

Exercise 2 - Part B

November 19, 2021

Machine Learning Lab

Lab 02

Exercise 2 - Part B

Importing Packages

```
[1]: import pandas as pd      #Importing Pandas
import numpy as np          #Importing Numpy
import math                 #Importing Math
```

Reading Training CSV data into the Dataframe

```
[2]: train_df = pd.read_csv('train.csv',low_memory=False)
#Setting Store column as my Index in Dataframe
train_df.set_index('Store',inplace=True)
train_df.head()
```

```
[2]:
```

	DayOfWeek	Date	Sales	Customers	Open	Promo	StateHoliday	\
Store								
1	5	2015-07-31	5263	555	1	1	0	
2	5	2015-07-31	6064	625	1	1	0	
3	5	2015-07-31	8314	821	1	1	0	
4	5	2015-07-31	13995	1498	1	1	0	
5	5	2015-07-31	4822	559	1	1	0	

SchoolHoliday

Store	
1	1
2	1
3	1
4	1
5	1

Reading Store CSV data into the Dataframe

```
[3]: store_df = pd.read_csv('store.csv')
#Setting Store column as my Index in Dataframe
store_df.set_index('Store',inplace=True)
store_df.head()
```

```
[3]:      StoreType Assortment  CompetitionDistance  CompetitionOpenSinceMonth \
Store
1          c          a          1270.0          9.0
2          a          a          570.0          11.0
3          a          a         14130.0          12.0
4          c          c          620.0          9.0
5          a          a         29910.0          4.0

      CompetitionOpenSinceYear  Promo2  Promo2SinceWeek  Promo2SinceYear \
Store
1          2008.0          0          NaN          NaN
2          2007.0          1          13.0          2010.0
3          2006.0          1          14.0          2011.0
4          2009.0          0          NaN          NaN
5          2015.0          0          NaN          NaN

      PromoInterval
Store
1          NaN
2      Jan, Apr, Jul, Oct
3      Jan, Apr, Jul, Oct
4          NaN
5          NaN
```

Merging Training and Store Dataframes into a single Dataframe

```
[4]: #Merging train and store dataframes on Store column
merged_df = pd.merge(train_df, store_df, how='inner', on='Store')
merged_df
```

```
[4]:      DayOfWeek      Date  Sales  Customers  Open  Promo  StateHoliday \
Store
1          5  2015-07-31   5263         555     1     1          0
1          4  2015-07-30   5020         546     1     1          0
1          3  2015-07-29   4782         523     1     1          0
1          2  2015-07-28   5011         560     1     1          0
1          1  2015-07-27   6102         612     1     1          0
...      ...      ...      ...      ...      ...      ...
1115      6  2013-01-05   4771         339     1     0          0
1115      5  2013-01-04   4540         326     1     0          0
1115      4  2013-01-03   4297         300     1     0          0
1115      3  2013-01-02   3697         305     1     0          0
1115      2  2013-01-01      0          0     0     0          a

      SchoolHoliday  StoreType Assortment  CompetitionDistance \
Store
1          1          c          a          1270.0
1          1          c          a          1270.0
```

1	1	c	a	1270.0
1	1	c	a	1270.0
1	1	c	a	1270.0
...
1115	1	d	c	5350.0
1115	1	d	c	5350.0
1115	1	d	c	5350.0
1115	1	d	c	5350.0
1115	1	d	c	5350.0

	CompetitionOpenSinceMonth	CompetitionOpenSinceYear	Promo2	\
Store				
1	9.0	2008.0	0	
1	9.0	2008.0	0	
1	9.0	2008.0	0	
1	9.0	2008.0	0	
1	9.0	2008.0	0	
...
1115	NaN	NaN	1	
1115	NaN	NaN	1	
1115	NaN	NaN	1	
1115	NaN	NaN	1	
1115	NaN	NaN	1	

	Promo2SinceWeek	Promo2SinceYear	PromoInterval
Store			
1	NaN	NaN	NaN
1	NaN	NaN	NaN
1	NaN	NaN	NaN
1	NaN	NaN	NaN
1	NaN	NaN	NaN
...
1115	22.0	2012.0	Mar, Jun, Sept, Dec
1115	22.0	2012.0	Mar, Jun, Sept, Dec
1115	22.0	2012.0	Mar, Jun, Sept, Dec
1115	22.0	2012.0	Mar, Jun, Sept, Dec
1115	22.0	2012.0	Mar, Jun, Sept, Dec

[1017209 rows x 17 columns]

Cleaning and Preparing Dataframe for Analysis

```
[5]: #For NA values in column Competition Distance, we are filling it with the
      ↪median value of the whole column
merged_df.CompetitionDistance.fillna(merged_df.CompetitionDistance.median(),
      ↪inplace = True)
#For NA in any other column, replacing NA with 0
merged_df.fillna(0, inplace = True)
```

Find all the stores that have sales recorded for 942 days

```
[6]: merged_df = merged_df[merged_df.groupby(by='Store').count() >= 942]
      #Taking only Store and Sales Columns
      merged_df = merged_df[['Sales']]
      merged_df
```

```
[6]:      Sales
      Store
1      5263.0
1      5020.0
1      4782.0
1      5011.0
1      6102.0
...      ...
1115    4771.0
1115    4540.0
1115    4297.0
1115    3697.0
1115         0.0
```

[1017209 rows x 1 columns]

Create a data matrix of the shape (#_of_stores, 942) for the daily sales record of these stores.

```
[7]: #First Grouping the dataframe by Store so to get (# of stores) rows
      store_sales = merged_df.groupby(['Store'])

      #For each store, converting its sales column to a list and storing it into a
      ↪ single cell
      store_sales = store_sales['Sales'].agg(lambda x: list(x))

      #Converting the list each cell into 942 different columns and each row now
      ↪ represent each store
      store_sales = pd.DataFrame(store_sales.values.tolist(), columns=[x+1 for x in
      ↪ range(942)])
      store_sales
```

```
[7]:      1      2      3      4      5      6      7      8  \
0      5263.0  5020.0  4782.0  5011.0  6102.0  0.0  4364.0  3706.0
1      6064.0  5567.0  6402.0  5671.0  6627.0  0.0  2512.0  3854.0
2      8314.0  8977.0  7610.0  8864.0  8107.0  0.0  3878.0  5080.0
3     13995.0 10387.0 10514.0 10275.0 11812.0  0.0  9322.0  8322.0
4      4822.0  4943.0  5899.0  6083.0  7059.0  0.0  2030.0  3815.0
...      ...      ...      ...      ...      ...      ...
1110    5723.0  5263.0  4907.0  6793.0  7742.0  0.0  2177.0  3918.0
1111    9626.0  9652.0  9179.0  9583.0 14383.0  0.0  6216.0  6220.0
1112    7289.0  7491.0  6640.0  6468.0  7582.0  0.0  4784.0  6399.0
```

1113	27508.0	24395.0	25840.0	25518.0	26720.0	0.0	21312.0	19627.0	
1114	8680.0	8405.0	7661.0	8093.0	10712.0	0.0	6897.0	5816.0	

	9	10	...	933	934	935	936	937	938	\
0	3769.0	3464.0	...	4892.0	5471.0	5580.0	7176.0	0.0	4997.0	
1	4108.0	5093.0	...	5618.0	6763.0	6318.0	6775.0	0.0	2342.0	
2	5702.0	5414.0	...	7772.0	8001.0	9800.0	12247.0	0.0	4523.0	
3	7286.0	8503.0	...	9472.0	8857.0	10031.0	12112.0	0.0	10338.0	
4	3713.0	3595.0	...	4999.0	5974.0	5718.0	6978.0	0.0	1590.0	
...	
1110	3587.0	4021.0	...	5887.0	5307.0	6472.0	9444.0	0.0	3325.0	
1111	6730.0	6029.0	...	14366.0	14724.0	17058.0	25165.0	0.0	9513.0	
1112	6410.0	4565.0	...	7508.0	6115.0	6866.0	8984.0	0.0	5194.0	
1113	20564.0	20424.0	...	18075.0	17073.0	18816.0	21237.0	0.0	18856.0	
1114	6150.0	5342.0	...	5007.0	4649.0	5243.0	6905.0	0.0	4771.0	

	939	940	941	942
0	4486.0	4327.0	5530.0	0.0
1	4484.0	4159.0	4422.0	0.0
2	6069.0	5902.0	6823.0	0.0
3	8290.0	8247.0	9941.0	0.0
4	4456.0	3465.0	4253.0	0.0
...
1110	4640.0	4579.0	5097.0	0.0
1111	9788.0	8716.0	10797.0	0.0
1112	5524.0	5563.0	6218.0	0.0
1113	18371.0	18463.0	20642.0	0.0
1114	4540.0	4297.0	3697.0	0.0

[1115 rows x 942 columns]

Use the first 800 stores in this data matrix for training and the rest for testing. Also split the sales data into 2 parts, the 1st part contains the information about the first 900 days of sales (these would be the features) and the 2nd contains the information about the last 42 days of sales (these would be the targets).

```
[8]: #Using iloc to split dataset and then converting this to numpy array for
      ↪ further processing
```

```
X_train = store_sales.iloc[:800, :900].to_numpy()
X_test = store_sales.iloc[800:, :900].to_numpy()
Y_train = store_sales.iloc[:800, 900:].to_numpy()
Y_test = store_sales.iloc[800:, 900:].to_numpy()
```

```
[9]: #Replacing every NaN value with 0 in training and test Dataset
```

```
X_train[np.isnan(X_train)] = 0
Y_train[np.isnan(Y_train)] = 0
X_test[np.isnan(X_test)] = 0
Y_test[np.isnan(Y_test)] = 0
```

Iteratively build multiple linear regression models for column vectors of X . You are allowed to use the numpy routines for calculating inverses, transposing of matrices and matrix multiplication. You would need to create 42 models in this case (1 model for each day in the target sales matrix)

```
[10]: #Calculating Matrix A which equals  $X^T \cdot X$ 
A = X_train.T @ X_train

#Creating a matrix which stores beta vector for next 42 days
all_beta = np.zeros(shape=(900,42))

#Iterating through the columns for Y train
for i in range(Y_train.shape[1]):
    #Initialize empty beta array
    beta = np.zeros(shape=(900,1))
    #Calculating beta vector using equation:  $(X^T \cdot X)^{-1} \cdot (X^T \cdot Y)$ 
    beta = np.array(np.dot(np.linalg.inv(A),np.dot(X_train.T,Y_train[:,i])))
    #Reshaping beta array to column vector
    beta = beta.reshape(-1,1)
    #Copying new beta values to beta matrix
    all_beta[:,i] = beta[:,0]
```

Verify that you have learned 0:900 for each of the 42 models and use these learned parameters to make predictions for each day ahead. In total 42 days.

```
[11]: #Calculating predicted y y hat using the X test and beta values
y_hat = X_train @ all_beta
```

Calculate and print the daily RMSE and MAE for all 42 sales values using test split (`X_test` as input). Also calculate and print overall average RMSE and MAE. (i.e. just the mean RMSE of all 42 models).

Function to calculate RMSE between Actual Y and Predicted Y

```
[12]: def calculate_rmse(actual,predicted):
    N = len(actual)
    summation = 0
    for i in range(len(actual)):
        summation += ((actual[i] - predicted[i]) ** 2)
    return math.sqrt(summation/N)
```

Function to calculate MAE between Actual Y and Predicted Y

```
[13]: def calculate_mae(actual,predicted):
    N = len(actual)
    summation = 0
    for i in range(len(actual)):
        summation += abs(actual[i] - predicted[i])
    return summation/N
```

```
[14]: #Initializing two empty array for storing RMSE and MAE
rmse = np.zeros(shape=(Y_train.shape[1],))
mae = np.zeros(shape=(Y_train.shape[1],))

#Iterating through Y values
for i in range(Y_train.shape[1]):
    rmse[i] = calculate_rmse(Y_train[:,i],y_hat[:,i])
    mae[i] = calculate_mae(Y_train[:,i],y_hat[:,i])

#Converting RMSE and MAE list to Dataframe
error_df = pd.DataFrame(np.hstack((rmse.reshape(-1,1),mae.
    ↪reshape(-1,1))),columns=['RMSE','MAE'])
error_df
```

```
[14]:
```

	RMSE	MAE
0	4.731422e+05	305195.909448
1	1.728305e+05	106405.221263
2	5.946421e+05	360909.887114
3	7.034829e+05	437619.131678
4	7.345277e+05	435543.805615
5	6.432622e+05	423011.717900
6	7.981136e+05	478594.333921
7	9.807624e+05	587478.966126
8	1.806327e+05	108853.805682
9	6.210497e+05	374447.000432
10	7.538311e+05	448565.176230
11	6.681774e+05	400354.796431
12	5.720995e+05	370470.913420
13	4.916015e+05	306657.210576
14	5.553930e+05	337416.307653
15	1.438492e+05	90126.687726
16	5.382004e+05	326645.534836
17	6.743641e+05	449194.804973
18	6.755049e+05	406534.428682
19	6.922066e+05	425230.854253
20	7.876939e+05	475979.539648
21	7.310623e+05	479163.659818
22	1.671382e+05	105600.794973
23	5.580886e+05	341107.885112
24	5.901033e+05	341277.665779
25	4.808007e+05	308412.184117
26	4.986938e+05	316512.642878
27	5.233060e+05	318318.903058
28	5.327361e+05	331078.892981
29	1.502887e+05	92746.161345
30	4.857587e+05	319835.723291
31	6.749813e+05	443260.238391

32	7.028667e+05	438025.457057
33	7.412883e+05	425917.227332
34	8.806699e+05	500656.773381
35	1.007064e+06	602554.784827
36	1.469232e+05	91284.073994
37	5.342813e+05	338508.310549
38	6.215749e+05	375212.543530
39	6.546487e+05	384561.950083
40	6.343508e+05	391866.106794
41	1.054245e+05	65956.638679

Reason why or why not Linear Regression is a good choice for this task. I think linear regression is not a good choice for this task, instead we can use time series forecast method Autoregressive model (AR) because it predict future behaviour based on past behaviour. The linear regression model uses the linear combination of predictors for predicting future values whereas AR model uses all the past values in time and then predict the future values.