An Ontology Artifact for Information Systems Sentiment Analysis

Completed Research Paper

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Abstract

As companies and organizations increasingly rely on on-line, user-supplied data to obtain valuable insights into their operations, sentiment analysis of textual data has proven to be a most valuable resource. To understand how sentiment analysis can be used effectively, it is important to identify what types of sentiment analysis could be employed during the analysis of a given situation. This research proposes an Information Systems Sentiment Ontology, the purpose of which is to provide a basis for mining and understanding sentiment, specifically from text provided by customers as online content. The Information Systems Sentiment Ontology is developed by analyzing the literature on emotion, sentiment analysis, and ontology development and from prior research on online forum analysis. A traditional design science approach is followed to the ontology development. Details on the creation and application of the ontology artifact are provided.

Keywords: sentiment, ontology, emotion, Information Systems Sentiment Ontology, repurchase, online consumer forums

Introduction

The explosion of social media and other forms of user-contributed content on the World Wide Web has lead to the need to text mine large amounts of data to identify trends and sentiments of web citizens. Organizations find this increasingly useful because it provides managers with an indication of how well they are performing from a customer perspective. Sentiment analysis is opinion mining or subjectivity analysis, which involves the applications of natural language processing, computational linguistics, and text analytics (Pang and Lee 2008). Its goals include enabling computers to extract opinion, sentiment, and subjectivity in text. There have been many different approaches, however, to understanding and analyzing sentiments. A few attempts have been made to organize the different concepts related to sentiment, which has resulted in several taxonomies. However, most research projects tend to develop their own taxonomies before the actual research can be carried out. A common ontology of concepts for sentiment analysis from which appropriate ones for a given project could be retrieved and applied would be helpful.

The objectives of this research, therefore, are to:

- Develop an Information Systems Sentiment Ontology based upon an analysis of the literature on ontologies, sentiment analysis, and emotion.
- Describe the ontology artifact produced and the process by which it was created.
- Demonstrate the effectiveness of the ontology.

To carry out the research, an analysis of the literature on ontology, sentiment analysis, and theory of emotion process (e.g., Frijda 2007; Frijda et al. 1989; Frijda and Mesquita 1998) is performed. From this the Information Systems Sentiment Ontology is developed as an artifact. The contributions of this research are to:

- Develop an Information Systems Sentiment Ontology that captures concepts of sentiment that can be useful when performing sentiment analysis.
- Demonstrate how the ontology can be applied in a marketing application to understand customers' perceptions of products and to predict consumer behavior, such as repurchase intentions or the desire to switch to another product.

Related Research and Research Motivation

Ontology

An ontology is a specification of a conceptualization and includes a vocabulary together with a specification of the intended interpretations (meanings) of the terms in the vocabulary (Gruber 1993). This specification includes:

- Identification of the fundamental categories in the domain
- Identification of the ways in which members of the categories are related to each other
- Identification and specification of constraints on the ways in which the relationships can be used.

Ontologies appear as many different types of created artifacts and used in different communities to represent entities and their relationships for a variety of purposes including annotating datasets, supporting natural language understanding, integrating information sources, semantic interoperability and to serve as a background knowledge in various applications (Gruninger et al. 2008). There is also an intended semantic dimension to ontologies which is to characterize how a given approach specifies the meanings of terms, which includes the expressiveness of the ontology representation language, structural properties, and the representational granularity of the ontology's specification. For sentiment analysis, the semantic interpretation of text data is desired to understand the creator's attitude towards a particular subject.

Sentiment Analysis

Web 2.0 has motivated the need for sentiment analysis, which has proven to be valuable with applications to marketing and customer relationship management. However, the 'emotion' part has been under-represented, even though there are compelling theories of emotion (e.g., Frijda 2007; Frijda et al. 1989) to be considered and sentiment analysis focuses on the role of emotion.

There have been many calls for the inclusion of sentiment analysis for Web 2.0 and the Semantic Web, for example, the benefits of social media such as blogs and web forums has created interest in sentiment analysis. As the variety of forms of online expression (e.g., reviews, ratings, and recommendations) proliferate, online opinions have become a critical indicator for businesses looking to promote their products, identify new opportunities, and increase their reputations (Kontopoulos et al. 2013). Businesses attempt to filter out noise (useless or not helpful comments), understand conversations, identify relevant content, and use the content to understand customers' needs and reaction. This has led firms to adopt sentiment analysis (e.g., Bollen et al. 2011; Spangler et al. 2008). Although Web 2.0 focuses on democratizing publishing, the next stage of web activities includes democratizing data mining of the content published (Liu 2007).

Sentiment analysis, then, is an attempt to effectively use content from the Web to understand sentiment expressed by web citizens in order to react to the concerns of customers of companies and to provide direction for product additions and modifications. Sentiment analysis could also assist in understanding why certain e-communities die or fade away (e.g., MySpace), whereas others seem to grow without limits (e.g., Facebook).

Sentiment analysis, in general, aims to assess the attitude of a speaker or a writer with respect to some topic or the overall contextual polarity of a document. The attitude may be his or her judgment or evaluation (see appraisal theory), affective state (emotional state of the author), or the intended emotional communication (emotional effect the author wishes to have on the reader). Emotion, thus, plays a dominant role in sentiment analysis (Larue et al. 2013). Sentiment has been classified based on various features (Abbasi et al. 2008). First, 'syntactic' feature uses word n-grams and punctuation and extracts phrase patterns of phrase (e.g., Fei et al. 2004; Pang et al. 2002). Second, the 'semantic' feature, which is our focus in the present study, uses such features as polarity, semantic orientation, appraisal group, and subjectivity (e.g., Riloff et al. 2003; Whitelaw et al. 2005). Third, 'link based' feature uses web link, citation, and patterns of send and reply (e.g., Agrawal et al. 2003; Efron 2004). Finally, 'stylistic feature' employs lexical and structural style measures (e.g., Mishne 2005; Zhang and Varadarajan 2006).

Specifically, the semantic features of taxonomies attempt to capture and represent information about how the real world operates with respect to the identification and use of circumstances to provide meaning (Whitelaw et al. 2005). One of the most frequently employed semantic features, the appraisal group, uses four types of attributes (e.g., Argamon et al. 2009; Fletcher and Patrick 2005; Maas et al. 2011; Whitelaw et al. 2005). (1) *Attitude* can be extracted by affect (emotional state), appreciation (evaluation of intrinsic object properties) or judgment (evaluation of social esteem and social sanction). (2) *Orientation* indicates whether an appraisal is positive or negative. (3) *Graduation* indicates the intensity of an appraisal based upon two dimensions, force (increased force versus decreased force) and focus (sharpened focus versus softened focus). (4) *Polarity* uses a polarity marker to capture negation.

Ontology-based Sentiment Analysis

One critical question in Web mining is how to index resources and retrieve them efficiently and effectively (Baldoni et al. 2012). To address this question, prior studies have proposed various approaches to extracting sentiments of tagged resources that involve combining available sentiment lexicons with an ontology of emotional categories.

As can be seen from the Table 1, most of the prior studies focus on proposing mining approaches to extract ontologies and attributes and to analyze sentiments. For instance, an ontology-supported polarity mining (OSPM) method is proposed to analyze semantic orientations and provides detailed topic-specific information such as positive or negative movie reviews (Zhou and Chaovalit 2008). A support vector machines algorithm based on a lexical variable ontology is used to classify and analyze online product

Table 1. Studies of Ontology-based Sentiment Analysis

Study	Ontology	Sentiment Analysis	Unique Features
(Zhou and Chaovalit 2008)	• Online products and services ontology	• Polarity mining: N-gram language modeling • Semantic orientation	• Movie review context • Ontology-supported polarity mining (OSPM) approach • Supervised and unsupervised techniques for sentiment analysis
(Polpinij and Ghose 2008)	• Lexical variation ontology	• Sentiment classifier based on support vector machine algorithm	• Online product review context • Lexical ontology acquisition for variation of the noun and the verb
(Lau et al. 2009)	• Product domain ontology	• Context-sensitive polarity • Semantic orientation	• Fuzzy domain ontology • Ontology extraction by a variant of Kullback-Leibler divergence • Context-sensitive opinion mining system • Contextual sentiment knowledge across various product domains
(Garcia-Crespo et al. 2010)	• Customer emotion ontology • Customer relationship management (CRM) ontology	• Latent semantic analysis: TF-IDF (term frequency-inverse document frequency)	• CRM context • Vector space model applied in natural language documents • Sentiment analysis engine • Customer emotion ontology: negative affect (anger, fear, sadness, shame) and positive affect (contentment, happiness, love, pride)
(Wei and Gulla 2010)	• Product ontology	• Hierarchical learning (HL)-sentiment ontology tree (SOT) algorithm	• Sentiment ontology tree (SOT) – tree-like ontology structure • HL-SOT approach: attributes identification task & sentiment annotation task
(Baldoni et al. 2012)	• Emotion ontology • Word ontology	• Emotional semantics from tagged resources • Polarity-sentiment score	• Ontology structured emotional categories in a taxonomy (87 emotional concepts) • Collections of tags
(Kontopoulos et al. 2013)	• Product domain ontology	• Sentiment score based on the intensity of the sentiment expression (OpenDover)	• Micro-blogging context • Ontology created and attributes detected by formal concept analysis and ontology learning

reviews (Polpinij and Ghose 2008). A context-sensitive opinion mining method with a novel fuzzy domain ontology is developed to extract sentiment knowledge in product domains (Lau et al. 2009). Employing natural language processing, a customer emotion ontology and a customer relationship management ontology are used for semantic annotation and sentiment classification (Garcia-Crespo et al. 2010). Ontology structured emotional categories are proposed to identify tags bearing emotional content and to create ontology structured emotional categories (Baldoni et al. 2012).

However, there has been little attempt to develop meaningful ontologies to understand customers' perceptions on products and associated emotions and further to predict their behaviors, particularly repurchase and switch to another product for marketing application. Our approach addresses this knowledge gap.

Framework Development

The methodology to develop the Information Systems Sentiment Ontology described in this research follows that of Uschold and King (1995) who generically prescribe the following stages for ontology development: (1) identify the purpose (and scope), (2) build the ontology, and (3) evaluate and document the ontology. The first stage involves defining the boundaries of the ontology. Ontology construction occurs in the second stage. Once completed, the ontology is evaluated to assess its usefulness. Finally, the ontology is documented so that those developing applications for its use can do so effectively.

For the first two stages of the development of the Information Systems Sentiment Ontology, we adopt the ontology definition and construction methodology proposed by Noy and McGuinness (2001). The steps followed are: (1) deciding upon the domain and scope of the ontology; (2) formulating the ontology based upon existing taxonomies (here, of sentiment analysis and the emotion literature); (3) defining the classes and their position within their hierarchies based upon a combination of the top-down and bottom-up approaches; (4) defining the properties of classes; (5) defining the facets of the slots; and (6) creating instances. Completion of these six steps constitutes the completion of Uschold and King's first two stages of ontology development.

Ontology Development

Weber (2002) distinguishes between formal ontologies, used to describe reality in general, and material ontologies, used to describe specific aspects of reality. Material ontologies include: application ontologies (specify definitions needed for a particular application); domain ontologies (specify conceptualizations specific to a domain), generic ontologies (specify conceptualizations generic to several domains); and representation ontologies (specify conceptualizations that underlie knowledge representation formalisms). The Information Systems Sentiment Ontology is classified under this scheme as an application ontology because it expresses definitions and concepts for the "sentiment analysis" domain.

Step 1. Identify the domain and scope of the ontology

The first step involves addressing the pragmatic questions associated with identifying the domain and scope of the ontology. Prior research (Gruninger and Fox 1995; Noy and McGuinness 2001; Uschold and King 1995) suggests that competency questions help determine the scope of an ontology. Based on this, the patterns in the type of knowledge and competency questions were identified through an iterative process which combined top-down and bottom-up approaches. Table 2 summarizes the types of knowledge needed, and the competency questions for the general and specific levels of the knowledge types. Representative example cases for evaluation are also given. The questions in both the general and detail levels dictate the domain and scope as well as provide guidance on how the ontology will evolve and be maintained.

The Information Systems Sentiment Ontology is constructed for the purposes of assessing and understanding the sentiments of customer feedback as mined from online product discussion forums. This application is important to marketing as the trend towards mining customer sentiment continues. Eventually, the ontology may evolve to other applications or include, for example, services.

Table 2. Type of Knowledge and Competency Questions

Type of Knowledge	Competency Questions	Examples
Target Environment	• Which environment do we target? • Which characteristics of the environment should we consider?	• Target environment: online technology supporting forums. • Characteristics: types of supporting forums, types of functions in online forums
Target Users	• Who are the target users? • Which characteristics of users should we consider?	• Target users: (1) consumers who experience technology malfunctions and (2) supporters who are either staff from vendors or voluntary experts. • Characteristics: profile of consumers and supporters
Target Domain	• What is the target domain? • Which characteristics of the specific domain should we consider?	• Target domain: online technology support forums • Target products: notebooks and desktops. • Characteristics: product type, brand name
Target Information	• What is the target information that we are looking for? • What is the specific information that we are looking for?	• Target: achieve sentiments and opinions of consumers. • Specific information: (1) prediction on 'repurchase' and 'switch' intentions based on outcomes. (2) patterns of types of issues, appraisals, emotions. (3) patterns of supporters' activities.

Step 2. Identify sources of input for artifact development

Existing emotion theories can be classified broadly into three approaches (e.g., Gross 1998; Hudlicka 2011; Mauss and Robinson 2009; Reisenzein et al. 2013): discrete emotion approach, dimensional approach, and componential approach. First, the *discrete emotion approach* focuses on a small set of fundamental emotions such as anger, disgust, fear, joy, and shame (Izard 1993; Panksepp 1982; Tomkins 1962). It suggests that such emotions have their own physiological and behavioral characteristics (Mauss and Robinson 2009). In sentiment analysis studies, Chen et al. (2009), for instance, create an emotion annotation scheme based on basic types of emotions. To mine emotional semantics of tagged resources, Baldoni et al. (2012) develop the ontology OntoEmotion, in which predominant emotions are organized by levels.

Second, the *dimensional approach* defines emotional states in terms of multiple dimensions such as valance and arousal (e.g., Barsade and Gibson 2007; Mauss and Robinson 2009). Valence means "a subjective feeling of pleasantness or unpleasantness (Barrett 1998, p. 580) while arousal regards "a subjective state of feeling activated or deactivated." In prior studies on sentiment analysis (e.g., Argamon et al. 2009; Whitelaw et al. 2005), that mine rich emotional semantics, the valence has been measured with an 'orientation' attribute in appraisal groups, using a sentiment classification method suggested by Whitelaw et al. (2005). The energy level of emotion that relates to arousal has been measured with a 'graduation' attribute.

Most sentiment analysis studies have employed discrete emotion or dimensional approach. However, they miss rich information on what triggers particular emotion(s) and what is the outcome. The *componential approach* describes emotion as a process that consists of a combination of components: event, appraisal, arousal, action readiness, behavior, and regulation (Frijda 2007; Mesquita et al. 1997). This approach does not confine emotion analysis to a set of basic emotions. Rather, it considers a process that encompasses the precedence (event, appraisal) triggering emotions and the outcome (arousal, action readiness), by decomposing emotional expressions into detailed components (Ortony and Turner 1990; Scherer and Ellgring 2007). According to Ortony et al. (1990), the componential approach is "more profitable to analyze emotional expressions and responses in terms of dissociable components and subcomponents than basic emotions…[It] permits not only a more fruitful decoding of emotion expressions than does a basic-emotion [discrete emotion] approach but also permits a systematic and detailed account of formation of new emotions by creation of new combinations of such elements" (p. 322-23).

In this study, we employ a componential approach to develop the concepts and structure of the Information Systems Sentiment Ontology (see Table 3 and Figure 1). This approach enables us, not only to extract information on an event that causes a particular emotion(s) and customers' perceptions of products, but also to predict customer behaviors such as repurchase intentions and switch intentions.

The development of the ontology proceeds from consideration of existing ontologies, taxonomies of sentiment analysis, and the literature on emotion. Doing so, we combine the results of previous work in a meaningful way. Table 3 presents the top level concept of the Information Systems Sentiment Ontology. It also enumerates important concepts identified from the three types of sources, which become important properties in the subsequent step.

Table 3. Top Level Concepts of Information Systems Sentiment Ontology

Ontology	Important Term Identified	Sources Informed
Event	Type of event	(Frijda 1996) (Frijda 2007) (DAML.org 2004)
Appraisal	Type of appraisals, graduation, orientation, polarity, attitude	(Frijda et al. 1989) (Frijda 2007) (Whitelaw et al. 2005)
Affect	Type of emotion, graduation, orientation, polarity	(Frijda et al. 1989) (Frijda 2007) (Whitelaw et al. 2005) (Pang and Lee 2008) (Garcia-Crespo et al. 2010) (Baldoni et al. 2012)
Behavioral Intention	Type of behavioral intention (adapted from action readiness)	(Frijda 1996) (Frijda 2007)
Regulation	Type of regulator	(Frijda 1996) (Frijda 2007)

First, the emotion literature provides insights on a basic set of ontologies. Specifically, the theory of emotion process (Frijda 1986; Frijda 1996; Frijda 2007) describes spontaneous occurrences of emotions and their influence on the behavior of an individual. The theory further suggests that emotionally significant events (e.g., information technology hardware malfunction) can generate an affect and action readiness after events are appraised by an individual. Elicited affect and action readiness can lead an individual to take an action (e.g., no repurchase, switch vendor) to change his/her environment. Regulation processes from an external origin (e.g., vendor's support, expert support) influence such components as appraisal, affect, action readiness, and behavior in either an attenuating or enhancing direction.

- *Event*: refers to various types of contexts (such as problem or issue context, product context, organizational context, or industry context) that an individual encounters.
- *Appraisal*: an individual perceives an event and evaluates it. The appraisal leads to continuous evaluation process about events and can be understood by a set of appraisal dimensions (Frijda 2007; Frijda et al. 1989).
- *Affect*: is a broad term that indicates feelings of an individual's experience. In this research, our focus narrows to identifying discrete emotions (e.g., anger, frustration, happiness).
- *Action readiness*: refers to an individuals' "readiness for achieving a particular aim" (Frijda 2007, p. 27). This concept of action readiness guides us to explore various types of *behavioral intentions* (e.g., repurchase, no repurchase, or switch vendor) in the present study.
- *Regulation*: indicates "attenuation or inhibition of emotions caused by anticipated adverse effects of uncontrolled emotion, as well as to enhancement of emotion because of anticipated advantageous effect" (Frijda and Mesquita 1998, p. 289). There are two types of regulation sources: (1) internal regulation sources (e.g., self-control, conscience) and external regulation sources (e.g., social norm, social support). This study focuses on external regulation sources because of how difficult it would be to attempt to extract patterns from internal regulation.

Second, the present study uses 'semantic' features of sentiment analysis such as polarity, attitude, and semantic orientation. Whitelaw et al. (2005)'s study uses an effective method, 'appraisal group,' for sentiment classification. An appraisal group refers to "a set of attribute values in several task-independent semantic taxonomies, based on appraisal theory" (Whitelaw et al. 2005, p. 625). Note, however, that the meaning of 'appraisal' in Whitelaw et al. (2005)'s study is different from the one used in the present study. They define 'appraisal' as "how language is used to adopt or express an attitude of some kind towards some target" (Whitelaw et al. 2005, p. 626). In addition, their study uses four types of attributes (polarity, graduation, orientation, and attitude) mentioned above to appraise languages. We adopt the three types of semantic features (polarity, graduation, and orientation) to classify languages. In most of sentiment analysis (e.g., Argamon et al. 2009; Fletcher and Patrick 2005; Maas et al. 2011; Whitelaw et al. 2005), 'attitude' includes various types of appraisal such as affect, appreciation, or judgment. However, in this study, the concept of 'affect' differs in that we consider 'affect' as an independent ontology, rather than a type of appraisal, as literature on emotion suggests (e.g., Barsade and Gibson 2007; Frijda 1986; Frijda 2007).

Finally, the reusable ontology from the DAML library (DAML.org 2004) is adopted and refined to the context of this research.

Step 3. Define classes and class hierarchy

Figure 1 presents the top-level structure of the Information Systems Sentiment Ontology for products. The classes and structure of the class hierarchy are defined following a hybrid ontology development approach (Noy and McGuinness 2001). This approach uses a combination of top-down and bottom-up development, starting with the top-down development of classes and subclasses and iterating bottom-up. The top-level concepts are identified and defined, based upon the emotion literature, and consist of: event, appraisal, affect, behavioral intention, and regulation. An event leads to an appraisal, which then triggers an affect that results in an intended behavior. The subclasses of event are product and issue, with product being a prerequisite for issue. Appraisal, affect, and behavioral intention are all dependent, in different ways, upon regulation, which becomes a subclass in the ontology.

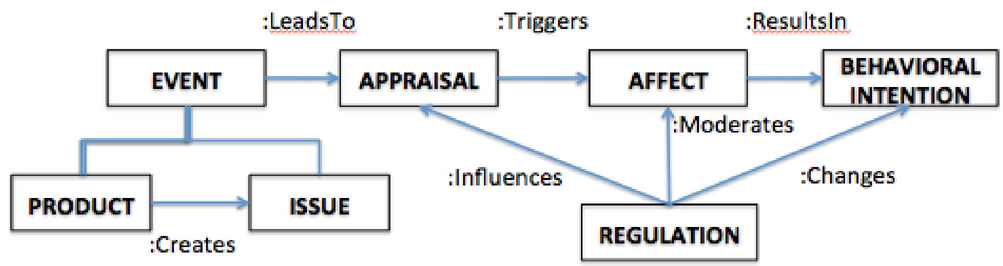

Figure 1. Structure Diagram of Ontology

Step 4. Define the properties of classes

For each class, we identify the properties that describe that class. Representative properties for the event class are shown in Table 4. (Other information about classes is provided in Appendix A). In the event class, TitleOfEvent is a property naming the event. These properties, or slots, represent the elements of data that constitute each class.

Table 4. Properties of the Event Class

Event [Class]		
Property	Description	Example
EventUserID	Initiator of discussion	Z_Klaus
TitleOfEvent	Title of event	Why are download speed so slow with my notebook
StartingTime	Starting time of discussion	06-05-2012 01:10 PM
EndingTime	Ending time of discussion	09-25-2012 09:50 PM
TotNumberOfPages	Total number of pages in discussion	5

Step 5. Define the facets of the slots

Each slot, or property, may have rules governing the values it can assume. These are called facets. In the example above, there can only be one TitleOfEvent. Therefore, the :MAXIMUM-CARDINALITY facet would be assigned a value of 1. Another facet common to all slots is data type. The data type for TitleOfEvent is "string." Facets are determined for each slot in each table. Some may be assigned at the slot level, for slots occurring in more than one class. Others may be assigned at the class-slot level if the facet is specific to the occurrence of the slot in a particular class.

Step 6. Create instances

The ontological structure, once designed, is instantiated using Protégé (Noy and McGuinness 2001). Protégé is a software application that allows for the creation of ontology structures, as well as storage of instances of ontology classes. It can work with several types of ontology representations through code, including the Web Ontology Language (OWL) (Motik et al. 2009). Classes are created either through a visual interface, or through OWL scripting. The classes of our ontology are represented by the XML code in Figure 2 with screenshots of Protégé shown in Figure 3.

```
<owl:Class rdf:ID="Affect"/>
<owl:Class rdf:ID="Appraisal"/>
<owl:Class rdf:ID="BehavioralIntention"/>
<owl:Class rdf:ID="Event"/>
   <owl:Class rdf:ID="Product">
      <rdfs:subClassOf rdf:resource="#Event" />
   </owl:Class>
   <owl:Class rdf:ID="Issue"/>
      <rdfs:subClassOf rdf:resource="#Event" />
   </owl:Class>
<owl:Class rdf:ID="RegulationProcess"/>
```

Figure 2. Class Creation through OWL XML

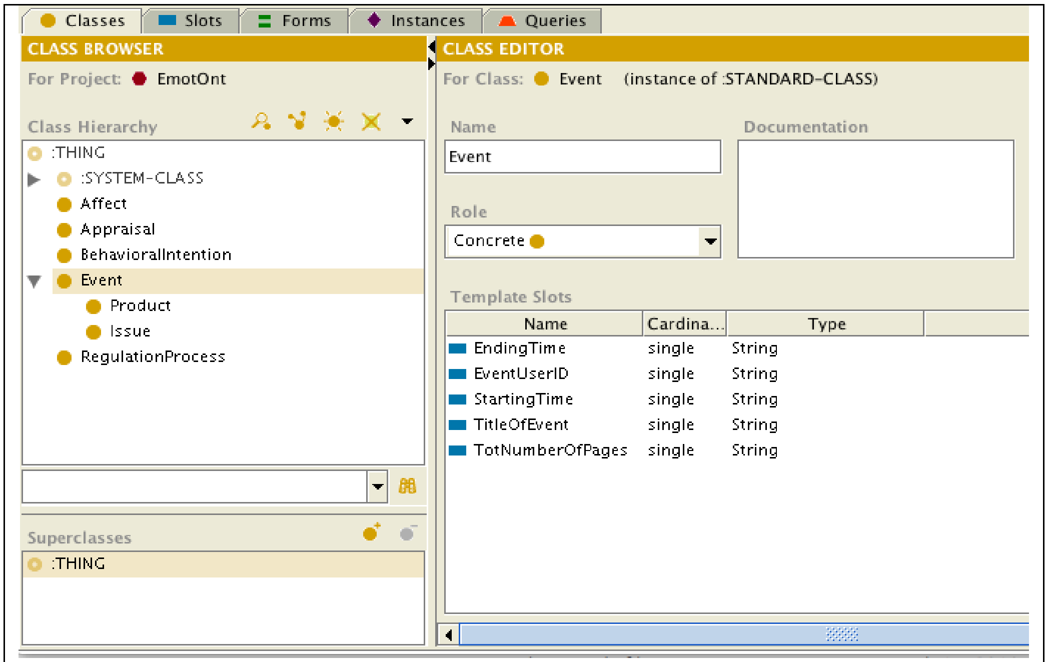

Figure 3. Protégé Console (Class)

Once the ontological structure is complete, including classes, properties (or slots), and facets, the data can be collected and stored. Data for this study is collected from online forums for computer support help of two global IT companies[1]. The companies provide customers and businesses with technologies and software for laptops, desktops, and printing equipment. In the forums, customers with IT malfunctions and other customers exchange their opinions, experiences and knowledge to resolve technology problems. Also staff in the companies (e.g., technicians, administrators) and experts participate in the dialogue and provide customers with technical supports for IT problem resolution.

The data are collected to reflect the spontaneous occurrences and changes of the components (event, appraisal, affect, regulation, and behavioral intention) experienced by participants. The target dialogues include affective word(s) based on WordNet-Affect (Bentivogli et al. 2004; Strapparava and Valitutti 2004).

The data for the basic set of ontology terms are collected from each posting of a dialogue. The emotion(s) of a participant are captured in the record of an affect class (Table 5E). The data on the precedence that triggers the particular emotion(s) are captured in the records of event (Table 5A), product (Table 5B), and appraisal (Table 5D) classes. The data on the outcome of appraisal and emotion, as a behavioral intention,

[1] The identity of the online support forums is concealed.

Table 5A. An Example Record of Event Class

EventI	EventUserID	TitleOfEvent	StartingTime	EndingTime	Pages
1	XXXX	Touch screen display stopped working and no audio device detected	xx-xx-xxxx xx:xx PM	xx-xx-xxxx xx:xx PM	1

Table 5B. An Example Record of Product Class

ProductID	BrandName	GeneralProductType	SpecificProductType	ProductName
1	XXXX	Laptop	Audio	X-132

Table 5C. An Example Record of Issue Class

IssueII	IssueUserID	UserType	TimeOfIssue	NumInPostings	IssueResolved
2	VVVVV	HonorStudent	xx-xx-xxxx xx:xx PM	1 of 430	Is_Not_Resolved

Table 5D. An Example Record of Appraisal Class

Appraisal	AppraisalType	AppraisalPolarity	AppraisalOrientation	AppraisalGraduation	TimeOfAppraisal
1	Appraisal_N3	Appraisal_Pol_UnMarked	Appraisal_Neg	Appraisal_Grad_2	xx-xx-xxxx xx:xx

Table 5E. An Example Record of Affect Class

AffectI	AffectType	AffectPolarity	AffectOrientation	AffectGraduation	TimeOfAffect
2	Frustrated	Affect_Pol_UnMarked	Affect_Pos	Affect_Grad_1	xx-xx-xxxx xx:xx

Table 5F. An Example Record of BehavioralIntention Class

BIID	BIType	BIPolarity	BISpecify	TimeOfBI
1	BtAct_1	BI_Pol_Marked	BITntentSpe_1	xx-xx-xxxx xx:xx

Table 5G. An Example Record of Regulation Class

Regu	nID	RegulatorUserID	RegulatorType
1		YYYYY	Administrator

are shown in the record of behavioral intention (Table 5F). The record of regulation class (Table 5G) collects the data on supporters who help the participant resolve a technology problem. Table 5C is filled with data on whether the issue raised is resolved. Records for each class are filled in, linking records according to the ontological structure given in Figure 1.

In detail, a given topic in the forum represents an *event* in the ontology. The first record of data for the event class (Table 5A) captures the title of an event, the starting/ending time, and the total number of pages in the dialogue.

Data about a specific *product* that generates participant's emotion are captured in the record of product class (Table 5B). The company's online supporting forum is organized based on general (e.g., laptop, desktop) and specific (e.g., network, audio) product categories. Such product categories data are captured.

The *issue* class (Table 5C) captures information about a participant who posts his/her issue and opinion such as user id and type of user from the profile. Also information on the time the post was issued, the number of postings, and the status of issue resolved are collected.

The record of *appraisal* class (Table 5D) shows participants' perception on events and products. The appraisal class is different with the 'appraisal groups' proposed by Whitelaw et al. (2005) in two ways: first, the dimensions of AppraisalType and AppraisalOrientation are formed based on the theory of emotion process (see the detail in Appendix A). Second, the dimensions of the appraisal types are particularly known as triggering emotions in studies in psychology (e.g., Frijda 1996; Frijda 2007; Frijda et al. 1989). Guided by the theory, lists of words for each dimension of AppraisalType and AppraisalOrientation are collected manually through qualitative research sampling and pooled. Although the lexicon created is small, it is enough to evaluate the usefulness of our ontological structure. AppraisalPolarity and AppraisalGraduation are created based on the polarity and the graduation attributes suggested by Whitelaw et al. (2005).

The record of *affect* class (Table 5E) is filled with emotion(s) of a participant. The types of emotion are retrieved based on the list of affective words provided by WordNet-Affect (Bentivogli et al. 2004;

Strapparava and Valitutti 2004) and are stored as the value of AffectType. To achieve the value of AffectOrientation, SentiWordNet is used to retrieve the associated positivity and negativity scores of an affective word (Baccianella et al. 2010). The values of AffectPolarity and AffectGraduation are retrieved as suggested by Whitelaw et al. (2005) in the polarity and graduation attributes.

In the record of *behavioralintention* class (Table 5F), specific types of behavioral intentions (repurchase and switch to other vendor's product) are retrieved and saved as the values of BIType. Polarity marker (such as 'not' and 'never') is used to retrieve the value f BIPolarity (Whitelaw et al. 2005). To retrieve the value of BISpecify, we use typical English word-ordering and pre-modifiers (e.g., will, would, is going to). This allows groups such as "will repurchase," or "is going to buy", where 'will' and 'is going to' modify 'purchase' and 'buy', respectively. We can capture the intention of no purchase, repurchase and switch behaviors. This allows us to expect future repurchase and switch behaviors.

The *regulation* class is created based on the theory of emotion process, suggesting that supporters (e.g., staff, technician, expert), which are types of external regulation, play important roles in (1) attenuating or inhibiting of emotions of customers; (2) changing negative appraisal to positive one; and (3) transforming negative behavioral intentions and behaviors and positive ones. Capturing data on the existence of regulation and the types of regulation (Table 5G) allows us to track not only a change of emotion and behavioral intention, but also effectiveness of regulation. The values of RegulatorUserID and regulationType are captured from the profile information in web pages.

In Appendix B, example outcomes are organized in a table format. A brief description on how to analyze such data collected and the objective of doing so are provided.

Structure diagrams are presented in Figures 4 and 5. The first represents an example of collected data at a time point when no regulation has occurred. The second represents the same example after a regulation has occurred and the issue is resolved. The application of this regulation changed the appraisal, thereby changing the affect and the behavioral intention.

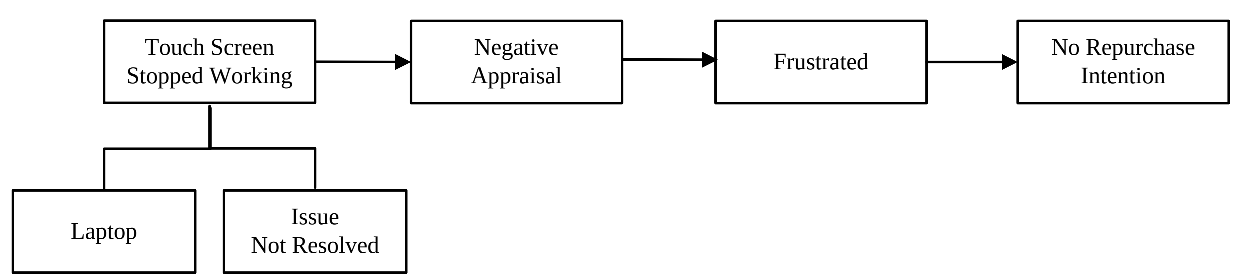

Figure 4. Structure Diagram of Ontology Example without Regulation

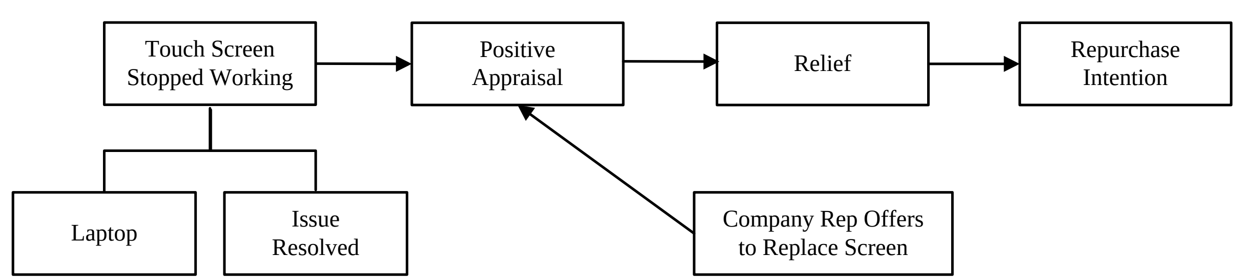

Figure 5. Structure Diagram of Ontology Example with Regulation

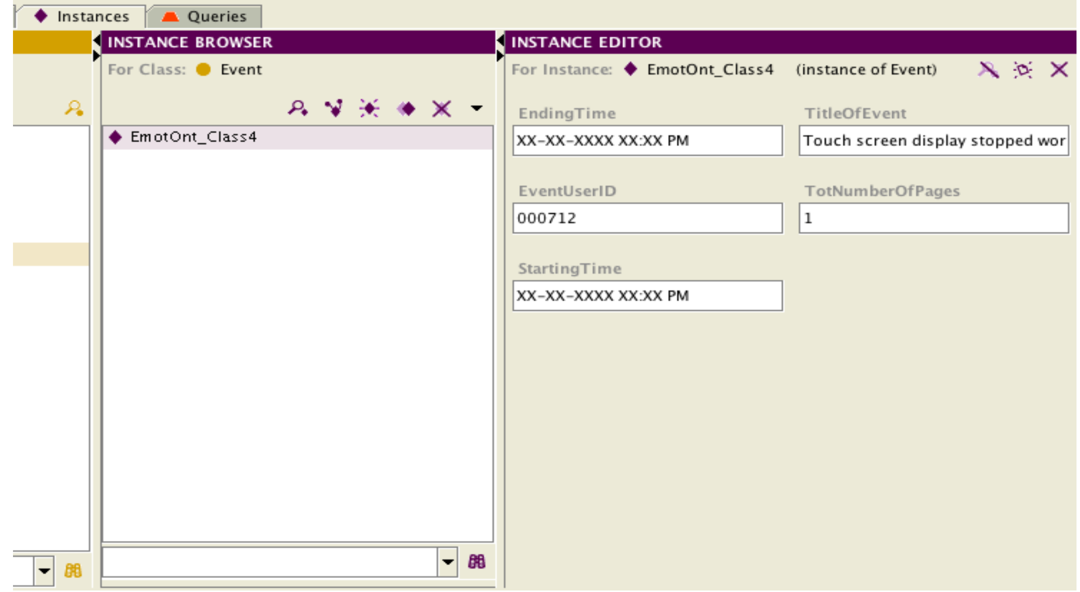

Figure 6. Protégé Console (Instance)

The data are entered into the ontology structure created in Protégé once it has been collected. Instances of each record are stored in the pre-created structure to allow for a standard, open format for access to the sum of collected data. An example of an Event instance is presented in Figure 6.

The Ontology Artifact

The main contribution of this research is the Information Systems Sentiment Ontology. The artifact development is based upon traditional design science requirements which include the development and assessment of an artifact (March and Storey 2008). It is novel in the sense that it: (a) develops an ontology based upon existing research in multiple areas of information systems (computer science, management information systems) and (b) it has been applied to real world applications (e.g., web form data). More noteworthy, though, the Information Systems Sentiment Ontology could be used in an open source way to gather information on sentiment analysis that could be used and built upon by other researchers on sentiment analysis.

The practical contribution of the research is to show how the ontology might be used to help businesses better mine data from people's online comments. In particular the research contributes to understanding how business can better understand the users' emotions and concerns when contributing to social media which, presumably the business is then able to respond to appropriately.

Evaluation

To evaluate the research, the ontology is applied in a use case for extraction of sentiment from web forms, to illustrate the usefulness of the research. It is also evaluated by ontology developers, who provide an expert assessment.

Use Case: Application to Web Forum for Text Extraction

The ontology is applied to text mining for sentiment analysis that is performed for extracting text from an online forum, the purpose of which is to assess repurchase intention of information technology products. Sample snippets are shown in Figure 7. Application of the ontology shows that it is effective in, first, identifying the important concepts that could be dealt with for sentiment analysis of content extracted from a web forum. In other words, it successfully provides a roadmap of concepts which an analyst should

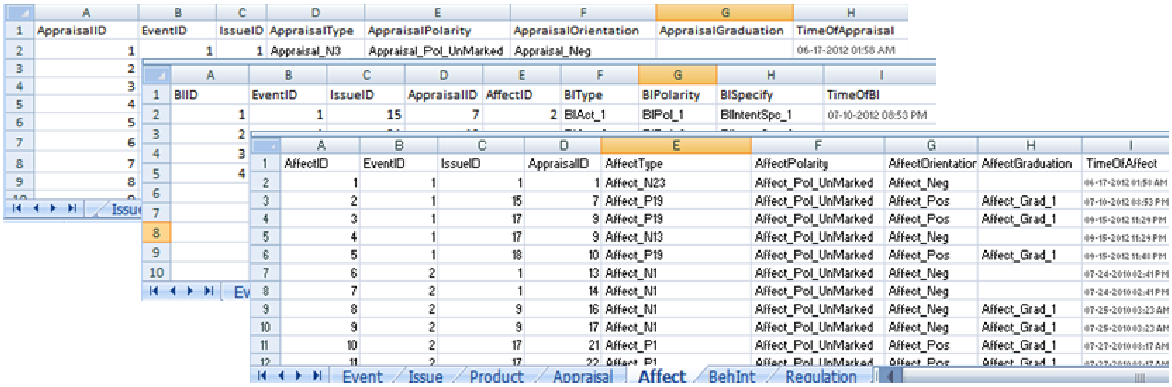

Figure 7. Sample Snippet

search when undertaking sentiment analysis on a web forum or related document. Second, it is useful for extracting useful concepts in the instances to which it is applied (specific web forums on information technology product analysis).

Expert Assessment: Ontology Developers

The ontology is evaluated on: (1) meta-level classification of the ontology type which included domain, expressiveness, temporality, and extensibility; as well as (2) a semiotics-based set of assessment criteria (Burton-Jones et al. 2005) of syntactic, semantic, pragmatic, and social quality. Two experts in ontology development and assessment are recruited to evaluate the Information Systems Sentiment Ontology. One of the experts has carried out prior research in sentiment analysis in addition to research on ontology development.

The expert evaluations are coded with a summary of the results given in Table 6. Each evaluation is coded by two independent coders. Codes are applied at the item-response level and aggregated to the criterion level as seen in Table 7. At the item-response level, inter-rater agreement (Miles and Huberman 1994) for the first evaluator is 84%, while inter-rater agreement for the second evaluator is 82%.

Overall, the experts assert that the structural elements of the ontology capture the appropriate types of information needed to support sentiment analysis, at least in the given domain. One evaluator states that the relationships in the schema need to be defined more clearly, with attempted clarification in Figure 1.

The evaluators also provide insightful feedback regarding the need to capture heuristics for inferences and appraisal patterns in an effort to provide more complete support for the decision inference purposes of the ontology.

Table 6. Evaluator Feedback Summary

Evaluation Criterion	**Evaluator 1**	**Evaluator 2**
Category of Ontology	Domain	Domain
Expressiveness	Good	Good
Temporality	Good	Good
Extensibility	Good	Good
Objectivity	Potentially Good	Fair
Syntactic Quality	Good	Acceptable
Semantic Quality	Acceptable/Good	Good/Acceptable
Pragmatic Quality	Deficient/Good	Acceptable
Social Quality	Acceptable	NA
Use Objectives	External systems would be needed to support decision making, unless this ontology captures appraisal patterns in its structure	Heuristics need to be developed to support inferences based on the sentiments extracted

Table 7: Coding Example				
Item	**Evaluator**	**Response**	**Coder 1 Coding**	**Coder 2 Coding**
Does the ontology identify appraisal patterns that lead to a specific emotion	1	Yes – However, I have my doubts about whether the way the information is stored in the ontology is the best way to support the discovering of patterns.	Yes, with concerns	Concerns about pattern discovery
	2	Yes	Yes	Yes

Conclusion

This research has developed, as a design science artifact, an Information Systems Sentiment Ontology by analyzing theories and applications in emotion, ontology, and sentiment analysis. The ontology development follows a traditional design science approach, drawing upon concepts from existing taxonomies as well as methodologies for ontology creation. The resulting artifact was applied, as a use case, to text mining of consumer sentiment as expressed in online product support forums. One implication from the development process is that the ontology creation can be expanded into an area that has broad implications for the use of information systems technology. As the assessment of the ontology was made by two ontology developers, the research, to a small extent, has tried to capture and represent semantics which could be useful for research on the Semantic Web (Berners-Lee et al. 2001), where ontologies play a central role in its development and evolution. Practitioners can also meaningfully use the Information Systems Sentiment Ontology in a marketing application to understand consumers' perceptions of products and services and to predict consumer behavior. Future work is required to apply the ontology to other real-world applications, and to carry out further assessment and refinement in an iterative development process. Additional terms also need to be added to the appraisal pool.

Appendix A

Description of Class and Its Properties

*Note: only the **main** properties and descriptions are presented in the tables. Sample snippets appear in Figure 7.

Product [SubClass]		
Property	Description	Example
BrandName	Name of company	LargeITCompany
GeneralProductType	General product type	Laptop & Notebook
SpecificProductType	Specific product type	Network/Wireless
ProductName	Name of product	Product1

Issue [SubClass]		
Property	Description	Example
IssueUserID	UserID of issue	S_Timmy
UserType	User type in profile	Top student
TimeOfIssue	Time of issue posted	06-18-2012 01:30 PM
NumInPostings	Message number in total pages	3 of 56
IssueResolved	Issue is resolved (Is_Resovled) or not (Is_Not_Resolved)	Is_Not_Resolved

Appraisal [Class]		
Property	Description	Example
AppraisalType	Appraisal type based on appraisal dimension of (Frijda 2007; Frijda et al. 1989) (pleasantness (Appraisal_P1), unpleasantness (Appraisal_N1), bearable (Appraisal_P2), Unbearable (Appraisal_N2), goal-conducive (Appraisal_P3), goal-obstructiveness (Appraisal_N3), etc.)	Appraisal_N3

AppraisalPolarity	Appraisal is marked if it is scoped in a polarity marker (such as 'not') (Appraisal_Pol_Marked), or unmarked otherwise (Appraisal_Pol_UnMarked).	Appraisal_Pol_UnMarked
AppraisalOrientation	Appraisal is positive (Appraisal_Pos) or negative (Appraisal_Neg).	Appraisal_Neg
AppraisalGraduation	Intensity of appraisal in terms of two independent dimensions of force (or 'intensity') and focus ('prototypicality'). Graduation is largely expressed via modifiers such as 'very' (increased force)(Appraisal_Grad_1), 'slightly' (decreased force) (Appraisal_Grad_2), 'truly' (sharpened focus) (Appraisal_Grad_3), or 'sort of' (softened focus) (Appraisal_Grad_4), but may also be expressed lexically in a head adjective, e.g., 'greatest' vs. 'great' vs. 'good'.	Appraisal_Grad_1

Affect [Class]		
Property	Description	Example
AffectType	Types of emotion	anger
AffectPolarity	Polarity marker (such as 'not') (Affect_Pol_Marked), or unmarked otherwise (Affect_Pol_UnMarked).	Affect_Pol_UnMarked
AffectOrientation	Positive (Affect_Pos) vs. negative emotion (Affect_Neg)	Affect_Neg
AffectGraduation	The intensity of affect in terms of two independent dimensions of force (or 'intensity') and focus ('prototypicality'). Graduation is largely expressed via modifiers such as 'very' (increased force) (Affect_Grad_1), 'slightly' (decreased force) (Affect_Grad_3), 'truly' (sharpened focus) (Affect_Grad_3), or 'sort of' (softened focus) (Affect_Grad_4), but may also be expressed lexically in a head adjective, e.g., 'greatest' vs. 'great' vs. 'good'.	Affect_Grad_1

BehavioralIntention [Class]		
Property	Description	Example
BIType	Types of behavioral intention; Target BI (1) Repurchase: (e.g., buy, buy again, purchase again, repurchase,) Mentioned (BIAct_1); (2) Switch: mentioned switch to other vendor's product (e.g., buy from other vendor) (BIAct_2); Not mentioned (BIAct_0)	BIAct_1
BIPolarity	Polarity marker (such as 'not')(BI_Pol_Marked), or unmarked otherwise (BI_Pol_UnMarked).	BI_Pol_Marked
BISpecify	(e.g., will, would, going to) mentioned (BIIntentSpc_1); not mentioned (BIIntentSpc_0)	BIIntentSpc_1

Regulation [Class]		
Property	Description	Example
RegulatorUserID	User ID of regulator	Bg_Ang
RegulatorType	Regulator type in profile	Teacher

Appendix B

Example Outcomes

Issue	Event	Product	Appraisal	Affect	Regulation	Behavioral Intention
• Customer N • Issue not resolved	Touch screen display stopped working and no audio device detected	X-132 (laptop & Notebook/ Sound/ Audio)	• Unpleasantness • Goal obstructiveness	Frustrated	No vendor or expert involved	No repurchase intention

Issue	Event	Product	Appraisal	Affect	Regulation	Behavioral Intention
• Customer T • Issue not resolved	Touch screen display stopped working and no audio device detected	X-132 (laptop & Notebook/ Sound/ Audio)	• Uncertainty • Goal obstructiveness • Uncontrollability	Annoying	No vendor or expert involved	Not mentioned

Issue	Event	Product	Appraisal	Affect	Regulation	Behavioral Intention
• Customer F • Issue not resolved	Touch screen display stopped working and no audio device detected	X-132 (laptop & Notebook/ Sound/ Audio)	• Unfairness • Uncertainty • Goal obstructiveness	Extremely unhappy	No vendor or expert involved	No repurchase intention

Note * The examples that were posted at similar time points are retrieved from one of the data collection sites. Over 100 customers who have the events of IT malfunction participate in this dialogue.
* The identities of the customers, company, and product are concealed.

These examples are analyzed based on the theory of emotion process (Frijda 1986; Frijda 1996; Frijda 2007). The event topic is "touch screen display stopped working and no audio device detected." Because of the technology malfunction, the customer N, T, and F experience negative emotions, frustration, annoyance, and extreme unhappiness. The affect class captures the properties of the emotions of the customers. The data indicates that the customers have the same issue that has not been resolved. The examples show that the particular precedence (event, product, and appraisal) triggers the specific emotions of the customers. Both customer N and F express no repurchase intentions. The examples indicate no vendor or expert support for this event. According to the theory, regulation plays a role in attenuating or inhibiting emotions. As time progresses, if there is no regulation and the issue is not resolved, customers' emotions may not change to positive emotions or even be worse. In the given situation, we also can predict the customers' actual behaviors of no repurchase based on the emotional intensity function. The basic idea is that high intensity is more likely to lead to a particular behavior. The basic function is adapted from the theory (Frijda 1996; Frijda 2007):

Emotional intensity = f (Event, Issue, Appraisal, Affect, Behavioral Intention, Regulation)

Objective of data analysis

- Identify types of event, product, and appraisal that raise particular emotion
- Identify types of event, product, appraisal, and affect that lead to a particular behavioral intention, e.g., repurchase, no repurchase, or switch intention
- Expect an actual behavior
- Check the effectiveness of the regulation by vendor or expert on changing negative customers' appraisal, affect, and behavioral intention to positive ones

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