# Fuzzy clustering to encode contextual information in artistic image classification *

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**Abstract.** Automatic art analysis comprises of utilizing diverse processing methods to classify and categorize works of art. When working with this kind of pictures, we have to take under consideration different considerations compared to classical picture handling, since works of art alter definitely depending on the creator, the scene delineated or their aesthetic fashion. This extra data improves the visual signals gotten from the images and can lead to better performance. However, this information needs to be modeled and embed alongside the visual features of the image. This is often performed utilizing deep learning models, but they are expensive to train. In this paper we utilize the Fuzzy C-Means algorithm to create a embedding strategy based on fuzzy memberships to extract relevant information from the clusters present in the contextual information. We extend an existing state-of-the-art art classification system utilizing this strategy to get a new version that presents similar results without training additional deep learning models.

**Keywords:** Clustering · Image Classification · Fuzzy C Means · Representation learning.

## 1 Introduction

The digitalization of various artworks and collections all around the world has utilized well known methods of computer vision and image processing on creative information [5]. One of the most encouraging themes toward this path is the

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programmed examination of compositions. These strategies are applied in tasks generally performed on most of the galleries and museums. For example, author verification [14], style investigation [25] or restauration [47].

Automatic art analysis examination can be performed utilizing hand-created features [10] [39], or automatically extracted features using deep-learning [22] [41]. Utilizing a Convolutional Neural Network to extract visual features from a picture is extremely well known and popular [4] [3], [35]. But for the instance of imaginative and creative pictures, human experts perform their examination using not only visual cues. They also rely on their insight on the chronicled setting, other artworks, materials, and so on [27].

There are numerous ways in which this information can be used. One of the the most popular ones is a knowledge graph [19] [18]. An knowledge graph models the connection between various ideas and attributions utilizing the construction of an network [40] [12]. Networks are a successful way to model interactions [29] and they have been utilized to tackle a heap of issues in various subject matters, from computer science [16] [30] [8], to biology [31] and the social sciences [2] [17]. The network connections can be utilized to capture all the information connected with a painting that trascends the visual cues,like the author or the artistic style. The most popular way to use this information is to develop continuous space representation from the nodes in the graph [28] [21]. These sort of representation are popular since they can work with conventional AI approaches [20].

The combination of visual and contextual features stands for a promising direction in which to perform automatic artistic images analysis [19] [18] [44]. However, even though visual features have been widely studied in the context of deep learning, there is not a straightforward procedure to model the contextual information associated with each image. The different possibilities of representation and fusion of this information can result in a wide range of different performances, as some modelizations can be more suitable for one task than others.

The mix of visual and context oriented elements represents a promising direction in which to perform automatic artistic images analysis [19] [18] [44]. However, despite the fact that visual elements have been broadly considered using deep learning, there is certainly not a direct methodology to show the relevant data related with each picture. he different possibilities of representation and fusion of this information can result in a wide range of different performances, as some modelizations can be more appropriate for one errand than others.

The aim of this paper is to propose different methods of representing the contextual embeddings from different works of art utilizing different traditional strategies, less complex and quicker than the development of a deep learning model. In order to so, we shall study different representation space obtained, and the various clusters obtained utilizing the Fuzzy C-Means [7]. Thus, we can develop an implanting strategy where each aspect is an embedding method where each dimension is a fuzzy membership to each of the relevant groups found in the original representation space.

The rest of the paper goes as follows: in Section 2 we displayed some of the previous concepts required to understand this work. In Section 3 we show our new method to obtain contextual embeddings from textual annotations using the Fuzzy C-Means clustering. Subsequently, in Section 4 we display our proposed framework for artistic image classification using contextual embeddings. In Section 5 we show the results of our experimentation and of other classification frameworks compared to ours. Finally, in Section 6 we give our final conclusions and future lines for this work.

## 2 Background

In this section we revise some previous works regarding knowledge graphs, the Fuzzy C-Means clustering algorithm and context aware embeddings.

### 2.1 Knowledge graphs

Knowledge graphs are a form of knowledge representation in which each concept is modeled as a node that is related to others with different relationships that are represented as edges. Knowledge graphs have been very popular in fuzzy literature because of fuzzy cognitive maps, and they have been instrumental in the development on a many systems.

There are different strategies in which a knowledge graph can be constructed and exploit. One possibility is to form hierarchies of concepts detected in images, or exploiting semantic similarities between different concepts or to use external knowledge bases.

Once the knowledge graph is built, there are different ways in which it can be exploited. One possibility is to feed it directly to a graph neural network. It is also possible to extract embeddings using node2vec, that uses random walks to create representations of each node that balance local proximity and homophily. Sometimes, it is also possible to use inference methods directly in the graph.

### 2.2 Fuzzy C-Means

The Fuzzy C-Means (FCM) is a well known fuzzy clustering algorithm, in which each element is assigned not only to one group, but rather, presents a membership to each of the groups considered [7].

The FCM aims to minimize the corresponding objective function:

$$\arg\min \sum_{i=1}^{n} \sum_{j=1}^{c} w_{ij}^{m} ||\mathbf{x}_i - \mathbf{c}_j||^2 \tag{1}$$

where $n$ is the number of observations, $m$ is a constant, $\mathbf{c}$ is a cluster and $c$ is the number of different clusters, and $\mathbf{x}$ is an observation. Finally, $w_{ij}^{m}$ is the membership of the $i-th$ particle to the $j-th$ cluster, that follows this expression:

$$w_{ij} = \frac{1}{\sum_{k=1} c \left( \frac{||\mathbf{x}_i - \mathbf{c}_j||}{||\mathbf{x}_i - \mathbf{c}_k} \right)^{\frac{2}{m-1}}} \tag{2}$$

The algorithm assigns randomly a coefficient for each observation to each cluster. Then, computes the centroid for each cluster, and the computes each membership again. It repeats this process until it has converged.

### 2.3 Multi-task learning

Similarly to transfer learning, the idea of multi-task learning (MTL) is that features can be useful for more tasks than they were originally intended to [43]. MTL is based on training for more than one task at a time, so that the resulting features will generalize better [11] [13].

MTL can be performed using hard parameter [38] and soft parameter sharing [36]. In the first case, the parameters for all the tasks are shared until the last layer, while in the latter one, each task has its own set of parameters, but they are encouraged to stay similar using different regularization methods. MTL is a popular deep-learning approach that has been successfully applied in different environments [48].

### 2.4 Representation learning

Representation learning consist of automatically extracting and computing features suitable for machine learning tasks from unstructured data like text, video or image [6]. Deep learning is one of the most popular fields in which feature learning is performed. Convolutional neural networks have been massively popular tools to embed images and video into vector spaces [15] [26] [32] [23] as well as text [33].

Just as image, video and text, networks can also be embed into vector space using deep learning models [21] [37] [46]. The deep learning models can be combined with other classical methods in text, using TF-IDF or latent Dirichlet allocation [9] [24].

## 3 Fuzzy representations for contextual information using Fuzzy C-Means

In this section we present our new proposal to substitute and enhance the contextual information extraction in two steps: first, we discuss how can we obtain bag of words representations from each contextual image, and how can we use the Fuzzy C-Means algorithm to extract the relevant information from the chosen feature extraction method.

### 3.1 Encoding context using Bag of Words

Contextual information in artistic images is usually encoded using textual representation (Figure 2). Textual representation can be encoded in different ways. The most classical one is the Bag of Words (BoW) in which each phrase is represented as a vector of numbers in the $[0, 1]$ where each position is associated with one word.

This representation is usually computed using the term frequency-inverse document frequency (TF-IDF) metric represent each word [1]. TF-IDF has been very popular in other artistic image processing tasks [19] and in text processing tasks in general [34] [45].

However, this representation presents some issues for our application. The vocabulary of these kind of contextual annotations is usually full of personal names and words that are present in very few samples. We are interested in a representation that scales well with the number of features, so that the vocabulary can be easily fixed. It can also be problematic that the TF-IDF ponders most words that are frequent in a description but absent in others. The idea is that those words are most discriminative than others, but this is not necessarily true in our case. "Landscape", for example, is a word that appears in many descriptions but is also very discriminative. This also happens with other words such as "Portrait".

In order to solve these problems, we have opted to use only the top $k$ most common words and a standard BoW representation. In this representation each contextual information is coded as a vector of size $k$ in which each position $n$ is 1 if the $n$-th most common word is present in the text. We shall fine-tune the $k$ value empirically.

### 3.2 Extracting relevant context information using Fuzzy C-Means

The idea of using FCM for this task is that the space formed using our embedding method can be a faithful representation of the original domain, bur not useful to solve the task at hand. Since we are interested in using these features to discriminate between classes, we are more interested in the topology of the representation obtained and the groups that are naturally present in them.

We expect that these groups should agglomerate categories that are not mutually exclusive. For example, in the case of artistic representation, style and year can be very correlated, because of artistic movements. Sometimes artists just don't follow their contemporary trends. There are many more possible examples in this case: landscapes can be together but belong to different authors, etc.

The FCM is the most suitable clustering algorithm for this task, since we intend to express the membership to different, not mutually exclusive groups. For each observation, the FCM returns a fuzzy membership degree for each of the pertinent groups. We can use this information to better characterize each observation with respect to the rest of them: each feature will correspond to one of the different relevant groups found using the FCM algorithm, instead of just encoding the original contextual information.

## 4 Artistic Image Classification Framework

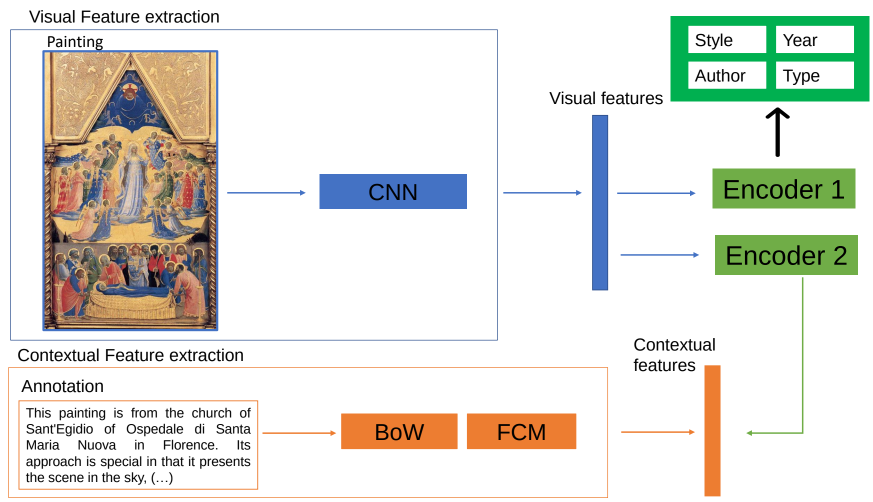


**Fig. 1.** Scheme of the proposed classification framework.

Our proposed framework consists of two different parts. On one hand, we compute the contextual embeddings in two step process:

1. Compute the BoW encoding for each annotation.
2. Compute the FCM over the BoW encodings in order to obtain the fuzzy memberships to each of the clusters founds.

On the other hand, we use a ResNet 50 [42] to compute visual features for each image. This ResNet is trained in a multi-task setting, so that it must learn at the same time style, year, author and type of each painting. It also trained to learn a reconstruction of the contextual embeddings computed alongside the classification problem. In order to do so, we have two "final" layers: one encoder that transforms the final feature vector of the network into the contextual features, and another one that performs the classification. These encoders are single full connected layers with a Rectified Linear Unit activation function.

The loss for each class $c$ is the standard cross-entropy:

$$l_c(y, \hat{y}) = -\frac{1}{n} \sum_{i=1}^{n} y_{ci} \log \hat{y}_{ci} + (1 - y_{ci}) \log(1 - \hat{y}_{ci}) \tag{3}$$

Given $r$, the final embedding obtained from the ResNet, $m$ the number of clusters obtained with the FCM, the loss function for the reconstruction of the fuzzy memberships vector is the Smooth L1:

$$\delta_{emb}(i,j) = \begin{cases} \frac{1}{2}(i-j), & \text{if } |i-j| \leq 1 \\ |i-j| - \frac{1}{2}, & \text{otherwise} \end{cases} \tag{4}$$

$$l_{emb} = \sum_{i=1}^{n} \sum_{j=1}^{m} \delta_{emb}(w_{ij}, r_{ij}) \tag{5}$$

A visual scheme of our proposed framework is displayed in Figure 1.

## 5 Experimentation

"Tiepolo painted this altarpiece during his stay in Germany. Because of the damp climate, he could only work on the frescoes in the Wurzburg Residenz in the spring and summer. So in the fall and winter he had to concentrate on painting in oil on canvas. He produced some fantastic and exotically beautiful works in which the religious subject seems merely a pretext for eye-catching, showy images, but he himself was genuinely religious. The style of the age, however, meant that even religious topics often became theatrical"

**Fig. 2.** An example of a Semart painting alongside its contextual information.

In this section we have computed the results with our proposed method, using the visual embeddings from the ResNet and the context aware embeddings enhanced using the Fuzzy C-means algorithm. We have also compared our solution with other proposals that use both visual and contextual embeddings.

For our experimentation we have used the SemArt dataset [19]. This dataset consists of 21,384 painting images, from which 19,244 are used for training, 1,069 for validation and 1,069 for test. Each painting has associates an artistic comment, alongside the following attributes: Author, Title, Date, Technique, Type, School and Timeframe.

In this experimentation three different classification tasks are proposed:

- Type: each painting is classified according to 10 different common types of paintings: portrait, landscape, religious, etc.
- School: each painting is identified with different schools of art: Italian, Dutch, French, Spanish, etc. There are a total of 25 classes of this kind.
- Timeframe: The attribute Timeframe, which corresponds to periods of 50 years evenly distributed between 801 and 1900, is used to classify each painting according to its creation date. We consider only the timeframes where at least 10 are present. This corresponds to 18 classes.
- Author: corresponds to the author of each paintings. We consider a total of 350 painters, that comprise the set of authors with more than 10 paintings in the dataset.

Our first experimental study was finding the optimal number of dimensions to use in the BoW embedding. Since we are interested in using the FCM on the computed embeddings, we are interested in finding a representation that clearly shows cluster of observations. We found the optimal number using visual inspection with the PCA algorithm, as the results were straightforward enough to interpret (Figure 5).

After the ideal number was stablished as $k = 5$, we computed the FCM for different numbers of clusters, and we computed the silhouette index in each case. We use the "elbow rule" to choose the optimal number of clusters, which we established as 13 (Figure 5d).

Once we have stablished the dimensionality of the BoW vectors and the number of clusters for the FCM, we can train our model using the computed contextual embeddings. We show the results obtained using our method in Table 1. In order to check the importance of the Bow and FCM parameters we also trained our proposed framework using a bigger number of words for the BoW model and a bigger number of clusters for the FCM.

Besides our method, we have also shown the results obtained with other classification methods:

1. The ResNet50, ResNet152 and the VGG16 using their correspondent pre-trained weights. We adapt the last layer to match the number of target classes. These solutions consider only the visual information for each image.
2. The ResNet50, ResNet152 and the VGG16 fine-tuning their weights. We also adapt the last layer to match the number of target classes. These solutions consider only the visual information for each image.
3. The ResNet50 precomputed weights with information captured from contextual annotations using node2vec representations using a Knowledge graph [18].

From the results obtained, we can conclude that pre-trained models using only visual features performed the worst. When taking into account contextual features using both FCM or KGM, the performance improved substantially for all classes. Comparing the context-aware proposals, the FCM-based frameworks performed better than their KGM counterparts in the "Type" and "Author" classes, where they also obtained the vest result overall. The best results for the two other classes were obtained using a fine-tuned ResNet50 model.

**Table 1.** Classification results for the different attributes on SemArt Dataset.

| Method | Type | School | TF | Author |
|---|---|---|---|---|
| VGG16 pre-trained | 0.706 | 0.502 | 0.418 | 0.482 |
| ResNet50 pre-trained | 0.726 | 0.557 | 0.456 | 0.500 |
| VGG16 fine-tuned | 0.768 | 0.616 | 0.559 | 0.520 |
| ResNet50 fine-tuned | 0.765 | **0.655** | **0.604** | 0.515 |
| ResNet50 pre-trained+KGM | 0.786 | 0.647 | 0.597 | 0.548 |
| ResNet50 pre-trained+$\text{FCM}_{5-15}$ | 0.778 | 0.625 | 0.591 | **0.564** |
| ResNet50 pre-trained+$\text{FCM}_{100-150}$ | **0.793** | 0.630 | 0.586 | 0.559 |

## 6 Conclusions and future lines

In this work we have presented a new method to extract features from the contextual annotations of a dataset of artistic images. We have shown the classification framework used, that uses a fine-tuned ResNet 50 in a multi-task environment. This network learns to solve a classification problem and to reconstruct the features extracted from the contextual image for each image, which helps the network generalize better, as it cannot rely only on visual cues to classify each sample.

In order to construct the contextual representations, we extract the $k$ most common words and we construct use a bag of words method. Then, we use Fuzzy C-Means clustering on these features to obtain a fuzzy membership for each of the natural clusters formed in this representation. In this way, the network is forced to learn a representation for each sample that is useful to solve the classification problem, but it is also a faithful representation of the different coalitions present in the contextual information embeddings.

We have compared our proposal with other similar classification frameworks. We found that contextual works using a knowledge graph surpass our performance, but are considerably more expensive to compute. We also found that our framework performed better than others using only visual features. Future lines of our research shall study the use of fuzzy linguistic variables to characterize the images in order to find a more expressive space in which to represent some of the images characteristics and attributes.

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