Features of Conceptual Blending in the Context of Visualisation

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Abstract: Computational creativity is a multi-disciplinary area of research that investigates what aspects of computing can be considered as an analogue to the human creative process. One premise is that humans come up with new concepts or creative ideas by combining two or more other concepts together. Conceptual blending is one of the creativity theories that has been modelled by computer programs attempting to emulate creativity. The current paper is part of a larger project that wishes to explore whether computer programs that automate the creation of data visualisations – such as pie charts, bar graphs and time series plots – can be enhanced by artificial intelligence methods that model human creative processes. One objective of the larger project is to explore and describe conceptual blending – and the techniques used to implement conceptual blending – in the context of applicability to visualisation. Metaphor emerges as a frequent emergent feature of conceptual blending with potential for creating useful visual features. Compression of information and iteration are shared and potentially exploitable features.

Keywords: Visualisation, Conceptual Blending.

1. Introduction

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 seen in existing computer programs [1]. Humans are still much better at quickly determining what context and which aspects of the data, and at what granularity, will successfully highlight what the data represents [2]. Humans may expect to find certain things in the data and they learn about their data as they go along; adapting the visualisation according to what they see [3]. Computational implementations of theories of creativity could enhance the visualisation process by supporting the choice of what data to visualise, or facilitating the choice of relevant and interesting data combinations, or by introducing graphical elements that draw attention to the patterns in the data. Boden and Mujumdar [4] suggest that one of the reasons for studying artificial creativity is the hope that it can contribute toward understanding human creativity. The introduction of artificial creativity, when applied to the production of data visualisations, could highlight how humans go about the task, or potentially improve existing programs that assist humans with this activity.

The paper is laid out as follows: Section 2 will describe how the literature review was conducted, after which the literature is presented in Section 3. The discussion in Section 4 connects the result of the literature to prior investigations on human creativity in data visualisation. This section also highlights the steps that are generally followed between the raw data and the final rendered visualisation.

2. Methodology

This paper explores and describes implementations of computer models of creativity that are based on the creativity theory known as conceptual blending. Only implementations that have also been used to generate visualisations (or that may contribute toward the techniques or heuristics of an artificial intelligence routine whose purpose is to automate the creation of visualisations) are considered. This is done by means of a critical literature review.

The sources of literature and motivation for keywords used for the search, as well as how the literature was prioritised, is described in Section 2. Various sources were consulted on the recommended procedure for conducting a critical literature review [5]–[8].

2.1 – Search procedure

An initial search was done on Google scholar using the phrases "conceptual blend" and "visualisation" or "visualization". Additional searches were done at Taylor and Francis, at World Wide Science, Science Direct, SpringerLink and IEEE Explore. This produced additional metaphor orientated keywords, since the results that matched both "conceptual blending" and "visualisation" frequently discussed metaphor. Visualisation results were not restricted to just "data" visualisation due to the sparseness of the results. Any content referencing a generated visualisation (such as art or image manipulation) were therefore also considered. Fauconnier and Turner are cited frequently in this paper to explain concepts and justify search terms, since they are the founders of conceptual blending and as such are frequently referenced in the literature.

An attempt was made to expand the search by combining the phrase "conceptual blend" with various authors that surface in the visualisation literature (such as Tufte and Graves-Morris [9], Shneiderman [10] and others. Various types of common visualisations (data maps, bar graphs, time series, etc.) and visualisation related keywords (plot, graph, etc.). The former returned only references to the use of conceptual blending when generating narrative. Keywords from the visualisation pipeline (varset, scales, geometry, nominal, ordinal, etc.) were added to the search. Geometry returned one partially relevant result describing the combining of images using conceptual blending and the Grabcut algorithm [11]. Other keywords and phrases (dataviz, visual analytics) were tried.

The sparse results were possibly due to the fact that many computational implementations of creativity theory do not mention the specific theory on which they are based [12]. An example of this is "The painting fool" [13] (a computer program that generates paintings) is well represented in the computational creativity literature, but does not explicitly mention any specific creativity theory. The sparsity could also be due to the recent focus on human assisted data visualisation, as is seen in the field of Visual Analytics.

2.2 Prioritisation and quality

Literature was included when it was specifically related to conceptual blending or closely related concepts. Literature focusing only on the history of creativity or psychological aspects of it was given lower priority. Focus was given to existing computational implementations of conceptual blending – and in particular those implementations where the computational methods used could be suitable to generation of visualisations or can assist with creative choices at any stage in the data visualisation pipeline.

Computational creativity and data visualisation journals and conferences as well as artificial intelligence journals and conferences were targeted first, since those are the areas of interest of the larger project. Newer resources were prioritised over older ones and higher cited sources were preferred. The sparse results necessitated the inclusion of older literature.

The literature is laid out as follows: Background information on conceptual blending is presented in Section 3. The pertinent literature on conceptual blending with regard to visualisation is presented in Section 3.3. Section 4 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. Metaphor is discussed in Section 3.3 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.

3. Literature

3.1 – Bisociation

Koestler [14] labelled the intersection of ideas from from two unrelated domains “bisociation of matrices”. He indicated that it is the overlap of domains that potentially produces creativity. He termed this overlap bisociation. A main aspect of bisociation is the discovery of hidden similarities between domains [15].

The nature of the overlap of the domains affects how it is perceived. Koestler [14] 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 [14], [15]. Examples include juxtaposing expectation versus surprise, or balance versus exaggeration, or decorum versus vulgarity. Similarly, creativity in science emerges when the overlap of domains of knowledge contains unifying aspects [14]. 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 [16].

Fauconnier and Turner [16] expand on the concept of bisociation, pointing out that blending 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 that extends bisociation 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. There are four of these spaces in conceptual blending, namely two input spaces, a generic space, and the blend [16].

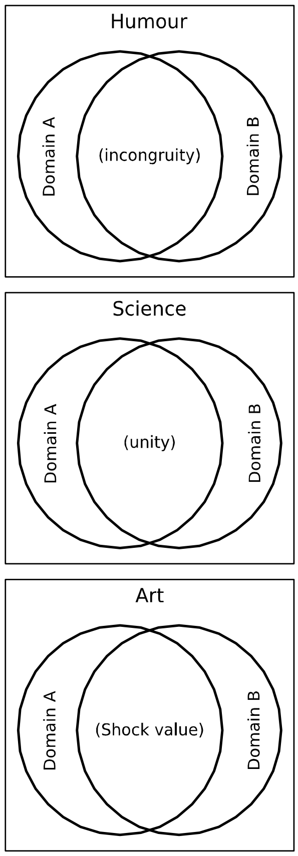

Figure 1: Venn diagram illustrating how Koestler’s theory of bisociation forms the overlap of unrelated domains resulting in creativity for humour, science and art [14]

3.2 – Conceptual blending

A conceptual blend consists of input spaces, partial cross mappings between the input 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 [16].

The computer desktop is an example of conceptual blending [16]. 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 exist in either input space. For example, you cannot perform a mouse click on a folder on a physical desktop, and a graphic user interface without the concept of folders cannot facilitate renaming or moving them. The computer desktop blending 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 2.

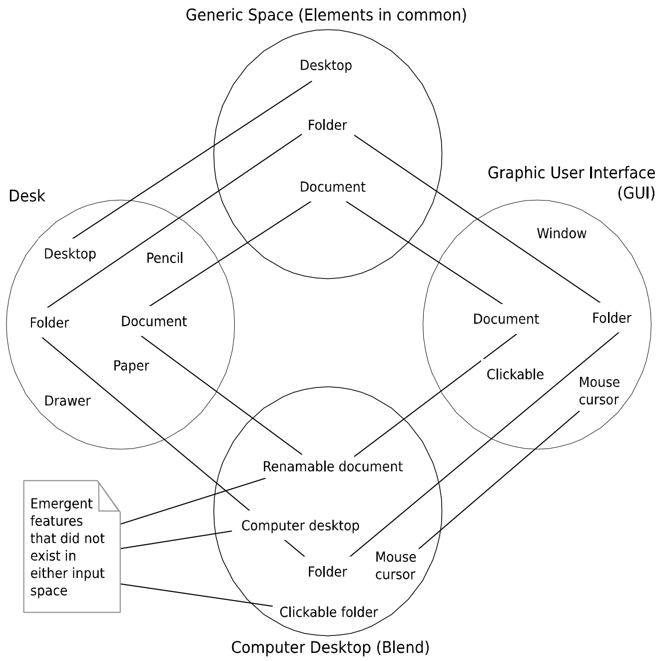

Figure 2: The four mental spaces in a conceptual blend as they pertain to the concept of a computer desktop

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 [16]. Fauconnier and Turner refer to the act of elaboration as, "running the blend" [16]. In the computer desktop example, the fact that a folder can be renamed is an example of emergent structure through composition.

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. Choosing which elements to include, or exclude, from the generic space is nondeterministic and is known as selective projection [16]. Elaboration can be achieved through the use of semantic frames or analogy tools.

3.3 – Conceptual blending and visualisation

Fauconnier and Turner [16] 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. Matching and aligning two domains by finding commonalities and analogies is central to creative work [16].

It has been suggested that iteration plays a large role in the blend of concepts [17]. Iteration is another overlapping feature of conceptual blending and data visualisation. The latter features iteration due to how humans not only anticipate certain patterns in the data, but also learn about their data as they go along, iteratively adjusting the visualisation to align with what they see and wish to communicate [18].

Metaphor is a word or phrase used in a non-literal manner, which when added to other words, suggests a resemblance [19]. Similarly, visual metaphor is an image of a subject (a person or place) depicted in a manner that suggests that it has additional attributes.

Metaphor has been linked to creativity and promotes convergent thinking and divergent thinking [20]–[22]. Metaphor can emerge from repeated iteration of conceptual blends [23]. Fauconnier and Turner call the resulting network of blends integration networks. Metaphor does not always emerge since blends can also contain counterfactuals and elements that clash [24] (refer to Figure 1). Conceptual integration blending operations also use metonymy, category, and analogy [25]. 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 [26]. Specifically they can connect subject orientated terms to visual metaphor. Examples of such metaphors are, “quantity is size”, and “similarity is proximity”. Primary metaphors can be used to communicate insight to the viewer of a visualisation by supporting the intended narrative behind a visualisation [26]. For example, “more is up” connects quantity and height [27], [28]. Purpose and narrative are important to data visualisation [29], [12], [30]–[32]. 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 [26].

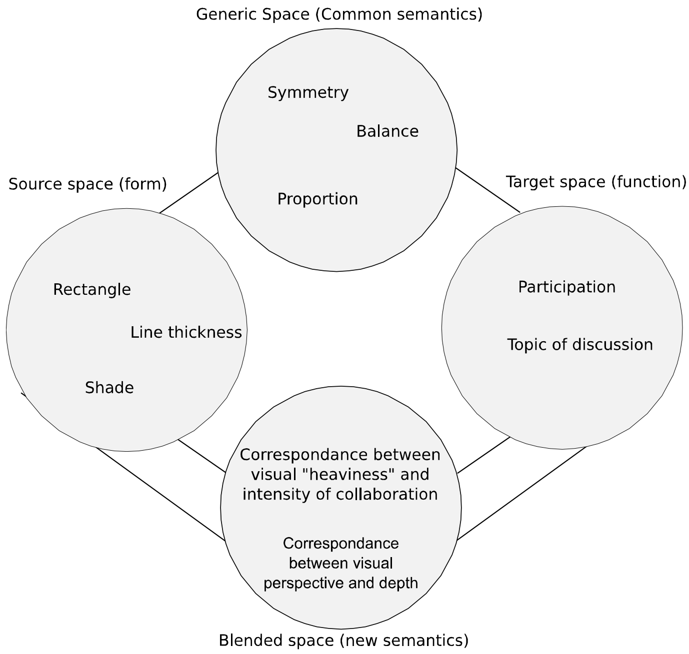

Figure 3: Form-semantic-function mapping for visualising bulletin discussion threads according to Simoff [33]

Simoff [33] suggests that the success of visual data mining is tied to the development of a computational model of metaphor. His model uses a conceptual blend over a textual data set and is illustrated in Figure 3. One of the input spaces (the form space) contains 2D and 3D shapes and their attributes (coordinates, geometry, colour). The second blend input (the function 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.

Time, event and action metaphors pertain to temporal data [26]. Time-space metaphors and mappings are relevant to both data visualisation and conceptual blending as they share attributes. Time-series visualisations are good at comparing multiple variables against each other, thereby illuminating smart comparisons or revealing causality [25], [34], [35]. Emerging novel features in visualised timelines result from compression of temporal relationships into spatial relationships [34]. Compression of multiple blend inputs spaces into one, and the potential compression of time are features of certain types of blends [25], [16]. Time metaphors, such as, “time is a river” and “time is space” exhibit geometry (circles, curves, lines) that can be connected with narrative when blended with culture – also called material anchors (a circle can be mapped to a clockface) [25], [34]. Useful timelines frequently emerge in an iterative manner [25]. Time-space metaphors often appear with motion verbs that indicate front, back, or rate of change [25].

Goguen and Harrell [36] introduce the concept of structural blending, which extends conceptual blending and incorporates syntax, metaphor and narrative [28], [36]. Structural blending 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 in the appropriate choice of visualisation [37].

A strong blend retains tight connections to the input space and can reconstruct how the blend is connected to the input. An item in the blend should have some sort of meaning [28], [38], [39].

Visual metaphor can be used to map concepts to physical objects and also to attributes of the concept (location, colour or texture) [26]. An implementation of visual metaphor mapped to objects is used in the program Virgilio [40]. Virgilio 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, or 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 [40]. The authors give the example of a search for the text "Sting". The dictionary connects this word to the musician "Sting", and returns the following 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.

Conceptual spaces and input spaces can be built computationally in a number of ways. They can be predefined by a human [41], [42], or they can be built from text documents using techniques from natural language processing [33], [40]. There are a variety of techniques for "running the blend". Analogy can be constructed using semantic networks, such as ConceptNet [43] or predefined relationships [40]. Background information can be inferred using semantic frames [28]. An example of a frame is the concept of an illumination device [42]. Both candle and light bulb fit this concept and therefore can be inferred to have the attributes belonging to the frame, such as the ability to make dark places lighter and the ability to be turned off. FrameNet is an example of a tool that provides a dictionary for looking up frames and tools for using the dictionary [44]. Ribeiro, Pereira, Marques et al. [42] use a genetic algorithm that chooses the merit of solutions by scoring 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 Riedl [41] is an open source machine learning toolkit [45], sprites, and probabilistic models learned from visuals. It is possible to connect a concept to a visual representation of the concept [46]. 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 [47]. Cunha, Martins, Cardoso et al. [46] attempted to computationally generate symbols from concepts using text as input and a semantic network repository. ConceptNet is an example of such a repository [43]. ConceptNet stores information about knowledge in the world in the form of relationships. Colours can frequently be associated with concepts. Examples include:

1. bananas ↔ yellow
2. anger ↔ red
3. money ↔ green

Lin, Fortuna, Kulkarni et al. [48] made use of Google's image search to find images related to the concept, after which they analyse the colour distributions in the returned images in order to find concept-colour associations.

4. Discussion

Computational models of metaphor have emerged as one way to connect conceptual blending and data visualisation. Concrete metaphors could potentially be used to connect the data to the visualisation of the data, using the results from the chosen computational model of metaphor with the assistance of semantic dictionaries. An implementation was described where items with a relationship type of "is a" string were mapped to the choice of labels (chosen for the axis on a graph or pie chart). Items with a relationship type of "is a" image could be used as background images. Relationships found using semantic dictionaries such as ConceptNet have been used to identify suitable colours and sentiment. There may be other semantic relationships, specifically geared toward enhancing the automated generation of data visualisation by a computer, that could have relevance. This requires further investigation.

Also described was the use of visual metaphor to aid in making the semantic connection between visual forms and text data, as well as the use of visual metaphor to aid in the understanding or intent of a visualisation. Other types of metaphors, including nominal metaphors (such as "time is money") may apply [49]. This suggests that further investigation of how metaphors can be computationally created and mapped to the data visualisation pipeline could be a topic for further investigation.

Compression of information is a shared feature of data visualisation, narrative, as well as conceptual spaces and should be taken into consideration when trying to marry them. Narrative is a feature of many successful visualisations [2], [29], [31], [50]–[52].

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 [2]. Rather than deciding which variables are chosen for the visualisation in a brute force manner, the operations used to choose which data is interesting, could be driven from the semantic information that emerges when "running the blend". Time information emerging from "running the blend" could potentially contribute toward a more informed choice of scales for the visualisation.

Previous work exploring the data visualisation pipeline highlighted storytelling as important [29], [30]–[32], [52]. Storytelling is a theme that emerges in the literature on conceptual blending as it relates to visualisation. The literature in the current paper suggests that the use of various types of metaphor can contribute to highlighting the intended narrative of a visualisation.

As indicated by Simoff [33], one possible way to generate visualisations using conceptual blends is to blend an input space generated from text documents, using natural language processing techniques (such as stop word removal, and word frequency counting), with an input space consisting of geometric shapes and their attributes. For other types of data involving numbers, a description of what the data is about could function as input to the blend. Since humans have background information about the data they are trying to visualise [51], suitable inputs for the blend could include a textual source of information (such as Wikipedia or Project Gutenberg), or a source of current news. The emergent structure in such a blend could be used to suggest what variables within the data are important or relevant. Such a blend could also identify relevant images or colours. Another possibility is using other data sets and their descriptions in the second input of the blend. The act of "running the blend" over other data sets has potential to discover variables in the data sets that are interesting when visualised side by side.

5. Conclusion

The features of computer models of a theory of creativity known as conceptual blending were reviewed to investigate whether they may be able to facilitate better heuristics for computer programs trying to automate the generation of visualisations. The review is part of a larger project exploring a prototype computer program that uses conceptual blending as part of the algorithm that creates visualisations from a provided data set. Prior investigation of the data visualisation process indicates that computer automated visualisation algorithms fall short because some aspects of the visualisation process (such as knowing what data is novel or interesting) are uniquely human. This is due to human creativity as well as the strong connection between human visual perception and data visualisation [29].

Compression, iteration, storytelling and metaphor are features of both conceptual blending as well as visualisation. Whilst the literature is sparse, different types of metaphor emerge as a means to discover mappings from words (or attributes) to visual elements. Storytelling and metaphor are both considered to be creative acts. Leveraging off commonalities between conceptual blending and visualisation could provide insight into why humans are still much better at creating visualisations than existing computer programs. The compression and metaphor that emerge when "running a blend" have potential to enhance the generation of visualisations, regardless of whether the visualisation are generated solely by computers, or whether the computer program's role is just to assist the user in discovering features of their data. Non-metaphor methods of conceptual blending, such as the use of analogy, should not be discarded because of conceptual blends whose intention is humour or shock value.

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