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Segmentation and Representation of Data Dependent Label Distribution Learning for Age Estimation using CNN

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Abstract— In the age estimation, apparent ages of images are provided. Uncertainty of each apparent age is induced because each image is labeled by multiple individuals. Such uncertainty makes this age estimation task different from common chronological age estimation tasks. In this paper, we propose a method using deep CNN (Convolutional Neural Network) with distribution-based loss functions. Using distributions as the training tasks can exploit the uncertainty induced by manual labeling to learn a better model than using ages as the target. To the best of our knowledge, this is one of the first attempts to use the distribution as the target of deep learning. In our method, two kinds of deep CNN models are built with different architectures. After pre-training each deep CNN model with different datasets as one corresponding stream, the competition dataset is then used to fine-tune both deep CNN models. Moreover, we fuse the results of two streams as the final predicted ages. In the final testing dataset provided by competition, the age estimation performance of our method is 0.3057, which is significantly better than the human-level performance (0.34) provided by the competition organizer

Keywords: CNN, AGE Estimation

1. INTRODUCTION

Two deep CNN models in different architectures are separately trained as two corresponding streams on different datasets. Moreover, the distribution based loss function, i.e., the KL divergence loss function, is used in our model as the training target to exploit the information of the standard deviations. In order to improve the estimation performance of both two streams, performance in diverse visible popularity tasks. A massive classified schooling set is one of the most essential elements for its success. However, it's miles difficult to collect enough training images with particular labels in some domain names which includes obvious age estimation, head pose estimation, multi-label category and semantic segmentation. Fortunately, there's ambiguous information among labels, which makes those tasks different from conventional classification. Based on this commentary, we convert the label of each image into a discrete label distribution, and study the label distribution via minimizing a Kullback-Leibler divergence between the expected and groundtruth label distributions the usage of deep ConvNets. The proposed DLDL (Deep Label Distribution Learning) method efficiently makes use of the label ambiguity in each function gaining knowledge of and classifier mastering, which help save you the community from over-fitting even if the schooling set is small. Experimental outcomes show that the proposed approach produces extensively higher outcomes than state-of-the-art methods for age estimation and head pose estimation. At the equal time, it additionally improves popularity overall performance for multi-label class and semantic segmentation tasks Age estimation overall performance has been substantially advanced by using using convolutional neural community. However, current techniques have an inconsistency between the training goals and evaluation metric, so they will be suboptimal. In addition, these strategies always undertake photo class or face popularity models with a massive quantity of parameters, which convey pricey computation fee and storage overhead. To alleviate these troubles, we layout a lightweight community architecture and propose a unified framework that could together analyze age distribution and regress age. The effectiveness of our technique has been confirmed on obvious and actual age estimation obligations. Our approach achieves new today's results using the single model with 36�fewer parameters and 2.6�discount in inferen ce time. Moreover, our approach can gain comparable consequences because the trendy despite the fact that version parameters are further decreased to zero.9M (three.8MB disk garage). We also examine that Ranking methods are implicitly gaining knowledge of label distributions

The not unusual assessment metric of age estimation is the Mean Absolute Error (MAE) among the expected value and ground-fact age. Thus, it is very natural to deal with age estimation as a metric regression trouble which minimizes the MAE. However, such techniques usually can't obtain high-quality performance due to the fact a few outliers might also cause a big errors time period which leads to an risky schooling technique. Later, trained deep convolutional neural network (CNN) for age estimation as multi-class class, which maximizes the possibility of floor-reality class without considering other training. This approach effortlessly falls into over-fitting because of the imbalance problem among instructions and restricted education images. Recently, rating CNN and deep label distribution gaining knowledge of (DLDL) strategies accomplished today's overall performance on age estimation. The rating method transforms age estimation to a series of binary classification problems in the training degree. Then, the output of the rankers are aggregated at once from these binary outputs for estimating age. The DLDL first of all converts real-price age to a discrete age distribution. Then, the aim of the training is to suit the complete distribution. At inference degree, an predicted price over the expected distribution is taken as the final output. We can without problems find that there is an inconsistency between the schooling targets and assessment metric in most of these strategies. Thus, they may be suboptimal. We anticipate to enhance their overall performance if the inconsistency can be alleviated. (1) Low-rank channel covariance matrices based methods, such as the finite scattering environment and small angular spread result in high correlation of different paths between the user and the BS and low-rank channel covariance matrix. We choose the deep CNN model as our basic model because of its satisfactory performance in various areas of face-related tasks, e.g., face recognition [16], face alignment, face verification, age and gender classification, etc. In this paper, we build two deep CNNs of different architectures as two streams to solve the apparent age estimation problem. The first one is based on a popular pre-trained deep network, i.e., VGG-16. For this deep CNN model, it is fine-tuned three times with different datasets in our method. The second deep CNN model is based on a novel architecture; we utilize different types of inputs, i.e., different augmentation methods used on our own collected data, to train this deep CNN model. After that, we use the competition dataset to fine-tune this model. Finally, we fuse the results of two streams as the final predicted ages. In the final evaluation phase, our method achieved 0.3057 age estimation performance, which is significantly better than the human-level performance

II. OBJECTIVES

The primary objectives of this study can be summarized as follows:

1 By using distribution-based loss functions as training targets in deep CNN models, the uncertainty information induced by standard deviation is exploited to solve the apparent age estimation problem. In addition, by using distribution as the target can make a face image contribute to not only the learning of its own age, but also the learning of its neighboring ages. Therefore, we can use the data more sufficiently.

2 We totally downloaded 119,539 face images from Internet and labeled these images manually. By using these additionally collected face images, the deep CNNs used in our method have a stronger prediction ability compared with the model only trained on the images provided by this competition

In the first stream of our method, we use the popular pretrained CNN model, i.e., VGG, as the basic model for age estimation. The whole process of training and predicting is listed as follows:

1) Fine-tuning on the MORPH dataset. In this step, we fine-tune VGG-16 on the pre-processed MORPH dataset which contains 55,134 images.

2) Fine-tuning again on two datasets collected from search engines and public facial datasets. In this step, we fine-tune the deep model obtained in the first step on two different datasets separately, then two different deep CNN models are obtained. The first dataset includes 27,197 images downloaded from Google. The second dataset includes 37,606 images downloaded from Baidu, Bing, FG-Net [1] and Adience

3) The last fine-tuning on the competition dataset with two different loss functions. In this step, we use 3,615 competition images (training and validation datasets) to fine-tune two deep CNN models obtained in the second step. Two different loss functions are used in these two deep CNN models separately. The first one is the KL divergence loss function, which is a distribution-based loss function. By using the KL divergence loss function, instead of considering each face image as an example with one label/age, each face image is treated as an example associated with a label distribution to exploit the uncertainty information. Given the mean age mn and standard deviation σn of the nth face from the competition dataset, a Gaussian distribution with mean and standard deviation σn is generated for the nth face. The second loss function is the softmax loss functionWe choose the deep CNN model as our basic model because of its satisfactory performance in various areas of face-related tasks, e.g., face recognition [16], face alignment, face verification, age and gender classification, etc. In this paper, we build two deep CNNs of different architectures as two streams to solve the apparent age estimation problem.

III. BLOCK DIAGRAM

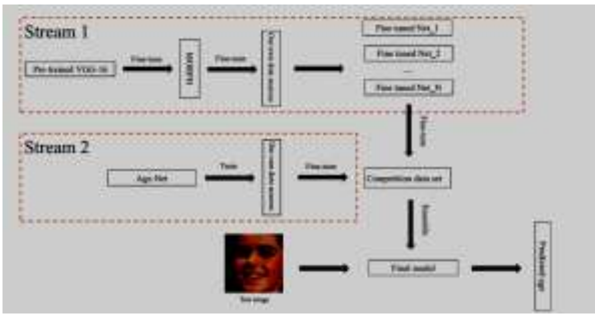

Fig III System model for the Age Estimation

IV. Conclusion

In this paper, we firstly analyze that Ranking-based methods are implicitly learning label distribution. This result unifies two existing popular state-of-the-art age estimation methods into the DLDL framework. Second, we propose a DLDL-v2 framework which alleviates the inconsistency between training and evaluation stages via jointly learning age distribution and regressing single age with a thin and deep network architecture. The proposed approach creates new state-of-the-art results on apparent and real age estimation tasks with fewer parameters and faster speed. In addition, our DLDL-v2 is also an interpretable deep framework which employs different patterns to estimate age...

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