Introduction

The data is provided with historical sales data for 1,115 Rossmann stores. The task is to forecast the "Sales" column for the test set.

```
Importing Basic Libraries
In [1]: import numpy as np import pandas as pd
         import matplotlib.pyplot as plt
from pandas import datetime as dt
         import seaborn as sns
         c:\users\user\anaconda3\lib\site-packages\ipykernel_launcher.py:4: FutureWarning: The pandas.datetime class is deprecated and will be removed from pandas in a future version. Import from datetime module instead.

after removing the cwd from sys.path.
        Reading Data:
 In [3]: train = pd.read_csv('train.csv',low_memory = False)
 In [4]: train.head()
Out[4]: Store DayOfWeek Date Sales Customers Open Promo StateHoliday SchoolHoliday
                  5 2015-07-31 5263
                                              555
         1 2 5 2015-07-31 6064 625 1
                                                                      0
         2 3 5 2015-07-31 8314 821
                                                                      0
         3 4 5 2015-07-31 13995 1498 1 1
                                                                      0
         4 5 5 2015-07-31 4822 559 1
        Converting Date Column to DateTime Data type :
 In [5]: train['Date'] = pd.to_datetime(train['Date'])
        Extracting Date Features :
         train['Year'] = train['Date'].dt.year
train['Month'] = train['Date'].dt.month
train['Day'] = train['Date'].dt.day
 In [7]: train = train.drop('Date',axis=1)
        Exploratory Data Analysis
 In [8]: train.shape
Out[8]: (1017209, 11)
 In [9]: train.columns
In [10]: train.info()
```

In [11]: train.describe().T

L]:		count	mean	std	min	25%	50%	75%	max
	Store	1017209.0	558.429727	321.908651	1.0	280.0	558.0	838.0	1115.0
	DayOfWeek	1017209.0	3.998341	1.997391	1.0	2.0	4.0	6.0	7.0
	Sales	1017209.0	5773.818972	3849.926175	0.0	3727.0	5744.0	7856.0	41551.0
	Customers	1017209.0	633.145946	464.411734	0.0	405.0	609.0	837.0	7388.0
	Open	1017209.0	0.830107	0.375539	0.0	1.0	1.0	1.0	1.0
	Promo	1017209.0	0.381515	0.485759	0.0	0.0	0.0	1.0	1.0
	SchoolHoliday	1017209.0	0.178647	0.383056	0.0	0.0	0.0	0.0	1.0
	Year	1017209.0	2013.832292	0.777396	2013.0	2013.0	2014.0	2014.0	2015.0
	Month	1017209.0	5.846762	3.326097	1.0	3.0	6.0	8.0	12.0
nJax]/extensions/Safe.js								

SchoolHoliday 1017209 non-null int64
Year 1017209 non-null int64
Month 1017209 non-null int64
Day 1017209 non-null int64

10 Day 1017209 dtypes: int64(10), object(1) memory usage: 85.4+ MB

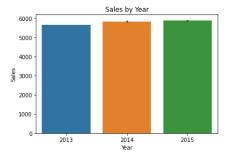
Loading [Math

```
Day 1017209.0 15.702790 8.787638 1.0 8.0 16.0 23.0 31.0
```

Plots

```
In [13]:
sns.barplot(x = train['Year'], y = train['Sales'])
plt.title('Sales by Year')
```

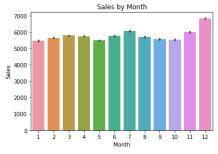
Out[13]: Text(0.5, 1.0, 'Sales by Year')



Maximum Sales was in Year 2014 and 2015

```
In [14]:
    sns.barplot(x = train['Month'], y = train['Sales'])
    plt.title('Sales by Month')
```

Out[14]: Text(0.5, 1.0, 'Sales by Month')



highest sales was in 12th month i.e, December

Creating Function to check various aspects of the dataset :

```
In [18]:
    def sniff_modified(df):
        data = pd.DataFrame()
        data['Data Type'] = df.dtypes
        data['Percent_Missing'] = (df.isnull().sum()*100)/len(df)
        data['Unique_values'] = df.apply(lambda x: x.unique())
        data['Count_Unique_values'] = df.apply(lambda x: len(x.unique()))
        return data.sort_values('Data Type')
```

In [19]: sniff modified(train)

Out[19]:	Data Type		Percent_Missing Unique_val		Count_Unique_values	
	Store int64 0.0		0.0	[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	1115	
	DayOfWeek	int64	0.0	[5, 4, 3, 2, 1, 7, 6]	7	
	Sales	int64	0.0	[5263, 6064, 8314, 13995, 4822, 5651, 15344, 8	21734	
	Customers	int64	0.0	[555, 625, 821, 1498, 559, 589, 1414, 833, 687	4086	
	Open	int64	0.0	[1, 0]	2	
	Promo	int64	0.0	[1, 0]	2	
	SchoolHoliday	int64	0.0	[1, 0]	2	
	Year	int64	0.0	[2015, 2014, 2013]	3	
	Month	int64	0.0	[7, 6, 5, 4, 3, 2, 1, 12, 11, 10, 9, 8]	12	
	Day	int64	0.0	[31,30,29,28,27,26,25,24,23,22,21,2	31	
	StateHoliday	object	0.0	[0, a, b, c]	4	

```
import category_encoders as ce
encoder = ce.OrdinalEncoder(mapping=[{'col':'StateHoliday','mapping':{'0':0,'a':1,'b':2,'c':3}}])
Loading[MathJax]extensions/Safe.js
```

```
encoder.fit(train)
train = encoder.transform(train)
```

Training The Model

```
from sklearn.ensemble import RandomForestRegressor
            from sklearn.metrics import rainconnectestreequesor
from sklearn.metrics import r2_score,accuracy_score,mean_absolute_error
from sklearn.model_selection import train_test_split
x = train.drop('Sales',axis = 1)
y = train('Sales')
            X_train,X_test,y_train,y_test = train_test_split(x,y,test_size = 0.20)
rf = RandomForestRegressor(n_jobs = -1,n_estimators=100)
             rf.fit(X_train,y_train)
Out[23]: RandomForestRegressor(n_jobs=-1)
            prediction = rf.predict(X_test)
             r2 = r2_score(y_test,prediction)
e = mean_absolute_error(y_test,prediction)
             ep = e*100 / y_test.mean()
In [25]: print(f"R^2 Score :{r2:.2f}")
            R^2 Score :0.96
In [26]: print(f"${e:.0f} error; {ep:.2f}% error")
            $470 error; 8.14% error
In [27]: output = pd.DataFrame({'Actual_Values':y_test,'Predictions':prediction})
In [28]: output.head(20)
                 Actual_Values Predictions
            876867
                             9225
                                      9027.68
            934965
                             3745 3641.16
            275889
                             4983
                                      5345.60
            627106
                            16353 17958.03
            918021
                             9562
                                      11022.88
            968817
                             7118
                                      6963.04
            928003
                             5653
                                       5806.58
            103893
                            10171
                                       7934.71
             76761
                               0
                                         0.00
            316936
                             8725 8133.48
            681209
                             6190
                                       6455.90
                             7932 6981.23
            264176
            705656
                             7655
                                       8108.53
            80492
                             9124
                                      8802.82
            491768
                             7540
                                       8409.51
            488844
                             7438
                                       7503.38
            188351
                             9934
                                       8958.75
             64489
                             6462
                                       6911.31
             73749
                             5083
                                       5496.78
            379215
                             7992
                                       8185.42
```