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In [138…

```python
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder,OrdinalEncoder
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
np.set_printoptions(suppress=True)
from scipy import stats
pd.options.display.float_format = '{:.3f}'.format
np.set_printoptions(threshold=3)
from sklearn.preprocessing import MinMaxScaler
from sklearn.ensemble import StackingRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import r2_score,mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
import xgboost as xgb
```

In [139…

```python
dataset = pd.read_csv('cars.csv')
dataset
```

Out[139…

	year_bought	km_driven	transmission	owner	selling_price
0	2007	70000	Manual	First Owner	60000
1	2007	50000	Manual	First Owner	135000
2	2012	100000	Manual	First Owner	600000
3	2017	46000	Manual	First Owner	250000
4	2014	141000	Manual	Second Owner	450000
...	...	...	...	...	...
4335	2014	80000	Manual	Second Owner	409999
4336	2014	80000	Manual	Second Owner	409999
4337	2009	83000	Manual	Second Owner	110000
4338	2016	90000	Manual	First Owner	865000
4339	2016	40000	Manual	First Owner	225000

4340 rows × 5 columns

In [140…

```python
# Data Analysis
print(dataset['transmission'].unique())
print(dataset['owner'].unique())
```

```
['Manual' 'Automatic']
['First Owner' 'Second Owner' 'Fourth & Above Owner' 'Third Owner'
 'Test Drive Car']
```

In [141…

```
# Data Preprocessing

le = LabelEncoder()
dataset['transmission'] = le.fit_transform(dataset['transmission'])
oe = OrdinalEncoder(categories=[['Test Drive Car','First Owner','Second Owner',
                                  'Third Owner','Fourth & Above Owner']],dtype=int)
dataset[['owner']] = oe.fit_transform(dataset[['owner']])
dataset
```

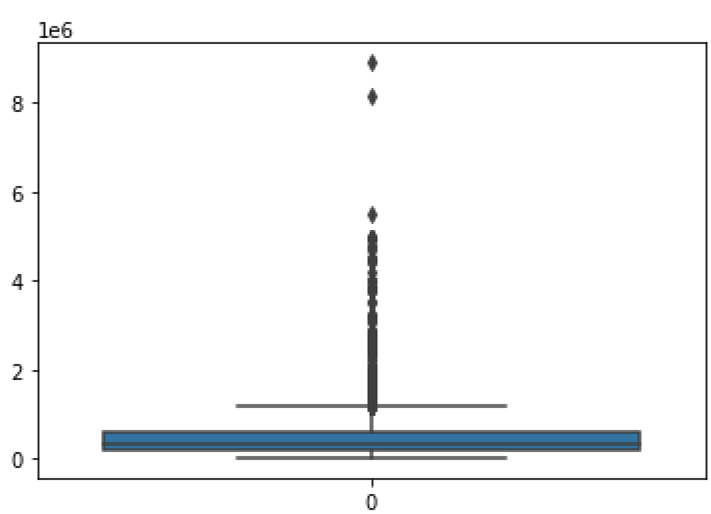
Out[141…

	year_bought	km_driven	transmission	owner	selling_price
0	2007	70000	1	1	60000
1	2007	50000	1	1	135000
2	2012	100000	1	1	600000
3	2017	46000	1	1	250000
4	2014	141000	1	2	450000
...	...	...	...	...	...
4335	2014	80000	1	2	409999
4336	2014	80000	1	2	409999
4337	2009	83000	1	2	110000
4338	2016	90000	1	1	865000
4339	2016	40000	1	1	225000

4340 rows × 5 columns

In [142…

```
# Outlier Removal
sns.boxplot(data = dataset['selling_price'])
plt.show()
z = np.abs(stats.zscore(dataset['selling_price']))
outliers = np.where(z>3)[0]
print('Outlier Indexes :',outliers)
dataset.drop(outliers,inplace = True)
```



```
Outlier Indexes : [  89   96  101 ... 4224 4304 4313]
```

In [143…

```
X = dataset[['year_bought','km_driven','transmission','owner']]
y = dataset['selling_price']
X
```

Out[143…

	year_bought	km_driven	transmission	owner
0	2007	70000	1	1
1	2007	50000	1	1
2	2012	100000	1	1
3	2017	46000	1	1
4	2014	141000	1	2
...	...	...	...	...
4335	2014	80000	1	2
4336	2014	80000	1	2
4337	2009	83000	1	2
4338	2016	90000	1	1
4339	2016	40000	1	1

4248 rows × 4 columns

In [144…

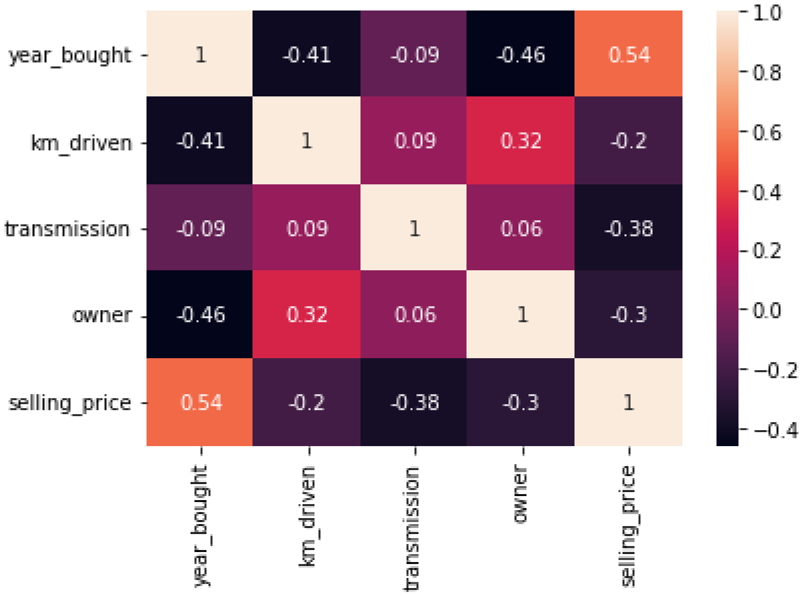
```
y
```

Out[144…

```
0        60000
1       135000
2       600000
3       250000
4       450000
         ...
4335    409999
4336    409999
4337    110000
4338    865000
4339    225000
Name: selling_price, Length: 4248, dtype: int64
```

In [145…

```
# Feature Importance
correl_matrix = dataset.corr().round(2)
sns.heatmap(data=correl_matrix, annot=True)
plt.show()
```



Hence 'year_bought' is most important feature to predict 'selling_price'

In [146…

```
# Split dataset into train and test set
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=13)
X_train
```

Out[146…

	year_bought	km_driven	transmission	owner
1863	2018	40000	1	1
2172	2016	40000	1	1
2553	2016	138925	1	1
965	2014	120000	1	1
2244	2015	11918	1	1
...	...	...	...	...
158	2020	120000	1	1
890	2018	10500	1	1
2863	2018	30000	1	1
74	2009	120000	1	3
345	2018	20000	1	1

2973 rows × 4 columns

In [147…

```
# Normalization

scaler = MinMaxScaler()
X_train[['year_bought','km_driven']] = scaler.fit_transform(
    X_train[['year_bought','km_driven']])
X_test[['year_bought','km_driven']] = scaler.transform(
    X_test[['year_bought','km_driven']])
X_train
```

Out[147…

	year_bought	km_driven	transmission	owner
1863	0.920	0.050	1	1

	year_bought	km_driven	transmission	owner
2172	0.840	0.050	1	1
2553	0.840	0.172	1	1
965	0.760	0.149	1	1
2244	0.800	0.015	1	1
...	...	...	...	...
158	1.000	0.149	1	1
890	0.920	0.013	1	1
2863	0.920	0.037	1	1
74	0.560	0.149	1	3
345	0.920	0.025	1	1

2973 rows × 4 columns

Stacking

In [148...

```
# Choosing the base models : Decision Tree, Support Vector Regressor, KNN Regressor
estimators = [('dt', DecisionTreeRegressor(random_state=13)),('svr', SVR()),
             ('knr',KNeighborsRegressor(n_neighbors = 40))]
```

In [149...

```
# Choosing the meta model : Linear Regression
stacker = StackingRegressor(estimators=estimators,final_estimator=LinearRegression())
stacker.fit(X_train,y_train)
```

Out[149...

```
StackingRegressor(estimators=[('dt', DecisionTreeRegressor(random_state=13)),
                              ('svr', SVR()),
                              ('knr', KNeighborsRegressor(n_neighbors=40))],
                  final_estimator=LinearRegression())
```

In [150...

```
# Evaluating performance of model

y_train_pred = stacker.predict(X_train)
y_test_pred = stacker.predict(X_test)

print('Training set performance :')
print('R2 Score : ',round(r2_score(y_train,y_train_pred),3))
print('RMSE : ',np.sqrt(mean_squared_error(y_train,y_train_pred)))
print()
print()
print('Test set performance :')
print('R2 Score : ',round(r2_score(y_test,y_test_pred),3))
print('RMSE : ',np.sqrt(mean_squared_error(y_test,y_test_pred)))
pred_stack = y_test_pred
```

```
Training set performance :
R2 Score :  0.65
RMSE :  194436.95481424822


Test set performance :
R2 Score :  0.451
RMSE :  251726.81985057672
```

Bagging

In [125…
```
# Using Random Forest for Bagging which contain homogeneous models : Decision Trees

bagger = RandomForestRegressor(random_state=13,n_estimators=200)
bagger.fit(X_train,y_train)
```

Out[125…
```
RandomForestRegressor(n_estimators=200, random_state=13)
```

In [151…
```
# Evaluating performance of model

y_train_pred = bagger.predict(X_train)
y_test_pred = bagger.predict(X_test)

print('Training set performance :')
print('R2 Score : ',round(r2_score(y_train,y_train_pred),3))
print('RMSE : ',np.sqrt(mean_squared_error(y_train,y_train_pred)))
print()
print()
print('Test set performance :')
print('R2 Score : ',round(r2_score(y_test,y_test_pred),3))
print('RMSE : ',np.sqrt(mean_squared_error(y_test,y_test_pred)))
pred_rf = y_test_pred
```

```
Training set performance :
R2 Score :  0.778
RMSE :  154930.07982554229


Test set performance :
R2 Score :  0.363
RMSE :  271146.0655493607
```

Boosting - AdaBoost

In [152…
```
# Using AdaBoost with Decision Trees as base estimator

ada_booster = AdaBoostRegressor(random_state=13,n_estimators=100)
ada_booster.fit(X_train,y_train)
```

Out[152…
```
AdaBoostRegressor(n_estimators=100, random_state=13)
```

In [153…
```
# Evaluating performance of model

y_train_pred = ada_booster.predict(X_train)
y_test_pred = ada_booster.predict(X_test)

print('Training set performance :')
print('R2 Score : ',round(r2_score(y_train,y_train_pred),3))
print('RMSE : ',np.sqrt(mean_squared_error(y_train,y_train_pred)))
print()
print()
print('Test set performance :')
print('R2 Score : ',round(r2_score(y_test,y_test_pred),3))
print('RMSE : ',np.sqrt(mean_squared_error(y_test,y_test_pred)))
pred_ada = y_test_pred
```

```
Training set performance :
```

```
R2 Score :  0.434
RMSE :  247483.17435028765


Test set performance :
R2 Score :  0.395
RMSE :  264230.2568571042
```

Boosting - XGBoost

In [154…

```
xg_booster = xgb.XGBRegressor(objective ='reg:squarederror',
                              learning_rate = 0.1,n_estimators = 250)
xg_booster.fit(X_train,y_train)
```

Out[154…

```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=250, n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, ...)
```

In [155…

```
# Evaluating performance of model

y_train_pred = xg_booster.predict(X_train)
y_test_pred = xg_booster.predict(X_test)

print('Training set performance :')
print('R2 Score : ',round(r2_score(y_train,y_train_pred),3))
print('RMSE : ',np.sqrt(mean_squared_error(y_train,y_train_pred)))
print()
print()
print('Test set performance :')
print('R2 Score : ',round(r2_score(y_test,y_test_pred),3))
print('RMSE : ',np.sqrt(mean_squared_error(y_test,y_test_pred)))
pred_xg = y_test_pred
```

```
Training set performance :
R2 Score :  0.74
RMSE :  167664.88955831496


Test set performance :
R2 Score :  0.41
RMSE :  260973.64632438868
```

Comparison of Results

In [156…

```
result = pd.DataFrame({'Stacking':[0.65,0.451],'Bagging (RF)':[0.778,0.363],
                        'Boosting (AdaBoost)':[0.434,0.395],
                       'Boosting (XGBoost)':[0.74,0.41]},
                       index=['R2 (Train)','R2 (Test)'])
result
```

Out[156…

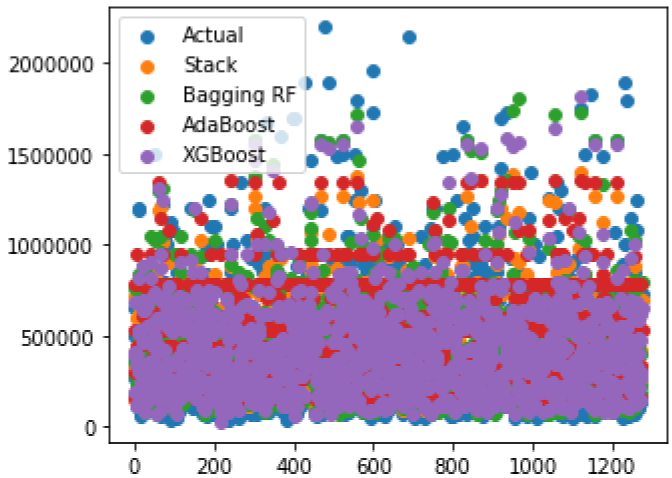
	Stacking	Bagging (RF)	Boosting (AdaBoost)	Boosting (XGBoost)
R2 (Train)	0.650	0.778	0.434	0.740

	Stacking	Bagging (RF)	Boosting (AdaBoost)	Boosting (XGBoost)
R2 (Test)	0.451	0.363	0.395	0.410

In [157…

```
# Actual vs Predicted

plt.figure(figsize=(5, 4))
ax = plt.axes()
ax.scatter(range(len(y_test)),y_test)
ax.scatter(range(len(y_test)),pred_stack)
ax.scatter(range(len(y_test)),pred_rf)
ax.scatter(range(len(y_test)),pred_ada)
ax.scatter(range(len(y_test)),pred_xg)
ax.ticklabel_format(style='plain')
plt.legend(['Actual','Stack','Bagging RF','AdaBoost','XGBoost'])
plt.show()
```



Hence XGBoost performed better than other models and AdaBoost performed the worst