Natural Language Processing Review Project Analysis

Report and Source Code

Import the dataset, **"K8 Reviews v0.2.csv"** from the location it saved in your computer in Jupyter Notebook and other basic libraries required for the analysis and building recommendation model.

Tasks:

1. Read the .csv file using Pandas. Take a look at the top few records.

Solution: Importing Libraries:

Input code: import pandas as pd

Reading and saving the file in dataframe variable:

Input Code:

df = pd.read_csv("K8 Reviews v0.2.csv")

df

Output: The output has 14675 rows and 2 columns displaying the sentiment and reviews with 0 value of sentiment as negative and 1 value to be positive review as shown below:

sentiment		review
0	1	Good but need updates and improvements
1	0	Worst mobile i have bought ever, Battery is dr
2	1	when I will get my 10% cash back its alrea
3	1	Good
4	0	The worst phone everThey have changed the last
5	0	Only I'm telling don't buyI'm totally disappoi
6	1	Phone is awesome. But while charging, it heats
7	0	The battery level has worn down
8	0	It's over hitting problemsand phone hanging
9	0	A lot of glitches dont buy this thing better $g_{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol{\boldsymbol$
10	0	Wrost
11	1	Good phone but charger not working / damage wi
12	0	Don't purchase this item, It is so much of hea

2. Normalize casings for the review text and extract the text into a list for easier manipulation.

Input Code:

```
df["review"] = df["review"].str.lower()
df["review"]
```

Output: Contains a list of reviews with 14675 rows of only review text. A glimpse is shown in the image below:

```
good but need updates and improvements
          worst mobile i have bought ever, battery is dr...
         when i will get my 10% cash back.... its alrea...
         the worst phone everthey have changed the last...
         only i'm telling don't buyi'm totally disappoi...
         phone is awesome. but while charging, it heats...
                               the battery level has worn down
       it's over hitting problems...and phone hanging...
        a lot of glitches dont buy this thing better g...
10
        good phone but charger not working / damage wi...
don't purchase this item, it is so much of hea...
i have faced the battery problem and motherboa...
11
        very good phone slim good battry backup good s..
15
                                       headset is not available
        every time automatic on and off so kindly sugg...
best product according to their prize range an...
16
17
         battery draining very rapidly i don't know why...
                                                 good smartphone
       galery problem and there is not atmos speakern...
excellent camera , excellent speed.excellent f...
22
23
                                               it ok good product
        it is not a very good product camera are very ...
         does not have many options like cast screen, w...
```

Extracting to list:

Input code: reviewData = df["review"].tolist()

3. Tokenize the reviews using NLTKs word_tokenize function.

Input Code:

```
from nltk import word_tokenize, pos_tag
tokenizedReviews = [word_tokenize(x) for x in reviewData]
tokenizedReviews
```

Output: A glimpse of is shown in the image below:

4. Perform parts-of-speech tagging on each sentence using the NLTK POS tagger.

Input Code:

posReviews = [pos_tag(x) for x in tokenizedReviews]
posReviews

Output: A glimpse of using the POS tagger is shown in the image below:

```
[[('good', 'JJ'),
    ('but', 'CC'),
    ('need', 'VBP'),
    ('updates', 'NNS'),
    ('and', 'CC'),
    ('improvements', 'NNS')],
[('worst', 'JJS'),
    ('mobile', 'NN'),
    ('i', 'NN'),
    ('have', 'VBP'),
    ('bought', 'VBN'),
    ('ever', 'RB'),
    (',',','),
    ('battery', 'NN'),
```

- 5. For the topic model, we want to include only nouns.
 - a. Find out all the POS tags that correspond to nouns.
 - b. Limit the data to only terms with these tags.

Solution: Tags corresponding to the nouns are NN, NNS, NNP and NNPS

Input Code:

```
nounPosReviews = []
```

for posReview in posReviews:

```
temp = []
```

for x in posReview:

```
if x[-1][0] == 'N':
```

temp.append(x)

nounPosReviews.append(temp)

nounPosReviews

Output: Limiting the data to these tags, glimpse is shown in the image below:

```
[[('updates', 'NNS'), ('improvements', 'NNS')],
[('mobile', 'NN'),
    ('i', 'NN'),
    ('battery', 'NN'),
    ('backup', 'NN'),
    ('backup', 'NNS'),
    ('uses', 'NNS'),
    ('idle', 'NN'),
    ('dicharged.this', 'NN'),
    ('lie', 'NN'),
    ('amazon', 'NN'),
    ('lenove', 'NN'),
    ('charger', 'NN'),
    ('charger', 'NN'),
    ('charger', 'NNS'),
    ('don', 'NN')],
    [('i', 'NN')],
    [('i', 'NN'), ('%', 'NN'), ('cash', 'NN'), ('january..', 'NN')],
    [['i', 'NN'), ('%', 'NN'), ('cash', 'NN'), ('january..', 'NN')],
    [['i', 'NN'), ('%', 'NN'), ('cash', 'NN'), ('january..', 'NN')],
    [['i', 'NN'), ('%', 'NN'), ('cash', 'NN'), ('january..', 'NN')],
    [['i'], 'NN'), ('%', 'NN'), ('cash', 'NN'), ('january..', 'NN')],
    [['i'], 'NN'],
```

- 6. Lemmatize.
 - a. Different forms of the terms need to be treated as one.
 - b. No need to provide POS tag to lemmatizer for now.

from nltk.stem import WordNetLemmatizer

lemmatizer = WordNetLemmatizer()

lemmatized NounPosReviews = [[(lemmatizer.lemmatize(x[0]),x[1]) for x in i] for i in nounPosReviews]

lemmatizedNounPosReviews

Output: A glimpse of using the lemmatizer is shown below:

```
[[('update', 'NNS'), ('improvement', 'NNS')],
[('mobile', 'NN'),
    ('i', 'NN'),
    ('battery', 'NN'),
    ('battery', 'NN'),
    ('backup', 'NN'),
    ('backup', 'NNS'),
    ('us', 'NNS'),
    ('idle', 'NN'),
    ('discharged.this', 'NN'),
    ('lie', 'NN'),
    ('amazon', 'NN'),
    ('lenove', 'NN'),
    ('battery', 'NN'),
    ('charger', 'NN'),
    ('charger', 'NN'),
    ('hour', 'NNS'),
    ('don', 'NNS'),
    ('don', 'NN')],
[('i', 'NN'), ('%', 'NN'), ('cash', 'NN'), ('january..', 'NN')],
[['i', 'NN'), ('%', 'NN'), ('cash', 'NN'), ('january..', 'NN')],
[['i', 'NN'), ('%', 'NN'), ('cash', 'NN'), ('january..', 'NN')],
[['i', 'NN'), ('%', 'NN'), ('cash', 'NN'), ('january..', 'NN')],
[]]
```

7. Remove stopwords and punctuation (if there are any).

Input Code:

from nltk.corpus import stopwords

stopwordList = stopwords.words('english')

cleanedNounPosReviews = [[(x[0],x[1]) for x in i if x[0] not in stopwordList] for i in lemmatizedNounPosReviews]

cleanedNounPosReviews

Output: A glimpse is shown in the image below:

```
[[('update', 'NNS'), ('improvement', 'NNS')],
[('mobile', 'NN'),
    ('battery', 'NN'),
    ('hell', 'NN'),
    ('backup', 'NNS'),
    ('us', 'NNS'),
    ('us', 'NNS'),
    ('idle', 'NN'),
    ('discharged.this', 'NN'),
    ('lie', 'NN'),
    ('amazon', 'NN'),
    ('lenove', 'NN'),
    ('battery', 'NN'),
    ('charger', 'NN'),
```

- 8. Create a topic model using LDA on the cleaned-up data with 12 topics.
 - a. Print out the top terms for each topic.
 - b. What is the coherence of the model with the c_v metric?

import gensim

import gensim.corpora as corpora

Lda = gensim.models.ldamodel.LdaModel

Drop tags:

lemmatizedReviews = [[i[0] for i in x] for x in cleanedNounPosReviews]

lemmatizedReviews

Output:

```
[['update', 'improvement'],
  ['mobile',
  'battery',
  'hell',
  'backup',
  'hour',
  'us',
  'idle',
  'discharged.this',
  'lie',
  'amazon',
  'lenove',
  'battery',
  'charger',
```

Input Code:

id2word = corpora.Dictionary(lemmatizedReviews)

texts = lemmatizedReviews

corpus = [id2word.doc2bow(text) for text in texts]

lda_model = Lda(corpus=corpus, id2word=id2word, num_topics=12)

lda_model.top_topics(corpus)

Output: Printing out terms for each topic:

```
[([(0.08434804, 'issue'),
(0.051711515, 'phone'),
(0.03998527, 'network'),
(0.039461244, 'battery'),
(0.021033444, 'hour'),
(0.020168453, 'sim'),
(0.019357868, 'time'),
(0.01911929, 'note'),
(0.018062659, '%'),
(0.016989574, 'charge'),
(0.016362302, 'call'),
(0.0130618755, 'option'),
(0.012135512, 'data'),
```

```
topTerms = [max(x[0], key=lambda l:l[0]) for x in lda_model.top_topics(corpus)] topTerms
```

Output: Printing out top terms:

```
[(0.08434804, 'issue'),
(0.13116528, 'phone'),
(0.16186793, 'battery'),
(0.055123806, 'camera'),
(0.2119095, 'camera'),
(0.094949976, 'note'),
(0.28875387, 'phone'),
(0.07933463, 'phone'),
(0.22034127, 'mobile'),
(0.31723484, 'product'),
(0.17752673, 'price'),
(0.05279111, 'screen')]
```

Input Code:

```
from gensim.models.coherencemodel import CoherenceModel coherence_model_lda = CoherenceModel(model=lda_model, texts=texts, dictionary=id2word, coherence='c_v') coherence_lda = coherence_model_lda.get_coherence() print('\nCoherence Score: ', coherence lda)
```

Output: The coherence score is 0.5165950021693836

Output: The coherence score is 0.5083485963025702

9. Analyse the topics through the business lens. Determine which of the topics can be combined.

Solution: From top terms 1st, 2nd, 9th and 12th topics can be combined.

10. Create topic model using LDA with what you think is the optimal number of topics. What is the coherence of the model?

Input Code:

```
Ida_model_optimal = Lda(corpus=corpus, id2word=id2word, num_topics=9)
coherence_model_lda_optimal = CoherenceModel(model=lda_model_optimal,
texts=texts, dictionary=id2word, coherence='c_v')
coherence_lda_optimal = coherence_model_lda_optimal.get_coherence()
print('\nCoherence Score: ', coherence_lda_optimal)
```

- 11. The business should be able to interpret the topics.
 - a. Name each of the identified topics.
 - b. Create a table with the topic name and the top 10 terms in each to present to the business.

topTermsOptimal = [max(x[0], key=lambda l:l[0]) for x in lda_model_optimal.top_topics(corpus)]

topTermsOptimal

Output: The identified topics are:

```
[(0.15009189, 'phone'),
(0.11674714, 'battery'),
(0.093986794, 'problem'),
(0.12803072, 'phone'),
(0.057888333, 'battery'),
(0.17438711, 'camera'),
(0.19824827, 'mobile'),
(0.06061089, 'camera'),
(0.27671534, 'product')]
```

Input Code:

Ida model optimal.top topics(corpus)

Output: A glimpse of the optimal LDA model is shown below:

```
[([(0.15009189, 'phone'), (0.055172645, 'note'), (0.055172645, 'note'), (0.02833446, 'k8'), (0.02223797, 'lenovo'), (0.02181811, 'call'), (0.02032657, 'feature'), (0.015543854, 'speaker'), (0.012190103, 'screen'), (0.01354237, 'option'), (0.010253569, 'camera'), (0.009346517, 'issue'), (0.0083459988, 'app'), (0.008317331, 'sound'), (0.00837331, 'sound'), (0.0071287374, 'software'), (0.0069468925, 'dolby'), (0.0065248418, 'apps'), (0.0065248418, 'apps'), (0.0062497235, 'problem')],
```

```
topicMap = dict()
for i in range(len(lda_model_optimal.top_topics(corpus))):
    entry = lda_model_optimal.top_topics(corpus)[i]
    temp = sorted(entry[0], key = lambda x:x[0], reverse=True)
    temp2 = [t[1] for t in temp]
    if temp2[0] not in topicMap:
        topicMap[temp2[0]] = temp2[1:11]
    else:
        topicMap[temp2[0]+str(i)] = temp2[1:11]

pd.DataFrame.from_dict(topicMap)
```

Output: Table representing the business: Topics with top 10 terms.

phone	battery	problem	phone3	battery4	camera	mobile	camera7	product
note	phone	phone	issue	performance	quality	price	quality	hai
k8	backup	service	time	problem	phone	phone		ho
lenovo	camera	charger	network	network	battery	product	photo	cam
call	day	money	battery	camera	h	range	picture	piece
feature	issue	amazon	screen	issue	feature	feature	display	lenovo
speaker	life	heating	everything	handset	money	camera	product	bhi
screen	%	day	heat	work	waste	superb	sound	ko
option	device	product	budget	product	mode	performance	set	ye
camera	hour	battery	sim	hr	performance	buy	super	tha
issue	update	delivery	lot	speed	depth	box	excellent	yesterday
	note k8 lenovo call feature speaker screen option camera	note phone k8 backup lenovo camera call day feature issue speaker life screen % option device camera hour	note phone phone k8 backup service lenovo camera charger call day money feature issue amazon speaker life heating screen % day option device product camera hour battery	note phone phone issue k8 backup service time lenovo camera charger network call day money battery feature issue amazon screen speaker life heating everything screen % day heat option device product budget camera hour battery sim	note phone phone issue performance k8 backup service time problem lenovo camera charger network network call day money battery camera feature issue amazon screen issue speaker life heating everything handset screen % day heat work option device product budget product camera hour battery sim hr	note phone phone issue performance quality k8 backup service time problem phone lenovo camera charger network network battery call day money battery camera h feature issue amazon screen issue feature speaker life heating everything handset money screen % day heat work waste option device product budget product mode camera hour battery sim hr performance	note phone phone issue performance quality price k8 backup service time problem phone phone lenovo camera charger network network battery product call day money battery camera h range feature issue amazon screen issue feature feature speaker life heating everything handset money camera screen % day heat work waste superb option device product budget product mode performance camera hour battery sim hr performance buy	note phone phone issue performance quality price quality k8 backup service time problem phone phone lenovo camera charger network network battery product photo call day money battery camera h range picture feature issue amazon screen issue feature feature display speaker life heating everything handset money camera product screen % day heat work waste superb sound option device product budget product mode performance set camera hour battery sim hr performance buy superb