In [1]:
```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
sns.set_theme(color_codes=True)
```

In [2]:
```
df = pd.read_csv('Sport car price.csv')
df.head()
```

Out[2]:

	Car Make	Car Model	Year	Engine Size (L)	Horsepower	Torque (lb-ft)	0-60 MPH Time (seconds)	Price (in USD)
0	Porsche	911	2022	3	379	331	4	101,200
1	Lamborghini	Huracan	2021	5.2	630	443	2.8	274,390
2	Ferrari	488 GTB	2022	3.9	661	561	3	333,750
3	Audi	R8	2022	5.2	562	406	3.2	142,700
4	McLaren	720S	2021	4	710	568	2.7	298,000

Data Preprocessing Part 1

In [3]:
```
df.select_dtypes(include='object').nunique()
```

Out[3]:
```
Car Make                    38
Car Model                  176
Engine Size (L)             45
Horsepower                 124
Torque (lb-ft)              93
0-60 MPH Time (seconds)     43
Price (in USD)             367
dtype: int64
```

Remove Comma from Price (in USD)

In [4]:
```
# remove commas from the Price column
df['Price (in USD)'] = df['Price (in USD)'].str.replace(',', '')
# convert the Price column to integer
df['Price (in USD)'] = df['Price (in USD)'].astype(int)
df['Price (in USD)'].dtypes
```

Out[4]:
```
dtype('int32')
```

In [5]:
```
df.head()
```

Out[5]:

	Car Make	Car Model	Year	Engine Size (L)	Horsepower	Torque (lb-ft)	0-60 MPH Time (seconds)	Price (in USD)
0	Porsche	911	2022	3	379	331	4	101200
1	Lamborghini	Huracan	2021	5.2	630	443	2.8	274390
2	Ferrari	488 GTB	2022	3.9	661	561	3	333750
3	Audi	R8	2022	5.2	562	406	3.2	142700
4	McLaren	720S	2021	4	710	568	2.7	298000

Change numerical data into integer

In [6]:
```
# remove commas from 0-60 MPH Time (seconds) column
df['0-60 MPH Time (seconds)'] = df['0-60 MPH Time (seconds)'].str.replace(',', '')

# check if the Horsepower column contains string values
if df['Horsepower'].dtype == 'object':
    # remove strings from the Column A column
    df['Horsepower'] = df['Horsepower'].str.replace('[^0-9]+', '', regex=True)

    # convert the remaining values to integers and fill empty strings with 0
    df['Horsepower'] = df['Horsepower'].apply(lambda x: int(x) if x != '' else 0)
else:
    # do something else if the Column A column does not contain string values
    pass

# check if the Horsepower column contains string values
if df['Torque (lb-ft)'].dtype == 'object':
    # remove strings from the Column A column
    df['Torque (lb-ft)'] = df['Torque (lb-ft)'].str.replace('[^0-9]+', '', regex=True)

    # convert the remaining values to integers and fill empty strings with 0
    df['Torque (lb-ft)'] = df['Torque (lb-ft)'].fillna(0)
    df['Torque (lb-ft)'] = df['Torque (lb-ft)'].apply(lambda x: int(x) if x != '' else 0)
else:
    # do something else if the Column A column does not contain string values
    pass

# check if the Horsepower column contains string values
if df['0-60 MPH Time (seconds)'].dtype == 'object':
    # remove strings from the Column A column
    df['0-60 MPH Time (seconds)'] = df['0-60 MPH Time (seconds)'].str.replace('[^0-9]+', '', r

    # convert the remaining values to integers and fill empty strings with 0
    df['0-60 MPH Time (seconds)'] = df['0-60 MPH Time (seconds)'].apply(lambda x: int(x) if x
else:
    # do something else if the Column A column does not contain string values
    pass


# Change numerical data into integer
df['Horsepower'] = df['Horsepower'].astype(int)
df['Torque (lb-ft)'] = df['Torque (lb-ft)'].astype(int)
df['0-60 MPH Time (seconds)'] = df['0-60 MPH Time (seconds)'].astype(float)

# convert the remaining values to integers and fill empty strings with 0
#df['Torque (lb-ft)'] = df['Torque (lb-ft)'].apply(lambda x: int(x) if x != '' else 0)

df.dtypes
```

Out[6]:
```
Car Make                    object
Car Model                   object
Year                         int64
Engine Size (L)             object
Horsepower                   int32
Torque (lb-ft)               int32
0-60 MPH Time (seconds)    float64
Price (in USD)               int32
dtype: object
```

Change Engine Size into integer

In [7]:
```
df['Engine Size (L)'].unique()
```

Out[7]:
```
array(['3', '5.2', '3.9', '4', '4.4', '6.2', '3.8', '8', '5', '3.5',
       '4.7', '2', '2.9', '6', 'Electric', '6.5', '3.7', 'Electric Motor',
       '2.5', '1.5 + Electric', '6.8', '8.4', nan, '6.6', '7', '1.7',
       '3.3', '-', '6.7', '1.8', 'Electric (tri-motor)', '5.5',
       'Electric (93 kWh)', 'Electric (100 kWh)', 'Hybrid (4.0)', '4.6',
       '3.6', '1.5', 'Hybrid', '5.7', '2.0 (Electric)', '4.0 (Hybrid)',
       '0', '6.4', '6.3', '2.3'], dtype=object)
```

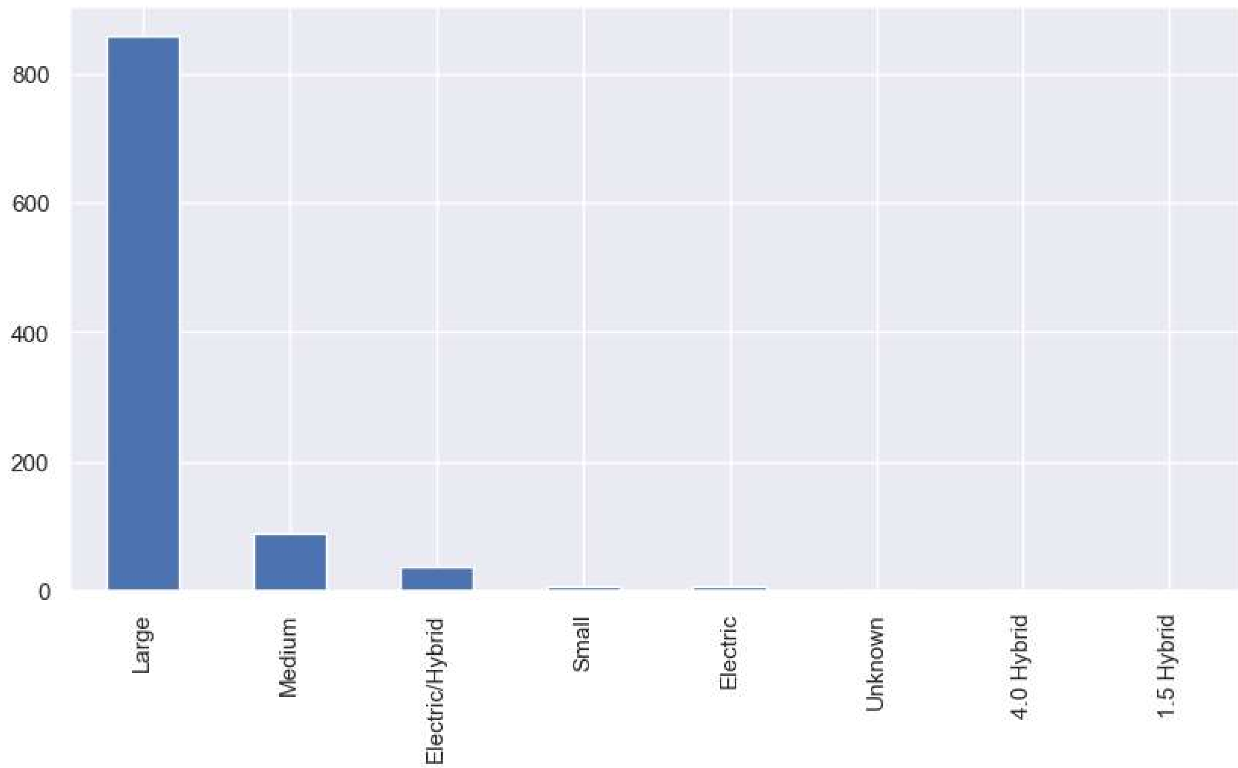
In [8]:
```
def segment_engine_size(engine_size):
    if engine_size in ['Electric', 'Hybrid']:
        return 'Electric/Hybrid'
    elif engine_size in ['Electric Motor', 'Electric (tri-motor)', 'Electric (93 kWh)', 'Electr
        return 'Electric'
    elif engine_size == '1.5 + Electric':
        return '1.5 Hybrid'
    elif engine_size in ['Hybrid (4.0)', '4.0 (Hybrid)']:
        return '4.0 Hybrid'
    elif engine_size == '0':
        return 'Unknown'
    elif engine_size == '-':
        return 'Unknown'
    elif float(engine_size) < 2:
        return 'Small'
    elif float(engine_size) < 3:
        return 'Medium'
    else:
        return 'Large'
df['Engine Size (L)'] = df['Engine Size (L)'].apply(segment_engine_size)
```

In [9]:
```
df['Engine Size (L)'].unique()
```

Out[9]:
```
array(['Large', 'Medium', 'Electric/Hybrid', 'Electric', '1.5 Hybrid',
       'Small', 'Unknown', '4.0 Hybrid'], dtype=object)
```

In [10]:
```
plt.figure(figsize=(10,5))
df['Engine Size (L)'].value_counts().plot(kind='bar')
```

Out[10]: <AxesSubplot:>



Remove Car Model because its irrelevant and have alot of unique value

In [11]:
```
df.drop(columns='Car Model', inplace=True)
df.head()
```

Out[11]:

	Car Make	Year	Engine Size (L)	Horsepower	Torque (lb-ft)	0-60 MPH Time (seconds)	Price (in USD)
0	Porsche	2022	Large	379	331	4.0	101200
1	Lamborghini	2021	Large	630	443	28.0	274390
2	Ferrari	2022	Large	661	561	3.0	333750
3	Audi	2022	Large	562	406	32.0	142700
4	McLaren	2021	Large	710	568	27.0	298000

Segment Car Make

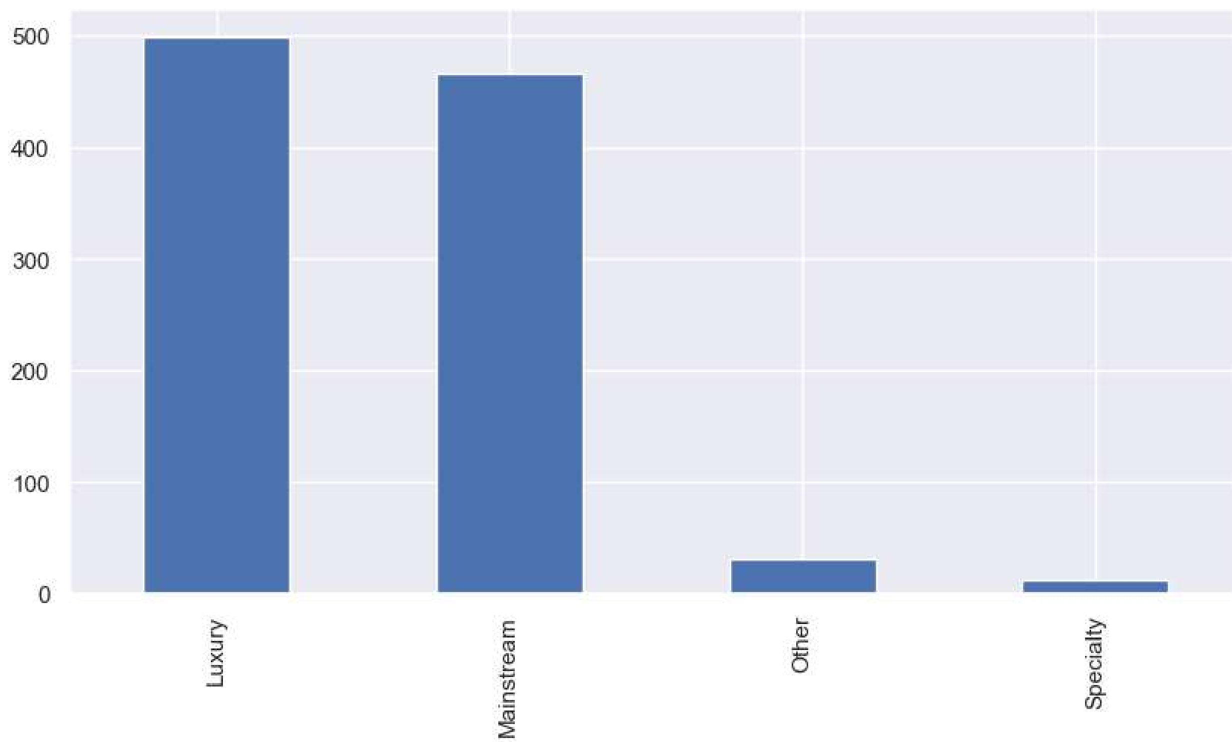
In [12]:
```
df['Car Make'].unique()
```

Out[12]:
```
array(['Porsche', 'Lamborghini', 'Ferrari', 'Audi', 'McLaren', 'BMW',
       'Mercedes-Benz', 'Chevrolet', 'Ford', 'Nissan', 'Aston Martin',
       'Bugatti', 'Dodge', 'Jaguar', 'Koenigsegg', 'Lexus', 'Lotus',
       'Maserati', 'Alfa Romeo', 'Ariel', 'Bentley', 'Mercedes-AMG',
       'Pagani', 'Polestar', 'Rimac', 'Acura', 'Mazda', 'Rolls-Royce',
       'Tesla', 'Toyota', 'W Motors', 'Shelby', 'TVR', 'Subaru',
       'Pininfarina', 'Kia', 'Alpine', 'Ultima'], dtype=object)
```

In [13]:
```
# define a function to segment the values
def segment_car_make(value):
    if value in ['Porsche', 'Lamborghini', 'Ferrari', 'McLaren', 'Aston Martin', 'Bugatti', 'Ko
        return 'Luxury'
    elif value in ['Audi', 'BMW', 'Mercedes-Benz', 'Chevrolet', 'Ford', 'Nissan', 'Dodge', 'Ja
        return 'Mainstream'
    elif value in ['Ariel', 'W Motors', 'Shelby', 'TVR', 'Subaru', 'Alpine', 'Ultima']:
        return 'Specialty'
    else:
        return 'Other'

# apply the function to the Car Make column
df['Car Make'] = df['Car Make'].apply(segment_car_make)
```

In [14]:
```
plt.figure(figsize=(10,5))
df['Car Make'].value_counts().plot(kind='bar')
```

Out[14]: <AxesSubplot:>



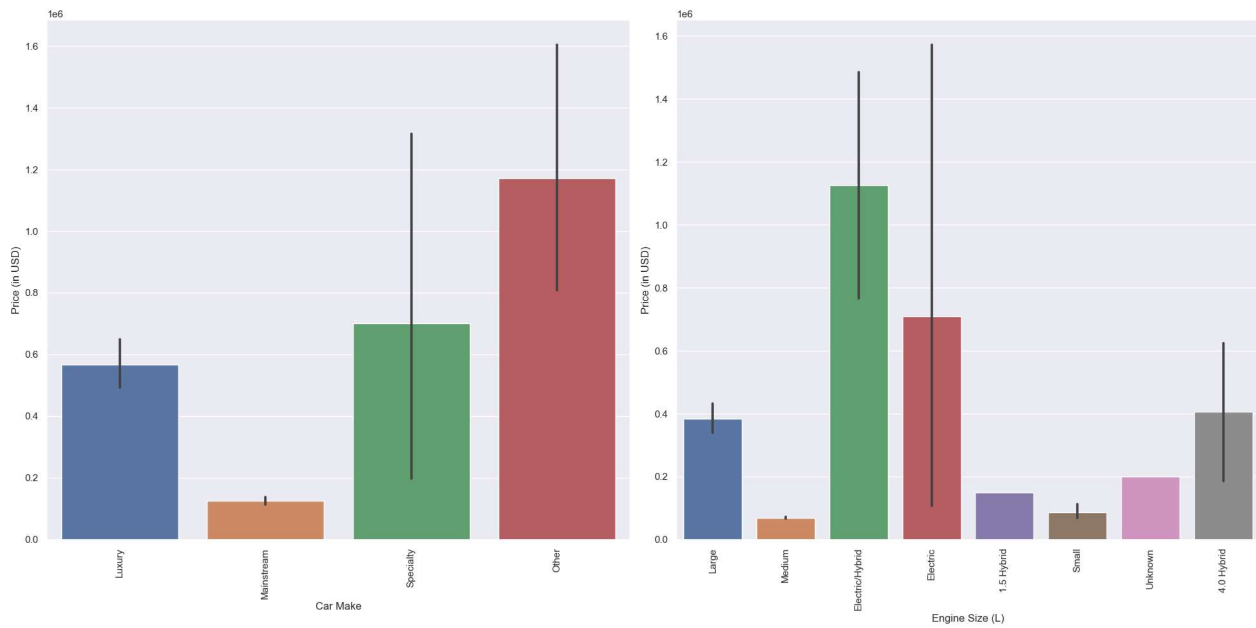
In [15]:
```
df.head()
```

Out[15]:

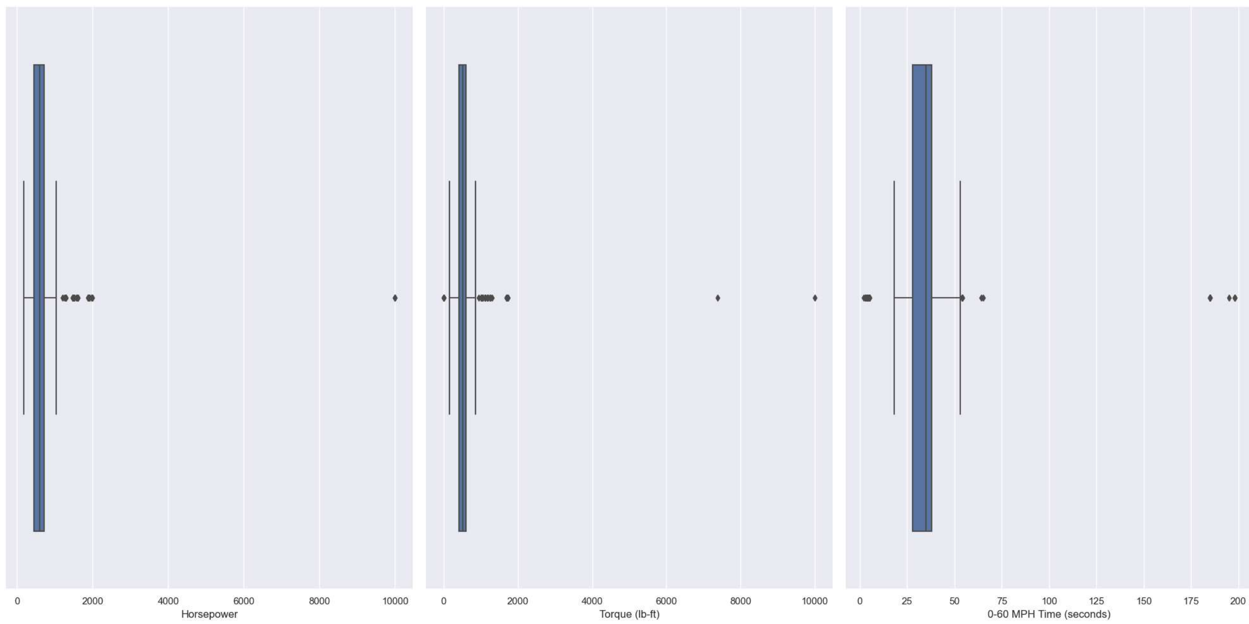
	Car Make	Year	Engine Size (L)	Horsepower	Torque (lb-ft)	0-60 MPH Time (seconds)	Price (in USD)
0	Luxury	2022	Large	379	331	4.0	101200
1	Luxury	2021	Large	630	443	28.0	274390
2	Luxury	2022	Large	661	561	3.0	333750
3	Mainstream	2022	Large	562	406	32.0	142700
4	Luxury	2021	Large	710	568	27.0	298000

Exploratory Data Analysis

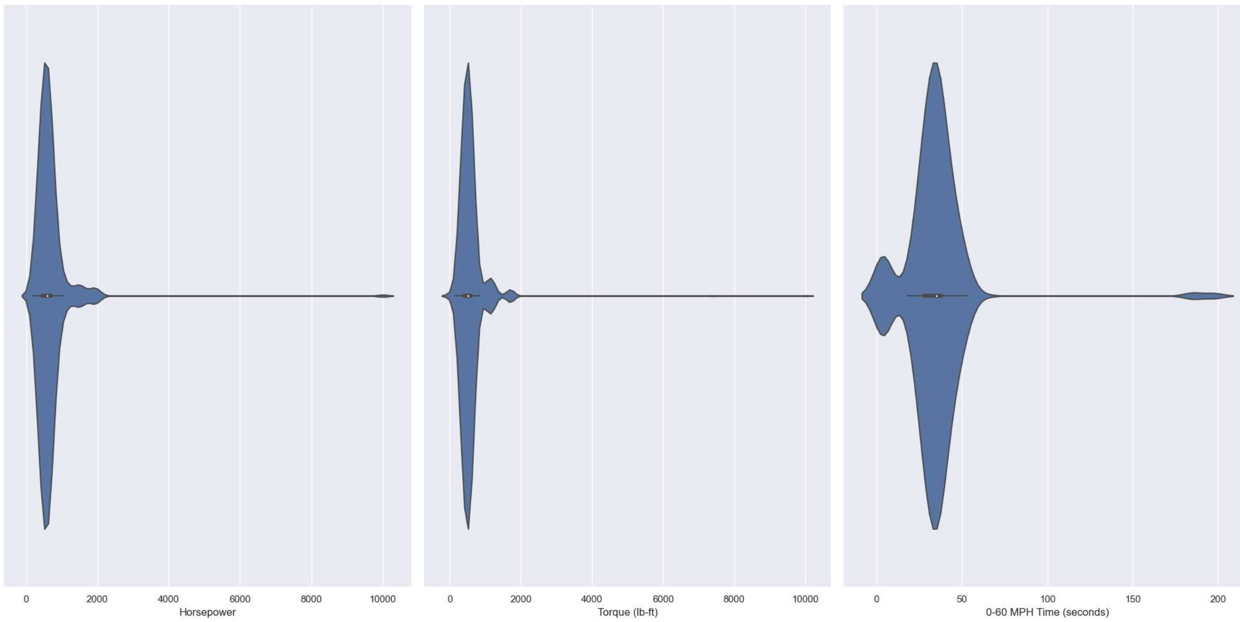
In [16]:
```
# list of categorical variables to plot
cat_vars = ['Car Make', 'Engine Size (L)']

# create figure with subplots
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20, 10))
axs = axs.flatten()

# create barplot for each categorical variable
for i, var in enumerate(cat_vars):
    sns.barplot(x=var, y='Price (in USD)', data=df, ax=axs[i])
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# adjust spacing between subplots
fig.tight_layout()

# show plot
plt.show()
```



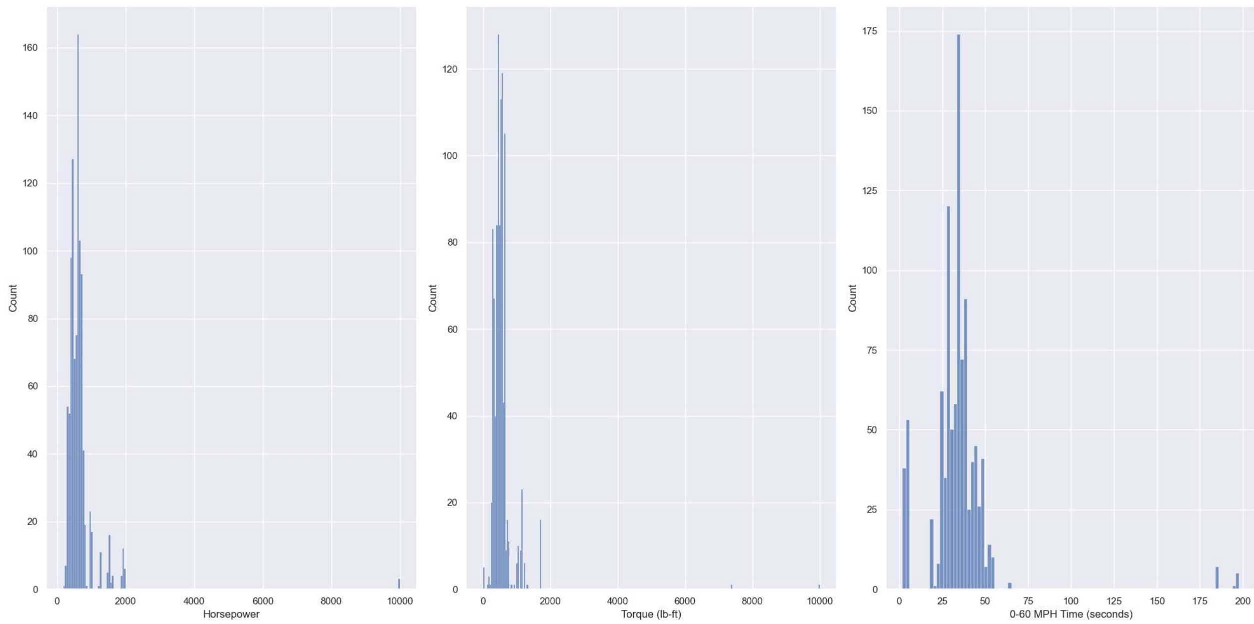
In [17]:
```
num_vars = ['Horsepower', 'Torque (lb-ft)', '0-60 MPH Time (seconds)']

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 10))
axs = axs.flatten()

#Show the boxplot
for i, var in enumerate(num_vars):
    sns.boxplot(x=var, data=df, ax=axs[i])

# adjust spacing between subplots
fig.tight_layout()

plt.show()
```



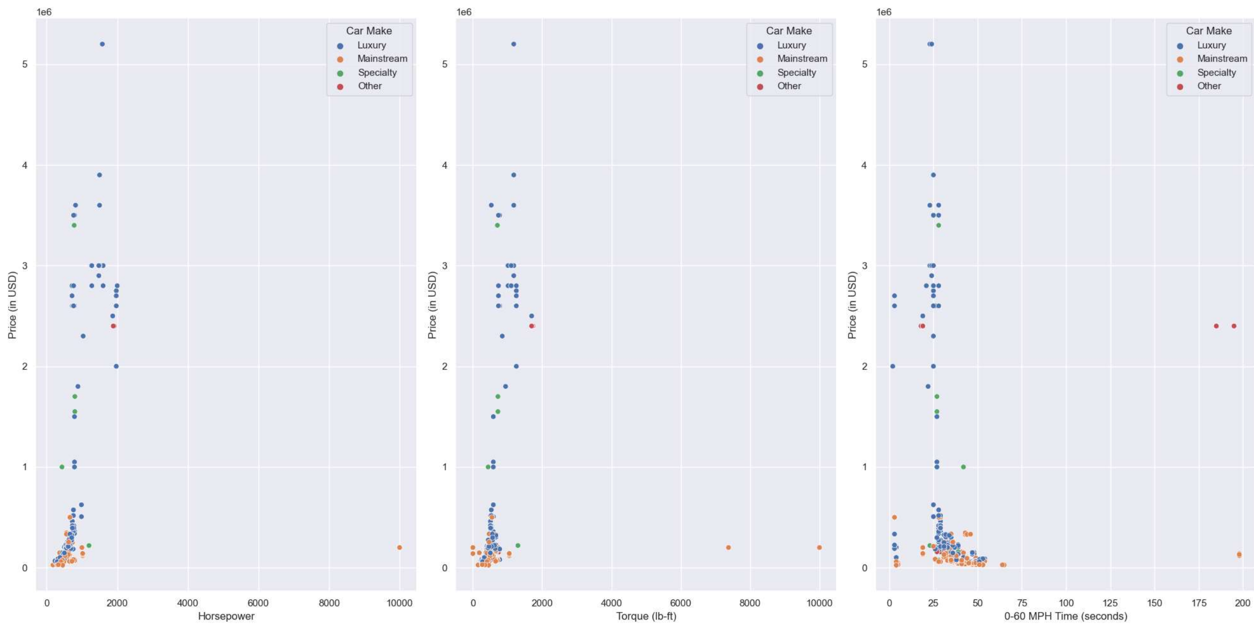
In [18]:
```
num_vars = ['Horsepower', 'Torque (lb-ft)', '0-60 MPH Time (seconds)']

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.violinplot(x=var, data=df, ax=axs[i])

fig.tight_layout()

plt.show()
```



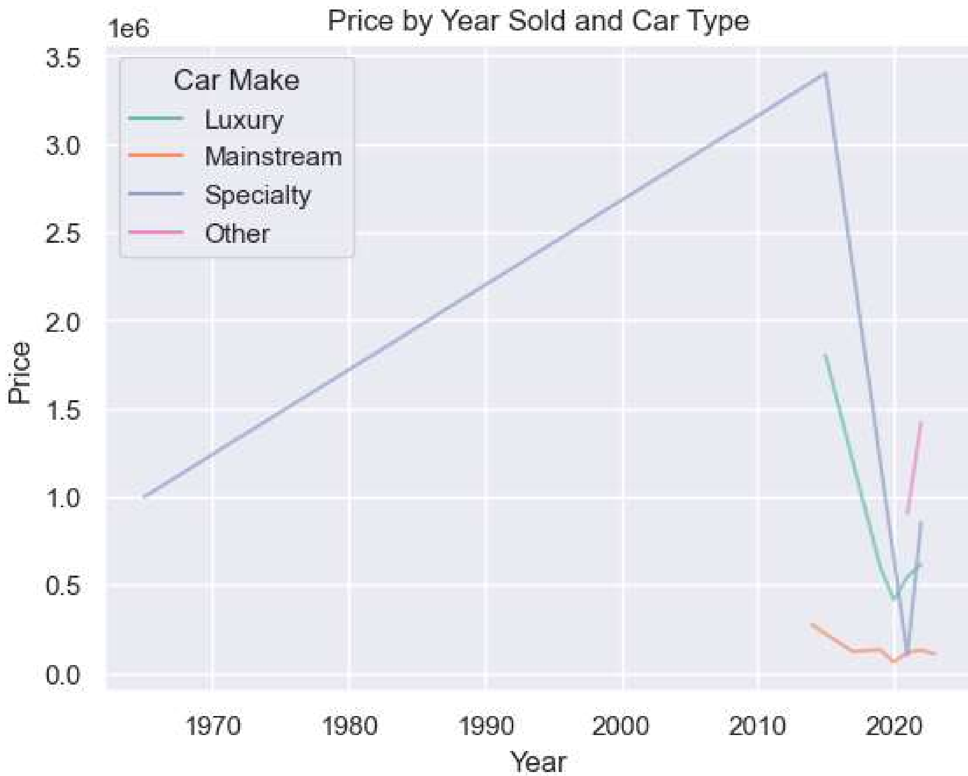
In [19]:
```
num_vars = ['Horsepower', 'Torque (lb-ft)', '0-60 MPH Time (seconds)']

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.histplot(x=var, data=df, ax=axs[i])

fig.tight_layout()

plt.show()
```



In [20]:
```
num_vars = ['Horsepower', 'Torque (lb-ft)', '0-60 MPH Time (seconds)']

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.scatterplot(x=var, y='Price (in USD)', hue='Car Make', data=df, ax=axs[i])

fig.tight_layout()

plt.show()
```



In [21]:
```
sns.set_style("darkgrid")
sns.set_palette("Set2")

sns.lineplot(x='Year', y='Price (in USD)', hue='Car Make', data=df, ci=None, estimator='mean',

plt.title("Price by Year Sold and Car Type")
plt.xlabel("Year")
plt.ylabel("Price")

plt.show()
```



Data Preprocessing Part 2

In [22]:
```
df.head()
```

Out[22]:

	Car Make	Year	Engine Size (L)	Horsepower	Torque (lb-ft)	0-60 MPH Time (seconds)	Price (in USD)
0	Luxury	2022	Large	379	331	4.0	101200
1	Luxury	2021	Large	630	443	28.0	274390
2	Luxury	2022	Large	661	561	3.0	333750
3	Mainstream	2022	Large	562	406	32.0	142700
4	Luxury	2021	Large	710	568	27.0	298000

In [23]:
```
#Check missing value
check_missing = df.isnull().sum() * 100 / df.shape[0]
check_missing[check_missing > 0].sort_values(ascending=False)
```

Out[23]:
```
Series([], dtype: float64)
```

Label Encoding for Object datatype

In [24]:
```
# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Print the column name and the unique values
    print(f"{col}: {df[col].unique()}")
```

```
Car Make: ['Luxury' 'Mainstream' 'Specialty' 'Other']
Engine Size (L): ['Large' 'Medium' 'Electric/Hybrid' 'Electric' '1.5 Hybrid' 'Small'
 'Unknown' '4.0 Hybrid']
```

In [25]:
```
from sklearn import preprocessing

# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Initialize a LabelEncoder object
    label_encoder = preprocessing.LabelEncoder()

    # Fit the encoder to the unique values in the column
    label_encoder.fit(df[col].unique())

    # Transform the column using the encoder
    df[col] = label_encoder.transform(df[col])

    # Print the column name and the unique encoded values
    print(f"{col}: {df[col].unique()}")
```

```
Car Make: [0 1 3 2]
Engine Size (L): [4 5 3 2 0 6 7 1]
```

Train Test Split

In [26]:
```
from sklearn.model_selection import train_test_split

X = df.drop('Price (in USD)', axis=1)
y = df['Price (in USD)']

# split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

Remove Outlier from Train data using IQR

In [27]:
```
# calculate the interquartile range for each feature
q1 = np.percentile(X_train, 25, axis=0)
q3 = np.percentile(X_train, 75, axis=0)
iqr = q3 - q1

# identify outliers using the IQR method
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr
outliers = np.logical_or(X_train < lower_bound, X_train > upper_bound)

# remove the outliers from the training set
X_train = X_train[~np.any(outliers, axis=1)]
y_train = y_train[~np.any(outliers, axis=1)]
```

In [28]:
```
X_train.shape
```

Out[28]:
```
(560, 6)
```

In [29]:
```
y_train.shape
```

Out[29]:
```
(560,)
```

In [30]:
```
X_train.head()
```

Out[30]:

	Car Make	Year	Engine Size (L)	Horsepower	Torque (lb-ft)	0-60 MPH Time (seconds)
767	1	2022	4	444	406	38.0
764	0	2021	4	612	561	34.0
529	1	2021	4	720	590	31.0
252	0	2021	4	592	457	28.0
451	0	2021	4	626	664	33.0

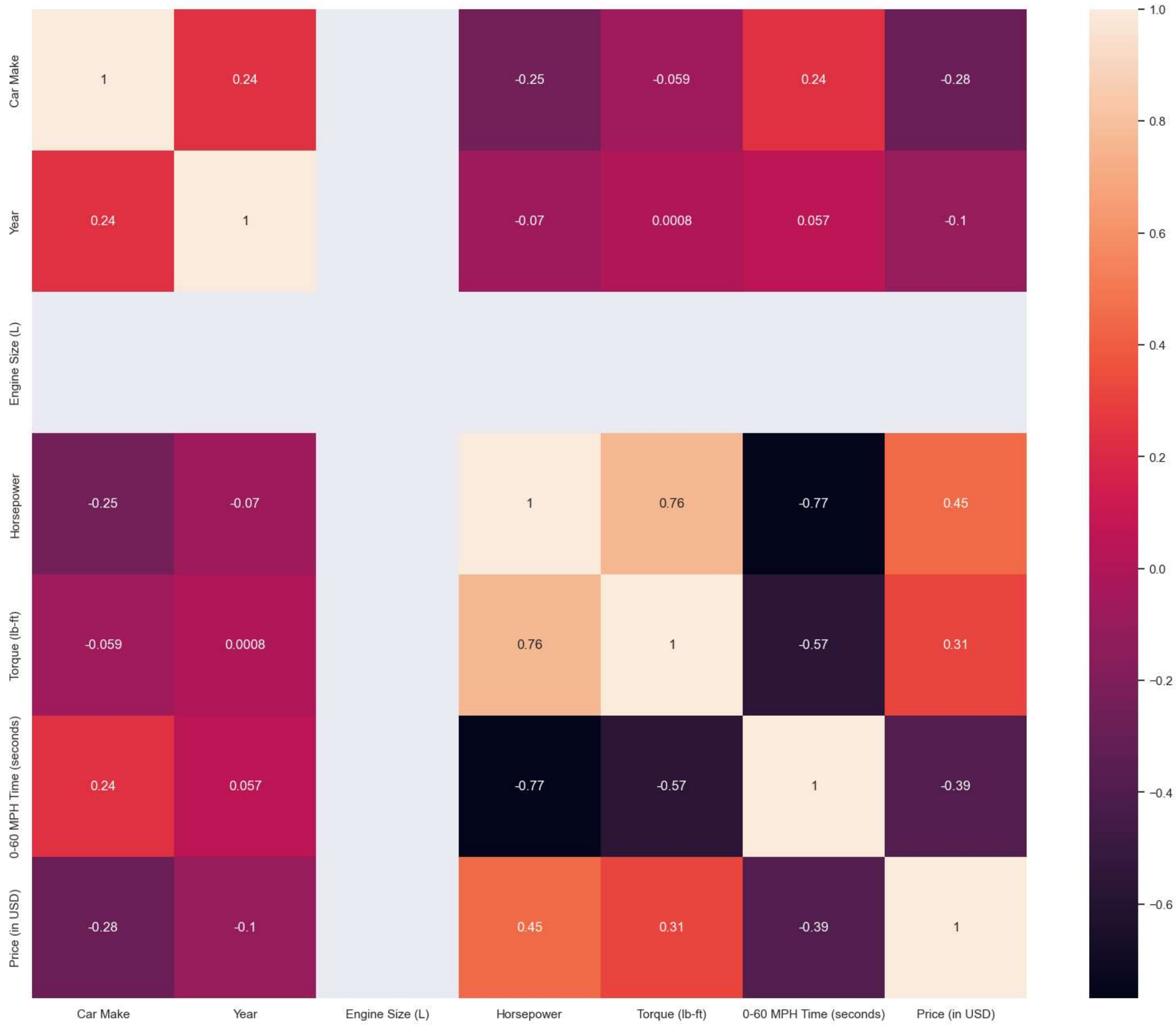
In [31]:
```
y_train.head()
```

Out[31]:
```
767     84595
764    235000
529    325000
252    256500
451    220000
Name: Price (in USD), dtype: int32
```

Correlation heatmap

In [32]:
```
# concatenate X_train and y_train
train_data = pd.concat([X_train, y_train], axis=1)

#Correlation Heatmap
plt.figure(figsize=(20, 16))
sns.heatmap(train_data.corr(), fmt='.2g', annot=True)
```

Out[32]: <AxesSubplot:>



In [33]:
```
# Remove Engine Size (L) because it has 0 correlation
X_train.drop(columns='Engine Size (L)', inplace=True)
X_train.head()
```

Out[33]:

	Car Make	Year	Horsepower	Torque (lb-ft)	0-60 MPH Time (seconds)
767	1	2022	444	406	38.0
764	0	2021	612	561	34.0
529	1	2021	720	590	31.0
252	0	2021	592	457	28.0
451	0	2021	626	664	33.0

In [34]:
```
# Remove Engine Size (L) because it has 0 correlation
X_test.drop(columns='Engine Size (L)', inplace=True)
X_test.head()
```

Out[34]:

	Car Make	Year	Horsepower	Torque (lb-ft)	0-60 MPH Time (seconds)
799	0	2021	503	505	35.0
311	1	2021	650	650	35.0
85	0	2022	1500	1180	24.0
435	0	2021	1262	1106	25.0
204	0	2022	325	332	53.0

In [35]:
```
X_train.shape
```

Out[35]:
```
(560, 5)
```

Decision Tree Regressor

In [36]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.datasets import load_boston


# Create a DecisionTreeRegressor object
dtree = DecisionTreeRegressor()

# Define the hyperparameters to tune and their values
param_grid = {
    'max_depth': [2, 4, 6, 8],
    'min_samples_split': [2, 4, 6, 8],
    'min_samples_leaf': [1, 2, 3, 4],
    'max_features': ['auto', 'sqrt', 'log2'],
    'random_state':[0, 42]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(dtree, param_grid, cv=5, scoring='neg_mean_squared_error')

# Fit the GridSearchCV object to the data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)
```

```
{'max_depth': 8, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_split': 6, 'rand
om_state': 0}
```

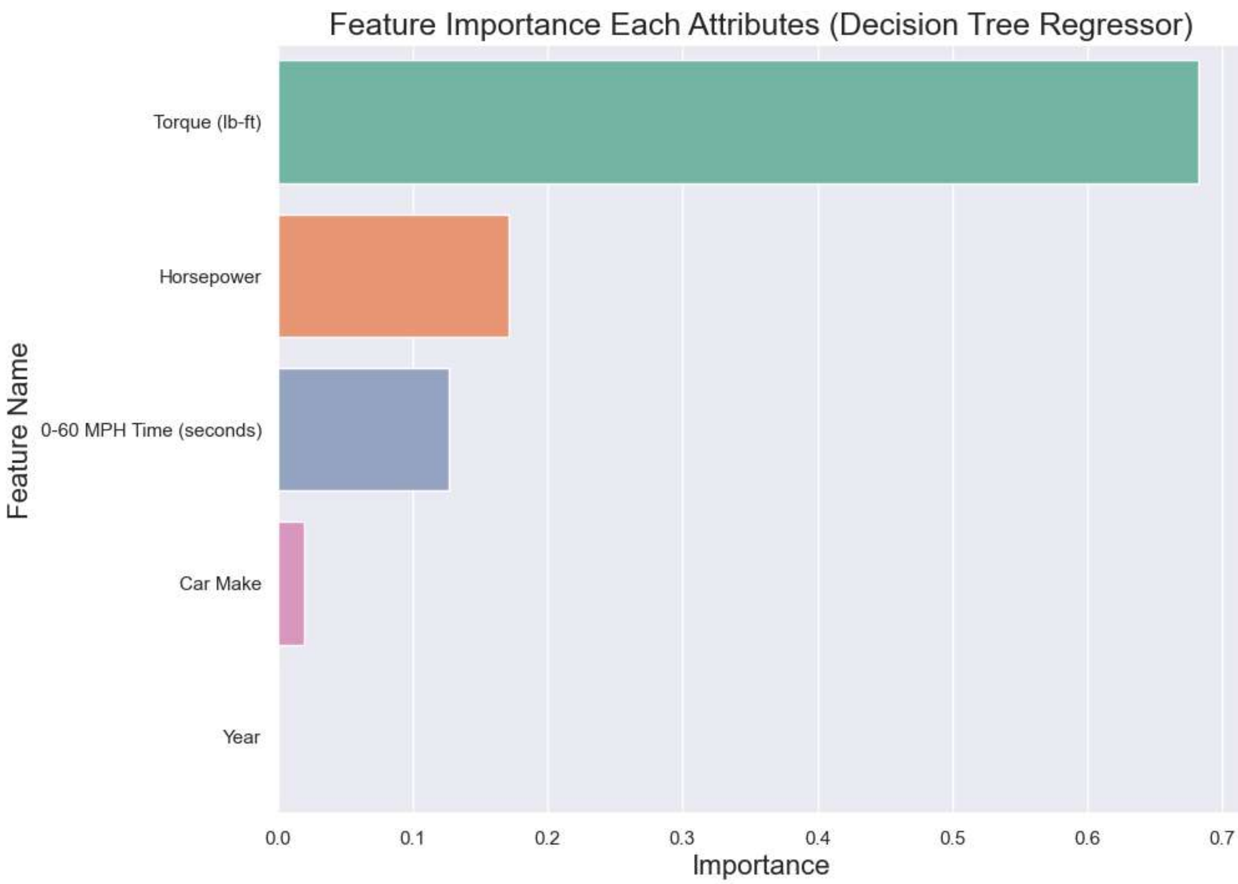
In [37]:
```
from sklearn.tree import DecisionTreeRegressor
dtree = DecisionTreeRegressor(random_state=0, max_depth=8, max_features='auto', min_samples_lea
dtree.fit(X_train, y_train)
```

Out[37]:
```
DecisionTreeRegressor(max_depth=8, max_features='auto', min_samples_split=6,
                      random_state=0)
```

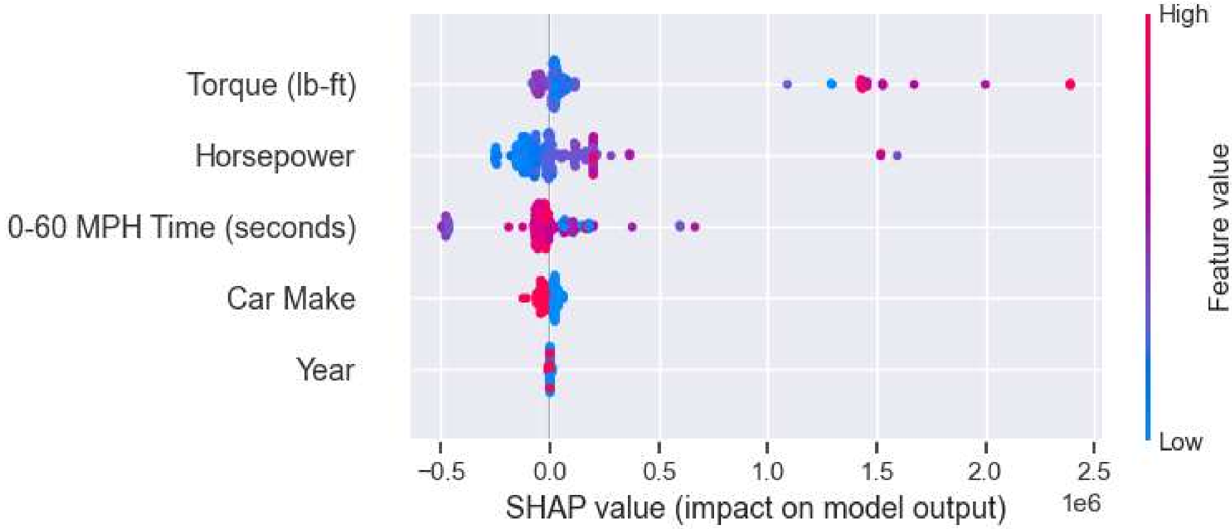
In [38]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = dtree.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 236035.63646431145
MAPE is 0.8031919449888023
MSE is 446587710382.5396
R2 score is 0.24660092968005953
RMSE score is 668272.1828585563
```

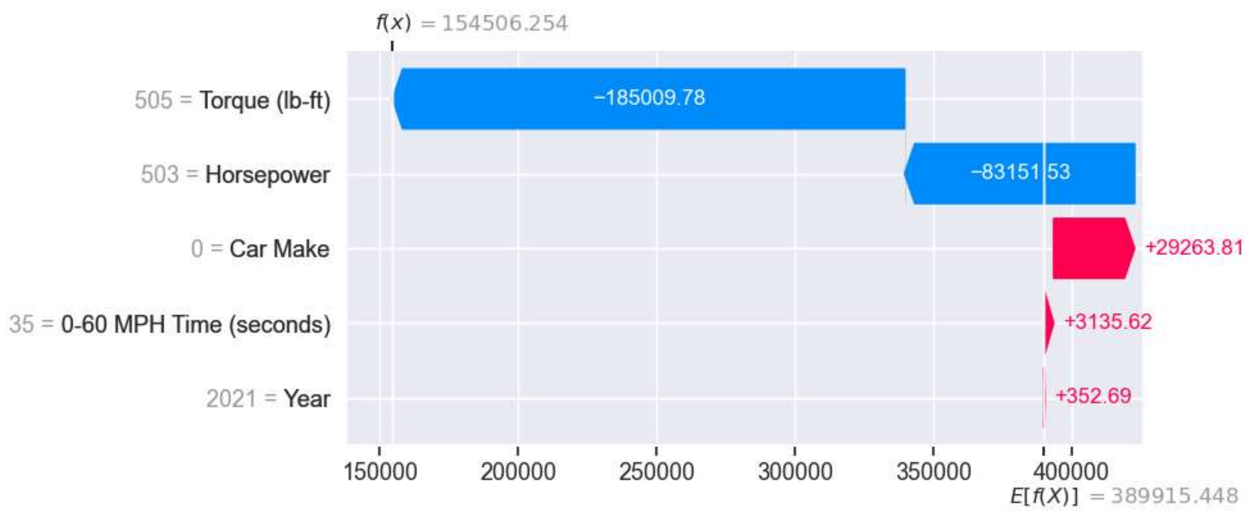
In [39]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (Decision Tree Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [40]:
```
import shap
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



In [41]:
```
explainer = shap.Explainer(dtree, X_test)
shap_values = explainer(X_test)
shap.plots.waterfall(shap_values[0])
```



Random Forest Regressor

In [42]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV

# Create a Random Forest Regressor object
rf = RandomForestRegressor()

# Define the hyperparameter grid
param_grid = {
    'max_depth': [3, 5, 7, 9],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt'],
    'random_state': [0, 42]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='r2')

# Fit the GridSearchCV object to the training data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print("Best hyperparameters: ", grid_search.best_params_)
```

```
Best hyperparameters:  {'max_depth': 9, 'max_features': 'sqrt', 'min_samples_leaf': 2, 'min_s
amples_split': 2, 'random_state': 0}
```

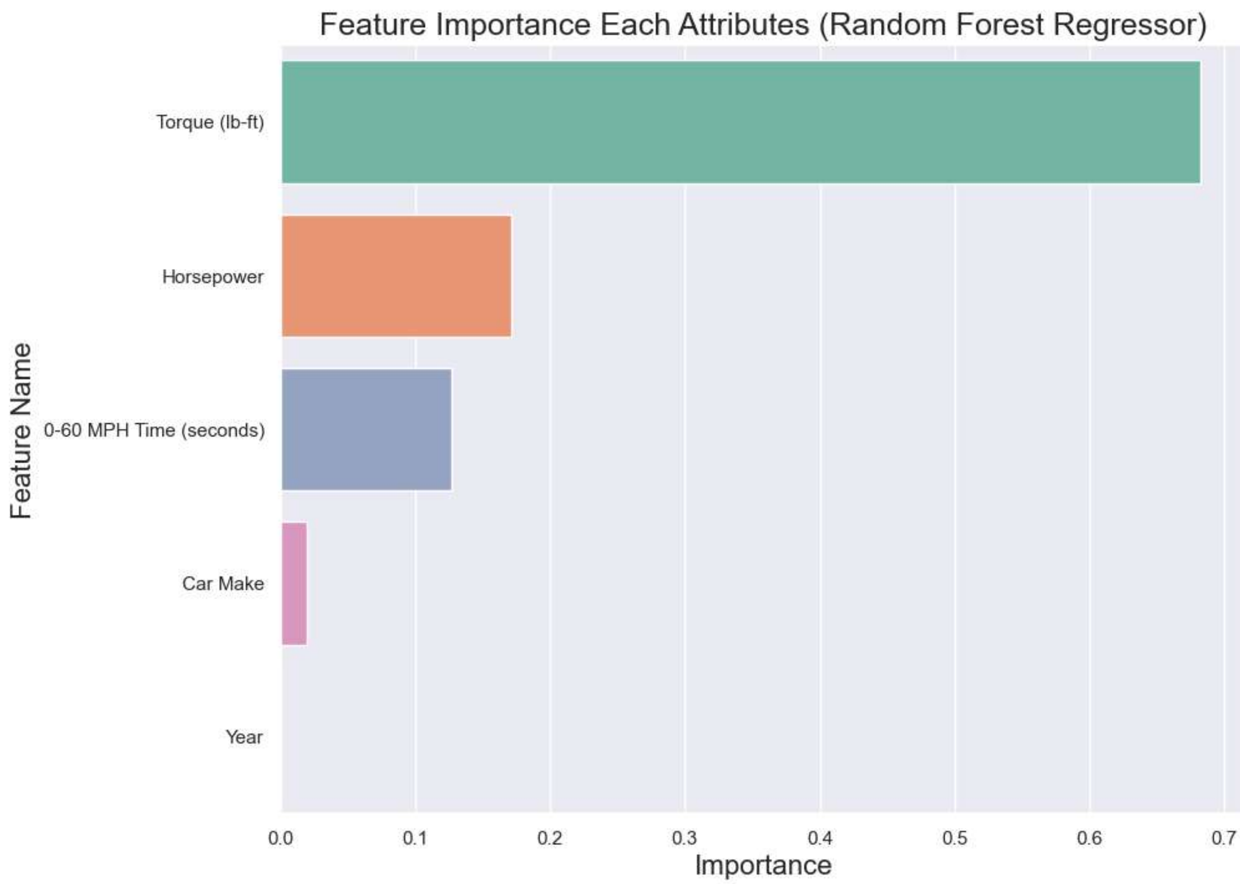
In [43]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(random_state=0, max_depth=9, min_samples_split=2, min_samples_leaf=:
                           max_features='sqrt')
rf.fit(X_train, y_train)
```

Out[43]:
```
RandomForestRegressor(max_depth=9, max_features='sqrt', min_samples_leaf=2,
                      random_state=0)
```

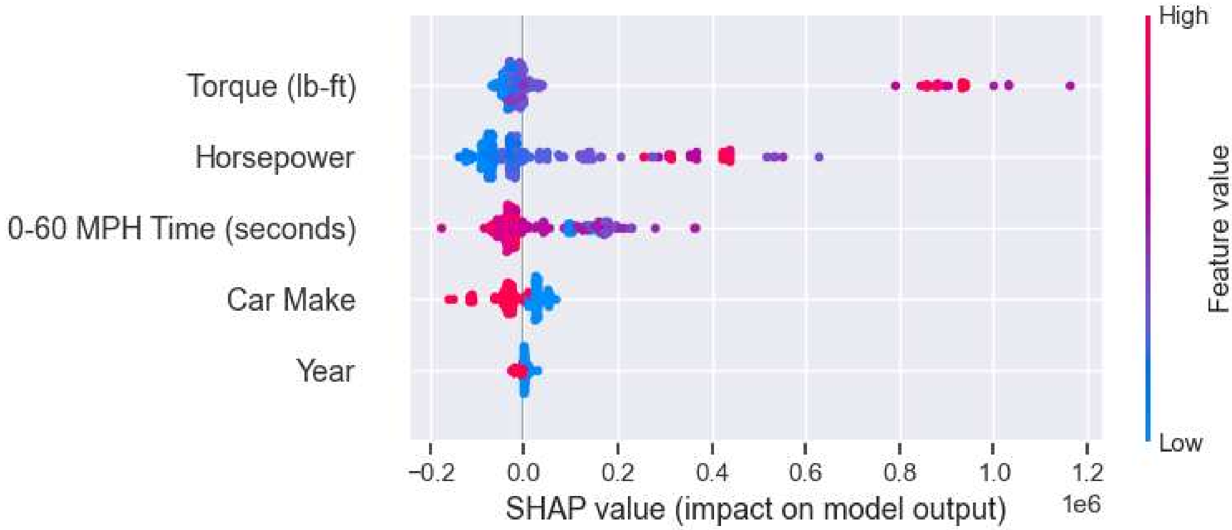
In [44]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = rf.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 179245.95197674824
MAPE is 0.6496436466127951
MSE is 232902640718.41104
R2 score is 0.6070903231035927
RMSE score is 482599.87641773286
```

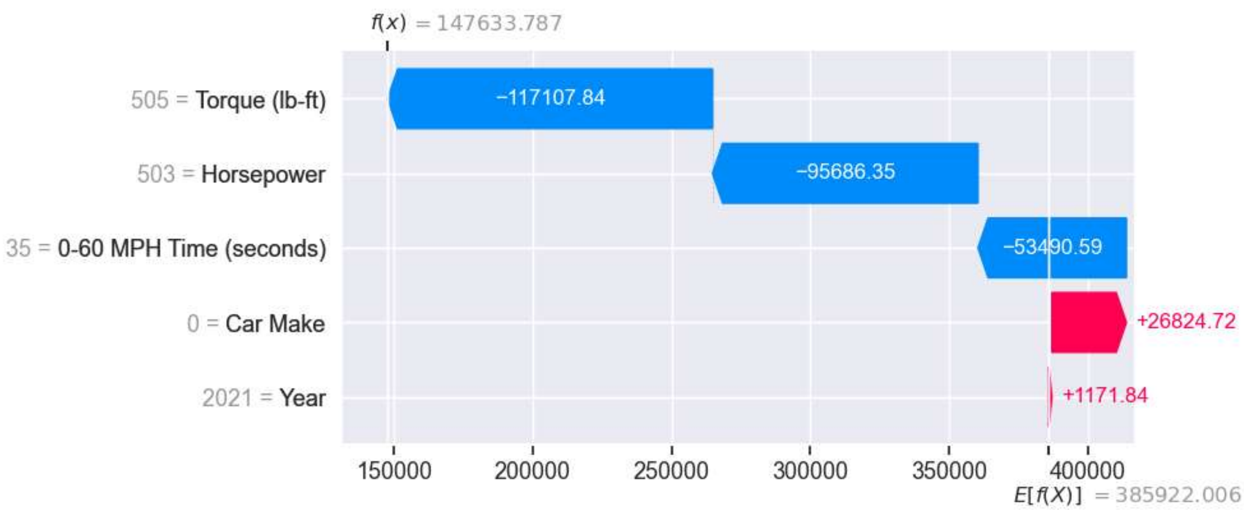
In [45]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (Random Forest Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [46]:
```
import shap
explainer = shap.TreeExplainer(rf)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



In [47]:
```
explainer = shap.Explainer(rf, X_test, check_additivity=False)
shap_values = explainer(X_test, check_additivity=False)
shap.plots.waterfall(shap_values[0])
```



AdaBoost Regressor

In [48]:
```
from sklearn.ensemble import AdaBoostRegressor
from sklearn.model_selection import GridSearchCV

# Define AdaBoostRegressor model
abr = AdaBoostRegressor()

# Define hyperparameters and possible values
params = {'n_estimators': [50, 100, 150],
          'learning_rate': [0.01, 0.1, 1, 10],
          'random_state': [0, 42]
         }

# Perform GridSearchCV with 5-fold cross validation
grid_search = GridSearchCV(abr, param_grid=params, cv=5, scoring='neg_mean_squared_error')
grid_search.fit(X_train, y_train)

# Print best hyperparameters and corresponding score
print("Best hyperparameters: ", grid_search.best_params_)
```

```
Best hyperparameters:  {'learning_rate': 0.1, 'n_estimators': 50, 'random_state': 0}
```

In [49]:
```
from sklearn.ensemble import RandomForestRegressor
abr = AdaBoostRegressor(random_state=0, learning_rate=0.1, n_estimators=50)
abr.fit(X_train, y_train)
```

Out[49]:
```
AdaBoostRegressor(learning_rate=0.1, random_state=0)
```

In [50]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = abr.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 246415.8167423268
MAPE is 0.8351811509347421
MSE is 408285348756.478
R2 score is 0.31121749428595646
RMSE score is 638972.1032693665
```

In [51]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": abr.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (AdaBoost Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```