Week_05_Quiz-qm2162

October 13, 2021

1 Week 5 Quiz

1.1 Qi Meng - qm2162

1.1.1 Due Sunday Oct 17th, 11:59pm

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

sns.set_style('darkgrid')
%matplotlib inline
```

[2]:
```
# Sklearn provides a set of commonly used example datasets.
# They can be accessed through the datasets submodule.
from sklearn import datasets

# We're going to use the Linnerud dataset to practice Regression in sklearn.

# The Linnerud dataset is a tiny multi-output regression dataset. It consists
# of three excercise (data) and three physiological (target) variables
# collected from twenty middle-aged men in a fitness club.
linnerud = datasets.load_linnerud()

# The features of the dataset contain data on 3 exercises
# Chins - number of chinups
# Situps - number of situps
# Jumps - number of jumping jacks

# Note that the features and target come as numpy matrices.
# We'll first load the features into a pandas dataframe.
df = pd.DataFrame(linnerud.data,columns=linnerud.feature_names)

# We'll also add the target to our dataframe.
# Note also that this dataset contains multiple targets.
# We'll only consider one of them: Weight
df['Weight'] = linnerud.target[:,linnerud.target_names.index('Weight')]
```

```python
# For more information on the dataset, uncomment the print command below
#print(linnerud.DESCR)

# print the first 3 rows
df.head(3)
```

[2]:

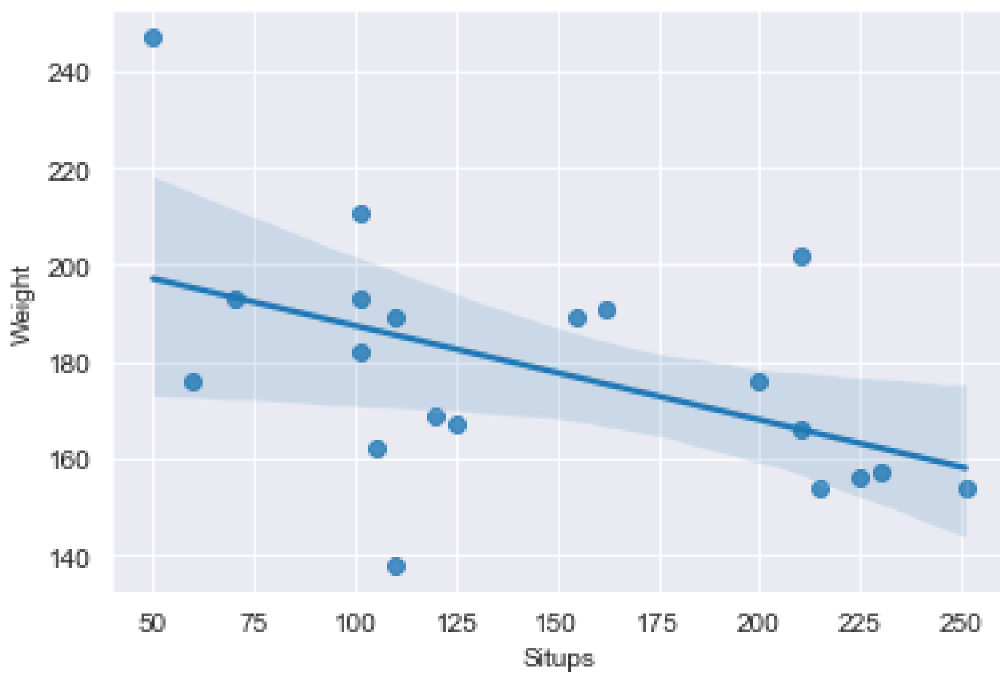
	Chins	Situps	Jumps	Weight
0	5.0	162.0	60.0	191.0
1	2.0	110.0	60.0	189.0
2	12.0	101.0	101.0	193.0

[3]:

```python
# What is the relationship between Situps and Weight?

# Plot a scatterplot and best-fit line for x=Situps vs y=Weight
#    using seaborn sns.regplot()
sns.regplot(x='Situps', y='Weight', data=df)
```

[3]: <AxesSubplot:xlabel='Situps', ylabel='Weight'>



[4]:

```python
# The above plot should indicate a negative relationship
#    between Situps and Weight
# How much does Weight go down if Situps goes up?
# To answer this we'll train a simple linear model.
```

```python
# First import LinearRegression from sklearn.linear_model
from sklearn.linear_model import LinearRegression

# Create a variable X containing the independent variable 'Situps'
# Note that sklearn expects X to be two dimensional
#   so you must use one of the methods discussed in class
#   to return a two dimensional object
X = df.Situps.values.reshape(-1, 1)

# Create a variable y containing the dependent variable 'Weight'
# Note that y should only be one dimensional,
#    so a Series (single column of a dataframe) works fine here
y = df.Weight

# Instantiate a LinearRegression object with default parameter settings
#   and store as lr
lr = LinearRegression()

# Fit lr using the X and y defined above
lr.fit(X=X, y=y)

# Using the learned parameters in coef_ and intercept_,
#   by how much do we expect Weight to go down when Situps goes up by 1?
# Print with a precision of 2
print(f"We expect Weight to go down by {np.abs(lr.coef_[0]):0.2f} when Situps␣
 ↪goes up by 1.")

# Using the learned parameters in coef_ and intercept_,
#   what should we expect weight to be when when Situps is 0?
# Print with a precision of 2
print(f"We should expect weight to be {lr.intercept_:0.2f} when Situps is 0.")
```

```
We expect Weight to go down by 0.19 when Situps goes up by 1.
We should expect weight to be 206.92 when Situps is 0.
```

[5]:
```python
# How is Weight related to all 3 features?

# Create a list containing the 3 feature names we're interested in
#    as strings: Chins, Situps, Jumps
# Store as feature_names
# We'll do this to make sure we don't include 'Weight' in the
#    regression as an independent variable
feature_names = ['Chins', 'Situps', 'Jumps']

# Instantiate a second LinearRegression model with default parameters
#    and store as mlr
# Fit this model using all of the columns in feature_names
```

```
# Note that here we can pass the 2D dataframe without needing to .reshape(),␣
↪etc.
mlr = LinearRegression()
mlr.fit(df[feature_names], y=y)

# For each feature name in feature_names, print out the name and
#    corresponding learned coefficient
# It looks like one of the features actually has a positive relationship.
# Print coefficient values with a precision of 2.
for (name, coef) in zip(feature_names, mlr.coef_):
    print(f'{name:10s} : {coef:0.2f}')
```

```
Chins      : -0.48
Situps     : -0.22
Jumps      : 0.09
```

[6]:

```
# NOT REQUIRED

# For those that are interested exploring how statsmodels works

# Import the statsmodels api as sm
import statsmodels.api as sm

# Store the 3 features from df as X
X = df[feature_names].copy()

# Add a constant to X (in order to learn the bias term) using sm.add_constant()
sm.add_constant(X)


# Instantiate and fit an OLS model using X and df.Weight as y
#   and store as sm_model
# Note that in OLS, the target y is the first parameter!
sm_model = sm.OLS(y, X).fit()

# Display the model summary
# Note that the coefficients in the summary match the values
#    found above using sklearn
sm_model.summary()
```

```
/Users/mengqi/opt/anaconda3/envs/eods-f21/lib/python3.8/site-
packages/statsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of
pandas all arguments of concat except for the argument 'objs' will be keyword-
only
  x = pd.concat(x[::order], 1)
```

[6]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                 Weight   R-squared (uncentered):
0.791
Model:                            OLS   Adj. R-squared (uncentered):
0.755
Method:                 Least Squares   F-statistic:
21.50
Date:                Wed, 13 Oct 2021   Prob (F-statistic):
5.07e-06
Time:                        03:40:45   Log-Likelihood:
-116.59
No. Observations:                  20   AIC:
239.2
Df Residuals:                      17   BIC:
242.2
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Chins          1.6422      5.376      0.305      0.764      -9.701      12.985
Situps         0.9735      0.442      2.201      0.042       0.041       1.906
Jumps         -0.1295      0.535     -0.242      0.812      -1.259       1.000
==============================================================================
Omnibus:                        0.243   Durbin-Watson:                   1.462
Prob(Omnibus):                  0.886   Jarque-Bera (JB):                0.412
Skew:                           0.185   Prob(JB):                        0.814
Kurtosis:                       2.402   Cond. No.                         47.8
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```