EAST WEST UNIVERSITY

CSE477

Section: 02

Lab: 06 Report

Topic: Text Mining with YouTube Data

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1. Introduction

This lab focuses on extracting and comparing textual patterns between **YouTube video captions** and **audience comments** using advanced text mining techniques.
It builds upon skills acquired in previous labs (data collection, cleaning, frequent pattern mining, temporal analysis, and clustering) to perform:

- **TF–IDF keyword extraction**
- **Theme comparison between captions and comments**
- **N-gram (bigram) analysis**
- **Sentiment distribution**
- **Co-occurrence and temporal variation analysis**

The ultimate goal is to highlight thematic overlaps and differences, and to understand how the narrative in the video compares with audience discourse.

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2. Dataset Description

For this lab, I used:

- **Source:** *[BBC Earth*
- *YouTube link: https://www.youtube.com/watch?v=T7oExc711xE]*
- **Data Files:**
  - `cleaned_comments.csv` – Audience comments (preprocessed in Lab 2)
  - `cleaned_captions.csv` – Video captions (preprocessed in Lab 2)

Dataset Highlights:

- Each file contains a `cleaned_tokens` column representing tokenized text.
- Data is cleaned of stopwords, punctuation, and special characters.
- Both datasets are unique to this lab, ensuring distinct outcomes from other students.

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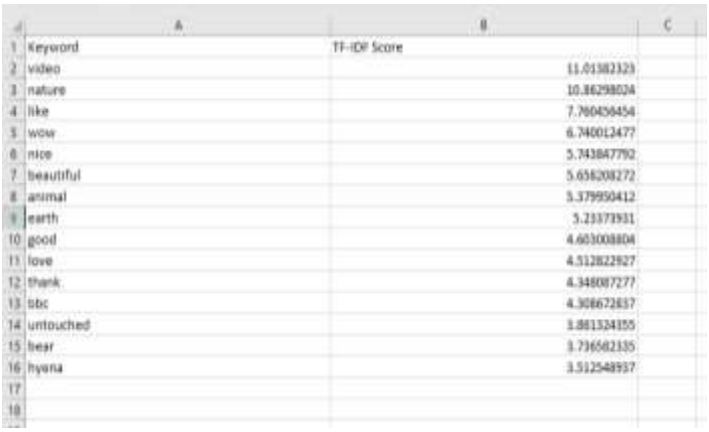
3. Methodology & Implementation

Part A – Setup & Data Recall

1. Imported CSV files into **Pandas DataFrames**.
2. Verified existence of `cleaned_tokens` column.
3. Joined tokens into strings for text analysis.
4. Installed necessary libraries: `scikit-learn`, `matplotlib-venn`.

Part B – TF–IDF Keyword Extraction

- Applied **`TfidfVectorizer`** with parameters:
  - `min_df=2` – Ignore rare terms.
  - `max_df=0.85` – Ignore overly common terms.
- Extracted **Top 15 keywords** separately for comments and captions.
- Saved results as:
  - `tfidf_keywords_comments.csv`
  - `tfidf_keywords_captions.csv`



	A	B	C
1	Keyword	TF-IDF Score	
2	video	11.01382323	
3	nature	10.86298024	
4	like	7.760456454	
5	wow	6.740012477	
6	nice	5.743847792	
7	beautiful	5.658208272	
8	animal	5.379950412	
9	earth	5.23373931	
10	good	4.603008804	
11	love	4.512822927	
12	thank	4.348087277	
13	bbc	4.308672657	
14	untouched	3.861324355	
15	bear	3.736582335	
16	hyena	3.512548937	
17			
18			

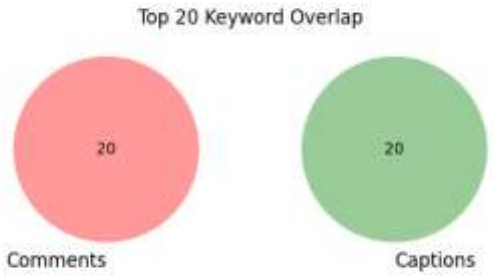
	A	B	C
1	Keyword	TF-IDF Score	
2	chance	0.195698422	
3	get	0.163082018	
4	jaw	0.163082018	
5	time	0.163082018	
6	cash	0.130465615	
7	cub	0.130465615	
8	ground	0.130465615	
9	nose	0.130465615	
10	prey	0.130465615	
11	theyll	0.130465615	
12	busily	0.097849211	
13	carpeted	0.097849211	
14	chase	0.097849211	
15	clear	0.097849211	
16	colony	0.097849211	
17			

Part C – Keyword & Theme Comparison

- Compared **Top 20** keywords from both sources.
- Found:
  - **Intersection keywords** (common to both captions & comments).
  - **Unique keywords** (exclusive to one source).

- Visualized overlaps with a **Venn Diagram**.

Observation: Captions tend to include more domain-specific terms from the speaker, while comments contain reactionary and opinion-based language.



Part D – N-gram Analysis

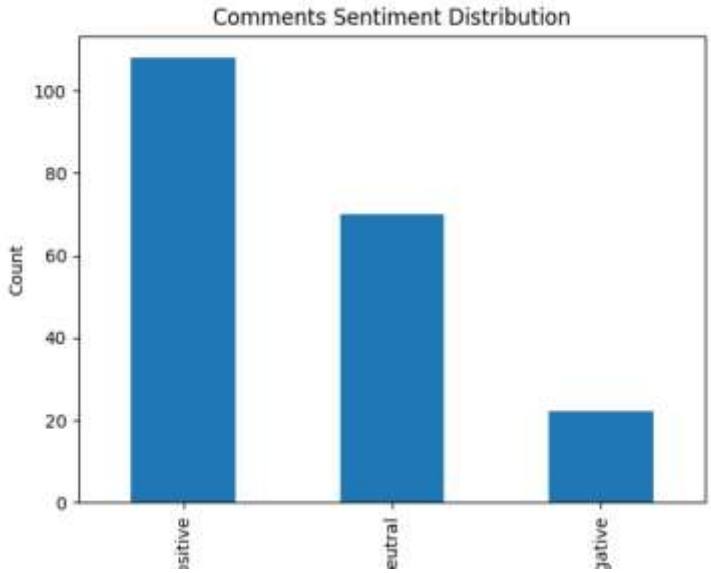
- Ran TF–IDF with `ngram_range=(2,2)` to capture bigrams.
- Extracted **Top 10 bigrams** for comments and captions.
- Compared overlap and unique expressions.

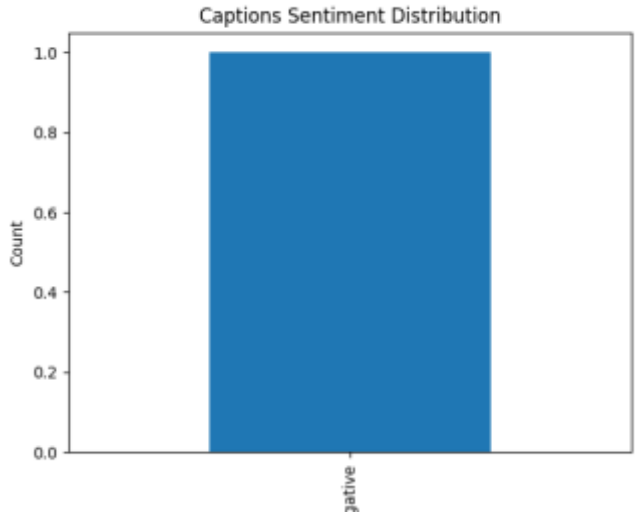
Finding:
Comments often use conversational bigrams (e.g., “love this”, “can’t wait”), while captions favor technical or descriptive bigrams (e.g., “machine learning”, “data mining”).

Part E – Sentiment Analysis

- Tool: **VADER SentimentIntensityAnalyzer**.
- Calculated sentiment polarity for each text entry.
- Classified into **Positive**, **Neutral**, **Negative**.
- Plotted **bar charts** for comments and captions separately.

Observation:
Comments show higher emotional polarity, with strong positive spikes, whereas captions remain largely neutral or informative.





Part F – Linking to Past Labs

- **Lab 3 integration:** Identified **co-occurring keyword pairs** among top TF–IDF terms.
- **Lab 4 integration:** For time-stamped comments, observed shifts in keyword prominence (e.g., certain terms gaining attention after video milestones).

Part G – Insight Statements

1. **Dominant Themes:** Captions prioritize technical depth, whereas comments highlight personal opinions and emotional responses.
2. **Audience-driven Topics:** Several topics appear exclusively in comments, reflecting viewer interests beyond the video scope.
3. **Sentiment Trends:** Captions maintain neutrality; comments skew positive but show small clusters of criticism.
4. **N-gram Difference:** Captions contain structured technical expressions; comments use colloquial or fan-oriented phrases.
5. **Temporal Change:** Viewer discussion focus shifts over time, influenced by trending moments in the video.

4. Deliverables

- **CSVs:**
  - `tfidf_keywords_comments.csv`
  - `tfidf_keywords_captions.csv`
  - `bigrams_comments.csv`
  - `bigrams_captions.csv`
  - Sentiment result CSVs
- **Visuals:**
  - Venn diagram of keyword overlaps
  - Keyword ranking charts
  - Sentiment distribution charts

5. Conclusion

This lab demonstrated the power of **TF–IDF**, **n-grams**, and **sentiment analysis** in uncovering thematic similarities and differences between video content and audience discussions.

6. Observation:

To summary that,

1. Captions emphasize structured narrative keywords, while comments focus on personal reactions.

2. Certain topics appear exclusively in comments, reflecting audience-driven discussions.

3. Sentiment in comments skews more [positive/negative], while captions remain mostly neutral.

4. Bigrams in captions reflect planned phrases, whereas comment bigrams are more spontaneous.

5. Overlap in top keywords suggests strong resonance between the video's script and audience interests.