Netflix Analysis

Problem Statement : Explore out the briefer analysis on Netflix Dataset with an access to noticeable feature attributes for Movies/TV Shows with Viewership Score and present the justifiable insights in points along with an overall summary.

Dataset:'netflix daily top 10.csv'. (Netflix Top 10 Shows for the period 2020-2022)

In [44]:
```
import pandas as pd, matplotlib.pyplot as plt, seaborn as sns
```

In [46]:
```
#Loading the dataset
df = pd.read_csv('netflix daily top 10.csv')
df.head()
```

Out[46]:

	As of	Rank	Year to Date Rank	Last Week Rank	Title	Type	Netflix Exclusive	Netflix Release Date	Days In Top 10	Viewership Score
0	2020-04-01	1	1	1	Tiger King: Murder, Mayhem ...	TV Show	Yes	Mar 20, 2020	9	90
1	2020-04-01	2	2	-	Ozark	TV Show	Yes	Jul 21, 2017	5	45
2	2020-04-01	3	3	2	All American	TV Show	NaN	Mar 28, 2019	9	76
3	2020-04-01	4	4	-	Blood Father	Movie	NaN	Mar 26, 2020	5	30
4	2020-04-01	5	5	4	The Platform	Movie	Yes	Mar 20, 2020	9	55

📊 Data Overview

The dataset comprises the following columns:

- As of: Date of ranking.
- Rank: Current rank on that date.

- Year to Date Rank: Cumulative rank for the year.
- Last Week Rank: Rank from the previous week.
- Title: Name of the movie or TV show.
- Type: Whether it's a TV Show or Movie.
- Netflix Exclusive: Indicates if it's exclusive to Netflix.
- Netflix Release Date: Release date on Netflix.
- Days In Top 10: Number of days the title remained in the Top 10.
- Viewership Score: A metric quantifying popularity.

In [48]:
```
# Size or the shape of dataset
df.shape
```

Out[48]:
```
(7100, 10)
```

Pre process cleaning and orgainzing data

In [50]:
```
# checking if there is any missing or null value
df.isnull().sum()
```

Out[50]:
```
As of                      0
Rank                       0
Year to Date Rank          0
Last Week Rank             0
Title                      0
Type                       0
Netflix Exclusive       2501
Netflix Release Date       0
Days In Top 10             0
Viewership Score           0
dtype: int64
```

In [52]:
```
# check if there is any duplicate values
df[df.duplicated(keep=False)]
```

Out[52]:

As of	Rank	Year to Date Rank	Last Week Rank	Title	Type	Netflix Exclusive	Netflix Release Date	Days In Top 10	Viewership Score

In [54]:
```
# Remove any blank space in the column variable
df.columns = df.columns.str.strip()
df.columns
```

Out[54]:
```
Index(['As of', 'Rank', 'Year to Date Rank', 'Last Week Rank', 'Title', 'Type',
       'Netflix Exclusive', 'Netflix Release Date', 'Days In Top 10',
       'Viewership Score'],
      dtype='object')
```

In [56]:
```
# converting the 'as of' and 'netflix release date' to datetime format
df['As of']= pd.to_datetime(df['As of'])
df['Netflix Release Date'] = pd.to_datetime(df['Netflix Release Date'], errors =
```

In [58]:
```
# Filling the missing values in the 'netflix exclusive'
df['Netflix Exclusive'] = df['Netflix Exclusive'].fillna('No')
```

```
df['Netflix Exclusive'].head()
```

Out[58]:

```
0    Yes
1    Yes
2     No
3     No
4    Yes
Name: Netflix Exclusive, dtype: object
```

In [60]:

```
df.head(10)
```

Out[60]:

	As of	Rank	Year to Date Rank	Last Week Rank	Title	Type	Netflix Exclusive	Netflix Release Date	Days In Top 10	Viewership Score
0	2020-04-01	1	1	1	Tiger King: Murder, Mayhem ...	TV Show	Yes	2020-03-20	9	90
1	2020-04-01	2	2	-	Ozark	TV Show	Yes	2017-07-21	5	45
2	2020-04-01	3	3	2	All American	TV Show	No	2019-03-28	9	76
3	2020-04-01	4	4	-	Blood Father	Movie	No	2020-03-26	5	30
4	2020-04-01	5	5	4	The Platform	Movie	Yes	2020-03-20	9	55
5	2020-04-01	6	6	-	Car Masters: Rust to Riches	TV Show	Yes	2018-09-14	4	14
6	2020-04-01	7	10	-	Unorthodox	TV Show	Yes	2020-03-26	2	5
7	2020-04-01	8	7	5	Love is Blind	TV Show	Yes	2020-02-13	9	40
8	2020-04-01	9	8	-	Badland	Movie	No	2020-03-26	4	11
9	2020-04-01	10	9	-	Uncorked	Movie	Yes	2020-03-27	4	15

Considering the use cases that align well with the data at hand. Potential use cases could include:

- Trends in Viewership Scores: How do viewership scores change over time?
- Effectiveness of Netflix Exclusives: Do Netflix exclusives perform better than non-exclusives?
- TV Shows vs Movies: Which type tends to perform better in the top 10?

- Popular Titles: Which titles consistently appear in the Top 10 with high viewership?

In [62]:

```python
# Describe the stats for all numberical columns
df.describe()
```

Out[62]:

	As of	Rank	Netflix Release Date	Days In Top 10	Viewership Score
count	7100	7100.000000	7100	7100.000000	7100.000000
mean	2021-03-21 12:00:00.000000256	5.500000	2020-06-21 08:05:32.619718144	24.123662	122.790141
min	2020-04-01 00:00:00	1.000000	2007-01-15 00:00:00	1.000000	1.000000
25%	2020-09-25 00:00:00	3.000000	2020-04-26 00:00:00	3.000000	19.000000
50%	2021-03-21 12:00:00	5.500000	2020-10-02 00:00:00	7.000000	50.000000
75%	2021-09-15 00:00:00	8.000000	2021-05-14 00:00:00	18.000000	128.000000
max	2022-03-11 00:00:00	10.000000	2022-03-04 00:00:00	428.000000	1474.000000
std	NaN	2.872484	NaN	58.473789	213.861642

In [64]:

```python
# Groupby 'title' aggregation on 'viewership score' and 'days in top 10'

title_st = df.groupby('Title').agg({
    'Viewership Score' : 'max',
    'Days In Top 10' : 'max'
}).sort_values('Viewership Score', ascending = False)

# Top 10 by viewership score
top_10 = title_st.head(10).reset_index()
top_10
```

Out[64]:

	Title	Viewership Score	Days In Top 10
0	Cocomelon	1474	428
1	Manifest	590	80
2	Cobra Kai	582	81
3	Ozark	536	89
4	Outer Banks	534	72
5	Squid Game	495	66
6	The Queenâ□□s Gambit	446	73
7	Bridgerton	432	58
8	All American	416	66
9	Lucifer	415	57

In [66]:

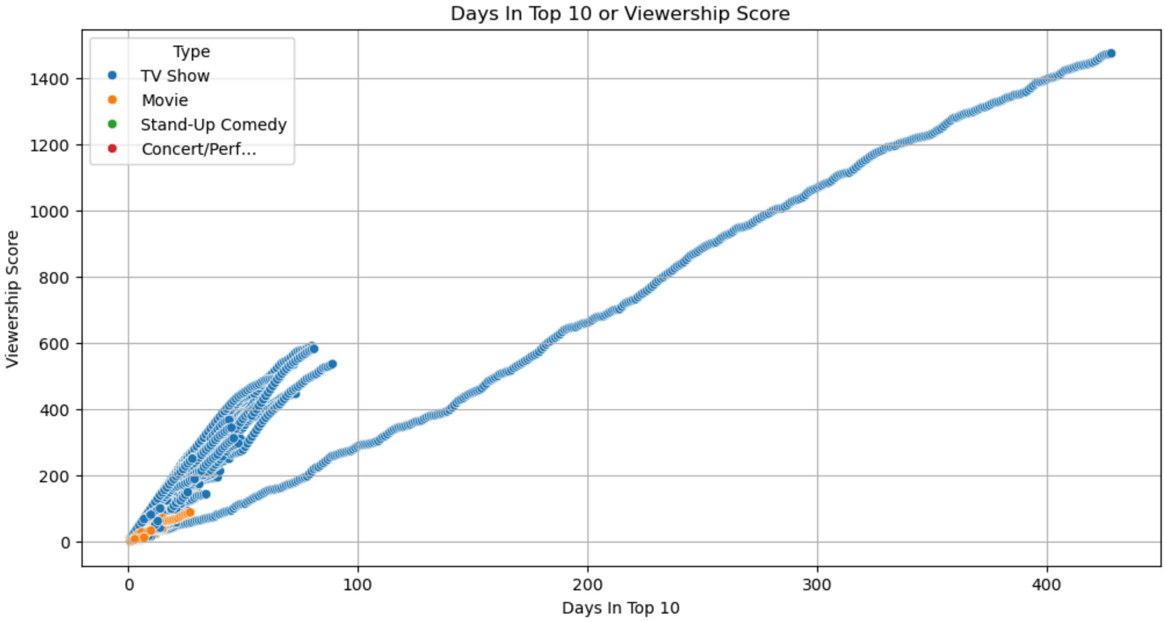
```
print(df['Type'].value_counts(),'\n')
print(df['Title'].value_counts())
```

```
Type
TV Show            4446
Movie              2611
Stand-Up Comedy      41
Concert/Perf…         2
Name: count, dtype: int64

Title
Cocomelon                          428
Ozark                               85
Cobra Kai                           81
Manifest                            80
The Queenâ□□s Gambit                73
                                  ...
The Office                           1
Animals on the Loose: A You…         1
Dark                                 1
The Secret Life of Pets 2            1
Step Up Revolution                   1
Name: count, Length: 645, dtype: int64
```

Above we can see the frequency of tv shows are majority in netflix than the Movies " Tv show > Movie > Stand-Up Comedy > Concert/perf "

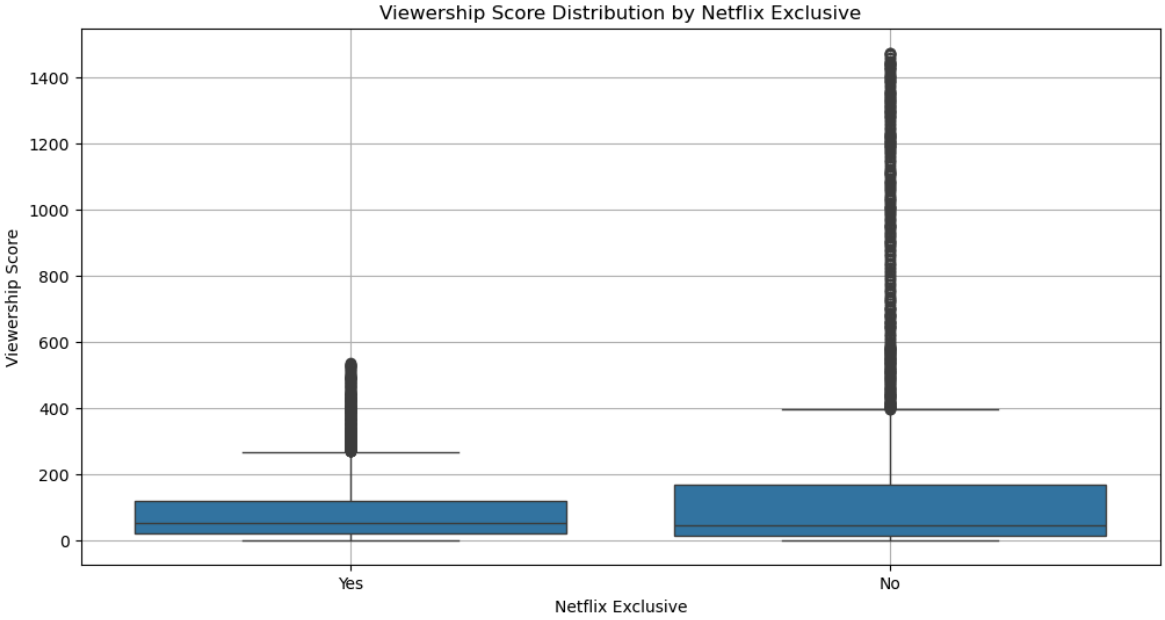
In [70]:

```
# Scatter plot of days in Top 10 vs viwership score

plt.figure(figsize = (12, 6))
sns.scatterplot(data = df, x = 'Days In Top 10', y = 'Viewership Score', hue = '
plt.title('Days In Top 10 or Viewership Score')
plt.xlabel('Days In Top 10')
plt.ylabel('Viewership Score')
plt.legend(title = 'Type')
plt.grid(True)
plt.show()
```



- The tv show viewership score dominant in netflix
- Comparing to movie or other genre the Tv show majority of Top 10 Days

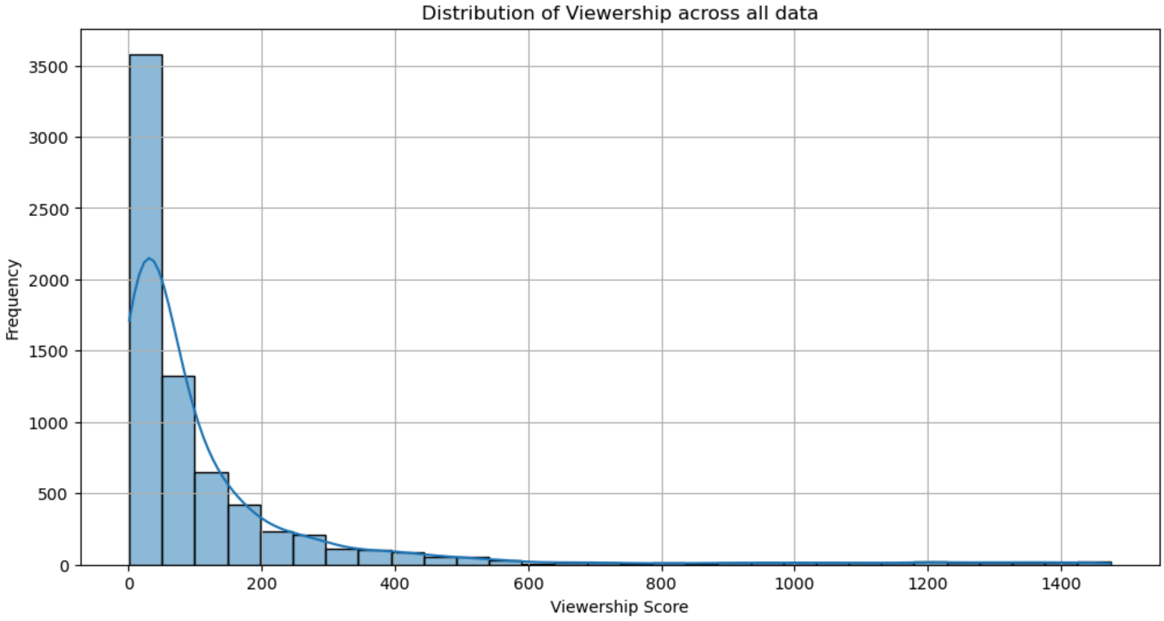
In [72]:
```
# Netflix Exclusive vs Viewership Score

plt.figure(figsize = (12,6))
sns.boxplot(data = df, x = 'Netflix Exclusive', y = 'Viewership Score')
plt.title('Viewership Score Distribution by Netflix Exclusive')
plt.xlabel('Netflix Exclusive')
plt.ylabel('Viewership Score')
plt.grid(True)
plt.show()
```



- Above boxplot the average viewership in the non-netflix exclusive has a higher than netflix exclusive
- And the outlier and extreme are also the higher viewership score in non-netflix exclusive

In [74]:

```
# Distribution of Viewership Score across all data

plt.figure(figsize = (12,6))
sns.histplot(df['Viewership Score'], bins=30, kde=True)
plt.title('Distribution of Viewership across all data')
plt.xlabel('Viewership Score')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



📊 Key Insights:

Cocomelon as an Outlier

- Cocomelon stands out with unusually high longevity and viewership scores.
- This is likely due to frequent, repeated viewership by younger audiences.

Squid Game vs. Sustained Hits

- Although Squid Game was a viral sensation, it spent fewer days in the Top 10 compared to shows like Cobra Kai or Ozark.
- This highlights how quick spikes in popularity can differ from long-term performance.

Correlation Between Viewership Score and Days in Top 10

- Generally, shows with more days in the Top 10 tend to have higher viewership scores.
- However, viral outliers like Squid Game may skew this trend.

Netflix Exclusive vs. Non-Exclusive Content

- Netflix Originals show steady viewership, but Non-Netflix titles sometimes have even higher scores.
- This could be influenced by strong external fanbases or outliers like Cocomelon.

Impact of Duration and Branding

- Shows with longer availability and catchy or recognizable titles tend to perform better in terms of viewership.
- Duration on the platform may directly influence cumulative viewership scores.

Conclusion:

- The analysis of Netflix content performance reveals nuanced dynamics between virality, longevity, and content origin. Outliers like Cocomelon underscore the impact of repeat viewership and niche audiences, while Squid Game illustrates how viral phenomena can achieve massive short-term success without sustained chart presence. A general correlation exists between viewership scores and time spent in the Top 10, but exceptions highlight the complexity of audience behavior. Interestingly, Non-Netflix titles can outperform Originals, suggesting external fanbases and brand recognition play a crucial role. Overall, duration on the platform and effective branding emerge as key drivers of long-term engagement and viewership.

In [ ]:

Starbucks Analysis

Problem Statement : Do an exploratory data analysis for the Starbuck Dataset with feature attributes that focuses on Food Menu and Drinks Menu considering the Nutrition Facts along. Wrap the analysis by subjecting favorable points with a final conclusion that ejects from the complete understanding.

In [81]:
```python
import pandas as pd, matplotlib.pyplot as plt, seaborn as sns
```

Loading dataset

In [83]:
```python
sb_drink = pd.read_csv('starbucks-menu-nutrition-drinks.csv')
sb_drink.head()
```

Out[83]:

	Unnamed: 0	Calories	Fat (g)	Carb. (g)	Fiber (g)	Protein	Sodium
0	Cool Lime Starbucks Refreshers™ Beverage	45	0	11	0	0	10
1	Ombré Pink Drink	-	-	-	-	-	-
2	Pink Drink	-	-	-	-	-	-
3	Strawberry Acai Starbucks Refreshers™ Beverage	80	0	18	1	0	10
4	Very Berry Hibiscus Starbucks Refreshers™ Beve...	60	0	14	1	0	10

In [85]:
```python
sb_drink.shape
```

Out[85]:
```
(177, 7)
```

In [87]:
```python
sb_food = pd.read_csv('starbucks-menu-nutrition-food.csv', encoding='utf-16')
sb_food.head()
```

Out[87]:

	Unnamed: 0	Calories	Fat (g)	Carb. (g)	Fiber (g)	Protein (g)
0	Chonga Bagel	300	5.0	50	3	12
1	8-Grain Roll	380	6.0	70	7	10
2	Almond Croissant	410	22.0	45	3	10
3	Apple Fritter	460	23.0	56	2	7
4	Banana Nut Bread	420	22.0	52	2	6

In [89]:
```python
sb_food.shape
```

Out[89]:
```
(113, 6)
```

📊 Data Overview

This dataset provides nutritional information for various menu items. The key columns include:

- Items: The name or description of the menu item.
- Calories: Total caloric content per item.
- Fat (g): Total fat content, measured in grams.

- Carb. (g): Carbohydrates content in grams.
- Fiber (g): Dietary fiber content in grams.
- Protein (g): Protein content in grams.
- Sodium: Sodium content, typically measured in milligrams.

In [91]:

```
# Rename the unnamed column
sb_drink.rename(columns = {'Unnamed: 0':'Items'}, inplace = True)
sb_food.rename(columns = {'Unnamed: 0':'Items'}, inplace = True)
sb_drink.rename(columns = {'Protein':'Protein (g)'}, inplace = True)
```

In [93]:

```
# Replace the '-' with NaN
sb_drink.replace('-', pd.NA, inplace = True)
sb_food.replace('-', pd.NA, inplace = True)

# Adding missing sodium column to sb_food(fill with NaN)
if 'Sodium' not in sb_food.columns:
    sb_food['Sodium'] = pd.NA

# Adding new column 'category'
sb_drink['Category'] = 'Drink'
sb_food['Category'] = 'Food'
```

In [95]:

```
# Strip down the extra spaces in columns name
sb_food.columns = sb_food.columns.str.strip()
sb_drink.columns = sb_drink.columns.str.strip()
```

In [99]:

```
# Print the columns name
print(sb_food.columns)
print(sb_drink.columns)
```

```
Index(['Items', 'Calories', 'Fat (g)', 'Carb. (g)', 'Fiber (g)', 'Protein (g)',
       'Sodium', 'Category'],
      dtype='object')
Index(['Items', 'Calories', 'Fat (g)', 'Carb. (g)', 'Fiber (g)', 'Protein (g)',
       'Sodium', 'Category'],
      dtype='object')
```

In [101…

```
# Combine the two menu into one
sb_combine = pd.concat([sb_drink, sb_food], ignore_index = True)
print(sb_combine.head())
print('\n',sb_combine.shape)
```

```
                                               Items Calories Fat (g)  \
0           Cool Lime Starbucks Refreshers™ Beverage       45       0
1                                   Ombré Pink Drink     <NA>    <NA>
2                                         Pink Drink     <NA>    <NA>
3     Strawberry Acai Starbucks Refreshers™ Beverage       80       0
4  Very Berry Hibiscus Starbucks Refreshers™ Beve...       60       0

  Carb. (g) Fiber (g) Protein (g) Sodium Category
0        11         0           0     10    Drink
1      <NA>      <NA>        <NA>   <NA>    Drink
2      <NA>      <NA>        <NA>   <NA>    Drink
3        18         1           0     10    Drink
4        14         1           0     10    Drink

(290, 8)
```

In [ ]:

In [103…

```
#checking if there is still any null values
sb_combine.isnull().sum()
```

Out[103…

```
Items            0
Calories        85
Fat (g)         85
Carb. (g)       85
Fiber (g)       85
Protein (g)     85
Sodium         198
Category         0
dtype: int64
```

In [105…

```
# Droping the missing value
sb_combine.dropna(subset = ['Calories', 'Fat (g)',      'Carb. (g)',    'Fiber (
sb_combine
```

Out[105…

	Items	Calories	Fat (g)	Carb. (g)	Fiber (g)	Protein (g)	Sodium	Category
0	Cool Lime Starbucks Refreshers™ Beverage	45	0	11	0	0	10	Drink
3	Strawberry Acai Starbucks Refreshers™ Beverage	80	0	18	1	0	10	Drink
4	Very Berry Hibiscus Starbucks Refreshers™ Beve...	60	0	14	1	0	10	Drink
8	Evolution Fresh™ Organic Ginger Limeade	110	0	28	0	0	5	Drink
9	Iced Coffee	0	0	0	0	0	0	Drink
...	...	...	...	...	...	...	...	...
285	Justin's Chocolate Hazelnut Butter	180	14.0	12	3	4	NaN	Food
286	Justin's Classic Almond Butter	190	18.0	6	3	7	NaN	Food
287	Lemon Chiffon Yogurt	340	13.0	38	0	18	NaN	Food
288	Organic Avocado (Spread)	90	8.0	5	4	1	NaN	Food
289	Seasonal Fruit Blend	90	0.0	24	4	1	NaN	Food

205 rows × 8 columns

In [107…

```
# Shows the duplicate values
sb_combine[sb_combine.duplicated(keep = False)]
```

Out[107…

	Items	Calories	Fat (g)	Carb. (g)	Fiber (g)	Protein (g)	Sodium	Category
11	Iced Espresso Classics - Vanilla Latte	130	2.5	21	0	5	65	Drink
12	Iced Espresso Classics - Caffe Mocha	140	2.5	23	0	5	90	Drink
13	Iced Espresso Classics - Caramel Macchiato	130	2.5	21	0	5	65	Drink
19	Tazo® Bottled Berry Blossom White	60	0	15	0	0	10	Drink
20	Tazo® Bottled Black Mango	150	0	38	0	0	15	Drink
21	Tazo® Bottled Black with Lemon	140	0	35	0	0	10	Drink
22	Tazo® Bottled Brambleberry	140	0	35	0	0	15	Drink
23	Tazo® Bottled Giant Peach	150	0	37	0	0	15	Drink
24	Tazo® Bottled Iced Passion	70	0	17	0	0	10	Drink
25	Tazo® Bottled Lemon Ginger	120	0	31	0	0	10	Drink
26	Tazo® Bottled Organic Black Lemonade	140	0	35	0	0	10	Drink
27	Tazo® Bottled Organic Iced Black Tea	60	0	15	0	0	10	Drink
28	Tazo® Bottled Organic Iced Green Tea	120	0	31	0	0	10	Drink
29	Tazo® Bottled Plum Pomegranate	140	0	35	0	0	10	Drink
30	Tazo® Bottled Tazoberry	150	0	38	0	0	15	Drink
31	Tazo® Bottled White Cranberry	140	0	35	0	0	10	Drink
39	Iced Espresso Classics - Vanilla Latte	130	2.5	21	0	5	65	Drink

	Items	Calories	Fat (g)	Carb. (g)	Fiber (g)	Protein (g)	Sodium	Category
40	Iced Espresso Classics - Caffe Mocha	140	2.5	23	0	5	90	Drink
41	Iced Espresso Classics - Caramel Macchiato	130	2.5	21	0	5	65	Drink
77	Tazo® Bottled Berry Blossom White	60	0	15	0	0	10	Drink
78	Tazo® Bottled Black Mango	150	0	38	0	0	15	Drink
79	Tazo® Bottled Black with Lemon	140	0	35	0	0	10	Drink
80	Tazo® Bottled Brambleberry	140	0	35	0	0	15	Drink
81	Tazo® Bottled Giant Peach	150	0	37	0	0	15	Drink
82	Tazo® Bottled Iced Passion	70	0	17	0	0	10	Drink
83	Tazo® Bottled Lemon Ginger	120	0	31	0	0	10	Drink
84	Tazo® Bottled Organic Black Lemonade	140	0	35	0	0	10	Drink
85	Tazo® Bottled Organic Iced Black Tea	60	0	15	0	0	10	Drink
86	Tazo® Bottled Organic Iced Green Tea	120	0	31	0	0	10	Drink
87	Tazo® Bottled Plum Pomegranate	140	0	35	0	0	10	Drink
88	Tazo® Bottled Tazoberry	150	0	38	0	0	15	Drink
89	Tazo® Bottled White Cranberry	140	0	35	0	0	10	Drink
134	Latte Macchiato	190	7	19	0	12	160	Drink
135	Latte Macchiato	190	7	19	0	12	160	Drink

In [109…

```
# Delete the duplicate value latte Macchiato
latte_dupes = sb_combine[sb_combine['Items'] == 'Latte Macchiato']

if len(latte_dupes)>1:
    index_to_drop = latte_dupes.index[0]
    sb_combine = sb_combine.drop(index = index_to_drop)
```

In [ ]:

In [111…

```
sb_combine[sb_combine['Items']  == 'Latte Macchiato']
```

Out[111…

	Items	Calories	Fat (g)	Carb. (g)	Fiber (g)	Protein (g)	Sodium	Category
135	Latte Macchiato	190	7	19	0	12	160	Drink

In [113…

```
sb_combine
```

Out[113…

	Items	Calories	Fat (g)	Carb. (g)	Fiber (g)	Protein (g)	Sodium	Category
0	Cool Lime Starbucks Refreshers™ Beverage	45	0	11	0	0	10	Drink
3	Strawberry Acai Starbucks Refreshers™ Beverage	80	0	18	1	0	10	Drink
4	Very Berry Hibiscus Starbucks Refreshers™ Beve...	60	0	14	1	0	10	Drink
8	Evolution Fresh™ Organic Ginger Limeade	110	0	28	0	0	5	Drink
9	Iced Coffee	0	0	0	0	0	0	Drink
...	...	...	...	...	...	...	...	...
285	Justin's Chocolate Hazelnut Butter	180	14.0	12	3	4	NaN	Food
286	Justin's Classic Almond Butter	190	18.0	6	3	7	NaN	Food
287	Lemon Chiffon Yogurt	340	13.0	38	0	18	NaN	Food
288	Organic Avocado (Spread)	90	8.0	5	4	1	NaN	Food
289	Seasonal Fruit Blend	90	0.0	24	4	1	NaN	Food

204 rows × 8 columns

In [115…

```
# checking if there still any null values
print(sb_combine['Calories'].isna().sum())
print(sb_combine['Calories'].dtype)
print(sb_combine['Category'].dtype)
```

```
0
object
object
```

In [117…

```
# check frequecy of same item appearance
print(sb_combine['Items'].value_counts())
```

```
Items
Tazo® Bottled Plum Pomegranate          2
Tazo® Bottled Black with Lemon          2
Tazo® Bottled White Cranberry           2
Tazo® Bottled Tazoberry                 2
Tazo® Bottled Organic Iced Green Tea    2
                                       ..
8-Grain Roll                            1
Almond Croissant                        1
Apple Fritter                           1
Banana Nut Bread                        1
Seasonal Fruit Blend                    1
Name: count, Length: 187, dtype: int64
```

In [119…

```
# Checking if there is still any duplicates
sb_combine[sb_combine.duplicated()].count()
```

Out[119…

```
Items          16
Calories       16
Fat (g)        16
Carb. (g)      16
Fiber (g)      16
Protein (g)    16
Sodium         16
Category       16
dtype: int64
```

In [121…

```
# Drop the duplicates and shows the table
sb_cleaned_menu = sb_combine.drop_duplicates(keep = False)
print(sb_cleaned_menu.head())
print('\n', sb_cleaned_menu.shape)
```

```
                                                Items Calories Fat (g)  \
0            Cool Lime Starbucks Refreshers™ Beverage       45       0
3      Strawberry Acai Starbucks Refreshers™ Beverage       80       0
4  Very Berry Hibiscus Starbucks Refreshers™ Beve...       60       0
8             Evolution Fresh™ Organic Ginger Limeade      110       0
9                                          Iced Coffee        0       0

  Carb. (g) Fiber (g) Protein (g) Sodium Category
0        11         0           0     10    Drink
3        18         1           0     10    Drink
4        14         1           0     10    Drink
8        28         0           0      5    Drink
9         0         0           0      0    Drink

 (172, 8)
```

In [295…

```
# check for duplicates
sb_cleaned_menu[sb_cleaned_menu.duplicated()].count()
```

Out[295…

```
Items          0
Calories       0
Fat (g)        0
Carb. (g)      0
Fiber (g)      0
Protein (g)    0
Sodium         0
Category       0
dtype: int64
```

In [123…

```
# Stat analysis
sb_cleaned_menu.groupby('Category')['Calories'].describe()
```

Out[123…

Category	count	unique	top	freq
Drink	59	28	5	7
Food	113	44	360	7

In [125…

```
sb_cleaned_menu.columns
```

Out[125…

```
Index(['Items', 'Calories', 'Fat (g)', 'Carb. (g)', 'Fiber (g)', 'Protein (g)',
       'Sodium', 'Category'],
      dtype='object')
```

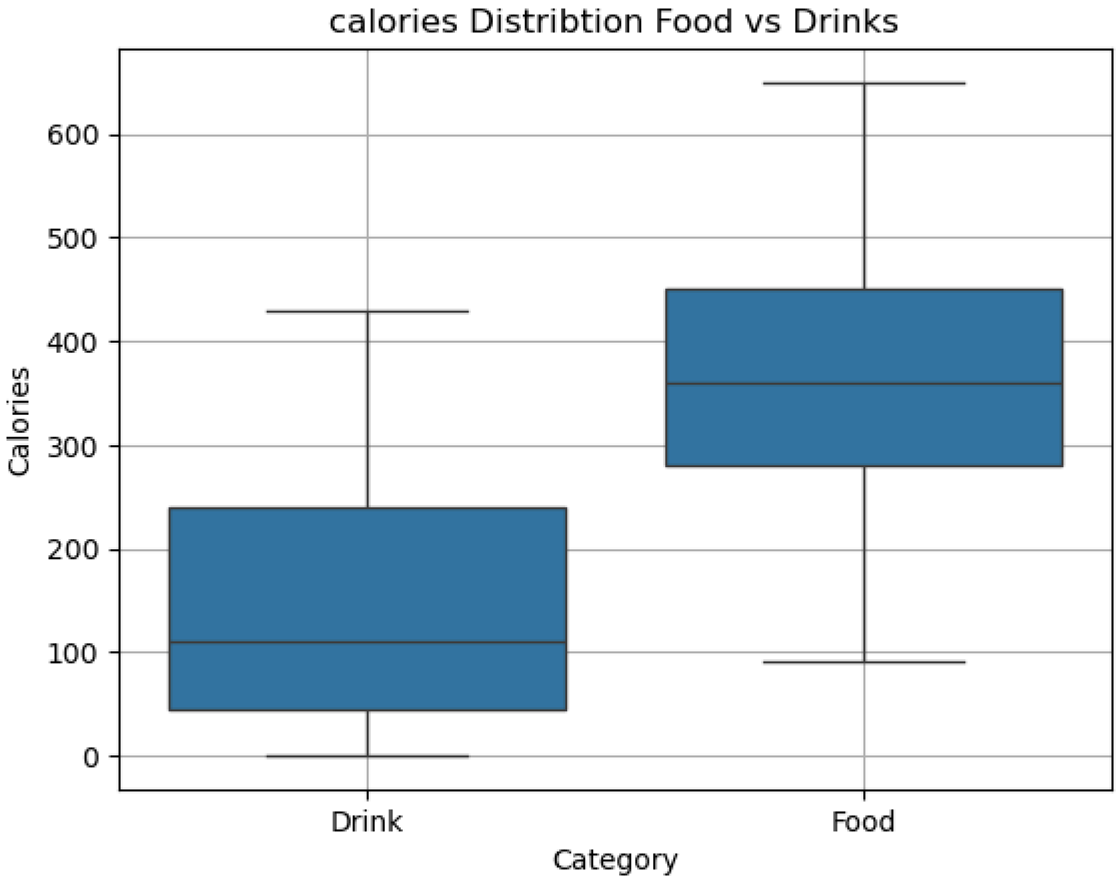
In [129…

```
# convert columns value to numeric for consistency
col_names = ['Calories', 'Fat (g)', 'Carb. (g)', 'Fiber (g)', 'Protein (g)', 'Sc

for col in col_names:
    sb_cleaned_menu[col] = pd.to_numeric(sb_cleaned_menu[col], errors='coerce')
```

```
C:\Users\gemin\AppData\Local\Temp\ipykernel_14604\4203541213.py:5: SettingWithCop
yWarning:
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/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  sb_cleaned_menu[col] = pd.to_numeric(sb_cleaned_menu[col], errors='coerce')
```

In [131…

```
# Calories Food vs Drinks
sns.boxplot(data=sb_cleaned_menu, x='Category', y='Calories')
plt.title('calories Distribtion Food vs Drinks')
plt.grid(True)
```



Insight

- Food has higher calorific variability
- Drinks have average of 100 calorific value
- Minimum of drinks rival the food in calorie content

In [ ]:

In [133…

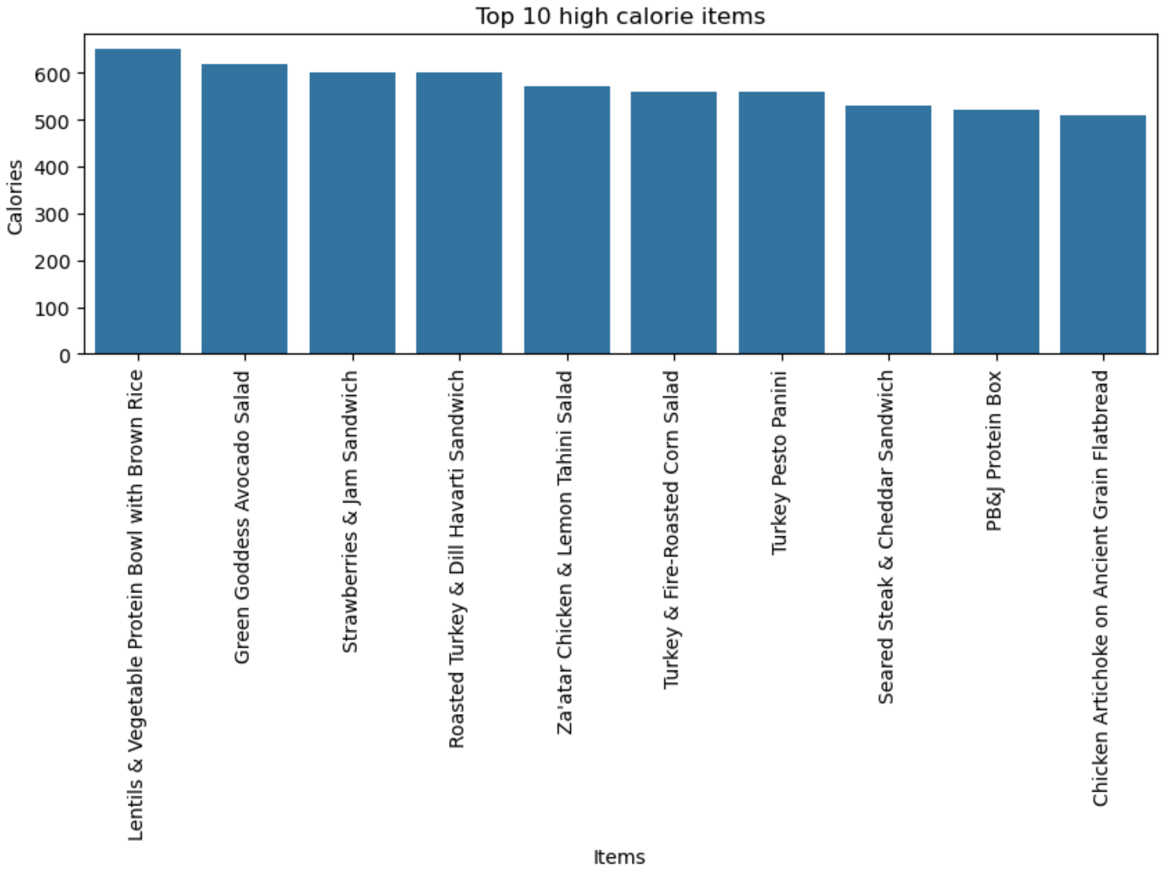
```
# Identifying top 10 high cal items
high_cal_items = sb_cleaned_menu[sb_cleaned_menu['Calories'] > 500].head(10)
high_cal_items
```

Out[133…

	Items	Calories	Fat (g)	Carb. (g)	Fiber (g)	Protein (g)	Sodium	Category
231	Strawberries & Jam Sandwich	600	25.0	80	10	19	NaN	Food
238	Green Goddess Avocado Salad	620	37.0	62	10	13	NaN	Food
242	Roasted Turkey & Dill Havarti Sandwich	600	32.0	47	6	32	NaN	Food
243	Seared Steak & Cheddar Sandwich	530	29.0	44	2	23	NaN	Food
246	Turkey & Fire-Roasted Corn Salad	560	29.0	53	7	24	NaN	Food
247	Za'atar Chicken & Lemon Tahini Salad	570	23.0	67	11	27	NaN	Food
252	PB&J Protein Box	520	26.0	53	5	20	NaN	Food
274	Chicken Artichoke on Ancient Grain Flatbread	510	27.0	37	5	24	NaN	Food
279	Lentils & Vegetable Protein Bowl with Brown Rice	650	29.0	80	21	23	NaN	Food
282	Turkey Pesto Panini	560	23.0	55	3	34	NaN	Food

In [135…

```
# Plotting the top 10 high calories items
plt.figure(figsize = (10,3))
sns.barplot(data=high_cal_items.sort_values('Calories', ascending=False), x='Ite
plt.title('Top 10 high calorie items')
plt.xticks(rotation=90)
plt.show()
```

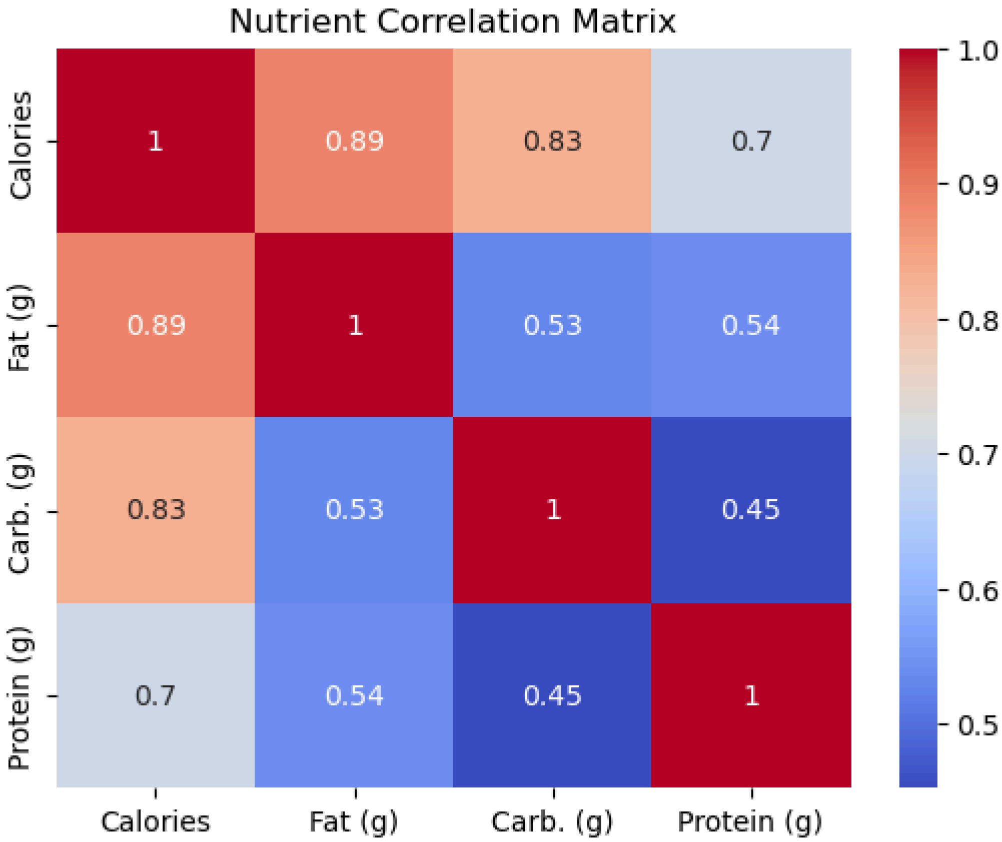


In [ ]:

```
- High calories item in the menu are foods.
- The top ten high calories item all are foods.
```

In [137…

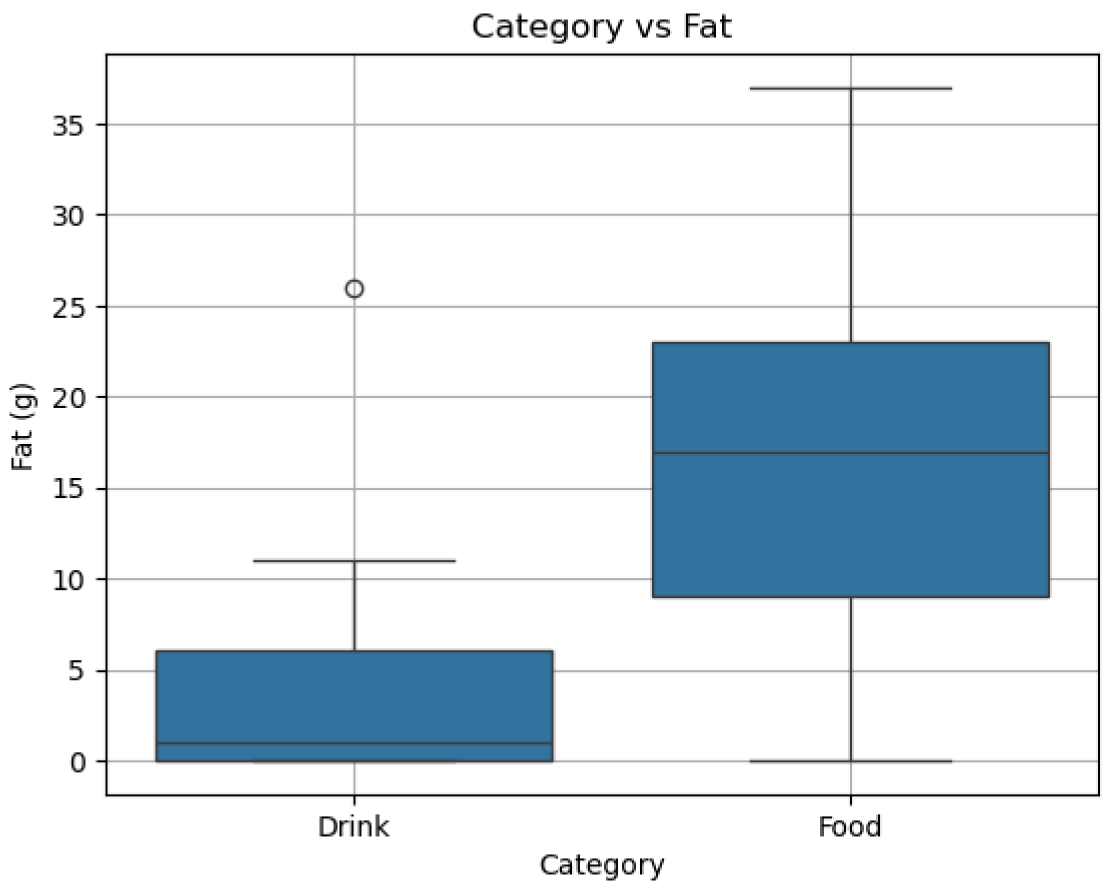
```
# Nutrient composition analysis
# Examine the correlation between different nutrients
correlation_matrix = sb_cleaned_menu[['Calories', 'Fat (g)', 'Carb. (g)', 'Prote
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Nutrient Correlation Matrix')
plt.show()
```



- Carbohydrates and protein has lower correlation rate.
- Fat and calories has higher correlation rate.

In [139…

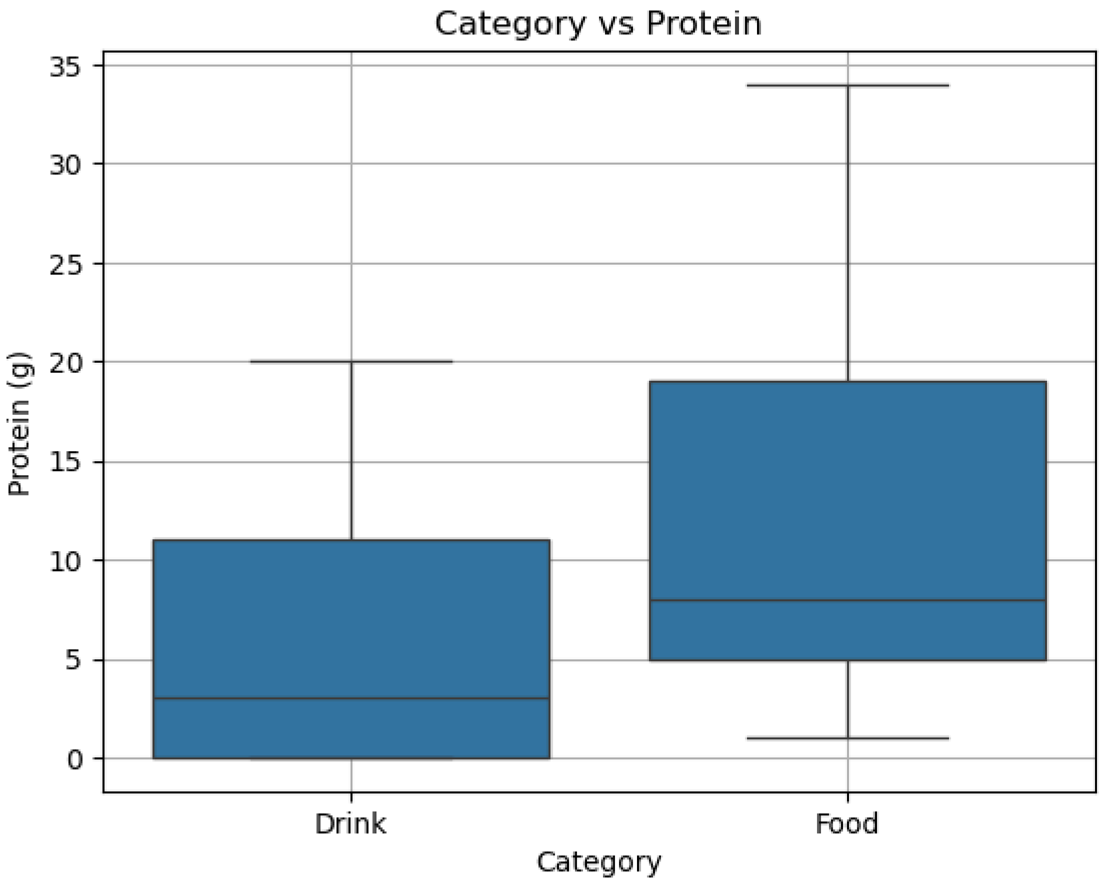
```
# Category vs Fat
sns.boxplot(data=sb_cleaned_menu, x='Category', y='Fat (g)')
plt.title('Category vs Fat')
plt.grid(True)
plt.show()
```



- In here food clearly dominate the drink in fat content.

In [141…

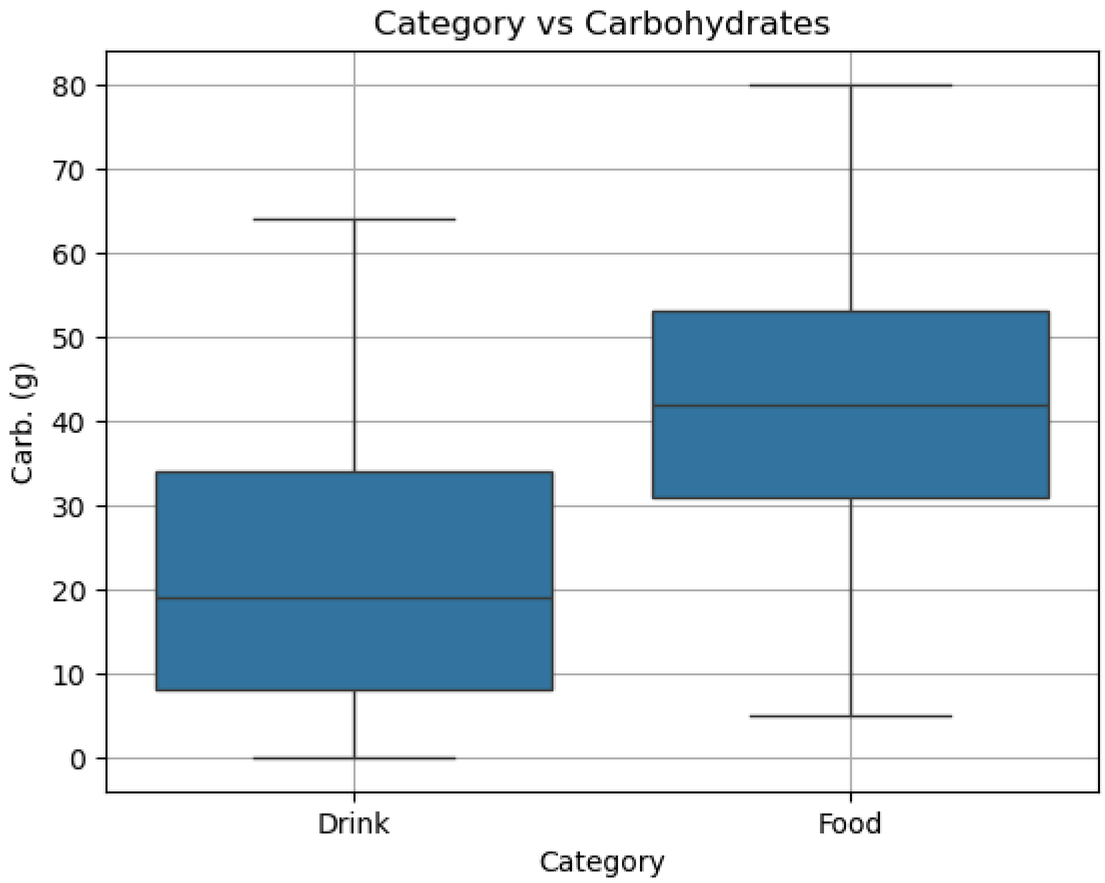
```
# Category vs protein
sns.boxplot(data=sb_cleaned_menu, x='Category', y='Protein (g)')
plt.title('Category vs Protein')
plt.grid(True)
plt.show()
```



- It clearly show the food has higher in protein and there is some outlier drinks that have higher protein content.

In [143…

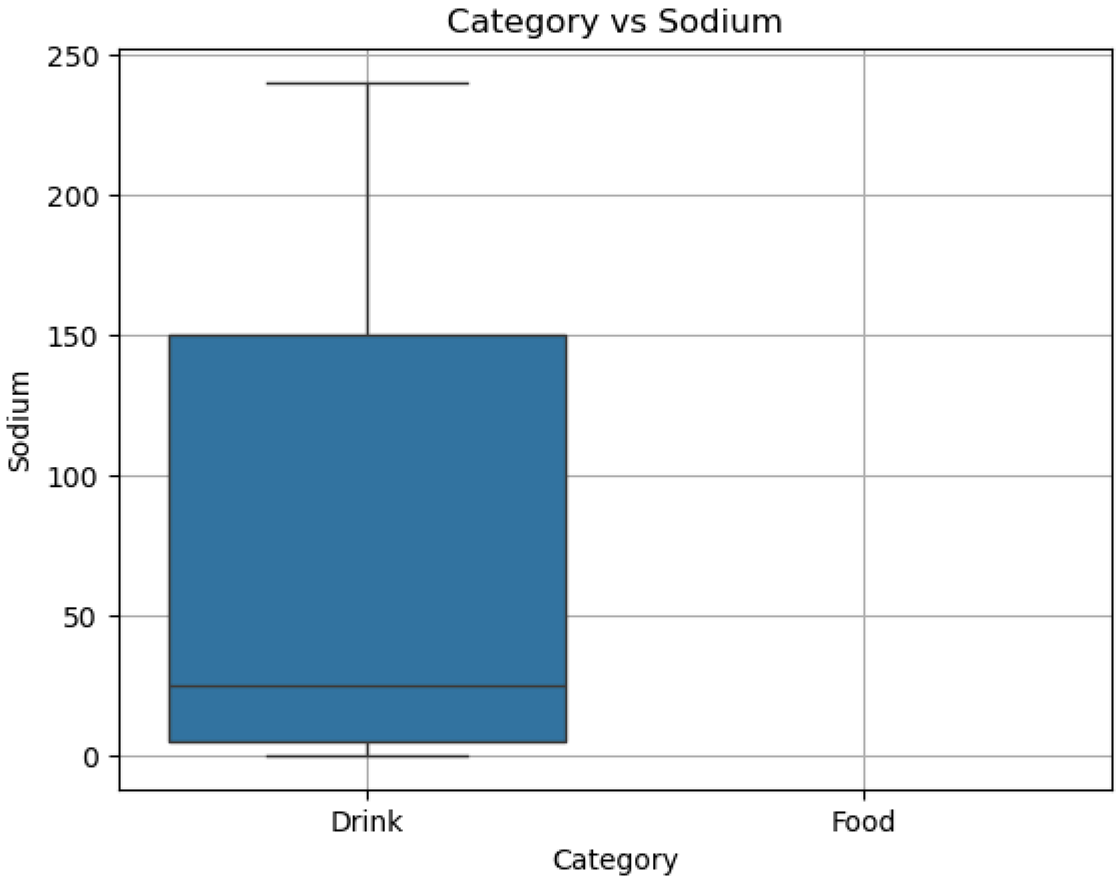
```
# Category vs Carb
sns.boxplot(data=sb_cleaned_menu, x='Category', y='Carb. (g)')
plt.title('Category vs Carbohydrates')
plt.grid(True)
plt.show()
```



- The carbohydrates content are higher in foods then drinks. But some drink rivial the food in carbohydrates content.

In [145…

```
# Category vs sodium
sns.boxplot(data=sb_cleaned_menu, x='Category', y='Sodium')
plt.title('Category vs Sodium')
plt.grid(True)
plt.show()
```



- Sodium content are only present in Drinks

```
In [ ]:
```

📊 Key Insights from Starbucks Menu Analysis:

High Protein and Carbohydrates in Food:

- Starbucks food items tend to be rich in both protein and carbohydrates.

Greater Caloric Variability in Food:

- Food items show a wide range in calorie content, indicating diverse nutritional profiles.

Drinks Average ~100 Calories:

- Most beverages have a relatively low average caloric value, around 100 calories.

Few Drinks Match Food in Calories:

- Only a small number of beverages have calorie levels comparable to food items.

Carbohydrate Content in Drinks Comparable to Food:

- Many beverages, especially sugary ones, contain carbohydrate levels similar to those found in solid food items.

Sodium Found Exclusively in Drinks:

- Interestingly, sodium appears to be present only in drinks, not in food items.

Conclusion

- The analysis of the Starbucks menu reveals distinct nutritional trends between food and beverages. Food items are generally higher in protein, carbohydrates, and exhibit a wide range in caloric content, reflecting their role as more substantial meal components. In contrast, drinks typically have lower calories on average, though some rival food in carbohydrate levels. The unexpected presence of sodium exclusively in drinks highlights the importance of examining beverages closely when considering overall dietary intake. These insights can guide more informed choices for customers seeking to balance taste with nutrition.

In [ ]: