In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
import statsmodels.api as sm
```

In [2]:
```python
# import data
df = pd.read_csv('Automobile_data.csv')
```

Clean the data

In [3]:
```python
# Remove null values
df = df.replace('?', np.nan)
df = df.dropna()
df['horsepower'] = pd.to_numeric(df['horsepower'])
df['price'] = pd.to_numeric(df['price'])
```

In [4]:
```python
# Fix column names
df['avg_mpg'] = (df['city-mpg'] + df['highway-mpg']) / 2
df['curb_weight'] = df['curb-weight']
df['body_style'] = df['body-style']
df['fuel_type'] = df['fuel-type']
df['drive_wheels'] = df['drive-wheels']
df['wheel_base'] = df['wheel-base']
```

In [5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 159 entries, 3 to 204
Data columns (total 32 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   symboling          159 non-null    int64
 1   normalized-losses  159 non-null    object
 2   make               159 non-null    object
 3   fuel-type          159 non-null    object
 4   aspiration         159 non-null    object
 5   num-of-doors       159 non-null    object
 6   body-style         159 non-null    object
 7   drive-wheels       159 non-null    object
 8   engine-location    159 non-null    object
 9   wheel-base         159 non-null    float64
 10  length             159 non-null    float64
 11  width              159 non-null    float64
 12  height             159 non-null    float64
 13  curb-weight        159 non-null    int64
 14  engine-type        159 non-null    object
 15  num-of-cylinders   159 non-null    object
 16  engine-size        159 non-null    int64
 17  fuel-system        159 non-null    object
 18  bore               159 non-null    object
 19  stroke             159 non-null    object
 20  compression-ratio  159 non-null    float64
 21  horsepower         159 non-null    int64
 22  peak-rpm           159 non-null    object
 23  city-mpg           159 non-null    int64
 24  highway-mpg        159 non-null    int64
 25  price              159 non-null    int64
 26  avg_mpg            159 non-null    float64
 27  curb_weight        159 non-null    int64
 28  body_style         159 non-null    object
 29  fuel_type          159 non-null    object
 30  drive_wheels       159 non-null    object
 31  wheel_base         159 non-null    float64
dtypes: float64(7), int64(8), object(17)
memory usage: 41.0+ KB
```

Simple Linear Regression

Target variable: `price` Feature variable: `avg_mpg`

In [6]:
```python
# make model
slr_model = smf.ols('price ~ avg_mpg', data=df).fit()
slr_model.summary()
```

Out[6]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.506
Model:	OLS	**Adj. R-squared:**	0.503
Method:	Least Squares	**F-statistic:**	161.0
Date:	Sun, 03 Oct 2021	**Prob (F-statistic):**	7.63e-26
Time:	15:59:45	**Log-Likelihood:**	-1548.9
No. Observations:	159	**AIC:**	3102.
Df Residuals:	157	**BIC:**	3108.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3.11e+04	1583.646	19.641	0.000	2.8e+04	3.42e+04
avg_mpg	-670.9148	52.870	-12.690	0.000	-775.343	-566.487

Omnibus:	56.883	**Durbin-Watson:**	1.026
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	123.064
Skew:	1.608	**Prob(JB):**	1.89e-27
Kurtosis:	5.870	**Cond. No.**	145.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [7]:
```python
# plot slr model
fig, ax = plt.subplots(figsize=(6,6))

ax.scatter(df['avg_mpg'], df['price'])
ax.set_xlabel('avg mpg')
ax.set_ylabel('price')
ax.set_title('Price over Average MPG')

# regression line
beta, y_inter = np.polyfit(df['avg_mpg'], df['price'], 1)
ax.plot(df['avg_mpg'], beta * df['avg_mpg'] + y_inter, c='red', lw=2)

#clean up plot
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

plt.show()
```

In [8]:
```python
# Find slope and parameters
b_0, b_1 = slr_model.params
```

In [9]:
```python
print(f'price = {np.round(b_0, 2)} {np.round(b_1, 2)} * avg_mpg')
```

```
price = 31104.8 -670.91 * avg_mpg
```

In [10]:
```python
def estimate_price_from_avg_mpg(avg_mpg_new):
    return np.round(b_0 + b_1 * avg_mpg_new,2)
```

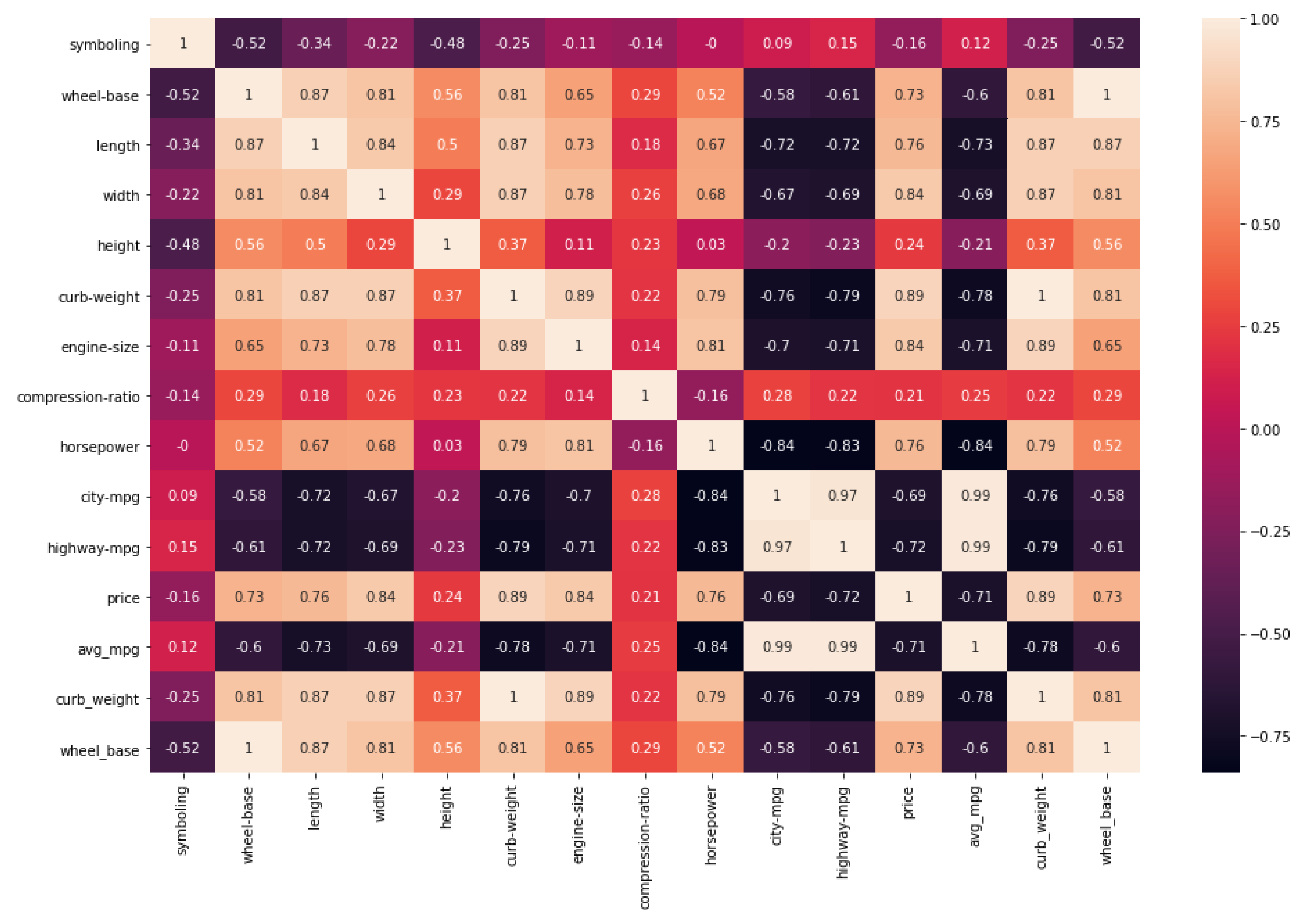
In [11]:
```python
estimate_price_from_avg_mpg(30)
```

Out[11]: 10977.36

Multiple Linear Regression

In [12]:
```python
# Check correlation of numeric variables
import seaborn as sns
correlation_matrix = df.corr().round(2)
plt.figure(figsize = (16, 10))
sns.heatmap(data=correlation_matrix, annot=True)

plt.show()
```



Target: `price` Feature variables: `avg_mpg` , `wheel_base` , `fuel_type`

In [13]:
```python
# Makde mlr model
mlr_model = smf.ols('price ~ avg_mpg + wheel_base + fuel_type', data=df).fit()
mlr_model.summary()
```

Out[13]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.700
Model:	OLS	**Adj. R-squared:**	0.694
Method:	Least Squares	**F-statistic:**	120.3
Date:	Sun, 03 Oct 2021	**Prob (F-statistic):**	2.76e-40
Time:	15:59:46	**Log-Likelihood:**	-1509.4
No. Observations:	159	**AIC:**	3027.
Df Residuals:	155	**BIC:**	3039.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-682.8180	9442.703	-0.072	0.942	-1.93e+04	1.8e+04
fuel_type[T.gas]	-5304.4989	1089.712	-4.868	0.000	-7457.103	-3151.895
avg_mpg	-548.1451	60.307	-9.089	0.000	-667.275	-429.015
wheel_base	335.7716	76.119	4.411	0.000	185.407	486.137

Omnibus:	81.635	**Durbin-Watson:**	1.267
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	382.088
Skew:	1.900	**Prob(JB):**	1.07e-83
Kurtosis:	9.576	**Cond. No.**	3.77e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.77e+03. This might indicate that there are strong multicollinearity or other numerical problems.