DATA 606 - Final Project

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0.1 Detection of Obesity Among the Population

Group Members: Aditya Jain, Ahmed Omar, Divine Ahuchogu, Yedu Krishnan

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0.2 Introduction

Today, many people around the world struggle with obesity, along with the complications that may arise with a higher body weight. Studies have shown that obesity increases the risk of several debilitating and deadly diseases, including diabetes, heart disease, and some cancers [2]. Over the years, obesity levels have been increasing. In fact, based on data from 1975 till now, the levels have tripled [3]. Our question is: what is the reason for such a difference in the increasing obesity levels in just few decades? According to the World Health Organization(WHO), obesity is estimated to be a contributing factor in approximately 44% of the global burden of type 2 diabetes, 23% of ischemic heart disease burden, and 7-41% of certain cancer burdens [3]. Our goal is to find out how factors like age, gender, height, and weight is correlated with the obesity levels in people. Our main objective is to use our acquired knowledge from the dataset found to predict the levels of obesity in people based on their lifestyle choices.

0.3 Dataset

The dataset we chose has been obtained from the UC Irvine Machine Learning Repository, with 2111 rows and 17 columns [1]. Furthermore, the dataset focuses on the estimation of obesity levels from three countries, including Mexico, Peru, and Colombia and is based on their physical health as well as their eating habits. The variables include:

1) Gender
2) Age
3) Height
4) Weight
5) family_history_with_overweight
6) FAVC (Do you eat high caloric food frequently?)
7) FCVC (Do you usually eat vegetables in your meals?)
8) NCP (How many main meals do you have daily?)
9) CAEC (Do you eat any food between meals?)
10) SMOKE (Do you smoke?)

11) CH2O (how much water do you drink daily?)
12) SCC (Do you monitor the calories you eat daily?)
13) FAF (How often do you have physical activity?)
14) TUE (How much time do you use technology like phones, videogames, etc.)
15) CALC (How often do you drink alcohol?)
16) MTRANS (Which transportation do you usually use?
17) NObeyesdad (Obesity level)

0.4 Data Cleaning

Most of the data was somewhat clean, but the inclusion of multiple categorical variables required us to convert these columns into dummy variables to ensure numerical values were used for the logistic regression analysis. All columns were therefore converted into integers/dummies. Columns were renamed below to simplify what each column is meant to represent. Lastly, we converted the outcome(obesity) into two number of classes to simplify the analysis instead of having 7 different classes. Outcome 0 included the classes 'Normal_Weight', 'Insufficient_Weight', 'Overweight_Level_I', 'Overweight_Level_II' whereas outcome 1 (obesity) was composed of 'Obesity_Type_I', 'Obesity_Type_II', 'Obesity_Type_III'. Therefore, class sizes for the outcome 0 and 1 group were 1,139 and 972 respectively.

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import ttest_ind
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import plotly.express as px
import statsmodels.api as sm
```

[2]:
```
data = pd.read_csv("ObesityDataSet_raw_and_data_sinthetic.csv")
data
```

[2]:
```
      Gender        Age    Height      Weight family_history_with_overweight  \
0     Female  21.000000  1.620000   64.000000                            yes
1     Female  21.000000  1.520000   56.000000                            yes
2       Male  23.000000  1.800000   77.000000                            yes
3       Male  27.000000  1.800000   87.000000                             no
4       Male  22.000000  1.780000   89.800000                             no
…        …         …         …          …                               …
2106  Female  20.976842  1.710730  131.408528                            yes
2107  Female  21.982942  1.748584  133.742943                            yes
2108  Female  22.524036  1.752206  133.689352                            yes
2109  Female  24.361936  1.739450  133.346641                            yes
```

```
2110  Female  23.664709  1.738836  133.472641                            yes

     FAVC  FCVC  NCP       CAEC SMOKE      CH2O  SCC       FAF       TUE  \
0      no   2.0  3.0  Sometimes    no  2.000000   no  0.000000  1.000000
1      no   3.0  3.0  Sometimes   yes  3.000000  yes  3.000000  0.000000
2      no   2.0  3.0  Sometimes    no  2.000000   no  2.000000  1.000000
3      no   3.0  3.0  Sometimes    no  2.000000   no  2.000000  0.000000
4      no   2.0  1.0  Sometimes    no  2.000000   no  0.000000  0.000000
…     …    …    …          …     …         …    …
2106  yes   3.0  3.0  Sometimes    no  1.728139   no  1.676269  0.906247
2107  yes   3.0  3.0  Sometimes    no  2.005130   no  1.341390  0.599270
2108  yes   3.0  3.0  Sometimes    no  2.054193   no  1.414209  0.646288
2109  yes   3.0  3.0  Sometimes    no  2.852339   no  1.139107  0.586035
2110  yes   3.0  3.0  Sometimes    no  2.863513   no  1.026452  0.714137

            CALC                 MTRANS           NObeyesdad
0             no  Public_Transportation        Normal_Weight
1      Sometimes  Public_Transportation        Normal_Weight
2     Frequently  Public_Transportation        Normal_Weight
3     Frequently                Walking   Overweight_Level_I
4      Sometimes  Public_Transportation  Overweight_Level_II
…            …                    …                  …
2106   Sometimes  Public_Transportation     Obesity_Type_III
2107   Sometimes  Public_Transportation     Obesity_Type_III
2108   Sometimes  Public_Transportation     Obesity_Type_III
2109   Sometimes  Public_Transportation     Obesity_Type_III
2110   Sometimes  Public_Transportation     Obesity_Type_III

[2111 rows x 17 columns]
```

[3]:
```
data['NObeyesdad'].value_counts()
```

[3]:
```
NObeyesdad
Obesity_Type_I         351
Obesity_Type_III       324
Obesity_Type_II        297
Overweight_Level_I     290
Overweight_Level_II    290
Normal_Weight          287
Insufficient_Weight    272
Name: count, dtype: int64
```

[4]:
```
# Categorize 'NObeyesdad' as either 1 for "obese/overweight" or 0 for "normal"
data['NObeyesdad'] = data['NObeyesdad'].apply(lambda x: 0 if x in
 ↪['Normal_Weight', 'Insufficient_Weight', 'Overweight_Level_I',
 ↪'Overweight_Level_II'] else 1)
```

```python
# Verify the changes by displaying the unique values of the modified␣
↪'NObeyesdad' column
data['NObeyesdad'].unique(), data.head()
```

[4]:
```
(array([0, 1]),
    Gender   Age  Height  Weight family_history_with_overweight FAVC  FCVC  \
 0  Female  21.0    1.62    64.0                            yes   no   2.0
 1  Female  21.0    1.52    56.0                            yes   no   3.0
 2    Male  23.0    1.80    77.0                            yes   no   2.0
 3    Male  27.0    1.80    87.0                             no   no   3.0
 4    Male  22.0    1.78    89.8                             no   no   2.0

    NCP       CAEC SMOKE  CH2O  SCC  FAF  TUE        CALC  \
 0  3.0  Sometimes    no   2.0   no  0.0  1.0          no
 1  3.0  Sometimes   yes   3.0  yes  3.0  0.0   Sometimes
 2  3.0  Sometimes    no   2.0   no  2.0  1.0  Frequently
 3  3.0  Sometimes    no   2.0   no  2.0  0.0  Frequently
 4  1.0  Sometimes    no   2.0   no  0.0  0.0   Sometimes

                   MTRANS  NObeyesdad
 0  Public_Transportation           0
 1  Public_Transportation           0
 2  Public_Transportation           0
 3                Walking           0
 4  Public_Transportation           0  )
```

[5]:
```python
from sklearn.preprocessing import LabelEncoder

# Initialize LabelEncoder
dummy_variable = LabelEncoder()

# Define categorical columns excluding 'NObeyesdad'
categorical_columns = data.select_dtypes(include=['object']).columns

# Apply LabelEncoder to each categorical column
for col in categorical_columns:
    data[col] = dummy_variable.fit_transform(data[col])
```

[6]:
```python
# Convert the Age column to int
data['Age'] = data['Age'].astype(int)
data['FCVC'] = data['FCVC'].astype(int)
data['NCP'] = data['NCP'].astype(int)
data['CH2O'] = data['CH2O'].astype(int)
data['FAF'] = data['FAF'].astype(int)
data['TUE'] = data['TUE'].astype(int)
data['CAEC'] = data['CAEC'].astype(int)
```

```
data.head(), data.dtypes
```

[6]:
```
(   Gender  Age  Height  Weight  family_history_with_overweight  FAVC  FCVC  \
 0       0   21    1.62    64.0                               1     0     2
 1       0   21    1.52    56.0                               1     0     3
 2       1   23    1.80    77.0                               1     0     2
 3       1   27    1.80    87.0                               0     0     3
 4       1   22    1.78    89.8                               0     0     2

    NCP  CAEC  SMOKE  CH2O  SCC  FAF  TUE  CALC  MTRANS  NObeyesdad
 0    3     2      0     2    0    0    1     3       3           0
 1    3     2      1     3    1    3    0     2       3           0
 2    3     2      0     2    0    2    1     1       3           0
 3    3     2      0     2    0    2    0     1       4           0
 4    1     2      0     2    0    0    0     2       3           0  ,
 Gender                              int64
 Age                                 int64
 Height                            float64
 Weight                            float64
 family_history_with_overweight      int64
 FAVC                                int64
 FCVC                                int64
 NCP                                 int64
 CAEC                                int64
 SMOKE                               int64
 CH2O                                int64
 SCC                                 int64
 FAF                                 int64
 TUE                                 int64
 CALC                                int64
 MTRANS                              int64
 NObeyesdad                          int64
 dtype: object)
```

[7]:
```
# Save the modified dataset to a new CSV file
# newfile = 'Obesity_Dataset.csv'
# data.to_csv(newfile, index=False)

# Return the path of the new file for download
# newfile
```

[8]:
```
data.isna().sum()
```

[8]:
```
Gender                            0
Age                               0
Height                            0
```

```
Weight                            0
family_history_with_overweight    0
FAVC                              0
FCVC                              0
NCP                               0
CAEC                              0
SMOKE                             0
CH2O                              0
SCC                               0
FAF                               0
TUE                               0
CALC                              0
MTRANS                            0
NObeyesdad                        0
dtype: int64
```

[9]:
```
# Number of classes and size

num_classes = len(data['NObeyesdad'].unique())
class_sizes = data['NObeyesdad'].value_counts()
```

[10]:
```
# Number of Classes
num_classes
```

[10]:
```
2
```

[11]:
```
# Size of Classes
class_sizes
```

[11]:
```
NObeyesdad
0    1139
1     972
Name: count, dtype: int64
```

[12]:
```
data = data.rename(columns={"FAVC": "High_Calorie",
                        "FCVC": "Vegetables",
                        "NCP" :"Number_of_meals",
                        "SMOKE" :"Smoke",
                        "CH2O":"Water_consumption",
                        "CALC":"Alcohol_consumption",
                        "MTRANS": "Transportation_method",
                        "FAF": "Physical_Acitivity",
                        "TUE": "Time_on_Technology",
                        "SCC": "Calorie_Monitoring",
                        "NObeyesdad": "Outcome",
                        "CAEC": "Food_Between_Meals"})
```

```
data
```

[12]:

```
      Gender  Age    Height      Weight  family_history_with_overweight  \
0          0   21  1.620000   64.000000                               1
1          0   21  1.520000   56.000000                               1
2          1   23  1.800000   77.000000                               1
3          1   27  1.800000   87.000000                               0
4          1   22  1.780000   89.800000                               0
…        …   …       …         …                              …
2106       0   20  1.710730  131.408528                               1
2107       0   21  1.748584  133.742943                               1
2108       0   22  1.752206  133.689352                               1
2109       0   24  1.739450  133.346641                               1
2110       0   23  1.738836  133.472641                               1

      High_Calorie  Vegetables  Number_of_meals  Food_Between_Meals  Smoke  \
0                0           2                3                   2      0
1                0           3                3                   2      1
2                0           2                3                   2      0
3                0           3                3                   2      0
4                0           2                1                   2      0
…              …         …               …                 …    …
2106             1           3                3                   2      0
2107             1           3                3                   2      0
2108             1           3                3                   2      0
2109             1           3                3                   2      0
2110             1           3                3                   2      0

      Water_consumption  Calorie_Monitoring  Physical_Acitivity  \
0                     2                   0                   0
1                     3                   1                   3
2                     2                   0                   2
3                     2                   0                   2
4                     2                   0                   0
…                   …                 …                 …
2106                  1                   0                   1
2107                  2                   0                   1
2108                  2                   0                   1
2109                  2                   0                   1
2110                  2                   0                   1

      Time_on_Technology  Alcohol_consumption  Transportation_method  Outcome
0                      1                    3                      3        0
1                      0                    2                      3        0
2                      1                    1                      3        0
3                      0                    1                      4        0
4                      0                    2                      3        0
```

```
...                   ...                 ...                  ...     ...
2106                    0                   2                      3       1
2107                    0                   2                      3       1
2108                    0                   2                      3       1
2109                    0                   2                      3       1
2110                    0                   2                      3       1

[2111 rows x 17 columns]
```

0.5 ## Exploratory Data Analysis For Numeric Variables

To get a better sense of the data, simple visual analysis was conducted for the numerical variables which include Age, Height, and Weight. For the first visual, a correlation matrix was produced to look at the relationship between all the variables in the dataset. To follow, histograms were able to provide a better outline on the distribution of the variables for both outcome groups when it came to the numerical variables. Box plots were then created to get a better visual on the interquartile range and median for the two outcome groups. Since visuals are not enough to form a solid conclusion, t-test analysis was conducted to see whether there was a statistically significant difference between the two means for both groups for Age, Height, and Weight. This required bootstrapping to meet the assumption of normality for the t-test difference in means analysis.

[13]:
```python
# Describe basic statistics of the data
stats = data[['Age', 'Height', 'Weight']].describe()
stats
```

[13]:

	Age	Height	Weight
count	2111.000000	2111.000000	2111.000000
mean	23.972525	1.701677	86.586058
std	6.308664	0.093305	26.191172
min	14.000000	1.450000	39.000000
25%	19.000000	1.630000	65.473343
50%	22.000000	1.700499	83.000000
75%	26.000000	1.768464	107.430682
max	61.000000	1.980000	173.000000

0.5.1 Correlation Between Variables

[14]:
```python
# Create a correlation matrix
correlation_matrix = data.corr()
correlation_matrix
```

[14]:

```
                               Gender       Age    Height    Weight  \
Gender                       1.000000  0.050677  0.618466  0.161668
Age                          0.050677  1.000000 -0.030738  0.190263
Height                       0.618466 -0.030738  1.000000  0.463136
```

```
Weight                          0.161668  0.190263  0.463136  1.000000
family_history_with_overweight  0.102512  0.195552  0.247684  0.496820
High_Calorie                    0.064934  0.055872  0.178364  0.272300
Vegetables                     -0.317272 -0.013240 -0.070032  0.201087
Number_of_meals                 0.023921 -0.070632  0.214633  0.126058
Food_Between_Meals              0.091543  0.074851  0.048818  0.287493
Smoke                           0.044698  0.097897  0.055499  0.025746
Water_consumption               0.194832 -0.090672  0.191061  0.052705
Calorie_Monitoring             -0.102633 -0.111882 -0.133753 -0.201906
Physical_Acitivity              0.174468 -0.163307  0.234248 -0.158726
Time_on_Technology              0.071148 -0.234951 -0.006181 -0.274960
Alcohol_consumption             0.007616 -0.043344 -0.129732 -0.206677
Transportation_method          -0.137537 -0.601020 -0.073609  0.004610
Outcome                        -0.001436  0.205189  0.137413  0.793652

                                family_history_with_overweight  High_Calorie  \
Gender                                                0.102512      0.064934
Age                                                   0.195552      0.055872
Height                                                0.247684      0.178364
Weight                                                0.496820      0.272300
family_history_with_overweight                        1.000000      0.208036
High_Calorie                                          0.208036      1.000000
Vegetables                                            0.008332     -0.073482
Number_of_meals                                       0.052504     -0.019162
Food_Between_Meals                                    0.169787      0.150068
Smoke                                                 0.017385     -0.050660
Water_consumption                                     0.053889     -0.082638
Calorie_Monitoring                                   -0.185422     -0.190658
Physical_Acitivity                                   -0.128375     -0.156302
Time_on_Technology                                   -0.097283     -0.054783
Alcohol_consumption                                   0.036676     -0.089520
Transportation_method                                -0.101540     -0.069800
Outcome                                               0.416607      0.278355

                                Vegetables  Number_of_meals  \
Gender                           -0.317272         0.023921
Age                              -0.013240        -0.070632
Height                           -0.070032         0.214633
Weight                            0.201087         0.126058
family_history_with_overweight    0.008332         0.052504
High_Calorie                     -0.073482        -0.019162
Vegetables                        1.000000         0.138510
Number_of_meals                   0.138510         1.000000
Food_Between_Meals               -0.100727        -0.122478
Smoke                             0.025567         0.035825
Water_consumption                 0.037495         0.067431
Calorie_Monitoring                0.070328        -0.006166
```

Physical_Acitivity	0.019344	0.126888
Time_on_Technology	-0.150120	0.028048
Alcohol_consumption	-0.085690	-0.116039
Transportation_method	0.105084	-0.012480
Outcome	0.136075	0.056340

	Food_Between_Meals	Smoke \
Gender	0.091543	0.044698
Age	0.074851	0.097897
Height	0.048818	0.055499
Weight	0.287493	0.025746
family_history_with_overweight	0.169787	0.017385
High_Calorie	0.150068	-0.050660
Vegetables	-0.100727	0.025567
Number_of_meals	-0.122478	0.035825
Food_Between_Meals	1.000000	-0.055282
Smoke	-0.055282	1.000000
Water_consumption	0.048315	0.014689
Calorie_Monitoring	-0.109179	0.047731
Physical_Acitivity	-0.098121	0.022590
Time_on_Technology	-0.157565	0.063889
Alcohol_consumption	-0.047540	-0.082471
Transportation_method	-0.048535	-0.010702
Outcome	0.232819	0.011578

	Water_consumption	Calorie_Monitoring \
Gender	0.194832	-0.102633
Age	-0.090672	-0.111882
Height	0.191061	-0.133753
Weight	0.052705	-0.201906
family_history_with_overweight	0.053889	-0.185422
High_Calorie	-0.082638	-0.190658
Vegetables	0.037495	0.070328
Number_of_meals	0.067431	-0.006166
Food_Between_Meals	0.048315	-0.109179
Smoke	0.014689	0.047731
Water_consumption	1.000000	0.070662
Calorie_Monitoring	0.070662	1.000000
Physical_Acitivity	0.266097	0.094120
Time_on_Technology	0.095753	0.032761
Alcohol_consumption	-0.041402	-0.003463
Transportation_method	0.044987	0.043157
Outcome	-0.038913	-0.187952

	Physical_Acitivity	Time_on_Technology \
Gender	0.174468	0.071148
Age	-0.163307	-0.234951

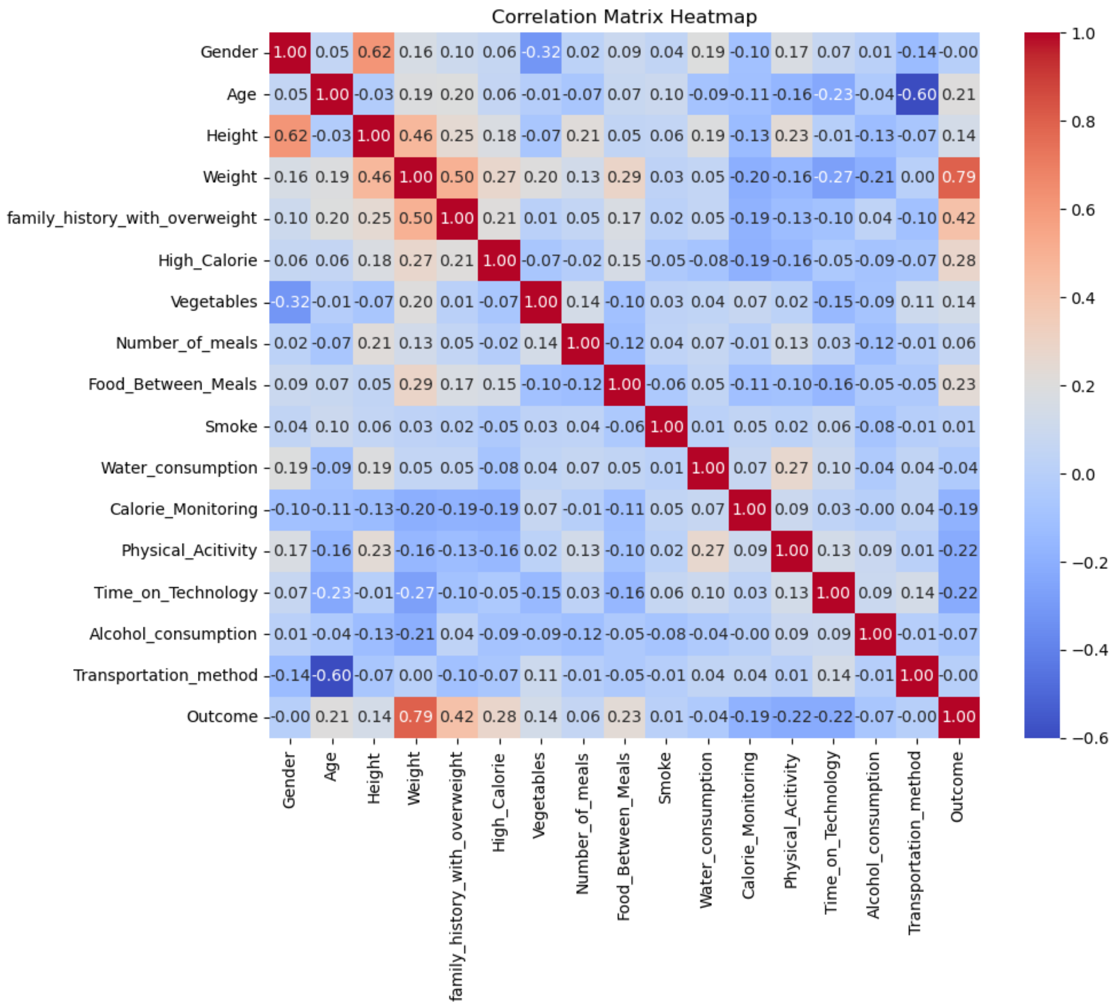
Height	0.234248	-0.006181
Weight	-0.158726	-0.274960
family_history_with_overweight	-0.128375	-0.097283
High_Calorie	-0.156302	-0.054783
Vegetables	0.019344	-0.150120
Number_of_meals	0.126888	0.028048
Food_Between_Meals	-0.098121	-0.157565
Smoke	0.022590	0.063889
Water_consumption	0.266097	0.095753
Calorie_Monitoring	0.094120	0.032761
Physical_Acitivity	1.000000	0.134370
Time_on_Technology	0.134370	1.000000
Alcohol_consumption	0.085458	0.091194
Transportation_method	0.008359	0.138015
Outcome	-0.221615	-0.221377

	Alcohol_consumption	Transportation_method \
Gender	0.007616	-0.137537
Age	-0.043344	-0.601020
Height	-0.129732	-0.073609
Weight	-0.206677	0.004610
family_history_with_overweight	0.036676	-0.101540
High_Calorie	-0.089520	-0.069800
Vegetables	-0.085690	0.105084
Number_of_meals	-0.116039	-0.012480
Food_Between_Meals	-0.047540	-0.048535
Smoke	-0.082471	-0.010702
Water_consumption	-0.041402	0.044987
Calorie_Monitoring	-0.003463	0.043157
Physical_Acitivity	0.085458	0.008359
Time_on_Technology	0.091194	0.138015
Alcohol_consumption	1.000000	-0.012452
Transportation_method	-0.012452	1.000000
Outcome	-0.073897	-0.002263

	Outcome
Gender	-0.001436
Age	0.205189
Height	0.137413
Weight	0.793652
family_history_with_overweight	0.416607
High_Calorie	0.278355
Vegetables	0.136075
Number_of_meals	0.056340
Food_Between_Meals	0.232819
Smoke	0.011578
Water_consumption	-0.038913

```
Calorie_Monitoring             -0.187952
Physical_Acitivity             -0.221615
Time_on_Technology             -0.221377
Alcohol_consumption            -0.073897
Transportation_method          -0.002263
Outcome                         1.000000
```

[15]:
```python
# Plot the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
 ↪annot_kws={"size": 10})
plt.title('Correlation Matrix Heatmap')
plt.show()
```

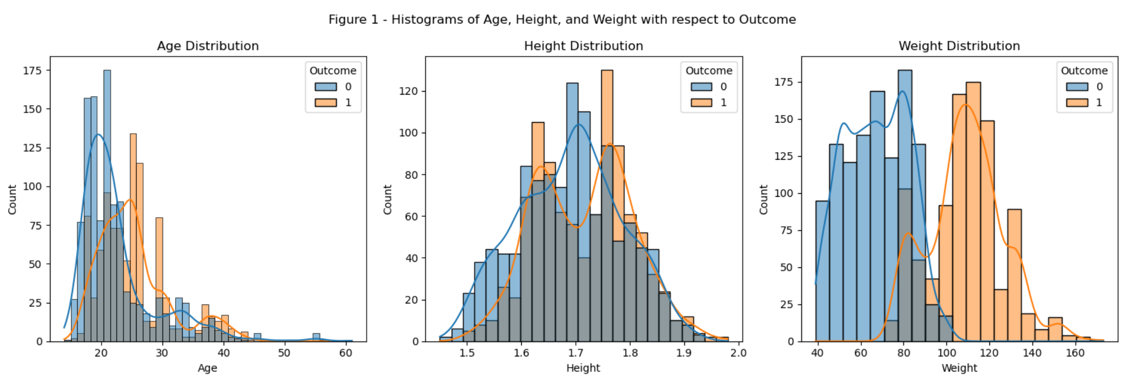


The above correlation matrix opens up a wide opportunity to correlate all attributes of the dataset. The main insights are the strong positive correlation between Outcome

and Weight, and strong negative correlation between Age and Transportation method which have a correlation coefficient of 0.79 and -0.60 respectively. The correlation between Weight and Height as well as Weight and Family history with Overweight are also strong with a correlation coefficient of 0.46 and 0.50 respectively.

Histogram

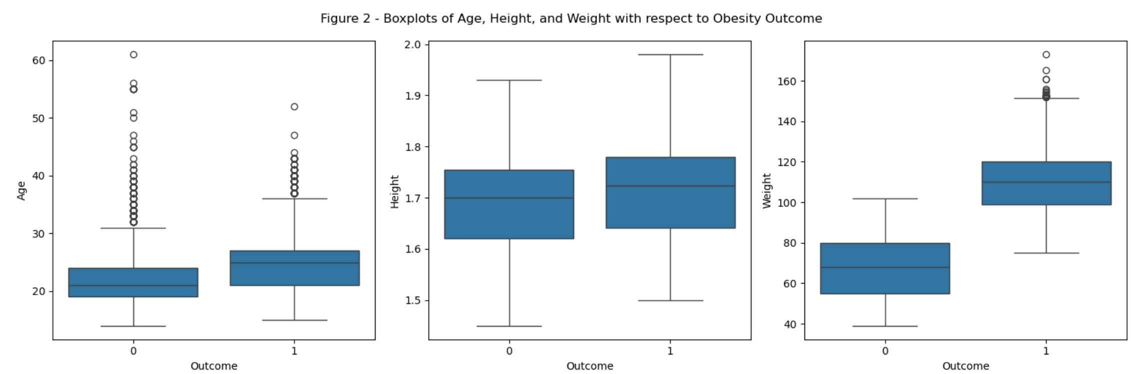
[16]:
```python
# Create subplots
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

# Create Histograms
sns.histplot(data=data, x='Age', hue='Outcome', ax=axes[0], kde=True)
sns.histplot(data=data, x='Height', hue='Outcome', ax=axes[1], kde=True)
sns.histplot(data=data, x='Weight', hue='Outcome', ax=axes[2], kde=True)

# Set titles
axes[0].set_title('Age Distribution')
axes[1].set_title('Height Distribution')
axes[2].set_title('Weight Distribution')

# Addtitle
plt.suptitle('Figure 1 - Histograms of Age, Height, and Weight with respect to␣
↪Outcome')
plt.tight_layout()
plt.show()
```



The histograms above display the distribution of Age, Height, and Weight for two different outcomes (0 and 1). Outcome 1 is generally associated with younger people who are taller and heavier, while Outcome 0 has a more diverse age distribution with a tendency towards lighter and shorter people. Both height distributions are normally distributed, whereas age and weight are right-skewed for Outcome 1, indicating a younger and heavier subset of the population in that category.

0.5.2 Boxplots

[17]:
```
# Create subplots
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

# Create boxplots
sns.boxplot(x='Outcome', y='Age', data=data, ax=axes[0])
sns.boxplot(x='Outcome', y='Height', data=data, ax=axes[1])
sns.boxplot(x='Outcome', y='Weight', data=data, ax=axes[2])

# Add title
plt.suptitle('Figure 2 - Boxplots of Age, Height, and Weight with respect to␣
↪Obesity Outcome')

# Show plot
plt.tight_layout()
plt.show()
```



The boxplots compare Age, Height, and Weight distributions across two outcomes related to obesity.

- **Age**: For Outcome 0, the median age is lower, and the age range is narrower compared to Outcome 1. There are also several outliers indicating people older than the typical range for Outcome 0.
- **Height**: Both outcomes have similar medians and interquartile ranges for height, suggesting height may not be significantly different between the two groups.
- **Weight**: There is a noticeable difference in weight between the two outcomes. Outcome 1 has a higher median weight and a larger interquartile range, indicating that people with this outcome tend to be heavier.

In general, these boxplots suggest that people with Outcome 1 are generally older and heavier, which could imply a higher risk or prevalence of obesity, while height appears to be consistent across both outcomes. Just from the visuals, assumptions cannot be made and therefore t-test analysis was performed to see if a significant difference

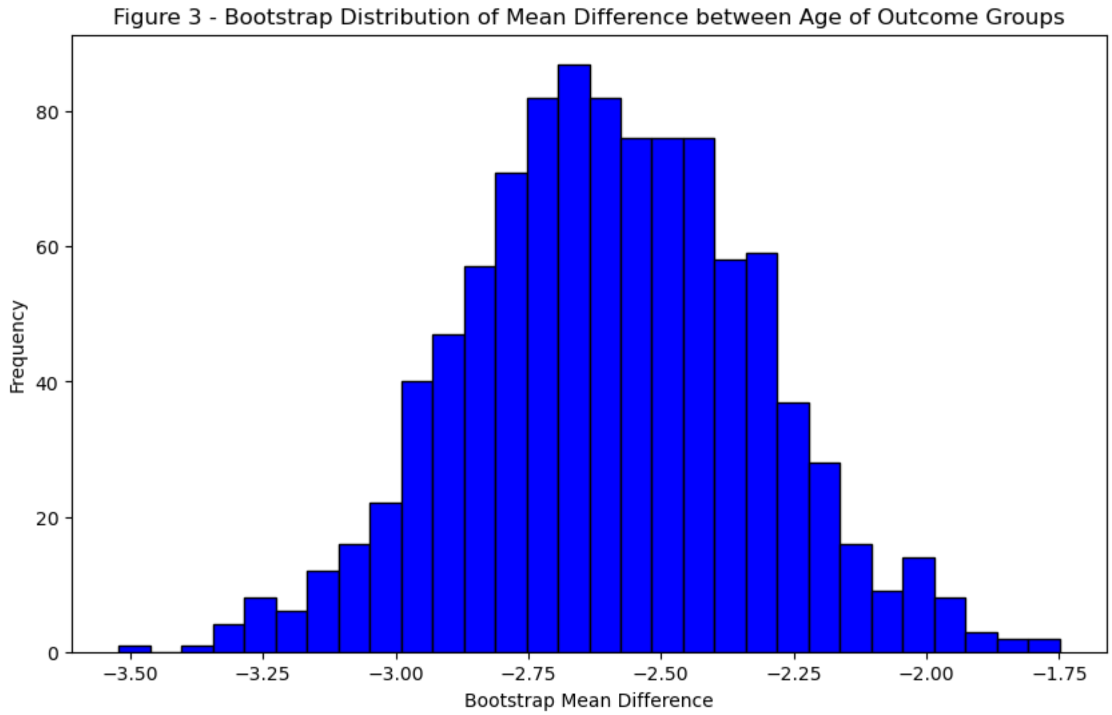
exists for each variables between the two groups.

0.5.3 T-test Analysis

H0: The difference between the two means for each variable's outcome group is equal to 0

HA: The difference between the two means for each variable's outcome group is NOT equal to 0

[18]:
```
# Bootstrapping
outcome_0_age = data[data['Outcome'] == 0]['Age']
outcome_1_age = data[data['Outcome'] == 1]['Age']
n_outcome_0_age = data[data['Outcome'] == 0]['Age'].count()
n_outcome_1_age = data[data['Outcome'] == 1]['Age'].count()

# Number of simulations
nsims = 1000

# Generate bootstrap samples and calculate the mean difference
bootstrap_mean_difference = np.zeros(nsims)
for i in range(nsims):
    sample_0_age = np.random.choice(outcome_0_age, size = n_outcome_0_age,␣
 ↪replace=True)
    sample_1_age = np.random.choice(outcome_1_age, size = n_outcome_1_age,␣
 ↪replace=True)
    bootstrap_mean_difference[i] = np.mean(sample_0_age) - np.mean(sample_1_age)

# Plot bootstrap distribution
plt.figure(figsize=(10, 6))
plt.hist(bootstrap_mean_difference, bins=30, color='blue', edgecolor='black')
plt.xlabel('Bootstrap Mean Difference')
plt.ylabel('Frequency')
plt.title('Figure 3 - Bootstrap Distribution of Mean Difference between Age of␣
 ↪Outcome Groups')
plt.show()
```



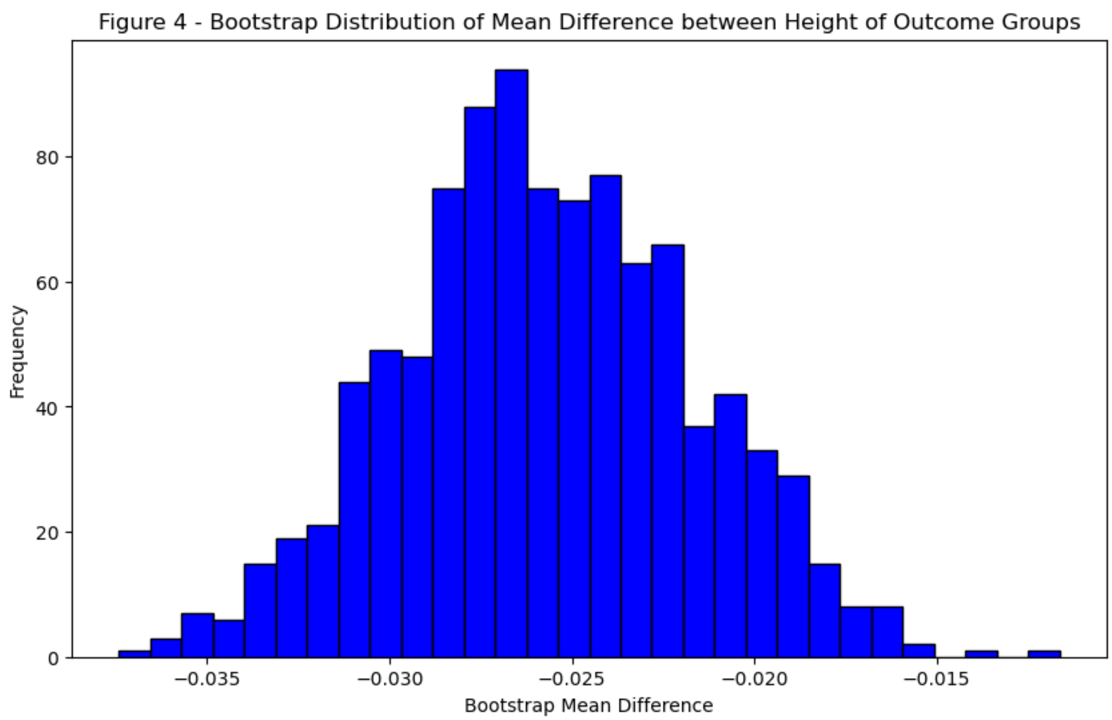
[19]:
```
# Perform independent t-test
t_statistic, p_value = ttest_ind(outcome_0_age, outcome_1_age, equal_var=False)

# Print results
print("t-statistic:", t_statistic)
print("p-value:", p_value)

# Interpret results
alpha = 0.05
if p_value < alpha:
    print("The p-value is less than the significance level ({}).".format(alpha))
    print("We reject the null hypothesis.")
    print("There is a statistically significant difference in the mean age␣
 ↪between the two outcome groups.")
else:
    print("The p-value is greater than or equal to the significance level ({}).
 ↪".format(alpha))
    print("We fail to reject the null hypothesis.")
    print("There is insufficient evidence to conclude a statistically␣
 ↪significant difference in the mean age between the two outcome groups.")
```

```
t-statistic: -9.691464196822928
p-value: 9.30274829436022e-22
The p-value is less than the significance level (0.05).
```

```
We reject the null hypothesis.
There is a statistically significant difference in the mean age between the two
outcome groups.
```

The t-statistic of -9.69 and the tiny p-value (9.30e-22) show a big difference in average ages between the two groups. Since the p-value is way below 0.05, we're confident in rejecting the null hypothesis. This means there's a significant age gap between the outcome groups, a key finding in our project.

[20]:
```python
# Extract data for each outcome group
outcome_0_height = data[data['Outcome'] == 0]['Height']
outcome_1_height = data[data['Outcome'] == 1]['Height']
n_outcome_0_height = data[data['Outcome'] == 0]['Height'].count()
n_outcome_1_height = data[data['Outcome'] == 1]['Height'].count()

# Number of simulations
nsims = 1000

# Generate bootstrap samples and calculate the mean difference
bootstrap_mean_difference = np.zeros(nsims)
for i in range(nsims):
    sample_0_height = np.random.choice(outcome_0_height, size =␣
 ↪n_outcome_0_height, replace=True)
    sample_1_height = np.random.choice(outcome_1_height, size =␣
 ↪n_outcome_1_height, replace=True)
    bootstrap_mean_difference[i] = np.mean(sample_0_height) - np.
 ↪mean(sample_1_height)

# Plot bootstrap distribution
plt.figure(figsize=(10, 6))
plt.hist(bootstrap_mean_difference, bins=30, color='blue', edgecolor='black')
plt.xlabel('Bootstrap Mean Difference')
plt.ylabel('Frequency')
plt.title('Figure 4 - Bootstrap Distribution of Mean Difference between Height␣
 ↪of Outcome Groups')
plt.show()
```



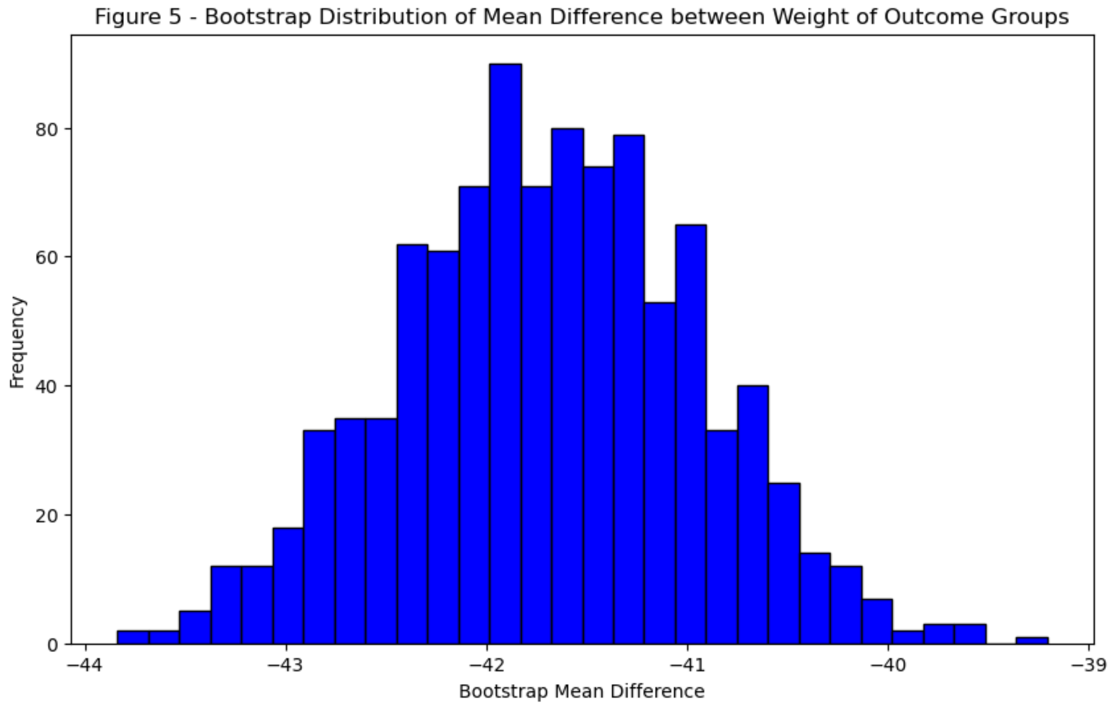
[21]:
```
# Perform independent t-test
t_statistic, p_value = ttest_ind(outcome_0_height, outcome_1_height,␣
↪equal_var=False)

# Print results
print("t-statistic:", t_statistic)
print("p-value:", p_value)

# Interpret results
alpha = 0.05
if p_value < alpha:
    print("The p-value is less than the significance level ({}).".format(alpha))
    print("We reject the null hypothesis.")
    print("There is a statistically significant difference in the mean height␣
↪between the two outcome groups.")
else:
    print("The p-value is greater than or equal to the significance level ({}).
↪".format(alpha))
    print("We fail to reject the null hypothesis.")
    print("There is insufficient evidence to conclude a statistically␣
↪significant difference in the mean height between the two outcome groups.")
```

```
t-statistic: -6.405435192046915
p-value: 1.8464734842511456e-10
```

```
The p-value is less than the significance level (0.05).
We reject the null hypothesis.
There is a statistically significant difference in the mean height between the
two outcome groups.
```

With a t-statistic of -6.41 and a p-value of 1.85e-10, we observe a substantial difference in average heights between the two groups. Since the p-value is much lower than the standard threshold of 0.05, we confidently reject the null hypothesis. This indicates a statistically significant contrast in height distribution among the outcome groups, emphasizing a noteworthy finding in our project analysis.

[22]:
```python
# Extract data for each outcome group
outcome_0_weight = data[data['Outcome'] == 0]['Weight']
outcome_1_weight = data[data['Outcome'] == 1]['Weight']
n_outcome_0_weight = data[data['Outcome'] == 0]['Weight'].count()
n_outcome_1_weight = data[data['Outcome'] == 1]['Height'].count()

# Number of simulations
nsims = 1000

# Generate bootstrap samples and calculate the mean difference
bootstrap_mean_difference = np.zeros(nsims)
for i in range(nsims):
    sample_0_weight = np.random.choice(outcome_0_weight, size =␣
 ↪n_outcome_0_weight, replace=True)
    sample_1_weight = np.random.choice(outcome_1_weight, size =␣
 ↪n_outcome_1_weight, replace=True)
    bootstrap_mean_difference[i] = np.mean(sample_0_weight) - np.
 ↪mean(sample_1_weight)

# Plot bootstrap distribution
plt.figure(figsize=(10, 6))
plt.hist(bootstrap_mean_difference, bins=30, color='blue', edgecolor='black')
plt.xlabel('Bootstrap Mean Difference')
plt.ylabel('Frequency')
plt.title('Figure 5 - Bootstrap Distribution of Mean Difference between Weight␣
 ↪of Outcome Groups')
plt.show()
```



[23]:
```
# Perform independent t-test
t_statistic, p_value = ttest_ind(outcome_0_weight, outcome_1_weight,␣
↪equal_var=False)

# Print results
print("t-statistic:", t_statistic)
print("p-value:", p_value)

# Interpret results
alpha = 0.05
if p_value < alpha:
    print("The p-value is less than the significance level ({}).".format(alpha))
    print("We reject the null hypothesis.")
    print("There is a statistically significant difference in the mean weight␣
↪between the two outcome groups.")
else:
    print("The p-value is greater than or equal to the significance level ({}).
↪".format(alpha))
    print("We fail to reject the null hypothesis.")
    print("There is insufficient evidence to conclude a statistically␣
↪significant difference in the mean weight between the two outcome groups.")
```

```
t-statistic: -59.109812874108115
p-value: 0.0
```

```
The p-value is less than the significance level (0.05).
We reject the null hypothesis.
There is a statistically significant difference in the mean weight between the
two outcome groups.
```

The t-statistic of -59.11 coupled with a p-value of 0.0 reveals an immense contrast in average weights between the two groups. Given the p-value's insignificance below the customary threshold of 0.05, we confidently reject the null hypothesis. This solidifies the presence of a statistically significant divergence in weight distribution among the outcome groups, marking a crucial insight in our project's findings.

0.6 Principal Commponent Analysis (PCA)

---

[24]:
```
data_copy = data.copy()
data_copy
```

[24]:
```
      Gender  Age    Height      Weight  family_history_with_overweight  \
0          0   21  1.620000   64.000000                               1
1          0   21  1.520000   56.000000                               1
2          1   23  1.800000   77.000000                               1
3          1   27  1.800000   87.000000                               0
4          1   22  1.780000   89.800000                               0
…        …   …      …       …                            …
2106       0   20  1.710730  131.408528                               1
2107       0   21  1.748584  133.742943                               1
2108       0   22  1.752206  133.689352                               1
2109       0   24  1.739450  133.346641                               1
2110       0   23  1.738836  133.472641                               1

      High_Calorie  Vegetables  Number_of_meals  Food_Between_Meals  Smoke  \
0                0           2                3                   2      0
1                0           3                3                   2      1
2                0           2                3                   2      0
3                0           3                3                   2      0
4                0           2                1                   2      0
…            …           …               …                  …      …
2106             1           3                3                   2      0
2107             1           3                3                   2      0
2108             1           3                3                   2      0
2109             1           3                3                   2      0
2110             1           3                3                   2      0

      Water_consumption  Calorie_Monitoring  Physical_Acitivity  \
0                     2                   0                   0
1                     3                   1                   3
2                     2                   0                   2
```

```
3                    2                   0                   2
4                    2                   0                   0
…                …                 …                 …
2106                 1                   0                   1
2107                 2                   0                   1
2108                 2                   0                   1
2109                 2                   0                   1
2110                 2                   0                   1

      Time_on_Technology  Alcohol_consumption  Transportation_method  Outcome
0                      1                    3                      3        0
1                      0                    2                      3        0
2                      1                    1                      3        0
3                      0                    1                      4        0
4                      0                    2                      3        0
…                  …                  …                    …      …
2106                   0                    2                      3        1
2107                   0                    2                      3        1
2108                   0                    2                      3        1
2109                   0                    2                      3        1
2110                   0                    2                      3        1

[2111 rows x 17 columns]
```

[25]:
```python
#saving diagnosis data
outcomedata = data["Outcome"]
outcomedata
```

[25]:
```
0       0
1       0
2       0
3       0
4       0
       ..
2106    1
2107    1
2108    1
2109    1
2110    1
Name: Outcome, Length: 2111, dtype: int64
```

[26]:
```python
# Standardarize/normalize the data
scaler = StandardScaler()
standardized_data = scaler.fit_transform(data_copy)
selected_data_standardized = pd.DataFrame(data_copy)
selected_data_standardized
```

[26]:
```
      Gender  Age    Height      Weight  family_history_with_overweight  \
0          0   21  1.620000   64.000000                               1
1          0   21  1.520000   56.000000                               1
2          1   23  1.800000   77.000000                               1
3          1   27  1.800000   87.000000                               0
4          1   22  1.780000   89.800000                               0
…        …   …       …           …                             …
2106       0   20  1.710730  131.408528                               1
2107       0   21  1.748584  133.742943                               1
2108       0   22  1.752206  133.689352                               1
2109       0   24  1.739450  133.346641                               1
2110       0   23  1.738836  133.472641                               1

      High_Calorie  Vegetables  Number_of_meals  Food_Between_Meals  Smoke  \
0                0           2                3                   2      0
1                0           3                3                   2      1
2                0           2                3                   2      0
3                0           3                3                   2      0
4                0           2                1                   2      0
…              …          …               …                  …    …
2106             1           3                3                   2      0
2107             1           3                3                   2      0
2108             1           3                3                   2      0
2109             1           3                3                   2      0
2110             1           3                3                   2      0

      Water_consumption  Calorie_Monitoring  Physical_Acitivity  \
0                     2                   0                   0
1                     3                   1                   3
2                     2                   0                   2
3                     2                   0                   2
4                     2                   0                   0
…                   …                  …                  …
2106                  1                   0                   1
2107                  2                   0                   1
2108                  2                   0                   1
2109                  2                   0                   1
2110                  2                   0                   1

      Time_on_Technology  Alcohol_consumption  Transportation_method  Outcome
0                      1                    3                      3        0
1                      0                    2                      3        0
2                      1                    1                      3        0
3                      0                    1                      4        0
4                      0                    2                      3        0
…                    …                   …                    …      …
2106                   0                    2                      3        1
```

```
2107                       0                    2                      3        1
2108                       0                    2                      3        1
2109                       0                    2                      3        1
2110                       0                    2                      3        1

[2111 rows x 17 columns]
```

[27]:
```python
pca = PCA()
data_pca = pca.fit_transform(selected_data_standardized)
df_pca = pd.DataFrame(data_pca)
pca_columns = ['PC' + str(i) for i in range(1, len(df_pca.columns) + 1)]
df_pca.columns = pca_columns
df_pca.head()
```

[27]:
```
         PC1       PC2       PC3       PC4       PC5       PC6       PC7  \
0 -22.709820 -1.939526  0.495874 -0.022072 -0.703023  0.510098  0.378575
1 -30.699533 -1.605241 -0.415082  2.257081  0.765597 -1.227531  0.726818
2  -9.629767 -0.621617 -0.130150  1.487604  0.476610  0.481650  0.224382
3   0.553425  2.734607  1.206184  2.274976  0.368643 -0.512349  0.285335
4   3.100795 -2.157025  0.869733 -1.094432  0.923761 -0.032532  0.587451

        PC8       PC9      PC10      PC11      PC12      PC13      PC14  \
0  0.490067 -0.797356 -0.376037  0.069622  0.251601  0.851246  0.114182
1 -0.576931 -0.162361 -0.492708  0.222395 -0.146497  0.667976  0.542222
2 -0.342200  1.206393 -0.183944 -0.260577 -0.108071  0.827981  0.473206
3 -0.953158  1.076812  0.189930 -0.771080  0.634112  0.366372  0.205883
4 -0.571811  0.276876  0.594465 -0.413511  1.022195  0.565357 -0.027731

       PC15      PC16      PC17
0 -0.166648 -0.011428  0.016304
1  0.809193  0.892627 -0.115483
2 -0.165085 -0.098948  0.039065
3 -0.222600 -0.092612  0.043056
4 -0.215253 -0.016801  0.052122
```

[28]:
```python
pca_variances = pca.explained_variance_ratio_
pca_variances = pd.DataFrame(pca_variances)
pca_variances.columns = ['Explained Variance']
pca_variances.index = pca_columns
print(pca_variances)
```

```
      Explained Variance
PC1             0.940773
PC2             0.053241
PC3             0.001432
PC4             0.001051
PC5             0.000854
```

```
PC6          0.000565
PC7          0.000431
PC8          0.000389
PC9          0.000339
PC10         0.000255
PC11         0.000216
PC12         0.000145
PC13         0.000124
PC14         0.000100
PC15         0.000053
PC16         0.000027
PC17         0.000004
```

[29]:

```
pca_variances["cumulative Variance"] = pca_variances['Explained Variance'].
  ↪cumsum()
print(pca_variances)
```

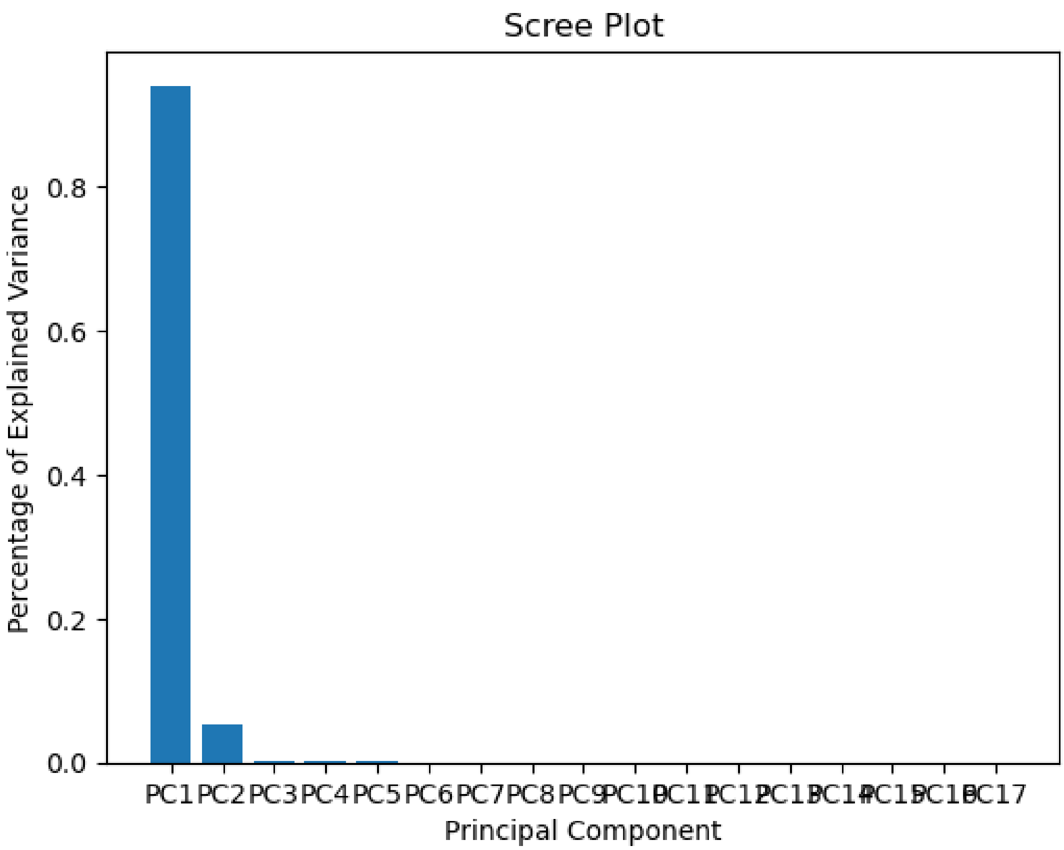
```
      Explained Variance  cumulative Variance
PC1             0.940773             0.940773
PC2             0.053241             0.994014
PC3             0.001432             0.995446
PC4             0.001051             0.996498
PC5             0.000854             0.997351
PC6             0.000565             0.997916
PC7             0.000431             0.998348
PC8             0.000389             0.998737
PC9             0.000339             0.999076
PC10            0.000255             0.999331
PC11            0.000216             0.999547
PC12            0.000145             0.999692
PC13            0.000124             0.999816
PC14            0.000100             0.999916
PC15            0.000053             0.999969
PC16            0.000027             0.999996
PC17            0.000004             1.000000
```

This table represents the explained variance for each principal component (PC) in our project. PC1 explains 94.08% of the variance, followed by PC2 with 5.32%. As we progress down the list, each subsequent PC contributes a smaller proportion to the cumulative variance. By the time we reach PC17, the cumulative variance sums up to 100%, indicating the complete variance explanation by all the principal components. This breakdown provides valuable insights into the contribution of each PC to our project's overall variance.

[30]:

```
#Now plot a scree plot
plt.bar(x = range(1,pca_variances.index.size+1), height =␣
  ↪pca_variances["Explained Variance"], tick_label = pca_columns)
plt.xlabel("Principal Component")
```

```
plt.ylabel("Percentage of Explained Variance")
plt.title("Scree Plot")
plt.show()
```



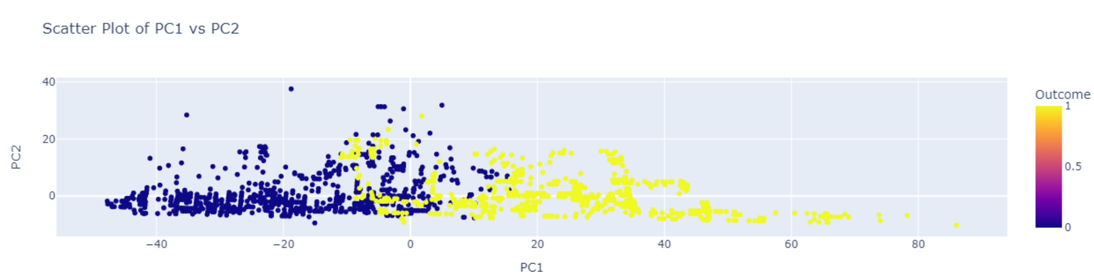
[31]:
```
pca_df = pd.DataFrame(data_pca,index = outcomedata,columns = pca_columns)
pca_df = pca_df.reset_index()

pca_df
```

[31]:

	Outcome	PC1	PC2	PC3	PC4	PC5	PC6	\
0	0	-22.709820	-1.939526	0.495874	-0.022072	-0.703023	0.510098	
1	0	-30.699533	-1.605241	-0.415082	2.257081	0.765597	-1.227531	
2	0	-9.629767	-0.621617	-0.130150	1.487604	0.476610	0.481650	
3	0	0.553425	2.734607	1.206184	2.274976	0.368643	-0.512349	
4	0	3.100795	-2.157025	0.869733	-1.094432	0.923761	-0.032532	
…	…	…	…	…	…	…	…	
2106	1	44.582790	-6.178975	-0.099500	0.167386	-0.427989	-0.899902	
2107	1	46.963652	-5.311653	-0.110869	0.478902	-0.158482	-0.771878	
2108	1	46.958625	-4.318864	-0.007107	0.555410	-0.148110	-0.753435	
2109	1	46.713339	-2.321869	0.202368	0.708375	-0.129165	-0.717400	

```
2110        1  46.790678 -3.318162  0.098101  0.631816 -0.139048 -0.735704

           PC7       PC8       PC9      PC10      PC11      PC12      PC13  \
0     0.378575  0.490067 -0.797356 -0.376037  0.069622  0.251601  0.851246
1     0.726818 -0.576931 -0.162361 -0.492708  0.222395 -0.146497  0.667976
2     0.224382 -0.342200  1.206393 -0.183944 -0.260577 -0.108071  0.827981
3     0.285335 -0.953158  1.076812  0.189930 -0.771080  0.634112  0.366372
4     0.587451 -0.571811  0.276876  0.594465 -0.413511  1.022195  0.565357
…          …         …         …         …         …         …         …
2106 -0.692728  0.117322  0.289681 -0.207723  0.035629  0.020995  0.111163
2107  0.150159  0.048331  0.021024 -0.201532  0.244076  0.080800  0.053612
2108  0.148724  0.050459  0.021943 -0.205622  0.238856  0.082045  0.049898
2109  0.146628  0.053782  0.022737 -0.215897  0.229034  0.082997  0.040469
2110  0.147832  0.051988  0.022088 -0.211353  0.234244  0.082314  0.044774

          PC14      PC15      PC16      PC17
0     0.114182 -0.166648 -0.011428  0.016304
1     0.542222  0.809193  0.892627 -0.115483
2     0.473206 -0.165085 -0.098948  0.039065
3     0.205883 -0.222600 -0.092612  0.043056
4    -0.027731 -0.215253 -0.016801  0.052122
…          …         …         …         …
2106 -0.152590 -0.015967 -0.008215 -0.037411
2107 -0.220022 -0.039572 -0.006526 -0.004215
2108 -0.226346 -0.037018 -0.010291  0.001610
2109 -0.234656 -0.031852 -0.018186 -0.005957
2110 -0.229487 -0.034404 -0.014366 -0.008991

[2111 rows x 18 columns]
```

[32]:
```
# Create a scatter plot using Plotly Express
fig = px.scatter(pca_df, x="PC1", y="PC2", color="Outcome",
                 title="Scatter Plot of PC1 vs PC2")
# Show the plot
fig.show()
```



The above visualization represents the data's varaiblity in a reduced dimensionality.The inference from the PCA is that PC1 accounts for the most significant variations in the data followed by PC2. PC1 and PC2 together provide a meaningful representation, highlighting distinct clusters within data

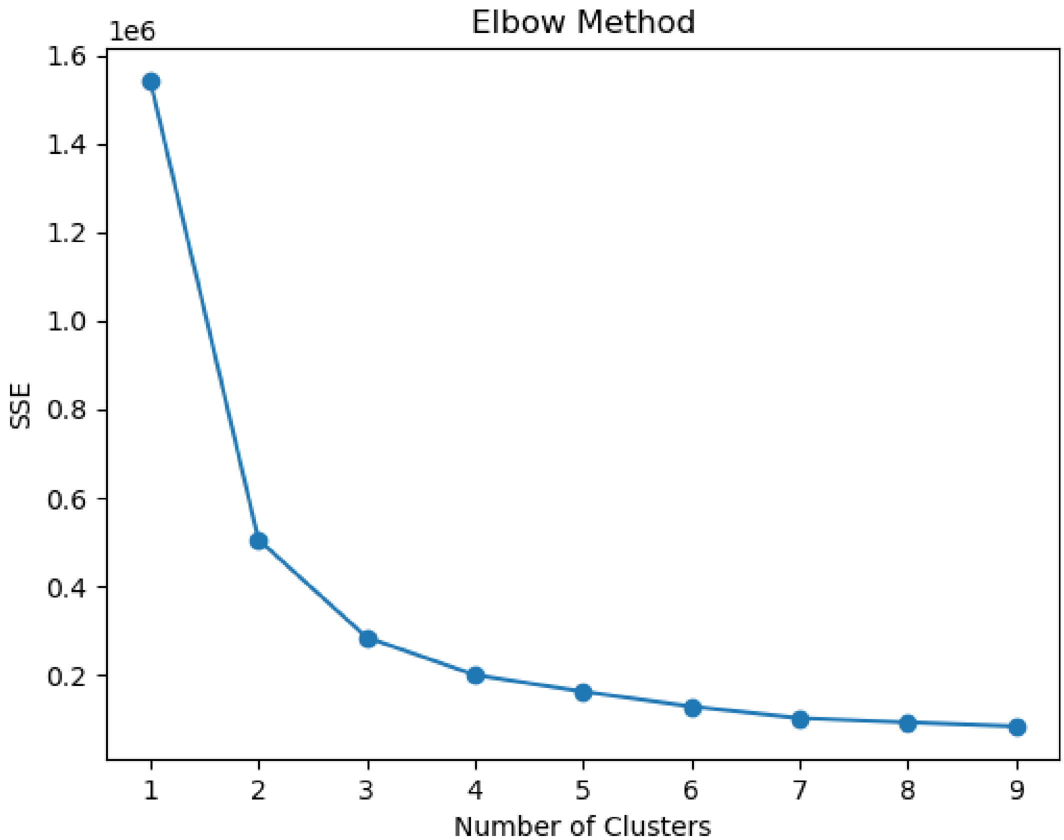
0.7 K-Means Clustering

---

[33]:
```
def find_best_no_cluster(df_dummy,k_max):
  means=[]
  sse = []
  for k in range(1,k_max):
    kmeans = KMeans(n_clusters = k)
    kmeans.fit(data_copy)

    means.append(k)
    sse.append(kmeans.inertia_)

  #draw elbow graph
  plt.plot(means,sse,'o-')
  plt.xlabel("Number of Clusters")
  plt.ylabel("SSE")
  plt.title("Elbow Method")
  plt.show()


find_best_no_cluster(selected_data_standardized,10)
```

```
/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning

/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning

/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning

/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
```

```
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning

/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning

/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning

/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning

/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning

/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning
```



The inference drawn from the above plot(number of clusters VS Sum if squared errors) is that at K=2, there is a noticable elbow or bent in the plot indicating the significant reduction in SSE for the preceding number of clusters. Beyond K=2, the reduction in SSE becomes less, suggesting diminishing returns in clustering performance. Therefore, selecting K=2 is likely to provide a good balance between minimizing SSE and avoiding overfitting, making it a suitable choice for clustering the data.

[34]:
```
# Applying Kmeans clustering
kmeans = KMeans(n_clusters=2)
kmeans.fit(selected_data_standardized)
selected_data_standardized['cluster']  = kmeans.labels_
selected_data_standardized
```

```
/opt/conda/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning
```

[34]:

```
      Gender  Age    Height      Weight  family_history_with_overweight  \
0          0   21  1.620000   64.000000                               1
1          0   21  1.520000   56.000000                               1
2          1   23  1.800000   77.000000                               1
3          1   27  1.800000   87.000000                               0
4          1   22  1.780000   89.800000                               0
…        …   …        …           …                              …
2106       0   20  1.710730  131.408528                               1
2107       0   21  1.748584  133.742943                               1
2108       0   22  1.752206  133.689352                               1
2109       0   24  1.739450  133.346641                               1
2110       0   23  1.738836  133.472641                               1

      High_Calorie  Vegetables  Number_of_meals  Food_Between_Meals  Smoke  \
0                0           2                3                   2      0
1                0           3                3                   2      1
2                0           2                3                   2      0
3                0           3                3                   2      0
4                0           2                1                   2      0
…              …          …               …                  …     …
2106             1           3                3                   2      0
2107             1           3                3                   2      0
2108             1           3                3                   2      0
2109             1           3                3                   2      0
2110             1           3                3                   2      0

      Water_consumption  Calorie_Monitoring  Physical_Acitivity  \
0                     2                   0                   0
1                     3                   1                   3
2                     2                   0                   2
3                     2                   0                   2
4                     2                   0                   0
…                   …                  …                  …
2106                  1                   0                   1
2107                  2                   0                   1
2108                  2                   0                   1
2109                  2                   0                   1
2110                  2                   0                   1

      Time_on_Technology  Alcohol_consumption  Transportation_method  Outcome  \
0                      1                    3                      3        0
1                      0                    2                      3        0
2                      1                    1                      3        0
3                      0                    1                      4        0
4                      0                    2                      3        0
…                    …                   …                     …       …
2106                   0                    2                      3        1
```

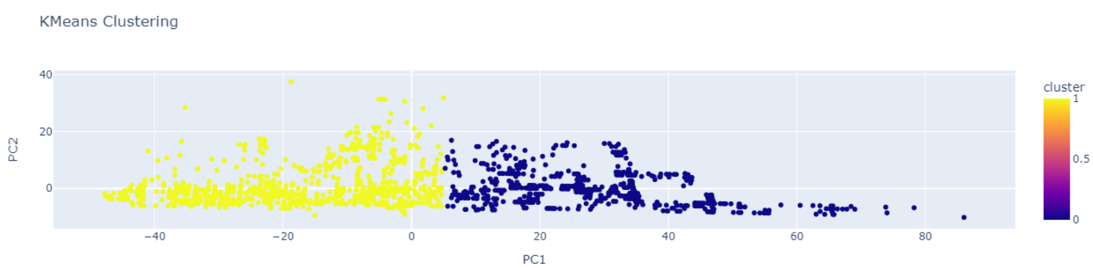
```
2107                    0                    2                      3        1
2108                    0                    2                      3        1
2109                    0                    2                      3        1
2110                    0                    2                      3        1

      cluster
0           1
1           1
2           1
3           1
4           1
…        …
2106        0
2107        0
2108        0
2109        0
2110        0

[2111 rows x 18 columns]
```

[35]:
```
pca_df["cluster"] =  kmeans.labels_

pca_df
```

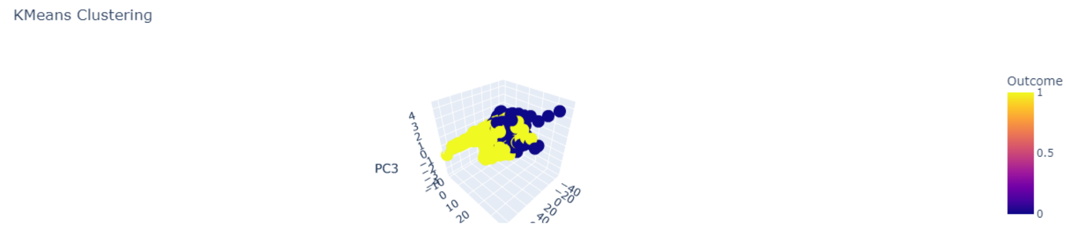
[35]:
```
      Outcome        PC1       PC2       PC3       PC4       PC5       PC6  \
0           0 -22.709820 -1.939526  0.495874 -0.022072 -0.703023  0.510098
1           0 -30.699533 -1.605241 -0.415082  2.257081  0.765597 -1.227531
2           0  -9.629767 -0.621617 -0.130150  1.487604  0.476610  0.481650
3           0   0.553425  2.734607  1.206184  2.274976  0.368643 -0.512349
4           0   3.100795 -2.157025  0.869733 -1.094432  0.923761 -0.032532
…        …       …         …         …         …         …         …
2106        1  44.582790 -6.178975 -0.099500  0.167386 -0.427989 -0.899902
2107        1  46.963652 -5.311653 -0.110869  0.478902 -0.158482 -0.771878
2108        1  46.958625 -4.318864 -0.007107  0.555410 -0.148110 -0.753435
2109        1  46.713339 -2.321869  0.202368  0.708375 -0.129165 -0.717400
2110        1  46.790678 -3.318162  0.098101  0.631816 -0.139048 -0.735704

           PC7       PC8       PC9      PC10      PC11      PC12      PC13  \
0     0.378575  0.490067 -0.797356 -0.376037  0.069622  0.251601  0.851246
1     0.726818 -0.576931 -0.162361 -0.492708  0.222395 -0.146497  0.667976
2     0.224382 -0.342200  1.206393 -0.183944 -0.260577 -0.108071  0.827981
3     0.285335 -0.953158  1.076812  0.189930 -0.771080  0.634112  0.366372
4     0.587451 -0.571811  0.276876  0.594465 -0.413511  1.022195  0.565357
…          …         …         …         …         …         …         …
2106 -0.692728  0.117322  0.289681 -0.207723  0.035629  0.020995  0.111163
2107  0.150159  0.048331  0.021024 -0.201532  0.244076  0.080800  0.053612
2108  0.148724  0.050459  0.021943 -0.205622  0.238856  0.082045  0.049898
```

```
2109  0.146628  0.053782  0.022737 -0.215897  0.229034  0.082997  0.040469
2110  0.147832  0.051988  0.022088 -0.211353  0.234244  0.082314  0.044774

          PC14      PC15      PC16      PC17  cluster
0     0.114182 -0.166648 -0.011428  0.016304        1
1     0.542222  0.809193  0.892627 -0.115483        1
2     0.473206 -0.165085 -0.098948  0.039065        1
3     0.205883 -0.222600 -0.092612  0.043056        1
4    -0.027731 -0.215253 -0.016801  0.052122        1
…          …        …        …        …        …
2106 -0.152590 -0.015967 -0.008215 -0.037411        0
2107 -0.220022 -0.039572 -0.006526 -0.004215        0
2108 -0.226346 -0.037018 -0.010291  0.001610        0
2109 -0.234656 -0.031852 -0.018186 -0.005957        0
2110 -0.229487 -0.034404 -0.014366 -0.008991        0

[2111 rows x 19 columns]
```

[36]:
```python
fig = px.scatter(pca_df, x="PC1", y="PC2", color="cluster",
                 title="KMeans Clustering")
fig.show()
```



[37]:
```python
# Create a scatter plot with three principal components
fig = px.scatter_3d(pca_df, x="PC1", y="PC2", z="PC3", color="Outcome",
                    title="KMeans Clustering")
# Show the plot
fig.show()
```



The above plots, where the former is a 2D visualization and latter is a 3D visulization of K-means clustering. For the 2D visulization, the data points were positioned along the first two principal components (PC1 and PC2) with colors indicating assigned clusters. The same with 3D visulization but PC3 was added to that. The insights from the analysis reveal distinct groupings within the data based on similarities between data points. These clusters may represent different patterns, behaviors, or characteristics present in the dataset. By identifying and understanding these groupings, we can gain valuable insights into the underlying structure of the data and potentially uncover hidden relationships or trends.

0.8 Logistic Regression Model

The overall objective of the report was creating a logistic regression model to predict the outcome variable using the variables present in the dataset. Below, steps have been taken to account for predictions by testing, training, and validating the model created.

[38]:
```
data
```

[38]:
```
      Gender  Age    Height      Weight  family_history_with_overweight  \
0          0   21  1.620000   64.000000                               1
1          0   21  1.520000   56.000000                               1
2          1   23  1.800000   77.000000                               1
3          1   27  1.800000   87.000000                               0
4          1   22  1.780000   89.800000                               0
…        …    …         …           …                               …
2106       0   20  1.710730  131.408528                               1
2107       0   21  1.748584  133.742943                               1
2108       0   22  1.752206  133.689352                               1
2109       0   24  1.739450  133.346641                               1
2110       0   23  1.738836  133.472641                               1

      High_Calorie  Vegetables  Number_of_meals  Food_Between_Meals  Smoke  \
0                0           2                3                   2      0
1                0           3                3                   2      1
```

```
2                 0          2                 3                   2      0
3                 0          3                 3                   2      0
4                 0          2                 1                   2      0
…             …          …               …                 …    …
2106              1          3                 3                   2      0
2107              1          3                 3                   2      0
2108              1          3                 3                   2      0
2109              1          3                 3                   2      0
2110              1          3                 3                   2      0

      Water_consumption  Calorie_Monitoring  Physical_Acitivity  \
0                     2                   0                   0
1                     3                   1                   3
2                     2                   0                   2
3                     2                   0                   2
4                     2                   0                   0
…                   …                 …                 …
2106                  1                   0                   1
2107                  2                   0                   1
2108                  2                   0                   1
2109                  2                   0                   1
2110                  2                   0                   1

      Time_on_Technology  Alcohol_consumption  Transportation_method  Outcome
0                      1                    3                      3        0
1                      0                    2                      3        0
2                      1                    1                      3        0
3                      0                    1                      4        0
4                      0                    2                      3        0
…                    …                  …                    …      …
2106                   0                    2                      3        1
2107                   0                    2                      3        1
2108                   0                    2                      3        1
2109                   0                    2                      3        1
2110                   0                    2                      3        1

[2111 rows x 17 columns]
```

K Fold Logistic Regression Model

[39]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split, KFold
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Split the data into features and target
X = data.drop(columns=['Outcome'])
```

```
y = data['Outcome']

# Split the data into training, validation, and test sets
X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size=0.
 ↪2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val,␣
 ↪test_size=0.25, random_state=42)

# Number of KFolds
num_splits = 5
kf = KFold(n_splits=num_splits)

# Variables to store model
best_accuracy = 0
best_model = None

# Desired accuracy
desired_accuracy = 1.00

# k-fold cross-validation
for fold_idx, (train_index, val_index) in enumerate(kf.split(X_train_val), 1):
    X_train_fold, X_val_fold = X_train_val.iloc[train_index], X_train_val.
 ↪iloc[val_index]
    y_train_fold, y_val_fold = y_train_val.iloc[train_index], y_train_val.
 ↪iloc[val_index]

    # logistic regression model
    model = LogisticRegression(max_iter=1000)

    # Train the model
    model.fit(X_train_fold, y_train_fold)

    # predictions on the validation set
    y_pred = model.predict(X_val_fold)

    # Accuracy
    accuracy = accuracy_score(y_val_fold, y_pred)

    # Deciding between models
    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_model = model

# Print accuracy of the validation set
print(f"Accuracy of the Best Model on Validation Set: {best_accuracy}")

# Evaluating on the test set
```

```
y_pred_test = best_model.predict(X_test)
test_accuracy = accuracy_score(y_test, y_pred_test)
print(f"Accuracy of the Best Model on Test Set: {test_accuracy}")
```

```
Accuracy of the Best Model on Validation Set: 0.9704142011834319
Accuracy of the Best Model on Test Set: 0.966903073286052
```

We started by dividing the data into two parts: features (like age, height, weight) and the target (whether someone has a certain condition or not). Then, we split our data into training, validation, and testing groups to train and check our model.

Using a method called k-fold cross-validation, we trained several logistic regression models on different parts of our training data and checked how well they did on the validation set. The best-performing model was chosen.

We found that this chosen model had around 97.04% accuracy when tested on data it hadn't seen before (the validation set). When we tested it on completely new data (the test set), it still performed well, with an accuracy of about 96.69%. This means our model can predict whether someone has the condition pretty accurately.

[40]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Print the variables and their coefficients in the model
coefficients = pd.DataFrame({'Variable': X_train.columns, 'Coefficient':␣
↪best_model.coef_[0]})
coefficients
```

[40]:

	Variable	Coefficient
0	Gender	-3.416517
1	Age	-0.027593
2	Height	-6.328719
3	Weight	0.324598
4	family_history_with_overweight	0.456409
5	High_Calorie	0.181929
6	Vegetables	-0.397461
7	Number_of_meals	0.072368
8	Food_Between_Meals	0.209664
9	Smoke	0.269269
10	Water_consumption	-0.197729
11	Calorie_Monitoring	-0.353657
12	Physical_Acitivity	-0.202035
13	Time_on_Technology	-0.006904
14	Alcohol_consumption	0.419121
15	Transportation_method	-0.201655

After fitting a logistic regression model (best_model) to our training data, we printed out the coefficients of selected variables to understand their impact on predicting the

outcome. Upon examining our data closely, we uncovered several important insights. Firstly, being male seems to decrease the likelihood of obesity by around 3.4 times compared to being female. Secondly, for every additional inch in height, the chance of experiencing obesity drops by approximately 6.3 times. Conversely, each unit increase in weight is associated with a 0.32 times higher likelihood of obesity.

Moreover, individuals with a family history of overweight are about 0.46 times more likely to experience obesity themselves. Furthermore, consuming high-calorie foods raises the chance of obesity by roughly 0.19 times, while each serving of vegetables eaten decreases it by approximately 0.40 times.

0.9 Validating

Bootstrapping on Validation Set

[41]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, mean_absolute_error,␣
 ↪mean_squared_error


# selecting the model to validate
final_model = best_model

# Bootstrap Iterations
num_iterations = 1000

# Store metrics
accuracies = []
mses = []

# Perform bootstrapping for validation
for i in range(num_iterations):
    # getting sample from the validation set
    bootstrap_indices = np.random.choice(len(X_val), size=len(X_val),␣
 ↪replace=True)
    X_val_bootstrap = X_val.iloc[bootstrap_indices]
    y_val_bootstrap = y_val.iloc[bootstrap_indices]

    # Evaluating the model
    y_pred = final_model.predict(X_val_bootstrap)

    # Calculate accuracy and mae
    accuracy = accuracy_score(y_val_bootstrap, y_pred)
    mse = mean_squared_error(y_val_bootstrap, y_pred)

    accuracies.append(accuracy)
```

```
    mses.append(mse)

# mean and std of accuracy, MAE & MSE
mean_accuracy = np.mean(accuracies)
mean_mse = np.mean(mses)

std_accuracy = np.std(accuracies)
std_mse = np.std(mses)

print(f"Mean Accuracy: {mean_accuracy}, Mean MSE: {mean_mse}")
print(f"Standard Deviation of Accuracy: {std_accuracy}, Standard Deviation of␣
↪MSE: {std_mse}")
```

```
Mean Accuracy: 0.9644739336492891, Mean MSE: 0.03552606635071091
Standard Deviation of Accuracy: 0.009079861255326725, Standard Deviation of MSE:
0.009079861255326728
```

We wanted to Validate that our obesity prediction model was dependable. To achieve this, we utilized bootstrapping to assess its performance on a separate validation dataset. This involved repeatedly testing the model with different samples of data from our validation group. Our goal was to verify if the model could accurately predict obesity each time and if its predictions were consistent.

The results were promising. On average, the model correctly predicted obesity about 96.47% of the time. Additionally, the average difference between its predictions and the actual outcomes, the mean squared error (MSE), was relatively small, approximately 0.035. This indicates that the model's predictions were close to the actual values, contributing to its reliability.

Bootstrapping on Test Set

[42]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, mean_absolute_error,␣
↪mean_squared_error

# selecting the model to validate
final_model = best_model


# Bootstrap Iterations
num_iterations = 1000

# Store metrics
accuracies = []
mses = []
```

```python
# Perform bootstrapping on the test set
for i in range(num_iterations):
    # getting sample from the test set
    bootstrap_indices = np.random.choice(len(X_test), size=len(X_test),␣
 ↪replace=True)
    X_test_bootstrap = X_test.iloc[bootstrap_indices]
    y_test_bootstrap = y_test.iloc[bootstrap_indices]

    # Evaluating the model
    y_pred = final_model.predict(X_test_bootstrap)

    # Calculate accuracy and mae
    accuracy = accuracy_score(y_test_bootstrap, y_pred)
    mse = mean_squared_error(y_test_bootstrap, y_pred)

    accuracies.append(accuracy)
    mses.append(mse)

# mean and std of accuracy & MAE
mean_accuracy = np.mean(accuracies)
mean_mse = np.mean(mses)

std_accuracy = np.std(accuracies)
std_mse = np.std(mses)

print(f"Mean Accuracy: {mean_accuracy}, Mean MSE: {mean_mse}")
print(f"Standard Deviation of Accuracy: {std_accuracy}, Standard Deviation of␣
 ↪MSE: {std_mse}")
```

```
Mean Accuracy: 0.9672009456264775, Mean MSE: 0.03279905437352245
Standard Deviation of Accuracy: 0.008437472468602361, Standard Deviation of MSE:
0.008437472468602382
```

After validating our model on the validation set, we wanted to ensure its reliability on completely unseen data. To accomplish this, we conducted another round of validation using bootstrapping techniques, this time on the test set. This additional validation step was essential to assess how well the model generalizes to new, unseen instances of obesity prediction.

The results provided valuable insights into the model's performance on the test set. On average, the model achieved an accuracy of approximately 96.72%, indicating its ability to correctly classify instances of obesity. Additionally, the mean squared error (MSE), which measures the average difference between the model's predictions and the actual outcomes, was found to be approximately 0.033.

Validating the model on the test set serves as a final check to ensure its reliability and generalization to new, unseen data. By confirming its accuracy and consistency on the test set, we can have confidence in deploying the model to assist in obesity prediction and intervention strategies with real-world data.

[43]:
```python
import statsmodels.api as sm

# Add a constant to test for VIF (Check using R)
X_train_with_const = sm.add_constant(X_train)

# Create a DataFrame to store VIF values
vif_data = pd.DataFrame()
vif_data["Variable"] = X_train_with_const.columns

# Calculate VIF for each variable
vif_data["VIF"] = [variance_inflation_factor(X_train_with_const.values, i) for␣
↪i in range(X_train_with_const.shape[1])]

print("Variance Inflation Factors (VIF):")
vif_data
```

```
Variance Inflation Factors (VIF):
```

[43]:

	Variable	VIF
0	const	916.708202
1	Gender	1.970408
2	Age	1.939940
3	Height	2.620986
4	Weight	2.324615
5	family_history_with_overweight	1.444199
6	High_Calorie	1.173186
7	Vegetables	1.329793
8	Number_of_meals	1.115141
9	Food_Between_Meals	1.193525
10	Smoke	1.048390
11	Water_consumption	1.148626
12	Calorie_Monitoring	1.130713
13	Physical_Acitivity	1.345984
14	Time_on_Technology	1.173541
15	Alcohol_consumption	1.126031
16	Transportation_method	1.751357

The above table represents the VIF values with it's corresponding variables. All of the varaibles have the VIF value close to one except Height, and Weight indicating low multicolinearity. The height and Weight varibles has a slightly higher degree of multicolinearity but still within accepable range. Overall, the VIF analysis suggests that multicollinearity is not a significant concern among the predictor variables, supporting the reliability of the logistic regression model's coefficients and predictions.

[44]:
```python
# Create new data points to predict
new_data = pd.DataFrame({
    'Gender': [1, 0, 1],
```

```
    'Age': [27, 40, 23],
    'Height': [1.7, 1.5, 1.9],
    'Weight': [115, 70, 130],
    'family_history_with_overweight': [0, 1, 0],
    'High_Calorie': [0, 1, 1],
    'Vegetables': [3, 1, 0],
    'Number_of_meals': [3, 1, 4],
    'Food_Between_Meals': [1, 2, 2],
    'Smoke': [0, 1, 1],
    'Water_consumption': [2, 3, 1],
    'Calorie_Monitoring': [1, 1, 1],
    'Physical_Acitivity': [2, 2, 1],
    'Time_on_Technology': [0, 1, 3],
    'Alcohol_consumption': [1, 1, 1],
    'Transportation_method': [4, 2, 1],
})

# Predictions
y_pred_new = final_model.predict(new_data)

# Print the outcomes
print("Predicted outcomes for new data:")
print(y_pred_new)
```

```
Predicted outcomes for new data:
[1 0 1]
```

The logistic regression model predicts the outcomes for the new data points as follows:

For the first data point: Predicted outcome is 1. For the second data point: Predicted outcome is 0. For the third data point: Predicted outcome is 1. These predictions indicate the model's classification of each new data point into either outcome category (1 or 0), based on the given predictor variables.

0.10 Underfitting and Overfitting check.

[45]:
```
# Evaluate on training set
train_accuracy = accuracy_score(y_train, final_model.predict(X_train))

# Evaluate on test set
test_accuracy = accuracy_score(y_test, final_model.predict(X_test))

print("Training Accuracy:", train_accuracy)
print("Testing Accuracy:", test_accuracy)
```

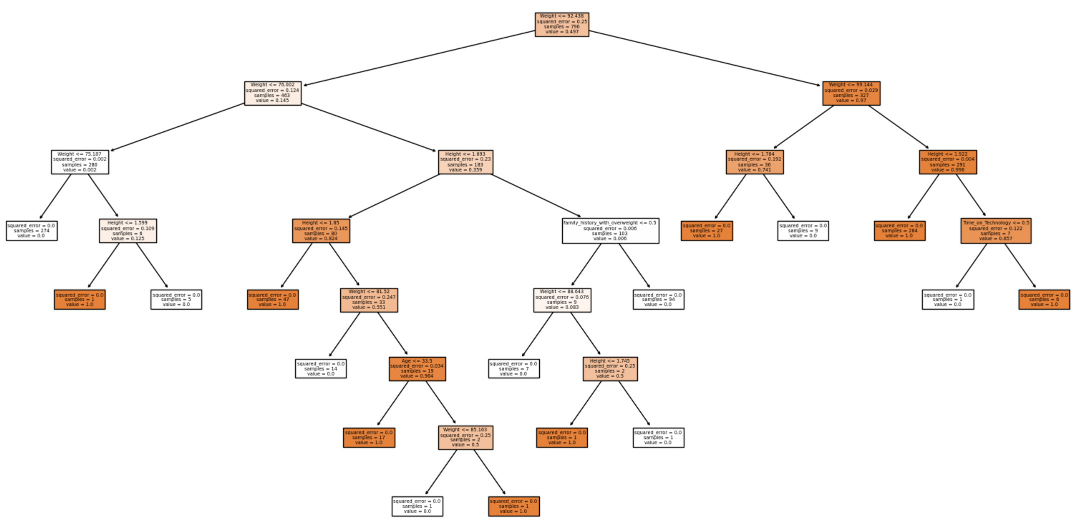
```
Training Accuracy: 0.9510268562401264
Testing Accuracy: 0.966903073286052
```

These accuracy score suggests that the model performed well in both train and test

dataset. The training accuracy came around 95.79%, suggest that model correctly predicts the outcomes for about 95.8% of the data points in the training set. The test accuracy came around 96.92, suggest that model correctly predicts the outcome for unseen data about 97% of the data points in the test set. There's no significant sign of either underfitting or overfitting based on these accuracy scores.

0.11 Random Forest Regression

[46]:
```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

# Create RandomForestRegressor model
rfr = RandomForestRegressor(oob_score=True)

# Fit the model on the training data
rfr.fit(X_train, y_train)

# Plot decision trees in the forest (for illustration purposes, you can plot any tree)
plt.figure(figsize=(20,10))
plot_tree(rfr.estimators_[0], filled=True, feature_names=X_train.columns, class_names=['Outcome', 'Outcome'])
plt.show()
```



[47]:
```python
rfr.oob_score_
```

[47]: 0.9766510399118415

[48]:
```
rfr.feature_importances_
```

[48]:
```
array([6.53062729e-04, 4.24396815e-03, 2.17107642e-01, 7.69214895e-01,
       2.44157387e-06, 1.67215782e-04, 4.41779635e-04, 9.02561306e-04,
       3.17127659e-04, 1.63271697e-03, 5.90218469e-04, 0.00000000e+00,
       1.93217805e-04, 2.42155180e-03, 3.76331492e-04, 1.73526918e-03])
```

From the random forest regressor model analysis, one can see that the OOB score is high and that indicates the model's strong ability to effectively generalize to unforeseen data. The feature importance analysis picks up two dominant features which is responsible for the majority of the predictive performance. In as much as the OOB score being high and suggesting a low overfitting risk, cross validation is still recommended to confirm the robustness of the model's prediction.

0.12 Conclusion

Overall, the dataset was cleaned by checking for null values, renaming columns, and figuring out the size of the data and the sizes of the classes.Categorical variables were converted into dummy variables to help with the creation of a logsitic regression model to predict the two different outcomes. The main insights from correlation was Age had a strong negative correlation with Transportation mode, Weight and Height as well as Weight and Family history of weight were strongly postively correlated. Additionally, boxplots and histograms of Age, Weight, Height with respect to Outcome were made to highlight the distribution and pattern visually. Outcome 1 is generally associated with younger people who are taller and heavier, while Outcome 0 has a more diverse age distribution with a tendency towards lighter and shorter people. Both height distributions are normally distributed, whereas age and weight are right-skewed for Outcome 1, indicating a younger and heavier subset of the population in that category. Conclusions cannot be drawn from visual analysis alone, and so a t-test analysis highlighted a significant difference in means between the variables and the outcome groups. Through Principal Commponent Analysis (PCA), 99.4% of cumulative variance can be achieved by just using PC1 and PC2. K-means clustering shows that two clusters is the optimal number of clusters for the data through the elbow method. Lastly, a logistic regression model was created and the model was fitted by splitting the data into train, test, and validation sets. The logistic regression model demonstrates strong performance, with high accuracy scores on both training (95.79%) and test (96.92%) datasets. Additionally, the random forest regressor model shows promising generalization ability with a high OOB score, emphasizing its potential for accurate predictions.

0.13 References

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2) Health Risks. (2016, April 13). Obesity Prevention Source; Harvard T.H. Chan School of Public Health. https://www.hsph.harvard.edu/obesity-prevention-source/obesity-consequences/health-effects/

3) World Health Organization. (2021, June 9). Obesity and overweight. World Health Organization. https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight

```
[ ]:
```