Joint Estimation of Age and Gender from Unconstrained Face Images using Lightweight Multi-task CNN for Mobile Applications

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Abstract

Automatic age and gender classification based on unconstrained images has become essential techniques on mobile devices. With limited computing power, how to develop a robust system becomes a challenging task. In this paper, we present an efficient convolutional neural network (CNN) called lightweight multi-task CNN for simultaneous age and gender classification. Lightweight multi-task CNN uses depthwise separable convolution to reduce the model size and save the inference time. On the public challenging Adience dataset, the accuracy of age and gender classification is better than baseline multi-task CNN methods.

1 Introduction

Understanding age and gender from the human face plays an essential role in social interaction. To make communication proper and efficient, people subconsciously judge others’ age or gender. Thus, age and gender estimation is important in several applications, including re-identification in surveillance videos, intelligent advertising and human-computer interaction. Nevertheless, accurately and efficiently estimating age and gender from unconstrained face images is difficult.

Prior to deep neural network era, several approaches estimate age and gender from face images using designed image features and machine learning. In [4], Eidinger et al. combine four-patch local binary patterns (FPLBP) [14] and support vector machine (SVM) to achieve the joint-estimation of age and gender. Han et al. [5] use biologically inspired features (BIF) and their designed hierarchical estimator for this task. Since deep CNNs get a great success in object classification, Rothe et al. [11] develop the DEX method which consists of the face detector in [10] and a deep CNN architecture VGG-16 [13] for age estimation. Levi_Hassner [8] introduce a five-layer CNN architecture that achieves the most favorable performance on the unconstrained public Adience dataset [4].

2 Related Work

There are two types of structures commonly used in multi-task learning with deep neural networks [12], hard parameter sharing and soft parameter sharing of hidden layers. Soft parameter sharing means that each task has its own deep neural network with same structure, and then a similarity function is utilized to regularize these models [15]. Thus the space required at run time is proportional to the number of tasks. To reduce the space complexity, the structure of hard parameter sharing is most commonly used in deep multi-task learning. It only employs one shared deep neural network and keeps several task-specific output layers [18]. The hard parameter sharing can not only reduce the space complexity, but can also decrease the risk of over-fitting [2].

The getting popular mobile device motivates researchers to develop deep neural networks for mobile applications [6, 9, 17, 7]. MobileNet [6] is one of the most interesting approaches about speedup of a deep neural network. The MobileNet is depended on a streamlined architecture that uses depthwise separable convolutions to factorize a general convolution into a depthwise convolution and a pointwise convolution. By combining the output values of the depth-
wise convolution with pointwise convolution, a lightweight deep neural network thus can be constructed. To further parameterize the tradeoff between latency and accuracy, they use two global hyper-parameters, width multiplier and resolution multiplier to adjust the computational cost of the neural network.

3 Lightweight Multi-Task CNN

We refine the state-of-the-art approach [8] on two aspects: simultaneous inference and model reduction, which are critical for mobile applications. Unlike LeviHassner CNN [8] that uses two independent models to recognize age and gender, only one single CNN for feature extraction is used for multiple tasks in our system. Thus, the memory requirement for deep neural networks is reduced. We employ a hard parameter sharing paradigm to learn the single CNN for both tasks. To further decrease the computation cost, we decompose the general CNN in [8] into depthwise and pointwise convolution networks. The pointwise convolution is a convolution with $1 \times 1$ kernel’s size, and it combines the output values of the depthwise convolution.

3.1 Depthwise Separable Convolution

Before detailing our network architecture, we give a brief review of the depthwise separable convolution in this section. First, we consider the computational complexity of a general convolution. Let us denote the size of a general convolutional layer by $D_K \times D_K \times C_I \times C_O$, where $D_K$ is the size of kernel $K$, and $C_I$ and $C_O$ are the number of input and output channels, respectively. The dimension of input map is $W_I \times H_I \times C_I$, where $W_I$ and $H_I$ are the width and height of the input feature map, respectively. The size of output map $O$ is $W_O \times H_O \times C_O$, where $W_O$ and $H_O$ are the width and height of the map, respectively. Figure 2(a) shows a common feature convolutional layer. The computational cost of the common convolution layer is $W_I \times H_I \times C_I \times D_K \times D_K \times C_O$.

In depthwise separable convolution, we split the general convolution layer into two layers. One is the depthwise convolution layer with size $D_K \times D_K \times 1$ of a 2D kernel filter per each input channel $C_I$, and the other is the pointwise convolution layer with $1 \times 1$ convolution used to generate a linear combination of the output of the depthwise layer, as shown in Figure 2(b). The computational cost of the depthwise separable convolution layer can be derived by the following equation: $W_I \times H_I \times C_I \times (D_K \times D_K + C_O)$.

Dividing the computational cost of general convolution by depthwise separable convolution, we can obtain the computational cost ratio is $\frac{D_K \times C_O}{D_K \times D_K + C_O}$. The greater the number of channels, the greater the speedup the depthwise separable convolution can be achieved. In [6], Howard et al. demonstrate that simplifying the architecture of a CNN in this manner can considerably increase the inference speed without sacrificing the classification performance.

3.2 Lightweight Multi-Task Network

The Lightweight Multi-Task CNN (LMTCNN) is composed of one general convolution layer, two depthwise separable convolution layers and two fully connected layers. Thus, it can accomplish multiple tasks while reducing the memory cost. The system overview is shown in Figure 1. To handle the age and gender classification on the Adience dataset [4], our proposed method consists of three steps.

First, input color face image is scaled to the $256 \times 256$ and then cropped into the $227 \times 227$ in size using over-sampling. The over-sampling here means that the system extracts five cropped regions from the scaled color face image, four cropped regions from the corners and one from the center of the scaled color face image. The LMTCNN processes five cropped regions with their horizontal reflections and estimates the final result by the average score of these regions.

Second, the size $3 \times 7 \times 7$ pixel values of 96 kernel filters are applied to the input in the first general convolution layer, followed by a rectified linear unit (ReLU), a max pooling layer with window size equals to $3 \times 3$ and strides equal to two pixels and a local response normalization layer. The output feature map (size $28 \times 28 \times 96$) of the first general convolution layer is processed by the two subsequent depthwise separable convolution layers defined in Table 1. The output feature map of the last depthwise separable convolution layer is fed to the kernel size $3 \times 3$ of a max pooling layer that partitions the input feature map into a set of non-overlapping regions.

Finally, the output feature map of the max pooling layer is fed to the two fully connected layers which contain 512 neurons, followed by a ReLU and a dropout layer. To achieve both the age classification for eight age classes and the gender classification for two gender classes, two separate softmax layers are followed by the output feature map of the average pooling layer. The first softmax layer assigns a probability for each class of the age and the other assigns a probability for each class of the gender. Figure 1 shows...
Table 1. The architecture of the two depth-wise separable convolution layers used in the lightweight multi-task CNN

| Type      | Filter Shape | Input Size   |
|-----------|--------------|--------------|
| dw Conv1  | 3 x 3 x 96   | 28 x 28 x 96 |
| pw Conv1  | 1 x 1 x 96 x 256 | 28 x 28 x 96 |
| dw Conv2  | 3 x 3 x 256  | 14 x 14 x 256 |
| pw Conv2  | 1 x 1 x 256 x 384 | 14 x 14 x 256 |

4 Experiment and Result

Our proposed network is implemented using the Tensorflow framework [1]. Training and Testing are executed on the desktop with Intel Xeon E5 3.5 GHz CPU, 64G RAM and GeForce GTX TITAN X GPU. Training our proposed network takes approximately six hours. When testing on the desktop, predicting age and gender on a single image requires approximately 7.6 milliseconds.

4.1 The Result of Adience Dataset

The Adience dataset [4] is composed of pictures taken by camera from smartphone or tablets. The images of Adience dataset capture extreme variations, including extreme blur (low-resolution), occlusions, out-of-plane pose variations, expressions. The entire Adience dataset includes 26,580 unconstrained images of 2,284 subjects. Its age labels contain eight groups, including (0−2), (4−6), (8−13), (15−20), (25−32), (38−43), (48−53), (60+).

Unlike other datasets (such as Morph II) where the face images are taken in a controlled environment, the Adience dataset is an in-the-wild benchmark for joint age and gender estimation, and is thus more demanding. Because our purpose is to develop a mobile system that can estimate age and gender in real environments, testing this benchmark can reflect the performance more appropriately.

For age and gender classification, we measure and compare the accuracy using a five-fold cross validation. The number of images in each fold of training, validation and testing are shown in Table 2. The in-plane aligned version of the faces defined in [4] is used.

We compare our proposed method with baseline Levi_Hassner CNN [8] by using five-fold cross validation with the number of images shown in Table 2 to train by the training set and test by the testing set in each fold. Our proposed method is LMTCNN with the width multiplier of each depthwise separable convolution equals to 1 or 2. In Table 3, we demonstrate that the accuracy of the LMTCNN with width multiplier = 2 of the first depthwise separable convolution and width multiplier = 1 of the second depthwise separable convolution for age and gender classification. As can be seen, although our architectures are more compact, their performance are comparable to that of the Levi_Hassner CNN [8].

4.2 Mobile Applications

To run a deep neural network model on mobile devices with Android operation system, we convert deep neural network model into the computational graph of Tensorflow library [1] and we compare the model size of each method, as shown in Table 4. The model size of LMTCNN with width multiplier = 1 of the first depthwise separable convolution and width multiplier = 1 of the second depthwise separable convolution is approximately nine times smaller than that of Levi_Hassner CNN [8], and the model size of LMTCNN with width multiplier = 2 of the first depthwise separable convolution and width multiplier = 1 of the second depthwise separable convolution is approximately half smaller.

For mobile application, we port the system with face detection, age recognition, and gender recognition on mobile devices, such as smartphone, tablet and smart robot. The face detection is implemented using the method of the MTCNN [16]. Then the region the facial regions are

Table 2. The number of images in each fold of the training, validation and testing sets

| Fold | Training | Validation | Testing |
|------|----------|------------|---------|
| First| 11,136   | 1,242      | 3,879   |
| Second| 11,905 | 1,348      | 3,005   |
| Third| 11,814   | 1,323      | 3,121   |
| Forth| 12,056   | 1,335      | 2,866   |
| Fifth| 11,593   | 1,277      | 3,387   |

Table 3. The accuracy of the age and gender classification generated by five-fold cross validation in Adience dataset

| Methods               | Age Top-1 (Acc.%) | Gender Top-1 (Acc.%) |
|-----------------------|-------------------|----------------------|
| Levi_Hassner CNN [8]  | 44.14             | 69.98                |
| LMTCNN-1-1            | 40.84             | 66.10                |
| LMTCNN-2-1            | 44.26             | 70.78                |

Table 4. The model size of each method

| Methods               | Model Size |
|-----------------------|------------|
| Levi_Hassner CNN [8]  | 9 times    |
| LMTCNN-1-1            | Half smaller |
| LMTCNN-2-1            | Half smaller |
cropped from each frame for LMTCNN or Levi_Hassner CNN [8] to recognize the age and gender. Figure 3 demonstrates our system on the ASUS Zenbo and ASUS Zenfone 3. The ASUS Zenbo is a smart robot developed by the ASUS incorporation with Intel Atom x5-Z8550 2.4GHz CPU, 4G RAM and Android 6.0.1 system and The ASUS Zenfone 3 is a smartphone developed by the ASUS incorporation with Qualcomm Snapdragon 625 2.02GHz CPU, 3G RAM and Android 7.0 system. We also calculate the processing time of each method on the ASUS Zenbo and ASUS Zenfone 3, as shown in Table 5.

In summary, the above results (Table 3, 4 and 5) reveal that LMTCNN can decrease the size of model and speed up the inference on mobile devices while maintaining the accuracy of age and gender classification.

5 Conclusion

We introduce the new network structure, LMTCNN, which accomplishes multiple tasks while maintaining the accuracy of age and gender classification. We also show that our architecture can be realized on mobile devices with limited computational resources. In the future, we will improve the performance of LMTCNN and reduce the size of model for the datasets of unconstrained face images with face attributes.

Table 4. The Comparison of the model size

| Methods       | Model size (MB) |
|---------------|-----------------|
| Levi_Hassner CNN [8] | 70.8            |
| LMTCNN-1-1    | 8.7             |
| LMTCNN-2-1    | 30.0            |

Table 5. The speed of each method executed in the mobile devices

| Methods       | Asus Zenbo Speed (ms/frame) | Asus Zenfone 3 Speed (ms/frame) |
|---------------|-----------------------------|---------------------------------|
| Levi_Hassner CNN [8] | ≈ 4800                      | ≈ 4800                          |
| LMTCNN-1-1    | 204.7                       | 204.9                           |
| LMTCNN-2-1    | 297.6                       | 367.2                           |

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