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PROJECT ON

Building a Semantic Based Search Engine Relevance for Video Subtitles

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Objective

- Developing an advanced search engine algorithm
- Leveraging Natural language processing and machine learning
- Enhancing relevance and accuracy of search results for video subtitles

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Summary

- In the fast-evolving landscape of digital content, effective search engines play a pivotal role in connecting users with relevant information. For Google, providing a seamless and accurate search experience is paramount. This project focuses on improving the search relevance for video subtitles, enhancing the accessibility of video content.

Core logic of this project

- Preprocessing of Data
- Cosine similarity calculation for relevance assessment
- Importance of document chunking for large documents

Step by Step Process

➢ Ingesting Documents

- Reading and decoding the database file
- Understand the encoding language
- Cleaning and preprocessing steps
- Experimenting with BOW/TFIDF and SentenceTransformers
- Implementing document chunking
- Storing embeddings in ChromaDB

- ➢ Retrieving Documents
- Take User query
- Preprocessing user queries
- Creating query embeddings
- Calculating cosine similarity scores
- Retrieving relevant candidate documents

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- Reading and Decoding the Database File:
  - The subtitle data is provided in a Database file format. Ingesting begins by reading this file and understanding its structure
  - Subtitles Data encoded with “Latin-1” and in a compressed format , so decoding is necessary to access the actual subtitle text
- Cleaning and Preprocessing Steps:
  - We **took a random sample 30% of the data for cleaning**
  - Before analysis The subtitles text require cleaning to remove irrerelevant elements include removing Timestamps,Special characters,stopwords ,apply lemmetaization

```python
def clean_subtitles(text):
    pattern = r'\d+\s*[\r\n]+\s*\d+:\d+:\d+,\d+\s*-->\s*\d+:\d+:\d+,\d+\s*[\r\n]+'
    cleaned_text = re.sub(pattern, " ",text)
    return cleaned_text

from tqdm import tqdm, tqdm_notebook
tqdm.pandas()
new_df['clean_subtitles'] = new_df['file_content'].progress_apply(lambda x:clean_subtitles(x))
```

Python

```
100%|██████████████████████████████████████████████████| 24749/24749 [01:47<00:00, 230.24it/s]
```

```python
from tqdm import tqdm, tqdm_notebook

def preprocess(raw_text, flag):
    # Removing special characters and digits
    sentence = re.sub("[^a-zA-Z]", " ", raw_text)

    # Change sentence to lowercase
    sentence = sentence.lower()

    # Tokenize into words
    tokens = sentence.split()

    # Lemmatization
    clean_tokens = [lemmatizer.lemmatize(word) for word in tokens]

    return pd.Series([" ".join(clean_tokens)])

tqdm.pandas()
new_df['clean_data'] = new_df['clean_subtitles'].progress_apply(lambda x:preprocess(x,'lemma'))
```

Python

Document Chunking

- Document chunking involves dividing large subtitle documents into smaller,more manageable chunks
- This is important because embedding entire documents as single vectors may lead to information loss,especially with long documents
- Overlapping windows with a specified number of tokens can be used to ensure continuity and context preservation across chunks

```python
from tqdm import tqdm, tqdm_notebook
tqdm.pandas()
def chunk_text(text, chunk_size=500, overlap_size=50):
    chunks = []
    words = text.split()
    start_idx = 0
    while start_idx < len(words):
        end_idx = min(start_idx + chunk_size, len(words))
        chunk = ' '.join(words[start_idx:end_idx])
        chunks.append(chunk)
        start_idx += chunk_size - overlap_size
    return chunks

# Apply chunking function to the 'clean_subtitles' column
chunk_size = 500  # Number of tokens per chunk
overlap_size = 50  # Number of tokens to overlap between chunks

df['chunks'] = df['clean_data'].progress_apply(lambda x: chunk_text(x, chunk_size, overlap_size))
```

[6]

Python

```
100%|██████████| 24749/24749 [00:05<00:00, 4780.00it/s]
```

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➢ Experimenting with BOW/TFIDF and SentenceTransformers

- After cleaning,the subtitle documents are prepared for analysis by converting them into numerical representations
- We used BERT-based “Sentence Transformers” vectorization technique.
- This Technique generate embeddings that encode semantic information,capturing the meaning and context of the text. They are suitable for building semantic search engines.

```python
from sentence_transformers import SentenceTransformer, util
model = SentenceTransformer('all-MiniLM-L6-v2')
```

Python

```
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update jupyter a
  from .autonotebook import tqdm as notebook_tqdm
```

```python
from tqdm import tqdm
tqdm.pandas()

def encode_and_convert_to_list(text):
    encoded_vector = model.encode(text).tolist()
    return encoded_vector

# Apply the function to each element of 'chunks'
df_exploded['doc_vector_pretrained_bert'] = df_exploded['chunks'].progress_apply(encode_and_convert_to_list)
```

Python

```
100%|██████████| 311548/311548 [1:23:35<00:00, 62.12it/s]
```

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Storing Embeddings in a chromadb vectors database

- Once the subtitles documents are processed and converted into embeddings,they need to be stored for efficient retrieval during the search process.
- Chromadb is efficient in handling large-scale vector data and enabling fast retrieval
- Chroma gives you the tools to:
- store embeddings and their metadata
- embed documents and queries
- search embeddings on the basis of cosine similarity scores

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```
from tqdm import tqdm

batch_size = 5000
total_batches = (len(documents) + batch_size - 1) // batch_size

for i in tqdm(range(total_batches), desc="Adding batches"):
    start_idx = i * batch_size
    end_idx = min((i + 1) * batch_size, len(documents))

    batch_doc = documents[start_idx:end_idx]
    batch_metadatas = metadatas[start_idx:end_idx]
    batch_ids = ids[start_idx:end_idx]
    embed = df_bert_pretrained[start_idx:end_idx]

    collection.add(
        embeddings=embed,
        documents=batch_doc,
        metadatas=batch_metadatas,
        ids=batch_ids
    )
```

```
Adding batches: 100%|██████████| 63/63 [08:16<00:00,  7.87s/it]
```

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Retrieving Documents

- ➢ Taking User query
- The process begins with the user inputting a query into the search engine . This query represents the information the user is seeking from the subtitle database.
- ➢ Preprocessing User queries:
- Before the query can be used for retrieval, it undergoes preprocessing steps to standardize and clean the text
- ➢ Creating Query Embeddings:
- After preprocessing, the user query is converted into a numerical representation,known as an embedding

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- Bert-based Sentence Transformers is used to generate embeddings that encode the semantic information of the query.
- This embedding captures the semantic meaning and context of the query,allowing it to be compared to the embeddings of subtitle documents
- ➢ Calculating cosine similarity scores:
- Now Connection is created to the path of that chromadb database
- Once the query has been embedded, the next step is to compare it to the embeddings of the subtitle documents in the database.
- Cosine similarity scores is calculated by chromadb between the query embedding and the embeddings of all subtitle documents.

```python
# Query Point
query_point = "what happened last night when we were fully drunk"

# Encode query point
doc_vector = clean_and_encode_query(query_point, model)

# Query the collection
result = collection.query(
    query_embeddings=doc_vector,
    n_results=10,
)

# Print movie names
print_movie_names(result)
```

[7] Python

```
Movie Names:
csi.miami.s03.e03.under.the.influence.(2004).eng.1cd
friends.s07.e16.the.one.with.the.truth.about.london.(2001).eng.1cd
working.class.heroes.(2022).eng.1cd
murdoch.mysteries.s09.e06.the.local.option.(2015).eng.1cd
revenge.for.daddy.(2020).eng.1cd
workin.moms.s07.e07.its.all.gone.(2023).eng.1cd
mister8.s01.e05.komediaperjantai.(2021).eng.1cd
brutal.bridesmaids.(2021).eng.1cd
50.first.dates.(2004).eng.1cd
according.to.jim.s08.e07.the.ego.boost.(2009).eng.1cd
```

Retrieving Relevant candidate Documents

- Finally ,based on the calculated cosine similarity scores , the search engine retrieves the most relevant Top N candidate documents from the stored data in Chromadb database

- **Web application.**

  We used Flask to build a web application that searches for a specific part of a subtitle and returns the top ten results. Linking each filename to the OpenSubtitles page allows for easy download of the subtitles.

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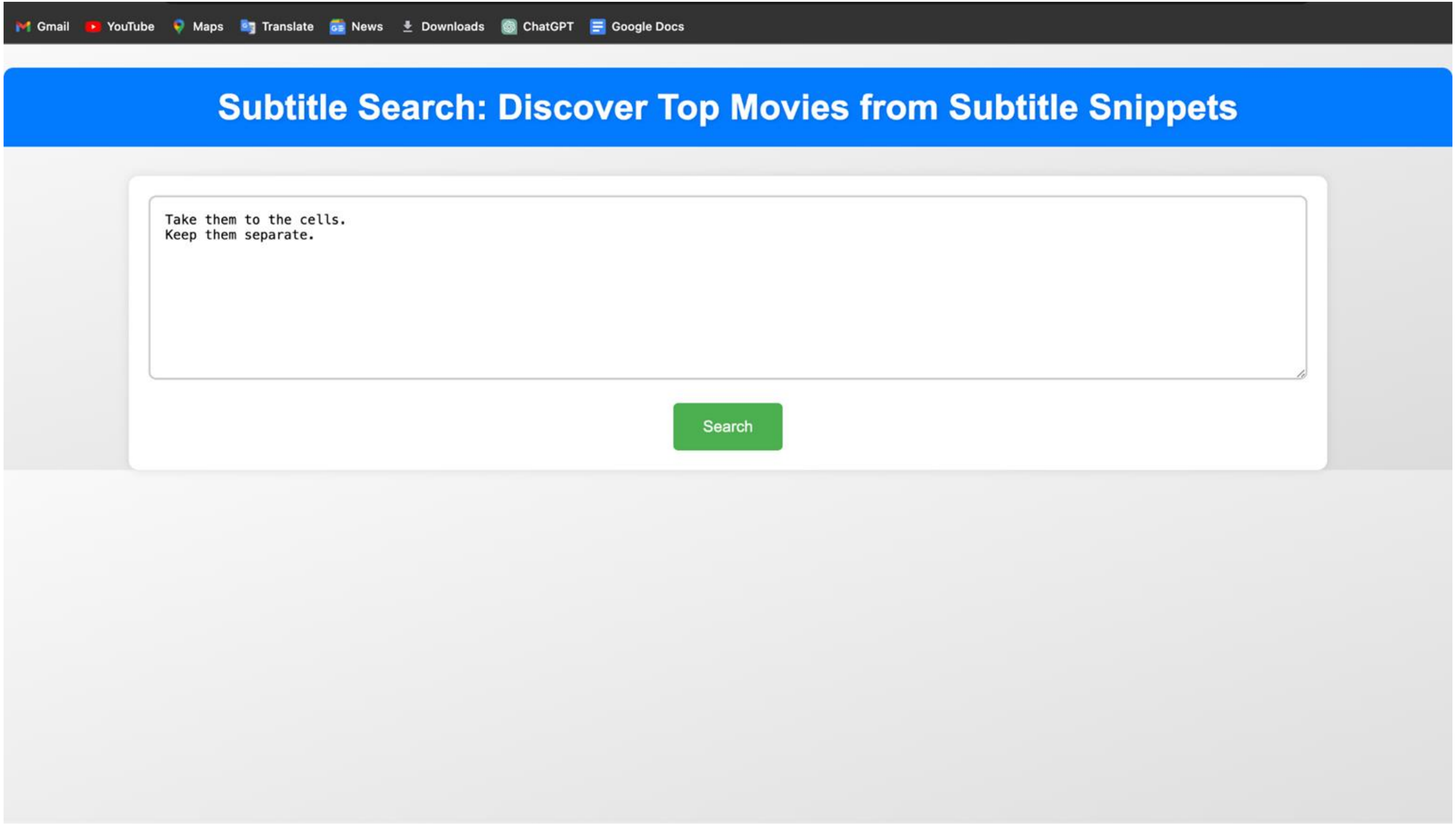
Gmail
YouTube
Maps
Translate
News
Downloads
ChatGPT
Google Docs
Subtitle Search: Discover Top Movies from Subtitle Snippets
Take them to the cells.
Keep them separate.
Search

Gmail YouTube Maps Translate News Downloads ChatGPT Google Docs

Top Movies Related to Subtitle Snippet:

magino.story.raising.silkworms.(1977).eng.1cd

View Subtitles

csi.crime.scene.investigation.s04.e16.getting.off.(2004).eng.1cd

View Subtitles

csi.crime.scene.investigation.s04.e16.getting.off.(2004).eng.1cd

View Subtitles

magino.story.raising.silkworms.(1977).eng.1cd

View Subtitles

the.makery.s01.e08.wakey.wakey.(2023).eng.1cd

View Subtitles

the.repair.shop.s08.e01.charles.ii.portrait.(2021).eng.1cd

THANK YOU