Research Article

Age Label Distribution Learning Based on Unsupervised Comparisons of Faces

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Although label distribution learning has made significant progress in the field of face age estimation, unsupervised learning has not been widely adopted and is still an important and challenging task. In this work, we propose an unsupervised contrastive label distribution learning method (UCLD) for facial age estimation. This method is helpful to extract semantic and meaningful information of raw faces with preserving high-order correlation between adjacent ages. Similar to the processing method of wireless sensor network, we designed the ConAge network with the contrast learning method. As a result, our model maximizes the similarity of positive samples by data enhancement and simultaneously pushes the clusters of negative samples apart. Compared to state-of-the-art methods, we achieve compelling results on the widely used benchmark, i.e., MORPH.

1. Introduction

Human face is a basic biological feature of human beings, and its image contains a lot of useful information, such as age, gender, identity, race, and emotion [1]. Face age estimation is aimed at using computer technology to predict the accurate age values for the given facial images. However, variations of the shape of the skull, the position of the facial features, wrinkles, lighting, expressions, and movements of videos likely give rise to bias prediction in the wild conditions [2]. Particularly when a small amount of training data is used, the accuracy of age prediction is generally not high.

Recently, although people have been working on age estimation research, the performance is still very limited. This is mainly affected by two factors. On the one hand, because the existing dataset is not complete enough, most methods are trained in a supervised way, which requires manual annotations. On the other hand, the relationship of face data and age labels is usually complexly heterogeneous and nonlinear [3, 4]. Hence, this urgently prompts us to propose robust and accurate facial age estimation particularly under unconstrained environments.

Conventional age estimation methods could be roughly categorized into two major ingredients: feature representation and age predictor. Feature representation-based methods [5–7] are aimed at seeking discriminative feature descriptors for ages based on the face images. Respectively, age predictor-based methods [8, 9] basically learn to classify the age ranker based on the input feature representation. Apart from that, label distribution has emerged as the widely employed and state-of-the-art methods such as [10–12]. The algorithm typically encodes a range of age labels to a symmetrical distribution, e.g., Gaussian or triangle distribution, reflecting the smoothness for high-performance age estimation. Nevertheless, they are constrained to take only fixed-structural form to model the ambiguous properties of age labels, which are usually nonrobust to complex cross-
population face data domains. In order to solve this problem, most scholars usually adopt feature fusion methods, such as [13, 14], but these methods seldom pay attention to the high correlation between adjacent samples and often require a lot of annotation data to achieve. Therefore, we propose a flexible unsupervised comparison of label distribution learning age estimation method, which can solve the above problems.

Similar to the wireless sensor network in the space to monitor and record the physical conditions of the environment and organize the collected data in a central location. In this article, we propose a label distribution learning method based on unsupervised comparison, dubbed UCLD, which typically models heterogeneous face aging data for robust face age estimation. Compared with the traditional fixed and inflexible label distribution methods, our method not only takes into account the high correlation between adjacent samples but also reduces the dependence of the model on the data. In this article, we believe that the learned distribution is determined by the relationship between the samples, as shown in Figure 1. Technically, we first construct the embedding space of each anchored sample based on the facial appearance information. Then, the age feature is extracted through the constraints of the two projection layers and the contrast loss. Our network structure uses the improved VGG-16 [15] for effective feature learning. Figure 2 illustrates the flow chart. In order to further evaluate the effectiveness of our proposed method, we conduct extensive experiments on two field datasets. Compared with the existing facial age estimation methods, it achieves significantly superior performance.

2. Methodology

In this section, we present a detailed description of our problem formulation, the proposed UCLD model, and finally its alternatively associated optimization procedure.

Considering the size and efficiency of the model, the convolutional neural network used in this article is an improved network from four aspects based on the VGG-16 [15] architecture. First, the three fully connected layers of the VGG-16 [15] architecture contain approximately 90% of the parameters of the entire model. In this paper, only two fully connected layers are used and the dimensionality is reduced sequentially, and the mixed layer constructed by the maximum pooling layer and the global average pooling layer is retained. Second, in order to further reduce the model size, the number of filters in each convolutional layer is reduced by half to make it thinner than the original VGG-16 [15] architecture. Third, in order to speed up the training, a batch normalization layer is added after each convolutional layer [17]. Finally, the pretraining model is obtained through the comparison learning module, and then, the label distribution learning module and the expectation regression module are added to jointly learn the age distribution. The algorithm will be described in detail in the following.

2.1. Problem Setting. Assume the input space \( X = \mathbb{R}^{h \times w \times c} \), where \( h, w, \) and \( c \) represent the height, width, and number of channels of the input image, respectively. The label \( Y = R \) represents the actual age value. On the training set \( \mathcal{D} = \{ (x^i, y^i) \}_{i=1}^{N} \) with the number of samples \( N \), define \( x^i \in X \) as the \( i \)th input image, and \( y^i \in Y \) as the corresponding age. The age estimation problem is to learn the mapping function \( \mathcal{F} : X \rightarrow Y \) in order to make the error between the predicted value \( \hat{y} \) and the true value \( y \) as small as possible on a given input image \( x \).

Gao et al. [18] defined \( l = \lfloor 0 : \Delta l : 100 \rfloor \) as an ordered label vector, where \( \Delta l \) is a fixed real number. Using an equal step size \( \Delta l \) to quantize \( y \), the probability density function of the normal distribution that generates the true value \( p \) through \( y \) and \( \sigma \) is

\[
p^k = \frac{1}{\sqrt{2\pi}\sigma} \exp \left( -\frac{(l_k - y)^2}{2\sigma^2} \right),
\]

where \( \sigma \) is a hyperparameter and \( p^k \) is the probability that the true age is \( l_k \) years old. This article is aimed at maximizing the similarity between the true value \( p \) and the predicted value \( \tilde{p} \) generated by the convolutional neural networks.

2.2. Contrastive Loss. For a set of \( N \) randomly sampled sample pairs \( \{ x_k, y_k \}_{k=1 \ldots N} \), the corresponding batch used for training consists of 2N sample pairs \( \{ x_k, y_k \}_{k=1 \ldots 2N} \), where \( x_{2k} \) and \( y_{2k-1} \) are two random enhanced views of \( x_k \) and \( y_{2k-1} = y_{2k} = y_k \).

In the data processing of 2N extended samples, let \( i \in I = \{ 1 \ldots 2N \} \) be the index of an arbitrary augmented sample, and let \( j(i) \) be the index of the other augmented sample originating from the same source sample. In unsupervised contrastive learning [19–21], the loss takes the following form:

\[
\mathcal{L}_{\text{self}} = \sum_{i \in I} \mathcal{L}_{\text{self}}^i = \sum_{i \in I} \log \frac{\exp \left( \frac{Z_i \cdot Z_{j(i)}}{\tau} \right)}{\sum_{a \in A(i)} \exp \left( \frac{Z_i \cdot Z_a}{\tau} \right)}. \tag{2}
\]

Here, \( Z_i = \text{Proj}(\text{Enc}(x_i)) \in \mathbb{R}^D \), the \( \cdot \) symbol denotes the inner product, \( \tau \in \mathbb{R}^+ \) is a scalar temperature parameter, and \( A(i) = I \setminus \{ i \} \). The index \( i \) is called the anchor, index \( j(i) \) is called the positive, and the other \( 2(N - 1) \) indices \( k \in A(i) \setminus \{ j(i) \} \) are called the negatives. Note that for each anchor \( i \), there is 1 positive pair and \( 2N - 2 \) negative pairs. The denominator has a total of \( 2N - 1 \) terms (the positive and negatives).

2.3. Label Distribution Learning. If the true ages of the two input images are similar, the two images are considered similar. In other words, input images with similar outputs are theoretically highly correlated. In order to use the features extracted from these correlations, the label distribution learning module quantifies the range of possible \( y \) values into labels in \( l \).

Specifically, given the input image \( x \) and the corresponding label distribution \( p \), it is assumed that \( f = \mathcal{F}(x; \theta) \) is the activation of the last layer of the convolutional neural network, where \( \theta \) represents the parameters of the convolutional neural network. A fully connected layer passes \( f \) to \( x \in \mathbb{R}^K \) through
Then, we use the softmax function to convert $x$ into a probability distribution as follows:

$$\hat{p}_k = \frac{\exp (x_k)}{\sum_i \exp (x_i)}.$$  \hfill (4)

For a given input image, the goal of label distribution learning is to find $\theta$, $W$, and $b$ to generate $\hat{p}$ similar to $p$.

Finally, the KL divergence is used as a measure of the difference between the real label and the predicted label. Therefore, the following loss function is defined on the training sample:

$$L_{ld} = \sum_k p_k \ln \frac{\hat{p}_k}{\hat{p}_k}.$$  \hfill (5)

### 2.4. Expectation Regression

Using only the label distribution learning module cannot accurately predict the age of the
The error metric uses the $\hat{y}$ between the expected value $\hat{y}$ and the true value $y$ is minimized. The error metric uses the $L_\text{reg}$ loss function, as shown in the following:

$$L_{\text{reg}} = \left| \tilde{y} - y \right|,$$

where $\tilde{y}$ represents the predicted probability that the input image belongs to label $l_k$. Given the input image, the error between the expected value $\tilde{y}$ and the true value $y$ is minimized. The error metric uses the $L_\text{reg}$ loss function, as shown in the following:

$$L = L_{\text{ld}} + L_{\text{er}},$$

where $\lambda$ is the weight that weighs the importance of the two losses. Substituting (5), (6), and (7) into (8), we get

$$L = -\sum_k p_k \ln \tilde{p}_k + \lambda \sum_k \tilde{p}_k l_k - y.$$

In this framework, optimization variables include $\theta$, $W$, and $b$. First, backpropagation through the network, and then use the stochastic gradient descent algorithm to optimize the parameters. The derivative of $L$ with respect to $\tilde{p}_k$ is

$$\frac{\partial L}{\partial \tilde{p}_k} = -\frac{p_k}{\tilde{p}_k} + \lambda \text{sign}(\tilde{y} - y).$$

For any $k$ and $j$, the derivative of the softmax function (4) is as follows:

$$\frac{\partial \tilde{p}_k}{\partial x_j} = \tilde{p}_k \left( \delta_{(k=j)} - \tilde{p}_j \right).$$

Among them, if $k = j$, then $\delta_{(k=j)}$ is 1; otherwise, it is 0. Then,

$$\frac{\partial L}{\partial x} = \tilde{p} - p + \lambda \text{sign}(\tilde{y} - y) \tilde{p} \circ (1 - \tilde{y}).$$

Applying the chain rule to (3) again, the derivative of $L$ with respect to $\theta$, $W$, and $b$ can be easily obtained

$$\frac{\partial L}{\partial W} = \frac{\partial L}{\partial \tilde{p}} \frac{\partial \tilde{p}}{\partial x} = \frac{\partial L}{\partial b} = \frac{\partial L}{\partial \theta} = \frac{\partial L}{\partial x} W^\top \frac{\partial \mathcal{F}}{\partial \theta}.$$
3. Album2 dataset, where 80% of the data is used as the training set and 20% of the data is used as the test set.

3.2. Evaluation Metric. In the experiment, we use Mean Absolute Error (MAE) \[24\] to calculate the difference between the estimated age value and the true age value. Obviously, the smaller the value of MAE, the smaller the error between the predicted age and the true age, and the better the performance of the model, as shown in Table 1.

Please note that the DLDL-v2 \[18\] mentioned in this article is all source codes released by them. Compare our method with the experimental results of DLDL-v2 on the FGNET and MORPH datasets. Obviously, our method is more advantageous. In addition, we also changed the experimental settings several times as shown in Table 2.

Among them, linear represents the number of projection layers used. Despite using different settings, the experimental results of our method on the MORPH dataset still maintain the most advanced performance.

3.3. Implementation Details. For each face image, the size is adjusted to 224 × 224 before being input to the network. Then, select one of the five data enhancement methods: random horizontal flip, random zoom, random rotation, color distortion, and Gaussian blur to process the image. The comparative learning module of the network is used to generate a pretraining model on the MORPH dataset. The initial learning rate is set to 0.001, and it is reduced by 10 times every 30 iterations. After the pretraining is completed, delete the contrast learning module of the network and add the label distribution learning module and the expectation regression module to test the face age dataset. During the
In this article, in view of the high correlation between adjacent age samples and the strong dependence of existing methods on data, we combine contrast loss and label distribution learning to learn abstract representations in an unsupervised manner. An unsupervised contrast label distribution (UCLD) learning method is proposed, which is similar to the processing form of wireless sensor networks. Extensive experiments on two datasets have proved the effectiveness of the method, especially the MORPH dataset reflects the advanced nature of the method. In future work, we will focus on efficiently distinguishing similar images to solve the problem of age prediction accuracy.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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