Predicting A Creator's Preferences In, and From, Interactive Generative Art

Devi Parikh
Georgia Tech & Facebook AI Research
parikh@gatech.edu

Abstract

As a lay user creates an art piece using an interactive generative art tool, what, if anything, do the choices they make tell us about them and their preferences? Both within the generative art form, and otherwise? As a preliminary study, we collect preferences from 311 subjects, in a specific generative art form and in other walks of life. We train machine learning models to predict a subset of preferences from the rest. We find that preferences in the generative art form cannot predict preferences in other walks of life better than chance (and vice versa). However, preferences within the generative art form are reliably predictive of each other.

Introduction

Generative art is art that has at least some of its features determined by a non-human autonomous system. The autonomous system is typically a computer, and it frequently relies on randomization to determine the art features. In the example in Figure 1 for instance, the start and end points of each curve are selected randomly. Among the human-defined features, some might be fixed by a generative artist (e.g., the fact that the piece is formed by a sequence of random points connected via Bezier curves), and other parameters might be open to manipulation (e.g., thickness of the strokes, color palette). Different settings of these open parameters, combined with the machine-defined features, leads to different instances of the generative art form. Generative artists often make interactive tools available so a lay person can set values of these open parameters and create their own generative art piece. We refer to these tools as interactive generative art tools, and they are the subject of this study.

We ask the question: what does the choices a lay person makes while creating art using an interactive generative art tool tell us about them – about their personality or preferences in food, fashion, interior design, etc., as well as about their preferences in the specific generative art form?

Effectively predicting their preferences in the specific generative art form can lead to a smarter interactive generative art tool. It can help the user create an art piece they like faster by encouraging them to explore a certain part of the parameter space. It can prevent the user from losing interest by discouraging them to explore a different part of the parameter space. Predicting their preferences in other aspects of life can position interactive art generation as a generic personality assessment tool for products and experiences recommendations. Finally, predicting their preferences in generative art from other other known preferences in life can lead to improved art recommendation.

Figure 1: Interactive generative art tool for creating Strokes. Video: `https://youtu.be/YzfzjK8NNMg`.

As a preliminary study, we conducted a survey where 311 subjects consented to participate and self-reported their preferences along various parameters in a generative art form (Strokes, Figure 1), as well as in various walks of life such as food, chocolate, alcoholic beverages, music, interior design, fashion, paintings and their other traits such as gender, personality type, exposure to design principles, artistic inclination, and introspectiveness. We train machine learning models to predict subsets of these preferences from other preferences. We find that user's preferences in other aspects of life cannot be reliably predicted from their preferences in the generative art form (and vice versa). However, their preferences in the generative art form can be predicted with statistical significance from other preferences in the generative art form. This is a promising result towards demonstrating the feasibility of smarter interactive generative art tools which guide a user through parts of the design space more likely to lead to an outcome they like.

Related Work

Preferences in art and personality. (Öz, Ozpolat, and Taşkesen 2015) study the correlations between five personality traits and art preferences among 24 visuals from Renaissance, Cubism, Abstract Art, Traditional Art, Impressionism and Surrealism. (Chamorro-Premuzic et al. 2008)

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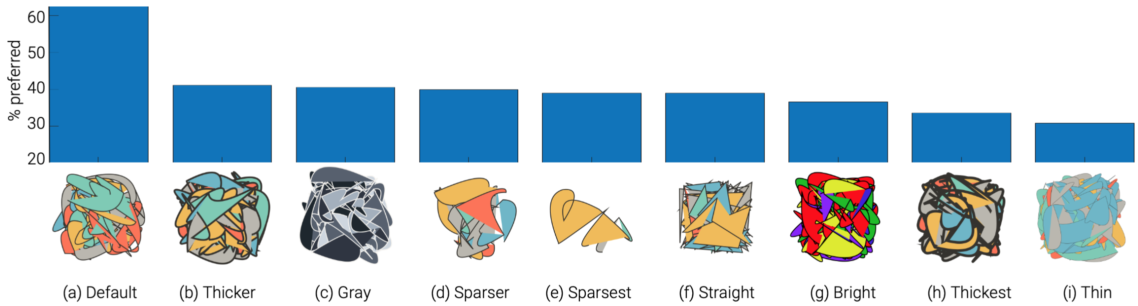

Figure 2: Configurations of Strokes we studied and % times each alternative (b-i) was preferred by subjects over the default (a).

performed a similar study across over 90,000 individuals in the UK. (Chamorro-Premuzic et al. 2010) find that personality traits correlate better with art categories when these categories are defined based on emotional valence and complexity as assessed by a collection of observers, than categories defined by researchers or historical art taxonomies. (Ercegovac, Dobrota, and Kuščević 2015) also study the relationship between personality traits and art preferences, but for both visual art and music. They also investigate correlations between music and visual art preferences. (Gridley 2013) study correlations of visual art preferences with personality traits as well as styles of thinking. They also find evidence for cross-modal relations in aesthetic preferences across food, music, and visual stimuli. (Lyssenko, Redies, and Hayn-Leichsenring 2016) study how participants describe abstract artwork and the relationship of these descriptions to various image properties. They also investigate the correlation between personality traits and preferences. To the best of our knowledge, connections between art perception and preferences has not been studied in the context of generative art (the focus of this work) or even digital art in general. As the landscape of art changes with the incorporation of digital tools and more recently AI, it is valuable to consider how these tools can be made smarter to better assist a human in their creative process. The ability to predict a user's preferences is central to such smart tools.

(Bhattacharjya 2016) discusses models of preferences in the context of computational creativity to embrace the subjective nature of evaluating creative value. (Cook and Colton 2015) design a software system capable of having preferences – to make and justify subjective decisions beyond using random chance or a pre-defined external heuristic.

Casual creators. The interactive generative art tools we study fall in the category of "Casual Creators". This is in contrast with tools that are designed to assist professionals or amateurs in their creative process towards a specific goal. Casual creators on the other hand are autotelic creativity tools that cater to enjoyable explorative creativity over task completion. (Compton and Mateas 2015), who coined the term, stress the interactive aspect of casual creators where the user is the driver, and the creating *process* as being core to the experience. A casual creator is an effective tool if it helps users find desirable artifacts without getting stuck in a local minima or being lost in a vast space of bad artifacts. Our work addresses exactly this. The various parameters in the interactive generative art tool define the space of artifacts, of possibilities, that a user can explore. Our work predicts the user's preferences. A computational model that uses these predictions can influence the path the user takes in this space; it affects the probability that a user will encounter a certain artifact in their creating process. By effectively predicting their preferences, we increase the chances that users will find a desirable artifact when using a casual creator.

Individual user preferences. Existing work, e.g., (Zsolnai-Fehér, Wonka, and Wimmer 2018), models *individual* preferences of a user as they explore a parametrized design space. Our work learns correlations between preferences across parameters from a *population* of users. The two directions have a common goal – helping a user find designs they like – but are complementary. Game content generation has been personalized for both designers (Liapis, Yannakakis, and Togelius 2013) and players (Shaker, Yannakakis, and Togelius 2010).

Interactive Generative Art: Strokes

We design our study around Strokes (Figures 1 and 2) as the generative art form. We chose Strokes because it is an abstract form, allowing us to focus our study on visual preferences rather than semantic associations.

A Strokes piece is a series of overlaid shapes. A shape is started by connecting two random points on a square canvas via a curve of a certain thickness (T). The curve may be a straight line, or a quadratic Bezier curve using a third point as a control point. This control point is the midpoint between the two end points perturbed by random noise. The noise is uniformly random in the range R, which is 10% to 20% the width of the canvas. This noise is either added or subtracted to the x and y co-ordinates of the mid-point. Each of these 4 possibilities has a probability ν of 0.25.

Having placed the first curve, the end point of the curve is connected to another random point on the canvas via a curve. This process is repeated. After each curve is drawn, the shape either continues (with probability $P = 0.5$) or the shape ends and a new shape begins. When the shape ends, the canvas enclosed by the curves and a straight line connecting the start point of the first curve in the shape and end point of the last curve in the shape is colored by a random color from a palette. The color of the curves themselves is a pre-defined background color in the palette. When a total of N curves have been drawn, the last shape ends and the piece is complete. Any pixel covered by more than one shape is colored by the most recent color.

The generative artist designed this generative process, chose the colors in each palette, the probability P with which a new shape starts after each curve, the range R that determines the amount of noise added to a mid point, and the probability ν of adding noise to each of the 4 directions to form the control point of the quadratic Bezier curve (when applicable). The machine picks the random end points and noise added to the mid point to form the control point of the quadratic Bezier curve (when applicable). The color palette, number of curves N in the piece, thickness of curves T and whether the curves should be a straight line or a quadratic Bezier curve are free parameters. These parameters are provided as options on an interactive tool as seen in Figure 1. The random seed is kept fixed when a user is changing parameters on the interface so that the only influence changing the piece is input from the user. The user can click on the "Generate" button to change the random seed that determines the machine's influence. A video demonstrating the interface is provided here `https://youtu.be/YzfzjK8NNMg`.

As options, the tool provides 6 color palettes, 11 densities which determine the number of curves ($N = 2^{\text{density}}$), 15 line thicknesses, and a binary option of curved or straight lines. In our study, we restrict the number of palettes to 3, densities to 3, line thicknesses to 4, and retain the straight vs. curved lines option. We start with a "default" configuration for each of these options and generate 8 versions of the piece by changing one property at a time (Figure 2).

Collecting Preferences

We collected 36 preferences – 24 in Strokes interactive generative art, 12 in other walks of life – from 311 subjects on Amazon Mechanical Turk. Subjects were from the US, had completed $\geq$5000 tasks on AMT with an approval rating of $\geq$95%, and were paid higher than minimum wage in the US.

For Strokes, we generate 8 pairs of comparisons: default in Figure 2a vs. each of the 8 edited versions in Figure 2b-i. Both pieces in each pair are generated with the same random seed so that there is only one cause of variation between the two pieces, but different seeds are used across pairs to ensure that the preferences we collect are generic across seeds. We randomly order the default and the edited version within a pair. The 8 pairs are also randomly ordered. We generate a total of 3 sets of these comparisons with different random seeds. This gives us 24 two-way forced choice pairs in the context of interactive generative art. For each pair, subjects were asked "Which visual pattern appeals to you more?" Including options for no or equal preference may be better.

For other walks of life, we ask subjects for 12 preferences. (1) Do you reflect on a regular basis (e.g., write in a journal)? Yes/No (2) Which do you prefer? Milk vs. dark chocolate (3) Which do you prefer? Wine vs. beer (4) Which do you prefer? Country vs. rock music (5) Do you have any exposure to design principles? Yes/No (6) Are you artistically inclined? Yes/No (7) Which gender do you associate with more? Male/female (8) What personality type do you associate with more? Introvert/extrovert (9) Which do you prefer? Sweet vs. savory food (10) Which of these styles of painting appeals to you more? Cubism vs. Renaissance (examples were shown) (11) If you could setup your home however you liked, which of these styles would you go with? Modern vs. traditional (with examples) (12) Irrespective of your gender, which of these fashion styles do you relate to more? Bohemian Chic vs. business casual (with examples).

Are people self-consistent in their preferences in generative art? Recall that 311 subjects were shown 8 generative art comparisons for 3 seeds. Across these 2488 sets of 3 responses, we check how accurately a response to a 3rd seed can be predicted by assuming the same response to the other 2 seeds. The prediction accuracy is 81%. When the response to the 2 seeds is different, we broke ties using the prior. Recall that each pair contains the default configuration and one of the eight alternative versions (Figure 2). Across subjects, the default configuration is preferred 62% of the time, and was used to break ties. Note that always predicting that subjects prefer the default option would result in a prediction accuracy of 62% – significantly lower than 81% reported above. Overall, it is clear that subjects frequently prefer alternative configurations *and* they are consistent in this preference across seeds. Thus, there is scope for predicting the personal preferences of a user automatically. Figure 2 shows the % of times each alternative is preferred over the default.

Which preferences are related? We omit detailed statistics for space considerations. We find that gender is the best predictor for wine vs. beer preference. Preferring gray palette over the default is the best predictor for preferring straight lines over the curved lines in Strokes. Preference for the bright palette is a good indicator of preferring thicker lines. Unsurprisingly, preference for the sparser pattern is the best predictor for preference for the sparsest pattern. Overall, we see promising correlations across preferences.

Predicting Preferences

To predict preferences from other preferences, we train a variety of ML models. We create three groups of preferences; $\mathcal{A}$: 8 art (Strokes), $\mathcal{L}$: 12 other walks of life, $\mathcal{U}$: all 20. Each group can be used as features $\mathcal{F}$ to predict preferences in the other group (target $\mathcal{T}$). A group can also be used as features to predict a preference from the same group by excluding that target preference from the input features. This results in a total of 9 settings $(\mathcal{F}, \mathcal{T}) \in \{\mathcal{A}, \mathcal{L}, \mathcal{U}\} \times \{\mathcal{A}, \mathcal{L}, \mathcal{U}\}$ where $\times$ denotes the cartesian product. We train and test our models via leave-one-out cross validation; train on preferences from 310 of 311 subjects, test on the remaining subject, repeated 311 times. To normalize for different priors for different preferences, we report class normalized accuracies. We experiment with: nearest neighbor, logistic regression, linear Support Vector Machines (SVMs), polynomial SVMs, Radial Basis Function (RBF) SVMs, neural networks, decision trees, and a matrix completion approach. Models for learning from preference data specifically may be better.

Linear SVMs perform the best. Models are unable to predict interactive generative art (Strokes) preferences based on other life preferences (50.00%) and vice versa (48.80%). Chance performance is 50%. However Strokes preferences predict other Strokes preferences well (64.33%). Knowing other preferences in life further helps predict Strokes preferences (65.11%). We focus on these two settings: using

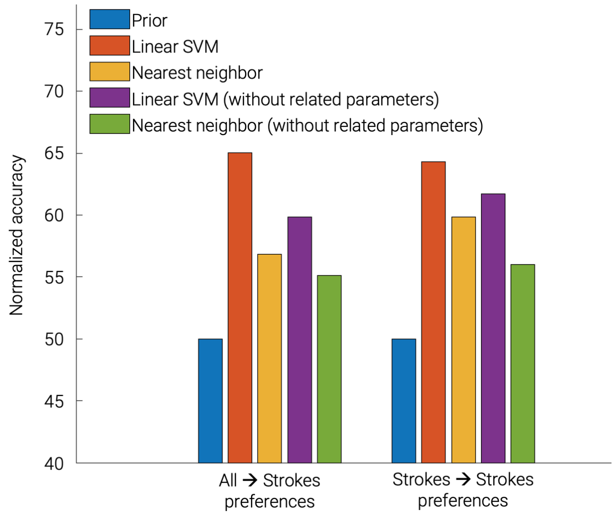

Figure 3: Accuracies of ML models at predicting Strokes preferences with and without Strokes preferences that are linearly related (e.g., thicker vs. thickest lines).

Strokes preferences to predict other Strokes preferences, and using all preferences (Strokes + other walks of life) to predict a held out Strokes preference. Nearest neighbor is an informative point of comparison. It assumes that a test subject's preference is the same as the training subject who has the most other preferences is common with. Figure 3 (three left bars) shows a comparison of SVM with nearest neighbor and the prior baseline. We use 1,000 bootstrap samples and find the 95% confidence interval to be $\pm{\sim}0.1\%$.

Looking at interpretable rules from decision trees, we noticed that a preference for the thickest or thin lines is used to predict a preference for thicker lines. Same for sparse vs. dense patterns. These preferences along a linear ordering are obviously (and hence uninterestingly) related. To verify that our models are not relying primarily on these uninteresting correlations, we reduced our set of Strokes preferences down to 5. We removed the sparsest, thickest lines and thin lines alternatives from Figure 2 because those were the least preferred alternatives along the thickness and density parameters. We retrained our models. Their performance is shown in Figure 3 (right two bars). We see that while model accuracies go down a little, they continue to be significantly better than the prior baseline. This suggests that we can indeed predict meaningful dependences between a user's preferences when interactively creating generative art (Strokes).

Conclusion and Future Work

Future work includes expanding the study to more configurations and generative art forms, and translating the ML models to a smart interactive tool. This leads to more complex ML problems of modeling the sequence of interactions, and determining if the models should be used to eliminate part of the parameter space or promote a part of the parameter space. This involves focussing on either precision or recall of the models. Grounding this study in models of aesthetic experience (Leder and Nadal 2014) is future work.

To summarize, while we have not yet found evidence for it, given the narrow scope of our study, there may still be potential in the use of interactive generative art creation as an engaging and creative "personality test". In fact, it may be possible to design generative art that explicitly optimizes for correlation with personality traits or preferences in other walks of life. We *do* find evidence that preferences of a user creating art using an interactive generative art tool are predictable from choices they make. This opens up opportunities for smart casual creators that make it easier for a lay person to create a piece they are personally excited about!

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