Convolutional neural network for image classification

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Abstract

Convolutional Neural Networks (CNN) have become the most widely used system to address the image classification task today. Due to their powerful ability to learn patterns have acquired great importance for the realization of a lot of problems in the field of computer vision. Because of this, a CNN was implemented with four convolutional layers and two fully connected layers, applying max pooling on the first layer and a nonlinear activation function on the final layer output. The model was trained with 3000 images of the database training set, 50 images per batch and 70 epochs from the Large-scale CelebFaces Attributes (CelebA) Dataset.

1. Introduction

Image classification is defined as the task of categorizing images into one of several predefined classes and it is a fundamental problem in computer vision [9]. Likewise, it forms the basis for other computer vision tasks such as localization, detection, and segmentation [2]. Even though the action of discriminating objects is a natural activity develop by humans, it represents a challenging task for computer due to some complications encountered in the representation of real world by digital images such as viewpoint-dependent object variability and the high in-class variability of having many object types [1]. However, deep learning models that exploit multiple layers of nonlinear information processing, for feature extraction for pattern analysis and classification, have been shown to overcome these challenges and exposed promising results [9].

One of the most implemented architectures to carry out an image recognition task corresponds to the convolutional neural networks (CNN). Neural networks are computational techniques for recognizing patterns, which consists of simple processing units, called neurons or nodes, connected to other neurons in the network by unidirectional connections of different strength or weight [8]. Usually, the neurons are arranged in a series of layers, bounded by input and output layers encompassing a variable number of hidden layers,

connected in a structure according to the complexity of the problem addressed [8]. The most common architecture of a standard feedforward CNN consists of a convolutional and pooling layers grouped into modules and one or more fully connected layer [9].

The convolutional layers serve as feature extractors, and thus they learn the feature representations of their input images. The neurons in the convolutional layers are arranged into feature maps and inputs are convolved with the learned weights in order to compute a new feature map, and the convolved results are sent through a nonlinear activation function [3]. On the other hand, the purpose of the pooling layers is to reduce the spatial resolution of the feature maps and achieving spatial invariance to input distortions and translations. Finally, a layer is fully connected if each node in the layer is connected to all the nodes in an adjacent layer [5], [4].

CNNs are feedforward networks, that is information flow takes place in one direction only, from their inputs to their outputs [9]. In addition, two of the main particular characteristics of these models is that the input is the image without any processing and that the representation space and the classifier used are the network itself. On the other hand, these models implement learning algorithms during training stage to adjust their parameters such as weights and biases in order to obtain a desired output. Therefore, an image is input directly to the network, and this is followed by several stages of convolution and pooling. Later, representations from these operations feed one or more fully connected layers and the last fully connected layer outputs the class label [9]. Finally, backpropagation algorithm is employed to compute the gradient of an objective to determine an adjustment factor to update the parameters in order to minimize errors that affects performance [6].

Keeping this in mind, the most important aspect of networks are their ability to learn from examples, and because the learnt information is stored across the network weights, to generalize, achieving accurate classifications even for input patterns not included in the training set [8]. In this order of ideas, a convolutional neural network was implemented to address a multi-class and multi-label classification prob-

Figure 1. Sample images of different classes among the whole dataset

Figure 2. Qualitative performance of the model implemented in the multi-label classification of images of the test set

lem of celebrities with different attributes.

2. Methods

2.1. Database

Large-scale CelebFaces Attributes (CelebA) Dataset was used. It consists of 200.000 images of celebrities and it is labeled with 40 different attributes (not-mutually exclusive) such as wearing eyeglasses, smiling, arched eyebrows, male/female (do not judge about binary genders), pale skin, young/old. The images in the dataset cover large pose variations and background clutter [7]. For this study, only 10 out 40 attributes were used to train the model. Figure 1 shows examples of the images employed for the training stage.

2.2. Algorithm

A CNN was implemented with four convolutional layers and two fully connected layers. In the first convolutional layer max pooling was performed, and it was applied down-sampling in the first two layers and up sampling in the last two. Each batch was normalized. Additionally, a dropout was applied to convolutional layers 2, 3 and 4. Likewise, in the layer where max pooling is passed from down-sampling to up-sampling a greater dropout than in the other layers was applied in order to avoid the overfitting of the model. Finally, since it is a multilabel classification problem, non-linear layers were not used within the network architecture but a sigmoid activation function was used to normalize the predictions at the output of the last layer fully Connected.

3. Results

In figure 2 it is shown the performance of the implemented model in the classification task for sample images of the test set. For each image a vector of zeros and ones is depicted which one correspond to an attributed recognized in the image and zero means that the attribute is not present. The attributes Eyeglasses, Bangs, Black Hair, Blond Hair, Brown Hair, Gray Hair, Male, Pale Skin, Smiling and Young refers to the same order positions of the vector, respectively.

4. Discussion

Alternatively to the implemented model, another mechanism to address this problem is by implementing a model with Bag of Words (BoW), whose main objective is to design visual words and to represent the image by its distribution of visual words. First of all, the local features of the image are extracted by sweeping with a pixel to pixel slider by computing Sift dense across the whole set of training images. At the same time, this process is carried out at the different levels of the Gaussian pyramid with the aim of making the model invariant at the scale. Once the Features are extracted, the dictionary of visual words is constructed by clustering with k-Means in the Sift space. Next, the pyramid of visual word histograms is computed for each image and the corresponding classifier is trained, in this case Random Forest could be a good alternative. Finally, to evaluate the performance of the model the pyramid of visual word histograms is computed for each test image and evaluated with the classifier, assigning the label of the class with a higher level of confidence.

The challenges faced in the design of the model's architecture are summarized in two main factors. The first is due to the adjustment of the dimensions at the outputs of each of the convolutional layers and the entry of the next layer, so that the sizes of the image display match and are appropriate to extract the necessary characteristics of the objects for correct network learning. The second challenge concerns the design of a sufficiently deep architecture taking into ac-

count the limited resources available, so that the amount of layers was appropriate for learning the main characteristics of each of the classes to be evaluated.On the other hand, compared to the original design, a convolutional layer was added with respect to the three initials of the network implemented in the previous challenge and it was decided to use a detector of faces as input of the neural network, so that it forces the network to learn patterns related to the expressions and attributes of the person ignoring as much as possible the background noise of the image and artifacts that are not points of interest and do not contribute to the learning.

5. Conclusions

It was not possible to conclude regarding the performance of the method in this classification task because errors occurred at the time of submission of the model to the challenge server as it was not available

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