Optimality Principles for Conceptual Blending:
A First Computational Approach

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Abstract

We propose an implementation of the eight Optimality Principles from the framework of Conceptual Blending, as presented by (Fauconnier and Turner, 1998). Conceptual Blending explains several cognitive phenomena in the light of the integration of knowledge from different mental spaces onto a single mental space: the Blend. The Optimality Principles express general pressures that compete in the generation of the Blend.

The work we present now corresponds to the Constraints module of our computational model of Conceptual Blending, also described in other papers.

1 Introduction

One big challenge for Computational Creativity is the generation of new concepts and a very interesting source of inspiration for approaching this issue comes from the framework of Conceptual Blending, from (Fauconnier and Turner, 1998). The Conceptual Blending (CB) framework suggests processes and principles that may be at work within the cognitive integrations of knowledge needed in reasoning. We are developing a model of computational creativity that takes an approach to CB as a fundamental pillar. This system has been described in earlier papers ((Pereira and Cardoso, 2001), (Pereira and Cardoso, 2003b)) as well as its first experiments ((Pereira and Cardoso, 2002)), where the need for developing the Optimality Principles of Conceptual Blending was evident as an urgent improvement. These are the general guidelines that drive the process of blending and allow the differentiation between a “good” and a “bad” blend. Here, we propose a formal realization for each of the eight principles. Experimentations around these principles have already been published in (Pereira and Cardoso, 2003b). Although in the present paper we provide some results of these experiments, we strongly advise the interested reader to explore this previous publication.

In the first sections, we give an overview of Conceptual Blending, so as to provide the reader with the motivation and background for our approaches to the Optimality Principles. We made some exploratory experiments which are informally reported at the end of the discussion of each principle. We finalize this paper with reflections regarding the relevant aspects of this work for Computational Creativity.
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2 Conceptual Blending

Conceptual Blending (CB) was initially proposed by (Fauconnier and Turner, 1998) as part of a major framework concerning cognition and language and had the role of explaining the integration of knowledge coming from distinct sources onto a single, independent and coherent unit, the Blend. A blend is a concept or web of concepts whose existence and identity, although attached to the pieces of knowledge that participated in its generation (the inputs), conquers gradual independence through time and use.

We find examples of blends in many sorts of situations. A blend can be an effective way to get attention and curiosity towards advertising a product (e.g. Sony’s AIBO robot uses all sorts of Sony products behaving as if it were a real human) or spreading a message (e.g. the Marlboro cowboy with impotence problems). People have been making blends with creatures from the times of Greek mythology (e.g. *pegasus*) till today (e.g. *the pokemons*), natural language discourse (e.g. “John digested the book”, “Sue sneezed the napkin off the table”), poetry (see (Freeman, 1999)). Many more examples and situations could be listed and studied in detail, demonstrating the ubiquity of CB as observed by its community.

It is noticeable that Conceptual Blending and its research community are growing, and possibly still in its early stages. It is an elegant proposal for modelling a creative process and its relationships with language and cognition, but it carries formal vagueness across its several aspects, making it difficult even to be considered as a theory, in a Popperian sense. Indeed, if the big hole between the general model and the specific examples does not show any incoherence, it also does not allow falsifiability, leaving very much undefined the boundary between what is and what is not a blend. These criticisms intend to motivate work that, from our point of view, is fundamental. They also support our own motivation for the present project, which is that of contributing with a formal model and implementation based on Conceptual Blending. We hope it can be useful in shedding some light on a number of issues.

In order to understand the CB framework, we must introduce a fundamental concept: the mental space. According to (Fauconnier and Turner, 1998), mental spaces are partial structures that proliferate when we think and talk, allowing a fine-grained partitioning of our discourse and knowledge structures. For simplifying, let us consider a mental space as a partial selection of knowledge from a domain, a memory of a situation, an imagined scenario or entity, essentially a knowledge structure of inter-related concepts that is explicitly or implicitly necessary for a reasoning. As AI researchers, we see a mental space representable as a semantic network, a frame, a case or any other symbolic knowledge structure that gathers a set of inter-related concepts towards a specific situation. In the four space model, Conceptual Blending is described as involving two input mental spaces that, recurring to a cross-space mapping between them and a generic space that has general knowledge relevant for both the input domains, will generate a fourth one, called Blend. This new domain will maintain partial structure from the input domains and have emergent structure of its own.

The process of generation of a blend can be summarized according to three general steps ((Fauconnier, 1997)): Composition, where new relations become available that did not exist in the separate inputs; Completion, when generic knowledge is projected into the blend, to "complete" the emergent structure; and Elaboration, in which cognitive work is performed in the blend, according to its own emergent logic. The order of these steps may be changed and several iterations of the process may be necessary. There is a set of governing principles, the Optimality Pressures, that should drive the process of generating
Figure 1: The Conceptual Blending Model

a “good blend” ((Fauconnier and Turner, 2002)):

- Integration - The blend must constitute a tightly integrated scene that can be manipulated as a unit. More generally, every space in the blend structure should have integration.

- Pattern Completion - Other things being equal, complete elements in the blend by using existing integrated patterns as additional inputs. Other things being equal, use a completing frame that has relations that can be the compressed versions of the important outer-space vital relations between the inputs.

- Topology - 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.

- Maximization of Vital Relations - Other things being equal, maximize the vital relations in the network. In particular, maximize the vital relations in the blended space and reflect them in outer-space vital relations. Turner and Fauconnier identify 15 different vital relations: change, identity, time, space, cause-effect, part-whole, representation, role, analogy, disanalogy, property, similarity, category, intentionality and uniqueness.

- Intensification of Vital Relations - Other things being equal, intensify vital relations.

- Web - Manipulating the blend as a unit must maintain the web of appropriate connections to the input spaces easily and without additional surveillance or computation.

- Unpacking - The blend alone must enable the understander to unpack the blend to reconstruct the inputs, the cross-space mapping, the generic space, and the network of connections between all these spaces.

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- Relevance - Other things being equal, an element in the blend should have relevance, including relevance for establishing links to other spaces and for running the blend. Conversely, an outer-space relation between the inputs that is important for the purpose of the network should have a corresponding compression in the blend.

As far as we know, there is no work yet towards an objective study of the optimality pressures, measuring examples of blends or specifying these principles in detail. This, we believe, disturbs considerably the appreciation and application of Conceptual Blending in scientific research, and therefore testing and specifying a formal proposal for the optimality pressures is also a particular motivation for this work.

3 Basic Notions from our model

We present now some basic notions that are necessary to understand this document. We use a specific type of mental space, that is static, modeless and non attached to discourse, which is closer to the notion of domain knowledge in AI. We call it a domain, comprising a theory and a set of instances. In this paper, we consider only the theory, which is represented by a concept map that explains the structural and causal organization of the domain. A concept map is a semantic network, with binary directed relations between the concepts. In CB, there is a set of vital relations that take a special role in the blending process. We also consider these relations, but allow the choice of a different set of relations. In principle, these vital relations can be the source for establishing mappings between the input spaces, fundamental for the projection operation (two objects mapped to each other can be projected to the same concept, e.g. horse and bird projected to pegasus). Each mapping projection consists of a ternary relation \( m/3 \). For example, a mapping algorithm based on “property” could try to map pairs of concepts that make a valid pair of property/object (e.g. \( m(\text{property, dark, bird}) \)), a different one based on analogy could link pairs of analogical counterparts (e.g. \( m(\text{analogy, leg, wing}) \)). As far as our research goes, we are applying mapping algorithms that find 1-to-1 structures mapping between the concept maps of the two domains based on analogy, identity, space and time. Knowing this is a strong limitation, we hope to address other mapping algorithms in future developments. Currently, for the sake of validation and experimentation of the system, we allow user-defined mappings, so as to allow conclusions independent from the mapping choice.

Finally, another important notion is that of frames. A frame comprises a set of concepts and relations that should be tightly integrated according to a situation, structure, cause-effect or any other relation that ties a set of concepts onto one, more abstract or broad, composite concept. We envisage different kinds of frames, in terms of level of abstraction. The more specific ones correspond to concepts easily identifiable as familiar objects or situation (which we can see as a kind of prototypes). For example, the (very much simplified) frame of “transport means” corresponds to a set of concepts and relations that, when connected together, represent something that has a container and a subpart (e.g. an

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1 First order logic predicates with arity 2, e.g. isa(bird, aves); purpose(wing, fly))

2 Analogy: the algorithm searches for a structure alignment between the two domains; Identity: equal or synonymous elements from the two domains get mapped together; Space: Spatial data (e.g. location) at the same level of detail are mapped together; Time: Temporal data (e.g. a date) at the same level are mapped together.

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The more abstract frames can consist of top-level decisions or directives that decide the underlying philosophy of the blend construction. For example, if a blend satisfies the "aframe" frame, it means it maintains the structure of the input domain. If it satisfies the "bprojection" frame, then the concepts of input space all get projected unchanged to the blend (e.g. “bird” is projected to “bird”, “wing” is projected to “wing”). If a blend satisfies “aframe” and “bprojection” simultaneously, then it should have the concepts from input space organized according to the structure of input space. It is more complex to design these more abstract frames, thus we allow the use of programming (in prolog language, inside curly brackets) within a frame specification. Below we can see the programming of the “aframe”.

```
frame(aframe(A)) :  
aframe(A, Blend) ←  
  { stats(domain1, A), current_blend(Bl1), ∧  
  { findall(R/X/Y, rel(A, X, A, R, Y, A), pro- 
    jection(Bl, A, X, A, X), projection(Bl, A, 
    Y, A, Y)), L1 } } ∧ op(exists(L))
```

Basically, “aframe” searches for all relations of domain 1 (A) and obtains a list (L) containing their projections to the blend. The $\text{op(exists}(L))$ condition is an operator that, when interpreted by the frame processor, expands L into a set of concept map relations (like those in the “transport_means” frame). For “aframe” to be totally satisfied, it is necessary that all relations from input space 1 also exist in the blend.

There are also frames of intermediate level of abstraction, which aren’t either as specific as “transport_means” or as abstract as “aframe”. For example, “new creature” is concerned with finding a “creature” (thus having its specific properties - e.g. being a “living being”) that didn’t exist before in either domains or existed but not as a “creature” (e.g. a “flying snout”).

When we say that a frame $f$ is satisfied in the blend $b$, we mean all its premises are true in the domain $b$. We see frames as information molds and building a blend for a given situation should depend much on the choice of these structures, either being structures towards which the blend self-organizes or as pragmatic goals or query specifiers that the blend is expected to accomplish.

## 4 Optimality Principles

Following the F&T notion of Optimality Principles, the pressures that should lead towards stable, integrated new blends, we propose now a set of measures that should reflect as much as possible the rationale behind each principle. In order to give a clearer idea of the mappings, the concepts considered in aframe and bprojection may become separate in the inputs (and so there wouldn’t be any systematic relation between concepts from input spaces 1 and 2), yet this would receive little value in the measures presented in this paper.

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of its individual effect in our blending system, we present a brief report of experiments we made. These experiments consisted in running a parallel search method, a genetic algorithm, to retrieve blends from the search space. The input domains were the domains of *horse* and *bird* (see tables 1 and 2 - in the end of this paper), meaning that the expected results range from the unchanged copy of one (or both) of the concepts to a horse-bird (or bird-horse) which is a combination of selected features from the input domains. The construction of these domains was subject to the following constraints: they should be concept networks in which nodes are concepts and arcs are relations; the concepts should be connected to the ontology in the generic space through an “isa” relation; the relations used should be present in the Generalized Upper Model (GUM) hierarchies ((Bateman et al., 1995)) or be subtypes of them. GUM is a general top-level ontology that has two hierarchies (elements and relations) that comprise abstract relations, properties, spatial relationships, among others. Although allowing a normalization of the concept maps, the constraints in the construction of the domains do not avoid, per se, the biasing or ingenious tailoring. For this reason, in this paper and in the exploratory experiments we show, we do not give special attention to a qualitative reading of the results or use them to demonstrate its validity, instead we are interested in reporting the effects that each measure has on the results and on the search landscape.

The generic domain (in tables 3 and 4, in the end of this paper) consists of a simple general ontology, a set of frames and integrity constraints. We applied 3 different mappings (figure 6), all generated automatically (via a structure alignment algorithm - read (Pereira and Cardoso, 2001) to know more). These mappings range from very small (only four mapping correspondence) to large (21 mapping correspondences), from non-surprising associations (e.g. “animal” and “animal”) to nonsense (e.g. snout and lung). For each mapping, we tested the seven optimality pressures, each of these comprising 30 runs⁴.

### 4.1 Integration

Frames have a natural integration role because they gather knowledge around abstractions, tightening the links between concepts. Assuming the set $F$ of frames that are satisfied in a blend, we define the *frame coverage* of a domain to be the set of relations from its concept map that belong to the set of conditions of one or more frames in $F$. The larger the frame coverage of the blend, the more it is integrated. Yet, a blend that is covered by many frames should be less integrated than a frame with the same coverage, but with less frames. In other words, if a single frame covers all the relations of a blend, it should be valued with the maximal integration, whereas if it has different frames being satisfied and covering different sets of relations, it should be considered less integrated. The intuition behind this is that the unity around an integrating concept (the frame) reflects the unity of the domain. The Integration measure we propose varies according to this idea. It also takes integrity constraints into account so that, when a frame violates such a constraint, it is subject to penalty.

### Definition 4.1

For a frame $f$ with a set $C$ of conditions $B_i \cup \neg B_i$, a blend $b$, with a concept map $CM_b$, a blendoid⁵ $CM_{b^\omega}$, the concept map of the blendoid and $VI$, the set of

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⁴ A run is an entire evolutive cycle, from the initial population to the population in which the algorithm stopped

⁵ The concept map that contains all the possible relations that the blend may have

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integrity constraints that are violated in the frame, the integration value, $I_f$, is defined by:

$$I_f = \left( \frac{\#C}{\#CM_b} \times (1 - \xi) \right) \times \left( 1 + \frac{\#CM_b}{\#CM_b} \right) / 2$$

where $\xi$ is a penalty factor between 0 and 1, a value that penalizes a frame for each violation to 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 $i$ if the conditions $Ci$ of $i$ are verified and $Ci \cap C \neq \emptyset$. In other words, $f$ needs to violate $i$ in order to be integrated.

We would like to clarify the above formula: the first factor represents the ratio of coverage of $C$ w.r.t. $CM_b$; the second factor means that each integrity constraint violation implies an exponential discount; the third factor serves the purpose of maximizing the size of the blend (if two frames have the same ratio of coverage, the one that contains more relations should have higher integration); the division by 2 aims to normalize the result between 0 and 1.

While the value for a single frame integration is described above, the integration measure of a domain w.r.t. a set of frames is not necessarily straightforward. At a first sight, it is appealing to just sum the values of integration of all frames, or of the union of them, or even their intersection. But this would lead to wrong results, because a set of frames could not be reduced to a single frame from the point of view of integration. In this measure, we want to stimulate unity, coverage and take into account the strength of each frame individually. In terms of unity, we argue that the set of relations that make the “core” of all the frames that are satisfied, i.e. the intersection of the sets $C$ of conditions of all frames, should be highly valued. On the other side, the coverage of this “core” will be smaller than the overall coverage (or equal, if the frames have equivalent $C$ sets), which leads us to take into account the disjoint sets of relations of the frames. Finally, the integration of each individual frame (as defined above) should also be present in the overall measure.

These last two issues (the overall coverage and the integration of individual frames) are subject to a disintegration factor because they reflect the existence of different, not totally intersected, frames. We propose this factor, $\alpha$, to be a configurable value from the interval $[1, 0]$. It is now time to present our proposal for the Integration Measure of a blend:

**Definition 4.2** For a set of frames $f_i \in F_b$, where $F_b$ is the set of the frames that have their conditions $C_i$ satisfied in the blend $b$

$$\text{Integration} = I \bigcap_{i} C_i + \alpha \times \text{Uncoverage} \times \sum_{i} I_{f_i}$$

The $\text{Uncoverage}$ 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:

$$\text{Uncoverage} = \frac{\# \bigcup_{i} C_i - \# \bigcap_{i} C_i}{\# \bigcup_{i} C_i}$$

We think the integration measure is a fundamental brick of the blending process. It leads the choice of the blend to something recognizable as a whole, fitting patterns that

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6Rules with false conclusion as in table 3

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help to determine and understand what a new concept is.
In order to illustrate this reasoning, in figure 2, we show 4 blends and the respective frame coverage. Blend A gets clearly the highest Integration value (all the relations are covered by a single frame); B is also totally covered, but by two different frames; Blend C should get lower Integration value than B because it does not cover every relation (Uncoverage is bigger than 0); finally, blend D would possibly get the lowest value (depending on the value of $\alpha$) because, although covering every relation, there is a high dispersion of frames.

**Experiments:** An immediate conclusion about the effect of Integration is that frames behave as attractor points in the search space. Moreover, the frames with a larger coverage tend to be preferred, although when too large (like a projection or a frame) they are dropped away. The evolution is directed to a compromise of coverage and satisfiability. More specifically, when it satisfies a frame like $pw_{based}\_explanation$, the resulting Integration value is a local maximum or a point in its neighborhood (because sometimes other, related, frames were also found) and “jumping” to another area of the search space becomes difficult.

Another conclusion to draw concerns to the observation that the complexity of the search space landscape grows with mapping size. In fact, when we have a mapping of size 2, the algorithm only finds two different solutions and the better rated (possibly a global maximum) is achieved in 77% of the runs, but with a mapping of size 5, it returns six different blends, with the best choice retrieved only 43% of the times. To confirm this conclusion, the mapping of size 21 led the algorithm to 16 different maxima, with the best one found only 7% of the times. A good compensation for this apparent loss of control is that the returned values are clearly higher (0.68, for the best) than in the small mappings (0.22), meaning that with big mappings there are many more possibilities to find integrated blends.

The resulting concept maps consist of exactly the relations that are covered by the satisfied frame or combination of them, more specifically there were two frames that were very persistent: $pw_{based}\_explanation$ and $purposeful\_subpart$. In some blends, the former was present multiple times (e.g. a part-whole explanation of a horse, with part-whole explanations of its subparts) and both were plenty of times combined.

### 4.2 Topology

The Topology optimality pressure brings inertia to the blending process. It is the constraint that drives against change in the concepts because, in order to maintain the same topological configuration as in the inputs, the blend should maintain exactly the same neighborhood relationships between every concept, ending up being a projected copy of the inputs. In real blends, this pressure is normally one that is disregarded without big loss in the value of the blend. This is due to the imagination context that normally in-
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volves blends, i.e., novel associations are more tolerable.
In our Topology measure, we follow the principle that, if a pair of concepts, \( x \) and \( y \), is 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. We say that such relation, \( r(x, y) \), is **topologically correct**. Thus, the value of Topology corresponds to the ratio of topologically correct relations in the concept map of the blend.

**Definition 4.3** For a set \( TC \subseteq CM_b \) of topologically correct relations, defined as

\[ TC = \{ r(x, y) : r(x, y) \in CM_1 \cup CM_2 \} \]

where \( CM_1 \) and \( CM_2 \) correspond to the concept maps of inputs 1 and 2, respectively\(^7\).

The topology measure is calculated by the ratio:

\[
\text{Topology} = \frac{\#TC}{\#CM_0}
\]

Intuitively, this measure represents the amount of relations from the inputs that got projected onto the topologically equivalent position in the blend. At the moment, the only way to violate topology is by having a pair of concepts projected to the same one (e.g. “horse” and “bird” projected to “horse”), bringing a new relation that was exclusive to one of the domains (e.g. ability(bird, fly) projects to ability(horse, fly)). Topology thus decreases as fusion or transfer projections are made.

**Experiments:** In all the experiments with Topology, the final results were valued 100%, meaning that this constraint is easily fully accomplished, independently of the mapping. An interesting fact is that there is a multitude of solutions in the search landscape of Topology, showed by the amount of different final results in each mapping. Intuitively, and observing the short duration of each run, this means that, wherever the search starts, there is always a Topology optimal point in the neighborhood.

Topology is more an inertia than a transformation force because it values knowledge that remains the same. In our horse-birds, this pressure projects wings, beaks and claws (i.e. concepts from the bird domain) to the blend but isolates them unless there is strong evidence to connect to horses, legs and snouts (i.e. concepts from the horse domain).

### 4.3 Pattern Completion

The Pattern Completion pressure brings the influence of patterns, being them present in the inputs or coming from the generic space. Sometimes a concept (or a set of concepts) may seem incomplete but making sense when “matched against” a pattern.

At present, in the context of this work, a pattern is described by a frame, i.e. we do not distinguish these two concepts, and therefore pattern completion is basically frame completion. Here, as in the definition of this principle, the completing knowledge becomes available from “outside”, not as a result of projection. This means that the act of completing a frame consists of asserting the truth of the ungrounded premises, a process that happens only after a sufficient number of premises is true. We call this the **evidence**

\(^7\)In other words, \( TC \) is the intersection of the concepts maps of the blend and the input spaces

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threshold. The evidence threshold $e$ of a frame $f_i$ with regard to a blend $b$ is calculated according to the following.

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

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

As in the integration pressure, we have the problem of taking into account multiple frames. This time, given that we are evaluating possible completion of subsets of relations, instead of sets of relations that are actually verified in the domain, it is difficult to find such a linear rationale (e.g. would two patterns each with individual completion $x$ value higher than three having each slightly less than $x$?). As a result, we propose to find the union of the patterns and then estimate its own evidence threshold:

**Definition 4.4** The Pattern Completion measure of a blend $b$ with regard to a set $F$ with $n$ frames is calculated by

$$PatternCompletion = e(\bigcup^n_{i=1} f_i, b)$$

This measure has a very important role in increasing the potential of the blend, for it brings the “seeds” that may be used in the Completion and Elaboration phases. In figure 3, we illustrate Pattern Completion with two examples. Assuming a frame with three conditions, on the left it has an evidence threshold of 66.6% (two relations are already accomplished), whereas on the right the evidence threshold is only 33.3%. For both, since we consider only one frame (i.e. one pattern), the value of Pattern Completion is the same as of the evidence threshold.

**Experiments:** The first conclusion to take from the experiments with Pattern Completion is that the size of the resulting concept maps tend to grow as the evolution progresses, although there is no linear correlation found. This has a simple interpretation, given that this measure stimulates the appearance of patterns (frames) that are only partially completed. In doing so, it drives the blend to partially complete (i.e., instantiate partially its conditions) the highest possible number of frames, leading, in each case, to several sets of relations that fit into those frames without satisfying them (e.g. wings are projected, they serve to fly, but they are not attached to anything).

In which respects to the search landscape, it seems to be very rich in local maxima. This fact was not unexpected, considering the discussion of the previous paragraphs, the number of different frames available (9) and all their different combinations. The most constant results came from mapping 2, with 13% of the best result obtained and 20% of the second best. An interesting remark is that the resulting local maxima always fall within a very strict range of values (of maximum amplitude 0.11).
4.4 Maximization of Vital Relations

For the maximization of vital relations, we estimate the impact of the vital relations to the blend calculated by the ratio of vital relations w.r.t. the whole set of possible vital relations, the blendoid. The blendoid is the largest possible blend that can be obtained from a given mapping and is calculated by projecting every concept to it (i.e., there is no selective projection) regardless of integrity constraint violation or any other constraint. Since it has the largest set of potential relations, it also has the maximum possible of vital relations.

**Definition 4.5** Let \( \Upsilon \) be a set of vital relations. From the concept map of the blend \( b \), we may obtain the set of vital relations in \( b \), \( B_{VR} \):

\[
B_{VR} = \{ r(x, y) : r(x, y) \in CM_B \land r \in \Upsilon \}
\]

From the blendoid (the largest possible blend), \( B^+ \), we have \( B_{VR}^+ \):

\[
B_{VR}^+ = \{ r(x, y) : r(x, y) \in CM_B^+ \land r \in \Upsilon \}
\]

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

\[
\text{Maximization}_\Upsilon R = \frac{\#B_{VR}}{\#B_{VR}^+}
\]

**Experiments:** The influence of Maximization of Vital Relations in the results is straightforward, given that its highest value (1) reflects the presence, in the blend, of all the vital relations that exist in the inputs, independently of the projections of the concepts or non-vital relations (which become noise in the sense that these appear randomly and making no difference to the value of the measure, yet confusing the “reading” of the concept map). As the evolution goes on in each run, the value grows until reaching the maximum reasonably early. For each set of 30 runs, it reached the value 1 a minimum of 93% of the times, and the remaining times achieved at least a value of 0.95. As in Topology, the search space of Maximization of Vital Relations is very simple since there is a global maximum in the neighborhood of (almost) every point. On the other hand, since there is no control on noise, the resulting concept maps show unity only in the subset of vital relations.

4.5 Intensification of Vital Relations

Intensification of Vital Relations is the principle that maximizes the concentration around a specific vital relation. I.e., while the Maximization of Vital Relations favors the creation in the blend of vital relations in general as opposed to “regular” relations, Intensification is based on focussing a specific vital relation. The former relates “new” vital relations with “new” relations in the blend; the latter relates vital relations with themselves. Thus, we need a notion of “intensity” of a vital relation. For such, we argue that a vital relation is considered more “intense” when there is more evidence of its strength. This evidence should be dependent on the kind of vital relation we are dealing with. For example, an “analogy” vital relation between two concepts is stronger when there is also a systematical association between the neighborhood concepts (the systematicity principle). In fact, systematicity is the only “intensity” heuristic we have now and its calculation (\( \text{Int}_{\text{analogy}} \)) is straightforward. For a mapping (of size \( n \))

\[
\text{Int}_{\text{analogy}} = \frac{\#\text{analagical transfers}}{n}
\]

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where an *analogue transfer* consists of a projection of a concept $x$ from input space 1 to $y$ in the blend (where $y$ is the analogue counterpart of $x$ in the input space 2).

Considering several different “intensity” heuristics, the evaluation of this pressure takes the point of view that a blend that applies only one vital relation, with intensity $x$, should have higher measure than a blend with $n$ vital relations, each with intensity $x/n$ (the sum would thus be $x$). So we want to favor “concentration” of vital relations.

**Definition 4.6** Let $v_i \in \mathcal{Y}$ be a vital relation and the set $VRB_{v_i}$, of the instances of vital relation $v_i$ in the blend, defined by $VRB_{v_i} = \{v_i(x, y) : v_i(x, y) \in \mathcal{C} \mathcal{M}_b\}$

Assuming a value $\text{Int}_{v_i}$ of intensity of the vital relation $v_i$, the measure of Intensification of Vital Relations is calculated by:

$$\text{Intensification}_{\text{VR}} = \frac{\sum_{i=1}^{n} \text{Int}_{v_i}^2}{\left(\sum_{i=1}^{n} \text{Int}_{v_i}\right)^2}, \quad n = \# \mathcal{Y}$$

Intensification is thus higher when there is more “concentration” (e.g. $\text{Int}_{v_1} = 2$, $\text{Int}_{v_2} = 2 \Rightarrow \text{Intensification} = 8/16$; $\text{Int}_{v_1} = 4 \Rightarrow \text{Intensification} = 1$). In figure 4, we intend to illustrate the reasoning behind this measure. On the left, we see that the only mapping function (vital relation) used in building the projections of $A$ and $B$ is *analogy*, whereas on the right there are two kinds of connections (*analogy* and *property*). Assuming that the number of mapped concepts of both examples remains the same, the one on the left gets a higher $\text{Intensification}_{\text{VR}}$ value because every mapping contributes to the intensity of a single vital relation, whereas on the right, we see that intensity is spread over two different relations. As a result, the former is more “concentrated” than the latter, yielding a bigger value.

**Experiments:** The behavior of Intensification of Vital Relations is similar to that of Maximization in the sense that the search landscape is not very complex. From wherever the search starts, there is a high probability (of at least 70%, in the worst case) of finding the maximum value in the neighborhood. It is important to point, though, that we are only applying one heuristic (analogue transfer), and so the results could not be different. Given this fact, we must say that we cannot claim or discuss much about this Intensification of V.R. proposal unless we find other heuristics than based on analogy systematicity.

### 4.6 Unpacking

Unpacking is the ability to reconstruct the whole process starting from the blend. In our view, such achievement underlies the ability to reconstruct the input spaces, specifically. The complete reconstruction of the input spaces from the blend would demand the assessment of the cross-space mappings, the generic space and other connections. However,
Unpacking should take the point of view of the “blend reader”, i.e., someone or something that is not aware of the process of generation, thus not having access to the actual projections. This “reader” should look for patterns pointing to the “original” concepts. Thus, what we are proposing is that Unpacking can be reduced to the ability to reconstruct the inputs. This is so because there is no way to properly reconstruct the inputs without a reconstruction of the cross-space mappings, generic space and the connections between spaces.

Once again we use the idea of frames, more specifically the defining frame of a concept, which comprises its immediately surrounding concepts and relations. For example, if the concept “wing” were projected onto /DC in blend, the defining frame with regard to the “bird” domain would consist of purpose(x, fly), conditional(x, fly), quantity(x, 2) and pw(x, 2). The more of these relations are found in the blend, the more likely it is that the “reader” will find easy to understand the relationship between /DC and “wing”.

Definition 4.7 Given a blend b and an input space d, the concept x (which is the projection of the element x^d of input space d to the b), has a defining frame f_{x,d} in d consisting of

\( f_{x,d} = C_0, C_1 \ldots C_n \rightarrow \text{true} \)

where \( C_i \in \{ r(x, y) : r(x^d, y) \in C M_d \} \).

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

\( \xi(x, d) = \frac{k}{n} \)

We calculate the total estimated unpacking value of x corresponding to the average of the unpacking values with regard to the input spaces. Thus, having input spaces 1 and 2, we have

\( \xi(x) = \frac{\xi(x, 1) + \xi(x, 2)}{2} \)

Definition 4.8 Let \( X \) be the set of n concepts of the blend b, generated from input spaces 1 and 2. The Unpacking value of b is calculated by

\( \text{Unpacking} = \frac{\sum_{i=0}^{n} \xi(x_i)}{n}, x_i \in X \)

In Figure 5, we present the defining frame for “horse”, in the “Horse” domain. In Blend 1, the concept “horse-bird” (the projection of “horse”) will have the highest Unpacking value because it fits exactly its defining frame. In Blend 2, the value is lower because there are two new relations (with “fly” and “wings”), meaning it is not the exact same concept. Blend 3 will get the lowest Unpacking value of all three because it also lacks some relations (e.g. with “run” and “grass”).

Experiments: The results of the Unpacking measure show that it has a notorious side effect on the size of the blend, since it drives it to very small sets (between 0 and 5) of relations. The interpretation here is straightforward: the ratio of unpackageable concepts is highly penalized in bigger sets because of the projected relations that come as side effect of the projection of (unpackageable or not) concepts. These relations confuse the unpacking algorithm so that it leads the evolution to gradually select the smaller results.

The maxima points also correspond to the value 1, but it seems, from the experiments, that there is a very limited set of such individuals, achieved in the majority (at least 93% for each mapping) of the experiments.

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4.7 Web

The Web principle concerns to being able to “run” the blend without cutting the connections to the inputs. In our opinion, this is not an independent principle, it is co-related to those of Topology and Unpacking because the former brings a straightforward way to “maintain the web of appropriate connections to the input spaces easily and without additional surveillance or computation” and the latter measures exactly the work needed to reconstruct the inputs from the blend. It is not to say that Web is the same as Topology or Unpacking, what we are arguing is that, on one side, Topology provides a pressure to maintain the most fundamental connection to the input: the same structure; on the other side, Unpacking evaluates the easiness of reestablishing the links to the inputs. These two values combined in a weighted sum yield, we propose, an estimation of the strength of the web of connections to the inputs:

\[ \text{Web} = \alpha \times \text{Topology} + \beta \times \text{Unpacking} \]

with \( \alpha + \beta = 1 \). Since this is not an independent variable, making independent experiments with the Web measure would not add any valuable conclusion. In a subsequent publication, we plan to focus on correlation of measures, where we may explore the behavior of this measure.

4.8 Relevance

The notion of “relevance” or “good reason” for a blend is tied to the context and goal of the blending generation. A blend, or a part of it, may be more or less relevant dependent of what it is for. Once again, frames take a fundamental role as “context” specifiers, (i.e., the set of constraints within a frame describe the context upon which the frame is fulfilled). Therefore, having a set of goal frames, which could be selected from any of the existent domains or specified externally, a blend gets the maximum Relevance value if it is able to satisfy all of them.

An aspect of the goal frames is that they allow the application of queries. For example, if we want to find a concept that “flies”, we could build a goal frame with the relation \( \text{ability}(x, \text{fly}) \). The blends that satisfy this frame would have high relevance.

Definition 4.9 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 \( b \), as described in section 4.3, we have

\[
\text{Relevance} = \frac{\#(F_g \cap F_b) + \#F_b \times PCN_{F_b}}{\#F_g}
\]
where $F_u$, the set of unsatisfied goal frames, consists of $F_u = F_g - F_b$.

From the point of view of creativity, we propose the use of Relevance as a “usefulness” measure, as we already made in some experiments ((Pereira, 2003) and (Pereira and Cardoso, 2003a)).

Experiments: The first part of the test on Relevance focussed on making a single relation query. In this case, we asked for “something that flies” (ability(., fly)). The results were straightforward in any mapping, accomplishing the maximum value (1) in 100% of the runs, although the resulting concept maps did not reveal necessarily any overall quality or unity. In other words, the evolution took only two steps: when no individual has a relation “ability(., fly)“, therefore with value 0; when a relation “ability(., fly)” is found, yielding a value 1, independently of the rest of the concept map.

The second part of the test on Relevance, by adding a frame (ability explanation) to the query, revealed similar conclusions. There was no sufficient knowledge in any of the input domains to satisfy this new frame completely, so the algorithm searched for the maximum satisfaction and reached it 100% of times in every mapping. So the landscape seems to have one single global and no local maxima, reflecting the integration of the two parts of the query. If there were separate frames, local maxima might be expected. Intuitively, the search landscapes of Integration and Relevance seem to be similar.

5 Discussion and further work

A first conclusion we draw from this work is that the eight optimality principles can be reduced to seven (since Web is not independent). Even more, given the power of language that we use in frames, some of the principles can be coded within a frame, namely Topology and Unpacking, and accomplished via a query measured by Relevance. This reduces our number to five. Yet, we do not know whether this reduction reflects a fault in the CB framework or in our interpretation of it.

It is important to say that the system is being already tested and some the experiments were published (e.g. in (Pereira, 2003), we used the same set of nouns used in the $C^3$ Conceptual Combination framework (Costello and Keane, 2000) to generate noun-noun combinations), the general conclusions confirming the same behavior we showed in this paper.

Regarding the creative aspects of this system, there are some issues we may discuss concerning the role of the optimality principles. Since different configurations may lead to considerably different results, an obvious question emerges: Is there any “specific” configuration (or configurations) that produces more creative results? If we assume a “creative result” as something that is novel (i.e., not existent in the list of previous results) and useful (according to a context), as a simple definition, we may at the least try to understand what configurations bring better results, and which optimality principles are more influential. From the experiments we have already taken, we can say that there are no precise patterns for “creative results”. However, it has been clear that usefulness is very much dependent on Relevance and, at a lesser extent, Integration. Novelty seems to be related to how strong is an optimality principle in a given context. For example, if Topology is important for the generation of a well known kind of blends (e.g. creatures), then diminishing its weight on the configuration will bring novel results more often. Naturally, these also tend to be less useful. This competition is a possible justification for the variability we have been observing in experiments so far.

We have already stated that the main motivation of our system is to generate new concepts out of previous knowledge. Two works under development include the application

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of the system to a game environment and increasing the emergence of knowledge within the blend. The latter will certainly improve the creativity potential of the system since it consists of the generation of new relations and concepts (not present in the inputs) within the blend, this new knowledge coming from outside (generic space and other domains in the knowledge base).

6 Acknowledgements

We would like to thank the reviewers for their constructive comments.

References


Figure 6: The three mappings

Table 1: The domain theory of horse
Optimality Principles for Conceptual Blending

isa(bird, aves) existence(bird, house) isa(parrot, bird)
isa(aves, oviparous) purpose(bird, pet) isa(nest, container)
lay(oviparous, egg) existence(bird, wilderness) role(playering(bird, freedom)
purpose(bird, food) purpose(bird, see) ability(parrot, speak)
smaller_than(bird, human) purpose(beak, chirp) purpose(claw, catch)
pw(lung, bird) motion_process(bird, fly) purpose(wing, fly)
purpose(lung, breathe) quantity(eye, 2) pw(claw, leg)
isa(paradise, bird) quantity(wing, 2) pw(beak, bird)
isa(owl, bird) quantity(claw, 2) pw(eye, bird)
ability(bird, fly) pw(wing, bird) quantity(leg, 2)
pw(feathers, bird) conditional(wing, fly) pw(leg, bird)
purpose(beak, eat) sound(bird, chirp) purpose(leg, stand)
pw(straw, nest)

Table 2: The domain theory of bird

isa(entity, something) isa(mammal, animal) isa(house, human setting)
isa(situation, something) isa(animal, living entity) isa(setting, space location)
isa(state, situation) isa(oviparous, animal) isa(space location, spatial entity)
isa(process, situation) isa(bird, human setting) isa(space location, spatial entity)
isa(temporal entity, entity) isa(human setting, setting) isa(physical entity, spatial entity)
isa(spatial entity, entity) isa(bird, existence, wilderness) isa(property measure, information entity)
isa(information entity, entity) isa(wilderness, setting) isa(imaginary spatial entity, spatial entity)
isa(human, primate) isa(farm, human setting) isa(property, information entity)
isa(primate, mammal) isa(equinae, mammal) isa(living entity, physical entity)

shape(X, Y), shape(X, Z), Y ≠ Z → false
quantity(X, Y), quantity(X, Z), Y ≠ Z → false
behavior(X, friendly), behavior(X, dangerous) → false
actor(X, _), not isaN(X, action) → false
pw(A, A) → false

Table 3: The generic space concept map and integrity constraints

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<table>
<thead>
<tr>
<th>Frame name</th>
<th>Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>aframe</td>
<td>The blend contains identical structure from input 1</td>
</tr>
<tr>
<td>aprojection</td>
<td>The blend contains the same concepts of input 1</td>
</tr>
<tr>
<td>bframe</td>
<td>The blend contains identical structure from input 2</td>
</tr>
<tr>
<td>bprojection</td>
<td>The blend contains the same concepts of input 2</td>
</tr>
<tr>
<td>pw\textunderscore explanation</td>
<td>The blend contains a concept that has associated a set of part-whole relations (i.e. it is explained by a set of these relations)</td>
</tr>
<tr>
<td>transport_means</td>
<td>The blend contains a concept that has associated the set of features of a generic transport means</td>
</tr>
<tr>
<td>purposeful_subpart</td>
<td>The blend contains a concept that has a subpart that has associated a set of relations that justify its existence (e.g. purpose, cause-effect)</td>
</tr>
<tr>
<td>new_ability</td>
<td>A concept has an ability relation not existent in any of the inputs</td>
</tr>
<tr>
<td>new_creature</td>
<td>A concept is a living thing that did not exist (or wasn’t such) in any of the inputs</td>
</tr>
<tr>
<td>new_feature</td>
<td>A concept has a feature relation not existent in any of the inputs</td>
</tr>
</tbody>
</table>

Table 4: Frames of the generic space