Week 5 Quiz

Zichen Zhao - zz3119

Due Monday Oct 21st, 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 consist
# 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]:

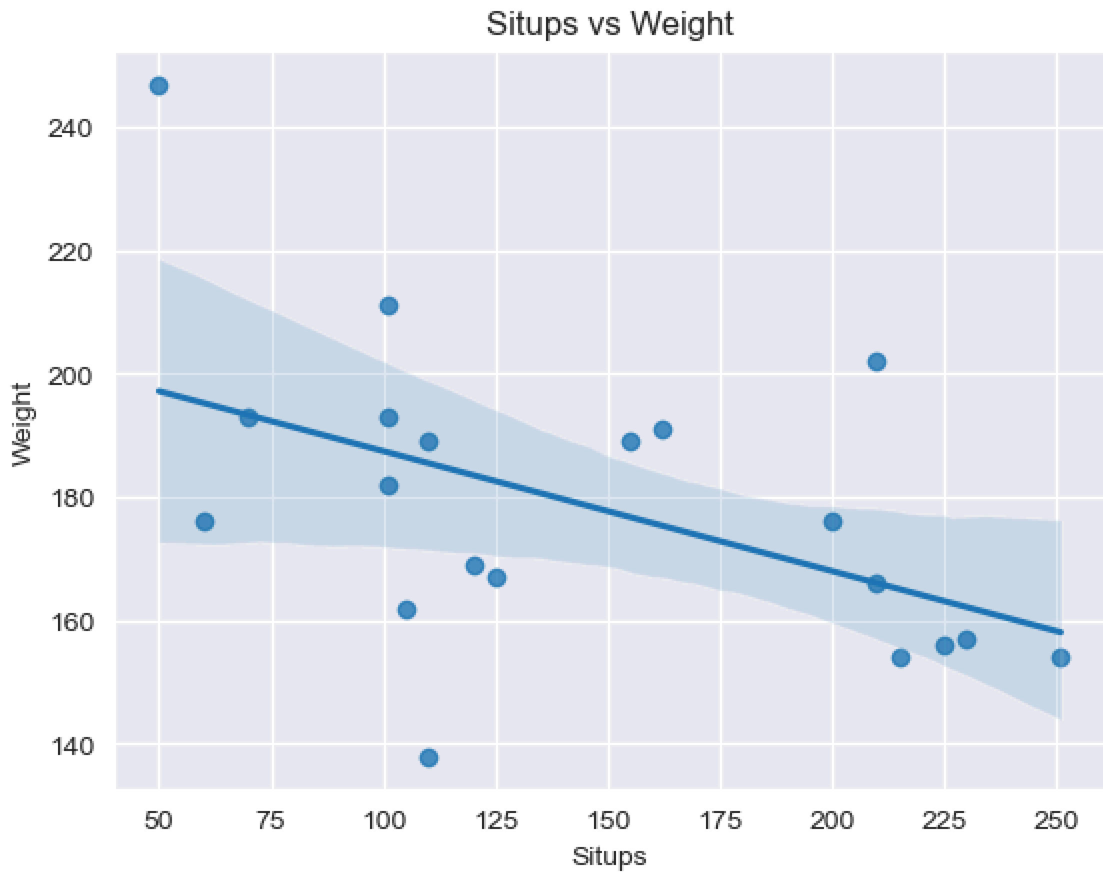
	Chins	Situps	Jumps	Weight
0	5.0	162.0	60.0	191.0
1	2.0	110.0	60.0	189.0
2	12.0	101.0	101.0	193.0

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(x="Situps", y="Weight", data=df)
plt.title("Situps vs Weight")
plt.xlabel("Situps")
plt.ylabel("Weight")
plt.show()
```



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']]

# 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?
```

```python
# Print with a precision of 2
print(f"Weight goes down by {lr.coef_[0]:.2f} when Situps goes up by 1.")

# 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"Expected weight when Situps is 0 is {lr.intercept_:.2f}.")
```

```
Weight goes down by -0.19 when Situps goes up by 1.
Expected weight when Situps is 0 is 206.92.
```

In [8]:
```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 do this to make sure we don't include 'Weight' in the
#    regression as an independent variable
from sklearn.linear_model import LinearRegression

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 ab
mlr = LinearRegression()
mlr.fit(df[feature_names], 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 feature, coef in zip(feature_names, mlr.coef_):
    print(f"{feature}: {coef:.2f}")
```

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

In [12]:
```python
# NOT REQUIRED

# For those that are interested exploring how statsmodels works
! pip install statsmodels

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

# Store the 3 features from df as X
X = df[feature_names]

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

```
Requirement already satisfied: statsmodels in /Users/jacksonzhao/miniconda3/
envs/eods/lib/python3.9/site-packages (0.14.4)
Requirement already satisfied: numpy<3,>=1.22.3 in /Users/jacksonzhao/minico
nda3/envs/eods/lib/python3.9/site-packages (from statsmodels) (1.26.4)
Requirement already satisfied: scipy!=1.9.2,>=1.8 in /Users/jacksonzhao/mini
conda3/envs/eods/lib/python3.9/site-packages (from statsmodels) (1.13.1)
Requirement already satisfied: pandas!=2.1.0,>=1.4 in /Users/jacksonzhao/min
iconda3/envs/eods/lib/python3.9/site-packages (from statsmodels) (2.2.2)
Requirement already satisfied: patsy>=0.5.6 in /Users/jacksonzhao/miniconda
3/envs/eods/lib/python3.9/site-packages (from statsmodels) (0.5.6)
Requirement already satisfied: packaging>=21.3 in /Users/jacksonzhao/minicon
da3/envs/eods/lib/python3.9/site-packages (from statsmodels) (24.1)
Requirement already satisfied: python-dateutil>=2.8.2 in /Users/jacksonzhao/
miniconda3/envs/eods/lib/python3.9/site-packages (from pandas!=2.1.0,>=1.4->
statsmodels) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /Users/jacksonzhao/miniconda
3/envs/eods/lib/python3.9/site-packages (from pandas!=2.1.0,>=1.4->statsmode
ls) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in /Users/jacksonzhao/minicond
a3/envs/eods/lib/python3.9/site-packages (from pandas!=2.1.0,>=1.4->statsmod
els) (2023.3)
Requirement already satisfied: six in /Users/jacksonzhao/miniconda3/envs/eod
s/lib/python3.9/site-packages (from patsy>=0.5.6->statsmodels) (1.16.0)
```

Out[12]:

OLS Regression Results

Dep. Variable:	Weight	**R-squared:**	0.268
Model:	OLS	**Adj. R-squared:**	0.131
Method:	Least Squares	**F-statistic:**	1.952
Date:	Fri, 11 Oct 2024	**Prob (F-statistic):**	0.162
Time:	21:36:23	**Log-Likelihood:**	-88.876
No. Observations:	20	**AIC:**	185.8
Df Residuals:	16	**BIC:**	189.7
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	208.2335	13.451	15.481	0.000	179.718	236.749
Chins	-0.4750	1.393	-0.341	0.738	-3.428	2.478
Situps	-0.2177	0.138	-1.583	0.133	-0.509	0.074
Jumps	0.0931	0.139	0.671	0.512	-0.201	0.387

Omnibus:	1.292	**Durbin-Watson:**	2.213
Prob(Omnibus):	0.524	**Jarque-Bera (JB):**	0.219
Skew:	0.077	**Prob(JB):**	0.896
Kurtosis:	3.489	**Cond. No.**	463.

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