main

September 14, 2024

[155]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[156]:
```
df = pd.read_csv("cars.csv")
df.head()
```

[156]:
```
    make model  priceUSD  year     condition  mileage(kilometers) fuel_type  \
0  mazda     2      5500  2008  with mileage             162000.0    petrol
1  mazda     2      5350  2009  with mileage             120000.0    petrol
2  mazda     2      7000  2009  with mileage              61000.0    petrol
3  mazda     2      3300  2003  with mileage             265000.0    diesel
4  mazda     2      5200  2008  with mileage              97183.0    diesel

   volume(cm3)     color transmission         drive_unit segment
0       1500.0  burgundy    mechanics  front-wheel drive       B
1       1300.0     black    mechanics  front-wheel drive       B
2       1500.0    silver         auto  front-wheel drive       B
3       1400.0     white    mechanics  front-wheel drive       B
4       1400.0      gray    mechanics  front-wheel drive       B
```

[157]:
```
# to check shape of the dataset
df.shape
```

[157]: (56244, 12)

[158]:
```
df.dtypes
```

[158]:
```
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
```

[159]:
```
# dropping unnecssary tables from the dataset for the anaylsis
df.drop(columns = ['model','segment'], inplace=True)
```

[160]:
```
# to find the unique values in the columns
df.nunique()
```

[160]:
```
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
```

[161]:
```
# gives me all knind of makes/types from the dataset
# it can be done for all the columns
print(df['make'].unique())
print("colors")
print(df['color'].unique())
```

```
['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']
colors
['burgundy' 'black' 'silver' 'white' 'gray' 'blue' 'other' 'purple' 'red'
 'green' 'brown' 'yellow' 'orange']
```

Since there are many cars, it is difficult to analyze them so i will group them into categories: Luxury

European, Mainstream European, Russina/ Eastern European, Asian, American, Speciality, and Other.

[162]:
```
#categorizing the car make according to the categoires
def car_make(make):
    if make in['mazda', 'mg', 'rover','alfa-romeo', 'audi', 'peugeot',␣
 ↪'chrysler', 'bmw', 'aston-martin','jaguar', 'land-rover']:
        return 'Luxury European'
    elif make in ['renault','dacia', 'citroen', 'volvo', 'fiat', 'opel',␣
 ↪'seat', 'volkswagen', 'citroen', 'skoda', 'mini', 'smart' ]:
        return 'Mainstream European'
    elif make in ['gaz', 'aro', 'lada-vaz', 'izh', 'raf', 'bogdan', 'moskvich',␣
 ↪'uaz', 'luaz', 'wartburg', 'trabant', 'proton', 'fso', 'jac', 'iran-khodro',␣
 ↪'zotye', 'tagaz', 'saipa', 'brilliance']:
        return 'Russian/Eastern European'
    elif make in ['toyota', 'nissan','asia', 'mitsubishi', 'chery', 'hyundai',␣
 ↪'honda', 'ssangyong', 'suzuki', 'daihatsu', 'kia', 'changan', 'lexus',␣
 ↪'isuzu', 'great-wall', 'daewoo', 'vortex', 'infiniti', 'byd', 'geely',␣
 ↪'haval', 'acura', 'scion', 'tata', 'datsun', 'ravon', 'proton', 'jac']:
        return 'Asian'
    elif make in ['oldsmobile', 'gmc', 'chrysler', 'plymouth', 'ford',␣
 ↪'cadillac', 'jeep', 'mercury', 'lincoln', 'buick', 'saturn', 'pontiac',␣
 ↪'chevrolet']:
        return 'American'
    elif make in ['porsche','bentley', 'maserati', 'tesla', 'mclaren']:
        return 'Specialty'
    else:
        return 'Other'
    # this below functions is used for creating a column (car_segment) to␣
 ↪display the categories in the dataets
df['make_segment'] = df['make'].apply(car_make)
```

[163]:
```
df.describe()
```

[163]:

	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

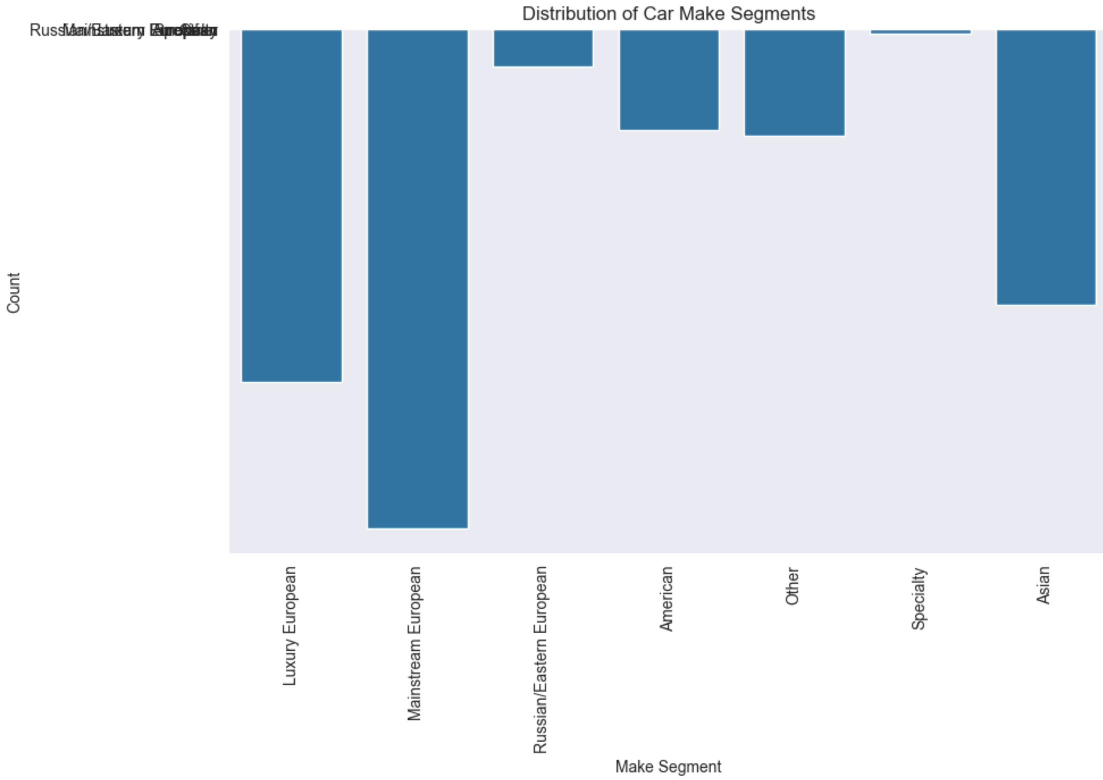
[164]:
```
df.head()
```

[164]:

```
    make  priceUSD  year     condition  mileage(kilometers) fuel_type  \
0  mazda      5500  2008  with mileage             162000.0    petrol
1  mazda      5350  2009  with mileage             120000.0    petrol
2  mazda      7000  2009  with mileage              61000.0    petrol
3  mazda      3300  2003  with mileage             265000.0    diesel
4  mazda      5200  2008  with mileage              97183.0    diesel

  volume(cm3)     color transmission        drive_unit     make_segment
0      1500.0  burgundy    mechanics  front-wheel drive  Luxury European
1      1300.0     black    mechanics  front-wheel drive  Luxury European
2      1500.0    silver         auto  front-wheel drive  Luxury European
3      1400.0     white    mechanics  front-wheel drive  Luxury European
4      1400.0      gray    mechanics  front-wheel drive  Luxury European
```

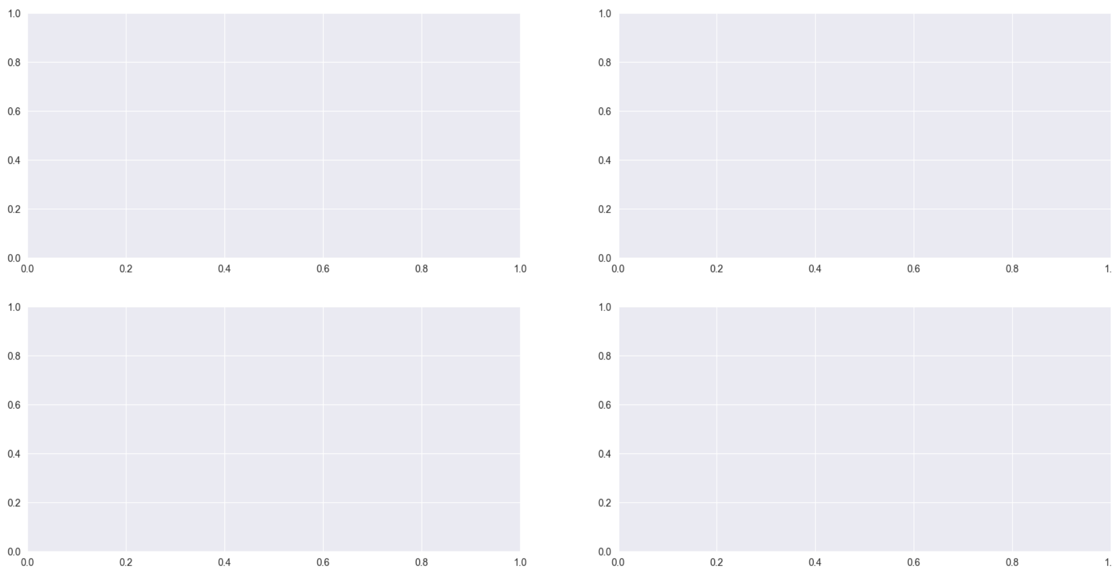
[165]:

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming you have a DataFrame 'df' with a column 'make_segment'
plt.figure(figsize=(10, 6))
sns.barplot(x='make_segment', y='make_segment', data=df, estimator=len)

plt.title('Distribution of Car Make Segments')
plt.xlabel('Make Segment')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.show()
```



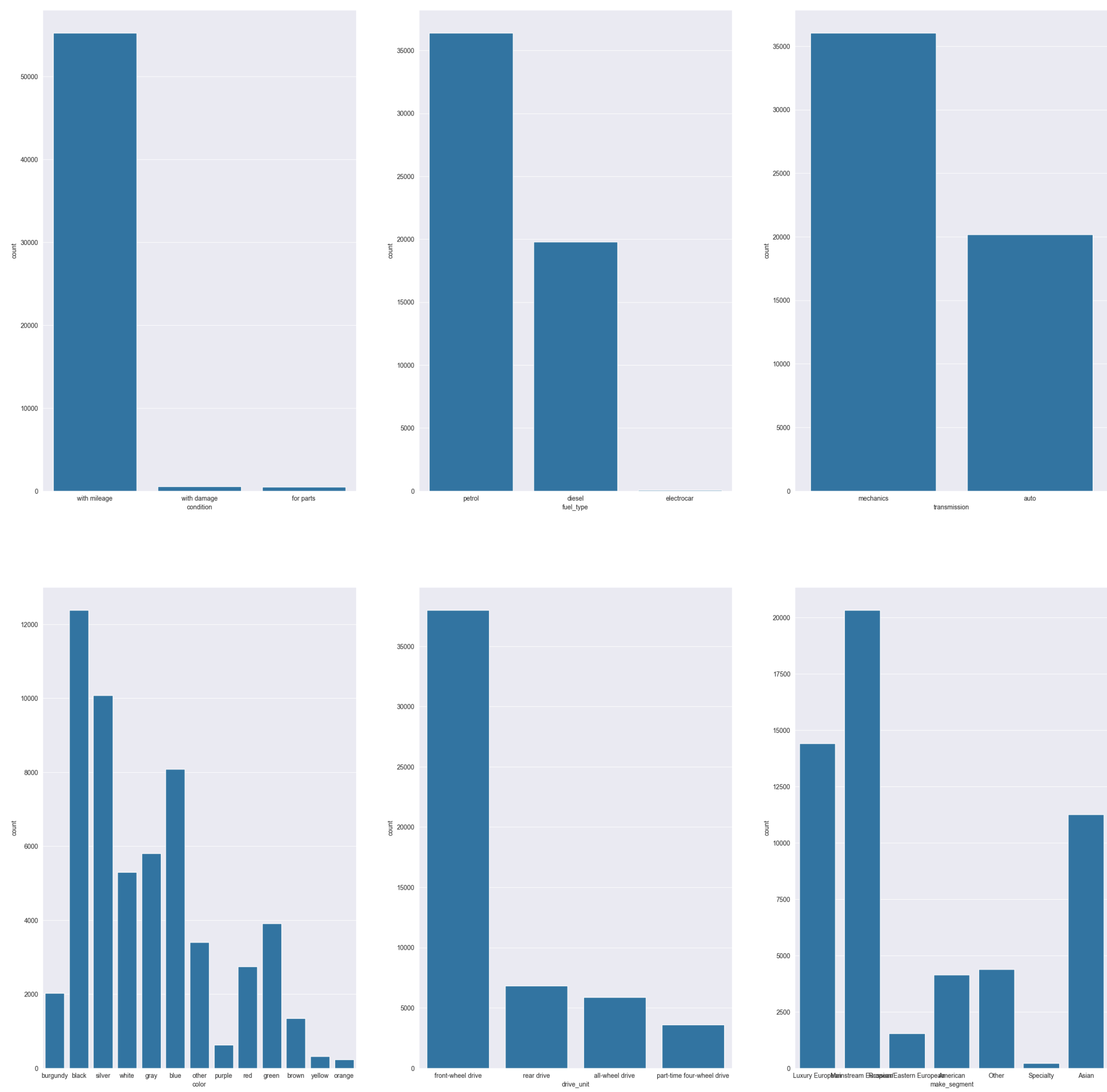
Categorical variable Distribution

[166]:
```
# creates empty the 2x2 matrix graphs with empty values
fig, ax = plt.subplots(2,2,figsize=(20,10))
```



[167]:
```
fig, ax = plt.subplots(2,3,figsize=(30,30))
# plots the graph acc to axis the data from df
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])
sns.countplot(x='drive_unit', data=df, ax=ax[1,1])
sns.countplot(x='make_segment', data=df, ax=ax[1,2])
```

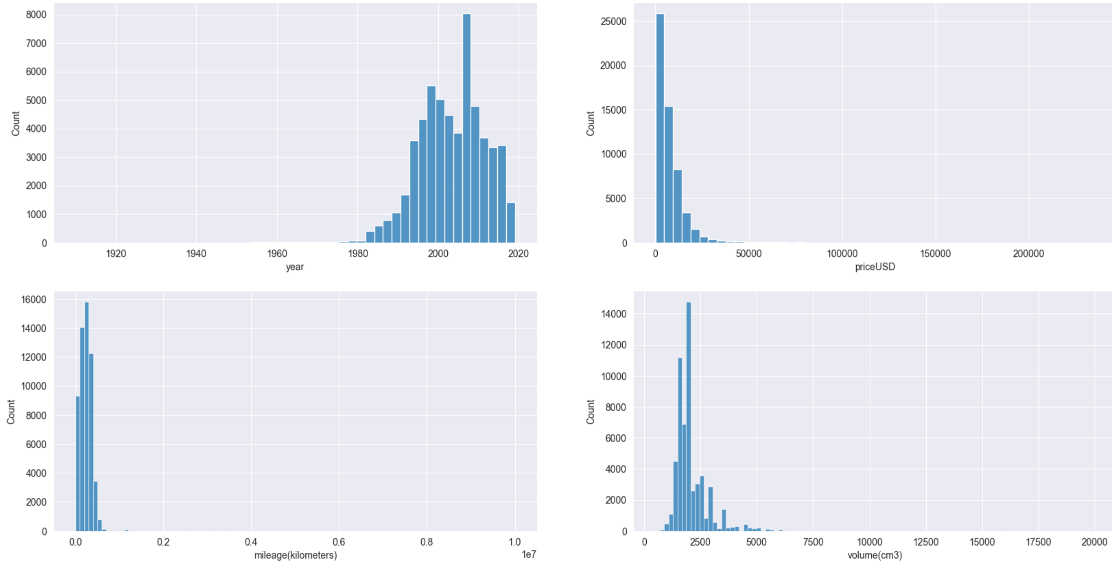
[167]: <Axes: xlabel='make_segment', ylabel='count'>



Continous variable Distribution

[168]:
```
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],bins=50)
sns.histplot(df['mileage(kilometers)'],ax=ax[1,0],bins =100)
sns.histplot(df['volume(cm3)'],ax=ax[1,1],bins=100)
```

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



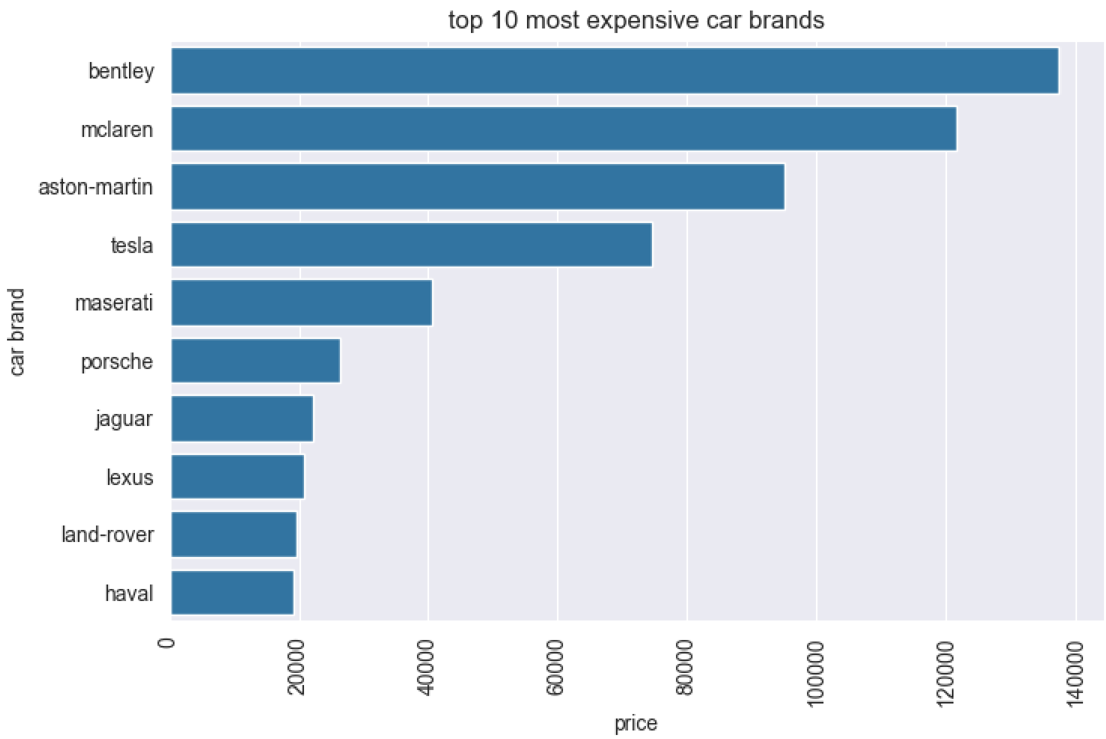
[169]:
```
df = df[df['year']>1980]
```

Price and Make

[170]:
```
demodf = df.groupby('make')['priceUSD'].mean().reset_index()
demof = demodf.sort_values(by='priceUSD',ascending=False).head(10)

# This code is performing the following operations:
#It groups the original dataframe df by the 'make' column.
#For each group (i.e., each unique car make), it calculates the mean of the 'priceUSD' column.
#The result is reset to a new dataframe demodf with two columns: 'make' and 'priceUSD' (which now contains the mean prices).
#The demodf is then sorted by the 'priceUSD' column in descending order (highest price first).
#Finally, it selects only the top 10 rows using .head(10).
#demodf = df.groupby('make')['priceUSD'].mean().reset_index()
```

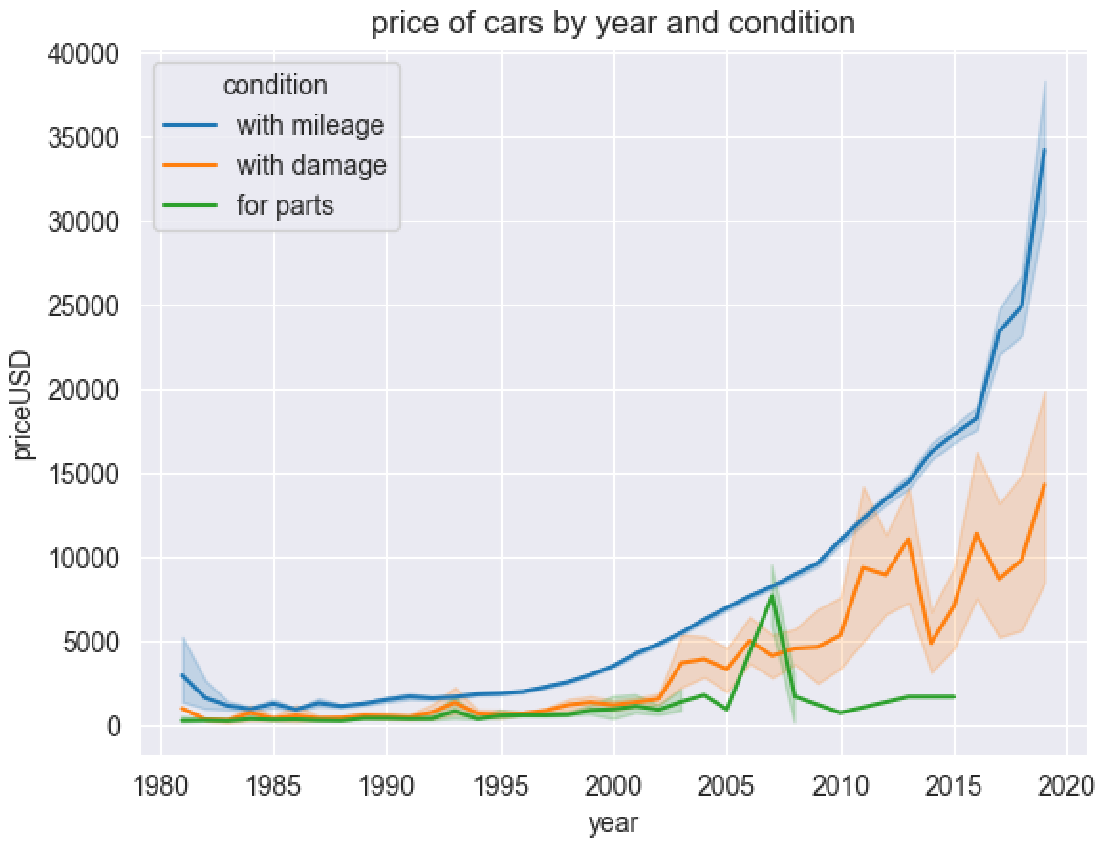
[171]:
```
demodf = df.groupby('make')['priceUSD'].mean().reset_index()
demof = demodf.sort_values(by='priceUSD',ascending=False).head(10)
```

```
#bar plot
plt.figure(figsize=(8,5))
sns.barplot(y='make', x='priceUSD', data=demof)
plt.xticks(rotation=90)
plt.title("top 10 most expensive car brands")
plt.xlabel("price")
plt.ylabel("car brand")
plt.show()
```



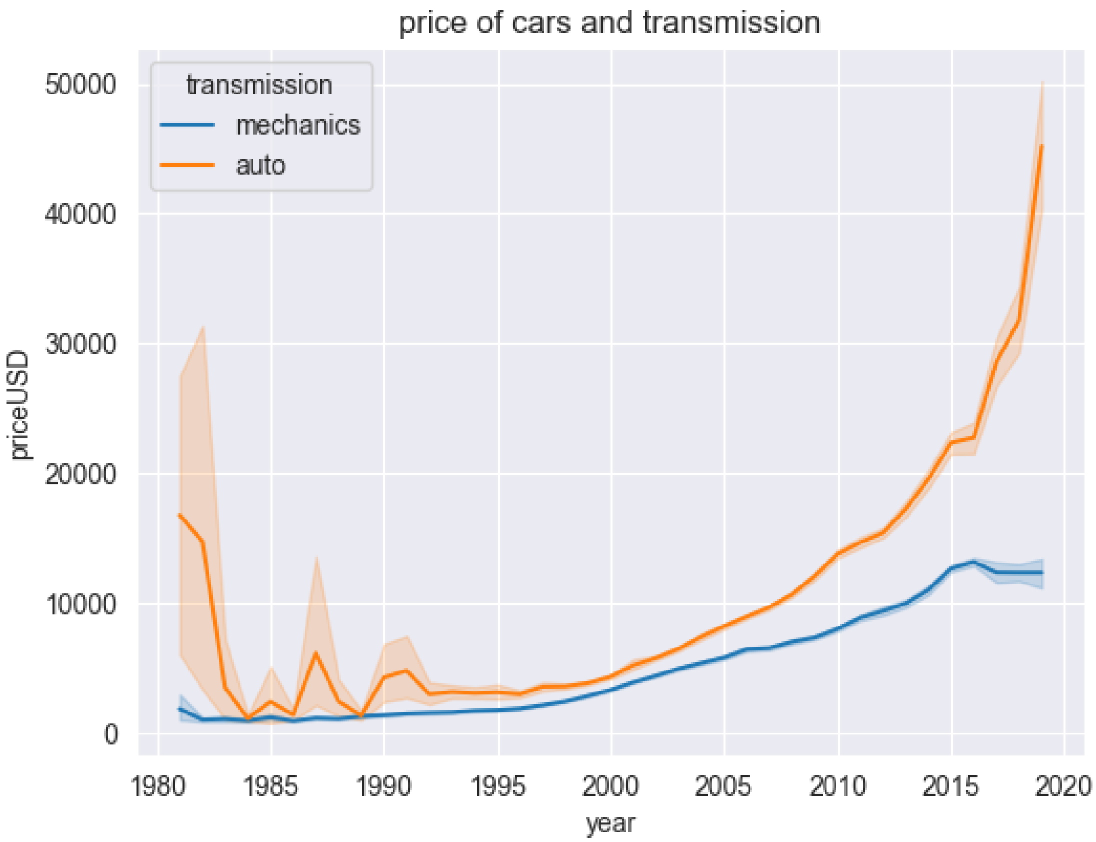
Price and Condition

[172]:
```
sns.lineplot(x='year', y='priceUSD', data=df, hue = 'condition')
plt.title("price of cars by year and condition")
plt.show()
```



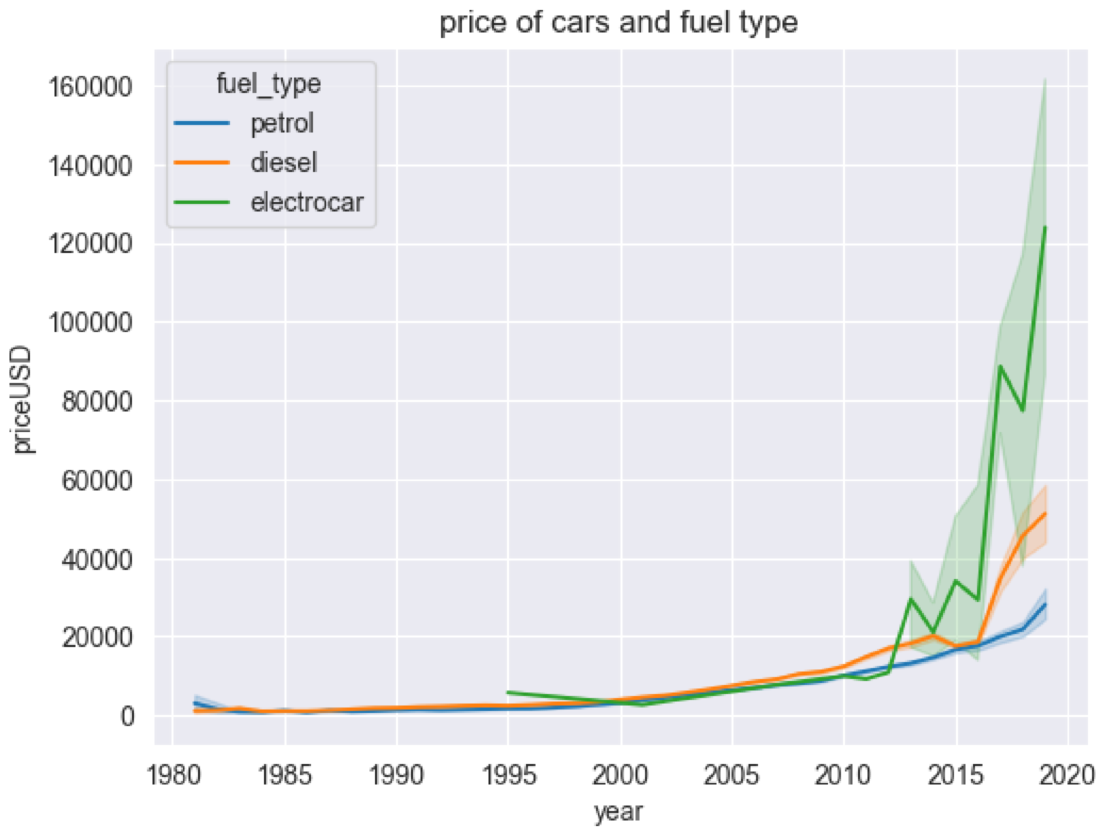
Price and Transmission

[173]:
```
sns.lineplot(x = 'year', y='priceUSD', data=df, hue = 'transmission')
plt.title("price of cars and transmission")
plt.show()
```



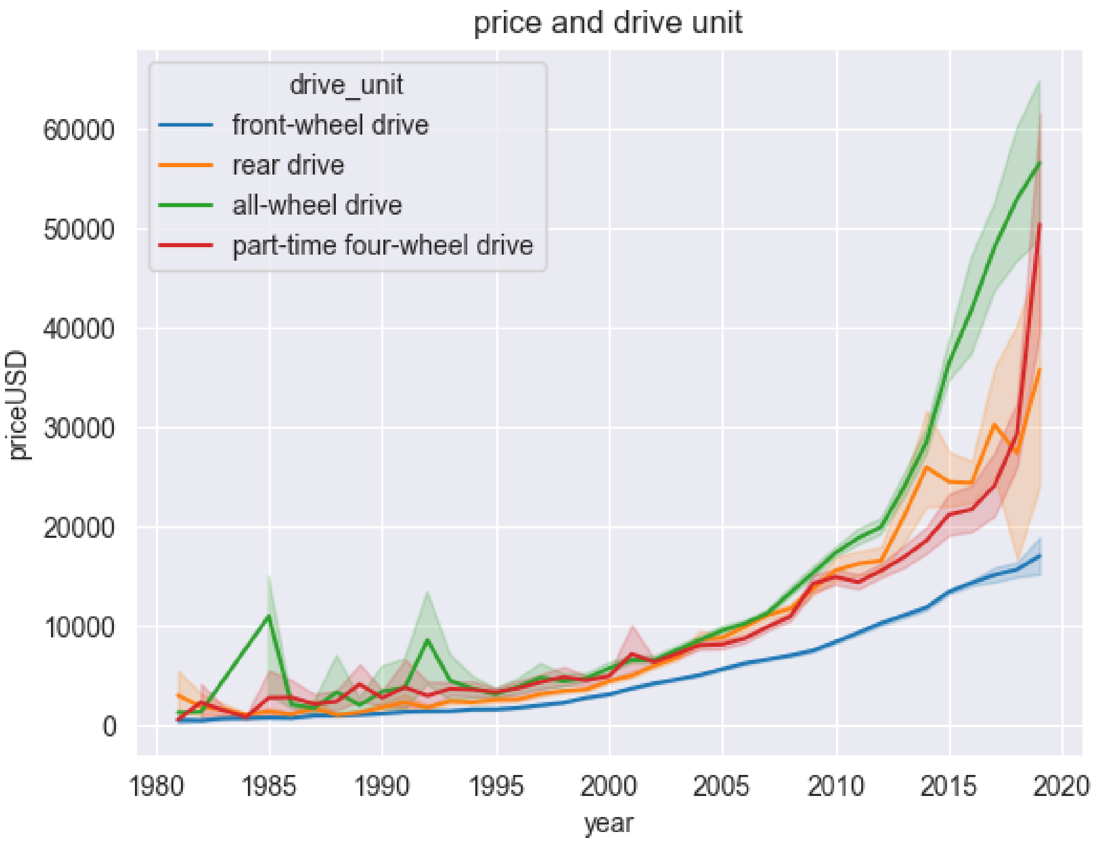
Price and Fuel_type

[174]:
```
sns.lineplot(x = 'year', y = 'priceUSD',data = df,hue = 'fuel_type')
plt.title("price of cars and fuel type")
plt.show()
```



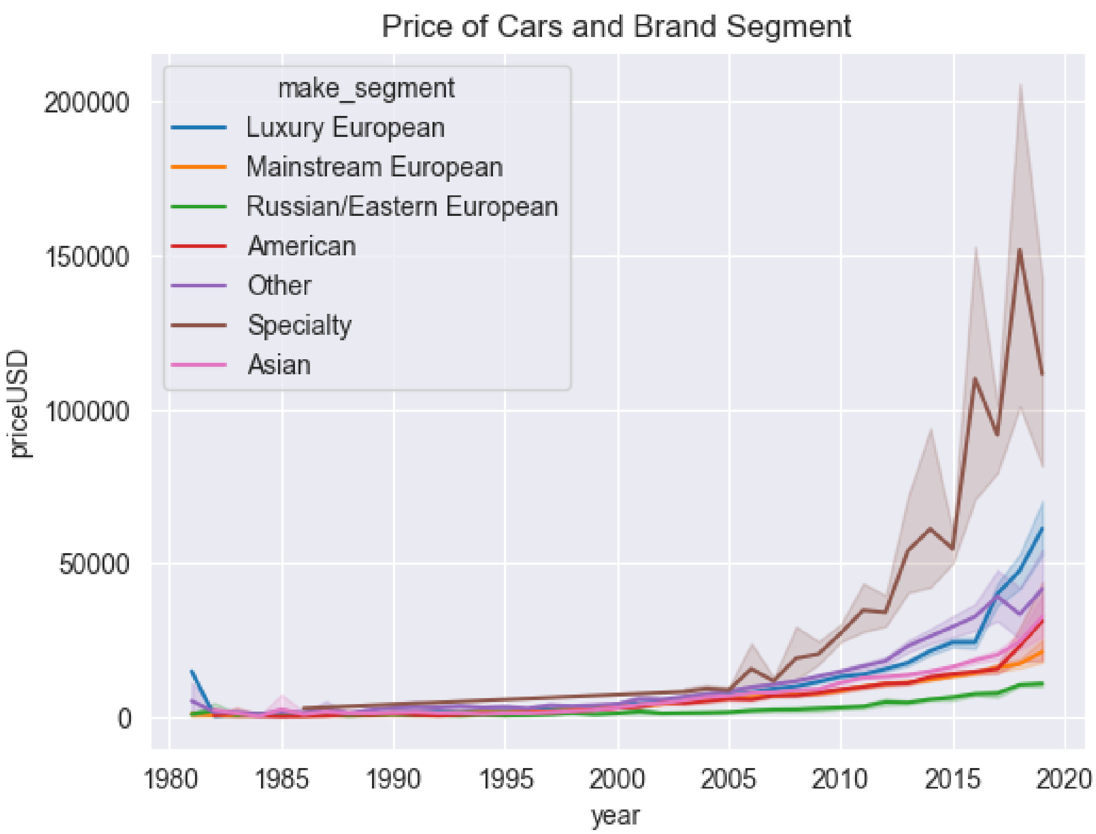
Price and drive_unit

[175]:
```
sns.lineplot(x='year', y='priceUSD', data=df, hue='drive_unit')
plt.title("price and drive unit")
plt.show()
```



Price and Brand Segment

[176]:
```
sns.lineplot(x = 'year', y = 'priceUSD', data = df, hue = 'make_segment')
plt.title('Price of Cars and Brand Segment')
plt.show()
```



Data Preprocessing Part 2

[177]:
```
#gives the no of null values totally
df.isnull().sum()
```

[177]:
```
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
```

[178]:
```
# drops the null values from the columns
df.dropna(inplace=True)
```

[179]:
```
df.isnull().sum()
```

[179]:
```
make                  0
priceUSD              0
year                  0
condition             0
mileage(kilometers)   0
fuel_type             0
volume(cm3)           0
color                 0
transmission          0
drive_unit            0
make_segment          0
dtype: int64
```

[180]:
```
#to drop null values from the columns(make)
df.drop(columns=['make'], inplace=True)
```

[181]:
```
df.isnull().sum()
```

[181]:
```
priceUSD              0
year                  0
condition             0
mileage(kilometers)   0
fuel_type             0
volume(cm3)           0
color                 0
transmission          0
drive_unit            0
make_segment          0
dtype: int64
```

Label encoding for object data type

[182]:
```
from sklearn.preprocessing import LabelEncoder

# columns to encode
cols = ['condition', 'fuel_type', 'transmission', 'color', 'drive_unit',␣
↪'make_segment']

# Label encoding Object is created
le = LabelEncoder()

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

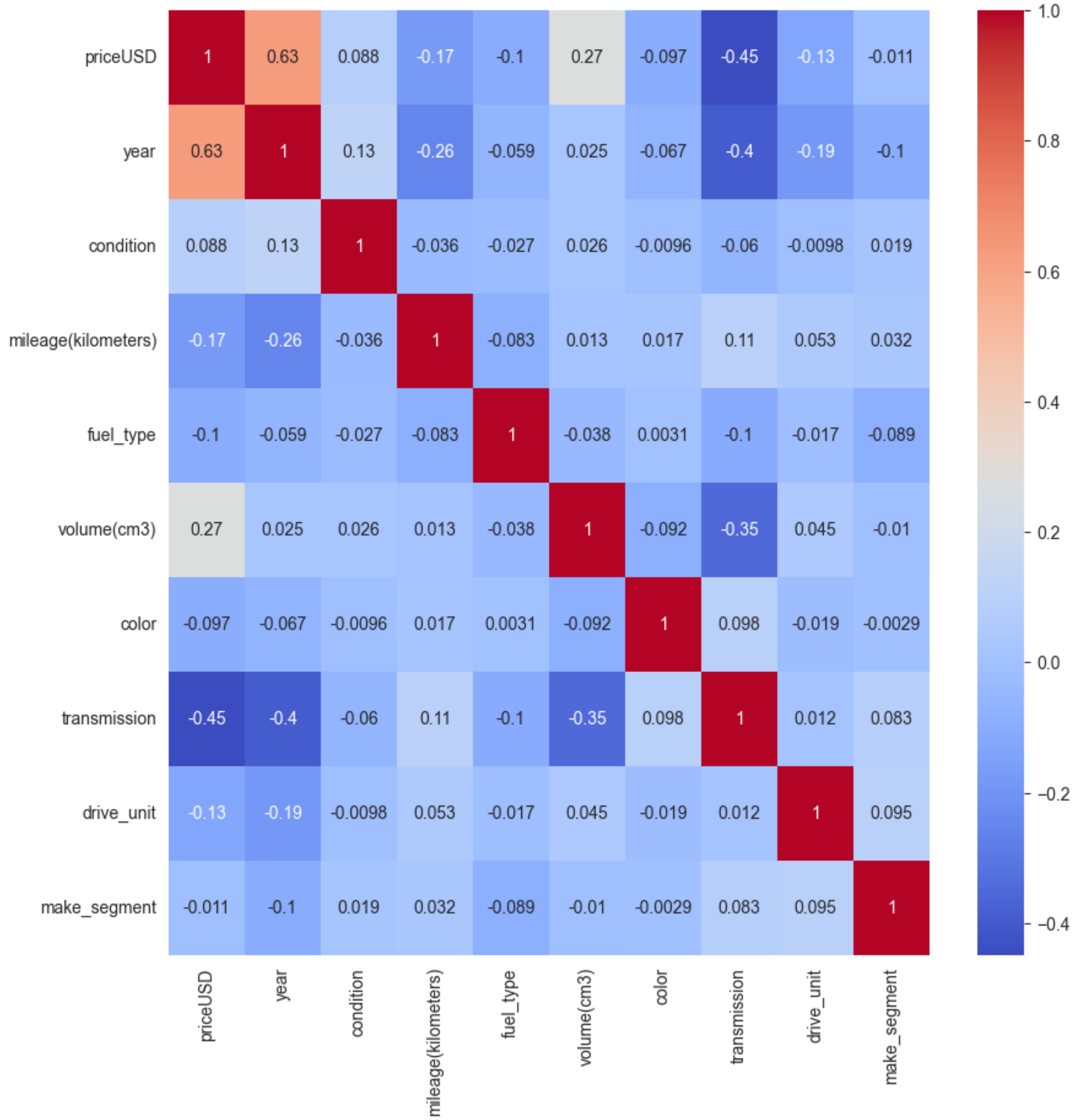
```
    print(col, df[col].unique())
```

```
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

[183]:
```
#sns.heatmap(): Creates the heatmap using seaborn.
#df.corr(): The correlation matrix to visualize.
#annot=True: Adds numerical annotations to each cell.
#cmap='coolwarm': Sets the color scheme (blue for negative correlations, red␣
 ↪for positive).
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
```

[183]:
```
<Axes: >
```



Outlier Removal

Removing outliers is a data preprocessing technique used to eliminate extreme values from a dataset that may skew analysis or model performance.

method for removing Outlier Z-score method: Removes data points that are a certain number of standard deviations away from the mean.

[184]:
```
# 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

Train-test split is an important technique in machine learning for evaluating model performance.

[185]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(df.
  ↪drop(columns=['priceUSD']),df['priceUSD'], test_size=0.2, random_state=42)
```

Model Building

Decision Tree Regressor

How It Works The model splits the data into subsets based on feature values, creating a tree-like structure. At each node, it chooses the feature and split point that minimizes the variance in the target variable. The process continues recursively until a stopping criterion is met (e.g., maximum depth reached). Predictions are made by traversing the tree and using the average target value in the leaf node.

GridSearchCV

GridSearchCV is a powerful tool for hyperparameter tuning in machine learning models. Here are the key points about using GridSearchCV for hyperparameter tuning:

How GridSearchCV Works GridSearchCV performs an exhaustive search over a specified parameter grid. It trains the model using every combination of parameters in the grid. Each model is evaluated using cross-validation. The best performing parameter combination is selected.

Hyperparameter Tuning

Important hyperparameters to consider: max_depth: Controls the maximum depth of the tree min_samples_split: Minimum number of samples required to split a node min_samples_leaf: Minimum number of samples required in a leaf node Tuning these parameters helps balance model complexity and performance.

[186]:
```
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]
}
```

```python
# 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': 'sqrt', 'min_samples_leaf': 3,
'min_samples_split': 2, 'random_state': 0}
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/model_selection/_validation.py:540: FitFailedWarning:
640 fits failed out of a total of 1920.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
352 fits failed with the following error:
Traceback (most recent call last):
  File "/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/model_selection/_validation.py", line 888, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/base.py", line 1466, in wrapper
    estimator._validate_params()
  File "/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/base.py", line 666, in _validate_params
    validate_parameter_constraints(
  File "/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/utils/_param_validation.py", line 95, in
validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features'
parameter of DecisionTreeRegressor must be an int in the range [1, inf), a float
in the range (0.0, 1.0], a str among {'log2', 'sqrt'} or None. Got 'auto'
instead.

--------------------------------------------------------------------------------
288 fits failed with the following error:
Traceback (most recent call last):
  File "/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/model_selection/_validation.py", line 888, in _fit_and_score
```

```
    estimator.fit(X_train, y_train, **fit_params)
  File "/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/base.py", line 1466, in wrapper
    estimator._validate_params()
  File "/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/base.py", line 666, in _validate_params
    validate_parameter_constraints(
  File "/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/utils/_param_validation.py", line 95, in
validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features'
parameter of DecisionTreeRegressor must be an int in the range [1, inf), a float
in the range (0.0, 1.0], a str among {'sqrt', 'log2'} or None. Got 'auto'
instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/numpy/ma/core.py:2820: RuntimeWarning: invalid value encountered in
cast
  _data = np.array(data, dtype=dtype, copy=copy,
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/model_selection/_search.py:1102: UserWarning: One or more of
the test scores are non-finite: [       nan        nan        nan        nan
nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan 0.30902003 0.293469   0.30902003 0.293469
 0.30902003 0.293469   0.30902003 0.293469   0.30902003 0.293469
 0.30902003 0.293469   0.30902003 0.293469   0.30902003 0.293469
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 0.30902003 0.293469   0.30902003 0.293469   0.30902003 0.293469
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 0.30902003 0.293469   0.30902003 0.293469   0.30902003 0.293469
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan 0.61141652 0.43704915 0.61141652 0.43704915
 0.61141652 0.43704915 0.61141652 0.43704915 0.61141652 0.43704915
 0.61141652 0.43704915 0.61141652 0.43704915 0.61141652 0.43704915
```

```
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 0.71432582 0.66764212 0.71435735 0.66764125 0.71435735 0.66764125
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  warnings.warn(
```

[187]:
```python
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeRegressor

# Create the base model
dtr = DecisionTreeRegressor()
```

```python
# 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': ['sqrt', 'log2', None],  # Removed 'auto', added None
    'random_state': [0, 42]
}

#This creates a GridSearchCV object:
#estimator=dtr: The model to use
#param_grid=params: The hyperparameter grid
#cv=5: Use 5-fold cross-validation
   #Cross-validation is a statistical method used to evaluate machine-
   #learning models by testing them on multiple subsets of data
#verbose=1: Print progress
#n_jobs=-1: Use all available CPU cores
#error_score='raise': Raise errors for debugging


# Grid Search Object
grid = GridSearchCV(
    estimator=dtr,
    param_grid=params,
    cv=5,
    verbose=1,
    n_jobs=-1,
    error_score='raise'  # This will raise errors for debugging
)

# Fitting the grid search
grid.fit(x_train, y_train)

# Best parameters
print("Best parameters found:")
print(grid.best_params_)

# Best score
print("\nBest cross-validation score: {:.4f}".format(grid.best_score_))

# Best estimator
print("\nBest estimator:")
print(grid.best_estimator_)
```

```
Fitting 5 folds for each of 384 candidates, totalling 1920 fits
Best parameters found:
```

```
{'max_depth': 8, 'max_features': None, 'min_samples_leaf': 4,
'min_samples_split': 2, 'random_state': 0}

Best cross-validation score: 0.8573

Best estimator:
DecisionTreeRegressor(max_depth=8, min_samples_leaf=4, random_state=0)
```

[188]:
```
#decision tree regressor with best parameters
dtr = DecisionTreeRegressor(max_depth=8, max_features='sqrt',␣
↪min_samples_leaf=4, min_samples_split=2, random_state=0)

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

[188]:
```
DecisionTreeRegressor(max_depth=8, max_features='sqrt', min_samples_leaf=4,
                      random_state=0)
```

[189]:
```
dtr.score(x_train, y_train)
```

[189]:
```
0.7883902435486847
```

[190]:
```
y_pred = dtr.predict(x_test)
```

Model Evaluation

Model evaluation is a critical process in machine learning that assesses the performance and quality of trained models

Purpose of Model Evaluation

1.Assess model performance and accuracy 2.Determine how well a model generalizes to unseen data 3.Compare different models or algorithms 4.Identify strengths and weaknesses of a model 5.Guide model selection and optimization

[ ]:
```

```

[191]:
```
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:  0.7701494431533182
Mean Squared Error:  7355859.020309841
Mean Absolute Error:  1869.2406549663542
Root Mean Squared Error:  2712.168693188136
```

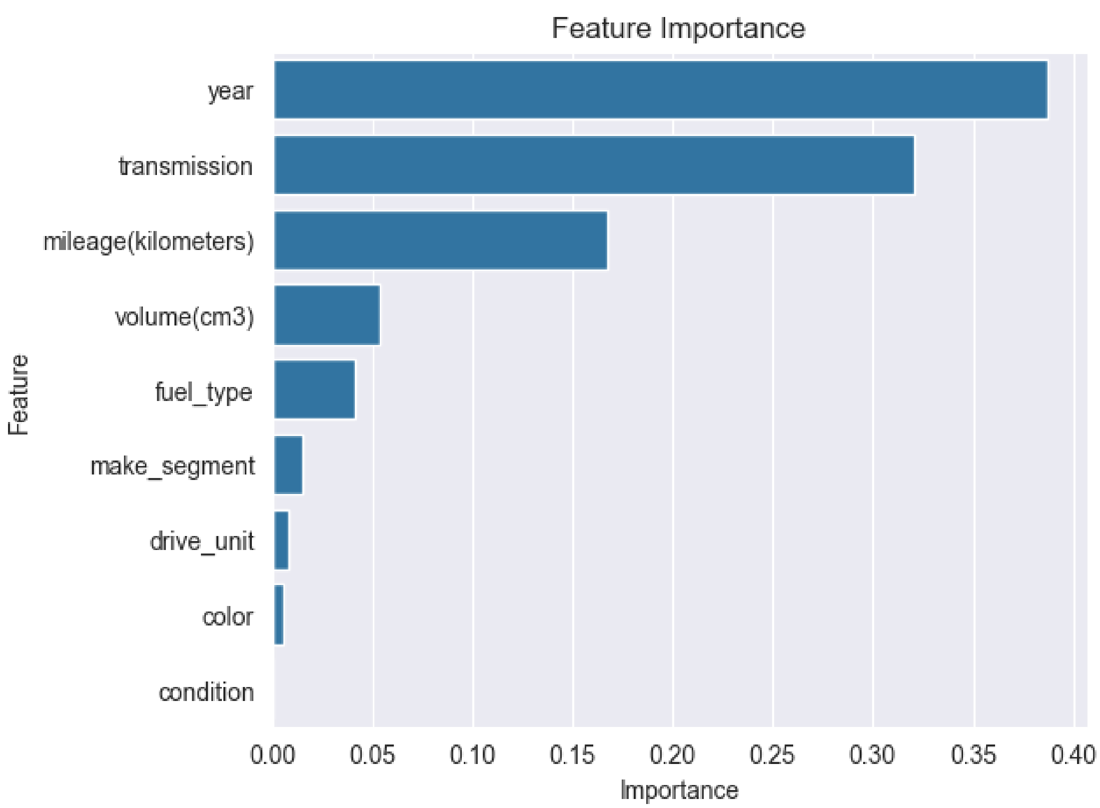
Feature Importance

[192]:
```
feat_df = pd.DataFrame({'Feature': x_train.columns, 'Importance': dtr.
 ↪feature_importances_})
feat_df = feat_df.sort_values(by='Importance', ascending=False)
feat_df
```

[192]:

	Feature	Importance
0	year	0.387447
6	transmission	0.320538
2	mileage(kilometers)	0.167548
4	volume(cm3)	0.053433
3	fuel_type	0.041817
8	make_segment	0.015295
7	drive_unit	0.008188
5	color	0.005734
1	condition	0.000000

[193]:
```
# Bar Plot
sns.set_style('darkgrid')
plt.figure(figsize=(6,5))
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.