In [ ]:
```
#DESCRIPTION

#Help a leading mobile brand understand the voice of the customer by analyzing the reviews of their product on Amazon and the topics that cu
stomers are talking about. You will perform topic modeling on specific parts of speech. You’ll finally interpret the emerging topics.

#Problem Statement:

#A popular mobile phone brand, Lenovo has launched their budget smartphone in the Indian market. The client wants to understand the VOC (voi
ce of the customer) on the product. This will be useful to not just evaluate the current product, but to also get some direction for develop
ing the product pipeline. The client is particularly interested in the different aspects that customers care about. Product reviews by custo
mers on a leading e-commerce site should provide a good view.

#Domain: Amazon reviews for a leading phone brand

#Analysis to be done: POS tagging, topic modeling using LDA, and topic interpretation

#Content:

#Dataset: ‘K8 Reviews v0.2.csv’

#Columns:

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

#Reviews: The main text of the review

#Steps to perform:

#Discover the topics in the reviews and present it to business in a consumable format. Employ techniques in syntactic processing and topic m
odeling.

#Perform specific cleanup, POS tagging, and restricting to relevant POS tags, then, perform topic modeling using LDA. Finally, give business
-friendly names to the topics and make a table for business.

#Tasks:

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

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

#Tokenize the reviews using NLTKs word_tokenize function.

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

#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.

#Lemmatize.

#Different forms of the terms need to be treated as one.
```

```
#No need to provide POS tag to lemmatizer for now.

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

#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?

#Analyze the topics through the business lens.

#Determine which of the topics can be combined.

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

#What is the coherence of the model?

#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 [ ]:

```python
from google.colab import drive
drive.mount('/content/drive')
```

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

In [135]:

```python
#!pip install pyldavis
#!pip install spacy
#!pip install gensim

#loading and installing neccessary library and packages
```

```
Collecting pyldavis
  Downloading https://files.pythonhosted.org/packages/a5/3a/af82e070a8a96e13217c8f362f9a73e82d61ac8fff3a2561946a97f96266/pyLDAvis-2.1.2.tar.gz (1.6MB)
     |████████████████████████████████| 1.6MB 2.6MB/s
Requirement already satisfied: wheel>=0.23.0 in /usr/local/lib/python3.6/dist-packages (from pyldavis) (0.35.1)
Requirement already satisfied: numpy>=1.9.2 in /usr/local/lib/python3.6/dist-packages (from pyldavis) (1.18.5)
Requirement already satisfied: scipy>=0.18.0 in /usr/local/lib/python3.6/dist-packages (from pyldavis) (1.4.1)
Requirement already satisfied: pandas>=0.17.0 in /usr/local/lib/python3.6/dist-packages (from pyldavis) (1.1.3)
Requirement already satisfied: joblib>=0.8.4 in /usr/local/lib/python3.6/dist-packages (from pyldavis) (0.17.0)
Requirement already satisfied: jinja2>=2.7.2 in /usr/local/lib/python3.6/dist-packages (from pyldavis) (2.11.2)
Requirement already satisfied: numexpr in /usr/local/lib/python3.6/dist-packages (from pyldavis) (2.7.1)
Requirement already satisfied: pytest in /usr/local/lib/python3.6/dist-packages (from pyldavis) (3.6.4)
Requirement already satisfied: future in /usr/local/lib/python3.6/dist-packages (from pyldavis) (0.16.0)
Collecting funcy
  Downloading https://files.pythonhosted.org/packages/66/89/479de0afbbfb98d1c4b887936808764627300208bb771fcd823403645a36/funcy-1.15-py2.py3-none-any.wh
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.17.0->pyldavis) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.17.0->pyldavis) (2018.9)
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.6/dist-packages (from jinja2>=2.7.2->pyldavis) (1.1.1)
Requirement already satisfied: py>=1.5.0 in /usr/local/lib/python3.6/dist-packages (from pytest->pyldavis) (1.9.0)
Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.6/dist-packages (from pytest->pyldavis) (20.2.0)
Requirement already satisfied: atomicwrites>=1.0 in /usr/local/lib/python3.6/dist-packages (from pytest->pyldavis) (1.4.0)
```

```
Requirement already satisfied: pluggy<0.8,>=0.5 in /usr/local/lib/python3.6/dist-packages (from pytest->pyldavis) (0.7.1)
Requirement already satisfied: setuptools in /usr/local/lib/python3.6/dist-packages (from pytest->pyldavis) (50.3.2)
Requirement already satisfied: six>=1.10.0 in /usr/local/lib/python3.6/dist-packages (from pytest->pyldavis) (1.15.0)
Requirement already satisfied: more-itertools>=4.0.0 in /usr/local/lib/python3.6/dist-packages (from pytest->pyldavis) (8.5.0)
Building wheels for collected packages: pyldavis
  Building wheel for pyldavis (setup.py) ... done
  Created wheel for pyldavis: filename=pyLDAvis-2.1.2-py2.py3-none-any.whl size=97712 sha256=6218842ec7483df6ffb42d4c053aab6ccb0a24528c609d1e3690bd7ec94
  Stored in directory: /root/.cache/pip/wheels/98/71/24/513a99e58bb6b8465bae4d2d5e9dba8f0bef8179e3051ac414
Successfully built pyldavis
Installing collected packages: funcy, pyldavis
Successfully installed funcy-1.15 pyldavis-2.1.2
```

In [287]:

```
import pandas as pd
import numpy as np
from textblob import TextBlob

import nltk
import string
import warnings
warnings.filterwarnings('ignore')
from nltk import tokenize,WordNetLemmatizer, PorterStemmer
from nltk.corpus import wordnet

from string import punctuation
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.feature_extraction.text import TfidfVectorizer,CountVectorizer
from nltk.corpus import stopwords
import re, nltk, spacy, gensim
from sklearn.decomposition import LatentDirichletAllocation, TruncatedSVD
from pprint import pprint
from sklearn.model_selection import GridSearchCV
import nltk

# Plotting tools
import pyLDAvis
import pyLDAvis.sklearn
import matplotlib.pyplot as plt
from gensim.models import CoherenceModel
```

In [288]:

```
#pip install --user -U nltk
#nltk.download('stopwords')
#nltk.download('punkt')
#nltk.download('wordnet')
#nltk.download('averaged_perceptron_tagger')

#Data Preprocessing
#With stopword and punctuation removal
```

In [289]:

```
stopwords1 = list(stopwords.words('english'))
print(stopwords1[0:11])
```

```
print('\nlength of stopwords list: ', len(stopwords1))
type(stopwords1)
```

```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've"]

length of stopwords list:  179
```

Out[289]: list

In [290]:
```
punctuation
```

Out[290]: `'!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'`

In [291]:
```
stopwords1 = list(stopwords.words('english'))+list(punctuation)
```

In [292]:
```
print(len(stopwords1),stopwords1,sep='\n\n')
```

```
211

['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves',
'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what
hich', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'havir
'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about',
st', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under',
in', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 's
'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now',
'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't"
ven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', '
n't", 'weren', "weren't", 'won', "won't", 'wouldn', "wouldn't", '!', '"', '#', '$', '%', '&', "'", '(', ')', '*', '+', ',', '-', '.', '/', ':', ';', '<
'=', '>', '?', '@', '[', '\\', ']', '^', '_', '`', '{', '|', '}', '~']
```

In [293]:
```
#Read the .csv file using Pandas. Take a look at the top few records.
reviews = pd.read_csv('/content/drive/My Drive/K8 Reviews v0.2.csv')
reviews = reviews[:8000]
reviews.head()
```

Out[293]:

	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 [298]:
```
#checking for null values although it is not neccessary to do
print(reviews.isnull().sum(),reviews.shape,sep='\n\n')
```

```
sentiment    0
review       0
dtype: int64
```

```
(8000, 2)
```

In [299]:
```python
reviews.dropna(inplace = True)
```

In [300]:
```python
#checking the shape of the data
reviews.shape
```

Out[300]:
```
(8000, 2)
```

In [301]:
```python
reviews.sentiment.value_counts()
```

Out[301]:
```
0    4209
1    3791
Name: sentiment, dtype: int64
```

In [302]:
```python
#stemming and lemmatization
#here we have build a custom function that will first get the noun pos tag and then
#do the lemmatization

ps=PorterStemmer()

lemmatizer = WordNetLemmatizer()
```

In [303]:
```python
# function to convert nltk tag to wordnet tag
def nltk_tag_to_wordnet_tag(nltk_tag):

    if nltk_tag.startswith('N'):
        return wordnet.NOUN
    else:
        return None

def lemmatize_sentence(sentence):
    #tokenize the sentence and find the POS tag for each token
    nltk_tagged = nltk.pos_tag(nltk.word_tokenize(sentence))
#     print(list(nltk_tagged))

    #tuple of (token, wordnet_tag)
    wordnet_tagged = map(lambda x: (x[0], nltk_tag_to_wordnet_tag(x[1])), nltk_tagged)


    lemmatized_sentence = []

    for word, tag in wordnet_tagged:
        if tag is None:
            #if there is no available tag, append the token as is
            lemmatized_sentence.append(word)
#             print('IN CASE OF NONE: ', lemmatized_sentence)

        else:
            #else use the tag to lemmatize the token
            lemmatized_sentence.append(lemmatizer.lemmatize(word, tag))
#             print('IN CASE OF ELSE : ',lemmatized_sentence)
```

```
    return " ".join(lemmatized_sentence)

# print(lemmatize_sentence(" i have been working on my skills ")) #I be love it
```

In [304]:
```
# Removing Stopwords and punctuatons
def clean_text(a):
    ls = [i.lower() for i in tokenize.word_tokenize(a) if i not in stopwords1]
    if len(ls)>3:
        val= ' '.join(ls)
        return val
    else :
        return None


# Lemmatization without POS Tags
def clean_text_lemma(a):
    val= ' '.join([lemmatizer.lemmatize(i.lower()) for i in tokenize.word_tokenize(a) if i not in stopwords1])
    return val


# Stemming
def clean_text_stem(a):
    val= ' '.join([ps.stem(i.lower()) for i in tokenize.word_tokenize(a) if i not in stopwords1])
    return val
```

In [305]:
```
reviews['clean_txt'] = reviews['review'].apply(clean_text)
reviews.dropna(inplace = True)
len(reviews)
```

Out[305]: 5827

In [306]:
```
reviews.head()
```

Out[306]:

	sentiment	review	clean_txt
0	1	Good but need updates and improvements	good need updates improvements
1	0	Worst mobile i have bought ever, Battery is dr...	worst mobile bought ever battery draining like...
2	1	when I will get my 10% cash back.... its alrea...	i get 10 cash back ... already 15 january..
4	0	The worst phone everThey have changed the last...	the worst phone everthey changed last phone pr...
5	0	Only I'm telling don't buyI'm totally disappoi...	only i 'm telling n't buyi 'm totally disappoi...

In [307]:
```
reviews['clean_lemma'] = reviews['clean_txt'].apply(clean_text_lemma)
reviews['clean_lemma_pos'] = reviews['clean_txt'].apply(lemmatize_sentence)
reviews['clean_stem_txt'] = reviews['clean_txt'].apply(clean_text_stem)
```

In [308]:
```
reviews.head()
```

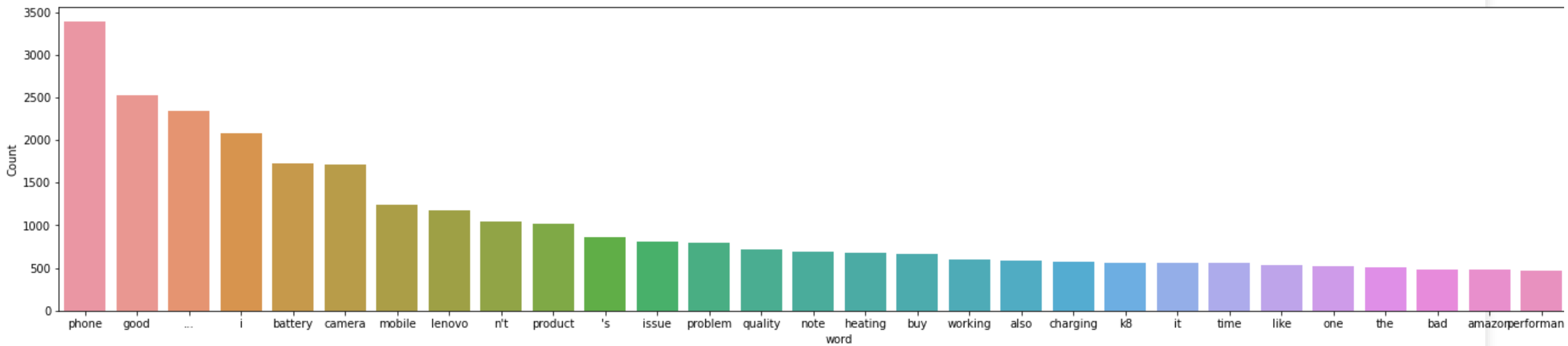
Out[308]:

	sentiment	review	clean_txt	clean_lemma	clean_lemma_pos	clean_s
0	1	Good but need updates and improvements	good need updates improvements	good need update improvement	good need update improvement	good need upda
1	0	Worst mobile i have bought ever, Battery is dr...	worst mobile bought ever battery draining like...	worst mobile bought ever battery draining like...	worst mobile bought ever battery draining like...	worst mobil bought ever batteri d
2	1	when I will get my 10% cash back.... its alrea...	i get 10 cash back ... already 15 january..	get 10 cash back ... already 15 january..	i get 10 cash back ... already 15 january..	get 10 cash back ... alreadi 15 j
4	0	The worst phone everThey have changed the last...	the worst phone everthey changed last phone pr...	worst phone everthey changed last phone proble...	the worst phone everthey changed last phone pr...	worst phone everthey chang las pro
5	0	Only I'm telling don't buyI'm totally disappoi...	only i 'm telling n't buyi 'm totally disappoi...	'm telling n't buyi 'm totally disappointedpoo...	only i 'm telling n't buyi 'm totally disappoi...	'm tell n't buyi 'm total disappoin

In [309]:
```
#converting into list for better computation
data = reviews.clean_lemma_pos.values.tolist()
```

In [354]:
```
#checking the distribution of the frequent words
import matplotlib.pyplot as plt
from nltk import FreqDist
# function to plot most frequent terms
def freq_words(x, terms = 30):
  all_words = ' '.join([text for text in x])
  all_words = all_words.split()

  fdist = FreqDist(all_words)
  words_df = pd.DataFrame({'word':list(fdist.keys()), 'count':list(fdist.values())})

  # selecting top 20 most frequent words
  d = words_df.nlargest(columns="count", n = terms)
  plt.figure(figsize=(25,5))
  ax = sns.barplot(data=d, x= "word", y = "count")
  ax.set(ylabel = 'Count')
  plt.show()
```

In [355]:
```
freq_words(reviews['clean_lemma_pos'])
```



In [310]:
```
#count vectorizer
#It is used to transform a given text into a vector on the basis of the frequency (count) of each word that occurs in the entire text.
#This is helpful when we have multiple such texts, and we wish to convert each word in each text into vectors (for using in further
                                                                                                                text analysis).
vectorizer = CountVectorizer(analyzer='word',
                             min_df=10,                          # minimum reqd occurences of a word
                             stop_words='english',               # remove stop words
                             lowercase=True,                     # convert all words to lowercase
                             token_pattern='[a-zA-Z0-9]{3,}',   # num chars > 3
                             # max_features=50000,               # max number of uniq words
                            )
```

In [356]:
```
data_vectorized = vectorizer.fit_transform(data)
type(data_vectorized)
```

Out[356]:
```
scipy.sparse.csr.csr_matrix
```

In [312]:
```
# Materialize the sparse data
data_dense = data_vectorized.todense()
```

In [313]:
```
# Compute Sparsicity = Percentage of Non-Zero cells
print("Sparsicity: ", ((data_dense > 0).sum()/data_dense.size)*100, "%")
```

```
Sparsicity:  1.0751104804729859 %
```

In [ ]:
```
#LDA's approach to topic modeling is to classify text in a document to a particular topic. Modeled as Dirichlet distributions, LDA builds -

#A topic per document model and
#Words per topic model
```

In [314]:
```
# Build LDA Model
lda_model = LatentDirichletAllocation(n_components=12,           # Number of topics
                                      max_iter=10,               # Max learning iterations
                                      learning_method='online',
                                      random_state=100,          # Random state
                                      batch_size=128,            # n docs in each learning iter
                                      evaluate_every = -1,       # compute perplexity every n iters, default: Don't
                                      n_jobs = -1,               # Use all available CPUs
                                     )
```

In [315]:
```
lda_output = lda_model.fit_transform(data_vectorized)

print(lda_model)  # Model attributes
```

```
LatentDirichletAllocation(batch_size=128, doc_topic_prior=None,
                          evaluate_every=-1, learning_decay=0.7,
                          learning_method='online', learning_offset=10.0,
                          max_doc_update_iter=100, max_iter=10,
                          mean_change_tol=0.001, n_components=12, n_jobs=-1,
                          perp_tol=0.1, random_state=100, topic_word_prior=None,
                          total_samples=1000000.0, verbose=0)
```

In [316]:
```
# Log Likelyhood: Higher the better
print("Log Likelihood: ", lda_model.score(data_vectorized))

# Perplexity: Lower the better. Perplexity = exp(-1. * log-likelihood per word)
print("Perplexity: ", lda_model.perplexity(data_vectorized))

# See model parameters
pprint(lda_model.get_params())
```

```
Log Likelihood:  -414579.66305578593
Perplexity:  413.92799356552376
{'batch_size': 128,
 'doc_topic_prior': None,
 'evaluate_every': -1,
 'learning_decay': 0.7,
 'learning_method': 'online',
 'learning_offset': 10.0,
 'max_doc_update_iter': 100,
 'max_iter': 10,
 'mean_change_tol': 0.001,
 'n_components': 12,
 'n_jobs': -1,
 'perp_tol': 0.1,
 'random_state': 100,
 'topic_word_prior': None,
 'total_samples': 1000000.0,
 'verbose': 0}
```

In [317]:
```
# Define Search Param
search_params = {'n_components': [10, 15, 20, 25, 30], 'learning_decay': [.5, .7, .9]}
```

In [318]:
```
# Init the Model
lda = LatentDirichletAllocation()
```

In [319]:
```
# Init Grid Search Class
model = GridSearchCV(lda, param_grid=search_params)
```

In [320]:
```
# Do the Grid Search
model.fit(data_vectorized)
```

Out[320]:
```
GridSearchCV(cv=None, error_score=nan,
             estimator=LatentDirichletAllocation(batch_size=128,
                                                 doc_topic_prior=None,
                                                 evaluate_every=-1,
                                                 learning_decay=0.7,
                                                 learning_method='batch',
                                                 learning_offset=10.0,
                                                 max_doc_update_iter=100,
                                                 max_iter=10,
                                                 mean_change_tol=0.001,
                                                 n_components=10, n_jobs=None,
```

```
                                            perp_tol=0.1,
                                            random_state=None,
                                            topic_word_prior=None,
                                            total_samples=1000000.0,
                                            verbose=0),
                      iid='deprecated', n_jobs=None,
                      param_grid={'learning_decay': [0.5, 0.7, 0.9],
                                  'n_components': [10, 15, 20, 25, 30]},
                      pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                      scoring=None, verbose=0)
```

In [321]:
```
# Best Model
best_lda_model = model.best_estimator_

# Model Parameters
print("Best Model's Params: ", model.best_params_)

# Log Likelihood Score
print("Best Log Likelihood Score: ", model.best_score_)

# Perplexity
print("Model Perplexity: ", best_lda_model.perplexity(data_vectorized))
```

```
Best Model's Params:  {'learning_decay': 0.5, 'n_components': 10}
Best Log Likelihood Score:  -90614.66296496465
Model Perplexity:  366.12561539068935
```

In [322]:
```
model.cv_results_['params'][0]
```

Out[322]:
```
{'learning_decay': 0.5, 'n_components': 10}
```

In [323]:
```
model.cv_results_['params'], model.cv_results_['mean_test_score']
```

Out[323]:
```
([{'learning_decay': 0.5, 'n_components': 10},
  {'learning_decay': 0.5, 'n_components': 15},
  {'learning_decay': 0.5, 'n_components': 20},
  {'learning_decay': 0.5, 'n_components': 25},
  {'learning_decay': 0.5, 'n_components': 30},
  {'learning_decay': 0.7, 'n_components': 10},
  {'learning_decay': 0.7, 'n_components': 15},
  {'learning_decay': 0.7, 'n_components': 20},
  {'learning_decay': 0.7, 'n_components': 25},
  {'learning_decay': 0.7, 'n_components': 30},
  {'learning_decay': 0.9, 'n_components': 10},
  {'learning_decay': 0.9, 'n_components': 15},
  {'learning_decay': 0.9, 'n_components': 20},
  {'learning_decay': 0.9, 'n_components': 25},
  {'learning_decay': 0.9, 'n_components': 30}],
 array([ -90614.66296496,  -93697.54661115,  -96303.55612368,
         -98741.80602119, -101229.7864391 ,  -90737.82543642,
         -93581.23602517,  -96589.71199452,  -98700.86624457,
        -100835.94516789,  -90740.04887767,  -93745.80818375,
         -96502.87469865,  -98973.91767886, -100832.71371895]))
```

In [324]:
```
model.cv_results_['mean_test_score']
```
Out[324]:
```
array([ -90614.66296496,  -93697.54661115,  -96303.55612368,
        -98741.80602119, -101229.7864391 ,  -90737.82543642,
        -93581.23602517,  -96589.71199452,  -98700.86624457,
       -100835.94516789,  -90740.04887767,  -93745.80818375,
        -96502.87469865,  -98973.91767886, -100832.71371895])
```

In [325]:
```
model.best_params_
```
Out[325]:
```
{'learning_decay': 0.5, 'n_components': 10}
```

In [326]:
```
# Create Document - Topic Matrix
lda_output = best_lda_model.transform(data_vectorized)
```

In [327]:
```
# column names
topicnames = ["Topic" + str(i) for i in range(best_lda_model.n_components)]
topicnames
```
Out[327]:
```
['Topic0',
 'Topic1',
 'Topic2',
 'Topic3',
 'Topic4',
 'Topic5',
 'Topic6',
 'Topic7',
 'Topic8',
 'Topic9']
```

In [328]:
```
# index names
docnames = ["Doc" + str(i) for i in range(len(data))]
```

In [329]:
```
# Make the pandas dataframe
df_document_topic = pd.DataFrame(np.round(lda_output, 2), columns=topicnames, index=docnames)
df_document_topic.head(5)
```
Out[329]:

	Topic0	Topic1	Topic2	Topic3	Topic4	Topic5	Topic6	Topic7	Topic8	Topic9
Doc0	0.02	0.02	0.02	0.02	0.02	0.02	0.82	0.02	0.02	0.02
Doc1	0.66	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.32
Doc2	0.05	0.05	0.05	0.05	0.05	0.55	0.05	0.05	0.05	0.05
Doc3	0.01	0.01	0.20	0.01	0.01	0.01	0.01	0.01	0.01	0.73
Doc4	0.03	0.03	0.22	0.51	0.03	0.03	0.03	0.03	0.03	0.03

In [330]:
```
# Get dominant topic for each document
dominant_topic = np.argmax(df_document_topic.values, axis=1)
df_document_topic['dominant_topic'] = dominant_topic

# Styling
def color_green(val):
    color = 'green' if val > .1 else 'black'
```

```
    return 'color: {col}'.format(col=color)

def make_bold(val):
    weight = 700 if val > .1 else 400
    return 'font-weight: {weight}'.format(weight=weight)

# Apply Style
df_document_topics = df_document_topic.head(15).style.applymap(color_green).applymap(make_bold)
df_document_topics
```

Out[330]:

	Topic0	Topic1	Topic2	Topic3	Topic4	Topic5	Topic6	Topic7	Topic8	Topic9	dominant_topic
Doc0	0.020000	0.020000	0.020000	0.020000	0.020000	0.020000	**0.820000**	0.020000	0.020000	0.020000	**6**
Doc1	**0.660000**	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	**0.320000**	0
Doc2	0.050000	0.050000	0.050000	0.050000	0.050000	**0.550000**	0.050000	0.050000	0.050000	0.050000	**5**
Doc3	0.010000	0.010000	**0.200000**	0.010000	0.010000	0.010000	0.010000	0.010000	0.010000	**0.730000**	**9**
Doc4	0.030000	0.030000	**0.220000**	**0.510000**	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	**3**
Doc5	**0.190000**	0.010000	0.010000	0.010000	**0.300000**	0.010000	0.010000	0.010000	**0.440000**	0.010000	**8**
Doc6	**0.700000**	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0
Doc7	0.010000	0.010000	0.010000	**0.220000**	0.010000	0.010000	0.010000	0.010000	**0.280000**	**0.460000**	**9**
Doc8	0.010000	0.010000	0.010000	**0.870000**	0.010000	0.010000	0.010000	0.010000	0.010000	0.010000	**3**
Doc9	0.010000	0.010000	**0.350000**	0.010000	**0.220000**	**0.330000**	0.010000	0.010000	0.010000	0.010000	**2**
Doc10	**0.550000**	0.010000	0.010000	**0.340000**	0.010000	0.010000	0.010000	0.010000	0.010000	0.010000	0
Doc11	**0.900000**	0.010000	0.010000	0.010000	0.010000	0.010000	0.010000	0.010000	0.010000	0.010000	0
Doc12	0.010000	0.010000	0.010000	0.010000	**0.740000**	0.010000	0.010000	**0.160000**	0.010000	0.010000	**4**
Doc13	0.020000	0.020000	**0.240000**	0.020000	0.020000	0.020000	0.020000	0.020000	**0.600000**	0.020000	**8**
Doc14	0.010000	0.010000	0.010000	**0.470000**	0.010000	**0.480000**	0.010000	0.010000	0.010000	0.010000	**5**

In [331]:
```
df_topic_distribution = df_document_topic['dominant_topic'].value_counts().reset_index(name="Num Documents")
df_topic_distribution.columns = ['Topic Num', 'Num Documents']
df_topic_distribution
```

Out[331]:

	Topic Num	Num Documents
0	4	1150
1	0	947
2	6	595
3	8	537
4	1	462
5	9	455
6	5	455

	Topic Num	Num Documents
7	2	454
8	3	434
9	7	338

In [332]:

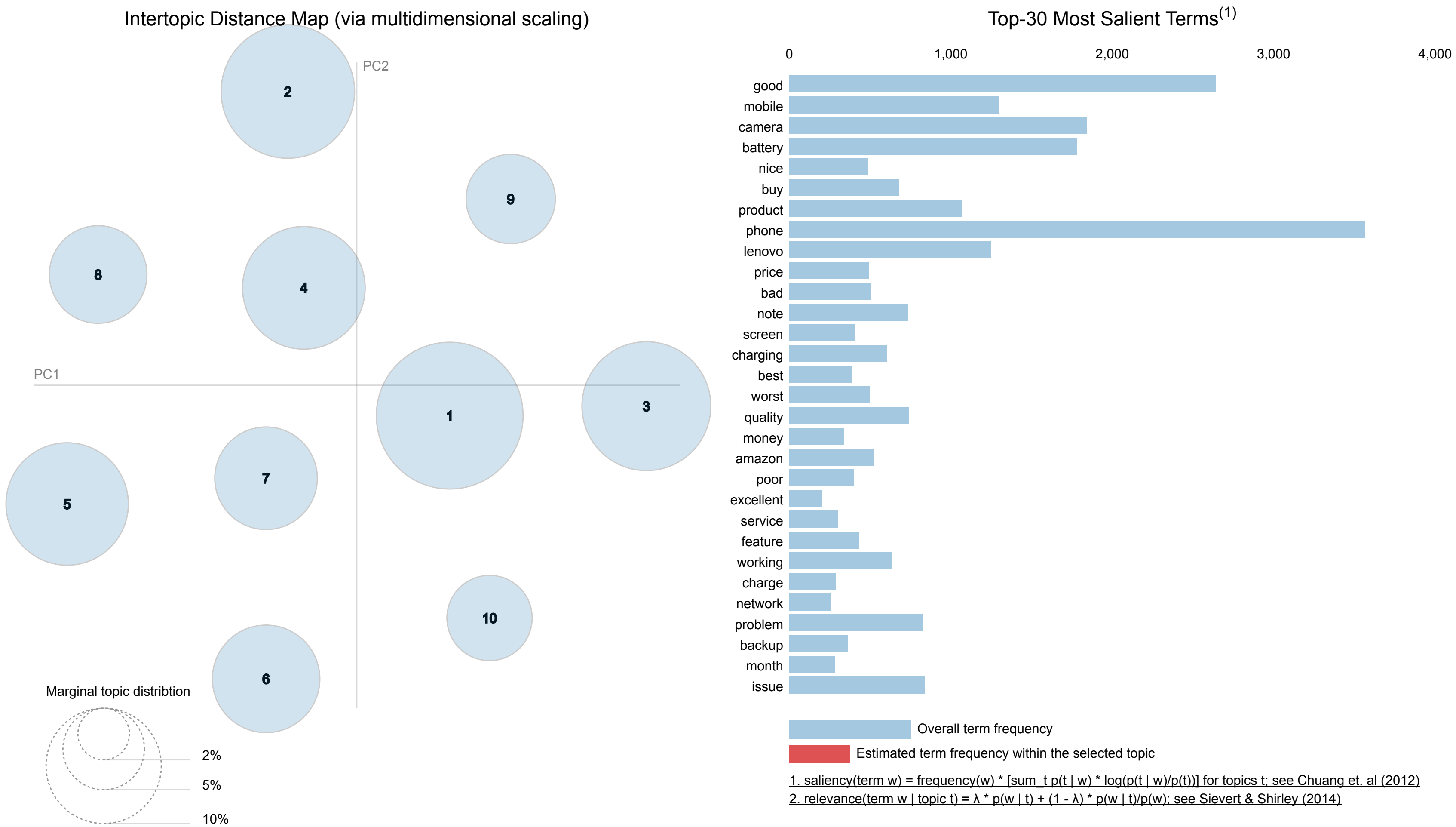
```
pyLDAvis.enable_notebook()
panel = pyLDAvis.sklearn.prepare(best_lda_model, data_vectorized, vectorizer, mds='tsne')
panel
```

Out[332]:

Selected Topic: 0 Previous Topic Next Topic Clear Topic

Slide to adjust relevance metric:(2)
$\lambda = 1$

0.0 0.2 0.4 0.6 0.8 1



In [333]:
```
# Topic-Keyword Matrix
df_topic_keywords = pd.DataFrame(best_lda_model.components_)

# Assign Column and Index
df_topic_keywords.columns = vectorizer.get_feature_names()
df_topic_keywords.index   = topicnames
```

```python
# View
df_topic_keywords.head()
```

Out[333]:

	100	1000	12000	13999	13mp	14k	15k	1st	2000	2017	2018	2nd	3gb	3rd	4000	4000mah	4gb	5mp	64gb
Topic0	61.840087	0.100013	0.100012	0.100008	0.100002	3.687455	1.234250	0.100007	0.100026	2.995907	0.100008	0.100032	1.422084	1.162489	55.462698	64.365008	7.552752	0.106815	0.100009
Topic1	0.100003	0.100021	0.100051	0.100000	0.100004	12.154314	0.100008	0.100000	0.100072	3.384224	0.100008	2.335768	0.100019	1.214770	0.100008	0.100004	0.100013	0.100004	0.100010
Topic2	0.100006	0.100009	1.880827	0.100042	5.325077	0.100025	0.100000	0.100003	1.147278	2.188324	0.100003	0.100012	3.606575	4.976819	0.100009	1.834882	8.200336	28.093073	16.647935
Topic3	0.100000	2.462933	0.100002	0.100038	0.100008	1.309040	8.965665	0.100005	7.914635	0.100006	0.100007	2.474342	0.100160	6.606933	0.100006	0.100010	0.100015	0.100005	0.100000
Topic4	0.100007	5.609898	0.100021	7.659555	0.100038	0.100041	0.100015	0.100011	3.099904	0.100011	0.100002	0.100008	2.158553	0.100009	0.100012	0.100029	0.100015	0.100006	0.100021

5 rows × 951 columns

In [334]:

```python
# Show top n keywords for each topic
def show_topics(vectorizer=vectorizer, lda_model=lda_model, n_words=20):
    keywords = np.array(vectorizer.get_feature_names())
    topic_keywords = []

    for topic_weights in lda_model.components_:
        top_keyword_locs = (-topic_weights).argsort()[:n_words]
        topic_keywords.append(keywords.take(top_keyword_locs))

    return topic_keywords
```

In [335]:

```python
topic_keywords = show_topics(vectorizer=vectorizer, lda_model=best_lda_model, n_words=15)
```

In [336]:

```python
# Topic - Keywords Dataframe
df_topic_keywords = pd.DataFrame(topic_keywords)
df_topic_keywords.columns = ['Word '+str(i) for i in range(df_topic_keywords.shape[1])]
df_topic_keywords.index = ['Topic '+str(i) for i in range(df_topic_keywords.shape[0])]
df_topic_keywords
```

Out[336]:

	Word 0	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10	Word 11	Word 12	Word 13	Word 14
Topic 0	battery	charging	phone	charge	heating	time	fast	hour	issue	turbo	day	mobile	good	problem	backup
Topic 1	mobile	nice	good	phone	excellent	best	feature	dolby	killer	product	camera	performance	working	look	budget
Topic 2	camera	money	product	poor	phone	worst	quality	return	bad	buy	amazon	waste	value	want	battery
Topic 3	phone	buy	mobile	price	worst	product	range	hanging	earphone	dont	best	purchase	box	heating	problem
Topic 4	good	phone	camera	battery	heating	quality	product	awesome	price	performance	backup	nice	problem	issue	overall
Topic 5	product	bad	working	amazon	month	problem	hai	got	mobile	speaker	properly	phone	day	happy	glass
Topic 6	camera	good	phone	dual	quality	mode	depth	battery	better	rear	sound	music	performance	average	low
Topic 7	phone	screen	lenovo	feature	great	cast	note	price	android	stock	really	display	best	core	glass
Topic 8	lenovo	note	mobile	network	problem	phone	sim	working	option	time	signal	issue	jio	like	app

	Word 0	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10	Word 11	Word 12	Word 13	Word 14
Topic 9	phone	lenovo	issue	service	amazon	buy	update	bought	customer	day	center	problem	worst	time	month

In [337]:

```
# Construct the k-means clusters
from sklearn.cluster import KMeans
clusters = KMeans(n_clusters=15, random_state=100).fit_predict(lda_output)

# Build the Singular Value Decomposition(SVD) model
svd_model = TruncatedSVD(n_components=2)  # 2 components
lda_output_svd = svd_model.fit_transform(lda_output)

# X and Y axes of the plot using SVD decomposition
x = lda_output_svd[:, 0]
y = lda_output_svd[:, 1]

# Weights for the 15 columns of lda_output, for each component
print("Component's weights: \n", np.round(svd_model.components_, 2))

# Percentage of total information in 'lda_output' explained by the two components
print("Perc of Variance Explained: \n", np.round(svd_model.explained_variance_ratio_, 2))
```

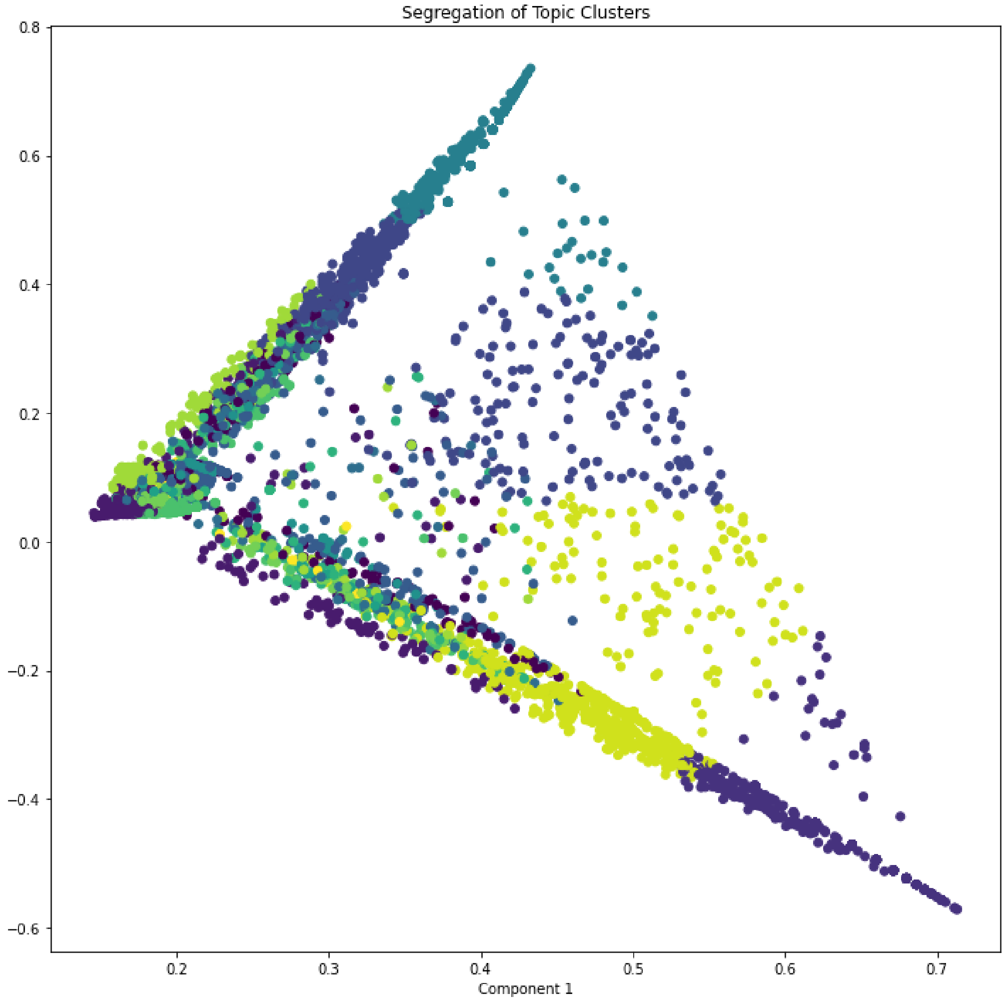
```
Component's weights:
 [[ 0.44  0.19  0.18  0.17  0.74  0.18  0.22  0.14  0.21  0.16]
 [ 0.75  0.04  0.08  0.06 -0.61  0.08  0.12  0.04  0.12  0.12]]
Perc of Variance Explained:
 [0.06 0.19]
```

In [338]:

```
# Plot
plt.figure(figsize=(12, 12))
plt.scatter(x, y, c=clusters)
plt.xlabel('Component 2')
plt.xlabel('Component 1')
plt.title("Segregation of Topic Clusters", )

#these are the clusters that we acn group together.
```

Out[338]:

```
Text(0.5, 1.0, 'Segregation of Topic Clusters')
```



In [ ]:
```
#here is another approach to apply lda model on the lemmatized data and get the coherence score for the LDA model
```

In [339]:
```
#using gensim simple preprocess funtion to clean the data
def sent_to_words(sentences):
    for sentence in sentences:
        yield(gensim.utils.simple_preprocess(str(sentence), deacc=True))  # deacc=True removes punctuations
```

```
data_words = list(sent_to_words(data))

print(data_words[:1])
```

[['good', 'need', 'update', 'improvement']]

In [340]:

```
#converting the data into a list for better computation
data = reviews.clean_lemma_pos.values.tolist()
data_words = list(sent_to_words(data))

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

['good', 'need', 'update', 'improvement']

In [341]:

```
# Build the bigram and trigram models
bigram  = gensim.models.Phrases(data_words, min_count=5, threshold=100) # higher threshold fewer phrases.
trigram = gensim.models.Phrases(bigram[data_words], threshold=100)

# Faster way to get a sentence clubbed as a trigram/bigram
bigram_mod  = gensim.models.phrases.Phraser(bigram)
trigram_mod = gensim.models.phrases.Phraser(trigram)
```

In [342]:

```
#user defined funtion for making the bigram trigram and lemmatization
def make_bigrams(texts):
    return [bigram_mod[doc] for doc in texts]

def make_trigrams(texts):
    return [trigram_mod[bigram_mod[doc]] for doc in texts]

def lemmatization(texts):
    """https://spacy.io/api/annotation"""
    texts_out = []
    for sent in texts:
        doc = nlp(" ".join(sent))
        texts_out.append([token.lemma_ for token in doc])
    return texts_out
```

In [343]:

```
# Do lemmatization
nlp = spacy.load("en_core_web_sm", disable=['parser', 'ner'])
data_lemmatized = lemmatization(data_words)

print(data_lemmatized[:1])
```

[['good', 'need', 'update', 'improvement']]

In [344]:

```
import gensim.corpora as corpora

# Create Dictionary
id2word = corpora.Dictionary(data_lemmatized)

# Create Corpus
texts = data_lemmatized

# Term Document Frequency
```

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

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

```
[(0, 1), (1, 1), (2, 1), (3, 1)]
```

In [345]:
```
# Build LDA model
lda_model = gensim.models.LdaMulticore(corpus=corpus,
                                       id2word=id2word,
                                       num_topics=10,
                                       random_state=100,
                                       chunksize=100,
                                       passes=10,
                                       per_word_topics=True)
```

In [346]:
```
from pprint import pprint

# Print the Keyword in the 10 topics
pprint(lda_model.print_topics())
doc_lda = lda_model[corpus]
```

```
[(0,
  '0.056*"product" + 0.041*"amazon" + 0.034*"bad" + 0.033*"problem" + '
  '0.030*"return" + 0.028*"lenovo" + 0.028*"service" + 0.023*"mobile" + '
  '0.016*"buy" + 0.016*"purchase"'),
 (1,
  '0.109*"camera" + 0.088*"good" + 0.045*"battery" + 0.044*"quality" + '
  '0.040*"phone" + 0.018*"backup" + 0.016*"performance" + 0.016*"dual" + '
  '0.013*"poor" + 0.012*"sound"'),
 (2,
  '0.129*"good" + 0.085*"phone" + 0.051*"mobile" + 0.051*"product" + '
  '0.045*"very" + 0.045*"price" + 0.031*"-PRON-" + 0.026*"nice" + '
  '0.023*"money" + 0.023*"awesome"'),
 (3,
  '0.069*"phone" + 0.033*"issue" + 0.032*"get" + 0.028*"buy" + 0.028*"use" + '
  '0.027*"-PRON-" + 0.021*"do" + 0.019*"time" + 0.017*"update" + 0.016*"heat"'),
 (4,
  '0.045*"work" + 0.021*"phone" + 0.020*"screen" + 0.018*"-PRON-" + '
  '0.017*"properly" + 0.016*"gb" + 0.016*"speaker" + 0.015*"device" + '
  '0.014*"app" + 0.014*"sim"'),
 (5,
  '0.025*"photo" + 0.021*"ok" + 0.021*"notification" + 0.021*"no" + '
  '0.019*"always" + 0.018*"earphone" + 0.017*"send" + 0.016*"gallery" + '
  '0.014*"possible" + 0.013*"improve"'),
 (6,
  '0.030*"delivery" + 0.029*"be" + 0.029*"touch" + 0.024*"thank" + '
  '0.021*"high" + 0.020*"amazon" + 0.018*"for" + 0.015*"at" + 0.013*"response" '
  '+ 0.013*"become"'),
 (7,
  '0.116*"battery" + 0.061*"charge" + 0.043*"drain" + 0.034*"fast" + '
  '0.031*"hour" + 0.025*"take" + 0.020*"low" + 0.019*"-PRON-" + 0.015*"full" + '
  '0.015*"poor"'),
 (8,
  '0.062*"call" + 0.033*"hai" + 0.023*"option" + 0.023*"cast" + 0.021*"screen" '
  '+ 0.020*"set" + 0.019*"not" + 0.017*"feature" + 0.017*"record" + '
```

```
 '0.015*"app"'),
 (9,
  '0.126*"lenovo" + 0.100*"note" + 0.035*"better" + 0.032*"android" + '
  '0.022*"dolby" + 0.017*"power" + 0.017*"like" + 0.016*"stock" + '
  '0.014*"atmos" + 0.013*"pls"')]
```

In [347]:
```
lda_model = gensim.models.LdaMulticore(corpus=corpus,
                                       id2word=id2word,
                                       num_topics=10,
                                       random_state=100,
                                       chunksize=100,
                                       passes=10,
                                       per_word_topics=True)
```

In [348]:
```
from gensim.models import CoherenceModel

# Compute Coherence Score
coherence_model_lda = CoherenceModel(model=lda_model, texts=data_lemmatized, dictionary=id2word, coherence='c_v')

coherence_lda = coherence_model_lda.get_coherence()
print('Coherence Score: ', coherence_lda)
```

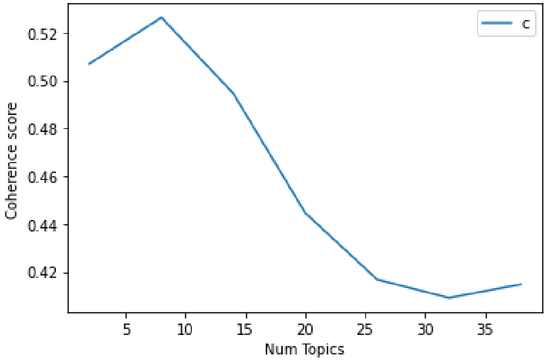
```
Coherence Score:  0.49113291932882
```

In [349]:
```
#checking for optimal number of topics
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 respective number of topics
    """
    coherence_values = []
    model_list = []
    for num_topics in range(start, limit, step):
        model = gensim.models.LdaMulticore(corpus=corpus,
                                       id2word=id2word,
                                       num_topics=num_topics,
                                       random_state=100,
                                       chunksize=100,
                                       passes=10,
                                       per_word_topics=True)
        model_list.append(model)
        coherencemodel = CoherenceModel(model=model, texts=texts, dictionary=dictionary, coherence='c_v')
        coherence_values.append(coherencemodel.get_coherence())
```

```
    return model_list, coherence_values
```

In [350]:
```
model_list, coherence_values = compute_coherence_values(dictionary=id2word, corpus=corpus, texts=data_lemmatized, start=2, limit=40, step=6)
```

In [351]:
```
limit=40; start=2; step=6;
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()
```



In [352]:
```
# Print the coherence scores
for m, cv in zip(x, coherence_values):
    print("Num Topics =", m, " has Coherence Value of", round(cv, 4))
    #we can observe that 8 is the number of topics for getting the optimal number of topics
```

```
Num Topics = 2  has Coherence Value of 0.507
Num Topics = 8  has Coherence Value of 0.5263
Num Topics = 14  has Coherence Value of 0.4945
Num Topics = 20  has Coherence Value of 0.4446
Num Topics = 26  has Coherence Value of 0.4168
Num Topics = 32  has Coherence Value of 0.4091
Num Topics = 38  has Coherence Value of 0.4147
```

In [353]:
```
# Select the model and print the topics
optimal_model = model_list[1]
model_topics = optimal_model.show_topics(formatted=False)
pprint(optimal_model.print_topics(num_words=10))
```

```
[(0,
  '0.034*"service" + 0.030*"amazon" + 0.028*"call" + 0.024*"hai" + '
  '0.017*"support" + 0.016*"product" + 0.016*"network" + 0.013*"replace" + '
  '0.013*"customer" + 0.012*"return"'),
 (1,
  '0.105*"camera" + 0.067*"good" + 0.042*"battery" + 0.040*"quality" + '
  '0.028*"phone" + 0.018*"performance" + 0.017*"dual" + 0.016*"low" + '
  '0.016*"poor" + 0.015*"backup"'),
```

```
 (2,
  '0.023*"money" + 0.022*"value" + 0.015*"jack" + 0.014*"wise" + '
  '0.013*"already" + 0.010*"anyone" + 0.010*"headphone" + 0.010*"nhi" + '
  '0.010*"ho" + 0.010*"bhi"'),
 (3,
  '0.065*"phone" + 0.051*"buy" + 0.037*"bad" + 0.031*"problem" + '
  '0.029*"product" + 0.028*"-PRON-" + 0.028*"issue" + 0.028*"mobile" + '
  '0.025*"do" + 0.024*"lenovo"'),
 (4,
  '0.032*"phone" + 0.023*"lenovo" + 0.022*"work" + 0.019*"note" + '
  '0.018*"-PRON-" + 0.018*"use" + 0.015*"get" + 0.014*"one" + 0.013*"month" + '
  '0.012*"app"'),
 (5,
  '0.138*"good" + 0.075*"phone" + 0.037*"price" + 0.030*"mobile" + '
  '0.030*"nice" + 0.027*"camera" + 0.026*"product" + 0.022*"awesome" + '
  '0.021*"feature" + 0.020*"great"'),
 (6,
  '0.036*"work" + 0.028*"come" + 0.024*"update" + 0.021*"properly" + '
  '0.020*"bluetooth" + 0.016*"device" + 0.014*"problem" + 0.013*"change" + '
  '0.012*"screen" + 0.011*"pls"'),
 (7,
  '0.092*"battery" + 0.068*"charge" + 0.032*"drain" + 0.027*"get" + '
  '0.026*"time" + 0.026*"day" + 0.024*"fast" + 0.024*"take" + 0.023*"hour" + '
  '0.019*"heat"')]
```

In [ ]:

```
-------------------------End-----------------------------
```