```
# Importing required libraries

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

```
# --Data loading--

data = pd.read_csv('/content/used-car-price.csv')
df = data.copy()
```

```
df.head().T
```

	0	1	2	3	4
make_year	2001	2014	2023	2009	2005
mileage_kmpl	8.17	17.59	18.09	11.28	12.23
engine_cc	4000	1500	2500	800	1000
fuel_type	Petrol	Petrol	Diesel	Petrol	Petrol
owner_count	4	4	5	1	2
price_usd	8587.64	5943.5	9273.58	6836.24	4625.79
brand	Chevrolet	Honda	BMW	Hyundai	Nissan
transmission	Manual	Manual	Automatic	Manual	Automatic
color	White	Black	Black	Blue	Red
service_history	NaN	NaN	Full	Full	Full
accidents_reported	0	0	1	0	0
insurance_valid	No	Yes	Yes	Yes	Yes

Next steps: Generate code with df New interactive sheet

```
df.shape
```

```
(10000, 12)
```

```
df.duplicated().sum()
```

```
np.int64(0)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   make_year           10000 non-null  int64  
 1   mileage_kmpl        10000 non-null  float64
 2   engine_cc           10000 non-null  int64  
 3   fuel_type           10000 non-null  object 
 4   owner_count         10000 non-null  int64  
 5   price_usd           10000 non-null  float64
 6   brand               10000 non-null  object 
 7   transmission        10000 non-null  object 
 8   color               10000 non-null  object 
 9   service_history     7962 non-null   object 
 10  accidents_reported  10000 non-null  int64  
 11  insurance_valid     10000 non-null  object 
dtypes: float64(2), int64(4), object(6)
memory usage: 937.6+ KB
```

```
# Splitting into Numerical and Categorical features
df_num = df.select_dtypes(include='number')
df_cat = df.select_dtypes(exclude='number')
```

```
df_num.head()
```

	make_year	mileage_kmpl	engine_cc	owner_count	price_usd	accidents_reported
0	2001	8.17	4000	4	8587.64	0
1	2014	17.59	1500	4	5943.50	0
2	2023	18.09	2500	5	9273.58	1
3	2009	11.28	800	1	6836.24	0
4	2005	12.23	1000	2	4625.79	0

Next steps: Generate code with df_num New interactive sheet

```
df_cat.head()
```

	fuel_type	brand	transmission	color	service_history	insurance_valid
0	Petrol	Chevrolet	Manual	White	NaN	No
1	Petrol	Honda	Manual	Black	NaN	Yes
2	Diesel	BMW	Automatic	Black	Full	Yes
3	Petrol	Hyundai	Manual	Blue	Full	Yes
4	Petrol	Nissan	Automatic	Red	Full	Yes

Next steps: Generate code with df_cat New interactive sheet

```
df_num.describe()
```

	make_year	mileage_kmpl	engine_cc	owner_count	price_usd	accidents_reported
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	2009.206900	17.960753	2287.130000	3.003500	7179.754532	0.492200
std	8.373858	5.025486	1291.276927	1.418904	2795.270940	0.694109
min	1995.000000	5.000000	800.000000	1.000000	1000.000000	0.000000
25%	2002.000000	14.540000	1200.000000	2.000000	5176.547500	0.000000
50%	2009.000000	17.970000	1800.000000	3.000000	6961.260000	0.000000
75%	2016.000000	21.352500	3000.000000	4.000000	8993.732500	1.000000
max	2023.000000	35.000000	5000.000000	5.000000	17647.630000	5.000000

```
print('-------- Missing value count in Numerical features ----------')
print(df_num.isna().sum().sum())
```

```
-------- Missing value count in Numerical features ----------
0
```

```
print('-------- Missing value count before Imputation ----------')
print(df_cat.isna().sum().sum())

# Imputing missing values of categorical feature with mode
impute_cols = ['service_history']
for col in df_cat.columns:
    if col in impute_cols:
        df_cat[col] = df_cat[col].fillna(df_cat[col].mode()[0])

print('-------- Missing value count before Imputation ----------')
print(df_cat.isna().sum().sum())
```

```
-------- Missing value count before Imputation ----------
2038
-------- Missing value count before Imputation ----------
0
```

```
# Clipping Outliers of numerical features using IQR method

# Detecting Outliers using boxplot
for col in df_num.columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(df_num[col])
    plt.title(col)
    plt.show()

# Clipping using IQR for (price_usd)
for col in df_num.columns:
    q1 = df_num[col].quantile(0.25)
    q3 = df_num[col].quantile(0.75)
    iqr = q3 - q1
    lower = q1 - 1.5*iqr
    upper = q3 + 1.5*iqr
```

```
# Visualize 'price_usd' distribution across categorical feature levels


for col in df_cat.columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=col, y='price_usd', data=df)
    plt.title(f'{col} vs price_usd')
    plt.xlabel(col)
    plt.ylabel('price_usd')
    plt.show()
```

- **INSIGHTS**
  - Strong Predictors: Boxes have step up
    - fuel_type
  - Weak Predictors: Boxes are at 'almost' same place
    - brand
    - color
  - Negligible: Boxes at same range
    - insurance_valid
    - service_history
    - transmission

```
# Visualize 'price_usd' across numerical features


for col in df_num.columns:
    plt.figure(figsize=(6, 4))
    sns.scatterplot(x=col, y='price_usd', data=df_num)
    plt.title(f'{col} vs price_usd')
    plt.xlabel(col)
    plt.ylabel('price_usd')
    plt.show()
```

- **INSIGHTS**
  - Strong Predictors
    - engine_cc
    - make_year
    - owner_count
    - accidents_reported
  - Weak Predictor
    - mileage_kmpl

```
print("-------- Unique values of Categorical feature Before Encoding --------")
for col in df_cat.columns:
    print(col, df_cat[col].unique())
```

```
-------- Unique values of Categorical feature Before Encoding --------
fuel_type ['Petrol' 'Diesel' 'Electric']
brand ['Chevrolet' 'Honda' 'BMW' 'Hyundai' 'Nissan' 'Tesla' 'Toyota' 'Kia'
 'Volkswagen' 'Ford']
transmission ['Manual' 'Automatic']
color ['White' 'Black' 'Blue' 'Red' 'Gray' 'Silver']
service_history ['Full' 'Partial']
insurance_valid ['No' 'Yes']
```

```
# Label encoding binary features
from sklearn.preprocessing import LabelEncoder
```

```
df_bin = ['insurance_valid', 'service_history', 'transmission']
for col in df_cat.columns:
    if col in df_bin:
        le = LabelEncoder()
        df_cat[col] = le.fit_transform(df_cat[col])


# One hot encoding multi-category features (nominal)
df_cat = pd.get_dummies(df_cat, columns=['fuel_type', 'color', 'brand'], drop_first=True, dtype='int')
```

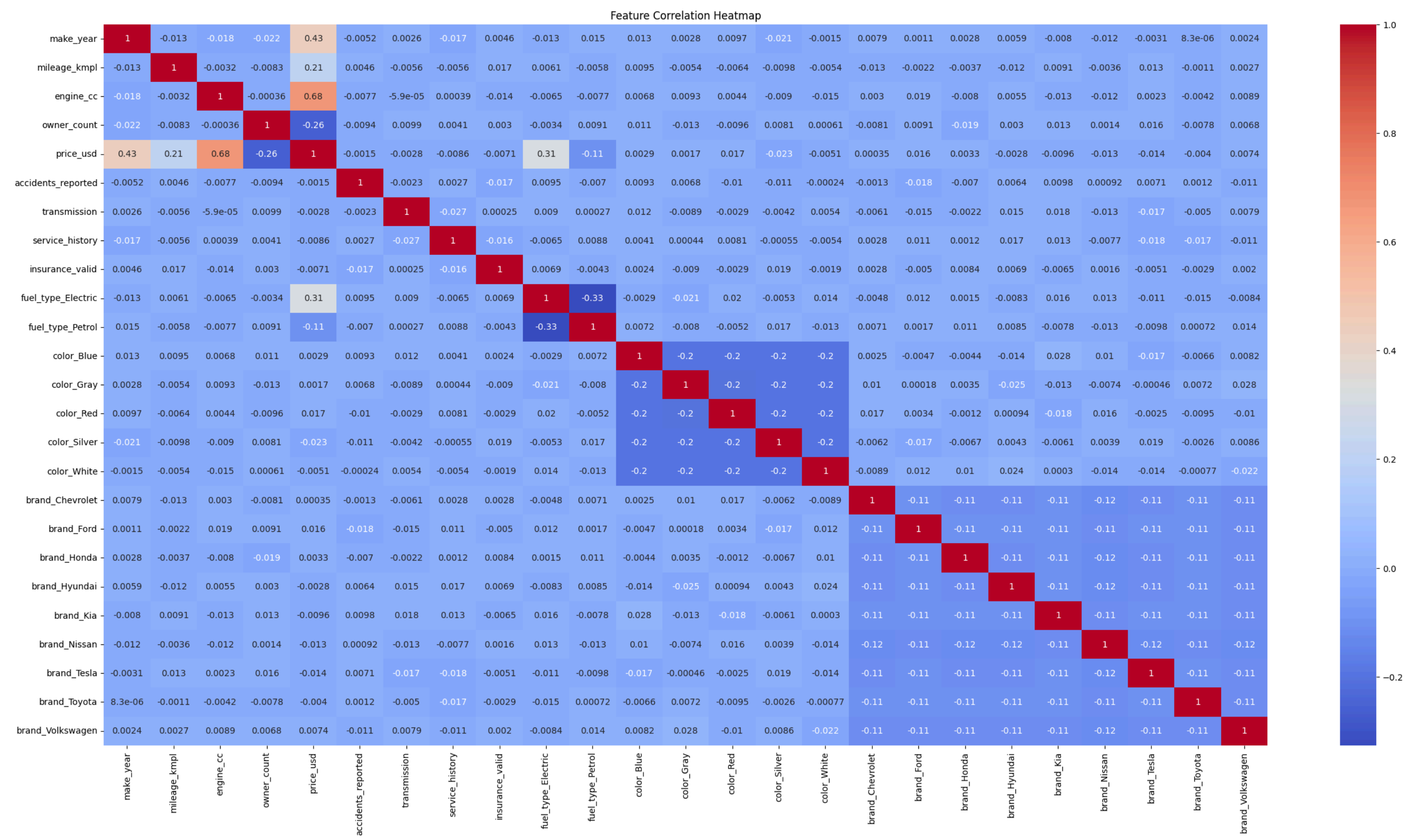
```
print("-------- Unique values of Categorical feature After Encoding --------")
for col in df_cat.columns:
    print(col, df_cat[col].unique())
```

```
-------- Unique values of Categorical feature After Encoding --------
transmission [1 0]
service_history [0 1]
insurance_valid [0 1]
fuel_type_Electric [0 1]
fuel_type_Petrol [1 0]
color_Blue [0 1]
color_Gray [0 1]
color_Red [0 1]
color_Silver [0 1]
color_White [1 0]
brand_Chevrolet [1 0]
brand_Ford [0 1]
brand_Honda [0 1]
brand_Hyundai [0 1]
brand_Kia [0 1]
brand_Nissan [0 1]
brand_Tesla [0 1]
brand_Toyota [0 1]
brand_Volkswagen [0 1]
```

```
df = pd.concat([df_num, df_cat], axis=1)
```

```
# Visualizing correlation between features

plt.figure(figsize=(30, 15))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title('Feature Correlation Heatmap')
plt.show()
```




```
# Splitting into training and testing data

from sklearn.model_selection import train_test_split
```

```
X = df.drop(['price_usd'], axis=1)
y = df['price_usd']

# Standardization of training data
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, shuffle=True, random_state=42)
```

```
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error, root_mean_squared_error


models = {
    'Linear Regression':LinearRegression(),
    'Ridge':Ridge(alpha=2),
    'Lasso':Lasso(alpha=2)
}


results = {}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    results[name] = {
        'R2 Score':r2_score(y_test, y_pred),
        'MAE':mean_absolute_error(y_test, y_pred),
        'MSE':mean_squared_error(y_test, y_pred),
        'RMSE':root_mean_squared_error(y_test, y_pred)
    }
```

```
results_df = pd.DataFrame(results)
print(results_df.T)
```

```
                   R2 Score         MAE            MSE        RMSE
Linear Regression  0.876648  790.800540  981328.481566  990.620251
Ridge              0.876648  790.811695  981327.280484  990.619645
Lasso              0.876628  791.160844  981490.924595  990.702238
```

```
poly = PolynomialFeatures(degree=2)
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)

model.fit(X_train_poly, y_train)
y_pred = model.predict(X_test_poly)

results['Polynomial Regression'] = {
        'R2 Score':r2_score(y_test, y_pred),
        'MAE':mean_absolute_error(y_test, y_pred),
        'MSE':mean_squared_error(y_test, y_pred),
        'RMSE':root_mean_squared_error(y_test, y_pred)
}
```

```
results_df = pd.DataFrame(results)
print(results_df.T)
```

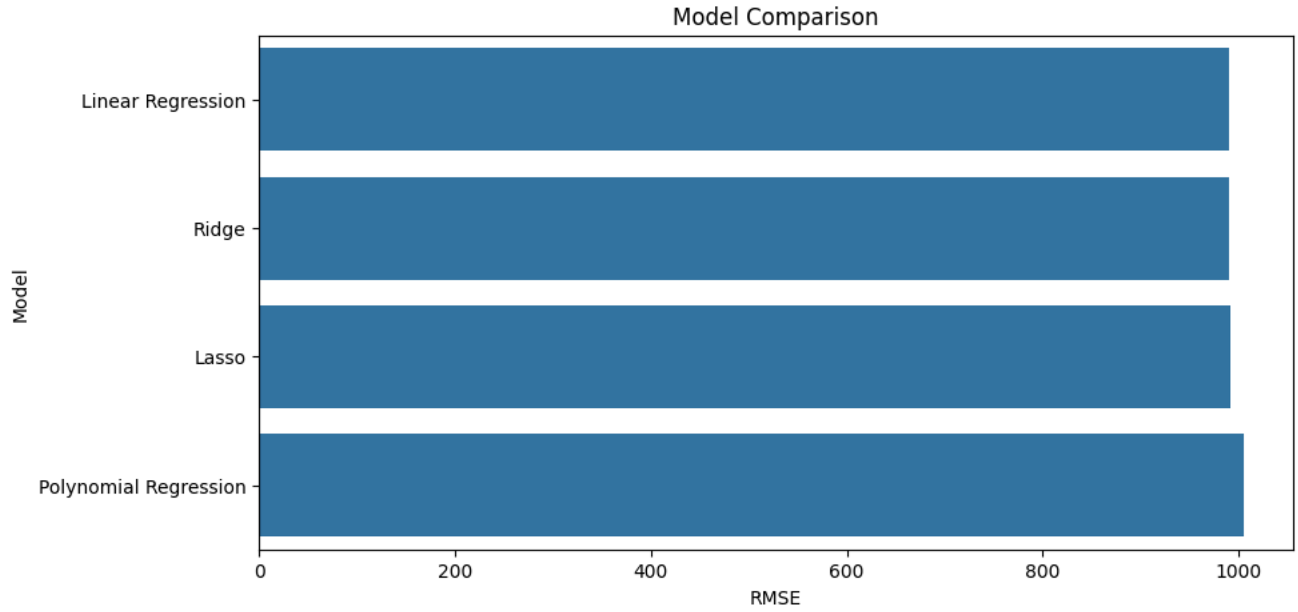
```
                       R2 Score         MAE           MSE         RMSE
Linear Regression      0.876648  790.800540  9.813285e+05   990.620251
Ridge                  0.876648  790.811695  9.813273e+05   990.619645
Lasso                  0.876628  791.160844  9.814909e+05   990.702238
Polynomial Regression  0.873007  800.210429  1.010298e+06  1005.135824
```

```
best_model = results_df.T['RMSE'].idxmax()
print(best_model)
```

```
Polynomial Regression
```

```
# Visualize model comparison

rmse = results_df.loc['RMSE']
plt.figure(figsize=(10, 5))
sns.barplot(x=rmse.values, y=rmse.index)
plt.xlabel('RMSE')
plt.ylabel('Model')
plt.title('Model Comparison')
plt.show()
```


Model Comparison
Linear Regression
Ridge
Lasso
Polynomial Regression
Model
0
200
400
600
800
1000
RMSE