Deep Convolutional Embedding for Digitized Painting Clustering

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Art & Science

Cultural heritage, in particular **visual arts**, are of inestimable importance for the cultural, historical and economic growth of our societies

In recent years, a large scale digitization effort has led to an increasing availability of large digitized art collections, e.g. WikiArt

This availability, coupled with the recent advances in Pattern Recognition and Computer Vision, has opened new opportunities for computer science research to assist the art community with automatic tools

Motivations

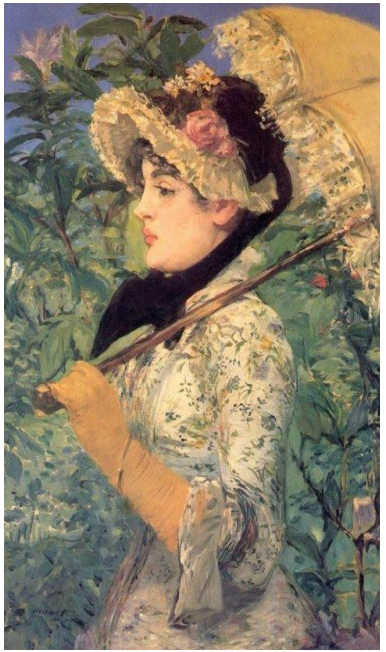
Human beings find similarity relationships among paintings based on their **aesthetic perception**

This perception (which can also be influenced by subjective experience) is:

- ➔ extremely hard to conceptualize
- ➔ difficult to translate into features and labels

Our **goal** is to develop an automatic tool to group digital paintings based on:

- ➔ “visual” features
- ➔ an unsupervised approach



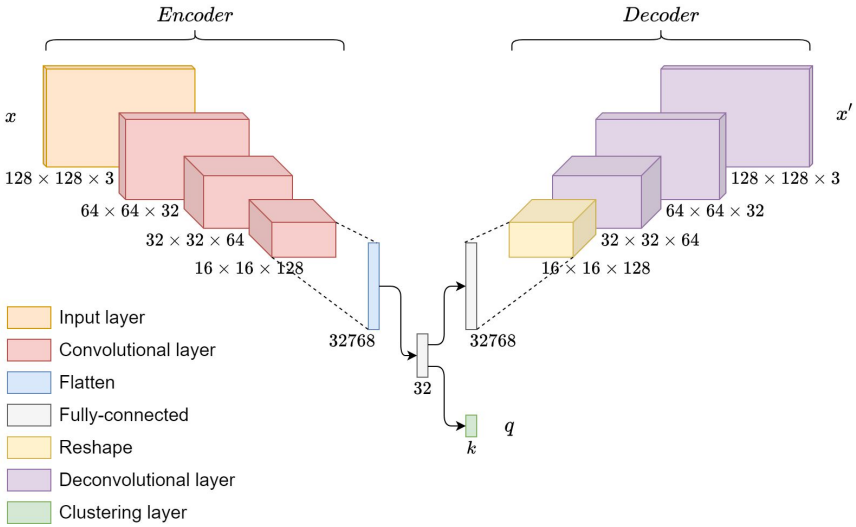
Limitations of traditional methods

- ➔ Applying traditional algorithms like k-means on the high-dimensional raw pixel space can be ineffective
- ➔ The application of reduction techniques, such as PCA, can ignore nonlinear relationships between the original input and the latent space
- ➔ Some variants of k-means (e.g., spectral clustering) are computationally expensive as the data grows
- ➔ Engineering meaningful features based on domain knowledge is extremely difficult

Deep Convolutional Embedding Clustering

We propose to use a **deep convolutional embedding** model for digitized painting **clustering**

Mapping the raw input data to an abstract, latent space is jointly optimized with the task of finding a set of cluster centroids in this latent feature space



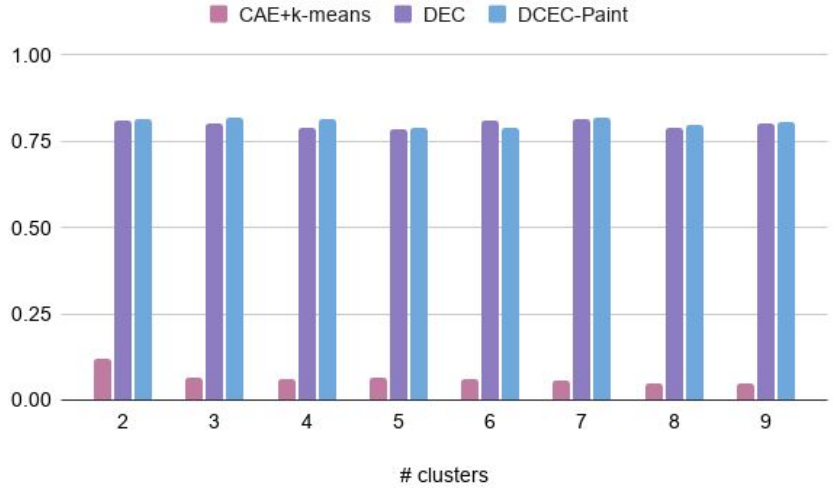
Experiment

To evaluate the effectiveness of the method, we used a database that collects paintings of 50 very popular artists belonging to 9 stylistic periods:

- ➔ Gothic
- ➔ Renaissance
- ➔ ...

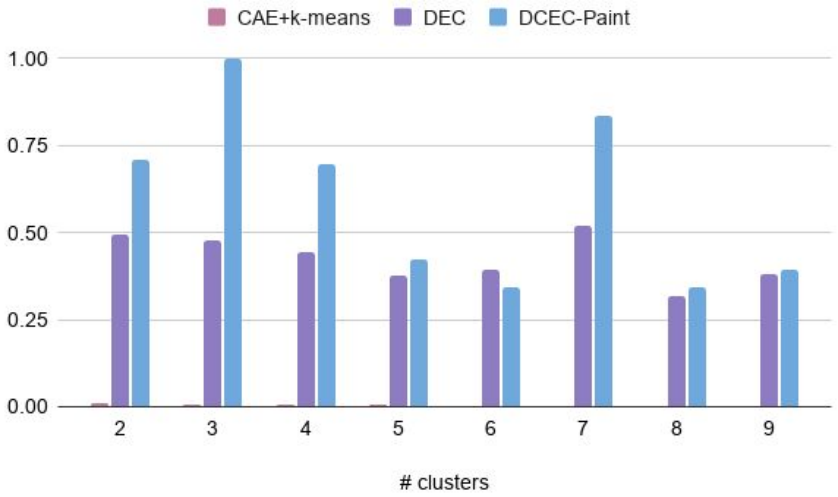
Quantitative results

Silhouette coefficient (compared to other deep clustering methods)



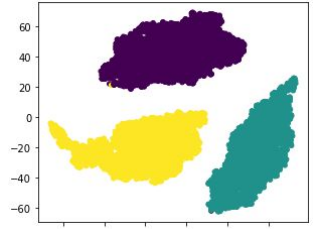
Quantitative results

Calinski-Harabasz index (compared to other deep clustering methods)



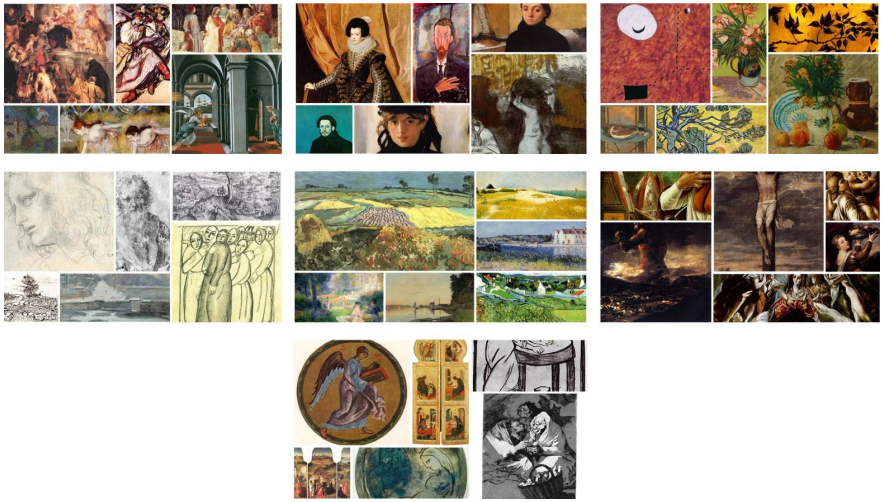
Qualitative results

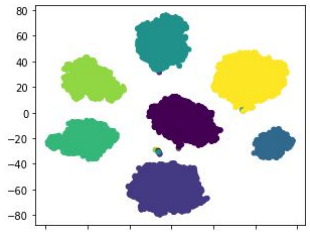
With **3 clusters**, these look well separated



Qualitative results

The same holds for **7 clusters**





Conclusion

Encouraging results have been obtained, which confirm the effectiveness of the deep clustering approach to address highly complex image domains, such as the artistic one

When the granularity of clustering is *coarse*, the model takes into account more general features, mainly related to the artistic style

When the granularity is *finer*, the model begins to use content features and tends to group works regardless of the corresponding painting school

In the future, we would like to discard traditional distance measures to find clusters in the feature space, relying on a metric learning approach

Thank you!