Week 5 Quiz

Clarissa Tai - rt2822

Due Tuesday Oct 11th, 11:59pm

Instructions

Replace the Name and UNI in cell above and the notebook filename

Replace all '__' below using the instructions provided.

When completed,

1. make sure you've replaced Name and UNI in the first cell and filename
2. Kernel -> Restart & Run All to run all cells in order
3. Print Preview -> Print (Landscape Layout) -> Save to pdf
4. post pdf to GradeScope

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

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

In [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')]

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

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

Out[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

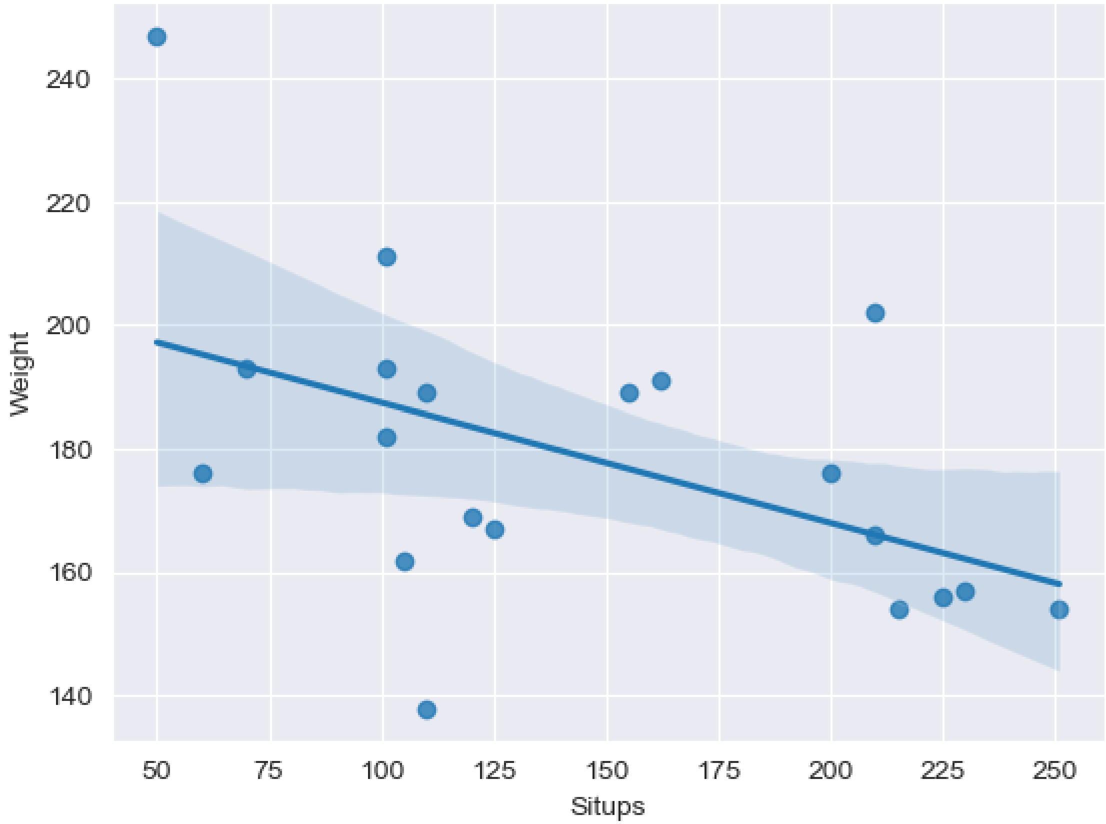
In [3]:

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

# Plot a scatterplot and best-fit line with
#    Situps on the x-asix vs Weight on the y=axis
#    using seaborn sns.regplot()
sns.regplot(df, x='Situps', y='Weight')
```

Out[3]:

```
<AxesSubplot: xlabel='Situps', ylabel='Weight'>
```



In [4]:
```
# The above plot should indicate a potentially 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.

# 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,y)

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

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

```
coef: -0.19
intercept: 206.92
```

In [5]:

```
# 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 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 and our y from above
mlr = LinearRegression()
mlr.fit(df[feature_names],df.Weight)

# 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 i in range(3):
    print("{}: {}".format(feature_names[i],np.round(mlr.coef_[i],2)))
```

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

In [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[['Chins', 'Situps', 'Jumps']]

# 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(df.Weight,X).fit()

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

Out[6]:

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:	Tue, 11 Oct 2022	**Prob (F-statistic):**	5.07e-06
Time:	16:17:54	**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] R^2 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.

In [ ]: