Report on Data Science project

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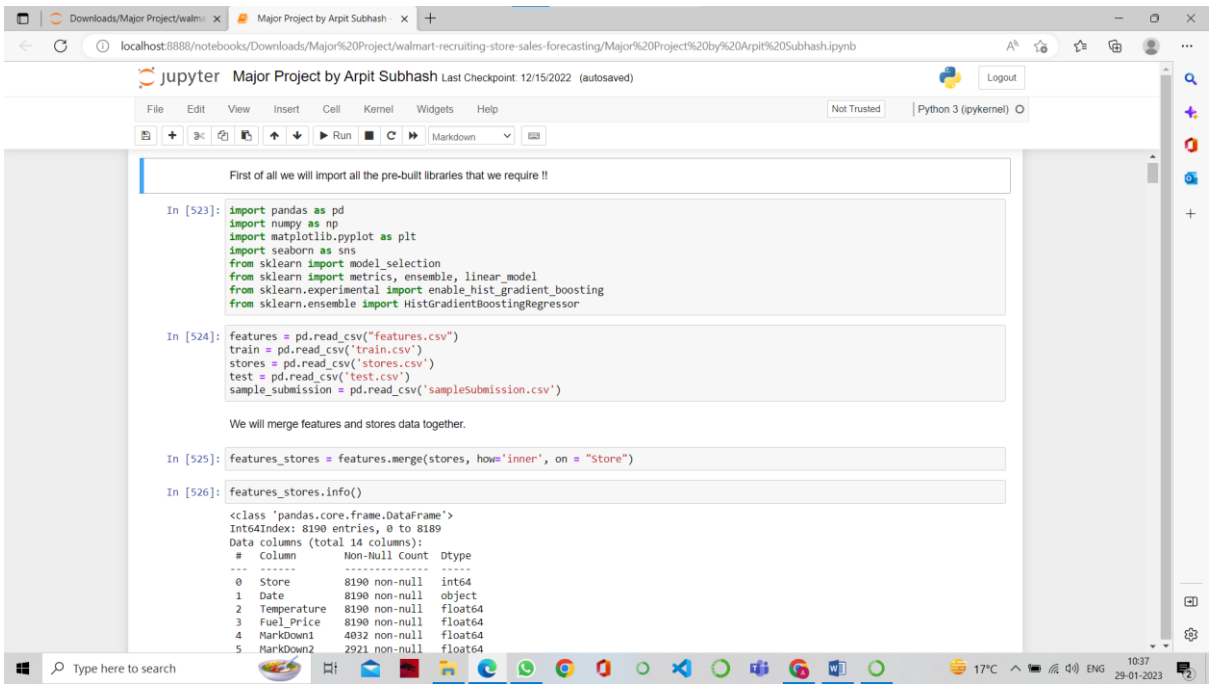
Topic: Prediction on Walmart's departments of different stores through all of the world

Table of contents:

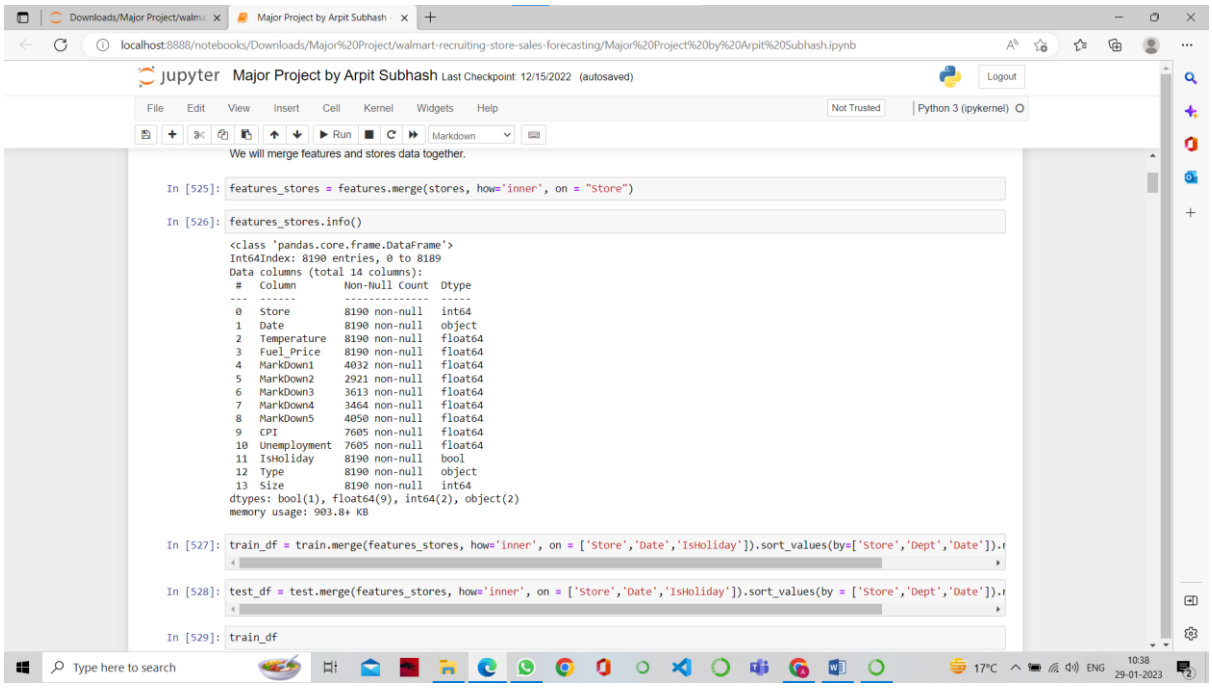
1. Libraries – I have used libraries like pandas, numpy, matplotlib, seaborn, sklearn kit (model_selection, ensemble, linear_model, eli5).

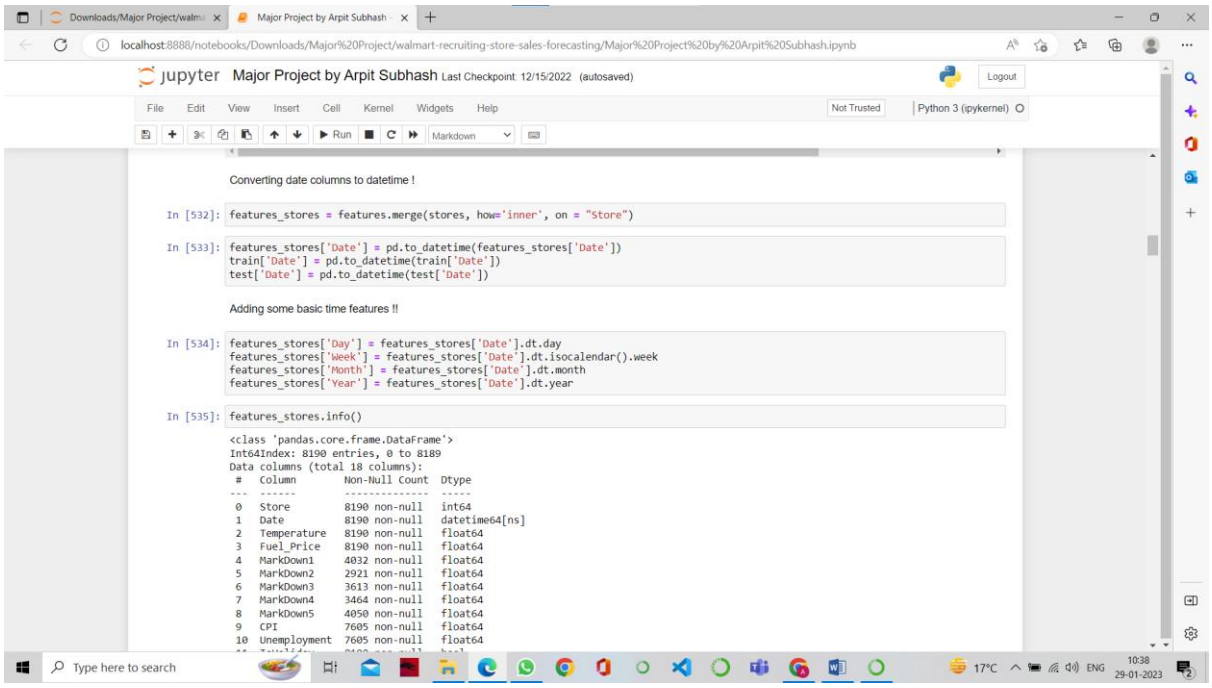
2. Data loading – features, stores, train, test (csv files).



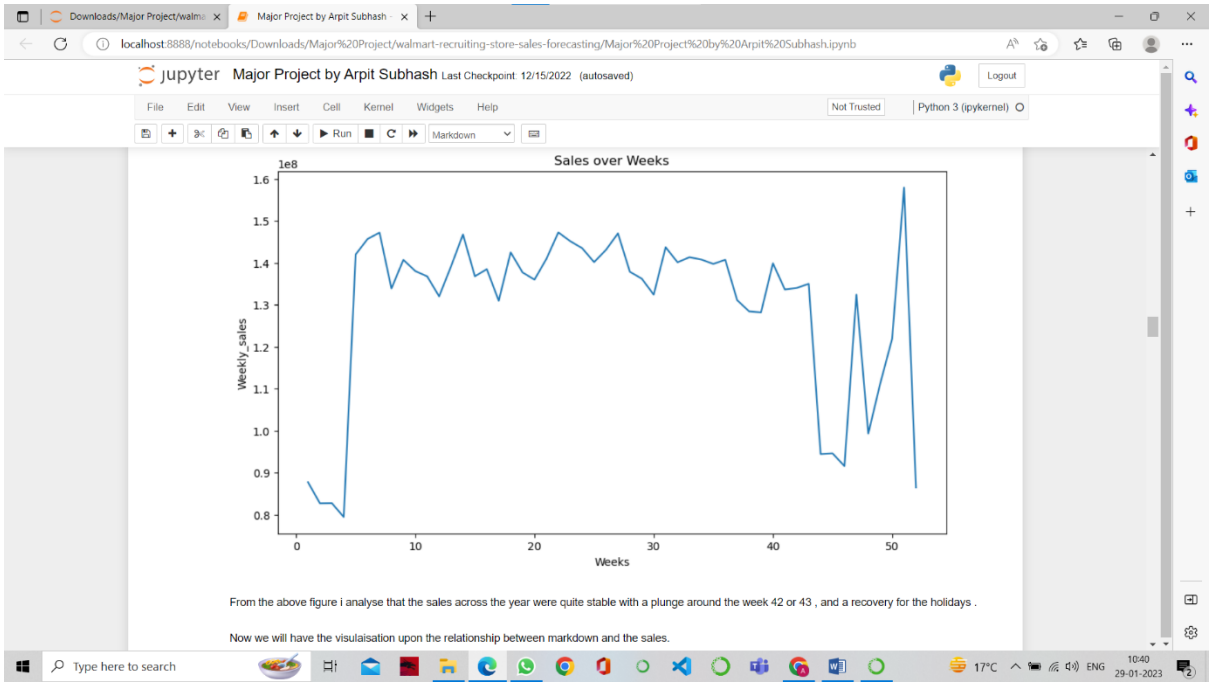
3. EDA – First of all I converted the date columns to date time, then I added some basic features related to all types of days that is, data, time, week, month, year and I merged four data sets to form two

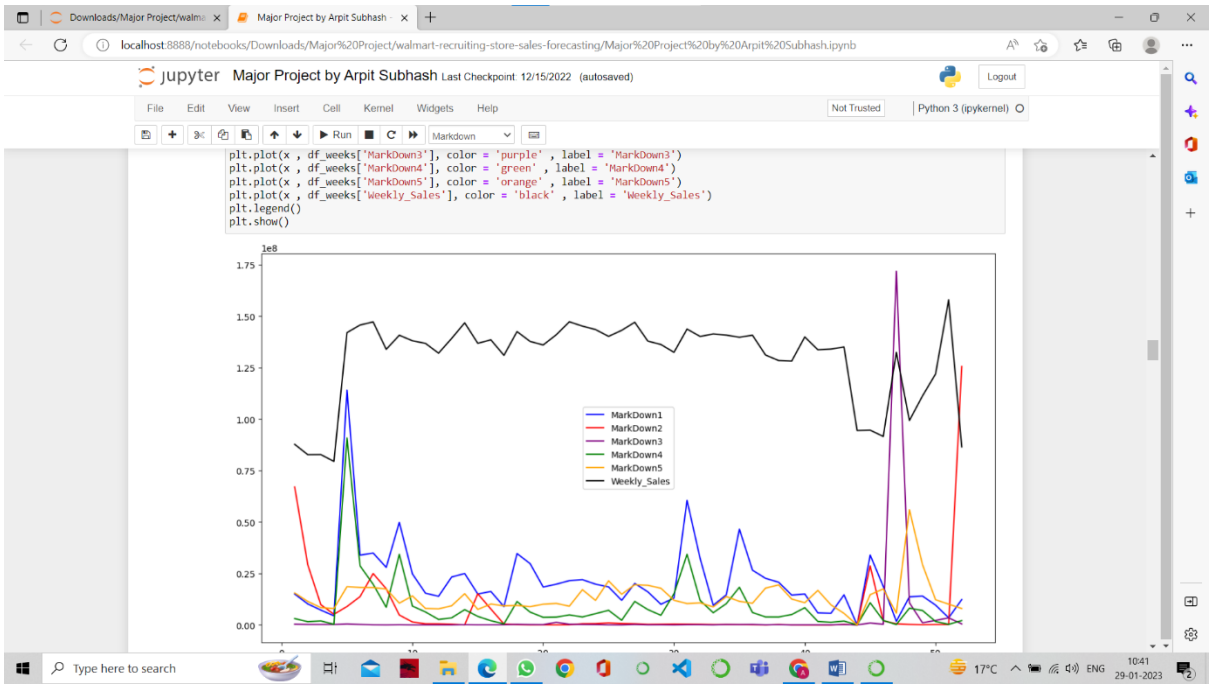
new data sets that is, train with features and stores and test with features and stores.

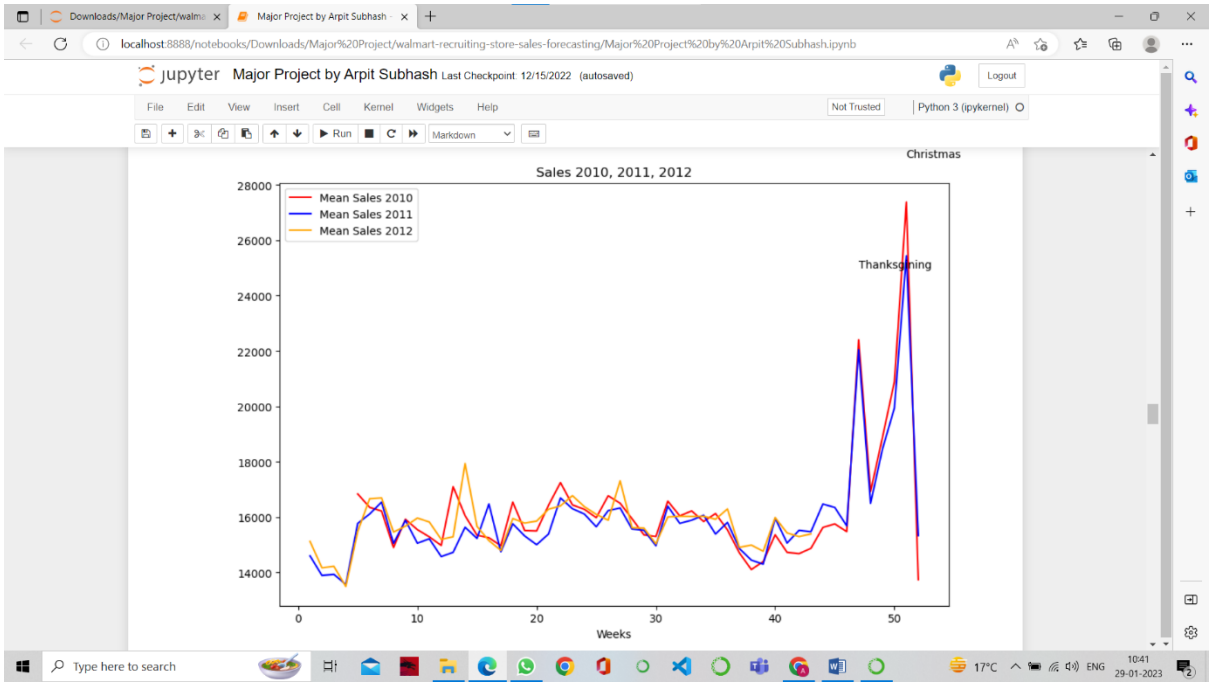


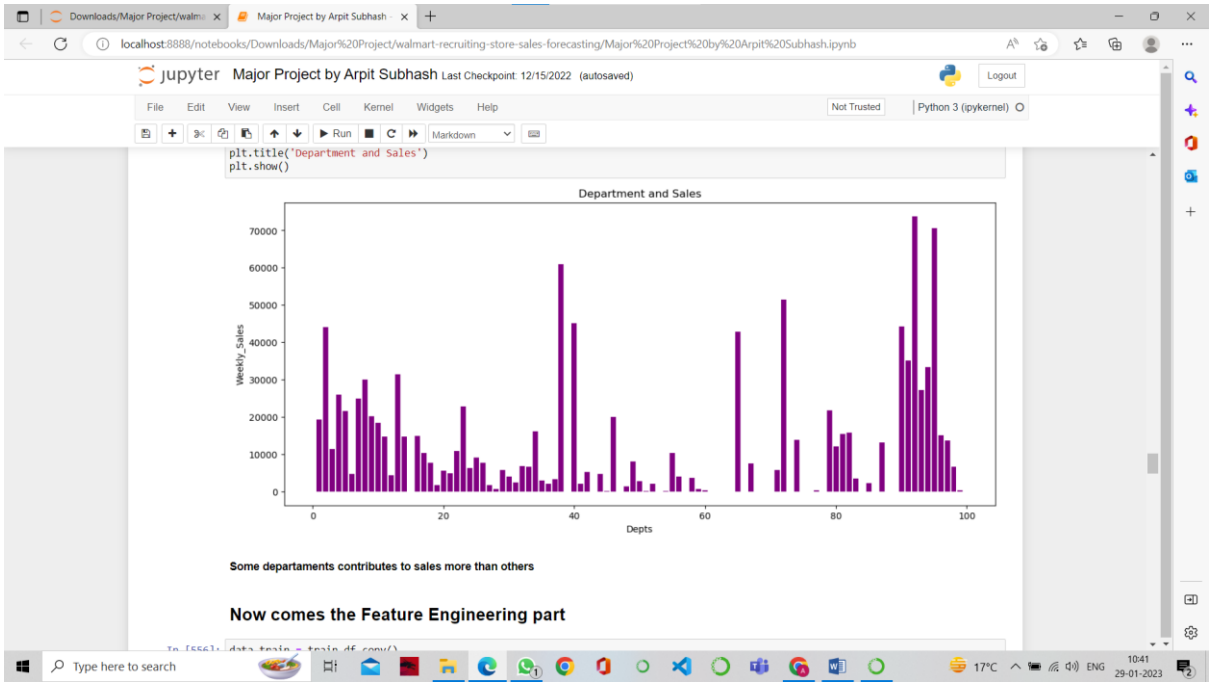


4. <u>Data Visualisation</u> – sales over weeks, sales vs all the markdowns, sales over weeks of year 2010, 2011, 2012 and relationship between store size and sales and relationship between department and sales.

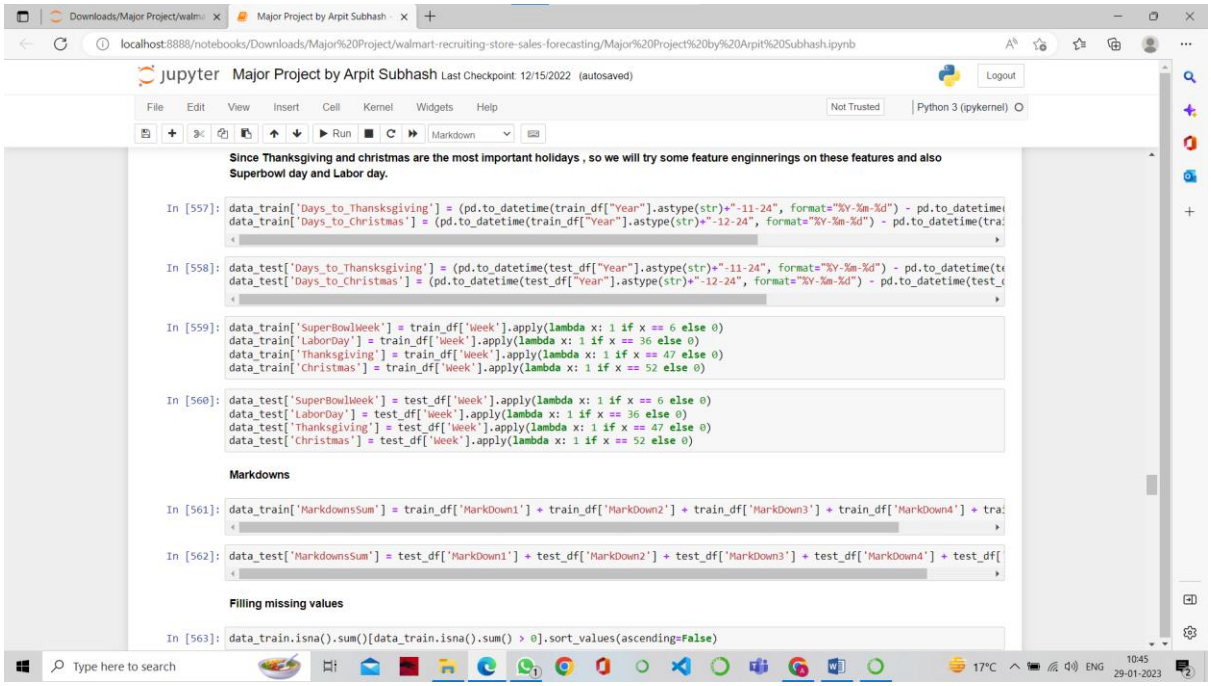

Major Project by Arpit Subhash Last Checkpoint: 12/15/2022 (autosaved)
Sales over Weeks
1e8
Weekly_sales
Weeks
From the above figure i analyse that the sales across the year were quite stable with a plunge around the week 42 or 43 , and a recovery for the holidays .
Now we will have the visulaisation upon the relationship between markdown and the sales.


plt.plot(x , df_weeks['MarkDown3'], color = 'purple' , label = 'MarkDown3')
plt.plot(x , df_weeks['MarkDown4'], color = 'green' , label = 'MarkDown4')
plt.plot(x , df_weeks['MarkDown5'], color = 'orange' , label = 'MarkDown5')
plt.plot(x , df_weeks['Weekly_Sales'], color = 'black' , label = 'Weekly_Sales')
plt.legend()
plt.show()
1e8
MarkDown1
MarkDown2
MarkDown3
MarkDown4
MarkDown5
Weekly_Sales





5. <u>Feature Engineering</u> – Since Thanksgiving and Christmas were the most important holidays, I tried some basic feature engineering on the days like Super Bowl day and Labor day. Also I added all the markdown to form two parts data train and data test.



Since Thanksgiving and christmas are the most important holidays , so we will try some feature enginnerings on these features and also Superbowl day and Labor day.

```
In [557]: data_train['Days_to_Thansksgiving'] = (pd.to_datetime(train_df["Year"].astype(str)+"-11-24", format="%Y-%m-%d") - pd.to_datetime(
          data_train['Days_to_Christmas'] = (pd.to_datetime(train_df["Year"].astype(str)+"-12-24", format="%Y-%m-%d") - pd.to_datetime(tra

In [558]: data_test['Days_to_Thansksgiving'] = (pd.to_datetime(test_df["Year"].astype(str)+"-11-24", format="%Y-%m-%d") - pd.to_datetime(te
          data_test['Days_to_Christmas'] = (pd.to_datetime(test_df["Year"].astype(str)+"-12-24", format="%Y-%m-%d") - pd.to_datetime(test_

In [559]: data_train['SuperBowlWeek'] = train_df['Week'].apply(lambda x: 1 if x == 6 else 0)
          data_train['LaborDay'] = train_df['Week'].apply(lambda x: 1 if x == 36 else 0)
          data_train['Thanksgiving'] = train_df['Week'].apply(lambda x: 1 if x == 47 else 0)
          data_train['Christmas'] = train_df['Week'].apply(lambda x: 1 if x == 52 else 0)

In [560]: data_test['SuperBowlWeek'] = test_df['Week'].apply(lambda x: 1 if x == 6 else 0)
          data_test['LaborDay'] = test_df['Week'].apply(lambda x: 1 if x == 36 else 0)
          data_test['Thanksgiving'] = test_df['Week'].apply(lambda x: 1 if x == 47 else 0)
          data_test['Christmas'] = test_df['Week'].apply(lambda x: 1 if x == 52 else 0)
```

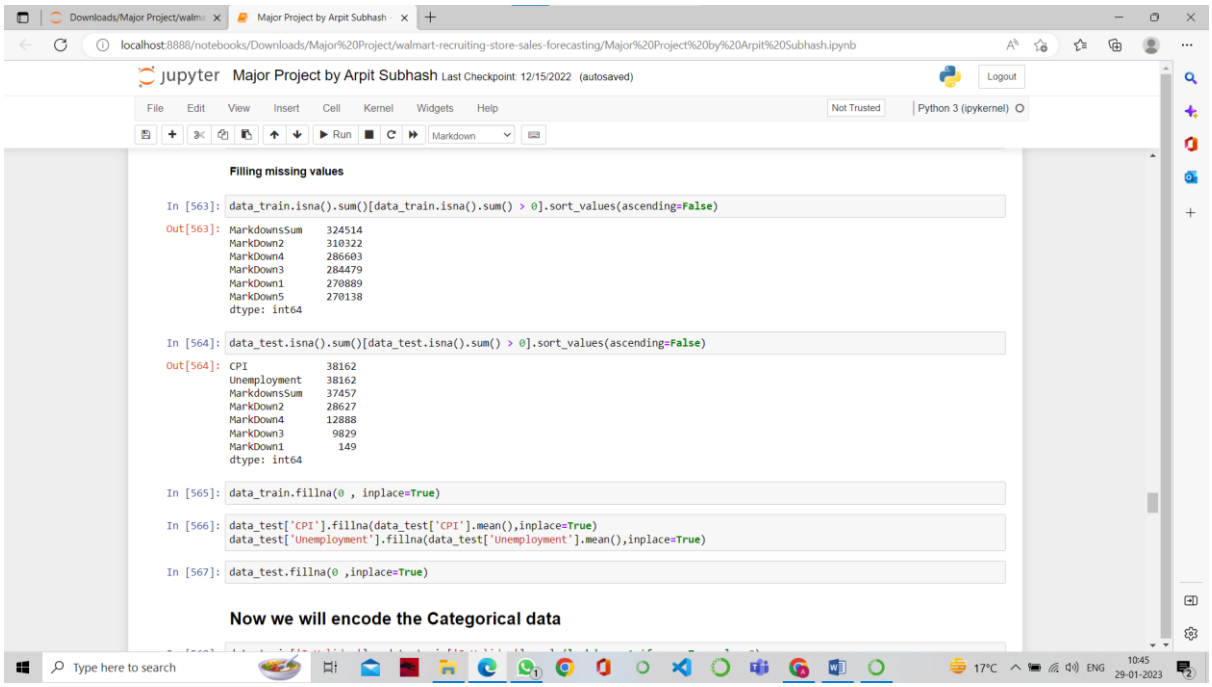
Markdowns

```
In [561]: data_train['MarkdownsSum'] = train_df['MarkDown1'] + train_df['MarkDown2'] + train_df['MarkDown3'] + train_df['MarkDown4'] + tra

In [562]: data_test['MarkdownsSum'] = test_df['MarkDown1'] + test_df['MarkDown2'] + test_df['MarkDown3'] + test_df['MarkDown4'] + test_df[
```

Filling missing values

```
In [563]: data_train.isna().sum()[data_train.isna().sum() > 0].sort_values(ascending=False)
```

6. <u>Preprocessing</u> – Since all the Markdowns were having null values so I filled all the null values.

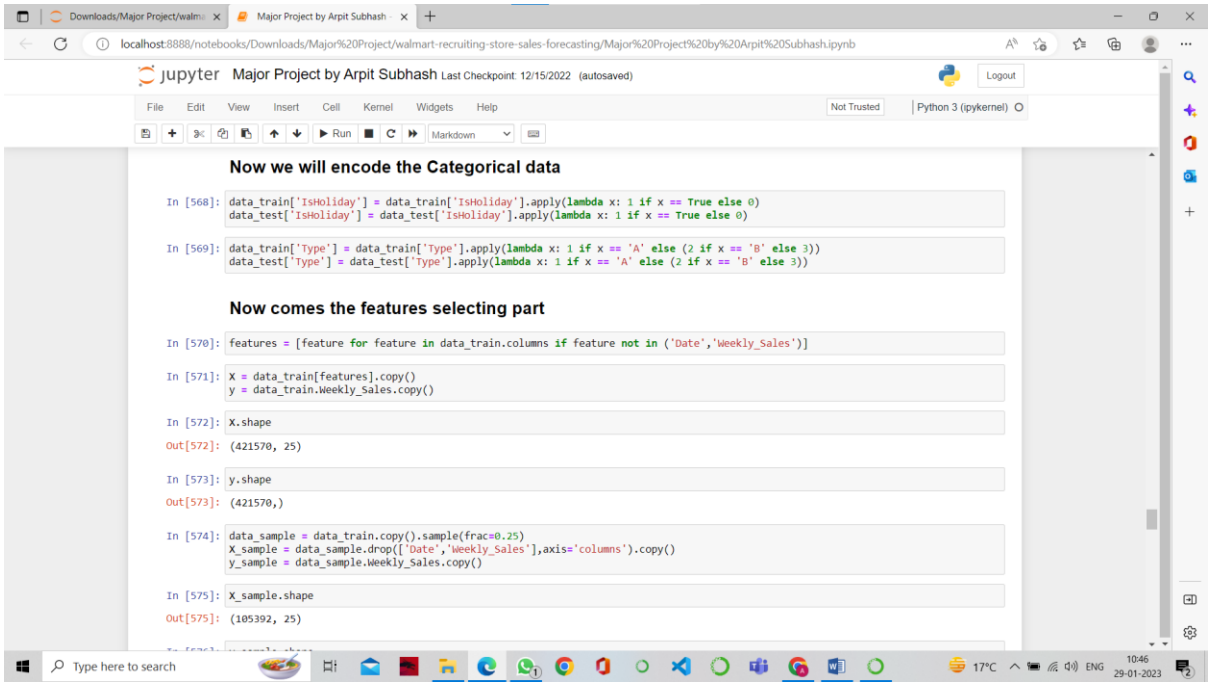


Filling missing values

```
In [563]: data_train.isna().sum()[data_train.isna().sum() > 0].sort_values(ascending=False)

Out[563]: MarkdownsSum    324514
          MarkDown2       310322
          MarkDown4       286603
          MarkDown3       284479
          MarkDown1       270889
          MarkDown5       270138
          dtype: int64

In [564]: data_test.isna().sum()[data_test.isna().sum() > 0].sort_values(ascending=False)

Out[564]: CPI             38162
          Unemployment    38162
          MarkdownsSum    37457
          MarkDown2       28627
          MarkDown4       12888
          MarkDown3        9829
          MarkDown1         149
          dtype: int64

In [565]: data_train.fillna(0 , inplace=True)

In [566]: data_test['CPI'].fillna(data_test['CPI'].mean(),inplace=True)
          data_test['Unemployment'].fillna(data_test['Unemployment'].mean(),inplace=True)

In [567]: data_test.fillna(0 ,inplace=True)
```

Now we will encode the Categorical data

7. <u>Encoding the categorical data</u> – Like if there is holiday then it is 1 otherwise 0 and some more.



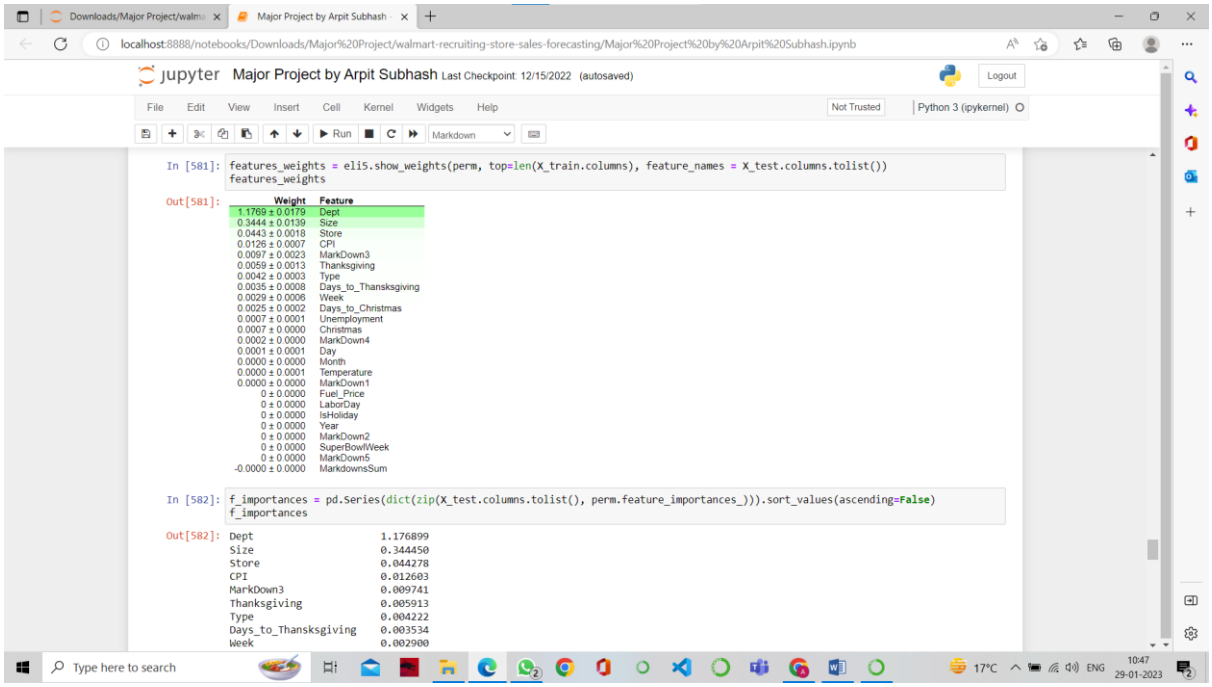
Now we will encode the Categorical data

```
In [568]: data_train['IsHoliday'] = data_train['IsHoliday'].apply(lambda x: 1 if x == True else 0)
          data_test['IsHoliday'] = data_test['IsHoliday'].apply(lambda x: 1 if x == True else 0)

In [569]: data_train['Type'] = data_train['Type'].apply(lambda x: 1 if x == 'A' else (2 if x == 'B' else 3))
          data_test['Type'] = data_test['Type'].apply(lambda x: 1 if x == 'A' else (2 if x == 'B' else 3))
```

Now comes the features selecting part

```
In [570]: features = [feature for feature in data_train.columns if feature not in ('Date','Weekly_Sales')]

In [571]: X = data_train[features].copy()
          y = data_train.Weekly_Sales.copy()

In [572]: X.shape
Out[572]: (421570, 25)

In [573]: y.shape
Out[573]: (421570,)

In [574]: data_sample = data_train.copy().sample(frac=0.25)
          X_sample = data_sample.drop(['Date','Weekly_Sales'],axis='columns').copy()
          y_sample = data_sample.Weekly_Sales.copy()

In [575]: X_sample.shape
Out[575]: (105392, 25)
```

8. <u>Feature Selection</u> - First I selected the top 5 features that were Dept, Size, Store, CPI, Markdown3 by using one library eli5.



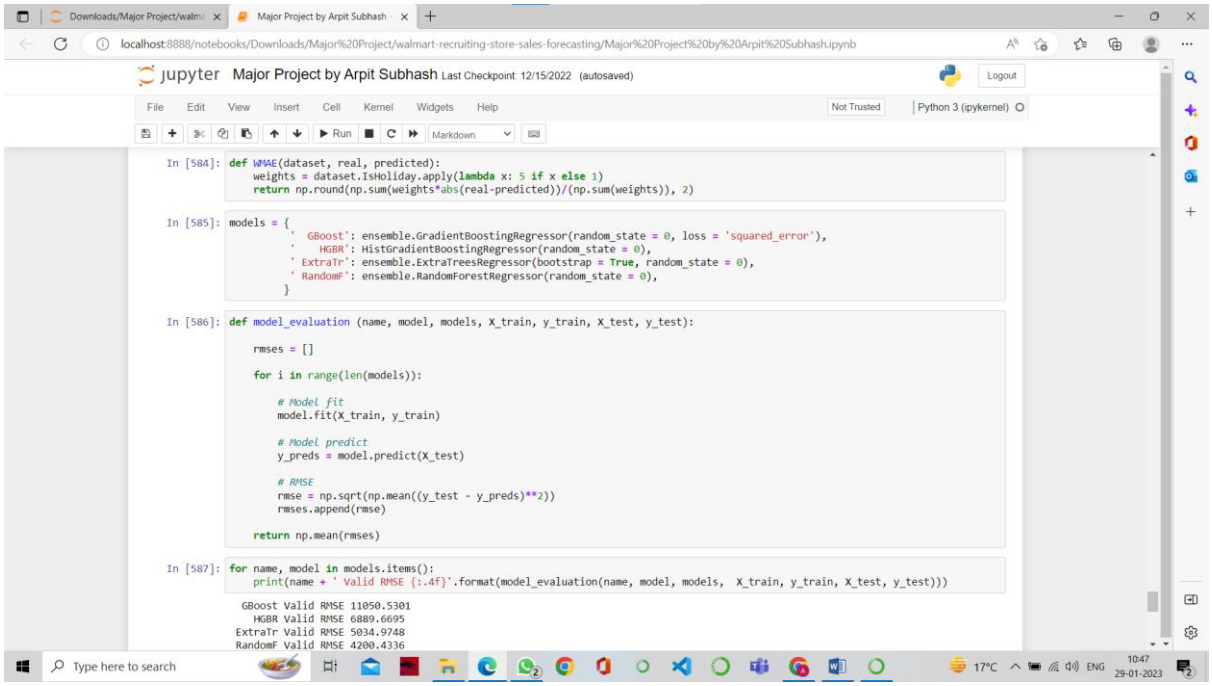
```
In [581]: features_weights = eli5.show_weights(perm, top=len(X_train.columns), feature_names = X_test.columns.tolist())
          features_weights
```

Out[581]:

Weight	Feature
1.1769 ± 0.0179	Dept
0.3444 ± 0.0139	Size
0.0443 ± 0.0018	Store
0.0126 ± 0.0007	CPI
0.0097 ± 0.0023	MarkDown3
0.0059 ± 0.0013	Thanksgiving
0.0042 ± 0.0003	Type
0.0035 ± 0.0008	Days_to_Thansksgiving
0.0029 ± 0.0006	Week
0.0025 ± 0.0002	Days_to_Christmas
0.0007 ± 0.0001	Unemployment
0.0007 ± 0.0000	Christmas
0.0002 ± 0.0000	MarkDown4
0.0001 ± 0.0001	Day
0.0000 ± 0.0000	Month
0.0000 ± 0.0001	Temperature
0.0000 ± 0.0000	MarkDown1
0 ± 0.0000	Fuel_Price
0 ± 0.0000	LaborDay
0 ± 0.0000	IsHoliday
0 ± 0.0000	Year
0 ± 0.0000	MarkDown2
0 ± 0.0000	SuperBowlWeek
0 ± 0.0000	MarkDown5
-0.0000 ± 0.0000	MarkdownsSum

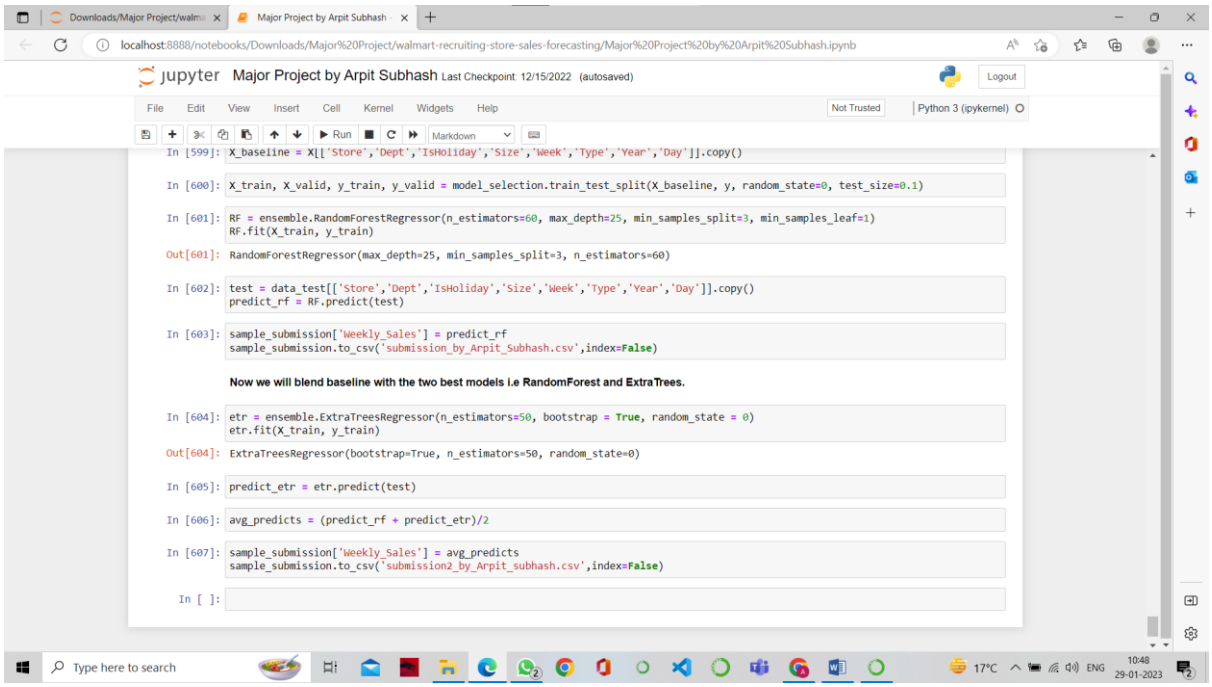
```
In [582]: f_importances = pd.Series(dict(zip(X_test.columns.tolist(), perm.feature_importances_))).sort_values(ascending=False)
          f_importances
Out[582]: Dept                  1.176899
          Size                  0.344450
          Store                 0.044278
          CPI                   0.012603
          MarkDown3             0.009741
          Thanksgiving          0.005913
          Type                  0.004222
          Days_to_Thansksgiving 0.003534
          Week                  0.002900
```

9. <u>Models</u> – Then I used the models like GBoost, HGBR, ExtraTrees, Random Forest and it comes out that the Random Forest was giving most accurate value or the least error.



```
In [584]: def WMAE(dataset, real, predicted):
              weights = dataset.IsHoliday.apply(lambda x: 5 if x else 1)
              return np.round(np.sum(weights*abs(real-predicted))/(np.sum(weights)), 2)

In [585]: models = {
                '  GBoost': ensemble.GradientBoostingRegressor(random_state = 0, loss = 'squared_error'),
                '    HGBR': HistGradientBoostingRegressor(random_state = 0),
                ' ExtraTr': ensemble.ExtraTreesRegressor(bootstrap = True, random_state = 0),
                ' RandomF': ensemble.RandomForestRegressor(random_state = 0),
                }

In [586]: def model_evaluation (name, model, models, X_train, y_train, X_test, y_test):

              rmses = []

              for i in range(len(models)):

                  # Model fit
                  model.fit(X_train, y_train)

                  # Model predict
                  y_preds = model.predict(X_test)

                  # RMSE
                  rmse = np.sqrt(np.mean((y_test - y_preds)**2))
                  rmses.append(rmse)

              return np.mean(rmses)

In [587]: for name, model in models.items():
              print(name + ' Valid RMSE {:.4f}'.format(model_evaluation(name, model, models,  X_train, y_train, X_test, y_test)))

  GBoost Valid RMSE 11050.5301
    HGBR Valid RMSE 6889.6695
 ExtraTr Valid RMSE 5034.9748
 RandomF Valid RMSE 4200.4336
```

10. <u>Baseline model</u> – At last I created a baseline model with Random Forest and Extra Trees Regressor.



```
In [599]: X_baseline = X[['Store','Dept','IsHoliday','Size','Week','Type','Year','Day']].copy()

In [600]: X_train, X_valid, y_train, y_valid = model_selection.train_test_split(X_baseline, y, random_state=0, test_size=0.1)

In [601]: RF = ensemble.RandomForestRegressor(n_estimators=60, max_depth=25, min_samples_split=3, min_samples_leaf=1)
          RF.fit(X_train, y_train)

Out[601]: RandomForestRegressor(max_depth=25, min_samples_split=3, n_estimators=60)

In [602]: test = data_test[['Store','Dept','IsHoliday','Size','Week','Type','Year','Day']].copy()
          predict_rf = RF.predict(test)

In [603]: sample_submission['Weekly_Sales'] = predict_rf
          sample_submission.to_csv('submission_by_Arpit_Subhash.csv',index=False)
```

Now we will blend baseline with the two best models i.e RandomForest and ExtraTrees.

```
In [604]: etr = ensemble.ExtraTreesRegressor(n_estimators=50, bootstrap = True, random_state = 0)
          etr.fit(X_train, y_train)

Out[604]: ExtraTreesRegressor(bootstrap=True, n_estimators=50, random_state=0)

In [605]: predict_etr = etr.predict(test)

In [606]: avg_predicts = (predict_rf + predict_etr)/2

In [607]: sample_submission['Weekly_Sales'] = avg_predicts
          sample_submission.to_csv('submission2_by_Arpit_subhash.csv',index=False)

In [ ]:
```