ML - Simple Regression Model.

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In [1]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import os
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
```

In [2]:
```
os.chdir(r'D:\Sagun Shakya\Python\Data Sets')
df = pd.read_csv('weight-height.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	Gender	Height	Weight
0	Male	73.847017	241.893563
1	Male	68.781904	162.310473
2	Male	74.110105	212.740856
3	Male	71.730978	220.042470
4	Male	69.881796	206.349801

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

Out[4]:
```
(10000, 3)
```

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
Gender    0
Height    0
Weight    0
dtype: int64
```

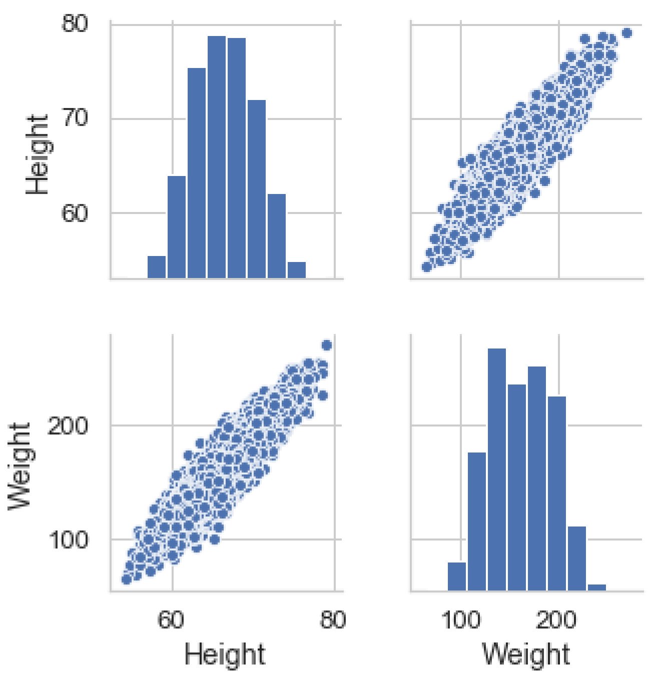
In [6]:
```
df.corr()
```

Out[6]:

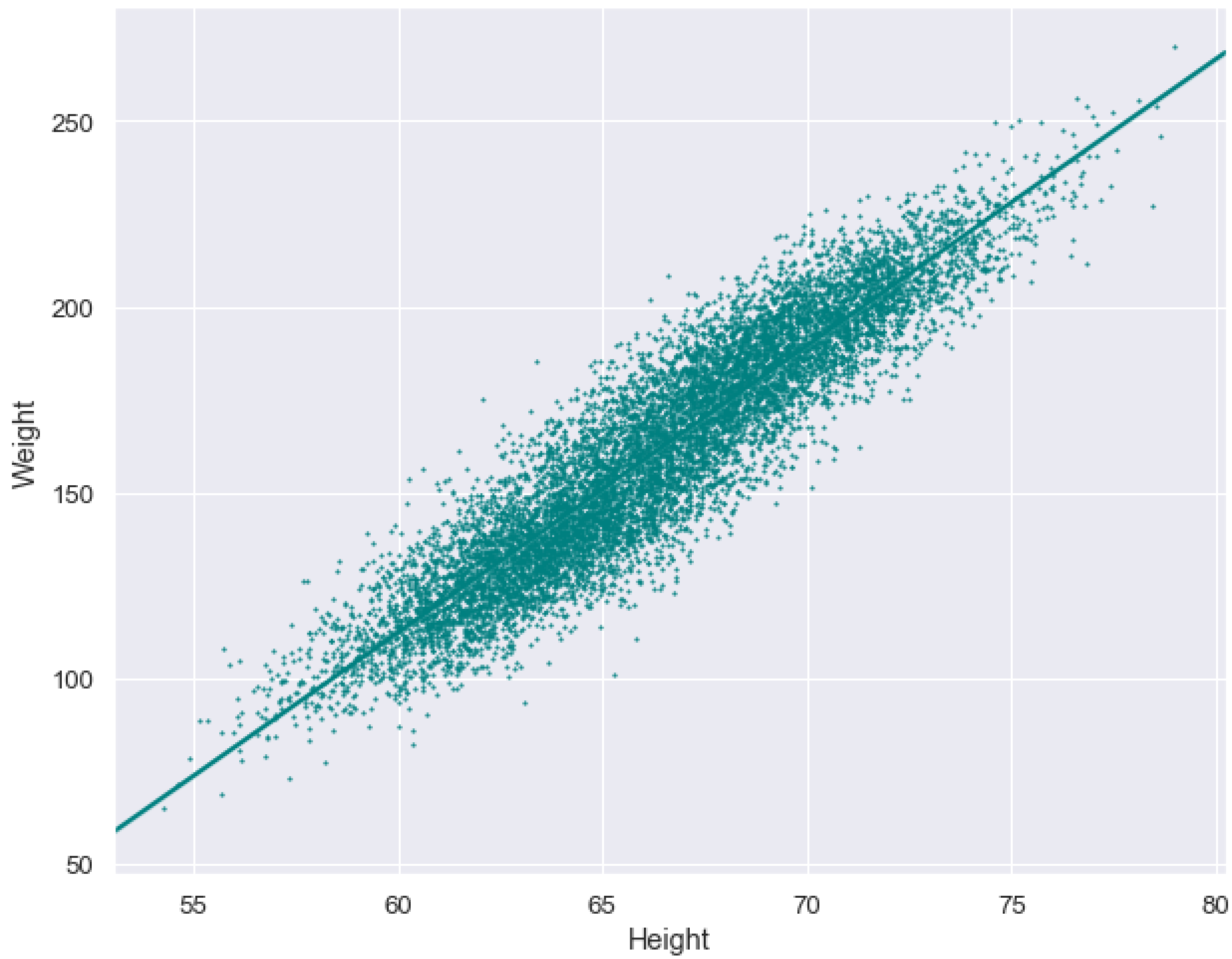
	Height	Weight
Height	1.000000	0.924756
Weight	0.924756	1.000000

In [7]:
```
plt.figure( figsize = (10,8) )
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.pairplot(df)
plt.show()
```

```
<Figure size 720x576 with 0 Axes>
```



In [8]:
```
plt.figure( figsize = (10,8) )
sns.set(style = 'darkgrid', font_scale = 1.2)

sns.regplot(x = df.Height, y = df.Weight, marker = '*', color = '#008080', scatter_kws={'s':2})
plt.show()
```



Fitting a Linear Model.

In [9]:
```
model = LinearRegression()
```

Test train split.

Test train split:

- *arrays: sequence of indexables with same length / shape[0]
  - Allowed inputs are lists, numpy arrays, scipy-sparse matrices or pandas dataframes.
- test_size: float, int or None, optional (default=None)
  - If float, should be between 0.0 and 1.0 and represent the proportion of the dataset to include in the test split. If int, represents the absolute number of test samples. If None, the value is set to the complement of the train size. If train_size is also None, it will be set to 0.25.
- train_size: float, int, or None, (default=None)
  - If float, should be between 0.0 and 1.0 and represent the proportion of the dataset to include in the train split. If int, represents the absolute number of train samples. If None, the value is automatically set to the complement of the test size.
- random_state: int, RandomState instance or None, optional (default=None)
  - If int, random_state is the seed used by the random number generator; If RandomState instance, random_state is the random number generator; If None, the random number generator is the RandomState instance used by np.random.

In [10]:
```
x_train, x_test, y_train, y_test = train_test_split(df.Height, df.Weight, test_size = 0.3, random_state = 42)
```

In [11]:
```
x_train_mod = np.array(x_train).reshape(-1,1)
x_test_mod = np.array(x_test).reshape(-1,1)
y_train_mod = np.array(y_train).reshape(-1,1)
y_test_mod = np.array(y_test).reshape(-1,1)
```

Fitting a Linear Regression Model using 70% of the data (test_size = 0.3).

In [12]:
```
model.fit(x_train_mod, y_train_mod)
```

Out[12]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Predicting the test results using 30% of the data.

In [13]:
```
y_predicted = model.predict(x_test_mod)
```

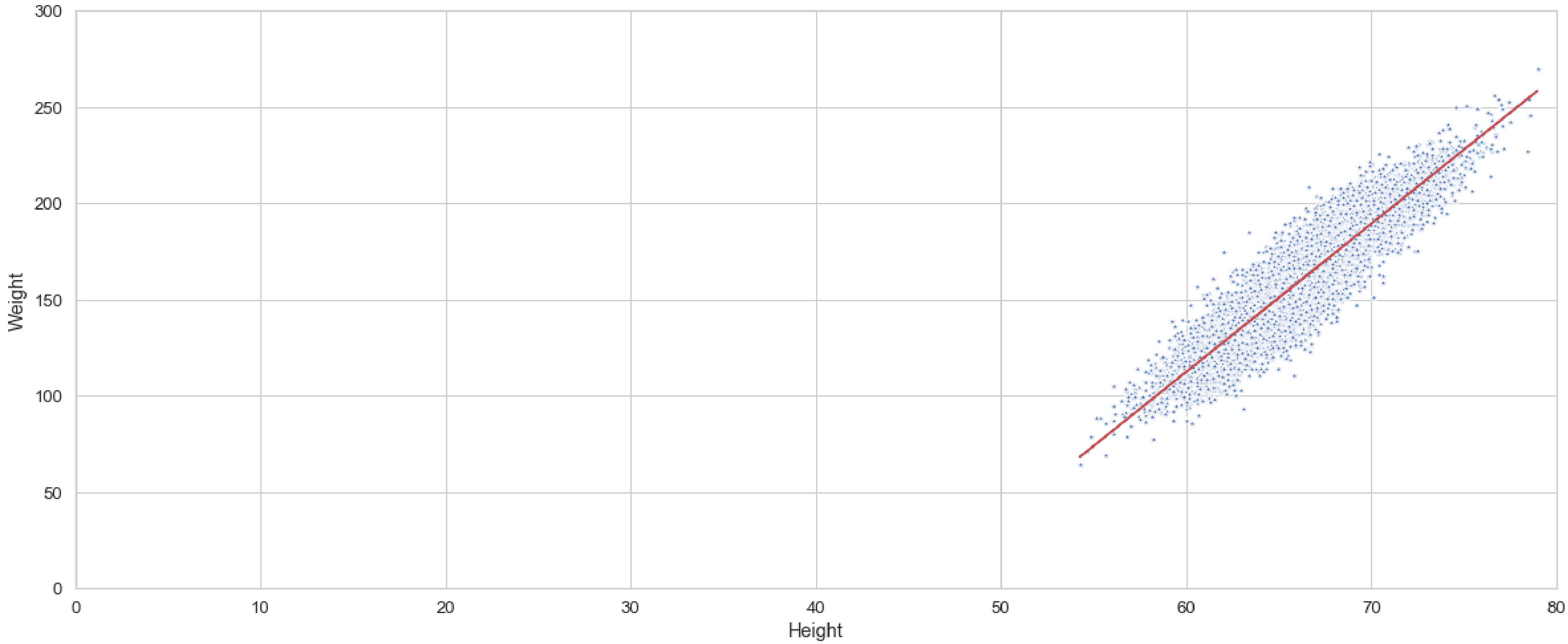
In [14]:
```
y_predicted
```

Out[14]:
```
array([[179.25411946],
       [180.34765156],
       [161.63849193],
       ...,
       [188.45953085],
       [129.84456058],
       [201.11830118]])
```

Data visualization.

1. Training set results.

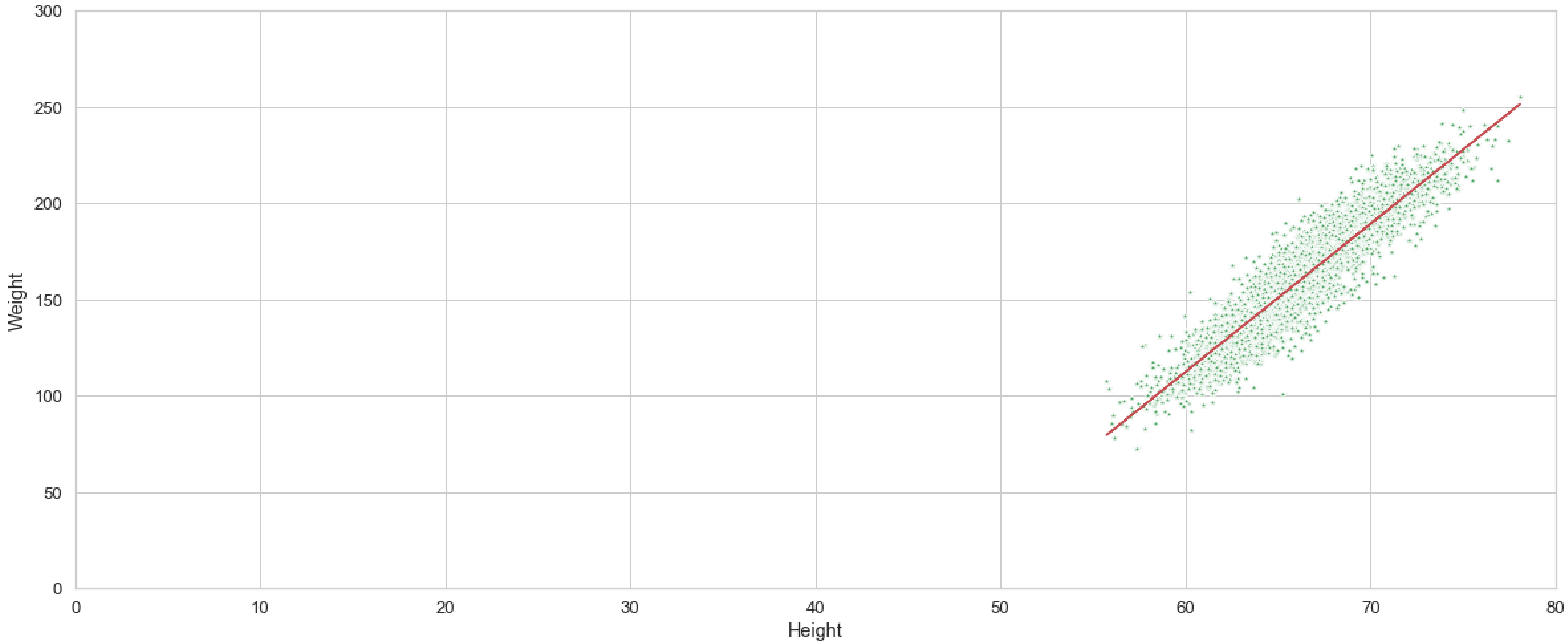
In [15]:
```
plt.figure( figsize = (20,8) )
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.scatterplot(x=x_train, y = y_train, color = 'b', marker = '*')
plt.plot(x_train, model.predict(x_train_mod), color = 'r')
plt.xlim(0,80)
plt.ylim(0,300)
plt.show()
```



2. Test set results.

In [75]:

```
plt.figure( figsize = (20,8) )
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.scatterplot(x=x_test, y = y_test, color = 'g', marker = '*')
plt.plot(x_test, model.predict(x_test_mod), color = 'r')
plt.xlim(0,80)
plt.ylim(0,300)
plt.show()
```



To determine the slope and the intercept of the regression line.

In [17]:
```
print('Slope = ', model.coef_)
print('Intercept = ', model.intercept_)
```

```
Slope =  [[7.69542535]]
Intercept =  [-349.32334861]
```

Prediction using a sample data point.

In [18]:
```
model.predict([[75.32]])
```

Out[18]:
```
array([[230.29608901]])
```

Using various regression metrics.

1. Mean Absolute Error:

$$\text{MAE}(y, \hat{y}) = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}-1} |y_i - \hat{y}_i|.$$

In [20]:
```
from sklearn.metrics import mean_absolute_error as mae
```

In [21]:
```
mae(y_test, y_predicted)
```

Out[21]:
```
9.709435604300088
```

2. Mean Squared Error:

$$\text{MSE}(y, \hat{y}) = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}-1} (y_i - \hat{y}_i)^2.$$

In [23]:
```python
from sklearn.metrics import mean_squared_error as mse
```

In [24]:
```python
mse(y_test, y_predicted)
```

Out[24]: 148.3622953279399

3. R^2 score, the coefficient of determination:

- It represents the proportion of variance (of y) that has been explained by the independent variables in the model.
- It provides an indication of goodness of fit and therefore a measure of how well unseen samples are likely to be predicted by the model, through the proportion of explained variance.
  - Note that r2_score calculates unadjusted R^2 without correcting for bias in sample variance of y.

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

In [26]:
```python
from sklearn.metrics import r2_score as r2
```

In [27]:
```python
r2(y_test, y_predicted)
```

Out[27]: 0.8577298529881874

4. P - value:

In [28]:
```python
from scipy.stats import linregress

slope, intercept, r_value, p_value, std_err = linregress(x_train,y_train)
```

In [36]:
```
print('Slope = ', round(slope,2),
      '\nIntercept = ', round(intercept,2),
      '\nr_value = ', round(r_value,2),
      '\np - value = ', p_value,
      '\nStandard Error = ', round(std_err,2))
```

```
Slope =  7.7
Intercept =  -349.32
r_value =  0.92
p - value =  0.0
Standard Error =  0.04
```

Since the p - values is very less than α = 0.05, we reject the Null hypothesis that the gradient = 0.

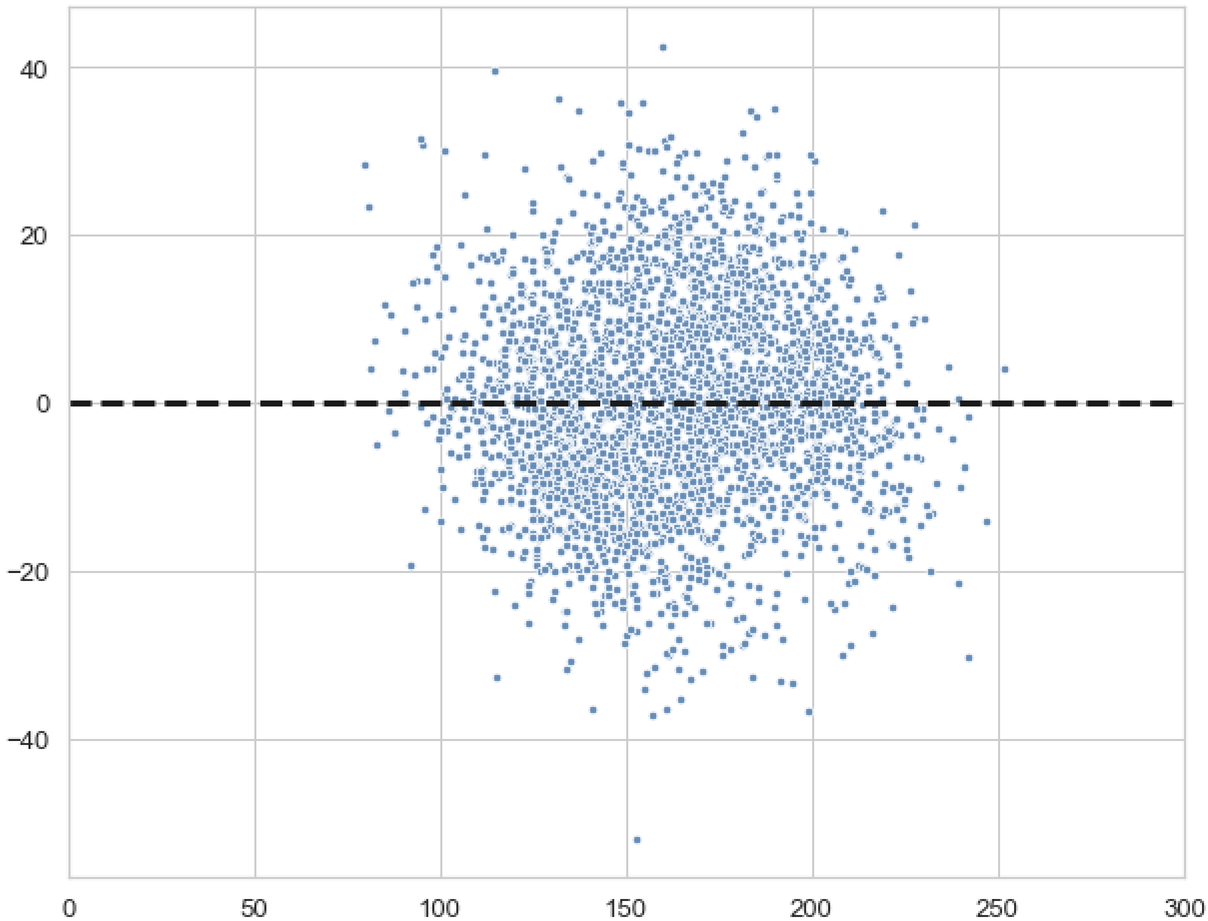
- This means that there exists a significant linear relationship between height and weight.

5. Residual analysis:

- We can plot the residuals versus each of the predicting variables to look for independence assumption.
  - If the residuals are distributed uniformly randomly around the zero x-axes and do not form specific clusters, then the assumption holds true.
- When we plot the fitted response values (as per the model) vs. the residuals, we clearly observe that the variance of the residuals increases with response variable magnitude.
  - Therefore, the problem does not respect homoscedasticity and some kind of variable transformation may be needed to improve model quality.

In [51]:
```
error = y_test_mod - y_predicted
```

In [73]:
```
plt.figure( figsize = (10,8) )
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.scatterplot(x = y_predicted.reshape(3000,), y = error.reshape(3000,), color = '#658cb7', s = 20)
plt.plot(np.arange(300), np.zeros(300), 'k--', linewidth = 3)
plt.xlim(0,300)
plt.show()
```



For more info:

[github (https://github.com/SSaishruthi/Linear_Regression_Detailed_Implementation/blob/master/Linear_Regression.ipynb)](https://github.com/SSaishruthi/Linear_Regression_Detailed_Implementation/blob/master/Linear_Regression.ipynb)

The End.