In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.linear_model import LinearRegression
```

In [2]:
```
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib import pyplot
from scipy import stats
```

In [3]:
```
df = pd.read_csv('E:\\projects\\automobile.csv')
```

In [4]:
```
df.dtypes
```

Out[4]:
```
symboling              int64
normalized-losses    float64
make                  object
fuel-type             object
aspiration            object
num-of-doors          object
body-style            object
drive-wheels          object
engine-location       object
wheel-base           float64
length               float64
width                float64
height               float64
curb-weight            int64
engine-type           object
num-of-cylinders      object
engine-size            int64
fuel-system           object
bore                 float64
stroke               float64
compression-ratio    float64
horsepower           float64
peak-rpm             float64
city-mpg               int64
highway-mpg            int64
price                  int64
dtype: object
```

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

Out[5]:

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	
count	201.000000	164.000000	201.000000	201.000000	201.000000	201.000000	201.000000	20
mean	0.840796	122.000000	98.797015	174.200995	65.889055	53.766667	2555.666667	12
std	1.254802	35.442168	6.066366	12.322175	2.101471	2.447822	517.296727	4
min	-2.000000	65.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	6
25%	0.000000	94.000000	94.500000	166.800000	64.100000	52.000000	2169.000000	9
50%	1.000000	115.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	12
75%	2.000000	150.000000	102.400000	183.500000	66.600000	55.500000	2926.000000	14
max	3.000000	256.000000	120.900000	208.100000	72.000000	59.800000	4066.000000	32

In [6]:
```
df.describe(include="all")
```

Out[6]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wh b
count	201.000000	164.000000	201	201	201	199	201	201	201	201.000
unique	NaN	NaN	22	2	2	2	5	3	2	N
top	NaN	NaN	toyota	gas	std	four	sedan	fwd	front	N
freq	NaN	NaN	32	181	165	113	94	118	198	N
mean	0.840796	122.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	98.797
std	1.254802	35.442168	NaN	NaN	NaN	NaN	NaN	NaN	NaN	6.066
min	-2.000000	65.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	86.600
25%	0.000000	94.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	94.500
50%	1.000000	115.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	97.000
75%	2.000000	150.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	102.400
max	3.000000	256.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	120.900

11 rows × 26 columns

In [7]:

```
df1 = df.replace("?",np.nan,inplace = True)
df.head(10)
```

Out[7]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base
0	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6
1	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6
2	1	NaN	alfa-romero	gas	std	two	hatchback	rwd	front	94.5
3	2	164.0	audi	gas	std	four	sedan	fwd	front	99.8
4	2	164.0	audi	gas	std	four	sedan	4wd	front	99.4
5	2	NaN	audi	gas	std	two	sedan	fwd	front	99.8
6	1	158.0	audi	gas	std	four	sedan	fwd	front	105.8
7	1	NaN	audi	gas	std	four	wagon	fwd	front	105.8
8	1	158.0	audi	gas	turbo	four	sedan	fwd	front	105.8
9	2	192.0	bmw	gas	std	two	sedan	rwd	front	101.2

10 rows × 26 columns

In [8]:

```
missing_data = df.isnull()
missing_data.head(5)
```

Out[8]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	e
0	False	True	False	False	False	False	False	False	False	False	...	
1	False	True	False	False	False	False	False	False	False	False	...	
2	False	True	False	False	False	False	False	False	False	False	...	
3	False	False	False	False	False	False	False	False	False	False	...	
4	False	False	False	False	False	False	False	False	False	False	...	

5 rows × 26 columns

In [9]:
```
for column in missing_data.columns.values.tolist():
    print(column)
    print(missing_data[column].value_counts())
    print("")
```

```
symboling
symboling
False    201
Name: count, dtype: int64

normalized-losses
normalized-losses
False    164
True      37
Name: count, dtype: int64

make
make
False    201
Name: count, dtype: int64

fuel-type
fuel-type
False    201
```

In [10]:
```
avg_norm_loss = df["normalized-losses"].astype("float").mean(axis = 0)
print("Average of normalized-losses:",avg_norm_loss)
```

```
Average of normalized-losses: 122.0
```

In [11]:
```
df["normalized-losses"].replace(np.nan,avg_norm_loss,inplace=True)
```

In [12]:
```
avg_bore = df["bore"].astype("float").mean(axis = 0)
print("Average of bore:",avg_bore)
```

```
Average of bore: 3.330710659898477
```

In [13]:
```
df["bore"].replace(np.nan,avg_bore,inplace=True)
```

In [14]:
```
avg_horsepower = df["horsepower"].astype("float").mean(axis = 0)
print("Average of horsepower:",avg_horsepower)
```

```
Average of horsepower: 103.39698492462311
```

In [15]:
```
df["horsepower"].replace(np.nan,avg_horsepower,inplace = True)
```

In [16]:
```
avg_peak_rpm = df["peak-rpm"].astype("float").mean(axis = 0)
print("Average of peak_rpm:",avg_peak_rpm)
```

```
Average of peak_rpm: 5117.587939698493
```

In [17]:
```
df["peak-rpm"].replace(np.nan,avg_peak_rpm,inplace = True)
```

In [18]:
```
avg_stroke = df["stroke"].astype("float").mean(axis = 0)
print("Average of stroke:",avg_stroke)
```

```
Average of stroke: 3.256903553299492
```

In [19]:
```
df["stroke"].replace(np.nan,avg_stroke,inplace = True)
```

In [20]:
```
df["num-of-doors"].value_counts()
```

Out[20]:
```
num-of-doors
four    113
two      86
Name: count, dtype: int64
```

In [21]:
```
df["num-of-doors"].value_counts().idxmax()
```

Out[21]:
```
'four'
```

In [22]:
```
df["num-of-doors"].replace(np.nan,"four",inplace=True)
```

In [23]:
```
df["num-of-doors"].value_counts()
```

Out[23]:
```
num-of-doors
four    115
two      86
Name: count, dtype: int64
```

In [24]:
```
df.dropna(subset=["price"],axis= 0,inplace=True)

df.reset_index(drop=True, inplace=True)
```

In [25]:
```
df.head()
```

Out[25]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base
0	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6
1	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6
2	1	122.0	alfa-romero	gas	std	two	hatchback	rwd	front	94.5
3	2	164.0	audi	gas	std	four	sedan	fwd	front	99.8
4	2	164.0	audi	gas	std	four	sedan	4wd	front	99.4

5 rows × 26 columns

In [26]:
```
df['city-L/100km']= 235/df["city-mpg"]
```

In [27]:
```
df.head()
```

Out[27]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base
0	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6
1	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6
2	1	122.0	alfa-romero	gas	std	two	hatchback	rwd	front	94.5
3	2	164.0	audi	gas	std	four	sedan	fwd	front	99.8
4	2	164.0	audi	gas	std	four	sedan	4wd	front	99.4

5 rows × 27 columns

In [28]:
```
df["highway-mpg"] = 235/df["highway-mpg"]

df.rename(columns={'"highway-mpg"':"highway-L/100km"},inplace = True)

df.head()
```

Out[28]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base
0	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6
1	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6
2	1	122.0	alfa-romero	gas	std	two	hatchback	rwd	front	94.5
3	2	164.0	audi	gas	std	four	sedan	fwd	front	99.8
4	2	164.0	audi	gas	std	four	sedan	4wd	front	99.4

5 rows × 27 columns

In [29]:
```
# Define a function to convert price to dollars
def convert_to_dollars(price):
    return '$' + str(price)

# Apply the conversion function to the price column and store the result in a r
df['price_in_dollars'] = df['price'].apply(convert_to_dollars)
```

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

Out[30]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base
0	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6
1	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6
2	1	122.0	alfa-romero	gas	std	two	hatchback	rwd	front	94.5
3	2	164.0	audi	gas	std	four	sedan	fwd	front	99.8
4	2	164.0	audi	gas	std	four	sedan	4wd	front	99.4

5 rows × 28 columns

In [31]:
```
df.describe()
```

Out[31]:

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	
count	201.000000	201.00000	201.000000	201.000000	201.000000	201.000000	201.000000	20
mean	0.840796	122.00000	98.797015	174.200995	65.889055	53.766667	2555.666667	12
std	1.254802	31.99625	6.066366	12.322175	2.101471	2.447822	517.296727	4
min	-2.000000	65.00000	86.600000	141.100000	60.300000	47.800000	1488.000000	6
25%	0.000000	101.00000	94.500000	166.800000	64.100000	52.000000	2169.000000	9
50%	1.000000	122.00000	97.000000	173.200000	65.500000	54.100000	2414.000000	12
75%	2.000000	137.00000	102.400000	183.500000	66.600000	55.500000	2926.000000	14
max	3.000000	256.00000	120.900000	208.100000	72.000000	59.800000	4066.000000	32

In [32]:
```
df[["length","width","height"]].head()
```

Out[32]:

	length	width	height
0	168.8	64.1	48.8
1	168.8	64.1	48.8
2	171.2	65.5	52.4
3	176.6	66.2	54.3
4	176.6	66.4	54.3

In [33]:
```
df['length']= df['length']/df['length'].max()
df['width']= df['width']/df['width'].max()
df['height']= df['height']/df['height'].max()
```

In [34]:
```
df[["length","width","height"]].head()
```

Out[34]:

	length	width	height
0	0.811148	0.890278	0.816054
1	0.811148	0.890278	0.816054
2	0.822681	0.909722	0.876254
3	0.848630	0.919444	0.908027
4	0.848630	0.922222	0.908027

In [35]:
```
# Binning means

df[["horsepower"]]
```

Out[35]:

	horsepower
0	111.0
1	111.0
2	154.0
3	102.0
4	115.0
...	...
196	114.0
197	160.0
198	134.0
199	106.0
200	114.0

201 rows × 1 columns

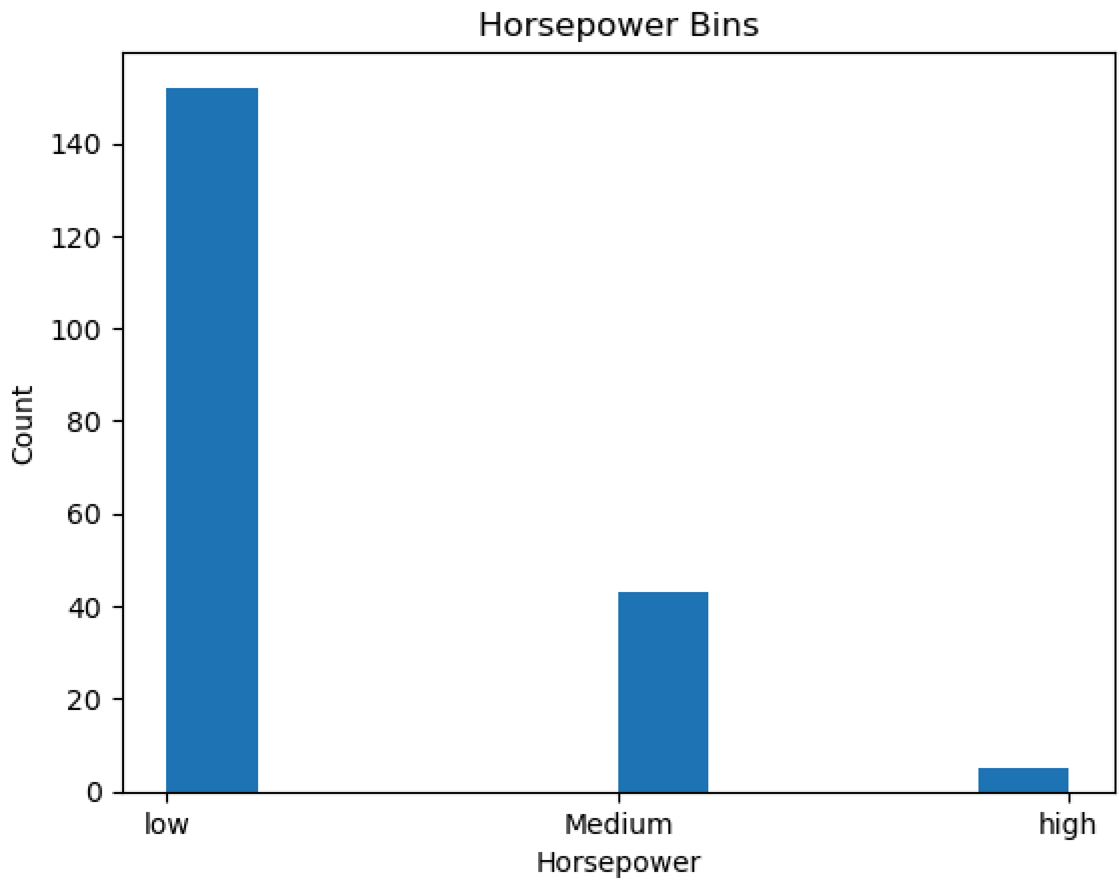
In [36]:
```
df["horsepower"]= df["horsepower"].astype(int, copy=True)

df["horsepower"]

bins = np.linspace(min(df["horsepower"]), max(df["horsepower"]),4)
group_names = ['low','Medium','high']
df['horsepower-binned'] = pd.cut(df['horsepower'],bins, labels=group_names)
df.dropna(subset=['horsepower-binned'], inplace=True)
df[['horsepower','horsepower-binned']].head(20)
```

Out[36]:

	horsepower	horsepower-binned
0	111	low
1	111	low
2	154	Medium
3	102	low
4	115	low
5	110	low
6	110	low
7	110	low
8	140	Medium
9	101	low
10	101	low
11	121	Medium
12	121	Medium
13	121	Medium
14	182	Medium
15	182	Medium
16	182	Medium
18	70	low
19	70	low
20	68	low

In [ ]:

In [37]:
```
import matplotlib.pyplot as plt

# Assuming 'df' is your DataFrame
df['horsepower-binned'] = df['horsepower-binned'].astype(str)

plt.hist(df["horsepower-binned"])
plt.xlabel("Horsepower")
plt.ylabel("Count")
plt.title("Horsepower Bins")
plt.show()
```



In [38]:
```
#  EXPLORTORY-DATA-ANALYSIS (EDA)
```

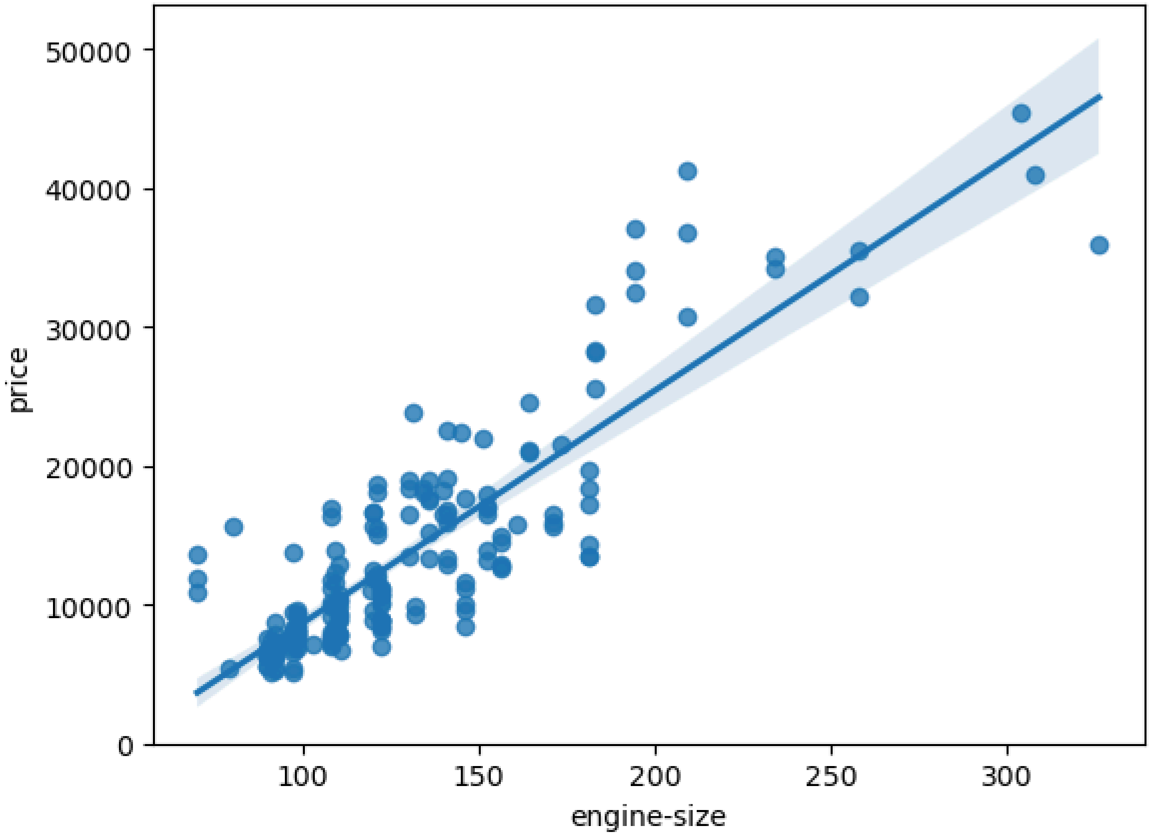
In [39]:
```
#correlation

df[['bore','stroke','compression-ratio','horsepower']].corr()
```

Out[39]:

	bore	stroke	compression-ratio	horsepower
bore	1.000000	-0.061513	-0.000059	0.561673
stroke	-0.061513	1.000000	0.187511	0.092884
compression-ratio	-0.000059	0.187511	1.000000	-0.216843
horsepower	0.561673	0.092884	-0.216843	1.000000

In [40]:
```
# positive linear relationship

sns.regplot(x="engine-size", y="price", data=df)
plt.ylim(0,)
```

Out[40]: (0.0, 53201.8756275018)



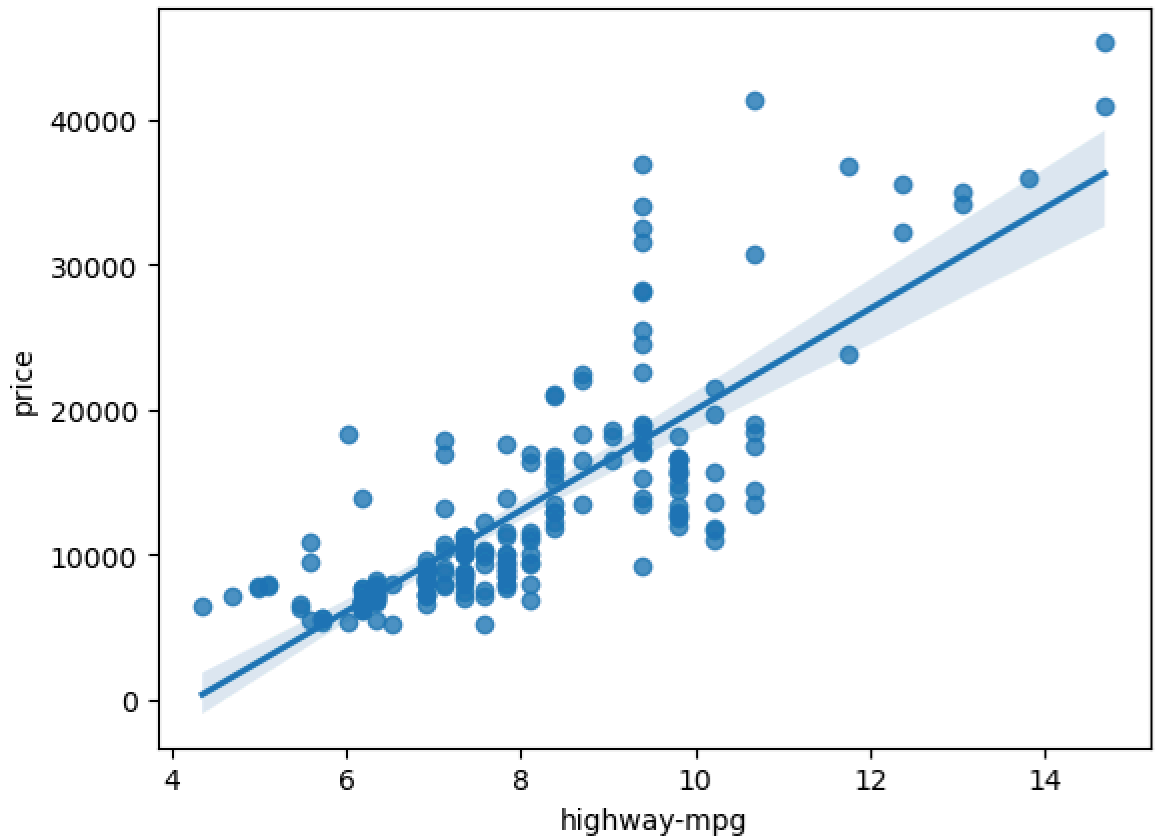
In [41]:
```
df[["engine-size","price"]].corr()
```

Out[41]:

	engine-size	price
engine-size	1.000000	0.872024
price	0.872024	1.000000

In [42]:
```
sns.regplot(x = "highway-mpg", y = "price", data = df)
```

Out[42]: <Axes: xlabel='highway-mpg', ylabel='price'>



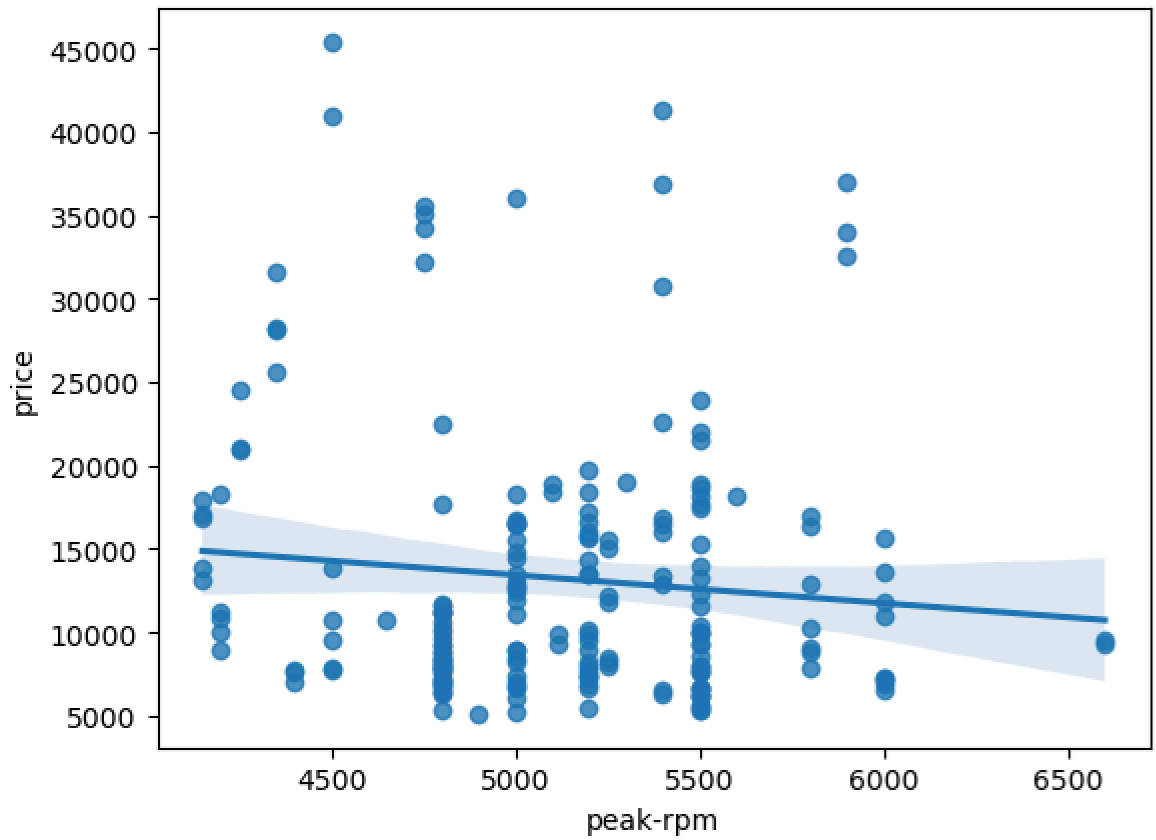
In [43]:
```
df[["highway-mpg","price"]].corr()
```

Out[43]:

	highway-mpg	price
highway-mpg	1.000000	0.800957
price	0.800957	1.000000

In [44]:
```
sns.regplot(x = "peak-rpm", y = "price", data = df)
```

Out[44]: <Axes: xlabel='peak-rpm', ylabel='price'>



In [45]:
```
df[["peak-rpm","price"]].corr()
```

Out[45]:

	peak-rpm	price
peak-rpm	1.000000	-0.101993
price	-0.101993	1.000000

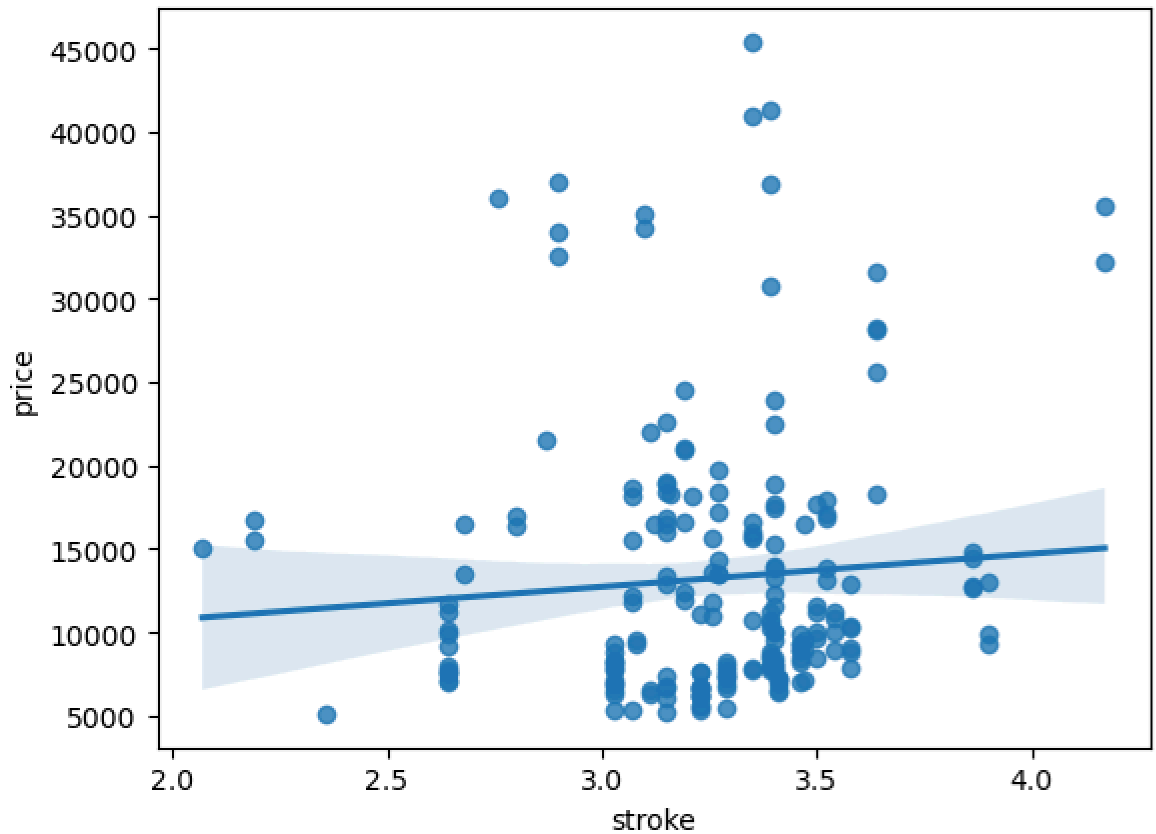
In [46]:
```
df[["stroke","price"]].corr()
```

Out[46]:

	stroke	price
stroke	1.000000	0.078916
price	0.078916	1.000000

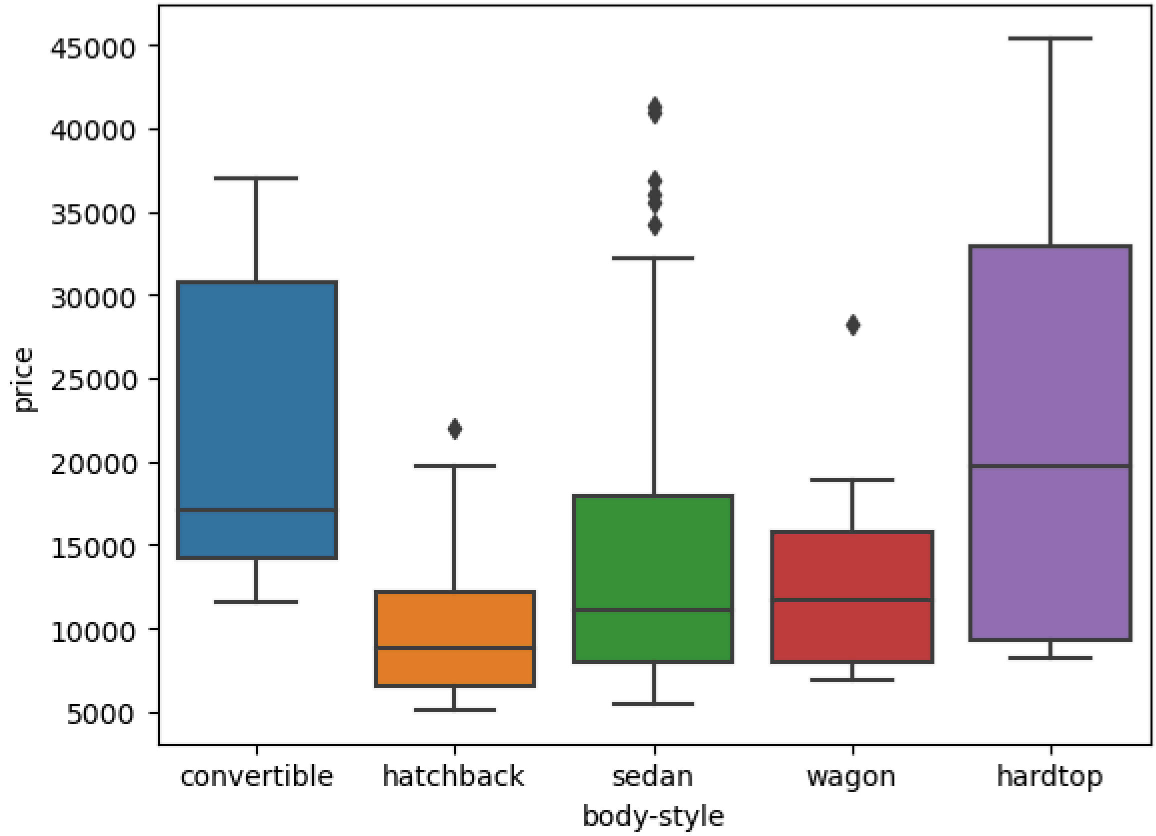
In [47]:
```
sns.regplot(x = "stroke", y = "price", data = df)
```

Out[47]: <Axes: xlabel='stroke', ylabel='price'>



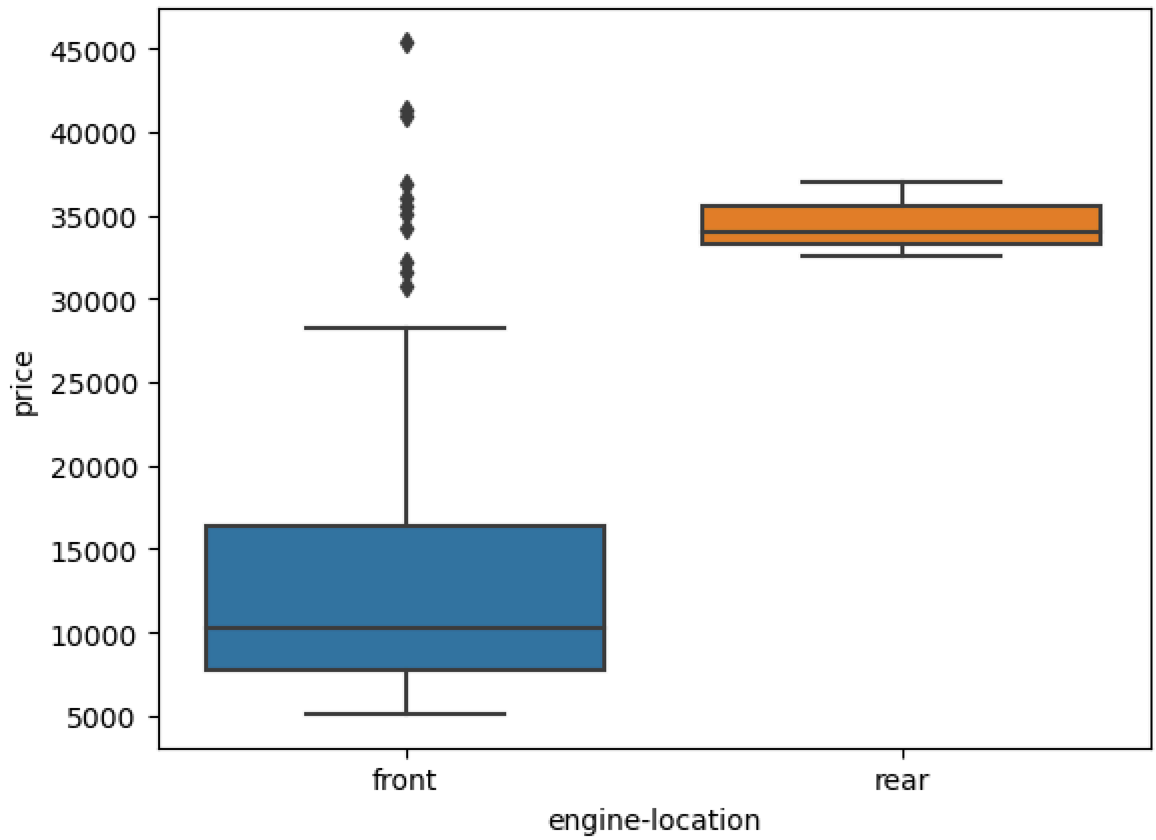
In [48]:
```
# Co-relationship

sns.boxplot(x="body-style", y="price", data=df)
```

Out[48]: <Axes: xlabel='body-style', ylabel='price'>



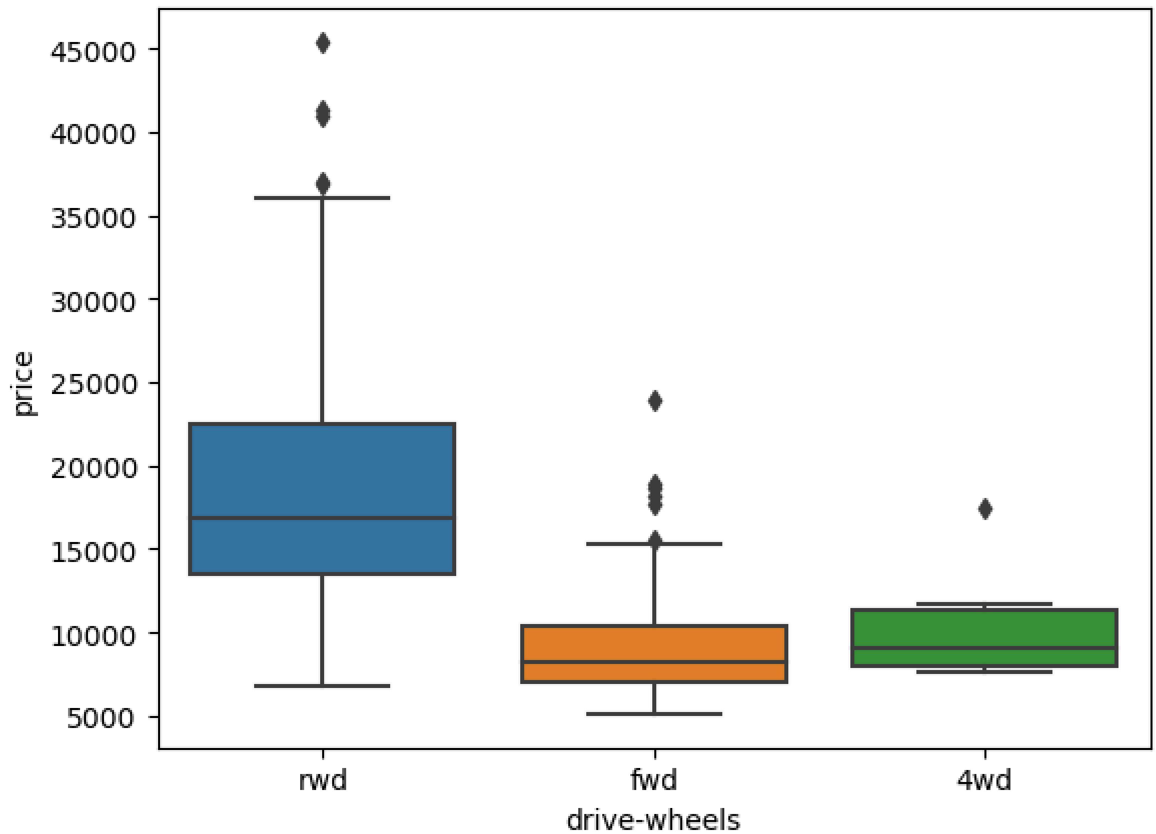
In [49]:
```
sns.boxplot(x = "engine-location", y = "price", data = df)
```

Out[49]: <Axes: xlabel='engine-location', ylabel='price'>



In [50]:
```
sns.boxplot(x = "drive-wheels", y = "price", data = df)
```

Out[50]: <Axes: xlabel='drive-wheels', ylabel='price'>



In [51]:
```
# Descriptive statistical analysis

df.describe()
```

Out[51]:

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	
count	200.00000	200.000000	200.000000	200.000000	200.000000	200.000000	200.000000	200
mean	0.83500	122.005000	98.849000	0.837898	0.915514	0.899156	2561.005000	127
std	1.25525	32.076463	6.036539	0.058275	0.028736	0.041031	513.014389	41
min	-2.00000	65.000000	86.600000	0.694858	0.858333	0.799331	1713.000000	70
25%	0.00000	100.250000	94.500000	0.801538	0.891319	0.869565	2184.750000	98
50%	1.00000	122.000000	97.000000	0.832292	0.909722	0.904682	2417.000000	120
75%	2.00000	138.250000	102.400000	0.881788	0.926042	0.928512	2928.250000	142
max	3.00000	256.000000	120.900000	1.000000	1.000000	1.000000	4066.000000	326

In [52]:
```
df.describe(include = ['object'])
```

Out[52]:

	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	engine-type	num-of-cylinders	fuel-system	pric
count	200	200	200	200	200	200	200	200	200	200	
unique	22	2	2	2	5	3	2	6	6	8	
top	toyota	gas	std	four	sedan	fwd	front	ohc	four	mpfi	
freq	32	180	164	115	94	117	197	145	157	92	

In [53]:
```
df['drive-wheels'].value_counts()
```

Out[53]:
```
drive-wheels
fwd    117
rwd     75
4wd      8
Name: count, dtype: int64
```

In [54]:
```
drive_wheels_counts = df['drive-wheels'].value_counts().to_frame()
drive_wheels_counts.rename(columns={'drive-wheels1': 'value_counts'})
drive_wheels_counts
```

Out[54]:

drive-wheels	count
fwd	117
rwd	75
4wd	8

In [55]:
```
engine_loc_counts = df['engine-location'].value_counts().to_frame()

engine_loc_counts.head(10)
```

Out[55]:

engine-location	count
front	197
rear	3

In [56]:
```
# basics of Grouping

df['drive-wheels'].unique()
```

Out[56]:
```
array(['rwd', 'fwd', '4wd'], dtype=object)
```

In [57]:
```
df_group_one = df[["drive-wheels","price"]]
df_group_one
```

Out[57]:

	drive-wheels	price
0	rwd	13495
1	rwd	16500
2	rwd	16500
3	fwd	13950
4	4wd	17450
...	...	...
196	rwd	16845
197	rwd	19045
198	rwd	21485
199	rwd	22470
200	rwd	22625

200 rows × 2 columns

In [58]:
```
grouped_test = df_group_one.groupby(['drive-wheels'],as_index=False).mean()
grouped_test
```

Out[58]:

	drive-wheels	price
0	4wd	10241.000000
1	fwd	9279.769231
2	rwd	19757.613333

In [59]:
```
df_gptest = df[['drive-wheels','body-style','price']]
grouped_test1 = df_gptest.groupby(['drive-wheels','body-style'],as_index=False)
grouped_test1
```

Out[59]:

	drive-wheels	body-style	price
0	4wd	hatchback	7603.000000
1	4wd	sedan	12647.333333
2	4wd	wagon	9095.750000
3	fwd	convertible	11595.000000
4	fwd	hardtop	8249.000000
5	fwd	hatchback	8464.000000
6	fwd	sedan	9811.800000
7	fwd	wagon	9997.333333
8	rwd	convertible	23949.600000
9	rwd	hardtop	24202.714286
10	rwd	hatchback	14337.777778
11	rwd	sedan	21711.833333
12	rwd	wagon	16994.222222

In [60]:
```
grouped_pivot = grouped_test1.pivot(index='drive-wheels',columns='body-style')
grouped_pivot = grouped_pivot.fillna(0)
grouped_pivot
```

Out[60]:

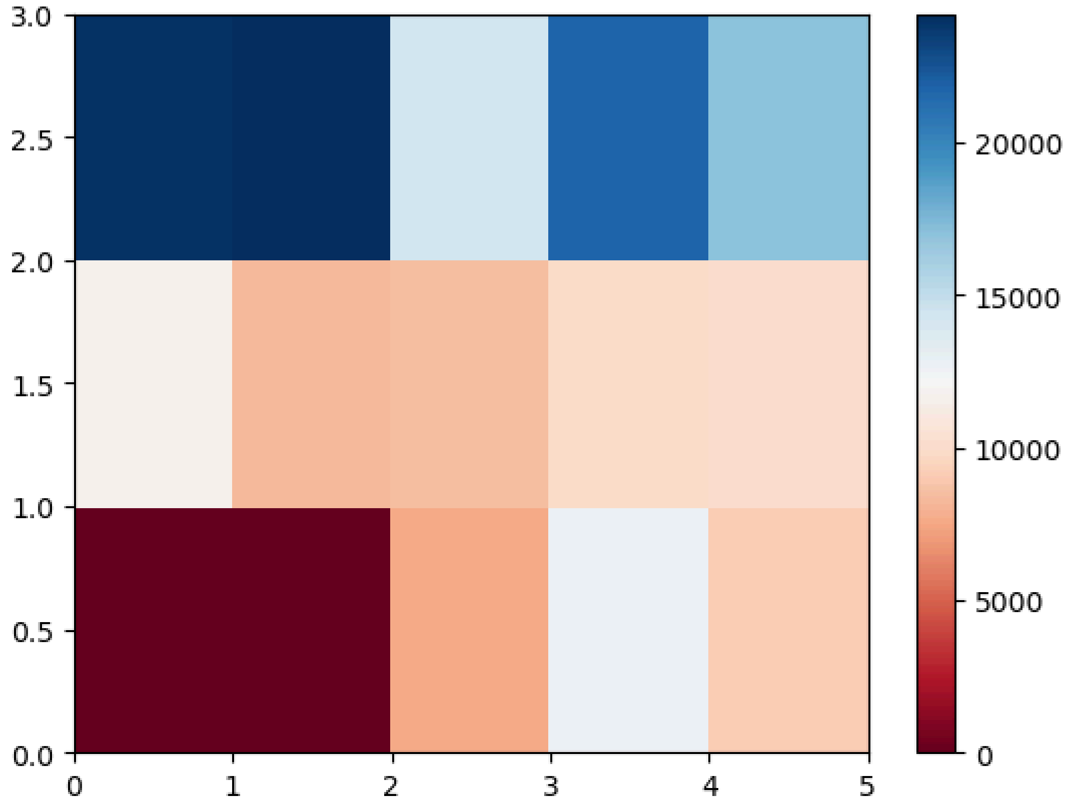
					price
body-style	**convertible**	**hardtop**	**hatchback**	**sedan**	**wagon**
drive-wheels					
4wd	0.0	0.000000	7603.000000	12647.333333	9095.750000
fwd	11595.0	8249.000000	8464.000000	9811.800000	9997.333333
rwd	23949.6	24202.714286	14337.777778	21711.833333	16994.222222

In [61]:
```
df_gptest2 = df[,'price']]
grouped_test_bodystyle = df_gptest2.groupby(['body-style'],as_index= False).mea
grouped_test_bodystyle
```

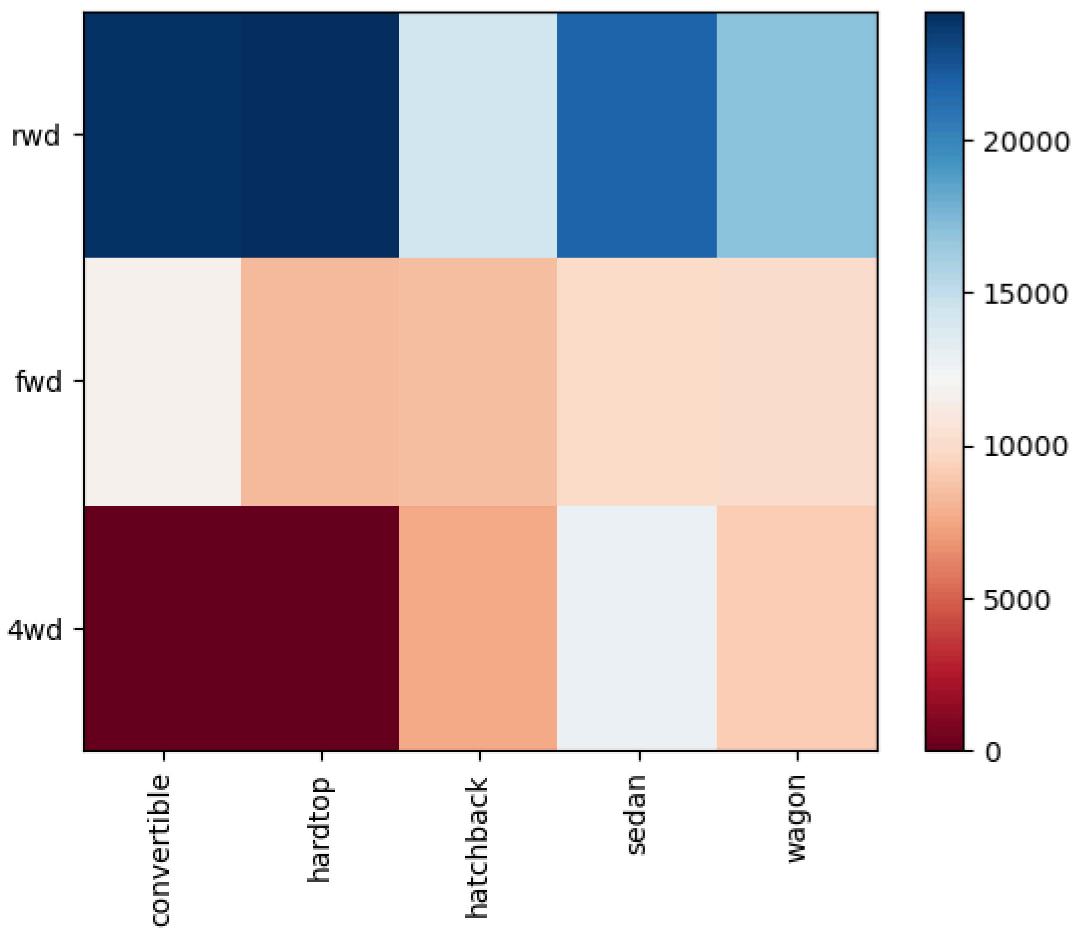
Out[61]:

	body-style	price
0	convertible	21890.500000
1	hardtop	22208.500000
2	hatchback	10029.179104
3	sedan	14459.755319
4	wagon	12371.960000

In [62]:
```
# Releationship with Drive Wheels and Body Style vs. Price

plt.pcolor(grouped_pivot, cmap='RdBu')
plt.colorbar()
plt.show()
```



In [63]:
```
fig, ax = plt.subplots()
im = ax.pcolor(grouped_pivot, cmap='RdBu')

#label names
row_labels = grouped_pivot.columns.levels[1]
col_labels = grouped_pivot.index

#move ticks and labels to the center
ax.set_xticks(np.arange(grouped_pivot.shape[1]) + 0.5, minor=False)
ax.set_yticks(np.arange(grouped_pivot.shape[0]) + 0.5, minor=False)

#insert labels
ax.set_xticklabels(row_labels, minor=False)
ax.set_yticklabels(col_labels, minor=False)

#rotate label if too long
plt.xticks(rotation=90)

fig.colorbar(im)
plt.show()
```



In [64]:
```
# Correlation and Causation
```

In [ ]:

```

```

In [65]:

```
pearson_coef, p_value = stats.pearsonr(df['wheel-base'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value
```

```
The Pearson Correlation Coefficient is 0.5817132408753356  with a P-value of
P = 1.6741233030208197e-19
```

In [66]:

```
nan_values = df.isna().sum()
print("NaN values in DataFrame:")
print(nan_values)

inf_values = df.isin([np.inf, -np.inf]).sum()
print("\nInfinite values in DataFrame:")
print(inf_values)

pearson_coef, p_value = stats.pearsonr(df['horsepower'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value
```

```
NaN values in DataFrame:
symboling            0
normalized-losses    0
make                 0
fuel-type            0
aspiration           0
num-of-doors         0
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
fuel-system          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
highway-mpg          0
price                0
city-L/100km         0
price_in_dollars     0
horsepower-binned    0
dtype: int64

Infinite values in DataFrame:
symboling            0
normalized-losses    0
make                 0
fuel-type            0
aspiration           0
num-of-doors         0
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
fuel-system          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
```

```
highway-mpg          0
price                0
city-L/100km         0
price_in_dollars     0
horsepower-binned    0
dtype: int64
The Pearson Correlation Coefficient is 0.808734646342276  with a P-value of P
=  1.6077454704877677e-47
```

In [67]:
```
pearson_coef, p_value = stats.pearsonr(df['length'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value
```

```
The Pearson Correlation Coefficient is 0.6913494781494154  with a P-value of
P =  9.190889116345163e-30
```

In [68]:
```
pearson_coef, p_value = stats.pearsonr(df['width'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value
```

```
The Pearson Correlation Coefficient is 0.7531354467954671  with a P-value of
P = 7.339912613026282e-38
```

In [69]:
```
pearson_coef, p_value = stats.pearsonr(df['curb-weight'], df['price'])
print( "The Pearson Correlation Coefficient is", pearson_coef, " with a P-value
```

```
The Pearson Correlation Coefficient is 0.835021883197705  with a P-value of P
=  2.858346147718497e-53
```

In [70]:
```
pearson_coef, p_value = stats.pearsonr(df['engine-size'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value
```

```
The Pearson Correlation Coefficient is 0.8720241350189741  with a P-value of
P = 2.3788186066775877e-63
```

In [71]:
```
pearson_coef, p_value = stats.pearsonr(df['bore'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value
```

```
The Pearson Correlation Coefficient is 0.5398978954125515  with a P-value of
P =   1.5844832015568345e-16
```

In [72]:
```
pearson_coef, p_value = stats.pearsonr(df['city-mpg'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value
```

```
The Pearson Correlation Coefficient is -0.6913465948945459  with a P-value of
P =  9.197877971831629e-30
```

In [73]:
```
pearson_coef, p_value = stats.pearsonr(df['highway-mpg'], df['price'])
print( "The Pearson Correlation Coefficient is", pearson_coef, " with a P-value
```

```
The Pearson Correlation Coefficient is 0.8009574869278472  with a P-value of
P =  5.479311669257528e-46
```

In [74]:
```
grouped_test2=df_gptest[['drive-wheels', 'price']].groupby(['drive-wheels'])
grouped_test2.head(2)
```

Out[74]:

	drive-wheels	price
0	rwd	13495
1	rwd	16500
3	fwd	13950
4	4wd	17450
5	fwd	15250
136	4wd	7603

In [75]:
```
df_gptest
```

Out[75]:

	drive-wheels	body-style	price
0	rwd	convertible	13495
1	rwd	convertible	16500
2	rwd	hatchback	16500
3	fwd	sedan	13950
4	4wd	sedan	17450
...	...	...	...
196	rwd	sedan	16845
197	rwd	sedan	19045
198	rwd	sedan	21485
199	rwd	sedan	22470
200	rwd	sedan	22625

200 rows × 3 columns

In [76]:
```
grouped_test2.get_group('4wd')['price']
```

Out[76]:
```
4      17450
136     7603
140     9233
141    11259
144     8013
145    11694
150     7898
151     8778
Name: price, dtype: int64
```

In [77]:
```
# ANOVA :- Analysis of Variance

       # The Analysis of Variance (ANOVA) is a statistical method used to test
       # there are significant differences between the means of two or more grc

       # F-test score: ANOVA assumes the means of all groups are the same,
       # calculates how much the actual means deviate from the assumption, and
       # A larger score means there is a larger difference between the means.

       # P-value: P-value tells how statistically significant our calculated sc

       # If our price variable is strongly correlated with the variable we are
       # we expect ANOVA to return a sizeable F-test score and a small p-value.
```

In [78]:
```
f_val, p_val = stats.f_oneway(grouped_test2.get_group('fwd')['price'],
               grouped_test2.get_group('rwd')['price'], grouped_test2.get_group

print( "ANOVA results: F=", f_val, ", P =", p_val)
```

```
ANOVA results: F= 67.12684882259785 , P = 5.876123262694183e-23
```

In [79]:
```
f_val, p_val = stats.f_oneway(grouped_test2.get_group('fwd')['price'], grouped_

print( "ANOVA results: F=", f_val, ", P =", p_val )
```

```
ANOVA results: F= 128.8734744035462 , P = 3.9200364546279194e-23
```

In [80]:
```
f_val, p_val = stats.f_oneway(grouped_test2.get_group('4wd')['price'], grouped_

print( "ANOVA results: F=", f_val, ", P =", p_val)
```

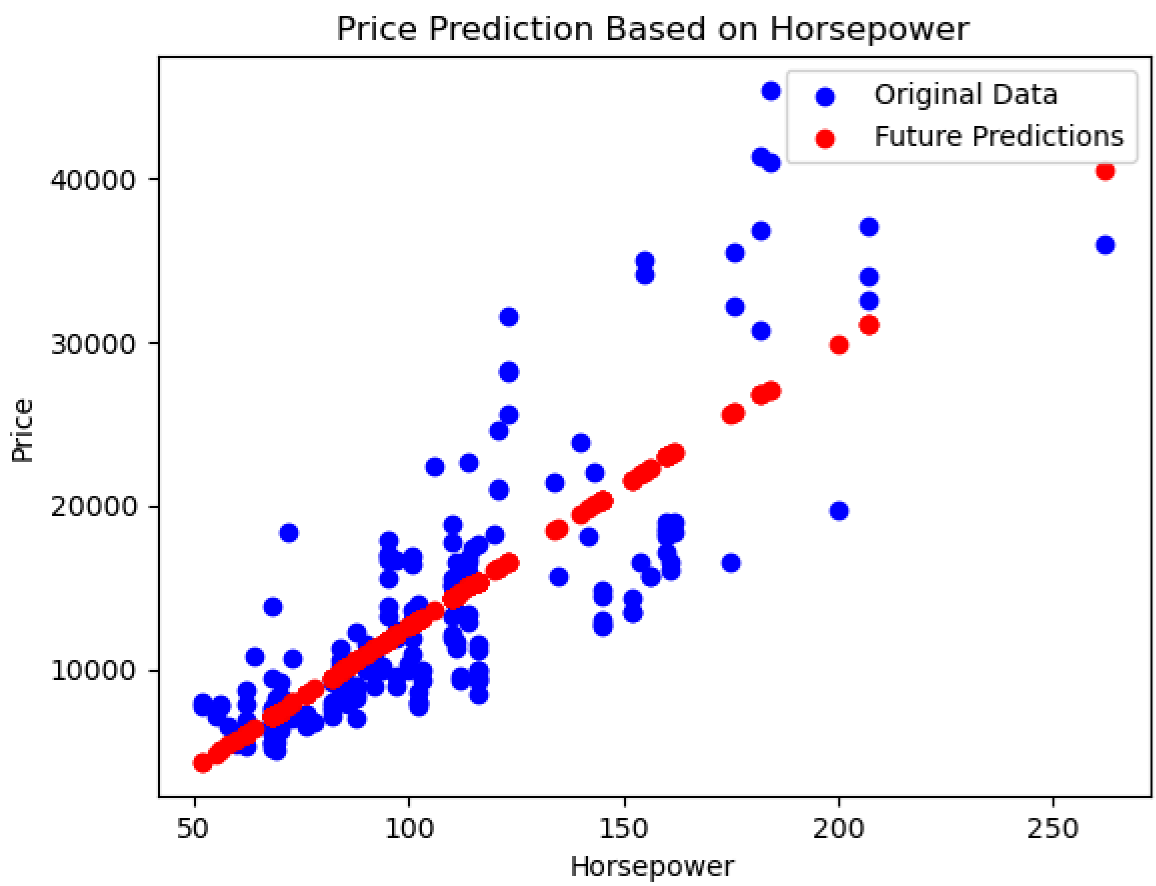
```
ANOVA results: F= 8.580681368924756 , P = 0.004411492211225333
```

In [81]:
```
f_val, p_val = stats.f_oneway(grouped_test2.get_group('4wd')['price'], grouped_

print("ANOVA results: F=", f_val, ", P =", p_val)
```

```
ANOVA results: F= 0.6217971622651529 , P = 0.43189741227446377
```

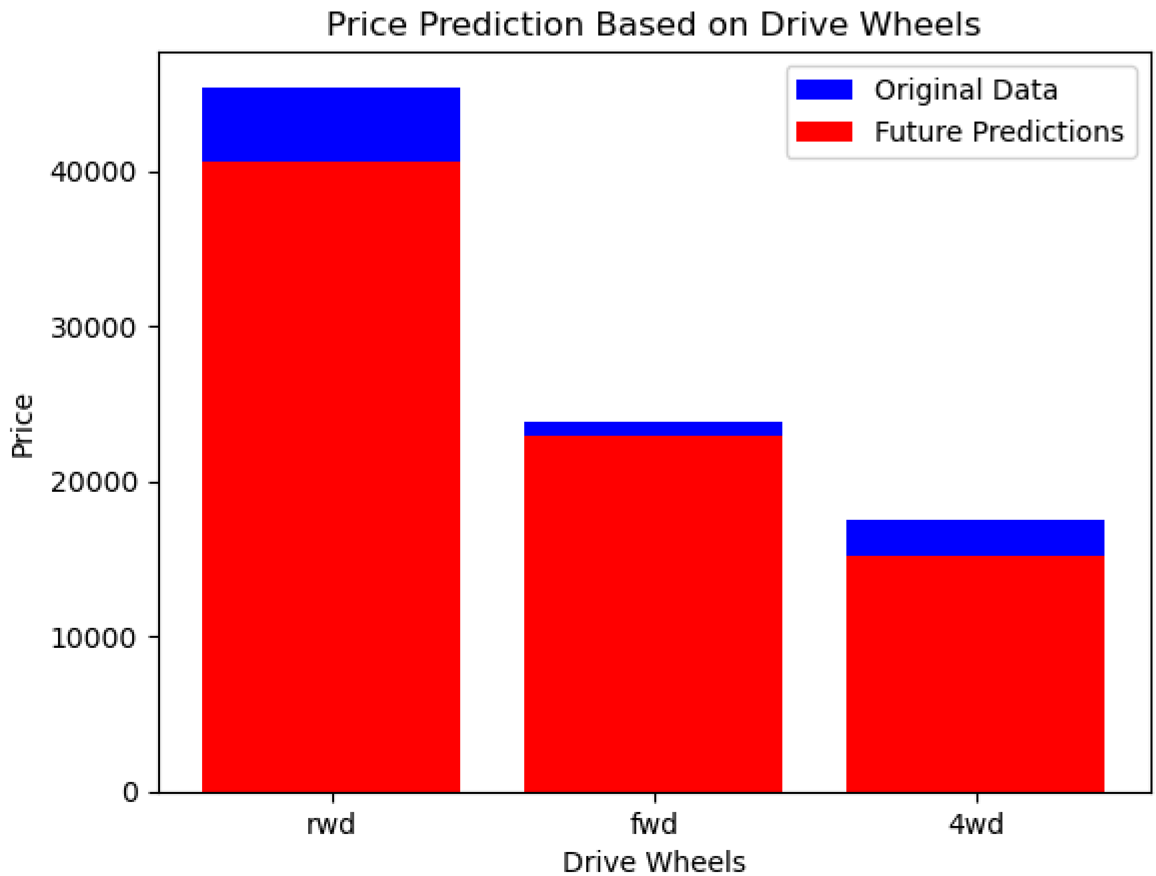
In [97]:

```
plt.scatter(df["horsepower"], y_train, color='blue', label='Original Data')  #
plt.scatter(df["horsepower"], future_predictions, color='red', label='Future Pr
plt.xlabel("Horsepower")
plt.ylabel("Price")
plt.title("Price Prediction Based on Horsepower")
plt.legend()
plt.show()
```

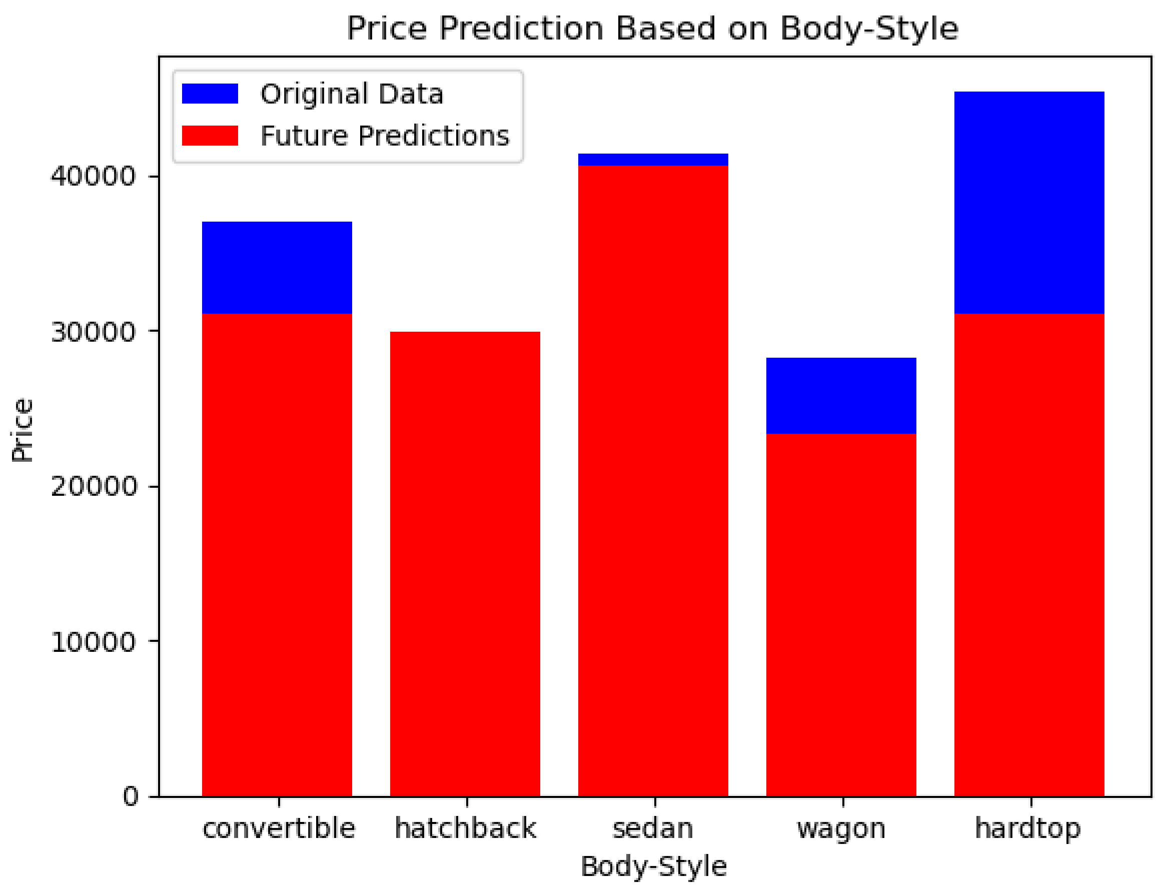


In [ ]:

In [92]:
```
# Step 5: Plot the updated data
# Use a bar plot to visualize the relationship between categorical features and
plt.bar(df["drive-wheels"], y_train, color='blue', label='Original Data')  # Ba
plt.bar(df["drive-wheels"], future_predictions, color='red', label='Future Pred
plt.xlabel("Drive Wheels")
plt.ylabel("Price")
plt.title("Price Prediction Based on Drive Wheels")
plt.legend()
plt.show()
```



In [93]:
```
plt.bar(df["body-style"], y_train, color='blue', label='Original Data')  # Bar
plt.bar(df["body-style"], future_predictions, color='red', label='Future Predic
plt.xlabel("Body-Style")
plt.ylabel("Price")
plt.title("Price Prediction Based on Body-Style")
plt.legend()
plt.show()
```



In [ ]:

In [ ]:

In [ ]: