Face Recognition
through a Siamese Network

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Sommario

1. Introduction

Face Detection and Recognition are one of the most popular fields in the study of Artificial Intelligence studies. But what’s the difference between them? Many people still make a mistake in differencing the two approaches.

- When somebody is talking about Face Detection, it is referring to a task in which the goal is to find some faces in a given image (ie: is this a face / is there a face in this image?)
- On the contrary, Face Recognition is applied when there is the necessity to identify the person on a given image (ie: who is this?)

But that is not where Face Recognition stops. In fact, it can be divided into sub-categories:

1. Identification: Given a face image, the objective is to match that file on a database – hence – identifying from this database to who that face belongs to (most common mean of Face Recognition)
2. Verification: Given an image and an identity, confirm that the given face belongs to the given identity (typical authentication / authorization task).

In this paper, we faced the problem of performing a Face Recognition (via Verification) of a given image through a Siamese Network.
Why a Siamese Network? How did we reach it? And what is it?
In the following chapters, we will going to describe our architectural choices also by providing the source code and we will see some “numerical facts” to see if our model has been a good choice or not for our task.

2. Theoretical overview

Before going deeper with describing the problem, let us first describe what a Convolutional Neural Network is and give just a quick example on how it is possible to implement one with the most used Deep Learning technologies.

2.1 Convolutional Neural Networks

A Convolutional Neural Network is a Neural Network that is part of the "Deep Learning branch" (since it holds, usually, a minimum of 7 layers) and is considered one of the most powerful network when it comes to image processing, thanks to the key its structure:

1. Neurons are distributed in 3 dimensions and not all of them are connected to the next layer: only the next to last is fully connected
2. Weights are shared all along the net

Why is all of this important? As an example, let's assume that we want to process a 48x48x3 image with a Multilayer Neural Network with Sigmoid as its activation function: this would mean to have, just for a single neuron in the first hidden layer, about 6912 weights (not to mention also the problem of the Vanishing / Exploding Gradient)! By exploiting the strong spacially local correlation that each hidden layer can hold, CNN have been proven to be the best choice against Multilayer Neural Networks.
As far as the type of layers that a Convolutional Neural Networks can have, there can be 3 types:

- Convolutional: they compute the output of neurons connected to the input thanks to a kernel, which slides over the input and perform the dot product between the entry of the filter and the postions that are close to the input computed; the output is influenced by some hyperparameters
- Pooling: usually inserted between one convulational layer and another, they are used to reduce the amount of parameters and computation in the network, in order to avoid overfitting
- Fully-connected layer: usually placed at the end of the Convolutation Neural Network. Since the neurons are fully connected, the layer is goingn to be threated as a normal neural network.

2.2 Siamese Networks

Since, sometimes, image datasets can contain few training samples of the same photo, **one-shot learning** techniques may be the best option for the Face Recognition task: in this approach, as it may be easy to guess, the objective is to learn information about object categories from one or just a few training samples.

One of the most common "exploiter" of the one-shot learning is the **Siamese Network**, which was first reported in the '90s researchs' papers as a new model of Neural Network, in which there are two or more twin nets that make predictions and then "merge" towards a guess: something like an ensemble method.

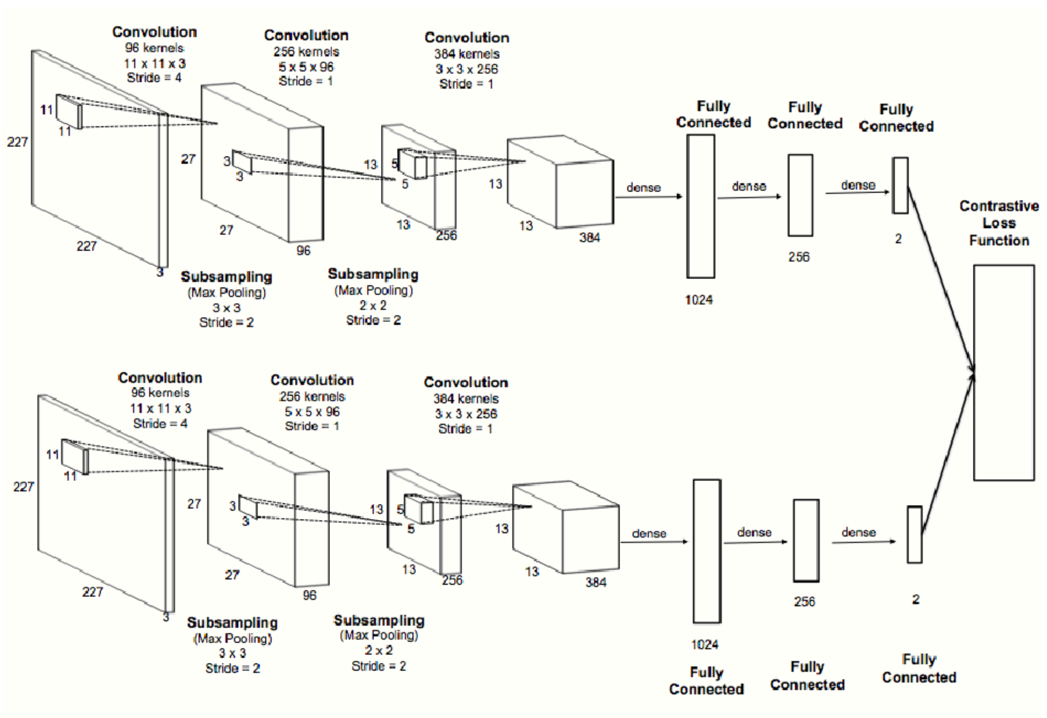


Figure 1 An example of a Siamese Network

Being that the networks are twins with each other, not only they share the same architecture, they also share the very same weights.

The overall architecture of a Siamese Network, and its features, holds two key properties:

1. It ensures predictions' consistency. Since the parameters between the networks are tied (and so are weights), there is a guarantee that two very similar images will have the same locations in the feature space, as per the activation function of the twin networks, since the calculations will always be the same
2. Since the network is symmetric, no matter to which network first an image is presented, it will always calculate the same metric (because of the above point)

But what about its predictive model? Essentially, the twin networks will compute n feature vectors from the input image (depending on how many pairs are in the network) and then it will calculate the similarity d between the two images. There are two possible outputs allowed:

- If d is small, then it is possible to say that the images are similar between them. That's because the twin networks calculated the same values through their neurons, so it is safe to assume that the images might be the same
- On the contrary, if d holds an high value, it is safe to assume that the the images are not similar.

2.3 TensorFlow

Tensorflow is probably the most famous framework for working out any large-scale Machine Learning: originally created by the *Google Brain Team*, it is an open-source library which bundles mainly Deep Learning models and algorithms.
The library can train and run Deep Neural Networks for many tasks, starting from the digit classification and arriving to the image recognition.
But how does it work?
Tensorflow allows to create the so-called “dataflow graphs”, structures that describe how data moves through a graph. Here:

- A node represents a mathematical operation
- An edge between two nodes symbolize a “Tensor” (short for multidimensional array)

The nodes, though, are not executed in Python: to ensure much more speed in terms of calculations, in fact, the library executes these operations in C++, so that they can work at a low-level context.
Another great advantage is that the developer can choose if to execute the calculations either on the CPU or the GPU, to ensure more calculation power to the program.
As of 2019, Tensorflow is accreditated as one of the most used libraries for Deep Learning and it keeps growing, even with a release for JavaScript.

As we felt that Tensorflow was what we needed for this task (since it is more powerful than Keras), we decided to abandon the advantage of having less and more concise code lines in favour of more computational power.
For this reason, we will not list a code example here as our project was entirely made with Tensorflow.
Please refer to Chapter 5 to immediately see our implementation of the Convolutional Neural Network.

3. Project setup

Let us know enlist the technologies that we used while working on this project.

- **Python 3.x**
- **PyCharm as our IDE**
- **Numpy**
- **PIL**
- **tqdm**
- **Tensorflow**
- **The CFPW dataset** (which is a collection of front and profile face images that belongs to many celebrities)

To check out the full project, please refer to this GitHub repository, which also contains all the papers from which we were inspired for this work.

3.1 The CFPW Dataset

The **CFPW dataset**, as already stated, is a dataset that is a collection of front and profile face images that belongs to many celebrities.
The set of images, as a whole, contains 500 celebrities and, each of them, has 14 images (10 from frontal point of view and 4 of their profiles) of himself/herself: this means that, as a grand total, the dataset has 7000 samples.
For our purposes we decided to discard the part of the dataset that contains the profile images, so our working dataset contains 5000 samples.

The dataset is organized in the following way: there is a folder for each person, where each one has a unique integer ID (numbered from 001 to 500). Each one of these folders contains two separate folders for the frontal and the profile points of view.

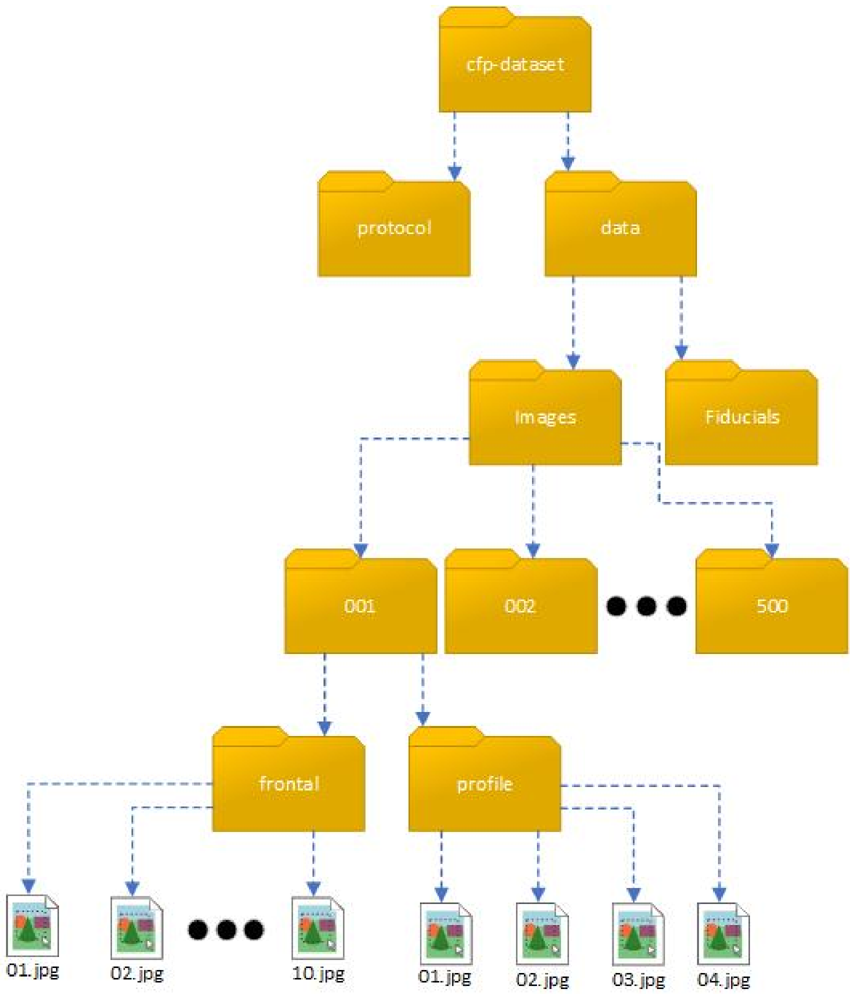


Figure 2 CFPW dataset structure

As stated above, we ignore the profile one. Finally, every frontal folder contains 10 photos of that person, taken in different lighting conditions, and with differing sized images.
As can be seen in the examples below, the images are already cropped.

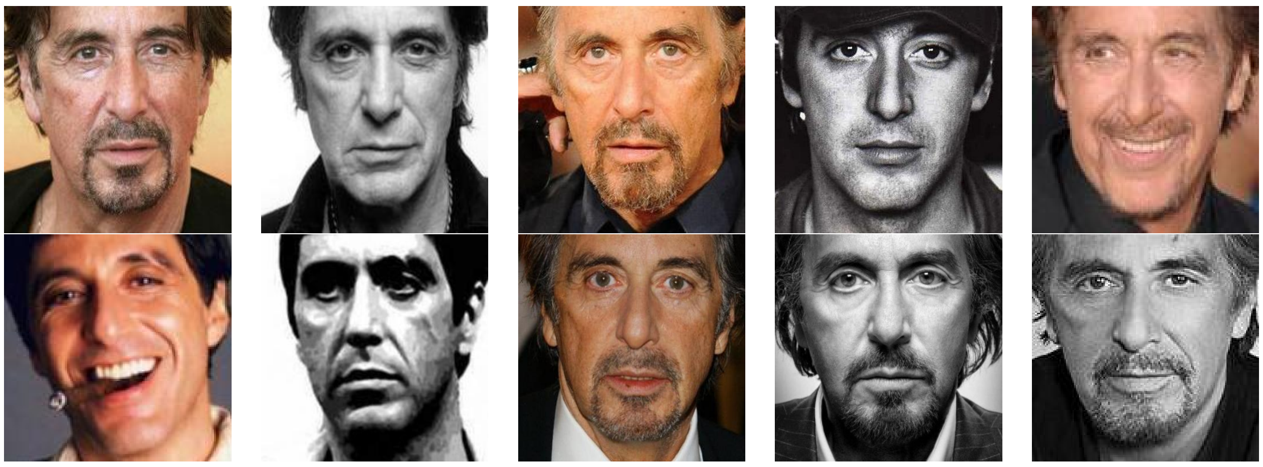


Figure 3 An example of frontal images (Al Pacino, id 012)

4. Data Pre-processing

Before we can operate on the dataset, we must load it in memory and apply some pre-processing techniques.
Our procedure consists of initializing two empty lists (one used for training the model, and the other one will be used for testing purposes) that will contain all the images in the dataset, grouped by person.
We decided to use 70% of the images of each person (chosen randomly) for training the model, while keeping the remaining 30% for the testing phase.

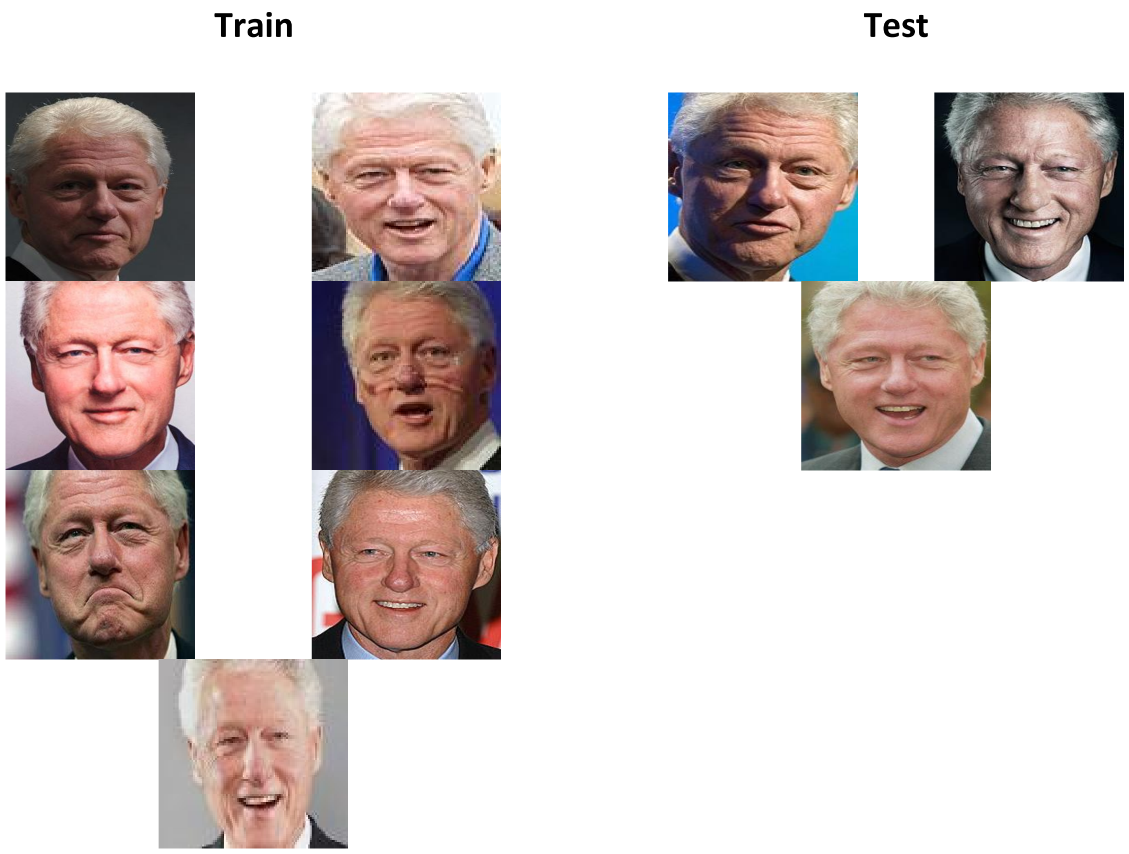


Figure 4 An example of how train-test splitting is done (Bill Clinton, id 067)

When loading each image, there are some steps done before saving it in our list:

- We load the image in RGB, through the PIL library;
- Each image is then resized to 105x105 using the LANCZOS resampling technique;
- Finally it is converted into a numpy array for use with Tensorflow.

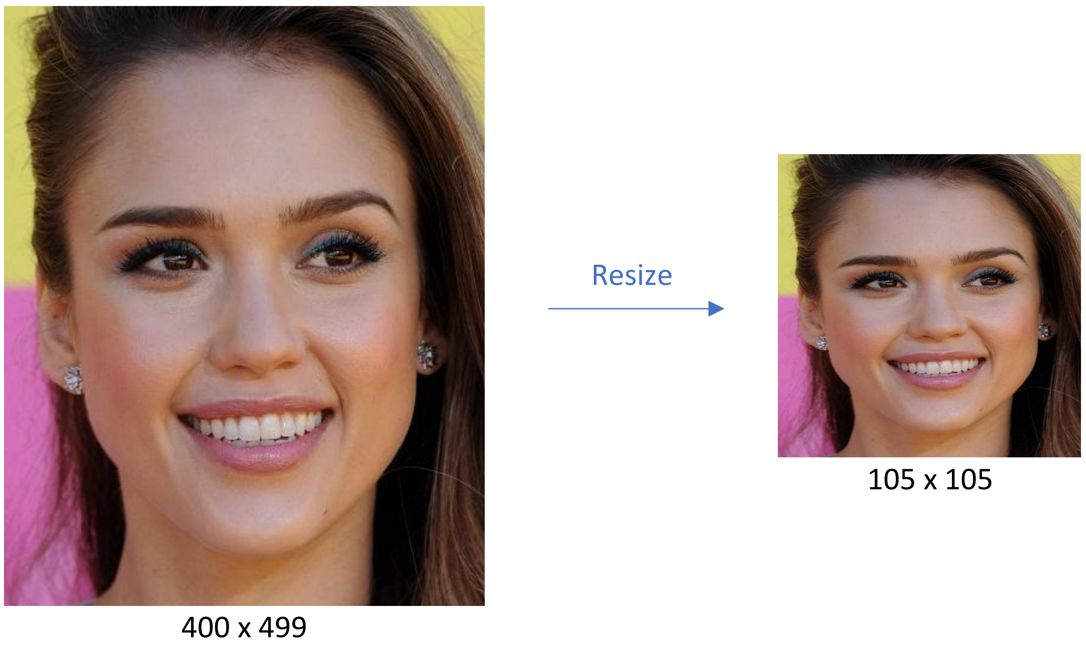


Figure 5 An example of how image resizing is done (Jessica Alba, id 225)

5. Implementation of a Siamese Neural Network

The implementation takes free inspiration from this paper.
The first thing we do is, of course, initializing the class: we decided to build it in a not really pythonic way to have a better reuse in Jupyter Notebooks. The full class can be seen in in Appendix A.
As it can be seen, after loading the collection of images, we also make a small copy of the train and test set, so that it can be easier to load it at the next run: loading the collection means, to us, converting the image to an Image object in Python, convert it as a 3x3 Numpy Array (because we load it with a 3 color channels), cast it to a simple array and then split it depending on the **subject** (will be explained later why).
After that, we define the core of the Siamese Neural Network, as it is possible to see in Appendix B.
Through Tensorflow, we use a layer variable that, everytime, it may seem that it is getting reinitialized with a new layer but it is, actually, not like that: by using the **with** statement, the Deep Learning framework allows us to create a new layer and give to it a name. When the layer is assigned, it **also** gets executed: this means that the user don't have to use something like a .build() method and have everything executed all at once. Tensorflow allows to inspect the progress of the calculations while the input flows from a layer to another.
Following are the list of the used layers:

- At every **with** statement, we initialize a **Convolutional Layer** with **ReLu** as the activation function. The kernel size starts as a 10x10 array and it shrinks, at every new Conv Layer, of 3x3 units less and the filters are, at the beginning, 64: a number that decreases by its half everytime it is initialized a new Convolutional layer.
- Immediately after the Convolutional layer, we have a **Max Pooling** layer which purpose is to decrease by its half the input. We also add a stride of 2, so that the algorithm can shift over the input matrix by a factor of 2 pixel at a time.
- Right after the fully connected layer, there is a **Flatten Layer** that allows to have the input "collapse" in just one dimension
- The final layer is a **Fully Connected**, which actually symbolize the fully connected Neural Network, is made of 4096 units and holds **Sigmoid** as the activation function. As per the input, it takes what the layer variable holds on that point of the program, which should by now represent an image that has now just one dimension.

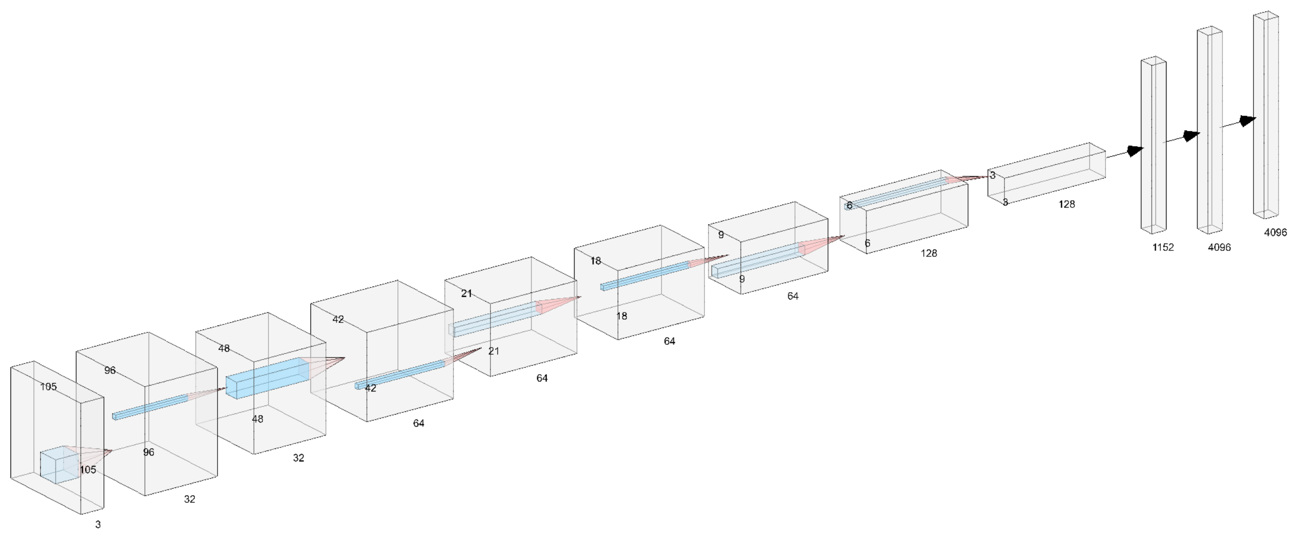


Figure 6 3D representation of our Siamese Network

The Siamese Network architecture follows the pattern:

```
INPUT -> [[CONV -> RELU] -> POOL]*4 -> FLATTEN -> [FC -> SIGMOID]*2
```

Notice that the latest Fully Connected layer is the absolute value subtraction between the first image and the second image passed as input.

5.1 The Weight inizialization problem

In the beginning, we initialized all the Convolutional Layers' biases with the following value

```
weights_initializer=tf.truncated_normal_initializer(mean=0.0, stddev=0.01)
```

which didn't allow us to produce any satisfying predictions as output. We then decided to change this part of our implementation and opted for the **Glorot-Bengio weight initialization technique**, which is the standard way with which Tensorflow initialize the weights of a Convolutional Layer: as specified both in the paper (formula #16) and in the official Tensorflow's documentation for this technique, weights are going to hold a value that has a range that starts from minus the square root of 6 divided by the input units + the output units until the positive of this very formula.

$$W \sim U\left[[-\frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}, \frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}\right]$$

By doing so, we achieve greater results, also in term of accuracy.

5.2 Minimizing loss

In order to minimize the loss that each layer produces at any epoch, we decided to not apply a standard Optimizer but to use the **Adam's** one. Adam is an optimization algorithm that can be used instead of the stochastic gradient descent procedure to update network weights.
The main reasons on why anybody should use this procedure might be:

- It is **easy** to implement;
- It is **computationally** efficient
- It requires just a little bit of memory
- Invariant to diagonal rescale of the gradients

But how does it work? At its core, Adam takes inspiration from two other extensions of the stochastic gradient descent, that are, the **AdaGrad** and the **RMSProp** (both maintains a per-parameter learning rate, while RMSProp also adapts that value to the average of the magnitude of the gradients for the weights) but, in its calculations, it also considers the uncentered variance (meaning we don't subtract the mean during variance calculation): this means that the algorithm will calculate an exponential *moving average* of the gradient and the squared gradient, while having two other parameters (namely, beta1 and beta2) that will control the decay rates of these moving averages.

$$m_t = (1-\beta_1)\sum_{i=0}^{t} \beta_1^{t-i} g_i$$

Figure 7 the moving average calculated with Adam formulation

The loss function, instead, is defined through the **binary cross entropy** formula, which is as it follows:

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1-y_i) \cdot log(1-p(y_i))$$

Figure 8 The Binary Cross Entropy Formula

5.3 Training and accuracy testing

In order to create our batch to be given to the Siamese Network for testing and metrics purposes, we go under two processes: first, we need to generate the batch and the labels, which will then be fed to the network. Our batch size is a hyper-parameter that we set to 32.
This is done by randomly initializing a list with its first half made of positive pairs and the second half with negative ones.
After that, every 500 iterative steps, we run a test to understand what the metrics of the Siamese Network at that stage are. We do this by giving to the algorithm a sample of the test set (in our case a support set of 10 samples) that is made just by one correct pair and, the rest, is made of wrong pairs: this is done to certify that the network is able to verify in a good way the person that is presenting right now.
Given this support set, the model is tasked to score the similarity of each sample in it, then we select the most similar one, using the argmax function (explained below).

Formally speaking, this is known as a **n-way one-shot learning** (our n being 10). Given a tiny labelled training set S, which will hold N examples, each vectors of the same dimension with a distinct label y.

$$S = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\,\}$$

And given x̂ (the test example it must classify), we need to classify the examples in the support set with the right class. But since exactly one example in the support set has the right class, the aim then becomes to correctly predict which y ∈ is the same as x̂ ‘s label, ŷ. Should we ignore this, then the task would become to try all the possible combinations for a single image, hence, a training epoch *would never meet its natural end*. Suppose, in fact, that we get to pass the full dataset to it: the full thing is composed of 500 classes C, each having 14 examples E (we will use 10 examples per person, since we use only the frontals). Then, we would have

$$N_{pairs} = \binom{C\ *\ E}{2} = \frac{(C * E)!}{2!\ (C * E - 2)!} = 12497500$$

In an epoch, the Siamese Network would then need to iterate over all the 12497500 N_{pairs}: this might be inefficient and time wasting. We will go, for this reason, under the assumption that an epoch of ours will last 3000 * 32 iterations: this means that we will check 96000 pairs per epoch, which is a more reasonable amount.

5.4 Prediction

After the optimization process, there is the prediction step, which gets calculated with the **argmax** function. By argmax, we mean the points of the domain of some function in which the function values gets maximized. It is defined in the following way:

$$argmax_x\, f(x) := \{\, x \mid \forall y : f(y)\ \leq\ f(x)\}$$

We use this approach because it generates the value, in our opinion, that best represents the image that got the highest similarity score, by comparing it to the other template, that is, the person that is the closest from the one we want to find, given the other persons used for the comparing (and so, possibly, the same person).
The code for this is available in Appendix C.

6. Model Evaluation

The evaluation process starts by initializing a Tensorflow's Session and assigning to it the graph variable that was previously created.
After that, we make all the Graph's variables initialize through the

session.run(tf.global_variables_initializer())

function. The specified input to .run() allows the Graph to have all its variables initialized, while the .run() method performs the specified action in input.
We then start the computation of the Siamese Network, by iterating to perform a good training. To get the dataset for training, we decided to generate a function (which can be read in Appendix E) that will dynamically (and randomly) select a portion of the dataset and give it to the Network.
Every 500 iterations, there is also a "check step": at that point, the algorithm will pick up a new portion of the dataset (Appendix F), totally random, so that it can perform the **one-shot testing**.

6.1 Test Run

By making a test run of our Network, we reach the following results, expressed in terms of Accuracy and Loss

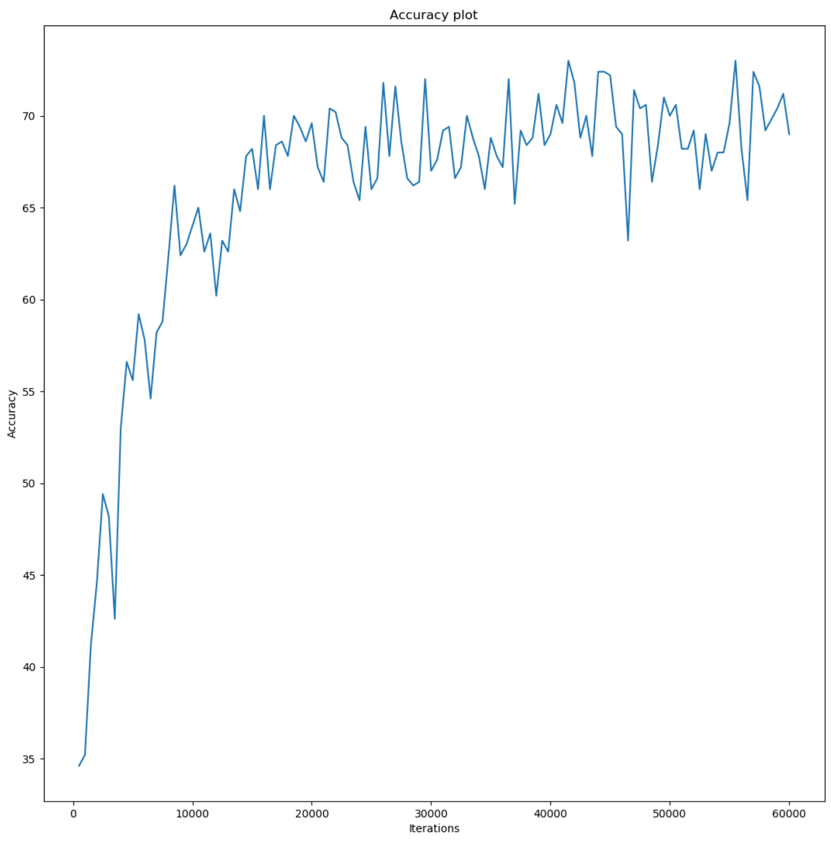


Figure 9 The Accuracy Plot after 60000 iterations of the network

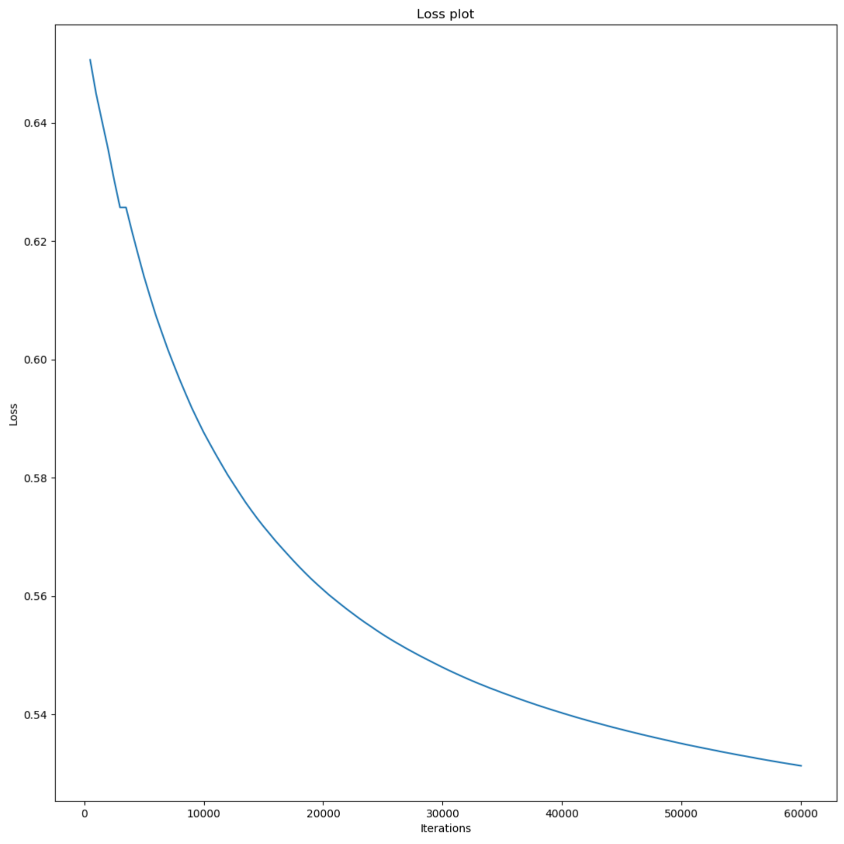


Figure 10 The Loss plot after 60000 iterations of the network

As it is possible to see from Figure 9, the accuracy that the Siamese Network can provide is immediately very high and it can reach in just a few iterations a value between the 65-70%. If we make it run, though, we reach a maximum value of **73%**, which seems a good compromise, considering also the fact that we are performing a One Shot Testing.
Even the loss has an interesting plot: we could say that it has a decrease process like an exponential function.

6.2 Real Test Example

After testing the accuracy of our Siamese Network, it is now time for testing it on a real environment. Usually, there are two cases under which this occurs:

1. **Closed Set**, meaning that the Network will receive as an input images that are somehow known to the dataset (hence, to the network as well);
2. **Open Set**, meaning that our network could be tasked to also evaluate samples of users which are not registered in the dataset

For this project, we decided to stay focused on the **Verification with Multiple Templates:** this means that the network will have to make a match of a person against his/her stored templates on the

dataset (based on the person's identity claim) and, if the outcome is greater or equal than the threshold value, the system will consider that person *who it claims to be*.
The closed set operation will be implemented according to the following pseudocode (where TI = total number of impostor attemps, TG = total number of genuine attempts):

```
for each threshold t do
  for each row I do
    for each group $M_{label}$ of cells $M_{i,j}$ with same label(j) excluding $M_{i,i}$
      select diff = min($M_{label}$ )
      if diff $\leq$ t then
        if label(i)=label($M_{label}$) then GA++
        else FA++
      else if label(i)=label($M_{label}$) then FR++
           else GR++
  GAR(t)=GA/TG; FAR(t)=FA/TI;
  FRR(t)=FR/TG; GRR(t)=GR/TI
```

We now write our way of implementing the *One vs All* pseudocode, which can be seen in the next snippet. Instead of having a matrix, though, we will just iterate over our samples and have the network make its prediction.

```python
# 1 VS ALL
os.path.exists(tmp_dir + '/rates.txt') and os.remove(tmp_dir + '/rates.txt')
threshold_list = [1e-8, 3e-8, 5e-8, 7e-8, 9e-8,
                  1e-7, 3e-7, 5e-7, 7e-7, 9e-7,
                  1e-6, 3e-6, 5e-6, 7e-6, 9e-6,
                  1e-5, 3e-5, 5e-5, 7e-5, 9e-5]
for threshold in threshold_list:
    print("Threshold:", threshold)
    TP, FP, FN, TN = 0, 0, 0, 0
    for i, x in tqdm.tqdm(enumerate(X), total=len(X)):
        if i != 0 and i % 250 == 0:
            print("Threshold:", threshold)
            print("TP:", TP, "FP:", FP, "FN:", FN, "TN:", TN)
            print("True Positive Rate:", TP / i)
            print("False Positive Rate:", FP / (i * (len(Y) // 3 - 1)))
            print("False Negative Rate:", FN / i)
            print("True Negative Rate:", TN / (i * (len(Y) // 3 - 1)))
        for category in range(0, len(Y), 3):
            if not Y[i] == category // 3:
                scores = s.predict([x * 3], X[category: category + 3])
            else:
                scores = s.predict([x * 2], X[category: i] + X[i + 1: category + 3])
            max_val = np.max(scores)
            if max_val >= threshold:
                if Y[i] == category // 3:
                    TP += 1
                else:
                    FP += 1
            else:
                if Y[i] == category // 3:
                    FN += 1
                else:
                    TN += 1
    GAR[threshold] = TP / len(X)
    FAR[threshold] = FP / (len(X) * (len(Y) // 3 - 1))
    FRR[threshold] = FN / len(X)
    GRR[threshold] = TN / (len(X) * (len(Y) // 3 - 1))
    with open(tmp_dir + '/rates.txt', 'a', encoding='utf-8') as w:
        w.write(str(threshold) + '\n')
        w.write(str(TP) + ' ' + str(FP) + ' ' + str(FN) + ' ' + str(TN) + '\n')
        w.write(str(GAR[threshold]) + '\n')
        w.write(str(FAR[threshold]) + '\n')
        w.write(str(FRR[threshold]) + '\n')
        w.write(str(GRR[threshold]) + '\n\n')
```

6.3 Real Test Example – Execution

This is how we proceed: after having loaded our dataset into the main memory, we initialize the Siamese Network, using the dump that was created once the training process was finished.
We started then to run our implementation of the One vs All Algorithm, given the following thresholds:

```
threshold_list = [1e-8, 3e-8, 5e-8, 7e-8, 9e-8,
                  1e-7, 3e-7, 5e-7, 7e-7, 9e-7,
                  1e-6, 3e-6, 5e-6, 7e-6, 9e-6,
                  1e-5, 3e-5, 5e-5, 7e-5, 9e-5]
```

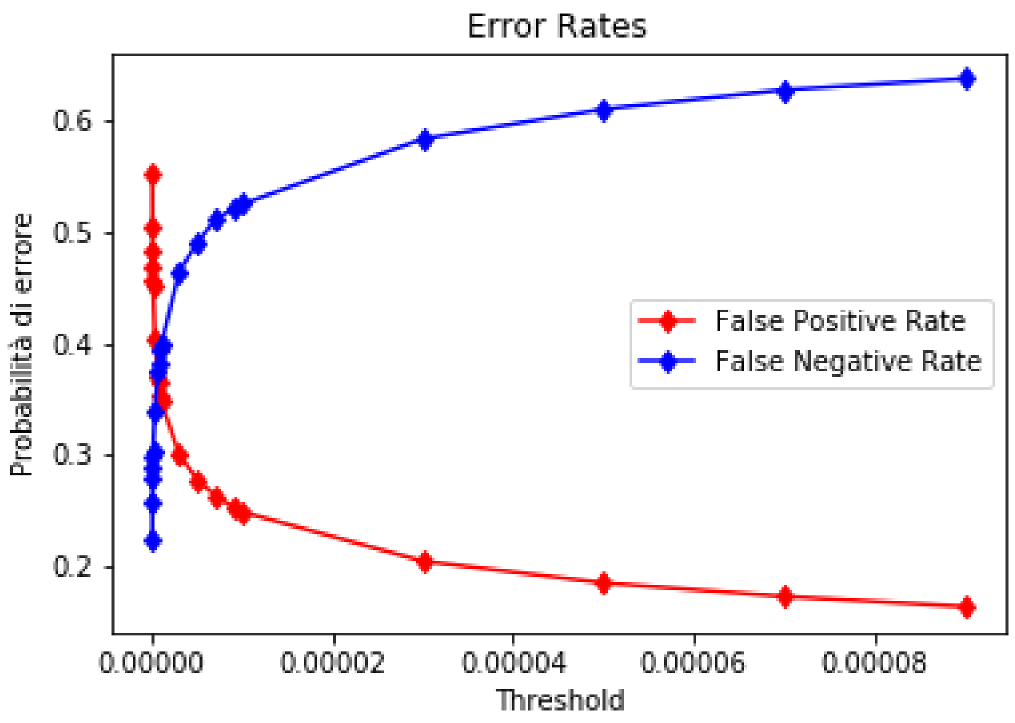
As the first iteration started, we saw that on a consumer grade computer a complete test of all those thresholds would have taken too much time. For this very reason, we decided to migrate our code on a **p2.xlarge** instance of **AWS**, which is configured in the following way:

1. 61GB of RAM
2. 4 vCPUs
3. 1 nVidia K80

By using AWS, we were able to reduce the calculation time from 20 days to just 9 days.

Our implementation of the *One vs All* algorithm works like this: by iterating on the test set, we take 3 images (3 of, say, a person X if X is not the person we are using to make the comparison; 2 otherwise) that will be compared to the one currently analyzed: the network will then perform its prediction. If one of these three predictions are greater or equal than the current threshold, then it is safe to assume that we have a positive prediction. This will be either true or false, based on the matching of the compared identities. The same holds true if the prediction is negative.

After finishing our iteration on the thresholds' list, we then used all the collected values in that process to build the final graph which shows how the FAR and the threshold curve intersects each other. Our objective is to find the best Equal Error Rate (ERR) possible and, by analyzing the following image, it is possible to see that it is located between 0.37 and 0.38.



We can see, also, through this plot, that the more the threshold is smaller, the more it is possible to have a high value for the Genuine Acceptance Rate. To enforce this thought, please consult Appendix G, where it is possible to find all the values that were calculated for each threshold (in order of appearance: GAR, FAR, FRR, GRR).

7. Conclusions

With our work, we managed to adapt a network that was initially created only for recognizing the handwriting also for the task of image recognition.
As per future work, it might be interesting to try to tweak the network more in order to reach an accuracy value of 75%-80% or more.
An interesting method that we can apply to our project, in order to achieve better results, is to retrain the Siamese Network using the data augmentation technique, like random shift, rotation, zoom, etc…
Very often this trick is used to permit to the model to get 5%-10% more of accuracy score and, at the same time, have greater power of generalization.

Appendix A – The Siamese Network class

```python
import os
import numpy as np
import tqdm
import tensorflow as tf
import data_preprocessing as dp
from cnn import siamese_network
import plot_generator as pg

class SiameseNetwork:

    def __init__(self):
        self.__DATA_DIR = 'cfp-dataset/Data/Images'
        self.__TMP_DIR = 'tmp'

        self.__BATCH_SIZE = 32
        self.__ITERATIONS = 3000

        if not os.path.exists(self.__TMP_DIR):
            os.makedirs(self.__TMP_DIR)

        self.__GLOBAL_ITER = dp.global_iteration(self.__TMP_DIR + '/iteration.txt')

        print('Global iteration:', self.__GLOBAL_ITER)

        self.__train_set = []
        self.__test_set = []

        self.__shape = (105, 105, 3)

        self.__graph = tf.Graph()

        with self.__graph.as_default():
            self.__img_1 = tf.placeholder(tf.float32, shape=[None, self.__shape[0], self.__shape[1], self.__shape[2]])
            self.__img_2 = tf.placeholder(tf.float32, shape=[None, self.__shape[0], self.__shape[1], self.__shape[2]])
            self.__flags = tf.placeholder(tf.float32, shape=[None])

            self.__embeddings_1 = siamese_network(self.__img_1, reuse_variables=False)
            self.__embeddings_2 = siamese_network(self.__img_2, reuse_variables=True)

            self.__distance = tf.abs(tf.subtract(self.__embeddings_1, self.__embeddings_2))

            self.__scores = tf.contrib.layers.fully_connected(inputs=self.__distance, num_outputs=1, activation_fn=tf.nn.sigmoid,
                                                              biases_initializer=tf.truncated_normal_initializer(mean=0.5,
                                                                                                                 stddev=0.01))

            self.__losses = tf.nn.sigmoid_cross_entropy_with_logits(labels=self.__flags,
                                                                    logits=tf.reshape(self.__scores, shape=[self.__BATCH_SIZE]))
            self.__loss = tf.reduce_mean(self.__losses)

            self.__optimizer = tf.train.AdamOptimizer(learning_rate=0.00005)
            # optimizer = tf.train.MomentumOptimizer(learning_rate=0.0001, momentum=0.95, use_nesterov=True)
            self.__train_op = self.__optimizer.minimize(self.__loss)

            self.__prediction = tf.cast(tf.argmax(self.__scores, axis=0), dtype=tf.int32)

            self.__saver = tf.train.Saver()

            init = tf.global_variables_initializer()

            ### SESSION ###
            self.__session = tf.Session(graph=self.__graph)

            # We must initialize all variables before we use them.
            init.run(session=self.__session)

            # reload the model if it exists and continue to train
            try:
                self.__saver.restore(self.__session, os.path.join(self.__TMP_DIR, 'model.ckpt'))
                print('Model restored')
            except:
                print('Model initialized')

    def train(self, epochs=1):
        if self.__train_set and self.__test_set:
            pass
        else:
            self.__train_set, self.__test_set = dp.load_dataset(self.__TMP_DIR, self.__DATA_DIR)

        # Open a writer to write summaries.
        self.__writer = tf.summary.FileWriter(self.__TMP_DIR, self.__session.graph)

        average_loss = 0

        for step in tqdm.tqdm(range(self.__ITERATIONS * epochs), desc='Training Siamese Network'):
            batch, label = dp.get_batch(self.__train_set, self.__BATCH_SIZE)

            pair_1 = np.array([b[0] for b in batch])
            pair_2 = np.array([b[1] for b in batch])

            # Define metadata variable.
            run_metadata = tf.RunMetadata()

            _, l = self.__session.run([self.__train_op, self.__loss], feed_dict={self.__img_1: pair_1, self.__img_2: pair_2, self.__flags: label},
                                      run_metadata=run_metadata)

            average_loss += l

            # print loss and accuracy on test set every 500 steps
            if (step % 500 == 0 and step > 0) or (step == (self.__ITERATIONS - 1)):
                       correct = 0
                       k = len(self.__test_set)
                       for _ in range(k):
                           test, label = dp.get_one_shot_test(self.__test_set)
                           pair_1 = np.array([b[0] for b in test])
                           pair_2 = np.array([b[1] for b in test])

                           run_metadata = tf.RunMetadata()

                           pred = self.__session.run(self.__prediction, feed_dict={self.__img_1: pair_1, self.__img_2: pair_2}, run_metadata=run_metadata)
                           if pred[0] == 0:
                               correct += 1

                       print('Loss:', str(average_loss / step), '\tAccuracy:', correct / k)

                       with open(self.__TMP_DIR + '/log.txt', 'a', encoding='utf8') as f:
                           f.write(str(correct / k) + ' ' + str(average_loss / step) + '\n')

                   if step == (self.__ITERATIONS - 1):
                       self.__writer.add_run_metadata(run_metadata, 'step%d' % step, global_step=self.__GLOBAL_ITER + step + 1)

               self.__saver.save(self.__session, os.path.join(self.__TMP_DIR, 'model.ckpt'))
               dp.global_iteration(self.__TMP_DIR + '/iteration.txt', update=self.__GLOBAL_ITER + step + 1)

               pg.generate_accuracy_plot(self.__TMP_DIR + '/')
               pg.generate_loss_plot(self.__TMP_DIR + '/')

               self.__writer.close()

           def predict(self, imgs1, imgs2):
               run_metadata = tf.RunMetadata()
               similarity_scores = self.__session.run(self.__scores, feed_dict={self.__img_1: imgs1, self.__img_2: imgs2}, run_metadata=run_metadata)
               return similarity_scores
```

Appendix B – Creation of the Model

```python
import tensorflow as tf

# MODEL #

def siamese_network(img, reuse_variables=False):

    with tf.name_scope('siamese'):

        with tf.variable_scope('conv1') as scope:
            layer = tf.contrib.layers.conv2d(inputs=img, num_outputs=32, kernel_size=[10, 10], padding='VALID', activation_fn=tf.nn.relu,
                                             biases_initializer=tf.truncated_normal_initializer(mean=0.5, stddev=0.01), scope=scope,
                                             reuse=reuse_variables)
            layer = tf.contrib.layers.max_pool2d(layer, kernel_size=[2, 2], stride=2, padding='VALID')

        with tf.variable_scope('conv2') as scope:
            layer = tf.contrib.layers.conv2d(inputs=layer, num_outputs=64, kernel_size=[7, 7], padding='VALID', activation_fn=tf.nn.relu,
                                             biases_initializer=tf.truncated_normal_initializer(mean=0.5, stddev=0.01), scope=scope,
                                             reuse=reuse_variables)
            layer = tf.contrib.layers.max_pool2d(layer, kernel_size=[2, 2], stride=2, padding='VALID')

        with tf.variable_scope('conv3') as scope:
            layer = tf.contrib.layers.conv2d(inputs=layer, num_outputs=64, kernel_size=[4, 4], padding='VALID', activation_fn=tf.nn.relu,
                                             biases_initializer=tf.truncated_normal_initializer(mean=0.5, stddev=0.01), scope=scope,
                                             reuse=reuse_variables)
            layer = tf.contrib.layers.max_pool2d(layer, kernel_size=[2, 2], stride=2, padding='VALID')

        with tf.variable_scope('conv4') as scope:
            layer = tf.contrib.layers.conv2d(inputs=layer, num_outputs=128, kernel_size=[4, 4], padding='VALID', activation_fn=tf.nn.relu,
                                             biases_initializer=tf.truncated_normal_initializer(mean=0.5, stddev=0.01), scope=scope,
                                             reuse=reuse_variables)
            layer = tf.contrib.layers.max_pool2d(layer, kernel_size=[2, 2], stride=2, padding='VALID')

        with tf.variable_scope('flatten') as scope:
            layer = tf.contrib.layers.flatten(inputs=layer)

        with tf.variable_scope('fc') as scope:
            layer = tf.contrib.layers.fully_connected(inputs=layer, num_outputs=4096, activation_fn=tf.nn.sigmoid,
                                                      biases_initializer=tf.truncated_normal_initializer(mean=0.5, stddev=0.01),
                                                      scope=scope, reuse=reuse_variables)

        return layer
```

Appendix C – Evaluation Process

```python
with self.__graph.as_default():
    self.__img_1 = tf.placeholder(tf.float32, shape=[None, self.__shape[0], self.__shape[1], self.__shape[2]])
    self.__img_2 = tf.placeholder(tf.float32, shape=[None, self.__shape[0], self.__shape[1], self.__shape[2]])
    self.__flags = tf.placeholder(tf.float32, shape=[None])

    self.__embeddings_1 = siamese_network(self.__img_1, reuse_variables=False)
    self.__embeddings_2 = siamese_network(self.__img_2, reuse_variables=True)

    self.__distance = tf.abs(tf.subtract(self.__embeddings_1, self.__embeddings_2))

    self.__scores = tf.contrib.layers.fully_connected(inputs=self.__distance, num_outputs=1, activation_fn=tf.nn.sigmoid,
                                                      biases_initializer=tf.truncated_normal_initializer(mean=0.5,
                                                                                                          stddev=0.01))

    self.__losses = tf.nn.sigmoid_cross_entropy_with_logits(labels=self.__flags,
                                                            logits=tf.reshape(self.__scores, shape=[self.__BATCH_SIZE]))
    self.__loss = tf.reduce_mean(self.__losses)

    self.__optimizer = tf.train.AdamOptimizer(learning_rate=0.00005)
    # optimizer = tf.train.MomentumOptimizer(learning_rate=0.0001, momentum=0.95, use_nesterov=True)
    self.__train_op = self.__optimizer.minimize(self.__loss)

    self.__prediction = tf.cast(tf.argmax(self.__scores, axis=0), dtype=tf.int32)

    self.__saver = tf.train.Saver()
```

Appendix D – Accuracy Calculation

```python
def train(self, epochs=1):
    if self.__train_set and self.__test_set:
        pass
    else:
        self.__train_set, self.__test_set = dp.load_dataset(self.__TMP_DIR, self.__DATA_DIR)

    # Open a writer to write summaries.
    self.__writer = tf.summary.FileWriter(self.__TMP_DIR, self.__session.graph)

    average_loss = 0

    for step in tqdm.tqdm(range(self.__ITERATIONS * epochs), desc='Training Siamese Network'):
        batch, label = dp.get_batch(self.__train_set, self.__BATCH_SIZE)

        pair_1 = np.array([b[0] for b in batch])
        pair_2 = np.array([b[1] for b in batch])

        # Define metadata variable.
        run_metadata = tf.RunMetadata()

        _, l = self.__session.run([self.__train_op, self.__loss], feed_dict={self.__img_1: pair_1, self.__img_2: pair_2, self.__flags: label},
                                  run_metadata=run_metadata)

        average_loss += l

        # print loss and accuracy on test set every 500 steps
        if (step % 500 == 0 and step > 0) or (step == (self.__ITERATIONS - 1)):
            correct = 0
            k = len(self.__test_set)
            for _ in range(k):
                test, label = dp.get_one_shot_test(self.__test_set)
                pair_1 = np.array([b[0] for b in test])
                pair_2 = np.array([b[1] for b in test])

                run_metadata = tf.RunMetadata()

                pred = self.__session.run(self.__prediction, feed_dict={self.__img_1: pair_1, self.__img_2: pair_2}, run_metadata=run_metadata)
                if pred[0] == 0:
                    correct += 1

            print('Loss:', str(average_loss / step), '\tAccuracy:', correct / k)

            with open(self.__TMP_DIR + '/log.txt', 'a', encoding='utf8') as f:
                f.write(str(correct / k) + ' ' + str(average_loss / step) + '\n')

        if step == (self.__ITERATIONS - 1):
            self.__writer.add_run_metadata(run_metadata, 'step%d' % step, global_step=self.__GLOBAL_ITER + step + 1)

    self.__saver.save(self.__session, os.path.join(self.__TMP_DIR, 'model.ckpt'))
    dp.global_iteration(self.__TMP_DIR + '/iteration.txt', update=self.__GLOBAL_ITER + step + 1)

    pg.generate_accuracy_plot(self.__TMP_DIR + '/')
    pg.generate_loss_plot(self.__TMP_DIR + '/')

    self.__writer.close()
```

Appendix E – Training Dataset Generation

```python
def get_batch(train_set, batch_size):
    cat = np.random.choice(list(range(len(train_set))), size=batch_size, replace=False)
    #print(cat)
    label = np.zeros(batch_size)
    # If the inputs are from the same class, then the value of label is 1, otherwise label
  is 0
    label[:batch_size // 2] = 1
    batch = []
    for i in range(batch_size // 2):
        category = cat[i]
        random_index = np.random.randint(0, len(train_set[category]))
        img_1 = train_set[category][random_index]
        random_index = np.random.randint(0, len(train_set[category]))
        img_2 = train_set[category][random_index]
        batch.append((img_1, img_2))
    for i in range(batch_size // 2, batch_size):
        category_1 = cat[i]
        random_index = np.random.randint(0, len(train_set[category_1]))
        img_1 = train_set[category_1][random_index]
        category_2 = (category_1 + np.random.randint(1, len(train_set))) % len(train_set)

        img_2 = train_set[category_2][random_index]
        batch.append((img_1, img_2))
    return batch, label
```

Appendix F – One Shot Testing Dataset Generation

```python
def get_one_shot_test(test_set, n_examples=10):
    # Questa funzione ritorna una lista di 10 coppie, dove la prima � con la medesima per
sona, le altre sono persone diverse
    n_classes = len(test_set)
    # n_examples = len(test_set[0])
    cat = np.random.choice(list(range(n_classes)), size=n_classes, replace=False)
    random_indexes = np.random.randint(0, len(test_set[0]), size=n_examples)
    true_cat = cat[0]
    ex1, ex2 = np.random.choice(len(test_set[0]), replace=False, size=2)
    test = []
    label = np.zeros(n_classes)
    img_1 = test_set[true_cat][ex1]
    for k, random_index in enumerate(random_indexes):
        if k == 0:
            img_2 = test_set[cat[k]][ex2]
        else:
            img_2 = test_set[cat[k]][random_index]
        test.append((img_1, img_2))
    label[0] = 1
    return test, label
```

Appendix G – Threshold values

```
5e-05
584 138617 916 609883
0.3893333333333333
0.1851930527722111
0.6106666666666667
0.8148069472277889

7e-05
558 129523 942 618977
0.372
0.17304342017368068
0.628
0.8269565798263193

9e-05
543 122758 957 625742
0.362
0.1640053440213761
0.638
0.8359946559786239

6e-07
936 278201 564 470299
0.624
0.3716780227120908
0.376
0.6283219772879092

5e-08
1081 361678 419 386822
0.7206666666666667
0.48320374081496326
0.2793333333333333
0.5167962591850367

7e-08
1066 350497 434 398003
0.7106666666666667
0.46826586506346024
0.28933333333333333
0.5317341349365398

9e-08
1053 342245 447 406255
0.702
0.45724114896459583
0.298
0.5427588510354041

1e-07
1045 338693 455 409807
0.6966666666666667
0.4524956579826319
0.30333333333333334
0.5475043420173681

7e-06
733 197443 767 551057
0.4886666666666667
0.26378490313961256
```

```
0.5113333333333333
0.7362150968603874

9e-06
718 189560 782 558940
0.4786666666666667
0.25325317301269207
0.5213333333333333
0.746746826987308

1e-05
712 186319 788 562181
0.4746666666666667
0.24892317969271877
0.5253333333333333
0.7510768203072812

3e-05
624 153278 876 595222
0.416
0.2047802271209085
0.584
0.7952197728790915

9e-07
909 264519 591 483981
0.606
0.3533987975951904
0.394
0.6466012024048097

1e-06
902 260935 598 487565
0.6013333333333334
0.3486105544422178
0.39866666666666667
0.6513894455577822

3e-06
803 224821 697 523679
0.5353333333333333
0.3003620574482298
0.4646666666666667
0.6996379425517703

5e-06
764 208208 736 540292
0.5093333333333333
0.27816700066800265
0.49066666666666664
0.7218329993319973

7e-07
925 272996 575 475504
0.6166666666666667
0.36472411489645956
0.38333333333333336
0.6352758851035404

1e-08
1163 413607 337 334893
0.7753333333333333
0.5525811623246493
0.22466666666666665
0.4474188376753507

3e-08
```

```
1113 378439 387 370061
0.742
0.5055965263861055
0.258
0.4944034736138945
```

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