homework 1

October 10, 2021

1 Tasks — Regression (week 1):

1.0.1 Task 2:

```
[134]: import pandas as pd
       import numpy as np
       reviews = pd.read_json('https://cseweb.ucsd.edu/classes/fa21/cse258-b/data/
       →fantasy_10000.json.gz', lines=True)
[135]: ratings = [review for review in reviews["rating"]]
       lengths = [len(review) for review in reviews["review_text"]]
       y = np.matrix(ratings).T
       X = np.matrix([[1,length] for length in lengths])
       theta = np.linalg.inv(X.T*X)*X.T*y
       print("Theta([Theta_0; Theta_1]): \n", theta)
      Theta([Theta_0; Theta_1]):
       [[3.68568136e+00]
       [6.87371675e-05]]
[136]: sse = sum([x**2 for x in (y - X*theta)]) #Summing up all square errors
       mse = sse / len(y) #Dividing by length to get mean square error
       print("MSE = ", mse)
      MSE = [[1.55220866]]
      1.0.2 Task 3:
[137]: import dateutil.parser
       dates = [dateutil.parser.parse(review_time) for review_time in_
        →reviews["date_added"]]
```

(3) To use the prelewise function implementation of one-hot encoding the weekdays, we need a 1×6 vector: [0 0 0 0 0 0] is morday [100000] is tuesday [O 1 0 0 0 0] is wednesday [QQQQQI] it Sunday To one-hot encode the years in the Same general manner is a bit worse, since there in theory might be an insinite amount of years. However, since I know the years in this dataset ranges from 2006 to 2017, I took the liberty of limiting the encoding to these years. We then need a 1×11 vector: F005 M [0000000] M 2007 8005 N [000000000 N 2008

F105 th [10000000] it 2017

```
The feature vectors for the first two samples
     then becomes as follows:
lengtin day (sunday) year (2017)
X1=[1 2086 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0]
```

1.0.3 Task 4:

```
[138]: #Using values directly as features
def feature(index):
    feature = [1]
    feature.append(lengths[index])
```

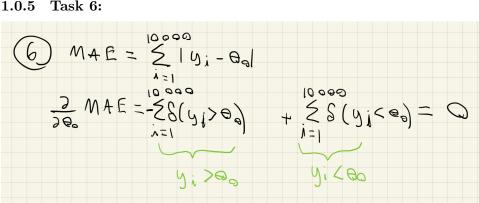
```
feature.append(dates[index].weekday())
           feature.append(dates[index].year-2006)
           return feature
       y = np.matrix(ratings).T
       X = np.matrix([feature(index) for index in range(0, len(lengths))])
       theta = np.linalg.inv(X.T*X)*X.T*y
       print("Theta_1: \n", theta[0],
       "\nTheta_2: \n", theta[1],
       "nTheta_3: n", theta[2],
       "nTheta_4: n", theta[3])
       sse = sum([x**2 for x in (y - X*theta)]) #Summing up all square errors
       mse = sse / len(y) #Dividing by length to get mean square error
       print("MSE = ", mse)
      Theta_1:
       [[3.29014782]]
      Theta_2:
       [[5.50923292e-05]]
      Theta_3:
       [[0.00875072]]
      Theta_4:
       [[0.05235923]]
      MSE = [[1.53677405]]
[139]: #Using one-hot encoding
       days = [date.weekday() for date in dates]
       years = [date.year for date in dates]
       def oneHotFeature(index):
           feature = [1]
           length = lengths[index]
           feature.append(length)
           day = dates[index].weekday()
           dayEncoded = [0]*6
           if day != 0:
               dayEncoded[day-1] = 1
           for elem in dayEncoded:
               feature.append(elem)
           year = dates[index].year
           yearEncoded = [0]*11
           if year != 2006:
```

```
yearEncoded[year-2007] = 1
    for elem in yearEncoded:
        feature.append(elem)
    return feature
y = np.matrix(ratings).T
X = np.matrix([oneHotFeature(index) for index in range(0, len(lengths))])
theta = np.linalg.inv(X.T*X)*X.T*y
print("Theta_1: \n", theta[0],
"\nTheta_2: \n", theta[1],
"\nTheta_3: \n", theta[2:8],
"\nTheta_4: \n", theta[8:])
sse = sum([x**2 for x in (y - X*theta)]) #Summing up all square errors
mse = sse / len(y) #Dividing by length to get mean square error
print("MSE = ", mse)
Theta_1:
 [[4.87171479]]
Theta_2:
 [[5.15709386e-05]]
Theta_3:
 [[0.04890034]
 [0.1457098]
 [0.1066464]
 [0.12616832]
 [0.03834177]
 [0.1028469]]
Theta_4:
 [[-1.58244783]
 [-1.70447417]
 [-1.68316056]
 [-1.67023905]
 [-1.62877001]
 [-1.19956705]
 [-1.10444816]
 [-1.09162361]
 [-1.20861354]
 [-1.23647487]
 [-1.23331225]]
MSE = [[1.51235787]]
```

1.0.4 Task 5:

```
[147]: # distributing "random" indices to each set
       training_indices = [i for i in range(0, len(lengths), 2)]
       test_indices = [i for i in range(1, len(lengths), 2)]
       training_ratings = [ratings[i] for i in training_indices]
       test_ratings = [ratings[i] for i in test_indices]
[148]: #Using values directly as features
       training_y = np.matrix(training_ratings).T
       test_y = np.matrix(test_ratings).T
       training_X = np.matrix([feature(index) for index in training_indices])
       trained_theta = np.linalg.inv(training_X.T*training_X)*training_X.T*training_y
       sse = sum([x**2 for x in (training_y - training_X*trained_theta)]) #Summing_up_
       →all square errors
       mse = sse / len(test_y) #Dividing by length to get mean square error
       print("MSE(training data) = ", mse)
       sse = sum([x**2 for x in (test_y - training_X*trained_theta)]) #Summing up all_
       ⇒square errors
       mse = sse / len(test_y) #Dividing by length to get mean square error
       print("MSE(test data) = ", mse)
      MSE(training data) = [[1.54991753]]
      MSE(test data) = [[1.52654798]]
[149]: #Using one-hot encoding
       training_y = np.matrix(training_ratings).T
       test_y = np.matrix(test_ratings).T
       training X = np.matrix([oneHotFeature(index) for index in training indices])
       trained_theta = np.linalg.inv(training_X.T*training_X)*training_X.T*training_y
       sse = sum([x**2 for x in (training_y - training_X*trained_theta)]) #Summing up_{\sqcup}
       →all square errors
       mse = sse / len(test_y) #Dividing by length to get mean square error
       print("MSE(training data) = ", mse)
       sse = sum([x**2 for x in (test_y - training_X*trained_theta)]) #Summing up all_U
       ⇒square errors
       mse = sse / len(test_y) #Dividing by length to get mean square error
       print("MSE(test data) = ", mse)
      MSE(training data) = [[1.52069864]]
      MSE(test data) = [[1.51164629]]
```

1.0.5 Task 6:



y; > eo and y; < eo hoppens exactly the same amount of times the two terms above will land each other out, and 2 MAE will be Q.

This has to be a global minima, since it does not makes sense that increasing or decreasing to the extreme will lead to a smaller MAE, which it would have some is it was a global maxima or a Saddle Point.

The only way to make the two terms cancel each other out, i.e. that yi>00 and yi 400 occurs the same amount of times, is in On hos the value of the median of y.

2 Tasks — Classification (week 2):

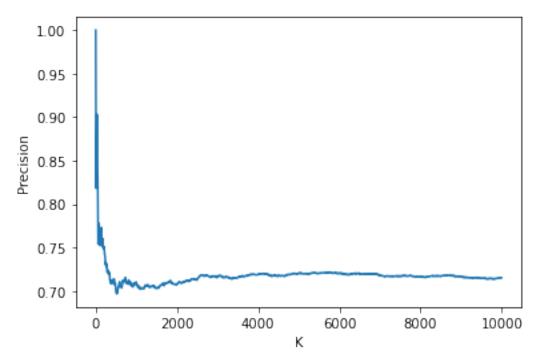
2.0.1 Task 7:

```
[152]: lengths = [len(review) for review in reviews["review/text"]]
       X = np.matrix([[1,length] for length in lengths])
       y = [rating >= 4 for rating in reviews["review/overall"]]
       model = sklearn.linear_model.LogisticRegression(class_weight='balanced')
       model.fit(X,y)
       predictions = model.predict(X)
       truePos = sum([(predictions[i] and y[i]) for i in range(0, len(y))])
       fakePos = sum([(predictions[i] and not y[i]) for i in range(0, len(y))])
       trueNeg = sum([(not predictions[i] and not y[i]) for i in range(0, len(y))])
       fakeNeg = sum([(not predictions[i] and y[i]) for i in range(0, len(y))])
       FPR = fakePos/(fakePos+trueNeg)
       FNR = fakeNeg/(fakeNeg+truePos)
       BER = 0.5*(FPR + FNR)
       print("True Positive = ", truePos)
       print("Fake Positive = ", fakePos)
       print("True Negative = ", trueNeg)
       print("Fake Negative = ", fakeNeg)
       print("Balanced Error Rates = ", BER)
```

```
True Positive = 14201
Fake Positive = 5885
True Negative = 10503
Fake Negative = 19411
Balanced Error Rates = 0.46830315259572763
```

2.0.2 Task 8:

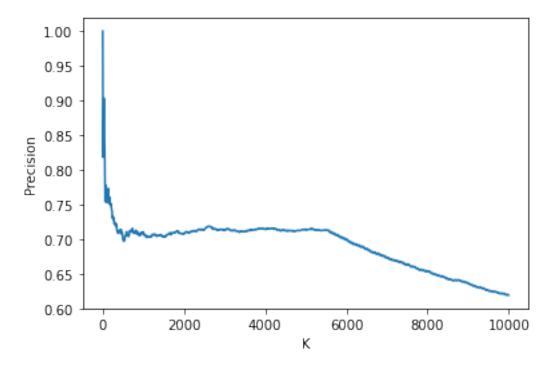
```
[154]: import matplotlib.pyplot as plt
       confidences = model.decision_function(X)
       sortedByConfidence = list(zip(confidences, y))
       sortedByConfidence.sort(reverse=True)
       K = [K \text{ for } K \text{ in range}(1, 10000+1, 10)]
       precisionsK = []
       for k in K:
           retrievedLabels = [x[1] for x in sortedByConfidence[:k]]
           precisionK = sum(retrievedLabels)/len(retrievedLabels)
           precisionsK.append(precisionK)
       plt.plot(K, precisionsK)
       plt.xlabel("K")
       plt.ylabel("Precision")
       plt.show()
       print(f"precision@K for k=1: {precisionsK[0]}, k=100: {precisionsK[100//10-1]}, u
        \rightarrowk=10000: {precisionsK[10000//10-1]}")
```



precision@K for k=1: 1.0, k=100: 0.7692307692307693, k=10000: 0.7152437193474127

2.0.3 Task 9:

```
[155]: import matplotlib.pyplot as plt
       confidences = model.decision_function(X)
       sortedByConfidence = list(zip(abs(confidences), y, predictions))
       sortedByConfidence.sort(reverse=True)
       K = [K \text{ for } K \text{ in range(1, } 10000+1, 10)]
       precisionsK = []
       for k in K:
           retrievedLabels = [[x[1], x[2]] for x in sortedByConfidence[:k]]
           precisionK = 0
           for elem in retrievedLabels:
               precisionK += (int)(elem[0] == elem[1])
           precisionK = precisionK/k
           precisionsK.append(precisionK)
       plt.plot(K, precisionsK)
       plt.xlabel("K")
       plt.ylabel("Precision")
       plt.show()
       print(f"precision@K for k=1: {precisionsK[0]}, k=100: {precisionsK[100//10-1]},_u
        \rightarrowk=10000: {precisionsK[10000//10-1]}")
```



precision@K for k=1: 1.0, k=100: 0.7692307692307693, k=10000: 0.6188569712741467