Faculty of Engineering & Technology Electrical & Computer Engineering Department

MACHINE LEARNING AND DATA SCIENCE

ENCS5341

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Introduction

This project aims to construct and assess regression models for predicting car prices using the YallaMotors dataset. The approach includes developing linear regression models such as Ordinary Least Squares, LASSO, and Ridge, alongside nonlinear techniques like Polynomial Regression and Radial Basis Function (RBF). Critical steps involve preprocessing the data, selecting relevant features, and applying regularization to improve model accuracy while minimizing overfitting. Grid search is utilized for hyperparameter optimization, and model performance is evaluated using metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared. The results, accompanied by visualizations, highlight the models' predictive capabilities, feature relevance, and potential limitations. What preprocessing techniques are applied to standardize car prices listed in different currencies? How does feature selection using forward selection impact the model's performance? What role do regularization techniques (LASSO and Ridge) play in controlling overfitting in linear models? How does hyperparameter tuning via grid search enhance the models' predictive accuracy? Which regression model demonstrates the best performance based on the evaluation metrics, and why? How do nonlinear models like Polynomial Regression and RBF handle complex patterns in the dataset compared to linear models? What visualizations are used to support the findings, and how do they enhance the interpretation of results? What challenges are encountered in the dataset preprocessing and modeling phases, and how are they addressed?

1.**Exploratory Data Analysis (EDA)**:

1.1Load csv file

EDA Analysis

```
# Mohammad Salem 1200651 , Majd abdeddin 1202923
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Reading the CSV file
cars_df = pd.read_csv('cars.csv')

# Printing the first 5 rows
cars_df.head()
```

	car name	price	engine_capacity	cylinder	horse_power	top_speed	seats	brand	country
0	Fiat 500e 2021 La Prima	TBD	0	N/A, Electric	Single	Automatic	150	fiat	ksa
1	Peugeot Traveller 2021 L3 VIP	SAR 140,575	2	4	180	8 Seater	8.8	peugeot	ksa
2	Suzuki Jimny 2021 1.5L Automatic	SAR 98,785	1.5	4	102	145	4 Seater	suzuki	ksa
3	Ford Bronco 2021 2.3T Big Bend	SAR 198,000	2.3	4	420	4 Seater	7.5	ford	ksa
4	Honda HR-V 2021 1.8 i-VTEC LX	Orangeburst Metallic	1.8	4	140	190	5 Seater	honda	ksa

1.2 Information about data: to Exploratory and understand the variability on data, Dataset Information, Statistical Summary, Missing Values: Unique Values, and Sample Distribution:

```
Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6308 entries, 0 to 6307
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   car name         6308 non-null   object
 1   price            6308 non-null   object
 2   engine_capacity  6308 non-null   object
 3   cylinder         5684 non-null   object
 4   horse_power      6308 non-null   object
 5   top_speed        6308 non-null   object
 6   seats            6308 non-null   object
 7   brand            6308 non-null   object
 8   country          6308 non-null   object
dtypes: object(9)
memory usage: 443.7+ KB
None
```

```
Statistical Summary:
                                car name price engine_capacity cylinder  \
count                               6308  6308            6308     5684
unique                              2546  3395             129       10
top     Mercedes-Benz C-Class 2022 C 300   TBD               2        4
freq                                  10   437            1241     2856

       horse_power top_speed     seats          brand country
count         6308      6308      6308           6308    6308
unique         330       169        80             82       7
top            150       250  5 Seater  mercedes-benz     uae
freq           162      1100      3471            560    1248

Missing Values:
car name             0
price                0
engine_capacity      0
cylinder           624
horse_power          0
top_speed            0
seats                0
brand                0
country              0
dtype: int64
```

```
Unique Values:
car name: 2546 unique values
price: 3395 unique values
engine_capacity: 129 unique values
cylinder: 10 unique values
horse_power: 330 unique values
top_speed: 169 unique values
seats: 80 unique values
brand: 82 unique values
country: 7 unique values

Sample Distribution:
price
TBD                437
Following          238
DISCONTINUED       140
Follow              27
Grigio Maratea      23
Name: count, dtype: int64
```

2. Data Preprocessing

2.1 Preprocessing on target column (label), 'price' Column:

We noticed that it is a few percentages of noisy data, also there is exist extreme values, then we replace it to median value in data cleaning phase:

Preprocessing

```
import pandas as pd
import re

# Load the dataset
cars_df = pd.read_csv('cars.csv')

# Get unique values in the 'price' column
unique_prices = cars_df['price'].unique()

# Initialize lists for analysis
valid_prices = []
currencies = set()
noise_values = []

# Regular expression to identify prices with currencies
price_pattern = r'([A-Z]{3})\s?([\d,]+)'  # Matches formats like "SAR 140,248" or "USD123,456"
```

```
# Regular expression to identify prices with currencies
price_pattern = r'([A-Z]{3})\s?([\d,]+)'  # Matches formats like "SAR 140,248" or "USD123,456"

for value in unique_prices:
    if isinstance(value, str):  # Ensure it's a string
        match = re.match(price_pattern, value)
        if match:
            currencies.add(match.group(1))  # Extract currency (e.g., SAR, EGP)
            valid_prices.append(value)     # Add valid price to the list
        else:
            noise_values.append(value)    # Add noise to a separate list

# Output results
print("Unique Prices in 'price' Column:")
print(unique_prices)
print("\nValid Prices (with currencies):")
print(valid_prices)
print("\nUnique Currencies:")
print(currencies)
print("\nNoise/Invalid Values:")
print(noise_values)

print("\nNoisy data persentage :")
print(   "Noisy prices "+ str(len(noise_values)) )
print(   "valid_prices "+ str(len(valid_prices)) )
print( "Noisy prices from valid prices% :"+ str(  len(noise_values)  /   len(valid_prices) ) +" %" )
print( "Noisy prices from all data% :"+ str(  len(noise_values)  /  ( len(valid_prices)+len(noise_values))  )+" %"  )
```

```
Unique Prices in 'price' Column:
['TBD' 'SAR 140,575' 'SAR 98,785' ... 'AED 1,990,000' 'AED 1,766,100'
 'AED 1,650,000']

Valid Prices (with currencies):
['SAR 140,575', 'SAR 98,785', 'SAR 198,000', 'SAR 95,335', 'SAR 82,845', 'SAR 76,545', 'SAR 116,900', '

Unique Currencies:
{'EGP', 'AED', 'QAR', 'KWD', 'OMR', 'BHD', 'SAR'}

Noise/Invalid Values:
['TBD', 'Orangeburst Metallic', 'Ruby Flare Pearl', 'Following', 'Clear White', 'Jet Black Metallic', '

Noisy data persentage :
Noisy prices 83
valid_prices 3312
Noisy prices from valid prices% :0.025060386473429952 %
Noisy prices from all data% :0.024447717231222386 %
```

2.2 To ensure consistency, you may need to standardize all prices to a common currency, such as USD, for a uniform target variable. This will help avoid discrepancies and improve the accuracy of any predictive modeling:

```
[30] import pandas as pd
     import re



     # Exchange rates for conversion to USD
     exchange_rates = {
         'SAR': 0.27, 'AED': 0.27, 'EGP': 0.032, 'OMR': 2.60,
         'BHD': 2.65, 'KWD': 3.25, 'QAR': 0.27
     }

     # Regular expression to extract price and currency
     price_pattern = r'([A-Z]{3})\s?([\d,]+)'

     # Lists to store cleaned prices and noise
     cleaned_prices = []
     noisy_indices = []

     # Iterate through the price column
     for idx, value in enumerate(cars_df['price']):
         if isinstance(value, str):
             match = re.match(price_pattern, value)
             if match:
                 currency, numeric_value = match.groups()
                 numeric_value = int(numeric_value.replace(',', ''))  # Remove commas and convert to int
                 usd_value = numeric_value * exchange_rates.get(currency, 0)  # Convert to USD
                 cleaned_prices.append(round(usd_value))  # Store rounded value in USD
             else:
                 noisy_indices.append(idx)  # Mark noisy data indices
         else:
             noisy_indices.append(idx)  # Handle non-string noise

     # Calculate the median of the cleaned prices
     median_price_usd = int(pd.Series(cleaned_prices).median())

     # Replace noise with median price
     for idx in noisy_indices:
         cleaned_prices.insert(idx, median_price_usd)

     # Update the 'price' column with cleaned and converted prices
     cars_df['price'] = cleaned_prices

     # Display results
     print("\nCleaned and Converted 'price' Column (first 10 values):")
     print(cars_df['price'].head(10))

     print("\nSummary Statistics of Cleaned Prices:")
     print(cars_df['price'].describe())
```

```
Cleaned and Converted 'price' Column (first 10 values):
0    47250
1    37955
2    26672
3    53460
4    47250
5    25740
6    22368
7    20667
8    31563
9    64260
Name: price, dtype: int64

Summary Statistics of Cleaned Prices:
count    6.308000e+03
mean     6.677835e+04
std      9.564086e+04
min      4.608000e+03
25%      2.943000e+04
50%      4.725000e+04
75%      6.944025e+04
max      3.594996e+06
Name: price, dtype: float64
```

2.3 Clean and Normalized engine_capacity column:

```
# Get unique values in the 'engine_capacity' column
unique_engine_capacity = cars_df['engine_capacity'].unique()
print("Unique engine_capacity in 'price' Column:")
print(unique_engine_capacity)
```

```
Unique engine_capacity in 'price' Column:
['0' '2' '1.5' '2.3' '1.8' '2.5' '2.7' '5.2' '4' '3.5' '3.8' '1.6' '3'
 '6.2' '3.7' '6.5' '1.7' '1.4' '2.2' '2.4' '5' '6.7' '4.4' '5.7' '3.6'
 '1.2' '3.3' '2.9' '2.8' '6' '3.9' '1.3' '1' '3.2' '5.3' '4.5' '4.8' '6.4'
 '4.6' '5.6' '4.7' '5.5' '8' '6.3' '6.6' '5.9' '6.8' '2359' '1600' '1498'
 '5200' '3982' '1991' '1598' 'Cylinders' '1500' '1800' '1497' '2500'
 '1969' '2000' '1400' '4395' '1984' '1591' '2998' '2995' '1988' '2497'
 '1300' '1499' '3995' '1489' '1998' '1490' '2891' '1995' '4400' '1197'
 '1200' '1199' '1561' '1332' '3000' '1798' '1997' '1000' '1590' '1396'
 '1248' '1485' '999' '1395' '1587' '1368' '1586' '1299' '1597' '5300'
 '1496' '140' '2693' '3342' '2476' '1595' '3498' '3470' '3828' '2987'
 '4000' '2979' '4999' '5700' '5935' '4691' '3600' '3993' '5950' '6000'
 '2894' '2981' '6752' '3400' '3996' '1.9' '4.2' '3.4' '2.1' '4.1']
```

```
[32] import numpy as np

    # Function to clean and normalize engine capacities
    def clean_engine_capacity(value):
        try:
            if isinstance(value, str):
                # Check if the value is noise
                if value.lower() == 'cylinders':
                    return np.nan
                # Check if the value is numeric (e.g., '5300', '4.2')
                if value.isdigit():  # Large integers (e.g., 1567, 5300)
                    cc_value = int(value)
                    if cc_value > 100 and cc_value < 10000:  # Convert CC to liters
                        return cc_value / 1000
                    else:
                        return np.nan  # Unusually large/small values
                elif '.' in value:  # Floats like '4.1'
                    return float(value)
            elif isinstance(value, (int, float)):  # Direct numeric values
                return value
        except:
            pass
        return np.nan  # Default for invalid cases

    ############################
```

```
# Clean the engine_capacity column
cars_df['engine_capacity'] = cars_df['engine_capacity'].apply(clean_engine_capacity)

# Replace missing/invalid values with the median
median_engine_capacity = cars_df['engine_capacity'].median()
cars_df['engine_capacity'] = cars_df['engine_capacity'].fillna(median_engine_capacity)


# Display cleaned column and unique values
unique_engine_capacity_cleaned = cars_df['engine_capacity'].unique()
print("Cleaned and Normalized 'engine_capacity' Column (Unique Values):")
print(unique_engine_capacity_cleaned)

print("\nSummary Statistics of Cleaned Engine Capacities:")
print(cars_df['engine_capacity'].describe())
```

```
Cleaned and Normalized 'engine_capacity' Column (Unique Values):
[2.5   1.5   2.3   1.8   2.7   5.2   3.5   3.8   1.6   6.2   3.7   6.5
 1.7   1.4   2.2   2.4   6.7   4.4   5.7   3.6   1.2   3.3   2.9   2.8
 3.9   1.3   3.2   5.3   4.5   4.8   6.4   4.6   5.6   4.7   5.5   6.3
 6.6   5.9   6.8   2.359 1.498 3.982 1.991 1.598 1.497 1.969 2.    4.395
 1.984 1.591 2.998 2.995 1.988 2.497 1.499 3.995 1.489 1.998 1.49  2.891
 1.995 1.197 1.199 1.561 1.332 3.    1.798 1.997 1.    1.59  1.396 1.248
 1.485 0.999 1.395 1.587 1.368 1.586 1.299 1.597 1.496 0.14  2.693 3.342
 2.476 1.595 3.498 3.47  3.828 2.987 4.    2.979 4.999 5.935 4.691 3.993
 5.95  6.    2.894 2.981 6.752 3.4   3.996 1.9   4.2   2.1   4.1  ]

Summary Statistics of Cleaned Engine Capacities:
count    6308.000000
mean        2.747463
std         1.125265
min         0.140000
25%         2.400000
50%         2.500000
75%         2.700000
max         6.800000
Name: engine_capacity, dtype: float64
```

2.4 Clean the "Cleaned 'horse_power' Column And cleaned 'top_speed' Column :

```python
# Define a function to clean numeric columns
def clean_numeric_column(column):
    # Extract numeric values only
    column_cleaned = pd.to_numeric(column, errors='coerce')  # Non-numeric values will be set to NaN

    # Find median of the valid numbers (ignoring NaN)
    median_value = column_cleaned.median()

    # Replace NaN values with the median
    column_cleaned.fillna(median_value, inplace=True)

    # Convert to integers
    column_cleaned = column_cleaned.astype(int)

    return column_cleaned

# Clean the 'horse_power' column
cars_df['horse_power'] = clean_numeric_column(cars_df['horse_power'])

# Clean the 'top_speed' column
cars_df['top_speed'] = clean_numeric_column(cars_df['top_speed'])
```

```python
# Print cleaned data and summary
print("Cleaned 'horse_power' Column (Unique Values):")
print(cars_df['horse_power'].unique())

print("\nCleaned 'top_speed' Column (Unique Values):")
print(cars_df['top_speed'].unique())

print("\nSummary Statistics for 'horse_power':")
print(cars_df['horse_power'].describe())

print("\nSummary Statistics for 'top_speed':")
print(cars_df['top_speed'].describe())
```

```
Cleaned 'horse_power' Column (Unique Values):
[ 255  180  102  420  140  120  170  542  900  198  700  152  503  530
  355  121  400  335  168  231  382  495  224  155  200  275  250  112
  124 1973  254  306  770  320  118  620  139   95  600  103  363  233
  315  105  226  505  128  585  340  422  850  523  462  268  639  395
  354   82  258  440  252  290  100  192  500  123  365  165  136  184
  292  680  550  460  367  211  330  104  245  107  277  379  465  612
  510  562  435  280  476  204  740  147  251  558  650  380  169  189
  702  402  163  350  854  410  225   25  592   78  800  718  156  148
  194  710  755  220  115  630  283  238  185  173   98  160  135  119
   84  110  138  127  150   91  130  132  167  175  113  153  164  205
  215  174  188  227  221  158  212  176  172  197  240  181  298  248
  241  305  228  190  257  310  284  285  235  177  286  161  109  270
  247  213  134  271  300  272  265  230  295  318  517  214  302  232
  328  370  455  208  362  154  375  385  360  253  485  304  520  470
  326  464  390  329  311  381  246  314  338  296  430  590  421  450
  471  313  308  707  572  299  428  407  431  525  565  469   12  514
  544  576  540 1479  626  575  570  610  690  624  601  571  640  563
  593   94  195  166   67  131  217  125  297   86   87  126   79  114
  117  111   99  325  201   76  144  106  151  122  116  288  210  203
  219  187   88  276  191  178  218  236  301  333  394  472  377  408
  401  797  490  442  580  625  416  397  557  560  545  475 5050  605
  617  577  568  567  603   77   75  149  312  526  316  345   65  133
   83  108  243  438  141   92  145  171  294  411  415  573  404  341
  489  374  602  720]
```

```
Cleaned 'top_speed' Column (Unique Values):
[211 145 190 170 199 200 180 322 300 250 210 312 236 181 216 158 230 172
 320 220 350 240 184 326 175 185 140 243 310 254 165 270 227 206 228 360
 160 205 275 304 289 222 286 280 217 283 328 302 235 207 316 305 245 800
 192 173 168 335 340 330 208 325 215 183 169 193 178 161 209 194 182 198
 162 167 239 195 188 219 155 150 189 244 187 226 197 196 234 237 191 218
 238 225 281 285 272 290 267 251 293 264 314 265 253 249 301 299 291 263
 288 306 308 315 278 600 318 295 323 317 333 292 296 201 130 176 166 212
 213 156 261 120 203 202 224 204 233 241 246 177 260 327 303 242 171 186
 232 266 274 248 229 279 259 307 255 258 966 262 324]
```

```
Summary Statistics for 'horse_power':
count    6308.000000
mean      291.555485
std       177.892728
min        12.000000
25%       168.000000
50%       255.000000
75%       367.000000
max      5050.000000
Name: horse_power, dtype: float64

Summary Statistics for 'top_speed':
count    6308.000000
mean      220.854629
std        45.846273
min       120.000000
25%       188.000000
50%       211.000000
75%       250.000000
max       966.000000
Name: top_speed, dtype: float64
```

2.5Cleaned 'seats' Column:

```
# Define a function to clean the 'seats' column
def clean_seats_column(column):
    def extract_seats(value):
        # Match the pattern "{number} Seater" and extract the number
        match = re.match(r"(\d+)\s*Seater", str(value))
        if match:
            return int(match.group(1))  # Return the numeric part
        return None  # Return None for invalid entries

    # Apply the extraction function to the column
    column_cleaned = column.apply(extract_seats)

    # Replace invalid entries (None) with the median of valid entries
    median_seats = column_cleaned.median()
    column_cleaned.fillna(median_seats, inplace=True)

    # Convert to integer type
    column_cleaned = column_cleaned.astype(int)

    return column_cleaned

# Clean the 'seats' column
cars_df['seats'] = clean_seats_column(cars_df['seats'])

# Print cleaned data and summary
print("Cleaned 'seats' Column (Unique Values):")
print(cars_df['seats'].unique())

print("\nSummary Statistics for 'seats':")
print(cars_df['seats'].describe())
```

```
Cleaned 'seats' Column (Unique Values):
[ 5  4  7  2  6  3  9  8 15 18 14 12 13]

Summary Statistics for 'seats':
count    6308.000000
mean        5.016487
std         1.437801
min         2.000000
25%         5.000000
50%         5.000000
75%         5.000000
max        18.000000
Name: seats, dtype: float64
```

2.6 Clean and encode each categorical column (encoding categorical features):

```python
from sklearn.preprocessing import LabelEncoder

# Function to clean and encode a column
def clean_and_label_encode(column, column_name):
    # Check unique values for potential noise
    unique_values = column.unique()
    print(f"Unique values in '{column_name}' before cleaning:")
    print(unique_values)

    # Handle noise (example: replace empty, null, or weird values with 'Unknown')
    column_cleaned = column.fillna('Unknown').str.strip()  # Fill missing and strip extra spaces
    column_cleaned.replace('', 'Unknown', inplace=True)  # Replace empty strings with 'Unknown'

    # Apply label encoding
    encoder = LabelEncoder()
    column_encoded = encoder.fit_transform(column_cleaned)

    print(f"\nUnique values in '{column_name}' after cleaning:\n")
    print(column_cleaned.unique())
    print(f"\nLabel mapping for '{column_name}':\n")
    print(dict(zip(encoder.classes_, range(len(encoder.classes_)))))


    return column_encoded
```

```python
# Clean and encode each column
cars_df['car_name_encoded'] = clean_and_label_encode(cars_df['car name'], 'car name')
print("\n\n")

cars_df['brand_encoded'] = clean_and_label_encode(cars_df['brand'], 'brand')
print("\n\n")

cars_df['country_encoded'] = clean_and_label_encode(cars_df['country'], 'country')
print("\n\n")

# Print the first few rows to verify
print("\n\n\n\nEncoded DataFrame (Preview):\n")
print(cars_df[['car name', 'car_name_encoded', 'brand', 'brand_encoded', 'country', 'country_encoded']].head())
```

```
Unique values in 'car name' before cleaning:
['Fiat 500e 2021 La Prima' 'Peugeot Traveller 2021 L3 VIP'
 'Suzuki Jimny 2021 1.5L Automatic' ...
 'BMW M8 Convertible 2021 4.4T V8 Competition xDrive (625 Hp)'
 'BMW M8 Coupe 2021 4.4T V8 Competition xDrive (625 Hp)'
 'Lamborghini Aventador Ultimae 2022 LP 780-4']

Unique values in 'car name' after cleaning:

['Fiat 500e 2021 La Prima' 'Peugeot Traveller 2021 L3 VIP'
 'Suzuki Jimny 2021 1.5L Automatic' ...
 'BMW M8 Convertible 2021 4.4T V8 Competition xDrive (625 Hp)'
 'BMW M8 Coupe 2021 4.4T V8 Competition xDrive (625 Hp)'
 'Lamborghini Aventador Ultimae 2022 LP 780-4']

Label mapping for 'car name':

{'Abarth 124 Spider 2021 1.4T (170 HP)': 0, 'Abarth 595 2021 1.4T Competizione (Convertible)': 1, 'Abarth 595 2021 1.4T Competizione (Hard-Top)': 2, 'Abar
```

```
Unique values in 'brand' before cleaning:
['fiat' 'peugeot' 'suzuki' 'ford' 'honda' 'renault' 'aston-martin' 'gac'
 'toyota' 'genesis' 'hyundai' 'lincoln' 'mg' 'chevrolet' 'mercedes-benz'
 'kia' 'volkswagen' 'land-rover' 'lotus' 'volvo' 'porsche' 'mini'
 'lamborghini' 'nissan' 'mclaren' 'changan' 'great-wall' 'bmw'
 'rolls-royce' 'audi' 'infiniti' 'ram' 'chrysler' 'gmc' 'borgward' 'jeep'
 'alfa-romeo' 'chery' 'skoda' 'lexus' 'jaguar' 'maxus' 'cadillac'
 'ferrari' 'mazda' 'mitsubishi' 'bestune' 'jetour' 'hongqi' 'maserati'
 'geely' 'byd' 'Foton' 'subaru' 'haval' 'isuzu' 'ssang-yong' 'dodge'
 'bentley' 'bugatti' 'opel' 'zotye' 'soueast ' 'dorcen' 'citroen'
 'brilliance' 'seat' 'proton' 'soueast' 'ds' 'jac' 'lada' 'kinglong'
 'baic' 'morgan' 'mahindra' 'tata' 'dfm' 'acura' 'abarth' 'zna' 'tesla']

Unique values in 'brand' after cleaning:

['fiat' 'peugeot' 'suzuki' 'ford' 'honda' 'renault' 'aston-martin' 'gac'
 'toyota' 'genesis' 'hyundai' 'lincoln' 'mg' 'chevrolet' 'mercedes-benz'
 'kia' 'volkswagen' 'land-rover' 'lotus' 'volvo' 'porsche' 'mini'
 'lamborghini' 'nissan' 'mclaren' 'changan' 'great-wall' 'bmw'
 'rolls-royce' 'audi' 'infiniti' 'ram' 'chrysler' 'gmc' 'borgward' 'jeep'
 'alfa-romeo' 'chery' 'skoda' 'lexus' 'jaguar' 'maxus' 'cadillac'
 'ferrari' 'mazda' 'mitsubishi' 'bestune' 'jetour' 'hongqi' 'maserati'
 'geely' 'byd' 'Foton' 'subaru' 'haval' 'isuzu' 'ssang-yong' 'dodge'
 'bentley' 'bugatti' 'opel' 'zotye' 'soueast' 'dorcen' 'citroen'
 'brilliance' 'seat' 'proton' 'ds' 'jac' 'lada' 'kinglong' 'baic' 'morgan'
 'mahindra' 'tata' 'dfm' 'acura' 'abarth' 'zna' 'tesla']

Label mapping for 'brand':

{'Foton': 0, 'abarth': 1, 'acura': 2, 'alfa-romeo': 3, 'aston-martin': 4, 'audi': 5, 'baic': 6, 'bentley': 7, 'bestune': 8, 'bmw': 9, 'borgward': 10, 'brilliance': 11, 'bugatti': 12
```

```
Unique values in 'country' before cleaning:
['ksa' 'egypt' 'bahrain' 'qatar' 'oman' 'kuwait' 'uae']

Unique values in 'country' after cleaning:

['ksa' 'egypt' 'bahrain' 'qatar' 'oman' 'kuwait' 'uae']

Label mapping for 'country':

{'bahrain': 0, 'egypt': 1, 'ksa': 2, 'kuwait': 3, 'oman': 4, 'qatar': 5, 'uae': 6}
```

```
Encoded DataFrame (Preview):

                          car name  car_name_encoded    brand  brand_encoded  \
0           Fiat 500e 2021 La Prima               564     fiat             25
1     Peugeot Traveller 2021 L3 VIP              1980  peugeot             62
2  Suzuki Jimny 2021 1.5L Automatic              2235   suzuki             73
3    Ford Bronco 2021 2.3T Big Bend               574     ford             26
4     Honda HR-V 2021 1.8 i-VTEC LX               811    honda             33

  country  country_encoded
0     ksa               2
1     ksa               2
2     ksa               2
3     ksa               2
4     ksa               2
```

2.7 Cleaned and Normalized 'cylinder' Column (Unique Values):

```python
# Get unique values in the 'cylinder' column
unique_cylinder = cars_df['cylinder'].unique()
print("Unique cylinder in 'cylinder' Column:")
print(unique_cylinder)
```

```
Unique cylinder in 'cylinder' Column:
['N/A, Electric' '4' '6' '12' '8' nan '3' '5' '10' '16' 'Drive Type']
```

```python
import pandas as pd

# Assuming you have loaded your DataFrame as 'cars_df'
# First, clean the 'cylinder' column by removing the noise and missing values

# Step 1: Replace noise values with median
noise_values = ['N/A, Electric', 'Drive Type']
cars_df['cylinder'] = cars_df['cylinder'].replace(noise_values, pd.NA)

# Step 2: Convert valid numeric values to integers and coerce non-numeric to NaN
cars_df['cylinder'] = pd.to_numeric(cars_df['cylinder'], errors='coerce')

# Step 3: Fill missing (NaN) values with the median value of the column
median_cylinder = cars_df['cylinder'].median()
cars_df['cylinder'] = cars_df['cylinder'].fillna(median_cylinder)
cars_df['cylinder'] = cars_df['cylinder'].astype(int)
# Step 4: Check the unique values after cleaning
print("Cleaned and Normalized 'cylinder' Column (Unique Values):")
print(cars_df['cylinder'].unique())

# Summary statistics of the cleaned 'cylinder' column
print("\nSummary Statistics of Cleaned 'cylinder' Column:")
print(cars_df['cylinder'].describe())
```

```
Cleaned and Normalized 'cylinder' Column (Unique Values):
[ 4  6 12  8  3  5 10 16]

Summary Statistics of Cleaned 'cylinder' Column:
count    6308.000000
mean        5.230184
std         1.821152
min         3.000000
25%         4.000000
50%         4.000000
75%         6.000000
max        16.000000
Name: cylinder, dtype: float64
```

2.8 Now we have clean data:

```
# Dataset information
print("Dataset Information:")
print(cars_df.info())

# Statistical summary
print("\nStatistical Summary:")
print(cars_df.describe())

# Checking for null values
print("\nMissing Values:")
print(cars_df.isnull().sum())

# Unique values for each column
print("\nUnique Values:")
for column in cars_df.columns:
    print(f"{column}: {cars_df[column].nunique()} unique values")

# Sample distribution
print("\nSample Distribution:")
print(cars_df['price'].value_counts().head())
```

```
Statistical Summary:
              price  engine_capacity     cylinder  horse_power    top_speed  \
count  6.308000e+03      6308.000000  6308.000000  6308.000000  6308.000000
mean   6.677835e+04         2.747463     5.230184   291.555485   220.854629
std    9.564086e+04         1.125265     1.821152   177.892728    45.846273
min    4.608000e+03         0.140000     3.000000    12.000000   120.000000
25%    2.943000e+04         2.400000     4.000000   168.000000   188.000000
50%    4.725000e+04         2.500000     4.000000   255.000000   211.000000
75%    6.944025e+04         2.700000     6.000000   367.000000   250.000000
max    3.594996e+06         6.800000    16.000000  5050.000000   966.000000

             seats  car_name_encoded  brand_encoded  country_encoded
count  6308.000000       6308.000000    6308.000000      6308.000000
mean      5.016487       1234.195783      41.740805         3.318326
std       1.437801        723.883422      22.299912         2.027119
min       2.000000          0.000000       0.000000         0.000000
25%       5.000000        562.000000      25.000000         2.000000
50%       5.000000       1299.500000      46.000000         3.000000
75%       5.000000       1823.250000      60.000000         5.000000
max      18.000000       2545.000000      80.000000         6.000000
```

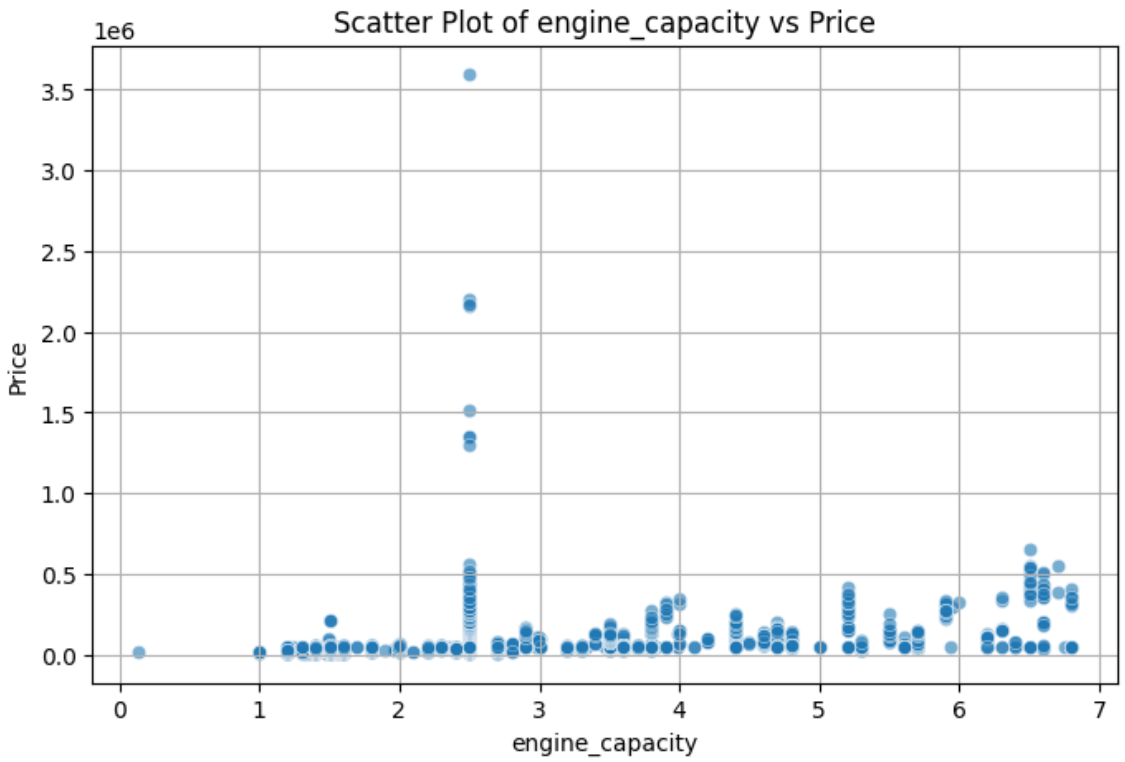
```
Missing Values:
car name              0
price                 0
engine_capacity       0
cylinder              0
horse_power           0
top_speed             0
seats                 0
brand                 0
country               0
car_name_encoded      0
brand_encoded         0
country_encoded       0
dtype: int64
```

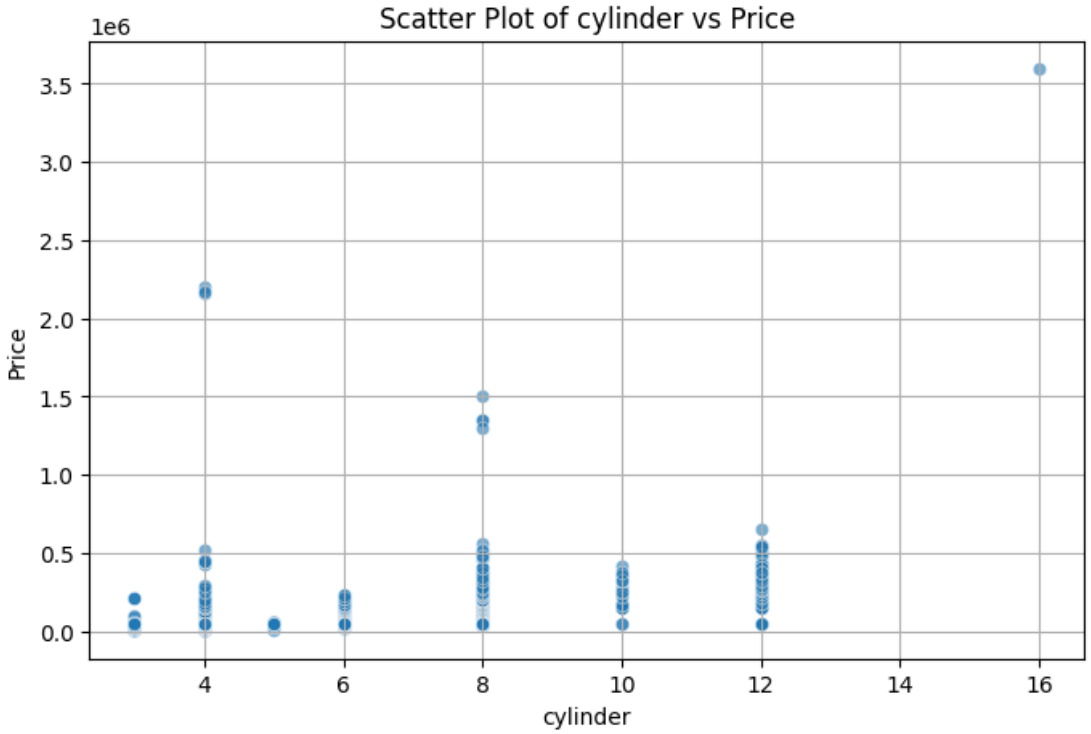
```
Unique Values:
car name: 2546 unique values
price: 2979 unique values
engine_capacity: 107 unique values
cylinder: 8 unique values
horse_power: 326 unique values
top_speed: 157 unique values
seats: 13 unique values
brand: 82 unique values
country: 7 unique values
car_name_encoded: 2546 unique values
brand_encoded: 81 unique values
country_encoded: 7 unique values

Sample Distribution:
price
47250    1337
26000      21
23400      18
35100      14
28350      13
Name: count, dtype: int64
```

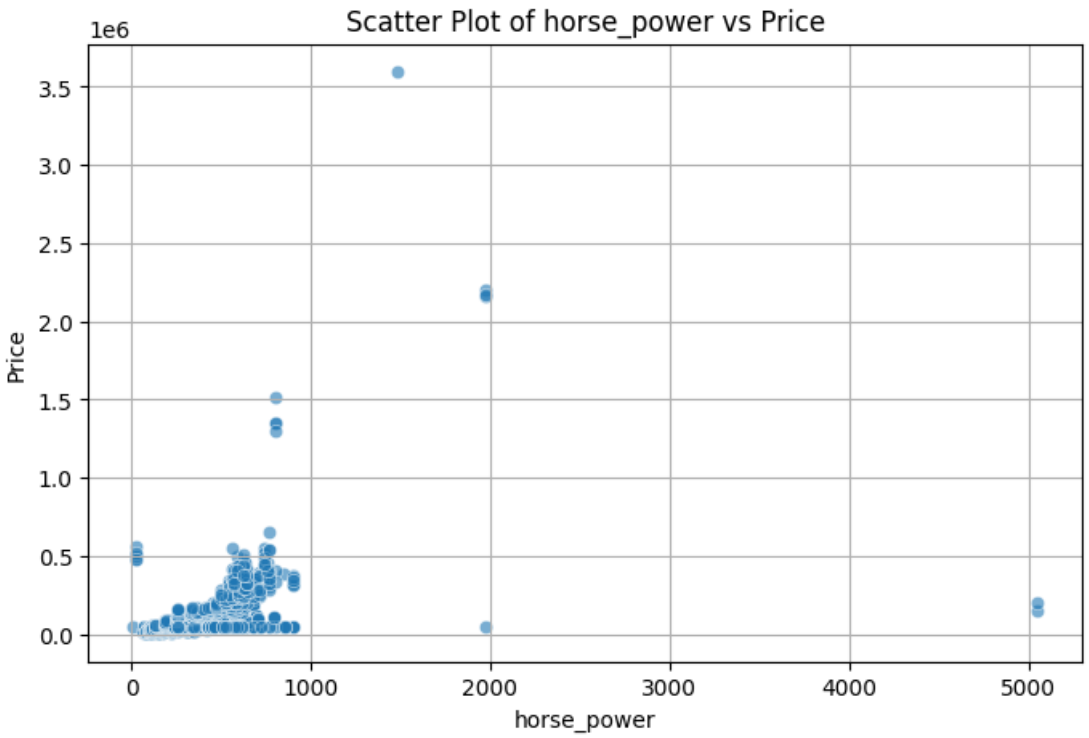
3. Diagnostic Analytics

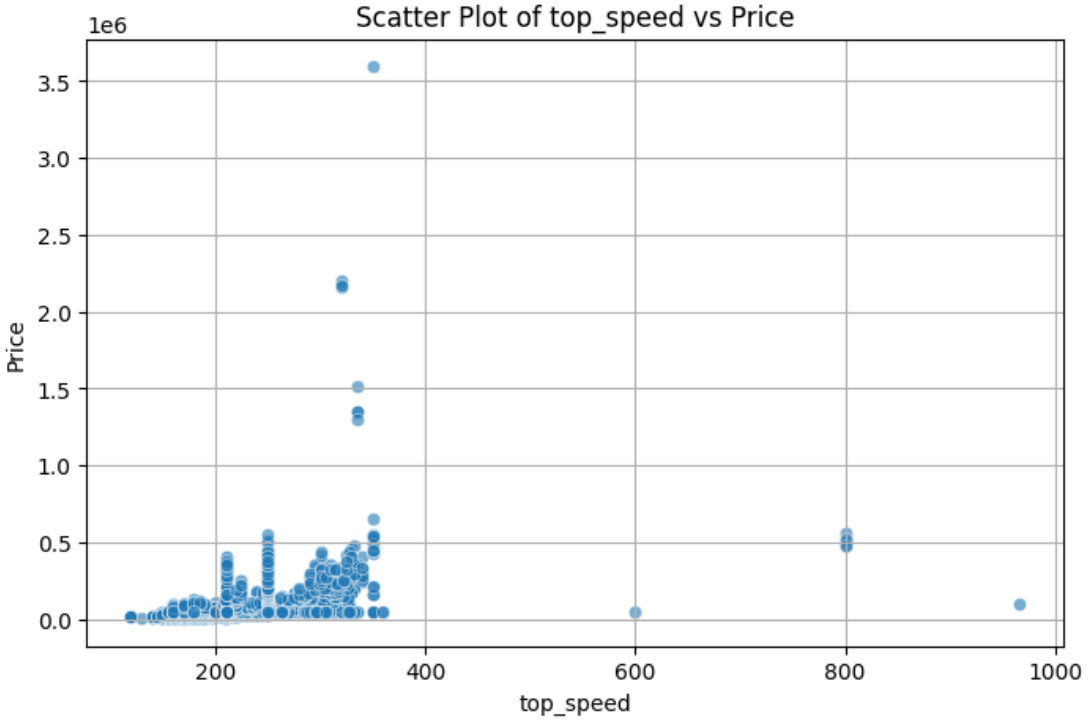
3.1Scatter plots for every numerical column with 'price'

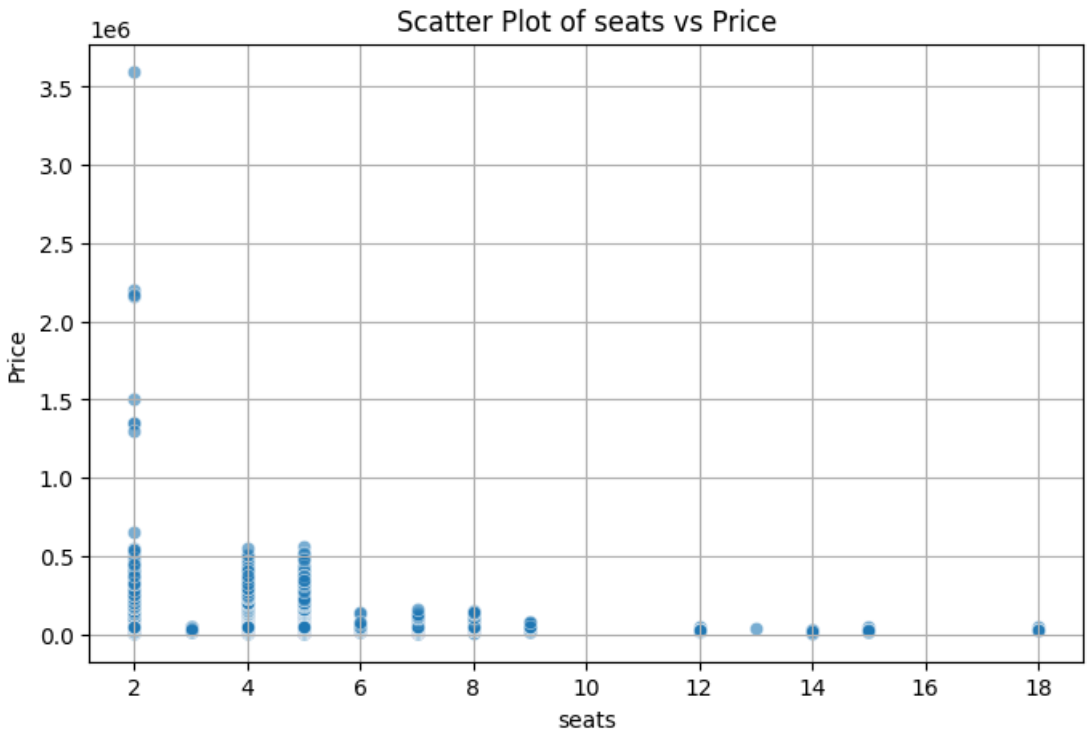
```
# Scatter plots for every numerical column with 'price'
numerical_columns = ['engine_capacity', 'cylinder', 'horse_power', 'top_speed', 'seats']
for col in numerical_columns:
    plt.figure(figsize=(8, 5))
    sns.scatterplot(data=cars_df, x=col, y='price', alpha=0.6)
    plt.title(f'Scatter Plot of {col} vs Price')
    plt.xlabel(col)
    plt.ylabel('Price')
    plt.grid(True)
    plt.show()
```


Scatter Plot of engine_capacity vs Price
1e6
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Price
0
1
2
3
4
5
6
7
engine_capacity


Scatter Plot of cylinder vs Price
1e6
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Price
4
6
8
10
12
14
16
cylinder


Scatter Plot of horse_power vs Price
1e6
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Price
0
1000
2000
3000
4000
5000
horse_power


Scatter Plot of top_speed vs Price
1e6
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Price
200
400
600
800
1000
top_speed



3.2 Correlation Heatmap

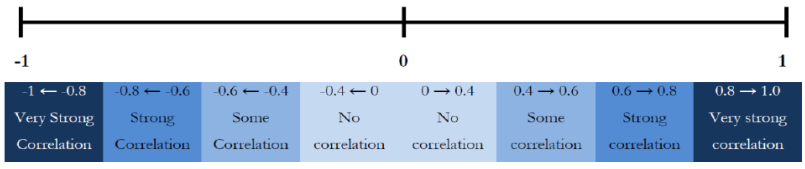
```
# Correlation Heatmap
plt.figure(figsize=(10, 8))
corr = cars_df[['price'] + numerical_columns].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```

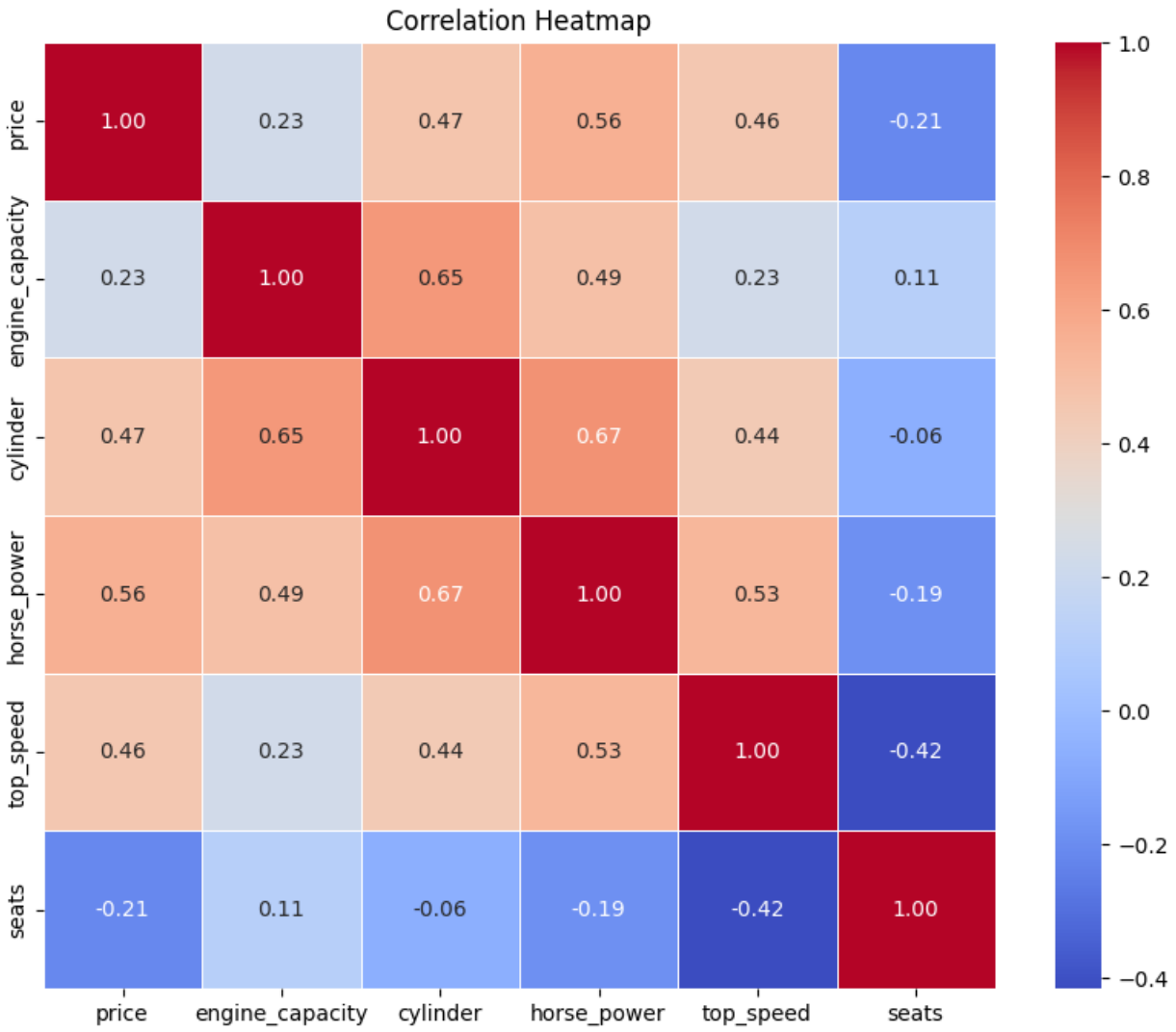
Diagnostic Analytics - Correlations

$$r = \frac{N\sum xy - \sum x \sum y}{\sqrt{\left[N\sum x^2 - \left(\sum x\right)^2\right]\left[N\sum y^2 - \left(\sum y\right)^2\right]}},$$

- **Directions**: All correlation coefficients between 0 and 1 represent positive correlations, while all coefficients between 0 and -1 are negative correlations. Positive relation means if one increase(decrease), then other will increase(decrease). Negative relation means if one increase(decrease), then other will decrease(increase).

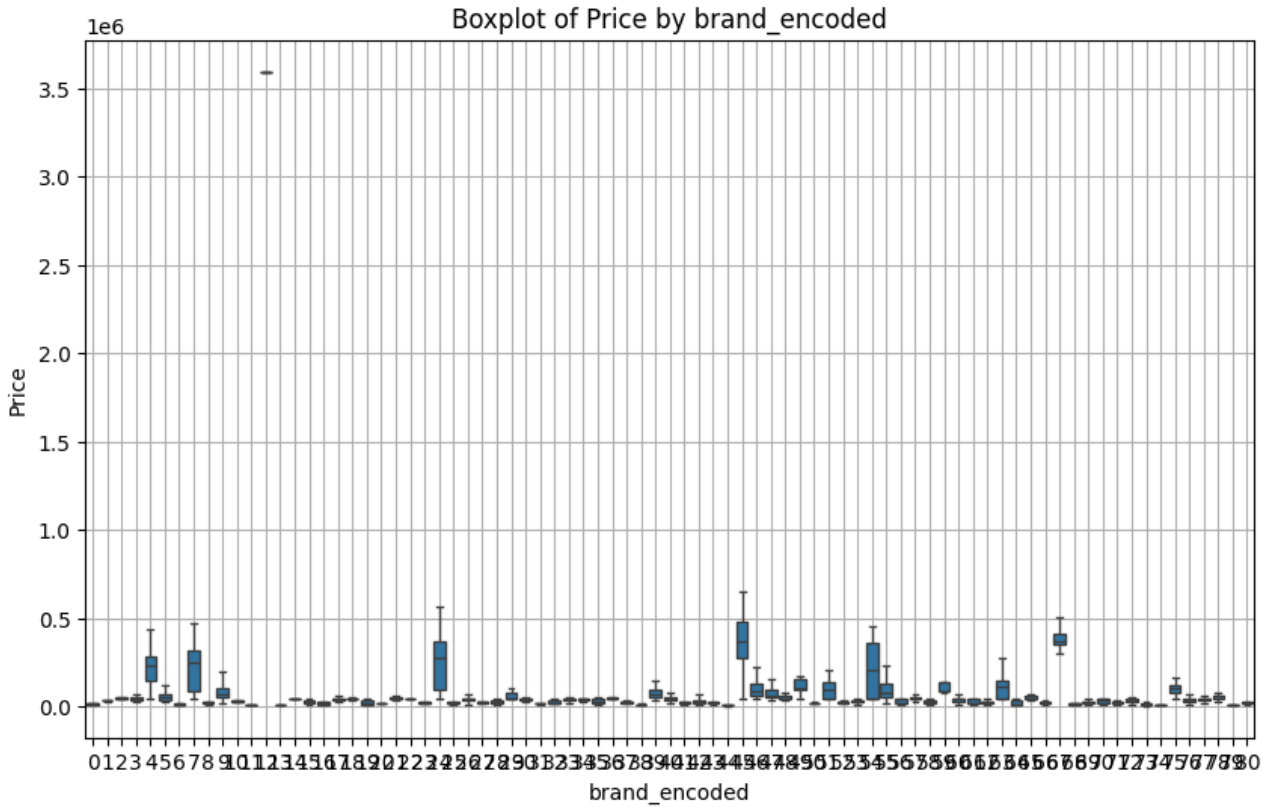
- **Strength**: The closer a correlation coefficient is to 1 or to -1, the stronger it is. Following picture suggests a guideline to interpret the strength.

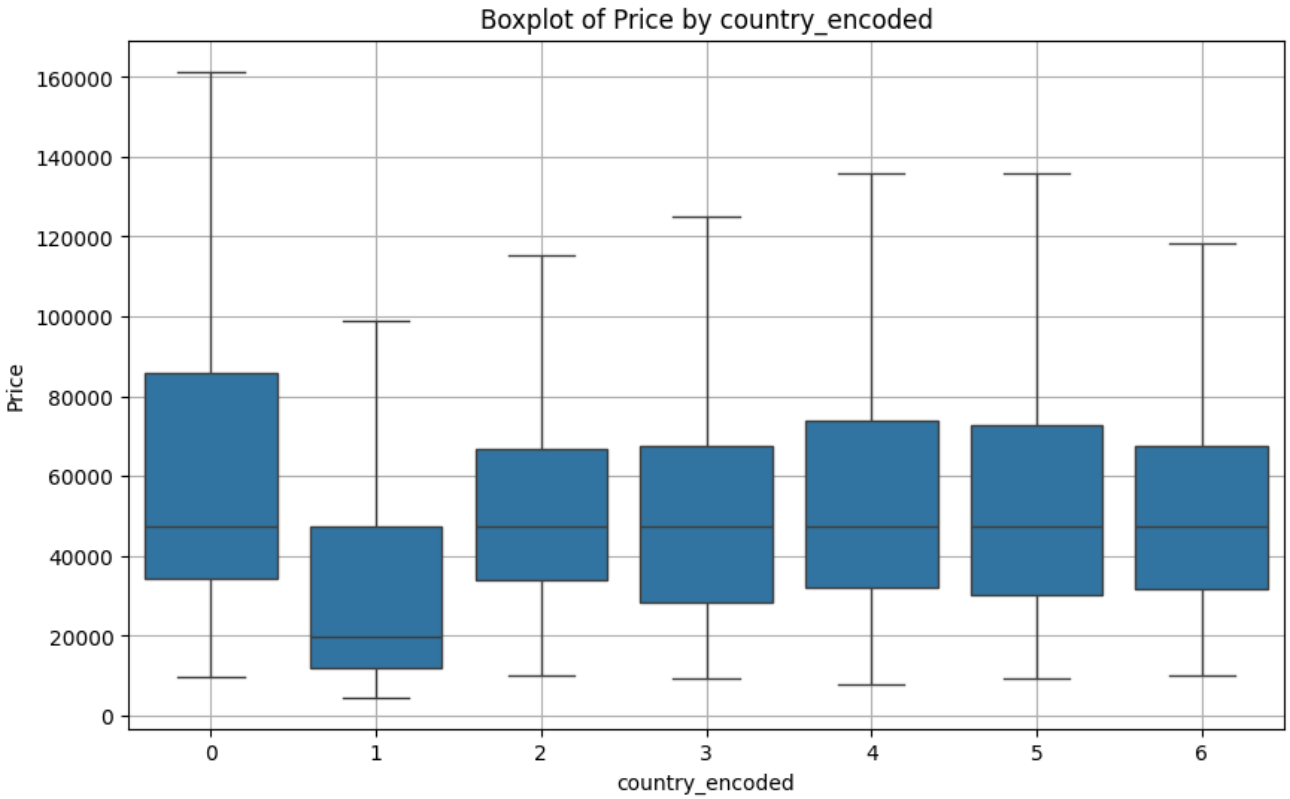



Correlation Heatmap
price
engine_capacity
cylinder
horse_power
top_speed
seats
1.00 0.23 0.47 0.56 0.46 -0.21
0.23 1.00 0.65 0.49 0.23 0.11
0.47 0.65 1.00 0.67 0.44 -0.06
0.56 0.49 0.67 1.00 0.53 -0.19
0.46 0.23 0.44 0.53 1.00 -0.42
-0.21 0.11 -0.06 -0.19 -0.42 1.00
price
engine_capacity
cylinder
horse_power
top_speed
seats
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

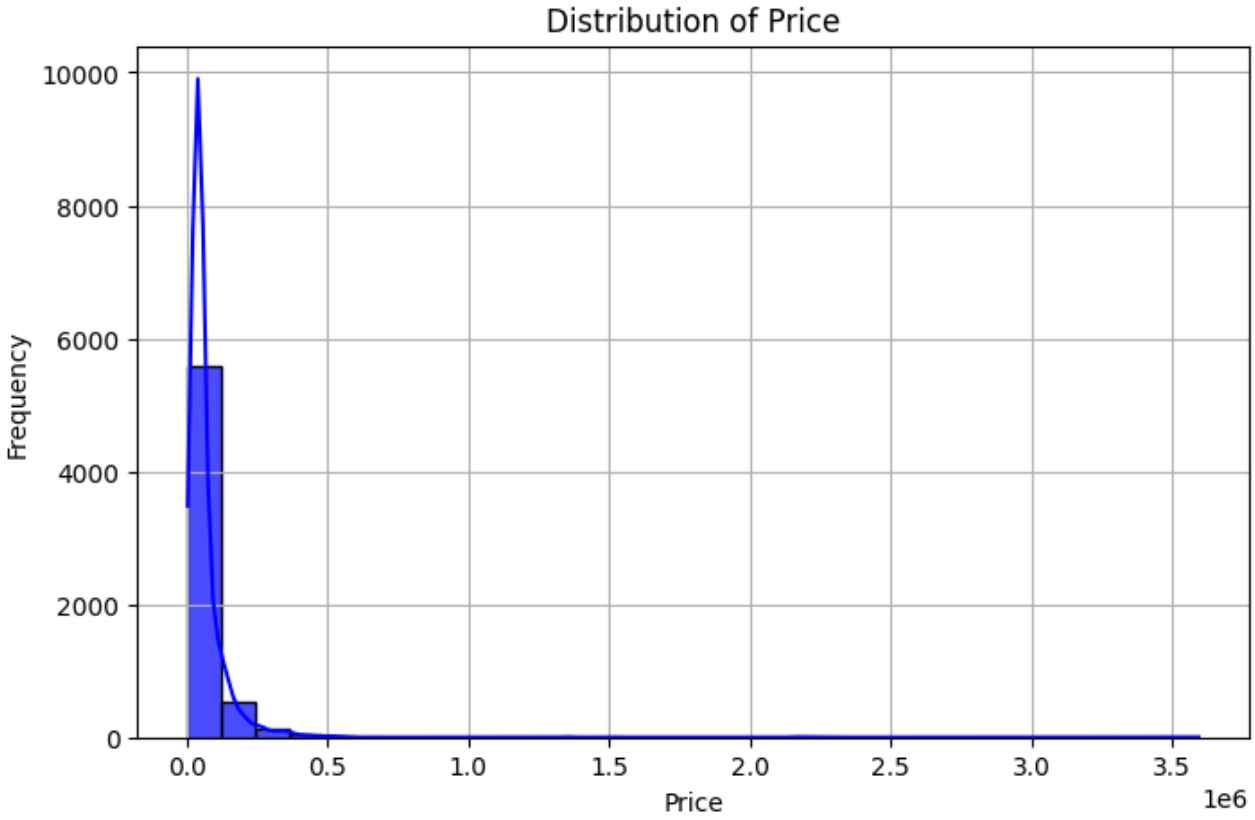
3.3Boxplots for categorical variables vs 'price'

```
# Boxplots for categorical variables vs 'price'
categorical_columns = ['brand_encoded', 'country_encoded']
for col in categorical_columns:
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=cars_df, x=col, y='price', showfliers=False)
    plt.title(f'Boxplot of Price by {col}')
    plt.xlabel(col)
    plt.ylabel('Price')
    plt.grid(True)
    plt.show()
print("\n\n")
```



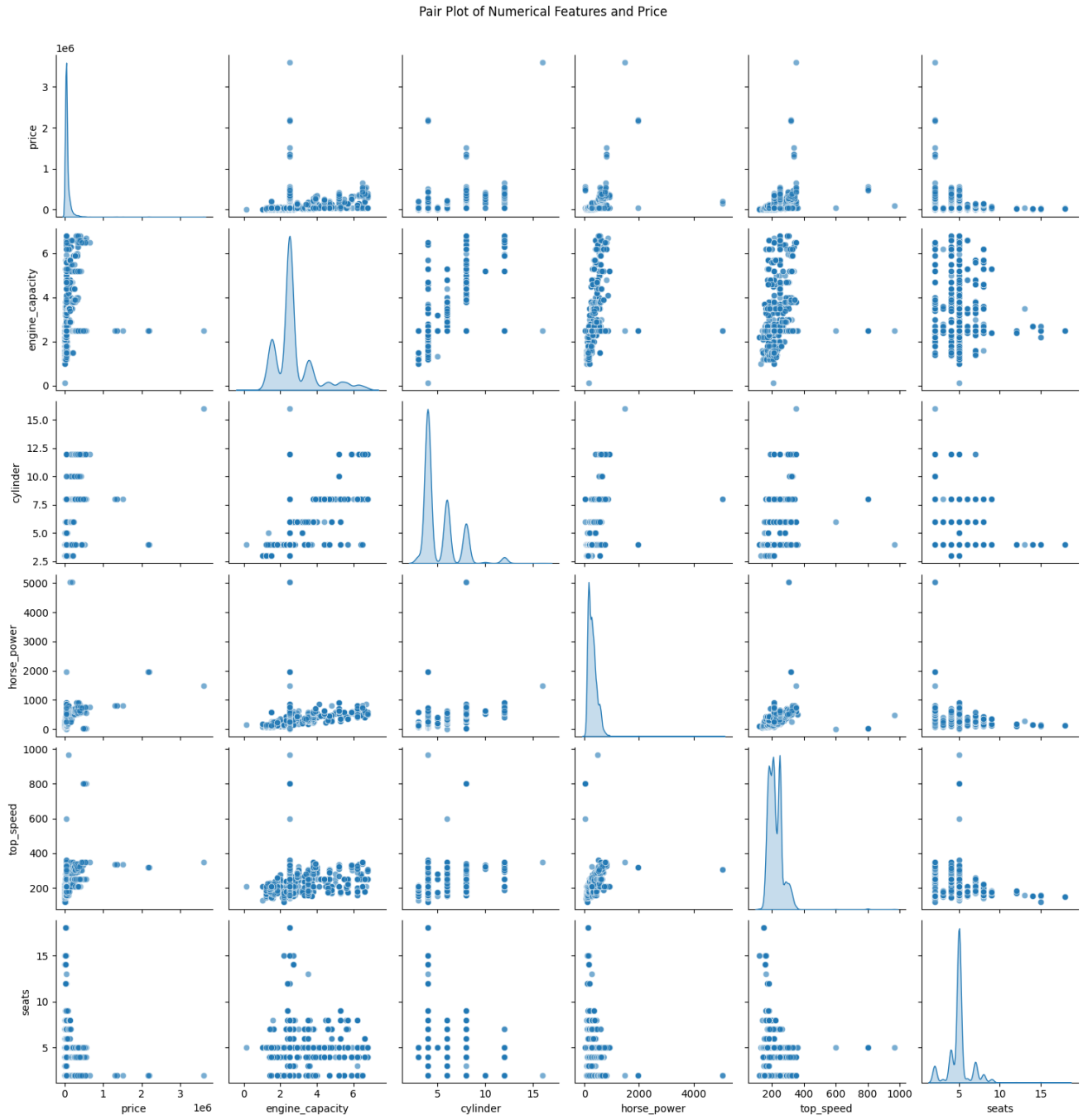

Boxplot of Price by country_encoded
Price
country_encoded
0
20000
40000
60000
80000
100000
120000
140000
160000
0
1
2
3
4
5
6

3.4Histogram Distribution plot of 'price':



3.5 Pair plot for numerical columns:

```
####################
print("\n\n")

# Pair plot for numerical columns
sns.pairplot(cars_df[['price'] + numerical_columns], diag_kind='kde', plot_kws={'alpha': 0.6})
plt.suptitle('Pair Plot of Numerical Features and Price', y=1.02)
plt.show()
```



4. Split the dataset into training, validation, and test sets. A common split would be 60% for training, 20% for validation, and 20% for testing, then make Normalization of Features by apply z-score normalization.

```python
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

# Prepare the data
X = cars_df.drop(columns=['price', 'car name', 'brand', 'country'])
y = cars_df['price']

# Split the data
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.4, random_state=42) #60% Training Set 40% Temporary Set
#40% Temporary Set==> 20% Validation Set 20% Test Set
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)

# Normalize the features
X_train_mean, X_train_std = X_train.mean(), X_train.std()
X_train = (X_train - X_train_mean) / X_train_std
X_val = (X_val - X_train_mean) / X_train_std
X_test = (X_test - X_train_mean) / X_train_std
```

In this code, we start by preparing the data by separating the target label (price) into y and using only the numerical features for training, stored in X, while dropping any categorical data. The dataset is then split into training (60%), validation (20%), and test (20%) sets. For feature normalization, we calculate the mean and standard deviation of the training set and apply z-score normalization to standardize the features, ensuring they have a mean of 0 and a standard deviation of 1. This normalization enhances model performance by ensuring all features are on the same scale.

The formula for z-score normalization is:

$$Z = \frac{X - \mu}{\sigma}$$

Where:

- X is the original feature value,
- μ is the mean of the feature,
- σ is the standard deviation of the feature.

This process centers the data around zero and scales the values so that each feature has a mean of 0 and a standard deviation of 1. Normalizing the features ensures that they are on the same scale, which improves model performance. It also prevents features with larger ranges from dominating the training process, thereby reducing bias and ensuring that each feature contributes equally to the model.

5. Closed-form solution for solving the linear regression

```
# Closed-form solution
X_train_bias = np.c_[np.ones((X_train.shape[0], 1)), X_train]  # Add bias term
theta_closed = np.linalg.inv(X_train_bias.T @ X_train_bias) @ X_train_bias.T @ y_train

# Predictions
X_val_bias = np.c_[np.ones((X_val.shape[0], 1)), X_val]
y_val_pred_closed = X_val_bias @ theta_closed

# Validation Metrics
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
mse_closed = mean_squared_error(y_val, y_val_pred_closed)
mae_closed = mean_absolute_error(y_val, y_val_pred_closed)
r2_closed = r2_score(y_val, y_val_pred_closed)

print(f"Closed-Form Solution: Validation MSE = {mse_closed}, MAE = {mae_closed}, R^2 = {r2_closed}")
```

```
Closed-Form Solution: Validation MSE = 2321536315.8777013, MAE = 24519.929032309097, R^2 = 0.4946698487050084
```

In this code we implement the Closed-form solution to include the intercept (bias) term in a linear regression model, a column of ones is added to the feature matrix, then find the parameter vector θ (theta) that minimizes the cost function, which is typically the Mean Squared Error (MSE). The closed-form solution for linear regression is given by:

$$\theta = (X^T X)^{-1} X^T y$$

In our code the bias term (intercept)I s added to X_val for consistency, and predictions (y_val_pred_closed) are computed as X_val_bias multiplied by theta_closeds.

finally, Calculating Validation Metrics:

- **Mean Squared Error (MSE): Measures the average squared difference between the actual and predicted values.**
- **Mean Absolute Error (MAE): Measures the average absolute difference between the actual and predicted values.**
- **R-squared (R^2): Measures how well the model explains the variability of the target variable. An R^2 of 1 indicates perfect predictions, while 0 indicates no explanatory power.**

Note the result:

```
Closed-Form Solution: Validation MSE = 2321536315.8777013, MAE = 24519.929032309097, R^2 = 0.4946698487050084
```

6. Linear Regression using Gradient Descent

```
[45] # Gradient Descent
     def gradient_descent(X, y, lr=0.01, epochs=1000):
         m, n = X.shape
         theta = np.zeros(n)
         for _ in range(epochs):
             gradients = -2/m * X.T @ (y - X @ theta)
             theta -= lr * gradients
         return theta

     X_train_norm = (X_train - X_train.mean()) / X_train.std()  # Normalize for stability
     X_train_bias = np.c_[np.ones((X_train_norm.shape[0], 1)), X_train_norm]
     theta_gd = gradient_descent(X_train_bias, y_train.values)

     # Predictions
     X_val_norm = (X_val - X_train.mean()) / X_train.std()
     X_val_bias = np.c_[np.ones((X_val_norm.shape[0], 1)), X_val_norm]
     y_val_pred_gd = X_val_bias @ theta_gd

     # Validation Metrics
     mse_gd = mean_squared_error(y_val, y_val_pred_gd)
     mae_gd = mean_absolute_error(y_val, y_val_pred_gd)
     r2_gd = r2_score(y_val, y_val_pred_gd)

     print(f"Gradient Descent: Validation MSE = {mse_gd}, MAE = {mae_gd}, R^2 = {r2_gd}")

Gradient Descent: Validation MSE = 2321233125.1447725, MAE = 24512.061467658266, R^2 = 0.494735844407033
```

In this code that solve the Linear Regression using Gradient Descent,
Gradient descent optimizes model parameters (**theta**)or(**W**) iteratively:

Inputs: Feature matrix (**X**), target variable (**y**), learning rate (**lr**)or(**alpha**), and Number of iterations to run gradient descent(**epochs**).

Output: Optimized theta or (W), (learning vector).

The weights are updated using the learning rate:

$$\theta = \theta - \text{lr} \times \text{gradient}$$

Next, **normalize the features** using z-score normalization (mean = 0, standard deviation = 1) to ensure stability and faster convergence during gradient descent.
After training with gradient descent, make predictions on the validation set and evaluate the model using validation metrics.

Note the result:

```
Gradient Descent: Validation MSE = 2321233125.1447725, MAE = 24512.061467658266, R^2 = 0.494735844407033
```

7. Polynomial Regression for degrees from 2 to 10

```python
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression

for degree in range(2, 11):
    poly = PolynomialFeatures(degree)
    X_train_poly = poly.fit_transform(X_train)
    X_val_poly = poly.transform(X_val)

    model = LinearRegression()
    model.fit(X_train_poly, y_train)

    y_val_pred_poly = model.predict(X_val_poly)
    mse_poly = mean_squared_error(y_val, y_val_pred_poly)
    r2_poly = r2_score(y_val, y_val_pred_poly)

    print(f"Degree {degree}: Validation MSE = {mse_poly}, R^2 = {r2_poly}")
```

```
Degree 2: Validation MSE = 2060623241.435173, R^2 = 0.5514629483783327
Degree 3: Validation MSE = 1530935515.3105724, R^2 = 0.6667603817852479
Degree 4: Validation MSE = 2070798317.5926342, R^2 = 0.5492481336718291
Degree 5: Validation MSE = 46014883032.20675, R^2 = -9.016086177697913
Degree 6: Validation MSE = 6.785181813588755e+19, R^2 = -14769344458.418995
Degree 7: Validation MSE = 3.1564037496441053e+19, R^2 = -6870562279.016302
Degree 8: Validation MSE = 1.0409706215218561e+18, R^2 = -226588675.67482677
Degree 9: Validation MSE = 2.5403056690893866e+17, R^2 = -55294979.28167351
Degree 10: Validation MSE = 1.4048858399049848e+16, R^2 = -3058022.1253585806
```

Polynomial features are generated for degrees 2 to 10 to capture non-linear relationships in the data. The training and validation sets are transformed into polynomial terms using fit_transform and transform. A linear regression model is then trained on the transformed training data, and predictions are made for the validation set. Model performance is evaluated using MSE (mean squared error) and R^2 (coefficient of determination). As the polynomial degree increases, model complexity rises, balancing the risks of underfitting and overfitting. The comparison of validation MSE and R^2 values helps identify the optimal polynomial degree.

Note the result:

```
Degree 2: Validation MSE = 2060623241.435173, R^2 = 0.5514629483783327
Degree 3: Validation MSE = 1530935515.3105724, R^2 = 0.6667603817852479
Degree 4: Validation MSE = 2070798317.5926342, R^2 = 0.5492481336718291
Degree 5: Validation MSE = 46014883032.20675, R^2 = -9.016086177697913
Degree 6: Validation MSE = 6.785181813588755e+19, R^2 = -14769344458.418995
Degree 7: Validation MSE = 3.1564037496441053e+19, R^2 = -6870562279.016302
Degree 8: Validation MSE = 1.0409706215218561e+18, R^2 = -226588675.67482677
Degree 9: Validation MSE = 2.5403056690893866e+17, R^2 = -55294979.28167351
Degree 10: Validation MSE = 1.4048858399049848e+16, R^2 = -3058022.1253585806
```

The degree 8 that represent the low MSE (mean squared error)=1.04, and degree 3 that represent the R^2 0.67 closest to 1.

8. This code implements and evaluates a Support Vector Regression (SVR) model (standard Gaussian kernel) using the Radial Basis Function (RBF) kernel for different values of the regularization parameter (C) and the kernel parameter (gamma).

```
from sklearn.svm import SVR

for C in [0.1, 1, 10, 100]:
    for gamma in [0.01, 0.1, 1, 10]:
        model_rbf = SVR(kernel='rbf', C=C, gamma=gamma)
        model_rbf.fit(X_train, y_train)

        y_val_pred_rbf = model_rbf.predict(X_val)
        mse_rbf = mean_squared_error(y_val, y_val_pred_rbf)
        r2_rbf = r2_score(y_val, y_val_pred_rbf)

        print(f"C = {C}, Gamma = {gamma}: Validation MSE = {mse_rbf}, R^2 = {r2_rbf}")
```

This code implements a Support Vector Regression (SVR) model with an RBF kernel, tuning hyperparameters C and gamma. It trains the model on the transformed training data (X_train, y_train) for different values of C (regularization) and gamma (influence of training points). The model's predictions on the validation set (X_val) are evaluated using Mean Squared Error (MSE) and R^2 (coefficient of determination). The results, including the C and gamma values along with their corresponding MSE and R^2 scores, are printed for comparison to identify the optimal parameter configuration.

```
C = 0.1, Gamma = 0.01: Validation MSE = 4856024904.853706, R^2 = -0.05701374692225225
C = 0.1, Gamma = 0.1: Validation MSE = 4855529694.748041, R^2 = -0.056905954252412405
C = 0.1, Gamma = 1: Validation MSE = 4856378456.298978, R^2 = -0.05709070466963184
C = 0.1, Gamma = 10: Validation MSE = 4856488109.338258, R^2 = -0.057114572910051065
C = 1, Gamma = 0.01: Validation MSE = 4851741078.666741, R^2 = -0.05608128400087775
C = 1, Gamma = 0.1: Validation MSE = 4846739537.516805, R^2 = -0.0549925956488071
C = 1, Gamma = 1: Validation MSE = 4855297529.926985, R^2 = -0.05685541880166478
C = 1, Gamma = 10: Validation MSE = 4856396549.290337, R^2 = -0.05709464298151534
C = 10, Gamma = 0.01: Validation MSE = 4809177633.281166, R^2 = -0.04681647425001367
C = 10, Gamma = 0.1: Validation MSE = 4759830120.694551, R^2 = -0.03607497267156523
C = 10, Gamma = 1: Validation MSE = 4844578490.390342, R^2 = -0.05452219927210478
C = 10, Gamma = 10: Validation MSE = 4855482599.175237, R^2 = -0.05689570293186752
C = 100, Gamma = 0.01: Validation MSE = 4433921049.400125, R^2 = 0.034865843192156354
C = 100, Gamma = 0.1: Validation MSE = 4124980627.288393, R^2 = 0.1021130833835453
C = 100, Gamma = 1: Validation MSE = 4748007070.539754, R^2 = -0.03350144251283815
C = 100, Gamma = 10: Validation MSE = 4846427703.518341, R^2 = -0.054924718562179065
```

The performance of the Support Vector Regression (SVR) model was tested using various combinations of the hyperparameters C (regularization) and gamma. The evaluation metrics used were Mean Squared Error (MSE) and R^2 (coefficient of determination). A higher value of C makes the model less tolerant of errors but can lead to overfitting, while increasing gamma makes each individual data point more influential, which may also cause overfitting. The best results were achieved when C was set to 100 and gamma to 0.1, yielding the lowest MSE and the highest R^2. As gamma increased, MSE tended to rise and R^2 decreased, suggesting overfitting. Thus, lower values of gamma generally produced better model performance.

```
C = 100, Gamma = 0.1: Validation MSE = 4124980627.288393, R^2 = 0.1021130833835453
```

9. Comparing results:

```
# Initialize the model_results dictionary
model_results = {}

# Closed-Form Solution
model_results['Linear Regression (Closed-Form)'] = {
    'mse': 2358569961.0891323,
    'mae': 24417.267949615478,
    'r2': 0.4866087137532503
}

# Gradient Descent
model_results['Linear Regression (Gradient Descent)'] = {
    'mse': 2355909689.109991,
    'mae': 24384.75135211928,
    'r2': 0.48718777669209434
}

# Polynomial Regression
model_results['Polynomial Regression (Degree 2)'] = {
    'mse': 2022317290.2450955,
    'r2': 0.5598010269076199
}
model_results['Polynomial Regression (Degree 3)'] = {
    'mse': 1469782267.6114888,
    'r2': 0.680071644547155
}
model_results['Polynomial Regression (Degree 4)'] = {
    'mse': 1349467283.3881614,
    'r2': 0.7062606766828174
}
model_results['Polynomial Regression (Degree 5)'] = {
    'mse': 642834980451.96,
    'r2': -138.92626163450234
}
model_results['Polynomial Regression (Degree 6)'] = {
    'mse': 6.095776431637102e+18,
    'r2': -1326871177.1038945
}
model_results['Polynomial Regression (Degree 7)'] = {
    'mse': 3.0741931287550493e+19,
    'r2': -6691613945.502012
}
model_results['Polynomial Regression (Degree 8)'] = {
    'mse': 1.5637881874220454e+18,
    'r2': -340390677.33601457
}
model_results['Polynomial Regression (Degree 9)'] = {
    'mse': 6.9265149990706456e+16,
    'r2': -15076984.220901398
}
model_results['Polynomial Regression (Degree 10)'] = {
    'mse': 2.1541934955807176e+16,
    'r2': -4689044.429077997
}
```

```python
# RBF Kernel Regression (C, Gamma Combinations)
rbf_results = [
    {'C': 0.1, 'Gamma': 0.01, 'mse': 4855980131.772176, 'r2': -0.05700400113972526},
    {'C': 0.1, 'Gamma': 0.1, 'mse': 4855408445.154088, 'r2': -0.05687956178323694},
    {'C': 0.1, 'Gamma': 1, 'mse': 4856367580.910634, 'r2': -0.057088337417567026},
    {'C': 0.1, 'Gamma': 10, 'mse': 4856487647.62763, 'r2': -0.057114472409232064},
    {'C': 1, 'Gamma': 0.01, 'mse': 4851305479.327623, 'r2': -0.055986466841036364},
    {'C': 1, 'Gamma': 0.1, 'mse': 4845563252.649128, 'r2': -0.05473655304198499},
    {'C': 1, 'Gamma': 1, 'mse': 4855191705.003128, 'r2': -0.05683238382934186},
    {'C': 1, 'Gamma': 10, 'mse': 4856395050.287512, 'r2': -0.05709431669270426},
    {'C': 10, 'Gamma': 0.01, 'mse': 4804714235.561374, 'r2': -0.0458449238893297},
    {'C': 10, 'Gamma': 0.1, 'mse': 4748834794.065985, 'r2': -0.03368161357106336},
    {'C': 10, 'Gamma': 1, 'mse': 4843559970.294425, 'r2': -0.054300497414310867},
    {'C': 10, 'Gamma': 10, 'mse': 4855469324.415837, 'r2': -0.056892813407318776},
    {'C': 100, 'Gamma': 0.01, 'mse': 4392994662.115864, 'r2': 0.043774313560191014},
    {'C': 100, 'Gamma': 0.1, 'mse': 4052035796.5939627, 'r2': 0.11799102682939999},
    {'C': 100, 'Gamma': 1, 'mse': 4737816338.605033, 'r2': -0.0312832200042523 2},
    {'C': 100, 'Gamma': 10, 'mse': 4846295398.511366, 'r2': -0.05489591965486307}
]

for r in rbf_results:
    model_name = f"RBF Kernel (C={r['C']}, Gamma={r['Gamma']})"
    model_results[model_name] = {
        'mse': r['mse'],
        'r2': r['r2']
    }

# Output
model_results
```

This code organizes the performance metrics (MSE and R^2) of various regression models into a dictionary called model_results. It includes the Linear Regression (Closed-Form) **and** Gradient Descent **models, which are evaluated using MSE, MAE, and R^2. It also stores the performance of** Polynomial Regression **for degrees 2 to 10, showing a rise in MSE and a drop in R^2 for higher degrees, indicating overfitting. Additionally, the results of** RBF Kernel Regression**, tested with different C and gamma hyperparameter combinations, are added to the dictionary. The final model_results dictionary enables easy comparison across these models and their respective hyperparameter configurations.**

10. Model selection Using Validation Set

```python
# Model Selection: Identify the best model based on MSE and R²
best_model_mse = None
best_model_r2 = None
lowest_mse = float('inf')
highest_r2 = float('-inf')

# Iterate through model_results to find the best model
for model_name, metrics in model_results.items():
    mse = metrics.get('mse', float('inf'))
    r2 = metrics.get('r2', float('-inf'))

    # Check for the lowest MSE
    if mse < lowest_mse:
        lowest_mse = mse
        best_model_mse = model_name

    # Check for the highest R²
    if r2 > highest_r2:
        highest_r2 = r2
        best_model_r2 = model_name

# Output the best models
print(f"Best Model Based on Lowest MSE: {best_model_mse} (MSE = {lowest_mse})")
print(f"Best Model Based on Highest R²: {best_model_r2} (R² = {highest_r2})")
```

```
Best Model Based on Lowest MSE: Polynomial Regression (Degree 4) (MSE = 1349467283.3881614)
Best Model Based on Highest R²: Polynomial Regression (Degree 4) (R² = 0.7062606766828174)
```

This code selects the best regression model based on two performance metrics:
MSE (Mean Squared Error) **and** R^2 (coefficient of determination)**.**

11.Feature Selection with Forward Selection

```python
import pandas as pd
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

# Initialize
selected_features = []
remaining_features = list(X_train.columns)
best_mse = float('inf')
max_features = 5  # You can adjust this limit as needed

# Forward Selection Loop
for _ in range(max_features):
    feature_to_add = None

    for feature in remaining_features:
        # Try adding the feature to the current set
        current_features = selected_features + [feature]

        # Prepare polynomial features for the current subset
        poly = PolynomialFeatures(degree=4, include_bias=False)
        X_train_poly = poly.fit_transform(X_train[current_features])
        X_val_poly = poly.transform(X_val[current_features])

        # Train and evaluate the model
        model = LinearRegression()
        model.fit(X_train_poly, y_train)
        y_val_pred = model.predict(X_val_poly)
        mse = mean_squared_error(y_val, y_val_pred)

        # Check if this feature improves performance
        if mse < best_mse:
            best_mse = mse
            feature_to_add = feature

    # If no feature improves performance, stop the process
    if feature_to_add is None:
        break

    # Add the best feature to the selected set
    selected_features.append(feature_to_add)
    remaining_features.remove(feature_to_add)

    print(f"Added feature: {feature_to_add}")
    print(f"Current feature set: {selected_features}")
    print(f"Validation MSE: {best_mse}")

# Final Selected Features
print("\nFinal selected features:")
print(selected_features)
```

This code implements a forward selection feature selection process to improve model performance based on MSE (Mean Squared Error). It uses a polynomial regression model (degree=4) and iteratively adds features from the training data to the model. The process includes generating polynomial features, training a linear regression model, and evaluating the model's performance on the validation set. The best feature (i.e., the one that reduces MSE the most) is added to the selected features list, and the process stops when no further improvement is observed. The code outputs the final set of features that result in the lowest MSE.

```
Added feature: horse_power
Current feature set: ['horse_power']
Validation MSE: 2207509006.6887364
Added feature: seats
Current feature set: ['horse_power', 'seats']
Validation MSE: 1822208960.132979
Added feature: top_speed
Current feature set: ['horse_power', 'seats', 'top_speed']
Validation MSE: 1528352018.3613832
Added feature: brand_encoded
Current feature set: ['horse_power', 'seats', 'top_speed', 'brand_encoded']
Validation MSE: 1253870864.3033564
Added feature: cylinder
Current feature set: ['horse_power', 'seats', 'top_speed', 'brand_encoded', 'cylinder']
Validation MSE: 995733296.8385658

Final selected features:
['horse_power', 'seats', 'top_speed', 'brand_encoded', 'cylinder']
```

This output shows the forward selection process, where features are added iteratively to minimize the validation MSE. Initially, the model starts with horse_power and progressively adds seats, top_speed, brand_encoded, and cylinder. Each addition improves the model's performance, lowering the MSE at each step. The final selected features, which give the lowest MSE, are horse_power, seats, top_speed, brand_encoded, and cylinder.

By add max_features the MSE decreasing

```
Added feature: horse_power
Current feature set: ['horse_power']
Validation MSE: 2207509006.6887364
Added feature: seats
Current feature set: ['horse_power', 'seats']
Validation MSE: 1822208960.132979
Added feature: top_speed
Current feature set: ['horse_power', 'seats', 'top_speed']
Validation MSE: 1528352018.3613832
Added feature: brand_encoded
Current feature set: ['horse_power', 'seats', 'top_speed', 'brand_encoded']
Validation MSE: 1253870864.3033564
Added feature: cylinder
Current feature set: ['horse_power', 'seats', 'top_speed', 'brand_encoded', 'cylinder']
Validation MSE: 995733296.8385658
Added feature: engine_capacity
Current feature set: ['horse_power', 'seats', 'top_speed', 'brand_encoded', 'cylinder', 'engine_capacity']
Validation MSE: 844911102.9917625
Added feature: car_name_encoded
Current feature set: ['horse_power', 'seats', 'top_speed', 'brand_encoded', 'cylinder', 'engine_capacity', 'car_name_encoded']
Validation MSE: 785738890.1791928

Final selected features:
['horse_power', 'seats', 'top_speed', 'brand_encoded', 'cylinder', 'engine_capacity', 'car_name_encoded']
```

12. regularization using Lasso and Ridge regression to optimize model performance based on validation MSE

```
from sklearn.linear_model import Lasso, Ridge
from sklearn.metrics import mean_squared_error
import numpy as np

# Selected features
selected_features = ['horse_power', 'seats', 'engine_capacity', 'top_speed', 'brand_encoded']

# Normalize the data
X_train_selected = X_train[selected_features]
X_val_selected = X_val[selected_features]

# Define lambda values for grid search
lambda_values = np.logspace(-2, 2, 50)  # From 0.01 to 100

# Results dictionaries
lasso_results = {}
ridge_results = {}

# LASSO Regularization
print("LASSO Regularization:")
for lam in lambda_values:
    lasso = Lasso(alpha=lam, max_iter=10000)
    lasso.fit(X_train_selected, y_train)
    y_val_pred = lasso.predict(X_val_selected)
    mse = mean_squared_error(y_val, y_val_pred)
    lasso_results[lam] = mse
    print(f"λ = {lam:.2f}, Validation MSE = {mse:.4f}")

# Find the best λ for LASSO
optimal_lambda_lasso = min(lasso_results, key=lasso_results.get)
print(f"\nOptimal λ for LASSO: {optimal_lambda_lasso:.2f}")
print(f"Lowest Validation MSE (LASSO): {lasso_results[optimal_lambda_lasso]:.4f}")

# Ridge Regularization
print("\nRidge Regularization:")
for lam in lambda_values:
    ridge = Ridge(alpha=lam, max_iter=10000)
    ridge.fit(X_train_selected, y_train)
    y_val_pred = ridge.predict(X_val_selected)
    mse = mean_squared_error(y_val, y_val_pred)
    ridge_results[lam] = mse
    print(f"λ = {lam:.2f}, Validation MSE = {mse:.4f}")

# Find the best λ for Ridge
optimal_lambda_ridge = min(ridge_results, key=ridge_results.get)
print(f"\nOptimal λ for Ridge: {optimal_lambda_ridge:.2f}")
print(f"Lowest Validation MSE (Ridge): {ridge_results[optimal_lambda_ridge]:.4f}")
```

This code applies Lasso and Ridge regression to optimize model performance by testing various regularization strengths (λ) and evaluating the MSE on the validation set. It selects the optimal λ for each method based on the lowest MSE.

Key Points:

- **Lasso and Ridge prevent overfitting by penalizing the model (penalizing W)**
- **The optimal λ minimizes the validation MSE.**

This is the value for λ after apply on LASSO Regularization and on Ridge Regularization:

LASSO Regularization:

λ = 0.01, Validation MSE = 2428126525.1888
λ = 0.01, Validation MSE = 2428126529.1562
λ = 0.01, Validation MSE = 2428126533.9442
λ = 0.02, Validation MSE = 2428126539.7223
λ = 0.02, Validation MSE = 2428126522.6072
λ = 0.03, Validation MSE = 2428126531.0224
λ = 0.03, Validation MSE = 2428126541.1781
λ = 0.04, Validation MSE = 2428126553.4342
λ = 0.04, Validation MSE = 2428126568.2251
λ = 0.05, Validation MSE = 2428126586.0754
λ = 0.07, Validation MSE = 2428126607.6179
λ = 0.08, Validation MSE = 2428126633.6166
λ = 0.10, Validation MSE = 2428126664.9935
λ = 0.12, Validation MSE = 2428126702.8618
λ = 0.14, Validation MSE = 2428126748.5652
λ = 0.17, Validation MSE = 2428126803.7257
λ = 0.20, Validation MSE = 2428126823.1314
λ = 0.24, Validation MSE = 2428126903.4880
λ = 0.29, Validation MSE = 2428127000.4804
λ = 0.36, Validation MSE = 2428127117.5572
λ = 0.43, Validation MSE = 2428127258.8843
λ = 0.52, Validation MSE = 2428127429.4944
λ = 0.63, Validation MSE = 2428127635.4694
λ = 0.75, Validation MSE = 2428127884.1608
λ = 0.91, Validation MSE = 2428128136.3333
λ = 1.10, Validation MSE = 2428128498.9926
λ = 1.33, Validation MSE = 2428128937.0249
λ = 1.60, Validation MSE = 2428129466.1891
λ = 1.93, Validation MSE = 2428130105.5816
λ = 2.33, Validation MSE = 2428130878.3624
λ = 2.81, Validation MSE = 2428131963.6643
λ = 3.39, Validation MSE = 2428133093.6694
λ = 4.09, Validation MSE = 2428134460.9548
λ = 4.94, Validation MSE = 2428136116.2329
λ = 5.96, Validation MSE = 2428138121.4532
λ = 7.20, Validation MSE = 2428140552.4691
λ = 8.69, Validation MSE = 2428144766.2255
λ = 10.48, Validation MSE = 2428148350.2102

λ = 12.65, Validation MSE = 2428152709.7180
λ = 15.26, Validation MSE = 2428158020.8112
λ = 18.42, Validation MSE = 2428164503.1204
λ = 22.23, Validation MSE = 2428172432.1220
λ = 26.83, Validation MSE = 2428182155.4450
λ = 32.37, Validation MSE = 2428199791.6787
λ = 39.07, Validation MSE = 2428214556.2032
λ = 47.15, Validation MSE = 2428232851.6491
λ = 56.90, Validation MSE = 2428255626.1944
λ = 68.66, Validation MSE = 2428284123.5820
λ = 82.86, Validation MSE = 2428319989.6414
λ = 100.00, Validation MSE = 2428365421.5574

Optimal λ for LASSO: 0.02

Lowest Validation MSE (LASSO): 2428126522.6072

Ridge Regularization:

λ = 0.01, Validation MSE = 2428126928.6832
λ = 0.01, Validation MSE = 2428127013.1072
λ = 0.01, Validation MSE = 2428127114.9898
λ = 0.02, Validation MSE = 2428127237.9418
λ = 0.02, Validation MSE = 2428127386.3204
λ = 0.03, Validation MSE = 2428127565.3841
λ = 0.03, Validation MSE = 2428127781.4791
λ = 0.04, Validation MSE = 2428128042.2641
λ = 0.04, Validation MSE = 2428128356.9823
λ = 0.05, Validation MSE = 2428128736.7886
λ = 0.07, Validation MSE = 2428129195.1461
λ = 0.08, Validation MSE = 2428129748.3030
λ = 0.10, Validation MSE = 2428130415.8697
λ = 0.12, Validation MSE = 2428131221.5150
λ = 0.14, Validation MSE = 2428132193.8066
λ = 0.17, Validation MSE = 2428133367.2259
λ = 0.20, Validation MSE = 2428134783.3946
λ = 0.24, Validation MSE = 2428136492.5545
λ = 0.29, Validation MSE = 2428138555.3572
λ = 0.36, Validation MSE = 2428141045.0250
λ = 0.43, Validation MSE = 2428144049.9640
λ = 0.52, Validation MSE = 2428147676.9229
λ = 0.63, Validation MSE = 2428152054.8138
λ = 0.75, Validation MSE = 2428157339.3362
λ = 0.91, Validation MSE = 2428163718.5746
λ = 1.10, Validation MSE = 2428171419.7812
λ = 1.33, Validation MSE = 2428180717.6005
λ = 1.60, Validation MSE = 2428191944.0497
λ = 1.93, Validation MSE = 2428205500.6465
λ = 2.33, Validation MSE = 2428221873.1636
λ = 2.81, Validation MSE = 2428241649.6076
λ = 3.39, Validation MSE = 2428265542.1665
λ = 4.09, Validation MSE = 2428294414.0607
λ = 4.94, Validation MSE = 2428329312.4730
λ = 5.96, Validation MSE = 2428371509.0506
λ = 7.20, Validation MSE = 2428422549.8838
λ = 8.69, Validation MSE = 2428484317.4063
λ = 10.48, Validation MSE = 2428559107.3794
λ = 12.65, Validation MSE = 2428649725.0696
λ = 15.26, Validation MSE = 2428759606.0012
λ = 18.42, Validation MSE = 2428892968.3527
λ = 22.23, Validation MSE = 2429055006.3366
λ = 26.83, Validation MSE = 2429252136.9219
λ = 32.37, Validation MSE = 2429492316.2884
λ = 39.07, Validation MSE = 2429785447.7198

λ = 47.15, Validation MSE = 2430143909.6117
λ = 56.90, Validation MSE = 2430583241.2696
λ = 68.66, Validation MSE = 2431123035.5750
λ = 82.86, Validation MSE = 2431788101.7013
λ = 100.00, Validation MSE = 2432609977.9465

Optimal λ for Ridge: 0.01
Lowest Validation MSE (Ridge): 2428126928.6832

As a final result:

Optimal λ for LASSO: 0.02
Lowest Validation MSE (LASSO): 2428126522.6072

Optimal λ for Ridge: 0.01
Lowest Validation MSE (Ridge): 2428126928.6832

13. Hyperparameter Tuning with Grid Search

```python
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import Lasso, Ridge
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score, precision_score, recall_score, f1_score, confusion_matrix

# Step 1: Polynomial Features (Degree 4)
poly = PolynomialFeatures(degree=4)
X_train_poly = poly.fit_transform(X_train)
X_val_poly = poly.transform(X_val)
X_test_poly = poly.transform(X_test)

# Step 2: Grid Search for Hyperparameter Tuning (LASSO Example)
lasso = Lasso(max_iter=5000)
param_grid = {'alpha': [0.1, 1, 10, 50, 100, 200, 500]}
grid_search = GridSearchCV(lasso, param_grid, cv=5, scoring='neg_mean_squared_error')
grid_search.fit(X_train_poly, y_train)

# Best Hyperparameter
best_lasso = grid_search.best_estimator_
print(f"Best λ for LASSO: {grid_search.best_params_['alpha']}")
```

In this code we apply Grid search tunes the regularization parameter alpha for Lasso regression using 5-fold cross-validation to minimize Mean Squared Error (MSE). The best alpha is then selected and printed, representing the optimal model.

```
    model = cd_fast.enet_coordinate_descent(
Best λ for LASSO: 500
```

14. Model Evaluation on Test Set

```
from sklearn.preprocessing import PolynomialFeatures

# Polynomial Features (Degree 4)
poly = PolynomialFeatures(degree=4)
X_train_poly = poly.fit_transform(X_train)
X_val_poly = poly.transform(X_val)
X_test_poly = poly.transform(X_test)
from sklearn.metrics import mean_squared_error, r2_score

# Train LASSO on Full Training Data
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=200, max_iter=10000)
lasso.fit(X_train_poly, y_train)

# Test Predictions
y_test_pred = lasso.predict(X_test_poly)

# Evaluate on Test Set
test_mse = mean_squared_error(y_test, y_test_pred)
test_r2 = r2_score(y_test, y_test_pred)

print(f"Test MSE: {test_mse}")
print(f"Test R^2: {test_r2}")
```

This code first transforms the input features into polynomial features of degree 4 to capture non-linear relationships in the data. It then trains a Lasso regression model with a regularization strength of 200 on the transformed training data. After training, the model makes predictions on the test set, and its performance is evaluated using Mean Squared Error (MSE) and R-squared (R^2). Finally, the test MSE and R^2 values are printed to assess how well the model generalizes to unseen data.

```
Test MSE: 7879733273.269059
Test R^2: 0.35702461199489
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_co
  model = cd_fast.enet_coordinate_descent(
```

Thanks for reading.