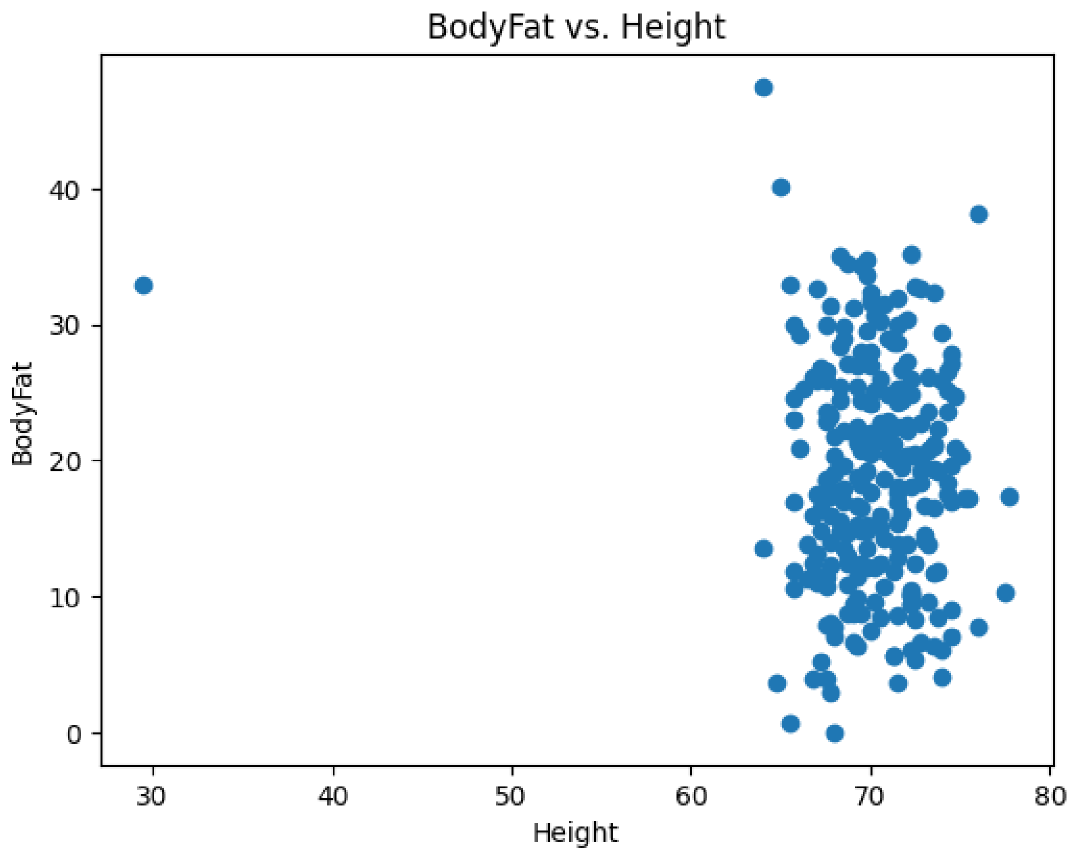
```
!pip install pandas
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
import statsmodels.api as sm
import numpy as np
```

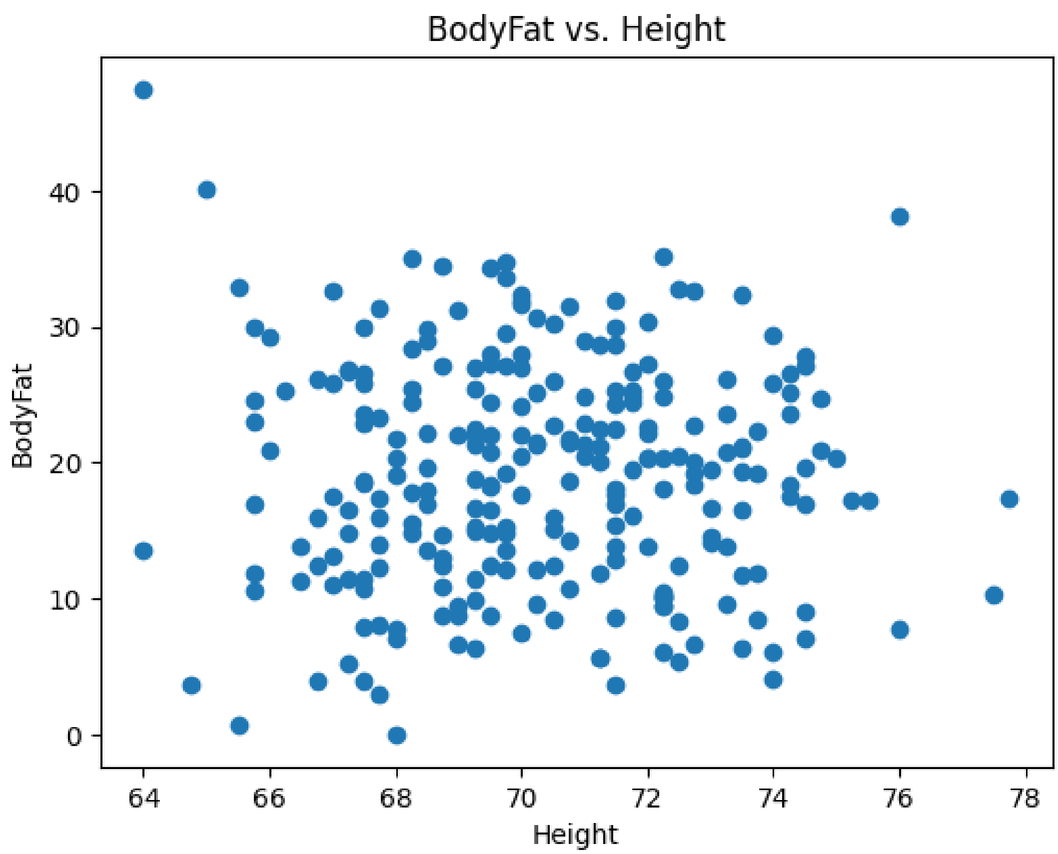
```
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages
(2.2.2)
Requirement already satisfied: numpy>=1.22.4 in
/usr/local/lib/python3.10/dist-packages (from pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.10/dist-packages (from pandas) (2024.2)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2->pandas)
(1.16.0)
```

```
# Body fat percentage refers to the relative proportions of body weight in terms
of lean body mass (muscle, bone, internal organs, and connective tissue) and body
fat. You probably already know that body fat percentage is an important indicator
of overall health - too little or too much body fat is associated with several
health issues. This assignment is about estimating body fat percentage from other
body measurements.
# a. Why is there a need to estimate body fat percentage instead of directly
measuring it (e.g., we can directly measure a person’s weight, we don’t have to
calculate it)? Do an internet search and answer in 2-3 sentences.
# ANSWER: Directly measuring it with extreme accuracy requires specialized
equipment and expertise, making it impractical for most people to access
regularly. Simply measuring a person's weight doesn't give insight as to how much
of that weight is from other sources such as muscles, bones, etc.
```

```
# b. The bodyfat.csv file in the Linear Regression module on Canvas contains 13
measurements from subjects (all men) along with their body fat percentage. Read
the file using pd.read_csv(). Plot BodyFat vs. Height (code, plot) Which should
be the dependent variable? Which is the independent variable?
df = pd.read_csv('bodyfat.csv')
plt.scatter(df['Height'], df['BodyFat'])
plt.xlabel('Height')
plt.ylabel('BodyFat')
plt.title('BodyFat vs. Height')
plt.show()
# ANSWER: BodyFat is the dependent variable since BodyFat can change based on
Height. Height is the independent variable because BodyFat has no bearing on
Height.
```




```
# c. There is one obvious outlier in the Height column. Remove the corresponding
row from the data and plot again. This will be the data used for the following
questions. Confirm that the mean Height is now 70.31076. (Show: code to remove
the row, plot, and calculate mean; plot).
mean_height = df['Height'].mean()
std_height = df['Height'].std()
outlier_condition = (df['Height'] > mean_height + 3*std_height) | (df['Height']
< mean_height - 3*std_height)
df_no_outlier = df[~outlier_condition]
plt.scatter(df_no_outlier['Height'], df_no_outlier['BodyFat'])
plt.xlabel('Height')
plt.ylabel('BodyFat')
plt.title('BodyFat vs. Height')
plt.show()
mean_height_no_outlier = df_no_outlier['Height'].mean()
mean_height_no_outlier
```




```
70.31075697211155
```

```
# d. Create a linear model of BodyFat vs. Height. (code, output of
summary(model))
X = df_no_outlier['Height']
Y = df_no_outlier['BodyFat']
X = sm.add_constant(X)
model = sm.OLS(Y, X).fit()
print(model.summary())
# i. What is the R2 value?
# ANSWER: 0.001
# ii. Is this a "good" model? Why or why not?
# ANSWER: No. The R^2 value is very small, meaning Height does not explain much
of the variability in BodyFat. Furthermore, the p-value is .712, which is much
greater than 0.05, suggesting that Height is not a statistically significant
predictor of BodyFat in this model.
# iii. What is the linear equation relating BodyFat and Height according to this
model?
# ANSWER: BodyFat = 24.3412 - 0.0746 × Height
```

```
                            OLS Regression Results
==============================================================================
```

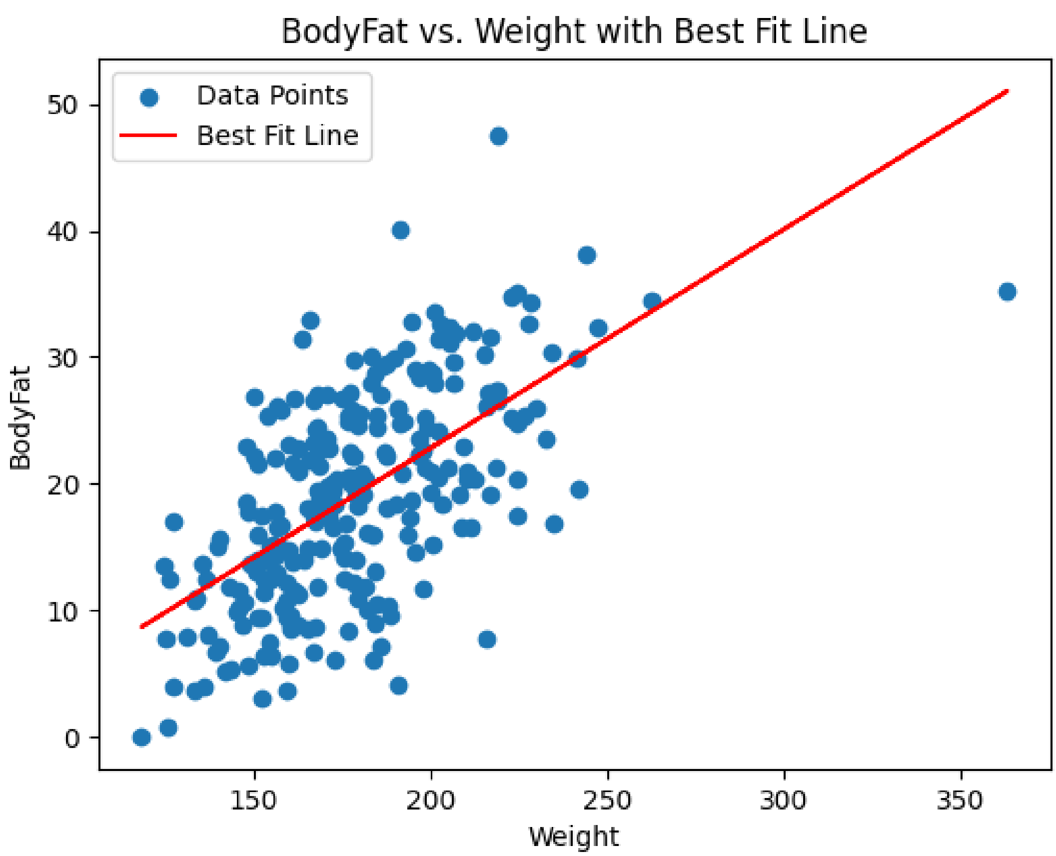
```
Dep. Variable:                BodyFat   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.003
Method:                 Least Squares   F-statistic:                    0.1362
Date:                Sat, 26 Oct 2024   Prob (F-statistic):              0.712
Time:                        21:16:21   Log-Likelihood:                -887.97
No. Observations:                 251   AIC:                             1780.
Df Residuals:                     249   BIC:                             1787.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         24.3412     14.221      1.712      0.088      -3.667      52.349
Height        -0.0746      0.202     -0.369      0.712      -0.473       0.323
==============================================================================
Omnibus:                        2.244   Durbin-Watson:                   1.463
Prob(Omnibus):                  0.326   Jarque-Bera (JB):                2.059
Skew:                           0.134   Prob(JB):                        0.357
Kurtosis:                       2.646   Cond. No.                     1.90e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.9e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

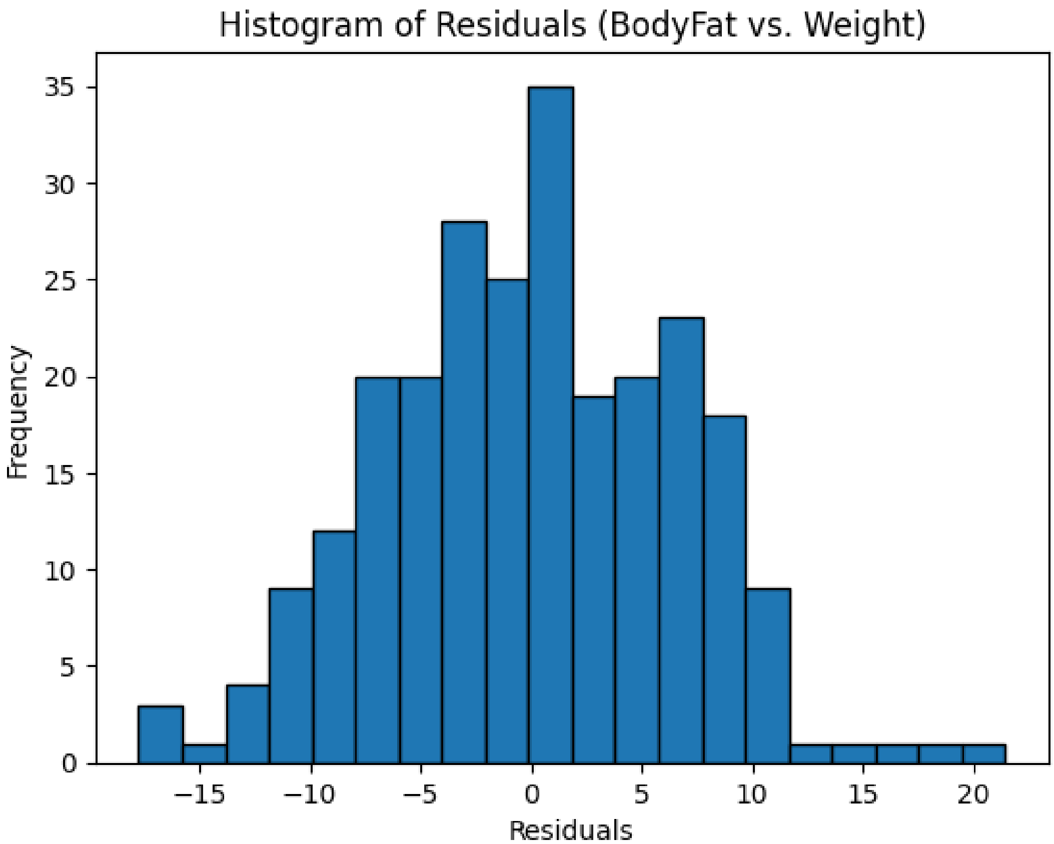
```python
# e. Create a linear model of BodyFat vs. Weight. (code, output of
summary(model))
X = df_no_outlier['Weight']
Y = df_no_outlier['BodyFat']
X = sm.add_constant(X)
model = sm.OLS(Y, X).fit()
print(model.summary())
# i. What is the R2 value?
# ANSWER: 0.373
# ii. Is this a better model than that based on Height? Why or why not?
# ANSWER: Yes. The R^2 value is significantly higher than the R^2 value from the
previous model. The p value is significantly smaller than the p value from the
previous model.
# iii. What is the linear equation relating BodyFat and Weight according to this
model?
# ANSWER: BodyFat = −11.8889 + 0.1733 × Weight
# iv. Plot BodyFat vs. Weight and overlay the best fit line. Use a different
color for the line. (plot, code)
plt.scatter(df_no_outlier['Weight'], df_no_outlier['BodyFat'], label='Data
Points')
```

```
plt.xlabel('Weight')
plt.ylabel('BodyFat')
plt.title('BodyFat vs. Weight with Best Fit Line')
best_fit_line = model.params['const'] + model.params['Weight'] *
df_no_outlier['Weight']
plt.plot(df_no_outlier['Weight'], best_fit_line, color='red', label='Best Fit
Line')
plt.legend()
plt.show()
# v. Plot the histogram of residuals (plot, code). Does this show an
approximately normal distribution?
residuals = model.resid
plt.hist(residuals, bins=20, edgecolor='black')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Histogram of Residuals (BodyFat vs. Weight)')
plt.show()
# ANSWER: Yes
# vi. From the model, predict the BodyFat for two persons: Person A weighs 150
lbs, Person B weighs 300 lbs. Include the 99% confidence intervals for the
predictions. In which prediction (for Person A or B), are you more confident?
Why?
new_weights = pd.DataFrame({'const': 1, 'Weight': [150, 300]})
predictions = model.get_prediction(new_weights)
predicted_summary = predictions.summary_frame(alpha=0.01)
predicted_summary
# ANSWER: The prediction for Person A is more precise because the weight of 150
lbs is closer to the mean range of the dataset, leading to a tighter confidence
interval. In contrast, the prediction for 300 lbs is less precise, reflected by a
much wider interval, indicating higher uncertainty.
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                BodyFat   R-squared:                       0.373
Model:                            OLS   Adj. R-squared:                  0.371
Method:                 Least Squares   F-statistic:                     148.2
Date:                Sat, 26 Oct 2024   Prob (F-statistic):           4.60e-27
Time:                        21:16:23   Log-Likelihood:                -829.43
No. Observations:                 251   AIC:                             1663.
Df Residuals:                     249   BIC:                             1670.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -11.8889      2.579     -4.610      0.000     -16.969      -6.809
Weight         0.1733      0.014     12.174      0.000       0.145       0.201
```

```
==============================================================================
Omnibus:                        0.065   Durbin-Watson:                   1.610
Prob(Omnibus):                  0.968   Jarque-Bera (JB):                0.109
Skew:                           0.038   Prob(JB):                        0.947
Kurtosis:                       2.933   Cond. No.                     1.12e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.12e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```





	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	14.102173	0.585383	12.582684	15.621663	-3.139442	31.343789
1	40.093254	1.774558	35.487003	44.699504	22.311747	57.874761

```
# f. Create a linear model of BodyFat vs. Weight and Height. (code, output of
summary(model))
X = df_no_outlier[['Weight', 'Height']]
Y = df_no_outlier['BodyFat']
X = sm.add_constant(X)
model = sm.OLS(Y, X).fit()
print(model.summary())
# i. What is the R2 value?
# ANSWER: 0.509
# ii. Is this a better model than that based only on Weight or Height? Why or why
not?
# ANSWER: Yes. The R^2 value is significantly higher than the R^2 value from the
previous models. The p value is significantly smaller than the p value from the
previous models.
# iii. What is the linear equation relating BodyFat, Weight and Height according
to this model?
# ANSWER: BodyFat = 72.5244 + 0.2319 × Weight − 1.3498 × Height
```

```
# iv. From the model, predict the BodyFat for two persons: Person A weighs 150
lbs, Person B weighs 300 lbs. Both persons have height=70". Include the 99%
confidence intervals for the predictions. In which prediction (for Person A or
B), are you more confident? Why?
new_data = pd.DataFrame({'const': 1, 'Weight': [150, 300], 'Height': [70, 70]})
predictions = model.get_prediction(new_data)
predicted_summary = predictions.summary_frame(alpha=0.01)
predicted_summary
# ANSWER: The model is more confident in predicting BodyFat for Person A because
their weight is closer to the typical range observed in the dataset, resulting in
a tighter confidence interval.
```

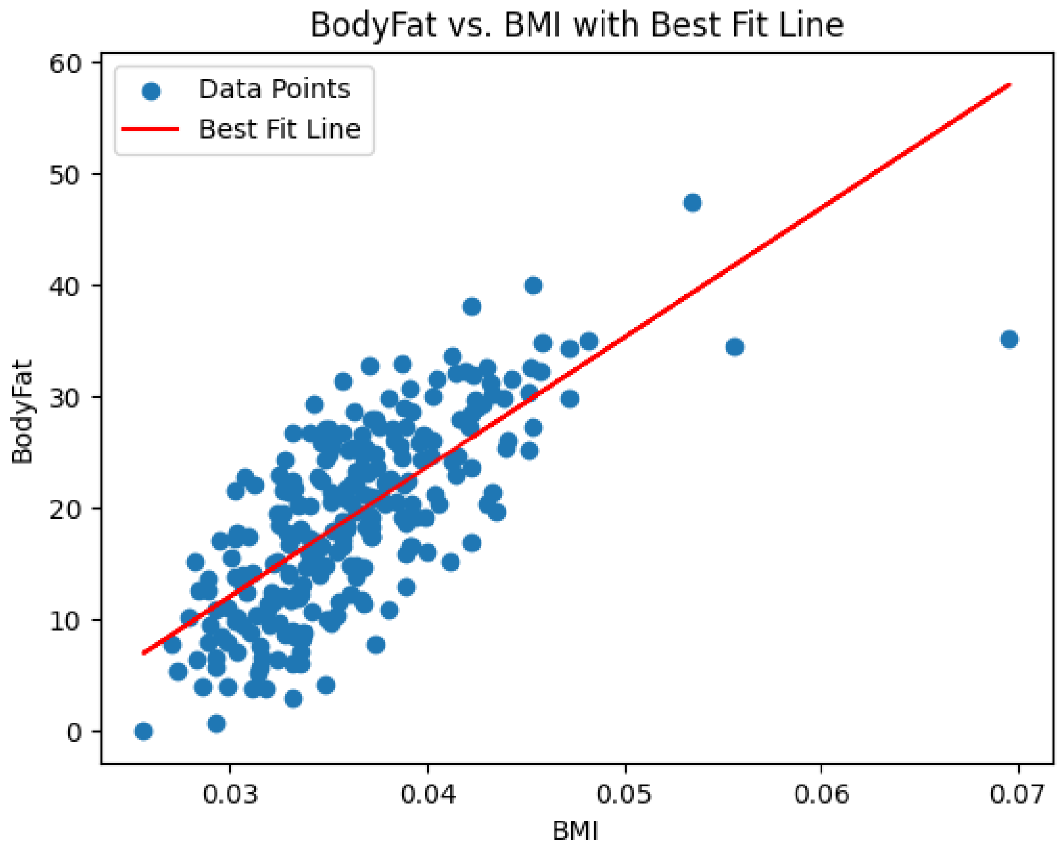
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                BodyFat   R-squared:                       0.509
Model:                            OLS   Adj. R-squared:                  0.505
Method:                 Least Squares   F-statistic:                     128.7
Date:                Sat, 26 Oct 2024   Prob (F-statistic):           4.50e-39
Time:                        21:16:27   Log-Likelihood:                -798.68
No. Observations:                 251   AIC:                             1603.
Df Residuals:                     248   BIC:                             1614.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         72.5244     10.426      6.956      0.000      51.990      93.059
Weight         0.2319      0.014     16.037      0.000       0.203       0.260
Height        -1.3498      0.163     -8.299      0.000      -1.670      -1.029
==============================================================================
Omnibus:                        3.956   Durbin-Watson:                   1.667
Prob(Omnibus):                  0.138   Jarque-Bera (JB):                3.595
Skew:                          -0.262   Prob(JB):                        0.166
Kurtosis:                       3.263   Cond. No.                     5.47e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.47e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	12.830683	0.541069	11.426176	14.235190	-2.459063	28.120429
1	47.622514	1.815980	42.908596	52.336432	31.684361	63.560667

```
# g. Add a new transformed variable BMI = Weight/Height2 to the dataset. Create a
linear model of BodyFat vs. BMI.
# i. Give sm.formula.ols() code, output of results.summary()
df_no_outlier['BMI'] = df_no_outlier['Weight'] / (df_no_outlier['Height'] ** 2)
model = smf.ols('BodyFat ~ BMI', data=df_no_outlier).fit()
print(model.summary())
# ii. Is this a better model than the previous models? Why or why not?
# ANSWER: Yes, this is a better model than the previous models. The R^2 value is
0.525, which is higher than the R^2 values of the earlier models. The p value is
smaller than the values of the earlier models.
# iii. What is the equation relating BodyFat, Weight, and Height according to
this model? Is this a linear or nonlinear equation?
# ANSWER: BodyFat = −22.8594 + 1161.9732 × BMI
# iv. Plot BodyFat vs. BMI and overlay the best fit model as a straight line.
(code, plot)
plt.scatter(df_no_outlier['BMI'], df_no_outlier['BodyFat'], label='Data Points')
plt.xlabel('BMI')
plt.ylabel('BodyFat')
plt.title('BodyFat vs. BMI with Best Fit Line')
bmi_values = df_no_outlier['BMI']
best_fit_line = model.params['Intercept'] + model.params['BMI'] * bmi_values
plt.plot(bmi_values, best_fit_line, color='red', label='Best Fit Line')
plt.legend()
plt.show()
# v. From the model, predict the BodyFat for two persons: Person A weighs 150
lbs, Person B weighs 300 lbs. Both persons have height=70". Include the 99%
confidence intervals for the predictions.
person_a_bmi = 150 / (70 ** 2)
person_b_bmi = 300 / (70 ** 2)
new_data_bmi = pd.DataFrame({'BMI': [person_a_bmi, person_b_bmi]})
predictions_bmi = model.get_prediction(new_data_bmi)
predicted_summary_bmi = predictions_bmi.summary_frame(alpha=0.01)
predicted_summary_bmi
# vi.Body Mass Index (BMI) is actually defined as a person’s weight in kilograms
divided by the square of height in meters but your data has Weight in pounds and
Height in inches. Thus, the correct BMI transformation should have been BMI =
(Weight/2.20)/(Height*0.0254)2. Would using this correct BMI transformation
result in a different model from what was calculated? Why or why not?
# ANSWER: Scaling transformations typically do not change the overall fit of the
model, meaning the R² value and significance should remain the same. The
coefficients would adjust to match the scaled BMI variable, but the quality of
the model would not fundamentally change.
```

```
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a
  df_no_outlier['BMI'] = df_no_outlier['Weight'] / (df_no_outlier['Height'] ** 2)

                            OLS Regression Results
==============================================================================
Dep. Variable:                BodyFat   R-squared:                       0.525
Model:                            OLS   Adj. R-squared:                  0.524
Method:                 Least Squares   F-statistic:                     275.7
Date:                Sat, 26 Oct 2024   Prob (F-statistic):           3.44e-42
Time:                        21:16:30   Log-Likelihood:                -794.49
No. Observations:                 251   AIC:                             1593.
Df Residuals:                     249   BIC:                             1600.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -22.8594      2.553     -8.955      0.000     -27.887     -17.832
BMI         1161.9732     69.977     16.605      0.000    1024.152    1299.795
==============================================================================
Omnibus:                        2.558   Durbin-Watson:                   1.672
Prob(Omnibus):                  0.278   Jarque-Bera (JB):                2.285
Skew:                          -0.226   Prob(JB):                        0.319
Kurtosis:                       3.115   Cond. No.                         193.
==============================================================================

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



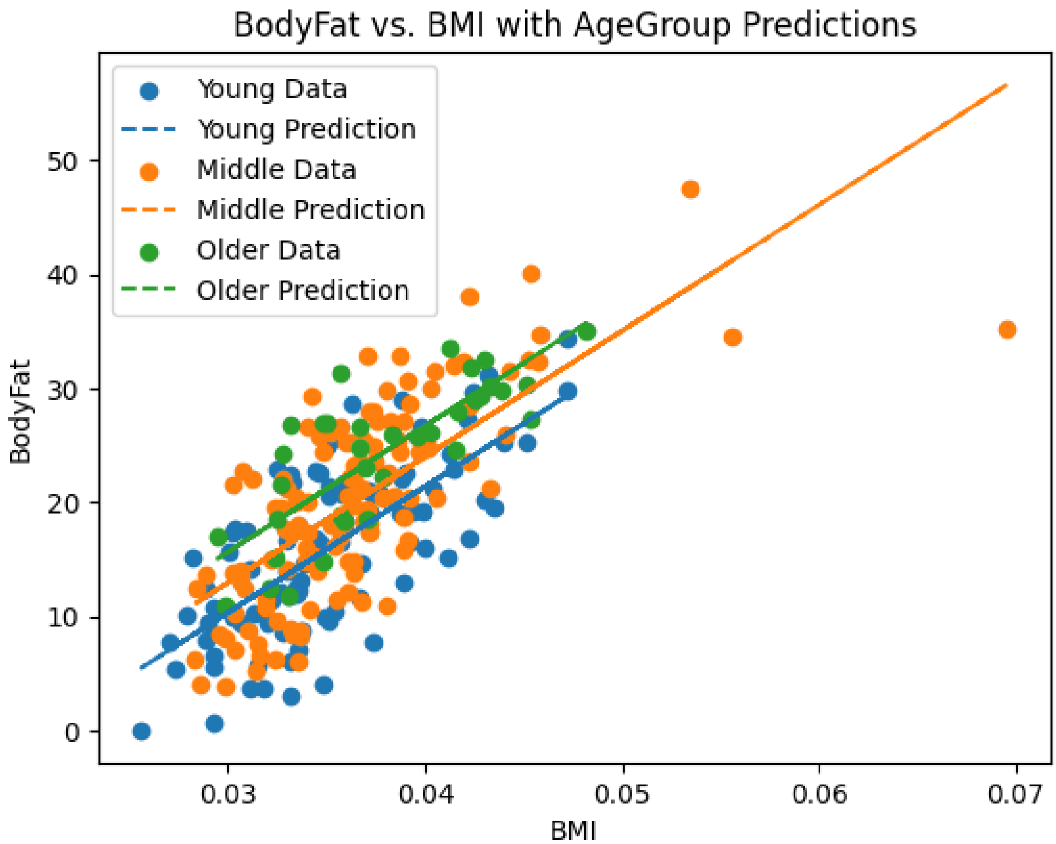
	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	12.711243	0.529030	11.338030	14.084457	-2.294409	27.716896
1	48.281853	1.794802	43.623053	52.940652	32.629751	63.933955

```
# h. Add a new categorical variable (factor) AgeGroup to the dataset. AgeGroup
should have three values: "Young" for Age 40, "Middle" for Age between 40 and 60,
and "Older" for Age>60.
# i. Show Pandas code that adds the AgeGroup variable. This can be done with
assign and the cut() function like so: pd.cut(bodyfat.Age, bins=[-np.inf, 40, 60,
np.inf], labels=["Young", "Middle", "Older"])[Code]
df_no_outlier['AgeGroup'] = pd.cut(
    df_no_outlier['Age'],
    bins=[-np.inf, 40, 60, np.inf],
    labels=["Young", "Middle", "Older"]
)
# ii. Create a linear model of BodyFat vs. BMI and AgeGroup.[Code, output of
summary(model)]
model = smf.ols('BodyFat ~ BMI + AgeGroup', data=df_no_outlier).fit()
print(model.summary())
# iii. How many dummy (i.e., 0-1) variables were created in the model?
# ANSWER: Two dummy variables were created for the AgeGroup category:
AgeGroup[T.Middle] and AgeGroup[T.Older]
```

```
# iv. Is this a better model than the previous models? Why or why not?
# ANSWER: Yes, this is a better model than the previous models. The R^2 value is
0.525, which is higher than the R^2 values of the earlier models. The p value is
smaller than the values of the earlier models.
# v. What are the set of equations relating BodyFat, BMI, and AgeGroup according
to this model?
# ANSWER: For "Young": BodyFat = − 22.8344 + 1105.0576 × BMI. For "Middle":
BodyFat = −22.8344 + 1105.0576 × BMI + 2.6113. For "Older": BodyFat = −22.8344 +
1105.0576 × BMI + 5.3074.
# vi. Plot BodyFat vs. BMI and overlay the model predictions (Hint: add a new
column with predictions and plot the predictions using geom_line. You should see
multiple lines, one for each value of the discrete variable). [Code, plot]
df_no_outlier['PredictedBodyFat'] = model.predict(df_no_outlier)
for age_group in df_no_outlier['AgeGroup'].unique():
    group_data = df_no_outlier[df_no_outlier['AgeGroup'] == age_group]
    plt.scatter(group_data['BMI'], group_data['BodyFat'], label=f'{age_group}
Data')
    plt.plot(group_data['BMI'], group_data['PredictedBodyFat'],
label=f'{age_group} Prediction', linestyle='--')
plt.xlabel('BMI')
plt.ylabel('BodyFat')
plt.title('BodyFat vs. BMI with AgeGroup Predictions')
plt.legend()
plt.show()
```

```
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a
  df_no_outlier['AgeGroup'] = pd.cut(
<ipython-input-79-ab2c96d9f236>:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a
  df_no_outlier['PredictedBodyFat'] = model.predict(df_no_outlier)

                            OLS Regression Results
==============================================================================
Dep. Variable:                BodyFat   R-squared:                       0.570
Model:                            OLS   Adj. R-squared:                  0.565
Method:                 Least Squares   F-statistic:                     109.2
Date:                Sat, 26 Oct 2024   Prob (F-statistic):           5.09e-45
Time:                        21:16:33   Log-Likelihood:                -782.11
```

```
No. Observations:                 251   AIC:                             1572.
Df Residuals:                     247   BIC:                             1586.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================================
                         coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------------------
Intercept            -22.8344      2.455     -9.301      0.000     -27.670
-17.999
AgeGroup[T.Middle]     2.6113      0.761      3.433      0.001       1.113
4.110
AgeGroup[T.Older]      5.3074      1.108      4.792      0.000       3.126
7.489
BMI                 1105.0576     67.831     16.291      0.000     971.456
1238.659
==============================================================================
Omnibus:                        0.954   Durbin-Watson:                   1.839
Prob(Omnibus):                  0.621   Jarque-Bera (JB):                0.869
Skew:                          -0.144   Prob(JB):                        0.648
Kurtosis:                       2.998   Cond. No.                         224.
==============================================================================

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


BodyFat vs. BMI with AgeGroup Predictions
Young Data
Young Prediction
Middle Data
Middle Prediction
Older Data
Older Prediction
BodyFat
BMI
0
10
20
30
40
50
0.03
0.04
0.05
0.06
0.07