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Towards a Model of Creative Understanding

Deconstructing and Recreating Conceptual Blends using Image Schemas and Spatial Descriptors

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Abstract Computational models of creativity are addressed from the viewpoint of conceptual blending theory (CBT) in this paper. Specifically, in our scenario, an unknown blend (a new/unknown concept) is addressed in a communication setting, where the blend is transmitted from a generator agent to a receiver agent.

In this paper, we first posit that understanding new blends is also a creative process in the framework of CBT. Albeit different from generating blends, understanding a novel blend involves the disintegration and decompression of that blend, in such a way that the receiver of that blend is able to re-create the conceptual network supposedly intended by the emitter of the blend. Secondly, we also propose image schemas as a tool that agents can use to interpret the spatial information obtained when disintegrating/unpacking blends.

This process is studied in a communication setting where semiotics and meaning are conveyed by visual and spatial signs (instead of the usual setting of natural language or text). In this case study, qualitative spatial descriptors are applied for obtaining a formal description of an icon, which is later assigned a meaning by blending with an image schema in a way that the received blend can be recreated.

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1 Motivation

Computational creativity is a multidisciplinary field originated in Artificial Intelligence (AI) research and strongly related to cognitive psychology, philosophy and arts. Summarily, the goal of computational creativity is to develop computational models and systems that address tasks that can be considered creative when undertaken by humans. This paper addresses a particular topic of interest in computational creativity, namely Concept Blending Theory (CBT) [20]. The theory of concept blending (or integration) originates from cognitive science, specifically, cognitive linguistics. CBT explains the process by which a new concept (also called a mental space) can be created from two existing concepts (or mental spaces). CBT was first formalised in category theory by Goguen [23], as shown in Fig. 1. Succinctly, given two concepts or mental spaces I_1 and I_2, conceptual blending is characterised by (1) a generic mental space G, that embodies some similarities or correspondences between I_1 and I_2, and (2) a new mental space B (the blend) that integrates two partial projections from the content of I_1 and I_2 following correspondences determined in G. A classical example is this: given the input mental spaces of *house* and *boat*, two different blends (with corresponding generic spaces) can be created: *houseboat* and *boathouse*. The *houseboat* blend is shown in Fig. 2.

$$\begin{tikzcd}
& G \arrow[dl] \arrow[dr] \arrow[dd] & \\
I_1 \arrow[dr] & & I_2 \arrow[dl] \\
& B &
\end{tikzcd}$$

Fig. 1 An overview of conceptual blending by Goguen [23].

A comprehensive computational model of conceptual blending was developed recently [12]. This is a computationally feasible cognitively-inspired formal model of concept invention developed in the CoInvent project [4]. This model follows Goguen's category theoretical approach [23] and, by incorporating the notion of amalgams [39], it develops a feasible computational model that can effectively create blends in different representation formalisms of AI. Another computational model of conceptual blending is the seminal Divago system [40] which later evolved into the Blendville system [25]. Other approaches related to this paper are Divago's approach applied to visual blending [8] and previous work on generating new computer icons using computational models of conceptual blending [6, 3].

However, although most computational models of conceptual blending focus on the *generation of novelty*, this paper focuses on the dual problem: that regarding understanding and integrating novelty by agents different from the "creative agent". This dual problem is in fact envisaged by CBT in cognitive linguistics. In concept-blending theory, understanding a (new/unknown) concept that is the result of a blend

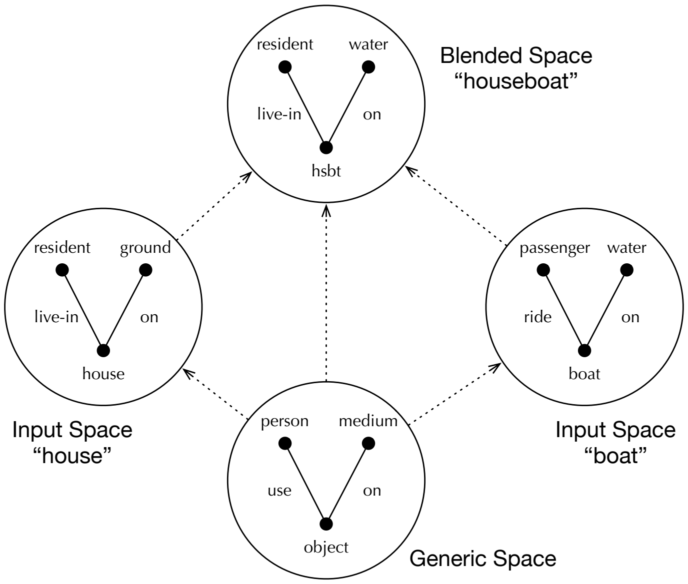


Fig. 2 The 'houseboat' blend, adapted from Goguen [24].

involves disintegration and decompression of that blend and reconstructing the network of concepts linked to that blend. In the example above, *houseboat* or *boathouse* could be understood by an agent who did not already knew them if that agent has the *house* and *boat* metal spaces and applies a process of disintegration and decompression of that blend.

Nevertheless, this is not a well-defined task, specially if we intend to create a computational model for (novel) concept understanding. A main goal of this paper is to better understand such task and to advance in the development of such a computational model.

A relevant aspect in this paper is that we are dealing with unknown/novel concepts, that is with a blend network created by an agent but which is new or unknown by another agent. To deal with this novelty we have to add the level of communication on top of the level of creative processes based on conceptual blending. The communication level requires the transmission of signs or descriptions of concepts, not the concepts themselves (the mental spaces in CBT). In this scenario, a creative agent generates a novelty by means of a blend network where a new concept is constructed, and then the communication level is used to transmit a sign (encoded information) about this novelty to a receiver agent.

Note that, if the concept is a novelty, then the blend network does not exist in the receiver since what is transmitted by communication is a name (or sign, in the more general semiotic sense). The CBT may say the receiving agent understands the new concept when capable of "reconstructing" the blend network (e.g. the network in Fig. 1). However, the communication layover added between the creative agent and the receiver agent implies that there is a less direct relation between receiving not a new concept (mental space), but a new name or sign for a novelty and the process required by the receiver to Understand that novelty. For instance, upon receiving a word like *houseboat*, if it is a novel/unknown concept for the receiver, he/she first needs to identify that by splitting this word in a specific way (e.g. *house-boat*) then the words *house* and *boat* can be associated to known mental spaces, and only then the agent can reconstruct the blending network that yields *houseboat* (the blend). While the CBT may take this for granted in cognitive linguistics because humans seem to do this effortlessly, developing a computational model is not so simple.

This paper is a first step towards a computational theory of understanding novelty. We use the CBT and the CoInvent project computational model of blending, but we argue that understanding a novelty requires "disintegration and decompression", but also a creative process by the receiver agent too —the receiver agent *creates* a blend in the process, using its own cognitive resources (e.g. image schemas in the case study developed in this paper). Note that, understanding involves re-creation rather than re-construction, that is, it involves not simply "disintegrating" a mental space which will not yet exist in the receiving agent, if the concept is a novelty.

For this purpose, let us briefly examine some statements used in the literature regarding the CBT in order to explain understanding a (new) blend. For instance, "disintegration and decompression" are mentioned twice in [20]. One mention appears in the definition of an optimisation principle:

> *The Unpacking Principle: Other things being equal, the blend all by itself should prompt for the reconstruction of the entire network. (...) Unpacking is often facilitated by disintegrations and incongruities in the blended space.*

Also, section "How networks do compression and decompression" in [20] states that:

> *In principle, a conceptual integration network contains its compressions and decompressions. Typically, in use and processing, only parts of the network are available and the rest must be constructed dynamically. In some cases, decompression will be the main avenue of construction, and in other cases, compression will.*

However, our viewpoint is that we cannot assume as inputs the mental spaces from which the blend is obtained by concept integration. If the blended concept is really new, then unpacking the new concept into a full-fledged conceptual network is not trivial. Although such a network may exist in the generation side of blends (e.g. the speaker, the writer), it is not trivial how it can be (re-)created by the receiver agent (e.g. the listener, the reader). We posit here that understanding is also a creative task when it involves unpacking real novelty (a new blended concept). Certainly this process requires disintegration and decompression, in this case with the goal of recreating a (valid, adequate) concept network that is hopefully the one intended by the utterer. Our intuition is that this requires not only unpacking the blended spaces (that does not yet exist in the receivers agent), but also it requires harnessing internal cognitive resources (like image schemas) to find the possible candidates to be the input mental spaces that –if blended in an appropriate way (finding an adequate Generic Space and two adequate partial projections)– create the same (or equivalent) concept. Thus, similarly, reading a novel or a poem is a creative process. Of course, it is a different process than that undertaken by the writer, but it is a creative process and this might be the reason why readers find novels and poems pleasant but also challenging at the same time.

Dealing with the complexity of natural language and the various theories of meaning is a very complex task. The approach presented in this paper focuses on a more straightforward and meaning-bearing language: graphical signs used in our society to convey meaning, such as icons and signage. Thus, let us focus on how a receiver can "decode the meaning" of graphical signs (i.e. understand that sign). Essentially, iconic meaning involves spatial relations between lines which form shapes that are interpreted as signs (e.g. interpreting a shape "$\leftarrow$" as an "arrow" or as a "left arrow"). We propose to use qualitative spatial descriptors to analyse complex spatial relations in signs and image schemas to ascertain the meaning of those signs (e.g. interpreting "left arrow" with the image schema "source-path-goal" may yield the meaning "moving on a path to the left"). Only after semiotic interpretation is performed, the receiver can build the concept-blending process upon that basis. As far as we are aware, none of the papers in the literature has dealt with this topic before.

The rest of the paper is organised as follows. Section 2 explains how understanding can be interpreted as a creative process starting from a new concept B, which is a novelty for the receiver agent who receives a semiotic sign (utterance) denoting B (but not B itself, being a mental space). If the semiotic sign is an icon in a digital image, the process of deconstruction can be done using tools such as qualitative image descriptors (presented in Section 4) which can deconstruct the icon by colour segmentation, identify its components and then describe its shape, location, topology and direction qualitatively, that is, using concepts. Then, the process of re-creation can be carried out by the receiver using tools such as image schemas (presented in Section 3). Section 5 shows the deconstruction process of the presented icon use case by applying qualitative spatial descriptors. Then, Section 6 integrates spatial qualitative descriptions with image schemas for extracting the meaning of elementary signs, and finally, those are blended together obtaining the mental space corresponding to the understanding (or interpretation) of the novelty concept B (icon use case). Finally, Section 7 discusses the main issues addressed in the paper.

2 Understanding novelty as a creative process

This section describes the computational task of concept-blending by following the computational model in [12]. It also introduces the computational task of blend understanding. Then it highlights the commonalities and differences of these tasks.

Let us define the task of blend generation, shown in Fig. 3, as follows:

Given Two (input) mental spaces I_1, I_2.
Find 1. G, a generic space of I_1 and I_2, and
2. B, a blended mental space of I_1, I_2 and G (that satisfies some optimality criteria)

Note that the arrows in Fig. 3 indicate how the information flows in the task, and they are different from the arrows in Fig. 2.

Blend "disintegration and decompression" can be considered the dual case of blending (blend generation), that is, given the blend (a blended mental space), the task

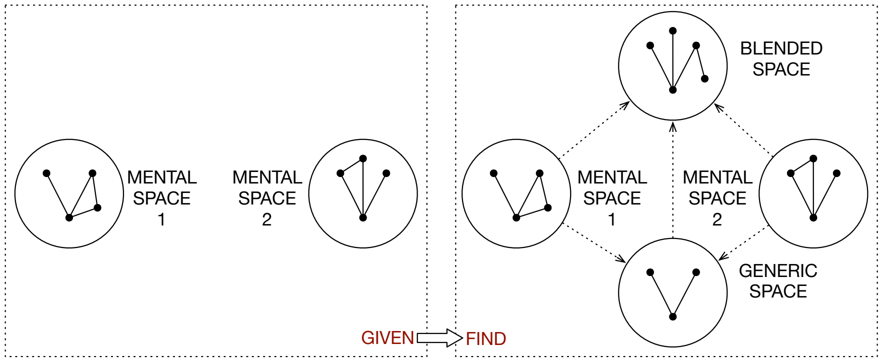


Fig. 3 The task of blend generation: two input spaces are assumed as given (I_1, I_2) and the task is, from I_1 I_2, finding an adequate generic space G and a blend (B). Arrows indicate information flow.

is to find the input spaces and an adequate generic space. However, the task of blend understanding, as shown in Fig. 4, is not exactly the dual task of blending because the input (the "blend") is not a complete and full-fledged mental space, but a semiotic sign denoting the blend. The mental space of the blend exists in our computational model only after re-constructing the blending network that yields the blend, that is, when the receiver agent understands that blend. Otherwise, if the complete mental space is available, there is no novelty for the receiving agent and therefore there is no need to reconstruct the blending network since the agent already knows it, the task is then recognising a sign (linking a sign with an existing mental space).

Therefore, let us define the task of novel blend understanding as follows:

Given 1. An (incomplete) description that refers to the mental space of a new concept blend B, and
2. a collection of image schemas.

Find 1. two adequate mental spaces I_1 and I_2,
2. an adequate generic space G of I_1 and I_2,
3. a mental space for B created by blending I_1 and I_2 following G.

Note that last line is *exactly* the definition of conceptual blending. Hence, if the blending process of the CBT is a model for creativity (combinatorial creativity to be precise [12]), then we claim that novel blend understanding should also be considered a creative process.

It is important to remark that arrows indicating information flow in Fig. 4 are bidirectional: the incomplete blend B yields some information to find the adequate input mental spaces, but then those input mental spaces are used to generate the actual blend as a complete mental space.

As a case study, the process of understanding the icon shown in Fig. 5 has been chosen. Notice that the input here is the visual sign, and the understanding task consists on obtaining its meaning. In the case of computational agents, perceiving the visual sign in Fig. 5 may not yield a blend immediately (i.e. the mental space built by perception is not complete), only after reconstructing the blending network, they

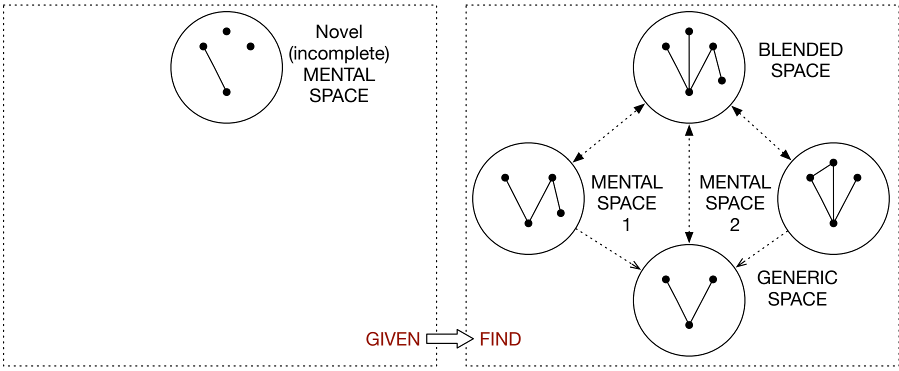


Fig. 4 The task of blend understanding: a blend is given (but as an incomplete mental space) and the task is finding an adequate blending network that completes the mental space of the blend. Arrows indicate information flow.

really have the (mental space of the) blend —which is equivalent, in our approach, to understand the input, that is, to understand what the image in Fig. 5 means.

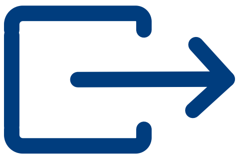


Fig. 5 Example of an icon: A concept visually representated by an arrow and a C-shaped area.

Thus, in the approach presented, the blend is not merely "unpacked" since that blend is still not *complete* (i.e. as a mental space). The input is, like a *word* in linguistic approaches such those of Wittgenstein or Grice[1], not immediately given as a concept (as a specific meaning), but as an index to concepts, and the relationship between language and concepts is better modelled as a mapping between two separate domains. In our case of study, we have a visual sign (instead of a word or a sentence), but the same principle applies: the meaning of the concept is not immediately and unequivocally given by the visual sign: we understand it by being able to construct a blending network that works, and that maps some lines to an "arrow" (i.e. concept usually indicating direction) and other lines to a delimited C-shaped space/area. These two elements generate a new meaning[2] together. For that,

[1] Grice [26, 27] contends sentence and word meaning can be analyzed in terms of what utterers mean.

[2] We are assuming the visual sign is *not* already known, in which case no blending reconstruction is needed, since it is just recalled from memory. The same is true of blends like "houseboat": if we know what a houseboat is we do not need to blend "house" and "boat". Another example is "shipwreck", that is commonly understood as concept, without knowing whether it is (or historically originated from) a blend of "ship" and "wreck" —Latin languages for this concept use words deriving from *naufragium* whose etymology is from *navis* ("a ship") and *frangō* ("I break"). Creative understanding addresses giving meaning to signs that are novel with respect to an agent.

agents can use tools such as: image schemas (see Section 3) and spatial descriptors of shape/topology/location/direction (see Section 4) to indicate the relations of the elements in the icon/sign.

3 Image Schemas

The definition of the term *image schema* in [34] and [30] emphasises the bodily, sensory-motor nature of various structures of our conceptualisation and reasoning. Image schemas are defined in [31] as:

> recurring patterns of our sensory-motor experience by means of which we can make sense of that experience and reason about it, and that can also be recruited to structure abstract concepts and to carry out inferences about abstract domains of thought.

As [31] pointed out, different types of image schemas exist, and some reflect properties of space:

- **Verticality schema**: we give great significance to standing up, rising and falling down because of the gravitational field we perceive.
- **Source-path-goal**: we experience and draw inferences about rectilinear/curved and even deviating motions that have no obvious goal.
- **Scale schema**: we continuously monitor our degree, intensity and quality of feelings or body states which is the basis of our sense of scales of intensity of a quality.
- **Container schema**: we interact with containers of all shapes and sizes, and we naturally learn the logic of containment, also hearing or reading the word *in* activates our container image schema to understand the scene.
- **Center-Periphery schema**: we project right, left, back, near and far throughout the horizon of our perceptual interactions, because of our embodiment.

There is also a logic in image-schemas, for example, as [31] says, via the transitive logic of containment, if the car keys are in your hand and your hand is in your pocket, then we infer that the car keys are in your pocket. That is, image schemas arise in our perception and bodily movement and have their own logic, which can be applied to abstract conceptual domains. The book by Lakoff and Núñez [33] shows examples of the use of image-schematic structure in abstract reasoning in mathematics. They prove that image schemas (operating within conceptual metaphors) make it possible for us to employ the logic of our sensory-motor experience to perform high-level cognitive operations for abstract entities and domains. Each image schema can be conceived of as a cluster of related schemas, as shown in [28], where a family of schemas around the notion of path, following in the *Source-path-goal* image schema, are analysed from a computational point of view.

Research on image schemas is an active area of study in cognitive science that has not yet been comprehensively formalised. This paper formalises two image schemas to apply them to our case study (see Sections 5 and 6). Note that it is out of the scope of this paper to formalise all image schemas in general.

Apart from image schemas, next section presents other tools that agents can use for obtaining an interpretation of an icon: spatial descriptors. Many image schemas are also related to spatial descriptors as the following section shows.

4 Qualitative Spatial Descriptors and its Relation to Image Schemas

Qualitative modelling [21] concerns the representations and reasoning that people use to understand continuous aspects of the world. Qualitative Spatial Representations and Reasoning (QSR) [42, 2, 35] models and reasons about properties of *space* (i.e. topology, location, direction, proximity, geometry, intersection, etc.) and their evolution between continuous neighbouring situations. Spatio-temporal reasoning models deal with imprecise and incomplete knowledge on a symbolic level. Qualitative spatial descriptors that represent properties of space are the following: (i) topology: 4IM [11], 9IM [10], RCC-8 [7]; (ii) shape: QSD [14], LogC-QSD [41]; (iii) location: [29, 22]; (iv) orientation: [37, 19]; (v) orientation and distance: [1], etc.

In the literature, qualitative models have been applied in AI, for example, the extended Qualitative Image Descriptor and Logics $QIDL^+$ apply computer vision algorithms to digital images and extract spatial logics automatically from them [16, 15]. Other qualitative spatial descriptors have also been used in cognitive science to solve perceptual tests for matching 3D perspective descriptions [18], for paper folding reasoning [13], for solving Raven Progressive Matrices intelligence test by analogical reasoning [36], etc. In the context of creativity, spatial descriptors and qualitative shape and colour descriptors and their similarity formulations were tools for object replacement and object composition in the theoretical approach presented by [38] to solve Alternative Uses Test. As qualitative descriptors are suitable for modelling human spatial reasoning [18, 13, 36], a relation can be established between image schemas and qualitative descriptors, as some examples are shown in Table 1.

Table 1 Relation between Images Schemas and Qualitative Descriptors

Image Schema	Qualitative Descriptor
Path-source-goal	orientation[37, 19], direction [19]
Scale	shape [14, 41], relative length [17]
Container	topology [11, 10, 7];
Verticality	location [29, 22], orientation[37, 19]
Centre-Periphery	orientation and distance [1]

Thus, qualitative spatial descriptors can link the digital representation of an icon with a conceptual representation which can be related to a more cognitive interpretation, for example, using image schemas. In the use case presented in Fig. 5, note that the lines in the icon may correspond to concepts with meaning by matching with corresponding shape descriptors (i.e. arrows); and, interior and exterior areas in icon-parts can be also identified by topology descriptors. All these is detailed in the next section.

5 Deconstructing a visual blend

Following the part-whole schema, let us consider that the meaning of a whole icon can be composed by the meaning of its parts and their relationships. Specifically, in our case of study, Fig. 6 shows the icon deconstructed in two parts: Part-I labelled as an arrow shape, and Part-II labelled as a C-shape. Note that these two parts can be easily extracted in the icon by the colour segmentation approach used by Qualitative Image Descriptors [16, 15]. Then, these two parts are both described qualitatively (as Fig. 10 and Fig. 11 show below) and then recognised as an arrow and a C-shape using pattern recognition algorithms (for more details see [14]).

Fig. 6 The use case icon decomposed in parts.

Each icon-part is further interpreted acquiring spatial meaning in relation to an image schema, as shown in Fig. 7. This relation is showed next.

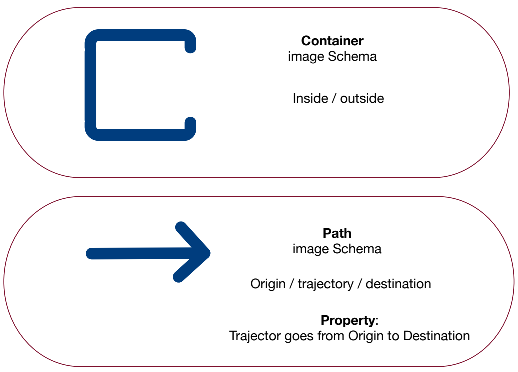


Fig. 7 A description of the two visual signs interpreted by two corresponding image schemas.

5.1 Part-I: Arrow-Icon Description

Arrows are visual signs that are very present in our daily lives. Fig. 9 reminds us

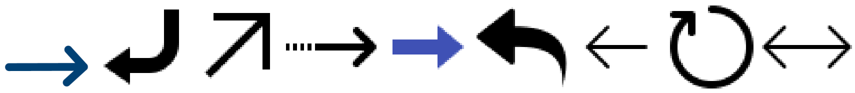


Fig. 8 Examples of Arrows: straight arrows, curved arrows, round arrows, dashed arrows and double-arrows.

of different examples of arrows. As it can be observed, all the examples of arrows provided have many shapes. However, studies on qualitative spatial reasoning about arrow description [32] determine that arrows in general can be defined by three component slots: the tail slot, the body slot and the head slot (Fig. 9).

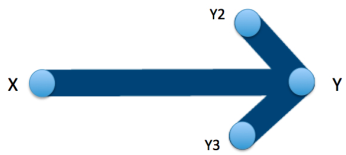


Fig. 9 Arrows are spatial signs that have a starting and ending point indicating a direction.

Thus, let us give a logical definition of an arrow a as follows:

$$\mathit{tail}(a,x) \wedge \mathit{head}(a,y) \wedge \mathit{body}(a,x,y) \Rightarrow \mathit{arrow}(a,x,y)$$

Another property that can be observed is that the head of the arrow is very characteristic and it is mostly defined by 3 points (i.e. y, y_2 y_3 in Fig. 9) — the main point in the head, and two other points that define a triangular shape:

$$\mathit{head}(a,y) \wedge \mathit{triangle}(y,y_2,y_3) \Rightarrow \mathit{triangular\text{-}shape}(a,y)$$

The body of the arrow is defined by the tail and the head. Thus it has a length, which can be calculated as the distance between both points.

$$\mathit{tail}(a,x) \wedge \mathit{head}(a,y) \wedge \mathit{distance}(x,y,l) \Rightarrow \mathit{has\text{-}length}(x,y,l)$$

When the tail and head of an arrow are the same point, then the arrow can be categorised as a round-arrow, which can be defined as:

$$\mathit{arrow}(a,x,y) \wedge \mathit{arrow}(a,y,x) \Rightarrow \mathit{round\text{-}arrow}(a,x,y)$$

A double arrow is characterised by having 2 heads and 2 tails, as follows:

$$\mathit{head}(a,x) \wedge \mathit{head}(a,y) \wedge \mathit{tail}(a,x) \wedge \mathit{tail}(a,y) \Rightarrow \mathit{double\text{-}arrow}(a,x,y)$$

The shape s of the arrow body can also be described –for example using a Qualitative Shape Descriptor (QSD) [14].

$$\textit{tail}(a,x) \wedge \textit{head}(a,y) \wedge \textit{body}(a,x,y) \Rightarrow \textit{has-shape}(a,x,y,s)$$

Different kinds of arrows can be categorised using shape, but this is beyond the scope of our paper.

The orientation o of the arrow is indicated by the location of its head with respect to its tail:

$$\textit{tail}(a,x) \wedge \textit{head}(a,y) \wedge \textit{has-orientation}(o,x,y) \Rightarrow \textit{orientation}(a,o)$$

Orientation Descriptor. In order to obtain the orientation of an object (i.e. an arrow), the coordinates of the front/head (p_1) and the back/tail (p_0) are compared. In 2D, their increasing or decreasing x and y values define the orientation of the object as indicated by the Orientation Reference System (O_{RS}) [19] summarised as follows:

Orientation	O_{RS}
towards-right	$\triangle x$
towards-right-up	$\triangle x$ $\triangle y$
towards-right-down	$\triangle x$ $\bigtriangledown y$
towards-left	$\bigtriangledown x$
towards-left-up	$\bigtriangledown x$ $\triangle y$
towards-left-down	$\bigtriangledown x$ $\bigtriangledown y$
towards-up	$\triangle y$
towards-down	$\bigtriangledown y$
cyclic	none

Thus, the Arrow-Icon part can be described using some of the previous predicates, as shown in Fig. 10.

tail(arrow-icon, x).
head(arrow-icon, y).
body(arrow-icon, x, y).
arrow(arrow-icon, x,y).
has-length(arrow-icon, x, y, 3).
has-shape(arrow-icon, x, y, straight).
orientation(arrow-icon, towards-right).

Fig. 10 Describing Arrow-Icon using qualitative descriptors.

5.2 Part-II: C-Icon Description

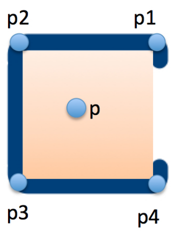
Let us describe the topology of the space delimited by C-Icon by taking into account the Gestalt closure principle and the study on open containers [9], which show that human perception tends to fill in the missing information in order to close shapes.

Thus, according to RCC-8 [7], it can be stated that a point p is part of the interior of an object (obj) if a line can be built using 2 points in the border of the object and this point P is included in that straight line:

$$\textit{border-point}(obj, b_1) \wedge \textit{border-point}(obj, b_2) \wedge \textit{line}(b_1, b_2, l) \wedge \textit{point-in-line}(p, l) \Rightarrow \textit{interior}(p, obj)$$

Therefore an interior space and an exterior space can be defined for the C-Icon shape.

Moreover, the shape of C-Icon can be described using a Qualitative Shape Descriptor (QSD) [14] as shown next in Fig. 11.



interior(c-icon,p).
...
hasQSD(c-icon,p_1,qsd(line-line,right,convex,much-larger)) $\wedge$
hasQSD(c-icon,p_2,qsd(line-line,right,convex,similar)) $\wedge$
hasQSD(c-icon,p_3,qsd(line-line,right,convex,similar)) $\wedge$
hasQSD(c-icon,p_4,qsd(line-line,right,convex,much-shorter))

Fig. 11 Describing C-Icon using qualitative descriptors.

5.3 Relating Arrow-Icon and C-Icon

The spatial relation of the Arrow-Icon and C-Icon parts (with respect to each other and with respect to the overall icon) can be described by qualitative descriptors of location and topology.

Topological Descriptors describe situations in space that are invariant under translation, rotation and scaling transformations. Some common topological relations used in describing the situation of an object a with respect to another object c (a wrt c) are the following:

$$\mathrm{T}_{Label} = \{\textit{disjoint, touching, inside, container}\}$$

In 2D space, an object a is *disjoint* from another object c, if they do not have any edge or vertex in common. In contrast, they are *touching* if, at least, there is a point from a (p_a) included in the border of c (b_c), or vice versa —i.e., if they have at least a point in their border in common. Note that *disjoint* and *touching* are inverse relations. This can be expressed logically as follows:

$$\textit{has-border}(a, b_a) \wedge \textit{has-point}(b_a, p_a) \wedge \textit{has-border}(c, b_c) \wedge \textit{has-point}(b_c, p_c) \wedge (\textit{point-in-border}(p_a, b_c) \vee \textit{point-in-border}(p_c, b_a)) \Rightarrow \textit{touching}(a, c)$$

$$\neg \textit{touching}(c, a) \Rightarrow \textit{disjoint}(a, c)$$

Location Descriptors. For obtaining the location of an object a (or a point of an object x) with respect to another object c, the following Location Reference System (LoRS) [29, 22] is used which divides the space into nine regions (see Fig. 12):

LoRS$_{Label}$= {*up, down, left, right, up-left, up-right, down-left, down-left, centre*}

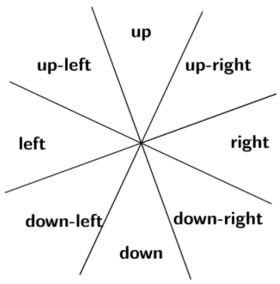
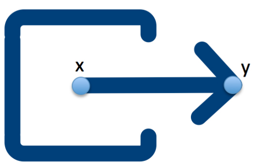


Fig. 12 Locations described by the $QIDL^+$.

An excerpt of the qualitative descriptors which relate the icon parts are shown in Fig. 13.



arrow(arrow-icon, x,y).

orientation(arrow-icon,towards-right).

...

interior(x,c-icon) $\wedge$ *exterior(y,c-icon)*

...

right(y,c-icon) $\wedge$ *centre(x,c-icon)*

...

up(c-icon, x) $\wedge$ *up-left(c-icon, x)* $\wedge$ *left(c-icon, x)* $\wedge$
down-left(c-icon,x) $\wedge$ *down(c-icon,x)*

Fig. 13 Some qualitative descriptors for the icon use case.

6 Recreating the novel blend

This section presents the relation between the two extracted icon parts (and its qualitative descriptors) with two image schemas. Intuitively, the goal to achieve is a blend that understands the icon meaning. For this purpose, this section will proceed as follows: the arrow-shape will be related to the $Source$-$Path$-$Goal$ image schema, the C-shape will be related to the $Container$ image schema, and thus the two input mental spaces needed for blending will be obtained. Finally, the last blend of this two input spaces will be undertaken; the result is a re-creation of the blending network with last blended space giving the meaning *exit* to our use case icon (see Fig. 14).

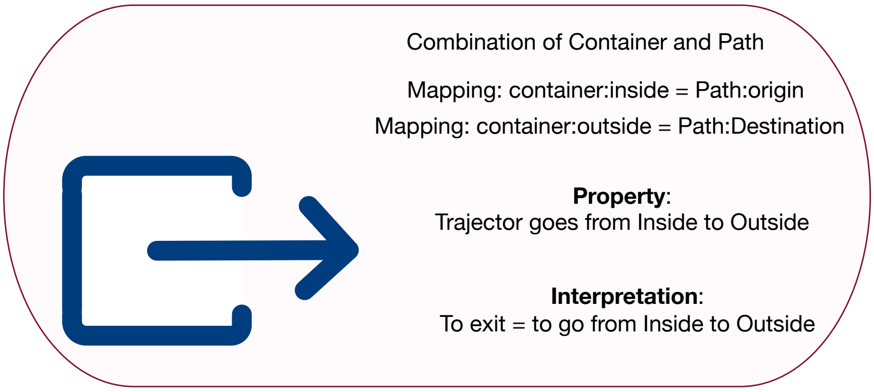


Fig. 14 A schema-based description of the Exit visual concept as a blend of visual signs interpreted as image schemas.

6.1 Container image schema

Let us define the Container image schema as:

$$\begin{aligned} &\forall x \in Space \\ \textbf{Ax}: &Within(x, Border) \Rightarrow x \in IN; \\ &x \in OUT \Leftrightarrow x \notin IN \end{aligned}$$

that is, a schema that defines two subspaces (IN and OUT) in a space with an abstract *Border* separating IN from OUT.

Blending the Container image schema with the C-Icon, as shown in Fig. 15, requires a generic space G_1 with mappings f and g that identify the elements in the two input spaces with the generalised elements a_1, a_2:

$$\begin{aligned} f(a_1) &= border & g(a_1) &= obj \\ f(a_2) &= x \in IN & g(a_2) &= interior(x, obj) \end{aligned}$$

where *obj* refers to the visual object with the C-shape icon part that is identified with the abstract *border*, and when being situated in the *interior* the C-shape is identified with being situated inside the container ($x \in IN$).

The blend B_1 that relates the Container schema and the C-shape part of the icon is directly obtained by the identifications made in G_1:

$$\begin{aligned} &\forall x \in Space \\ \textbf{Axioms}: &interior(x, obj) \Leftrightarrow x \in IN; \\ &exterior(y, obj) \Leftrightarrow y \in OUT \\ &x \in OUT \Leftrightarrow x \notin IN \end{aligned}$$

that is, the interior of the C-shape icon part (noted as *obj*) is identified with the IN subspace of the Container schema (and the rest with the OUT subspace).

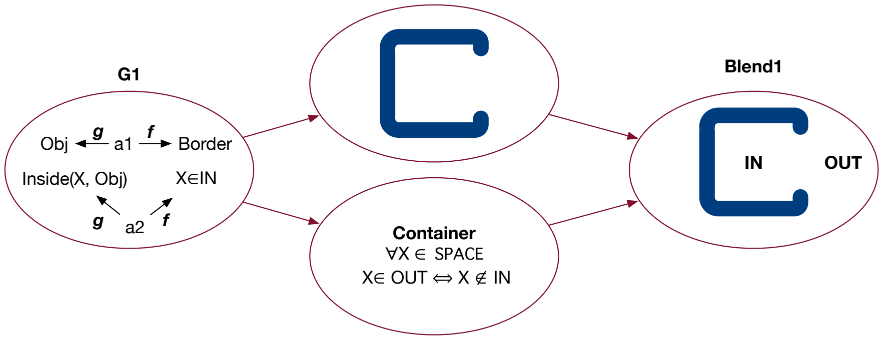


Fig. 15 A blend of a visual representation and the Container image schema.

6.2 Source-Path-Goal image schema

Let us define the Source-Path-Goal (SPG) image schema as follows[3]:

$$source(x) \wedge goal(y) \wedge path(x, y) \wedge trajector(p);$$
$$\textbf{Axioms}: loc(p, x, t) \wedge loc(p, y, t') \Rightarrow t < t'$$

where $loc(p, x, t)$ stands for the entity p located at place x in time t.

The generic space G_2 in Fig. 16 establishes the mappings f and g that identify the elements in the two input spaces with the generalised elements a_1, a_2, a_3, as follows:

$$\begin{aligned} f(a_1) &= source & g(a_1) &= tail \\ f(a_2) &= goal & g(a_2) &= head \\ f(a_3) &= path & g(a_3) &= body \end{aligned}$$

Let us rename, for clarity's sake, the generalised elements a_1, a_2, a_3 respectively as *origin*, *destination*, and *trajectory*; then the blend B_2 in Fig. 16 can be defined as:

$$arrow(a, x, y) \wedge origin(x) \wedge destination(y) \wedge$$
$$trajectory(x, y) \wedge trajector(p) \wedge$$
$$loc(p, x, t) \wedge loc(p, y, t') \wedge t < t'$$

that is to say, the arrow is interpreted as a visual metaphor for the SPG schema and this interpretation adopts some properties of the SPG (i.e. an implicit "trajector" and a temporal dimension).

[3] Note that this is not intended to be a general valid specification for the Source-Path-Goal (SPG) schema, just a consistent interpretation of SPG suitable for our purpose of study. Regarding the approach where an image schema is considered to be a family of similar but distinct schemas, e.g. see [28]. In this view, we use an image schema of the SPG family.

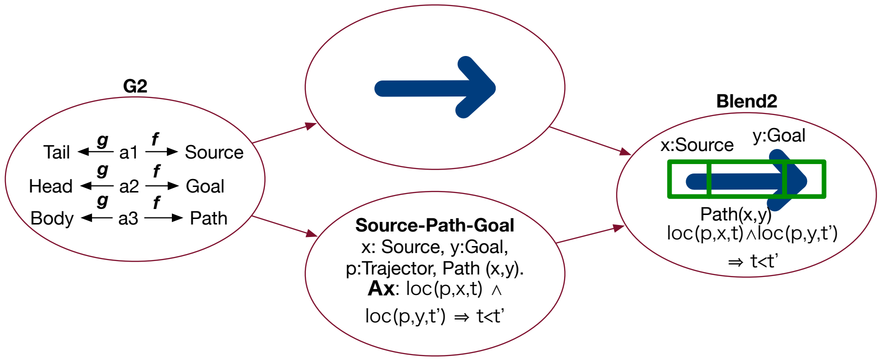


Fig. 16 A blend of a visual representation and the Source-Path-Goal image schema.

6.3 The "Exit" Blend

Let us explain that the final "Exit" blend may be achieved by taking as input spaces the two previous blends, B_1 and B_2, as shown in Fig. 17. For that purpose, let us first specify how B_1 and B_2 match in a new generic space G_3:

$$
\begin{array}{ll}
f(a_1) = origin(x) & g(a_1) = interior(x, obj) \\
f(a_2) = destination(y) & g(a_2) = exterior(y, obj)
\end{array}
$$

That is to say, G_3 maps the origin of the arrow (x) to an interior point of the C-shape icon part (obj) and that the arrows head (y) is mapped to an exterior point.

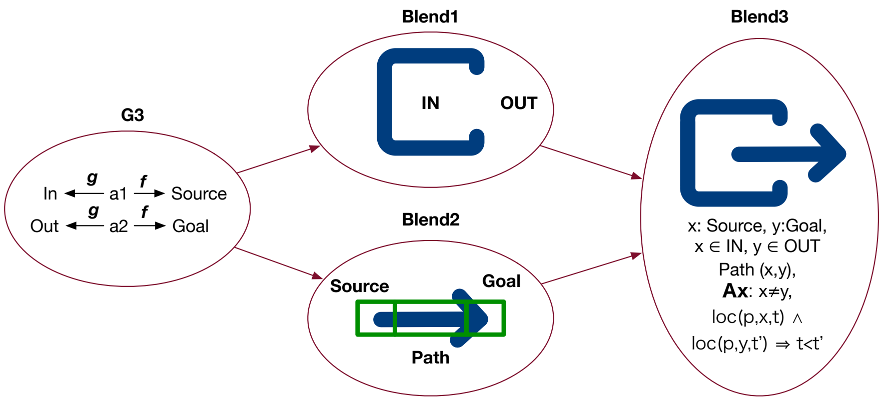


Fig. 17 Blending the two previous blends to *understand the meaning* of the icon "Exit".

Given the mappings at G_3, the blend B_3 is created as shown in Fig. 17. This blend B_3 gives meaning to the "exit" icon by projecting and fusing the two previous blends that serve as input spaces yielding the following:

$$\begin{aligned} arrow(a, x, y) \wedge origin(x) \wedge destination(y) \wedge \\ trajectory(x, y) \wedge trajector(p) \wedge \\ interior(x, obj) \wedge exterior(y, obj) \wedge \\ loc(p, x, t) \wedge loc(p, y, t') \wedge t < t' \end{aligned}$$

that is to say, the origin of the arrow is inside the container (a place, an inside), the destination is outside the container, and there is a trajector that starts inside the container and moves until reaching a place in the exterior of the container (an outside) at a later time. This is precisely equivalent to a conceptual description of the verb *exit* —"an act of going out of or leaving a place" (New Oxford American Dictionary). Notice that the blend B_3 mentions the arrow but not the place (or container): it states properties of places inside or outside of that elided place. This is consistent to the use of the visual sing "Exit", where the place is also implicit: it is the place where the sign is located (be it a building lobby, an airport lounge, etc.) that indicates (deictically) the place to be exited from. Similarly, the trajector is not explicitly given.

The overall process of re-creating the blend (or more technically the blended network) is shown in Fig. 18 (where generic spaces are omitted). Notice that the blended mental spaces, including the blend B_3, have visual information (qualitative spatial descriptors) and abstract properties (from the image schemas). Initially, creative understanding has only the visual information, that is perceived and characterised as a collection of qualitative spatial descriptors (finding out the "arrow" and the "C-shaped-Icon" shapes and their spatial relationship). Finding image schemas that fit well with the visual information gives a possible interpretation for the meaning of the "arrow" and the "C-shaped-Icon" by blending them to obtain the Exit-icon mental space by reconstruction of the blending network.

Finally, notice that there is more than one possible blend to be obtained when reconstructing the blending network. For example, for our use case, in addition to the blend B_3 "Exit", another blend B_3' could have been obtained with meaning "Exit to the right". That would be possible if the predicate *orientation(arrow-icon,towards-right)* in B_2 was included in the partial projection from B_2 to B_3', so that B_3' would include a further spatial LoRS predicate like this: *orientation(x,y,towards-right)*. This fact shows that the process of understanding a (novel) blend is more complex than a mere unpacking of information that is "already there". Instead, we view understanding (or interpreting) a novel visual sign as a full-fledged blending process (in the sense the computational blending model by [12]) that aims at creating the concept blend that corresponds to that novel sign.

7 Dicussion

In a communication setting, what is transmitted by the utterer is not a conceptual blend, but a (semiotic) sign: a blend, we shall recall here, is a mental space in CBT. Thus, the expression "unpacking the blend" may be misleading, in that it seems to assume we have already the blend we need to unpack. The approach taken in this

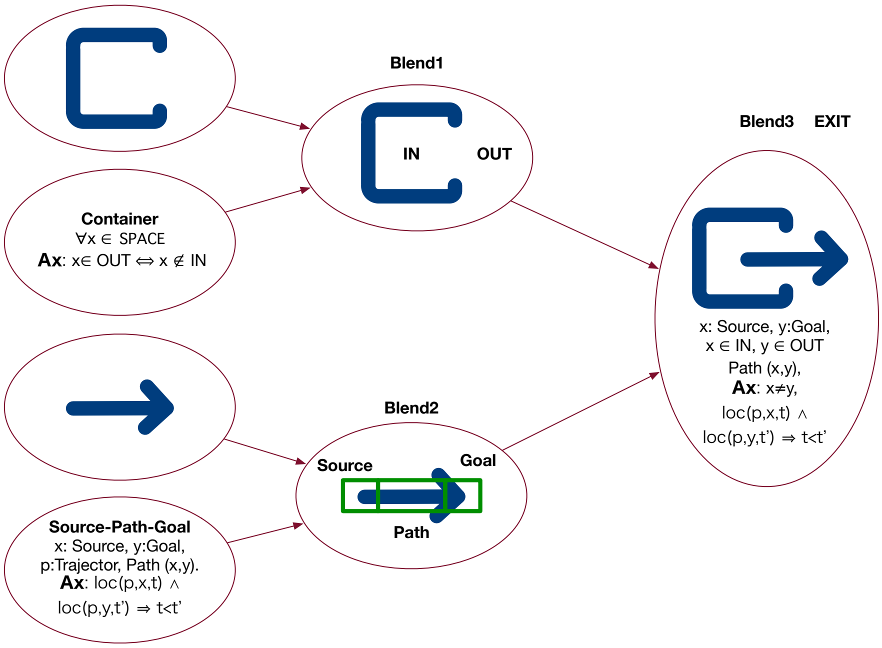


Fig. 18 The overall process of understanding the visual representation fro Exit. Generic spaces are omitted.

paper, at least for computational models of blending, requires some creative processes of blending whenever a received sign is novel/unknown, that is, does not have an already known meaning. The receiver hypothesises the elements of that sign (be it houseboat or "Exit") which can be understood if a blend that reconstructs the intended meaning of the sign is found by recreating the blending network that was used in generating that sign.

In the visual language scenario of icons, pictograms and signage, our approach shows that meaning can be grounded whenever pre-existing mental spaces can be used to reconstruct such blending network. Failure to find adequate mental spaces (e.g. for the visual information of Fig. 5) ends up in failing to create a blend and thus failing to understand the meaning of that visual sign.

Therefore, we assume that, understanding a new blended space is also a creative process, whether the blend is a new concept (e.g. "houseboat"), a new metaphor (e.g. "This surgeon is a butcher") or a new pictogram (e.g. the "Exit" icon). The reason is that understanding a "new blend" (that is in fact a sign charged with a not yet ascertained meaning) involves creating a new blended space that (if successful) reconstructs the blending network (and thus the meaning) of the utterer. Thus, understanding requires conceptual blending, and even more: it also requires to create the mental spaces that will serve as input spaces, together with the generic space that determines which elements and relations of both input spaces are identified. If this summary is correct, and we have shown here a case study with the "Exit" icon example, *blend understanding* requires the same components and processes as *blend* *generation*: (1) creating metal spaces for the two input spaces (note that this can be a complex process, including selecting an image schema and a specific blending process); (2) creating a generic space that determines what is identified as commonalities in both input spaces; and (3) blending the two input spaces.

In this paper, we argue that both generation and understanding of new blends are creative (in that they involve the same components and operations, at least from the point of view of a computational model). However, they are not the same, so the question of how they differ must also be clarified. A way to do so, is to take an approach to meaning such as Grice in our computational models: that the relationship between language (oral, textual or pictographic) and concepts is better modelled as a mapping between two separate domains. This approach is also consistent with construction grammar models of linguistics, where a construction (f, c) is a pairing of forms (sounds, pictograms) and content (conceptual structures having semantic and pragmatic meaning). In this view, generation is a process $c \longrightarrow f$ (from content to form) while understanding is a process $f \longrightarrow c$ (from form to content or meaning).

Thus, this involves that, for a pictographic sign like "Exit" to be understood, a process $f \longrightarrow c$, and creating c requires constructing a blending network that uses "unpackaged" information from f. However, we should not call f a blended mental space, instead it is better to consider f as a sign that constitutes a partial specification of a mental space that needs to be created. The blended mental space is a pairing (f, c) where c has been created by one or several blends, and it is successful if (or as long as) it reconstructs the intended meaning by the utterer of f. Previous work has been focused on designing computer icons by means of conceptual blending [3, 5], that is, going from an intended meaning to a pictogram the can express that meaning. That work considers icons as pairings (f, c) (visual form and concept structure), and it considers also icon understanding as the dual process (going from form to meaning). However, this duality goes further than expected: understanding was assumed to be 'simpler' than generating but, as we have tried to show in this paper, understanding requires the whole gamut of mental space creation, generic space determination, and blend generation. For this reasons we state that understanding of a novel/unknown concept, a creative artefact, is also a creative process in the sense of CBT.

As future work, we intend to evaluate our approach by asking designers to create novel icons which we will use as inputs for our system to obtain an interpretation. For that, designers may use a tool which may obtain automatically a qualitative description of the icons. This description will be the logic input to our approach. Finally, in order to validate the interpretations obtained by our approach, we will ask different people to find out the meaning of that novel icons and we will find out if they agree with our approach, with the designers or with both.

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