A Machine Learning Paradigm for Studying Pictorial Realism: How Accurate Are Constable's Clouds?

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Abstract—The British landscape painter John Constable is considered foundational for the Realist movement in 19th-century European painting. Constable's painted skies, in particular, were seen as remarkably accurate by his contemporaries, an impression shared by many viewers today. Yet, assessing the accuracy of realist paintings like Constable's is subjective or intuitive, even for professional art historians, making it difficult to say with certainty what set Constable's skies apart from those of his contemporaries. Our goal is to contribute to a more objective understanding of Constable's realism. We propose a new machine-learning-based paradigm for studying pictorial realism in an explainable way. Our framework assesses realism by measuring the similarity between clouds painted by artists noted for their skies, like Constable, and photographs of clouds. The experimental results of cloud classification show that Constable approximates more consistently than his contemporaries the formal features of actual clouds in his paintings. The study, as a novel interdisciplinary approach that combines computer vision and machine learning, meteorology, and art history, is a springboard for broader and deeper analyses of pictorial realism.

Index Terms—Pictorial realism, John Constable, cloud classification, feature fusion, style disentanglement.

1 Introduction

In this paper, we propose a new machine learning paradigm for studying the European art style known as realism. The specific case study we report here is the work of John Constable (1776-1837) whose landscape paintings are considered foundational for the Realist movement. Constable was especially renowned for his skies. Although there is general agreement that Constable's sky paintings are persuasive in their realism, the precise basis for his realism continues to be debated. The feasibility of quantitative analysis for studying pictorial realism, as exemplified here, demonstrates that computational approaches may augment traditional approaches to art-historical research.

Fig. 1: Two *Cloud Study* oil paintings by John Constable (1822). Left: Yale Center for British Art. Right: The Frick Collection.

1.1 The Art-Historical Questions

In 1821, Constable undertook a sustained campaign of "skying," as he called his outdoor sketching of clouds. There is general art-historical agreement that Constable's painted clouds became more life-like around this time (Fig. 1) [1], [2]. The significance of this period of concentrated effort has been debated [2], [3], [4]. Some see Constable's cloud paintings of this period as confirmation that the artist's powers of observation improved as a consequence of prolonged study, enabling him to execute more convincing clouds [5]. Yet faithful visual documentation of clouds is challenging because they are *constantly changing*. It seems reasonable to posit that Constable relied on certain artistic conventions or formal patterns for his paintings of these ever-shifting motifs, as painters often did. It has also been argued that the 1821 skying campaign was a belated response to the 1803 publication of Luke Howard's typology of clouds into cumulus, cirrus, stratus, etc. [6], though there is no direct evidence that Constable consulted Howard's publication [7]. Scholars remain in disagreement about the degree to which Constable relied strictly on empirical observation, on visual formulae that might escape the notice of human viewers, or on a new understanding of how to distinguish and thus represent different types of clouds [2], [3], [4]. To some extent, scholarly disagreement arises from the fact that human viewers may not perceive or may perceive only with difficulty qualities like cloud accuracy or visual conventions that have been naturalized through regular use by European artists. Our goal is to contribute to a more accurate understanding of Constable's realism via three paths of inquiry:

1) Do Constable's clouds correspond with the system of cloud typology introduced in 1803 by Luke Howard?
2) How closely do Constable's paintings emulate the appearance of actual clouds when compared to photographs of clouds?
3) How does the empirical accuracy of Constable's clouds compare with that of his contemporaries when judged against photographs of clouds?

1.2 Overview of Our Approach

These judgments about realism from art historians are highly subjective insofar as they record the opinion of a particular viewer at a particular moment. The perceived fidelity of a painting to the natural phenomena it represents cannot always be clearly explained, because it is guided by an immediate, intuitive response to a particular painting. This is especially true of hard-to-describe phenomena like clouds or crashing waves: for most human viewers, paintings of these subjects simply "look right" or not. To provide a more objective assessment of realism, we introduce a

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machine-learning-based analysis procedure. As shown in Fig. 2, this method comprises two components: classification of painted content (cloud in this case) and evaluation of painting style. In a nutshell, we evaluate pictorial realism by assessing the similarity between paintings and photographs in terms of both the painted content and painting style, which makes our evaluation system more thorough and unbiased [8].

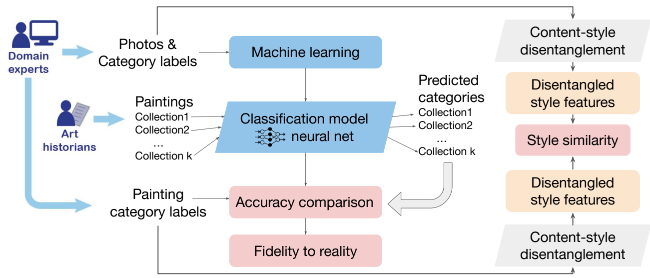


Fig. 2: The proposed machine learning paradigm for studying pictorial realism.

After obtaining a labeled dataset containing both photographic images of clouds and a collection of sky paintings, we first train a machine learning system using these photographs to classify cloud categories. We then apply this classifier to our painting set to predict their cloud categories. In the meantime, classification labels are created for the paintings by experts (meteorologists). The classification accuracy for the paintings is then computed and compared with the accuracy achieved for photographs. Our basic assumption is that the classification accuracy of paintings that imitate observed reality well will be close to that obtained for the photos. Further comparison can be conducted between different collections of paintings, allowing assessment of the relative fidelity of various collections to nature. One type of comparison across collections is between works by different artists. Our labeling relies on the expertise of meteorologists to categorize clouds documented in photographs and paintings according to the types defined by Howard [9]. We propose a semi-supervised learning model for cloud classification that merges classic features with edge features. The classification of clouds in Constable's paintings according to the standard typology allows for a more precise comparison with his contemporaries. By contrasting the AI system's predictions with the expert-created ground truth labels, we obtain an objective assessment of the degree to which painters are (knowingly or unknowingly) differentiating cloud types. Given the highly specialized skills and knowledge required to classify cloud types, the AI system offers an insight unattainable by the average human viewer.

Furthermore, to further explore painting styles, we examine pictorial realism from another perspective of painting style. Specifically, we first extract the encoded style features from each painter's collection by training a content-style-disentanglement model [10]. Using our newly developed evaluation metrics, we assess the pictorial realism based on these extracted style features. This allows us to compare the relative realism of various painting styles in our dataset against that of John Constable. These style features act as direct representations of the unique pictorial characteristics of each painter's collection in comparison to photographic images.

The **key contributions** of our work include:

- *Interdisciplinary framework:* We proposed a machine learning framework to study realism in art from an explainable and interdisciplinary perspective by leveraging computer vision techniques, meteorology expertise, and art history insights.
- *Methodology:* We developed several tools and models: a sky-ground segmentation algorithm, a new semi-supervised CNN model (named SFF-CNN) for cloud-type classification, and new evaluation metrics to quantify the style differences between images. Notably, this is the first effort to harness unlabeled sky photos to enhance cloud classification.
- *Dataset:* We curated a unique dataset consisting of 363 paintings featuring skies by John Constable and six of his contemporaries. Two expert meteorologists professionally annotated each piece, making it the inaugural dataset of paintings designed for computational analysis of skies. We are sharing our sky segmentation results and detailed annotations with the broader research community.
- *Insights:* Our findings furnish the art history domain with compelling evidence: *Constable's systematic adherence to cloud typologies is pivotal for the pronounced realism in his cloud artworks.*

1.3 Related Work

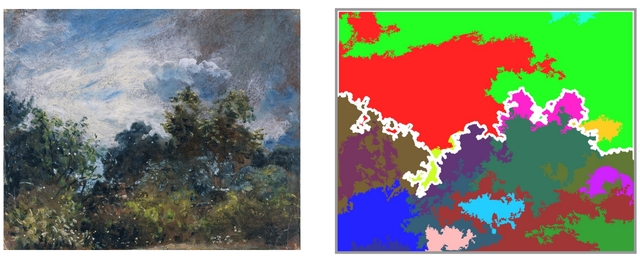
We briefly introduce related work on the art-historical study of Constable's sky paintings, computerized cloud-type classification, and content-style disentanglement.

Modern art-historical scholarship on Constable's clouds began with Kurt Badt's 1950 book on the subject [7]. Prior to this, accounts of Constable's clouds were largely descriptive as opposed to analytical, attributing their realism to Constable's emotional connection with nature, his devotion to sketching outdoors, or his largely rural childhood [11]. Badt was the first to argue that Constable's proficiency with painting realistic clouds was due to his familiarity with the recent development of a typology of clouds created by British chemist Luke Howard. Howard's typology was published in 1803 and was widely disseminated during Constable's lifetime, so it was available to him. But there is no evidence that Constable possessed Howard's typology, and the artist's extant correspondence makes no direct reference to Howard [12]. More recent scholars tend to cite instead Constable's dedication to sustained periods of empirical observation of clouds [1], [5] and his familiarity with earlier paintings of naturalistic landscapes by artists like Claude Lorrain or Willem van de Velde the Younger, both of whom were well represented in English art collections during Constable's lifetime [12], [13]. In addition, a Romantic explanation for Constable's naturalism likewise persists in the scholarly literature to this day, attributing his naturalism at least in part to an emotional or spiritual impulse toward accuracy in his depictions of natural phenomena [2].

We regard the accuracy of cloud-type classification as strong evidence of Constable's familiarity with Howard's typology, so building a trustworthy cloud-type classifier is indispensable. Recently, researchers have started to adopt CNNs for cloud-type classification. Zhang *et al.* [14], [15] built a large ground-based cloud dataset, called Cirrus Cumulus Stratus Nimbus (CCSN) with cloud type labels, and a CNN model for cloud classification. Huertas *et al.* [16] proposed a feature fusion model combining CNN features and handcrafted low-level textural features to boost classification accuracy. Departing from this fusion model, our approach aims to extract more task-relevant features such as the contours of clouds to improve classification on both the photo and painting datasets.

Another problem that we address is the lack of labeled cloud photos. The emergence of semi-supervised learning can enhance classification performance by utilizing a great amount of unlabeled data during the training process. The common semi-supervised classification models can be categorized into self-learning [17], co-training [18], graph-based semi-supervised learning [19], and semi-supervised supported vector machine [20]. Following the idea of self-learning, we generate pseudo labels (detailed in Section 2.1.3) for two unlabeled sky photo datasets and then add these new data to the labeled CCSN dataset to achieve dataset expansion.

Content-style disentanglement has been extensively applied for feature decoupling, with both the content and style feature representations useful for downstream problems, such as semantic segmentation [21], [22], image retrieval [23], [24], and image style transfer [25], [26]. In image translation, most CNN-based methods aim to learn latent space representations by extracting content or style information using autoencoder variants. However, utilizing these disentangled features for similarity or discrepancy comparison among paintings from different artists–as we have done in this study–is a relatively uncharted territory.



(a) John Constable, *Study of Sky and Trees*, 1821

(b) Eugène Boudin, *Etaples, les Bords de la Canche*, 1891

Fig. 3: Sky and ground segmentation illustrated with two paintings. Left: Original paintings. Right: Homogeneous patches (represented by different colors) generated using the A3C algorithm. Regions within the thin white contours are the sky regions after regression.

2 Algorithms

As we have discussed in Section 1.2, our paradigm for studying pictorial realism (Fig. 2) provides a novel perspective for comparing artworks with photographs and addresses the subjectivity of experts' opinions. Below, we elaborate on the technical components in the analysis pipeline.

2.1 Semi-Supervised Cloud-Type Classification

Our classification model consists of two main steps: clustering-based sky segmentation and classification by a *semi-supervised feature fusion CNN* (SFF-CNN) model. The sky segmentation step reduces the impact of irrelevant parts of an image on classification. SFF-CNN contains two streams of feature extraction, aptly called the *classic feature extractor* and *edge feature extractor*. The former generates features from low-level textures or patterns to high-level object-related characteristics, while the latter focuses on edge information. The fused features from the two encoders are utilized together for the ultimate class label prediction. We are motivated to extend a typical CNN model by incorporating edge features because (1) the contour information of cloud bases and updraft turrets is valuable for meteorologists to determine the cloud type, and (2) CNN models tend to focus on texture rather than shape for recognition [27] while paintings and photos have different texture characteristics. Our extended CNN model is trained iteratively by generating pseudo labels for unlabeled images and then refitting the model.

2.1.1 Sky Segmentation

The land, mountains, or other irrelevant regions in a painting can negatively affect cloud classification. Because only sky regions are used in the training photos, we eliminate the impact of other irrelevant parts in the paintings by excluding pixels outside the sky region from subsequent classification analysis. Specifically, a painting is segmented into two classes: sky versus non-sky (mostly land). The entire non-sky region of a painting image is replaced by black pixels and the modified image becomes the input to the CNN model, which we refer to as the *sky-selected image*.

Our sky segmentation algorithm includes two major steps: segmentation into homogeneous patches (aka, segment) and classification of each segment into sky versus non-sky. For the first step, we used the Agglomerative Connectivity Constrained Clustering (A3C) algorithm [28]. For the second step, we perform logistic regression on the features extracted from each segment to determine whether the segment is sky or non-sky. For each segment, a 10-dimensional feature vector including location and color-based features is computed. Details about the sky detection algorithm and some example results are provided in Supplementary Materials. Fig. 3 shows the clustering results of two paintings and the sky versus non-sky classification results of the segments.

2.1.2 Cloud-Type Classification

The sky-selected images are classified into different cloud types by the SFF-CNN model. Our neural network is custom-designed for cloud-type classification by incorporating pre-learned edge features into the layers of a typical CNN model as edge information is crucial in differentiating various types of clouds. The neural network consists of a bottom stream for classic feature extraction and a top stream for edge feature extraction. The classic feature extractor aims at extracting useful features from low-level textures or patterns to high-level object-related quantities, while the edge feature extractor only captures the characteristics of edges in the same input image. Both feature extractors take the three-color-channel sky-selected images as the input.

Classic Feature Extraction: Denote the kth sky-selected image by $\mathbf{I}_k$. The encoder for classic feature extraction takes the three-color-channel image $\mathbf{I}_k$ as the input. The first two convolutional blocks both consist of two Conv-BatchNorm-Relu layers and are followed by a 2×2 pooling layer to downsample the input feature maps (400×400). The convolutional layers in these two blocks all have stride set to 1 and the kernel size 3×3. The next two blocks are residual blocks with two convolutional layers with stride set to 1 and 2, respectively, and the same kernel size 3×3. Each of these blocks spatially downsamples the input feature maps to half of their size. The third residual convolutional module follows the same structure as the first two but sets stride to 1 for both convolutional layers. Then three fully-connected layers with feature dimensions 4096, 1024, and 10, respectively, are connected to the Resconv modules. The final layer of Softmax activation produces a distribution over the ten output probability classes for each category. Lastly, the cross-entropy (CE) loss [29] is applied to train the network.

Edge Feature Extraction: Visualization results using the Grad-cam method [30] (shown in Supplementary Materials) verified our expectation that edge information is important for classifying cloud types, which motivated our strategy to fuse edge features in the CNN. We compute the edge features by a pre-trained encoder named holistically-nested features for edge detection (HED) [31]. The side-output layer of each convolution module of HED generates an edge feature map at a particular receptive field size. These maps are concatenated with those generated by the CNN at corresponding layers. The two feature maps are ensured to have the same size (horizontally and vertically) such that the features at any location on one map can be combined with features at the same location on another map before convolution. In particular, we use the same setting for the HED and CNN architectures so that at every layer, their respective feature maps are generated with the same receptive field size. The augmented feature map is the input to the next convolution layer.

2.1.3 Semi-Supervised Learning

To further enhance cloud classification accuracy, we employ semi-supervised learning to leverage a large set of 9,883 unlabeled cloud photos from the SkyFinder dataset [32] and FindMeASky dataset [33]. We also apply data augmentation following the schemes of FixMatch [17]. For each unlabeled image, its flipped and shifted versions, called weak augmentation images, are created. Additionally, the so-called strong augmentation images are created by another two operations, namely, CTAugment followed by Cutout [17]. We first apply the classifier trained using only the labeled images to classify the weak augmentation images. The class that has the maximum predicted posterior probability is chosen as the predicted class (also called the one-hot pseudo label). To counter the negative effect of possibly incorrect pseudo labels, the maximum predicted posterior is compared with a pre-chosen threshold. If the threshold is not exceeded, this unlabeled image and its augmented versions will not be used further. Otherwise, the pseudo label is treated as the true label for the strong augmentation images, which we refer to as high-confidence unlabeled images. Finally, another round of training is performed using both labeled and high-confidence unlabeled images. The cross-entropy between the true class and the labeled images and between the pseudo-class generated from the weak-augmented images and the predicted class posteriors using the strong-augmented images are defined as the loss to train the model.

2.2 Style Disentanglement

In addition to comparing paintings based on how well they can be classified, we propose a methodology to assess the similarity in the "style" features of pictures. In MUNIT [10], an image is decomposed into two representations: content versus style. Both the content and style features are extracted by an encoding CNN, and they can be combined as input to a decoding CNN to reconstruct the original image. Roughly speaking, the content features capture the shared characteristics between two sets of images, whereas the style features pinpoint the unique attributes of each set. The encoders and decoders for both image sets are trained together to ensure that the content features correspond to traits shared by the two sets.

In our analysis, we treat the set of paintings of every artist as domain $\mathscr{A}$ and the set of cloud photographs as the reference domain $\mathscr{P}$. This training process yields a content encoder and a style encoder for each artist. The training algorithm generates photo-realistic images $I_{\mathscr{A}2\mathscr{P}}$ from images in domain $\mathscr{A}$ or painting-like images $I_{\mathscr{P}2\mathscr{A}}$ from those in domain $\mathscr{P}$, an operation called "cross-domain style translation." The translation is achieved by keeping the content features but adopting style features generated for an image in the other domain. These cross-domain features are fed into a decoder to reconstruct a translated picture. The training objective function used in [10] has been modified slightly in [34] by removing the learning regression loss because the authors of the latter found that better separation of content and style can be obtained and the style and input image will be more correlated. In subsequent discussions, we will refer to the style features computed via a style encoder simply as the "style" of an image.

2.2.1 Style Similarity Between Artists

First, to evaluate style similarity between artists, we consider two sets of paintings denoted by A and B. Suppose $A = \{a_i : i \in \{1, 2, ..., n_A\}\}$ contains n_A pictures and $B = \{b_j : j \in \{1, 2, ..., n_B\}\}$ contains n_B pictures. Denote the content and style encoder trained based on style transfer from painting set A to photo set $P = \{p_k : k \in \{1, 2, ..., n_P\}\}$ by E_C^A and E_S^A, respectively. Likewise, the encoders for B are E_C^B and E_S^B. For an image $a_i \in A$, denote its style features computed by E_S^A by $F_S^{a_i}$. Similarly, for any $b_j \in B$, let its style computed by E_S^B be $F_S^{b_j}$. If A and B are similar in style, we would expect $F_S^{a_i}$ and $F_S^{b_j}$ to be close on average. Use the normalized square of the L^2 norm of a style feature vector to indicate the signal strength: $I_S^{a_i} = \|F_S^{a_i}\|^2/d$, where d is the dimension of the style feature vector. The Mean Squared Error (MSE) between $F_S^{a_i}$ and $F_S^{b_j}$ is simply $\|F_S^{a_i} - F_S^{b_j}\|^2/d$. For each image $a_i \in A$, we define its average distance to images in B by

$$D_A^{a_i} = \frac{1}{n_B} \sum_{b_j \in B} \frac{\text{MSE}(F_S^{a_i}, F_S^{b_j})}{I_S^{a_i}} . \quad (1)$$

Conversely, for each image $b_j \in B$, we define its average distance to images in A as $D_B^{b_j}$ likewise. Finally, define $D_A = \frac{1}{n_A} \sum_{a_i \in A} D_A^{a_i}$, $D_B = \frac{1}{n_B} \sum_{b_j \in B} D_B^{b_j}$, and

$$D_{\text{style}}(A, B) = \frac{1}{2}(D_A + D_B). \quad (2)$$

The distance D_{style} is taken to measure the style difference between sets A and B.

2.2.2 Style Similarity Between an Artist and Photos

Next, we propose to use the metric "Information Over Bias (IOB)" [34] to measure the difference between the paintings of an artist and real photos. For an image $a_i \in A$, where a_i is treated as a vector, let its style feature vector be $F_S^{a_i}$. $\text{IOB}(a_i, F_S^{a_i})$ is defined to quantify the amount of information in a_i which is captured by $F_S^{a_i}$. Specifically, the informativeness of $F_S^{a_i}$ is measured by the ratio between $\text{MSE}(a_i, \widetilde{a_i}')$ and $\text{MSE}(a_i, \widetilde{a_i})$, where $\widetilde{a}_i{}'$ is a reconstructed image from an uninformative constant substitute style vector $\mathbb{1}$ combined with a_i's content feature vector, while $\widetilde{a}_i$ is generated from the informative style vector $F_S^{a_i}$ and the same content vector. Thus, we define $\text{IOB}(a_i, F_S^{a_i})$ by $\text{IOB}(a_i, F_S^{a_i}) = \text{MSE}(a_i, \widetilde{a}_i{}')/\text{MSE}(a_i, \widetilde{a}_i)$. With a slight abuse of notation, we also use $\text{IOB}(A)$ to denote the average IOB values for the images in A, i.e., $\text{IOB}(A) = \frac{1}{n_A}\sum_{i=1}^{n_A} \text{IOB}(a_i, F_S^{a_i})$. A lower value of $\text{IOB}(A)$ indicates that the style representation of the image is less important since a substitute default style vector can result in reconstruction with a similar level of disparity from the original image. Because the style feature vectors capture the distinct characteristics of one set of images from another set, less informative style vectors reflect a higher similarity between the two set of images. To form a basis of comparison, we also compute IOB for a mixed set containing both paintings and cloud photographs. Specifically, we first compute $\text{IOB}(A)$ for a set of paintings by an artist using the style transfer process from paintings to photographs. Then we mix images from the painting set A and the photo set P to form a new set $M = \{a_i : i \in \{1, 2, ..., n_A\},\ p_k : k \in \{1, 2, ..., n_P\}\}$. Again by the style transfer process from set M to P, we can compute $\text{IOB}(M)$. Finally, the style distance between an artist and the photographs is defined as $R_{\text{style}}(A) = \text{IOB}(M)/\text{IOB}(A)$.

3 Experimental Results

3.1 Painting and Photo Datasets

We curated a dataset of oil paintings by John Constable (1776-1837) and six of his near-contemporaries: Pierre Henri de Valenciennes (1750-1819), David Cox (1783-1859), Frederick Richard Lee (1798-1879), Frederick W. Watts (1800-1870), Eugène Boudin (1824-1898), and Lionel Constable (1828-1887). All of these images are either high-resolution scans of existing reproductions or digital photographs of landscape paintings with "finished" clouds or pure cloud studies.

Cloud types and detailed meteorological information for each painting in the dataset were labeled by two meteorologists with expertise in cloud classification. One annotator possesses basic knowledge of the history of European landscape painting, while the other does not. Post their initial round of labeling, the two experts reached consensus on 75.5% of the labels. They both recognized that the majority of different annotations were due to borderline cases. Following a discussion between the experts, the labels used in the subsequent experiments were mostly based on the senior annotator's annotations, while the labels of 15 paintings were in accordance with the junior annotator's opinion. Finally, an open dataset containing 363 images with detailed labeled metadata was established, which will be shared (to the extent that image licensing allows) in order to facilitate further analyses of the relation between painted clouds and actual meteorological phenomena.

We used the CCSN dataset to train the cloud classification model. The CCSN dataset contains 2,543 cloud images, in which cloud photographs were labeled into 10 cloud categories, thus we formulated cloud-type classification as a 10-class problem. For semi-supervised learning, we leveraged the SkyFinder [32] and FindMeASky [33] datasets, which came with the sky segmentation masks but no cloud-type labels. After eliminating duplicate images, our unlabeled dataset comprised 9,883 photos.

3.2 Cloud Classification on the Paintings

To evaluate our sky segmentation algorithm, we manually labeled sky regions for all 363 paintings, which serve as the ground truth. We then computed pixel accuracy, mean accuracy, and mean IoU as evaluation metrics, which were 0.9804, 0.9613, and 0.9427, respectively. Such accuracy levels are regarded as high.

Applying the trained SFF-CNN to the test photo images (20% of the CCSN dataset), we obtained a classification precision of 97.2% and recall of 96.9%. Detailed results on the test photos are provided in Section 3.5. Then, we re-trained the classification model on the entire CCSN dataset, which was then applied to the paintings. Because the painting dataset was small and the prevalence of different cloud types was highly unbalanced, to compute classification accuracy for the paintings, we only discriminated at the granularity of five common cloud types: cumuliform (cumulus), cumulonimbiform (cumulonimbus), cirriform (cirrus), stratiform (stratus, cirrostratus, altostratus, and nimbostratus), and stratocumuliform (cirrocumulus, altocumulus, and stratocumulus) [35]. The classification accuracy of each painter using the SFF-CNN model with or without feature fusion is shown in Fig. 4. For the accuracy achieved with feature fusion, the confidence interval for the accuracy at the significance level of 0.05 is shown. Except for Cox, all the other artists had a confidence interval of accuracy well above 60% (higher than the percentage of the most dominant cloud type), indicating that the clouds they painted correspond with Luke Howard's system of cloud categorization to a great extent. Moreover, clouds painted by Constable were the easiest to classify (highest accuracy) with a classification accuracy of 0.8452. Additionally, in Fig. 5, we show the classification confusion matrices for each artist's paintings. Constable's clouds achieved the highest classification accuracy in the cumuliform.

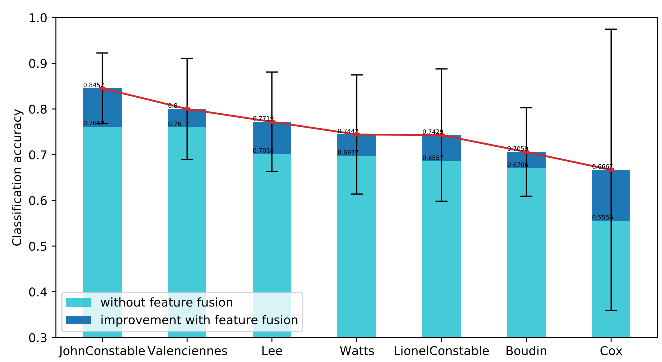
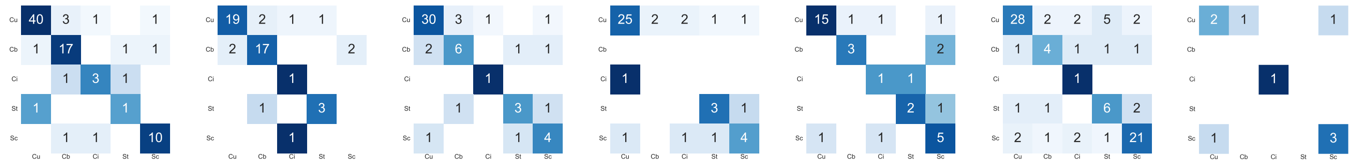


Fig. 4: The comparison in terms of classification accuracy of all seven painters using the SFF-CNN model with or without feature fusion. The error bars denote the confidence interval for the classification accuracy at the significance level of 0.05 for each painter.

To compare Constable with each of the other artists, we conducted hypothesis testing with the alternative hypothesis: Constable's paintings can be more accurately classified than those of other artists. We assigned identification numbers with Constable represented by 1 and the other artists labeled as $2, 3, ..., 7$. We modeled the classification decision on a painting of the ith artist by a Bernoulli random variable with 1 indicating the correct classification and 0 otherwise. Let p_i be the probability of correct classification. Thus, the distribution for the number of correctly classified paintings of artist i is a Binomial distribution. The null hypothesis we formulated is $p_1 \leq p_i, i \neq 1$. We used the one-tail



J. Constable | Valenciennes | Lee | Watts | L. Constable | Boudin | Cox

Fig. 5: The confusion matrices represent the classification results of all seven painters using the semi-supervised feature fusion model. The vertical axis represents the ground truth, while the horizontal axis represents the predicted labels. The abbreviations Cu, Cb, Cs, St, and Sc stand for cumuliform, cumulonimbiform, cirriform, stratiform, and stratocumuliform, respectively.

Z-test [36] with continuity correction. The p-values obtained for Valenciennes, Lee, Watts, Lionel, Boudin, and Cox were 0.332, 0.189, 0.128, 0.147, 0.024, and 0.189, respectively. At the significance level of 0.1, Constable's paintings were more accurately classified than Boudin's works, but not others. We conducted the same hypothesis testing to examine whether the inclusion of edge features could significantly improve the classification accuracy for any artist. The lowest p-value was 0.122, obtained for Constable, while the other p-values exceeded 0.25. This result indicates that the edge features improved classification most significantly for Constable.

From the results, it is evident that Constable's clouds correspond well with the system of cloud typology devised by Luke Howard. The 5% confidence interval for the classification accuracy of Constable's paintings was $[0.768, 0.923]$. The average classification accuracy was highest for Constable's paintings. Are Constable's clouds more reminiscent of photographs of real-world clouds than those of his contemporaries? The answer is mixed. At the significance level of 0.1, as indicated by the aforementioned p-values, Constable's clouds were more accurately classified than Boudin's, but not more than those by Valenciennes, Lee, Watts, Lionel Constable, and Cox. A potential explanation for the insignificant difference between Constable and these artists could be the limited number of paintings each of them had in the dataset.

We posit that Constable's technique, which involves strong contour lines rendered with a relatively continuous brushstroke, contributes to the realism of his clouds. In contrast, some artists, such as Boudin, tended to use dots and dashes in lieu of the clear-edged and smooth contours that define cloud shapes. Our computer model–trained on photographs–found Constable's cloud representations easier to classify and thus to recognize by viewers. Attention to precisely the morphological differences that Luke Howard highlighted when crafting his cloud typology in 1803 endowed Constable's clouds with a sufficiently striking degree of realism to set him apart from other landscape painters, at least in the eyes of his contemporaries–and in the eyes of our computer models. While our findings cannot confirm *definitively* that Constable was acquainted with Howard's cloud classification, they do confirm that systematic categorization is key for the visual impact of his realism.

3.3 Style Similarity Analysis

To train the style encoder for each artist, we used the MUNIT model [10] as the network backbone. We excluded Learning Regression loss during training as suggested in [34] for better disentanglement of content and style features. All the paintings of an artist formed set A, and a subset of cloud photographs formed set P. We selected 300 cloud photographs and ensured that the number of images in each cloud category was the same. For the paintings, instead of the original images, we used their sky-selected images. After obtaining the style encoders, we computed D_{style} and R_{style}.

3.3.1 *Style Distance Between Artists' Clouds and Cloud Photos*

We computed R_{style} (defined earlier) for each of the seven painters. To assess variation in R_{style} caused by randomness in the input images, for each painter, we randomly sampled five paintings to form a set and computed R_{style} for this set. The calculation was repeated for multiple random samples of five paintings. As our collection only contained nine paintings by Cox, there were a maximum of 126 different combinations of five paintings by Cox. We thus randomly sampled subsets of five paintings 126 times for every artist. Table 1 shows the average values of R_{style} for each artist as well as the standard deviation.

To assess whether the distance metrics vary significantly among artists, we conducted hypothesis testing with the alternative hypothesis: these distances are significantly different between the artists. Denote the set of paintings from each of the seven artists by C_i, with $i = 1, 2, ..., 7$, and the sampled subsets by C_i^n, where $n = 1, 2, ..., 126$. Let the set $R_{\text{style}}(C_i) = \{R_{\text{style}}(C_i^n) : n \in \{1, 2, ..., 126\}\}$. Assume that the distribution of $R_{\text{style}}(C_i^n)$ for each set C_i follow a Gaussian distribution $N(\mu_i, \sigma_i^2)$, where μ_i and σ_i^2 indicate the mean and variance, respectively. Our null hypothesis is: $\mu_1 = \mu_2, ..., = \mu_7$. We use an F-test for a one-way analysis of variance. With an F-statistic of 21.15 and a p-value below $2e - 16$, the null hypothesis (the sets have the same mean value) is rejected at the significance level 0.05. Then, we conducted another hypothesis test using the T-test to test if the paintings of Constable exhibit a style more akin to photographs compared with other artists. Let μ_1 denote the mean value of Constable's painting set. We conducted six hypothesis tests with the null hypothesis: $\mu_1 \geq \mu_i$ for $i = 2, 3, ..., 7$. Table 1 shows both the T-statistics and the corresponding p-values. At a significance threshold of 0.1, John Constable's painting style appears more similar to photographs than that of Boudin, Lee, and Cox. However, we cannot reject the null hypothesis that his painting style is less photo-like than that of Valenciennes, Lionel Constable, and Watt. In addition, we conducted the same T-test to determine whether, on average, R_{style} of Valenciennes surpassed that of the other artists. All the p-values fell below 0.1. This result suggests that Valenciennes' painting style is the most reminiscent of actual photos when compared with the other six painters, at a significance level of 0.1. Furthermore, the Pearson correlation coefficient between classification accuracy and style similarity is -0.782, with a p-value of 0.039. This strong negative correlation between the measurement of stylistic difference (paintings versus photos) and the accuracy of cloud classification aligns well with our heuristic understanding–paintings similar to photos tend to be classified more accurately into cloud types.

TABLE 1: R_{style} of the painting sets of each painter and T statistics of T-test about the difference of R_{style} between John Constable and other artists.

Artist	R_{style} (mean $\pm$ std)	T-statistic	p-value
Valenciennes	1.163 ± 0.132	1.590	0.944
Lionel Constable	1.188 ± 0.141	0.165	0.566
John Constable	1.191 ± 0.147	-	-
Watts	1.210 ± 0.146	-1.029	0.152
Boudin	1.254 ± 0.143	-3.448	3.310e-04
Lee	1.298 ± 0.151	-5.699	1.689e-08
Cox	1.319 ± 0.156	-6.703	6.775e-11

TABLE 2: Style distance D_{style} between painting set of John Constable with himself or others and T statistics of T-test about the difference of D_{style}.

Pair Comparison	D_{style} (mean $\pm$ std)	T-statistic	p-value
John Constable	0.351 ± 0.092	-	-
Lionel Constable	0.359 ± 0.095	-0.679	0.249
Valenciennes	0.373 ± 0.109	-1.730	0.042
Boudin	0.405 ± 0.108	-4.270	1.387e-05
Cox	0.408 ± 0.110	-4.462	6.225e-06
Watts	0.421 ± 0.113	-5.390	8.312e-08
Lee	0.439 ± 0.102	-7.190	3.797e-12

3.3.2 Style Similarity Between Paintings by Constable and His Contemporaries

Next, we used Eq. (2) to compute the style similarity between pairs of painters. The results are shown in Table 2. Again, we conducted hypothesis testing to verify whether these style distances were significantly different. We used C_1 to denote the set of paintings by John Constable, and C_i for those by another artist i. Similar to the approach in the previous subsection, we computed D_{style} between randomly sampled subsets of paintings by two artists. The same subsets used to generate R_{style} were used here. For the pair of sets C_1 and C_i, we obtained 126 values of D_{style}: $D_{\text{style}}(C_1, C_i) = \{D_{\text{style}}(C_1^n, C_i^n), n \in \{1, 2, ..., 126\}\}$. To establish a baseline, we also computed D_{style} for subsets of paintings within John Constable's collection. Specifically, in addition to the 126 subsets C_1^n that were already created, another 126 random subsets were sampled from C_1, each containing five paintings. Denote these new subsets by $C_{1,2nd}^n$, $n \in \{1, 2, ..., 126\}$. Then, $D_{\text{style}}(C_1, C_1) = \{D_{\text{style}}(C_1^n, C_{1,2nd}^n), n \in \{1, 2, ..., 126\}\}$. If Constable's style significantly diverges from that of other artists in terms of D_{style}, we would expect the values in $D_{\text{style}}(C_1, C_i)$ for $i \neq 1$ to surpass, at least on average, those in $D_{\text{style}}(C_1, C_1)$.

Denote the mean of $D_{\text{style}}(C_1, C_i)$ by μ_i'. In the first test, the null hypothesis is: $\mu_1' = \mu_2', ..., = \mu_7'$. Similarly, we used the F-test for one-way analysis of variance. The F-statistic obtained was 12.69 with a p-value of $9.21e-14$, suggesting a significant difference in the style features among these paired artists.

The style distances between other artists and John Constable are provided in Table 2. We also conducted a T-test between two data sets $D_{\text{style}}(C_1, C_1)$ and $D_{\text{style}}(C_1, C_i)$, where $i \in \{2, ...11\}$ to test if artist i's painting style is similar to John Constable's. The null hypothesis is: $\mu_1' \geq \mu_i'$ for $i \neq 1$. We tested at the confidence level of 0.95. The T-statistic and the corresponding p-value for the 6 tests are listed in Table 2, and we can observe that p-values are all below 0.05 except for Lionel Constable. We can therefore claim that Lionel Constable's paintings are the most stylistically similar to John Constable's of the group.

3.4 Insights for Art History

The key art-historical findings are: (1) John Constable's clouds can be more accurately classified than those of his contemporaries, which sustains the possibility that Constable possessed some knowledge of Luke Howard's classification of clouds but does not serve as definitive proof. (2) Fusing edge features boosts the classification performance of Constable's clouds more than it does for other artists. This underscores the significance of the pronounced structure in Constable's clouds as a contributing factor to their realistic portrayal. (3) John Constable's paintings are not the most realistic among the artists evaluated if realism is defined by relative approximation in appearance to a photograph. Valenciennes, according to our experiments, created clouds that bear the closest resemblance to photographs. (4) In terms of painting style, Lionel Constable aligns most closely with John Constable. This is consistent with his known practice of emulating his father's style.

3.5 Classification Results on Cloud Photos

We randomly selected 20% of the images from the CCSN dataset for testing. The other 80% of the labeled images from the CCSN dataset and all the unlabeled images were used together during the self-learning process. In the training process, only parameters in the encoder for classic feature extraction were learned by back-propagation, while the parameters of the edge feature encoder were fixed. We chose Adam as the optimizer with a learning rate of 0.0001 and batch size of 16, which provided the highest accuracy. We compared the classification results obtained by our model with two advanced methods, CloudNet [14] and ensemble-learning-based classification [16]. Our SFF-CNN model achieved the best performance with a precision of 0.972 and a recall of 0.969. The confusion matrix is shown in Fig. 6. In contrast, CloudNet (Ensemble learning) achieved a precision of 0.891 (0.953) and a recall of 0.868 (0.902). We also conducted the ablation study on the SFF-CNN model with results shown in Table 3. The improvement of the classification accuracy of SFF-CNN can be attributed to sky selection, the usage of unlabeled data, and edge feature fusion.

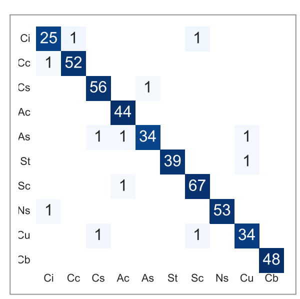


Fig. 6: Confusion matrix of the test results on the CCSN dataset using our SFF-CNN model.

TABLE 3: The ablation study of our model.

Method	Precision	Recall
SFF-CNN (w/o feature fusion)	0.955	0.953
SFF-CNN (w/o semi-supervised learning)	0.944	0.940
SFF-CNN (w/o sky selection)	0.938	0.934
SFF-CNN	**0.972**	**0.969**

4 CONCLUDING REMARKS

Moving beyond investigating this artistic movement solely through traditional methods of art history or via computer-aided stylometric analysis, we engage with meteorology both as a means of gaining ground truth and as a historical discipline that may have influenced visual arts.

Following the assumption that the more realistic the cloud painting is, the easier it is for the AI to determine its cloud type, we developed a new, specialized computer-based cloud-type classification method to determine if Constable's clouds or those of his contemporaries can be correctly categorized into different cloud types. Additionally, by content-style disentanglement, we defined two metrics to evaluate the style similarity between paintings and photos as well as the similarity among artists.

Further avenues for art-historical inquiry are indicated by our research. The stylistic similarity between Valenciennes and Constable invites a reconsideration of their relationship. Our experiments suggest that even artists closely associated with naturalism like Boudin were working in a less photographic mode than like-minded predecessors who died just before photography was invented. This raises the interesting possibility that a kind of photographic realism was highly prized around 1800, but was soon seen as less realistic when applied to painting once photographs were more or less ubiquitous after the 1850s. These possibilities can be investigated further using the presented style similarity analysis.

ACKNOWLEDGMENTS

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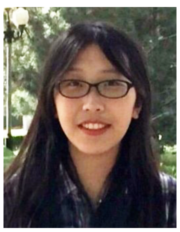

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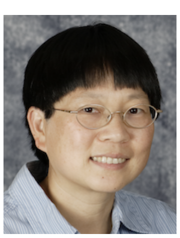

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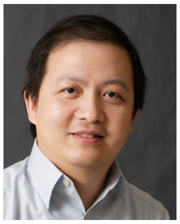

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Supplementary Materials for "A Machine Learning Paradigm for Studying Pictorial Realism: How Accurate Are Constable's Clouds?"

1 Art Historical Background

1.1 Artists' Use of Pictorial Conventions

As noted in Section 1.1 of our paper, artists may rely on visual codes, conventions, or symbols to convey information to a viewer. Viewers accustomed to the visual codes or visual symbols of a particular culture may not even be aware of the use of such conventions. An example is the tendency for children raised in some cultures, including in the U.S., to represent the sun as a circle with a smiley face and several lines emanating from the circle outward. Although this is not a life-like representation of the sun, it is immediately recognizable as the sun by most American viewers. Visual codes can be much subtler, of course. This phenomenon is readily evident in depictions of ocean waves, which are just as recognizable when they are represented through the use of an artistic convention familiar to the viewer as they are when they are portrayed in a highly naturalistic way (Fig. 1). So one art historical explanation for the perceived truthfulness of Constable's clouds is the fact that viewers who are familiar with the tradition of European landscape paintings are accustomed to seeing clouds depicted in this way and are also accustomed to attributing to such paintings a quality of life-likeness.

1.2 How Luke Howard's Essay on the Modification of Clouds Might Have Influenced John Constable?

This argument hypothesizes that Constable came to understand, by way of Luke Howard's account [1], the nomenclature, distinct physical structures of different types of clouds, and the atmospheric conditions that generate different types of clouds, and that this knowledge enabled Constable to paint clouds more persuasively. The 1803 publication of Howard's "On the Modifications of Cloud" included verbal descriptions and visual illustrations of different cloud types (Fig. 2). Howard's nomenclature continues to be used today.

2 Data

2.1 Painting Dataset

The key factors we used to select proper artistic works for comparison are as follows:

- We should maintain a dataset that is consistent in terms of medium. Because many of Constable's most renowned depictions of clouds were painted with oil rather than watercolor, we should find comparative works that are also oil paintings.
- It can be hard to know for certain that a cloud study was entirely executed outdoors or touched up in the studio, so we should use artists who worked out of doors as well as in the studio.
- We should use artists for whom clouds were of enduring interest. By focusing on artists whose oeuvres include many depictions of clouds, we may be able to collect a large enough dataset.

All of the artists in our dataset, worked in oil and all had a sustained interest in painting skies/clouds. For instance, Lionel, son of John Constable, emulated his father's technique; French artist Eugène Boudin was known as "king of skies" and encouraged a number of artists like Gustave Courbet and Claude Monet to paint clouds *en plein air* (*i.e.*, in the open air); Pierre-Henri de Valenciennes trained younger artists to paint out-of-doors and to practice making cloud studies. Other painters in our dataset were similarly attentive to the depiction of cloudy skies.

Fig. 3 shows the painting distribution in our dataset in terms of painters and cloud types. As can be seen, there are more paintings by Boudin and John Constable and more depictions of cumulus clouds in our dataset.

We illustrate some representative paintings of each artist in Fig. 4 and Fig. 5 to provide a general impression of these artists' landscape paintings.

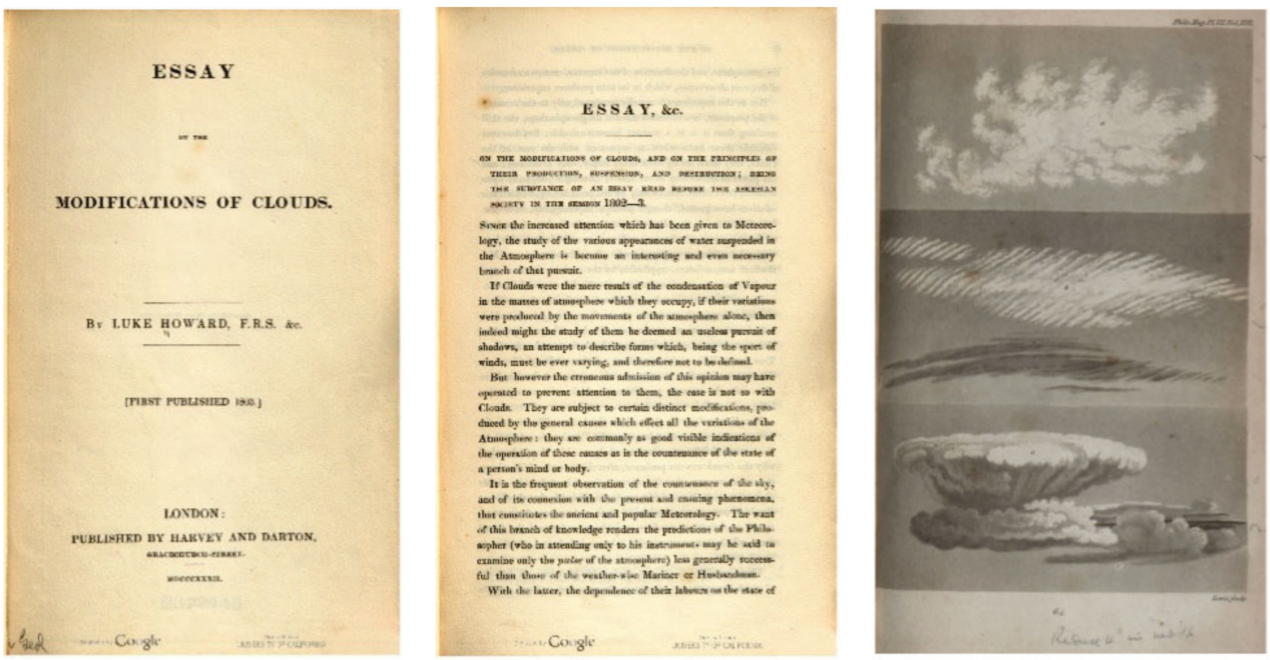
2.2 Photo Dataset

The CCSN dataset [2] contains 2,543 cloud images in total. According to the World Meteorological Organization's genera-based classification recommendation, all the collected images are divided into 11 different categories as shown in Table. 1. Representative sample images from each category are shown in Fig. 6. All images are fixed resolution 400×400 pixels in the JPEG format.

To achieve semi-supervised learning, we leverage the SkyFinder [3] and FindMeASky [4] datasets to boost the classification performance. The SkyFinder dataset contains over 90,000 outdoor sky photos in different weather situations with associated detailed weather data and annotated sky pixels. However, not all photos were taken in a cloudy situation and there are plenty of

(a) (b) (c)

Fig. 1: Waves in art: From engraved maps and woodblock prints to contemporary photography. (a) Detail from Abraham Ortelius, *Theatrum Orbis Terrarum*, The Netherlands, hand-colored engraving, 1570. (b) Katsushika Hokusai, *The Great Wave off Kanagawa*, Japan, woodblock print, 1830-33. (c) Detail from Luis Ramos, *David Mitchell Riding a Wave*, Puerto Rico, photograph, 2015.



(a) (b) (c)

Fig. 2: Luke Howard's *Essay on the Modifications of Clouds*, original 1803 edition. (a) Title page. (b) First page. (c) Plate VII.

repetitive views of the exact same cloud, so we only used images labeled as "cloudy," and we eliminated images taken from the same camera and on the same day to avoid including multiple images of the same cloud. In addition, the FindMeASky dataset consists of 6,679 outdoor sky images with corresponding binary masks filtered from the ADE20K Dataset [5] where the sky region occupies over 40% of the area of the whole image. Therefore, our unlabeled dataset has 9,883 images in total.

3 The Sky Segmentation Method

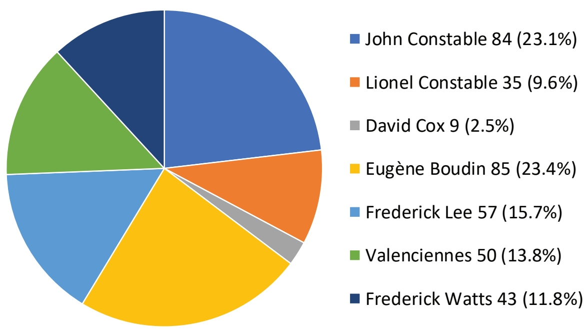
We refer to the idea developed by J. Li [6] as the basis of our segmentation algorithm. The proposed image segmentation algorithm by Li [6] is called agglomerative connectivity constrained clustering (A3C) which combines the top-down k-means clustering and a bottom-up agglomerative connectivity constrained merge method to achieve image segmentation. In our case, we first obtain the segments through the A3C algorithm and then apply a logistic regression on the location and color features extracted from each segment to achieve a two-class sky-land segmentation.

K-means Clustering: First, we apply multi-depth k-means clustering on the LUV color space of each image to get small segmented patches homogeneous in color. Suppose K clusters are generated after k-means clustering, then a graph G recording the connectivity between clusters is built using these K clusters C_k, $k = 1, 2, ..., K$ as nodes. If there exists one pixel from C_i that is 8-connected with a pixel in C_j, we consider C_i and C_j adjacent. If C_i and C_j are adjacent, edge (C_i, C_j) exists in G, represented as $(C_i, C_j) \in G$. Graph G is connected if there exists a path containing edges $(C_i, C_{m_1}), (C_{m_1}, C_{m_2}), ..., (C_{m_{n-1}}, C_{m_n}), (C_{m_n}, C_j)$ in G for any C_i and C_j.

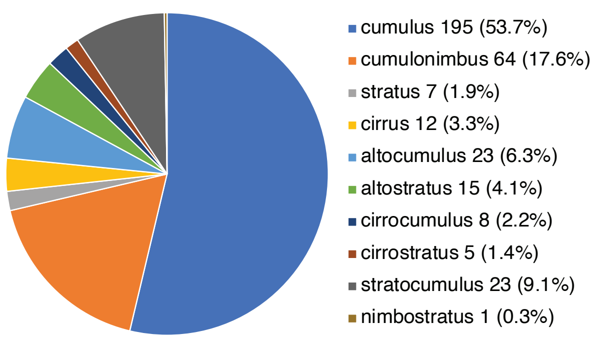
Agglomerative Merging: After the graph is established, some handcrafted features need to be extracted to compute the distance between every two nodes. These distances will then be used as criteria for merging adjacent nodes. Several types of distance are

TABLE 1: Descriptions of different cloud formations in the CCSN dataset.

Cloud Level	Cloud Genus	Abbreviation	Characteristics	Number of Images
High level	Cirrus	Ci	Fibrous,thin, white and transparent clouds	139
	Cirrocumulus	Cc	Small and white flakes arranged in groups	268
	Cirrostratus	Cs	Thin and translucent ice crystals	287
Mid level	Altocumulus	Ac	Thicker and gray line-arranged cloud sheets	221
	Altostratus	As	Opaque striped veil of grayish cloud	188
Low level	Stratus	St	Ragged and stratiform clouds that lay evenly	202
	Stratocumulus	Sc	Dark gray layered clouds	340
	Nimbostratus	Ns	Deep gray and fluffy rain clouds	274
Vertical level	Cumulus	Cu	grayish clouds with clear contours, flat bases and circular tops	182
	Cumulonimbus	Cb	Dark-gray rain clouds with blurry and doomed edges	242



(a) by artist



(b) by cloud type

Fig. 3: Painting dataset distributions. John Constable and Boudin's paintings have the highest percentages in the dataset. Cumulus and cumulonimbus are the two most dominant cloud types.

exploited in the A3C algorithm.

(1) Color. Let μ_i and μ_j be the average LUV color vectors in clusters C_i and C_j. $\|\cdot\|_2$ denote the Euclidean distance, and n_i, n_j be the number of pixels in the patches i and j, respectively. The color distance $d_c(i,j)$ is defined as:

$$d_c(i,j) = \|\mu_i - \mu_j\|^2 \, \frac{n_i n_j}{n_i + n_j} \, . \tag{1}$$

(2) Edge. Two Sobel filters are applied to obtain the horizontal and vertical derivatives g_x and g_y. The gradient is calculated by $\sqrt{g_x^2 + g_y^2}$, and the combined gradient of three color channels for each pixel is $g = (g_l + g_u + g_v)/3$. Let b_{ij} be the boundary pixel set, then the edge distance $d_e(i,j)$ is defined as:

$$d_e(i,j) = \frac{1}{|b_{ij}|} \sum_{k \in b_{ij}} g_k \, . \tag{2}$$

(3) Location. Same as the color feature, We define the Euclidean distance d_l between the average coordinates of each patch as:

$$d_l(i,j) = \|z_i - z_j\|^2 \, \frac{n_i n_j}{n_i + n_j} \, , \tag{3}$$

where z_i and z_j are average horizontal and vertical coordinates of patches i and j, respectively.

Then for patches i and j, their pairwise distance is defined as:

$$d(i,j) = \sqrt{\lambda_c d_c(i,j)^2 + \lambda_l d_l(i,j)^2} + \lambda_e d_e(i,j) \, . \tag{4}$$

This distance is used to merge patches that are connected with a pre-set threshold ϵ. The merging is from the patch in the smallest size at each iteration. We merge connected nodes C_i and C_j into a new node if $d(i,j) < \epsilon$. The pairwise distance will be computed iteratively after the graph is updated through the merging operation. Once no two more patches can be merged, the first-stage clustering is ended with visually similar patches. Then in the second-stage merging, we still follow the same merging strategy but incorporate the balanced partition measure and jaggedness measure [6] into the pairwise distance to achieve a better overall segmentation result. We refer to the generated segmented regions at the final state as segments.

Sky-versus-Land Classification: After obtaining these segments, we need to classify whether each segment belongs to the sky or land regions. To separate the sky and land or other irrelevant objects accurately, we perform a logistic regression for this two-class segmentation problem. For each segment, we need to extract some features to describe these two distinct regions. Through experiments, we notice that location and color-based features can have significant impacts on the regression performance. Thus, We collected a 10-dimensional feature vector for each segment, which contains: *normalized intensity, normalized saturation, normalized hue, the square of intensity, the square of saturation, the cosine of the average hue, average vertical position, top-most vertical position, bottom-most vertical position, and the ratio between width/height by bounding box*. These features are used for regression to decide whether the segment is one of the two classes, sky or land.

In addition, we show some more sky region segmentation results in Figs. 7 and 8. After obtaining the sky regions, we compute

Cloud Study, Hampstead, Tree at Right, 1821 — *Cloud Study: Stormy Sunset*, 1821 — *Clouds Study*, 1822 — *Study of Sky and Trees*, 1821

(a) John Constable

Landscape with the Pyramid of Gaius Cestius, Rome — *Rome: Study of a Cloudy Sky* — *At the Villa Borghese: White Clouds* — *At Villa Borghese: Trees and Buildings*

(b) Valenciennes

Strand-on-the-Green, London — *View of Barges on the Thames with Henley-on-Thames Beyond*, 1830 — *View of the Thames from Tilehurst* — *An English River*, circa 1830-1870

(c) Watts

View near Crediton, Devon, 1867 — *View near Crediton, Devon* — *Scottish Loch with Game Birds*, 1852 — *Le Pont du Gard*

(d) Lee

Fig. 4: Representative paintings of the seven artists in our dataset. The figure is continued in Fig. 5.

the hue distribution of each painting collection by converting the color space to HSV. Fig. 9 shows the hue distribution by counting the number of pixels in the sky region belonging to each hue value (0-360) and the Kernel Density Estimation (KDE) of each distribution.

4 Cloud Classification

Our neural network contains two parts, a pre-learned edge feature encoder and a classic feature encoder. The pipeline is shown in Fig. 10. An exemplary output of the edge feature encoder is shown in Fig. 11 (d).

To find what features are most important for the CNN classification model, we use the Grad-cam visualization method [7], which provides a heatmap indicating the significance of any location in the feature map for reaching the classification decision. In Figs. 11 (b) and (c), the visualization result for an example image based on the final convolution layer in the last Resconv module shows that the edge information of each cloud mass is important for classifying the cloud type. We are thus motivated to directly include edge- or contour-related features in the neural network to increase classification accuracy.

A schematic plot for the extraction of content and style features by MUNIT [8] is given in Fig. 12.

5 Multidimensional Scaling Results

To better understand the style distances between individual paintings in the entire collection, we generate two plots to show the

Dedham Water Meadows

View in Kent

View of Hampstead looking towards Harrow, circa 1860-1880

Beach near Yarmouth, circa 1850

(e) Lionel Constable

Venice, Santa Maria della Salute from San Giorgio, 1895

Harbor Scene

Beaulieu: The Bay of Fourmis, 1892

Port of Le Havre, 1886

(f) Boudin

Moorland Road, 1851

A Windy Day, 1850

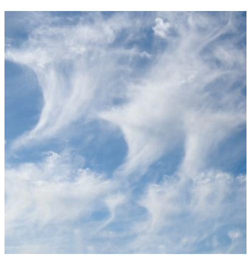
The Road across the Common, 1853

Rhyl Sands, 1854

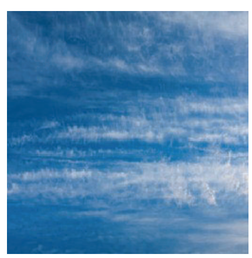
(g) Cox

Fig. 5: Representative paintings of the seven artists in our dataset. Continued from Fig. 4.

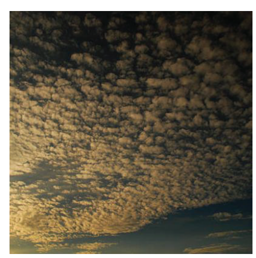
(a) Cirrus



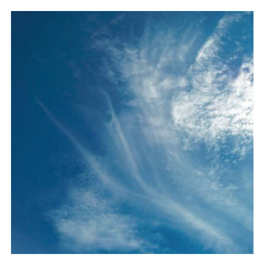
(b) Cirruocumulus



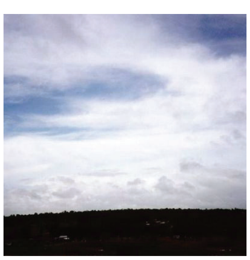
(c) Cirrostratus



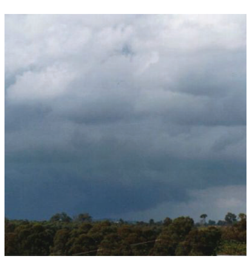
(d) Altocumulus



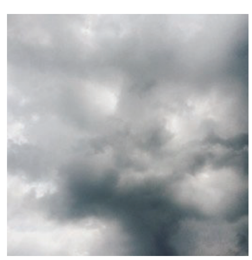
(e) Altostratus



(f) Stratus

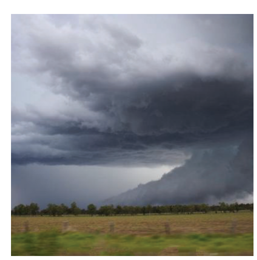


(g) Stratocumulus



(h) Nimbostratus

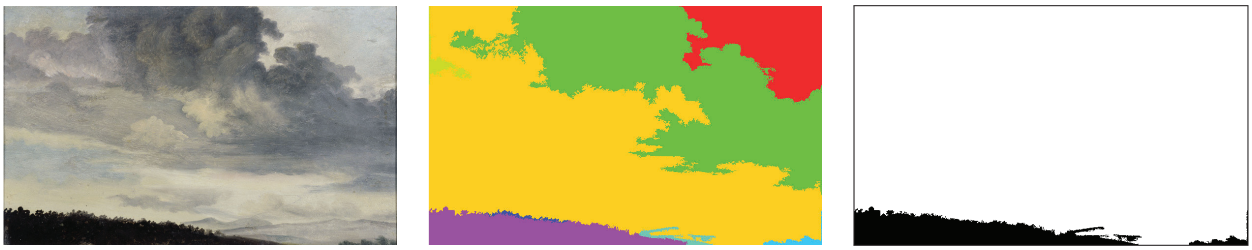
(i) Cumulus



(j) Cumulonimbus

Fig. 6: Representative photographs of different types of clouds in the CCSN dataset.

(a) *Road to the Spaniards, Hampstead*, John Constable, 1822



(b) *Rome: Study of a cloudy sky*, Valenciennes

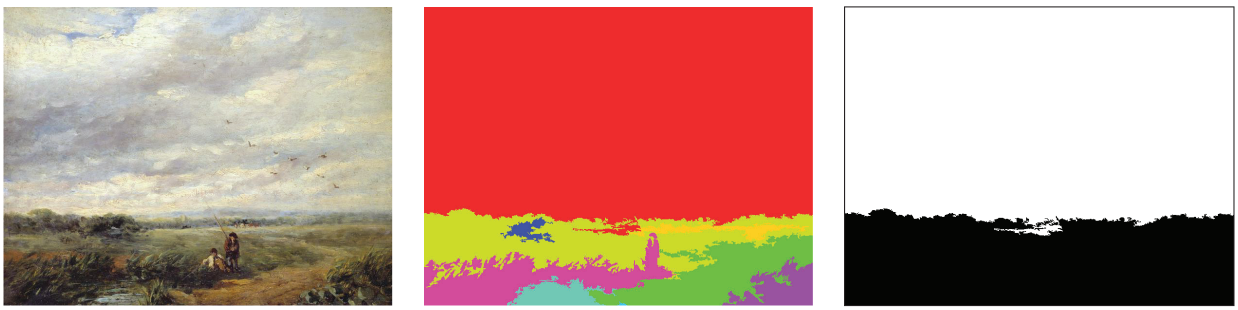
(c) *View of the Thames from Tilehurst*, Watts

(d) *A Quiet Nook, North Wales*, Lee, 1865

(e) *Landscape with Wheatfield*, Lionel Constable, circa 1850

Fig. 7: Sky and ground segmentation illustrated with a painting by each artist. Left: Original painting. Middle: Segments generated after a two-round merging. Right: Sky and land segmentation maps. This figure is continued in Fig. 8.

(f) *A Marine Scene*, Boudin, 1878

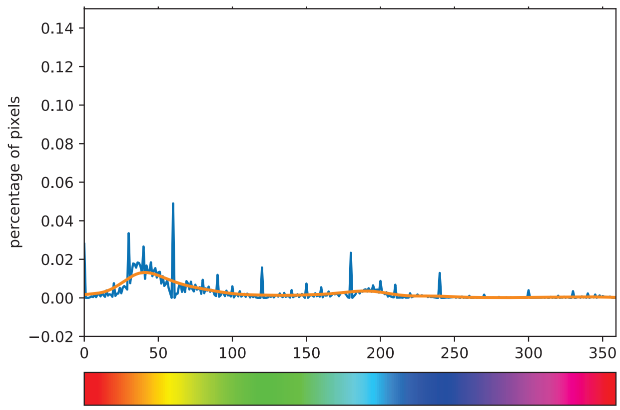


(g) *River Scene with Boys Fishing*, Cox

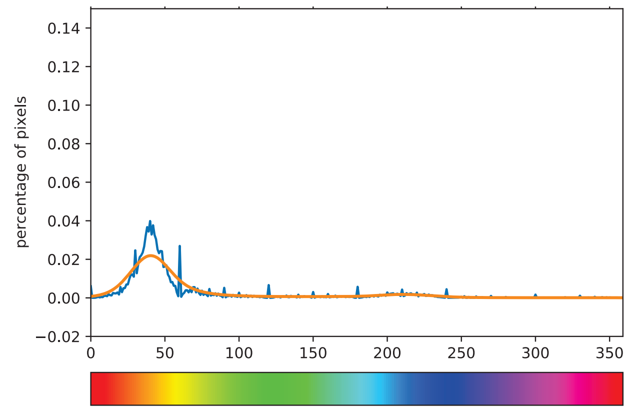
(g) Photo from the CCSN dataset

(g) Photo from the CCSN dataset

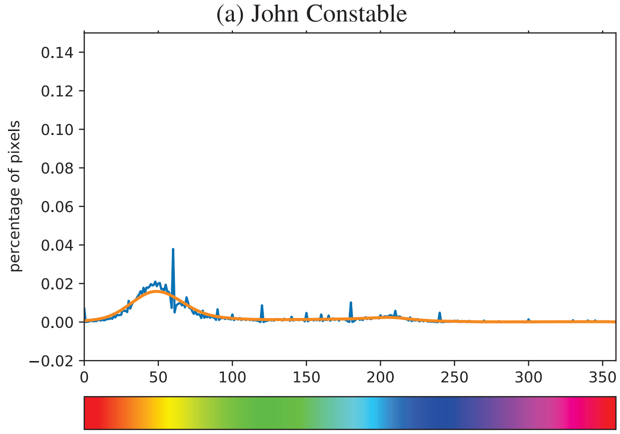
Fig. 8: Sky and ground segmentation illustrated with a painting by each artist and photos from the Middle: Segments generated after a two-round merging. Right: Sky and land segmentation maps. Continued from Fig. 7.



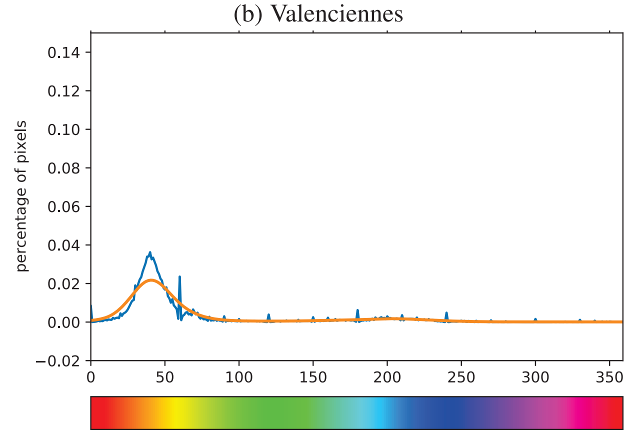
(a) John Constable



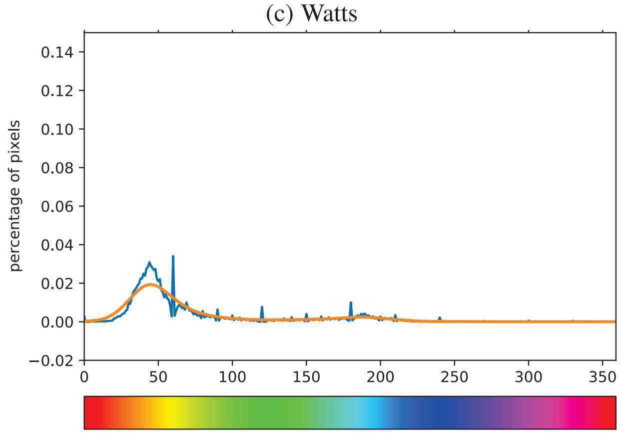
(b) Valenciennes



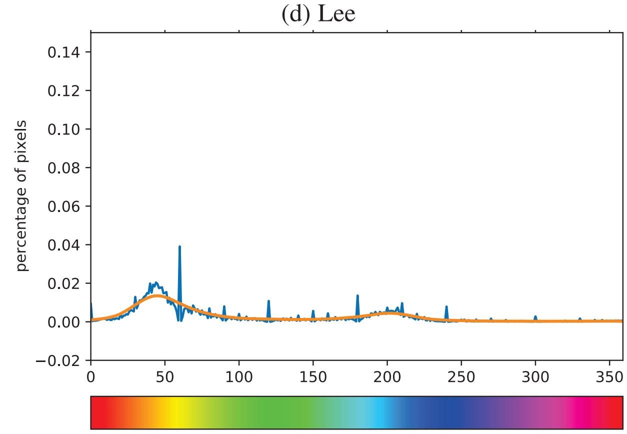
(c) Watts



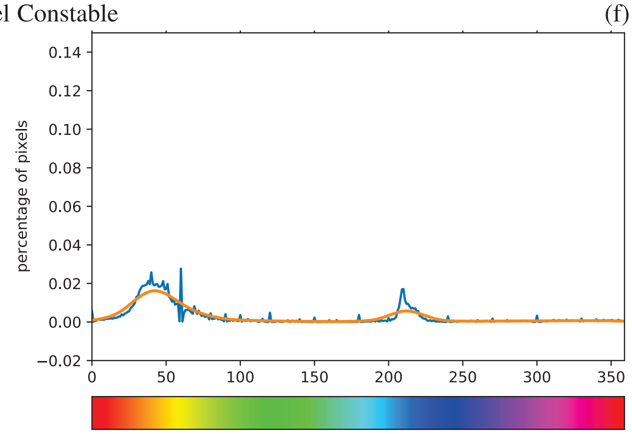
(d) Lee



(e) Lionel Constable



(f) Boudin



(g) Cox

Fig. 9: The hue distribution of all seven artists' painting collections and their corresponding kernel density estimate results.

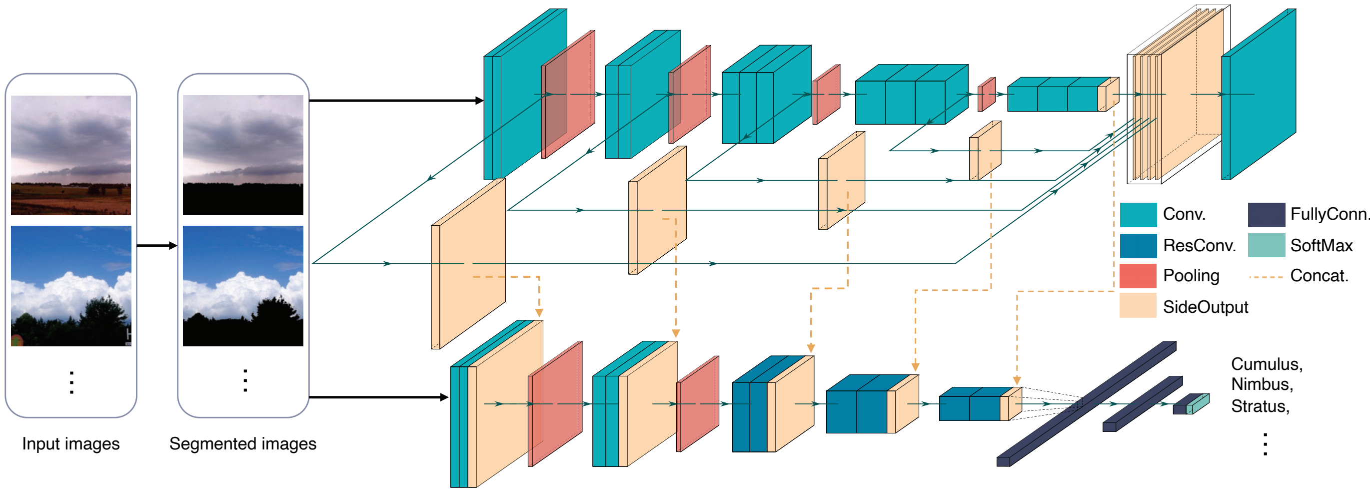


Fig. 10: The structure of our cloud classification. First, we need to get segmented images to use as input to the network. Then, two streams of encoders aim for extracting classic and edge features.

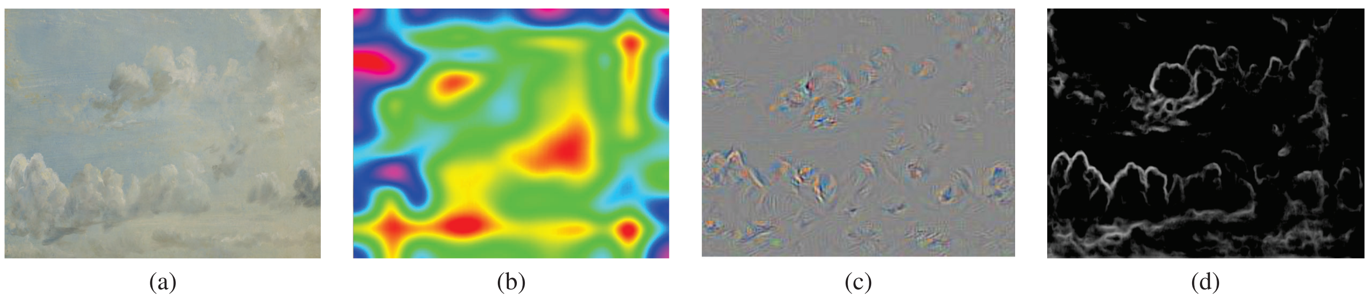


Fig. 11: Grad-cam visualization. (a) Example cloud painting. (b) The Grad-cam heatmap highlights where the model relies on the most to conclude the class of the image. Warmer colors indicate a higher significance of a location in the feature map. Red is the warmest, with yellow, green, blue, and purple becoming increasingly cooler. (c) The guided back-propagation plot is another way to show the contribution of features to the classification result. Brighter pixels indicate that the features at their positions are more important. (d) The output edge estimation of the HED model.

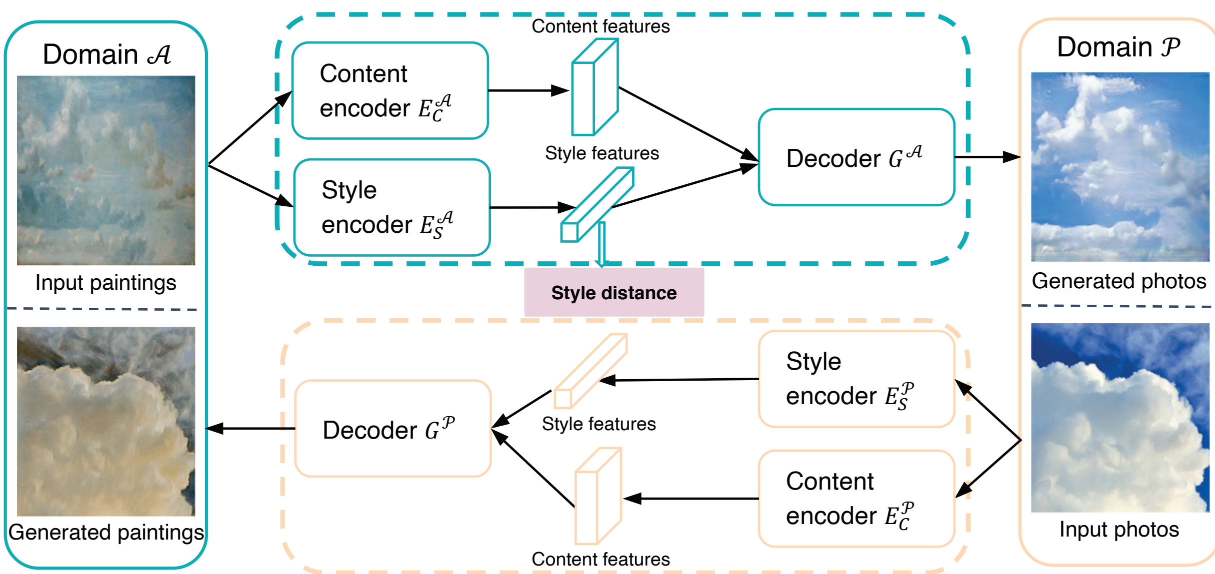


Fig. 12: The process of image translation from paintings to photos with content-style disentanglement.

multidimensional scaling (MDS) results of these paintings using the style distances between any pair of paintings applied to groups each containing a single painting). Figs. 13 and 14 show the MDS results in two dimensions.

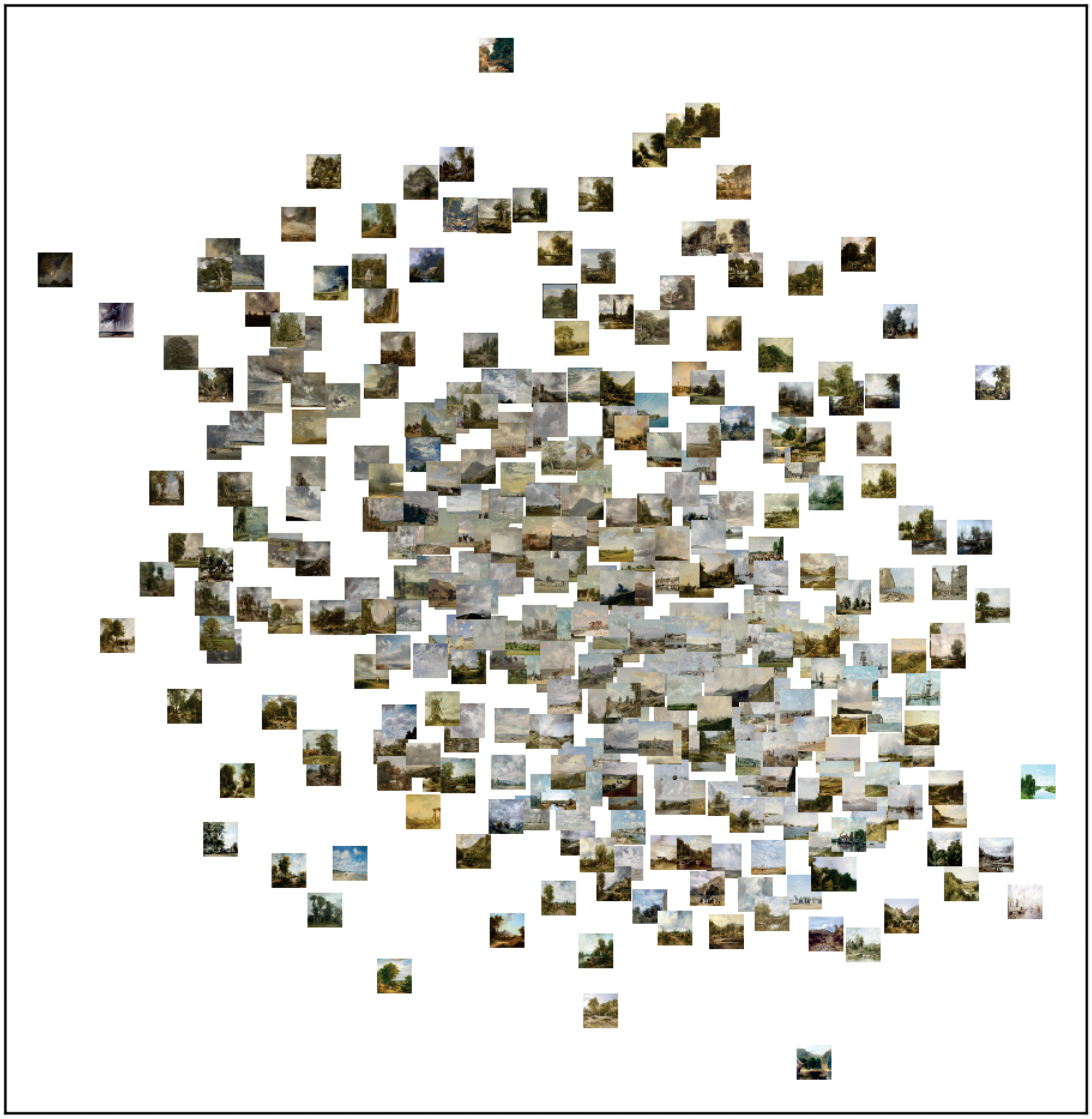


Fig. 13: Multidimensional scaling (MDS) results of paired paintings. The MDS plot shows all 363 paintings. Only the sky regions are used in the analysis.

6 Style Distance in the Expanded Dataset

Besides the seven painters discussed so far, we expanded our dataset to include landscape paintings by artists working in diverse styles from the Renaissance painter Titian (c. 1490-1576), to the 20th-century modernists Georgia O'Keeffe (1887-1986) and Thomas Hart Benton (1889-1975), and the popular contemporary landscapist Thomas Kinkade (1958-2012) as well as watercolors by John Constable to show that the proposed style distance can be applied to more artists and media. The style distances between these artists and John Constable are provided in Table 2. The statistics of T-test about whether these painting collections are similar to John Constable's are listed in Table 3.

TABLE 2: Style distance among different painting collections.

Pair of Painting Collections in Comparison	D_{style} (mean $\pm$ std)
(John Constable:oil, John Constable:watercolor)	0.606 ± 0.143
(John Constable, Benton)	0.835 ± 0.149
(John Constable, Titian)	0.843 ± 0.138
(John Constable, Kinkade)	0.881 ± 0.156
(John Constable, O'Keeffe)	0.926 ± 0.153

TABLE 3: T statistics of T-test about the difference of D_{style}

Artist	T-statistic	p-value
John Constable:watercolors	-16.834	<2.2e-16
Benton	-31.025	<2.2e-16
Titian	-33.298	<2.2e-16
Kinkade	-32.849	<2.2e-16
O'Keeffe	-36.153	<2.2e-16

7 Style Similarity of Whole Paintings

Instead of using only the sky regions to analyze the style transfer, we also obtained the trained style encoder using the whole images of both the paintings and photographs for training to measure the similarity to photos and style distance among the whole paintings of each artist. We utilized the same pipeline and settings in Section 5.4 to sample data and conduct hypothesis testing but using the style features generated from the style encoder trained with the

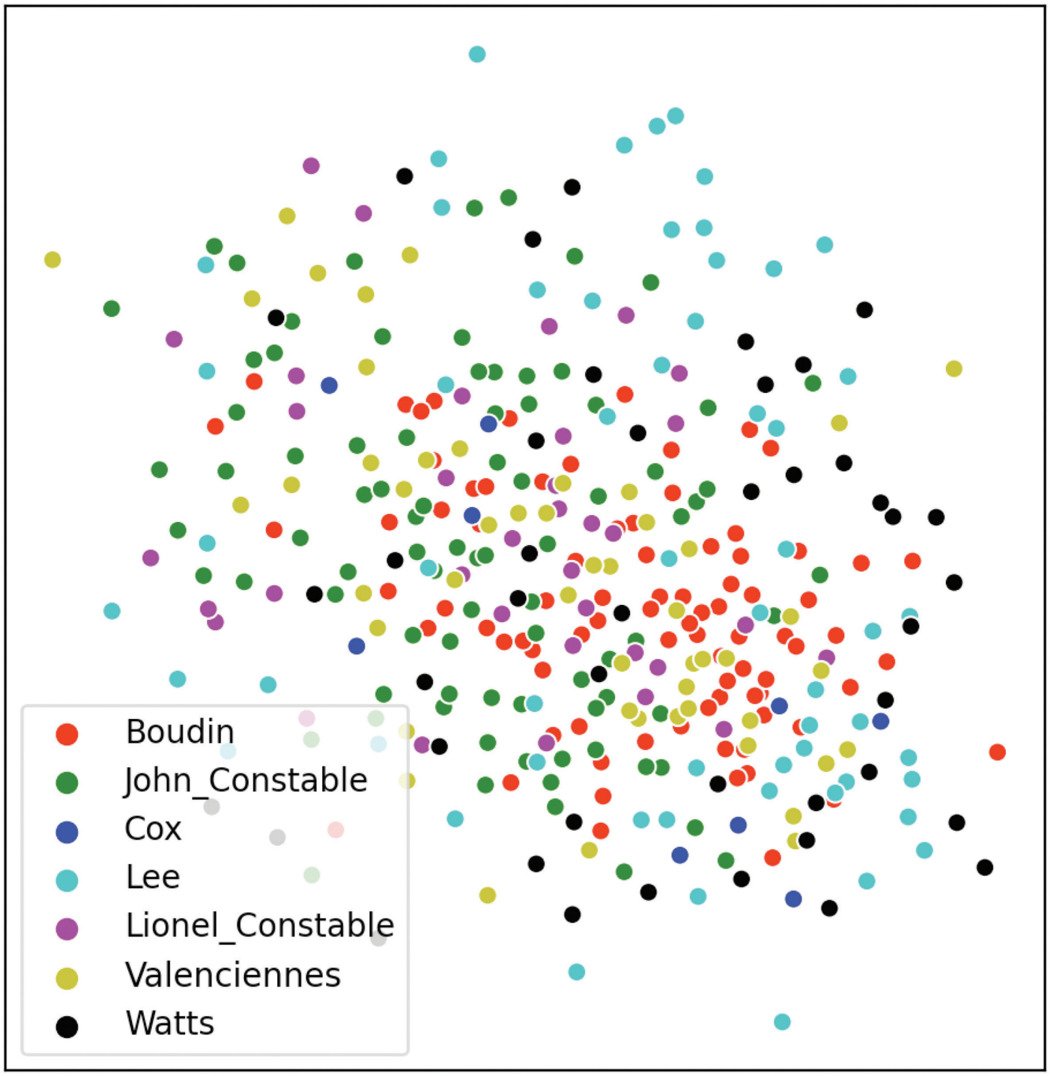


Fig. 14: Multidimensional scaling results of paired paintings. The colors of the scattered points indicate different painters.

whole paintings. The corresponding R_{style} and the statistics of T-test about whether John Constable's paintings are more similar to photos are listed in Tables 4 and 5. It is worth noting that John Constable's paintings are not significantly more similar to photographs than those painted by his son Lionel Constable at the significance level of 0.1, while do have a smaller style distance to photographs than other painters. In addition, D_{style} and the statistics of T-test about whether the other six artists' painting styles are similar to John Constable's are listed in Tables 6 and 7. We can still observe that John Constable and Lionel Constable shared a similar painting style at the significance level of 0.01. The Multidimensional scaling (MDS) results of D_{style} computed using the whole paintings are shown in Figs. 15 and 16.

TABLE 4: R_{style} of the painting collection of each painter using the whole painting. These R_{style}s are generated with the same sampling method, but using the whole images of both paintings and photos to train the style encoder.

Artist	R_{style} (mean $\pm$ std)
John Constable	1.381 ± 0.169
Lionel Constable	1.403 ± 0.162
Valenciennes	1.492 ± 0.178
Watts	1.515 ± 0.176
Lee	1.548 ± 0.181
Boudin	1.562 ± 0.183
Cox	1.581 ± 0.179

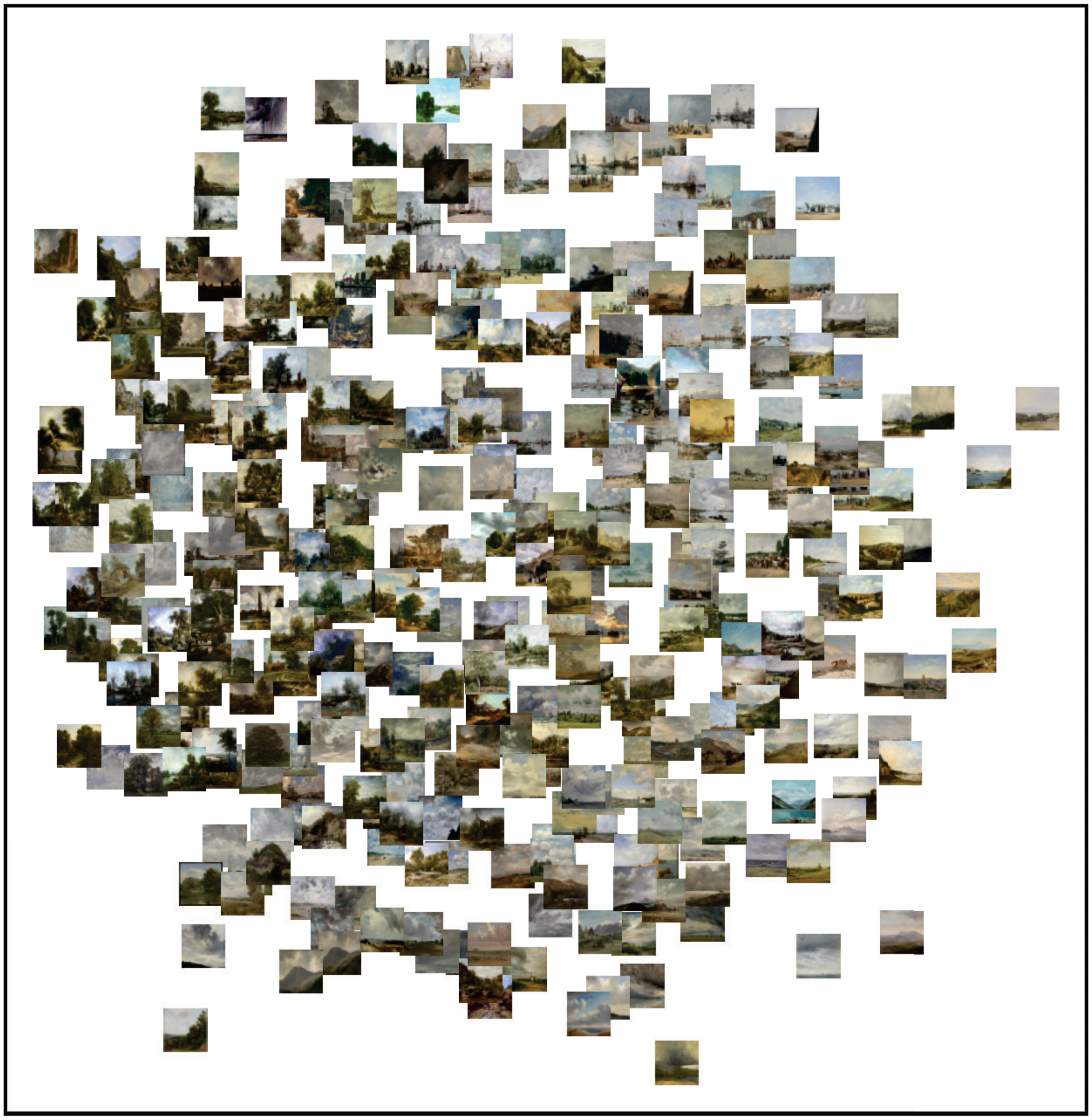


Fig. 15: Multidimensional scaling (MDS) results of paired paintings using the style distances between any pair of paintings. The style features are generated using the style encoder trained with the whole images. The MDS plot shows all 363 paintings.

TABLE 5: T statistics of T-test about the difference of R_{style} between John Constable and other artists using the whole images. Based on these statistics, John constable's painting style of landscape paintings is more similar to real-world scenes than all other artists except Lionel Constable at significance level 0.1.

Artist	T-statistic	p-value
Lionel Constable	-1.055	0.146
Valenciennes	-5.0763	3.767e-07
Watts	-6.165	1.412e-09
Lee	-7.570	3.636e-13
Boudin	-8.156	8.601e-15
Cox	-9.112	<2.2e16

TABLE 6: Style distance among different painting collections. These D_{style}'s are generated with the same sampling method, but using the whole images of both paintings and photos to train the style encoder.

Pair of Artists in Comparison	D_{style} (mean $\pm$ std)
(John Constable, John Constable)	0.491 ± 0.112
(John Constable, Lionel Constable)	0.522 ± 0.120
(John Constable, Boudin)	0.548 ± 0.131
(John Constable, Valenciennes)	0.556 ± 0.139
(John Constable, Cox)	0.576 ± 0.136
(John Constable, Watts)	0.592 ± 0.141
(John Constable, Lee)	0.610 ± 0.145

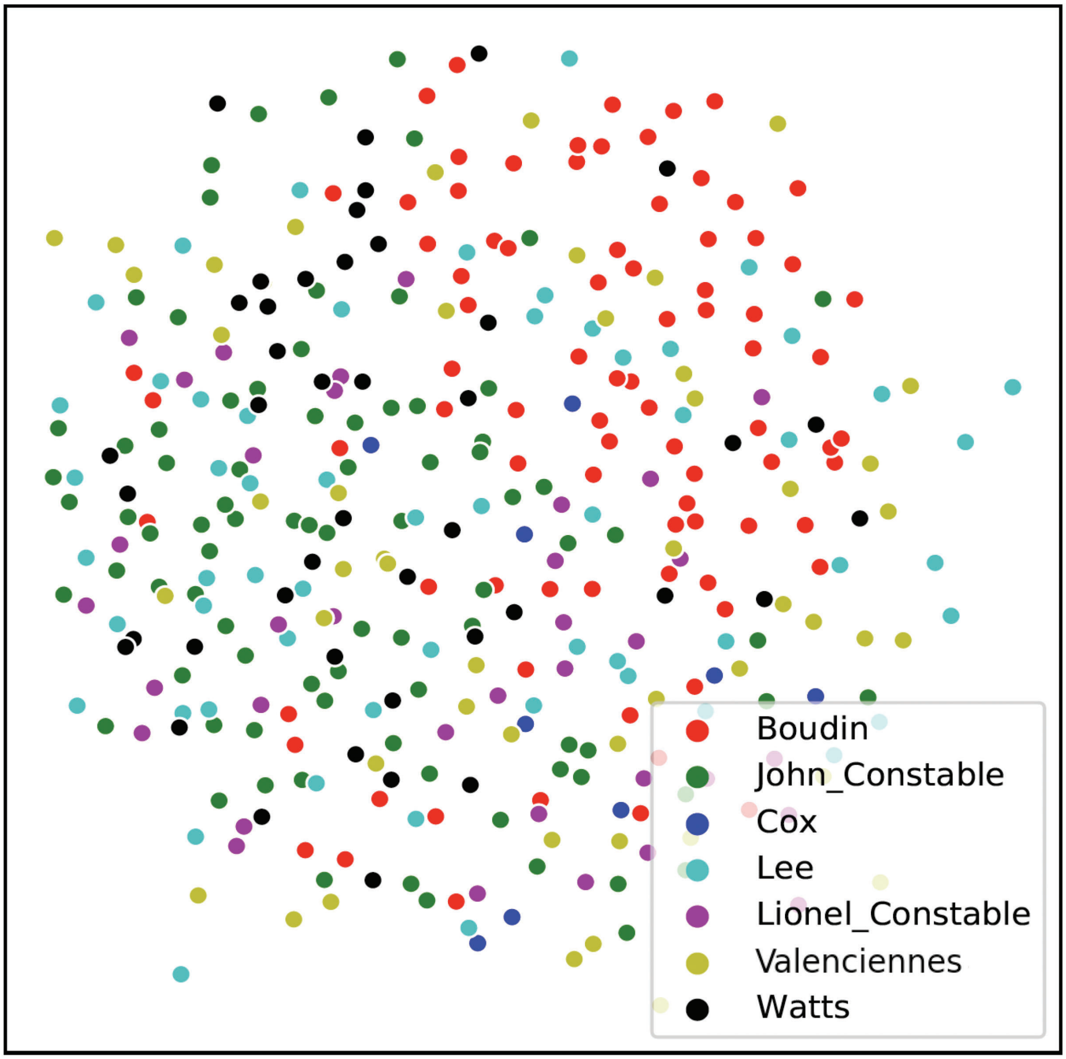


Fig. 16: MDS results of paired paintings using the style distances between any pair of paintings. The style features are generated using the style encoder trained with the whole images. The colors of the scattered points indicate different painters.

TABLE 7: T statistics of T-test about the difference of D_{style} using the whole image. Based on these statistics, John Constable's painting style of landscape paintings is similar to Lionel Constable's at the significance level of 0.01.

Artist	T-statistic	p-value
Lionel Constable	-2.120	0.018
Valenciennes	-3.712	1.27e-4
Boudin	-4.087	2.980e-05
Cox	-5.416	7.380e-08
Watts	-6.296	7.300e-10
Lee	-7.291	2.339e-12

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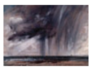
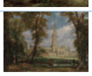
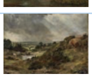
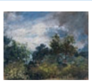
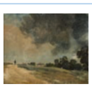
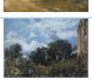
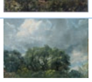
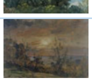
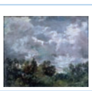
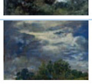
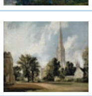
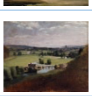
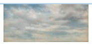
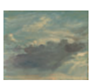
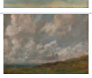
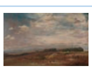
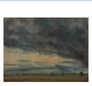
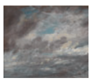
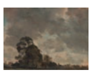
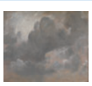
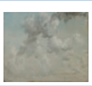
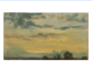
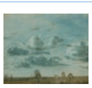
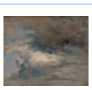
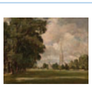
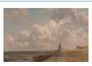
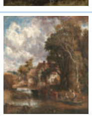
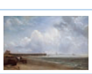
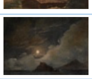
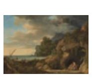
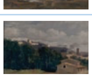
TABLE 8: Paintings in our dataset and their main cloud and weather types as determined by an expert meteorologist. Instead of only providing cloud types for each painting, the detailed cloud structure, corresponding painting environments and the evaluation of realism are also offered. 'NG' denotes 'Not given'.

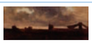
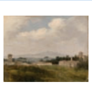
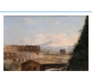
Painter	Painting	Cloud type	Cloud structure	Weather	Time	Wind direction	Assessment of Accuracy
John Constable		Cumulus	Cumulus clouds have reasonable representation of the flat and dark bases. Very good representation of the lumpy turreted cloud tops.	NG	Summer	NG	It's more stylized but recognizable.
John Constable		Cumulonimbus	Not a lot of detail in the cumulus, but as much detail in the rain as it really would be.	Raining.	Afternoon	NG	It's stylized but good for figuring out what the meteorology is.
John Constable		Cumulus	We see various cloud turrets coming up with some detail in there.	Cloudy	Noon	NG	It is enough that you can tell what genus the clouds are, but it is not super realistic.
John Constable		stratocumulus	The clouds are made up with flat bases and are overcast.	NG	NG	NG	The detail is accurate.
John Constable		Cumulus	We have three sizes of cumulus here. The tallest ones are cumulus congestus, medium sized ones are cumulus mediocris and some wispy clouds are cumulus humulus.	Cloudy	NG	NG	Three sizes of cumulus all coexisting is quite reasonable.
John Constable		Cumulus	We can see the dark and flat cloud bases and multi turreted tops.	NG	NG	NG	This is a perfectly reasonable depiction.
John Constable		Cumulus	The cumulus congestus here is weak and highly sheared.	NG	NG	NG	This is a very accurate depiction of the cumulus.
John Constable		Cumulus	The smallest flattest ones are cumulus humulus. The larger multi-turreted lumpy ones are probably mediocris, the next size up.	NG	NG	NG	It is not a terribly accurate depiction, but it's very clear that it's cumulus.
John Constable		Cumulonimbus	On the distant horizon we can see vertical edges and maybe vertical strips and dark surface.	Thunderstorm	NG	NG	The depiction is lack of details.
John Constable		Stratocumulus	The clouds have flat bases. It is the borderline case between stratocumulus and cumulus.	NG	NG	NG	It is a decent depiction of a perfectly reasonable skyscape.
John Constable		Cirrostratus	There is a large-scale cyclone here and there is an anvil flowing out from the top of a thunderstorm	Thunderstorm	NG	NG	It is very hard to tell what's going on in this picture. The view is blocked by the trees in the foreground.
John Constable		Cumulonimbus	We see clouds getting just big enough to be starting to rain.	Raining	March	Right to left	It is perfectly reasonable.
John Constable		Altocumulus	It's rather lumpy and convoluted. It's probably giving a start in something bigger.	Hazy	Afternoon	NG	Poorer than reality but the clouds could be easily distinguished.
John Constable		Cumulus	It is noted basically by their curving turrets.	NG	NG	NG	Perfectly identifiable cloud types.
John Constable		Cumulus	We can see well-depicted good turret structure	Warm day	Spring noon	NG	It is a good capture in terms of being able to tell what cloud type is here.
John Constable		Altocumulus	The overall structure of the cloud deck is quite good. Wind is shearing on these clouds. Clouds will start to rain in 12 to 24 hours.	Raining soon	NG	NG	Capturing the spirit of the day well.
John Constable		Cumulus	We have large cloud bulks here with well-depicted base and top.	Raining soon	Summer afternoon	NG	We can clearly see what type of cloud is.
John Constable		Cirrus	We can see clouds hitting the top of the troposphere. And being blown out by the jet stream.	Raining soon	Night	Left to right	We can give an accurate forecast based on it.
John Constable		Cumulonimbus	We see somewhat lumpy clouds, white from one side and dark on the other, very tall and with some vertical stripes.	Raining	NG	NG	It has very low amount of details in the structure but the cloud type is clear.
John Constable		Cumulus	We can see the flat bases on every cloud and lumpy tops but squashed vertically, and the clouds are much wider than their vertical sizes.	NG	NG	NG	It is a near perfect depiction of cumulus humulus.

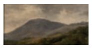
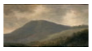
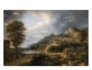
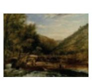
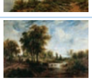
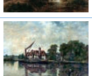
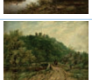
John Constable		cumulus	Good job of capturing the flat draft base of all the cumulus clouds	Sunny	Afternoon	Right to left	It is a perfect capture.
John Constable		Cumulus	They are medium-sized mediocris.	NG	NG	NG	It is a good depiction as usual.
John Constable		Stratocumulus	We have flat-based, lumpy-topped clouds, not nearly as tall as they are wide with small surfaces.	NG	NG	NG	The lower cumulus humulus is done really well.
John Constable		Cirrus	The streaks just below the jet stream are dominating the picture. It is a reasonably good picture of capturing the shape and texture of the streaks.	Snowing	NG	Left to right	It's clearly identifiable what's it.
John Constable		Cumulonimbus	We can see the lumpy cloud bases with fairly tall vertical development.	Thundershowers	NG	NG	Although some details are blocked by trees, it is not hard to see exactly what's going on.
John Constable		Cumulus	There is a good depiction of the flat bases and sub-turrets at the right scale.	NG	NG	NG	Overall, it is a really nice depiction of cumulus mediocris.
John Constable		Cirrocumulus	A few scattered puffs are lit up by sun lights.	NG	NG	Left to right	It is quite realistic, but also slightly stylized.
John Constable		Cumulus	This is a reasonably typical painting of constable. There aren't a whole lot of effort to show the flat bases of the cumulus. How the upper turrets break down into smaller scales is handled quite well.	Sunny	NG	NG	It is a perfect picture.
John Constable		Cumulonimbus	The edge is not as sharp as a strong thunderstorm	Sunny	Afternoon	NG	It is one of the better shots for realism and certainly we can tell exactly what club type you've got.
John Constable		Cumulonimbus	The clouds are densely packed, highly sheared and towering vertically.	NG	NG	NG	It is a perfectly reasonable sky scape.
John Constable		Cumulus	We have good flat cloud bases going back in perspective to horizon.	NG	NG	NG	It is a good capture of the cumulus.
John Constable		Cumulus	It's typical in a warm tropical air mass. Because there's some large-scale updrafts going on, we can see it destabilizing the atmosphere and then allowing that form cumulus at those middle levels.	Sunny	Summer	NG	Overall, it is just an excellent painting.
John Constable		Cirrus	We can see snowflakes coming down and generating fall streaks.	Sunny	Midday or afternoon	NG	It is a reasonably realistic picture.
John Constable		Stratocumulus	Good capture of cloud bases and cloud base perspectives and the accurate scale of sub-turrets.	Fair weather.	Summer	NG	It is overall a good capture of a very typical summer day.
John Constable		Cumulonimbus	It's a vibrating before reaching the ground which suggests that this is a fairly young storm just beginning to release its precipitation and has a very flat dark base of the updraft.	Cloudy	NG	NG	It is a pretty good record of cumulonimbus.
John Constable		Cumulus	We can see good turret structure with detailed depiction.	NG	NG	NG	It is one of the better teams here in this constable group.
John Constable		Altocumulus	Flat cloud base is darker, getting rain or snow falling out.	Heavy cloudy	NG	NG	It is a medium good picture going to high accuracy in the bottom half of the atmosphere here.
John Constable		Cumulonimbus	We have two thunderstorms here, a young cumulonim bus calvus with a lumpy top and not yet reaching the stratosphere we expect from young thunderstorm and then a mature thunderstorm on the left with streaky anvil-like dome.	Raining	NG	NG	The details are a bit lacking, but the cloud type is accurately depicted.
John Constable		Altostratus	The cloud is just growing and tilting to the left.	Raining.	NG	Right to left	The capture is accurate.

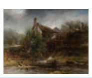
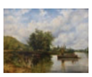
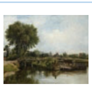
John Constable		Cirrus	We can see high thin sheets.	Sunny	NG	NG	It is a beautiful photographic picture.
John Constable		Cumulus	A bunch of clouds that is cumulus drawing moisture from the air between them the sea surface.	Sunny	Summer	NG	Tt looks like real clouds.
John Constable		Cumulus	Cumulus congestus is rising up through the background.	NG	NG	NG	It all looks very reasonable, but the painting perspective is spooky.
John Constable		Cumulus	They are close enough together and tall enough.	Sunny	Summer afternoon	NG	The work is beautifully done and it's hard to miss what they are.
John Constable		Cumulonimbus	The thunderstorm has large flat updraft bases, getting smaller when be closer. Clouds are tilting off to the right indicating a strong wind from left to right and a little bit from back to front.	Storming.	NG	Left to right.	It is an accurate capture.
John Constable		Cumulus	We can see the succession of turrets growing higher with the oldest.	NG	NG	NG	It's a good capture of a growing multi-cell cumulus cloud.
John Constable		Altocumulus	They are middle level degree of older clouds.	Ng	Summer afternoon	NG	It is a reasonably good capture of that sort of day except flat cloud bases.
John Constable		Cumulus	The cumulus clouds range from fairly small to wider and taller. We can even see the breakdown of old turrets starting to get wispy and evaporated.	NG	Noon	Summer	It is realistic.
John Constable		Altocumulus	We can see flat sheet of the cloud s. The cloud bases are at the same level, tall and narrow. We've got a large-scale low-pressure system where the cyclone is coming towards.	Cloudy and raining.	NG	NG	It is relatively clear what's going on here.
John Constable		Cumulus	The curving structure and the process of fading out are all done perfectly	Rainy	Summer	Left to right	It is very clear what's going on and most of the details here is accurate.
John Constable		Cumulonimbus	We can see dark cloud bases and lumpy but not detailed tops.	Rainy	NG	Along the cloud line	It is somewhat impressionistic quality and not detailed at all.
John Constable		Cumulus	The turret scaling is perfect.	Murky	NG	NG	It is a good depiction turrets and subgroups.
John Constable		Cumulus	We can see pinkish haze in the blue sky.	NG	Summer	NG	Everything is perfect.
John Constable		Cumulus	We can see stripes of cumulus clouds.	Sunny	Summer evening	NG	The capture is good.
John Constable		Cumulus	Clouds are all have lumpy tops and flat bases. The taller ones are cumulus mediocris with the others are cumulus humulus.	NG	NG	NG	There's a fair number of details in it.
John Constable		Cirrus	The thin bright clouds are in long streaks with sun leaking through.	NG	NG	NG	It is oretty clear what's being depicted but the details are very much lacking.
John Constable		Cumulonimbus	The heights and the number of turrets and sub-turrets, how they pile up on each other and the lumpy round tops indicate it is a cumulonimbus calvus.	NG	NG	NG	It's very clear what's being depicted.
John Constable		Cumulus	The cloud has right number of sub-turrets so it will let energy cascades well.	NG	NG	NG	All the features are depicted fairly well.
John Constable		Cumulus	The cloud shadow along with the flat bases and multi-cell turrets are well depicted.	NG	NG	NG	It is both stylistic and photograph-like.
John Constable		Cumulus	It is a reasonably correctional capture of cloud bases but not perfect.	NG	NG	NG	It's clear what cloud type is.
John Constable		Cumulus	We have more cumulus mediocris with more tattered bottoms.	NG	NG	NG	It is overall a good picture meteorologically.

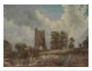
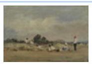
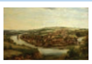
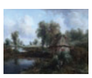
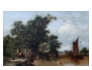
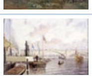
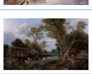
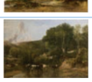
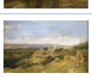
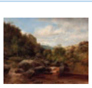
John Constable		Stratocumulus	We can see a thin sheet of cloud looks like a whole bunch of cotton balls.	NG	NG	NG	It's poorly depicted.
John Constable		Cumulus	The clouds have dark flat bases and right number of sub-turrets per turret.	NG	NG	NG	This is a really accurate depiction of clouds
John Constable		Cumulonimbus	The clouds are starting to spread out.	Raining	NG	NG	It's an accurate enough picture for telling what the cloud types are.
John Constable		Cumulus	The painter wimped out on drawing the cloud bases but paided more attention on drawing the multi-turreted tops.	NG	NG	NG	It is clear enough to identify what cloud type it is.
John Constable		Cumulus	It is a good capture of flat bases looking from the horizon.	Raining	NG	NG	It's meteorologically accurate.
John Constable		Cumulus	Most clouds here are cumulus congestus with tall vertical development.	NG	NG	NG	The cloud type can be positively identified.
John Constable		Cumulonimbus	Little effort is made to do the flat updraft bases.	NG	NG	NG	This is nothing like a real-life portrait.
John Constable		Cumulus	The clouds have flat bases and multi-turreted tops.	NG	NG	NG	We have here a very accurate picture.
John Constable		Cumulus	We see small cumulus here with flat bases at the same level and lumpy tops. Most of them are dying and starting to evaporate, maybe in the peak of life.	NG	NG	NG	It's a reasonably good picture of a very common cloud type.
John Constable		Cumulus	We can see the lumpy turreted tops and flat black bases in fairly large size.	NG	NG	NG	It is certain what cloud type the artist is trying to paint.
John Constable		Cumulus	We see almost no detail on the cloud's tops. There's almost no updraft strength in these clouds.	NG	NG	NG	It's a fairly half-hearted artwork.
John Constable		Cumulonimbus	We have some bigger and darker clouds to the left with rain starting to come out of it.	Raining	NG	NG	It's a perfectly reasonable picture.
John Constable		Cumulus	We have surely cumulus congestus here, taller than wider. Clouds are tilting somewhat towards to the left.	NG	NG	Right to Left	It's reasonably accurate.
John Constable		Cumulus	We can see here the indications of flat bases and tattered tops.	NG	NG	NG	The cloud type is obvious, but it's not depicted with any significant amount of detail.
John Constable		Cumulonimbus	The cloud is much bigger and with more turrets. It is in the transition from young thunderstorm to mature thunderstorm.	Thundershowers	NG	Right to left	This is pretty close to a photo realistic picture of thunderstorms starting to break out.
John Constable		Stratocumulus	There have flat bases and lumpy turreted tops. The updraft speed is about 10 meters per second.	NG	NG	NG	There's almost no detail here, but the detail he put in is very wisely chosen to make it completely unambiguous what cloud types they are.
John Constable		Cumulus	Mostly are cumulus congestus, wider than higher.	NG	NG	Left to right	It is a good capture of cumulus congestus.
John Constable		Cumulus	We see the lumpy tops with some sub-turrets going to turrets. The older clouds are starting to tilt to the left.	NG	NG	Right to left	We have here a nearly photographic painting.
John Constable		Cumulonimbus	A cumulonimbus calvus's just starting to rain out, not very tall or big for heavy rain but just barely big enough to start raining.	Raining.	NG	NG	IT is a reasonably good depiction of the skyscape.
John Constable		Cumulus	They have flat bases and lumpy turreted tops. The older clouds are starting to be evaporated.	NG	NG	Left to right.	It's a really nice sky painting.
John Constable		Cumulus	It's a mixture of three cumulus cloud types. The tops are all multi-turreted. The crepuscular rays are not done with any physical accuracy.	NG	NG	NG	The cloud part is done quite well.

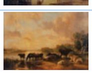
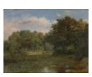
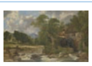
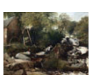
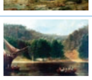
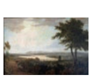
John Constable		Cumulonimbus	We can see turreted tops and white flat bases, a lightning within it and a rainbow outside it.	Raining	NG	NG	The phenomenon is physically correct.
John Constable		Cumulonimbus	Nice capture of the turret structures. It isn't a very strong thunderstorm and the decay of the anvil top here is happening faster than it is being replenished.	Cloudy	NG	Right to left	It is a good capture of the thunderstorms.
John Constable		Cumulus	Good catching of the sub-turrets within some of the turrets and reasonable indication of the flat cloud bases.	NG	NG	NG	The detail of a picture is about 70 or 80 percent right.
Valenciennes		Cirrus	We have thin sheets of clouds with sharp edges in the mist.	NG	Early morning	NG	The painting is realistic but maybe a little more large-scale structure than the typical altocumulus.
Valenciennes		Cumulus	We have cumulus congestus here. The scale of the decay from large cloud turrets to turrets is perfect.	Raining	Summer late afternoon	NG	It's a photographic picture.
Valenciennes		Cumulus	We have cumulus congestus here with flat bases, but the depiction of the cloud tops is not detailed.	NG	Summer late afternoon	NG	It's overall not a bad job of capturing the clouds.
Valenciennes		Cumulonimbus	IT is a good capture of the turrets and then the sub-turrets within. The rain is dropping from the middle levels where dry air is being mixed in from the sides.	Raining	Warm season	NG	A nice capture of that somewhat mushroom cloud shape of cumulonimbus.
Valenciennes		Cumulonimbus	We can see the turreted structure on the top, but the base is too lumpy and turreted.	NG	Warm season late afternoon	NG	It is basically a photographic stylistic image.
Valenciennes		Cumulus	The cloud edges are starting to get tattered and mixed with the dry air around them. The clouds are formed by the typical meso-scale mountain-valley circulation.	NG	About the sunset in the summer	NG	The depiction is accurate.
Valenciennes		Cumulonimbus	Reasonably good indication of the flat updraft base and decent job on the number of turrets or sub-turrets within turrets and the number of large turrets within the cloud.	NG	Dawn	NG	They are perfectly normal looking clouds.
Valenciennes		Cumulonimbus	The cloud bases are cloud and the clouds' turrets are tilting up to the left. Really good job on the flat updraft we can see the sheets of rain coming down.	Raining	Early morning in Summer	Left to right	It's a perfectly reasonable picture.
Valenciennes		Cumulonimbus	The clouds have reached the level of stratospheric stability and have formed the characteristic flat, anvil-top shape.	NG	NG	Left to right	The painting is a little sketchy.
Valenciennes		Cumulus	We have cumulus mediocris here. The cloud tops are lumpy, but the bases are lumpy too which they should not be. Vertical development is not very big.	NG	NG	NG	It is in lower quality and the cloud structure is wrong.
Valenciennes		Cumulus	We have the whole spectrum of small to medium cumulus clouds here with lumpy tops and flat bases.	Sunny	Afternoon	NG	They're perfectly identifiable for cloud types but the details are lacking.
Valenciennes		Altostratus	The sky is kind of hazy.	NG	Night	Left to right	It's not terribly well depicted.
Valenciennes		Cumulus	We have cumulus congestus and cumulus mediocris here with lumpy tops and flat bases. To clouds are assembled by the mesoscale circulation	NG	Summer afternoon	NG	The cloud structure is correct.
Valenciennes		Cumulonimbus	The cloud base is a little bit too lumpy. The odd angles of the turrets indicate it's not a really strong thunderstorm. The clouds are lit by the sun to the left.	NG	Afternoon	NG	It's a fairly realistic picture.
Valenciennes		Cumulus	The cloud structure is okay, but the position of the clouds to the mountain peak is a little odd.	NG	NG	Left to right	The details are lacking.
Valenciennes		Cumulus	The clouds are wider than they are tall. We can see turreted tops and flat wispy-edged bases.	NG	NG	NG	It's a perfectly reasonable picture but there is very low detail in the cloud here.
Valenciennes		Cumulus	The cloud structure is correct.	NG	NG	NG	Not a lot of detail but quite clear what clouds are intended.

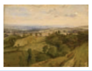
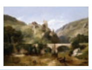
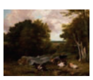
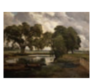
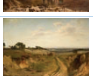
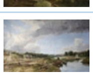
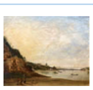
Valenciennes		Cumulonimbus	It's a young thunderstorm.	NG	Afternoon	NG	The cloud type is identifiable.
Valenciennes		Cumulonimbus	We can see lumpy turreted tops of the cumulonimbus, not too terribly tall, precip coming out of the bottom. The cloud walls are clearly going from right to left.	Snowing	Warm season	NG	The details are lacking.
Valenciennes		Cumulus	Clouds have lumpy tops and somewhat wispy bottoms.	NG	NG	NG	It's a very challenging picture to tell the cloud types.
Valenciennes		Cumulonimbus	We can see very fuzzy snow falling out of the clouds which are formed over the mountain and then freezed by the cold front.	Snowing.	NG	NG	It's moderately challenging to identify the cloud type.
Valenciennes		Cumulus	We can see a line of clouds with the lumpy turreted tops and flat bases. These clouds are all well-sheared.	NG	NG	Right to left	The drawing is sketchy but quite representative.
Valenciennes		Altostratus	The clouds are in a generally uniform gray sheet	NG	NG	NG	It is accurate meteorologically.
Valenciennes		Cumulonimbus	The cloud structure is correct given with the lumpy turreted tops and flat bases and the position is also accurate.	NG	NG	NG	This is a nice capture.
Valenciennes		Cumulus	We can see the broken fields of cumulus mediocris. Fairly good attempt at the flat cloud bases and somewhat sketchy but still nice turreted cloud top. The wind speed is about 12 miles an hour	Windy	NG	NG	It's a reasonable picture.
Valenciennes		Cumulonimbus	Good capture of the flat updraft bases. There are flanking lines building up into the main cumulonimbus. It's just a strong thunderstorm and the whole storm is moving away from us to the right.	Cloudy	NG	Front to back.	Accurate capture of this setup.
Valenciennes		Cumulonimbus	Not much effort done to do the flat cloud bases. We've got crepuscular rays shining out from the sun located right. It is a strong storm.	NG	NG	NG	It's overall a perfectly reasonable picture that anyone can tell what's going on quite easily.
Valenciennes		Cumulus	The flat cloud bases are nicely done with a rich group of turrets.	NG	NG	NG	This painting is almost photographically accurate.
Valenciennes		Cumulonimbus	We can see flat updraft bases on the left with airs going up and on the right rain falling out of the cloud in shapes.	Raining	NG	NG	Accurate capture of what it is.
Valenciennes		Cumulus	Very smallest ones are cumulus mediocris, most of them are cumulus humulus, the next size bigger, and over the highest mountain here we have cumulus congestus, two sizes bigger. The dying clouds are becoming sort of ragged at edges.	NG	Afternoon	NG	The depiction is very precise.
Valenciennes		Cumulus	This painting primarily has cumulus mediocris with a few small cumulus humulus and one cumulus congestus over the mountain on the left.	NG	NG	NG	A realistic artwork.
Valenciennes		Cumulonimbus	We've got 3 scales of the energy cascade from cloud scale down to turbulence, which indicate this is a strong and intense storm.	NG	Afternoon	NG	The depicted structure is fairly detailed.
Valenciennes		Cumulus	We have cumulus congestus here, with three or four sub-turrets per cell.	NG	Mid afternoon	NG	It is a perfectly reasonable picture but without too many details.
Valenciennes		Cumulonimbus	We have cumulonimbus calvus with reasonable number of turrets and accurate number of sub-turrets within that. There are two levels of the energy cascade down scale.	Snowing	NG	NG	It is a perfectly reasonable picture.
Valenciennes		Cumulus	We can see cumulus mediocris with lumpy turreted tops and flat bases	NG	NG	NG	The depiction is accurate.
Valenciennes		Cumulonimbus	We have dark clouds here, wider on top and narrower on bottom.	NG	NG	NG	It has the barely minimum amount of details that are needed for identification.
Valenciennes		Cumulus	It's a mixture of cumulus congestus and cumulus mediocris with turreted tops but sketchy bases.	NG	NG	NG	It's not meteorologically precise but the cloud type is straightforward to get.

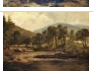
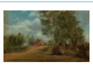
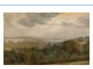
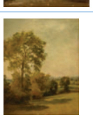
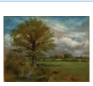
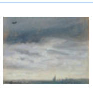
Valenciennes		Cumulonimbus	Sky is clearly about nine tenth covered with very dark clouds. We can just see enough lumpy turrets in the background.	Raining	NG	NG	The details are quite lacking.
Valenciennes		Cumulus	It's a mixture of cumulus congestus and cumulus mediocris. The cloud tops are turreted, but the cloud bases are not at the same level.	NG	NG	NG	It's very pretty picture but the clouds are a little bit fictitious.
Valenciennes		Stratus	It's a young but strong cloud given levels of the energy cascade.	Raining	NG	NG	It's a nice shooting.
Valenciennes		Cumulus	Only a little effort is done at capturing flat cloud bases.	NG	NG	NG	It's not meteorologically accuracy but easy to tell the cloud type.
Valenciennes		Cumulus	We have the whole spectrum of three sizes of cumulus clouds here with accurate depiction of cloud bases and tops. All cloud bases are the same height	NG	NG	NG	It is a perfectly reasonable painting.
Valenciennes		Cumulonimbus	It's a mature thunderstorm.	NG	Summer afternoon	NG	The picture is reasonable and detailed.
Valenciennes		Cumulus	We see the early large vertical extent, indicating it is cumulus congestus.	Windy	Afternoon	NG	It's a very accurate depiction.
Valenciennes		Altocumulus	The clouds are puffy and reasonably distributed.	NG	NG	NG	It's a reasonably good depiction of clouds.
Valenciennes		Cumulus	We have the mix of three sizes of cumulus clouds here with precise depiction of cloud bases and tops.	NG	Afternoon	NG	It shows perfectly reasonable meteorology overall.
Valenciennes		Cumulonimbus	We can see the very dark underside of the cloud most of which is just precipitation as rain falling out of the cloud.	Raining	Afternoon	Left to right	It's not terribly realistic.
Valenciennes		Altostratus	The clouds are in the form of thin sheets.	NG	NG	NG	It's a pretty good picture of capturing a very reasonable day.
Valenciennes		Cumulonimbus	It's probably a cumulonimbus calvus given how dark it is and how big it is. It's a young thunderstorm.	NG	NG	Back to front	The depiction is reasonable.
Valenciennes		Cumulonimbus	We can see the anvil spreading out above the dark clouds.	Raining	Late afternoon to evening	NG	This picture captures a unified whole of what's going on in the flow.
Watts		Cumulus	We can see cumulus mediocris with lumpy tops and flat bases, but some older clouds are a little tattered.	NG	Summer	NG	It's a good capture.
Watts		Stratus	It has lumby and is distributed evenly.	Hazy	NG	NG	It's a reasonable depiction of cumulus clouds over hazy day.
Watts		Cumulus	We can see lumpy tops, flat bases and fuzzy edges. The species of cumulus is unclear.	NG	NG	NG	The details are lacking.
Watts		Altocumulus	We can see clouds with lumpy tops and flat bases, wider than the depth.	NG	NG	NG	This is not the clearest cloud depiction.
Watts		Cumulus	It's a humid hazy day. We have cumulus mediocris here with lumpy tops and flatter bases, being torn by the wind shear.	NG	Late afternoon	Left to right	Meteorologically it is a perfectly reasonable picture.
Watts		Cumulus	We can see cumulus humulus with lumpy turreted tops and flat bases.	NG	NG	NG	The depiction is not very accurate.
Watts		Cumulus	There are some puffs of clouds in a distance.	NG	NG	NG	Details are not terribly accurate.
Watts		Cumulus	We have cumulus mediocris with turreted tops and sub-turrets within them. The depiction of flat bases is sketchy. The clouds have been torn to pieces by wind shear.	NG	Summer	Left to right	Meteorologically it is a reasonable picture.
Watts		Stratocumulus	We can see patches of cloud with gaps in it.	NG	NG	NG	The detail here is generally lacking.

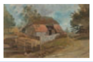
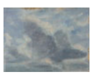
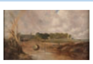
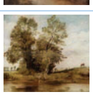
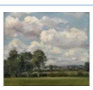
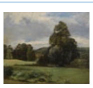
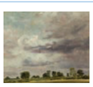
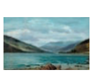
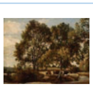
Watts		Cumulus	We have cumulus humulus here with good depiction of cloud tops. Wind speed is 12 miles an hour.	NG	NG	Left to right.	It's a reasonable picture.
Watts		Stratocumulus	It's a humid day. There are large dark and tattered clouds here.	NG	Early morning	NG	The depiction is not very detailed.
Watts		Cumulus	The cloud tops are lumpy are turreted. The cumulus is starting to get fairly large.	Humid	NG	Mid to late afternoon	Accurate depiction of a perfectly reasonable day.
Watts		Cumulus	We have most cumulus humulus with an updraft within. The cloud bases are very close to the ground. It's a very humid day.	NG	NG	NG	Meteorologically it's a perfectly reasonable setting.
Watts		Cumulus	We have cumulus congestus there with flat bases and lumpy turreted tops. The details of sub-turrets are limited as the use of very broad brushstrokes.	NG	NG	Right to left	Despite the lack of detail, the large-scale detail is really nice.
Watts		Cumulus	We have cumulus congestus with rotated flat bases and turreted tops. The capture of the decaying debris of some of the older clouds is really nice.	NG	Spring or summer afternoon	Left to right	The depiction is fairly good.
Watts		Cumulus	It's clear cumulus congestus and cumulus mediocris. Wind speed is 12 miles an hour.	NG	NG	Left to right	It's not a very detailed picture
Watts		Cumulus	We have here cumulus mediocris with vertical extent. We've got about 2 scales of the energy cascade in there.	NG	Early to midafterno on on a summer day	NG	It's a good depiction.
Watts		Cumulus	All the clouds are cumulus congestus with turreted tops. There is not a whole lot of detail on cloud bases. The clouds are tilting to right.	Windy	NG	Left to right	The detail is quite lacking.
Watts		Cumulus	We have cumulus mediocris here with turrets. There are about two levels of the energy cascade from cloud scale down to turbulence. Many of the clouds are slanted to the right. The clouds are breaking up into separate bubbles.	Windy	NG	Left to right	It's a nice depiction.
Watts		Cumulus	We have cumulus mediocris here with cumulus congestus behind the biggest boat. You see the tops being quite tattered. The updrafts are not strong yet.	NG	Mid of late morning on a summer day	NG	It's a perfectly reasonable picture.
Watts		Cumulus	We have two small sorts of cumulus here, cumulus mediocris and cumulus humulus with not detailed depiction of tops and bottoms.	NG	Mid to late morning in Summer	NG	It's really clear what cloud type is going on
Watts		Cumulus	We have cumulus mediocris with lumpy cloud tops. The details of cloud bases are fairly sketchy and vague.	Raining	NG	NG	The clouds are more likely painted from big memories of what clouds look like rather than any particular sky scape.
Watts		Cumulus	We have most cumulus mediocris here and couple of cumulus humulus with a great number of turrets. Good capture of the aging clouds and the way they've evaporated.	NG	NG	Left to right	The detail of cloud bases is limited.
Watts		Cumulus	We have here cumulus mediocris. We have decent flat dark updraft bases on some of these clouds.	NG	NG	NG	The cloud type is certainly detectable but it's not a high-accuracy painting.
Watts		Cumulus	Clouds here are cumulus mediocris with lumpy tops and dark flat bases.	NG	Summer	NG	It's decent capture of cumulus.
Watts		Cumulus	We have more cumulus mediocris here with three-level turreted lumpy tops and dark flat bases.	NG	NG	Right to left	Clouds are quite well painted.
Watts		Cumulus	The cloud top of cumulus mediocris is lumpy but the base is quite vague.	Hazy	NG	NG	The cloud type is obvious, but the details are really lacking.
Watts		Cirrocumulus	We have white, thin and patchy clouds here.	NG	Late afternoon in Summer	NG	The depiction is perfect.
Watts		Cumulus	They are small cumulus humulus with lumpy turrets in most of them. The effort put in drawing the sub-turrets and flat bases is limited.	NG	NG	NG	The depiction is accurate, but the details are lacking.

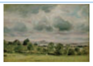
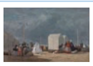
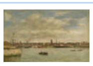
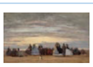
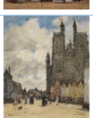
Watts		Cumulus	We can see flat bases here.	NG	NG	NG	Despite the course brushstrokes, it's a reasonably accurate painting.
Watts		Stratocumulus	We can see thin wispy clouds with gaps in them.	NG	NG	NG	The details are lacking.
Watts		Cumulus	We have tall cumulus congestus with lumpy tops. Winds are blowing towards us and maybe a bit towards the left.	Windy	NG	Towards us	The depiction is quite accurate.
Watts		Cumulus	We have cumulus mediocris with dark flat bases and wispy lumpy tops. It's humid day. These updrafts make clouds gradually evaporate away and once the updraft stops, we can get a new updraft with sharped cloud edges and turbulences.	NG	Summer afternoon	NG	It's a perfectly reasonable capture.
Watts		Altostratus	The image is occupied by thick layers.	NG	NG	NG	Really not much detail in this picture.
Watts		Altostratus	We can see day grey cloud layers here.	NG	NG	NG	The amount of detail in here is very low.
Watts		Altocumulus	The cloud type is determined given how far it is up off the ground. The clouds are lined up as small puffs.	NG	NG	NG	The details are lacking.
Watts		Cumulus	We can see cumulus mediocris with turreted tops and flat dark bases. The cloud bases are very low. It's very humid day.	Raining soon	Morning	Left to right	The depiction is accurate.
Watts		Cumulus	The smaller ones are cumulus mediocris and the larger ones in a distance are cumulus congestus. Good capture of the fragmented tattered appearance of the dying older clouds.	NG	Summer afternoon	NG	The cloud type is easy to tell but some details are wrong.
Watts		Cumulus	We can see tall cumulus congestus and the tattered evaporated debris from dying Cumulus congestus.	NG	Summer	Left to right	Overall, it's a reasonably accurate picture.
Watts		Stratocumulus	The cloud tops are very vague.	NG	NG	NG	This isn't a terribly accurate depiction of clouds.
Watts		Cumulus	Clouds here are cumulus mediocris. The low cloud bases mean it's a humid day. The tattered edges imply that many of these clouds have updrafts being fed are dying out.	NG	NG	NG	It captures the weather accurately.
Watts		Cumulus	We can see cumulus mediocris and the debris of dying Cumulus mediocris with very low flat cloud bases and lumpy tops.	NG	NG	NG	Overall, it's a good picture.
Watts		Altostratus	The whole sky is occupied by fairly uniform light grey.	NG	NG	NG	The details are lacking.
Lee		Cumulonimbus	They are young and not terribly intense cumulonimbus clouds with accurately depicted turrets.	Raining soon	NG	NG	It's a very reasonable picture.
Lee		Cumulus	We have the mix of cumulus in reasonable shapes.	Raining soon	NG	NG	It's a very accurate painting.
Lee		Cumulonimbus	We can see turreted tops and pretty good scaling of sub-turrets. We can also see a rainbow and rain falling to the right.	Raining	NG	Left to right	The distribution of clouds is not correct.
Lee		Cirrocumulus	These puffy clouds are white and patchy.	NG	NG	NG	It's a good picture meteorologically.
Lee		Cumulonimbus	There are three or four turrets per cloud	Overcast	NG	NG	It's a reasonably good picture except for how little attention is paid to cloud bases.
Lee		Cumulus	We can see cumulus humulus with lumpy turreted tops and flat bases	NG	NG	Right to left	It's a reasonably good painting including all the individual features.
Lee		Cumulus	We can see cumulus humulus and cumulus mediocris with turreted tops and flat bases.	NG	NG	NG	The depiction is really accurate.

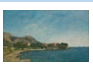
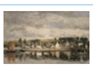
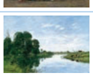
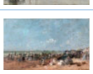
Lee		Cumulonimbus	Good depiction of flat cloud bases.	NG	NG	NG	It's a really nice picture.
Lee		Cumulus	We have cumulus congestus with flat bases and tattered edges.	NG	NG	NG	It's a decent depiction of what's going on here.
Lee		Altostratus	These scattered clouds are translucent and brightly lit by the sun.	Sunny	NG	Right to left	It's a precise capture of a weak-sunshine day.
Lee		Cirrostratus	The clouds are brightly lit. There is a warm front approaching.	NG	NG	NG	Really good capture of the cloud types.
Lee		Altostratus	The clouds are translucent and wispy.	Raining soon	NG	NG	It's pretty easy to figure out what's going on from this picture.
Lee		Cumulus	The smaller and scattered ones are cumulus humulus and the larger ones are cumulus mediocris. It's a humid and hazy day.	NG	September late morning	NG	It's a good picture of that phenomenon.
Lee		Cumulonimbus	The clouds are tilting to the left. The cloud tops are starting to be sheared off. There is a really strong large-scale cyclone nearby.	Raining	NG	Right to left	It's a very reasonable thunderstorm.
Lee		Stratus	The clouds have ragged edges like this and gaps through them.	NG	NG	NG	This is a poor representation of this type of clouds.
Lee		Cumulus	We can see fairly narrow clouds, tattered and almost completely shredded. The cloud tops are mixed with dry air.	NG	NG	Left to right	This capture is very detailed.
Lee		Cumulus	We have cumulus congestus mixed with dry air around it.NG	NG	Sunset	NG	It's a decent and accurate capture.
Lee		Cirrus	The sky is overcast by thin and wispy clouds.	NG	NG	Right to left	It's a reasonably good depiction of the cloud types but not many details are included here.
Lee		Cirrocumulus	We can see the turret tops but the flat bases for terribly accurate.	NG	NG	NG	The cloud types can be easily identified but there are only so little details.
Lee		Cumulus	We have cumulus congestus here mixed with dry air. It is towering and relatively narrow.	NG	NG	NG	It's a perfect capture.
Lee		Cumulus	The smaller and scattered ones are cumulus humulus and the larger ones are cumulus congestus. There is not much attempt to get the structure of the sub-turrets within the turrets. Just one level of the energy cascade down from cloud scale to turbulence	Sunny	NG	NG	It's a reasonable work but without accurate depiction of cloud structure.
Lee		Cumulus	We can see the turrets of cumulus clouds.	NG	NG	NG	It's good picture although only there is only a tiny patch of the sky here.
Lee		Cumulus	We have cumulus humulus here, wider than they are tall. Some cloud bases are flat, while others are tattered.	NG	Summer	Right to left	It's a reasonable sky picture being depicted logically.
Lee		Cumulus	We can see lumpy cloud tops. The clouds directly over the tree is very fuzzy and more tattered. A cold front is approaching.	NG	NG	NG	It's reasonable meteorologically.
Lee		Cumulus	We quite a bit of vertical development here, suggesting they are cumulus congestus.There is a warm layer in the atmosphere that is abruptly stopping the rise and causing them to spread out.	NG	NG	NG	The artist depicted everything correctly.
Lee		Cumulus	The energy cascade down from cloud turrets to sub-turrets is done well and the dark flat cloud bases are also well depicted.	NG	NG	NG	The cloud structure is correct, but the position of these three types of cumulus is wrong.
Lee		Altocumulus	These altocumulus castellanus are consistent and narrow.	NG	NG	NG	The depiction is reasonable.
Lee		Cumulus	We can see lumpy cloud tops and flat bases. The cumulus humulus are on the top and the cumulus mediocris are on the bottom.	NG	NG	NG	The presented features are enough to tell the cloud types.

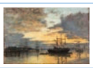
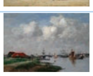
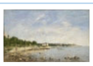
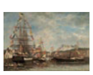
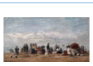
Lee		Cumulonimbus	We have a line of young thunderstorms and given the smaller cells in front. It could be intense rain particularly given how sharp and detailed the sub-turret structure is.	Raining soon	NG	NG	It's easy to forecast from this painting.
Lee		Cumulus	You can see some flat dark bases and lumpy tops.	NG	NG	NG	What sort of cumulus is extremely hard to tell sincce we have a tiny little view of the sky.
Lee		Cumulus	We have a variety of cumulus clouds here without detailed depiction.	NG	NG	NG	It's not a particularly good representation.
Lee		Altostratus	The clouds are translucent and thin.	NG	NG	NG	It's a reasonable depiction.
Lee		Cumulus	We have cumulus humulus here, wider than they are tall. The cloud bases are all on the same level. It's under warm front.	NG	NG	NG	Not a whole lot of effort went into making realistic clouds here.
Lee		Cumulus	We can see dark base and white lumpy turrets.	NG	NG	NG	The upper picture is not terribly well done.
Lee		Cumulus	We can see turreted tops but no sign of the cloud bases back behind the mountains. It's probably a cold front coming at us.	Raining soon	Noon	NG	It's a reasonably good picture and very subtle painting of the cloud shadows.
Lee		Cumulus	The sub-turrets in the main turret are towards to divergent directions, which makes the depiction a little bit exaggerated	NG	NG	NG	The cloud type is easy to tell.
Lee		Altostratus	The clouds are in uniform gray sheet.	NG	NG	Right to left	It's a challenging picture.
Lee		Altocumulus	The clouds are densely packed look like puffy pillows.	NG	NG	South wind	Not terribly clear what's going on here, but the cloud type is obvious
Lee		Cumulus	We can see flat dark bases and lumpy tops	NG	NG	NG	The depiction is accurate.
Lee		Cumulus	We can see clouds with lumpy tops. Some older clouds are fragmented.	NG	NG	NG	The details are lacking.
Lee		Cumulonimbus	The clouds are tilted and scattered.	NG	NG	Right to left	It's not a good representation.
Lee		Cumulonimbus	The clouds are darker to the right and lighter to the left, which implies that the air comes through the flat black bases and then rises and comes out to form the altostratus later.	NG	NG	NG	Clouds in this picture are so vaguely painted.
Lee		Cumulus	We can see lumpy turreted tops but no sign of the bases of the updrafts.	NG	NG	NG	This is not a terribly good depiction.
Lee		Cumulus	We see flat dark bases and lumpy turreted tops.	NG	Late morning	NG	It's a pretty nice although not very detailed painting.
Lee		Cumulus	There is very little cloud visible in here but there's a lot of detailed variation in brightness, so it can't be cirrus or stratus.	NG	NG	NG	It's a very challenging painting.
Lee		Cumulus	Good capture of the turreted tops but bad at the flat bases.	Raining soon	NG	NG	It's pretty realistic.
Lee		Cirrocumulus	This is a bunch of white color in the blue sky	NG	NG	NG	The cloud type is hard to tell and it's not a good depiction of clouds at all.

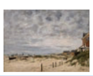
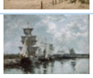
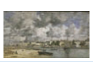
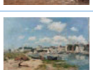
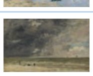
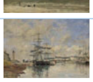
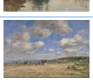
Lee		Cumulus	We have cumulus congestus here with really tall and narrow towers, sunlight on the top and dark on the bottom.	NG	NG	NG	The details are lacking.
Lee		Cumulus	We have cumulus humulus here with lumpy tops and flat bases. , perhaps with larger cumulus in the background obscured by haze.	NG	NG	NG	It's a good capture.
Lee		Cumulus	We have cumulus congestus and Cumulus mediocris here.	NG	NG	NG	The details are enough to tell the cloud type.
Lee		Cumulonimbus	We have cumulonimbus calvus here. Snow is falling, but more of them are melting and evaporating on the way down. This is some attempt to capture a squall line with the anvil back behind the new troops coming up in front.	Snowing	NG	NG	This is not a meteorologically realistic painting.
Lee		Cumulus	Good depiction of the flat cloud bases and the turreted cloud tops with the subgroups.	Humid	Summer afternoon	NG	It's an overall perfectly reasonable picture.
Lee		Altocumulus	We've got a more or less solid cloud deck with a few cracks through it.	NG	NG	NG	The details are limited.
Lee		Cumulus	We have cumulus mediocris in the front and cumulus congestus back over the trees. Good capture of the cloud shadows.	NG	NG	Left ot right	It's a reasonably good painting.
Lee		Cumulus	We have lumpy cumulus mediocris here, but they look like some sort of corals rather than cumulus clouds.	NG	NG	NG	It's a very awful painting.
Lee		Cumulonimbus	We have cumulonimbus calvus with lumpy turrets.	NG	NG	NG	Very little details are shown here.
Lee		Cumulus	The cumulus species is unclear.	NG	NG	NG	The depiction is very sketchy.
Lionel Constable		Cumulus	We have cumulus humulus and smaller mediocris here with flat dark bases and lumpy turrets.	NG	Summer	NG	The depiction is good.
Lionel Constable		Cumulus	We have mediocris here with flat dark bases and lumpy turrets	NG	Mid-morning to midafterno on on a summer day	NG	It's not terribly detailed but reasonably accurate.
Lionel Constable		Stratocumulus	We can see well-defined dark cloud bases with gaps between them.	Windy	NG	NG	IT's a very meteorologically reasonable picture
Lionel Constable		Cumulonimbus	Cloud tops are not detailed	NG	NG	NG	The details are lacking.
Lionel Constable		Cumulonimbus	Good capture of the black cloud bases going into those updrafts. We can see turreted tops on some of the smaller cells building up into the mass and we can see rain coming out here on the right.	Raining	NG	NG	Cloud tops are not detailed depicted, but a good picture overall meteorologically.
Lionel Constable		Cumulus	Clouds present white puffy tops and flat darker bases.	NG	NG	NG	It's a reasonably accurate picture without any meteorological problems in it.
Lionel Constable		Cumulus	Clouds are in scattered field and only the cloud bases can be identified.	NG	NG	NG	Not a whole lot of detail on the clouds.
Lionel Constable		Cirrus	They are little wisps arc-shaped twists.	NG	NG	NG	The depiction is not accurate.
Lionel Constable		Stratocumulus	The clouds have broken decks.	NG	NG	Left to right	Overall, it's a really great overcast.

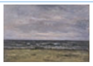
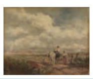
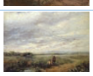
Lionel Constable		Cumulus	Reasonable job of capturing the black cloud bases and turreted cloud tops. The orange blocks are in the wrong parts of the clouds	Raining	Summer afternoon	NG	Overall, it's a reasonable painting.
Lionel Constable		Cumulus	Three sorts of cumulus are all represented here.	NG	NG	NG	The details are very lacking.
Lionel Constable		Cumulus	We can see scattered field of cumulus mediocris here.	NG	NG	NG	Not a lot of details here.
Lionel Constable		Cirrus	We can see vertical streaky lines.	Raining	NG	NG	This painting is kind of sketchy.
Lionel Constable		Cumulus	The cloud base structure and how the clouds lined up are painting accurately.	NG	NG	Right to left	It's very nice painting meteorologically.
Lionel Constable		Cumulus	We have two smallest types of cumulus clouds here. We've got some hint of the turreted structure on the top and the darker flat bases.	NG	NG	NG	The details are very sketchy.
Lionel Constable		Stratocumulus	Little puffs of clouds being evaporated at edges.	NG	NG	NG	These clouds have fairly accurate details.
Lionel Constable		Cumulus	These congestus clouds are rising and tilting to the left	NG	NG	Right to left	It's not highly accurate.
Lionel Constable		Cumulus	We can see dark cloud bases and lumpy towering cloud tops. There are some evaporating remanences of some large cumulus.	NG	NG	NG	There is not nearly enough detail for realism.
Lionel Constable		Cumulus	We can see gets flat bases of the cumulus clouds, but only minimal attempt is put to get the lumpy tops.	NG	NG	NG	The detail level is extremely low, and the realism is not terribly high.
Lionel Constable		Stratocumulus	We can see a broken field of stratocumulus here with a rainbow coming through.	NG	Sunset or sunrise	Left to right	It's an accurate capture despite the really bad depiction on the rainbow optics.
Lionel Constable		Cumulus	We have here cumulus humulus with lumpy tops and dark bases.	NG	Late morning in Summer	NG	There is not much detail here, but the cloud predictions are quite clear.
Lionel Constable		Cumulus	We have cumulus mediocris with lumpy tops and dark bases. All the cloud bases are at the same level.	NG	Mid-day in early summer	NG	It's a perfect depiction.
Lionel Constable		Stratocumulus	We can see a gap in the clouds here in the middle. The sky is covered by a fairly flat sheet.	NG	NG	NG	It's a reasonable depiction.
Lionel Constable		Cumulonimbus	We can see the flat and very dark updraft bases and lumpy tops. We have young storms on left old storms on right.	Raining soon	Summer afternoon	NG	It's a good depiction.
Lionel Constable		Cumulonimbus	We can see flat updraft bases and lumpy tops with turrets and sub-turrets, all perfectly scaled to each other.	NG	NG	NG	It's reasonably accurate but not a lot of detail is here.
Lionel Constable		Altocumulus	They are altocumulus given how broken they are.	NG	NG	NG	The details are quite lacking.
Lionel Constable		Altocumulus	The clouds are cumulus humulus with flat bases and lumpy tops. The latter wispy clouds are dying cumulus.	NG	Late afternoon in Summer	NG	It's a good depiction but details are so limited.
Lionel Constable		Cumulus	We have cumulus mediocris and cumulus congestus here with the flat black bases and the turreted structure and some sub-turrets within. There are 2 scales of the energy cascade in there.	NG	NG	NG	It's a perfect cloud depiction.
Lionel Constable		Cumulonimbus	It's a good capture of the way the mountaintop is obscured when it rises up into the cloud bases.	NG	NG	NG	It's a perfectly reasonable picture meteorologically.
Lionel Constable		Cumulus	It's a very little sky visible here. We have cumulus mediocris with lumpy tops.	NG	NG	NG	It's very sketchy.

Lionel Constable		Cumulus	We can see generally a dark flat up draft base and a line of early large cumulus clouds.	NG	NG	NG	Very little effort in detail and much of what's there doesn't make a lot of sense.
Lionel Constable		Cirrostratus	The clouds have gaps in the cloud decks and faded edges.	NG	Summer	NG	It's a pretty good depiction.
Lionel Constable		Cumulus	The clouds are tattered by wind shear.	NG	NG	NG	This is certainly nowhere near photo realistic.
Lionel Constable		Stratus	The clouds are wispy edged.	NG	NG	NG	This picture does not show anything like realistic clouds.
Lionel Constable		Cumulus	We have medium and big sized cumulus here, but the species is unclear as the lack of details here.	NG	NG	NG	It's a bit of sketchy.
Boudin		Cumulus	The cloud base structure is only done really well on that distant cloud. The turbulence structure is sort of not too much detail.	Fair weather	NG	NG	It's a bit blurry and under detailed.
Boudin		Cumulus	We have cumulus mediocris here with the flat dark bases lumpy cloud tops.	NG	NG	NG	NG
Boudin		Cumulonimbus	We can see the lumpy cloud tops and large area of flat dark cloud bases with the updraft going through.	Raining	NG	NG	It's a pretty good picture.
Boudin		Cumulus	These clouds cumulus mediocris. They are so tattered and so few of them have flat updraft bases, indicating they are fractocumulus that is cumulus torn apart by wind shear.	NG	NG	Right to left	The details are not terribly accurate.
Boudin		Stratocumulus	Dark grey clouds covered by milky white haze.	NG	NG	NG	This is an ill-defined skyscape with little details here.
Boudin		Cumulus	Cumulus clouds are merging into stratocumulus near top.	NG	NG	NG	Not a lot of detail here, but it is enough to tell what's going on.
Boudin		Cumulus	The clouds are wind tattered.	NG	NG	NG	None of these clouds really look like anything in nature.
Boudin		Cumulus	It's clearly cumulus humulus given the cloud top and cloud size.	NG	NG	NG	There are so little details.
Boudin		Altocumulus	The size of the cells within the altocumulus is well done.	NG	NG	NG	This is an accurate sketch of capturing the cloud type.
Boudin		Cumulus	Clouds here are cumulus mediocris. We can see the lumpy cloud tops and flat dark bases.	NG	NG	NG	Not a whole lot of detail but the features are perfectly correct.
Boudin		Stratocumulus	We have the even mixture of clouds.	NG	NG	NG	The cloud types can be easily identified.
Boudin		Stratus	We have flat, grey and pure stratus here.	Overcast	NG	NG	Reasonably good depiction of this cloud type.
Boudin		Stratocumulus	The clouds are barely solid and lit by the sun.	NG	NG	NG	NG
Boudin		Stratocumulus	Good capture of the flat updraft bases.	Fair	NG	NG	All the settings are pretty good.
Boudin		Cumulus	The smallest ones are cumulus humulus and the larger ones or cumulus mediocris.	NG	NG	NG	Cloud types can be clearly identified, but the details are sadly lacking.

Boudin		Cumulus	Here we have both the cumulus humulus and cumulus mediocris, different in sizes.	NG	NG	NG	It's an overall perfectly reasonable picture.
Boudin		Nimbostratus	Clouds here are bigger, taller, and darker and we can see streaks reaching from them to the sea surface.	Raining	NG	Right to left	Not a lot of detail here but is meteorologically reasonable.
Boudin		Altocumulus	We can see flat bottoms and lumpy tops. The clouds are not very tall.	NG	NG	NG	Not much effort is put into the clouds in this painting.
Boudin		Cirrocumulus	The dark clouds are cirrocumulus humulus. The bright ones are in the same type but with more sun lights going through.	NG	NG	NG	It's really clear what the cloud type is.
Boudin		Cumulus	Here we have both the dark cumulus humulus and bright white cumulus mediocris.	NG	NG	NG	It's clear what cloud type it is.
Boudin		Cumulus	The smallest one is cumulus humulus and the biggest one is cumulus mediocris. The turreted tops are not so detailed, but the scale is correct.	NG	NG	NG	The capture of the cloud shape is reasonable.
Boudin		Stratocumulus	There's a possibility of smog from early industrialization.	NG	NG	NG	Too much haze to tell cloud type for sure.
Boudin		Stratocumulus	The sky is completely overcast.	NG	NG	NG	It's clear what cloud type it is.
Boudin		Cumulus	We have here is cumulus mediocris. The cloud puffs are tall and wide.	NG	NG	NG	Fairly low effort is put in painting.
Boudin		Cirrocumulus	They're small puffs of cloud. Their transparency makes it pretty clear they are cirrocumulus.	NG	NG	NG	The depiction is accurate.
Boudin		Cumulus	We have cumulus mediocris with flat bases and wide cloud puffs.	NG	NG	NG	It shows perfectly reasonable weather setting but the details are lacking.
Boudin		Cumulus	We have cumulus mediocris in bands, which is called cloud streets	NG	NG	NG	It is perfectly reasonable.
Boudin		Altocumulus	We see opaque clouds made up of many small elements all in sheets. We can see altocumulus almost becoming altostratus.	NG	NG	NG	It is a perfectly reasonable picture of these clouds but not a lot of details here.
Boudin		Cirrus	Translucent and wispy clouds.	NG	NG	NG	It's an accurate depiction of this cloud type.
Boudin		Cumulus	We have cumulus mediocris here in the same widths and heights.	NG	NG	NG	The details are not terribly accurate.
Boudin		Cumulus	Here we have both the cumulus humulus and cumulus mediocris. Reasonably good capture of the flat cloud bases tops.	NG	NG	NG	It's quite clear about the depicted cloud species.
Boudin		Stratocumulus	They are somewhat puffy clouds.	NG	NG	NG	Not much detail but the cloud types are ambiguous.
Boudin		Cumulus	Here we can see cumulus humulus given the flat and grey cloud bases.	NG	NG	NG	The detail is quite low.
Boudin		Altostratus	There's some texture in the patch of clouds and the degree of of transparency is various. The clouds might be transitioning to altocumulus.	NG	NG	NG	The detail is quite lacking.
Boudin		Cumulonimbus	The clouds are large, puffy and nearly gray or blackish. We can see some crepuscular rays coming through the gap in the clouds and hitting the sun positioned back behind.	Raining and windy	NG	NG	It is a good capture of the meteorological situation.

Boudin		Cumulonimbus	We can see very black cloud bottom. The shady sides are lumpy turreted and black, while the sunny sides are white.	Raining	NG	Left to right	The painting is accurately depicted.
Boudin		Altocumulus	We see a scattered field of small cumulus clouds.	NG	NG	NG	It's not a terribly precise picture.
Boudin		Stratocumulus	The clouds are mashed tightly together and are distributed unevenly.	NG	NG	NG	It's a pretty good depiction of this cloud type.
Boudin		Stratocumulus	The clouds are fairly solid. The wind blows on shore.	Sunny	Summer afternoon	NG	It's very detailed depiction.
Boudin		Stratocumulus	They are patches of clouds vary in colors.	NG	NG	Towards us and to the right	They're not drawn with any great degree of details.
Boudin		Cumulus	Clouds have dark and flat bottom some with rounded tops. Here we have both the cumulus humulus and cumulus mediocris.	NG	NG	NG	All of the key features that are exploited to find the cloud type are here.
Boudin		Altocumulus	We can see translucent and textured clouds with puffy tops.	NG	NG	NG	None of the clouds here look particularly like real clouds.
Boudin		Cumulus	We have cumulus congestus here with lumpy tops and dark flat bases.	NG	NG	NG	It's detailed enough to tell the cloud type.
Boudin		Altostratus	These patchy clouds are arranged like broken fields. The edges are wispy.	NG	NG	NG	It's a nearly photo realistic painting.
Boudin		Cirrocumulus	We have mostly translucent and very small puffs of cloud here in ordered sheets.	NG	NG	NG	Not a lot of details here.
Boudin		Stratocumulus	The clouds are densely packed with well-painted multi-turreted tops.	NG	NG	NG	The depictions are in low detail.
Boudin		Cirrocumulus	There are translucent patchy clouds in the blue and white sky.	NG	NG	NG	It's hard to guess the cloud types without glasses.
Boudin		Cumulus	We cumulus mediocris near the horizon with lumpy tops and dark bases.	NG	NG	NG	It's a pretty good painting of sky.
Boudin		Cumulus	We have cumulus humulus here. They are dark and flat on the bottom, puffy and white on the top.	NG	NG	NG	There are little details.
Boudin		Cumulus	We have primally cumulus mediocris here. They are rather tattered and have ragged edges. A wind driven by a turbulence tears up the clouds.	Windy	NG	NG	NG
Boudin		Cumulus	They are cumulus mediocris, not drawn with any precision.	NG	NG	NG	It has really low accuracy in terms of details.
Boudin		Cumulus	We have cumulus mediocris. We've got the lumpy multi-turreted cloud tops and flatter and darker cloud bases. The painting is drawn from a good perspective so that can capture all the bases at the same level.	NG	NG	NG	Not a whole lot of detail in there.
Boudin		Altocumulus	The puffy sheets are so thin and flat.	NG	NG	NG	There is so little detail in clouds.
Boudin		Cumulus	Smaller ones are cumulus mediocris and the larger ones are cumulus congestus. All the flat cloud bases are at the same level.	NG	NG	NG	It shows perfectly reasonable club field and perfectly reasonable mix of clouds to find together.
Boudin		Cumulus	We have low-level cumulus mediocris with flat bases and lumpy turreted tops.	Windy	NG	NG	Not much detail, but given their shapes, sizes and coloring there's nothing else that could cloud be.
Boudin		Stratocumulus	We can see the flat bases and lumpy turreted tops that are completely overcast.	NG	NG	NG	Details are lacking but the depiction is accurate.
Boudin		Stratus	The sky is hazy and fog-like.	NG	NG	NG	It doesn't look like real clouds.

Boudin		Cumulonimbus	We can see the lumpy turreted tops, flat bases, rain coming out of the bottom and really strong wind feeding into the cumulonimbus, and we can see the avil cloud blowing up to the right.	Raining	NG	Left to right	Not a whole lot of detail, but the depiction here is accurate meteorologically.
Boudin		Stratocumulus	The clouds are fairly densely packed.	NG	NG	NG	This do not look like real clouds.
Boudin		Altocumulus	All we have here are small puffy clouds.	NG	NG	NG	The cloud type is very hard to determine.
Boudin		Cumulonimbus	It's a young but strong thunderstorm given the number of turrets.	Cloudy	NG	NG	The cloud type is quite obvious.
Boudin		Altocumulus	The cloud deck is solid and opaque. The scale of the patches and the transparency are correct.	NG	NG	NG	The details are perfectly captured.
Boudin		Cumulus	The clouds are cumulus mediocris with the lumpy turreted tops and flat bases.	Windy and raining	NG	Right to left.	It's a reasonably good depiction of a very windy day.
Boudin		Cumulonimbus	The main updraft is invisible. We can see angled bottoms and ragged shape.	Windy	NG	Right to left.	It's a perfectly reasonable picture.
Boudin		Stratocumulus	The clouds are patchy and puffy. The cloud deck is solid and fairly dark.	NG	NG	NG	The details are quite lacking.
Boudin		Cirrocumulus	The clouds are transparent.	NG	NG	NG	The cloud type is not 100 percent accurate.
Boudin		Cumulus	The smaller ones are cumulus mediocris and the taller and wider ones are cumulus Congestus	NG	NG	NG	NG
Boudin		Altocumulus	We have clouds packed tightly in the thin sheet.	Raining	NG	NG	The details are not terribly accurate.
Boudin		Cumulus	We have cumulus congestus, tall and wide, white on the top, dark on the bottom.	NG	NG	NG	Too few brushstrokes are used to capture it.
Boudin		Cumulus	We have cumulus congestus with the flat bases and lumpy turreted tops.	NG	NG	NG	It's a perfectly decent picture of a reasonable sky, but not a lot of details here.
Boudin		Cumulus	Clouds are cumulus mediocris a few smaller cumulus humulus.	NG	NG	NG	It's an accurate depiction.
Boudin		Cumulus	We can see cumulus mediocris with lumpy tops.	NG	NG	NG	The cloud type is unambiguous.
Boudin		Cumulus	We can see cumulus humulus with flat dark bases.	NG	Summer morning	NG	There is very little detail here.
Boudin		Altocumulus	We can see a solid overcast layer of grey clouds	NG	NG	NG	The details are really lacking.
Boudin		Cumulus	The clouds here are scattered cumulus humulus with flat bases and lumpy tops.	NG	NG	NG	It's a very good painting for capturing meteorology.
Boudin		Cumulonimbus	The clouds have flat black updraft bases, and we can see very intense rain sliding out of the anvil.	Raining	NG	NG	Details in here are enough to tell exactly what's going on.
Boudin		Cumulus	We have a mix of cumulus humulus and cumulus mediocris here.	NG	NG	NG	It's an accurate capture of the skyscape.
Boudin		Cumulus	We can see cumulus humulus here in a tall and wide shape.	NG	NG	NG	The cloud type is obvious.
Boudin		Stratocumulus	The clouds vary from opaque to translucent.	NG	NG	NG	There's not much detail here.
Boudin		Cumulus	We can see cumulus mediocris with the lumpy turreted tops and flat bases. Sizes are about right.	NG	NG	NG	It's a reasonable skyscape.

Boudin		Stratocumulus	We can see a solid overcast here, but because of the turbulence within it, the cloud deck isn't totally uniform.	NG	NG	NG	The depiction is reasonable.
Boudin		Cumulonimbus	A large mass above the horizon with lumpy sub-turrets.	NG	NG	NG	Not much details but it is inconsistent with any other cloud types.
Boudin		Cumulus	The mix of smaller cumulus mediocris and taller cumulus humulus is here.	NG	NG	NG	It's a nearly photo realistic picture.
Boudin		Cumulus	We can see cumulus mediocris with the lumpy turreted tops and flat bases.	NG	NG	NG	The cloud type is obvious, but the details are lacking.
Boudin		Altostratus	Clouds are long and streaky and are in uniform colors.	NG	NG	NG	The capture is accurate.
Cox		Altocumulus	The hazy clouds are in sheets.	NG	NG	NG	The details are quite lacking.
Cox		Cumulus	It has white lumby tops and flat bases.	NG	NG	NG	Good capture of this cloud type.
Cox		Stratocumulus	Streaks that are fairly close to each other.	A fine day	NG	NG	Not a whole lot of detail here and not a lot of precision on the detail that is there.
Cox		Cumulus	The cloud bases are near the sea level and the tops are lumpy.	NG	NG	NG	The depiction can tell what cloud type it is.
Cox		Stratocumulus	The clouds are strongly tilting to the right.	NG	NG	NG	Not super realistic.
Cox		Cumulus	Good depiction of the flat bases and lumpy tops.	Thunderstorm	Spring afternoon	NG	Reasonable depiction of the weather situation.
Cox		Cirrus	The clouds are in the form of white, thin and wispy strands.	NG	NG	NG	It's very stylistic and lacking in detail.
Cox		Cumulus	They are very small puffy clouds.	NG	NG	NG	It's not a high-accuracy picture but that is clearly an attempt of that sort of clouds.
Cox		Altocumulus	The clouds have scattered tops.	Cloudy	NG	NG	The cloud structure is not accurately depicted.