P4DS: Assignment 3 (Autumn 2020)

Data Analysis Project

Notebook template design: Brandon Bennett (2020/11/3)

Analysis and Predict the Price of the Used Car

Project participants:

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Project Plan

The Data (10 marks)

This dataset contains the data and details of used cars of the UK. BMW manufactures these used cars. This information is being gathered in order to create a tool that will forecast how much individuals should sell their old vehicles for by comparing it to other items on the market. It has records of 24 models of cars from the year 1996 to 2020. Also, it contains the features of the cars like engine size, mileage, price etc. This dataset is downloaded from Kaggle (https://www.kaggle.com/adityadesai13/used-car-dataset-ford-and-mercedes?select=bmw.csv).This dataset was published by Aditya who is Student at the University of Oxford. In this project, I am going to use only one CSV file.

- BMW.csv

This CSV file will provide all the necessary information that helps us predict the used cars' price.

Column Description

- **Model:** Model of the cars
- **Year:** It tells the year of the car in which it is Registered
- **Price:** Price of the used cars in pounds (£)
- **Transmission:** It tells the Gearbox type of the cars
- **Mileage:** Miles travelled
- **FuleType:** car's Engine fule
- **Tax:** Road tax(£) that paid for the car

- **mpg:** Miles per gallon of the car
- **EnginSize:** Size of the engine in (L)

This CSV contains 10781 rows and 9 columns without any null values. This dataset is already cleaned and split from the car dataset, which contains all the Manufacturers.

The price column has numbers in the range of 1200 to 123456, whereas the year column covers data from 1996 to 2020. There are three different types of car gearboxes (Automatic, Manual, Semi-Auto). There are 43 percent of semi-automatic automobiles and 33 percent of automatic cars in this statistics.There are two primary items in the fule type column: one is petrol, and the other is diesel. In this dataset, 32 percent of automobiles are gasoline and 65 percent are diesel.

Project Aim and Objectives (5 marks)

The project's goal is to do a visual analysis of the BMW used car dataset in the United Kingdom and estimate car prices, which will assist individuals in determining the value of their old vehicles.

Specific Objective(s)

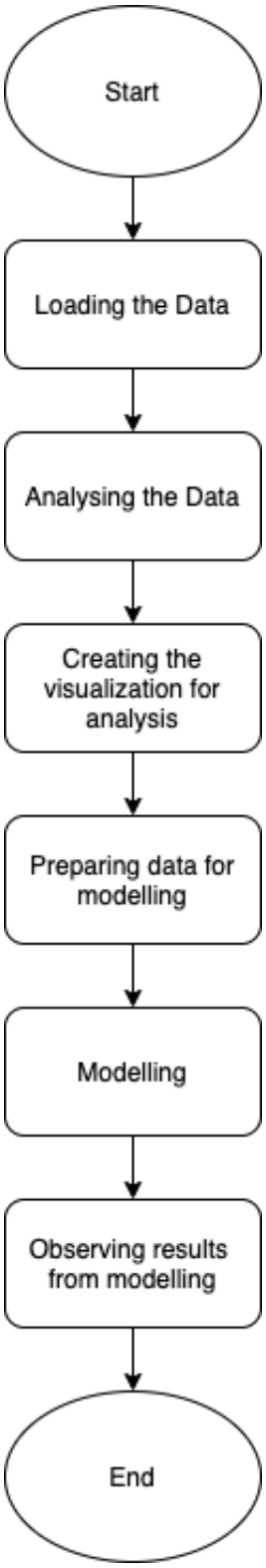
- **Objective 1:** *Virtual analysis of the data of the used cars*
- **Objective 2:** *Predicting the price of the Used BMW Cars*

System Design (5 marks)

Architecture

In [3]:
```
from IPython.display import Image
Image("PDS flow chart.png")
```

Out[3]:



Processing Modules and Algorithms

- *Data is loaded from a CSV file as a data frame.*
- *Analyzing the data frame to know how to proceed with visualization.*
- *Creating a visualization of comparing different attributes.*
- _Preparing the data for modelling. _
- *Developing models to predict the price of cars.*

Program Code (15 marks)

Data Processing

Importing the packages

The following packages must be imported in order to do data analysis and visualisation.

In [5]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statistics
import seaborn as sns
```

Loading the data

Loading the data "bmw.csv" from the filesystem to carryout the next step.

In [6]:
```
bmw = pd.read_csv('/Users/raghulsekar/Desktop/Programming for D
```

Checking the dataset loaded.

In [7]:
```
bmw.head()
```

Out[7]:

	model	year	price	transmission	mileage	fuelType	tax	mpg	engineSize
0	5 Series	2014	11200	Automatic	67068	Diesel	125	57.6	2.0
1	6 Series	2018	27000	Automatic	14827	Petrol	145	42.8	2.0
2	5 Series	2016	16000	Automatic	62794	Diesel	160	51.4	3.0
3	1 Series	2017	12750	Automatic	26676	Diesel	145	72.4	1.5
4	7 Series	2014	14500	Automatic	39554	Diesel	160	50.4	3.0

Finding the number of unique car models in the dataset.

In [18]:
```
n_model = bmw["model"].nunique()
print('Number of car models in this dataset is',n_model)
```

```
Number of car models in this dataset is 24
```

To checking the shape of the file.

In [9]:
```
bmw.shape
```

Out[9]:
```
(10781, 9)
```

Checking null values

In [11]:
```
bmw.isna().any()
```

Out[11]:
```
model           False
year            False
price           False
transmission    False
mileage         False
fuelType        False
tax             False
mpg             False
engineSize      False
dtype: bool
```

Creating a new column "age"

To know the age of the column, I am creating a new column age by subtracting the year column from the current year.

In [21]:
```
bmw["age"] = 2021 - bmw["year"]
```

Summary of the data

In [22]:
```
1 bmw.describe().T
```

Out[22]:

	count	mean	std	min	25%	50%	75%	ma
year	10781.0	2017.078935	2.349038	1996.0	2016.0	2017.0	2019.0	2020
price	10781.0	22733.408867	11415.528189	1200.0	14950.0	20462.0	27940.0	123456
mileage	10781.0	25496.986550	25143.192559	1.0	5529.0	18347.0	38206.0	214000
tax	10781.0	131.702068	61.510755	0.0	135.0	145.0	145.0	580
mpg	10781.0	56.399035	31.336958	5.5	45.6	53.3	62.8	470
engineSize	10781.0	2.167767	0.552054	0.0	2.0	2.0	2.0	6
age	10781.0	3.921065	2.349038	1.0	2.0	4.0	5.0	25

We may deduce the following from the given summary statistics:

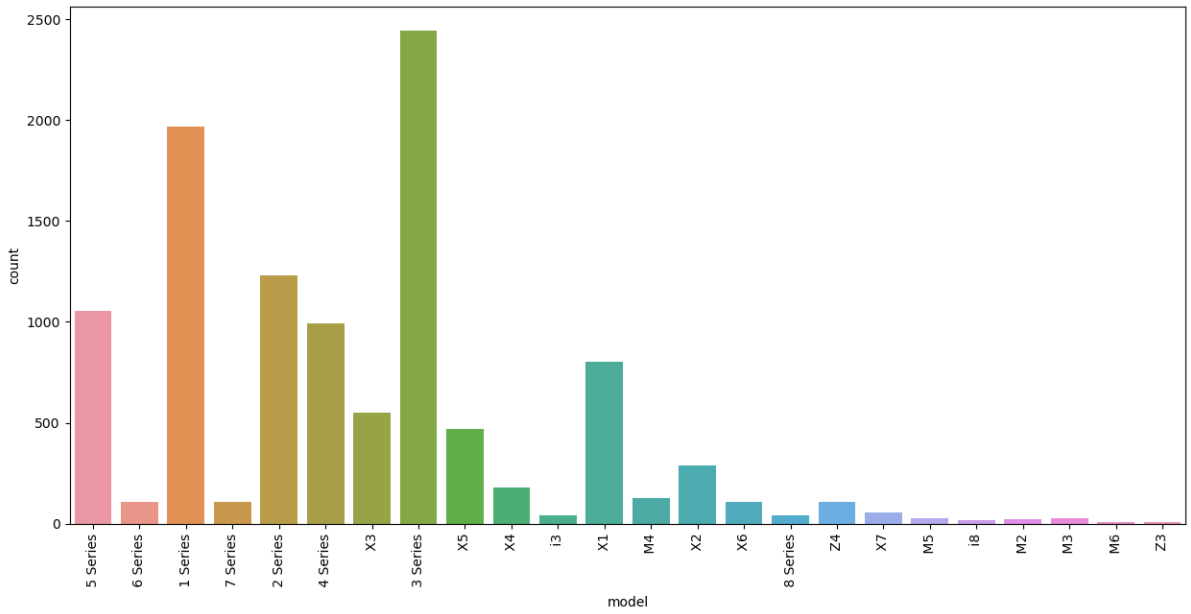
- Count column has a value 10781 in all rows, this mean there are 10781 rows in the dataset and there is no null value in the table.
- min shows all the minimum values in all respective columns.
- In the year row, we can see the min value is 1996, and the max value is 2020. This means data is in between the range of 1996 to 2020.
- Average age of the cars in this dataset is around four years.

Objective 1

Virtual analysis of the data of the used cars

Count Plot for the Car Models:

In [35]:
```
plt.figure(figsize=(15,7))
count_model = sns.countplot(x = bmw["model"])
count_model.tick_params(axis='x', rotation=90)
```

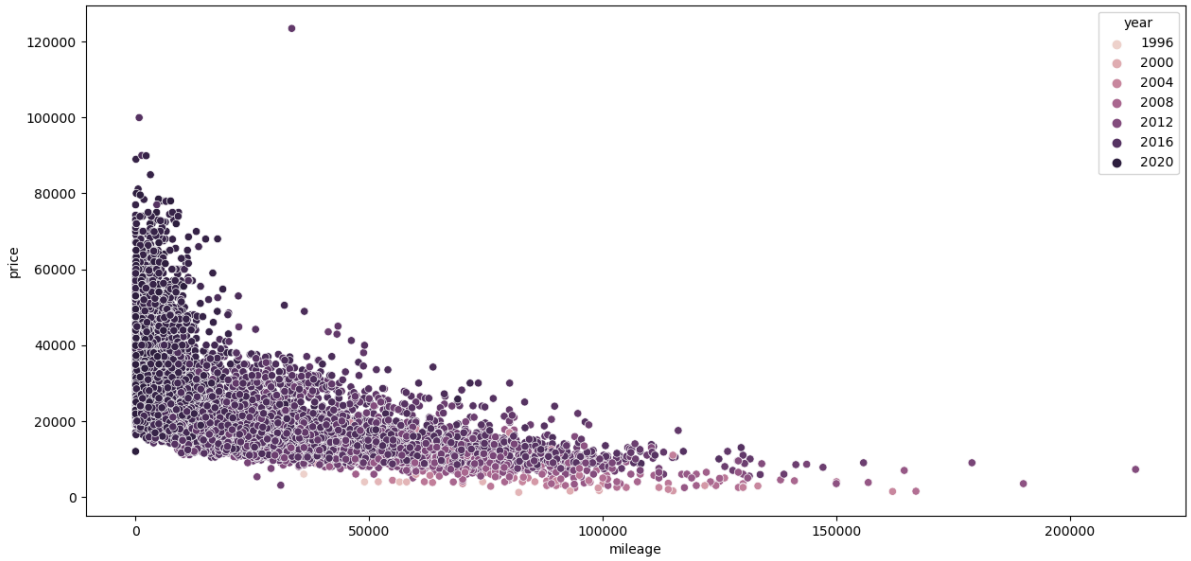


The above bar chart compares the number of cars in each model with other models.

Scatter plot of mileage and price with year as hue:

In [28]:
```
plt.style.use('default')
plt.figure(figsize=(15,7))
sns.scatterplot( x = bmw["mileage"], y = bmw["price"], hue = bm
```

Out[28]: <AxesSubplot:xlabel='mileage', ylabel='price'>

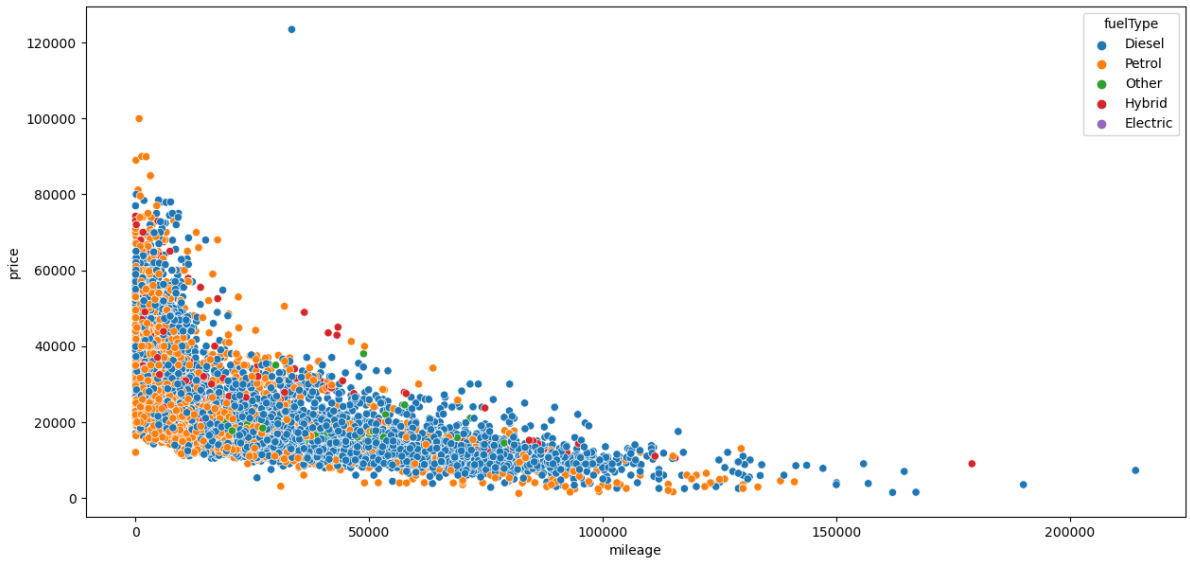


From the above plot, we can see the price is high when the mileage is less. As the mileage gets increases price of the cars are getting decreases. And also we can note that most of the cars having high milage are from the early years. Most of the new cars price is high then the old cars.

Scatter plot of mileage and price with fule type as hue:

In [26]:
```
plt.figure(figsize=(15,7))
sns.scatterplot(x = bmw["mileage"], y = bmw["price"], hue = bmw
```

Out[26]:
```
<AxesSubplot:xlabel='mileage', ylabel='price'>
```

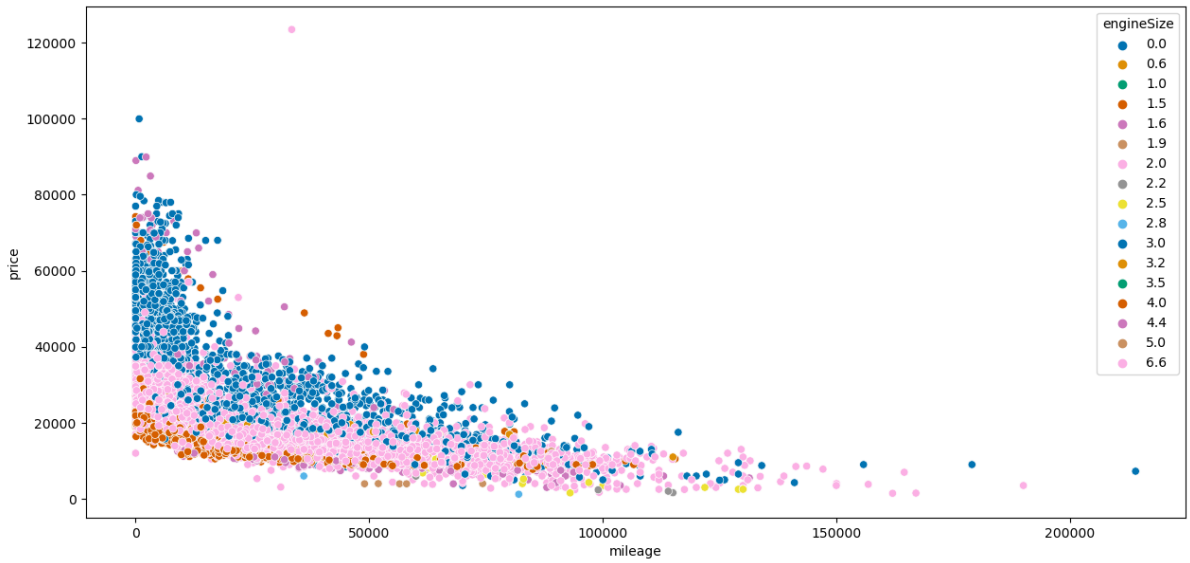


This scatter plot shows that most diesel cars are less price and have driven high miles than petrol cars. The price of petrol cars is higher than diesel cars in less mileage, as the mileage increases the price of diesel cars is high.

Scatter plot of mileage and price with engine size as hue:

In [36]:
```
plt.figure(figsize=(15,7))
sns.scatterplot(x = bmw["mileage"], y = bmw["price"], hue = bmw
```

Out[36]: <AxesSubplot:xlabel='mileage', ylabel='price'>

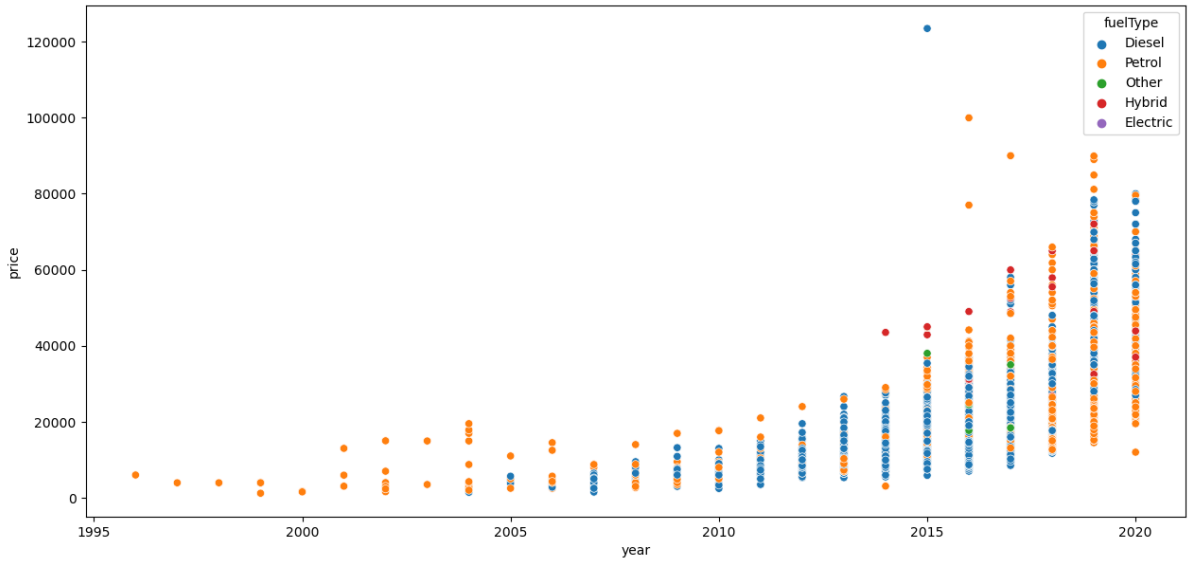


From the above chart, we can see the size of the engine is less price of the car is high and as the size of the engine is getting high, price of the car is less. Also, only cars with large engine sizes are driven for long miles.

Scatter plot of year and price with fuel type as hue:

In [37]:
```
plt.figure(figsize=(15,7))
sns.scatterplot(x = bmw["year"],y = bmw["price"], hue = bmw["fu
```

Out[37]: <AxesSubplot:xlabel='year', ylabel='price'>



We can see that price of the car is high when the car is new. As the age of the car is increasing price of the car is decreasing. Also, most of the oldest cars are petrol engines. So petrol car is lasting for a long period.

Depending on the year, determining which vehicles are the most popular:

Here BMW data is grouped by year column and count the number of cars in each year.

In [38]:
```
bmw_gy = bmw
bmw_gy = bmw_gy.groupby("year")
bmw_yb = bmw_gy["model"].count()
bmw_yb = pd.DataFrame(bmw_yb)
bmw_yb.sort_values(by=['model'], ascending=False, inplace=True)
bmw_yb.head(10)
```

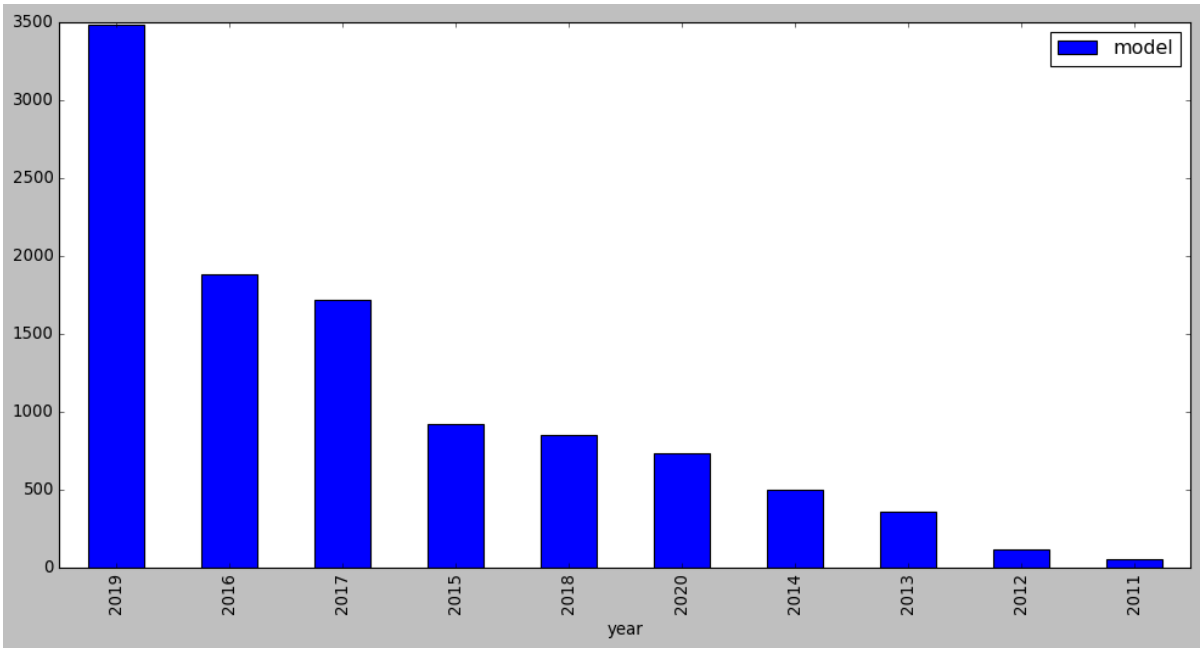
Out[38]:

year	model
2019	3485
2016	1882
2017	1721
2015	922
2018	848
2020	733
2014	501
2013	357
2012	119
2011	51

I am plotting a bar chart for the number of models in each year.

In [39]:
```
plt.style.use('classic')
bmw_yb.head(10).plot.bar(figsize=(15,7))
```

Out[39]: <AxesSubplot:xlabel='year'>



This bar chart shows there cars in the our data is mostly from 2019, 2016 and 2017.

The average amount spent on a model year after year:

BMW data is grouped by year and have taken the mean of each year. This will give the average price of the cars based on the registered year.

In [42]:
```
bmw_gy = bmw
bmw_gy = bmw_gy.groupby("year")
bmw_py = bmw_gy["price"].mean()

bmw_py = pd.DataFrame(bmw_py)
bmw_py = bmw_py.round(1)
bmw_py.sort_values(by=['price'], ascending=False, inplace=True)
bmw_py_2 = bmw_py.head(11)
bmw_py_2
```

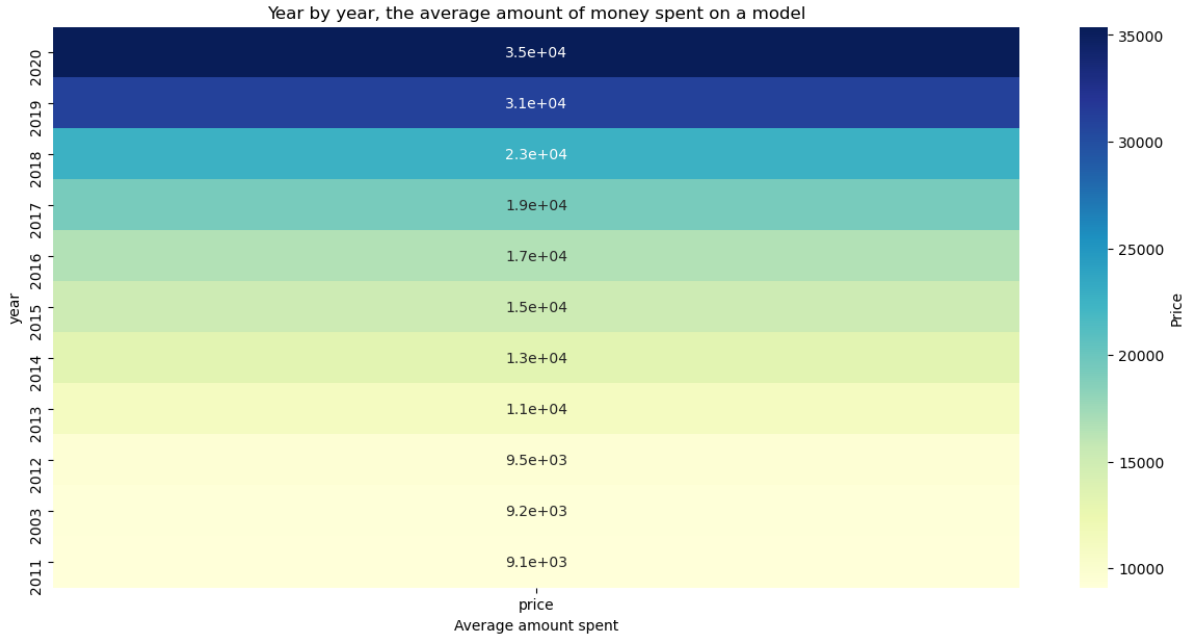
Out[42]:

year	price
2020	35377.7
2019	31025.9
2018	22721.7
2017	19267.2
2016	16638.4
2015	15199.8
2014	13323.6
2013	11118.4
2012	9533.7
2003	9222.5
2011	9099.1

Plotting the heatmap for the average price of the cars in each years.

In [44]:
```
plt.style.use('default')
plt.figure(figsize=(15,7))
sns.heatmap(data=bmw_py_2, cmap="YlGnBu", cbar_kws={'label': 'P
plt.title("Year by year, the average amount of money spent on a
plt.xlabel("Average amount spent")
```

Out[44]: Text(0.5, 47.7222222222222, 'Average amount spent')

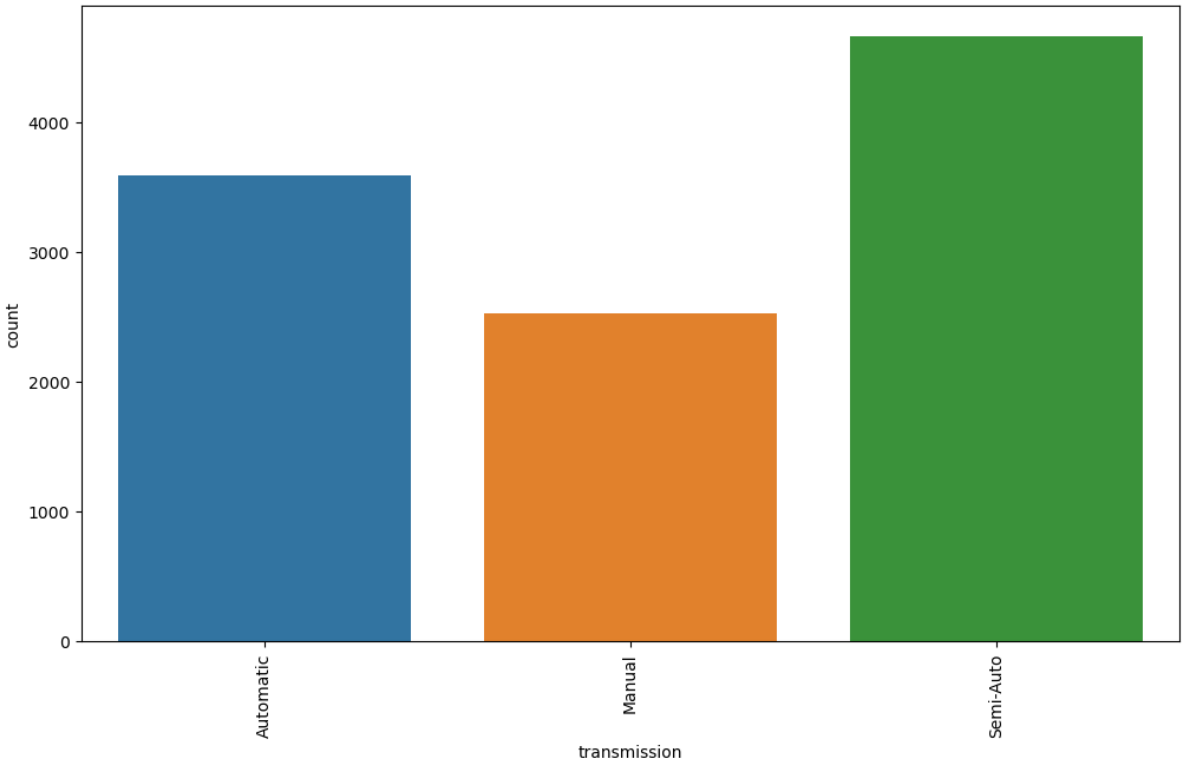


From above, the new cars are costly than the old cars.

Analysing the gear box over the years

To start with it, First count plot is plotted to find the number of counts of each gearbox.

In [48]:
```
plt.figure(figsize=(12,7))
count_model = sns.countplot(x = bmw["transmission"])
count_model.tick_params(axis='x', rotation=90)
```



In [49]:
```
bmw_gt = bmw
bmw_gt = bmw_gt.groupby("transmission")
bmw_mt = bmw_gt["model"].count()

bmw_mt = pd.DataFrame(bmw_mt)

bmw_mt
```

Out[49]:

transmission	model
Automatic	3588
Manual	2527
Semi-Auto	4666

Above result shows the count of each transmission.

Now, splitting the BMW dataset into a different dataset for each transmission. Each dataset is grouped by year. Cars in each years are counted and created a new dataset for count.

In [53]:
```
automatic_data = bmw[bmw["transmission"]=="Automatic"]
automatic_data_gy = automatic_data.groupby("year")
automatic_data_gy_c = automatic_data_gy["model"].count()
automatic_data_gy_c = pd.DataFrame(automatic_data_gy_c)


Manual_data = bmw[bmw["transmission"]=="Manual"]
Manual_data_gy = Manual_data.groupby("year")
Manual_data_gy_c = Manual_data_gy["model"].count()
Manual_data_gy_c = pd.DataFrame(Manual_data_gy_c)


Semi_Auto_data = bmw[bmw["transmission"]=="Semi-Auto"]
Semi_Auto_data_gy = Semi_Auto_data.groupby("year")
Semi_Auto_data_gy_c = Semi_Auto_data_gy["model"].count()
Semi_Auto_data_gy_c = pd.DataFrame(Semi_Auto_data_gy_c)
```

In [54]:
```
automatic_data_gy_c2 = automatic_data_gy_c
#reset the index
automatic_data_gy_c2 = automatic_data_gy_c2.reset_index()
automatic_data_gy_c2.describe()
```

Out[54]:

	year	model
count	23.000000	23.000000
mean	2008.913043	156.000000
std	6.940743	275.450045
min	1996.000000	1.000000
25%	2003.500000	3.000000
50%	2009.000000	11.000000
75%	2014.500000	170.500000
max	2020.000000	997.000000

In [55]:
```
Manual_data_gy_c2 = Manual_data_gy_c
Manual_data_gy_c2 = Manual_data_gy_c2.reset_index()
Manual_data_gy_c2.describe()
```

Out[55]:

	year	model
count	23.000000	23.000000
mean	2008.739130	109.869565
std	7.130073	178.360795
min	1997.000000	1.000000
25%	2003.000000	3.000000
50%	2009.000000	20.000000
75%	2014.500000	149.500000
max	2020.000000	637.000000

In [56]:
```
Semi_Auto_data_gy_c2 = Semi_Auto_data_gy_c
Semi_Auto_data_gy_c2 = Semi_Auto_data_gy_c2.reset_index()
Semi_Auto_data_gy_c2.describe()
```

Out[56]:

	year	model
count	11.000000	11.000000
mean	2014.090909	424.181818
std	4.657350	582.025054
min	2006.000000	1.000000
25%	2011.000000	32.000000
50%	2015.000000	252.000000
75%	2017.500000	551.500000
max	2020.000000	2005.000000

We are now joining all counted datasets into one dataset so that we can plot the line chart.

In [58]:
```
ty_dataset = Manual_data_gy_c2.merge(automatic_data_gy_c2, how=
ty_dataset = ty_dataset.merge(Semi_Auto_data_gy_c2, how= "left"
ty_dataset = ty_dataset.rename({"model_x": "manual", "model_y":
ty_dataset = ty_dataset.fillna(0)
ty_dataset.dtypes
```

Out[58]:
```
year           int64
manual         int64
automatic    float64
semi-auto    float64
dtype: object
```

In [61]:
```
ty_dataset["automatic"] = ty_dataset["automatic"].astype('int64
ty_dataset["semi-auto"] = ty_dataset["semi-auto"].astype('int64
ty_dataset.head()
```

Out[61]:

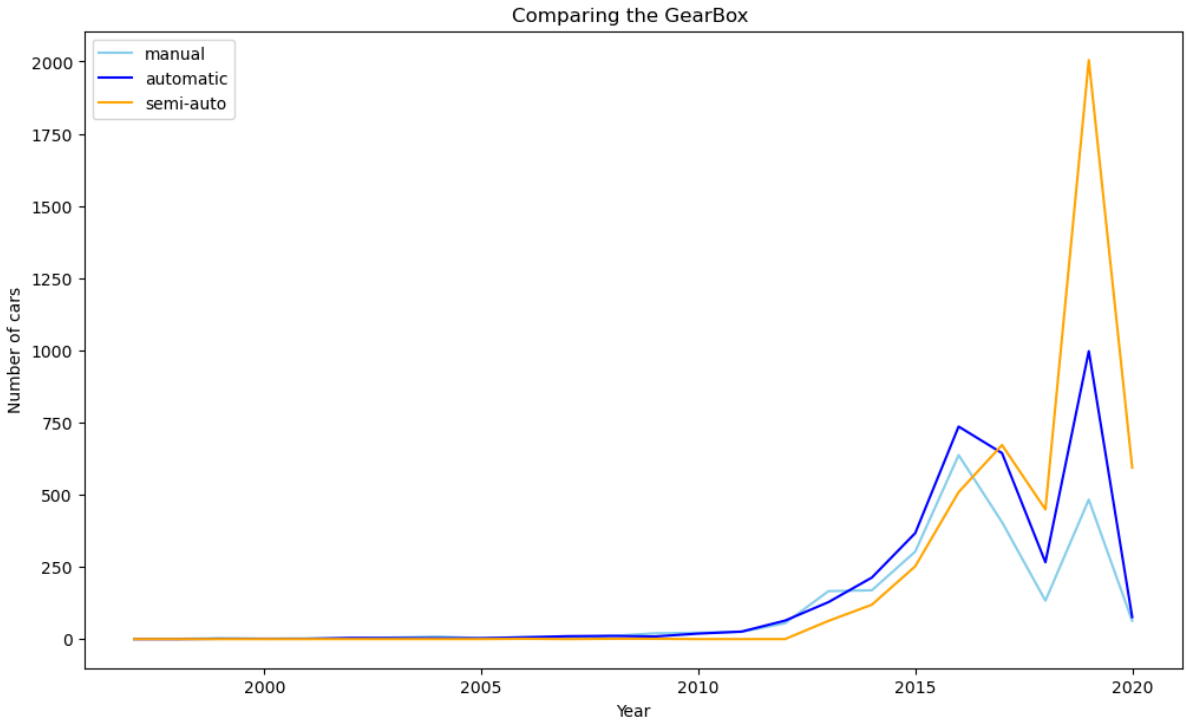
	year	manual	automatic	semi-auto
0	1997	1	0	0
1	1998	1	0	0
2	1999	3	1	0
3	2000	1	1	0
4	2001	2	1	0

Plotting the line chart

In [62]:
```
plt.figure(figsize=(12,7))
plt.plot( 'year', 'manual', data=ty_dataset,  color='skyblue')
plt.plot( 'year', 'automatic', data=ty_dataset, color='blue')
plt.plot( 'year', 'semi-auto', data=ty_dataset, color='orange')
# show legend
plt.legend()

plt.title('Comparing the GearBox ')
plt.xlabel('Year')
plt.ylabel('Number of cars')

# show graph
plt.show()
```

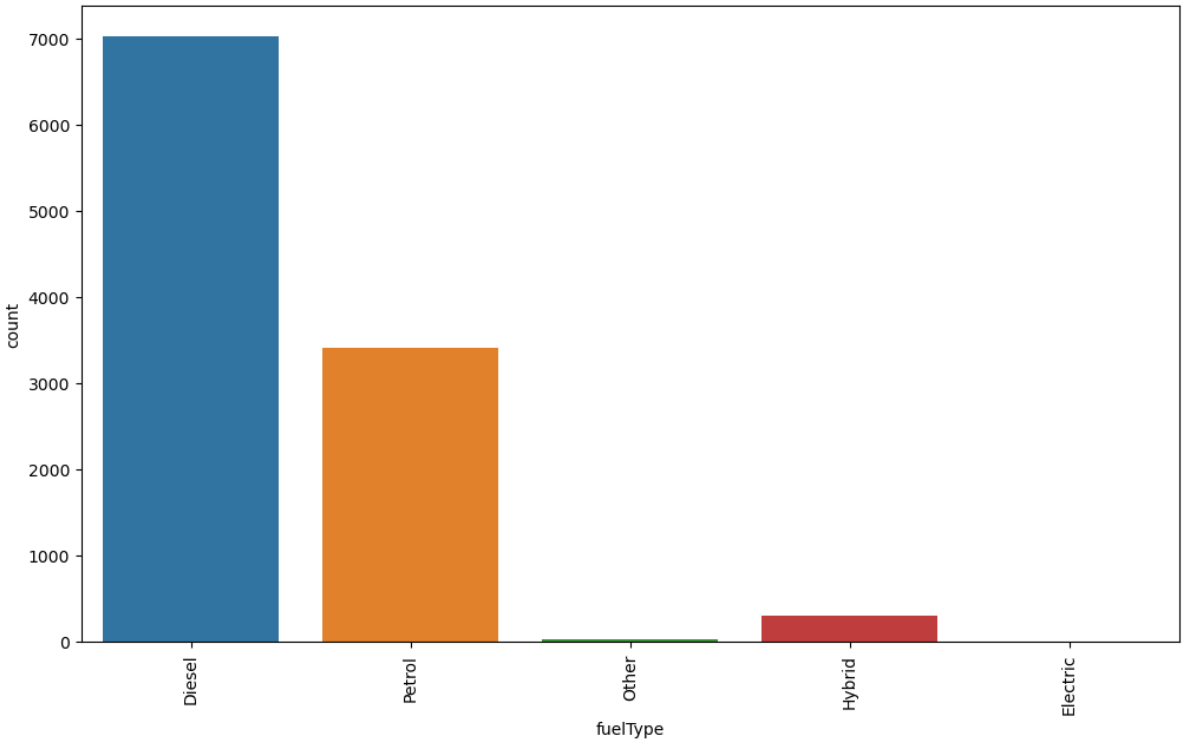


The above chart shows that new cars are mostly semi-auto cars in the UK, followed by automatic cars and then manual cars. From here, we can clearly see that people are turning to use automatic cars than manual cars.

Analysing the fule type over the years

To start with it, Count plot is plotted to find the number of counts of each fule type.

In [64]:
```
plt.figure(figsize=(12,7))
count_model = sns.countplot(x = bmw["fuelType"])
count_model.tick_params(axis='x', rotation=90)
```



In [65]:
```
bmw_gf = bmw
bmw_gf = bmw_gf.groupby("fuelType")
bmw_mf = bmw_gf["model"].count()

bmw_mf = pd.DataFrame(bmw_mf)

bmw_mf
```

Out[65]:

fuelType	model
Diesel	7027
Electric	3
Hybrid	298
Other	36
Petrol	3417

Above result shows the count of each fule type.

Now, splitting the BMW dataset into a different dataset for each fule types. Each dataset is grouped by year. Cars in each years are counted and created a new dataset for count.

In [66]:
```
Diesel_data = bmw[bmw["fuelType"]=="Diesel"]
Diesel_data_gy = Diesel_data.groupby("year")
Diesel_data_gy_c = Diesel_data_gy["model"].count()
Diesel_data_gy_c = pd.DataFrame(Diesel_data_gy_c)


Hybrid_data = bmw[bmw["fuelType"]=="Hybrid"]
Hybrid_data_gy = Hybrid_data.groupby("year")
Hybrid_data_gy_c = Hybrid_data_gy["model"].count()
Hybrid_data_gy_c = pd.DataFrame(Hybrid_data_gy_c)


Petrol_data = bmw[bmw["fuelType"]=="Petrol"]
Petrol_data_gy = Petrol_data.groupby("year")
Petrol_data_gy_c = Petrol_data_gy["model"].count()
Petrol_data_gy_c = pd.DataFrame(Petrol_data_gy_c)
```

In [67]:
```
Diesel_data_gy_c2 = Diesel_data_gy_c
Diesel_data_gy_c2 = Diesel_data_gy_c2.reset_index()
Diesel_data_gy_c2.head()
```

Out[67]:

	year	model
0	2004	2
1	2005	3
2	2006	5
3	2007	10
4	2008	11

In [68]:
```
Hybrid_data_gy_c2 = Hybrid_data_gy_c
Hybrid_data_gy_c2 = Hybrid_data_gy_c2.reset_index()
Hybrid_data_gy_c2.head()
```

Out[68]:

	year	model
0	2013	1
1	2014	6
2	2015	6
3	2016	78
4	2017	66

In [69]:
```
Petrol_data_gy_c2 = Petrol_data_gy_c
Petrol_data_gy_c2 = Petrol_data_gy_c2.reset_index()
Petrol_data_gy_c2.head()
```

Out[69]:

	year	model
0	1996	1
1	1997	1
2	1998	1
3	1999	4
4	2000	2

We are now joining all counted datasets into one dataset so that we can plot the line chart.

In [70]:
```
fy_dataset = Petrol_data_gy_c2.merge(Hybrid_data_gy_c2, how= "l
fy_dataset = fy_dataset.merge(Diesel_data_gy_c2, how= "left", o
fy_dataset = fy_dataset.rename({"model_x": "Petrol", "model_y":
fy_dataset = fy_dataset.fillna(0)
fy_dataset.dtypes
```

Out[70]:
```
year        int64
Petrol      int64
Hybrid    float64
Diesel    float64
dtype: object
```

In [71]:
```
fy_dataset["Hybrid"] = fy_dataset["Hybrid"].astype('int64')
fy_dataset["Diesel"] = fy_dataset["Diesel"].astype('int64')
fy_dataset.head()
```

Out[71]:

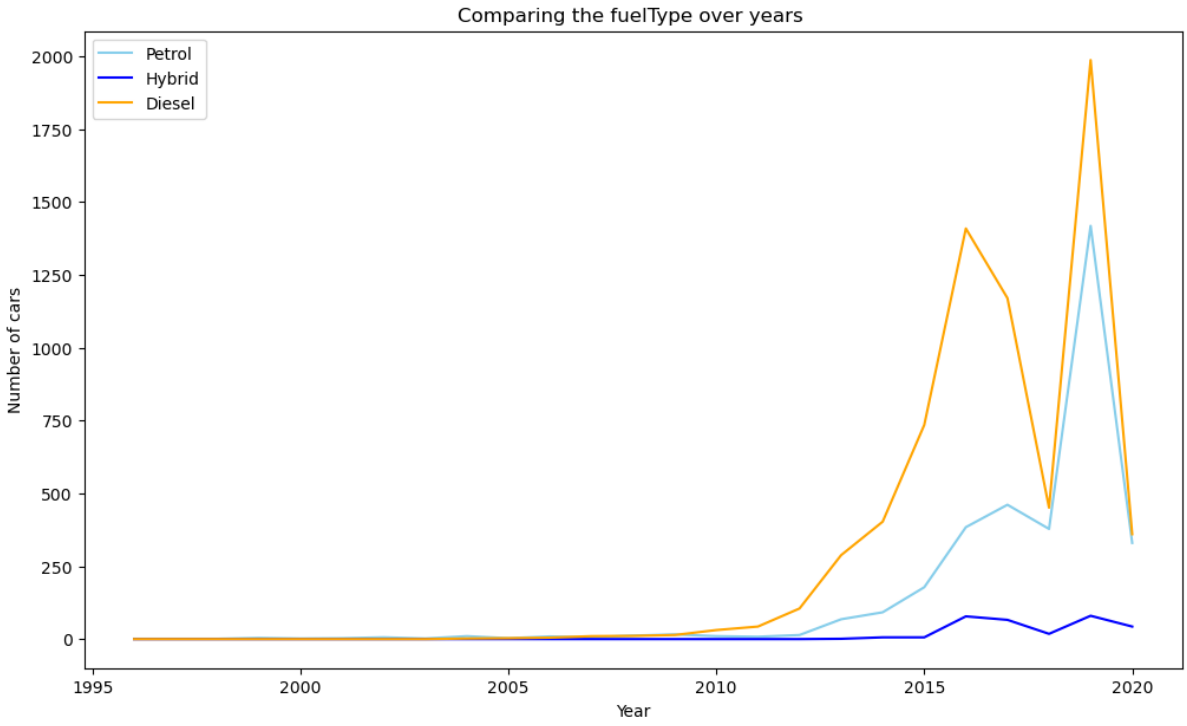
	year	Petrol	Hybrid	Diesel
0	1996	1	0	0
1	1997	1	0	0
2	1998	1	0	0
3	1999	4	0	0
4	2000	2	0	0

Plotting the line chart for fuel types over the years.

In [72]:
```
plt.figure(figsize=(12,7))
plt.plot( 'year', 'Petrol', data=fy_dataset,  color='skyblue')
plt.plot( 'year', 'Hybrid', data=fy_dataset, color='blue')
plt.plot( 'year', 'Diesel', data=fy_dataset, color='orange')
# show legend
plt.legend(loc='upper left')

plt.title('Comparing the fuelType over years ')
plt.xlabel('Year')
plt.ylabel('Number of cars')

# show graph
plt.show()
```



The above line chart shows the sale of diesel cars are high in count than the petrol cars. The sale of diesel cars of 2016 is facing the peak then suddenly there is a dip in the sales, and again sale of the cars get increased on car Registered in 2019. From hear we can clearly say that new cars are more soled.

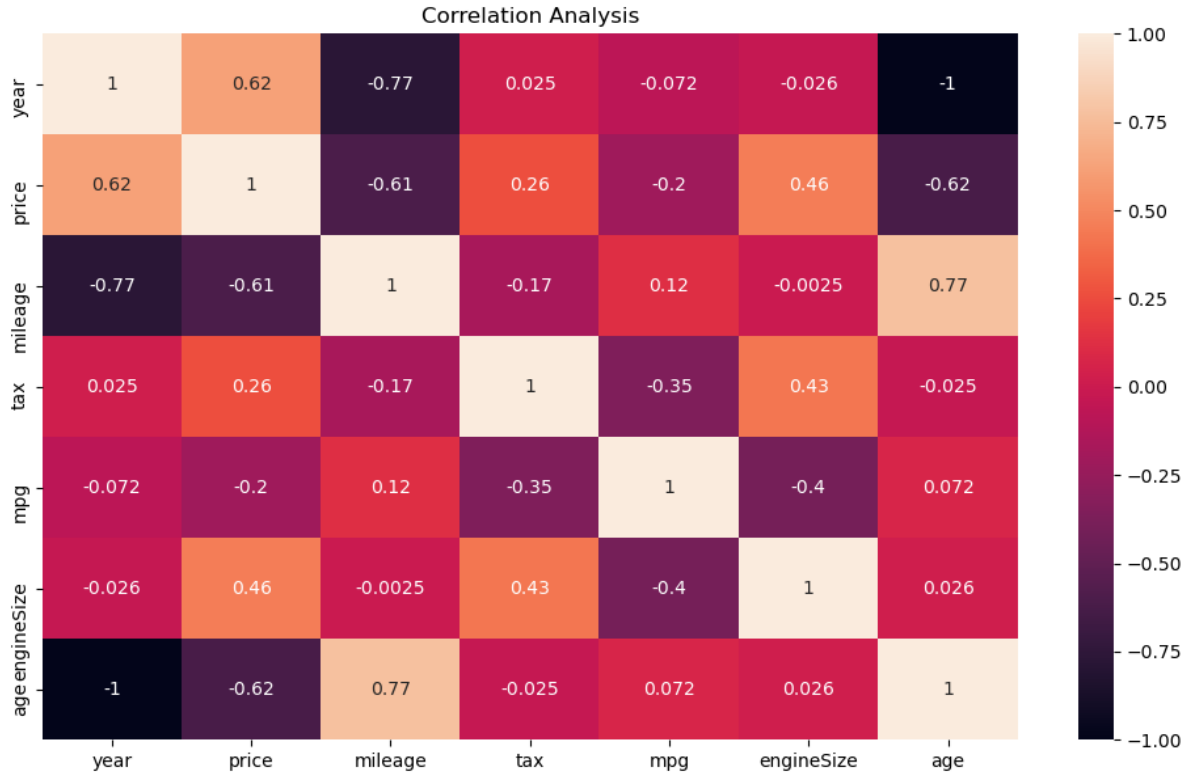
Objective 2

Predicting the price of the Used BMW Cars

To start with modelling, we need to prepare the data for it.

First, we are checking the correlation between each column. This will show how much columns are related to each other.

In [87]:
```
plt.figure(figsize=(12,7))
sns.heatmap(bmw.corr(), annot=True)
plt.title("Correlation Analysis")
plt.show()
```



The above Correlation shows that mileage, mpg columns are not related to the price columns.

In [74]:
```
bmw_d = bmw
bmw_d.head()
```

Out[74]:

	model	year	price	transmission	mileage	fuelType	tax	mpg	engineSize	age
0	5 Series	2014	11200	Automatic	67068	Diesel	125	57.6	2.0	7
1	6 Series	2018	27000	Automatic	14827	Petrol	145	42.8	2.0	3
2	5 Series	2016	16000	Automatic	62794	Diesel	160	51.4	3.0	5
3	1 Series	2017	12750	Automatic	26676	Diesel	145	72.4	1.5	4
4	7 Series	2014	14500	Automatic	39554	Diesel	160	50.4	3.0	7

Now we are creating the dummies for all characters columns because, in machine learning, we can feed the input through the numerical values only. So, we are converting all the characters columns into numerical and dropping the characters columns.

In [75]:
```
bmw_d = pd.concat([bmw_d, bmw_d['model'].str.get_dummies(sep=",
bmw_d = pd.concat([bmw_d, bmw_d['transmission'].str.get_dummies
bmw_d = pd.concat([bmw_d, bmw_d['fuelType'].str.get_dummies(sep


bmw_d = bmw_d.drop('model', 1)
bmw_d = bmw_d.drop('transmission', 1)
bmw_d = bmw_d.drop('fuelType', 1)
```

We are dropping the year column because we have an age column.

In [76]:
```
bmw_d.drop('year',axis=1,inplace=True)
bmw_d.head()
```

Out[76]:

	price	mileage	tax	mpg	engineSize	age	1 Series	2 Series	3 Series	4 Series	...	i3	i8	A
0	11200	67068	125	57.6	2.0	7	0	0	0	0	...	0	0	
1	27000	14827	145	42.8	2.0	3	0	0	0	0	...	0	0	
2	16000	62794	160	51.4	3.0	5	0	0	0	0	...	0	0	
3	12750	26676	145	72.4	1.5	4	1	0	0	0	...	0	0	
4	14500	39554	160	50.4	3.0	7	0	0	0	0	...	0	0	

5 rows × 38 columns

In [77]:
```
from sklearn.model_selection import train_test_split
```

Dataset is ready to create models. Now, I am splitting the dataset into a training dataset and a testing dataset.

In [78]:
```
X = bmw_d.drop('price',axis=1)
y = bmw_d['price']
```

In [79]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_
```

The following packages must be imported in order to create models.

In [80]:
```
from sklearn.linear_model import LinearRegression,Lasso,Ridge
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn.ensemble import RandomForestRegressor

from sklearn.svm import SVR
```

Now, we are fitting the training dataset in different models and predicting the test score. With this score, we can find the best models which suit this problem.

In [81]:
```
lr = LinearRegression()
lr.fit(X_train,y_train)
y_test_pred = lr.predict(X_test)

LR_Score = r2_score(y_test_pred,y_test)
LR_Score
```

Out[81]: 0.85970040228781

In [82]:
```
rf = RandomForestRegressor(random_state=50)
rf.fit(X_train,y_train)
y_test_pred2 = rf.predict(X_test)

RF_score = r2_score(y_test_pred2,y_test)
RF_score
```

Out[82]: 0.9558273093611489

In [83]:
```
r = Ridge()
r.fit(X_train,y_train)
y_test_pred3 = r.predict(X_test)

r_score = r2_score(y_test_pred3,y_test)
r_score
```

Out[83]: 0.8585020055211864

In [84]:
```
l = Lasso()
l.fit(X_train,y_train)
y_test_pred4 = l.predict(X_test)

l_score = r2_score(y_test_pred4,y_test)
l_score
```

```
/Users/raghulsekar/opt/anaconda3/lib/python3.8/site-packages/sklea
rn/linear_model/_coordinate_descent.py:530: ConvergenceWarning: Ob
jective did not converge. You might want to increase the number of
iterations. Duality gap: 62519446507.83631, tolerance: 112790724.7
1875542
  model = cd_fast.enet_coordinate_descent(
```

Out[84]: 0.8592052249172866

In [85]:
```
output = {
  "Linear Regression": LR_Score,
  "Random Forest Regressor": RF_score,
  "Ridge": r_score,
  "Lasso": l_score
}

output = pd.DataFrame.from_dict(output, orient='index')

output = output.rename_axis("model", axis="columns")
output.rename(columns = {0: "r2 Score"}, inplace=True)
output
```

Out[85]:

model	r2 Score
Linear Regression	0.859700
Random Forest Regressor	0.955827
Ridge	0.858502
Lasso	0.859205

The accuracy score of all the models for this dataset is shown in the table above. We can see that the random forest regressor has the greatest accuracy rate of 95.5 percent, indicating that it is the best model of the four.

Project Outcome (10 + 10 marks)

Overview of Results

In general, results from this BMW dataset are all about finding the Attributes that affect the price of the used cars and predicting the price of the used cars in the united kingdom. For this, I have virtualized the different type charts. From these charts, we can get the exact information needed by looking at it.

A Scatter plot is plotted to find how mileage affects the price with years, fule types and engine size. Also, there is another scatter plot and heat map which shows how a car's year of registration affects the price. Line chart from our result will compare each transmission of the cars with the cars years which will have the result to know which year car model has how many cars of transmission. Same like that, there is another line chat that will compare with fule types. Many people are willing to know their car price, so that I used this dataset to create four models that will predict the price of the used cars in the united kingdom based on the attributes.

Objective 1

Explanation of Results

Objective 1 is all about Virtual analysis of the data of the used BMW cars in the United Kingdom. From this analysis, we came to know that majority of the used BMW cars are from the last ten years. In comparison to older automobiles, cars with less miles travelled are more expensive. Diesel engines are the most often utilised, followed by petrol engines.

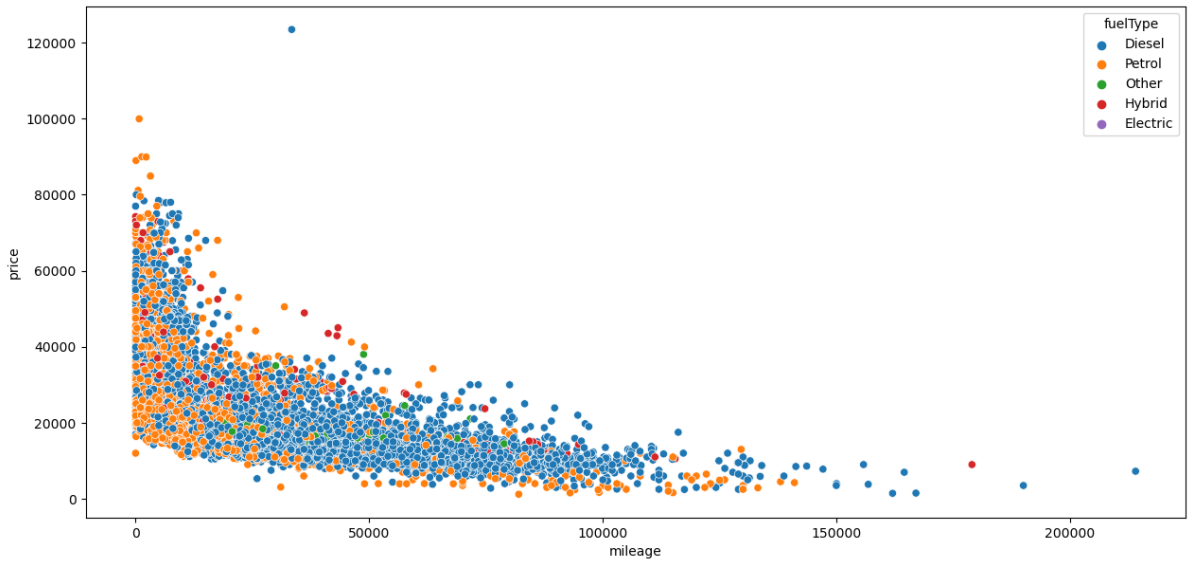
In addition, we can see that as the size of the engine grows larger, the automobiles last longer. 2019 model cars are the car model which sold in high quantities then followed by 2016 and 2017. As previously said, the price of the automobiles for the 2020 model year is rather expensive. Semi-auto vehicles have been utilised more than automatic or manual cars in terms of transmission. The majority of the cars in the 2019 model year are semi-automobiles. We can also see that the dataset is dominated by diesel vehicles.

Visualisation

This scatter plot demonstrates that most diesel automobiles are less expensive and have logged more kilometres than petrol vehicles. Petrol vehicles have a greater price than diesel cars with lower mileage, and as the mileage grows, the price of diesel cars decreases. When the mileage is low, we can tell that the price is high. As the mileage of an automobile grows, the price of the car lowers.

In [89]:
```
plt.figure(figsize=(15,7))
sns.scatterplot(x = bmw["mileage"], y = bmw["price"], hue = bmw
```

Out[89]: <AxesSubplot:xlabel='mileage', ylabel='price'>



Objective 2

Explanation of Results

The second objective is to forecast the price of used BMW automobiles based on the supplied attitudes. The mileage and mpg columns are unrelated to the price column, according to the correlation matrix. Then, for the character columns, dummies are produced so that the data may be utilised to create the models.

I made four models in order to choose the best one. Ridge, Lasso, Linear Regression, Random Forest Regressor These machine learning methods are trained using a separate training set from the data used to create the model. The testing dataset is used to put the trained model to the test. The best model is one that has a high accuracy score. The Random Forest Regressor is the best model that forecasts the price of used BMW cars with the greatest accuracy rate and best performance among the models that I have created here.

Visualisation

There is no visualization in this objective.

But there is a table that shows the Accuracy value of all models. From this, we can see the random forest regressor is the best model which predicts the accurate price.

In [88]:
```
1 output
```

Out[88]:

model	r2 Score
Linear Regression	0.859700
Random Forest Regressor	0.955827
Ridge	0.858502
Lasso	0.859205

Conclusion (5 marks)

Acheivements

From the result, we are able to predict the price of the used BMW cars in the united kingdom. The Random Forest Regressor model is the best model for reliably predicting the price of secondhand automobiles. As a result, understanding the price of their used cars using this approach makes individuals more helpful. In addition, the virtualization we created allows us to discover that recently purchased automobiles are sold at a premium price on the used market. We learned about the characteristics that influence the pricing of secondhand automobiles.

The price is influenced by so many factors that pinpointing the primary cause of price fluctuation is difficult. we can see, the 3 series is the most popular BMW vehicle in the United Kingdom. The majority of automobiles have been purchased in the previous three to four years.

Future Work

In the future, we'd like to collect more data on used automobiles from other manufacturers and develop a machine learning model that can better forecast the price. Apart from secondhand cars, we can also acquire data on buses, lorries, and other vehicles. This will aid the used car industry in estimating the value of vehicles based on their condition.

Grading

Feedback and marks will be given here.

Feedback

Marks

In [56]:
```
DATA   = 10
AIMS   =  5
DESIGN = 5

CODE = 15

OUTCOME_EXPLANATION   = 10
OUTCOME_VISUALISATION = 10

CONCLUSION = 5

TOTAL = ( DATA + AIMS + DESIGN + CODE
          + OUTCOME_VISUALISATION + OUTCOME_VISUALISATION
          + CONCLUSION )
TOTAL
```

Out[56]: 60

In [ ]:
```

```