

# Situated Novelty in Computational Creativity Studies

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## Abstract

This paper furthers the study of creative design by taking a situated view of novelty. A set of computational experiments is performed utilizing an agent-based model of a design team, and resulting data is used to examine the influence of a change in a situation (or a design frame) on the perception of a design's novelty in terms of its difference from existing or possible designs. The experiments demonstrate that, over the course of designing, solutions which were regarded as novel, can become not novel. They also show that a solution which was not seen as novel in one situation can be assessed as novel when a situation changes. The results, therefore, emphasize the importance of studying novelty as a situated measure.

## Introduction

Design has long been recognized as a situated act (Gero 1998; Gero and Kannengiesser 2004; Suwa, Gero, and Purcell 2000). Empirical findings (Suwa, Gero, and Purcell, 2000) suggest that throughout designing, designers use their past experiences and expectations to develop interpretations of their tasks. To further the studies on creativity, Kelly and Gero (2015) developed the notion of situated interpretation and used it for studies on framing in creative tasks. Their work builds on Boden's (1996; 2004) theory of creativity and emphasizes that to understand the creative aspects of design activity it is essential to understand how the conceptual space changes. In their later work, Kelly and Gero (2017) elaborated the notion of situated interpretation and build on it to develop a paradigm of generate and situated transformation, where a situated transformation is defined as a process that draws on previous experiences to create a new design space or to modify the existing one.

To further the studies on the relationship between situatedness and creativity, this research utilized computational experiments to explore how novelty – a key aspect of creativity - is influenced by the situated changes in the conceptual space in which the design occurs.

## Novelty

Novelty, its definition, assessment or reinforcement, constitutes an inevitable part of every study on creativity. Earlier work on creativity (e.g., Besemer 2006; Boden 1996) viewed novelty as a term covering aspects of originality and surprise. However, recently researchers (e.g., Maher, Brady, and Fisher 2013) argued that novelty, as a measure of difference of a design relative to the set of existing designs, does not necessarily imply violation of expectations (i.e., surprise) in a space of projected designs. Following this distinction between surprise and novelty, Maher and Fisher (2012) and Grace et al. (2015) proposed measures of novelty and surprise based on k-means clustering. Their approach includes representing each design with a set of features determining its position within the conceptual space. The measure is particularly important for computational studies of creativity as it relies on well-known and easy-to-implementation mechanisms. Many additional methods for novelty detection and measurement can be found in, for example, the field of signal processing (for a review, see Pimentel et al. 2014); while for an overview of measures used in design one can consult the work of Ranjan, Siddharth, and Chakrabarti (2018).

## Hypothesis

Following this brief theoretical background and empirical findings, and building on previous computational studies of novelty, this work studies novelty in design through the lens of situatedness. The notion that situational change can introduce differences in novelty assessment can be detailed through the formulation of two hypotheses:

*H1: Over the time course of designing, (some of) the solutions that were previously recognized as novel, will become not novel.*

*H2: Over the time course of designing, (some of) the solutions that were previously not regarded as novel, can be recognized as novel.*

These hypotheses are tested through a series of experiments conducted by utilizing a computational model of a design team.

## Model

Within a computational model used in this study, a design team is represented as a set of cognitively rich, social agents, where each agent portrays an individual designer (Perišić et al. 2017; 2018; 2019). An agent’s mental model consists of three layers: the function layer, the behavior layer, and the structure layer. At each layer, the set of nodes (of the corresponding type) represents functions, behaviors or structures known to the agent. Links between functions and behaviors, and behaviors and structures represent the associative relationships between elements known to the agent. There are no links among nodes of the same type (Gero and Kannengiesser 2004).

An agent’s reasoning mechanisms are based on cognitive theories: dual system theory (Kahneman 2011) and a theory distinguishing reflexive, reactive and reflective modes of reasoning (Maher and Gero 2002). As described in (Perišić et al. 2017; 2018; 2019), each structure node is associated with a network, while each behavior node represents a range of one network property (e.g. a behavior node may represent having a clustering coefficient between 0.1 and 0.2). In this manner, one can derive structure’s behavior by calculating the respective network’s properties. When an agent is faced with a task (a set of requirements – i.e., required functions or behaviors), an activation impulse is generated in the function node which is deemed as relevant and passed through the links. If a structure node becomes sufficiently activated, the associated network is analyzed (i.e., its properties are calculated) and the behaviors obtained are compared to the required and expected ones. If a mismatch from the expectations is encountered, an activation impulse is sent to the function nodes relevant for the unmet requirements.

To enable agents to expand the structure space, two mechanisms were implemented: *union* – which can occur if two structures are simultaneously sufficiently active and it consists of overlaying their respective networks; and *contraction* - in which two network nodes (i.e., nodes within the structure node’s network) can be collapsed into one (thus creating a new network node). Additionally, agents can learn through communication with others. If a structure node is sufficiently active and determined to meet the requirements, an agent can propose it as a solution to other agents, which in turn learn it, evaluate it in against their mental models, and rate its suitability for the task. Similarly, if two nodes are sufficiently active and the link between them is of sufficient weight, an agent can decide to communicate this link to others which can then learn the link and use it in subsequent reasoning. Through structure space expansion and processes of learning, grounding and forgetting of links, the agent’s mental model develops and shapes its reasoning.

Further details on the model’s implementation and performance can be found in previous work (Perišić et al. 2017;

2018; 2019). For the present study, however, one modification of the prior implementation was made. As initially modeled, a simulation was considered over when the agents found and agreed upon a single structure that satisfied the requirements. The scope of the present study requires continuous exploration and extension of the solution space. Therefore, the mechanism to avoid team fixation on a single feasible structure was implemented as follows: if a unique structure has been proposed repeatedly over the course of 10 simulation steps, and the links from relevant (i.e., required) behavior nodes to the structure are well-grounded (i.e., more than 98% of maximal link weight) in the mental models of every agent, then the structure is inhibited and the weight of relevant behavior–structure links is reduced in each of the agents’ mental models. Although this results in the structure not being used in (at least some) subsequent steps, the activation level of behaviors connected to the structure remains unchanged, therefore influencing the further search. This mechanism corresponds to the situation where members of a design team all agree upon one solution and “leave it aside” to produce additional ideas, while still remembering the behavior and properties of the solution.

## Design of the Experiments

For each simulation run, a task is represented as a set of network properties which a structure (i.e. structure’s respective network) has to meet to be considered as a solution (i.e., to be found *useful*). To enable comparison and novelty assessment of structures, each structure is characterized by its respective network’s properties. To avoid high correlations among structures’ properties due to task requirements, in the present work the tasks pose requirements on the properties of the largest connected component of a structure network, while the structure’s properties were calculated on the whole respective network. Each structure’s characterizations consist of three values: network degree centrality, clustering coefficient and hierarchy value, based on the measure for undirected networks defined by Mones, Vicsek, and Vicsek (2012). Tasks were defined as combinations of requirements regarding diameter, closeness and/or betweenness centralities of the structure network’s largest connected component.

Throughout a simulation, details on all of the agent-generated structures were collected. Further, at each time step, a reachable structure space was calculated. Reachable structure space at a time step  $t$  ( $RSS_t$ ) is defined as a space of all structures which can be created by agents in a time step  $t+1$ . In other words, it is a space of all structures derived from the structures known to agents at the step  $t$  by utilizing union and contraction mechanisms described in the previous section. A subset of a reachable structure space consists of all reachable feasible solutions ( $RFSS_t$ ), i.e., a space of all structures meeting the requirements which can be generated in the next step. Finally, a subset of all reachable feasible solutions can be considered as novel, thus constituting a space denoted as  $RNSS_t$ . To derive  $RNSS_t$  from its corresponding  $RFSS_t$ , Mahalanobis distance was used. Mahalanobis distance is a measure frequently used for detection of outliers in multivariate data and has often been utilized in

machine learning systems to identify data distinct from the samples used for system’s training (Pimentel et al. 2014).

Overall, 300 simulation experiments were run, each terminating when the size of the RSS reached 100,000 nodes. The average sizes and standard deviations of the size of reachable structure space (RSS) and reachable feasible structure space (RFSS) over time are shown in Figure 1.

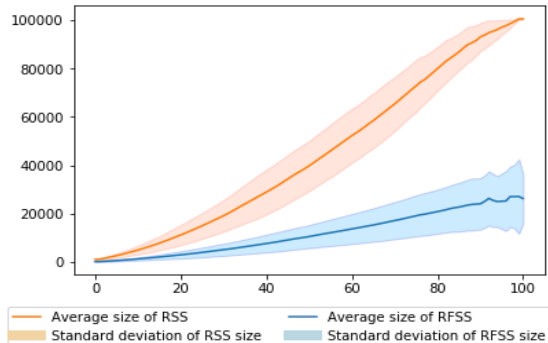


Figure 1. Average size and standard deviations of RSS and RFSS over time

## Results

To test for the hypotheses posed in this paper, the number of novel structures which, over the course of the simulation, turned not novel, was counted. Similarly, the statistics include the number of structures which were initially (i.e., at the time of their first occurrence within reachable structure space) not marked as novel, only to be labeled as novel as the simulation progressed. The respective average (aggregate) numbers and standard deviations are presented in Table 1. Finally, to illustrate the dynamics of the simulated experiments and to provide deeper insights in the obtained results, a series of snapshots for one simulation experiment are extracted and presented in Figure 2. In the figure, feasible solutions are shown, and further differentiated based on their novelty status. Structures more than two standard deviations apart from the sample mean were marked as novel.

Number of Novel -> Not Novel nodes per simulation		Number of Not Novel -> Novel nodes per simulation	
Average	Standard deviation	Average	Standard deviation
187	167.06	653	256.88

Table 1. Statistics on the number of novel solutions turned not novel and not novel solutions turned novel

## Discussion

As shown in Figure 1, the mechanisms which agents use to extend the solution space enable them to create new – feasible or not – structures over time. The number of novel solutions found in each simulation step increases over the course of the simulation. However, the percentage of feasible solutions which is recognized as novel slowly declines over time. More precisely, at the early stages of simulation (first

10%) when the number of novel solutions is small (less than 100), the percentage of novel solutions shows several increases and decreases, and a large standard deviation. This reflects the differences between simulation runs. Namely, while in some cases agents needed more steps to find novel solutions, at other runs some of the structures generated at the early stages of simulation were already significantly different from others. As the simulation progresses, the percentage stabilizes and starts to decline.

Interestingly, significantly more structures turned from not novel to novel, than the other way around. To explain this, one may take a closer look at the dynamics of the simulation depicted in Figure 2. At the simulation start, several nodes on the left side of the space are marked as novel. However, as the agents learn and create more structures, the space of reachable feasible solutions changes to include structures closer to those previously regarded as new. As a consequence, the notion of what is novel (i.e., different from others) gradually shifts from the left to the far right of the space (third subfigure). As the process continues, the RFSS grows, and the majority of reachable structures concentrate in a cluster on the left of the space. As a consequence, the standard deviation of the population decreases, and a (relatively) large number of structures which are outside of the cluster but were previously not regarded as novel, now become assessed as such. This example serves to show how agent-produced solutions, after some time, start to converge to “similar looking” structures satisfying the requirements. Such a process is a consequence of two factors: first, the novelty detection algorithm was not implemented in the agents themselves, therefore restricting them from detecting that subsequently generated structures moved the space towards increasingly similar structures. Secondly, the synthesis mechanisms (union and contraction, among which union is more frequently applied) led to the generation of larger, well-connected networks for which calculated measures differ to a lesser extent. Due to these characteristics (arguably, limitations) of the system, over time, the majority of reachable structures “concentrates”. This means that the number of structures which will be marked as novel and then changed to not novel decreases over time. However, as the simulation progresses, the large proportion of the previously not novel structures will become assessed as novel.

Despite the limitation that agents do not assess novelty, the results enable interesting insights. If a task is reframed to broaden the solution space, the difference in characteristics between the initial and newly obtained space may cause some solutions to no longer be regarded as novel. Perhaps more surprisingly, broadening the solution space can also cause some (previously uninteresting) solutions to stand out. This effect may likewise be discussed through the notion of “norms” and development of immutable expectations.

Finally, it would be interesting to observe whether the similar results would be obtained if the agents were modelled as the robot with real-time novelty-detection mechanism implemented in (Marsland, Nehmzow, and Shapiro 2000). Marsland et al. (2000)’s robot utilizes habituation and recovery mechanisms enabling it to get accustomed to

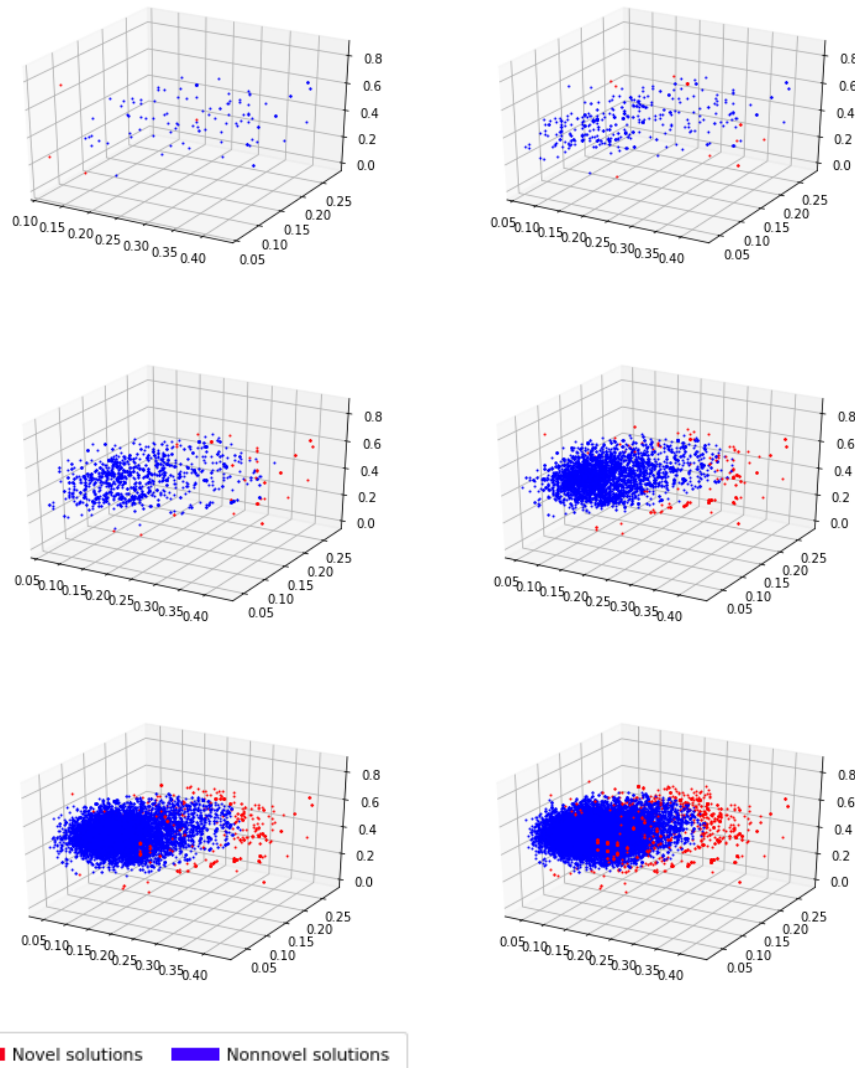


Figure 2. An example of the simulation run

stimuli, develop different value systems and forget, which results in it being able to mark the stimuli as novel even though the stimuli has already been encountered in previous stages of the simulation.

## Conclusion

This work builds on the notion of situatedness and uses it to study creative aspects of design. Relying on empirical findings and computational models of creativity in design, this work explores how a vital part of creativity – novelty – changes with respect to the situation. A series of computational experiments demonstrated the importance of a frame within which the design occurs in assessing novelty. As a design frame (or a situation as defined by Kelly and Gero 2017) is changing to broaden the solution space, a design may turn from appearing as novel to being regarded as not different from the majority of others. In contrast, a change of a design frame may cause a design previously marked as

‘typical’ (i.e., not sufficiently different from other solutions), to be seen as interesting and different from others.

The simulations utilized the Mahalanobis distance to detect structures distant from the general distribution of designs. In future, experiments using different measures could be compared and assessed based on their capability to capture the notion of novelty, therefore determining whether the observed trends are emerging from the chosen novelty measure. Additionally, one may note that the current framework does not enable the dynamic introduction of new variables along which solutions can differ. It is likely that some of the subsequently added structures that were labeled as not novel would be found as novel based on some additional dimension (i.e., different network characteristic). In the present study, difference in designs is manifested through either new values for a certain attribute or as a novel combination of attributes. But, as Gero (1990) postulated and Maher and Fisher (2012) demonstrated with the example of Bloom Laptop design, new (and surprising) designs can introduce new variables (i.e., dimensions) along which designs can differ.

Nevertheless, this work demonstrates the importance of regarding novelty as a situated measure. Nu-

merous examples from fashion (Bianchi 2002), or even the healthcare industry (Janssen, Stoopendaal and Putters 2015), show how “old” designs can again come under the spotlight due to the change in their contextual factors. In future studies, an approach similar to the one taken here can be applied to study how assessment of another creativity aspect – surprise – is influenced by situational changes.

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