Belarus Car Price Prediction

The aim of this project is to predict the price of the car in Belarus, by analyzing the car features such as brand, year, engine, fuel type, transmission, mileage, drive unit, color, and segment. The project also aims to find out the set the of variables that has most impact on the car price.

The dataset has been taken from kaggle. It has 56244 rows and 12 columns.

Data Dictionary

Variable	Description
make	machine firm
model	machine model
price USD	price in USD (target variable)
year	year of production
condition	represents the condition at the sale moment (with mileage, for parts, etc)
mileage	mileage in kilometers
fuel type	type of the fuel (electro, petrol, diesel)
volume(cm3)	volume of the engine in cubic centimeters
color	color of the car
transmission	type of transmission
drive unit	drive unit
segment	segment of the car

In [ ]:
```
# Loading the Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
# Loading the dataset
df = pd.read_csv('cars.csv')
df.head()
```

Out[ ]:

	make	model	priceUSD	year	condition	mileage(kilometers)	fuel_type	volume(cı
0	mazda	2	5500	2008	with mileage	162000.0	petrol	15(
1	mazda	2	5350	2009	with mileage	120000.0	petrol	13(
2	mazda	2	7000	2009	with mileage	61000.0	petrol	15(
3	mazda	2	3300	2003	with mileage	265000.0	diesel	14(
4	mazda	2	5200	2008	with mileage	97183.0	diesel	14(

Data Preprocessing Part 1

In [ ]:

```
# Checking the shape of the dataset
df.shape
```

Out[ ]: (56244, 12)

In [ ]:

```
# Checking the data types of the columns
df.dtypes
```

Out[ ]:

```
make                    object
model                   object
priceUSD                 int64
year                     int64
condition               object
mileage(kilometers)    float64
fuel_type               object
volume(cm3)            float64
color                   object
transmission            object
drive_unit              object
segment                 object
dtype: object
```

In [ ]:

```
# Droping the columns that are not needed for the analysis
df.drop(columns = ['model','segment'], inplace=True)
```

In [ ]:

```
# Unique values in the columns
df.nunique()
```

Out[ ]:
```
make                   96
priceUSD             2970
year                   78
condition               3
mileage(kilometers)  8400
fuel_type               3
volume(cm3)           458
color                  13
transmission            2
drive_unit              4
dtype: int64
```

In [ ]:
```
# Unqiue car make
df['make'].unique()
```

Out[ ]:
```
array(['mazda', 'mg', 'renault', 'gaz', 'aro', 'rover', 'uaz',
       'alfa-romeo', 'audi', 'oldsmobile', 'saab', 'peugeot', 'chrysler',
       'wartburg', 'moskvich', 'volvo', 'fiat', 'roewe', 'porsche', 'zaz',
       'luaz', 'dacia', 'lada-vaz', 'izh', 'raf', 'bogdan', 'bmw',
       'nissan', 'mercedes-benz', 'mitsubishi', 'toyota', 'chery', 'gmc',
       'hyundai', 'honda', 'ssangyong', 'suzuki', 'opel', 'seat',
       'volkswagen', 'daihatsu', 'chevrolet', 'geely', 'saturn', 'kia',
       'lincoln', 'eksklyuziv', 'citroen', 'dong-feng', 'pontiac', 'ford',
       'subaru', 'bentley', 'faw', 'cadillac', 'lifan', 'plymouth',
       'hafei', 'shanghai-maple', 'mini', 'jeep', 'skoda', 'mercury',
       'changan', 'lexus', 'isuzu', 'aston-martin', 'lancia',
       'great-wall', 'land-rover', 'jaguar', 'buick', 'daewoo', 'vortex',
       'infiniti', 'byd', 'smart', 'maserati', 'haval', 'acura', 'scion',
       'tata', 'datsun', 'tesla', 'mclaren', 'ravon', 'trabant', 'proton',
       'fso', 'jac', 'asia', 'iran-khodro', 'zotye', 'tagaz', 'saipa',
       'brilliance'], dtype=object)
```

Since there are you many car make, and it is difficult to analyze them individually, so I will group them into categories : Luxury European, Mainstream European, Russina/ Eastern European, Asian, American, Speciality, and Other. The grouping is based on the car make and the country of origin.

In [ ]:
```
# Categorizing the car make
def car_make(make):
    if make in ['mazda', 'mg', 'rover','alfa-romeo', 'audi', 'peugeot', 'chrysle
        return 'Luxury European'
    elif make in ['renault','dacia', 'citroen', 'volvo', 'fiat', 'opel', 'seat',
        return 'Mainstream European'
    elif make in ['gaz', 'aro', 'lada-vaz', 'izh', 'raf', 'bogdan', 'moskvich',
        return 'Russian/Eastern European'
    elif make in ['toyota', 'nissan','asia', 'mitsubishi', 'chery', 'hyundai', '
        return 'Asian'
    elif make in ['oldsmobile', 'gmc', 'chrysler', 'plymouth', 'ford', 'cadillac
        return 'American'
    elif make in ['porsche','bentley', 'maserati', 'tesla', 'mclaren']:
        return 'Specialty'
    else:
        return 'Other'

df['make_segment'] = df['make'].apply(car_make)
```

Descriptive statistics

In [ ]:
```
df.describe()
```

Out[ ]:

	priceUSD	year	mileage(kilometers)	volume(cm3)
count	56244.000000	56244.000000	5.624400e+04	56197.000000
mean	7415.456440	2003.454840	2.443956e+05	2104.860615
std	8316.959261	8.144247	3.210307e+05	959.201633
min	48.000000	1910.000000	0.000000e+00	500.000000
25%	2350.000000	1998.000000	1.370000e+05	1600.000000
50%	5350.000000	2004.000000	2.285000e+05	1996.000000
75%	9807.500000	2010.000000	3.100000e+05	2300.000000
max	235235.000000	2019.000000	9.999999e+06	20000.000000

In [ ]:
```
df.head()
```

Out[ ]:

	make	priceUSD	year	condition	mileage(kilometers)	fuel_type	volume(cm3)	
0	mazda	5500	2008	with mileage	162000.0	petrol	1500.0	bui
1	mazda	5350	2009	with mileage	120000.0	petrol	1300.0	
2	mazda	7000	2009	with mileage	61000.0	petrol	1500.0	
3	mazda	3300	2003	with mileage	265000.0	diesel	1400.0	
4	mazda	5200	2008	with mileage	97183.0	diesel	1400.0	

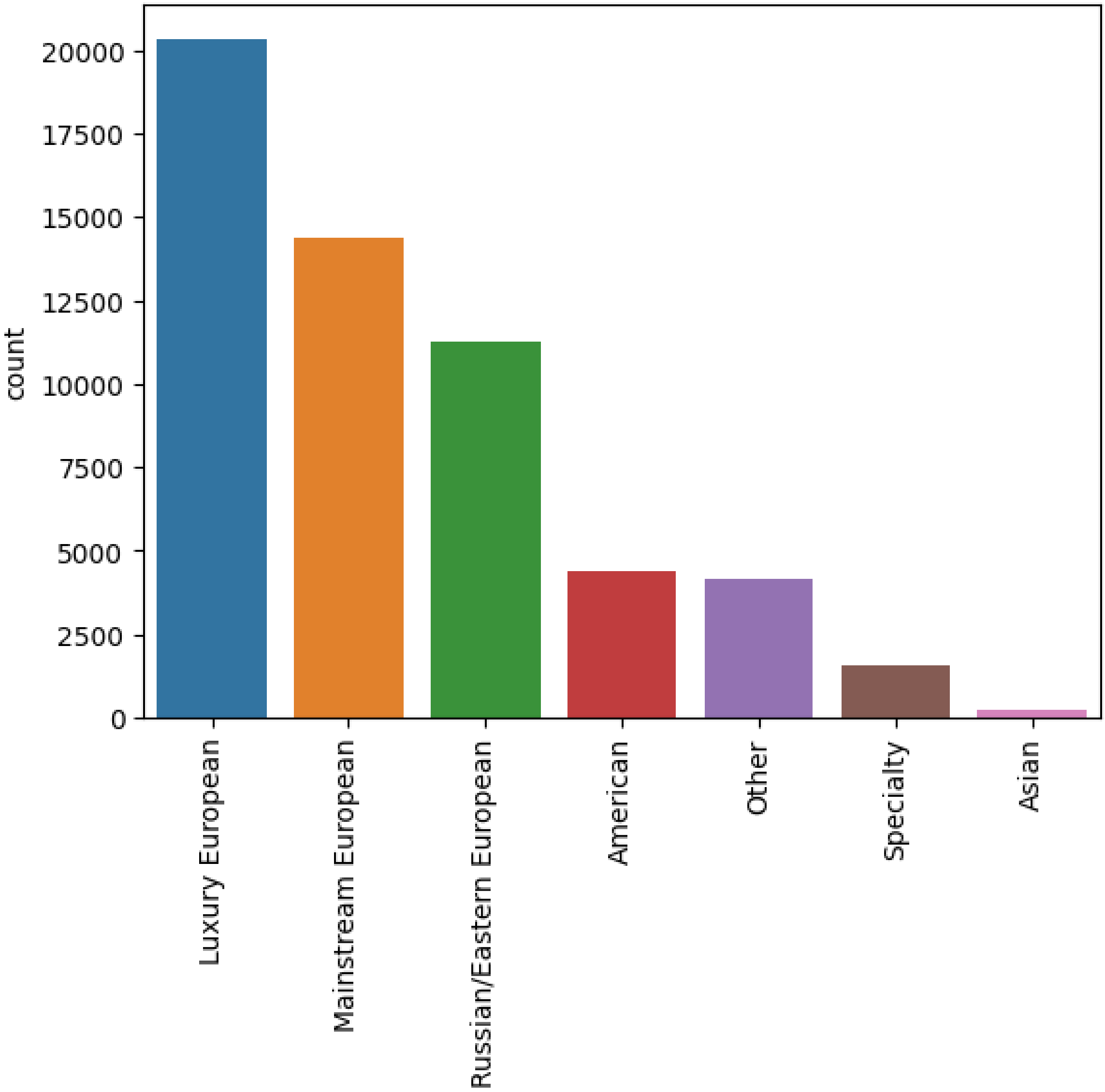
Exploratory Data Analysis

In the exploratory data analysis, I will analyze the relationship between the target variable and the independent variables. I will also analyze the relationship between the independent variables. This will help me to understand the data better and to find out the variables that have most impact on the target variable.

Car Make Segment

In [ ]:
```
sns.barplot(x=df['make_segment'].unique(), y=df['make_segment'].value_counts(),
plt.xticks(rotation=90)
```

```
Out[ ]: (array([0, 1, 2, 3, 4, 5, 6]),
         [Text(0, 0, 'Luxury European'),
          Text(1, 0, 'Mainstream European'),
          Text(2, 0, 'Russian/Eastern European'),
          Text(3, 0, 'American'),
          Text(4, 0, 'Other'),
          Text(5, 0, 'Specialty'),
          Text(6, 0, 'Asian')])
```

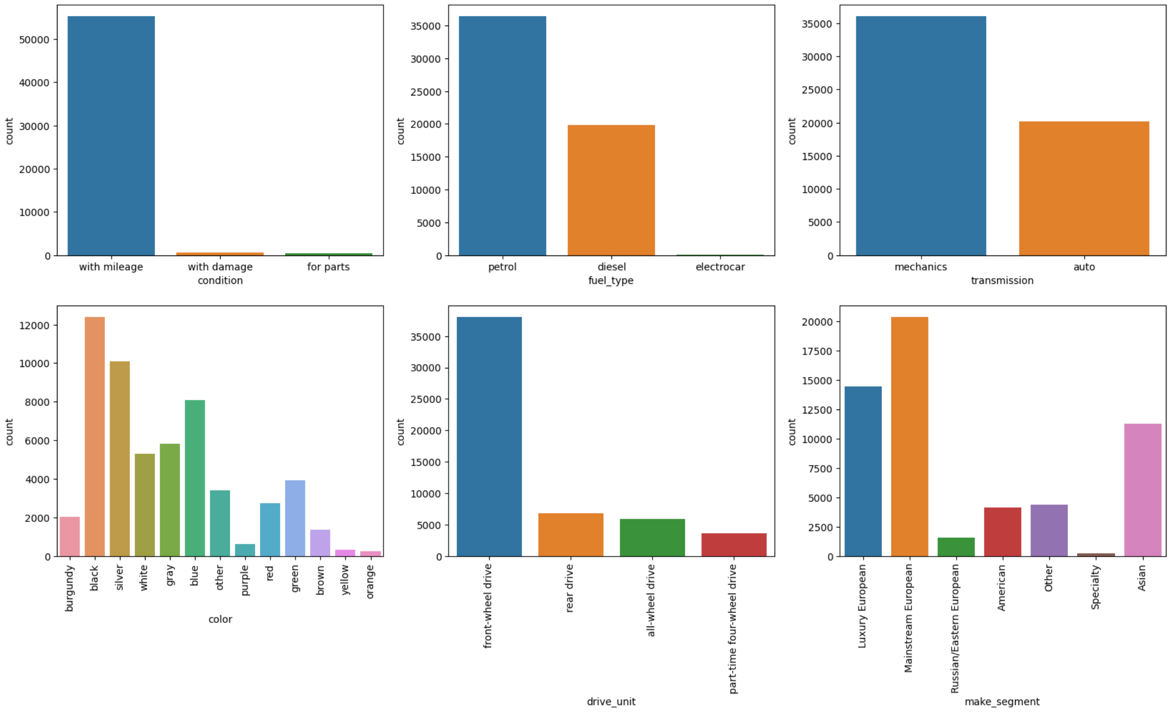


In the dataset, most of the cars are european (particulary majority of the are Luxury followed by Mainstream and Russian/Eastern European). However the dataset also has american as well asian cars. There are also some speciality cars such as Tesla, McLaren, Bentley, etc. The dataset also has some cars that are not categorized into any of the above categories.

Categorical Variable Distribution

```
In [ ]: fig, ax = plt.subplots(2,3,figsize=(20,10))
        sns.countplot(x='condition', data=df, ax=ax[0,0])
        sns.countplot(x='fuel_type', data=df, ax=ax[0,1])
        sns.countplot(x='transmission', data=df, ax=ax[0,2])
        sns.countplot(x='color', data=df, ax=ax[1,0])
        ax[1,0].tick_params(axis='x', rotation=90)
```

```
sns.countplot(x='drive_unit', data=df, ax=ax[1,1])
ax[1,1].tick_params(axis='x', rotation=90)
sns.countplot(x='make_segment', data=df, ax=ax[1,2])
ax[1,2].tick_params(axis='x', rotation=90)
```

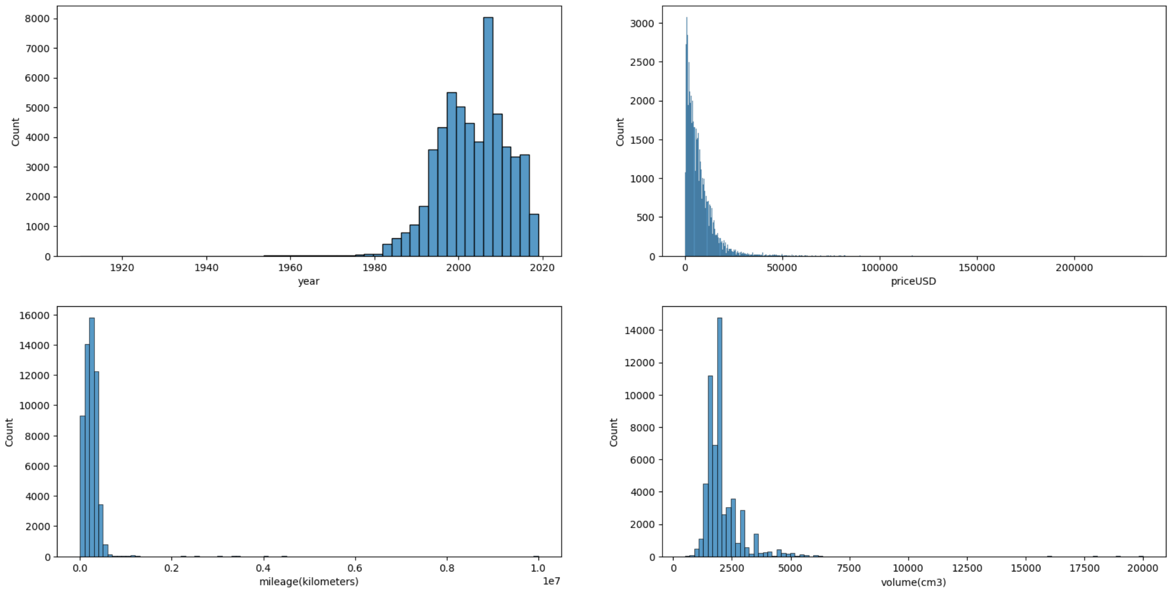


From the above graphs, we can get an overview regarding the data across the categorical variables in the data set. The from the above graphs it is clear that majority of the cars are being sold are in working condition, majority of them run on petrol, followed by diesel and hardly any of them runs on electricity. Most of the cars have manual transmission, with front wheel drive, having colors such as balck, silver, blue, white, and grey.

Continuous Variable Distribution

In [ ]:
```
fig, ax = plt.subplots(2,2,figsize=(20,10))
sns.histplot (df['year'], ax=ax[0,0], bins = 50)
sns.histplot(df['priceUSD'], ax=ax[0,1])
sns.histplot(df['mileage(kilometers)'], ax=ax[1,0], bins = 100)
sns.histplot(df['volume(cm3)'], ax=ax[1,1], bins = 100)
```

Out[ ]: <Axes: xlabel='volume(cm3)', ylabel='Count'>



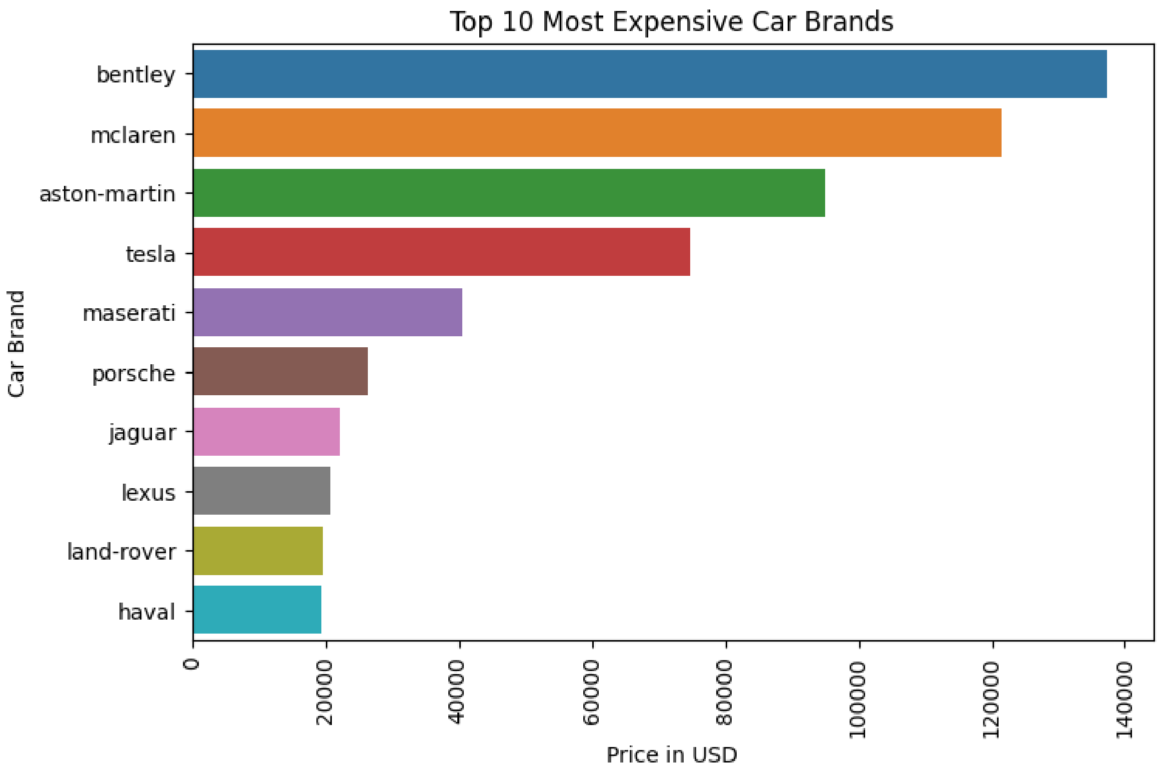
The above graphs shows the distribution of the data across continuous variables. Majority of the cars are manufactured between 1990 to 2019,having price less than 50k USD, mileage less than 1 million km, engine volume between 1750 to 2000 cm3.

Since most of the cars are manufactured after 1980, so I will only consider the cars manufactured after 1980.

In [ ]:
```
df= df[df['year']>1980]
```

Price and Make

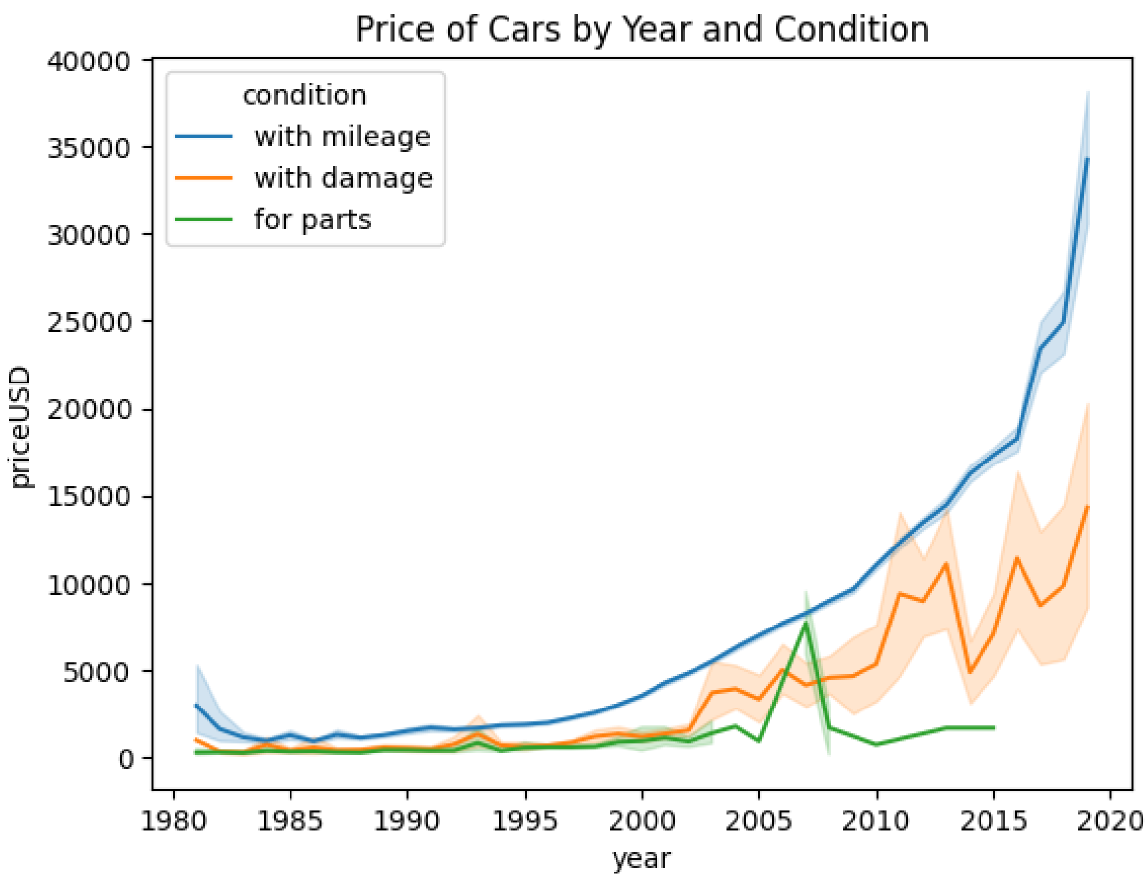
In [ ]:
```
demodf = df.groupby('make')['priceUSD'].mean().reset_index()
demodf = demodf.sort_values(by='priceUSD', ascending=False).head(10)

#b Bar Plot
plt.figure(figsize=(8,5))
sns.barplot(y='make', x='priceUSD', data=demodf)
plt.xticks(rotation=90)
plt.title('Top 10 Most Expensive Car Brands')
plt.ylabel('Car Brand')
plt.xlabel('Price in USD')
plt.show()
```



This graph shows top 10 most expensive car brands in the data set. The top 5 most expensive car brands are Bentley, Mclaren, aston-martin, Tesla and meserati.

Price and Condition

In [ ]:
```
sns.lineplot(x = 'year', y = 'priceUSD', data = df, hue = 'condition')
plt.title('Price of Cars by Year and Condition')
plt.show()
```

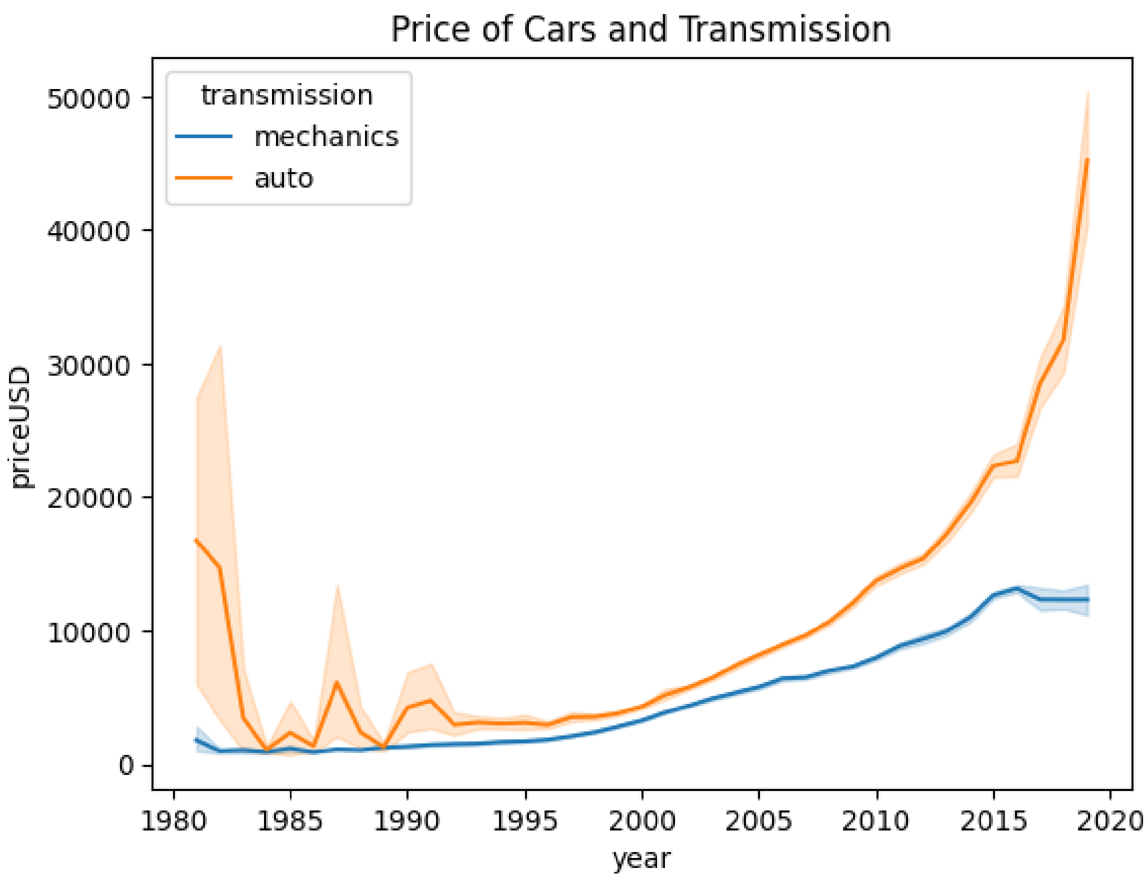


This graph shows the relationship between the price and the year of the car along with selling codition of the car. Cars, which are sold in working condition, are more expensive and their price increased with time, having exponential increase between 2015 to 2020. Cars, which were damaged, had a similar price to tha cars which were sold for parts between 1980 to 2000. However, the price of the damaged cars increased significanlty after 2000. Cars, which were sold for parts, tend to have minimal price and their price increased very little with time.

The cars running on petrol and diesel have similar mileage, however their prices are quite different. The cars running on petrol tend to have higher price than the diesel ones. The cars running on electricity tend to have very high prices and low mileage.

Price and Transmission

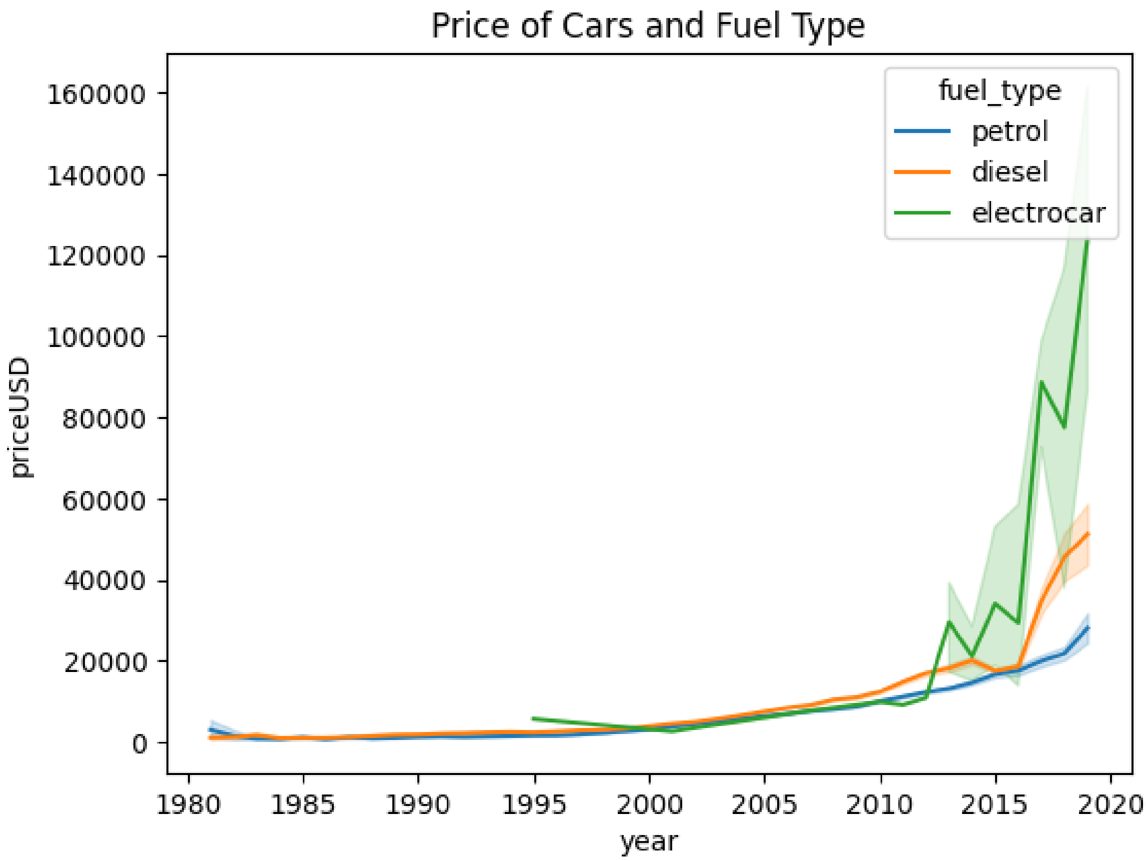
In [ ]:
```
sns.lineplot(x = 'year', y = 'priceUSD', data = df, hue = 'transmission')
plt.title('Price of Cars and Transmission')
plt.show()
```



This graph reveals the changes in the car price based on their transmission. The price of the cars with automatic transmission decreased significantly after 1983, however its price increased exponentially after 2000. However, the price of the cars with manual transmission is always less than the cars with automatic transmission showing similar increase in price after 2000.

Price and Fuel Type

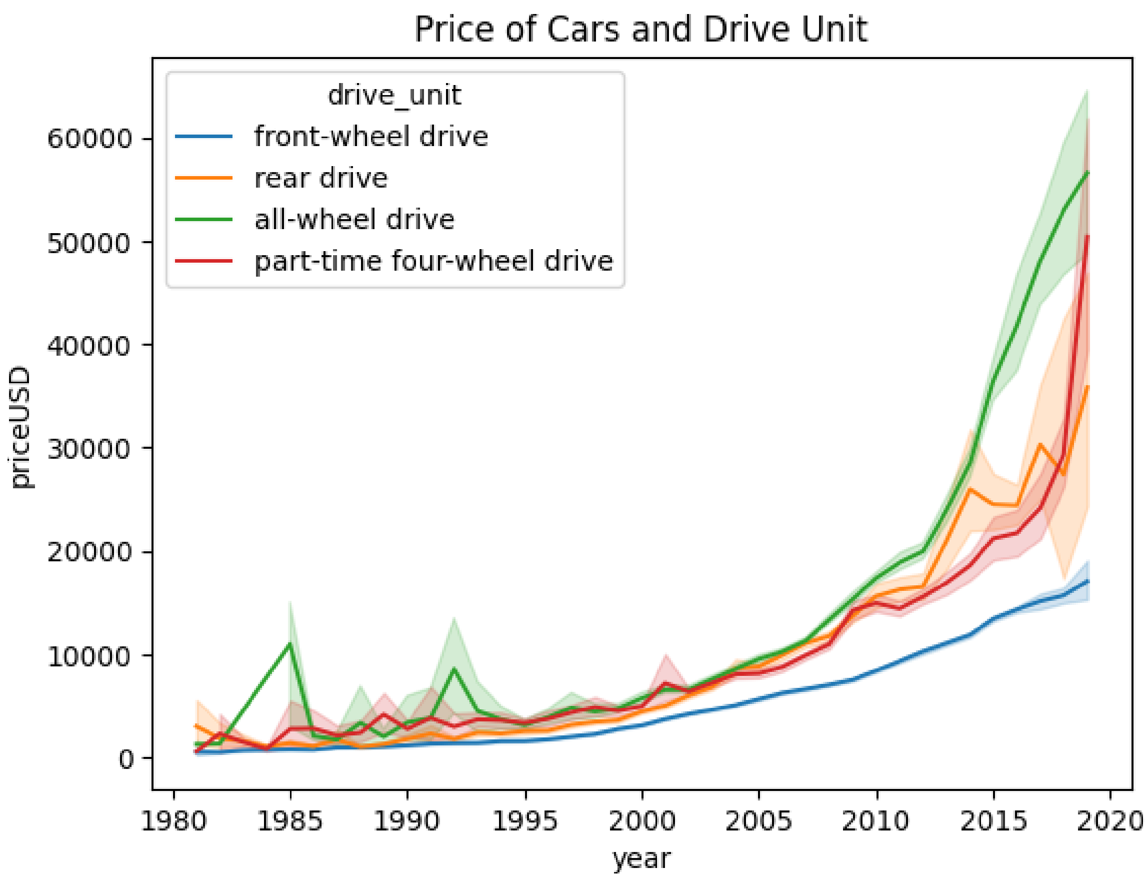
In [ ]:
```
sns.lineplot(x = 'year', y = 'priceUSD', data = df, hue = 'fuel_type')
plt.title('Price of Cars and Fuel Type')
plt.show()
```



Till 2005, there was no major difference in car price of cars running on petrol and diesel. However, after 2015, the price of the cars running on petrol increased significantly, whereas the price of the cars running on diesel increased with a very small margin. The graph also highloghts the introducttion of electro cars, which runs on electricity in 1995. However, the price of the electro cars increases exponentially after 2015, having the highest car price based on fuel type

Price and Drive Unit

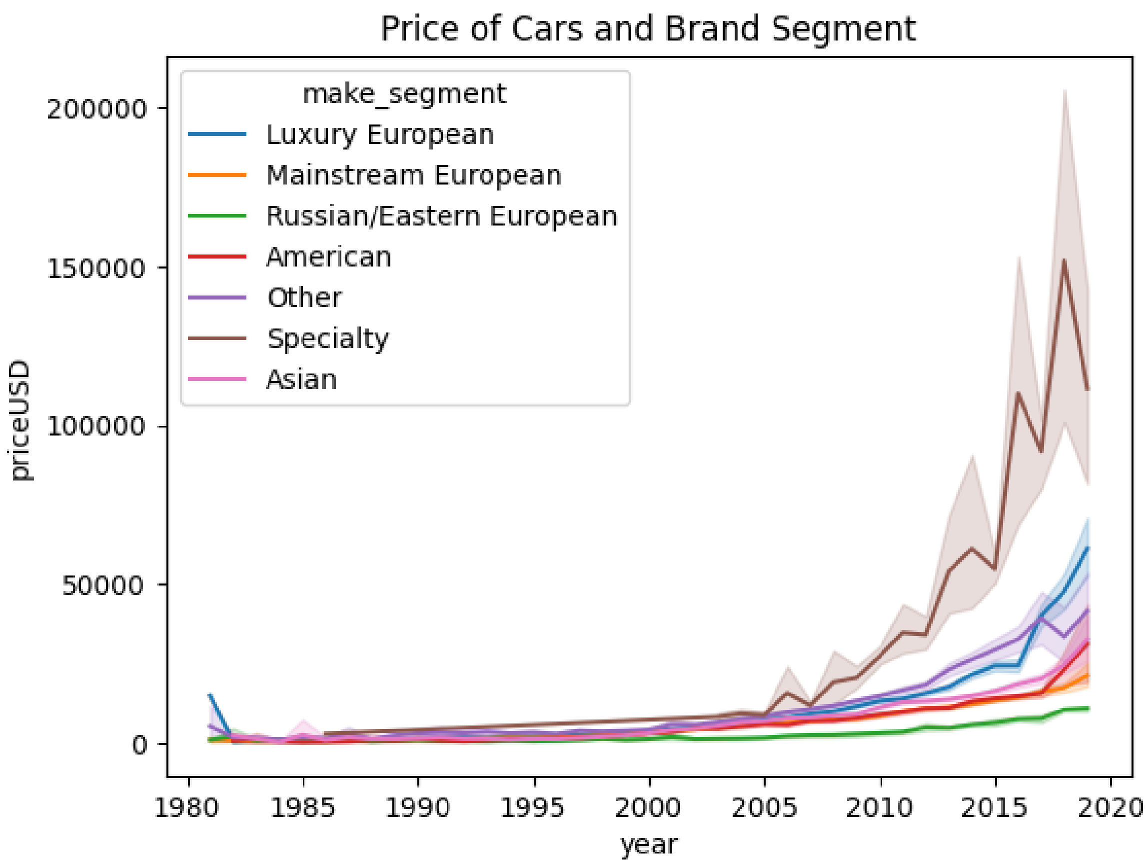
In [ ]:
```
sns.lineplot(x = 'year', y = 'priceUSD', data = df, hue = 'drive_unit')
plt.title('Price of Cars and Drive Unit')
plt.show()
```



Between 1980 to 1995, there was not much difference in the price of the cars based on the drive unit. However after 1995, the price of the cars with front wheel drive increased at a slower pace as compared to other drive units. The price of the cats with all wheel drive increased significantly after 2005, having the highest price among all the drive units, followed by part-time four wheel drive and rear wheel drive.

Price and Brand Segment

In [ ]:
```
sns.lineplot(x = 'year', y = 'priceUSD', data = df, hue = 'make_segment')
plt.title('Price of Cars and Brand Segment')
plt.show()
```



This graph shows the surge in car prices after 2005, where we can seen that the price of the specialty car segment increased significanlty followed by the luxury european car, American, Asian and Mainstream European car segment. The price of the Russian/Eastern European car segment increased at a slower pace as compared to other segments and is lowest among all the segments.

Data Preprocessing Part 2

In [ ]:
```
# checking for null values
df.isnull().sum()
```

Out[ ]:
```
make                   0
priceUSD               0
year                   0
condition              0
mileage(kilometers)    0
fuel_type              0
volume(cm3)           47
color                  0
transmission           0
drive_unit          1874
make_segment           0
dtype: int64
```

Since, the count of null values in small in comparison to that dataset size, I will be dropping the null values from the dataset.

In [ ]:
```
df.dropna(inplace=True)
```

In [ ]:
```
df.drop(columns=['make'], inplace=True)
```

Label encoding for object data type

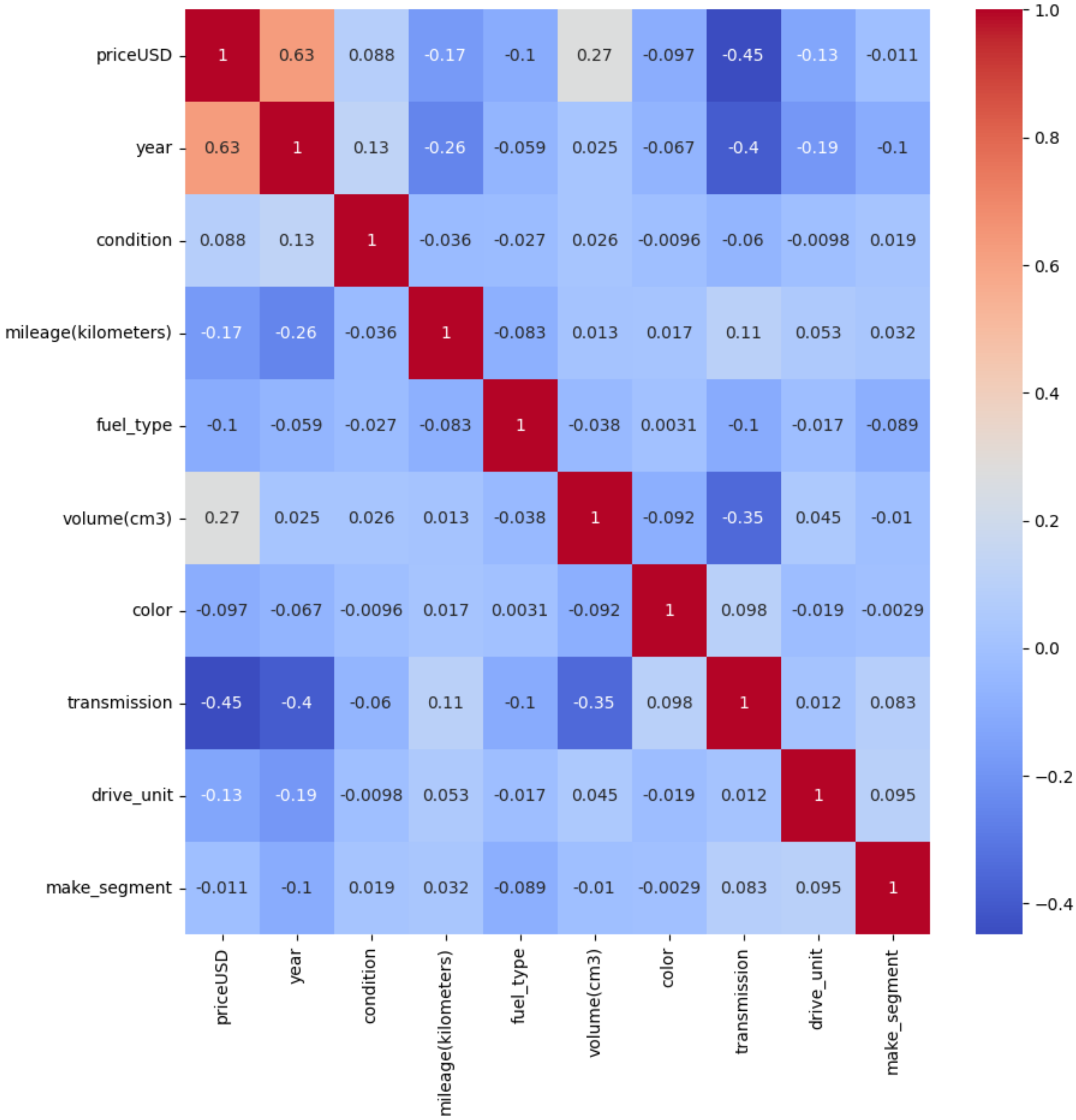
In [ ]:
```
from sklearn.preprocessing import LabelEncoder

# columns to encode
cols = ['condition', 'fuel_type', 'transmission', 'color', 'drive_unit', 'make_s

# Label encoding Object
le = LabelEncoder()

#label encoding for each column
for col in cols:
    le.fit(df[col])
    df[col] = le.transform(df[col])
    print(col, df[col].unique())
```

```
condition [2 1 0]
fuel_type [1 0]
transmission [1 0]
color [ 3  0 10 11  4  1  7  8  9  5  2 12  6]
drive_unit [1 3 0 2]
make_segment [2 3 5 0 4 6 1]
```

Correlation Matrix Heatmap

In [ ]:
```
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
```

Out[ ]: `<Axes: >`



Outlier Removal

In [ ]:

```
# Using Z-score to remove outliers
from scipy import stats

z = np.abs(stats.zscore(df))

threshold = 3

#columns with outliers
cols = ['year', 'mileage(kilometers)', 'volume(cm3)']

#removing outliers
df = df[(z < 3).all(axis=1)]
```

Train Test Split

In [ ]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df.drop(columns=['priceUSD']
```

Model Building

Decision Tree Regressor

In [ ]:
```
from sklearn.tree import DecisionTreeRegressor

# Decision Tree Regressor Object
dtr = DecisionTreeRegressor()
```

Hypertuning using GridSearchCV

In [ ]:
```
from sklearn.model_selection import GridSearchCV

#parameters for grid search
params = {
    'max_depth': [2,4,6,8],
    'min_samples_split': [2,4,6,8],
    'min_samples_leaf': [1,2,3,4],
    'max_features': ['auto', 'sqrt', 'log2'],
    'random_state': [0,42]
}
# Grid Search Object
grid = GridSearchCV(dtr, param_grid=params, cv=5, verbose=1, n_jobs=-1)

#fitting the grid search
grid.fit(X_train, y_train)

#best parameters
print(grid.best_params_)
```

```
Fitting 5 folds for each of 384 candidates, totalling 1920 fits
{'max_depth': 8, 'max_features': 'auto', 'min_samples_leaf': 4, 'min_samples_spli
t': 2, 'random_state': 0}
```

```
C:\Users\DELL\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2k
fra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\tree\_classes.p
y:277: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will b
e removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0'`.
  warnings.warn(
```

In [ ]:
```
#decision tree regressor with best parameters
dtr = DecisionTreeRegressor(max_depth=8, max_features='auto', min_samples_leaf=4

#fitting the model
dtr.fit(X_train, y_train)
```

```
C:\Users\DELL\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2k
fra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\tree\_classes.p
y:277: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will b
e removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0'`.
  warnings.warn(
```

Out[ ]:

```
▾ DecisionTreeRegressor
DecisionTreeRegressor(max_depth=8, max_features='auto', min_samples_lea
f=4,
                      random_state=0)
```

In [ ]:

```
#training score
dtr.score(X_train, y_train)
```

Out[ ]: 0.8689232243678456

In [ ]:

```
#predicting the test set
y_pred = dtr.predict(X_test)
```

Model Evaluation

In [ ]:

```
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
print('R2 Score: ', r2_score(y_test, y_pred))
print('Mean Squared Error: ', mean_squared_error(y_test, y_pred))
print('Mean Absolute Error: ', mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error: ', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
R2 Score:  0.8529954473045238
Mean Squared Error:  4704555.776616746
Mean Absolute Error:  1414.2804910704947
Root Mean Squared Error:  2168.9987959002524
```

Feature Importance

In [ ]:

```
feat_df = pd.DataFrame({'Feature': X_train.columns, 'Importance': dtr.feature_im
feat_df = feat_df.sort_values(by='Importance', ascending=False)
feat_df
```

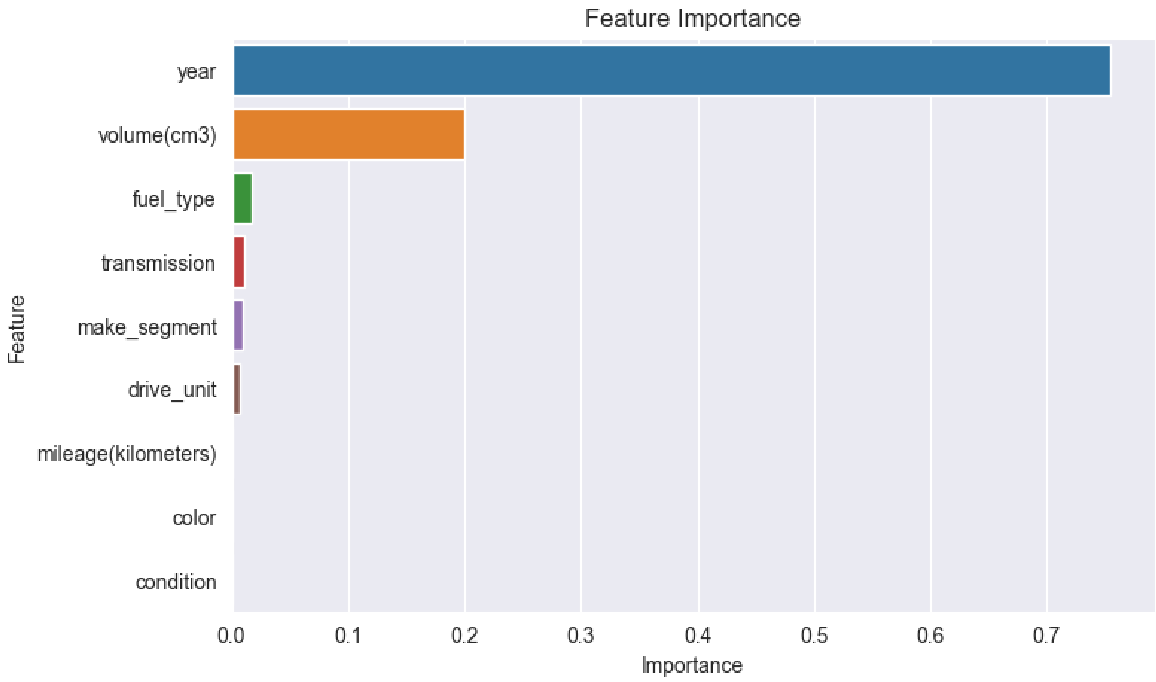
Out[ ]:

	Feature	Importance
0	year	0.754301
4	volume(cm3)	0.200413
3	fuel_type	0.017333
6	transmission	0.010267
8	make_segment	0.009639
7	drive_unit	0.006883
2	mileage(kilometers)	0.000872
5	color	0.000292
1	condition	0.000000

In [ ]:

```
# Bar Plot
sns.set_style('darkgrid')
plt.figure(figsize=(8,5))
```

```
sns.barplot(x='Importance', y='Feature', data=feat_df)
plt.title('Feature Importance')
plt.show()
```



Conclusion

The aim of this project was to predict the price of the car in Belarus, by analyzing the car features such as brand, year, engine, fuel type, transmission, mileage, drive unit, color, and segment. During the exploratory data analysis, it was found that there has been a significant increase in car prices in Belarus after the year 2000. The cars which runs on petrol have automatic transmission have higher price has compared to diesel cars with manual transmission. However, the elctric cars are distinctively expensive than the other cars. The cars with all wheel drive have the highest price among all the drive units. The speciality segment cars have the highest price among all the segments followed by luxury european, american, asian car segments.

The decision tree regressor model was used to predict the car price. The model was able to predict the car price with 85.29% accuracy. The most important features for predicting the car price were found to be year and volume of the engine.