Marginal loss for deep face recognition

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Abstract

In recent years, scientists apply convolutional neural networks (CNN) to face recognition. Due to that CNN bless with the feature of high capacity in learning discriminative features, it can improve the performance of face recognition. According this feature, the results of this study is that researchers proposed a new supervision signal named marginal loss for deep face recognition.

1. Marginal Loss

The most widely used classification loss function, softmax loss, is presented as follows:

$$L_s = \sum_{i=1}^{m} log \frac{e^{W_{y_i}^T x_i + b_{y_i}}}{\sum_{j=1}^{n} e^{W_{J}^T x_i + b_{j}}}$$
(1)

In this paper, scientists have improved the marginal loss function to minimize the intra-class variations and keep inter-classes distances within the batch, as follows:

$$L_{m} = \frac{1}{m^{2} - m} \sum_{i,j,i \neq j}^{m} \left(\xi - y_{ij} \left(\theta - \left\| \frac{x_{i}}{\|x_{i}\|} - \frac{x_{j}}{\|x_{j}\|} \right\| \right) \right)$$
(2)

Scientists adopt the joint supervision of softmax loss and marginal loss to train the CNNs for discriminative feature learning.

$$L = L_s + \lambda L_m \tag{3}$$

Where λ is used for balancing the two loss function-

2. Experiment

2.1. Experiments on the LFW and YTF datasets

Scientists evaluate the proposed marginal loss model on two famous face recognition benchmarks, Labelled Faces in the Wild (LFW, image) and Y-ouTube Faces (YTF, video) datasets, under unconstrained environments. And the experiment results is shown in Table 1. In Table 1, scientists compare the proposed marginal loss method against many existing advanced models. From the results, the proposed marginal loss can enhance the discriminative power of the deeply learned face features [1].

Table 1: Verification performance of different methods on LFW and YTF datasets.

| Methods | Images | LFW(%) | YTF(%) |
|-----------------|--------|--------|--------|
| Deep ID [4] | | 99.47 | 93.20 |
| VGG Face [2] | 2.6M | 98.95 | 97.30 |
| Deep Face [5] | 4M | 97.35 | 91.40 |
| Fusion [6] | 500M | 98.37 | |
| FaceNet [3] | 200M | 99.63 | 95.10 |
| Baidu | 1.3M | 99.13 | |
| Center Loss [7] | 0.7M | 99.28 | 94.9 |
| Range Loss | 1.5M | 99.52 | 93.70 |
| Multibatch | 2.6M | 98.8 | |
| Aug | 0.5M | 98.06 | |
| Softmax Loss | 4M | 98.87 | 94.16 |
| Marginal Loss | 4M | 99.48 | 95.98 |

Reference

- [1] J. Deng, Y. Z, and S. Zafeiriou. Marginal loss for deep face recognition. In *The IEEE Conference on Computer Vision and Pattern Recognition Workshop-s*, July 2017. 1
- [2] O. M. Parkhi, A. Vedaldi, and A. Zisserman. Deep face recognition. In *British Machine Vision Conference*, volume 1, page 6, 2015. 1
- [3] F. Schroff, D. Kalenichenko, and J. Philbin. Facenet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE Conference on Com*puter Vision and Pattern Recognition, pages 815– 823, 2015. 1
- [4] Y. Sun, Y. Chen, X. Wang, and X. Tang. Deep learning face representation by joint identificationverification. In *Advances in Neural Information Pro*cessing Systems, pages 1988–1996, 2014. 1
- [5] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf. Deepface: Closing the gap to human-level performance in face verification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1701–1708, 2014.
- [6] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf. Webscale training for face identification. In *Proceedings* of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2746–2754, 2015.
- [7] Y. Wen, K. Zhang, Z. Li, and Y. Qiao. A discriminative feature learning approach for deep face recognition. In *European Conference on Computer Vision*, pages 499–515, 2016.