DEEP CONVOLUTIONAL EMBEDDING FOR DIGITIZED PAINTING CLUSTERING

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ABSTRACT

Clustering artworks is difficult because of several reasons. On one hand, recognizing meaningful patterns in accordance with domain knowledge and visual perception is extremely hard. On the other hand, the application of traditional clustering and feature reduction techniques to the highly dimensional pixel space can be ineffective. To address these issues, we propose a deep convolutional embedding model for clustering digital paintings, in which the task of mapping the input raw data to an abstract, latent space is optimized jointly with the task of finding a set of cluster centroids in this latent feature space. Quantitative and qualitative experimental results show the effectiveness of the proposed method. The model is also able to outperform other state-of-the-art deep clustering approaches to the same problem. The proposed method may be beneficial to several art-related tasks, particularly visual link retrieval and historical knowledge discovery in painting datasets.

Keywords Cultural heritage · Visual arts · Computer vision · Deep clustering · Convolutional autoencoders

1 Introduction

Cultural heritage, in particular visual arts, have invaluable importance for the cultural, historic and economic growth of our societies. In the last years, due to technology improvements and drastically declining costs, a large scale digitization effort has been made leading to a growing availability of large digitized fine art collections. Remarkable examples include WikiArt[1] and the MET collection[2]. This availability, along with the recent advancements in Pattern Recognition and Computer Vision, has opened new opportunities to computer science researchers to assist the art community with intelligent tools to analyze and further understand visual arts. Among the others, a deeper understanding of visual arts has the potential to make them accessible to a wider population, both in terms of fruition and creation, thus supporting the spread of culture.

The ability to recognize meaningful patterns in visual artworks inherently falls within the domain of human perception [1]. Recognizing stylistic and semantic attributes of a painting, in fact, originates from the composition of the colour, texture and shape features visually perceived by the human eye. These attributes, which typically concern the distribution of colours, the spatial complexity of the painted scene, etc., together are responsible for the overall “visual appearance” of the artwork [2]. Unfortunately, this visual perception can be extremely hard to conceptualize. However, visual-related features, particularly those learned by Convolutional Neural Network (CNN) models [3], can be effective to tackle the problem of extracting automatically useful patterns from the low-level colour and texture features. These patterns can assist various art-related tasks, ranging from object detection in paintings [4] to artistic style categorization [5].

[1] https://www.wikiart.org
[2] https://www.metmuseum.org/art/collection
While several successful attempts have been made towards the use of Pattern Recognition and Computer Vision in art-related supervised tasks (e.g., [6][8]), little work has been done in the clustering setting [2][9][10]. Having a model capable of clustering artworks in accordance with their visual appearance, without the need of collecting labels and metadata, can be useful for many applications. It can be used to support art experts in findings trends and influences among painting schools, i.e. in performing historical knowledge discovery. Analogously, it can be used to discover different periods in the production of a same artist. The model may discover which artworks influenced mostly the work of current artists. It may support interactive navigation on online art galleries by finding visually linked artworks, i.e. visual link retrieval. It can help curators in better organizing permanent or temporary expositions in accordance with their visual similarities rather than historical motivations.

In this paper, starting from the deep convolutional embedding clustering (DCEC) model introduced in [11], we propose DCEC-Paint as a method for grouping digitized paintings in an unsupervised fashion. To derive DCEC-Paint we introduced some changes to the original DCEC architecture’s definition which makes the model better suited to the specific image domain. We report the results of some experiments, aimed at evaluating the effectiveness of the method in finding meaningful clusters in a dataset of paintings spanned across different epochs. The method is also applied to a sub-sample including only the works of a single artist, namely Pablo Picasso, to evaluate its effectiveness in finding clusters in the production of a specific artist. Finally, comparative results between the proposed method and other deep clustering approaches to the same problem are reported.

The rest of this paper is structured as follows. Section 2 is about related work. Section 3 describes the proposed method. Section 4 is devoted to the experimental results. Section 5 concludes the work.

2 Related work

In the literature, automatic art analysis has been done by using either hand-crafted features (e.g., [12][13][14]) or features automatically learned by deep learning models (e.g., [4][7][8]). Despite the encouraging results of applying feature engineering techniques to this specific domain, early attempts were affected by the difficulty of capturing explicit knowledge on the attributes to be associated to a particular artist or artwork. This difficulty arises because this knowledge is typically associated with implicit and subjective expertise human experts may find hard to verbalize. An expert draws his judgment based on the historical context of the work and on the understanding of the metaphors beyond what is immediately perceived. In addition, art experts, as well as untrained enthusiasts, may experience subjective reactions to the artwork’s stylistic properties [1]; in other words, emotions may contribute to their aesthetic perception.

Conversely, several successful applications in a number of Computer Vision tasks (e.g., [15][16][17][18]) have shown that representation learning is an effective alternative to feature engineering to extract meaningful patterns from complex raw data. In particular, one of the main reasons of the recent success of deep neural network models, such as deep Convolutional Neural Networks, in solving tasks too hard for classic algorithms is the availability of large human annotated datasets, such as ImageNet [19]. The aggregation of all currently available art collections would result in a significantly smaller number of images compared to ImageNet. Instead, a model built on these data often provides a sufficiently general knowledge of the “visual world”, which can be transferred to specific visual domains profitably.

One of the first attempts of using CNNs in the visual art domain was reported in [4]. The authors developed a CNN-based system that can learn object classifiers from Google images and use these classifiers to find previously unseen objects in a large painting database. Other works, focusing on object recognition and detection in artworks, have also been reported [20][21][22][23][24][25]. The main issue to be addressed in this kind of research is the so-called cross-depiction problem, that is the problem of recognizing visual objects regardless of whether they are photographed, painted, drawn, etc. The variance across photos and artworks is greater than either domains if considered alone, thus classifiers usually trained on traditional photographic images may find difficulties when used on painting images, due to the domain shift.

Another task frequently addressed by computer science researchers in this domain is learning to recognize artists by their style. In a pioneering work [5] van Noord et al. proposed PigeoNET, a CNN trained on a large collection of paintings to perform the task of automatic artist recognition based on visual characteristics. Classifying unique characteristics of an artist is a complex task, even for an expert. This because there may be low inter-variability among different artists and high intra-variability in the style of the same artist. Encouraging results from the application of deep CNNs to artistic style classification have been recently reported [6][8][26]. In other works, e.g. [27][28], experiments were performed by considering also additional metadata, for example time period, reporting improved results.

Another task that drew attention is to find similarity relationship between visually linked paintings. In [29], Seguin et al. proposed a pre-trained CNN model for predicting pairs of paintings an expert considered them to have a visual relation with each other. Similarly, in [30], Shen et al. used a deep neural network model to identify near duplicate patterns in a dataset of artworks attributed to Jan Brueghel.
Most of the existing literature reports the use of machine learning/deep learning-based solutions requiring a form of supervision. Conversely, very little work has been done from an unsupervised perspective. In [9], Barnard et al. proposed a clustering approach to fine art images by exploiting textual descriptions through natural language processing. Spehr et al. [2], instead, applied a computer vision approach to the problem of grouping paintings by using traditional hand-crafted features. Saleh et al. [31] proposed an unsupervised approach for finding similarities among paintings, based on traditional hand-crafted features. They trained discriminative and generative models for the supervised task of classifying the painting style to ascertain which type of features would be more useful in the artistic domain. Then, once the most appropriate features were found, they used these features to judge the similarity between paintings by using distance measures. In [10], Gultepe et al. applied an unsupervised feature learning method based on $k$-means to extract features that were then fed to a spectral clustering algorithm for the purpose of grouping paintings. In [32], we proposed a method aimed at finding visual links among paintings in a completely unsupervised way. The method is solely based on the visual attributes automatically learned by a deep pre-trained model, thus it may be particularly effective when additional information, such as textual metadata, are either scarce or unavailable.

The contributions previously described confirm the applicability of a deep learning-based strategy to the problem of visual pattern extraction in painting datasets. Inspired by this success, in this paper we propose to use a deep clustering model to group paintings based on their visual similarity.

## 3 Proposed method

Clustering is one of the fundamental tasks in Machine Learning. It is notoriously difficult, mainly because of the absence of supervision in evaluating what an algorithm discovers. In particular, since its appearance, $k$-means has been extensively used for its ease of implementation and effectiveness [33]. However, especially in a complex image domain, the application of $k$-means may be unfeasible. On one hand, it is well-known that clustering with traditional distance measures in the highly multi-dimensional raw pixel space is completely ineffective. Moreover, as previously remarked, extracting meaningful feature vectors according to domain-specific knowledge can be extremely difficult when dealing with artistic data. On the other hand, applying well-known dimensionality reduction techniques, such as PCA [34], either to the original space or to a manually engineered feature space, can ignore possible nonlinear transformations from the original input to the latent space, thus decreasing clustering performance.

In recent years, a deep clustering paradigm has emerged which takes advantage of the capability of deep neural networks of finding complex nonlinear relationships among data for clustering purposes [11, 35, 36]. The idea is to jointly optimize the task of mapping the input data to a lower dimensional space and the task of finding a set of centroids in this latent feature space.

Inspired by the deep convolutional embedding clustering (DCEC) framework recently proposed by Guo et al. in [11], we propose DCEC-Paint, a neural network framework for clustering images of digitized paintings. The proposed architecture is depicted in Fig. 1. Starting from the DCEC model, we made some architectural changes to the original formulation so as to adapt the model to the specific image domain. In summary: (i) the activation function ELU is used instead of ReLU, to speed up learning; (ii) the latent embedding space is enlarged so as to address the higher complexity of the input images; (iii) the loss importance weights are reversed to put more emphasis to the clustering loss instead of the reconstruction loss.

The network is based on a convolutional autoencoder and on a clustering layer attached to the embedded layer of the autoencoder. Autoencoders are neural networks that learn to reconstruct their input [37]. An autoencoder is made up of two parts: an encoder $\phi$, which learns a nonlinear function that maps the input data to a smaller hidden latent space, and a decoder $\psi$, which learns to reconstruct the original input by using this latent representation. The parameters of the autoencoder are updated by minimizing a mean squared reconstruction loss:

$$\mathcal{L}_r = \frac{1}{n} \sum_{i=1}^{n} (x'_i - x_i)^2 = \frac{1}{n} \sum_{i=1}^{n} (\psi (\phi (x_i)) - x_i)^2,$$

where $n$ is the cardinality of the dataset, $x_i$ is the $i$-th input sample and $x'_i$ its reconstruction. We assume an input consisting of $128 \times 128$ three-channel scaled images, normalized in the range $[0, 1]$. This input is then propagated through a stack of convolutional layers which learn to extract hierarchical visual features. The first convolutional layer has 32 filters, with kernel size $5 \times 5$. The second convolutional layer has 64 filters, with kernel size $5 \times 5$. The third convolutional layer has 128 filters, with kernel size $3 \times 3$. The number of filters in the last two layers is higher mainly because the number of low level features (i.e., circles, edges, lines, etc.) is typically low, but the number of ways to combine them to obtain higher level features can be high. All convolutional layers adopt strides 2 and zero-padding, and they are followed by an exponential linear unit (ELU) nonlinearity [38]. We preferred this activation function to the
originally proposed ReLU, as ELU tries to make the mean activations closer to zero, thus speeding up learning:

\[
f(x) = \begin{cases} 
  x & \text{if } x > 0, \\
  \alpha (e^x - 1) & \text{otherwise}, 
\end{cases}
\]

where \( x \) is the input to a neuron and \( \alpha = 1 \) is an extra constant. All units in the last convolutional layer are flattened and given as an input to a fully-connected layer with 32 units, which constitutes the latent embedding space. In the original formulation [11], the number of units in this layer was set to 10. However, we found that this dimension is too constraining, making the reconstruction of complex artistic images slower. The embedding features are then reshaped and propagated through deconvolutional layers, which mirror, in a reverse layer-wise order, the hyper-parameters of the encoder and restore the embedding features back to the original input.

As in [11], the formulation of the clustering layer is based on the Deep Embedded Clustering (DEC) proposed in [35]. This layer is connected to the bottleneck of the autoencoder and its task is to assign the embedding features of each sample to a cluster. Given an initial estimate of the nonlinear mapping \( \phi : X \rightarrow Z \) and initial cluster centroids \( \{\mu_j\}_{j=1}^k \), the clustering layer maps each embedded point, \( z_i \), to a cluster centroid, \( \mu_j \), by using Student’s t distribution:

\[
q_{ij} = \left( \frac{1 + \| z_i - \mu_j \|^2}{\sum_j (1 + \| z_i - \mu_j \|^2)^{-1}} \right)^{-1},
\]

where \( q_{ij} \) represents the membership probability of \( z_i \) to belong to cluster \( j \); in other words, it can be viewed as a soft assignment. The membership probabilities are used to compute an auxiliary target distribution \( P \):

\[
p_{ij} = \frac{q_{ij}^2 / \sum_i q_{ij}}{\sum_j (q_{ij}^2 / \sum_i q_{ij})},
\]

where \( \sum_i q_{ij} \) are soft cluster frequencies. Clustering is performed by minimizing the Kullback-Leibler (KL) divergence between \( P \) and \( Q \):

\[
L_c = KL(P \parallel Q) = \sum_i \sum_j p_{ij} \log \left( \frac{p_{ij}}{q_{ij}} \right).
\]

In practice, the \( q_{ij} \)'s provide a measure of the similarity between each data point and the different \( k \) centroids. Higher values for \( q_{ij} \) indicate higher confidence in assigning a data point to a particular cluster. The auxiliary target distribution is conceived to put more emphasis on the data points assigned with higher confidence while normalizing the loss contribution of each centroid. Hence, by minimizing the divergence between the membership probabilities and the target distribution, the network improves upon the initial estimate by learning from previous high confidence predictions, in a form of self-supervised training.
In [35], the network abandons the decoder and fine-tunes the encoder by using only the clustering loss $L_c$. However, this approach could distort the embedded space, harming the clustering performance. Instead, as in [11], we propose to keep the decoder attached to the encoder during training. This can help DCEC-Paint to preserve the data structure of the latent feature space. Overall, the network attempts to minimize the following composite objective function:

$$
L = \lambda L_r + (1 - \lambda) L_c,
$$

where $\lambda \in [0, 1]$ is a hyper-parameter that balances $L_r$ and $L_c$. In the original formulation [11], $\lambda = 0.1$ and weights were inverted, thus giving more importance to the reconstruction loss rather than the clustering loss. However, since the accuracy of the reconstruction is not the primary goal of the model, we found that putting more emphasis on the clustering term improves cluster assignment.

The overall training works in two steps. In an initial pre-training step, the convolutional autoencoder is trained to learn an initial set of embedding features, by minimizing $L_r$ and keeping $\lambda = 1$. After this pre-training, the learned features are used to initialize the cluster centroids $\mu_j$ by using traditional $k$-means. Finally, embedding feature learning and cluster assignment are simultaneously optimized by setting $\lambda = 0.1$. The overall weights are updated by backpropagation. It is worth noting that, to avoid instability, $P$ is not updated at each iteration using only a batch of data, but by using all embedded points every $t$ iterations. The training procedure stops when the change of cluster assignments between two consecutive updates is less than a given threshold $\delta$.

### 4 Experimental results

To evaluate the effectiveness of the proposed DCEC-Paint method, we employed a database collecting paintings of 50 very popular painters. More precisely, we used data provided by the Kaggle platform [3], scraped from an art challenge website [2]. Artists belong to very different epochs and painting schools, ranging from Giotto di Bondone and Renaissance painters such as Leonardo da Vinci and Michelangelo, to more modern exponents, such as Pablo Picasso and Salvador Dalí. In particular, nine periods can be recognized: Gothic, Renaissance, Baroque, Romanticism, Impressionism, Post-impressionism, Expressionism, Surrealism, Art Nouveau/Modern Art. Painting images are non-uniformly distributed among painters for a total of 8,446 images of different sizes. To speed up calculations, each image was scaled to $128 \times 128$ pixels; moreover, to improve the network’s performance, images were normalized in the range $[0, 1]$ before training.

Experiments were run on an Intel Core i5 equipped with the NVIDIA GeForce MX110, with dedicated memory of 2GB. As deep learning framework, we used TensorFlow 2.0 and the Keras API [39].

In the following subsections, the results of some experiments are reported. In the first experiment, we evaluated the effectiveness of DCEC-Paint in clustering the dataset. In addition, we run our method on a sub-sample of paintings belonging to Pablo Picasso. This was done to evaluate the effectiveness of the proposed method in finding meaningful clusters inside the production of a same artist. In the second experiment, we compared the proposed solution to its original formulation to justify the modification we made to the loss weights. Then, we fairly compared the proposed method with other deep clustering approaches, to evaluate if it provides a better solution to the problem of clustering paintings. In particular, we considered the following two alternative approaches:

1. Performing $k$-means on the embedded features of the proposed pre-trained convolutional autoencoder (CAE), from now onwards referred to as CAE+$k$-means;

2. The deep embedding clustering (DEC) method proposed by Xie et al. [35], in which, after the pre-training stage, the decoder is abandoned and only the clustering loss is minimized. It is worth noting that, for a fair comparison, DEC was not set as a fully-connected multi-layer perceptron as in [35], but mirrored the same architecture of the proposed CAE.

In all cases, CAE was pre-trained end-to-end for 200 epochs using the AdMax optimizer [40] and mini-batches of size 128. To initialize cluster centroids, we run $k$-means with 20 restarts, picking the best solution. For DEC and DCEC-Paint, the convergence threshold $\delta$ was set to 0.001 and the update interval $t$ to 140.

Since clustering is unsupervised, we do not know a priori what the best grouping of paintings is. In addition, since two artworks of a same artist could have been produced in different stylistic periods, it is very difficult to assign a precise label to a given painting, thus providing a form of supervision on the cluster assignments. For this reason, for clustering evaluation, we used two standard internal metrics, i.e. the silhouette coefficient [41] and the Calinski-Harabasz index

[3]: https://www.kaggle.com/ikarus777/best-artworks-of-all-time
[2]: http://artchallenge.ru
where \( C \) is the set of points in cluster \( q \), \( c_q \) the center of cluster \( q \), \( c_D \) the center of \( D \), and \( n_q \) the cardinality of cluster \( q \). It is worth noting that the Calinski-Harabasz index is not bounded within a given interval, instead its value tends to grow. For this reason, in the following, only relative values are reported normalized by the maximum value obtained. Finally, we also drew qualitative observations on the cluster assignments provided by the method.

### 4.1 Clustering evaluation

In the following subsections, we report the results obtained by clustering the overall dataset and those obtained by focusing only on the artworks produced by a single artist, namely Pablo Picasso.

#### 4.1.1 Overall dataset

Table 1 reports the clustering performance of the proposed DCEC-Paint over the whole dataset by varying the number of clusters \( k \). We varied \( k \) between 2, i.e. the minimum number of clusters, and 9, which is the grouping suggested by the nine different painting schools the artworks in the dataset historically belong to. By looking at the silhouette coefficient \( ss \), it can be seen that well-defined clusters are obtained in all cases, with the two highest values at \( k = 3 \) and \( k = 7 \). The values for the the Calinski-Harabasz index \( chs \) tend to increase or decrease accordingly. After training the two best models till convergence, we used the learned embedding features to fit t-distributed Stochastic Neighbors Embedding (t-SNE) representations for purposes of data visualization. t-SNE is a nonlinear dimensionality reduction technique which is suited for embedding high-dimensional data in a low-dimensional space of two or three dimensions. Specifically, it converts similarities between data points to joint probabilities and tries to minimize the Kullback-Leibler divergence between the joint probabilities of the low-dimensional embedding and the original high-dimensional data. Figures 2 and 3 show the t-SNE visualizations for \( k = 3 \) and \( k = 7 \). The graphical representation confirms the effectiveness of the model in finding clusters which look well-separated. From a qualitative point of view, both figures also show sample images from the clusters obtained with DCEC-Paint when \( k = 3 \) and \( k = 7 \). In the case of three clusters, the cluster assignment suggests that the model was able to separate artworks into three macro-periods:

1. More classic works, including Renaissance, Romanticist and Baroque paintings;
2. Artworks mostly belonging to the Impressionist and Post-Impressionist period, such as paintings from van Gogh and Degas;
3. More modern samples, including works by Picasso and Dalí.

In other words, with this low number of clusters, the model looked at stylistic attributes of paintings to group them. Conversely, by increasing the number of clusters to 7, it is more likely to find works from very different periods in the same clusters but sharing some other visual characteristics. In fact, in the case of 7 clusters, it seems that seven distinctive features were looked for by the model. Two clusters appear to be related to people: groups of more
individuals in one cluster; and single individuals, typically in portraits, in the other cluster. Another cluster mostly contains drawings: the dataset, in fact, includes several drawing works by Da Vinci, Duerer, and so on. A cluster mostly concerns with landscapes, independently of the stylistic school. Another one is made up of iconic works, mostly from the Gothic period. A cluster seems to be concerned with dark, Romanticist scenes. Finally, a cluster appears to include still-life paintings, flowers and, more in general, household items. These findings suggest that by increasing the number of clusters the model starts looking at content-based characteristics to group artworks.

4.1.2 Single artist data

We run DCEC-Paint on the 439 artworks painted by Pablo Picasso the dataset we used was provided with. We set $k = 3$ because historically three clearly distinguishable macro-periods can be recognized in the Picasso’s artistic production: blue period; rose period; and cubism. Although forms of proto-cubism can be traced in the first two periods, signing a transition from the earlier works towards the more mature production, the three periods present clear stylistic (and color) differences. In performing the clustering, DCEC-Paint achieves a high value of ss equals to 0.9356 and a chs of 10730.87. The latter value is not normalized as it concerns a much smaller dataset. These performance, together with the corresponding t-SNE visualization of the embedding features learned by the model (Fig. [4]), shows that the proposed approach is really effective in finding well-defined clusters. The figure also shows sample images from the
Table 1: Performance of DCEC-Paint on the overall dataset.

| k | ss  | chs  |
|---|-----|------|
| 2 | 0.8164 | 0.7092 |
| 3 | 0.8207 | 1.0000 |
| 4 | 0.8155 | 0.6965 |
| 5 | 0.7911 | 0.4235 |
| 6 | 0.7905 | 0.3434 |
| 7 | 0.8186 | 0.8340 |
| 8 | 0.7988 | 0.3415 |
| 9 | 0.8058 | 0.3916 |

Table 2: Effects of loss weights on cluster assignments.

| k | Original | No-weights | DCEC-Paint |
|---|----------|------------|------------|
|   | ss | chs | ss | chs | ss | chs |
| 2 | 0.7065 | 0.3787 | 0.8102 | 0.5608 | 0.8164 | 0.7092 |
| 3 | 0.6848 | 0.4099 | 0.7942 | 0.4260 | 0.8207 | 1.0000 |
| 4 | 0.7581 | 0.4382 | 0.8062 | 0.5952 | 0.8155 | 0.6965 |
| 5 | 0.7102 | 0.2375 | 0.7723 | 0.4999 | 0.7911 | 0.4235 |
| 6 | 0.7541 | 0.2749 | 0.8070 | 0.4397 | 0.7905 | 0.3434 |
| 7 | 0.7402 | 0.2930 | 0.8076 | 0.3544 | 0.7988 | 0.3415 |
| 8 | 0.7230 | 0.2358 | 0.8077 | 0.3511 | 0.8058 | 0.3916 |

Table 3: Comparison with other deep clustering methods.

| k | CAE+\(k\)-means | DEC | DCEC-Paint |
|---|----------------|-----|------------|
|   | ss | chs | ss | chs | ss | chs |
| 2 | 0.1214 | 0.0094 | 0.8105 | 0.4941 | 0.8164 | 0.7092 |
| 3 | 0.0649 | 0.0064 | 0.8031 | 0.4797 | 0.8207 | 1.0000 |
| 4 | 0.0619 | 0.0051 | 0.7873 | 0.4451 | 0.8155 | 0.6965 |
| 5 | 0.0636 | 0.0043 | 0.7861 | 0.3755 | 0.7911 | 0.4235 |
| 6 | 0.0603 | 0.0038 | 0.8081 | 0.3938 | 0.7905 | 0.3434 |
| 7 | 0.0564 | 0.0034 | 0.8126 | 0.5178 | 0.8186 | 0.8340 |
| 8 | 0.0467 | 0.0030 | 0.7905 | 0.3167 | 0.7988 | 0.3415 |
| 9 | 0.0486 | 0.0028 | 0.8036 | 0.3820 | 0.8058 | 0.3916 |

clusters obtained by the method. Thanks to the very different color distribution, the model was pretty good in grouping together works belonging to the same stylistic period of the artist.

4.2 Comparison with original formulation

We studied the effects of the loss weights assigned to the composite loss function \(L\) on the clustering performance. In the original formulation of DCEC, weights are inverted and the joint loss assumes the following form: \(\hat{L} = (1-\lambda)L_r + \lambda L_c\), with \(\lambda\) evaluating 0.1. This form puts more emphasis on the reconstruction loss rather than the clustering loss during backpropagation. However, since the accurate image reconstruction is not the primary task of the model, we reversed the weights. Table 2 shows the results obtained in terms of ss and chs between the original DCEC and the proposed one, by varying the number of clusters \(k\). Note that also the results of applying no weights, i.e. using a joint loss in which the reconstruction and clustering term have the same importance, are reported. As it can be observed, a trend emerges in which giving gradually more importance to the clustering term rather than the reconstruction term improves performance.
4.3 Comparison with Other Methods

Table 3 shows the comparison between DCEC-Paint and CAE+$k$-means and DEC. The clustering performance of CAE+$k$-means clearly indicates that this approach is completely ineffective, with performance decreasing as $k$ increases. Instead, DEC compares favorably with our approach with quite similar values for what concerns $ss$ and lower performance in terms of $chs$. Both DCEC-Paint and DEC agree that the partitions into 3 and 7 clusters are among the best solutions, even if the second highest performance of DEC is obtained with $k = 2$.

5 Conclusion

In this paper, we addressed the problem of grouping together digitized paintings in a completely unsupervised fashion. To this end, we proposed a deep convolutional embedding clustering model which relies only on visual features automatically learned by the deep network model. The model was able to find well-separated clusters both when considering an overall dataset spanned across different epochs and when focusing on the works produced by a same artist. Quantitative and qualitative results confirmed the effectiveness of the method. In particular, from a qualitative point of view, it seems that the model is able to recognize stylistic or semantic attributes of paintings to group them. When the granularity of clustering is coarse, the model looks at more general features, mostly concerning with the artistic style. Instead, when the granularity is finer, the model starts looking at content features and tends to group works independently of the corresponding painting school. The method may be beneficial to several art-related tasks, particularly historical knowledge discovery, visual link retrieval and museum logistics. More in general, the experimental results here reported confirm the effectiveness of applying the deep clustering approach to very complex image domains, such as the artistic one.

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