In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

from functions import sugar_classifier
from preprocessor_class import Preprocessor
```

Project Outline and Goal

The goal of this project is to build a supervised machine learning model that can predict the sugar content of a menu item. This model will be able to read the text-based information printed on a menu and make a prediction that can allow you to make an informed decision.

Business Problem

Have you ever been on a diet and been invited out to dinner or wanted take-out? It can be frustrating to lose track of nutritional intake when eating at a restaurant and you stand the risk of unwittingly ordering something that is unhealthy or outside of your diet's restrictions.

Some menus will provide calorie counts, but that is only helpful for weight gain/loss and does not take into account other health concerns such as diabetes and some forms of heart disease. What can you do when the only information you have is the title of a dish, short description, and a price?

The Data

The data for this project was collected by the Department of Health and Mental Hygiene (DOHMH) and is available to the public from the NYC OpenData website. The .csv contains over 60,000 menu items available at chain restaurants throughout New York City. All data was collected between 2017-2018 and was made public on 5/10/2018. For more information or to download, visit [NYC OpenData's webpage for this dataset](#)

The menus contained within my data are large chains with one or more franchises within New York City borders. Overall, there were 86 restaurants represented with a combined total of 65,219 menu items. Each menu item had information on the restaurant, menu text, food category, serving size, and nutrition facts such as calories, sugar, fats, sodium, and more.

In [2]:

```
df_raw = pd.read_csv('Data/menu_items.csv', low_memory = False)
df_raw.head()
```

Out[2]:

	Menu_Item_ID	Year	Restaurant_Item_Name	restaurant	Restaurant_ID	Item_Name	Item_Description	Food_Category	Ser
0	35005	2017	7 Eleven Mocha Iced Coffee	7 Eleven	1	Mocha Iced Coffee	Mocha Iced Coffee, Chillers Iced Coffee, Drinks	Beverages	
1	35008	2017	7 Eleven French Vanilla Iced Coffee	7 Eleven	1	French Vanilla Iced Coffee	French Vanilla Iced Coffee, Chillers Iced Coff...	Beverages	
2	35027	2017	7 Eleven French Vanilla Cappuccino	7 Eleven	1	French Vanilla Cappuccino	French Vanilla Cappuccino, Coffee, Drinks, Fla...	Beverages	
3	35028	2017	7 Eleven Peppermint	7 Eleven	1	Peppermint	Peppermint Mocha, Coffee, 8	Beverages	

	Menu_Item_ID	Year	Restaurant_Item_Name	restaurant	Restaurant_ID	Item_Name	Item_Description	Food_Category	Ser
			Mocha			Mocha	fl oz		
4	35029	2017	7 Eleven Pumpkin Spice Latte	7 Eleven	1	Pumpkin Spice Latte	Pumpkin Spice Latte, Coffee, 8 fl oz	Beverages	

5 rows × 49 columns

In [3]:

```
df_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 65219 entries, 0 to 65218
Data columns (total 49 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Menu_Item_ID             65219 non-null  int64
 1   Year                     65219 non-null  int64
 2   Restaurant_Item_Name     65219 non-null  object
 3   restaurant               65219 non-null  object
 4   Restaurant_ID            65219 non-null  int64
 5   Item_Name                65219 non-null  object
 6   Item_Description         65219 non-null  object
 7   Food_Category            65219 non-null  object
 8   Serving_Size             26899 non-null  float64
 9   Serving_Size_text        39 non-null     object
 10  Serving_Size_Unit        26927 non-null  object
 11  Serving_Size_household   15238 non-null  object
 12  Calories                 55315 non-null  float64
 13  Total_Fat                54846 non-null  float64
 14  Saturated_Fat            54143 non-null  float64
 15  Trans_Fat                51503 non-null  float64
 16  Cholesterol              53219 non-null  float64
 17  Sodium                   54991 non-null  float64
 18  Potassium                1098 non-null   float64
 19  Carbohydrates            54288 non-null  float64
 20  Protein                  54233 non-null  float64
 21  Sugar                    52931 non-null  float64
 22  Dietary_Fiber            53440 non-null  float64
 23  Calories_100g            25878 non-null  float64
 24  Total_Fat_100g           25686 non-null  float64
 25  Saturated_Fat_100g       25285 non-null  float64
 26  Trans_Fat_100g           23828 non-null  float64
 27  Cholesterol_100g         25126 non-null  float64
 28  Sodium_100g              25853 non-null  float64
 29  Potassium_100g           623 non-null    float64
 30  Carbohydrates_100g       25592 non-null  float64
 31  Protein_100g             25531 non-null  float64
 32  Sugar_100g               25207 non-null  float64
 33  Dietary_Fiber_100g       25391 non-null  float64
 34  Calories_text            303 non-null    object
 35  Total_Fat_text           69 non-null     object
 36  Saturated_Fat_text       50 non-null     object
 37  Trans_Fat_text           10 non-null     object
 38  Cholesterol_text         358 non-null    object
 39  Sodium_text              93 non-null     object
 40  Potassium_text           2 non-null      object
 41  Carbohydrates_text       634 non-null    object
 42  Protein_text             467 non-null    object
 43  Sugar_text               591 non-null    object
 44  Dietary_Fiber_text       811 non-null    object
 45  Kids_Meal                65219 non-null  int64
 46  Limited_Time_Offer       65219 non-null  int64
 47  Regional                 65219 non-null  int64
 48  Shareable                65219 non-null  int64
dtypes: float64(23), int64(7), object(19)
memory usage: 24.4+ MB
```

Data Cleaning

The first step was to clean the data and set it up in a way that it can be used to train the model. The steps I took were:

1. Feature Selection
2. Deal with Missing Data
3. Bin Sugar Contents
4. Explore/Understand Data
5. Prepare Text
6. Save to .csv

Step 1: Feature Selection

First, I isolated the data to all of the text information and the target variable, 'Sugar'. Most of the text was used for NLP, but I specifically kept the 'restaurant' column, or restaurant name, so that I could later remove that specific string from the item descriptions.

In [4]:

```
relevant_columns = ['Restaurant_Item_Name', 'restaurant', 'Item_Name', 'Item_Description
', 'Food_Category', 'Sugar']
df_relevant = df_raw.loc[:, relevant_columns]
df = df_relevant.sort_values(by = 'Sugar', ascending = False)
df = df.reset_index(drop = True)
```

Step 2: Missing Data

There were several rows throughout the dataset with various parts of nutrition facts omitted. In this case, there were 12,288 items with missing sugar values.

I decided it was best to remove these rows. Although more data will always be helpful, especially for supervised learning models, I didn't want to impute the data and have various word tokens lose or gain inappropriate levels of significance. Ultimately, this left me with 52,931 rows with the data I needed.

In [5]:

```
df.isna().sum()
```

Out[5]:

```
Restaurant_Item_Name        0
restaurant                  0
Item_Name                   0
Item_Description            0
Food_Category               0
Sugar                   12288
dtype: int64
```

In [6]:

```
df.dropna(inplace = True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 52931 entries, 0 to 52930
Data columns (total 6 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Restaurant_Item_Name  52931 non-null  object
 1   restaurant            52931 non-null  object
 2   Item_Name             52931 non-null  object
 3   Item_Description      52931 non-null  object
 4   Food_Category         52931 non-null  object
 5   Sugar                 52931 non-null  float64
dtypes: float64(1), object(5)
memory usage: 2.8+ MB
```

Step 3: Binned Sugar Values

Initially, I considered a regression model to make predictions on specific sugar values given input text. However, I felt that the amount of data I had was insufficient to make accurate predictions on that level. In addition, I wanted my results to be interpretable for an end user who just wants to know at a glance which menu items would be appropriate to order. Practically speaking, the target user doesn't need to know whether the menu item has 75 or 80g of sugar. They just need to know that it's too much sugar!

I binned the sugar values into 5 categories according to the quartiles represented in the data with a 5th added category for menu items with 0g sugar. These quartiles were conveniently in accordance with recommended sugar intake.

The [USDA 2020-2025 Dietary Guidelines fo Americans](), defines a healthy diet as having no more than 10% of daily calorie intake coming from sugar. Most people's daily recommended calorie intake is between 2,000 and 2,500, limiting diets to no more than 200-250 calories in sugar. This equates to about 50-60g, so this class of menu item would be half or more of a day's healthy sugar intake. Further, the American Heart Association (AHA) [recommends no higher than 6% of daily calorie intake coming from sugar]().

This left me with the following categories:

1. **Very High Sugar (5) - Menu items with greater than 30g sugar. These items would either make up 50+% of your daily sugar intake according to the USDA. If you were to follow the AHA's recommendations, an item in this category would exceed your entire day's sugar intake!**
2. **High Sugar (4) - Menu items with between 7 and 30 grams of sugar. Choosing an item in this category would mean consuming a substantial portion of your daily sugar, but not all.**
3. **Medium Sugar (3) - Menu items with between 2 and 7 grams of sugar. These items definitely contain some sugar and may be important for diabetics or those with medical concerns to be aware of.**
4. **Low Sugar (2) - Menu items with between 0 and 2 grams of sugar. These items are pretty safe! However, if you are looking for choices that are completely sugar free, it would be important to know that these items are not 100% sugar-free.**
5. **Zero Sugar (1) - Menu items with exactly 0g sugar.**

In [7]:

```
df.describe()
```

Out[7]:

	Sugar
count	52931.000000
mean	21.902446
std	34.088833
min	0.000000
25%	2.000000
50%	7.000000
75%	30.000000
max	783.000000

In [8]:

```
df['sugar_class'] = df['Sugar'].apply(sugar_classifier)
df.sample(n = 5, random_state = 300)
```

Out[8]:

	Restaurant_Item_Name	restaurant	Item_Name	Item_Description	Food_Category	Sugar	sugar_class
49053	Zaxby's Unsweet Tea	Zaxby's	Unsweet Tea	Unsweet Tea, Beverages, 42 oz	Beverages	0.0	1
	Yard House Guacamole	Yard	Guacamole &	Guacamole & Chips w/	Appetizers &		

	Restaurant_Item_Name	restaurant	Item_Name	Item_Description	Food_Category	Sugar	sugar_class
39101	Yard House Guacamole & Chips	Yard House	Guacamole & Chips	Pico de Gallo & Feta, Snacks	Appetizers & Sides	2.0	2
5673	Culver's Vanilla Cake Cone, 3 Scoops	Culver's	Vanilla Cake Cone, 3 Scoops	Vanilla Cake Cone w/ Vanilla Fresh Frozen Cust...	Desserts	63.0	5
7410	Panera Bread Pumpkin Muffin	Panera Bread	Pumpkin Muffin	Pumpkin Muffin, Muffins & Muffies, Pastries & ...	Baked Goods	52.0	5
20417	California Pizza Kitchen Quinoa & Arugula Sala...	California Pizza Kitchen	Quinoa & Arugula Salad w/ Grilled Chicken Brea...	Quinoa & Arugula Salad w/ Grilled Chicken Brea...	Salads	13.0	4

Step 4: Explore/Understand Data

At this point, I wanted to take a minute to look at the data with a wider perspective. Although the text will processed in a way that will be universal, I thought it was important for intepreting results to look at some statistics. For instance, we see that Starbucks and Dunkin' Donuts provide the most information out of all the represented restaurants. This means that we are going to have lots of data on words like "whipped", "caramel", "mocha", and "chocolate". Although this is not necessarily problematic, it is worth noting and something I will address in my conclusion's "Next Steps" findings.

In [9]:

```
df
```

Out[9]:

	Restaurant_Item_Name	restaurant	Item_Name	Item_Description	Food_Category	Sugar	sugar_class
0	Dairy Queen Cookie Dough Blizzard Cake, 10 in	Dairy Queen	Cookie Dough Blizzard Cake, 10 in	Cookie Dough Blizzard Cake, 10 in w/ Vanilla S...	Desserts	783.0	5
1	Dairy Queen Reeses Peanut Butter Cups Blizzard...	Dairy Queen	Reeses Peanut Butter Cups Blizzard Cake, 10 in	Reeses Peanut Butter Cups Blizzard Cake, 10 in...	Desserts	737.0	5
2	Dairy Queen Chocolate Xtreme Blizzard Cake, 10 in	Dairy Queen	Chocolate Xtreme Blizzard Cake, 10 in	Chocolate Xtreme Blizzard Cake, 10 in w/ Brown...	Desserts	735.0	5
3	Dairy Queen Oreo Blizzard Cake, 10 in	Dairy Queen	Oreo Blizzard Cake, 10 in	Oreo Blizzard Cake, 10 in w/ Oreo Cookie Piece...	Desserts	720.0	5
4	Dairy Queen DQ Round Cake, 10 in	Dairy Queen	DQ Round Cake, 10 in	DQ Round Cake w/ Cake Crunch Filling, Chocolat...	Desserts	569.0	5
...	...	...	...	...	...	...	...
52926	Popeyes 6 Nuggets	Popeyes	6 Nuggets	6 Nuggets, Tenders	Entrees	0.0	1
52927	Popeyes Breast, Bonafide Spicy Chicken	Popeyes	Breast, Bonafide Spicy Chicken	Breast, Bonafide Spicy Chicken	Entrees	0.0	1
52928	Popeyes Thigh, Bonafide Spicy Chicken	Popeyes	Thigh, Bonafide Spicy Chicken	Thigh, Bonafide Spicy Chicken, 300 Calories or...	Entrees	0.0	1
52929	Popeyes Leg, Bonafide Spicy Chicken	Popeyes	Leg, Bonafide Spicy Chicken	Leg, Bonafide Spicy Chicken, 200 Calories or U...	Entrees	0.0	1
52930	Sheetz Black Pepper, for MTO Shnack Wrapz	Sheetz	Black Pepper, for MTO Shnack Wrapz	Black Pepper, for MTO Shnack Wrapz & MTO Slide...	Toppings & Ingredients	0.0	1

52931 rows × 7 columns

In [92]:

```python
value_counts = df['restaurant'].value_counts()
for value, count in value_counts.items():
    print(f'{value}: {count}')
top_15_restaurants = dict(value_counts.iloc[:15])
print("")
print("==================================")
print("")

average_no_menu_items = value_counts.mean()

print("Average number of menu items per restaurant:")
print(average_no_menu_items)
```

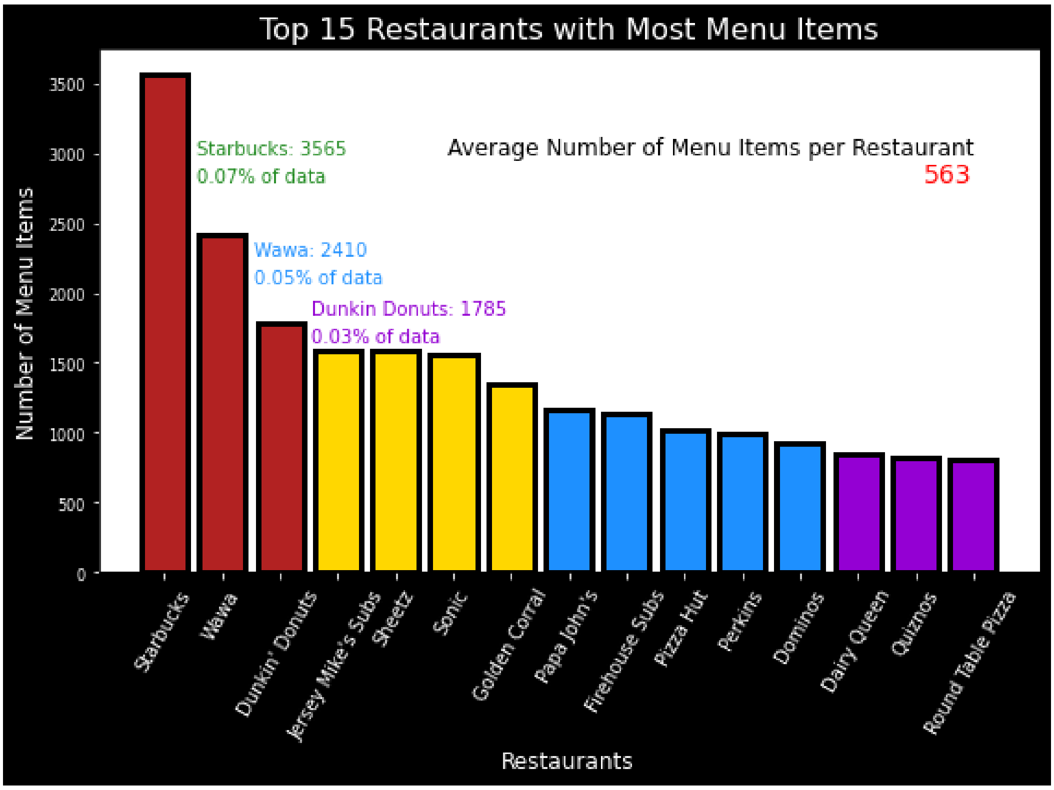
```
Starbucks: 3565
Wawa: 2410
Dunkin' Donuts: 1785
Jersey Mike's Subs: 1585
Sheetz: 1584
Sonic: 1553
Golden Corral: 1351
Papa John's: 1165
Firehouse Subs: 1134
Pizza Hut: 1017
Perkins: 991
Dominos: 927
Dairy Queen: 847
Quiznos: 816
Round Table Pizza: 814
Jason's Deli: 813
BJ's Restaurant & Brewhouse: 813
IHOP: 774
Chili's: 725
Red Robin: 719
White Castle: 715
Frisch's Big Boy: 707
Steak 'N Shake: 685
Bob Evans: 667
Culver's: 654
Baskin Robbins: 650
Taco Bell: 638
Whataburger: 632
California Pizza Kitchen: 622
Tim Hortons: 600
Red Lobster: 594
Papa Murphy's: 591
Yard House: 590
Denny's: 582
Panera Bread: 578
Marco's Pizza: 577
Famous Dave's: 575
Friendly's: 574
Jack in the Box: 552
Applebee's: 536
Einstein Bros: 517
McDonald's: 515
McAlister's Deli: 510
Zaxby's: 504
TGI Friday's: 457
Subway: 443
LongHorn Steakhouse: 432
Ruby Tuesday: 429
Olive Garden: 419
Krispy Kreme: 417
Wendy's: 412
KFC: 393
O'Charley's: 390
Carrabba's Italian Grill: 389
Burger King: 388
Jamba Juice: 387
PF Chang's: 376
Joe's Crab Shack: 375
Auntie Anne's: 372
```

```
Bonefish Grill: 344
Carl's Jr.: 343
Hardee's: 317
El Pollo Loco: 306
Del Taco: 272
Potbelly Sandwich Shop: 264
Arby's: 262
Outback Steakhouse: 259
Panda Express: 257
Sbarro: 257
Romano's Macaroni Grill: 254
Krystal: 240
Church's Chicken: 240
Moe's Southwest Grill: 239
Hooters: 239
Bojangles: 233
Casey's General Store: 228
Chuck E. Cheese: 225
Chick-Fil-A: 223
Checker's Drive-In/Rallys: 220
The Capital Grille: 219
Boston Market: 189
Noodles & Company: 178
Popeyes: 174
Long John Silver's: 173
Captain D's: 144
Qdoba: 144
Chipotle: 131
Wingstop: 114
Ci Ci's Pizza: 91
Little Caesars: 90
Dickey's Barbeque Pit: 75
In-N-Out Burger: 72
Five Guys: 61
7 Eleven: 22

================================

Average number of menu items per restaurant:
563.0957446808511
```

In [115]:

```python
fig, ax = plt.subplots(figsize = (8, 6), facecolor = 'black')
x = list(top_15_restaurants.keys())
y = list(top_15_restaurants.values())
colors = ['firebrick', 'firebrick', 'firebrick',
          'gold', 'gold', 'gold', 'gold',
          'dodgerblue', 'dodgerblue', 'dodgerblue', 'dodgerblue', 'dodgerblue',
          'darkviolet', 'darkviolet', 'darkviolet']
border_thickness = 3
ax.bar(x, y, color = colors, edgecolor = 'black', linewidth = border_thickness)
ax.set_title('Top 15 Restaurants with Most Menu Items', fontsize = 16, color = 'white')
ax.set_ylabel('Number of Menu Items', color = 'white', fontsize = 12)
ax.set_xlabel('Restaurants', color = 'white', fontsize = 12)
ax.tick_params(axis = 'x', rotation = 60, colors = 'white', labelsize = 10)
ax.tick_params(axis = 'y', colors = 'white', labelsize = 8)
plt.text(0.55, 3000, 'Starbucks: 3565', ha = 'left', color = 'forestgreen')
plt.text(0.55, 2800, f"{(3565 / 52931):.2f}% of data", ha = 'left', color = 'forestgreen
')
plt.text(1.55, 2275, 'Wawa: 2410', ha = 'left', color = 'dodgerblue')
plt.text(1.55, 2075, f"{(2410 / 52931):.2f}% of data", ha = 'left', color = 'dodgerblue'
)
plt.text(2.55, 1850, 'Dunkin Donuts: 1785', ha = 'left', color = 'darkviolet')
plt.text(2.55, 1650, f"{(1785 / 52931):.2f}% of data", ha = 'left', color = 'darkviolet'
)
plt.text(14, 3000, 'Average Number of Menu Items per Restaurant', ha = 'right', fontsize
= 12)
plt.text(14, 2800, f"{round(average_no_menu_items)}", ha = 'right', color = 'red', fonts
ize = 14)
plt.tight_layout()
plt.savefig('Images/top_15_restaurants_graph.png')
```

```
plt.show()
```



Step 5: Prepare Text

To prepare the text, I combined the strings together and removed the restaurant names from the text. It is important to note that some words will appear multiple times in each text block. This will be addressed in my imported Preprocessor class that can be found in the preprocessor_class.py file in the repo. However, it does help form the raw text block that makes up the independent variable.

In [163]:

```
df['text'] = df['Restaurant_Item_Name'] + " " + df['Item_Name'] + " " + df['Item_Descrip
tion'] + " " + df['Food_Category']
df.drop(columns = ['Restaurant_Item_Name', 'Item_Name', 'Item_Description', 'Food_Catego
ry', 'Sugar'], inplace = True)
```

In [164]:

```
df['restaurant'] = df['restaurant'].str.split()
for index, row in df.iterrows():
    for string in row['restaurant']:
        df.at[index, 'text'] = df.at[index, 'text'].replace(string, '')
df.drop(columns = 'restaurant', inplace = True)
```

In [165]:

```
df.sample(n = 5, random_state = 200)
```

Out[165]:

	sugar_class	text
21688	4	Deconstructed Breakfast Taco Deconstructed Br...
42983	2	Lay's Kettle Cooked 40% Less Fat Original La...
26327	4	Chicken Maui Zaui w/ Polynesian Sauce, Pan,...
31076	3	All Meat Pizza on Gluten Free Crust, Medium,...
13655	4	El Nino Margarita El Nino Margarita El Nino M...

Step 6: Save to .csv

At this point, I saved the data to a new .csv file that can be referenced later so the above code does not need to be re-ran in each notebook.

In [169]:

```
df.to_csv('Data/prepared_text_data_sugar.csv', index = False)
```