Annals of Mathematics and Artificial Intelligence
https://doi.org/10.1007/s10472-019-09619-9

Towards a model of creative understanding: deconstructing and recreating conceptual blends using image schemas and qualitative spatial descriptors

Zoe Falomir[1] · **Enric Plaza**[2]

Published online: 14 February 2019

Abstract

Computational models of novel concept understanding and creativity are addressed in this paper from the viewpoint of conceptual blending theory (CBT). In our approach, a novel, unknown concept is addressed in a communication setting, where this novel concept, created as a blend by an emitter agent, sends a communicative object (words, or in this paper, a visual representation of that concept) to another agent. When received by a computational agent, a novel concept for that communicative object can only be understood by blending concepts already known by that agent. In this paper, we first posit that understanding new concepts via blending is also a creative process. Albeit different from generating conceptual blends, understanding a novel concept via blending involves the disintegration and decompression of that novel concept, in such a way that the receiver of that concept is able to re-create the conceptual network supposedly intended by the emitter of the novel concept. Secondly, we also propose image schemas as a tool that agents can use to interpret the spatial information obtained when disintegrating/unpacking novel concepts and then re-create the new blend. 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 or pictogram, which is later assigned a meaning by a process of conceptual blending using image schemas.

Keywords Computational creativity · Concept blending · Qualitative spatial descriptors · Image schemas · Concept understanding · Novel concepts

✉ Enric Plaza
enric@iiia.csic.es

Zoe Falomir
zfalomir@uni-bremen.de

[1] Bremen Spatial Cognition Centre (BSCC), University of Bremen, Enrique-Schmidt-Str. 5, 28359 Bremen, Germany

[2] IIIA, Artificial Intelligence Research Institute CSIC, Spanish Council for Scientific Research, Campus U.A.B., 08193 Bellaterra, Catalonia, Spain

Mathematics Subject Classification 2010 68T01

1 Motivation

Computational creativity is a multidisciplinary field originated in Artificial Intelligence (AI) research and strongly related to cognitive psychology, philosophy and the 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 conceptual blending (or conceptual 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.

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 [38], 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 [39] which later evolved into the Blendville system [24]. 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 [3, 6].

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

Fig. 1 An overview of conceptual blending by Goguen [23]. Notice here the blend is on the bottom

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

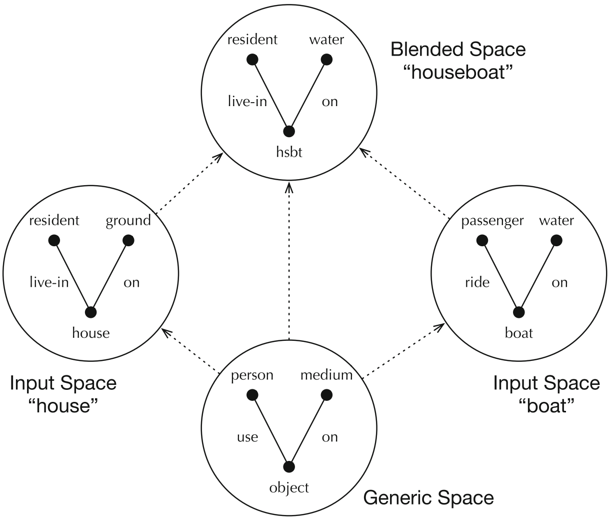


Fig. 2 An illustration of the 'houseboat' blend. Notice here the blend is on the top

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. It's worth noticing that both creativity and novelty can be defined (a) with respect to an individual, or (b) in absolute terms. Generally speaking, CBT focuses on the cognitive process of an individual person, so creating a new blend in CBT is understood as a creative process for that individual. Moreover, this new concept created by blending can be a novelty in absolute terms or only with respect to that individual.

A relevant aspect in this paper is that we are dealing with unknown/novel concepts, that is with a blend network (like that of Fig. 2) created by an agent but that is new or unknown to another agent. To deal with this novelty we have to add the level of communication on top of the level of (internal) 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 approach, 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 (at least to the receiver agent), then the blend network does not exist in the receiver agent, since what is transmitted by communication is a word or an image (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. 2). However, the communication layover added between the creative agent and the receiver agent implies that there is a less direct relation between generating and understanding a concept via blending. This is because the receiving agent has not access to a new concept (mental space), but to a new word or sign for a novelty and thus there is some process required by the receiver to understand that novelty, to make sense of it by connecting this new concept with previously know concepts. 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 more complicated since we need to make explicit these tacit subtasks.

This paper is a first step towards a computational theory of understanding novel concepts by a computational agent. 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 reconstruction, that is, it involves not simply "disintegrating" a mental space which does 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:

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 (for the receiver), 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 receiver 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 pictograms used in signage. Thus, we will 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 that have some meaning (e.g. interpreting a shape "←" as an "arrow" or as a "left arrow"). We propose to use qualitative spatial descriptors to analyse complex spatial relations in visual signs, together with *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 concept 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 their shape, location, topology and direction qualitatively, that is, using spatial descriptions. 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 our use case icon by applying qualitative spatial descriptors. Then, Section 6 integrates spatial qualitative descriptions with image schemas for assigning some meaning to elementary signs (creating their corresponding concepts or mental spaces). Finally, those mental spaces are blended together obtaining the mental space corresponding to the understanding (or interpretation) of the novel concept B (in this paper, our use case will be an icon introduced in the next section). Finally, Section 7 discusses the main issues addressed in the paper and discusses future work.

2 Understanding novel concepts 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, and then it highlights the commonalities and differences between these two 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 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 novel concept (the "blend") is not a complete and full-fledged mental space, but a semiotic sign denoting the concept 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).

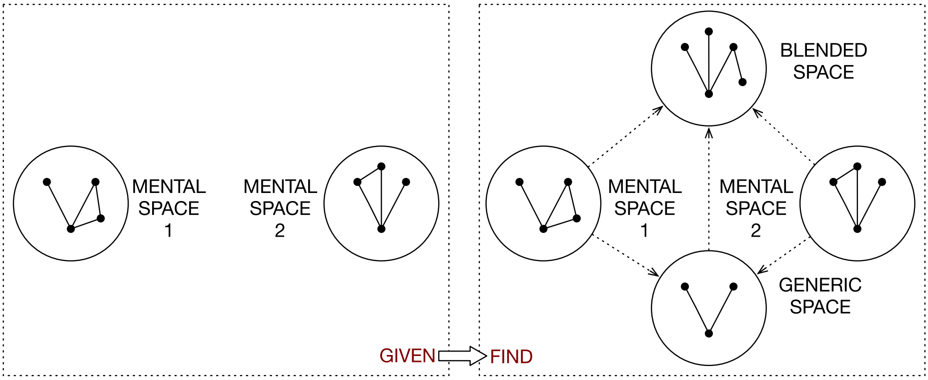


Fig. 3 The task of blend generation: two input spaces are assumed as given (I_1, I_2) and the task is, from I_1 I_2, finding an adequate generic space (G) and a blend (B). Arrows indicate information flow

Next we define the task of novel concept understanding using blending, as follows:

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

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 B for the novel concept created by blending I_1 and I_2 following G.

Note that the last line is exactly the definition of conceptual blending: creating a blend from two input spaces following a generic space. Hence, if the blending process of the CBT is a model for creativity (combinatorial creativity to be precise [12]), then we claim that when novel concept understanding (creating a mental space for the novel concept) requires blending, then we should also consider it to be a creative process.

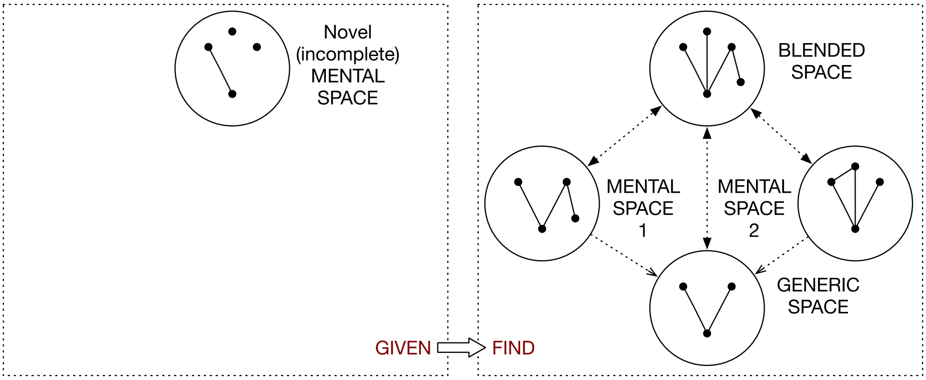


Fig. 4 The task of novel concept understanding by blending: when a novel concept is given (and only an incomplete mental space can be created for it), then the task is finding an adequate blending network that creates a complete mental space for the novel concept. Arrows indicate information flow

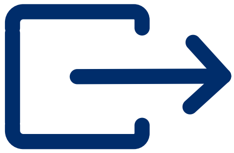


Fig. 5 Example of an icon: A concept visually represented by an arrow shape and a C-like shape

It is important to remark that three arrows indicating information flow in Fig. 4 are bidirectional: the novel concept B has an incomplete mental state, which yields some information to find the adequate input mental spaces, and then those input mental spaces are used to generate the actual blend for B (thus completing B's 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 adjudicating a meaning to that visual sign. In the case of a computational agent, perceiving the visual sign in Fig. 5 may not yield a concept immediately (i.e. the mental space built by perception is not complete), only after reconstructing a blending network the agent may have the mental space of the new concept —which is equivalent, in our approach, to understand the input; in other words, to understand what the image in Fig. 5 means.

Thus, in the approach presented, understanding a novel concept in a computational agent is not directly equivalent to having a blend that needs to be "unpacked" —since that blend (mental space) is still not *complete* —it is just a novel concept with an incomplete representation in its 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 icon space/area. These two elements generate a new meaning[2] together. For that, 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 [33] and [29] emphasises the bodily, sensory-motor nature of various structures of our conceptualisation and reasoning. That is, if our

[1] Grice [25, 26] 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.

cognitive reasoning operations are embodied (i.e. meaning, imagination and reasoning emerge from our body interactions with the environment), then structures of perceiving and doing must shape our acts of understanding and knowing. And these structures of perceiving and doing, or structures of sensory-motor experience (e.g. image schemas) can be used to understand abstract concepts and to perform abstract reasoning [30]. So, according to this, image schemas are defined in [30] 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.

Different types of image schemas exist, as pointed out in [30], 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**: underlies our understanding of bodily motion along a path, where there is a starting point (Source), a continuous set of steps (Path), taken toward the destination (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 inherent to image-schemas, for example via the transitive logic of containment [30]: 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 [32] shows examples of the use of image-schematic structure in abstract reasoning in mathematics. They show 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. Moreover, each image schema can be conceived of as a cluster of related schemas, as shown in [27], 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.

In addition to image schemas, the next section presents other tools that a computational agent can use for adjudicating an interpretation of an icon: qualitative spatial descriptors.

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) [2, 34, 41] 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 [40]; (iii) location: [22, 28]; (iv) orientation: [19, 36]; (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 [15, 16]. 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 [35], 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 [37] to solve Alternative Uses Test. As qualitative descriptors are suitable for modelling human spatial reasoning [13, 18, 35], a relation can be established between image schemas and qualitative descriptors, as some examples shown in Table 1.

Thus, qualitative spatial descriptors can link the visual 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-elements can be also identified by topology descriptors. All these is detailed in the next section.

5 Extracting the spatial description of the icon structure

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.

In our study case regarding visual signage, let us highlight that icon elements can be identified and described separately. As an example, Fig. 6 shows our icon use case deconstructed in: Element-I labelled as an Arrow-Icon, and Element-II labelled as a C-shaped icon or C-Icon for short. Note that these two elements can be easily extracted from the icon by a digital image colour segmentation approach, e.g. that used by Qualitative Image Descriptors [15, 16].

Table 1 Relation between images schemas and qualitative descriptors

Image schema	Qualitative descriptor
Path-source-goal	orientation [19, 36], direction [19]
Scale	shape [14, 40], relative length [17]
Container	topology [7, 10, 11];
Verticality	location [22, 28], orientation [19, 36]
Centre-Periphery	orientation and distance [1]

Fig. 6 The use case icon decomposed in two visual elements

These two icon elements are both described qualitatively (as Figs. 10 and 11 show below) and then recognised as an Arrow-Icon and a C-Icon using pattern recognition algorithms (for more details see [14]). Each icon element is further interpreted acquiring spatial meaning in relation to an image schema, as shown in Fig. 7. The following subsections address these relations.

5.1 Spatial description of element I: Arrow-icon

Arrows are visual signs that are very present in our daily lives. Figure 8 reminds us 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 [31] determine that arrows in general can be defined by three component slots: the tail slot, the body slot and the head slot (Fig. 9).

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

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

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,

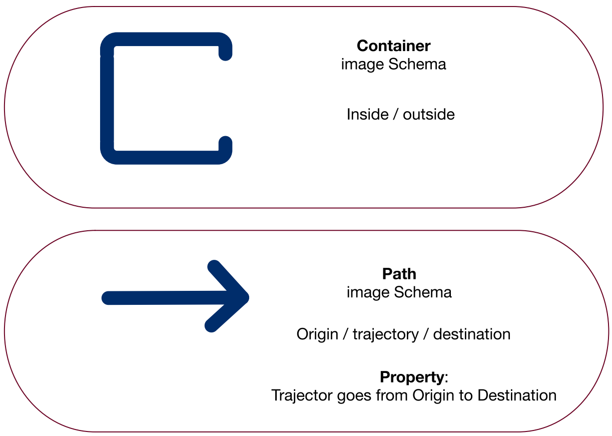


Fig. 7 A description of the two icon visual elements interpreted by two image schemas

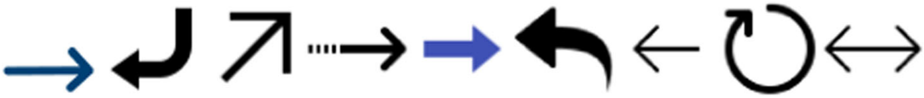


Fig. 8 Examples of Arrows: straight arrows, curved arrows, round arrows, dashed arrows and double-arrows

and two other points that define a triangular shape:

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

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.

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

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:

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

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

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

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

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

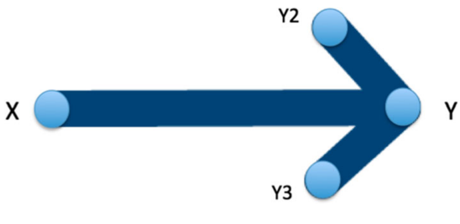
Different kinds of arrows can be categorised using shape, but this is beyond the scope of our paper.

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

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

Orientation descriptor (O_D) In order to obtain the orientation of an element of an icon (i.e. an arrow), the coordinates of the front/head (p_1) and the back/tail (p_0) are compared. In 2D,

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



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

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:

O_D	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	$\bigtriangledown y$

Note that if, e.g. the arrow is circular, its orientation is composed by all the orientations defined by O_{RS}, since they have all been taken at some point in the cycle.

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

5.2 Spatial description of element-II: C-icon

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.

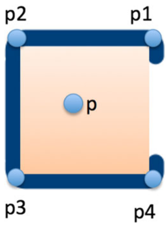
Thus, according to RCC-8 [7], it can be stated that a point p is in the interior of an object (obj) if a line can be built using 2 points in the border of the object and this point p is included in that straight line:

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

Therefore an interior space and an exterior space can be defined for the C-Icon as shown in Fig. 11. Moreover, the shape of C-Icon can be described using a Qualitative Shape Descriptor (QSD) as shown in Fig. 11, that is: how many lines or curves are connected, what kind of angles they define, its lengths, etc. (for definitions and a more detailed description see [14, 40]).

5.3 Spatial relation between the icon elements: Arrow-icon and C-icon

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



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 the shape and topology of C-Icon using qualitative descriptors

Topological descriptors (T_D) Situations in space that are invariant under translation, rotation and scaling transformations of elements are described by topology. 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:

T_D = {*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 there is a point from a (p_a) included in the border of c (b_c) at least, or vice versa —i.e., if they have a point at least in their common border. Note that *disjoint* and *touching* are inverse relations. This can be expressed logically as follows:

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

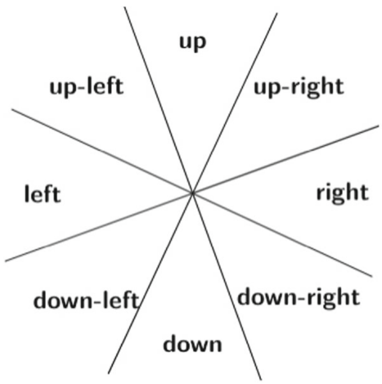
$$\neg \textit{touching}(c, a) \Rightarrow \textit{disjoint}(a, c)$$

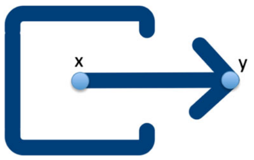
Location descriptors (L_D) For obtaining the location of an object a (or a point of an object x) with respect to another object c, the following Location Reference System (LoRS) [22, 28] is used which divides the space into nine regions (see Fig. 12):

L_D= {*up, down, left, right, up-left, up-right, down-left, down-left, centre*}

Figure 13 presents an excerpt of the qualitative descriptors which relate the icon elements.

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





arrow(arrow-icon, x,y).
orientation(arrow-icon,towards-right).
...
interior(x,c-icon) ∧ *exterior(y,c-icon)*
...
right(y,c-icon) ∧ *centre(x,c-icon)*
...
up(c-icon, x) ∧ *up-left(c-icon, x)* ∧ *left(c-icon, x)* ∧
down-left(c-icon,x) ∧ *down(c-icon,x)*

Fig. 13 An excerpt of the qualitative spatial descriptors generated for our icon use case

6 Recreating the novel concept blend

This section presents the relation between the two extracted icon elements (and its qualitative spatial descriptors) with two image schemas. Intuitively, the goal to achieve is a blend that generates the icon meaning. For this purpose, this section proceeds as follows: the C-Icon is related to the *Container* image schema (Section 6.1), the Arrow-Icon is related to the *Source-Path-Goal* image schema (Section 6.2), and thus the two input mental spaces needed for blending are obtained. Finally, the last blend of this two input spaces is 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).

6.1 Relating C-icon with the container image schema

Let us define the Container image schema as follows:

$$\forall x \in Space$$
$$\textbf{Axioms}: Within(x, Border) \Rightarrow x \in IN;$$
$$x \in OUT \Leftrightarrow x \notin IN$$

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

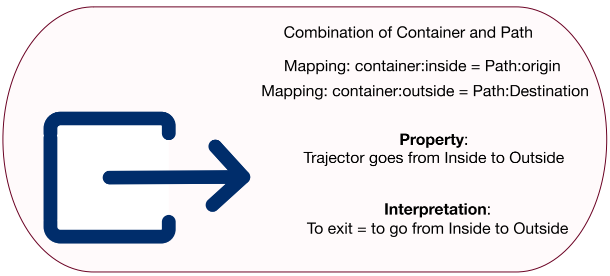


Fig. 14 An interpertation of the *Exit* visual sign combining *Container* and *Source-Path-Goal* image schemas

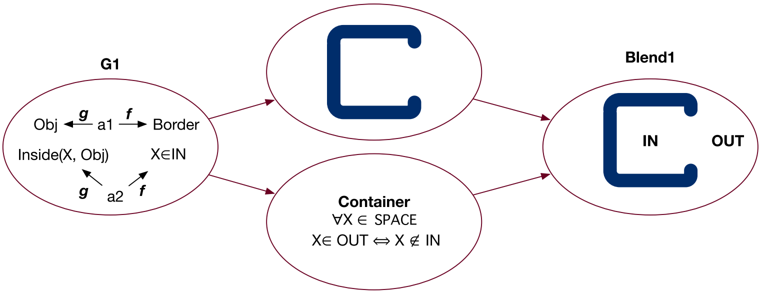


Fig. 15 A blend of the C-Icon element and the Container image schema

with the generalised elements a_1, a_2:

$$f(a_1) = border \qquad g(a_1) = obj$$
$$f(a_2) = x \in IN \qquad g(a_2) = interior(x, obj)$$

where obj refers to the visual element C-Icon that is identified with the abstract *Border*, and when x is situated in the *interior* of the C-Icon is identified with being situated inside the container ($x \in IN$).

The blend B_1 that integrates the Container schema and the C-Icon is directly obtained by the identifications made in G_1:

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

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

6.2 Relating arrow-icon with 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:

$$f(a_1) = source \qquad g(a_1) = tail$$
$$f(a_2) = goal \qquad g(a_2) = head$$
$$f(a_3) = path \qquad g(a_3) = body$$

[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 [27]. In this view, we use an image schema of the SPG family.

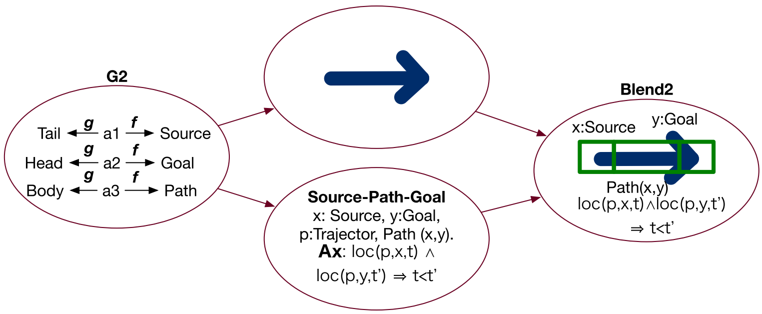


Fig. 16 Blending a spatial description of the Arrow-Icon with the Source-Path-Goal image schema

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:

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

that is to say, the Arrow-Icon 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).

6.3 Generating the meaning of *Exit* by a concept blend

The meaning *Exit* may be achieved by blending the input spaces from 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:

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

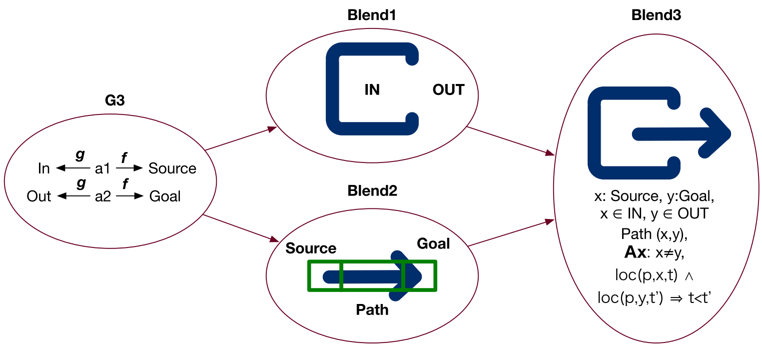


Fig. 17 Blending the two previous blends to *understand the meaning* of the icon *Exit*

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

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 integrating the two previous blends that serve as input spaces yielding the following:

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

that is to say, the origin of the Arrow-Icon 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 being 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 (deictically) indicates 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 (generic spaces are omitted for simplicity). 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 (defining the Arrow-Icon and the C-Icon and their spatial relations). Finding image schemas that fit well with the visual information gives a possible interpretation for

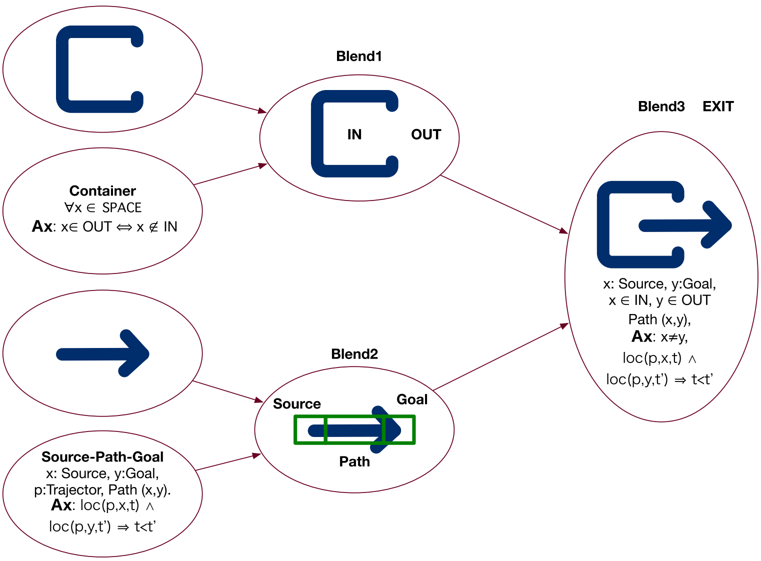


Fig. 18 The overall process of understanding the visual representation for *Exit*. Generic spaces are omitted

the meaning of the Arrow-Icon and the C-Icon by blending them to obtain the *Exit*-icon mental space by reconstruction of the blending network.

Moreover, note that more than one possible blend may 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 location 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 Discussion

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 the 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 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 which can be understood (be it houseboat or *Exit*) 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. to extract the visual information of each element of an icon) ends up in failing to create a blend and thus failing to understand the meaning of that complete visual sign/icon.

Therefore, we assume that, understanding a new concept via blending 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 select or create the mental spaces (if they do not already exist) 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 mental 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 conceptual blends are (individually) creative. The reason is that they involve the same components and operations (at least from the point of view of a computational model, which is our interest here). However, they are not the same, so the question of how they differ must also be clarified.

For this, we may take an approach to meaning such as Grice [25, 26] 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 f (sounds, pictograms) and content c (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, for a pictographic sign like *Exit* to be understood, this involves that there is 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 the 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.

Acknowledgments This research has been partially supported by *Cognitive Qualitative Descriptions and Applications* (CogQDA) of the Central Research Development Fund (CRDF) at University of Bremen through the *04-Independent Projects for Postdocs action* and project DIVERSIS (CSIC Intramural 201750E064).

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

1. Clementini, E., Felice, P.D., Hernandez, D.: Qualitative representation of positional information. Artif. Intell. **95**(2), 317–356 (1997)
2. Cohn, A.G., Renz, J.: Qualitative spatial reasoning, handbook of knowledge representation. Elsevier, Wiley-ISTE, London (2007)
3. Confalonieri, R., Corneli, J., Pease, A., Plaza, E., Schorlemmer, M.: Using argumentation to evaluate concept blends in combinatorial creativity. In: Toivonen, H., Colton, S., Cook, M., Ventura, D. (eds.) Proceedings of the 6th international conference on computational creativity, pp. 174–181, Park City (2015)

4. Confalonieri, R., Pease, A., Schorlemmer, M., Besold, T., Kutz, O., Maclean, E., Kaliakatsos-Papakostas, M. (eds.): Concept invention: Foundations, implementation, social aspects and applications. Springer, Berlin (2018)
5. Confalonieri, R., Eppe, M., Schorlemmer, M., Kutz, O., Pe naloza, R., Plaza, E.: Upward refinement operators for conceptual blending in the description logic EL++. Annals of Mathematics and Artificial Intelligence, 1–31. https://doi.org/10.1007/s10472-016-9524-8 (2016)
6. Confalonieri, R., Plaza, E., Schorlemmer, M.: A process model for concept invention. In: Pachet, F., Cardoso, A., Corruble, V., Ghedini, F. (eds.) Proceedings of the 7th international conference on computational creativity, pp. 338–345, Paris (2016)
7. Cui, Z., Cohn, A.G., Randell, D.A.: Qualitative and topological relationships in spatial databases. In: Abel, D.J., Ooi, B.C. (eds.) Advances in spatial databases, 3rd international symposium, SSD'93, June 23-25, 1993 Proceedings, volume 692 of lecture notes in computer science, pp. 296–315. Springer, Singapore (1993)
8. Cunha, J.M., Gonċalves, J., Martins, P., Machado, P., Cardoso, A.: A pig, an angel and a cactus walk into a blender: A descriptive approach to visual blending. arXiv:1706.09076 (2017)
9. Davis, E., Marcus, G., Chen, A.: Reasoning from radically incomplete information: The case of containers. Advances in Cognitive Systems **2**, 1–18 (2013)
10. Egenhofer, M., Herring, J.: Categorizing binary topological relationships between regions, lines, and points in geographic databases. Department of Surveying Engineering, University of Maine, Orono ME (1991)
11. Egenhofer, M.A.X.J., Franzosa, R.: Point-set topological spatial relations. Int. J. Geogr. Inf. Syst. **5**(2), 161–174 (1991)
12. Eppe, M., Maclean, E., Confalonieri, R., Kutz, O., Schorlemmer, M., Plaza, E., Kühnberger, K.-U.: A computational framework for conceptual blending. Artif. Intell. **256**, 105–129 (2018)
13. Falomir, Z.: Towards a qualitative descriptor for paper folding reasoning. In: Proc. of the 29th International Workshop on Qualitative Reasoning, 2016. Co-located with IJCAI'2016 in New York, USA
14. Falomir, Z., Gonzalez-Abril, L., Museros, L., Ortega, J.: Measures of similarity between objects from a qualitative shape description. Spat. Cogn. Comput. **13**, 181–218 (2013). https://doi.org/10.1080/13875868.2012.700463
15. Falomir, Z., Museros, L., Castelló, V., Gonzalez-Abril, L.: Qualitative distances and qualitative image descriptions for representing indoor scenes in robotics. Pattern Recogn. Lett. **38**, 731–743 (2013). https://doi.org/10.1016/j.patrec.2012.08.012
16. Falomir, Z., Olteţeanu, A.-M.: Logics based on qualitative descriptors for scene understanding. Neurocomputing **161**, 3–16 (2015). https://doi.org/10.1016/j.neucom.2015.01.074
17. Falomir, Z., Pich, A., Costa, V.: Spatial reasoning about qualitative shape compositions: Composing qualitative lengths and angles. Annals of mathematics and artificial intelligence, page submitted (2018)
18. Falomir, Z.: A qualitative model for reasoning about 3D objects using depth and different perspectives. In: Lechowski, T., Wałęga, P., Zawidzki, M. (eds.) LQMR 2015 Workshop, volume 7 of annals of computer science and information systems, pp. 3–11, PTI. https://doi.org/10.15439/2015F370. (2015)
19. Falomir, Z., Rahman, S.: From qualitative descriptors of movement towards spatial logics for videos. In: Azzopardi, G. et al. (eds.) Proc. 3rd Workshop on Recognition and Action for Scene Understanding (REACTS), co-located at 16th Int. Conf. Computer Analysis of Images and Patterns (CAIP), ISBN 978-84-606-9592-9, pp. 119–128 (2015)
20. Fauconnier, G., Turner, M.: The way we think: Conceptual blending and the mind's hidden complexities. Basic Books, New York (2003)
21. Forbus, K.D.: Qualitative modeling. Wiley Interdisciplinary Reviews. Cognit. Sci. **2**(4), 374–391 (2011)
22. Frank, A.U.: Qualitative spatial reasoning with cardinal directions. In: Kaindl, H. (ed.) 7. Österreichische artificial intelligence tagung. Springer, Berlin (1991)
23. Goguen, J.: An introduction to algebraic semiotics, with applications to user interface design. In: Nehaniv, C.L. (ed.) Computation for metaphors, analogy, and agents, volume 1562 of lecture notes in computer science, pp. 242–291. Springer (1999)
24. Gonċalves, J., Martins, P., Cardoso, A.: Blend city, blendville. In: Goel, A., Jordanous, A., Peas, A. (eds.) Proceedings of the Eighth International Conference on Computational Creativity, pp. 112–119 (2017)
25. Grice, P.: Meaning. Philos. Rev. **66**, 377–88 (1957). Reprinted in [26] pages 213–223
26. Grice, P.: Studies in the way of words. Harvard University Press, Harvard (1989)
27. Hedblom, M.M., Kutz, O., Neuhaus, F.: Choosing the right path Image schema theory as a foundation for concept invention. J. Artificial General Intelligence **6**(1), 21–54 (2015)
28. Hernández, D.: Relative representation of spatial knowledge: The 2-D case. In: Mark, D.M., Frank, A.U. (eds.) Cognitive and linguistic aspects of geographic Space, pp. 373–385. NATO Advanced Studies Institute, Kluwer (1991)

29. Johnson, M.: The body in the mind: The bodily basis of meaning, imagination, and reason. University Of Chicago Press, Chicago (1987)
30. Johnson, M.: The philosophical significance of image schemas. In: Hampe, B., Grady, J.E. (eds.) From perception to meaning: Image schemas in cognitive linguistics, pp. 15–33. Mouton de Gruyter, Berlin & New York (2005). ISBN-13: 978-3-11-018311-5
31. Kurata, Y., Egenhofer, M.J.: The arrow-semantics interpreter. Spatial Cognition & Computation: An Interdisciplinary Journal **8**(4), 306–332 (2008)
32. Lakoff, G., Núñez, R.E.: Where mathematics comes from: How the embodied mind brings mathematics into being basic books (2000)
33. Lakoff, G.: Women, fire and dangerous things: What categories reveal about the mind. University of Chicago Press, Chicago (1987)
34. Ligozat, G.: Qualitative spatial and temporal reasoning. MIT Press, Wiley-ISTE, London (2011)
35. Lovett, A., Forbus, K.: Modeling visual problem solving as analogical reasoning. Psychol. Rev. **124**(1), 60–90 (2017)
36. Moratz, R., Dylla, F., Frommberger, L.: A relative orientation algebra with adjustable granularity. In: Proceedings of the workshop on agents in real-time and dynamic environments (IJCAI 05) (2005)
37. Olteteanu, A.-M., Falomir, Z.: Object replacement and object composition in a creative cognitive system. A computational counterpart of the alternative use test. Cogn. Syst. Res. **39**, 15–32 (2016)
38. Ontañón, S., Plaza, E.: Amalgams: A formal approach for combining multiple case solutions. In: ICCBR'10: 18th international conference on case-based reasoning, volume 6176 of lecture notes in artificial intelligence, pp. 257–271. Springer (2010)
39. Pereira, F.C., Cardoso, A.: Experiments with free concept generation in divago. Knowl.-Based Syst. **19**(7), 459–470 (2006)
40. Pich, A., Falomir, Z.: Logical composition of qualitative shapes applied to solve spatial reasoning tests. Cogn. Syst. Res. **52**, 82–102 (2018)
41. Stock, O.: Spatial and temporal reasoning. Kluwer Academic Publishers, Norwell (1997)