Learning Redundant Codes with Deep CNN for Cross-Dataset Age Estimation

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2 Contribution details

- Title of the contribution
  Learning Redundant Codes with Deep CNN for Cross-Dataset Age Estimation
- Final score
  0.285 on Validation Set
- General method description
  We cast the age estimation problem as multi-label classification of some age codes. The code labels characterize age groups at several granularities, cumulative age groups and gender. We train deep convolutional neural networks (CNN) to predict the labels accurately, on multiple large age databases. The learned redundant codes are demonstrated to be generalizable to the contest dataset, and not so sensitive to cross-dataset bias. Finally the codes are regressed to age values using the contest data.
- Describe data preprocessing techniques applied (if any)
  The faces are detected and the facial landmarks are located with a commercial Face Software Development Kit. We normalize the faces geometrically using these facial landmarks. A linear SVM classifier is trained to remove false positive detections and background faces.

3 Apparent Age Estimation Stage

3.1 Features / Data representation

On multiple large age databases, we train deep CNN features guided by the above-mentioned age codes. We combine several features learned by different configurations of VGG networks.

3.2 Dimensionality reduction

We use PCA and LDA to reduce the dimension of our features.

3.3 Learning strategy

We use Caffe to train our CNN models. The models are pretrained for the face recognition task on Celebface+ dataset, and then fine-tuned to predict age codes. The training faces are augmented using multiple approaches, such as flipping, grayscale conversion, and small random translation, so that the models can handle many variations.

3.4 Other techniques

Ages are predicted by fusing several regressors, such as lasso, global and local quadratic regressor, and random forest.

3.5 Method complexity

We haven't evaluated the complexity of our pipeline.

4 Global Method Description

- Total method complexity:
  haven't been evaluated
- Which pre-trained or external methods have been used
  We use external face detector and facial landmark detector.
- Which additional data has been used in addition to the provided ChaLearn training and validation data (at any stage, if any)
  We use academic face age databases, such as Morph, FGNet, and Adience.
- Qualitative advantages of the proposed solution
  1) High accuracy; 2) Generalizability to new datasets
- Results of the comparison to other approaches (if any)
  Will do it later.
- Novelty degree of the solution and if is has been previously published
  We will summarize our solution for future publication.

5 Other details

- Language and implementation details (including platform, memory, parallelization requirements)
  C++ (caffe), Matlab and Python

- Human effort required for implementation, training and validation?
  The whole pipeline is automatic, with no human efforts even for training.

- Training/testing expended time?
  About one day needed for training.

- General comments and impressions of the challenge? what do you expect from a new challenge in face and looking at people analysis?
  The provided age estimation dataset is valuable, although it is small due to the cost of collecting such data. The allocation of training, validation and test sets may leak some information, as there are duplicate person identities (or even near-duplicate images) among them. The person identities are probably the same for consecutive image IDs. Although we didn't utilize this information, but the quantitative evaluation can indeed be affected.
  We are also interested in other interesting topics related to face, such as emotion recognition and spoofing detection.