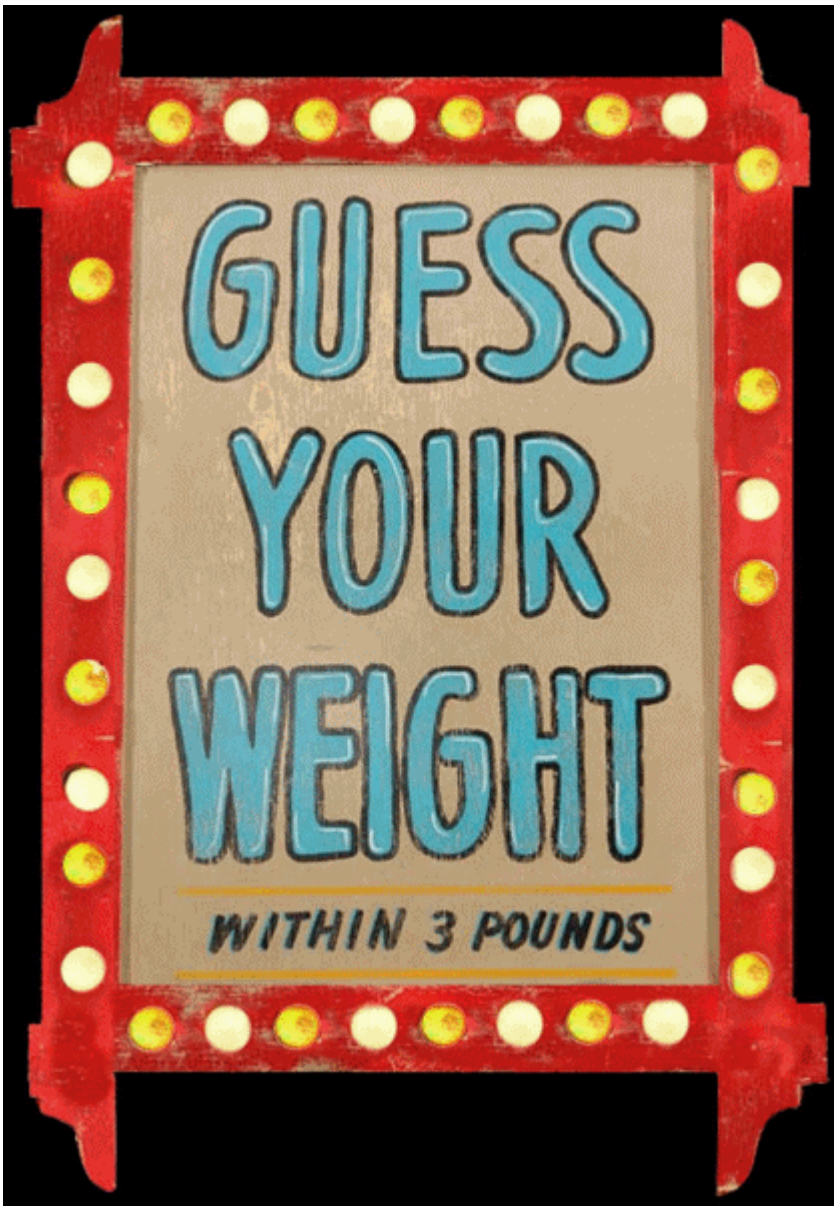
GUESS MY WEIGHT

Welcome to Guess My Weight!

Next Day Weight Loss Prediction Model. If you're looking to run in Google Colab. Please follow the instructions below.



Overview

Health and Wellness is a $142 billion dollar industry designed to help people managed their weight. This model is intended as a feature to guide users tracking lifestyle data (diet, exercise, sleep) with recommendations to target weight loss. A machine learning Decision Tree algorithm analyzed captured lifestyle data with emphasis on precision and accuracy metrics. The model determined a Carbohydrate threshold, or Carb Number, which corresponded to next day weight loss or gain. At under 221g (for this user) nearly 74 percent of the next days weigh-in showed a

loss. This increased to nearly 82 eprcent when acheiving a minimum fiber intake around 14.5 grams as well. Conversely, at over 221g, nearly 66 percent of the weigh-ins showed a gain. This increased to 79 percent when less than 6.9hrs of sleep was recorded in addition to the carb threshold. Based on these findings, it's recommended that these analytics be used to prompt/guide users through out the day to course correct on encourage certain habits.

Instructions for Google Colab

To run this notebook, you'll need a Kaggle log-in and web access to Google Colab. Google Colab is a free, user-friendly platform to run software, specifically data models. Kaggle is a website popular with data industry that hosts databases and runs data analytics competition. To access the database for this model, you will need to create a Kaggle account and follow the instructions (https://www.kaggle.com/docs/api) to download your 'token' and 'key'. This model will prompt you to have that information.

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1. Business Case

According to a CDC study, the obesity prevalence rate in the US was 42 percent in 2020. The Health and Wellness industry, valued at around $142 billion, has a plethora of systems, apps, and protocols to address this, yet it's still a problem. On a human level, we all know that managing our weight is both critical to health and happiness but also incredible challenging. The average person has dieted over 6 times in their life, according to a survey by the Mayo Clinic. There's a demand among users as well as a basic human earn to feel in control of our health. Creating additional, more intuitive tools to manage weight loss is a vast importance.

In this model, we focus on a small short term goals to determine if daily diet, exercise, and sleep goals can impact your weigh-in the next day. To simplify this task, we'll utilize binary prediction, either weight loss or weight gain, to determine if the sum of these daily habits to determine how they predicted this binary outcome.

2. Data Understanding

2a. Data Source

The data source for this analysis is my personal health information. Over the course of 6 months, I lost approximately 20 lbs. Tracking my calories and weight was a big part of it, as well data captured from my devices (Iphone, Apple Watch). The dataset contains both the information that I logged (daily weigh-ins and food journaling) as well as workouts, heart rate, sleep, etc tracked passively.

Quality Concerns Because it’s my personal data there’s more clarity about data entry methods. This is more subjective, than a controlled experiment with many participants. I know what data I was diligent about collecting so I should be able to scrub it appropriately. For instance, I didn’t record my fluids consistently - water, tea, coffee. Water weight can be a big part of total weight, so the data is far from flawless.

2b. Data Collection

Data Logging Protocol:

The protocol is as follows: A person (in this case, me, but anyone can follow) records their weight in the morning, tracks their data during the day, and wakes up the next day to record their sleep and weigh-in. The idea of a "day" with regard to activities ends the mornign log-in and starts with the first cup of water (usually right after). A day starts AFTER the morning weigh-in, even though it will be recorded on that day.

Devices:

I have much (and probably too much) of this data in my iphone and Apple Watch. It contains the weight information, workouts, heart rate, meals - broken down into subcategories (proteins, fats, etc). Most importantly is the weight. That will be the feature that I primarily use for classification.

Quality Concerns - Preliminary Note

Because it’s my data, there’s more clarity about how it was collected. This is more subjective, than say a controlled experiment with many participants. This data is considered found data, even though I was personally involved with the collection. I know the data I was focused on and which was ignored. For instance, I didn’t record my fluids consistently - water, tea, coffee. Water consumption is a big part of this so I’ll have to be clear about the gaps in the data.

Data Extraction

Prior to a csv datafile accessible on Kaggle, the raw data files from the smartphone were preprocessed. They were stored on an xml file on a phone. That file was transferred to a local harddrive for further analysis. It was uploaded to a jupyter notebook where it was converted from a table of individual entries, to a table of daily sums. Data, as say a recurring pulse reading (any data in a unit/time for instance) where you could potentially extract data like daily averages, daily minimums and maximums were not converted into the clean dataset. Once the entire set had been converted to a daily sum over the approximate 6 months duration. It was uploaded to Kaggle for analysis. return to TOC

To begin our analysis, we start with the Kaggle download. Per Kaggle instructions above, you must have your Kaggle API Key and Token to work on this file.

Collect Data from Kaggle

In [2]:
```
#install latest modules to facilitate Kaggle Download
! pip install opendatasets
! pip install kaggle
```

```
Requirement already satisfied: opendatasets in c:\users\benne\anaconda3\envs
\learn-env\lib\site-packages (0.1.22)
Requirement already satisfied: tqdm in c:\users\benne\anaconda3\envs\learn-en
v\lib\site-packages (from opendatasets) (4.50.2)
Requirement already satisfied: kaggle in c:\users\benne\anaconda3\envs\learn-
env\lib\site-packages (from opendatasets) (1.6.11)
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nv\lib\site-packages (from opendatasets) (7.1.2)
Requirement already satisfied: python-dateutil in c:\users\benne\appdata\roam
ing\python\python38\site-packages (from kaggle->opendatasets) (2.9.0.post0)
Requirement already satisfied: requests in c:\users\benne\anaconda3\envs\lear
n-env\lib\site-packages (from kaggle->opendatasets) (2.24.0)
Requirement already satisfied: certifi>=2023.7.22 in c:\users\benne\anaconda3
\envs\learn-env\lib\site-packages (from kaggle->opendatasets) (2024.2.2)
Requirement already satisfied: urllib3 in c:\users\benne\anaconda3\envs\learn
-env\lib\site-packages (from kaggle->opendatasets) (1.25.10)
Requirement already satisfied: bleach in c:\users\benne\anaconda3\envs\learn-
env\lib\site-packages (from kaggle->opendatasets) (3.2.1)
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s\learn-env\lib\site-packages (from kaggle->opendatasets) (8.0.4)
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4)
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\learn-env\lib\site-packages (from requests->kaggle->opendatasets) (2.10)
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rn-env\lib\site-packages (from bleach->kaggle->opendatasets) (24.0)
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3\envs\learn-env\lib\site-packages (from python-slugify->kaggle->opendataset
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env\lib\site-packages (1.6.11)
Requirement already satisfied: tqdm in c:\users\benne\anaconda3\envs\learn-en
v\lib\site-packages (from kaggle) (4.50.2)
Requirement already satisfied: python-dateutil in c:\users\benne\appdata\roam
ing\python\python38\site-packages (from kaggle) (2.9.0.post0)
Requirement already satisfied: bleach in c:\users\benne\anaconda3\envs\learn-
env\lib\site-packages (from kaggle) (3.2.1)
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n-env\lib\site-packages (from kaggle) (2.24.0)
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-env\lib\site-packages (from kaggle) (1.25.10)
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s\learn-env\lib\site-packages (from kaggle) (8.0.4)
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rn-env\lib\site-packages (from bleach->kaggle) (24.0)
Requirement already satisfied: chardet<4,>=3.0.2 in c:\users\benne\anaconda3
```

```
\envs\learn-env\lib\site-packages (from requests->kaggle) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in c:\users\benne\anaconda3\envs
\learn-env\lib\site-packages (from requests->kaggle) (2.10)
Requirement already satisfied: text-unidecode>=1.3 in c:\users\benne\anaconda
3\envs\learn-env\lib\site-packages (from python-slugify->kaggle) (1.3)
```

In [3]:
```
#import libraries and prompts to access Kaggle API and download dataset. Add Ka
import opendatasets as od

od.download("https://www.kaggle.com/datasets/andrewmbennett/guess-my-weight-4-2
```

```
Skipping, found downloaded files in ".\guess-my-weight-4-25" (use force=True
to force download)
```

We have successfully downloaded the data. We will now begin our data inspection

In [4]:
```
#import standard python libraries and modules
import pandas as pd
import datetime as dt
import numpy as np
from statsmodels.tsa.stattools import adfuller
import tensorflow as tf
from sklearn.model_selection import train_test_split
import seaborn as sns
```

In [5]:
```
df = pd.read_csv('/content/guess-my-weight-4-25/merge_health_4_25.csv')
```

In [6]:
```
df
```

Out[6]:

	date	BodyMass_lb	StepCount_count	DistanceWalkingRunning_mi	BasalEnergyBurned_Cal
0	2023-08-24	196.9	8895.0	4.163569	2055.322
1	2023-08-25	195.1	9276.0	4.512434	2174.950
2	2023-08-26	195.1	10883.0	4.948209	2074.476
3	2023-08-27	192.9	19174.0	9.909258	2187.383
4	2023-08-28	192.9	13636.0	6.833914	2186.244
...	...	...	...	...	...
193	2024-03-04	175.7	8191.0	4.051709	1983.933
194	2024-03-05	174.2	8882.0	4.448750	2009.083
195	2024-03-06	173.3	2610.0	1.272886	759.761
196	2023-08-23	NaN	7325.0	3.399540	2057.531
197	2023-08-22	NaN	NaN	NaN	NaN

198 rows × 46 columns

2b. Data Description

From the description above, we have 198 rows, 46 columns, and data ranges from 2023-08-24 to 2024-03-06, with two extra rows at the rear.

Preliminary Inspection

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 198 entries, 0 to 197
Data columns (total 46 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   date                            198 non-null    object 
 1   BodyMass_lb                     196 non-null    float64
 2   StepCount_count                 197 non-null    float64
 3   DistanceWalkingRunning_mi       197 non-null    float64
 4   BasalEnergyBurned_Cal           197 non-null    float64
 5   ActiveEnergyBurned_Cal          197 non-null    float64
 6   FlightsClimbed_count            197 non-null    float64
 7   DietaryFatTotal_g               196 non-null    float64
 8   DietaryFatPolyunsaturated_g     196 non-null    float64
 9   DietaryFatMonounsaturated_g     196 non-null    float64
 10  DietaryFatSaturated_g           196 non-null    float64
 11  DietaryCholesterol_mg           196 non-null    float64
 12  DietarySodium_mg                196 non-null    float64
 13  DietaryCarbohydrates_g          196 non-null    float64
 14  DietaryFiber_g                  196 non-null    float64
 15  DietarySugar_g                  196 non-null    float64
 16  DietaryEnergyConsumed_Cal       196 non-null    float64
 17  DietaryProtein_g                196 non-null    float64
 18  DietaryVitaminA_mcg             196 non-null    float64
 19  DietaryVitaminB6_mg             196 non-null    float64
 20  DietaryVitaminB12_mcg           196 non-null    float64
 21  DietaryVitaminC_mg              196 non-null    float64
 22  DietaryVitaminD_mcg             196 non-null    float64
 23  DietaryVitaminE_mg              196 non-null    float64
 24  DietaryVitaminK_mcg             196 non-null    float64
 25  DietaryCalcium_mg               196 non-null    float64
 26  DietaryIron_mg                  196 non-null    float64
 27  DietaryThiamin_mg               196 non-null    float64
 28  DietaryRiboflavin_mg            196 non-null    float64
 29  DietaryNiacin_mg                196 non-null    float64
 30  DietaryFolate_mcg               196 non-null    float64
 31  DietaryBiotin_mcg               180 non-null    float64
 32  DietaryPantothenicAcid_mg       196 non-null    float64
 33  DietaryPhosphorus_mg            196 non-null    float64
 34  DietaryIodine_mcg               182 non-null    float64
 35  DietaryMagnesium_mg             196 non-null    float64
 36  DietaryZinc_mg                  196 non-null    float64
 37  DietarySelenium_mcg             196 non-null    float64
 38  DietaryCopper_mg                196 non-null    float64
 39  DietaryManganese_mg             196 non-null    float64
 40  DietaryPotassium_mg             196 non-null    float64
 41  AppleExerciseTime_min           197 non-null    float64
 42  SleepAnalysis_AsleepDeep_hrs    197 non-null    float64
 43  SleepAnalysis_AsleepCore_hrs    197 non-null    float64
 44  SleepAnalysis_AsleepREM_hrs     197 non-null    float64
 45  SleepAnalysis_Awake_hrs         197 non-null    float64
dtypes: float64(45), object(1)
memory usage: 71.3+ KB
```

As we can see, the data is represented by the description of the variable and the unit. Our second variable (after data) is our critical label `BodyMass_lb` where `Body Mass` is the variable name and `lb` is the variable unit.

So we have all floats, except our data information, with the most of our entries with only one or two null entries. `DietaryBiotin_mcg` and `DietaryIodine_mcg` have 16-18 null entries. Because we have floats, we can do some preliminary inspection of the shape of the numbers.

In [8]:
```
#show the numeric distribution of the numbers using the describe function
df.describe()
```

Out[8]:

	BodyMass_lb	StepCount_count	DistanceWalkingRunning_mi	BasalEnergyBurned_Cal	Acti
count	196.000000	197.000000	197.000000	197.000000	
mean	127.684184	13800.162437	7.204382	2073.072868	
std	88.425096	5590.992597	3.323999	174.647851	
min	0.000000	2610.000000	1.272886	409.967000	
25%	0.000000	9770.000000	4.845659	2039.642000	
50%	181.100000	12651.000000	6.202475	2096.636000	
75%	188.300000	16396.000000	9.263240	2137.858000	
max	388.500000	42434.000000	21.039808	2259.292000	

8 rows × 45 columns

Our first column, 'BodyMass_lb' appears to have both 0s for the minimum and 25 percentile. This is obviously not correct, and likely explains days where no weight was logged. THis is tricky - at least 25% of our critical data is missing. We also see 0s for `FlightsClimbed_count` which could be accurate, and for dietary data, like `DietaryFatTotal_g` , which represents days where no dietary information was logged. We will have to address this in our data preparation.

Reset index column to dates

To continue, let's convert the date column to a datetime object and make it the index. We will also delete entries for Aug 22, and 23, as those dates appear on the fringe of our sample and have incomplete data.

In [10]:
```
#convert the date
df['date'] = pd.to_datetime(df['date'], format='%Y-%m-%d')
```

In [11]:
```
# Make Date the index
df.set_index('date', inplace=True)
```

In [12]:
```
# delete the last row
df.drop(['2023-08-22', '2023-08-23'], axis=0,inplace=True)
```

In [13]:
```
df
```

Out[13]:

date	BodyMass_lb	StepCount_count	DistanceWalkingRunning_mi	BasalEnergyBurned_Cal	Activ
2023-08-24	196.9	8895.0	4.163569	2055.322	
2023-08-25	195.1	9276.0	4.512434	2174.950	
2023-08-26	195.1	10883.0	4.948209	2074.476	
2023-08-27	192.9	19174.0	9.909258	2187.383	
2023-08-28	192.9	13636.0	6.833914	2186.244	
...	...	...	...	...	
2024-03-02	174.6	13416.0	6.533640	2048.925	
2024-03-03	175.0	15876.0	7.722016	2048.189	
2024-03-04	175.7	8191.0	4.051709	1983.933	
2024-03-05	174.2	8882.0	4.448750	2009.083	
2024-03-06	173.3	2610.0	1.272886	759.761	

196 rows × 45 columns

Now that we have done preliminary data description, let's explore in detail.

2c. Data Exploration

Let's start with our most critical column, our target `BodyMass_lb` .

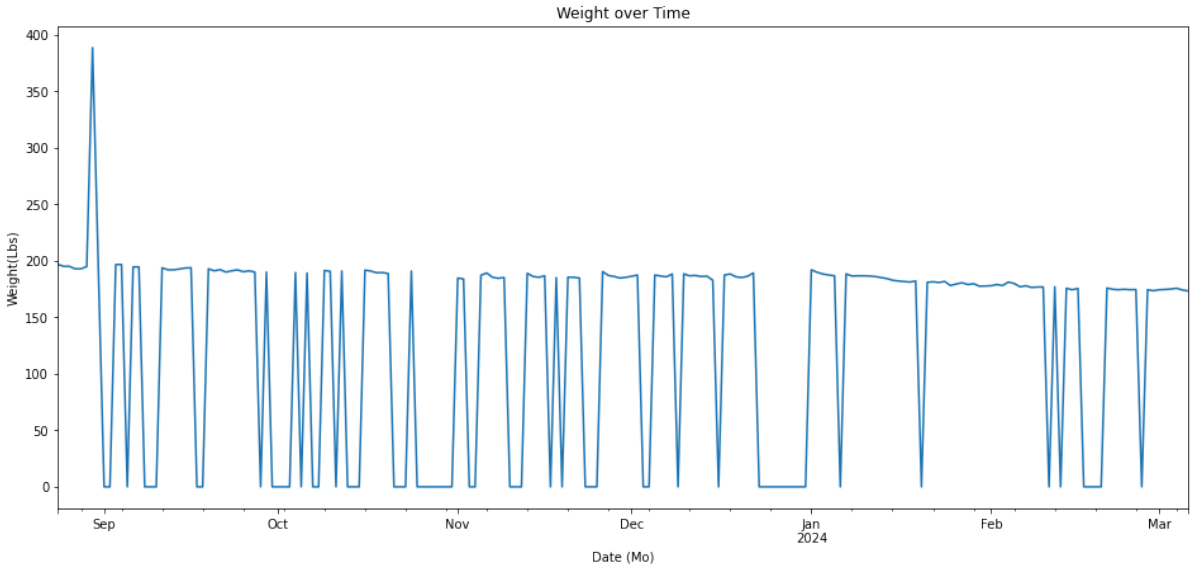
`BodyMass_lb` Inspection

In [211]:
```
df['BodyMass_lb'].describe()
```

Out[211]:
```
count    196.000000
mean     127.684184
std       88.425096
min        0.000000
25%        0.000000
50%      181.100000
75%      188.300000
max      388.500000
Name: BodyMass_lb, dtype: float64
```

As we mentioned, there seem to be considerable missing data. Also, the maximum says 388.5, which is clearly a mistake. Let's do a time plot to get a better sense of it.

In [21]:
```
import matplotlib.pyplot as plt
%matplotlib inline

df['BodyMass_lb'].plot(figsize = (16,7));
plt.xlabel('Date (Mo)')
plt.ylabel('Weight(Lbs)')
plt.title('Weight over Time')
plt.show()
```



So it appears as we suspected. There are considerable moments of missing data. I see the last week in December looks pretty bare. Let's see how many of these points are missing.

In [16]:
```
#calculate ratio of null (or 0 wieghts)
null_weights = len(df[df['BodyMass_lb'] < 100])
total = len(df['BodyMass_lb'])
null_weights/total
```

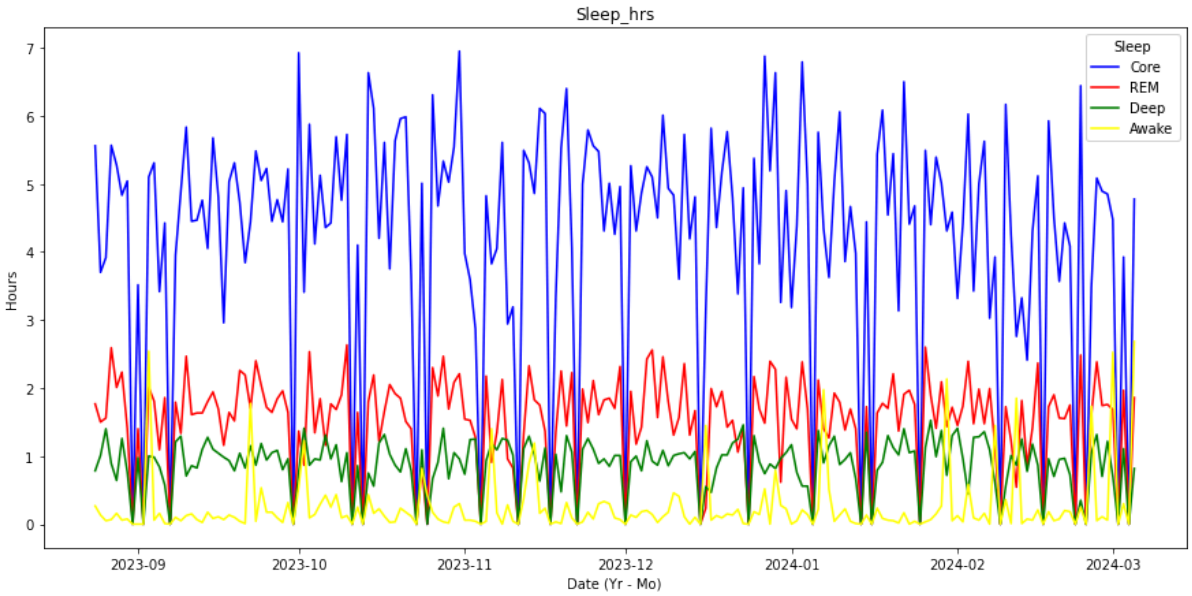
Out[16]:
```
0.3163265306122449
```

We have a few issues to resolve. 32% of the Body_Mass lbs are missing. Based on our knowledge of human weight fluctation, we know it's impossible to weight 0 pounds. More than likely, these are the dates when a wiegh-in was never performed. We should convert these values to NaN to make our graph appear better.

Sleep Inspection

Let's inspect the sleep column

In [23]:
```
#plot the relevant sleep categories
plt.rcParams['figure.figsize']=(15,7)

plt.plot(df['SleepAnalysis_AsleepCore_hrs'], color='blue', label = 'Core')
plt.plot(df['SleepAnalysis_AsleepREM_hrs'], color='red', label = 'REM')
plt.plot(df['SleepAnalysis_AsleepDeep_hrs'], color='green', label = 'Deep')
plt.plot(df['SleepAnalysis_Awake_hrs'], color='yellow', label = 'Awake')

plt.title('Sleep_hrs')
plt.xlabel('Date (Yr - Mo)')
plt.ylabel('Hours')
plt.legend(title = 'Sleep')
plt.show()
```

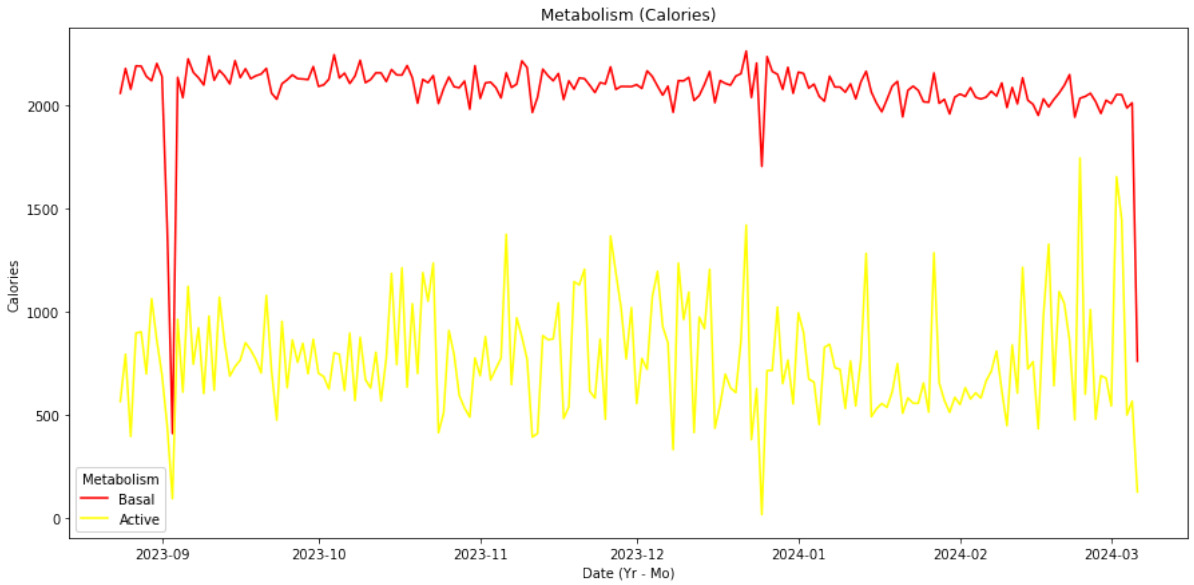


Much like the Body_Mass, we see considerable date with 0. However, the numbers appear relatively consistent, with Core average between 4-5hrs, REM under 2 hours, and Deep sleep around 1 hour.

Metabolism Inspection

Let's review the metabolism column. We'll limit this to only Basal and Active Energy for now. Basal, as Apple perceives it, is the same as your resting Calories. Active Calories, are those exercises done at a higher heart rate. While there's some medical disagreement about the difference between Basal and Resting Metabolism, for our purposes, we'll use Apple's definition. Basal/Resting Metabolism utilizes your weight, height, and age to factor this data. As I lost weight over time, there a slight trend in the downward direction

In [27]:
```
#plot the data
plt.rcParams['figure.figsize']=(15,7)

plt.plot(df['BasalEnergyBurned_Cal'], color='red', label = 'Basal')
plt.plot(df['ActiveEnergyBurned_Cal'], color='yellow', label = 'Active')

plt.title('Metabolism (Calories)')
plt.xlabel('Date (Yr - Mo)')
plt.ylabel('Calories')
plt.legend(title = 'Metabolism')
plt.show()
```

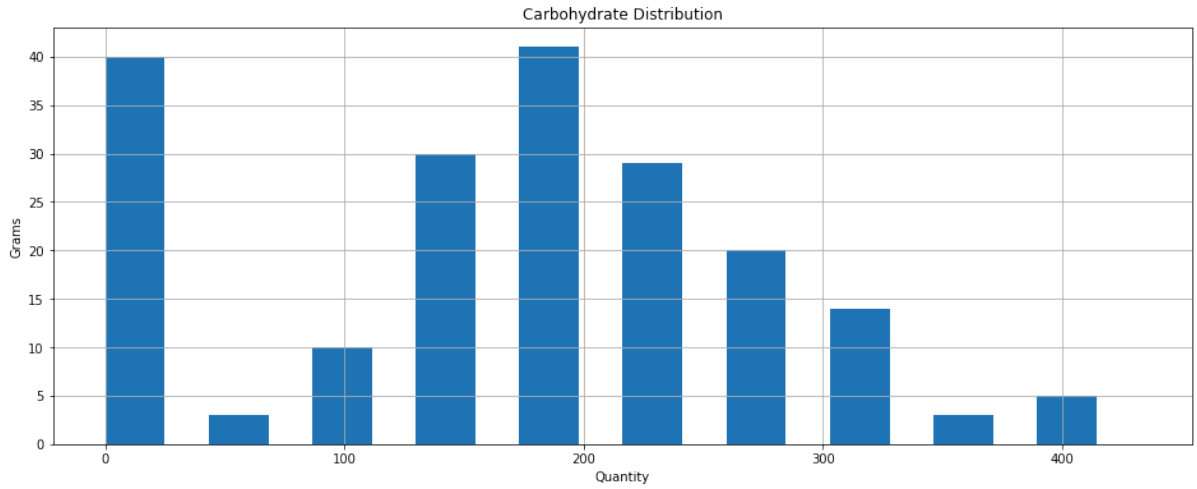


Metabolism data looks consistent except for a few 0 entries, again, these are just days where the data wasn't captured. Most likely because devices weren't properly charged. This data is captured passively.

Dietary Inspection

Now let's look at the diet information. For this, we'll focus on Carbohydrates and use a histogram.

In [34]:
```
df['DietaryCarbohydrates_g'].hist(figsize = (16,6), width = 25);

plt.title('Carbohydrate Distribution')
plt.xlabel('Quantity')
plt.ylabel('Grams')

plt.show()
```



Yes, again we have nearly 40 days where we didn't record Carbohydrate data.

In [37]:
```
null_weights = len(df[df['DietaryCarbohydrates_g'] == 0])
total = len(df['DietaryCarbohydrates_g'])
null_weights/total
```

Out[37]:
```
0.18877551020408162
```

19 percent missing data. This would correspond to other diet data as well, as the calories were entered by food item (ie Salmon Portion, Cheddar Rockets, etc.)

2d. Data Quality Assessment

The data contains numerous gaps which will have to be addressed to perform any analysis. Some of our most important columns, relying on manual entry, show over 31% and 19% for critical columns 'BodyMass_lb' and 'DietaryCarbohydrates_g' respectively.

Our 'BodyMass_lb' data is considered Missing Completely at Random (MCAR). This means that there's no pattern to the data gaps. It's totally random and independent of other variables. In this case, it's whenever I forgot to step on the scale and log my weight.

Regarding our Carbohydrate data, it is considered Missing at Random (MAR). We define these as data points that are missing, depending on observed values in other variables, but not on the missing values themselves. Meaning, because Carbohydrate data is missing, other Dietary data will be missing as well, so it's not completely random.

With the data that is apparent, it appears accurate and relevant and in the right format.

The passively (or automated) data tracking by my devices (sleep, metabolism) has fewer gaps.

3. Data Preparation

So we know we to address our missing columns. But we'll have to adjust our target column as well. Remember... we're looking to predict weight loss or weight gain. We'll have to do some feature engineering as well.

3a. Data Selection

Our target data is Body_mass. Our feature data will be the data that pertains to metabolism or diet or sleep. The data will be segmented into those sections further in this section. First, let's fill in the missing data, which currently expresses as 0. The challenge here, is that the data point of 0.0 will affect our analysis, because it represents an actual number.

For most of our feature data within each category, we can utilize the mean as an appopriate number. Take sleep (for instance), the data appears consistent over time and appears totally as noise. Same with dietary and metabolism data. Whether we sleep for 6 hours or 9 hours does not appear dependent on other data (outside of our sleep data). The same for our diet data - whether I have 200g of carbs one day or 300g the next day, it doesn't matter. It seems appropirate for this data that I use the mean.

Body Mass data is different. We know our weigh-in data is highly correlated to the previous days data - it's time dependent. So we'll need to do some brief analysis to verify that our data is in fact not totally correlated before we determine how to replace it.

3b. Data Clean

Sleep

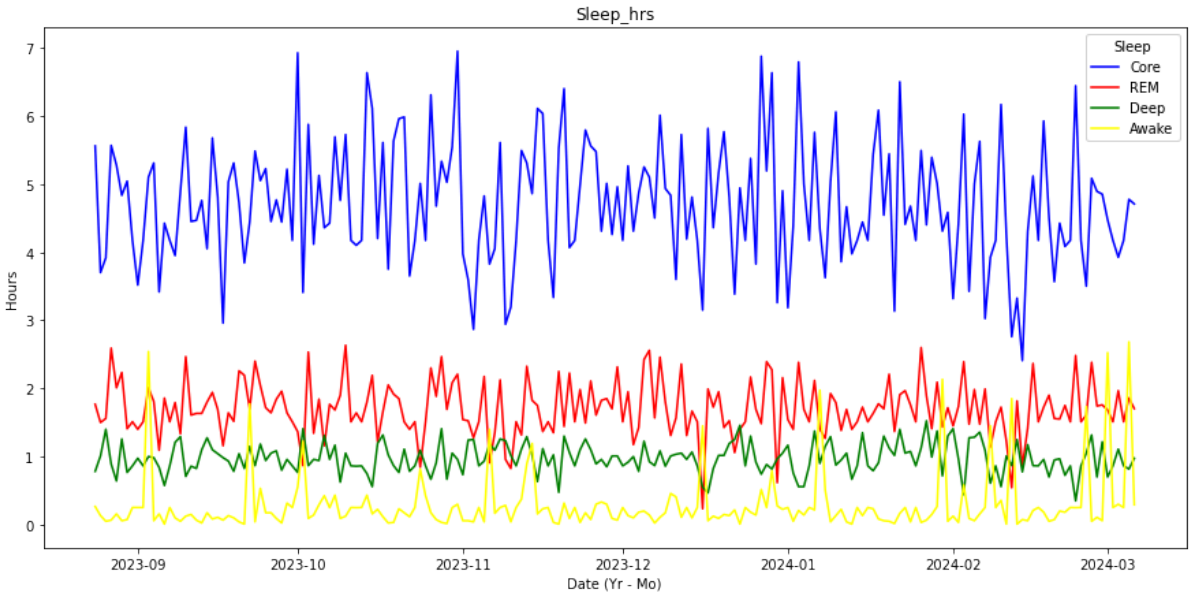
For sleep, we have a little more comfort converting this data to the mean for each sleep category, as we mentioned above.

In [44]:
```
#create a sleep column
col_sleep = ['SleepAnalysis_AsleepDeep_hrs', 'SleepAnalysis_AsleepCore_hrs', 'S
```

In [46]:
```
#if there are any null values, we will replace them and make them the mean
df[col_sleep] = df[col_sleep].fillna(df[col_sleep].mean())
```

In [47]:
```
#replace each sleep column with a 0 to the mean of that column
df['SleepAnalysis_AsleepDeep_hrs'].replace(to_replace=0,value = df['SleepAnalys
df['SleepAnalysis_AsleepCore_hrs'].replace(to_replace=0,value = df['SleepAnalys
df['SleepAnalysis_AsleepREM_hrs'].replace(to_replace=0,value = df['SleepAnalysi
df['SleepAnalysis_Awake_hrs'].replace(to_replace=0,value = df['SleepAnalysis_Aw
```

In [48]:
```
#plot the relevant sleep categories
plt.rcParams['figure.figsize']=(15,7)

plt.plot(df['SleepAnalysis_AsleepCore_hrs'], color='blue', label = 'Core')
plt.plot(df['SleepAnalysis_AsleepREM_hrs'], color='red', label = 'REM')
plt.plot(df['SleepAnalysis_AsleepDeep_hrs'], color='green', label = 'Deep')
plt.plot(df['SleepAnalysis_Awake_hrs'], color='yellow', label = 'Awake')

plt.title('Sleep_hrs')
plt.xlabel('Date (Yr - Mo)')
plt.ylabel('Hours')
plt.legend(title = 'Sleep')
plt.show()
```



Looks much better. Making this data the mean doen't appear to have much impact, at least visually. Let's go to metabolism.

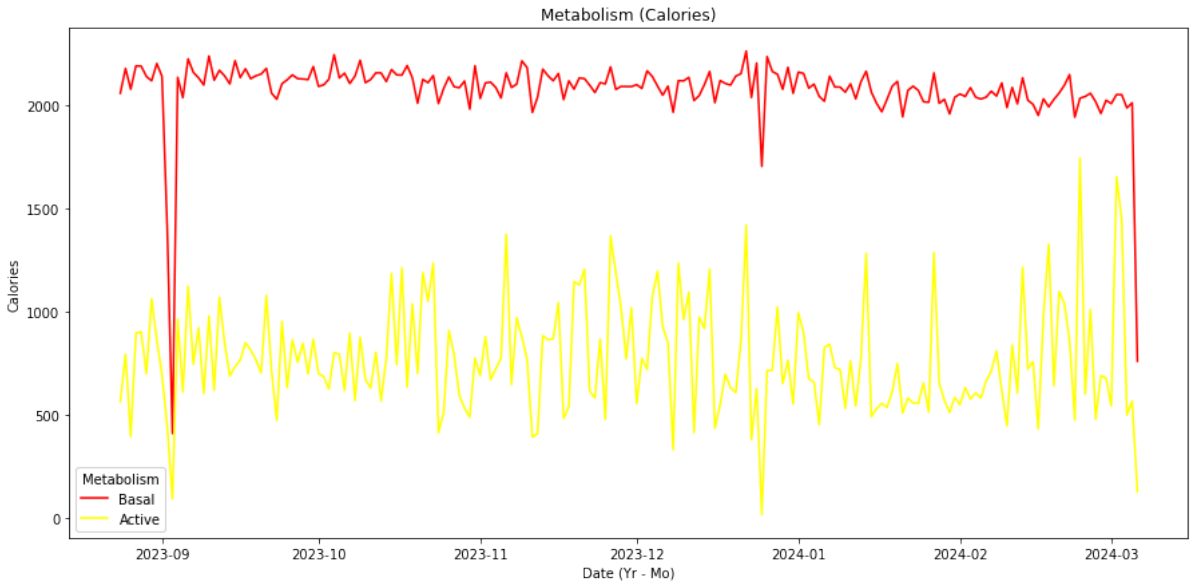
Metabolism

For metabolism, we have a little more comfort converting this data to the mean for each metabolism category. It's important to note that we have some exercise data as well. For the time being, we'll focus on metabolism. We feel comfortable replacing this data with the mean.

In [50]:
```
col_exercise = ['StepCount_count', 'DistanceWalkingRunning_mi', 'BasalEnergyBur
col_exercise = ['BasalEnergyBurned_Cal', 'ActiveEnergyBurned_Cal']
```

Let's take another quick inspection of the data.

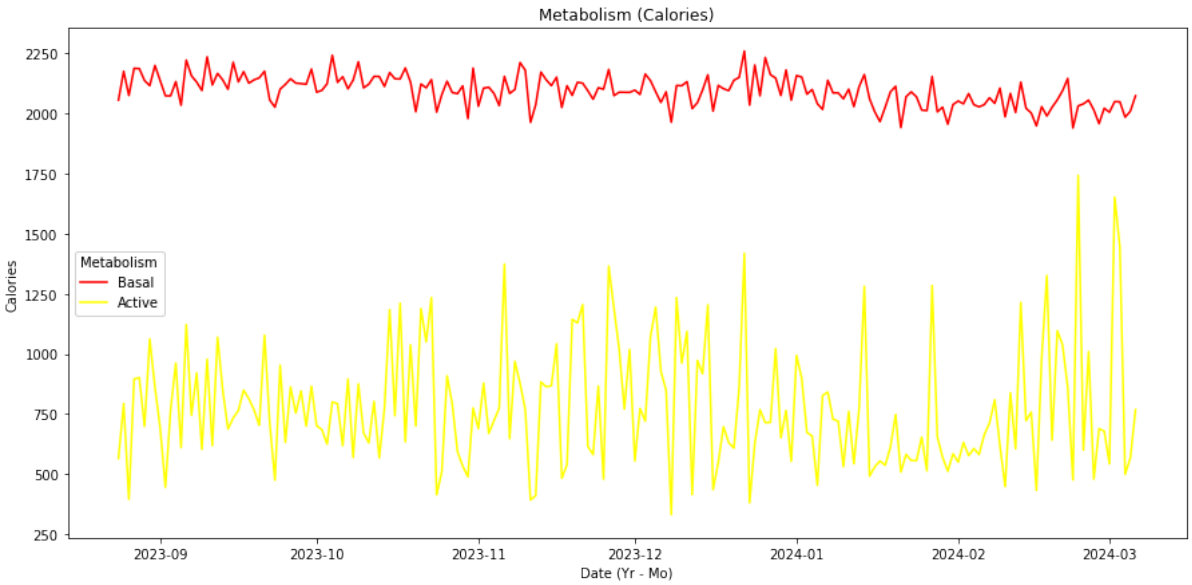
In [51]:
```
#plot the data
plt.rcParams['figure.figsize']=(15,7)

plt.plot(df['BasalEnergyBurned_Cal'], color='red', label = 'Basal')
plt.plot(df['ActiveEnergyBurned_Cal'], color='yellow', label = 'Active')

plt.title('Metabolism (Calories)')
plt.xlabel('Date (Yr - Mo)')
plt.ylabel('Calories')
plt.legend(title = 'Metabolism')
plt.show()
```



Here was can see that our data is never actually 0, but certain drop-off looks suspicious. It looks as though moments where Basal Metabolism falls below 1750 calories (or so) represents faulty data. Same for Active Energy below 250 calories.

In [52]:
```
#let's convert those low values to mean
df.loc[df['ActiveEnergyBurned_Cal'] < 250, 'ActiveEnergyBurned_Cal'] = df['Acti
df.loc[df['BasalEnergyBurned_Cal'] < 1750, 'BasalEnergyBurned_Cal'] = df['Basal
```

In [53]:
```
#plot the data
plt.rcParams['figure.figsize']=(15,7)

plt.plot(df['BasalEnergyBurned_Cal'], color='red', label = 'Basal')
plt.plot(df['ActiveEnergyBurned_Cal'], color='yellow', label = 'Active')

plt.title('Metabolism (Calories)')
plt.xlabel('Date (Yr - Mo)')
plt.ylabel('Calories')
plt.legend(title = 'Metabolism')
plt.show()
```



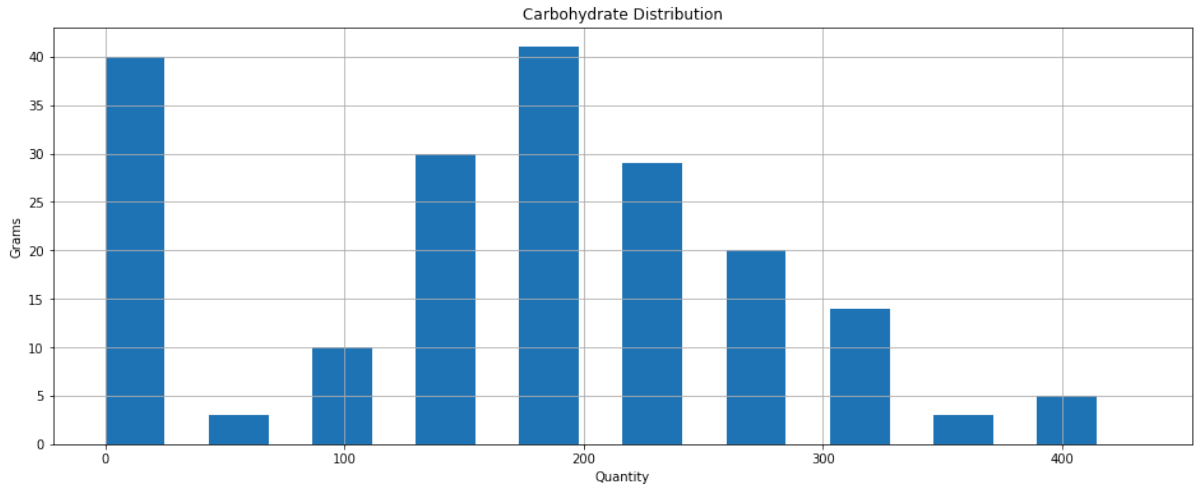
This looks better. Let's move on to Dietary.

Dietary

For dietary concerns, we can still convert this data to the mean for each feature, including all of the small micronutrients. The challenge here is not only the 0 data, but also data that looks exceptionally small. Recall that the dietary information comes from manually logging food data. Were meals skipped? Snacks missed? Sure. The trick is determining how many of those meals were incomplete and how many were just low consumption days.

First, let's recall our carbohydrate histogram

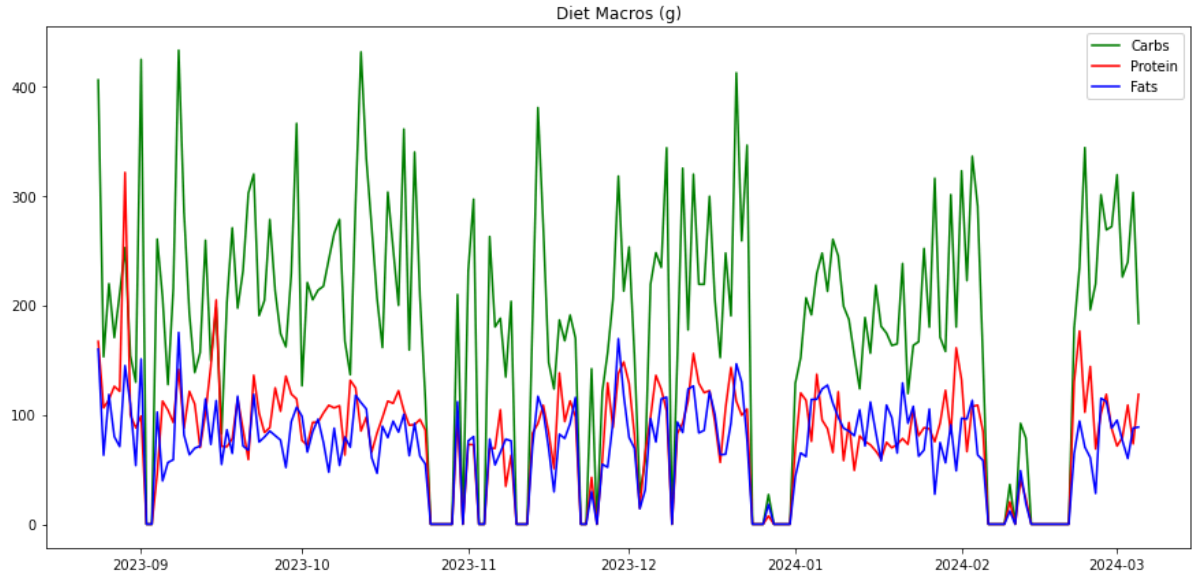
In [54]:
```
df['DietaryCarbohydrates_g'].hist(figsize = (16,6), width = 25);

plt.title('Carbohydrate Distribution')
plt.xlabel('Quantity')
plt.ylabel('Grams')

plt.show()
```



As we can see here, there are considerable 0 days. And also, as we mentioned above, a few days where the carbs appear less than 75 grams.

Let's plot all the Carbs, Proteins, and Fats together to see if our theory's accurate. Namely, that low Carbohydrate days correspond to low dietary days all around.

In [55]:
```
plt.rcParams['figure.figsize']=(15,7)

plt.plot(df['DietaryCarbohydrates_g'], color='green', label = 'Carbs')
plt.plot(df['DietaryProtein_g'], color='red', label = 'Protein')
plt.plot(df['DietaryFatTotal_g'], color='blue', label = 'Fats')

plt.title('Diet Macros (g)')
plt.legend()
plt.show()
```

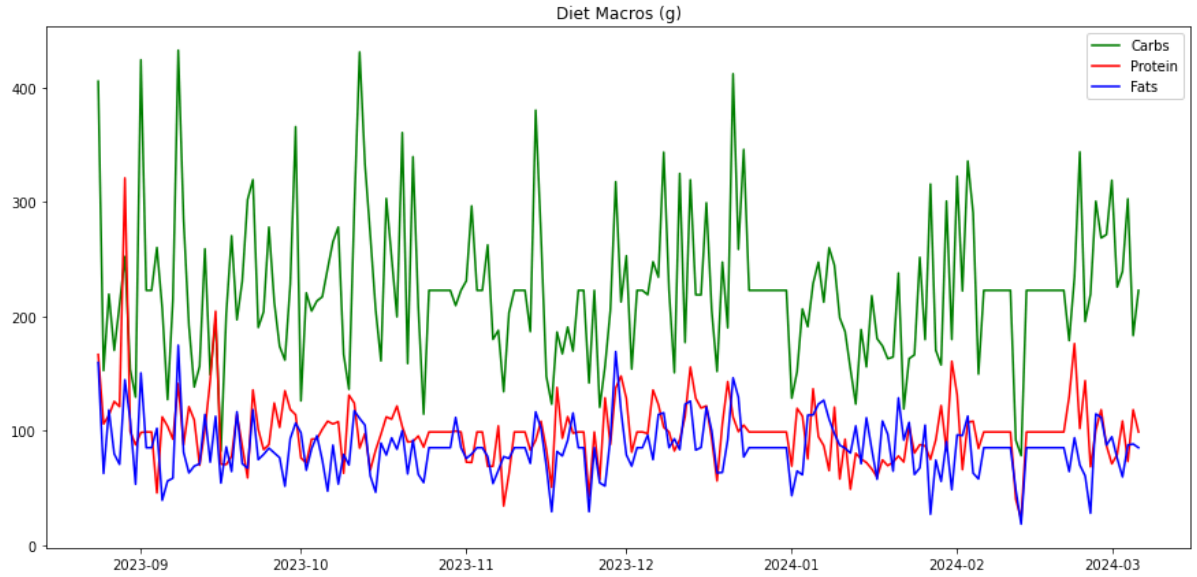


Yes. It looks as though it's consistent across the board. We need to convert these areas (under 75 grams) to mean across all of the Dietary information.

In [56]:
```
#we'll go ahead and convert all dietary data to Nan where the Carbs are less th
col_dietary = [col for col in df.columns if "Dietary" in col]
df.loc[df['DietaryCarbohydrates_g'] < 75.0, col_dietary] = np.nan
```

In [57]:
```
df[col_dietary] = df[col_dietary].fillna(df[col_dietary].mean())
```

In [58]:
```
plt.rcParams['figure.figsize']=(15,7)

plt.plot(df['DietaryCarbohydrates_g'], color='green', label = 'Carbs')
plt.plot(df['DietaryProtein_g'], color='red', label = 'Protein')
plt.plot(df['DietaryFatTotal_g'], color='blue', label = 'Fats')

plt.title('Diet Macros (g)')
plt.legend()
plt.show()
```

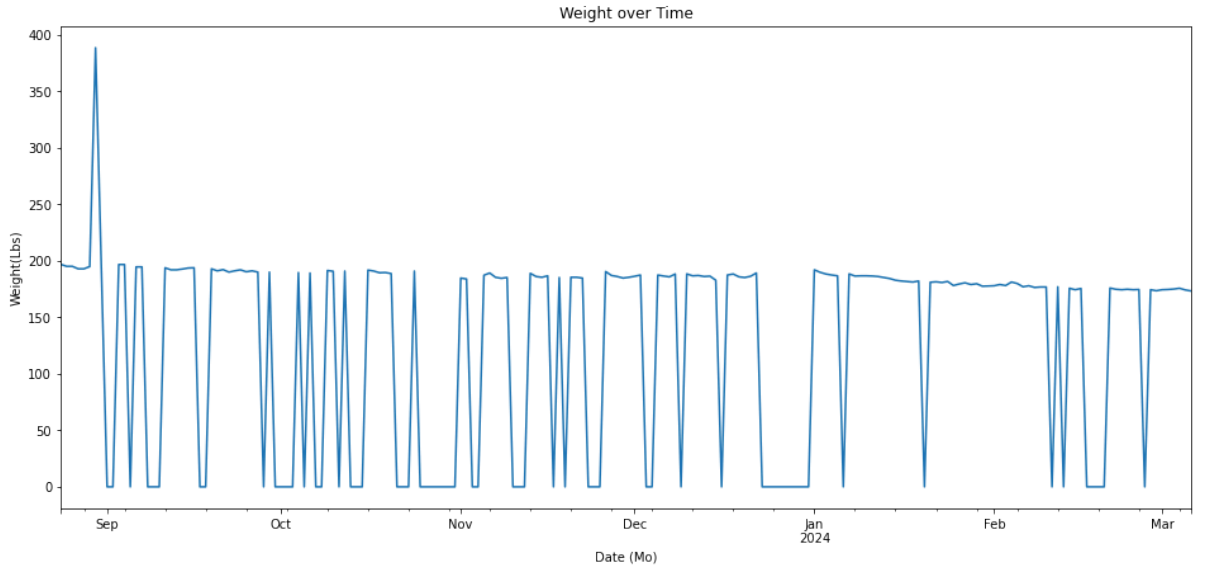


This data looks better. Even though it's not perfect. There are still a few dips but better.

Body Mass

As we mentioned previously, Body Mass is a partially time dependent feature. We can not simply impute the mean, because we know the value is affected by the previous days number. So let's look at our mass again and sort through it.

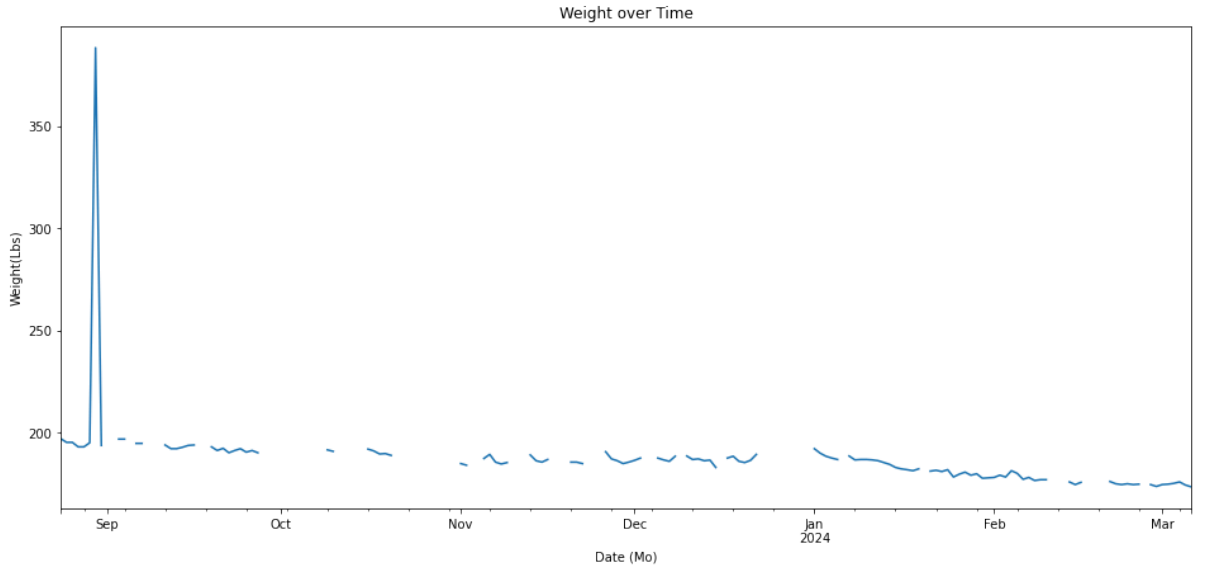
In [59]:
```
df['BodyMass_lb'].plot(figsize = (16,7));
plt.xlabel('Date (Mo)')
plt.ylabel('Weight(Lbs)')
plt.title('Weight over Time')
plt.show()
```



As we mentioned, we can not feasibly have 0.0s in our weight column, so let's convert those to Nans.

In [60]:
```
df.loc[df['BodyMass_lb'] == 0.0,'BodyMass_lb'] = np.nan
```

In [61]:
```
df['BodyMass_lb'].plot(figsize = (16,7));
plt.xlabel('Date (Mo)')
plt.ylabel('Weight(Lbs)')
plt.title('Weight over Time')
plt.show()
```

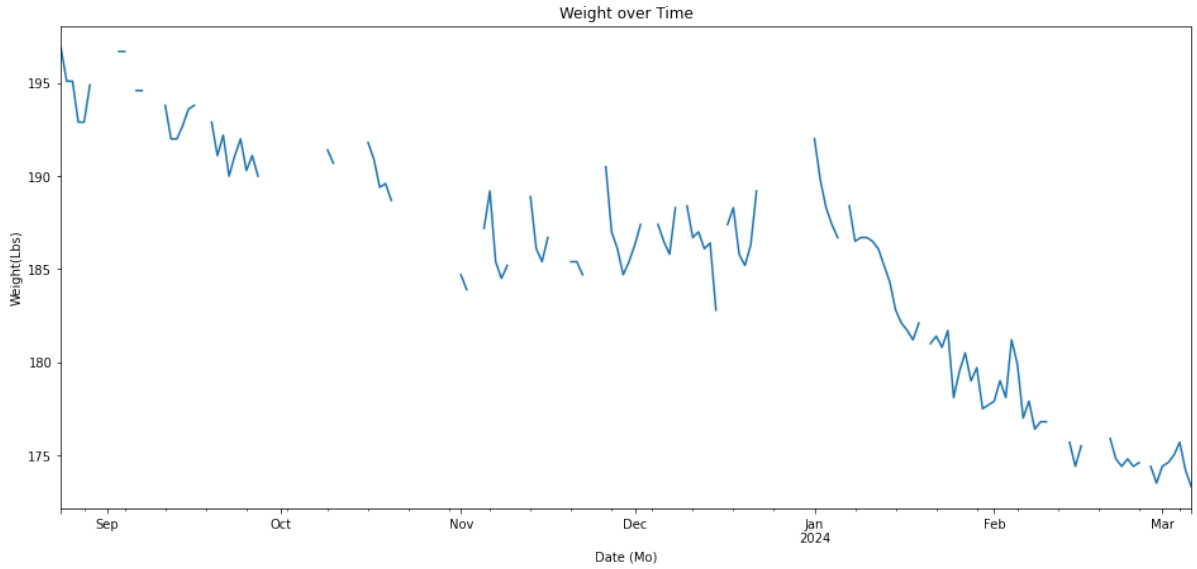


Our weights appear better, except for one errant reading. We know that 388.5 is not possible. So we'll go ahead and make that null as well.

In [62]:
```
df.loc[df['BodyMass_lb'] == 388.5,'BodyMass_lb'] = np.nan
```

Now, let's plot the graph

In [63]:
```
df['BodyMass_lb'].plot(figsize = (16,7));
plt.xlabel('Date (Mo)')
plt.ylabel('Weight(Lbs)')
plt.title('Weight over Time')
plt.show()
```



So, as we've established, we can't impute the mean for this. Instead we can try to interpolate the results and evaluate whether this is reasonable. The interpolation takes the two known points on either sife of missing data and attempts to find points in between. We'll use the `spline` option in the iterpolate capabilities of the dataframe. `spline` attempts to smooth out the data.

In [64]:
```
#create new column for interpolated data
df['BodyMass_lb_inter'] = df['BodyMass_lb'].interpolate(option='spline')
```

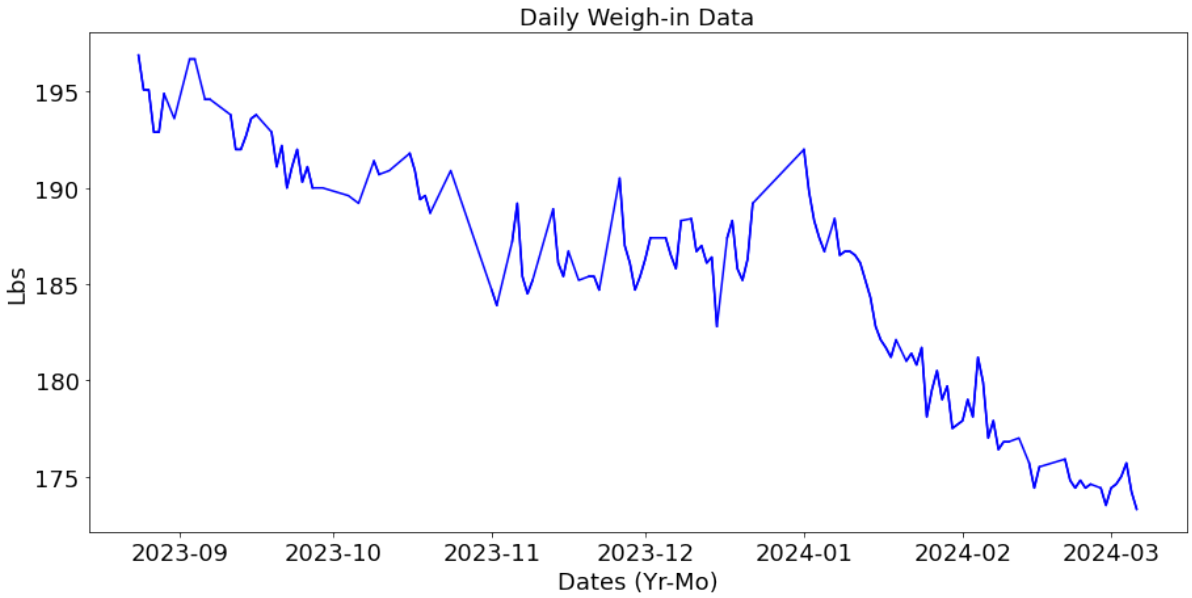
In [66]:
```
#let's inspect the results
df.head(5)
```

Out[66]:

date	BodyMass_lb	StepCount_count	DistanceWalkingRunning_mi	BasalEnergyBurned_Cal	Activ
2023-08-24	196.9	8895.0	4.163569	2055.322	
2023-08-25	195.1	9276.0	4.512434	2174.950	
2023-08-26	195.1	10883.0	4.948209	2074.476	
2023-08-27	192.9	19174.0	9.909258	2187.383	
2023-08-28	192.9	13636.0	6.833914	2186.244	

5 rows × 46 columns

In [71]:
```
plt.rcParams['figure.figsize']=(15,7)

plt.plot(df['BodyMass_lb_inter'], color='blue', label = 'Interpolated_Data')
plt.plot(df['BodyMass_lb'], color='blue', label = 'Actual')

#plt.xaxis.set_major_formatter(mdates.DateFormatter("%Y-%b"))

SMALL_SIZE = 8
MEDIUM_SIZE = 10
BIGGER_SIZE = 18

plt.rc('axes', titlesize=SMALL_SIZE, labelsize=MEDIUM_SIZE)

plt.rc('font', size=MEDIUM_SIZE)          # controls default text sizes
plt.rc('axes', titlesize=BIGGER_SIZE)     # fontsize of the axes title
plt.rc('axes', labelsize=BIGGER_SIZE)    # fontsize of the x and y labels
plt.rc('xtick', labelsize=MEDIUM_SIZE)    # fontsize of the tick labels
plt.rc('ytick', labelsize=MEDIUM_SIZE)    # fontsize of the tick labels
#plt.rc('legend', fontsize=SMALL_SIZE)    # legend fontsize
#plt.rc('figure', titlesize=BIGGER_SIZE)  # fontsize of the figure title

#matplotlib.rc('font', size=BIGGER_SIZE)
#matplotlib.rc('axes', titlesize=BIGGER_SIZE)

plt.title('Daily Weigh-in Data')
plt.xlabel('Dates (Yr-Mo)')
plt.ylabel('Lbs')
#plt.legend()
plt.show()
```



This looks good, we can move on to the next task.

Recall our protocol from above: The idea of a "day" with regard to activities ends the mornign log-in and starts with the first cup of water (usually right after). A day starts AFTER the morning weigh-in, even though it will be recorded on that day.

Our data as it's listed there lists the morning weigh-in as if it's a result of the food we're eating AFTER we weighed in. To rectify this, we have to adjust our weight data "up" by a day. Meaning, if we have a weigh-in on Sept. 8, it really reflects the food, sleep, and metabolism, from the night before.

In [72]:
```
#initialize a blank series series without the date index
series = df['BodyMass_lb_inter'].reset_index()

#loop through series and move the interpolated weight one index (data) up
for ind in range(0,len(series)-1):
    series.loc[ind, 'BodyMass_lb_inter'] = series.loc[ind+1, 'BodyMass_lb_inter

#make the last value Nan
series.loc[ind+1, 'BodyMass_lb_inter'] = np.NaN

#re-stablish date index
series.set_index('date', inplace = True)

#create new feature in df to represent the new lagged body mass
df['BodyMass_lb_inter'] = series['BodyMass_lb_inter']
```

okay, let's see how it looks

In [77]:
```
df[['BodyMass_lb', 'BodyMass_lb_inter']].head(5)
```

Out[77]:

date	BodyMass_lb	BodyMass_lb_inter
2023-08-24	196.9	195.1
2023-08-25	195.1	195.1
2023-08-26	195.1	192.9
2023-08-27	192.9	192.9
2023-08-28	192.9	194.9

Okay, so we've got interpolated weight data that we feel comfortable with.

Checking Weight Difference - Time Dependency

The main feature we have to create is our weight loss column. Recall that our goal is to predict weight_loss or weight_gain. TO do this, we have to create a column with the weight difference. We also use this column to test for stationality, just to make sure our time dependent target appears as noise.

In [78]:
```
#let's create the weight difference in a new column
df['BodyMass_lb_diff'] = df['BodyMass_lb_inter'].diff()
```

In [79]:
```
#review column
df['BodyMass_lb_diff'].head(5)
```

Out[79]:
```
date
2023-08-24    NaN
2023-08-25    0.0
2023-08-26   -2.2
2023-08-27    0.0
2023-08-28    2.0
Name: BodyMass_lb_diff, dtype: float64
```

Here, we can replace the first Nan with the actual value (from our original BodyMass_lb column)

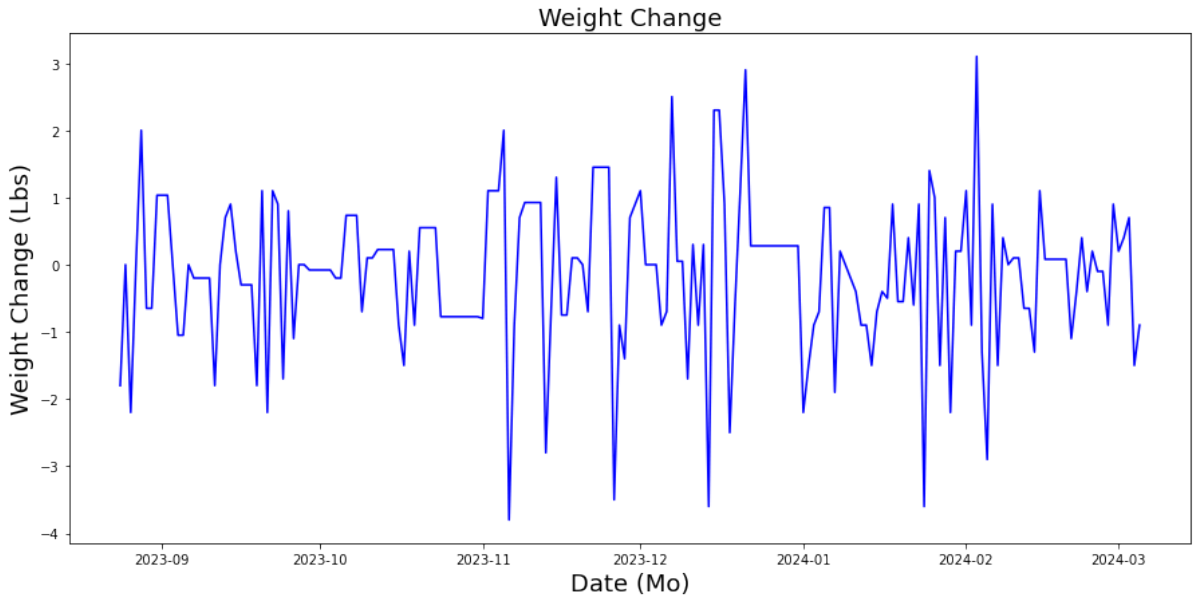
In [81]:
```
#provide the first differenced entry
df.iloc[0,len(df.columns)-1] = df.iloc[0,len(df.columns)-2] - df.iloc[0,0]
```

In [80]:
```
#let's review the last columns
df['BodyMass_lb_diff'].tail(5)
```

Out[80]:
```
date
2024-03-02    0.4
2024-03-03    0.7
2024-03-04   -1.5
2024-03-05   -0.9
2024-03-06    NaN
Name: BodyMass_lb_diff, dtype: float64
```

the Nan here on the last column is expected. We don't have the data from March 7th. So this is normal.

In [83]:
```
#Let's plot the results
plt.rcParams['figure.figsize']=(15,7)

plt.plot(df['BodyMass_lb_diff'], color='blue', label = 'Weight Diff')

plt.title('Weight Change')
plt.xlabel('Date (Mo)')
plt.ylabel('Weight Change (Lbs)')
plt.show()
```



Now that we have differenced the data, and have nothing null, let's go ahead and test for Dickey-Fuller

Test for Stationality

The Dickey-Fuller Test shows if we have Stationality. We're going to use the Dickey-Fuller test in the stats model. This function does not permit null values. So let's see how we're doing. We'll create a new dataframe to test.

In [84]:
```
#drop null values
new_df = df.dropna(subset=['BodyMass_lb_diff'])
```

In [87]:
```
dftest = adfuller(new_df['BodyMass_lb_diff'])
```

In [88]:
```
# Print Dickey-Fuller test results
print('Results of Dickey-Fuller Test: \n')

dfoutput = pd.Series(dftest[0:4], index=['Test Statistic', 'p-value',
                                         '#Lags Used', 'Number of Observati
for key, value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value
print(dfoutput)
```

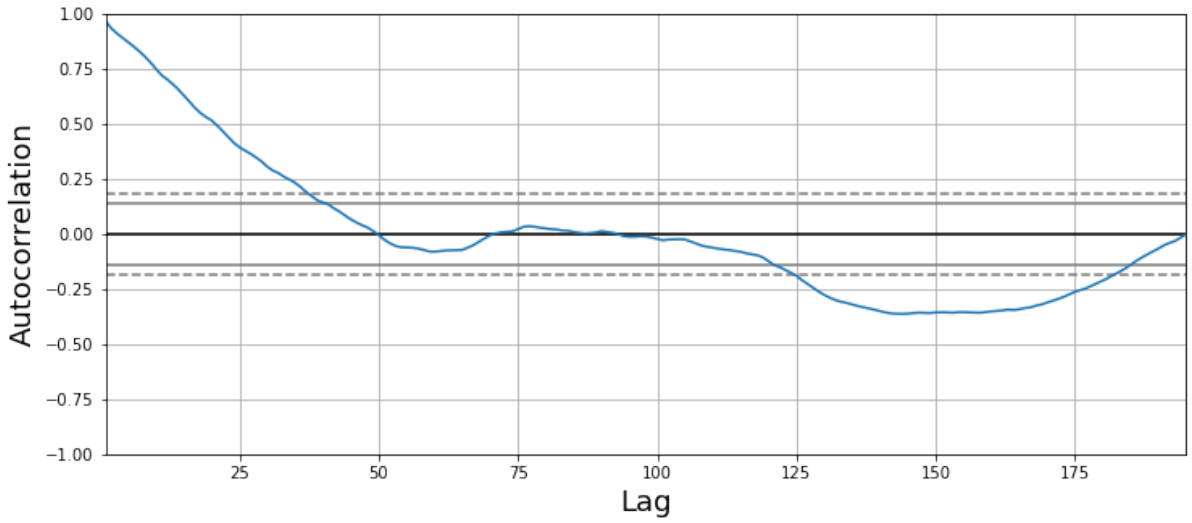
```
Results of Dickey-Fuller Test:

Test Statistic                -9.581410e+00
p-value                        2.153488e-16
#Lags Used                     3.000000e+00
Number of Observations Used    1.910000e+02
Critical Value (1%)           -3.465059e+00
Critical Value (5%)           -2.876794e+00
Critical Value (10%)          -2.574901e+00
dtype: float64
```

Fantastic, we have a low P-Value. So, we've confirmed our weight data can be considered noise, even though we did have a slight trend of weight loss over time. We don't need any decomposition before we begin our analysis.

Autocorrelation Checks

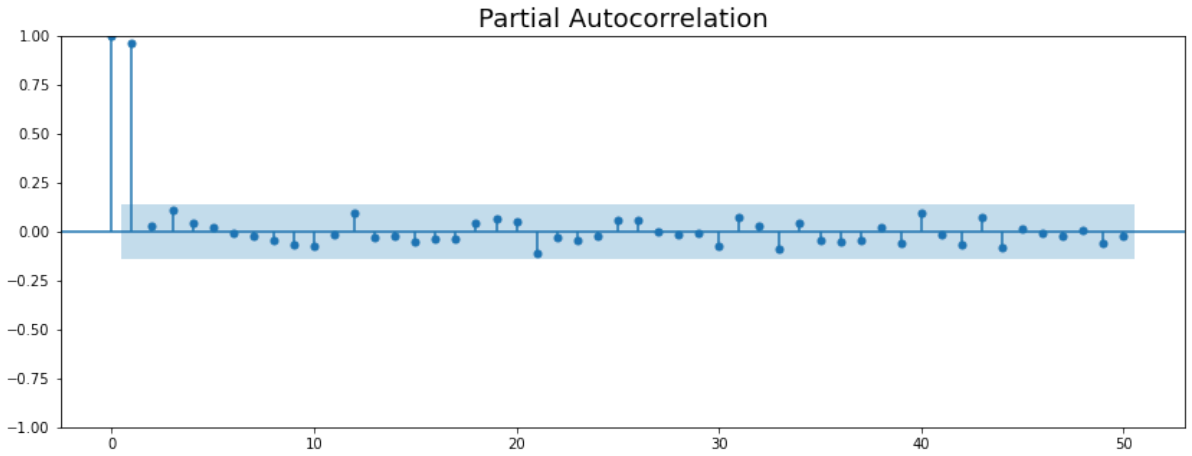
Let's check autocorrelation to make sure there's no additional time dependency

In [89]:
```
#plot autocorrelation
plt.figure(figsize=(12,5))
pd.plotting.autocorrelation_plot(new_df['BodyMass_lb_inter']);
```



This is what we would expect, essentially a declining correlation over time. What we weigh each day has a declining reliance on the previous day. Let's check the Partial Autocorrelation.

In [90]:
```
from statsmodels.graphics.tsaplots import plot_pacf
from matplotlib.pylab import rcParams

rcParams['figure.figsize'] = 14, 5

plot_pacf(new_df['BodyMass_lb_inter'], lags=50);
```



Both plots look pretty stationary. So that's great. Our PACF plot shows high correlation with the 1st order, which is exactly what we would expect. The difference in what we weigh from one day to the next is what we care about.

Let's go ahead and start Feature Engineering

3.c Feature Engineering

So, now that we added have scrubbed our data, interpolated the weight loss, and verified no difference beyond our previous day weight loss, we can dig into the feature engineering.

Weight Loss column

Let's create a new weight loss column that we will use as our target variable for the classification models.

In [91]:
```
#let's rename original Body Mass data and call it raw
df['BodyMass_lb_raw'] = df['BodyMass_lb']
```

Let's also drop our Nans on the last row of our differenced column (recall, we only did this for our new_df)

In [92]:
```
#drop NAs from the last row
df = df.dropna(subset=['BodyMass_lb_diff'])
```

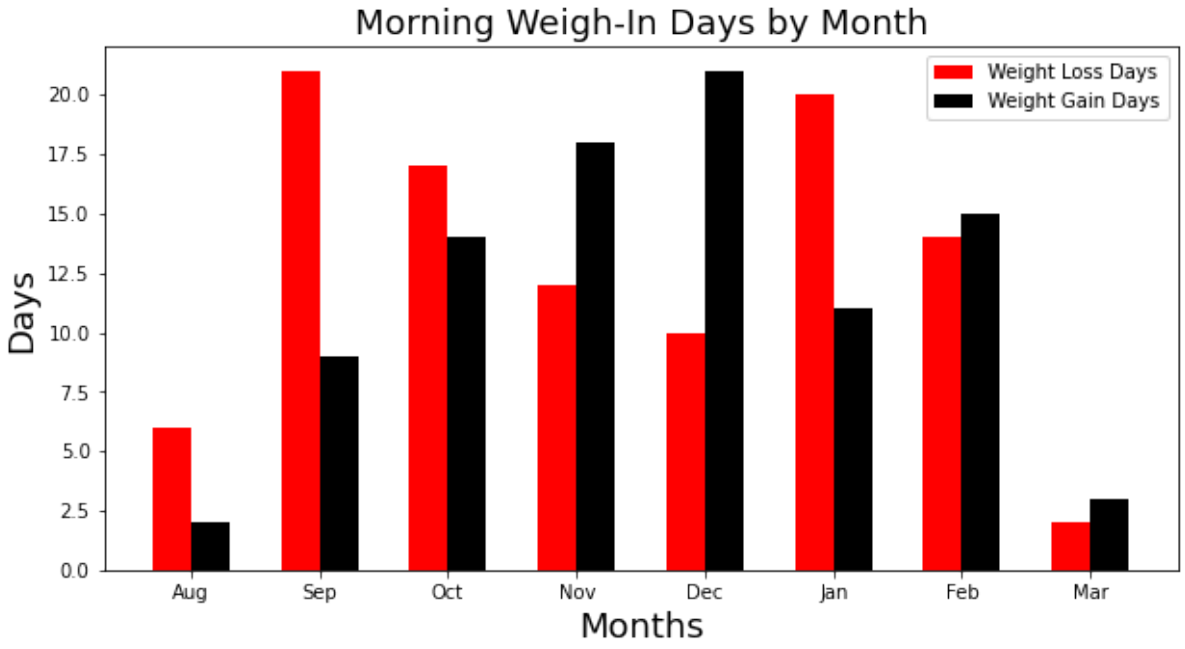
Let's make our category to determine if weight loss occurred. This is relatively simple. Let's call it weight loss, and we'll give it a 1, if there's was weight loss, and 0 if there wasn't. In this scenario, even 0 lbs would be the same as weight gain.

In [95]:
```
#create column and make it an integer
df.loc[:,'weight_loss'] = df.loc[:,'BodyMass_lb_diff'] < 0.01
df.loc[:,'weight_loss'] = df.loc[:,'weight_loss'].astype(int)
```

Now that we have a new weight loss column, we can track the weight by weight loss days, and not a time dependent variable. Let's show a new graph to detail this.

In [101]:
```
#create wieght days dataframe for plotting
weight_days = pd.DataFrame(df[df['weight_loss'] == 1]['weight_loss'].resample('
weight_days['weight_gain'] = df[df['weight_loss'] == 0]['weight_loss'].resample
weight_days.reset_index(inplace = True)
weight_days['date'] = weight_days['date'].dt.month_name().str[:3]
weight_days.set_index('date', inplace = True)
```

In [102]:
```
# Specify the values of black bars (height)
weight_gain = weight_days['weight_gain']

# Specify the values of red bars (height)
weight_loss = weight_days['weight_loss']

# Position of bars on x-axis
ind = np.arange(len(weight_days['weight_gain']))

# Figure size
plt.figure(figsize=(10,5))

# Width of a bar
width = 0.3

# Plotting
plt.bar(ind, weight_loss, width, label='Weight Loss Days', color = 'red')
plt.bar(ind + width, weight_gain, width, label='Weight Gain Days', color = 'bla

plt.xlabel('Months')
plt.ylabel('Days')
plt.title('Morning Weigh-In Days by Month')

# xticks()
# First argument - A list of positions at which ticks should be placed
# Second argument -  A list of labels to place at the given locations
plt.xticks(ind + width/2, weight_days.index)

# Finding the best position for legends and putting it
plt.legend(loc='best')
plt.show()
```



In [264]:
```
#let's see the total
weight_days.loc['totals'] = [weight_days['weight_loss'].sum(), weight_days['wei
weight_days
```

Out[264]:

date	weight_loss	weight_gain
Aug	6	2
Sep	21	9
Oct	17	14
Nov	12	18
Dec	10	21
Jan	20	11
Feb	14	15
Mar	2	3
totals	102	93

3d. PCA Analysis

Now that we have all of these feature variables, and we believe we're in good shape. Let's figure out if there's any PCA or correlation issues with our data. To do that, we'll separate between what the potential targets are from the features.

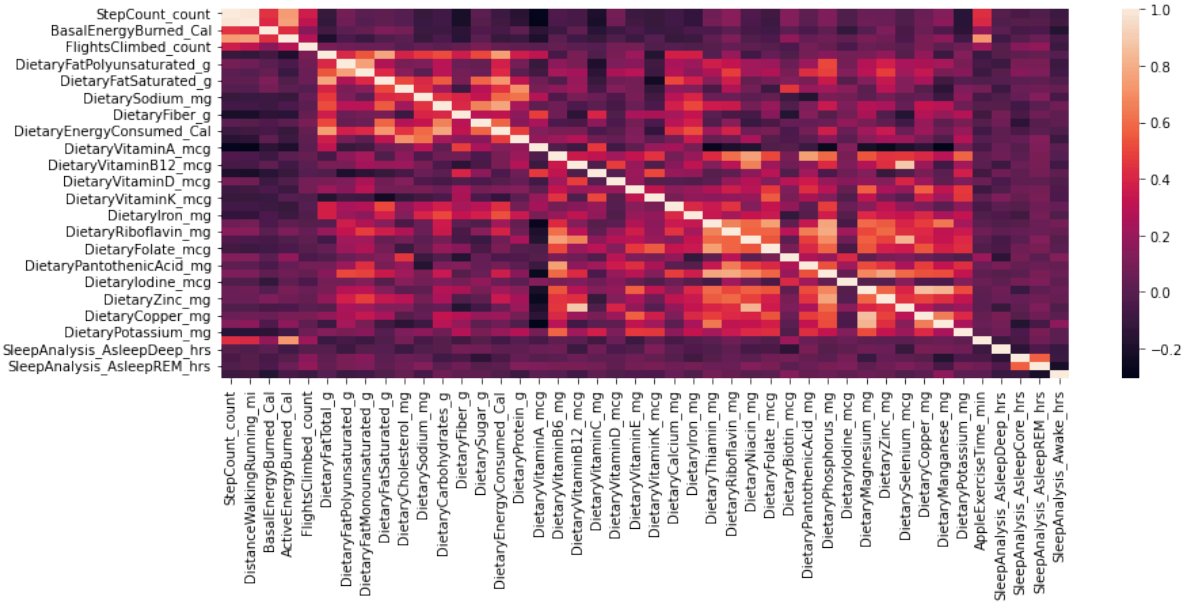
In [103]:
```
targets = df.loc[:,'BodyMass_lb_inter':'weight_loss']
features = df.loc[:,'StepCount_count':'SleepAnalysis_Awake_hrs']
```

Now that we've done that, let's review the correlation of the features via a heatmap. We will utilize the heatmap function. We'll use the standardization of the data here.

In [104]:
```
from sklearn.preprocessing import StandardScaler

scaler_std = StandardScaler()
features_std = pd.DataFrame(scaler_std.fit_transform(features), columns = featu
```

In [105]:
```
# Your code here
import seaborn as sns
sns.heatmap(features_std.corr())
```

Out[105]: <Axes: >



There appears to be significant correlation here, especially among the micronutrients. Let's do a quick PCA analysis to understand the variance.

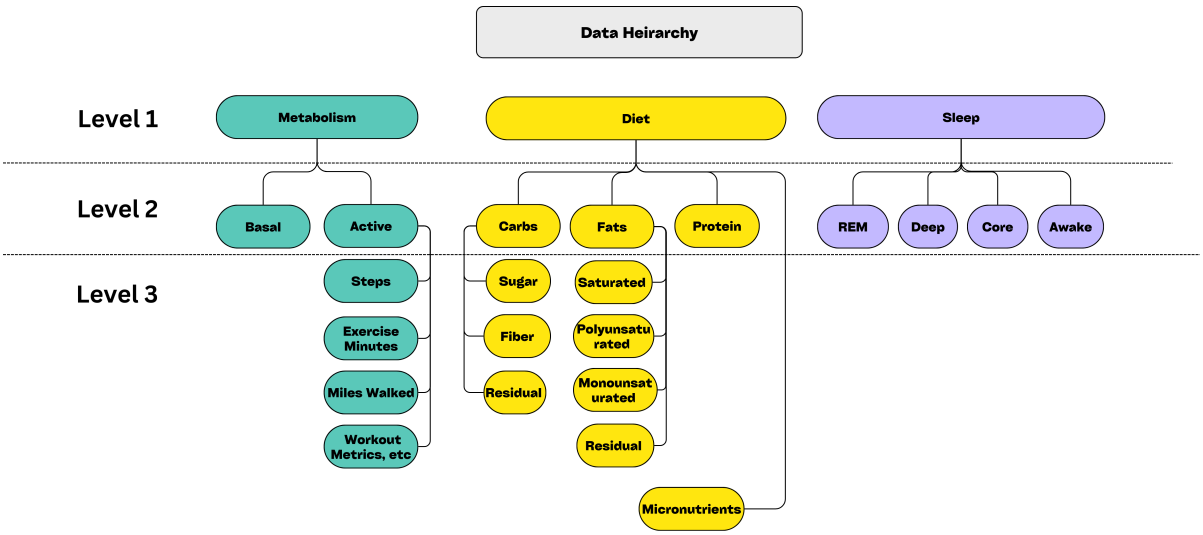
In [106]:
```
#PCA analysis to locate possible variance reduction
from sklearn.decomposition import PCA

pca_1 = PCA(n_components=12)
pca_2 = PCA(n_components=24)
pca_3 = PCA(n_components=36)

principalComponents = pca_1.fit_transform(features_std)
principalComponents = pca_2.fit_transform(features_std)
principalComponents = pca_3.fit_transform(features_std)

print(np.sum(pca_1.explained_variance_ratio_))
print(np.sum(pca_2.explained_variance_ratio_))
print(np.sum(pca_3.explained_variance_ratio_))
```

```
0.7718141093403272
0.9424805670117009
0.9928075952307182
```

Wow, okay, so we can maintain about 80% of our data through 12 components, down from 45. That's an improvement, but still suggests a lot of variation in the data. At the same time, a lot of correlation (the heat in our correlation map). It's probably a good time to delve into the data a bit more. Previously, we divided our data into dietary, exercise, and sleep. It turns out, we may need to create further subsets through segmenting.

3e. SEGMENTING FEATURE DATA

In order to better sort all of the correlation here, it might be a good time to segment the data. To do this, we'll utilize a heirarchal arrangement of data points.



For dietary information, it's useful to think of it in levels. It starts with Level 1 - `DietaryEnergyConsumed_Cal`, from there we go to Level 2 - macronutrients `DietaryFatTotals_g`, `DietaryCarbohydrates_g`, `DietaryProtein_g`. But fortunately for us, we have, what I call, Level 3 - sub-macronutrients still measured in grams, which includes things like `DietarySugar_g` which is a carbohydrate, and `DietarySaturatedFats_g` which is a fat. Going further, we have micronutrients, or Level 4 - measured in milligrams (or even micrograms) of things like `DietarySodium_mg` and `DietaryCholesterol_mg`.

Same with sleep. With sleep, we have level 2 data - REM, Core, Deep. We also have awake hours as well. Level 1 data, if we wanted it, would consist of the total hours of sleep we got. So, if we chose to include only Level 1 diet data in our analysis, it might be better to be consistent with sleep as well. Same with exercise. We have basal and active calories, or Level 2, and we have exercise minutes. Exercise minutes are even a collary category of workout.

There's a big correlative overlap between Level 1, 2, & 3. So, we have to make a decision on what we want to include. Given where we are, let's start with Level 1 and go from there.

To do that, let's start with Level 1. For sleep and metabolism, we'll have to feature engineer our total numbers (sleep hours and metabolic calories burned).

Level 1 - Correlation Check

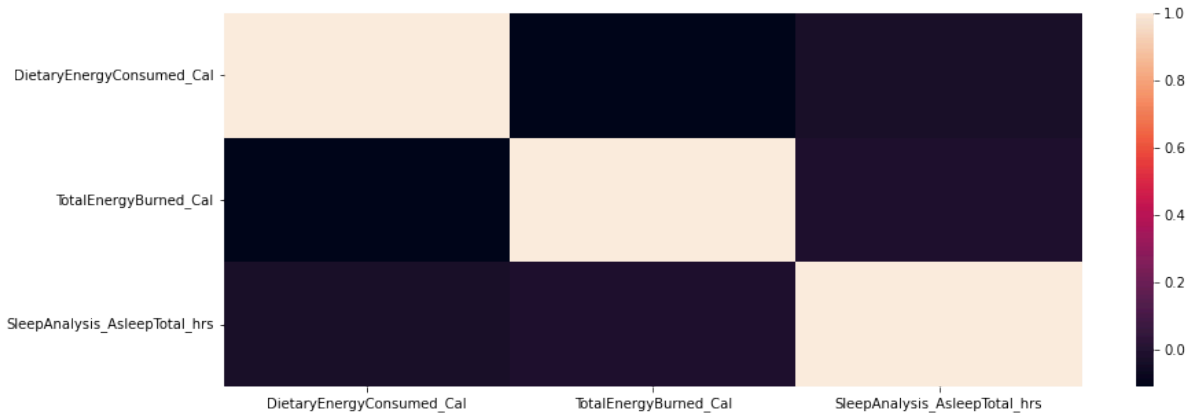
In [107]:
```
#let's add totals for sleep and energy burned
df.loc[:,'SleepAnalysis_AsleepTotal_hrs'] = df.loc[:,'SleepAnalysis_AsleepDeep_
df.loc[:,'TotalEnergyBurned_Cal'] = df.loc[:,'BasalEnergyBurned_Cal'] + df.loc[
```

```
<ipython-input-107-33e7c8ea61eb>:2: 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/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  df.loc[:,'SleepAnalysis_AsleepTotal_hrs'] = df.loc[:,'SleepAnalysis_AsleepD
eep_hrs'] + df.loc[:,'SleepAnalysis_AsleepCore_hrs'] + df.loc[:,'SleepAnalysi
s_AsleepREM_hrs']
<ipython-input-107-33e7c8ea61eb>:3: 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/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  df.loc[:,'TotalEnergyBurned_Cal'] = df.loc[:,'BasalEnergyBurned_Cal'] + df.
loc[:,'ActiveEnergyBurned_Cal']
```

In [108]:
```
#combine all 3 - Level 1
level_1 = ['DietaryEnergyConsumed_Cal', 'TotalEnergyBurned_Cal', 'SleepAnalysis
level_1_diet = ['DietaryEnergyConsumed_Cal']
level_1_exer = ['TotalEnergyBurned_Cal']
level_1_sleep = ['SleepAnalysis_AsleepTotal_hrs']

feature_1 = df[level_1]
```

In [109]:
```
#let's check our heatmap
import seaborn as sns
sns.heatmap(feature_1.corr())
```

Out[109]: <Axes: >



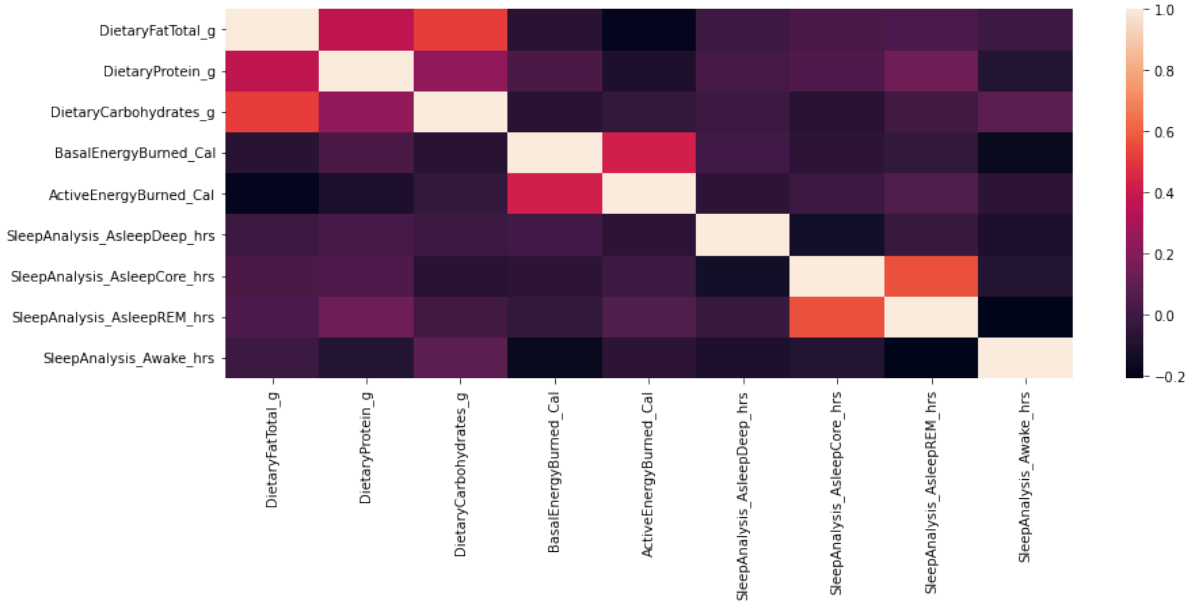
aha, so very little correlation between dietary energy, total energy, and sleep analysis. Now, let's run some models on our data and see which performs the best. Because we're worried about whether we've gained weight or lost weight, accuracy is going to be or relevant prediction.

Level 2 - Correlation Check

In [110]:
```
#combine - Level 2
level_2_diet = ['DietaryFatTotal_g', 'DietaryProtein_g', 'DietaryCarbohydrates_
level_2_exer = ['BasalEnergyBurned_Cal','ActiveEnergyBurned_Cal']
level_2_sleep = ['SleepAnalysis_AsleepDeep_hrs','SleepAnalysis_AsleepCore_hrs',
level_2 = level_2_diet + level_2_exer + level_2_sleep
feature_2 = df[level_2]
```

In [111]:
```
sns.heatmap(feature_2.corr())
```

Out[111]: <Axes: >



There is some correlation above espeicially between `DietaryFatTotal_g` and `DietaryCarbohydrates_g` , as well `DietaryFatTotal_g` and `DietaryProtein_g` . Also some between Sleep variables.

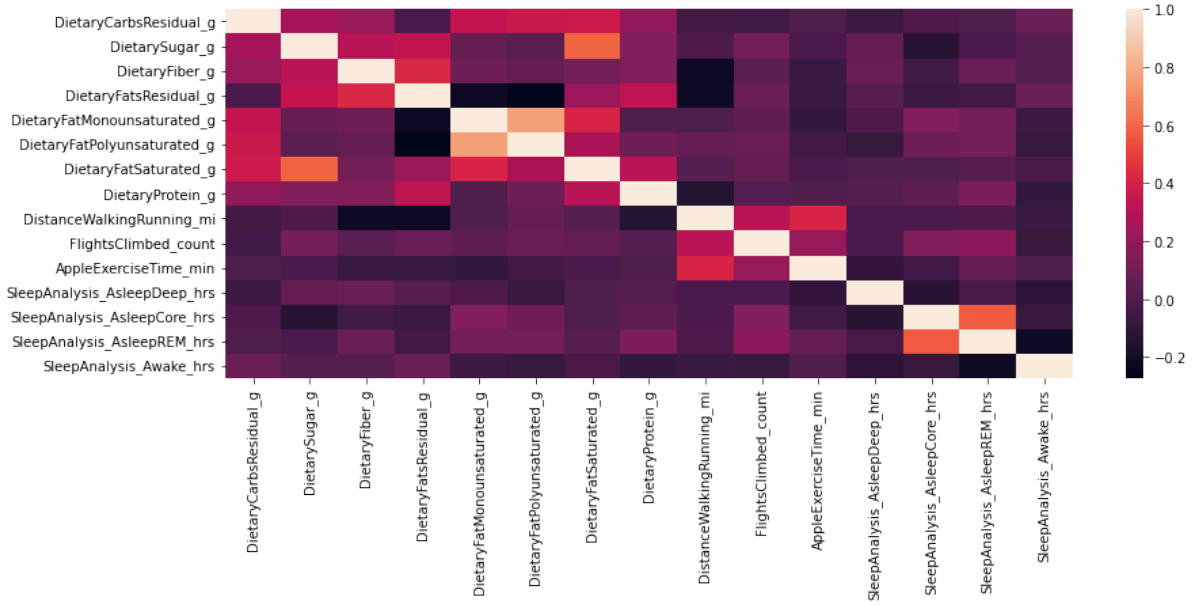
Level 3 - Correlation Check

In [112]:
```
#feature engineering - let's create some of the categories for dietary 3
df.loc[:,'DietaryCarbsResidual_g'] = df.loc[:,'DietaryCarbohydrates_g'] - df.lo
df.loc[:,'DietaryFatsResidual_g'] = df.loc[:,'DietaryFatTotal_g'] - df.loc[:,'D

#let's aggregate the level 3 dietary information
level_3_diet_carbs = ['DietaryCarbsResidual_g', 'DietarySugar_g', 'DietaryFiber
level_3_diet_fat = ['DietaryFatsResidual_g', 'DietaryFatMonounsaturated_g', 'Di
level_3_diet_protein = ['DietaryProtein_g']
level_3_diet = level_3_diet_carbs + level_3_diet_fat + level_3_diet_protein

#our exercise categories have both stepCount and DistanceWalking, we'll get ria
level_3_exer = ['DistanceWalkingRunning_mi', 'FlightsClimbed_count', 'AppleExer

#combine - Level 3, please note, there is no level 3 for sleep and exercise, we
level_3 = level_3_diet + level_3_exer + level_2_sleep
feature_3 = df[level_3]
```

```
<ipython-input-112-25beb2d6ea9d>:2: 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/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  df.loc[:,'DietaryCarbsResidual_g'] = df.loc[:,'DietaryCarbohydrates_g'] - d
f.loc[:,'DietarySugar_g'] - df.loc[:,'DietaryFiber_g']
<ipython-input-112-25beb2d6ea9d>:3: 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/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  df.loc[:,'DietaryFatsResidual_g'] = df.loc[:,'DietaryFatTotal_g'] - df.loc
[:,'DietaryFatMonounsaturated_g'] -  df.loc[:,'DietaryFatPolyunsaturated_g']
- df.loc[:,'DietaryFatSaturated_g']
```

In [113]:
```
sns.heatmap(feature_3.corr())
```

Out[113]: <Axes: >



We see some correlation between sleep, as well as a bit of correlation between the sub-macronutrients of both Carbs and Fats. Despite some correlation here, we've significantly cut down on both the overall correlation we saw with all of our variables. We will leave out our Micronutrients for now.

3f. Data Preparation Summary

We have successfuly completed our Data Preparation. We filled in the missing values, we feature engineered a few target categories. We also verified that our data was stationary and that there were no correlations in our time dependent weight loss category. Furthermore, we analyzed the data to check for variance and correlation and were able to segment our data into smaller, more manageable segments. We are ready to model!

4. Modeling

In order to select the best model, we will use a variety of traditional algorithms and use our different feature segments (level 1, level 2, and level 3). We'll start with KNN, Logistic Regression, Decision Tree, Naive Bayes, SVM, and Neural Network. Evaluation metrics will be tallied in one table and then we will select on optimal model based on the evaluation metrics. Each model will get a set of trianing data and a set of test for which to report. We will try to optimize hyperparameters when available.

4.1 Level 1 Modeling

Baseline Random Algorithm

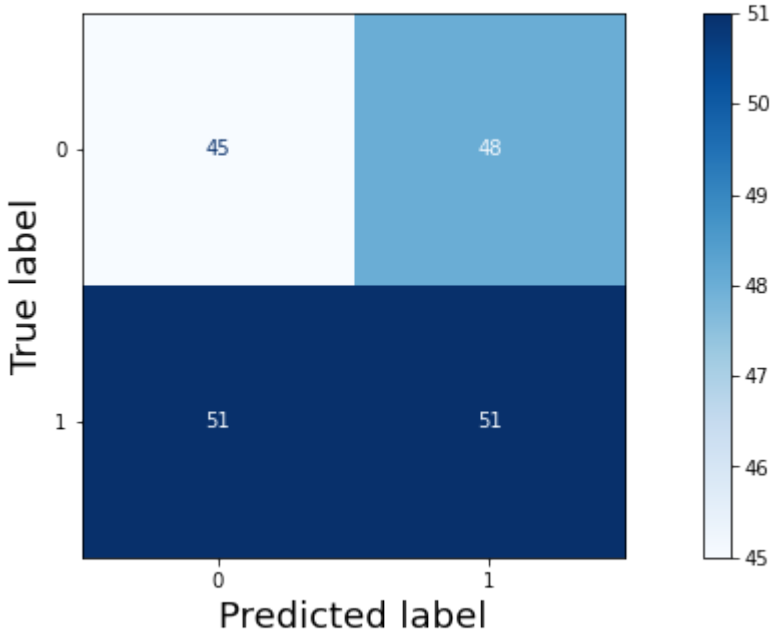
Prior to that, let's perform a very simple, random test, to randomly select whether an observation is a weight loss day or a weight gain day.

In [114]:
```
#import random module
import random

#initialize baseline dataframe from the weight loss column
baseline = pd.DataFrame(df['weight_loss'])

#create a predictions column that randomly chooses 0 or 1
baseline['Predictions'] = [random.randrange(0, 2, 1) for i in range(len(baselir

#create another column which determines which are correct
baseline['Correct?'] = (baseline['weight_loss'] == baseline['Predictions'])

#count the true and false answers
baseline['Correct?'].value_counts(normalize=True)
```

Out[114]:
```
Correct?
False    0.507692
True     0.492308
Name: proportion, dtype: float64
```

In [115]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay

target = baseline['weight_loss']
preds = baseline['Predictions']

cnf = confusion_matrix(target, preds)

disp = ConfusionMatrixDisplay(confusion_matrix=cnf)
disp.plot(cmap=plt.cm.Blues)
```

Out[115]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1de18e01a
90>
```



This make sense, as we have a 50-50 model (basically) with skew towards predicting weight loss (Label = 1). Recall that we have more weight loss days than weight gain days. Let's see how this compares with our evaluation metrics.

In [116]:
```
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_s

# Complete the function
def print_metrics(labels, preds):
    print("Precision Score: {}".format(precision_score(labels, preds)))
    print("Recall Score: {}".format(recall_score(labels, preds)))
    print("Accuracy Score: {}".format(accuracy_score(labels, preds)))
    print("F1 Score: {}".format(f1_score(labels, preds)))

print_metrics(target, preds)
```

```
Precision Score: 0.5151515151515151
Recall Score: 0.5
Accuracy Score: 0.49230769230769234
F1 Score: 0.5074626865671642
```

So, we have what we thought... a roughly 50-50 model which skews higher in precision because we have more weight loss days. Make sense. Let's create a dataframe, called level 1, which puts our results in one table for comparison.

In [117]:
```
level_1_df = pd.DataFrame(columns=['Model', 'Precision', 'Recall', 'Accuracy',
level_1_df.loc[0] = ['Baseline - Random',
                     precision_score(target, preds),
                     recall_score(target, preds),
                     accuracy_score(target, preds),
                     f1_score(target, preds),
                     'N/A']
level_1_df
```

Out[117]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	Baseline - Random	0.515152	0.5	0.492308	0.507463	N/A

okay, now let's go ahead and create something for each algorithm.

Standard Imports and Custom Scoring Functions for each algorithm

In [118]:
```
# Import train_test_split
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score

# Split the data
X_train, X_test, y_train, y_test = train_test_split(feature_1, df['weight_loss'
```

In [119]:
```
#scoring function to score different results and append to the dataframe
def scoring (name, model, X_train, X_test, y_train, y_test):
    preds = model.predict(X_test)
    val_score = cross_val_score(model, X_train, y_train, cv=5) #5 fold cross va
    eval_df = pd.DataFrame(columns=['Model', 'Precision', 'Recall', 'Accuracy',
    eval_df.loc[0] = [name,
                  precision_score(y_test, preds),
                  recall_score(y_test, preds),
                  accuracy_score(y_test, preds),
                  f1_score(y_test, preds),
                  val_score.mean()]
    return eval_df
```

In [120]:
```
def nn_scoring (name, model, X_test, y_test):

    preds = np.round(model.predict(X_test))
    eval_df = pd.DataFrame(columns=['Model', 'Precision', 'Recall', 'Accuracy',
    eval_df.loc[0] = [name,
                  precision_score(y_test, preds),
                  recall_score(y_test, preds),
                  accuracy_score(y_test, preds),
                  f1_score(y_test, preds),
                  'n/a']
    return eval_df
```

KNN (Level 1 Data)

Okay let's start with KNN level 1. We'll use a function to optimize n_neighbors parameter.

In [121]:
```
def find_best_knn(name, X_train, X_test, y_train, y_test):

    # Instantiate StandardScaler
    scaler = StandardScaler()

    # Transform the training and test sets
    scaled_data_train = scaler.fit_transform(X_train)
    scaled_data_test = scaler.fit_transform(X_test)

    #algorithm for k
    best_k = 0
    best_score = 0.0
    min_k=1
    max_k=25

    for k in range(min_k, max_k+1, 2):
        knn = KNeighborsClassifier(n_neighbors=k)
        knn.fit(X_train, y_train)
        preds = knn.predict(X_test)
        f1 = f1_score(y_test, preds)
        if f1 > best_score:
            best_k = k
            best_score = f1

    # Instantiate KNeighborsClassifier
    knn = KNeighborsClassifier(n_neighbors=best_k)

    # Fit the classifier
    knn.fit(scaled_data_train, y_train)

    results = scoring ((f'{name}, k = {best_k}'), knn, scaled_data_train, scale
    return results
```

In [122]:
```
results = find_best_knn('knn', X_train, X_test, y_train, y_test)
level_1_df = level_1_df._append(results, ignore_index = True)
```

In [123]:
```
level_1_df
```

Out[123]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	Baseline - Random	0.515152	0.5	0.492308	0.507463	N/A
1	knn, k = 19	0.720000	0.6	0.612245	0.654545	0.637241

Logistic Regression

For Logistic Regression, and models following, I built a pipeline to expedite testing.

In [124]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline

# Build a pipeline with StandardScaler and Logistic Regression
lr_pipeline = Pipeline([('ss', StandardScaler()),
                        ('LR', LogisticRegression(random_state=42))])

# Define the grid
grid = [{'LR__C': [1, 1E6, 1E12],
         'LR__solver': ['liblinear', 'newton-cg', 'lbfgs', 'sag', 'saga']}]

# Define a grid search
gridsearch = GridSearchCV(estimator=lr_pipeline,
                          param_grid=grid,
                          scoring='accuracy',
                          cv=10)

# Fit the training data
gridsearch.fit(X_train, y_train)

results = scoring ((f'logreg'), gridsearch, X_train, X_test, y_train, y_test)
level_1_df = level_1_df._append(results, ignore_index = True)
```

In [125]:
```
level_1_df
```

Out[125]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	Baseline - Random	0.515152	0.500000	0.492308	0.507463	N/A
1	knn, k = 19	0.720000	0.600000	0.612245	0.654545	0.637241
2	logreg	0.703704	0.633333	0.612245	0.666667	0.685057

Decision Tree

In [126]:
```
from sklearn.tree import DecisionTreeClassifier

# Build a pipeline with StandardScaler and DecisionTree
dt_pipeline = Pipeline([('DT', DecisionTreeClassifier())])

# Define the grid
grid = [{'DT__criterion': ['gini', 'entropy'],
         'DT__max_depth': [2, 4, 6],
         'DT__min_samples_split': [5, 10, 15]}]

# Define a grid search
gridsearch = GridSearchCV(estimator=dt_pipeline,
                          param_grid=grid,
                          scoring='accuracy',
                          cv=5)

# Fit the training data
gridsearch.fit(X_train, y_train)
```

Out[126]:
```
GridSearchCV(cv=5, estimator=Pipeline(steps=[('DT', DecisionTreeClassifier
())]),
             param_grid=[{'DT__criterion': ['gini', 'entropy'],
                          'DT__max_depth': [2, 4, 6],
                          'DT__min_samples_split': [5, 10, 15]}],
             scoring='accuracy')
```

In [127]:
```
results = scoring ('dec_tree', gridsearch, X_train, X_test, y_train, y_test)
level_1_df = level_1_df._append(results, ignore_index = True)
```

In [128]:
```
level_1_df
```

Out[128]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	Baseline - Random	0.515152	0.500000	0.492308	0.507463	N/A
1	knn, k = 19	0.720000	0.600000	0.612245	0.654545	0.637241
2	logreg	0.703704	0.633333	0.612245	0.666667	0.685057
3	dec_tree	0.736842	0.466667	0.571429	0.571429	0.69908

Naive Bayes - Level 1

In [129]:
```
from sklearn.naive_bayes import GaussianNB

# Build a pipeline with StandardScaler and Logistic Regression
GNB_pipeline = Pipeline([('ss', StandardScaler()),
                         ('GNB', GaussianNB())])

# Define parameters
parameters = {
    'GNB__priors': [None],
    'GNB__var_smoothing': [0.00000001, 0.000000001, 0.00000001]}

# Define a grid search
gridsearch = GridSearchCV(estimator=GNB_pipeline,
                          param_grid=parameters,
                          scoring='accuracy',
                          cv=10)

# Fit the training data
gridsearch.fit(X_train, y_train)

results = scoring ((f'GNB'), gridsearch, X_train, X_test, y_train, y_test)
level_1_df = level_1_df._append(results, ignore_index = True)
```

In [130]:
```
level_1_df
```

Out[130]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	Baseline - Random	0.515152	0.500000	0.492308	0.507463	N/A
1	knn, k = 19	0.720000	0.600000	0.612245	0.654545	0.637241
2	logreg	0.703704	0.633333	0.612245	0.666667	0.685057
3	dec_tree	0.736842	0.466667	0.571429	0.571429	0.69908
4	GNB	0.703704	0.633333	0.612245	0.666667	0.712414

SVM

In [131]:
```
from sklearn import svm

# Build a pipeline with StandardScaler and Logistic Regression
SVM_pipeline = Pipeline([('ss', StandardScaler()),
                         ('SVM', svm.SVC(kernel='linear'))])

# Define parameters
parameters = {
    'SVM__coef0': [0.01, 1, 10],
    'SVM__gamma': [0.001, 0.01, 0.1]}

# Define a grid search
gridsearch = GridSearchCV(estimator=SVM_pipeline,
                          param_grid=parameters,
                          scoring='accuracy',
                          cv=10)

# Fit the training data
gridsearch.fit(X_train, y_train)

results = scoring ((f'SVM'), gridsearch, X_train, X_test, y_train, y_test)
level_1_df = level_1_df._append(results, ignore_index = True)
```

In [132]:
```
level_1_df
```

Out[132]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	Baseline - Random	0.515152	0.500000	0.492308	0.507463	N/A
1	knn, k = 19	0.720000	0.600000	0.612245	0.654545	0.637241
2	logreg	0.703704	0.633333	0.612245	0.666667	0.685057
3	dec_tree	0.736842	0.466667	0.571429	0.571429	0.69908
4	GNB	0.703704	0.633333	0.612245	0.666667	0.712414
5	SVM	0.655172	0.633333	0.571429	0.644068	0.698621

In [133]:
```
import keras
from keras.models import Sequential
from keras.layers import Dense
#from sklearn.preprocessing import StandardScaler, LabelBinarizer
```

In [134]:
```
# Instantiate StandardScaler
scaler = StandardScaler()

# Transform the training and test sets
scaled_data_train = scaler.fit_transform(X_train)
scaled_data_test = scaler.fit_transform(X_test)
```

In [135]:
```
model_1 = Sequential()

#we'll try the 8-4-2 neurons, and an input shape of 3
model_1.add(Dense(8, activation='tanh', input_shape=(3,)))
model_1.add(Dense(4, activation='tanh'))
model_1.add(Dense(2, activation='tanh'))

#output classification layer
model_1.add(Dense(1, activation='sigmoid'))
```

In [136]:
```
from keras import optimizers
# Compile the model
model_1.compile(loss='binary_crossentropy', optimizer='sgd', metrics=[tf.keras.
```

In [137]:
```
#fit model
results_1  = model_1.fit(scaled_data_train,
                    y_train,
                    epochs=100,
                    validation_split=0.25)
```

```
Epoch 1/100
4/4 [==============================] - 3s 119ms/step - loss: 0.7666 - binar
y_accuracy: 0.4128 - val_loss: 0.7760 - val_binary_accuracy: 0.3514
Epoch 2/100
4/4 [==============================] - 0s 16ms/step - loss: 0.7619 - binary
_accuracy: 0.4128 - val_loss: 0.7721 - val_binary_accuracy: 0.3243
Epoch 3/100
4/4 [==============================] - 0s 17ms/step - loss: 0.7576 - binary
_accuracy: 0.4128 - val_loss: 0.7668 - val_binary_accuracy: 0.3243
Epoch 4/100
4/4 [==============================] - 0s 20ms/step - loss: 0.7523 - binary
_accuracy: 0.4220 - val_loss: 0.7621 - val_binary_accuracy: 0.3243
Epoch 5/100
4/4 [==============================] - 0s 19ms/step - loss: 0.7478 - binary
_accuracy: 0.4404 - val_loss: 0.7578 - val_binary_accuracy: 0.3514
Epoch 6/100
4/4 [==============================] - 0s 18ms/step - loss: 0.7435 - binary
_accuracy: 0.4404 - val_loss: 0.7534 - val_binary_accuracy: 0.3514
Epoch 7/100
```

In [138]:
```
#scoring for NN
preds = np.round(model_1.predict(scaled_data_test))

eval_df = pd.DataFrame(columns=['Model', 'Precision', 'Recall', 'Accuracy', 'F1

eval_df.loc[0] = ['NN',
                  precision_score(y_test, preds),
                  recall_score(y_test, preds),
                  accuracy_score(y_test, preds),
                  f1_score(y_test, preds),
                  'n/a']
level_1_df = level_1_df._append(eval_df, ignore_index = True)
```

```
2/2 [==============================] - 0s 4ms/step
```

In [139]:
```
level_1_df
```

Out[139]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	Baseline - Random	0.515152	0.500000	0.492308	0.507463	N/A
1	knn, k = 19	0.720000	0.600000	0.612245	0.654545	0.637241
2	logreg	0.703704	0.633333	0.612245	0.666667	0.685057
3	dec_tree	0.736842	0.466667	0.571429	0.571429	0.69908
4	GNB	0.703704	0.633333	0.612245	0.666667	0.712414
5	SVM	0.655172	0.633333	0.571429	0.644068	0.698621
6	NN	0.689655	0.666667	0.612245	0.677966	n/a

OKay, so, kind of a mixed bag. OUr best F1 and accuracy scores came from GNB and Log Reg. Let's look at feature 2 and see if we can see anything better.

4. 2 - Level 2 Algorithms

Recall our Level 2 data. We have the next layer of macronutrients, exercise, and sleep. We'll do the same thing we did above. Will run through each model and see if anything pops out.

So, there is some correlation between these sublayers. There appears to be correlation between Protein and Fat, Carbs and Fat, Basal and Active Calories, and Core and REM sleep. Let's go ahead and split the data, and run through our algorithms. Then we'll put them in a spreadsheet.

In [141]:
```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(feature_2, df['weight_loss'
```

KNN

In [142]:
```
results = find_best_knn('knn', X_train, X_test, y_train, y_test)
level_2_df = results
```

Logistic Regression

In [143]:
```
# Build a pipeline with StandardScaler and Logistic Regression
lr_pipeline = Pipeline([('ss', StandardScaler()),
                        ('LR', LogisticRegression(random_state=42))])

# Define the grid
grid = [{'LR__C': [1, 1E6, 1E12],
         'LR__solver': ['liblinear', 'newton-cg', 'lbfgs', 'sag', 'saga']}]

# Define a grid search
gridsearch = GridSearchCV(estimator=lr_pipeline,
                          param_grid=grid,
                          scoring='accuracy',
                          cv=10)

# Fit the training data
gridsearch.fit(X_train, y_train)

results = scoring ((f'logreg'), gridsearch, X_train, X_test, y_train, y_test)
level_2_df = level_2_df._append(results, ignore_index = True)
```

In [144]:
```
level_2_df
```

Out[144]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	knn, k = 21	0.680000	0.566667	0.571429	0.618182	0.671494
1	logreg	0.545455	0.400000	0.428571	0.461538	0.651034

Decision Tree

In [145]:
```
# Build a pipeline with StandardScaler and DecisionTree
dt_pipeline = Pipeline([('DT', DecisionTreeClassifier())])

# Define the grid
grid = [{'DT__criterion': ['gini', 'entropy'],
         'DT__max_depth': [2, 3, 4, 5, 6],
         'DT__min_samples_split': [5, 10, 15]}]

# Define a grid search
gridsearch = GridSearchCV(estimator=dt_pipeline,
                          param_grid=grid,
                          scoring='accuracy',
                          cv=5)

# Fit the training data
gridsearch.fit(X_train, y_train)
```

Out[145]:
```
GridSearchCV(cv=5, estimator=Pipeline(steps=[('DT', DecisionTreeClassifier
())]),
             param_grid=[{'DT__criterion': ['gini', 'entropy'],
                          'DT__max_depth': [2, 3, 4, 5, 6],
                          'DT__min_samples_split': [5, 10, 15]}],
             scoring='accuracy')
```

In [146]:
```
results = scoring ('dec_tree', gridsearch, X_train, X_test, y_train, y_test)
level_2_df = level_2_df._append(results, ignore_index = True)
```

SVM

In [147]:
```
# Build a pipeline with StandardScaler and Logistic Regression
SVM_pipeline = Pipeline([('ss', StandardScaler()),
                         ('SVM', svm.SVC(kernel='linear'))])

# Define parameters
parameters = {
    'SVM__coef0': [0.01, 1, 10],
    'SVM__gamma': [0.001, 0.01, 0.1]}

# Define a grid search
gridsearch = GridSearchCV(estimator=SVM_pipeline,
                          param_grid=parameters,
                          scoring='accuracy',
                          cv=10)

# Fit the training data
gridsearch.fit(X_train, y_train)

results = scoring ((f'SVM'), gridsearch, X_train, X_test, y_train, y_test)
level_2_df = level_2_df._append(results, ignore_index = True)
```

In [148]:
```
level_2_df
```

Out[148]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	knn, k = 21	0.680000	0.566667	0.571429	0.618182	0.671494
1	logreg	0.545455	0.400000	0.428571	0.461538	0.651034
2	dec_tree	0.789474	0.500000	0.612245	0.612245	0.732644
3	SVM	0.590909	0.433333	0.469388	0.500000	0.650805

GNB

In [149]:
```
# Build a pipeline with StandardScaler and Logistic Regression
GNB_pipeline = Pipeline([('ss', StandardScaler()),
                         ('GNB', GaussianNB())])

# Define parameters
parameters = {
    'GNB__priors': [None],
    'GNB__var_smoothing': [0.00000001, 0.000000001, 0.00000001]}

# Define a grid search
gridsearch = GridSearchCV(estimator=GNB_pipeline,
                          param_grid=parameters,
                          scoring='accuracy',
                          cv=10)

# Fit the training data
gridsearch.fit(X_train, y_train)

results = scoring ((f'GNB'), gridsearch, X_train, X_test, y_train, y_test)
level_2_df = level_2_df._append(results, ignore_index = True)
```

In [150]:
```
level_2_df
```

Out[150]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	knn, k = 21	0.680000	0.566667	0.571429	0.618182	0.671494
1	logreg	0.545455	0.400000	0.428571	0.461538	0.651034
2	dec_tree	0.789474	0.500000	0.612245	0.612245	0.732644
3	SVM	0.590909	0.433333	0.469388	0.500000	0.650805
4	GNB	0.700000	0.466667	0.551020	0.560000	0.644368

Nueral Network

In [151]:
```
# Instantiate StandardScaler
scaler = StandardScaler()

# Transform the training and test sets
scaled_data_train = scaler.fit_transform(X_train)
scaled_data_test = scaler.fit_transform(X_test)
```

In [152]:
```
model_1 = Sequential()

#we'll start with 10 neurons, and an input shape of 14
model_1.add(Dense(8, activation='tanh', input_shape=(9,)))
model_1.add(Dense(4, activation='tanh'))
model_1.add(Dense(2, activation='tanh'))

#output classification layer
model_1.add(Dense(1, activation='sigmoid'))
```

In [153]:
```
from keras import optimizers
# Compile the model
model_1.compile(loss='binary_crossentropy', optimizer='sgd', metrics=[tf.keras.
```

In [156]:
```
#fit model
results_1  = model_1.fit(scaled_data_train,
                    y_train,
                    epochs=33,
                    validation_split=0.25)
```

```
Epoch 1/33
4/4 [==============================] - 0s 35ms/step - loss: 0.5363 - binary_a
ccuracy: 0.7706 - val_loss: 0.6707 - val_binary_accuracy: 0.6216
Epoch 2/33
4/4 [==============================] - 0s 16ms/step - loss: 0.5357 - binary_a
ccuracy: 0.7706 - val_loss: 0.6700 - val_binary_accuracy: 0.6216
Epoch 3/33
4/4 [==============================] - 0s 16ms/step - loss: 0.5350 - binary_a
ccuracy: 0.7706 - val_loss: 0.6698 - val_binary_accuracy: 0.6216
Epoch 4/33
4/4 [==============================] - 0s 17ms/step - loss: 0.5345 - binary_a
ccuracy: 0.7706 - val_loss: 0.6698 - val_binary_accuracy: 0.6216
Epoch 5/33
4/4 [==============================] - 0s 19ms/step - loss: 0.5340 - binary_a
ccuracy: 0.7706 - val_loss: 0.6700 - val_binary_accuracy: 0.6216
Epoch 6/33
4/4 [==============================] - 0s 16ms/step - loss: 0.5333 - binary_a
ccuracy: 0.7706 - val_loss: 0.6702 - val_binary_accuracy: 0.6216
Epoch 7/33
4/4 [==============================] - 0s 18ms/step - loss: 0.5328 - binary_a
ccuracy: 0.7706 - val_loss: 0.6700 - val_binary_accuracy: 0.6486
Epoch 8/33
4/4 [==============================] - 0s 18ms/step - loss: 0.5321 - binary_a
ccuracy: 0.7615 - val_loss: 0.6708 - val_binary_accuracy: 0.6216
Epoch 9/33
4/4 [==============================] - 0s 18ms/step - loss: 0.5317 - binary_a
ccuracy: 0.7706 - val_loss: 0.6718 - val_binary_accuracy: 0.6216
Epoch 10/33
4/4 [==============================] - 0s 25ms/step - loss: 0.5313 - binary_a
ccuracy: 0.7706 - val_loss: 0.6724 - val_binary_accuracy: 0.6216
Epoch 11/33
4/4 [==============================] - 0s 24ms/step - loss: 0.5307 - binary_a
ccuracy: 0.7706 - val_loss: 0.6734 - val_binary_accuracy: 0.6216
Epoch 12/33
4/4 [==============================] - 0s 21ms/step - loss: 0.5302 - binary_a
ccuracy: 0.7706 - val_loss: 0.6739 - val_binary_accuracy: 0.6216
Epoch 13/33
4/4 [==============================] - 0s 19ms/step - loss: 0.5295 - binary_a
ccuracy: 0.7706 - val_loss: 0.6744 - val_binary_accuracy: 0.6216
Epoch 14/33
4/4 [==============================] - 0s 21ms/step - loss: 0.5295 - binary_a
ccuracy: 0.7706 - val_loss: 0.6737 - val_binary_accuracy: 0.6216
Epoch 15/33
4/4 [==============================] - 0s 17ms/step - loss: 0.5285 - binary_a
ccuracy: 0.7706 - val_loss: 0.6742 - val_binary_accuracy: 0.6216
Epoch 16/33
4/4 [==============================] - 0s 16ms/step - loss: 0.5281 - binary_a
ccuracy: 0.7706 - val_loss: 0.6747 - val_binary_accuracy: 0.6486
Epoch 17/33
4/4 [==============================] - 0s 19ms/step - loss: 0.5276 - binary_a
ccuracy: 0.7706 - val_loss: 0.6751 - val_binary_accuracy: 0.6486
Epoch 18/33
4/4 [==============================] - 0s 18ms/step - loss: 0.5272 - binary_a
ccuracy: 0.7706 - val_loss: 0.6753 - val_binary_accuracy: 0.6486
Epoch 19/33
4/4 [==============================] - 0s 23ms/step - loss: 0.5267 - binary_a
ccuracy: 0.7706 - val_loss: 0.6755 - val_binary_accuracy: 0.6486
```

```
Epoch 20/33
4/4 [==============================] - 0s 17ms/step - loss: 0.5263 - binary_a
ccuracy: 0.7706 - val_loss: 0.6760 - val_binary_accuracy: 0.6486
Epoch 21/33
4/4 [==============================] - 0s 16ms/step - loss: 0.5259 - binary_a
ccuracy: 0.7706 - val_loss: 0.6756 - val_binary_accuracy: 0.6486
Epoch 22/33
4/4 [==============================] - 0s 15ms/step - loss: 0.5253 - binary_a
ccuracy: 0.7706 - val_loss: 0.6759 - val_binary_accuracy: 0.6486
Epoch 23/33
4/4 [==============================] - 0s 18ms/step - loss: 0.5251 - binary_a
ccuracy: 0.7706 - val_loss: 0.6779 - val_binary_accuracy: 0.6486
Epoch 24/33
4/4 [==============================] - 0s 18ms/step - loss: 0.5245 - binary_a
ccuracy: 0.7798 - val_loss: 0.6773 - val_binary_accuracy: 0.6486
Epoch 25/33
4/4 [==============================] - 0s 22ms/step - loss: 0.5239 - binary_a
ccuracy: 0.7798 - val_loss: 0.6777 - val_binary_accuracy: 0.6486
Epoch 26/33
4/4 [==============================] - 0s 16ms/step - loss: 0.5236 - binary_a
ccuracy: 0.7798 - val_loss: 0.6776 - val_binary_accuracy: 0.6486
Epoch 27/33
4/4 [==============================] - 0s 15ms/step - loss: 0.5231 - binary_a
ccuracy: 0.7798 - val_loss: 0.6789 - val_binary_accuracy: 0.6486
Epoch 28/33
4/4 [==============================] - 0s 16ms/step - loss: 0.5225 - binary_a
ccuracy: 0.7890 - val_loss: 0.6791 - val_binary_accuracy: 0.6486
Epoch 29/33
4/4 [==============================] - 0s 17ms/step - loss: 0.5222 - binary_a
ccuracy: 0.7890 - val_loss: 0.6793 - val_binary_accuracy: 0.6486
Epoch 30/33
4/4 [==============================] - 0s 18ms/step - loss: 0.5218 - binary_a
ccuracy: 0.7890 - val_loss: 0.6794 - val_binary_accuracy: 0.6486
Epoch 31/33
4/4 [==============================] - 0s 17ms/step - loss: 0.5214 - binary_a
ccuracy: 0.7890 - val_loss: 0.6798 - val_binary_accuracy: 0.6486
Epoch 32/33
4/4 [==============================] - 0s 18ms/step - loss: 0.5211 - binary_a
ccuracy: 0.7890 - val_loss: 0.6803 - val_binary_accuracy: 0.6486
Epoch 33/33
4/4 [==============================] - 0s 50ms/step - loss: 0.5206 - binary_a
ccuracy: 0.7890 - val_loss: 0.6801 - val_binary_accuracy: 0.6486
```

In [157]:
```
results = nn_scoring ('nn', model_1, scaled_data_test, y_test)
level_2_df = level_2_df._append(results, ignore_index = True)
```

```
2/2 [==============================] - 0s 3ms/step
```

In [158]:
```
level_2_df
```

Out[158]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	knn, k = 21	0.680000	0.566667	0.571429	0.618182	0.671494
1	logreg	0.545455	0.400000	0.428571	0.461538	0.651034
2	dec_tree	0.789474	0.500000	0.612245	0.612245	0.732644
3	SVM	0.590909	0.433333	0.469388	0.500000	0.650805
4	GNB	0.700000	0.466667	0.551020	0.560000	0.644368
5	nn	0.636364	0.700000	0.571429	0.666667	n/a

4.3 - Level 3 Algorithms

In [159]:
```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(feature_3, df['weight_loss'
```

KNN

In [160]:
```
results = find_best_knn('knn', X_train, X_test, y_train, y_test)
level_3_df = results
```

Log Reg

In [161]:
```
# Build a pipeline with StandardScaler and Logistic Regression
lr_pipeline = Pipeline([('ss', StandardScaler()),
                        ('LR', LogisticRegression(random_state=42))])

# Define the grid
grid = [{'LR__C': [1, 1E6, 1E12],
         'LR__solver': ['liblinear', 'newton-cg', 'lbfgs', 'sag', 'saga']}]

# Define a grid search
gridsearch = GridSearchCV(estimator=lr_pipeline,
                          param_grid=grid,
                          scoring='accuracy',
                          cv=10)

# Fit the training data
gridsearch.fit(X_train, y_train)
```

Out[161]:
```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('ss', StandardScaler()),
                                       ('LR',
                                        LogisticRegression(random_state=4
2))]),
             param_grid=[{'LR__C': [1, 1000000.0, 1000000000000.0],
                          'LR__solver': ['liblinear', 'newton-cg', 'lbfgs',
                                         'sag', 'saga']}],
             scoring='accuracy')
```

In [162]:
```
results = scoring ((f'logreg'), gridsearch, X_train, X_test, y_train, y_test)
level_3_df = level_3_df._append(results, ignore_index = True)
```

```
C:\Users\benne\anaconda3\envs\learn-env\lib\site-packages\sklearn\linear_mode
l\_sag.py:352: ConvergenceWarning: The max_iter was reached which means the c
oef_ did not converge
  warnings.warn(
C:\Users\benne\anaconda3\envs\learn-env\lib\site-packages\sklearn\linear_mode
l\_sag.py:352: ConvergenceWarning: The max_iter was reached which means the c
oef_ did not converge
  warnings.warn(
```

Decision Tree

In [163]:
```
# Build a pipeline with StandardScaler and DecisionTree
dt_pipeline = Pipeline([('DT', DecisionTreeClassifier())])

# Define the grid
grid = [{'DT__criterion': ['gini', 'entropy'],
         'DT__max_depth': [2, 3, 4, 5, 6],
         'DT__min_samples_split': [5, 10, 15]}]

# Define a grid search
gridsearch = GridSearchCV(estimator=dt_pipeline,
                          param_grid=grid,
                          scoring='accuracy',
                          cv=5)

# Fit the training data
gridsearch.fit(X_train, y_train)
```

Out[163]:
```
GridSearchCV(cv=5, estimator=Pipeline(steps=[('DT', DecisionTreeClassifier
())]),
             param_grid=[{'DT__criterion': ['gini', 'entropy'],
                          'DT__max_depth': [2, 3, 4, 5, 6],
                          'DT__min_samples_split': [5, 10, 15]}],
             scoring='accuracy')
```

In [164]:
```
results = scoring ((f'dec_tree'), gridsearch, X_train, X_test, y_train, y_test)
level_3_df = level_3_df._append(results, ignore_index = True)
```

SVM

In [165]:
```
# Build a pipeline with StandardScaler and Logistic Regression
SVM_pipeline = Pipeline([('ss', StandardScaler()),
                         ('SVM', svm.SVC(kernel='linear'))])

# Define parameters
parameters = {
    'SVM__coef0': [0.01, 1, 10],
    'SVM__gamma': [0.001, 0.01, 0.1]}

# Define a grid search
gridsearch = GridSearchCV(estimator=SVM_pipeline,
                          param_grid=parameters,
                          scoring='accuracy',
                          cv=10)

# Fit the training data
gridsearch.fit(X_train, y_train)

results = scoring ((f'SVM'), gridsearch, X_train, X_test, y_train, y_test)
level_3_df = level_3_df._append(results, ignore_index = True)
```

GNB

In [166]:
```
# Build a pipeline with StandardScaler and Logistic Regression
GNB_pipeline = Pipeline([('ss', StandardScaler()),
                         ('GNB', GaussianNB())])

# Define parameters
parameters = {
    'GNB__priors': [None],
    'GNB__var_smoothing': [0.00000001, 0.000000001, 0.00000001]}

# Define a grid search
gridsearch = GridSearchCV(estimator=GNB_pipeline,
                          param_grid=parameters,
                          scoring='accuracy',
                          cv=10)

# Fit the training data
gridsearch.fit(X_train, y_train)

results = scoring ((f'GNB'), gridsearch, X_train, X_test, y_train, y_test)
level_3_df = level_3_df._append(results, ignore_index = True)
```

In [167]:
```
level_3_df
```

Out[167]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	knn, k = 7	0.750000	0.400000	0.551020	0.521739	0.685747
1	logreg	0.789474	0.500000	0.612245	0.612245	0.692644
2	dec_tree	0.800000	0.533333	0.632653	0.640000	0.603448
3	SVM	0.714286	0.500000	0.571429	0.588235	0.664828
4	GNB	0.736842	0.466667	0.571429	0.571429	0.630345

Neural Network

In [168]:
```
# Instantiate StandardScaler
scaler = StandardScaler()

# Transform the training and test sets
scaled_data_train = scaler.fit_transform(X_train)
scaled_data_test = scaler.fit_transform(X_test)
```

In [169]:
```
model_1 = Sequential()

#we'll start with 8-4-2 neurons, and an input shape of 15
model_1.add(Dense(8, activation='tanh', input_shape=(15,)))
model_1.add(Dense(4, activation='tanh'))
model_1.add(Dense(2, activation='tanh'))

#output classification layer
model_1.add(Dense(1, activation='sigmoid'))
```

In [170]:
```
from keras import optimizers
# Compile the model
model_1.compile(loss='binary_crossentropy', optimizer='sgd', metrics=[tf.keras.
```

In [171]:
```
#fit model
results_1  = model_1.fit(scaled_data_train,
                         y_train,
                         epochs=50,
                         validation_split=0.25)
```

```
Epoch 1/50
4/4 [==============================] - 1s 84ms/step - loss: 0.9377 - binary
_accuracy: 0.4220 - val_loss: 0.8836 - val_binary_accuracy: 0.4324
Epoch 2/50
4/4 [==============================] - 0s 17ms/step - loss: 0.9243 - binary
_accuracy: 0.4312 - val_loss: 0.8741 - val_binary_accuracy: 0.4595
Epoch 3/50
4/4 [==============================] - 0s 18ms/step - loss: 0.9099 - binary
_accuracy: 0.4404 - val_loss: 0.8648 - val_binary_accuracy: 0.4595
Epoch 4/50
4/4 [==============================] - 0s 17ms/step - loss: 0.8972 - binary
_accuracy: 0.4495 - val_loss: 0.8564 - val_binary_accuracy: 0.4595
Epoch 5/50
4/4 [==============================] - 0s 19ms/step - loss: 0.8861 - binary
_accuracy: 0.4312 - val_loss: 0.8488 - val_binary_accuracy: 0.4595
Epoch 6/50
4/4 [==============================] - 0s 19ms/step - loss: 0.8752 - binary
_accuracy: 0.4312 - val_loss: 0.8419 - val_binary_accuracy: 0.4865
Epoch 7/50
```

In [172]:
```
results = nn_scoring ('nn', model_1, scaled_data_test, y_test)
level_3_df = level_3_df._append(results, ignore_index = True)
```

```
2/2 [==============================] - 0s 4ms/step
```

In [173]:
```
level_3_df
```

Out[173]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc
0	knn, k = 7	0.750000	0.400000	0.551020	0.521739	0.685747
1	logreg	0.789474	0.500000	0.612245	0.612245	0.692644
2	dec_tree	0.800000	0.533333	0.632653	0.640000	0.603448
3	SVM	0.714286	0.500000	0.571429	0.588235	0.664828
4	GNB	0.736842	0.466667	0.571429	0.571429	0.630345
5	nn	0.560000	0.466667	0.448980	0.509091	n/a

Algorithms Complete

We have successfully run through our algorithms. It's now time to select our best model.

5 Model Evaluation

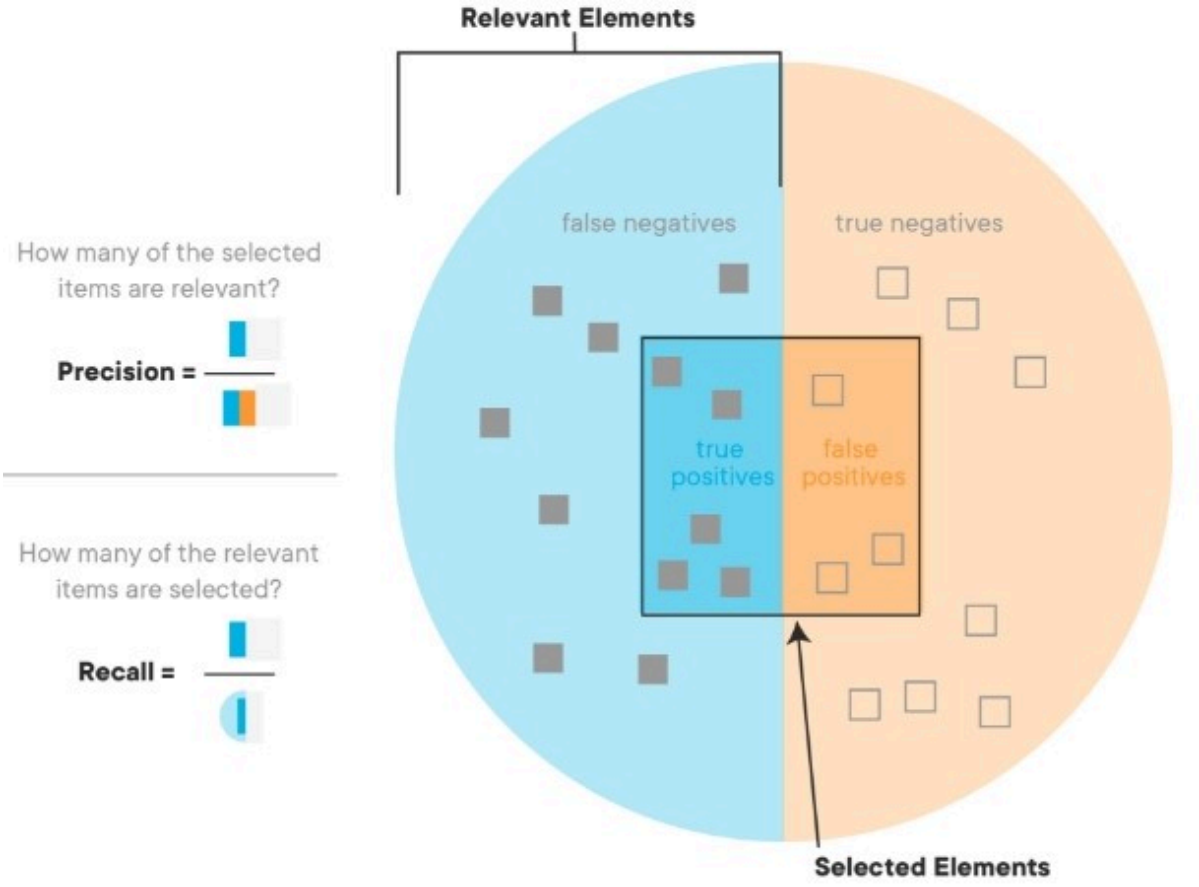
We have performed a preliminary review of our feature segmentation with various models. To select the best model to use, we'll consider two factors.

1. Precision

This reflects the strength of our True Positives. Which is what we care about, right? We want to predict for our end-users the best chance of losing weight. We care less about considering ALL of the ways they can lose weight, and want to focus on SURE FIRE way - True Positives. Are we will to sacrifice some instances where weight loss occured? Sure For instance, do we care about False Negatives? So precision is a good metric for this.

2. Accuracy

As a secondary consideration, accuracy is important. It measures both True Positives and True Negatives. It's helpful to provide certainty for both how to LOSE weight and how to GAIN weight. However, this is really secondary to the goal.



Let's combine the results of all 3 into one table, then we will evaluate for Precision and Accuracy.

In [174]:
```
#combine evaluation tables into 1
level_1_df['features'] = '1'
level_2_df['features'] = '2'
level_3_df['features'] = '3'

total_df = pd.concat([level_1_df, level_2_df, level_3_df], axis = 0)
```

In [175]:
```
#let's look at the top models, sorting by Precision
precision = total_df.sort_values('Precision', ascending = False).head(5)
precision
```

Out[175]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc	features
2	dec_tree	0.800000	0.533333	0.632653	0.640000	0.603448	3
2	dec_tree	0.789474	0.500000	0.612245	0.612245	0.732644	2
1	logreg	0.789474	0.500000	0.612245	0.612245	0.692644	3
0	knn, k = 7	0.750000	0.400000	0.551020	0.521739	0.685747	3
3	dec_tree	0.736842	0.466667	0.571429	0.571429	0.69908	1

Interesting. Both of our decision Tree odels provided the best Precision, while sacrificing Recall, or False Negatives. Let's look at accuracy.

In [176]:
```
#let's look at the top models, sorting by Precision
accuracy = total_df.sort_values('Accuracy', ascending = False).head(5)
accuracy
```

Out[176]:

	Model	Precision	Recall	Accuracy	F1	Cross-Val-Acc	features
2	dec_tree	0.800000	0.533333	0.632653	0.640000	0.603448	3
2	dec_tree	0.789474	0.500000	0.612245	0.612245	0.732644	2
2	logreg	0.703704	0.633333	0.612245	0.666667	0.685057	1
4	GNB	0.703704	0.633333	0.612245	0.666667	0.712414	1
6	NN	0.689655	0.666667	0.612245	0.677966	n/a	1

Both of our decision tree models are in the top 5. With our decision tree model for feature 3 having the best accuracy at 63%. This is an improvement of nearly 20% of our random model. Let's dig in to our Decision Tree.

5.1 Evaluation and Decision Tree Fine Tuning

Now let's perform some fine tuning on our Decision Tree. Let's bring back our best performing tree and take a deeper look.

5.1.1 Review Decision Tree at Feature 3.

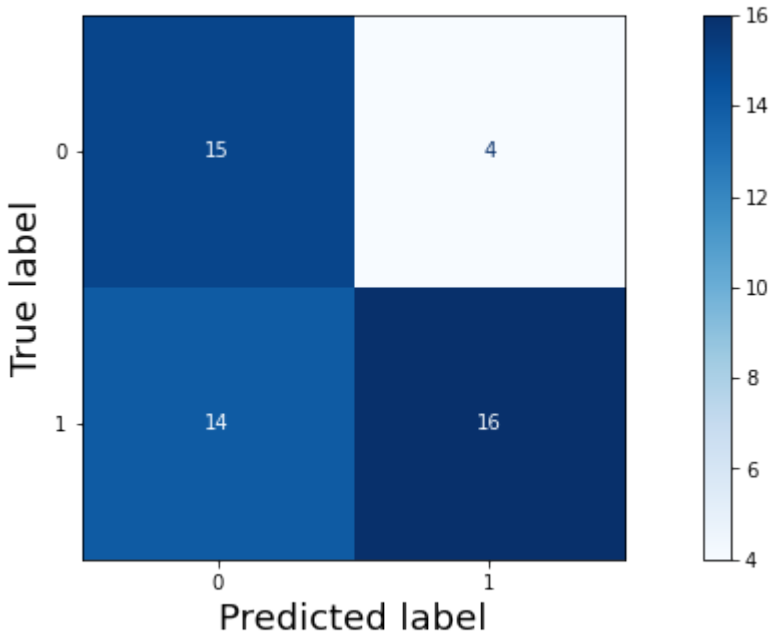
In [223]:
```
# Split the data
X_train_3, X_test_3, y_train_3, y_test_3 = train_test_split(feature_3, df['weig
```

In [250]:
```
# Build a pipeline with StandardScaler and DecisionTree
dt_pipeline_3 = Pipeline([('DT_3', DecisionTreeClassifier())])

# Define the grid
grid = [{'DT_3__criterion': ['gini', 'entropy'],
         'DT_3__max_depth': [2, 3, 4, 5, 6],
         'DT_3__min_samples_split': [5, 10, 15]}]

# Define a grid search
gridsearch_3 = GridSearchCV(estimator=dt_pipeline_3,
                            param_grid=grid,
                            scoring='accuracy',
                            cv=5)

# Fit the training data
gridsearch_3.fit(X_train_3, y_train_3)
print("Best Parameters: \n{}\n".format(gridsearch_3.best_params_))
```

```
Best Parameters:
{'DT_3__criterion': 'entropy', 'DT_3__max_depth': 4, 'DT_3__min_samples_spli
t': 15}
```

In [251]:
```
preds = gridsearch_3.predict(X_test_3)

cnf = confusion_matrix(y_test_3, preds)

disp = ConfusionMatrixDisplay(confusion_matrix=cnf)
disp.plot(cmap=plt.cm.Blues)
```

Out[251]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1de216627
f0>
```



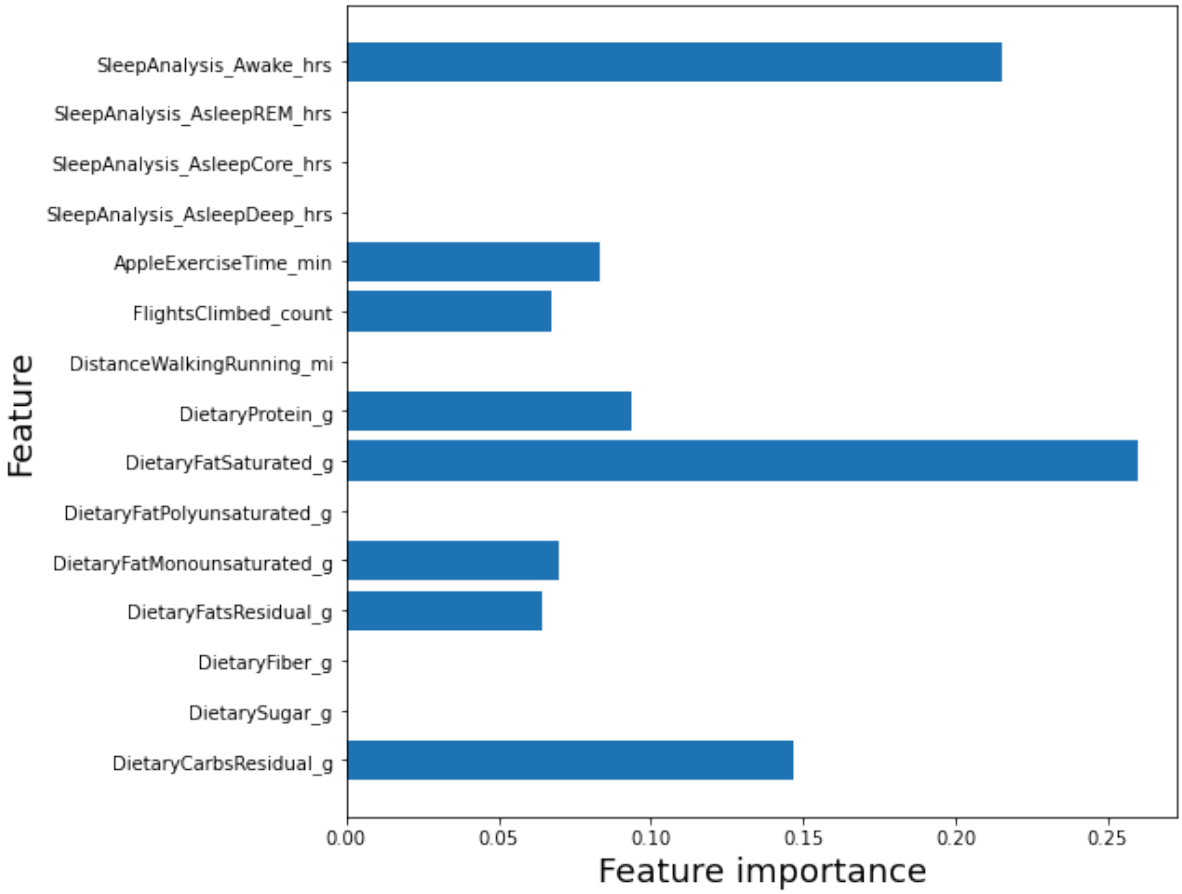
We can see a very strong precision. Of 20 predicted weight loss days, we predicted 16 correctly. Let's review the leafs.

In [226]:
```
DT_3 = DecisionTreeClassifier(criterion='entropy', max_depth = 4, min_samples_s
DT_3.fit(X_train_3, y_train_3)
```

Out[226]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=4, min_samples_split=1
5)
```

Let's look at the feature importance.

In [227]:
```
def plot_feature_importances(model):
    n_features = X_train_3.shape[1]
    plt.figure(figsize=(8,8))
    plt.barh(range(n_features), model.feature_importances_, align='center')
    plt.yticks(np.arange(n_features), X_train_3.columns.values)
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')

plot_feature_importances(DT_3)
```



We have Saturated Fat as greatest feature importance, let's look at other model for feature 2 and see results.

5.1.2 Review Decision Tree at Feature 2.

In [228]:
```
# Split the data
X_train_2, X_test_2, y_train_2, y_test_2 = train_test_split(feature_2, df['weig
```

In [255]:
```
# Build a pipeline with StandardScaler and DecisionTree
dt_pipeline_2 = Pipeline([('DT_2', DecisionTreeClassifier())])

# Define the grid
grid = [{'DT_2__criterion': ['gini', 'entropy'],
         'DT_2__max_depth': [2, 3, 4, 5, 6],
         'DT_2__min_samples_split': [5, 10, 15]}]

# Define a grid search
gridsearch_2 = GridSearchCV(estimator=dt_pipeline_2,
                            param_grid=grid,
                            scoring='accuracy',
                            cv=5)

# Fit the training data
gridsearch_2.fit(X_train_2, y_train_2)
print("Best Parameters: \n{}\n".format(gridsearch_2.best_params_))
```

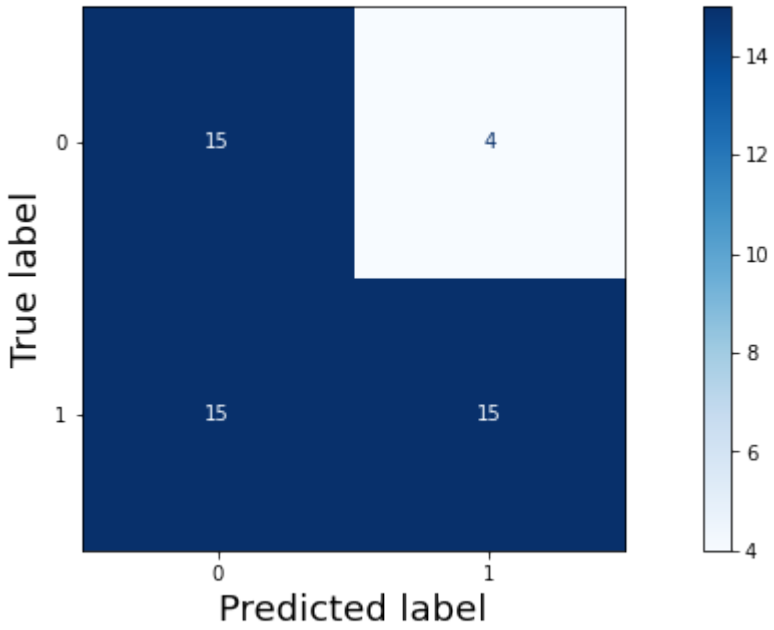
```
Best Parameters:
{'DT_2__criterion': 'gini', 'DT_2__max_depth': 2, 'DT_2__min_samples_split':
5}
```

In [256]:
```
DT_2 = DecisionTreeClassifier(criterion='gini', max_depth = 2, min_samples_spli
DT_2.fit(X_train_2, y_train_2)
```

Out[256]:
```
DecisionTreeClassifier(max_depth=2, min_samples_split=5)
```

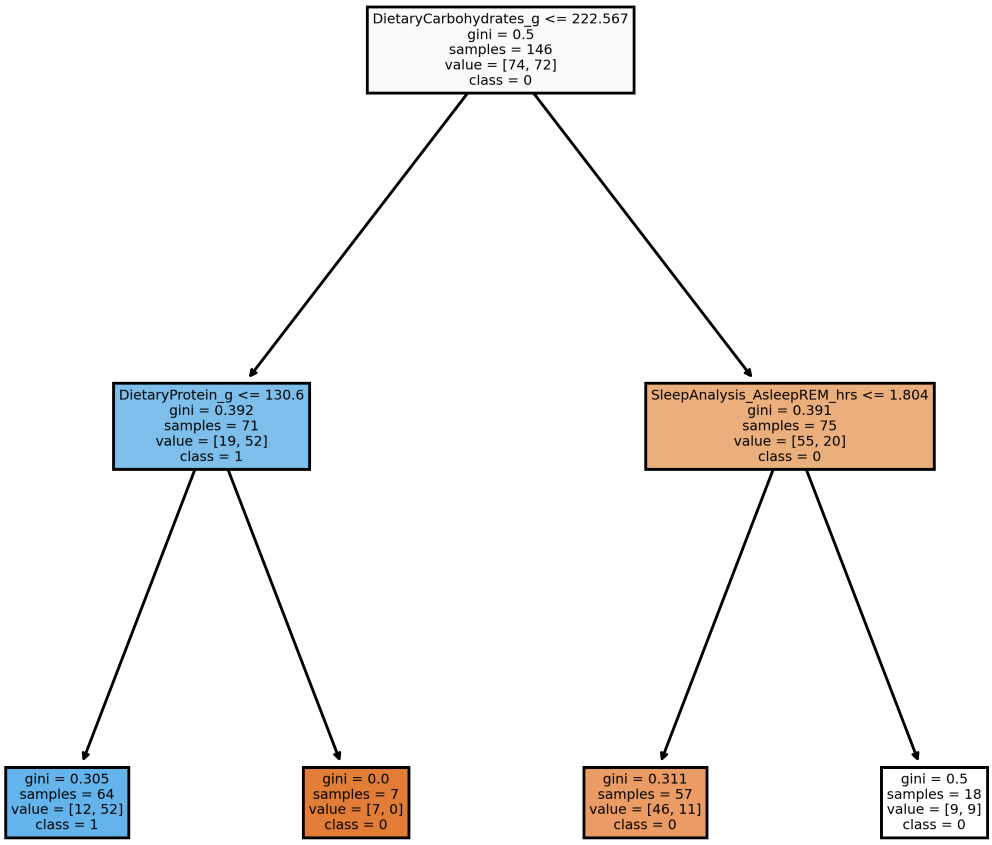
In [257]:
```
preds = gridsearch_2.predict(X_test_2)

cnf = confusion_matrix(y_test_2, preds)

disp = ConfusionMatrixDisplay(confusion_matrix=cnf)
disp.plot(cmap=plt.cm.Blues)
```

Out[257]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1de239d4f
d0>
```

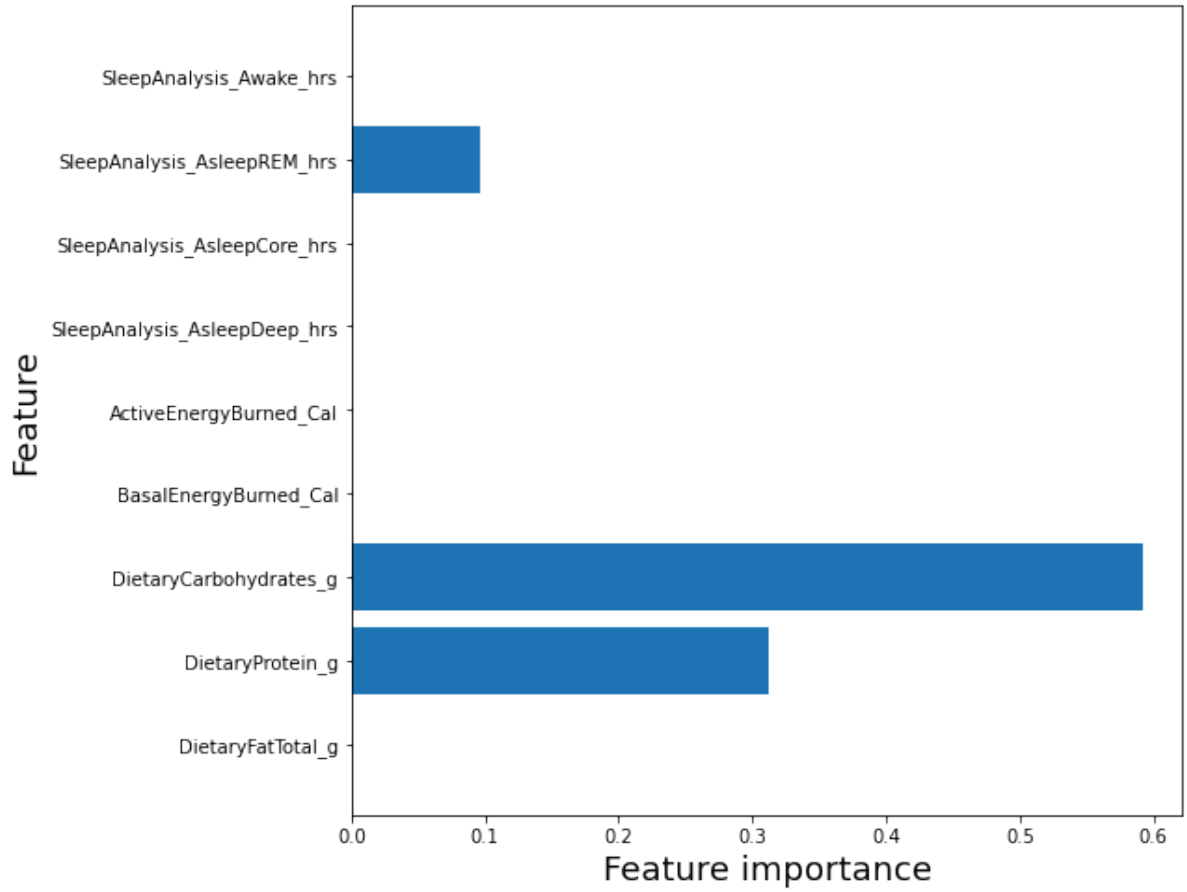


So we can see that our precision went down slightly 15 out of 19 correct predictions, but only because we predicted on less. Let's look at the leafs>

In [258]:
```
from sklearn import tree
fig, axes = plt.subplots(nrows = 1,ncols = 1, figsize = (7,7), dpi=500)
tree.plot_tree(DT_2,
               feature_names = X_train_2.columns,
               class_names=np.unique(y_train_2).astype('str'),
               filled = True)
plt.show()
```



In [259]:
```
def plot_feature_importances(model):
    n_features = X_train_2.shape[1]
    plt.figure(figsize=(8,8))
    plt.barh(range(n_features), model.feature_importances_, align='center')
    plt.yticks(np.arange(n_features), X_train_2.columns.values)
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')

plot_feature_importances(DT_2)
```



THis is fascinating. In this particular model, when less Dietary Carbohydrates than 222.5 g were consumed, 73% of the days there was wieght loss the next day. When above, 73% of the next days experienced weight gains. That's regardless of any other considerations! That one factor alone is staggering.

RECOMMENDATION #1 - Carbs

Utilize decision tree model with Dietary Carbohydrate Split. We'll delve into this one a little deeper.

Now let's see what happens when we combined this data with our Feature 3 data.

5.1.2 Review Decision Tree with both Feature 2 & Feature 3.

In [260]:
```
feature_2_3 = pd.concat([feature_2, df[level_3_diet_carbs], df[level_3_diet_fat
feature_2_3
```

Out[260]:

date	DietaryFatTotal_g	DietaryProtein_g	DietaryCarbohydrates_g	BasalEnergyBurned_Cal	Active
2023-08-24	159.7455	166.7683	405.4413	2055.322	
2023-08-25	62.9275	106.1325	152.7750	2174.950	
2023-08-26	118.3000	113.6000	219.5000	2074.476	
2023-08-27	79.9300	125.8100	170.3400	2187.383	
2023-08-28	70.8500	121.2500	210.4000	2186.244	
...	...	...	...	...	
2024-03-01	94.9000	71.3000	319.0000	2004.932	
2024-03-02	76.2000	79.3000	225.7000	2048.925	
2024-03-03	59.9000	108.7000	239.3000	2048.189	
2024-03-04	87.7000	73.3000	302.8000	1983.933	
2024-03-05	88.6000	118.5000	183.3000	2009.083	

195 rows × 16 columns

In [261]:
```
# Split the data
X_train_2_3, X_test_2_3, y_train_2_3, y_test_2_3 = train_test_split(feature_2_3
```

To get a depth of response, I'm going to raise the ceiling of the max_depth. Let's see if we can get some additional information.

In [267]:
```
# Build a pipeline with StandardScaler and DecisionTree
dt_pipeline_2_3 = Pipeline([('DT_2_3', DecisionTreeClassifier())])

# Define the grid
grid = [{'DT_2_3__criterion': ['gini', 'entropy'],
         'DT_2_3__max_depth': [3, 4, 5, 6],
         'DT_2_3__min_samples_split': [5, 10, 15]}]

# Define a grid search
gridsearch_2_3 = GridSearchCV(estimator=dt_pipeline_2_3,
                              param_grid=grid,
                              scoring='accuracy',
                              cv=5)

# Fit the training data
gridsearch_2_3.fit(X_train_2_3, y_train_2_3)
print("Best Parameters: \n{}\n".format(gridsearch_2_3.best_params_))
```

```
Best Parameters:
{'DT_2_3__criterion': 'entropy', 'DT_2_3__max_depth': 3, 'DT_2_3__min_samples
_split': 5}
```

In [ ]:
```
```

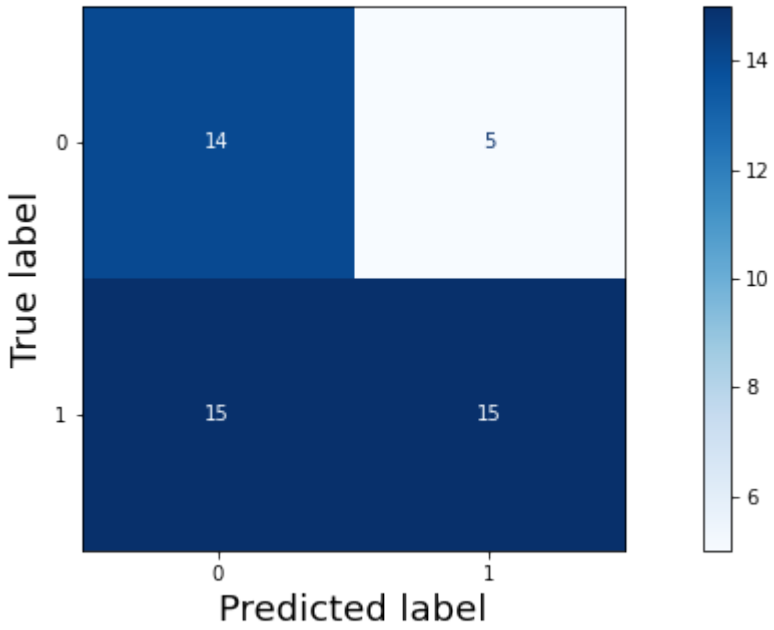
So... it appears that our precision went down, to 75%. Our accuracy drops slightly, but not by much. Let's look at the leafs.

In [268]:
```
DT_2_3 = DecisionTreeClassifier(criterion='entropy', max_depth = 3, min_samples
DT_2_3.fit(X_train_2_3, y_train_2_3)
```

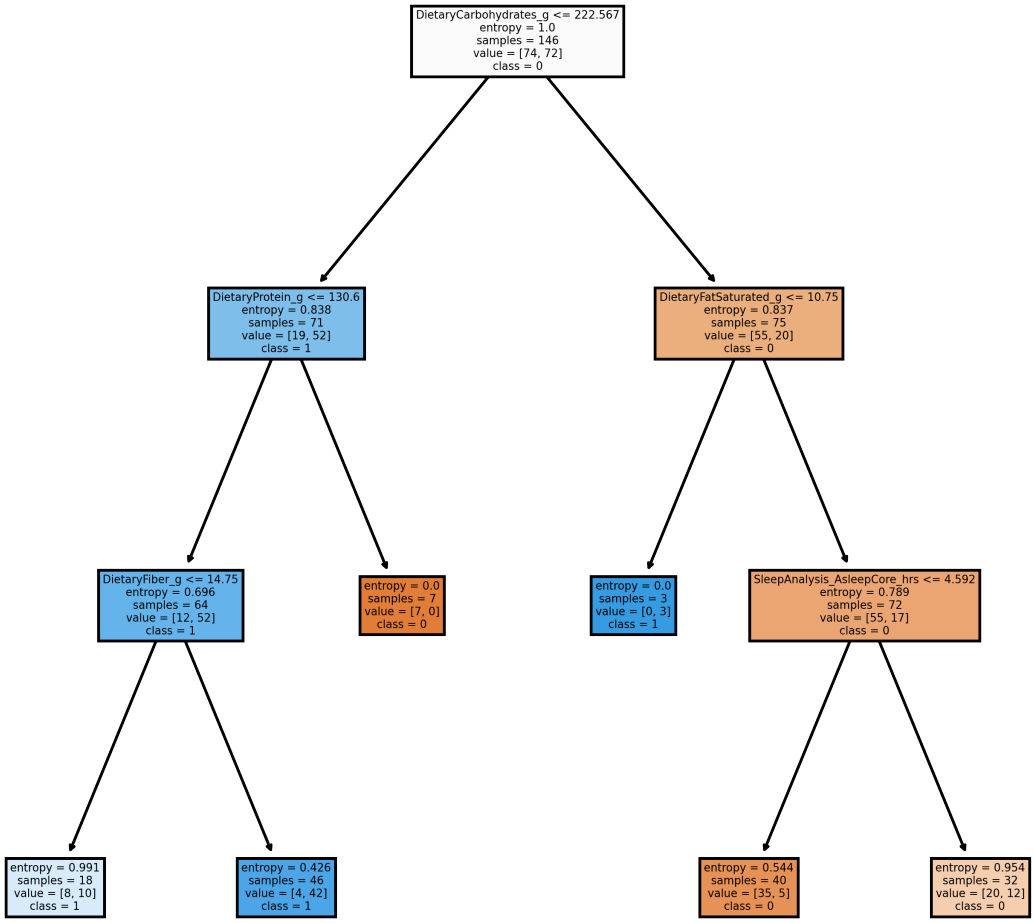
Out[268]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=3, min_samples_split=5)
```

In [269]:
```
preds = DT_2_3.predict(X_test_2_3)

cnf = confusion_matrix(y_test_2_3, preds)

disp = ConfusionMatrixDisplay(confusion_matrix=cnf)
disp.plot(cmap=plt.cm.Blues)
```

Out[269]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1de18a447
30>
```



In [270]:
```
from sklearn import tree
fig, axes = plt.subplots(nrows = 1,ncols = 1, figsize = (7,7), dpi=500)
tree.plot_tree(DT_2_3,
               feature_names = X_train_2_3.columns,
               class_names=np.unique(y_train_2_3).astype('str'),
               filled = True)
plt.show()
```



This is fascinating. It appears that the fiber we have contributes to weight loss.

RECOMMENDATION #2 - Carbs & Fiber.

In fact, days where we are under our Carb threshold, but have a minimum of 14.75 grams of Fiber, we are experience weight loss 42 out of 53 days. That's nearly 80% We'll touch on this more in the Results Section

In [201]:
```
from scipy.stats import percentileofscore

percentile_of_protein = percentileofscore(df['DietaryProtein_g'], 121)
print(percentile_of_protein)
```

```
83.58974358974359
```

In [202]:
```
percentile_of_protein = percentileofscore(df['DietaryCarbohydrates_g'], 222.5)
print(percentile_of_protein)
```

```
47.17948717948718
```

As we can see, 222.5 grams of Carbohydrates is the 47% percentile. Basically the median. This thresholds splits our data nearly evenly, with fairly strong results after that.

The protein threshold is really high, and after our carbs split, only accounts for 11 samples, 8 of which are weight gains.

On the weight loss side, a lack of Core Sleep turns out to lead to certain weight loss. Let's see what the data looks like with sleep combined.

5.1.4 Review Decision Tree with both Feature 2 & Feature 3, but combined Sleep.

In [271]:
```
feature_sleep = pd.concat([df[level_2_diet + level_2_exer], df[level_3_diet_car
```

In [272]:
```
# Split the data
X_train_sleep, X_test_sleep, y_train_sleep, y_test_sleep = train_test_split(fea
```

In [277]:
```
# Build a pipeline with StandardScaler and DecisionTree
dt_pipeline_sleep = Pipeline([('DT_sleep', DecisionTreeClassifier())])

# Define the grid
grid = [{'DT_sleep__criterion': ['gini', 'entropy'],
         'DT_sleep__max_depth': [3, 4, 5, 6],
         'DT_sleep__min_samples_split': [5, 10, 15]}]

# Define a grid search
gridsearch_sleep = GridSearchCV(estimator=dt_pipeline_sleep,
                          param_grid=grid,
                          scoring='accuracy',
                          cv=5)

# Fit the training data
gridsearch_sleep.fit(X_train_sleep, y_train_sleep)
print("Best Parameters: \n{}\n".format(gridsearch_sleep.best_params_))
```

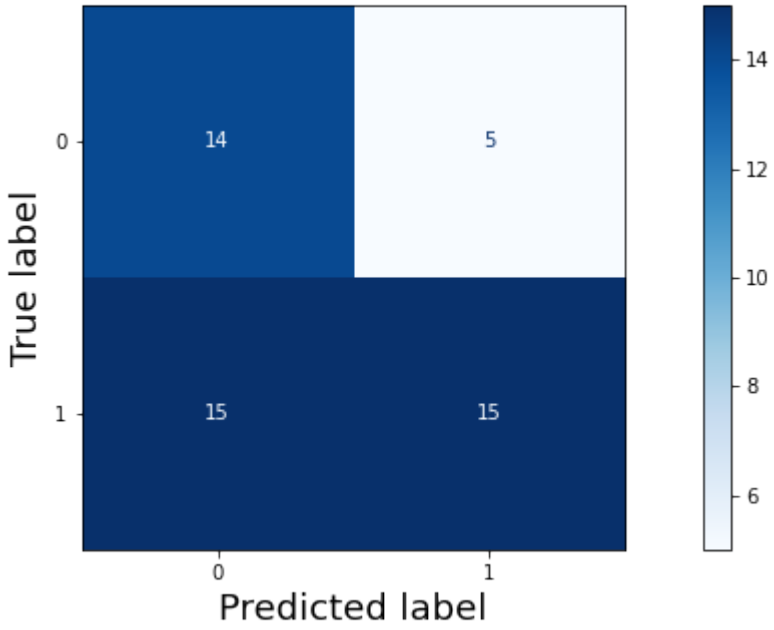
```
Best Parameters:
{'DT_sleep__criterion': 'entropy', 'DT_sleep__max_depth': 3, 'DT_sleep__min_s
amples_split': 5}
```

In [278]:
```
DT_sleep = DecisionTreeClassifier(criterion='gini', max_depth = 3, min_samples_
DT_sleep.fit(X_train_sleep, y_train_sleep)
```

Out[278]:
```
DecisionTreeClassifier(max_depth=3, min_samples_split=5)
```

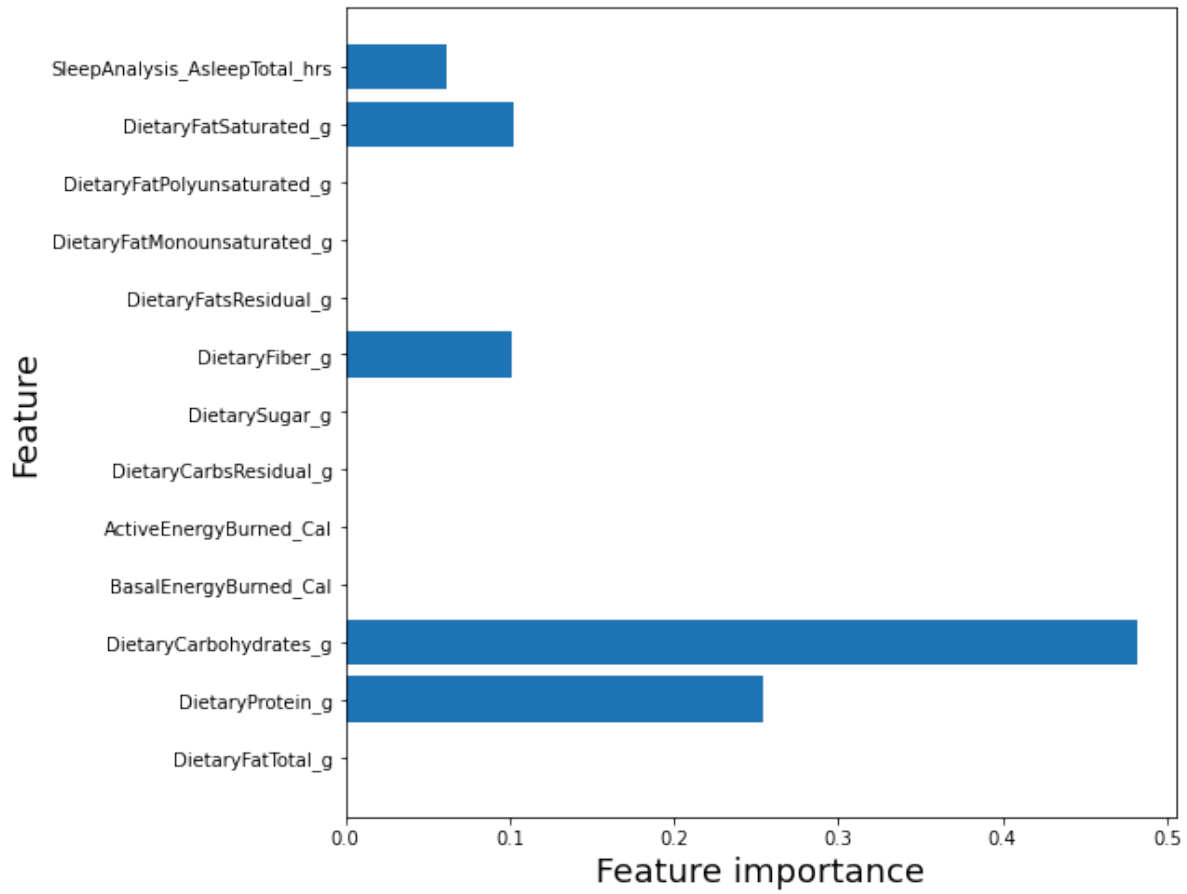
In [279]:
```
preds = DT_sleep.predict(X_test_sleep)

cnf = confusion_matrix(y_test_sleep, preds)

disp = ConfusionMatrixDisplay(confusion_matrix=cnf)
disp.plot(cmap=plt.cm.Blues)
```

Out[279]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1de1b29b2
80>
```

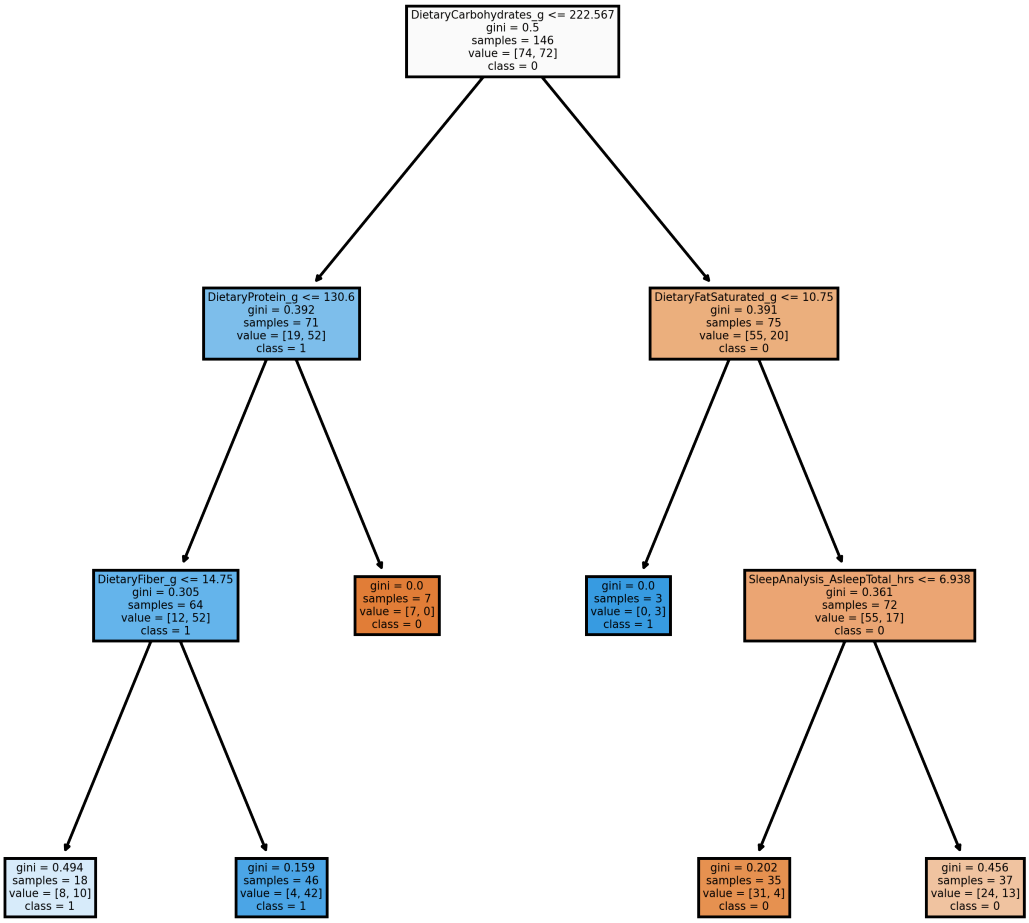


So, we have still sacrificed some precision. We're at 75%. This is the difference of 1 or 2 predictions. Let's look at the leafs

In [280]:
```
def plot_feature_importances(model):
    n_features = X_train_sleep.shape[1]
    plt.figure(figsize=(8,8))
    plt.barh(range(n_features), model.feature_importances_, align='center')
    plt.yticks(np.arange(n_features), X_train_sleep.columns.values)
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')

plot_feature_importances(DT_sleep)
```



In [249]:
```
from sklearn import tree
fig, axes = plt.subplots(nrows = 1,ncols = 1, figsize = (7,7), dpi=500)
tree.plot_tree(DT_sleep,
               feature_names = X_train_sleep.columns,
               class_names=np.unique(y_train_sleep).astype('str'),
               filled = True)
plt.show()
```



Recommendation #3 - Sleep, When carbs are over 121g.

When over the Carb limit, getting less than 7 hours of sleep almost guarantees weight gain, with it occuring 31 out of 37 instances.

5.2 Three Recommendations - Key Findings

Based on our preliminary modeling iterations, we selected the Decision Tree model to fine tune. We reviewed a few different versions of it, but ultimately decided on a model that had a precision of 75%, which was slightly lower than the version that we tested in the previous section (80%).

This is because of the findings associate with the model led to strong predictors of both weight gain and weight loss utilizing only a few key variables. We will review them here.

5.2.1 The Carb Number

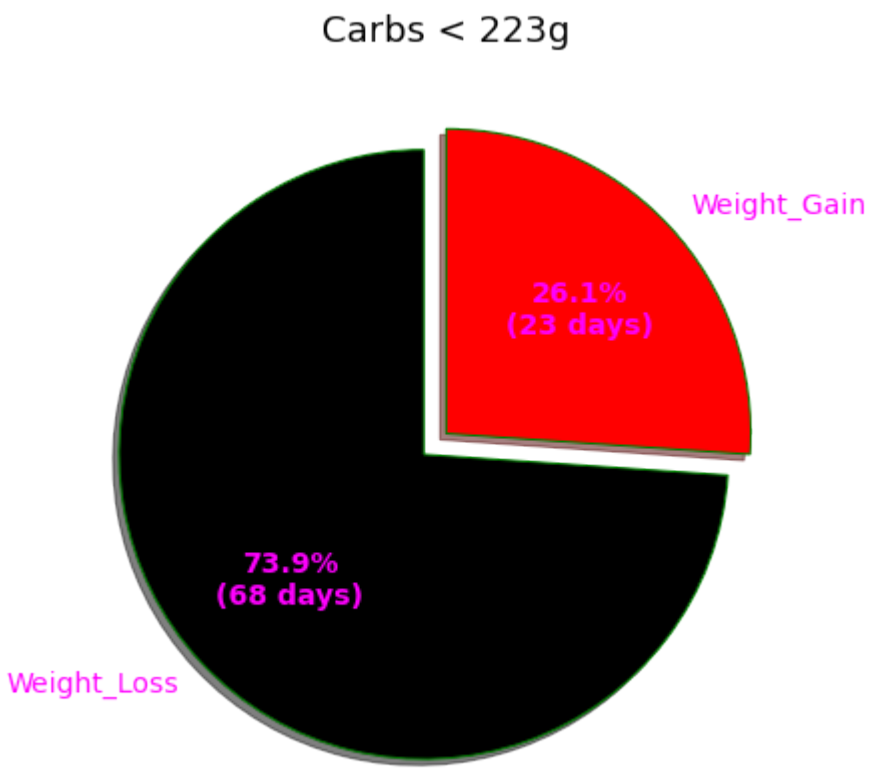
Best on the Decision Tree model where we account for Total Carbs, this number had a impactful effect on whether a person experience next day weight loss. To illustrate this, let's generate a few pie charts.

In [281]:
```
#create multiple arrays containing the tallies of the weight loss and weight ga
carb_under_loss = df[(df['DietaryCarbohydrates_g'] < 222.567) & (df['weight_los
carb_under_gain = df[(df['DietaryCarbohydrates_g'] < 222.567) & (df['weight_los
carb_over_loss = df[(df['DietaryCarbohydrates_g'] > 222.567) & (df['weight_loss
carb_over_gain = df[(df['DietaryCarbohydrates_g'] > 222.567) & (df['weight_loss

carb_over = [carb_over_loss, carb_over_gain]
carb_under = [carb_under_loss, carb_under_gain]
```

In [282]:
```
carb_under
```

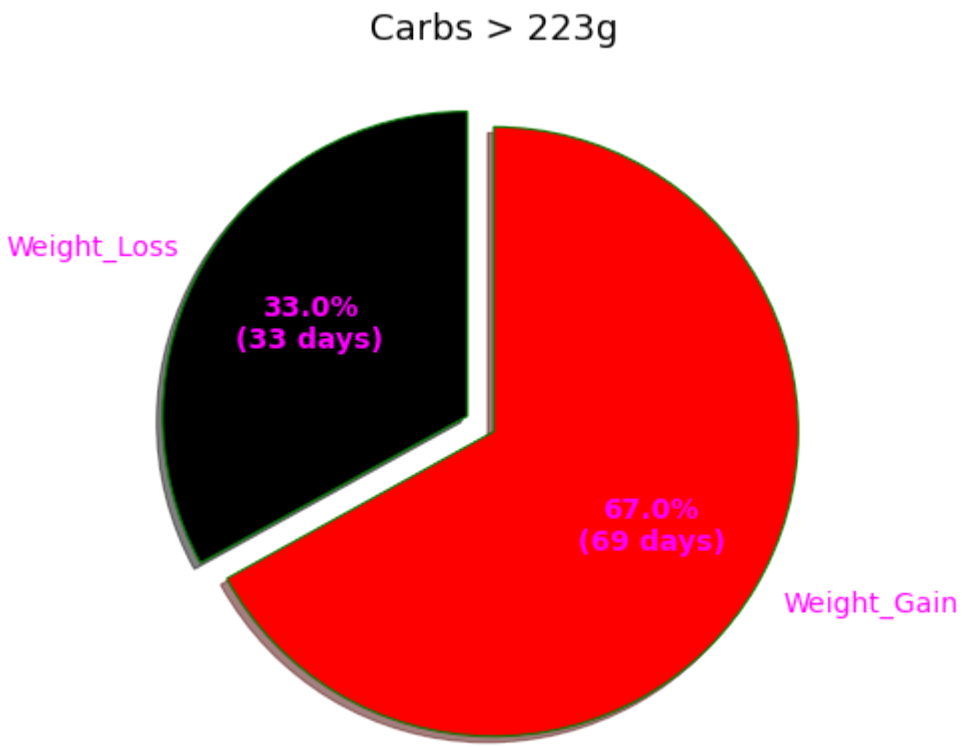
Out[282]:
```
[68, 24]
```

In [286]:
```
# Creating explode data
explode = (0.1, 0.0)

# Creating color parameters
colors = ("black", "red")

# Wedge properties
wp = {'linewidth': 1, 'edgecolor': "green"}

# Creating autocpt arguments


def func(pct, allvalues):
    absolute = int(pct / 100.*np.sum(allvalues))
    return "{:.1f}%\n({:d} days)".format(pct, absolute)


# Creating plot
fig, ax = plt.subplots(figsize=(10, 7))
wedges, texts, autotexts = ax.pie(carb_under,
                                  autopct=lambda pct: func(pct, carb_under),
                                  explode=explode,
                                  labels=['Weight_Loss', 'Weight_Gain'],
                                  shadow=True,
                                  colors=colors,
                                  startangle=90,
                                  wedgeprops=wp,
                                  textprops=dict(color="magenta", size=14))

plt.setp(autotexts, size=14, weight="bold")
ax.set_title(f'Carbs < 223g')

# show plot
plt.show()
```



As you can see, this single factor alone corresponds to experiencing next day weight loss. And it also applies for weight gain.

In [288]:
```
# Creating plot
fig, ax = plt.subplots(figsize=(10, 7))
wedges, texts, autotexts = ax.pie(carb_over,
                                  autopct=lambda pct: func(pct, carb_over),
                                  explode=explode,
                                  labels=['Weight_Loss', 'Weight_Gain'],
                                  shadow=True,
                                  colors=colors,
                                  startangle=90,
                                  wedgeprops=wp,
                                  textprops=dict(color="magenta", size=14))

plt.setp(autotexts, size=14, weight="bold")
ax.set_title(f'Carbs > 223g')

# show plot
plt.show()
```



5.2.1 Lack of Sleep and Weight Gain

It turns out that the lack of sleep may aid in weight gain! On days when the carb threshold was exceeded, getting less than 7 hours of sleep corresponding with nearly 80% occurrences of weight gain days.

In [289]:
```
##create multiple arrays containing the tallies of the weight loss and weight g
carb_over_sleep_loss = df[(df['DietaryCarbohydrates_g'] > 222.567) & (df['Sleep
carb_over_sleep_gain = df[(df['DietaryCarbohydrates_g'] > 222.567) & (df['Sleep
carb_over_sleep = [carb_over_sleep_loss, carb_over_sleep_gain]
```

In [290]:
```
# Creating plot
fig, ax = plt.subplots(figsize=(10, 7))
wedges, texts, autotexts = ax.pie(carb_over_sleep,
                                  autopct=lambda pct: func(pct, carb_over_sleep
                                  explode=explode,
                                  labels=['Weight_Loss', 'Weight_Gain'],
                                  shadow=True,
                                  colors=colors,
                                  startangle=90,
                                  wedgeprops=wp,
                                  textprops=dict(color="magenta", size=14))

plt.setp(autotexts, size=14, weight="bold")
ax.set_title(f'Carbs > 221g, Sleep < 6.9 hrs')

# show plot
plt.show()
```

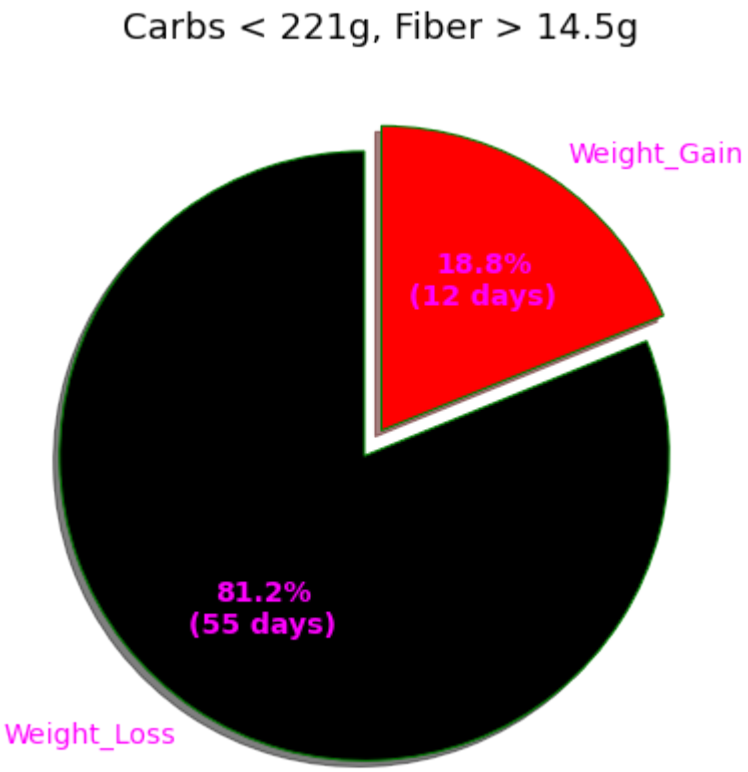
5.2.3 Fiber and Weight Loss

Fiber may help with weight loss. On days below the carb threshold, having a minimum amount of carbs increased next weight loss occurences of up to 81.2%.

In [291]:
```
carb_under_fiber_loss = df[(df['DietaryCarbohydrates_g'] < 222.567) & (df['Diet
carb_under_fiber_gain = df[(df['DietaryCarbohydrates_g'] < 222.567) & (df['Diet
carb_under_fiber = [carb_under_fiber_loss, carb_under_fiber_gain]
carb_under_fiber
```

Out[291]:
```
[56, 13]
```

In [292]:
```
# Creating plot
fig, ax = plt.subplots(figsize=(10, 7))
wedges, texts, autotexts = ax.pie(carb_under_fiber,
                                  autopct=lambda pct: func(pct, carb_under_fibe
                                  explode=explode,
                                  labels=['Weight_Loss', 'Weight_Gain'],
                                  shadow=True,
                                  colors=colors,
                                  startangle=90,
                                  wedgeprops=wp,
                                  textprops=dict(color="magenta", size=14))

plt.setp(autotexts, size=14, weight="bold")
ax.set_title(f'Carbs < 221g, Fiber > 14.75g')

# show plot
plt.show()
```



6 Summary

To aid in the struggle to lose weight, this model was able to analyze data and create 3 key finding that could be used to help people reach their goals. Through lifestyle analytics, a user can track their eating over the case of the day and receive notifications about how to course correct. The model utilized a database from apps and devices that was tracking the user's lifestyle analytics. There was also manual data entry to log calories and weigh-in data.

6.1 Modeling

This model surveyed a number of machine learning algorithms to best predict weight loss. A Decision Tree model was utilized as it had the best performance in preliminary testing, with primary emphasis on precision, but also accuracy as a secondary metric. Once the model was selected, it was refined through feature experimentation and model tuning. The model yielded three findings that corresponding with nearly 82% occurences of weight loss, and 79% occurences of weight gain. The model that utilized these findings descreased in precision, but these was due to one additional incorrect prediction in the test data.

6.2 Key Findings

Carbs

The strongest indicator in the model of potential weight loss. When under the carbohydrate threshold (223 g) the user experienced 74% of their weigh-ins the next day showed weight loss. Vice-Versa, when the user was over the threshold (223g), 67% of the weigh-ins next day showed a gain.

Lack of Sleep

Lack of sleep may contribute to weight gain. In instances when the user was over the carbohydrate threshold, and slept less than 6.9hrs, almost 80% of the weigh-ins showed a gain. That's a 12% increase.

Fiber

Having a minimum intake of Fiber could help with weight loss. In instances when the user was under the carbohydrate threshold, and consumed more than 15.75 grams of Fiber, almost 82% of their next day weigh-ins showed a loss. That's an 8% increase over just the carbs.

6.3 Next Steps

Additional Data

We need to continue to refine the model to boost performance. Typically, over 1000 observations are needed to have confidence in a model. We only had 195 observations, nearly 30% of which had gaps in weight data. With more data we can optimize the success we already have.

Test UI Prompts

Recommendations for course correction are only as effective as how the message is delivered. For carb tracking, perhaps the user could monitor their carb intake through the day and receive a notification when intake is high. With Fiber, the user could be pinged at the end of the day if their fiber intake is low. When carb intake increases, the user could be reminded to get enough sleep.

Try Calorie Counting

Increase awareness around calorie counting. It's hard at first but then it becomes second nature. It's very helpful to track what one eats.

In [ ]: