Setup

In [ ]:
```
import os
import datetime
import pandas as pd
from pandas import json_normalize
import numpy as np
import re
import json
import requests
import time
from bs4 import BeautifulSoup
from collections import defaultdict, Counter
import random
import pprint
from string import punctuation
from wordcloud import WordCloud
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.decomposition import NMF, TruncatedSVD, LatentDirichletAllocation
from sklearn.model_selection import train_test_split
import pyLDAvis
import pyLDAvis.lda_model
import pyLDAvis.gensim_models

from nltk.corpus import stopwords

from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

```
/Users/viviando/.local/lib/python3.10/site-packages/pandas/core/computation/expressions.py:21: UserWarnin
g: Pandas requires version '2.8.4' or newer of 'numexpr' (version '2.8.3' currently installed).
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  from pandas.core import (
/var/folders/b8/4ntn3_wd1wg59r0lmbfgfmwc0000gn/T/ipykernel_8959/1341059295.py:3: DeprecationWarning:
Pyarrow will become a required dependency of pandas in the next major release of pandas (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better interoperability with othe
r libraries)
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If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
/opt/miniconda3/envs/ADS500B/lib/python3.10/site-packages/scipy/__init__.py:146: UserWarning: A NumPy vers
ion >=1.16.5 and <1.23.0 is required for this version of SciPy (detected version 1.24.4
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

In [ ]:
```
# subdue warnings
import warnings
warnings.filterwarnings('ignore')
```

In additional to traditional stopwords, common cooking terminologies were also filtered out.

In [ ]:
```
sw = stopwords.words("english")

recipe_based_stopwords = ['teaspoon', 'tablespoon', 'fluid ounce',
                          'cup', 'pint', 'quart', 'gallon', 'milliliter',
                          'liter', 'gram', 'kilogram', 'ounce', 'pound',
                          'pinch', 'dash', 'recipe', 'recipes', 'tin', 'tbsp',
                          'tablespoons', 'chopped', 'cups','oz.','teaspoons','finely',
                          'minced','taste','cut','tsp','&']

#len(recipe_based_stopwords)
#recipe_based_stopwords[10]

for rbs in recipe_based_stopwords:
    sw.append(rbs)
```

Defined functions to obtain descriptive statistics, process data (including tokenization, remove stopwords) and create wordcloud visualizations.

In [ ]:
```
# define functions

punctuation = set(punctuation) # speeds up comparison
tw_punct = punctuation


def descriptive_stats(tokens, verbose=True) :
    """
        Given a list of tokens, print number of tokens, number of unique tokens,
        number of characters, lexical diversity, and num_tokens most common
        tokens. Return a list of
    """


    num_tokens=len(tokens)
    num_unique_tokens = len(set(tokens))
    lexical_diversity = num_unique_tokens/num_tokens
    num_characters = sum(len(token) for token in tokens)

    if verbose :
        print(f"There are {num_tokens} tokens in the data.")
        print(f"There are {num_unique_tokens} unique tokens in the data.")
        print(f"There are {num_characters} characters in the data.")
        print(f"The lexical diversity is {lexical_diversity:.3f} in the data.")

        # print the five most common tokens
        counter = Counter(tokens)
        top_5_tokens = counter.most_common(5)
        print("Top 5 most common tokens:")
        for token, count in top_5_tokens:
            print(f"{token}: {count} occurrences")

    return([num_tokens, num_unique_tokens,
            lexical_diversity,
            num_characters])


def remove_stopwords(tokens) :
    return [token for token in tokens if token not in sw]
    return(tokens)

def remove_punctuation(text, punct_set=tw_punct) :
    """
        Function takes two arguments: (1) text, which is the input string, and (2) the punctuation set, wh
        Returns all characters not found in the punctuation set and concatenates them back into a string u
        string "" as the separator.
    """
    return("".join([ch for ch in text if ch not in punct_set]))

def tokenize(text) :
    """
        Splitting on whitespace rather than the book's tokenize function. That
        function will drop tokens like '#hashtag' or '2A', which we need for Twitter.
    """
    tokens = text.split()
    return(tokens)

def prepare(text, pipeline) :
    tokens = str(text)

    for transform in pipeline :
        tokens = transform(tokens)

    return(tokens)
def display_topics(model, features, no_top_words=5):
    for topic, words in enumerate(model.components_):
        total = words.sum()
        largest = words.argsort()[::-1] # invert sort order
        print("\nTopic %02d" % topic)
        for i in range(0, no_top_words):
            print("  %s (%2.2f)" % (features[largest[i]], abs(words[largest[i]]*100.0/total)))
```

In [ ]:
```
from matplotlib import pyplot as plt

def wordcloud(word_freq, title=None, max_words=200, stopwords=sw):

    wc = WordCloud(width=800, height=400,
                   background_color= "black", colormap="Paired",
                   max_font_size=150, max_words=max_words)

    # convert data frame into dict
    if type(word_freq) == pd.Series:
        counter = Counter(word_freq.fillna(0).to_dict())
    else:
        counter = word_freq

    # filter stop words in frequency counter
    if stopwords is not None:
        counter = {token:freq for (token, freq) in counter.items()
                              if token not in stopwords}
    wc.generate_from_frequencies(counter)

    plt.title(title)

    plt.imshow(wc, interpolation='bilinear')
    plt.axis("off")


def count_words_ingredients(df, column='Ingredients_tokens', preprocess=None, min_freq=2):

# process tokens and update counter
    def update(doc):
        tokens = doc if preprocess is None else preprocess(doc)
        counter.update(tokens)

    # create counter and run through all data
    counter = Counter()
    df[column].map(update)

    # transform counter into data frame
    freq_df = pd.DataFrame.from_dict(counter, orient='index', columns=['freq'])
    freq_df = freq_df.query('freq >= @min_freq')
    freq_df.index.name = 'token'

    return freq_df.sort_values('freq', ascending=False)

def count_words_title(df, column='Recipe_tokens', preprocess=None, min_freq=2):

    # process tokens and update counter
    def update(doc):
        tokens = doc if preprocess is None else preprocess(doc)
        counter.update(tokens)

    # create counter and run through all data
    counter = Counter()
    df[column].map(update)

    # transform counter into data frame
    freq_df = pd.DataFrame.from_dict(counter, orient='index', columns=['freq'])
    freq_df = freq_df.query('freq >= @min_freq')
    freq_df.index.name = 'token'

    return freq_df.sort_values('freq', ascending=False)
```

Data import

Recipes were obtained from the Edamam Recipe Search API (https://developer.edamam.com/edamam-recipe-api).

In [ ]:
```
# data import
recipes = pd.read_csv("all_recipes.csv")
recipes.head(5)
```

Out[ ]:

	Recipe	URL	Ingredients
0	Michela's tuna with cannellini beans (no cook)	http://www.jamieoliver.com/recipes/fish-recipe...	1 x 400 g tin of cannellini beans\n1 x 80 g ti...
1	Haddock with cannellini beans & artichokes	https://www.bbcgoodfood.com/recipes/haddock-ca...	400g can cannellini beans , drained and rinsed...
2	Grilled Bruschetta - Cannellini Beans with Fet...	https://food52.com/recipes/10069-grilled-brusc...	1 loaf bread\n1 15 oz. can cannellini beans\n8...
3	Escarole with Cannellini Beans	https://www.epicurious.com/recipes/food/views/...	1 sweet onion, halved\n1 head of garlic, halve...
4	Broccoli Rabe with Cannellini Beans	http://www.eatingwell.com/recipe/255758/brocco...	1 bunch broccoli rabe (1-1¼ pounds), trimmed a...

In [ ]:

```
#regex = For all numbers, single letters, numbers + single letters
import re

# Function to remove numbers, single letters, and numbers + single letters
def remove_patterns(text):
    pattern = r'(\b(?:\d+|\b\w\b|\d+\s*\w)\b)|[/\n%()]'
    #(\b(?:\d+|\b\w\b|\d+\s*\w)\b)|\n'
    return re.sub(pattern, '', text)

# Apply the function to the DataFrame column
recipes['Ingredients'] = recipes['Ingredients'].apply(remove_patterns)

recipes.head(5)
```

Out[ ]:

	Recipe	URL	Ingredients
0	Michela's tuna with cannellini beans (no cook)	http://www.jamieoliver.com/recipes/fish-recipe...	tin of cannellini beans tin of tuna in ...
1	Haddock with cannellini beans & artichokes	https://www.bbcgoodfood.com/recipes/haddock-ca...	can cannellini beans , drained and rinsed sma...
2	Grilled Bruschetta - Cannellini Beans with Fet...	https://food52.com/recipes/10069-grilled-brusc...	loaf bread oz. can cannellini beans ounces f...
3	Escarole with Cannellini Beans	https://www.epicurious.com/recipes/food/views/...	sweet onion, halved head of garlic, halved cr...
4	Broccoli Rabe with Cannellini Beans	http://www.eatingwell.com/recipe/255758/brocco...	bunch broccoli rabe - pounds, trimmed and coa...

Tokenization

In [ ]:

```
# store tokens in new dataframe 'df'
df=pd.DataFrame()

# fold to lowercase
df['Recipe_tokens']=recipes['Recipe'].str.lower()
df['Ingredients_tokens']=recipes['Ingredients'].str.lower()

# tokenize
df['Recipe_tokens']=tokenize(df['Recipe_tokens'].str)
df['Ingredients_tokens']=tokenize(df['Ingredients_tokens'].str)

# remove stopwords
df['Ingredients_tokens']=df['Ingredients_tokens'].apply(remove_stopwords)
df['Recipe_tokens']=df['Recipe_tokens'].apply(remove_stopwords)

df
```

Out[ ]:

	Recipe_tokens	Ingredients_tokens
0	[michela's, tuna, cannellini, beans, (no, cook)]	[cannellini, beans, tuna, spring, water, added...
1	[haddock, cannellini, beans, artichokes]	[cannellini, beans, ,, drained, rinsed, small,...
2	[grilled, bruschetta, -, cannellini, beans, fe...	[loaf, bread, cannellini, beans, ounces, feta,...
3	[escarole, cannellini, beans]	[sweet, onion,, halved, head, garlic,, halved,...
4	[broccoli, rabe, cannellini, beans]	[bunch, broccoli, rabe, -, pounds,, trimmed, c...
...	...	...
1059	[creamy, yogurt, porridge]	[porridge, oat, pot, fat, probiotic, yogurt]
1060	[twice-baked, truffled, potatoes-, appetizer]	[uniformly, sized, fingerling, potatoes, asiag...
1061	[frozen, strawberry, yogurt]	[strawberries, light, condensed, milk, tub, -f...
1062	[blueberry, honey, yogurt, parfait]	[plain, greek, yogurt, blueberries, sliced, al...
1063	[twice, baked, truffled, potato, boats, (my, v...	[uniformly, sized, fingerling, potatoes, asiag...

1064 rows × 2 columns

Descriptive statistics

In [ ]:
```
Recipe_combined_tokens = [token for sublist in df['Ingredients_tokens'] for token in sublist]
descriptive_stats(Recipe_combined_tokens)
```

```
There are 19169 tokens in the data.
There are 2799 unique tokens in the data.
There are 116342 characters in the data.
The lexical diversity is 0.146 in the data.
Top 5 most common tokens:
salt: 440 occurrences
oil: 396 occurrences
pepper: 347 occurrences
fresh: 332 occurrences
olive: 315 occurrences
```

Out[ ]:
```
[19169, 2799, 0.1460170066252804, 116342]
```

In [ ]:
```
ingredient_count= count_words_ingredients(df)
print('Wordcloud for Ingredients')
wordcloud(ingredient_count['freq'])
```

```
Wordcloud for Ingredients
```

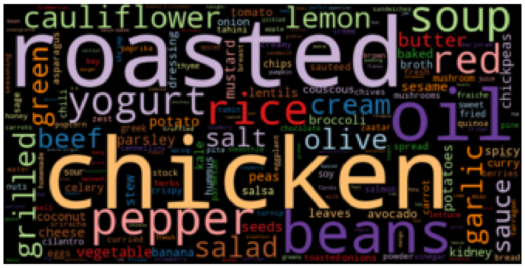
In [ ]:
```
title_combined_tokens = [token for sublist in df['Recipe_tokens'] for token in sublist]
descriptive_stats(title_combined_tokens)
```

```
There are 3444 tokens in the data.
There are 958 unique tokens in the data.
There are 21570 characters in the data.
The lexical diversity is 0.278 in the data.
Top 5 most common tokens:
chicken: 54 occurrences
roasted: 51 occurrences
oil: 48 occurrences
beans: 47 occurrences
pepper: 44 occurrences
```

Out[ ]:
```
[3444, 958, 0.2781649245063879, 21570]
```

In [ ]:
```
title_count=count_words_title(df)
print('Wordcloud for Recipe Titles')
wordcloud(title_count['freq'])
```

Wordcloud for Recipe Titles



Topic Modeling using NMF, LSA, LDA, and LDA with Gensim

In [ ]:
```
# Count Vectorizer
count_title_vectorizer = CountVectorizer(stop_words='english', min_df=5, max_df=0.7)
count_title_vectors = count_title_vectorizer.fit_transform(title_combined_tokens)
count_title_vectors.shape
```

Out[ ]:
```
(3444, 171)
```

In [ ]:
```
# TF-IDF Vectorizer
tfidf_title_vectorizer = TfidfVectorizer(stop_words='english', min_df=5, max_df=0.7)
tfidf_title_vectors = tfidf_title_vectorizer.fit_transform(title_combined_tokens)
tfidf_title_vectors.shape
```

Out[ ]:
```
(3444, 171)
```

NMF

In [ ]:
```
# NFM Model
nmf_title_model = NMF(n_components=5, random_state=314)
W_title_matrix = nmf_title_model.fit_transform(tfidf_title_vectors)
H_title_matrix = nmf_title_model.components_

# Display NMF Model
display_topics(nmf_title_model, tfidf_title_vectorizer.get_feature_names_out())
```

```
Topic 00
  roasted (91.23)
  garlic (2.18)
  soy (2.15)
  sesame (1.36)
  thyme (1.02)

Topic 01
  chicken (97.56)
  grilled (2.44)
  rice (0.00)
  lemon (0.00)
  soup (0.00)

Topic 02
  beans (99.99)
  soup (0.01)
  rice (0.01)
  cauliflower (0.00)
  yogurt (0.00)

Topic 03
  pepper (84.58)
  red (10.38)
  lemon (3.09)
  hot (0.89)
  cucumber (0.87)

Topic 04
  oil (93.65)
  olive (5.10)
  fried (1.24)
  lemon (0.00)
  rice (0.00)
```

LSA

In [ ]:
```
# Fitting LSA Model
svd_title_model = TruncatedSVD(n_components=5, random_state=314)
W_svd_title_matrix = svd_title_model.fit_transform(tfidf_title_vectors)
H_svd_title_matrix = svd_title_model.components_
# Display LSA Model
display_topics(svd_title_model, tfidf_title_vectorizer.get_feature_names_out())
```

```
Topic 00
  roasted (97.11)
  garlic (2.69)
  soy (2.31)
  soup (1.97)
  sesame (1.50)

Topic 01
  chicken (92.61)
  rice (2.07)
  cauliflower (1.17)
  lemon (1.16)
  soup (1.12)

Topic 02
  beans (96.39)
  soup (3.29)
  rice (2.88)
  cauliflower (2.55)
  sauce (2.14)

Topic 03
  pepper (60.57)
  oil (33.51)
  red (4.37)
  beans (2.75)
  soup (1.98)

Topic 04
  oil (195.87)
  olive (11.64)
  lemon (8.90)
  cauliflower (5.77)
  rice (3.69)
```

LDA

In [ ]:
```
# Fitting LDA Model
lda_title_model = LatentDirichletAllocation(n_components=5, random_state=314)
W_lda_title_matrix = lda_title_model.fit_transform(count_title_vectors)
H_lda_title_matrix = lda_title_model.components_

# Display LDA Model
display_topics(lda_title_model, count_title_vectorizer.get_feature_names_out())
```

```
Topic 00
  pepper (8.91)
  beans (8.42)
  rice (6.61)
  soup (6.45)
  garlic (6.28)

Topic 01
  chicken (10.18)
  yogurt (6.92)
  salad (5.83)
  cheese (4.38)
  seeds (4.20)

Topic 02
  oil (10.50)
  red (8.08)
  grilled (7.28)
  olive (6.68)
  beef (5.87)

Topic 03
  roasted (11.99)
  cream (6.61)
  salt (5.42)
  chickpeas (4.82)
  lentils (3.82)

Topic 04
  lemon (8.34)
  green (6.06)
  sauce (5.64)
  sesame (4.81)
  mustard (4.60)
```

In [ ]:
```
lda_display = pyLDAvis.lda_model.prepare(lda_title_model, count_title_vectors, count_title_vectorizer, sor
pyLDAvis.display(lda_display)
```

```
/Users/viviando/.local/lib/python3.10/site-packages/pandas/core/computation/expressions.py:21: UserWarnin
g: Pandas requires version '2.8.4' or newer of 'numexpr' (version '2.8.3' currently installed).
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/Users/viviando/.local/lib/python3.10/site-packages/pyLDAvis/_prepare.py:9: DeprecationWarning:
Pyarrow will become a required dependency of pandas in the next major release of pandas (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better interoperability with othe
r libraries)
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```
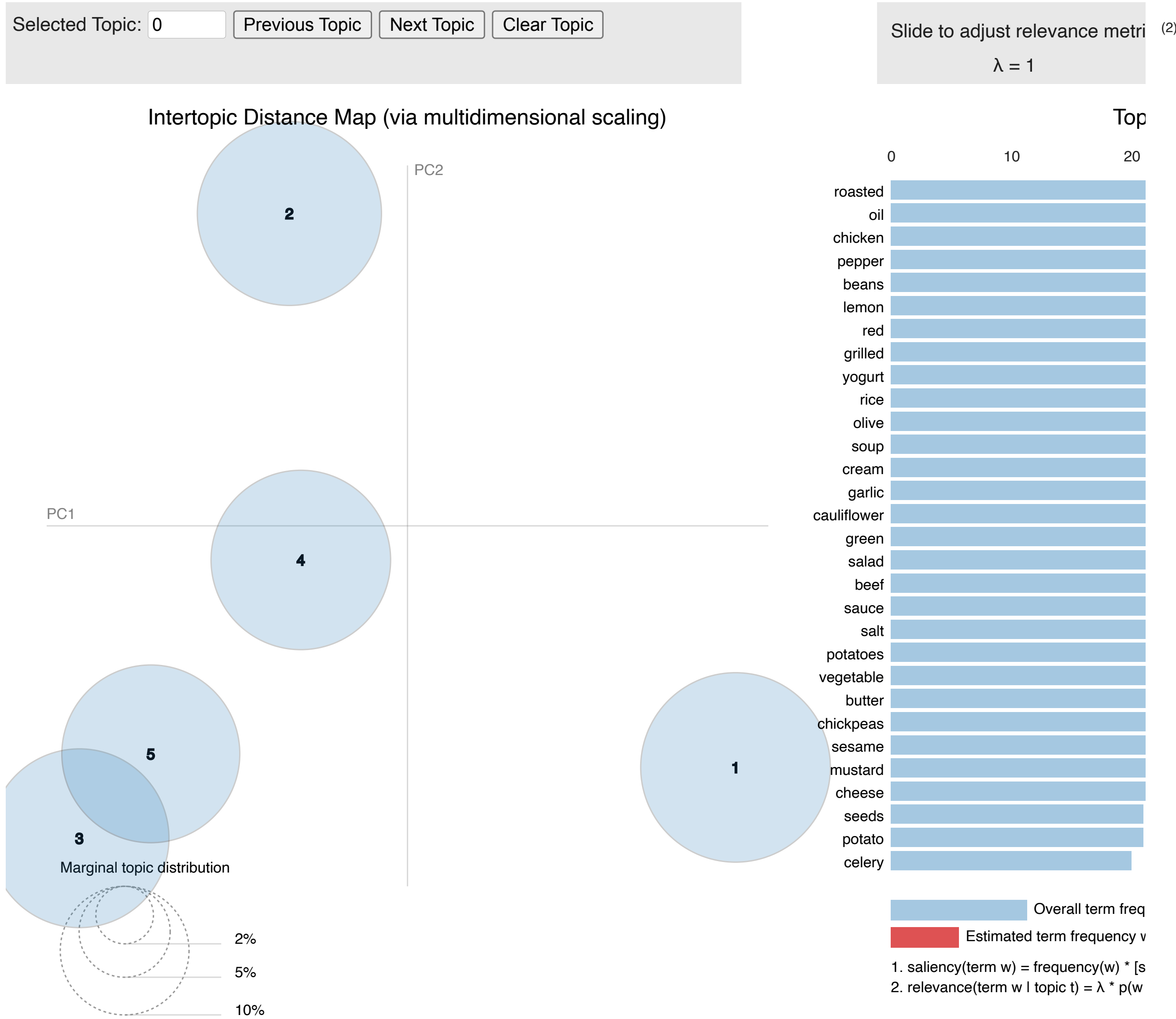

Out[ ]:



Observations:

- Topics 3 and 5 are most related to each other
- Each topic uses roughly 20% of all tokens

LDA w/ Gensim

In [ ]:

```
# tokens stored in df['Recipe_tokens']
gensim_tokens = df['Recipe_tokens']

# initialize Gensim dictionary
from gensim.corpora import Dictionary
dict_gensim = Dictionary(gensim_tokens)

# filter for words that appear in: at least 5 recipes, but not more than 70% of all recipes
dict_gensim.filter_extremes(no_below=5, no_above=0.7)

# calculate bag of words matrix
bow_gensim = [dict_gensim.doc2bow(token) for token in gensim_tokens]

# perform TF-IDF transformation
from gensim.models import TfidfModel
```

```
tfidf_gensim = TfidfModel(bow_gensim)
vectors_gensim = tfidf_gensim[bow_gensim]
```

In [ ]:
```
# using LDA with Gensim
from gensim.models import LdaModel
lda_gensim = LdaModel (corpus = bow_gensim,
                       id2word = dict_gensim,
                       chunksize = 2000,
                       alpha = 'auto',
                       eta = 'auto',
                       iterations = 400,
                       num_topics = 5,
                       passes = 20,
                       eval_every = None,
                       random_state = 509)
```

In [ ]:
```
# get topic probabilites for each recipe
topic_probabilities = [lda_gensim.get_document_topics(item) for item in bow_gensim]

# see example output
topic_probabilities[0]
```

Out[ ]:
```
[(0, 0.069617294),
 (1, 0.76808125),
 (2, 0.04583999),
 (3, 0.067112684),
 (4, 0.049348757)]
```

Classification model

Labeling the data

Topic modeling using LDA with Gensim identified 5 topics, or food categories. For each recipe, the topic model outputted the probabilities of each dish belonging to each of the 5 food categoeies. These categories will be used to label the recipes based on the dish type.

In [ ]:
```
# extract highest probability and add to dataframe
for i, row in enumerate(topic_probabilities):
    max_index = max(row, key=lambda x: x[1])[0]
    df.at[i, 'topic'] = max_index

# see topic distribution
df['topic'].value_counts()
```

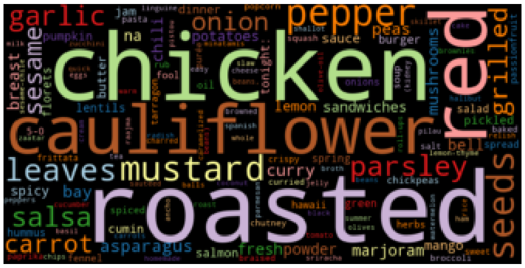
Out[ ]:
```
topic
0.0    317
3.0    249
1.0    218
4.0    153
2.0    127
Name: count, dtype: int64
```

In [ ]:
```
# see word distribution of topics
#display_topics_gensim(lda_gensim)
lda_gensim_topics = lda_gensim.show_topics(num_topics=5, num_words=10)

# Display the topics
for topic_idx, topic in lda_gensim_topics:
    print(f"Topic #{topic_idx + 1}: {topic}")
```

```
Topic #1: 0.083*"roasted" + 0.069*"chicken" + 0.059*"red" + 0.053*"cauliflower" + 0.041*"pepper" + 0.036
*"seeds" + 0.035*"mustard" + 0.026*"parsley" + 0.026*"leaves" + 0.025*"salsa"
Topic #2: 0.057*"soup" + 0.057*"cream" + 0.055*"salad" + 0.055*"beef" + 0.043*"potato" + 0.039*"stew" + 0.
036*"baked" + 0.033*"beans" + 0.032*"dressing" + 0.028*"hummus"
Topic #3: 0.094*"lemon" + 0.081*"yogurt" + 0.079*"salt" + 0.056*"pepper" + 0.047*"banana" + 0.047*"kale" +
0.044*"celery" + 0.032*"parmesan" + 0.029*"tarragon" + 0.029*"zest"
Topic #4: 0.082*"oil" + 0.057*"olive" + 0.046*"butter" + 0.045*"chickpeas" + 0.037*"cheese" + 0.037*"sauc
e" + 0.033*"coconut" + 0.032*"garlic" + 0.030*"avocado" + 0.027*"lentils"
Topic #5: 0.098*"rice" + 0.078*"beans" + 0.075*"green" + 0.062*"vegetable" + 0.039*"couscous" + 0.036*"pot
atoes" + 0.034*"spread" + 0.032*"kidney" + 0.029*"stock" + 0.029*"chives"
```

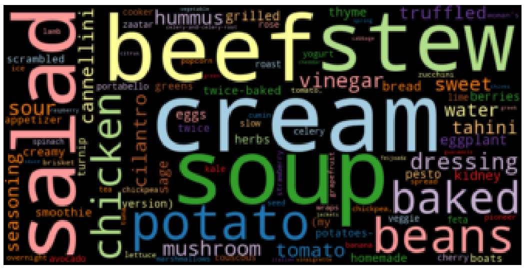
In [ ]:
```
## visualize each topic
topic0_count= count_words_title(df[df['topic']==0])
print('Wordcloud for Topic ')
wordcloud(topic0_count['freq'])
```

```
Wordcloud for Topic
```



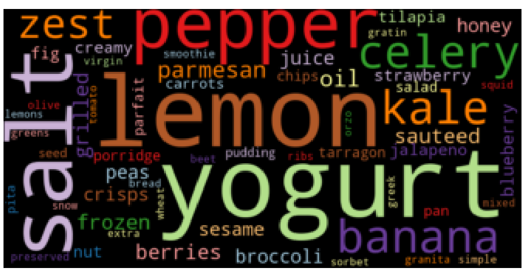

```
In [ ]: ## visualize each topic
topic1_count= count_words_title(df[df['topic']==1])
print('Wordcloud for Topic 1')
wordcloud(topic1_count['freq'])
```

```
Wordcloud for Topic 1
```



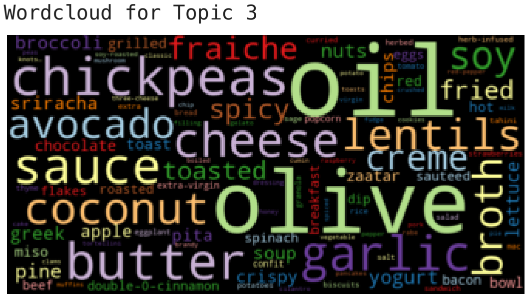

```
In [ ]: ## visualize each topic
topic2_count= count_words_title(df[df['topic']==2])
print('Wordcloud for Topic 2')
wordcloud(topic2_count['freq'])
```

```
Wordcloud for Topic 2
```



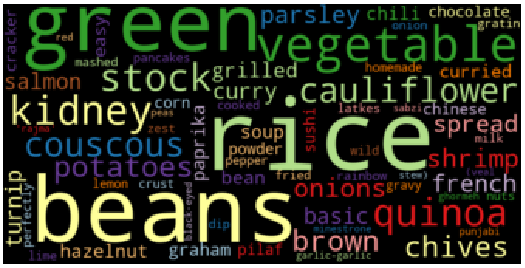

```
In [ ]: ## visualize each topic
topic3_count= count_words_title(df[df['topic']==3])
print('Wordcloud for Topic 3')
wordcloud(topic3_count['freq'])
```

```
Wordcloud for Topic 3
```




```
In [ ]: ## visualize each topic
topic4_count= count_words_title(df[df['topic']==4])
print('Wordcloud for Topic 4')
wordcloud(topic4_count['freq'])
```

```
Wordcloud for Topic 4
```



Based on the most-salient terms identified, recipes were categorized as follows:

```
**Topic 0:** Chicken dishes

**Topic 1:** Meat dishes

**Topic 2:** Desserts and other sweets

**Topic 3:** Sauces and sides

**Topic 4:** Vegetarian
```

In [ ]:
```
# export labeled recipes

# copy recipes into new dataframe
labeled_recipes=recipes

# add topic label
labeled_recipes['Type']=df['topic']

# add food categories to labeled_recipes
labeled_recipes.loc[labeled_recipes['Type'] == 0, 'Type'] = 'Chicken dishes'
labeled_recipes.loc[labeled_recipes['Type'] == 1, 'Type'] = 'Meat dishes'
labeled_recipes.loc[labeled_recipes['Type'] == 2, 'Type'] = 'Desserts and other sweets'
labeled_recipes.loc[labeled_recipes['Type'] == 3, 'Type'] = 'Sauces and sides'
labeled_recipes.loc[labeled_recipes['Type'] == 4, 'Type'] = 'Vegetarian'

labeled_recipes.head(5)

# export to csv
labeled_recipes.to_csv('labeled_recipes.csv', index=False)
```

In [ ]:
```
labeled_recipes.sample(10)
```

Out[ ]:

	Recipe	URL	Ingredients	Type
480	Grilled Spring Green Onions	https://food52.com/recipes/4043-grilled-spring...	bunch spring green onions " or soExtra virgi...	Vegetarian
222	Chicken Casserole with Campbell's Canned Soup ...	https://www.tastingtable.com/cook/recipes/chic...	boneless, skinless chicken breasts package eg...	Meat dishes
4	Broccoli Rabe with Cannellini Beans	http://www.eatingwell.com/recipe/255758/brocco...	bunch broccoli rabe - pounds, trimmed and coa...	Meat dishes
673	Oven Beef Stew	http://www.myrecipes.com/recipe/oven-beef-stew	pounds stew beef, cubed carrots, peeled and ...	Meat dishes
172	Graham Cracker Crust	http://www.cookstr.com/recipes/graham-cracker-...	cups graham cracker crumbs about squares; se...	Vegetarian
55	Roasted Asparagus with Parmesan	https://www.marthastewart.com/1155393/roasted-...	bunches pounds asparagus Asparagus Fresh $....	Chicken dishes
354	Garlic-Garlic Mashed Potatoes	https://food52.com/recipes/14611-garlic-garlic...	pounds Yukon gold potatoes, peeled and cut in...	Vegetarian
424	Creamy Corn with Chives	https://www.epicurious.com/recipes/food/views/...	ears corn, shucked teaspoon kosher salt teasp...	Vegetarian
107	Olive Oil Popcorn	https://www.foodnetwork.com/recipes/daphne-bro...	tablespoons olive oil cup popcorn kernelsKosh...	Sauces and sides
1012	Simple Pita Chips recipes	http://www.foodrepublic.com/recipes/simple-pit...	pita rounds tablespoons olive olivepinch of c...	Sauces and sides

Use TF-IDF vectors as feature inputs into classification models

In [ ]:
```
# convert tfidf vectors into numpy array to be used
# as features in classification model

# determine the number of features (maximum index + 1)
num_features = max(index for vector in vectors_gensim for index, _ in vector) + 1

# create an empty NumPy array
features_array = np.zeros((len(vectors_gensim), num_features))

# fill the array with TF-IDF values
for i, vector in enumerate(vectors_gensim):
    for index, value in vector:
        features_array[i, index] = value

print(features_array)
```

```
[[0.55570766 0.83137777 0.         ... 0.         0.         0.        ]
 [0.55570766 0.83137777 0.         ... 0.         0.         0.        ]
 [0.47478478 0.71031144 0.51965091 ... 0.         0.         0.        ]
 ...
 [0.         0.         0.         ... 0.         0.         0.        ]
 [0.         0.         0.         ... 0.         0.         0.        ]
 [0.         0.         0.         ... 0.         0.         0.65583592]]
```

In [ ]:
```
# data split
X = features_array
y = df['topic']
train_x, test_x, train_y, test_y =train_test_split(X, y, test_size=0.20,
                                random_state=6,
                                shuffle=True,
                                stratify=df['topic'])

print(len(train_x))
print(len(train_y))
print(len(test_x))
print(len(test_y))
```

```
851
851
213
213
```

In [ ]:
```
# confirm stratified split--see topic distribution in training set
train_y.value_counts()
```

Out[ ]:
```
topic
0.0    254
3.0    199
1.0    174
4.0    122
2.0    102
Name: count, dtype: int64
```

Build classification models

Logistic Regression and Naive Bayes achieved the highest overall accuracy (89.2%)

In [ ]:
```
# Logistic Regression
# Initialize the Logistic Regression model
logreg = LogisticRegression()

# Fit the model on the training data
logreg.fit(train_x, train_y)

# Make predictions on the testing data
logreg_pred = logreg.predict(test_x)

# Evaluate the model
accuracy_logreg = accuracy_score(test_y, logreg_pred)
conf_matrix_logreg = confusion_matrix(test_y, logreg_pred)
classification_rep_logreg = classification_report(test_y, logreg_pred)

# Print the results
print("Accuracy:", accuracy_logreg)
print("\nConfusion Matrix:")
```

```
print(conf_matrix_logreg)
print("\nClassification Report:")
print(classification_rep_logreg)
```

```
Accuracy: 0.892018779342723

Confusion Matrix:
[[59  1  1  2  0]
 [ 0 40  1  0  3]
 [ 2  1 21  1  0]
 [ 1  1  0 48  0]
 [ 4  1  1  3 22]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.89      0.94      0.91        63
         1.0       0.91      0.91      0.91        44
         2.0       0.88      0.84      0.86        25
         3.0       0.89      0.96      0.92        50
         4.0       0.88      0.71      0.79        31

    accuracy                           0.89       213
   macro avg       0.89      0.87      0.88       213
weighted avg       0.89      0.89      0.89       213
```

In [ ]:
```
nb_model = MultinomialNB()
nb_model.fit(train_x, train_y)
nb_pred = nb_model.predict(test_x)

accuracy_nb = accuracy_score(test_y, nb_pred)
conf_matrix_nb = confusion_matrix(test_y, logreg_pred)
classification_rep_nb = classification_report(test_y, logreg_pred)

# Print the results
print("Accuracy:", accuracy_nb)
print("\nConfusion Matrix:")
print(conf_matrix_nb)
print("\nClassification Report:")
print(classification_rep_nb)
```

```
Accuracy: 0.892018779342723

Confusion Matrix:
[[59  1  1  2  0]
 [ 0 40  1  0  3]
 [ 2  1 21  1  0]
 [ 1  1  0 48  0]
 [ 4  1  1  3 22]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.89      0.94      0.91        63
         1.0       0.91      0.91      0.91        44
         2.0       0.88      0.84      0.86        25
         3.0       0.89      0.96      0.92        50
         4.0       0.88      0.71      0.79        31

    accuracy                           0.89       213
   macro avg       0.89      0.87      0.88       213
weighted avg       0.89      0.89      0.89       213
```

Decision Tree, Random Forest, SVC, K-Nearest Neighbors Models

In [ ]:
```
dt_model = DecisionTreeClassifier()
dt_model.fit(train_x, train_y)
dt_pred = dt_model.predict(test_x)

accuracy = accuracy_score(test_y, dt_pred)
print("Decision Tree Accuracy:", accuracy)
```

```
Decision Tree Accuracy: 0.7793427230046949
```

In [ ]:
```
rf_model = RandomForestClassifier()
rf_model.fit(train_x, train_y)
```

```
rf_pred = rf_model.predict(test_x)

accuracy = accuracy_score(test_y, rf_pred)
print("Random Forest Accuracy:", accuracy)
```

```
Random Forest Accuracy: 0.8450704225352113
```

In [ ]:

```
svc_model = SVC()
svc_model.fit(train_x, train_y)
svc_pred = svc_model.predict(test_x)

accuracy = accuracy_score(test_y, svc_pred)
print("SVM Accuracy:", accuracy)
```

```
SVM Accuracy: 0.8873239436619719
```

In [ ]:

```
knn_model = KNeighborsClassifier()
knn_model.fit(train_x, train_y)
knn_pred = knn_model.predict(test_x)

accuracy = accuracy_score(test_y, knn_pred)
print("KNN Accuracy:", accuracy)
```

```
KNN Accuracy: 0.8075117370892019
```