One Shot Learning with Siamese Networks using Keras

Harshall Lamba Follow
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1. Introduction

Deep Convolutional Neural Networks have become the state of the art methods for image classification tasks. However, one of the biggest limitations is they require a lots of labelled data. In many applications, collecting this much data is sometimes not feasible. One Shot Learning aims to solve this problem.

2. Prerequisites

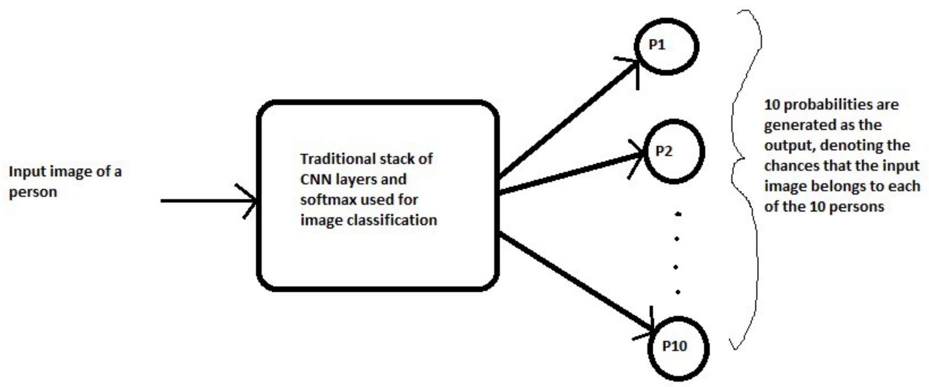
In this post, I will assume that you are already familiar with the basics of machine learning and you have some experience on using Convolutional Neural Networks for image classification using Python and Keras.

3. Classification vs One Shot Learning

In case of **standard classification**, the input image is fed into a series of layers, and finally at the output we generate a probability distribution over all the classes (typically using a Softmax). For example, if we are trying to classify an image as cat or dog or horse or elephant, then for every input image, we generate 4 probabilities, indicating the probability of the image belonging to each of the 4 classes. Two important points must be noticed here. **First**, during the training process, we require a **large** number of images for each of the class (cats, dogs, horses and elephants). **Second**, if the network is trained only on the above 4 classes of images, then we cannot expect to test it on any other class, example "zebra". If we want our model to classify the images of zebra as well, then we need to first get a lot of zebra images and then we must **re-train** the model again. There are applications wherein we neither have enough data for each class and the total number classes is huge as well as dynamically changing. Thus, the cost of data collection and periodical re-training is too high.

On the other hand, in a **one shot classification**, we require only one training example for each class. Yes you got that right, just one. Hence the name **One Shot**. Let's try to understand with a real world practical example.

Assume that we want to build face recognition system for a small organization with only 10 employees (small numbers keep things simple). Using a traditional classification approach, we might come up with a system that looks as below:


Input image of a person
Traditional stack of CNN layers and softmax used for image classification
P1
P2
P10
10 probabilities are generated as the output, denoting the chances that the input image belongs to each of the 10 persons

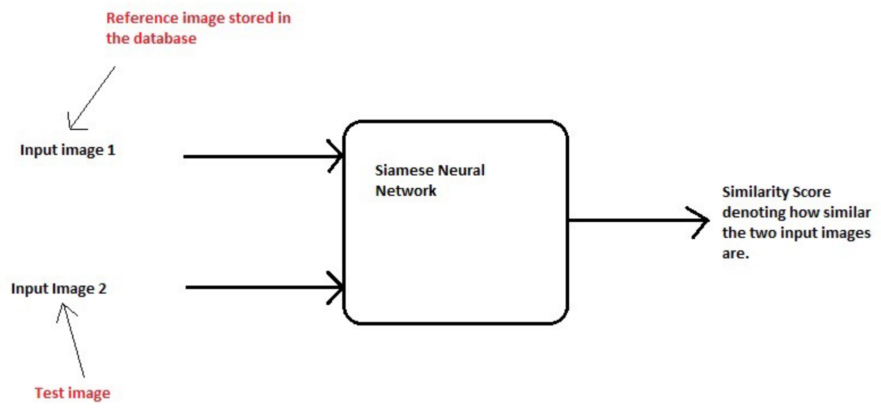
Standard classification using CNN

Problems:

a) To train such a system, we first require a lot of **different** images of each of the 10 persons in the organization which might not be feasible. (Imagine if you are doing this for an organization with thousands of employees).

b) What if a new person joins or leaves the organization? You need to take the pain of collecting data again and re-train the entire model again. This is practically not possible specially for large organizations where recruitment and attrition is happening almost every week.

Now let's understand how do we approach this problem using one shot classification which helps to solve both of the above issues:


Reference image stored in the database
Input image 1
Input Image 2
Test image
Siamese Neural Network
Similarity Score denoting how similar the two input images are.

One Shot Classification

Instead of directly classifying an input(test) image to one of the 10 people in the organization, this network instead takes an extra reference image of the person as input and will produce a similarity score denoting the chances that the two input images belong to the same person. Typically the similarity score is squished between 0 and 1 using a sigmoid function; wherein 0 denotes no similarity and 1 denotes full similarity. Any number between 0 and 1 is interpreted accordingly.

Notice that this network is not learning to classify an image directly to any of the output classes. Rather, it is learning a **similarity function**, which takes two images as input and expresses how similar they are.

How does this solve the two problems we discussed above?

a) In a short while we will see that to train this network, you do not require too many instances of a class and only few are enough to build a good model.

b) But the biggest advantage is that , let's say in case of face recognition, we have a new employee who has joined the organization. Now in order for the network to detect his face, we only require a **single** image of his face which will be stored in the database. Using this as the reference image, the network will calculate the similarity for any new instance presented to it. Thus we say that network predicts the score in **one shot**.

Don't worry if the above details seem a bit abstract at the moment, just continue ahead and we will solve a problem in full detail and I promise you will develop an in-depth understanding of the subject matter.

4. Applications

Before we proceed, I would like to mention a few applications of one shot learning in order to motivate you so that you develop more keen interest in understanding this technology.

a. As I have already mentioned about face recognition above, just go to this *link* wherein the AI Guru Andrew Ng demonstrates how Baidu (the Chinese Search Giant) has developed a face recognition system for the employees in their organization.

b. Read this *blog* to understand how one shot learning is applied to drug discovery where data is very scarce.

c. In this *paper*, the authors have used one shot learning to build an offline signature verification system which is very useful for Banks and other Government and also private institutions.

5. Omniglot Dataset

For the purpose of this blog, we will use the Omniglot dataset which is a collection of 1623 hand drawn characters from 50 different alphabets. For every character there are just 20 examples, each drawn by a different person. Each image is a gray scale image of resolution 105x105.

Before I continue, I would like to clarify the difference between a character and an alphabet. In case of English the set A to Z is called as the alphabet while each of the letter A, B, etc. is called a character. Thus we say that the English alphabet contains 26 characters (or letters).

So I hope this clarifies the point when I say 1623 characters spanning over 50 different alphabets.

Let's look at some images of characters from different alphabets to get a better feel of the dataset.

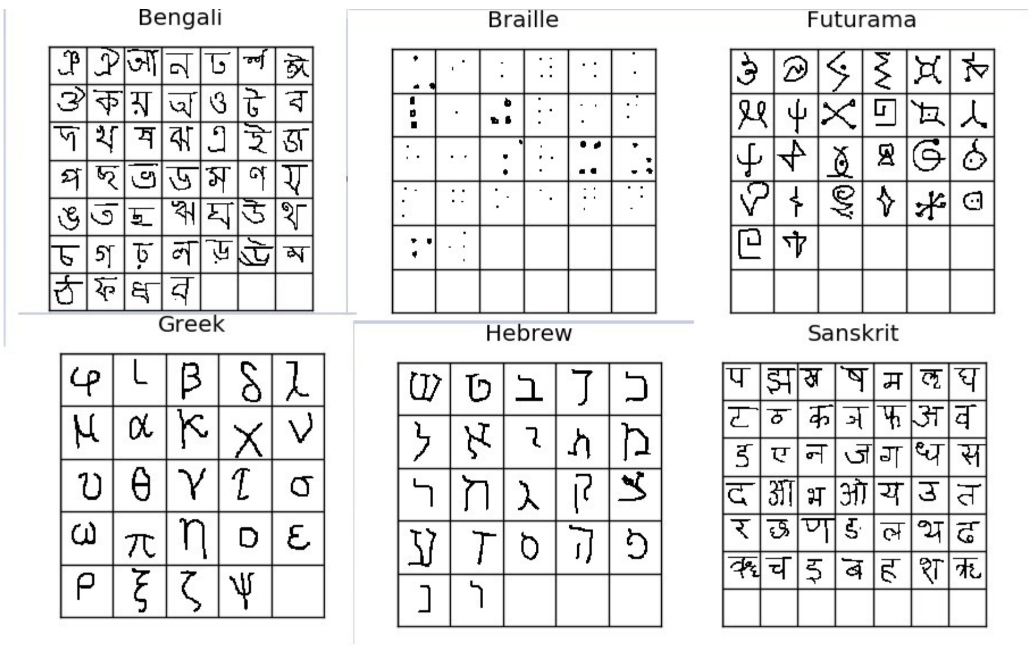


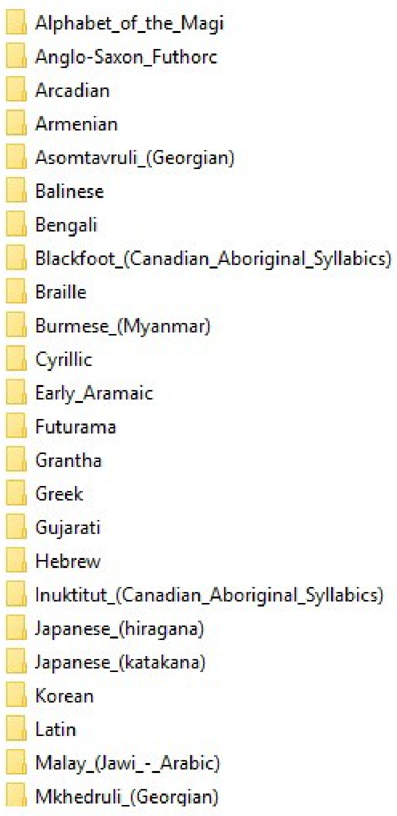
Image Source: https://sorenbouma.github.io/blog/oneshot/

Thus we have 1623 different classes(each character can be treated as a separate class) and for each class we have only 20 images. Clearly, if we try to solve this problem using the traditional image classification method then definitely we won't be able to build a good generalized model. And with such less number of images available for each class, the model will easily overfit.

You can download the dataset by cloning this *GitHub repository*. The folder named "Python" contains two zip files: images_background.zip and images_evaluation.zip. Just unzip these two files.

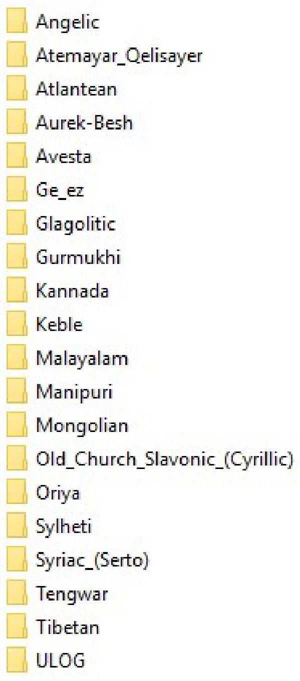
images_background folder contains characters from 30 alphabets and will be used to train the model, while images_evaluation folder contains characters from the other 20 alphabets which we will use to test our system.

Once you unzip the files, you will see below folders (alphabets) in the images_background folder(used for training purpose):


Alphabet_of_the_Magi
Anglo-Saxon_Futhorc
Arcadian
Armenian
Asomtavruli_(Georgian)
Balinese
Bengali
Blackfoot_(Canadian_Aboriginal_Syllabics)
Braille
Burmese_(Myanmar)
Cyrillic
Early_Aramaic
Futurama
Grantha
Greek
Gujarati
Hebrew
Inuktitut_(Canadian_Aboriginal_Syllabics)
Japanese_(hiragana)
Japanese_(katakana)
Korean
Latin
Malay_(Jawi_-_Arabic)
Mkhedruli_(Georgian)

Contents of images_background directory

And you will see below folders (alphabets) in the images_evaluation folder (used for testing purpose):


Angelic
Atemayar_Qelisayer
Atlantean
Aurek-Besh
Avesta
Ge_ez
Glagolitic
Gurmukhi
Kannada
Keble
Malayalam
Manipuri
Mongolian
Old_Church_Slavonic_(Cyrillic)
Oriya
Sylheti
Syriac_(Serto)
Tengwar
Tibetan
ULOG

Contents of images_evaluation directory

Notice that we will train the system on one set of characters and then test it on a completely different set of characters which were never used during the training. This is not possible in a traditional classification cycle.

6. Loading the dataset

First we need to load the images into tensors and later use these tensors to provide data in batches to the model.

We use below function to load images into tensors:

```python
def loadimgs(path,n = 0):
    '''
    path => Path of train directory or test directory
    '''
    X=[]
    y = []
    cat_dict = {}
    lang_dict = {}
    curr_y = n

    # we load every alphabet seperately so we can isolate them later
    for alphabet in os.listdir(path):
        print("loading alphabet: " + alphabet)
        lang_dict[alphabet] = [curr_y,None]
        alphabet_path = os.path.join(path,alphabet)

        # every letter/category has it's own column in the array, so  load seperately
        for letter in os.listdir(alphabet_path):
            cat_dict[curr_y] = (alphabet, letter)
            category_images=[]
            letter_path = os.path.join(alphabet_path, letter)

            # read all the images in the current category
            for filename in os.listdir(letter_path):
                image_path = os.path.join(letter_path, filename)
                image = imread(image_path)
                category_images.append(image)
                y.append(curr_y)
            try:
                X.append(np.stack(category_images))
            # edge case  - last one
            except ValueError as e:
                print(e)
                print("error - category_images:", category_images)
            curr_y += 1
            lang_dict[alphabet][1] = curr_y - 1
    y = np.vstack(y)
    X = np.stack(X)
    return X,y,lang_dict
```

Code to load images from disk

To call this function as follows, pass the path of the train directory as the parameter as follows:

```
X,y,c = loadimgs(train_folder)
```

The function returns a tuple of 3 variables. I won't go through each line of the code, but I will provide you some intuition what exactly the function is doing by understanding the values it returns. Given this explanation you should be in a good position to understand the above function, once you go through it.

Let's understand what is present in 'X':

```
X.shape
(964, 20, 105, 105)
```

This means we have **964** characters (or letters or categories) spanning across 30 different alphabets. For each of this character, we have **20** images, and each image is a gray scale image of resolution **105x105.** Hence the shape (964, 20, 105, 105).

Let's now understand how the labels 'y' are populated:

```
y.shape
(19280, 1)
```

Total number of images = 964 * 20 = 19280. All the images for one letter have the same label., i.e. The first 20 images have the label 0, the next 20 have the label 1, and so on, … the last 20 images have the label 963.

Finally the last variable 'c' stands for categories and it is a dictionary as follows:

```
c.keys() # 'c' for categories

dict_keys(['Alphabet_of_the_Magi', 'Anglo-Saxon_Futhorc', 'Arcadian',
'Armenian', 'Asomtavruli_(Georgian)', 'Balinese', 'Bengali',
'Blackfoot_(Canadian_Aboriginal_Syllabics)', 'Braille',
'Burmese_(Myanmar)', 'Cyrillic', 'Early_Aramaic', 'Futurama',
'Grantha', 'Greek', 'Gujarati', 'Hebrew',
'Inuktitut_(Canadian_Aboriginal_Syllabics)', 'Japanese_(hiragana)',
'Japanese_(katakana)', 'Korean', 'Latin', 'Malay_(Jawi_-_Arabic)',
'Mkhedruli_(Georgian)', 'N_Ko',
'Ojibwe_(Canadian_Aboriginal_Syllabics)', 'Sanskrit',
'Syriac_(Estrangelo)', 'Tagalog', 'Tifinagh'])
```

```
c['Alphabet_of_the_Magi']
[0, 19]

c['Anglo-Saxon_Futhorc']
[20, 48]
```

Since there are 30 different alphabets, this dictionary 'c' contains 30 items. The key for each item is the name of the alphabet. The value for each item is a list of two numbers: [low, high], where 'low' is the label of the first character in that alphabet and 'high' is the label of the last character in that alphabet.

Once we load the train and test images, we save the tensors on the disk in a pickle file, so that we can utilize them later directly without having to load the images again.

7. Mapping the problem to binary classification task

Let's understand how can we map this problem into a supervised learning task where our dataset contains pairs of (Xi, Yi) where 'Xi' is the input and 'Yi' is the output.

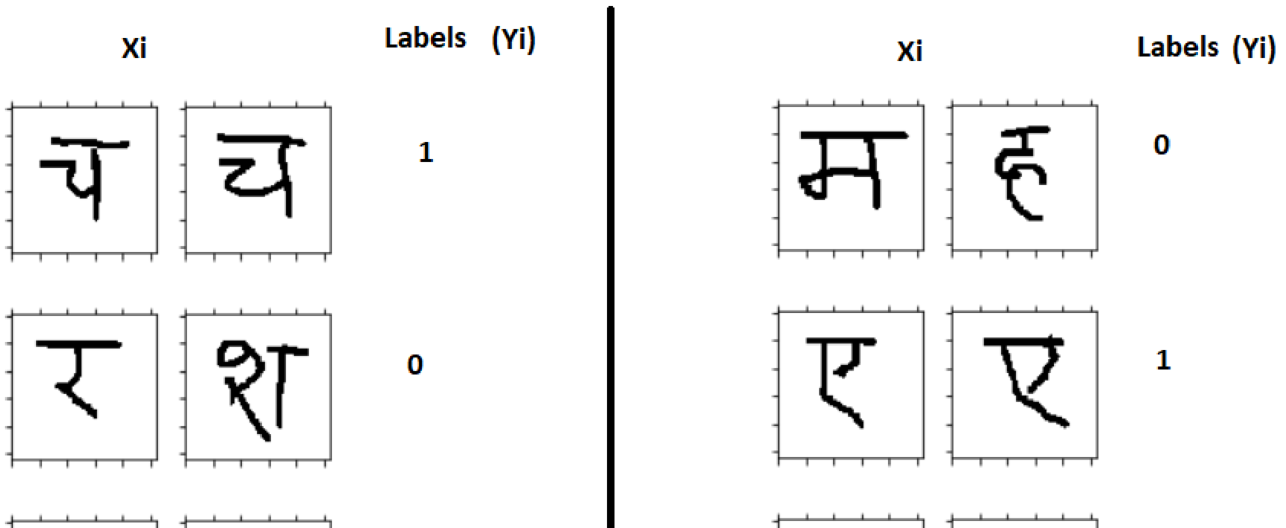
Recall that the input to our system will be a pair of images and the output will be a similarity score between 0 and 1.

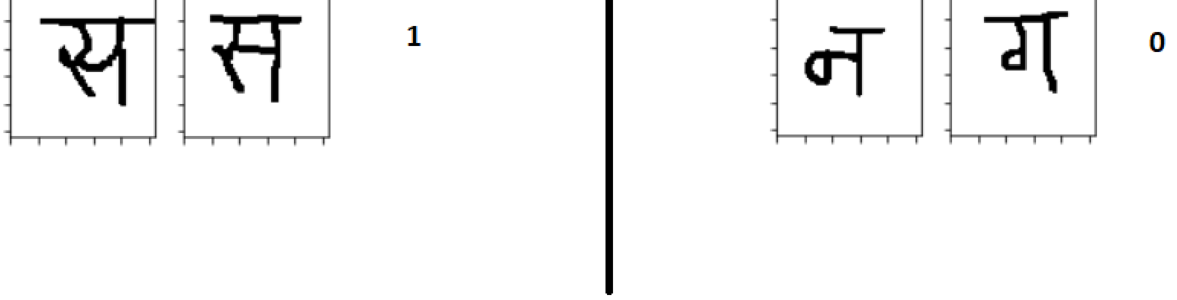
Xi = Pair of images

Yi = 1 ; if both images contain the same character

Yi = 0; if both images contain different characters

Let's have a better understanding by visualizing the dataset below:





Sample of 6 data points

Thus we need to create pairs of images along with the target variable, as shown above, to be fed as input to the Siamese Network. Note that even though characters from Sanskrit alphabet are shown above, but in practice we will generate pairs **randomly** from all the alphabets in the training data.

The code to generate these pairs and targets is shown below:

```python
def get_batch(batch_size,s="train"):
    """
    Create batch of n pairs, half same class, half different class
    """
    if s == 'train':
        X = Xtrain
        categories = train_classes
    else:
        X = Xval
        categories = val_classes
    n_classes, n_examples, w, h = X.shape

    # randomly sample several classes to use in the batch
    categories = rng.choice(n_classes,size=(batch_size,),replace=False)

    # initialize 2 empty arrays for the input image batch
    pairs=[np.zeros((batch_size, h, w,1)) for i in range(2)]

    # initialize vector for the targets
    targets=np.zeros((batch_size,))

    # make one half of it '1's, so 2nd half of batch has same class
    targets[batch_size//2:] = 1
    for i in range(batch_size):
        category = categories[i]
        idx_1 = rng.randint(0, n_examples)
        pairs[0][i,:,:,:] = X[category, idx_1].reshape(w, h, 1)
        idx_2 = rng.randint(0, n_examples)

        # pick images of same class for 1st half, different for 2nd
        if i >= batch_size // 2:
            category_2 = category
        else:
            # add a random number to the category modulo n classes to ensure 2nd image has a dif
            category_2 = (category + rng.randint(1,n_classes)) % n_classes

        pairs[1][i,:,:,:] = X[category_2,idx_2].reshape(w, h,1)

    return pairs, targets
```

Code to load data in batches

We need to call the above function by passing the batch_size and it will return “batch_size” number of image pairs along with their target variables.

We will use the below generator function to generate data in batches during the training of the network.

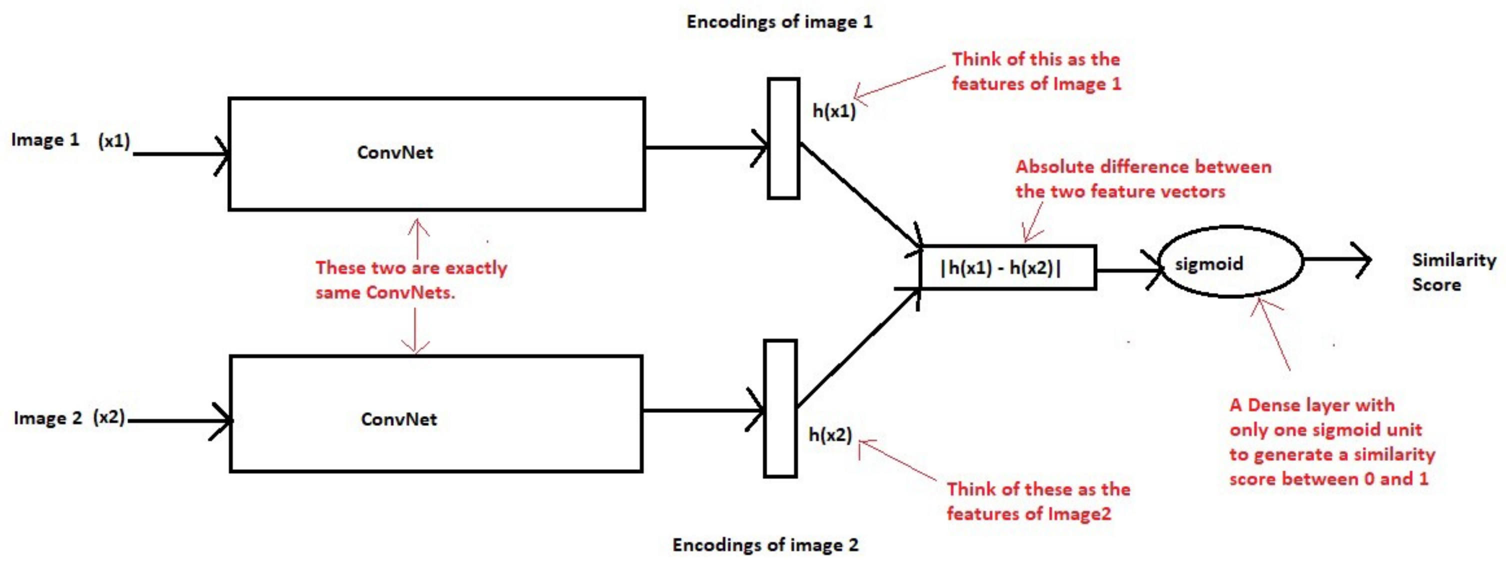
```python
def generate(batch_size, s="train"):
    """
    a generator for batches, so model.fit_generator can be used.
    """
    while True:
        pairs, targets = get_batch(batch_size,s)
        yield (pairs, targets)
```

generator_one_shot.py hosted with ♡ by GitHub view raw

8. Model Architecture and Training

This code is an implementation of the methodology described in this *research paper* by Gregory Koch et al. Model architecture and hyper-parameters that I have used are all as described in the paper.

Let’s first understand the architecture on a high level before diving into the details. Below I present an intuition of the architecture.



Encodings of image 1
Think of this as the features of Image 1
Image 1 (x1)
ConvNet
h(x1)
Absolute difference between the two feature vectors
These two are exactly same ConvNets.
|h(x1) - h(x2)|
sigmoid
Similarity Score
Image 2 (x2)
ConvNet
h(x2)
A Dense layer with only one sigmoid unit to generate a similarity score between 0 and 1
Think of these as the features of Image2
Encodings of image 2

A high level architecture

Intuition: The term Siamese means twins. The two Convolutional Neural

Networks shown above are not different networks but are two copies of the same network, hence the name Siamese Networks. Basically they share the same parameters. The two input images (x1 and x2) are passed through the ConvNet to generate a fixed length feature vector for each (h(x1) and h(x2)). Assuming the neural network model is trained properly, we can make the following hypothesis: If the two input images belong to the same character, then their feature vectors must also be similar, while if the two input images belong to the different characters, then their feature vectors will also be different. Thus the element-wise absolute difference between the two feature vectors must be very different in both the above cases. And hence the similarity score generated by the output sigmoid layer must also be different in these two cases. This is the central idea behind the Siamese Networks.

Given the above intuition let's look at the picture of the architecture with more finer details taken from the research paper itself:

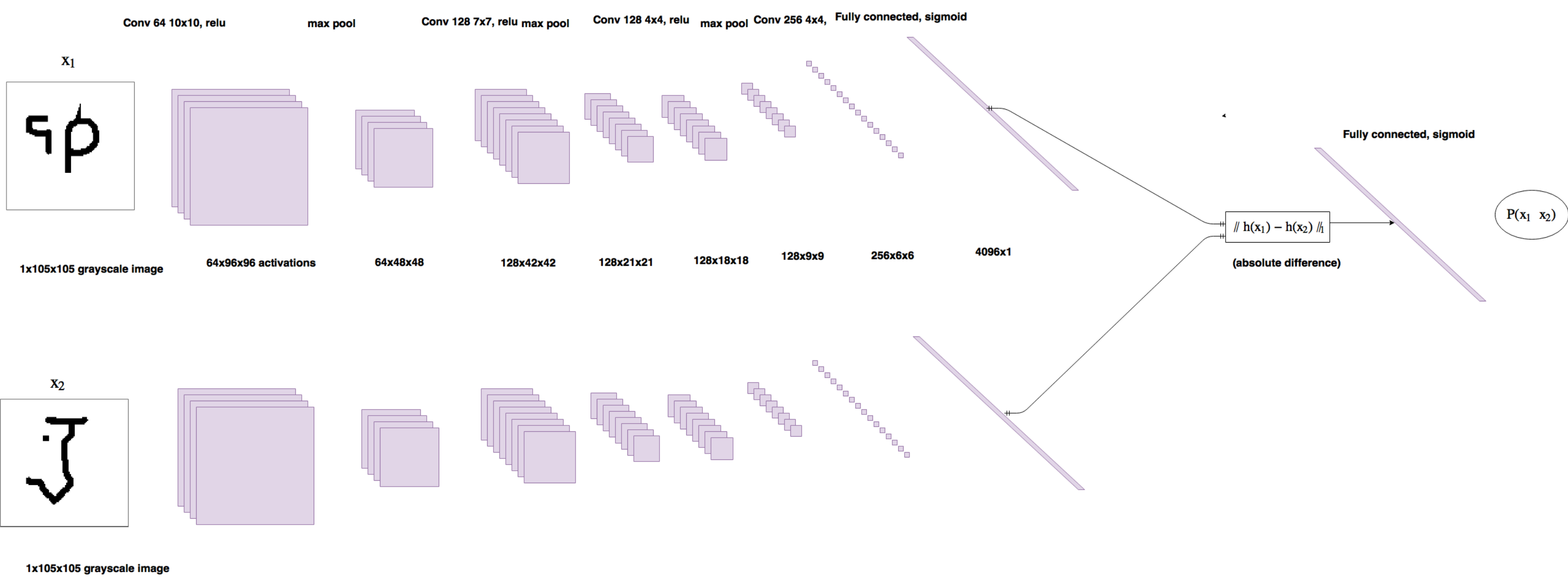


Image Source: https://www.cs.cmu.edu/~rsalakhu/papers/oneshot1.pdf

The below function is used to create the model architecture:

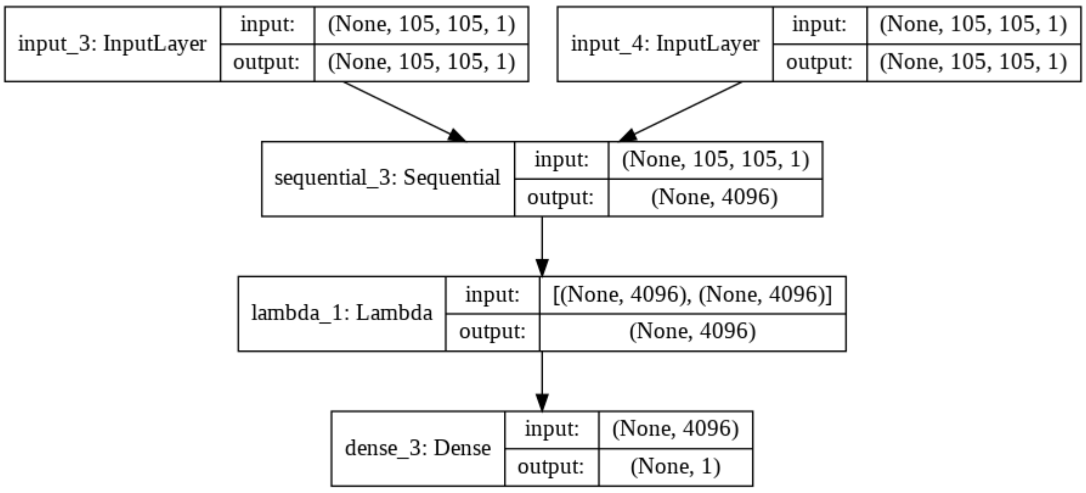
```python
def get_siamese_model(input_shape):
    """
        Model architecture
    """

    # Define the tensors for the two input images
    left_input = Input(input_shape)
    right_input = Input(input_shape)

    # Convolutional Neural Network
    model = Sequential()
    model.add(Conv2D(64, (10,10), activation='relu', input_shape=input_shape,
                   kernel_initializer=initialize_weights, kernel_regularizer=l2(2e-4)))
    model.add(MaxPooling2D())
    model.add(Conv2D(128, (7,7), activation='relu',
                     kernel_initializer=initialize_weights,
                     bias_initializer=initialize_bias, kernel_regularizer=l2(2e-4)))
    model.add(MaxPooling2D())
    model.add(Conv2D(128, (4,4), activation='relu', kernel_initializer=initialize_weights,
                     bias_initializer=initialize_bias, kernel_regularizer=l2(2e-4)))
    model.add(MaxPooling2D())
    model.add(Conv2D(256, (4,4), activation='relu', kernel_initializer=initialize_weights,
                     bias_initializer=initialize_bias, kernel_regularizer=l2(2e-4)))
    model.add(Flatten())
    model.add(Dense(4096, activation='sigmoid',
                   kernel_regularizer=l2(1e-3),
                   kernel_initializer=initialize_weights,bias_initializer=initialize_bias))

    # Generate the encodings (feature vectors) for the two images
    encoded_l = model(left_input)
    encoded_r = model(right_input)

    # Add a customized layer to compute the absolute difference between the encodings
    L1_layer = Lambda(lambda tensors:K.abs(tensors[0] - tensors[1]))
    L1_distance = L1_layer([encoded_l, encoded_r])

    # Add a dense layer with a sigmoid unit to generate the similarity score
    prediction = Dense(1,activation='sigmoid',bias_in译alizer=initialize_bias)(L1_distance)

    # Connect the inputs with the outputs
    siamese_net = Model(inputs=[left_input,right_input],outputs=prediction)

    # return the model
    return siamese_net
```

siamese_model_one_shot.py hosted with ♡ by GitHub view raw

Siamese Model Architecture

Notice that there is no predefined layer in Keras to compute the absolute difference between two tensors. We do this using the Lambda layer in Keras which is used to add customized layers in Keras.

To understand the shape of the tensors passed at different layers, refer the below image generated using the plot_model utility of Keras.



Tensor shapes at every level

The model was compiled using the adam optimizer and binary cross entropy loss function as shown below. Learning rate was kept low as it was found that with high learning rate, the model took a lot of time to converge. However these parameters can well be tuned further to improve the present settings.

```
optimizer = Adam(lr = 0.00006)
model.compile(loss="binary_crossentropy",optimizer=optimizer)
```

The model was trained for 20000 iterations with batch size of 32.

After every 200 iterations, model validation was done using 20-way one shot learning and the accuracy was calculated over 250 trials. This concept is explained in the next section.

9. Validating the Model

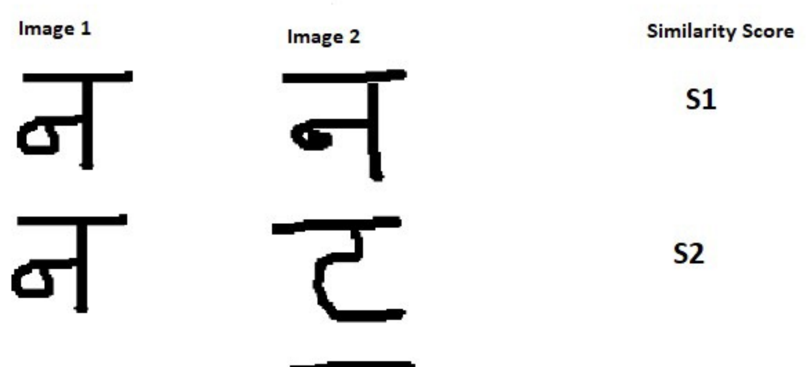
Now that we have understood how to prepare the data for training, model architecture and training; it's time we must think about a strategy to validate and test our model.

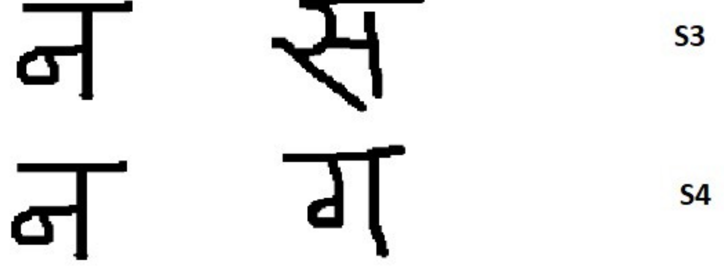
Note that, for every pair of input images, our model generates a similarity score between 0 and 1. But just looking at the score its difficult to ascertain whether the model is really able to recognize similar characters and distinguish dissimilar ones.

A nice way to judge the model is **N-way one shot learning**. Don't worry, it's much easier than what it sounds to be.

An example of 4-way one shot learning:

We create a dataset of 4 pairs of images as follows:





Example of a 4-way one shot learning

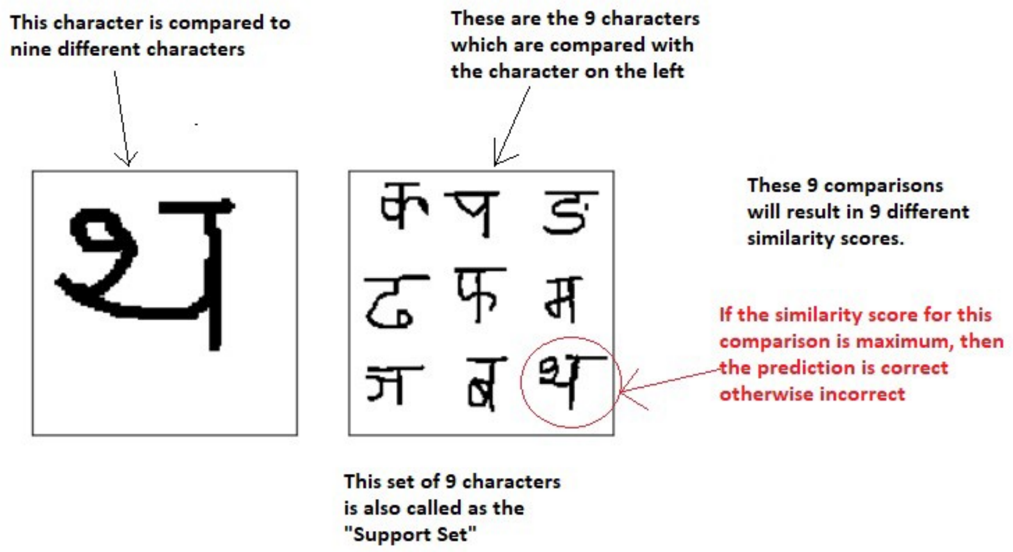
Basically the same character is compared to 4 different characters out of which only one of them matches the original character . Let's say by doing the above 4 comparisons we get 4 similarity scores S1, S2, S3 and S4 as shown. Now if the model is trained properly, we expect that S1 is the maximum of all the 4 similarity scores because the first pair of images is the only one where we have two same characters.

Thus if S1 happens to be the maximum score, we treat this as a correct prediction otherwise we consider this as an incorrect prediction. Repeating this procedure 'k' times, we can calculate the percentage of correct predictions as follows:

percent_correct = (100 * n_correct) / k

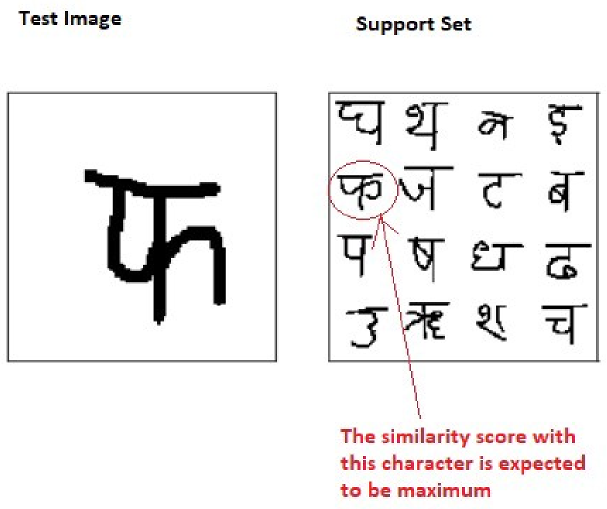
where k => total no. of trials and n_correct => no. of correct predictions out of k trials.

Similarly a 9-way one shot learning will look as follows:


This character is compared to nine different characters
These are the 9 characters which are compared with the character on the left
These 9 comparisons will result in 9 different similarity scores.
If the similarity score for this comparison is maximum, then the prediction is correct otherwise incorrect
This set of 9 characters is also called as the "Support Set"

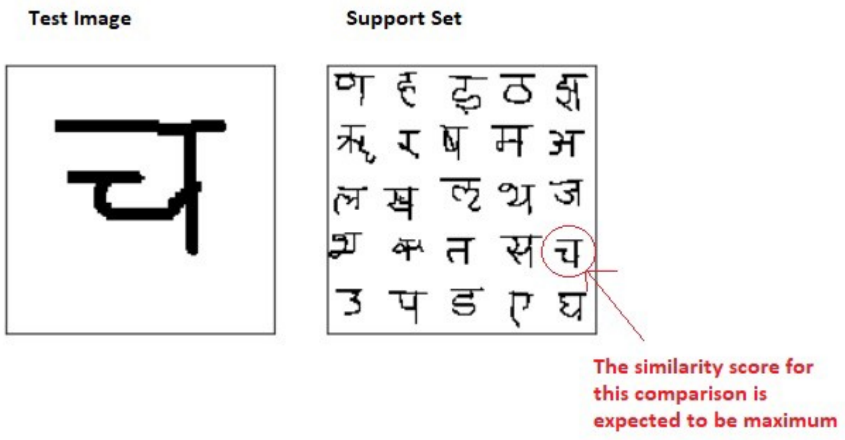
Example of a 9-way one shot learning

A 16-way one shot leaning will be as shown below:


Test Image
Support Set
The similarity score with this character is expected to be maximum

Example of a 16-way one shot learning

Below is how a 25-way one shot learning would look like:


Test Image
Support Set
The similarity score for this comparison is expected to be maximum

Example of a 25-way one shot learning

Note that the value of 'N' in N-way one shot learning need not necessarily be a perfect square. The reason for me taking values 4, 9, 16 and 25 was because it just looks good for presentation when the square is filled completely.

It's quite obvious that smaller values of 'N' will lead to more correct predictions and larger values of 'N' will lead to relatively less correct predictions when repeated multiple times.

Just a reminder again: All the examples shown above are from the Sanskrit Alphabet but in practice we will generate the test image and the support set randomly from all the alphabets of the test/validation dataset images.

The code to generate the test image along with the support set is as follows:

```python
def make_oneshot_task(N, s="val", language=None):
    """Create pairs of test image, support set for testing N way one-shot learning. """
    if s == 'train':
        X = Xtrain
        categories = train_classes
    else:
        X = Xval
        categories = val_classes
    n_classes, n_examples, w, h = X.shape

    indices = rng.randint(0, n_examples,size=(N,))
    if language is not None: # if language is specified, select characters for that language
        low, high = categories[language]
        if N > high - low:
            raise ValueError("This language ({}) has less than {} letters".format(language, N))
        categories = rng.choice(range(low,high),size=(N,),replace=False)
        else: # if no language specified just pick a bunch of random letters
        categories = rng.choice(range(n_classes),size=(N,),replace=False)

    true_category = categories[0]
    ex1, ex2 = rng.choice(n_examples,replace=False,size=(2,))
    test_image = np.asarray([X[true_category,ex1,:,:]]*N).reshape(N, w, h,1)
    support_set = X[categories,indices,:,:]
    support_set[0,:,:] = X[true_category,ex2]
    support_set = support_set.reshape(N, w, h,1)
    targets = np.zeros((N,))
    targets[0] = 1
    targets, test_image, support_set = shuffle(targets, test_image, support_set)
    pairs = [test_image,support_set]
    return pairs, targets


  def test_oneshot(model, N, k, s = "val", verbose = 0):
    """Test average N way oneshot learning accuracy of a siamese neural net over k one-shot task
    n_correct = 0
    if verbose:
        print("Evaluating model on {} random {} way one-shot learning tasks ... \n".format(k,N))
    for i in range(k):
        inputs, targets = make_oneshot_task(N,s)
        probs = model.predict(inputs)
        if np.argmax(probs) == np.argmax(targets):
            n_correct+=1
    percent_correct = (100.0 * n_correct / k)
    if verbose:
        print("Got an average of {}% {} way one-shot learning accuracy \n".format(percent_correc
    return percent_correct
```

Code to generate a test image along with the support set

10. Base Line 1 — Nearest Neighbor Model

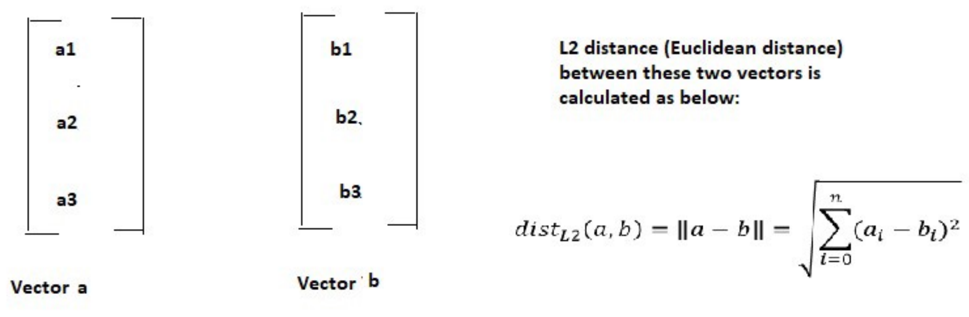
It is always a good practice to create simple baseline models and compare their results with complex model you are trying to build.

Our first baseline model is the Nearest Neighbor approach. If you are familiar with K-Nearest Neighbor algorithm, then this is just the same thing.

As discussed above, in an N-way one shot learning, we compare a test image with N different images and select that image which has highest similarity with the test image as the prediction.

This is intuitively similar to the KNN with K=1. Let's understand in detail how this approach works.

You might have studied how we can compute the L2 distance (also called as the Euclidean distance) between two vectors. If you do not recall, below is how it is done:

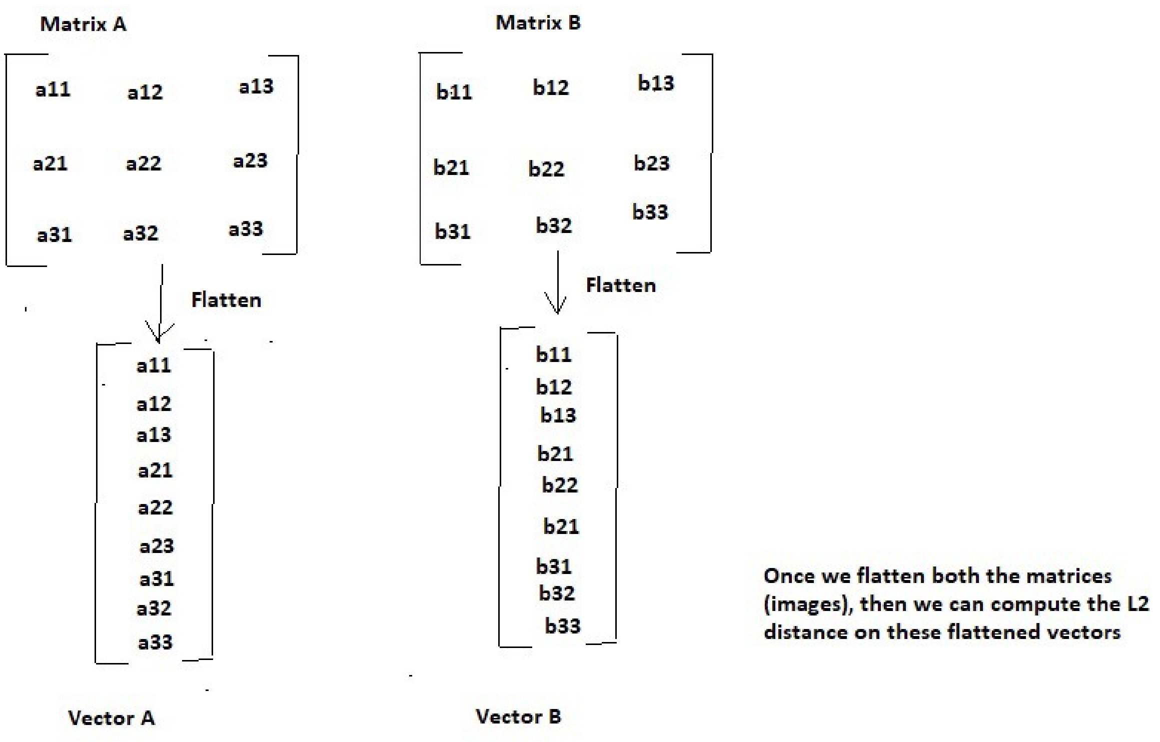

a1
a2
a3
Vector a
b1
b2
b3
Vector b
L2 distance (Euclidean distance) between these two vectors is calculated as below:
$dist_{L2}(a,b) = ||a-b|| = \sqrt{\sum_{i=0}^{n}(a_i-b_i)^2}$

L2 distance between two vectors

Let's say we compare L2 distance of a vector X with 3 other vectors say A, B and C. Then one way to compute the most similar vector to X is check which vector has the least L2 distance with X. Because distance is inversely proportional to similarity. Thus for example if the L2 distance between X and B is minimum, we say that the similarity between X and B is maximum.

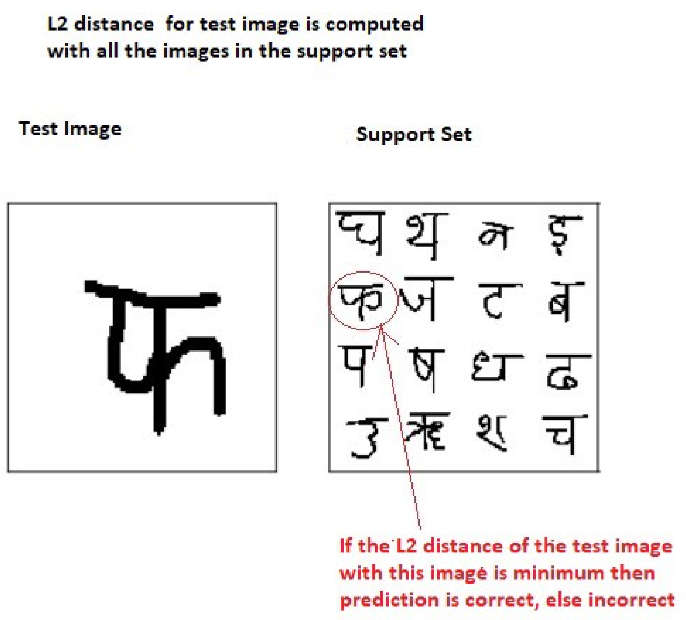
However, in our case we do not have vectors but gray scale images, which can be represented as matrices and not vectors. Then how do we compute L2 distance between matrices?

That’s simple, just flatten the matrices into vectors and then compute the L2 distance between these vectors. For example:


Matrix A
a11 a12 a13
a21 a22 a23
a31 a32 a33
Matrix B
b11 b12 b13
b21 b22 b23
b31 b32 b33
Flatten
Flatten
a11 a12 a13 a21 a22 a23 a31 a32 a33
b11 b12 b13 b21 b22 b21 b31 b32 b33
Once we flatten both the matrices (images), then we can compute the L2 distance on these flattened vectors
Vector A
Vector B

Computing L2 distance between images

Thus in N-way One Shot learning, we compare the L2 distance of the test image with all the images in the Support Set. Then we check the character for which we got the minimum L2 distance. If this character is the same as the character in the test image, then the prediction is correct, else the prediction is incorrect. For example:


L2 distance for test image is computed with all the images in the support set
Test Image
Support Set
If the L2 distance of the test image with this image is minimum then prediction is correct, else incorrect

N way Nearest Neighbor Approach

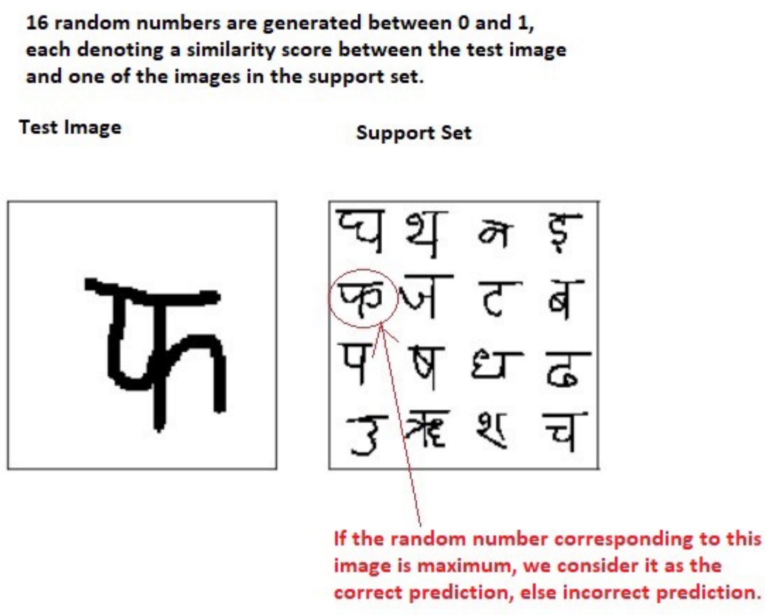
Similar to N way one shot learning, we repeat this for multiple trials and compute the average prediction score over all the trials. The code for nearest neighbor approach is below:

```python
def nearest_neighbour_correct(pairs,targets):
    """returns 1 if nearest neighbour gets the correct answer for a one-shot task
        given by (pairs, targets)"""
    L2_distances = np.zeros_like(targets)
    for i in range(len(targets)):
        L2_distances[i] = np.sum(np.sqrt(pairs[0][i]**2 - pairs[1][i]**2))
    if np.argmin(L2_distances) == np.argmax(targets):
        return 1
    return 0


  def test_nn_accuracy(N_ways,n_trials):
    """Returns accuracy of NN approach """
    print("Evaluating nearest neighbour on {} unique {} way one-shot learning tasks ...".format(
    n_right = 0

    for i in range(n_trials):
        pairs,targets = make_oneshot_task(N_ways,"val")
        correct = nearest_neighbour_correct(pairs,targets)
        n_right += correct
    return 100.0 * n_right / n_trials
```

Code to compute Nearest Neighbors

11. Base Line 2 — Random Model

Creating a random model which makes prediction at random is a very common technique to make sure that the model we created is at least better than a model which makes completely random predictions. It's working can be summarized in the below diagram:

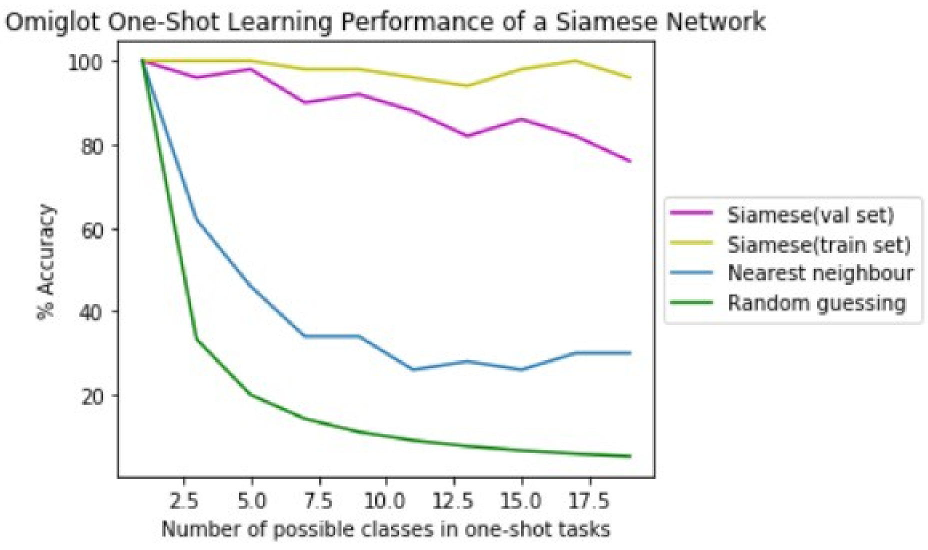

16 random numbers are generated between 0 and 1, each denoting a similarity score between the test image and one of the images in the support set.
Test Image
Support Set
If the random number corresponding to this image is maximum, we consider it as the correct prediction, else incorrect prediction.

12. Test Results and Inference

The N-way testing was done for N = 1, 3, 5, …., 19.

For each N-way testing, 50 trials were performed and the average accuracy was computed over these 50 trials.

Below is the comparison between the 4 models:



Test Results

Inference: Clearly the Siamese Model performed much better than the Random Model and the Nearest Neighbor Model. However there is some gap between the results on training set and validation set which indicate that model is over fitting.

13. Conclusion

This is just a first cut solution and many of the hyper parameters can be tuned in order to avoid over fitting. Also more rigorous testing can be done by increasing the value of 'N' in N-way testing and by increasing the number of trials.

I hope this helped you in understanding the one shot learning methodology using Deep Learning.

Source Code: Please refer my source code in Jupyter Notebook on my GitHub Repository *here*.

Note: The model was trained on Cloud with a P4000 GPU. If you train it on a CPU, then you need to be very patient.

Comments, suggestions, criticism are welcomed. Thanks.

14. References

a. https://github.com/akshaysharma096/Siamese-Networks

b. https://sorenbouma.github.io/blog/oneshot/

c. https://www.cs.cmu.edu/~rsalakhu/papers/oneshot1.pdf

d. Andrew Ng's deeplearning.ai Specialization Course on Coursera

Machine Learning Siamese Networks One Shot Learning Convolution Neural Net