Exploring the Evolution of Artistic Styles Using Generative AI and Influence Modeling

Keywords: generative AI, cultural evolution, artistic concepts, computational creativity, historic creativity

Extended Abstract

Understanding the evolution of human creative expression is central to art history, and instrumental to the progress of algorithmic creativity [1, 2]. Recent advances in generative AI, such as Stable Diffusion, Midjourney, and DALL-E, show great promise in generating detailed images based on textual prompts blending visual concepts and art styles. However, whether these models can produce truly novel outputs beyond recombination remains unclear. Measuring creativity and cultural progress in subjective domains like the arts is challenging, but generative AI can help deconstruct art into distinct concepts, such as style, content, and composition, and measure their similarity. In this ongoing work, we propose a method to measure the similarity of visual concepts and thereby the cultural evolution of artist styles. We also present a simple influence model to represent the cultural processes and discuss the potential of generative AI to explore new, unseen art styles.

Our work is based on the Stable Diffusion model [3], which comprises a text interpreter (CLIP) and an image generator. Our focus is on the first layer of CLIP, which tokenizes the textual input and embeds each token into a token space. This process encodes linguistic concepts, such as "cat" or "Van Gogh," into a shared embedding. As a result, the model implicitly deconstructs images into concepts based on, e.g., the objects depicted, specific colors, or various stroke techniques.

We introduce a new dataset of artistic style embeddings for 1,114 artists from the 1400s to 2000s, using the refined WikiArt dataset as a basis [4]. By applying textual inversion, we recompute a single vector $\vec{v} \in \mathbb{R}^{768}$ representing the style of each artist in the data. Textual inversion involves finding a representation of a concept $\vec{v}$ in the token space based on a set of example images and a prompt blueprint (i.e. "a painting in the style of $\vec{v}$") [5].

We conducted a preliminary analysis of the evolution of artistic styles in the latent space. As shown in Figure 1.a, artists are located in the vicinity of their contemporary peers. Moreover, we observed that the convex hull of artistic styles expands over time, indicating that new styles emerge beyond the distribution of existing styles.

We model an artist's style as a linear combination of pre-dating artists using an influence model and find that an artist's style can be well described as being influenced by only a few predating artists. An important caveat is that the data we analyze is already curated and thus the measures we present are computed from a contemporary, historical perspective.

Our work showcases novel methods for computing the stylistic similarity of different artists and measuring stylistic creativity. The findings shed light on the prospects of discovering new art styles in the latent space of generative AI. Our study contributes to the growing field of computational creativity, linking generative AI and cultural evolution.

References

[1] Byunghwee Lee, Min Kyung Seo, Daniel Kim, In-Seob Shin, Maximilian Schich, Hawoong Jeong, and Seung Kee Han. Dissecting landscape art history with information theory. Proc. Natl. Acad. Sci. U. S. A., 117(43):26580–26590, October 2020.

[2] Ahmed Elgammal and Babak Saleh. Quantifying creativity in art networks. June 2015.

[3] Jascha Sohl-Dickstein, Eric A. Weiss, Niru Maheswaranathan, and Surya Ganguli. Deep unsupervised learning using nonequilibrium thermodynamics. CoRR, abs/1503.03585, 2015.

[4] Wei Ren Tan, Chee Seng Chan, Hernan Aguirre, and Kiyoshi Tanaka. Improved artgan for conditional synthesis of natural image and artwork. IEEE Transactions on Image Processing, 28(1):394–409, 2019.

[5] Rinon Gal, Yuval Alaluf, Yuval Atzmon, Or Patashnik, Amit H Bermano, Gal Chechik, and Daniel Cohen-Or. An image is worth one word: Personalizing Text-to-Image generation using textual inversion. August 2022.

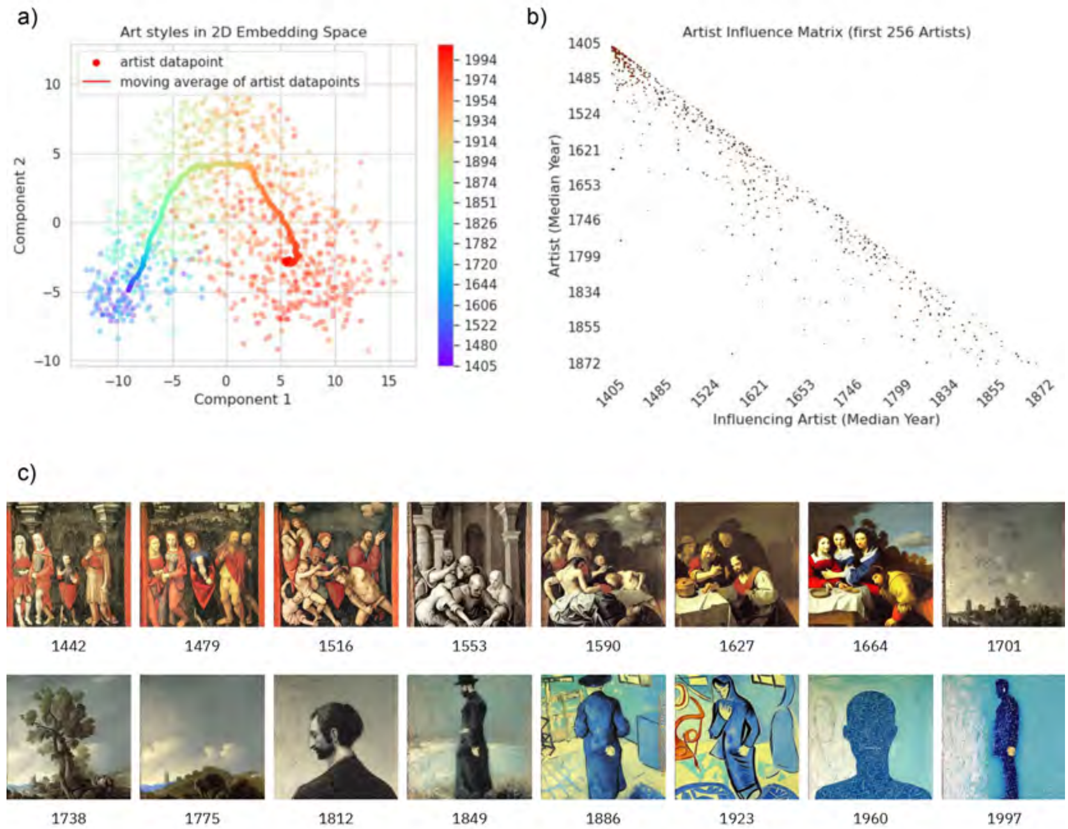

Figure 1: [Preliminary Results] (a) A projection of the first two PCA dimensions of the artists' embeddings with colors representing the median year of the artists' artworks. A rainbow-colored line shows the moving average of the embeddings. (b) Non-zero weights of the linear influence model, as described in equation ??. A non-zero weight can be interpreted as one artist influencing another artist style. Empirically we found a concentration close to the diagonal. Therefore the model suggests that artist in the dataset are predominantly influenced by peers of the same period. (c) Images generated with the prompt "a painting in the style of <avg. year>" with the vector <avg. year> corresponding to the moving average as depicted in (a).