

cmeps320_inclass_assignment1_SammanBhetwal

September 27, 2024

```
[1]: ### Import appropriate libraries
```

```
[5]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sn
import statsmodels.formula.api as smf

# plot the graph directly in the notebook
%matplotlib inline
```

```
[48]: df = pd.read_excel("Wire_bond.xlsx", header=1, index_col=0)
```

df

```
[48]:
```

	pull strength	die height	post height	loop height	wire length	\
1	8.0	5.2	17.0	28.6	83.0	
2	8.0	5.2	19.6	29.6	94.9	
3	8.3	5.8	19.8	32.4	89.7	
4	8.5	6.4	19.6	31.0	96.2	
5	8.8	5.8	19.4	32.4	95.6	
6	9.0	5.2	18.6	28.6	86.5	
7	9.3	5.6	18.8	30.6	84.5	
8	9.3	6.0	20.4	32.4	88.8	
9	9.5	5.2	19.0	32.6	85.7	
10	9.8	5.8	20.8	32.2	93.6	
11	10.0	6.4	19.9	31.8	86.0	
12	10.3	6.0	18.0	32.6	87.1	
13	10.5	6.2	20.6	33.4	93.1	
14	10.8	6.2	20.2	31.8	83.4	
15	11.0	6.2	20.2	32.4	94.5	
16	11.3	5.6	19.2	31.4	83.4	
17	11.5	6.0	17.0	33.2	85.2	
18	11.8	5.8	19.8	35.4	84.1	
19	12.0	6.5	19.4	32.2	88.5	
20	12.3	5.6	18.8	34.0	86.9	
21	12.5	18.6	18.6	34.2	83.0	

22	12.5	18.6	20.8	35.4	96.2
----	------	------	------	------	------

	bond width on the die	bond width on the post
1	1.9	1.6
2	2.1	2.3
3	2.1	1.8
4	2.0	2.0
5	2.2	2.1
6	2.0	1.8
7	2.1	2.1
8	2.2	1.9
9	2.1	1.9
10	2.3	2.1
11	2.1	1.8
12	2.0	1.6
13	2.1	2.1
14	2.2	2.1
15	2.1	1.9
16	1.9	1.8
17	2.1	2.1
18	2.0	1.8
19	2.1	1.9
20	2.1	1.8
21	1.9	2.0
22	2.3	2.3

```
[51]: # renaming the columns
df.columns = ['y', 'x1', 'x2', 'x3', 'x4', 'x5', 'x6']

df.describe()
```

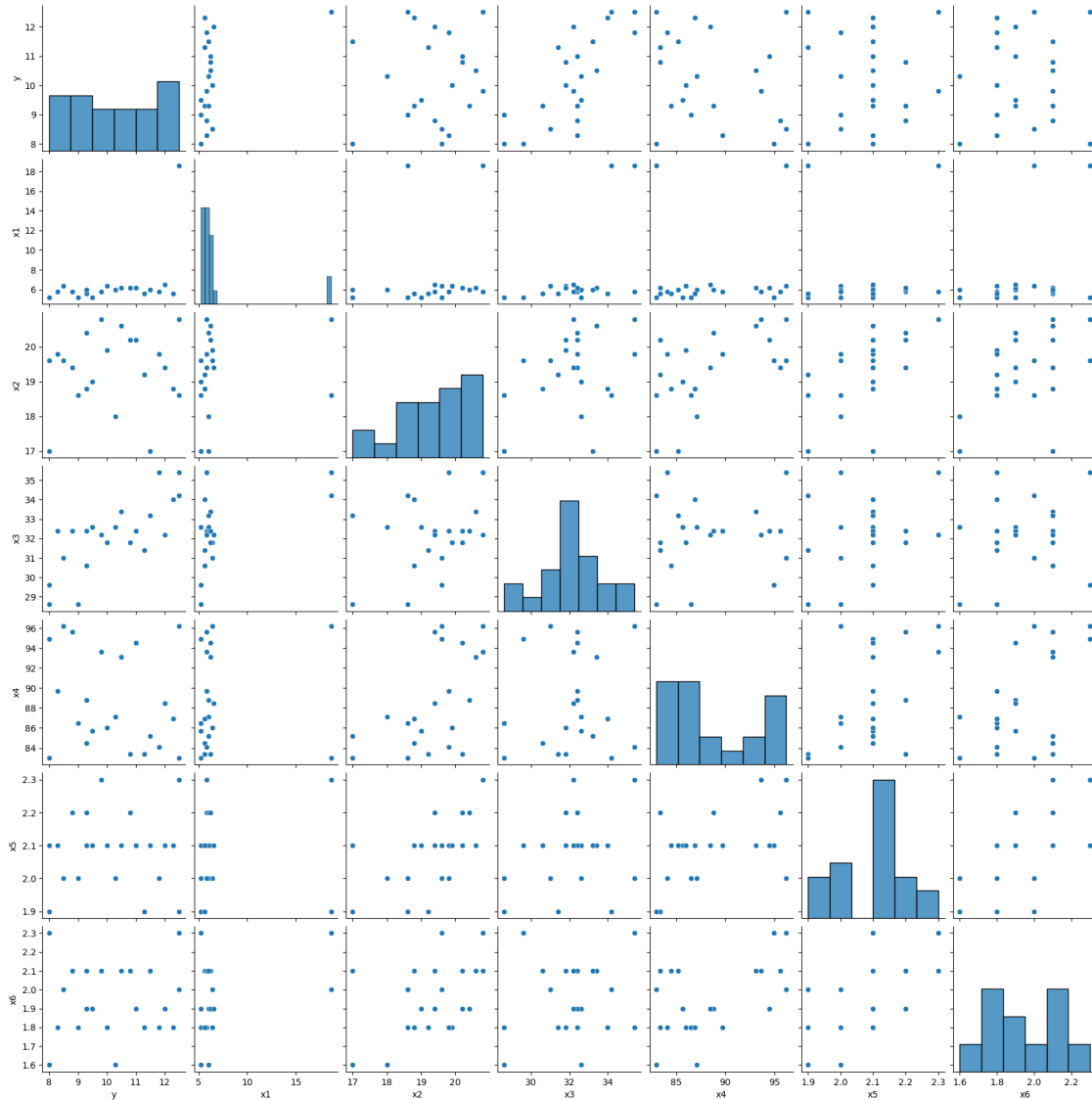
```
[51]:
```

	y	x1	x2	x3	x4	x5 \
count	22.000000	22.000000	22.000000	22.000000	22.000000	22.000000
mean	10.227273	6.995455	19.340909	32.190909	88.631818	2.086364
std	1.490664	3.777184	1.066663	1.803148	4.759190	0.112527
min	8.000000	5.200000	17.000000	28.600000	83.000000	1.900000
25%	9.075000	5.600000	18.800000	31.500000	84.675000	2.000000
50%	10.150000	5.900000	19.500000	32.400000	87.000000	2.100000
75%	11.450000	6.200000	20.125000	33.050000	93.475000	2.100000
max	12.500000	18.600000	20.800000	35.400000	96.200000	2.300000

	x6
count	22.000000
mean	1.945455

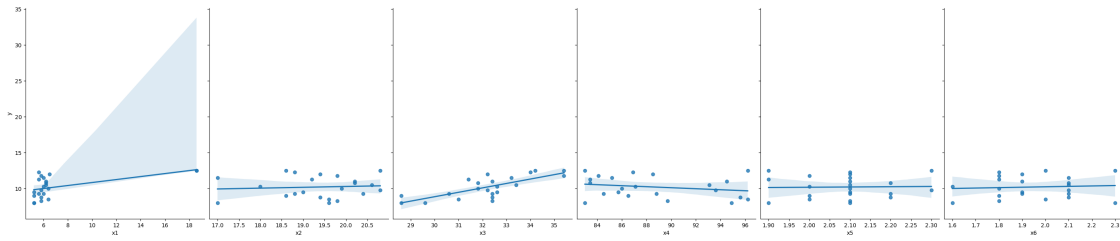
```
std      0.192050
min      1.600000
25%      1.800000
50%      1.900000
75%      2.100000
max      2.300000
```

```
[52]: sn.pairplot(df)
plt.show()
```



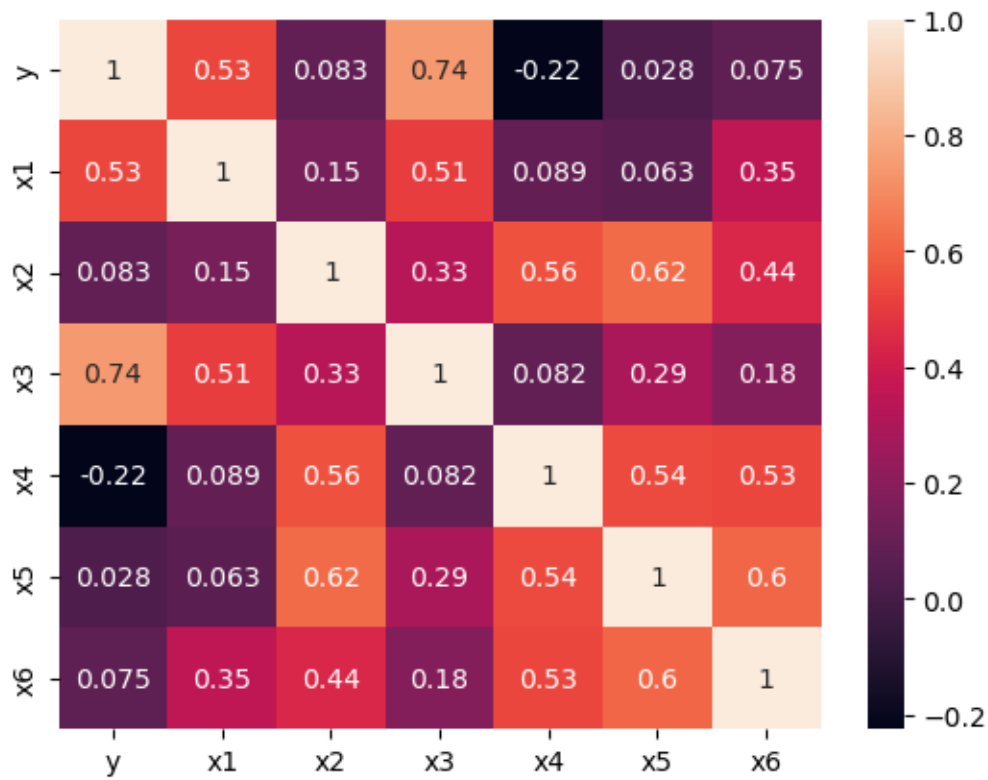
```
[53]: sn.pairplot(data = df, x_vars=['x1','x2','x3','x4','x5','x6'], y_vars=['y'],
        height = 6, aspect = 0.8, kind='reg')
```

[53]: <seaborn.axisgrid.PairGrid at 0x216d02eac70>



```
[54]: # Compute the correlation matrix
corrMatrix = df.corr()

# Plot the heatmap
sn.heatmap(corrMatrix, annot=True)
plt.show()
```



1 Single regression Model

```
[55]: import warnings
warnings.filterwarnings("ignore")
```

```
[75]: lm_linear = smf.ols(formula='y ~ x3', data=df).fit()
print(lm_linear.summary())
```

```

                        OLS Regression Results
=====
Dep. Variable:          y      R-squared:                0.554
Model:                  OLS    Adj. R-squared:           0.531
Method:                 Least Squares    F-statistic:        24.82
Date:                  Fri, 27 Sep 2024    Prob (F-statistic):    7.16e-05
Time:                  23:06:25    Log-Likelihood:       -30.611
No. Observations:      22    AIC:                65.22
Df Residuals:          20    BIC:                67.40
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-9.5769	3.981	-2.406	0.026	-17.881	-1.273
x3	0.6152	0.123	4.982	0.000	0.358	0.873

```
=====
Omnibus:                0.253    Durbin-Watson:           1.122
Prob(Omnibus):          0.881    Jarque-Bera (JB):         0.439
Skew:                   -0.133    Prob(JB):                 0.803
Kurtosis:               2.361    Cond. No.                 591.
=====
```

Notes:

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

1.0.1 Trying with Multiple regression model now

```
[62]: lm_mul = smf.ols(formula= 'y ~ x1+ x2 +x3+ x4 + x5 +x6', data=df).fit()
lm_mul.summary()
```

```
[62]: <class 'statsmodels.iolib.summary.Summary'>
"""
```

```

                        OLS Regression Results
=====
Dep. Variable:          y      R-squared:                0.677
Model:                  OLS    Adj. R-squared:           0.548
Method:                 Least Squares    F-statistic:        5.244
Date:                  Fri, 27 Sep 2024    Prob (F-statistic):    0.00430

```

```

Time:                22:56:48    Log-Likelihood:        -27.051
No. Observations:    22          AIC:                68.10
Df Residuals:        15          BIC:                75.74
Df Model:            6
Covariance Type:     nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.6737	5.891	0.114	0.910	-11.883	13.231
x1	0.0723	0.076	0.956	0.354	-0.089	0.233
x2	0.0226	0.286	0.079	0.938	-0.587	0.633
x3	0.5602	0.156	3.601	0.003	0.229	0.892
x4	-0.0978	0.061	-1.592	0.132	-0.229	0.033
x5	-1.0217	3.021	-0.338	0.740	-7.461	5.417
x6	0.7078	1.664	0.425	0.677	-2.839	4.255
Omnibus:	0.490		Durbin-Watson:	1.438		
Prob(Omnibus):	0.783		Jarque-Bera (JB):	0.288		
Skew:	0.265		Prob(JB):	0.866		
Kurtosis:	2.814		Cond. No.	2.67e+03		

Notes:

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

[2] The condition number is large, 2.67e+03. This might indicate that there are strong multicollinearity or other numerical problems.

"""

1.0.2 a)

The summaries of both models indicate that the simple linear regression model is a better fit. In comparing the p-values of all the coefficients in the multiple regression model, only loop height has a p-value below 0.05, while the other coefficients are closer to 1, suggesting they are not highly significant. Additionally, the simple linear model exhibits better F statistics and a low p-value, indicating its significance. Although the multiple regression model shows a higher R-squared value, the difference is not substantial compared to the simple model, as multiple models typically have higher R-squared values. Furthermore, the Adjusted R-squared values are also similar, showing no significant disparity.

1.0.3 b)

The R-squared value indicates how well the model explains the variation in the dependent variable, with values closer to 1 indicating a better fit. In the case of the simple linear regression model, 55% of the variation in pull strength (Y) is explained by the loop height (X).

1.0.4 (c)

```
[65]: # With 95% confidence interval
      lm_linear.conf_int(0.05)
```

```
[65]:
```

	0	1
Intercept	-17.880939	-1.272886
x3	0.357634	0.872787

Intercept (Pull Strength when Loop Height is Zero): The 95% confidence interval for the intercept is [-17.88, -1.27]. This implies that when the loop height (the independent variable) is 0, the pull strength of a wire bond is expected to fall within this range, indicating a potential for negative values.

Effect of Loop Height (x4): The confidence interval for the coefficient of loop height is [0.358, 0.873]. This suggests that for each unit increase in loop height, the pull strength is anticipated to increase by an amount between 0.358 and 0.873 units, reflecting a significant positive effect of loop height on pull strength.

1.0.5 (d)

Effect of Wire Length (x4): The coefficient for wire length (x4) is negative, indicating that increasing its value will result in a decrease in the average pull strength (y) by approximately 0.0978 units for each unit increase in wire length. This suggests an inverse relationship between wire length and pull strength, highlighting the importance of managing this variable in wire bond applications.

1.0.6 (e)

```
[76]: data = pd.DataFrame({
      'x1': [5.5],
      'x2': [19.3],
      'x3': [30.2],
      'x4': [90],
      'x5': [2],
      'x6': [1.85] })
```

```
[77]: predicted = lm_linear.predict(data)
      print(lm_linear.predict(data))
```

```
0    9.002445
dtype: float64
```

9.002445

```
[ ]:
```