MassFace: an efficient implementation using triplet loss for face recognition

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Abstract

In this paper we present an efficient implementation using triplet loss for face recognition. We conduct the practical experiment to analyze the factors that influence the training of triplet loss. All models are trained on CASIA-Webface dataset and tested on LFW. We analyze the experiment results and give some insights to help others balance the factors when they apply triplet loss to their own problem especially for face recognition task. Code has been released in https://github.com/yule-li/MassFace.

1. Introduction

Face recognition has achieved significant improvement due to the power of deep representation through convolutional neural network. Convolutional neural network (CNN) based method first encodes the image which contains face into deep presentation and then apply the loss function to train the CNN such that the distance of feature vectors of the same persons is smaller than that of the different persons. Almost all of these loss functions can be divided into two categories: 1) softmax classification based loss and its variants such as Sphere face [6], Arcface [9] and Cosface [10]; 2) metric learning based loss such as contrastive loss [8] and Triplet loss [7]. The previous one recently draw more attentions and has achieved great progress with the development of angular softmax loss and larger margin softmax loss to enhance the discriminative power of softmax loss. However, the last one is hard to train and heavily depends on people’s experiences of hard example mining due to high computational complexity such as $O(N^3)$ of triplet loss for a dataset with $N$ samples.

In this work, we present an efficient implementation of triplet loss on face recognition task and conduct several experiments to analyze the factors that influence the training of triplet loss. The overview of our implementation can be seen in figure 1. Unlike the softmax loss, data sample of triplet loss need ensure that the valid triplet pair can be constructed as much as possible. In order to achieve this, we follow [3] and the total $P*K$ images are sampled for $P$ persons with $K$ images each. The sampled images are mapped into feature vector $F_p^k$ through deep convolutional network such as Resnet [2] or Mobilenet [4]. Then the triplet pairs are selected by a hard mining process based on the embedded feature vectors. For convenience of implementation, we first get the indexes of triplet pairs and then gather their responding features. Finally, the gathered features of triplet pairs are fed into triplet loss to train the CNN.

The contributions of our paper can be summarized as: 1) we present an efficient implementation of our proposed framework which provides variant choices for the component of our proposed framework such as different CNN feature extractor, different triplet pair selection method as in figure 1 and also support multi-gpus to accelerate training process. 2) we practically analyze a series of factors that influence training of triplet loss by experiments.

2. Related Work

FaceNet: A Unified Embedding for Face Recognition and Clustering [7]. FaceNet uses triplet loss to train the CNN model and mines semi-hard examples to train the triplet loss. It utilized on a dataset with 8M identities and trained on a cluster of cpu for thousands of hours. FaceNet achieves remarkable result on LFW [5] while it’s not practical because it relies on such large dataset and need a large mount of time to train.

In Defense of the Triplet Loss for Person Re-Identification [3]. This work applies triplet loss on person re-identification problem. It constructs image batch efficiently by sampling $P$ persons with $K$ images each. It also proposed batch hard and batch all hard example mining strategies. This work achieves the start-of-the-art in person re-identification.

3. Framework

The overview of our proposed framework can be viewed as figure 1. The framework include the following module: data sample, feature embedding, triplet selection and triplet loss. We will describe them in details as follow.

Data Sample. Following [3], a batch of input images consists of $P$ persons and each person includes $K$ images. So in each iteration, we sample total $P*K$ images. Using
such data sampling method, it’s convenient to select valid triplet pairs and mine hard examples.

**Feature Extraction.** We use MobileFacenets [1] to extract the feature $F$ of the input image $x$ as a deep representation. We also fix the feature $\|F_i\| = 1$ by L2-normalization. It only has about 6.0MB parameters and can be inferred very fast as well.

**Triplet Loss** Through the feature extraction powered by CNN, the input image $x$ can be mapped into a feature vector with $d$ dimension, and the map function is denoted as $f(x)$. The goal of the triplet loss is to make sure that the feature vector $f_i^a(x)$ of image $x_i^a$ (called anchor) is close to $f_i^p(x)$ of image $x_i^p$ (called positive) which has the same identity as image $x_i^a$ while $f_i^a(x)$ is far away from $f_i^n(x)$ of the image $x_i^n(x)$ (called negative) that has the different identity as $x_i^a$. We can formulate this loss as:

$$\|f_i^a(x) - f_i^p(x)\|^2_2 + \alpha < \|f_i^a(x) - f_i^n(x)\|^2_2$$

(1)

where $\alpha$ is the margin to avoid the collapse of $f_i(x)$. And the loss that will be optimized can become $L$

$$L = \max(0, \|f_i^a(x) - f_i^p(x)\|^2_2 + \alpha - \|f_i^n(x) - f_i^n(x)\|^2_2)$$

(2)

**Triplet Selection** Triplet selection aims to choose the valid triplet $(i, j, k)$ which is used as input of triplet loss. The valid triplet means that $i$, $j$ have the identity and $i$, $k$ have different identity. As see in Data sample, the input is composed of $P$ persons with $K$ images each and total $B = P * K$ images. In order to obtain the all possible valid triplets, we iterate each image $x_{ik}^a$ in person $k$ and any other image $x_{ij}^p$ in person $k$ can be positive. Thus the negative can be from all images of other persons except k. We summary this as algorithm 1. So there are about $O(P * K * P * K)$ valid triplet pairs but not every triplet pair can contribute to the triplet loss. As we see in formula 2 only the triplet pair that satisfies $\|f_i^a(x) - f_i^p(x)\|^2_2 + \alpha - \|f_i^n(x) - f_i^n(x)\|^2_2 > 0$ has loss value. We develop algorithm to mine such triplet pairs. We also develop different kinds of strategies to mine the ‘hard’ examples based on algorithm 1 and our experiment shows that these hard mining strategies can achieve better performance for triplet loss. We summary all these mining strategies as follow.

- **Batch All.** As we can see in formula 2 only the triplet pair $(i, j, k)$ that satisfy $\|f_i(x) - f_j(x)\|^2_2 + \alpha > \|f_i(x) - f_k(x)\|^2_2$ has the loss value. So we choice all of these triplet pairs as "hard" examples. We just modify algorithm 1 a little to obtain the Batch All algorithm 2

- **Batch Random** If there are many negatives for some anchor and positive, we randomly select a negative. That can be described as algorithm 3

- **Batch Min Min** There may be many negatives for some $(anchor, positive)$ and we select the negative that has the least distance with anchor. There may be also many positives for some anchor, and we continue to select the positive in which the responding negative has least distance with anchor. That can be shown as algorithm 4

- **Batch Min Max** There may be many negatives for some $(anchor, positive)$ and we select the negative that has the least distance with anchor. There may be also many positives for some anchor, and we just select the positivein which the responding negative has the biggest distance with anchor. That can be shown as algorithm 5

- **Batch Hardest** There may be many valid triplet pairs for some person, and we select only one pair in which negative has the least distance with anchor. This can be seen as algorithm 6
Algorithm 1 Select all possible valid triplets

1: Random choice $B$ input images for $P$ persons with $K$ images each
2: Initialize list $T$ to hold all selected triplet pairs
3: for Each person $p \in [1, P]$ do
4:  for Each image $i$ in person $p$ as anchor do
5:   for Each image $j$ in person $p$ and $j! = i$ as positive do
6:     for Each image $k \in [1, B]$ and $k$ is not in person $p$ do
7:       $T.append((i, j, k))$
8:     end for
9:   end for
10: end for
11: end for

Algorithm 2 Batch All

1: Random choice $B$ input images for $P$ persons with $K$ images each
2: Forwarding $B$ input images to obtain the feature pool $F$
3: Compute distance matrix $M_{B \times B}$ between $F$
4: Initialize list $T$ to hold all selected triplet pairs
5: for Each person $p \in [1, P]$ do
6:  for Each image $i$ in person $p$ as anchor do
7:   for Each image $j$ in person $p$ and $j! = i$ as positive do
8:     for Each image $k \in [1, B]$ and $k$ is not in person $p$ as negative do
9:       if $M(i, j) + \alpha > M(i, k)$ then
10:         $T.append((i, j, k))$
11:       end if
12:     end for
13:   end for
14: end for
15: end for

Algorithm 3 Batch Random

1: Random choice $B$ input images for $P$ persons with $K$ images each
2: Forwarding $B$ input images to obtain the feature pool $F$
3: Compute distance matrix $M_{B \times B}$ between $F$
4: Initialize list $T$ to hold all selected triplet pairs
5: for Each person $p \in [1, P]$ do
6:  for Each image $i$ in person $j$ as anchor do
7:   for Each image $j$ in person $p$ and $j! = i$ as positive do
8:     if $M(i, j) + \alpha > M(i, k)$ then
9:       $T.append((i, j, k))$
10:     end if
11:   end for
12: end for
13: end for

Algorithm 4 Batch Min Min

1: Random choice $B$ input images for $P$ persons with $K$ images each
2: Forwarding $B$ input images to obtain the feature pool $F$
3: Compute distance matrix $M_{B \times B}$ between $F$
4: Initialize list $T$ to hold all selected triplet pairs
5: for Each person $p \in [1, P]$ do
6:  for Each image $i$ in person $p$ as anchor do
7:   Initialize list $t$
8:   for Each image $j \in [1, B]$ and $k$ is not in person $p$ as negative do
9:     if $M(i, j) + \alpha > M(i, k)$ then
10:       $t.append((i, j, k))$
11:     end if
12:   end for
13: end for
14: $k_{min\_min} = \arg\min_{(i, j, k)} \{M(i, k)|(i, j, k) \in t\}$
15: $T.append(k_{min\_min})$
16: end for
17: end for
18: end for

Mining methods. The triplet selection is based on a pool of the feature vectors $F$. There are severeral methods to obtain the pool of feature vectors with size $B$.

- **Online mining.** We obtain the pool of features by forwarding a batch of input images with size of $B$ once a time.

- **Offline mining.** We forward all images in dataset to get the pool of features and select triplet pairs. Then we train these triplet pairs by a sequence of iterations.

- **Semi-online mining.** We generate the pool of features by forwarding CNN model in several iterations like 10 times and then select triplet pairs. That can choice more triplet pairs while it doesn’t consume too much time.
Algorithm 5 Batch Min Max
1: Random choice $B$ input images for $P$ persons with $K$
2: images each
3: Forwarding $B$ input images to obtain the feature pool $F$
4: Compute distance matrix $M_{B \times B}$ between $F$
5: Initialize list $T$ to hold all selected triplet pairs
6: for Each person $p \in [1, P]$ do
7: for Each image $i$ in person $p$ as anchor do
8: for Each image $j$ in person $p$ and $j! = i$ as positive do
9: Initialize list $t_2$
10: for Each image $k \in [1, B]$ and $k$ is not person $p$ as negative do
11: if $M(i, j) + \alpha > M(i, k)$ then
12: $t_2.append((i, j, k))$
13: end if
14: end for
15: $k_{\min} = \arg\min_{(i, j, k)} \{M(i, k) | (i, j, k) \in t_2\}$
16: $t_1.append(k_{\min})$
17: end for
18: $k_{min, max} = \arg\max_{(i, j, k)} \{M(i, k) | (i, j, k) \in t_2\}$
19: $T.append(k_{min, max})$
20: end for
21: end for

Algorithm 6 Batch Hardest
1: Random choice $B$ input images for $P$ persons with $K$
2: images each
3: Forwarding $B$ input images to obtain the feature pool $F$
4: Compute distance matrix $M_{B \times B}$ between $F$
5: Initialize list $T$ to hold all selected triplet pairs
6: for Each person $p \in [1, P]$ do
7: Initialize list $t$
8: for Each image $i$ in person $p$ as anchor do
9: for Each image $j$ in person $p$ and $j! = i$ as positive do
10: for Each image $k \in [1, B]$ and $k$ is not in person $p$ as negative do
11: if $M(i, j) + \alpha > M(i, k)$ then
12: $t.append((i, j, k))$
13: end if
14: end for
15: end for
16: $k_{\min, min} = \arg\min_{(i, j, k)} \{M(i, k) | (i, j, k) \in t_2\}$
17: $T.append(k_{\min, min})$
18: end for

4. Experiment

We train all models on CASIA-Webface [11] and test them on LFW. We first train the model with Softmax and CosFace respectively, as our pretrained model. Then all models based on triplet loss are optimized by ADAGRAD optimizer with learning rate 0.001 and $\alpha$ is set as 0.2.

Results with different mining strategies. We first pretrain CNN model with softmax classifier. Then we finetune the deep CNN model using triplet loss with different mining strategies. Every model is trained with 60k iterations and each iteration is optimized with batch size 210. The results of triplet loss with different mining strategy can be seen as table 1. All mining strategies can boost the performance of softmax classifier. The $BH_{min, min}$ strategy and $BH_{min, max}$ strategy improve performance more than BR and BA, while $B_{hardest}$ is close to $BH_{min, min}$ and $BH_{min, max}$. The $BH_{min, min}$ strategy and $BH_{min, max}$ strategy is 'hard' strategy but not the 'hardest' strategy, which may make it easy to train for triplet loss.

| strategy       | acc(%) |
|----------------|--------|
| softmax pretrain | 97.1   |
| BH_{Min, Min}    | 98.0   |
| BH_{Min, Max}    | 98.0   |
| BH_{Hardest}     | 97.9   |
| BH_{Random}      | 97.8   |
| BH_{All}         | 97.5   |

Table 1: Accuracy on LFW with different mining strategies.

Results with different initial models. We also compare the models with different initial methods. We pretrained two model with softmax classifier and CosFace respectively. Then we used these pretrained model as initial models and finetuned it using triplet loss with $BH_{min, max}$ strategy which shows best performance in all strategies. The result can be viewed as table 2. The model with pretrain is more better than that without pretrain. The pretrained model gives a good start for triplet loss, which is essential for training of triplet loss. We also can see that pretrained model with CosFace is better than softmax because it has a better initialization.

| pretrain       | iters | acc(%) |
|----------------|-------|--------|
| softmax pretrain | 6w    | 97.1   |
| cosface pretrain | 6w    | 98.3   |
| with softmax    | 6w    | 98.0   |
| with cosface    | 6w    | 98.6   |
| without pretrain| 6w    | 92.2   |

Table 2: Accuracy on LFW with different initial models.
Results with different \((P, K)\) combinations. In this experiment, we use the pretrained model trained by softmax and finetue it by triplet loss with the \(BH_{\text{min max}}\) strategy. The result of different combination can be seen as tabel\[3\]. When we keep \(B(B = P \times K)\) as constant \((210)\). From the tabel\[3\] we can know that the larger the \(P\) is, the better the performance is. For larger \(P\), the anchor can see more negative from other persons, which may avoid the model trapped in local optimization.

| \(P\) | \(K\) | acc(\%) |
|---|---|---|
| 42 | 5 | 98.0 |
| 30 | 7 | 98.0 |
| 14 | 15 | 97.7 |
| 10 | 21 | 97.5 |

Table 3: Accuracy on LFW with different \(P\) and \(K\) settings.

Results with different mining methods. In this experiment, we compare the models trained in online and semi-online. All models are pretrained by Softmax and finetue with \(Batch_{\text{min max}}\) strategy. In semi-online, we forwared the model by 10 iterations with 210 images each and then selected the triple pairs based on features of 10 iterations. The results can be seen as table\[4\]. The semi-online training is better than online. This may be understood by that semi-online training increase the \(P\) to improve the performance as we see in tabel\[5\]. We demostrate this by add a experiment with multi-gpus. We increase batch size to \(210 \times 4\) by rising \(P\) from 30 to \(30 \times 4\) with 4 gpus. The accuracy of mutli-gpus is 98.3\%, a similar accuracy with semi-online. We can use semi-online method to acheive the approaching performance of mutli-gpus when our computing resource is limited.

| training | acc(\%) |
|---|---|
| softmax pretrain | 97.1 |
| online | 98.0 |
| semi-online | 98.2 |
| online with multi-gpus | 98.3 |

Table 4: Accuracy on LFW with different mining methods.

5. Conclusion

We present an efficient implementation based on triplet loss for face recognition. We analyze the important factors that influence the performance of triplet loss by experiment. The results of experiment shows: 1) the pretrained model is very important for training CNN model with triplet loss; 2) hard example mining is essencial and we proposal two new mining methods: \(BH_{\text{min min}}\) and \(BH_{\text{min max}}\); 3) we can improve the performance by increasing \(P\) and a better way to do this is to train model with multi-gpus or in semi-online if the computing resource is limited.

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