A Data-Driven Architecture for Social Behavior in Creator Networks

Berkeley Andrus, Nancy Fulda
Computer Science Department
Brigham Young University
Provo, UT 84602 USA
berkeleyandrus@gmail.com, nfulda@cs.byu.edu

Abstract

Previous Computational Social Creativity work has improved the performance of automated creators using social mechanics inspired by human behavior. However, these simulations have often focused on generic or assumed human behaviors rather than on specific anthropoligical data. In this work we take a more focused approach by comparing simulated social behavior to observed behavior in large social networks of human creators. We analyze social patterns among human creators by defining metrics for social behavior within creative communities and collecting data for three online communities of creators: Scratch, FanFiction, and r/ArtCrit. We introduce the Architecture for Multi-Agent Creative Societies (AMACS), a modeling tool which controls the social activity of automated creators and can be adapted to any creative discipline. We demonstrate AMACS's ability to recreate a wide range of network-level social behaviors, including the behaviors observed in three human societies.

Introduction

Social interaction has long been understood to be an essential component of the creative process (Csikszentmihalyi 2014; Boden 1992; Glăveanu 2013; Jennings 2010). Social interactions help creators in many disciplines by facilitating encouragement, correction, inspiration, and mentorship. A creator's social circles provide opportunities to test out new ideas, collaborate, and hone skills. This is true in disciplines ranging from pottery to programming to dance.

Past research on the role of social interaction in the creative process has typically taken one of two approaches. The first approach has been to analyze social networks of creators directly and identify quantitative and qualitative trends relevant to specific facets of creativity (Sylvan 2007; Sylvan 2010; Xu and Bailey 2012; Crain and Bailey 2017; Marlow and Dabbish 2014; Campbell et al. 2016; Evans et al. 2017; Pace et al. 2013). The second approach has been to simulate networks of creators in fully automated social environments (Linkola and Hantula 2018; Hantula and Linkola 2018; Gómez de Silva Garza and Gero 2010; Greenfield and Machado 2009; Alnajjar and Hämäläinen 2018; Hämäläinen, Alnajjar, and others 2019). These simulations tend to focus on generic or assumed rules of human behavior rather than on quantitative data, and while they have the potential to inform our understanding of human creativity (Saunders and Bown 2015) they are often more concerned with improving the performance of simulated creators. Surprisingly, these approaches have rarely - if ever - been mixed. Researchers have attempted to *observe* or *simulate* the social behavior of creators, but not both.

In this work we combine these two approaches of measuring and simulating user behavior. To our knowledge it is the first attempt to quantitatively measure and then replicate the social behaviors of creators acting in a social network. This data-driven and focused approach allows for more meaningful analysis of simulated creators, making simulation a viable tool for understanding human creativity and potentially improving automated creative social systems.

We also introduce an Architecture for Multi-Agent Creative Societies (AMACS), a simulation architecture implemented in Python that controls the social activity of automated creators and can be adapted to any creative discipline. We make AMACS publicly available and hope it will act as a common test bed for future researchers experimenting with social mechanics for automated creative agents.

Related Work

Many researchers, both in the field of psychology and in artificial intelligence, have sought to define and understand the role of social interaction in creativity. For example, Csikszentmihalyi (2014) argued that creativity is only possible when a creator interacts with a domain of cultural knowledge and a field of peers, making creativity an inherently social process. Boden (1992) discussed creativity in terms of conceptual spaces, which she defined as being "familiar to (and valued by) a certain social group" rather than belonging solely to an individual. Jennings (2010) proposed using socialization as a tool for increasing the autonomy of simulated creators. Glăveanu's framework of creativity (2013) elevated the importance of socialization in creativity by including *audience* as a key member of the creative process.

Parallel to the effort to define the social aspects of creativity has been the effort to quantitatively observe them, specifically in online social environments. Sylvan (2007; 2010) used the term 'Online Community of Creators' (OCOCs) to describe social network sites where creators share and receive feedback on their work. She selected two OCOCs - The Village and Scratch - and attempted to track how ideas spread through these online communities by finding qualities correlated with influential individuals and artifacts. Xu and Bailey (2012) analyzed interactions between users in the online photography critique community PhotoSIG, focusing specifically on critique mechanisms. Crain and Bailey (2017) analyzed how users engage with criticism on three art critique subreddits, focusing on the quality of feedback and how it impacted a creator's willingness to iterate on published artifacts. Marlow and Dabbish (2014) investigated how users of Dribble gradually become more skilled at their craft. Campbell and associates (Campbell et al. 2016; Evans et al. 2017) also explored how OCOCs allow creators to improve, framing their findings with a model they call *distributed mentoring*. Pace et. al. (2013) mapped theories concerning more traditional (i.e. offline) creative communities to OCOCs while analyzing the role of leaders in the Etsy community.

There has also been much work done to simulate the social behavior of creators, a task which Saunders and Brown (2015) describe as 'Computational Social Creativity'. Hantula and Linkola (Linkola and Hantula 2018; Hantula and Linkola 2018) study *collaborator selection* in a simulated society of image-generating agents with various changing tastes. Gómez de Silva Garza and Gero (2010) introduce a network in which agents are engaged in either creating or evaluating simple visual designs. Greenfield and Machado (2009) use the same distinction between agents, calling their agents 'artists' and 'critics'. Critics in their system compare agent-generated artifacts to human-generated ones via representative vectors. Alnajjar and Hämäläinen (2018; 2019) use a social network which contains only a master and an apprentice. The master generates training data for the apprentice and curates a dataset of human-generated examples for the apprentice to learn from.

There are examples in which multiple simulated agents work together to generate a single artifact (Pérez y Pérez et al. 2010; Boyd, Hushlak, and Jacob 2004; Wright, Purver, and others 2020). Because these social networks are focused only on collaborating (rather than sharing and evaluating finished artifacts, forming relationships, etc.) they fall outside the scope of the creative societies we are interested in here.

To our knowledge, the present work is the first attempt to both observe and simulate the social interactions between creators, an important bridge between these previously disjointed approaches. It also introduces the first discipline-agnostic simulation tool for creative societies of which we are aware. Our hope is that this combined approach and the accompanying software package will add more meaning and focus to future approaches at social simulation.

Analyzing Creative Societies

The purpose of this work is to create a data-driven simulation of the social behaviors of creators. In order to validate that simulations are acting in a human-like manner, we need a framework for analyzing and describing both human and automated societies so that different societies can be meaningfully compared with one another.

To this end we introduce a quantitative analysis framework that consists of four metrics: Creator to Agent Ratio, Reciprocity, Clustering, and Attention Concentration (each defined below). These metrics were chosen because they each affect the experience of individual agents and can be calculated based on publicly available information as described below.

Creator to Agent Ratio (CAR) is the percentage of community members that create original artifacts (paintings, songs, programs, etc.) as opposed to only commenting on the artifacts of others. CAR is defined as $\frac{|C|}{|A|} \times 100$, where C is the set of all creators in the network and A is the set of all agents (both creators and non-creators) in the network.

A network's CAR is important in defining the relationship between creators and fans. A high CAR can make it difficult for creators to build audiences because the have more competition, while a low CAR might make it difficult for fans to find creators they like.

Reciprocity is the tendency for an agent to return the favor when another agent gives feedback on one of their artifacts. In an online setting, feedback can include comments, 'Likes', or any other publicly observable recognition of the artifact. We define reciprocity as $P(A \triangleright B \mid B \triangleright A) \times 100$, where A and B are distinct creators in the network and $X \triangleright Y$ denotes that an agent X has provided feedback for an artifact generated by agent Y at some point in the past.

Reciprocity describes one way in which network agents form relationships with one another. If agents are inclined to reciprocate positive attention or feedback, then it becomes easier for a relationship to form out of a single agent's desire for a connection. High reciprocity also means that a network rewards good behavior through reciprocation, which incentivizes agents to be generous with one another.

Clustering is the tendency for an agent to be friends with its own friends-of-friends. Highly clustered networks indicate the presence of cliques and sub-communities within the larger network. The definition of clustering depends on a definition of 'friendship', which takes different forms in different types of communities. For consistency, we notate that two distinct agents A and B are friends using $A \diamond B$ and say that $A \diamond B \iff (A \triangleright B) \cap (B \triangleright A)$. In other words, if two creators have commented on each others artifacts at least once each, we call them friends.

Given a definition of friendship, we define clustering as $P(B \diamond C \mid A \diamond B, A \diamond C) \times 100$ for any three distinct creators A, B, and C in the network. This is equivalent to the global clustering coefficient for graphs if we consider each agent as a node and each friendship as an undirected edge.

A network's clustering rate can serve as an indicator for how opinions and ideas spread through a population of agents (Malik and Mucha 2013; Centola 2010; Jackson 2019). Tight clusters can cause agents to become more similar to their direct contacts, but they can also insulate agents and slow the spread of globally popular beliefs (Granovetter 1973).

Attention Concentration measures how popular the most popular artifacts in the network are, where popularity is defined as the volume of comments received. We measure attention concentration using the Gini coefficient (Gini 1912), a metric commonly used to describe the wealth in-

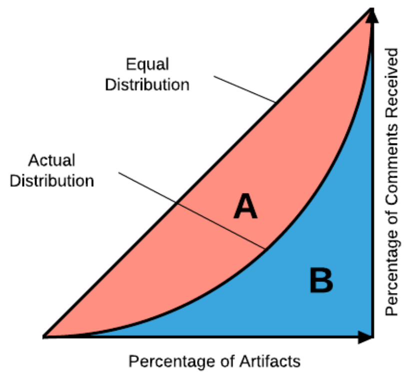

Figure 1: Visualization of the Gini Coefficient, used to measure the concentration of attention within a network of creators. The curved line shows the percentage of all comments received by the corresponding percentage of artifacts, which are sorted by ascending popularity. The diagonal line shows a hypothetical society where all artifacts receive an equal number of comments. The Gini Coefficient is the area of A divided by the sum of the areas of A and B.

equality of a population. We refer to (Dorfman 1979) for a mathematical definition, but a basic explanation is provided in Figure 1. The Gini Coefficient can be understood as a real number in the range [0, 1] where 0 indicates that all artifacts receive an equal amount of feedback and 1 indicates that all feedback is directed at a single artifact.

Attention concentration can be a significant pain point for human creators, especially in online environments. Xu and Bailey (2012) found that over 80% of artifacts on a photography sharing community received fewer comments than average users considered useful, while other artifacts received many comments. If most attention is being directed at a small handful of popular artifacts, it can be difficult for new creators to feel engaged with the network.

Data Collection

In order to understand the social behavior of human communities, we apply this analysis framework to several communities of creators. Our purpose is to collect quantitative data that can then be used to validate simulations of social behavior. In this work we focus on online communities of creators that are large, include mechanisms for artistic critique in the form of comments, and permit legal scraping of user and artifact data. After considering nearly a dozen communities, we select three that best fit the above criteria: Scratch, FanFiction, and the r/ArtCrit community on Reddit. These communities are oriented towards programming projects, creative writing, and visual artwork respectively.

To collect data for Scratch, we use a Selenium-based web scraper to collect several thousand of the most recent artifacts published in the 'Music' category of coding projects. For each recent project we then find the user who created that project and collect data on each project published by that user. For each project we collect the project ID and the list of all users who have commented on that project. We collect a total of 91,506 projects and 82,952 comments posted by 39,631 users.

Table 1: Observed behavior in three online communities of creators using four network-level metrics.

Community	CAR	Reciprocity	Clustering	AC
Scratch	17.1	1.2	6.3	0.901
FanFiction	23.2	11.0	15.6	0.762
r/ArtCrit	59.6	0.5	1.0	0.489

Following (Milli and Bamman 2016), we scrape FanFiction data using Python-generated HTTP requests and parse responses with the BeautifulSoup library. We select 32 of the most popular book 'canons' (the original works that FanFiction stories are based on) and scrape all stories and comments related to those canons, excluding anonymous comments. We collect 189,076 stories and 7,789,744 comments posted by 387,253 users.

We access r/ArtCrit data using Cornell University's ConvoKit toolkit (Chang et al. 2020). The dataset includes 14,201 posts and 33,451 comments made by 11,992 users. We filter out posts or comments made by users who have since deleted their accounts (as these are effectively anonymous), comments that are responses to other comments rather than to posts, and comments made by the same user as the post being commented on.

Anonymized copies of the collected data are available upon request. In accordance with the privacy policies of Scratch and FanFiction, this anonymized data will include only the metadata necessary to calculate the four metrics described above, not user data or content of the posted artifacts or comments themselves. All scraping that we performed was in accordance with the respective site policies.

Human Analysis Results

The results of applying our framework to these three communities are found in Table 1. We note that there is a wide variance in the behavior of these three communities. For example, r/ArtCrit's CAR is more than double the other two communities' and FanFiction has a much higher Reciprocity and Clustering rate than the other two. Further analysis of these results are provided in (Andrus 2021), but for our purposes here we are primarily interested in recreating these quantitative behaviors in a simulated environment.

AMACS: the Architecture for Multi-Agent Creative Societies

Having observed several human creative societies, we are now prepared to simulate them. To this end we introduce AMACS: the Architecture for Multi-Agent Creative Societies. AMACS is a flexible, task-agnostic architecture implemented in Python that defines how automated agents generate and evaluate creative artifacts. It also defines how agents form relationships with and are influenced by one another. Any designer who desires to use AMACS to simulate the behavior of agents in a given creative discipline need only implement functions for evaluating and generating artifacts within that discipline; AMACS handles the rest, including content discovery, social mechanics, and the changing aesthetic tastes of agents. We hope that it will serve as a test bed and reference point for future researchers who wish to perform experiments in a common setting. The full AMACS implementation and three example instantiations are provided online at `https://github.com/bandrus5/amacs`.

AMACS Methodology

An AMACS network, similar to previous simulated creative societies (Hantula and Linkola 2018; Linkola and Hantula 2018; Gómez de Silva Garza and Gero 2010; Greenfield and Machado 2009), is composed of a pool of agents capable of generating and evaluating creative artifacts. Agent aesthetic tastes change over time as agents interact with and are influenced by one another. Unlike previous works, an AMACS network can be implemented for any creative task (e.g. writing poetry, designing furniture, or composing music), and it includes hyperparameters that can be tuned to elicit specific human-like behaviors.

Following Hantula and Linkola (Hantula and Linkola 2018), each agent in an AMACS network has individual aesthetic tastes represented by numeric scores. In Hantula and Linkola's simulations, which use image generation as the creative task, each agent's tastes are represented by a single number that corresponds to their preferred value along some evaluative spectrum such as Symmetry, Contrast, etc. We expand this evaluative paradigm with a multidimensional "artifact space". Unlike in Hantula and Linkola's simulations, the AMACS artifact space can have as many dimensions as needed, and all agents share the same artifact space. We consider the artifact space to be an application of Boden's *conceptual space* (Boden 1992), albeit a relatively simple one.

Each dimension of the artifact space corresponds to some evaluative function. The nature of these evaluation functions will depend on the creative task of the network. For example, in a music-generation AMACS network, dimensions of the artifact space might correspond to tempo, key, and sentiment. Dimensions can represent binary distinctions (e.g. whether or not a poem conforms to a 5-7-5 syllabic pattern) or real value measurements (e.g. the type-token ratio of a short story). They can even be unbounded (e.g. the length of a song), though in many cases there will be an inherent lower and upper limit (e.g. the percentage of image pixels that are blue cannot fall outside the range [0, 100]).

Points within the artifact space can be used to describe both artifacts and agent preferences. Each artifact is assigned a score vector S which situates that artifact within the artifact space. We represent an agent's preferences with a taste vector T and a taste weight vector W. T describes which point within the space the agent considers to be 'perfect', and W allows the agent to scale the artifact space and choose which dimensions it cares most about. S, T, and W each have the same dimensionality as the artifact space.

Some dimensions of the artifact space may have a "correct" answer, meaning that all agents share the same taste values in those dimensions. This allows an AMACS designer to enforce artistic constraints, such as that all poems must rhyme or that all songs must be in a major key. In the other dimensions agents are free to set their own tastes, giving them creative freedom to choose, for example, the key a song is written in or the dominant color used in a painting. The fact that agents are fixed in some dimensions and not in others allows for a shared understanding of which artifacts are valid but individual understanding of which artifacts are good. This is partially inspired by Wiggins's (2006) rule sets $\mathscr{R}$ and $\mathscr{T}$ for constraining and traversing a conceptual space respectively. In AMACS, agents and artifacts are constrained in membership dimensions (analogous to Wiggins's $\mathscr{R}$) and are free to traverse attribute dimensions (analogous to Wiggins's $\mathscr{T}$). Future work may attempt to simulate more transformative creativity by allowing agents to ignore membership dimensions of the artifact space under specific conditions or invent new attribute dimensions and add them to the global artifact space. This latter approach was described but not implemented by Ventura (2019).

On each network time step, each existing agent has an opportunity to generate a new artifact, analogous to a human creator sharing a new piece of artwork with their social network. The decision of whether to produce an artifact is based on whether the agent produced anything on the previous time step and the average value of W, which along with scaling the artifact space is used to model the agent's confidence in its own tastes.

Once all agents have had an opportunity to generate artifacts, each agent evaluates a small number of artifacts from the current or past time steps. Each agent is given a list of recommended artifacts, and the agent randomly samples from the recommendations based on its own criteria. It then evaluates each chosen artifact a using the following value definition:

$$value(a) = -\sum_{i=1}^{n} |\boldsymbol{S}_i - \boldsymbol{T}_i| * \boldsymbol{W}_i \quad (1)$$

where n is the number of dimensions in the artifact space and S is the vector representing a's location in the artifact space. This is equivalent to the negative weighted Manhattan distance between T and S.

The agent can then choose whether to leave publicly observable feedback for the artifact, which can take several different forms. The simplest form of feedback, which we use in our experiments, is a binary feedback system analogous to the 'Like' button found on many online platforms for creators. If an agent's evaluation of an artifact falls above some threshold, the agent gives the artifact a 'Like' and the evaluation is classified as favorable. A more ambitious feedback system could include agents leaving some sort of comment on the artifact with details about what they liked or didn't like. Alternatively, an agent could provide feedback on an artifact by editing it to something the evaluating agent likes better and sharing the 'enhanced' version of the artifact with the original creator. We leave these more complex mechanisms to future work.

The final process on each time step is for agents to adapt based on what they've experienced on the current time step. First, agents change their taste weights to reflect their changing confidence. Taste weights go up if agents received positive feedback from their peers and/or they evaluated artifacts that they liked. Otherwise taste weights go down. Next, agents have a small probability of changing their tastes. The higher their taste weights, the lower probability their tastes will change. If an agent chooses to change its tastes, it typically moves towards its most recently evaluated artifacts, although in some cases it will move away. Finally, agents choose whether or not they will generate an artifact on the next time step. All changes to tastes and taste weights happen independently in each dimension of the artifact space.

In our experiments we initialize each AMACS network with a pool of 42 agents with random tastes and taste weights. We run the network for 30 time steps, adding 4 new agents to the network on each time step to simulate the community growing over time. There are many other population mechanics that could be explored in future work depending on the specific human behavior being simulated.

We increase AMACS's flexibility by defining 11 hyperparameters that affect agent behavior, specifically in how they select new artifacts to interact with. Each hyperparameter loosely corresponds to design decision that community administrators control, which makes them useful for tuning AMACS networks to resemble specific communities. They are:

- **Agent Taste** controls how personalized the recommendations made to AMACS agents are. This is analogous to the level of customization on websites used by human creators to find new content.
- **Creator Familiarity** controls how much an AMACS agent prefers to review artifacts created by other agents is has interacted with in the past, regardless of whether those interactions were positive or negative. **Creator Favorability** is similar, but it includes only positive interactions.
- **Mutual Contact** controls an agent's preference to review artifacts created by other agents who share a mutual contact. **Mutual Friend** is similar, but it includes only contacts where most interactions have been positive.
- **New Artifact** controls the extent to which AMACS promotes artifacts generated on the most recent time steps.
- **Popular Artifact** controls whether AMACS promotes artifacts based on their number of positive reviews.
- **New Creator** controls the extent to which AMACS promotes artifacts generated by agents who have not generated many artifacts in the past.
- **Popular Creator** controls the extent to which AMACS promotes artifacts generated by agents who have generated other popular artifacts.
- **Gratitude** controls an agent A's willingness to view artifacts generated by agent B because B has done the same for A in the past. Note that this is highly related with the concept of Reciprocity introduced in the previous section, but in AMACS Gratitude only becomes Reciprocity when the reciprocated reviews end up being positive.
- **Recommender Ranking** controls an agent's willingness to evaluate the first artifacts that are recommended to them as opposed to considering many options.

We experiment with the effects of each of these hyperparameters and show how they can induce specific behaviors later in the paper.

AMACS Instantiations

In order to demonstrate the diversity of tasks to which AMACS can be applied we present three instantiations, each focused on a different creative discipline. Creating a new AMACS instantiation is as simple as implementing the agents' generation process and defining an artifact space by writing evaluation functions. The examples provided here are relatively simple, allowing us to focus on the social mechanics of AMACS rather than the generation and evaluation details which will vary from application to application. AMACS is equally capable of modeling interactions between creative agents with more sophisticated processes than those described here.

We provide only brief descriptions of the creative tasks and the evaluation functions used in each instantiation. Further details on how agents generate and evaluate artifacts can be found in the AMACS code repository.

AMACS for Image Generation In this AMACS instantiation agents generate 16x16 grayscale images. All agents try to generate images that are symmetrical and that have a small cross pattern in any of the four corners. We note that these constraints are arbitrary and were chosen only to demonstrate the idea of a universal aesthetic standard amongst agents. There are two dimensions along which agents can choose their tastes: the overall brightness of the image and the average contrast between columns in the image. Generation is accomplished using a genetic algorithm.

AMACS for Title Generation In this AMACS instantiation agents generate plausible titles for academic papers. "Plausibility" was measured using two methods: a neural network trained on 46,198 examples, and hand-coded rules designed to detect failure modes of the neural network. Agents chose their own tastes along three dimensions, each measuring the degree to which artifacts belong in one of three subclasses: Computer Science papers, Medicine papers, and Humanities papers. Each dimension is measured with an LSTM trained to detect whether a title belongs to the corresponding subclass. We train the LSTMs separately (though on overlapping data) so that a single title could theoretically score high on all three classifiers, although it is easier to earn a high score on just one. See Elgammal et. al. (2017) for a demonstration of why subclass membership is a powerful consideration for creative agents. Title generation is accomplished using a genetic algorithm.

AMACS for Policy Generation Agents in this AMACS instantiation create policy look-up tables for a robot control problem inspired by (Mitchell 2009, p. 130–142). In

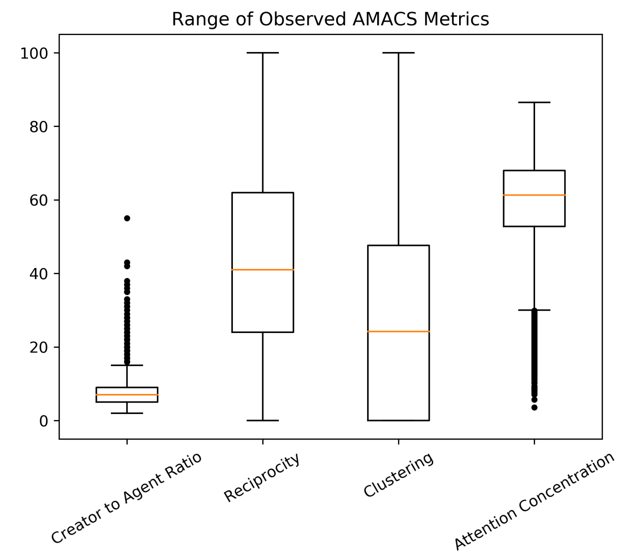

Figure 2: Full range of behavior observed in AMACS using all three instantiations and both SPM and TPM. AMACS demonstrates considerable flexibility in Reciprocity, Clustering, and Attention Concentration. It has limited flexibility in the Creator to Agent Ratio metric.

our version of this problem, a simulated robot lives in a 4 x 4 grid with blue and red trash scattered throughout. The AMACS agents compose instructions for the robot on how to navigate through the world and collect trash. All agents want to help the robot avoid running into walls, and each agent gets to choose the percentage of red and blue trash the robot collects. Agents generate policies using a genetic algorithm. We also implemented a Monte Carlo Tree Search approach for policy generation, but found that it was slower and caused agents to be less satisfied with their own artifacts.

Demonstrating the Flexibility and Applicability of AMACS

Given the human social behavior data and the simulated networks described earlier, we are ready to quantitatively validate that AMACS is capable of exhibiting human-like social behavior. Specifically, in this section we will demonstrate that by manipulating AMACS hyperparameters we can induce a wide range of behaviors, including the behaviors observed in human communities. Our purpose is not to demonstrate that AMACS always acts the same way as human or responds to stimuli in the same way as humans; rather, we seek to show that AMACS has enough flexibility that it can be coaxed into demonstrating the same network-level behavior as specific human social networks.

Experiment Setup

We discover the range of possible AMACS behavior with two sets of experiments in which we manipulate the 11 hyperarameters described in the previous section. In the first set of experiments, we change one hyperparameter's value at a time while keeping all other hyperparameter values fixed, which we refer to as Single Parameter Modulation (SPM). In the second set of experiments we introduce more noise by randomly and independently modulating the values of all 11 hyperparameters simultaneously, which we refer to as Total Parameter Modulation (TPM).

To perform SPM, we define a set of hyperparameter values $V = \{$-20, -10, -1.0, -0.5, 0.0, 0.5, 1.5, 2.0, 10, 20, 30, 40$\}$. The purpose in selecting these specific values is to measure what happens when we go far below, slightly below, slightly above, and far above a default value of 1.0. We refer to the set of all hyperparameters as P. For each hyperparameter $p \in P$ and each hyperparameter value $v \in V$, we produce a combination c of network inputs where p is set to v and all other hyperparameters are set to 1.0. For each generated combination c, we run all 3 AMACS instantiations 4 times, after which we record the four resultant network-level metrics. In total this requires 1,584 network runs.

To perform TPM, we split V into two subsets, $V_S = \{$-1.0, 0.5, 0.0, 0.5, 1.0, 1.5, 2.0$\}$ and $V_L = \{$-20, -10, 0, 10, 20, 30, 40$\}$, where S and L stand for "small" and "large" and refer to the magnitudes of the included values. For each subset, we generate 700 random combinations of hyperparameter values in which each value is used 100 times for each hyperparameter. The purpose of splitting V into two subsets for TPM is to avoid situations in which large value changes in one hyperparameter drown out small value changes in other hyperparameters, i.e. we first modulate all hyperparameters on a small scale and then again on a large scale. We run each combination of hyperparameters for 30 generations each on all 3 AMACS instantiations. In total this involves 4,200 network runs.

Between SPM and TPM we perform a total of 5,784 network runs. Collectively these give us a broad understanding of the types of behavior AMACS is capable of modelling.

Simulation Results

Figure 2 shows the full range of metric values observed in all AMACS runs. We can see that AMACS is remarkably flexible with respect to observed Reciprocity and Clustering values; AMACS has produced the full range of possible values, and the spread is wide enough that no possible value can be classified as an outlier. AMACS also exhibits a fairly wide Attention Concentration spread, with values ranging from 3.6 to 86.5 including outliers. AMACS appears to be the least flexible in its Creator to Agent Ratio (CAR). The vast majority of AMACS runs had CARs less than 20, and even the highest magnitude outlier is only 55.5. This is lower than the r/ArtCrit CAR, meaning that some human behavior is outside the range of what AMACS can produce, at least with the instantiations and hyperparameters tested here. Future efforts to model a wider spread of CAR behaviors may consider changing the rules for how agents choose whether to be creators.

In order to validate AMACS's relevance as a tool for modelling human behavior, we compare AMACS runs to the human communities analyzed (Scratch, FanFiction, and r/ArtCrit). For each community we find the AMACS run which was the most similar to human behavior in each indi-

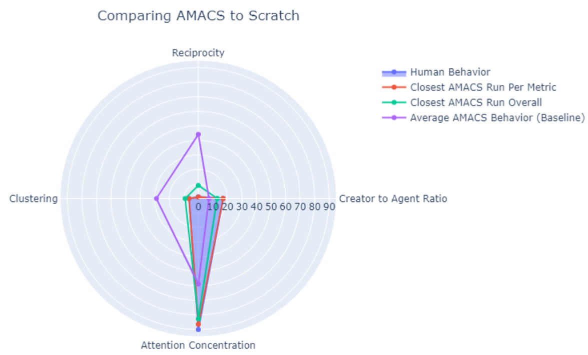

Figure 3: Comparison of AMACS behavior to the Scratch community. The blue shaded area represents human behavior. The red and green lines show the AMACS runs most similar to the human community in each individual metric and over all four metrics, respectively. The purple line shows average AMACS behavior and is included for reference.

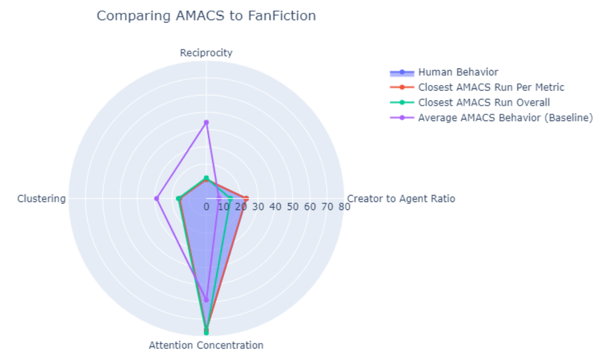

Figure 4: Comparison of AMACS behavior to the FanFiction community. The blue shaded area represents human behavior. The red and green lines show the AMACS runs most similar to the human community in each individual metric and over all four metrics, respectively. The purple line shows average AMACS behavior and is included for reference.

vidual metric and which was the most similar over all four metrics (measured with Euclidean distance). These results are visualized in Figures 3-5. We see that AMACS does fairly well at replicating the behavior of the Scratch and FanFiction communities, including nearly matching Scratch's remarkably high Attention Concentration. It is less successful at replicating r/ArtCrit's behavior, particularly in the CAR metric which, as noted earlier, is where AMACS is currently the least adaptable. AMACS is largely able to replicate the behavior of these three communities, indicating that it will likely be successful at modelling many other human creator networks.

Implications for Human Creators

The described parameter modulation experiments demonstrate the range of possible AMACS behaviors, but they also enable us to analyze the quantitative relationships between each hyperparameter and each network-level metric. Understanding these relationships is helpful for future AMACS designers hoping to induce specific behaviors from automated agents. This information can also help administrators of human creative communities to maximize the experiences of their members, provided that AMACS trends hold for human communities as well. Trends found in AMACS are not guaranteed to exist in human communities, but they indicate possibilities that may warrant further investigation.

To analyze the effects of each hyperparameter, we find the Pearson correlation between each hyperparameter and each network-level metric over all 5,784 network runs described above. Results are shown in Figure 6.

The strongest correlation observed is between the Popular Artifact hyperparameter (AMACS's tendency to promote popular content) and Attention Concentration. This is unsurprising, as recommending popular artifacts creates a positive feedback loop that keeps a few artifacts at the center of attention. This relationship matches the recommendation in (Xu and Bailey 2012) that administrators of online communities of creators can spread attention by increasing the personalization of user's 'Browse' or 'Explore' pages, as opposed to only recommending globally popular artifacts. New Artifact (AMACS's tendency to promote new content) shows a strong negative correlation with Attention Concentration, indicating another possible way that online platforms could spread attention when increased personalization is not possible.

The strongest indicator of a network's Reciprocity is the Gratitude hyperparameter (which represents how willing an agent is to review a peer's work because that peer has given positive reviews in the past). If administrators of online platforms want to increase the reciprocity of their communities, they might consider adding features that encourage gratitude, such as notifying users of generous actions and encouraging them to return the favor. For example, when a Reddit user receives a new follower, they receive a notification saying "[USERNAME] just followed you. Go check them out to learn more about them." This type of call to action encourages gratitude and, by extension, reciprocity.

For Clustering, the strongest indicator is the Mutual Contact hyperparameter (which controls an agent's desire to view artifacts created by agents with whom they share a mutual contact). There are two ways an administrator of an online social platform might use this information to increase Clustering. The first is by explicitly calling out the existence of mutual contacts in the site's UI. Facebook does this by listing the number of mutual friends user's have with each other, encouraging users with many mutual friends to connect. The second, more subtle approach is to use mutual contacts in determining which artifacts to recommend to a user on their "Browse" or "Explore" pages, which many social media sites already do.

Perhaps the most surprising strong correlation is between

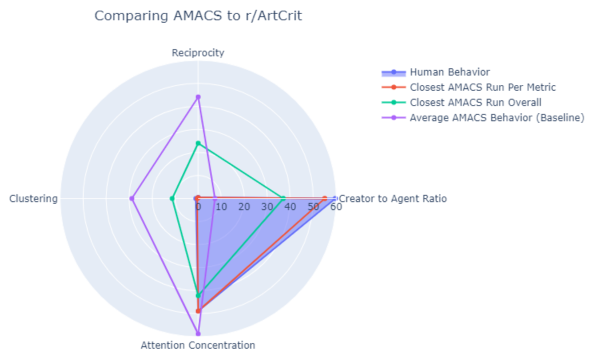

Figure 5: Comparison of AMACS behavior to the r/ArtCrit community. The blue shaded area represents human behavior. The red and green lines show the AMACS runs most similar to the human community in each individual metric and over all four metrics, respectively. The purple line shows average AMACS behavior and is included for reference.

Agent Taste (the personalization of AMACS's artifact recommendations) and Creator to Agent Ratio. AMACS agents become creators when they are confident in their own tastes, so the most likely reason for this correlation is that increased personalization leads to increased confidence, as agents consistently find artifacts that reinforce their current tastes.

Out of the eleven hyperparameters tested, ten showed statistically significant correlations with at least one metric, and 8 showed significant correlations with more than one metric.

We look forward to future work that may validate the degree to which these trends hold for human societies and discover other ways in which modelling tools can help inform our understanding of human behavior.

Ethical Considerations

One might reasonably ask if it is wise to study the ways in which community administrators can induce desired behaviors in their communities, as this might be interpreted as manipulation. The authors of this paper believe that studying the power of platform administrators in a public and academic setting adds transparency and accountability to the larger discussion of ethical platform administration. Design decisions affect users whether we understand their effects or not; this line of research empowers administrators to be more deliberate and thoughtful with the influence they already have. It is our hope that educating both users and administrators will help both parties make decisions that are beneficial to everybody.

Conclusion

In this work we have introduced a data-driven and task-agnostic architecture for modelling the social behavior of creative agents. We have studied real-world communities of creators and replicated many of their behaviors in an automated setting using AMACS: the Architecture for Multi-Agent Creative Societies. AMACS is designed to be flexible and user-friendly, and we hope it will provide a useful test bed and common setting for future experiments. Future areas of improvement could include defining more robust and descriptive metrics for understanding network-level social behavior, collecting data on more human creator communities, and investigating the experience of individual network participants rather than analyzing aggregated data.

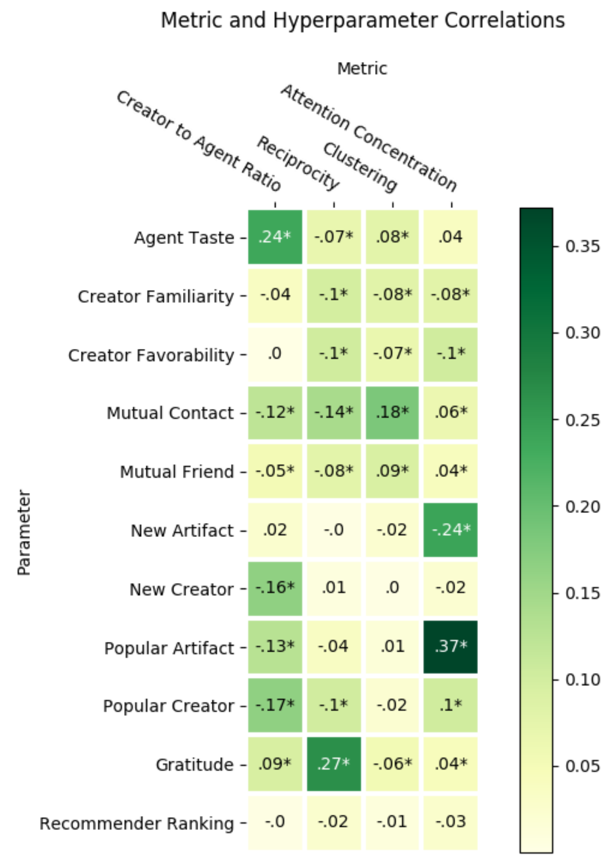

Figure 6: Pearson correlation between each hyperparameter and metric in AMACS. Darker colors indicate larger magnitudes, and $*$ indicates significant relationships ($\alpha = 0.01$).

We look forward to future work that will use socialization both to improve the efficacy of artificial creative agents and also "to contribute to the understanding of human creativity" (Saunders and Bown 2015). Learning from from human behavior, as we have done here, has the potential to improve our models and the performance of computational creativity systems. Using real-world data to validate automated systems also allows information to flow the other way; phenomena that emerge in our simulations give us clues about how human creativity may work. We hope that this and future work continues to improve the experience of human creators and the performance of automated ones.

Author Contributions

Berkeley Andrus wrote the paper and designed and conducted the experiments described, with Nancy Fulda advising and editing.

Acknowledgements

We would like to thank Dan Ventura for his advice and feedback that contributed to the design of AMACS. We would also like to thank Jacob Crandall for his advice throughout the project and for inspiring the four metrics used in our analysis.

References

[Alnajjar and Hämäläinen 2018] Alnajjar, K., and Hämäläinen, M. 2018. A master-apprentice approach to automatic creation of culturally satirical movie titles. In *Proceedings of the 11th International Conference on Natural Language Generation*, 274–283.

[Andrus 2021] Andrus, B. 2021. Modeling user relationships in online communities of creators. Master's thesis, Brigham Young University.

[Boden 1992] Boden, M. 1992. *The Creative Mind*. London: Abacus.

[Boyd, Hushlak, and Jacob 2004] Boyd, J. E.; Hushlak, G.; and Jacob, C. J. 2004. Swarmart: Interactive art from swarm intelligence. In *Proceedings of the 12th Annual ACM International Conference on Multimedia*, 628–635.

[Campbell et al. 2016] Campbell, J.; Aragon, C.; Davis, K.; Evans, S.; Evans, A.; and Randall, D. 2016. Thousands of positive reviews: Distributed mentoring in online fan communities. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, 691–704.

[Centola 2010] Centola, D. 2010. The spread of behavior in an online social network experiment. *science* 329(5996):1194–1197.

[Chang et al. 2020] Chang, J. P.; Chiam, C.; Fu, L.; Wang, A.; Zhang, J.; and Danescu-Niculescu-Mizil, C. 2020. Convokit: A toolkit for the analysis of conversations. In *Proceedings of the 21th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, 57–60.

[Crain and Bailey 2017] Crain, P. A., and Bailey, B. P. 2017. Share once or share often? exploring how designers approach iteration in a large online community. In *Proceedings of the 2017 ACM SIGCHI Conference on Creativity and Cognition*, 80–92.

[Csikszentmihalyi 2014] Csikszentmihalyi, M. 2014. Society, culture, and person: A systems view of creativity. In *The Systems Model of Creativity*. Springer. 47–61.

[Dorfman 1979] Dorfman, R. 1979. A formula for the gini coefficient. *The review of economics and statistics* 146–149.

[Elgammal et al. 2017] Elgammal, A.; Liu, B.; Elhoseiny, M.; and Mazzone, M. 2017. Can: Creative adversarial networks generating "art" by learning about styles and deviating from style norms. In *8th International Conference on Computational Creativity, ICCC 2017*. Georgia Institute of Technology.

[Evans et al. 2017] Evans, S.; Davis, K.; Evans, A.; Campbell, J. A.; Randall, D. P.; Yin, K.; and Aragon, C. 2017. More than peer production: Fanfiction communities as sites of distributed mentoring. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 259–272.

[Gini 1912] Gini, C. 1912. Variabilità e mutabilità. *Reprinted in Memorie di Metodologica Statistica (Ed. Pizetti E.*

[Glăveanu 2013] Glăveanu, V. P. 2013. Rewriting the language of creativity: The five a's framework. *Review of General Psychology* 17(1):69–81.

[Gómez de Silva Garza and Gero 2010] Gómez de Silva Garza, A., and Gero, J. S. 2010. Elementary social interactions and their effects on creativity: A computational simulation. In *ICCC*, 110–119. Citeseer.

[Granovetter 1973] Granovetter, M. S. 1973. The strength of weak ties. *American journal of sociology* 78(6):1360–1380.

[Greenfield and Machado 2009] Greenfield, G., and Machado, P. 2009. Simulating artist and critic dynamics. In *Proceedings of the International Joint Conference on Computational Intelligence, Funchal, Madeira, Portugal, October*, 5–7.

[Hämäläinen, Alnajjar, and others 2019] Hämäläinen, M.; Alnajjar, K.; et al. 2019. Modelling the socialization of creative agents in a master-apprentice setting: The case of movie title puns. In *Proceedings of the 10th International Conference on Computational Creativity*. Association for Computational Creativity.

[Hantula and Linkola 2018] Hantula, O., and Linkola, S. 2018. Towards goal-aware collaboration in artistic agent societies. In *Proceedings of the Ninth International Conference on Computational Creativity ICCC 2018, Salamanca, 25-29 June*. Association for Computational Creativity (ACC).

[Jackson 2019] Jackson, M. O. 2019. *The Human Network: How Your Social Position Determines Your Power, Beliefs, and Behaviors*. Vintage.

[Jennings 2010] Jennings, K. E. 2010. Developing creativity: Artificial barriers in artificial intelligence. *Minds and Machines* 20(4):489–501.

[Linkola and Hantula 2018] Linkola, S., and Hantula, O. 2018. On collaborator selection in creative agent societies: An evolutionary art case study. In *International Conference on Computational Intelligence in Music, Sound, Art and Design*, 206–222. Springer.

[Malik and Mucha 2013] Malik, N., and Mucha, P. J. 2013. Role of social environment and social clustering in spread of opinions in coevolving networks. *Chaos: An Interdisciplinary Journal of Nonlinear Science* 23(4):043123.

[Marlow and Dabbish 2014] Marlow, J., and Dabbish, L. 2014. From rookie to all-star: Professional development in a graphic design social networking site. In *Proceedings of the*

17th ACM Conference on Computer Supported Cooperative Work & Social Computing, 922–933.

[Milli and Bamman 2016] Milli, S., and Bamman, D. 2016. Beyond canonical texts: A computational analysis of fanfiction. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, 2048–2053.

[Mitchell 2009] Mitchell, M. 2009. *Complexity: A Guided Tour*. Oxford University Press.

[Pace et al. 2013] Pace, T.; O'Donnell, K.; DeWitt, N.; Bardzell, S.; and Bardzell, J. 2013. From organizational to community creativity: Paragon leadership & creativity stories at etsy. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work*, 1023–1034.

[Pérez y Pérez et al. 2010] Pérez y Pérez, R.; Negrete, S.; Peñalosa, E.; Ávila, R.; Castellanos-Cerda, V.; and Lemaitre, C. 2010. Mexica-impro: A computational model for narrative improvisation. In *ICCC 2010*, 90–99.

[Saunders and Bown 2015] Saunders, R., and Bown, O. 2015. Computational social creativity. *Artificial life* 21(3):366–378.

[Sylvan 2007] Sylvan, E. 2007. *The Sharing of Wonderful Ideas: Influence and Interaction in Online Communities of Creators*. Ph.D. Dissertation, Massachusetts Institute of Technology.

[Sylvan 2010] Sylvan, E. 2010. Predicting influence in an online community of creators. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1913–1916.

[Ventura 2019] Ventura, D. 2019. Autonomous intentionality in computationally creative systems. In *Computational Creativity*. Springer. 49–69.

[Wiggins 2006] Wiggins, G. A. 2006. A preliminary framework for description, analysis and comparison of creative systems. *Knowledge-Based Systems* 19(7):449–458. Creative Systems.

[Wright, Purver, and others 2020] Wright, G.; Purver, M.; et al. 2020. Creative language generation in a society of engagement and reflection. In *Proceedings of the Eleventh International Conference on Computational Creativity*. Association for Computational Creativity (ACC).

[Xu and Bailey 2012] Xu, A., and Bailey, B. 2012. What do you think? a case study of benefit, expectation, and interaction in a large online critique community. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, 295–304.