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Import useful libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re

from sklearn.metrics import root_mean_squared_error
from sklearn.preprocessing import RobustScaler
from sklearn.model_selection import train_test_split

random_state = 42
```

Load the data and print some stats

I decided to load only the "train.csv" file because I think it is better to have the ground truth for the evaluation of the results and therefore have a rmse for training and testing (I splitted the "train.csv" in train set and test set, having the file a consistent number of samples.).

- Brand & Model: Identify the brand or company name along with the specific model of each vehicle.
- Model Year: Discover the manufacturing year of the vehicles, crucial for assessing depreciation and technology advancements.
- Mileage: Obtain the mileage of each vehicle, a key indicator of wear and tear and potential maintenance requirements.
- Fuel Type: Learn about the type of fuel the vehicles run on, whether it's gasoline, diesel, electric, or hybrid.
- Engine Type: Understand the engine specifications, shedding light on performance and efficiency.

- Transmission: Determine the transmission type, whether automatic, manual, or another variant.
- Exterior & Interior Colors: Explore the aesthetic aspects of the vehicles, including exterior and interior color options.
- Accident History: Discover whether a vehicle has a prior history of accidents or damage, crucial for informed decision-making.
- Clean Title: Evaluate the availability of a clean title, which can impact the vehicle's resale value and legal status.
- Price: Access the listed prices for each vehicle, aiding in price comparison and budgeting.

In [2]:
```
data = pd.read_csv('train.csv')
```

In [3]:
```
print(f"Training set: \t{data.shape[0]} rows \t{data.shape[1]} columns")
```

```
Training set:   188533 rows     13 columns
```

In [4]:
```
data.head()
```

Out[4]:

	id	brand	model	model_year	milage	fuel_type	engine	transmission	ext_col	int_col	accident	clean_title	pric
0	0	MINI	Cooper S Base	2007	213000	Gasoline	172.0HP 1.6L 4 Cylinder Engine Gasoline Fuel	A/T	Yellow	Gray	None reported	Yes	420
1	1	Lincoln	LS V8	2002	143250	Gasoline	252.0HP 3.9L 8 Cylinder Engine Gasoline Fuel	A/T	Silver	Beige	At least 1 accident or damage reported	Yes	499
2	2	Chevrolet	Silverado 2500 LT	2002	136731	E85 Flex Fuel	320.0HP 5.3L 8 Cylinder Engine Flex Fuel Capab...	A/T	Blue	Gray	None reported	Yes	1390
3	3	Genesis	G90 5.0 Ultimate	2017	19500	Gasoline	420.0HP 5.0L 8 Cylinder Engine Gasoline Fuel	Transmission w/Dual Shift Mode	Black	Black	None reported	Yes	4500
4	4	Mercedes-Benz	Metris Base	2021	7388	Gasoline	208.0HP 2.0L 4 Cylinder Engine Gasoline Fuel	7-Speed A/T	Black	Beige	None reported	Yes	9750

Thorugh the print of the first 5 rows of the dataset we can already gather some useful information.

- "id" column can be dropped as it refers only to the index of the car.
- "brand" and "model" columns seem to have a lot of different unique values.
- "engine" column has useful and different information abridged in one string.
- "ext_col" and "int_col" columns are the colors of the cars and they may be not so useful.
- "price" column, the target feature, seems to have a wide range of values.

In [5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 188533 entries, 0 to 188532
Data columns (total 13 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   id            188533 non-null  int64
 1   brand         188533 non-null  object
 2   model         188533 non-null  object
 3   model_year    188533 non-null  int64
 4   milage        188533 non-null  int64
 5   fuel_type     183450 non-null  object
 6   engine        188533 non-null  object
 7   transmission  188533 non-null  object
 8   ext_col       188533 non-null  object
 9   int_col       188533 non-null  object
 10  accident      186081 non-null  object
 11  clean_title   167114 non-null  object
 12  price         188533 non-null  int64
dtypes: int64(4), object(9)
memory usage: 18.7+ MB
```

In [6]:
```
data.describe(include='all')
```

Out[6]:

	id	brand	model	model_year	milage	fuel_type	engine	transmission	ext_col	int_col	a
count	188533.000000	188533	188533	188533.000000	188533.000000	183450	188533	188533	188533	188533	
unique	NaN	57	1897	NaN	NaN	7	1117	52	319	156	
top	NaN	Ford	F-150 XLT	NaN	NaN	Gasoline	355.0HP 5.3L 8 Cylinder Engine Gasoline Fuel	A/T	Black	Black	r
freq	NaN	23088	2945	NaN	NaN	165940	3462	49904	48658	107674	
mean	94266.000000	NaN	NaN	2015.829998	65705.295174	NaN	NaN	NaN	NaN	NaN	
std	54424.933488	NaN	NaN	5.660967	49798.158076	NaN	NaN	NaN	NaN	NaN	
min	0.000000	NaN	NaN	1974.000000	100.000000	NaN	NaN	NaN	NaN	NaN	
25%	47133.000000	NaN	NaN	2013.000000	24115.000000	NaN	NaN	NaN	NaN	NaN	
50%	94266.000000	NaN	NaN	2017.000000	57785.000000	NaN	NaN	NaN	NaN	NaN	
75%	141399.000000	NaN	NaN	2020.000000	95400.000000	NaN	NaN	NaN	NaN	NaN	
max	188532.000000	NaN	NaN	2024.000000	405000.000000	NaN	NaN	NaN	NaN	NaN	

With the data description we can see that the analysis done before are valid and that there are some missing values. Thus, the missing values have to be dealt with and also the many unique values in some columns.

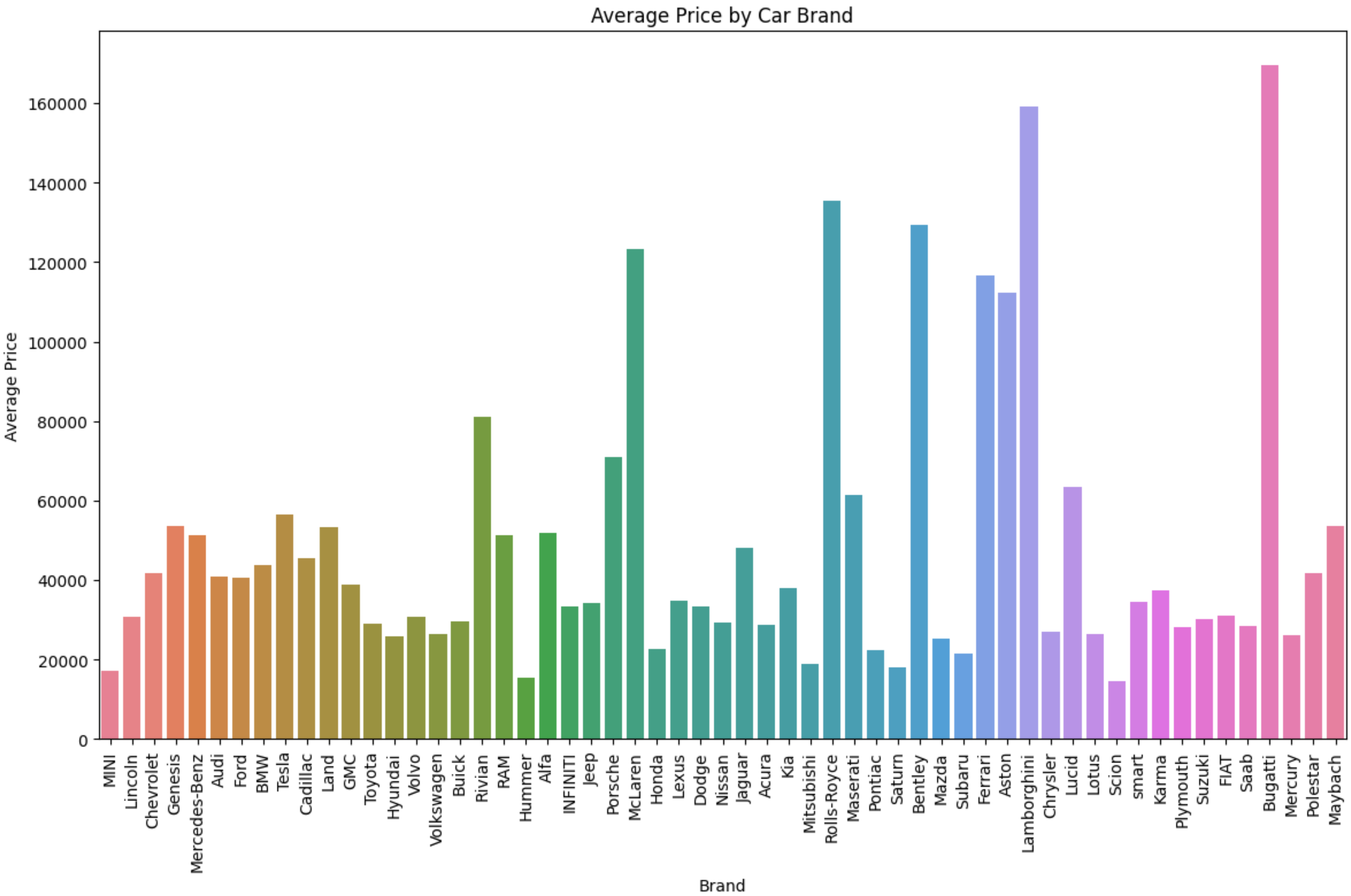
In [7]:
```
print(data.isnull().sum())
```

```
id                 0
brand              0
model              0
model_year         0
milage             0
fuel_type       5083
engine             0
transmission       0
ext_col            0
int_col            0
accident        2452
clean_title    21419
price              0
dtype: int64
```

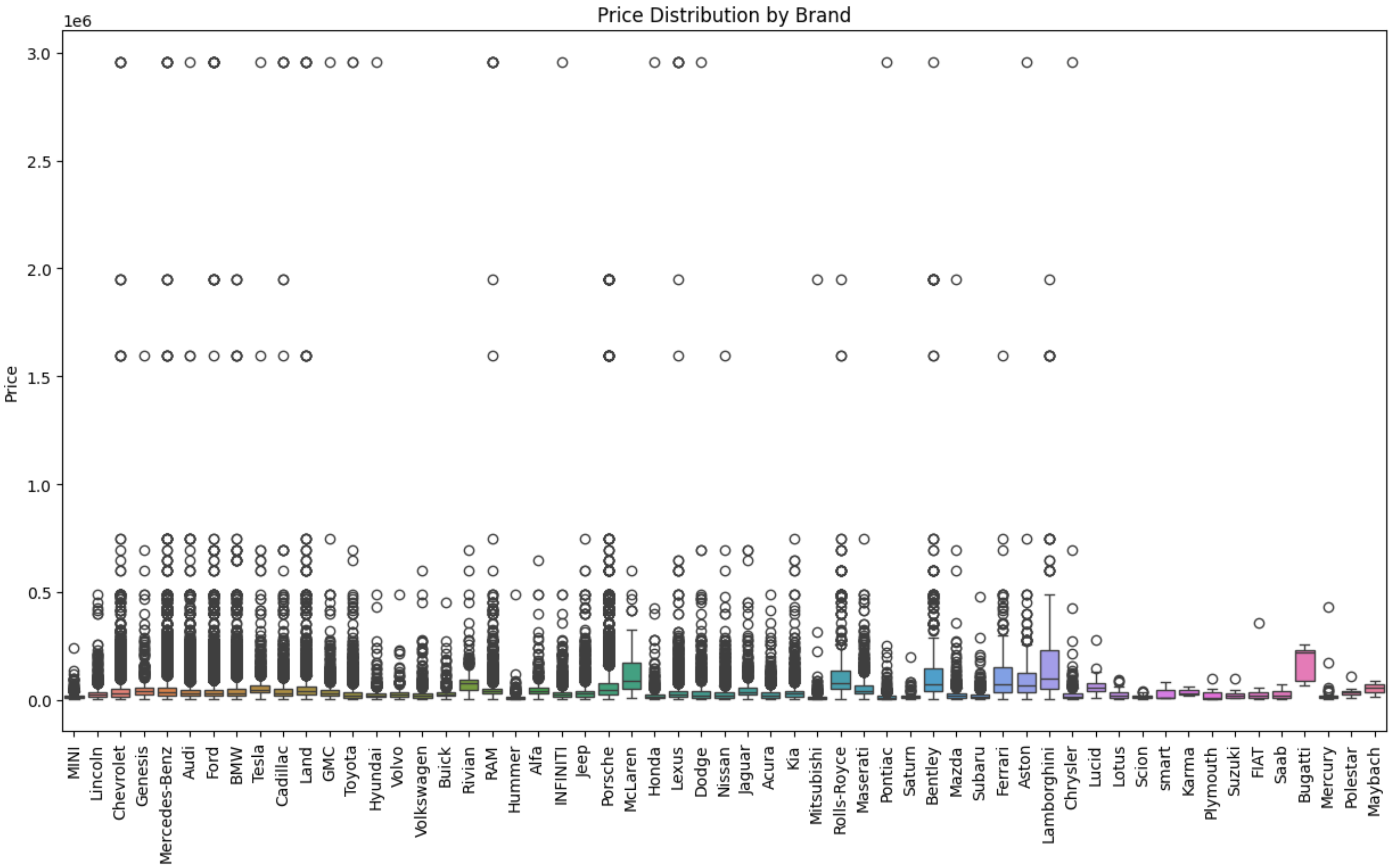
Plot the data

Visualize the data to have a better understanding of the distribution and outliers

In [8]:
```
plt.figure(figsize=(14, 8))
sns.barplot(x='brand', y='price', data=data, errorbar=None, hue='brand', legend=False)
plt.title('Average Price by Car Brand')
plt.xlabel('Brand')
plt.ylabel('Average Price')
plt.xticks(rotation=90)
plt.show()
```


Average Price by Car Brand
Average Price
160000
140000
120000
100000
80000
60000
40000
20000
0
MINI
Lincoln
Chevrolet
Genesis
Mercedes-Benz
Audi
Ford
BMW
Tesla
Cadillac
Land
GMC
Toyota
Hyundai
Volvo
Volkswagen
Buick
Rivian
RAM
Hummer
Alfa
INFINITI
Jeep
Porsche
McLaren
Honda
Lexus
Dodge
Nissan
Jaguar
Acura
Kia
Mitsubishi
Rolls-Royce
Maserati
Pontiac
Saturn
Bentley
Mazda
Subaru
Ferrari
Aston
Lamborghini
Chrysler
Lucid
Lotus
Scion
smart
Karma
Plymouth
Suzuki
FIAT
Saab
Bugatti
Mercury
Polestar
Maybach
Brand

In [9]:
```
# Box plot for price by car brand
plt.figure(figsize=(15, 8))
sns.boxplot(data=data, x='brand', y='price', hue='brand', legend=False)
plt.xticks(rotation=90)
plt.title("Price Distribution by Brand")
plt.xlabel("Brand")
plt.ylabel("Price")
plt.show()
```


Price Distribution by Brand
1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Price
MINI
Lincoln
Chevrolet
Genesis
Mercedes-Benz
Audi
Ford
BMW
Tesla
Cadillac
Land
GMC
Toyota
Hyundai
Volvo
Volkswagen
Buick
Rivian
RAM
Hummer
Alfa
INFINITI
Jeep
Porsche
McLaren
Honda
Lexus
Dodge
Nissan
Jaguar
Acura
Kia
Mitsubishi
Rolls-Royce
Maserati
Pontiac
Saturn
Bentley
Mazda
Subaru
Ferrari
Aston
Lamborghini
Chrysler
Lucid
Lotus
Scion
smart
Karma
Plymouth
Suzuki
FIAT
Saab
Bugatti
Mercury
Polestar
Maybach
Brand

Visualizing the boxplot of the price with reference to the brand, we can see that there are outliers, and also that some of them seem to be errors. There are three lines (2.9e6, 1.6e6 and 1.9e6) that are all isolated and at the same value, so they are likely errors. To be sure about that let investigate the "Chevrolet" brand. It is known that it's a normal brand, not of luxury, but it can have some car models with a price value consistently above the average. We can analyze that by printing the 5 rows of Chevrolet brand that have higher price.

In [10]:
```
chevrolet_cars = data[data['brand'] == 'Chevrolet']
chevrolet_cars.sort_values(by='price', ascending=False).head(5)
```

Out[10]:

	id	brand	model	model_year	milage	fuel_type	engine	transmission	ext_col	int_col	accident	clean_tit
118167	118167	Chevrolet	Corvette Base	2007	54323	Gasoline	430.0HP 6.2L 8 Cylinder Engine Gasoline Fuel	A/T	White	Red	None reported	Y
85611	85611	Chevrolet	Silverado 1500 Custom Trail Boss	2022	5072	Gasoline	5.3L V8 16V GDI OHV	Automatic	White	Jet Black	None reported	Na
66224	66224	Chevrolet	Corvette Base	2005	23133	Gasoline	400.0HP 6.0L 8 Cylinder Engine Gasoline Fuel	6-Speed M/T	Gold	Beige	None reported	Y
46159	46159	Chevrolet	Tahoe LT	2018	83858	E85 Flex Fuel	5.3L V8 16V MPFI OHV Flexible Fuel	6-Speed Automatic	Silver	Jet Black	None reported	Na
31429	31429	Chevrolet	Corvette Base	2002	15443	Gasoline	400.0HP 6.0L 8 Cylinder Engine Gasoline Fuel	6-Speed A/T	Black	Beige	None reported	Y

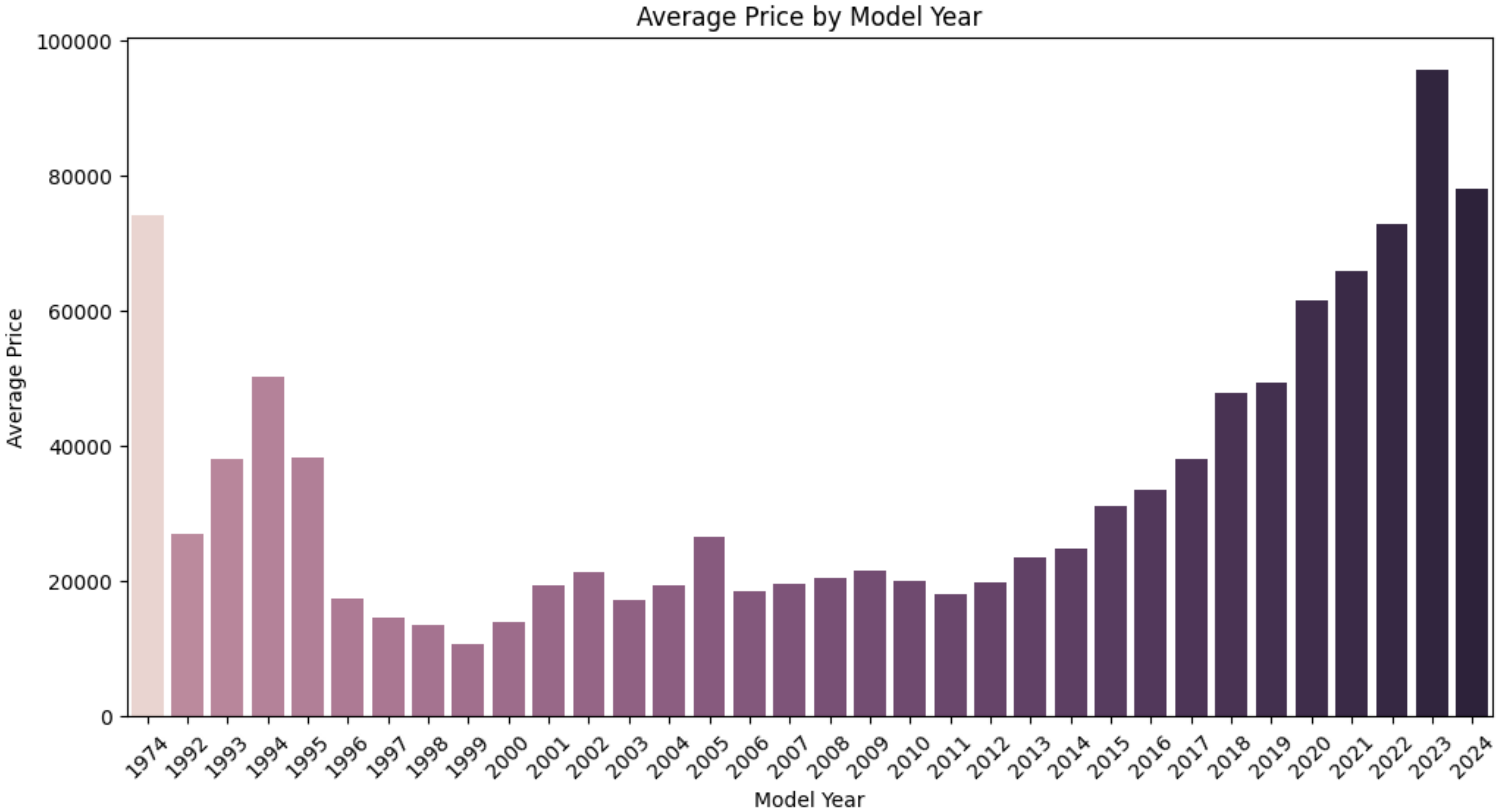
These cars have a very high price and making some searchs over the internet, it appers clearly that the price reported is an error: the

Silverado 2022 model can be found at about 50k €, not 2954k.

So, in the data processing phase these data entries errors should be dealt.

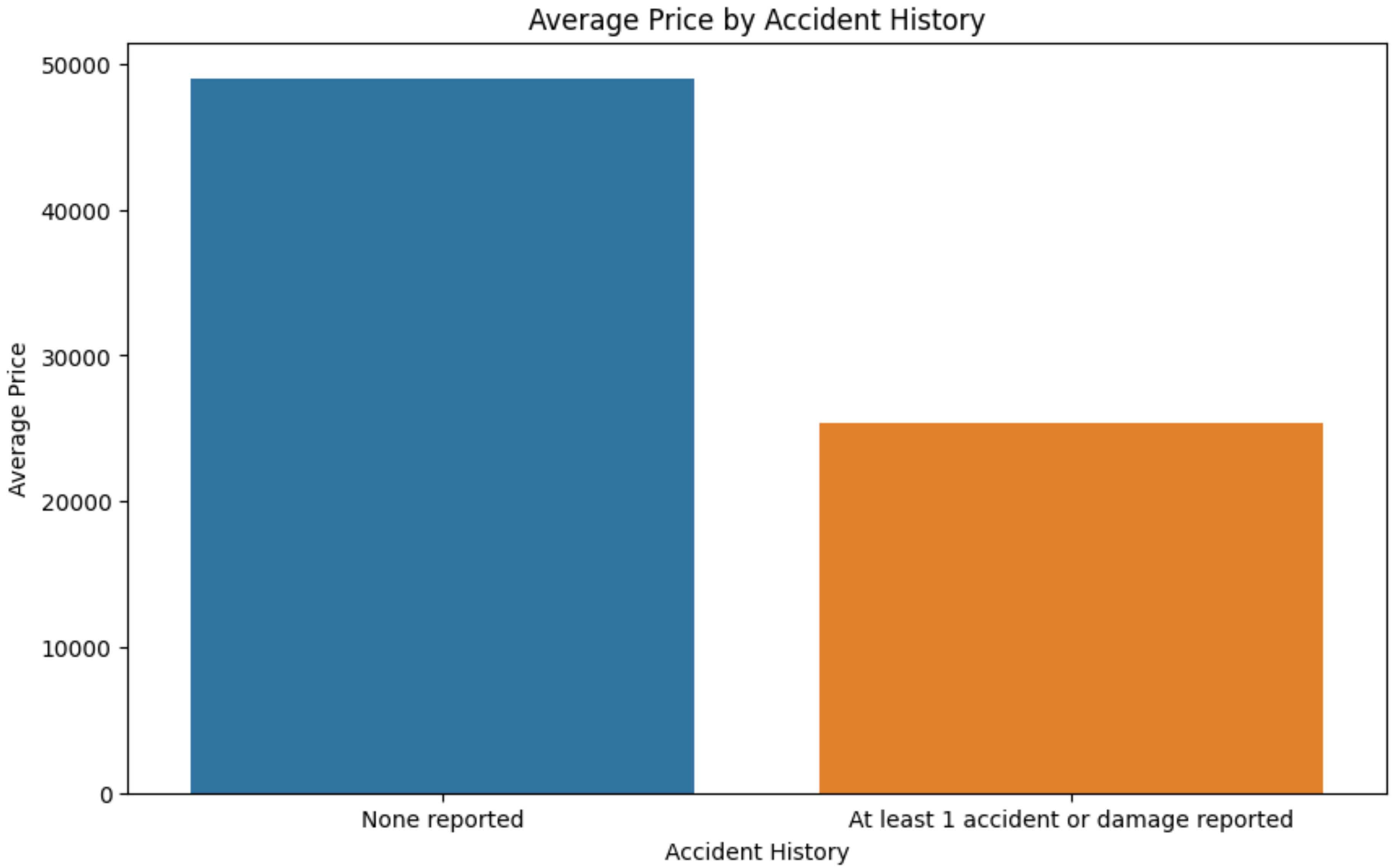
But, before doing the data processing, let's have a look to the other features.

In [11]:
```
plt.figure(figsize=(12, 6))
sns.barplot(x='model_year', y='price', data=data, errorbar=None, hue='model_year', legend=False)
plt.title('Average Price by Model Year')
plt.xlabel('Model Year')
plt.ylabel('Average Price')
plt.xticks(rotation=45)
plt.show()
```



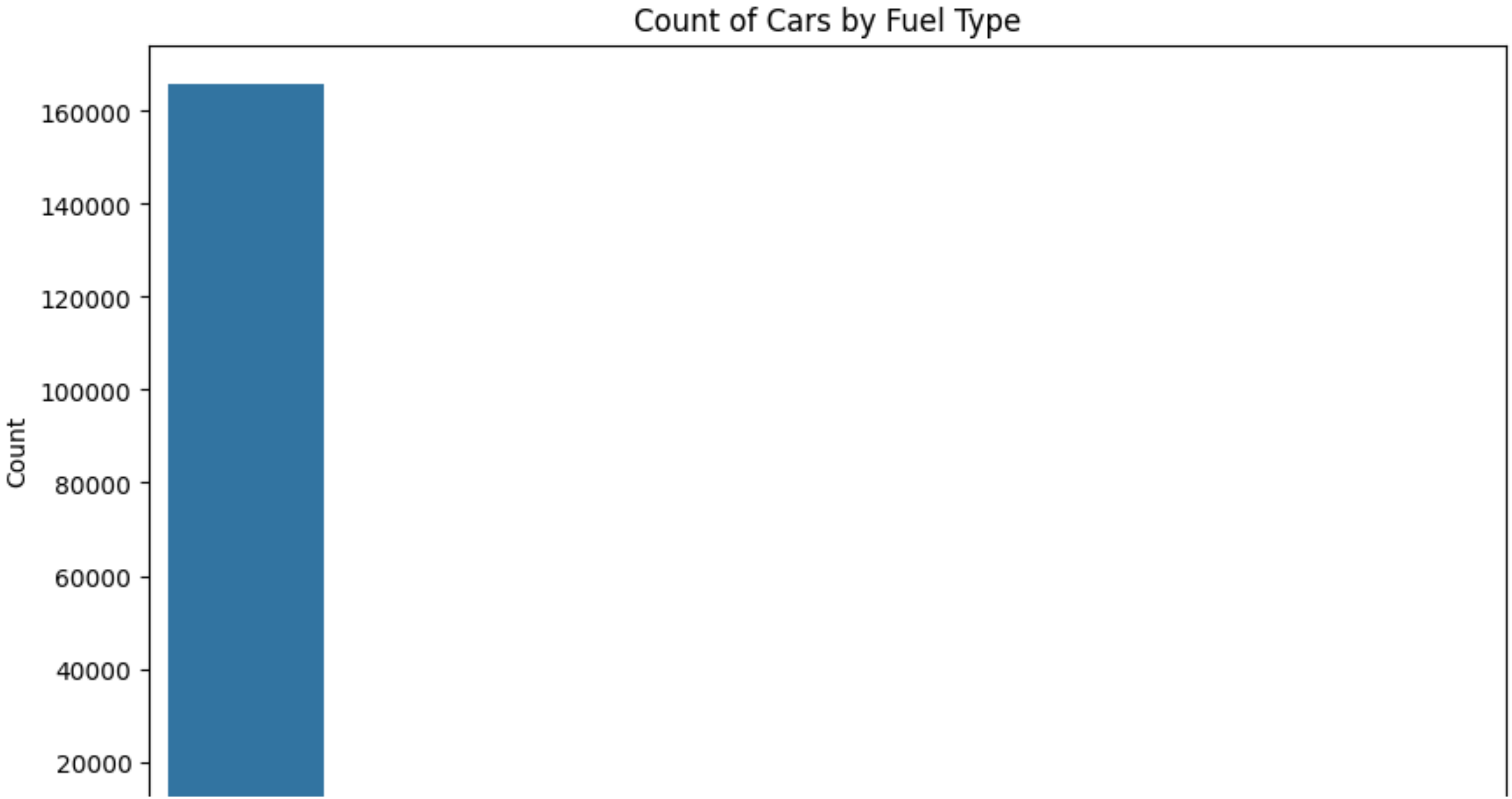
Although the price is altered due to the previous considerations, from the "Average Price by Model Year" barplot we can see that the "model_year" feature is an important feature: new cars and pretty old cars (maybe because out of production and difficult to find) have significantly higher prices.

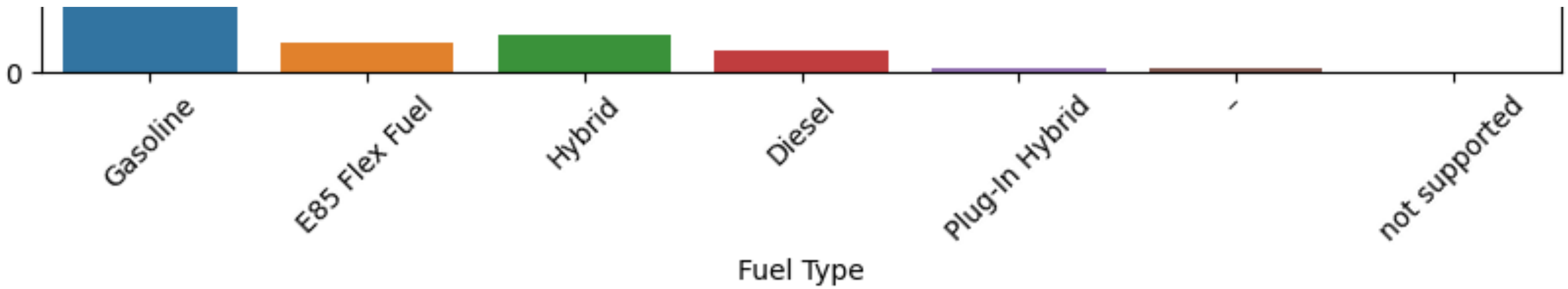
In [12]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x='accident', y='price', data=data, errorbar=None, hue='accident', legend=False)
plt.title('Average Price by Accident History')
plt.xlabel('Accident History')
plt.ylabel('Average Price')
plt.show()
```



Also the "accident" column seems to be important in the definition of the price: cars with at least 1 accident have lower average price, and this is pretty plausible according to the fact that cars with an accident history can have some damages.

In [13]:
```
plt.figure(figsize=(10, 6))
sns.countplot(x='fuel_type', data=data, hue='fuel_type', legend=False)
plt.title('Count of Cars by Fuel Type')
plt.xlabel('Fuel Type')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```





From the plot of the count of "fuel_type" we can evaluate that more than 90% of the cars have "Gasoline" fuel and there is a "-" value that almost surely represent the "Electric" fuel type. In fact, in the Dataset Card on kaggle, under the explanation of the "fuel_type" feature, the "Electric" value is mentioned and it can definitely represented by the "-" value.

Data Processing

Deal with outliers

Below I remove the outliers with the IQR method within each brand, in order to remove outliers considering the brand in analysis (a Chevrolet that has 200k as price is an outlier, a Bugatti is not)

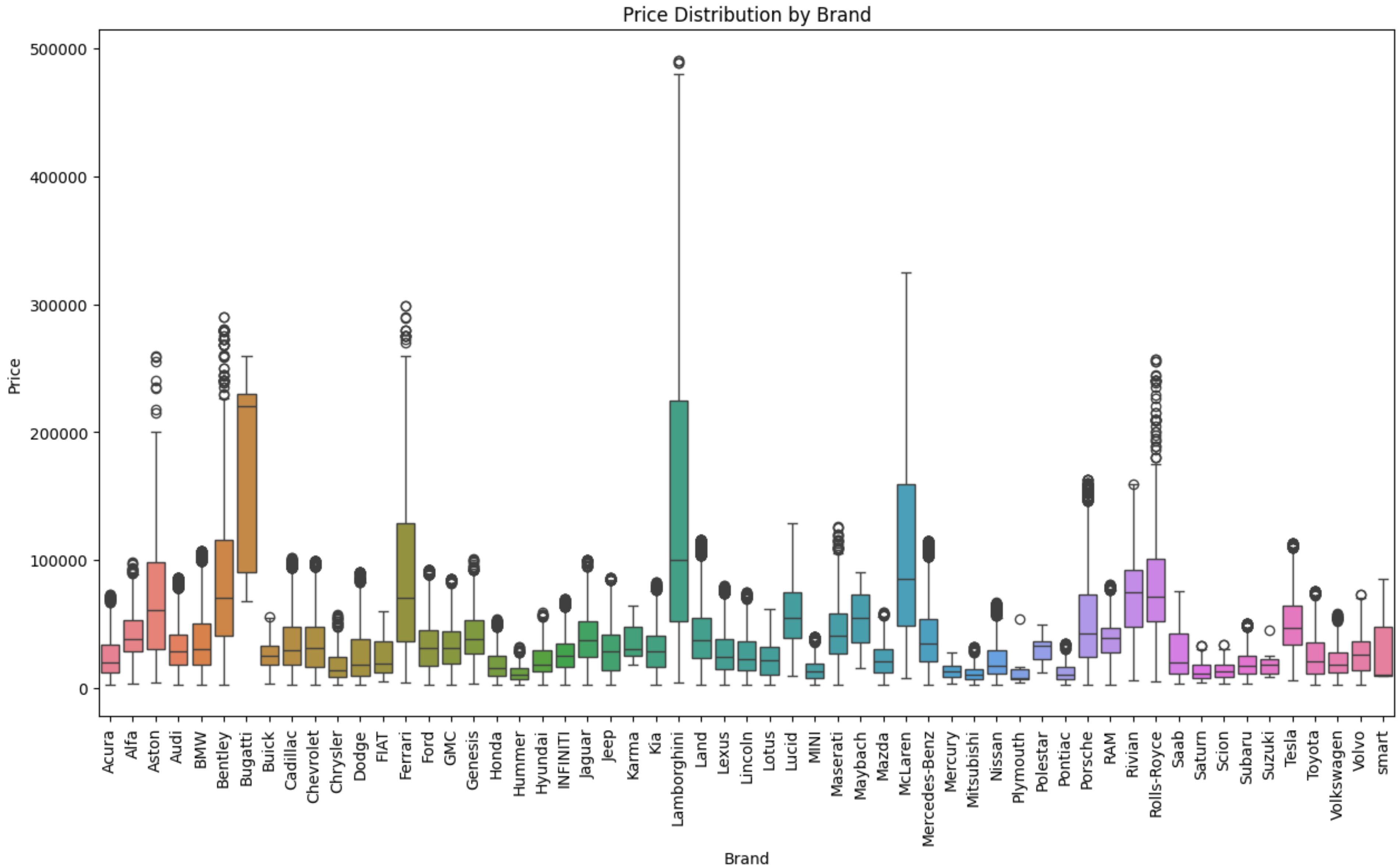
In [14]:
```
# Remove the outliers
def remove_outliers(df, column, threshold=1.5):
    def remove_outliers_from_group(group):
        Q1 = group[column].quantile(0.25)
        Q3 = group[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - threshold * IQR
        upper_bound = Q3 + threshold * IQR
        return group[(group[column] >= lower_bound) & (group[column] <= upper_bound)]
```

```
    return df.groupby('brand').apply(remove_outliers_from_group).reset_index(drop=True)

# Apply the function to remove outliers from the 'price' column
data = remove_outliers(data, 'price')
```

```
/var/folders/_g/7s4z636d67z67rlmmnqgx5mm0000gn/T/ipykernel_4136/3797912126.py:11: DeprecationWarning: DataFrameGr
oupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the
grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings
or explicitly select the grouping columns after groupby to silence this warning.
  return df.groupby('brand').apply(remove_outliers_from_group).reset_index(drop=True)
```

In [15]:

```
# Box plot for price by car brand
plt.figure(figsize=(15, 8))
sns.boxplot(data=data, x='brand', y='price', hue='brand', legend=False)
plt.xticks(rotation=90)
plt.title("Price Distribution by Brand")
plt.xlabel("Brand")
plt.ylabel("Price")
plt.show()
```



In [16]:
```
# Print the top 5 Lamborghini rows by price
```

```python
top_5_lamborghini = data[data['brand'] == 'Lamborghini'].nlargest(5, 'price')
top_5_lamborghini
```

Out[16]:

	id	brand	model	model_year	milage	fuel_type	engine	transmission	ext_col	int_col	accident	cl
99775	160977	Lamborghini	Urus Base	2021	4283	Gasoline	4.0L V8 32V GDI DOHC Twin Turbo	8-Speed Automatic	Rosso Mars Metallic	Nero Ade	None reported	
99827	172563	Lamborghini	Murcielago Base	2006	10000	Gasoline	571.0HP 6.2L 12 Cylinder Engine Gasoline Fuel	M/T	Red	Black	None reported	
99881	187262	Lamborghini	Gallardo LP570-4 Superleggera	2014	816	Gasoline	5.2L V10 40V GDI DOHC	6-Speed Manual	White	Nero Ade	None reported	
99536	104212	Lamborghini	GTO Base	2005	1795	Gasoline	6.5L V12 48V MPFI DOHC	7-Speed Manual	Balloon White	Nero Ade	NaN	
99159	14865	Lamborghini	Huracan EVO Base	2022	2750	Gasoline	5.2L V10 40V PDI DOHC	7-Speed Automatic with Auto-Shift	Kemora Gray Metallic	Beige	None reported	

Feature extraction

In [ ]:

```python
def vehicle_age(df):
```

```
    current_year = 2024

    df['vehicle_age'] = current_year - df['model_year']
    df = df.drop(columns=['model_year'])

    return df

def engine_info(engine_total):
    HP_str = re.search(r'(\d+\.?\d*)HP', engine_total)
    size_str = re.search(r'(\d+\.?\d*)L', engine_total)
    cylinder_str = re.search(r'(\d+) Cylinder', engine_total)

    HP = float(HP_str.group(1)) if HP_str else None
    size = float(size_str.group(1)) if size_str else None
    cylinder = int(cylinder_str.group(1)) if cylinder_str else None

    return HP, size, cylinder

def process_transmission_data(data):
    data_transmission = pd.DataFrame(data['transmission'].unique().tolist(), columns=['Transmission'])

    # Feature 1: Extract the number of gears
    data_transmission['speed'] = data_transmission['Transmission'].apply(lambda x: re.search(r'\d+', x).group() :

    # Feature 2: Identify transmission type (automatic, manual, CVT)
    data_transmission['transmission_type'] = data_transmission['Transmission'].apply(
        lambda x: 'Automatic' if 'A/T' in x or 'Automatic' in x or 'CVT' in x
                  else 'Manual' if 'M/T' in x or 'Manual' in x
                  else 'Other'
    )

    data = pd.concat([data, data_transmission[['speed', 'transmission_type']]], axis=1)

    data = data.drop(columns=['transmission'])
```

```
    return data

def extract_brand_features(df):
    luxury_brands = ['Bugatti', 'Lamborghini', 'McLaren', 'Ferrari', 'Bentley', 'Rolls-Royce', 'Aston', 'Rivian'
    economy_brands = ['Toyota', 'Acura', 'FIAT', 'Lotus', 'Mazda', 'Hyundai', 'Nissan', 'Volkswagen', 'Suzuki',

    df['luxury_brand'] = df['brand'].apply(lambda x: 2 if x in luxury_brands else 0 if x in economy_brands else 
    df = df.drop(columns=['brand'])

    return df
```

Through 3 function I extracted some features:

- the 'vehicle_age' from the 'model_year'
- 'speed' and 'transmission_type' from the 'transmission' column
- the type of the 'brand', divided in luxury, economy and other in the middle

In [18]:
```
# Add a column "vehicle_age" and drop the column "model_year"
data = vehicle_age(data)

# Add the columns "HP", "engine_size" and "cylinders" and drop the column "engine"
data[['HP', 'engine_size', 'cylinders']] = data['engine'].apply(lambda x: pd.Series(engine_info(x)))

data = data.drop(columns=['engine'])

# Add the columns "speed" and "transmission_type" and drop the column "transmission"
data = process_transmission_data(data)

# Add the columns "luxury_brand", "premium_brand" and "economy_brand" and drop the column "brand"
data = extract_brand_features(data)
```

In [19]:
```
def group_models(model_name):
    if any(term in model_name.lower() for term in ['sport', 'gt', 'rs', 'amg']):
        return 'Sport'
```

```
    elif any(term in model_name.lower() for term in ['luxury', 'premium']):
        return 'Luxury'
    elif any(term in model_name.lower() for term in ['base', 'standard']):
        return 'Base'
    return 'Other'

data['model_category'] = data['model'].apply(group_models)
```

In [20]:
```
data.head()
```

Out[20]:

	id	model	milage	fuel_type	ext_col	int_col	accident	clean_title	price	vehicle_age	HP	engine_size	cylinders
0	111	ILX Premium Package	16113	Gasoline	Ebony Twilight Metallic	Ebony	None reported	NaN	29998	3	NaN	2.4	NaN
1	122	TLX	60854	Gasoline	Platinum White Pearl	Ebony	At least 1 accident or damage reported	NaN	19425	4	NaN	NaN	NaN
2	164	RDX w/A-Spec Package	39517	Gasoline	Gray	Black	NaN	NaN	29645	1	NaN	NaN	NaN
3	270	TL Type S	123500	Gasoline	Beige	Beige	None reported	Yes	12800	19	290.0	3.5	6.0
4	282	TLX	3389	Gasoline	Platinum White Pearl	Black	None reported	NaN	40798	4	NaN	NaN	NaN

Deal with missing values

Fill all the missing values with 'Unknown' and than deal with it

In [21]:
```
# Replace '-' with 'Electric' in the "fuel_type" because electric is mentioned in the "Data card" of the dataset
print('Fuel types pre processing:', data['fuel_type'].unique())
data['fuel_type'] = data['fuel_type'].fillna('Unknown')
data['fuel_type'] = data['fuel_type'].replace('–', 'Electric')
print('Fuel types post processing:', data['fuel_type'].unique())

print()

# Accidents
print('Accidents pre processing:', data['accident'].unique())
data['accident'] = data['accident'].fillna('Unknown')
print('Accidents post processing:', data['accident'].unique())

print()

# Clean title
print('Clean title pre processing:', data['clean_title'].unique())
data['clean_title'] = data['clean_title'].fillna('Unknown')
print('Clean title post processing:', data['clean_title'].unique())

print()

# HP
print('HP pre processing:', data['HP'].unique())
data['HP'] = data['HP'].fillna(0)
print('HP processing', data['HP'].unique())

print()

# Engine size
print('Engine size pre processing:', data['engine_size'].unique())
data['engine_size'] = data['engine_size'].fillna(0)
print('Engine size processing', data['engine_size'].unique())
```

```
print()

# Cylinders
print('Cylinders pre processing:', data['cylinders'].unique())
data['cylinders'] = data['cylinders'].fillna(0)
print('Cylinders processing', data['cylinders'].unique())

print()

# Speed
print('Speed pre processing:', data['speed'].unique())
data['speed'] = data['speed'].fillna('0')
print('Speed post processing', data['speed'].unique())

print()

# Transmission type
print('Transmission type pre processing:', data['transmission_type'].unique())
data['transmission_type'] = data['transmission_type'].fillna('Unknown')
print('Transmission type post processing', data['transmission_type'].unique())
```

```
Fuel types pre processing: ['Gasoline' 'E85 Flex Fuel' '–' 'Hybrid' nan 'Diesel' 'Plug-In Hybrid'
 'not supported']
Fuel types post processing: ['Gasoline' 'E85 Flex Fuel' 'Electric' 'Hybrid' 'Unknown' 'Diesel'
 'Plug-In Hybrid' 'not supported']

Accidents pre processing: ['None reported' 'At least 1 accident or damage reported' nan]
Accidents post processing: ['None reported' 'At least 1 accident or damage reported' 'Unknown']

Clean title pre processing: [nan 'Yes']
Clean title post processing: ['Unknown' 'Yes']

HP pre processing: [  nan  290.  150.  280.  270.  355.  206.  201.  200.  300.  400.  140.
  258.  272.  305.  268.  260.  295.  239.  444.  279.  160.  302.  310.
  286.  321.  306.  291.  220.  151.  210.  265.  420.  560.  320.  240.
```

```
  147.  285.  180.  250.  275.  245.  252.  158.  263.  190.  153.  563.
  136.  182.  215.  349.  316.  155.  390.  303.  261.  284.  106.  386.
  271.  835.  505.  424.  255.  503.  380.  710.  582.  523.  490.  430.
  340.  605.  715.  542.  483.  379.  577.  440.  385.  630.  562.  460.
  641.  521.  330.  247.  335.  500.  333.  211.  248.  292.  591.  450.
  354.  482.  610.  184.  188.  550.  788.  525.  225.  360.  329.  405.
  375.  186.  228.  429.  401.  475.  170.  445.  518.  241.  230.  315.
  296.  365.  382.  425.  759.  325.  402.  536.  348.  437.  543.  161.
  276.  616.  115.  235.  308.  174.  395.  435.  480.  350.  463.  455.
  567.  212.  603.  202.  617.  389.  414.  453.  601.  600.  540.  456.
  326.  134.  510.  449.  473.  369.  282.  357.  624.  362.  555.  199.
  454.  328.  407.  148.  181.  322.  288.  526.  416.  273.  381.  410.
  175.  383.  469.  412.  120.  611.  313.  218.  485.  552.  621.  571.
  556.  640.  467.  651.  573.  138.  197.  179.  172.  237.  283.  173.
  304.  195.  293.  277.  318.  403.  264.  397.  345.  760.  422.  204.
  670.  301.  650.  217.  443.  281.  312.  366.  323.  169.  426.  353.
  332.  132.  319.  324.  191.  393.  278.  638.  394.  143.  645.  166.
  287.  342.  122.  242.  256.  470.  341.  717.  246.  130.  363.  222.
  707.  154.  797.  808.  370.  372.  471.  565.  236.  101.  131.  164.
  118.  111.  602.  660.  553.  729.  493.  411.  156.  266.  171.  346.
  262.  231.  207.  221.  152.  253.  534.  557.  159.  187.  177.  495.
  168.  193.  311.  192.  185.  244.  109.  205.  227.  208.  165.  126.
  298.  243.  104.  141.  378.  344.  198.  145.  139.  214.  226.  142.
  294.  575.  146.  317.  107.  496.  409.  620.  189.  404.  232.  167.
  178.  451.  545.  778.  580.  572.  162.   78.  520.  502.  415.  533.
  702.  133.  224. 1020.  417.  691.  203.  219.  137.  121.  176.   76.
   70.]
HP processing [   0.  290.  150.  280.  270.  355.  206.  201.  200.  300.  400.  140.
  258.  272.  305.  268.  260.  295.  239.  444.  279.  160.  302.  310.
  286.  321.  306.  291.  220.  151.  210.  265.  420.  560.  320.  240.
  147.  285.  180.  250.  275.  245.  252.  158.  263.  190.  153.  563.
  136.  182.  215.  349.  316.  155.  390.  303.  261.  284.  106.  386.
  271.  835.  505.  424.  255.  503.  380.  710.  582.  523.  490.  430.
  340.  605.  715.  542.  483.  379.  577.  440.  385.  630.  562.  460.
  641.  521.  330.  247.  335.  500.  333.  211.  248.  292.  591.  450.
```

```
  354.  482.  610.  184.  188.  550.  788.  525.  225.  360.  329.  405.
  375.  186.  228.  429.  401.  475.  170.  445.  518.  241.  230.  315.
  296.  365.  382.  425.  759.  325.  402.  536.  348.  437.  543.  161.
  276.  616.  115.  235.  308.  174.  395.  435.  480.  350.  463.  455.
  567.  212.  603.  202.  617.  389.  414.  453.  601.  600.  540.  456.
  326.  134.  510.  449.  473.  369.  282.  357.  624.  362.  555.  199.
  454.  328.  407.  148.  181.  322.  288.  526.  416.  273.  381.  410.
  175.  383.  469.  412.  120.  611.  313.  218.  485.  552.  621.  571.
  556.  640.  467.  651.  573.  138.  197.  179.  172.  237.  283.  173.
  304.  195.  293.  277.  318.  403.  264.  397.  345.  760.  422.  204.
  670.  301.  650.  217.  443.  281.  312.  366.  323.  169.  426.  353.
  332.  132.  319.  324.  191.  393.  278.  638.  394.  143.  645.  166.
  287.  342.  122.  242.  256.  470.  341.  717.  246.  130.  363.  222.
  707.  154.  797.  808.  370.  372.  471.  565.  236.  101.  131.  164.
  118.  111.  602.  660.  553.  729.  493.  411.  156.  266.  171.  346.
  262.  231.  207.  221.  152.  253.  534.  557.  159.  187.  177.  495.
  168.  193.  311.  192.  185.  244.  109.  205.  227.  208.  165.  126.
  298.  243.  104.  141.  378.  344.  198.  145.  139.  214.  226.  142.
  294.  575.  146.  317.  107.  496.  409.  620.  189.  404.  232.  167.
  178.  451.  545.  778.  580.  572.  162.   78.  520.  502.  415.  533.
  702.  133.  224. 1020.  417.  691.  203.  219.  137.  121.  176.   76.
   70.]

Engine size pre processing: [2.4   nan 3.5  1.4  3.2  3.   3.7  2.   4.2  1.8  3.8  2.9  2.5  2.2
 3.3  4.   4.8  5.   3.4  2.3  6.6  1.5  5.3  4.6  1.6  5.2  3.6  3.9
 4.4  4.3  6.   5.9  6.5  6.2  4.7  5.7  5.5  5.8  7.3  0.65 5.6  6.7
 2.7  2.1  2.8  6.4  6.1  5.4  6.75 8.   6.8  6.3  7.   8.3  1.3  1.2
 8.1  7.4  8.4  1.7  4.5  1.  ]
Engine size processing [2.4  0.   3.5  1.4  3.2  3.   3.7  2.   4.2  1.8  3.8  2.9  2.5  2.2
 3.3  4.   4.8  5.   3.4  2.3  6.6  1.5  5.3  4.6  1.6  5.2  3.6  3.9
 4.4  4.3  6.   5.9  6.5  6.2  4.7  5.7  5.5  5.8  7.3  0.65 5.6  6.7
 2.7  2.1  2.8  6.4  6.1  5.4  6.75 8.   6.8  6.3  7.   8.3  1.3  1.2
 8.1  7.4  8.4  1.7  4.5  1.  ]

Cylinders pre processing: [nan  6.  4.  8.  5. 12. 10.  3.]
```

```
Cylinders processing [ 0.  6.  4.  8.  5. 12. 10.  3.]

Speed pre processing: ['6' None '9' '10' '8' '2' '7' '4' '5' '1' nan]
Speed post processing ['6' '0' '9' '10' '8' '2' '7' '4' '5' '1']

Transmission type pre processing: ['Automatic' 'Manual' 'Other' nan]
Transmission type post processing ['Automatic' 'Manual' 'Other' 'Unknown']
```

In [22]:
```
print(data.isnull().sum())
```

```
id                  0
model               0
milage              0
fuel_type           0
ext_col             0
int_col             0
accident            0
clean_title         0
price               0
vehicle_age         0
HP                  0
engine_size         0
cylinders           0
speed               0
transmission_type   0
luxury_brand        0
model_category      0
dtype: int64
```

Drop columns

Drop:

- 'id' beacuse it is not useful as said before.

- 'clean_title'
- 'ext_col' and 'int_col' because they plausibily do not change the price so much, maybe in some rare cases, but it is not worth it.
- 'model' beacause there are a lot of different values for each brand and the encoding would create a sparse matrix.
- 'fuel_type' because almost all are 'Gasoline' and it does not contribute per the evaluation.

In [23]:
```
# drop columns that I think that are not useful (the color of the car can be changed and usually it is a cheap op
data = data.drop(columns=['id', 'ext_col', 'int_col'])
```

In [24]:
```
data.head()
```

Out[24]:

	model	milage	fuel_type	accident	clean_title	price	vehicle_age	HP	engine_size	cylinders	speed	transmission_ty
0	ILX Premium Package	16113	Gasoline	None reported	Unknown	29998	3	0.0	2.4	0.0	6	Autom
1	TLX	60854	Gasoline	At least 1 accident or damage reported	Unknown	19425	4	0.0	0.0	0.0	0	Autom
2	RDX w/A-Spec Package	39517	Gasoline	Unknown	Unknown	29645	1	0.0	0.0	0.0	0	Autom
3	TL Type S	123500	Gasoline	None reported	Yes	12800	19	290.0	3.5	6.0	6	Mar
4	TLX	3389	Gasoline	None reported	Unknown	40798	4	0.0	0.0	0.0	0	Ot

In [25]:
```
data = data.drop(columns=['model'])
```

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

Out[26]:

	milage	fuel_type	accident	clean_title	price	vehicle_age	HP	engine_size	cylinders	speed	transmission_type	luxur
0	16113	Gasoline	None reported	Unknown	29998	3	0.0	2.4	0.0	6	Automatic	
1	60854	Gasoline	At least 1 accident or damage reported	Unknown	19425	4	0.0	0.0	0.0	0	Automatic	
2	39517	Gasoline	Unknown	Unknown	29645	1	0.0	0.0	0.0	0	Automatic	
3	123500	Gasoline	None reported	Yes	12800	19	290.0	3.5	6.0	6	Manual	
4	3389	Gasoline	None reported	Unknown	40798	4	0.0	0.0	0.0	0	Other	

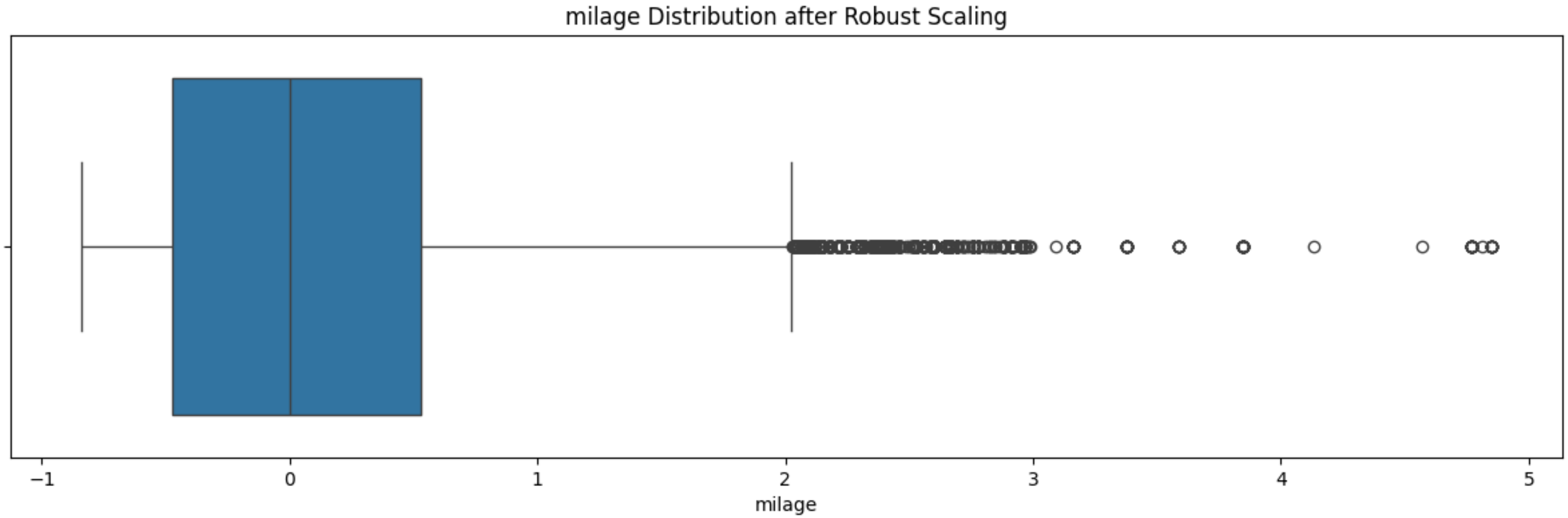
Scale some columns

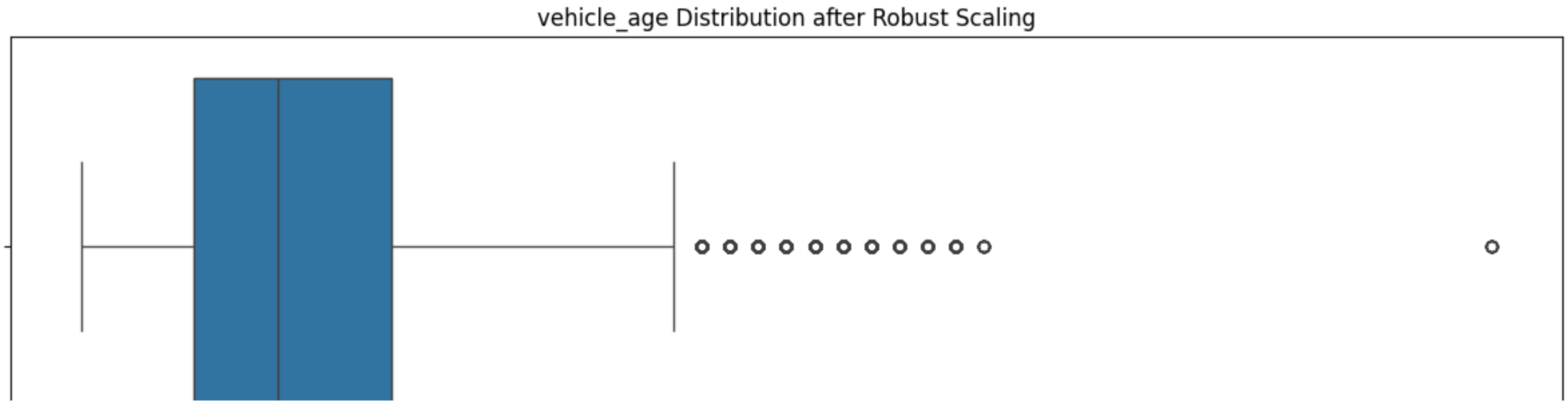
Scale some numerical columns with RobustScaler() in order to have a better range for training.

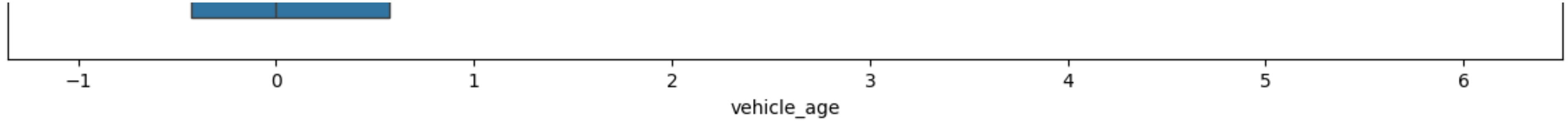
In [27]:
```
columns_to_scale = ['milage', 'vehicle_age', 'HP', 'engine_size']

scaler = RobustScaler()
data[columns_to_scale] = scaler.fit_transform(data[columns_to_scale])
```

In [28]:
```
fig, axes = plt.subplots(len(columns_to_scale), 1, figsize=(12, 4*len(columns_to_scale)))

for i, column in enumerate(columns_to_scale):
    sns.boxplot(data=data, x=column, ax=axes[i])
```

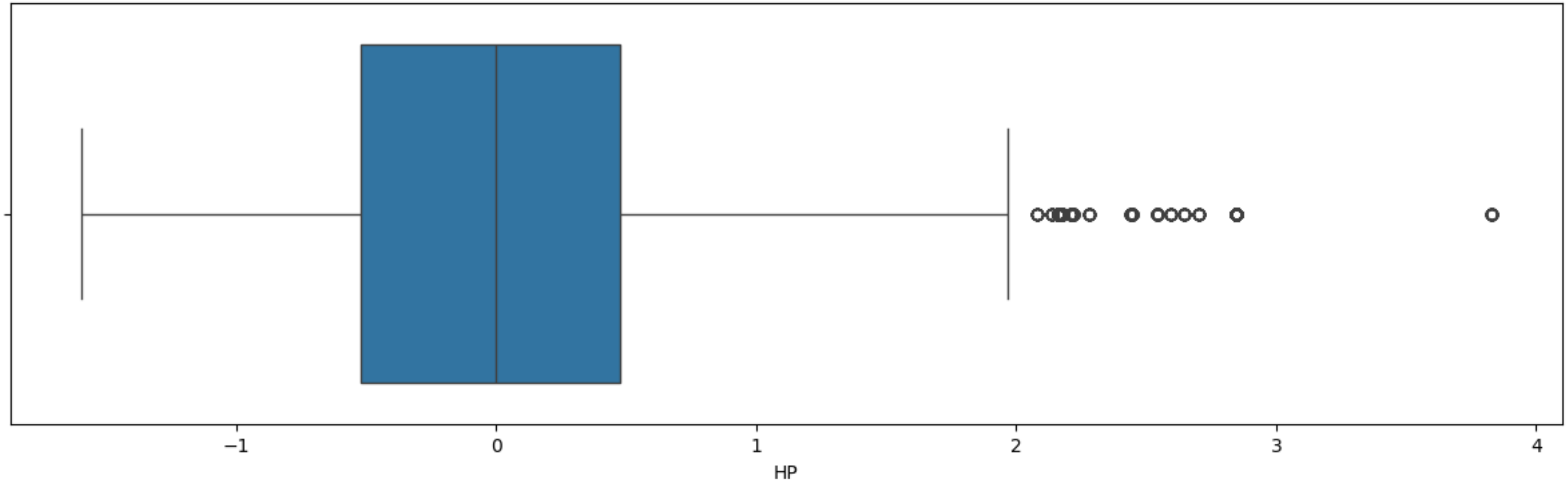
```
    axes[i].set_title(f'{column} Distribution after Robust Scaling')

plt.tight_layout()
plt.show()
```



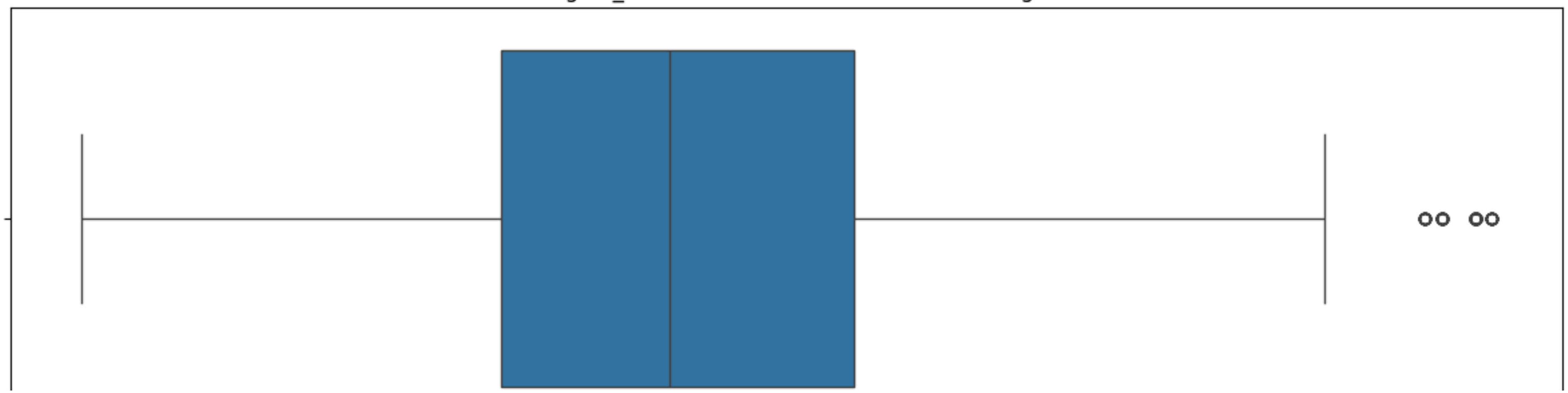


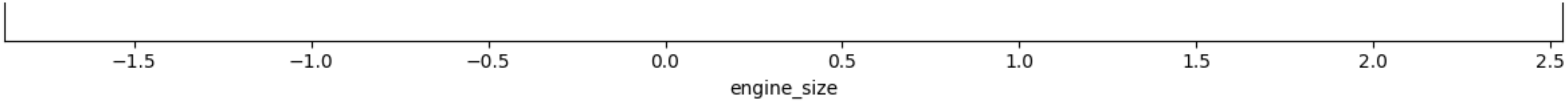


HP Distribution after Robust Scaling



engine_size Distribution after Robust Scaling





In [29]:
```python
data.head()
```

Out[29]:

	milage	fuel_type	accident	clean_title	price	vehicle_age	HP	engine_size	cylinders	speed	transmission_type
0	-0.617136	Gasoline	None reported	Unknown	29998	-0.571429	-1.595745	-0.523810	0.0	6	Automatic
1	0.012009	Gasoline	At least 1 accident or damage reported	Unknown	19425	-0.428571	-1.595745	-1.666667	0.0	0	Automatic
2	-0.288030	Gasoline	Unknown	Unknown	29645	-0.857143	-1.595745	-1.666667	0.0	0	Automatic
3	0.892932	Gasoline	None reported	Yes	12800	1.714286	-0.053191	0.000000	6.0	6	Manual
4	-0.796060	Gasoline	None reported	Unknown	40798	-0.428571	-1.595745	-1.666667	0.0	0	Other

Encode the non-numerical features

In [30]:
```python
# Encode the accident column as 1 if 'At least 1 accident or damage reported', else 0
data['accident'] = data['accident'].apply(lambda x: 1 if x=='At least 1 accident or damage reported' else 0)
```

In [31]:
```python
# Transform the column 'speed' to numerical data, it was a column of strings before
data['speed'] = data['speed'].replace('Unknown', 0)
data['speed'] = pd.to_numeric(data['speed'])
```

In [32]:
```
# Encode the 'transmission_type' as 1 if it is 'Automatic', 0 if it is 'Manual' or else
data['transmission_type'] = data['transmission_type'].apply(lambda x: 1 if x=='Automatic' else 0)
```

In [33]:
```
# Encode the 'clean_title' as 1 if it is 'Yes', 0 otherwise
data['clean_title'] = data['clean_title'].apply(lambda x: 1 if x == 'Yes' else 0)
```

In [34]:
```
# Keep only fewer differentiations of 'fuel_type'
data['fuel_type'] = data['fuel_type'].apply(lambda x: 0 if x == 'Gasoline'
                                              else 1 if x =='Electric'
                                              else 2 if x == 'Diesel'
                                              else 3 if (x == 'Hybrid' or x == 'Plug-In Hybrid')
                                              else 4)
```

In [35]:
```
# Make One-Hot Encoding of the 'luxury_brand', 'fuel_type' and 'model_category'
categorical_columns = ['luxury_brand', 'fuel_type', 'model_category']

data_encoded = pd.get_dummies(data, columns=categorical_columns, drop_first=True)
data_encoded = data_encoded.replace({True: 1, False: 0})
```

```
/var/folders/_g/7s4z636d67z67rlmmnqgx5mm0000gn/T/ipykernel_4136/1712994280.py:5: FutureWarning: Downcasting behav
ior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly ca
ll `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_dow
ncasting', True)`
  data_encoded = data_encoded.replace({True: 1, False: 0})
```

In [36]:
```
data_encoded.head()
```

Out[36]:

	milage	accident	clean_title	price	vehicle_age	HP	engine_size	cylinders	speed	transmission_type	luxury_br
0	-0.617136	0	0	29998	-0.571429	-1.595745	-0.523810	0.0	6	1	
1	0.012009	1	0	19425	-0.428571	-1.595745	-1.666667	0.0	0	1	
2	-0.288030	0	0	29645	-0.857143	-1.595745	-1.666667	0.0	0	1	
3	0.892932	0	1	12800	1.714286	-0.053191	0.000000	6.0	6	0	
4	-0.796060	0	0	40798	-0.428571	-1.595745	-1.666667	0.0	0	0	

In [37]:

```
data_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178861 entries, 0 to 178860
Data columns (total 19 columns):
 #   Column                  Non-Null Count   Dtype  
---  ------                  --------------   -----  
 0   milage                  178861 non-null  float64
 1   accident                178861 non-null  int64  
 2   clean_title             178861 non-null  int64  
 3   price                   178861 non-null  int64  
 4   vehicle_age             178861 non-null  float64
 5   HP                      178861 non-null  float64
 6   engine_size             178861 non-null  float64
 7   cylinders               178861 non-null  float64
 8   speed                   178861 non-null  int64  
 9   transmission_type       178861 non-null  int64  
 10  luxury_brand_1          178861 non-null  int64  
 11  luxury_brand_2          178861 non-null  int64  
 12  fuel_type_1             178861 non-null  int64  
 13  fuel_type_2             178861 non-null  int64  
 14  fuel_type_3             178861 non-null  int64  
 15  fuel_type_4             178861 non-null  int64  
 16  model_category_Luxury   178861 non-null  int64  
 17  model_category_Other    178861 non-null  int64  
 18  model_category_Sport    178861 non-null  int64  
dtypes: float64(5), int64(14)
memory usage: 25.9 MB
```

Create X_train and y_train

Divide the data in 80% training set and 20% test set

In [38]:
```
X = data_encoded.drop(columns=['price'])
y = data_encoded['price']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=random_state)
```

Create, train and evaluate model

In [ ]:
```
def plot_results(train_rmse, test_rmse, ytrain, ytest, ytrainpred, ytestpred):
    rmse_values = [train_rmse, test_rmse]
    labels = ['Train RMSE', 'Test RMSE']

    # Plot RMSE Comparison
    plt.figure(figsize=(8, 5))
    plt.bar(labels, rmse_values, color=['blue', 'orange'])
    plt.ylabel('RMSE')
    plt.title('RMSE Comparison')
    plt.show()

    # Determine the y-axis limits for training and test sets
    train_ylim = (min(min(ytrain), min(ytrainpred)), max(max(ytrain), max(ytrainpred)))
    test_ylim = (min(min(ytest), min(ytestpred)), max(max(ytest), max(ytestpred)))

    plt.figure(figsize=(14, 10))

    plt.subplot(2, 2, 1)
    plt.plot(range(len(ytrain)), ytrain, 'o', color='blue', markersize=5, label='True Values')
    plt.xlabel('Element')
    plt.ylabel('Value')
    plt.title('Training Set: True Values')
    plt.ylim(train_ylim)
    plt.grid()
    plt.legend()

    plt.subplot(2, 2, 2)
    plt.plot(range(len(ytrainpred)), ytrainpred, 'o', color='red', markersize=5, label='Predicted Values')
    plt.xlabel('Element')
    plt.ylabel('Value')
```

```
    plt.title('Training Set: Predicted Values')
    plt.ylim(train_ylim)
    plt.grid()
    plt.legend()

    plt.subplot(2, 2, 3)
    plt.plot(range(len(ytest)), ytest, 'o', color='blue', markersize=5, label='True Values')
    plt.xlabel('Element')
    plt.ylabel('Value')
    plt.title('Test Set: True Values')
    plt.ylim(test_ylim)
    plt.grid()
    plt.legend()

    plt.subplot(2, 2, 4)
    plt.plot(range(len(ytestpred)), ytestpred, 'o', color='red', markersize=5, label='Predicted Values')
    plt.xlabel('Element')
    plt.ylabel('Value')
    plt.title('Test Set: Predicted Values')
    plt.ylim(test_ylim)
    plt.grid()
    plt.legend()

    plt.tight_layout()
    plt.show()
```

In [40]:
```
def train_evaluate_model(model, model_name, X_train, X_test, y_train, y_test, results, has_feature_importance=Fa

    # Train model
    model.fit(X_train, y_train)

    if is_grid_search:
        print(f"Best parameters found: {model.best_params_}")

    # Make predictions
```

```
    train_y_pred = model.predict(X_train)
    test_y_pred = model.predict(X_test)

    # Calculate RMSE
    train_rmse = root_mean_squared_error(train_y_pred, y_train)
    test_rmse = root_mean_squared_error(test_y_pred, y_test)

    print(f'Train rmse {train_rmse}')
    print(f'Test rmse {test_rmse}')

    # Store results
    results.loc[len(results)] = [model_name, train_rmse, test_rmse]

    # Plot prediction results
    plot_results(train_rmse, test_rmse, y_train, y_test, train_y_pred, test_y_pred)

    # Plot feature importance if available
    if has_feature_importance:
        importance_values = model.feature_importances_ if hasattr(model, 'feature_importances_') else abs(model.c
        importances = pd.DataFrame({
            'feature': X_train.columns,
            'importance': importance_values
        })
        importances = importances.sort_values('importance', ascending=False)

        plt.figure(figsize=(12,6))
        plt.bar(importances['feature'], importances['importance'])
        plt.xticks(rotation=45, ha='right')
        plt.xlabel('Features')
        plt.ylabel('Importance')
        plt.title(f'Feature Importance from {model_name}')
        plt.tight_layout()
        plt.show()
```

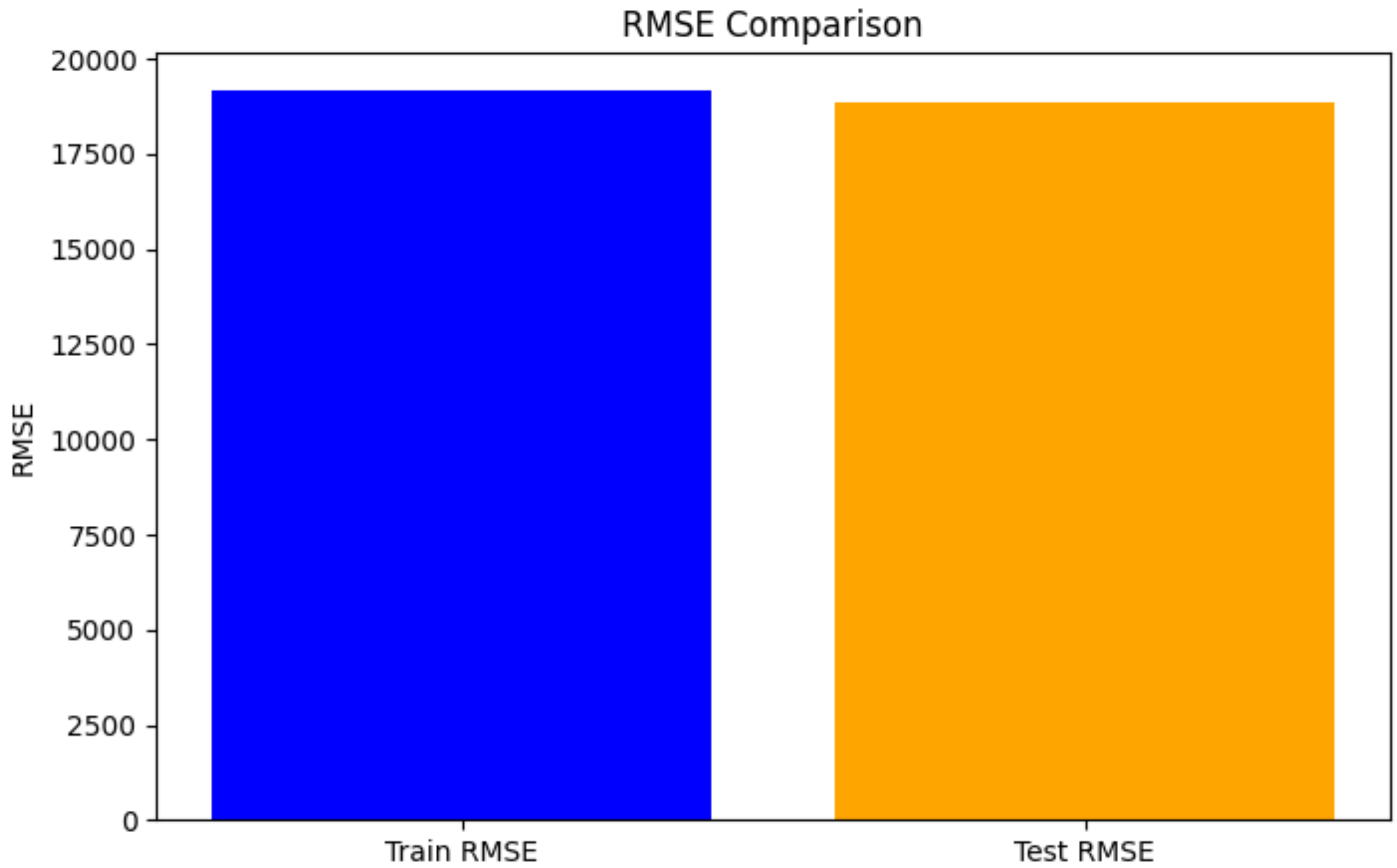
Initialize a dataframe for the results

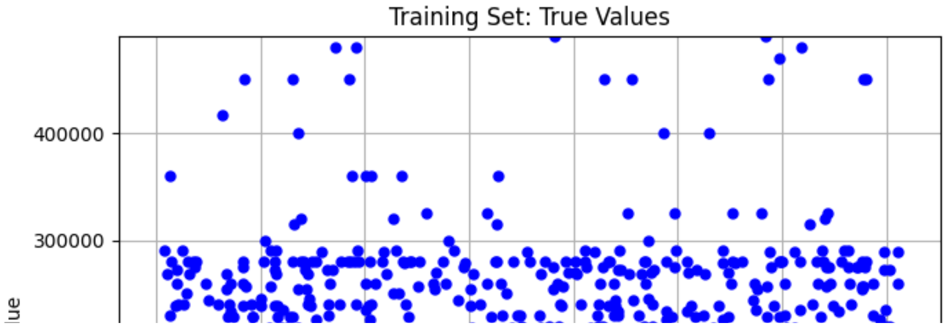
In [41]:
```
results = pd.DataFrame(columns=['Model','Train RMSE','Test RMSE'])
```

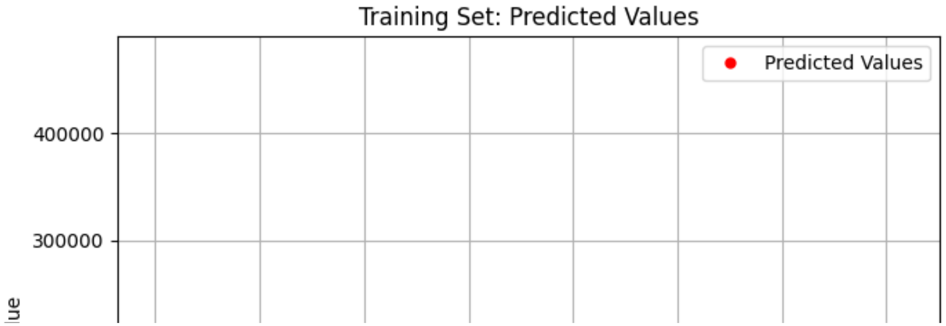
Ridge Regressor: linear least squares using l2 regularization.

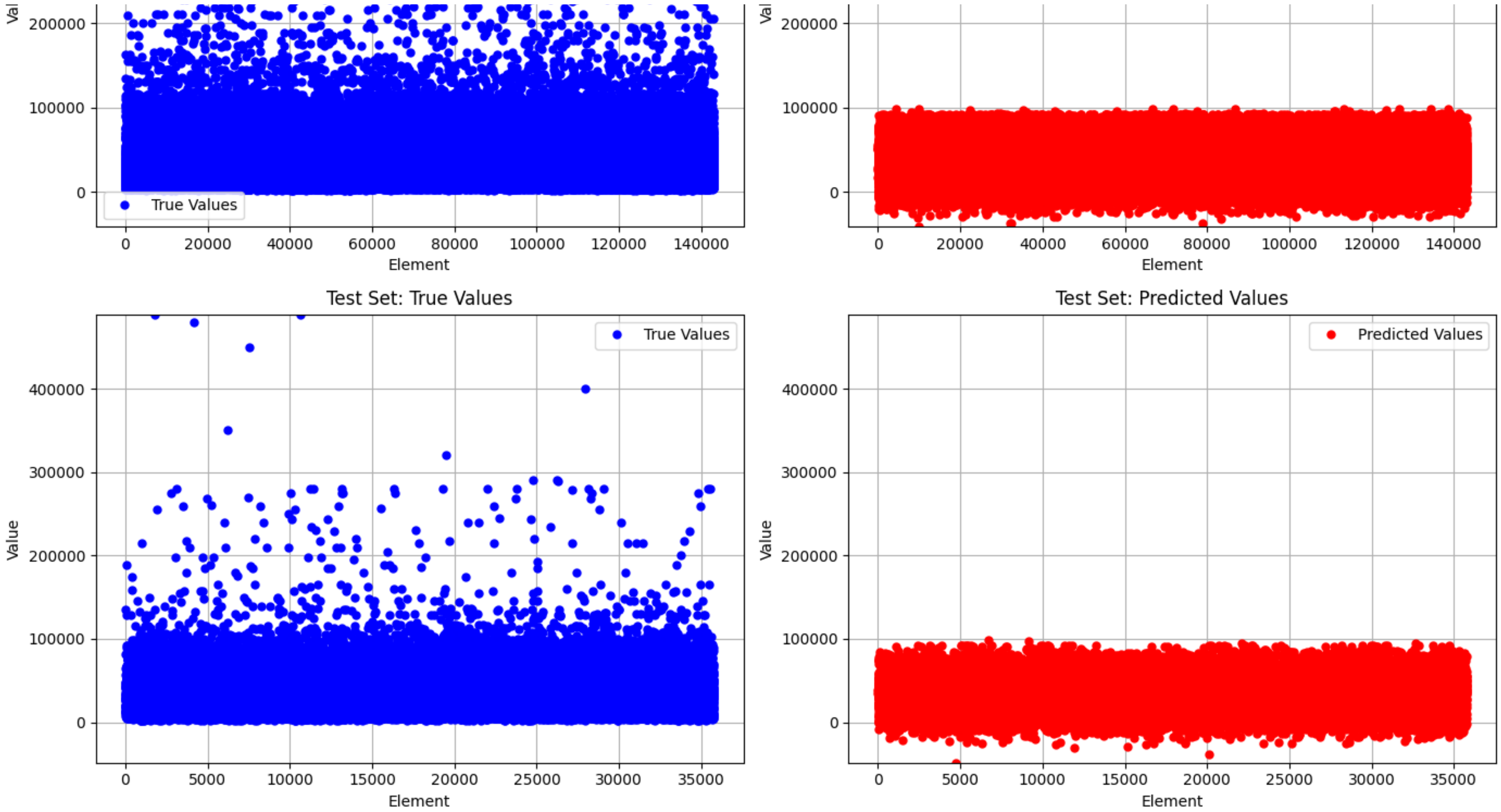
In [42]:
```
from sklearn.linear_model import Ridge

lr = Ridge(random_state=random_state)
train_evaluate_model(lr, 'Ridge Regressor', X_train, X_test, y_train, y_test, results, has_feature_importance=Tru
```

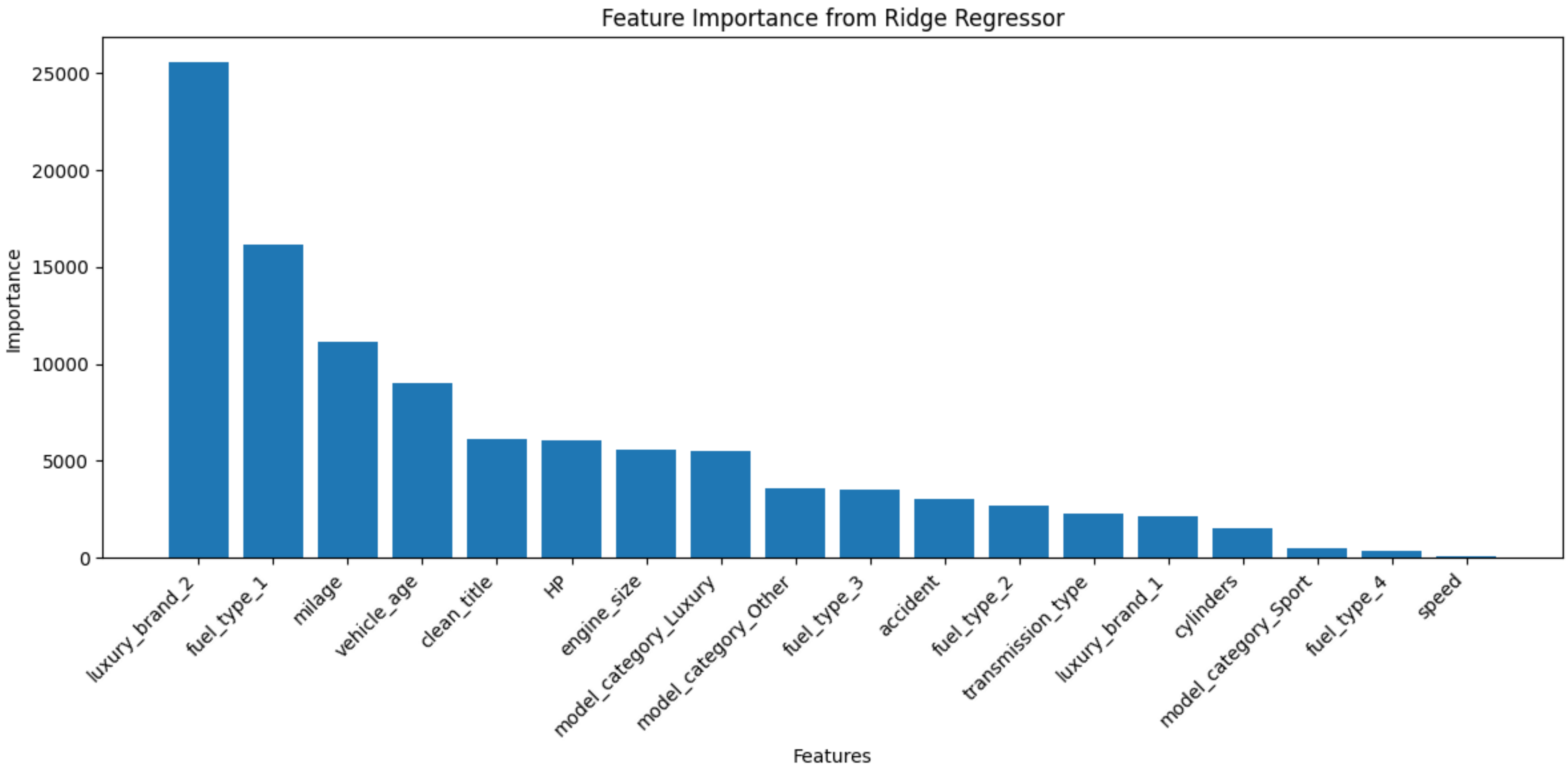
```
Train rmse 19192.26292188491
Test rmse 18877.630774308625
```


RMSE Comparison
20000
17500
15000
12500
10000
7500
5000
2500
0
RMSE
Train RMSE
Test RMSE


Training Set: True Values
400000
300000


Training Set: Predicted Values
Predicted Values
400000
300000

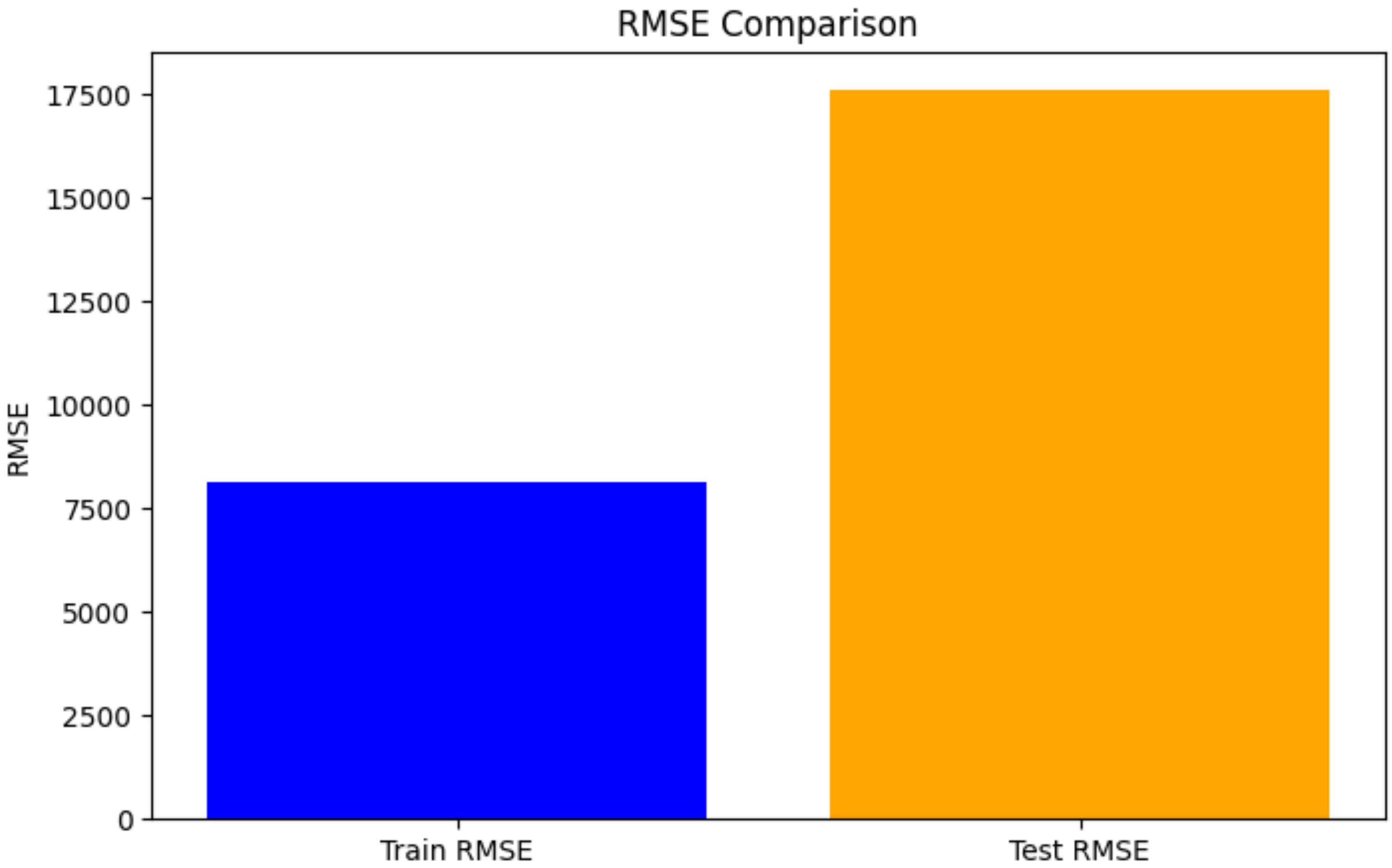

Val
200000
100000
0
True Values
0
20000
40000
60000
80000
100000
120000
140000
Element
Val
200000
100000
0
0
20000
40000
60000
80000
100000
120000
140000
Element
Test Set: True Values
True Values
400000
300000
200000
100000
0
Value
0
5000
10000
15000
20000
25000
30000
35000
Element
Test Set: Predicted Values
Predicted Values
400000
300000
200000
100000
0
Value
0
5000
10000
15000
20000
25000
30000
35000
Element

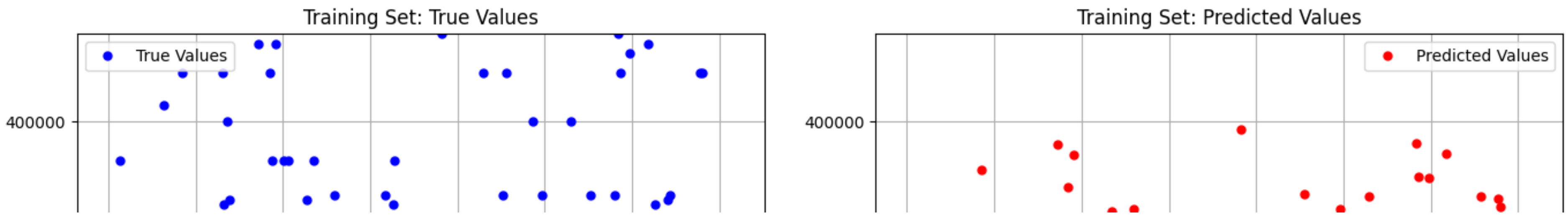


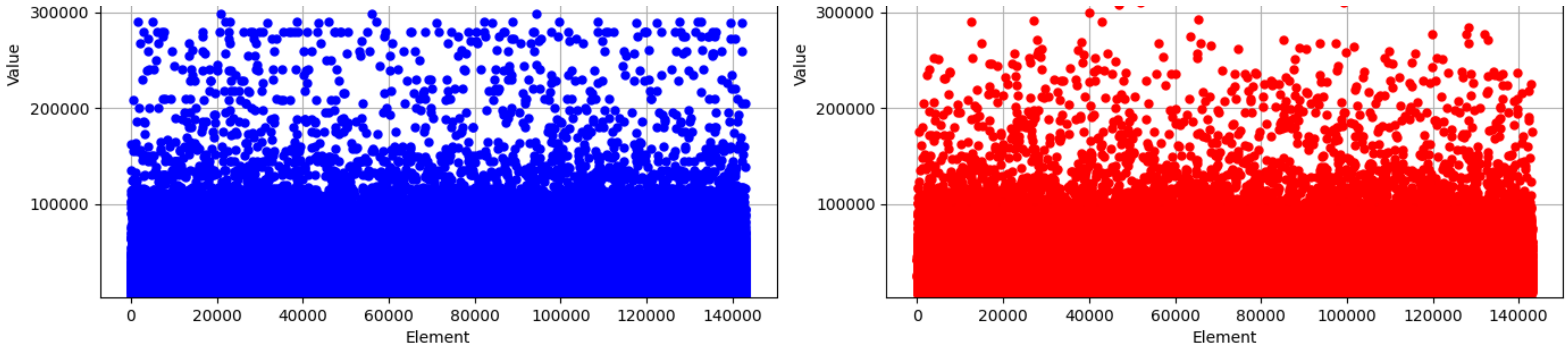
Random Forest Regressor used in its default configuration.

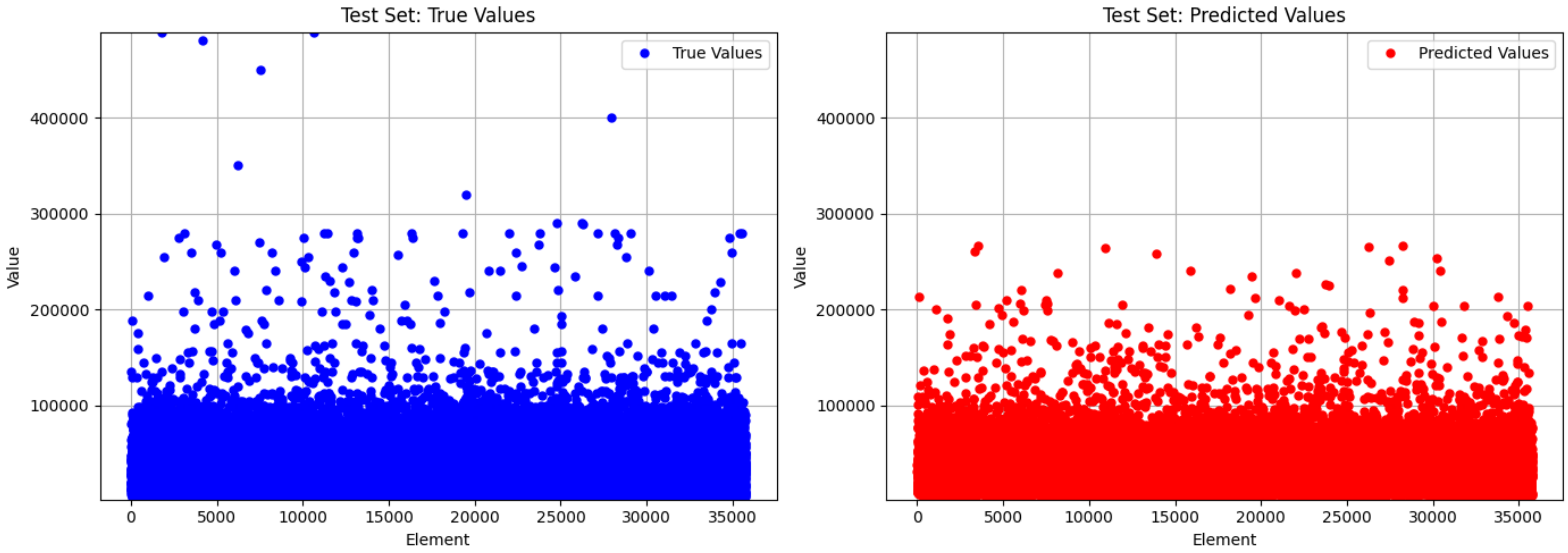
In [53]:
```
from sklearn.ensemble import RandomForestRegressor

rf = RandomForestRegressor(random_state=random_state)
train_evaluate_model(rf, 'Random Forest Regressor', X_train, X_test, y_train, y_test, results, has_feature_impor
```

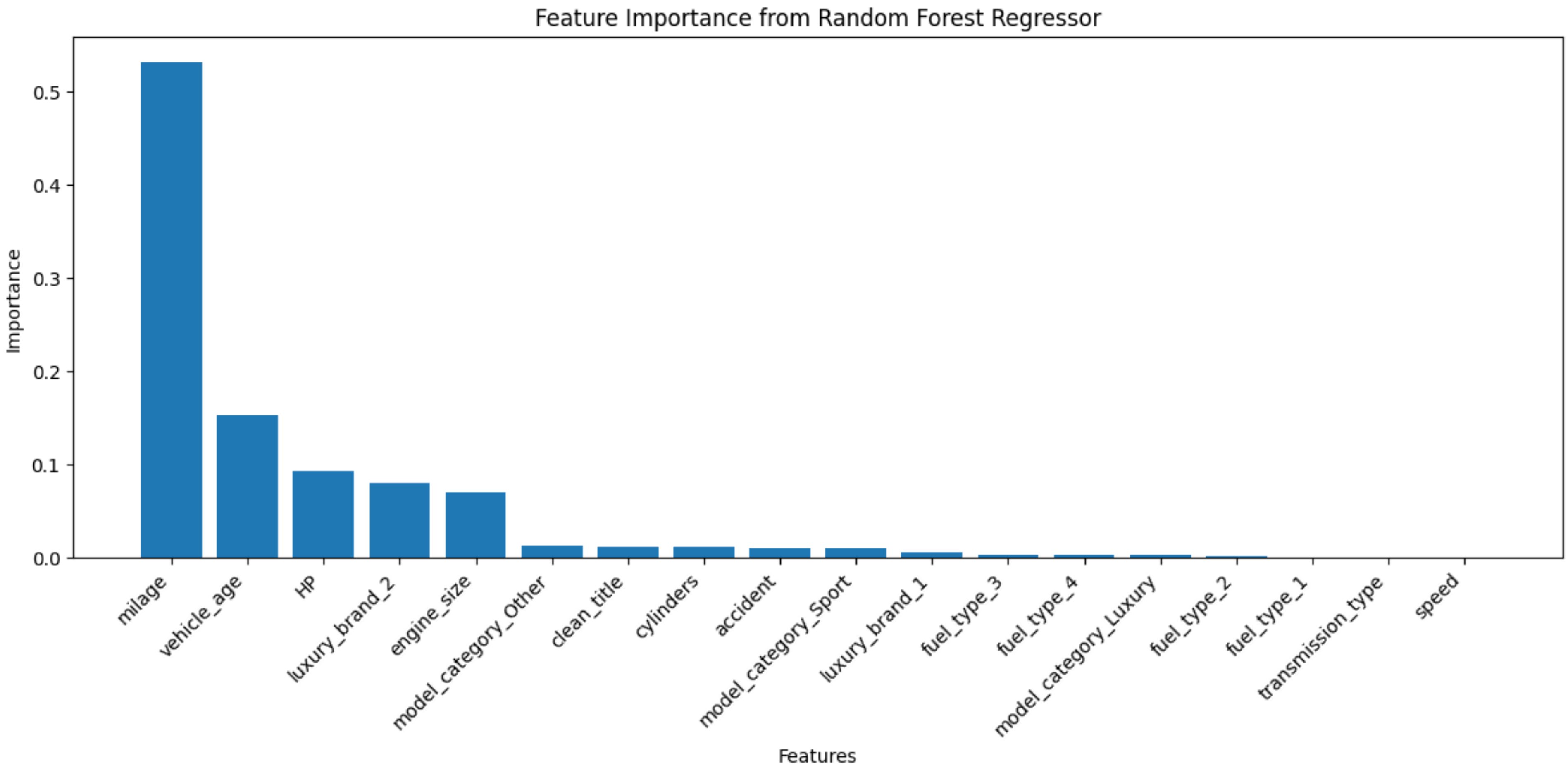
```
Train rmse 8134.419781733904
Test rmse 17625.011145229026
```






Value
300000
200000
100000
0
20000
40000
60000
80000
100000
120000
140000
Element


Test Set: True Values
True Values
Test Set: Predicted Values
Predicted Values
Value
400000
300000
200000
100000
0
5000
10000
15000
20000
25000
30000
35000
Element

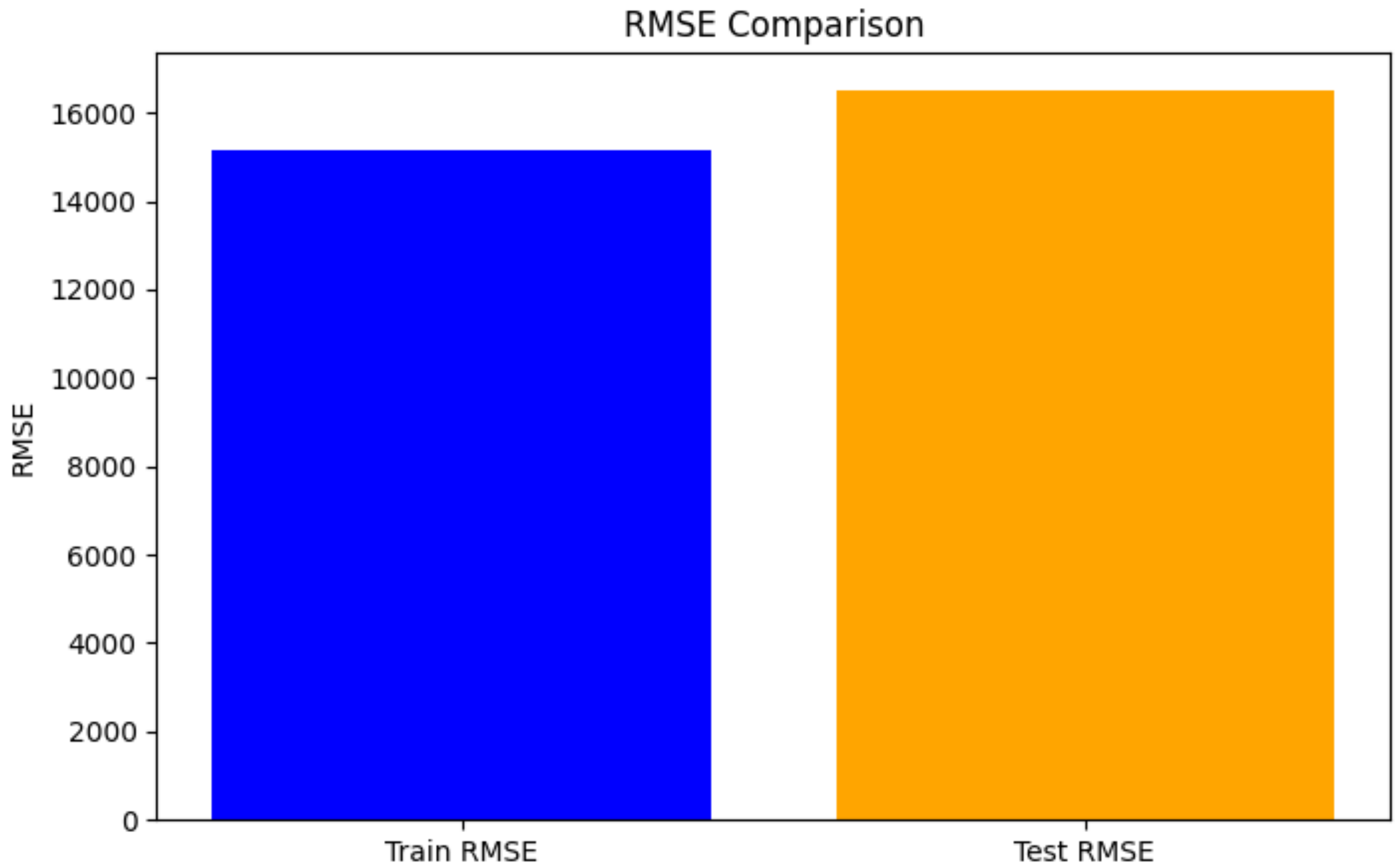


Random Forest Regressor with best parameters found through a grid search. The feature importance plot did not work for the grid search model, so i kept the error being the run of the cell very very long.

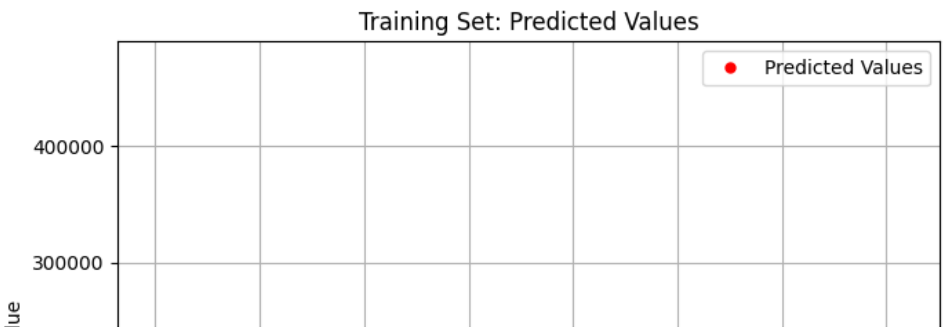
In [ ]:
```
from sklearn.model_selection import GridSearchCV

rf_regr = RandomForestRegressor()
```

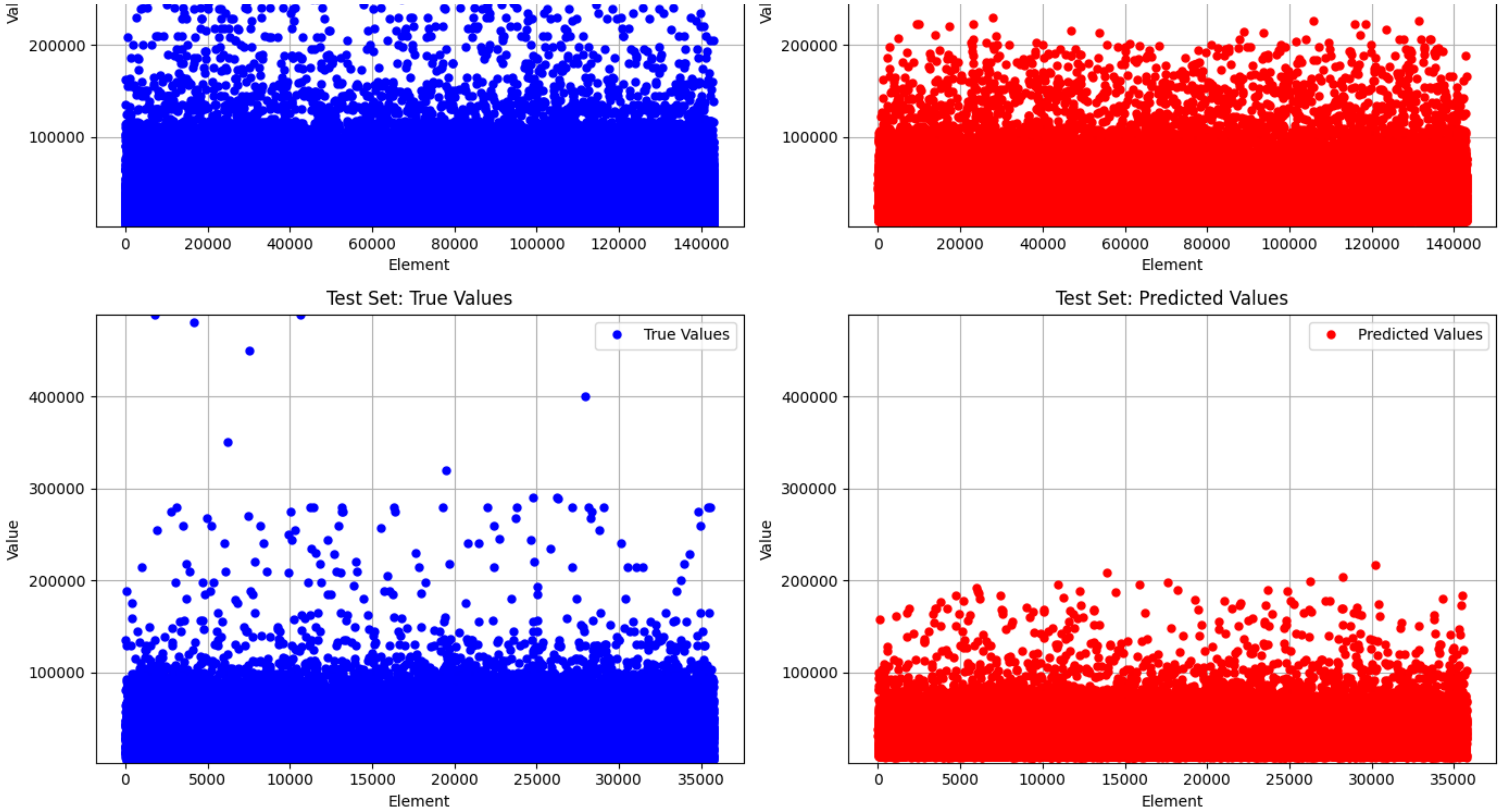
```
# Define the hyperparameter grid
param_grid = {
    'n_estimators': [50, 100],
    'max_depth': [3, 5, 7, 10, 12, 15],
    'min_samples_split': [6, 8, 10, 12, 14, 16, 18],
    'min_samples_leaf': [1, 2, 3, 4]
}

# Initialize GridSearchCV with RandomForestRegressor and param_grid
grid_search = GridSearchCV(estimator=rf_regr, param_grid=param_grid,
                           cv=5, scoring='neg_root_mean_squared_error')

train_evaluate_model(grid_search, 'Random Forest Regressor GS', X_train, X_test, y_train, y_test, results, has_fe
```

```
Best parameters found: {'max_depth': 12, 'min_samples_leaf': 3, 'min_samples_split': 14, 'n_estimators': 100}
Train rmse 15129.661061150095
Test rmse 16518.339963396436
```


RMSE Comparison
16000
14000
12000
10000
8000
6000
4000
2000
0
RMSE
Train RMSE
Test RMSE


Training Set: True Values
True Values
400000
300000


Training Set: Predicted Values
Predicted Values
400000
300000


Test Set: True Values
Test Set: Predicted Values
True Values
Predicted Values
Value
Element

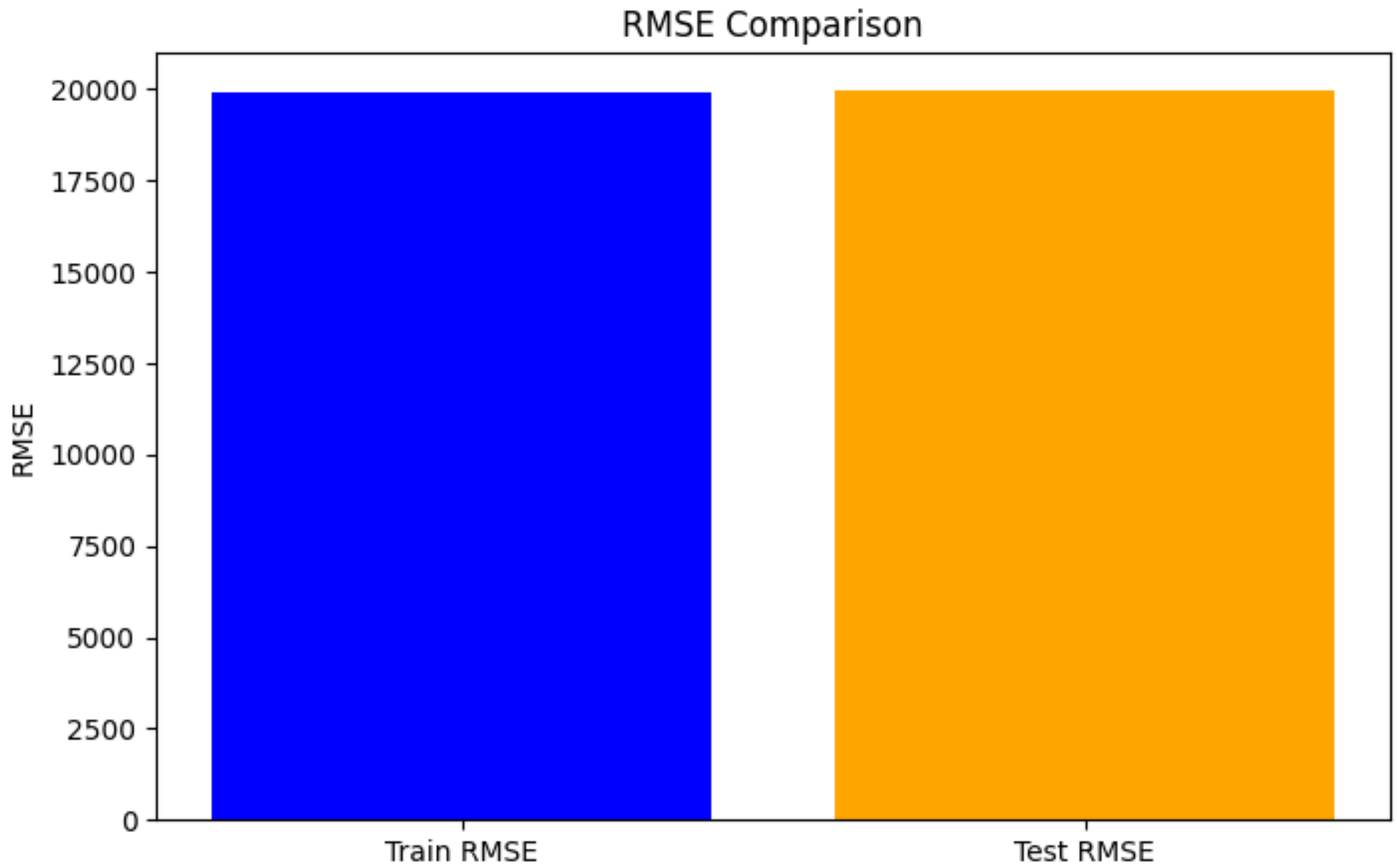
```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[55], line 18
     14 # Initialize GridSearchCV with RandomForestRegressor and param_grid
     15 grid_search = GridSearchCV(estimator=rf_regr, param_grid=param_grid,
     16                            cv=5, scoring='neg_root_mean_squared_error')
---> 18 train_evaluate_model(grid_search, 'Random Forest Regressor GS', X_train, X_test, y_train, y_test, result
s, has_feature_importance=True, is_grid_search=True)

Cell In[41], line 28, in train_evaluate_model(model, model_name, X_train, X_test, y_train, y_test, results, has_f
eature_importance, is_grid_search)
     26 # Plot feature importance if available
     27 if has_feature_importance:
---> 28     importance_values = model.feature_importances_ if hasattr(model, 'feature_importances_') else abs(mod
el.coef_)
     29     importances = pd.DataFrame({
     30         'feature': X_train.columns,
     31         'importance': importance_values
     32     })
     33     importances = importances.sort_values('importance', ascending=False)

AttributeError: 'GridSearchCV' object has no attribute 'coef_'
```

AdaBoost Regressor used in its default configuration, so using Decision Trees.

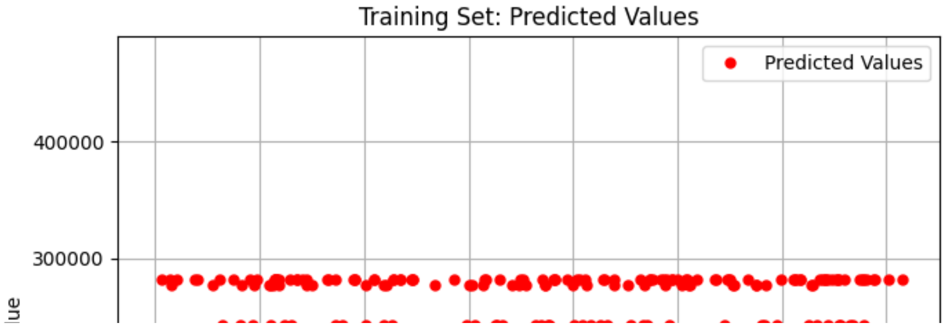
In [58]:

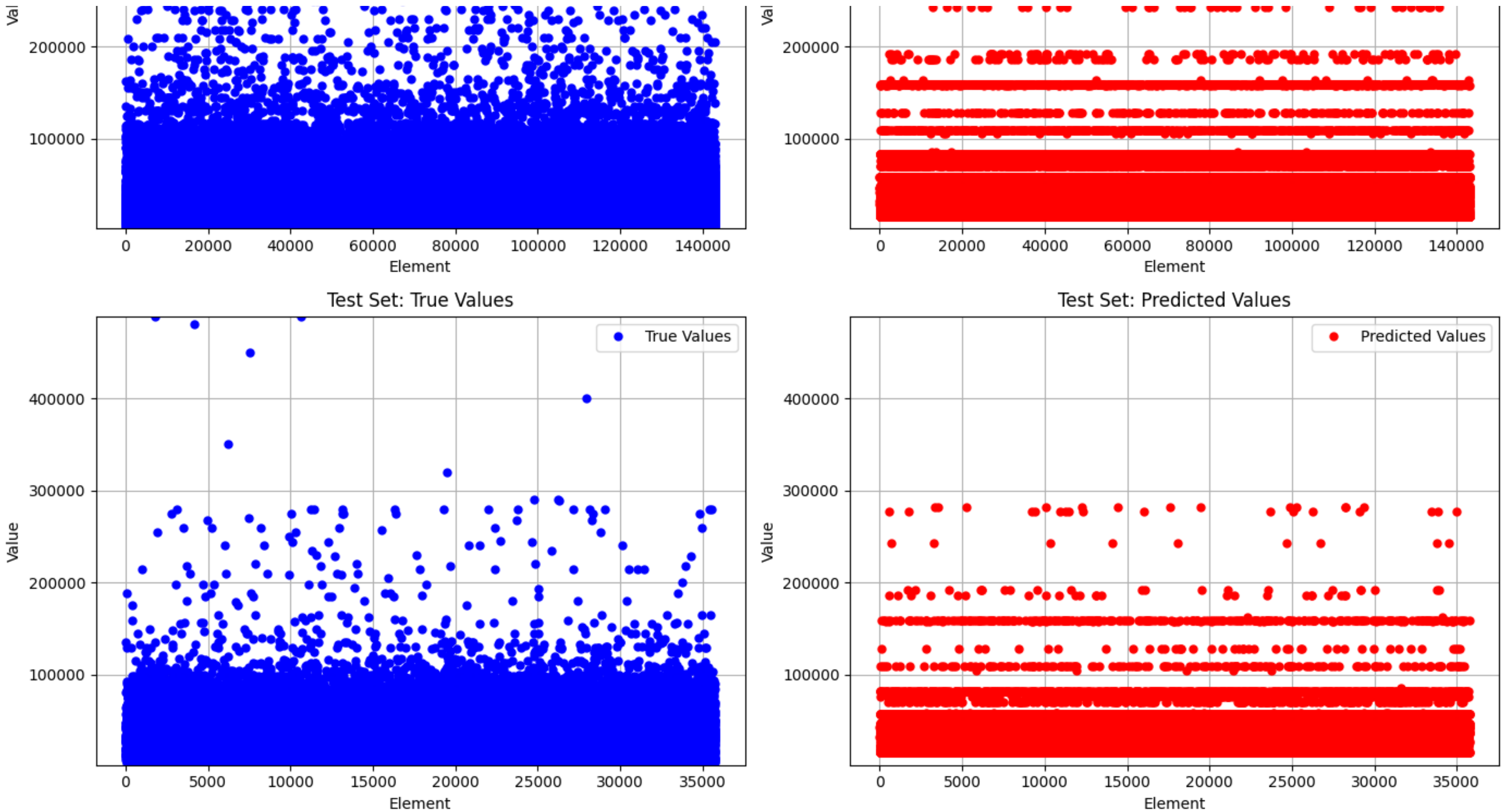
```
from sklearn.ensemble import AdaBoostRegressor

ab = AdaBoostRegressor(random_state=random_state)

train_evaluate_model(ab, 'Ada Boost Regressor', X_train, X_test, y_train, y_test, results, has_feature_importance
```

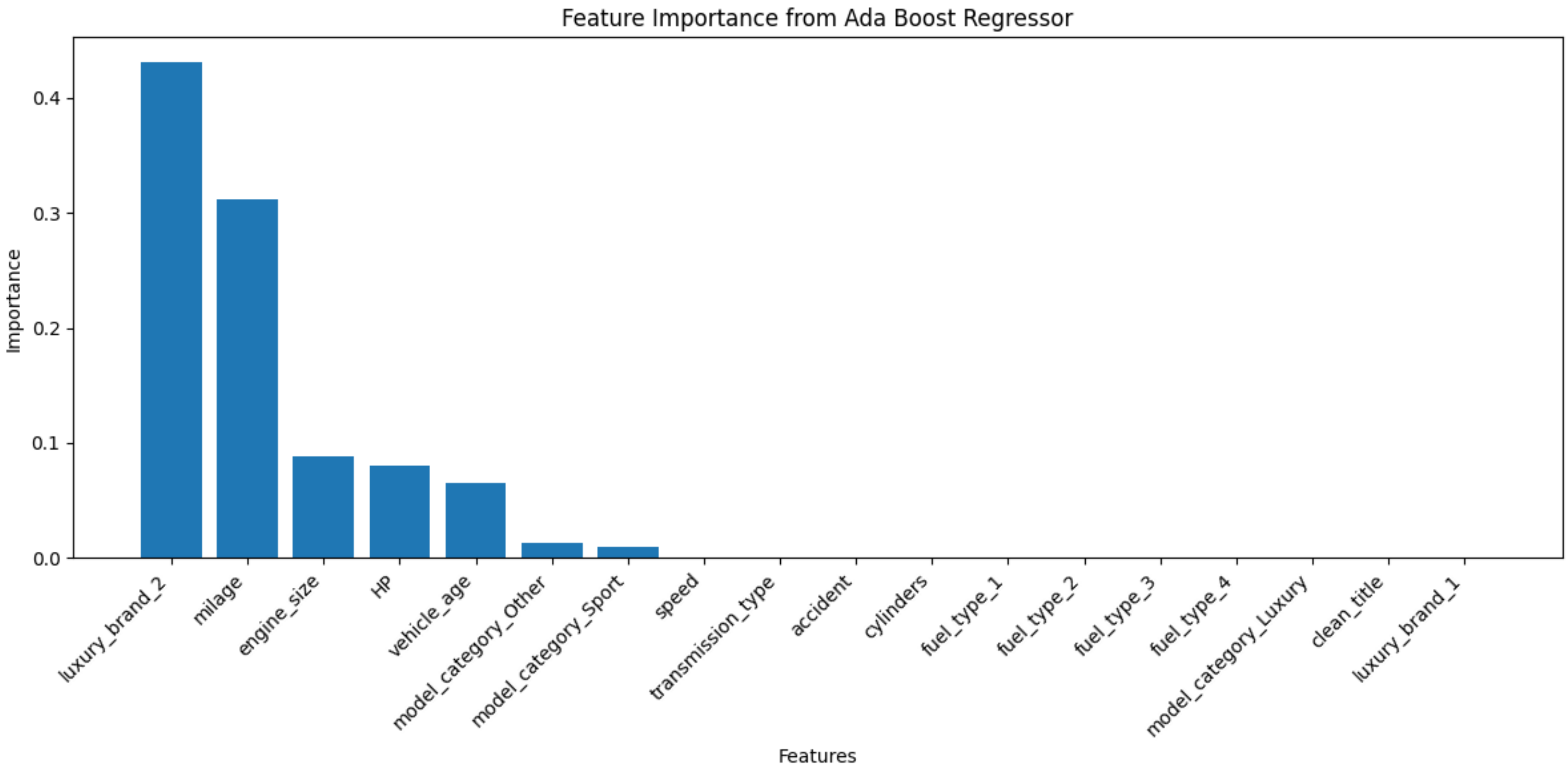
```
Train rmse 19941.286400888504
Test rmse 19990.2614383597
```


RMSE Comparison
RMSE
20000
17500
15000
12500
10000
7500
5000
2500
0
Train RMSE
Test RMSE


Training Set: True Values
True Values
400000
300000


Training Set: Predicted Values
Predicted Values
400000
300000


Val
200000
100000
0
20000
40000
60000
80000
100000
120000
140000
Element
Test Set: True Values
True Values
Value
400000
300000
0
5000
10000
15000
20000
25000
30000
35000
Test Set: Predicted Values
Predicted Values

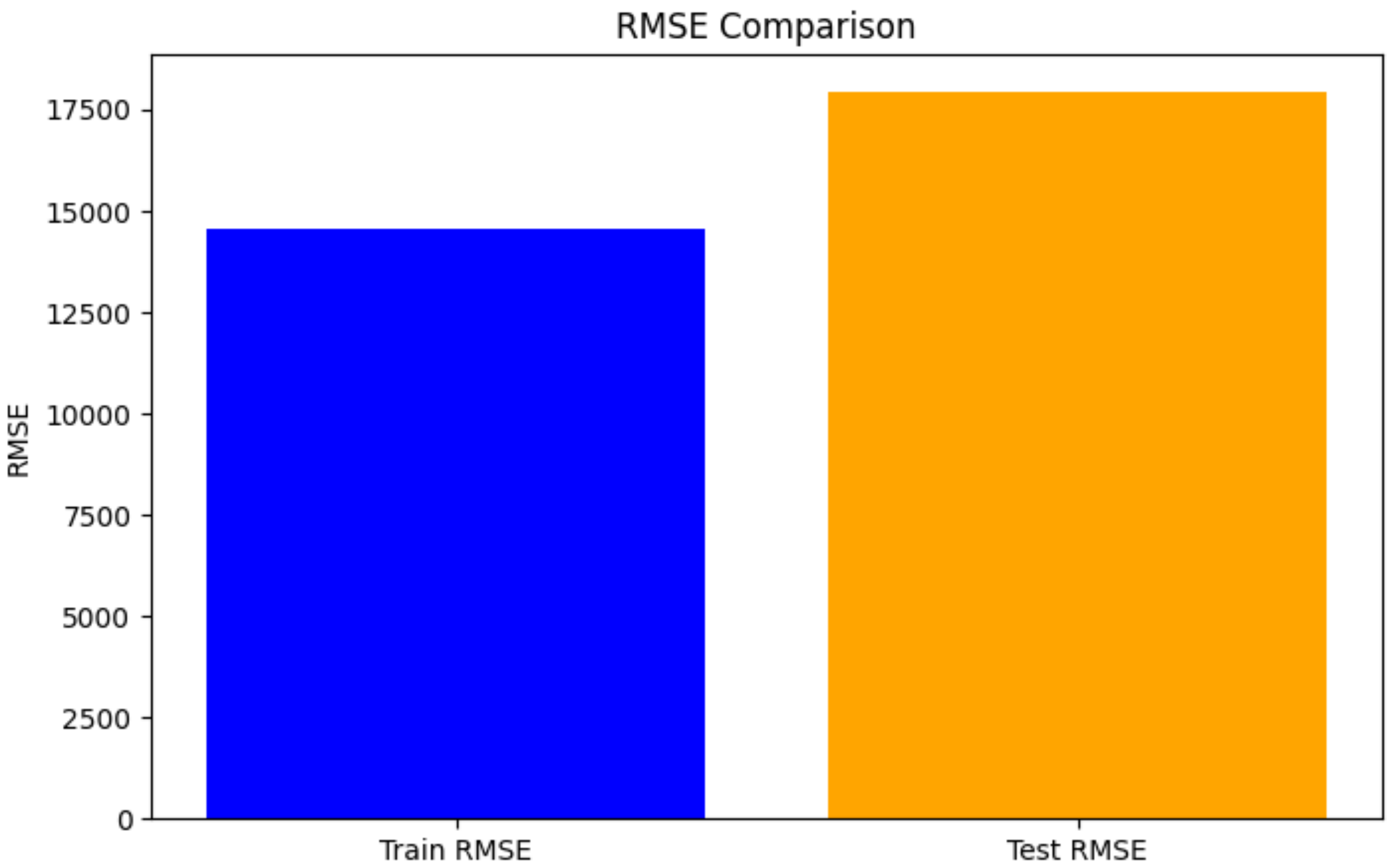


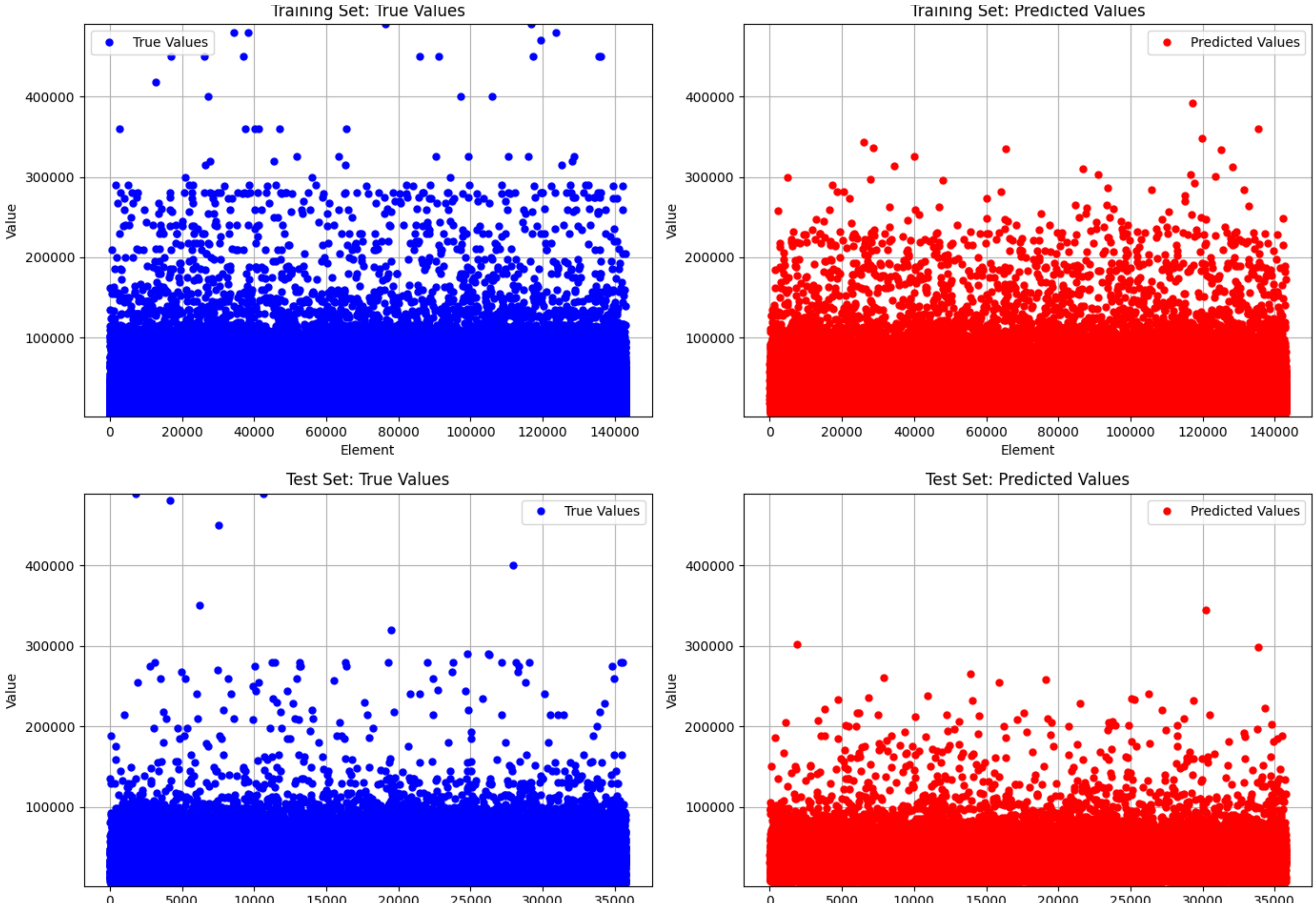
Multi Layer Perceptron Regressor used with Adama optimizer (default), adaptive learning rate and some hidden layers to capture non linearities (i tried using less layers but the model could not predict high prices, performing similarly to the Ridge Regressor). As for Grid Search, this model run into an error for the feature importance plot, but I had to keep the output that way due to the long time of the running.

In [61]:
```
from sklearn.neural_network import MLPRegressor
```

```
mlpr = MLPRegressor(random_state=random_state,
                    hidden_layer_sizes=(128, 256, 512, 256, 128),
                    max_iter=1000,
                    learning_rate='adaptive')

train_evaluate_model(mlpr, 'MLP Regressor', X_train, X_test, y_train, y_test, results, has_feature_importance=Tru
```

```
Train rmse 14572.15991344441
Test rmse 17955.450583250138
```



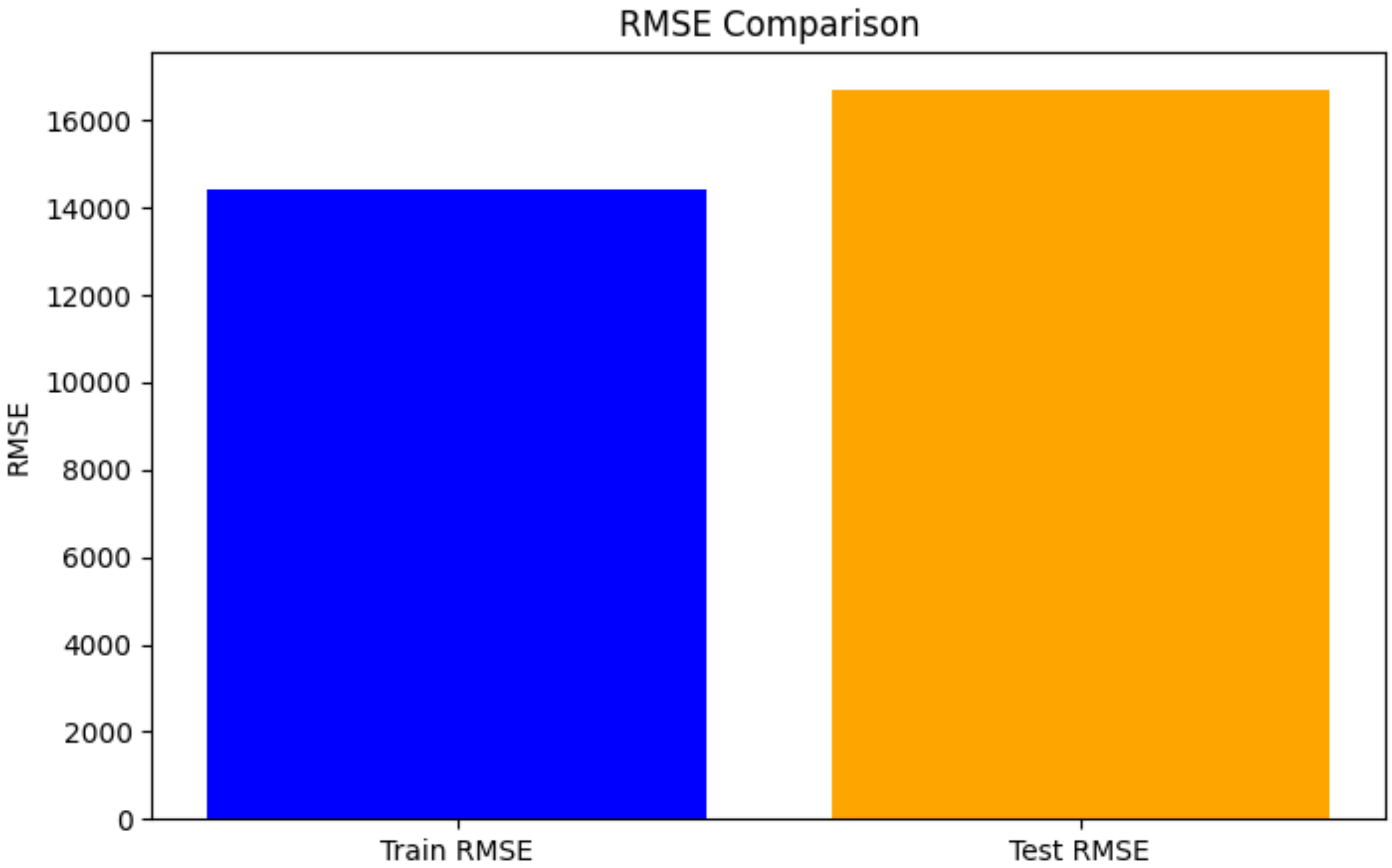

Training Set: True Values
True Values
Value
Element
Training Set: Predicted Values
Predicted Values
Value
Element
Test Set: True Values
True Values
Value
Test Set: Predicted Values
Predicted Values
Value

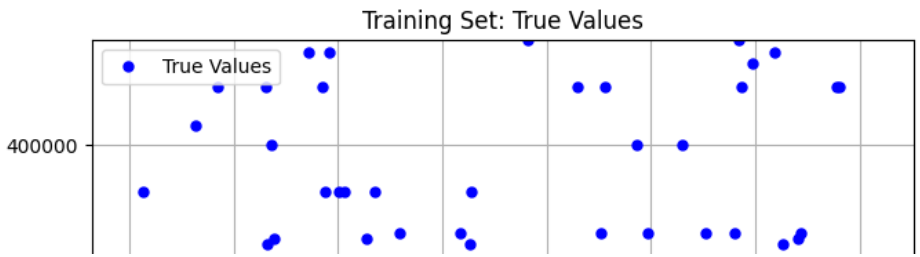

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[61], line 8
      1 from sklearn.neural_network import MLPRegressor
      3 mlpr = MLPRegressor(random_state=random_state,
      4                     hidden_layer_sizes=(128, 256, 512, 256, 128),
      5                     max_iter=1000,
      6                     learning_rate='adaptive')
----> 8 train_evaluate_model(mlpr, 'MLP Regressor', X_train, X_test, y_train, y_test, results, has_feature_import
ance=True)

Cell In[41], line 28, in train_evaluate_model(model, model_name, X_train, X_test, y_train, y_test, results, has_f
eature_importance, is_grid_search)
     26 # Plot feature importance if available
     27 if has_feature_importance:
---> 28     importance_values = model.feature_importances_ if hasattr(model, 'feature_importances_') else abs(mod
el.coef_)
     29     importances = pd.DataFrame({
     30         'feature': X_train.columns,
     31         'importance': importance_values
     32     })
     33     importances = importances.sort_values('importance', ascending=False)

AttributeError: 'MLPRegressor' object has no attribute 'coef_'
```

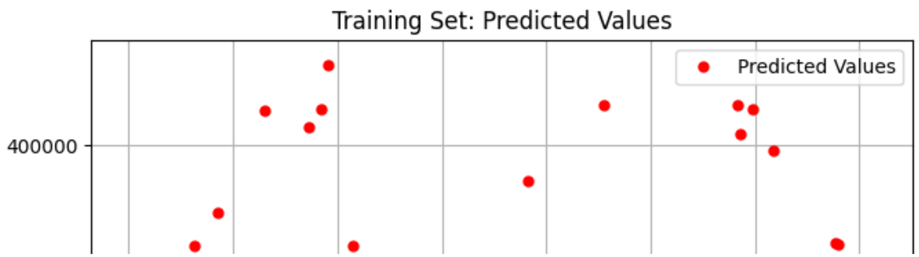
AdaBoost Regressor using Random Forest Regressor, in particular the one found previusly with the grid search.

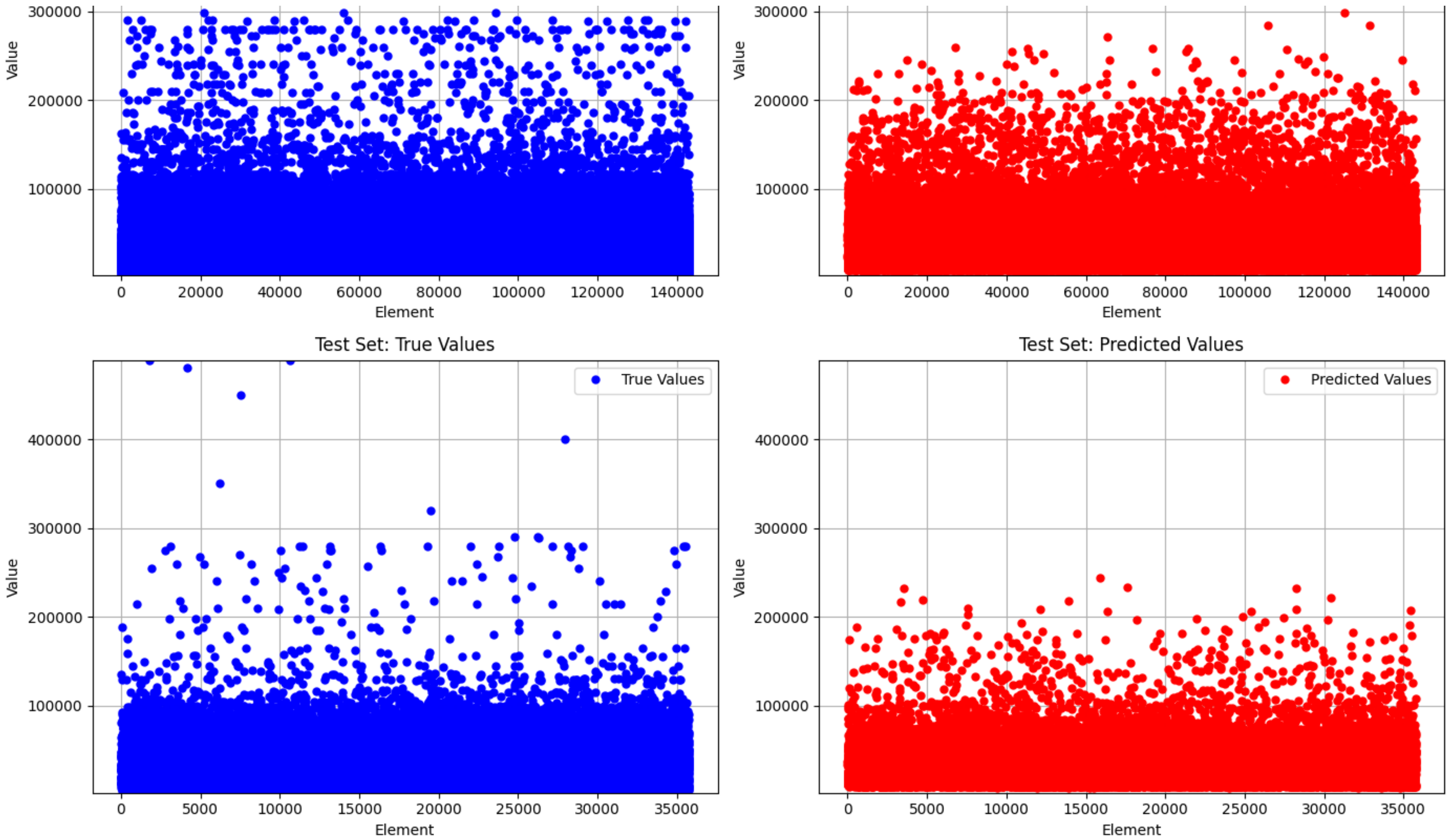
In [45]:
```
ab = AdaBoostRegressor(estimator=RandomForestRegressor(max_depth=12, min_samples_leaf=3, min_samples_split=14, ra
                       n_estimators=200,
                       random_state=random_state)

train_evaluate_model(ab, 'AdaBoost RF Regressor', X_train, X_test, y_train, y_test, results, has_feature_importa
```

```
Train rmse 14432.919157178276
Test rmse 16710.486194398163
```

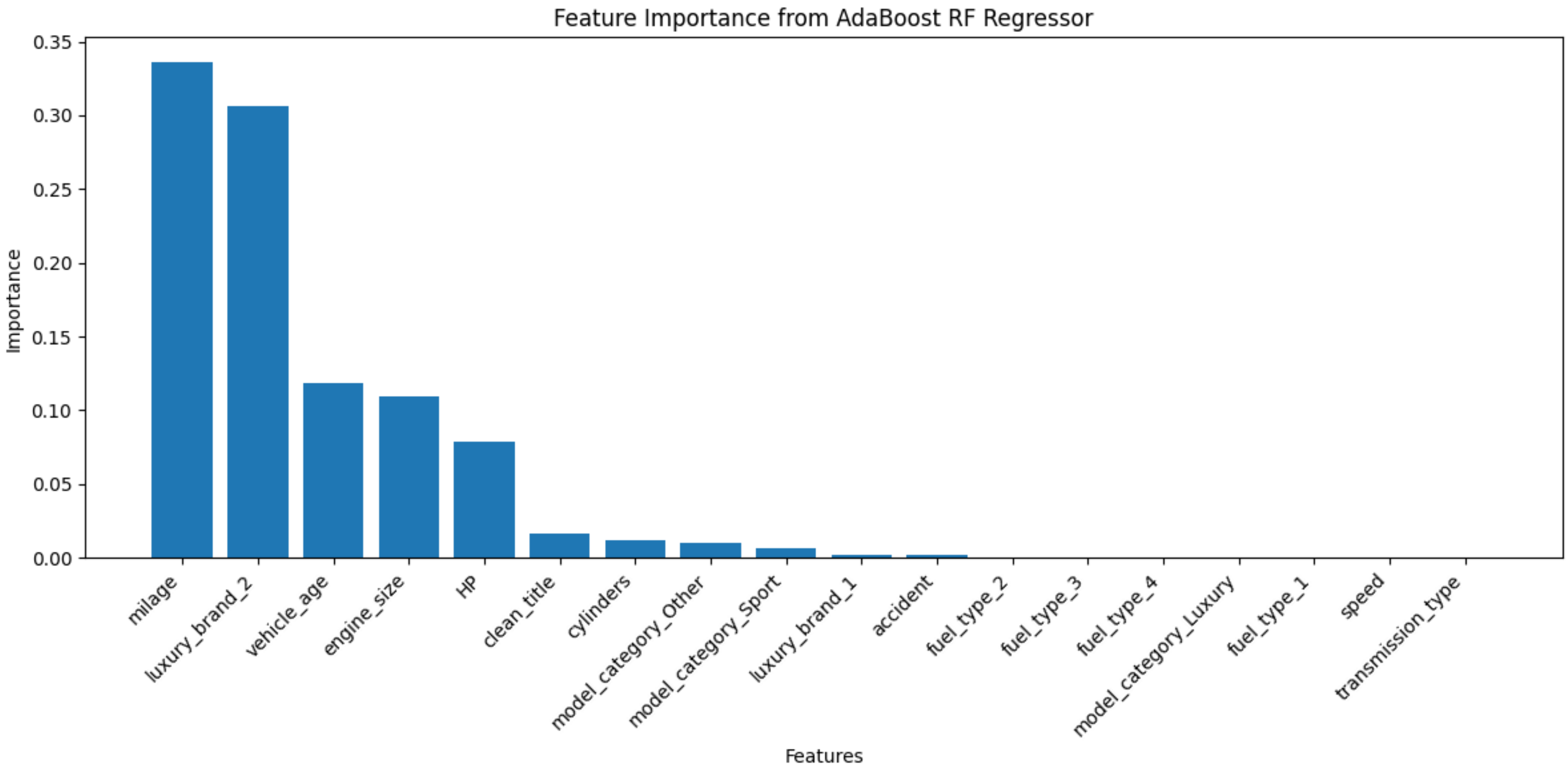








Value
Element
Test Set: True Values
True Values
Test Set: Predicted Values
Predicted Values



Below, the results obtained in the whole analysis

In [42]:
```
results.style.format(precision=0)
```

Out[42]:

	Model	Train RMSE	Test RMSE
0	Ridge Regressor	19192	18878
1	Random Forest Regressor	8134	17625
2	Random Forest Regressor GS	15130	16518
3	Ada Boost Regressor	19941	19990
4	MLP Regressor	17049	17043
5	AdaBoost RF Regressor	14433	16710

We can see that the best approach is using RandomForest Resgressor. In particular, the results found with the use of grid search is the best one (it also took a lot of running time being the search between many parameters). This approach does not suffer of overfitting, being the tran RMSE only 8% lower than the test RMSE. Also Adaboost using Random Forest performs very well, it overfits a bit. I think MLP could reach better results, but doing a grid search on it is time consuming being the scikit learn library not optimized to train them. The Rigde Regressor performed surprisingly well, probably due to the fact that most of the car prices are grouped in a small range of values (<30000) and therefore it predict them with a close value. This simple model do not catch the high prices as we can see from the plot of the predictions.