Optimality Principles in Computational Approaches to Conceptual Blending: Do We Need Them (at) All?

P. Martins[1], S. Pollak[2], T. Urbančič[3,2], A. Cardoso[1]
[1] CISUC, Department of Informatics Engineering, University of Coimbra, Coimbra, Portugal
[2] Jožef Stefan Institute, Ljubljana, Slovenia
[3] University of Nova Gorica, Nova Gorica, Slovenia

Abstract

Optimality principles are a key element in the Conceptual Blending (CB) framework, as they are responsible for guiding the integration process towards 'good blends'. Despite their relevance, these principles are often overlooked in the design of computational models of CB. In this paper, we analyse the explicit or implicit presence and relevance of the optimality principles in three different computational approaches to the CB, known from the literature. The approaches chosen for the analysis are Divago, Blending from a generalisation-based analogy model, and blending as a convolution of neural patterns. The analysis contains a discussion on the relevance of the principles and how some of absent principles can be introduced in the different models.

Introduction

Fauconnier and Turner (2002) proposed *Conceptual Blending* (CB) as a general and basic cognitive mechanism that leads to the creation of new meaning and insight. It integrates (or blends) two or more *mental spaces* in order to produce a new mental space, the *blend(ed) space*. Here, mental space means a temporary knowledge structure created for the purpose of local understanding as opposed to *frames*, which are more stable knowledge structures (Fauconnier 1994).

CB is not a simple combination of the initial mental spaces; it involves a network of mental spaces in which knowledge is transferred and meaningfully integrated (see Figure 1). At least two of the mental spaces correspond to the *input spaces* (the initial spaces). A partial matching between the input spaces is constructed (*cross-space mapping*). The matching between elements is then reflected in another mental space, the *generic space*, which contains elements common to the different input spaces. The latter space captures the conceptual structure that is shared by the input spaces. The outcome of the blending process is the blend, a mental space that simultaneously maintains partial structures from the input spaces and has an emergent structure of its own.

Integration of input elements in the blend space results from three operations: *composition*, *completion*, and *elaboration*. Composition occurs when the elements from the input spaces are projected into the blend space, allowing for new relations to become available in the blended space. This implies not only the matched elements, but also other neighbouring elements to be projected into the blend. Completion occurs when existing knowledge in long-term memory, i.e., knowledge from *background frames*, is used to create meaningful structures in the blend. Elaboration is an operation closely related to completion; it involves cognitive work to perform a simulation of the blended space.

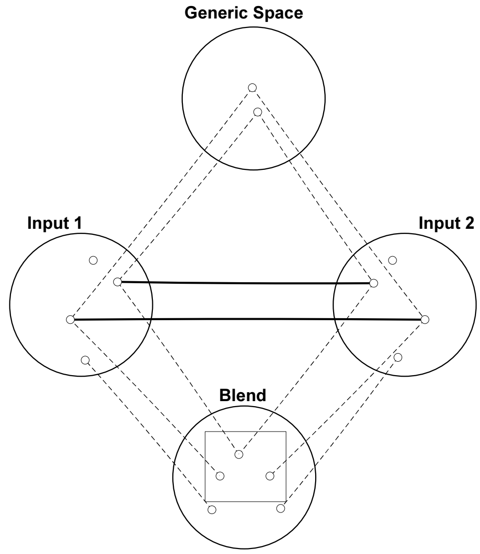


Figure 1: The original four-space CB network (Fauconnier and Turner 2002).

The possibilities for blending are apparently infinite and the quality of blends can be quite diverse. The *optimality principles* (also known as *optimality constraints*) have a key role in blending, namely in the integration process. They are responsible for providing guidance towards highly integrated, coherent and easily interpreted blends.

Despite the challenge in designing a computational model of the CB mechanism, several formalisations and computational models of the CB mechanism have been proposed. The inclusion of the optimality principles in formal and computational models has arguably been one of the most challenging tasks, manly due to the subjectivity and the computational inefficiency associated with these principles.

Bou et al. (2014) have presented a survey of computational approaches to conceptual blending where the presence of the optimality principles was assessed. To the best of our knowledge, the work of Bou et al. offers the most detailed discussion on the computational modelling of the optimality principles. In this paper, we analyse the presence and relevance of the optimality principles in three considerably different approaches to the CB mechanism. Instead of solely basing our analysis on the assessment of the presence or absence of the optimality principles, we discuss the relevance of the principles and how some of the absent principles can be introduced in the different models. We include in our discussion suggestions from our previous study on the quality of blends (Martins et al. 2015). It is particularly relevant to analyse the importance of optimality principles in scenarios where creative blends are a goal.

The remainder of this paper is structured as follows. In the upcoming section, we describe the optimality principles of CB theory. Then, we analyse optimality principles in computational models of CB. Finally, we draw the main conclusions of this study and suggest lines of further research.

Optimality principles

Originally, Fauconnier and Turner (1998) have presented a list of five optimality principles (integration, topology, web, relevance, and unpacking). Later, the same authors have extended the list by including three more principles (maximisation of vital relations, intensification of vital relations, and pattern completion) (Fauconnier and Turner 2002). This paper focuses on the latter.

The Principles

Integration The *integration* principle states that the blend must be perceived and manipulated as a unit. Every element in the blend structure should have integration.

Topology *Topology* acts as a force that attempts to maintain the topological structure of the input spaces in the resulting blend. For any input space and any element in that space projected into the blend, it is optimal for the relations of the element in the blend to match the relations of its counterpart.

Intensification of Vital Relations A key characteristic of the blending process is the ability to *compress* a diffuse conceptual structure into more intelligible and manipulable human-scale situations in the blended space (Fauconnier 2005; Turner 2006). Such compression is likely to occur when mental spaces are connected by *vital relations*, such as time, space, cause-effect, analogy or a part-whole relation. The principle known as *intensification of vital relations* states that diffuse structures should be compressed by scaling a single vital relation (e.g. scale down an interval of time) or transforming vital relations into others.

Maximisation of Vital Relations The *maximisation of vital relations* principle states that the number of vital relations in the blended space should be maximised in order to create human scale.

Pattern Completion The *pattern completion* principle forces the introduction of integrated patterns either from the input spaces or from frames. The elements in the blend should be completed using existing integrated patterns as additional inputs. The principle dictates the use of a completing frame having relations that can be the compressed versions of the important *outer-space vital relations* (space, time, etc.) between the inputs.

Web The *web* principle states that manipulating the blend as a unit must maintain the web of appropriate connections to the input spaces easily and without additional surveillance or computation.

Relevance (or Good Reason) The *relevance* principle dictates that an element in the blend should be relevant, which includes being relevant to establish links to other spaces and for running the blend.

Unpacking The *unpacking* principle imposes the ability to 'deconstruct' the whole blending process starting from the blended space. This principle takes exclusively the perspective of the 'blend reader', who is expected to recognise the input spaces and the results of intermediate operations, namely the cross-space mappings.

Optimal blends vs. creative blends

All of the listed principles try to ensure an easy interpretation of the blend and trigger a prompt cognitive response. Additionally, they intend to provide integrity and coherence, namely by the integration, web, and topology principles. However, there is a tension among the principles, which includes different levels of incompatibility between them (Grady, Oakley, and Coulson 1999). For example, an intensification of vital relations might hinder the ability to reconstruct the entire blending network (unpacking principle).

The aforementioned tension among principles makes the construction of a blend satisfying all the principles impossible. However, we cannot simply regard these principles as 'rigid laws', but as something with a reasonable degree of flexibility (Kowalewski 2008). Furthermore, the optimality of a blend depends on its purpose: different purposes imply distinct levels of priority for each principle.

While the optimality principles can provide guidance towards consistent, useful, and easily interpreted blends, we cannot ensure that they contribute to defining novel and surprising blends. Thus, the criteria conveyed by the optimality principles cannot dictate whether a blend is creative or not. Nonetheless, they help defining other 'good characteristics' of a creative blend.

Optimality Principles and Computational Approaches to Conceptual Blending

'*Conceptual blending is not a compositional algorithmic process and cannot be modeled as such for even the most rudimentary cases. Blends are not predictable solely from the structure of the inputs. Rather, they are highly motivated by such structure, in harmony with independently available background and* *contextual structure; they comply with competing optimality constraints ... and with locally relevant functional goals. In this regard, the most suitable analog for conceptual integration is not chemical composition but biological evolution. Like analogy, metaphor, translation, and other high-level processes of meaning construction, integration offers a formidable challenge for explicit computational modeling.*'(Fauconnier and Turner 1998).

Despite the challenge in computationally modelling the CB mechanism, several formalisations and computational models of the CB mechanism have been proposed. The inclusion of the optimality principles in such models has arguably been one of the most challenging tasks, manly due to the subjectivity and the computational inefficiency associated with these principles. According to Goguen (1999), who proposed one of the first formalisations of CB theory, the optimality principles are one of the components of CB theory that cannot be formalised and straightforwardly implemented, as they require human judgment.

In this section, we analyse the role implicitly or explicitly played by the optimality constraints in three different computational models: (1) Divago (Pereira 2005), which is strongly inspired by CB theory and contains quantitative metrics for the optimality principles; (2) a model that follows a neuro-computational approach (Thagard and Stewart 2010), with blending being performed via the convolution of mental representations; and, finally, (3) a model constructed using a generalisation-based approach to analogy (Guhe et al. 2011).

We have opted for these three models because they simultaneously illustrate the heterogeneity and the maturity of computational approaches to CB. For an updated and a more complete overview of computational approaches to CB, we refer the reader to the works of Martins et al. (2014), Bou et al. (2014), or Li et al. (2012).

When analysing the relevance of some principles, we take into account also suggestions from our previous study in which we investigated the quality of blends as perceived by humans in a web-based questionnaire (Martins et al. 2015). The participants were asked to rate criteria related to the optimality principles (e.g., coherence) and creativity (e.g., novelty and surprise).

Divago

The Divago system (Pereira 2005) is one of the earliest computational approaches to CB and is, to the best of our knowledge, the only system to date that uses a thorough formalisation of the optimality principles. The architecture of the system is depicted in Figure 2.

In Divago, the first step corresponds to selecting a pair of input spaces (domains) from the *Knowledge Base*. The input spaces are represented as concept maps, i.e., graphs where vertices are concepts and edges represent relations. The selection of such spaces is performed by the user or randomly generated. Then, the *Mapper* module preforms the selection of elements for projection. Such selection is achieved by means of a partial mapping between the input spaces using *structural alignment*. This operation looks for the largest isomorphic pair of sub-graphs contained in the input spaces.

For each mapping provided by the Mapper, the *Blender* performs a projection into the blend space. At this stage, all the possible projections resulting from each mapping must be represented in the blend space. The whole set of projections summarises the *Blendoid*, which is the set of all possible blends.

The *Factory* module is responsible for exploring the space of all possible blends provided by the Blender. The Factory interacts both with the *Elaboration* and *Constraints* modules: it is based on a genetic algorithm (GA) that looks for the elaborations that best fulfill the requirements dictated by the Constraints module. At each iteration, the GA sends each blend to the Elaboration module, which is responsible for applying context-dependent knowledge, and then sends the result to the Constraints module, which applies the optimality principles in order to evaluate the elaborated blend. When the GA finds an adequate solution (or a pre-defined number of iterations is reached), the Factory stops the execution of the genetic algorithm and returns the best blend.

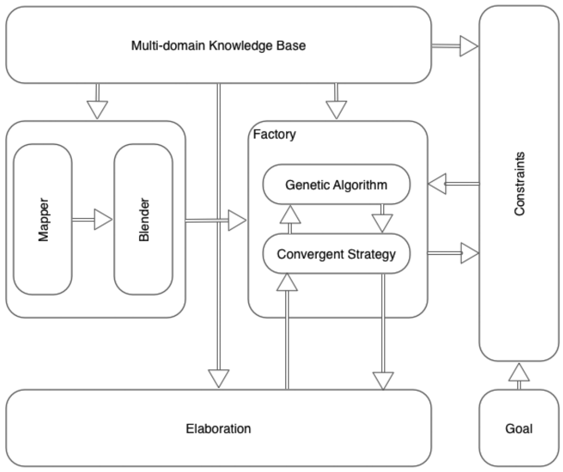


Figure 2: Divago architecture.

The Constraints module contains an implementation of the optimality principles based on quantitative metrics.

Integration

The measure of integration is based on the idea of *frame coverage*. If F is the set of frames that are satisfied in a blend, frame coverage corresponds to the set of relations from its concept map that belong to the set of conditions of one or more frames in F.

Definition 1 ($SingleFrameIntegration$)**.** For a frame f with a set C of conditions, a blend b, with a concept map CM_b, its blendoid with a concept map, CM_{B+}, and VI, the set of integrity constraints that are violated in the frame, the *integration* value, I_f, is defined by:

$$I_f = \frac{\#C}{\#CM_b} \times (1-\iota)^{\#VI} \times (1 + \frac{\#CM_b}{\#CM_{B^+}})/2, \quad (1)$$

where ι is a penalty factor between 0 and 1, a value that penalises a frame for each violation of integrity constraints. An integrity constraint is violated if its premises are true. In the context of the integration measure of frame f above, f violates integrity ic if the conditions C_{ic} of ic are met and $C_{ic} \bigcap C \neq \emptyset$.

Integration is estimated through the following equation:

Definition 2 ($Integration$)**.** Let $F_b = \{f_1, f_2, ..., f_i\}$ be the set of the frames that have their conditions (C_i) satisfied in the blend b, α, the disintegration factor (with $0 < \alpha < 1$), and I_{f_i}, the single frame integration value, as in Eq. (1).

$$Integration = I_{\bigcap_0^i C_i} + \alpha \times Uncoverage \times \sum_0^i I_{f_i}. \quad (2)$$

The $Uncoverage$ value consists of the ratio of relations that do not belong to the intersection of all frames w.r.t. the total number of relations considered in the frames:

$$Uncoverage = \frac{\# \bigcup_0^i C_i - \# \bigcap_0^i C_i}{\# \bigcup_0^i C_i}. \quad (3)$$

Topology

The topology measure follows the principle that if a pair of concepts x and y are associated in the blend by a relation r, then the same relation must exist in the inputs between the elements from which x and y were projected. In this case, the relation $r(x, y)$ is *topologically correct*. The topology measure corresponds to the ratio of topologically correct relations in the concept map of the blend:

Definition 3 ($Topology$)**.** For a set $TC \subseteq CM_b$ of *topologically correct* relations, defined as

$$TC = \{r(x, y) : r(x, y) \in CM_1 \cup CM_2\}, \quad (4)$$

where CM_1 and CM_2 correspond to the concept maps of inputs 1 and 2, respectively. The topology measure is calculated by the ratio:

$$Topology = \frac{\#TC}{\#CM_b}. \quad (5)$$

Maximisation/Intensification of Vital Relations

In Divago, intensification is treated as maximisation, i.e., there is only one measure for the principles related to the vital relations. To define the maximisation measure, the impact of the vital relations to the blend is given by the ratio of vital relations w.r.t. the whole set of possible vital relations, contained within the blendoid:

Definition 4 ($Maximisation\_VR$)**.** Let Υ be a set of *vital relations*. From the concept map of the blend b, we may obtain the set of vital relations in b, B_{VR}:

$$B_{VR} = \{r(x, y) : r(x, y) \in CM_b \wedge r \in \Upsilon\}.$$

From the blendoid (the union of all possible blends), B^+, we have B^+_{VR}:

$$B^+_{VR} = \{r(x, y) : r(x, y) \in CM^+_B \wedge r \in \Upsilon\}.$$

Finally, the Maximisation of Vital Relations measure is calculated by the ratio

$$Maximisation\_VR = \frac{\#B_{VR}}{\#B^+_{VR}}.$$

Pattern Completion

In Divago, pattern completion is viewed as frame completion, as a pattern is described by a frame. The act of completing a frame consists in asserting the truth of the ungrounded premises, a process that happens only after a sufficient number of premises is true (*completion threshold*). The measure that indicates the conditions that are actually satisfied by a frame f in a blend b is called *completion evidence* of f, $e(f, b)$. (Frame) completion can only happen when the completion evidence is higher than the completion threshold.

Definition 5 ($Completion\ Evidence$)**.** The Completion Evidence e of a frame f_i with regard to a blend b is calculated according to the following:

$$e(f_i, b) = \frac{\#Sat_i}{\#C_i} \times (1-\iota)^{\#VI}, \quad (6)$$

where Sat_i contains the conditions of each f_i that are satisfied in b, C_i contains the conditions of f_i, ι is the integrity constraint violation factor and VI the set of violated integrity constraints.

In the end, pattern completion is computed by finding the union of all the conditions contained within the patterns and estimating its own completion evidence:

Definition 6 ($Pattern\ Completion$)**.** The Pattern Completion measure of a blend b with regard to a set of frames F is calculated by

$$PatternCompletion = e(\bigcup_{f_i \in F} f_i, b). \quad (7)$$

Web

The web principle is not treated as an independent principle; it is co-related to topology and unpacking. As a result, it is given as an estimation of the strength of the web of connections to the inputs:

Definition 7 (Web)**.**

$$Web = \lambda \times Topology + \beta \times Unpacking, \quad (8)$$

with $\lambda, \beta \geq 0$ and $\lambda + \beta = 1$.

Relevance

The idea of relevance is strongly associated with the goal of blending:

Definition 8 ($Relevance$)**.** Assuming a set of goal frames, F_g, the set F_b of the satisfied frames of blend b and the value PCN_F for the pattern completion of a set of frames F in blend b, relevance is given by:

$$Relevance = \frac{\#(F_g \cap F_b) + \#F_u \times PCN_{F_u}}{\#F_g}, \quad (9)$$

where F_u, the set of unsatisfied goal frames, consists of $F_u = F_g - F_b$. This formula gives the ratio of satisfied and partially satisfied goal frames w.r.t. the entire set, F_g of goal frames.

Unpacking

Unpacking is reduced to the ability to reconstruct the input spaces. To measure it, the definition of *defining frame* is required:

Definition 9 ($DefiningFrame$)**.** Given a blend b and an input space d, the element x (which is the projection of the element x_d of input concept map d to b) has a defining frame $f_{x,d}$ consisting of

$$f_{x,d} = C_0, C_1, \ldots, C_n \longrightarrow true, \tag{10}$$

where $C_i \in \{r(x,y) : r(x_d, y) \in CM_d\}$. Assuming that k is the number of conditions (C_i) of $f_{x,d}$ that are satisfied in the blend, the unpacking value of x with regard to d (represented as $\xi(x,d)$) is

$$\xi(x,d) = \frac{k}{n'}, \tag{11}$$

where n' is the number of elements to which x is connected. The *total estimated unpacking value* of x as being the average of the unpacking values with regard to the input spaces:

$$\xi(x) = \frac{\xi(x,1) + \xi(x,2)}{2}. \tag{12}$$

Definition 10 ($Unpacking$)**.** Let $\mathcal{X}$ be the set of m elements of the blend b, generated from input concept maps 1 and 2. The *Unpacking* value of b is calculated by

$$Unpacking = \frac{\sum_{i=0}^{m} \xi(x_i)}{m}, x_i \in \mathcal{X}. \tag{13}$$

Blending as a convolution of neural patterns

Thagard and Stewart (2010) propose a neuro-computational approach based on a mechanism that combines neural activity patterns by a process of *convolution*, a mathematical operation that interweaves structures. The main idea behind such approach is to build combinations of neural activity patterns that are probably useful and novel. The work aims at modelling the so-called *AHA! moment*, which occurs when humans discover surprising relations between apparently unrelated pieces of information.

Concepts are represented as activity patterns of vectors of neurons, which are convoluted in order to combine patterns (the use of convolution to combine neural representations is based on the assumption that any representation can be treated as a vector). Although the authors do not explicitly claim that their approach models the CB mechanism, they highlight the similarities between the proposed account of creativity and the blending mechanism. A key feature of this model is the ability to combine several multimodal representations, including information that can be sensorial, kinesthetic, and verbal, as well as emotional (see Figure 3). As for the latter, it is worth mentioning that emotional reactions play a key role in creative thought; in particular, the reaction of pleasure/approval that is associated with the generation of novel and surprising ideas. As a result, the AHA! experience is presented as a convolution of a novel combined representation with patterns of brain activity for emotion.

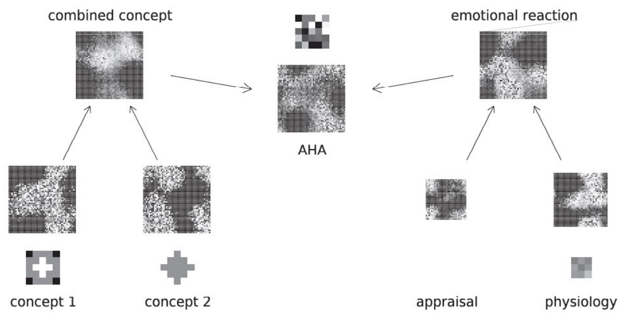


Figure 3: The AHA! experience as a convolution of neural patterns (combination of four representations into a single one). The arrows indicate the flow of information although many reentry feedback loops may occur (Thagard and Stewart 2010).

Another relevant feature of this model is the ability to reverse the process of convolution, using neural connections similar to those required for performing the convolution. This reverse process, which is known as *deconvolution*, implies loss of information: the output is an approximation of the original patterns.

Blending from a Generalisation-Based Analogy Model

Guhe et al. (2011) present an account of blending based on the *Heuristic-Driven Theory Projection* (HDTP) (Schwering et al. 2009; Gust, Kühnberger, and Schmid 2006), which was originally proposed as a framework for analogy making. HDTP represents knowledge about the domains as *first-order logic theories*, whose analogical mapping is established via *anti-unification*, i.e., an analogical relation is built by associating terms with a common generalisation.

In the HDTP framework, knowledge is mapped and transferred from a source domain S to a a target domain T. To create an analogy, two stages are required: *mapping phase* and *transfer phase*. In the former, the two domains are compared to find structural commonalities, leading to the creation of a generalised description G that contains the matching parts of both domains. In the final phase, unmatched knowledge in S can be mapped to the target domain to create new hypotheses.

The first phase is similar to the cross-space mapping and the generation of the generic space in the CB framework. In fact, the authors turn the HDTP framework into a CB framework by modifying the second phase: the knowledge transfer is replaced by a process that creates a new knowledge domain B, the blend. Knowledge from S and T is merged to create B based on the following mapping: '*in the ideal case, B respects the shared features of S and T (those with common generalisations), and inherits independently the other* *features of S and T.*'.

Since unmatched parts of the domains will be transferred into the blend, which may introduce incoherence, the framework has the ability to either discard conflicting knowledge or reduce the coverage of the generalisation.

Figure 4 depicts a diagram illustrating the extension of the HDTP framework to CB.

In this model, the mental spaces are represented by *many-sorted first-order theories*. To blend two theories, three steps are required: (i) definition of *core (blend) laws*, which unite input signatures to generate new signatures ; (ii) addition of *preferred conjectures* (generation and addition of laws that concern equality of analogous entities, functions and relations) ; (iii) definition of *extra conjectures* (addition of laws from the input spaces) (Bou et al. 2014).

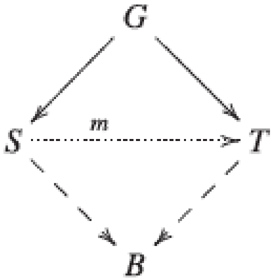


Figure 4: HDTP as a blending framework. Top arrows denote substitutions resulting from the computation of the analogical relation m. Dashed arrows indicate the heuristic-driven construction of the conceptual blend (Guhe et al. 2011).

Discussion

Among the three models previously described, Divago is the one that encapsulates more elements of CB theory. Despite the inherent subjectivity involved, the Constraints module in Divago tries to be consistent with theory regarding the optimality principles. This gives Divago a certain modularity, as different principles and weights can be considered as a function of the task at hand. The inclusion of metrics to assess the presence of vital relations is probably the most noteworthy characteristic of the constraints module. However, it is important to note that Divago does not perform compression (of vital relations).

The neuro-computational approach based on the convolution of neural patterns is not directly inspired by CB theory. Its inspiration comes from findings in the field of neuroscience that can be related to blending (neural combination and binding). This kind of approach does not take into consideration the optimality principles. However, we believe that the inclusion of those principles in the model of emotional reactions would make the whole model more complete, as it would define emotional reactions that are associated not only with novelty and surprise but also with the coherence and interpretation of ideas. Here, the challenging task is to model neural processes that can generate inputs to assess the presence of the optimality principles.

The blending model developed from a generalisation-based analogy model is particularly suitable for generating blends that are mostly analogical constructions. The preferred and extra conjectures that can be added during the generation of blends share some similarities with the optimality principles in terms of role in the blending process, as they help discard unwanted blends.

While some models try to include the optimality principles, others do not take them into consideration. But are all the principles relevant? And, when they are not an obvious part of the model, could they be implicitly defined? We present our view on these questions for each one the optimality principles and for each one of the computational approaches described herein.

Integration

Integration is a principle that most contributes to the integrity of a blend and it cannot be completely disregarded. Our experiments with visual blends showed the importance of integrity to the quality of a blend; there was a high correlation between integrity (or coherence) and the overall impression of the blend (Martins et al. 2015). Figure 5 depicts two examples of visual blends (fictional hybrid animals) used in our survey: *Guorse* and *Pengwhale*. The former was among the blends with the lowest overall impression and coherence scores, whereas the latter was among the favourite blends (with high overall impression and coherence scores).

Integration is present in each one of the models but in apparently varying degrees. Divago performs integration both in an explicit and implicit way. The former corresponds to the maximisation of the criterion given by Equation (2). However, integration is also achieved to some extent through the strategy used to perform cross-space mapping, as Divago basis its mapping on structural alignment, which ensures a certain degree of integration.

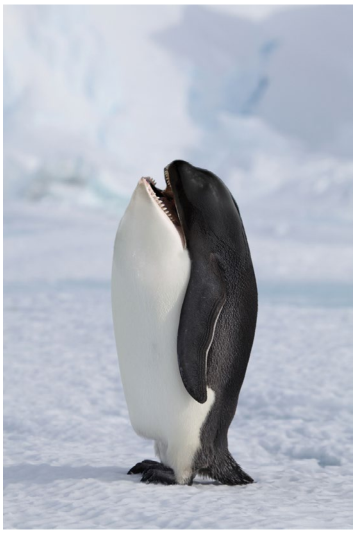
The blending model based on the HDTP framework tries to ensure integration by constructing the generalisation model and in subsequent stages the integrity criterion is still taken into consideration.

In the neuro-computational model, the convolution of neural activity patterns is by definition an integration operation. However, to ensure a higher level of integration, it is fundamental to assess integration through the emotions module.

Topology

As for the Topology principle, we can argue that its relevance is somewhat relative. On one hand, it can ensure consistency to some extent, as it contributes to the external coherence of the blend. On the other hand, it tends to inhibit the inclusion of more uncommon associations. However, as observed by Pereira (2005), the importance of maintaining the same topological arrangement depends on the type of the blend we are aiming at. For example, if our construction pursues an analogy, then topology becomes crucial; if we are pursuing less strict combinations, then it should become secondary.

Guorse
(guinea pig, horse)



Pengwhale
(penguin, whale)

Figure 5: Two examples of fictional hybrid animals used in the online questionnaire (Martins et al. 2015). Each subcaption contains the corresponding name of the blend as well as the input spaces. The author of both blends is Arne Fredriksen (`http://gyyp.imgur.com/`).

The model based on the HDTP framework follows an approach that tries to build externally coherent blends, despite the absence of an implementation of the optimality principles. With regard to the neuro-computational approach, topology could be assessed via the emotions module.

Maximisation/Intensification of Vital Relations
A maximisation or an intensification of vital relations contributes to make the blend easier to understand and to trigger a prompt cognitive response. However, maximisation (or intensification) is not always possible, as the mental spaces are not always connected by vital relations. Furthermore, computationally modelling the phenomenon of compression, i.e., bringing appropriate relations from different inputs to the blend can be challenging.

Pattern Completion
We do not view pattern completion as a fundamental principle. It can enrich the blend, but it is not the type of constraint that, by itself, contributes more to the integrity and easy understanding of a blend. However, we believe it cannot be completely disregarded, especially when there is some incompleteness associated with the blend. Additionally, frame pattern completion can increase the capabilities and relevance of the blend.

Any of the computational models described in this paper can accommodate an implementation of this principle. In the HDTP-based approach, this can be achieved via the definition of extra conjectures. In the neuro-computational model, pattern combination could be assessed by inputs related to the incompleteness of patterns.

Web
The web principle ensures that elaboration is performed without removing links to the input spaces. This constraint has a direct relation with the topology and unpacking principles, as they try to maintain the connections to the input spaces. More particularly, the topology principle tries to maintain the web of relevant connections to the input spaces, whereas unpacking tries to reduce the cognitive work associated with the reconstruction of the input spaces.

In our view, this is a relevant principle in most of the scenarios, as it promotes the easy understanding of the blended space and tends to produce an immediate cognitive effect. However, it does not have to be directly applied, as it depends on the topology and unpacking principles.

Relevance
Relevance is a principle that is associated with the usefulness of the blend. Since the quality of a blend depends on its purpose, it is fundamental to understand the usefulness of the various elements of a blend. An inexistent blending goal can be detrimental to the assessment of the relevance. It is therefore advantageous to have additional knowledge regarding the blending goal and how it relates to the elements of the blend. This principle is usually implicitly present. For example, the HDTP-based model can use the preferred and extra conjectures to define goals.

Unpacking
Our previous series of experiments on the evaluation of visual blends suggested that unpacking is relevant in order to better understand the blend. The participants tended to emphasise the importance of recognising the input spaces (Martins et al. 2015). However, there was also a generalised opinion that the favourite blends were those whose unpacking took some time to occur. The unpacking act can give a hint on the level of surprise of a blend: a longer unpacking tends to suggest a higher level of surprise. However, too much surprise can be detrimental to the quality of the blend.

As for the external coherence of the blend, we believe that unpacking is a fundamental criterion. However, for some approaches, it can become challenging to evaluate the easiness of reconstructing the integration network or simply determining the input spaces. In those cases, a topology measure is required to account for external coherence.

Since the convolution of neural patterns can be reverted (via deconvolution), we can say that the neuro-computational approach follows the unpacking principle.

We also argue that HDTP-based CB model tries to follow this principle, as it tries to add the maximum number of symbols of the input spaces to the blends.

Conclusions and further work

The optimality principles are a fundamental element in CB theory. They are responsible for guiding the integration process towards highly integrated, coherent and easily interpreted blends. While several computational models of the CB mechanism have been proposed and successfully used as creative systems, the inclusion of the optimality principles in those models has been overlooked, manly due to the subjectivity and the computational inefficiency associated with this element of CB theory.

In this paper, we have analysed the presence as well as the relevance of the optimality principles in three different approaches to the CB mechanism. Three substantially different computational models were studied: Divago (explicit presence), CB as a convolution of neural patterns (implicit presence) and CB from a Generalization-Based Analogy Model (implicit presence).

From our analysis, we believe that not all principles are relevant. Integration, topology, unpacking, relevance, and intensification/maximisation of vital relations appear to be the most crucial ones. In fact, principles such as integration and topology tend to be implicitly present in models that apparently overlook the optimality principles.

Integration is the most vital principle to establish the integrity of the blend. Topology and unpacking are responsible for defining the external coherence of the blend. However, if we want to favour the introduction of uncommon associations, topology and unpacking can be treated as secondary principles.

Maximisation (and intensification) of vital relations can contribute to an easier understanding of the blend and a create a more immediate cognitive effect. As such, they are also fundamental principles.

Relevance is related to the usefulness of the blend and, as a result, we believe it cannot be disregarded in most cases.

As future work, we will continue our investigation on the relevance of the optimality principles. We also plan to reimplement the Constraints module in the Divago framework using some of the discoveries made during our study.

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