Logistic_Regression

November 27, 2020

Group Member Name(Master Data Science): Suresh Kumar Choudhary, Sofya Laskina, Emilio Kuhlmann

Import necessary packages: Numpy, Pandas, matplotlib

[59]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report
```

Mount your google drive (if you have a google account) or upload files (go on the file icon on the left -> right click). Copy path of zip.train and zip.test and load them as numpy arrays using the following code (insert the path as string).

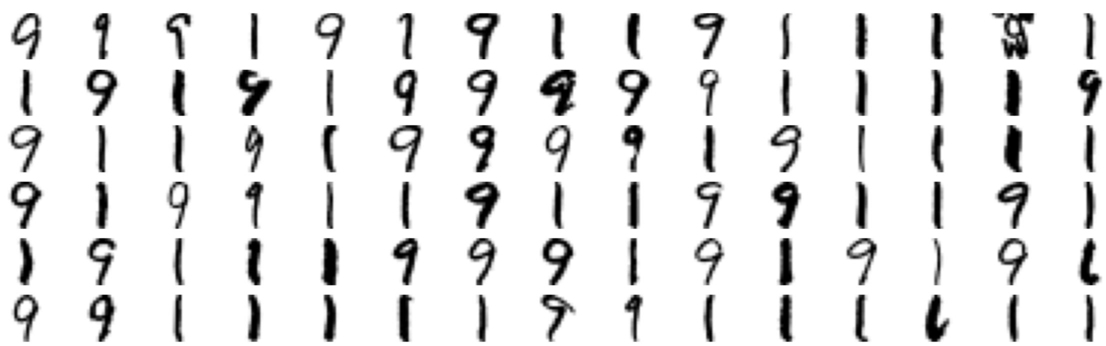
[60]:
```
path_to_train = './zip.train'
path_to_test = './zip.test'
training_data = np.array(pd.read_csv(path_to_train, sep=' ', header=None))
test_data = np.array(pd.read_csv(path_to_test, sep =' ',header=None))

X_train, y_train = training_data[:,1:-1], training_data[:,0]
X_test, y_test = test_data[:,1:], test_data[:,0]

# We only want to classify two different digits. You can choose which digits you␣
↪want to classify youself

X_train = X_train[np.logical_or(y_train == 1, y_train == 9)]
X_test = X_test[np.logical_or(y_test == 1, y_test == 9)]
y_train = y_train[np.logical_or(y_train == 1, y_train == 9)].reshape(-1,1)
y_train=np.where(y_train> 5, 1, 0)
#print(y_train)
y_test = y_test[np.logical_or(y_test == 1, y_test == 9)].reshape(-1,1)
y_test=np.where(y_test> 5, 1, 0)
```

[61]:
```
def show_numbers(X):
    num_samples = 90
    indices = np.random.choice(range(len(X)), num_samples)
    print(indices.shape)
```

```
    sample_digits = X[indices]

    fig = plt.figure(figsize=(20, 6))

    for i in range(num_samples):
        ax = plt.subplot(6, 15, i + 1)
        img = 1-sample_digits[i].reshape((16, 16))
        plt.imshow(img, cmap='gray')
        plt.axis('off')
```

[62]:
```
show_numbers(X_test)
```

(90,)



Implement Logistic Regression, do gradient descent until training converges (find a good criterion for when that is the case yourself) and test the accuracy on your test data.

[79]:
```
class LogisticRegression:
  def __init__(self, w, b):
    self.w = w
    self.b = b

  def mean_squared_error(self,x,y):
    mse=1/y.shape[0]*np.sum((y-self.sigmoid_function(x))**2)
    return mse


  def sigmoid_function(self,x):
    return 1 / (1 + np.exp(-(np.dot(x,self.w) +self.b)))

  def cross_entropy_loss(self, x,y):
    sigmoid = self.sigmoid_function(x)
    CE = -1/x.shape[0]*np.sum(np.multiply(y, np.log(sigmoid))+ np.
 ↪multiply((1-y),np.log(1-sigmoid)))
    return CE
```

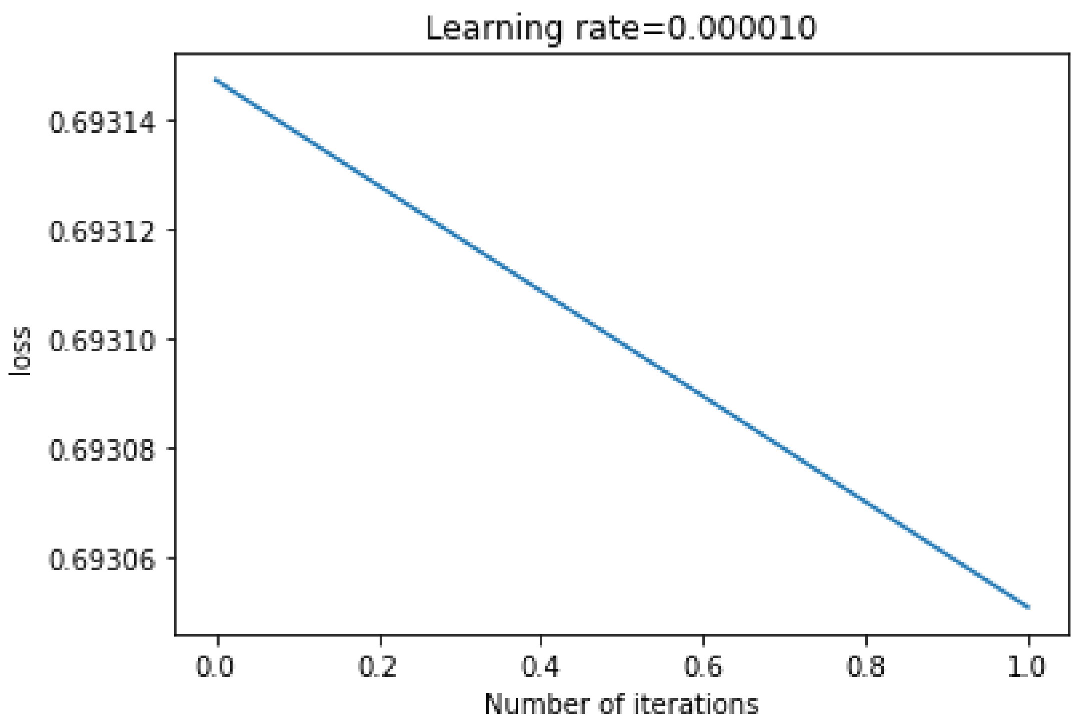
```
 def gradient_descent(self, x,y):
   dw = 1/x.shape[0] * np.dot(x.T, (self.sigmoid_function(x)  - y))
   db = 1/x.shape[0] * np.sum(self.sigmoid_function(x)  - y)
   return  (dw,db)

 def fit(self,x,y, learning_rate,num_iter):
   counter = 0
   loss = [self.cross_entropy_loss(x,y)]
   loss_difference = 1
   while loss_difference > 0.001 and counter < num_iter:
     gradient_updated = self.gradient_descent(x,y)
     #print(gradient_updated[0][:10])
     #print(gradient_updated[0].shape[0],self.w.shape[0])
     w_updates = self.w - learning_rate*gradient_updated[0]
     b_updates = self.b - learning_rate*gradient_updated[1]
     self.w = w_updates
     self.b = b_updates
     loss.append(self.cross_entropy_loss(x,y))
     #print(current_loss)
     loss_difference = abs(loss[-2]-loss[-1])

     counter+=1
   self.plot_loss(loss,np.arange(0,counter+1,1),learning_rate)
   return LogisticRegression(self.w,self.b)

#gradient for mean squared error model
 def greadient_meansquared(self,x,y):
   dw = 1/x.shape[0] *np.dot(x.T,self.sigmoid_function(x)*(1-self.
↪sigmoid_function(x).T)*(self.sigmoid_function(x)  - y))
   db = 1/x.shape[0] * np.sum(self.sigmoid_function(x)  - y)
   return  (dw,db)

 #means quared error model fit function
 def fit_mse(self,x,y, learning_rate,num_iter):
   counter = 0
   error = [self.mean_squared_error(x,y)]
   error_difference = 1
   while error_difference > 0.001 and counter < num_iter:
     gradient_updated = self.greadient_meansquared(x,y)
     #print(gradient_updated[0][:10])\
     print('gradient shape',gradient_updated[0].shape[0],'weight shape',self.w.
↪shape[0])
     w_updates = self.w - learning_rate*gradient_updated[0]
     b_updates = self.b - learning_rate*gradient_updated[1]
     self.w = w_updates
     self.b = b_updates
```

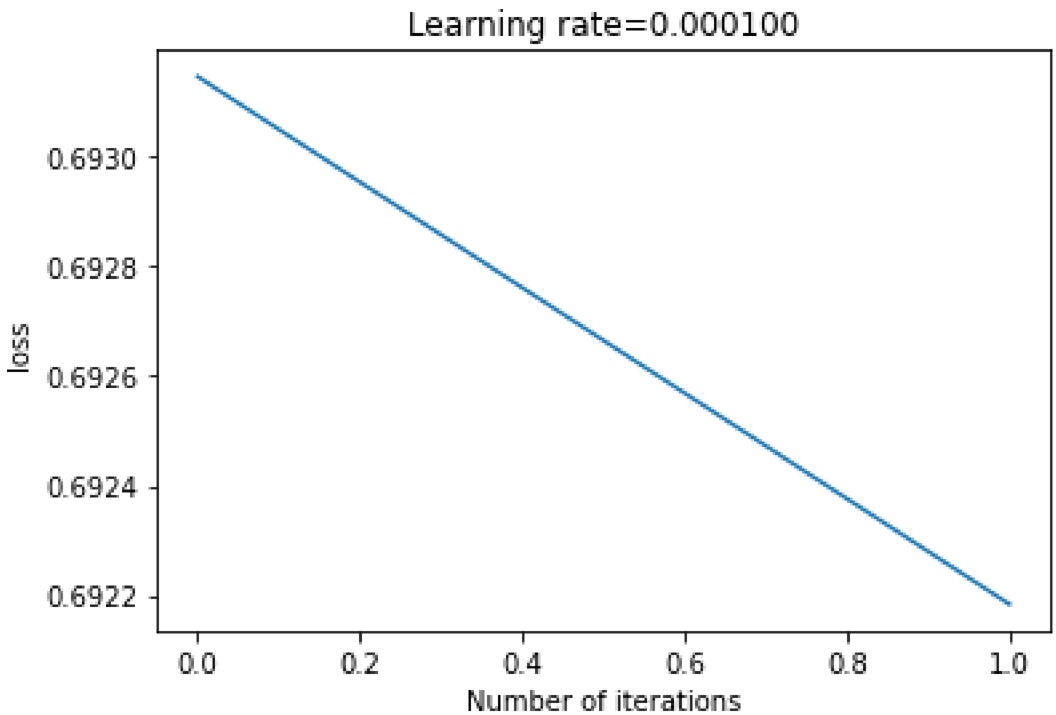
```
      error.append(self.mean_squared_error(x,y))
      #print(current_loss)
      error_difference = abs(error[-2]-error[-1])

      counter+=1
    self.plot_mse(error,np.arange(0,counter+1,1),learning_rate)
    return LogisticRegression(self.w,self.b)

  def predict(self,x):
    y = self.sigmoid_function(x)
    return y
  def plot_loss(self,loss,num_iter,learning_rate):
      #print(loss)
      #print(num_iter)
      plt.plot(num_iter,loss)
      plt.title('Learning rate=%f'%learning_rate)
      plt.xlabel('Number of iterations')
      plt.ylabel('loss')
      plt.show()
  def plot_mse(self,loss,num_iter,learning_rate):
      #print(loss)
      #print(num_iter)
      plt.plot(num_iter,loss)
      plt.title('Learning rate=%f, Mean Squared Error vs Iterations␣
↪'%learning_rate)
      plt.xlabel('Number of iterations')
      plt.ylabel('Mean Squared Error')
      plt.show()
```

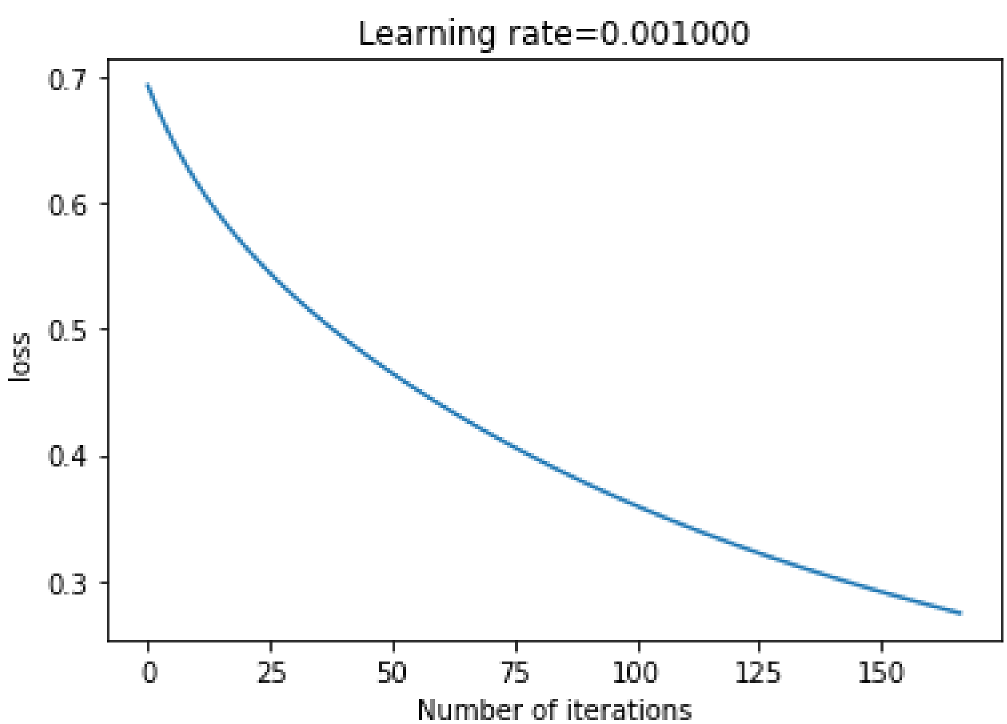
[64]:
```
def weight_initiliazitation(x):
    w = np.zeros((x.shape[1], 1))
    b = 0
    return (w,b)

def find_optimum_lr(lr_list,X_train,y_train,X_test,y_test,w,b):
    lr_acc=[]
    for lr in lr_list:
        model = LogisticRegression(w,b)
        model.fit(X_train,y_train,lr,num_iter)
        predictions = model.predict(X_test)
        y_pred_binary = np.where(predictions > 0.5, 1, 0)
        #we are using f-score as no of digits are not balanced
        accuracy_score=f1_score(y_test,y_pred_binary)
        lr_acc.append([accuracy_score,lr])
    x=[str(x[1]) for x in lr_acc]
    y=[x[0] for x in lr_acc]
    plt.plot(x,y)
```

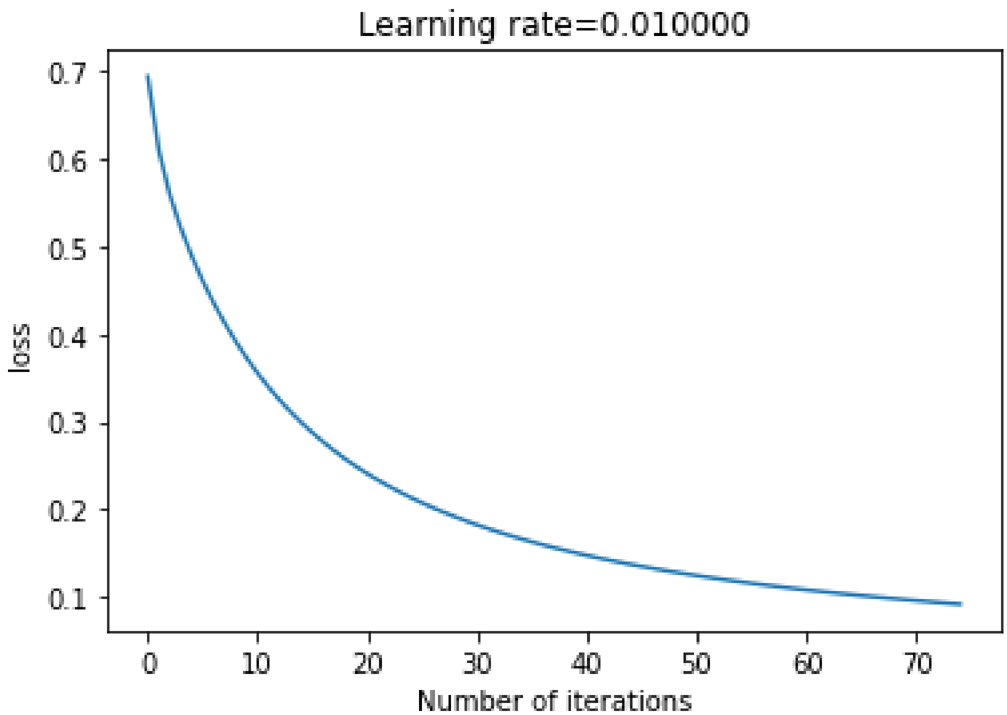
```
    plt.xlabel('learning rate')
    plt.ylabel('Accuracy score(F-score)')
    plt.show()
    lr_acc.sort(reverse=True)
    return lr_acc[0][1]
```

[65]:
```
num_iter=500
w,b=weight_initiliazitation(X_train)
lr_list=[0.00001,0.0001,0.001,0.01,0.1,0.2,0.3,0.4]
optimum_learning_rate=find_optimum_lr(lr_list,X_train,y_train,X_test,y_test,w,b)
model = LogisticRegression(w,b).
 ↪fit(X_train,y_train,optimum_learning_rate,num_iter)
```

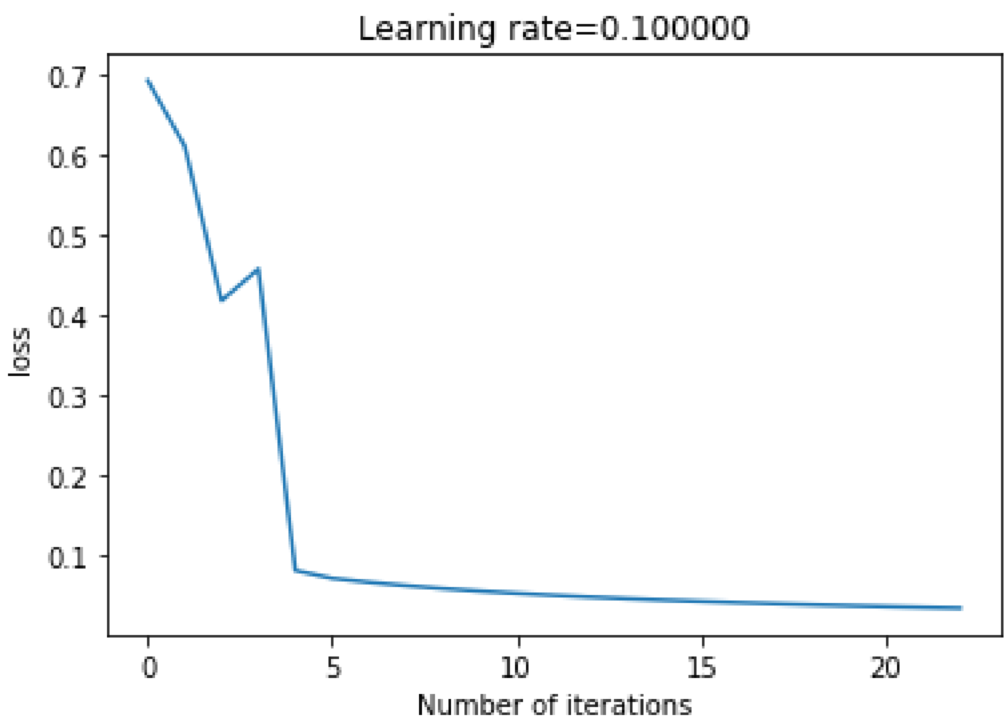



Learning rate=0.000100
loss
0.6930
0.6928
0.6926
0.6924
0.6922
0.0
0.2
0.4
0.6
0.8
1.0
Number of iterations

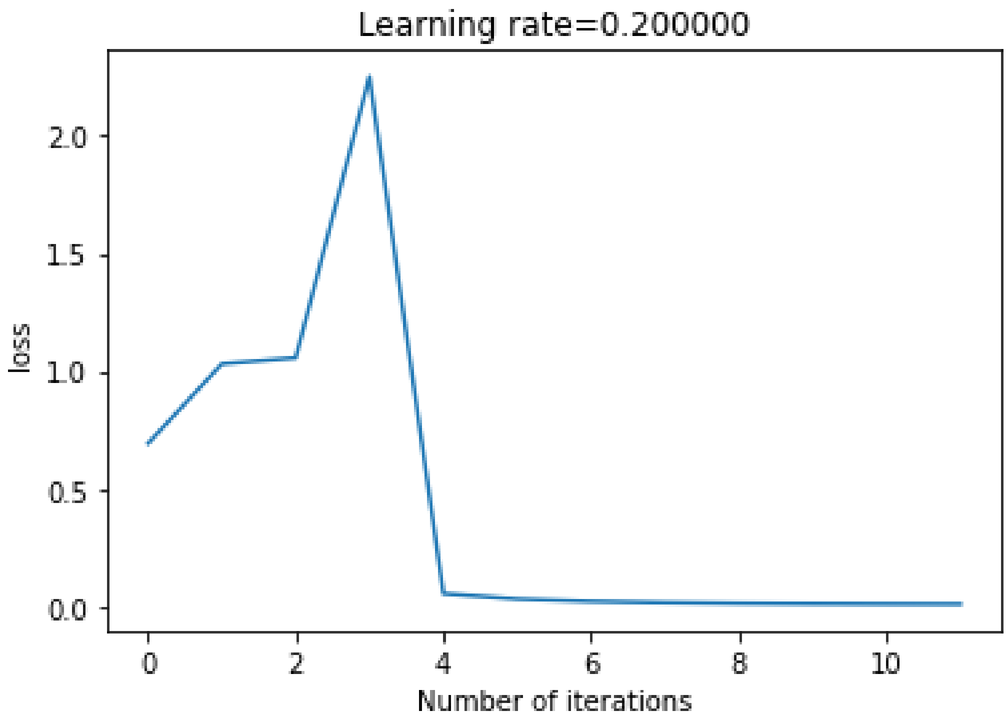

Learning rate=0.001000
loss
0.7
0.6
0.5
0.4
0.3
0
25
50
75
100
125
150
Number of iterations

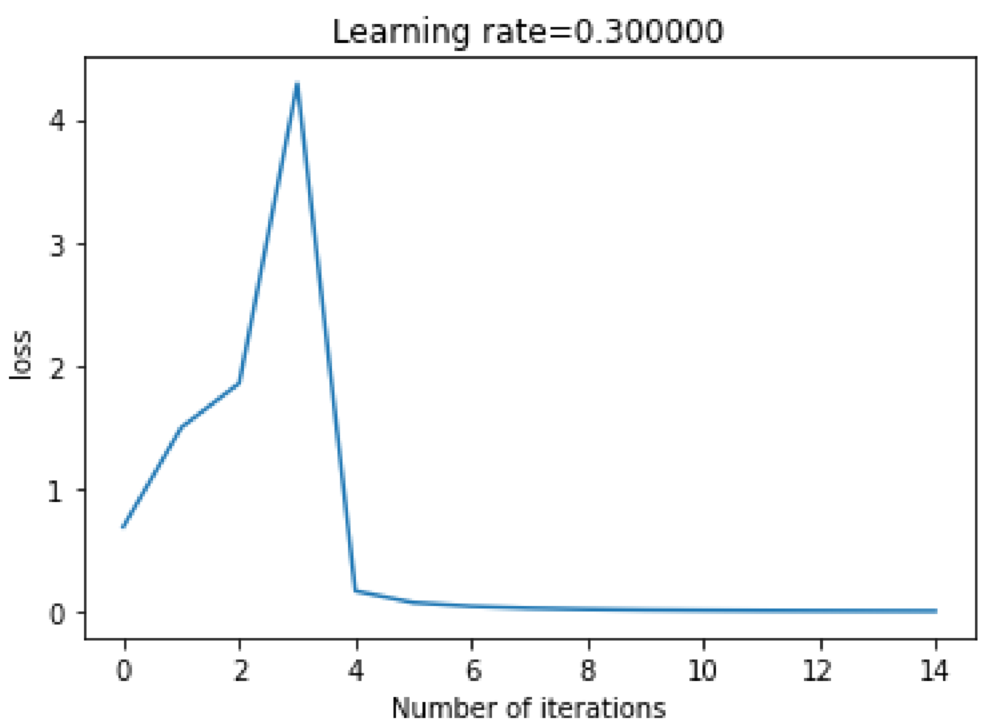


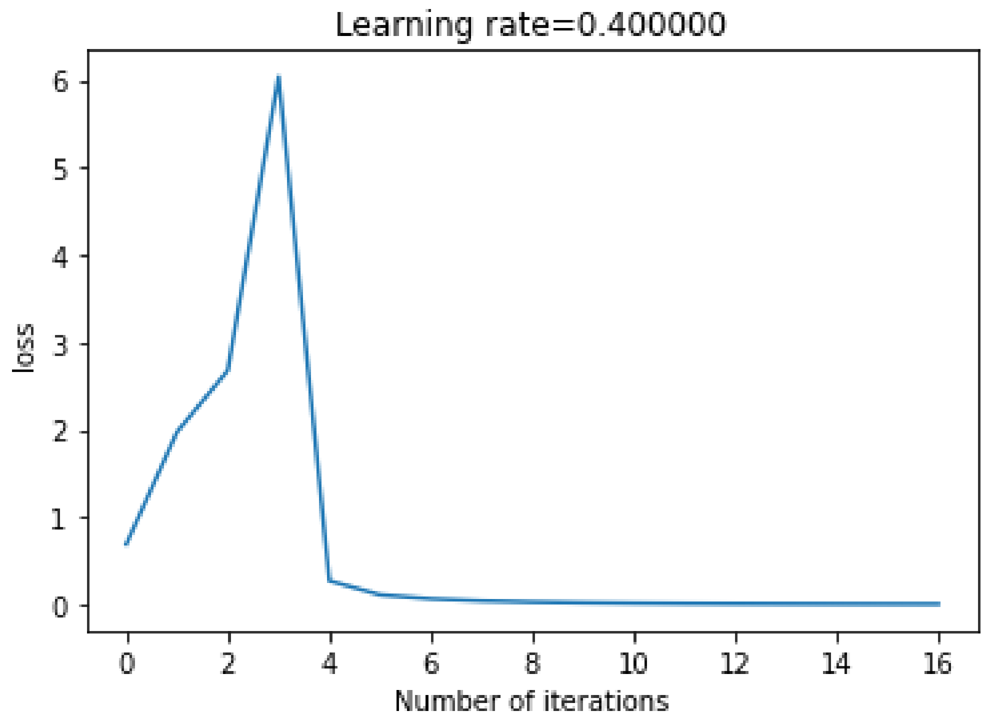
Learning rate=0.010000
0.7
0.6
0.5
0.4
0.3
0.2
0.1
loss
0
10
20
30
40
50
60
70
Number of iterations

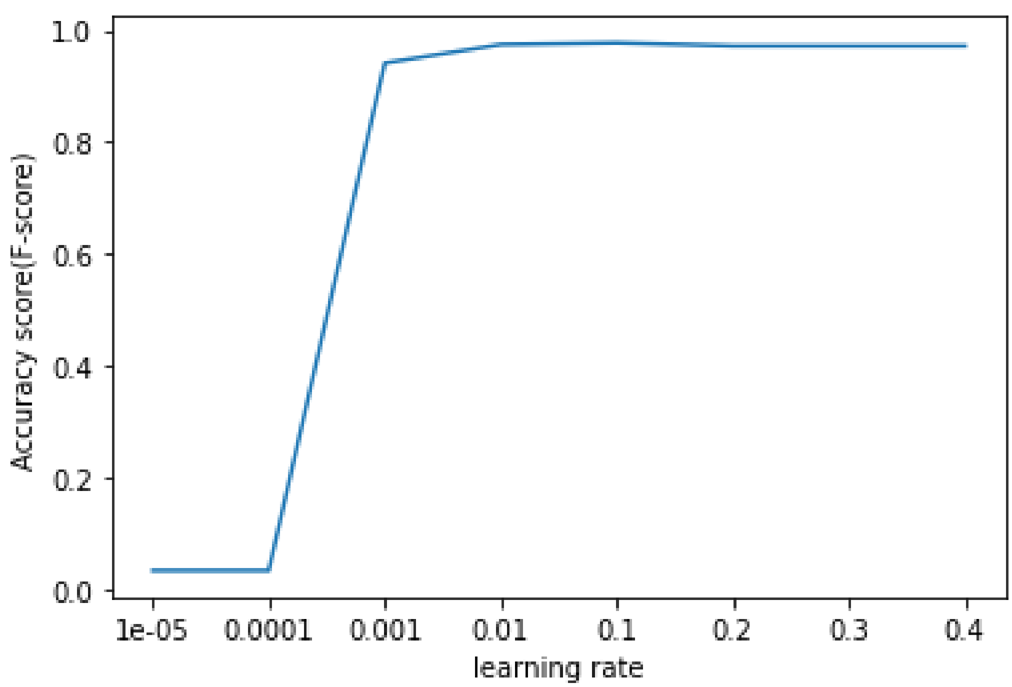


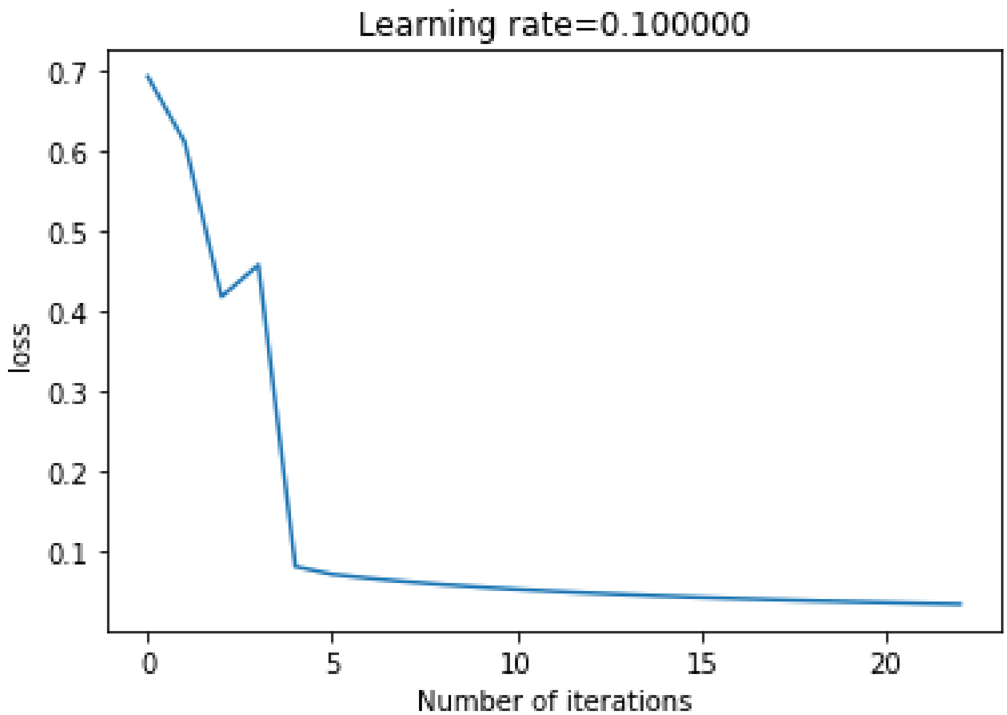
Learning rate=0.100000
0.7
0.6
0.5
0.4
0.3
0.2
0.1
loss
0
5
10
15
20
Number of iterations


Learning rate=0.200000
loss
Number of iterations

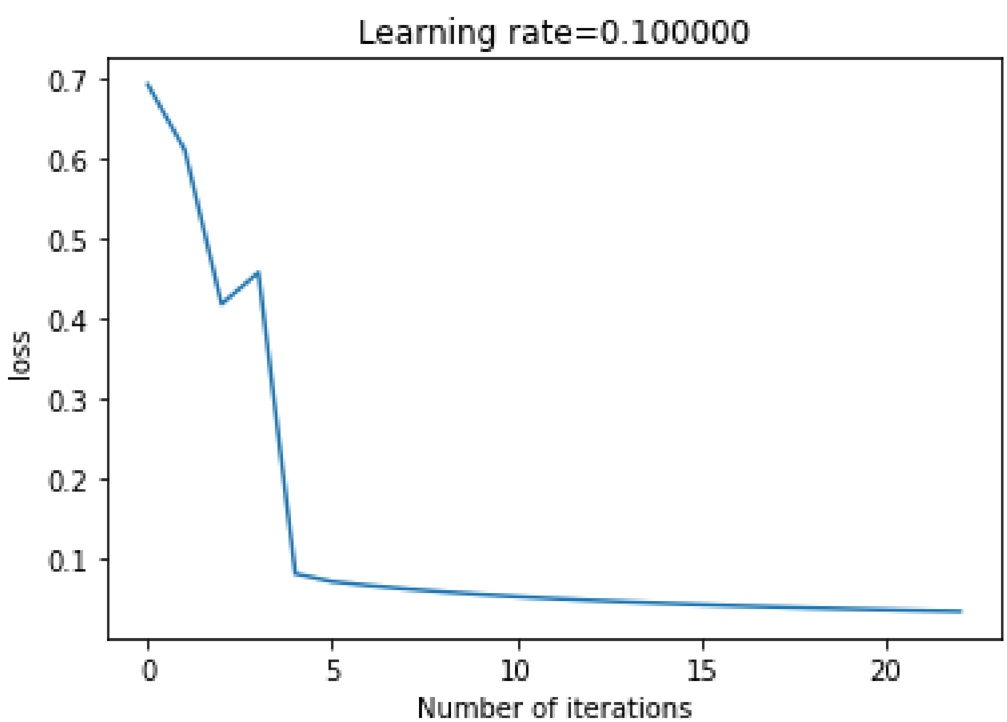

Learning rate=0.300000
loss
Number of iterations


Learning rate=0.400000
loss
Number of iterations


Accuracy score(F-score)
learning rate
1e-05
0.0001
0.001
0.01
0.1
0.2
0.3
0.4



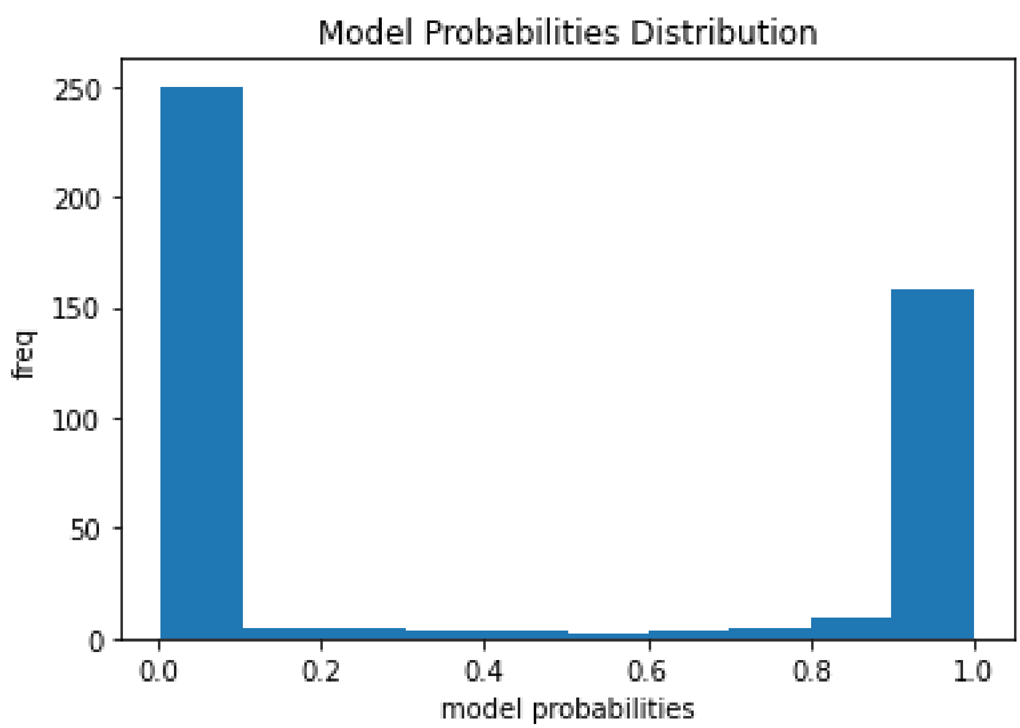
[66]:
```
model = LogisticRegression(w,b).
 ↪fit(X_train,y_train,optimum_learning_rate,num_iter)
```



[67]:
```
predictions = model.predict(X_test)
y_pred_binary = np.where(predictions > 0.5, 1, 0)
accuracy_score=f1_score(y_test,y_pred_binary)
print('accuracy score(F-score)%.2f'%accuracy_score)
```

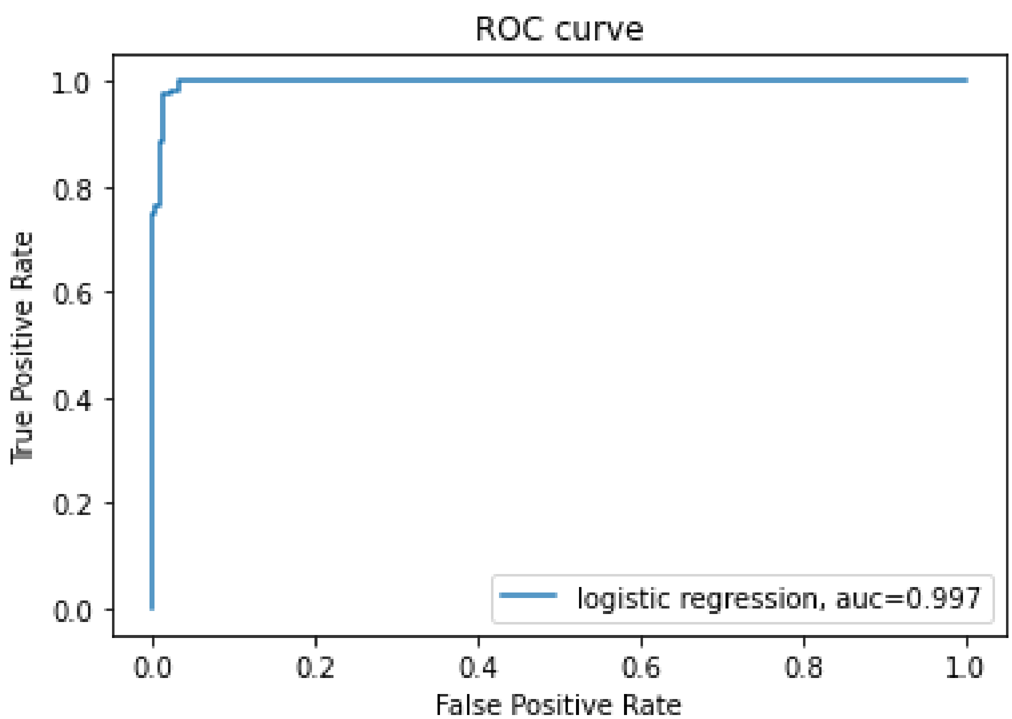
```
accuracy score(F-score)0.98
```

[68]:
```
plt.hist(predictions, bins = 10)
plt.title('Model Probabilities Distribution')
plt.xlabel('model probabilities')
plt.ylabel('freq')
plt.show()

# Generate a classification report
cm_plot_labels = ['digit 1', 'digit 9']
# For this to work we need y_pred as binary labels not as probabilities
y_pred_binary = np.where(predictions > 0.5, 1, 0)

report = classification_report(y_test, y_pred_binary,␣
↪target_names=cm_plot_labels)

print(report)
```



```
              precision    recall  f1-score   support

     digit 1       0.98      0.98      0.98       264
     digit 9       0.98      0.98      0.98       177

    accuracy                           0.98       441
   macro avg       0.98      0.98      0.98       441
weighted avg       0.98      0.98      0.98       441
```

[69]:
```
from sklearn import metrics
fpr, tpr, _ = metrics.roc_curve(y_test,  predictions)
auc = metrics.roc_auc_score(y_test, predictions)
plt.plot(fpr,tpr,label="logistic regression, auc=%.3f"%auc)
plt.legend(loc=4)
plt.title('ROC curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```



Logistic Regression can be interpreted as a neural network with just a single layer. It uses the Cross Entropy to measure the performance of the layer (i.e. of the "trained" weight **w**). In ML we call this the **Loss function**.

What happens when you take the Means Squared Error (MSE) instead of the Cross Entropy? Does this also work? Implement MSE and try for yourself.

Answer: If we take MSE instead of the Cross Entropy then It will not converge as the cost function is not convex and there are a lot of local minima.

[81]:
```
num_iter=100
w,b=weight_initiliazitation(X_train)
#lr_list=[0.00001,0.0001,0.001,0.01,0.1,0.2,0.3,0.4]
#optimum_learning_rate=find_optimum_lr_mse(lr_list,X_train,y_train,X_test,y_test,w,b)
model = LogisticRegression(w,b).fit_mse(X_train,y_train,0.05,num_iter)
```

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[ ]:
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