

Multiple Linear Regression

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In [1]: import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

from sklearn import linear_model
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split

In [2]: # 1. Import data
df = pd.read_csv("baseball.csv")
df.columns = ['x1','x2','x3','x4','x5','x6']
print(df.describe())
```

	x1	x2	x3	x4	x5	x6
count	45.000000	45.000000	45.000000	45.000000	45.000000	45.000000
mean	0.280467	0.150889	0.046356	0.011289	0.024267	0.104333
std	0.044002	0.042009	0.010452	0.006960	0.022260	0.063057
min	0.188000	0.064000	0.025000	0.001000	0.000000	0.000000
25%	0.248000	0.119000	0.039000	0.007000	0.009000	0.062000
50%	0.290000	0.150000	0.045000	0.009000	0.013000	0.095000
75%	0.308000	0.189000	0.053000	0.016000	0.039000	0.138000
max	0.367000	0.259000	0.068000	0.030000	0.085000	0.264000

```
In [5]: df.shape
```

```
Out[5]: (45, 6)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45 entries, 0 to 44
Data columns (total 6 columns):
#   Column       Non-Null Count  Dtype  
--- 
#   x1           45 non-null    float64
#   x2           45 non-null    float64
#   x3           45 non-null    float64
#   x4           45 non-null    float64
#   x5           45 non-null    float64
#   x6           45 non-null    float64
dtypes: float64(6)
memory usage: 2.2 KB
```

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In [3]: # 2. Observe the correlation of dependent variables to the independent variable and
# independent variables to each other to avoid multi-collinearity
cor = sns.PairGrid(df)
cor.map(plt.scatter);
plt.show()
```



```
In [4]: #3. Prepare data
# Remove the dependent variable and build an input dataset
X = df.iloc[:,df.columns != 'x1']
#Create a df of dependent variable by itself
Y = df.iloc[:, 0]
#Split the data into train and test sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,
random_state= 0)
```

```
In [7]: #4. Create the model
# Call the model function
model = linear_model.LinearRegression()

# Fit the data to model
model.fit(X_train, Y_train)
```

```
# Build the dataframe with coefficients
coeff_df = pd.DataFrame(model.coef_, X.columns, columns=['Coef'])
print(coeff_df)
```

Coef
x2 0.518154
x3 1.027110
x4 0.518150
x5 0.175801
x6 -0.248293

```
In [ ]: x1 = .51 * x2 + 1.02 * x3 + .5 * x4 + .17 * x5 + -0.24 * x6
```

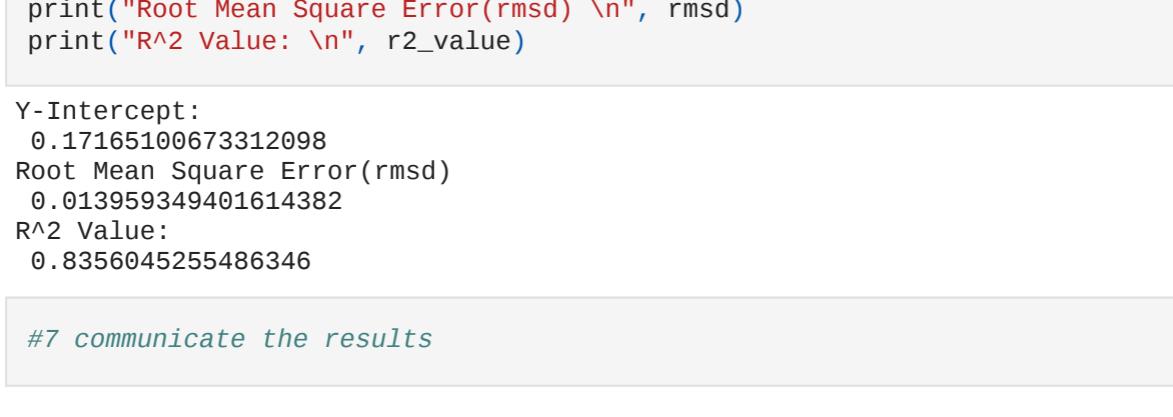
```
In [8]: model.coef_
```

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Out[8]: array([ 0.51815391,  1.0271097 ,  0.51814958,  0.17580108, -0.24829316])
```

```
In [9]: #5. Test the model
y_pred = model.predict(X_test)
df = pd.DataFrame({'Actual': Y_test, 'Predicted': y_pred})
print(df.head(10))
```

	Actual	Predicted
30	0.243	0.233866
37	0.304	0.317188
27	0.318	0.333119
4	0.290	0.299402
10	0.269	0.276333
25	0.244	0.242289
28	0.207	0.239242
11	0.300	0.294018
38	0.297	0.290114

```
In [10]: #6. Observe the performance of the model
df.plot(kind='bar', figsize=(10,8))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='red')
# plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```



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In [11]: #6. Observe the performance of the model
# Root Mean Squared Error or Deviation
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# Lower the rmse(rmsd) is, the better the fit
rmsd = np.sqrt(mean_squared_error(Y_test, y_pred))
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# The closer towards 1, the better the fit
r2_value = r2_score(Y_test, y_pred)
```

```
print("Y-Intercept: \n", model.intercept_)
```

```
print("Root Mean Square Error(rmsd) \n", rmsd)
```

```
print("R^2 Value: \n", r2_value)
```

```
Y-Intercept:
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```
0.17165100673312098
```

```
Root Mean Square Error(rmsd)
```

```
0.013959349401614382
```

```
R^2 Value:
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```
0.8356045255486346
```

```
In [ ]: #7 communicate the results
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