Two Ways of Understanding Social Dynamics: Analyzing the Predictability of Emergence of Objects in Reddit r/place Dependent on Locality in Space and Time

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Abstract
Lately, studying social dynamics in interacting agents has been boosted by the power of computer models, which bring the richness of qualitative work, while offering the precision, transparency, extensiveness, and replicability of statistical and mathematical approaches. A particular set of phenomena for the study of social dynamics is Web collaborative platforms. A dataset of interest is r/place, a collaborative social experiment held in 2017 on Reddit, which consisted of a shared online canvas of 1000 pixels by 1000 pixels co-edited by over a million recorded users over 72 hours. In this paper, we designed and compared two methods to analyze the dynamics of this experiment. Our first method consisted in approximating the set of 2D cellular-automata-like rules used to generate the canvas images and how these rules change over time. The second method consisted in a convolutional neural network (CNN) that learned an approximation to the generative rules in order to generate the complex outcomes of the canvas. Our results indicate varying context-size dependencies for the predictability of different objects in r/place in time and space. They also indicate a surprising peak in difficulty to statistically infer behavioral rules towards the middle of the social experiment, while user interactions did not drop until before the end. The combination of our two approaches, one rule-based and the other statistical CNN-based, shows the ability to highlight diverse aspects of analyzing social dynamics.

Introduction
The field of social dynamics studies behaviors that result from groups of interacting individuals that self-organize in particular ways. It is also one of the pillars of complexity science, and has ramifications in sociology, psychology, economics, animal behavior, and numerous fields. One of the most data-rich areas for the study of such social phenomena can be found in online communities, in particular on collaborative platforms such as wikis, Q&A websites, and social media. This project focuses on Reddit, an online discussion platform that also hosted a collaborative social experiment on April Fools’ Day of 2017, called Place (or r/place, the sub-community created for the occasion). The experiment involved an online canvas, which registered users could edit by changing the color of a single pixel from a 16-color palette. After each pixel was placed, a timer prevented the user from placing any pixels for a period of time between 5 and 20 minutes (Simpson et al., 2017).

In just 72 hours, over a million registered Reddit users placed 16.5 million pixels to transform a simple, blank, 1000 \times 1000-pixel canvas into a surprisingly beautiful clash of communities, nations, and ideologies. Because each user could only place one pixel every 5-20 minutes, any single individual would have struggled to create a meaningful image on their own. However, through community collaboration, users quickly produced complex creations, surpassing all of our expectations about how this project would turn out once the 72 hours were up. Reddit released pixel-by-pixel placement data and additional community efforts were spurred to produce additional canvas analysis. The r/place Atlas project (Rytz, 2017) identified almost 1500 different objects and phenomena on the final state of the canvas, although does not identify objects and phenomena in intermediate canvas states.

Although most of the placement happened within a span of 72 hours, the full dataset from u/Drunken Economist (2017) included pixels placed prior to the 72 hours. As a result, the full dataset includes pixel placements from 2017-03-21 21:03:09 UTC - 2017-04-03 16:58:55 UTC. In addition, some users were unable to place new pixels after 5 minutes and needed to wait up to 20 minutes (see posts such as u/nlscrub (2017)).

Previous work and motivation
In the current literature, there are some studies that have addressed the dynamics of this experiment. One example is Litherland and Mørch (2021), who studied the r/place event through the evolution of two types of objects, visual artifacts and social artifacts, that changed continuously over 72 hours. But because of the complex nature of the data, this study mainly focuses on a single image on the final canvas, along with its corresponding social community on the forums: The Mona Lisa replication. The Mona Lisa was present throughout most of the 72-hour span of r/place which makes it ideal to study its dynamics in comparison...
to post/comment activity that users used to coordinate pixel placement.

The authors found interesting and complex interactions between the visual and social artifacts that supported the creation, stabilization, and preservation of the Mona Lisa image. These interactions are similar to top-down and bottom-up dynamics seen across several scales of biology (Walker and Davies, 2013): bottom-up pixel placement of the initial image spurred social interactions, which lead to further image development and preservation from attacks in a top-down approach. On one hand, parts of the image (such as the face) initially appeared spontaneously, while on the other hand, the rest of the image was filled by a coordinated effort to complete and maintain the image against attacks. In context of emergence, the authors argue that the robustness of the Mona Lisa image is due to organized efforts on multiple levels, not only on a pixel-by-pixel basis, but also as a result of dynamics within the social artifact. These results suggest it may not be possible to understand the dynamics of emergent r/place structures based only on the pixel-by-pixel dataset. Instead, emergent structures are more fully understood using additional data, particularly on a social level as captured by subreddit posts, comments, and upvotes. In addition, Rappaz et al. (2018) proposed a predictive method based on the graph of user interaction clustering that captures the latent structure of the emergent collaborative efforts, and showed that the method provides an interpretable representation of the social structure.

So far, these approaches rely on visual and social artifacts that are annotated externally and robust over time. Structures like the Mona Lisa image are static and do not change location on the canvas, however there are several documented objects that do not have well-defined borders, move location over time, or change shape and structure drastically over the course of their evolution. For example, “The Void” is an amorphous block spot that is defined as behavior that simply changes adjacent pixels from their current color to black. “Rainbow Road” is a rainbow path that spans a large area of the canvas and is moved throughout its evolution. In addition, objects such as national flags are documented to expand and collide with other objects. Objects and images compete for space, invade one another, and can spawn inside each other. Not all of these events are documented or have a corresponding social artifact to represent them.

In our analysis, we further generalize these approaches by developing a framework aimed at detecting emergent objects and artifacts over time without relying on external annotations or social artifacts. Not all objects are given names, timestamps, and coordinate locations on the r/place canvas, therefore we are interested in a framework that can identify a wide variety of object types over the canvas evolution. We introduce a framework inspired by Krakauer et al. (2020), which demonstrates that individuals (like objects, images, and artifacts) can be defined in many different ways by constants throughout time or space. Within some time series data, particularly pixel-by-pixel placements in r/place, we generalize the concept of an “individual” image or object as a set of spatially local rules that don’t change over time.

However, we recognize the shortcomings of this approach. Because images that are reproduced in this canvas are defined externally, it is very unlikely that any image can be predicted before pixels are placed. In addition, each image is composed of its own set of rules; the ruleset that defines the instantiation of one image (or object) is different from any other. As a result, the “rules” of the whole canvas are inconsistent because it is a sum of multiple, externally-defined images. Temporally, the evolution of the canvas lends itself to different types of spatially local rulesets that are being implemented. At the beginning of the canvas, for example, users may be placing tiles randomly, which can later be used as “seeds” to scaffold an externally-existing image. During later stages, present images/objects are well-defined and pixel placement may be less random. Thus, the beginning and end stages of the canvas evolution maybe be more predictable given the state of the canvas than in the middle stage.

To explore whether this framework lends itself to the predictability of future canvas states, we trained a convolutional neural net (CNN) on certain temporal subsets of the canvas evolution and test its ability to predict future canvas states. We then compare its ability to make predictions with the results of the rule-based approach. Our reasoning is that if dynamics that emerge without external coordination from social constructs should be derived simply from the canvas evolution, where objects that are a result of coordinated social efforts in subreddits can’t. The CNN model is used to demonstrate different areas of space and time over the canvas that can and can’t be predicted by training on previous canvas frames.

We recognize that several extrinsic collaborations – by which we mean interactions having taken place between users outside of the direct activity of editing the canvas – contributed to the state of the canvas, which cannot be predicted from the state-evolution of the canvas alone. Litherland and Mørch (2021) discusses the close relationship between objects that emerge and activity within some subreddits. Due to this, we cannot predict the emergence of objects that form due to collaboration and planning that occurred within subreddits, unless such information is fed into our training, including both social interactions (e.g. private discussion among factions of users outside the canvas painting activity) and cultural objects (a database of relevant images, flags, and logos, ideally including some attached cultural semantics). Here, we focus on collaboration “rules” that are purely spatial-based. In other words, this analysis tries to estimate “rules” that users use to decide which pixel to place where based on the current state of the canvas. Since both
types of rules contribute to the state-evolution of the canvas, we acknowledge that our current approach is limited to only spatial state-based rules. In the future, we could use data from subreddits that hosted the external collaboration for the emergence of objects to gain a more complete predictive analysis.

In summary, our approach is aimed at addressing the following questions: What are the conditions that lead to an emergent structure? Are some structures emergent based on pixel-by-pixel interactions without social coordination? Finally, how do these objects differ from objects that are a direct result of social coordination?

**Statistical rule-based approach**

We rendered snapshots of the canvas in 10-minute intervals to create a coarse-grained time-evolution of the canvas. This resulted in 682 total snapshots of the canvas over the whole dataset. In the times between each snapshot, we also counted the number of pixels placed and the number of unique users who placed pixels. What “rules” do users use to place a new pixel on the canvas, given the current state of the canvas? If the dynamics of the canvas state are open-ended, then these rules could change over time, possibly as a function of the state of the canvas. Regardless if this evolution fits the requirements of open-endedness described by [Adams et al., 2017], we leave open the possibility that the update rules from one frame to the other could change over time.

Artificial life’s approach advocates for the understanding of complex systems from the bottom-up, by studying emergent properties in a generative way ([Bedau et al., 2000] and [Frans et al., 2021]). The analysis may profit in from starting with the restricted frame of discrete dynamical systems such as cellular automata ([Beer, 2014]), which give us access to a large range of tools from computer science and complex systems, such as counting the number of ways a finite region may transform from a defined region to another ([Biehl and Witkowski, 2021]). If we assume the canvas snapshots behave similarly to a synchronous 2-dimensional cellular automata (2D CA) with local interaction rules, then a static object that persists throughout snapshots are locally a static, unchanging set of rules. Here, we use a slightly different interpretation for “rule” than for 2D CA. For cellular automata, a rule is the set of single-pixel outcomes for all possible neighborhood states. Here, we take a more fine-grained definition of rule and assume a rule is a single neighborhood state and an outcome for the center pixel. Using this interpretation, a cellular automata rule is a set of “rules” using our definition.

The Mona Lisa, for example, can be mapped to an area of pixels, each in a single state from a set of discreet colors. As a result, it is defined as a static set of rules that is only applied to the area that spans the image. The set of rules can have contradictory outcomes for the same neighborhood state, depending on how a neighborhood is defined. Over time, the pixels within the image do not change since it is a static image, and any pixel that is perturbed would be changed back according to the set of rules that define the static image, according to the image’s set of rules. Our goal is to estimate the rule set for each image (and the canvas overall) and understand how these rule sets change over time as images appear, disappear, and compete for limited space in r/place.

We understand that it is possible (and likely) that rule-sets that define images could include rules based on non-local neighborhood states. In addition, individual rules are likely to have different neighborhood sizes depending on the outcome pixel location in relation to the whole image. For example, a corner pixel of the Mona Lisa does not care about its immediate neighboring pixels outside of the image boundary. But the pixels in the center of the image do depend on the state of all its immediate neighbors, because the neighbors are within the boundary of the image. Images that are not as well-defined, such as the spreading “Blue Corner” and spreading black “Void,” have a simpler rule set: Simply to change any neighboring pixel to the image boundary blue or black, respectively. Different images and objects in the canvas will have different sets of rules that are intrinsic to the object type. But no matter the object, we argue that *in order for an object to persist, the set of rules that define it must persist over time in that local space.*

Given 10-minute interval snapshots of the canvas, we map whatever local and non-local rules between snapshots as a 2D nearest-neighbor CA, with a nearest-neighbor radius of 1 and 2. Given the current color of a pixel and its 8 ($n = 1$) or 24 ($n = 2$) nearest neighbors, what color will the pixel be at the next time step? Regardless of the actual set of rules that govern the transition between canvas snapshots, even if these rules are changing over time, we encode all rules from one snapshot to the other using the 2D CA rule space. As a result, whichever rules are driving the evolution of the canvas, we understand that they are mapped into 2D CA rule spaces. Rules along the edges are excluded. Figures 1 and 2 show the rank-order frequency distributions of these rules over time, encoded in 2D CA rule spaces. Each line represents the rank-order distribution of rules between a snapshot and the snapshot at the next 10-minute interval. The line thickness represents the number of pixels placed during that time frame. If the thickness denoted the number of unique users that placed pixels instead, the results are visually identical in these plots.

To better understand the relationship between these rule frequency distributions and the objects present in the canvas, we have also included canvas snapshots in Figure 3. These snapshots correspond to the same time period in Figures 1 and 2 that spans the two “groups” of lines (red-orange to yellow-blue).
CNN-based neural network approach

Next, we let a neural network learn the generative rules in order to generate the complex outcomes of the art canvas. This approach is similar to some works on growing neural cellular automata (Mordvintsev et al., 2020), but with the following design changes. To learn the set of rules, we have trained a convolutional neural network (CNN) which, given a $3 \times 3$-pixel kernel of a canvas snapshot in time, outputs the value of the central pixel of one of the successive frames. Running this neural network over all $3 \times 3$ fragments for one frame of the $1000 \times 1000$-pixel canvas, we end up with a $998 \times 998$-pixel canvas that may then be compared to the original art output in the r/place experiment. Similarly to the convolutional part of Mordvintsev et al. (2020), we have divided each of the RGB colors for the training in order to (1) simplify the learning process of the neural network, and (2) use the SSIM method (explained later) to measure the performance of the model.

To deepen the analysis, we have trained the neural network under different conditions. We have first trained the model to predict not only the next frame, but also the 6th, 18th, and 36th frame. Considering that the time gap between frames is 10 minutes, these frame gaps correspond to 10 minutes, 1 hour, 3 hours, and 6 hours, respectively. Figure 4 shows the results of the model for this predictive task. The results indicate that the further the frame to be predicted, the less significantly similar the frame created by the neural network is compared to the ground truth. Figure 5 shows two different outputs of the model for the last frame compared to the last frame of the original social experiment.

We have also compared the prediction of the model in different timestamps of the video, assessing the model performance every 50 frames ($\sim$ 8 hours). When predicting one frame ahead, we observed that the accuracy changed over time as it significantly decreased for the 400th and 500th frame when compared to the 450th frame (p-value < 0.001), and significantly increased for the 250th and 300th frame (p-value < 0.001). Instead, when predicting 36 frames ahead, the model became significantly better at predicting the last frames compared to the first frames of the video. Compared
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also change over the space of the canvas as well. The “Blue
Corner” (seen in snapshots 300–400 in Figure 5) may use a
set of rules based on nearest-neighbor states, but the Mona
Lisa appearing in snapshot 400 may use a much more con-
strained rule set based on an external, well-defined pattern
mapped to a set of pixels. Future analyses could compare
these rule frequency distributions with distributions based
on random neighborhoods, including non-local neighbor-
hoods with non-adjacent pixels.
The results from the CNN-based neural network approach
indicate that the collaboration rules become easier to infer
as we decrease the time gap between the input frame and
desired frame to reconstruct. Perhaps more surprisingly, the
behavioral rules followed by the users to modify the art piece
were not kept constant over time, being statistically more
difficult to infer for the middle time frame of the experiment,
in spite of edits and interactions remaining intense until the
end of the experiment (Simpson et al., 2017). This implies
that the user decisions to modify a pixel are more based on
short-term rather than long-term contexts in time, while be-
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tained in the image, as they increase over time until the last
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there were “outside” collaborations between users that can-
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findings indicate that there were general trends over the art
piece that were found by the model. Hence, it was possible
to get some predictability over certain objects of the canvas,
such as the ones growing linearly over time such as the blue
corner or the German flags. One example is the output im-
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cies were predicted by the model while global dependencies,
such as the dove on the EU flag, were not inferred.
Nevertheless, this predictability would probably increase
if analyzing each subset of users that were collaborating to-
gether to create new objects. So, we leave to future work
the implementation of this same model for sets of users to
gain a more complete understanding of the decisions taken
in relation with complex interactions.

**Conclusion**
This work focused on the study of the social dynamics of
interacting agents who are able to collectively create an art
piece such as the r/place. To gain a better understanding
of these dynamics, we use a statistical 2D cellular-automata
rule-based approach to address spatially local rules that
don’t change over time as a rough estimation of the num-
ber of objects present in the canvas during that snapshot and
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For the rule-based approach, we mapped the rules be-
tween snapshots using a 2D nearest-neighbor CA with a ra-
dius of 1 and 2 and have found that rules that rules encoded
in the \( n = 1 \) 2D CA space are more frequently repeated
Figure 4: Model performance when predicting the following
frame (10 minutes), the 6\textsuperscript{th} frame (1 hour), 18\textsuperscript{th} frame (3
hours), and 36\textsuperscript{th} frame (6 hours).
Results from the statistical rule-based approach indicate that
rules for the overall canvas encoded in the \( n = 1 \) 2D CA
space are more frequently repeated than for \( n = 2 \). How-
ever, this could be due to the fact that the size of the rule
space is considerably smaller for \( n = 1 \) than it is for \( n = 2 \).
In the future, we plan on comparing rule frequencies based
on canvas snapshots with rule frequencies between white
noise images. In the case of white noise images, the rule
space would be sampled at random. But since the size of the
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Overall, our results may bring about many interesting questions about the dynamics of the art piece and social cooperation within a digital medium. We think that further work could profit from focusing on finding which rule encodings are more deterministic. For example, one may implement these same methods for each set of users, to then compare their outcomes and inferred rules to make sense of local and global dynamics in social behavior. Having combined the insights of a rule-based approach with a machine learning one, we were able to discover diverse aspects of the social dynamics from a promising dataset. This seems to constitute a clear indication that both tools may be advantageously combined for this field of research.

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Figure 6: Model performance when predicting different frames of the video. On the top image, results when predicting one time frame ahead. On the bottom image, results when predicting 36 time frames ahead.

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