CONCEPTUAL BLENDING TECHNIQUES FOR DATA VISUALISATION

by

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13 # DECLARATION

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CONCEPTUAL BLENDING TECHNIQUES FOR DATA VISUALISATION

14 I declare that the above dissertation/thesis is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

SIGNATURE DATE

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List of publications from this research

1. Featherstone, C. & Van der Poel, E. (2017a, June). Features of conceptual blending in the context of visualisation. *IST Africa 2017*. Retrieved November 29, 2017, from http://ieeexplore.ieee.org/document/8102296/,https://researchspace.csir.co.za/dspace/handle/10204/9306

2. Featherstone, C. & Van der Poel, E. (2017b). Human creativity in the data visualisation pipeline. *African Conference on Information Science and Technology (ACIST)*. retrieved November 29, 2017, from https://researchspace.csir.co.za/dspace/handle/10204/9505

Abstract

Computational creativity is an active area of research within the artificial intelligence domain that investigates what aspects of computing can be considered as an analogue to the human creative process. Computers can be programmed to emulate the type of things that the human mind can. Artificial creativity is worthy of study for two reasons. Firstly, it can help in understanding human creativity and secondly it can help with the design of computer programs that appear to be creative. Although the implementation of creativity in computer algorithms is an active field, much of the research fails to specify which of the known theories of creativity it is aligning with.

The combination of computational creativity with computer generated visualisations has the potential to produce visualisations that are context sensitive with respect to the data and could solve some of the current automation problems that computers experience. In addition theories of creativity could theoretically compute unusual data combinations, or introducing graphical elements that draw attention to the patterns in the data. More could be learned about the creativity involved as humans go about the task of generating a visualisation.

The purpose of this dissertation was to develop a computer program that can automate the generation of a visualisation, for a suitably chosen visualisation type over a small domain of knowledge, using a subset of the computational creativity criteria, in order to try and explore the effects of the introduction of *conceptual blending* techniques. The problem is that existing computer programs that generate visualisations are lacking the creativity, intuition, background information, and visual perception that enable a human to decide what aspects of the visualisation will expose patterns that are useful to the consumer of the visualisation.

The main research question that guided this dissertation was, “How can criteria derived from theories of creativity be used in the generation of visualisations?”. In order to answer this question an analysis was done to determine which creativity theories and artificial intelligence techniques could potentially be used to implement the theories in the context of those relevant to computer generated visualisations. Measurable attributes and criteria that were sufficient for an algorithm that claims to model creativity were explored. The parts of the visualisation pipeline were identified and the aspects of visualisation generation that humans are better at than computers was explored. Themes that emerged in both the computational creativity and the visualisation literature were highlighted.

Finally a prototype was built that started to investigate the use of computational creativity methods in the ‘variable choice’, and ‘aesthetics’ stages of the data visualisation pipeline.

1 Introduction

1.1 Background information

What is CC

Computational creativity is an active area of research that investigates what aspects of computing can be considered as an analogue to the human creative process (Colton, Cook, Hepworth & Pease, 2014). Boden and Mujumdar (1998) argue that computers can be programmed to emulate the type of things that the human mind can. Computational creativity is a sub-field within the artificial intelligence domain.

controversy but worthy

While the *Chinese room argument* of artificial intelligence (Searle, 1990) attracted both proponents and controversy and continues to be topical (Maruyama, 2016), it's hard to deny that the study of artificial intelligence is not a worthwhile exercise, because techniques involving, logic, reasoning, machine learning and natural language processing are used in everything from self-driving cars (Petrovskaya & Thrun, 2009), to computer game enhancements (Millington & Funge, 2016), to speech recognition, drug discovery, and object recognition (LeCun, Bengio & Hinton, 2015). Although *strong artificial intelligence* was never achieved, most researches are more interested in the application and usefulness of the results (Hauer, 2018).

Similarly, computational creativity falls into two realms. One that tries to simulate creativity, and another that is more concerned with the produced artefacts and their implication (Hoover, Szerlip & Stanley, 2013). The analogue of the *Chinese room argument* is the *Lovelace test* of creativity (Boden & Mujumdar, 1998; Bringsjord, Bello & Ferrucci, 2003; M. Riedl, 2014).

examples

Examples of computational creativity are computer programs and computational methods that:

- Investigate new searching techniques (Yannakakis & Liapis, 2016)
- Draw and paint artworks and create images (H. Cohen, 1995; Colton, 2014; Joao M Cunha, Gonçalves, Martins, Machado & Cardoso, 2017; Heath & Ventura, 2016; McCaig, DiPaola & Gabora, 2016)
- Generate poetry (Hrešková & Machová, 2018; Lamb, Brown & Clarke, 2016; Oliveira & Alves, 2016)
- Tell stories (Gervás & León, 2016; Llano, Guckelsberger et al., 2016; McKeown & Jordanous, 2018)
- Generate humour (Barros, Liapis & Togelius, 2016; Gabora & Kitto, 2017; Wen et al., 2015)
- Create culinary recipes (Grace, Maher, Davis & Eltayeby, 2018; Pinel, Varshney & Bhattacharjya, 2015; Shao, Murali & Sheopuri, 2014)
- Automate the creation of computer games (Guzdial & M. Riedl, 2016; Pollak, Wiggins, Žnidaršič & Lavrač, 2018) and characters (Correia, Martins, Martins & Machado, 2016)
- Create music (Chirita & Fiadeiro, 2016; Zbikowski, 2018)
- Create dance moves (Carlson et al., 2016; Manfré, Augello, Pilato, Vella & Infantino, 2016)

overview

purpose

This research explored the development of a computational system that used theories of creativity to enhance the process of automating computer generated visualisations. Francisco Câmara Pereira (2007) argues that due to the lack of formal approaches it may be 'impossible to say a system is creative without controversy'; however, it is possible to classify the computer program based on criteria from formal theories. Specifically the purpose of the dissertation was to develop a method whereby a computer program can introduce techniques from the field of computational creativity into the data visualisation pipeline, in order to explore the locations in the pipeline in which humans are currently indispensable, in an attempt to emulate creativity. The terms *useful* and *novel* are defined and there is consensus in the computational creativity literature (Boden & Mujumdar, 1998; Diedrich, Benedek, Jauk & Neubauer, 2015), but for the purposes of this dissertation the intent is as follows:

The specific meanings of the word *useful* (as it is applied in the creativity literature) was aligned with that of data visualisation. The dissertation made use of existing theories of creativity with a grounding in how the theory had already been successfully applied in the artificial intelligence field.

1.2 Rationale and research problem

Visualisation is important

Visualisation is important because it has been shown that – due to the *Gestalt principals* of human visual perception – new insight and discoveries are quickly identified from visualised data. Human visual perception is faster and more efficient than our cognitive processes (Kirk, 2012). Visualisation is powerful at helping with the problem of data overload, because human vision is adept at detecting patterns (Myatt & W. P. Johnson, 2011). The connection between the data set and its meaning is important for a successful visualisation (Yau, 2013).

human limits to auto. Vis.

Whilst computer algorithms can create visualisations from data in a brute force combinatorial manner, humans are still much better at quickly determining what context and which aspects of the data, at what granularity, will successfully highlight what the data represents. This is because human visual perception as well as cognition contribute toward understanding visual representations (Yau, 2013). This is important because what one knows about one's data can drive elements of the visualisation (Francisco Câmara Pereira, 2007), and combining data visualisation with domain-specific knowledge is considered to be challenging even for a human (Kalogerakis, Christodoulakis & Moumoutzis, 2006). One research area that tries to address the fact that computers are still unable to generate the quality of visualisations produced by humans, is the field of *visual analytics*. *Visual analytics* solves the limit by involving humans in the process using interactive visual interfaces (Cybulski, Keller, L. Nguyen & Saundage, 2015; Keim et al., 2008).

creativity is important

There are two reasons artificial creativity is worthy of study (Boden & Mujumdar, 1998). Firstly, it can help in understanding human creativity and secondly it can help with the design of computer programs that appear to be creative. Although the implementation of creativity in computer algorithms is an active field of research, computational creativity literature that specifically mentions the creativity theory on which the implementation of the algorithm is modelled, is diverse and scant (Francisco Câmara Pereira, 2007).

combined is important

The combination of computational creativity with computer generated visualisations has the potential to produce visualisations that are context sensitive with respect to the data and could solve some of the current automation problems that computers experience. In addition theories of creativity could enhance the visualisations by computing unusual data combinations or introducing graphical elements that draw attention to the patterns in the data. Finally the creativity aspect could highlight the creativity involved as humans go about the task of generating visualisations.

aim

The intention of the dissertation was to develop a computer program that introduced criteria from the theories of creativity into an automated data visualisation pipeline, in order to explore the effects of the introduction of computational creativity techniques – whilst retaining the qualities required of a successful visualisation. A specific focus was given to a computational creativity model known as *conceptual blending*.

problem

The problem is that existing computer programs that generate visualisations are lacking the intuition, context, creativity and visual perception that enable a human to decide what aspects of the visualisation will expose patterns that are useful to the consumer of the visualisation (Keim et al., 2008; Myatt & W. P. Johnson, 2011).

1.3 Research question and objective

The main research question that will guide this dissertation is, "How can criteria derived from theories of creativity be used in the generation of visualisations?".

1.3.1 Secondary research questions

The following questions support answering the primary research question. In particular, the output of these questions will help determine how to design the computer program.

1. "How have the currently accepted theories of creativity been applied in the artificial intelligence and computational realms, with an emphasis on those that generate creative data visualisations?"

   The results of this question will establish which artificial intelligence methods are applicable and to establish the criteria for models that can support computer generated visualisations.

2. "What scope do computer generated data visualisations have for the introduction of criteria deemed to be creative?"

   The results of this question will establish the current techniques used to computer generate visualisations in order to establish which techniques are able to support creativity criteria. It will also identify where in the graphics pipeline creativity criteria can effectively be introduced.

Having enumerated the research questions the following section will elaborate on objectives that support these questions.

1.3.2 Research objectives

The following objectives have been identified:

1.3.3 Primary research question objectives

A) Develop a computer program that can automate the generation of a visualisation, for a suitably chosen visualisation type over a small domain of knowledge, using a subset of the computational creativity criteria, in order to explore the effects of the introduction of *conceptual blending* techniques.

This objective will be achieved by developing a computer program that can demonstrate the introduction of computational creativity into the process of generating visualisations.

1.3.4 Secondary objectives - Creativity oriented objectives

A) Explore and describe creativity theories and the artificial intelligence techniques used to implement the theories in the context of those relevant to computer generated visualisations.

B) Determine what measurable attributes are sufficient for an algorithm that claims to be creative.

1.3.5 Secondary objectives - Visualisation oriented objectives

A) Explore and describe the current state of computer generated visualisations, with the aim of identifying suitable methods and data representations.

B) Identify any parts of the visualisation pipeline suitable for introducing creativity theories.

C) Identify what aspects of the human visualisation process are considered to be creative.

The secondary research question objectives will be achieved through a review of the literature. A chosen subset of criteria will also be motivated from the literature.

Layout of this dissertation

This dissertation is structured as follows:

overview of layout

Ethical considerations are communicated in Section 1.4. Project limitations and scope are discussed in Section 1.5. The literature is presented in Section 2. The creativity literature is explored first, after which the visualisation literature is presented. A discussion,in Section 3, concludes the literature survey. Thereafter, the research design and chosen methods are elaborated on, and the reason for the choice is expounded in Section 4. The implementation and design of the prototype is described in Sections 4.3, 4.4 and 4.5. The findings and conclusion follow in Section 5, with detail in Sections 5.2 and 5.2, respectively. The conclusion in Section 7, begins with a review and summary of each chapter, and the main outcomes of each section (Section 7.2). In Section 7.3 each research question and objective is revisited and the findings are presented. These findings are summarises in Section 7.4. Potential future research is discussed in Section 7.5.

Finally, acknowledgements to persons involved in the dissertation process and acknowledgements of data-sources and open source software is given (Section 8). There is a table of definitions in Addendum 10.

lead out

The next section discusses any relevant ethical issues that are relevant to this dissertation.

1.4 Ethical considerations

The majority of the work involved finding specific data that could be used to generate graphics. Care was taken not to infringe on the copyright of any text, clipart, or image that was used. The dataset was chosen so as not to infringe on any copyright. The considerations on dataset choice are discussed in Section 4.3. Open data in the public domain was used. The relevant open source licenses are iterated, where applicable, in the acknowledgements (Section 8).

The dissertation contents acknowledge and conform to the ethics requirements of UNISA. An ethical clearance certificate from UNISA's Research Ethics Committee was obtained prior to the commencement of the work.

1.5 Project limitations and scope

focus

The focus was on the process of generating visualisations using the theories of creativity and not on generating visualisations per se. With this in mind, existing datasets, tools, methods, knowledge bases, semantic networks, and any other sources of data, were used. Where existing tools were used, an extensive literature review of the tools was not conducted, and the first one that had enough features to represent or tweak the visualisations enough for the purposes of the project was chosen.

blending

specifically

As seen in the preliminary literature review many of the theories of creativity are extensions of a concept known as *bisociation*. *Bisociation* has been refined to a more concrete theory known as *conceptual blending*. The literature indicates that *conceptual blending* has been implemented in the artificial intelligence space for many projects. Examples include, 'Divago' (Francisco C Pereira, 1998), 'CoInvent' (Schorlemmer et al., 2014) and 'The Blender' (Joao M Cunha et al., 2017). This project was constrained to implementations of *conceptual blending*. The reason for this choice was to limit the project to a feasible scope. *Conceptual blending* was chosen since the literature contains many descriptions of computer implementations, and the concept is well supported in the literature. There was no attempt to investigate every single possible entry point in the visualisation pipeline. The intent was to choose one stage in the visualisation pipeline, but two stages of the pipeline were ultimately explored.

data

The narrowing of the base of expertise for the dataset was determined by the applicability of the visualisation type, the access to data about the chosen knowledge domain, the ability to use existing methods to represent that data and the ability of those frameworks to allow the introduction of mechanisms, such as specific graphics that could support the data.

tool limits

There are many visualisation tools in the literature. Examples include Gephi (Bastian, Heymann & Jacomy, 2009), and R ‘The R Project for Statistical Computing’ (2015). The JavaScript framework D3.js (Teller, 2013) was chosen, firstly because it allowed a lot of graphic manipulation and is extensively documented, complete and still under active development. Enumerating the advantages and disadvantage of all existing tools would have contributed nothing to the purpose of this dissertation.

No documented existing implementations of *bisociation* or *conceptual blending* were found that would have been suitable for the project.

graph types

Types of visualisations (bar charts, histograms etc.) were not extensively reviewed, and their properties are not discussed. These visualisation types have been around a long time and are well known. A Bar Chart and Histogram were the basis of the prototype. No effort was made to introduce creativity into large amount of different visualisations. Trying to do this would have made the project infeasible. The intended focus was not on coming up with new visualisations, but rather on finding out whether models of creativity and creative traits could be useful when creating visualisations. More than one type of visualisation was required because some data attributes were more suitable to one visualisation type than another. This is discussed in more detail when the mapping of the dataset to a visualisation is discussed in Section 4.5.2.

lead in

The next section will focus on the literature. A summary of the literature is presented in the following chapter (Section 3).

2 Literature

lead in

The literature survey is divided into creativity literature (Sections 2.1 through 2.3) and visualisation literature (Section 2.4).

explain Overview

Section 2.1 gives a broad overview of commonly accepted theories of creativity, without considering computers. The literature on theories of creativity provides the background required to understand the models on which the computer algorithms, that form part of computational creativity, are built. Section 2.2 is where the literature's focus turns to how these models of creativity are modelled in the computer science realm. The aim is to establish criteria that existing models of creativity feature, that can be introduced into a computer program, method or model aiming to produce creative outputs. Some of these criteria are presented in Section 2.2.2.

Some sections of the literature in this section have been published previously in the form of systematic literature reviews (Featherstone & Van der Poel, 2017a, 2017b).

2.1 Theories of creativity

history

The domain of creativity lies within psychology. It is crucial background information for why certain techniques are used when trying to introduce creativity into artificial intelligence methods. The literature in Sections 2.1 through 2.2.2 concentrates on briefly describing the most widely cited and accepted theories without attempting to dispute, argue or rationalise the findings. The literature starts with a discussion of some of the theories and ends with a summary of the terminology used in the various theories (2.1.11). The literature provides context for the computer algorithms that attempt to emulate these theories gives the background required to understand why computer algorithms are focusing on the methods that they do. Another aim is to establish criteria that can be used to evaluate any computer program, method or model aiming to produce creative outputs. These criteria specific to *conceptual blending* is presented in Section 2.2.2.

Other theories

Other theories of creativity include the concepts of *Convergent and Divergent Production* as described in Guilford's *Structure of Intellect* (Sternberg & Grigorenko, 2001), the Geneplore model by Finke (Finke, 2014; Finke, Ward & Smith, 1992; Lubart, 2001), *Confluence theories* (Sternberg & Lubart, 1999), the *Four C Model* (Kaufman & Beghetto, 2009), the *Systems model of creativity* as suggested by Csikszentmihalyi (1997, 2014c) and more recently *Honing theory* (Gabora, 2016). Many theories of creativity result from combining of spaces of mental ideas (Thagard & Stewart, 2011).

current implementations

Sections 2.2 briefly investigates current artificial intelligence implementations of these theories and highlights those that have relevance to data visualisations and gives an indication of some of the measurable criteria of these implementations of creativity theories. Section 2.1.10, narrows the discussion of these theories to *conceptual blending* – addressing the specific scope of this dissertation – and establishes creativity objectives **A** and **B**.

scope of theory discussion

Many computational implementations of creativity theory often do not mention the creativity theory on which they are based (Francisco Câmara Pereira, 2007). An example of this is *The painting fool* (Colton, 2014), a computer program that generates paintings, which is well represented in the literature. This literature touches on the theories for context and only goes into more detail on those theories with existing representations in the computational creativity literature. The last creativity model discussed is *conceptual blending* 2.1.10, which is the main focus in this dissertation (Refer to project limitations in Section 1.5).

terminology

A note on terminology; There is a review of terminology in Addendum A.

2.1.1 Bisociation

creativity as intersection

Koestler (1964) described creativity as the intersection of ideas from two unrelated domains, which he referred to as *bisociation of matrices*. The premise is that humans come up with new concepts or creative ideas by combining two or more other concepts together. Koestler (1964) indicated that it is the overlap of domains of knowledge that have potential to produce creativity. He termed this overlap *bisociation*. A main concern of *bisociation* is the discovery of hidden similarities between domains (Paulos, 2008).

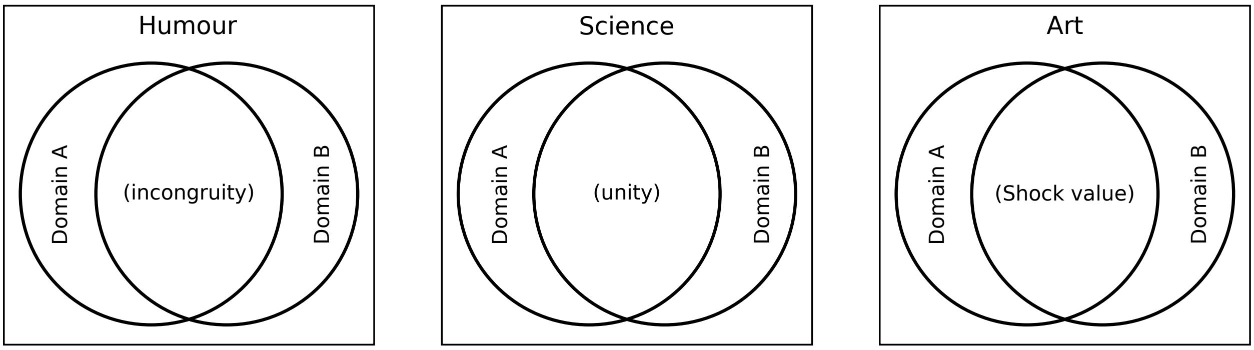


Figure 1: Venn diagram illustrating how Koestler's theory of *bisociation* forms the overlap of unrelated domains resulting in creativity for humour, science and art (Koestler, 1964).

Nature of overlap

The nature of the overlap of the domains affects how it is perceived. Koestler (1964) constrained the focus to three types of overlap that are creative, namely: humour, science, and art. Creativity in humour emerges when the overlap highlights two incongruous ways of viewing something (Koestler, 1964; Paulos, 2008). Examples include juxtaposing expectation versus surprise, or balance versus exaggeration, and decorum versus vulgarity. An example of the former is illustrated in Figure 2. An example of exaggeration is illustrated in Figure 3. Similarly, creativity in science emerges when the overlap of domains of knowledge contains unifying aspects (Koestler, 1964). Art relies on sensory and emotive potential. The overlap of domains as explained by the theory of *bisociation* is illustrated in the Venn diagrams in Figure 1.

Koestler's description of *bisociation* stopped short of prescribing how the matrices were found or how to model them and this is where other authors picked up the topic (Fauconnier & Turner, 2008b).

Q: What do you get when you cross a mosquito with a mountain climber?
A: Nothing. You can't cross a vector and a scalar.

Figure 2: A joke demonstrating a *bisociation* of three conceptual spaces, namely: insects, mountain climbing, and mathematics. In this case, 'vector' has a different meaning in the mathematics and insect conceptual spaces. Similarly, 'scalar' has a different meaning in the mathematics and mountain climbing conceptual spaces. This is an example of a *bisociation* contrasting expectation versus surprise.

Johnny Carson: You know, I was visiting a small town last week.
'How small was it?'
Johnny Carson: The Enter and Exit signs for the town were on the same pole.

Figure 3: A joke demonstrating balance versus exaggeration. The conceptual spaces are 'small towns' and 'road signs'. The joke is attributed to talk-show host, 'Johnny Carson'.

2.1.2 Structure of intellect

SOI overview

The structure of intellect is a model of intelligence, within which Guilford incorporates a model of creativity (Sternberg & Grigorenko, 2001). It is an associative theory, which means it investigates how ideas are materialised and chained together. This is in contrast to theories that are analogy or combinatorial based, such as *conceptual blending* and the Geneplore model (Mark A. Runco, 2014). Guilford essentially broke intelligence down into three dimensions, thereby modelling how intellectual processes mapped onto contents thereby producing *products* (G. Domino & M. L. Domino, 2006). These dimensions were then broken into smaller categories that can be represented by a cube. The cube can then be explored and sliced. There are five processes mapped to the *process* dimension, including convergent thinking and divergent thinking. The former process answers problems that have a correct answer and the latter problems that may have multiple solutions, with some of those solutions being more pleasing or reasonable than others. Guilford's Structure of intellect model has fallen out of favour. However, Guilford's concepts of convergent and divergent production are topics that persist in the creativity literature (G. Domino & M. L. Domino, 2006). Divergent and convergent production, and why they are important in creativity, are discussed next.

Divergent and convergent production

Divergent and convergent production

Problems requiring creativity generally have multiple solutions (Pétervári, Osman & Bhattacharya, 2016). Creative thinking is sometimes measured by the ability to produce *novelty*, which is measured using tests for divergent production, and by *usefulness*, which is evaluated using convergent production. Convergent production is heavily influenced by knowledge and has the goal of trying to find a correct answer (Cropley, 2006). Both are required since too much *novelty*, can result in solutions that are inappropriate to the problem at hand (Cropley, 2006), and divergence tests are not enough on their own to test for creativity (Mark A Runco & Acar, 2012). Tests for divergent thinking involve the presentation of a problem with many solutions and scoring the results for fluency, flexibility and originality (Huang, Peng, Chen, Tseng & Hsu, 2017). Fluency is a count of how many solutions were given, flexibility is the number of categories of the response, and originality measures the unusualness of the responses (Huang et al., 2017). An example of such a test is a provided row of circles, with the instruction to draw as many things as possible in the circles within 2 minutes. One test subject may draw in all the provided circles and another in just two of them. The first student would score higher for fluency. The first student may draw smiley faces in the circles and the second student draws a face and a string on one circle so that it depicts a balloon. The second student would score higher on flexibility. An illustration of this example is depicted in Figure 4.

Convergent thinking emerges both during the creation of ideas, and when evaluating the ideas (Pétervári et al., 2016). Generating large amounts of ideas has a statistically greater change of producing rare or unusual ones (Guilford, 1984).

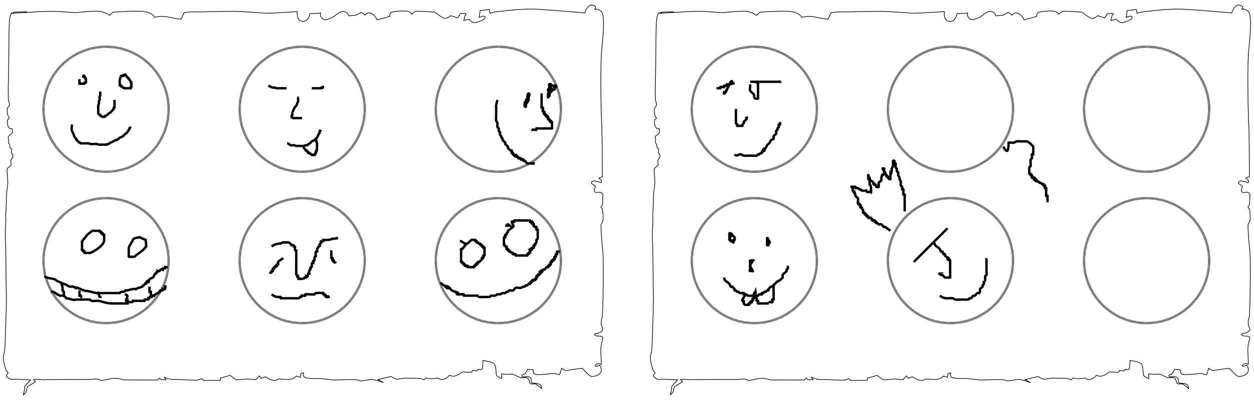


Figure 4: An illustration of a possible outcome of a test for divergent thinking using circles. The students are given a sheet of paper containing circles, with the instruction to draw as many things as possible in the circles within 2 minutes. The student producing the result on the left has drawn in all the provided circles and the student on the right in just two of them per line. The first student would score higher for fluency. The first student has drawn smiley faces in all the circles and the second student has drawn a face, and a string on one circle, so that it depicts a balloon. The second student would score higher on flexibility.

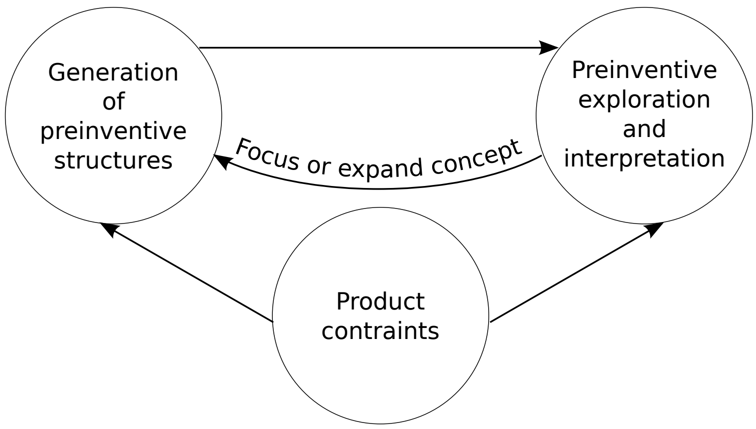


Figure 5: The Geneplore model of creative cognition.

2.1.3 Geneplore model of creative cognition

Geneplore model

The Geneplore model breaks creativity down into two phases, a generative process and an exploratory process (Finke, 1996). In the first phase (the generative phase), the seeds of creative ideas (preinventive forms) are spawned through processes such as mental blends, mental models, category exemplars and verbal combinations. The generative phase's mental processes can be spontaneous or planned, and conscious or unconscious. These preinventive forms are not necessarily fully formed ideas – the 'Half-baked idea'. During the exploratory phase, the forms are interpreted, extended, and evaluated for suitability of solving the task (Mark A. Runco, 2014). Cycling through the generate and explore phases potentially results in the final products. The Geneplore model, according to Finke (1996), is illustrated in Figure 5.

The next section discusses two theories of creativity that are grouped under the umbrella of confluence theories.

2.1.4 Confluence theories

intro

Sternberg developed two theories of creativity, which he described as confluence theories (Sternberg, 2006, 2012). Investment theory, to which other authors contributed (Sternberg, O'Hara & Lubart, 1997), and propulsion theory which was mostly the work of Sternberg. A confluence, according to the dictionary (Dictionary, 2010), is the point at which two rivers join. Sternberg's theories investigate the circumstances that have to co-occur for the emergence of creativity (Sternberg, 2012).

investment theory

1. **Investment theory** is a theory of creativity which borrows theories from the financial domain. The theory proposes that creative individuals are those that seek out unpopular, unfavourable or old, but yet potential, ideas and despite resistance pursue these ideas to potential until they bear fruition (Sternberg, 2006). The investment analogue to this is, 'buy low and sell high'. In order to achieve this, the individual requires three specific abilities: They need to be able to make connections between concepts and redefine obstacles, they need to be able to make accurate judgements on potential, and they require the ability to sell their ideas (Sternberg, 2006). All three of these individual intellectual skills are required. As with Csikszentmihalyi's system model (Csikszentmihalyi, 2014c), an investment theory creative individual needs to have motivation and subject knowledge. The individual is also a risk-taker and is able to generate, evaluate and execute ideas and choose appropriate environments in which to pursue them. In summary investment theory requires a confluence of six ideas, namely: intellectual ability, domain knowledge, styles of thinking, certain personality traits, motivation, and a supportive environment (Sternberg, 2006).

propulsion theory

2. **Propulsion theory** addressed how creative individuals make decisions and how they articulate and push forward their creative ideas (Sternberg, 2006). It focusses on the types of contributions that propel creative ideas within a particular domain or paradigm. There are three categories of contributions: contributions that accept current paradigms, contributions that reject current paradigms, and paradigms that attempt to integrate multiple current paradigms.

2.1.5 The four (or six) P model

intro

The P's of creativity are less about creativity theory and more a perspective of what drives and affects a creative individual. The initial four P's of creativity were proposed by Rhodes (Glăveanu, 2013). The four P's are *person* (or personality), *process*, *product*, and *press* (or place) (Glăveanu, 2013; Kozbelt, Beghetto & Runco, 2010). *Person* encompasses personality, intellect, habits, temperament, physique and so forth. *Process* refers to motivation, learning, thinking and communication. It queries why creative individuals strive for original answers and don't just accept the status quo. *Press* concerns how the environment affects creative production. *Product* is the communicated idea, such as art, music or poetry that can be judged for newness, value or originality. Jordanous (2015) put this succinctly as the individual that is creative, what they do to be creative, what they produce and in what environment. The four P model is illustrated in Figure 6 Jordanous.

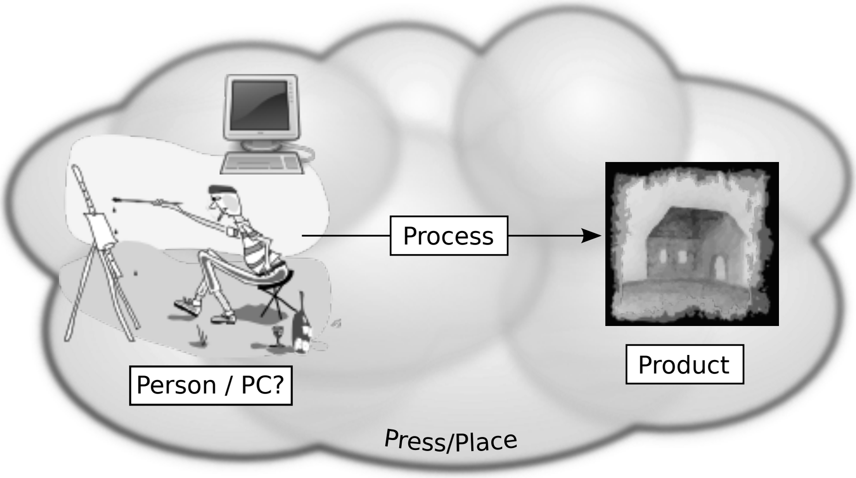


Figure 6: The four P model according to Jordanous. .

Two additional dimensions, *persuasion* and *potential*, have subsequently been suggested (Jordanous, 2015; Kozbelt et al., 2010). *Persuasion* describes the effect an individual has on their environment (Jordanous, 2016). Creative *potential* tries to account for creative individuals who have not yet produced creative products. Mark A Runco and Acar (2012) argues that divergence tests are a good indication of *potential*. In terms of the computational investigation of creativity, there is frequently a question about where to measure the creativity. Do you measure of the system itself or the systems output (Jordanous, 2015)? Jordanous argue that computational creativity should be explored from the four P model perspective.

Section 2.1.6 introduces the Systems Model perspective of creativity as proposed by Csikszentmihalyi (2014c). Unlike the *four P model*, Csikszentmihalyi's model of creativity is not focused entirely on one creative individual.

2.1.6 The Systems model

Systems model of creativity

The Systems model of creativity posits that while personality makes some contribution, creativity is not the property of an individual. Creativity emerges from an interacting system made up of the domain, the field, and the person (Csikszentmihalyi, 2014b, 2014c). Examples of domain include: mathematics or chemistry, or on a more fine grained level, algebra or statistics. The field includes the individuals or organisations that drive choices within the field. The field is the gateway that decides what is considered creative or relevant in the domain (Csikszentmihalyi, 2014a). These could be thought of as the domain experts or industry leaders. The person is only a part of the system involved in generating creativity; Creativity is a social construct and all three systems are necessary for it's emergence (Csikszentmihalyi, 2014c).

time/social

Time and social constructs are also key features of the systems model. This is because all three systems evolve over the passage of time and are affected by social constructs and culture (Csikszentmihalyi, 2014a). Culture and the individual's capacity to act can change over time affecting the emergence of creativity (Csikszentmihalyi & Robinson, 2014). The description of how *domains* evolve over time is succinctly captured by Kuhn in his work on the Structure of Scientific revolutions (Kuhn, 2012).

insight

Insight – another key characteristic of the systems model, as well as creative systems in general – may involve time, requiring input from social experiences. Here time is frequently referred to as the gestation period (Csikszentmihalyi, 2014b). The most significant insights span multiple domains which can be far apart or as close as neighbouring branches within a larger domain (such as statistics and algebra within the larger domain of mathematics) (Csikszentmihalyi & Sawyer, 2014). This suggests that *bisociation* is involved in the process of insight. Insight requires prior knowledge. The insight process is discussed in more detail when creative insight and other key characteristics of creativity are discussed in more detail in Section 2.1.8.

person traits

The attributes of the person that ends up contributing to the model include: curiosity, strong interest, motivation, sensitivity to information, and the ability to act on information and seize opportunity. These attributes can be driven by social constructs and experiences. In addition, it is the ability to find information, over the ability to problem-solve, that facilitates more creative acts. The difference between problem-solving versus problem-finding individuals is still under investigation. However, the latter is an essential trait of artists (Csikszentmihalyi, 2014b).

example

In the context of desktop blend (discussed when *bisociation* was reviewed in Section 2.1.1), the domain is computer science. The drive to find a user friendly user interface, combined with the individuals determination to solve the problem is what constituted the act of inventing the computer desktop, which was then accepted as a creative solution by domain experts who were driving the need for useful user interfaces, at a time when computers were becoming more available in society. The insight in this example occurred with the realisation that documents and filing are activities of both the office desk, and the computer.

2.1.7 Honing theory

Honing theory

Honing theory suggests that creativity is the process, driven by entropy and arousal, that drives cultures to evolve over time (Gabora, 2016). It is a self-organising system driven by the communal exchange of ideas. As a self-organising system it self-organises, self-maintains and self-reproduces. The creative process is started by what Gabora refers to as, 'high psychological entropy material', and evolves iteratively considering new material until the entropy and arousal have been dispelled. It is a theory of creativity that addresses why creativity begins and what guides the process. Gabora suggests evidence for Honing theory from evolving agent-based computer models that replicate the evolution of culture. She suggests that these computer models use concept combinations, once again suggesting that *bisociation* and *conceptual blending* is involved. Honing theory tries to formalise the Geneplore model's *pre-inventive forms* (Gabora, 2016).

QM vs Bayesian

Gabora mentions that prior research has indicated that models of human reasoning based on quantum probabilities may have advantages over classical probability and statistical reasoning using Bayesian inference. This is because quantum amplitudes – the quantum equivalent to probabilities – also interfere with each other and can exist in a linear superpositions of non-separable states (known as entanglement). The models using concepts from quantum mechanics also successfully model scenarios where multiple co-existing solutions exist as well as the effects that context has on concepts. One of these quantum concept models goes under the name of the *state-context-property theory* or sometime the *SCOP formalism* (Busemeyer, Pothos, Franco & Trueblood, 2011; Gabora & Aerts, 2002).

lead in/purpose

Attempts to formalise the measurement of computationally creative systems is necessary since earlier research on these systems is not systematic enough, and therefore hard to replicate and easily criticised (Jordanous, 2013). Part of the problem is coming to a consensus on the key characteristics of creativity – as discussed in Section 2.1.8. Section 2.2.2 discusses the efforts to rectify this issue and formalise the process.

2.1.8 Key characteristics of creativity

overview

The characteristics of creativity are broken down into necessary attributes and desirable attributes. Necessary attributes include *novelty* and *utility*. Desirable attributes include *surprise*, *divergence* and *incubation*. The necessary attributes were described in an early model known as the 'creative product analysis model (CPAM)' (Burns, 2015). Both types of attributes are discussed individually in more detail below.

novelty

Novelty

Theories of creativity indicate that creative acts need to produce some form of *novelty* (Newell, Shaw & Simon, 1959; Pétervári et al., 2016; Ritchie, 2007; Varshney et al., 2013). *Novelty* has an agreed upon definition in the literature. Specifically; a created and appropriate artefact is considered novel when it differs in characteristics from other artefacts in the same class. *Unexpectedness* is a measure of the degree to which *novelty* has occurred (Maher, 2010). *Novelty* is necessary but not sufficient for an artefact to be considered creative (Mark A Runco & Kim, 2011).
Methods of evaluating novelty are discussed in Section 2.2.2 when creativity evaluation techniques are discussed.

Usefulness

Another accepted characteristic of creative artefacts is that of *utility*. *Utility* is also often referred to as *value* or *usefulness* or *relevance* and, in the case of the creative product analysis model, *resolution* (Burns, 2015). The produced creative artefact needs to have the appropriate level of utility (or performance) within the genre or space it inhabits – and within the social group within which the artefact is relevant **??**. Some authors consider *novelty* more important that usefulness (McCormack & d'Inverno, 2012).

The creative insight pipeline

description

Several researchers have described models that attempt to encapsulate the mental processes that result in insight (Csikszentmihalyi, 2014c; Csikszentmihalyi & Sawyer, 2014; Hadamard, 1954; Simonton, 2009). Hadamard's model of the insight pipeline is illustrated in Figure 7. Other two and three stage models are shown in Figure 8. There was terminology differences between these models; For example Simonton used the terms, *variation*, *selection* and *retention*. Existing models of insight should - but currently don't – describe or model how interpersonal contact, politics and external events affect when and how insight occurs (Csikszentmihalyi & Sawyer, 2014).

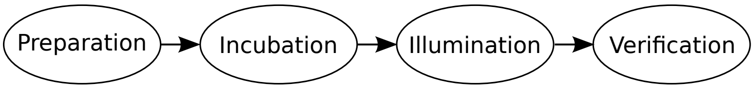


Figure 7: Hadamard's model of the insight pipeline.

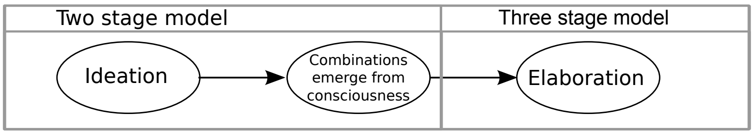


Figure 8: Two and three stage versions of the insight pipeline (Csikszentmihalyi & Sawyer, 2014).

Incubation

The fact that there frequently appears to be an amount of time between the beginning of a creative idea and the final produced novel artefact for that idea, is also frequently mentioned in the creativity literature. There are a number of suggested reasons for this *incubation* period. Csikszentmihalyi suggested that the time was required to interact with other domains, fields and societal influences. Gilhooly mention that some of the theories about the benefits of *incubation* are *Intermittent Conscious Work*, *Beneficial Forgetting* and *Unconscious Work*. *Beneficial Forgetting*, is the idea that forgotten detail facilitates looking at the problem from a new perspective. A popular explanation for *intuition*, is that the truth or solution, emerges from unconscious processes during the incubation stage (Gilhooly, 2016). It was already mentioned above that Boden; Fauconnier and Turner and Koestler were all in agreement that there is a *hidden* aspect or *unconscious association* in creativity, which emerges in the form of intuition or hunches (Francisco Câmara Pereira, 2007). The role and specific characteristics of intuition are still being investigated (Pétervári et al., 2016).

The AHA moment

Sudden Insight, or illumination, is that moment in the insight pipeline where a previously partly formed idea, suddenly materialises into a fully formed creative idea. Researchers have taken to referring to this part of the *insight pipeline* as *the 'AHA' moment* (A. Anderson et al., 2016; Kudrowitz, 2010; Martins, Urbancic, Pollak, Lavrac & Cardoso, 2015; Thagard & Stewart, 2011). In Figures 7 and 8 this insight occurs at the *illumination* and *combinations emerging* stages. Insight, sometimes occurs after a restructuring of the representation of the unknown problem (Mark A. Runco, 2014) .

Elaboration

or verification is that final part of the insight pipeline in which partly formed ideas are developed and shared Csikszentmihalyi.

unexpectedness or surprise other

Unexpectedness or *surprise* is considered a desirable trait of creative systems, but is not an essential requirement (Maher, 2010).

In addition to these necessary and desirable traits of creative artefacts specific models of creativity may have their own necessary requirements. For example; *bisociation* requires an artefact to be generated using input from more than one domain of knowledge.

2.1.9 The creativity pipeline

The stages in the creativity process include, *finding the problem* – and often overlooked part of creativity (Csikszentmihalyi & J. W. Getzels, 2014; Csikszentmihalyi & J. Getzels, 1970; Varshney et al., 2013), *amassing knowledge*, *collecting related knowledge*, *incubation*, *generation of ideas*, *combining ideas*, *prioritising* the most relevant ideas and producing creative output (*externalising*) (Varshney et al., 2013). This is diagrammed in Figure 9.

Csikszentmihalyi even goes as far as to point at that problem finding is more creative than problem solving (Csikszentmihalyi, 2014c; Csikszentmihalyi & J. Getzels, 1970; Mark A Runco, 2009).

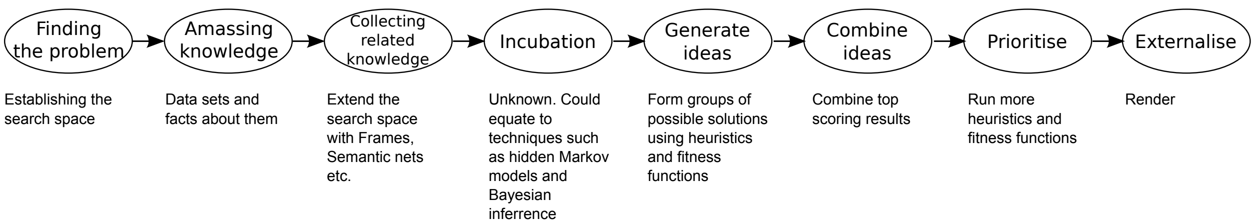


Figure 9: The creativity pipeline, with potential computational creativity tasks at each stage of the pipeline.

CC lead in

Having discussed some of the main theories of creativity and the common characteristics within those theories, the discussion now turns to computational creativity and how the theories of creativity have been implemented in the artificial intelligence field.

The following section outlines the theory of *conceptual blending* which builds upon the concept of *bisociation*.

2.1.10 Conceptual blending

overview

Fauconnier and Turner (2008b) expand on the concept of *bisociation* by pointing out that *bisociation* is not constrained to human creativity and is a fundamental part of the way humans think. They point out that for *bisociation* to be creative it needs to occur within certain boundaries and certain rules. They propose *conceptual blending* as an extension to *bisociation* that combines form with mental spaces and clarifies the patterns of blending between conceptual spaces in order to find the emergent behaviour. Mental spaces are groups of concepts that humans construct as they think and there are four of these spaces in *conceptual blending* (Fauconnier & Turner, 2008b).

Definition 2.1. *A conceptual blend consists of input spaces (matrices), partial cross mappings of spaces, a generic space – which contains only the elements that the inputs have in common – and a fourth space which is the resulting blend. The blend contains new features that do not exist in the other spaces (Fauconnier & Turner, 2008b).*

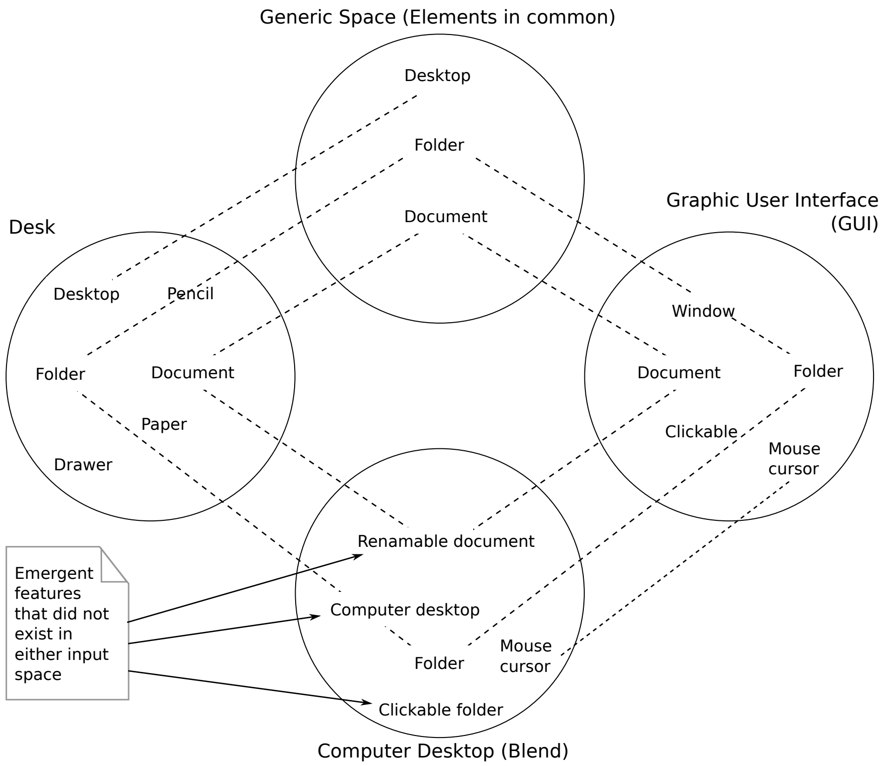


Figure 10: The four mental spaces in a *conceptual blend* as they pertain to the concept of a computer desktop.

example

The computer desktop is given as an example of conceptual blending (Fauconnier & Turner, 2008b). The one mental space is a normal desk and the items you would normally find on it. The other space is the computer's Graphic User Interface (GUI). The common items are folders and documents. The emergent behaviours that exists in the blend are the ability to name, drag and click on folders. None of these behaviours exists in either input space. You cannot click on a folder on a physical desktop using a mouse cursor. A GUI without the concept of folders cannot rename or move them. This example also demonstrates how blending is often unnoticed. Even computer scientists may not be aware of the blend. The four input spaces of the *conceptual blend*, as related to the computer desktop example, are illustrated in Figure 10.

Emergent structure

Emergent structure in the blend materialises in three ways: through *composition* of projected elements from the input spaces, through *completion* based on background information (such as that provided by semantic frames), and through *elaboration* (Fauconnier & Turner, 2008b). Fauconnier and Turner refer to the act of *elaboration* as, "running the blend". In the computer desktop example, the fact that a folder can be renamed is an example of emergent structure through composition.

Types of blends

A question that remains regards how choices are made as to what to cross map and project into generic space and hence the blend? This is where the patterns of blending and the types of blends come to the fore. Aspects of only one of the input spaces can be brought into the blend, for example using one input space's time-frame and discarding time from the other input. Concepts from both inputs can be equally projected into the generic space or one input space can provide most of the elements. This is called an asymmetric blend and is also known as selective projection (Fauconnier & Turner, 2008b). Elaboration can be achieved through various methods including the use of analogy tools and semantic networks. Goguen and Harrell (2010) indicate that metaphoric blends are asymmetric, in that more concepts are brought in from one of the input spaces than the other.

Compression

Visualisation of data allows a compressed and compact view of the data due to the *Gestalt principals* of human visual perception – resulting in human visual perception being faster and more efficient than our cognitive processes (Kirk, 2012). Similarly, *conceptual blending* also exhibits emergent *compression* of information (Fauconnier & Turner, 2008b). The *compression* is apparent when there are relationships in the blend containing scales, or when significant portions of data are dropped from one of the input spaces by selective projection (Fauconnier & Turner, 2008b). For example, the dropping of most of the information from one of the input spaces can cause a quantised or summarised view in the blend. When relationships with scales (such as time, nominals, ordinals, intervals or ratios) differ between the inputs it can expand or compress one of the input spaces in the blend, resulting in a compressed view of the result (Fauconnier & Turner, 2008b). For example, a blend between a historic event, that took place over many years, with an event that occurred at lunchtime yesterday. Conceptual blends have been used to facilitate navigation between concepts of visualisations of large networks of data (Cybulski, Keller & Saundage, 2015; Liu & Yang, 2014).

how to blend is NB

Fauconnier and Turner (2008b) insist that the way concepts are formalised and how the concepts are blended is important in distinguishing between a *bisociation* that is involved in all human thought processes, and one that is creative. Formal structures and their transforms are important and certain themes recur within the rules of those forms (Fauconnier & Turner, 2008b). Form, in creativity turns out to be much harder to model on a computer than it would seem. Formal approaches, such as formal logic, rule based production, fuzzy logic or algorithmic systems don't quite capture the process (Fauconnier & Turner, 2008b). Parallel distributed processing was successful at representing cognitive phenomena. But even parallel distributed processing had problems capturing identities and linking roles. Matching and aligning two domains by finding commonalities and analogies is not trivial and is central to creative work (Fauconnier & Turner, 2008b). Analogy is hard to recognise and tends to occur at hidden layers within the form. The emergent structure is generated by *composition* of projections and the emergent behaviours are generated based on *elaboration* (Fauconnier & Turner, 2008b). It has also been suggested that iteration also plays a large role in the blend of concepts (Chan & Schunn, 2015).

Optimality principles

An Optimal blend has specific characteristics. A strong blend retains tight connections to the input space and can reconstruct how the blend is connected to the input. Blended elements should share similar relations to the items in the input. An item in the blend should have some sort of meaning (Fauconnier & Turner, 1998; Goguen & Harrell, 2004; Grady, Oakley & Coulson, 1999)

superimposed images

Images when combined also exhibit emerging structures (Finke, 1996). As an example of this see Figure 11. The letter 'X' and the letter 'N' when superimposed exhibit new shapes including the letter 'M'.

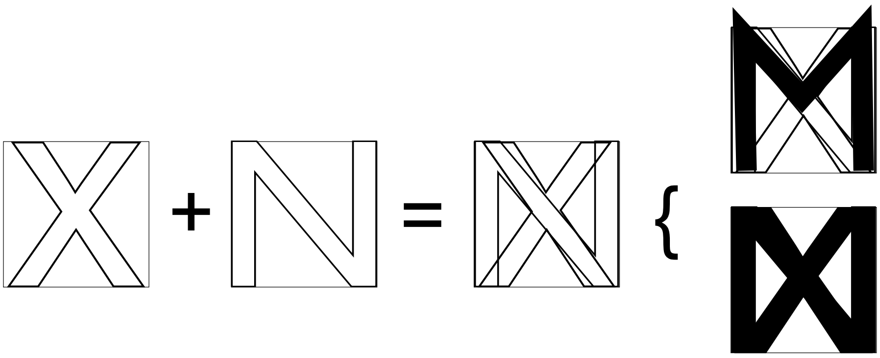


Figure 11: Emergent features of superimposed images.

2.1.11 Summary and creativity terminology

The terminology varies between creativity theories, but many of the definitions have a heavy overlap with the earlier theory of *bisociation*. This overlap between the terminology of the theories is summarised in Table 1.

Creativity theory	Term	Meaning of term	Creativity emerges with
Bisociation	matrices of knowledge	Any pattern of activity defined by a set of rules	Overlap between multiple matrices of knowledge containing originality through carefully chosen exaggerations or omission or implied relationships (Koestler, 1964)
Conceptual Blending	conceptual space	A collection of related concepts	Bisociation is not sufficient. Correspondences between conceptual spaces require overlap between the spaces where the overlap contains emergent elements that were non existent in the input spaces (Fauconnier & Turner, 2008b).
Boden's Taxonomies	conceptual space	Structured style of thought driven by culture, peer groups or tragedy	Her focus was on artificial intelligence implementations. The correspondence between the conceptual spaces is brought about in three ways: 1. unusual combinations of familiar ideas in the spaces. 2. exploration outside one or both of the conceptual spaces 3. transformation of one or both of the conceptual space/s

Table 1: Summary of the terminology overlap between creativity theories based on *bisociation*.

Section 2.2 covers some of the issues that arise while implementing creativity on computers and gives an overview of the field. Margaret Boden's theories are discussed, since her work is found prominently in the literature. The section then covers the issue of how to measure computational creativity and presents some of the formal models have been suggested.

2.2 Computational creativity

The following section discusses the ideas and work of Margaret Boden. Her work extended the concept of *conceptual blending* by focusing on the theory from an artificial intelligence point of view. Examples of programs that illustrate Boden's theories are given.

2.2.1 Boden's taxonomies

overview

Boden (2004) built onto the concept of *conceptual blending*. She believed that *bisociation* was not just found in creative thoughts but was in fact part of every day thought processes. Boden is widely cited because she provided an analysis based on how creativity translates into the artificial intelligence field thereby providing a framework for analysing the results (Francisco Câmara Pereira, 2007).

computer problems

Boden made clear why implementing *bisociation* on a computer was not that straight forward. She describes the aspects of *bisociation*, that elevate the combinations of *conceptual spaces* above the realm of simple combinatorics; pointing out that combining conceptual spaces in a combinatorial manner isn't as straight forward for a computer as you would expect it to be, particularly as the search space grows. It is not enough for an idea to be random, unusual, useful or even statistically rare (Boden, 2004).

human traits

Unconscious thoughts, inference and societal paradigms – human traits that are difficult for a computer – would need to be addressed. Boden (2004), Fauconnier and Turner (2008b) and Koestler were all in agreement that there is a *hidden* aspect or *unconscious association* in creativity, which emerges in the form of intuition or hunches (Francisco Câmara Pereira, 2007). Societal shared knowledge and paradigms have a role to play and this accounts for why discoveries are frequently made concurrently by several individuals (Boden, 2004). Environmental events such as floods or trauma can also contribute to creative discoveries. Boden points out that humans can recognise creativity. For this reason, a program simulating creativity should be able to account for how it's creativity came about and be able to recognise that some solutions are more appropriate than others.

desirable charac. of creativity

Boden highlighted many desirable aspects that computer programs should strive for in order to achieve some of the characteristics of creativity. Artificial intelligence techniques can produce new ideas in three ways: by producing novel *combinations* of well known ideas; by *exploring* the potential within the conceptual spaces and by making *transformations* that enable the generation of previously unachievable solutions (Boden, 1998; Thagard & Stewart, 2011).

types of creativity

Combinatorial creativity

Novel combinations can be generated by developing analogies or using artificial intelligence heuristic techniques as described by Michalski, Carbonell and Mitchell (2013) and Boden (1998). Heuristics also help with the exploding search space problem in combinatorial creativity. More general heuristics such as those described by Polya can also be used (Boden & Mujumdar, 1998). Polya's heuristics include analogy, auxiliary problems, contradiction, generalisation, variation of a problem and working backward (Polya, 2014, pp. 37-225). Most combinational creativity studied in artificial intelligence requires a knowledge base or semantic network as a base; Examples of knowledge bases are *ConceptNet* (Llano, Colton, Hepworth & Gow, 2016; 'ConceptNet 5', 2016) and AnalogySpace (Lieberman & Henke, 2015; Speer, Havasi & Lieberman, 2008a). The knowledge base also requires some way of linking the concepts in a useful, rather than random manner. The originality of the combinations needs to be determinable (Thagard & Stewart, 2011). An example of a creative program of the combinatorial type is Jape, which generates riddles using puns (Ritchie, 2003).

Exploratory creativity

Exploratory programs explore the domain of the search space looking for potential. Something that is considered novel can generally be described by a known set of generative rules, but something that is genuinely creative cannot; Ideally exploratory models of creativity should be able to expand, explore or move outside of the provided search space (Boden, 1998). This is also the case for Genetic Algorithms (GAs) since they only seek a solution within a provided space (Boden, 1998). GAs used to generate graphics may tweak the conceptual space; However, the resulting images – although they may be novel – still belong to the same family as the GA's prior generations of images. BACON, which tries to generate scientific theories is an examples of an explorative creative program (H. A. Simon, 1992). BACON has carefully pre-structured data and conceptual spaces as do many exploratory models of creativity. AARON, which produces digital paintings, is another example of this type – earning H. Cohen a lifetime achievement award (H. Cohen, 1995, 2014).

Transformational creativity

Transformational creativity is the successor to exploratory creativity (Boden, 2016). Transforms involve one or more of the dimensions of the space. Transforms add, remove or change aspects of the space. Transformation need not be creative because it is possible for a transform to produce uninteresting results. Vast changes are hard to evaluate suggesting that an evolving fitness function may be required (Boden, 1998). The COPYCAT program is an example of transformational creativity (Hofstadter, 1984). COPYCAT is a program that when given an example input and output string of characters, will – when prompted with a new string – generate a set of outputs by looking for patterns in the provided example and its own previous outputs.

overlap/
summary

All of these techniques can overlap with one another. In computer models of creativity, the exploratory type is the most successful, but is hard to reproduce since it requires considerable amounts of domain expertise (Boden, 1998). Combinational and transformational creativity are even harder to model (Boden, 1998). Most combinational creativity studied in artificial intelligence requires a knowledge base or semantic network as a foundation (Thagard & Stewart, 2011). The knowledge base requires some way of linking the concepts in a useful, rather than random manner. Large knowledge bases, containing many combinations require heuristics to eliminate the combinations that may not be particularly interesting. The originality of the combinations needs to be determinable.

terminology

The terminologies between these creative theories vary but the meanings overlap significantly. The terminologies used in each theory are summarised in Table 1. *Bisociation* was originally introduced by Koestler (1964) in a book called 'The act of creation'. The following section summarises the main ideas behind *bisociation*.

2.2.2 Measuring computational creativity

measurement probs

The application of the knowledge of creativity into the computer science realm is difficult to assess (Van der Velde, Wolf, Schmettow & Nazareth, 2015). This is largely due to the large amount of methods, and thus wide scope of assessment, used in the existing research which makes them difficult compare (Francisco Câmara Pereira, 2007). Francisco Câmara Pereira (2007) also mentions that they do not all follow similar methodologies or relate the methodologies back to the currently accepted theories of creativity and for this reason this dissertation will try to focus on computational literature where the methodologies closely align with one of the known theories of creativity or where the methodology contributes to the generation of graphics, visualisation and/or domain specific *novelty*.

work arounds

Some authors work around this problem by assessing other aspects of their computational systems, such as the quality(M. Riedl, 2014). Others use predefined criteria against which to test their results **??**. Solving the creativity measurement problem also requires that the evaluation is measured against a working definition of creativity (Colton, Pease, Corneli, Cook & Llano, 2014).

Measuring creativity criteria

Measuring novelty

The calculation of novelty is one of distance and is therefore a metric in the mathematical sense (Maher, 2010). One manner to quantify *novelty* is the use of Bayesian inference techniques from statistics (Shao et al., 2014). For example, the Kullback–Leibler test for divergence, which is an expectation calculation that measures the differences between probability distributions. The probability distribution of existing examples typical in the class, is calculated and subtracted from the probability distribution of the artefacts that are being tested for *novelty*. This measurement has come to be known as *Bayesian surprise* (Correll & Heer, 2017; Evans, 1997; Gkioulekas, Evangelopoulos & Maragos, 2010; Itti & P. F. Baldi, 2005; Maher, 2010; Varshney et al., 2013). *Bayesian surprise* also shows promise as a model for human visual attention, giving

category	description	criteria
typicality	A score of how typical the output is when is when measured against examples in the domain it is intended to represent	1. On average, the system should produce suitably typical output. 2. A decent proportion of the output should be suitably typical. 3. A decent proportion of the valuable output is suitably atypical. 4. The system can replicate many of the example artefacts that guided construction of the system (An inspiring set). 5. Much of the output of the system is not in the inspiring set, so is novel to the system. 6. Novel output of the system (i.e. not in the inspiring set) should be suitably typical. 7. A decent proportion of the output should be suitably typical items that are novel. 8. A decent proportion of the novel output of the system should be suitably typical.
value	A score of the level of quality of the output when measured against other examples of it's genre	1. A decent proportion of the novel output of the system should be highly valued. 2. A decent proportion of the output should be highly valued items that are novel. 3. Novel output of the system (i.e. not in the inspiring set) should be highly valued. 4. A decent proportion of the atypical output is highly valued. 5. On average, the system should produce highly valued output. 6. A decent proportion of the output should be highly valued.
both		1. A decent proportion of the output should be both suitably typical and highly valued. 2. A decent proportion of the output is suitably atypical and highly valued. 3. A decent proportion of the novel output of the system should be suitably typical and highly valued. 4. A decent proportion of the novel output of the system should be suitably atypical and highly valued.

Table 2: The empirical scoring criteria used for assessment in Ritchie's method of creativity assessment (Ritchie, 2007).

prominence to anomalies such as outliers (Correll & Heer, 2017). As mentioned in Section 2.1.2, novelty can also be measured using the combination of tests for divergent production, and tests for *usefulness*.

bayesian surp. Equation

The *Bayesian surprise* equation is given in Figure 12. The former equation is simpler in practice (P. Baldi & Itti, 2010). As can be seen from the equation, the Kullback–Leibler test is a generalisation of Claude Shannon's test for entropy (Figure 13). The main difference is that Shannon's theory is for one data set, whereas the Kullback–Leibler test is the average over the entire model (P. Baldi & Itti, 2010). *Bayesian surprise* is always positive (P. Baldi & Itti, 2010). The integrals generalise to summation in the discrete case.

A simpler approach to detecting novelty is to detect outliers since these have a low probability. This is also related to Shannon's theory since rare events score high in Shannon's equation (P. Baldi & Itti, 2010). The problem with this approach is that the resulting artefacts are unlikely to be very useful. The work around it to introduce a surprise index that takes the other examples into consideration (P. Baldi & Itti, 2010).

$$\begin{aligned} \textit{Bayesian surprise} &= KL\,(P(X)\,,\;P(X|Y)) && (1)\\ &= \int_X P(X)\log\frac{P(X)}{P(X|Y)}dX && (2)\\ &= \log P(Y) - \int_X P(X)\log P(X|Y)dX && (3) \end{aligned}$$

Or equivalently

$$\begin{aligned} \textit{Bayesian surprise} &= KL\,((P(X|Y)\,,\;P(X)) && (4)\\ &= \int_X P(X|Y)\log\frac{P(X|Y)}{P(X)}dX && (5) \end{aligned}$$

For the discrete case

$$\begin{aligned} \textit{Bayesian surprise} &= KL\,((P(X|Y)\,,\;P(X)) && (6)\\ &= \sum_X P(X|Y)\log\frac{P(X|Y)}{P(X)}dX && (7) \end{aligned}$$

Figure 12: *Bayesian surprise* calculations using the Kullback–Leibler relative entropy test. Two equivalent continuous equations and the discrete version .

$$\textit{Entropy} = -\int_X p(x)\log\frac{P(x,y)}{P(x)P(y)}dxdy$$

Figure 13: *Shannon's entropy* (Shannon, 2001).

$$\textit{Surprise index} = \sum\frac{X^2}{Y}$$

measuring divergence

The measurement of divergence, when testing human subjects, was briefly discussed in Section 2.1.2. The measurements are transferable into the computational realm since that are measurable. Tests for divergence apply when there are multiple potentially suitable answers. The test for divergence comprises: tests for fluency, tests for flexibility, and tests for originality (Huang et al., 2017). Fluency is a count of how many solutions were given within a given time frame, flexibility is the number of categories of the response, and originality measures the unusualness of the responses (Huang et al., 2017).

measuring usefulness

Usefulness cannot always be a fixed metric since a useful artefact can be produced, that has a function that was not a feature of the existing class of artefacts. In this instance, *usefulness* can be measured using adaptive performance functions (Maher, 2010). *Usefulness* can also be the easiest creativity criteria to measure. A computer program is *useful*, if it is designed to solve a problem and the program produces a suitably appropriate answer. In the case of data visualisation, the *usefulness* criteria is achieved if the program produces an effective visualisation.

Formalised frameworks for measurement

Formalised frameworks

Formalised frameworks for the measurement of computational creativity are a matter of ongoing investigation. Elgammal and Saleh (2015) suggest using an adaptation of network centrality – from graph theory – to infer the originality of computer generated art works. Van der Velde et al. (2015) uses semantic maps, which are a visual display of connections between similarly related concepts, to build up a collection of words associated with creativity. The resulting maps were then used to generate rating scales. Automated fitness functions for evolutionary art and music are being explored under the concept of *computational aesthetic evaluation* (Bodily & Ventura, 2018; den Heijer & Eiben, 2014; Galanter, 2013a), but this concept is also an open problem (Galanter, 2013b). Generally evaluations are based on criteria set by the researchers (Jordanous, 2013).

measurement models

Some of the recent formal models for measuring creative systems include, the *FACE* (Colton, Pease & Charnley, 2011), *Standardised Procedure for Evaluating Creative Systems (SPECS)* (Colton, Pease et al., 2014; Jordanous, 2013), Ritchie's criteria approach (Ritchie, 2007) and *DECIDE* (Kantosalo, Toivanen, H. T. T. Toivonen et al., 2015; Rogers, Sharp & Preece, 2011) models.

The IDEA model

works around the fact that creative artificial intelligence programs can produce multiple correct 'solutions' and potentially don't have specific enough criteria to label solutions as correct or incorrect. This was discussed when divergent thinking and divergent production were introduced in Section 2.1.2. The model replaces the idea of solutions to the artificial intelligence program with the notion of the impact of the program output (artefacts).

The FACE model

consists of tuples, labelled 'creative acts', that represent scores for both the processes and the generated artefacts. Scored aspects of the program, labelled 'generative acts' include, execution, the method the program uses, the frames (which provide contextual, historical or aesthetic background information about the domain) and the function that calculates the aesthetic score. The generated output from these four 'generative acts' is also scored. Each 'generative act' of the program feeds the resulting output into the next 'generative act' so that the scoring is chained. Not all 'generative acts' need to exist in the program and can be null in the tuple. The resulting tuples can then be compared and the average, best and worst, range and yield of acceptable scores can be calculated mathematically (Colton et al., 2011).

Ritchie's empirical criteria approach

typicality and quality

Ritchie's approach uses *typicality* and *quality* as criteria against which the output of a creative system can be assessed (Colton, Pease et al., 2014). *Typicality* criteria test how dissimilar the item is from examples of it's genre. *Quality* criteria test for the extent to which an item meets the desirable criteria for membership within it's genre. These eighteen criteria indirectly encompass *novelty* (Colton, Pease et al., 2014). The criteria are listed in Table 2.

appropriateness for use

Ritchie's model disregards how the artefacts were generated and measures them after their creation (Jordanous, 2013). It is therefore better suited to measuring systems that produce concrete observable artefacts, as opposed to abstract, output (Jordanous, 2013; Ritchie, 2007). Ritchie claims that the model doesn't test for creativity, but instead tests for criteria that indicate evidence of

scoring

The scoring against the eighteen criteria is done by what ever measures are pertinent to that particular artefact, and the artefacts are defined by their inclusion in a particular class or genre (such as poems, stories, drawings etc.) (Ritchie, 2007). Ritchie does mention that quality ratings of these classes can be somewhat subjective and therefore the scores for his criteria are treated as fuzzy sets (refer to Table 29), and scored on the interval $[0, 1]$. The intent is to capture how the artefacts can be distinguished from typical examples of the class.

summary of eval meth.

Graeme Ritchie's formal empirical criteria appear to be the most widely adopted (Jordanous, 2013; Misztal-Radecka & Indurkhya, 2016). It is one feasible option of measurement for the output of the prototype since we know what makes a successful visualisation. Ritchie measures the output of a creative system relative to the search space and specifically tries to measure – amongst other criteria – *novelty* (Raczinski & Everitt, 2016). Criteria and qualities of a successful visualisation are discussed in Section 2.4.1. It should also be easy to find existing typical existing visualisations if the data is chosen from sources that already have existing visualisations. The choice of evaluation technique will ultimately need to be determined by the design of the prototype, based on which stage of the pipeline is chosen against which evaluation technique may be suitable.

creativity criteria

There are two types of attributes that creative programs exhibit, namely: attributes that are *sufficient* for the program to demonstrate creativity, and attributes that are *essential* for the program to demonstrate creativity (Francisco Câmara Pereira, 2007). The following paragraph summarises some of the attributes – specific to *bisociation* – that are sufficient to satisfy the theories of creativity.

bisociation criteria

One of the primary attributes of *bisociation*, as described by Koestler (1964), is the notion that two or more domains of knowledge need to overlap. The goal then is to find a suitable relationship between the domains. Measurable programs, therefore need to keep track of which domain the concepts they are combining are from and describe how the concepts are related. Concepts from more than one domain need to exist in the resulting output and the relation between the concepts needs to be describable. This attribute is fundamental and hence required. As mentioned in Section 2.2.1, Boden (2004) indicates that a truly creative program should ideally be able to generate knowledge that was not part of the original data, or search space, however she provided an example showing that this is not a necessary requirement in order for a program to appear to be creative. Combining domains in unusual ways and the illumination of how the domains were combined is a key factor in creativity theories based on the concept of *bisociation*. Methods claiming to be based on these theories would require a mechanism, such as history tracking, so they could account for their results. A software program that is grounded in creativity theories based on the theory of *bisociation* would need to show that two diverse domains have been combined in some unique manner to create the program output. The program would therefore be required to produce a history of what domains it combined and why – or how – it chose to combine them.

lead out

Having given a brief overview of how creativity materialises in the computational space and what the issues are, the conversation now turns to more specific techniques.

2.3 Computational methods of blending

2.3.1 Representating concepts

In order to model concepts, one has to first define them. There are a number of theories on how to define concepts. The psychological theories of concepts described here are those that have been adapted for use in existing computational creativity programs.

Prototype Theory

The Prototype view of concepts was described by Rosch (Rosch, 1975). Concepts are prototypes and are not defined by detailed definitions. They are defined by the features that are necesary and sufficient to assign an item to a category. In order to belong to the concept 'bird', for example, the item being assigned to the 'bird' concept must have wings, feathers and be bipedal. The more attributes that the item has in common with the features of 'bird', the more likely it is to belong to the concept. How many of the attributes of the item are in agreement with the features of the prototype also provides a score of how well the item fits the concept.

The prototype view of concepts is well suited to artificial intelligence machine learning techniques that classifies instances in terms of attribute value sets. Version space learning and decision trees are two examples (Francisco Câmara Pereira, 2007) of these techniques.

Exemplar Theory

Concepts are represented by their most typical examples. Exemplar and Prototype theory are similar. Where they differ is that in the protoype theory there is only one prototype per category, whereas Exemplar theory uses multiple typical examples (or exemplars) against which it confirms concept membership. In AI is case based reasoning

Theory View

Concepts are represented by facts about them. Ie Airoplanes have wings and can fly. Techniques suitable for modelling the theory view of concepts include Inductive logic programs and programs that use Semantic Networks, such as Divago and Copycat (Francisco Câmara Pereira, 2007) .

Having built up sets that represent conceptual spaces, the next task is to find a way of blending them. Methods of implementing *bisociation* 2.3.2 and more advanced techniques 2.3.3 are discussed.

TODO fix grammar

2.3.2 How to Blend: Bisociation

Bisociation

Bisociation has been applied in the natural language processing area. Collections of words, commonly referred to as 'bags of words', can be generated from any data source using algorithms such as topic modelling. Frequently they are generated from text documents using standard natural language processing

$$\sin(\theta) = \frac{tf_i^A \cdot tf_i^B}{\|tf_i^A\| \|tf_i^B\|}$$

where the values in the denominator are calculated using the Euclidean norm.

Figure 14: The Cosine measure .

techniques, such as document parsing, after which stop word removal, stemming and inverse document term frequency calculations are performed (Jurafsky & Martin, 2014; Francisco Câmara Pereira, 2007). Document similarity based on the frequency of items is a technique suitable for *bisociation* because it can calculate the similarity of two unrelated documents (Segond & Borgelt, 2012a). Various measures that calculate the distance between vectors can be used to determine how closely two collections of words overlap. A *Bison Index* or *Bison measure* (Figure 15) has been developed (Borgelt, 2012; Juršič, 2015; Segond & Borgelt, 2012b). This measurement attempts to address some of the shortcomings of other measurements – such as the cosine measurement (Figure 14) (Berthold, 2012; Berthold, Dill, Kötter & Thiel, 2008). The Bison measure increases the similarity score for documents sharing higher frequently values (Segond & Borgelt, 2012b). When generating *bisociations* over text documents in this way, the measurement calculation frequently involves the 'term frequency-inverse document frequency (tf-idf)' vectors.

An examples of a program using these techniques is the work by Nagel, Thiel, Kötter, Piątek and Berthold who demonstrated how to find and how to score *bisociation* using graphs. They demonstrate their results against the Schools-Wikipedia dataset ('Wikipedia for Schools', 2013).

BisoNets are semantic networks that represent the relationships across more than one domain. *Bisociations* that use semantic networks have resulted in a computer program known as BISON. BISON generates semantic graphs from text documents. It specialises in producing graphs that combine unrelated domains using analogical reasoning, metaphorical reasoning and other approaches. These graphs are known as *BisoNets* (Segond & Borgelt, 2012b). (Berthold, 2012; Handl & Schmid, 2011; Imaz & Benyon, 2007; Francisco Câmara Pereira, 2007; Veale, Feyaerts & Forceville, 2013).

Conceptual blending

In order to implement conceptual blending, and infer new knowledge in the blended domain - known as 'running the blend' - authors build concepts out of predicates or build ontologies and then use reasoners to infer new knowledge. When using semantic dictionaries these predicates become hierarchical and take the form of graphs. The task of joining the two graphs that form the input spaces to the blend then becomes one of combining two graphs. Combining nodes can be as simple as just finding nodes that match and joining them or matching on the physical similarities of the nodes; However, *conceptual blending* is looking for more creative and unusual matches.

$$B(A,B) = (tf_i^A \cdot tf_i^B)^k \times \left(1 - \frac{|\arctan(\|tf_i^A\|) - \arctan(\|tf_i^B\|)|}{\arctan(1)}\right)$$

where $tf_i^A, tf_i^B \in [0,1]$
and k adjusts the importance of low frequency terms.

Figure 15: The Bison measure .

2.3.3 How to Blend: More advanced techniques

In order to implement some of the more advanced techniques of conceptual blending, and infer new knowledge in the blended domain - known as 'running the blend' - authors build concepts out of predicates or build ontologies and then use reasoners to infer new knowledge. When using semantic dictionaries these predicates become hierarchical and take the form of graphs. The task of joining the two graphs that form the input spaces to the blend then becomes one of combining two graphs. Combining nodes can be as simple as just finding nodes that match and joining them or matching on the physical similarities of the nodes; However, *conceptual blending* is looking for more creative and unusual matches. Some models of *conceptual blending* use models of analogy to connect the graphs. Sapper is an algorithm that is frequently used for this purpose (Veale & O'Donoghue, 2000). Blending two graphs has the potential to explode computationally and known methods for bridging graphs such as edge trimming and spreading-activation are appropriate.

Existing implementations of Conceptual Blending do not always fully account for every mechanism described in the Conceptual Blending literature Martinez et al., 2011. How to select the input space, selective projects and how to 'Run the blend' are sometimes neglected Li, Zook, Davis and Riedl, 2012.

existing description

Table 3 summarises some of the existing implementations of blending. The table summarises how the input spaces are represented, how items are chosen from the input spaces for selective projection, and how elaboration occurs in the resulting conceptual blend.

visualisation lead-in

The discussion now turns to the visualisation side of the project. The *success*2.4.1, *usefulness*, *process* (visualisation pipeline B) and *shortcomings of existing computational tools* 2.6. Visualisation objective C need to be established. The next section begins to attempt to address these issues.

2.4 Information visualization

lit. visualisation lead-in

Section 2.4 starts by pointing out how closely the success of a visualisation is related to human visual perception and discusses what makes a successful visualisation (Section 2.4.1). This section also clarifies what is meant when this dissertation discusses visualisation. The visualisation pipeline is discussed – since it exposes potential entry points in the software for the introduction of creativity (Section 2.5.1).

out of Scope

Out of scope in this discourse is the exploration of knowledge versus information in visualisations (M. Chen et al., 2009), the controversial dispute on when a visualisation becomes art (Kosara, 2007; Yau, 2013), what

Name	Input Space representation	Selective projection & blend technique	Elaboration
PRINCE (Hervás, Pereira, Gervás & Cardoso, 2006)	PRINCE made use of previously generated Ontologies	Uses predicates against Wordnet 'Princeton University "About WordNet." WordNet.' 2010	
Martinez et al.'s extension of the **Heuristic-Driven Theory Projection Framework** Martinez et al., 2011	Input spaces are sets of first-order logic axioms	Axioms that match between spaces are selected (Unification)	Mechanisms of Analogy (such as generalisation, specialisation and structural congruences and isomorphisms), anti-unification.
Divago (Francisco C Pereira, 1998)	Divago used predefined conceptual spaces	Generic space is built using predicate logic production rules that evaluate to true	Attributes are added based on relevant semantic frames
Gadget generation algorithm Li and M. O. Riedl, 2011a, 2011b; Li, Zook, Davis and Riedl, 2012	Goals (derived from the story), represented as first order logic predicates, are used to identify input spaces. Objects and properties relevant to the goal are also included.	1. Projects true predicates common to both spaces that are a preconditions for achieving the goal predicate 2. Actions from both/either spaces are also projected The analogical reasoning engine, Sapper (Veale & O'Donoghue, 2000) establishes mapping across input spaces	Simulated with closure actions
The Mapper component of **the Blender** (Joao M Cunha, Gonçalves, Martins, Machado & Cardoso, 2017)	Semantic maps composed of triples of the form $< concept_0, relation, concept_1$	The same routine Sapper (Veale & O'Donoghue, 2000) uses is described, but not specifically mentioned	

Table 3: A non-exhaustive list of methods that have previously been used to implement Conceptual blending.

makes any visualisation better that any other (since there is more than one way to visualise the same set of data (Yau, 2013)), or detailed reviews of the types of visualisation (Cleveland, 1985).

Section 2.6.4 focuses on the criteria and measurables for evaluating visualisations independently of any measurables required for creativity. The literature in this section attempts to address the visualisation objectives B and C. The section establishes what criteria can be used to assess the success of a visualisation that has been computationally generated.

The focus of Section 2.6 is objective A. Existing tools for the creation of visualisations are presented 2.6.1, computational techniques are discussed 2.6.2. It also explores the existing artificial intelligence techniques that have successfully been used to generate visualisations.

2.4.1 What makes a visualisation successful

overview

A successful visualisation is able to make smart comparisons, show causality and present multivariate data in a manner that exposes useful information such as size, direction or position. Ideally a visualisation should be able to highlight aspects of the data that were not visible before (Yau, 2013). It also needs to retain the integrity if data and be respectful of the credibility of the data (Tufte, 2006). There are different ways of visualising data, such as data maps, bar graphs, time series and many others (Tufte & Graves-Morris, 1983). There can be multiple attributes, such as who, what, where and when, that can be viewed within the same dataset (Yau, 2013). The connection between the data and its meaning is very important for a successful visualisation (Yau, 2013). Labelling and context is critical without which a visualisation is meaningless (Tufte, 2006; Yau, 2013).

Visualisation unique to human

There are some aspects of visualisation that are uniquely human. This is because data visualisation are heavily influenced by the science of human visual perception, much of which emerged from the Gestalt School of Psychology (Kirk, 2012). The Gestalt principals – such as the *Law of Similarity*, *Law of Closure* and the *Law of Proximity* – emerged from studies of how our brains form a global sense of patterns. Critical to this understanding is the fact that our visual perception is faster and more efficient than our cognitive processes. Exploiting these features of visual perception has significant influence on how well a visualisation is interpreted (Kirk, 2012; Kosslyn, 2006; Meirelles, 2013).

Visualisation is iterative

Humans may expect to find certain things in the data but they also learn about their data as they go along; adapting the visualisation according to what they see (Sugiyama, 2002). Choosing which data will produce a useful visualisation can require an exploration phase (Yau, 2013). Iteration and experimentation are important because some aspects in the data only show shortcomings when graphed and one successful graph can suggest an idea for a better one (Cleveland, 1985). Visualisation designers infer and induct information about the data as they work and make adjustments (Kirk, 2012). These adjustments could be based on the realisation that another axis scale would be better or that the data is showing outliers or has gaps in the information (Kirk, 2012).

purpose/story

Visualisations have both a purpose and a storyline. Humans are aware of the purpose (underlying intention) and storyline of a particular visualisation (Grammel, Tory & Storey, 2010; Kirk, 2012; Kosslyn, 2006; Munzner, 2009; Yau, 2013); the reason for its existence (Kirk, 2012). Whether the intention is to convince the viewer of something, such as visualisations used for advertising, or summarise results, the purpose will affect the decisions made during the design (such as the variables chosen, or whether to introduce artistic elements) as well as the final outcome (Kosslyn, 2006; Meirelles, 2013). Storylines compress information in the same way that visualisations do, conveying large amounts of inferred information with very few words (Gershon & Page, 2001). Marrying facts to the story behind them makes the data memorable (Kosara & Mackinlay, 2013) and allows viewers to relate to the information (Figueiras, 2014). Adding story-like features to a visualisation, such as continuity and context, can also help guide a user's focus and highlight the intended purpose of the visualisation (Gershon & Page, 2001). Starting a visualisation without first clarifying why it matters to the audience is a recipe for failure (Sykes, Malik & West, 2012). Visual designers should know what the design needs to achieve and should aspire to emulate journalists' propensity for uncovering important and relevant information (Kirk, 2012). What one knows about one's data can drive elements of the visualisation (Francisco Câmara Pereira, 2007) and combining data visualisation with domain-specific knowledge is considered to be challenging even for a human (Kalogerakis et al., 2006). Storytelling can make sure that the author's objective message is delivered (Khataei & Lau, 2013). There is a specific style of visualisation known as, 'narrative visualisation', that intentionally embeds rhetorical techniques into visualisation (Figueiras, 2014; Hullman & Diakopoulos, 2011). Narrative visualisation does attracts controversy, as some suggest that it is another contributor to information bias (Hullman & Diakopoulos, 2011).

story how to

Stories are found in comparisons (range, ranking), measurements (magnitude), context (deviation, forecasts, averages), trends (direction, rate of change, fluctuations), intersections, relationships (exceptions, correlations, association, gaps) and in hierarchies (Katz, 2012). Information overload needs to be avoided since it obscures purpose (Katz, 2012). A story can be defined as an ordered sequence of steps and can be aligned with the visualisation pipeline (Kosara & Mackinlay, 2013). In fact order (such as time and causality) are key features of some stories (Kosara & Mackinlay, 2013; Segel & Heer, 2010). Techniques from film making are used (Hullman & Diakopoulos, 2011; Khataei & Lau, 2013). Stories told in visualisations are generally not interactive (Gershon & Page, 2001). The three main ways of calling attention to storytelling in visualisations is the use of genres, visual clues that direct attention or orient (called anchoring) and tactics such as ordering (Hullman & Diakopoulos, 2011; Segel & Heer, 2010). Other storytelling techniques include: excluding variables, or including extra contextual information, emphasising data using redundancy, contrasting opposing information (or comparing similar information), the use of visual metaphor to provide visual clues and implicit suggestions, the use of phrasing or graphics aimed at a particular audience, and visual clues indicating uncertainty in the data (Hullman & Diakopoulos, 2011). There are linguistic storytelling techniques as well. Bolding or italicizing fonts is known to convey meaning. Irony, and quotation marks, and understatements can be used to indicate alternative insinuated meaning (Hullman & Diakopoulos, 2011).

narrative vis

In narrative visualisation, additional textual annotations are sometimes directly added to the visualisation, specifically to guide the user, or emphasise points, or outliers, and provide contextual information. These textual annotations usually provide extra information, or add observational information (Hullman, Diakopoulos & Adar, 2013). The annotations can be connected to time points on a graph or regions within the visualisation or to the entire graphic. Exactly what components and process form a story, within the context of a visualisation, is still a matter of ongoing investigation (Badawood, 2012; Lee, Riche, Isenberg & Carpendale, 2015).

type after purpose

Once the story and purpose are known a suitable graphic type can be chosen for its suitability. Different visualisation types have their own strengths and weaknesses. The mix of statistical data with geographic maps are known as Data maps (Tufte, 2006); They are good for directing attention toward relevant detail. Time-series – where a variable, or variables are plotted against some regular variable of time (seconds, months, years) – is well suited to big data sets with variable, or non-linear data (Tufte, 2006). Time-series is also good at comparing multiple variables against each other (that share the time axis) – in this way illuminating smart comparisons or revealing causality (Cristóbal Pagán Cánovas, Coulson & Jensen, 2011; Tufte, 2006). Emerging novel features in time-series result from compression of temporal relationships into spatial relationships (Cristóbal Pagán Cánovas et al., 2011). A chosen data type can also have shortcomings. The shortcomings of data maps is that the comparison of area of the map with the density of the variables that is being plotted can distort the importance of the data (Tufte, 2006). Time-series does not elucidate causality although plotting other aspects of the data can help with this (Tufte, 2006). Humans are aware of semantic and structural rules and drawing conventions and know which drawing rules produce *good* graphics (Sugiyama, 2002).

distortion

Information can be distorted by incorrect presentation. The visualisation produced needs to accurately present the data whilst highlighting patterns within the data without distortion (Tufte & Graves-Morris, 1983; Yau, 2013). Care is needed to retain data integrity. Over decorating or exaggerating data distorts what is presented (Tufte, 2006). Good visualisations avoid distortion, present many numbers in a small space, make large data sets coherent, reveal several levels of detail and concur with a verbal description of the data (Tufte, 2006). Changing the increments on the ticks on an axes or altering graphics half way through a visualisation can distort what truths are seen (Tufte, 2006). Labelling and context is also essential for integrity (Tufte, 2006). Accompanying graphics should be sized relative to the size of the variable in the data they are representing (Tufte, 2006). A graphic's aspect ratio can make a huge difference to what is seen in statistical data. It can influence both the sample depth as well as distort the evidence presented by the data. As a general rule the width should be wider than the height (Tufte, 2006). Badly placed links or arrows can cause ambiguity (Tufte, 2006). Integrity is more likely if the following rules are adhered to (Tufte, 2006):

1. Representation of numerical data should retain proportions.
2. Labelling should be clear enough to resolve ambiguity.
3. Visualisations should show data changes and not design changes.
4. Standardise units of measure.
5. The number of aspects of the data visualised should not exceed those actually found in the data.
6. Graphics used must be in context.

pipeline
why/lead-out

The following sections discuss the data visualisation process. In order for methods that demonstrate creative traits to integrate with the visualisation process, one or more of the activities in the visualisation pipeline has to be identified. The literature will expose which parts of the pipeline process are suitable places for the introduction of creativity.

2.5 The visualisation pipeline

pipeline
why/lead-in

Sections 2.5.1, 2.5.2 and 2.5.3 begin to address the visualisation objectives B and C. The sections focus on identifying the *visualisation pipeline* (the process that occur between the point where the data to visualise is supplied, up until the point where a visualisation has been created from the data), in order to identify where in the visualisation pipeline, human creativity and other distinctly human traits – such as intuition and human visual perception – occur. The literature will expose which parts of the pipeline process are suitable places for the introduction of creativity.

The following questions are investigated:

1. Which steps in the visualisation pipeline require human creativity?

2. How are computers facilitating creativity in the visualisation pipeline?

3. Which stages in the visualisation pipeline are affected by storytelling and purpose?

3 angles

The literature for Sections 2.5.1,2.5.2, 2.5.3 was reviewed from three angles. The visualisation process that a human would follow is investigated in Section 2.5.1. Thereafter, the visualisation process that a computer algorithm or machine learning solution would follow is investigated (Section 2.5.2). Finally, the visualisation pipeline of an area of research known is *visual analytics* is explored (Keim et al., 2008). Visual analytics is a method of automating visualisations and analytical reasoning by combining the strengths of computers and humans (Shrinivasan & van Wijk, 2008) (Section 2.5.3).

Data is transformed, in stages, until it can be rendered (Wickham et al., 2009). Specific phases within the pipeline showing the stages of the process have been identified and acknowledged (Myatt & W. P. Johnson, 2011; Ware, 2004; Wickham et al., 2009; Wilkinson, 2006).

2.5.1 The basic visualisation pipeline

Data is transformed, in stages, until it can be rendered (Wickham et al., 2009). Specific phases within the pipeline showing the stages of the process have been identified and acknowledged (Myatt & W. P. Johnson, 2011; Ware, 2004; Wickham et al., 2009; Wilkinson, 2006).

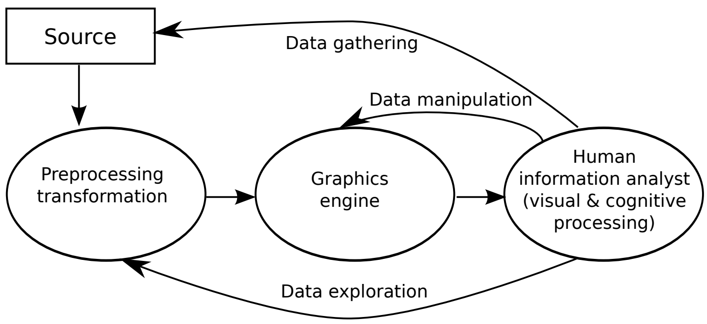


Figure 16: The graphics pipeline according to Ware (Ware, 2004).

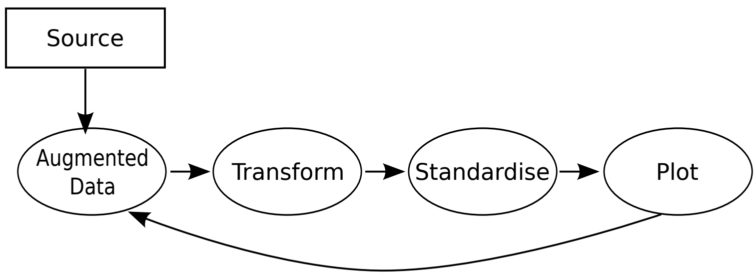


Figure 17: The simple pipeline according to Wickham (Wickham et al., 2009).

At its most basic, the visualisation process only has four stages, namely: collection of data, data pre-processing, standardising, and rendering (See Figures 16 and 17). The process involves cleaning the data, understanding what the data is about, deciding on the context and what aspects of the data can (or should) be presented and then choosing a graphic representation for display (Kirk, 2012; Spence, 2001; Yau, 2013). The purpose of this work-flow is to distil and highlight patterns within the data, that are useful to humans (Myatt & W. P. Johnson, 2011; Spence, 2001; Yau, 2013).

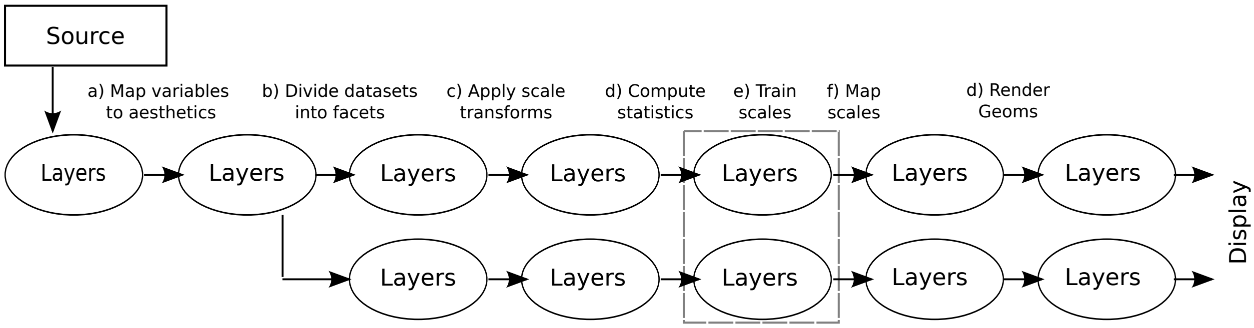


Figure 18: The layered graphics pipeline according to Wickham et al. (2009) reproduced from Making Sense of data III (Myatt & W. P. Johnson, 2011).

Vis is iterative

As indicated in Ware's diagram (Figure 16), this process is iterative. The iteration exists because humans may expect to find certain things in the data, but they also learn about their data as they go along; adapting the visualisation according to what they see (Myatt & W. P. Johnson, 2011). Choosing which data will produce a useful visualisation can require an exploration phase (Yau, 2013). Iteration and experimentation are important because some aspects in the data only show shortcomings when graphed and one successful graph can suggest an idea for a better one (Cleveland, 1985). Visualisation designers infer and induct information about the data as they work and make adjustments (Kirk, 2012). These adjustments could be based on the realisation that another axis scale would be better or that the data is showing outliers or has gaps in the information (Kirk, 2012). A visualisation is not constrained to one set of data, and could include other data such as predictions from a statistical model (Wickham, 2010).

why iter

Much of this iterative design is entirely due to the close link between visualisation and human visual skills (Myatt & W. P. Johnson, 2011). Humans can easily detect things in data, such as outliers and symmetry, but some artificial intelligence methods find these patterns hard to detect (Boden, 2004; Myatt & W. P. Johnson, 2011).

human backg. knowledge

In addition to background knowledge and intended purpose, humans are aware of background to the data as well as vocabulary in the data that emerges from the particular domain in which the data exists (such as e-commerce or politics) (Munzner, 2009). Humans are aware of relationships between concepts, data attributes and data values and know how to calculate some values from others (Grammel et al., 2010). This facilitates the addition of calculated variables, in a manner that contributes to the intended storyline or purpose of the visualisation.

2.5.2 Computer only visualisation pipeline

CFG

The process of data visualisation has been formalised as a formal grammar known as a context free grammar (Chomsky, 1956). This particular context free grammar is called the "*grammar of graphics*" (Wilkinson,

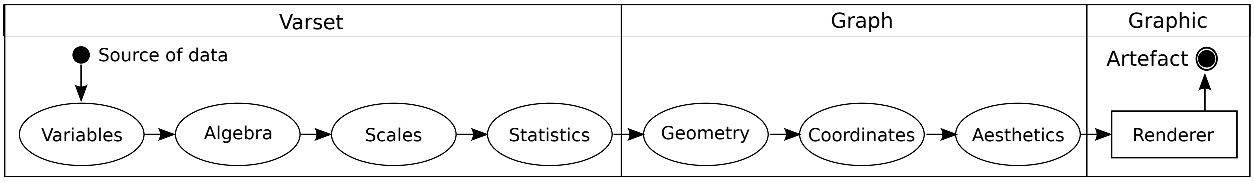


Figure 19: Diagram of grammar rules used for the visualisation of a pie chart as described by the *grammar of graphics* (Wilkinson, 2006).

Category	stage	brief description of activity
Varset	Variables	Converting the raw data into variables. Includes activities such as calculating ranges, assigning ordering and deciding how to assign size to non numeric data. Transforming the data so that statistical operations can be performed. Sorting (Patterns can be more obvious with sorted data (Yau, 2013)), aggregating and calculating statistics.
	Algebra	Various set theoretic operations to combine variables. These operations have equivalent database structured query language (SQL) statements.
	Scales	These are activities that decide how variables map to a scale or axis in the visualisation. Scales can be nominal, ordinal, intervals or ratios and they can have a measurement unit (seconds) but not always (towns). The choice of scale is critical to whether patterns emerge in the visualisation. Scales can also be transformed into other scales.
	Statistics	Statistical methods applied to the scales. Includes calculations such as average, smooth, sum, mean and so on.
Graph	Geometry	These are functions that convert the variables into geometric objects such as point, line, contour, area and polygon.
	Coordinates	Coordinates are functions that decide location in space (Cartesian, polar, spherical). They can also be transformed (dilate, stretch, rotate).
	Aesthetics	The application of various aesthetic elements such as choice of colour, hue, texture, brightness and labels.
Graphic	Renderer	The final conversion of all of the previous stages into the visualisation

Table 4: The types of activities that occur in each of the stage of the visualisation pipeline as per the "*grammar of graphics*" (Wilkinson, 2006).

2006). The grammar formalises the data pipeline into a formal reproducible process. The grammar identifies three graphical elements that make up a visualisation: the data, the scales and coordinates, and plot annotations – such as title and background (Wickham, 2010). The formalisation of the visualisation pipeline into a context free grammar allows the abstraction of the task in a manner that focusses on the structure of the graphic process rather than on specific representations (Wickham, 2010). The grammar facilitates moving away from specific chart types – such as pie chart or scatterplot – and focus instead on the underlying structure as well as composition; It also facilitates insight into how seemingly different graphics can be related to each other (Wickham, 2010).

what is CFG

A context free grammar consists of a set of rules for generating allowed transforms in a language; it can be thought of as a set of nested production rules (Wilkinson, 2006). This has specific meaning in linguistics. Formal grammars are also the basis of theories of computation (Chomsky, 1956; D. I. A. Cohen & Chibnik, 1991; Jurafsky & Martin, 2014). The "*grammar of graphics*" is a set of rules by which data can be transformed into graphics (Wilkinson, 2006). Wilkinson et al. (2000) also show that sections of the grammar can be executed in parallel (Wilkinson, Rope, Carr & Rubin, 2000). Wickham (2010) refers to this as layering (Refer to Figure 18). Breaking the graphics pipeline into further layers – or individual plots – facilitates the plotting of multiple datasets against multiple types of geometries on the same visualisation (Wickham, 2010). The rules of the grammar are independent so any of the steps can be swapped out with an equivalent production rule without effecting the rest of the pipeline (Wickham, 2010). This allows for complex visualisations to be produced – such as the reproduction of Minard's famous 1869 visualisation of Napoleon's march (Wickham, 2010). Formal grammars are not deterministic and there is more than one way to get from the data to a visualisation, which makes sense insomuch as there is more than one way to visualise a set of data (D. I. A. Cohen & Chibnik, 1991; Yau, 2013).

CFG recognised

The *grammar of graphics* is widely recognised and is used by various visualisations tools (Wickham, 2010). Some of these tool are mentioned in Section 2.6.1. Wilkinson does not claim that the *grammar of graphics* can be used to produce every visualisation possible (Wickham, 2010; Wilkinson, 2006), but his comprehensive book suggests that it covers most aspects of the process (Wilkinson, 2006). An activity diagram of the visualisation pipeline for a pie chart, as described by the *grammar of graphics*, is shown in Figure 19. An indication of the types of activities occurring in each of the stages of the "*grammar of graphics*" are shown in Table 4.

CFG three groups

There are three groups within the grammar (See Figure 19). Production rules (the *Varset* group) are all related to preparing the variables in the dataset. A significant part of the pipeline involves choosing which variables to display. The second group (labelled *Graph* in Figure 19), contains rules pertaining to the choice of graph type and aspects of the graph such as axis and scale. The final group of rules belong to the *rendering* stage of the visualisation, and include things such as the overall title and background images. The order of events in the grammar is fixed and does not change for other types of visualisations and therefore variables are always chosen before algebra, which is always completed before attending to scale (Wilkinson, 2006).

Shortcomings

Although widely recognised, some authors are working on improvements with respect to the shortcomings of the "*grammar of graphics*". It lacks the ability to address abstract attributes such as information density and does not support strategies to come up with multiple representations of the same information (Redström, Skog & Hallnäs, 2000). Control over graphical output needs to be addressed and graphic customisations are not supported (Bostock & Heer, 2009); although, Wilkinson mentions that this is by design (Wilkinson, 2006). Many visualisation systems propose methods on how to apply the graphics pipeline, but fail to address when a particular method should be chosen (Munzner, 2009) – in other words the process is non-deterministic. The grammar also requires a steep learning curve due to complexity (Bostock & Heer, 2009) and does not support dynamic graphics (Young, Valero-Mora & Friendly, 2011).

Other techniques

Other automation mechanisms include the use of data-flow diagrams (Senay & Ignatius, 1994), genetic algorithms (Bouali, Guettala & Venturini, 2015) and machine learning techniques such as t-distributed stochastic neighbour embedding (van der Maaten & Hinton, 2008). Many machine learning tools, which feature visualisation, facilitate the display of multiple dimensions, but still leave the interpretation to a human (van der Maaten & Hinton, 2008).

2.5.3 Human-and-computer visualisation pipeline

what is va

One research area that tries to address the gap between the creativity of visualisation that a human produces and the creativity of visualisation a computer produces is the field of *visual analytics*. *Visual analytics* combines the creativity of individuals with the computational strengths of computers, using interactive visual interfaces (Cybulski, Keller, L. Nguyen & Saundage, 2015; Keim et al., 2008; Myatt & W. P. Johnson, 2011).

Visual analytics adds data analysis (informational, geospatial, scientific or statistical) to the process of data visualisations and combines three visualisation tasks, *reasoning* (sense-making), *interactive visualisations* and *analytical processes* (such as statistics and data mining techniques) (Keim et al., 2008). This adds additional iterative cycles to the visualisation pipeline. The knowledge generation model for visual analytics is composed of a two parts. The first part concerns the data model and the second human part is specific to the view of the data, and facilitates hypothesis finding, insight and knowledge generation (Ed Huai-hsin Chi & J. T. Riedl, 1998; Grammel et al., 2010; X. Wang, Zhang, Ma, Xia & Chen, 2016). Visual analytics shares some of the usual visualisation challenges, such as scalability, uncertainty and difficulty with evaluation; It also has its own challenges, including, hardware support and the difficulty in the design of intuitive graphic user-interfaces (Kohlhammer, Keim, Pohl, Santucci & Andrienko, 2011). One model of the visualisation pipeline in visual analytics – the data state reference model – also has four stages (Data, models, knowledge and visualization) (X. Wang et al., 2016).

GUI

The graphic user-interfaces for visual highlighting and interrogation of data, support seven manipulation tasks. Shneiderman (1996) identifies these tasks as overview, zoom, filter, details-on-demand, relate, history and extract. The tasks help a user navigate data in a visual manner using dynamic feedback, thereby facilitating iteration, but also points at human perception (Shneiderman, 1996). Users choose where to zoom because they know what they are interested in seeing, and the visualisation gives them perceptual clues as to patterns in the data. Filtering out uninteresting items, requesting more detail and viewing relationships requires knowledge and intuition of what is important and what is un/interesting after getting a broad overview of the data. Some interfaces offer editing of the transformations (Jankun-Kelly, Ma & Gertz, 2002). The interactive user-interface facilitates the incorporation of human intelligence into the process, but the combination of knowledge and visual feedback produces more satisfying and intuitive visualisations (X. Wang et al., 2016).

Iterative loops

The visual analytics pipeline, like the non-interactive visualisation pipeline, also contains iterative feedback loops. The key feature is that the user controls the iteration (X. Wang et al., 2016). Since the graphic user-interface controls are attached to the visualisation transformation changes, the changes in visualisation transforms between iterations should probably be part of the pipeline (Jankun-Kelly et al., 2002). These iterations continually refine the visual towards the intended purpose of the visualisation (Grammel et al., 2010).

Unsolved

The problem of prior knowledge is an unsolved problem with automated visualisation, so is the matter of human insight (C. Chen, 2005). The combination of machine learning and visualisation is still a topic with many open topics and models available for exploration Endert et al., 2017.

creativity support

One of the ways in which computers can support creativity in the visual analytics pipeline is by suggesting visual mappings and alerting the user to the advantages and features of the suggested mappings (Grammel et al., 2010). In the visual analytics environment, rapidly allowing the user to switch visualisation types and visual mappings and facilitating backtracking also facilitates creativity support while automated wizards stifle creativity (Grammel et al., 2010). Novel user-interfaces focussing on visual design, such as *Visualization-*

by-Sketching, have also been suggested (Schroeder & Keefe, 2016) to facilitate creativity for artistic, but non visualisation-expert individuals.

other pipelines

Other visualisation pipelines include the information visualization data state reference (Ed H Chi, 2000; Ed Huai-hsin Chi & J. T. Riedl, 1998), the generic visualization model (Van Wijk, 2005), the reference model (S. K. Card, Mackinlay & Shneiderman, 1999) and the nested model of visualization creation (Munzner, 2009). They are similar to those discussed here and the reader is referred to X. Wang et al. (2016) for a comprehensive discussion of these pipelines.

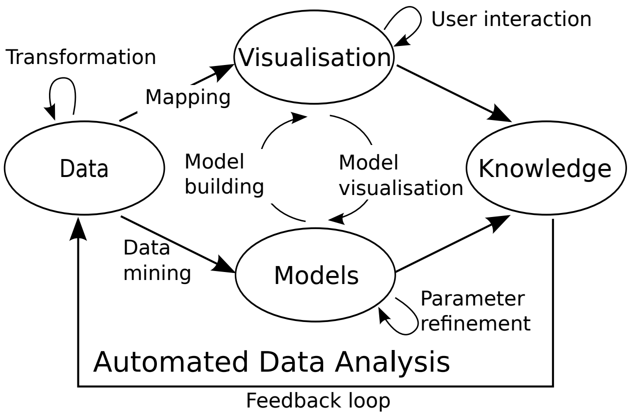


Figure 20: Visual analytics pipeline (Kohlhammer, Keim, Pohl, Santucci & Andrienko, 2011).

pipeline implementation

The interactive visualisation system, VisTrails, makes the pipeline visible in the graphic user-interface by providing a breadcrumb trail as well as multiple possible views of that pipeline, the comparison of which provide insight into the data (Bavoil et al., 2005). Many interactive visualisation systems build the visualisation pipeline out of smaller modules – a process referred to as the data flow module (Bavoil et al., 2005) or flow networks.

Sense/provenance

Sense-making is the process of foraging through information in order to generate and identify meaning and gain insight (P. H. Nguyen et al., 2016; Xu et al., 2015). Attempts to model the sense-making process are referred to as analytic provenance (P. H. Nguyen et al., 2016). Proposed sense-making pipelines include, the *sense-making model* (Pirolli & S. Card, 2005), the *knowledge-generating model* (Sacha et al., 2014), the *knowledge generation and synthesis model* (Endert et al., 2017), the *data/frame theory of sense-making* (Klein, Moon & Hoffman, 2006), *human cognition model* (Green, Ribarsky & Fisher, 2009) and *a pipeline of the knowledge discovery in databases* (Han, Pei & Kamber, 2011). Analytic provenance incorporates levels of semantic information. It has been suggested that sense-making is the result of collation of stories and the result is a narrative (Baber, Andrews, Duffy & McMaster, 2011). The section concludes with a discussion on various methods that can be used to measure the *success* of a visualisation (Section 2.6.4).

2.6 Computer generated visualisations

summary over entire subsection

Section 2.6.1 discusses tools that, when given a dataset, can produce a visualisations. Techniques used for parts of the visualisation process, such as those used for pre-processing data and finding the distribution of the data are discussed next in Section 2.6.2. Then visualisation measurement is discussed in more detail (Section 2.6.4). As mentioned in the project limitations (Section 1.5), the literature on tools and techniques is not intended as a critical survey of all possible tools; The purpose is to highlight those with potential for the purposes of this dissertations prototype.

Finally, Section 2.6.5 discussion computer-only visualisations. Those embedded into machine learning applications, such as WEKA (Hall et al., 2009), as a secondary function, are also discussed.

2.6.1 Existing visualisation tools

tools

Various data visualisation tools exist. Gephi (Bastian et al., 2009), Treemap (Shneiderman, 2015), Flotr2 ('Flotr2', 2017) and D3.js (Teller, 2013) combined with a vector graphics program are frequently used. They still require some low level programming on the part of the user and are not fully automatic (Wu, Battle & Madden, 2014). Some visualisation tools use a specialised visualisation tool on top of a database. Activities such as aggregation and filtering get duplicated with this approach (Wu et al., 2014). In order to create an algorithm that produces a visualisation the pipeline needs to be abstracted and modelled (Munzner, 2009).

tools using GOG

Tools that acknowledge the "*grammar of graphics*" model of the pipeline include, the Graphics Production Library (GPL) (Wilkinson et al., 2000), nViZn (Wilkinson, 2006), ggplot2 (Wickham, 2010), Proto-Vis (Bostock & Heer, 2009), Grammar of graphics in D3 (Braşoveanu, Sabou, Scharl, Hubmann-Haidvogel & Fischl, 2009; Hunter, 2016), Vega (Braşoveanu et al., 2009), nViZn (Jones & Symanzik, 2001), VizQL (Mackinlay, Hanrahan & Stolte, 2007) and VizJSON (Malaika & Brunssen, 2015).

Mach. Learning techniques

Other automation mechanisms include the use of data-flow diagrams (Senay & Ignatius, 1994), Genetic Algorithms (Bouali et al., 2015) and machine learning techniques such as t-distributed stochastic neighbour embedding (van der Maaten & Hinton, 2008). Many machine learning tools, which feature visualisation, facilitate the display of multiple dimensions, but still leave the interpretation to a human (van der Maaten & Hinton, 2008).

general

D3.js stands out from many other visualisation tools because it is much better at customised visualisation than other libraries that focus on off-the-rack data visualisation (Thomas, 2015).

Vis tools at http://www.cc.gatech.edu/gvu/ii/citevis/VIS25/ (CiteVis2, CiteMatrix, and VISLists)

2.6.2 Varset: Variable processing, algebra, scales and statistics

intro

Humans explore the data, looking for trends. In the absence of eyesight computers achieve this through statistical methods and techniques for pattern recognition. Terms include, Knowledge mining, Data mining or Data analytics, and both data visualisation and data mining can be used to discover patterns (AbdulRahman R Alazmi & AbdulAziz R Alazmi, 2012).

Data to vars

The first stage of the Visualisation pipeline is the conversion of raw data to variables and choosing which we are interested in using. This is not as simple as it would seems since, variables also include calculation between variables and projection of data into lower dimensions (known as *Projection pursuit*). There is

$$b = c_1 \log_2 n + 1 \quad \text{for } n > 30 \tag{8}$$

Figure 21: Sturges' formula for calculating bin width. n is the number of instances and c_1 can be manipulated to adjust the level of compression.

potentially an explosion of possible sets and subsets that can be calculated (Leban, Zupan, Vidmar & Bratko, 2006).

Data distribution

Histograms

Histograms are a quick and easy way to learn about the statistical distribution of the data and can give a quick indication of the most common themes (Piegorsch, 2015). Used big data to lower dimensions and uncover outliers. Histograms are created using a technique called *binning*. Binning is the process of dividing data into intervals and then using the counts of items in each interval in a visualisation (Wickham, 2013). It effectively quickly filters the data and can prevent over plotting. Commonly a fixed interval width (fixed width binning) is chosen and the counts are visualised using a bar graph, but, this is not necessarily the case (Wickham, 2013). An easy way to spot outliers is to calculate the intervals with the least data (Wickham, 2013). Items in these intervals can then be focussed on or discarded as required. Wickham refers to this as *peeling*. Binning can also be used to avoid over-plotting – the situation where too many points drawn at the same location on a visualisation are so dense that they obscure the density of the data (Dang, Wilkinson & Anand, 2010).

bin width

The bin width controls smoothing of data and an interval that is too wide can hide data (Wand, 1997). The number of bins,and therefore the interval width, can be calculated using a number of techniques. Scott's (1979) normal reference rule is a commonly chosen as it handles asymmetrically distributed data (Piegorsch, 2015; Wand, 1997). A simpler rule that assumes a normal distribution is Sturges' formula which is illustrated in Figure 21 (Anand, Wilkinson & Dang, 2012; Sturges, 1926).

Other

There are many other statistical and machine learning techniques for calculating data distribution include clustering, topic modelling, kernel density estimation, weighted mean and reduced chi-squared statistics (Endert et al., 2017; Spencer, Yakymchuk & Ghaznavi, 2017).

subsets

Sometimes analysing a subset of the data is useful. Sampling can often give an indication of patterns in the full dataset without the computational effort and time involved in processing the entire set. It can also sometimes highlight patterns that only exist in a subset of the data (R. K. Anderson, 2012).

data correlation

A Correlation Matrix can be used to figure out which variables are highly correlated. A Scatterplot Matrix can also highlight correlation.

projection

Projection pursuit

VizRank (Data Visualization Guided by Machine Learning) is a tool that aids in finding useful data projections (Leban et al., 2006). It does this by calculating a rank for each potential data projections (variable choices). Rank is calculated by classifying the data projection's x and y values and correlating it against the machine learned classifications over the entire data set. In other words it concerns itself with identifying projections that preserve the already discovered classification class. VizRank is restricted to methods that map attributes to points (Leban et al., 2006).

lead in

Having briefly indicated some of the techniques used to explore data and variable choice, attention is turned to the graphing section of the visualisation pipeline according to the *grammar of graphics*. Graphing also includes geometry, and coordinate choices, but the focus in this section is more specifically on aesthetics – since manipulating aesthetics is potentially a creative endeavour.

2.6.3 Graph: Aesthetics

intro define overview graph

Graphing is concerned with how to map data into visual elements, and includes: geometry, coordinate choices, and aesthetics. Geometry concerns mapping magnitude into n-dimensional space, and is a mathematical function that produces shapes like: points, lines, contours and polygons. Coordinates are sets of mapping functions that establish points in space by mapping coordinates from one space into another. Examples of coordinates are Cartesian, and Polar. A change of coordinates can reshape the graphic and change how it is perceived (Wilkinson, 2006).

intro aesthetics

This section will focus on aesthetics. Aesthetics are those elements of the visualisation relating to perception, beauty, taste and artistic criteria (Wilkinson, 2006). Aesthetics concern the mapping of quantitative and qualitative values into features of perception. They map values to visual element that are aligned with human perceptual processes. Aesthetics include: position, length, angle, size, categories, colour, texture, and dimensions.

Scales: colour

colour choice

The choice of colour for a visualisation – for both the data and the background – can affect how easily and quickly the data is seen (Healey, 1996). Colour distance, linear separation and colour category, within a colour model, have been identified as important in the choice of effective colours and all three are required for effective colour discernment (Healey, 1996). The colour also needs to share intensity, since deviation in intensity can result in interfering with the perception of the data (Healey, 1996). The *CIE LUV* colour model has three dimensions – two that together specify chromaticity and one for luminescence (Healey, 1996). Two colours are considered isoluminant if their luminescence values are equal (Healey & Enns, 1996).

colour category

Colour category involves placing individual colours within named colour regions (Healey, 1996). The *Munsell* colour system, which splits colour into *hue*, *value* (lightness), and *chroma* (saturation) can be used since the hue divides colour into Red (R), Yellow-Red (YR), Yellow (Y), Green-Yellow (GY), Green (G), Blue-Green (BG), Blue (B), Purple-Blue (PB), Purple (P) and Red-Purple (P) and allows for identification of equal intensity. Colour discernment becomes increasingly difficult the more variables there are in the visualisation (Healey, 1996). More saturated colours are best for small lines and symbols, whilst larger

$$\textit{Euclidean distance} = \sqrt{\sum_{X} x_i} \tag{9}$$

Figure 22: The Euclidean distance calculation over all the variables is a chosen colour model can be used to calculate colour distance.

areas should use less saturation (Ware, 2004). Red is not as easily distinguished as other colour categories (Ware, 2004)

Colour distance

Colour distance is a simple Euclidean distance calculation (Figure 22) over all the variables is a chosen colour model (Healey, 1996). It cannot be used in isolation of the other two calculations, since fixing the distance between two chosen colours cannot guarantee that the colours will be equally easy to discern (Healey, 1996).

Scales: dimensions

Dimensions within the data as they relate to aesthetics have importance because human vision needs to be able to separate and identify these dimensions. Visualisation sometime like to convey as much information as possible but there are limits as to how many dimensions can be perceived. For example: colour, and symbols can be used simultaneously to compare multiple variables. In summary colours supporting best performance in a visualisation (Y, G, B, P) are isoluminant and those with the greatest distance and linear separation (Healey, 1996). The The *Munsell* and *CIE luv* colour models can be used to calculate colour perception for automated colour choice for a data visualisation (Healey, 1996; Healey & Enns, 1996; Ware, 2004).

summary

2.6.4 Evaluating visualisations

difficulty

Visualisations are tricky to evaluate (C. Chen & Czerwinski, 2000; Y. Zhu, 2007). One reason is that visualisation is not an exact science; there is no one right way to produce a visualisation for a given data set (Kirk, 2012). Another reason visualisation evaluation is problematic is that there is varying agreement as to what constitutes effective visualisation. Where quantitative measures exists, they are still not perfect. This is due to influence by user's subjectiveness and their domain knowledge, which could affect assumptions hidden in visualisation made for data in a specific domain. Imperfection in quantitative measures also exists because there is some disagreement over the validation of accepted visualisation rules (Y. Zhu, 2007).

chart junk

Visual embellishments, also sometimes known as known chart junk, demonstrate an example of the disagreements that occur in evaluating visualisation. Bateman et al. (2010) gives an example of an embellished visualisation in which the visualisation shows the number of drinks consumed in Manhattan on a Friday night by alcohol type. The visualisation shows human figures standing and sitting at a bar, holding recognisable glass shapes (Wine, Beer, Champagne, and Martini) representing each alcohol type. The figures are standing, sitting and sometimes holding a tray above their head. The height of the relevant cup (read against the ticks on the y-axis) clearly indicates the consumed number of the applicable alcohol type. Some argue that chart junk causes problems with interpreting the data and introduces bias and is not backed by psychology (Wilkinson, 2006). Bateman et al. (2010) have shown that embellishments can help with memorability. Visual embellishments vary in how extreme the embellishment is. Yet, examples exist of seemingly successful and memorable embellished visualisations, such as the example given above. Connotation that is hidden in embellishments can also draw a stronger value judgement from the user (Hullman & Diakopoulos, 2011). Hullman and Diakopoulos (2011) present compelling evidence that story telling is unavoidable in all visualisation due to overlap in the techniques used.

overcoming difficulty

One way to overcome the evaluation difficulty of data visualisation – and a method frequently also used in implementations of the theories of creativity – is to pre-determined the desirable output criteria and then used this pre-determined criteria to evaluate the resulting visualisation. Successful visualisations can be tested empirically against predefined criteria, or against performance measures (Nazemi, Burkhardt, Hoppe, Nazemi & Kohlhammer, 2015). It is also helpful to test visualisations against datasets where the content of the datasets is already known. One such source of datasets is the ‘UCI Machine Learning Repository’ (Lichman, 2013). The ‘UCI Machine Learning Repository’ is a database of datasets that also includes references to research that has already used the datasets. It is used by artificial intelligence researchers to test their machine learning algorithms. Other visualisation projects generate their test data (Keim, Bergeron & Pickett, 1994). The resulting visualisation can then be compared against the manipulated data and thereby tested.

Two ways 2 measure

Visualisations can be measured heuristically or with user studies. Heuristic evaluation tends to use lists of rules and principles that are frequently qualitative, but there are some that are quantitative (Y. Zhu, 2007). Rules that are frequently used are those of Kosslyn (1989), Shneiderman’s, ‘information-seeking mantra’ (Shneiderman, 1996), Tufte and Graves-Morris’s (sometimes controversial) data/ink ratio (Tufte & Graves-Morris, 1983), Bertin’s perceptual properties of visual variables (Bertin, 2000; Meirelles, 2013), and the Gestalt principles.

eval narrative vis

Hullman and Diakopoulos (2011), highlighted and justified many technique that occur in narrative visualisation. They are discussed in Section 2.4.1. The top ten most frequently used techniques were presented. Ranked from most frequent to least frequently used they were: grouping by colour, aggregating values, suggestive spatial mappings, goal suggestions, bold fonts, data source citations, metaphoric statements, colour mappings, apostrophe, and variable splices. As pointed out, this is interesting because some of these techniques are commonly found in visualisations that do not contain narrative elements (Hullman & Diakopoulos, 2011). These techniques frequently co-occur (Hullman & Diakopoulos, 2011). Counting how many of these techniques are present could be a a useful gauge.

measure bisoc

Since this investigation is exploring the aspects of visualisation that are uniquely human, the target criteria will also aim to improve these shortcomings. Measurements against a visualisation process attempting to emulate a specific theory of creativity would still need to prove that the method producing the visualisation adheres to that theories’ objectives. For *bisociation*, this would mean keeping a history of how the graphic was produced. This is because the computer program would need to be able to show that there was a cross domain element to the result, that there are multiple domains involved, and that there are emergent features.

Bayesian surprise

Correll and Heer used an adapted version of *Bayesian surprise*, effectively modelling anticipated versus observed events. They built probability models of expected event distributions to look for surprising data. This effectively also overcome shortcomings of visualisations called thematic maps – such as sampling errors, and atypical regions. Thematic maps are visualisations which connect data to geographic locations. They created discrete density maps from density variables – optionally using binning – and calculated the results against expected event density – such as calculation of population size, visualising the resulting surprise values. Another technique for calculating expected distributions is to generate them from smaller samples of the data set. The authors uses both spatial and temporal data to calculate expected data distributions and do not restrict themselves to comparing the same data between the two distributions in the *Bayesian surprise* calculation.

Quantitative

Quantitative measures can fall under three general types, accuracy, utility, and efficiency (Y. Zhu, 2007). Accuracy includes things such as the measurement of errors. Utility benchmarks use predefined goals. Efficiency measures are concerned with things like how long it took to generate the visualisation, and whether the process was abandoned. Some quantitative measures include some Tufte and Graves-Morris's data/ink ratio (Tufte & Graves-Morris, 1983), and some of Kosslyn's rules (Y. Zhu, 2007). Kosslyn (1989)'s rules are intended to identify design flaws, and are therefore accuracy rules.

Data/ink ratio

Tufte and Graves-Morris referred to the graphic elements that make up the visualisation as, 'the ink'. Tufte and Graves-Morris stated that the the ink that represents the data should be the bulk of the ink in the graphic. In other words, the bulk of the graphic elements should change when the data changes and be non-erasable, in the sense that erasing them would remove information. The ink that transports data excludes scales, grid-lines, labels, redundant information, meta-data, borders that don't have tick marks, and decorations. Tufte and Graves-Morris's data/ink ratio (Tufte & Graves-Morris, 1983) is shown in Figure. As mentioned, some authors suggest a balance between minimalism and other psychological factors such as recall, and the abilities of the user (Bateman et al., 2010).

$$\text{Data-ink ratio} = \frac{\text{Data-ink}}{\text{Total ink used to print the graphic}}$$

$$1.0 - \text{Ink that does directly represent data}$$

Figure 23: Tufte and Graves-Morris's data/ink ratio.

measuring Aesthetics

Aesthetics, include position, size, shape, resolution, colour and texture. Some of these are easier to evaluate than others. Colour, for example, has attributes such as must be friendly for colour-blind individuals and must be distinguishable from each other. Psychophysics, a field concerned with how physical stimuli relates to perception (Dictionary, 2010), contributes to formulas and theories in pursuit of understanding visual perception (Wilkinson, 2006).

Aesthetics:colour

Healey (1996) has developed a formula that uses three measurements for choosing colours for effective visualisation. The measurements calculate the distance between two colours (using a Euclidean distance function over the CIELUV colour model), colour separation (using linear separation), and categories (defined by distance from previously named colour regions). Ordering, which can make outliers more obvious can be measured using various similarity/distance measures such as Euclidean distance, Pearson's correlation, Pearson's chi squared, relative entropy or Kullback Leibler distance ($D(p||q) = sum_x p(x) log(p(c)/q(c))$ where p and q are mass functions), but comparing every dimension in the data is considered a hard problem in higher dimensions and is best left to heuristics driven algorithms such as genetic algorithms and neural networks (Ameur, Benblidia & Oukid-Khouas, 2013).

Aesthetics:position

Cleveland and McGill (1984)'s hierarchy is sometimes used to evaluate aesthetics. Cleveland found that human's numerical judgements, when mapped to visual elements, formed a hierarchy. Position along a common scale was perceived most accurately, followed by position on non-aligned scales, length, angle, area, volume, and colour. Colour is the least effective at conveying the magnitude of a number. The low level of area in Cleveland and McGill (1984)'s hierarchy is being contested in the era of big data. This is due to the effective use of area in big data visualisation types (Kostelnick, 2017).

Cawthon and Moere (2007) mentions that minimising of bends and edges that cross and maximising angles, orthogonality and symmetry has previously been shown to be better received by the target audience. They also show that there is likely a correlation between aesthetics and utility.

measure other stages of pipel.

Quality metrics can be calculated for other stage of the pipeline and can be done on the data or the image space or both (Bertini, Tatu & Keim, 2011).

1. Clustering metrics measure the extent to which the visualization or the data contain groupings.
2. Correlation relates to two or more data dimensions and captures the extent to which systematic changes to one dimension are accompanied by changes in other dimensions.
3. Outlier metrics capture the extent to which the data segment under inspection contains elements that behave differently from the large majority oft he data

The purpose of these metrics is to spot outliers, find correlation, and find projected subsets that may expose useful patterns in the data (Bouali et al., 2015).

summary

In summary, knowing what you expect to see in the data, along with scoring against known good practises for visualisation, is a commonly used, but imperfect method of measuring visualisation due to human preferences and domain knowledge and the fact that data visualisation is not an exact science.

lit both

Section 3.5 begins to explore and describe *conceptual blending* techniques in the context of those relevant to visualisation; starting to address creativity objective A.

This section presents what aspects can be built into a computer program so that the resulting prototype can be evaluated against the chosen visualisation criteria and techniques.

2.6.5 Machine learning and artificial intelligence methods

Genetic algorithms

There are ways humans and computers can generate visualisations other than using a human driven, interactive graphic user-interface. Bouali et al. generated visualisations using a genetic algorithm, but using a human to assess and score the result. They started with a model of possible mappings between the visual and data attributes – encoded as a vector of weights. Standard operations, such as crossover and mutation, produced potential visualisations. The genetic algorithm used the human-supplied scores to iteratively produce another set of improved visualisations (Bouali et al., 2015). Visualisation can also be a part of machine learning tools (such as *WEKA*). These tools also facilitate some data pre-processing and filtering choices before learning the data and visualising the result (Hall et al., 2009).

lead out

The literature concludes, in the next section, with a discussion of the overlaps between visualisation and computational creativity, and a summary of the research questions and objectives that have been addressed.

3 Literature Summary and discussion

This section summarises the creativity and visualisation literature and highlights the most promising criteria that could be applied to develop a basic computer program to demonstrate the results. The key results of the intended objectives are also highlighted.

Section 3.1 summarises the alteration in the pipeline between human generated, computer generated and visual analytics identified in Sections 2.5.1, 2.5.2 and 2.5.3 are compared to identify the primary differences between the same task executed with and without a human. The section summarises the results and concludes with a short discussion suggesting some options.

3.1 Visualisation discussion

Complete automation of visualisations appear to be restricted to specific data types (such as medical imaging) and dashboard type charts. Completely automated production of visualisations appear to have been abandoned in favour of human-in-the-loop solutions provided by visual analytics. While visualisation is a part of machine learning software, those visualisations are presented without intent of storyline leaving the interpretation to the user.

two human loops

The two additional, human orientated, stages of the visual analytics' visualisation pipeline – the knowledge generation and user interactive stages – hint at where a fully automated computer generated visualisation algorithm could attempt to address the shortcomings of existing automated visualisation algorithms. All visualisation pipelines have data pre-processing, clean-up and variable choice; however, background knowledge of the data, purpose, intended storyline as well as recognition of outliers or elements of interest are human attributes. What is not clear from the *grammar of graphics* diagram in Figure 20, is that user interaction and knowledge generating loops can occur between each stage in the visualisation pipeline.

How are computers facilitating creativity in the visualisation pipeline

Computers currently facilitate creativity during the visual analytic pipeline by assisting with choices at every stage of the visualisation pipeline and aiding with filtering and transforming data, visual comparisons, backtracking, memory aids and quick access to high and low level detail of the visualisation.

storytelling + vis pipeline

Storytelling and purpose also emerge from choices made in all the steps in the visualisation pipeline, but how effective the visualisation is at relaying the story, is refined in the iteration between steps. Choosing which variables to use, such as time or causality, begin the story, but the emergence of patterns or recognition that the graphic is not conveying the intended purpose – either because there are outliers, or because the geometry, variables or chosen aesthetics don't effectively communicate the intent – drives new choices of algebra, scale, statistics, geometry, coordinates or aesthetics. Comparing the final rendering of two different choices against the intended purpose, can end the iteration, or drive another loop to refine one of the choices. Stories emerge from creative combinations of diverse variables, visualised against each other in relevant ways. This task is generally performed by a computer in a combinatorial manner, with no regard to why particular choices are novel or unusual. The choice of genre, or attention seeking visual clues are driven by purpose or storyline, yet don't appear in the "*grammar of graphics*".

storytelling and CC+vis

Storytelling is one of the targets of existing computer programs attempting to emulate creativity and these existing techniques may come in use for computationally generating visualisations. Among the techniques used, are scripts and semantic frames (which are used to provide background information and fill in missing data) or semantic networks (which are used to establish meaning and relationships between concepts) (Boden, 1998). These techniques are among those currently used to automate the creation of poetry (Colton, Goodwin & Veale, 2012; Lamb et al., 2016) and computer generated stories (Gervás & León, 2016; M. Riedl, 2016). Klein et al. (2006) even mentions the potential role of frames in artificial intelligence methods whose purpose is the generation of visualisations from data.

story plus artificial intelligence

The awareness of a story behind the data, the intent of a visualisation, intentional attention-grabbing aesthetics or *novelty* does not appear to be modelled in computer-only visualisation generating machine learning tools or computer algorithms that automate the generation of visualisations; they would likely benefit from fitness functions and heuristics that can drive the visualisation towards a storyline or purpose by including a sense-making pipeline, that is optionally executed, between each step in the visualisation pipeline after the first rendering of a visualisation has been made. Figure 24 attempts to illustrate how the "*grammar of graphics*" could be adjusted to facilitate the addition of a sense-making pipeline. Constraining a computer generated visualisation to a predefined grammar or wizard may be too limiting when attempting to emulate human creativity and information seeking. In a computational visualisation generation process, introduction of a sense-making cycle could drive a more informed heuristic and validate choices as to why a particular grammar production rule or model is chosen over another, seemingly just as suitable substitution.

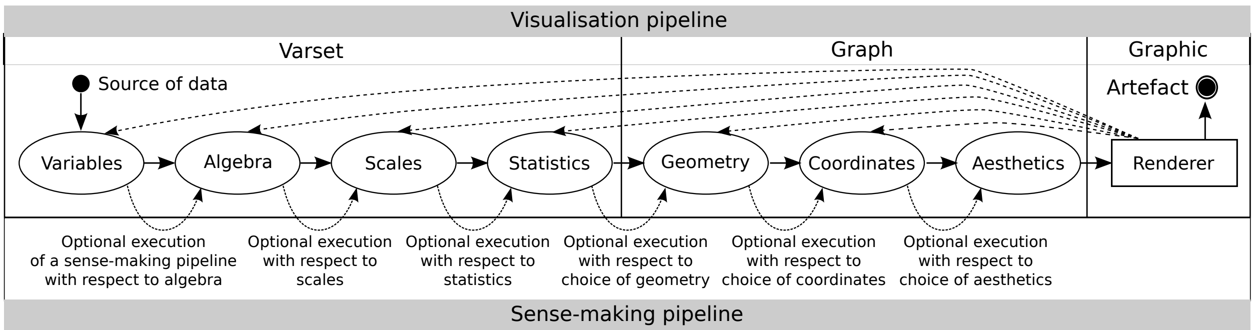


Figure 24: The *grammar of graphics* adjusted to indicate iterations into (some choice of) sense-making pipeline.

Incorporating story lines and purpose into the computational algorithms that generate visualisations, and incorporating insight provenance between each step in the visualisation pipeline, are potentially good techniques to add to existing visualisation algorithms that are attempting to produce the same kind of novel, purposeful and creative visualisations that humans can. Sense-making pipelines will need to be reviewed in more detail.

Combining data

Combining data from other data sets on the same graph can highlight patterns. An example of an existing visualisation demonstrating combined data is the graph of the 1854 Broad Street cholera outbreak – shown in Figure 25. The graph shows the location and number of deaths. It also shows the location of water pumps on the map. The combination highlighted that the deaths were clustered around the water points. In a time-series plot, including another shared variables on the same axis as time can be particularly effective at exposing evidence (Tufte, 2006). This is also an area where the cross domain knowledge particular to *bisociation* could be useful; multiple inputs into a blend can be mapped onto the same time-series graph (Cristóbal Pagán Cánovas et al., 2011).

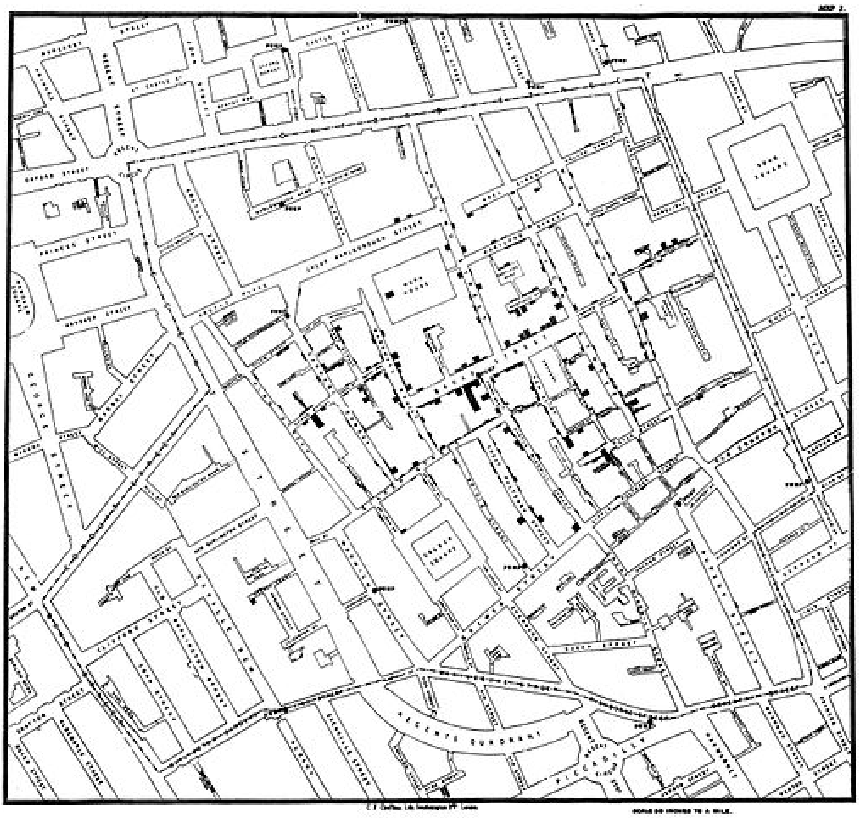


Figure 25: John Snow's original visualisation of the 1854 Broad Street cholera outbreak. (The image is in the public domain due to its age.)

what to graph

Choosing what aspects of the data can or should be represented is a task requiring domain knowledge and creativity and is therefore a task difficult for computers and still mostly done by humans (Kalogerakis et al., 2006; Myatt & W. P. Johnson, 2011; Yau, 2013). Domain knowledge in the visualisation can also allow the user to change the graphic based on what they are trying to extract (Kalogerakis et al., 2006). This suggests that the activities and their associated production rules in the *Varset* group (Figure 19) are appropriate targets. D. Zhu and Porter (2002) suggest that blending various forms of knowledge can enhance the utility of the resulting data. This suggests that choosing what aspects within the data are chosen for the visualisation is a potential target for the introduction of creativity.

purpose of pipeline in discussion

In summary, the purpose of the initial review of the visualisation pipeline was to investigate parts of the process suitable for the introduction of computational methods based on creativity theories, based on *bisociation*. From the creativity discussion earlier in the literature (Section 2.2), it is clear that concepts from differing data sets could make a useful blend. to be blended. There is no requirement that both sets of data suggestion: choosing data

are visualised – but they could be. From the discussion of the graphics pipeline in Section 3.1, it can be inferred that one of the locations in an automated visualisation, suitable for the introduction of computational creativity, is in the iteration between the collection of data and the first stage of the pipeline – the choice of variables; This is because a suitable choice of a data, such as a news website or an online encyclopaedia, could be blended with the data for the visualisation (or a description of the data for the visualisation). The resulting combination of the two sets of data can then used to infer heuristics about what aspects of the data are useful to the viewer, or point out useful facts about the data that were not present, or obvious, in the original dataset. This would need to be done, without distorting the data, though careful choice of document closeness matching and related concepts from semantic databases. Two contrasting sources of external data, such as a source of news or a collection of children's books have potential to highlight very different attributes in the data against which they are to be blended. This has potential to expose or highlight storylines by exposing different important aspects of the data. An additional dataset that is calculated to be similar to the data to be visualised can be used to fill in missing aspects of the data set to be visualised.

suggestion: filling in detail

Another part of the pipeline with potential is the aesthetics stage; The blend with a suitably chosen external data-source could facilitate the use of colour or visual clues that highlight the purpose of the visualisation. Background graphics could be discovered, by extracting the images from an original document that very closely matched the data to be visualised. The inclusion of external aesthetics would need to occur without interfering with the human perception of the data.

suggestion: aesthetics

The next section summarises the creativity literature and points out the overlaps with visualisation.

3.2 Creativity discussion

blend visual metaphor discussion

Computational models of metaphor in natural language processing – also called *Computational metaphor identification* – has emerged as one way to connect *conceptual blending* and data visualisation. Concrete metaphors would need to be found that connect the data, to the visualisation of the data, using the results from the chosen metaphor dictionary or tool. An implementation was described where items of metaphor type *"isa" string* were mapped to the choice of labels (chosen for the axis on a graph or pie chart). Items of metaphor type *"isa" image* could be used as background images. There may be other relationships, specifically geared toward enhancing the automated-generation of data visualisation by a computer, that could contribute; Relationships found using tools such as 'ConceptNet', could be discovered via the same technique to identify colour or sentiment. Compression in the blend could aid with the identification of axis ticks and choice of geometry and coordinates.

visual metaphor

Also described was the use of a predefined visual metaphor or metaphors to aid in making the semantic connection between visual forms and attributes and text data as well as the use of visual metaphor to aid in understanding or intent of a visualisation. Other types of metaphors, such as *nominal metaphors* – such as 'time is money' – may also apply (Su, Huang & Chen, 2016). This suggests that further investigation of how metaphors can be computationally created and mapped to a data visualisation could be a topic for further investigation. It is interesting to note that metaphor can occur as the result of a change of semantic frame, and therefore appears in the computational metaphor literature (Jang, Maki, Hovy & Rose, 2017).

blend compressions discussion

Compression of information is a feature of both data visualisation, narrative as well as conceptual spaces and should be taken into consideration when trying to connect the two. The emergence of compression in a blend, can be used at various points in the visualisation pipeline. The algebra step in the pipeline aligns with emergent structure materialising from composition of elements that have been projected into the blend. Time information emerging from a blend could potentially contribute toward a more informed choice of scales for a set of data (such as time, nominals, ordinals, intervals or ratios).

Sections 2.5.1, 2.5.2 and 2.5.3, explored the data visualisation pipeline, highlighting storytelling as important. Storytelling is also a theme that emerges in the literature on *conceptual blending* as it relates to visualisation. What has emerged is that the use of various types of metaphor can contribute to highlighting narrative in visualisations and selected use of compression of time-frames between inputs can also facilitate narrative. Colours could be chosen by calculating average values from images returned from a Google image search or from colours related to concepts via metaphor.

results of vis+conceptBlending

Compression, iteration, storytelling and metaphor are features of both *conceptual blending* as well as data visualisation. Structured mappings can be found, from words or attributes in the conceptual space to visual elements, through the use of different types of metaphor. Story telling and metaphor are both considered to be creative acts. Leveraging off the commonalities between *conceptual blending* and visualisation could provide a suitable entry point for the prototype. The compression and metaphor that emerges when ‘running a blend’ has potential to enhance the no-human-in-the-loop generation of visualisation by addressing some of these shortcomings; however, non metaphor methods of blending, such as the use of analogy, should not be dis-guarded because of *bisociations* whose intention is humour or shock value.

A final point about iteration and when to stop; Thagard and Stewart (2011) point out that when multiple experiences (input from external sources, memory, touch, hearing) blend in previously unconnected ways it induces an emotional response (Thagard & Aubie, 2008). If their ‘EMOCON’ model is correct then it is this emotional response that elicits the recognition of creativity or the surprise – “the AHA moment” – that emerges in creativity literature. They are not the only ones to posit this theory. The *Honing theory*, which is based on the *Geneplore* model of creativity – another blending theory – asserts that blends of concepts continue iteratively until emotional arousal subsides. This is suggestive of a potential role for valence both for recognising which blends have creative outputs, as well as deciding when to stop a *conceptual integration*. Valence and effect dictionaries used for computation, such as the *NRC Word-Emotion Association Lexicon* (‘NRC Word-Emotion Association Lexicon’, 2011) could be used alongside the metaphor calculations for this purpose.

3.3 Creativity in the visualisation pipeline

Storytelling and narrative was highlighted in the literature as being an important and distinctly human part of the visualisation process. Since storytelling is an addressed aspect of computational creativity the combination of narrative with the distinctly human parts of the visualisation pipeline are promising choices. The following questions emerge:

1. Can conceptual blending/storytelling help with variable choice by identifying what we want to see in the data?
2. Can *conceptual blending* identify interesting data to contrast?
3. Can *conceptual blending* help with Image choice?
4. Can conceptual blending/storytelling help with deciding what to filter?
5. Can conceptual blending/storytelling help with deciding what range to visualisation and what tick choice?
6. Can *conceptual blending* and frames identify items in the visualisation to draw appropriate attention to?
7. Can frames and *conceptual blending* identify target audience?
8. Can *conceptual blending* help with visualisation display type choice?
9. Can *conceptual blending* or storytelling supply prior knowledge and context?
10. Can frames and visual metaphor be useful for data visualisation
11. Can storytelling contribute to the semantics associated with visualisation aesthetics?
12. Trend detection, causality, inference make data useful. What is conceptual blending's role?

Prior knowledge is an unsolved problem with automated data visualisation that may be solved by conceptual blending.

Frames, that could provide context may offer solutions for image and variable choice and metaphor discovery as well as fill in missing information. Bisociative knowledge discovery could make for unusual contrasts of information sources and can drive narrative. Contrasting data, lends itself to very specific visualisation types.

The next section summarises the evaluation techniques from the literature that could be suitable in the context of the dissertation objectives.

3.4 Suitable evaluation techniques

The *Bayesian surprise* formula has already been used, outside of a computational creativity application, to improved shortcomings of visualisation techniques and find unexpected data. It therefore stands out as a potentially appropriate technique for a heuristic, fitness function or evaluation technique for the prototype (Correll & Heer, 2017). Not only did this technique overcome some of the shortcomings of the chosen visualisation type, but the technique highlighted relevant outliers and also could compare heterogeneous data in order to do this. In addition, the technique effectively modelled how humans know a little bit about what they are expecting to see in the data.

3.5 Conceptual blending in the context of visualisation

Metaphor is discussed in Section 3.5.1 since it emerges in the literature not only as a frequently emergent feature of a blend and a technique to create the blend but also as a means of creating visual features, by associating visuals and graphics to a given concept. Section 3.2 summarises the key points that correlate with the objective of exploring *conceptual blending* implementations in the context of those relevant to computer generated visualisation. Suitable techniques are suggested that could be integrated into a computer program attempting to introduce *conceptual blending* into a computational method that emulates the data visualisation pipeline.

3.5.1 Metaphor in blends

Metaphors in blend

Metaphor is a word or phrase used in non-literal manner, which when added to other words or phrases, suggests a resemblance. Similarly, *Visual metaphor* is an image of a subject (such as a person or place) depicted in a manner that suggests that the subject has some additional attributes. Metaphor has been linked to creativity and promotes convergent thinking and divergent thinking (Leung et al., 2012; Marin, Reimann & Castaño, 2014; Sternberg & Grigorenko, 2001). Metaphor can emerge from repeated iteration of conceptual blends (Fauconnier & Turner, 2008a). Fauconnier and Turner call the resulting network of blends, *integration networks*; although, metaphor does not always emerge since blends can also contain counterfactuals and elements that clash (Ox, 2015) (Refer to the *bisociation* Venn diagram in Figure 1). Conceptual integration blending operations also use metonymy, category, analogy and counterfactual reasoning (Coulson & Cristobal Pagán Cánovas, 2009). *Primary metaphors* are metaphors that connect concrete subjects to abstract or subjective terms, such as, *happy*, *bad* and *touch*. While no concrete proof is supplied by the authors, it has been suggested that *primary metaphors* can support more intuitive visualisations (Cybulski, Keller & Saundage, 2015). Specifically they can connect subject orientated terms to visual metaphor. Examples of such metaphors are, ‘quantity is size’, and ‘similarity is proximity’. Time, event and action metaphors pertain to temporal data (Cybulski, Keller & Saundage, 2015). *Primary metaphors* can also be used to communicate insight to the viewer of a visualisation (Cybulski, Keller & Saundage, 2015), supporting the intended narrative behind a visualisation. For example, ‘More is up’ connects quantity and height (Goguen & Harrell, 2004; Grady, 2005). Purpose and narrative are important to data visualisation (Katz, 2012; Kirk, 2012; Kosslyn, 2006; Meirelles, 2013; Francisco Câmara Pereira, 2007). Well designed visualisations frequently contain visual metaphor designed around the narrative intended for the visualisation audience and these visual metaphors also aid in facilitating multiple views of the same information (Cybulski, Keller & Saundage, 2015). Blending differs from metaphor in that it allows more than one relationship to exist in the blend (Grady et al., 1999).

computational model of metaphor

Simoff (2001) suggests that the success of visual data mining is tied to the development of a computational model of metaphor. He suggests a model that uses a *conceptual blend* over a textual data set. His model is illustrated in Figure 26. One of the input spaces (the form and *source space*) contains 2D and 3D shapes as well as their attributes (coordinates, geometry, colour, texture, brightness). The second blend input (the function and *target space*) contains functions generalising patterns discovered in the data. The blend emerges from establishment of relationships and semantics links between the elements common to both input spaces through the exploration of common terms emerging from word statistics, as well as topics emerging from the text and the association with a particular pre-chosen metaphor such as *Euclidean space* or *Tree*.

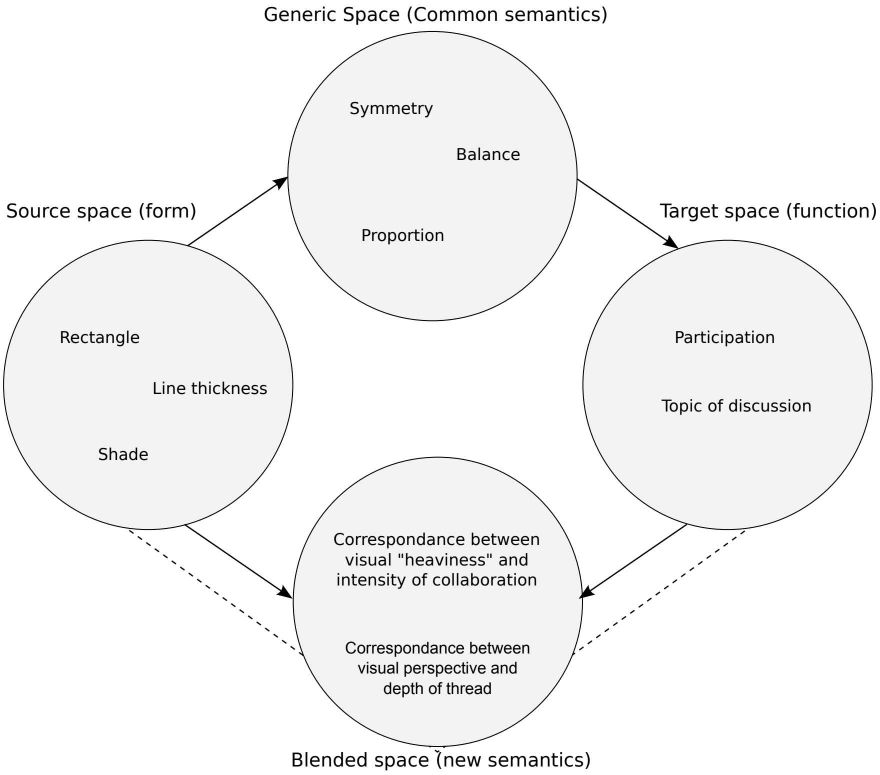


Figure 26: Form-semantic-function mapping for visualising bulletin discussion threads facilitating team collaboration according to Simoff (2001).

Time metaphor

Time-space metaphors and mappings are also relevant to both data visualisation and *conceptual blending*. Time-series data visualisations and blending share attributes. Time-series visualisations are good at comparing multiple variables against each other (that share the time axis) – in this way illuminating smart comparisons or revealing causality (Cristóbal Pagán Cánovas et al., 2011; Coulson & Cristobal Pagán Cánovas, 2009; Tufte, 2006). Emerging novel features in visualised timelines result from compression of temporal relationships into spatial relationships (Cristóbal Pagán Cánovas et al., 2011). Compression of multiple blend inputs spaces onto one, and the potential compression of time are possible features of certain types of blends (Coulson & Cristobal Pagán Cánovas, 2009; Fauconnier & Turner, 2008b). Time metaphor, such as, 'time is a river' and 'time is space' exhibit geometry (circles, curves, lines) that can also be connected with narrative when blended with culture – also called material anchors (a circle can be mapped to a clockface) (Cristóbal Pagán Cánovas et al., 2011; Coulson & Cristobal Pagán Cánovas, 2009). Useful timelines frequently emerge in an iterative manner (Coulson & Cristobal Pagán Cánovas, 2009). Time-space metaphors also often appear with motion verbs that indicate front, back as well as rate of change (Coulson & Cristobal Pagán Cánovas, 2009).

Goguen and Harrell (2010) introduce the concept of *structural blending*, which extends *conceptual blending* and incorporates syntax, metaphor and narrative (Goguen & Harrell, 2004, 2010). *Structural blending* also incorporates iteration, semiotic morphisms and media morphisms allowing the output media of the blend to be mapped to different types of outputs – such as text or graphics. Semiotic morphisms – the mapping of one set of signs into another – can aid with appropriate choice of visualisation (Goguen & Harrell, 2005).

concrete metaphor

Data-orientated or visual metaphors

Visual metaphor can be used to map concepts to physical objects and also to attributes of the concept (location, colour or texture) (Cybulski, Keller & Saundage, 2015). An implementation of visual metaphor mapped to objects is the program Virgilio (L'Abbate & Hemmje, 1998). Virgilio is a tool that generates Virtual Reality Modelling Language (VRML) worlds from a database. The program does this by using a metaphor dictionary/repository to connect the data returned from a database query – the metaphor input – to the visual side of Virgilio – the metaphor output. The metaphor output consists of simple objects known to users (such as desk, chair, book). The metaphor dictionary looks up the keywords in the metaphor input and calculates relationships between input and output concepts in order to find the simple objects that can be visualised. It follows relationships until it finds a relationship that can be visualised. In the case of Virgilio, this relationships consisted of objects that have an 'isof' relationship (L'Abbate & Hemmje, 1998). The authors give the example of a search for the text 'Sting'. The metaphor dictionary, connects this word to the musician and returns the following metaphor relationships:

1. Sting (owns) photo (isof) image
2. Sting (contains) CDs (contains) CD (owns) CD title (isof) string
3. Sting (contains) CDs (contains) CD (contains) Songs (owns) Song title (isof) string

In this example the *photo*, *CD title* and *song title* are all mapped to items that the tool knows how to visualise, namely: strings, and images.

computational input Spaces

Conceptual spaces and input spaces can be built computationally in a number of ways. They can be predefined by a human (Guzdial & M. Riedl, 2016; Ribeiro, Pereira, Marques, Leitão & Cardoso, 2003); they can be built from documents (L'Abbate & Hemmje, 1998; Simoff, 2001).

computational blends

There are a variety of techniques for "running the blend". Analogy can be constructed using semantic networks, such as 'ConceptNet' ('ConceptNet 5', 2016) or predefined relationships (L'Abbate & Hemmje, 1998). 'ConceptNet' stores information about knowledge in the world in the form of relationships. 'ConceptNet' is also available in matrix form (Speer, Havasi & Lieberman, 2008b). Background information can be inferred using semantic frames (Goguen & Harrell, 2004). FrameNet is an example of a tool that provides a dictionary for looking up frames and has tools for using the dictionary (Baker, Fillmore & Lowe, 1998). Ribeiro et al. (2003) use a genetic algorithm whose fitness function scores and verifies the blend. The program does this by verifying if the blended result matches predefined frames without contradicting a small set of restrictions. Thereafter, the program uses a predefined knowledge base to search for additional concepts to add to the blend. Included in the blending model of Guzdial and M. Riedl (2016), is an open source machine learning tool-kit ('OpenCV (Open source computer vision)', 2015) which uses sprites, and probabilistic models learned from visuals.

connecting concept to a symbol

It is possible to connect a concept to a visual representation of the concept (Joao Miguel Cunha, Martins, Cardoso & Machado, 2015). This is known as Semantography and is a sub-field within the field of Semiotics. An implementation of concept to symbol mapping is the set of symbols known as Blissymbolics (Bliss, 2016). Joao Miguel Cunha et al. (2015) attempted to computationally generate symbols from concepts using text as input and a semantic network repository. Colours can frequently be associated with concepts. Examples include:

1. bananas $\longleftrightarrow$ yellow
2. anger $\longleftrightarrow$ red
3. money $\longleftrightarrow$ green

Lin, Fortuna, Kulkarni, Stone and Heer (2013) made use of Google's image search to find images related to a concept, after which they analyse the colour distributions in the returned images in order to find concept-colour associations.

4 Research design and methods

4.1 Methodology

introduce DSRM

This process will followed the design science research methodology (DSRM) (Aier, Winter & Zhao, 2010; Dresch, Lacerda & Antunes, 2015; Hevner & Chatterjee, 2010; Peffers et al., 2006; Vaishnavi & Kuechler, 2015). Unlike natural science, which tries to understand reality, DSRM tries to create artefacts that serve human purposes (Peffers, Tuunanen, Rothenberger & Chatterjee, 2007). DSRM is based in artificial rather that natural phenomena (Hevner & Chatterjee, 2010).

applicability

This methodology is applicable to information systems research in that it helps to elevate it from a design process into a form that can be recognised as quality research and that can be evaluated for validity and value. It does this by providing a consistent model and process to follow with specific guidelines on what the output should look like (Peffers et al., 2007). It differs from the standard systems development life cycle in that the process is exploratory, can terminate at in time during the process, and generates new design science knowledge such as invention, improvement or adaptation (Vaishnavi & Kuechler, 2015). DSRM can be used in combination with various research methods (Gregory, 2011).

4.1.1 The Design Science Research Methodology Process (DSRM)

Goals of

One of the goals of DSRM is to establish process and mental models or templates for the structure of research outputs (Peffers et al., 2007). The process model should guide reviewers about what to expect from the DSRM output, while the mental model can help researchers carry out the process (Peffers et al., 2007). The accepted process model consists of six activities namely:- *Problem identification and motivation*, *Solution objectives*, *Design and development*, *Demonstration*, *Evaluation* and *communication* (Peffers et al., 2007). Solution objectives can include validity, utility, quality, and efficacy. An illustration of this process model, taken from Peffers et al. (2007), is depicted in Figure 27. This particular dissertation will be entering the DSRM process at the *problem-centered* initiation point.

Knowledge contributions

Knowledge contributions, such as design principles, models, methods and rules, emerge from the process used to create the artefact (Gregor & Hevner, 2013). As an example, a word processor is useful for generating and editing text documents but any specific implementation of a word processor can't be said to be more "correct" than any other; However, that implementation may be more useful in some aspect of text processing than another (Iivari, 2007). The process can stop at any time, as knowledge is gained or when a sub-problem is found, that requires more literature, or invalidates a suggested solution. This *drilling down* or re-scoping of the research is part of the DSRM (Vaishnavi & Kuechler, 2015).

this DSRM

The DSRM process pertinent to this dissertation is illustrated in Figure 28.

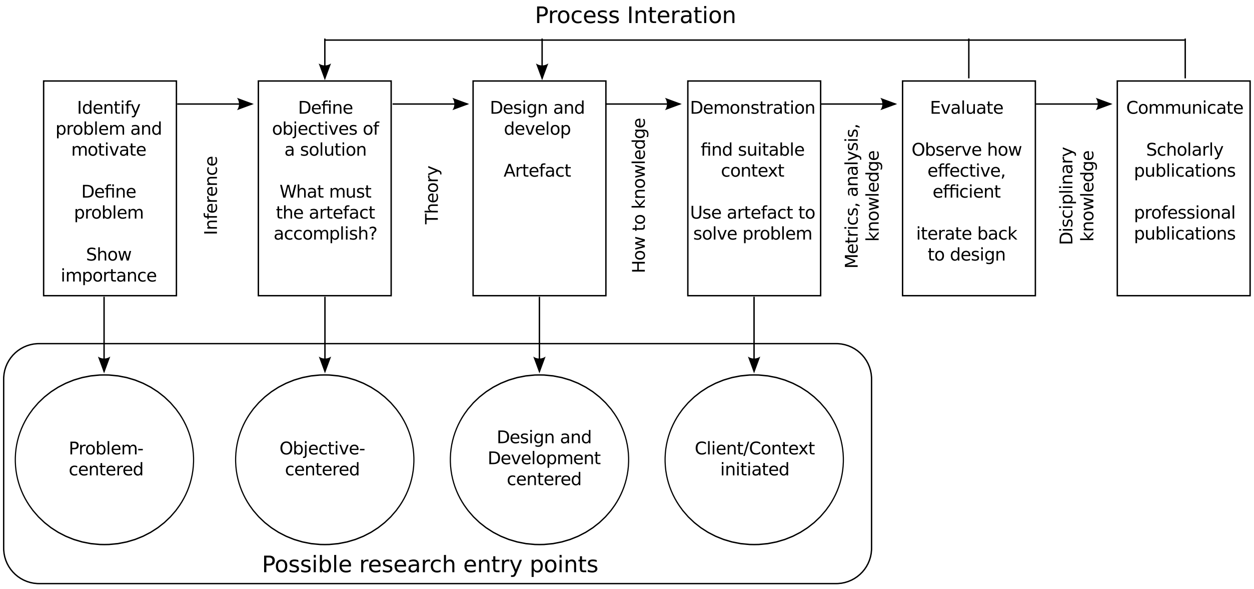


Figure 27: Design Science Research Methodology (DSRM) process model from Peffers, Tuunanen, Rothenberger and Chatterjee (2007).

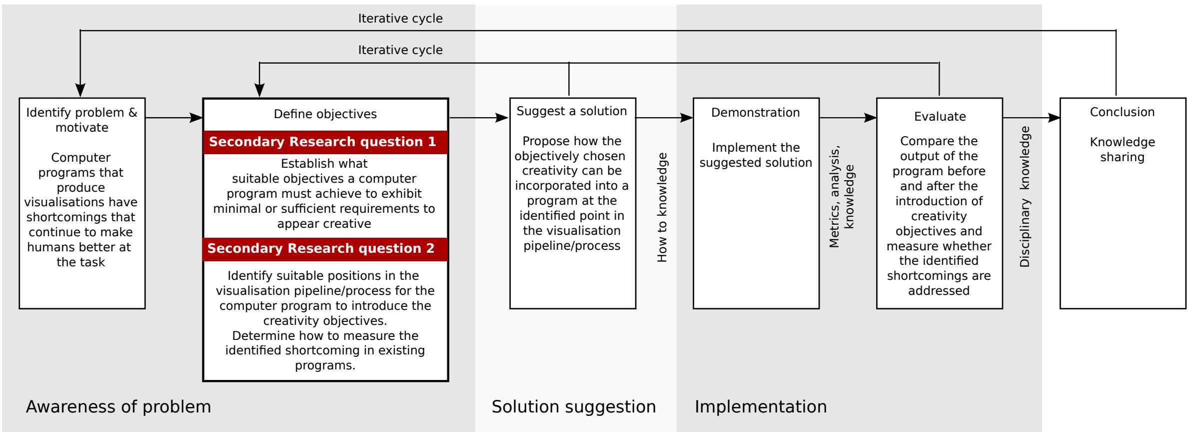


Figure 28: Design Science Research Methodology (DSRM) as it applies to this dissertation.

4.1.2 Iterative cyles within the DSRM

The DSRM contains three distinct iterative cycles which distinguish the methodology from others (Hevner, 2007; S. Wang & H. Wang, 2010). A diagram of these cycles, is depicted in Figure 29.

cycles

The *relevance cycle* initiates the DSRM by identifying potential opportunities for addressing problems. The *relevance cycle* also defines the acceptance criteria for evaluation of the research results. Evaluation of deficiencies or qualities of the artefact (such as usability or performance) can necessitate iterations back into the *relevance cycle* (Hevner, 2007). The *rigor cycle* ensures that past knowledge is taken into account in such a manner that the produced artefact is guaranteed to demonstrate something new; elevating it from the standard IT development (Hevner, 2007). The *design cycle* iterates between artefact development, evaluation and refinement, and facilitates the development of alternative designs (Hevner, 2007). Together the three cycles support rigorous evaluation of an artefact demonstrating an original contribution.

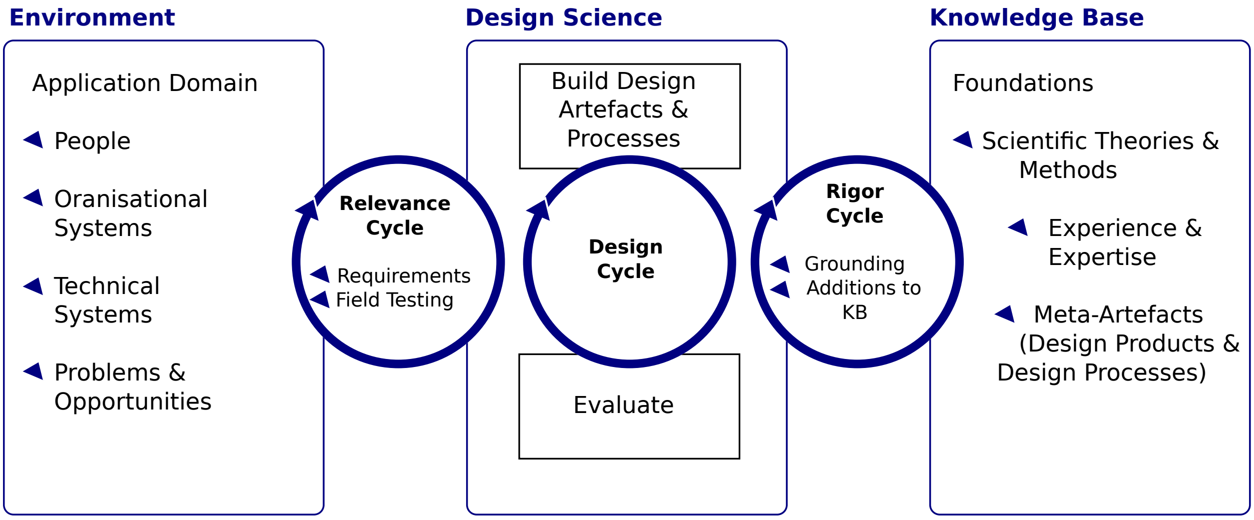


Figure 29: DSRM research cycles, taken from Hevner (2007).

4.1.3 Motivation for the choice of Methodology

Motivation

Table 5 is adapted from the work of van der Merwe, Kotzé and Cronje (2005). The table facilitates the identification of the most suitable methodology supporting the research questions. The list of methodologies used are not exhaustive, but cover the more common choices of methodologies in the computer science realm (van der Merwe et al., 2005). Where entries have been adjusted or added to the table, citations are provided. The first column in the table contains the methodology name and the second column lists the most common characteristics of that methodology. Each research question has its own column. A mark is then made in the intersection where the methodology's characteristic is applicable to the associated research question. The applicable methodologies are the ones with the highest number of characteristics that are applicable.

		Secondary research question - creativity	Secondary research question - visualisation	Primary research question
Approach	Characteristics	How have the currently accepted theories of creativity been applied in the artificial intelligence and computational realms, with an emphasis on those that generate creative data visualisations?	What scope do computer generated data visualisations have for the introduction of criteria deemed to be creative?	How can computer generated visualisations be enhanced using criteria as guided by theories of creativity?
Experiments	Control and experimental groups			
	Treats situations like a laboratory			
	Causes due to experimental investigation			
	Does not judge worth			
Survey	Describe and explain	✓	✓	✓
	Represents wide population			
	Gathers numerical data			
Case Study	In-depth data from wide data sources			
	Participant and non-participant observation			
	Non-interventionist			
	Empathic			
	Holistic treatment of phenomena			
	What can be learned from a particular case			
Grounded Theory	Theory emerges from empirical data (Gregory, 2011)			✓
	Collection and analysis of data occurs simultaneously			
	Hierarchical coding processes			
	Discovery of concepts and their properties from data			✓
	Discovery of conceptual relationships grounded in the data			✓
	Data collection proceeds until so called theoretical saturation is achieved			
Action Research	Context-specific	✓	✓	✓
	Participant as researcher			
	Reflection on practice	✓	✓	✓
	Interventionist-leading to solution of 'real' problems			
	Empowering for participants			
	Collaborative			
	Promoting praxis and equality			
	Stakeholder research			
	Change orientated			
Design Science	Identifies and solves real world problems (Gregory, 2011; Hevner & Chatterjee, 2010)	✓	✓	✓
	Solution is mostly a local solution and may not be generalized to other settings (Gregory, 2011)			✓
	Usefulness is more important than the search for truth (Iivari, 2007; Peffers, Tuunanen, Rothenberger & Chatterjee, 2007)	✓	✓	✓
	Develops understanding of a problem domain that extends beyond explicit business needs (Hevner & Chatterjee, 2010; S. Wang & H. Wang, 2010)	✓	✓	✓
	Construction and innovation is addressed in addition to improvement (Iivari, 2007; S. Wang & H. Wang, 2010)			✓

Table 5: Research methodology guidance as driven by the main characteristics of the methodology — as adapted from the techniques described by van der Merwe, Kotzé and Cronje (2005).

Iivari (2007) provides a comparison of Action Research to DSRM and Gregory (2011) can be consulted for further clarification on the differences between Grounded Theory and DSRM. Action Research has similarities to DSRM – including rigor, cyclical phases, theory, evaluation and reflection – and the two methodologies are not necessarily mutually exclusive (Hevner & Chatterjee, 2010). Action Research is stakeholder and intervention driven and action research is applied to existing problems (Hevner & Chatterjee, 2010). Design Science can also identify and develop innovative constructions that are useful but whose requirements were not necessarily driven by stakeholder requirements (Hevner & Chatterjee, 2010).

As can be seen from Table 5, DSRM was an appropriate choice of methodology considering the primary and secondary research questions of this dissertation.

4.1.4 Evaluation methods

Evaluation

Evaluation in the DSRM takes place continuously in small increments as the design process is cycled between suggested solutions to the problem and the evaluation of those solutions (Vaishnavi & Kuechler, 2015). The suggested solutions were evaluated to see whether the addition of the creative aspects in the computer program has improved any parts of the visualisation process – in which humans still outperform computers – thereby addressing some of the shortcomings that are seated in the software's lack of human inference and visual perception. The suggested software solution will need to know what objectives it needs to achieve in order to prove that creative criteria have been introduced. Adherence to the predetermined criteria will be used to determine whether the software is adhering to the chosen creativity theory; These criteria – established by the secondary research objectives – may be adjusted as the DSRM is followed.

4.2 Method

introduce

The applicability of the introduction of computational creativity techniques into a program automating the generation of visualisations, will be demonstrated with the design and creation of a prototype (Verschuren & Hartog, 2005). The *variable choice* and *aesthetics* stages of the pipeline were investigated as potential points at which to demonstrate the introduction of bisociative methods.

eval

The types of criteria that could be measured are items such as, "How long the resulting visualisations take to generate?", "How relevant the visualisations are to the data?", "Did the computer program learn about the data in successive visualisations?", "Does the visualisation demonstrate the story behind the data?", "Does the resulting visualisation highlight aspects that were known to be features of the dataset" and "How many visualisations had to be generated to produce a successful visualisation?". These suggested criteria are based on the current visualisation and creativity literature presented here.

not going to

Since this is an initial exploration of the topic, the prototypes will be presented, but no attempt will be made to quantify or assess the outcome. The use of *conceptual blending* techniques will be shown. The prototype will be demonstrated before and after the introduction of bisociation. The techniques that demonstrate that *conceptual blending* have been introduced will be indicated when the prototype design is discussed.

4.3 Prototype Design

lead in

The intent is to explore how useful some of the bisociative techniques of computational creativity can be used in the data visualisation pipeline. Two stages of the pipeline were chosen for exploration, specifically, *variable choice* and *aesthetics*. The prototype design of these two stages is discussed in Sections 4.4 and 4.5 respectively. Before discussing these two prototyes, the next section begins with a discussion on data choice, since the choice is applicable to all prototypes for both stages of the pipeline.

4.3.1 Sources of data

open data

The data sets under consideration were Worldbank Open Data ('World Bank Open Data', 2017), the UCI Machine learning repository (Lichman, 2013), and United state census data ('United Status Census Bureau', 2016) and The Visual Analytics Benchmark Repository, which contains the datasets from the InfoViz contest ('Visual Analytics Benchmark Repository', 2016). The CSV files presented with D3 templates were also considered ('Popular Blocks', 2018). The reason for the choice was that all these are copyright free and several have some sort of existing visualisations, including some really well known examples (such as the Iris data set). Worldbank Open Data, the UCI Machine learning repository, Visual Analytics Benchmark Repository and InfoViz contest also describe the data sets. Table 6 enumerates several publicly accessible, license free sources of data and compares their attributes so that the most appropriate data set could be chosen for the chosen *conceptual blending* method. at were suitable for the methods chosen.

lead out

The next Section describes an initial attempt to explore the use of *bisociation* targeting the *variable choice* stage of the graphics pipeline. An attempt was made to use bisociation as a mechanism with which to choose the variables that were to be visualised. Section 5.1.3 explores adding additional techniques of conceptual blending.

The technique showed some indication that divergence and convergence is useful, but was not successful enough for comparison or measurement. The result is discussed in Section 5.1.

A second prototype, targeting *bisociation* and elements of *conceptual blending*, and targeting the *aesthetics* stage of the visualisation pipeline is then discussed in Section 4.5. The results of the second prototype are explored in Section 4.4.3.

lead into next two sections

Two stages in the data visualisation pipeline were chosen for exploration of the introduction of *conceptual blending*, namely, variable chose and *aesthetics*. The design of the variable choice stage of the pipeline is the subject of Section 4.4, and Section 4.5 presents the design choices at the aesthetics stage of the pipeline.

4.4 Prototype Design : Variable choice

lead in

The intention of the variable choice prototype was to find two different datasets that may be interesting to visualise on the same visualisation. The datasets with the highest scoring bisociation were calculated,

Dataset	URL	Attributes	Conditions of use
The UCI Machine learning repository	http://archive.ics.uci.edu/ml	The UCI Machine learning repository has 383 data sets. Links to papers that have previously used a particular data set are available so there is access to information that is expected in the data. Data sets can be filtered by attribute type (nominal, numerical mixed) and type of data (multivariate, time-series, text etc.). Data subject area is large.	The library must be acknowledged and a citations is required (Lichman, 2013). Some datasets have additional citation requirements.
Worldbank Open Data	https://data.worldbank.org	Dataset is large and has a number of variables. The descriptions of the datasets are long and comprehensive. The website provides existing visualisations of the data that can be filtered. Data is consistently available in Excel and CSV. There are links to other data sets. There is also a 'REST-compliant Web Service Application Programming Interface (API)' that allows easy querying of the available datasets by a computer program. The datasets are Census data orientated, which makes them a bit limiting for the purposes of this project, however the ability to access the data programmatically is an advantage.	Attribution to The World Bank is to be given in the following format: The World Bank: Dataset name: Data source (if known). There are addition requirements if the data is reshared or sub licensed.
United state census data	http://www.census.gov		
The Visual Analytics Benchmark Repository	http://hcil2.cs.umd.edu/newvarepository	The advantage of the Visual Analytics Benchmark Repository, is that it also contains information on what anomalies are expected in the data. There are data sets from 2002 to 2015. The sets of data include CSV files, images and websites (HTML). The data descriptions contain named entities.	
Popular Blocks	https://bl.ocks.org	GNU General Public License, version 3.	

Table 6: Publicly accessible, license free sources of data, with a description of attributes and suitability.

but not visualised, because visualisation is not part of the variable choice stage of the data visualisation pipeline.

brief overview

The prototypes used natural language processing techniques to break down descriptions of the datasets into collections of words representing the dataset, thereby forming conceptual spaces. The techniques used to perform the bisociation between the conceptual spaces were discussed in Section 2.3.2. A simple *bisociation* was attempted first, after which 'ConceptNet' was added with the purpose of finding words to expand the conceptual spaces.

choice of data

Considering the attributes in Table 6, the Worldbank Open Data was chosen as suitable. Desired features included as open source availability, large amount of datasets, programmatic access, and descriptions of both the dataset, as well as the individual attributes of the dataset. The Worldbank data contains long descriptions of the data, which makes it suited to the natural language processing techniques being used. The Worldbank Open Data was used due to programmatic availability of the descriptions of the topics covered by the data as well as the descriptions of the variables available for each topic.

The world bank API

The world bank API allows you to query various aspects of their data, via internet requests (REST). Depending on the URL that is requested, various aspects of their data can be queried. For the purposes of the initial experiments only two queries were made and the results were requested in XML format. A request was made for available 'topics' and their descriptions. An example of partial results from this type of query can be seen in Figure 30. The topic query returns a unique identifier for each topic that can then be used to fetch information about what is known about the data for the topic – the variables. The variables describe data such a total population, gross income, energy use and others. World bank refers to these descriptions of the data as 'indicators'. Indicators can be requested for each topic, using the unique identifier. An example of such a query for the topic 'Trade' is shown in Table 31. Note that the The world bank API's topics are equivalent to what this dissertation refers to as datasets and the The world bank API's indicators are refered to here, and in the visualisation literature as variables.


```xml
<?xml version="1.0" encoding="utf-8"?>
<wb:topics page="1" pages="1" per_page="50" total="21" xmlns:wb="http://www.worldbank.org">
  <wb:topic id="17">
    <wb:value>Gender</wb:value>
    <wb:sourceNote>Gender equality is a core development objective in its own right. It is also smart
    development policy and sound business practice. It is integral to economic growth, business growth
    and good development outcomes. Gender equality can boost productivity, enhance prospects for the
    next generation, build resilience, and make institutions more representative and effective.
    In December 2015, the World Bank Group Board discussed our new Gender Equality Strategy 2016-2023,
    which aims to address persistent gaps and proposed a sharpened focus on more and better gender data.
    The Bank Group is continually scaling up commitments and expanding partnerships to fill significant
    gaps in gender data. The database hosts the latest sex-disaggregated data and gender statistics
    covering demography, education, health, access to economic opportunities, public life and
    decision-making, and agency.
    </wb:sourceNote>
  </wb:topic>
  <wb:topic id="18">
    <wb:value>Millenium development goals</wb:value>
    <wb:sourceNote/>
  </wb:topic>
</wb:topics>
```


Figure 30: Partial result of the REST call from http://api.worldbank.org/v2/topics requesting topics.

4.4.1 Bisociative method

Ten topics were initially chosen for input space creation, namely: Health, Social Protection & Labor, Gender, Energy And Mining, Environment, Science & Technology, Public Sector, Private Sector, External Debt and Infrastructure. Further topics, such as Infrastructure and Social Development, were added later to investigate symmetry. This is discussed shortly.

Potential spaces, chosen by *bisociation* consisted on all the spaces returned by the World data query. All three experiments used the same topics but vary with respect to what the input spaces consist of. The experiments are an implementation of the 'theory view' of concepts as previously discussed in Section 2.3.1.

first attempt

```xml
<?xml version="1.0" encoding="utf-8"?>
<wb:indicators page="1" pages="4" per_page="50" total="152" xmlns:wb="http://www.worldbank.org">
  <wb:indicator id="MS.MIL.XPRT.KD">
    <wb:name>Arms exports (SIPRI trend indicator values)</wb:name>
    <wb:unit />
    <wb:source id="2">World Development Indicators</wb:source>
    <wb:sourceNote>Arms transfers cover the supply of military weapons through sales, aid, gifts, and
      those made through manufacturing licenses. Data cover major conventional weapons such as aircraft,
      armored vehicles, artillery, radar systems, missiles, and ships designed for military use.
      Excluded are transfers of other military equipment such as small arms and light weapons, trucks,
      small artillery, ammunition, support equipment, technology transfers, and other services.
    </wb:sourceNote>
    <wb:sourceOrganization>Stockholm International Peace Research Institute (SIPRI), Arms Transfers
      Programme (http://portal.sipri.org/publications/pages/transfer/splash).
    </wb:sourceOrganization>
    <wb:topics>
      <wb:topic id="13">Public Sector </wb:topic>
      <wb:topic id="21">Trade</wb:topic>
    </wb:topics>
  </wb:indicator>
  <wb:indicator id="IC.CUS.DURS.EX">
    <wb:name>Average time to clear exports through customs (days)</wb:name>
    <wb:unit />
    <wb:source id="2">World Development Indicators</wb:source>
    <wb:sourceNote>Average time to clear exports through customs is the average number of days to clear
      direct exports through customs.
    </wb:sourceNote>
    <wb:sourceOrganization>World Bank, Enterprise Surveys (http://www.enterprisesurveys.org/).
    </wb:sourceOrganization>
    <wb:topics>
      <wb:topic id="12">Private Sector</wb:topic>
      <wb:topic id="21">Trade</wb:topic>
    </wb:topics>
  </wb:indicator>
</wb:indicators>
```


Figure 31: Partial result of the RESTful webservice call to http://api.worldbank.org/v2/topics/21/indicators showing indicators that are available for the topic ‘Trade’.

4.4.2 Bisociation over dataset descriptions

Initially, a simple *bisociation* was created using using the Bison measure. The process that was followed is illustrated in Figure 32. The conceptual spaces consist of vectors of words that were built using the descriptions of Worldbank Open Data’s topics and natural language processing techniques.

4.4.3 Bisociation over dataset descriptions and variable descriptions

Experiment two was also a simple *bisociation*, but the indicator descriptions are also used when forming the collection of words that make up the conceptual space. As with experiment one, the input spaces contain the words built from the topic description. The topic is then queried for the available indicators (variables). The conceptual spaces are expanded with the description of the indicators. The blend and choice of second input space is then calculated in the same manner as was done in experiment one.

First input space An input space is represented by a bag of words. A bag of words is generated using natural language processing techniques from a description of the topic we wish to visualise

Potential spaces Build a bag of words for each of the other topic descriptions from the Worldbank Open Data topics.

Run the Blend Score the *bisociation* between the First Topic and each of the other potential conceptual spaces using the Bison Measure.

Second input space The second input space is the highest scoring *bisociation*.

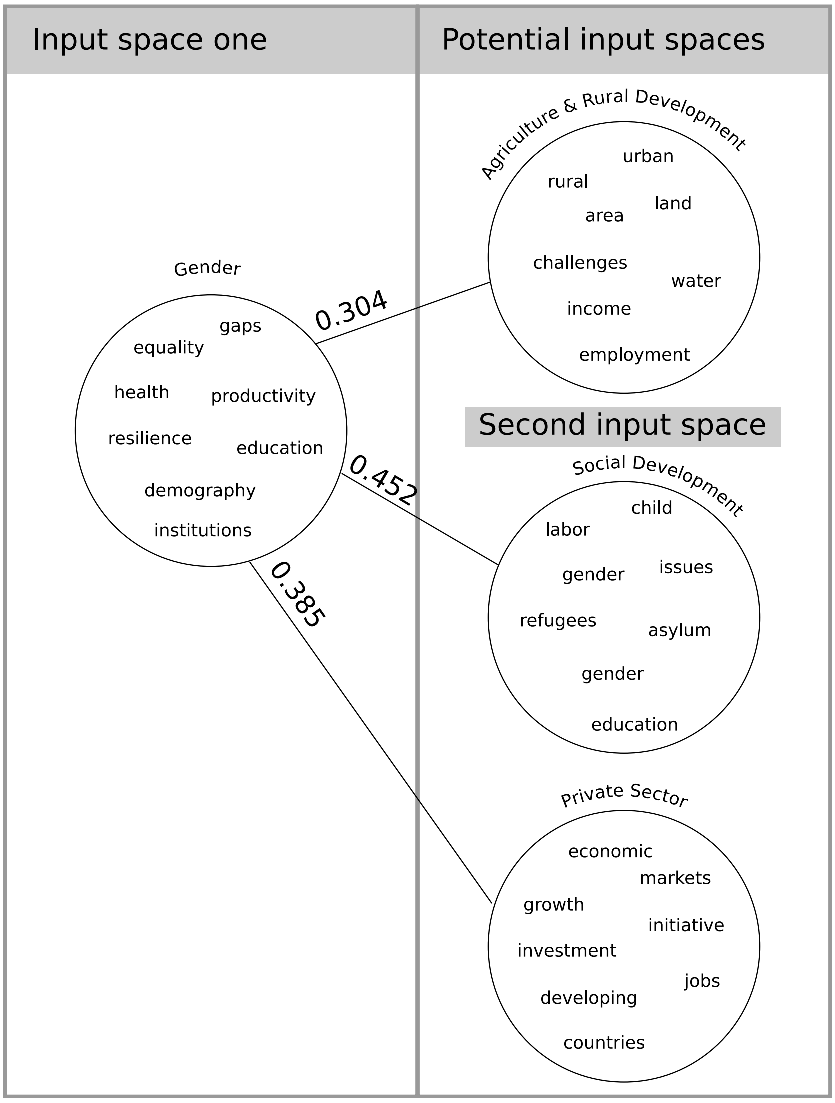


Figure 32: The process followed to explore potentially compatible data sets via *bisociation*, using the Bison Measure.

4.4.4 Adding words from ConceptNet

Experiment three was an attempt to begin introducing *conceptual blending* processes. By introducing queries from the semantic dictionary, ‘ConceptNet’, selective projection and elaboration was introduced. The experiment is not a full implementation of conceptual blending; It misses aspects such as divergent production, and iteration, and is a simplification of the process. The blend itself is also simple as the Bison measure is still performed. A more complete implementation of *conceptual blending* could introduce other forms of blending such as the computational metaphor implementation of the Sapper algorithm.

'ConceptNet' was introduced (expanding the generic space of the blend), in preparation for the introduction of further blending techniques. 'ConceptNet' was used to add words to First input space and the other potential spaces based on attributes and relationships such as, 'IsA', 'HasA', 'AtLocation', 'HasProperty', 'MadeOf', and others. The process followed is the same as that in experiment one and two (32) except that before running the blend the *bag of words* representing each input space is expanded by 'ConceptNet'. For each word in the original *bag of words* a request is made to 'ConceptNet' and the resulting attribute is added to the *bag of words*.

To make this concrete, if the *bag of words* contains the word 'labor', a query is sent to 'ConceptNet' for 'labor'. The result of the query contains the relationship ,'*unemployed* SimilarTo *out of work*'. From this relationship the phrase 'out of work' is broken into words and stop-words are removed so that 'out' and 'work' are added to the *bag of words*.

lead out

Having described the prototypes used to explore *variable choice*, attention is now turned to the design of the *aesthetics* prototype.

Aesthetics

lead in

The next Section describes an initial attempt to build a prototype that explores using *bisociation* and computational creativity techniques that target the *aesthetics* stage of the graphics pipeline.

4.5 Prototype design : Aesthetics

lead in

The present section begins by describing the creation of a visualisation based on the data, without any blending present. The visualisation is then cloned and embellished using *conceptual blending* techniques. The discussion of this second part of the prototype begins in Section 4.5.10.

intro

Recall from Section 2.6.3 that aesthetics are those elements of the visualisation relating to perception, beauty, taste and artistic criteria (Wilkinson, 2006). Aesthetics are an compelling target for exploring computational creativity since there is a relationship to art and beauty, albeit restrained to remaining within constraints that retain the conveyance of information. Aesthetics also have storytelling potential and storytelling featured strongly in the literature.

target question

The prototype targeted the question brought up in Section 3.3, namely, 'Can *conceptual blending* help with image choice?'. The prototype introduced a second conceptual space and attempted to use the resulting conceptual blend to add image based aesthetics to the visualisation. The prototype was designed as an example of 'combinatorial creativity' using a blend.

proto without blend

As mentioned in the method section (Section 4.1.4), the plan was to build a prototype that produces visualisations for a pre-chosen data set for pre-chosen graph types that can be used for comparison. In this section, this initial visualisation against which the altered visualisations can be compared will be referred to as the base prototype. The prototype will then be extended to perform a subset of the criteria required of *bisociation* and *conceptual blending*.

choice of data

Considering the attributes in Table 6, the D3 example datasets was chosen as suitable. The D3 examples already existed for each dataset and these examples were useful as a starting point for the prototype. The datasets are in the public domain.

The architecture common to both prototypes is presented first, with brief justifications for the choices (Section 4.5.1). Section 4.5.2 is dedicated to conveying how the gap between data and suitable graphic representations was bridged. The base prototype is presented next (Section 4.5.9), followed by the blending prototype in Section 4.5.10. The blending prototype will from now on be referred to as, 'VisBrew'.

4.5.1 General Architecture

D3 justification

The visualisation was designed using the D3 JavaScript framework ('D3.js', 2018). D3 was used to generate the graphic user interface (referred to here as the view). The prototype was designed as a web application. D3 was chosen due to it being a well maintained and recent framework, and due to the fact that it is very flexible in terms of graphics manipulation. The flexibility is a result of the framework directly manipulating HTML and SVG using JavaScript. This flexibility does come with overhead, so the prototype used predefined D3 visualisation templates for bar charts and line charts. A subset of existing bar charts and various line charts were pre-chosen. The visualisation types were chosen based on their simplicity and scope for playing with aesthetics such as height, texture, colour and labels. The grammar of graphics in D3 (Hunter, 2016) was abandoned as an option because it hasn't been maintained for a while and due to some missing features, such as chart labels.

Java justification

Java provided the web server, was used to code the logic, provided access to data sources and drove the navigation. The Java coordinated the required stages of the visualisation pipeline. Java was chosen because it is easier to find, and make use of, existing word natual language processing libraries, if needed, and to programmatically make calls to 'ConceptNet' and 'Wikipedia'. This would have been far harder to implement and debug in a loosely typed scripting language like JavaScript.

MVC

The architecture made use of a commonly occurring software design pattern, wherein the view is connected to, but independent of, the logic and the navigation. This particular reusable solution for implementing user interfaces, is referred to by programmers as the model-view-controller pattern (Gamma, 1995). The view was coded in D3 and JavaScript, and the controller and model were implemented in Java. The architecture of the initial visualisation and the extended visualisations that attempt to demonstrate *conceptual blending* was the same and is illustrated in Figure 33.

VizAssist justification

The initial visualisation was based on the program VizAssist (Bouali et al., 2015) (a version of which is available for demonstration online ('VizAssist - Your visualization Web assistant', 2018)). VizAssist was chosen since VizAssist demonstrates how to use the user's choice of priorities within the data, to choose how to present the attributes in a visualisation. It further demonstrates how to connect this process to an artificial intelligence algorithm - in their case a genetic algorithm - and demonstrates how to score the result. The score provides the genetic algorithm with fitness score and therefore heuristics to drive evolution of the genetic algorithm's population. VizAssist, and the programs it is based on, make use of Cleveland and

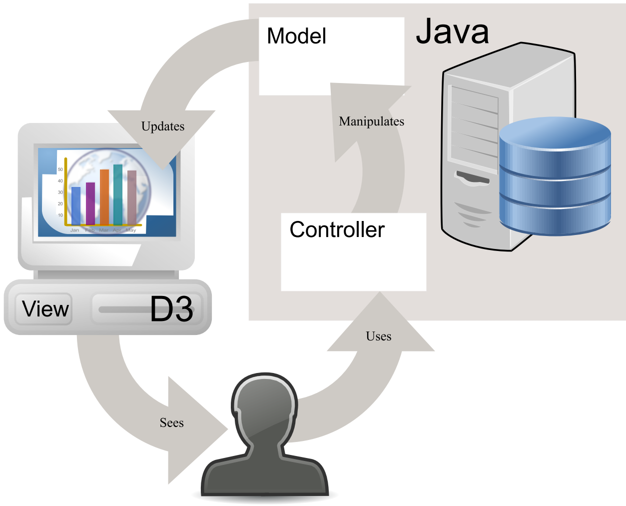


Figure 33: The architecture of the base prototype. Java was used for the controller and model and D3 and JavaScript were used for the view.

McGill (1984)'s hierarchy and Kosslyn's rules (Y. Zhu, 2007). These were discussed in Section 2.6.4, when the literature covering measuring visualisations was presented. How this is done is presented in detail in the next section.

4.5.2 Architecture: Bridging the gap between data and a suitable graphic representations

Intro

We know from Cleveland and McGill (1984)'s hierarchy, that some visual representations of data are more easily perceived than others. As a reminder, position along a common scale is perceived more accurately, than position on non-aligned scales. This, in turn, is perceived more easily than length, angle, area, volume, and colour (in that order). Colour is the least effective at conveying the magnitude of a number. These rules are leveraged to bridge the gap between what data attribute the user most wants represented in the visualisation and how it is presented. Four elements are used to bridge the gap between what the user wishes to visualise and how the visualisation is chosen and scored.

These elements are:

1. The data type of the attributes the user wishes to visualise.
2. The data types the visualisation type is capable of representing.
3. What attributes the visualisation type has at it's disposal to present each data type.
4. Which attributes the user is most interested in seeing in the visualisation.

This section describes these four elements, and explains how they are used to match the data to a suitable representation.

4.5.3 The data type of the data attributes

Data attr. types

The attributes of the 'Iris' data set are, 'sepal length in cm', 'sepal width in cm', 'petal length in cm', 'petal width in cm' and 'Name'. Data attributes can be classified into three data attribute types, namely, quantitative, ordinal and nominal. Quantitative data attributes are numerical, whereas ordinal data attributes are categorical in nature, and divide the data into sets. Nominal attributes –like quantitative data attributes – can be ordered, and have size; But, they can also be represented in a categorical manner. Quantitative, ordinal and nominal data have slightly different ordering when it comes to perceptual tasks (Mackinlay, 1986). For example, colour scores much higher for nominal values than it does for quantitative values, when scored for perceptual significance.

In the 'Iris' data set, 'Name', categorises the data into a class, based on the type of Iris, and is therefore nominal. The other four attributes are quantitative in nature.

4.5.4 The data types the visualisation type is capable of representing

Visualisation types

The number of attributes the user wishes to visualise and whether those attributes are quantitative, ordinal or nominal determines what visualisation types can be used. As an example of this, a simple histogram is only able to chart one attribute at a time (or some composition of attributes) and can only represent quantitative data. Illustrating multiple attributes would require the display of multiple histograms. On the other hand, a stacked histogram, or a simple bar chart, that makes use of multiple colours and a key/legend, is capable of representing nominal attributes against associated quantitative data. Obviously this differs for each visualisation type. These rules are pre-defined and programmed into both prototypes.

4.5.5 What attributes the visualisation type has at it's disposal to present each data type

Visualisation type avail attributes

Each visualisation type also has rules that indicate if it has facility for x-position, y-position, symbol, size, colour, texture, angle, slope, area, tooltip and so on. Let's refer to these as the visualisation type's attributes, sometimes referred to as visual variables. These are visual elements in the graphic that change based on the data. Again, this differs from type to type. A histogram can only represent quantity, which manifests as bar height in the histogram. It's only attribute, therefore is y-position. A Scatterplot on the other hand can make use of x-position, y-position, symbol, size (of symbol), colour (of symbol) and texture (of symbol). Of course there are different templates for Scatterplots and one Scatterplot may make use of all of these attributes, while another only uses x-position, y-position, and colour.

vis types scores

Visualisation types that are able to present every attribute the user wishes to see are scored higher. Visualisation types that are only able to show some of the attributes requested are still allowed, but are penalised.

4.5.6 Which attributes the user is most interested in seeing in the visualisation

After the system knows which data set the user wished to visualise, it presents the attributes of the data set to the user and asks the user to give each a quantitative value out of one hundred. This value is used to order the attributes. An attribute with a higher value than another is considered higher priority in the visualisation.

Since the user is allowed to prioritise which attributes they would like visualised, the attributes the user is least interested in are left out of any visualisation type that is unable to present all the data.

4.5.7 How they are used to match the data to a suitable representation

VizAssist scores

The rules and scoring use Bertin's perceptual properties of visual variables. The following Table 7, adapted from Meirelles's book, demonstrates how the scoring was used as a fitness function for the genetic algorithm (Meirelles, 2013). The darker the attribute, the more the characteristic contributes to visual perception. If one then assigns a score based on this colouring, with three being the highest and 1 being the lowest, then one has a way to score a visualisation based on these attributes.

justify subset

The table presented here is a subset of the table in Meirelles's book. This was in order to make the project manageable and keep things simple.

Point Line Area	quantitative	ordered	selective	associative	dissociative
Variables of the image					
2 Dimensions (x, y)	3	3	3	3	1
Size	3	3	3	1	3
Value	1	3	3	1	3
Differential variables. The ability					
Colour	1	1	3	3	1
Orientation	2	2	3	3	1
Texture	2	2	3	3	3
Shape	1	1	3	1	1

Table 7: Summary of the scoring that determines which visualisation attributes are mapped to which. Scoring is based on Bertin's perceptual properties of visual variables (also called attributes).

Note that the table is in agreement with Cleveland and McGill (1984)'s hierarchy, rows higher in the table are higher in this hierarchy and garner higher scores. So same scale needs to score higher than differing scale, needs to score higher than position, needs to score higher than length, needs to score higher than angle, needs to score higher than area, needs to score higher than volume, needs to score higher than colour. Texture, colour, orientation and shape give the same visibility (Bertin, 1981). The meaning of the attributes presented in the table are provided in Figure 34.

4.5.8 An illustration of how this works

example

To illustrate how this works, let's say the user has chosen the iris data set, and wishes to visualise sepal length and width as well as the iris name. They have given an importance of 80 to sepal length and 50 to iris name and sepal width. Since the most important attribute the user wishes to visualise is sepal length which is quantitative, the prototype immediately eliminates all the visualisation types that are incapable of representing quantitative data. The iris name is ordinal (or categorical), and as such, charts that are unable to represent ordinal data are penalised in terms of score. Visualisation types with enough visualisation

Quantitative A variable that is quantitative can be interpreted numerically (as opposed to a nominal value).

Ordered The variable can be ordered, and if it is ordered, there is no need for a legend in order to understand the data. All the variables of the image have this attribute. Orientation and texture have it to a lessor extent.

Selective If a variable is selective, the variable can be used to distinguish among areas or lines (Bertin, 1981). So for example, every variable (size, colour, texture, etc.) in Table 7, can be used to distinguish one variable in the data, from another variable in the data.

Associative Changing the value of the associative variables does not change their visibility.

Dissociative Changing the size, value or texture of a variable changes it's visibility. For example the number of colours that can be perceived shrinks as the size diminishes.

Figure 34: The meaning of the attributes presented in the Table 7.

attributes (colour, position, size etc) to be able to represent both quantitative values and the ordinal are given higher scores. The user is presented with the top scoring visualisation types and is asked to choose the ones they like.

For our example, let's assume the user has chosen a bar chart that makes use of colour, height of the bar (ie position-y) and a labelled legend to associate the colour to the nominal. The template for this particular visualisation type (a bar chart) has two available visualisation type attributes. One of those visualisation type attributes (colour) can only be used to represent nominal attributes, since it has a grouping function, and the other (position-y) is unable to represent nominal types since position is quantitative and can therefore only be used to represent quantitative data attributes.

As an aside, another bar chart could have the facility to use colour to represent quantitative amounts, it depends on the D3 template that is used. Hue and saturation can also represent quantitative values.

At this point the system has calculated four ordered lists for each visualisation type that hasn't been eliminated. The four lists are as follows:

1. The desired nominal and ordinal attributes the user wishes to visualise, ordered most important first (as ranked by the user)
2. The desired quantitative attributes the user wishes to visualise, ordered most important first (as ranked by the user)
3. The attributes the visualisation type has at it's disposal for presenting nominal and ordinal data attribute types ranked according to Table 7 and ordered largest ranking first
4. The attributes the visualisation type has at it's disposal for presenting quantitative data attribute types ranked according to Table 7 and ordered largest ranking first

There are now two quantitative lists which can be paired with each other. The two highest scoring items in the two lists are assigned to each other, and then the next highest scoring pair and so on. The same is done for the other two lists.

In our scenario above, the nominal/ordinal list as ranked by the user only contains the iris name. The bar chart the user chose only has one way to represent nominal data (colour combined with a legend). Colour is paired to iris name. When rendered, a colour is created for each unique nominal and a legend is added to the bar chart showing each colour next to each iris name.

The second list in our scenario contains sepal length and sepal width. Since the user prioritises sepal length, it appears first in the list. The highest item in visualisation attributes quantitative list, according to Table 7, is position-y. Sepal length is therefore paired with position-y. When the visualisation is rendered, sepal length is the data attribute used to determine the height of the bars and is placed into the bar with the associated iris name. Sepal width on the other hand is discarded as there are no remaining visualisation type attributes for the bar chart in the example presented.

VizAssist GA

The reader may be wondering at this point how VizAssist's genetic algorithm, generated and mutated visualisations for a chosen data set. The answer is, that the initial choice of data type, and applicable visualisation types, and prioritisation of the data attributes by the user was used to generate the starting population. The genetic algorithm created a population using only the chosen visualisation types against the user's chosen prioritisation. The algorithm then used mutation, to alter the numeric priorities and crossover to swap the the visualisation types. The techniques described in this section were used to calculate each populations fitness, with the fittest populations generating the next population. The highest population at the end of this process was then presented to the user. VizAssist also allows the user to choose whether each attribute is nominal, ordinal or quantitative, since some attributes can be both. This is not used here for simplicity.

lead out

Having described how a data set can be mapped to a visual representation, we now describe the prototypes.

4.5.9 Architecture: Initial visualisation prototype

base overview

The base prototype was designed to walk the user through choosing a dataset, choosing what aspects of the data visualise and then selecting an appropriate visualisation.

The program execution was developed as follows and is illustrated in Figure 35:

1. The user is presented with a list of the available data sets and chooses one of them.
2. The system presents the user with the attributes of the chosen dataset. The user chooses which attributes they wish to visualise by adjusting a slider. The user can choose some, or all of the attributes.
3. The system determines from the chosen data set which types of visualisations are appropriate for displaying the chosen attributes and presents them to the user. The user chooses some of the visualisation types and clicks submit.
4. The system presents the user with the attributes chosen at step 2 and asks the user to indicate the importance of each attribute by scoring each attribute out of 100. A score of fifty indicates a neutral importance and a higher score indicates that the user would like that particular attribute to feature more predominantly.
5. The system uses the data set to visual mapping described in the previous section and renders the six highest scoring visualisations, alongside their score.

Note, that the reason more than one non-blended visualisation is presented in the base prototype, is for comparison with the blended results. This is because the models for scoring creativity assume that there is no one correct answer and frequently score collections of results. This discussion on multiple correct answers appears in Section 2.6.4.

To make this more concrete, let's suppose the user chooses the famous 'Iris' data set (which was mentioned previously in Section 4.3.1). The program flow would go something like this:

1. The user is presented with a list of the available data sets and chooses 'Iris' (Figure 36a).
2. The attributes of the 'Iris' dataset are, 'sepal length in cm', 'sepal width in cm', 'petal length in cm', 'petal width in cm' and 'Name'. These five attributes are presented to the user in a manner that allows the user to adjust the sliders to indicate how important each attribute is. The user clicks submit (Figure 36b).
3. The system needs to determine which predetermined visualisation types are suitable for visualising the chosen attributes for the chosen data set. The system considers whether the chosen attribute is numeric or nominal in nature and narrows the available list of visualisation types (Figure 37a).
4. All variables were equally scored for importance, but because the only available visualisation type is a Histogram, only one of the attributes is chosen for visualisation(Figure **??**).

4.5.10 Architecture: VizBrew

lead in

This section present how the blending was introduced into the visualisation. The section starts by describing what the criteria were for the blend. The section briefly mentions an initial attempt at a *bisociation* (that was not able to produce anything meaningful), before going on to present a different blend that became the final prototype.

Change vis based on the four elements that bridge data and representation

Ideas

1) data attributes Can add new ones? maybe Can blend data sets

2) vis type available capabilities

a) Change symbol based on blend b) Change colours based on rules about things found in concept net cold-> blue etc metaphor c) Change line width? d) Choose texture based onflickr

3) Affect data attribute importance based on result of blend or some or other feature found in blend

4) Affect scoring of color, position, texture etc based on result of blend

The prototype extends the base prototype, and adds a 'ConceptNet' query service, a graphic query service, a blending method and the ability to use the results from the blend in the visualisation. The program takes as input a

The graphic service either queries Flickr for photographs or openclipart for scalar vector graphics clipart.

blend evaluation

The blending itself was not measured with any advanced criteria (such as Ritchie's criteria) as the prototype was still very exploratory. Some of the criteria demonstrating techniques of *conceptual blending* are apparent from the prototype's design. The following traits are present:

1. *ConceptNet* provided divergence from the 'IsA' relationships

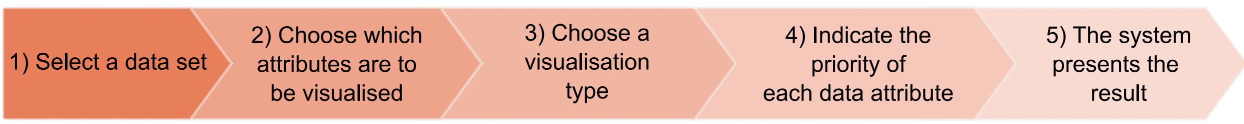
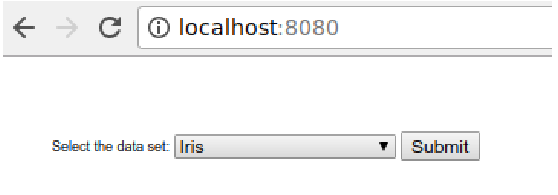
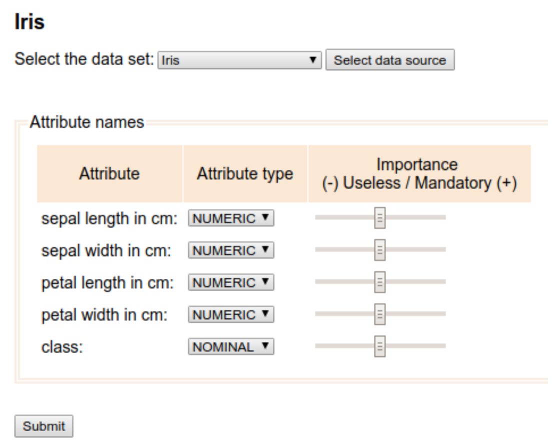


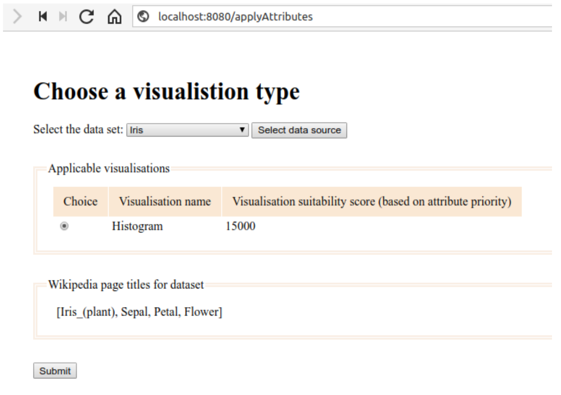
Figure 35: The process the base prototype uses to walk a user through visualising a data set.



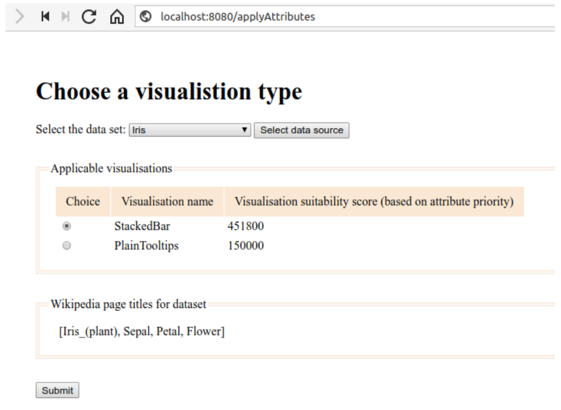
(a) The starting page of the prototype presents the user with a predefined list of datasets.



(b) The prototype presents the user with the attributes of the datasets and asks the user to choose how important each variable is to them.



(a) The prototype presents the user with the visualisation types that are suitable based on which variable where chosen as important. In this case a histogram.



(b) The prototype presents the user with the visualisation types that are suitable based on which variable where chosen as important. In this case a histogram and a bar chart with tooltips.

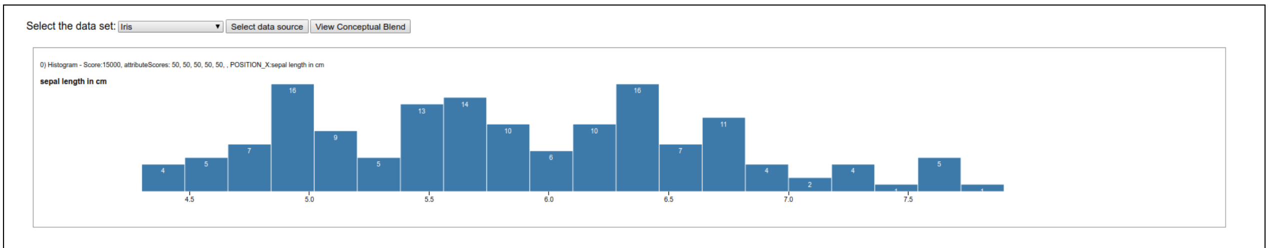


Figure 38: The prototype presents the user with the visualisation using the chosen chart type.

2. The Wikipedia search provided second conceptual spaces

3. The is a blend that occurs between the dataset conceptual spaces and the other pages found through the search on Wikipedia for the 'IsA' pages.

4. The process can be repeated which proves how it came to the blends found.

lead in

The next Section will discuss how choices were made about what was going to be updated in each visualisation.

4.5.11 Updating visualisations with blending results

restrict to aesthetics

In keeping with the limitations discussed in Section 1.5, no attempt is made to explore every possible change that could be made to every visualisation type. A subset was used. Since the focus is on the aesthetics stage of the pipeline, rules are restricted to the visual elements including, shape, position, length, angle, size, categories, colour, texture, and dimensions (Refer to Section 2.6.3. The resulting rules are used to alter the aesthetics of the visualisations generated in the first stage of the application.

aesthetics in cNet

A brief exploration of the 'ConceptNet' revealed that some of the rules restricted to aesthetics can actually be identified by 'ConceptNet'. No attempt was made to find these rules programmatically. The exploration was performed by querying 'ConceptNet' for the paths starting with words describing aesthetics.

elaborate/eg.

As an example, starting with the aesthetic keyword, 'shape', and limiting the length of the path to depth two, the result contains the entries illustrated in Table 8.

aesthetics rules+available

The prototype uses Wikipedia ('Wikipedia (en)', 2018) and Openclipart ('Openclipart', 2016) so the rules are further restricted to data which can be fetched from these two sources, Namely, text, images, and clipart.

name	start edge	relation	end edge	weight	relation	end edge	weight
shape	/c/en/shape/n	/r/IsA	/c/en/attribute/n	2.0	/r/IsA	/c/en/abstraction/n	2.0
shape	/c/en/shape/n	/r/IsA	/c/en/concretism/n	2.0	/r/IsA	/c/en/representation/n	
shape	/c/en/shape/n	/r/Synonym	/c/en/form/n	2.0	/r/Synonym	/c/en/class/n	2.0
shape	/c/en/shape/n	/r/Synonym	/c/en/form/n	2.0	/r/Synonym	/c/en/shape/n	2.0
shape	/c/en/shape/n	/r/IsA	/c/en/attribute/n	2.0	/r/IsA	/c/en/abstraction/n	1.0
shape	/c/en/shape/n	/r/IsA	/c/en/attribute/n	2.0	/r/RelatedTo	/c/en/noun	1.0
shape	/c/en/shape/n	/r/IsA	/c/en/attribute/n	2.0	/r/RelatedTo	/c/en/decorate	1.0
shape	/c/en/shape/n	/r/IsA	/c/en/attribute/n	2.0	/r/RelatedTo	/c/en/colour	1.0
shape	/c/en/shape/n	/r/Synonym	/c/en/form/n	2.0	/r/HasContext	/c/en/geometry	1.0
shape	/c/en/shape/n	/r/Synonym	/c/en/form/n	2.0	/r/RelatedTo	/c/en/plane	1.0
shape	/c/en/shape/n	/r/Synonym	/c/en/form/n	2.0	/r/RelatedTo	/c/en/ordinal_number	1.0
shape	/c/en/shape	/r/RelatedTo	/c/en/form	1.418	/r/CapableOf	/c/en/change_shape	1.0
shape	/c/en/shape	/r/RelatedTo	/c/en/form	1.418	/r/RelatedTo	/c/en/fill	0.507
shape	/c/en/shape/n	/r/RelatedTo	/c/en/name	1.0	/r/RelatedTo	/c/en/label	3.569
shape	/c/en/shape	/r/RelatedTo	/c/en/square	2.154	/r/IsA	/c/en/rectangle/n	1.0

Table 8: Partial results for a 'ConceptNet' query, starting with the aesthetic keyword, 'shape', and limiting the length of the path to depth two.

The following, non-exhaustive, set of rules can be inferred by a human from Table 8:

1. Shape can be an abstraction
2. Shape can represent a form
3. Shapes can be decorated
4. Shapes can be changed
5. Shapes can be filled
6. Shapes can be labelled
7. Shapes are interchangeable with other shapes

Similarly, running the same query from the word, 'texture', returns the entries in Table 9.

name	start edge	relation	end edge	weight	relation	end edge	weight
texture	/c/en/texture/n	/r/IsA	/c/en/quality/n	2.0	/r/RelatedTo	/c/en/position	1.0
texture	/c/en/texture/n	/r/RelatedTo	/c/en/shape	1.0	/r/RelatedTo	/c/en/square	2.154
texture	/c/en/texture/n	/r/RelatedTo	/c/en/surface	1.0	/r/AtLocation	/c/en/geometry	2.0
texture	/c/en/texture/n	/r/RelatedTo	/c/en/shape	1.0	/r/IsA	/c/en/geometric_figure	2.0
texture	/c/en/texture/n	/r/RelatedTo	/c/en/shape	1.0	/r/RelatedTo	/c/en/triangle	1.478
texture	/c/en/texture/n	/r/RelatedTo	/c/en/shape	1.0	/r/RelatedTo	/c/en/circle	1.371
texture	/c/en/texture/n	/r/RelatedTo	/c/en/substance	1.0	/r/AtLocation	/c/en/container	1.0
texture	/c/en/texture/n	/r/RelatedTo	/c/en/surface	1.0	/r/AtLocation	/c/en/solid	1.0
texture	/c/en/texture/n	/r/RelatedTo	/c/en/text	1.0	/r/CapableOf	/c/en/fade	1.0
texture	/c/en/texture/n	/r/RelatedTo	/c/en/text	1.0	/r/CapableOf	/c/en/sequence_of_words	1.0
texture	/c/en/texture/n	/r/RelatedTo	/c/en/smoothness	1.0	/r/DerivedFrom	/c/en/smooth/a	1.0
texture	/c/en/texture/n	/r/RelatedTo	/c/en/image	1.0	/r/DerivedFrom	/c/en/imagemapping	1.0

Table 9: Partial results for a 'ConceptNet' query, starting with the aesthetic keyword, 'texture', and limiting the length of the path to depth two.

Again, it is possible to find replacement rules from Table 9, that can be used to make replacements in the visualization.

Similar rules can be established for hue, texture, position, image, saturation, size, tooltip, label, and so on.

Hue

1. One hue can replace or marry_another_color (Hues can be combined)
2. Two items can exchange hues
3. Hues can be replaced with grey
4. Hue can be darkened or lightened
5. Any area can get hue

Labels

1. Labels can be replaced with symbols
2. Labels can be notes
3. Labels can describe
4. Labels have a location (that can be moved)
5. Labels can change font (cursive)
6. Labels can be attached

rule subset choice

Position

1. X can be represented in other rationalize_organizational_units
2. X can be replaced by a symbol or another shape indicating size
3. X related to quantity and can be replaced with other quantities

Tooltips

1. Tooltips can be any shape
2. Tooltips can contain amounts
3. Tooltips can have extra information
4. Tooltips can contain detail
5. Any container can have a tooltip

A subset of these rules keeps the project size manageable. The rule subset was chosen by narrowing he choice to rules which could be easily used with the information that is already available. Rules easily implemented were selected. The type of data that can be retrieved from Wikipedia and Open Clipart are images and text and so rules that focused on images were chosen. In addition, the available attributes of the visualisation type are heeded.

final rules

The following rules are used.

1. Shapes are interchangeable
2. Shapes can be decorated
3. Texture can be applied to any shape or surface
4. Position X (Y) can be replaced by a symbol or another shape indicating size

D3 template aesthetics

The available visualisation types in VizBrew and their aesthetic attributes are

visualisation types	aesthetic attributes	embedded shapes	applicable rules
Histogram	POSITION_X, LABEL	rectangle	1, 2, 3
Parallel Chart	LABEL, POSITION_Y, COLOUR_HUE	line	1, 2, 3, 4
Plain Bar Chart with Tooltips	LABEL, POSITION_X, POSITION_Y	rectangle	1, 2, 3, 4
Stacked Bar Chart	LABEL, POSITION_X, POSITION_Y, COLOUR_HUE	rectangle	1, 2, 3, 4
2D Scatter Plot	LABEL, POSITION_X, POSITION_Y, SHAPE, COLOUR_HUE	symbol	1, 2, 3, 4

Table 10: Visualisation types and their attributes as used by the system. These types came from pre-existing D3 templates.

As discussed in Section 5.3, polymorphic relationships within 'ConceptNet' are much more prominent than other types of paths, such as attributes. It was noted that the polymorphic relationships in 'ConceptNet' can diverge. Using this knowledge – and the understanding that truly creative concepts both converge and diverge – it was decided to try a *bisociation* based on the polymorphic relationships within 'ConceptNet'. The isA relationships were used to make up a second conceptual space .

The procedure (illustrated in Figure 39) is as follows:

1. An initial visualisation of the data is generated. The method is described in Section 4.5.1.
2. Each dataset is assigned keywords describing the data.
3. These keywords are used to find all keywords in 'ConceptNet' with the relationship *isA*.
4. The keywords are also used to find pages on Wikipedia whose words become the first conceptual space.
5. The *isA* words found in step 3 are also used to search for Wikipedia pages
6. The words from each page found from searching for the *isA* words formed the potential second conceptual spaces.
7. A bisociation is then performed between the first conceptual space and each of the potential second conceptual spaces
8. The highest scoring bisociation becomes the chosen second conceptual space
9. The highest scoring words within the chosen bisociation are used to look up scalar vector graphic clipart on Openclipart.org
10. The keywords and graphic that are returned from Openclipart.org are used to make substitutions as described in Section 4.5.11.

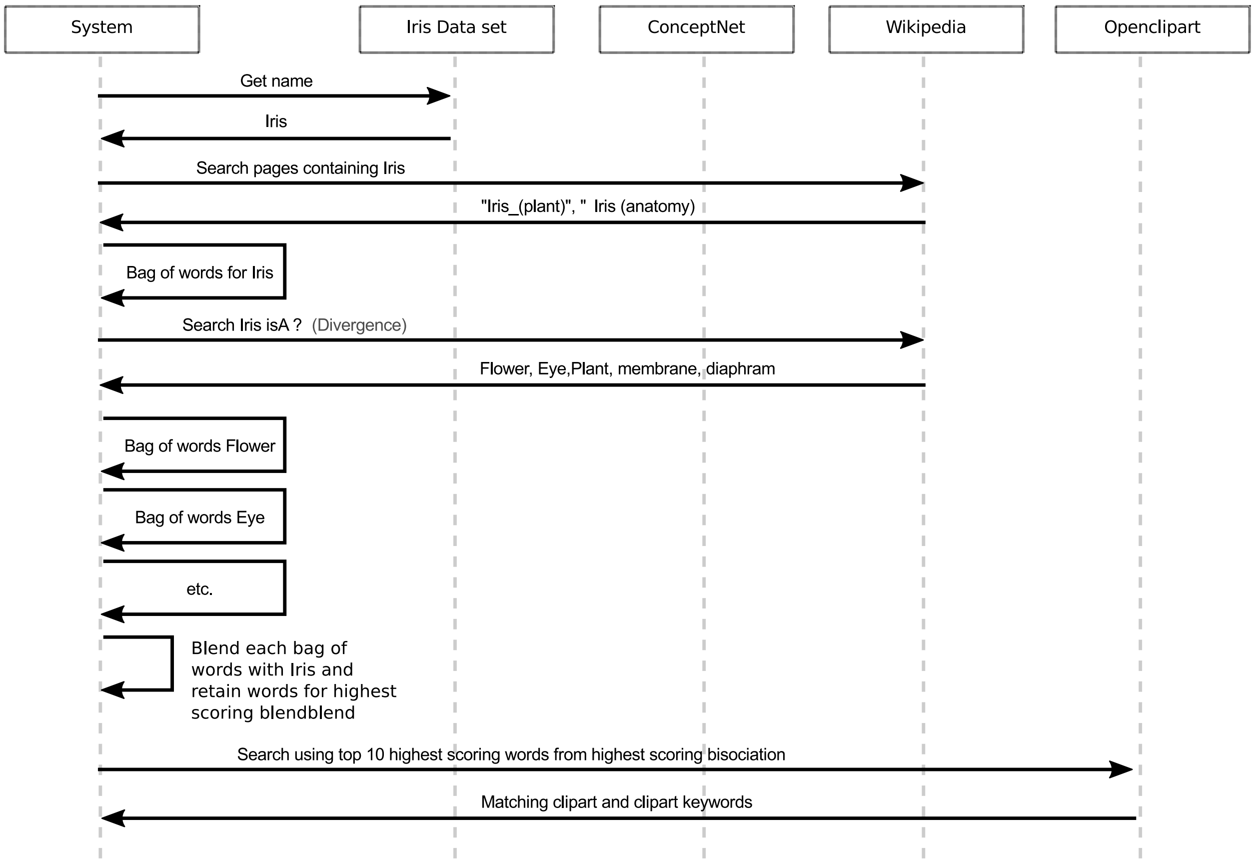


Figure 39: Sequence diagram indicating the process of finding a conceptual blend and using the result to find clipart.

5 Findings and analysis

5.1 Findings and analysis: variable choice

lead in

Recall that intention of the variable choice prototype was to find two different datasets that may be interesting to visualise on the same visualisation (Section 4.4). The results of a bisociation formed over the description of a chosen dataset against other datasets is presented first in Section 5.1.1, the results of the addition of the description of the variables in the dataset is presented in Section 5.1.3, and the augmentation with words from *ConceptNet* is described in Section 5.1.3.

5.1.1 Results: Bisociation over dataset descriptions

Topic Blending 'Private Sector' had the highest scoring Bison measure of all the input topics with a score of 0.611 matching the topic 'Trade'. Table 11 shows the top and bottom scoring results for 'Private Sector'. Table 12 contains the descriptions that were returned from World bank for these two topics. The input topic 'External Debt' was the lowest scoring *bisociation* for the topic 'Financial Sector' at 0.379.

Topic name	Bison measure score	shared keywords and tf-idf scores
Trade	0.611	trade(0.152,0.235) initiative(0.038,0.059) markets(0.027,0.041) developing(0.020,0.031) international(0.021,0.016) world(0.020,0.010) development(0.005,0.017) bank(0.010,0.016) data(0.002,0.004)
External Debt	0.442	database(0.063,0.027) sector(0.046,0.039) financial(0.031,0.027) statistics(0.018,0.030) markets(0.027,0.023) various(0.027,0.023) developing(0.020,0.017) world(0.020,0.006) countries(0.010,0.018) bank(0.010,0.009) data(0.002,0.006)
Financial Sector	0.436	financial(0.031,0.137) markets(0.027,0.087) sector(0.046,0.025) growth(0.024,0.039) economic(0.031,0.017) international(0.021,0.011) indicators(0.018,0.019) countries(0.010,0.011) development(0.005,0.006)
...		
Urban Development	0.294	people(0.023,0.026) international(0.021,0.012) sources(0.018,0.020) world(0.020,0.015) organization(0.014,0.015) development(0.005,0.006) data(0.002,0.003)
Poverty	0.257	growth(0.024,0.012) world(0.020,0.013) development(0.005,0.011) countries(0.010,0.011) bank(0.010,0.011) data(0.002,0.005)
Agriculture & Rural Development	0.218	organization(0.014,0.018) development(0.005,0.007) data(0.002,0.003)

Table 11: Highest scoring *bisociations* for the topic Private Sector using the Bison measure.

Indicator blending Recall that once the highest scoring potential topic has been calculated for a given input topic, the indicators of these two topics get queried. The indicators of the input topic and highest scoring potential topic are used to generate new conceptual spaces. The conceptual spaces consist of the *bag of words* created from each indicator's description. Each conceptual space created from the input topic's indicator's are then scored against each conceptual space created from the indicator of the highest scoring potential topic. The *bisociation* of two indicator's with the highest score are considered the final blended space and suggest variables that are potentially interesting between the two topics. The final

Topic name	Topic description
Private Sector	Private markets drive economic growth, tapping initiative and investment to create productive jobs and raise incomes. Trade is also a driver of economic growth as it integrates developing countries into the world economy and generates benefits for their people. Data on the private sector and trade are from the World Bank Group's Private Participation in Infrastructure Project Database, Enterprise Surveys, and Doing Business Indicators, as well as from the International Monetary Fund's Balance of Payments database and International Financial Statistics, the UN Commission on Trade and Development, the World Trade Organization, and various other sources.
Trade	Trade is a key means to fight poverty and achieve the Millennium Development Goals, specifically by improving developing country access to markets, and supporting a rules based, predictable trading system. In cooperation with other international development partners, the World Bank launched the Transparency in Trade Initiative to provide free and easy access to data on country-specific trade policies.

Table 12: Detail of the descriptions of the highest scoring *bisociation* for the input topic 'Private Sector'.

blended space also contains the words that the two highest scoring indicators have in common. Words with low tf-idf scores were discarded (less than 0.001). The number 0,001 was arbitrary; However, words with low scores are unlikely to be relevant unless the *bisociation* is attempting to simulate Guilford's divergent creativity. These words indicate why the two variables from the two topics were calculated as similar.

For 'Private Sector', the indicators scoring the highest *bisociation* with the indicators for 'Trade' were, 'Average time to clear exports through customs (days)' and 'New businesses registered (number)' (Table 13). 'Average time to clear exports through customs (days)' was an indicator on both topics. The source of the surveys for this indicator was the World Bank's Enterprise Surveys (enterprisesurveys.org).

The only word in common for the second highest scoring pair (Table 14) is the word, 'number', which is a little too generic to be useful. The next few highest scoring pairs of indicators also only have one word in common, but it is the word 'year' which is something that can be visualised. Another single scoring word, for the indicators, 'Average time to clear exports through customs (days)' and 'Ease of doing business index (1=most business-friendly regulations)' also hint at data variable manipulation of interest. Table 15 contains the results for the second highest scoring pair of indicators. It is only the fifth highest scoring pairs of indicators (Table 16) that finally match on more that three words. Many of the indicator pairs scored zero.

Indicator name	Indicator description	shared words and their tf-idf scores	Bison Measure
Average time to clear exports through customs (days)	Average time to clear exports through customs is the average number of days to clear direct exports through customs.	average(0.072,0.652)	0.752
Ease of doing business index (1=most business-friendly regulations)	Ease of doing business ranks economies from 1 to 190, with first place being the best. A high ranking (a low numerical rank) means that the regulatory environment is conducive to business operation. The index averages the country's percentile rankings on 10 topics covered in the World Bank's Doing Business. The ranking on each topic is the simple average of the percentile rankings on its component indicators.		

Table 13: Detail of the highest scoring *bisociation* for the indicator 'Average time to clear exports through customs (days)'.

Indicator name	Indicator description	words in common against tf-idf scores	Bison Measure
Average time to clear exports through customs (days)	Average time to clear exports through customs is the average number of days to clear direct exports through customs.	number(0.424,0.156)	0.615
New businesses registered (number)	New businesses registered are the number of new limited liability corporations registered in the calendar year.		

Table 14: Detail of the highest scoring *bisociation* for the indicator 'Average time to clear exports through customs (days)'

Indicator name	Indicator description	words in common against tf-idf scores	Bison Measure
Travel services (% of service exports, BoP)	Travel covers goods and services acquired from an economy by travelers for their own use during visits of less than one year in that economy for either business or personal purposes. Travel includes local transport (i.e., transport within the economy being visited and provided by a resident of that economy), but excludes international transport (which is included in passenger transport. Travel also excludes goods for resale, which are included in general merchandise.	year(0.236,0.070)	0.264
New businesses registered (number)	New businesses registered are the number of new limited liability corporations registered in the calendar year.		

Table 15: Detail of the second highest scoring *bisociation* for the indicator 'Travel services (% of service exports, BoP)'.

Indicator name	Indicator description	words in common against tf-idf scores	Bison Measure
Logistics performance index: Ease of arranging competitively priced shipments (1=low to 5=high)	Data are from Logistics Performance Index surveys conducted by the World Bank in partnership with academic and international institutions and private companies and individuals engaged in international logistics. 2009 round of surveys covered more than 5,000 country assessments by nearly 1,000 international freight forwarders. Respondents evaluate eight markets on six core dimensions on a scale from 1 (worst) to 5 (best). The markets are...	private(0.091,0.019) based(0.049,0.020) surveys(0.049,0.041)	0.190
Firms with female top manager (% of firms)	Firms with female top manager refers to the percentage of firms in the private sector who have females as top managers. Top manager refers to the highest ranking manager or CEO of the establishment. This person may be the owner if he/she works as the manager of the firm. The results are based on surveys of more than 100,000 private firms.		

Table 16: Detail of the highest scoring *bisociation* for the indicator 'Logistics performance index: Ease of arranging competitively priced shipments (1=low to 5=high)'.

5.1.2 Results: Bisociation over dataset descriptions and variable descriptions

Topic Blending 'Private Sector' was not the input space with the highest bison score, as was the case with experiment one. 'Private Sector' scored 0.375 against a different topic, namely, 'Education'. 'Trade' scored fifth highest with a score of 0.196.

Instead, 'External Debt' had the highest scoring Bison measure of all the input topics with a score of 0.464 matching the output topic 'Environment'. Table 17 shows the top and bottom scoring results for 'External Debt'. The additional words added to the topic input spaces significantly add to the amount of shared words; however, the tf-idf scores are not high. 'Private Sector' score last against the input topic 'External Debt' with a bison score of 0.187. Table 17 contains the descriptions that were returned from World bank for these two topics.

Topic name	Bison measure score	shared keywords and tf-idf scores
Environment	0.464	long-term(0.017,0.001) equivalent(0.003,0.007) defined(0.007,0.003) year(0.007,0.002) amount(0.006,0.001) change(0.001,0.006) bodies(0.005,0.004) excluding(0.001,0.004) excludes(0.000,0.003) percentage(0.002,0.003) bank(0.002,0.000) shows(0.000,0.002) during(0.001,0.002) those(0.000,0.002) include(0.002,0.001) primary(0.002,0.001) international(0.002,0.000)
Agriculture & Rural Development	0.374	current(0.018,0.001) long-term(0.017,0.001) specified(0.011,0.001) goods(0.011,0.001) dollars(0.009,0.001) u.s(0.009,0.001) defined(0.007,0.007) year(0.007,0.003) services(0.007,0.001) public(0.007,0.000) bodies(0.005,0.003) due(0.005,0.002) income(0.004,0.001) regional(0.004,0.001) value(0.002,0.004) agency(0.003,0.001) category(0.000,0.003)
Energy & Mining	0.371	currency(0.021,0.002) current(0.018,0.002) banks(0.014,0.003) amounts(0.013,0.001) dollars(0.009,0.002) u.s(0.009,0.002) private(0.008,0.001) stock(0.002,0.008) reserve(0.002,0.007) equivalent(0.003,0.007) services(0.007,0.000) public(0.007,0.000) commitments(0.006,0.001) economy(0.005,0.001) government(0.005,0.002) resources(0.001,0.005) due(0.005,0.002) covers(0.000,0.005) value(0.002,0.005) 25(0.002,0.005) projects(0.001,0.005) imports(0.002,0.004) investment(0.004,0.003) converted(0.001,0.004) service(0.004,0.001) agency(0.003,0.002)
Urban Development	0.320	currency(0.021,0.003) dollars(0.009,0.001) u.s(0.009,0.001) defined(0.007,0.008) services(0.007,0.001) public(0.007,0.001) statistical(0.001,0.007) national(0.001,0.006) percentage(0.002,0.005) bodies(0.005,0.004) due(0.005,0.001) residents(0.005,0.001) closer(0.001,0.003) converted(0.001,0.003) organization(0.003,0.001) local(0.001,0.003) bank(0.002,0.001) value(0.002,0.002) part(0.001,0.002) households(0.002,0.002) percent(0.002,0.001) include(0.002,0.000) refers(0.000,0.002) international(0.002,0.000) cost(0.002,0.002) resources(0.001,0.002) end(0.001,0.002) individuals(0.000,0.001) measure(0.001,0.001) having(0.000,0.001) available(0.001,0.001) includes(0.001,0.001) major(0.000,0.001) excluding(0.001,0.001)
Poverty	0.253	rate(0.001,0.027) take(0.001,0.017) income(0.004,0.015) agencies(0.012,0.001) account(0.002,0.011) private(0.008,0.002) public(0.007,0.002) official(0.005,0.004)
...		
Trade	0.199	principal(0.040,0.001) markets(0.002,0.020) repayments(0.020,0.001) current(0.018,0.004) cost(0.002,0.016) banks(0.014,0.002) export(0.007,0.013) services(0.007,0.013) amounts(0.013,0.001) agencies(0.012,0.006) goods(0.011,0.012) paid(0.011,0.000) economy(0.005,0.011) dollars(0.009,0.003) u.s(0.009,0.003) border(0.001,0.009) low(0.009,0.008) service(0.004,0.008)
Gender	0.184	principal(0.040,0.001) primary(0.002,0.032) 25(0.002,0.016) secondary(0.001,0.016) understanding(0.001,0.012) rate(0.001,0.011) percentage(0.002,0.011) private(0.008,0.003) expressed(0.001,0.007) year(0.007,0.002) official(0.005,0.007) public(0.007,0.002) commitments(0.006,0.001) cumulative(0.003,0.005) net(0.002,0.005) due(0.005,0.003) skills(0.001,0.004)

Table 17: Highest scoring *bisociations* for the topic External Debt.

Topic name	Topic description
External Debt	Debt statistics provide a detailed picture of debt stocks and flows of developing countries. Data presented as part of the Quarterly External Debt Statistics takes a closer look at the external debt of high-income countries and emerging markets to enable a more complete understanding of global financial flows. The Quarterly Public Sector Debt database provides further data on public sector valuation methods, debt instruments, and clearly defined tiers of debt for central, state and local government, as well as extra-budgetary agencies and funds. Data are gathered from national statistical organizations and central banks as well as by various major multilateral institutions and World Bank staff.
Environment	Natural and man-made environmental resources – fresh water, clean air, forests, grasslands, marine resources, and agro-ecosystems – provide sustenance and a foundation for social and economic development. The need to safeguard these resources crosses all borders. Today, the World Bank is one of the key promoters and financiers of environmental upgrading in the developing world. Data here cover forests, biodiversity, emissions, and pollution. Other indicators relevant to the environment are found under data pages for Agriculture & Rural Development, Energy & Mining, Infrastructure, and Urban Development.

Table 18: Detail of the highest and lowest scoring *bisociations* for the topic External Debt.

Indicator blending For 'External Debt', the indicators scoring the highest *bisociation* with the indicators for 'Environment' were, 'Access to electricity (% of population)' and 'PPG, IBRD (AMT, current US$)' (Table 19). 'Year' and 'data' where frequently the highest scoring tf-idf scores. It became clear that lower scoring words are more relevant and that words common when describing data should probably be removed with the stopwords.

'Methane emissions (% change from 1990)' and 'PPG, IBRD (AMT, current US$)' indicators scored 0.519 – the same as 'Other greenhouse gas emissions (% change from 1990)' and 'PPG, private creditors (AMT, current US$)' (Tables 20 and 21). This is another example of similar 'indicators' attaining close scores (as was mentioned in discussed in the general results when currency differences between indicators was discussed).

Indicator name	Indicator description	words in common against tf-idf scores	Bison Measure
Access to electricity (% of population)	Access to electricity is the percentage of population with access to electricity. Electrification data are collected from industry, national surveys and international sources.	international(0.079,0.231) data(0.057,0.137)	0.617
PPG, IBRD (AMT, current US$)	Public and publicly guaranteed debt outstanding from the International Bank for Reconstruction and Development (IBRD) is nonconcessional. Nonconcessional debt excludes loans with an original grant element of 25 percent or more. Principal repayments are actual amounts of principal (amortization) paid by the borrower in currency, goods, or services in the year specified. Data are in current U.S. dollars.		

Table 19: Detail of the highest scoring *bisociation* for the indicator 'Access to electricity (% of population)'.

Indicator name	Indicator description	words in common against tf-idf scores	Bison Measure
Methane emissions (% change from 1990)	Methane emissions are those stemming from human activities such as agriculture and from industrial methane production. Each year of data shows the percentage change to that year from 1990.	year(0.057,0.242) data(0.057,0.111)	0.519
PPG, IBRD (AMT, current US$)	Public and publicly guaranteed debt outstanding from the International Bank for Reconstruction and Development (IBRD) is nonconcessional. Nonconcessional debt excludes loans with an original grant element of 25 percent or more. Principal repayments are actual amounts of principal (amortization) paid by the borrower in currency, goods, or services in the year specified. Data are in current U.S. dollars.		

Table 20: Detail of the highest scoring *bisociation* for the indicator 'Methane emissions (% change from 1990)'.

Indicator name	Indicator description	words in common against tf-idf scores	Bison Measure
Other greenhouse gas emissions (% change from 1990)	Other greenhouse gas emissions are by-product emissions of hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride. Each year of data shows the percentage change to that year from 1990.	year(0.041,0.242) data(0.041,0.111)	0.491
PPG, private creditors (AMT, current US$)	Public and publicly guaranteed debt from private creditors include bonds that are either publicly issued or privately placed; commercial bank loans from private banks and other private financial institutions; and other private credits from manufacturers, exporters, and other suppliers of goods, and bank credits covered by a guarantee of an export credit agency. Principal repayments are actual amounts of principal (amortization) paid by the borrower in currency, goods, or services in the year specified. Data are in current U.S. dollars.		

Table 21: Detail of the highest scoring *bisociation* for the indicator 'Other greenhouse gas emissions (% change from 1990)'.

5.1.3 Results: Adding words from ConceptNet

Topic Blending The highest scoring input topics for Experiment three was not 'Private Sector' (per experiment one) or 'External Debt' (per experiment two). The previously high scoring topics were not even in the top four scores. Interestingly, the simple *bisociation* over topics, and the *bisociation* over topics plus indicators and *ConceptNet* were in closer agreement over the higher scoring topics than experiments one and two.

'Gender' had the highest scoring Bison measure of all the input topics with a score of 0.464 matching the topic 'Social Protection & Labor'. Table 11 'External Debt' scored tenth highest against the input topic 'Gender'.

The input spaces are much larger with approximately 15 000 extra words in each input space. This explosion of extra words would have been much more significant had an attempt been made to iterate or chain calls to *ConceptNet*. Only one lookup was made for each word in the original input space. *ConceptNet* was not called again to iterate or follow concept relationships. The words scored much higher in terms of tf-idf and the high scoring words are logical for the topics. For example for the top scoring topics for ‘Gender’ (*school* and *male*) had high scores against the topic ‘Social Protection & Labor’. For ‘Education’, the words, *age*, *education*, and *female* scored high. These words and their scores have been highlighted in Table 22.

Topic name	Bison measure score	shared keywords and tf-idf scores
Social Protection & Labor	0.464	school(0.031,0.096) 24(0.006,0.096) ages(0.018,0.087) 15(0.007,0.073) youth(0.004,0.055) share(0.001,0.051) male(0.026,0.048) female(0.023,0.032) students(0.013,0.003) rate(0.011,0.001) population(0.005,0.011) top(0.004,0.008) works(0.001,0.003) surveys(0.001,0.002) social(0.002,0.001) while(0.001,0.002) establishment(0.001,0.002) people(0.002,0.001) participation(0.001,0.001)
Education	0.434	age(0.033,0.094) education(0.044,0.041) female(0.023,0.038) primary(0.032,0.001) school(0.031,0.013) gender(0.022,0.003) educational(0.017,0.003) ratio(0.017,0.001) population(0.005,0.017) 25(0.016,0.014) 15(0.007,0.014) percentage(0.011,0.013) rate(0.011,0.002) literacy(0.010,0.001) 24(0.006,0.009) official(0.007,0.001) understanding(0.007,0.004) music(0.006,0.003) year(0.002,0.005) number(0.005,0.000) group(0.005,0.000) index(0.005,0.002) university(0.002,0.005)
...		
Trade	0.184	primary(0.032,0.001) completed(0.016,0.003) gross(0.008,0.000) official(0.007,0.001) core(0.002,0.006) level(0.006,0.000) index(0.005,0.006) high(0.003,0.005) number(0.005,0.001) surveys(0.001,0.005) net(0.005,0.002) completion(0.004,0.003) time(0.000,0.004) required(0.002,0.004) expected(0.004,0.001) reach(0.004,0.002) private(0.003,0.002) institutions(0.001,0.003) entering(0.003,0.001) ownership(0.001,0.003) based(0.002,0.002) indicates(0.002,0.001) calculation(0.002,0.001) business(0.001,0.002) sum(0.002,0.001) country(0.000,0.002) year(0.002,0.000)
Climate Change	0.169	primary(0.032,0.001) percentage(0.011,0.002) parity(0.010,0.001) gross(0.008,0.000) years(0.007,0.001) natural(0.003,0.006) population(0.005,0.000) group(0.005,0.000) net(0.005,0.001) expected(0.004,0.001) year(0.002,0.003) result(0.002,0.003) final(0.002,0.002) once(0.001,0.002) those(0.001,0.002) during(0.001,0.002) share(0.001,0.002) refers(0.000,0.002) sum(0.002,0.000) shown(0.002,0.001) relevant(0.002,0.001) resilience(0.002,0.002) people(0.002,0.000) while(0.001,0.001) includes(0.001,0.001) minus(0.001,0.001) divided(0.001,0.001)
Environment	0.168	primary(0.032,0.001) percentage(0.011,0.003) years(0.007,0.000) natural(0.003,0.006) level(0.006,0.001) population(0.005,0.002) access(0.001,0.003) final(0.002,0.002) during(0.001,0.002) based(0.002,0.002) year(0.002,0.002) those(0.001,0.002) definition(0.002,0.001) result(0.002,0.002) social(0.002,0.000) relevant(0.002,0.001) share(0.001,0.002) once(0.001,0.002) including(0.000,0.001) includes(0.001,0.001) total(0.001,0.001) excluded(0.001,0.001) refers(0.000,0.001)

Table 22: Highest scoring *bisociations* for the topic Gender.

Indicator blending

5.1.4 General discussion

The REST calls that fetch the indicators for each topic are paginated, and returned only fifty results at a time. Since the investigation was exploratory, the pagination was not used and only the first fifty results were used. Figure 31, shows the first couple of indicators for the topic ‘Trade’. There are 152 indicators for this topic

It was not entirely unexpected that a *bisociation* over just the topic description resulted in the same kind of problems experienced by natural language algorithms exploring microblogging text such as Twitter and Facebook Featherstone, 2013. The problems are due to the sparseness of the results which is due to the small amount of words. Adding the indicators to the topics and then introducing 'ConceptNet' increased the positivity of the scores, but did not always change the highest scoring topics. For example, for an input topic **Education** the highest scoring topic was always **Social Protection & Labor**. This was despite a Bison score of -0.129, 0.646, and 0.643 for experiments 1, 2, and 3, respectively. The simple *bisociation* was the least likely to agree with the other two methods. For example, for the topic **Social Protection & Labor** the highest scoring topic for the *bisociation* was **Energy & Mining**, but this topic was only the second highest score when indicators and conceptNet supplemented the keywords. In the latter cases, **Science & Technology** scored the highest. The highest scoring words were still interesting however. Under Labour, coal, fuels one would expect to discover keywords associated with **Labour** intensive industries, such as coal, oil, fuel and minerals as well as the keyword production. **Science & Technology** better matched the **Social Protection** side of the topic, with words such as **trademark**, **patent**, and **protection**.

The *bisociation*s producing the highest scoring indicators were not necessarily the most interesting. This was because the indicators sometimes only differed by the unit it was measured in (for example currency in Rands, versus currency in Dollars). The rest of the currency indicator description was worded almost the same, and as a result, they scored a very high bisociative score.

A high score when matching topics did not translate into a high score when matching indicators.

Adding results from 'ConceptNet' into the input spaces (selective projection) upped the count of matching words on topics but did this did not necessarily equate to high tf-idf scores for the words.

anomaly

The topic 'Millenium development goals' caused anomalies in the output, scoring very high over just one word. It turns out that the XML returned from the REST call made to World bank did not contain a description for this topic. The topic was therefore discarded in the discussion that follows. Refer to Figure 30.

Cosine and symmetry

After the initial data was extracted it became obvious that the results were asymmetric. That is, if topic *A* returned topic *B* as it's highest scoring result, not only did topic *B* not necessarily return topic *A* as it's highest scoring topic, but the scores were not the same. The experiments were rerun with the cosine measure, which is symmetric, in order to check these results. The cosine measure fixed the mismatch on the scores, but the asymmetry remained. If topic *B* was the highest scoring *bisociation* for topic *A*, it was frequently the case that some topic **C** scored highest on a *bisociation* when topic *B* was used as the first input space.

Tables 23 and 24 illustrate this for the input topic 'Gender' using the Bison measure. The relevant topics and scores are highlighted. Table 23 shows the (partial) results for the highest scoring *bisociations* when the chosen input topic is 'Gender'. Abandoning the anomaly mentioned above, it can be seen from the table that 'Social Development' is the highest scoring topic, with a score of 0.452. Table 24 shown the results for the input topic 'Social Development'. The score for 'Gender' is 0.464 – which differs from the previous score for 'Gender' – and it is only the third highest scoring topic for 'Social Development'.

Tables 25 and 26 illustrate a similar outcome for the input topic 'Gender' using the Cosine measure. As

Topic name	Bison measure score	shared keywords and tf-idf scores
Millenium development goals	0.467	development(0.011,0.112)
Social Development	0.452	gender(0.187,0.064) agency(0.022,0.026) statistics(0.012,0.015) education(0.012,0.015) bank(0.015,0.009) health(0.011,0.013) development(0.011,0.005) data(0.005,0.008) world(0.005,0.005)
Private Sector	0.385	database(0.022,0.063) business(0.053,0.038) economic(0.022,0.031) growth(0.017,0.024) world(0.005,0.020) statistics(0.012,0.018) bank(0.015,0.010) development(0.011,0.005) data(0.005,0.002)
Education	0.373	education(0.012,0.134) outcomes(0.027,0.057) statistics(0.012,0.027) economic(0.022,0.024) growth(0.017,0.018) bank(0.015,0.016) world(0.005,0.010) data(0.005,0.008)
External Debt	0.358	public(0.016,0.039) statistics(0.012,0.030) database(0.022,0.027) institutions(0.019,0.023) bank(0.015,0.009) data(0.005,0.006) world(0.005,0.006)
...		
Infrastructure	0.249	education(0.012,0.020) health(0.011,0.018) growth(0.017,0.014) data(0.005,0.003)
Social Protection & Labor	0.123	data(0.005,0.003)

Table 23: Highest scoring *bisociations* for the topic Gender using the Bison measure.

can be seen in the tables, the score (0.120) is now in agreement; however, ‘Gender’s’ highest scoring topic, ‘Social Development’, does not have ‘Gender’ as the highest scoring *bisociation*.

The results shown in Tables 23, 24, 25, and 26 are from experiment one. The behaviour was the same for all three experiments.

While Cosine Measure and Bison Measures, did not always agree on the top scoring Topics to regard as the second conceptual space, the order of the scores of the topics, when scored from highest to lowest, was similar.

Topic name	Bison measure score	shared keywords and tf-idf scores
Social Protection & Labor	0.530	labor(0.064,0.168) surveys(0.022,0.059) work(0.058,0.026) labour(0.032,0.042) ilo(0.032,0.042) force(0.032,0.042) works(0.032,0.042) often(0.026,0.035) social(0.015,0.020) organization(0.011,0.015) countries(0.009,0.012) international(0.009,0.012) data(0.008,0.003)
Health	0.466	health(0.013,0.104) united(0.067,0.077) nations(0.067,0.077) many(0.032,0.036) children's(0.032,0.036) fund(0.026,0.030) cover(0.019,0.022) countries(0.009,0.020) organization(0.011,0.013) data(0.008,0.005) here(0.006,0.007) world(0.005,0.006) development(0.005,0.005)
Gender	0.464	gender(0.064,0.187) agency(0.026,0.022) education(0.015,0.012) statistics(0.015,0.012) bank(0.009,0.015) health(0.013,0.011) development(0.005,0.011) data(0.008,0.005) world(0.005,0.005)
...		
Financial Sector	0.252	social(0.015,0.019) countries(0.009,0.011) international(0.009,0.011) here(0.006,0.008) development(0.005,0.006)
Agriculture & Rural Development	0.238	here(0.006,0.020) organization(0.011,0.018) data(0.008,0.003) development(0.005,0.007)

Table 24: Highest scoring *bisociations* for the topic Social Development using the Bison measure.

Topic name	Cosine measure score	shared keywords and tf-idf scores
Social Development	0.120	gender(0.187,0.064) agency(0.022,0.026) statistics(0.012,0.015) education(0.012,0.015) bank(0.015,0.009) health(0.011,0.013) development(0.011,0.005) data(0.005,0.008) world(0.005,0.005)
Private Sector	0.041	database(0.022,0.063) business(0.053,0.038) economic(0.022,0.031) growth(0.017,0.024) world(0.005,0.020) statistics(0.012,0.018) bank(0.015,0.010) development(0.011,0.005) data(0.005,0.002)
Education	0.040	education(0.012,0.134) outcomes(0.027,0.057) statistics(0.012,0.027) economic(0.022,0.024) growth(0.017,0.018) bank(0.015,0.016) world(0.005,0.010) data(0.005,0.008)
...		
Social Protection & Labor	0.000	data(0.005,0.003)

Table 25: Highest scoring *bisociations* for the topic Gender.

Topic name	Cosine measure score	shared keywords and tf-idf scores
Social Protection & Labor	0.162	labor(0.064,0.168) surveys(0.022,0.059) work(0.058,0.026) labour(0.032,0.042) ilo(0.032,0.042) force(0.032,0.042) works(0.032,0.042) often(0.026,0.035) social(0.015,0.020) organization(0.011,0.015) countries(0.009,0.012) international(0.009,0.012) data(0.008,0.003)
Health	0.154	health(0.013,0.104) united(0.067,0.077) nations(0.067,0.077) many(0.032,0.036) children's(0.032,0.036) fund(0.026,0.030) cover(0.019,0.022) countries(0.009,0.020) organization(0.011,0.013) data(0.008,0.005) here(0.006,0.007) world(0.005,0.006) development(0.005,0.005)
Gender	0.120	gender(0.064,0.187) agency(0.026,0.022) education(0.015,0.012) statistics(0.015,0.012) bank(0.009,0.015) health(0.013,0.011) development(0.005,0.011) data(0.008,0.005) world(0.005,0.005)
Education	0.106	education(0.015,0.134) united(0.067,0.040) nations(0.067,0.040) participation(0.053,0.047) surveys(0.022,0.040) statistics(0.015,0.027) organization(0.011,0.021) bank(0.009,0.016) world(0.005,0.010) data(0.008,0.008)
...		
Millenium development goals	0.001	development(0.005,0.112)

Table 26: Highest scoring *bisociations* for the topic Social Development.

The next section will elaborate on the success and shortfalls of the resulting prototypes. The evaluation of the prototypes against the chosen criteria will be presented, and the results discussed.

5.2 Findings and analysis: aesthetics

5.2.1 Results - the blend

divergence and conv

The location in the prototype of convergence and divergence was a little unexpected. The prototype was designed in a way that expected the divergence to come about from *ConceptNet*. Instead both divergence and convergence came from the Openclipart search. This is illustrated in Table 40 which shows the words found as *ConceptNet* IsA relations against the page titles that were returned from a Wikipedia search. Table reftable:irisBlendWithFlowerShows the highest scoring words from the highest scoring Wikipedia page .While *ConceptNet* words, such as diaphragm, and membrane diverge from from the concept Iris, the related Wikipedia pages whose words form potential conceptual spaces were eliminated as they did not score highest when the blend was run. There is some divergence that occurs when the top scoring Wikipedia page's words are used to search Openclipart. This is because the human tags added to the clipart, sometimes diverge from the graphic itself. This can be seen in Table 27 which contains a sample of the results from the search. To illustrate this Table 27's entry for the word flower, has a result that also contains children, circus and horse. These items of clipart have something in the graphic was related to flowers, such as the saddle on the elephant, which has an edge decorated with flowers. Some of the tags converge with what one would expect to find in an Iris conceptual space. Words such as leaves, pollen and picking (as in picking flowers) seem to belong.

Clipart technical

There were some limits to the use of scalar vector graphics (SVG) clipart. When used as SVG images, the items scaled but the results were blurry (as one would expect from scaled bitmaps). When the SVG was nested in the SVG visualisation, the browser could only handle a limited number of included files before throwing an error.

didnt work

An initial attempt with made to blend chart characteristics provided by a set of Wikipedia page describing the attributes of the chart, with the dataset description. The dataset description also consisted of provided Wikipedia pages describing the data. Conceptual spaces were made up from the words. One conceptual space from the dataset pages and one conceptual space for each visualisation type. The bisociation between the dataset and each visualisation type was performed and the the highest scoring bisociation determined the visualisation type. Unfortunately, the highest scoring words formed with this bisociation were not particularly relevant or meaningful in terms of contribution to the visualisation and so this prototype was abandoned.

infographics

It is acknowledged that the result of the prototype is probably more in the infographic category of visualisations rather than pure data visualisation.

iris IsA diaphragm	Matching Wikipedia page title
diaphragm	Diaphragm (birth control)
diaphragm	Diaphragmatic rupture
diaphragm	Diaphragmatic breathing
diaphragm	Diaphragm pacing
diaphragm	Diaphragmatic hernia
diaphragm	Diaphragm (optics)
diaphragm	Diaphragm pump
diaphragm	Diaphragm valve
diaphragm	Diaphragm (acoustics)

(a) Wikipedia pages matching a search for diaphragm.

iris IsA flower	Matching Wikipedia page title
flower.	Flower
flower	Flowering plant
flower	Flower-class corvette
flower	Flower Boy
flower	Flowers for Algernon
flower	Flower Drum Song
flower	Flowers in the Dirt
flower	Flower Mound, Texas
flower	Flowers of the Prison
flower	Flowers in the Attic (2014 film)

(b) Wikipedia pages matching a search for flower.

iris IsA membrane	Matching Wikipedia page title
membrane	Membrane
membrane	Membrane potential
membrane	Membrane transport protein
membrane	Membrane gas separation
membrane	Membrane bioreactor
membrane	Membrane distillation
membrane	Membrane protein
membrane	Membrane technology
membrane	Membrane transport
membrane	Membrane progesterone receptor

(c) Wikipedia pages matching a search for membrane.

Highest scoring words	TD-IDF score of word
flowers	0.04197152357711407
pollen	0.03082099399434306
flower	0.02690690917978509
flowering	0.02054732932956204
plants	0.018429389849167865
species	0.01349065969580521
plant	0.01339221379699548
floral	0.01219997678942746
whorl	0.011327594260048285
color	0.009551966355052566

(d) The strongest blend was with the Flower Wikipedia page which achieved a bison score of 0.6264376449022712. The table lists the highest scoring words from this blend.

Figure 40: Example of Wikipedia pages matching a search for the word returned from an IsA query in *ConceptNet* for the Iris dataset and the resulting scoring.

5.2.2 Results - applied to the visualisation

Background images

Search word	tags	image url
flowers	floral, flower, flowery, leaf, leafy, leaves, plant	https://openclipart.org/download/304716/1533192841.svg
	botanical, floral, flower, Flowers, leaf, leafy, leaves, petal, plant, remix+278391, rose, Wild for Flowers	https://openclipart.org/download/304693/1533013185.svg
	child, children, country, countryside, flower, kid, picking, rural, scene, Semi-Realistic People	https://openclipart.org/download/304584/1532680609.svg
	Circus, Female, flowers, Girl, Horse, isolated, lady, Poster, remix+224457, ride, roses, Semi-Realistic People, Vintage, woman	https://openclipart.org/download/303235/1529040492.svg
pollen	floral, flower, flowery, leaf, leafy, leaves, plant	https://openclipart.org/download/304716/1533192841.svg
	botanical, floral, flower, Flowers, leaf, leafy, leaves, petal, plant, remix+278391, rose, Wild for Flowers	https://openclipart.org/download/304693/1533013185.svg
	child, children, country, countryside, flower, kid, picking, rural, scene, Semi-Realistic People	https://openclipart.org/download/304584/1532680609.svg
	Flowers, FlowerMarket	https://openclipart.org/download/303564/1529730388.svg
	antique, botanical, floral, flower, leaf, leafy, leaves, magazine, petal, plant, vintage, yellow, upright, ixia	https://openclipart.org/download/302713/1527826025.svg
	animal, animals - cute, bee, Bees, bug, bumblebee, cartoon, children, environment, funny, happy, hive, honey, insect, kids, kindergarten, pollen, remix+3243, remix+174840, spring, summer	https://openclipart.org/download/293996/bee04.svg
flower	floral, flower, flowery, leaf, leafy, leaves, plant	https://openclipart.org/download/304716/1533192841.svg
	animal, animals - cute, bee, Bees, bug, bumblebee, cartoon, children, environment, funny, happy, hive, honey, insect, kids, kindergarten, pollen, remix+3243, remix+174840, spring, summer	https://openclipart.org/download/293996/bee04.svg
	Flower, Pink, Plue,	https://openclipart.org/download/184592/pinkandblueflower.svg
	bee, bumblebee, flowers, gate, pollen, summer,	https://openclipart.org/download/183614/bee-scene.svg

Table 27: The strongest blend for the Iris dataset was with the Flower Wikipedia page which achieved a bison score of 0.6264376449022712. Listed here are some of the results from an Openclipart search for the these words.

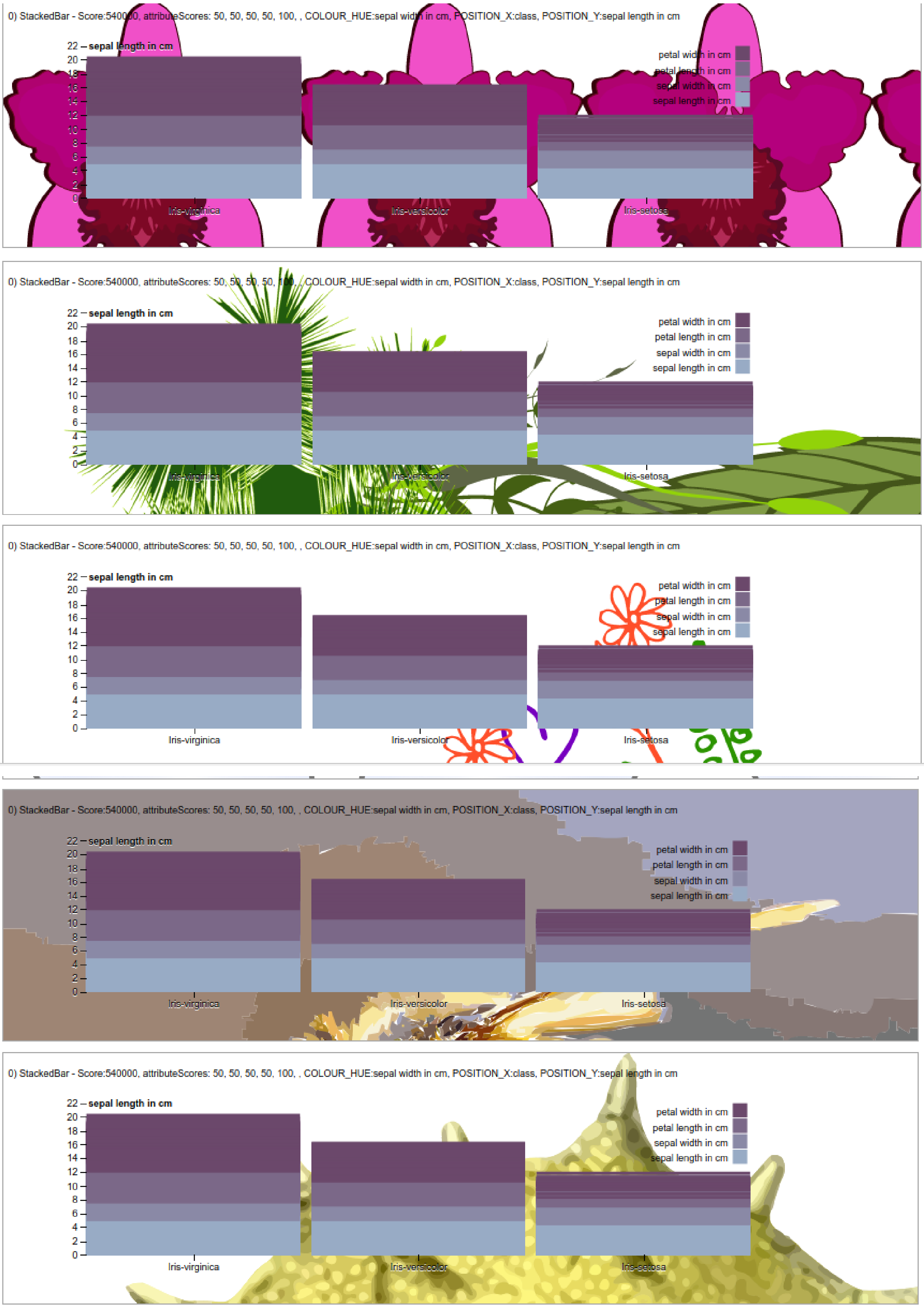


Figure 41: Reasonably convergent blend results for the stacked bar chart visualisation type for the iris dataset, consisting of flowers, plants and pollen.

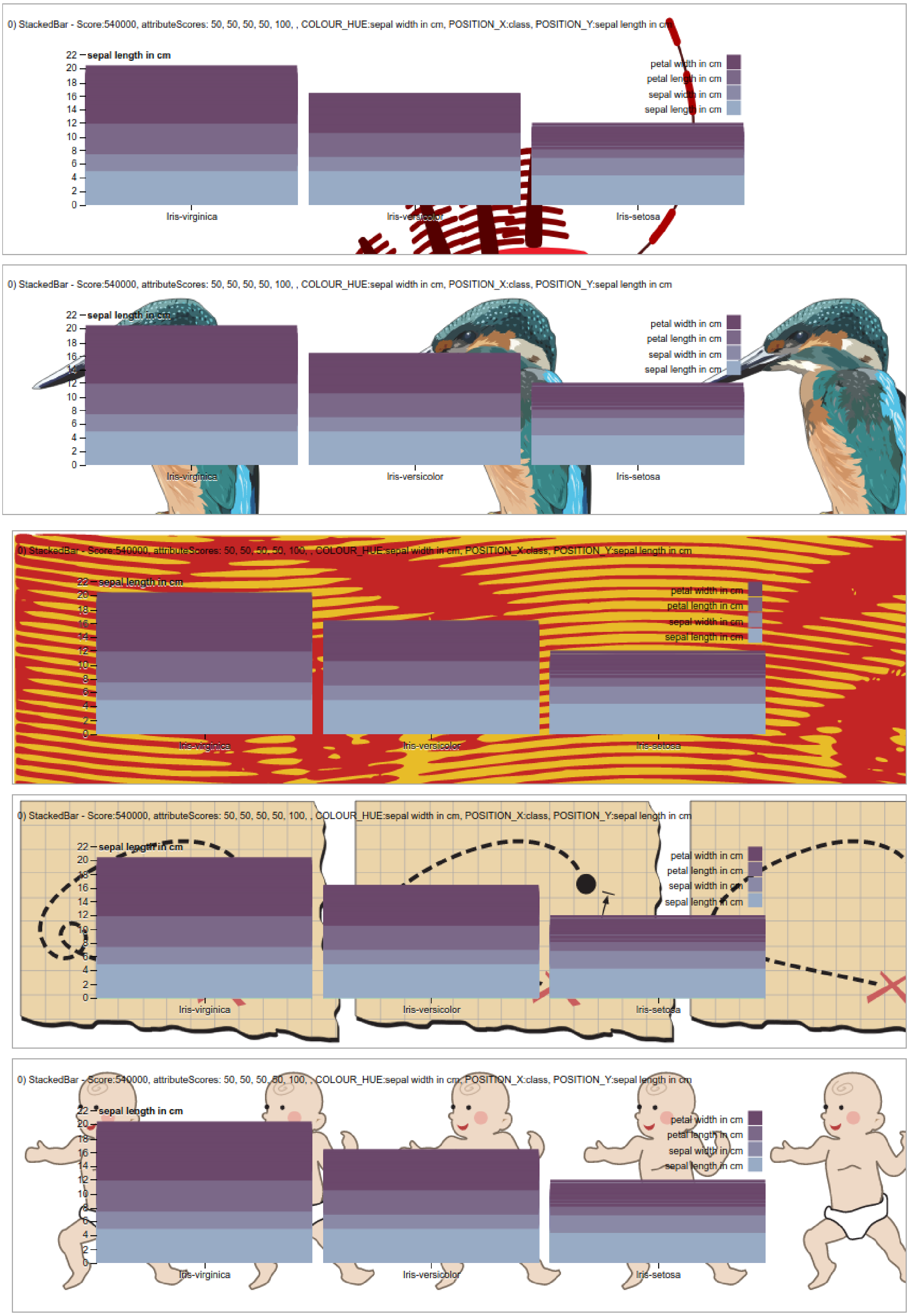


Figure 42: More abstract and divergent blend results for the stacked bar chart visualisation type for the iris dataset.

Figure 43: TODO. Get better screenshot

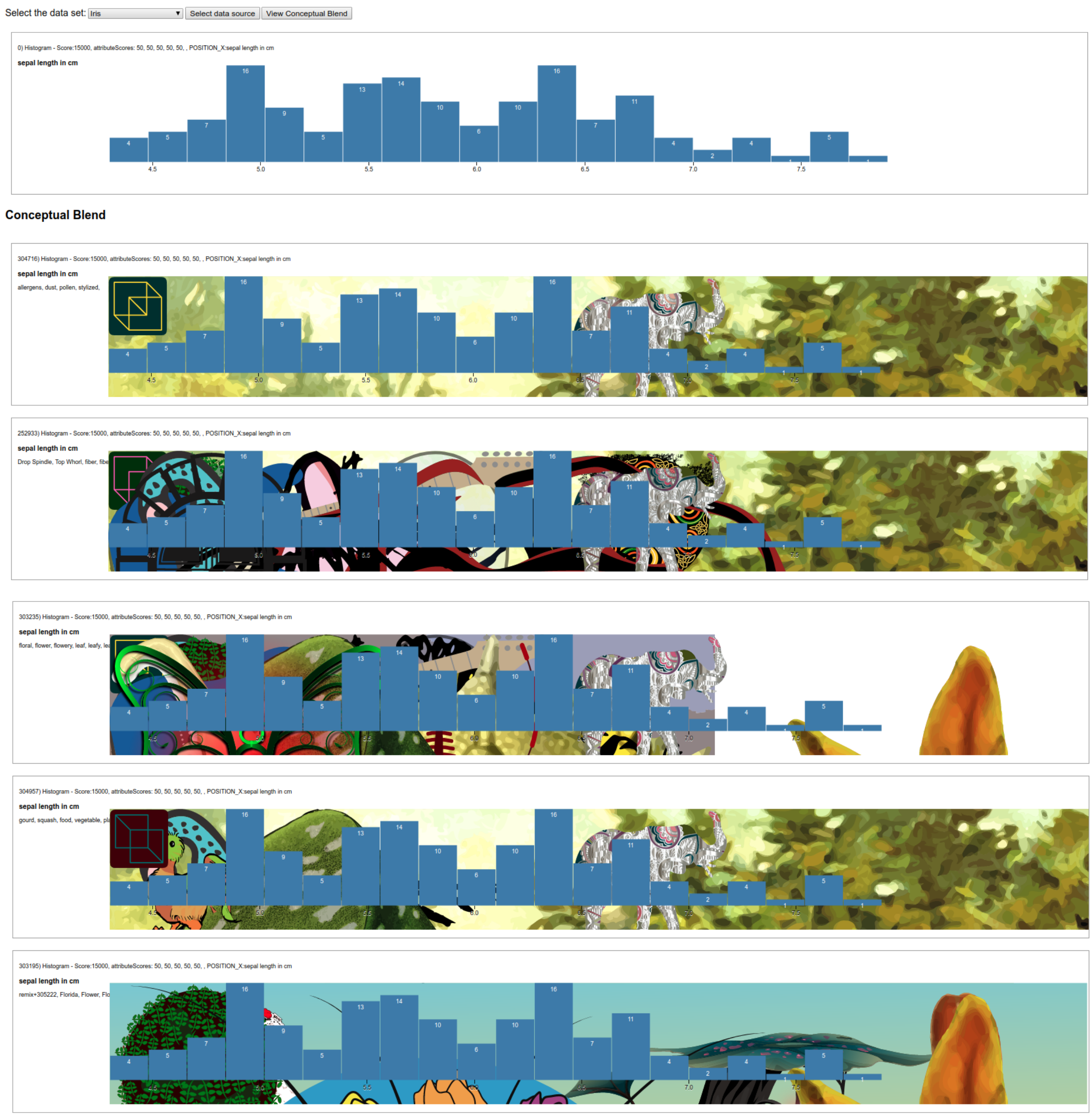


Figure 44: The visualisation background was altered to contain a collection of scalar vector graphics calculated by the prototype.

Multiple background images

Replace histogram bars

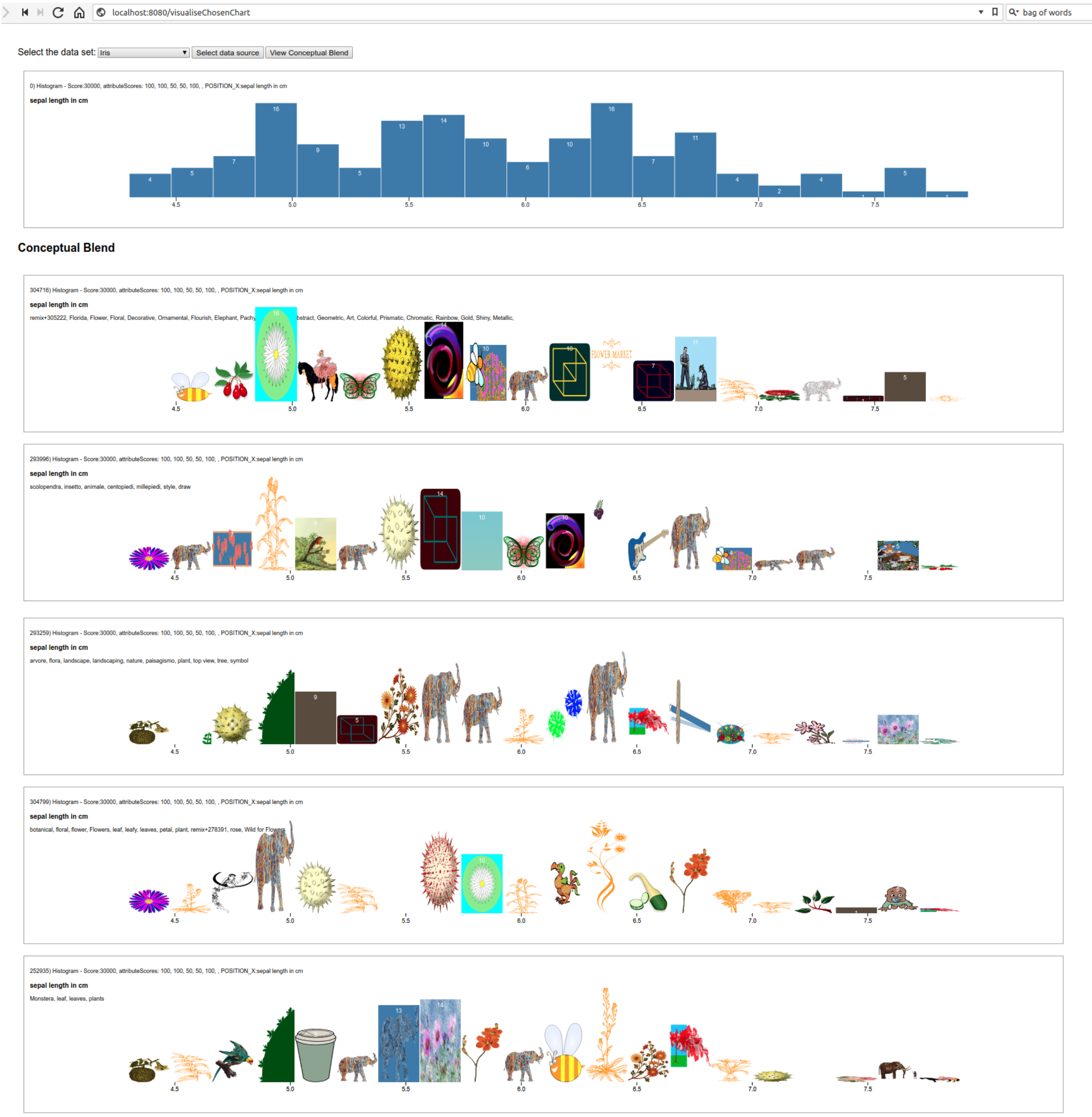


Figure 45: TODO.

5.2.3 Evaluation of VizBrew

vis eval

In Section 4, where the research design was presented, the following questions were asked when mentioning tangible visualisation evaluation criteria. “How long the resulting visualisations take to generate?”, “How relevant the visualisations are to the data?”, “Does the visualisation demonstrate the story behind the data?”, “Does the resulting visualisation highlight aspects that were known to be features of the dataset” and “How many visualisations had to be generated to produce a successful visualisation?”. These questions can now be answered.

time

The blended visualisations took approximately a minute to display. The majority of the delay was in the fetching and external information from Wikipedia and fetching the clipart from Openclipart. The word processing and bisociation calculations took very little time. Caching speeded the fetching of external up, but not enough to make the prototype feasable. Wikipedia is available for download, but the Openclipart database is not.

relevance/story/highlight

Many clipart images were convergent with the data when the initial dataset was more concrete. For example the Iris dataset returned results containing pollen, pollinators, petals and flowers, but while these concepts are relevant to Iris' they are not particularly useful in the visualisation in that they don't demonstrate the story behind the data. More abstract datasets, like the ‘Population age by state’ dataset, contains more concepts (population, age, state) and therefore returned a large number of Wikipedia pages and a large amount of clipart. The divergent results, such as the flowers on the elephant saddle, were interesting but completely irrelevant to the visualisation.

how many

The count of visualisations was restricted by the size of the scalar vector graphics returned to the browser. Once the text of the page got too large the browser simply threw an error. The amount varied depending on the file size of the clipart, how many of the clipart were used on the visualisation and the count of visualisation. The bisociations returned the most divergent clipart first and the divergent visualisations started appearing after approximately the 10th visualisation.

blend evaluation

The blending itself was not measured with any advanced criteria (such as Ritchie's criteria) as the prototype was still very exploratory. Some of the criteria demonstrating techniques of *conceptual blending* are apparent from the prototype's design. The following traits are present:

1. *ConceptNet* provided divergence from the ‘IsA’ relationships
2. The Wikipedia search provided second conceptual spaces
3. The is a blend that occurs between the dataset conceptual spaces and the other pages found through the search on Wikipedia for the ‘IsA’ pages.
4. The process can be repeated which proves how it came to the blends found.

5.3 Discussion

lead in

This Section begins by briefly observing problems and choices that applied to both prototypes. The abandonment of Sapper as the choice of for performing the bisociation is mentioned first. The results of the exploration of each prototype was covered separately in Sections 5.1 and 5.2 respectively. This section summarises those results and makes some observations on the output.

Dropping Sapper

Sapper It would've been ideal to perform the *bisociation* using the Sapper algorithm, as described in the literature (Section 2.3.3). The pseudocode for the Sapper algorithm was clear. Since Sapper – an implementation of computational metaphor – has been used to generate more interesting blends it was considered for the prototype. The algorithm was easy enough to implement. The problems arose when attempting to test the use of Sapper in combination with 'ConceptNet' to produce the desired metaphor.

How sapper works

An implementation of computational metaphor should be able to reproduce commonly used metaphors. An attempt was made to blend concepts that are known to produce metaphor. The concept, 'Butcher' with the concept, 'Surgeon', should be able to recreate the, 'My surgeon is a butcher' metaphor. The problem was that the Sapper algorithm only matches paths that share relational attributes (*has a*, *is a*, *provides*, etc.). The algorithm collapses polymorphic paths to produce the required metaphors. As an example, if all doctors take many years to get a degree and my surgeon is a doctor, then it follows that s/he studied for many years. Figure 46 illustrates the idea of how Sapper works.

CNet and Sapper

Figure 47 illustrate one of the initial problems that occurred when running the algorithm using 'ConceptNet' as a source of concepts. 'ConceptNet' forms mathematical graphs, which can be followed as paths. Breaks in these paths get handled using word forms and word derivations to find additional attributes. In the case of 'butcher', the word forms are 'butcher','butches', and 'butchest' and the root word is 'butch'. The former figure shows how Sapper ideally constructs metaphor, and the latter figure illustrates how queries to 'ConceptNet' sometimes require word forms to connect the two graphs.

reason not used

The main reason Sapper with 'ConceptNet' was abandoned, was due to the fact that following the paths generated by the relations in 'ConceptNet' and including word form relations still could not produce the required metaphor. An investigation of a the count of the relationships in 'ConceptNet' revealed why. Over 60 percent of the relationships in 'ConceptNet' are polymorphic in nature, and there are fewer relationships describing object attributes. Sapper ended up collapsing to paths consisting of just polymorphic relationships, and the paths that matched were divergent and not useful. The resulting paths were made up almost entirely of 'isA' relationships and matched paths were divergent. Sapper with 'ConceptNet' was abandoned in favour of a simpler *bisociation* working towards more advanced blends that contained some of the attributes required by a full implementation of conceptual blending.

var choice

While the variable choice prototype did not produce very useful results, the aesthetic prototype was more interesting. Some of the results have potential to be relevant elsewhere. For example *ConceptNet* or Openclipart could be used for suggesting a second dataset against which to compare the current dataset. For example, the aesthetic blend for the Iris dataset, returned images and keywords for pollen and bees, and datasets for pollen and bees may be interesting when viewed against the attributes in the Iris dataset ('Sepal length' versus pollen count for example).

speed

Both exploratory prototypes suffered from speed problems. The lag was experienced when looking up data

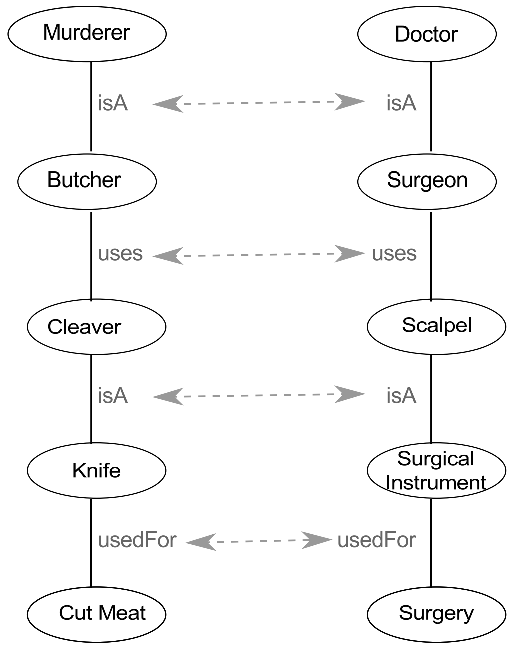


Figure 46: An illustration of how the Sapper algorithm would (ideally) use chains of matching relations to find metaphor. Illustrated is the, 'My surgeon is a butcher' metaphor.

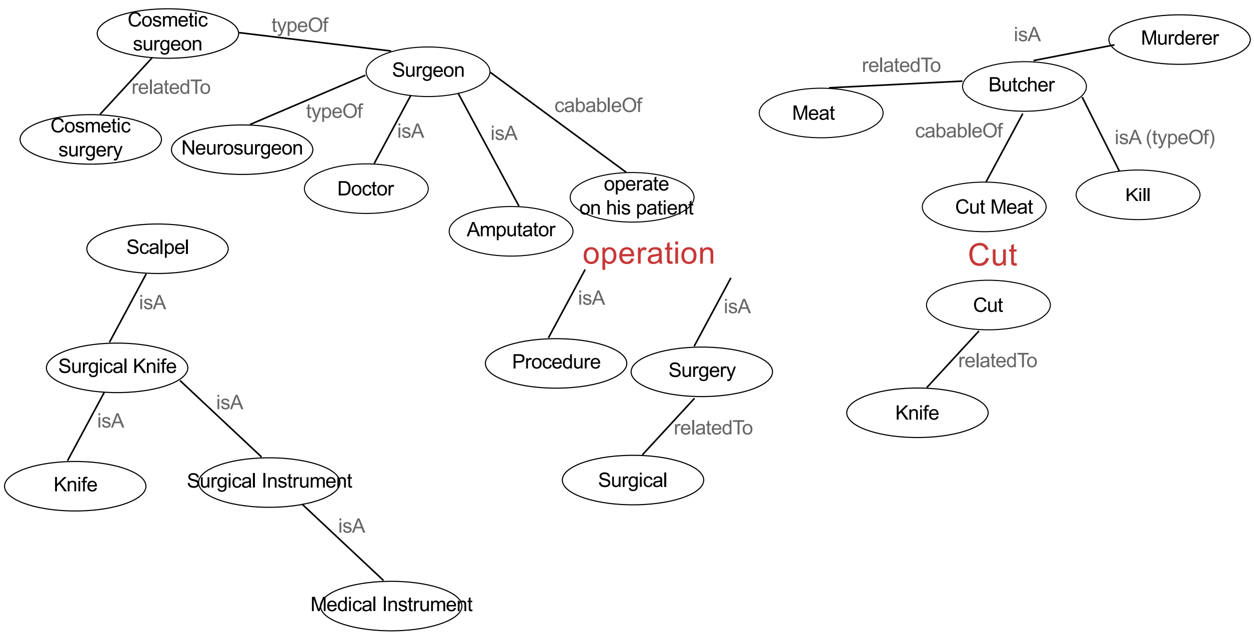


Figure 47: The intended implementation of the surgeon-butcher metaphor against the actualisation using 'ConceptNet'. As can be seen in the figure, surgeon could not be connected to surgery and butcher could not be connected to cleaver or knife. This occurred even though word forms and the root forms of words were considered.

2598 from external sources and when doing the blending calculations. The aesthetic prototype took approxim-
2599 ately a minute to do these calculations. A system built with more caching would improve or eliminate this
2600 issue.

Cross-space mapping

The process of borrowing attributes and features between conceptual spaces was limited by the chosen prototypes. The lack of attributes in *ConceptNet* was one constraint. Another was the inability to use parts of the scalar vector graphic (SVG) clipart files. While SVG has the concept of groups (and groups can be nested), there was no way to reliably identify whether the groups within the file formed cohesive human recognisable features.

lead out

The limitations and scope of the dissertation were presented in Section 1.5. The next section briefly revisits these limitations in the context of what has been done.

6 Limitations of research

no justif 4 tool

It was indicated in Section 1.5 (when project limitations were discussed) that the project scope needed to be limited for feasibility. It was mentioned that existing suitable datasets would be chosen. World bank's data was chosen and justification was provided in Section 4.3.1. The section also mentioned that suitable tools would be chosen without doing a comprehensive analysis that compared similar tools. 'ConceptNet' was chosen as the tool providing of a Semantic Network. It was chosen since it was easily accessible and had a convenient programming language independent REST Application Program Interface.

may not produce vis

It was also indicated that only one entry point in the visualisation pipeline would be chosen. The dependency of each stage on previous stages in the pipeline made this a logical choice. The first stage in the pipeline is that of variable choice. Variable choice is not sufficient to produce a full visualisation. The limitations did indicate that there was a possibility that the stage of the pipeline explored did not necessarily result in graphic output.

existing implementations

The literature indicated that there were existing implementations of *bisociation* and *conceptual blending*. Some of the instances were not available as open source software. Other instances were not well documented. Most instances for which code was available required that the input spaces exist as Ontologies (Definition in Table 29). It was felt that the descriptions of the datasets were too sparse in content to facilitate a full exercise of auto-generating (or even manually generating) suitable ontologies.

7 Conclusion

lead in purpose

As discussed in Section 1.2, the purpose of this dissertation was to introduce criteria from the theories of creativity into the process of automating the creation of visualisations of a data set. The intent was to explore whether the introduction of computational creativity could contribute to overcoming the shortcomings inherent in existing computer programs. Existing programs lack human insight and don't understand what aspects of the data may be important. This final section revisits the purpose and objectives of the dissertation, and presents the findings. A discussion of the success of the objectives and research questions takes place. Suggestions for future work is also highlighted.

lead in structure

The structure of this section is as follows: A run-down of what each section covered and how the sections contributed to objectives is give in Section 7.1. Section 7.2 summarises the research process that was followed. Section 7.3 revisits the objectives and research questions. Section 6 contains a digest of potential contributions emerging from the dissertation. The scope and limitations of the dissertation leave much more to explore, and an overview of open questions and objectives is the topic of Section 7.5. The final Section (7.6) offers some final thoughts.

7.1 Summary of chapters

Section 1

Section 1 introduced the dissertation and laid out background information, the problem, and the purpose. The research questions and objectives were introduced and limitation were presented. Specific limitations on scope were presented to ensure that the project was feasible.

Section 2

Section 2 contained the literature for the dissertation. The first half of the literature covered creativity objectives and the second half data visualisation. The literature specifically addressed some of the research objectives. The section also emphasised some of the discoveries. Detail of where specific objectives have been addressed, is discussed in an upcoming section (Section 7.3).

Some sections of the literature have been published at conferences in the form of systematic literature reviews (Featherstone & Van der Poel, 2017a, 2017b) and have been through a double-blind peer review process.

Section 3

Section 3 summarised the literature presented in Section 2, specifically highlighting aspects of the literature that contributed towards addressing objectives and justifying options that with potential, that drove choices made in designing the prototype. The literature connecting visualisation and computational creativity was sparse, but it is summarised in this section.

Section 4

Section 4 justified the choice of *Design Science Research* as a methodology and specified the intended prototype method. The section continued with a discussion on the identified sources of data sets that could be used as input. The section acquainted the reader with the design of the prototypes. The final choice of data sets was justified and specific details of design for two prototypes targeting two separate stages of the visualisation pipeline were put forward.

Section 5

Section 5 discussed the resulting output of the prototypes. The variable choice prototype was presented first after which the aesthetic prototype's results were observed. General observations and findings were then presented.

Section 6

Section 6 revisited the limitations and scope in the context of the final prototypes.

Section 7

Section 7 summarises the research, deliberates on the findings and suggests possibilities for future research.

The conversation now turns to how the research process was executed and where the difficulties arose.

7.2 Summary of research process

At the initial conclusion of the first round of literature review, potential data sources had been identified and it had been established that the first stage of the data visualisation pipeline – as specified by the *grammar of graphics* – was a logical place to start. The reason it seemed like a good starting point was because the *grammar of graphics* seemed to enjoy a good deal of recognition as a valid visualisation pipeline. The *grammar of graphics* also is implemented in a number of the visualisation tools. The intent was implement a reasonably chosen set of attributes required to implement conceptual blending. The first step in the pipeline was chosen because the literature mentioned that the order of the grammar is fixed. Stages of the grammar can be revisited; However each stage is dependant on the previous one. A prototype was built, but it fell short of useful results and a second prototype targeting the aesthetics stage of the pipeline was built.
The literature was expanded as various questions arose as to how to concretely implement the theory. A section defining concepts and motivating the choice, had to be added, along with sections discussing how

many of the features of blending various authors had achieved and how their concepts were implemented and how the actual concepts were blended.

For the variable choice prototype, it would have been useful to have had access to open data that was presented using some sort of predefined specification. A predefined specification for open data would allow access in a standardised manner and would allow multiple sources of data to be accessed in the same manner. This would have aided in the comparison of a more diverse and potentially more creative combination of concepts. The data sources found all seemed to offer the entire data set as a manually downloadable document, usually as an spreadsheet, CSV file or XML. Other sources, such as InfoViz also had images and other non-computer accessible information that was not suitable. A data source that facilitated *non-manual* download of only specific attributes of the data, was not found.

Implementations of blending were discussed in the literature. It was hoped that some of the implementations would be available online. It was known at the start of the prototype design stage, that projects such as COINVENT ('The infrastructure software for the CoInvent computational creativity project', 2017) have source code that is available in the open source software space. The implementations of blending that were found, seemed in many cases to have adopted a model that required ontologies as the input spaces to the blend, requiring additional investigation. The automated creation of ontologies did not seem appropriate for the simple prototype that was being considered. In addition, the software that was found was often not documented well enough for an outside individual, not familiar with the design choices of the software.

The discussion that follows, concentrates on the research objectives and research questions in the context of the prototype results and the findings.

7.3 Deliberation on findings

The primary and secondary questions and objectives are visited one by one. The sections specifically addressing the objects and questions are referenced and findings are summarised.

7.3.1 Secondary objectives - Creativity oriented objectives

Explore and describe creativity theories and the artificial intelligence techniques used to implement the theories in the context of those relevant to computer generated visualisations.

The literature covering this objective spanned several sections of the literature section of this dissertation. Creativity theories were presented in in Sections 2.1.1 through 2.1.8 and Section 2.1.10, and the creativity pipeline was introduced in Section 2.1.9. Honing theory (Section 2.1.7) is relatively new and only discussed by one or two authors, and therefore was the shortest Section. Considerably more attention was given to the description of *conceptual blending* (Section 2.1.10). This was due to the fact that *conceptual blending* still appears to be dominant in the computational creativity literature where the creativity theory is specifically mentioned. Conceptual Blending also refines *bisociation* to the point that it is easier to target specific components of *bisociation* as it tries to explain types of *bisociations* and their features. Understanding selective projection and emergent features helps to drive programming choices when building computational methods that are generating bisociative knowledge.

Necessary considerations for algorithmically implementing creativity, such as how to measure the resulting output of the computer program, and tools and techniques were presented in Sections 2.2.1,2.2.2, and **??**. Section 2.3.1 detailed how the theories of concepts translated into computer models. Specific implementations and techniques for blending were then presented in Sections 2.3.2 and 2.3.3.

The literature specifically combining visualisation and computational creativity was sparse. That literature was presented in Section 3.5.

Determine what measurable attributes are sufficient for an algorithm that claims to be creative.

Novel/useful

The literature covering creativity theories and computational creativity solidified how the concepts of *Novelty*, *Usefulness* and *Surprise* can be built into a computer algorithm (Section 2.1.8). *Usefulness* is very easy to measure. A program is *Useful*, if it is designed to solve a problem and the program produces a suitably appropriate answer. *Usefulness* is covered in Section 2.1.8, *Surprise* (*The AHA moment*) and *Novelty* and are also essential criteria against which to measure creativity. *Surprise* is discussed in the text at 2.1.8 and again in the discussion on how to measure computation creativity (Section 2.2.2). *Novelty* is discussed in Section 2.1.8. A key technique for measuring these criteria lies in finding ways to score the output of the computer program against representative and typical examples of the domain. Formal frameworks for measuring computation creativity are still under active investigation. The literature also discussed measurements for divergent and convergent production which, when measured together, are useful measurable tests for creativity. Divergent and convergent production were described in Section 2.1.2.

surprise

divergent and convergent production

There are several models under development for testing for, and scoring, creative attributes. Scoring was discussed more generally in Section 2.2.2, after which the IDEA, FACE and SPECS models were described in Sections 2.2.2, 2.2.2 and **??**. These three models are fairly recent models (Jordanous, 2013). Sometimes one model is more suitable that another for scoring a particular project. This is due to differences in what the model expects is available for measurement. Ritchie's model is a quantitative model that is frequently used (Jordanous, 2013), and was described in Section 2.2.2.

models to test

controversy

Measuring computer programs that claim to be creative, continues to be open to controversy. Especially, since different individuals can differ in what they consider to be creative (Jordanous, 2013). Some individuals argue that a computer can only be as creative as the programmer writing the program (Jordanous, 2013). As a result, some authors, such as Wiggins, choose not to measure creativity at all and instead measure the quality of output of their program (Jordanous, 2013).

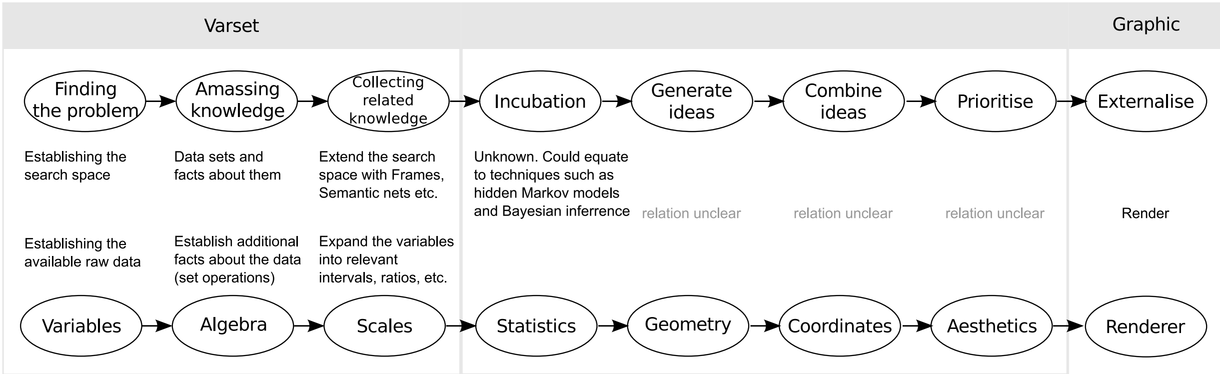


Figure 48: The stages of the creativity pipeline and potential parallels to the data visualisation pipeline.

7.3.2 Secondary Objectives - Visualisation oriented objectives

Explore and describe the current state of computer generated visualisations with the aim of identifying suitable methods and data representations.

The current state of computer generated visualisations was described in Section 2.6. Literature discussing visualisation of specific domains, such as visualising a particular type of medical data, genomics, spectrometry data, and so on, were excluded. They were excluded because they appeared to follow processes that were very specific to the type of data that was being visualised. It seems that most tools for data visualisation, assist a human or programmer with the generation of the visualisation, but are not likely to produce a visualisation end to end. Some machine learning tools and visual analytics tools statistically produce histograms and identify outliers and missing data using various mathematical methods. The resulting visualisations are not necessarily always useful. Visual analytics tries to fill this gap by involving a human in the process.

Identifying any parts of the visualisation pipeline suitable for introducing creativity theories.

The parts of the data visualisation process, which this dissertation refers to as the visualisation pipeline were discussed in Sections 2.5.1, 2.5.2, and 2.5.3. It was discovered that several authors (Csikszentmihalyi & J. W. Getzels, 2014; Csikszentmihalyi & J. Getzels, 1970; Varshney et al., 2013) also acknowledge a creativity pipeline 2.1.9. There appear to be potential parallels between the two pipelines. These associations are illustrated in Figure 48.

Identify what aspects of the human visualisation process are considered to be creative.

Sections 2.5.1, 2.5.2, and 2.5.3 compared how a computer would go about creating a visualisation versus how a human would go about the same process.

The main takeaway from this question appears to be that humans understand their data, and understand why they may be creating a particular visual. This understanding of storyline and data drives the choices at each stage of the visualisation pipeline. Humans are also better at identifying why certain outliers or emergent features within the visualised data may be interesting. The understanding of the data and its context facilitates the natural drive to compare and contrast data (blend) and understand features and attributes of the data that are not necessarily provided in the data itself. There is also an understanding of the expectation and culture of the intended audience of the visualisation as well as the intended purpose of the visualisation, whether it be marketing, shock value, or trends. This framed information provides input into the visualisation that would not be normally available to a computer.

This dissertation's literature did not explore the feature, but the literature also described the role of the human visual system in being able to understand, succinctly, patterns emerging when the data is visualised, that are not obvious before the data is visualised.

7.3.3 Secondary research questions

The secondary research questions aimed to support the primary research question by identifying the overlap where theories of creativity and creativity in the visualisation process covered common ground. Ultimately this overlap was intended to determine which criteria from creativity theories could be used, and how they could be used to determine the creativity of a computer generated visualisation. Each secondary question is addressed separately.

How have the currently accepted theories of creativity been applied in the artificial intelligence and computational realms, with an emphasis on those that generate creative data visualisations?

Bisociation and *conceptual blending* are discussed in the literature. Specific functions and methods used to perform *bisociation*, such as the Bison measure and the Sapper algorithm are found in the literature. No full implementation of *bisociation* or *conceptual blending* were found in the open source software space. The implementations that were found were based on ontologies and either not available publicly or difficult to understand or use.

What scope do computer generated data visualisations have for the introduction of criteria deemed to be creative?

This question was intended to establish the current techniques used to generate visualisations in order to establish which techniques could support creativity criteria. It also aimed to identify where in the graphics pipeline, creativity criteria can effectively be introduced.

The parts of the visualisation pipeline was investigated and it was found that many parts of the pipeline have potential for the introduction of *bisociation* and conceptual blending. The prototypes for this dissertation only addressed variable choice and one aspect of the aesthetics stage of the pipeline. Both stages of the pipeline could be explored further.

7.3.4 Primary Research question

How can criteria derived from theories of creativity be used in the generation of visualisations?

The literature reviewed has suggested that bisociative creativity theories could contribute toward a computer program knowing more about why the data is important to a human, and establishing useful associations between data sets that may not be immediately obvious as having a connection. The literature also indicated that the intended purpose of a visualisation (it's story) could be discovered or driven by blending theories.
It was demonstrated that the polymorphic relationships in *ConceptNet* can actually be used to make rules for the aesthetic alterations of the visualisation, but no attempt was made to automate this or implement all the rules found 4.5.11. Semantic networks on their own aren't criteria for a conceptual blend, but they are one of the tools used. Also demonstrated was how human tagged clipart can identify unrelated conceptual spaces. The example of a search for the word 'flower' returning an elephant because it had flowers on it's saddle.
This dissertation did not progress far enough to enumerate all possibilities. Open research questions that show potential were listed in the literature summary in Section 3.3.

7.3.5 Primary objectives

Develop a computer program that can generate a visualisation for a suitably chosen visualisation type over a small domain of knowledge using a subset of the creativity criteria in order to try and address the shortcomings of computer automated visualisation caused by lack of human cognition and visual perception

The limitations on the dissertation, were introduced in Section 1.5, and have been summarised again in Section 6. It was indicated that only one of the stages in the visualisation pipeline would be chosen for investigation. It made sense to begin with the first stage of the data visualisation pipeline, because stages further along the pipeline, were dependant on the earlier stages of the pipeline. This is not to say that stages in the pipeline could not be revisited, but you cannot visualise data if you do not have all of the data that you wish to visualise, in a form that can be used.
A prototype was produced that investigated the choice of variables using the World Bank data set ('World Bank Open Data', 2017). All stages of the visualisation pipeline would ideally need to be implemented to produce an end-to-end program that produced a fully developed visualisation. It was hoped that the variable choice would be sufficient to pass to an existing program to temporarily fill in the missing parts. *R* and *ggplot2* were investigated and found to suitable as they were able to produce fairly complete visualisations from a source of data such as a CSV file. The World Bank data API facilitates querying the data topics and the fields/indicators that are available for the data's topic. The API, which was fairly extensively documented, did not contain documentation describing the facility to request the actual data. Unfortunately technical difficulties prevented the prototype from getting to the point where there was data to pass to *ggplot2*. As a result, no visualisations were produced.

7.3.6 Other questions

In Section 3.3 – after storytelling and narrative emerged as part of the human visualisation process and also as potential targets for computational creativity – additional question were enumerated. The majority of those questions could be addressed by future research. This dissertation began to contribute to answering some of those questions.

1. Can conceptual blending/storytelling help with variable choice by identifying what we want to see in the data?
2. Can *conceptual blending* identify interesting data to contrast?
3. Can *conceptual blending* help with Image choice?
4. Can *conceptual blending* or storytelling supply prior knowledge and context?

Whilst Questions 1 and 2 were not fully answered, they show promise. The experiments show that *bisociation* can find common themes between data sets by finding words that correlate. Using larger sources of information about the data may answer the question fully. Question 1 shows potential because computational creativity has already been used to generate storylines, intent, and narrative – as the literature showed – is something humans have in mind when creating a visualisation.

Question 4 has promise because *Semantic Networks* and *Frames* are useful for exactly that purpose. They supply background information and additional attributes.

lead out

In the next section a summary of the key findings is given and conclusions are discussed.

7.4 Summary of contributions

lead in Iteration

The literature drew attention to iteration as a feature of computational creativity models and the process humans follow when creating a visualisation. Ideally humans gain insight into features within the data in the process. They revisit earlier parts of the pipeline. Tests for when and how to iterate, may be a useful feature to include into the fitness function of an artificial intelligence algorithm that generates visualisations. The literature that was found did not describe any attempts to replicate this cycling and sense making into the visualisation process without involving a human.

rest calls + iterate

Ideally, to use 'ConceptNet' efficiently, the triples (made up of relations and attributes between concepts), need to be followed. Using the REST method, whether 'ConceptNet' is installed locally or not, is too slow practically. Using 'ConceptNet' as a database still had issues with large graphs and the problems that are known to be related to large graphs.

Combining diverse concepts

The ability to connect datasets that are not obviously related is encouraging. This ability is facilitated by the use of tools such as *Semantic Networks* and *Frames*. The tools also allow the interrogation of how the concepts were found to be related. The ability to connect Irises to pollinators (birds, bees) and pollen, as a convergent example, and the connection to ornament and elephant as more divergent. Lakoff and M.

computation metaphor

Johnson pointed out that metaphor may be strongly linked to human cognition. Metaphor is strongly represented in the *conceptual blending* literature, but does not appear in the visualisation literature presented in this dissertation. If metaphor is linked to how humans think, it seems reasonable to propose that the awareness and use of computational metaphor could potentially make computer generated visualisations more interesting and *novel*.

As only two stages of the visualisation pipeline were investigated – and could potentially be explored further – there is a large scope for future research. Questions that came out of the literature are also potentially interesting. The next section summarises the most relevant opportunities.

lead out

7.5 Future research

lead in

The unexplored stages of the visualisation pipeline are discussed first. The section also suggests less obvious potential targets for interrogation. It was mentioned in Section 3.1 that exploring the automating

pipeline visA

of the 'knowledge generation' and 'user interaction' parts of visual analytics process in terms of creativity models is open for exploration. Directly investigating computational creativity models' scope for addressing storytelling and purpose, was mentioned in the same section. The aspects of visualisation that specifically drive storytelling and purpose were identified, but not explored.

pipeline var choice

This investigation did not finish covering potential options for exploring variable choice, due to limitations with the chosen data set; Specifically with limitations due to the sparsity of text when using such small descriptions. There is potential scope to continue exploring this stage of the pipeline. Especially, if more diverse sets of data can be compared. It was pointed out that variable choice continues to be difficult for computers. The aesthetics stage of the pipeline offers scope for exploring the use of computational creativity theories for identifying colour choice, visual clues and accompanying graphics.

pipeline aesthetics

unanswered identified Qs

Some of the questions identified in Section 3.3 can still be explored.

Visual metaphor

There is room to explore the mapping of visual and spatial metaphor against the visualisations pipeline. Especially since it has been identified that visual metaphor has stronger links between two aligned concepts than the links found in linguistic metaphor (Bolognesi, 2016). The same study found that additional attributes of the relationships between terms encode additional semantic information. None of the creativity models discussed here incorporate this additional semantic information when performing *bisociation*.

Honing

Future research could consider applying the SCOP-formalism and Honing theory (Discussed in Section 2.1.7) to models of conceptual blending. While Gabora mentions it as a method to blend concepts, she does not specifically mention *conceptual blending* or any existing formal models of *conceptual blending*. Gabora also suggests that entropy and arousal could be driving forces of creativity. Incorporating some sort of computational valence calculation into blending operations could be interesting to explore.

intuition

Since the specific characteristics of intuition are still under investigation (Pétervári et al., 2016), it may be worth exploring whether metaphor and metaphoric language has any role to play, particularly since it has been suggested that metaphor underlies the way humans think (Lakoff & M. Johnson, 2008).

blending not nlp

Most of the *conceptual blending* literature is working with conceptual spaces that are formed by collecting words in documents. Other conceptual space models could be considered. As an example, it may be interesting to consider a conceptual space to consist of the training results of a machine learning algorithm. It may be interesting to find a way to blend the results of the trained data, with the results of the trained data of a second machine learning algorithm that performing a different task. Or it may be interesting to combine two neural networks that are simultaneously learning different tasks.

7.6 Concluding remarks

purpose

The aim of the research was to explore the introduction of criteria from the theories of creativity into computer generated data visualisations. In the process a computer prototype was built using the creativity models and attempting to reproduce the, ‘variable choice’ and ‘aesthetic’ visualisation pipeline activities. Creativity theories and measurable attributes were described, computer generated visualisation was touched on, and the parts of the visualisation pipeline, the creativity pipeline, and the visual analytics pipeline were presented.

what was achieved

Findings and analysis indicated that metaphor, iteration, compression of information and knowing one’s data are overlapping themes between computational creativity models and the data visualisation pipeline. Existing tools and algorithms would be helpful in driving computational creativity research forward.

limitations

Limitations included inconsistency in manner in which to access to the data between diverse datasets, the shortcomings of the chosen tools, as well as access to existing implementations of computational creativity tools and algorithms. Exploring every stage of the visualisation pipeline and every creativity model was not a feasible goal and this was indicated as a limitation beforehand.

future work

The research leaves a large scope for future exploration. Other stages of the visualisation pipeline are open to explore, as are other creativity models, and other ways of tackling blending, variable choice and aesthetics. The findings leave a large amount of room for further exploration.

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8.2 Data attribution

I would like to thank the World Bank Group, who made their data available for use (in such an accessible manner). None of the findings, interpretations or conclusions in this dissertation reflect the views of the World Bank Group, and there is no association or liability. This dissertation made use of topics, and the indicator queries for those topics. The topics used were:

1. Education
2. Energy And Mining
3. Environment
4. External Debt
5. Gender
6. Health
7. Public Sector
8. Private Sector
9. Science And Technology
10. Social Development
11. Social Protection And Labor
12. Science And Technology
13. Infrastructure

The World Bank's, 'Terms of use for datasets listed in the World Bank Data Catalog', indicates that any data sets that have been used, are given attribution. The data sets were not used; However, the topics used in the dissertation appear in the following data sets:

1. The Atlas of Social Protection: Indicators of Resilience and Equity, World Bank Group
2. Country Opinion Survey Data
3. Climate Change Data, World Bank Group
4. Data Resources for Structural Economic Analysis, World Bank Group

5. Development Research Group, The World Bank
6. EBRD-World Bank Business Environment and Enterprise Performance Survey (BEEPS)
7. Gender Statistics, The World Bank
8. Global Development Finance, The World Bank
9. HealthStats, World Bank Group
10. IDA Results Measurement System, the World Bank
11. Joint External Debt Hub, The World Bank
12. Landmine Contamination, Casualties and Clearance Database, The World Bank
13. Logistics Performance Index, The World Bank
14. Millennium Development Goals, The World Bank
15. PPI Database, World Bank and PPIAF
16. Private Participation in Infrastructure (PPI) database
17. Privatization Barometer
18. Projects related data from SAP, other data from IW
19. Rural Access Index, World Bank Group
20. Quarterly External Debt Statistics, The World Bank
21. World Bank EdStats
22. World Development Indicators, The World Bank
23. World Development Report 2011, The World Bank
24. World Development Report 2013 on Jobs Statistical Tables, World Bank Group
25. WDR2013 Survey on Good Jobs, World Bank Group

8.3 Open source software

The following software was used for the prototypes. The licenses and terms of use are indicated in Table 28.

Software	terms of use and license
ConceptNet	The complete data in ConceptNet is available under the Creative Commons Attribution-ShareAlike 4.0 license. http://creativecommons.org/licenses/by-sa/4.0/
D3js	D3 is Copyright 2010-2017 Mike Bostock and is licensed under the BSD 3-Clause "New" or "Revised" License. Redistributed binaries need to contain a copy of the license. https://github.com/d3/d3/blob/master/LICENSE
Openclipart	Openclipart is in the public domain and is free even for unlimited commercial use. Openclipart is licensed under the Creative Commons Zero 1.0 Public Domain License https://openclipart.org/share
Wikipedia	Wikipedia uses multi open source licenses including the Creative Commons Attribution-ShareAlike 3.0 Unported License and the GNU Free Documentation License (GFDL) https://en.wikipedia.org/wiki/Wikipedia:Reusing_Wikipedia_content

Table 28: Software used for this project and the relevant license and terms of usage

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10 Addendum A

Table 29 contains definitions for common terms that have been used in this dissertation, that may require explanation for non experts. The terms are well known in the computer science, artificial intelligence and visualisation fields.

API	Application programming interface. A set of methods, specifications, or tools for facilitating communication between various pieces of software. The software may not necessarily reside on the same machine or be in the same computer programming language.
Artificial intelligence	Artificial intelligence is a sub-field of computer science dedicated to producing human-like intelligent behaviour using computational techniques and methods (Shi, 2011)
Artificial neural networks	Artificial neural networks are a set of techniques from the field of artificial intelligence that attempt to model the neurons of the nervous system (Graupe, 2013; Kattan, Abdullah & Geem, 2011)
Binning	The data visualisation variable preparing process whereby the data is split into intervals and the resulting counts of items within each interval is used in the visualisation
Bag of words	A document that is represented by the collection of words that it contains.
CSV	A text file containing data in the form of comma-separated values.
CIELUV color model	A colour model consisting of three dimensions, namely, luminance and two values which together encode chromaticity)
Entropy	The amount of chaos, disorder or uncertainty in a system
Evolutionary algorithm	Evolutionary algorithms are, artificial intelligence software programs which attempt to emulate processes observed in nature, such as evolution, species migration and bird and insect swarming behaviour (D. Simon, 2013)
Fitness function	A term used in the artificial intelligence community to describe an evaluation calculation that can be used to provide estimations of the quality of the program's suggested solutions and establish heuristics that drive the program towards the most suitable candidates for a solution (Kattan, Abdullah & Geem, 2011)
Ontologies	A formal specification naming properties and relationships between entities
Fuzzy set	In mathematics, fizzy sets are sets in which the members of the sets have degrees of membership
REST	Representational state transfer or RESTful Web Services are a way of facilitating request over the internet using basic machine readable text formats such as XML.
Software agent (or intelligent agent)	Artificial intelligent software components designed to simulate human behaviour are frequently referred to as intelligent agents. These agents make use of Statistical inference, logic and logic rules to plan decisions, react and take appropriate action within the environment (Das, 2008).
Machine Learning Classifier	The name for a group of supervised algorithms whose function is that of classification; That is, to classify or categorise data into predefined related sets or classes based on common known attributes (AbdulRahman R Alazmi & AbdulAziz R Alazmi, 2012)
Model–view–controller architecture pattern	A software architecture pattern that divides the software into three independent, yet connected, parts. These parts separately control the graphic user interface, navigation, and functionality
Semantic frames	Frames are a type of graph, or semantic structure that describes a type of situation, object or event as well as all the parties involved in that event (Sullivan, 2013). They provide background knowledge against which word meaning can be interpreted (Boas, 2009)
XML	Extensible Markup Language is a language developed the World Wide Web Consortium, for sharing data in a format that describes the data in a manner that can be read by both humans and computers. Refer to https://www.w3.org/standards/xml

Table 29: Definitions of terms found in this dissertation.