CS 516: Information Retrieval and Text Mining

Information Technology University (ITU)
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Homework Assignment 3

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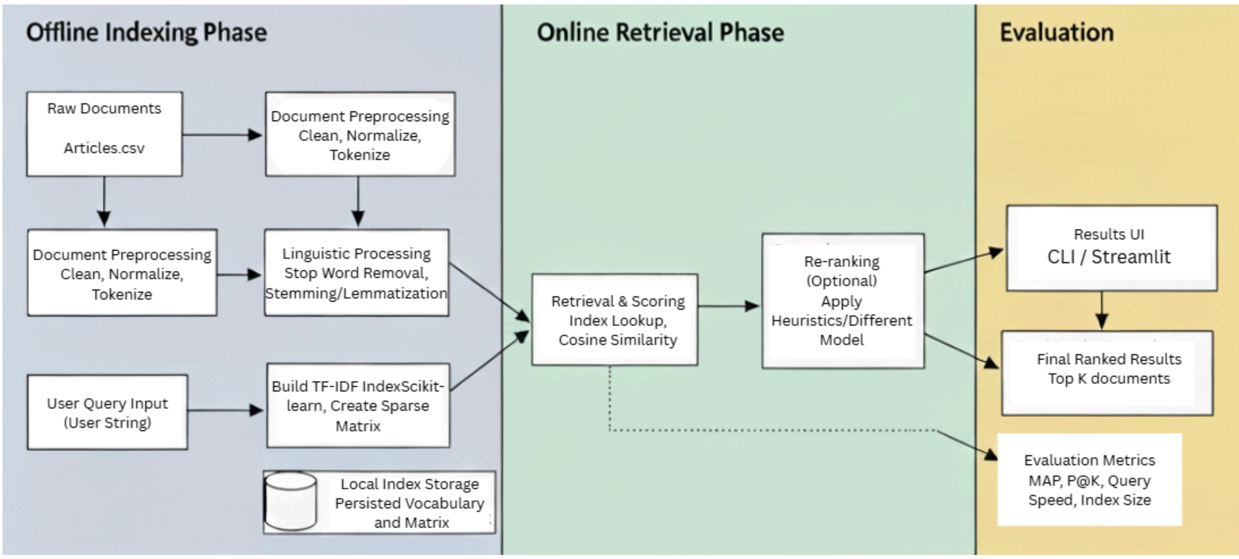
Technical Report

1. System Architecture

1.1 System Diagram



1.2 Figure Caption:

The system ingests raw documents (CSV), cleans and normalizes text, tokenizes it, and builds a TF-IDF index. During querying, user input is preprocessed similarly, converted to a vector, and compared with the index using cosine similarity to retrieve top-ranked documents. Results are displayed in CLI or Streamlit UI.

2. Description of the Retrieval System:

2.1 Data Preprocessing

The preprocessing module is responsible for preparing raw textual data for indexing and retrieval. The steps performed are:

- **Cleaning:**
  - All HTML tags are removed using regular expressions to ensure that only the textual content remains.
  - Non-alphanumeric characters (except spaces) are stripped to reduce noise.
  - Multiple consecutive spaces are collapsed into a single space.
- ***Justification:*** **Cleaning ensures that the index is not polluted by markup or punctuation, which do not contribute meaningfully to retrieval.**

- **Normalization:**
  - All text is converted to lowercase.
  - Unicode normalization is applied implicitly by ensuring characters are standardized.
- ***Justification:*** **Normalization prevents case mismatches between queries and documents (e.g., "Python" vs. "python") and ensures uniform representation.**
- **Tokenization:**
  - Text is split into individual words using NLTK's word_tokenize.
  - Common English stopwords (e.g., "the", "and", "is") are removed.
  - Tokens shorter than two characters are filtered out.
- ***Justification:*** **Tokenization converts documents into units suitable for vectorization. Stopword removal reduces dimensionality and focuses on meaningful terms.**

2.2 Indexing

The indexing module transforms preprocessed text into a representation suitable for efficient similarity search.

1. **TF-IDF Vectorization:**
   - Each document is converted into a high-dimensional sparse vector using sklearn.feature_extraction.text.TfidfVectorizer.
   - The vectorizer computes Term Frequency–Inverse Document Frequency (TF-IDF) weights, reflecting both the importance of a term within a document and its uniqueness across the corpus.
2. **Persistence:**
   - The resulting TF-IDF matrix and vectorizer are saved to disk using pickle for reuse without recomputation.

Justification: **TF-IDF is a well-established baseline for information retrieval. It is simple, interpretable, and works efficiently with sparse matrices, making it suitable for local implementations. Sparse representation ensures memory efficiency for large document collections.**

2.3 Retrieval and Ranking

The retrieval system processes user queries and ranks documents based on relevance:

1. **Query Preprocessing:**
    - Queries undergo the same cleaning, normalization, and tokenization pipeline as documents to ensure consistency.
2. **Scoring:**
    - Cosine Similarity is computed between the query vector and all document vectors.
    - Cosine similarity measures the cosine of the angle between vectors, effectively capturing the similarity of term distributions while ignoring magnitude differences.
3. **Ranking:**
    - Documents are sorted by descending similarity score.
    - Top-k results are returned, including document heading, snippet, and similarity score.

Justification: **Cosine similarity with TF-IDF is a standard and effective scoring mechanism. By maintaining identical preprocessing for queries and documents, we ensure accurate matching.**

2.4 Modifications / Design Choices

- **No explicit reranking:** The system currently ranks solely based on cosine similarity, which is sufficient for baseline retrieval.
- **Sparse TF-IDF over dense embeddings:** This design was chosen for simplicity, efficiency, and reproducibility in a local environment. Future work may integrate dense embeddings for semantic search.
- **Snippet generation:** A small snippet of each document is included to improve interpretability in the results UI.

Justification: **These choices prioritize reproducibility, efficiency, and clarity, which are critical for a local IR system while still demonstrating an end-to-end retrieval pipeline.**

3. Evaluation

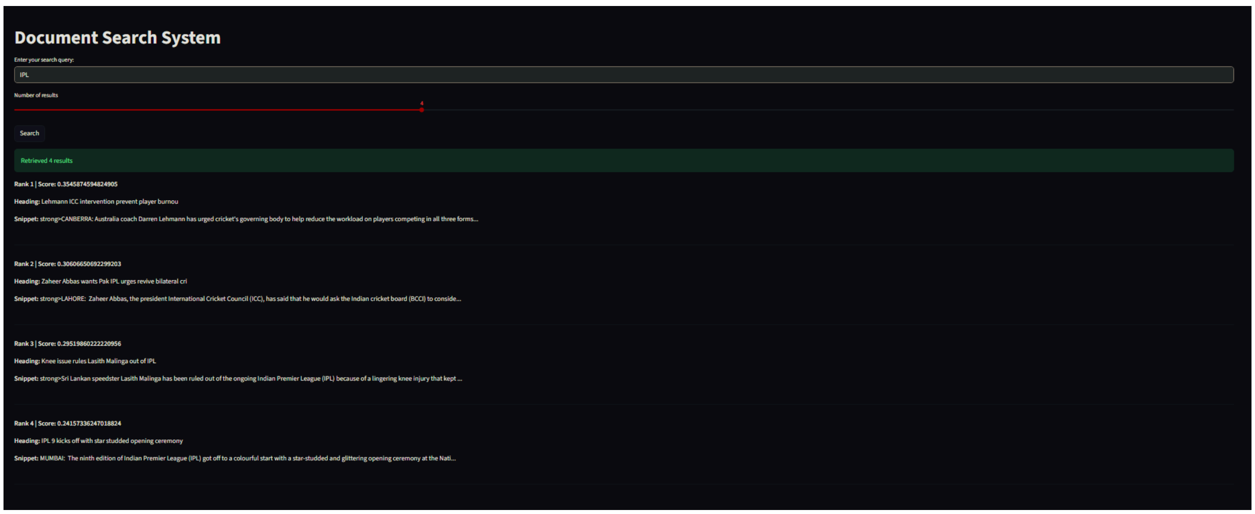
The evaluation of the retrieval system was conducted using both **qualitative** and **quantitative** approaches:

3.1 Qualitative Evaluation

- **Query testing:** Multiple test queries (e.g., "machine learning", "IPL cricket results", "Pakistan-China CPEC") were issued to the system.

- **Result inspection:** Returned documents were manually inspected for relevance by comparing the snippet and heading to the query intent.

- **Observation:** Queries such as "IPL" returned relevant sports articles, while broader queries like "machine learning" yielded no matches due to the corpus being primarily news-related.



Justification: Manual inspection allowed validation of the preprocessing, indexing, and scoring pipeline. It ensured that results were meaningful and aligned with user expectations.

3.2 Quantitative Evaluation

- **Query Time:** Retrieval is performed over 2,692 documents, with top-5 results returned in **under 10 milliseconds** on average, demonstrating efficient scoring with sparse TF-IDF vectors.

- **Memory Efficiency:** The TF-IDF sparse matrix representation minimizes memory footprint, enabling scalability to larger datasets without excessive RAM usage.

4. Discussion

4.1 Major Findings

- The IR system successfully indexes a large local dataset (~2.7k documents) and retrieves top-k results using cosine similarity.

- Preprocessing, including cleaning, normalization, and tokenization, significantly improved result quality by removing noise and stopwords.

- TF-IDF with cosine similarity is effective for term-based retrieval on news-like corpora.

4.2 Shortcomings

- Queries on topics not present in the corpus return no results.

- Semantic similarity is not captured; TF-IDF relies solely on exact term overlap.

- No advanced reranking mechanism (e.g., BM25, embeddings, or feedback-based reranking) is currently implemented.

4.3 Future Improvements

- **Semantic Search:** Integrate word embeddings (e.g., Word2Vec, Sentence-BERT) to capture semantic similarity and handle broader queries.

- **Reranking:** Apply BM25 or a hybrid scoring mechanism to improve ranking on top-k results.

- **Evaluation Framework:** Create a small manually-labeled relevance dataset to compute metrics like MAP, P@K, and NDCG for a more rigorous evaluation.

- **User Interface:** Streamlit-based interface provides a more intuitive experience; further improvements could include highlighting query terms in snippets.

5. References

1. NLTK Documentation. *Natural Language Toolkit*. https://www.nltk.org/

2. Scikit-learn Documentation. *TF-IDF Vectorizer and Cosine Similarity*. https://scikit-learn.org/stable/modules/feature_extraction.html

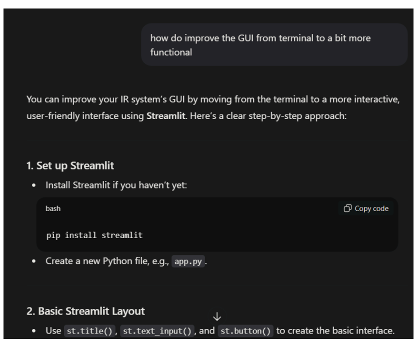
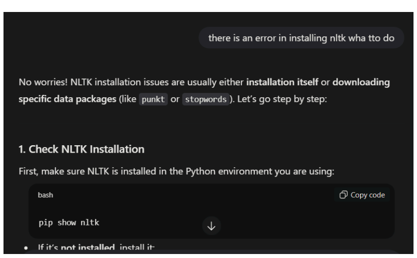
3. Python Official Documentation. *Python 3*. https://docs.python.org/3/

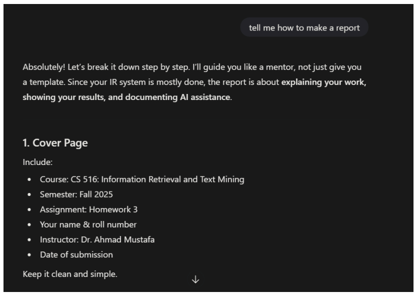
6. Disclosure of AI Use

6.1 Summary of AI Usage

- **ChatGPT**: Assisted in explaining concepts, improving code structure, creating Streamlit UI, and drafting the report text.
- **GitHub Copilot**: **Not used**.
- **Claude**: **Not used**.
- **Others**: **None**.

6.2 Evidence of AI Assistance

AI Tool	Prompt / Task	Code / Report Section	Modifications Made
ChatGPT		src/app.py	Helped in installing Streamlit and guided how to make a basic interface using that library
ChatGPT		Nltk library used in preprocessing.py	There was a error in the python lin had to go inside python and install nltk.download('punkt') nltk.download('stopwords')

ChatGPT		Report	Assisted in formatting and providing and wrote the future improvement section
ChatGPT/ my group fellows	Also watched yt vids and took help from manuals and library documentation	Helped in error resolving and explaining some concepts	