

```
pip install ucimlrepo
```

```
Collecting ucimlrepo
  Downloading ucimlrepo-0.0.6-py3-none-any.whl (8.0 kB)
Installing collected packages: ucimlrepo
Successfully installed ucimlrepo-0.0.6
```

```
!pip install hvplot
```

```
Collecting hvplot
  Downloading hvplot-0.9.2-py2.py3-none-any.whl (1.8 MB)
    1.8/1.8 MB 17.4 MB/s eta 0:00:00
Requirement already satisfied: bokeh>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: colorcet>=2 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: holoviews>=1.11.0 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: numpy>=1.15 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: panel>=0.11.0 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: param<3.0,>=1.12.0 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: Jinja2>=2.9 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: contourpy>=1 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: pillow>=7.1.0 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: PyYAML>=3.10 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: tornado>=5.1 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: xyzservices>=2021.09.1 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: pyviz-comms>=0.7.4 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: markdown in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: markdown-it-py in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: linkify-it-py in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: mdit-py-plugins in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: tqdm>=4.48.0 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: uc-micro-py in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from hvplot)
Installing collected packages: hvplot
Successfully installed hvplot-0.9.2
```

```
from ucimlrepo import fetch_ucirepo
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import hvplot.pandas

from sklearn.model_selection import train_test_split

from sklearn import metrics

from sklearn.linear_model import LinearRegression

%matplotlib inline

# fetch dataset
automobile = fetch_ucirepo(id=10)

# data (as pandas dataframes)
X = automobile.data.features
y = automobile.data.targets

# metadata
#print(automobile.metadata)

# variable information
#print(automobile.variables)

df = pd.concat([X,y], axis=1)

df
```

	price	highway- mpg	city- mpg	peak- rpm	horsepower	compression- ratio	stroke	bore	fuel- system	engine-size
0	13495.0	27	21	5000.0	111.0	9.0	2.68	3.47	mpfi	130
1	16500.0	27	21	5000.0	111.0	9.0	2.68	3.47	mpfi	130
2	16500.0	26	19	5000.0	154.0	9.0	3.47	2.68	mpfi	130
3	13950.0	30	24	5500.0	102.0	10.0	3.40	3.19	mpfi	130
4	17450.0	22	18	5500.0	115.0	8.0	3.40	3.19	mpfi	130
...
200	16845.0	28	23	5400.0	114.0	9.5	3.15	3.78	mpfi	130
201	19045.0	25	19	5300.0	160.0	8.7	3.15	3.78	mpfi	130
202	21485.0	23	18	5500.0	134.0	8.8	2.87	3.58	mpfi	130
203	22470.0	27	26	4800.0	106.0	23.0	3.40	3.01	idi	130
204	22625.0	25	19	5400.0	114.0	9.5	3.15	3.78	mpfi	130

205 rows × 26 columns

▼ Data Cleaning

```
# Imputing the missing values
```

```
df.fillna(df.select_dtypes(np.number).mean(), inplace=True)
```

```
# There are no more missing values in the dataframe
```

```
df.isnull().sum()
```

```
price          0
highway-mpg    0
city-mpg       0
peak-rpm       0
horsepower     0
compression-ratio  0
stroke         0
bore           0
fuel-system    0
engine-size    0
num-of-cylinders 0
engine-type    0
curb-weight    0
```

```

height      0
width       0
length      0
wheel-base  0
engine-location  0
drive-wheels  0
body-style  0
num-of-doors  0
aspiration  0
fuel-type    0
make         0
normalized-losses  0
symboling    0
dtype: int64

```

```

# Covertng categorical types into a numerical type
from sklearn.preprocessing import LabelEncoder

```

```

categorical_columns = ['fuel-system', 'engine-type', 'engine-location', 'drive-wheels', 'body-st

```

```

label_encoder = LabelEncoder()
for column in categorical_columns:
    encoded_column_name = column + '_encoded'
    df[encoded_column_name] = label_encoder.fit_transform(df[column])

```

```
df
```

	price	highway- mpg	city- mpg	peak- rpm	horsepower	compression- ratio	stroke	bore	fuel- system	en
0	13495.0	27	21	5000.0	111.0	9.0	2.68	3.47	mpfi	
1	16500.0	27	21	5000.0	111.0	9.0	2.68	3.47	mpfi	
2	16500.0	26	19	5000.0	154.0	9.0	3.47	2.68	mpfi	
3	13950.0	30	24	5500.0	102.0	10.0	3.40	3.19	mpfi	
4	17450.0	22	18	5500.0	115.0	8.0	3.40	3.19	mpfi	
...	
200	16845.0	28	23	5400.0	114.0	9.5	3.15	3.78	mpfi	
201	19045.0	25	19	5300.0	160.0	8.7	3.15	3.78	mpfi	
202	21485.0	23	18	5500.0	134.0	8.8	2.87	3.58	mpfi	
203	22470.0	27	26	4800.0	106.0	23.0	3.40	3.01	idi	
204	22625.0	25	19	5400.0	114.0	9.5	3.15	3.78	mpfi	

205 rows × 34 columns

```
# Dropping the categorical type in the dataframe for accurat linear regression analysis
categorical_columns = ['fuel-system', 'engine-type', 'engine-location', 'drive-wheels', 'body-style']
df = df.drop(columns=categorical_columns, axis=1)
df
```

	price	highway-mpg	city-mpg	peak-rpm	horsepower	compression-ratio	stroke	bore	engine-size	cylinders
0	13495.0	27	21	5000.0	111.0	9.0	2.68	3.47	130	
1	16500.0	27	21	5000.0	111.0	9.0	2.68	3.47	130	
2	16500.0	26	19	5000.0	154.0	9.0	3.47	2.68	152	
3	13950.0	30	24	5500.0	102.0	10.0	3.40	3.19	109	
4	17450.0	22	18	5500.0	115.0	8.0	3.40	3.19	136	
...
200	16845.0	28	23	5400.0	114.0	9.5	3.15	3.78	141	
201	19045.0	25	19	5300.0	160.0	8.7	3.15	3.78	141	
202	21485.0	23	18	5500.0	134.0	8.8	2.87	3.58	173	
203	22470.0	27	26	4800.0	106.0	23.0	3.40	3.01	145	
204	22625.0	25	19	5400.0	114.0	9.5	3.15	3.78	141	

205 rows × 26 columns

```
df.dtypes
```

```
price                float64
highway-mpg          int64
city-mpg             int64
peak-rpm             float64
horsepower           float64
compression-ratio    float64
stroke              float64
bore                float64
engine-size          int64
num-of-cylinders     int64
curb-weight          int64
height              float64
width               float64
length              float64
wheel-base          float64
num-of-doors         float64
normalized-losses    float64
symboling            int64
fuel-system_encoded  int64
engine-type_encoded  int64
```

```

engine-location_encoded    int64
drive-wheels_encoded       int64
body-style_encoded         int64
aspiration_encoded         int64
fuel-type_encoded          int64
make_encoded               int64
dtype: object

```

```
df.shape
```

```
(205, 26)
```

```
df.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   price                 205 non-null   float64
 1   highway-mpg           205 non-null   int64
 2   city-mpg              205 non-null   int64
 3   peak-rpm              205 non-null   float64
 4   horsepower            205 non-null   float64
 5   compression-ratio     205 non-null   float64
 6   stroke                205 non-null   float64
 7   bore                  205 non-null   float64
 8   engine-size           205 non-null   int64
 9   num-of-cylinders      205 non-null   int64
10   curb-weight           205 non-null   int64
11   height                205 non-null   float64
12   width                 205 non-null   float64
13   length                205 non-null   float64
14   wheel-base            205 non-null   float64
15   num-of-doors          205 non-null   float64
16   normalized-losses     205 non-null   float64
17   symboling              205 non-null   int64
18   fuel-system_encoded   205 non-null   int64
19   engine-type_encoded   205 non-null   int64
20   engine-location_encoded 205 non-null   int64
21   drive-wheels_encoded  205 non-null   int64
22   body-style_encoded    205 non-null   int64
23   aspiration_encoded     205 non-null   int64
24   fuel-type_encoded     205 non-null   int64
25   make_encoded          205 non-null   int64
dtypes: float64(12), int64(14)
memory usage: 41.8 KB

```

```
df.corr()
```

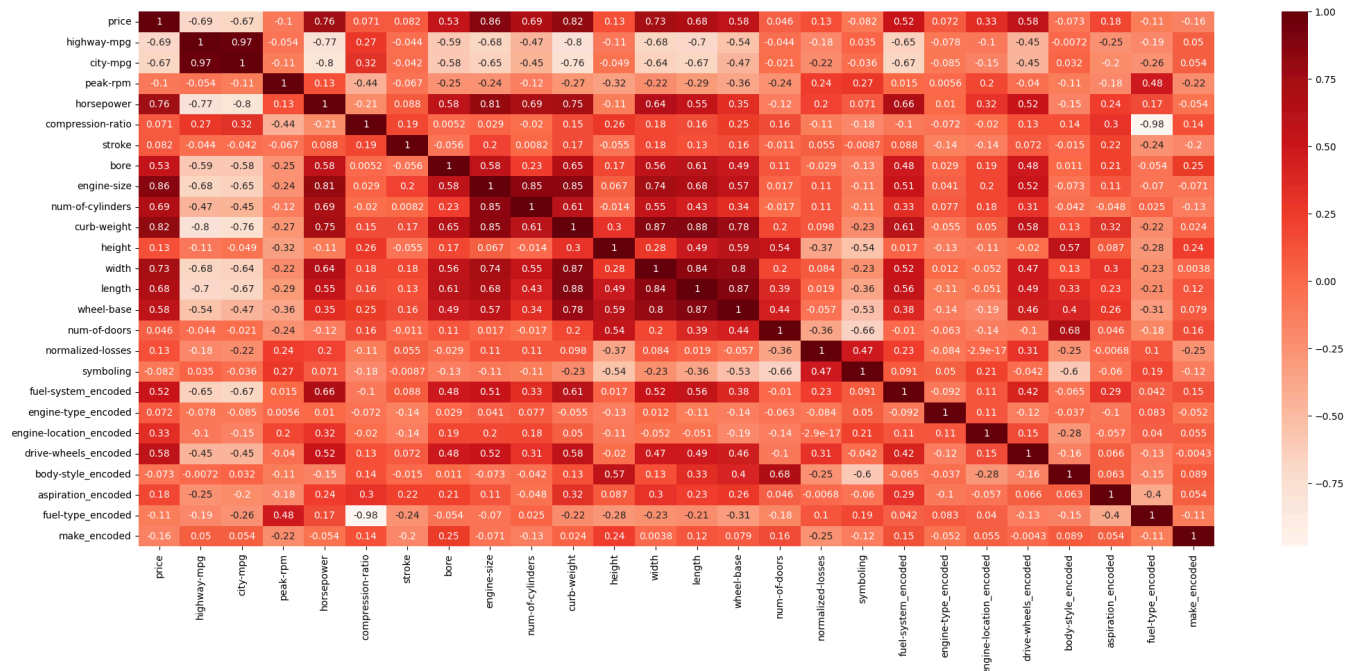
	price	highway- mpg	city-mpg	peak-rpm	horsepower	compression- ratio	
price	1.000000	-0.690526	-0.667449	-0.100854	0.757917	0.070990	0.
highway-mpg	-0.690526	1.000000	0.971337	-0.054257	-0.770903	0.265201	-0.
city-mpg	-0.667449	0.971337	1.000000	-0.113723	-0.803162	0.324701	-0.
peak-rpm	-0.100854	-0.054257	-0.113723	1.000000	0.130971	-0.435936	-0.
horsepower	0.757917	-0.770903	-0.803162	0.130971	1.000000	-0.205740	0.
compression-ratio	0.070990	0.265201	0.324701	-0.435936	-0.205740	1.000000	0.
stroke	0.082095	-0.043961	-0.042179	-0.066844	0.088264	0.186105	1.
bore	0.532300	-0.586992	-0.584508	-0.254761	0.575737	0.005201	-0.
engine-size	0.861752	-0.677470	-0.653658	-0.244599	0.810713	0.028971	0.
num-of-cylinders	0.687770	-0.466666	-0.445837	-0.124358	0.691208	-0.020002	0.
curb-weight	0.820825	-0.797465	-0.757414	-0.266283	0.750968	0.151362	0.
height	0.134388	-0.107358	-0.048640	-0.320602	-0.110137	0.261214	-0.
width	0.728699	-0.677218	-0.642704	-0.219859	0.642195	0.181129	0.
length	0.682986	-0.704662	-0.670909	-0.287031	0.554434	0.158414	0.
wheel-base	0.583168	-0.544082	-0.470414	-0.360704	0.351957	0.249786	0.
num-of-doors	0.046001	-0.044213	-0.020671	-0.240295	-0.124001	0.161502	-0.
normalized-losses	0.133999	-0.178221	-0.218749	0.237748	0.203434	-0.114525	0.
symboling	-0.082201	0.034606	-0.035823	0.273679	0.071389	-0.178515	-0.
fuel-system_encoded	0.516533	-0.645659	-0.671581	0.014714	0.659120	-0.100786	0.
engine-type_encoded	0.071535	-0.078456	-0.085004	0.005592	0.010258	-0.071873	-0.
engine-location_encoded	0.331013	-0.102026	-0.153487	0.198400	0.317610	-0.019762	-0.
drive-wheels_encoded	0.576866	-0.452220	-0.449581	-0.039724	0.516936	0.127479	0.
body-style_encoded	-0.072677	-0.007170	0.031697	-0.109410	-0.152438	0.136243	-0.

aspiration_encoded	0.177285	-0.254416	-0.202362	-0.183629	0.240182	0.295541	0.
fuel-type_encoded	-0.110207	-0.191392	-0.255963	0.477060	0.165190	-0.984356	-0.
make_encoded	-0.161471	0.050022	0.053642	-0.218342	-0.053654	0.138828	-0.

26 rows × 26 columns

```
fig, ax = plt.subplots(figsize = (25, 10))  
sns.heatmap(df.corr(), annot=True, cmap='Reds')
```


<Axes: >



✎ Exploratory Data Analysis

```
sns.pairplot(df)
```

The figure is a 25x25 grid of plots. The variables, listed on both the left and top axes, are: ΔT , ΔT_{eff} , ΔT_{eff}^2 , ΔT_{eff}^3 , ΔT_{eff}^4 , ΔT_{eff}^5 , ΔT_{eff}^6 , ΔT_{eff}^7 , ΔT_{eff}^8 , ΔT_{eff}^9 , $\Delta T_{\text{eff}}^{10}$, $\Delta T_{\text{eff}}^{11}$, $\Delta T_{\text{eff}}^{12}$, $\Delta T_{\text{eff}}^{13}$, $\Delta T_{\text{eff}}^{14}$, $\Delta T_{\text{eff}}^{15}$, $\Delta T_{\text{eff}}^{16}$, $\Delta T_{\text{eff}}^{17}$, $\Delta T_{\text{eff}}^{18}$, $\Delta T_{\text{eff}}^{19}$, $\Delta T_{\text{eff}}^{20}$, $\Delta T_{\text{eff}}^{21}$, $\Delta T_{\text{eff}}^{22}$, $\Delta T_{\text{eff}}^{23}$, $\Delta T_{\text{eff}}^{24}$, and $\Delta T_{\text{eff}}^{25}$. The diagonal of the grid contains histograms of each variable. The off-diagonal plots show scatter plots of pairs of variables, illustrating their correlations. The plots are arranged in a grid where the top-left plot is ΔT vs ΔT and the bottom-right plot is $\Delta T_{\text{eff}}^{25}$ vs $\Delta T_{\text{eff}}^{25}$.

✓ Training a Linear Regression Model

X and y arrays

```
X = df.drop('price',axis=1)
```

```
y = df['normalized-losses']
```

```
print("X-", X.shape, "\ny-", y.shape)
```

```
    X- (205, 25)
```

```
    y- (205,)
```

✓ Train Test Split

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 10)
```

```
X_train.shape
```

```
(143, 25)
```

```
X_test.shape
```

```
(62, 25)
```

✓ Linear Regression

```
model = LinearRegression()
```

```
model.fit(X_train, y_train)
```

```
▼ LinearRegression
```

```
LinearRegression()
```

✓ Model Evaluation

```
model.coef_
```

```
array([-2.78263758e-15,  1.47624968e-15, -1.09236736e-16,  2.71685639e-16,
       -1.31928379e-15, -8.49612120e-15,  3.35728726e-14,  4.75795023e-16,
        1.95259003e-15, -1.54871236e-16,  1.38015749e-15, -5.92406309e-16,
       -4.87730338e-16, -6.98331142e-16,  1.11063094e-14,  1.00000000e+00,
        1.32510326e-15, -5.11506256e-16, -3.98484956e-16, -3.35745331e-16,
        2.43758464e-15,  1.28467343e-15,  1.33107585e-15, -2.04532711e-14,
        1.31877948e-16])
```

```
model.fit(X_train, y_train)
```



```
▼ LinearRegression
```

```
LinearRegression()
```

```
model.coef_
```

```
array([-2.78263758e-15,  1.47624968e-15, -1.09236736e-16,  2.71685639e-16,
       -1.31928379e-15, -8.49612120e-15,  3.35728726e-14,  4.75795023e-16,
        1.95259003e-15, -1.54871236e-16,  1.38015749e-15, -5.92406309e-16,
       -4.87730338e-16, -6.98331142e-16,  1.11063094e-14,  1.00000000e+00,
        1.32510326e-15, -5.11506256e-16, -3.98484956e-16, -3.35745331e-16,
        2.43758464e-15,  1.28467343e-15,  1.33107585e-15, -2.04532711e-14,
        1.31877948e-16])
```

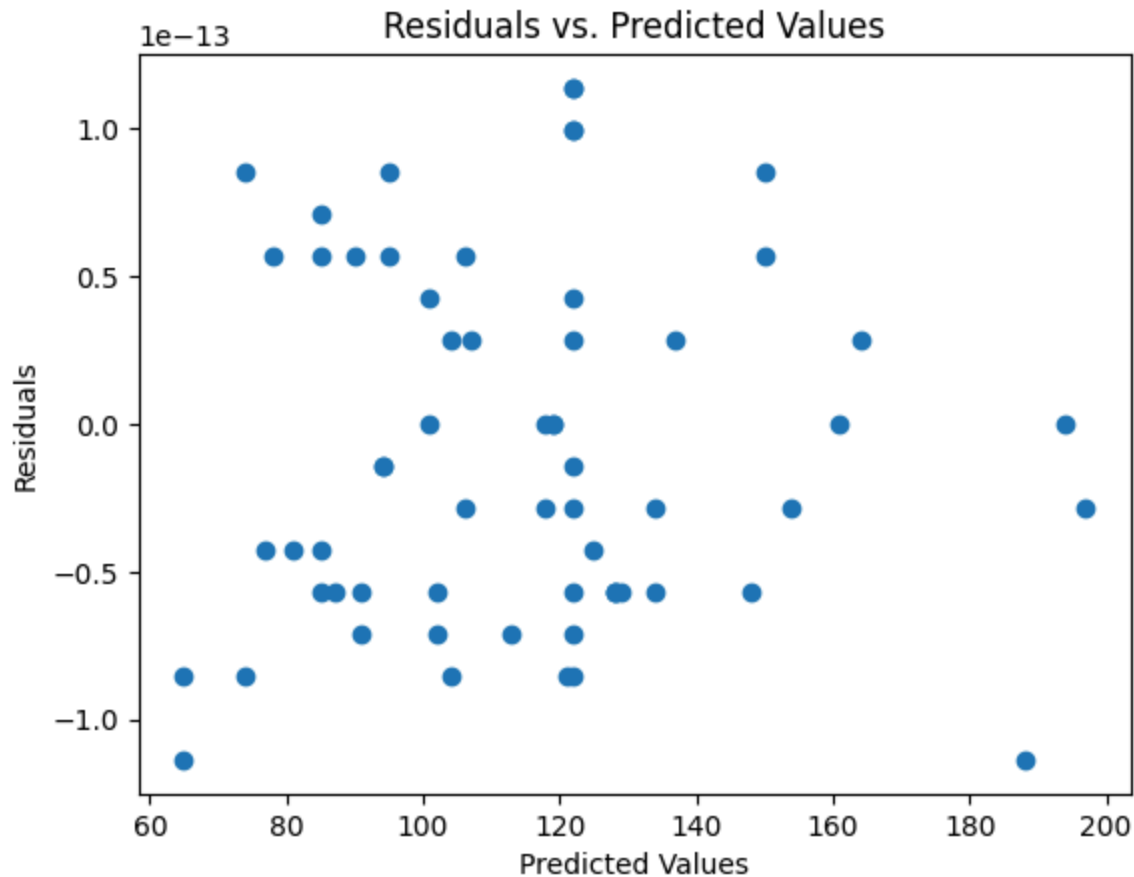
```
pd.DataFrame(model.coef_, X.columns, columns=['Coefficients'])
```

	Coeffieicients	
highway-mpg	-2.782638e-15	
city-mpg	1.476250e-15	
peak-rpm	-1.092367e-16	
horsepower	2.716856e-16	
compression-ratio	-1.319284e-15	
stroke	-8.496121e-15	
bore	3.357287e-14	
engine-size	4.757950e-16	
num-of-cylinders	1.952590e-15	
curb-weight	-1.548712e-16	
height	1.380157e-15	
width	-5.924063e-16	
length	-4.877303e-16	
wheel-base	-6.983311e-16	
num-of-doors	1.110631e-14	
normalized-losses	1.000000e+00	
symboling	1.325103e-15	
fuel-system_encoded	-5.115063e-16	
engine-type_encoded	-3.984850e-16	
engine-location_encoded	-3.357453e-16	
drive-wheels_encoded	2.437585e-15	
body-style_encoded	1.284673e-15	
aspiration_encoded	1.331076e-15	
fuel-type_encoded	-2.045327e-14	
make_encoded	1.318779e-16	

✓ Prediction from our Model

```
y_pred = model.predict(X_test)
residuals = y_test - y_pred

plt.scatter(y_pred, residuals)
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residuals vs. Predicted Values')
plt.show()
```



✓ Regression Evaluation Metrics

```
MAE = metrics.mean_absolute_error(y_test, y_pred)
MSE = metrics.mean_squared_error(y_test, y_pred)
RMSE = np.sqrt(MSE)
```

MAE

5.271768684671711e-14

MSE

3.713244622253227e-27

RMSE

6.093639817262937e-14

```
df['normalized-losses'].mean()
```

122.0

✓ Residual Analysis

```
test_residual = y_test - y_pred
```

```
pd.DataFrame({'Error Values': (test_residual)}).hvplot.kde()
```

```
/usr/local/lib/python3.10/dist-packages/holoviews/core/util.py:1585: PanelDeprecationWarning  
value = param_value_if_widget(value)
```

```
sns.displot(test_residual, bins=25, kde=True)
```

```
<seaborn.axisgrid.FacetGrid at 0x7c87c2a74310>
```