data_cleaning_wrangling

July 9, 2025

1 Data Cleaning and Wrangling Practice

1.0.1 Objectives:

- Load, clean, and explore real-world datasets using Python and pandas.
- Generate insights through descriptive statistics and visualizations.
- Communicate findings effectively via notebooks and charts.
- Apply data analysis skills to a project using a public dataset.

1.0.2 Public dataset source:

Kaggle Food choices and preferences of college students This dataset includes information on food choices, nutrition, preferences, childhood favorites, and other information from college students. There are 126 responses from students. Data is raw and uncleaned.

[48]:
```
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_selection import mutual_info_regression
```

1.1 Discovery: Understanding the data, its structure, and what it contains

[16]:
```
# Establish file path and import data
path = 'food_coded.csv'
data = pd.read_csv(path)

# Look at a snapshot of the data
data.head()
```

[16]:
```
     GPA  Gender  breakfast  calories_chicken  calories_day  calories_scone  \
0    2.4       2          1               430           NaN           315.0
1  3.654       1          1               610           3.0           420.0
2    3.3       1          1               720           4.0           420.0
3    3.2       1          1               430           3.0           420.0
4    3.5       1          1               720           2.0           420.0

   coffee                          comfort_food        comfort_food_reasons  \
0       1                             none       we dont have comfort
1       2         chocolate, chips, ice cream        Stress, bored, anger
2       2   frozen yogurt, pizza, fast food             stress, sadness
3       2  Pizza, Mac and cheese, ice cream                     Boredom
4       2      Ice cream, chocolate, chips   Stress, boredom, cravings

   comfort_food_reasons_coded  …  soup  sports  thai_food tortilla_calories  \
0                         9.0  …   1.0     1.0          1            1165.0
1                         1.0  …   1.0     1.0          2             725.0
2                         1.0  …   1.0     2.0          5            1165.0
3                         2.0  …   1.0     2.0          5             725.0
4                         1.0  …   1.0     1.0          4             940.0

   turkey_calories  type_sports veggies_day  vitamins  waffle_calories  \
0              345   car racing           5         1             1315
1              690  Basketball            4         2              900
2              500         none           5         1              900
3              690          NaN           3         1             1315
4              500     Softball           4         2              760

                 weight
0                   187
1                   155
2  I'm not answering this.
3         Not sure, 240
4                   190

[5 rows x 61 columns]
```

[27]:
```
df.describe()
```

[27]:
```
              GPA      Gender  grade_level  parents_cook      weight  \
count  125.000000  125.000000   125.000000    125.000000  125.000000
mean     3.418936    1.392000     2.376000      1.528000  158.360000
std      0.382553    0.490161     1.133536      0.746778   31.119022
min      2.200000    1.000000     1.000000      1.000000  100.000000
25%      3.200000    1.000000     1.000000      1.000000  135.000000
50%      3.500000    1.000000     2.000000      1.000000  155.000000
75%      3.700000    2.000000     3.000000      2.000000  180.000000
max      4.000000    2.000000     4.000000      5.000000  265.000000

             cook  eating_out  ethnic_food   fruit_day  veggies_day  \
count  125.000000   125.00000   125.000000  125.000000   125.000000
mean     2.792000     2.56000     3.744000    4.224000     4.008000
std      1.026236     1.13876     1.177093    0.923388     1.081337
min      1.000000     1.00000     1.000000    1.000000     1.000000
25%      2.000000     2.00000     3.000000    4.000000     3.000000
```

```
50%      3.000000     2.00000     4.000000     5.000000     4.000000
75%      3.000000     3.00000     5.000000     5.000000     5.000000
max      5.000000     5.00000     5.000000     5.000000     5.000000

       healthy_feeling  self_perception_weight    vitamins  fav_cuisine_coded
count       125.000000              125.000000  125.000000         125.000000
mean          5.456000                3.120000    1.512000           2.424000
std           2.585643                1.111523    0.501867           1.947968
min           1.000000                1.000000    1.000000           0.000000
25%           3.000000                2.000000    1.000000           1.000000
50%           5.000000                3.000000    2.000000           1.000000
75%           8.000000                4.000000    2.000000           4.000000
max          10.000000                6.000000    2.000000           8.000000
```

[9]:
```python
# Preview all the columns and their quantity
print(len(data.columns))
print(data.columns)
```

```
61
Index(['GPA', 'Gender', 'breakfast', 'calories_chicken', 'calories_day',
       'calories_scone', 'coffee', 'comfort_food', 'comfort_food_reasons',
       'comfort_food_reasons_coded', 'cook', 'comfort_food_reasons_coded.1',
       'cuisine', 'diet_current', 'diet_current_coded', 'drink',
       'eating_changes', 'eating_changes_coded', 'eating_changes_coded1',
       'eating_out', 'employment', 'ethnic_food', 'exercise',
       'father_education', 'father_profession', 'fav_cuisine',
       'fav_cuisine_coded', 'fav_food', 'food_childhood', 'fries', 'fruit_day',
       'grade_level', 'greek_food', 'healthy_feeling', 'healthy_meal',
       'ideal_diet', 'ideal_diet_coded', 'income', 'indian_food',
       'italian_food', 'life_rewarding', 'marital_status',
       'meals_dinner_friend', 'mother_education', 'mother_profession',
       'nutritional_check', 'on_off_campus', 'parents_cook', 'pay_meal_out',
       'persian_food', 'self_perception_weight', 'soup', 'sports', 'thai_food',
       'tortilla_calories', 'turkey_calories', 'type_sports', 'veggies_day',
       'vitamins', 'waffle_calories', 'weight'],
      dtype='object')
```

1.2 Cleaning: Modifying data that is incorrect, incomplete, irrelevant, duplicated, or improperly formatted

[17]:
```python
# Convert GPA and weight data from object to floats
data['GPA'] = pd.to_numeric(data['GPA'], errors='coerce')
# print(data['GPA'])

data['weight'] = pd.to_numeric(data['weight'], errors='coerce')
# print(data['weight'])
```

[18]:
```
# Identify open-ended questions and remove data entries
text_cols = data.select_dtypes(include=['object', 'string']).columns
print(text_cols)
print('Removing ',len(text_cols), ' columns')

df = data.drop(columns=text_cols)
print(df.columns)
print('Now with ',len(df.columns), ' columns')
```

```
Index(['comfort_food', 'comfort_food_reasons', 'diet_current',
       'eating_changes', 'father_profession', 'fav_cuisine', 'food_childhood',
       'healthy_meal', 'ideal_diet', 'meals_dinner_friend',
       'mother_profession', 'type_sports'],
      dtype='object')
Removing  12  columns
Index(['GPA', 'Gender', 'breakfast', 'calories_chicken', 'calories_day',
       'calories_scone', 'coffee', 'comfort_food_reasons_coded', 'cook',
       'comfort_food_reasons_coded.1', 'cuisine', 'diet_current_coded',
       'drink', 'eating_changes_coded', 'eating_changes_coded1', 'eating_out',
       'employment', 'ethnic_food', 'exercise', 'father_education',
       'fav_cuisine_coded', 'fav_food', 'fries', 'fruit_day', 'grade_level',
       'greek_food', 'healthy_feeling', 'ideal_diet_coded', 'income',
       'indian_food', 'italian_food', 'life_rewarding', 'marital_status',
       'mother_education', 'nutritional_check', 'on_off_campus',
       'parents_cook', 'pay_meal_out', 'persian_food',
       'self_perception_weight', 'soup', 'sports', 'thai_food',
       'tortilla_calories', 'turkey_calories', 'veggies_day', 'vitamins',
       'waffle_calories', 'weight'],
      dtype='object')
Now with  49  columns
```

[19]:
```
# Check for null values
print(df.isna().sum())
```

```
GPA                              5
Gender                           0
breakfast                        0
calories_chicken                 0
calories_day                    19
calories_scone                   1
coffee                           0
comfort_food_reasons_coded      19
cook                             3
comfort_food_reasons_coded.1     0
cuisine                         17
diet_current_coded               0
drink                            2
eating_changes_coded             0
```

```
eating_changes_coded1           0
eating_out                      0
employment                      9
ethnic_food                     0
exercise                       13
father_education                1
fav_cuisine_coded               0
fav_food                        2
fries                           0
fruit_day                       0
grade_level                     0
greek_food                      0
healthy_feeling                 0
ideal_diet_coded                0
income                          1
indian_food                     0
italian_food                    0
life_rewarding                  1
marital_status                  1
mother_education                3
nutritional_check               0
on_off_campus                   1
parents_cook                    0
pay_meal_out                    0
persian_food                    1
self_perception_weight          1
soup                            1
sports                          2
thai_food                       0
tortilla_calories               1
turkey_calories                 0
veggies_day                     0
vitamins                        0
waffle_calories                 0
weight                          5
dtype: int64
```

[22]:
```
# Decisions based on data visualization performed down below
# GPA and weight replace with either median because data are skewed and there␣
 ↪are several outliers
df['GPA'] = df['GPA'].fillna(df['GPA'].median())
df['weight'] = df['weight'].fillna(df['weight'].median())

# Self-perception of weight and Cook replace with most common class (mode) for␣
 ↪categorical
df['self_perception_weight'] = df['self_perception_weight'].
 ↪fillna(df['self_perception_weight'].mode()[0])
```

```
df['cook'] = df['cook'].fillna(df['cook'].mode()[0])

# Remove marital status, very heavily skewed and not useful for college student␣
 ↪population
# Remove more columns with too many missing values
remove_NAcolumns = ['marital_status','exercise','cuisine',␣
 ↪'comfort_food_reasons_coded']
df = df.drop(columns=remove_NAcolumns)
```

[ ]:
```
# Significantly cut down on the size of the dataset
# Keep only columns of interest
columns_of_interest =␣
 ↪['GPA','Gender','grade_level','parents_cook','weight','cook','eating_out','ethnic_food','fr
df = df[columns_of_interest]

# Verify no null values left
print(df.isna().sum())
```

```
GPA                     0
Gender                  0
grade_level             0
parents_cook            0
weight                  0
cook                    0
eating_out              0
ethnic_food             0
fruit_day               0
veggies_day             0
healthy_feeling         0
self_perception_weight  0
vitamins                0
fav_cuisine_coded       0
dtype: int64
```

[26]:
```
# Check to see if there are any duplicate rows
df.duplicated().sum()
```

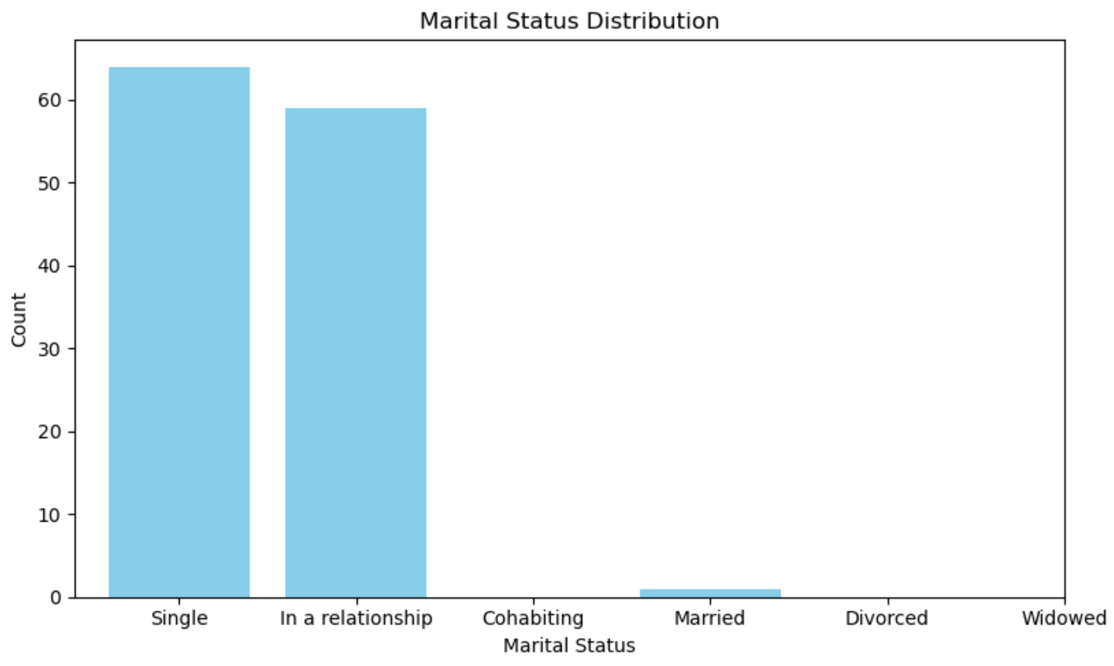
[26]:
```
0
```

1.3 Exploratory data analysis and Visualization: descriptive statistics, correlations, basic visualizations

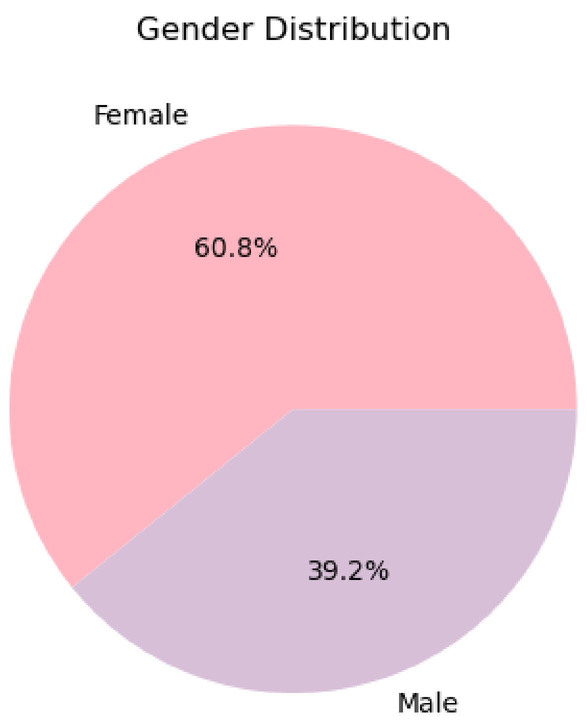
[28]:
```
# Display a few averages
ave_GPA = np.mean(df['GPA'])
ave_weight = np.mean(df['weight'])
print('Average GPA is:', ave_GPA)
print('Average weight is', ave_weight,'lbs')
```

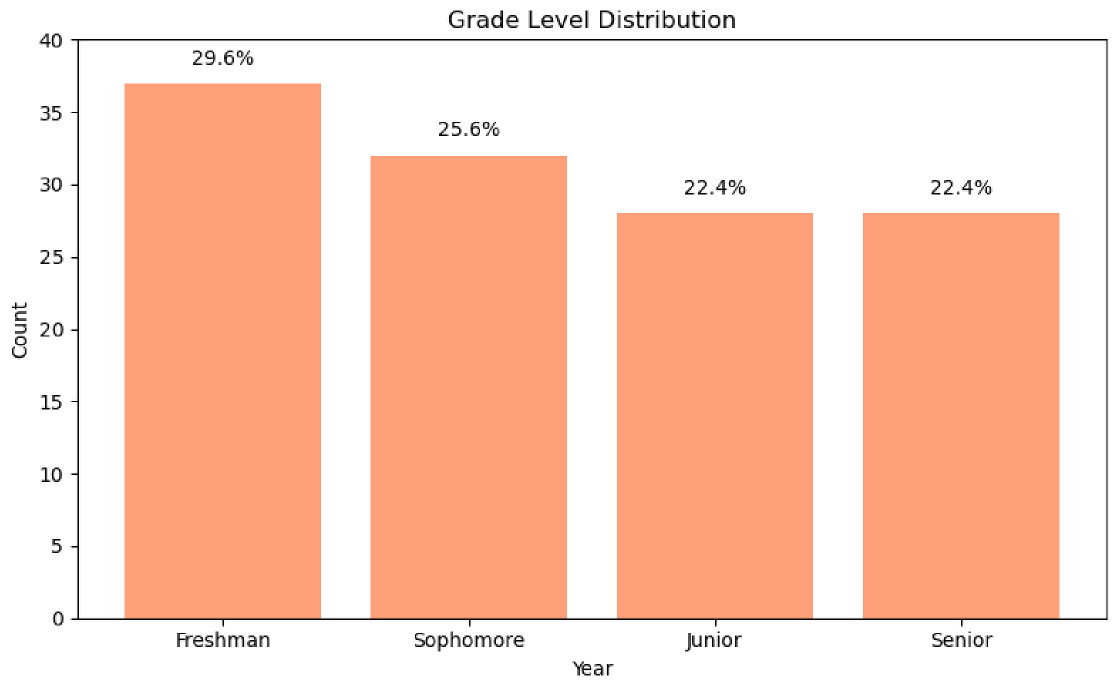
```
Average GPA is: 3.418936
Average weight is 158.36 lbs
```

[30]:
```
# Visualize marital status
# Count occurrences
marital_counts = data['marital_status'].value_counts()

labels = ['Single','In a␣
 ↪relationship','Cohabiting','Married','Divorced','Widowed']

# Plot bar chart
plt.figure(figsize=(8, 5))
plt.bar(marital_counts.index, marital_counts.values, color='skyblue')
plt.title('Marital Status Distribution')
plt.xlabel('Marital Status')
plt.ylabel('Count')
plt.tight_layout()
plt.xticks(ticks=range(1, 7), labels=labels)
plt.show()
```

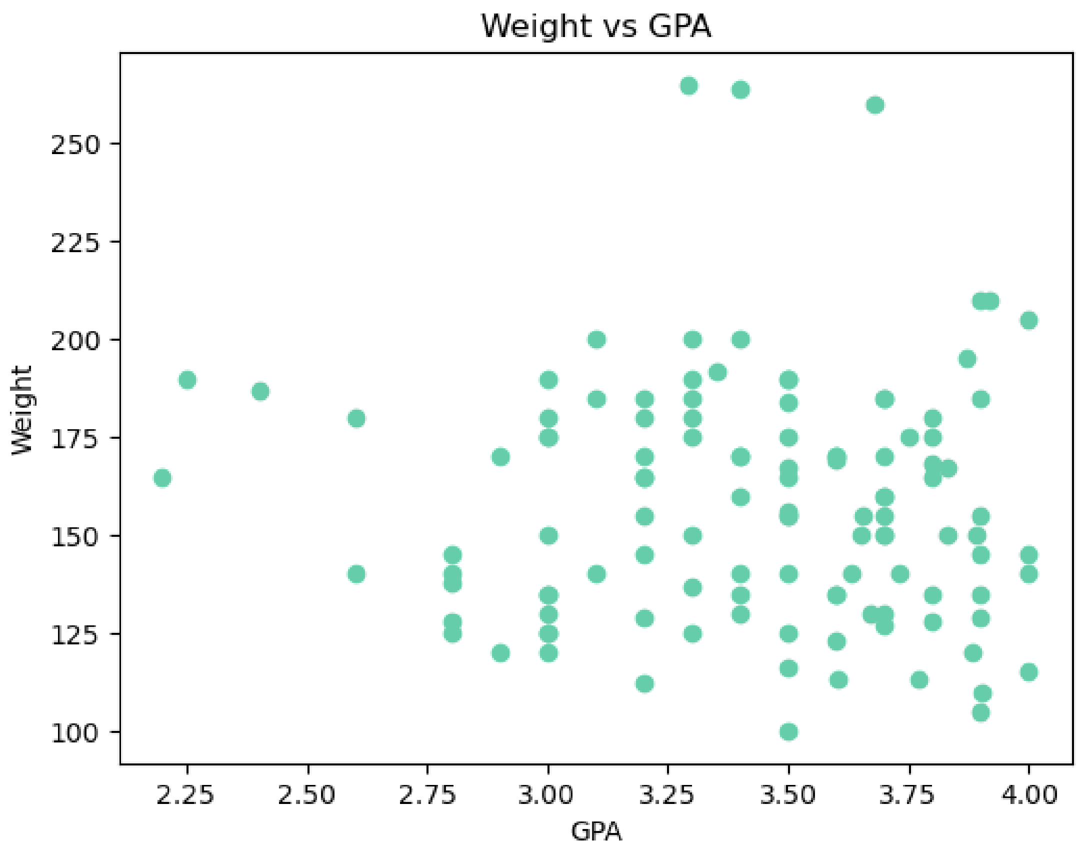


[32]:
```
# Visualize Gender
# Count occurrences
gender_counts = data['Gender'].value_counts()
# The index is the unique categories
# The values are the number of occurrences
# Plot pie chart
fig, ax = plt.subplots()
ax.pie(gender_counts.values, labels=['Female','Male'], autopct='%1.1f%%',␣
 ↪colors=['lightpink','thistle'])
ax.set_title('Gender Distribution')
plt.show()


# Count occurrences
grade_counts = data['grade_level'].value_counts()
# The index is the unique categories
# The values are the number of occurrences

labels = ['Freshman','Sophomore','Junior','Senior']

# Plot bar chart
plt.figure(figsize=(8,5))
bars = plt.bar(grade_counts.index, grade_counts.values, color='lightsalmon')
total = grade_counts.values.sum()
for bar in bars:
    height = bar.get_height()
    percentage = 100 * height / total
    plt.text(bar.get_x() + bar.get_width()/2, height + 1, f'{percentage:.1f}%',
             ha='center', va='bottom')

plt.title('Grade Level Distribution')
plt.xlabel('Year')
plt.ylabel('Count')
plt.tight_layout()
plt.ylim(0,40)
plt.xticks(ticks=range(1, 5), labels=labels)
plt.show()
```

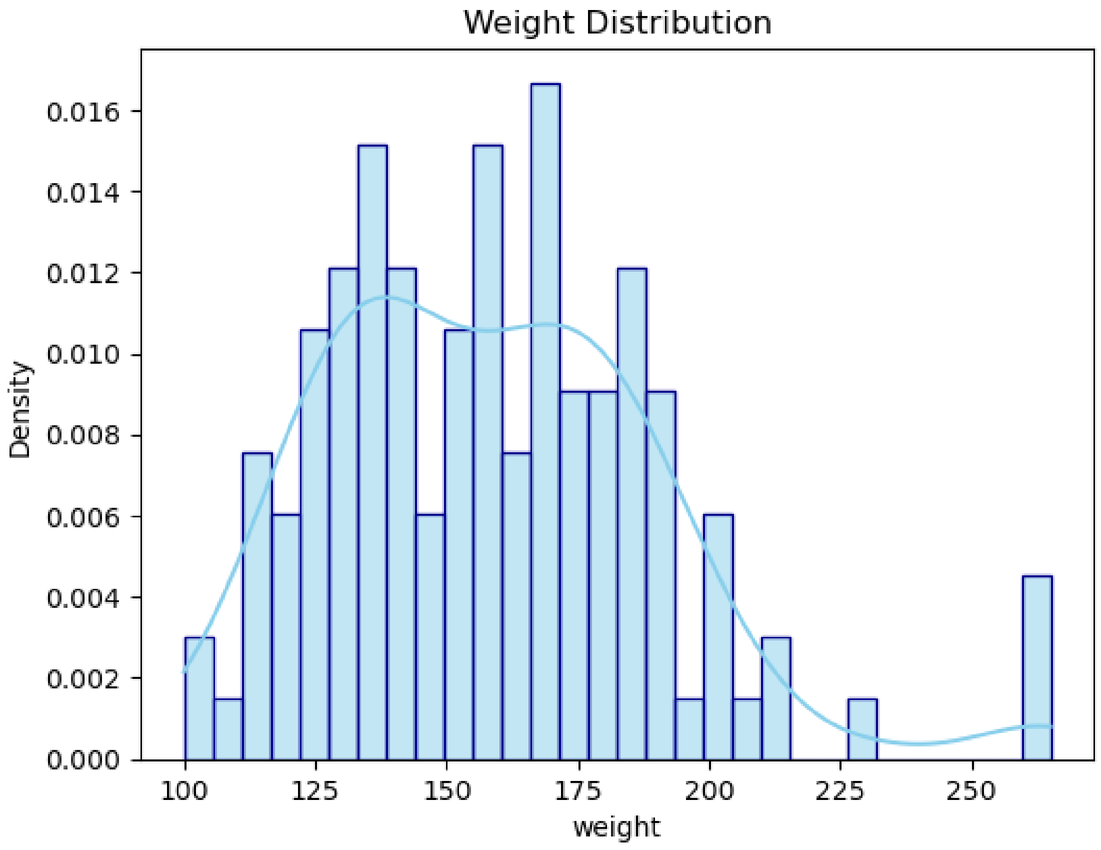

Gender Distribution
Female
60.8%
39.2%
Male

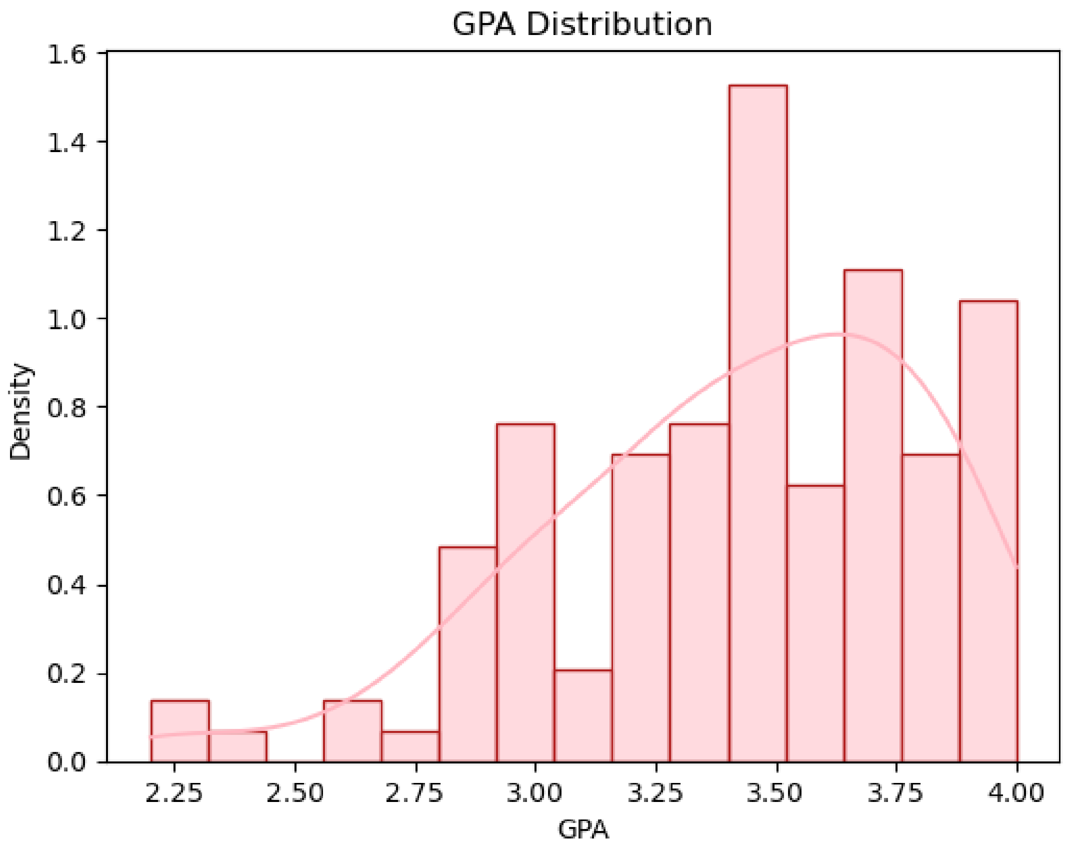

Grade Level Distribution
Count
40
35
30
25
20
15
10
5
0
29.6%
25.6%
22.4%
22.4%
Freshman
Sophomore
Junior
Senior
Year

```
[33]: # VIsualize GPA
      x = data['GPA']
      y = data['weight']
      plt.scatter(x, y, color = 'mediumaquamarine')
      plt.xlabel('GPA')
      plt.ylabel('Weight')
      plt.title('Weight vs GPA')
      plt.show()
```



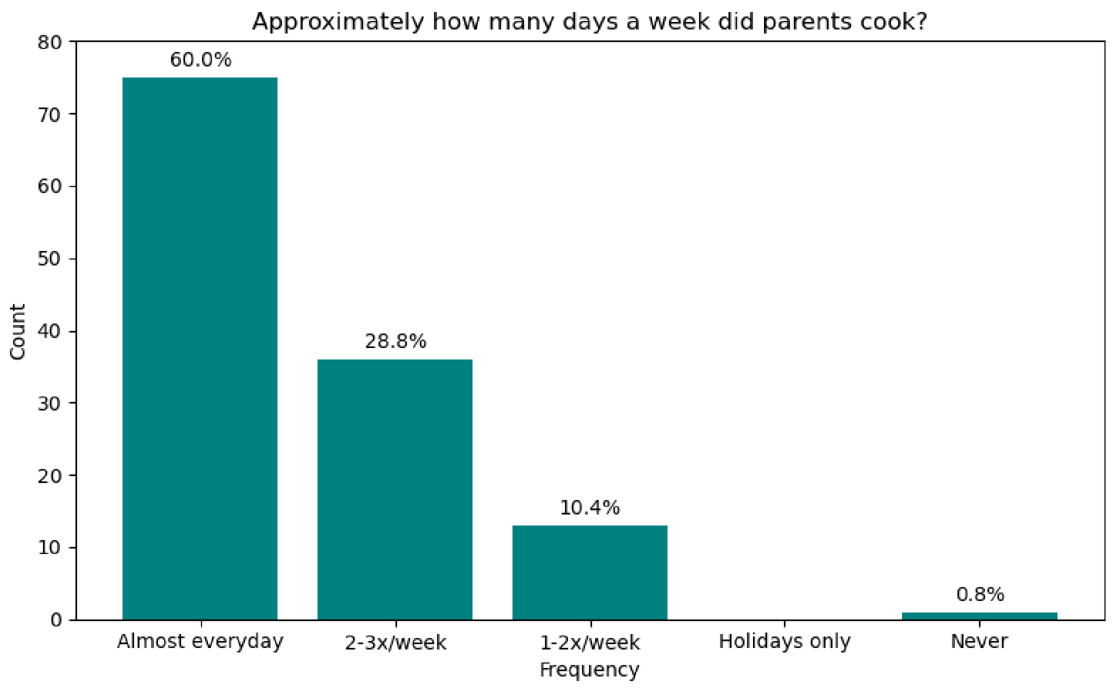
```
[34]: # Visualize distributions of weight and GPA
      sns.histplot(data['weight'], bins=30, kde=True, stat="density",␣
       ↪color='skyblue', edgecolor='darkblue')
      plt.title('Weight Distribution')
      plt.show()

      sns.histplot(data['GPA'], bins=15, kde=True, stat="density", color='lightpink',␣
       ↪edgecolor='firebrick')
      plt.title('GPA Distribution')
      plt.show()
```

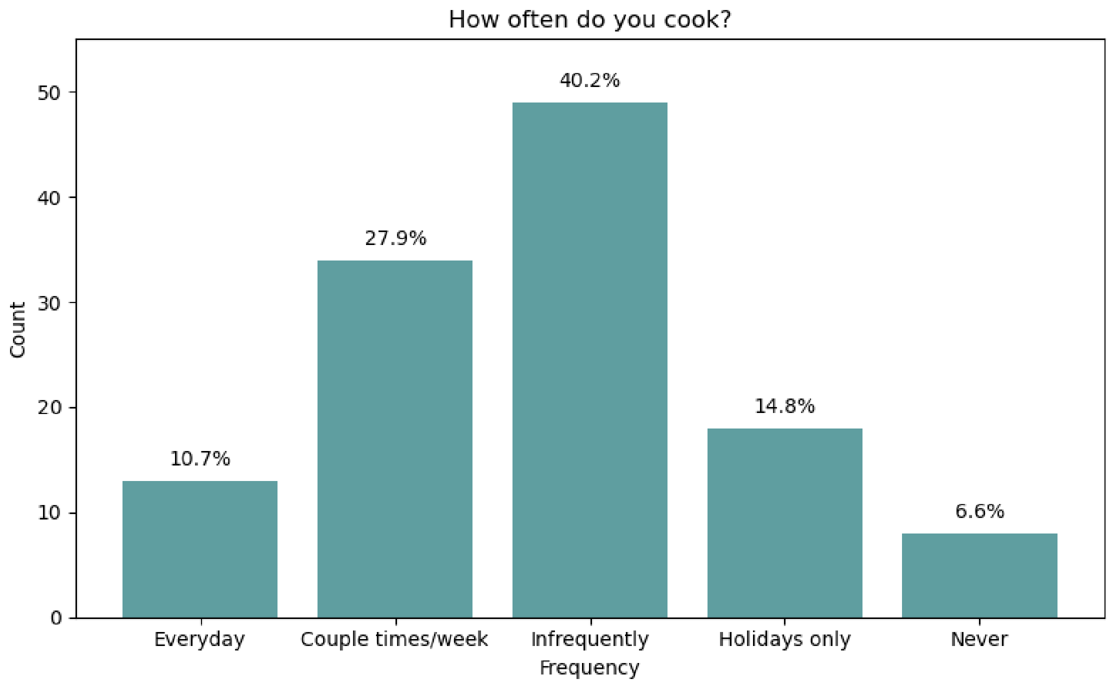

Weight Distribution
Density
weight
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0.014
0.016
100
125
150
175
200
225
250

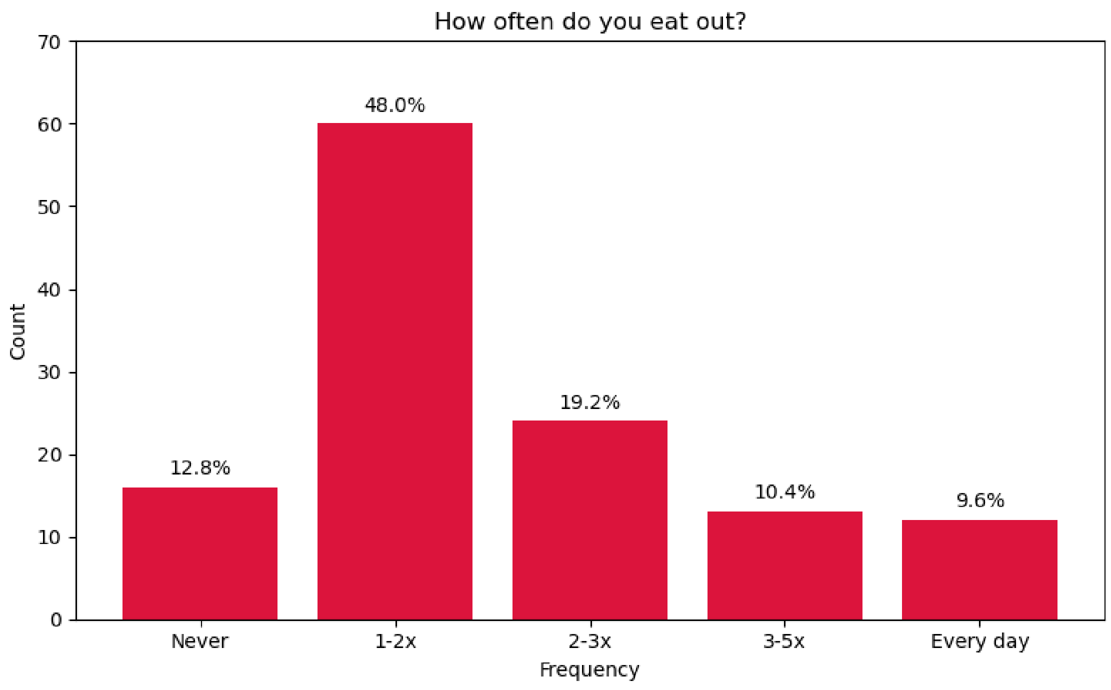


[37]:
```
# Visualizing cooking variables
parents_counts = data['parents_cook'].value_counts()
labels = ['Almost everyday','2-3x/week','1-2x/week','Holidays only','Never']
plt.figure(figsize=(8,5))
bars1= plt.bar(parents_counts.index, parents_counts.values, color='teal')
total = parents_counts.values.sum()
for bar in bars1:
    height = bar.get_height()
    percentage = 100 * height / total
    plt.text(bar.get_x() + bar.get_width()/2, height + 1, f'{percentage:.1f}%',
             ha='center', va='bottom')

plt.title('Approximately how many days a week did parents cook?')
plt.xlabel('Frequency')
plt.ylabel('Count')
plt.ylim(0,80)
plt.tight_layout()
plt.xticks(ticks=range(1, 6), labels=labels)
plt.show()
```

```python
cook_counts = data['cook'].value_counts()
labels = ['Everyday','Couple times/week','Infrequently','Holidays only','Never']
plt.figure(figsize=(8,5))
bars2 = plt.bar(cook_counts.index, cook_counts.values, color='cadetblue')
total = cook_counts.values.sum()
for bar in bars2:
    height = bar.get_height()
    percentage = 100 * height / total
    plt.text(bar.get_x() + bar.get_width()/2, height + 1, f'{percentage:.1f}%',
             ha='center', va='bottom')

plt.title('How often do you cook?')
plt.xlabel('Frequency')
plt.ylabel('Count')
plt.tight_layout()
plt.ylim(0,55)
plt.xticks(ticks=range(1, 6), labels=labels)
plt.show()

eatingout_counts = data['eating_out'].value_counts()
labels = ['Never','1-2x','2-3x','3-5x','Every day']

plt.figure(figsize=(8,5))
bars = plt.bar(eatingout_counts.index, eatingout_counts.values, color='crimson')
# Add percentage labels
total = eatingout_counts.values.sum()
for bar in bars:
    height = bar.get_height()
    percentage = 100 * height / total
    plt.text(bar.get_x() + bar.get_width()/2, height + 1, f'{percentage:.1f}%',
             ha='center', va='bottom')

# plt.bar(eatingout_counts.index, eatingout_counts.values, color='crimson')
plt.title('How often do you eat out?')
plt.xlabel('Frequency')
plt.ylabel('Count')
plt.ylim(0,70)
plt.tight_layout()
plt.xticks(ticks=range(1, 6), labels=labels)
plt.show()
```


Approximately how many days a week did parents cook?
Count
80
70
60
50
40
30
20
10
0
60.0%
28.8%
10.4%
0.8%
Almost everyday
2-3x/week
1-2x/week
Holidays only
Never
Frequency

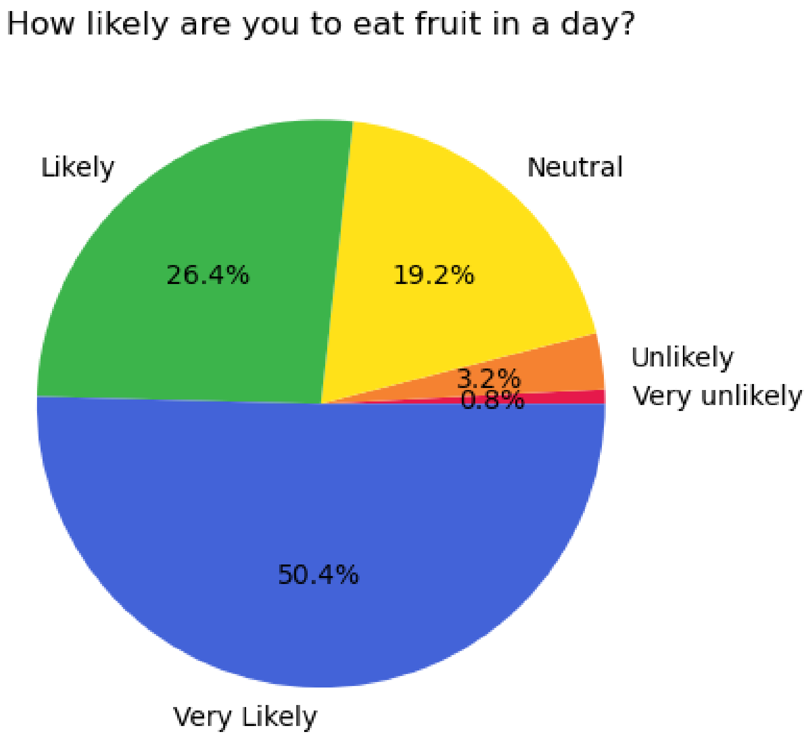

How often do you cook?
Count
50
40
30
20
10
0
10.7%
27.9%
40.2%
14.8%
6.6%
Everyday
Couple times/week
Infrequently
Holidays only
Never
Frequency

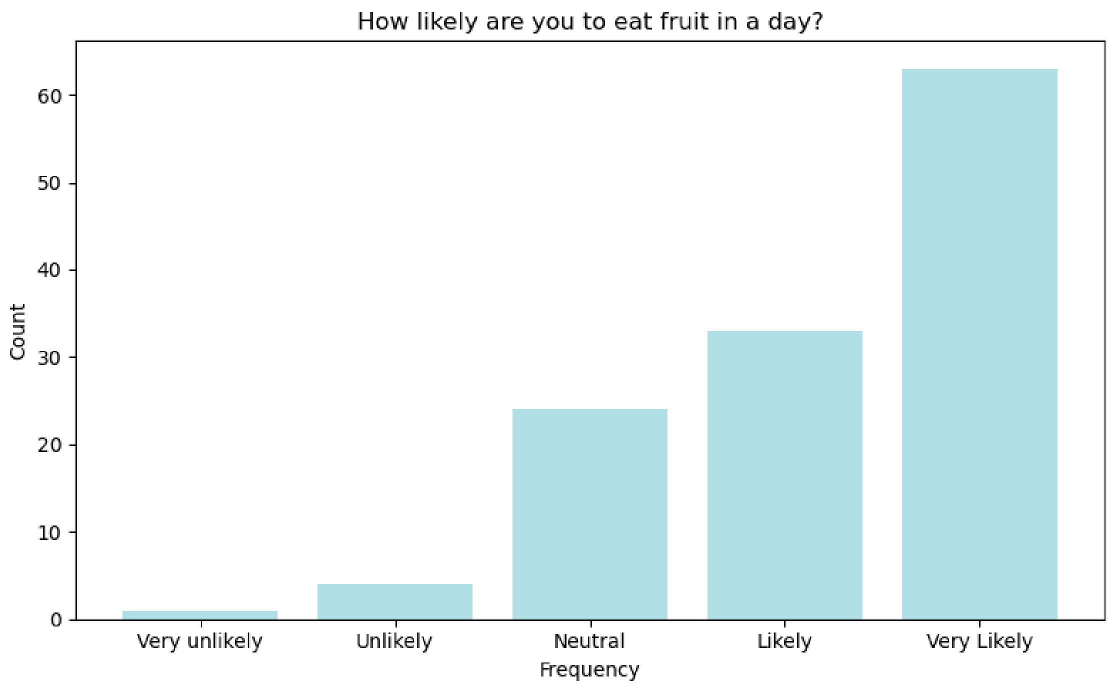


[38]:
```python
# Visualize fruit consumption
labels=['Very unlikely','Unlikely','Neutral','Likely','Very Likely']
fruit_counts = data['fruit_day'].value_counts().sort_index()
print(fruit_counts)

colors = ['#e6194b',  # red
          '#f58231',  # orange
          '#ffe119',  # yellow
          '#3cb44b',  # green
          '#4363d8']  # blue
fig, ax = plt.subplots()
ax.pie(fruit_counts.values, labels=labels, autopct='%1.1f%%', colors=colors)
ax.set_title("How likely are you to eat fruit in a day?")
plt.show()

plt.figure(figsize=(8,5))
plt.bar(fruit_counts.index, fruit_counts.values, color='powderblue')
plt.title('How likely are you to eat fruit in a day?')
plt.xlabel('Frequency')
plt.ylabel('Count')
plt.tight_layout()
plt.xticks(ticks=range(1, 6), labels=labels)
plt.show()
```

```
fruit_day
```

```
1     1
2     4
3    24
4    33
5    63
Name: count, dtype: int64
```

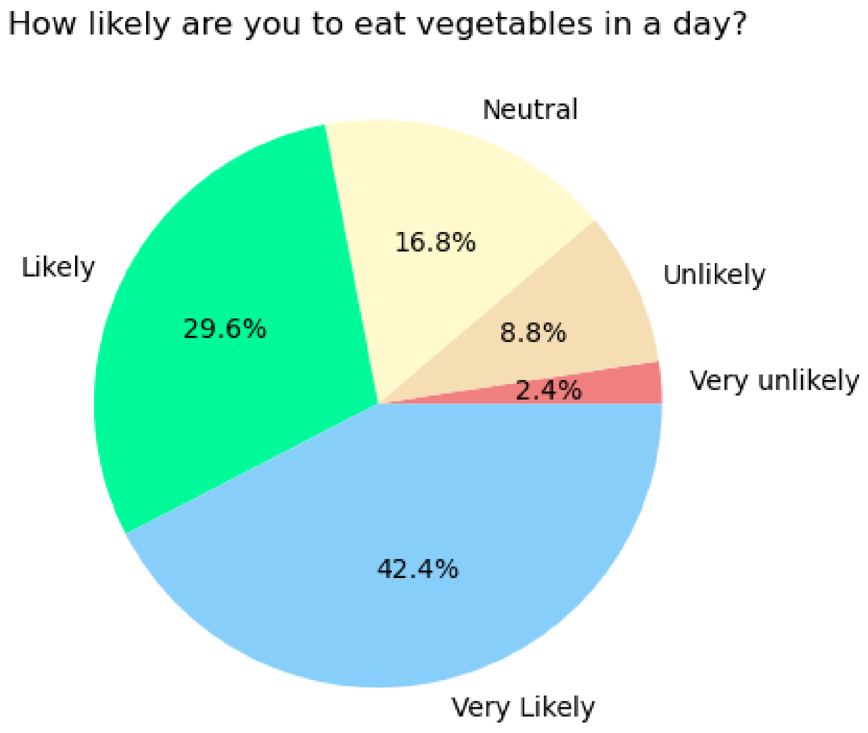


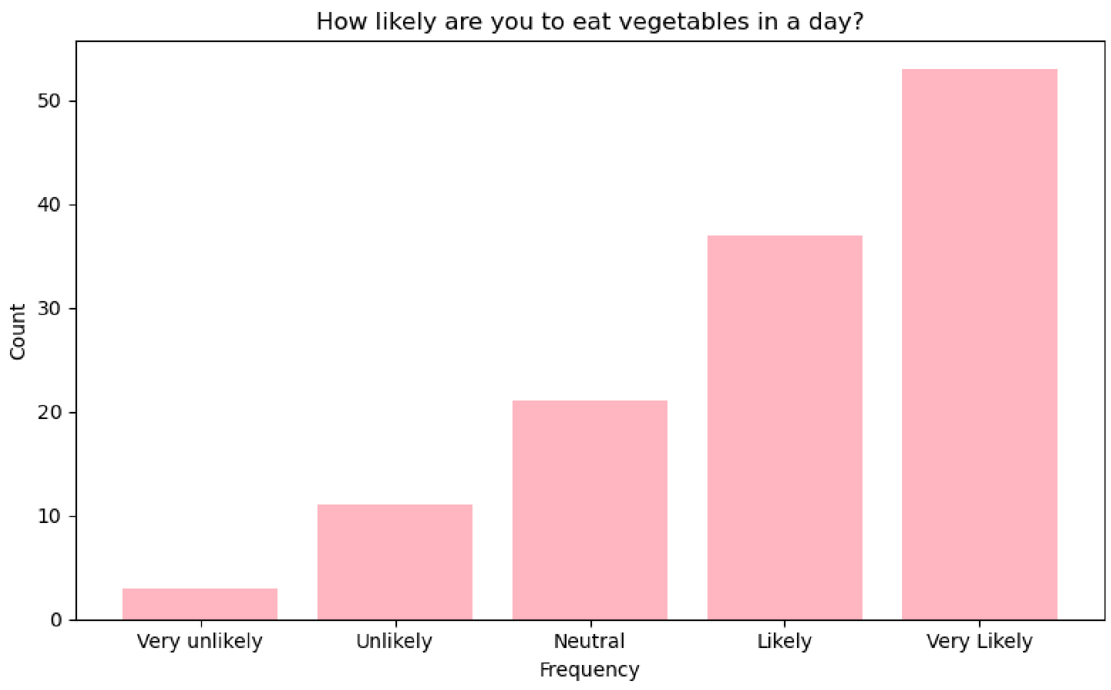


[39]:
```
# Visualize vegetable consumption
labels=['Very unlikely','Unlikely','Neutral','Likely','Very Likely']
veggies_counts = data['veggies_day'].value_counts().sort_index()
print(fruit_counts)

colors = ['lightcoral',  # red
          'wheat',  # orange
          'lemonchiffon',  # yellow
          'mediumspringgreen',  # green
          'lightskyblue']  # blue
fig, ax = plt.subplots()
ax.pie(veggies_counts.values, labels=labels, autopct='%1.1f%%', colors=colors)
ax.set_title("How likely are you to eat vegetables in a day?")
plt.show()

plt.figure(figsize=(8,5))
plt.bar(veggies_counts.index, veggies_counts.values, color='lightpink')
plt.title('How likely are you to eat vegetables in a day?')
plt.xlabel('Frequency')
plt.ylabel('Count')
plt.tight_layout()
plt.xticks(ticks=range(1, 6), labels=labels)
plt.show()
```

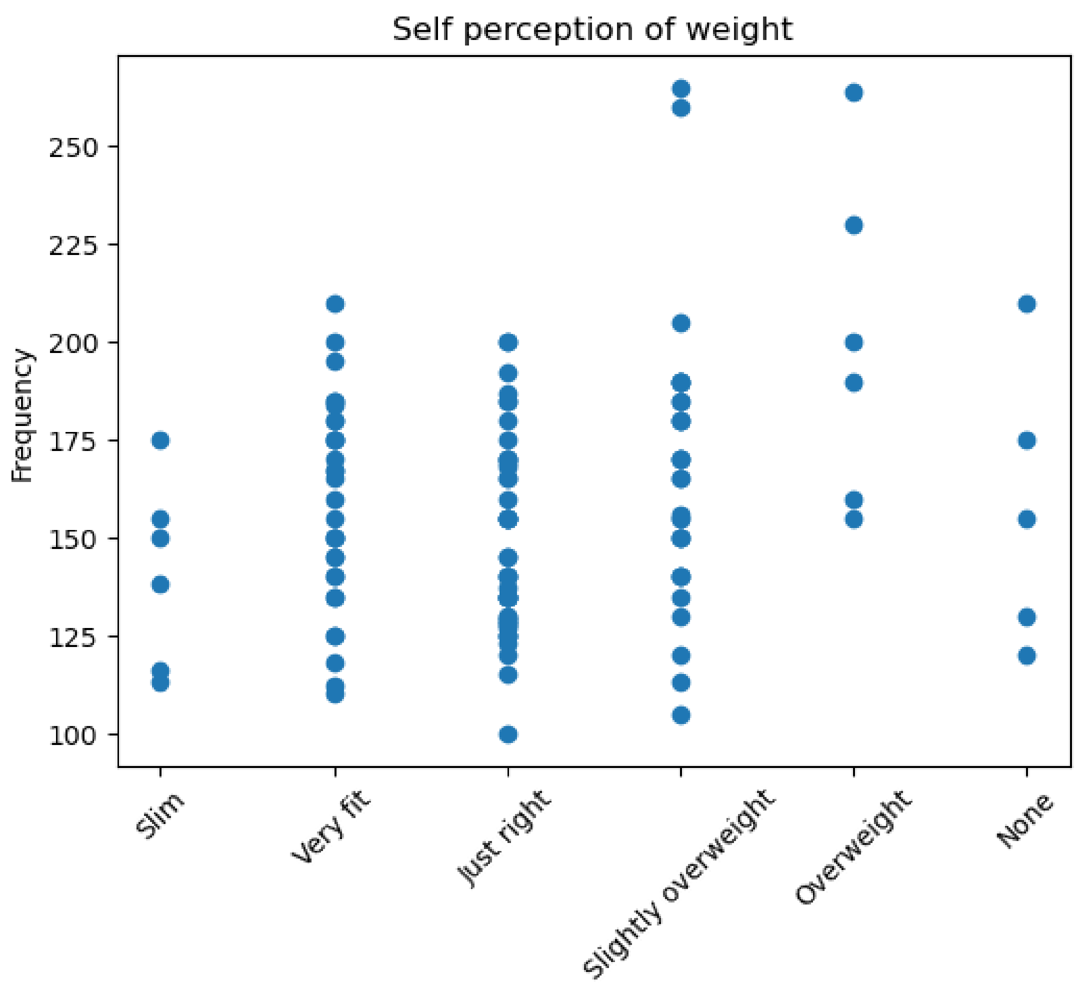
```
fruit_day
```

```
1     1
2     4
3    24
4    33
5    63
Name: count, dtype: int64
```



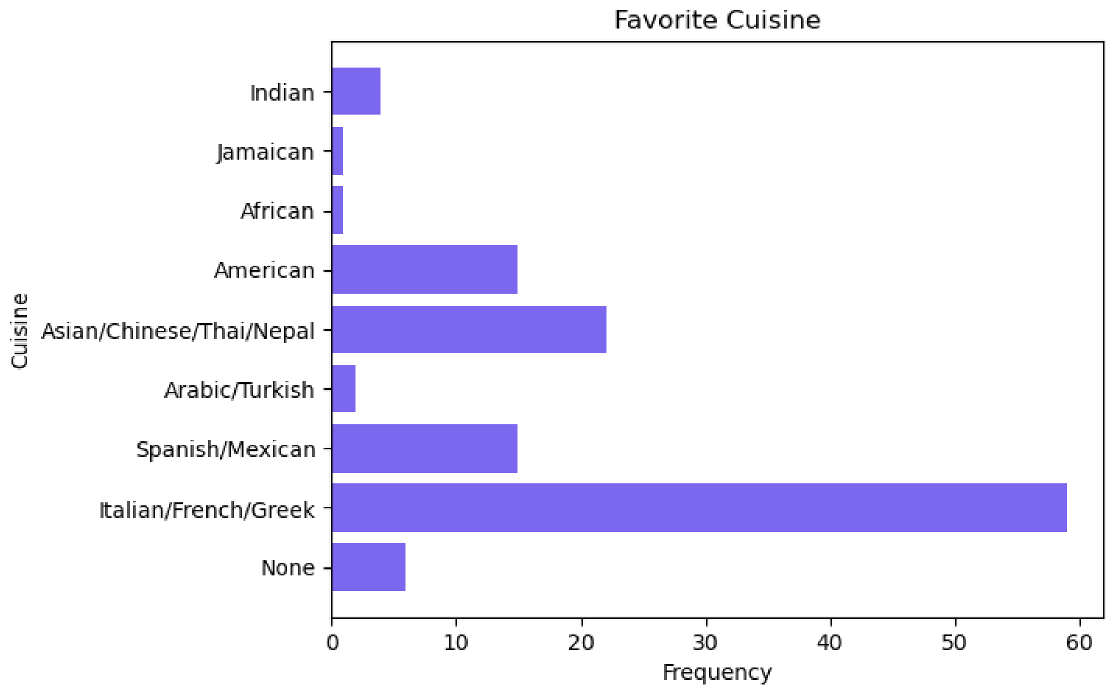


```
[40]: # Visualize self-perception of weight
perception_counts = data['self_perception_weight'].value_counts().sort_index()

labels = ['Slim','Very fit','Just right','Slightly␣
 ↪overweight','Overweight','None']
# 'None' corresponds to: "I don't think of myself in these terms"
plt.scatter(df['self_perception_weight'], df['weight'])
plt.xticks(ticks=range(1, 7), labels=labels, rotation=45)
plt.title('Self perception of weight')
plt.ylabel('Frequency')
plt.show()
```

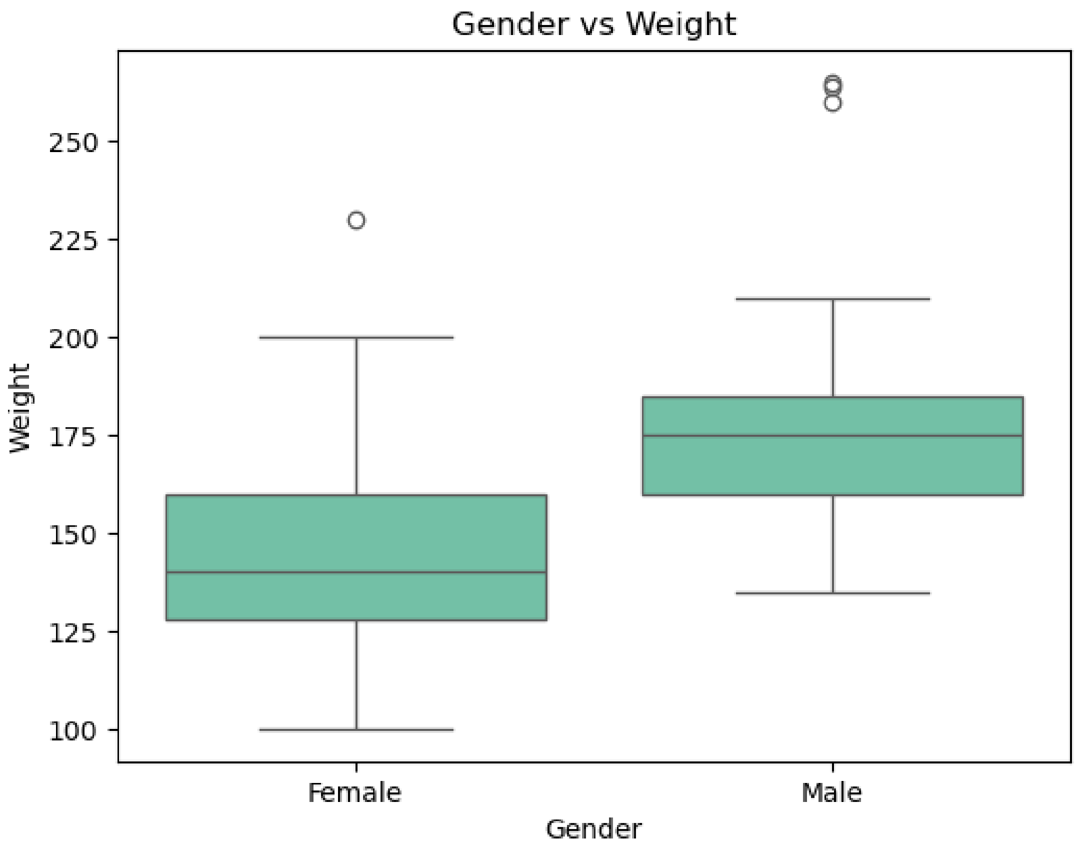


[42]:
```
# Visualize vitamins and favorite cuisine
vitamins_counts = data['vitamins'].value_counts().sort_index()
print(vitamins_counts)

favcuisine_counts = data['fav_cuisine_coded'].value_counts().sort_index()
labels = ['None','Italian/French/Greek','Spanish/Mexican','Arabic/
  ↪Turkish','Asian/Chinese/Thai/Nepal','American','African','Jamaican','Indian']
# 'None' corresponds to: "I don't think of myself in these terms"
plt.barh(favcuisine_counts.index, favcuisine_counts.values,␣
  ↪color='mediumslateblue')
plt.yticks(ticks=range(0, 9), labels=labels)
plt.title('Favorite Cuisine')
plt.ylabel('Cuisine')
plt.xlabel('Frequency')
plt.show()
```

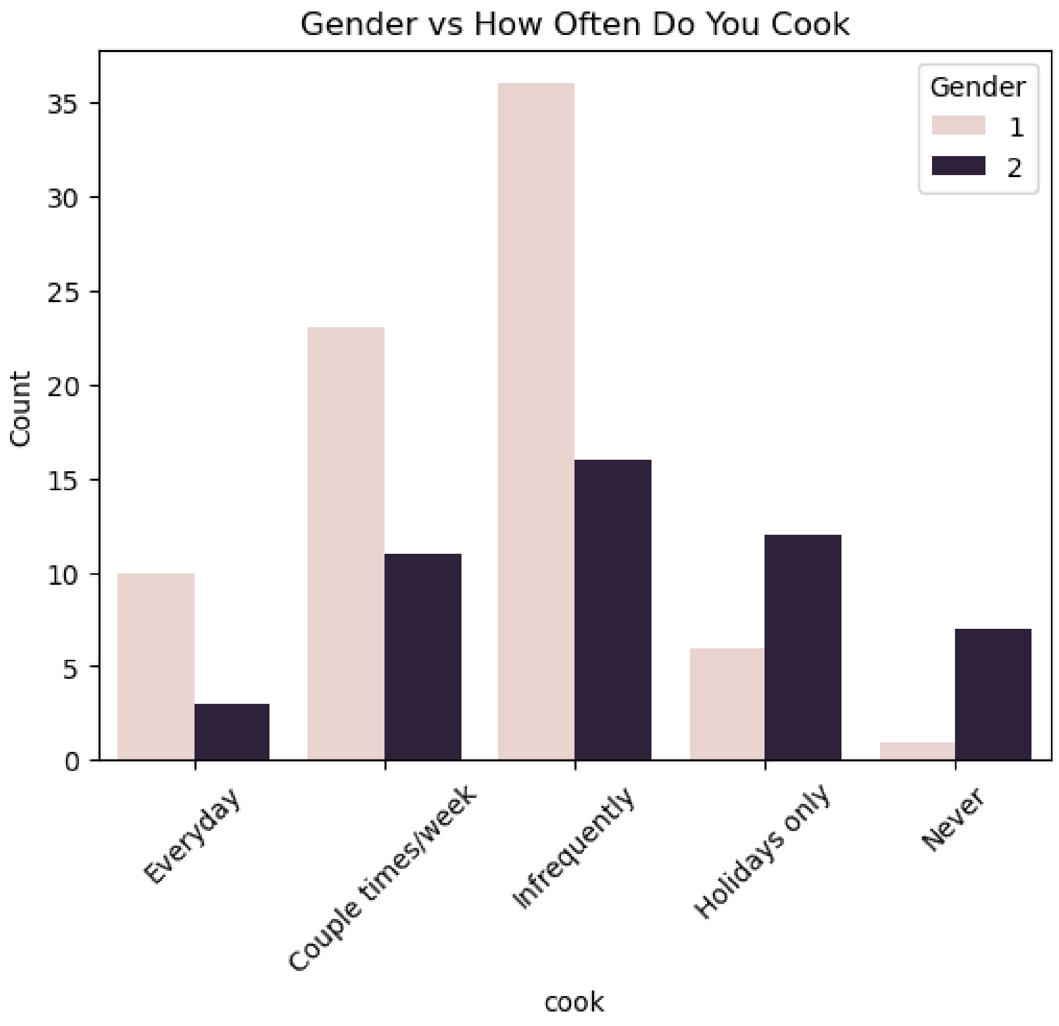
```
vitamins
1    61
2    64
Name: count, dtype: int64
```



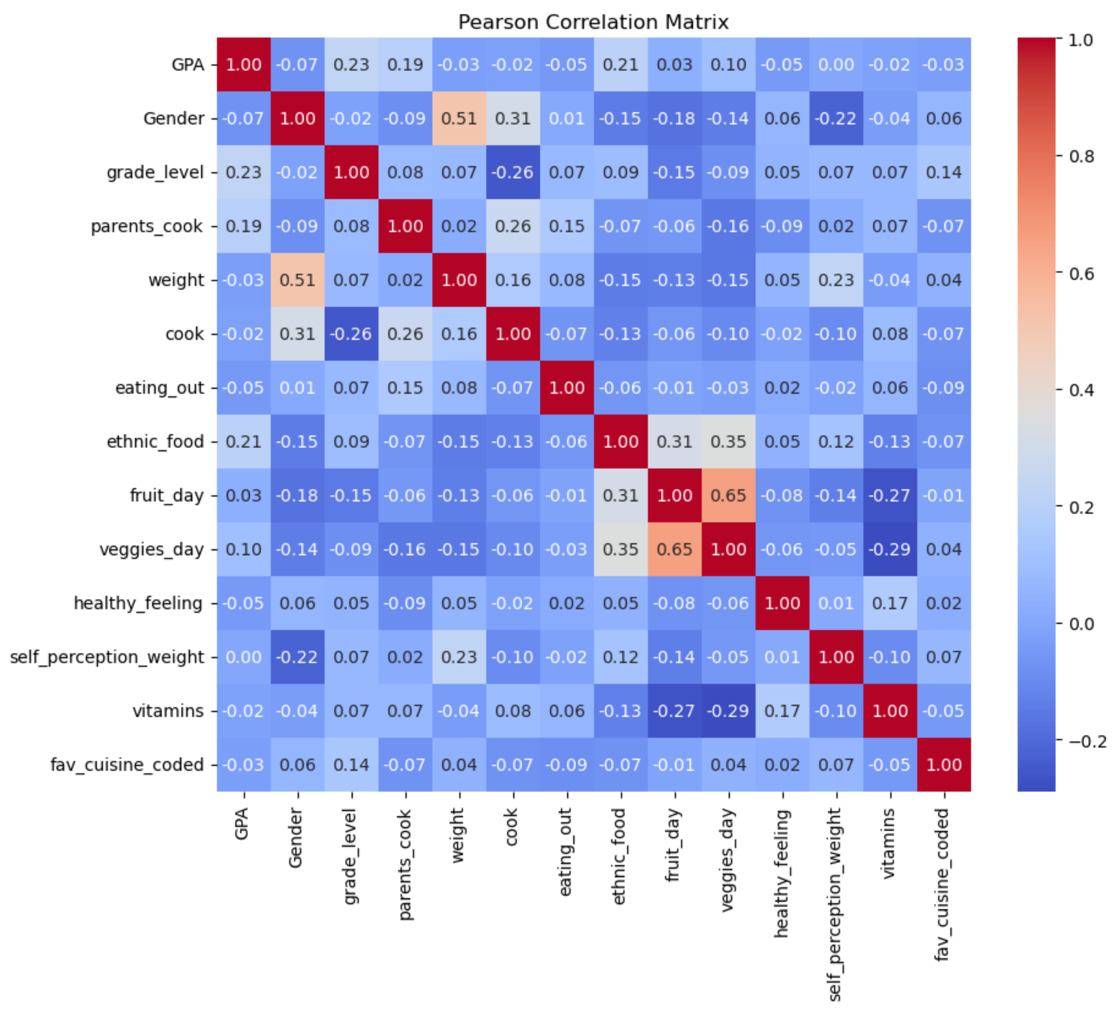
[44]:
```
# Visualize gender and weight
sns.boxplot(x=df['Gender'], y=df['weight'], color='mediumaquamarine')
plt.xlabel('Gender')
plt.ylabel('Weight')
plt.title('Gender vs Weight')
plt.xticks(ticks=[0, 1], labels=['Female','Male'])
plt.show()
```



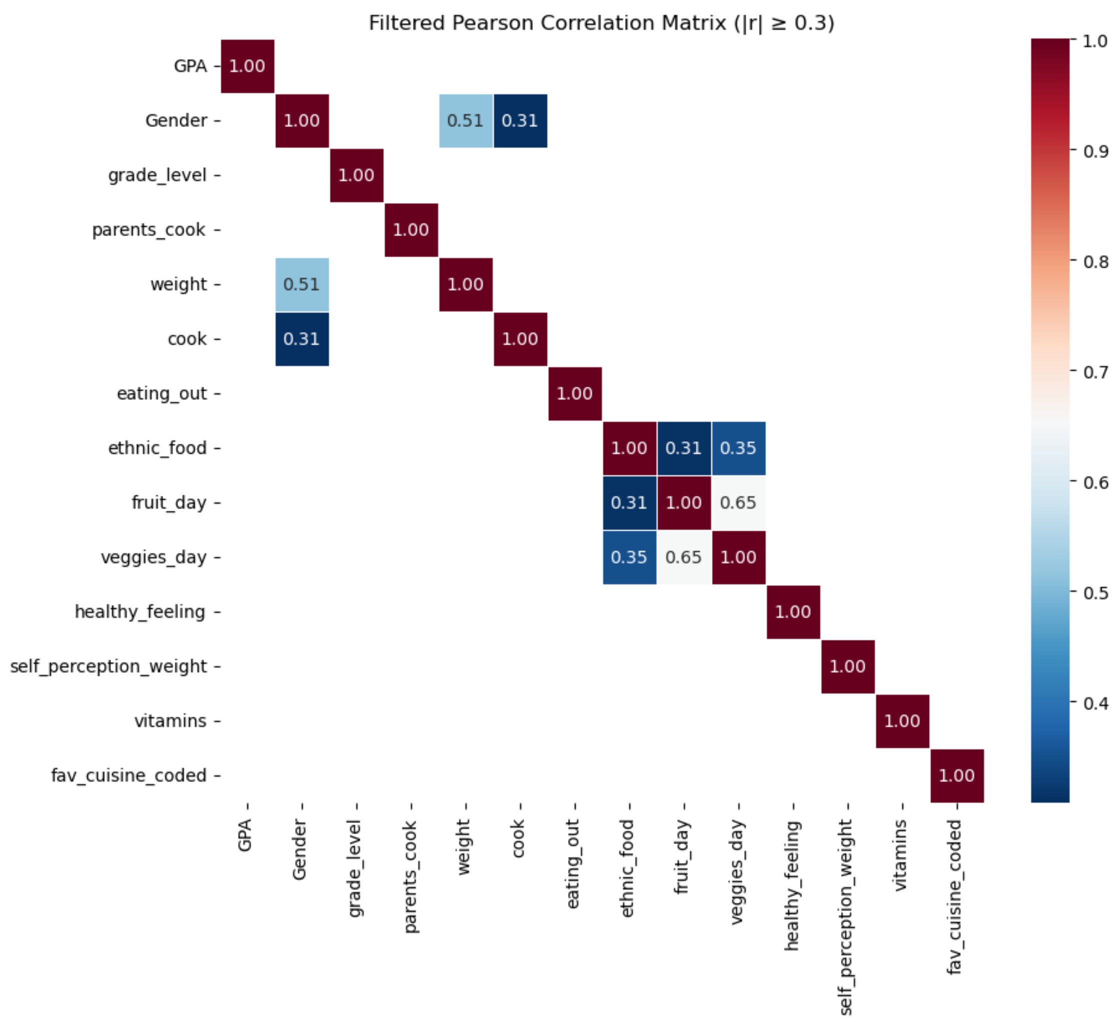
[45]:
```python
# Visualize gender and cooking
sns.countplot(x='cook', hue='Gender', data=df)
plt.title('Gender vs How Often Do You Cook')
plt.ylabel('Count')
plt.xticks(ticks=range(0,5), labels = ['Everyday','Couple times/
 ↪week','Infrequently','Holidays only','Never'], rotation=45)
plt.show()
```



```
[46]: #Pearson correlation
      corr_matrix = df.corr(method='pearson')

      plt.figure(figsize=(10, 8))
      sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f", square=True)
      plt.title("Pearson Correlation Matrix")
      plt.show()
```

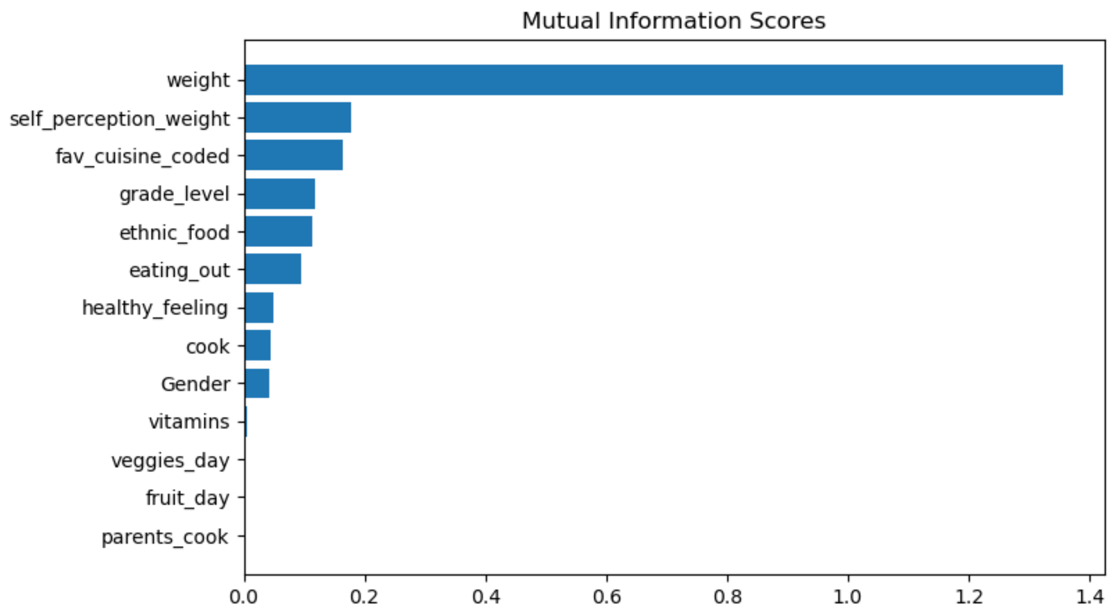


```
[47]: # Create a mask for correlations with abs value < 0.3
mask = (np.abs(corr_matrix) < 0.3)

# Plot
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix,
            mask=mask,
            annot=True,
            cmap='RdBu_r',
            fmt=".2f",
            square=True,
            linewidths=0.5,
            cbar=True)
plt.title("Filtered Pearson Correlation Matrix (|r|   0.3)")
plt.show()
```



```
[49]: X = df.copy() # make a copy
X = X.dropna() # remove rows with NA for now
X = X.apply(lambda col: col.astype(int) if col.dtype == 'float' else col) #␣
 ↪convert all floats to ints
y = X.pop("GPA")

# All discrete features should now have integer dtypes (double-check this␣
 ↪before using MI!)
discrete_features = X.dtypes == int

def make_mi_scores(X, y, discrete_features):
    mi_scores = mutual_info_regression(X, y,␣
 ↪discrete_features=discrete_features)
    mi_scores = pd.Series(mi_scores, name="MI Scores", index=X.columns)
    mi_scores = mi_scores.sort_values(ascending=False)
    return mi_scores

mi_scores = make_mi_scores(X, y, discrete_features)
print(mi_scores)

def plot_mi_scores(scores):
    scores = scores.sort_values(ascending=True)
    width = np.arange(len(scores))
    ticks = list(scores.index)
    plt.barh(width, scores)
    plt.yticks(width, ticks)
    plt.title("Mutual Information Scores")


plt.figure(dpi=100, figsize=(8, 5))
plot_mi_scores(mi_scores)
```

```
weight                       1.356273
self_perception_weight       0.176837
fav_cuisine_coded            0.163722
grade_level                  0.118304
ethnic_food                  0.112594
eating_out                   0.095915
healthy_feeling              0.048478
cook                         0.043687
Gender                       0.041797
vitamins                     0.006173
parents_cook                 0.000000
fruit_day                    0.000000
veggies_day                  0.000000
Name: MI Scores, dtype: float64
```



Interpretation: Mutual Information quantifies how much information one variable gives about another.
A higher MI score corresponds to a stronger non-linear and linear dependency with the target.
According to the plot above showing how much each feature contributes to predicting **GPA** using mutual information.

Most Informative Features:
* weight (MI 1.71): most informative variable for predicting the target * self_perception_weight (MI 0.32): moderately informative, reflects how someone's perception of their body relates to the target. healthy_feeling (MI 0.13): provides some predictive signal, although weaker.

Less Informative Features:
* veggies_day, cook, fruit_day, ethnic_food: have low MI values (< 0.1), suggesting a weak relationship with the target.

Non-informative Features:. * Gender, grade_level, parents_cook, eating_out, vitamins (MI = 0): these variables do not contribute any useful information about the target

1.4 Summarized notes, insights, and interpretation

- Most common favorite cuisine is Italian/French/Greek
- Gender and cooking were highly correlated (r=0.31), as was gender and weight (as expected) (r=0.51).
- Ethnic food and veggies day (r=0.35) and fruit day (r=0.31) are highly correlated
- Fruit day and veggies day are highly correlated (r=0.65)
- The distribution of population is 60.8% female, 39.2% male
- Weight distribution is skewed to the right
- GPA distribution is skewed to the left

- Grade level distribution is somewhat evenly distributed (29.6% freshman, 25.6% sophomores, 22.4% juniors, and 22.4% seniors)
- 60% of students reported that their parents cooked almost everyday of the week (parents_cook)
- 10% of students reported that they cook every day (cook)
- 42% of students reported that they cook infrequently
- 48% of students reported that they eat out 1-2 times a week (eating_out)
- 10% of students reported that they eat out every day