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import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler #for feature scaling
from sklearn.model_selection import train_test_split #train-test split
#for simple linear regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

```

```

df = pd.read_csv('/content/dataset.zip')
print("Shape of the dataset:", df.shape)
df.head()

```

Shape of the dataset: (15915, 23)

```

{"type": "dataframe", "variable_name": "df"}

```

```

df.info()
df.describe()

```

```

# Check for missing values
missing_values = df.isnull().sum()
missing_values[missing_values > 0]

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15915 entries, 0 to 15914
Data columns (total 23 columns):

```

#	Column	Non-Null Count	Dtype
0	make_model	15915 non-null	object
1	body_type	15915 non-null	object
2	price	15915 non-null	int64
3	vat	15915 non-null	object
4	km	15915 non-null	float64
5	Type	15915 non-null	object
6	Fuel	15915 non-null	object
7	Gears	15915 non-null	float64
8	Comfort_Convenience	15915 non-null	object
9	Entertainment_Media	15915 non-null	object
10	Extras	15915 non-null	object
11	Safety_Security	15915 non-null	object
12	age	15915 non-null	float64
13	Previous_Owners	15915 non-null	float64
14	hp_kw	15915 non-null	float64
15	Inspection_new	15915 non-null	int64
16	Paint_Type	15915 non-null	object
17	Upholstery_type	15915 non-null	object
18	Gearing_Type	15915 non-null	object

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19 Displacement_cc      15915 non-null float64
20 Weight_kg            15915 non-null float64
21 Drive_chain          15915 non-null object
22 cons_comb            15915 non-null float64
dtypes: float64(8), int64(2), object(13)
memory usage: 2.8+ MB

Series([], dtype: int64)

# Drop rows with missing values
df_cleaned = df.dropna()
# Select only numeric columns
numeric_df = df_cleaned.select_dtypes(include=[np.number])
# Check again
numeric_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15915 entries, 0 to 15914
Data columns (total 10 columns):
#   Column                Non-Null Count  Dtype
---  -
0   price                 15915 non-null  int64
1   km                    15915 non-null  float64
2   Gears                 15915 non-null  float64
3   age                   15915 non-null  float64
4   Previous_Owners       15915 non-null  float64
5   hp_kW                 15915 non-null  float64
6   Inspection_new        15915 non-null  int64
7   Displacement_cc       15915 non-null  float64
8   Weight_kg             15915 non-null  float64
9   cons_comb             15915 non-null  float64
dtypes: float64(8), int64(2)
memory usage: 1.2 MB

features = ['km', 'hp_kW', 'Displacement_cc', 'Weight_kg',
'Previous_Owners', 'cons_comb', 'Gears', 'age']
target = 'price'

X = df[features]
y = df[target]

# Splitting dataset
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

```

```

#Simple Linear Regression:km vs price
X_km = df[['km']] #one feature that most correlates with the target
variable
y_price = df['price']

X_train_km, X_test_km, y_train_km, y_test_km = train_test_split(X_km,
y_price, test_size=0.2, random_state=42)

# Model
lr_simple = LinearRegression()
lr_simple.fit(X_train_km, y_train_km)

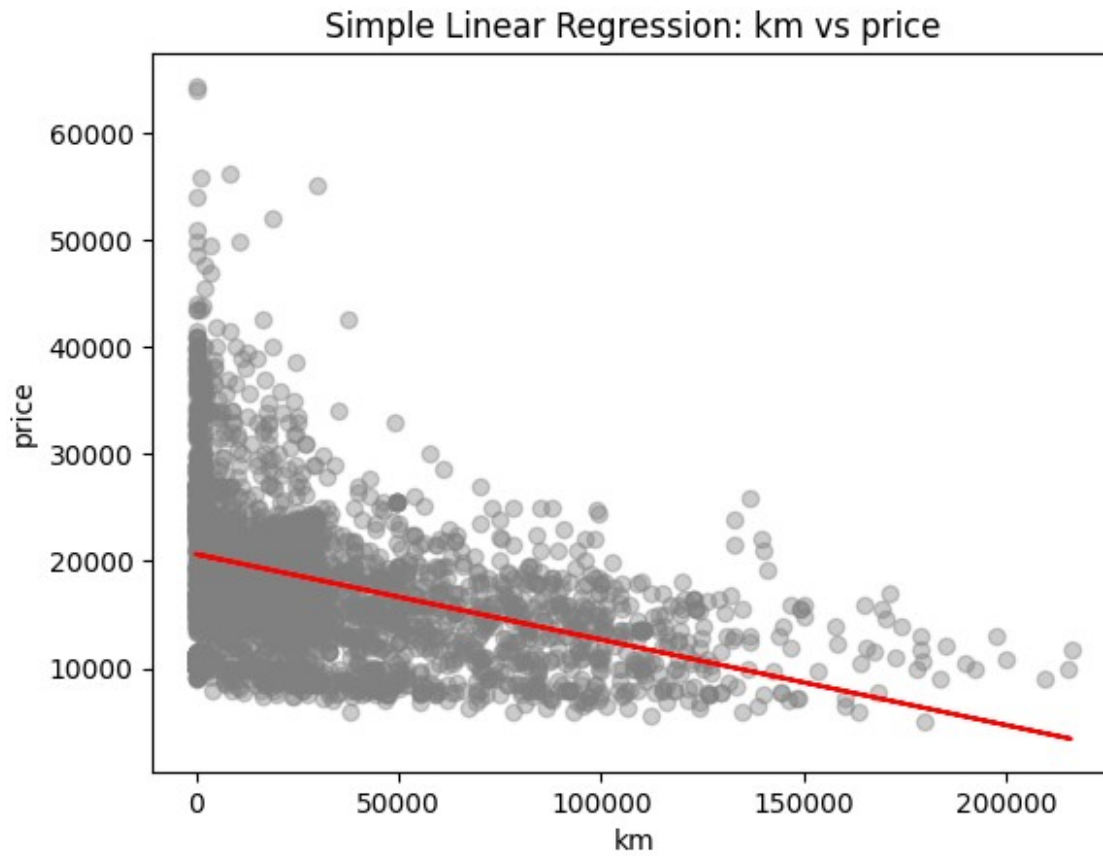
# Predict and evaluate
y_pred_km = lr_simple.predict(X_test_km)

print("Simple Linear Regression:")
print("R^2 Score:", r2_score(y_test_km, y_pred_km))
print("MSE:", mean_squared_error(y_test_km, y_pred_km))

# Visualization
plt.scatter(X_test_km, y_test_km, color='gray', alpha=0.4)
plt.plot(X_test_km, y_pred_km, color='red')
plt.xlabel('km')
plt.ylabel('price')
plt.title('Simple Linear Regression: km vs price')
plt.show()

Simple Linear Regression:
R^2 Score: 0.15181949886405333
MSE: 45774249.476677515

```



```
# Use already scaled and split data from earlier
# X_scaled, y, X_train, X_test, y_train, y_test

lr_multi = LinearRegression()
lr_multi.fit(X_train_scaled, y_train)

# Predict and evaluate
y_pred_multi = lr_multi.predict(X_test_scaled)

print("Multiple Linear Regression:")
print("R^2 Score:", r2_score(y_test, y_pred_multi))
print("MSE:", mean_squared_error(y_test, y_pred_multi))

Multiple Linear Regression:
R^2 Score: 0.757866741684256
MSE: 13067346.110765168

comparison_df = pd.DataFrame({
    "Model": ["Simple Linear Regression", "Multiple Linear
Regression"],
    "R^2 Score": [r2, r2_m],
    "MSE": [mse, mse_m]
})
```

comparison\_df

```
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            "Simple Linear Regression"
          ],
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            "semantic_type": "",
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              "min": 13053305.7226343,
              "max": 26323633.65733814,
              "num_unique_values": 2,
              "samples": [
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                26323633.65733814
              ],
              "semantic_type": "",
              "description": ""
            }
          }
        }
      }
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    "variable_name": "comparison_df"
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}
```