Homework 2 Part 2

Face Classification & Verification using Convolutional Neural Networks

11-785: Introduction to Deep Learning (Spring 2021)

DUE: **11:59PM (EST), March 21^{th}, 2021**

1 Introduction

Even though face recognition may sound quite trivial to us humans, it remained a challenging computer vision problem in the past decades. Thanks to deep learning methods, computers now can leverage huge dataset of faces to learn rich and compact representations of human faces, allowing models to even outperform the face recognition capabilities of humans.

Face recognition mainly consists of two parts. The task of classifying the ID of the face is known as **face classification**, which is a closed-set problem. The task of determining whether two face images are of the same person is known as **face verification**, which is an open-set problem[1].

In this assignment, you will use Convolutional Neural Networks (CNNs) to design an end-to-end system for both tasks (well, other techniques are required if you want to get an A.) For the classification task, your system will be given an image of a face as input and should output the ID of the face. For the verification task, your system will be given two images as inputs and should output a score that quantifies the similarity between the *faces* in the given images. A higher score means that the faces from the two images are more likely to be from a same person.

You will train your model on a dataset with a few thousand images of labelled IDs (i.e., a set of images, each labeled by an ID that uniquely identifies the person.) You will learn more about embeddings[2], several loss functions, and, of course, convolutional layers as effective shift-invariant feature extractors. You will also develop skills necessary for processing and training neural networks with $_{\text{big}}$ data, which is often the scale at which deep neural networks demonstrate excellent performance in practice.

Please NOTICE: this assignment comes with **two Kaggle** competitions. In this way, you can understand how *classification* and *verification* resembles and differs from each other.

- **Face classification**
  - Goal: Given a person's face, return the ID of the face
  - Kaggle: `http://www.kaggle.com/c/11785-spring2021-hw2p2s1-face-classification`
- **Face verification**
  - Goal: Given two faces, return whether they are from the same person
  - Kaggle: `http://www.kaggle.com/c/11785-spring2021-hw2p2s2-face-verification`

2 Face Classification

2.1 Face Embedding

Before we dive into implementation, let's ask ourselves a question: how do we differentiate faces? Yes, your answers may contain skin tone, eye shapes, etc. Well, these are called **facial features**. Intuitively, facial features vary extensively across people (and make you different from others). Your main task in this

[1] For close-set task, all testing identities are predefined in training set. For open-set task, testing identities typically do not appear in training set.

[2] In this case, embeddings for face information.

assignment is to train a CNN model to extract and represent such important features from a person. These extracted features will be represented in a *fixed-length* vector of features, known as a **face embedding**.

Once your model can encode sufficient discriminative facial features into face embeddings, you can pass the face embedding to a fully-connected(FC) layer to generate corresponding ID of the given face.

Now comes our second question: how should we train your CNN to produce high-quality face embeddings?

2.2 Multi-class Classification

It may sound fancy, but conducting *face classification* is just doing a multi-class classification: the input to your system is a face image and your model needs to predict the ID of the face.

Suppose the labeled dataset contains a total of M images that belong to N different people (where $M > N$). Your goal is to train your model on this dataset so that it can produce "good" face embeddings. You can do this by optimizing these embeddings for predicting the face IDs from the images. The resulting embeddings will encode a lot of discriminative facial features, just as desired. This suggests an N-class classification task.

A typical multi-class classifier conforms to the following architecture:

$$\text{Classic multi-class classifier} = \text{feature extractor(CNN)} + \text{classifier(FC)}$$

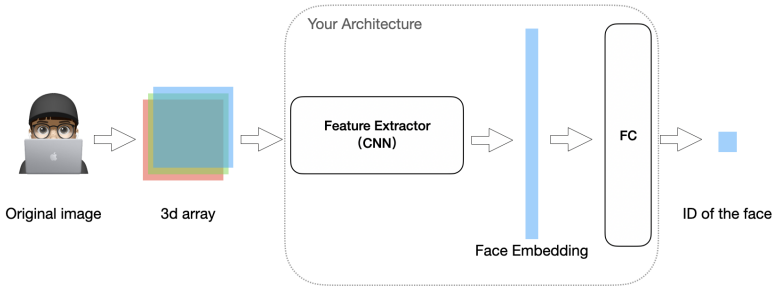

Figure 1: A typical face classification architecture

More concretely, your network consists of several (convolutional) layers for feature extraction. The input will be (possibly a part[3] of) the image of the face. The output of the last such feature extraction layer is the face embedding. You will pass this face embedding through a linear layer whose dimension is *embedding dim* $\times$ *num of faceids*, followed by Softmax, to classify the image among the N (i.e., num of faceids) people. You can then use cross-entropy loss to optimize your network to predict the correct person for every training image.

The ground truth will be provided in the training data (making it supervised learning). You are also given a validation set for fine-tuning your model. Please refer to the **Dataset section** where you can find more details about what dataset you are given and how it is organized. To understand how we (and you) evaluate your system, please refer to the **System Evaluation section**.

That's pretty much everything you need to know for your **first** Kaggle competition. Go for it!

3 Face Verification

Let's switch gear to face verification. Now, the input to your system will be a *trial*, i.e., a pair of face images that may or may not belong to the same person. Given a *trial*, your goal is to output a numeric score that quantifies how similar the faces in the two images are. A higher score indicates higher confidence that the faces in the two images are of the same person.

[3]It depends on whether you pre-process your input images

In the following sections, we will introduce you to a few approaches. But do not let us constrain your imagination. There are a lot of other ways to achieve great performance.

FAIR WARNING: We do not guarantee that all the methods listed below can help you pass the A cut-off. You need to experiment with your own judgement.

3.1 Building upon the multi-class classification

I hope you have not deleted your classification model. If your model yields high accuracy in face classification, you **might** already have a good Feature Extractor for free. That being said, if you remove the fully-connected/linear layer, this leaves you with a CNN that "can" (*probably can* should be more accurate here) generate discriminative face embeddings given arbitrary face images.

3.1.1 Feature extractor + distance calculator

We shall all agree that the face embeddings of a same person should be similar (the distance is short) even if they are extracted from different images. Assume our CNN is competent to generate accurate face embeddings, we only need to find a proper **distance metric** to evaluate how close given face embeddings are. If two face embeddings are close[4] in distance, they are more likely to be from a same person[5].

Here, we propose two prevalent distance metrics, but you have to experiment yourself from there. (Hint: check Appendix A)

- Cosine Similarity
- Euclidean Distance

If you follow this design, your system should look like this. Please notice that the Feature Extractor in Fig 2 is the same one even though it is drawn twice.

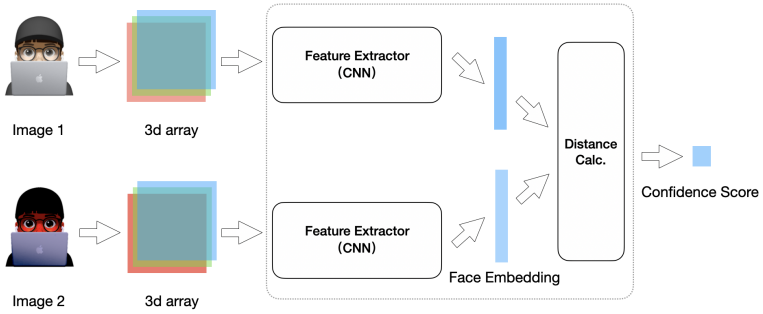

Figure 2: face verification architecture

3.1.2 Take a step further

We have heard a rumor that a good job in classification is only guaranteed to help you reach the B-cutoff in validation. Hence, you are encouraged to try other advanced loss functions such as Center-loss [1], LM [2], L-GM [3], and other architectures such as SphereFace [4], CosFace [5], ArcFace [6] and UniformFace [7] to go beyond this.

Alternatively, you can remove the layer entirely and optimize the net using comparator-losses that optimize the network for the verification task, e.g. triplet-loss[8], pair wise loss [9].

You are also encouraged to explore the interconnection between classification accuracy and verification performance.

[4]How close is close?

[5]Now, do you understand why we use fixed-length vector as face embeddings?

3.2 Metric Learning

The multi-class classification method has a flaw here: in the real world, we can not make our model to recognize every person on Earth. What if a new person is added to the dataset? Do you want to re-train the whole network whenever a new person is added?

The second approach is actually called deep metric learning(DML): instead of modeling the classes, you are directly modeling the similarity between two images. The general goal is to make the minimum distance between negative pairs larger than the maximum distance between positive pairs[6].

A potential approach is to build a Siamese Neural Network [10] and apply a Contrastive loss function as follows:

$$L = \frac{1}{N}\Sigma_{i=1}^{N}[y * d(P_i) + (1-y) * (m - d(P_i))] \tag{1}$$

Where d denotes Euclidean distance, and $y = 1/0$ indicates the pair P_i is positive/negative respectively. m is a margin. N denotes total number of training objectives.

There are two popular approaches to make pairs for your verification system. One is **offline selection**: pairs are generated before passed through the neural network. Another is **online selection**: pairs are generated in the mini-batch during training. For offline selection, please pay attention to the ratio of #negative pairs to #positive pairs. You are **advised** to set this ratio as 5:5, 6:4, 7:3. For online selection, one straightforward method is to select all $\frac{B(B-1)}{2}$ pairs within a mini-batch of size B. You can also just select *hard*[7] pairs within the mini-batch, which is also referred to as **Hard Sample Mining** [11, 12].

Instead of measuring the similarity between pairs, you can also apply Triplet loss [13] or Quadruplet loss [14] to model the similarities among triplets or quadruplets.

If you're wondering if there exists a Quintuplets, Sextuplets, Septuplets or even Octuplets loss, you can refer to the N-pair Loss [15], Lifted-Structure Loss [16], Softtriplet Loss [17] papers.

It may also be possible for other advanced loss functions such as Pair-Wise Loss [18], Multi-Similarity(MS) [19], Mask Proxy(MP) [20] to give SOTA verification performance.

4 Dataset

The data for the assignment can be downloaded from the Kaggle competition link. [8][9]. The dataset contains images of size 64×64 for all xyz channels. In this competition, we are dealing with faces from 4000 people (That being said, we have 4000 classes.) [10]

This assignment contains 2 parts.

- For **classification**, you will be given a human face image. What you need to do is to learn to classify this image into correct people IDs.
- For **verification**, you will be given two images, and you need to calculate the similarity score for those images using the embeddings generated by your classification network. Notice that for verification, the test identities are disjoint from the training identities, i.e. your network should be able to tell whether two images belong to the same person or not, even if it has never seen those people before. This is known as open-set protocol.

4.1 File Structure

The structure of the dataset folder is as follows:

[6]Two instances in the positive pair should be from the same identity. Two instances in the negative pair should be from different identities.

[7]Large similarity for negative pairs and small similarity for positive pairs.

[8]Classification: `http://www.kaggle.com/c/11785-spring2021-hw2p2s1-face-classification/data`

[9]Verification: `http://www.kaggle.com/c/11785-spring2021-hw2p2s2-face-verification/data`

[10]If you are using Kaggle API and the file hierarchy is not as desired, try upgrade your Kaggle API by running `!pipinstall--upgrade--force-reinstall--no-depskaggle`

4.1.1 Kaggle Classification

- `classification_data`: Each sub-folder in `train_data`, `val_data` and `test_data` contains images of one person, and the name of that sub-folder represents their ID.
  - `train_data`: You are supposed to use the `train_data` set to train your model **both for the classification task and verification task.**
  - `val_data`: You are supposed to use `val_data` to validate the classification accuracy.
  - `test_data`: You are supposed to assign IDs for images in `test_data` and submit your result.
- `classification_test.txt`: This file contains the trials for `Classification Test`. The first column is the images path. Your task is to assign ID to each image and generate submission file based on the order given here.
- `classification_sample_submission.csv`: This is a sample submission file for face classification competition.

4.1.2 Kaggle Verification

- `verification_data`: This is the directory that contains the images for both the `Verification Validation` and `Verification Test`.
- `verification_pairs_val.txt`: This file contains the trials for `Verification Validation`. The first two column are the images path of the trial. The third column contains the true label for the pair. You are supposed to use the data in this file to validate your AUC score.
- `verification_pairs_test.txt`: This file contains the trials for `Verification Test`. The first two column are the images path of the trial. You task is to compute the similarity between each two trials and to generate submission file based on this.
- `verification_sample_submission.csv`: This is a sample submission file for face verification competition.

4.2 Loading Training Data - ImageFolder

To load the images, we recommend that you look into the ImageFolder dataset class of PyTorch at `https://pytorch.org/docs/stable/torchvision/datasets.html#imagefolder`. The images in subfolders of `classification_data` are arranged in a way that is compatible with this dataset class. Note that `ImageFolder` is helpful for both `Multi-class classification`, and `Metric Learning` tasks.

Again, If you are using Kaggle API and the file hierarchy is not as desired, try upgrade your Kaggle API by running `!pipinstall--upgrade--force-reinstall--no-depskaggle`

5 System Evaluation

5.1 Kaggle 1: Face Classification

This is quite straightforward,

$$\text{accuracy} = \frac{\#\text{ correctly classified images}}{\#\text{ total images}}$$

5.2 Kaggle 2: Face Verification

Here, we briefly describes how the "quality" of your similarity scores will be evaluated. Given similarity scores for many trials, some *threshold* score is needed to actually accept or reject pairs as *same-person* pairs (i.e., when the similarity score is above the threshold) or *different-person* pairs (i.e., when the score is below the threshold), respectively. For any given threshold, there are four conditions on the results: some

percentage of the different-person pairs will be accepted (known as the *false positive* rate), some percentage of the same-person pairs will be rejected (known as the *false rejection* rate), some percentage of the different-person pairs will be rejected (known as the *true negative* rate), and some percentage of the same-person pairs will be accepted (known as the *true positive* rate).

The Receiver Operating Characteristic (ROC) curve is created by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings [11]. The Area Under the Curve (AUC) for the ROC curve is equal to the probability that a classifier will rank a randomly chosen similar pair (images of same people) higher than a randomly chosen dissimilar one (images from two different people) (assuming 'similar' ranks higher than 'dissimilar' in terms of similarity scores).

This is the metric which will be used to evaluate the performance of your model for the face verification task.

To track your progress, after an epoch of training, you can compute a similarity score for every trial in the validation set, write them to another file. One suggested approach to compute AUC is to use the function provided in sklearn library[12]:

- `sklearn.metrics.roc_auc_score(true_label, similarity_scores)`. This function is useful for Verification Validation. It loads the true label array and the generated similarity scores array and prints out the average AUC score. Please also pay attention to the difference between cosine similarity score and Euclidean distance score.

6 Submission

Following are the deliverables for this assignment:

- Kaggle submission for Face Classification.
- Kaggle submission for Face Verification.
- A one page write up describing your model architecture, loss function, hyper parameters, any other interesting detail led to your best result for the above two competitions. Please limit the write up to one page. The link for submitting the writeup will be posted later on piazza/Autolab.

7 Conclusion

Nicely done! Here is the end of HW2P2, and the beginning of a new world. As always, feel free to ask on Piazza if you have any questions. We are always here to help.

Good luck and enjoy the challenge!

[11] `https://en.wikipedia.org/wiki/Receiver_operating_characteristic`
[12] `https://scikit-learn.org/stable/`

Appendix A

Appendix A1: Cosine Similarity VS Euclidean Distance

You may struggle with selecting a proper distance metric for the verification task. The most two popular distance metrics used in verification are cosine similarity and Euclidean distance. We would tell you in that both two metrics are able to reach SOTA score, but at least you should get an intuition on how to choose one of them.

The metric should be training-objective-specific, where training objective refers to the loss function. Let us start with revisiting Softmax cross entropy:

$$Loss = -\frac{1}{N}\Sigma_{i=1}^{N} log \frac{e^{W_{Y_i}^T X_i}}{\Sigma_{j=1}^{N} e^{W_{Y_j}^T X_i}} \tag{2}$$

Where Y_i is the label of X_i. If you take a thorough look at this formula, you will find that the objective is to make the vector(embedding) X_i be closer to the vector W_{Y_i} and be far away from other vectors W_{Y_j}. Under this rule, the W_{Y_i} is actually the center of $i-th$ class. Because you are performing dot product between the class center and the embedding, then each embedding would be similar to its center in the **Angular Space**, which could be illustrated in the following Figure. 3. So during verification, you are strongly suggested to apply cosine similarity rather than Euclidean distance to compute the similarity score.

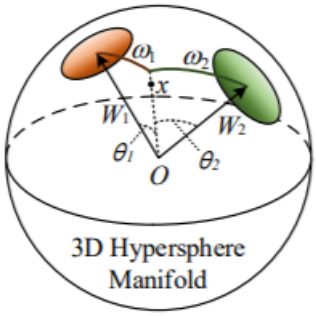

Figure 3: Angular Space [4]

Furthermore, if we design our own loss function e.g. in Eq. 3, you are suggested to apply Euclidean distance metric to compute similarity. (Is this RBF?)

$$Loss = -\frac{1}{N}\Sigma_{i=1}^{N} log \frac{e^{||W_{Y_i} - X_i||^2}}{\Sigma_{j=1}^{N} e^{||W_{Y_j} - X_i||^2}} \tag{3}$$

Question left to you, what metric is **probably** better if you start with metric learning and apply the loss function in Eq. 1?

However, the aforementioned conclusions are not definitely true. We would tell you that sometimes Euclidean distance is also good when you apply softmax XE in Eq. 2 and cosine similarity is also good when you apply Eq. 3 as loss function. We would just give you the following hint and let you explore it.

$$||U - V||_2^2 = ||U||_2^2 + ||V||_2^2 - 2U^T V \tag{4}$$

Appendix B

Appendix B1: B-way Classification

In this appendix, we are going to introduce you to a **metric learning** strategy called *B-way classification*, in which B refers to batch size. The following figure gives an intuition of this manner:

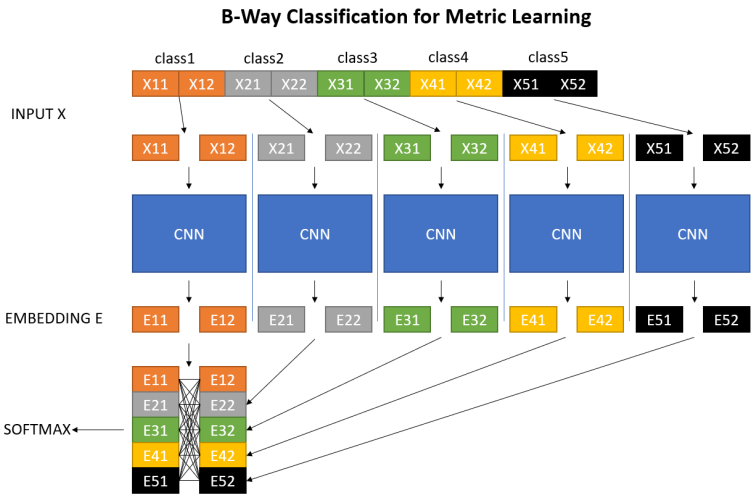

Figure 4: B-way classification for metric learning

Note that everything happens only within a mini-batch and batch size is 5 in this figure. For the notation, in X_{ij} and E_{ij}, i is the label information($1 \leq i \leq$ BatchSize) and j is the index of samples for each class. Here we set number of samples in each class as 2. To claim again, if the batchsize is B, then you will get $2 \times B$ embeddings and 2 for each class. Your task is just to classify these B classes:

$$L = -\sum_{i=0}^{B-1} \log \frac{\exp(E_{i1}^T E_{i2})}{\sum_{j=0}^{B-1} \exp(E_{i1}^T E_{j2})}$$

This is actually called *Prototypical loss*, which is one of the SOTA metric learning losses currently and which is likely to give you a better AUC score than classification methods(Even better than margin-based Softmax loss functions like CosFace/ArcFace). To apply this loss function, you may care about the following points:

1. There is only one CNN backbone within a mini-batch though we present 5 in the example. (You can also apply Siamese Network)
2. Label information is ignored when computing the loss objective. Labels are just 0,1,...B-1. Labels are only useful when building your dataset.
3. You need to build a powerful dataset/dataloader to pass these $B \times 2$ data points into the network, which is the most pivotal part in the whole work.
4. $E_{i1}^T E_{i2}$ could be replaced by $a \cdot E_{i1}^T E_{i2} + b$, in which a and b are learnable parameters. It would usually be better to normalize embeddings.
5. There is no supervision signal in the loss objective unlike multi-class classification. (Is this unsupervised learning?)

Just feel free to go through this method!

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