Data/Domain Understanding and Exploration

In [1]:
```
import pandas as pd
import warnings
warnings.filterwarnings('ignore')

# Load data
data = pd.read_csv("AutoTrader Dataset.csv")
```

In [2]:
```
data.head()
```

Out[2]:

	public_reference	mileage	reg_code	standard_colour	standard_make	standard_model	vehicle_condition	year_of_registration	price	body_type	crossover
0	202006039777689	0.0	NaN	Grey	Volvo	XC90	NEW	NaN	73970	SUV	
1	202007020778260	108230.0	61	Blue	Jaguar	XF	USED	2011.0	7000	Saloon	
2	202007020778474	7800.0	17	Grey	SKODA	Yeti	USED	2017.0	14000	SUV	
3	202007080986776	45000.0	16	Brown	Vauxhall	Mokka	USED	2016.0	7995	Hatchback	
4	202007161321269	64000.0	64	Grey	Land Rover	Range Rover Sport	USED	2015.0	26995	SUV	

In [3]:
```
data.shape
```

Out[3]: (402005, 12)

In [4]:
```
# Check data types of columns
print(data.dtypes)
```

```
public_reference           int64
mileage                  float64
reg_code                  object
standard_colour           object
standard_make             object
standard_model            object
vehicle_condition         object
year_of_registration     float64
price                      int64
body_type                 object
crossover_car_and_van       bool
fuel_type                 object
dtype: object
```

In [5]:
```
# Analyze the distribution of selling price
print(data["price"].describe())
```

```
count    4.020050e+05
mean     1.734197e+04
std      4.643746e+04
min      1.200000e+02
25%      7.495000e+03
50%      1.260000e+04
75%      2.000000e+04
max      9.999999e+06
Name: price, dtype: float64
```

In [13]:
```
# Analyze the distribution of mileage
print(data["mileage"].describe())
```

```
count    401878.000000
mean      37743.595656
std       34831.724018
min           0.000000
25%       10481.000000
50%       28629.500000
75%       56875.750000
max      999999.000000
Name: mileage, dtype: float64
```

In [14]:
```
# Analyze the distribution of year_of_registration
print(data["year_of_registration"].describe())
```

```
count    368694.000000
mean       2015.006206
std           7.962667
min         999.000000
25%        2013.000000
50%        2016.000000
75%        2018.000000
max        2020.000000
Name: year_of_registration, dtype: float64
```

In [15]:
```
# Identify missing values
print(data.isnull().sum())
```

```
public_reference            0
mileage                   127
reg_code                31857
standard_colour          5378
standard_make               0
standard_model              0
vehicle_condition           0
year_of_registration    33311
price                       0
body_type                 837
crossover_car_and_van       0
fuel_type                 601
dtype: int64
```

In [16]:
```
corr_matrix = data.corr()
print(corr_matrix["mileage"]["price"])
```

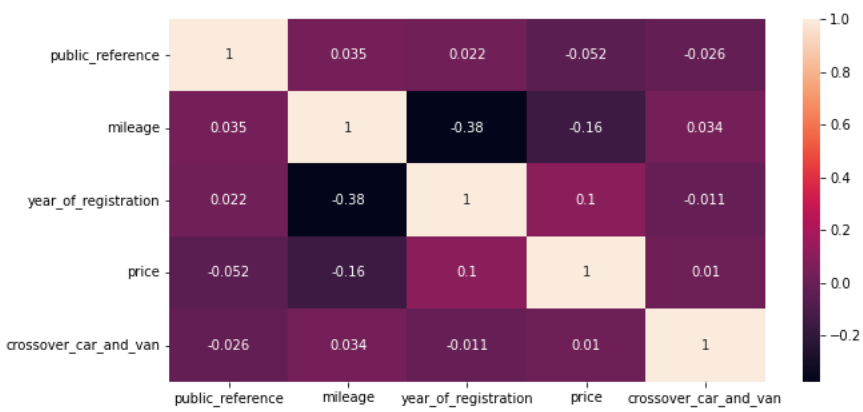
```
-0.1602037449776471
```

In [17]:
```
corr_matrix = data.corr()
print(corr_matrix["year_of_registration"]["price"])
```

```
0.10234109038334868
```

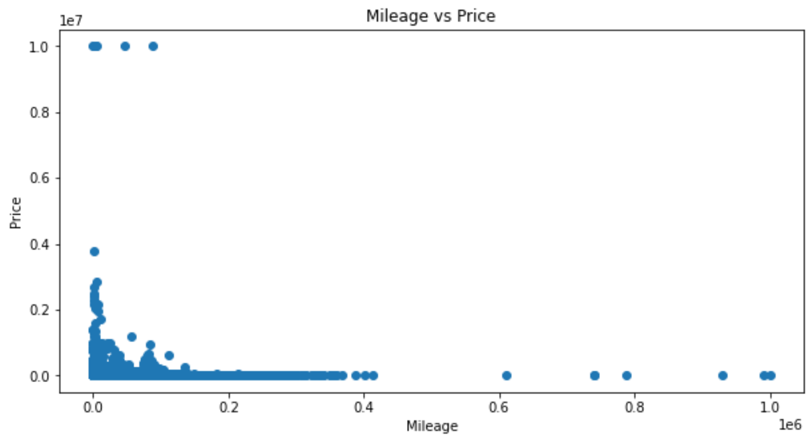
In [18]:
```
import seaborn as sns
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (10,5)

corr = data.corr()
sns.heatmap(corr,
            xticklabels=corr.columns.values,
            yticklabels=corr.columns.values,
            annot=True)
plt.show()
```

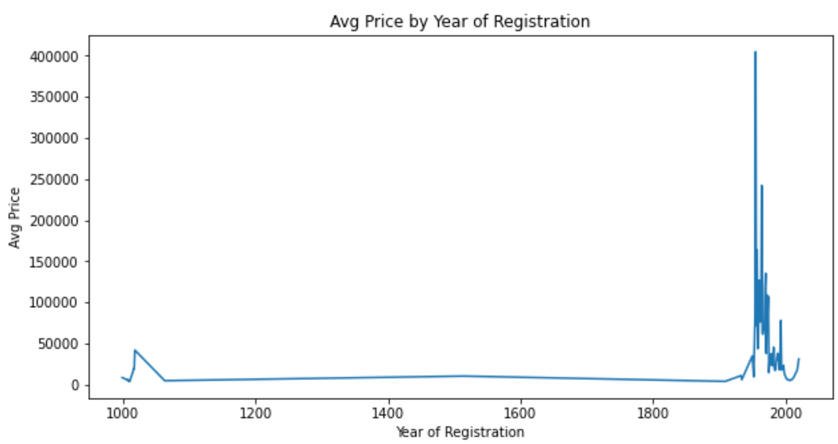


Data Processing for Machine Learning

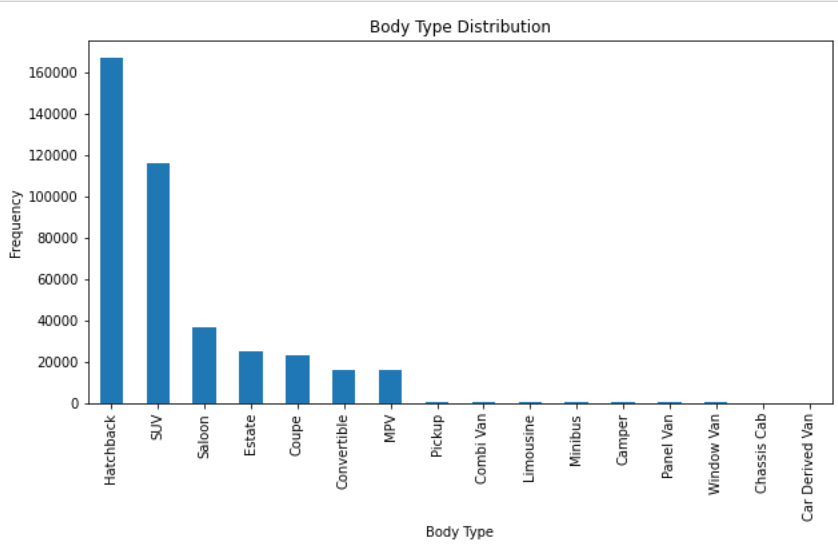
In [19]:
```
plt.scatter(data["mileage"], data["price"])
plt.xlabel("Mileage")
plt.ylabel("Price")
plt.title("Mileage vs Price")
plt.show()
```



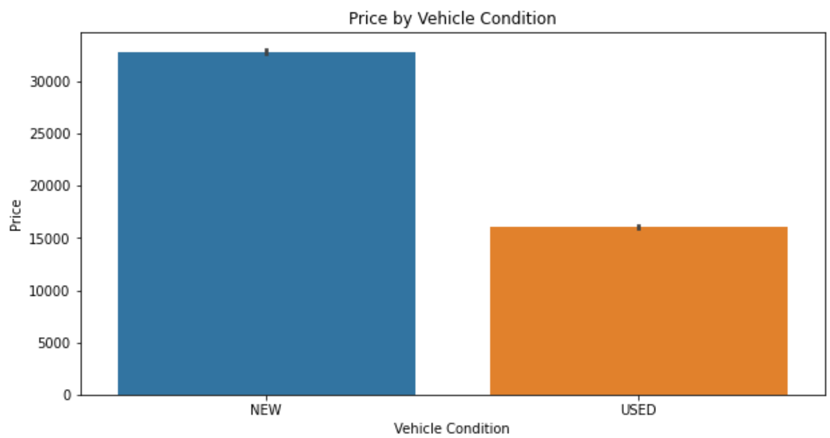
In [20]:
```
data.groupby("year_of_registration")["price"].mean().plot()
plt.xlabel("Year of Registration")
plt.ylabel("Avg Price")
plt.title("Avg Price by Year of Registration")
plt.show()
```



In [21]:
```
data["body_type"].value_counts().plot(kind="bar")
plt.xlabel("Body Type")
plt.ylabel("Frequency")
plt.title("Body Type Distribution")
plt.show()
```



In [22]:
```
import seaborn as sns
sns.barplot(x="vehicle_condition", y="price", data=data)
plt.xlabel("Vehicle Condition")
plt.ylabel("Price")
plt.title("Price by Vehicle Condition")
plt.show()
```



In [23]:
```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder

# create an imputer object with strategy as 'mean'
imputer = SimpleImputer(strategy='mean')

# fit and transform the imputer on numerical variables
data[['mileage', 'year_of_registration']] = imputer.fit_transform(data[['mileage', 'year_of_registration']])

# create an imputer object with strategy as 'most_frequent'
imputer = SimpleImputer(strategy='most_frequent')

# fit and transform the imputer on categorical variables
data[['reg_code', 'standard_colour', 'standard_make', 'standard_model','vehicle_condition','body_type','fuel_type']] = imputer.fi

# Create an object of LabelEncoder
le = LabelEncoder()

# fit and transform the label encoder on categorical variables
data[['reg_code', 'standard_colour', 'standard_make', 'standard_model','vehicle_condition','body_type','fuel_type']] = data[['reg
```

In [24]:
```
# set the lower and upper limits for the outliers
lower_limit = data["price"].quantile(0.05)
upper_limit = data["price"].quantile(0.95)
# clip the values outside the range
data["price"] = data["price"].clip(lower_limit, upper_limit)
```

In [33]:
```
# Identify missing values
print(data.isnull().sum())
```

```
public_reference         0
mileage                  0
reg_code                 0
standard_colour          0
standard_make            0
standard_model           0
vehicle_condition        0
year_of_registration     0
price                    0
body_type                0
crossover_car_and_van    0
fuel_type                0
dtype: int64
```

In [26]:
```
data.head()
```

Out[26]:

	public_reference	mileage	reg_code	standard_colour	standard_make	standard_model	vehicle_condition	year_of_registration	price	body_type	crossov
0	202006039777689	0.0	17	Grey	Volvo	XC90	NEW	2015.006206	43842.4	SUV	
1	202007020778260	108230.0	61	Blue	Jaguar	XF	USED	2011.000000	7000.0	Saloon	
2	202007020778474	7800.0	17	Grey	SKODA	Yeti	USED	2017.000000	14000.0	SUV	
3	202007080986776	45000.0	16	Brown	Vauxhall	Mokka	USED	2016.000000	7995.0	Hatchback	
4	202007161321269	64000.0	64	Grey	Land Rover	Range Rover Sport	USED	2015.000000	26995.0	SUV	

In [27]:
```
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split

data = data.apply(LabelEncoder().fit_transform)
data.head()

scaler = StandardScaler()
data[["mileage", "price"]] = scaler.fit_transform(data[["mileage", "price"]])

data.head()
```

Out[27]:

	public_reference	mileage	reg_code	standard_colour	standard_make	standard_model	vehicle_condition	year_of_registration	price	body_type	crossc
0	25073	-1.305400	15	8	106	1107	0	79	2.164823	13	
1	35623	1.775596	31	2	47	1110	1	74	-0.891413	14	
2	35630	-0.995415	15	8	91	1130	1	81	-0.032054	13	
3	38515	0.455116	14	4	104	702	1	80	-0.768110	7	
4	44297	1.030716	34	8	54	833	1	78	1.246145	13	

In [28]:
```
# Split data into training and testing sets
X = data.drop(["price",'public_reference'] , axis=1)
y = data["price"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Data Processing for Machine Learning

In [29]:
```
# Choose a suitable algorithm
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV

# Fit and tune the model
lasso = Lasso(random_state=42)
lasso.fit(X_train, y_train)

# predicting on test data
y_pred = lasso.predict(X_test)

# calculating mean absolute error and mean squared error
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("MAE: ", mae)
print("MSE: ", mse)
print("R2: ", r2)
```

```
MAE:  0.7129978548974307
MSE:  0.7670273454992862
R2:  0.2274797635158814
```

In [30]:
```
from sklearn.linear_model import LinearRegression

# Select algorithm
model = LinearRegression()

# Train model
model.fit(X_train, y_train)

# predicting on test data
y_pred = model.predict(X_test)

# calculating mean absolute error and mean squared error
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("MAE: ", mae)
print("MSE: ", mse)
print("R2: ", r2)
```

```
MAE:  0.5375137791367528
MSE:  0.4940699961313655
R2:  0.502391834540578
```

In [31]:
```
param_grid = {'normalize':[True,False], 'fit_intercept':[True,False]}
grid_search = GridSearchCV(model, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Select the best model
best_model = grid_search.best_estimator_

# predicting on test data
y_pred = best_model.predict(X_test)

# calculating mean absolute error and mean squared error
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("MAE: ", mae)
print("MSE: ", mse)
print("R2: ", r2)
```

```
MAE:  0.5375137791367528
MSE:  0.4940699961313655
R2:  0.502391834540578
```

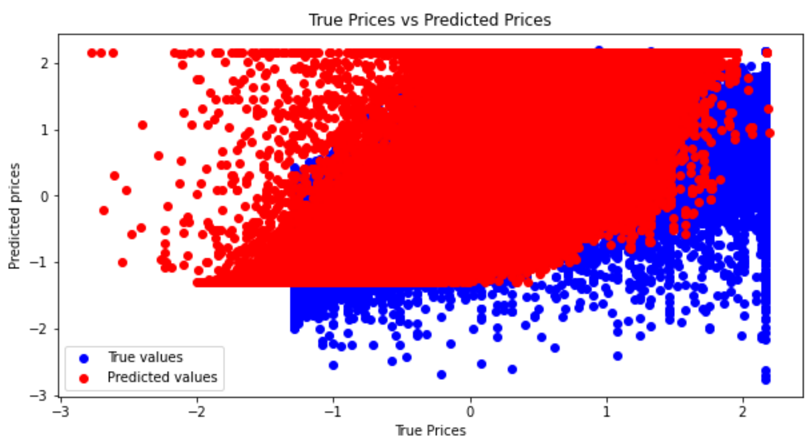
Model Evaluation and Analysis

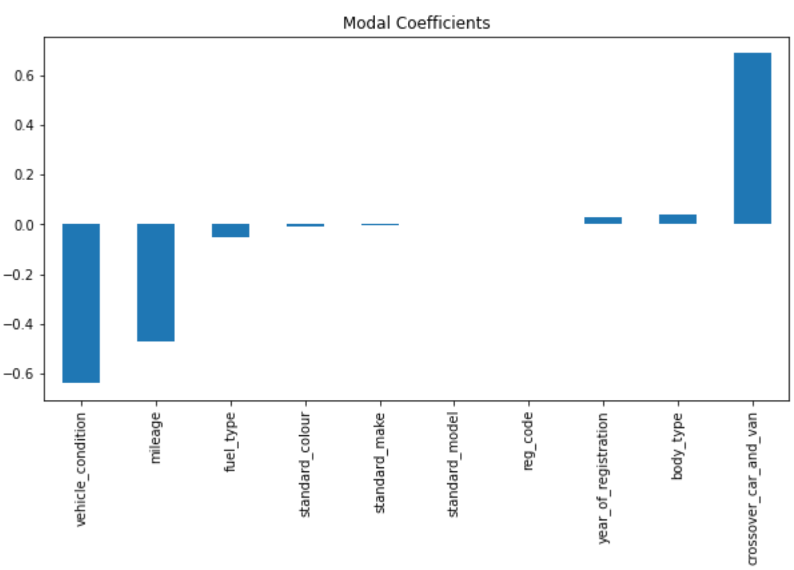
In [32]:
```
# Evaluate the model with cross-validation
from sklearn.model_selection import cross_val_score
scores = cross_val_score(best_model, X_test, y_test, cv=5)

# Analyze true vs predicted plot
y_pred = best_model.predict(X_test)
plt.scatter(y_test, y_pred, c='b', label='True values')
plt.scatter(y_pred,y_test, c='r', label='Predicted values')
plt.xlabel("True Prices")
plt.ylabel("Predicted prices")
plt.title("True Prices vs Predicted Prices")
plt.legend()
plt.show()

# Gain and discuss insights based on feature importance
coef = pd.Series(best_model.coef_, X_train.columns).sort_values()
plt.figure(figsize=(10,5))
coef.plot(kind='bar', title='Modal Coefficients')
plt.show()

# Analyze individual predictions and distribution of scores/losses
from sklearn.metrics import mean_absolute_error, mean_squared_error
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("MAE: ", mae)
print("MSE: ", mse)
print("R2: ", r2)
```






```
MAE:  0.5375137791367528
MSE:  0.4940699961313655
R2:  0.502391834540578
```

In [32]: