

Capstone Project Presentation on Topic Modeling On News Articles

Presented by: 1. Priyabrata Mohanty

2. Rahul Sharma

Pipeline

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Why Topic Modeling?

- 80% of data of the world is **unstructured**. Textual data is biggest example of it. Natural Language Processing is the very best step on structuring it.
- News rooms and editorials spend most of their times trying to figure out the preference of the audience and categories them vividly.
- Machine learning for topic modeling comes very handy to save time and work efficiently.



Problem statement

To identify major themes or topics across a collection of BBC news articles. You can use clustering algorithms such as Latent Dirichlet Allocation (LDA).

Data summary



The dataset contains a set of news articles for each major segment consisting of **business**, **entertainment**, **politics**, **sports** and **technology**.

- Number of Business articles: 510
- Number of Entertainment articles: 386
- Number of Politics articles: 417
- Number of Sports articles: 511
- Number of Technology articles: 401

Data cleaning & Processing



- Merged different articles together to form whole dataset.
- Removal of **stopwords**, **punctuations** & **unwanted** characters (e.g. "\n") from data.

Converted the texts into lower case & tokenization.

 Added few new columns number of sentences, complex words, average length of sentence to the dataframe.



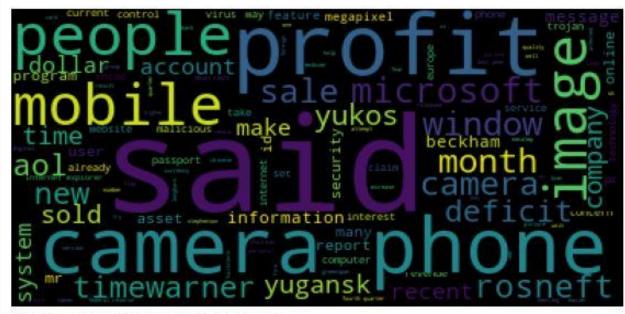
Exploratory Data analysis



Important Words In The Article

According to above graphs:

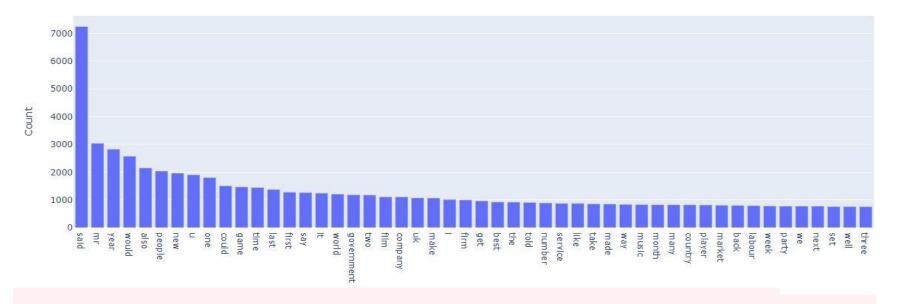
Said, Profit, Camera,
 Phone, Window,
 People, Image,, Sale
 are the most important
 words in this article.



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Word VS Frequency Graph





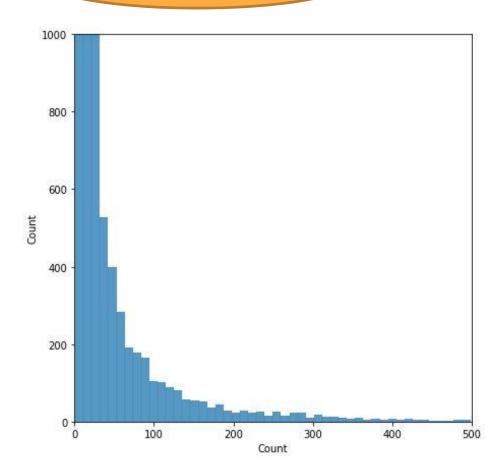
According to above graphs:

- Said is the most frequent word with frequency of 7253 (which is obvious verb)
- Other most frequent words are Camera, Phone, Profit, Mobile, Image.



Most of the articles word counts is in the range of 0-100.

Word Counts of articles Distribution





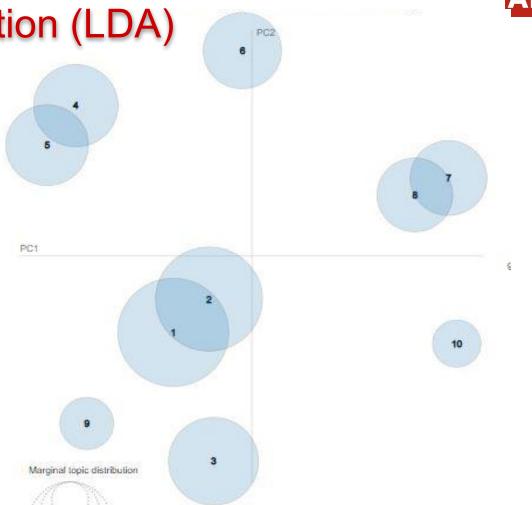
Machine Learning Model Building



Latent Dirichlet Allocation (LDA)

According to the above figure:

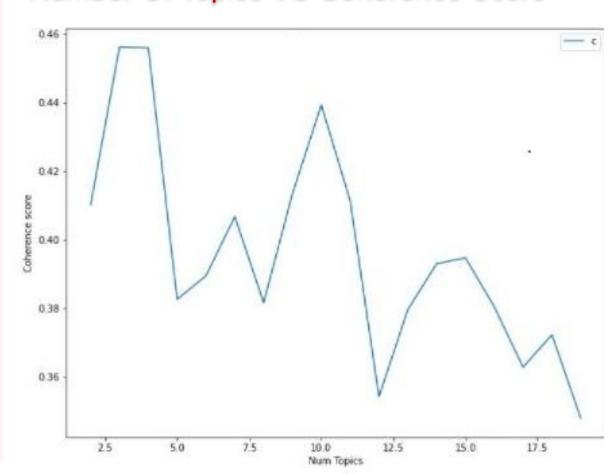
- When the number of topics is 10, most of the topics are overlapping with each other.
- The coherence score for Number of topics=10 is
 0.4126.



For the number of topics
 3 & 4, the coherence
 score is almost same
 (0.456) & it's the highest
 coherence score.

Number Of Topics VS Coherence Score

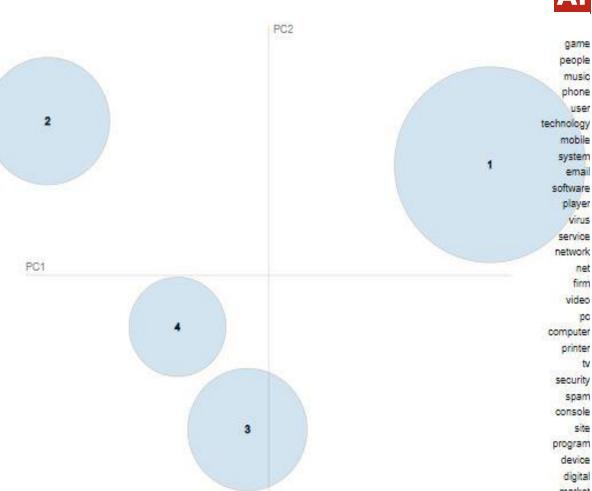






According to this graph:

 The topics are not overlapping with each other when the number of topics is 4.





These are the Top 10
words for the Topic-0 &
Topic-1.

Wordcloud of Top N words in each topic

```
election labour party year gamer party tax people leader government public retwork
```



 These are the Top 10 words for the Topic-2 & Topic-3.

Wordcloud of Top N words in each topic

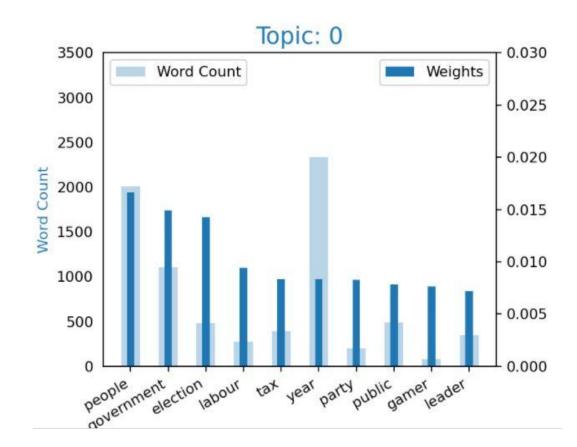
```
battery new company

club
audio malicious
lastrecord
year window
vehicle company

sale growth
firm
economy market
rate
year price
```

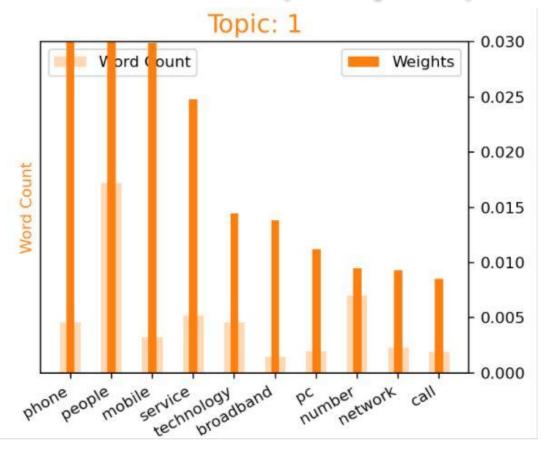
- These are the **Top 10** words for the **Topic-0**.
- These words are related to topic **government** & **Year** is the most frequent word.





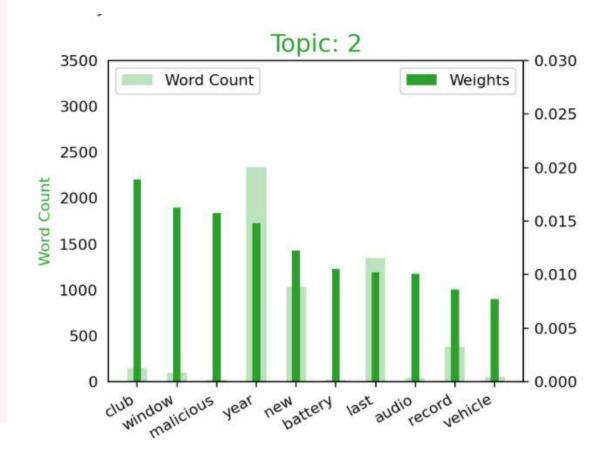
- These are the **Top 10** words for the **Topic-1**.
- These words are related to topic **Technology** & Phone, People, Mobile are the most frequent word.





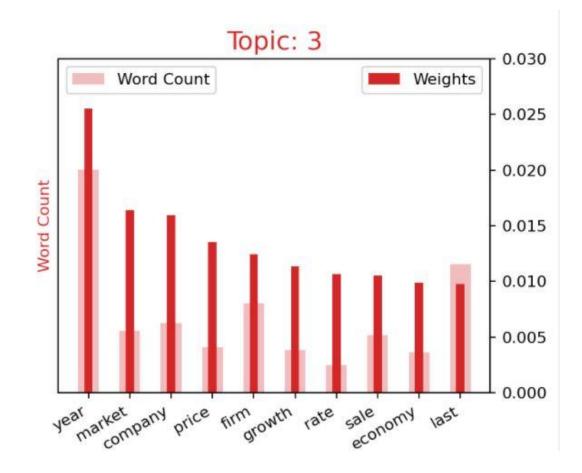
- These are the **Top 10** words for the **Topic-2**.
- These words are related to topic **Entertainment** & Club, Window are the most frequent word.





- These are the **Top 10** words for the **Topic-3**.
- These words are related to topic **Business** & Year, Market, Company, **Price** are the most frequent word.







Conclusion

- The data was highly unstructured. So removed unwanted characters, punctuations, stopwords.
- Articles were distinctly analysed by aggregating their sentence counts and words.
- Coherence score were showing varying results for each additional run time. The best it did with 5 topics was **0.5**. But in the last run we had to keep it at 4 clusters because 5 was making overlapping between topics.
- The results were different for every runtime.



Conclusion

- The **People**, **Music**, **Technology**, **Player**, **Game** were the most important word for the **Topic-0**.
- The **Software**, **Phone**, **User**, **System**, **Computer** were the most important word for the **Topic-1**.
- The Game, User, People, Firm, Mobile were the most important word for the Topic-2.
- The New, Year, Time, Price, Sale were the most important word for the Topic-3.



Appendix - Data sources

Here is a snapshot of data dictionary:

We used the past **BBC News** articles based on 5 major Segments.

- 1. Business
- 2. Entertainment
- 3. Politics
- 4. Sports
- 5. Technology



Appendix - Data Methodology

We conducted a thorough analysis & ML model building for Topic Modeling. The process includes:

- Data cleaning Removal of stopwords, unwanted characters.
- EDA Understanding data using different visualization methods.
- ML Modelling Built & tested the machine learning models to do the topic modeling.



Thank You!