USED CAR PRICE PREDICTION PROJECT

By
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INTRODUCTION

- The prices of new cars in the industry is fixed by the manufacturer with some additional costs incurred by the Government in the form of taxes.
- So, customers buying a new car can be assured of the money they invest to be worthy. But due to the increased price of new cars and the incapability of customers to buy new cars due to the lack of funds, used cars sales are on a global increase (Pal, Arora and Palakurthy, 2018).
- There is a need for a used car price prediction system to effectively determine the worthiness of the car using a variety of features.
- Even though there are websites that offers this service, their prediction method may not be the best. Besides, different models and systems may contribute on predicting power for a used car's actual market value. It is important to know their actual market value while both buying and selling

Objective or Problem Statement

The objective of this project is scrape data of used cars from websites such as olx, cardekho etc and use those features to predict the carprices.

With the covid 19 impact in the market, we have seen lot of changes in the car market. Now some cars are in demand hence making them costly and some are not in demand hence cheaper. Therefore we need a ML model in order to predict the price of the used car based on features such as Brand, model, variant, manufacturing year, driven kilometers, fuel, number of owners, location etc

Dataset

- This is a sample of the dataset which was scraped from olx.in. There are 5922 rows and 9 columns in the dataset.
- Here the target variable is ‘Price” which consist of continuous numerical values,Therefore we can see that it is a Regression problem.

```
df = pd.read_csv("dfcar.csv")
#importing the file which we have extracted using selenium
pd.set_option('display.max_columns', None) # displays maximum columns
df
```

	Brand	Model	Variant	Manufacturig year	Kilometers driven	Fuel	No of Owners	Location	Price
0	Toyota	Innova Crysta	2.4 V	2017	53,000 km	Diesel	2nd	Puthanathani, Malappuram, Kerala	₹ 18,50,000
1	BMW	5 Series	520d Luxury Line	2011	140,000 km	Diesel	1st	Koduvally, Kozhikode, Kerala	₹ 10,45,000
2	Renault	KWID	Climber 1.0 MT Opt	2018	13,000 km	Petrol	1st	Kazhakoottam, Thiruvananthapuram, Kerala	₹ 3,70,000
3	Renault	KWID	1.0 RXT AMT Opt	2017	23,000 km	Petrol	1st	Kazhakoottam, Thiruvananthapuram, Kerala	₹ 3,80,000

Exploratory data analysis

Checking for null or '-' values:

```
: print((df == '-').sum())

Brand                 0
Model                 0
Variant               0
Manufacturig year     0
Kilometers driven     0
Fuel                  0
No of Owners          0
Location              0
Price                 0
dtype: int64
```

```
: df.isnull().sum() #checking null values.

: Brand                 0
  Model                 0
  Variant               0
  Manufacturig year     0
  Kilometers driven     0
  Fuel                  0
  No of Owners          0
  Location              0
  Price                 0
  dtype: int64
```

There are no null values.

Location column

We can see from below that there are lot of unique values in the location column. Therefore, to simplify it we can only take out the states instead of the whole address.

```
df['Location'].nunique()
```

```
1191
```

```
# new data frame with split value columns
df["State"] = df["Location"].str.split(",", expand = True)[2]
```

```
df.drop('Location',axis=1,inplace=True)
```

We have now created a new column state and dropped location

“Kilometers driven” and “Price” columns

```
df.dtypes #checking data types
```

```
Brand                   object
Model                   object
Variant                 object
Manufacturig year        int64
Kilometers driven       object
Fuel                    object
No of Owners            object
Price                   object
State                   object
dtype: object
```

We can see that kilometers driver and price is object type. We need to convert them into integers

Removing unnecessary things from the column values

```
df['Kilometers driven']=df['Kilometers driven'].apply(lambda x: x.replace(',',''))
```

```
df['Kilometers driven'] = df['Kilometers driven'].str.extract(r'(\d+[.\d]*)')
```

```
df['Price']=df['Price'].apply(lambda x: x.replace(',',''))
```

```
df['Price'] = df['Price'].str.extract(r'(\d+[.\d]*)')
```

“Kilometers driven” and “Price” columns

```
df["Kilometers driven"] = pd.to_numeric(df["Kilometers driven"])
```

```
df["Price"] = pd.to_numeric(df["Price"])
```

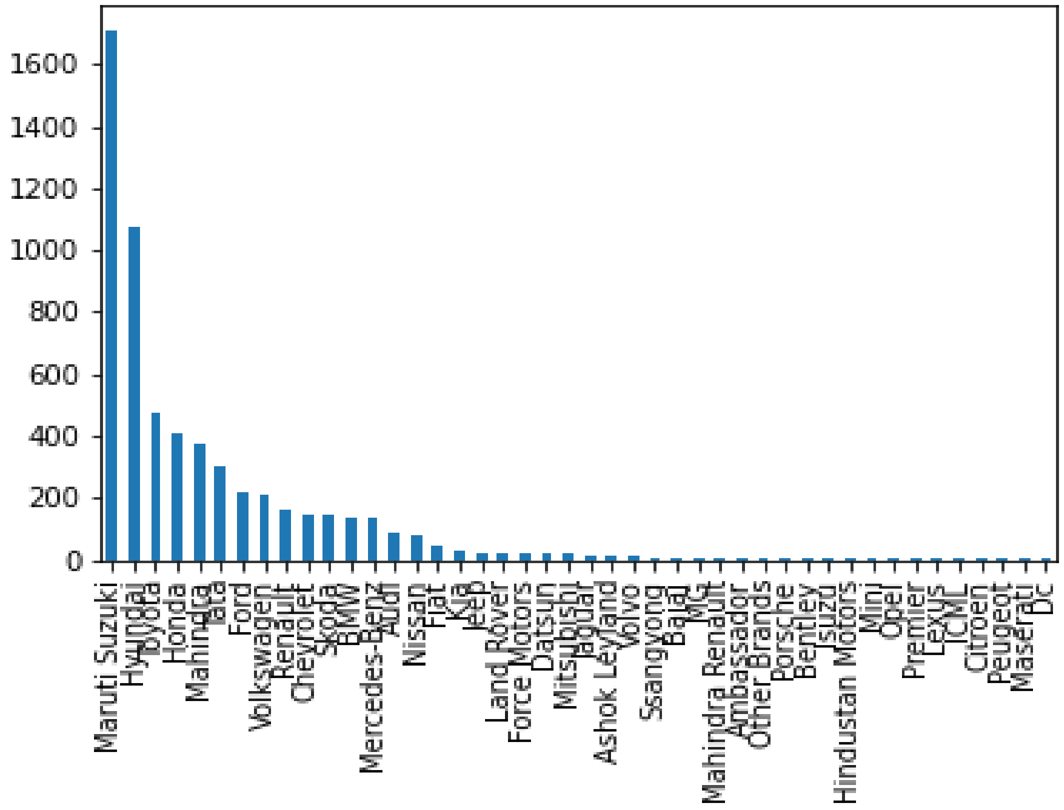
```
df.dtypes
```

```
Brand                  object
Model                  object
Variant                object
Manufacturig year       int64
Kilometers driven       int64
Fuel                   object
No of Owners           object
Price                   int64
State                  object
dtype: object
```

We have now converted kilometers driver and price into integers

“Brand” column

```
df['Brand'].value_counts().plot.bar()
plt.show()
```



We can see here that maximum of the people buy maruti suzuki brand cars

“Model” Column

```
df['Model'].value_counts()
```

```
Swift                           288
Swift Dzire                     183
Innova                          179
i10                             167
i20                             164
Wagon R                         152
City                            151
Polo                            122
XUV500                          119
Verna                           111
Santro Xing                     105
Others                           97
Grand i10                        96
Creta                            94
Alto                             90
Ertiga                           84
Baleno                           84
Ecosport                         84
800                              77
```

we can see that maximum people buy maruti suzuki swift car.

“Variant” column

```
df['Variant'].value_counts()
```

```
Others                340
VXI                   138
VDI                   114
LXI                   105
LXi                    47
GLS                    41
Magna                  33
2.5 V 7 STR            31
2011-2014 VDI          30
1.2 Kappa Magna        30
AC                     29
1.6 CRDi SX            29
VDi                    27
1.5 TDI Highline       27
LDI                    26
1.2 Spotz              24
Era                    23
LX                     23
Sportz                 22
```

Here others is highest which we cannot say and therefore is ambigous.

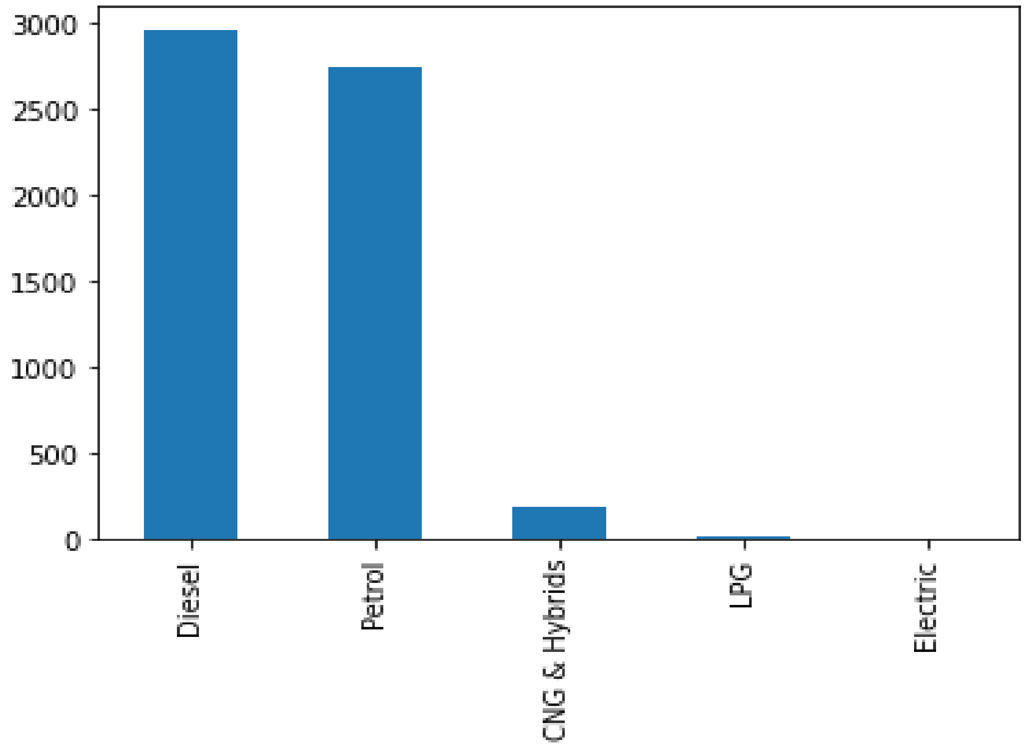
```
df['Variant'].nunique() #checking unique values
```

We can see that there are many unique values in "Variant" Column, and also from the above point we can just drop this column as it won't be helpful.

```
df.drop('Variant',axis=1,inplace=True)
```

“Fuel” Column

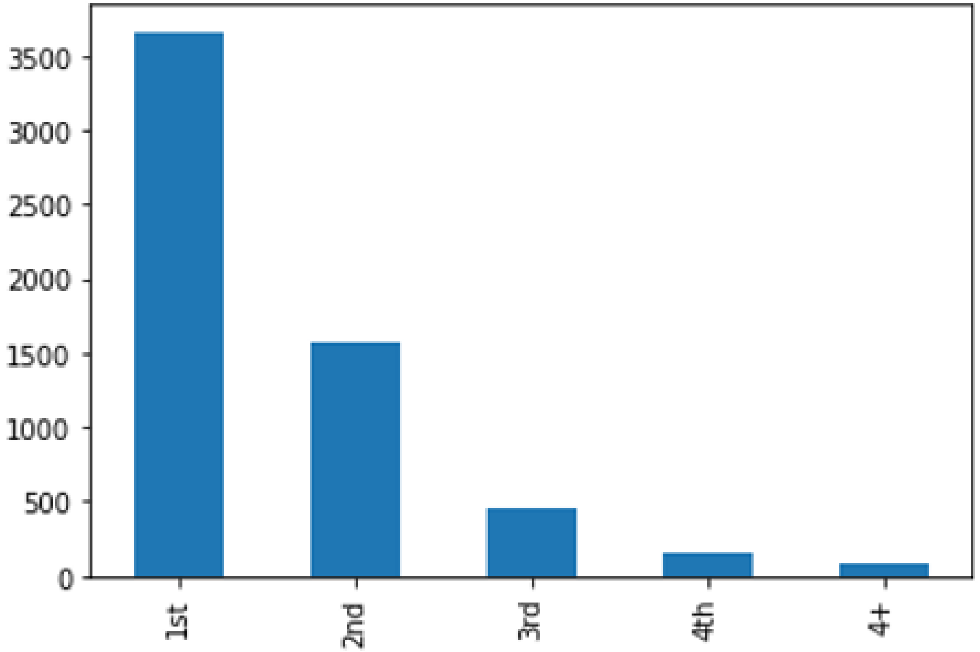
```
df['Fuel'].value_counts().plot.bar()
plt.show()
```



We can see that maximum people prefer to buy diesal cars.

“No of Owners” Column

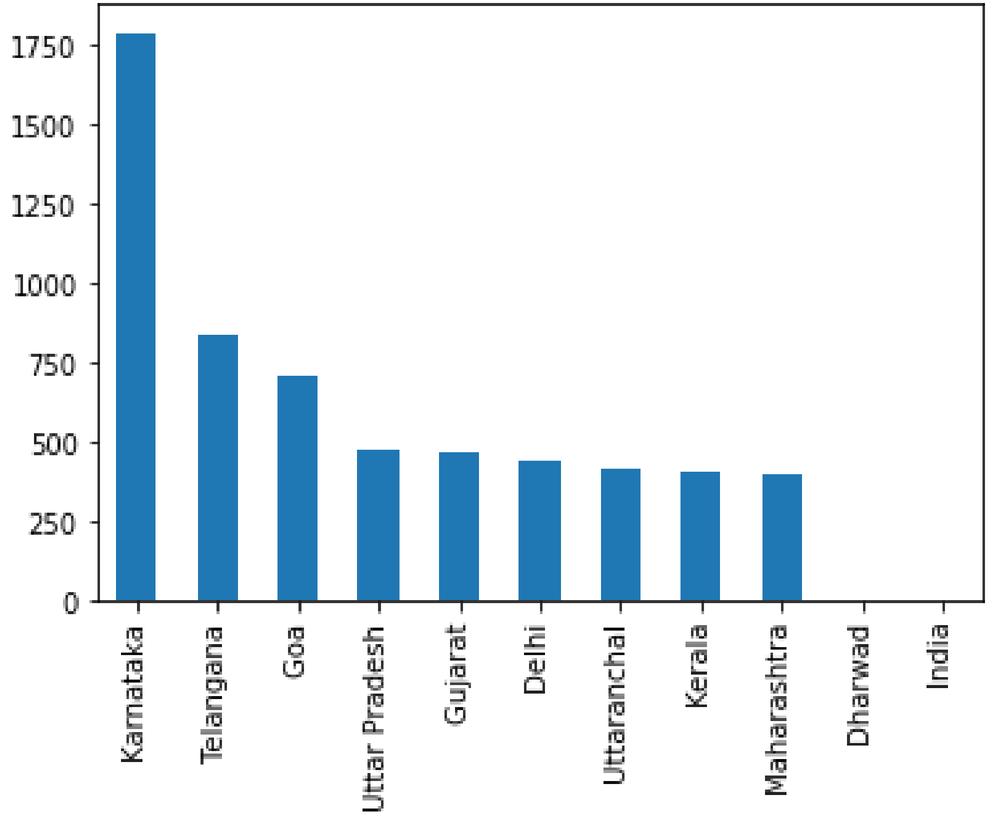
```
df['No of Owners'].value_counts().plot.bar()
plt.show()
```



We can see that maximum people buy car which was owned by only 1 person. Naturally this is because the lesser the owners owned before, better the condition of the car.

“State” Column

```
df['State'].value_counts().plot.bar()
plt.show()
```



We can see that maximum of the used cars are sold in Karnataka

Data Preprocessing

```
#Scaling
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

for i in ['Kilometers driven']:
    df[[i]]=scaler.fit_transform(df[[i]])
```

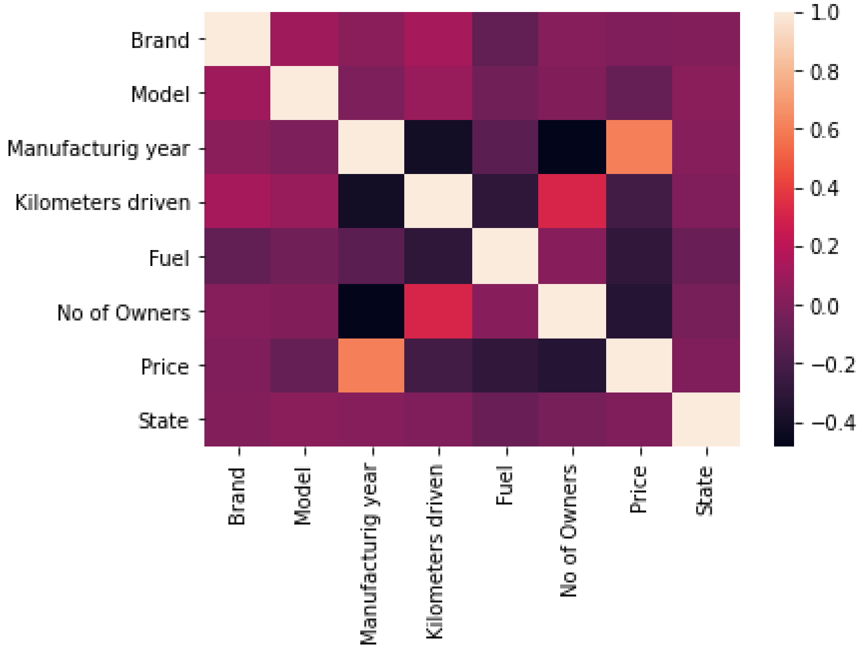
```
#Label Encoding
from sklearn.preprocessing import LabelEncoder
label = LabelEncoder()
for i in ['Brand','Model','Manufacturig year','Kilometers driven','Fuel','No of Owners','Price','State']:
    df[i]=label.fit_transform(df[i])
```

Correlation

```
df.corr()
```

	Brand	Model	Manufacturig year	Kilometers driven	Fuel	No of Owners	Price	State
Brand	1.000000	0.105976	0.030972	0.125512	-0.111909	0.018655	-0.005285	0.008898
Model	0.105976	1.000000	-0.012140	0.079423	-0.049528	0.000656	-0.092153	0.030636
Manufacturig year	0.030972	-0.012140	1.000000	-0.409764	-0.132295	-0.483513	0.601707	0.018801
Kilometers driven	0.125512	0.079423	-0.409764	1.000000	-0.298181	0.312665	-0.219021	-0.005153
Fuel	-0.111909	-0.049528	-0.132295	-0.298181	1.000000	0.021271	-0.292093	-0.078379
No of Owners	0.018655	0.000656	-0.483513	0.312665	0.021271	1.000000	-0.338083	-0.034446
Price	-0.005285	-0.092153	0.601707	-0.219021	-0.292093	-0.338083	1.000000	-0.002741
State	0.008898	0.030636	0.018801	-0.005153	-0.078379	-0.034446	-0.002741	1.000000

```
sns.heatmap(df.corr())
plt.show()
#Heat map of correlation between columns
```



We can see that there is no multicorralation.

Splitting of data into Independent and Target variables

```
ind=df.drop("Price",axis=1)
tar=df["Price"]
#splitting individual and target variable in ind and tar
```

```
from sklearn.model_selection import train_test_split

# splitting data into training and testing
ind_train, ind_test, tar_train, tar_test = train_test_split(ind, tar, test_size=0.33, random_state=42)
```

- Hardware and Software Requirements and Tools Used

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
import warnings
warnings.filterwarnings('ignore')
```

```python
from sklearn.preprocessing import MinMaxScaler
```

```python
from sklearn.preprocessing import LabelEncoder
```

```python
from sklearn.model_selection import train_test_split
```

```python
#Importing Machine Learning Models
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import make_scorer
from sklearn.metrics import r2_score,mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.ensemble import AdaBoostRegressor
```

```python
from sklearn.model_selection import cross_val_score
```

```python
from sklearn.model_selection import GridSearchCV
```

Algorithms used

- Testing of Identified Approaches (Algorithms)
- DecisionTreeRegressor
- RandomForestRegressor
- LinearRegression
- XGBRegressor
- AdaBoostRegressor

```
#Importing Machine Learning Models
from sklearn.neighbors import KNeighborsRegressor
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from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import make_scorer
from sklearn.metrics import r2_score,mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.ensemble import AdaBoostRegressor
```

```
dt = DecisionTreeRegressor()
rf = RandomForestRegressor()
lr= LinearRegression()
xg = XGBRegressor()
ad = AdaBoostRegressor()
```

Results:

```
for m in [rf,lr,xg,ad,dt]:
    m.fit(ind_train,tar_train)
    train_predict = m.predict(ind_train)
    test_predict = m.predict(ind_test)
    print('for',m)
    print("RMSE of train:", np.sqrt(mean_squared_error(tar_train, train_predict)))
    print("RMSE of test:", np.sqrt(mean_squared_error(tar_test, test_predict)))
    print("Train R^2: ", r2_score(tar_train, train_predict))
    print("Test R^2: ", r2_score(tar_test, test_predict))
    print("..........\n")
```

```
for RandomForestRegressor()
RMSE of train: 27.113481739416102
RMSE of test: 75.53616411645457
Train R^2:  0.9762729958535608
Test R^2:  0.8221423234277269
..........

for LinearRegression()
RMSE of train: 133.22525711955115
RMSE of test: 136.38377789940435
Train R^2:  0.42714400897223004
Test R^2:  0.4201866719070394
..........
```

Results:

```
for XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.300000012, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=4, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
RMSE of train: 22.955064326872662
RMSE of test: 67.44702623489738
Train R^2:  0.9829929357088604
Test R^2:  0.8581960352093563
..........

for AdaBoostRegressor(n_estimators=100, random_state=0)
RMSE of train: 128.30019991639577
RMSE of test: 134.18700835967067
Train R^2:  0.46871568881793235
Test R^2:  0.43871465573651824
..........

for DecisionTreeRegressor()
RMSE of train: 1.5547591000446013
RMSE of test: 103.11157639518838
Train R^2:  0.9999219813304426
Test R^2:  0.6685808384104553
..........
```

Cross Validation:

```
from sklearn.model_selection import cross_val_score
# function to get cross validation scores
def get_cv_scores(model):
    scores = cross_val_score(model,
                             ind_train,
                             tar_train,
                             cv=5,
                             scoring='r2')

    print('CV Mean: ', np.mean(scores))
    print('STD: ', np.std(scores))
    print('\n')
```

```
for i in [rf,lr,xg,ad,dt]:
    print('for',i)
    print(get_cv_scores(i))
```

```
for RandomForestRegressor()
CV Mean:  0.8226862969021852
STD:  0.009232137204687978


None
for LinearRegression()
CV Mean:  0.42447176553805105
STD:  0.019002041821895507


None
for XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.300000012, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=4, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
CV Mean:  0.867971955780202
STD:  0.0071791614567836394


None
for AdaBoostRegressor(n_estimators=100, random_state=0)
CV Mean:  0.46670838955503874
STD:  0.022068279936120327
```

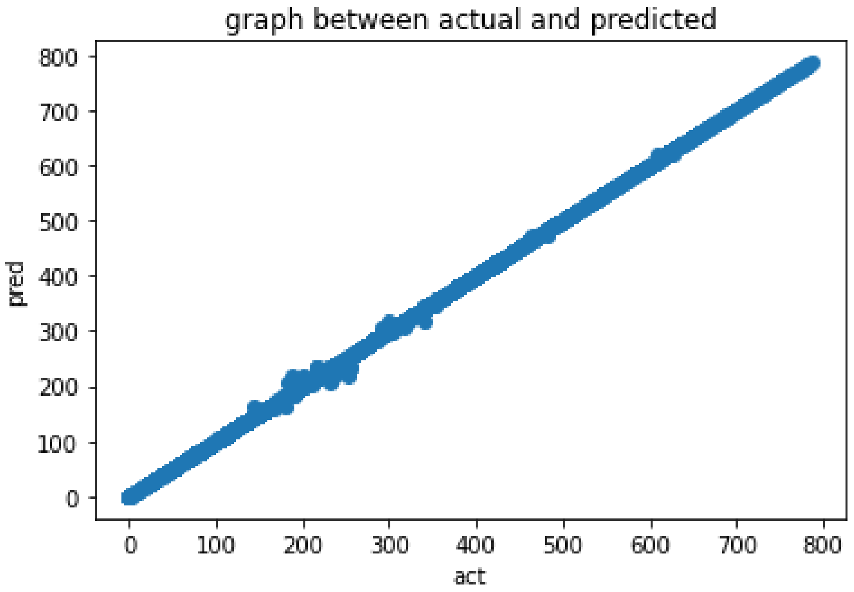
```
None
for DecisionTreeRegressor()
CV Mean:  0.6797734924948287
STD:  0.055965045725750145


None
```

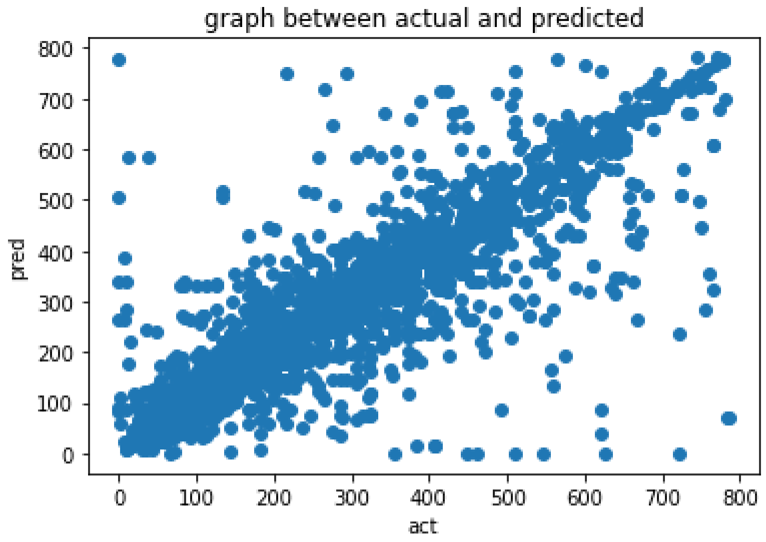
We can see that from the Accuracy score and Crossvalidation Score, XGBRegressor is performing the best. Therfore XGBRegressor is the best model

Graph between Actual and Predicted values

```
plt.scatter(tar_train, train_predict)
plt.title('graph between actual and predicted')
plt.xlabel('act')
plt.ylabel('pred')
plt.show()
```




```
plt.scatter(tar_test, test_predict)
plt.title('graph between actual and predicted')
plt.xlabel('act')
plt.ylabel('pred')
plt.show()
```



We can see that the above two graphs that the model is predicting well.

Hyperparameter tuning of XGBRegressor

```
# To find the best parameters by using GridSearchCV to improve the model
from sklearn.model_selection import GridSearchCV

parameters = {'min_child_weight':[4,5], 'gamma':[i/10.0 for i in range(3,6)],
              'subsample':[i/10.0 for i in range(6,11)],
            'colsample_bytree':[i/10.0 for i in range(6,11)], 'max_depth': [2,3,4]}

gs=GridSearchCV(xg,parameters)
gs.fit(ind_train,tar_train)
print(gs.best_params_)
#best parameters
```

```
{'colsample_bytree': 1.0, 'gamma': 0.3, 'max_depth': 4, 'min_child_weight': 5, 'subsample': 1.0}
```

```
gs.best_score_
```

```
0.8695142800886895
```

We can see that the score is good. Therefore the model is predicting well.

Conclusion

- Key Findings and Conclusions of the Study

  We have found that Logistic XGBRegressor model is the model that works best with this data among the other 4.

- Learning Outcomes of the Study in respect of Data Science

  Cleaning of the data is very important, also making them in the format they represent as it would affects the model training and thereby predict wrong results. We can eliminate features that have more no of unique values by keeping the importance of the feature in mind.

- Limitations of this work and Scope for Future Work

  The only limitation I have found is that we need to keep updating or making new models as condition change and few more features keep adding up. Therefore, we need to keep updating the model by using the new dataset.

Thank You