FaceNet

A Unified Embedding for Face Recognition and Clustering

The mean squares
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Problem Statement

Despite significant recent advances in the field of face recognition, implementing face verification and recognition efficiently at scale presents serious challenges to current approaches.

Solution Approach

- A system is described which converts an image to a fixed size embedding.
- Distances between any two embeddings is a measure of the similarity of the faces.
- The embedding is produced by training a siamese network with triplet loss.

Introduction to FaceNet

- A unified system for face verification (is this the same person), recognition (who is this person) and clustering (find common people among these faces).
- The embedding generated is an Euclidean embedding per image using a deep convolutional network.
- The network is trained such that the squared L2 distances in the embedding space directly correspond to face similarity.
- Faces of the same person have small distances and faces of distinct people have large distances.
- Face verification simply involves thresholding the distance between the two embeddings, recognition becomes a k-NN classification problem; and clustering can be achieved using off-the-shelf techniques such as k-means or agglomerative clustering.
- Dataset to be used for training:- Labeled Faces in the Wild (LFW).

Dataset Description

- Database of face photographs designed for studying the problem of unconstrained face recognition.
- For training, we are considering a subset of classes with 3 images each. That comes up to be 610 labels.
- All the images from LFW dataset are split into 2 sets -
  - For validation, to find appropriate threshold for distances of similar faces and different faces.
  - For testing, the images we are taking all labels in the LFW dataset and performing verification/recognition tasks.

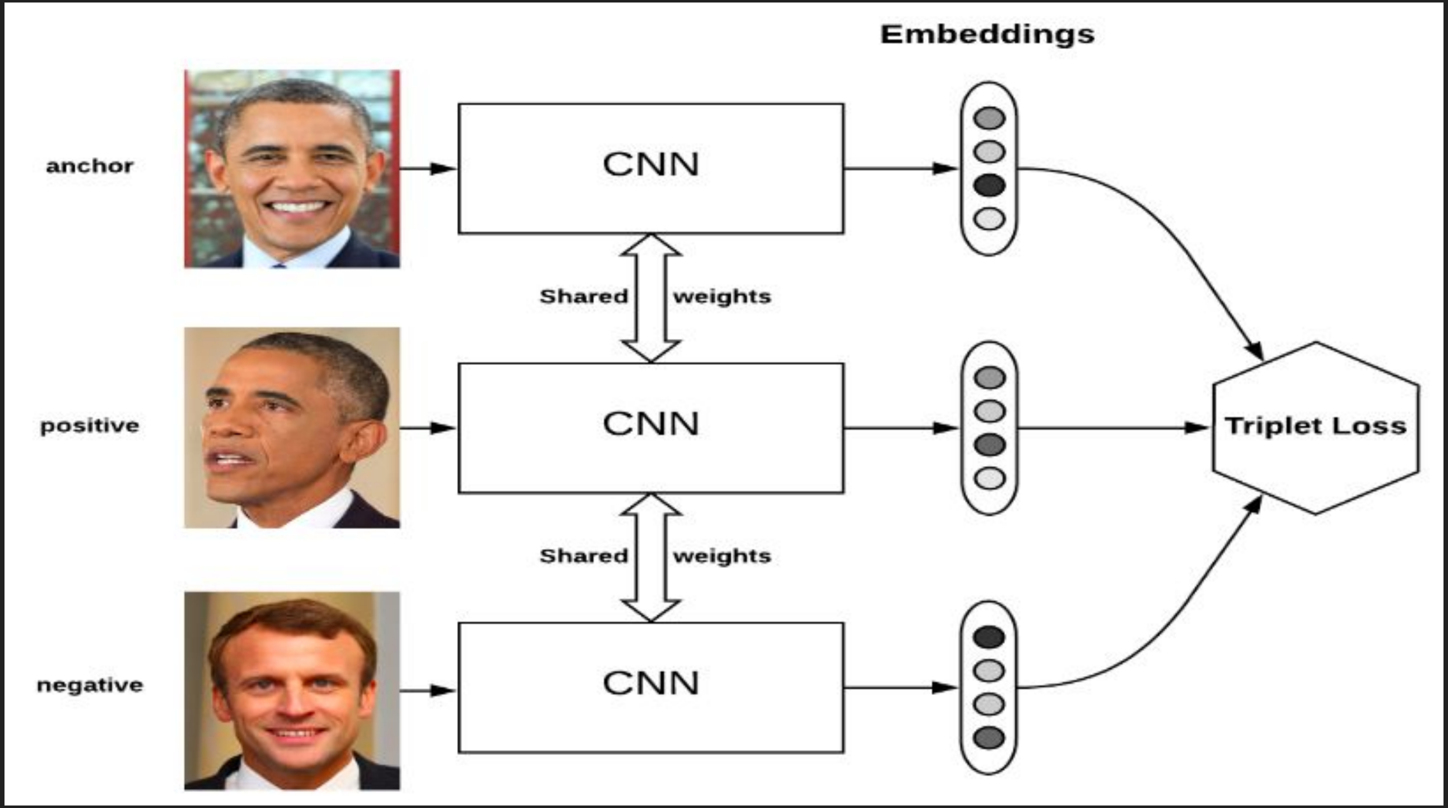
Expected Results

- The model will produce a fixed size embedding for a test data.
- If the test data belongs to a particular label then the distance between the embedding generated and stored embedding for that class should be less than a threshold.

Siamese Networks

- Siamese Networks are basically two same neural networks, the output of which are passed through the a function that calculates the distance between the inputs.
- For inputs belonging to same class, the outputs are close (i.e., distance is less) and for inputs belonging to different classes, the distance between outputs should be large.
- Triplet loss can be used to train a siamese network.

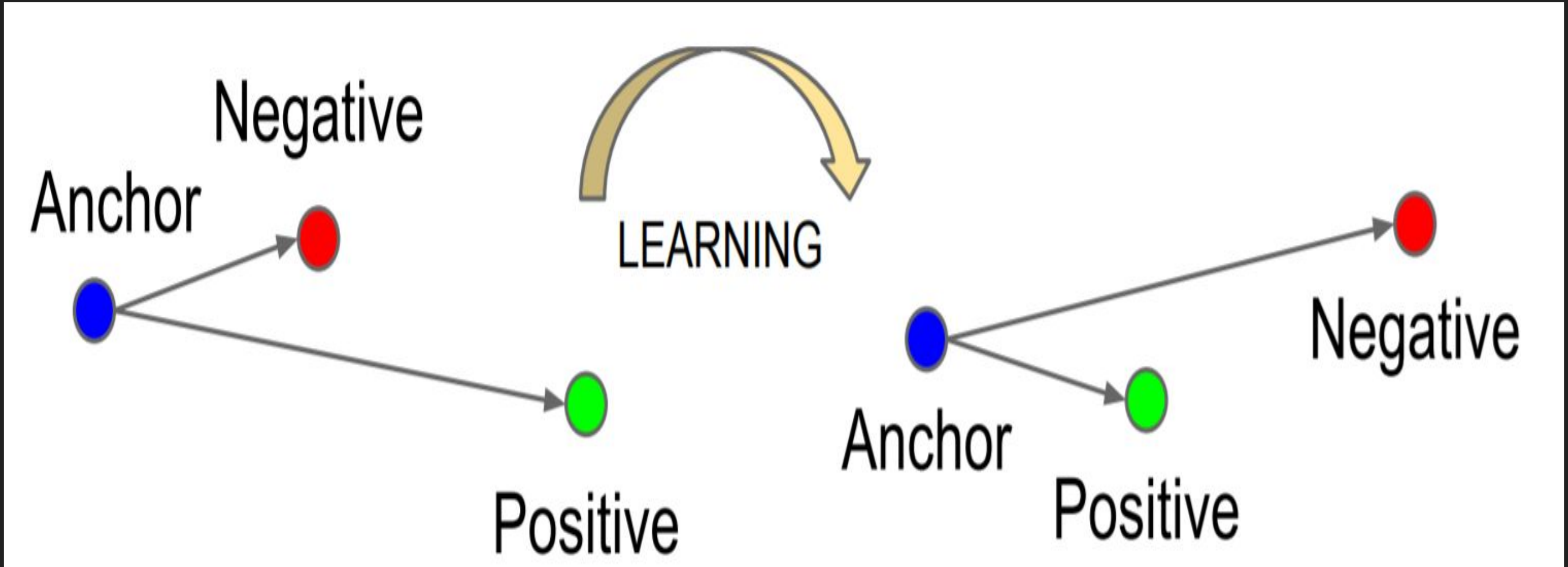
Siamese Network(Cont..)



Triplet loss

- It is a distance based loss function that operates on three inputs:
  1. anchor (a) : is any arbitrary data point,
  2. positive (p) : which is the same class as the anchor
  3. and negative (n) : which is a different class from the anchor
- Mathematically, it is defined as: $L=\max(d(a,p)-d(a,n)+margin,0)$.
- We minimize this loss, which pushes $d(a,p)$ to 0 and $d(a,n)$ to be greater than $d(a,p)+margin$.
- After the training, the positive examples will be closer to the anchor while the negative examples will be farther from it.

Triplet Loss(Cont..)



Triplet loss - loss function

$$\sum_{i}^{N} \left[\| f(x_i^a) - f(x_i^p) \|_2^2 - \| f(x_i^a) - f(x_i^n) \|_2^2 + \alpha \right]_+$$

Model Summary

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 30, 30, 64)        1792      
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 15, 15, 128)       73856     
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 8, 8, 64)          73792     
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 4, 4, 64)          4160      
_________________________________________________________________
flatten (Flatten)            (None, 1024)              0         
_________________________________________________________________
dense (Dense)                (None, 512)               524800    
_________________________________________________________________
dropout (Dropout)            (None, 512)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 256)               131328    
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_2 (Dense)              (None, 128)               32896     
=================================================================
Total params: 842,624
Trainable params: 842,624
Non-trainable params: 0
_________________________________________________________________
Model: "functional_1"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to                     
==================================================================================================
anchor_input (InputLayer)       [(None, 60, 60, 3)]  0                                            
__________________________________________________________________________________________________
positive_input (InputLayer)     [(None, 60, 60, 3)]  0                                            
__________________________________________________________________________________________________
negative_input (InputLayer)     [(None, 60, 60, 3)]  0                                            
__________________________________________________________________________________________________
sequential (Sequential)         (None, 128)          842624      anchor_input[0][0]               
                                                                 positive_input[0][0]             
                                                                 negative_input[0][0]             
__________________________________________________________________________________________________
merged_layer (Concatenate)      (None, 384)          0           sequential[0][0]                 
                                                                 sequential[1][0]                 
                                                                 sequential[2][0]                 
==================================================================================================
Total params: 842,624
Trainable params: 842,624
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```
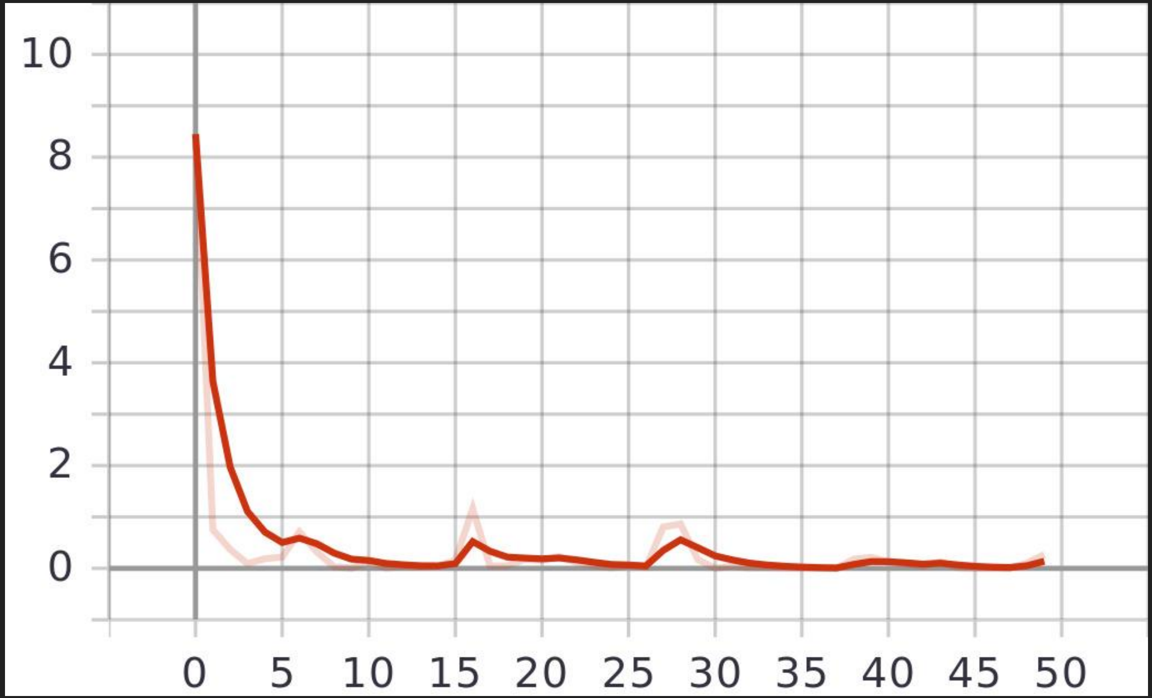
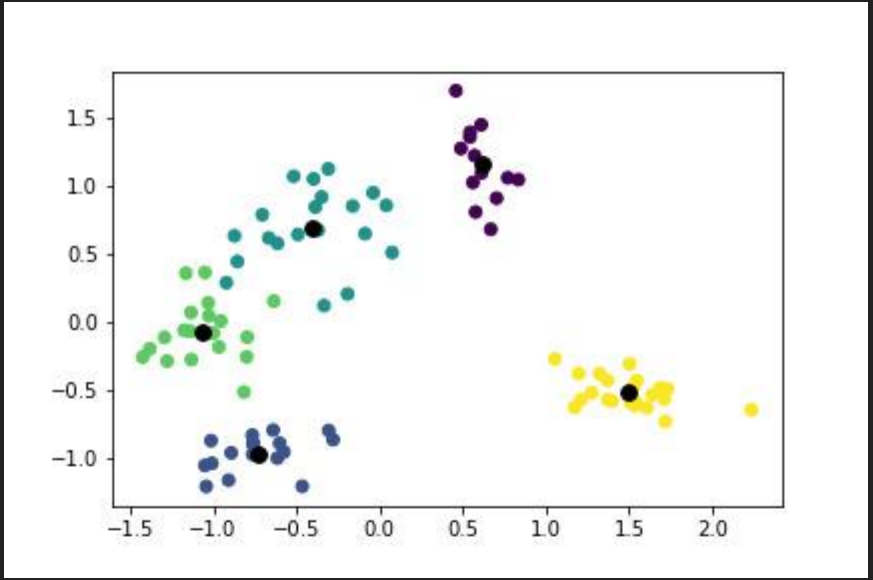

Training and Validation

- For training and validation, we have considered a small subset of the original dataset.
- For validation accuracy, we have used K-NN for better accuracy.

Epoch vs Loss



Scatter Plot for validation data and clusters



Validation Accuracy

K	Accuracy
1	83.33%
3	83.33%
5	79.16%
7	70.83%

Code Snippets

Triplet Generation

```
def generate_triplets(x, y, num_same = 4, num_diff = 4):
    anchor_images = np.array([]).reshape((-1,)+ x.shape[1:])
    same_images = np.array([]).reshape((-1,)+ x.shape[1:])
    diff_images = np.array([]).reshape((-1,)+ x.shape[1:])

    for i in range(len(y)):
        point = y[i]
        anchor = x[i]

        same_pairs = np.where(y == point)[0]
        same_pairs = np.delete(same_pairs , np.where(same_pairs == i))
        diff_pairs = np.where(y != point)[0]

        same = x[np.random.choice(same_pairs,num_same)]
        diff = x[np.random.choice(diff_pairs,num_diff)]

        anchor_images = np.concatenate((anchor_images, np.tile(anchor, (num_same * num_diff, 1, 1, 1) )), axis = 0)

        for s in same:
            same_images = np.concatenate((same_images, np.tile(s, (num_same, 1, 1, 1) )), axis = 0)

        diff_images = np.concatenate((diff_images, np.tile(diff, (num_diff, 1, 1, 1) )), axis = 0)

    return anchor_images, same_images, diff_images
```

Code Snippets

Triplet Loss Function

```python
def triplet_loss(y_true, y_pred, alpha = 0.2):
    total_length = y_pred.shape.as_list()[-1]
    anchor, positive, negative = y_pred[:,:int(1/3*total_length)], \
        y_pred[:,int(1/3*total_length):int(2/3*total_length)], y_pred[:,int(2/3*total_length):]

    pos_dist = tf.reduce_sum(tf.square(anchor - positive), axis=-1)
    neg_dist = tf.reduce_sum(tf.square(anchor - negative), axis=-1)
    basic_loss = pos_dist - neg_dist + alpha
    loss = tf.reduce_sum(tf.maximum(basic_loss,0.0))
    return loss
```

Models and experiments

- We have tried different deep learning structures and experimented with them.
  - Experiments on Batch Normalisation
  - Max/Min/Avg pooling
  - Dropout
  - optimizers
  - epochs and different batch sizes
- We tried different values of K in KNN classification.
- We trained our model to different numbers of triplets.
- We tried different subsets of LFW dataset for training model.

Accuracy on LFW

Model	Accuracy
Margin: 0.4, K=7, w/o dropout	52.70%
Margin: 0.4, K=9, with dropout	51.45%
Margin: 0.5, k = 1, w/o dropout	55.96%
Margin: 1, k = 7, w/o dropout, Batch normalization	52.74%

Final Model & Accuracy

Margin: 0.6, k=9, w/o dropout

Accuracy = 61.32%

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 30, 30, 64)	1792
max_pooling2d (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_1 (Conv2D)	(None, 15, 15, 128)	73856
max_pooling2d_1 (MaxPooling2	(None, 15, 15, 128)	0
conv2d_2 (Conv2D)	(None, 8, 8, 64)	73792
conv2d_3 (Conv2D)	(None, 4, 4, 64)	4160
max_pooling2d_2 (MaxPooling2	(None, 4, 4, 64)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 512)	524800
dense_1 (Dense)	(None, 256)	131328
dense_2 (Dense)	(None, 128)	32896

Total params: 842,624
Trainable params: 842,624
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Timeline

WEEK 1

Understanding the problem statement, Studying Research paper, Solution approach in research paper, Initial evaluation

WEEK 2

More exploration in research paper solution, Existing solutions for the problem statement, Finding different datasets

WEEK 3

Writing code of solution approach, Debugging code, Evaluation our model with parameters, Mid evaluation

WEEK 4

Tuning Parameters, Finalizing dataset, Preprocessing dataset, Final run on dataset

WEEK 5

Testing model, Experiments, Feedback from testing and make changes accordingly, Final results, Final evaluations

Individual contribution

- Data Preprocessing & face detection - Param and Sanyam
- Generating triplets - Shubham and Sanyam
- Siamese Network and Triplet Loss function - Param and Shubham
- Experimenting with Different parameters - All

References

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