

Learning how to reinterpret creative problems

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Abstract

This paper discusses a method, implemented in the domain of computational association, by which computational creative systems could learn from their previous experiences and apply them to influence their future behaviour, even on creative problems that differ significantly from those encountered before. The approach is based on learning ways that problems can be reinterpreted. These interpretations may then be applicable to other problems in ways that specific solutions or object knowledge may not. We demonstrate a simple proof-of-concept of this approach in the domain of simple visual association, and discuss how and why this behaviour could be integrated into other creative systems.

Introduction

Learning to be creative is hard. Experience is known to be a significant influence in creative acts: cognitive studies of designers show significant differences in the ways novices and experts approach creative problems (Kavakli and Gero, 2002). Yet each creative act is potentially so different from every other act that it is complex to operationalise the experience gained and apply it to subsequent acts of creating.

Systems that can, through experience, improve their own capacity to be creative are an interesting goal for computational creativity research as they are a rich avenue for improving system autonomy. While computational creativity research has coalesced over the last decade around quantified ways to evaluate creative output, there have been few attempts to imbue a system with methods of self-evaluation and processes by which it could learn to improve. This research presents one possible avenue for pursuing that goal.

A distinction should be drawn between learning about the various objects and concepts to be used in particular creative acts, which serves to aid those acts specifically, and learning about how to be a better creator more broadly. Knowledge about objects influences future creative acts with those objects, but the generalisability of that knowledge is suspect.

One example of where this learning challenge is particularly relevant is analogy-making, in which every mapping created between two objects is, by the definition of an analogy as a new relationship, in some way unique. Multiple analogies using the same object or objects are not guaranteed to be similar. This makes it very difficult to generalise

knowledge about making analogies and apply it to any future analogy-making act.

We propose to tackle this problem of learning to be (computationally) creative by learning ways to interpret problems, rather than learning solutions to problems or learning about objects used in problems. These interpretations can be learnt, evaluated, recalled and reapplied to other problems, potentially producing useful representations. This process is based on the idea that perspectives that have been adopted in the past and have led to some valuable creative output may be useful to adopt again if a compatible problem arises. While even quite similar creative problems may require very different solutions, quite different problems may be able to be reinterpreted in similar ways. We discuss this approach specifically for association and analogy-making but it may hypothetically apply to other components of computational creativity. We develop a proof-of-concept implementation in the domain of computational association, and outline some ways in which this learning of interpretations could be more useful than object- or solution-learning in creative contexts.

Models for how previous experiences can influence behaviour could be a valuable addition to learning in creative systems. A computational model able to learn ways to approach creative problems would behave in ways driven by its previous experiences, permitting kinds of autonomy of motivation and action currently missing from most models of computational creativity. For example, it would be possible to develop a creative system that could autonomously construct aesthetic preferences based on what it has (or has not) experienced, or to learn styles by which it can categorise the work of itself and others, such as described in (Jennings, 2010). A creative system capable using past experiences to influence its behaviour is a key step towards computationally creative systems that are embedded in the kind of rich historical and cultural contexts which are so valuable to human artists and scientists alike.

Learning interpretations in computational association

We have previously developed a model of computational association based on the reinterpretation of representations so as to render them able to be mapped. Our model, along with an implementation of it in the domain of ornamental

design, is detailed in (Grace, Gero, and Saunders, 2012). We distinguish association from analogy by the absence of the transfer process which follows the construction of a new mapping: analogy is, in this view, association plus transfer. Interpretation-driven association uses a cyclical interaction of re-representation and mapping search processes to both construct compatible representations of two objects and produce a new mapping between them. An interpretation is considered to be a transformation that can be applied to the representations of the objects being associated. These transformations are constructed, evaluated and applied during the course of a search for a mapping, transforming the space of that search and influencing its trajectory while the search occurs. This differs from the theory of rerepresentation in analogy-making presented in Yan, Forbus and Gentner 2003 as in our system representations are iteratively adapted in parallel with the search for mappings, rather than only after mapping has failed. This permits interpretation to influence the search for mappings, and for mapping to influence the construction, evaluation and use of interpretations in turn.

The implementation of this model presented here explores the process of *Interpretation Recollection*, through which interpretations that have been instrumental in creating past associations can be recalled to influence a current association problem. This process occurs in conjunction with the construction of interpretations from observations made about the current problem.

In the model interpretation recollection is a step in the iterative interpretation process in which the set of past, successful interpretations is checked for any interpretations appropriate to the current situation. These past interpretations will then be considered for application to the object representations alongside other interpretations that have previously been constructed or recalled. A successful interpretation – one that has previously led to an association – can thereby be reconstructed and reapplied to a new association problem. In this paper we demonstrate that this feature of the interpretation-driven model leads to previous experiences influencing acts of association-making, and claim that this is promising groundwork for future investigations into learning in creative contexts.

In the implementation described in this paper we use simplified approaches to determining the relevance of previously successful interpretations and reapplying them to the current context. The metric for determining appropriateness is straightforward: any previous interpretation which has a non-zero effect on a current object representation is determined to be capable of influencing the course of the current association problem and included. This simplifies the notion of "appropriate for future use" and leads to an obvious scalability issue, but we demonstrate that this very simple approach influences behaviour. More sophisticated methods for determining when and how known interpretations should be reapplied are an area of future investigation.

Experimenting with learnt interpretations

As a preliminary investigation into the potential of interpretation-based creative learning, we will demonstrate that the approach we have developed permits previous ex-

perience to influence the behaviour of an association system. To illustrate this we will prime the system to produce different results after having experienced different histories. In our system previously constructed associations can influence new association problems through interpretation learning; past associations can act to "prime" the system to produce particular results on future associations. By demonstrating that an association system's experience with one pair of objects can influence its behaviour associating different objects, we show the advantage of interpretation-based approach to learning. Comparatively an object-based approach to learning would not have permitted generalisation to an unfamiliar pair of objects.

In our experiments the system is exposed to a particular stimulus (either a simple unambiguous association problem or nothing in the case of the control trial) and then attempts to solve an ambiguous association problem that is the same between all trials. Our association system produces many different mappings between any two objects, so changes in the distribution of mappings produced on the second problem is used as an indicator of priming effects.

Three trials were conducted. In the first trial no priming association was performed, in the second trial a priming association between Objects 1 and 2 of Figure 1 was performed, and in the third trial a priming association Objects 1 and 3 of Figure 1 was performed. In each trial an association between Objects 4 and 5, depicted in Figure 2, followed the priming stage. Each trial was performed 100 times, with the system being re-initialised (and re-primed) between each one so that the histories are identical for every association. A distribution of the results of the association between Objects 4 and 5 was produced. All trials were conducted using three relationships: relationships of the relative orientation of shapes, such as ' $\sim 45^\circ$ difference in orientation'; relationships of the relative vertical separation of shapes, such as ' ~ 3 units of separation in the Y axis'; and simple binary relationships when two shapes share vertices.

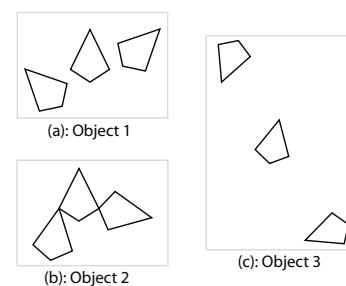


Figure 1: The three objects used in the priming associations. An association between either Objects 1 and 2 or Objects 1 and 3 is used to prime the interpretation system.

The two associations used for priming are designed to repeatedly produce a predictable association based on a predictable interpretation - making them well suited to testing the impact of priming an association system with that

interpretation. The system perceives Objects 1 and 2 and constructs a simple association based on equating the pattern of relative rotations between features in Object 1 with the pattern of shared vertices between features in Object 2. In the other trial, the system perceives Objects 1 and 3 and constructs another simple association, this time equating the pattern of relative rotations in Object 1 with the pattern of relative vertical positions in Object 3. These associations are depicted in Figure 3, with the thick dashed lines between features within the objects denoting relationships that were mapped, while solid lines between features joining the two objects denote which features were mapped to each other.

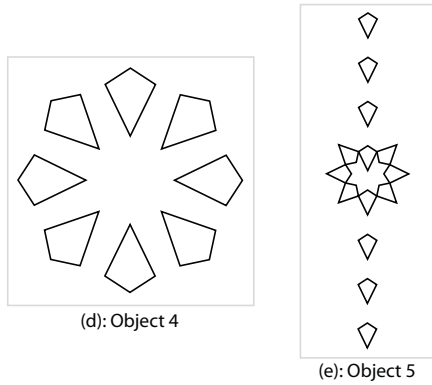


Figure 2: The two objects used in the test association of all three trials, which is used to measure the effects of the priming associations.

These simple associations effectively prime the system with an interpretation which will predictably bias the dependent association between Objects 4 and 5. This bias provides a proof-of-concept test of experiential influence. Future studies are needed to determine the scope of influences which historical context can exert in creative systems.

The post-priming association problem used in all three trials is designed to have two dominant solutions. Over many runs the system will produce many other associations in addition to these two, but these will occur relatively often. The two associations can be seen in Figure 4, with association (a) being between the radial arrangement of shapes in Object 4 and the similar arrangement of touching shapes in Object 5, and association (b) being between the same arrangement in Object 4 and the vertically spaced shapes in Object 5.

It is hypothesised that when the system is first primed with the association in Figure 3(a) the solution in Figure 4(a) will be more common (than when unprimed), and that when the system is first primed with the association in Figure 3(b) the solution in Figure 4(b) will instead be more common (than when unprimed). This outcome would demonstrate the feasibility of using interpretation-based learning to enable a creative system's experiences to influence its actions.

Experimental results

The distribution of associations produced in each trial can be seen in Figure 5. Each of the three bars represents one

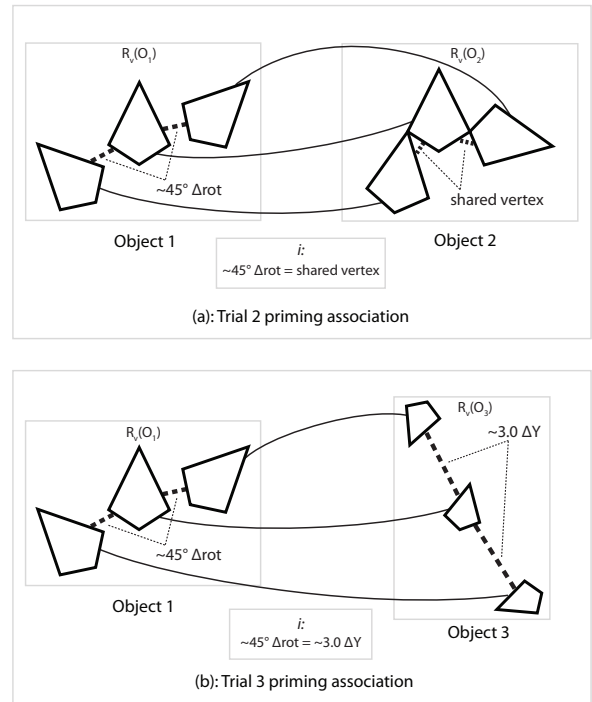


Figure 3: The solutions to the association problems used to prime the system in the second and third trials. These simple problems predictably influence the experiential component of the creative system in ways that can then be measured.

trial, and each of the three different shading tones represent a different result, with the darkest tone representing the solution seen in Figure 4(a), the middle tone representing Figure 4(b), and the lightest tone representing all other solutions. The latter category included fragmented mappings (those for which the system could not find a complete mapping of all the shapes in Object 4) based on relationships such as 90° and 135° orientation differences as well as similar varieties and combinations of vertical separation and vertex sharing relationships. Although they are irrelevant to this investigation of priming effects, at present this implementation has no way of evaluating associations other than the number of features which are mapped. See (Grace, Gero, and Saunders, 2012) for a discussion of the evaluative capabilities of this model and its current implementation.

It is clear from Figure 5 that priming the association system with previous problems that rely on compatible interpretations leads to a significant influence on the outcome of the association process. Trial 1, in which no priming is performed, serves as a control against which the frequency of different associations can be compared. In Trial 2 the system is primed with a problem that relies on the adoption of an interpretation equating a pattern of rotational relationships with a pattern of shared vertices. The result for Trial 2 clearly shows that the frequency of solutions relying on this interpretation (such as the one seen in Figure 4(a)) has

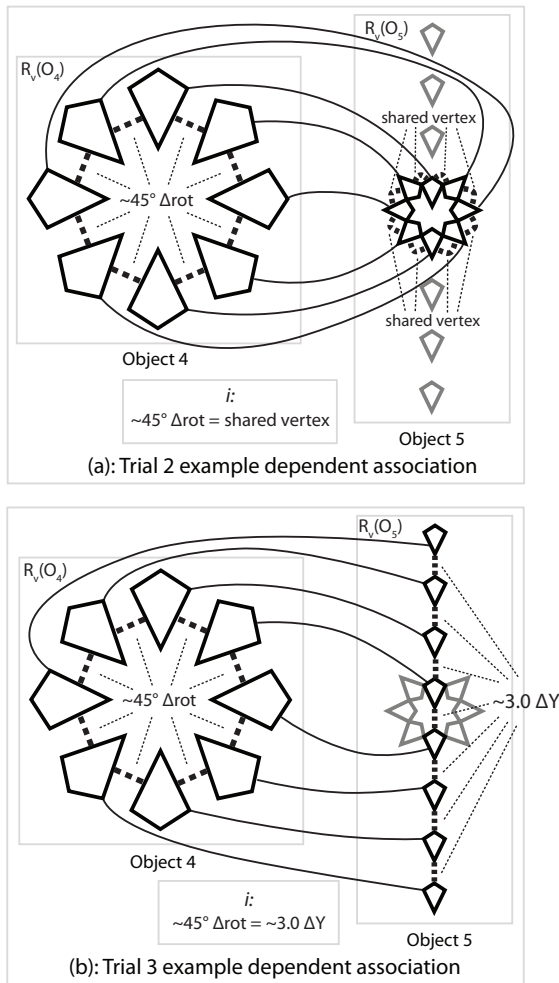


Figure 4: Two of the possible solutions to the dependent association performed in each trial. Solution (a) uses the same interpretation as used in Figure 3(a), while solution (b) uses the one found in Figure 3(b).

increased significantly, from 17% in the control to 63% in Trial 2. In Trial 3 the system is primed with a problem that relies on equating the same pattern of rotational relationships with a pattern of vertical separation, shown in Figure 4(b). The result for Trial 3 shows a similarly significant increase in frequency, with 36% frequency for the primed trial compared to only 3% in the control.

The difference in absolute frequency of the two associations shown in Figure 4 can be explained by the underlying graph structures and the process for searching them used in our model. The association primed for in Trial 2 is based on the “shared vertex” relationship, which is 50% more common in Object 5’s graph representation than the “3.0 difference in the Y axis” relationship used in the interpretation primed for in Trial 3. For information on how our system automatically extracts these and other relationships from vector representations of the objects see (Grace,

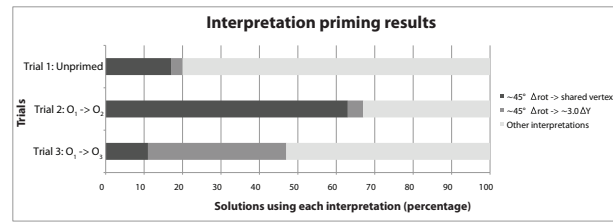


Figure 5: The distribution of association results in each trial, showing the influence of the priming in Trials 2 & 3.

Gero, and Saunders, 2012). The commonality of that relationship makes mappings that involve features connected by that relationship similarly more common, which makes it more likely to be utilised by both the mapping and interpretation processes. This bias makes the vertex-sharing relationships much more likely to feature in associations, but priming the system towards a less common result largely overrides it. This can be seen in the twelve-fold increase in the likelihood of the less-common association as compared to the only three-fold increase in the more common one.

These results show that it is possible for the learning of interpretations to influence the behaviour of a creative system, and demonstrate our model of association’s capacity for interpretation learning and experiential influence on behaviour. While the influence on behaviour produced in this implementation is limited, these experiments demonstrate that interpretation learning can influence behaviour on problems significantly different than those previously experienced. This shows the potential for more general learning than is possible by solution- or object-based methods, making this approach a valuable building block for modelling learning computational creativity.

Discussion

The experiments described in this paper are a demonstration that the behaviour of creative systems can be influenced by storing and reusing ways to interpret creative problems. This section discusses the impact on creativity of drawing from experience to reinterpret a problem and the ways interpretation can influence creative acts. For a more general discussion of our model and how it compares to other models see Grace et. al (2012).

Re-using interpretations for creativity?

There is an intuitive objection to the idea of re-using elements of a previous creative process: that process, or at least that element of the larger creative process, cannot by definition be p-creative. While the process may go on to produce p- or h-creative outputs, it will at least partially be based on things that have been experienced previously.

The p-creativity, or lack thereof, of any element of the creative process does not imply any impact on the creativity of the final product, but the objection bears discussion: if drawing on experience will only reduce the creativity of a process, what is its value? Investigations of the diversity

of solutions both with and without priming show that there is no significant reduction in the breadth of solutions produced, only in the order in which the system produces them. This is due to the novelty-favouring behaviour of our model, which over time discounts and eventually discards solutions to a particular problem which have repeatedly arisen. Such intrinsic motivations towards novelty are a necessary component of learning creative systems, balancing the desire to repeat the familiar against the desire to explore the new.

(Suwa, Gero, and Purcell, 1999) propose a third element to Boden's categorisation of creativity (1992), 'situational', or s-creativity, to describe when an object or process is not absolutely new to an agent, but is new within the current situation. This occurs when a familiar idea is considered for the first time in an unfamiliar context, a common outcome of analogy-making and a potent component of experiential learning. This is particularly applicable to the notion of re-using interpretations, which have the potential to transform the solution space of the current problem despite not being a novel process to the agent in question.

Kinds of interpretation and their influence

In the system presented here interpretations are simple transformations that are stored and re-applied verbatim. However, the notion that interpretations can influence future acts does not require that the previously useful interpretation be literally re-applied to the new context. It would be possible to develop a system in which exemplary, prototypical or generalised interpretations could be reconstructed from experience and applied to the current context.

We define interpretations as a transformations applied to the objects being associated, but this need not be a direct transformation of the object representations used by the system. Other elements of the model could be transformed, such as evaluative processes, which would change not the information being used in the creative process but its value metrics. This could lead to experiential influence on aesthetic judgement, similar to the idea of autonomously derived aesthetics proposed by Colton (2011). Alternatively, representational processes of the model could be transformed, for example relaxing thresholds for categorisation or similarity. This could lead to behaviours like satisficing, a common behaviour of human designers in which requirements are changed during the creative act (Simon, 1957).

Conclusions

This paper proposes the notion of interpretation-learning – the storage and recollection of ways to transform problems – as a complement to more familiar models of object- or solution-learning. Interpretation-learning is hypothesised as being of particular utility in creative contexts as each creative problem is unique in its solutions, but potentially not in the ways it can be perceived. These remembered interpretations can be thought of as granting a creative system more autonomy over its decision making than other means of deciding how to interpret problems such as provided heuristics or stochastic processes. We present a simple implementation of a creative system in which past experiences influ-

ence behaviour through interpretation, to serve as a proof-of-concept of the notion of interpretation-learning. With this approach demonstrated as feasible and promising, future work can explore its efficiency and effectiveness.

Incorporating learning is emerging as an important component of computational creativity due to growing prominence of desired behaviours like surprise (Maher, 2010), appreciation (Colton, Goodwin, and Veale, 2012) and autopoiesis (Saunders, 2012), which necessarily involve past experience. Learning about specific objects or outcomes is of limited utility in computational creativity, as creative problems are by definition unique. However, learning and recalling different perspectives through which to view objects is one process by which learning in creative contexts could be modelled.

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