Review Project Analysis

Description:

Help a leading mobile brand understand the voice of the customer by analyzing the reviews of their pr

Problem Statement:

A popular mobile phone brand, Lenovo has launched their budget smartphone in the Indian market. T useful to not just evaluate the current product, but to also get some direction for developing the produ Product reviews by customers on a leading e-commerce site should provide a good view.

Steps to perform:

Discover the topics in the reviews and present it to business in a consumable format. Employ techniq

Perform specific cleanup, POS tagging, and restricting to relevant POS tags, then, perform topic mod and make a table for business.

Latent Dirichlet Allocation

In [2]:
```
import pandas as pd
import numpy as np

import nltk
from nltk.stem import WordNetLemmatizer

import string

import seaborn as sns
import matplotlib.pyplot as plt

import logging
logging.basicConfig(format='%(asctime)s : %(levelname)s : %(message)s', level=log

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

Content:

Dataset: 'K8 Reviews v0.2.csv'

Columns: ['sentiment' , 'review']

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

In [3]:
```
df = pd.read_csv('K8 Reviews v0.2.csv')
df.head()
```

Out[3]:

	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...

In [4]:
```
df.columns
```

Out[4]:
```
Index(['sentiment', 'review'], dtype='object')
```

In [5]:
```
df.sentiment.value_counts()
```

Out[5]:
```
0    7712
1    6963
Name: sentiment, dtype: int64
```

The sentiment against the review (4,5 star reviews are positive, 1,2 are negative)

- number of negative review: 7712
- number of positive review: 6963

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

In [6]:
```
review_text = list(df['review'].values)
review_text = [item.lower() for item in review_text]
review_text[0]
```

Out[6]:
```
'good but need updates and improvements'
```

3) Tokenize the reviews using NLTKs word_tokenize function.

In [7]:
```
from nltk.tokenize import word_tokenize
review_tokens = [word_tokenize(review) for review in review_text]
review_tokens[0]
```

Out[7]:
```
['good', 'but', 'need', 'updates', 'and', 'improvements']
```

In [8]:
```
review_tokens[0]
```

Out[8]:
```
['good', 'but', 'need', 'updates', 'and', 'improvements']
```

In [9]:
```
clean_review_tokens = []
# remove remaining tokens that are not alphabetic
for list_token in review_tokens:
    clean_review_tokens.append([word for word in list_token if word.isalpha()])
```

In [10]:
```
clean_reviews = [[token for token in clean_review_token if len(token) > 1] for cl

#docs = [[token for token in doc if len(token) > 1] for doc in docs]
len(clean_reviews)
```

Out[10]:
```
14675
```

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

In [11]:
```
all_nouns = []

review_pos = [nltk.pos_tag(tokens) for tokens in clean_reviews]
review0_nouns = [term for term,pos in review_pos[0] if pos.startswith("NN")]
```

5) For the topic model, we should want to include only nouns.

- Find out all the POS tags that correspond to nouns.
- Limit the data to only terms with these tags.

In [12]:
```
for sent in review_pos:
    all_nouns.append([term for term,pos in sent if pos.startswith("NN")])
```

In [13]:
```
review0_nouns
```

Out[13]:
```
['updates', 'improvements']
```

In [14]:
```
all_nouns[0:2]
```

Out[14]:
```
[['updates', 'improvements'],
 ['battery',
  'hell',
  'backup',
  'hours',
  'internet',
  'uses',
  'lie',
  'amazon',
  'lenove',
  'battery',
  'charger',
  'hours',
  'don']]
```

In [15]:
```
print(len(review_text))
print(len(all_nouns))
```

```
14675
14675
```

6) Lemmatize.

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

In [16]:
```
lemmatizer = WordNetLemmatizer()

lemmatized_nouns = []
for nouns in all_nouns:
    lemmatized_nouns.append([lemmatizer.lemmatize(item) for item in nouns])
```

In [17]:
```
lemmatized_nouns[0:2]
```

Out[17]:
```
[['update', 'improvement'],
 ['battery',
  'hell',
  'backup',
  'hour',
  'internet',
  'us',
  'lie',
  'amazon',
  'lenove',
  'battery',
  'charger',
  'hour',
  'don']]
```

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

In [18]:
```
from nltk.corpus import stopwords
from string import punctuation
```

In [19]:
```
stop_nltk = stopwords.words("english")
stop_punct = list(punctuation)
stop_final = stop_nltk + stop_punct
print(len(stop_final))

text_clean = []
for term in lemmatized_nouns:
    text_clean.append([item for item in term if item not in stop_final])

text_clean[0:2]
```

```
211
```

Out[19]:
```
[['update', 'improvement'],
 ['battery',
  'hell',
  'backup',
  'hour',
  'internet',
  'us',
  'lie',
  'amazon',
  'lenove',
  'battery',
  'charger',
  'hour']]
```

Latent Dirichlet Allocation (LDA)

- LDA is used to classify text in a document to a particular topic. It builds a topic per document mo
- Each document is modeled as a multinomial distribution of topics and each topic is modeled as a
- LDA assumes that the every chunk of text we feed into it will contain words that are somehow rel produced from a mixture of topics. Those topics then generate words based on their probability d

8) Create a topic model using LDA on the cleaned-up data with 12 topics

- Print out the top terms for each topic.
- What is the coherence of the model with the c_v metric?

In [20]:
```
import gensim
from gensim.models import CoherenceModel

from tqdm import tqdm_notebook  as tqdm
```

In [21]:
```
dictionary = gensim.corpora.Dictionary(text_clean)

dictionary.filter_extremes(no_below=15, no_above=0.5)
print(dictionary)
```

```
Dictionary(517 unique tokens: ['improvement', 'update', 'amazon', 'backup', 'batte
```

In [22]:
```
# Bag-of-words representation of the documents.
bow_corpus = [dictionary.doc2bow(doc) for doc in text_clean]

print(bow_corpus[0])
```

```
[(0, 1), (1, 1)]
```

The doc2bow() function converts dictionary into a bag-of-words

- In each document vector is a series of tuples
- The tuples are (term ID, term frequency) pairs
- This includes terms that actually occur - terms that do not occur in a document will not appear in

In [23]:
```
# show the actual terms with the term frequency
[[(dictionary[id], freq) for id, freq in cp] for cp in bow_corpus[:1]]
```

Out[23]:
```
[[('improvement', 1), ('update', 1)]]
```

Hyperparameter Tuning for random_state

In [24]:
```
from tqdm import tqdm_notebook as tqdm

limit = 13
num_topics = 12
rand = list(np.arange(13,40,2))

b = 0.01
a = 0.61
for r in tqdm(rand):
    lm = gensim.models.LdaModel(corpus=bow_corpus, num_topics=num_topics, alpha='
    cm = CoherenceModel(model=lm, texts=text_clean, dictionary=dictionary,coheren

    print("{} - {} ".format(cm.get_coherence(),r))
```

100% 14/14 [07:34<00:00, 33.67s/it]

```
0.5393236674179007 - 13
0.5316661030445747 - 15
0.5125720811806537 - 17
0.5202565462213121 - 19
0.5517544942098908 - 21
0.5318244191743492 - 23
0.5184065953881257 - 25
0.5240136417847616 - 27
0.5438222672344666 - 29
0.5366056452675256 - 31
0.5173672311909299 - 33
0.5330179113186869 - 35
0.5325630849497399 - 37
0.4955822903959948 - 39
```

random_state with highest score: 21

Hyperparameter Tuning for Alpha and Eta

In [25]:
```
from tqdm import tqdm_notebook as tqdm

limit = 13
alpha=list(np.arange(0.01,1,0.3))
beta=list(np.arange(0.01,1,0.3))
num_topics = 12
r=21

for b in tqdm(beta):
    for a in alpha:
        #lm = gensim.models.LdaModel(corpus=bow_corpus, num_topics=num_topics, al
        lm = gensim.models.LdaModel(corpus=bow_corpus, num_topics=num_topics, alp
        cm = CoherenceModel(model=lm, texts=text_clean, dictionary=dictionary,coh
        print("{} - {} - {} - {}".format(cm.get_coherence(),b,a,r))
```

100% 4/4 [08:44<00:00, 132.14s/it]

```
0.5586497962557168 - 0.01 - 0.01 - 21
0.4956775745205788 - 0.01 - 0.31 - 21
0.4737986082958378 - 0.01 - 0.61 - 21
0.5153770090442823 - 0.01 - 0.9099999999999999 - 21
0.5678200935379377 - 0.31 - 0.01 - 21
0.5080016418237573 - 0.31 - 0.31 - 21
0.47740102053037586 - 0.31 - 0.61 - 21
0.5216276305628544 - 0.31 - 0.9099999999999999 - 21
0.582619689515261 - 0.61 - 0.01 - 21
0.5088670263531173 - 0.61 - 0.31 - 21
0.4821469004865648 - 0.61 - 0.61 - 21
0.4917114090982179 - 0.61 - 0.9099999999999999 - 21
0.5753184078345135 - 0.9099999999999999 - 0.01 - 21
0.5071666660217321 - 0.9099999999999999 - 0.31 - 21
0.48751600835564535 - 0.9099999999999999 - 0.61 - 21
0.4852180214267223 - 0.9099999999999999 - 0.9099999999999999 - 21
```

Best value for Alpha and Eta: (b = 0.91, a = 0.61)

- Alpha = 0.01
- Eta = 0.61

Building the LDA model using the Hyperparameters found for 12 topics

In [26]:
```
b = 0.61
a = 0.01
r = 21

model = gensim.models.LdaModel(corpus=bow_corpus, num_topics=num_topics, alpha=a,
```

In [27]:
```
for idx, topic in model.print_topics(-1):
    print("Topic: {} \nWords: {}".format(idx, topic))
    print("\n")
```

```
Topic: 0
Words: 0.440*"problem" + 0.152*"heating" + 0.030*"super" + 0.029*"smartphone" + 0


Topic: 1
Words: 0.231*"money" + 0.109*"waste" + 0.089*"value" + 0.057*"superb" + 0.042*"de


Topic: 2
Words: 0.322*"camera" + 0.206*"quality" + 0.043*"speaker" + 0.031*"sound" + 0.024
ture"


Topic: 3
Words: 0.507*"mobile" + 0.115*"performance" + 0.044*"expectation" + 0.034*"excell
*"superb"


Topic: 4
Words: 0.346*"battery" + 0.067*"backup" + 0.054*"hour" + 0.050*"day" + 0.039*"lif


Topic: 5
Words: 0.146*"price" + 0.101*"charger" + 0.078*"range" + 0.072*"heat" + 0.058*"mo


Topic: 6
Words: 0.082*"note" + 0.073*"lenovo" + 0.072*"phone" + 0.046*"service" + 0.042*"s


Topic: 7
Words: 0.059*"device" + 0.047*"option" + 0.045*"software" + 0.042*"update" + 0.03


Topic: 8
Words: 0.694*"phone" + 0.028*"issue" + 0.026*"price" + 0.024*"month" + 0.021*"fea


Topic: 9
Words: 0.105*"network" + 0.069*"issue" + 0.055*"call" + 0.053*"sim" + 0.041*"hai"


Topic: 10
Words: 0.351*"product" + 0.078*"amazon" + 0.030*"return" + 0.029*"service" + 0.02
0.016*"policy"


Topic: 11
Words: 0.091*"camera" + 0.076*"phone" + 0.039*"feature" + 0.033*"processor" + 0.0
18*"handset"
```

Coherence of model with c_v metric:

In [28]:
```
cm = CoherenceModel(model=model, texts=text_clean, dictionary=dictionary,coherenc
print("Coherence of model with c_v metric: {}".format(cm.get_coherence()))
```

```
Coherence of model with c_v metric: 0.582619689515261
```

9) Analyze the topics through the business lens.

```
Determine which of the topics can be combined.
```

- pyLDAvis result as shown in the visualization below.
- The area of circle represents the importance of each topic over the entire corpus.
- The distance between the center of circles indicate the similarity between topics.
- For each topic, the histogram on the right side listed the top 30 most relevant terms.
- LDA extracted 12 main topics.

From the visualization below we can see that only small overlap within 3 topics. Most topics are sprea
the Topic number or Topic Id in the visualization is assigned differently from my output. I will use the to

1 Topics 6 and 9 can be combined -- Network/Service/Signal (Connectivity) Issues

2 Topics 6 and 8 can be combined -- Phone and Usage Issues

3 Topics 4 and 5 can be combined -- Battery Related Issues

In [29]:
```
import pyLDAvis
import pyLDAvis.gensim_models as gensimvis
pyLDAvis.enable_notebook()

# feed the LDA model into the pyLDAvis instance
lda_viz = gensimvis.prepare(model, bow_corpus, dictionary)
lda_viz
```

```
C:\Users\mglee\Anaconda3\lib\site-packages\sklearn\decomposition\online_lda.py:29
his warning, use `float` by itself. Doing this will not modify any behavior and is
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs
l#deprecations)
  EPS = np.finfo(np.float).eps
```

Out[29]:

Selected Topic: 0 Previous Topic Next Topic Clear Topic

Compute c_v coherence for various number of topics

In [30]:
```
def compute_coherence_values(dictionary, corpus, texts, limit, start=2, step=3):
    """
    Compute c_v coherence for various number of topics
    Parameters:
    ----------
    dictionary : Gensim dictionary
    corpus : Gensim corpus
    texts : List of input texts
    limit : Max num of topics
    Returns:
    -------
    model_list : List of LDA topic models
    coherence_values : Coherence values corresponding to the LDA model with respe
    """
    # Set training parameters.
    b = 0.61
    a = 0.01
    # Use middle range random_state value
    r = 27
    # Make a index to word dictionary.
    #temp = dictionary[0]  # This is only to "load" the dictionary.
    #id2word = dictionary.id2token
    coherence_values = []
    model_list = []
    for num_topics in tqdm(range(start, limit, step)):
        #model = gensim.models.wrappers.LdaMallet(mallet_path, corpus=corpus, num_
        #model = gensim.models.LdaModel(corpus=bow_corpus, num_topics=num_topics,
        lm = gensim.models.LdaModel(corpus=bow_corpus, num_topics=num_topics, alp
        model_list.append(lm)
        coherencemodel = CoherenceModel(model=lm, texts=texts, dictionary=diction
        coherence_values.append(coherencemodel.get_coherence())

    return model_list, coherence_values
```

Generate the list of LDA topics with each corresponding coherence_values

- model_list : List of LDA topic models
- coherence_values : Coherence values corresponding to the LDA model with respective number o

In [31]:
```
from tqdm import tqdm_notebook as tqdm
# Can take a long time to run.
model_list, coherence_values = compute_coherence_values(dictionary=dictionary, co
```

```
C:\Users\mglee\Anaconda3\lib\site-packages\ipykernel_launcher.py:25: TqdmDeprecat
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
```

100% 9/9 [01:35<00:00, 11.43s/it]

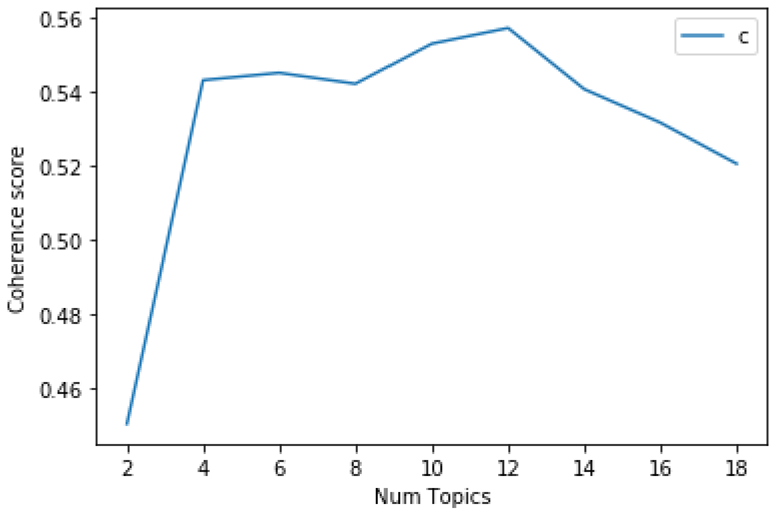
10) Create topic model using LDA with what you think is the optimal number of topics

- What is the coherence of the model?

made a plot showing: number of topics vs coherence score.

In [32]:
```
import matplotlib.pyplot as plt
%matplotlib inline

limit=20; start=2; step=2;
x = range(start, limit, step)
plt.plot(x, coherence_values)
plt.xlabel("Num Topics")
plt.ylabel("Coherence score")
plt.legend(("coherence_values"), loc='best')
plt.show()
```



- The plot shows the optimal number of topics.
- Here we see 12 (Num Topics) have highest Coherence score.
- 12 topics is optimal number of topics.

11) The business should be able to interpret the topics.

- Name each of the identified topics.
- Create a table with the topic name and the top 10 terms in each to present to the business.

In [33]:
```
topics=model.show_topics(formatted=False)
```

In [34]:
```
topics = sorted(topics)
```

In [35]:
```
top_terms=[]

top_id=[top for top,tl in topics]
terms =[tl for top,tl in topics]

for term in terms:
    top_terms.append([t for t,s in term])
#print(top_terms)
```

Give names to each of the identified topics

In [47]:
```
topic_names=['Problems','Value','Features','Positive','Battery Performance','Char
topics = pd.DataFrame({'ID': top_id, 'Name': topic_names, 'top terms':top_terms})
topics.style.hide_index()
```

Out[47]:

ID	Name	
0	Problems	['problem', 'heating', 'super', 'smartphone', 'set', 'pls', 'model', 'cell', 'cond
1	Value	['money', 'waste', 'value', 'superb', 'delivery', 'worth', 'ok', 'buy',
2	Features	['camera', 'quality', 'speaker', 'sound', 'speed', 'picture', 'performance', 'note', 'imag
3	Positive	['mobile', 'performance', 'expectation', 'excellent', 'item', 'plz', 'feature', 'purchase', 'ph
4	Battery Performance	['battery', 'backup', 'hour', 'day', 'life', 'charge', 'issue', 'time', 'drain', 'pe
5	Charging issues	['price', 'charger', 'range', 'heat', 'mode', 'turbo', 'camera', 'game', 'dc
6	Service issues	['note', 'lenovo', 'phone', 'service', 'screen', 'day', 'glass', 'issue', 'dis
8	Other Issues	['phone', 'issue', 'price', 'month', 'feature', 'time', 'hang', 'use', '
10	Amazon	['product', 'amazon', 'return', 'service', 'customer', 'replacement', 'delivery', 'experience', 'ti
11	Hardware Related	['camera', 'phone', 'feature', 'processor', 'everything', 'budget', 'ram', 'performance', 'clarity

table with the topic name and the top 10 terms

In [48]:
```
lda_viz
```

Out[48]:

Selected Topic: 0 | Previous Topic | Next Topic | Clear Topic

Intertopic Distance Map (via multidimensional scaling)

In [ ]: