Evolutionary Analysis and Cultural Transmission Models of Color Style Distributions in Painting Arts

Eita Nakamura* and Yasuyuki Saito†
* Kyoto University, Kyoto, Japan
E-mail: eita.nakamura@i.kyoto-u.ac.jp Tel/Fax: +81-75-753-5396
† National Institute of Technology, Kisarazu College, Chiba, Japan
E-mail: saito@j.kisarazu.ac.jp Tel/Fax: +81-438-30-4137

Abstract—**This paper studies the evolutionary dynamics and cultural transmission of color styles in painting arts. Creative cultures, such as visual arts, develop through repeated processes of knowledge transmission and modification, and characteristics of these processes can lead to macroscopic evolutionary patterns. While recent studies have found intriguing trends and dynamic patterns in the evolution of visual arts, the relationship between these trends and cultural transmission processes remains poorly understood. We first analyze the evolutionary dynamics of color distributions in oil paintings by applying a clustering method. The results reveal that some of the frequencies of the color style clusters exhibit synchronous changes that are related to creators' biases in producing paintings belonging to specific clusters. We subsequently construct models of cultural evolution to represent how these biases are transmitted between creators, based on two hypothetical transmission modes: one guided by influencer-to-descendant connections and another guided by community-to-descendant connections. Through statistical inference, we show that the influencer-guided transmission model better fits the historical data. Furthermore, highly influential creators, as inferred by the model purely from content data, remarkably align with those commonly mentioned in the literature on art history.**

I. Introduction

The recent advancement of generative AI [1]–[3] has drawn attention to the application of image processing in the field of arts, such as painting. The automatic creation technology based on machine learning enables the generation of images in diverse styles. While machine learning relies heavily on a large accumulation of image data historically created by humans, the generation of paintings in new creation styles remains a big challenge [4]. In fact, there is still limited quantitative and scientific understanding of the process in which humans develop new creation styles. If we can understand this human's creative intelligence, the knowledge can be utilized to realize automatically generating paintings in a much wider variety of styles than current systems.

Creative cultures have evolved through repeated processes of transmission and modification of creative knowledge. Cultural evolution including such cultural transmission processes has been studied based on theoretical analogies with biological evolution, and two factors, environmental and dynamical, in the evolution process are generally considered to shape evolutionary processes [5]. Environmental factors refer to various factors that generate selective pressure, and determine the direction and constraints of evolution. In the case of painting culture, these include people's preferences, the supply of painting materials, and social backgrounds such as economics and politics. On the other hand, dynamical factors refer to the effects caused by the processes of knowledge transmission, mutation, and selection, and are generally relevant for understanding the speed and regularities of evolution.

Research on the evolutionary analysis of painting art data, mainly focusing on Western art, has recently become an active field [6], thanks to the availability of large-scale digital data and the development of image analysis techniques including deep learning. Previous studies have found trends in certain time periods, in the entropy-complexity features used in physical system analysis [7] and in the features extracted by convolutional neural networks (CNNs) [8], [9]. It has also been shown that the characteristic temporal changes found in these analyses generally agree with the analysis by art experts, and the creators who represent the style of each era coincide with those widely mentioned in art history [7], [8], [10]. Another study suggested that there were significant changes in the average features of paintings, particularly during the 15th and 16th centuries, and in the late 19th century, from the analysis of color contrast, which can be associated with the popularization of oil paints and the increase in individuality in painting styles [11]. The existence of trends spanning several centuries and the presence of revolutionary periods with rapid changes have also been observed in music data, where similar evolutionary analysis has been conducted [12]–[15]. These quantitative results have revealed the relationship between the temporal changes in painting styles and social/environmental factors. However, the impact of dynamic factors due to cultural transmission on art evolution still remains poorly understood.

In this study, focusing on the fact that creators usually produce artworks in several creation styles, we investigate the impact of cultural transmission of these creative style distributions on macroscopic evolution of the painting culture. First, we analyze the color styles of oil paintings by using a clustering method and show that there are synchronous changes in the frequencies of certain color style clusters. We also confirm, through an analysis of the network of clusters obtained from creators belonging to multiple style clusters, that the creators' biased distribution of color styles had significant influence on the aforementioned synchrony.

To understand the process by which creators select the distribution of color styles, we construct cultural evolution models incorporating a transmission process of this distribution between creators and compare them with a random selection model. In cultural transmission, various modes of learning are generally possible, such as learning from a specific influencer, as in a master-descendant relationship, or learning from numerous creators or artworks. We here consider two extreme possibilities: *influencer-guided* transmission, where one influencer is mainly involved in the transmission, and *community-guided* transmission, where the average features from a community of creators are transmitted. We formulate the mathematical models to represent these hypothetical cases. Through statistical inference based on these models, we show that the influencer-guided transmission model better explains the historical data. Furthermore, we validate the potential of this model, which allows for the estimation of the creator's fitness (influence) from image data by unsupervised learning, by measuring the degree of match between creators with high estimated fitness and those mentioned in an influential textbook on art history.

II. Cluster analysis of color style

A. Materials and method

We used image data of mostly Western art paintings obtained from a public website WikiArt.org. Some meta data are associated with the obtained image data, including the year of production, creator's name, and media (materials). For our analysis, we extracted artworks with media labeled as "oil", resulting in 32 401 artworks. We then extracted color frequency statistics from each of the images as follows. First, all images were converted to 100×100 pixels by downsampling (Fig. 1). Second, we applied color reduction to $I = 40$ representative colors, which form a set of equally spaced points in the cone-shaped HSV color space. Third, the relative frequencies $\boldsymbol{\theta}_n = (\theta_{ni})_{i=1}^{I}$ of the representative colors i for each image n were computed. The tuple $(a_n, t_n, \boldsymbol{\theta}_n)$ of creator a_n, year of production t_n, and color statistics $\boldsymbol{\theta}_n$ was used for the following analysis. The years of production in the data ranged from 1270 to 2022. The number of distinct creators was 1128.

To quantitatively study the evolution of creation styles, we analyze the temporal changes in the distribution of color statistics. To deal with the high-dimensional space of the statistics, we first apply clustering in this space to identify several concentrated regions, which we call color style clusters. Specifically, we use for clustering the discrete distribution mixture model defined as

$$P(\boldsymbol{\theta}_n) = \sum_{k=1}^{K} \pi_k P(\boldsymbol{\theta}_n|\bar{\boldsymbol{\theta}}_k),$$

where K is the number of clusters, π_k denote the probabilities of clusters (called the mixture probabilities), and $\bar{\boldsymbol{\theta}}_k$ is the mean statistics of cluster k. The k-th component discrete distribution model $P(\boldsymbol{\theta}_n|\bar{\boldsymbol{\theta}}_k)$ is defined as

$$P(\boldsymbol{\theta}_n|\bar{\boldsymbol{\theta}}_k) = \prod_{i=1}^{I} \bar{\theta}_{ki}^{L\theta_{ni}},$$

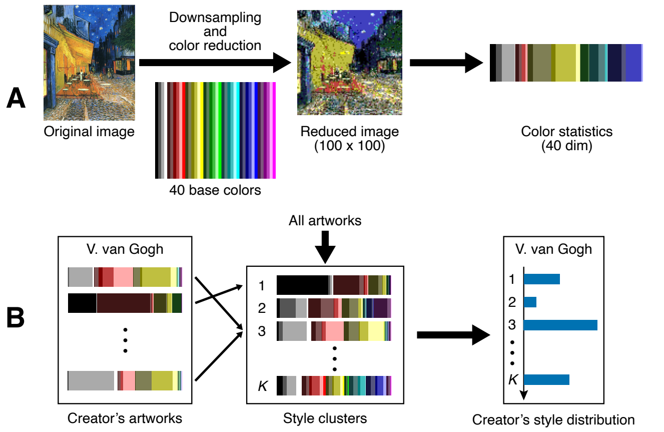

Fig. 1. Processes for analyzing color styles. A: Preprocessing for extracting color statistics. B: Color style clusters and creator's style distribution.

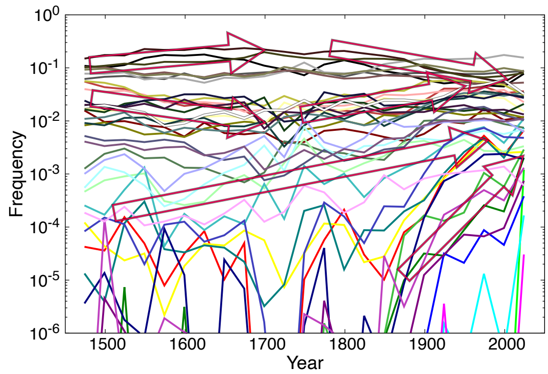

Fig. 2. Evolution of color frequencies. The plotted lines are colored in the indicating base colors (while line is shaded). Arrows indicate notable trends.

where L is an auxiliary parameter corresponding to a "sample size" to compute the probability. The clustering algorithm can be derived based on the expectation-maximization (EM) algorithm. In the E-step, the posterior probability is computed as $P(k|n) \propto \pi_k P(\boldsymbol{\theta}_n|\bar{\boldsymbol{\theta}}_k)$, where L is set as $L = 10\,t$ (t denotes the iteration time) and plays a similar role as the inverse temperature in the simulated annealing method. In the M-step, the mixture probability is updated as $\pi_k \leftarrow \sum_n P(k|n)$ and the mean statistics as $\bar{\theta}_{ki} \leftarrow \sum_n P(k|n)\theta_{ni}$. Note that we apply the clustering without using the temporal information t_n. After the convergence of the EM algorithm, we assign each artwork n to the most probable cluster $k_n = \mathrm{argmax}_k P(k|n)$, for subsequent analyses.

To get an overview of the temporal changes of the distribution of data samples, we also project the color statistics on a two-dimensional visualization space. For this purpose, we use the t-SNE method [16] with the Jensen-Shannon divergence used as the distance measure. This dimensional reduction process is conducted independently of the clustering and is used only for visualization.

B. Results

We used images whose year of production is 1450 or later because there were only a small number of images produced

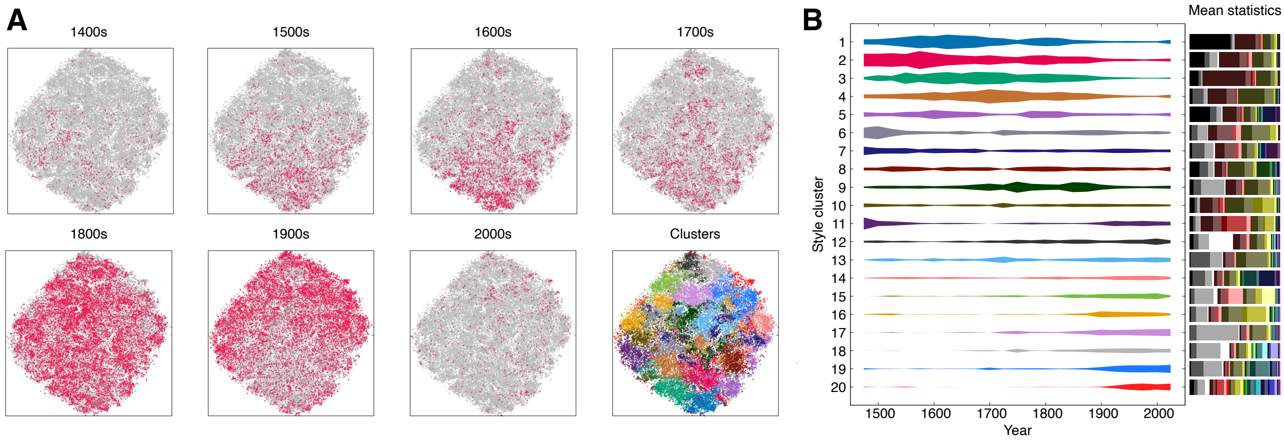

Fig. 3. A: Distribution of artworks in the visualization space. Red dots indicate artworks in each period and gray dots represent all the artworks. In the 'cluster' panel, artworks are illustrated in the colors of the clusters they belong to (cluster colors are arbitrary). B: Evolution of style cluster frequencies.

before the year. Fig. 2 shows the temporal evolution of the relative frequencies of colors, where the frequencies were calculated for each 25-years window. The most frequent colors have low brightness and low saturation, and bright and high-saturation colors are generally rare. Several trends can be observed in this figure, as indicated by arrows. First, from the 15th century to the 17th century, some of the most frequent colors increased their frequencies in the data, whereas some relatively frequent bright colors decreased their frequencies. The frequencies of these colors changed in opposite directions from the mid-18th century to the 20th century. Second, several rare bright colors had an overall gradual increase of the frequency from the 16th century to the 20th century. Last, the frequencies of vivid colors that were rarely used in early centuries increased rapidly from the mid-19th century onwards. While these general trends provide some insights, the periodwise average frequencies cannot represent variation and biases of color combinations in individual artworks. The analysis method based on style clusters solves this problem, as presented in the results below, thus providing a useful framework for studying underlying evolutionary processes.

The results of clustering and visualization of color statistics are shown in Fig. 3, where we used $K = 20$ clusters to approximate the distribution. In the visualization space, most artworks in early centuries are located in the lower half region, which represents color combinations containing mostly dark colors. Several important observations can be made in the evolution of the relative frequencies of color style clusters. First, we can observe concurrent and transient cluster structure [13], [17], that is, several clusters are active in each time period and active clusters gradually change over time. That there always exist several active clusters reflects the fact that there are usually multiple art styles and genres in any society. Second, there are two notable periods where multiple style clusters arose: from the 15th to the 16th centuries, and from the mid-19th to the mid-20th centuries. These time periods coincide with the previous result [11] showing periods with significant changes in color contrast. Third, we can observe some style clusters with synchronous rises and declines. For example, clusters 1 and 3, and clusters 17 and 18 respectively have synchronous rises in different centuries. These results indicate the presence of regularities in the evolution of color styles. In the next section, we analyze this synchrony in more detail and study its relationships with creators' behavior.

III. Synchronous Changes of Style Cluster Frequencies and Creators' Style Distributions

A. Analysis method

The relative frequencies of style clusters, as depicted in Fig. 3, can be expressed as a time-dependent mixture probability $\pi_k(t)$. The local synchrony $S_{kk'}(t)$ between the rises and declines of clusters k and k' can be formulated as

$$S_{kk'}(t) = \frac{1}{\sqrt{C_k C_{k'}}} \frac{\mathrm{d}\pi_k(t)}{\mathrm{d}t} \frac{\mathrm{d}\pi_{k'}(t)}{\mathrm{d}t},$$

where $C_k = \int \mathrm{d}t\, (\mathrm{d}\pi_k(t)/\mathrm{d}t)^2$ is a normalization constant. The (overall) synchrony can be defined as $S_{kk'} = \int \mathrm{d}t\, S_{kk'}(t)$. In the numerical analysis, the mixture probabilities are observed at discrete time steps, and the differentials and integration in these equations should be replaced with differences and summation w.r.t. time. It is noted that since the relative frequencies must sum up to unity, a rise of a cluster naturally induces a decline of another, and $S_{kk'}$ generally has a negative value if the relative frequencies of clusters k and k' fluctuate independently. Therefore, a positive value of $S_{kk'}$ indicates synchronous changes between the two clusters.

There are at least two possible factors that cause synchronous changes of cluster frequencies. First, some style clusters with similar mean color statistics, such as those located closely in the visualization space in Fig. 3, can represent separate parts of the same color style. In such a case, a change in the frequency of a color style can result in coherent changes in the frequencies of the relevant clusters. Second, the behavior of creators who usually produce artworks in several creation styles can induce the synchrony between clusters that do not necessarily represent similar color statistics. For

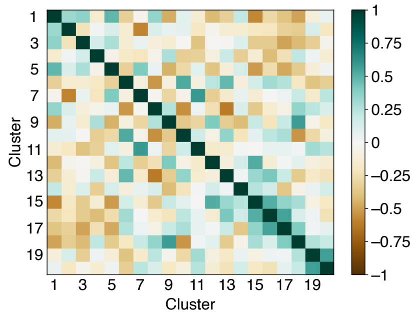

Fig. 4. Pairwise synchrony $S_{kk'}$ between clusters.

example, there are many creators who produced both portraits and landscapes, each of which are usually painted in different color combinations, and a change of artistic taste shared in a community can result in a synchronous change of color styles of both genres. To study this aspect, we calculate the *color style distribution* $\boldsymbol{\pi}_a = (\pi_{ak})_{k=1}^{K}$ of creator a, by counting the number of artworks by the creator belonging to cluster k and normalize the frequencies.

In both cases, some relations, feature similarity or association through creators, induce connections between clusters that lead to synchronous changes in the cluster frequencies. As in the case of association through creators, such connections can temporally change in general. These connections can be expressed as a weighted network $A(t) = \{A_{kk'}(t)\}$ of clusters, where edges $A_{kk'}(t)$ represent the degree of connection between clusters k and k' at time t. The contribution of a network on the synchrony can be quantified as $S(A) = \int \mathrm{d}t \sum_{kk'} A_{kk'}(t) S_{kk'}(t)$. To compare different networks, we impose conditions that self-connections are zero ($A_{kk}(t) = 0$) and that a normalization condition $\sum_{kk'} A_{kk'}(t) = 1$ holds.

To examine possible factors of the synchrony of style cluster frequencies, we consider the following four cluster networks. (i) Uniform network: $A_{kk'} = 1/(K-1)$ ($k \neq k'$). This is a null hypothesis. (ii) Feature similarity network: $A_{kk'} \propto \sum_i \bar{\theta}_{ki}\bar{\theta}_{k'i}$. This represents the cosine similarity between the mean statistics of the clusters. (iii) Creator-mediated association network: $A_{kk'}(t) \propto \sum_a D(t,a)\pi_{ak'}\pi_{ak'}$, where $D(t,a) = 1$ if creator a is relevant at time t and 0 otherwise. This represents the co-occurrence of style clusters in the artworks produced by individual creators. (iv) Frequency-based association network: $A_{kk'}(t) \propto \pi_k(t)\pi_{k'}(t)$. This represents a hypothetical situation where creators choose the style clusters of their artworks by randomly sampling from the cluster frequencies of the time, and consequently their style distributions π_{ak} coincide with $\pi_k(t)$ of time t when creators a are active. We compare these networks in terms of the derived synchrony $S(A)$; if a network $A_{kk'}(t)$ is relevant to the macroscopic evolution of the cluster frequencies, then $S(A)$ is expected to be large.

B. Results

Fig. 4 shows the pairwise synchrony $S_{kk'}$ between style clusters, where we have used discrete time steps of 25-year width. We see some off-diagonal elements with positive values, while a majority of the elements have negative values. Table I lists the derived synchronies for the four cluster networks. Only the creator-mediated association network yielded a positive synchrony, indicating that the creators' style distributions had an impact on the dynamics of style cluster frequencies and induced the synchronous changes. The result also suggests that the feature similarity of clusters also induced the synchrony. On the other hand, the small derived synchrony by the frequency-based network indicates that creators' style distributions deviated from the random selection case, in a biased and coherent (i.e. shared by many creators of the same time) way.

The creator-mediated cluster networks visualized in Fig. 5 clearly show that the association of clusters changed considerably over centuries. The connection weights between some clusters are much larger than others, and we can observe some edges between distant clusters with distinct styles also have large weights. Overall, these results show that creators' color style distributions are biased in a coherent way that cannot be simply explained by the feature similarity or random selection of style clusters, and as they vary over time these biased style distributions markedly affected the macroscopic evolution of color styles in painting arts.

TABLE I
DERIVED SYNCHRONIES FOR DIFFERENT CLUSTER NETWORKS.

Network A	Derived synchrony $S(A)$
Uniform	-0.042
Feature similarity	-0.007
Creator-mediated association	0.033
Frequency-based association	-0.034

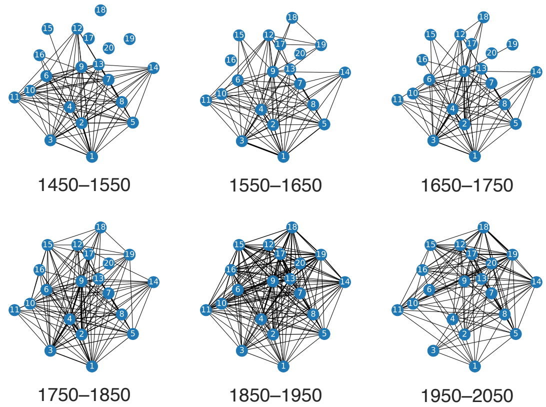

Fig. 5. Creator-mediated cluster networks in different centuries. The nodes are located similarly as the cluster centers in the visualization space in Fig. 3.

IV. CULTURAL TRANSMISSION OF COLOR STYLE DISTRIBUTIONS

A. Cultural evolution models for creators' style distributions

The biased and coherent color style distributions of creators discussed in the previous section pose an important question: How did the creators' style distributions determine? While certain social factors such as the demand from the church or patrons are conceivable, we here focus on a simple possibility of cultural transmission. Since complex knowledge about the art of paining is usually learned from other creators or their artworks, it is possible that the color style distribution is transmitted in this learning process.

We construct two models to examine what particular mode of cultural transmission is plausible to explain the data. In cultural phenomena, unlike in genetic evolution, the number of cultural parents is not limited to one (asexual) or two (sexual), and transmission from a varying number of cultural parents are possible. We thus consider two hypothetical situations that represent extreme cases within a broad range of possibilities. In the first *influencer-guided* transmission model, we suppose that a creator learns his/her creation style mainly from a specific influencer's artworks, as in a master-descendant relationship. In the second *community-guided* transmission model, we suppose that a creator learns the creation style from numerous creators' artworks belonging to some stylistic community. In the following, we mathematically formulate these models.

We formulate the cultural evolution models based on a stochastic description of the transmission-mutation-selection process [5]. This is a formulation similar to the models of biological evolution used in population genetics [18], except that the potential of a past creator to produce cultural offspring can in principle continue for long after his/her death. We denote by t^{s}_a the year that creator a started creation, which is defined as the earliest year of the creator's artworks in the data. Let $\tilde{\boldsymbol{\pi}}_a = (\tilde{\pi}_{ak})_{k=1}^K$ denote the frequency counts of style clusters in artworks of creator a. By normalizing these frequencies, we obtain the style distribution $\boldsymbol{\pi}_a$. We also denote by $\boldsymbol{\pi}_a^{<t}$ the style distribution obtained from the artworks of creator a produced before year t. Our cultural evolution models are formulated as explicit realizations of the probability distribution $P(\tilde{\boldsymbol{\pi}}_a)$ for all creators a.

B. Influencer-guided transmission model

In the influencer-guided transmission model, each learner creator selects an influencer creator among previous creators and learns the influencer's style distribution. This model can be formulated as

$$P(\tilde{\boldsymbol{\pi}}_a) = \sum_{a':t^{\mathrm{s}}_{a'}<t^{\mathrm{s}}_a} P^{t^{\mathrm{s}}_a}_{\mathrm{sel}}(a') P_{\mathrm{dis}}(\tilde{\boldsymbol{\pi}}_a|\boldsymbol{\pi}_{a'\to a}),$$

where the summation is taken over all potential creators a' with $t^{\mathrm{s}}_{a'} < t^{\mathrm{s}}_a$, $P^{t^{\mathrm{s}}_a}_{\mathrm{sel}}(a')$ is the selection probability of the influencer a' of creator a, $\boldsymbol{\pi}_{a'\to a}$ represents the style distribution transmitted from a' to a, and the last factor is given as a discrete probability distribution

$$P_{\mathrm{dis}}(\tilde{\boldsymbol{\pi}}_a|\boldsymbol{\pi}_{a'\to a}) = \prod_k [\pi_{(a'\to a)k}]^{\tilde{\pi}_{ak}}. \tag{1}$$

We incorporate two biases in the selection probability to represent potential tendencies of learner creators, which are similar to those used for modeling citation dynamics of scientific papers [19]. The first is the recency bias, which represents the creators' tendency to more likely choose a reference influencer that lived more recently. This bias can be represented by a weighting factor $\mathrm{e}^{-(t^{\mathrm{s}}_a - t^{\mathrm{s}}_{a'})/\tau_{\mathrm{c}}}$, where the time constant τ_{c} represents the time scale for the bias. The second bias is the (intrinsic) fitness of an influencer, which represents a time-independent likelihood of being learned by successors due to possible factors such as prestige and visibility. To represent this bias, we introduce a fitness parameter $v_{a'}$ for each creator. We also require that a potential influencer a' must have produced at least N_{bound} artworks (specifically, we set $N_{\mathrm{bound}} = 7$). The selection probability can then be given as

$$P^{t^{\mathrm{s}}_a}_{\mathrm{sel}}(a') \propto \mathbb{I}(t^{\mathrm{s}}_{a'} < t^{\mathrm{s}}_a)\, \mathbb{I}(N^{<t^{\mathrm{s}}_a}_{a'} \geq N_{\mathrm{bound}})\, \mathrm{e}^{-(t^{\mathrm{s}}_a - t^{\mathrm{s}}_{a'})/\tau_{\mathrm{c}} + v_{a'}}, \tag{2}$$

where $\mathbb{I}(\mathcal{C}) = 1$ if condition $\mathcal{C}$ is true and otherwise $\mathbb{I}(\mathcal{C}) = 0$, and $N^{<t}_{a'}$ denotes the number of artworks produced by creator a' before year t.

The transmitted style distribution represents the influencer's style distribution with modifications including mutations. Here, we include the influence of creators other than the influencer since it is certainly possible that a learner creator observes many others' artworks and is influenced by the average style distribution of the time. This situation can be formulated as

$$\boldsymbol{\pi}_{a'\to a} = (1 - \eta - \epsilon)\boldsymbol{\pi}^{<t^{\mathrm{s}}_a}_{a'} + \eta\, \boldsymbol{\pi}^{<t^{\mathrm{s}}_a} + \epsilon\, \mathbf{1}/K,$$

where $\boldsymbol{\pi}^{<t^{\mathrm{s}}_a}$ represents the average style distribution at (just before) time t^{s}_a, $\mathbf{1}/K = (1/K, \ldots, 1/K)$ denotes a uniform distribution, and η and ϵ are nonnegative constants. The first, second, and third terms on the right-hand side represent the transmission from the influencer, transmission from the average style distribution of the time, and random mutation, respectively. The average style distribution $\boldsymbol{\pi}^{<t}$ also incorporates the recency effect and is defined as

$$\pi^{<t}_k \propto \sum_{n:t_n<t} \mathbb{I}(t_n < t)\mathbb{I}(k_n = k)\, \mathrm{e}^{-(t-t_n)/\tau_{\mathrm{p}}}, \tag{3}$$

where the summation is taken over all artworks n produced before t, k_n denotes the cluster assigned to n, and τ_{p} denotes the time constant for artworks. The parameters η and ϵ represent the strength of the second and third terms and are called the oblique transmission coefficient and the random mutation rate, respectively. It is noted that the time-decaying factors in Eqs. (2) and (3) reduce the influence of past creators and artworks as time proceeds. Additionally, the restrictions on time in these equations ensure the causal constraint that future information is not used in the definition of probability $P(\tilde{\boldsymbol{\pi}}_a)$.

C. Community-guided transmission model

In the community-guided transmission model, we consider that a learner creator first analyzes previous artworks and finds communities of creators sharing similar style distributions. The learner creator then selects a community and learns the mean style distribution of the community. This model is described as

$$P(\tilde{\boldsymbol{\pi}}_a) = \sum_{c=1}^{C} \psi^{<t^{\mathrm{s}}_a}_c P_{\mathrm{dis}}(\tilde{\boldsymbol{\pi}}_a|\boldsymbol{\pi}_{c\to a}), \tag{4}$$

where c indexes communities of creators, C is the number of communities, $\psi^{<t}_c$ represents the selection probability of

communities at time t, and $\boldsymbol{\pi}_{c\to a}$ represents the style distribution transmitted from community c to creator a. The discrete probability distribution $P_{\rm dis}(\tilde{\boldsymbol{\pi}}_a|\boldsymbol{\pi}_{c\to a})$ is the same as in Eq. (1). The creator communities are formalized as a dynamic mixture model with the following log-likelihood:

$$\mathcal{L}(t) = \sum_{\substack{a:t_a^{\rm s}<t,\\ N_a^{<t}\geq N_{\rm bound}}} {\rm e}^{-(t-t_a^{\rm s})/\tau_{\rm c}} \ln\biggl[\sum_c \psi_c^{<t} P_{\rm dis}(\tilde{\boldsymbol{\pi}}_a^{<t}|\boldsymbol{\pi}_c^{<t})\biggr], \tag{5}$$

where $\tau_{\rm c}$ is the creator time constant, $\psi_c^{<t}$ is the mixture probability, and $\boldsymbol{\pi}_c^{<t}$ is the mean style distribution of community c. Assuming that how creators analyze the community structure is time-dependent and recent creators are given more attention in this process, the time-decaying factor ${\rm e}^{-(t-t_a^{\rm s})/\tau_{\rm c}}$ is introduced to weigh the creators' contributions on the likelihood. We use in Eq. (4) the parameter values of $\psi_c^{<t}$ and $\boldsymbol{\pi}_c^{<t}$ that maximize Eq. (5). See Sec. IV-D for the inference method.

The transmitted style distribution in Eq. (4) is formulated similarly as in the influencer-guided transmission model: we suppose that the mean style distribution of the selected community has the dominant influence, but the mean average style distribution of the time also has some influence and there is a small chance of random mutation. This situation can be formalized as

$$\boldsymbol{\pi}_{c\to a} = (1-\eta-\epsilon)\boldsymbol{\pi}_c^{<t_a^{\rm s}} + \eta\,\boldsymbol{\pi}^{<t_a^{\rm s}} + \epsilon\,\mathbf{1}/K,$$

where η represents the oblique transmission coefficient also in this model.

D. Inference method

The main purpose of the evolution models presented in the previous sections is to compare the two hypotheses on the cultural transmission process. Both models are formulated as realizations of the same probability distribution $P(\tilde{\boldsymbol{\pi}}_a)$, and we can compare them by their total log-likelihoods normalized by the total number of artworks

$$\mathcal{L}_{\rm tot} = \biggl(\sum_a \ln P(\tilde{\boldsymbol{\pi}}_a)\biggr)\bigg/\biggl(\sum_{a,k}\tilde{\pi}_{ak}\biggr),$$

or the exponentiated quantities $\kappa = \exp(\mathcal{L}_{\rm tot})$ called the perplexity. The perplexity can be interpreted as the effective number of style clusters to choose. The smaller this quantity is, the more predictive a model is. The log-likelihood value $\mathcal{L}_{\rm tot}$ depends on the model parameters in both evolution models. Following the maximum likelihood principle, we estimate the model parameters to maximize $\mathcal{L}_{\rm tot}$, that is, we compare the two models in their optimal conditions. Since the values of the mutation rate ϵ and artwork time constant $\tau_{\rm p}$ did not affect the likelihood so much, as they are effectively smoothing constants, we fixed them as $\epsilon = 10^{-6}$ and $\tau_{\rm p} = 20$ yrs. In the following, due to the lack of space, we briefly explain specific methods for the inference of model parameters.

In the influencer-guided model, the model parameters to be estimated are $\{v_a\}$, $\tau_{\rm c}$, and η. We use an iterative method for optimizing these parameters; when one parameter (set) is optimized the other parameters are fixed. For creators' fitness v_a, we use the expectation-maximization (EM) algorithm with the influencer variable a' treated as a latent variable for each learner creator a, which can be derived in a manner similar to the Gaussian mixture model. For parameters $\tau_{\rm c}$ and η, we use the grid search method.

TABLE II
PERPLEXITIES AND ESTIMATED PARAMETERS OF THE EVOLUTION MODELS. RESULT FOR THE MODEL USED FOR ANALYZING CREATOR FITNESS (SEE TEXT) IS ALSO SHOWN AT THE BOTTOM.

Model	Perplexity	$\tau_{\rm c}$ (yrs)	η
Random	19.1	NA	NA
Influencer-guided (optimal)	15.6	117	0.37
Community-guided ($C = 10$)	16.4	160	0.38
Community-guided ($C = 20$)	16.2	110	0.52
Community-guided ($C = 30$)	16.1	220	0.58
Influencer-guided (for analysis)	16.2	50	0.1

In the community-guided model, the model parameters to be estimated are $\{\psi_c^{<t}, \boldsymbol{\pi}_c^{<t}\}$, $\tau_{\rm c}$, and η. We again use an iterative method for optimizing these parameters, and the parameters $\tau_{\rm c}$ and η are optimized by grid search. We use the EM algorithm for estimating $\psi_c^{<t}$ and $\boldsymbol{\pi}_c^{<t}$ with the likelihood function in Eq. (5). To ensure the temporal consistency of the community estimation, we first perform community estimated on a coarse time scale of 25-years width and use this result to initialize the parameters $\psi_c^{<t}$ and $\boldsymbol{\pi}_c^{<t}$ for individual years.

E. Results

Table II shows the model comparison result. As a reference, we also compared the random model where a creator generates artworks with cluster frequencies $\tilde{\boldsymbol{\pi}}_a$ according to the temporal average style distribution $\boldsymbol{\pi}^{<t_a^{\rm s}}$: $P(\tilde{\boldsymbol{\pi}}_a) = P_{\rm dis}(\tilde{\boldsymbol{\pi}}_a|\boldsymbol{\pi}^{<t_a^{\rm s}})$. The creator time constant $\tau_{\rm c}$ was estimated in the resolution of approx. 1 year for the influencer-guided model, and 10 years for the community-guided model, due to the large computational cost of the latter model. We tested $C = 10$, 20, and 30 for the community-guided model. Compared to the random model, the influencer-guided and community-guided models both had significantly lower perplexities, indicating a clear effect of cultural transmission. We see that the number of communities C does not have much impact on the perplexity, while large values of the oblique transmission coefficient were estimated for $C = 20$ and 30, suggesting that these models overfitted the community structure. By comparison, the influencer-guided model had a smaller perplexity, which shows that influencer-guided transmission better fits our data. On the other hand, the oblique transmission coefficient was also relatively large for this model, implying that the color style distribution is learned not only from one influencer but also from others. The estimated value $\tau_{\rm c} = 117$ yrs suggests that the influence of past creators sustains for a relatively long time.

An interesting possibility of the influencer-guided model is that it can estimate the fitness (influence) of creators in an unsupervised manner. To examine the model's potential,

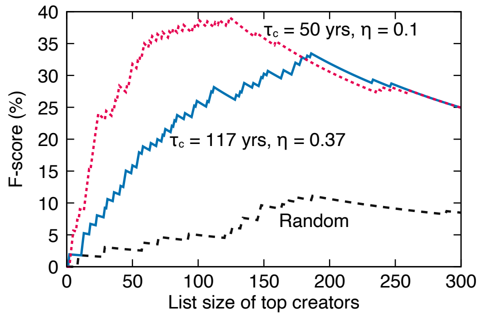

Fig. 6. Comparison of F-score measuring the accuracy of estimating influential creators in comparison with Gombrich's book [20].

we compared the list of creators with high estimated fitness with the list of creators appearing in Gombrich's classical textbook on art history [20]. Among the creators listed in [20], we removed a few who did not have major activities of painting and obtained a list of 101 creators. Using the model estimation, we made lists of varying sizes containing creators with the highest fitness, and we calculated the F-score to measure how much the results align with the Gombrich's list. We also conducted a similar calculation for a randomly sorted list of creators. The result in Fig. 6 shows that the F-score curve by the influencer-guided model with maximum likelihood parameters had significantly high values than that for the random list. While this result is already remarkable, we found that with alternative parameterization with a shorter time constant $\tau_c = 50$ yrs and a smaller oblique transmission constant $\eta = 0.1$, the F-score curve had even higher values (Fig. 6), even though the perplexity becomes higher (Table II). We discuss this mismatch between the optimized models for the likelihood measure and the accuracy of estimating "well-known" creators in the discussion section.

The 25 creators with the highest estimated fitness by the influencer-guided model with $\tau_c = 50$ and $\eta = 0.1$ are shown in Table III. We can see that the list includes creators active in various centuries. Importantly, the list contains creators with a relatively small number of artworks in the dataset, including such well-known creators as S. de Vlieger, R. Lichtenstein, and H. Hoffman. This result shows that the model predicts the fitness not merely from the number of artworks in the data, which although highly correlates with the creator's prestige. That this result was obtained purely from the image data and the meta data about the year of production for ensuring causal constraints demonstrates the potential of the present model for quantitatively and objectively analyzing painting art data and cultural evolution.

TABLE III
HIGHEST FITNESS CREATORS ESTIMATED BY THE INFLUENCER-GUIDED MODEL ($\tau_c = 50$ YRS, $\eta = 0.1$). NAMES IN BOLD FONTS INDICATE THOSE APPEARING IN GOMBRICH'S BOOK [20].

Fitness e^{v_a}	Creator a	Year t_a^s	No. of works
1.81	T. van Rysselberghe	1880	125
1.77	I. Aivazovsky	1835	238
1.75	**S. de Vlieger**	1629	29
1.70	**Titian**	1503	200
1.63	**C. Lorrain**	1630	62
1.62	C. Hernandez	2001	17
1.60	D. Teniers II	1633	54
1.58	**G. Bellini**	1455	56
1.57	M. Hafftka	1986	8
1.54	**P.-A. Renoir**	1858	913
1.53	H. Hofmann	1902	16
1.48	F. Boucher	1734	51
1.45	K. Malevich	1904	113
1.44	**P. Picasso**	1893	499
1.44	**D. Velazquez**	1616	127
1.43	**T. Gainsborough**	1745	125
1.43	**J. van Eyck**	1426	63
1.42	R. Lichtenstein	1961	26
1.42	**C. Monet**	1861	191
1.41	**H. Matisse**	1890	188
1.40	**V. van Gogh**	1881	747
1.38	**C. Corot**	1825	409
1.38	**P. Gauguin**	1873	460
1.38	**A. Altdorfer**	1507	25
1.37	R. Bujnowski	2001	9

V. CONCLUSIONS AND DISCUSSION

We have analyzed the evolution of color styles in painting arts using statistical machine learning and evolutionary modeling methods. By analyzing the dynamics of color style clusters, we have found synchronous changes in the cluster frequencies. We also found that creators' color style distributions are biased in a coherent way and this property is a major factor of this macroscopic phenomenon. We then constructed cultural evolution models incorporating transmission and selection processes of creators' color style distributions and found that the influencer-guided transmission model better fits the data than the community-guided transmission model. We also showed that the model can estimate the creators' fitness by unsupervised learning and automatically discover important figures in the history of painting art only from the image data. All together, these results indicate that in the cultural transmission of knowledge about painting styles, not only the average color combinations but also the distribution of different sets of color combinations is transmitted from creators to creators, and this microscopic process of individual creators can lead to the macroscopic patterns in the evolution of painting style.

It should be emphasized that the present models represent a simplified description of the real evolutionary process. For example, the model can be extended to include more than one cultural parent, or dynamic changes in the parameters such as the creator time constant and the oblique transmission coefficient. The mismatch of the preferred parameterizations by the maximum likelihood estimation and the optimal accuracy of reproducing the human expert's account, found in Sec. IV-E, may be an indication of such incompleteness of the current model. It may also be possible that the present model, which "analyzes" a much larger amount of data than a human can, can find objectively correct results that humans may not find easily. Therefore, future work should study more elaborated models and examine how these models will (or will not) alter the results, and additionally, conduct a benchmark test, for example, using synthetic data, to quantitatively measure the ability of the present model. It is also important to examine the influence of the number and values of representative colors, which were somewhat arbitrarily chosen in this study.

Our result has prospective applications for enhancing the generative AI technology. Using the evolution model with influencer-guided transmission, we can estimate the transmission paths of knowledge about creation style. In scientometrics, for example, such knowledge reference data (i.e. citation data) are used as fruitful sources for studying the dynamics of creative activities including the quantification of the scientific contribution [21], the formation of communities [22], and the nature of creativity [23], [24]. Since complete knowledge transmission paths are rarely provided in self-reports or historians' accounts especially in art fields [25], a data-driven method would provide useful complemental data for revealing the mechanisms by which new creation styles are developed. The found mechanisms can be integrated with machine learning techniques to realize "creative" generative AIs, for example, using the framework of evolutionary computation.

Finally, the present framework of applying a model integrating a probabilistic generative process and cultural evolution process can be applied to a wide domain of data. While we focused on the color style in this study, there are other important stylistic features such as spatial composition, brushstroke pattern, and painted objects. We can apply DNNs for analyzing these various features [8], [9] and with a modification of the data generation process, we can conduct a similar analysis on more general features. Other possible cultural domains of application include music [26]–[28] and literary art [29], and culinary art [30], where cultural transmission of complex knowledge is considered equally important to understand the creative aspect of human intelligence.

ACKNOWLEDGMENT

We thank Takayuki Itoh, Daichi Mochihashi, Hitomi Kaneko, and Gumpu Nakamura for useful discussions. This study was supported by JSPS KAKENHI Grant Numbers 21K12187, 21K02846, and 22H03661, and JST FOREST Program Grant Number JPMJPR226X.

REFERENCES

[1] T. Karras, S. Laine, and T. Aila, "A style-based generator architecture for generative adversarial networks," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019, pp. 4401–4410.

[2] R. Rombach *et al.*, "High-resolution image synthesis with latent diffusion models," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022, pp. 10 684–10 695.

[3] Y. Jiang, S. Chang, and Z. Wang, "TransGAN: Two pure transformers can make one strong GAN, and that can scale up," *Proc. Conference on Neural Information Processing Systems (NeurIPS)*, vol. 34, pp. 14 745–14 758, 2021.

[4] A. Elgammal *et al.*, "Can: Creative adversarial networks: Generating "art" by learning about styles and deviating from style norms," in *Proc. International Conference on Computational Creativity (ICCC)*, 2017, pp. 96–103.

[5] L. L. Cavalli-Sforza and M. W. Feldman, *Cultural Transmission and Evolution*. Princeton University Press, 1981.

[6] M. Perc, "Beauty in artistic expressions through the eyes of networks and physics," *Journal of Royal Society Interface*, vol. 17, p. 20190686, 2018.

[7] H. Y. D. Sigaki, M. Perc, and H. V. Ribeiro, "History of art paintings through the lens of entropy and complexity," *Proceedings of the National Academy of Sciences of the USA*, vol. 115, no. 37, pp. E8585–E8594, 2018.

[8] A. Elgammal *et al.*, "The shape of art history in the eyes of the machine," in *Proc. AAAI Conference on Artificial Intelligence*, vol. 32, no. 1, 2018, pp. 2183–2191.

[9] E. Cetinica, T. Lipica, and S. Grgic, "Learning the principles of art history with convolutional neural networks," *Pattern Recognition Letters*, vol. 129, pp. 56–62, 2020.

[10] H. Wölfflin, *Principles of Art History: The Problem of the Development of Style in Later Art*. Dover Publications Inc., 1950.

[11] B. Lee *et al.*, "Heterogeneity in chromatic distance in images and characterization of massive painting data set," *PLOS One*, vol. 13(9), no. e0204430, 2018.

[12] P. H. R. Zivic, F. Shifres, and G. A. Cecchi, "Perceptual basis of evolving Western musical styles," *Proceedings of the National Academy of Sciences of the USA*, vol. 110, no. 24, pp. 10 034–10 038, 2013.

[13] M. Mauch *et al.*, "The evolution of popular music: USA 1960–2010," *Royal Society Open Science*, vol. 2, no. 150081, 2015.

[14] C. Weiß *et al.*, "Investigating style evolution of Western classical music: A computational approach," *Musicae Scientiae*, vol. 23, no. 4, pp. 486–507, 2019.

[15] E. Nakamura and K. Kaneko, "Statistical evolutionary laws in music styles," *Scientific Reports*, vol. 9, no. 15993, 2019.

[16] L. Van der Maaten and G. Hinton, "Visualizing data using t-SNE," *Journal of Machine Learning Research*, vol. 9, pp. 2579–2605, 2008.

[17] R. Singh and E. Nakamura, "Dynamic cluster structure and predictive modelling of music creation style distributions," *Royal Society Open Science*, vol. 9, no. 220516, 2022.

[18] J. F. Crow and M. Kimura, *An Introduction to Population Genetics Theory*. Harper and Row Publishers, New York, NY, USA, 1970.

[19] D. Wang, C. Song, and A.-L. Barabási, "Quantifying long-term scientific impact," *Science*, vol. 342, no. 6154, pp. 127–132, 2013.

[20] E. H. Gombrich, *The Story of Art (16th ed.)*. Phaidon Press, 1995.

[21] O. Penner *et al.*, "On the predictability of future impact in science," *Scientific Reports*, vol. 3, no. 1, pp. 1–8, 2013.

[22] R. Klavans and K. W. Boyack, "Which type of citation analysis generates the most accurate taxonomy of scientific and technical knowledge?" *Journal of the Association for Information Science and Technology*, vol. 68, no. 4, pp. 984–998, 2017.

[23] V. Larivière, S. Haustein, and K. Börner, "Long-distance interdisciplinarity leads to higher scientific impact," *PLOS One*, vol. 10, no. 3, p. e0122565, 2015.

[24] L. Wu, D. Wang, and J. A. Evans, "Large teams develop and small teams disrupt science and technology," *Nature*, vol. 566, no. 7744, pp. 378–382, 2019.

[25] D. Park, J. Nam, and J. Park, "Novelty and influence of creative works, and quantifying patterns of advances based on probabilistic references networks," *EPJ Data Science*, vol. 9, no. 2, pp. 1–15, 2020.

[26] D. Park *et al.*, "Topology and evolution of the network of Western classical music composers," *EPJ Data Science*, vol. 4, no. 2, 2015.

[27] M. Interiano *et al.*, "Musical trends and predictability of success in contemporary songs in and out of the top charts," *Royal Society Open Science*, vol. 5, p. 171274, 2018.

[28] E. Nakamura, "Computational analysis of selection and mutation probabilities in the evolution of chord progressions," in *Proc. International Symposium on Computer Music Multidisciplinary Research (CMMR)*, 2023, to appear.

[29] C. O. Brand, A. Acerbi, and A. Mesoudi, "Cultural evolution of emotional expression in 50 years of song lyrics," *Evolutionary Human Sciences*, vol. 1, no. e11, 2019.

[30] O. Kinouchi *et al.*, "The non-equilibrium nature of culinary evolution," *New Journal of Physics*, vol. 10, no. 073020, 2008.