Part 1: Descriptive Analysis

DSC 483 Capstone Mini Project

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In [ ]:
```
# mount Google Drive to import data
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:
```
import numpy as np
import pandas as pd
import time
import datetime

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

# Load the regular expression library
import re
# Import the wordcloud library
from wordcloud import WordCloud

import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
# df = pd.read_csv('/content/drive/MyDrive/Mini Project/amazon_reviews.csv')
```

load after processed (part 1) amazon df to avoid time consuming

In [ ]:
```
%%time
df = pd.read_parquet("/content/drive/MyDrive/Mini Project/amazon_reviews.parquet.gzip")
```

Convert delta time to datetime format

In [ ]:
```
startdate = datetime.datetime.strptime('1970-01-01 00:00:00', '%Y-%m-%d %H:%M:%S')
df['Time'] = df['Time'].apply(lambda x: (startdate + datetime.timedelta(seconds = x)))
```

a)

Create a table that contains information on minimum, average, median, and maximum for the following: title length, summary length, score, helpfulness ratio (helpfulness nume
denominator) (Add your table to the report at the end.) (10 points for undergraduate students, 5 points for graduate students)

In [ ]:
```
df['Title_len'] = df['ProfileName'].str.len()
df['Summary_len'] = df['Summary'].str.len()
df['Helpful_ratio'] = df['HelpfulnessNumerator'] / df['HelpfulnessDenominator']
df['Review_len'] = df['Text'].str.len()
```

In [ ]:
```
feature_list = ['Title_len', 'Summary_len', 'Score', 'Helpful_ratio']
table1 = pd.DataFrame(index=['Title_len', 'Summary_len', 'Score', 'Helpful_ratio'], columns=['Min', 'Mean', 'Max', 'Medi
table1['Min'] = df[feature_list].min()
table1['Mean'] = df[feature_list].mean()
table1['Max'] = df[feature_list].max()
table1['Median'] = df[feature_list].median()
table1
```

Out[ ]:

	Min	Mean	Max	Median
Title_len	1.0	13.804964	49.0	11.0
Summary_len	1.0	23.446858	128.0	20.0
Score	1.0	4.183199	5.0	5.0
Helpful_ratio	0.0	0.776975	3.0	1.0

b)

Create four line graphs with the following variables aggregated by day over time: review length, summary length, score, helpfulness ratio (helpfulness numerator divided by help horizontal axis should correspond to time. Do you observe any patterns or interesting trends? Write your findings in the report. (Add the line graphs to the report at the end.) (1C 5 points for graduate students)

In [ ]:
```
table2 = df[['Time', 'Review_len', 'Summary_len', 'Score', 'Helpful_ratio']].groupby(['Time']).agg(['mean'])
table2.columns = ['Review_len_mean', 'Summary_len_mean', 'Score_mean', 'Helpful_ratio_mean']
table2 = table2.reset_index()
table2
```

Out[ ]:

	Time	Review_len_mean	Summary_len_mean	Score_mean	Helpful_ratio_mean
0	1999-10-08	375.000000	25.000000	5.000000	NaN
1	1999-10-25	407.000000	60.000000	5.000000	1.000000
2	1999-12-02	166.000000	20.000000	5.000000	NaN
3	1999-12-06	222.000000	23.000000	5.000000	0.500000
4	2000-01-03	244.000000	10.000000	5.000000	NaN
...	...	...	...	...	...
3163	2012-10-22	417.025492	23.512167	4.009270	0.854610
3164	2012-10-23	373.058126	22.456702	4.233689	0.796296
3165	2012-10-24	355.812941	21.910588	4.251765	0.964286
3166	2012-10-25	386.945274	24.500000	4.121891	0.812500
3167	2012-10-26	344.689716	21.574468	4.248227	1.000000

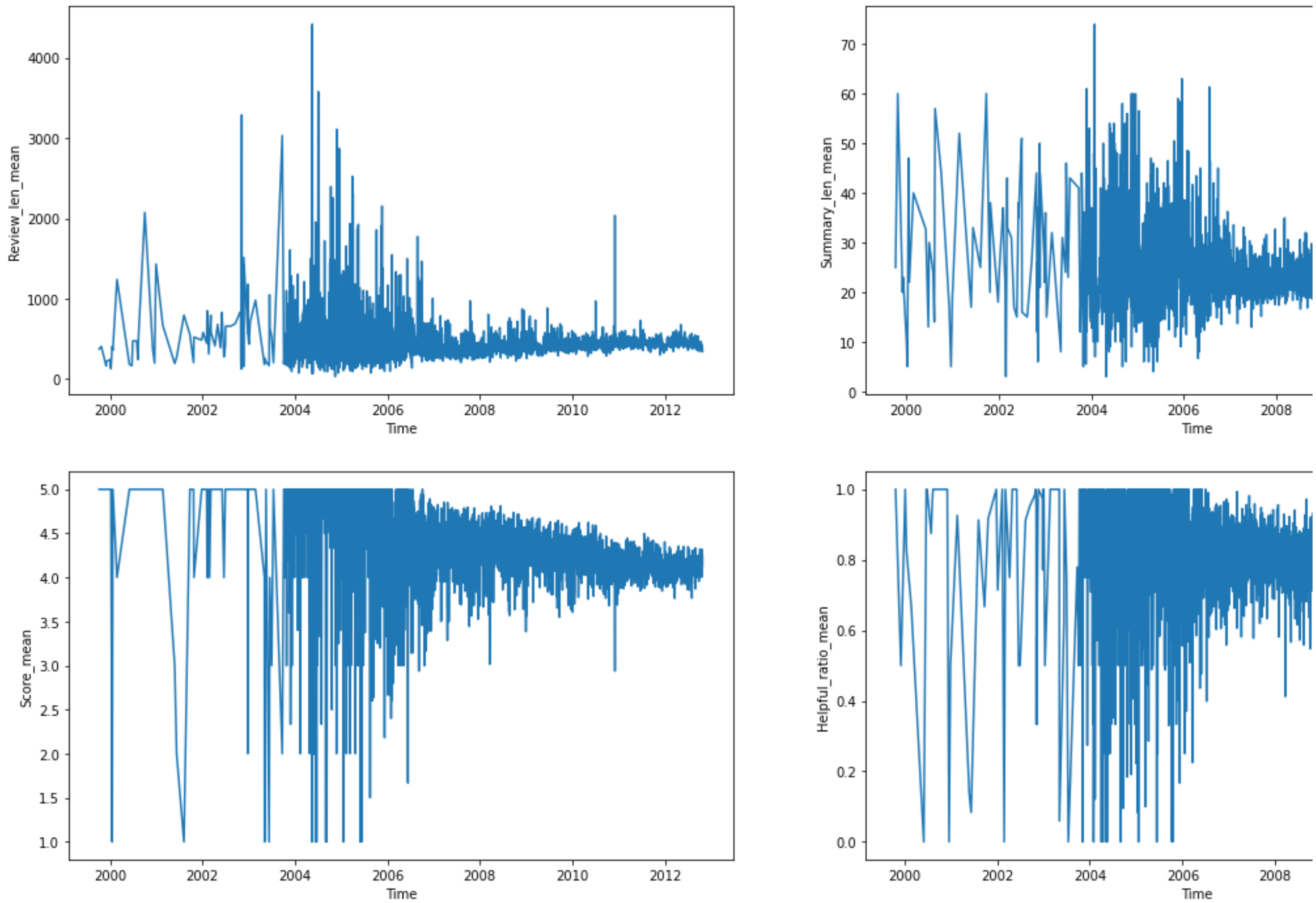
3168 rows × 5 columns

In [ ]:
```
table2['Review_len_mean'].mode(), table2['Summary_len_mean'].mode(), table2['Score_mean'].mode(), table2['Helpful_ratio_
```

Out[ ]:
```
(0    314.0
 dtype: float64, 0    20.0
 dtype: float64, 0    5.0
 dtype: float64, 0    1.0
 dtype: float64)
```

In [ ]:
```
fig, ax = plt.subplots(2, 2,figsize=[20,12])
sns.lineplot(x='Time', y='Review_len_mean', data=table2, ax=ax[0,0])
sns.lineplot(x='Time', y='Summary_len_mean', data=table2, ax=ax[0,1])
sns.lineplot(x='Time', y='Score_mean', data=table2, ax=ax[1,0])
sns.lineplot(x='Time', y='Helpful_ratio_mean', data=table2, ax=ax[1,1])
```

Out[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0aa7250090>
```



From all four-line graphs, we can see that from 2000 to 2003, the distributions of length of reviews, length of summary, score and helpfulness ratio all showed to be pretty sprea very large. From 2004 to 2006, they all reach to a peak. After 2006, everything gets to its consistent state. The range becomes dramatically smaller and the frequency remains h that from 1998-2004 is when amazon started to expand its services to fine food, the smaller group of customers made the rating range more fluctuated.

c)

Using the lda_tutorial.pdf file in the assignment folder, perform a Latent Dirichlet Allocation (LDA) analysis to extract the topics in the Text column in an unsupervised manner. Se (five). What are your observations? Does each cluster seem to form a meaningful subset? What do they seem to represent (Add the clusters and your observations to the report undergraduate students, 5 points for graduate students)

In [ ]:
```
# Remove punctuation
df['Text_processed'] = df['Text'].map(lambda x: re.sub(r'[^\w\s]', '', x))

# Convert the titles to lowercase
df['Text_processed'] = df['Text'].map(lambda x: x.lower())

# Print out the first rows of papers
df['Text_processed'].head()
```

Out[ ]:
```
0    i have bought several of the vitality canned d...
1    product arrived labeled as jumbo salted peanut...
2    this is a confection that has been around a fe...
3    if you are looking for the secret ingredient i...
4    great taffy at a great price.  there was a wid...
Name: Text_processed, dtype: object
```

In [ ]:

```python
# Join the different processed titles together.
long_string = ','.join(list(df['Text_processed'].values))

# Create a WordCloud object
wordcloud = WordCloud(background_color="white", max_words=1000, contour_width=3, contour_color='steelblue')

# Generate a word cloud
wordcloud.generate(long_string)

# Visualize the word cloud
wordcloud.to_image()
```

Out[ ]:

In [ ]:

```python
import gensim
from gensim.utils import simple_preprocess
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords

stop_words = stopwords.words('english')
stop_words.extend(['from', 'subject', 're', 'edu', 'use', 'br', 'http', 'com', 'www', 'href', 've'])


def sent_to_words(sentences):
    for sentence in sentences:
        # deacc=True removes punctuations
        yield(gensim.utils.simple_preprocess(str(sentence), deacc=True))

def remove_stopwords(texts):
    return [[word for word in simple_preprocess(str(doc))
             if word not in stop_words] for doc in texts]


data = df.Text_processed.values.tolist()
data_words = list(sent_to_words(data))

# remove stop words
data_words = remove_stopwords(data_words)

print(data_words[:1][0][:30])
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
['bought', 'several', 'vitality', 'canned', 'dog', 'food', 'products', 'found', 'good', 'quality', 'product', 'looks', '
ells', 'better', 'labrador', 'finicky', 'appreciates', 'product', 'better']
```

In [ ]:

```python
import gensim.corpora as corpora

# Create Dictionary
id2word = corpora.Dictionary(data_words)

# Create Corpus
texts = data_words

# Term Document Frequency
corpus = [id2word.doc2bow(text) for text in texts]

# View
print(corpus[:1][0][:30])
```

```
[(0, 1), (1, 2), (2, 1), (3, 1), (4, 1), (5, 1), (6, 1), (7, 1), (8, 1), (9, 1), (10, 1), (11, 1), (12, 1), (13, 1), (14
1), (19, 1), (20, 1)]
```

In [ ]:
```
from pprint import pprint

# number of topics
num_topics = 5

# Build LDA model
lda_model = gensim.models.LdaMulticore(corpus=corpus,
                                       id2word=id2word,
                                       num_topics=num_topics)

# Print the Keyword in the 5 topics
pprint(lda_model.print_topics())
doc_lda = lda_model[corpus]
```

```
[(0,
  '0.043*"coffee" + 0.038*"tea" + 0.017*"cup" + 0.015*"like" + 0.014*"flavor" '
  '+ 0.011*"good" + 0.011*"taste" + 0.010*"one" + 0.008*"cups" + '
  '0.008*"green"'),
 (1,
  '0.024*"food" + 0.016*"dog" + 0.010*"treats" + 0.009*"one" + 0.008*"dogs" + '
  '0.008*"like" + 0.007*"cat" + 0.007*"loves" + 0.007*"treat" + 0.006*"eat"'),
 (2,
  '0.018*"amazon" + 0.014*"product" + 0.012*"price" + 0.010*"great" + '
  '0.009*"buy" + 0.008*"box" + 0.008*"order" + 0.008*"good" + 0.008*"store" + '
  '0.008*"find"'),
 (3,
  '0.014*"like" + 0.012*"good" + 0.012*"great" + 0.010*"flavor" + '
  '0.010*"taste" + 0.009*"chips" + 0.008*"love" + 0.007*"salt" + 0.007*"oil" + '
  '0.007*"eat"'),
 (4,
  '0.021*"like" + 0.018*"taste" + 0.013*"sugar" + 0.010*"flavor" + '
  '0.009*"good" + 0.009*"water" + 0.008*"product" + 0.008*"one" + '
  '0.008*"sweet" + 0.007*"chocolate"')]
```

In [ ]:

Key text visualizaton

In [ ]:
```
!pip install gensim
!pip install pyLDAvis
!pip install vega
!pip install altair
```

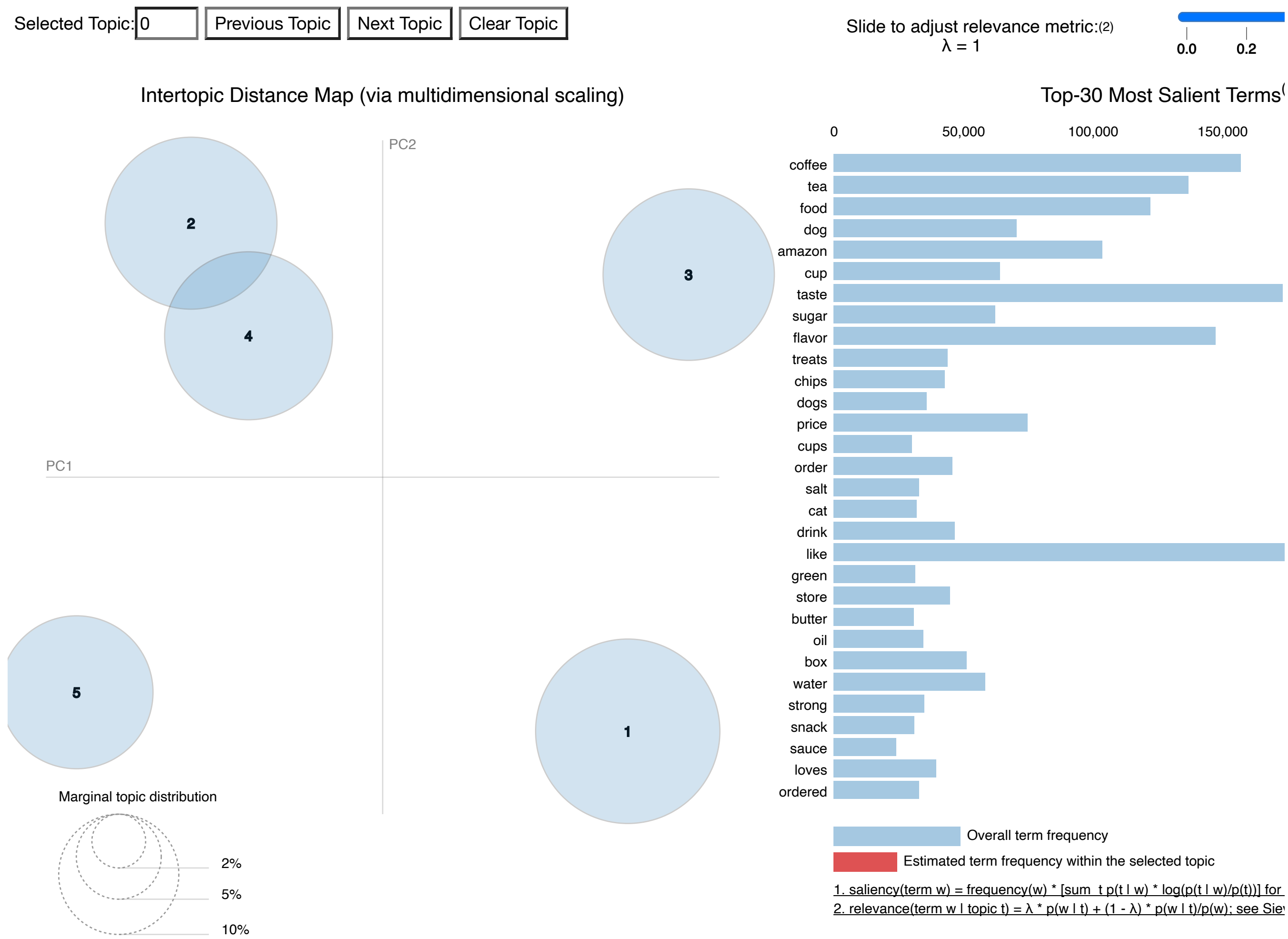
In [ ]:
```
import pyLDAvis
import pyLDAvis.gensim_models
import pickle
```

Warning: read this before you want to run below codes:

pyLDAvis.gensim_models.prepare occurs error "A result has failed to un-serialize. Please ensure that the objects returned by the function are always picklable." solution is to up
(because google colab's version is 1.15), then restart runtime and run below code again. reference: [https://github.com/bmabey/pyLDAvis/issues/144 (https://github.com/bmab](https://github.com/bmabey/pyLDAvis/issues/144)

```
In [ ]: pyLDAvis.enable_notebook()
        pyLDAvis.gensim_models.prepare(lda_model, corpus, id2word)
```

Out[ ]:



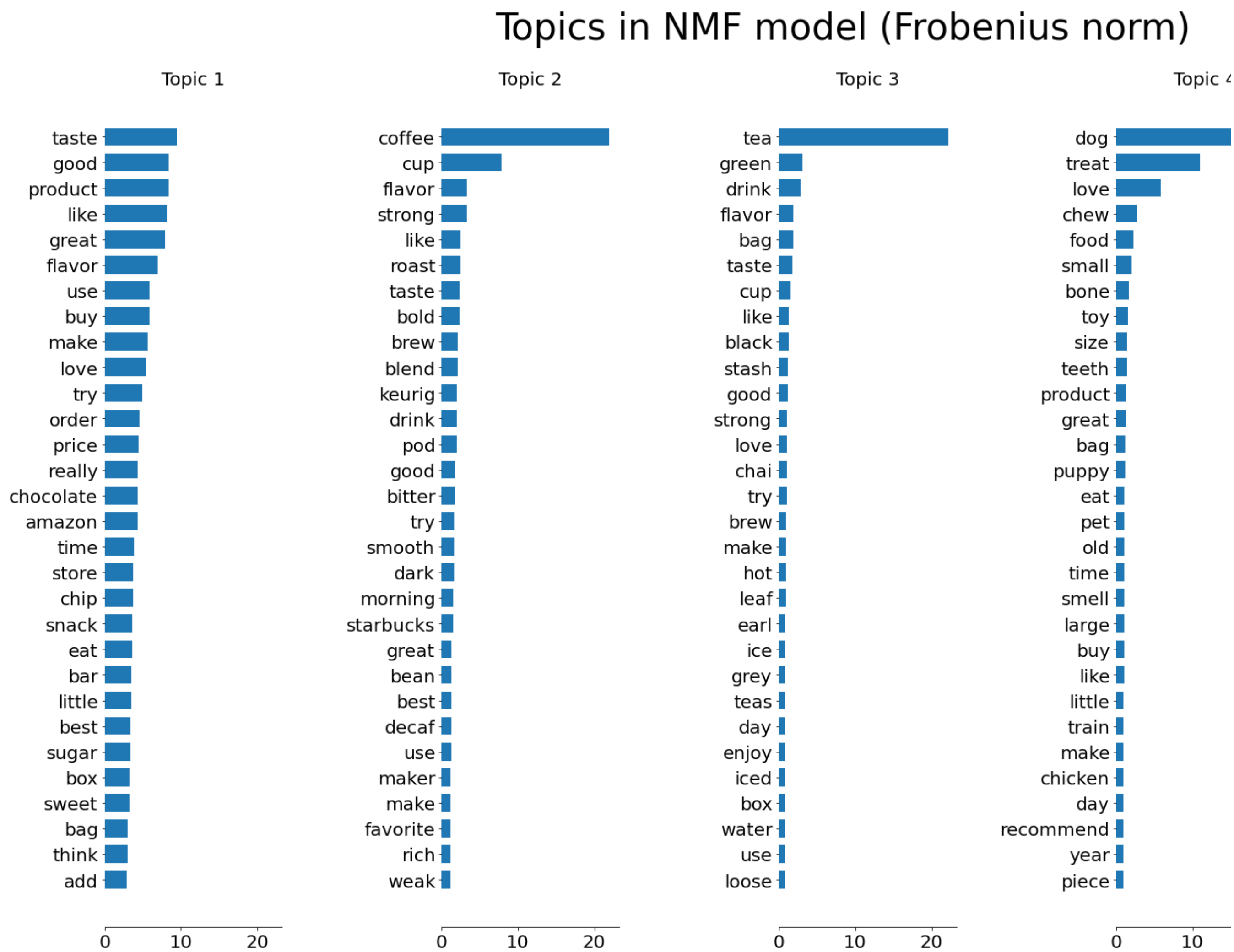
The overall percentages of each topic are pretty even. Each topic appears to from a meaningful subset. Topic 1 is centered around amazon service such as the price and produ snacks, mainly salty snacks such as chips. Topic 3 covers pet food, it's all about dog and cat foods. Topic 4 is about desserts, some of the key terms are sugar and chocolate. 2 and 4 overlap with each other on some of the terms. This is due to the characteristics of desserts and snacks have some similarities. Yet, topic 1, topic 3 and topic 5 are very four clusters that represent different category of foods.

d)

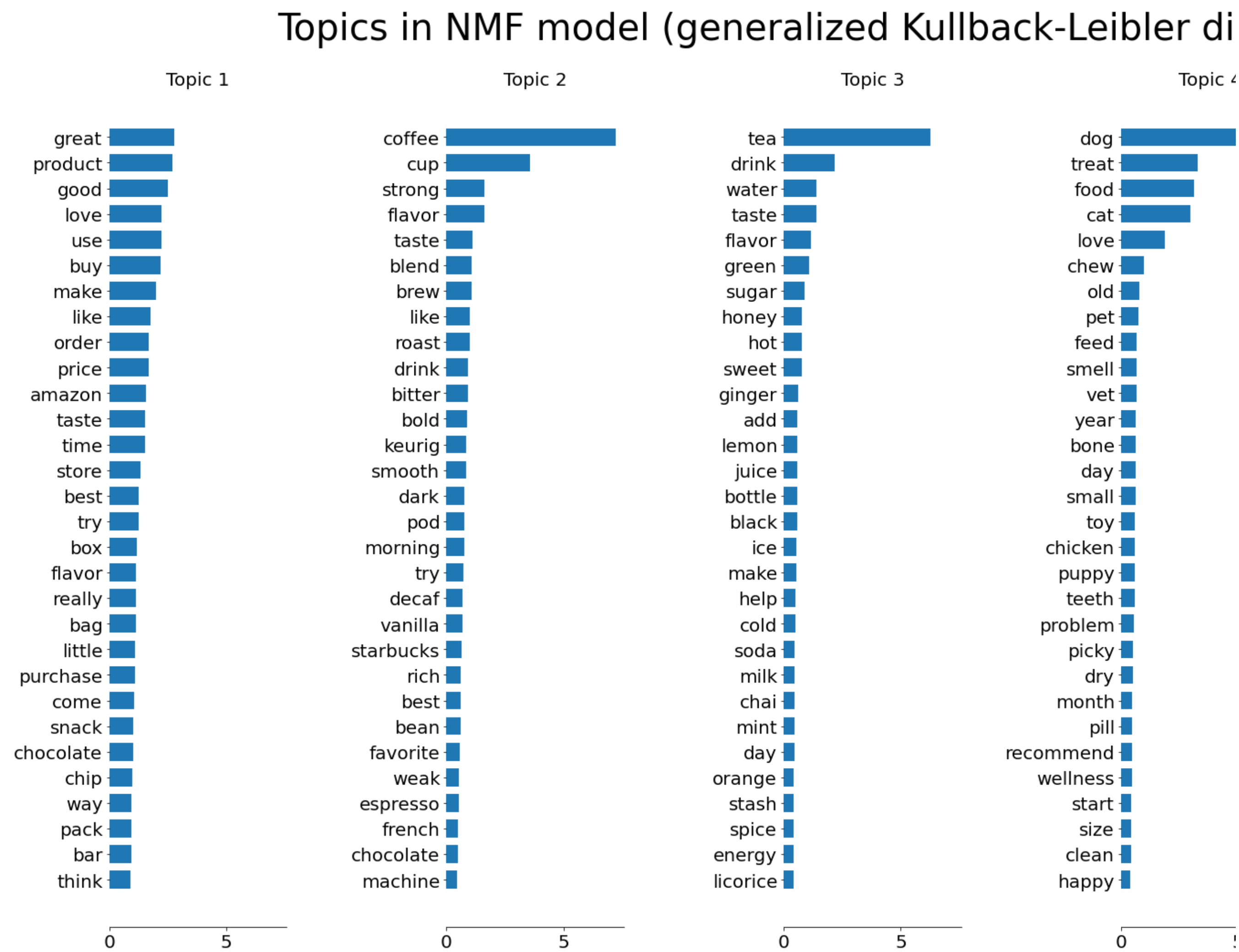
Following the code in the following link1, perform Non-negative Matrix Factorization for topic analysis. Again, like in question c), set the number of clusters/topics to 5 (five) and unsupervised manner. Analyze the results. Do you see any similarities or differences with respect to your results in c) ? Explain. (5 points)

In [ ]:
```python
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from time import time
from sklearn.decomposition import NMF, LatentDirichletAllocation
n_components = 5 #topic=5
n_features = 1000
n_top_words = 30



def plot_top_words(model, feature_names, n_top_words, title):
    fig, axes = plt.subplots(1, 5, figsize=(30, 15), sharex=True)
    axes = axes.flatten()
    for topic_idx, topic in enumerate(model.components_):
        top_features_ind = topic.argsort()[:-n_top_words - 1:-1]
        top_features = [feature_names[i] for i in top_features_ind]
        weights = topic[top_features_ind]

        ax = axes[topic_idx]
        ax.barh(top_features, weights, height=0.7)
        ax.set_title(f'Topic {topic_idx +1}',
                     fontdict={'fontsize': 20})
        ax.invert_yaxis()
        ax.tick_params(axis='both', which='major', labelsize=20)
        for i in 'top right left'.split():
            ax.spines[i].set_visible(False)
        fig.suptitle(title, fontsize=40)

    plt.subplots_adjust(top=0.90, bottom=0.05, wspace=0.90, hspace=0.3)
    plt.show()


# Use tf-idf features for NMF.
print("Extracting tf-idf features for NMF...")
tfidf_vectorizer = TfidfVectorizer(max_df=0.95, min_df=2,
                                   max_features=n_features,
                                   stop_words='english')
t0 = time()
tfidf = tfidf_vectorizer.fit_transform(df.Text_clean.values) # input text
print("done in %0.3fs." % (time() - t0))

# Fit the NMF model
# print("Fitting the NMF model (Frobenius norm) with tf-idf features, "
#       "n_samples=%d and n_features=%d..."
#       % (n_samples, n_features))
t0 = time()
nmf = NMF(n_components=n_components, random_state=1,
          alpha=.1, l1_ratio=.5).fit(tfidf)
print("done in %0.3fs." % (time() - t0))


tfidf_feature_names = tfidf_vectorizer.get_feature_names()
plot_top_words(nmf, tfidf_feature_names, n_top_words,
               'Topics in NMF model (Frobenius norm)')

# Fit the NMF model
# print('\n' * 2, "Fitting the NMF model (generalized Kullback-Leibler "
#       "divergence) with tf-idf features, n_samples=%d and n_features=%d..."
#       % (n_samples, n_features))
t0 = time()
nmf = NMF(n_components=n_components, random_state=1,
          beta_loss='kullback-leibler', solver='mu', max_iter=1000, alpha=.1,
          l1_ratio=.5).fit(tfidf)
print("done in %0.3fs." % (time() - t0))

tfidf_feature_names = tfidf_vectorizer.get_feature_names()
plot_top_words(nmf, tfidf_feature_names, n_top_words,
               'Topics in NMF model (generalized Kullback-Leibler divergence)')
```

```
Extracting tf-idf features for NMF...
done in 21.608s.
done in 50.551s.
```




```
done in 270.705s.
```



Based on the NMF model, there are some similarity in topics with the outputs in LDA. In the NMF model, there is a topic covers amazon service and pet foods. However, in the clustered into two different clusters. This is different with LDA model where coffee and tea are clustered into one cluster. In the NMF model, there is a topic that covers ingredie clustered into snacks and desserts. It appears that the clusters in the LDA results are centered in major food categories such as snacks, desserts, drinks and pet foods. Yet, the more specific level, such as tea, coffee, ingredients and pet foods. These four categories are what American people focus on daily. Coffee, tea and pet foods are necessities fo nowadays pay great attentions on the food ingredients. It is interesting to see that the NMF model is able to extract the differences between coffee and tea whereas the LDA is

e)

Write a ‘text cleaner’ function that does the following: (i) remove stopwords2, (ii) remove all words that are shorter than 3 characters, (iii) remove all links (starting with http), (iv) r punctuation. Attach the code you wrote to the lemmatizer.py file in the project folder. Run the lemmatizer function and create ‘cleaned and lemmatized’ versions of Summary ar new columns as Summary_clean and Text_clean). (5 points)

Text clean

1. Remove stopwords
2. remove all words are shorter than 3 characters
3. remove all links
4. Remove emojis
5. Remove punnctuation

In [ ]:

```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import re
import nltk
import string
from nltk.corpus import stopwords
nltk.download("stopwords")
stop_words = stopwords.words('english')

def text_clean(x):
  # lower case
  x = x.lower()
  # remove stop words
  x = ' '.join([word for word in x.split(' ') if word not in stop_words])
  # remove emoji
  x = x.encode(encoding="ascii", errors="ignore").decode()
  # remove hashtags
  x = re.sub("#\S+", " ", x)
  # remove mentions
  x = re.sub("@\S+", " ", x)
  # remove URL/links
  x = re.sub("https*\S+", " ", x)
  #remove punctuation
  x = re.sub('[%s]' % re.escape(string.punctuation), ' ', x)
  # remove overspaces
  x = re.sub('\s{2,}', " ", x)
  # remove ticks
  x = re.sub("\'\w+", '', x)
  # remove words shorter than 3
  x = re.sub(r'\b\w{1,2}\b', '', x)

  return x

df['clean_text'] = df.Text.apply(text_clean)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [ ]:

```python
df['clean_text']
```

Out[ ]:

```
0         bought several vitality canned dog food produc...
1         product arrived labeled jumbo salted peanuts t...
2         confection around centuries light pillowy citr...
3         looking secret ingredient robitussin believe f...
4         great taffy great price wide assortment yummy ...
                                ...
568449    great sesame chicken this good better resturan...
568450      disappointed flavor chocolate notes especial...
568451    stars small give   one training session tried ...
568452    best treats training rewarding dog good groomi...
568453    satisfied product advertised use cereal raw vi...
Name: clean_text, Length: 568454, dtype: object
```

In [ ]:

```python
df['clean_summary'] = df.Summary.astype(str).apply(text_clean)
```

In [ ]:
```python
from nltk.stem import WordNetLemmatizer
import nltk
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import re
import nltk
import string
from nltk.corpus import stopwords
from nltk.corpus import wordnet
nltk.download('wordnet')
nltk.download("stopwords")
stop_words = stopwords.words('english')
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
nltk.download("stopwords")

lemmatizer = WordNetLemmatizer()

##Tags the words in the tweets
def nltk_tag_to_wordnet_tag(nltk_tag):
    if nltk_tag.startswith('J'):
        return(wordnet.ADJ)
    elif nltk_tag.startswith('V'):
        return(wordnet.VERB)
    elif nltk_tag.startswith('N'):
        return(wordnet.NOUN)
    elif nltk_tag.startswith('R'):
        return(wordnet.ADV)
    else:
        return(None)

##Lemmatizes the words in tweets and returns the cleaned and lemmatized tweet
def lemmatize_tweet(tweet):
    #tokenize the tweet and find the POS tag for each token
    tweet = tweet_cleaner(tweet) #tweet_cleaner() will be the function you will write
    nltk_tagged = nltk.pos_tag(nltk.word_tokenize(tweet))
    #tuple of (token, wordnet_tag)
    wordnet_tagged = map(lambda x: (x[0], nltk_tag_to_wordnet_tag(x[1])), nltk_tagged)
    lemmatized_tweet = []
    for word, tag in wordnet_tagged:
        if tag is None:
            #if there is no available tag, append the token as is
            lemmatized_tweet.append(word)
        else:
            #else use the tag to lemmatize the token
            lemmatized_tweet.append(lemmatizer.lemmatize(word, tag))
    return(" ".join(lemmatized_tweet))


def tweet_cleaner(x):
    # lower case
  x = x.lower()
  # remove stop words
  x = ' '.join([word for word in x.split(' ') if word not in stop_words])

  # remove URL/links
  x = re.sub("https*\S+", " ", x)
  #remove punctuation
  x = re.sub('[%s]' % re.escape(string.punctuation), ' ', x)


  # remove words shorter than 3
  x = re.sub(r'\b\w{1,2}\b', '', x)

  return x
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [ ]:
```python
df['Text_clean'] = df.Text.apply(lemmatize_tweet)
```

In [ ]:
```python
df['Summary_clean'] = df.Summary.astype(str).apply(lemmatize_tweet)
```

In [ ]:
```
df['Summary_clean']
```

Out[ ]:
```
0                good quality dog food
1                           advertised
2                          delight say
3                       cough medicine
4                          great taffy
                       ...
568449                         without
568450                    disappointed
568451                perfect maltipoo
568452    favorite train reward treat
568453                     great honey
Name: Summary_clean, Length: 568454, dtype: object
```

In [ ]:
```
df['Text_clean']
```

Out[ ]:
```
0         buy several vitality can dog food product find...
1         product arrive labeled jumbo salt peanut the p...
2         confection around century light pillowy citrus...
3         look secret ingredient robitussin believe find...
4         great taffy great price wide assortment yummy ...
                                ...
568449    great sesame chicken this good good resturants...
568450    disappointed flavor chocolate note especially ...
568451    star small give one training session try train...
568452    best treat train reward dog good groom low cal...
568453    satisfied product advertise use cereal raw vin...
Name: Text_clean, Length: 568454, dtype: object
```

Save the Lemmatized and time transfered df

Load the lemmatized data from google drive, use parquet format to save time of loading data

f)

Using the cosine_similarity.py file in the project folder compute the similarity values between Summary_clean and Text_clean. Finally, create a density plot of the similarity value some of your observations? Is Summary predictive of Text? Are there any very large or very small values? (Add the graph you created to the report at the end.) (5 points)

In [ ]:
```
import math
import re
from collections import Counter

WORD = re.compile(r"\w+")


def get_cosine(vec1, vec2):
    intersection = set(vec1.keys()) & set(vec2.keys())
    numerator = sum([vec1[x] * vec2[x] for x in intersection])

    sum1 = sum([vec1[x] ** 2 for x in list(vec1.keys())])
    sum2 = sum([vec2[x] ** 2 for x in list(vec2.keys())])
    denominator = math.sqrt(sum1) * math.sqrt(sum2)

    if not denominator:
        return 0.0
    else:
        return float(numerator) / denominator


def text_to_vector(text):
    words = WORD.findall(text)
    return Counter(words)

##Example
##cosine_score = get_cosine(text_to_vector(clean_tweet), text_to_vector(" ".join(topic_words)))
##topic_words is a list of words; clean_tweet is a string
```

Convert word2vector:

In [ ]:
```
df['Summary_vec'] = df.Summary_clean.astype(str).apply(text_to_vector)
```

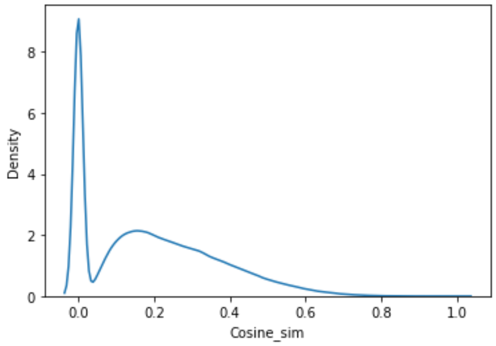
In [ ]:
```
df['Text_vec'] = df.Text_clean.apply(text_to_vector)
```

Compute Cosine Similarity

```
In [ ]: df['Cosine_sim'] = list(map(get_cosine, df['Summary_vec'], df['Text_vec']))
```

```
In [ ]: sns.kdeplot(df['Cosine_sim'])
```

```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f08cf24f390>
```



The similarity value between text and summary are not very high. The majority of the score stays below 0.6. In fact, the density is at its highest when cosine similarity is 0. The c
similarity ranges between -0.05 to 0.03. When cosine similarity is between 0.04 to 0.6, the density stays below 2. As the conclusion, summary does not predictive text, only ver
text says. For the majority of the summaries, they do not tell a good story of the texts.

Save the processed df:

```
In [ ]: df.to_parquet('amazon_reviews.parquet.gzip', compression="gzip")
        !cp amazon_reviews.parquet.gzip "/content/drive/MyDrive/Mini Project/"
```

```
In [ ]: %%time
        df = pd.read_parquet("/content/drive/MyDrive/Mini Project/amazon_reviews.parquet.gzip")

        CPU times: user 4.78 s, sys: 1.41 s, total: 6.19 s
        Wall time: 10.4 s
```

```
In [ ]: df.head(3)
```

Out[ ]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text	Title_len	Summary_le
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	2011-04-27	Good Quality Dog Food	I have bought several of the Vitality canned d...	10.0	21.(
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	2012-09-07	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...	6.0	17.(
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	2008-08-18	"Delight" says it all	This is a confection that has been around a fe...	31.0	21.(