semantic Augmentation. The component was evaluated in an experimental study using content collected in a controlled environment.

In Chapter 5, an experimental study to explore potential benefits of viewpoints analysis with learning simulator designers is discussed. In this study, further requirements for viewpoint representation were collected and summarised.

Chapter 6 presents the viewpoint focus modelling approach based on the elicited requirements. Formal Concept Analysis, a formal computational framework, is used for representation and Region Connection Calculus for comparison of focus models. The implementation of the methods and techniques are detailed with the presentation of a tool – ViewS Microscope which provides a visual-analytical tool for user generated content.

In Chapter 7, two studies are described and showcase the power of ViewS and ViewS Microscope. The first study used a dataset (with user generated content) from a closed social environment within a learning simulator. The second study used data from a selected set of videos in YouTube as an example of open social environment.

Chapter 8 concludes the thesis by summarising the key achievements as well as the limitations which will drive future research or technical work (immediate and long-term). Other potential application scenarios for this work are discussed.

Chapter 2
Related Work

2.1 Introduction

The goal of this Chapter is to position this research within the related work. Methods and technologies that could be used for user viewpoints capturing, representation and analysis are presented from three main research fields in computer science: Text Mining, Semantic Web technologies and User Modelling. Key research aspects and limitations of the state-of-the-art approaches are identified.

In Section 2.2 text mining methods and applications are presented focusing on opinion mining and sentiment analysis. Section 2.3 illustrates how conceptualisation of user opinions is enabled with semantic web technologies which overcome some of the limitations of data mining methods. In Section 2.4 the user modelling approaches are discussed and current limitations with respect to viewpoints representation for exploring diversity are highlighted. Section 2.5 summarises the key novelties that this research aims to bring.

2.2 Data Mining Methods for Analysing UGC

In the research field of *data mining*, with particular focus on its subfield *text mining*, computational methods closest to the need of viewpoint modelling are under the umbrella of *opinion mining* [19]. Chen and Zimbra [20] define opinion mining as the set of techniques for capturing and analysing opinions expressed in user generated content. The most prominent technique is *sentiment analysis (sometimes this term is used interchangeably with opinion mining)*. Sentiment analysis aims at identifying emotional trends, e.g. sentiment, affect and subjectivity, in text [20].

The key concepts of opinion mining and sentiment analysis are summarised including measurement attributes and methods. The review below draws from the survey articles of Pang and Lee [19], Liu and Zhang [21] and Liu [22].

2.2.1 Representation of Opinion

The most prominent type for measuring opinion and sentiment uses a *polarity scale* between a positive and a negative value [19]. The process of assigning a value for sentiment within the polarity scale is called *sentiment polarity classification*. The polarity scale can be either binary (positive or negative value) or continuous (taking values in the interval between positive and negative values). The application of this metric assumes that opinion and sentiment is identified on a single issue.

Another strand of opinion mining deals with opinionated text. In this case subjectivity of the expressed opinion is being investigated. *Subjectivity* measures whether a piece of text expressing an opinion (not necessarily sentimental [22]) is subjective or objective. Again, assuming a single issue, subjectivity analysis aims at identifying if a piece of text contains personal views or beliefs [22]. Although subjectivity has been mostly investigated using binary classification, Pang and Lee stress the fact that in many cases an opinion may be neutral [19].

Coarse grain document classification, either for sentiment or subjectivity classification, provides an overview analysis on a single subject or issue. However, as identified by Pang and Lee [19] and Riloff et al.[23], one could consider several sub-items that are related within a single document subject. This has been furthered by Liu [22] in providing more semantically enhanced opinion mining. Hu and Liu [24] focused on a more fine-grained level of analysis where a piece of text is processed to extract entities and their corresponding aspects (also called features). Each aspect is then investigated with opinion mining techniques presented above.

Extending the work on polarity classification of sentiment and subjectivity, another strand of opinion mining research investigates the notion of *viewpoints and perspectives* [19]. The aim of such approaches is to characterise user generated content with singular *concepts* which can depict, e.g. attitudes or beliefs, instead of positive or negative trends. The work by Lin et al. [25, 26] consists a representative example of identifying viewpoints and perspectives regarding the Israeli-Palestinian conflict.

Research has also emerged on extraction of fewer factual attributes for opinions from a piece of text. Pang and Lee [19] refer to this class of approaches as *non-factual information* extraction from text. A representative example classifies text into affective categories (e.g. the six universal emotions[27] - anger, disgust, fear, happiness, sadness and surprise). The related work for emotion annotation in text, relevant to the application domain of this PhD, will be further explored in Chapter 3, Section 3.4.

Viewpoints and perspectives analysis has been combined with entity-aspect representation in a recent modelling approach called the Topic-Aspect Model (TAM)[28]. TAM also provides a more fine-grained representation of opinions in documents. TAM aims at not only extracting the general *concept* (topic) associated with a viewpoint or perspective, but also identifying the topics and aspects associated with it. These descriptors can be used to distinguish between viewpoints or perspectives. TAM is a probabilistic model which assigns word distributions to topics based on word co-occurrences in the corpus.

2.2.2 Methods

The methods which are being used for opinion mining concern machine learning techniques, focusing mainly on text classification tasks. A comprehensive review has been presented by Liu in [22] (and earlier in Pang and Lee [19]) and will not be repeated here.

For sentiment classification, both supervised (more frequently) and unsupervised machine learning techniques have been applied. In the case of supervised machine learning, the researcher builds a training data set for the model, which is then tested on the testing data set(s). Both the training and testing data sets are described or examined by the model respectively with a set of features. These features can include terms and their frequencies, part of speech, predefined sentiment words and phrases, syntactic dependencies and sentiment shifters, e.g. negation. Most commonly, two types of machine learning models are being used: naive Bayes classification and support vector machines. These models integrate the selected features and build a probabilistic model for predicting the sentiment class. In the case of unsupervised machine learning, sentiment words and phrases are used for sentiment classification. Based on a set of positive and negative sentiment words and phrases, the model calculates the statistical dependencies of the document with either polarities based on probabilities to co-occur with other terms in the document. The co-occurrences usually follow syntactical patterns within the text document or term distances.

For subjectivity classification, the most common method to apply is supervised machine learning, using a variety of features as aforementioned. The application of features concerns the assigned subjectivity orientation either as subjective or objective. In the case of unsupervised modelling, predefined subjectivity expressions are used as seeds for the model, which can then be expanded with other resources, e.g. similar expressions and phrases.

For the more fine-grained classification of sentiment, which includes entities, topics and aspects as aforementioned, the classifier is build based on the target facet. A syntactical dependency parser is often utilised to correctly identify the selected feature(s) value with respect to the target. In the case of unsupervised learning, a lexicon of sentiment words or phrases is used together with the syntactic parse tree to discover dependencies with the target facet. In both cases, however, the facet (entity, topic or aspect) is not always known, therefore has to be extracted. A facet can be identified by using syntactical features and frequencies -e.g. nouns and noun phrases, extracting the target given an opinion phrase with syntactical parsing, using supervised machine learning and topic models - similar to the TAM presented earlier.

For viewpoints and perspectives modelling, supervised machine learning is commonly used. The technique involves manually annotated corpora with known viewpoint or perspective, from which related words (together with the associated sentences) are extracted and given a score (distributional frequency). The models are implemented with naive Bayes or support vector machine classifiers.

2.2.3 Applications of Opinion Mining for Viewpoints Diversity

The work by Lin et al. [25] aims at identifying perspectives in textual corpora. It followed the conventional approach of supervised machine learning using naive Bayes and SVM classifiers. The experimentation is performed on a corpus of text related to the Israeli-Palestinian conflict. Classification is presented both in document and sentence level. The corpus consists of more than 18,000 sentences. The classifiers have achieved high accuracy both at document and sentence level. The large volume of data required for such methods to perform has a counter effect however. Diversity of opinions or subjectivity in this case cannot be explored with high level views, which is offered by classification techniques. Identifying the differences, similarities and overlaps requires more work with qualitative instruments. Moreover, as the classification is based on words, terms and language features, extraction and analysis at the conceptual - deeper meaning- of such features can enable reasoning about the observed viewpoints.

Paul et al. [29] investigate how opinions can be summarised in text corpora, in order to represent contrastive viewpoints. The viewpoints, and consequently the diversity of viewpoints, are handled in a polarised - positive or negative - manner. Adopting the definition from WordNet, a viewpoint is "a mental position from which things are viewed". To model and extract the viewpoints, the Topic-Aspect Model (TAM) [28] is utilised, which has been discussed earlier. As TAM is an unsupervised model, it was enhanced with additional features including: retaining stop words, syntactical dependencies, negation and polarity of words. Viewpoints are summarised at a macro level - sets of sentences with each set corresponding to a viewpoint, and micro level - pairs of sentences with each sentence belonging to one viewpoint. Clusters of viewpoints have been randomly generated using the LexRank algorithm [30]. The evaluation include: a data set of 948 responses to a survey about the U.S Healthcare Bill in 2010, and a data set of 594 editorials about the Israeli-Palestinian conflict. The viewpoints extraction phase shows that the enhanced TAM model provides moderate accuracy for certain datasets (also commented in [28]). The comparison of viewpoints (contrastive summaries) aims at correctly identifying contrastive pairs - either sets of sentences (macro-level) or sentences (micro-level). Diversity of viewpoints, particularly differences in topics and aspects in the viewpoints model, has not been explored.

In [31] Pochampally and Karlapalem present a framework for mining diverse views (viewpoints) on related articles, in order to better organise content in the world wide web for faster information exploration. A viewpoint is defined as a set of semantically related sentences from textual corpora. Sentences are selected to represent views based on a ranking mechanism. This mechanism is based on frequency of terms relatively to the document (TF-IDF), as well as on the number of top ranked words in a sentence. Sentences are grouped to views based on a clustering algorithm which utilises as a feature the semantic relatedness of two sentences (WordeNet based). Ranking of views is based on the cohesion of the cluster of sentences it constitutes of. Cohesion is defined as the average pair-wise similarity of the sentences in the cluster. Cohesion of views is the parameter for evaluation of the framework - the higher cohesion, the better view representation. Diversity between views has not been explored however in this work. Differences between words at a set or sentence level are not examined. Moreover, the semantic similarity metric has not been further explored to identify potential overlap between different views (clusters of sentences).

Bizau et al. [32] focus their work on expressing opinion diversity in social media, by developing domain-dependent opinion vocabularies. An opinion is measured based on a 3-level polarity scale (positive, negative and neutral). Using seed sentiment words, they expand the vocabulary based on synonyms and antonyms normalised by the distance in the WordNet search tree of synsets. The use case includes building a domain dependent opinion vocabulary from the Internet Movie Data Base (IMDB) (27,886 reviews). The vocabulary is then tested against a collection of tweets (220,387 Twitter messages) related to movies based on word frequency (both positive and negative). The scoring of tweets based on polarity converge with the actual IMDB movie reviews, however not significantly. Positive and negative (or neutral) reviews have not been compared however, in order to explore diversity. Potential overlap could be identified based on the relations of words in WordNet, which would be interesting to test against the different sets of sentiment words identified in the Twitter messages. Implications regarding the diversity of opinions are not investigated with regard to the linguistic approach. Moreover, it is unclear whether all synsets for a seed word were taken. Each synset given a search token declares a different sense under which synonyms and antonyms are clustered.

2.2.4 Discussion

In the research field of text mining, viewpoints are captured and analysed with computational methods which concern opinion mining. Opinion is expressed through linguistic and statistical processing with sentiment, subjectivity and perspectives. Although notable effort has been put to extract and analyse viewpoints, exploration of diversity is hindered; the analysis stops at a shallow layer of representation. The main constructive components concern key terms which are associated either with polarised opinions (expressed with sentiment) or attitudes (expresses with subjectivity and perspectives). When facet models (e.g. [28]) are exploited, no work has been done to explore the viewpoint space and consequently diversity. *In order to explore diversity, a deeper layer of analysis is required to understand the similarities and differences between viewpoints.*

Moreover, the aforementioned methods and applications rely on large volumes of data. The classifiers are based either on parameters (unsupervised approaches) or large training data sets (supervised approaches). This requires high density distributions of features (e.g. bag of words, labelled phrases, linguistically annotated text frames) to build the classification model. However, when such large volumes are either not available or extensive manual work is needed for their production, the classification models are unsuitable. For example, as pointed out by Vassileva [33] in the context of online learning environments, despite the abundance of user generated content, it is challenging to elicit the "right stuff" with respect to personalisation, pedagogy, context and content types. Bontcheva and Rout [34] also highlight that when user generated content is small, corpus-based data mining methods cannot be applied successfully. *In order to process such content and extract viewpoints, deeper analysis is required for smaller volumes of data.*

The vision for this research is complementary to the data mining methods for opinion and sentiment analysis. *A conceptual layer is envisaged to characterise viewpoints and contextualise the data in order to understand differences and similarities of aspects and to analyse smaller volumes of content*. *The conceptual layer can be provided by exploiting Semantic Web technologies*. The semantic web technologies for content annotation are reviewed in the next section.

2.3 Semantic Web Technologies for Analysing UGC

> *"The Semantic Web is not a separate Web but an extension of the current one, in which information is given well-defined meaning, better enabling computers and people to work in cooperation."*
>
> **Tim Berners-Lee et al.**, **2001 [35]**

> *"...I would call the current state of the Social Web something else: collected intelligence..."*
> *...*
> *"I think it premature to apply term collective intelligence to these systems because there is no emergence of truly new levels of understanding."*
> *...*
> *" The challenge for the next generation of the Social and Semantic Webs is to find the right match between what is put online and methods for doing useful reasoning with the data."*
>
> **Tom Gruber**, **2008 [1]**

Gruber's inspirational article on blending Social and Semantic Web [1] is being realised with the design and implementation of semantic web methods to *"give well-defined meaning"* [35] to data. The focus in this research is on semantic annotation of textual user generated content using ontologies.

2.3.1 Semantic Annotation with Ontologies

Semantic annotation is "*the process of tying semantic models and natural language together*" [34]. In Semantic Web technologies a *semantic model* is expressed by an *ontology.* This thesis follows the conventional definition of ontology given by Gruber: "*an explicit specification of a conceptualization*"[36, 37]. Ontologies are used to describe knowledge about a domain of discourse[37].

An ontology includes a vocabulary of concepts, also called classes, which are related to a domain (e.g. the concepts *car*, *vehicle* and *driver*, are concepts related to the domain *transportation*). In an ontology, classes are organised in a taxonomic hierarchy with two relations: sub-class and super-class. A sub-class is a class more specific than its super class (e.g. *car* is a sub-class of *vehicle*). Each class in an ontology can define its members, called instances of the class (e.g. *BMW* is an instance of the class *car*). In this thesis, classes and instances are treated as entities. The taxonomic hierarchy of entities forms a tree structure. This structure is called an ontology space. An ontology can also define properties (called object properties or slots [37]) between classes that are realised with their member instances (e.g. a *driver* drives a *car*, drive is a property that can illustrate that, for example, *Thomas* drives *BMW*). The following notations are used: Ω for a set of ontologies; ω for a single ontology; $E(\omega)$ for the set of entities of an ontology, and we generalise to $E(\Omega) = \bigcup\{E(\omega) \mid \omega \in \Omega\}$ for a set of ontologies; and, $P(\omega)$ for the set of properties of an ontology, and we generalise to $P(\Omega) = \bigcup\{P(\omega) \mid \omega \in \Omega\}$ for a set of ontologies.

More specifically, semantic annotation is the process of linking ontology entities and properties with text elements (words or phrases). The annotation can be: manual – human annotators assign ontology entities; automatic – computer software automatically identifies links to ontology entities; or, semi-automatic – computer software automatically assigns links to ontology entities, which are then refined by human annotators. Because of the large effort that is required for manual, or even semi-automatic annotation, automatic methods are more suitable for user-generated content.

Automatic semantic annotation can be performed with Ontology-based Information Extraction (OBIE). OBIE involves natural language processing (NLP) of text to extract particular types of information (information extraction) related to a domain. This information is then connected with entities and properties from one or more ontologies which represents knowledge about the domain [38]. In OBIE, the used ontology (or ontologies) consists the Knowledge Organisation System (KOS)[39].

For OBIE systems, the input is text and ontologies, and the output is links from text to ontology entities. The text is firstly processed with NLP techniques to extract linguistic information, e.g. sentences, part of speech, phrases (verb or noun) and dependencies (e.g. adverbial modifiers). For this, a set of regular expressions based rules can be exploited (e.g. in the General Architecture for Text Engineering [GATE] [40]), or an NLP text parser based on grammar rules (e.g. the Stanford parser [41]). The text processing output is then linked to ontology entities with textual label matching (either with particular extracted keywords or patterns –e.g. noun phrases, extracted from the text processing phase).

2.3.2 Applications

The most commonly used ontology for semantic annotation is DBpedia [42], a cross-domain ontological knowledge base extracted from Wikipedia[5]. Similar to DBpedia, the YAGO knowledge base [43] is also derived from Wikipedia. These ontologies are being used in a variety of semantic annotation systems. OpenCalais[6], DBpedia Spotlight[7] and Zemanta[8], are widely used semantic annotation systems (offered as services). In the context of user generated content annotation, the semantic tagging aims at identifying keywords, topics, named entities (e.g. persons and locations) and events.

Keyword extraction for automatic semantic tagging has been applied in [44]. The work considers Twitter messages (also called microblogging posts), and their lining with Wikipedia article titles. Each article title represents a *concept* that can be used to add meaning to the tweet. N-gram word generation is performed on the textual message which are then processed with supervised machine leaning classification to link to Wikipedia concepts. Each concept is first ranked as candidate for matching based on a variety of matching algorithms, which are evaluated in the work.

Topic modelling is performed in [45], using a semantic approach. The work is distinctive in the way that *topic* is extracted. Compared to conventional methods which are based only on word co-occurrences, this modelling approach involves examination of the semantic relations of key words using the corresponding senses in WordNet. The text classification to topics is performed with supervised machine learning based on the semantically described data set. Compared with base-line classification, i.e. without applying semantics, the proposed framework performed significantly better in terms of accuracy of assigning a topic to textual content.

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[5] Wikipedia: http://en.wikipedia.org/wiki/Main_Page

[6] http://www.opencalais.com/

[7] https://github.com/dbpedia-spotlight/dbpedia-spotlight/wiki

[8] http://www.zemanta.com/

Named entity recognition (NER) and extraction is investigated in [46], in the context of research in the ARCOMEM EU Project[9]. The work considers a variety of web resources including web pages and microblogs. The textual content is pre-processed using GATE and with regular expression rules named entities are extracted. These entities are then linked (thus the web content is semantically enriched) with Linked Data resources including DBpedia and Freebase. The extracted named entities are related to events, locations, money, organisations, persons and time. NER with semantic web technologies has been also investigated in [47], where twitter posts are analysed and enriched with Linked Data to identify companies, persons products and movies, using OpenCalais.

Event detection from text using semantic web technologies and machine learning has been studied in [48]. Twitter posts are analysed and semantically linked and enriched with DBpedia using the Zemanta processing framework for keyword extraction. The processed tweet is then matched with an ontology for describing events and sub-events – Linking Open Descriptions of Events (LODE), using on machine learning classification. The semantic tags, represented with DBpedia URIs consists a feature for the classification task.

2.3.3 Discussion

This section has illustrated the application of semantic web technologies for the analysis of user generated content. Although semantically described content provides meaningful interpretation of data, explicit linking of textual elements to ontologies is not always possible. Semantic enrichment is needed for this reason in order to provide *extra information* and *context*, thus to increase the potential of linking with domain ontologies. For example, Abel et al. [49], enrich the Twitter posts with news articles using semantic web technologies, in order to contextualise a user's profile of interests. *It is therefore reasonable to consider that for capturing and analysing viewpoints in user generated content, semantic enrichment of textual content needs to be investigated.*

In the context of social media, enrichment has been applied on named entities (e.g. [46, 49]). In less specific language text, e.g. a person story about a journey, linguistic and semantic resources (such as ontologies, thesauri and corpora) can be utilised to augment the user generated content.

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[9] ARCOMEM EU Project: http://www.arcomem.eu/

In [50], Choudhury, et al. experiment with enrichment of a tag space for YouTube videos. A set of tags is gathered for each video and expanded with *contextual enrichment*: tags are added from the video title, description, related videos and playlists. The expanded set of tags is then linked with DBpedia concepts to provide a semantic layer. Promising results for enhanced search and retrieval for media content, as well as for data organisation, have been shown. *Semantic enrichment solutions can be engineered to expand the knowledge embedded in the user generated content in order to capture and analyse viewpoints.*

Semantic web technologies show their potential for adding meaning to user generated content. To enable users to access this enriched content, *a mechanism to provide structures for navigating around the semantic data is needed*. *User contributions in the content may provide useful indicators on the building blocks of semantic data to enable further analysis. These structures are investigated in User Modelling research community.* The related methods are described next.

2.4 User Modelling with UGC

User modelling is the research field which aims at understanding the user of a system. Semantic Web technologies facilitate the representation and processing of knowledge about a user through shared vocabularies and properties which can describe the user [51].

Two particularly relevant groups of user modelling approaches are discussed below. The first is the ontological user modelling approaches which represent a user model with an ontology. The second is ontology-based user modelling approaches which utilise ontologies as background knowledge about the user model.

2.4.1 Ontological User Models

The most prominent ontological user modelling approach for Web 2.0 is the *Friend-Of-a-Friend*(FOAF) specification [52]. FOAF provides a template for user profiling, consisting six main classes: *Person, Project, Group* and *Organisation* which are classified as *Agents*, and *Document* which aims at wrapping Social Web resources to connect with relevant *Agents.* In addition to defining and describing agents using contact information and demographics related attributes, FOAF connects these agents to construct a social network in the Linked Data cloud. This is achieved using the *knows* property in the ontology specification. Although a lightweight user modelling ontology, FOAF has been widely used and extended in several applications. One of the most desired user characteristic in the Social Web - user's *interest* - is described by the *e-foaf:interest* extension [53].

Heckmann et al. [54, 55] introduce the General User Model Ontology (GUMO) as a unified approach to model users and context. The main element of GUMO is *user's model dimension* representation using a triple <*auxiliary* - the user *property*, *predicate* - the *value* of the property, *range* - the quantifying attribute>. An example triple is <*hasInterest, music, high*>. GUMO defines a range of predicates including *emotional state, general characteristics,* and *personality.* The aim of GUMO is to provide a top-level uniform representation of user characteristics as a standard, or as an extendable template for user modelling.

Recent work by Plumbaum et al.[56] presents the semantic Social Web User Model (SWUM). SWUM aims to tackle user data sharing and aggregation across social web platforms. Again, SWUM is an ontological model that focuses on extending GUMO and FOAF (presented earlier) to explicitly include dimensions and attributes particularly important for the Social Web. Such properties include e.g. *interests*, *goals*, and *knowledge*, which are loosely defined in precedent models. SWUM attempts to resolve the problem of cross-platform modelling by exploiting WordNet, in order to derive similar sense alignment of dimensions and attributes.

2.4.2 Ontology-based User Models

The work by Abel et al. [6], segments of which have also been discussed in [49] and [57], deals with user modelling and personalisation on the Social Web. Apart from *form-based* user profiles (include e.g. demographics), the modelling approach also focuses on *tag-based* user profiles. A tag-based user profile is a set of *tag* (term) and *weight* pairs. The weight quantifies the importance of the specific term for a specific user. In a cross-system user modelling framework, Mypes[10], these profiles are aggregated based on the union set operation and weight adjustment. A key component of Mypes is the semantic enrichment method which meaningfully describes the assigned user tags. Two approaches are followed: the first concerns the use of WordNet categories (e.g. location and person) and the second the use of Linked Data and services (e.g. DBpedia and OpenCalais described in [49]).

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[10] http://mypes.groupme.com

This enables the classification of tags under semantic categories to support faceted search [58].

In research on personalised news or content recommendations in social media [59], a unique feature is the extended semantic annotation pipeline which includes three components: GATE - for term annotation, KEA [60] - for phrase annotation, and OpenCalais - for named entities annotation. The resulted semantically annotated contents are then matched with the user profile which includes explicitly defined interests.

The work presented above concerns the greater research application topic of social annotations (also called social tagging), although significant analysis has been done in Twitter as well. Social tags implicitly represent user's interests and preferences, therefore constitute a decisive element for user profiling[61]. The schema which emerges from user tagging resources in a social context is commonly known as *folksonomy* [62].

Semantic contextualisation of social tags has been presented in [63]. The work aims at resolving the problem of ambiguity and synonymy of tags which appear in a particular folksonomy. A framework (cTag) is developed, which utilises tag clustering to construct the desired context of use. The clustering takes into account the similarity of two tags, based on which a graph is constructed : nodes correspond to tags, while edges denote the similarity between the two connected tag nodes. The clustering then exploits graph-based algorithms (e.g. shortest-path) presented in [64]. User and item profiles include the semantically contextualised tag sets (clusters). Although ontologies are not used to provide an explicit semantic model, folksonomy are utilised as implicit semantic structures where from user modelling can be performed. Similarly, Szomszor et al. [65] utilise Wikipedia as a semantic model in order to derive user models of interests based on folksonomies.

User interests have also been studied in [66]. The authors consider a user model of interests as an overlay of the domain ontology. Starting with indirect user feedback, interests are matched to the corresponding ontology concepts and instances. Based on the taxonomical position of the initial domain – interest ontology items, interests are propagated as ancestors or descendants in the ontology hierarchy. In an empirical evaluation which involves comparison of propagated user interest models with explicit user feedback the proposed algorithm has showed promising results for a hypothetical scenario of recommending products in the gastronomy domain. In follow-up work [67], the identified limitation which concerns the richness of an ontology’s hierarchy was also further examined. The authors experiment with propagating interests based on ontology-properties as well. The evaluation study in the same domain has shown significant improvement in positively associating algorithmic results with explicit user feedback.

2.4.3 User Viewpoints

The work in [11] elaborates on media resources that represent real world events. Giunchiglia*,* et al. point out that when exploiting media resources for a particular event, there remains a semantic gap between different users' conceptualisations for the event, resulting from different real word experiences. When a user annotates a media resource that represents an event he/she has participated in, they will construct personal conceptualisation which will be different from other users, as each of them has experienced the event differently. Following this, a media aggregation methodology is proposed. The notion of user's perspective is informally introduced. However, the focus is on the representation of the event through media aggregation, and the actual individual conceptualisation and reasoning over the user's background has not been exploited.

The notion of individual viewpoints and perspectives appears also in [68] where a new dimension of functionality of recommender systems is proposed: recommend products (e.g. items, news and content) according to user beliefs, additionally to user characteristics. The underlying idea is that different people will develop different beliefs based on individuals' background. The *PerspectiveSpace* is presented which performs opinion mining based on agreement and disagreement of users statements from other user in the social space. As acknowledged by Alonso*, et al.*, semantic analysis of the actual statements (reviews of products) has not been performed in their work, but would potentially result in a better understanding of the users' beliefs.

Although not applied for user generated content, early work by Zuo and Posland [69] identify the need for different user viewpoints. The authors consider a domain (environmental data) represented by heterogeneous data sources, for which different views should be generated in order to better adapt to the information retrieval needs of particular individuals. These *targeted views* aim at presenting relevant content adapted to the user's expertise and preferences/interests. The key difference with current user modelling approaches is that the user model is predefined according to the domain model; instead, our goal is to automatically extract user viewpoints given domain models and user generated content.

More recently, in the research field of information retrieval again, Kang and Lerman [70] also embrace user viewpoints and diversity. Their work aims at identifying expert users based on their social annotations which form folksonomies, in order to further improve user profiling techniques based on folksonomy learning. Although the work builds on existing research for clustering users based on their annotation practices [71], it provides more detailed analysis to characterise users based on their expertise. A set of quantifiable features (e.g. directory depth and breadth, differences between directories) are exploited over the directory-like annotation schema of online resources (Flickr media). Using supervised machine learning classification with these features over the data set, moderate to high performance (F measure of precision and recall) has been achieved through iterations. This work is also affected however by the limitation of the data mining methods presented earlier in this Chapter: large data sets are needed and explanations at a conceptual level cannot be provided. The technique is not grounded to a reference domain model, therefore diversity cannot be uniformly explored.

In an attempt to semantically describe opinion mining results on the Social Web, Westerski et al. [72], build an ontology for opinion mining – Marl. Marl aims to bridge user generated content with scientific analysis (opinion sentiment analysis) in the Linked Data cloud by providing an organisation structure. Marl covers a wide range of opinion mining aspects, only implicitly provided in previous models (e.g. *opinion object* – the target object for analysis [a *car*], *opinion object part*– part of the object [*body* of the car], and *opinion feature* – a feature of the aspect [*shape* of the body of the car]). Although these features are linked to ontology concepts through DBpedia, Marl misses the user aspect as well as the user's viewpoint aspect. In order to explore diversity several opinions could be aggregated for an individual user or a group of users over the domain and contextualised as viewpoints. This semantic contextualisation in the domain ontology (e.g. portion of DBpedia) could offer potential for understanding similarities and differences between user viewpoints, thus to explore diversity.

Preliminary work by Osborne [73, 74] builds on the notion of *Personal-Ontology-Views* (POV) [75-77]. The work suggests adaptation and tailoring of the original domain ontology to individual (personal) views of the world. This aims at supporting information navigation and retrieval tasks. In its definition however, an ontology aims as well at a *shared conceptualisation of a domain*. Although identifying views of the domain for particular users (i.e.

viewpoints) is the research direction of this thesis, two questions are posed for tailoring existing ontologies to particular users: how does a user model – in this case a user's domain view – is related to the original shared conceptualisation (ontology); and, how can two user models be compared to explore diversity. It is worth noting at this stage that preserving the original ontology specification in the viewpoint representation and identifying personal views with reference to original model, would not only allow relative analysis potentially to expand the user's view of the domain, but would also enable understanding of similarities and differences between user views to explore diversity.

2.4.4 Discussion

A semantic representation of user models aims at relating user characteristics relative to a domain [51]. Two user modelling approaches have been discussed, which are based on semantic web technologies facilitated by the use of ontologies. Firstly, the *ontological user modelling* utilises ontologies as templates to instantiate user models. However, identifying viewpoints or exploring diversity is not possible because the user model is disconnected from the domain. In the absence of a reference domain model, users cannot be compared. Secondly, the *ontology-based user modelling* utilises ontologies as reference models to relate user characteristics. However, the user model's relation with the domain is only implicit, which hinders the identification of user viewpoints to explore diversity.

The presented user modelling approaches for capturing viewpoints fail to identify the user's projection within a greater spectrum of knowledge represented by the domain of modelling. Therefore, comparison of viewpoints to explore diversity is not possible based on the viewpoints characteristics.

2.5 Summary

In this Chapter related work on user viewpoints modelling was presented. Three main research fields were examined in detail focusing on representation, capturing and analysis of user viewpoints. Limitations of the state-of-the-art approaches for exploring diversity were identified.

Representation of User Viewpoints: Research in the user modelling community, despite the exploitation of semantic web technologies and domain models to relate user characteristics, has not explicitly identified user viewpoints in the domain of interest. In the text mining research field, the shallow representation of viewpoints hinders the exploration of diversity.

Capturing User Viewpoints: Semantic Web technologies can act as enablers to overcome the reasoning limitation posed by text mining techniques by providing a conceptual layer for representation. However, in order to be able to contextualise user generated content, semantic enrichment is needed when explicit linking to domain models is not possible, especially in domains which are described with less specific language text such as name entities. The semantic output can be used then to capture the viewpoint focus with respect to a domain model.

Analysis and Comparison of User Viewpoints: The addition of a conceptual layer to capture user viewpoints and focus on a domain of interest need intelligent mechanisms for analysis and comparison to explore diversity.

The next Chapter presents the research context and outlines the proposed framework for representing capturing and analysing viewpoints in user generated content **-** ViewS, for **View**point **S**emantics.

Chapter 3
Research Context

3.1 Introduction

The aim of this research is to formulate a mechanism for modelling user viewpoints in user generated content. The previous Chapter clarified the need for considering user viewpoints as part of existing user models in order to explicate the semantic gaps between different user conceptualisations. Key challenges were identified in the user modelling process.

This Chapter firstly proposes ViewS (a framework) which conceptually highlights the main components for modelling viewpoints in UGC (Section 3.2). The research methodology for realising and testing the components of the framework is then discussed (Section 3.3). Finally, the domain of experimentation is presented (Section 3.4).

3.2 An Overview of ViewS Framework

This Section outlines a framework for representing, capturing and analysing user viewpoints, called ViewS (Viewpoint Semantics). The formal viewpoint representation together with terms and notation to be adopted in this thesis are defined firstly.

3.2.1 User Viewpoints Representation

Definition of terms.

Social Space. A social space in ViewS includes not only open social web platforms (e.g. Twitter, Flickr) but can also refer to closed environments (e.g. a company's Wiki system, a Virtual Learning Environment) in which users participate and contribute. For referring to users in a social space, the notation U for a set of users and u for a single user are used.

User Statements. A user statement is a piece of textual content provided by a user. It is an example of user generated content as part of contribution in a social space. For examples, a statement can depict a user's description about an item in an on-line shop, an opinion about a product or an experience when participating in an event. For referring to user statements, the notation S for a set of statements and s for a single statement are used.

Domain and Topic. A domain refers to a *"specified sphere of activity or knowledge"*[11] in the world. When a domain is split into finer spheres, these are referred as topics.

Dimension. A dimension in this work is used to define a characteristic that can be used to describe a domain or topic.

Digital Object. A digital object is a digital resource about a topic for which user statements may be collected in a social space. Examples of digital objects include a forum thread about travelling to Greece, a YouTube video footage about a museum visit, a Flickr picture about a music performance during holidays and more. For referring to digital objects, the notation O for a set of digital objects and o for a single digital object are used.

A Definition for User Viewpoint.

Considering the definitions of terms listed above, a user viewpoint is defined as a tuple:

$$V = \langle U, O, S, \Omega, C, F \rangle, where:$$

- U is a set of users; $if\ |U| > 1,$ then the discussion concerns a *group* viewpoint;
- O is a set of digital objects;
- S is a set of statements made by the user(s), and
- Ω is a set of ontologies that represent one or more dimensions related to a domain or topic, or the domain itself;

$U, O, S\ and\ \Omega$ constitute the input for the viewpoints modelling process. The other two elements ($C\ and\ F$) constitute the output as following:

- C is a set of ontology entities annotated in S, $C \subseteq E(\Omega)$, representing the semantics of <u>user viewpoints</u> linking to Ω. Hereafter these entities will be called annotated ontology entities.
- F is a semantic representation of the <u>user viewpoint focus</u>. The focus is a semantic projection (overlay) of the annotated ontology entities C on the ontology space Ω where: $E(F) \subseteq E(\Omega)\ and\ P(F) \subseteq P(\Omega)$.

Figure 3.1 depicts and entity-relation diagram for the viewpoint representation.

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[11] Oxford Dictionaries Online entry for "*domain*": http://oxforddictionaries.com/definition/english/domain?q=domain

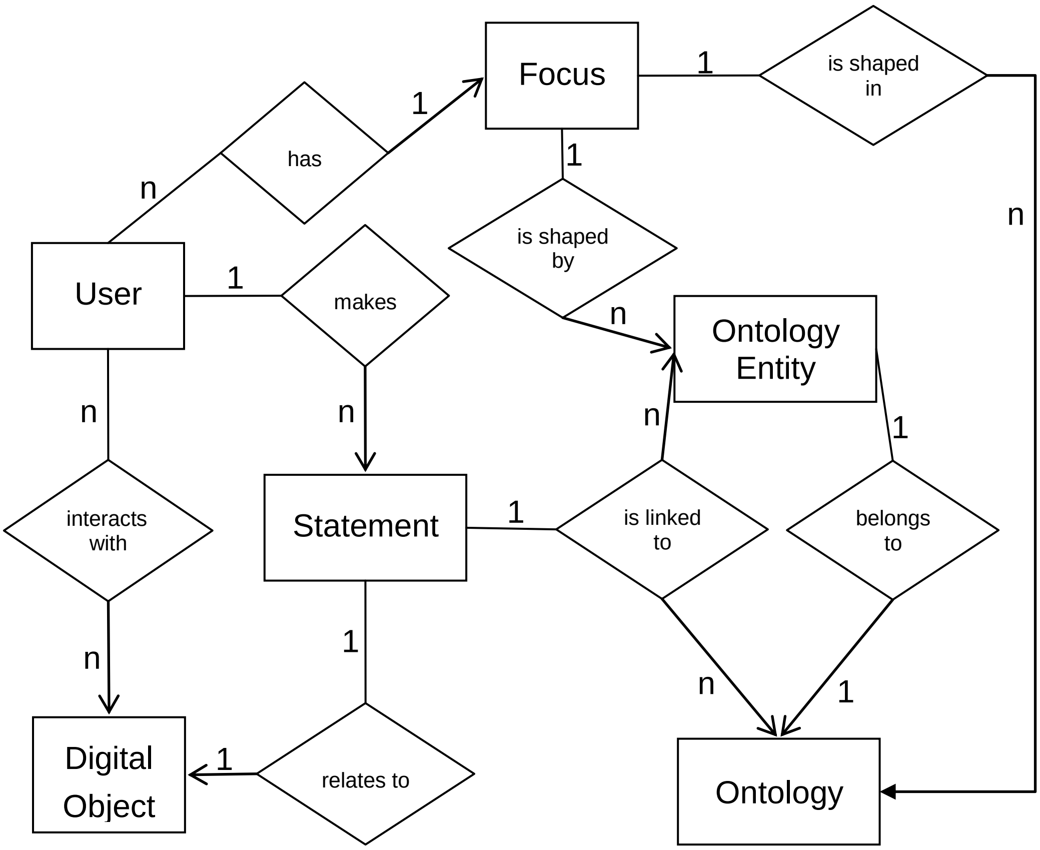

Figure 3.1 An entity-relation diagram describing the relationships between the viewpoint constituent concepts.

The outline of ViewS is presented in Figure 3.2. The collected UGC, which concerns textual user statements on digital objects, is first pre-processed and then semantically augmented (Component A). The semantic output, in turn, is used for capturing the viewpoint focus (Component B). Components A and B capture the user viewpoints which are then used for analysis and comparison. Each phase is detailed in the following Sections.

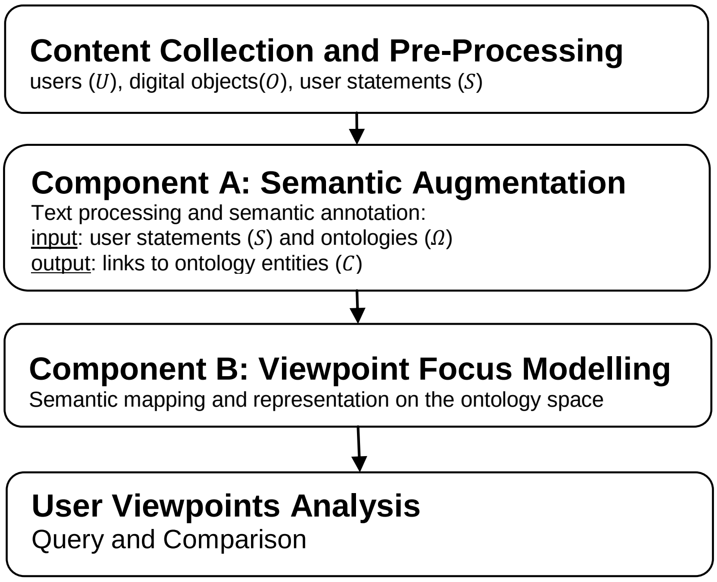

Figure 3.2 Outline of the ViewS framework.

3.2.2 Content Collection and Pre-processing

ViewS assumes that there is a way to collect UGC from social spaces – either in closed social spaces or by calling appropriate APIs to access Open Social Spaces, e.g. YouTube. The UGC concerns textual user statements on digital objects.

Digital objects and user statements have to be filtered in order to remove irrelevant or noisy content. The extracted content of interest is then converted to appropriate XML format (see Appendix A.3.1) in order to be semantically augmented in the next phase (Component A).

3.2.3 Component A for Viewpoint Capturing: Semantic Augmentation

The semantic augmentation component comprises three phases for semantic text analysis and annotation (details will be discussed in Chapter 4):

(a) *text processing* which involves traditional Natural Language Processing (NLP) modules executed on the input text from which the text surface form is extracted,
(b) *enrichment* of the surface form with linguistic and semantic resources to increase the probability for a textual term to be recognised and mapped to ontologies in the following semantic annotation phase; and
(c) *semantic annotation* to link the surface form and the enriched surface form to ontology entities.

The semantic augmentation component aims at capturing the semantics of user viewpoints by mapping and extending knowledge about the user statements in ontological spaces. The technical novelty of this component is in the integration of relevant tools to achieve this goal.

3.2.4 Component B for Viewpoint Capturing: Viewpoint Focus Modelling

The viewpoint focus modelling component aims at completing the capturing of user viewpoints for the representation by providing an intelligent mechanism to map and structurally represent the focus of a user or a group of users on the ontology space. The technical novelty of the viewpoint focus modelling is to engineer a computational method that can model the concept of *focus* as perceived by humans into a computer processable form (details will be discussed in Chapter 6).

3.2.5 User Viewpoints Analysis

The analysis of user viewpoints is directly dependent on the representation and includes querying and comparing user viewpoint models. The novelty of the analysis is to characterise and query viewpoints based on the focus coverage and complexity, as well as to qualitatively compare focus models to explicate similarities and differences.

The query and comparison are enabled with an implemented tool - ViewS Microscope (presented in Chapter 6), which has been used to illustrate the analysis made possible by the framework in the domain of experimentation (Chapter 7).

3.3 Methodology

An incremental approach was used in the formulation, design, and evaluation of the ViewS framework. The methodology followed is described below:

I. Selection of a domain for experimentation: In order to have suitable datasets for experimentation, a domain has to be selected. This provides a testbed to investigate the research hypotheses and illustrates the potential research contributions. The domain needs to fulfil the following three aspects:

(i) importance: need for further investigation in a computer science perspective, offering potential for resolving research problems and current trends;

(ii) relevance: comprise a context within which user opinions and experiences can be diverse;

(iii) feasibility and significance of research approach: provide sufficient research foundations to justify theoretical assumptions and technical solutions and provide evidence for improvement in knowledge, to which the proposed approach (modelling viewpoints in UGC) can contribute and extend.

II. Development - semantic augmentation: Engineering and fine tuning of an integration of existing solutions for text processing and semantic annotation to capture viewpoint semantics.

III. Evaluation of the semantic augmentation: evaluate the performance of semantic augmentation including: (i) accuracy-precision of semantic annotation in terms of correctly identifying key terms and phrases and linking them to ontology entities to describe user statements, (ii) critical assessment of the approach to identify strengths and limitations, (iii) proposed extensions of the research work in the future. The evaluation step comprises of a data set selection phase: experimental data set to test the computational methods for semantic augmentation, implementation of the study and fine tuning of the semantic Augmentation.

IV. Experimentation with a real-world application: investigate the potential benefit of the approach to capture viewpoints with semantic web technologies using a real-world application, and elicit requirements for viewpoint focus modelling and viewpoints analysis. This step comprises of a data selection phase (from real world application context), implementation of the study and the analysis of the results.

V. Development – viewpoint focus modelling and viewpoints analysis methods: based on the elicited requirements.

VI. Evaluation of viewpoint focus modelling and viewpoints analysis including: (i) comparative analysis of the elicited requirements and their fulfilment with the provided computational solution, (ii) critical assessment of the proposed method, and (iii) proposed extensions for future research work. If necessary, fine tuning of the viewpoints focus modelling and analysis computational methods will be done.

VII. Exploration of user viewpoints in a larger context: execution of the ViewS framework computational methods for user viewpoints modelling in the Social Web context. This step comprises of data set selection, implementation of study and evaluation which includes: (i) feasibility of

ViewS application in the Social Web context, (ii) implications for utilising Social Web content to model user viewpoints, and (iii) future research directions to address possible limitations.

The methodology presented above requires a series of data sets of UGC to be created or collected. This research considered three types of datasets:

(i) Experimental data set: collection of UGC in a controlled, custom-made social space to evaluate the semantic augmentation component of the ViewS framework;
(ii) Real–world application data set: collection of UGC from a social space within a real-world application to investigate the potential benefit of semantics as well as to elicit requirements for viewpoint focus modelling and viewpoints analysis;
(iii) Social Web data set: collection of UGC from Social Web media platforms to explore the application of ViewS.

Each data set as well as the rationale of creating/selecting it are presented in the appropriate Chapters. The next Section depicts the selected domain for experimentation and provides the rationale of its selection according to the criteria as set out in the first step of the methodology.

3.4 Domain for Experimentation

In this work Interpersonal Communication (IC) has been considered as the domain for experimentation. IC defines a communicative interaction between people, verbally or non-verbally. Non-verbal communication is instantiated through body language cues, often called non-verbal behavioural cues, and emotions are expressed in the context of social interaction between two or more individuals. These cues are transformed through the process of communication into social signals for other participants in this communication. This dimension of IC, social signals, is the focus of this thesis.

3.4.1 Motivation

Importance of the Domain. IC is regarded as a key soft skill required in the knowledge society of the 21st century [78], and is fundamental to everyday professional and social life. In IC, emotions and non-verbal cues (i.e. social signals) play a key role. Research has shown that non-verbal communication carries most of the social meaning (about two thirds comparing with verbal communication [79], while other studies show that non-verbal cues cover 90% of the communication [80]). Body language expresses emotions, regulates the flow of interaction and provides valuable feedback to every individual participating in IC activities.

One possible target application area is user-adaptive learning environments. Providing various perspectives on the same topic is highly beneficial for learning, and is seen as one of the challenges to the next generation of technology-enhanced learning systems [81]. More specifically one can consider informal learning environments for adults, which are growing in popularity in workplace contexts. In order to be effective, such environments should provide a range of real life examples and a variety of viewpoints [82]. We further examine this assumption and hypothesis in Chapter 5 where the potential benefit is explored in a learning context.

Relevance. Awareness and recognition of social signals is crucial in social interactions [83], and is linked to the development of emotional intelligence [84]. Different interpretations could be possible depending on the background and experience of the “observers” and “participants” in IC activities. Hence, personalised support can be offered exploiting the diversity of viewpoints, and thus showing a variation of social signal interpretations based on authentic examples from user-generated content.

In an IC learning context, interpreting those social signals can be complicated and highly subjective. For example, in a job interview, a gesture like “waving the hands in the air” might be interpreted by one person as exaggeration and by another person as enthusiasm and willing; or a “frowning facial expression” could be a sign of boredom or intensive contemplation. These diverse interpretations, if semantically captured and processed, can provide a rich resource for personalised learning experiences to improve awareness and promote reflection.

Feasibility and significance. This will be established in greater detail in the section below.

3.4.2 Related Work on Mining Social Signals in UGC

Social signals concern two human aspects: emotion and body language. Following we discuss related work on each aspect with respect to identifying it in UGC.

The emotional aspect is closely related to sentiment, for which related work on text mining approaches for analysis were discussed in Chapter 2. Here we list additional research work which consider more expressive representations of emotions.

In [85], a framework has been developed which aims to understand when a piece of text contains inflammatory content or not, in order to prevent "*trolling*" in social web spaces and to block insulting messages. This produces the AffectNet - vocabulary combining common sense knowledge from ConceptNet[12] and emotional attributes from WordNet represented by the emotion taxonomy WordNet- Affect [86]. Each concept in the vocabulary is either a common-sense concept or has an affective attribute. AffectNet is then partitioned into four main categories: pleasantness, attention, sensitivity and aptitude, which are further analysed into six basic emotions (with negative to positive valence) each. This modelling is called the Hour Glass of emotion. Concepts which identified in the text and can be matched with ConceptNet are mapped to affective valence in the Hour Glass model of emotions and are given a polarity score to identify "trollness".

Some research work have been done for annotating textual content with the six basic emotions defined by Ekman [27] - anger, disgust, fear, happiness, sadness and surprise. [87-90] constitute a representative sample in this research direction. The methodology being followed includes natural language processing on textual content and classification of text into one of the six basic emotions. Linguistic resources are being used to match term references with affective labels and valence, as well as to construct dictionaries and lexicons for training probabilistic classifiers. Features for classification often include, apart from words, punctuation, emoticons and syntactical rules associations with affective states.

Although richer representations of emotions are being exploited in the aforementioned research outlooks of emotion mining from text, such classification has not been applied to date for user viewpoints modelling. The particulars of affective classes, i.e. the key-words and concepts, which are used to describe the emotion label, have not been used to date to describe user models. Moreover, external resources for enrichment which are used in the classification process have not been considered as domain models to which an opinion or expression in text can instantiate a reflection of the user-contributor.

The feasibility of the approach for annotating emotion is related to the availability of resources which can describe emotion. In Chapter 4 we list state-of-the-art semantic models to represent emotion. For this work we

12 http://csc.media.mit.edu/conceptnet

have exploited WordNet-Affect, a taxonomy of emotion, which was also exploited in previous works, however not for user viewpoint modelling.

Regarding detection and recognition of social signals, a review of methods for capturing and analyzing non-verbal behavioural cues was provided in [91]. These methods involve audio and visual data processing which utilises statistical and probabilistic methods. Little has been done in utilising text UGC to extract body language related concepts. Similarly to [92], we focus on awareness and recognition of social signals for user modelling, but we consider textual content. The significance of the research in this work is based on the semantic augmentation component which is configured for body language in the context of interpersonal communication experimental domain, and the enrichment method that is offered.

Mining body language related terms is made feasible in this work with the design of an ontology for human-activity modelling [93], including body language, in the context of the ImREAL EU project. More details are discussed in Chapter 4.

3.5 Summary

In this Chapter we presented the research context. Firstly, the ViewS framework was outlined with respect to the research questions that this work aims to tackle: viewpoints capturing, representation and analysis. The research methodology used to develop and validate ViewS was then presented. Finally, the domain of experimentation, IC with focus on Social Signals, was discussed.

The following Chapters detail the accomplishment of the methodology steps with respect to the ViewS framework components.

Chapter 4
Semantic Augmentation of User Generated Content

4.1 Introduction

This chapter proposes a semantic augmentation pipeline to tackle the first research question: *How can we capture the semantics of user viewpoints?* Following the definition of user viewpoints (see Section 3.2) the goal of semantic augmentation is:

to extract a set of ontology entities $C \subseteq E(\Omega)$ *that can be used to describe a given set of user statements* S *with a set of ontologies* Ω*.*

In view of the existing technologies for text analysis and knowledge capturing, a decision was made to reuse these tools as much as possible. Consequently, Stanford parser, WordNet, DISCO and the Suggested Upper Merged Ontology (SUMO) were deployed and integrated for user viewpoints capturing. The technical novelty of this integration is to exploit different resources for semantic enrichment (WordNet and DISCO) based on sense detection and semantic mapping (with SUMO) with relevant to the selected domain concepts.

Semantic augmentation is the first component for capturing viewpoints in ViewS. Section 4.2 details the semantic augmentation pipeline in ViewS, while Section 4.3 illustrates an instantiation of the pipeline for the domain of social signals in interpersonal communication. The ViewS semantic augmentation component has been evaluated in an experimental study which is presented in Section 4.4. The Chapter is summarised in Section 4.5.

4.2 The ViewS Semantic Augmentation Pipeline

The semantic augmentation in ViewS is engineered as an integration of existing text processing methods and knowledge sources. Figure 4.1 presents the semantic augmentation pipeline which comprises three phases: (i) text processing to extract a surface form, (ii) enrichment of the surface form with linguistic and semantic resources, and (iii) semantic annotation for linking with ontology entities.

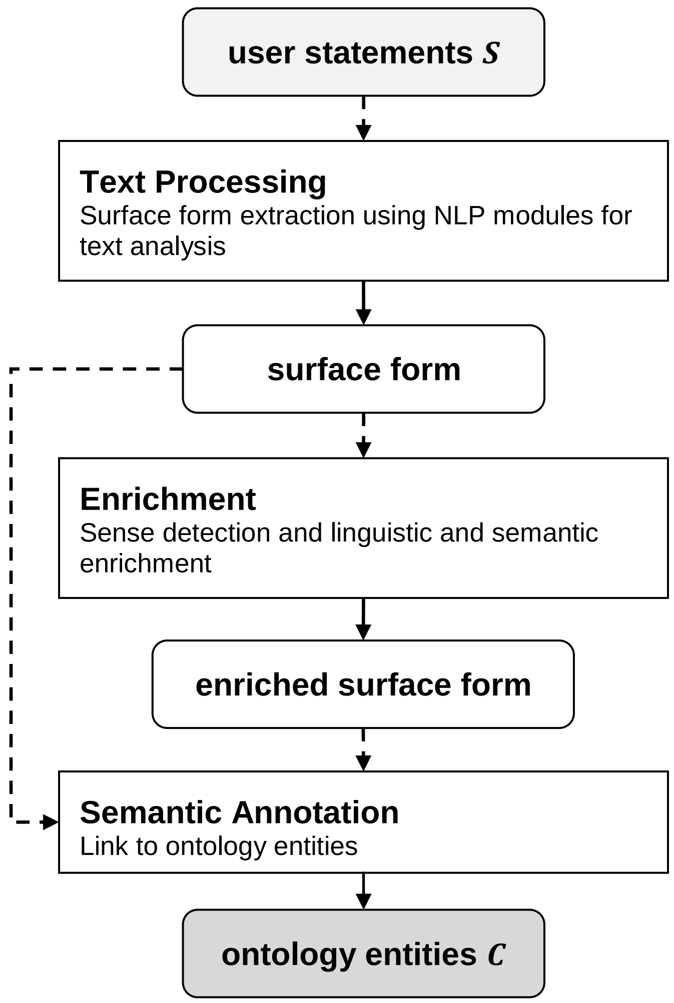

Figure 4.1 The ViewS semantic augmentation pipeline.

4.2.1 Text Processing

The goal of the text processing phase is to extract a surface form from given textual user statements. A surface form is the first form that a user statement takes in order to be further processed. It mainly concerns the understanding of the structure of the textual content including the organisation of the words into sentences and phrases as well as grammatical tagging, e.g. Part of Speech (POS) tagging.

In ViewS the Stanford Parser using a factored model [41] has been selected to tokenize the text, detect and split sentences, and tag the text tokens with Part of Speech (POS). The Stanford parser has also been used to extract typed dependencies from the text [94]. Alternatives such as the English Probabilistic Context-free Grammar Parser from Stanford [95] and the Link Grammar Parser for English [96] which is based on grammar-style formalism of English were considered. The Standford Parser was chosen because – (i) as the API states[13], it is faster and can produce better results when looking for typed dependencies; (ii) offers high precision for grammatical and syntactical labelling [97]; and (iii) as it is a statistical parser, it may be more appropriate for noisy input texts [97] which are expected in user generated content [98].

The POS for further processing include: nouns, verbs, adverbs and adjectives. Examples of typed dependencies considered include: negation, adjective complements and modifiers, noun compounds, phrasal verbs and conjunctions (full list can be found in Appendix A.1.1). From these dependencies which were selected based on combination of the selected POS tags, multi-word terms are constructed in the sense that they comprise more than one terms.

During the surface form extraction phase (for stemming), each token, together with the corresponding POS tag, are used to query WordNet in order to derive possible keyword matches. The POS tags as well as a list of commonly used stop-words comprised a filter for the text tokens to be used further. The selected text tokens are then stemmed and matched to keywords (w.r.t. the specific POS tag) defined in the WordNet lexical data base [99] version 3.0 using the MIT Java WordNet Interface (JWI) [100]. Other APIs that could be used include the Java WordNet Library[14] and Java API for WordNet Search[15] and Rita.WordNet[16]. JWI was selected based on its WordNet lookup functionality and memory management. The transition between WordNet versions is seamless and no additional plug-in is needed. The surface form (SF) of the text includes three kinds of lexical elements: exact tokens (ET) that precisely match the text terms, the stemmed terms (ST) and the derived - from the typed dependencies - multi-word terms (MWT) (see Figure 4.2).

[13] http://nlp.stanford.edu/software/parser-faq.shtml#y

[14] http://sourceforge.net/projects/jwordnet/

[15] http://lyle.smu.edu/~tspell/jaws/

[16] http://www.rednoise.org/rita/wordnet/documentation/

surface form **(SF)**

- exact text tokens **(ET)**
- stemmed tokens **(ST)**
- typed dependencies → multi-word terms **(MWT)**

Figure 4.2 Elements of the text surface form (SF).

4.2.2 Enrichment

The purpose of surface form enrichment is to extend the surface form with additional linguistically and semantically related terms. The output increases the probability of mapping a text term with the ontology entities.

The enrichment process also uses the WordNet lexical data base. For a given term and POS tag, WordNet defines a structure of senses called *lemma*. Each *lemma* comprises a set of senses for this term and is organised into a set of synonym sets (known as *synsets)*.

Sense Detection and Mapping.

WordNet semantically classifies each *synset* into lexical categories, e.g. *noun.animal* and *verb.motion* are categories that depict nouns related to animals and verbs related to motion respectively. A set of lexical categories is selected according to their relevance to the domain for which we want to model viewpoints. For example, for the domain of IC and social signals, verb.emotion is relevant but not noun.animal.

For more fine grain semantic classification to direct the linguistic and semantic enrichment at a word level, an Upper Ontology is utilised to further filter irrelevant linguistic data. The Suggested Upper Merged Ontology (SUMO) [101] is selected. SUMO offers two main advantages: (a) it covers a wide range of aspects, e.g. communication, people, physical elements etc., which is important for the generality of the approach and, (b) it provides direct mappings of ontology entities (including concepts, individuals and predicates) to WordNet *synsets* [102]. Other Upper ontologies that could be used include DOLCE [103] which also provides alignment with WordNet. However, the alignment is based on an early version and considers only the top-level of WordNet.

Mapping operators between a SUMO entity and a WordNet *synset* include: equivalence, subsuming and instance mapping. It is then possible to examine word senses (in *synsets*) from the text and link them to the appropriate domain-specific SUMO entities (similar method has been followed in [104, 105]). For example, in the music domain, the WordNet term "song" has an equivalent mapping with the SUMO concept "MakingVocalMusic" in the sense of "the act of singing". Hence "MakingVocalMusic" can be used to enrich the surface form “song” from the specific *synset*.

For a given token (ET/ST) or a multi-word term (MWT) in the surface form (SF), its senses-*synsets* SS are filtered to pick only the relevant senses to form SS_1 : $SS_1 \subseteq SS$. based on the pre-selected set of semantic lexical categories. These senses (in SS_1) are further filtered to pick only senses to form SS_2 covered by the relevant SUMO mappings: $SS_2 \subseteq SS_1 \subseteq SS$. SS_2 is used for the surface form enrichment.

Enrichment Types.

With the resulting senses synsets, $SS_{2,}$ four types of enrichment (Figure 4.3) are conducted by one of these two methods: (i) using semantically enhanced linguistics to retrieve lexical derivations, synonyms and antonyms, and (ii) using corpus statistical measurements to retrieve similar words.

$$\begin{array}{c}\text{enriched}\\ \text{surface form}\\ \textbf{(ESF)}\end{array} \begin{cases} \text{lexical derivations } \textbf{(DRV)} \\ \text{synonyms } \textbf{(SNM)} \\ \text{antonyms } \textbf{(ANT)} \\ \text{similar words from DISCO } \textbf{(DSC)} \end{cases}$$

Figure 4.3 Elements of the enriched text surface form (ESF).

(i) For lexical derivations, synonyms and antonyms. Words in SS_2 are used to query WordNet for lexical derivations, synonyms and antonyms. For each result set, the whole *synset* was exploited (i.e. the lexical derivatives of a word are organised again as a *synset*) and checked for relevancy using the aforementioned sense-detection and mapping. Antonyms are qualified with a negation attribute. From SF, MWT elements are also used to query WordNet and match keywords, and eventually enrich as discussed.

(ii) For similar words. For enriching the surface form with similar words, DISCO [106], which retrieves similar words from English language corpora using techniques based on statistical distributions, was exploited. This enables contextually (co-occurring in text) related terms to be retrieved, increasing the probability of such terms to be found in the ontologies for semantic annotation. DISCO has been used with the Wikipedia corpus, as it provides multi-disciplinary collective knowledge (compared with PubMed which is medicine oriented or the British National Corpus which is significantly smaller than Wikipedia provided with the tool[17]).

Figure 4.4 presents the pseudocode for the 'similar-word enrichment' algorithm used with DISCO for a given keyword in SS_2. The input to the includes: a keyword (*in*), relevant senses from WordNet for this keyword (*in.senses*) and the number of senses (*in.senses.count*). With this input the DISCO API is queried and returns a set of similar words (*out*) together with their similarity score (*Sim (out_word)*). At this stage, a threshold for similarity value is applied. For each of the similar words (*out_word*) which pass the declared threshold, WordNet is queried to retrieve its senses (*out_word.senses*) for every possible POS tag. Each of these senses (*out_word.sense*) is matched with the input senses (*in.senses*) using the weighted score of the following parameters: (a) lexical category of the sense from WordNet, (b) the SUMO mapping entity, and (c) the SUMO mapping operator (one of equivalence, subsuming or instance).

The threshold values SIM_THRESHOLD and SENSE_SCORE_THRESHOLD as well as the constant scoring values MAX_SENSE_SCORE, LEX_SCORE, SUMO_SCORE and SUMO_OP_SCORE can be set manually by the experimenter for comparisons. The process includes querying DISCO with words related to the selected domain and dimensions, retrieving the results, checking the results with respect to their possible senses according to the sense detection and sense mapping filters discussed earlier. When the resulting words match the selected domain, the experimenter retrieves the similarity scores and tunes the threshold accordingly[18].

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[17] http://www.linguatools.de/disco/disco-download_en.html

[18] Following the described process, for social signals (see Section 4.4) the threshold is set to 0.7

```
in                    //the word used to query DISCO in its base form
in.senses             //the senses of the word used to query DISCO
in.senses.count       //the number of senses
out                   //the set of resulted words
Sim (out_word)        //the similarity score for an output word
set SIM_THRESHOLD
FOR each out_word in out
  IF Sim (out_word)≤ SIM_THRESHOLD
  THEN EXCLUDE out_word;
  ELSE
    out_word.senses = Extract possible senses from WordNet;
    //including all the possible syntactic roles, i.e. noun, verb, adverb
    FOR each out_word.sense in out_word.senses
      //check if the word sense is in context
      maximum_score = MAX_SENSE_SCORE* in.senses.count;
      current_score = 0;
        FOR each in.sense in in.senses
          IF out_word.sense.lexical_category = in.sense.lexical_category
          THEN Current_score += LEX_SCORE;
          IF out_word.sense.SUMO_concept = in .sense.SUMO_concept
          THEN Current_score += SUMO_SCORE;
          IF out_word.sense.SUMO_operator = in.sense.SUMO_ operator
          THEN Current_score += SUMO_OP_SCORE;
        IF current_score/maximum_score ≥ SENSE_SCORE_THRESHOLD
        THEN INCLUDE out_word.sense
```

Figure 4.4 The 'similar-word enrichment' algorithm used with DISCO.

4.2.3 Semantic Annotation

The surface form (SF) is checked for matches with ontology entities. Top priority is given to exact tokens (ET) and then to stemmed tokens (ST). The multi-word terms (MWT) are always checked for matches with the ontologies as they consist a special type of surface form. If a match is found in SF, the enriched surface form (ESF) is not examined for matches. All enrichment types are checked if ESF is needed.

To perform the semantic annotation, ontology pre-processing routines are needed, e.g. stemming of concepts and removal of punctuation. Semantic technologies (such as reasoners) are also required to load ontologies, parse them and lookup ontology entities to match and map to the text processing output (i.e. surface form and enriched surface form). For MWT tokens annotation, the ontologies are queried at the pre-processing stage of the semantic annotation to check for concepts and entities that are formed by more than one term[19]. These concepts are named multi-word concepts (MWC) for simplicity. For a MWT token with MWT={t_1,t_2}v containing two words, and equally for a MWC with MWC = {$c_1,c_2,\ldots,c_n$}. containing a set of words, a set of possible grammatical stems is constructed for each of their words using WordNet lookup: MWT={{$t_{1.1}$,$t_{1.2}$,..$t_{1.m}$}, {$t_{2.1}$, $t_{2.2}$,…, $t_{2.q}$}} and MWC ={{$c_{1.1}$,$c_{1.2}$,..$c_{1.p}$}, {$c_{2.1}$, $c_{2.2}$,…, $c_{2.r}$},…, {$c_{n.1}$, $c_{n.2}$,…, $c_{n.k}$}}. The subsets of word stems are merged then to form a vector of words both for MWT and MWC. For these two vectors the cosine similarity of the two vectors of words is calculated and an experimental threshold of 0.65 is applied for matching the two vectors. This threshold is set as the two vectors have small cardinality of terms and words respectively, thus the probability of matching is becoming lower [107]. Experimentation with example ontologies and input MWT is also important to fine tune the similarity value.

4.2.4 Software Implementation

The ViewS Semantic Augmentation component has been implemented in Java as a class library providing API functionality for text processing and semantic annotation[20]. Appendix A.3 provides the XML Schema Definitions of the input and output data for the Semantic Augmentation in ViewS.

The semantic augmentation component can be characterised as semi-automatic as it involves two manual steps: (i) prior to the text-processing step, selection of relevant lexical categories from WordNet for sense detection and SUMO entities for sense mapping, and (ii) prior to the semantic annotation step, selection of ontologies describing the desired domain dimension(s).

[19] The label formats include camelcase (e.g. "MusicDomain") writing style as well as underscore (_) and hyphen (-) separated words

[20] The ViewS API can be accessed at: http://imash.leeds.ac.uk/services/ViewS/

4.3 Instantiation of ViewS Semantic Augmentation for IC and Social Signals

The domain for this research concerns interpersonal communication with particular focus on the social signals dimensions including emotion and body language (see also Section 3.4). In this Section, specific issues for the instantiation of Semantic Augmentation for this selected domain are described.

The ViewS semantic augmentation component requires two manual configuration steps which are described in the following subsections.

4.3.1 Sense Detection and Mapping Resource Configuration

The first manual step was conducted in collaboration with a domain expert[21] to select relevant semantic lexical categories form WordNet and concepts from SUMO. **WordNet Lexical Categories**. For IC activities (such as job interview and socializing with friends) and social signals, 31 lexical categories have been selected as relevant from the total of 44 in WordNet. Table 4.1 provides some examples (see Appendix A.2.1 for a full list).

Table 4.1 Examples of selected WordNet lexical categories, suitable for IC and social signals. (for a full list see Appendix A.2.1).

WordNet lexical category and meaning
[noun.body]: body parts
[noun.cognition]: cognitive processes and contents
[noun.communication]: communicative processes and contents
[verb.perception]: seeing, hearing, feeling
[verb.cognition]: thinking, judging, analyzing, doubting
[verb.emotion]: feeling

SUMO Entities. 346 entities from SUMO were selected as relevant by the domain expert. The expert was given the list of all SUMO entities and definitions, and was asked to indicate those which could be related to IC activity aspects. Table 4.2 shows a sample of selected SUMO concepts (for a full list see Appendix A.2.2).

21 The domain expert is a social scientist working on modelling interpersonal communication activities within the ImREAL EU project: http://www.imreal-project.eu.

Table 4.2 Example concepts from SUMO selected as relevant to IC and social signals (for a full list see Appendix A.2.2) .

SUMO concepts and meaning
[SubjectiveAssessmentAttribute]: a kind of normative attribute for a subject
[SocialInteraction]: interactions between cognitive agents such as humans
[BodyMotion]: any motion where the agent is an organism and the patient is a body part
[EmotionalState]: the class of attributes that denote emotional states of organisms
[StateOfMind]: transient features of a creature's behavioural/ psychological make-up
[BodyPart]: …small components of complex organs
[PsychologicalAttribute]: attributes that characterize the mental or behavioural life of an organism
[TraitAttribute]: attributes that indicate the behaviour/ personality traits of an organism
[Perception]: sensing some aspect of the material world

4.3.2 Selection of Ontologies for Social Signals

This is the second manual step. Two ontologies (in OWL or RDF format) were chosen to represent the social signals dimensions - emotion and body language.

To represent emotion, WordNet-Affect [86] was selected, which comprises a rich taxonomy of emotions including 304 concepts. The original XML format of WordNet-Affect was transformed to RDF/XML[22](see Figure 4.5, left) to enable semantic processing. Another candidate ontology could be the Emotion-Ontology [108]; however, a final release was only made recently. The OntoEmotion ontology described in [109] was also considered; however, although it was at a stable stage, it did not include the rich vocabulary of WordNet-Affect. Other vocabularies that could be used for augmentation of emotion include ConceptNet[23] and DBpedia[24], however they do not provide a fine grained taxonomy as WordNet-Affect does.

Note that the consistency between WordNet and WordNet-Affect in terms of conceptualisation, as the latter emanates from the former, is also an important factor for selection.

To represent body language, the Activity Modelling Ontology (AMOn) [93]

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22 A full version of the WNAffect taxonomy is available at: http://imash.leeds.ac.uk/ontologies/WNAffect/WNAffect.owl

23 ConceptNet, available at: http://conceptnet5.media.mit.edu/

24 DBpedia, available at: http://wiki.dbpedia.org/OnlineAccess

was used. AMOn contains a body language ontology[25] which was built as part of the ImREAL EU Project. It combines the literature presented in [91], a taxonomy of body language cues available on the web[26], and a portion of SUMO to link body postures, parts and body language signal meanings (see Figure 4.5, right). We exploited SUMO to provide an integrated solution with the provided WordNet mappings. The ontology comprises 130 concepts and 396 instances. Concepts are related to each other with 9 object properties (see Table 4.3). To the best of our knowledge, this is the first attempt to implement an ontology for body language. Further extension may consider reusing vocabularies from DBpedia:gesture[27] or DBpedia:list_of_gestures[28].

Table 4.3 Body language ontology object properties.

Object Property	Domain	Range
hasPossibleMeaning	Body Language Signal	Body Language Signal Meaning
involvesArtifact	Body Language Signal	Artifact
involvesBodyPart	Body Language Signal	Body Part
involvesMotion	Body Language Signal	Body Motion
involvesNonPhysicalObject	Body Language Signal	Non-physical Object
involvesPosition	Body Language Signal	Body Position
involvesSense	Body Language Signal	Body Sense Function
isStructuredBy	Body	Body Part
consistsOf	Body	Body Substance

25 A full version of the Body Language ontology is available at: http://imash.leeds.ac.uk/ontologies/BodyLanguage/BodyLanguage.owl

26 http://www.businessballs.com/body-language.htm

27 http://dbpedia.org/page/Gesture

28 http://dbpedia.org/page/List_of_gestures

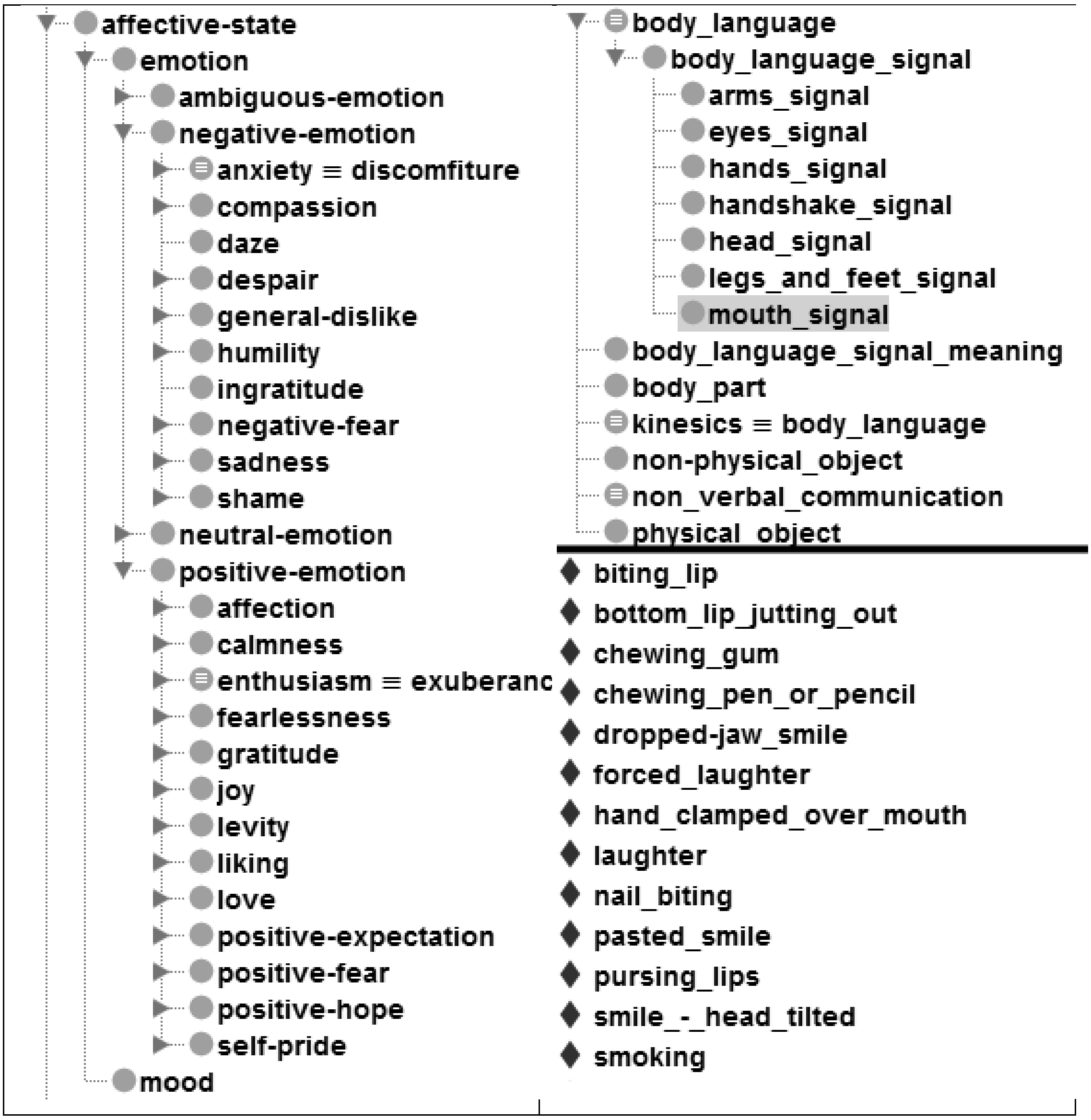

Figure 4.5 Snapshots of the ontologies used for representing social signals for the semantic annotation stage with ViewS: WordNet-Affect taxonomy of emotion (left) and Body Language ontology (right).

4.3.3 Example Semantic Augmentation

To illustrate the semantic augmentation process in ViewS, the following example piece of text T is used:

***T*:** " *The applicant is not anxious. She appears very confident, although she is not greeting the interviewer and then sits and crosses her legs. She does not respect the interviewer. The interviewer might feel discomfort with the applicant's manners.*"

Text processing and semantic enrichment phases

Table 4.4 shows the partial output of text processing and semantic enrichment phases for the first three terms in T (i.e. applicant, anxious and appear). For each term the linguistic sense (derived from the parser and query of WordNet according to the filtering criteria), the lexical category and the SUMO mapping are presented. As an example: for ‘*applicant’* - a lexical derivation (DRV) is ‘*apply*’ and a synonym (SNM) is ‘*applier*’; for ‘*anxious’* - DRV is ‘*uneasiness*’ and a DISCO similar word (DSC) is ‘*eager’*;, and for ‘*appear(s)’*: a DRV is ‘*facial_expression*’ and DSC is ‘*seem*’. For each enriched form (e.g. apply), the corresponding linguistic and semantic metadata (i.e. sense, category and SUMO) are shown.

Semantic annotation

Table 4.5 presents part of the output of this phase for the example comment *T*. For each semantic annotation record the text token(s), annotation type (one of SF or ESF elements), the ontology entity name, the ontology and SUMO concept are presented. The prefix '¬' at the front of an ontology entity name indicates negation.

Table 4.4 Sample output of the text processing stage including surface form (SF) and enriched surface forms (ESF).

SF	**Example ESF**
keyword: *applicant* **sense**: a person who requests or seeks something such as assistance or employment or admission **category**: noun.person **SUMO**: SocialRole(subsuming)	**DRV**: *apply* **sense**: ask (for something);"She applied for college"; "apply for a job" **category**: verb.communication **SUMO**: Requesting(subsuming) **SNM**: *applier* **sense**: a person who requests.. **category**: noun person **SUMO**: SocialRole(subsuming)
keyword: *anxious* **sense**: causing or fraught with or showing anxiety; **category**: adj.all **SUMO**: EmotionalState(subsuming)	**DRV**: *uneasiness* **sense**: inability to rest or relax or be still; **category**: noun.attribute **SUMO**: PsychologicalAttribute(subsuming) **DSC**: *eager* **sense**: having or showing keen interest or intense desire or impatient expectancy; **category**: adj.all **SUMO**: desires(equivalence)
keyword: *appear* **sense**: give a certain impression or have a certain outward aspect **category**: verb.perception **SUMO**: SubjectiveAssessmentAttribute(subsuming)	**DRV**: *facial_expression* **sense**: the feelings expressed on a person's face **category**: noun.attribute **SUMO**: FacialExpression(equivalence) **DSC**: *seem* **sense**: appear to one's own mind or opinion; **category**: verb.perception **SUMO**: believes(subsuming)

Table 4.5 An extract of the annotation set for comment T.

Text Token	Type	Ontology Entity	SUMO Entity Mapping	Ontology
not anxious	DRV	¬ anxiousness	EmotionalState+	WNAffect
not anxious	DRV	¬ anxiousness	EmotionalState+	BodyLanguage
not anxious	DRV	¬ nervousness	EmotionalState+	BodyLanguage
not anxious	DRV	¬ jitteriness	EmotionalState+	WNAffect
appears	DRV	facial_expression	FacialExpression=	BodyLanguage
confident	DRV	confidence	EmotionalState+	WNAffect
appears	DRV	face	FacialExpression=	BodyLanguage
confident	DRV	confidence	EmotionalState+	BodyLanguage
confident	DRV	authority	PsychologicalAttribute+	BodyLanguage
sits	DRV	sitting	BodyMotion+	BodyLanguage
not greeting	ET	¬ greeting	Greeting+ , Greeting+ ,	BodyLanguage
legs	ET	legs	SubjectiveAssessmentAttribute+ ,	BodyLanguage
not respect	DRV	¬ regard	IntentionalRelation+	WNAffect
not respect	DRV	¬ admiration	EmotionalState+	WNAffect
feel	DRV	belief	believes+	BodyLanguage
discomfort	DSC	nausea	EmotionalState+ ,	WNAffect
discomfort	DSC	distress	EmotionalState+ ,	WNAffect
discomfort	DSC	frustration	EmotionalState+ ,	WNAffect
discomfort	ANT	¬comfortableness	EmotionalState+	WNAffect
discomfort	DSC	confusion	EmotionalState+ ,	WNAffect
discomfort	DSC	frustration	EmotionalState+ ,	BodyLanguage
manners	DSC	behaviour	TraitAttribute+ ,	WNAffect
discomfort	DSC	anxiety	EmotionalState+ ,	WNAffect
{crosses, legs}	MWT	crossed_legs_sitting	legs_and_feet_signal	BodyLanguage

4.4 Evaluation Study for ViewS Semantic Augmentation

An experimental study was conducted to evaluate the semantic augmentation component of ViewS for textual user-generated content (UGC). The study had three main objectives: (a) examine how precisely the semantic augmentation output can describe the textual content based on the extracted annotations, (b) compare the performance of annotation between the surface form (SF) and the enriched surface form (ESF), and (c) identify further improvement of the semantic augmentation component.

The study included four stages: (i) collection of UGC, (ii) execution of semantic augmentation over the collected corpus, (iii) examination of the semantically annotated corpus by human annotators, and (iv) evaluation of ViewS with respect to the feedback from annotators.

4.4.1 UGC Corpus Collection

A closed social platform similar to YouTube was developed to collect relevant UGC for the study. The videos would act as stimuli for the participants to express their opinions and experiences in the form of textual comments.

We selected a representative Interpersonal Communication activity - job interview and queried YouTube to retrieve video exemplars of job interview situations (a screenshot of the prototype system is shown in Figure 4.6). Job interview was selected due to the high likelihood of finding participants with familiarity in this activity - people often participate in job interviews in their life, either as an interviewer or an applicant. Participants with different personal experience can bring diversity to the semantic output, hence viewpoints. Additionally, thought provoking job interview videos are more widely available.

The content collection was done in a controlled experimental setting involving ten participants (five male and five female). Participation was on a voluntary basis and was reimbursed with a small value Amazon voucher. Before joining the study, each participant was asked to complete a questionnaire about his/her experience in job interview and awareness of social signals. The participants were selected to represent diversity in terms of job interview experience, age, and educational levels (see Table 4.6). One participant had no experience in job interviews, and one had extensive experience as both interviewer and applicant. Each of the remaining eight participants had at least one job interview experience as an applicant, and four had no experience as interviewers.

Table 4.6 Summary of the user profiles of the participants in the study.

Profile variable	Proportion of users
Gender	5/10 [males] 5/10 [females]
Age	2/10 [18-23] 4/10 [24-30] 1/10 [31-40] 2/10 [over 41]
Academic level	3/10 [Honours Degree, level 6] 2/10 [Masters Degree, level 9] 5/10 [Doctoral Degree, level 10]
Experience as applicants	1/10 [no experience] 6/10 [1-5 interviews] 2/10 [6-10 interviews] 1/10 [more than 15 interviews]
Experience as interviewers	6/10 [no experience] 1/10 [1-5 interviews] 3/10 [more than 15 interviews]
Emotion is important	8/10 [Yes] 1/10 [No] 1/10 [I do not know]
Body language is important	9/10 [Yes] 1/10 [I do not know]
Body language consists a communication tool	9/10 [Yes] 1/10 [I do not know]

The users were asked to watch at least one video and provide comments by selecting particular video episodes, stating the subject of the comment (i.e. interviewer or applicant) and whether the comment was related directly to the video they watched or from their personal experience. These are properties-attributes that qualify the comments and extracted semantics, enabling thus more reasoning to be performed.

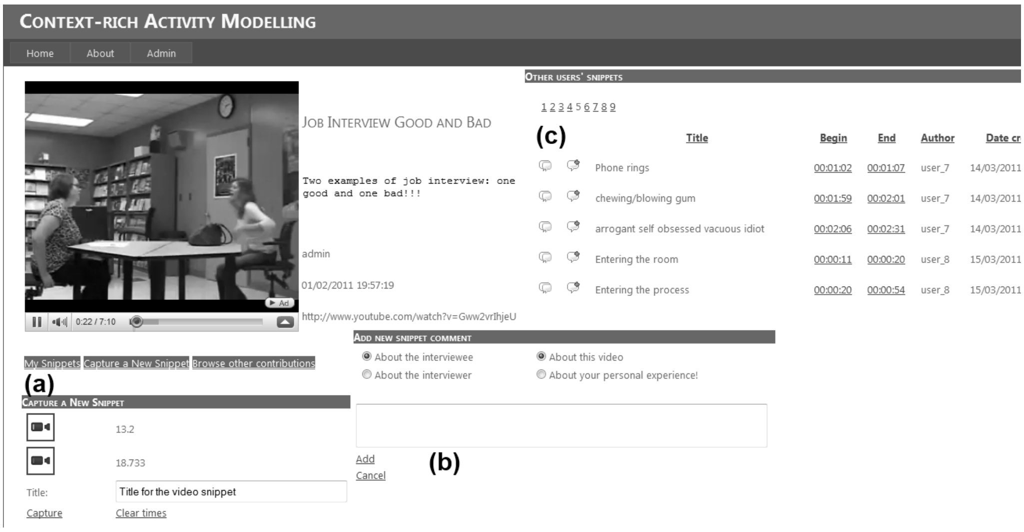

Figure 4.6 A screenshot of the interface for content collection.

Participants can (a) partition the video into video snippets (episodes) and (b) add comments on a chosen person in video based on their direct observation or from their personal experience. The participants were allowed to browse and contribute to video snippets captured from other participants (c).

In the study, participants annotated a total of 8 job interview videos and the resulted corpus included 193 textual comments (example comments are presented in Table 4.7[29]).

Table 4.7 Example comments from several users; the underlined phrases relate to social signals (emotions and body language).

"Avoids the handshaking. Shows a person without manners, completely rude and disrespectful and maybe inappropriate for the job."
"I had a similar situation when a candidate rushed to the interview showing little interest. This made me think immediately that I would not wish to work with them. However, I had to force myself to keep calm and positive, to ensure the candidate was given sufficient attention"
"The interviewer may feel discomfort and confusion due to the unexpected behaviour of the interviewee. The interviewer may be thinking that she would not wish to work with people who do not take her (or the job) seriously."
"She appears very understanding of the situation and tries to make the interviewee feel comfortable even though she is late."

29 The study material (content and input from the experts) is available at: http://imash.leeds.ac.uk/services/ViewS/#datasets

4.4.2 Semantic Augmentation with ViewS

The corpus collected was semantically augmented, using the instantiation described in Section 4.3. For the total of 193, 183 comments were annotated (at least one annotation)[30] and 1526 annotations were extracted (8.3 annotations per comment). 22.8% of the annotation were linked to emotion and 77.2% to body language ontology. For emotion, 115 distinct text terms were annotated with 75 distinct ontology entities, and for body language 273 and 153 respectively. Table 4.8 summarises the outcome for each group of methods (SF and ESF). From the figures, the enriched surface form produced more annotations than the surface form. Lexical derivations produced most of the annotated textual terms as well as ontology entities linked to them, followed by synonyms. The annotated corpus was then given to three experts for validation.

[30] 10 of the comments were not annotated and were not given to the experts for validation. We did not consider recall in our validation/evaluation as no gold-standard could be constructed. We acknowledge the subjectivity of freely annotating textual content and focus on how precisely the augmentation with ViewS performed as well as on examining each method separately.

Table 4.8 Summary of the semantic augmentation outcome with ViewS for the collected corpus in the study.

	Method	Annotation	#annotations	# distinct text terms	#distinct entities
SF	ET	Emotion	20	8	8
		Body Language	183	48	48
	ST	Emotion	4	2	2
		Body Language	18	9	8
	MWT	Emotion	4	4	2
		Body Language	117	27	26
	Total for SF		***346***	***98***	***94***
ESF	DRV	Emotion	230	76	56
		Body Language	570	156	87
	SNM	Emotion	61	24	16
		Body Language	205	51	34
	ANT	Emotion	9	5	4
		Body Language	10	7	4
	DSC	Emotion	21	9	13
		Body Language	74	27	17
	Total for ESF		***1180***	***355***	***231***
	SF+ESF		**1526**	**453**	**325**

4.4.3 Validation of the Semantic Output by Human Annotators

The validation methodology to include human annotators was selected based on the notion of *human computation* defined by von Ahn in his Doctoral Thesis [110]. According to von Ahn, human computation is *"…a paradigm for utilizing human processing power to solve problems that computers cannot yet solve.*" In a recent survey article , Quinn and Bederson [111] discuss among other examples where human computation can aid machine computation with the notion of (i) *output agreement* - which denotes acceptance of machine output based on human agreement, and (ii) *aggregation* - which denotes the summarisation of human contributions to validate machine output. In this light, human annotators were used for validating the output of the semantic augmentation component as described below.

Two social scientists (with experience in content annotation and activity modelling) and one psychologist were recruited as the expert annotators.

They manually examined the semantic augmentation output on the set of comments collected from the case study. Both social scientists had experience in qualitative analysis of human contributions (e.g. interviews or personal stories) to extract relevant concepts for an activity model in a range of domains. Particularly relevant to this study was their experience in analysing textual contributions and deriving a model of IC (in general) and job interview (specifically). The psychologist's expertise included psychology of emotion and non-verbal communication, as well as their application in Serious Games/simulated environments for learning.

Each expert was given the whole annotation set (all the comments with all the annotated entities). For each annotation both the text term and the corresponding annotated ontology entity were given and the experts were asked to follow the script below:

> The purpose of this study is to validate and measure how effectively the framework (a) identifies correct textual terms in the textual comment and (b) extracts concepts based on specific senses that the term can possibly have. The domain that the concepts and terms are related to is Interpersonal Communication, and particular focus has been given to social signals, including Emotion and Body Language. For each comment it is likely that you will see concepts and terms such as: "talk", "anxiety", "hands", "face", "understanding", "want", "expectation" etc..
>
> You are kindly asked to fill two of the columns (see the figure below for an example) in the attached spreadsheet for each of the extracted concepts and identified terms of each of the 183 comments. These columns are:
>
> (1) "ANNOTATION CORRECT?", which corresponds to whether or not the concept ("ANNOTATION") is correctly annotated through the sense given in the column "WITH THE SENSE" using the term ("THROUGH THE TEXT TERM") in the text presented in the column "TEXT".
>
> (2) "TEXT TERM CORRECT?", which corresponds to whether the identified term ("THROUGH THE TEXT TERM") can be annotated and used in order to describe the textual comment, based on the domain of Interpersonal Communication in general, or more particularly based on Social Signals.
>
> For each cell in the above 2 columns a drop down list will appear after clicking with the options (1) "YES", if you agree, (2) "NO" if you disagree" and (3) "NOT SURE" if you are not sure for the concept or term.
>
> You will also notice the column "Operator" which will have the value "Negation" if the concept and the term have been identified following a negation in the textual comment (through terms such as "no", "not" and "n't") (or "None" if there is not a negation).

The analysis of the responses included the validation of the annotated ontology entities, as well as the identified original text terms leading to annotations[31]. This enables the comparison of different annotation methods (surface form and enrichments) with respect to the original text input. Tables A.4.1 and A.4.2 in Appendix A.4 show the pair-wise contingency tables of responses of the experts for the text terms and annotated entities respectively. We name the experts as ExpA, ExpB and ExpC for simplicity.

In order to measure agreement we did not use the *Kappa* statistic[112] because of the prevalence of responses for each contingency table in both cases (text terms and annotated ontology entities); that is, imbalanced distribution of responses produces low *Kappa*, even though the observed agreement Po is high, because the expected agreement by chance is high[113, 114]. The problem is well defined and the proposed solution is to report on specific agreements per category (i.e. *YES*, *NO* and *NOT SURE*)[113, 115, 116]. Given a contingency table as below, of two experts' responses (Exp1 and Exp2) with three possible classification categories (cat1, cat2 and cat3)

		Exp1			
		cat1	**cat2**	**cat3**	**Total**
	cat1	a	b	c	a+b+c
Exp2	**cat2**	d	e	f	d+e+f
	cat3	g	h	i	g+h+i
	Total	a+d+g	b+e+h	c+f+i	N=a+b+c+d+e+f+g+h+i

the specific agreement for each category is given by the formula (adapted from [113]):

$$\mathrm{A}_{\mathrm{cat1}} = \frac{2\mathrm{a}}{\mathrm{N} + (a - e - f - h - i)}$$

for category *cat1* as an example. The formula is based on the following calculations:

The number of times in which Exp1 assigned the category cat1 is:

$f_1 = a + d + g$ (a)

The number of times in which Exp2 assigned the category cat1 is:

[31] Commonly named *spans* of annotated text.

$g_1 = a + b + c$ (b)

The average number of times for which both experts assigned the category cat1 is:

$$\frac{(f_1 + g_1)}{2} \quad \text{(c)}$$

The index average agreement (probability) in assigning the category cat1 is then:

$$\frac{a}{\frac{(f_1 + g_1)}{2}} = \frac{2a}{(f_1 + g_1)} \quad \text{(d)}$$

Substituting $(f_1 + \ g_1)$ from (a) and (b) in (d) we take:

$$f_1 + \ g_1 = (a + b + c) + (a + d + g) = a + (a + b + c + d + g) =$$
$$a + (N - e - f - h - i) = N + (a - e - f - h - i)$$

Table 4.9 presents the pair-wise specific agreement for each category of responses in the validation set for both text terms and ontologies entities. The proportional agreements presented in the table show that the experts agreed in a substantial degree - (81.2% on average for term extraction and 75.9% for ontology entity annotation; Krippendorff suggested a threshold of 67%[117] for tentative conclusions, however recent work [118], indicates that the cut-off point above 70%, e.g. in [119, 120], are considered reasonable, especially in cases of prevalence of responses) - on the system performance correctly capturing the text terms to describe the textual comments as well as on the annotated ontology entities (positive agreement - *YES* responses). For the cases of negative (*NO* responses) and neutral (*NOT SURE* responses) the agreement was low which resulted from the prevalence and sparsity of responses.

However, looking at the proportions of negative or neutral responses by each expert and comparing with the corresponding positives (i.e. computing the precision for each), we see that the associated precision for ExpB and ExpC is significantly larger (>90% *YES* responses, based on the margin totals for each response in Tables A.4.1 and A.4.2 in Appendix A.4) than the error and the neutral rates for both textual terms and annotated ontology entities. For ExpA the precision and error rates are close to 50% for the annotated entities and significantly in favour to precision for the textual terms (73% *YES* responses). The low precision considering ExpA was a result of 631 negative responses for which the other two experts provided either positive (*YES*) or neutral (*NOT SURE*) responses. In 588 of the cases both experts ExpB and ExpC provided a positive (YES) response which concerned mostly body language related entities (459 annotations out of 588). Most of the cases concerned lexical derivation directly extracted from the surface form text terms (379 annotations out of the 588).

Considering the majority of responses for the three experts, the above observations show that the semantic augmentation with ViewS performs precisely in most of the cases. Details are presented and discussed in the next Section.

Table 4.9 Pair-wise specific agreement and average scores.

	Text Terms (%)			Ontology Entities(%)		
	YES	NO	NOT SURE	YES	NO	NOT SURE
ExpA-ExpB	83.7	8.8	0	69	21	11.3
ExpA-ExpC	79.8	39.3	0.2	66	4.7	4.3
ExpB-ExpC	80.5	12.4	3.1	92.8	15.9	6.1
Average(%)	81.2	20.1	1.1	75.9	13.8	7.2

4.4.4 Evaluation of the Semantic Augmentation Methods

In order to evaluate in more details the performance of the semantic augmentation and the utilised methods, the majority of responses was taken to characterise each textual term and annotated ontology entity (similar method has been followed in [121]). The contingency Table 4.10 shows the number of responses by value after taking the majority of the three experts' validation sets for each annotation element in the corpus for textual terms and annotated ontology entities (pair-wise). From the table we identify six categories of annotations:

(a) correct: both the text term and ontology entity are correct[32];
(b) incorrect: both text term and ontology entity are incorrect;
(c) term-favouring: the text term is correct and the ontology entity is not;
(d) ontology-entity-favouring: the ontology entity is correct and the text term is not;
(e) text-term-neutral: the text term is correct and the ontology entity is neutral;
(f) ontology-entity-neutral: the ontology entity is correct and the text term is neutral.

32 'Correctness' indicates the case where a text term or an ontology entity can be used to describe the text.

Table 4.10 Number of responses considering the majority between the three annotators

		Text Terms			
		YES	**NO**	**NOT SURE**	**Total**
Ontology Entities	**YES**	1166 (correct)	127 (ontology-entity-favouring)	80 (ontology-entity-neutral)	1373
	NO	65 (term-favouring)	29 (incorrect)	11 (incorrect)	105
	NOT SURE	29 (text-term-neutral)	5 (incorrect)	14 (incorrect)	48
	Total	1260	161	105	1526

Correct annotations. The correct annotations covered most of the corpus (1166 - 76.4%). For these annotations the enrichment methods were more favourable than the surface form methods (73% compared to 27%). 48.2% of the annotations were extracted using lexical derivations (followed by synonyms - 17.4%). Most of the annotations concerned body language (75.4%). Figure 4.7 shows the distribution of each method for the correct annotations.

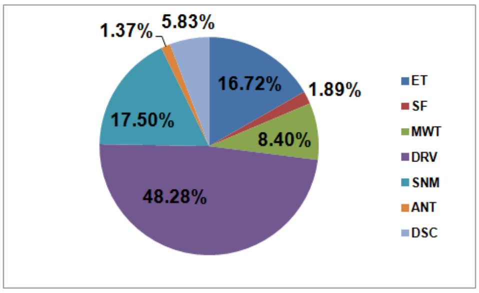

Figure 4.7 Distribution of correct annotations for each method.

The enrichment methods covered 73% of the correct annotations.

Incorrect annotations. For 29 (1.9%) of the annotations, neither the text term nor the annotated ontology entity could be used to describe the given text. Most of the ontology entities which concerned body language were linked through lexical derivations as SUMO: NormativeAttribute (e.g. *take-want*, *like-want*, *meeting* - *touching* and *playing* - *flirting*). Incorrect were also considered the cases where neutral and negative responses were combined (1.9%). Figure 4.8 shows the distribution of each method for the incorrect annotations.

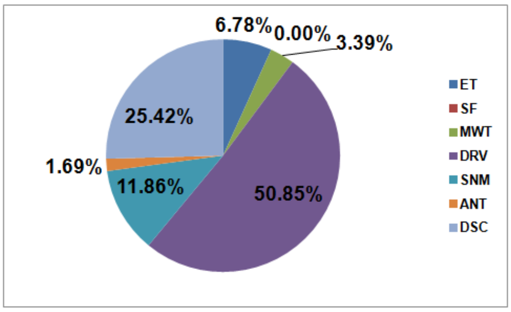

Figure 4.8 Distribution of incorrect annotations for each method.

Term-favouring annotations[33]. Annotations accepted for the identified text terms but not for the annotated ontology entities (4.2%) were equally spread between the surface form and enriched surface form methods. Most of the annotations concerned body language and the textual terms included words such as *impression*, *crucial*, *excuse*. For these cases the enrichment process did not correctly extract possible ontology entities to describe the comment. On the other hand, these cases also depict missing ontology entities from the utilised ontologies.

Text-term-neutral annotations[33]. Cases where the experts were not sure about the annotated ontology entities but positively responded for the text terms (1.9 %) concerned both emotions and body language mainly extracted by lexical derivations and synonyms. For the utilised ontologies, this possibly means that the corresponding ontology entities could be perceived with uncertainty with regard to the context of use in the user's statement. Example entities include *anticipation*, *doubt* and *vexation*, extracted though lexical derivations. Considering both text-term favouring and neutral annotations the implication for Views is that more contextualised methods are needed in some cases (see also discussion in Section 4.5). Although the sense detection and mapping mechanism performed well for the semantic annotation, future work should also consider additional disambiguation techniques, e.g. by examining more closely the text dependencies within phrases to derive context and more accurate meaning [122, 123]. Part of the annotations in this case also concerned the multi-word token matching (see Section 4.3.3). More sophisticated algorithms than cosine similarity for vector matching can also be considered for annotating multi-word tokens (see Section 4.3.3), e.g. [107] which utilises web search results to contextualise the input vectors. However, it is out of scope for this work.

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33 These annotations cannot be used for further analysis/reasoning and can be merged with incorrect category.

Ontology-entity-favouring. These annotations concerned cases that the annotated ontology entities could better describe the text than the text terms and were considerably more frequent as opposed to term-favouring annotations (8.3%). Most of the annotations were produced through the enrichment methods (99% of the cases, derivations - 90 cases, synonyms-28 cases, and DISCO similar words - 8 cases). Example pairs of text term-ontology entity include *trying-stress*, *patience-humility* and *question-doubt*. For ViewS, these cases show that the user's statement can be extended to include more reliable- to describe the content - concepts.

Ontology-entity-neutral annotations. Cases where the experts were not sure about the text terms but positively responded for the annotated ontology entities (5.2 %) concerned mainly body language produced by the enriched surface form methods.

To calculate the precision of the semantic augmentation in ViewS we considered the cases where the ontology entities were accepted as valid. Considering the margin totals in Table 4.10 the semantic augmentation with ViewS achieved a **micro-averaging** (average for the whole corpus) precision of 89.97% for correctly extracting ontology entities to describe the textual comments, and 82.5% for correctly identifying textual terms respectively. The overall performance of each semantic augmentation method is presented in Table 4.11 with regard to the correctly annotated ontology entities. The average precision of the enrichment methods' output annotations is 86.36% which indicates their effectiveness in describing the user statements for capturing the viewpoint semantics.

Table 4.11 The overall performance of each semantic augmentation method. The precision is calculated based on the valid annotated ontology entities.

	Method	Annotation	#annotations	#valid (% performance)
SF	ET	Emotion	20	20 (100%)
		Body Language	183	178 (97.2%)
	ST	Emotion	4	4 (100%)
		Body Language	18	18 (100%)
	MWT	Emotion	4	2 (50%)
		Body Language	117	96 (82.05%)
	Total for SF		***346***	***318 (91.9%)***
ESF	DRV	Emotion	230	207 (90%)
		Body Language	570	513 (90%)
	SNM	Emotion	61	55 (90.1%)
		Body Language	205	187 (91.2%)
	ANT	Emotion	9	7 (77.7%)
		Body Language	10	9 (90%)
	DSC	Emotion	21	17 (80.9%)
		Body Language	74	60 (81%)
	Total for ESF		***1180***	***1055 (89.4%)***
	Total		**1526**	**1373 (89.97%)**

The **macro-averaging** precision, i.e. the average performance of the semantic augmentation with ViewS for each textual comment was 89.55% for correctly annotating the comment text with ontology entities, and 82.72% for correctly identifying text terms to describe the comment.

4.4.5 Discussion

The additional concepts brought by the enrichment of the surface form broaden the captured semantics for viewpoints on social signals (76.83% of the accepted annotated entities). This shows that linguistic and semantic enrichment is valuable for describing the user statements. It is also worth noting that each enrichment method brought exclusive to other methods concepts form the ontologies, which shows that capturing the semantics of viewpoints can benefit from the proposed engineered integration individually by each method. Considering the total amount of annotations and valid annotated ontology entities in the evaluation study (see Table 4.11), the most beneficial method for capturing viewpoint semantics is the WordNet lexical derivations (DRV) followed by synonyms[34]. However, there was also benefit in using broader resources like DISCO, as it brought additional concepts that were approved by the domain experts.

Considering the discrepancies which occur between text terms and corresponding annotated ontology entities in the responses, it became possible to identify that diverse situational interpretations of terms from the domain experts which led to negative responses on the annotated ontology entities. That is, although the text term was correctly identified as relevant, the linked ontology entity could not be used to describe the situation implied in the comment[35]. The results also showed that experts interpreted social signals based on subjective opinions or used their tacit knowledge when assigning concepts to text based on the situations presented in the users' statements. Such cases are beyond the scope of traditional information extraction techniques employed in our framework. Example cases include *amusing* with *laugh* and *question* with *doubt* from lexical derivatives, *concern* with *interest* for synonyms, *knowing* with *want* for similar words, and *hope* with ¬*despair* for antonyms.

Cases where the framework would miss annotating ontology entities through text-terms[36] were also examined It was discovered that ontology entities could be missed due to algorithmic deficiencies of the linguistic parser or incorrect syntax of sentences given by the users. These introduced incorrect part of speech tagging during parsing, which led to incorrect search in the lexical resources to derive senses. The coverage of the ontologies is also an important factor to consider with respect to recall. A partial solution can be to introduce new ontology entities in the ontologies based on the extracted text terms, and with the guidance of the domain experts to include them in the ontology specifications.

Based on the evaluation study presented in this Section, the ViewS semantic augmentation is considered reliable for capturing viewpoint semantics on

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[34] The annotations through the lexical derivations (DRV) were significantly more than the annotations though synonyms (SNM) in total (800 for DRV and 266 for synonyms). Proportionally, 90% valid annotations for DRV compared to ~91% valid annotations for SNM, denotes that more semantics can be extracted when exploiting DRV enrichment.

[35] Validation categories: term-favoring and text-term-neutral.

[36] The empirical recall was calculated at 89%.

social signals from textual UGC. The comparative analysis in the evaluation study with a base-line (that is extracting surface form without semantics) showed that there was an increased potential for additional semantic enrichment methods, as more than 75% of the approved semantic annotations concerned the enriched surface form. It should be noted however that semantic enrichment could introduce noise which should not be overlooked. Details for generality of the approach for other domains is discussed in Chapter 8 of the thesis.

4.5 Summary

In this Chapter semantic web technologies for textual content annotation and augmentation were exploited and evaluated for the extraction of meaningful data able to describe the user-generated content. Technical details of the implementation were presented. In summary, the proposed pipeline provides an intelligent mechanism for augmenting UGC. ViewS allows for configuring the processing of content by tuning the knowledge resources according to the selected domain and dimensions, as well as by importing appropriate ontologies. The ViewS semantic augmentation is a reliable tool to semantically map and extend the knowledge embedded in user generated content in order to extract viewpoint semantics. Given the semantically augmented UGC with ViewS, semantics within user statements can be described in a machine processable form. To further investigate how to automatically model user viewpoints, the machine computational approach has to be aligned with human computation and perception to capture the viewpoint focus.

Chapter 5
Semantic Social Sensing in a Learning Context

5.1 Introduction

Having gained confidence in the technical performance of the Semantic Augmentation component, an exploratory study was set up with the following objectives:

(i) to illustrate the usefulness of semantic augmentation for gaining an insight into the UGC.
(ii) to inform the design of the Viewpoint Focus Modelling component.

This Chapter reports the design and outcome of this exploratory study which was conducted with a company which develops a learning simulator for interpersonal communication in business settings. This company wanted to explore a way to use the learners' free style comments while they were going through the simulation.

Section 5.2 outlines the application context which motivates the study. The content collection process is presented in Section 5.3. The instantiation of ViewS semantic augmentation was identical to the one presented in detail in Section 4.4. In short, specific WordNet semantic lexical categories and SUMO concepts were selected for the domain of IC and social signals, as well as the WordNet Affect taxonomy of emotions and the body language ontology. The semantic output is summarised in Section 5.4. The evaluation session with the simulation designers is presented together with the findings in Section 5.5. Section 5.6 discusses strengths and limitations of the approach and summarises the Chapter.

5.2 Application Context

Social spaces are radically transforming the educational landscape. A new wave of intelligent learning environments that exploit social interactions to enrich learning environments is forming [33]. Notable successes include using socially generated content to augment learning experiences [124], facilitate search [125], aid informal learning through knowledge discovery or interactive exploration of social content [126], and facilitate organisational learning [127] and knowledge maturing [128]. In the same line, social contributions are becoming invaluable source to augment existing systems, e.g. [129-131] and to build open user models [132, 133]. Social spaces and user generated content provide a wealth of authentic and unbiased collection of different perspectives resulting from diverse backgrounds and personal experiences. This can bring new opportunities for informal learning of soft skills (e.g. communicating, planning, managing, advising, negotiating), which are ill-defined domains requiring awareness of multiple interpretations and viewpoints [134]. There is a pressing demand for robust methods to get an insight into user generated content to empower learning of soft skills.

While semantic analysis of social content is revolutionising human practices in the many areas (e.g. policy making, disaster response, open government), little attention has been paid at exploiting semantic technologies to gain an understanding of social content in order to empower learning environments. The approach presented in this Chapter explores this direction. A *semantic social sensing* approach is proposed which explores ontologies and semantic augmentation of social content with ViewS to get an insight into diversity and identify interesting aspects that can be helpful for enriching a learning environment. While the approach can be seen as resembling open learner models of social interactions (e.g.[132, 133, 135], it has crucial differences - we link social user generated content to ontology entities and provide interactive visualizations in the form of semantic maps for exploring such content.

The semantic social sensing approach is applied to one of the ImREAL[37] use cases – a simulator for interpersonal communication in business settings. The potential for gaining an understanding of user reactions with the simulation and extending the simulation content is examined. This approach offers a new dimension in the established research strand on evaluating and extending simulated environments for learning by adding a novel way of *sensing* learners and content, in addition to traditional methods of log data analysis [136, 137], measuring the learning effect [138, 139] or eye tracking[140].

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[37] http://www.imreal-project.eu

5.3 Content Collection in a Simulated Environment for Learning

The study used a simulator developed by *imaginary Srl*[38] within the ImREAL EU project. The simulator is expected to promote awareness of the importance of cultural variations in IC, focusing on differences in social norms and use of body language, and how this may influence a person's expectations and emotions. It also aims to promote reflection on personal experiences in relevant IC context.

Semantic Augmentation was applied in this context and two main goals were derived:

(i) **investigate the potential benefit of *semantic social sensing*** in a learning context for the simulator designers to:
   (a) **get an insight into users' reactions** on the simulator's content;
   (b) **evaluate and improve the simulator** based on authentic UGC.

(ii) use the prototype to extract further requirements from the simulator designers to extend the analytic power, **hence informing the automatic viewpoint focus modelling (the next component in ViewS).**

Following was the learning scenario used in the simulator. The learner is the host who organises a business dinner involving several people from different nationalities. The simulated scenario includes four episodes:

- *Greetings* (situations embed arriving on time, different norms about greetings, first impression, and use of body language);
- *Dinner* (situations embed use of body language and different preferences about food and drink);
- *Bill* (situations embed use of body language and different norms about payment), and
- *Goodbye* (situations embed use of body language and different norms about greetings).

Figure 5.1 illustrates the interface and the interaction features in the simulator. The learner is expected to select a response and may read/write microblogging comments at each step. The simulator was used by 39 users

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[38] http://www.i-maginary.it/en/

who attended interactive sessions at learning technology workshops or responded to invitations sent to learning forums in Europe. The data were collected during the period 29 Oct 2012 – 15 Jan 2013, which provided 193 micro-blogging comments from 27 users.

Figure 5.1 A learner interaction screen in the simulator– the simulated situation is in the Dinner episode where the host has to decide about ordering food for his business guests.

The screen shows the options (main screen bottom) the learner can choose from, as well as the microblogging utility offered (right). These micro blogs were collected for processing.

5.4 Semantic Augmentation Output

Table 5.1 presents a summary of the results from semantic augmentation of the collected content. It was observed that the numbers of ontology entities extracted varied between episodes. A high proportion of entities was extracted from the first episode. It is interesting to note that the number of annotation was very low for emotional aspects but relatively high for body language in the "Bill" and "Goodbye" episodes, showing that different aspects may be triggered more readily in different situations.

In order to further explore the semantic output, **a visualisation tool – 'ViewS Microscope'** was developed. Input into the ViewS Microscope are (i) the ontologies used for semantic augmentation (i.e. WNAffect taxonomy of emotions and the body language ontology) and (ii) the annotation sets of user generated content. The Output of the ViewS Microscope is a set of semantic maps, each graphically represents the hierarchical structure of the related ontology entities (hierarchy (`owl:subClassOf`) and membership (`rdf:type`) relationships as edges) and highlights those entities that are picked out from the user generated content by using the semantic augmentation component in ViewS. For the visualisation of the semantic map, the radial tree layout is used, which enables to examine the depth of the hierarchy, but also provides clarity compared to a tree layout which would expand either horizontally or vertically distorting thus the spatial configuration of the visualisation panel. Details of the implementation are presented in Section 6.5.

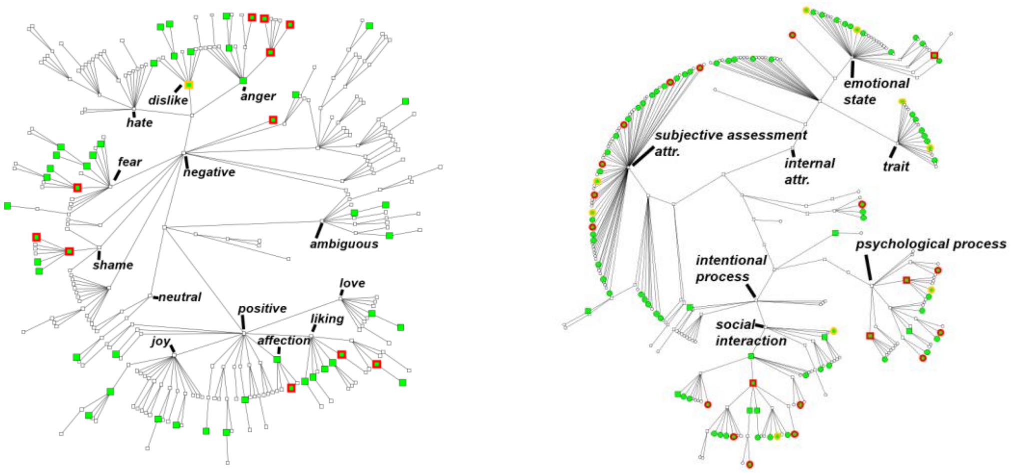
Table 5.1 Summary of the annotated content.

#Users	27					
#Comments	193					
#Annotations	**Episode**	**" Greetings"**	**"Dinner"**	**"Bill"**	**"Goodbye"**	**Total**
	Emotion	82	84	18	8	192
	Body Language	311	236	100	76	723
	Total	393	320	118	84	915
#Distinct Ontology Entities	**Episode**	**" Greetings"**	**"Dinner"**	**"Bill"**	**"Goodbye"**	**Total***
	Emotion	36	36	11	5	57 (31 common)
	Body Language	76	63	43	33	106 (109 common)
	Total*	109 (3 common)	94 (5 common)	53 (1 common)	38	157 (137 common)

**Distinct values are not exclusive between different episodes and some ontology entity labels are common in the two ontologies (e.g. Emotion and body_language_signal_meaning branch in the Body Language ontology).*

Figure 5.2 presents the semantic maps for the WNAffect taxonomy of emotions. On the left, the branch[39] with top node "*mental-state*" from the WNAffect taxonomy is under the microscope, while on the right the "*body-language signal meaning*" is under the microscope.

[39] **An ontology branch** is a sub-tree of the ontology hierarchy tree with top node being a sub-concept of `owl:Thing`.



(a) "*mental-state*" branch of the WNAffect taxonomy of emotions

(b) "*body language signal meaning*" branch of the body language ontology

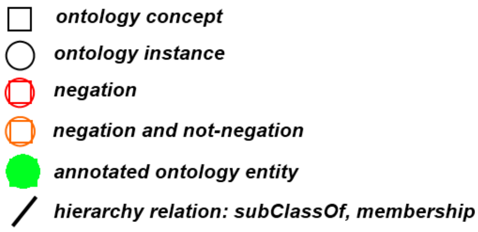


Figure 5.2 Overview of the semantic maps of the annotated user generated content from the simulator.

The ontology entities from the (a) WNAffect taxonomy of emotions and (b) body language signal meaning branch of the body language ontology which have been annotated in the textual corpus are highlighted in the semantic maps.

5.5 Exploration of the Semantic Output and Findings

The simulator designers were shown a collection of semantic maps of the domain ontologies providing: (i) overview of the annotations for simulation episodes and user groups, and (ii) comparison between different episodes and user groups. For each semantic map, the designers were asked if they could see anything interesting and, if so, how it could be helpful for them. Designers' observations and feedback were driven by the key challenges they were facing: (i) getting an insight of the user reactions with the simulator; and (ii) improving the simulation scenario to make it more realistic and engaging.

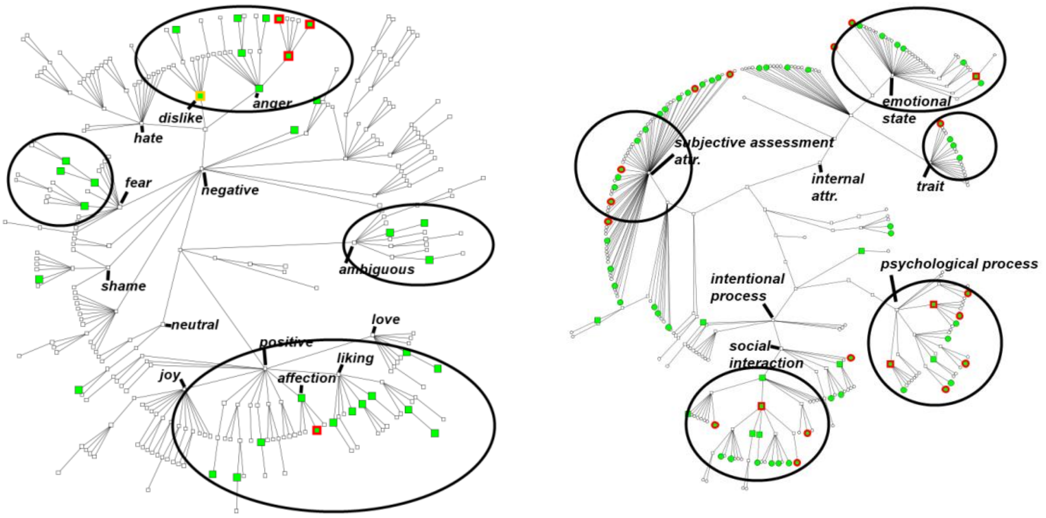
In the rest of this section, the findings are classified into one of these two groups: **"Potential Benefit for Simulator Designers:"** or **"Focus Requirement**:".

5.5.1 Overview of Semantic Maps

Figure 5.3 provides an example of the kind of semantic maps being shown to the simulator designers for their feedback. In this example, the annotated ontology entities for the *Greetings* episode for both emotion and body language signal meanings were highlighted by the microscope.

Potential Benefit 1 for Simulator Designers. The designers were able to very quickly identify clusters of annotated ontology entities formed in the areas of positive and negative emotions, social interactions and psychological processes in the body language signal meanings. The simulator designers noted additional desired user reactions picked up by ontology labels highlighted in the UGC. Semantics can be used to externalise learners' reactions to the simulator designers or tutors. From this observation the first requirement was elicited for computational representation of viewpoint focus:

Focus Requirement 1. *An automatic mechanism to identify clusters of annotated ontology entities in the ontology space.*



(a) "*mental-state*" branch of the WNAffect taxonomy of emotions

(b) "*body language signal meaning*" branch of the body language ontology

Figure 5.3 Semantic maps for the *Greetings* episode.

The simulator designers were able to very quickly identify clusters of annotated ontology entities using the semantic maps for (a) emotion and (b) body language signal meanings.

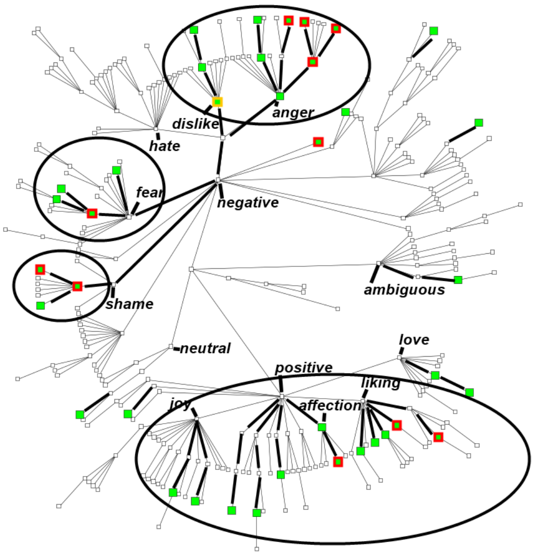
Potential Benefit 2 for Simulator Designers. The simulator designers noted the differences in the number of annotated ontology entities across the different clusters for both emotions and body language signal meanings. Clusters with higher cardinality are referred to as *hot topics by the designer*, e.g. the ‘positive emotion’ cluster (as opposed to the ‘ambiguous emotion’ cluster) in Figure 5.3. This prompted designers to consider if enough illustrations were provided, or indeed whether some of the less hot topics should be showcased more. This observation depicts the following requirement for viewpoints focus representation.

Focus Requirement 2. *Preserve the cardinality of the clusters of the annotated ontology entities*.

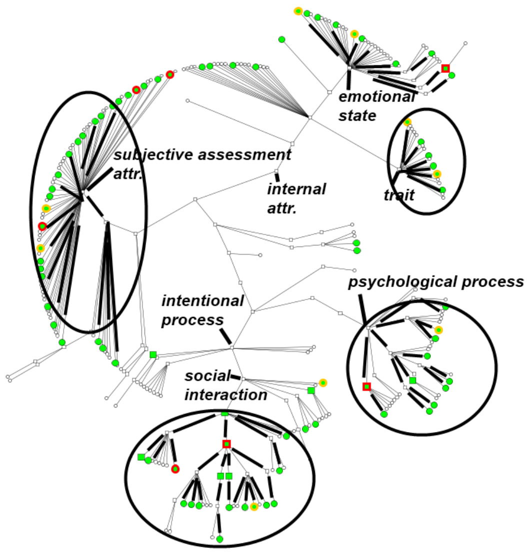
Potential Benefit 3 for Simulator Designers. Another filter was executed to visualise semantic maps for different user groups. From the 27 participants who had used the microblogging tool, 17 (8 female and 9 male) completed the anonymised user profile questionnaire. 13 participants were 22-35 years old and only 4 belonged to age groups >36. Figure 5.4 depicts two examples of semantic maps derived from microblogs of male participants that were shown to the simulator designers. The simulator designers again quickly identified clusters of ontology entities. In addition, they queried the parent node of the clustered annotated ontology entities, as well as the non-annotated ontology entities close to them. The extended set of annotated ontology entities, which include the entities close to those highlighted by the UGC, is hereafter called *an aggregate*. Labels for aggregates such as *positive*, *negative* and *ambiguous* emotions, as well as *social interaction* and *psychological process* were explicitly given to the designers, and thereafter their observations were based on them. The semantic map and the aggregates can be used together with the UGC to augment the simulation. For example, wider range of related words or concepts could now be considered in the dialogue design.

This observation complemented the identification of clusters with the notion of aggregates in the ontology space, from which the third requirement was elicited:

Focus Requirement 3. *Extract aggregates of ontology entities given the clusters of annotated ontology entities in the ontology spaces.*



(a) "*mental-state*" branch of the WNAffect taxonomy of emotions



(b) "*body language signal meaning*" branch of the body language ontology

Figure 5.4 Semantics maps for the male participants.

In addition to clusters, the simulator designers mentioned aggregates of ontology entities formed by the clustered ontology entities in the (a) emotion and (b) body language signal meaning semantic maps.

Potential Benefit 4 for Simulator Designers. The designers noted that the semantic maps could show how close ontology entities are related in the aggregates. This observation leads to the question of what distance should be used to form clusters and consequently aggregates. Longer distance will result in larger clusters and aggregates, while shorter distance in smaller clusters. With respect to the number of ontology entities in each cluster this affects how abstract of specific clusters can be identified. Following two requirements are drawn from this observation:

Focus Requirement 4. *Construct clusters and aggregates based on the distance of the annotated ontology entities.*

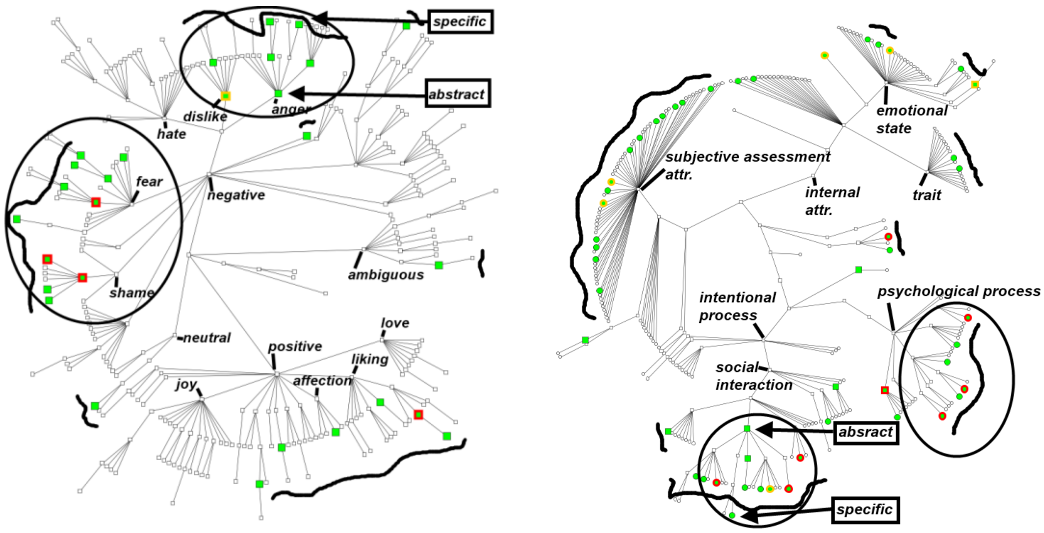
Focus Requirement 5. *Allow for clustering and aggregation using different distances between ontology entities.*

Potential Benefit 5 for Simulator Designers. Another example of semantic maps derived from user groups is shown in Figure 5.5, where the visualisations shown to the designers included semantics maps from young participants (age 17-26 years old) in the study.

While the simulator designers identified clusters and aggregates mainly regarding negative emotions (*dislike*, *anger*, *shame* and *fear*), they also commented on the breadth of emotions and body language signals meanings covered by the annotated ontology entities in the semantic maps. For example, the fact that all positive, negative and ambiguous emotions were partially covered by participants' comments was seen by the designers as an indication that a variety of emotions was triggered when interacting with the simulator. In addition to the breadth, the semantic map visualisation provided a tool for the designers to examine how abstract or specific are the triggered emotions and be able to adapt the simulator accordingly, e.g. by illustrating situations expressing more specific emotions when abstract ones have been triggered. From this observation, two requirements were elicited:

Focus Requirement 6. *Represent the breadth of annotated ontology entities.*

Focus Requirement 7. *Exploit the ontology hierarchy to be able to reason about specificity and generality of ontology entities.*



(a) "*mental-state*" branch of the WNAffect taxonomy of emotions

(b) "*body language signal meaning*" branch of the body language ontology

Figure 5.5 Semantics maps for the young participants.

With the semantic maps for (a) emotion and (b) body language signal meanings the simulator designers were also able to examine the breadth and depth of annotated ontology entities across and within the clusters respectively. The curved lines indicate areas from which ontology entities were extracted. The ellipses indicate the areas of interest for the simulator designers.

Potential Benefit 6 for Simulator Designers. By examining each cluster of annotated ontology entities closer, the designers also identified interesting sub-clusters inside the same aggregate. For example (see Figure 5.6 snapshot from Figure 5.5,b) , the *social interaction* concept in the body language signal meaning branch of the body language ontology is a super-class of *communication* (populated aggregate), *contest*, *cooperation* and *pretending*. In turn, communication is a super-class of *expressing*, *linguistic communication* (most populated) and *remembering*. Parsing the ontology hierarchy for a cluster (consequently aggregate) of annotated ontology entities, several sub-clusters can be extracted that compose the cluster in discussion with a decreasing cardinality of ontology entities. This property leads to the following requirement for viewpoints focus representation:

Focus Requirement 8 *Represent the composition of the clusters and consequently of the aggregates in the ontology space.*

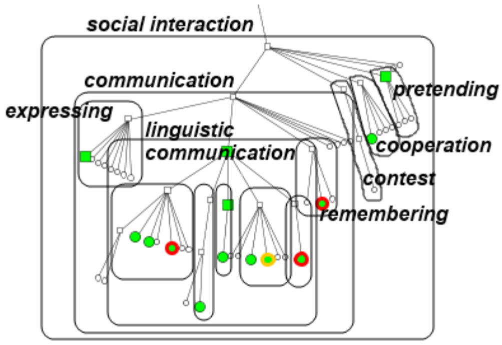


Figure 5.6 Composition of a cluster of annotated ontology entities with smaller sub-clusters.

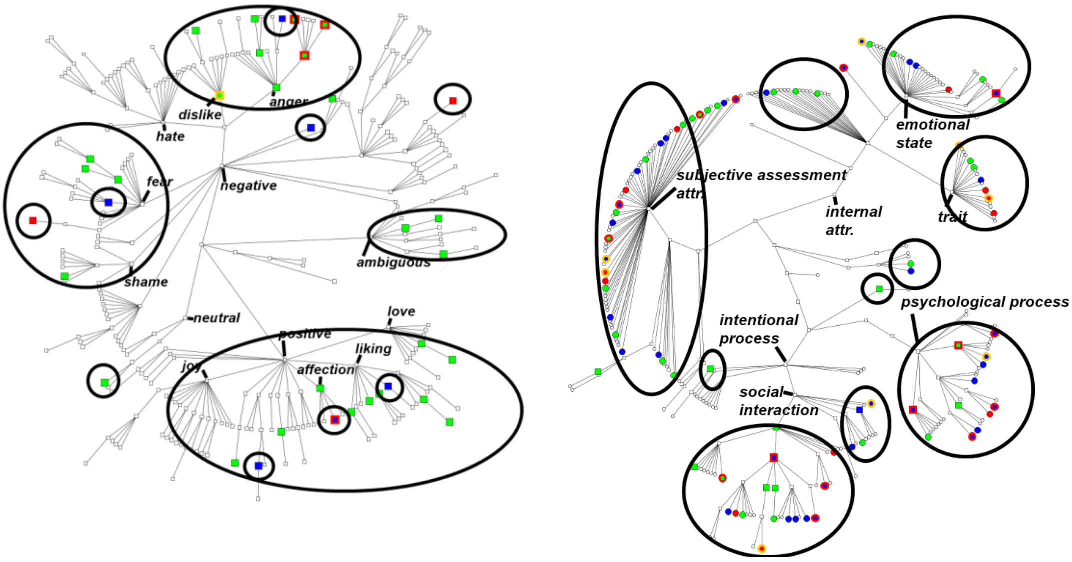
5.5.2 Comparison of Episodes and Users

The observations and requirements elicited in the above laid the foundation for comparing semantic maps for different episodes and user groups

Potential Benefit 7 for Simulator Designers. Comparison of semantic maps enabled the comparison of different episodes. For example, the content related to the *Bill* episode did not refer to many WNAffect ontology entities, compared with the *Greetings* episode (Figure 5.7,a). The designers found such comparison useful because it provided a tool to examine which simulation parts would require further improvement and in what direction (e.g. the designers noted that the Bill episode could be improved as it did not have many branches and situations, and hence did not provoke much user comments linking to emotion entities). Furthermore, semantic maps of different dimensions for the same episode were compared (Figure 5.7,b shows the comparative map of Greetings and Bill for the body language signal meaning branch, in which it is shown that the Bill episode was mostly associated by the participants with body language compared to emotion).

The designers found such comparisons helpful for balancing elements of the simulation in the same or different situations and for evaluating technicalities of the simulation by indicating which simulation content/part is quantitatively and qualitatively poor and improve. These observations depict a summarised requirement for viewpoint focus representation:

Focus Requirement 9 *Define scope of viewpoint focus modelling: the viewpoint model should be able to distinguish viewpoint focus, e.g. between different episodes, aspects and dimensions.*



(a) "*mental-state*" branch of the WNAffect taxonomy of emotions

(b) "*body language signal meaning*" branch of the body language ontology

only from the "Greetings" episode

only from the "Bill" episode

common to both episodes

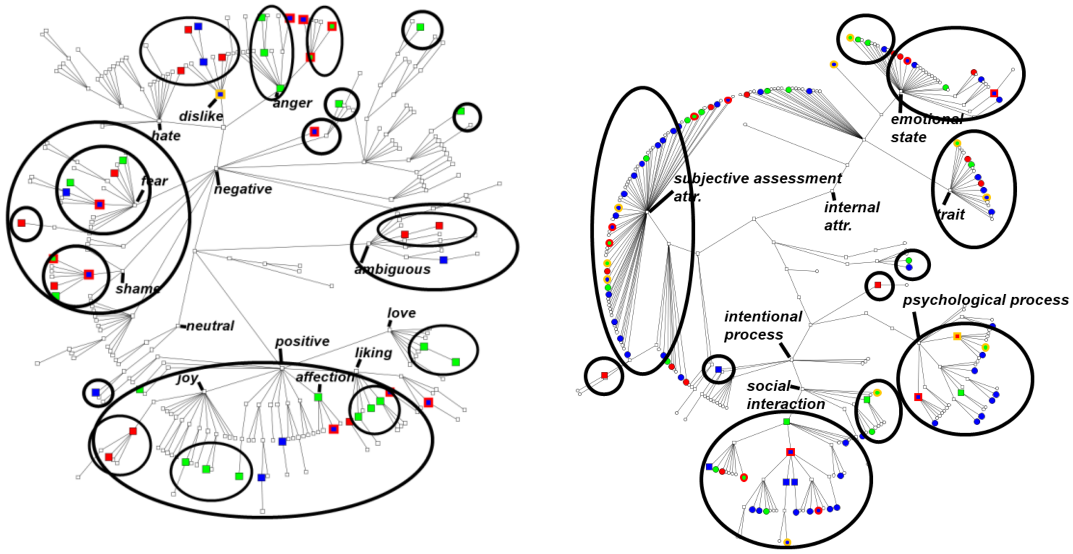
Figure 5.7 Comparative semantic maps for the "Greetings" and "Bill" simulation episodes.

Different situations can trigger different dimensions in participants' contributions. The Greetings episode triggered more emotion related terms (a) than the Bill episode, while more balanced in body language signal meanings. Comparing the two semantic maps only for the Bill episode it is shown that different dimensions can be triggered within a situation.

Potential Benefit 8 for Simulator Designers. The simulator designers were able to visually examine the contributions from different user groups and see the distribution in the semantic maps. The semantic maps with WNAffect annotations of comments by male and female users (Figure 5.8,a) were compared. It was noted that male referred to a broader set of WNAffect entities, while for body language signal meanings (Figure 5.8,b) the contributions were balanced among the two groups. Comparisons were also made between young participants (17-26 years old) and older ones (over 26 years old). Emotion related entities (Figure 5.9,a) by the second user group were broader (covering also positive emotions) and covered different levels of abstraction, while the first group linked to a more limited set of entities. The difference was also clear in body language signal meanings (Figure 5.9,b), where contributions from older users expanded to *social interactions* and *psychological processes*. The simulator designers pointed out that such comparison could useful particularly when thinking about target audiences for the simulator.

ViewS Microscope provided a helpful way to summarise and compare/contrast different user groups. Visualising contributions in the semantic space enables to quantify contributions and examine the distributions in different spaces. With ViewS, the designers were able to examine how close exclusive ontology entities are to the common ones and evaluate for improvement. Designers also stated that together with the clusters and aggregates diversity (illustrated with different colours in the figures) can be structurally explored. These observations led to the following requirement for user viewpoint focus representation:

Focus Requirement 10 *Enable comparison of viewpoint focus using the clusters and aggregates*.



(a) "*mental-state*" branch of the WNAffect taxonomy of emotions

(b) "*body language signal meaning*" branch of the body language ontology

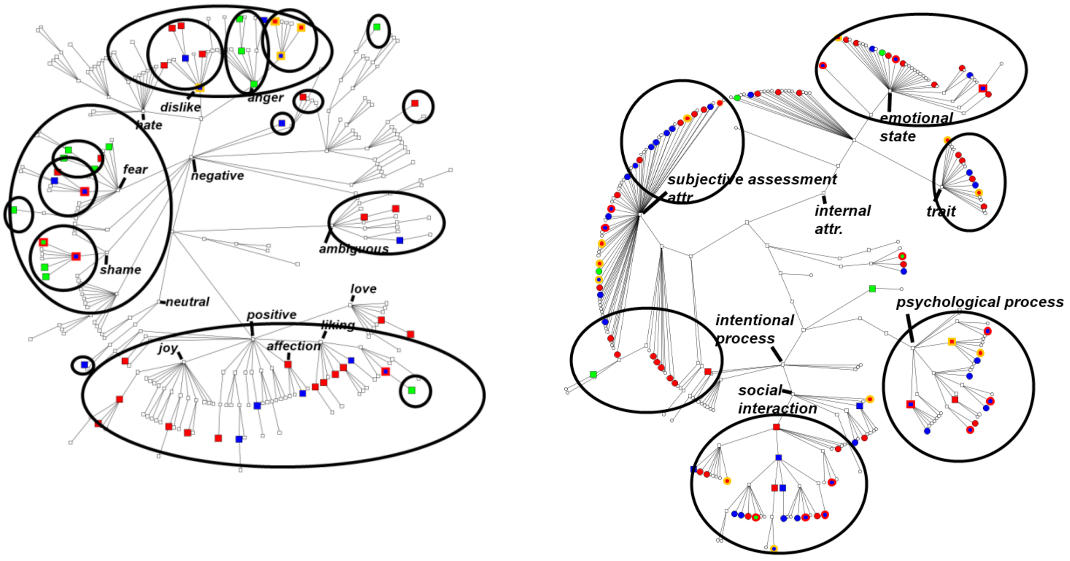
only from male participants

only from female participants

common to both male and female participants

Figure 5.8 Comparative semantic maps for the male and female participants.

Male users mentioned a broader set of emotion (a) related ontology entities, while contributions were more balanced in body language signal meanings (b). Using the distinguishable colour scheme, the simulator designers were able to very quickly identify common and exclusive entities mentioned by the different user groups.



(a) "*mental-state*" branch of the WNAffect taxonomy of emotions

(b) "*body language signal meaning*" branch of the body language ontology

only from young participants

only from older participants

common to both young and older participants

Figure 5.9 Comparative semantic maps for the young and older participants.

Older users mentioned a broader set of (a) emotion related ontology entities and (b) body language signal meanings. The simulator designers pointed that it was very helpful to quantify diverse contributions within the semantic clusters and aggregates, which can then be used to qualitatively analyse the observed diversity.

Early on during the study, the designers sought additional information about the content that could be useful to get a deeper insight into the user-generated content. Such information included mainly characterisation of user contributions as statements about personal experiences or about the situation presented in the simulator. The gateway to comments during the study is presented next.

5.5.3 Zoom into Comments

The designers found the grouping of content through the extracted ontology entities visualised in the semantic maps with ViewS Microscope very helpful. There was a strong desire from the simulator designers however to explore comments together with ontology concepts, as additional semantics were sought from an early point in the study. Of particular interest to the designers was whether an ontology entity, consequently a cluster of ontology entities, was linked with a comment or a set of comments that were referring to the participant's personal experience or the simulated situation.

Tables 5.2 and 5.3 present example user comments linked with ontology entities from different clusters in the Body Language ontology and WNAffect taxonomy of emotions for different simulation episodes and user groups. Some of the comments were seen as helpful to enrich the feedback provided to the learner or to add more options for response in the simulated situations. For example, in different simulation episodes (Table 5.2) there are different aspects discussed with respect to the situation presented (e.g. #1 and #2) that can be used to evaluate the presented scenario, as well as personal norms and suggestions (e.g. #3 and #4) that can be integrated to enrich the simulator. Personal experiences of people in different gender groups (Table 5.3, #1 and #2) can also be used to enrich the simulated situation with different negative emotions, or augment the options given to the user for appropriate behaviour according to users' suggestions linked to positive emotions (Table 5.3, #3 and #4).

Table 5.2 Example comments and annotated entities from body language signal meaning clusters in the Greetings and Bill simulation episodes.

Episode	#	User Comment	Semantic Tag
social interaction	*1*	*(**"Greetings" episode**)He is very <u>polite</u> and probably <u>greets</u> his partners as used in his culture.*	**respectful, greeting,**
	2	*(**"Bill" episode**)You can make a softer gesture with your palm when you want someone to hold and relax while you <u>take care</u> of things.*	**caution, attention**
psychological process	*3*	*(**"Greetings" episode**)I think that it's pretty rough-mannered to arrive with a significant delay in every situation, most of all in a business one. So I would <u>expect</u> the person to <u>apologize</u> and to come with a very good justification.*	**anticipation, defensive**
	4	*(**"Bill" episode**)If I <u>see</u> that not everyone agrees to share the bill equally, I would never do so. I would propose that everyone pays what he/she has exactly to pay.*	**confirmation**

Table 5.3 Example comments and annotated entities from WNAffect clusters in the male and female user groups.

WNAffect Cluster	#	User Comment	Semantic Tag
negative	*1*	(***male user***) *One year ago I was obliged to order a chip dish in order to not embarrass the diners, eventually I was angry and hungry!*	**anger, wrath, fury**
	2	(***female user***) *The gestures in multicultural environments are very risky, especially can be viewed as obscene or insulting. I always try to avoid them.*	**repugnance, abhorrence, contempt**
positive	*3*	(***male user***) *When people are more friendly you should never make them feel embarrassed for their behaviour. Especially when this is warm regards.*	**warm-heartedness, friendliness**
	4	(***female user***) *It is important in a team of different nationality to respect the request to order what they like to eat, so that it might suits everyone, even if it could cost extra money.*	**regard, admiration**

5.6 Discussion

The semantic maps with ViewS Microscope provided a useful tool for the simulator designers to get an insight into the UGC. The designers were able to quickly sense the user reactions with the simulator, thus to evaluate the intended effect of the simulator and also to sense which parts of the simulator may need improvement. It was also useful to facilitate summarisation, comparison and contrast of different simulation episodes or users groups, as ViewS Microscope provided a fast way to quantify contributions as well as to qualitatively present diversity of social-signal aspects. This shows that ViewS can be used to capture and compare different viewpoints expressed in UGC.

Although the designers provided overall very positive feedback, more information was sought in the study regarding the textual content, which ViewS was unable to capture. This information concerned additional semantics to attribute the UGC related to the intention of the users' contribution - e.g. whether they were referring to personal experiences and rules/norms, or providing statements about the situation presented in the simulation. To further investigate the potential of using UGC to augment digital environments for learning a hybrid approach was instantiated in [141] combining semantic analysis with ViewS and discourse analysis. While ViewS showcased its most prominent beneficial role - a gateway to UGC, the discourse analysis that aimed at annotating UGC with categories related to either improving the simulator (e.g. real-world stories and rules) or gathering information about the simulator (e.g. statements about the situation and feedback on the simulator) appeared very challenging: using three different content annotators the observed agreement in attributing UGC with discourse categories was classified as moderate to low, considering the subjectivity of assessing user contributions.

This research builds on the assumption that semantic augmentation of UGC with social signal related terms is helpful for getting an insight into the UGC to improve the simulated environment for learning. For this thesis, it is considered sufficient that ViewS acted as an effective and efficient gateway to UGC. Although promising, but yet challenging, as presented in [141], aiding the simulator designers with more sophisticated means to further examine UGC and its usefulness in improving the simulator (e.g. using discourse analysis) is out of the scope of this work.

The next Chapter concerns the support for the elicited requirements (summarised in Table 5.4) for viewpoint focus modelling with automatic computational methods.

Table 5.4 Viewpoint focus requirements (FRs) elicited during the exploratory study in Chapter 5.

FR-1	*Identify clusters of annotated ontology entities in the ontology space.*
FR-2	*Preserve the cardinality of the clusters of the annotated ontology entities.*
FR-3	*Extract aggregates of ontology entities given the clusters of annotated ontology entities in the ontology spaces.*
FR-4	*Construct clusters and aggregates based on the distance of the annotated ontology entities.*
FR-5	*Allow for clustering and aggregation using different distances between ontology entities.*
FR-6	*Represent the breadth of annotated ontology entities.*
FR-7	*Preserve the ontology hierarchy to be able to reason about specificity and generality of ontology entities.*
FR-8	*Represent the composition of the clusters and consequently of the aggregates in the ontology space.*
FR-9	*Allow for selective data partitioning: the viewpoint model should be able to distinguish focus spaces between e.g. different episodes, aspects and dimensions.*
FR-10	*Enable quantitative and qualitative comparison of focus spaces using the clusters and aggregates.*

Chapter 6
Viewpoint Focus Modelling

6.1 Introduction

The goal of this Chapter **is to transform the human observations and the formulated requirements** (obtained in Chapter 5) **into computational methods to automatically extract and represent the viewpoint focus.** An investigation is conducted on how the ontological knowledge structure can support the elicited requirements on the semantic augmentation output for modelling the viewpoint focus.

The Chapter is structured as follows: Section 6.2 examines the elicited focus requirements for viewpoint focus modelling in order to determine their interdependencies and organise them into logical steps for resolution. Section 6.3 presents the motivation and related work including key novelty aspects of utilising Formal Concept Analysis (FCA) [142] as a computational framework for viewpoint focus modelling, as well as the adaptation of FCA mathematical foundations. The algorithms for viewpoint focus construction are depicted in Section 6.4, while the implementation of the approach is presented in Section 6.5 by detailing the ViewS Microscope software and its usage. The comparison of viewpoint focus models is described in Section 6.6 together with the extension of ViewS Microscope. Finally in Section 6.7, the viewpoint focus modelling approach is discussed including: the foundational assumptions, implementation and output.

6.2 Focus Modelling Steps

In order to clarify what the viewpoint focus model should include, this Section organises the elicited requirements into logical steps for support and discusses the implications to support them. Figure 6.1 illustrates these steps as a sequence based on their interdependencies.

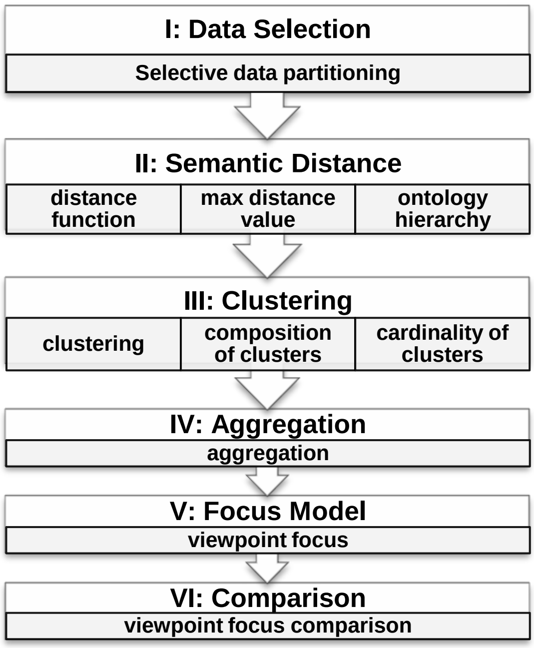
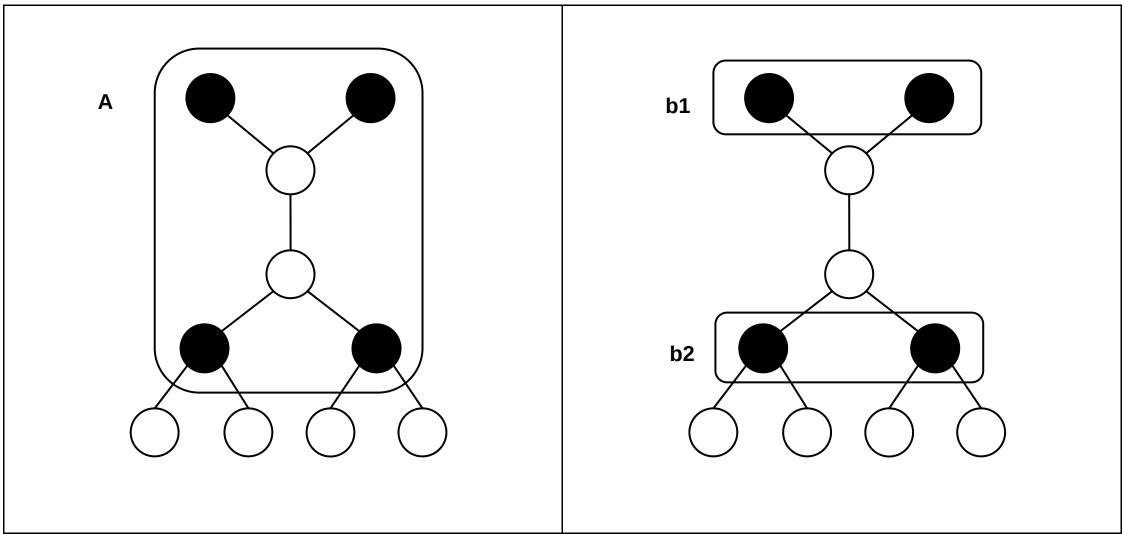


Figure 6.1 Sequence of steps to support the FRs based on their interdependencies.

I: Data Selection. The first requirement to support concerns the **selective data partitioning**. The representation model should be able to distinguish focus between different types of UGC partitions. For example, as presented in Chapter 5, Section 5.5, the data was partitioned based on the simulator's episodes (e.g. "Greetings" and "Bill") and user profile characteristics (e.g. age and gender groups). This allows for different ViewS to be constructed and more relevant comparisons can be made. Another type of partitioning includes different dimensions to be examined; focus spaces between emotions and body language signal meanings, for example, can be analysed.

II: Semantic Distance. The second part of the course concerns a block of requirements to support with respect to the **distance** between two ontology entities. Figure 6.2 presents a simple example of possible distance-wise grouping of ontology entities. The representation model should allow flexibility in **deciding the accorded distance**, as more ontology entities in the same group illustrate more abstract clusters (supersets), while, fewer entities more specific (subsets) respectively. For ontological knowledge representation, distance concerns the *semantic distance* between ontology entities [143]. In this work, the semantic distance is defined by the **hierarchy** of the ontology (counting edges between ontology entities[144], see also Section 6.6 for implementation). In Section 6.8 (discussion) considering other types of semantic distances between ontology entities -e.g.

considering ontology object properties -, is discussed both as a resolvable (based on the modelling approach) limitation and future research extension.



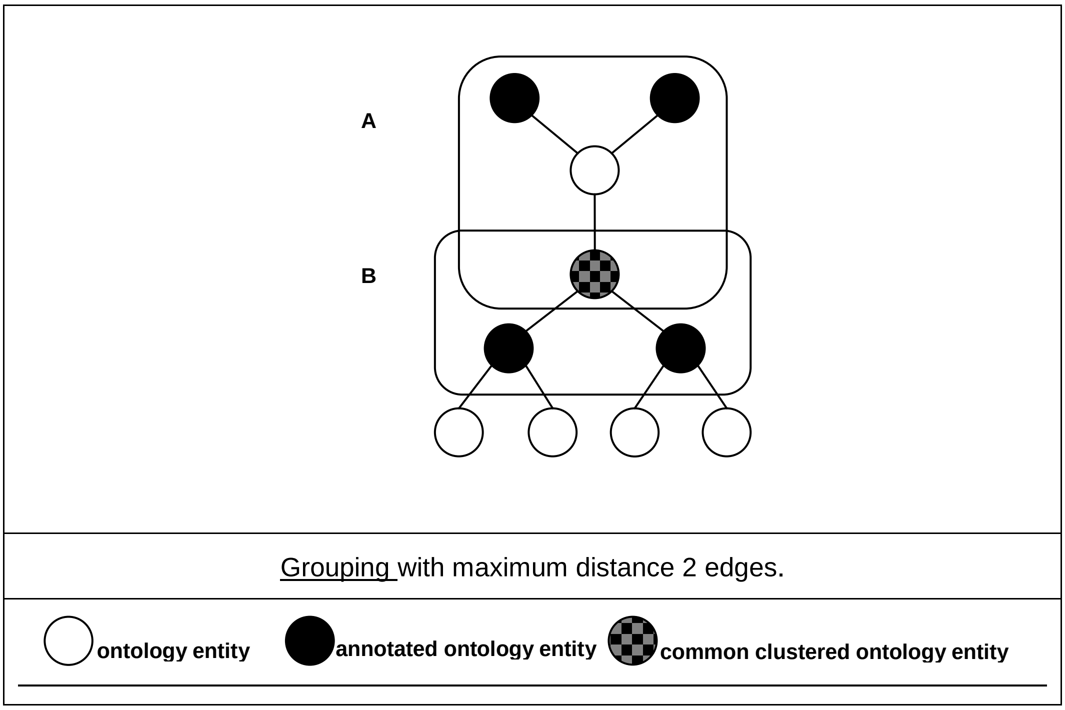
Grouping A with maximum distance 3 edges.	Grouping B with maximum distance 2 edges.

ontology entity   annotated ontology entity

Figure 6.2 Deciding the accorded distance between two ontology entities.

Based on the distance cap, two groupings are presented: A and B including b1and b2.

III: Clustering. The third part also concerns a block of requirements: for **clustering** (a), close in distance ontology entities should be grouped together, hence all the possible pairs of annotated ontology entities have to be checked. Figure 6.3 illustrates a case in which one ontology entity, based on the decided distance can belong into two different clusters. This observation concerns the **composition** (b) of the clusters based on the neighbourhood of close ontology entities, as well as the **cardinality** (c) (number of entities in the cluster) of the clusters.



<u>Grouping</u> with maximum distance 2 edges.

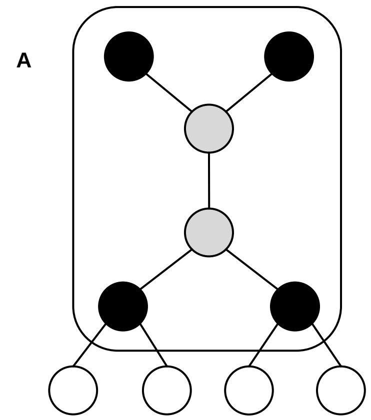
Figure 6.3 One (or more) ontology entities can belong to more than one clusters based on the accorded distance.

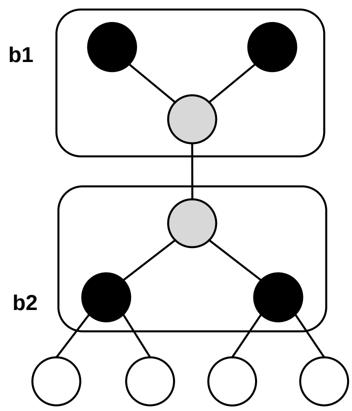
This observation illustrates the requirement for representing the composition of a cluster of ontology entities.

IV: Aggregation. The **aggregation** is directly dependent on the *distance*, *clustering* and *hierarchy preservation* requirements.

<u>An aggregate is defined</u> as the set of annotated ontology entities in a cluster together with the set of non-annotated ontology entities which belong in the hierarchy paths between the annotated ontology entities.

Longer distances result in larger clusters, which in turn results in different aggregates; difference can be identified quantitatively - considering the number of aggregates and the cardinality of the set of ontology entities in each aggregate, and qualitatively - considering the labels of the ontology entities. Figure 6.4 presents the resulted aggregates from the clusters presented in Figure 6.2 considering two different distance measures for the same set of annotated ontology entities. An aggregate of ontology entities reflects and inherits all the previously defined requirements including: distance, hierarchy (depth), cardinality, clustering and composition.





Grouping A and aggregate with maximum distance 3 edges.	Grouping B and aggregates (b1 and b2) with maximum distance 2 edges.

ontology entity **annotated ontology entity** **aggregated ontology entity**

Figure 6.4 Two different ontology entity aggregates which emanated by using different distance measures between ontology entities, thus different clusters (adapted from Figure 6.2).

V: Focus Model. The aggregates of ontology entities constitute the **viewpoint focus**.

VI: Comparison. Extracting the viewpoint focus consequently enables support for **comparison** of different viewpoint focus: different aggregates from the viewpoint focus can be contrasted to explore similarities and differences on the semantic maps.

To conclude, a computational framework which will allow clustering of ontology entities based on the semantic distance is needed. The framework should allow for intelligent processing including: aggregation, and composition of different ontology entity clusters with respect to the ontology hierarchy and desired cardinality, as well as comparison. The problem of solving the course for supporting the requirements presented in Figure 6.1 can then be considered as a methodology for conceptual processing of the knowledge represented with the selected ontologies. To do this Formal Concept Analysis is exploited in this thesis and is discussed next.

6.3 Modelling Viewpoint Focus with Formal Concept Analysis

In this Section the exploitation of Formal Concept Analysis (FCA) [145] as a computational framework for focus modelling is discussed. Firstly the selection of FCA is motivated and the relevant work is presented then.

6.3.1 Why FCA

Key FCA theoretical foundations are quoted below from Rudolf Wille's work [146] which **motivated the selection of the framework**, to address the research question this Chapter aims to tackle:

"FCA is a mathematisation of the philosophical understanding of a concept"
The notion of concept can be aligned with the notion of an ontology region as a viewpoint focus element. This work however acknowledges the distinction provided by Priss [147], with respect to the interpretation of human-cognition intuitive notions: the adoption of FCA does not intend to formally analyse human-cognition, instead to computationally (formally) interpret the observations made over the ontological space.

"FCA is a human-centred method to structure and analyze data"
Computational modelling of the human observations can be achieved based on the requirements for viewpoint focus modelling: including representation, overview analysis and comparison

"FCA is a method to visualize data and its inherent structures, implications and dependencies"
The composition of the viewpoint focus can be represented using FCA on the ontologies to meet the human observations. With FCA we can support semantic zooming for structural (de)composition based on the implications and dependencies of the viewpoint focus elements.

A machine learning approach could be followed for clustering ontology entities (e.g. hierarchical clustering [148]). However, in order to assign features to objects or relate observations, the knowledge exists and is represented by the ontologies, therefore no statistical inference and modelling is needed. Moreover, in this thesis we have considered the notion of semantic distance as a metric for ontology entities clustering, while in traditional data mining a variety of distance metrics can be considered (e.g. Euclidean distance for numerical data[149] and Levenshtein distance for textual data[150]). Ontology entities constitute objects and attributes in FCA.

The semantic distance between ontology entities attributes ontology entities to other entities to form semantic clusters.

Utilising ontologies as the knowledge source for FCA has been presented in [151]. This work also motivated the selection of FCA for viewpoint focus processing including support of navigation and analysis tasks that the simulator designers were aiming at. Uniquely in this thesis, ontologies are exploited for representing a domain, and parameters for extracting viewpoints and relating focus elements for user modelling with FCA are defined.

6.3.2 Relevant Work on FCA

FCA has been used for interest-based user profiling with bookmarks in social tagging systems (e.g. del.icio.us) in [152]. Bookmarks are organised into clusters based on shared tags associated with the resources. The set of tags for each cluster of bookmarks denotes a user interest space that are organised in a hierarchy. This hierarchy results from sub-clusters of bookmarks which share a sub-set of tags with their associated super-clusters. This organisation facilitates the navigation of user interests based on frequency of use of tags: the more bookmarks in one cluster the more times a tag is being used to annotated a resource. In [75] similar approaches to the aforementioned work has been followed. In order to facilitate search and navigation of personal resources FCA is applied on documents and extracted features from the documents. The documents are clustered based on the features they share (e.g. key-words, directory names of files etc.).

In both research works, the user is modelled based on his explicit organisation of documents (bookmarks and files respectively) using tags (bookmarking keywords and archiving features respectively). In this work we consider ontologies to build the user model (viewpoint focus) from the semantic tags extracted from the user generated textual content. Instead of deriving exclusive user models for each user, here, we project the user on the domain knowledge represented by ontologies.

The work in [153] uses concept lattices as user profiles to provide context-aware recommendations (product purchase based on context provided by services). The recommender engine utilises the lattice implications (rules). Although an ontology is used to deduce a query when the query parameters are obscure, the user profile construction mechanism does not consider the ontology to build the user profile. Rules for the recommender engine are derived then not based on the domain knowledge, instead, the comparison with the services is based on the similarity with individual user models. Ontologies could be used to describe the domain (e.g. as used for query deduction the context example ontology, or a ontology for the web services) and align the user models with the application context. In this work, we use the ontology space both for user viewpoint focus construction and analysis.

In the area of personalised web recommendations the authors in [154] exploited FCA to model web browsing sessions (web usage) to aid users in to access related web pages. The web pages are related based on sessions logs to build the web usage context and consequently the web usage lattice, from where association access rules can be derived based on the lattice implications. The authors did not consider other metrics for web page relatedness to build the web usage lattice. A potential approach related to this PhD could be to utilise ontologies to describe domain knowledge for the browsing sessions and related web pages in the web usage context (apart from session timeout thresholds for web page classification used in [154]). A user could then be described by the ontology overlay (entities related to the web pages he visited), and the association rules derived from the web usage lattice could be based on the ontology.

6.3.3 Mathematical Foundations of FCA

Formal Concept Analysis (FCA) was presented by Rudolf Wille in 1982 [146] as a method for data analysis, knowledge and information representation to "*support the rational communication of humans by mathematically developing appropriate conceptual structures"[145]*. These structures can be "*logically activated*" and modelled then to inform further analysis and understanding of the domain of analysis. FCA is based on three main notions: formal context, formal concept and formal concept lattice [142]. An example is used to illustrate each notion.

Formal Context. The basic notion of FCA is a formal context $\mathbb{K}$ represented by a triple $\langle G, M, I \rangle$. G is a set of objects, M is a set of attributes and I is a binary relation $I \subseteq G \times M$. For a formal object $g \in G$ and formal attribute $m \in M$, $(g, m) \in I$ is read : the object g has the attribute m. An example formal context is presented in Table 6.2 with a cross-table of objects and attributes assigned to objects via the binary relation I.

The notion of Formal Context can be used to support the first two steps of the focus extraction framework (Data Selection and Semantic Distance) by producing different formal contexts for different data partitions. A formal context can be constructed by relating ontology entities in I based on the semantic distance between them.

Table 6.2 An example Formal Context for a set of objects G and attributes M. "x" indicates that an object has an attribute (relation I)

Set of objects G		Set of attributes M					
		m1	m2	m3	m4	m5	m6
	g1	x		x	x		
	g2		x	x		x	
	g3	x	x		x	x	x
	g4	x		x		x	
	g5		x		x		x

Formal Concept. Given a formal context $\mathbb{K} = \langle G, M, I \rangle$, let $A \subseteq G$ and $B \subseteq M$. The pair (A, B) is called a formal concept $iff\ A = B' and\ B = A'$. A' is the set of attributes applying to all the objects belonging to $B, i.e.\ A' = \{m \in M | (g, m)\ \forall g \in A\}$, and B' is the set of objects having all the attributes belonging to $A, i.e.\ B' = \{g \in G | (g, m)\ \forall m \in B\}$. A and B represent the *extent* and the *intent* of the formal concept respectively. An example Formal concept given the Context in Table 6.2 is $(A, B) = (\{g3, g4\}, \{m1, m5\})$. The concept objects $g3, g4$ are conceptually clustered based on two shared attributes $m1, m5$.

Having objects and attributes ontology entities in the semantic map, and the semantic distance function, a Formal Concept can then represent a cluster of closely related ontology entities. Together with the cardinality requirement, the Formal Concept notion can be used to support Clustering (see Figure 6.1). Preserving the ontology hierarchy, Aggregation can also be supported given the ontology entity clusters. The hierarchy relations in the ontology connect ontology entities to each other in the ontology graph. Entities which are present in the path between two annotated entities can be aggregated in the cluster. The composition of clusters is supported with the notion of Formal Concept Lattice and is presented next.

(Formal) Concept Lattice. Given a formal context $\mathbb{K} = \langle G, M, I \rangle$, let (A_1, B_1) and (A_2, B_2) be two formal concepts of $\mathbb{K}$. If $A_1 \subseteq A_2$ and $B_2 \subseteq B_1$ then (A_1, B_1) is a sub-concept of (A_2, B_2). This inheritance relation is defined as $(A_1, B_1) \leq (A_2, B_2)$. For all the formal concepts in $\mathbb{K}$ denoted as $L(G, M, I)$(for short $L(\mathbb{K})$), $\underline{\mathfrak{B}}$ $(\mathbb{K})$ $= (L(G, M, I), \leq)$ is a complete lattice, called concept lattice. The Formal Concept Lattice for the Formal Context in Table 6.2 is depicted in Figure 6.5. A concept lattice (called lattice hereafter) is a complete lattice which has a supremum (concept with the most objects, top concept) and an infimum (concept with the most attributes, bottom concept). The conceptual hierarchy in the lattice is a direct effect of a central notion in FCA: the duality of extend and intend, also called "*Galois Connection*"[147] of concepts given the Formal Context. With a Galois connection, fewer attributes will result in more objects in the Formal Concept and vice versa. For example, for a set of documents as objects linked to keywords as attributes, the more documents a formal concept includes, the fewer keywords they share.

The inheritance relationship between Formal Concepts in the lattice, can be used to illustrate and support the composition of clusters as well as the different cardinalities and consequently the aforementioned requirements for Aggregation. The lattice structure as a whole can then be used to represent the Viewpoint Focus space, while the comparison of lattices given the semantic space can then be gathered as comparing different viewpoint focus.

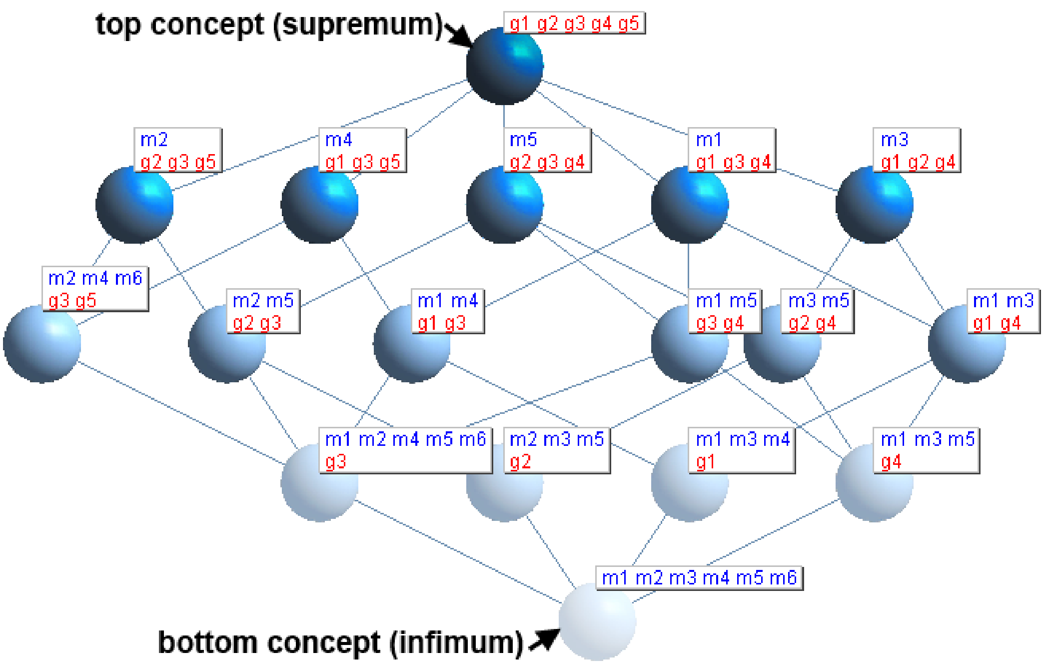


Figure 6.5 The Formal Concept Lattice[40] extracted from the Formal Context in Table 6.2.

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[40] The lattice structure was visualised using the Lattice Miner Software v1.4 available from: http://sourceforge.net/projects/lattice-miner/

The nodes represent the Formal Concepts and the edges the inheritance (order) relation: from bottom to top each Formal Concept has at least one super-concepts. The top most Formal concept represents the supremum (concept with the most objects) and the bottom most the infimum (concept with the most attributes).

6.3.4 Adaptation of FCA for Viewpoint Focus Modelling

Formal Context ≡ Formal Viewpoint Context. The formal viewpoint context $\mathbb{V}$ is a triple $\mathbb{V} = \langle C, C, I_{d,\theta} \rangle$ where $C \subseteq \Omega$ is a set of objects and attributes represented by the ontological entities. The binary relation $I_{d,\theta}$ attributes an ontology entity c_2 to an ontology entity c_1 using a semantic distance function d with the condition $d(c_1, c_2) \leq \theta$ over Ω (for each ontological space $\omega \in \Omega$) and θ is a threshold. The distance is calculated for every pair of annotated entities (the implementation of the semantic distance function is given in Section 6.4).

Formal Concept ≡ Viewpoint Focus Element. The objects A of a formal concept comprise ontology entities that share common attributes in B, i.e. are close in distance with respect to their commonly attributed entities though $I_{d,\theta}$, thus forming a cluster of annotated ontology entities.

Viewpoint Focus Element. Given a formal viewpoint context $\mathbb{V} = \langle C, C, I_{d,\theta} \rangle$, let $A, B \subseteq C$ and $v = (A, B)$ a formal concept of $\mathbb{V}, v \in L(\mathbb{V})$. A viewpoint focus element f is a sub-tree of the ontology hierarchy representing the result of the aggregation of all the possible paths between the objects-entities A. The focus element is defined as $f = (A, (\sqsubseteq, isa))$. B, i.e. the concept attributes, comprise features based on which the concept objects are clustered.

Concept Lattice ≡ Viewpoint Focus Lattice. $\underline{\mathfrak{B}}$ $(\mathbb{V})$ $= (L(\mathbb{V}), \leq)$ is a viewpoint focus lattice denoting super and sub-element relationships between viewpoint focus elements. A focus lattice is constructed for every ontology branch b of every ontology ω in Ω. These lattices represent the <u>viewpoint focus</u> F in the user viewpoint $\mathrm{V_U} = \langle \mathrm{U, O, S, \Omega, C, F} \rangle$.

6.4 Algorithms for Viewpoint Focus Construction

Overview. Following the formal model presented in Section 6.3, this section presents the algorithm for viewpoint focus construction (Figure 6.6). It is based on the following conventions:

- Viewpoint Focus is calculated for each ontology $\omega \in \Omega$.
- Viewpoint Focus is calculated for each ontology branch determined by the `owl:Thing` node (see also p4).

- The Viewpoint Context is constructed using the annotated ontology entities as both objects and attributes.
- An ontology entity is related to another ontology entity in the Viewpoint Context with a semantic distance function caped with an accorded threshold value. For this work only the subsumption (`rdfs:subClassOf`) and membership (`rdf:type`) relationships in the ontologies $\omega \in \Omega$ have been considered. A shortest path algorithm presented in Figure 6.7 has been implemented (adapted from[144]) based on two conventions: (a) the distance between an instance node and its parent (`rdf:type`) is zero, and (b) the distance between two ontology entities is infinity when the path that connects them via the subsumption or membership relationships includes the `owl:Thing` node. Note that the semantic paths for each pair of annotated ontology entities are used to extract the aggregates in the semantic spaces (see Section 6.5.2).
- The semantic distance value is capped with an accorded threshold θ in order to populate the Viewpoint Context with respect to the assigning binary function $I_{d,\Theta}$. This threshold can be manually accorded by the experimenter. Lower threshold results in smaller but more focus elements in the viewpoint focus, while, reversely, higher threshold to larger but fewer focus elements. Section 6.8 discusses how the distance threshold could also be decided based on ontology hierarchy including the depth and breadth of the tree. A conventional approach which includes calculation based on the weighted average of distances between the ontology entities is also discussed.

After populating the viewpoint context, in order to calculate the lattice structure, the Colibri- Java FCA [155][41] library has been utilised. The lattice calculation algorithm follows a bottom-up approach. Colibri was selected because it is open-source - allows examination of the implementation, it is intuitive – generalises programming objects and classes, and it was designed to achieve high performance – implemented with iterators on bit-sets (low level programming implementation). First the lattice includes only one concept, the bottom concept which contains all the attributes (intent) and (usually) no objects (extend). Then the upper neighbours of the concept are calculated recursively for each concept and the new concepts are

[41] Colibri-Java was implemented by Daniel Götzmann as part of his Bachelor Thesis and is freely available at: http://code.google.com/p/colibri-java/

added together with the hierarchy relationship (edges) in the lattice. The algorithm used is presented in [156].

$F = \boldsymbol{calculate\_F}(\Omega, C, \theta)$;

$\boldsymbol{calculate\_F}(\Omega, C, \theta)$:

  $\boldsymbol{foreach}\ \omega \in \Omega$:

    $F_\omega = \boldsymbol{calculate\_F_\omega}(\omega,\ C,\ \theta)$;

    $F = F \cup F_\omega$;

  $\boldsymbol{return}\ F$;

$\boldsymbol{calculate\_F_\omega}(\omega, C, \theta)$:

  $\boldsymbol{foreach}\ \{b \mid b \subseteq \omega, b\ an\ ontology\ branch\}$:

    $F_b = \boldsymbol{calculate\_F_b}(b,\ C,\ \theta)$;

    $F_\omega = F_\omega \cup F_b$;

  $\boldsymbol{return}\ F_\omega$;

$\boldsymbol{calculate\_F_b}(b, C, \theta)$:

  $\mathbb{V}_b = \boldsymbol{build\_viewpoint\_context}(b,\ C,\ \theta)$;

  $\underline{\mathfrak{B}}\ (\mathbb{V}_b) = \boldsymbol{run\_FCA}(\mathbb{V}_b)$//see note 32

  $\boldsymbol{return}\ \mathfrak{B}\ (\mathbb{V}_b)$;

$\boldsymbol{build\_viewpoint\_context}(b, C, \theta)$:

  $C_G = C_M = \{c \mid c \in b \cap C\}$;

  $I = \emptyset$;

  $\boldsymbol{foreach}\ c_1 \in C_G,\ \ c_2 \in C_M$:

    $\langle path, distance\rangle = \boldsymbol{calculate\_path}(c_1,\ c_2,\ b)$;

    $value = 0$;

    $\boldsymbol{if} distance \leq \theta\ \boldsymbol{then}: value = 1$;

    $I = I \cup \{\langle value,\ path\rangle\}$;

  $\boldsymbol{return}\ \langle C_G,\ C_M,\ I\rangle$;

Figure 6.6 The algorithm in pseudo-code to extract the Viewpoint Focus using ontologies and FCA.

$b \subseteq \omega, b\ an\ ontology\ branch$

$c_1 \in b, c_2 \in b, ontology\ entities$

$p = \boldsymbol{calculate\_path}(c_1, c_2, b);$

$\boldsymbol{calculate\_path}(c_1, c_2, b)$:

$\boldsymbol{if}\ \ (c_1\ \boldsymbol{equals}\ c_2)$:

$\boldsymbol{then}: \boldsymbol{return}\ \langle\{c_1\}, 0\rangle;$

$\boldsymbol{else\ if}\ (c_1\ \boldsymbol{isa}\ c_2)\ \boldsymbol{or}\ (c_2\ \boldsymbol{isa}\ c_1)$:

$\boldsymbol{then}: \boldsymbol{return}\ \langle\{c_1, c_2\}, 0\rangle;$

$\boldsymbol{else}$:

$p_1 = \boldsymbol{getPathToOWLThing}(c_1, b, \emptyset);$

$p_2 = \boldsymbol{getPathToOWLThing}(c_2, b, \emptyset);$

$p_0 = \ (p_1 \cap p_2);$

$P = (p_1 - p_0) \cup (p_2 - p_0) \cup p_0(0);$

$\boldsymbol{return}\ \langle P, |P| - 1 - \boldsymbol{InstanceCounter}(P)\rangle;$

$\boldsymbol{InstanceCounter}(P)$:

$counter = 0;$

$\boldsymbol{foreach}\ c \in P$:

$\boldsymbol{if}\ c\ \boldsymbol{hasType}\ Instance$:

$\boldsymbol{then}: counter = counter + 1;$

$\boldsymbol{return}\ counter;$

$\boldsymbol{getPathToOWLThing}(c, b, p)$:

$\boldsymbol{if}\ c\ \boldsymbol{equals}\ owl{:}Thing$:

$\boldsymbol{then}: \boldsymbol{return}\ p \cup c;$

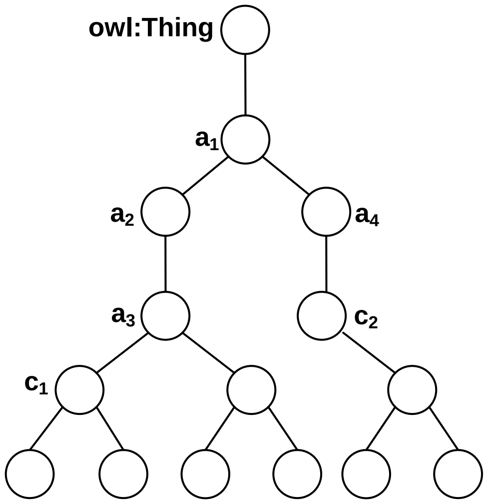
$\boldsymbol{else}$:

$p = p \cup c;$

$\boldsymbol{return}\ \boldsymbol{getPathToOWLThing}(\boldsymbol{getParent}(c), b, p);$

Figure 6.7 A shortest path algorithm to calculate the path between two ontology entities in an ontology branch[144]. $p_0(0)$ denotes the first common parent in the ontology hierarchy.

The path is constructed with ontology entities. Its cardinality indicates the semantic distance based on the hierarchy and membership relationships in the ontology, by subtracting 1 to calculate the connecting edges (relations) and the number of instance ontology entities in the path. Figure 6.8, presents an example for two ontology classes.



$$p_1 = \{c_1, a_3, a_2, a_1, owl{:}Thing\}$$

$$p_2 = \{c_2, a_4, a_1, owl{:}Thing\}$$

$$p_0 = \{a_1, owl{:}Thing\}$$

$$P(c_1, c_2,) = \{c_1, a_3, a_2, a_1, a_4, c_2\}$$

$$distance(P) = 5$$

Figure 6.8 An example path calculation and distance for two (class) ontology entities c_1 and c_2.

6.5 Implementation: ViewS Microscope

6.5.1 ViewS Microscope Architecture

The algorithms presented in Section 6.4 have been implemented in a tool called ViewS Microscope[42] in Java. ViewS Microscope enables visualisation of the ontologies and the annotated ontology entities in the user generated content, construction, visualisation and navigation of the viewpoint focus (lattice), as well as the visualisation of the focus regions on the ontologies. Figure 6.9 depicts the three-layered architecture of ViewS Microscope. ViewS Microscope is demonstrated with an example in the next Seciton.

[42] http://imash.leeds.ac.uk/services/ViewS/

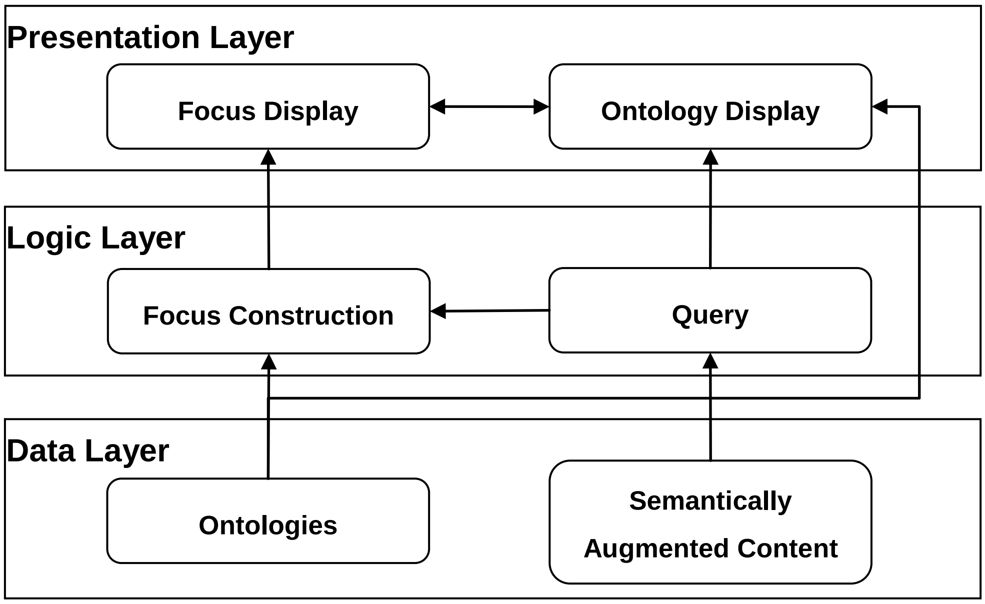


Figure 6.9 Architecture of ViewS Microscope

The data layer includes modules for loading ontologies (off and on-line in OWL/RDF format) and semantically augmented (with ViewS Semantic Augmentation) user generated content. The content is in XML format and includes information about the digital object, the user statements and the associated semantic annotations (see Appendix A.3.2 for the XML Schema Definition).

The logic layer includes modules for querying the content to select different digital objects and users based on their profile (age, gender and location) as well as the implementation of the algorithms for the viewpoint focus construction using the selected ontologies and semantically augmented content as input. The user can also define the semantic distance threshold to be applied for the clustering in the viewpoint context.

The presentation layer includes interactive visualisation modules (displays) for the ontologies and the viewpoint focus lattice. The user can map the semantic annotations on the ontologies and explore the user statements associated with each ontology entity. Using the viewpoint focus display, the user can visualise the focus regions (clusters and aggregates) by selecting different focus elements on the lattice structure and also explore the related ontology entities. The visualisation module has been implemented using the Prefuse visualisation toolkit[43]. The Prefuse classes have been extended to

[43] Prefuse: Open Source Information Visualisation Toolkit, available at: http://prefuse.org/

customise structures (e.g. ontology hierarchy graphs), layouts (e.g. lattice), decorators (e.g. coloring effects) and interactions (e.g. user clicks).

6.5.2 Example Viewpoint Focus Construction and Processing

Let:

- $C = \{anger, anticipation, diffidence, dislike, distance,$
  $easiness, fit, fury, identification, preference, regard,$
  $self - consciousness, shyness, timidity, wrath\}$

be a set of annotated ontology entities with ViewS Semantic Augmentation, and

- $\Omega = \{WNAffect\}$ the ontology space.

For simplicity of the example, only one dimension is considered –emotion-, represented by the WNAffect taxonomy. The semantic map of the annotation set for an ontology branch "*mental-state*" is shown below (Figure 6.10).

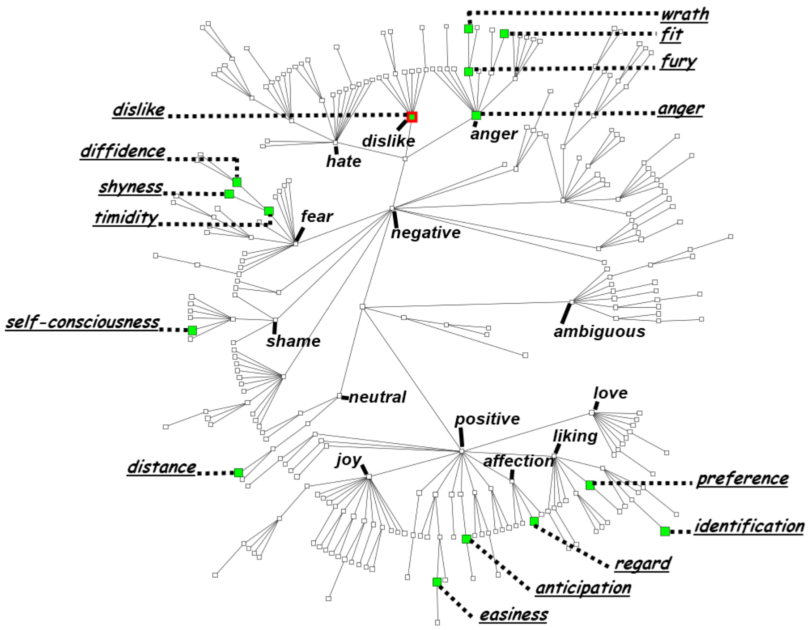


Figure 6.10 Example semantic map of the mental-state branch in the WNAffect taxonomy of emotions.

The annotation set (green highlighted nodes) comprises 15 ontology entities.

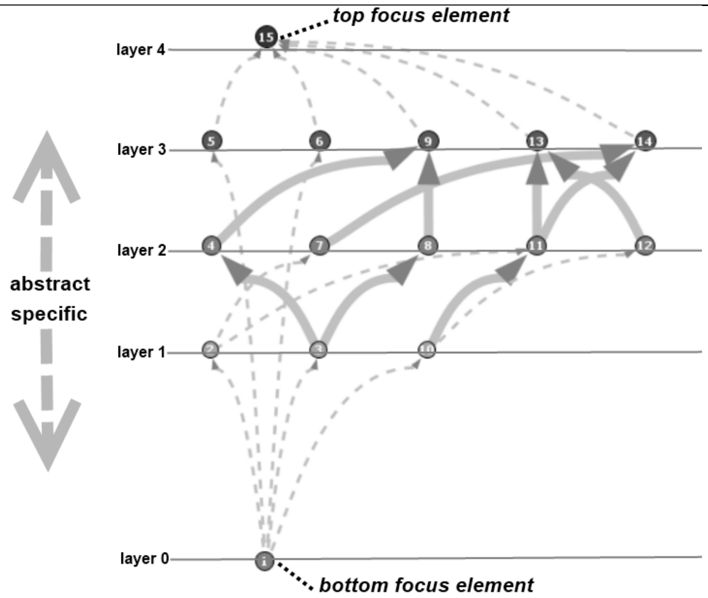
An example threshold for the semantic distance between ontology entity connecting paths is set to 4 (edges). Following the algorithm presented in Section 6.4 to construct the Viewpoint Focus using ontologies and FCA , one Viewpoint Context is constructed per ontology branch. The viewpoint context for this example is shown in Table 6.3.

Table 6.3 The Viewpoint Context which emanated from the semantic map in Figure 6.10 by setting the semantic distance threshold to 4.

objects	attributes: anger	anticipation	diffidence	dislike	distance	easiness	fit	fury	identification	preference	regard	self-consciousness	shyness	timidity	wrath
anger	x			x			x	x						x	x
anticipation		x								x	x				
diffidence			x										x	x	
dislike	x			x			x	x						x	x
distance					x										
easiness						x									
fit	x			x			x	x							x
fury	x			x			x	x							x
identification									x	x					
preference		x							x	x	x				
regard		x								x	x				
self-consciousness												x			
shyness			x										x	x	
timidity	x		x	x									x	x	
wrath	x			x			x	x							x

The input viewpoint context in Table 6.3 results in a viewpoint focus that is depicted by the lattice in Figure 6.11. The lattice can be described using the FCA properties (layers, hierarchy and concepts) presented in Section 6.3. ViewS Microscope supports these properties using respective visualisation.

Top and Bottom Focus Elements. The lattice has a top and bottom focus element concepts, each one representing a holistic view. The top focus element has all the ontology entities as objects, which for the bottom focus element appear as attributes based on the inheritance relationship in the lattice and the Galois connections (see Section 6.3).

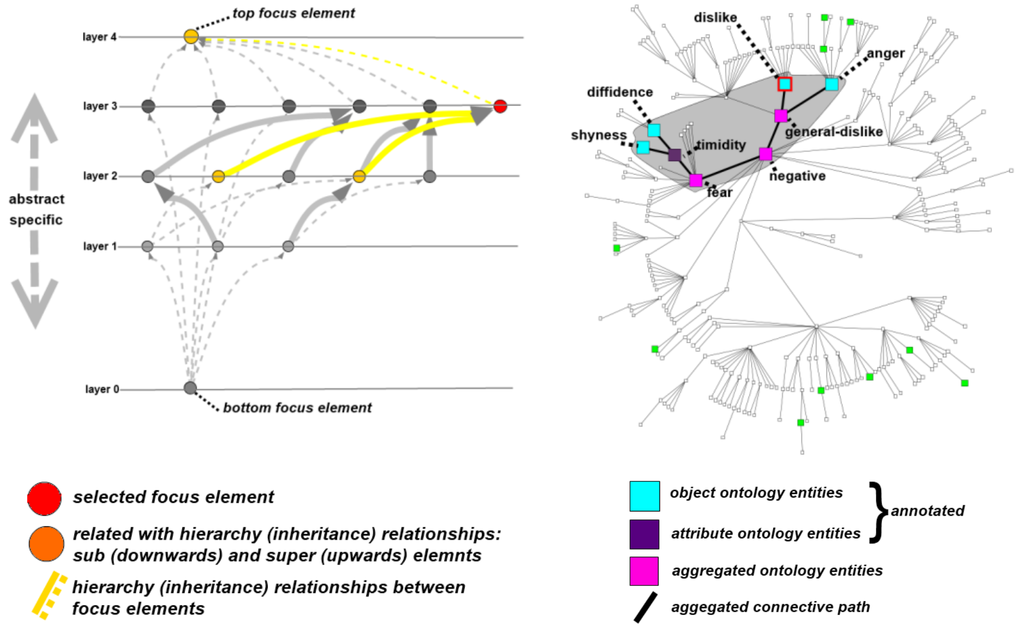


Element	Objects	Attributes
1	-	all
2	timidity	anger, diffidence, dislike, shyness, timidity
3	preference	anticipation, identification, preference
4	identification, preference	identification, preference
5	easiness	easiness
6	distance	distance
7	diffidence, shyness, timidity	diffidence, shyness, timidity
8	anticipation, preference	anticipation, preference
9	anticipation, identification, preference	preference
10	anger, dislike	anger, dislike, fit, fury, timidity, wrath
11	anger, dislike, timidity	anger, dislike, timidity
12	anger, dislike, fit, fury, wrath	anger, dislike, fit, fury, wrath
13	anger, dislike, fit, fury, timidity, wrath	anger, dislike
14	anger, diffidence, dislike, shyness, timidity	timidity
15	all	-

Figure 6.11 The viewpoint focus (lattice) derived from the formal context in Table 6.3.

> The lattice depicts 16 focus elements organised in 5 layers based on the hierarchy relations (edges) between them. The top (most abstract) and bottom (most specific) concepts represent a holistic view of the semantic space in the WNAffect branch.

Focus Elements. Each focus element (16 focus elements in total) in the viewpoint focus is the result of aggregation of the object ontology entities. Figure 6.12 illustrates the aggregation using a selected focus element from the lattice.



(a) (b)

Figure 6.12 Example selected focus element (a) and the corresponding aggregate (b) in the semantic map.

Hierarchy. The connections between the focus elements (nodes/ formal concepts) depict the inheritance relations in the lattice. Reading from top to bottom, a focus element is connected with its sub-elements (see Figure 6.13). Moving from top to bottom the focus elements' specificity (fewer object ontology entities) increases (reversely, the generality increases from bottom to top). This traversal depicts the decomposition of the viewpoint focus space starting from the top focus element. Reversely, reading from bottom to top, a focus elements is connected with its super-elements, allowing to explore the composition of the viewpoint focus space. The relation $\leq$ in $\mathfrak{B}(\mathbb{V})$ can be used to identify two types of implications in the concept lattice: (a) Direct Implications: In the viewpoint focus lattice the sub-concepts of the top node, as an example, can be used as direct implication factors: for two viewpoint focus elements $f_1 = (A(v_1), (\sqsubseteq, isa))$ and $f_2 = (A(v_2), (\sqsubseteq, isa))$: if $f_2 \leq f_1$ then $A_2 \rightarrow A_1$ (implies). This means that every viewpoint focus element is implied by the set of its sub-concept by having attributes a subset of the set of attributes of its sub-concepts (from above $B_1 \subseteq B_2$). Therefore, the sub-concepts of the top node can be used for querying and the implications can provide useful information regarding the construction of the viewpoint focus; (b) Indirect Implications. Indirect implication also hold in the lattice through transitivity : $f_1 = (A(v_1), (\sqsubseteq, isa))$, $f_2 = (A(v_2), (\sqsubseteq, isa))$ and $f_3 = (A(v_3), (\sqsubseteq, isa))$: if $f_3 \leq f_2 \leq f_1$ then $A_3 \rightarrow A_1$, allowing thus deeper querying to be executed.

Relation Confidence. The connections between the focus elements can be also characterised by a confidence indicator [142, 157]: the ratio of the number of object ontology entities of a focus element over the number of object ontology entities of its super-element. ViewS illustrates this characteristic using dotted-stroke edges for confidence levels below 0.5 and thickened else. Figure 6.14 illustrates this characteristic with three focus elements that contain only a single ontology entity (indeed, observing the semantic map in Figure 6.10, these three entities appear disconnected).

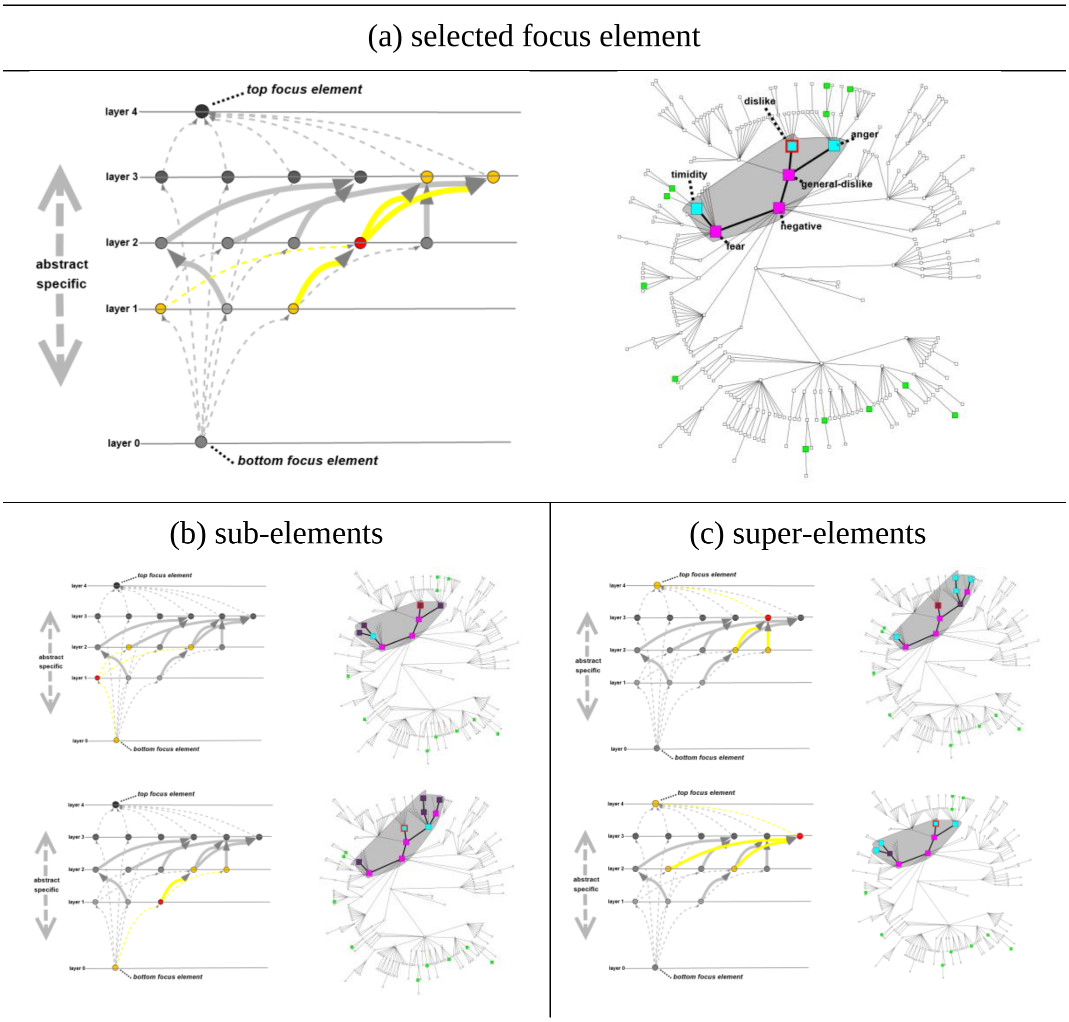


Figure 6.13 A focus element (a) can have sub-elements (b) and super-elements(c).

These relations show its decomposition (b) to more specific elements (fewer object attributes) and its composition (c) by more abstract elements (more object ontology entities) based on the implications between the corresponding attributed ontology entities.

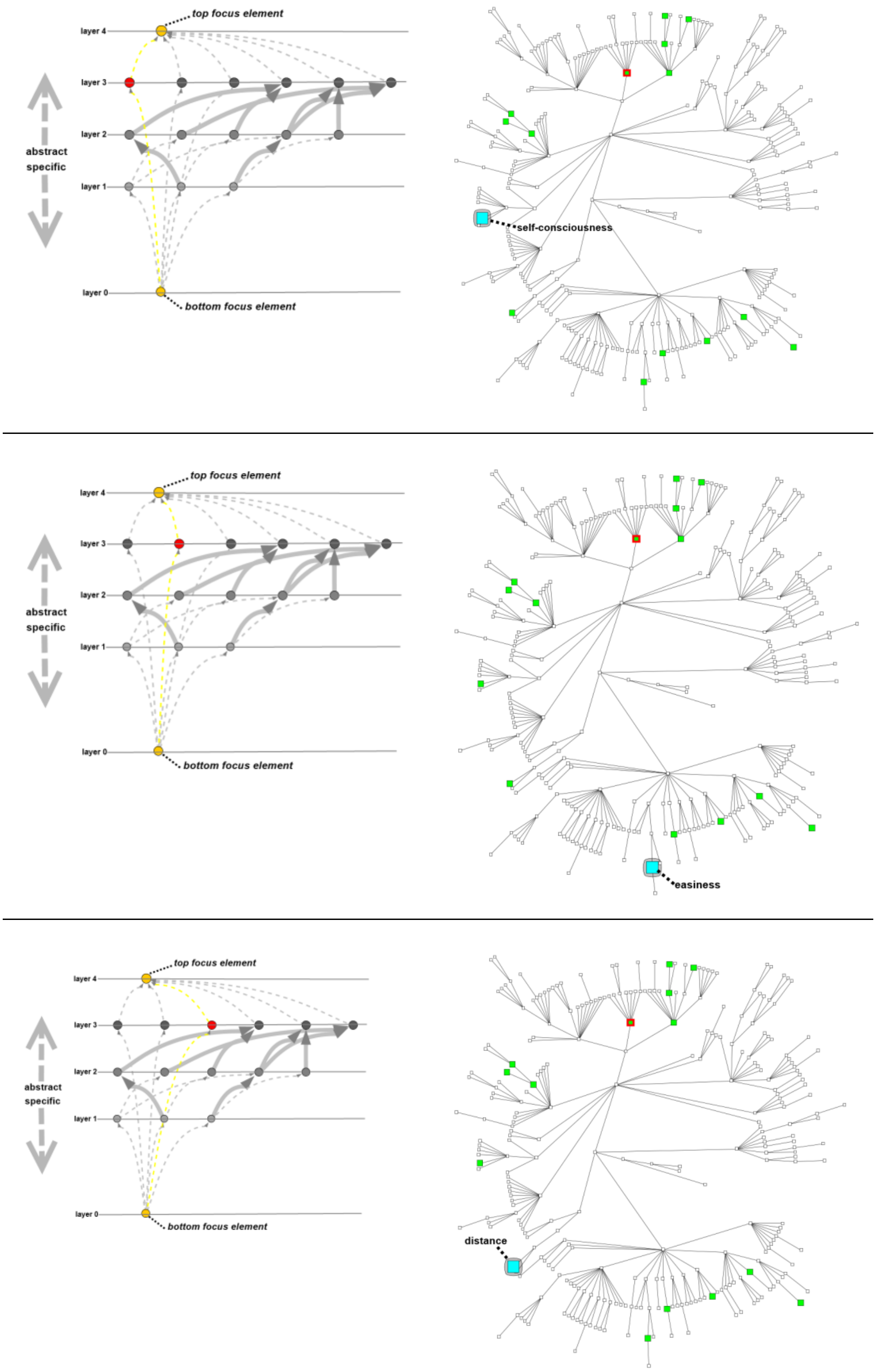


Figure 6.14 Focus elements connected with their sub and super-elements with low confidence relations (depicted with dotted-stroke edges).

Such elements comprise low cardinality aggregates in the semantic map, which consequently indicate outliers in the viewpoint focus.

Attribute Exploration. Implications, hierarchy and layers can be used for conceptual knowledge construction that can be reflected in querying and understanding the user's viewpoint focus [142]. Given a viewpoint focus (lattice), one, given the set of annotated ontology entities, can query the model to explore:

> *which are the focus elements in the semantic space that include the central ontology entities c_1 and c_2?*

In the FCA framework this query can be illustrated with two questions:

(a) *which objects have the attributes a_1 and a_2?*

This functionality is called *conjunction* of formal concepts or *meet*: finding the concepts from the top with the specific attributes and follow the edges downwards to where they meet.

(b) *which attributes are shared by objects o_1 and o_2?*

This functionality is called *disjunction* of formal concepts or *join*: find the concepts from the bottom with the specific objects and follow the lines upwards to where they join.

The maximum points (formal concepts) of meet and join are the bottom and top formal concepts respectively. As the bottom and top concepts comprise all attributes and objects respectively, it is not sensible to include them in the result set of formal concepts.

In ViewS, as both objects and attributes comprise ontology entities, the aforementioned queries are identical in their intention to derive focus elements and can be answered by either exploring focus elements from top to bottom looking at the attribute entities, or reversely, from bottom to top by looking at the object entities. An example is shown in Figure 6.15 for the entities *anger* and *timidity.* For the example, the bottom to top path is followed.

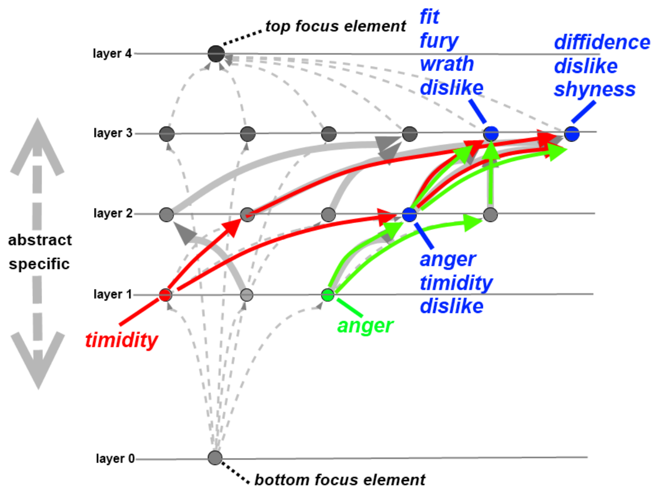
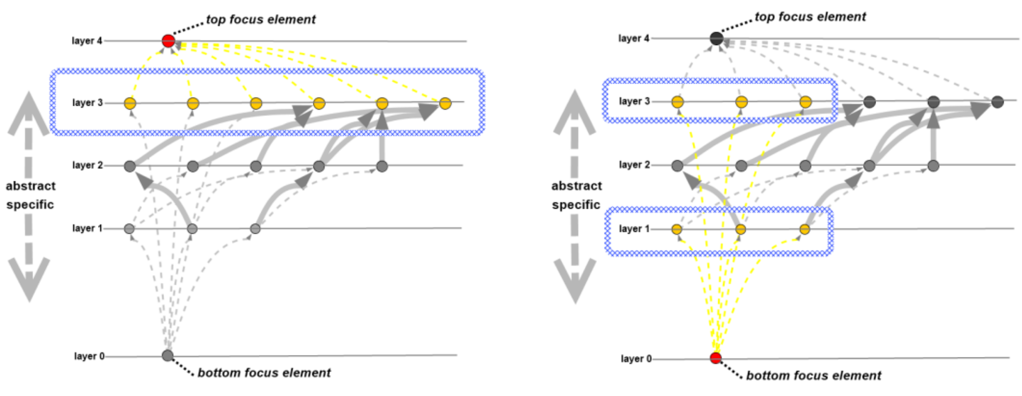


Figure 6.15 An example query for focus elements (blue), given specific central entities (timidity and anger, in red and green respectively).

Similarly the query can be resolved from top to bottom: the semantic space and the duality of the lattice will result to the same focus elements as the viewpoint context comprises ontology entities both as objects and attributes.

The presented viewpoint focus modelling framework allows for automatic representation of the semantic annotation set, based on the input ontologies. ViewS enables explicit structures to be extracted and also intelligent processing to explore the viewpoint focus space.

Main Focus Elements. The main focus elements (denoted hereafter as $main(F_b)$ for the focus lattice F of an ontology branch $b \subseteq \omega$) can be examined by either selecting consecutively focus elements form the second top or the second bottom layer of the lattice (see Figure 6.16, note that one element can belong to more than one layers depending on the its hierarchy relationships). Ontology entities will appear either as objects or attributes. The aforementioned layers also provide information about the central ontology entities - the entities based on which a clustered is formed, for each focus element (see Figure 6.17): for the second top layer, one should examine the attribute elements of the focus element, wile, reversely, for the second bottom layer the object ontology entities respectively. Layers below and up to the middle layer allow then for examination of the composition of the main focus elements. The middle layers therefore comprise focus elements with identical object and corresponding attribute entities.



(a) (b)

Figure 6.16 Main focus elements can be extracted from (a) the second top or (b) bottom layers. The middle layer(s) can then be used to explore the (de)composition of focus elements.

Note that a focus element can belong to more than one layers in the viewpoint focus lattice.

(a)

(b)

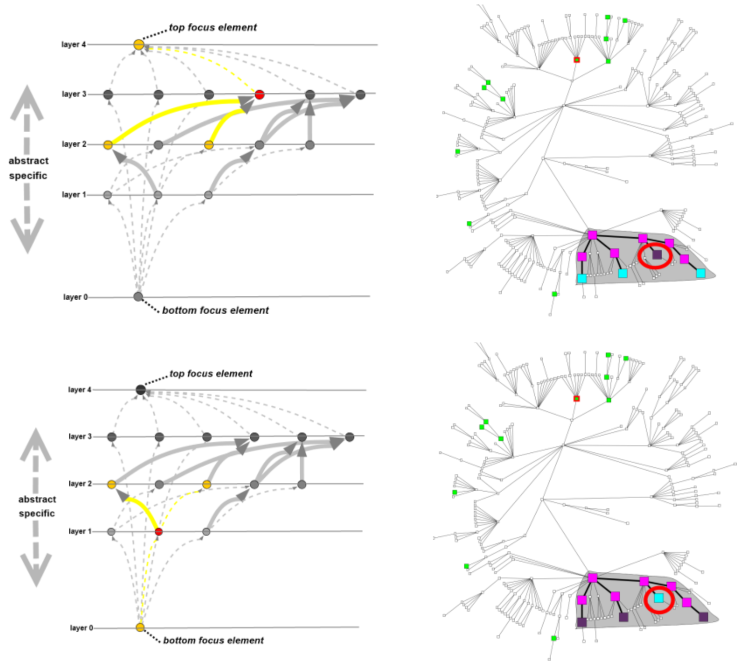


Figure 6.17 The second (a) top or (b) bottom layers can be used to examine the central ontology entities in each focus element.

From the two layers, similar focus elements are extracted in the FCA lattice, one having the objects as attributes from the other and vice versa. The middle layers can be used to explore the (de)composition of focus elements based on their hierarchy relationships.

The main focus elements play also a crucial role for the comparison of viewpoint focus models. Although quantitative and partially qualitative insight can be gained by observing the structural characteristics of two focus models (e.g. number of focus elements, number of main focus elements, number of layers), comparing the main focus elements in the semantic maps allows for more qualitative observations to be made. The next Section presents the metrics with which viewpoint focus model comparisons are enabled with ViewS.

6.6 Comparison of Viewpoint Focus Models

The lattice structures reveal differences between the focus models which can be further explored (structural comparison). More detailed comparison of the focus models is enabled with ViewS using the semantic aggregates and particularly the main focus elements (second top layer) of the models (regional comparison). The comparison can inform about where and how the viewpoint focus models differ with respect to the conceptual knowledge represented by the ontology branches.

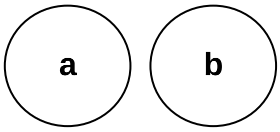
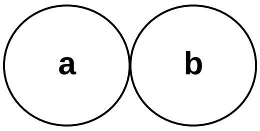
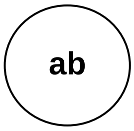
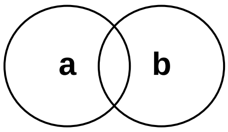
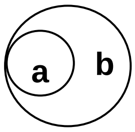
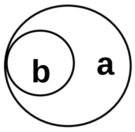
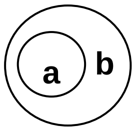
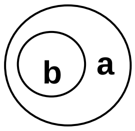
The set operations between clusters and aggregates can then result in this sense into spatial relations on the ontology graph between regions. Region Connection Calculus (RCC) has been adopted and adapted in this work to represent relations between ontology entity aggregates (focus elements) in order to enable qualitative comparison of viewpoint focus models.

A focus element is used in the same sense as a region in the (conceptual) space formed by the ontology hierarchy, for which primitive elements consist the ontology entities.

6.6.1 Outline of RCC

RCC originated in 1992 by Randell, Cui and Cohn [158], resulting to a set of 5 RC relations (known as RCC-5) and revisited in [159] to include more spatial relations (RCC-8). Table 6.4 depicts the 8 RC relations in RCC8 [159] including: *DC*(disconnection), *EC*(external connection), *EQ*(equality), *PO*(partial overlap), TPP(tangential proper part and its inverse) and *NTTP* (non-tangential proper part and its inverse).

Table 6.4 The 8 RCC basic relations and the corresponding visual topological interpretation.

RC Relation in RCC-8	Topological Interpretation
$DC(a, b)$: *disconnected*	
$EC(a, b)$: *externally − connected*	
$EQ(a, b)$: *equal*	
$PO(a, b)$: *partial overlap*	
$TPP(a, b)$: *tangential proper part*	
$TPP^{-1}(a, b)$: *inverse TPP*	
$NTPP(a, b)$: *non − tangential proper part*	
$NTPP^{-1}(a, b)$: *inverse NTPP*	

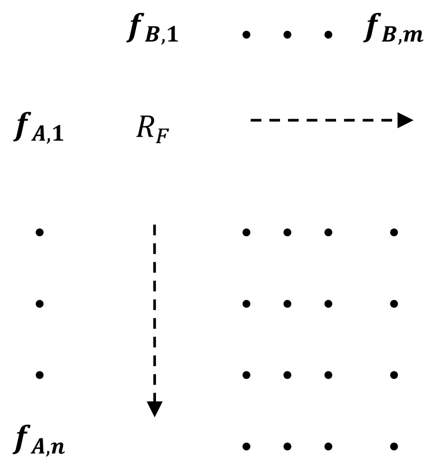
6.6.2 Adaptation of RCC to Compare Viewpoint Focus Models

The RCC-8 connection relations have been adapted in Views to represent a simplified set of 5 qualitative relations (denoted with R_F) between focus elements (see Table 6.5): *equal* (identical to *RCC-EQ*), *disconnected* (identical to *RCC-DC*), *included* (merging RCC-*TPP* and *RCC-NTTP*), *includes* (merging RCC-TPP^{-1} and *RCC-*$NTTP^{-1}$) and *overlap*(merging *RCC-PO* and *RCC-EC*).

Table 6.5 Adaptation of RCC-8 spatial relations to compare viewpoint focus elements f from viewpoint focus models F with respect to an ontology branch $b \in \omega$.

Viewpoint Focus Element Relations $\boldsymbol{f_A \in F_{A,b}, f_B \in F_{B,b},}$ $\boldsymbol{b \in \omega: an\ ontology\ branch}$	**Corresponding RCC-8 Relations**
$equal(\boldsymbol{f_A}, \boldsymbol{f_B})$	$EQ(a,b)$
$disconnected(\boldsymbol{f_A}, \boldsymbol{f_B})$	$DC(a,b)$
$included(\boldsymbol{f_A}, \boldsymbol{f_B})$	$TPP(a,b)\ or\ NTPP(a,b)$
$includes(\boldsymbol{f_A}, \boldsymbol{f_B})$	$TPP^{-1}(a,b)\ or\ NTPP^{-1}(a,b)$
$overlap(\boldsymbol{f_A}, \boldsymbol{f_B})$	$PO(a,b)$

Given the main focus elements $main(\boldsymbol{F_{A,b}})$ and $main(\boldsymbol{F_{B,b}})$ of two viewpoint focus models F with respect to the same ontology branch b of an ontology ω, a cross-table can be constructed that allows for exploration of the qualitative relations between the focus models.



$$f_A \in main(\boldsymbol{F_{A,b}}), n = |main(F_A)|$$

$$f_B \in main(\boldsymbol{F_{B,b}}), m = |main(F_B)|$$

ViewS Microscope has been extended to compare the regions of viewpoint focus. The illustrations in the example below are from this extension.

6.6.3 Example Viewpoint Focus Models Comparison

The modelling properties inherited from FCA over the ontologies provide quantitative (structural) and qualitative (regional) indicators for diversity between two or more viewpoint focus models.

Let us consider two viewpoints $V_A = \langle U_A, O, S_A, \Omega, C_A, F_A \rangle$ and $V_B = \langle U_B, O, S_B, \Omega, C_B, F_B \rangle$ on a set of digital objects , where:

$$C_A = \{fit, dislike, foreboding, apprehension, cruelty, embarrassment,$$
$$self - consciousness, satisfaction, fulfillment, confidence, easiness,$$
$$anticipation, regard, approval, preferences, gravity, earnestness, daze\}$$
$$C_B = \{dislike, nausea, wrath, fury, anger, pique, daze, guilt, foreboding,$$
$$abashment, shamefacedness, embarrassment, easiness, anticipation,$$
$$regard, preference\}$$

Figure 6.18 depicts the contrastive semantic map for two sets of annotated ontology entities in the *mental state* branch of the WNAffect taxonomy from the simulator dataset.

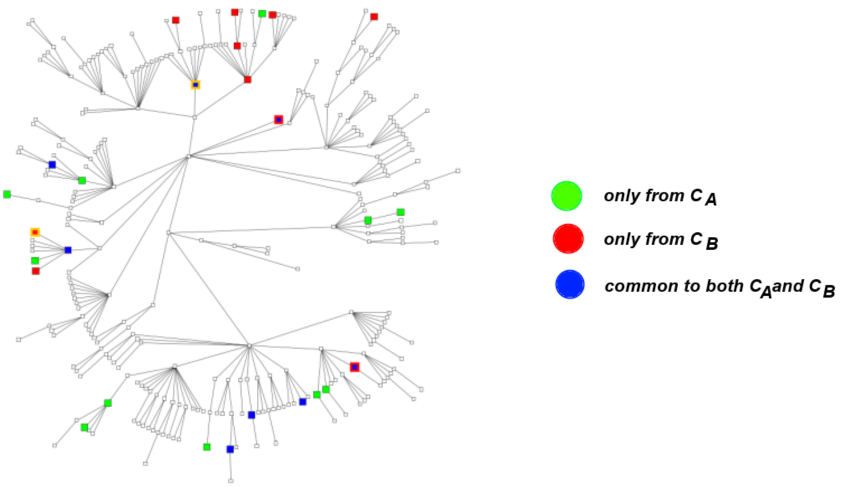


Figure 6.18 The contrastive semantic map of the annotated ontology entities sets C_A and C_B.

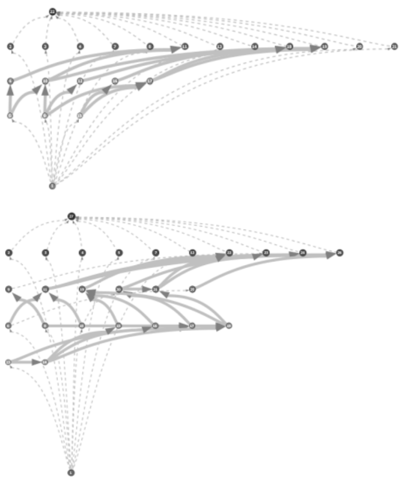
Given the two sets and using conventional set operations one can identify that:

- C_A has more entities annotated than C_B, ($|C_A| = 18, |C_B| = 16$);
- C_A has 8 common ($|C_A \cap C_B|$) entities with C_B;
- C_A has more distinct ontology entities than C_B compared to each other (differences of sets).

ViewS complements the comparison metrics by extracting, representing and comparing the viewpoint focus models from the annotation sets to identify what are the similarities and differences between the viewpoint focus.

Structural Comparison. The two viewpoint focus models for these annotation sets are depicted by the lattices in Figure 6.19 using a semantic distance threshold 3. The lattices indicate that F_A is broader than F_B as more main focus elements (see Section 6.5) are extracted (F_A:12, F_A:10). This observation does not necessarily reflect the fact that C_A includes more unique entities than C_B, as if these were aggregated together based on the distance threshold would result to fewer main focus elements. This comparison is enabled with ViewS as the focus models explicitly denote the difference. From the focus models it is also observed that F_B contains more focus elements in total than F_A, organised in more layers. This indicates that more implications exist between the focus elements in F_B, therefore closer aggregates are derived than from F_A. Although F_A appears broader, F_B seems more condensed considering the semantic space, again with respect to the application of the same distance threshold.

F_A



layers: 5, elements: 22, main elements: 12

F_B

layers: 7, elements: 27, main elements: 10

Figure 6.19 The viewpoint focus models derived from the annotated ontology entities sets.

Differences are observed in the structure characteristics. F_A appears broader than F_B, as more main focus elements are extracted. However, F_B appears more complex, as more elements occur in the lattice organised in more layers.

Regional Comparison. For the example focus models the corresponding cross-table for the comparison of the extracted main focus elements includes 120 pairs ($|main(F^A)| * |main(F^B)| = 12 * 10 = 120$), including: 3 *equal*, 2 *includes*, 12 *overlap* and 103 *disconnected*. Example illustrations of the qualitative comparison relations are shown in Figure 6.20 extracted with ViewS-Microscope. Note that in this example equality is not very helpful as it only concerns a single ontology entity in the focus elements.

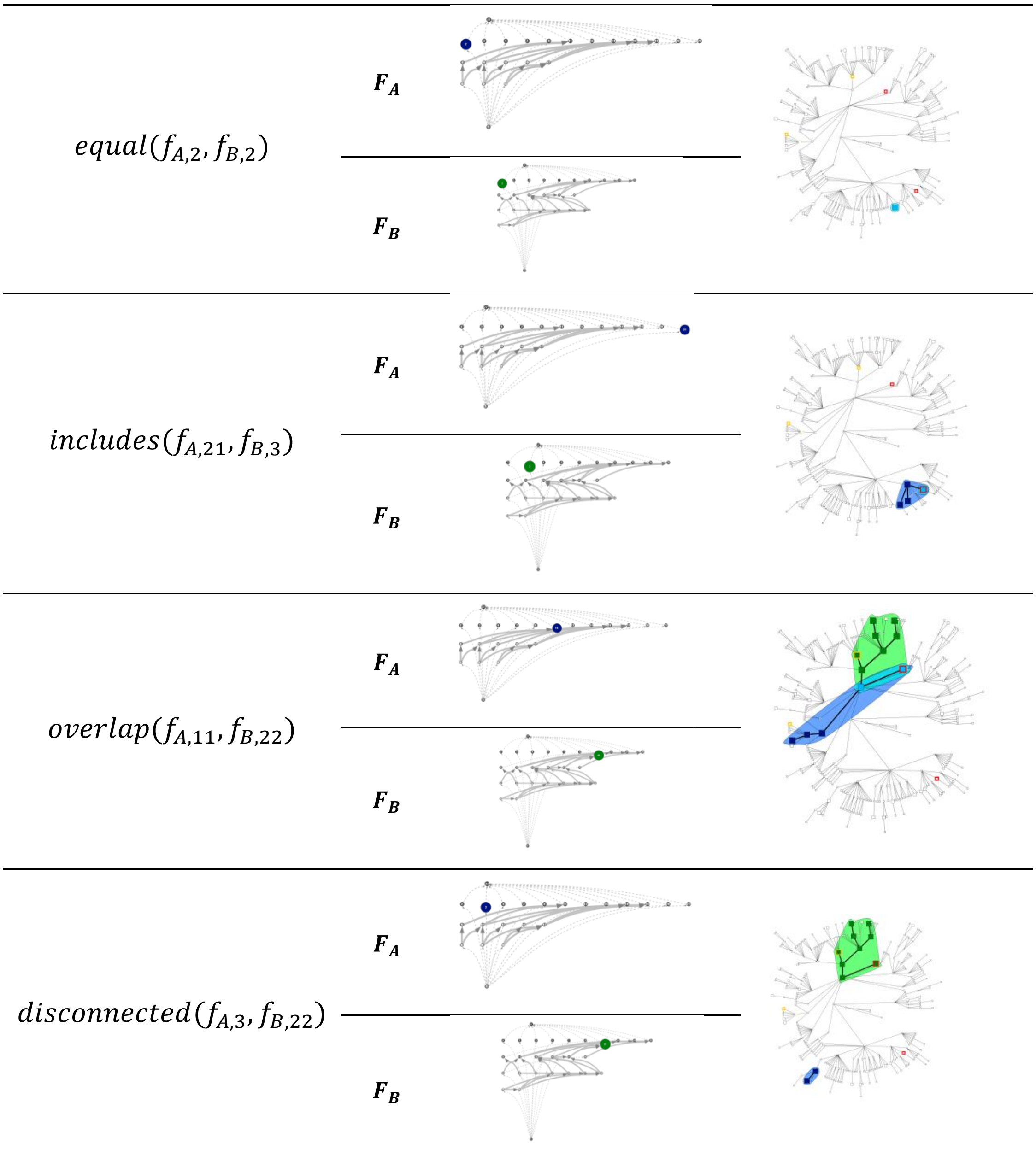


Figure 6.20 Example qualitative comparison relations for selected focus elements from two viewpoint focus models on the *mental-state* WNAffect taxonomy branch.

Using the comparison cross-table each focus element from a focus model (by row or similarly by column) can be examined across the focus elements of the other model. From such examination, conclusions can be drawn regarding which focus elements appear more equal, disconnected, inclusive, included and overlapping, as well as an overview of the similarities and differences. In the previous example, observing the contrastive semantic map (see Figure 6.18) the two viewpoint focus models appear very overlapping, especially around negative emotion. Indeed, all the 12 overlapping pairs of focus elements relate to this ontology branch (see Figure 6.21 below), between 3 main focus elements from the first model and 4 from the second respectively.

Using the ViewS viewpoint focus modelling presented in this Section, the UGC from the simulated environment can be examined by over viewing and comparing different focus models. The next Section illustrates the application of ViewS on the same content and setup used in the study with the simulator designers to validate their observations using the computational instruments of the focus modelling approach.

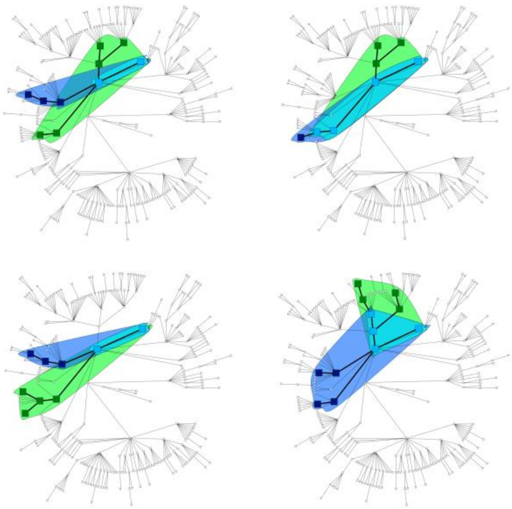


Figure 6.21 A sample of 4 pairs out of the 12 overlapping focus elements between the two focus models.

ViewS enables cross-table comparison to identify relations between focus elements and understand similarities and differences.

6.7 Discussion

In this chapter the viewpoint focus modelling with ViewS was presented. ViewS adapted the FCA computational framework using as input:

- ontologies to represent domain knowledge; and,
- semantically annotated data sets (which linked UGC to ontology entities);

and produced as output:

- semantic relations of the annotated ontology entities represented as formal contexts;
- viewpoint focus elements represented as semantic clusters and aggregates based on the derived relations; and,

- viewpoint focus models represented as formal concept (focus element) lattices for different ontology branches.

For comparison of viewpoint focus models RCC was exploited in a simplified version to include *equality*, *inclusion*, *overlap* and *disconnection*. Focus extraction and comparison were illustrated with an example. Particularly for comparison, two approaches were discussed: structural – which concerns the lattice structural characteristics, and regional – using the RCC on the main focus elements.

Using the main framework components i.e. viewpoint context (formal context), focus element(formal concept), focus model (concept lattice) and focus model comparison, several observation can be made to evaluate the underlying modelling assumptions. A reflection is following on each component of the model discussing strengths and limitations, as well as indication for future extension.

6.7.1 Viewpoint Context (Formal Context)

In order to build the viewpoint context, equality of importance was assumed in order to assigning ontology entities as objects and attributes. As all entities were used as objects and attributes, the focus model could be examined from top to middle layer and reversely from bottom to top. Although this approach supports objectivity, there exist other possible metrics on which decision can be made. Although identified, this thesis did not support and investigate further. One possible characteristic could be to separate as objects ontology entities that are most frequently annotated in the ontologies. In this scenario one can assign the importance of common entities to objects which can possible be related with other (attribute) entities less frequently annotated.

It was also depicted in the examples that in some cases the viewpoint focus models included as focus element aggregates with cardinality 1 based on the selected semantic distance threshold. These cases could possibly be omitted from the modelling to achieve simplicity of the focus lattice. It depends on their importance viewed by an expert (as the simulator designers in the study) or based on the qualitative comparison analysis with respect to other models.

Another possibility is to include as objects entities from the upper ontology hierarchy layers (more abstract) and as attributes entities from the lower (more specific). This approach, however, introduces subjectivity in the selection criteria and should be looked more thoroughly by an expert in the specific conceptualisation (e.g. a psychologist in the area of emotion).

Finally, with respect to the formal context, more options for branching the ontology space could be explored. The selective data partitioning supported by ViewS (and FCA) provides several possibilities for experts to analyse viewpoint focus models. For example, one can branch the WNAffect taxonomy of emotion to derive focus models related to each polarity scale, e.g positive, negative, ambiguous and neutral emotions (and similarly for body language signal meanings). The ontology branching method presented in this work followed the conventional modelling assumption stating that everything is a kind of (classified) *Thing* providing the top classification layer. Going deeper in the ontology hierarchy, mode detailed examination would be permitted at a more generic level in the viewpoint focus model (although this is can be achieved at lower layers in the current approach).

6.7.2 Viewpoint Focus Element (Formal Concept)

The viewpoint context is directly related with the focus elements that occur in the model as it consists the base of processing . Attributing ontology entities to others is done using the a binary function I. In this work this function was instantiated using the semantic distance based on the ontology hierarchy (subsumption and membership relationships).

The assumptions underlying this approach include that the ontology will offer a rich hierarchy taxonomy to be able to distinguish and also investigate the composition of focus elements. If this taxonomy is not rich, in breadth and depth, although the algorithms will work, the end result would not make necessarily sense considering the assigned thresholds. We could consider for example the body language ontology branch related to body language signals below (Figure 6.22). A semantic distance threshold of 3 , or even 2, would relate every class of signals (and instances) under the same aggregate. The focus elements, although qualitatively different would always at least *overlap*.

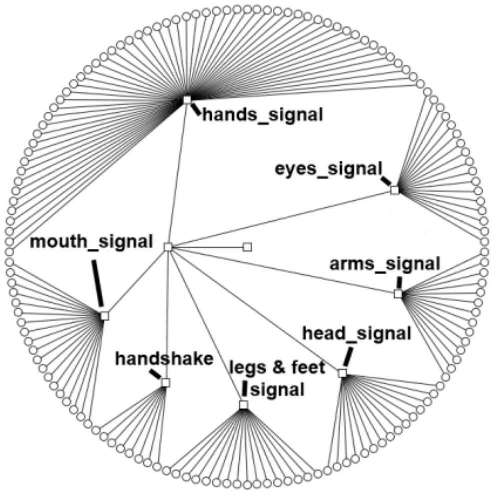


Figure 6.22 The body language ontology branch related to signals.

A distance threshold of 3 would relate all signals under the same aggregates, making the qualitative comparison less effective.

This case could be further explored by incorporating the ontology's object properties to build the viewpoint content and consequently the focus elements. This approach has also been investigating in ontology based user modelling to propagate interests for user profiling in recommender systems. Firstly calculating hierarchy based concept similarity, Cena et all [66] showed the potential of extracting interests for user profiles, while later on in [67], addressed the limitation poor-structured ontologies by investigating object properties. Similarly, the I binary assignment functions can vary in the construction of the viewpoint context. Significant importance also has the domain and dimensions under examination. Semantic similarity and relatedness[143] can also be further examined to attribute entities to other entities.

Another interesting work can also include experimentation with declaring the distance threshold. Investigate further the effect of the distance threshold relevant to the ontology topology or its value defined by different experts relatively to the output models could reveal significant qualitative changes between the focus models. Another possibility includes automatic assignment based on a heuristic approach. For example, the formula below calculates the weighted-based on frequency-average distance of annotated ontologies entities from the annotation:

$$\boldsymbol{\theta} = \frac{\sum_0^n \boldsymbol{w_i} * \boldsymbol{d_i}}{\sum_0^n \boldsymbol{w_i}}, \boldsymbol{\theta}: \left[\mathbf{1}, \max_i \boldsymbol{d_i}\right],$$

where d_i is an index distance value of all possible distances between annotated ontology entities and w_i is the frequency of it.

The focus model is the direct result of identifying the focus elements and analysing their inheritance and dependencies to derive the lattice structure.

6.7.3 Viewpoint Focus Model (Concept Lattice)

As aforementioned for the viewpoint context, counting for the frequency of annotated ontology entities can consequently also qualify focus elements with an importance indicator. This can complement the cardinality of the aggregated entities and provide better indicators of "hot topics" desired by experts.

The second point that was also identified in this work but not further investigated concerns the specification of the ontology, and particularly the possibility of occurred circles, i.e. multiple inheritance between classes and instances. Although ViewS caters for these cases, as a duplicate ontology entity will still be aggregated with closely related entities in the ontology graph (or even singularly), the visualisation and background computation of the semantic map could be improved. Referring to the body language ontology (*signal meanings* branch*)* the visualisations (as shown in the application of ViewS - Microscope in the next Chapter, e.g. in Figure 7.9) depict the different aggregated ontology parts for a single focus element, however, the convex hull for the corresponding aggregate summarises the ontology entities including the duplicates. A more sophisticated approach would be to further analyse the aggregate and introduce lower level sub-structures that can inherit the focus model structural dependencies. Further zooming can be achieved this way able to distinguish qualitative characteristics and consequently differences for focus model comparisons.

6.7.4 Focus Models Comparison

The comparison of focus models takes into account the structure of the focus lattice including the number of layers, elements and main focus elements, and can provide quantitative indicators to describe differences. The qualitative part of comparison however, investigates in detail the semantic enriched relations of the focus models by examining the main focus elements and assigning RCC-inspired connection tags. The main focus elements can then be further analysed to the sub-elements (decomposing) and compared with the components of another focus element in another model respectively.

Another possibility to extend the focus modelling and comparison would be to characterise the spatial relations between the focus elements. Preliminary work has been carried out, although has been not included in this thesis to attribute RCC relations with additional semantics. The possibilities summarised so far include the following ideas that could be possible further explored in future research work, considering the strength of the relation:

equality: attribute strength level relatively to the ratio of annotated ontology entities in the aggregate over the maximum cardinality aggregate. Aggregates with only few ontology entities in the focus models can be characterised as loosely equal (similarly moderately and strongly) compared to aggregates with higher cardinality ("hot topics") of ontology entities;

disconnection: the smallest semantic distance between possible pairs of ontology entities in different focus elements can provide a strength level indicator, with respect to the defined semantic distance threshold. For example, having threshold 3, two disconnected focus element in the focus models can be characterised moderately disconnected if the minimum distance between the pairs of the ontology entities is 2. The *disconnected* relation could also be characterised by the cardinalities of the disconnected focus elements as aforementioned (to capture less important aggregates also based on frequency of annotation), together with the distance metric.

includes/included: the proportional size of the included or inclusive ontology entities with respect to the cardinality of the focus elements can also characterise the strength of the relations. For example if only 20% of the aggregate covers the aggregate of the other focus model, the relation could be characterised as loose.

overlap: similarly to the *inclusion* relation, overlap can be characterised based on the proportional size of the shared ontology entities between the two focus elements.

6.7.5 Implementation

The algorithms for the viewpoint focus construction based on FCA, as well as the RCC based relations for comparison of focus models have been implemented with a tool – ViewS Microscope. ViewS Microscope provides visualisation of the focus models, and supports analysis and comparison. In the next Chapter, we illustrate the application of ViewS with two data sets of user generated content.

Chapter 7
Using ViewS to Explore UGC from Social Spaces

7.1 Introduction

In the previous Chapters we presented the ViewS framework for modelling viewpoints in user generated content. The goal of this Chapter is to illustrate the potential of ViewS for exploring UGC. ViewS is applied on content from two social spaces:

A closed social space (Section 7.2): content collected in the simulator presented in Chapter 5. This will illustrate how ViewS can support the elicited requirements for focus modelling. We demonstrate with ViewS Microscope how the framework can derive explicit structures - viewpoint focus models- of semantically augmented data sets from the overview semantic maps. Then, the viewpoint focus models are compared using the extracted lattice structures.

A Social Media platform (Section 7.3): content collected from YouTube. This will illustrate how ViewS can be applied for analysis of user viewpoints in larger-open data sets. A common approach for user modelling from social media is to extract user characteristics based on concept/term lists linked to an ontology (e.g. for recommender systems [6]). The user models are then quantitatively analysed to discover trends, similarities and differences. In this work we argue that semantic web technologies offer a greater potential for user modelling by providing an explicit structure to position a user model within the domain and complement the current conventional approaches. This can enable discovering similarity, complementarity and overlap between user models.

This Chapter concludes with a discussion (Section 7.4) with respect to implications for collection, analysis and application of user generated contents.

7.2 ViewS in a Closed social Space

The content collection and the semantic augmentation have been presented in Sections 5.3 and 5.4. The following Sections present overview (Section 7.2.1) and comparison (Section 7.2.2) of user viewpoints.

7.2.1 Overview of Viewpoint Focus Models

The overview semantic maps discussed in the exploratory study (see Section 5.5.1) are recalled here in order to show how the viewpoint focus (lattice) models extracted represent the observations made by the simulator designers and support the discussed requirements (see Section 6.1 for a summary). For each overview data set, the viewpoint focus lattice presented as well as the holistic focus element from the top focus element of the lattice. Each visualization is then discussed. For the calculation of the focus models, a semantic distance threshold is set to 3. Because of the size of the annotation sets, larger thresholds, although would result to fewer focus elements and fewer lattice layers, would not be distinguishable in the semantic map[44].

Figure 7.1 depicts the focus lattice and top focus element visualisations on *mental states* (WNAffect taxonomy of emotions) and *body language signal meanings* (Body Language ontology) *for* the “Greetings” simulation episode. The viewpoint focus model comprises two lattices with 46 focus elements structured in 7 layers and 198 focus elements structured in 15 layers respectively for each branch. It is clear from the illustration that different clusters are explicitly shaped on the semantic map with different number of annotated ontology entities.

Visualisation of Viewpoint Focus Lattices. The figures depicting the viewpoint focus lattices are based on a layout algorithm which used an index for the lattice layers starting from 0. Also, the layout algorithm positions a focus element in a layer relatively to the lattice hierarchy constraints. This leads to visually represent fewer layers than actually exist.

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[44] Setting the semantic distance threshold is relative to desired observations, e.g. the threshold should be considered if one wants to distinguish between positive and negative emotions to avoid overlaps within focus elements. Section 6.7 discussed the experimental settings and the matter of branching the ontologies.

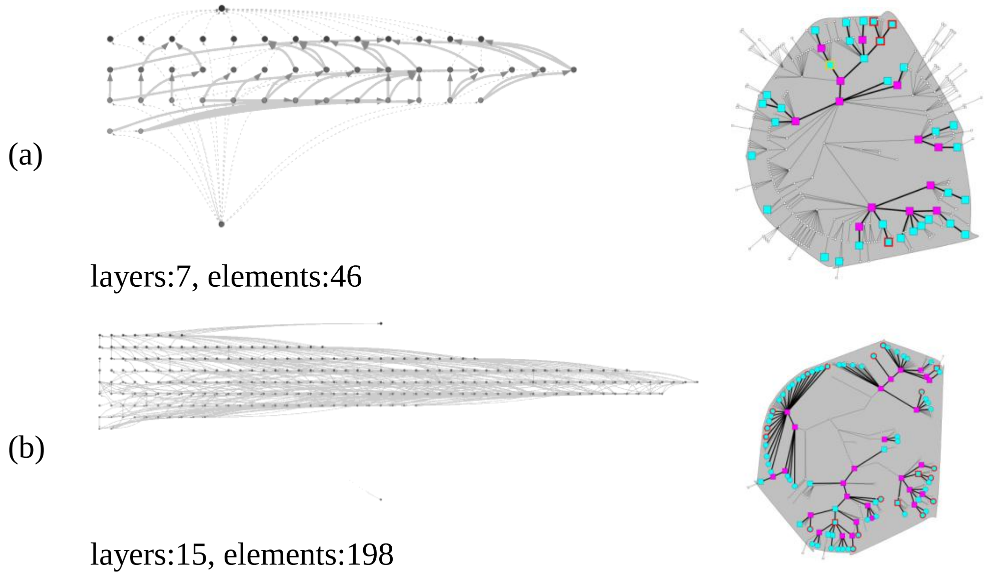
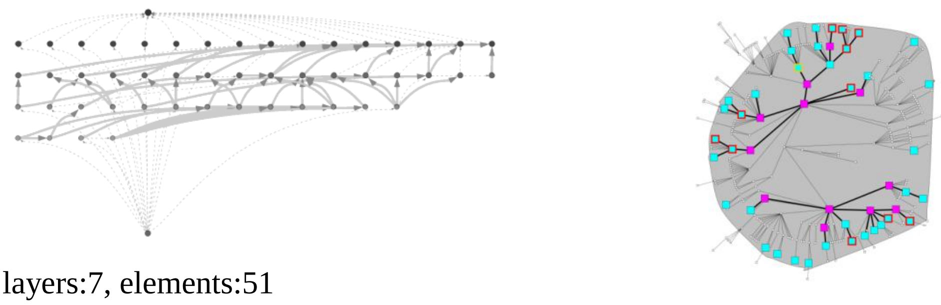


Figure 7.1 The viewpoint focus model for the “Greetings” simulation episode: The WNAffect *mental-state* branch (a) and the body language signal meaning branch from the Body Language ontology (b).

The semantic aggregates on the left represent the top focus element in the focus lattice, distinguishable from the thickened edges. The light-blue highlighted entities comprise the annotated ontology entities (object entities of the top focus element). Different clusters with different cardinalities of ontology entities are shaped.

Similarly, Figure 7.2 depicts the viewpoint focus model for the male participants. The semantic clusters are automatically expanded to semantic aggregates providing a more abstract description of the users’ viewpoint. The viewpoint focus model reflects the differences in clustering and aggregation results when the semantic distance threshold differs. Figure 7.3 illustrate this for the same data set (male participants) using a semantic distance threshold 2.

(a)



layers:7, elements:51

(b)

layers:19, elements:328

Figure 7.2 The viewpoint focus model for the male participants: The WNAffect *mental-state* branch (a) and the body language signal meaning branch from the Body Language ontology (b).

The semantic aggregates on the left represent the top focus element in the focus lattice, distinguishable from the thickened edges. The light-blue highlighted entities comprise the annotated ontology entities (object entities of the top focus element). For each cluster, the focus model allows for explicit representation of the aggregates of ontology entities.

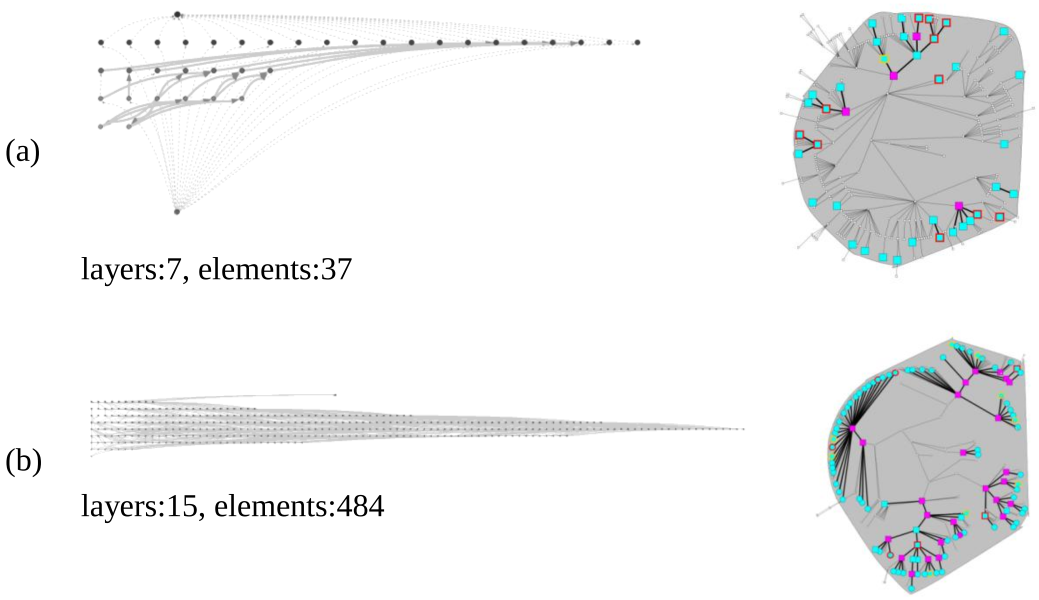


Figure 7.3 The viewpoint focus model for the male participants using a semantic distance threshold 2.

Changing the semantic distance threshold is reflected in the viewpoint focus model with respect to the focus elements (clusters and aggregates). Compared with the focus model in Figure 7.2 for the male participants, here more main focus elements (20 versus 16 in the second top layer) are extracted but fewer in total, as fewer implications occur for *mental-states*, while for *body language signal meanings* more main focus elements (11 versus 4) and more in total as well[45].

The viewpoint focus model of the young participants is shown in Figure 7.4. The focus lattice is also able to capture the breadth of the viewpoint focus which is reflected to the number of focus elements and the layers they are organised in, e.g. comparing the illustrations in Figures 7.4 (a) and 7.2(a) for emotions, the semantic map visualisation indicate more broad entities for the male partitioned data than the young one. This observation is validated with the number of main focus elements (second top layer). For the former (male), 16 main focus elements, while for the latter (young) 12 (same branch and semantic distance threshold). For each focus element, the ontology entities' hierarchy is preserved by qualifying the accorded ontology URI. Moreover, within a focus element, one can exploit the distance of the paths between the ontology entities and the `owl:Thing` class to derive generality and specificity.

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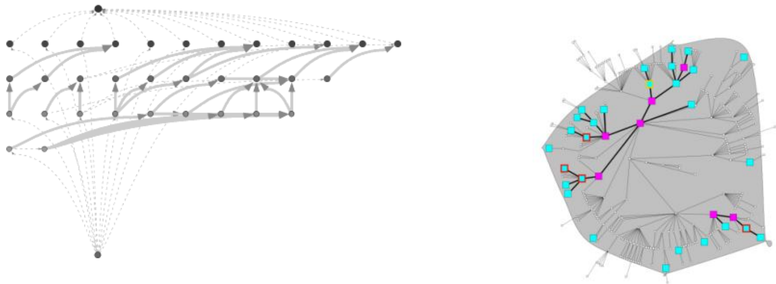
[45] The effect of adjusting the semantic distance threshold has not been examined in detail in this work. In Section 6.7 a discussion is included with pointers at the topology/hierarchy structure of the ontologies.

(a)



layers:7, elements:35

(b)

layers:9, elements:125

Figure 7.4 The viewpoint focus models for the young participants: the WNAffect *mental-state* branch (a) and the body language signal meaning branch from the Body Language ontology (b).

The semantic aggregates on the left represent the top focus element in the focus lattice, distinguishable from the thickened edges. The focus lattice is able to capture the breadth of the viewpoint focus which is reflected to the number of focus elements and the layers they are organised in.

Exploring the (de)composition of the aggregates (focus elements) is also possible with ViewS Microscope. Starting from a main (second top layer) focus element, Figure 7.5 illustrates the decomposition of an abstract focus element form the *mental states* WNAffect branch to smaller particulars for the young participants' viewpoint focus model presented in Figure 7.4. The (de) composition process utilises the hierarchy (inheritance) relations between focus elements across different layers based on the attribute entities implications. From top to bottom, the lattice offers a zoom-in functionality, desired by the simulator designers in the exploratory study. Reversely, from bottom to top, focus elements expand when following the accorded relationships. The semantic zooming complements the utility of ViewS Microscope, together with the attribute exploration presented in Section 6.5.2.

The utility offered by the ViewS Focus modelling approach can be used for comparing different viewpoint focus models. The next Section illustrates comparison of focus models extracted with ViewS following the examples presented in Section 5.5.2.

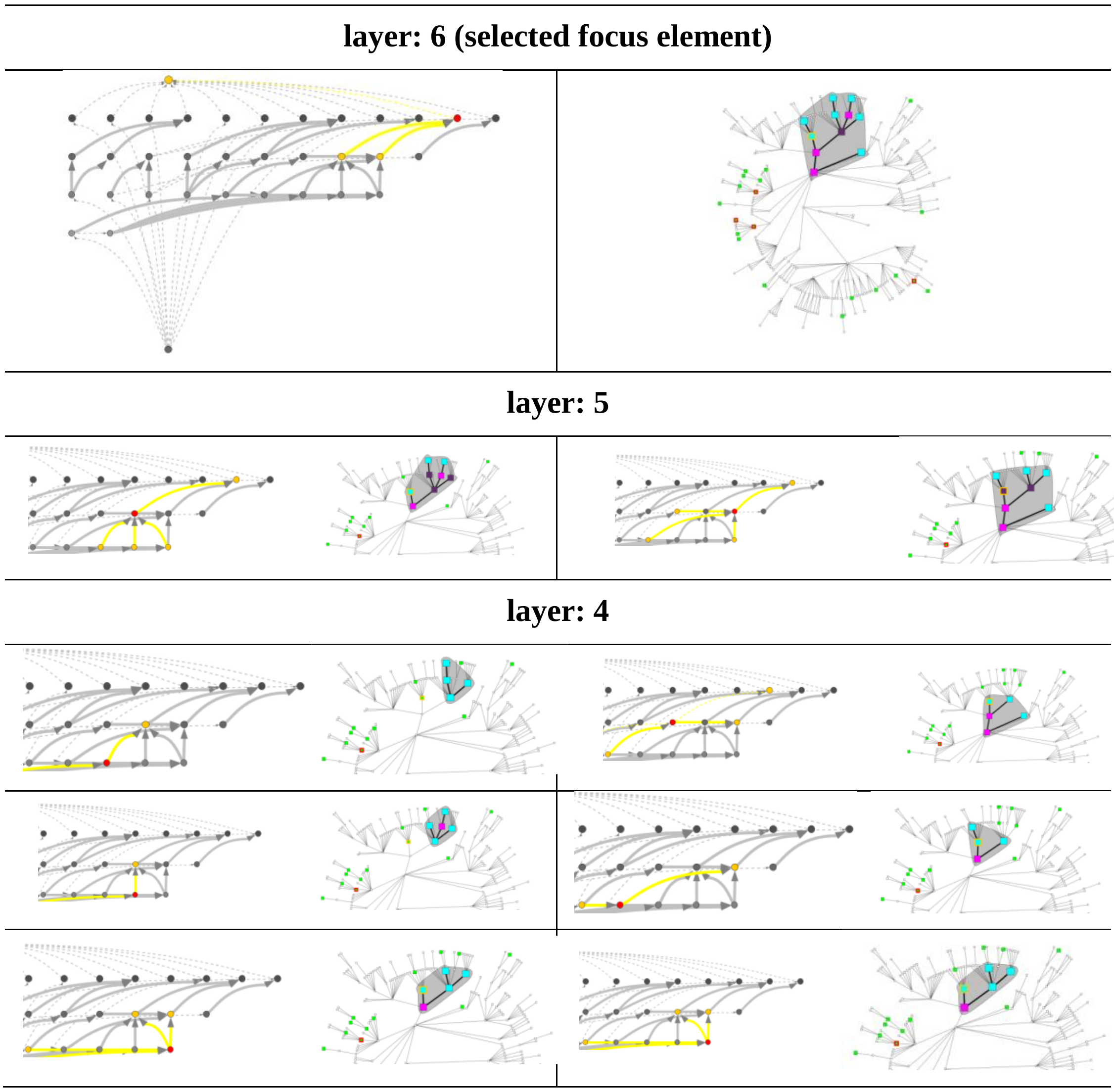


Figure 7.5 Decomposition of an abstract (second top layer) focus element from the *mental states* WNAffect branch to smaller particulars for the young participants' viewpoint focus model presented in Figure 6.20.

7.2.2 Comparison of Viewpoint Focus Models

In this Section, the comparison of viewpoint focus models is illustrated with the utility of ViewS Microscope[46]. The same data sets as in Section 5.5.2 are used: (I) simulation episodes, (II) male and female, and (III) young and older participants. The semantic distance threshold is also set to 3 as in the previous Section.

(I) Greetings and Bill simulation episodes. Figure 7.6 illustrates the focus models of the two simulation episodes *Greetings* and *Bill* (the contrastive semantic map can be seen in Figure 5.7), both the WNAffect *mental state* and Body Language Ontology *body language signal meaning* branches.

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[46] FR-9 - Selective data partitioning -, has been discussed in Section 6.2.

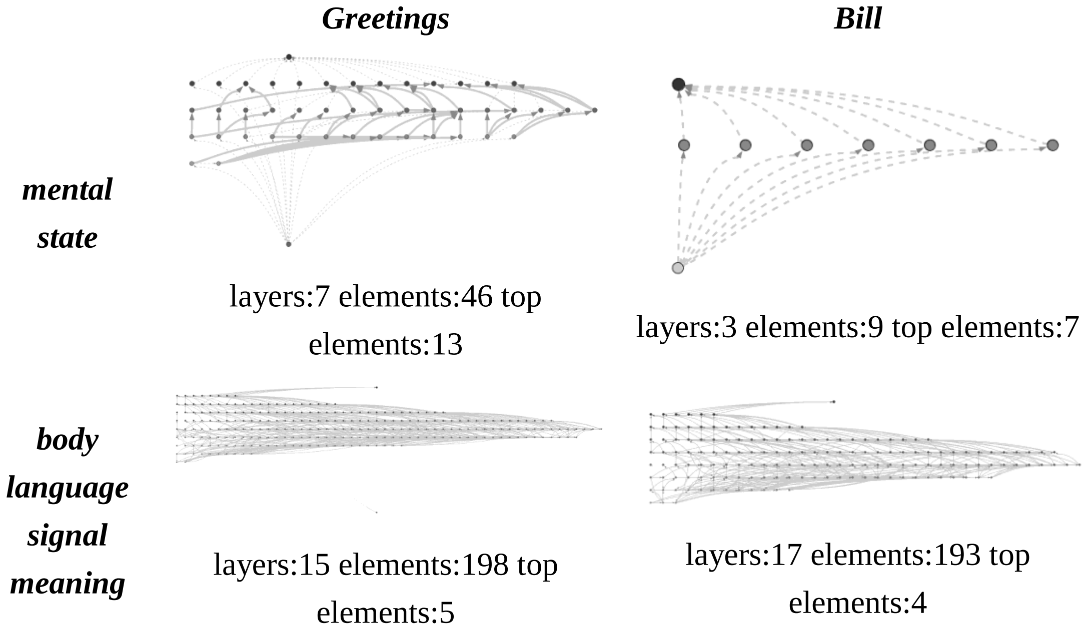


Figure 7.6 The viewpoint focus models for the *Greetings* and *Bill* simulation episodes.

The complexity and richness of the former is illustrated through the lattice properties including the number of layers, elements and (top) main elements.

Mental state : particularly for the emotion dimension, diversity is observed on focus models. More layers are extracted in the lattice as well as focus elements for the Greetings episode. It is shown therefore that the viewpoint focus model of the *Greetings* episode covers more aspects of emotions. To examine the particular differences the overview aggregates (extracted from the top focus element of the lattice) can be visualised (see Figure 7.7) and contrasted. More details can be gathered regarding the differences by browsing through the main focus elements of the focus lattices to investigate comparison relations. The comparison (see Section 6.6.2) defines 91 pairs of main focus elements from the models, including 1 *equal*, 81 *disconnected*, 7 *includes*, and 2 *overlap*. For example, Figure 7.8 illustrates *overlap* (similarity) and disconnection between two pairs of focus elements (relative to the focus models presented in Figure 7.7).

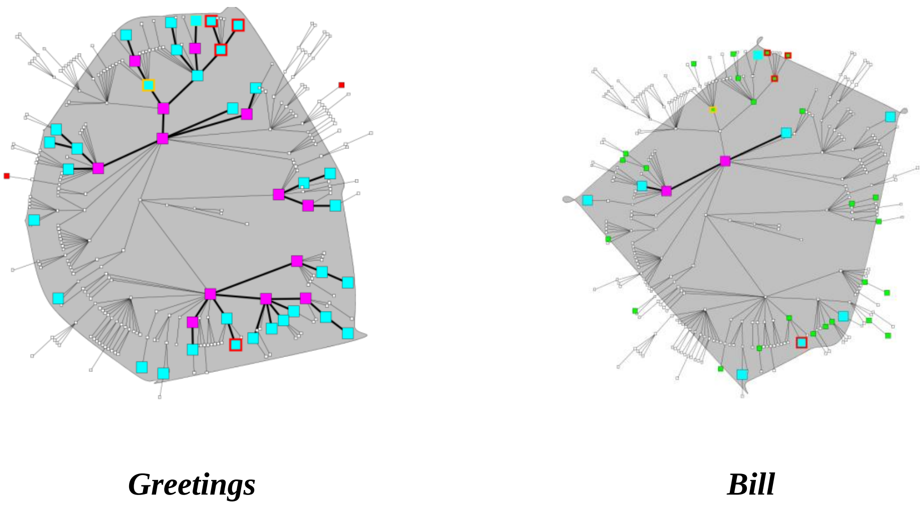


Figure 7.7 The contrastive viewpoint focus model holistic aggregates extracted from the two simulation episodes on *mental states*.

The number of main focus elements (both in terms of clusters and aggregates) are more and larger for the Greetings episode. Navigating through the main (top) focus elements enables comparison of the focus models.

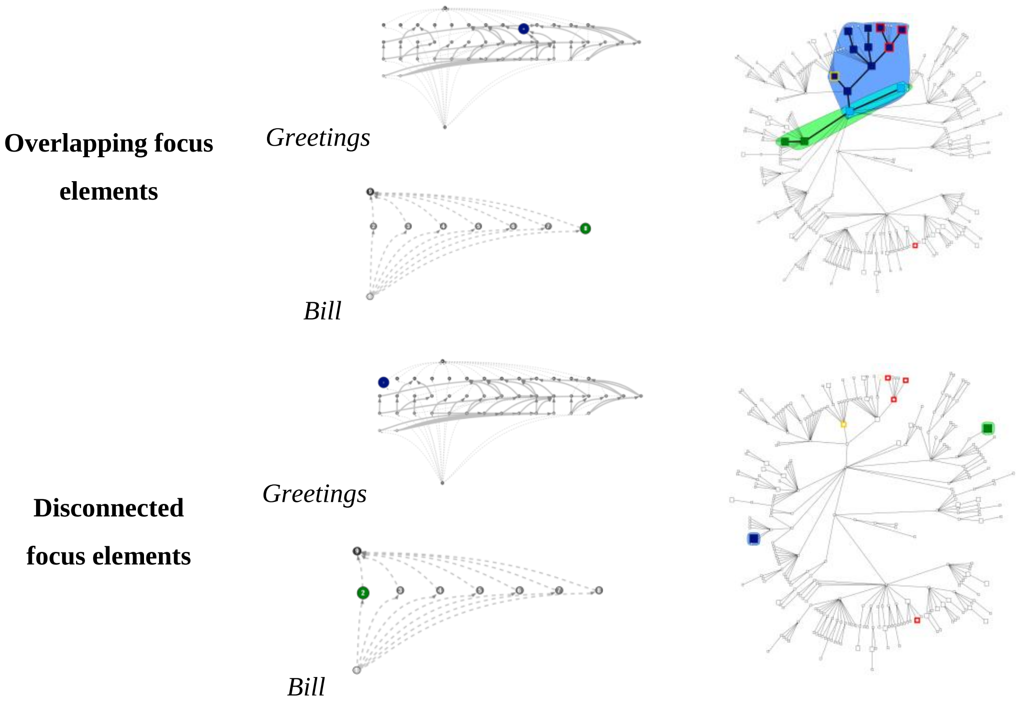
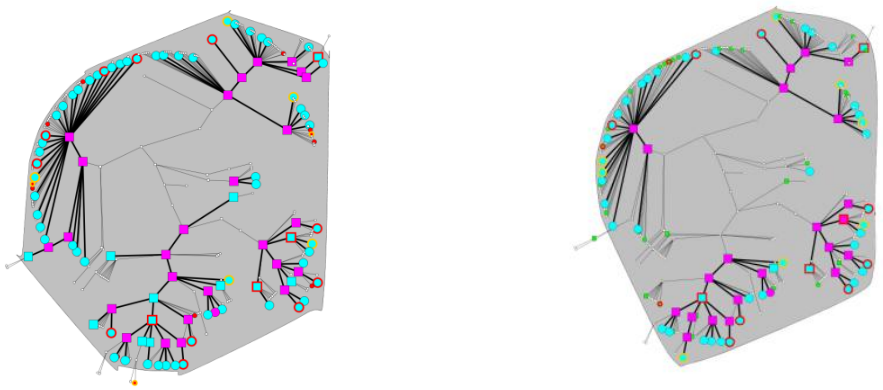


Figure 7.8 Similarity and difference in terms of focus elements in the viewpoint focus models. The *Greetings* and *Bill episodes* are selected for illustration.

Browsing through the main focus elements allows for closer exploration of the viewpoint focus models.

Body language signal meaning: for body language signal meanings the contrastive semantic maps as well as the viewpoint focus models (see Figure 7.9) illustrate similarities between the focus models. The lattice structures although different are very complicated to analyse as opposed in the *mental state* branch of emotions. The benefit of the modelling approach is to examine pair-wise focus element comparison. From the cross-table, all 20 possible pairs of focus elements overlap. This strongly recommends that there exist body language signal meanings shared between different simulation episodes. A closer look into an overlapping pair (see Figure 7.10) following the aggregates' cardinalities, shows the differences between the sets occur around *social interaction* and *psychological process* related terms as well as on *subjective assessment attributes* and *emotional states*. These consist exactly the points of interest of the simulator designers during the study.



Greetings ***Bill***

Figure 7.9 The contrastive viewpoint focus model holistic aggregates extracted from the two simulation episodes on *body language signal meanings*.

The number of main focus elements (both in terms of clusters and aggregates) are more and richer for the Greetings episode, however diversity is not clear on the conceptual space.

Greeting
s

Bill

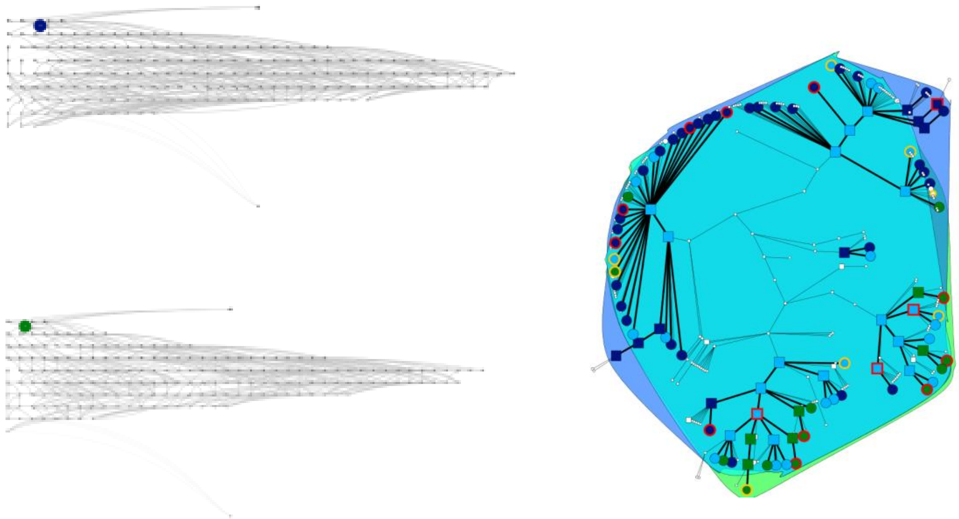


Figure 7.10 An example overlap between focus elements of the *Greetings (blue)* and *Bill(green)* simulation episode focus models.

Although overlapping the two focus elements distinguish to each other in parts that triggered the attention of the simulator designers. ViewS successfully captures the quantitative and qualitative diversity of the focus models.

(II) Male and female users. Similarly to the simulation episode comparison, the ViewS viewpoint focus modelling was applied for the male and female users of the simulator (the contrastive semantic map can be seen in Figure 5.8). The corresponding focus models are shown in Figure 7.11.

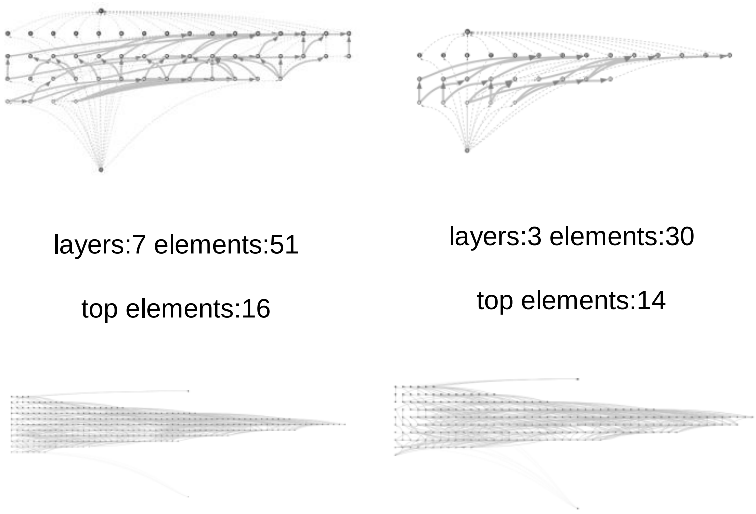


Figure 7.11 The viewpoint focus models for the *male* and *female* users of the simulator.

The complexity and richness of the former is illustrated through the lattice properties including the number of layers, elements and (top) main elements for *mental state*, while for *body language signals meanings* more balanced contributions are observed.

Mental state. Validating the observations of the simulator designers, the focus models' structures indicate that the viewpoint focus of the male users is broader and possible richer than the viewpoint focus of the female participants. Figure 7.12 illustrates the holistic (top) focus element for each user group. The cross-table comparison for the two groups showed that from the 224 comparison pairs 2 were *equal* (aggregates with cardinality 1), 4 *inclusive*, 1 *included*, 22 *overlap* and 195 *disconnected*. The *inclusive pairs as well as* the *overlapping* and *disconnected* reveal the richness of male user group as opposed to female user group. Zooming into the focus elements Figure 7.13 illustrates cases of *inclusion* and *overlap* between the focus elements of the two user groups. The selection is based on the cross-table for comparison where focus elements are examined in relation to the other focus model and characterised based on the frequency of the possible relations.

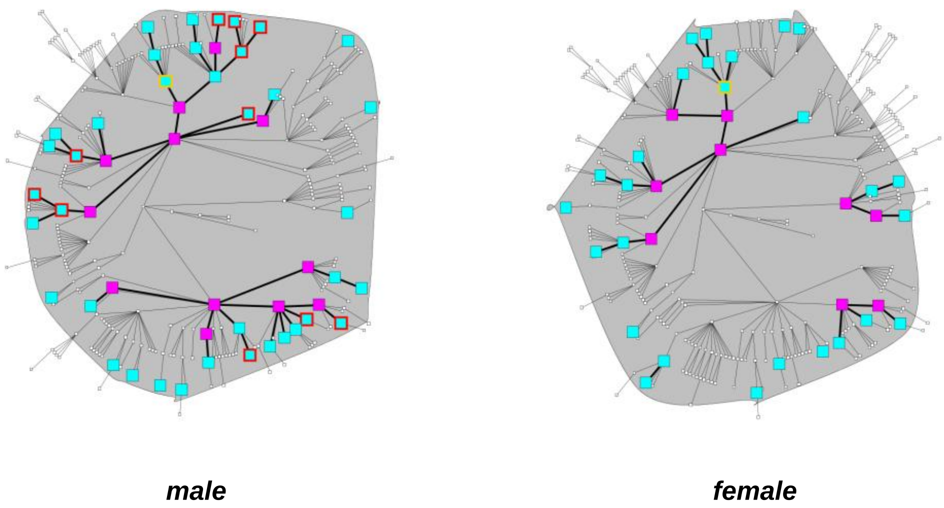


Figure 7.12 The contrastive viewpoint focus model holistic aggregates extracted from the male and female user groups on *mental states*.

The number of main focus elements (both in terms of clusters and aggregates) are more and richer for the Greetings episode.

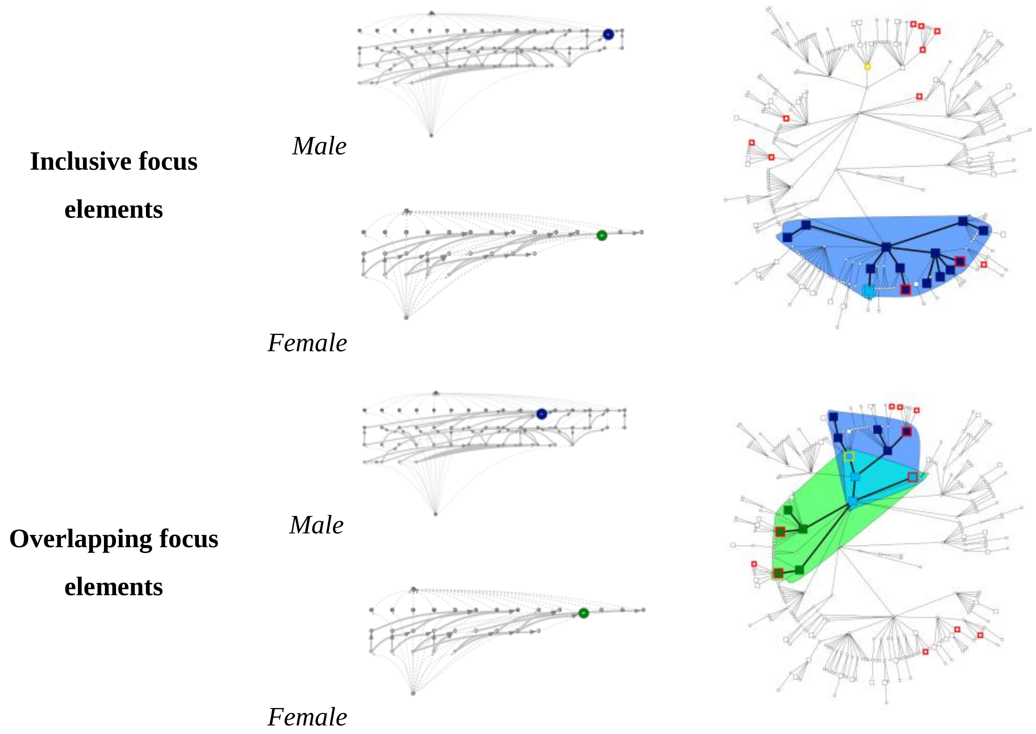
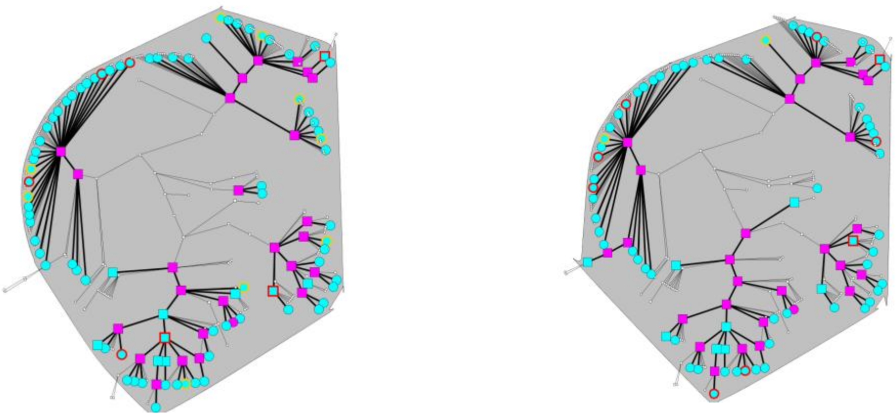


Figure 7.13 *Inclusion* and *overlap* of focus elements for the viewpoint focus models of male (blue) and female(green) participants.

The focus elements are selected based on the frequency of possible relations between focus elements in the cross-table for comparison.

Body language signal meaning. The contributions related to *body language signal meanings* were more balanced between the two user groups. This observation is validated by the contrastive semantic maps depicted in Figure 7.14 by visualising the holistic aggregates (top foucs elements) from the focus models. The cross-table comparison between focus elements showed that from the 24 main focus element pairs, the qualitative aggregates comparison resulted to equivalent number of overlaps. Figure 7.15 shows an example overlapping pair for the focus models of the two groups.



male ***female***

Figure 7.14 The contrastive viewpoint focus model holistic aggregates extracted from the male and female user groups on *body language signal meaning*.

Many similarities are observed between the focus models which validate the observations of the simulator designers.

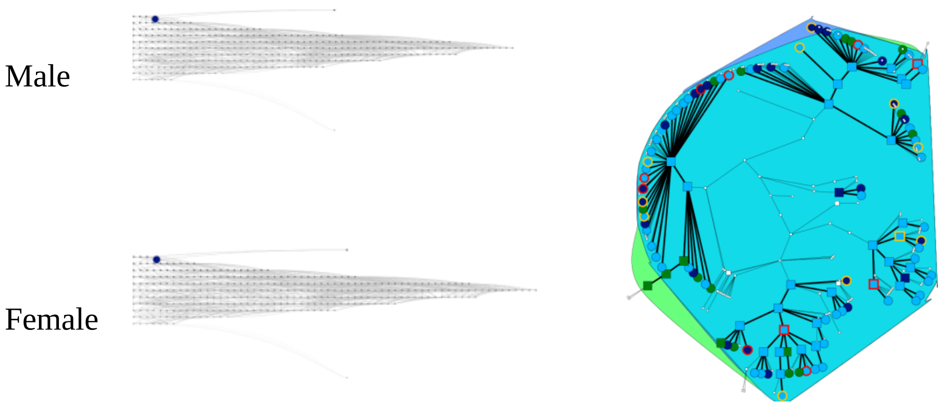


Figure 7.15 An example overlap between focus elements of the *male (blue)* and *female(green)* focus models.

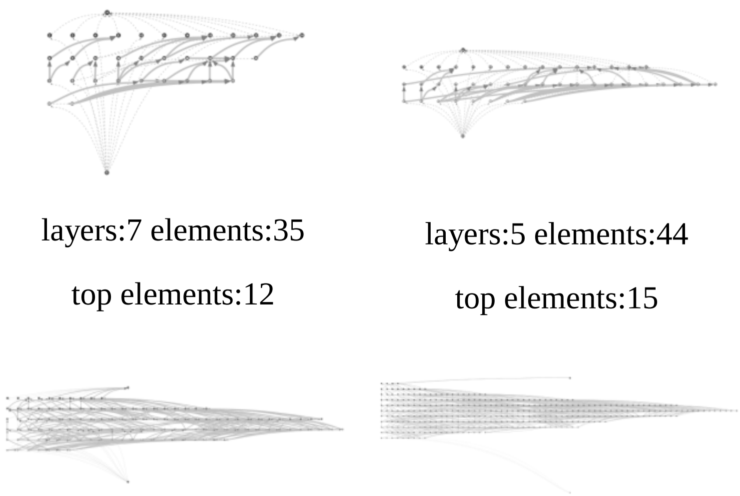
Although overlapping the two focus elements distinguish to each other in parts that triggered the attention of the simulator designers similarly to the simulation episode focus models.

(III) Young and older Users. The focus models of the young and older users of the simulator are depicted in Figure 7.16 (the contrastive semantic map can be seen in Figure 5.9).

Young ***Older***

mental state

body language signal meaning



layers:7 elements:35 top elements:12 — layers:5 elements:44 top elements:15

layers:9 elements:125 top elements:10 — layers:21 elements:355 top elements:4

Figure 7.16 The viewpoint focus models for the *young* and *older* users of the simulator.

More focus elements for the older user group indicate the broader and richer viewpoint than the younger group.

Mental state. Validating the observations of the simulator designers, the focus models' structures indicate that the viewpoint focus of the older users is broader and richer than the viewpoint focus of the younger users. Figure 7.17 illustrates the holistic (top) focus element for each user group. The cross-table comparison for the two groups showed that from the 180 comparison pairs 2 were *equal* (aggregates with cardinality 1), 3 *included*, 16 *overlap* and 159 *disconnected*. Zooming into the focus elements Figure 7.18 illustrates cases of *inclusion* and *overlap* between the focus elements of the two user groups. The selection is again based on the cross-table for comparison where focus elements are examined in relation to the other focus model and characterised based on the frequency of the possible relations. As observed from the simulator designers, the older group significantly associated the simulation situation with more positive emotions than the younger group. The aggregated focus elements depict this difference in the comparative semantic map.

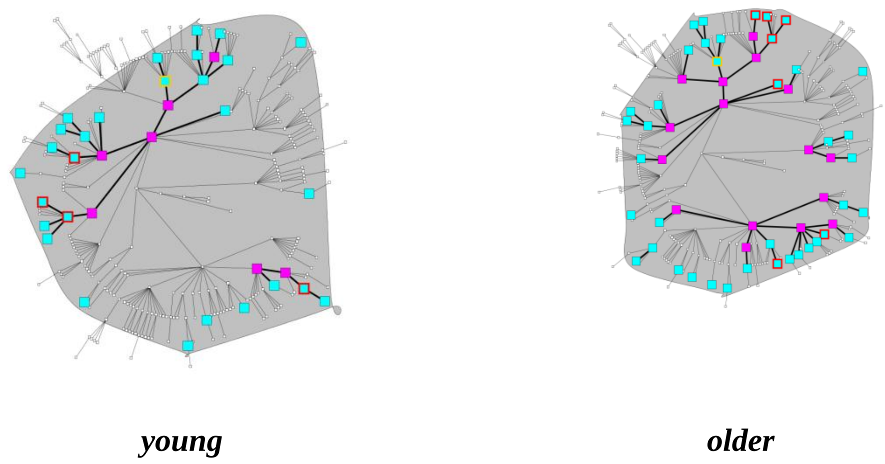


Figure 7.17 The contrastive viewpoint focus model holistic aggregates extracted from the young and older user groups on *mental states*.

The number of main focus elements (both in terms of clusters and aggregates) is richer for the older group.

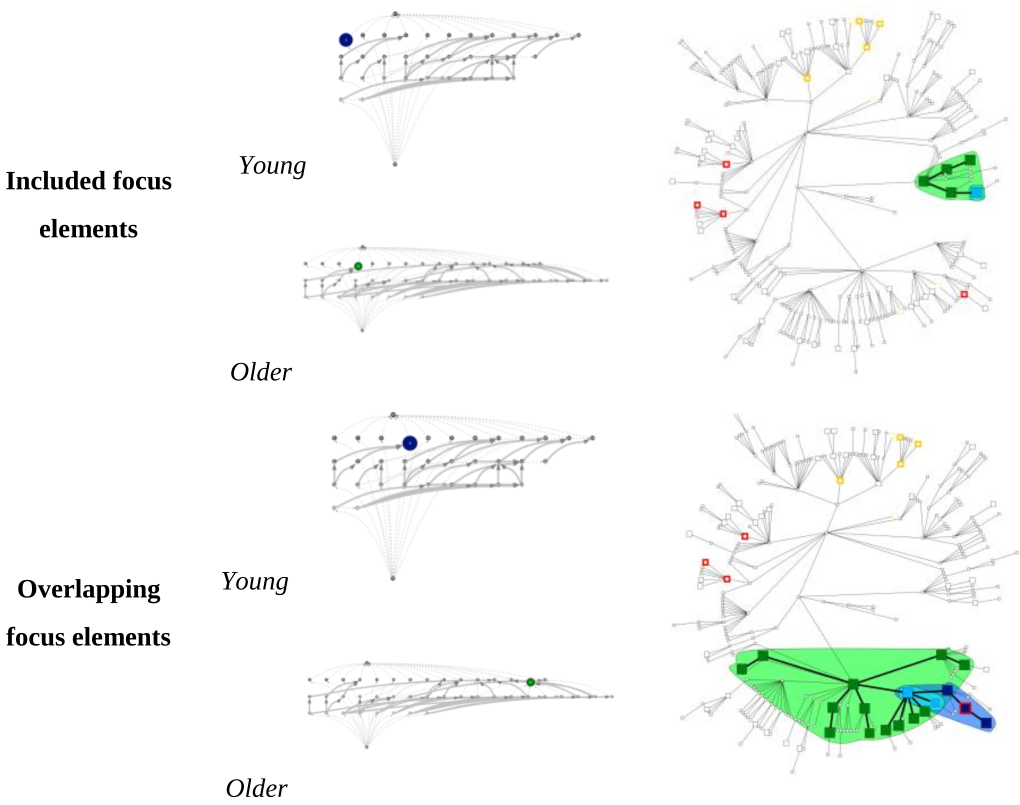


Figure 7.18 *Inclusion* and *overlap* of focus elements for the viewpoint focus models of young (blue) and older(green) participants on *mental states*.

The focus elements are selected based on the frequency of possible relations between focus elements in the cross-table for comparison. The comparative semantic map of aggregated focus elements clearly depicts the difference (overlap) in the positive emotion region, also observed by the simulator designers.

Body language signal meaning. The contributions related to *body language signal meanings* were significantly more by the older users again, similarly to the *mental states*. This observation is validated by the contrastive semantic maps depicted in Figure 7.19 by visualising the holistic aggregates (top focus elements) from the focus models. The cross-table comparison between focus elements showed that from the 40 main focus element pairs, the qualitative aggregates comparison resulted to 32 *overlaps* and 8 *disconnected* (aggregates with cardinality 1 from the young users' group). Figure 7.20 an example *overlap* pair for the focus models of the two user groups.

Figure 7.19 The contrastive viewpoint focus model holistic aggregates extracted from the young and older user groups on *body language signal meanings*.

The number of focus elements (both in terms of clusters and aggregates) are richer for the older group.

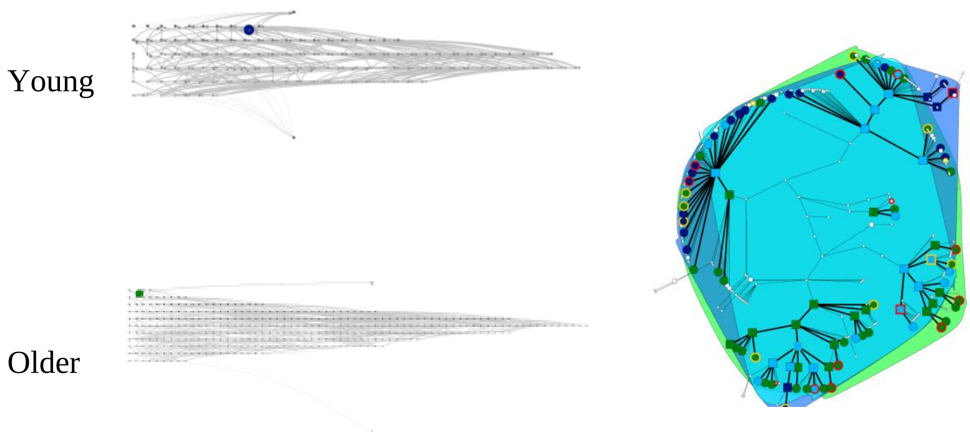


Figure 7.20 Example *overlap* focus elements for the viewpoint focus models of young (blue) and older(green) participants on *body language signal meanings*.

> The focus elements are selected based on the frequency of possible relations between focus elements in the cross-table for comparison. The comparative semantic map of aggregated focus elements clearly depicts the differences in observed by the simulator designers, where older users' viewpoint focus dominated the semantic map.

In this Section it was shown that ViewS can facilitate exploration of UGC. Diversity of viewpoints can be explored with the analytical utility of ViewS including: identification of focus elements, zooming and comparison, based on the elicited requirements for focus modelling.

7.3 Social Media Platform

To collect user generated content we selected YouTube as the data source. It was also decided to select job-interviews as an example of IC activity; an activity that every person experiences several times in his/her life, either as applicant or interviewer. In YouTube there is a plethora of digital objects including : (a) videos of job interviews (activity exemplars) and (b) videos about job interviews (guides and tips for successful job interviews and stories) which can stimulate discussions where some users contributed comments can include personal opinions and experiences. Moreover, there is a plethora of users registered at YouTube and the platform is up to date regarding new content being published and users registering. Because of the of the selected IC activity - job interviews - in real-life, ample user-generated content exists in the form of comments.

A recent survey[47] published in the Joint Information Systems Committee (JISC)[160] - a major UK organisation for digital technologies in education and research, showed that social media, and particularly YouTube, support and enhance the quality of the learning experience. In this context, ViewS application provides an analytical tool driven by semantic web technologies.

7.3.1 Content Collection From YouTube

The data was of two types: (a) content, including video URLs, video metadata and textual comments, and (b) user profiles.

The keywords used to construct queries for the YouTube search engine were collected from a study that aims at identifying competency questions related to job interviews to evaluate an ontology of activity models – AMOn

[47] Enhanced Training Needs Analysis (ETNA) 2012, available at http://www.rsc-scotland.org/?p=2945

[93] - including job interviews[48]. A script was provided to domain experts in the field of "job interviewing" in order to elicit competency questions. Five individuals considered experts including human resources managers with international experience and trainers at a staff development and recruitment centre, were consulted.

Each query is structured based on three components: `<activity>`, `<activity aspect>` and `<context dimension>`. Different combinations of these components were used to construct a set of 198 queries. Table 7.1 shows the templates used for constructing the queries and example(see Appendix B.1.1 for a full list). The queries were executed using the YouTube Data API[49].

Table 7.1 The query templates used to search YouTube for job interview related videos and corresponding examples.

Query template	Query examples	
<activity>	<“interview”>< “job interview”>	
<activity aspect>	<“applicant”>< “interviewer”>	22 queries
<activity>, <activity aspect>	<“interview"><"candidate”>, <“job interview"><"applicant”>	
<activity>, <dimension>	<“job interview"><"social signals”>, <“job interview"><"non verbal cues”>	176 queries
<activity>, <activity aspect>, < dimension>	<“job interview"><"interviewer"><"body language”>, <“interview"><"candidate"><"emotional”>	
	Total	198

Identifying videos relevant to the job interview activity included a pre-study task where a sample of 4,282 videos were manually checked for relevancy based on the following criteria: (i) the video is related to job interview and does not contain advertising material, (ii) it is not a video of celebrity persons, political figures or other personalities, (iii) it is not a video of interviews relating to either than job recruitment, (iv) it is in English language or at least has English subtitles, and the comments are in English. The

[48] ImREAL EU Project, deliverable D7.3: http://www.imreal-project.eu/

[49] https://developers.google.com/youtube/2.0/developers_guide_java

selected videos were examined, by checking the corresponding user-contributed tags. This allowed for automating the process of selecting relevant videos. The relevant videos were those which were tagged with combinations of the terms "job" and "interview" (including plural variations).

For each set of video results (each query produces one set of videos), the videos that had no comments contributed from users were removed from the corpus. For each video, the duplicate comments and the comments that included URIs were also removed. Also, comments provided by users that had unsubscribed from the service were excluded. We considered individuals for which age, gender and location were available and the provided age was between 13 and 85 years. Videos for which no comment was semantically annotated were also removed.

The analysis presented in the remainder of the Chapter is performed on the comments (and the users) that were semantically annotated.

Table 7.2 presents the summary of the collected content[50] (semantically augmented with ViewS). Most of the videos and the corresponding semantically annotated comments were collected from the "How to & Style" video category, which together with videos belonging to the "People & Blogging" category had the highest comments ratio.

Table 7.2 Summary of the collected content after the semantic augmentation.

Content	**Video Category**				**Total**
	How to & Style	Education	People & Blogging	Nonprofit & Activism	
# videos	324	149	116	11	600
# comments	6,730	1,662	2,113	151	10,656
Comments ratio	20.77	11.15	18.21	13.72	26.345

The collected profile variables included age, gender and location (profile properties as occupation, hometown and language for example were disregarded because the missing values were above 75% of the data). After the content filtering (both content and annotation based), 8,083 user profiles were collected. Table 7.3 presents the summary of the user profiles. Table 7.4 presents the summary of contributions to videos in different categories

[50] The data is available at http://imash.leeds.ac.uk/services/ViewS/

according to different profile characteristics. Age is discretised in six groups ([13-18], [19-21], [22-26], [27, 36], [37, 54] and [55, 85]) based on normal distribution of observations. For the location characteristic 79% of the population is presented by the top six countries.

Table 7.3 Summary of the collected YouTube demographic user profiles.

Profile variable	Summary
Age	**min**:13 **max**:85 **median**: 26 **mean**: 20.09 **sd**: 9.63
Gender	**male**: 4,460 **female**: 3,623
Location	**US**:53.9% **GB**:10.3% **CA**:7.1% **AU**:3.3% **PH**:2.0% **IN**:1.8%

Table 7.4 Summary of comments contributions in different video categories according to different user profile characteristics.

User Profiles			# comments per video category				Total
Profile Characteristic	**Group**	**#users**	**How to & Style**	**Education**	**People & Blogging**	**Nonprofit & Activism**	
Age	[13-18]	734	608	104	103	6	821
	[19-21]	1174	892	216	287	7	1402
	[22-26]	2518	1878	510	573	28	2989
	[27, 36]	2399	2286	536	633	54	3509
	[37, 54]	1053	912	229	405	40	1586
	[55, 85]	205	154	67	112	16	349
Gender	Male	4,460	3488	1233	1547	113	6381
	Female	3,623	3242	429	566	38	4275
Location*	US	4,357	3393	858	1262	94	5607
	GB	839	630	149	191	23	993
	CA	579	435	124	126	14	699
	AU	271	202	53	71	5	331
	PH	169	127	24	48	0	199
	IN	165	89	64	33	1	187

* 79% of the population is presented for location

7.3.2 Semantic Augmentation Output

The collected UGC was semantically augmented with ViewS using WN-Affect for emotion and the body language ontology (see Table 7.5 for a summary).

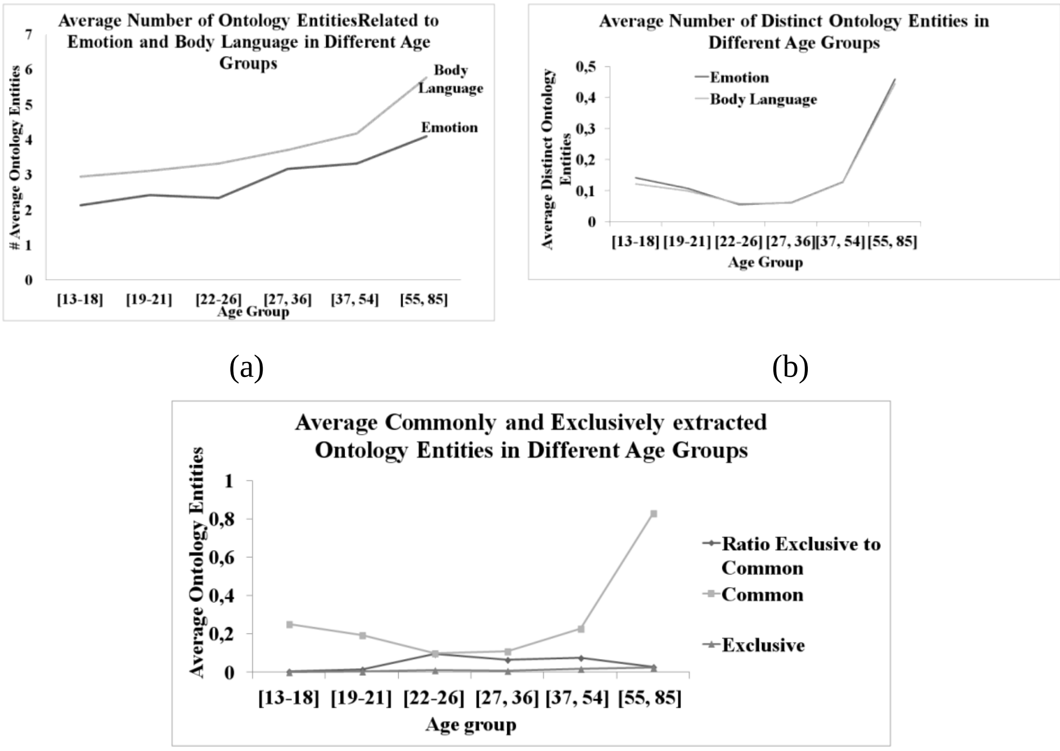
Table 7.5 Summary of the semantic augmentation of UGC in YouTube

User Group		Dimension	#Annotations	#Distinct Entities
By Age	[13-18]	Emotion	1572	129
		Body Language	4013	180
	[19-21]	Emotion	2840	158
		Body Language	7089	228
	[22-26]	Emotion	5690	166
		Body Language	15284	269
	[27-36]	Emotion	6890	171
		Body Language	16846	262
	[37-54]	Emotion	3408	164
		Body Language	8617	248
	[55-85]	Emotion	815	118
		Body Language	2224	189
By Gender	Male	Emotion	12632	192
		Body Language	32668	299
	Female	Emotion	8583	178
		Body Language	21405	266
By Location	US	Emotion	11272	192
		Body Language	29196	295
	GB	Emotion	1995	142
		Body Language	5125	220
	CA	Emotion	1609	136
		Body Language	4032	215
	AU	Emotion	660	109
		Body Language	1812	172
	PH	Emotion	355	58
		Body Language	826	113
	IN	Emotion	366	74
		Body Language	832	113

7.3.3 Quantitative Analysis

In this Section users' diversity is investigated using statistical indicators. The quantitative analysis aimed at gaining an insight into possible trends in the data set, rather than arriving at decisions for stereotyping. The analysis is based on the user profile variables (age, gender and location) in relation to the semantic augmentation output with ViewS. In the next Section we run ViewS Microscope to identify similarities and differences between user viewpoints and explicate the observed numerical relations.

Findings - Grouping by Age. Age (discretised in six groups: [13-18], [19-21], [22-26], [27, 36], [37, 54] and [55, 85]) was found strongly associated with both the social signal dimensions, i.e. emotion and body language (Pearson's χ^2 p = 1.252e-15) and the extracted ontology entities (Pearson's χ^2 p < 2.2e-16). Regarding the social signal dimensions, it was observed that as age increases, concepts related to body language and emotion were more frequently extracted in proportions between the different age groups (Figure 7.21a, Spearman's on emotion: *rho* = 0.94, p = 0.034, on body language: *rho* = 1, p = 0.025, total observations: *rho* = 1, p = 0.025). Regarding the ontology entities, as age increases, with respect to the number of users and comments ratio in different age groups, more distinct ontology entities were extracted related both to emotion and body language, however no significant correlation was detected as the data were skewed and balanced between the age groups of 22 and 36 years old (Figure 7.21b). It was also observed that the average number of ontology entities as well as the ratio of exclusive to common ontology entities was increasing as age was increasing (Figure 7.21c) particularly for the exclusively extracted ontology entities in different age groups (Spearman's *rho* = 0.94, p = 0.034). The above observations show that from older ages, larger breadth of social signal related terms were identified in the given data set.

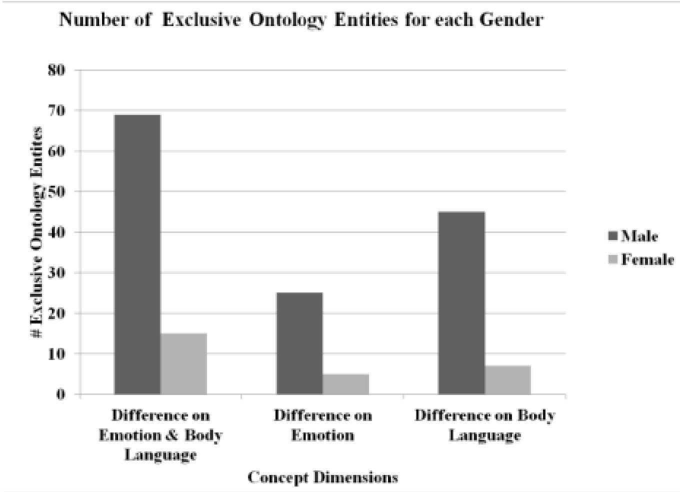


(c)

Figure 7.21 Ontology entities related to both emotion and body language social signal dimensions were extracted more frequently as age increases (a). The analysis also showed that as age increases more distinct emotion and body language (b) related ontology entities were extracted from comments provided by users in different age groups. The average number of commonly and exclusively extracted ontology entities is also increasing as age increases, having a stable score between ages of 22 to 36 years old (c). The ratio of exclusive to common number of ontology entities is increased in older ages.

Findings - Grouping by Gender. Gender was also found to be associated with social signals (for social signal dimensions: Pearson's χ^2 p = 1.53e-10 , for ontology entities: Pearson's χ^2 p = 2.2e-16). Regarding social signal dimensions, the ontology entities extracted with ViewS were mostly related to emotion for comments contributed by male users and for female users related to body language. Although the significant amount of ontology entities extracted by both male and females users, for both dimensions, more exclusive ontology entities were extracted by comments provided by male users (Figure 7.22a) in the given data set. To adjust for the number of contributions, the average number of exclusive ontology entities was calculated per user and comment in the data set for each dimension (Figure 7.22b), which again showed that larger breadth of social signal related terms was extracted from comments provided by male users in the given data set.

(a)



(b)

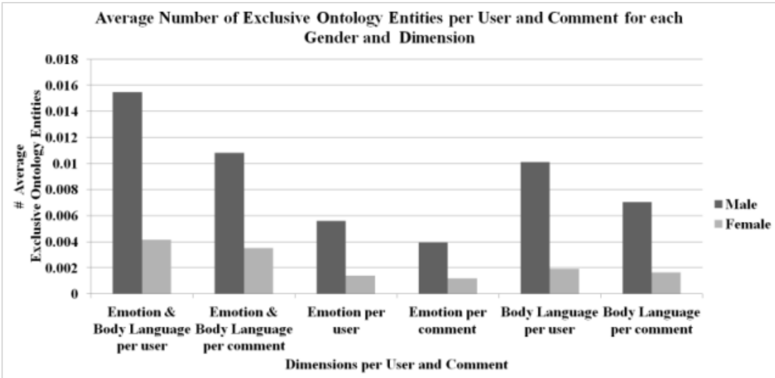
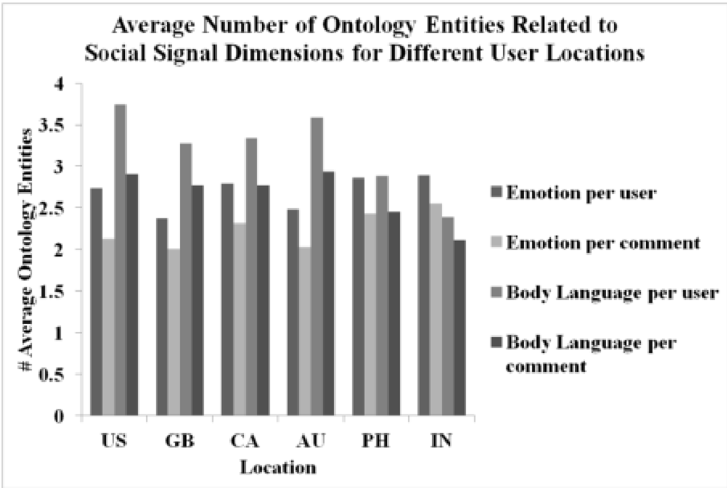


Figure 7.22 Number of ontology entities commonly (a) and exclusively (b) extracted from comments by each gender for each dimension, showing that for male users a larger breadth of social signal related terms was extracted by their comments . To adjust for the number of contributions the average number of exclusive ontology entities was calculated per user and comment for each gender and social signal dimension (c).

Findings - Grouping by Location. Location was also tested for dependency with the semantic output and found associated (Pearson's χ^2 p < 2.2e-16 for both social signal dimensions and specific ontology entities). As Figure 7.23a depicts, on average, from users in India and Philippines the extracted ontology entities were related to emotion mostly, while from users in the United States, Great Britain, Canada and Australia to body language. Sampling the users in the United States to balance the size of users located elsewhere did not affect the results significantly. Regarding specific ontology entities, although in total the number of distinctively extracted ontology entities for each group was in line with the number of contributions, the average number of distinctively extracted entities per user and comment in different groups was inversely proportional to the number of users and comments in the data set (see Figure 7.23b). Of particular interest is the comparison of users from Philippines and India which although constituted a small data sample, it was shown that the proportional density of social signal related terms was higher. However, regarding the coverage (exclusively defined entities from each group), users located in the United States contributed a larger breadth, followed by Canada, Great Britain and Australia, India and Philippines.

(a)



(b)

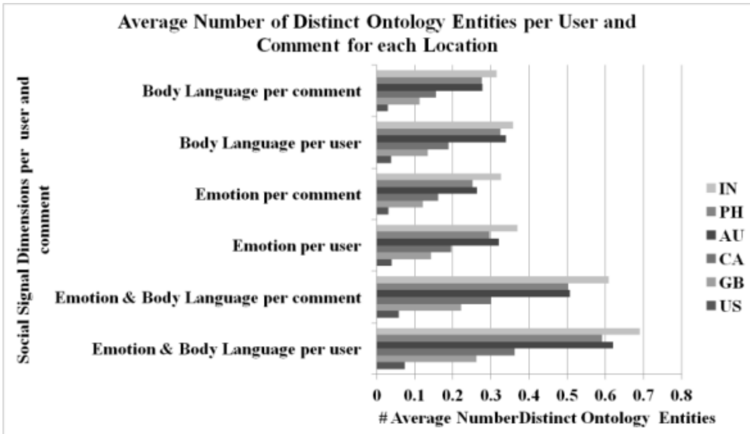


Figure 7.23 Average number of ontology entities related to social signals (a) and average number of distinct entities per user and comment from different location groups (b).

Diversity of viewpoints in the UGC was observed with the utilisation of statistical indicators. Trends – with association of user profiles variables with extracted semantic tags, as well as similarities and differences – with comparative descriptive statistics, were examined. However, in order to further reason about the diversity, a deeper layer of analysis is needed. In order to investigate where and how user viewpoints differ with respect to the domain of interest, zooming into the viewpoint semantics is enabled with ViewS.

7.3.4 Qualitative Analysis with ViewS Microscope

The qualitative analysis with ViewS Microscope is illustrated with a sample of 26 YouTube videos related to *how to prepare for a job interview*. ViewS

Microscope was ran for different user profile groupings as in the previous Section. For the construction of viewpoint focus models we used a semantic distance threshold 3 (edges).

(I) Findings - Grouping by Age. We selected two age groups to compare the viewpoint focus models. The first group (referred to as young) included 102 users with age between 18 and 23, based on the assumption that this is a period in their lives in which they study and do not have much experience in interviewing. The second group (referred to as older) included 109 users with age between 28 and 33, based on the assumption that during this period a person will be working and will have at least one job interview experience.

Mental-state. Figure 7.24 shows the contrastive semantic map for the mental-state branch (WNAffect taxonomy of emotions) together with the associated viewpoint focus models (lattices). The older group's focus included more elements (43 for young and 61 for older) in the structure as well as more main focus elements (9 for young and 12 for older). This shows that for the given data set a larger breadth of emotion related entities was extracted from comments of older YouTube users. As Figure 25a depicts, the young group's focus is included in the older group's viewpoint focus particularly around ambiguous -emotion. Around the region of negative emotions, the young group's viewpoint focus is either included or overlapping with the older group's. Figure 25b depicts two overlapping regions, showing the dominating coverage of the older group's focus. In the region of positive emotions, the two foci mostly overlap (an example is shown in Figure 25c).

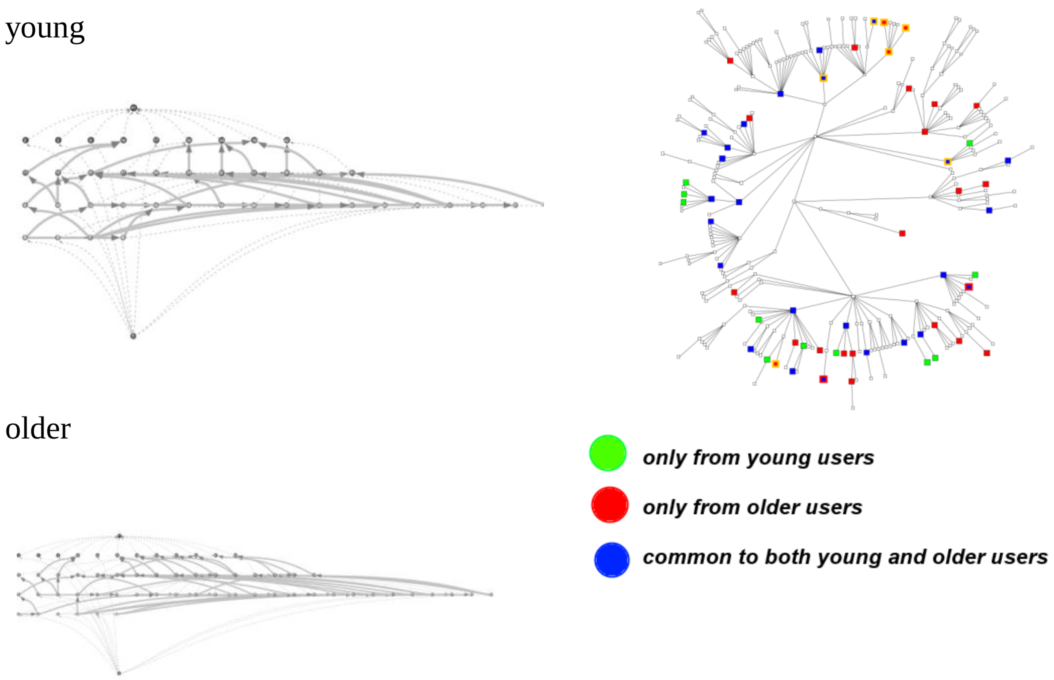


Figure 7.24 Contrastive semantic map of *mental states*(right) and focus models (left) for young and older users.

(a) young group's focus element included in older group's focus in the region of ambiguous emotion

(b) older group's focus covered a wider region of negative emotions

(c)only weak overlap was observed in the region of positive emotion. Exclusive ontology entities were extracted by comments of each group.

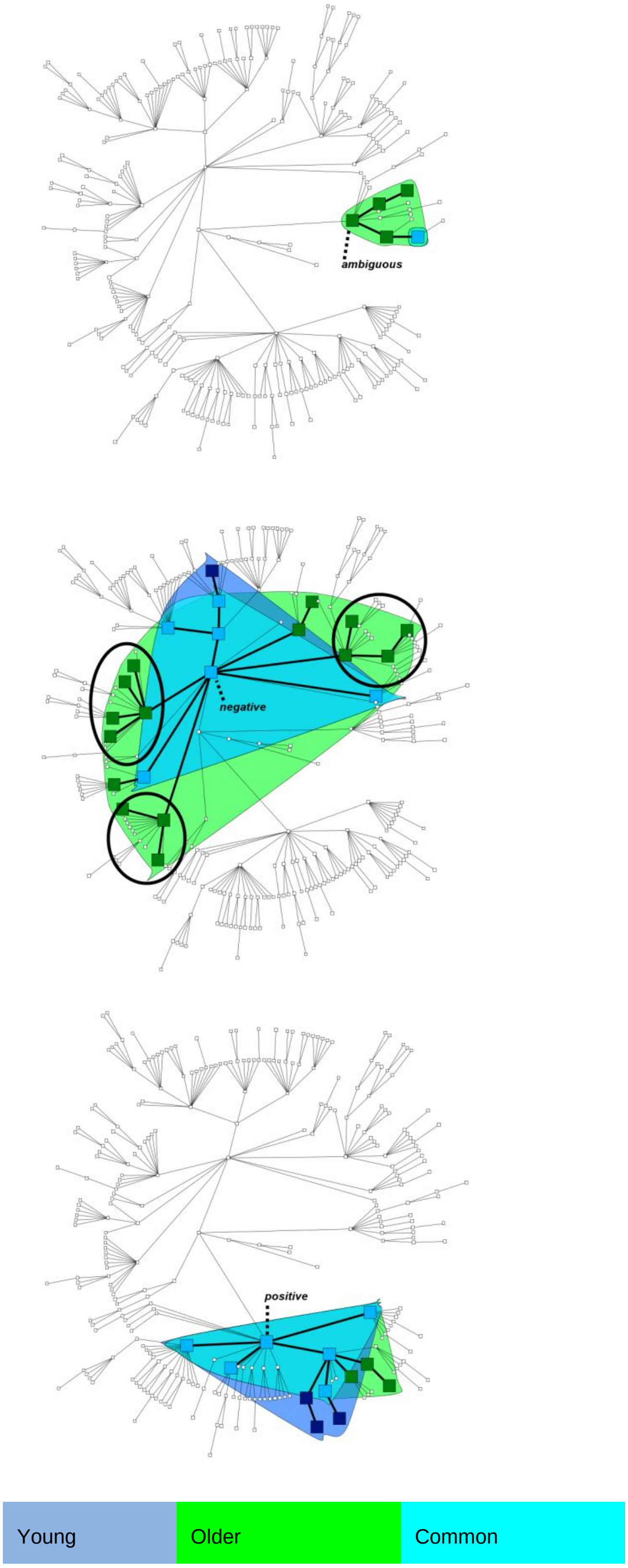


Figure 7.25 Comparison of focus models between young and older user groups.

Body language signal meaning. Figure 7.26 shows the contrastive semantic map for the *body language signal meaning* branch (body language ontology) together with the associated viewpoint focus models (lattices). The

older group's focus included more elements (195 for young and 348 for older) in the structure as well as more main focus elements (5 for young and 7 for older). Moreover, the older group's focus model is structured in more layers than the young group's (17 for young and 19 for older). The above observations show that the older group's viewpoint is covering a larger breadth f entities and includes more implications, thus more composite than the young group's respectively. Although both focus models overlap, particular differences are observed around the regions of social interactions and normative attributes (Figure 7.27). This shows that for the given data set a larger breadth of emotion related entities was extracted from comments of older YouTube users.

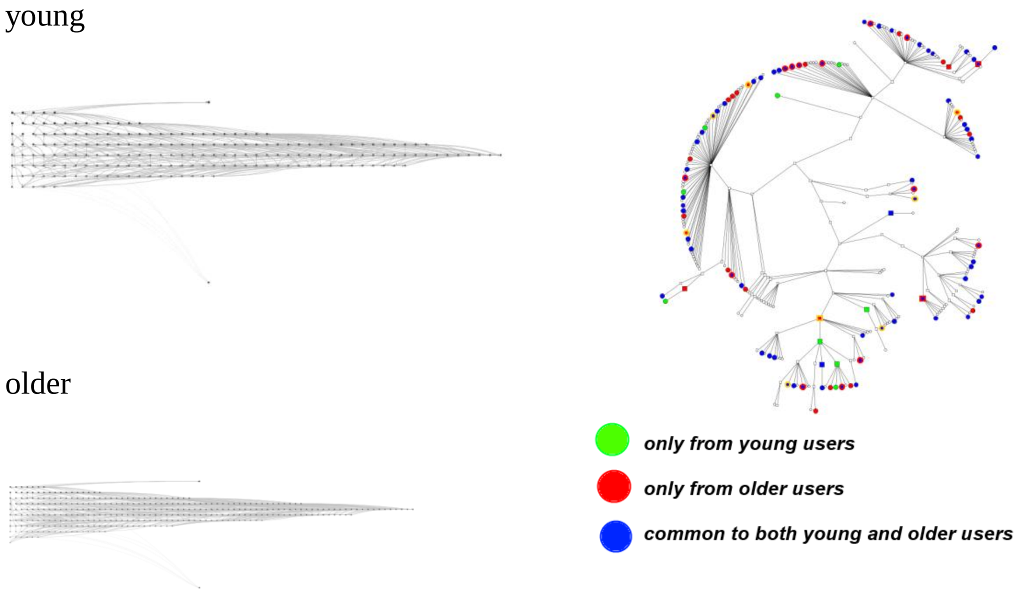


Figure 7.26 Contrastive semantic map of *body language signal meanings*(right) and focus models (left) for young and older users.

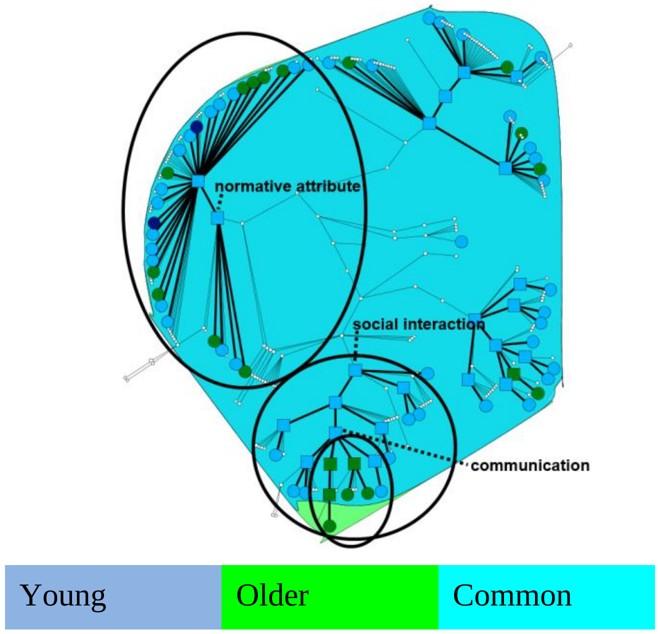


Figure 7.27 Overlap of focus models of young and older users.

Regions of ontology entities related to social interaction and normative attributes were extracted only by older users.

(II) Findings - Grouping by Gender. For the comparison of viewpoints based on gender, a random sample of male user profiles was selected to balance the with the female user profiles (105 users). A theoretical foundation for such a comparison includes that social signals (emotion and emotion expression) can be diverse between genders in particular contexts of interactions (e.g. job interviews)[161].

Mental-state. Figure 7.28 shows the contrastive semantic map for the mental-state branch (WNAffect taxonomy of emotions) together with the associated viewpoint focus models (lattices). The male group's focus included more elements (71 for male and 51 for female) in the structure as well as more main focus elements (15 for male and 12 for female). This shows that for the given data set a larger breadth of emotion related entities was extracted from comments of male YouTube users. Many singular entity regions of the male user's focus are disconnected from the female user's focus including *cruelty, identification, wonder* and *mood*. In the region of positive emotion, the viewpoints are very overlapping (Figure 29a). However, in the negative emotion, although overlapping, the male user's viewpoint focus includes elements around sadness (Figure 29b) and annoyance (Figure 29c) which are missing from the female user's viewpoint focus.

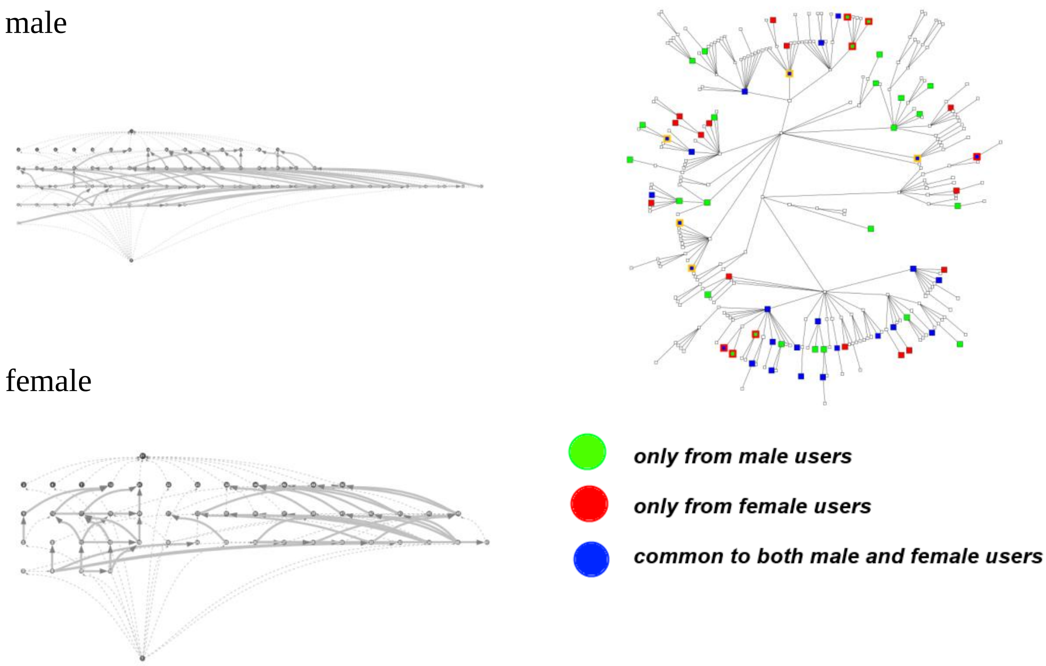
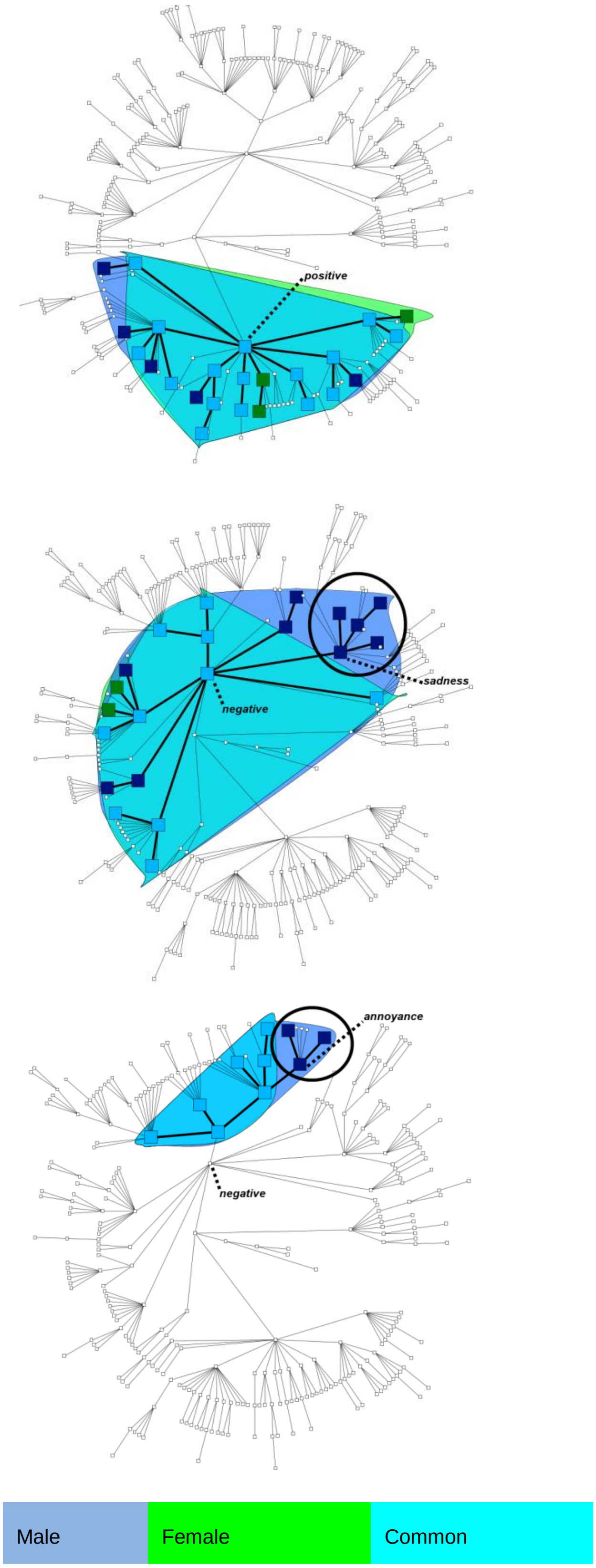


Figure 7.28 Contrastive semantic map of *mental states*(right) and focus models (left) for male and female users.



(a) in the region of positive emotion the focus models mostly overlap between the two user groups

(b) a focus region of ontology entities related to sadness was extracted only by the comments of male users

(c) in the region of negative emotion the focus of male users included the focus of female users. A sub-region of ontology entities related to annoyance was extracted only from male users.

Figure 7.29 Comparison of focus models between male and female user groups.

Body language signal meaning. Figure 7.30 shows the contrastive semantic map for the *body language signal meaning* branch (body language ontology) together with the associated viewpoint focus models (lattices). The

male user's focus included more elements (336 for male and 260 for female) in the structure. Although both focus models had the same number of main focus elements (6 in the second top layer), the male user's focus model is structured in more layers than the female group's (17 for male and 19 for female). The above observations show that the male group's viewpoint is slightly broader and more composite. Although both focus models overlap, particular differences are observed around the regions of normative attributes and psychological attributes (Figure 7.31). This shows that for the given data set a larger breadth of related entities was extracted from comments of male YouTube users.

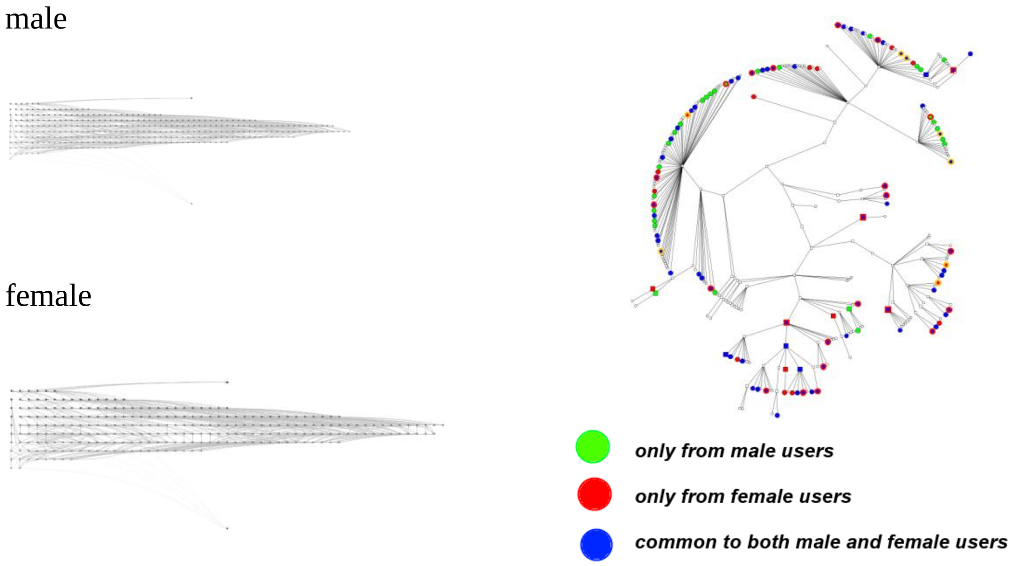


Figure 7.30 Contrastive semantic map of *body language signal meanings*(right) and focus models (left) for male and female users.

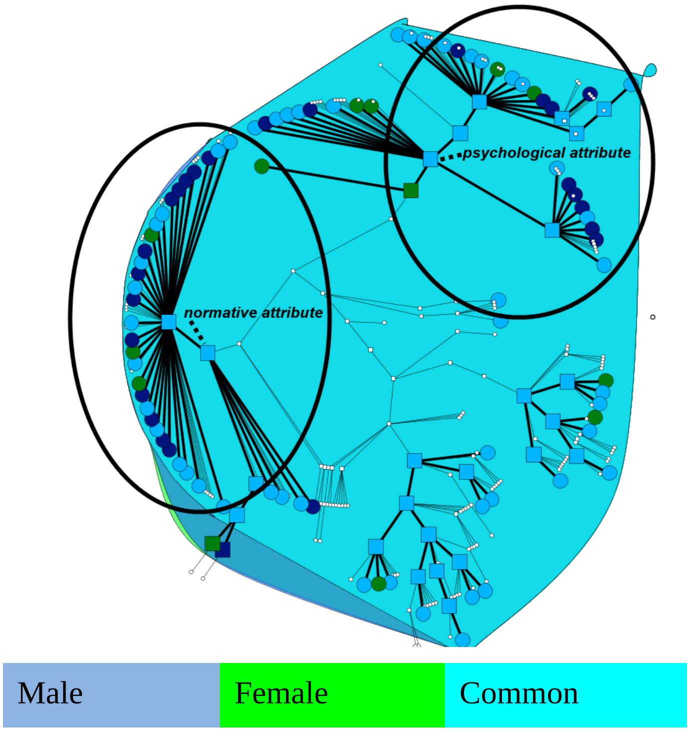


Figure 7.31 Overlap of focus models of male and female users.

Regions of ontology entities related to psychological and normative attributes were extracted only by male users.

(III) Findings - Grouping by Location. For the comparison of viewpoints based on location, a random sample of US user profiles was selected to balance with the GB YouTube users (36 users). similarly to the gender-social signals comparison, culture can also be a co-variant in peoples emotional experience according to particular contexts[161-163].

Mental-state. Figure 7.32 shows the contrastive semantic map for the mental-state branch (WNAffect taxonomy of emotions) together with the associated viewpoint focus models (lattices). The US group's focus included more elements (34 for US and 24 for GB) in the structure as well as more main focus elements (9 for US and 8 for female) and layers (7 for US and 5 for GB). This shows that for the given data set a larger breadth of emotion related entities was extracted from comments of US YouTube users. However, there is a region related to annoyance in negative emotions from which ontology entities were extracted from users in GB and missed from US (Figure 7.33a). Regions of ontology entities related to negative fear and sadness were not extracted by comments of users in GB (Figure 7.33b and c). In the region of positive emotion, the ontology entities extracted from comments of both groups of users were sparse.

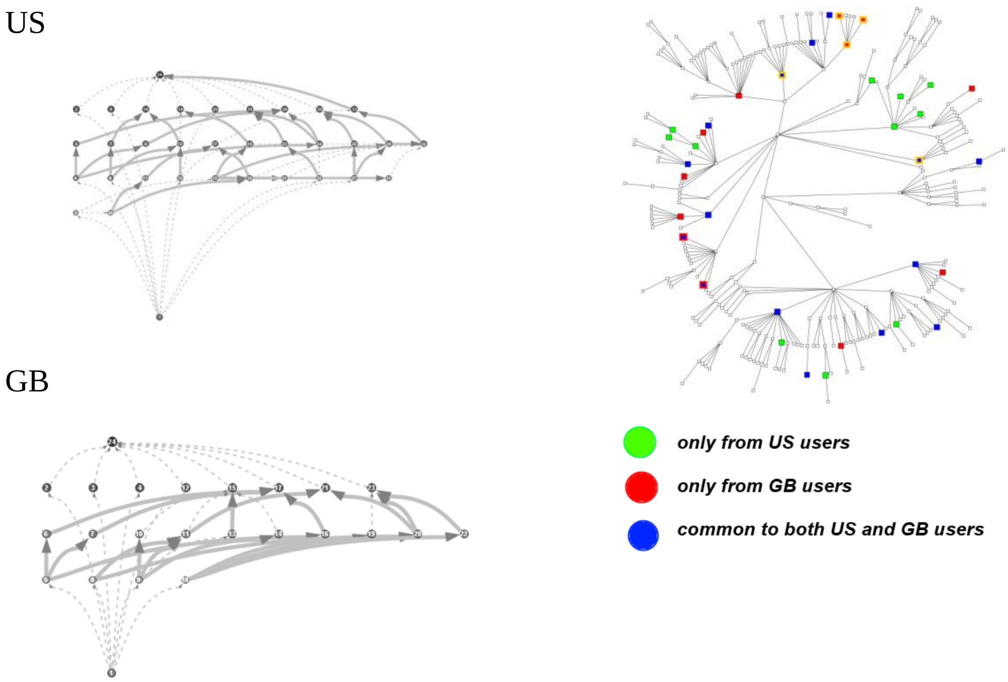


Figure 7.32 Contrastive semantic map of *mental states*(right) and focus models (left) for US and GB users.

(a) in the region of negative emotion, a focus region from the GB users' focus model included the focus of US users. A region of entities related to annoyance was exclusively extracted from comments provided by users in GB.

(b) a region of entities related to negative-fear was extracted in the focus model of US users, illustrated with the two overlapping focus elements.

(c) a region of entities related to sadness was extracted in the focus model of US users, illustrated with the two overlapping focus elements.

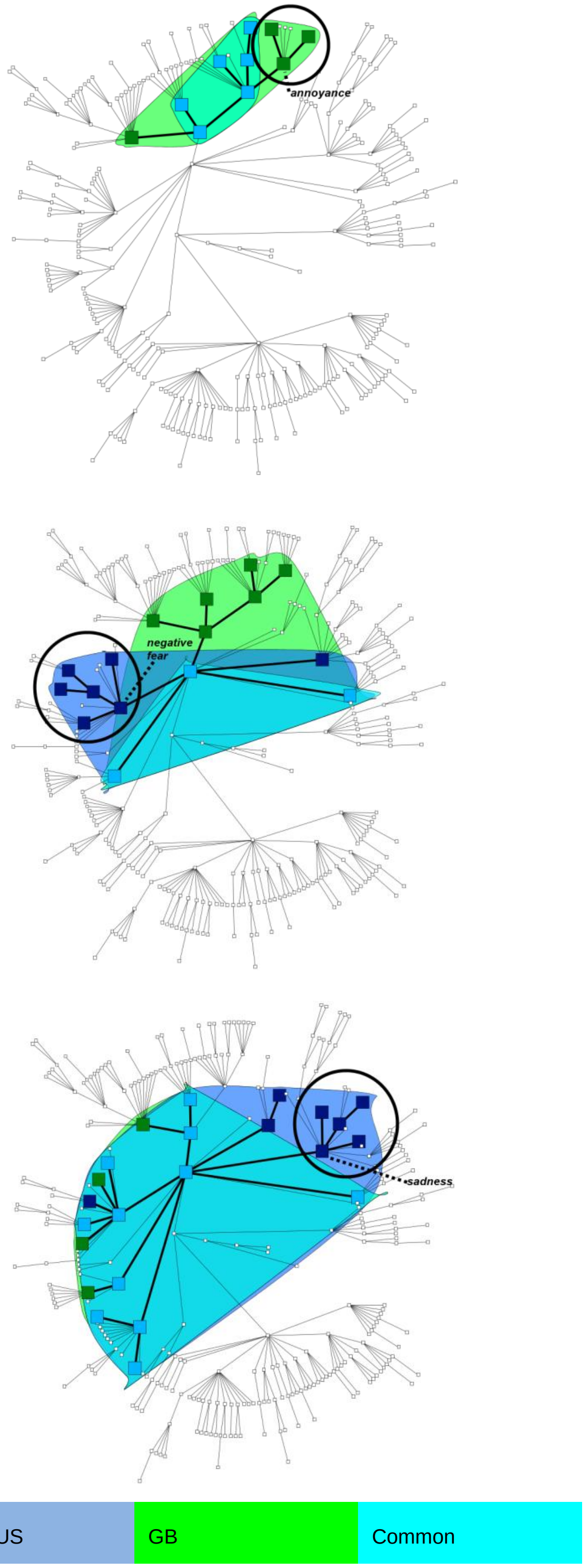


Figure 7.33 Comparison of focus models between US and GB user groups.

Body language signal meaning. Figure 7.34 shows the contrastive semantic map for the *body language signal meaning* branch (body language ontology) together with the associated viewpoint focus models (lattices). The

GB users' focus included more elements (88 for US and 100 for GB) in the structure. However, the focus model extracted from US users had more main focus elements (6 for US and 4 for GB) and the structure had more layers (13 for US and 11 for GB). Although both focus models had the same number of main focus elements (6 in the second top layer), the male user's focus model is structured in more layers than the female group's (17 for male and 19 for female). The above observations show that the male group's viewpoint is slightly broader and more composite. Although both focus models overlap, a particular difference is observed at the linguistic communication region of the ontology branch, where ontology entities extracted from GB user's comments were missed in US users' comments and reversely. Most overlap is observed in the region of psychological processes. Figure 7.35 depicts these observations.

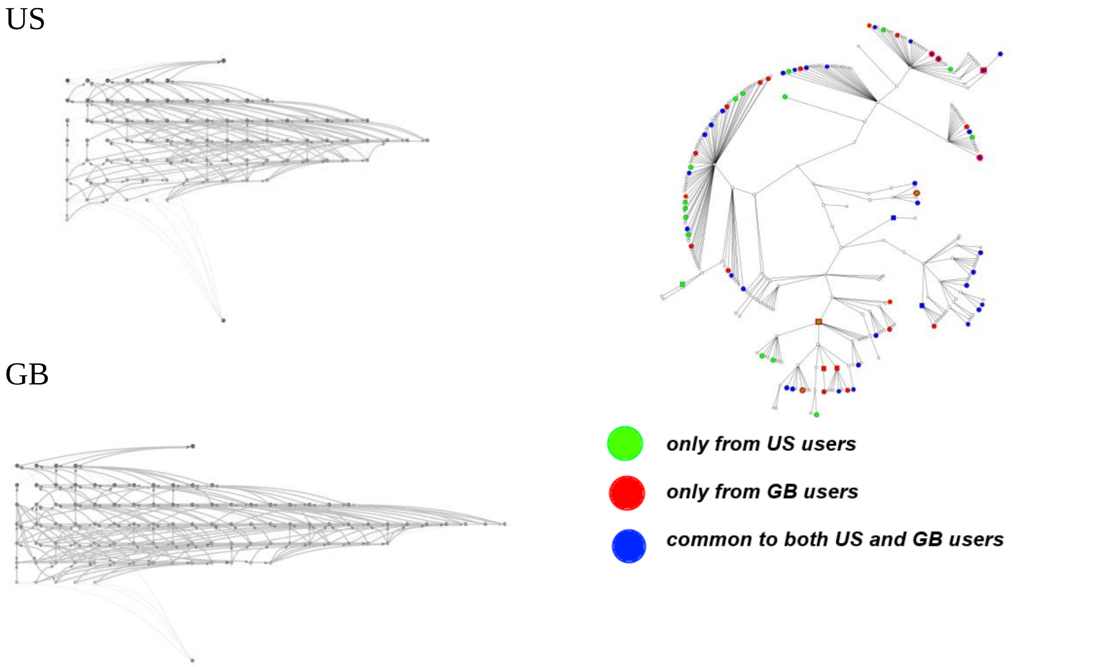


Figure 7.34 Contrastive semantic map of *body language signal meanings*(right) and focus models (left) for US and GB users.

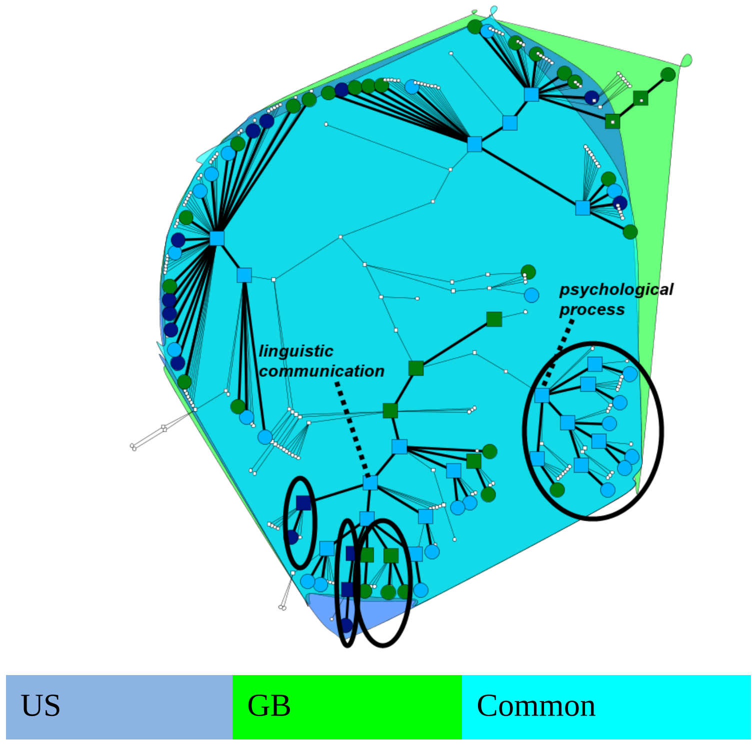


Figure 7.35 Overlap of focus models of US and GB users.

Regions of ontology entities related to linguistic communication were exclusively extracted from focus models of each user group. Strong overlap is observed in the region of entities related to psychological processes.

Using ViewS to extract and compare viewpoints in a small sample data set made possible to examine the similarities and differences of the viewpoints between different user groups. To explore diversity, domain aspects where viewpoints are similar or different were identified to better understand the users.

7.4 Discussion

In this Chapter ViewS Microscope was instantiated for two different types of user generated content: content collected in a closed social space, to illustrate the support of for the viewpoints focus representation requirements; and, content collected from a Social Media platform – YouTube, to illustrate the analytical utility for larger volumes of data. The application of Views is highly dependent on the data/content collection, from which particular implications have to be considered with respect to the methodology including required content features, purpose, application and quality.

Using closed social space. Content collection from closed social space allows for controlled elicitation of use generated content. Similarly to empirical evaluation methods for user modelling [164], the experiments/analysts can identify and elicit the features of user generated content that he/she is interested in. Guidelines are explicitly given to users, based on the purpose of the study, of which the users are aware off. The data is expected to be of higher quality, with reduced noise levels, however, achieving large volumes can be proved time consuming and resource expensive. How easy it is to avoid bias in the user model, therefore to increase authenticity[164]; To overcome this, open social spaces can be exploited, which however has its own disadvantages as a trade-off.

Using Social Media. Social Web provides an abundance of authentic user generated content. Making sense of its users has been proved beneficial and challenging in recent research streams, including user modelling with semantic web technologies [165]. However, Social Web does not provide the facility to collect all the possible desired features of user generated content, as the experimenters/analysts do not have direct control on the user interfaces for interaction.

In this work we acknowledge the benefit that can be produced with a synergy of semantic web technologies and machine learning or computational linguistic approaches, e.g. for topic detection. For example, given a user’s comment on job interview related video in YouTube, to whom does the comment refer: the interviewer or the applicant different viewpoint focus models can be constructed and analysed with intelligent text summarisation techniques [166].

Moreover, researchers have to deal with the noisy content that social media platforms are characterised by, especially when involving semantic annotation[98, 167]. The application of the extracted user models as well, has to be carefully monitored by domain experts; while in closed social spaces, the domain expert him/her self can control the content elicitation mechanism from the beginning of the study.

With ViewS Microscope, we demonstrated a semantic approach for user viewpoint modelling. It comprises an analytical tool for user generated content to support experimenters and analysts at the design stage of a system. ViewS can be extended in several directions. One of them, considering the large volumes of data especially concentrated in Social Web, concerns the frequency of annotations of particular ontology entities. As discussed in Section 6.7 regarding the focus model construction (and comparison of models), more frequent entities in the data set should be given more weight for analysis.

Moreover, one has to consider the distribution of user generated content with respect to different user profiles and digital objects. In the Social Web, as opposed to close-controlled social spaces, it can be found extremely difficult to balance the selected user profiles with the content contributed to digital objects. For example, exploiting YouTube, it is difficult to trace users that have contributed to several related videos. Although we acknowledge that no conclusive observations are aimed to be made (e.g. for stereotyping), the application of ViewS as an analytical tool, guided by a domain expert's input, can be proved useful for getting insights. Digital objects that complement viewpoint focus models can be suggested to users within a user group that is currently analysed. Similarly, focus models can be suggested to users within a group when they have interacted with the digital objects. This utility can be included by a domain expert in an adaptive system to expand and broaden the users' viewpoint (suggesting other digital objects) on one hand, and on the other hand to increase their awareness (using the same digital objects) respectively.

Chapter 8
Conclusions

8.1 Synopsis

This research dealt with the problem of modelling viewpoints in user generated content. The ultimate goal was to provide support for exploring diversity of user viewpoints.

Towards this goal, in Chapter 1, three main research questions were formulated: *how to represent, capture and analyse viewpoints in user generated content*.

In Chapter 2, related work was discussed and key limitations of state-of-the-art techniques were identified. Three main research fields were investigated: (i) *Text Mining* for classifying opinions and sentiments – however, these approaches only provide a shallow layer of representation, (ii) *Semantic Web technologies* which utilise ontologies to provide a conceptual layer to contextualise data – however, to be effective, semantic enrichment is needed especially when only small volume of content is available, and (iii) *User Modelling* which for a structure to represent a user using user generated content – although Semantic Web technologies are utilised, current approaches do not consider user viewpoints as part of the domain model, therefore diversity cannot be explored.

To provide solution for the research questions and to overcome limitations in current approaches, the ViewS framework was proposed in Chapter 3. ViewS represents user viewpoints with six elements: *users, digital objects, user statements, ontologies, semantic tags and viewpoint focus.* For capturing viewpoints two main components were introduced: (i) semantic augmentation of textual user generated content for extracting semantic tags from user statements, and (ii) viewpoint focus modelling for projecting the semantic tags as an overlay of the ontologies used to represent the domain knowledge. Social Signals in Interpersonal Communication was selected as a domain of experimentation and was discussed.

Semantic Augmentation was presented in Chapter 4, which includes three main steps: text-processing, enrichment and annotation using ontologies. The pipeline for semantic tagging integrates a number of existing software tools and resources. Semantic Augmentation was instantiated for the domain of social signals in interpersonal communication and was evaluated in an experimental study. High precision of annotation was demonstrated, and advantages and implications for semantic enrichment methods were identified.

In Chapter 5, an experimental study was presented which aimed at identifying potential benefits of semantic analysis of user generated content and eliciting requirements for focus representation. The study considered a learning context. User generated content was collected from a learning simulator and the semantic augmentation output was discussed with two simulator designers. The benefit of semantic analysis was illustrated together with the elicited requirements from the observations on the spread of annotated ontology entities over selected semantic maps of the domain.

The requirements were critically examined and a focus modelling framework was presented in Chapter 6. The focus modelling approach exploited Formal Concept Analysis to cluster annotated ontology entities in the ontologies and provide a structure for analysis. The viewpoints comparison method was also presented. The comparison method adapted the Region Connection Calculus framework which was applied for ontology regions (focus elements) defined by hierarchy relations between ontology entities. In order to be able to examine the output of the viewpoint focus modelling approach a visualisation tool was developed – ViewS Microscope. ViewS Microscope provides interactive visualisations for semantic maps of annotations, viewpoint focus models and comparison of viewpoints.

The support for analysis of user generated content offered by ViewS and ViewS Microscope was showcased in Chapter 7. Two social spaces were used: a closed social space – to illustrate the support of the requirements for focus modelling, and YouTube – to demonstrate the visual analytical power of ViewS for larger volumes of content in Social Media. For the first case study, ViewS was able to computationally model the observations made by the simulator designers. Discussion on extended the utility of ViewS Microscope is included in section 8.4. For the second case study, it was made possible to extract user viewpoints and support conceptual understanding of diversity found with preliminary statistical methods between different user groups. However, the selection of content to analyse has to be further considered. Primarily one should consider the relevancy of the content with respect to the interests of analysis. Moreover, it was not made possible in this research to provide a finer grained analysis which would include partitioning of the collected data according to specific features, e.g.

analyse comments related to the applicants in job interviews or to particular job interview phases (e.g. introduction, questions, salary negotiation).

8.2 Contributions

Contributions by this research are the results from the attempt to address the three research questions posed in Chapter 1. These are:

1) ***Views Framework***: The representation of user viewpoints blends the aspects of the infrastructure of the Social Web 2.0 with the vision of evolution to the Social Semantic Web 3.0 [1] including *users, digital objects in social spaces, user generated content, domain knowledge, extracted semantics,* and *user model projection in the domain knowledge*. This representation can be used as a starting point to semantically integrate (link) and aggregate (summarise) either users or digital online resources with respect to domains of interests. It is perceived as a way to better understands the users and their viewpoints related to experiences and opinions in a domain, but also to understand the domain itself in its specific instantiations based on user reflections [18]. The ViewS framework addresses mainly RQ1 for viewpoints representation and partly RQ2 and RQ3 for capturing and analysing viewpoints as it defines the necessary components and supports the analysis respectively.

2) ***Semantic Augmentation Pipeline***: The semantic augmentation pipeline provides *a technical solution for contextualising user generated content*. One of the main challenges is the amount and length of user contributions which result to less informative contents to extract knowledge from [165]. Direct links to ontologies which are exploited for semantic annotation are not possible in such cases, commonly present in Social Media. For this an integration of existing software tools was engineered in the semantic augmentation pipeline with the *semantic enrichment component*. Instead of language specific text, such as Named Entities (persons, locations and events), this research considered common sense language text. A linguistic and semantic approach was followed to link textual content (utilising WordNet) with semantically relevant (utilising SUMO) concepts (utilising WordNet linguistic variations, i.e. synonyms, antonyms and derivations, and DISCO similar words based on Wikipedia corpus).In the conducted evaluation study the semantic enrichment methods resulted to high precision of annotations in a common-sense field of experimentation – emotion and non-verbal communication. To further the application of semantic enrichment, the evaluation also included

identification of limitations and implications which should be considered in other research studies. The semantic augmentation pipeline addresses RQ2 for capturing user viewpoints.

3) ***Viewpoint Focus Modelling***: The viewpoint focus modelling approach utilising Formal Concept Analysis enables projecting the user in the domain of interest. Considering ontologies as domain knowledge representations the framework clusters and aggregates ontology entities extracted from user statements to form viewpoint focus elements. The analysis of viewpoint focus models is based on structural characteristics of the lattice graph and regional coverage over the ontology space. This allows for explicit qualitative processing of user viewpoints with respect to the domain knowledge. The comparison takes into account the regional coverage of focus elements and identifies similarities and differences using the Region Connection Calculus. The viewpoint focus modelling addresses RQ2 and RQ3 for capturing and analysing user viewpoints respectively.

4) ***ViewS Microscope***: ViewS Microscope was developed in order to be able to examine the output of ViewS including the semantic augmentation and focus extraction, as well as to practically analyse and compare user viewpoints. Although it consists a prototype software, it offers a creative solution for supporting visual analytics on user viewpoints. It is envisaged that it can be further extended as an initial tool for more generic solutions. ViewS Microscope contributes in tackling RQ3.

8.3 Generality of the Approach

This Section discusses the generality of the proposed semantic approach for viewpoints modelling with respect to the contributions by this research.

ViewS Framework. The representation of user viewpoints ($V = \langle U, O, S, \Omega, C, F \rangle$, Section 3.2.1), allows for a concise description of data and captures the main aspects of Social and Semantic Web. It is to be generic at a top level, namely no particular attributes are used to describe the specific modelling elements. For users, the current description includes a unique identifier, a username and basic demographic information (age, gender and location). The list of attributes can be extended however with an abstract list of properties. Similarly digital objects are described with a unique URI and metadata (title, author etc). User statements are bound to users and digital objects. Ontology description includes the ontology namespace and URI and a label to denote the corresponding domain or dimension. Semantic tags and focus extracted by the framework are described with entity URI (linking to the ontology) and the concept lattice structure which can be serialised to abstract XML graph structure.

The specificity of the framework lies on the data format needed to describe the input and the output of the semantic augmentation component. More generalised data formats will include RDF and standardised vocabularies (e.g. FOAF for users).

Semantic Augmentation. The generality of the semantic augmentation approach is bound to the application in common-sense domain knowledge. ViewS allows for configuration of the processing resources as well as appropriate ontologies with respect to the domain of interest; for example in this research, this included the selection of lexical categories and SUMO concepts for text processing and semantic enrichment..

It is acknowledged that for more specialised application domains, more specialised linguistic and semantic resources could be exploited. In the domain of health and medicine for example, for text- processing and semantic enrichment steps, the Unified Medical Language Thesauri could be exploited to derive related terms and PubMed corpus for deriving similar words with DISCO.

Viewpoint Focus Modelling. In the focus modelling approach a well established knowledge processing framework has been exploited - Formal Concept Analysis. The high level non-domain-specific conceptualisation used in this approach enables its generic application. Moreover, the requirements which led to exploit this framework were elicited on the basis of a structural representation of a domain – provided by ontologies, despite the fact the study considered the specific domain of social signals. The mechanism used to extract ontology regions is generic considering the flexibility to select arbitrary properties (I) to relate entities in the viewpoint context ($\mathbb{V} = \langle C, C, I_{d,\theta} \rangle$, see Section 6.3.4) as well as association metrics (e.g. in this research semantic distance was used to relate ontology entities and distance threshold as an association metric).

The specificity of the focus modelling approach resides in the hierarchy/taxonomy of the input ontology(ies). A rich ontology graph structure was assumed and tested for modelling; namely that the hierarchy tree has to be of reasonable depth and breadth in order to extract discernible ontology regions. Implications for adapting the proposed approach into less rich taxonomical structures in ontologies were discussed in Section 6.7.2.

Consequently, the comparison mechanism which is inspired by RCC would have limited application if a less rich hierarchy is exploited.

ViewS Microscope. ViewS Microscope can be as a generic tool for visual analysis of viewpoints. Any domain or dimension ontology(ies) can be loaded (domain independent) together with semantically augmented content (content independent). The focus extraction, visualisation and comparison mechanisms will effectively work in these settings.

The specificity of ViewS Microscope concerns the input data format. As discussed earlier the semantic augmentation component defines a custom non-standardised XML data schema.

8.4 Future Work

Based on the identified limitations of the proposed approach for user viewpoints modelling (Sections 4.5 and 6.7), this Section discusses immediate and future work.

8.4.1 Immediate

The immediate extensions of the work concern mainly technical improvements on the produced software for semantic augmentation and focus extraction, as well as visualisation for analysis with ViewS Microscope. The semantic augmentation pipeline has been implemented as a software library (API) which can be utilised from other software applications. However, implementation and wrapping as a web service would be ideal because of the size of the resources that need to be downloaded in a desktop based application (e.g. the Wikipedia corpus for extracting similar words with DISCO is approximately 5 Gigabytes). This will enable seamless integration with existing software or services.

ViewS Microscope will be extended to improve the visualisation of the semantic maps and viewpoint focus both at the presentation level (what is visible and accessible) as well as the layout level (how is it visible e.g. colours and graph layouts). The offered utility will be also enriched by providing access to user generated content based on annotated ontology entities and clusters or aggregates in the viewpoint focus model. The querying functionality will be designed to offer search on the semantically augmented content based on users, digital objects and semantic data, as well as to implement automatic methods for parsing the viewpoint focus lattice structure (e.g. for attribute exploration).

8.4.2 Long-term

In the long term plan for future research it envisaged to test and evaluate the framework in other domains. One possibility is to apply ViewS on data related to e-commerce and offer visual analytics functionality for product and service recommendations and social sensing of consumers' behaviour. The semantic based approach will utilise ontological specifications such as the GoodRelations ontology for e-commerce to semantically describe and relate user and company data.

Particular research focus will attract the investigation of the implications related to ontological knowledge processing for viewpoints modelling in user generated content. As discussed in the previous Section and earlier in Chapter 6, generalising the method to include additional structuring characteristics (e.g. object-properties) and content features (e.g. frequency of annotated entities) to relate entities will be challenging. Possible candidate research field to generalise the approach is the mathematical modelling and implications of Conceptual Graphs [168].

In a greater spectrum of application, of special interest would be to investigate the implications and design of the integration of the framework for user viewpoints modelling within the Social Semantic Web. One should consider not only the heterogeneity of the domain of application but also the heterogeneity of the current Social Media platforms [6]. One possible starting point would be to align the representational aspects with established standards, e.g. FOAF for user profiling and Linked Data for resource and user viewpoints linking. This implies the representation of the viewpoints model with OWL or RDF specification; which is also considered as an immediate extension.

Possible application scenarios are also envisaged for the proposed user viewpoint modelling approach and are discussed next.

8.5 Application Scenarios

This Section briefly discusses potential application scenarios of the proposed viewpoint modelling approach with user generated content.

Contextual Augmentation of Digital Objects. In the Social Web, user generated content related to a particular media, e.g. a video in YouTube or a picture in Flickr, can be used to contextually augment the digital object itself. Identifying user viewpoints can be helpful for the publisher of the digital object to augment its content based on observations and experiences contributed by other users. Diverse viewpoints can result to inclusion of digital objects where diverse situations are presented under the same scope, e.g. a video for responsibilities of volunteers in Africa could be augmented with content related to the perception and culture of the people who benefit from the volunteering. Moreover, personalised recommendations can be possible to broaden user perspectives by suggesting content and digital objects based on the viewpoints they stimulate.

Social Visual Analytics. A lot of work has been done on social network analysis based on online links between users, e.g. based on friendship in Facebook, commonly tagged pictures in Flickr, and shared interests on movies in IMDB. This research field could be augmented by integrating user viewpoint links to other people. A potential application can be to investigate cultural aspects between users and groups from different locations. Investigate how online communities are shaped or evolve by understanding similarities and differences of viewpoints and examine relations between existing social links (e.g. friendships and shared interests) together with viewpoints on particular domains. ViewS Microscope can be extended in this directions to include comparative or summary visualisations based on these two features and will support sense making by analysts.

Augmented User Modelling. Augmented user modelling is about getting insights about users from social web to improve adaptation in traditional systems. People nowadays are leaving digital traces in terms of blogs, tweets, comments etc. on the Social Web, providing a *sensor* of user activities and experiences, which can be a valuable source for personalisation. An application that can benefit from augmented user modelling is a user-adaptive simulated environment for learning which adapts the content to user profiles (discussion on this direction was included in Chapter 5). One of the known challenges for such adaptation is the *cold start* problem. Using ViewS, it is possible to create group profiles from social content by aggregating and representing various group viewpoints and focus spaces. Using ViewS viewpoints of groups (e.g. based on age) based on collective statements made on digital objects representing some activity (e.g. an activity in the simulator) can be derived. A new user of the simulated environment can be assumed to get *similar viewpoints* to a user group with the close demographics, i.e. the group viewpoints can be used in a stereotype-like way. If we have a viewpoint of the user (e.g. she has made a comment and it is linked to domain concepts) ViewS can help with mapping of the individual user’s viewpoint with the group viewpoint and finding complementary and similar viewpoint elements (and subsequent statements). This can be utilised to perform adaptation and broaden the user's perspective over the domain knowledge.

Adaptation Authoring. User-adaptive learning applications generally have a design phase where instructional designers plan scenarios, exploration paths and content to offer to users. Zooming through the viewpoint focus lattice over the focus space allows: (a) Path selection: the simulation scenario can be built over the viewpoint lattice given current situations represented by viewpoint and going from specific to more generic spaces, i.e. exploring broader aspects. A current situation can include a small number of entities and progressively, by following upward links, can expand the knowledge space based on the viewpoints structure. (b) Content presentation: different granularity aggregates of focus can be presented to users, e.g. of different expertise and awareness, and at a different progress stage. It is possible to analyse viewpoint focus of younger group and discover areas they concentrate on, areas they miss (for example, a particular category of emotion missed by this group). The instruction designer might decide to include a scenario and training content that include domain areas this group may be missing.

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List of Abbreviations

ANT	Antonym
DRV	Derivation
DSC	DISCO
ESF	Enriched Surface Form
ET	Exact Token
FR	Focus Requirement
IC	Interpersonal Communication
IE	Information Extraction
MWC	Multi-word Concept
MWT	Multi-word Token
NER	Named Entity Recognition
NLP	Natural Language Processing
OBIE	Ontology Based Information Extraction
SF	Surface Form
SNM	Synonym
ST	Stemmed Term
SUMO	Suggested Upper-merged Ontology
UGC	User Generated Content
ViewS	Viewpoint Semantics

Appendix A
Semantic Augmentation in ViewS

A.1 Text Processing

A.1.1 Typed Dependencies

Negation, Adjectival Complement, Adjectival Modifier, Direct Object, Noun Compound, Participial Modifier mod, Prepositional Object, Phrasal Verb, Open Clausal Complement, Nominal Subject, Noun Phrase As Adverbial, Conjunction Or, Conjunction And, Adverbial Modifier, Adverbial Clause Modifier

A.2 Enrichment

A.2.1 WordNet Lexical Categories for IC and Social Signals

1	adj.all	**17**	noun.possesion
2	adj.ppl	**18**	noun.process
3	adj.pert	**19**	noun.relation
4	adv.all	**20**	noun.state
5	noun.act	**21**	noun.time
6	noun.artifact	**22**	verb.body
7	noun.attribute	**23**	verb.cognition
8	noun.body	**24**	verb.communication
9	noun.cognition	**25**	verb.competition
10	noun.communication	**26**	verb.contact
11	noun.event	**27**	verb.emotion
12	noun.feeling	**28**	verb.motion
13	noun.location	**29**	verb.perception
14	noun.motive	**30**	verb.social
15	noun.object	**31**	verb.stative
16	noun.person		

A.2.2 SUMO Entities for IC and Social Signals

1	Accelerating	**90**	Eyelid	**179**	manner	**268**	Reserving
2	Agreement	**91**	EyeMotion	**180**	Matriculation	**269**	Resigning
3	Ambulating	**92**	Face	**181**	Meeting	**270**	Retired
4	Anger	**93**	FacialExpression	**182**	Memorizing	**271**	Retiring
5	Ankle	**94**	FacialHair	**183**	Motion	**272**	Running
6	Answering	**95**	Fact	**184**	MotionDownward	**273**	SalesPosition
7	Anxiety	**96**	Falling	**185**	MotionUpward	**274**	Seeing
8	Arguing	**97**	fears	**186**	Mouth	**275**	SensoryDisability
9	Argument	**98**	Female	**187**	Multilingual	**276**	ServiceContract
10	Arm	**99**	FinancialContract	**188**	Muscle	**277**	ServicePosition
11	Arriving	**100**	FinancialTransaction	**189**	Nail	**278**	Sharing
12	Artifact	**101**	Finger	**190**	Neck	**279**	Shirt
13	Asleep	**102**	finishes	**191**	needs	**280**	Shoe
14	attends	**103**	Fist	**192**	Negotiating	**281**	Shrugging
15	Awake	**104**	Foot	**193**	Nodding	**282**	Sign
16	believes	**105**	FormalAttribute	**194**	NormativeAttribute	**283**	SigningADocument
17	BiologicalAttribute	**106**	FormalMeeting	**195**	Nose	**284**	SittingDown
18	BiologicalProcess	**107**	Frightening	**196**	ObjectiveNorm	**285**	Skin
19	Biting	**108**	FullTimePosition	**197**	Obligation	**286**	Skull
20	Blind	**109**	FutureFn	**198**	OccupationalRole	**287**	Sleeve
21	BodyHair	**110**	Gesture	**199**	occupiesPosition	**288**	Smelling
22	BodyJoint	**111**	Grabbing	**200**	Offering	**289**	Smiling
23	BodyJunction	**112**	grasps	**201**	OpeningEyes	**290**	Smoke
24	BodyMotion	**113**	Greeting	**202**	Organization	**291**	Smoking
25	BodyPart	**114**	Guiding	**203**	OrganizationalProcess	**292**	SocialParty
26	BodySubstance	**115**	Hair	**204**	Pain	**293**	SocialRole
27	BodySubstance	**116**	Hand	**205**	Paper	**294**	Sock
28	BodyVessel	**117**	Hanging	**206**	Partnership	**295**	Speaking

29	Bone	**118**	Happiness	**207**	PartTimePosition	**296**	StandingUp
30	Bowing	**119**	hasExpertise	**208**	PastFn	**297**	Statement
31	Boy	**120**	hasPurpose	**209**	PathologicProcess	**298**	StateOfMind
32	Breast	**121**	hasSkill	**210**	Payment	**299**	Stating
33	Breathing	**122**	Head	**211**	Pencil	**300**	Stepping
34	Calculating	**123**	Hearing	**212**	Perception	**301**	Stomach
35	Chin	**124**	Heart	**213**	PerceptualAttribute	**302**	Stressed
36	Clamp	**125**	Hiring	**214**	Permission	**303**	SubjectiveAssessmentAttribute
37	Clapping	**126**	hopes	**215**	PhysicalAttribute	**304**	Supposing
38	ClosingEyes	**127**	Human	**216**	PhysicalState	**305**	Supposition
39	Combining	**128**	HumanChild	**217**	PhysiologicProcess	**306**	Surprise
40	Commenting	**129**	HumanLanguage	**218**	Plan	**307**	TasteAttribute
41	Communication	**130**	Imagining	**219**	Planning	**308**	Tasting
42	Comparing	**131**	Impacting	**220**	Pocket	**309**	Teenager
43	Composing	**132**	Inclining	**221**	Poking	**310**	Telephone
44	conclusion	**133**	Indicating	**222**	Position	**311**	Telephoning
45	conforms	**134**	Inflating	**223**	PositionalAttribute	**312**	Testament
46	considers	**135**	Inhaling	**224**	possesses	**313**	Testifying
47	containsInformation	**136**	IntentionalProcess	**225**	Predicting	**314**	Thanking
48	Contest	**137**	IntentionalPsychologicalProcess	**226**	prefers	**315**	Threatening
49	ContestAttribute	**138**	IntentionalRelation	**227**	PreparedFood	**316**	Throat
50	contestParticipant	**139**	InternalAttribute	**228**	Pretending	**317**	Throwing
51	Cooperation	**140**	InternalChange	**229**	prevents	**318**	Thumb
52	Corresponding	**141**	Interpreting	**230**	priceRange	**319**	time
53	Counting	**142**	Investigating	**231**	ProbabilityRelation	**320**	Tissue
54	Dancing	**143**	Investing	**232**	Procedure	**321**	Toe
55	Debating	**144**	Judging	**233**	Process	**322**	Tooth
56	Deciding	**145**	Jumping	**234**	Proliferation	**323**	Torso
57	Declaring	**146**	Kicking	**235**	Promise	**324**	Touching

58	Demonstrating	**147**	Kidney	**236**	Proposition	**325**	TraitAttribute
59	Demonstration	**148**	Kissing	**237**	PropositionalAttitude	**326**	Tranquility
60	describes	**149**	Knee	**238**	Proprietorship	**327**	Trembling
61	Designating	**150**	knows	**239**	Prostrate	**328**	Trousers
62	desires	**151**	Knuckle	**240**	PsychologicalAttribute	**329**	Unemployed
63	Directing	**152**	lacks	**241**	PsychologicalDysfunction	**330**	Unhappiness
64	disapproves	**153**	Language	**242**	PsychologicalOperation	**331**	Unlikely
65	dislikes	**154**	Laughing	**243**	PsychologicalProcess	**332**	Vacationing
66	doubts	**155**	Lead	**244**	Psychology	**333**	ViolentContest
67	DramaticActing	**156**	leader	**245**	Psychosis	**334**	Vocalizing
68	Dress	**157**	Learning	**246**	Pulling	**335**	Walking
69	dressCode	**158**	Leaving	**247**	Punishing	**336**	wants
70	Dressing	**159**	Lecture	**248**	Pursuing	**337**	Waving
71	Drinking	**160**	Lending	**249**	Pushing	**338**	wears
72	Ducking	**161**	Letter	**250**	Putting	**339**	Weeping
73	Ear	**162**	License	**251**	Question	**340**	Winking
74	Eating	**163**	LinguisticCommunication	**252**	Questioning	**341**	Won
75	Elbow	**164**	LinguisticExpression	**253**	RatingAttribute	**342**	Working
76	Embracing	**165**	Lip	**254**	Reading	**343**	Wrist
77	EmotionalState	**166**	Listening	**255**	Reasoning	**344**	Writing
78	EmploymentFiring	**167**	Liver	**256**	Reciting	**345**	FALSE
79	employs	**168**	Living	**257**	Registering	**346**	TRUE
80	enjoys	**169**	Looking	**258**	Regretting		
81	entails	**170**	loss	**259**	Relation		
82	expects	**171**	Lost	**260**	Releasing		
83	experiencer	**172**	Lung	**261**	RelievingPain		
84	Explanation	**173**	Maintaining	**262**	Remembering		
85	Expressing	**174**	Making	**263**	Reminding		
86	ExpressingApproval	**175**	Male	**264**	Report		

87	ExpressingDisapproval	176	Man	265	represents	
88	ExpressingFarewell	177	Manager	266	Request	
89	EyeGlass	178	Managing	267	Requesting	

A.3 ViewS Semantic Augmentation XSD

A.3.1 Input: User Generated Content XSD

```xml
<?xml version="1.0" encoding="utf-8"?>
<xs:schema attributeFormDefault="unqualified" elementFormDefault="qualified" xmlns:xs="http://www.w3.org/2001/XMLSchema">
  <xs:element name="map">
    <xs:complexType>
      <xs:sequence>
        <xs:element maxOccurs="unbounded" name="entry">
          <xs:complexType>
            <xs:sequence>
              <xs:element name="string" type="xs:string" />
              <xs:element name="views.Data.DigitalObject">
                <xs:complexType>
                  <xs:sequence>
                    <xs:element name="Id" type="xs:unsignedShort" />
                    <xs:element name="Environment__Id" type="xs:string" />
                    <xs:element minOccurs="0" name="Author">
                      <xs:complexType>
                        <xs:sequence>
                          <xs:element name="Id" type="xs:string" />
                          <xs:element name="Nickname" type="xs:string" />
                          <xs:element name="Age" type="xs:byte" />
                          <xs:element name="Gender" type="xs:string" />
                          <xs:element name="Location" type="xs:string" />
                          <xs:element name="Occupation" type="xs:string" />
                        </xs:sequence>
                      </xs:complexType>
                    </xs:element>
                    <xs:element name="Uri" type="xs:string" />
                    <xs:element name="Title" type="xs:string" />
                    <xs:element name="Description" type="xs:string" />
                    <xs:element name="Keywords" type="xs:string" />
                    <xs:element name="Category" type="xs:string" />
                    <xs:element name="IsActive" type="xs:boolean" />
                    <xs:element name="IsTimeSequenced" type="xs:boolean" />
                    <xs:element name="Tstart" type="xs:decimal" />
                    <xs:element name="Tend" type="xs:decimal" />
                    <xs:element name="Duration" type="xs:decimal" />
                    <xs:element name="ObjectEpisodes">
                      <xs:complexType>
                        <xs:sequence>
                          <xs:element name="entry">
                            <xs:complexType>
                              <xs:sequence>
                                <xs:element name="int" type="xs:unsignedByte" />
                                <xs:element name="views.Data.DigitalObjectEpisode">
                                  <xs:complexType>
                                    <xs:sequence>
                                      <xs:element name="Id" type="xs:unsignedByte" />
                                      <xs:element name="Environment__Id" type="xs:string" />
                                      <xs:element minOccurs="0" name="Author">
                                        <xs:complexType>
                                          <xs:sequence>
                                            <xs:element name="Id" type="xs:string" />
                                            <xs:element name="Nickname" type="xs:string" />
                                            <xs:element name="Age" type="xs:byte" />
                                            <xs:element name="Gender" type="xs:string" />
                                            <xs:element name="Location" type="xs:string" />
                                            <xs:element name="Occupation" type="xs:string" />
                                          </xs:sequence>
                                        </xs:complexType>
                                      </xs:element>
                                      <xs:element name="Uri" type="xs:string" />
                                      <xs:element name="Title" type="xs:string" />
                                      <xs:element name="Description" type="xs:string" />
                                      <xs:element name="Keywords" type="xs:string" />
                                      <xs:element name="Category" type="xs:string" />
                                      <xs:element name="IsActive" type="xs:boolean" />
                                      <xs:element name="IsTimeSequenced" type="xs:boolean" />
                                      <xs:element name="Tstart" type="xs:decimal" />
                                      <xs:element name="Tend" type="xs:decimal" />
                                      <xs:element name="Duration" type="xs:decimal" />
                                      <xs:element name="ObjectEpisodes" />
                                      <xs:element name="DigitalObject__Id" type="xs:unsignedShort" />
                                      <xs:element name="DigitalObjectTraces">
                                        <xs:complexType>
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                                            <xs:element maxOccurs="unbounded" name="entry">
                                              <xs:complexType>
                                                <xs:sequence>
                                                  <xs:element name="int" type="xs:unsignedShort" />
                                                  <xs:element name="views.Data.DigitalObjectTrace">
```

```xml
                                            <xs:complexType>
                                              <xs:sequence>
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                                                <xs:element name="DigitalObject__Id" type="xs:unsignedShort" />
                                                <xs:element name="ObjectEpisode__Id" type="xs:unsignedByte" />
                                                <xs:element name="Author">
                                                  <xs:complexType>
                                                    <xs:sequence>
                                                      <xs:element name="Id" type="xs:string" />
                                                      <xs:element name="Nickname" type="xs:string" />
                                                      <xs:element name="Age" type="xs:byte" />
                                                      <xs:element name="Gender" type="xs:string" />
                                                      <xs:element name="Location" type="xs:string" />
                                                      <xs:element name="Occupation" type="xs:string" />
                                                    </xs:sequence>
                                                  </xs:complexType>
                                                </xs:element>
                                                <xs:element name="Aspect">
                                                  <xs:complexType>
                                                    <xs:sequence>
                                                      <xs:element name="Operator" type="xs:string" />
                                                      <xs:element name="Label" type="xs:string" />
                                                      <xs:element name="Sense" />
                                                      <xs:element name="ResourceType" type="xs:string" />
                                                      <xs:element name="Resource__Id" type="xs:string" />
                                                      <xs:element name="Dimension" type="xs:string" />
                                                    </xs:sequence>
                                                    <xs:attribute name="class" type="xs:string" use="required" />
                                                  </xs:complexType>
                                                </xs:element>
                                                <xs:element name="Text" type="xs:string" />
                                                <xs:element name="Perspective" type="xs:string" />
                                              </xs:sequence>
                                            </xs:complexType>
                                          </xs:element>
                                        </xs:sequence>
                                      </xs:complexType>
                                    </xs:element>
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                              </xs:element>
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                      </xs:sequence>
                    </xs:complexType>
                  </xs:element>
                </xs:sequence>
              </xs:complexType>
            </xs:element>
          </xs:sequence>
        </xs:complexType>
      </xs:element>
    </xs:sequence>
  </xs:complexType>
  </xs:element>
</xs:schema>
```

A.3.2 Output: Semantically Augmented User Generated Content XSD

```xml
<?xml version="1.0" encoding="utf-8"?>
<xs:schema attributeFormDefault="unqualified" elementFormDefault="qualified" xmlns:xs="http://www.w3.org/2001/XMLSchema">
  <xs:element name="set">
    <xs:complexType>
      <xs:sequence>
        <xs:element maxOccurs="unbounded" name="views.SemanticAugmentation.SemanticAnnotation.DataAnnotation">
          <xs:complexType>
            <xs:sequence>
              <xs:element name="Id" type="xs:unsignedShort" />
              <xs:element name="Environment__Id" type="xs:string" />
              <xs:element minOccurs="0" name="Author">
                <xs:complexType>
                  <xs:sequence>
                    <xs:element name="Id" type="xs:string" />
                    <xs:element name="Nickname" type="xs:string" />
                    <xs:element name="Age" type="xs:byte" />
                    <xs:element name="Gender" type="xs:string" />
                    <xs:element name="Location" type="xs:string" />
                    <xs:element name="Occupation" type="xs:string" />
                  </xs:sequence>
                </xs:complexType>
              </xs:element>
              <xs:element name="Uri" type="xs:string" />
              <xs:element name="Title" type="xs:string" />
              <xs:element name="Description" type="xs:string" />
              <xs:element name="Keywords" type="xs:string" />
              <xs:element name="Category" type="xs:string" />
              <xs:element name="IsActive" type="xs:boolean" />
              <xs:element name="IsTimeSequenced" type="xs:boolean" />
              <xs:element name="Tstart" type="xs:decimal" />
              <xs:element name="Tend" type="xs:decimal" />
              <xs:element name="Duration" type="xs:decimal" />
              <xs:element name="ObjectEpisodes" />
```

```xml
<xs:element name="Elements">
  <xs:complexType>
    <xs:sequence>
      <xs:element maxOccurs="unbounded" name="entry">
        <xs:complexType>
          <xs:sequence>
            <xs:element name="int" type="xs:unsignedShort" />
            <xs:element name="views.SemanticAugmentation.SemanticAnnotation.AnnotationElement">
              <xs:complexType>
                <xs:sequence>
                  <xs:element name="Id" type="xs:unsignedShort" />
                  <xs:element name="Environment__Id" type="xs:string" />
                  <xs:element name="DigitalObject__Id" type="xs:unsignedShort" />
                  <xs:element name="ObjectEpisode__Id" type="xs:unsignedByte" />
                  <xs:element name="Author">
                    <xs:complexType>
                      <xs:sequence>
                        <xs:element name="Id" type="xs:string" />
                        <xs:element name="Nickname" type="xs:string" />
                        <xs:element name="Age" type="xs:byte" />
                        <xs:element name="Gender" type="xs:string" />
                        <xs:element name="Location" type="xs:string" />
                        <xs:element name="Occupation" type="xs:string" />
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                    <xs:complexType>
                      <xs:sequence>
                        <xs:element name="Operator" type="xs:string" />
                        <xs:element name="Label" type="xs:string" />
                        <xs:element name="Sense" />
                        <xs:element name="ResourceType" type="xs:string" />
                        <xs:element name="Resource__Id" type="xs:string" />
                        <xs:element name="Dimension" type="xs:string" />
                      </xs:sequence>
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                    </xs:complexType>
                  </xs:element>
                  <xs:element name="Text" type="xs:string" />
                  <xs:element name="Perspective" type="xs:string" />
                  <xs:element name="Annotations">
                    <xs:complexType>
                      <xs:sequence minOccurs="0">
                        <xs:element maxOccurs="unbounded" name="entry">
                          <xs:complexType>
                            <xs:sequence>
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                              <xs:element name="views.Semantics.Statement">
                                <xs:complexType>
                                  <xs:sequence>
                                    <xs:element name="ID" type="xs:unsignedShort" />
                                    <xs:element name="DigitalObject__Id" type="xs:unsignedShort" />
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                                    <xs:element name="Individual">
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                                          <xs:element name="Nickname" type="xs:string" />
                                          <xs:element name="Age" type="xs:byte" />
                                          <xs:element name="Gender" type="xs:string" />
                                          <xs:element name="Location" type="xs:string" />
                                          <xs:element name="Occupation" type="xs:string" />
                                        </xs:sequence>
                                      </xs:complexType>
                                    </xs:element>
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                                    <xs:element name="DigitalObject__Title" type="xs:string" />
                                    <xs:element name="DigitalObjectEpisode__Title" type="xs:string" />
                                    <xs:element name="DigitalObjectTrace__Text" type="xs:string" />
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                                          <xs:element name="Resource__Id" type="xs:string" />
                                          <xs:element name="Dimension" type="xs:string" />
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                                          <xs:element name="Domain" type="xs:string" />
                                          <xs:element name="ResourceType" type="xs:string" />
                                          <xs:element name="Resource__Id" type="xs:string" />
                                          <xs:element name="Dimension" type="xs:string" />
                                          <xs:element name="Uri" type="xs:string" />
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                                    </xs:element>
                                    <xs:element name="AnnotationTokenIDS" type="xs:string" />
                                    <xs:element name="AnnotationTokens" type="xs:string" />
```

```
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                                      </xs:complexType>
                                    </xs:element>
                                  </xs:sequence>
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                    </xs:complexType>
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              </xs:complexType>
            </xs:element>
          </xs:sequence>
        </xs:complexType>
      </xs:element>
    </xs:sequence>
  </xs:complexType>
</xs:element>
</xs:schema>
```

A.4 Evaluation of Semantic Augmentation

Table A.4.1 Pair-wise contingency tables of responses for the annotated text terms.

			ExpA			
			YES	NO	NOT SURE	Total
ExpA - ExpB	ExpB	YES	1080	378	8	1466
		NO	28	20	2	50
		NOT SURE	6	4	0	10
		Total	1114	402	10	1526
			ExpA			
			YES	NO	NOT SURE	Total
ExpA - ExpC	ExpC	YES	855	166	7	1028
		NO	177	142	1	320
		NOT SURE	82	94	2	178
		Total	1114	402	10	1526
			ExpB			
			YES	NO	NOT SURE	Total
ExpB - ExpC	ExpC	YES	1004	19	5	1028
		NO	295	23	2	320
		NOT SURE	167	8	3	178
		Total	1466	50	10	1526

Table A.4.2 Pair-wise Contingency tables of responses for the annotated ontology entities.

			ExpA			
			YES	NO	NOT SURE	Total
ExpA - ExpB	ExpB	YES	740	614	13	1367
		NO	32	90	1	123
		NOT SURE	5	28	3	36
		Total	777	732	17	1526
			ExpA			
			YES	NO	NOT SURE	Total
ExpA - ExpC	ExpC	YES	729	689	14	1432
		NO	44	19	2	65
		NOT SURE	4	24	1	29
		Total	777	732	17	1526
			ExpB			
			YES	NO	NOT SURE	Total
ExpB - ExpC	ExpC	YES	1299	99	34	1432
		NO	50	15	0	65
		NOT SURE	18	9	2	29
		Total	1367	123	36	1526

Appendix B
Application of ViewS on Social Spaces

B.1 YouTube Platform

B.1.1 YouTube Query Strings

interviewer
interviewee
job interviewer
job interviewee
applicant
candidate
job candidate
job applicant
interview
job interview
interview applicant
job interview applicant
interview candidate
job interview candidate
interview interviewer
interview interviewee
job interview interviewer
job interview interviewee
interview example
interview examples
job interview example
job interview examples
interview culture
job interview culture
interview applicant culture
interview candidate culture
interview interviewer culture
job interview applicant culture
job interview candidate culture
job interview interviewer culture
interview non-verbal communication
job interview non-verbal communication
interview applicant non-verbal communication
interview candidate non-verbal communication
interview interviewer non-verbal communication
job interview applicant non-verbal communication
job interview candidate non-verbal communication
job interview interviewer non-verbal communication
interview emotional
job interview emotional
interview applicant emotional
interview candidate emotional
interview interviewer emotional
job interview applicant emotional
job interview candidate emotional
job interview interviewer emotional
interview cultural difference
job interview cultural difference
interview applicant cultural difference
interview candidate cultural difference
interview interviewer cultural difference
job interview applicant cultural difference
job interview candidate cultural difference
job interview interviewer cultural difference
interview question
job interview question
interview applicant question
interview candidate question
interview interviewer question
job interview applicant question
job interview candidate question
job interview interviewer question
interview women
job interview women
interview applicant women
interview candidate women
interview interviewer women
job interview applicant women
job interview candidate women
job interview interviewer women
interview men
job interview men
interview applicant men
interview candidate men
interview interviewer men
job interview applicant men
job interview candidate men
job interview interviewer men
interview male
job interview male
interview applicant male
interview candidate male
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job interview applicant male
job interview candidate male
job interview interviewer male
interview female
job interview female
interview applicant female
interview candidate female
interview interviewer female
job interview applicant female
job interview candidate female
job interview interviewer female
interview foreign
job interview foreign
interview applicant foreign
interview candidate foreign
interview interviewer foreign
job interview applicant foreign
job interview candidate foreign
job interview interviewer foreign
interview tactics
job interview tactics
interview applicant tactics
interview candidate tactics
interview interviewer tactics
job interview applicant tactics
job interview candidate tactics
job interview interviewer tactics
interview non-verbal cues
job interview non-verbal cues
interview applicant non-verbal cues
interview candidate non-verbal cues
interview interviewer non-verbal cues
job interview applicant non-verbal cues
job interview candidate non-verbal cues
job interview interviewer non-verbal cues
interview communication
job interview communication
interview applicant communication
interview candidate communication
interview interviewee communication
job interview applicant communication
job interview candidate communication
job interview interviewer communication
interview answer
job interview answer
interview applicant answer
interview candidate answer
interview interviewer answer
job interview applicant answer
job interview candidate answer
job interview interviewer answer
interview behaviour
job interview behaviour
interview applicant behaviour
interview candidate behaviour
interview interviewer behaviour
job interview applicant behaviour
job interview candidate behaviour
job interview interviewer behaviour
interview skills
job interview skills
interview applicant skills

interview candidate skills
interview interviewer skills
job interview applicant skills
job interview candidate skills
job interview interviewer skills
interview interpersonal skills
job interview interpersonal skills
interview applicant interpersonal skills
interview candidate interpersonal skills
interview interviewer interpersonal skills
job interview applicant interpersonal skills
job interview candidate interpersonal skills
job interview interviewer interpersonal skills
interview interpersonal communication skills
job interview interpersonal communication skills
interview applicant interpersonal communication skills
interview candidate interpersonal communication skills
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job interview applicant interpersonal communication skills
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interview applicant communication skills
interview candidate communication skills
interview interviewer communication skills
job interview applicant communication skills
job interview candidate communication skills
job interview interviewer communication skills
interview social signals
job interview social signals
interview applicant social signals
interview candidate social signals
interview interviewer social signals
job interview applicant social signals
job interview candidate social signals
job interview interviewer social signals
interview body language
job interview body language
interview applicant body language
interview candidate body language
interview interviewer body language
job interview applicant body language
job interview candidate body language
job interview interviewer body language
interview emotion
job interview emotion
interview applicant emotion
interview candidate emotion
interview interviewer emotion
job interview applicant emotion
job interview candidate emotion
job interview interviewer emotion