

Falak_Jain_HW1

February 10, 2022

HW1 - Falak Jain

```
[16]: import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
```

1.

(i) Yes

(ii) 4 hours per week on average

(iii) Yes

2.

Model: $\log y = 1 + 70 \log x$

- This implies that for a 1% increase in x, there is a roughly 101% increase in y
- If x changes: the regression equation is $1 + 70 \log(x_{\text{new}})$
- Old equation : $\log(y_{\text{old}}) = 1 + 70\log(x_{\text{old}})$

Interpretation:

- $\log(y_{\text{new}}) = 1 + 70\log(x_{\text{new}})$
- Subtracting the old and new equations we get,
- $\log(y_{\text{new}}) - \log(y_{\text{old}}) = 70\log(x_{\text{new}}) - 70\log(x_{\text{old}})$
- $\log(y_{\text{new}}/y_{\text{old}}) = 70\log(x_{\text{new}}/x_{\text{old}})$
- $y_{\text{new}}/y_{\text{old}} = (x_{\text{new}}/x_{\text{old}})^{70}$
- Therefore, if there is a 1% increase in x,
- $y_{\text{new}}/y_{\text{old}} = 1.01^{70} = 2.01$

Therefore there is an increase of 101% in y

3.

```
[4]: housing = pd.read_csv('housing.csv')
housing.head()
```

```
[4]:      crim    zn  river    rm  ptratio  medv
0  0.00632  18.0     0  6.575    15.3   24.0
1  0.02731   0.0     0  6.421    17.8   21.6
2  0.02729   0.0     0  7.185    17.8   34.7
3  0.03237   0.0     0  6.998    18.7   33.4
4  0.06905   0.0     0  7.147    18.7   36.2
```

```
[3]: mms = MinMaxScaler()
X = mms.fit_transform(X)
```

Before Min Max Scaling

```
[5]: X = housing[['ptratio', 'rm']].values
y = housing['medv'].values
```

```
[11]: linear_model = LinearRegression()
linear_model.fit(X,y)
r_sq = linear_model.score(X,y)
print('Coefficient of determination: ', r_sq)
```

Coefficient of determination: 0.5612534621272917

After Min Max Scaling

```
[12]: X = housing[['ptratio', 'rm']].values.astype(float)
y = housing['medv'].values
mms = MinMaxScaler()
X_scaled = mms.fit_transform(X)
X_norm = pd.DataFrame(X_scaled, columns = ['ptratio', 'rm'])
X_norm
```

```
[12]:      ptratio    rm
0    0.287234  0.577505
1    0.553191  0.547998
2    0.553191  0.694386
3    0.648936  0.658555
4    0.648936  0.687105
..      ...      ...
501  0.893617  0.580954
502  0.893617  0.490324
503  0.893617  0.654340
504  0.893617  0.619467
505  0.893617  0.473079
```

[506 rows x 2 columns]

```
[14]: linear_model = LinearRegression()
X_norm_values = X_norm[['ptratio', 'rm']].values
linear_model.fit(X_norm_values, y)
r_sq = linear_model.score(X_norm_values, y)
print('Coefficient of determination: ', r_sq)
```

Coefficient of determination: 0.5612534621272917

We get the same R-sq value as Lecture 2b

4.

```
[5]: import statsmodels.api as sm
X = sm.add_constant(housing[['zn', 'river', 'rm', 'ptratio', 'medv']].values)
y = housing['crim'].values
ols = sm.OLS(y, X)
ols_result = ols.fit()
ols_result.summary()
```

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

```

                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared:                0.170
Model:                            OLS      Adj. R-squared:         0.161
Method:                 Least Squares      F-statistic:            20.43
Date:                Sun, 30 Jan 2022      Prob (F-statistic):      1.41e-18
Time:                  19:13:20      Log-Likelihood:         -1759.3
No. Observations:                506      AIC:                   3531.
Df Residuals:                    500      BIC:                   3556.
Df Model:                          5
Covariance Type:                nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-4.3579	5.449	-0.800	0.424	-15.064	6.348
x1	-0.0178	0.017	-1.054	0.293	-0.051	0.015
x2	0.4869	1.415	0.344	0.731	-2.294	3.268
x3	1.2903	0.698	1.850	0.065	-0.080	2.661
x4	0.4466	0.195	2.288	0.023	0.063	0.830
x5	-0.3644	0.058	-6.237	0.000	-0.479	-0.250

```

=====
Omnibus:                    557.602      Durbin-Watson:           1.009
Prob(Omnibus):                0.000      Jarque-Bera (JB):        32052.496
Skew:                          5.097      Prob(JB):                 0.00
Kurtosis:                     40.635      Cond. No.                 544.
=====

```

Notes:

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

"""

- R-sq = 0.17, adj-R-sq = 0.161
- We can reject the null for ptratio and medv predictors

```
[6]: import statsmodels.api as sm
X = sm.add_constant(housing[['ptratio', 'medv']].values)
y = housing['crim'].values
ols = sm.OLS(y, X)
ols_result = ols.fit()
ols_result.summary()
```

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

```

                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared:                  0.162
Model:                            OLS     Adj. R-squared:              0.159
Method:                 Least Squares   F-statistic:                 48.75
Date:                Sun, 30 Jan 2022   Prob (F-statistic):          4.43e-20
Time:                  19:13:20         Log-Likelihood:             -1761.5
No. Observations:                  506     AIC:                       3529.
Df Residuals:                      503     BIC:                       3542.
Df Model:                           2
Covariance Type:                nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          1.2931      4.087        0.316      0.752      -6.737      9.323
x1              0.4966      0.188        2.639      0.009       0.127      0.866
x2             -0.3038      0.044       -6.857      0.000      -0.391     -0.217
=====
Omnibus:                 562.630   Durbin-Watson:              0.998
Prob(Omnibus):              0.000   Jarque-Bera (JB):          34204.153
Skew:                      5.151   Prob(JB):                   0.00
Kurtosis:                  41.939   Cond. No.                   349.
=====
```

Notes:

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

"""

Interpretation of slopes:

- For every one unit increase in pupil teacher ratio, the crime rate increases by 0.4966 crimes per capita

- For every one thousand dollar increase in the median home price in a neighborhood, the crime rate reduces by 0.3038 crimes per capita

5.

```
[7]: from sklearn.model_selection import train_test_split
X,y = housing[['river','rm']].values,housing.iloc[:,-1].values
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.
↪3,random_state = 2)
```

```
[8]: linear_model = LinearRegression()
linear_model.fit(X_train,y_train)
r_sq = linear_model.score(X_train,y_train)
print('In-Sample Coefficient of determination: ', r_sq)
r_sq = linear_model.score(X_test,y_test)
print('Out-of-Sample Coefficient of determination: ', r_sq)
```

In-Sample Coefficient of determination: 0.4652498065943518

Out-of-Sample Coefficient of determination: 0.5582472793500367