Project: Exploring Food Nutrition Patterns

Objective: Analyze the nutritional content of various foods using the CORGIS Food dataset. The purpose is to discover patterns and answer key questions related to protein, fat, and carbohydrate content across different foods and categories, using data science tools and techniques.

Analytical Questions:

1. Which foods have the highest and lowest protein, fat, and carbohydrate content?
2. How do average nutrient values differ among the most common food categories?
3. What relationships exist between foods' protein and fat content?
4. Can similar foods be grouped by their nutrient profiles using clustering?

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
data = pd.read_csv('food.csv')
data.head()
```

Out[1]:

	Category	Description	Nutrient Data Bank Number	Data.Alpha Carotene	Data.Beta Carotene	Data.Beta Cryptoxanthin	Data.Carbohydr
0	Milk	Milk, human	11000000	0	7	0	6
1	Milk	Milk, NFS	11100000	0	4	0	4
2	Milk	Milk, whole	11111000	0	7	0	4
3	Milk	Milk, low sodium, whole	11111100	0	7	0	4
4	Milk	Milk, calcium fortified, whole	11111150	0	7	0	4

5 rows × 38 columns

Data Acquisition and Preparation

I used the CORGIS Food dataset, which provides nutrient information for thousands of foods. After loading the data, I performed basic cleaning, selecting relevant columns, checking for missing values, and focusing on the ten most common food categories to ensure clear visualization and comparison.

In [2]:
```
print(data.columns)
```

```
Index(['Category', 'Description', 'Nutrient Data Bank Number',
       'Data.Alpha Carotene', 'Data.Beta Carotene', 'Data.Beta Cryptoxanthin',
       'Data.Carbohydrate', 'Data.Cholesterol', 'Data.Choline', 'Data.Fiber',
       'Data.Lutein and Zeaxanthin', 'Data.Lycopene', 'Data.Niacin',
       'Data.Protein', 'Data.Retinol', 'Data.Riboflavin', 'Data.Selenium',
       'Data.Sugar Total', 'Data.Thiamin', 'Data.Water',
       'Data.Fat.Monosaturated Fat', 'Data.Fat.Polysaturated Fat',
       'Data.Fat.Saturated Fat', 'Data.Fat.Total Lipid',
       'Data.Major Minerals.Calcium', 'Data.Major Minerals.Copper',
       'Data.Major Minerals.Iron', 'Data.Major Minerals.Magnesium',
       'Data.Major Minerals.Phosphorus', 'Data.Major Minerals.Potassium',
       'Data.Major Minerals.Sodium', 'Data.Major Minerals.Zinc',
       'Data.Vitamins.Vitamin A - RAE', 'Data.Vitamins.Vitamin B12',
       'Data.Vitamins.Vitamin B6', 'Data.Vitamins.Vitamin C',
       'Data.Vitamins.Vitamin E', 'Data.Vitamins.Vitamin K'],
      dtype='object')
```

Exploratory Analysis: Nutrient Extremes

I identified the foods with the highest and lowest values for protein, fat, and carbohydrate. This comparison reveals which foods are most and least nutrient-dense and highlights differences in macronutrient profiles across products.

In [3]:
```
# Top 10 highest protein foods
protein_sorted = data[['Description', 'Data.Protein']].sort_values(by='Data.Protein
print('Top 10 highest protein foods:')
print(protein_sorted.head(10))

print('Bottom 10 lowest protein foods:')
print(protein_sorted.tail(10))
```

```
Top 10 highest protein foods:
                                           Description  Data.Protein
7022           Nutritional powder mix, whey based, NFS         78.13
7025              Nutritional powder mix, protein, NFS         78.13
1528                                Tuna, fresh, dried         76.25
7010  Nutritional powder mix (EAS Whey Protein Powder)         66.67
1468                                     Salmon, dried         64.06
1306                                Cod, dried, salted         62.82
1249                        Fish, NS as to type, dried         62.82
826                                    Pork skin rinds         61.30
1584                                      Squid, dried         58.94
7013                  Nutritional powder mix (Isopure)         58.14
Bottom 10 lowest protein foods:
                                            Description  Data.Protein
6880  Fruit flavored drink, powdered, not reconstituted           0.0
6882   Sports drink, dry concentrate, not reconstituted           0.0
6351                                          Olive oil           0.0
6742  Coffee, instant, decaffeinated, pre-lightened ...           0.0
6352                                         Peanut oil           0.0
6353                                         Canola oil           0.0
6348                                           Corn oil           0.0
6888                     Alcoholic malt beverage, sweetened           0.0
6889  Alcoholic malt beverage, higher alcohol, sweet...           0.0
7082                  Industrial oil as ingredient in food           0.0
```

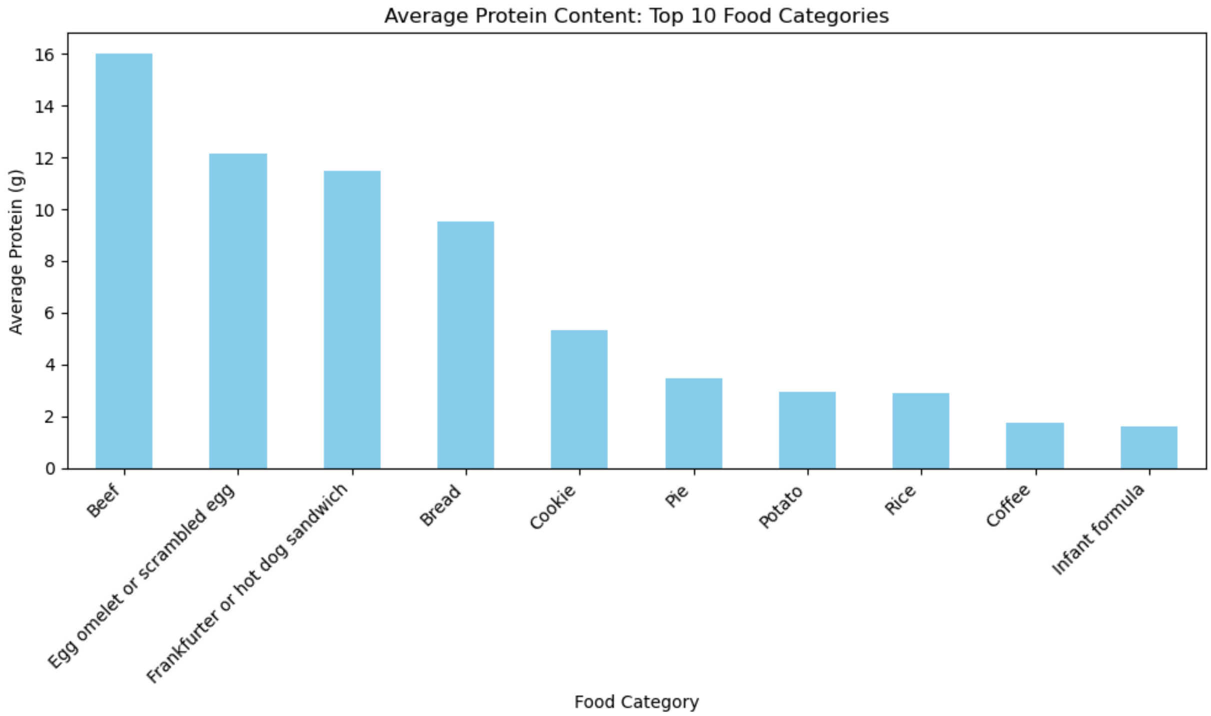
In [4]:
```
print(data['Category'].unique()[:20])  # See the first 20 unique values
print(len(data['Category'].unique()))  # Total number of unique categories
```

```
['Milk' 'Buttermilk' 'Kefir' "Goat's milk" 'Non-dairy milk' 'Soy milk'
 'Almond milk' 'Rice milk' 'Coconut milk' 'Yogurt' 'Chipotle dip'
 'Dill dip' 'Onion dip' 'Ranch dip' 'Spinach dip' 'Tzatziki dip'
 'Vegetable dip' 'Yogurt parfait' 'Frozen yogurt' 'Frozen yogurt sandwich']
2429
```

In [5]:
```
# Find the top 10 most common categories
top_categories = data['Category'].value_counts().head(10).index
subset = data[data['Category'].isin(top_categories)]

# Calculate average protein for just these groups
avg_protein = subset.groupby('Category')['Data.Protein'].mean().sort_values(ascendi

plt.figure(figsize=(10,6))
avg_protein.plot(kind='bar', color='skyblue')
plt.title('Average Protein Content: Top 10 Food Categories')
plt.ylabel('Average Protein (g)')
plt.xlabel('Food Category')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.savefig('test.png')
plt.show()
```



Interpretation: Average Protein by Food Category

The bar chart above shows the average protein content for the 10 most frequent food categories in the dataset. It is clear that animal-based protein sources like beef and eggs dominate the top ranks for protein. Processed foods like frankfurters and bread have moderate protein, while baked goods, starchy foods, and beverages have much lower averages. This visualization makes it easy to compare broad nutritional patterns across everyday foods.

In [6]:
```
# Sort foods by total fat content
totfat_sorted = data[['Description', 'Data.Fat.Total Lipid']].sort_values(by='Data.
print('Top 10 highest fat foods:')
print(totfat_sorted.head(10))
```

```python
print('Bottom 10 lowest fat foods:')
print(totfat_sorted.tail(10))
```

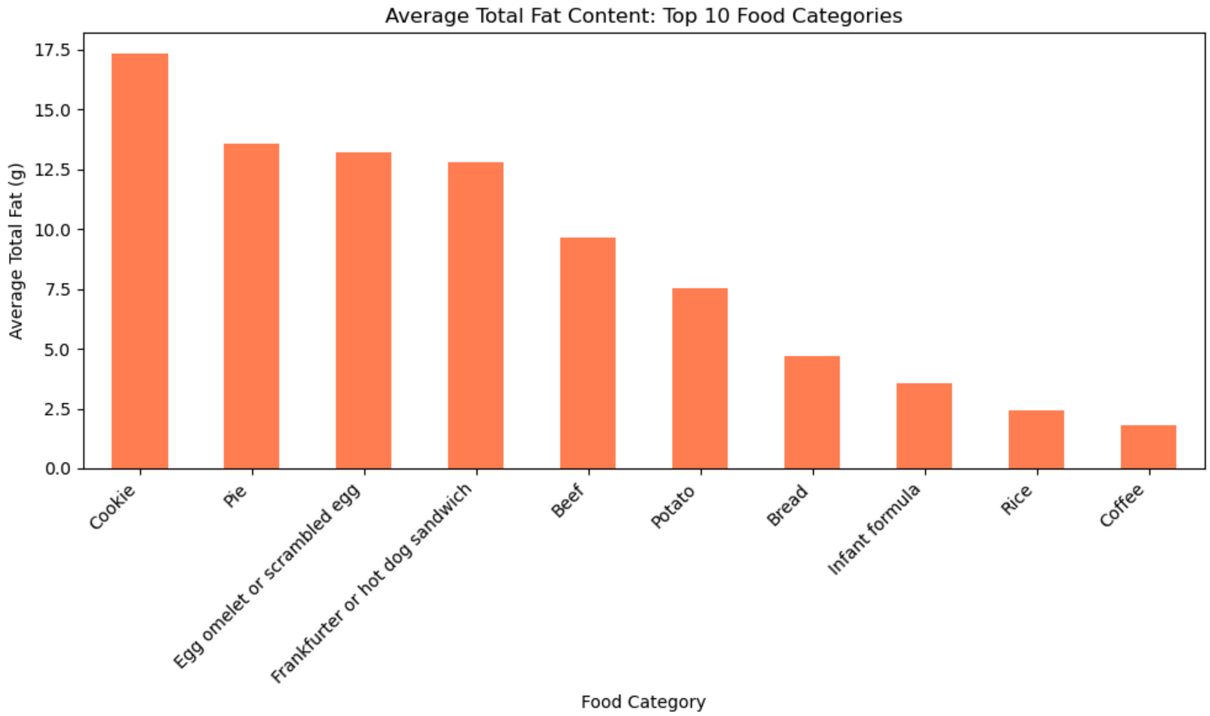
```
Top 10 highest fat foods:
                               Description  Data.Fat.Total Lipid
7082  Industrial oil as ingredient in food                 100.0
6354                         Safflower oil                 100.0
6345                     Vegetable oil, NFS                 100.0
6359                         Wheat germ oil                 100.0
6358                            Walnut oil                 100.0
6357                         Sunflower oil                 100.0
6356                           Soybean oil                 100.0
6346                            Almond oil                 100.0
6355                            Sesame oil                 100.0
6353                            Canola oil                 100.0
Bottom 10 lowest fat foods:
                                             Description  Data.Fat.Total Lipid
6859  Vegetable and fruit juice drink, with high vit...                    0.0
104   Chocolate milk, ready to drink, fat free (Nesq...                    0.0
6848  Fruit flavored drink, with high vitamin C, pow...                    0.0
6856                 Lemonade, fruit juice drink, light                    0.0
6440                                    Blueberry syrup                    0.0
6854          Orange juice beverage, 40-50% juice, light                    0.0
6852  Cranberry juice drink, with high vitamin C, light                    0.0
6851                           Fruit juice drink, diet                    0.0
6849      Fruit juice drink, with high vitamin C, light                    0.0
6819                     Soft drink, chocolate flavored                    0.0
```

In [7]:
```python
top_categories = data['Category'].value_counts().head(10).index
subset = data[data['Category'].isin(top_categories)]

avg_fat = subset.groupby('Category')['Data.Fat.Total Lipid'].mean().sort_values(asc

plt.figure(figsize=(10,6))
avg_fat.plot(kind='bar', color='coral')
plt.title('Average Total Fat Content: Top 10 Food Categories')
plt.ylabel('Average Total Fat (g)')
plt.xlabel('Food Category')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()

plt.show()
```



In [8]:

```
# Sort foods by carbohydrate
totcarb_sorted = data[['Description', 'Data.Carbohydrate']].sort_values(by='Data.Ca
print('Top 10 highest carbohydrate foods:')
print(totcarb_sorted.head(10))

print('Bottom 10 lowest carbohydrate foods:')
print(totcarb_sorted.tail(10))
```

```
Top 10 highest carbohydrate foods:
                                         Description  Data.Carbohydrate
6429                    Sugar substitute, stevia, powder             100.00
6431                Sugar substitute, monk fruit, powder             100.00
6424              Sugar, white, confectioner's, powdered              99.77
6423                    Sugar, white, granulated or lump              99.60
6422                                          Sugar, NFS              99.60
6427                    Sugar substitute and sugar blend              99.35
372   Strawberry beverage powder, dry mix, not recon...              99.10
6879  Fruit flavored drink, with high vitamin C, pow...              98.94
6602                                            Gumdrops              98.90
6617                   Dietetic or low calorie candy, NFS              98.60
Bottom 10 lowest carbohydrate foods:
                                         Description  Data.Carbohydrate
658   Beef steak, NS as to cooking method, lean and ...                0.0
976   Chicken leg, drumstick and thigh, fried, coate...                0.0
657   Beef steak, NS as to cooking method, NS as to ...                0.0
656            Beef, NS as to cut, fried, NS to fat eaten                0.0
6625                                Coffee, NS as to type                0.0
6626                     Coffee, NS as to brewed or instant                0.0
6627                                       Coffee, brewed                0.0
6628  Coffee, brewed, blend of regular and decaffein...                0.0
974   Chicken leg, drumstick and thigh, sauteed, ski...                0.0
7082                   Industrial oil as ingredient in food                0.0
```

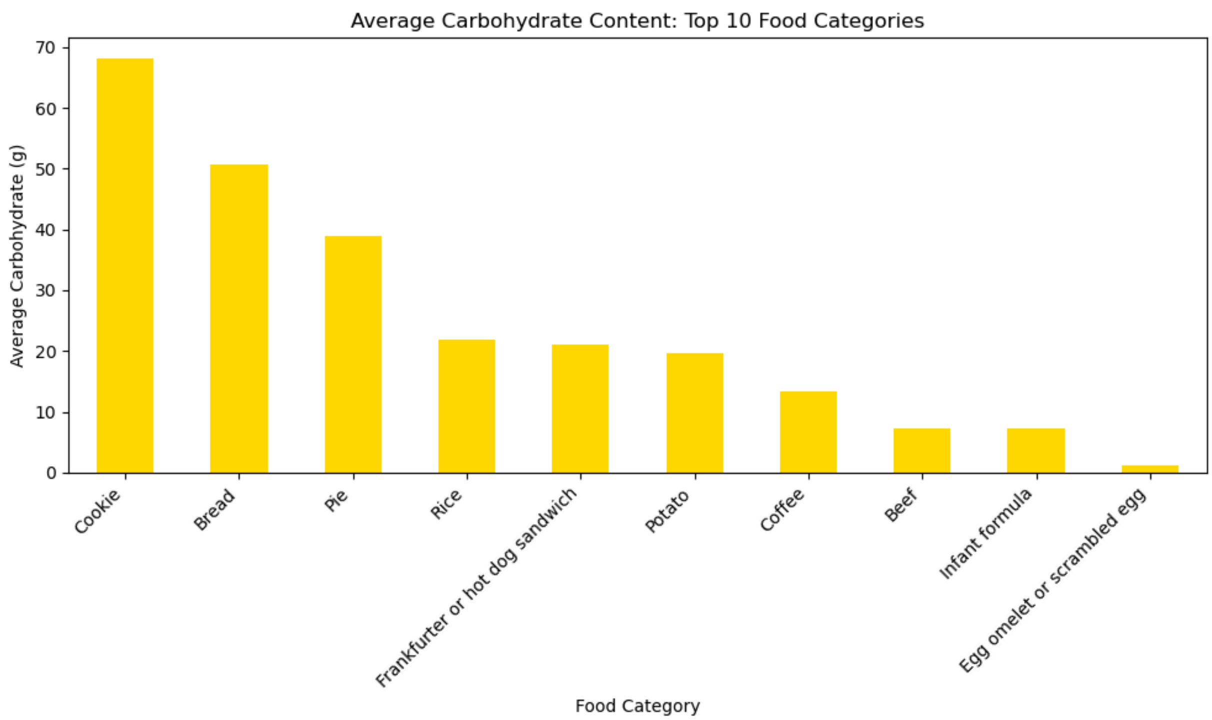
Mean Nutrient Content by Food Category

Bar charts below display the average protein, fat, and carbohydrate content for the ten most common food categories. Comparing these averages helps reveal broader nutrition trends and differences between food types.

In [9]:
```
top_categories = data['Category'].value_counts().head(10).index
subset = data[data['Category'].isin(top_categories)]

avg_carb = subset.groupby('Category')['Data.Carbohydrate'].mean().sort_values(ascen

plt.figure(figsize=(10,6))
avg_carb.plot(kind='bar', color='gold')
plt.title('Average Carbohydrate Content: Top 10 Food Categories')
plt.ylabel('Average Carbohydrate (g)')
plt.xlabel('Food Category')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



Interpretation: Nutritional Patterns by Food Category

By repeating this analysis for protein, fat, and carbohydrates, we can see how

different food types contribute to the macronutrient content of diets. High-protein foods cluster around animal products, while baked goods and processed foods tend to be higher in carbohydrates and/or fat. Visualizing by category helps identify trends that are useful for dietary planning and recommendation.

In [10]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Prepare features to cluster
top_categories = data['Category'].value_counts().head(10).index
subset = data[data['Category'].isin(top_categories)].copy()  # <--- .copy() removes

features = subset[['Data.Protein', 'Data.Fat.Total Lipid', 'Data.Carbohydrate']].fi
scaler = StandardScaler()
X_scaled = scaler.fit_transform(features)

kmeans = KMeans(n_clusters=3, random_state=42)
subset['Cluster'] = kmeans.fit_predict(X_scaled)

subset[['Description', 'Category', 'Data.Protein', 'Data.Fat.Total Lipid', 'Data.Ca
```

Out[10]:

	Description	Category	Data.Protein	Data.Fat.Total Lipid	Data.Carbohydrate	Cluster
190	Infant formula, NFS	Infant formula	1.38	3.56	7.12	1
191	Infant formula, NS as to form (Similac Expert ...	Infant formula	1.80	3.63	6.77	1
192	Infant formula, ready-to-feed (Similac Expert ...	Infant formula	1.80	3.63	6.77	1
193	Infant formula, powder, made with water, NFS (...	Infant formula	1.80	3.63	6.77	1
194	Infant formula, powder, made with tap water (S...	Infant formula	1.80	3.63	6.77	1
195	Infant formula, powder, made with plain bottle...	Infant formula	1.80	3.63	6.77	1
196	Infant formula, powder, made with baby water (...	Infant formula	1.80	3.63	6.77	1
197	Infant formula, NS as to form (Similac Advance)	Infant formula	1.37	3.62	6.87	1
198	Infant formula, ready-to-feed (Similac Advance)	Infant formula	1.37	3.62	6.87	1
199	Infant formula, liquid concentrate, made with ...	Infant formula	1.37	3.62	6.87	1

In this step, we prepare the food nutrition dataset for a clustering analysis. We select the ten most common food categories in

the data and focus on three key macronutrients: protein, fat, and carbohydrate. These features are standardized before using K-means clustering to assign each food to one of three nutrition-based clusters. This process helps uncover patterns in macronutrient profiles and allows us to group foods with similar nutritional characteristics.

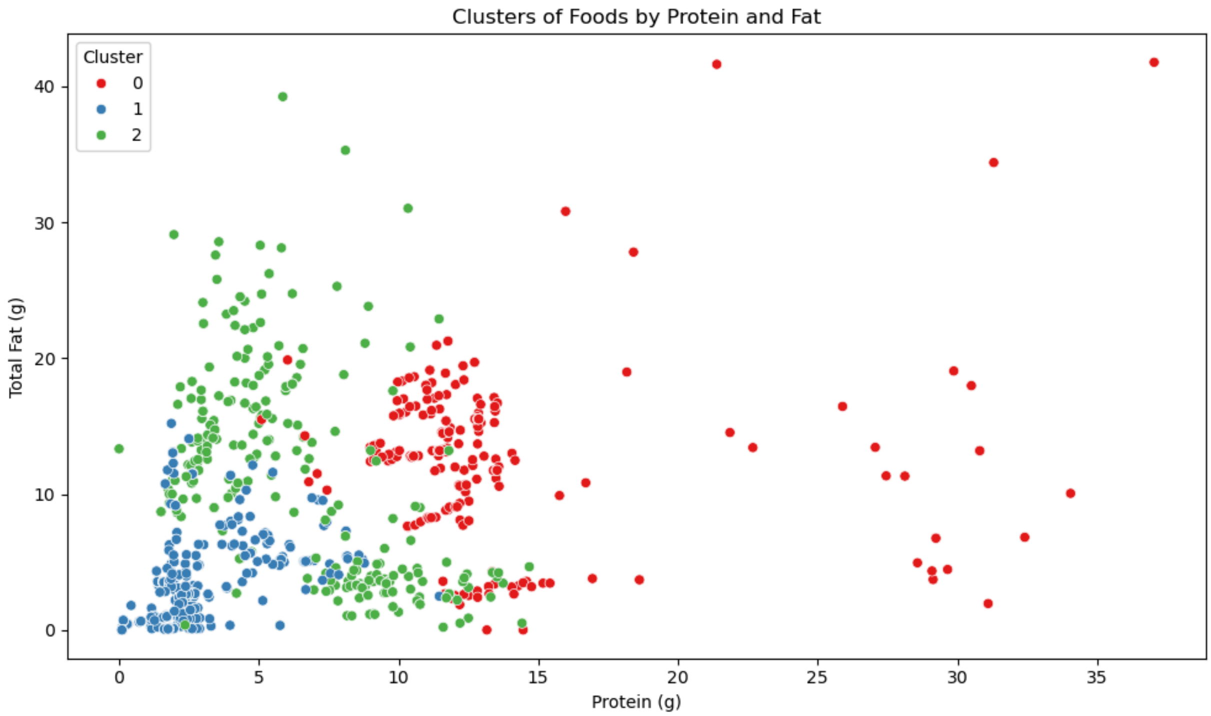
In [11]:
```
# Show foods from another cluster, e.g., cluster 0
subset[subset['Cluster'] == 0][['Description', 'Category', 'Data.Protein', 'Data.Fa
```

Out[11]:

	Description	Category	Data.Protein	Data.Fat.Total Lipid	Data.Carbohydrate
649	Beef, NS as to cut, cooked, NS as to fat eaten	Beef	29.23	6.75	0.00
650	Beef, NS as to cut, cooked, lean and fat eaten	Beef	27.06	13.44	0.00
651	Beef, NS as to cut, cooked, lean only eaten	Beef	29.23	6.75	0.00
655	Beef, pickled	Beef	18.17	18.98	0.47
656	Beef, NS as to cut, fried, NS to fat eaten	Beef	29.23	6.75	0.00
675	Beef, oxtails, cooked	Beef	30.80	13.19	0.00
676	Beef, neck bones, cooked	Beef	29.87	19.06	0.00
677	Beef, shortribs, cooked, NS as to fat eaten	Beef	30.50	17.98	0.00
678	Beef, shortribs, cooked, lean and fat eaten	Beef	21.39	41.63	0.00
679	Beef, shortribs, cooked, lean only eaten	Beef	30.50	17.98	0.00

In [12]:
```
import seaborn as sns
```

In [13]:
```
plt.figure(figsize=(10,6))
sns.scatterplot(data=subset,
                x='Data.Protein',
                y='Data.Fat.Total Lipid',
                hue='Cluster',
                palette='Set1')
plt.title('Clusters of Foods by Protein and Fat')
plt.xlabel('Protein (g)')
plt.ylabel('Total Fat (g)')
plt.tight_layout()
plt.show()
```



The scatter plot above displays the results of K-means clustering on foods from the most common categories in the dataset, based on their protein and total fat content. Each point is a food, and its color represents the cluster assigned by the algorithm.

The visualization reveals distinct nutrient profiles one cluster primarily contains foods high in both protein and fat (often animal-based or processed), another

groups items with low protein and fat (such as some infant formulas or lighter foods), and the third cluster lies between these extremes. Clustering helps simplify and highlight complex dietary data, making it clear which foods are nutritionally similar. This approach is valuable for recommendations, menu planning, or understanding broad patterns in the food supply.

In [ ]:

In [ ]: