

CIS 666 Artificial Intelligence

ASSIGNMENT 2

Submitted By

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Steps:

- 1. Apply the input Xi
- 2. Compute output Yj
- 3. Compute error Ej
- 4. If $ej \ge E$, modify $wji \ge Ej = Dj Yj$ if ej = 0, stop
- 5. $W_{ii}(t + 1) = W_{ii}(t) + change in (W_{ii}(t))$
- 6. Repeat steps 2 5 for all parameters
- 7. Repeat steps 2 6 till the error \leq = E(\sim 0)

The Perceptron is inspired by the information processing of a single neural cell called a neuron. In a similar way, the Perceptron receives input signals from examples of training data that we weight and combined in a linear equation called the activation. The activation is then transformed into an output value or prediction using a transfer function, such as the step transfer function. In this way, the Perceptron is a classification algorithm for problems with two classes (0 and 1) where a linear equation (like or hyperplane) can be used to separate the two classes.

It is closely related to linear regression and logistic regression that make predictions in a similar way (e.g. a weighted sum of inputs).

The weights of the Perceptron algorithm must be estimated from your training data using stochastic gradient descent.

- Learning Rate: Used to limit the amount each weight is corrected each time it is updated.
- **Epochs**: The number of times to run through the training data while updating the weight.

These, along with the training data will be the arguments to the function.

There are 3 loops we need to perform in the function:

- 1. Loop over each epoch.
- 2. Loop over each row in the training data for an epoch.
- 3. Loop over each weight and update it for a row in an epoch.

As you can see, we update each weight for each row in the training data, each epoch.

Design a fully connected network structure of 784 input nodes and 10 output nodes. The input to the single layer network architecture will be a set of binary pixels representing a 28×28 image of handwritten digits. The output should indicate which of the digits (0,....,9) is in the input image.

```
weights = np.random.uniform(0,1,(10,784))
```

Random weights are initialised based on the size of the input that is 28*28

```
1) Input data
f = gzip.open('mnist.pkl.gz', 'rb')
train_set, valid_set, test_set = p.load(f,encoding='iso-8859-1')
f.close()
```

This is used to load the input into train_set and

#Task 1: Repeat this experiment for different learning rate parameters #(at least 3 experiments. Start with a large value and gradually decrease to a small value).

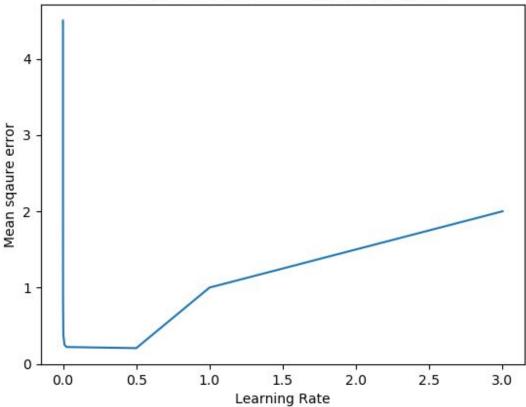
```
for nr in range(0,10):
       for i in range(0,50000):
       x = images[i]
       t = targets[i]
       z = np.dot(weights[nr],x)
       output = activation(z)
       if nr == t:
       target = 1
       else:
       target = 0
       adjust = np.multiply((target - output) * learningRate[e], x)
2. Output is generated using the activation function
def activation(x):
       if x > 0:
           return 1
       return 0
3. Compute the error
       temp += 0.5*(target - output)*(target - output)
#target is desired output dj and output is yj applying 0.5(dj - yj)^2
```

This the individual error and together makes it mean squared error which is marked against learning rate.

I used 10 different learning rate to better understand the scenario.

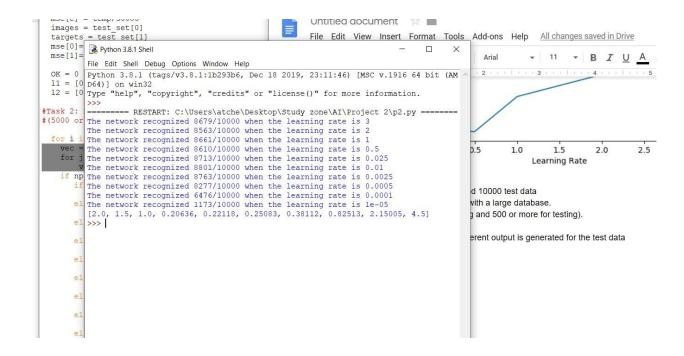
learningRate = [3,2,1,0.5,0.025,0.01,0.0025,0.0005,0.0001,0.00001]

the mean square error versus iterations



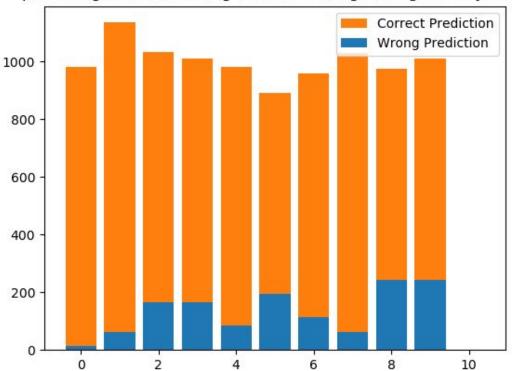
4.I used 50000 training and 10000 test data #Task 2: Repeat Task #1 with a large database. #(5000 or more for training and 500 or more for testing).

For each learning rate different output is generated for the test data

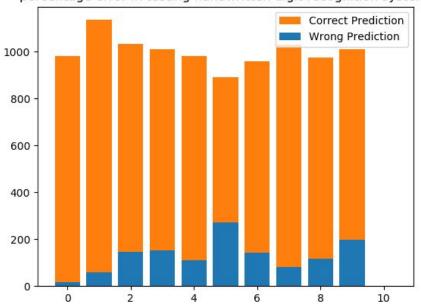


Plot the percentage error in testing your handwritten digit recognition system as a bar chart.

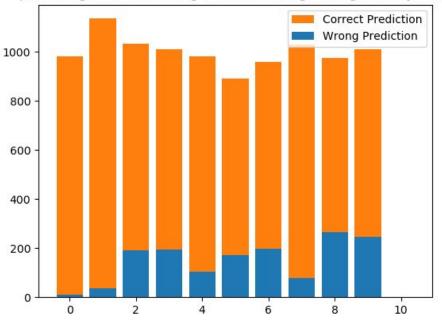
percentage error in testing handwritten digit recognition system







percentage error in testing handwritten digit recognition system



percentage error in testing handwritten digit recognition system

