# **Documentation Practical Exercise 3**

## Student:

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# Degree:

- MSc Computer Science

#### Module:

- Multimedia Retrieval

# GitHub Repo for this Project:

https://github.com/manuu1999/Ex3 NLTK-Transformers-TextTasks MultiMediaRetrieval

### A. Exercise Description

In this task, we will utilize NLTK and transformers to perform text analytics. You have the option to create custom Python classes and methods, or just create command blocks in a Jupyter notebook. The course material contains many code snippets that you can use as a starting point:

a)[easy] Use NLTK to determine the language of an input text. Download texts in Italian, German, and English (or any other language) with the same encoding for simplicity. Employ NLTK's stop word lists to identify the text's language based on stop word occurrences (pick the language with most stop words).

Solution Code:

```
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
nltk.download('stopwords')
nltk.download('punkt')
def detect_language(text):
    languages = ['english', 'german', 'italian']
    stopwords_count = {}
    tokens = word_tokenize(text.lower())
    for language in languages:
        lang_stopwords = set(stopwords.words(language))
        stopwords_count[language] = sum(1 for word in tokens if word in lang_stopwords)
    detected_language = max(stopwords_count, key=stopwords_count.get)
    return detected_language
text_italian = "Ciao, come stai? Questo è un esempio di testo in italiano."
print("Detected Language (Italian):", detect_language(text_italian))
text_english = "Hello, how are you? This is an example of text in English."
print("Detected Language (English):", detect_language(text_english))
text_german = "Hallo, wie geht es dir? Dies ist ein Beispieltext in Deutsch."
print("Detected Language (German):", detect_language(text_german))
```

# **Explanation of the code:**

detect\_language(text):

- **Purpose**: Detects the language of the given text by counting overlaps between the text and NLTK's predefined stopwords for English, German, and Italian.
- Steps:
  - 1. Tokenizes the text into lowercase words using nltk.word tokenize.
  - 2. Iterates through the stopword lists for the three languages.
  - 3. Counts how many tokens (words) from the input appear in each language's stopword list.
  - 4. Returns the language with the highest count.

# Output to test it:

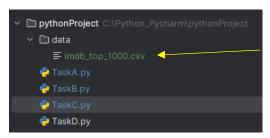
```
C:\Intelij_MultimediaRetrieval\Ex3_MultimediaRetrieval\Scripts\python.exe C:\Python_Pycharm\pythonProject\TaskA.py
[nltk_data] Downloading package stopwords to
[nltk_data] C:\Users\buser\AppData\Roaming\nltk_data...
[nltk_data] Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data] C:\Users\buser\AppData\Roaming\nltk_data...
[inltk_data] Package punkt is already up-to-date!
Detected Language (Italian): italian
Detected Language (English): english
Detected Language (German): german

Process finished with exit code 0
```

### **B.** Exercise Description

b)[intermediate] We once again work with the movie dataset from Kaggle.com. This time, we will exclusively use the movie titles and apply sub-word tokenization, which involves fixed-length sequences of 2, 3, or 4 characters within words. You may use special codes to indicate the start or end of words. To simplify the task, utilize <u>unidecode</u> to convert words into non-accented versions. Create a set-of-word representation (using Python's set) for the sub-tokens extracted from the titles and ignore all other fields. For searching, employ the same tokenization and set-of-word approach as for the titles, and establish an appropriate similarity function to match queries with movie titles.

https://www.kaggle.com/datasets/harshitshankhdhar/imdb-dataset-of-top-1000-movies-and-tv-shows.



#### 1. Functions:

- 2. tokenize\_to\_ngrams(text, n=3):
  - Purpose: Converts a string into sub-word sequences (n-grams).
  - o Steps:
    - 1. Converts the text to lowercase and removes accents using unidecode.
    - 2. Adds start (<) and end (>) markers to each word.
    - 3. Extracts all overlapping sequences of length n.
- 3. create\_title\_index(csv\_file\_path, n=3):
  - Purpose: Reads the CSV file of movie titles and tokenizes each title into ngrams, creating an index for later search.
  - Steps:
    - 1. Reads the CSV file.
    - 2. Processes each title using tokenize\_to\_ngrams and stores the n-grams as a set associated with the title.
- 4. search\_titles(query, index, n=3):
  - Purpose: Searches for movie titles similar to the query by comparing ngrams.
  - Steps:
    - 1. Tokenizes the query into n-grams.
    - 2. Calculates the Jaccard similarity between the query and each title in the index.
    - 3. Sorts and returns titles ranked by similarity.

## Testing:

```
C:\Intelij_MultimediaRetrieval\Ex3_MultimediaRetrieval\Scripts\python.exe C:\Python_Pycharm\pythonProject\TaskB.py
Search Results:
The Shawshank Redemption: 0.15
Forushande: 0.12
Pink: 0.09
Shaun of the Dead: 0.09
Shadow of a Doubt: 0.09
Shrek: 0.08
Shine: 0.08
Shine: 0.08
Sholay: 0.08
Hana-bi: 0.07
Kagemusha: 0.06
Process finished with exit code 0
```

This output from Task B shows the search results for a query based on n-gram similarity using trigrams (n=3). The numbers represent the similarity scores between the query and the movie titles, with higher numbers indicating a better match. For example, "The Shawshank Redemption" has the highest similarity score of 0.15, meaning 15% of the trigrams overlap with the query. The results are sorted by similarity, showing the top 10 closest matches.

### C. Exercise Description

c)[intermediate] We perform the same task as in b), but this time we will utilize sentence transformers. Select a suitable model for your hardware and explore various sentence transformer models. Encode the movie titles and proceed with a semantic search for your query:

from sentence\_transformers import SentenceTransformer, util model = SentenceTransformer('all-MiniLM-L6-v2')
a, b = model.encode(title\_a), model.encode(title\_b)
float(util.dot\_score(a, b))

```
🔷 TaskA.py
              🌏 TaskB.py
                                                    ♣ TaskC.py ×
                                                                   TaskD.py
     from sentence_transformers import SentenceTransformer, util
     def encode_movie_titles(csv_file_path):
         embeddings = []
         with open(csv_file_path, mode="r", encoding="utf-8") as file:
            reader = csv.DictReader(file)
             for row in reader:
                 title = row["Series_Title"] # Ensure this matches the CSV column
                 titles.append(title)
                 embeddings.append(model.encode(title)) # Encode each title
         return titles, embeddings
     def semantic_search(query, titles, embeddings, top_k=10):
         query_embedding = model.encode(query) # Encode the query
         scores = util.dot_score(query_embedding, embeddings).cpu().numpy()[0] # Compute similarity scores
         results = sorted(zip(titles, scores), key=lambda x: x[1], reverse=True)
         return results[:top_k] # Return top-k results
     csv_file_path = "data/imdb_top_1000.csv" # Path to the CSV file
     titles, embeddings = encode_movie_titles(csv_file_path) # Encode all movie titles
     results = semantic_search(query, titles, embeddings)
```

## 1. create\_title\_embeddings(titles):

- Purpose: Encodes movie titles into vector representations using a pre-trained SentenceTransformer model.
- o Steps:
  - 1. Loads the all-MiniLM-L6-v2 model.
  - 2. Encodes all titles from the dataset into vectors.

## 2. semantic\_search(query, title\_embeddings, model, titles):

- Purpose: Finds semantically similar titles to a query.
- o Steps:
  - 1. Encodes the query into a vector.
  - 2. Calculates the cosine similarity between the query and each title's vector.
  - 3. Sorts titles by similarity scores.

## 3. Testing:

```
Search Results:
The Social Network: 0.39
Network: 0.34
The Nightmare Before Christmas: 0.34
Requiem for a Dream: 0.32
Awakenings: 0.30
Waking Life: 0.28
Night on Earth: 0.28
The Big Sleep: 0.26
Home Alone: 0.25
Sleepers: 0.25
Process finished with exit code 0
```

This output represents the results of a semantic search on movie titles, where each title is given a similarity score. These scores are calculated using sentence-transformer embeddings, which convert the titles and query into numerical vectors. The similarity is determined by comparing these vectors using a dot-product score, where higher values (e.g., **0.39** for *The Social Network*) mean the query and title are more semantically similar. The results are sorted from the highest to the lowest similarity score.

### D. Exercise Description

d)[difficult] Let's revisit task a) with language detection. The approach in a) relies on having sufficiently long texts with an adequate number of stop words for accurate language prediction. In the script, we discussed a method based on Naive Bayes, which operates with sub-word sequences. You can reuse the method from b) to generate these sub-sequences, first for learning the Naive Bayes likelihoods, and then for language prediction. To simplify, you can choose an equal prior for all languages and select 3-5 languages that use the same alphabet (eliminating alphabet-related rules). Extract and count all sub-sequences, but only keep the top-n sub-sequences per language (choose n as relatively small, such as 100 or 1000). During prediction, disregard sub-sequences for which we lack likelihoods (to avoid 0-posteriors).

```
a TaskA.py
               TaskB.py
                                                     TaskC.py
                                                                     🥏 TaskD.py 🗵
        from collections import Counter
        from unidecode import unidecode
        # Function to generate n-grams
        def generate_ngrams(text, n=3):
            text = unidecode(text.lower())
        def train_naive_bayes(language_texts, n=3, top_n=1000):
            likelihoods = {}
            for lang, texts in language_texts.items():
                ngram_counts = Counter()
                for text in texts:
                    ngram_counts.update(generate_ngrams(text, n))
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                # Select top-n n-grams for the language
                top_ngrams = dict(ngram_counts.most_common(top_n))
                likelihoods[lang] = top_ngrams
            return likelihoods
        def predict_language(text, likelihoods, n=3):
            ngrams = generate_ngrams(text, n)
            scores = {lang: 0 for lang in likelihoods}
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            for lang, ngram_likelihoods in likelihoods.items():
                for ngram in ngrams:
                    if ngram in ngram_likelihoods:
                         scores[lang] += ngram_likelihoods[ngram]
            return max(scores, key=scores.get)
```

# 1) generate\_ngrams(text, n=3):

- Purpose: Converts text into trigrams.
- Steps:
- Similar to Task B, it uses unidecode to normalize text and extracts n-grams.

# 2) train\_naive\_bayes(language\_texts, n=3, top\_n=1000):

- Purpose: Trains a Naive Bayes likelihood model using text samples for each language.
- Steps:
- Tokenizes the text samples for each language into trigrams.
- · Counts the frequency of each trigram.
- Stores the top n most common trigrams for each language as the likelihoods.

## 3) predict\_language(text, likelihoods, n=3):

- Purpose: Predicts the language of a given text using the trained Naive Bayes model.
- Steps:
- Tokenizes the text into trigrams.
- Checks the likelihoods for each trigram and accumulates scores for each language.
- Returns the language with the highest score.

```
# Example usage

| if __name__ == "__main__":
| # Example texts for training
| language_texts = {
| 'english': ["Hello world", "This is an example of English text."],
| 'german': ["Hallo Welt", "Das ist ein Beispieltext in Deutsch."],
| 'italian': ["Ciao mondo", "Questo è un esempio di testo in italiano."]

| # Train Naive Bayes likelihoods
| likelihoods = train_naive_bayes(language_texts, n=3, top_n=100)

| # Input text for prediction
| text = "buonqiorno."
| text2 = "hello"
| text3 = "Hallo"

| predicted_language = predict_language(text, likelihoods)
| predicted_language2 = predict_language(text2, likelihoods)
| predicted_language3 = predict_language(text3, likelihoods)
| print("Predicted Language:", predicted_language)
| print("Predicted Language:", predicted_language2)
| print("Predicted Language:", predicted_language3)
| print("Predicted Language:", predicted_language3)
```

#### **Manuel Buser**

```
C:\Intelij_MultimediaRetrieval\Ex3_MultimediaRetrieval\Scripts\python.exe C:\Python_Pycharm\pythonProject\TaskD.py
Predicted Language: italian
Predicted Language: english
Predicted Language: german

Process finished with exit code 0
```

Now we can predict languages with a short input such as hello or hallo. I tried to input the same in the code for task A and the predictions there were not accurate since it needed more words to predict the language. But since we are using now a stronger predictor model we are able to predict shorter sequences.