```
# For data operations
import pandas as pd

# For visualisations
import seaborn as sns

# For visualisations
import matplotlib.pyplot as plt

# To set the styles for the visualisations
from matplotlib import style
style.use('seaborn')

# To find Optimal parameters for hyperparameter tuning
from sklearn.model_selection import GridSearchCV

# TO split the data into training and testing sets
from sklearn.model_selection import train_test_split

# To scale the Data
from sklearn.preprocessing import StandardScaler

#importing various Algorithms
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
from sklearn.neighbors import KNeighborsClassifier

# To measure the model performance
from sklearn.metrics import mean_absolute_error, r2_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
import warnings
warnings.filterwarnings('ignore')

# Reading the data from the csv file
car_data = pd.read_csv('C:/Users/Shubham/OneDrive - Teesside
University/Machine Learning Lab/ford.csv')

# Getting the idea of the data we are dealing with
car_data.head()
```

```
     model  year  price transmission  mileage fuelType  tax   mpg
engineSize
0   Fiesta  2017  12000    Automatic    15944   Petrol  150  57.7
1.0
1    Focus  2018  14000       Manual     9083   Petrol  150  57.7
1.0
2    Focus  2017  13000       Manual    12456   Petrol  150  57.7
```

```
1.0
3   Fiesta  2019  17500       Manual    10460   Petrol  145  40.3
1.5
4   Fiesta  2019  16500    Automatic     1482   Petrol  145  48.7
1.0
```

```
car_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17966 entries, 0 to 17965
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   model         17966 non-null  object 
 1   year          17966 non-null  int64  
 2   price         17966 non-null  int64  
 3   transmission  17966 non-null  object 
 4   mileage       17966 non-null  int64  
 5   fuelType      17966 non-null  object 
 6   tax           17966 non-null  int64  
 7   mpg           17966 non-null  float64
 8   engineSize    17966 non-null  float64
dtypes: float64(2), int64(4), object(3)
memory usage: 1.2+ MB
```

```
# checking any null entries
car_data.isnull().sum()
```

```
model           0
year            0
price           0
transmission    0
mileage         0
fuelType        0
tax             0
mpg             0
engineSize      0
dtype: int64
```

```
# Getting statistical information about the dataset
car_data.describe()
```

```
               year         price        mileage           tax
mpg  \
count  17966.000000  17966.000000   17966.000000  17966.000000
17966.000000
mean    2016.866470  12279.534844   23362.608761    113.329456
57.906980
std        2.050336   4741.343657   19472.054349     62.012456
10.125696
min     1996.000000    495.000000       1.000000      0.000000
```

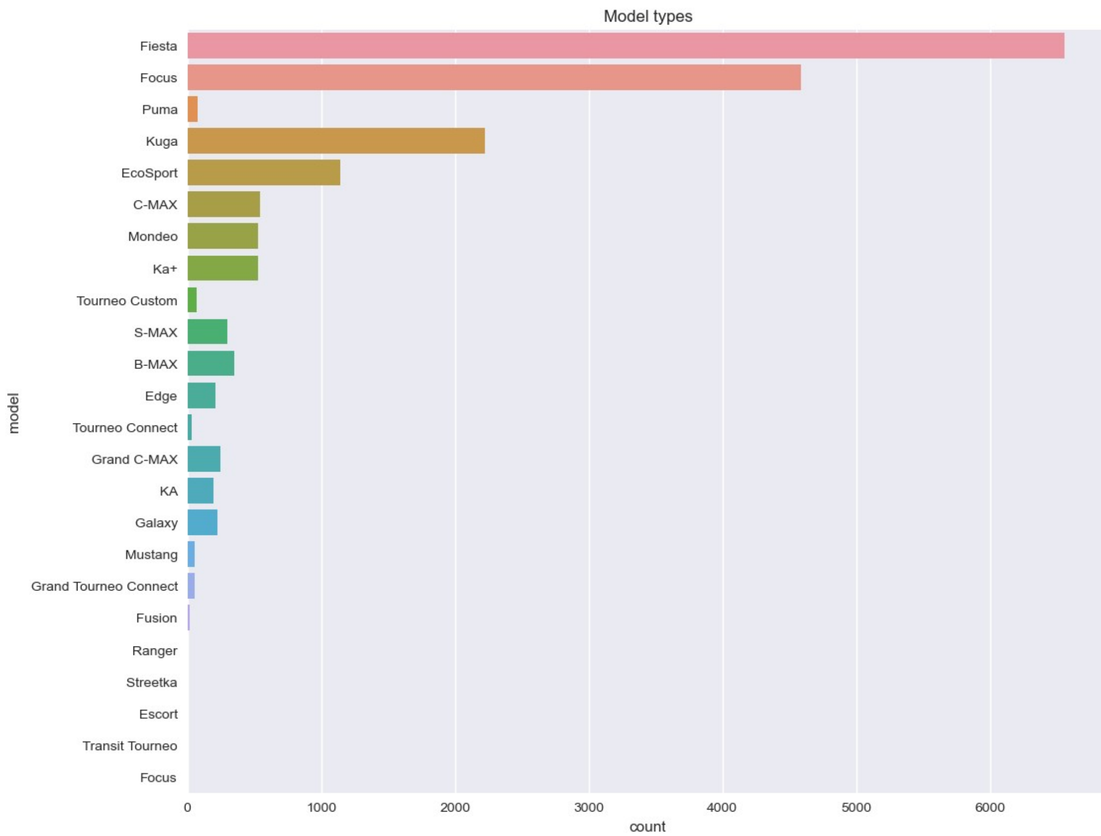
```
20.800000
25%     2016.000000   8999.000000    9987.000000     30.000000
52.300000
50%     2017.000000  11291.000000   18242.500000    145.000000
58.900000
75%     2018.000000  15299.000000   31060.000000    145.000000
65.700000
max     2060.000000  54995.000000  177644.000000    580.000000
201.800000

         engineSize
count  17966.000000
mean       1.350807
std        0.432367
min        0.000000
25%        1.000000
50%        1.200000
75%        1.500000
max        5.000000
```

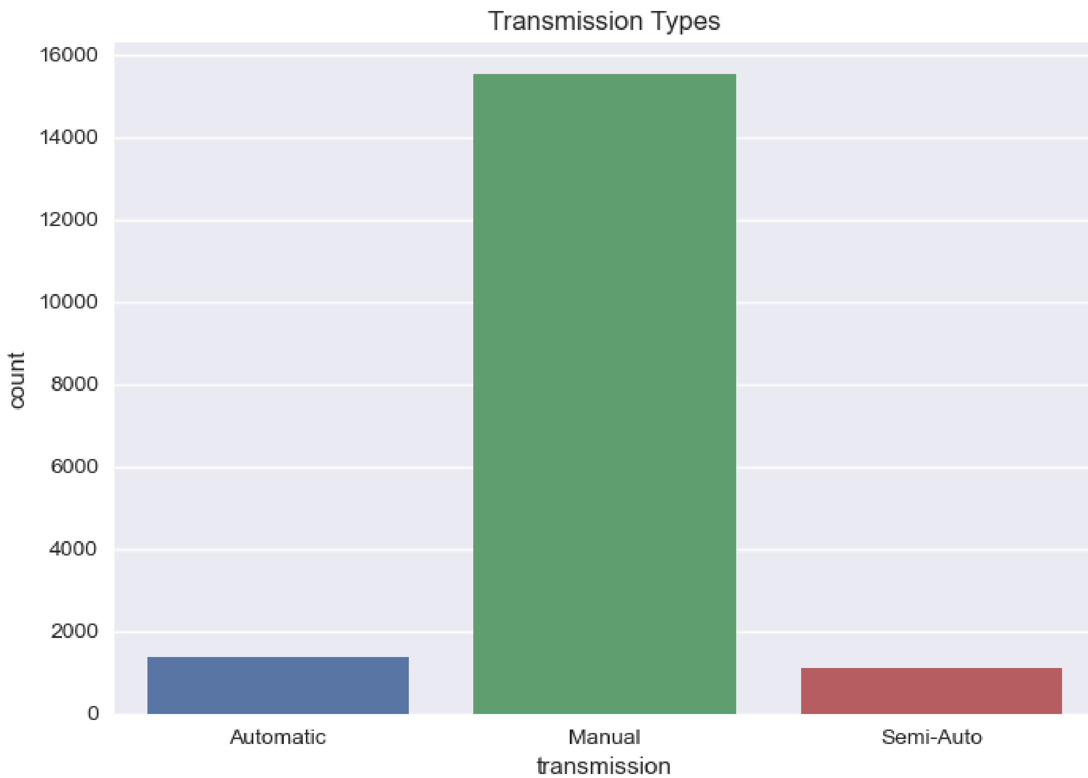
```
car_data.columns
```

```
Index(['model', 'year', 'price', 'transmission', 'mileage',
'fuelType', 'tax',
       'mpg', 'engineSize'],
      dtype='object')
```

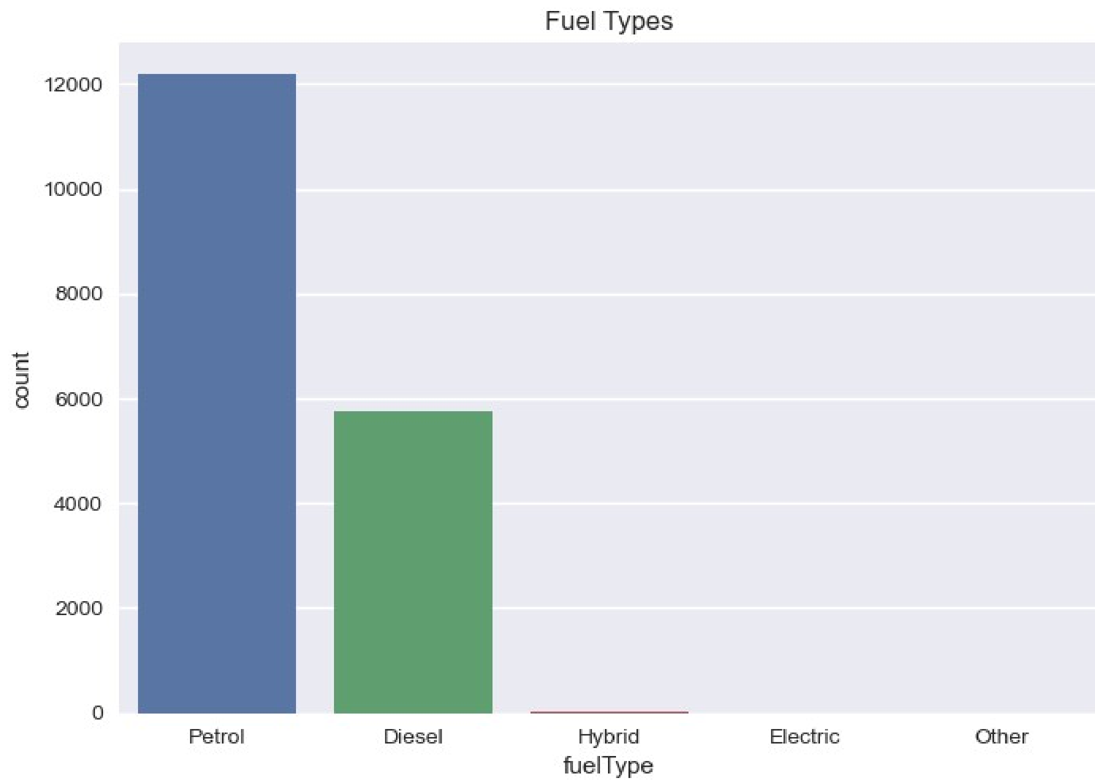
```
# Exploring the categorical data of model types
plt.figure(figsize=(12,10))
sns.countplot(y='model', data=car_data)
plt.title('Model types')
plt.show()
```




```
# Exploring the categorical data of transmission types
sns.countplot(x='transmission', data=car_data)
plt.title('Transmission Types')
plt.show()
```




```
# Exploring the categorical data of fuel types
sns.countplot(x='fuelType', data=car_data)
plt.title('Fuel Types')
plt.show()
```




```
# To see numerical values of different categorical data
print(car_data['model'].value_counts())
print("\n\n")
print(car_data['transmission'].value_counts())
print("\n\n")
print(car_data['fuelType'].value_counts())
```

```
 Fiesta                    6557
 Focus                     4588
 Kuga                      2225
 EcoSport                  1143
 C-MAX                      543
 Ka+                        531
 Mondeo                     526
 B-MAX                      355
 S-MAX                      296
 Grand C-MAX                247
 Galaxy                     228
 Edge                       208
 KA                         199
 Puma                        80
 Tourneo Custom              69
 Grand Tourneo Connect       59
 Mustang                     57
 Tourneo Connect             33
 Fusion                      16
```

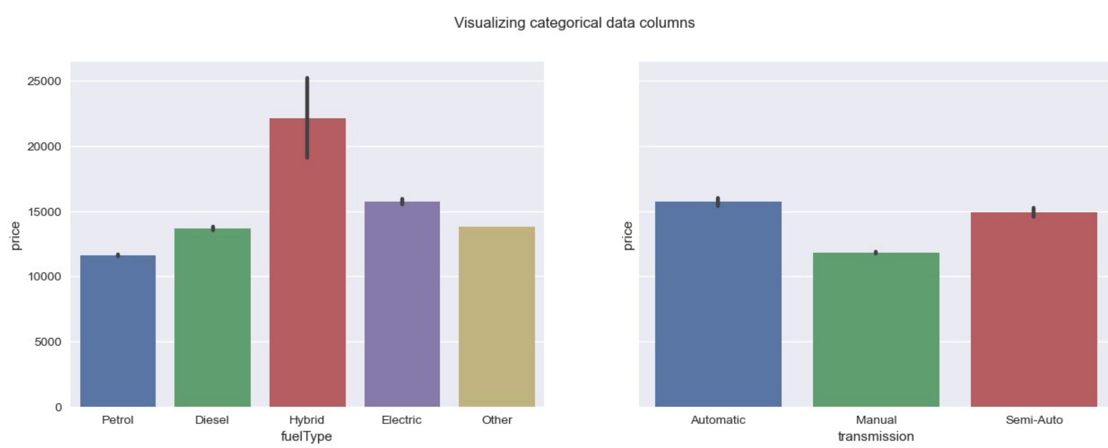
```
 Streetka                     2
 Ranger                       1
 Escort                       1
 Transit Tourneo              1
Focus                         1
Name: model, dtype: int64
```

```
Manual       15518
Automatic     1361
Semi-Auto     1087
Name: transmission, dtype: int64
```

```
Petrol      12179
Diesel       5762
Hybrid         22
Electric        2
Other           1
Name: fuelType, dtype: int64
```

```
# Creating a variable to store the data from the column
fuelType = car_data['fuelType']
transmission = car_data['transmission']
price = car_data['price']
fig, axes = plt.subplots(1,2, figsize=(15,5), sharey=True)
fig.suptitle('Visualizing categorical data columns')
sns.barplot(x=fuelType, y=price, ax=axes[0])
sns.barplot(x=transmission, y=price, ax = axes[1])
```

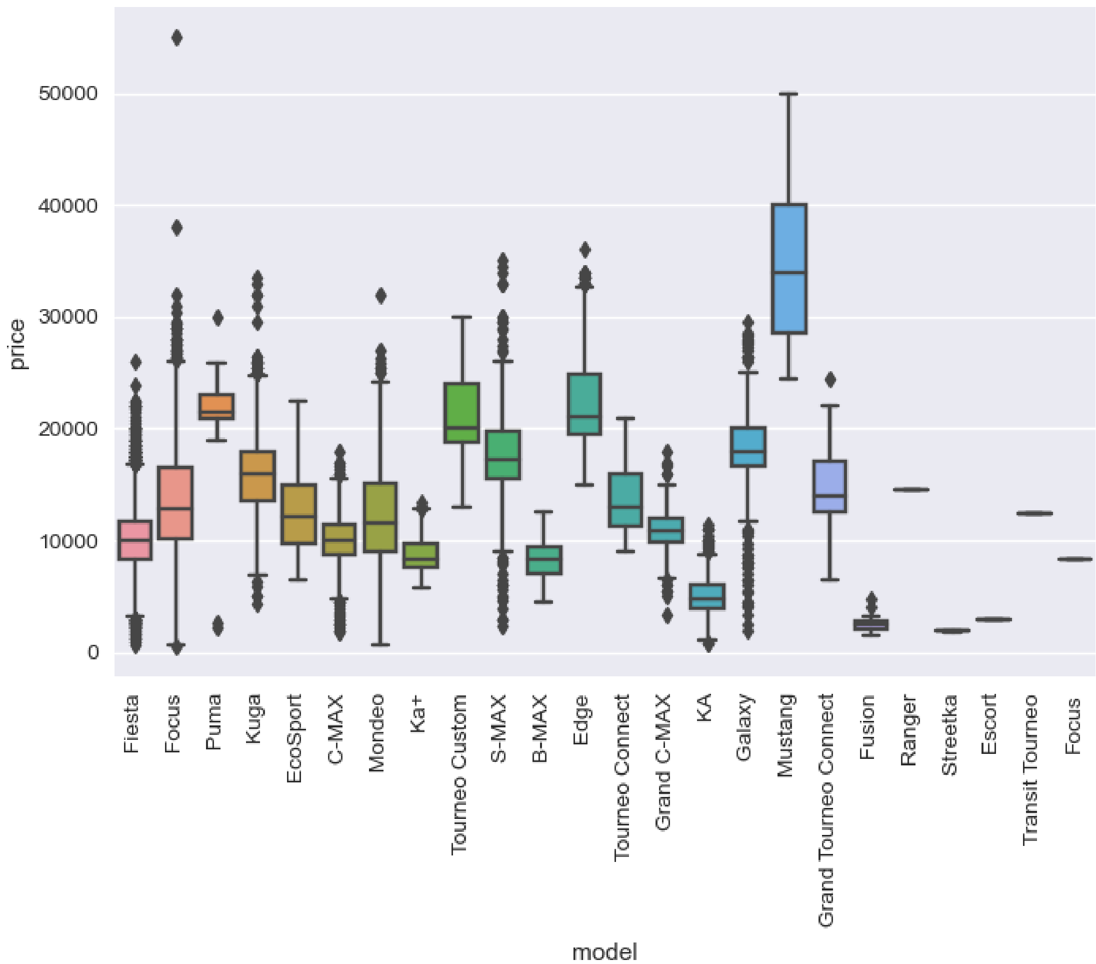
```
<AxesSubplot:xlabel='transmission', ylabel='price'>
```




```
# performing ordinal encoding on the data to convert into numerical
values.
```

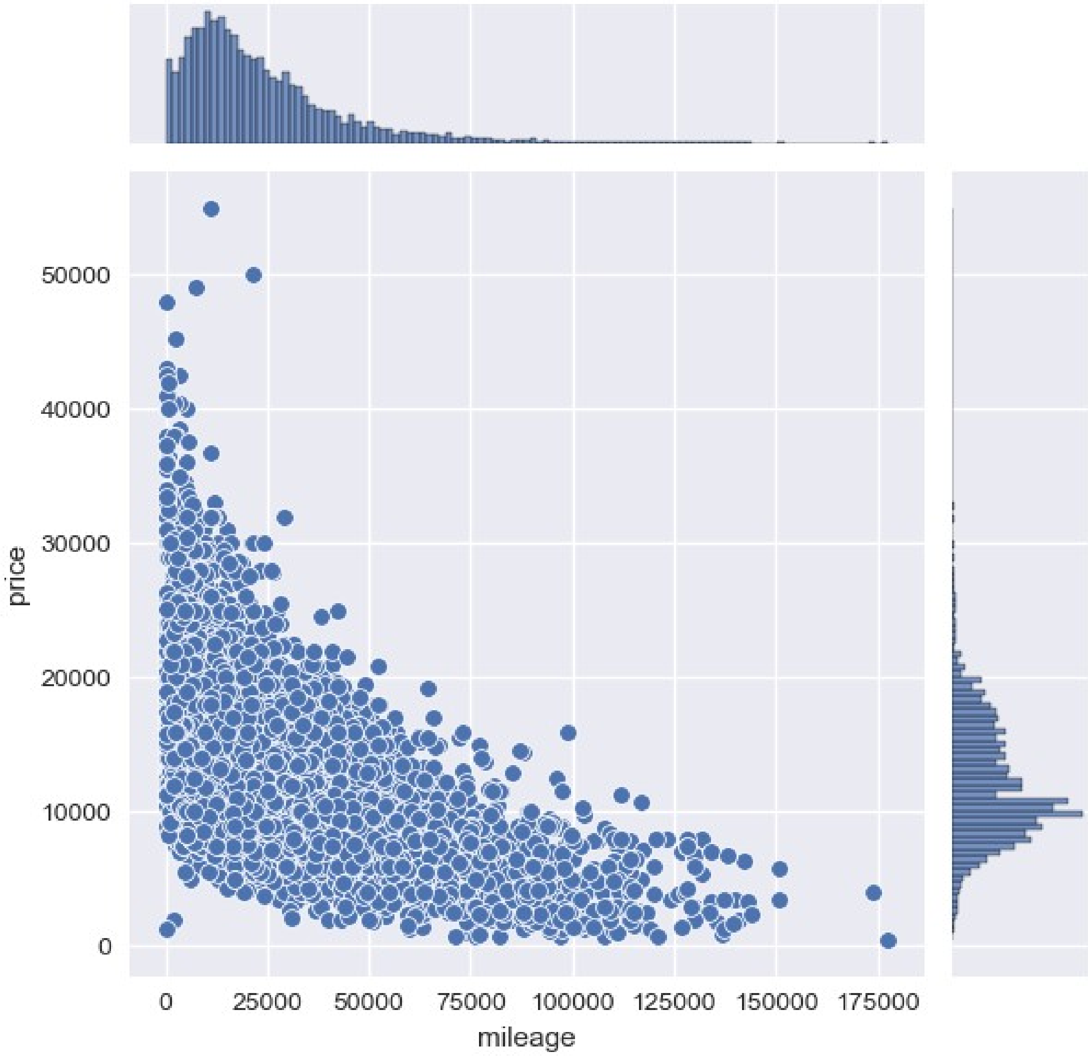
```
car_data.replace({'transmission':{'Manual':0, 'Automatic':1, 'Semi-
Auto':2}}, inplace=True)
car_data.replace({'fuelType':{'Petrol':0, 'Diesel':1, 'Hybrid':2,
'Electric':3, 'Other':4}}, inplace=True)

# car price value based on model
ax = sns.boxplot(data=car_data, x=car_data['model'],
y=car_data['price'])
ax.tick_params(axis='x', rotation=90)
```

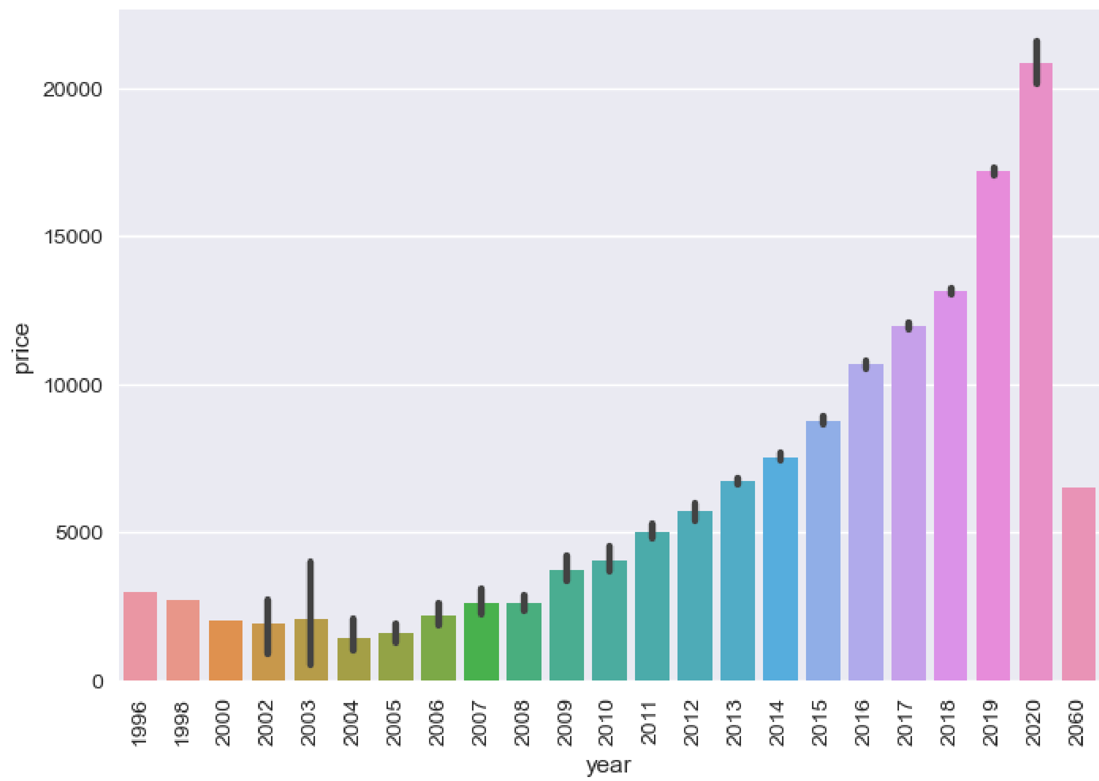



```
# car price value based on mileage driven
sns.jointplot(data=car_data, x=car_data['mileage'],
y=car_data['price'])
```

```
<seaborn.axisgrid.JointGrid at 0x1ef52af52b0>
```

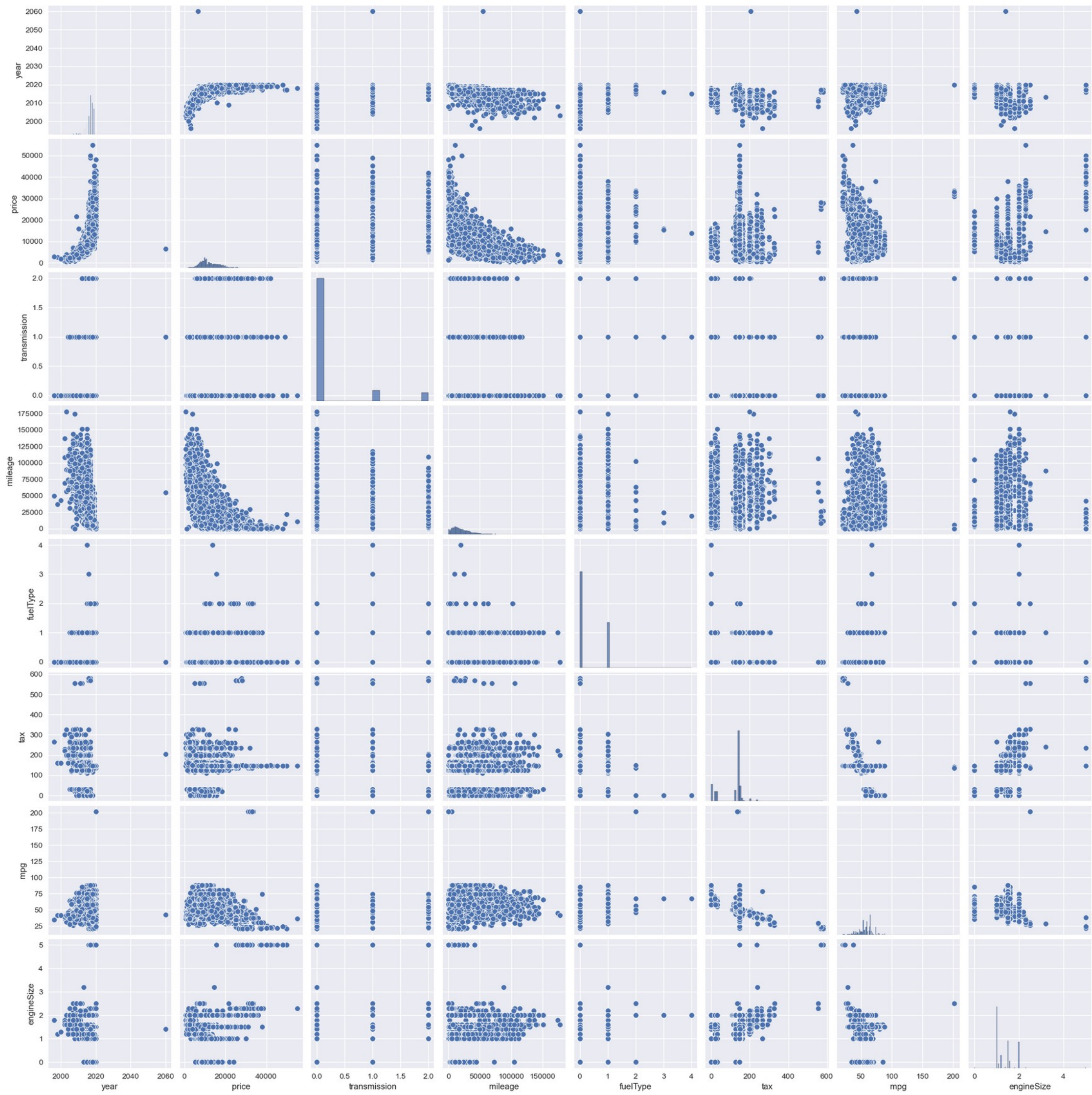



```
# car price value based on manufacured year
ax = sns.barplot(data=car_data, x=car_data['year'],
y=car_data['price'])
ax.tick_params(axis='x', rotation=90)
```



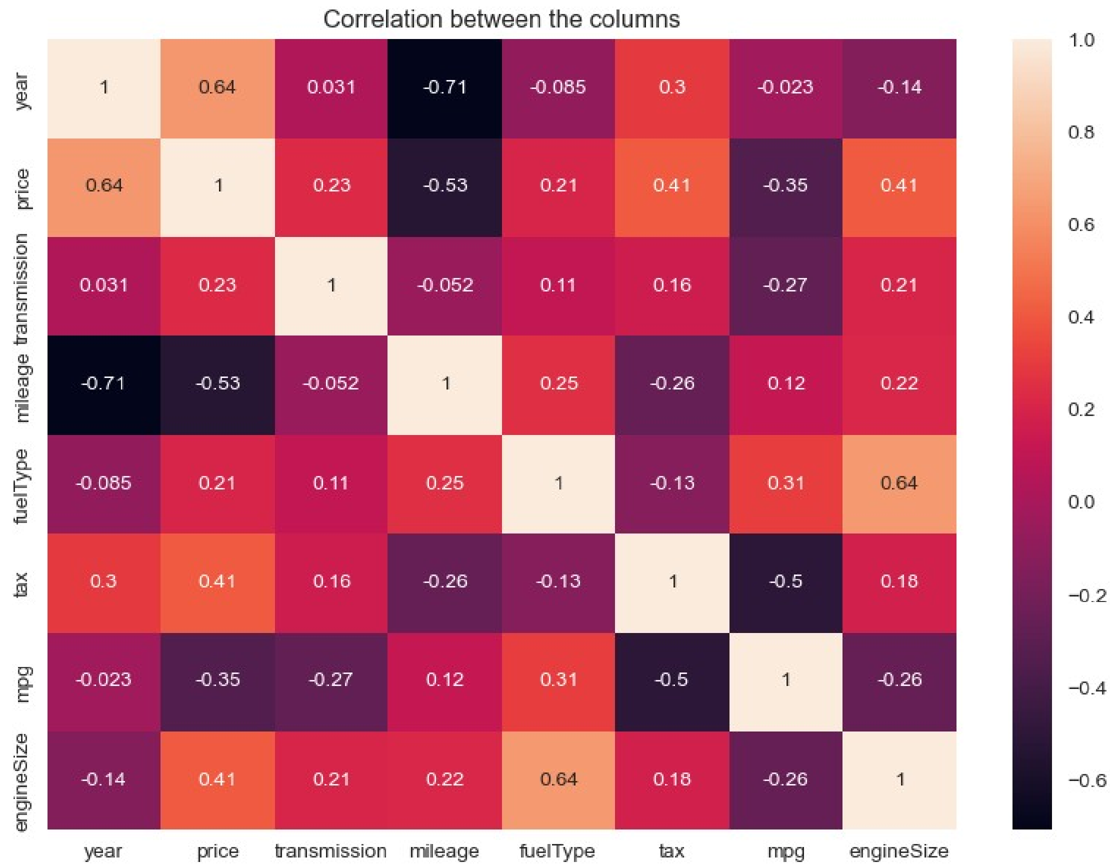

```
# pairplot
sns.pairplot(car_data)
```

<seaborn.axisgrid.PairGrid at 0x1ef520a0550>




```
# using the head function to see the modified data
car_data.head()
# dropping the model column
car_data = car_data.drop("model", axis=1)

# visualising heat map to show correlation between attributes and the
target column
plt.figure(figsize=(10,7))
sns.heatmap(car_data.corr(), annot=True)
plt.title('Correlation between the columns')
plt.show()
```

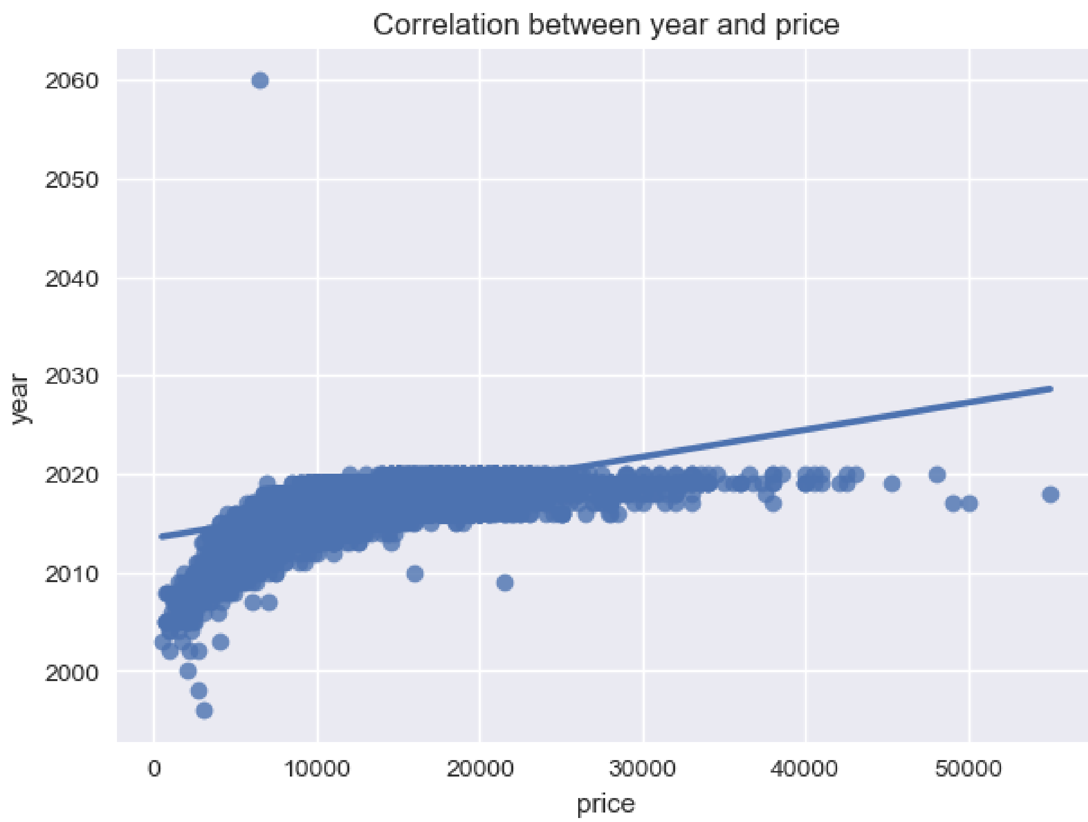



```
# sorting the correlation of the price column
car_data.corr()['price'].sort_values()
```

```
mileage        -0.530659
mpg            -0.346419
fuelType        0.209225
transmission    0.231806
tax             0.406857
engineSize      0.411178
year            0.636009
price           1.000000
Name: price, dtype: float64
```

```
# plotting regression plot
fig = plt.figure(figsize=(7,5))
plt.title('Correlation between year and price')
sns.regplot(x='price', y='year', data=car_data)
```

```
<AxesSubplot:title={'center':'Correlation between year and price'},
xlabel='price', ylabel='year'>
```




```
# splitting the data into x and y
X = car_data.drop('price', axis=1)
y = car_data['price']

# printing thee shape of x and y
print("Shape of X is :", X.shape)
print("Shape of y is :", y.shape)

Shape of X is : (17966, 7)
Shape of y is : (17966,)

# splitting the data into training and testing sets.
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# printing the shape of training and testing data
print("Shape of X_train is: ", X_train.shape)
print("Shape of y_train is: ", y_train.shape)
print("Shape of X_test is: ", X_test.shape)
print("Shape of y_test is: ", y_test.shape)

Shape of X_train is:  (14372, 7)
Shape of y_train is:  (14372,)
Shape of X_test is:  (3594, 7)
Shape of y_test is:  (3594,)
```

```
# normalising the data
scaler = StandardScaler()

# applying normalisation on X data
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# creating the liear regression model
linreg = LinearRegression()
linreg.fit(X_train, y_train)
linreg_pred = linreg.predict(X_test)

# evaluating the linear regression model performance
linreg_mae = mean_absolute_error(y_test, linreg_pred)
linreg_r2 = r2_score(y_test, linreg_pred)
print("MAE of linear regression model is:", linreg_mae)
print("R2 score of linear regression model is:", linreg_r2)
```

```
MAE of linear regression model is: 1778.2319322410349
R2 score of linear regression model is: 0.7379425731911509
```

```
# performing cross validation on test data
linreg_score = cross_val_score(linreg, X_test, y_test, cv=4)
print("Linear Regression model accuracy is:
{}".format(linreg_score.mean()*100))
```

```
Linear Regression model accuracy is: 73.87545898136361
```

```
# Defining the hyperparameters to tune
parameters = {'fit_intercept': [True, False],
             'normalize': [True, False],
             'copy_X': [True, False]}

# Creating the GridSearchCV object for linear regression model
linreg_cv = GridSearchCV(LinearRegression(), param_grid=parameters,
cv=5)

# Fitting the GridSearchCV object to training data
linreg_cv.fit(X_train, y_train)
```

```
GridSearchCV(cv=5, estimator=LinearRegression(),
             param_grid={'copy_X': [True, False],
                         'fit_intercept': [True, False],
                         'normalize': [True, False]})
```

```
# Printing the best hyperparameters found
print("Best hyperparameters:", linreg_cv.best_params_)
```

```
Best hyperparameters: {'copy_X': True, 'fit_intercept': True,
'normalize': True}
```

```
# Using the best hyperparameters to predict on the test data
linreg_pred = linreg_cv.predict(X_test)
```

```
# Calculating the MAE and R2 score for the model with the best
hyperparameters
linreg_mae = mean_absolute_error(y_test, linreg_pred)
linreg_r2 = r2_score(y_test, linreg_pred)
print("MAE of linear regression model with best hyperparameters:",
linreg_mae)
print("R2 score of linear regression model with best
hyperparameters:", linreg_r2)
```

```
MAE of linear regression model with best hyperparameters:
1778.2319322410349
R2 score of linear regression model with best hyperparameters:
0.7379425731911511
```

```
# creating the decision model
dtree = DecisionTreeRegressor()
dtree.fit(X_train, y_train)
dtree_pred = dtree.predict(X_test)

# evaluating the decision tree model performance
dtree_mae = mean_absolute_error(y_test, dtree_pred)
dtree_r2 = r2_score(y_test, dtree_pred)
print("MAE of decision tree model is:", dtree_mae)
print("R2 score of decision tree model is:", dtree_r2)
```

```
MAE of decision tree model is: 1174.6750602856614
R2 score of decision tree model is: 0.8597171999082486
```

```
# performing cross validation on test data
dtree_score = cross_val_score(dtree, X_test, y_test, cv=4)
print("Decision Tree model accuracy is:
{}".format(dtree_score.mean()*100))
```

```
Decision Tree model accuracy is: 82.3626463016493
```

```
# Defining the hyperparameters for the decision tree model
parameters = {
    'max_depth': [3, 5, 7, 10],
    'min_samples_split': [2, 5, 10, 15],
    'min_samples_leaf': [1, 2, 5, 10]
}

# Creating the GridSearchCV object for decision tree model
dtree_cv = GridSearchCV(DecisionTreeRegressor(),
param_grid=parameters, cv=5)

# Fitting the GridSearchCV object to training data
dtree_cv.fit(X_train, y_train)
```

```
GridSearchCV(cv=5, estimator=DecisionTreeRegressor(),
             param_grid={'max_depth': [3, 5, 7, 10],
```

```
                         'min_samples_leaf': [1, 2, 5, 10],
                         'min_samples_split': [2, 5, 10, 15]})

# Printing the best hyperparameters found
print("Best hyperparameters:", dtree_cv.best_params_)
```

```
Best hyperparameters: {'max_depth': 10, 'min_samples_leaf': 5,
'min_samples_split': 15}
```

```
# Using the best hyperparameters to predict on the test data
dtree_pred = dtree_cv.predict(X_test)

# Calculating the MAE and R2 score for the model with the best
hyperparameters
dtree_mae = mean_absolute_error(y_test, dtree_pred)
dtree_r2 = r2_score(y_test, dtree_pred)
print("MAE of decision tree model with best hyperparameters:",
dtree_mae)
print("R2 score of decision tree model with best hyperparameters:",
dtree_r2)
```

```
MAE of decision tree model with best hyperparameters:
1007.3313843147844
R2 score of decision tree model with best hyperparameters:
0.9031300534856432
```

```
# creating the XGBoost model
xgb = XGBRegressor()
xgb.fit(X_train, y_train)
xgb_prediction = xgb.predict(X_test)

# evaluating the XGBoost model performance
xgb_mae = mean_absolute_error(y_test, xgb_prediction)
xgb_r2 = r2_score(y_test, xgb_prediction)
print("MAE of xgboost model is:", xgb_mae)
print("R2 score of xgboost model is:", xgb_r2)
```

```
MAE of xgboost model is: 914.1581133384472
R2 score of xgboost model is: 0.9196627631595996
```

```
# performing cross validation on test data
xgb_score = cross_val_score(xgb, X_test, y_test, cv=4)
print("xgboost model accuracy is: {}".format(xgb_score.mean()*100))
```

```
xgboost model accuracy is: 89.60526998355522
```

```
#printing best cross validation score
print("best cross validation score: {:.2f}".format(grid.best_score_))
print("best parameters: ", grid.best_params_)
```

```
----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
```

```
last)
~\AppData\Local\Temp\ipykernel_20908\3877909406.py in <module>
      1 #printing best cross validation score
----> 2 print("best cross validation score:
{:.2f}".format(grid.best_score_))
      3 print("best parameters: ", grid.best_params_)

NameError: name 'grid' is not defined
```

```
# Defining the hyperparameters to tune
param_grid = {
    'learning_rate': [0.1, 0.01, 0.001],
    'max_depth': [3, 4, 5],
    'n_estimators': [50, 100, 150]
}

# Creating a GridSearchCV object with the XGBoost model and the
hyperparameters
xgb_grid = GridSearchCV(XGBRegressor(), param_grid=param_grid, cv=5)

# Fitting the GridSearchCV object to the training data
xgb_grid.fit(X_train, y_train)
```

```
GridSearchCV(cv=5,
             estimator=XGBRegressor(base_score=None, booster=None,
                                    callbacks=None,
colsample_bylevel=None,
                                    colsample_bynode=None,
                                    colsample_bytree=None,
                                    early_stopping_rounds=None,
                                    enable_categorical=False,
eval_metric=None,
                                    feature_types=None, gamma=None,
gpu_id=None,
                                    grow_policy=None,
importance_type=None,
                                    interaction_constraints=None,
                                    learning_rate=None, max_bin=None,
                                    max_cat_threshold=None,
                                    max_cat_to_onehot=None,
max_delta_step=None,
                                    max_depth=None, max_leaves=None,
                                    min_child_weight=None,
missing=nan,
                                    monotone_constraints=None,
n_estimators=100,
                                    n_jobs=None,
num_parallel_tree=None,
                                    predictor=None, random_state=None,
...),
             param_grid={'learning_rate': [0.1, 0.01, 0.001],
```

```
                         'max_depth': [3, 4, 5],
                         'n_estimators': [50, 100, 150]})

# Printing the best hyperparameters found
print("Best hyperparameters:", xgb_grid.best_params_)
```

```
Best hyperparameters: {'learning_rate': 0.1, 'max_depth': 5,
'n_estimators': 150}
```

```
# Using the best hyperparameters to predict on the test data
xgb_pred = xgb_grid.predict(X_test)

# Calculating the MAE and R2 score for the model with the best
hyperparameters
xgb_mae = mean_absolute_error(y_test, xgb_pred)
xgb_r2 = r2_score(y_test, xgb_pred)
print("MAE of XGBoost model with best hyperparameters:", xgb_mae)
print("R2 score of XGBoost model with best hyperparameters:", xgb_r2)
```

```
MAE of XGBoost model with best hyperparameters: 932.5599693506375
R2 score of XGBoost model with best hyperparameters:
0.9168357941605024
```

```
car_data.columns
```

```
Index(['year', 'price', 'transmission', 'mileage', 'fuelType', 'tax',
'mpg',
       'engineSize'],
      dtype='object')
```

```
car_data.head()
```

	year	price	transmission	mileage	fuelType	tax	mpg	engineSize
0	2017	12000	1	15944	0	150	57.7	1.0
1	2018	14000	0	9083	0	150	57.7	1.0
2	2017	13000	0	12456	0	150	57.7	1.0
3	2019	17500	0	10460	0	145	40.3	1.5
4	2019	16500	1	1482	0	145	48.7	1.0

```
# creating new data for the model to predict
data = {'year':2017, 'transmission':1, 'mileage':15944, 'fuelType':0,
'tax':150, 'mpg':57.7,
       'engineSize':1.0}
index= [0]
new_car_data = pd.DataFrame(data, index)
new_car_data
```

	year	transmission	mileage	fuelType	tax	mpg	engineSize
0	2017	1	15944	0	150	57.7	1.0

```
# implementing the data created to the XGB model
new_prediction = xgb_grid.predict(new_car_data)
print("The car price for the new data is: ", new_prediction)
```

```
The car price for the new data is:  [11068.842]
```