

LAUNCHED MOBILE USING:

THE TOPIC MODELLING APPROACH

Present By:

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AGENDA

Introduction

Problem Statement

Project progress

- Data summary
- Data analysis
- Topic Modelling
- Text classification

INTRODUCTION

E-commerce has revolutionized the way we shop. That phone you've been saving up to buy for months? It's just a search and a few clicks away. Items are delivered within a matter of days (sometimes even the next day!).

For online retailers, there are no constraints related to inventory management or space management They can sell as many different products as they want. Brick and mortar stores can keep only a limited number of products due to the finite space they have available.

But online shopping comes with its own caveats. One of the biggest challenges is verifying the authenticity of a product. Is it as good as advertised on the ecommerce site? Will the product last more than a year? Are the reviews given by other customers really true or are they false advertising? These are important questions customers need to ask before splurging their money.

- ☐ Consumers may learn a lot from online reviews of products.
- □ Online reviews may be used by vendors to get feedback from customers on the goods or services they are selling.
- ☐ Yet, because the volume and depth of these online evaluations are sometimes overwhelming.

- ❖ Let customers to rapidly go through the reviews' most important points without having to read all of them.
- ❖ Assist the merchants/retailers in obtaining consumer input in the form of topics

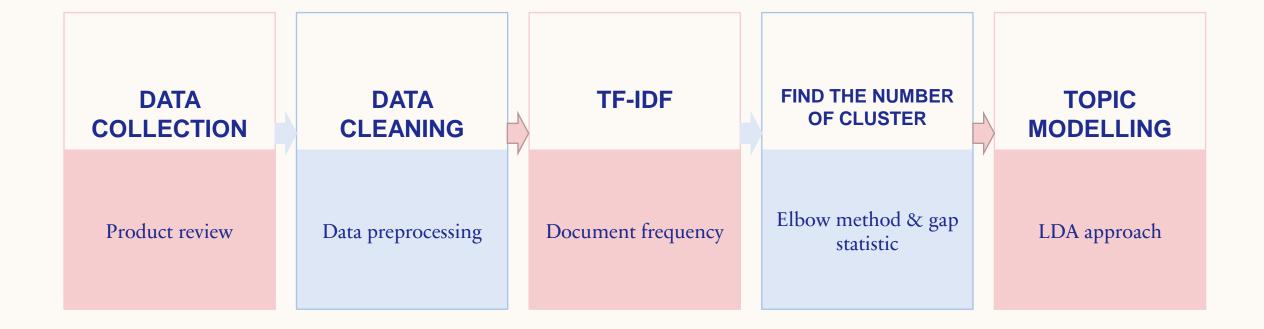


- ☐ In our case, we have thousands of online reviews for the newly launched mobile.
- ☐ Our aim here is to extract a certain number of groups of important words from the reviews.
- ☐ These groups of words are basically the topics which would help in ascertaining what the consumers are actually talking about in the reviews.

Programming language and algorithm

- Python Language
- ➤ Here we'll work on the problem statement defined above to extract useful topics from our online reviews dataset using the concept of Latent Dirichlet Allocation (LDA).

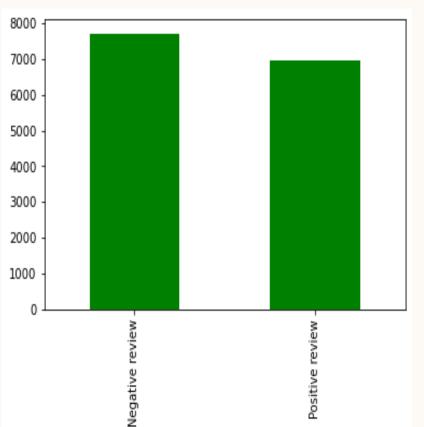
PROJECT FRAME WORK





Customer review about the mobile labeled with positive or negative sentiment.

Features	Count	Data type
Sentiment	14675	Integer
Reviews	14675	Object

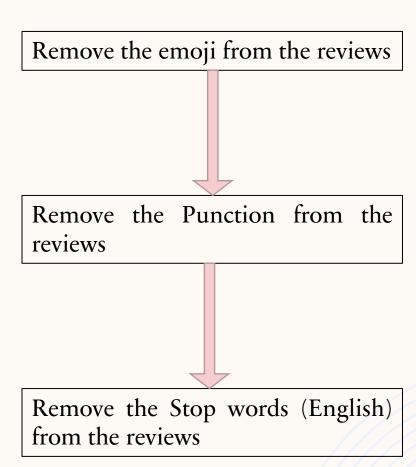


Negative	7712
Positive	6393

Python Code:

DATA CLEANING

```
from cleantext import clean
clean(data['review'], no emoji=True)
# function to remove punctuation
import string
def clean text(text):
  delete_dict = {sp_character: " for sp_character in string.punctuation}
  delete_dict[' '] = ' '
  table = str.maketrans(delete_dict)
  text1 = text.translate(table)
  textArr= text1.split()
  text2 = ''.join([w for w in textArr if ( not w.isdigit() and ( not w.isdigit() and len(w)>3))])
  return text2.lower()
data['review'] = data['review'].apply(clean_text)
#Let us pre-process the data
from nltk.corpus import stopwords
stop_words = stopwords.words('english')
# function to remove stopwords
def remove_stopwords(text):
  textArr = text.split(' ')
  rem_text = " ".join([i for i in textArr if i not in stop_words])
  return rem_text
df = data
# remove stopwords from the text
df['review']=df['review'].apply(remove_stopwords)
```



WORD CLOUD

Python Code

from wordcloud import WordCloud

```
text = " ".join(review for review in df['review'])
wordcloud = WordCloud(background_color="white").generate(text)
wordcloud.words_
```

```
# plot the WordCloud image
plt.figure(figsize = (10, 10), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)
plt.show()
```

{'phone': 1.0,

'good': 0.5716429107276819,
'mobile': 0.48799699924981244,
'lenovo': 0.3522130532633158,
'camera': 0.34433608402100524,
'battery': 0.3420855213803451,
'problem': 0.30195048762190546,
'issue': 0.2873218304576144,
'nice': 0.24118529632408103,

'feature': 0.24006001500375093,

'time': 0.231807951987997,

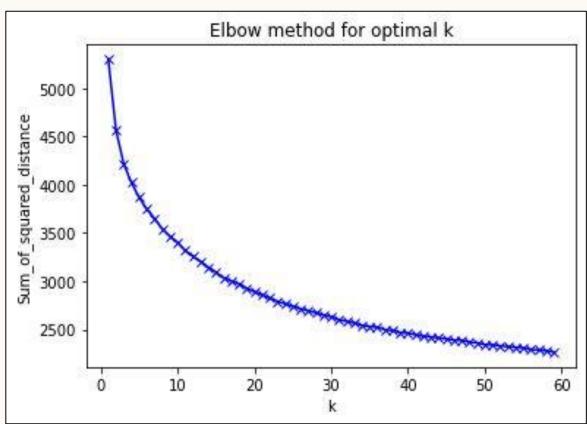
'working': 0.23143285821455364, 'good phone': 0.23143285821455364,

'even': 0.22918229557389347,

'amazon': 0.2250562640660165,.....}

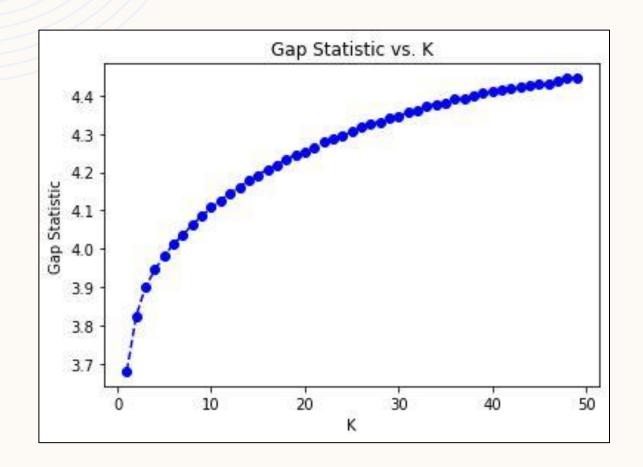


Elbow Chart And Gap Statistic



from sklearn.feature_extraction.text import TfidfVectorizer

```
tfidfconvert =
TfidfVectorizer(analyzer=clean_text,ngram_range=(1,3)).fit(df['review'])
len(tfidfconvert.vocabulary )
x transformed = tfidfconvert.transform(df['review'])
from sklearn.cluster import KMeans
Sum_of_squared_distance =[]
K = range(1,60)
for k in K:
      km = KMeans(n clusters=k)
      km = km.fit(x transformed)
      Sum of squared distance.append(km.inertia)
plt.plot(K,Sum of squared distance,'bx-')
plt.xlabel('k')
plt.ylabel('Sum_of_squared_distance')
plt.title('Elbow method for optimal k')
plt.show()
```



Based on the elbow chart and gap statistic:
Prefer to do the topic modelling using K=10

CREATING DICTIONARY

```
#lemmatization
import spacy
nlp = spacy.load('en core web md')
def lemmatization(texts,allowed_postags=['NOUN', 'ADJ']):
    output = []
    for sent in texts:
       doc = nlp(sent)
       output.append([token.lemma for token in doc if token.pos in
allowed_postags ])
    return output
text list=df['review'].tolist()
print(text_list[1])
tokenized reviews = lemmatization(text list)
print(tokenized reviews[1])
#Create vocabulary dictionary and document term matrix
dictionary = corpora.Dictionary(tokenized reviews)
doc term matrix = [dictionary.doc2bow(rev) for rev in tokenized reviews]
```

Length of dictionary =9371

Dictionary(9371 unique tokens: ['good', 'improvement', 'need', 'backup', 'bad']...)

TOPIC MODELLING - LDA

import gensim from gensim import corpora

Creating the object for LDA model using gensim library

LDA = gensim.models.ldamodel.LdaModel

Build LDA model

TOPIC MODELLING - LDA

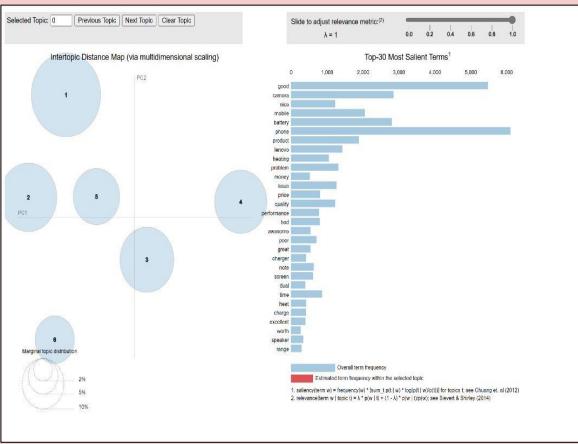
Result:

Topic 0	mobile, product, money, bad, nice, delivery, value, waste, amazon, worth
Topic 1	problem, heating, phone, issue, battery, heat, excellent, awesome, drain, network
Topic 2	poor, phone, issue, network, lenovo, video, range, time, quality, battery
Topic 3	phone, battery, time, charge, charger, hour, turbo, full, day, usage
Topic 4	good, battery, product, backup, performance, life, smartphone, thank, awesome, quality
Topic 5	camera, quality, sound, speaker, mode, average, music, dolby, depth, happy
Topic 6	update, software, working, worth, super, processor, oreo, experience, love, volte
Topic 7	camera, good, phone, price, quality, great, performance, dual, feature, overall
Topic 8	phone, nice, service, lenovo, screen, bad, month, glass, customer, day
Topic 9	lenovo, note, device, call, screen, many, option, problem, feature, available

TOPIC MODELLING - LDA

Result:





TOPIC MODELLING - LDA

Result:

Topic: 0 keywords are

nice, mobile, product, money, phone, worth, delivery, value, glass, waste

Topic: 1 keywords are

battery, phone, heating, problem, issue, bad, product, mobile, awesome, time

Topic: 2 keywords are

lenovo, phone, poor, note, issue, time, call, mobile, update, battery

Topic: 3 keywords are

phone, price, great, charger, screen, range, service, month, feature, turbo

Topic: 4 keywords are

good, phone, camera, battery, quality, performance, product, price, backup, life

Topic: 5 keywords are

camera, quality, dual, speaker, mode, front, sound, average, amazing, depth

Perplexity: -7.9740844536125355

Coherence Score: 0.55015485303433

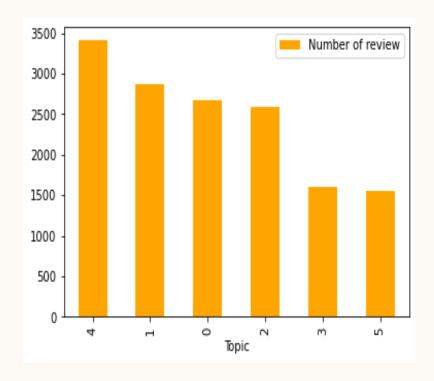
TOPIC MODELLING - LDA

Result:

Topic Number	Key word	Topic Label
Topic 0	nice, mobile, product, money, phone, worth, delivery, value, glass, waste	Value for Money
Topic 1	battery, phone, heating, problem, issue, bad, product, mobile, awesome, time	Battery
Topic 2	lenovo, phone, poor, note, issue, time, call, mobile, update, battery	Software
Topic 3	phone, price, great, charger, screen, range, service, month, feature, turbo	Design
Topic 4	good, phone, camera, battery, quality, performance, product, price, backup, life	Quality
Topic 5	camera, quality, dual, speaker, mode, front, sound, average, amazing, depth	Performance

DOMINANT TOPIC

Topic Number	Topic Label	Number of review
0	Value for Money	2669
1	Battery	2864
2	Software	2582
3	Design	1596
4	Quality	3406
5	Performance	1558



Topic 0:	
Positive review	1664
Negative review	1005

Topic 1:	
Positive review	2002
Negative review	842

Topic 2:	
Positive review	1938
Negative review	644

Topic 3:	
Positive review	801
Negative review	795

Topic 4:	
Positive review	2431
Negative review	975

Topic 5:	
Positive review	977
Negative review	581

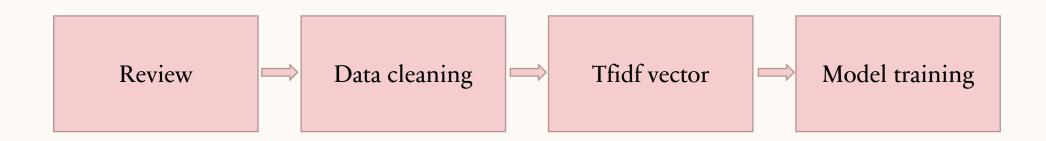
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TEXT CLASSIFICATION



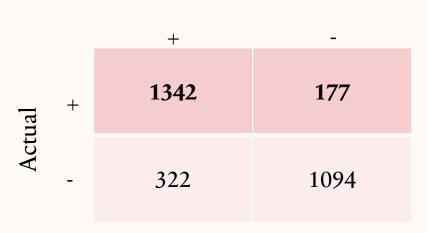
Text classification 21

FRAME WORK



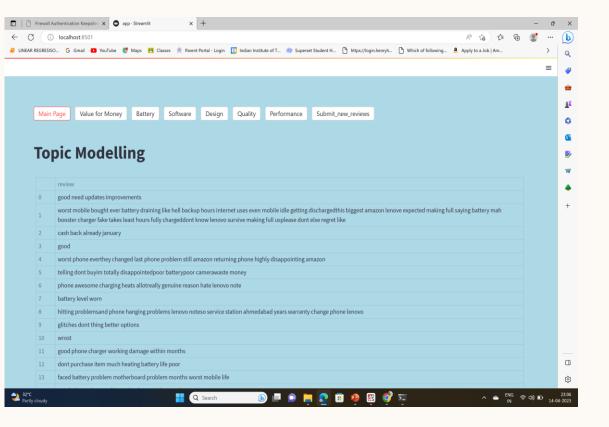
RESULT – RANDOM FOREST CLASSIFIER

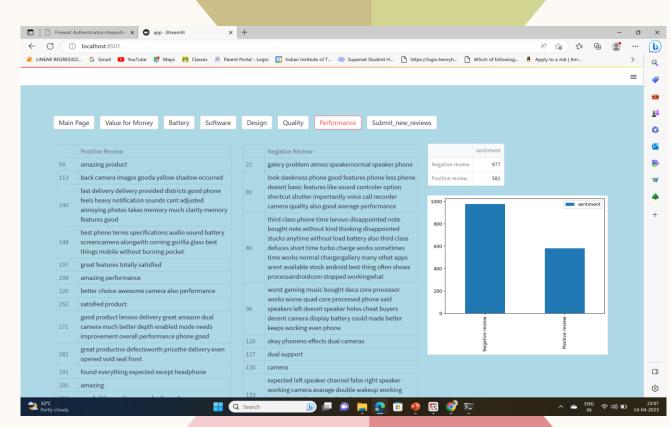
Predicted



precision recall f1-score support				
0	0.81	0.88	0.84	1519
1	0.86	0.77	0.81	1416
accuracy			0.83	2935
macro avg	0.83	0.83	0.83	2935
weighted avg	0.83	0.83	0.83	2935

WEB PAGE





THANK YOU