Conformal Alignment: Knowing When to Trust Foundation Models with Guarantees

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Github: https://github.com/Saarts21/Art-Conformal-Alignment

Abstract

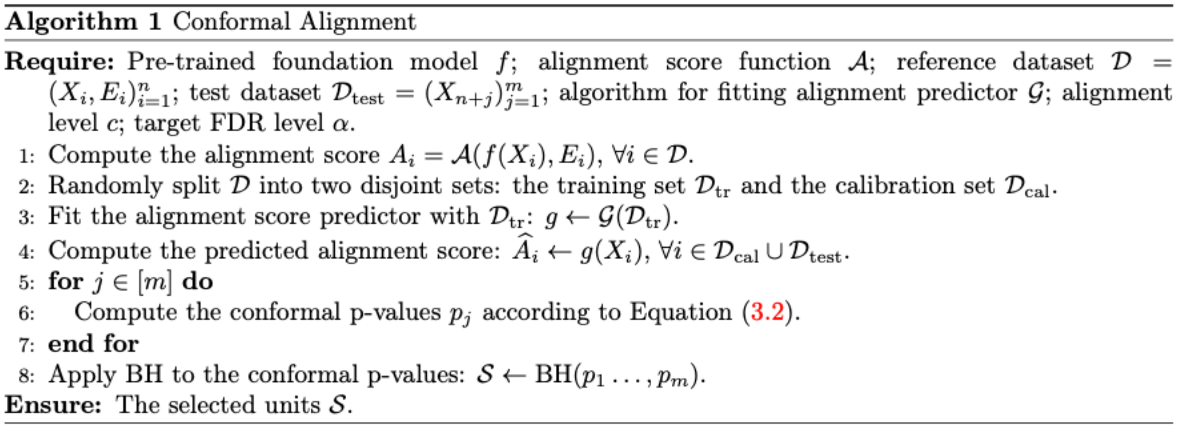
The paper we chose to present and explore written by Yu Gui et al,. (2024) introduces Conformal Alignment, a method that certifies aligned outputs of pre-trained foundation models in generating outputs for various tasks, with strict control over the false discovery rate (FDR). We chose to extend this framework to the domain of artworks, we explored whether a generative model like DALL-E can reliably generate art pieces that imitate the style of famous artists. We assessed the quality of model-generated reproductions of existing paintings using Conformal Alignment.

Section 1: Background and Problem Setup

The paper "Conformal Alignment: Knowing When to Trust Foundation Models with Guarantees" by Yu Gui et. al (2024) discusses the powerful capabilities of large-scale, pre-trained foundation models in providing outputs to a vast variety of tasks. However, these models often face issues like factual errors, hallucinations, and bias, which raise concerns regarding fostering such models for high-stakes tasks. In these crucial tasks, the model's outputs must align with human evaluations before their use. Trusting a foundation model blindly for such tasks is out of the question, building multiple testing procedures on its outputs is necessary to guarantee reliability. One of the most desired and practical properties to ensure is the ability to control the type I error: the expected proportion of erroneously rejected hypotheses among the rejected ones, which is the focus of the paper.

Section 2: The Conformal Alignment Procedure, Results and Limitations

Equipped with an understanding of the problem's background, let's dive into the paper's main contribution and analyze the results in detail. Conformal Alignment is a flexible, effective framework to select those aligned outputs, combining conformal prediction and hypothesis testing. In the figure below you can see the main algorithm presented in the article which aims to determine which outputs are aligned to human criterion:



Algorithm 1 Conformal Alignment

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Require: Pre-trained foundation model $f$; alignment score function $\mathcal{A}$; reference dataset $\mathcal{D} = (X_i, E_i)_{i=1}^n$; test dataset $\mathcal{D}_{\text{test}} = (X_{n+j})_{j=1}^m$; algorithm for fitting alignment predictor $\mathcal{G}$; alignment level $c$; target FDR level $\alpha$.
Compute the alignment score $A_i = \mathcal{A}(f(X_i), E_i)$, $\forall i \in \mathcal{D}$.
Randomly split $\mathcal{D}$ into two disjoint sets: the training set $\mathcal{D}_{\text{tr}}$ and the calibration set $\mathcal{D}_{\text{cal}}$.
Fit the alignment score predictor with $\mathcal{D}_{\text{tr}}$: $g \leftarrow \mathcal{G}(\mathcal{D}_{\text{tr}})$.
Compute the predicted alignment score: $\widehat{A}_i \leftarrow g(X_i)$, $\forall i \in \mathcal{D}_{\text{cal}} \cup \mathcal{D}_{\text{test}}$.
for $j \in [m]$ do
    Compute the conformal p-values $p_j$ according to Equation (3.2).
end for
Apply BH to the conformal p-values: $\mathcal{S} \leftarrow \text{BH}(p_1 \dots, p_m)$.
Ensure: The selected units $\mathcal{S}$.
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It begins by computing the ground-truth alignment score A_i for each sample in the reference dataset $i \in [n] i \in [n]$ (a computation that requires a human reference), followed by splitting it into training set $\mathcal{D}_{tr}$ and calibration set $\mathcal{D}_{cal}$. The alignment score predictor model g is then trained using the training set to compute the predicted alignment score $\hat{A}_i$ to each sample in the training and the calibration sets. The method yields conformal p-values for each test unit $X_{n+j}, j \in [m]$, indicating how likely it is that the output is aligned, according to the conformal p-value formula:
$p_j = \frac{1+\sum_{i\in\mathcal{D}_{cal}} \mathbb{1}\{A_i \leq c, \hat{A}_i \geq \hat{A}_{n+j}}{|\mathcal{D}_{cal}|+1} \hat{A}_i$

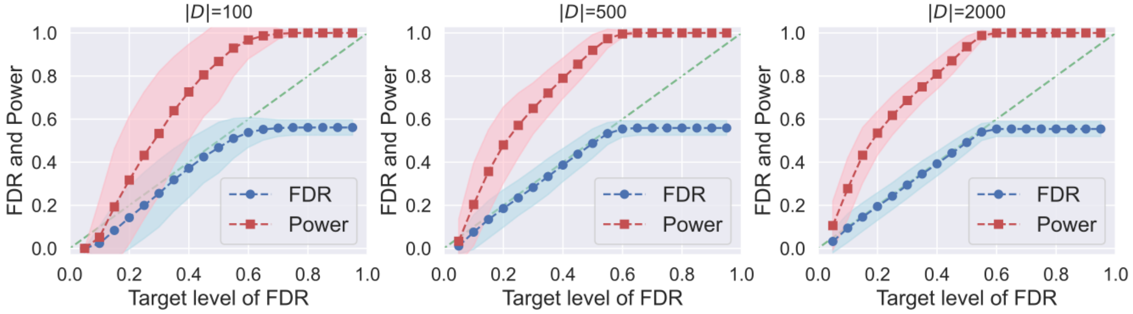
The p-value corresponds to the following null hypothesis: H_j: $A_{n+j} \leq c$. Rejecting H_j reflects evidence that the (true) alignment score of unit j is above the threshold c, and therefore the generated output $f(X_{n+j})$ is aligned. The threshold of p-values determined by the Benjamini-Hochberg procedure, as we saw in lecture 10: let $p_{(1)} \leq \cdots \leq p_{(m)}$ denote the ordered statistics of the conformal p-values, the rejection set is then $\mathcal{S} = \left\{ j \in [m] : p_j \leq \frac{\alpha k^*}{m} \right\}$, where $k^* = \max\left\{ k \in [m] : p_{(k)} \leq \frac{\alpha k}{m} \right\}$.

Overall, this framework aims to optimize the power, i.e. the proportion of selected aligned units out of all aligned test units: $Power = \mathbb{E}\left[\frac{\sum_{j\in[m]} \mathbb{1}\{A_{n+j} > c, j \in \mathcal{S}\}}{\max(\sum_{j\in[m]} \mathbb{1}\{A_{n+j} > c\}, 1)}\right]$, while strictly enforce the FDR constraint, i.e. the proportion of selected units that are not aligned: $FDR = \mathbb{E}\left[\frac{\sum_{j\in[m]} \mathbb{1}\{A_{n+j} \leq c, j \in \mathcal{S}\}}{\max(|\mathcal{S}|, 1)}\right] \leq \alpha$

Paper Results Analysis

The paper proposes two domains for testing their framework. One is the setting of generated radiology reports based on chest X-ray scans. Given a stream of reports, the goal is to select the most correct and aligned to human report, such that the proportion of false positives, i.e. selected reports that are not truly aligned, will be strictly controlled below a given α. The other domain is a question anwering task of LLMs, in which alignment means to select only correct answers.

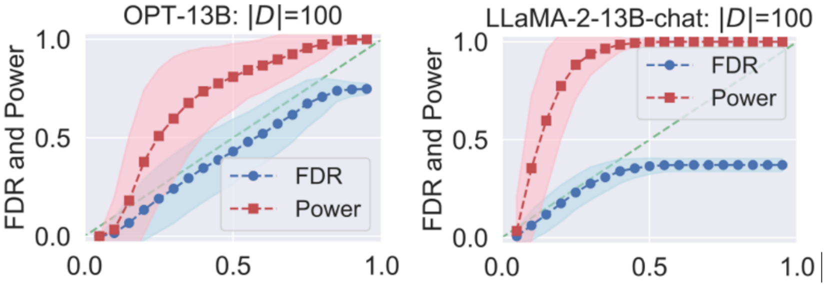
The results demonstrate that Conformal Alignment effectively controls the FDR, showing consistent error control even as the FDR target level increases. For example, Power vs. FDR levels of Conformal Alignment applied on the generated radiology reports of a pre-trained Vision-Transformer and GPT2 encoder-decoder model (figure 6):



Over 500 independent runs, the dots denote the expectancy, and the shaded area denotes the standard deviation. Each plot represents a different sample size of the reference set $|\mathcal{D}|$ used in the algorithm. It is noticeable that a few hundred high-quality samples are generally sufficient for effective procedure (500 on average), with larger sample sizes offering better stability in selection, demonstrating reduced variance in both FDR and Power.

Interestingly, the Power and the FDR curves converge simultaneously, i.e. for the same level of α; it's no coincidence. When the FDR becomes stably fixed, along with the Power that converges to 1, it means that all the test units were selected. It makes sense because we can't make more mistakes than the number of not aligned test samples exist.

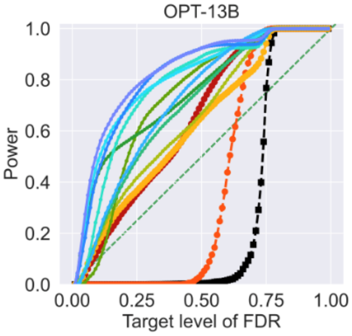
The writers also observed that more powerful model enables more powerful selection, especially when applying small values of α. For example, the question answering domain, they compared the results of the OPT-13B foundation model vs. the LlaMA-2-13B-chat (figure 3):



Clearly, the LlaMA-2-13B-chat is more powerful than OPT-13B: for $\alpha = 0.25$ the Power of the latter is almost 1, while the former results in slightly above 0.5.

In addition to the capability of the foundation model, the features used to train g also play a vital role in the power of selection. The writers divided them into 3 subgroups: **Self-evaluation likelihood** – the confidence level of f on its own generated outputs. **Input certainty scores** – the variability and uncertainty present in the inputs to the model. **Output confidence scores** – the consistency and confidence of the model's outputs based on their interrelationships. All the features for both domains in the paper were semantic and lexical properties of text using similarity measurements and LLMs, for example rouge-L similarity, the eigenvalues of the graph Laplacian of words embeddings, the pairwise distance based on a degree matrix, etc.

To test the informativeness of each feature and its effect on the Power curve, they conducted the same experiment but with a single feature at a time. In the right are the results on the question answering domain (figure 5). Each curve represents a feature. For the most effective features the Power quickly increases, wheras for the less informative features, no test units were selcted for $\alpha < 0.5$, but when $\alpha \geq 0.5$, the Power increases rapidly to 1, since all test units can be selected without violating the FDR constraint (as we saw in the previous plot, the number of not aligned test samples is 0.4-0.5).



Limitations

First of all, Conformal Alignment fits only on a large set of test units, as in multiple hypothesis testing. Therefore, for several tasks, we can't provide an imidiate decision. For example, a doctor who wishes to use a foundation model to generate a radiology report of an X-ray and test its reliability, must first collect another 400-500 scans before he can apply Conformal Alignment.

Secondly, the provided guerantee is only by expectancy: It's a game of chance. When using Conformal Alignment in practice with a single test set, it could return a selected set in which the FDR constraint really holds, but it might as well select only false positives. However, if we conduct continuous experiments as researchers, without employing the outputs for a practical use, it can help us evaluate the reliability of the foundation model in general.

Moreover, the framework requires to implement an algorithm that assigns a true alignment score to the reference dataset. Even though computer science research evolve with every passing day, sometimes it's just not possible for a computer to learn alignment to human values accurately. Even more challenging is engineer the features to train g. There are tasks that even humans can't deduce alignment without a reference. We met these limitations in our domain, which we will discuss further in the next sections.

Section 3: Creative Extension

For our creative extension, we chose to implement the Conformal Alignment framework in a different domain. While it was tempting to select a high-stakes task with the potential for real-world impact, we opted instead for a field we’re more familiar with, one that’s easier to explore and appreciate without expert assistance, and, quite frankly, a lot of fun: Art.

The golden era of visionary artists like Van Gogh and Rembrandt lies firmly rooted in the 19th century, stretching perhaps into the early 20th. With the advent of groundbreaking multimodal foundation models, particularly text-to-image generative models, a question naturally arises: might we now create new works reminiscent of Van Gogh's masterpieces?

This task was examined long before this project, but as far as we know, no one tried to apply conformal alignment to evaluate the quality of such generated paintings. We therefore formulated our goal: can we trust a model to generate a reliable art piece of the artist by our choice? To fit the domain to the Conformal Alignment framework, we focused on a slightly relaxed version of the task: instead of generating new paintings, we assessed the model’s ability to generate existing ones – those who have reference we can compare the generated paintings with.

f Pre-trained foundation model

DALL·E 3

We chose DALL-E3 as our foundation model. DALL-E is a text-to-image model developed by OpenAI using deep learning methodologies to generate digital images from natural language descriptions known as "prompts".

We chose DALL-E because it’s considered the state of the art for this task, aside from Midjourney and Stable Diffusion which were more expensive and harder to interface with. DALL-E can generate imagery in multiple styles, including photorealistic imagery and paintings. It can manipulate and rearrange objects in its images and correctly place design elements in novel compositions without explicit instruction.

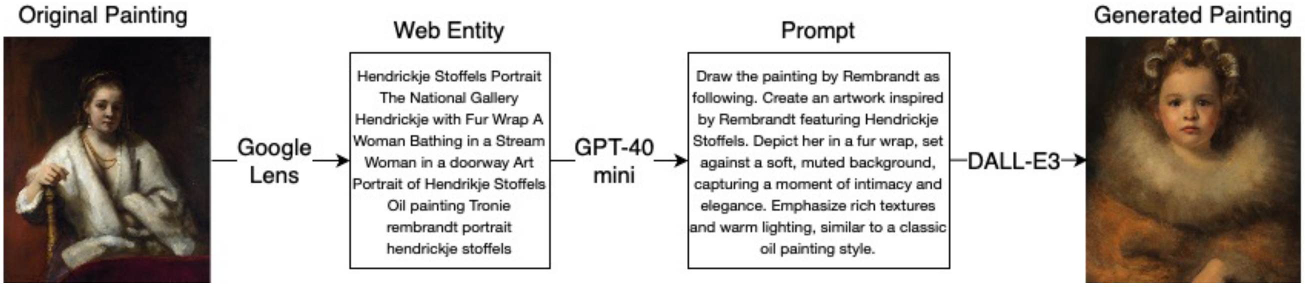
Dataset creation

One of the most challenging parts of our project was collecting the dataset. We needed at least 1000 paintings, each tagged with the piece’s name, artist name, and a prompt description of it. We started by downloading the Kaggle dataset “Best Artworks of All Time – Collection of Paintings of the 50 Most Influential Artists of All Time” [1]. We focused on 10 famous artists: Vincent van Gogh, Edgar Degas, Pablo Picasso, Pierre-Auguste Renoir, Albrecht Dürer, Paul Gauguin, Francisco Goya, Rembrandt, Alfred Sisley and Titian (Tiziano Vecellio).

Unfortunately, the paintings had only artists tags, without names or description. To cope, we took advantage of Google Lens, a deep learning model developed by Google, designed to bring up relevant information related to objects it identifies. For each painting, the model generated a web entity, which is a short summary of the painting: the piece’s name, the artist’s name, the style and the technique.

To generate the prompts, we used GPT-40 mini model. For each web entity, the model produced a short prompt that describes the painting: the objects, the colors and the general style.

Finally, we used DALL-E3 to generate paintings from the prompts. Aiming for 1000, we eventually managed to generate 898 samples. The reason is that some prompts were denied by DALL-E since they were inappropriate (for example nude art). A demonstration to summarize our pipeline with “Portrait of Hendrikje Stoffels” by Rembrandt:



Draw the painting by Rembrandt as following. Create an artwork inspired by Rembrandt featuring Hendrickje Stoffels. Depict her in a fur wrap, set against a soft, muted background, capturing a moment of intimacy and elegance. Emphasize rich textures and warm lighting, similar to a classic oil painting style.

Our data notations: X_i is a text prompt, $f(X_i)$ is a generated painting, and E_i is the reference (original painting). $\mathcal{D} = (X_i, E_i)_{i=1}^{n}$ is the reference dataset, $\mathcal{D}_{test} = \left(X_{n+j}\right)_{j=1}^{m}$ is the test dataset.

Dataset Split

The proportion of datasets in splitting was a key hyperparameter in the paper. We could have learned the optimal splitting, but we eventually decided to focus on more important tasks. We fixed $|\mathcal{D}_{test}| = 405$ so that the BH procedure will have a sufficient number of samples to conduct the statistical testing. Left with $|\mathcal{D}| = 493$, we split the train and calibration sets approximately similar to the experiments in the paper: $|\mathcal{D}_{calib}| = 0.6 \cdot |\mathcal{D}| = 296, |\mathcal{D}_{tr}| = 0.4 \cdot |\mathcal{D}| = 197$

$\mathcal{A}$ Alignment score function

To compute the true alignment score $A_i = \mathcal{A}(f(X_i), E_i), \forall i \in [n]$, we had to come up with a way to compare the generated images to their references. We experimented with a few similarity measurements to test if the generated image and the reference are visually akin, and eventually decided to measure 4 aspects of similarity:

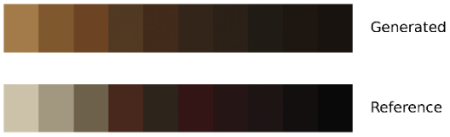
1. **Structural similarity –** we computed the SSIM index [3], which aims to approximate an objective image quality based on structures that are perceived by human visual system. It performed poorly on high dimensions, so we first resized the images to a smaller size and transformed them to black and white pixels.
2. **Style similarity –** inspired by the style loss formulation of the Neural Style Transfer task [5], which measures the correlation between features after each layer, we computed the L1 distance of the gram matrices of the images.
3. **Features similarity –** we used the pre-trained VGG16 deep learning model [4]. We fed the images to the model to extract features and produce image embeddings, which we then computed their cosine similarity.

4. **Color similarity** – we generated a color palette of the 10 most bold colors of each image and measured the palettes' distance after transforming the RGB colors to the CIELAB color space [(6)]. It is designed to be perceptually uniform; the Euclidean distance between two colors in this space more accurately reflects perceived differences.

For each aspect of the above, we calculated a score between the generated image and the reference. To determine the quality of the scores, we sampled another 10 independent images and 10 independent random noises and calculated the score between them and the generated image (total of 21 scores). If the generated image and the reference have better scores than the generated image and all the other samples, they are most likely to be aligned. We summed the indices of the former in the sorted scores array over each similarity aspect and normalized it to a value between 0 and 1. Formally: $A_i = \frac{\text{argsort}(S_{ssim}, s^*_{ssim}) + \text{argsort}(S_{style}, s^*_{style}) + \text{argsort}(S_{features}, s^*_{features}) + \text{argsort}(S_{color}, s^*_{color})}{4 \cdot 21}$

Where S_a is the array of scores of the aspect a, the a score between the generated image and the real reference is s^*_a, and $\text{argsort}(S_a, s^*)$ is the index of s^* in the sorted S_a.

Demonstrating again on the "Portrait of Hendrikje Stoffels" by Rembrandt, the SSIM score was 0.01476, the style distance was 2.9908, the features embeddings cosine similarity was 0.6715, and the palette distance was 9.4653. Those are not optimal scores by no means, but they were the highest among all the other false references, hence the alignment score was 1.0. Visually, they indeed seem very similar. To sense the color similarity, we displayed the color palettes below.



Features used for learning $\hat{A}$

As discussed in the previous section, identifying informative features for training the alignment predictor is crucial, since the power of Conformal Alignment depends on how well g discerns those $A > c$ against those $A \leq c$. Unlike in the paper's research, however, we could not extract DALL-E's confidence in its generated outputs. Furthermore, refining the semantic and lexical properties of text using similarity measures and LLMs, as applied in the paper, was not suitable for our context, since we needed to assess the alignment of an image. We needed to explore by trial and error how to formulate features suitable for g.

Our primary concern was whether the generated painting aligns with the original artist's style. To cope, we trained our own artist classifier[(2)] on Google Colab's GPUs. We implemented the architecture of ResNet50 neural network and trained it on the reference paintings dataset of the 10 artists we selected for our task. The output of the model's inference is softmax probabilities, indicating which artist has most likely drawn the input painting. We anticipated that if the generated painting is truly similar to the artist's art style, our model would be able to classify it correctly.

Our second task was to determine whether the generated painting matches the prompt requirements. To do so, we used Facebook's pre-trained DETR (DEtection Transformer) model with ResNet-50 backbone [7] to detect the objects in the generated painting. After receiving a list of detected objects (regardless of their positions), we counted how many of these objects the prompt and the image have in common as follows: For each object we checked if the prompt contains it. If not, it still doesn't mean that they are not aligned; For example, a common scenario was where the object detection model recognized a "person" in the image, while the prompt required a dancer. Even though the prompt doesn't contain the word "person", a dancer is semantically contained. To address this problem, we used Facebook's pre-trained NLI-based zero shot text classification model named BART-Large-MNLI [8] to infer whether the prompt was asking to generate the object.

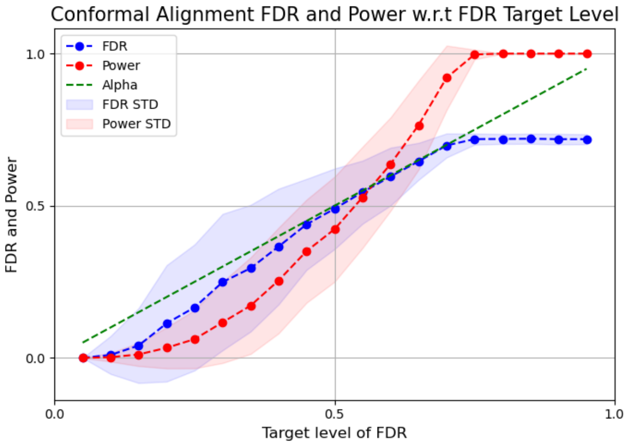
Overall, the feature vector of each generated painting was a concatenation of the artist classifier's output, a one hot vector indicating the ground truth artist (extracted from the prompt), and the number of shared objects between the prompt and the image.

$\mathcal{G}$ Alignment predictor fitting algorithm

To train the alignment predictor g, we used XGBoost, one of the most popular machine learning frameworks among data scientists for tabular data. We ran logistic regression with binary cross entropy loss, since $A_i \in [0,1]$ we can consider it as the probability to be aligned and learn its distribution.

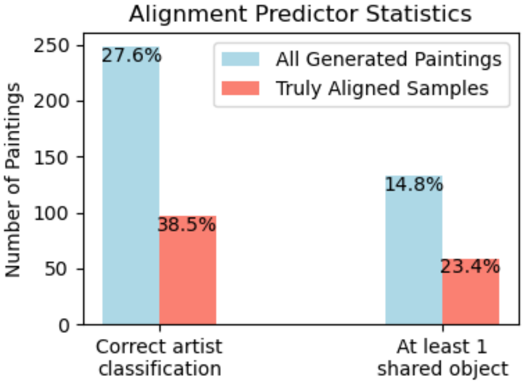
Results

With alignment level of $c = 0.8$, we conducted 500 independent random data-splits and computed the Power and the FDR over 20 different values of FDR target level:

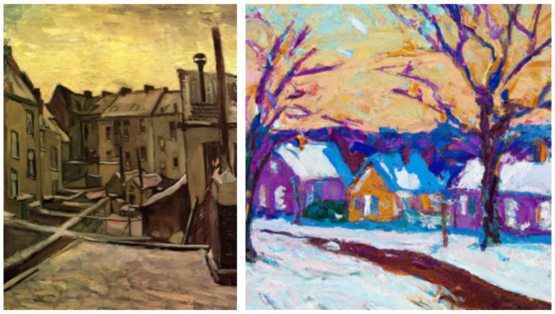


Although the results demonstrate strict control over the FDR level, the standard deviation is relatively large. As discussed in the paper, that might indicate that we didn't have a sufficient sample size. The Power we experience is also sub-optimal, compared to the results shown in the paper. As we mentioned in the previous section, the features used to train g play a vital role in the power of selection. The Power curve indeed reminds of the poor features curves in figure 5. Hence, we took a closer look at the ability of the features in measuring alignment.

Both the artist classification performance and the object detection performance were not in our favor: among all the 898 generated paintings, 248 were classified to the correct artist, while among 252 truly aligned samples, only 97 generated paintings were classified correctly. This means that it might mislead the alignment predictor to think that a true classification is reversely correlated to alignment. Furthermore, among all the 898 generated paintings, 133 share at least 1 semantic object with the prompt, whereas among 252 truly aligned samples, only 59 generated paintings hold that property. The reason is that many generated paintings feature abstract elements, lacking distinct lines or clear separation from the background.



However, the most obvious reason for the poor quality of the results is that DALL-E is generally not aligned to artist's style. It has a unique style of its own ☺ It's evidential that nearly all the generated paintings had brighter and more vivid colors than their reference. Most of the paintings displayed an impressionist brushstroke technique typical of oil paintings, despite the original reference having a different style. Furthermore, for some paintings, the prompts generated with GPT did not accurately describe the artwork, and the web entity data obtained from Google Lens was not always precise or detailed, resulting in less accurate generations. For example:



Van-Gogh's "Houses seen from the back" (the generated on the right), alignment score 0.4285. Th artist classifier decided it is a painting by Van-Gogh with probability 0.03, no objects detected. The prompt required to feature "charming houses in vibrant colors, contrasting the white snow". Obviously, that is not a good description of the painting.

Interestingly, 31 aligned samples were classified correctly and shared at least 1 semantic object with their prompt, 26 of them were paintings by Rembrandt, 4 Titian's and 1 Paul Gauguin's. This is not a surprise; Rembrandt's paintings are easy to learn, since they are more realistic (their objects are likely detectable) and their colors are uniformly in shades of brown, distinguishable from the others.

Conclusion and Future Works

To conclude, our work examines the application of Conformal Prediction in the complex domain of art imitation, specifically utilizing generative models like DALL-E to capture and evaluate stylistic fidelity. We observed the sensitivity of the Conformal Alignment framework, emphasizing challenges in performance when there is not a sufficient amount of data or when the data quality is poor. Those challenges raise questions about the framework's robustness in high-stakes applications. Another conclusion of ours is that implementing Conformal Prediction for art imitation poses significant challenges due to the complexity of the task of capturing artistic style.

Using DALL-E to generate imitated paintings, we found that the model has limited ability to capture a range of diverse art styles.

We suggest the following directions to extend and improve our work: Comparing the performance and stylistic versatility of DALL-E with other text-to-image generative models, such as Midjourney and Stable Diffusion; Investigate advanced feature sets to deepen the analysis of true alignment (A score) versus predicted alignment (g score) and refine predictive accuracy; Improve dataset quality by generating more precise prompts and enhancing web entity descriptions, thereby increasing the robustness of the generated outputs. Other directions that we think are interesting to further explore are: Explore the potential of applying Simes' procedure and try to control FWER rather than FDR, or alternatively, use Simes' to control the FDR, which aligns more closely with the objectives of the main algorithm in the article. Simes' procedure may be particularly useful here, as it handles dependent data effectively, a key consideration in our art-focused context and in high-stakes medical applications where dependencies are prevalent as well; Explore knockoffs to improve feature assessment for constructing g during the process.

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