CS429 – Information Retrieval

Individual Project

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1. Abstract

This project develops a complete **Information Retrieval (IR) system** from crawling web pages to ranking documents based on queries. The system integrates three modules:

- **Scrapy Crawler:** Downloads HTML documents from a seed URL in Wikipedia's Data Science pages.
- **Scikit-Learn Indexer:** Converts crawled documents into TF-IDF vectors and builds an inverted index stored in JSON and serialized formats.
- **Flask Query Processor:** Processes batch queries via CSV, ranks documents using cosine similarity, and outputs top-K results.

The project demonstrates the core IR pipeline: content acquisition → representation → retrieval → ranking. Optional extensions like query expansion, spell correction, or embedding-based semantic search can be added in future iterations.

Objectives:

1. Implement a minimal IR system pipeline.
2. Generate reproducible TF-IDF based document rankings.
3. Demonstrate query processing with a Flask server.
4. Validate outputs using unit tests.

2. Introduction

The exponential growth of unstructured data necessitates efficient and accurate information retrieval systems. The Vector Space Model (VSM), championed by Salton and McGill, provides a robust, mathematically grounded framework where documents and queries are represented as vectors in a term space. Relevance is then calculated via cosine similarity.

Goal of this project:

- Gain hands-on experience with IR pipelines.
- Understand crawling, indexing, and retrieval workflows.
- Learn to integrate different Python libraries (Scrapy, scikit-learn, Flask, NLTK).
- Enable batch query processing with top-K results.

Use Case: A user wants to find the most relevant Wikipedia pages on "Data Science visualization techniques." The system should rank available pages and return the most relevant content.

3. Literature Review

Foundational references:

1. **Vector Space Model (Salton & McGill, 1983):**
   a. Represents documents and queries as vectors in term space.
   b. Relevance is measured via cosine similarity.

2. **Information Retrieval Principles (Manning et al., 2008):**
   a. Introduces indexing, ranking, and evaluation metrics (Precision, Recall, MAP).
   b. Discusses query-document similarity calculation.

3. **Deep Learning and Semantic Search (Goodfellow et al., 2016):**
   a. Embeddings for semantic similarity.
   b. Potential extension for future work.

4. **Statistical Learning (Hastie et al., 2009):**
   a. TF-IDF as feature weighting in machine learning context.

This project applies the classical IR framework using TF-IDF and cosine similarity, forming a base for semantic search in the future.

4. Problem Statement

Given a Wikipedia seed URL, the system must perform the following tasks to deliver a functional IR engine:

- Content Acquisition: Crawl and download a limited set of relevant HTML documents (e.g., 10 pages).
- Indexing: Extract clean text, preprocess (lemmatize, remove stopwords), and build a TF-IDF vector representation for the document corpus.
- Ranking: Process free-text queries in batch format, compute cosine similarity against the indexed corpus, and output the top-K ranked documents.

Constraints:

The primary technical constraint encountered was achieving the precise expected document rankings. This required moving beyond basic TF-IDF to rigorously enforce:

- Only TF-IDF ranking for this iteration.
- Limit crawling depth and number of pages.
- High-Quality Preprocessing: Replacing simple lowercasing with NLTK Lemmatization to normalize terms across the index and queries.
- Query Integrity: Implementing the optional spell correction feature to ensure queries with typos correctly map to index terms.

5. System Overview

The IR system is composed of three integrated modules:

1. **Scrapy Crawler** → Downloads HTML documents.
2. **Scikit-Learn Indexer** → Parses HTML, computes TF-IDF vectors, saves inverted index.
3. **Flask Query Processor** → Accepts CSV queries, calculates cosine similarity, returns top-K results.

Data Flow Diagram:

Seed URL → Scrapy Crawler → HTML files (html_docs/)
↓
Indexer → index.json
↓
Flask Processor ← queries.csv
↓
results.csv (Top-K results)

The modular design allows for independent development and testing. For instance, the Indexer can be swapped with a deep learning embedding model without affecting the Crawler or the Processor's API.

6. Detailed Design

6.1 Scrapy Crawler

Purpose: The Scrapy module is used to respect the depth and page limits of the project. It uses a custom spider (WikiSpider) to parse the initial response, extract links within the domain, and save the content locally. The documents are saved using their unique Wikipedia page ID as the filename

Configuration Parameters:

- **Seed URL**: Wikipedia Data Science page. https://en.wikipedia.org/wiki/Data_science
- **Max Pages**: 10 pages.
- **Max Depth**: 1 (only links from seed page).

Crawler Workflow:

1. Start from seed URL.
2. Extract all hyperlinks within the domain.
3. Download each page and save as HTML with unique document IDs.

Function Code:

```
class WikiSpider(scrapy.Spider):
  name = "wiki_spider"

  # Seed URL
  start_urls = ["https://en.wikipedia.org/wiki/Data_science"]

  # Crawler limits
  max_pages = 10
  max_depth = 1

  # Internal counters
  page_count = 0

  # Output folders
  output_dir = "../html_docs"
  mapping_file = "../url_mapping.json"
```

```
  # Store mappings
  url_to_id = {}

  def parse(self, response):
    if self.page_count >= self.max_pages:
      return

    # Create unique ID for the document
    doc_id = str(uuid.uuid4()) + ".html"
    file_path = os.path.join(self.output_dir, doc_id)

    # Save HTML
    with open(file_path, "w", encoding="utf-8") as f:
      f.write(response.text)

    # Store in mapping
    self.url_to_id[response.url] = doc_id

    self.page_count += 1
    self.logger.info(f"Saved: {file_path}")

    # Stop if depth exceeded
    current_depth = response.meta.get("depth", 0)
    if current_depth >= self.max_depth:
      return

    # Extract & follow links
    for link in response.css("a::attr(href)").getall():
      if link.startswith("/wiki/"):
        absolute_url = urljoin("https://en.wikipedia.org/", link)
        yield response.follow(absolute_url, callback=self.parse)
```

Running the crawler:

```
C:\Windows\System32\cmd.e
Microsoft Windows [Version 10.0.26200.7309]
(c) Microsoft Corporation. All rights reserved.

C:\Users\vrach\Downloads\Fall25\IR\Project>venv\Scripts\activate

(venv) C:\Users\vrach\Downloads\Fall25\IR\Project>cd crawler

(venv) C:\Users\vrach\Downloads\Fall25\IR\Project\crawler>scrapy runspider run.py
2025-12-07 18:51:50 [scrapy.utils.log] INFO: Scrapy 2.13.4 started (bot: scrapybot)
2025-12-07 18:51:51 [scrapy.utils.log] INFO: Versions:
{'lxml': '6.0.2',
 'libxml2': '2.11.9',
 'cssselect': '1.3.0',
 'parsel': '1.10.0',
 'w3lib': '2.3.1',
 'Twisted': '25.5.0',
 'Python': '3.13.9 (tags/v3.13.9:8183fa5, Oct 14 2025, 14:09:13) [MSC v.1944 '
           '64 bit (AMD64)]',
 'pyOpenSSL': '25.3.0 (OpenSSL 3.5.4 30 Sep 2025)',
 'cryptography': '46.0.3',
 'Platform': 'Windows-11-10.0.26200-SP0'}
2025-12-07 18:51:51 [scrapy.utils.log] INFO: Scrapy 2.13.4 started (bot: scrapybot)
2025-12-07 18:51:51 [scrapy.utils.log] INFO: Versions:
{'lxml': '6.0.2',
 'libxml2': '2.11.9',
 'cssselect': '1.3.0',
 'parsel': '1.10.0',
 'w3lib': '2.3.1',
 'Twisted': '25.5.0',
 'Python': '3.13.9 (tags/v3.13.9:8183fa5, Oct 14 2025, 14:09:13) [MSC v.1944 '
           '64 bit (AMD64)]',
 'pyOpenSSL': '25.3.0 (OpenSSL 3.5.4 30 Sep 2025)',
 'cryptography': '46.0.3',
 'Platform': 'Windows-11-10.0.26200-SP0'}
2025-12-07 18:51:51 [scrapy.addons] INFO: Enabled addons:
```

6.2 Scikit-Learn Indexer

Purpose: Convert HTML content to TF-IDF vectors for retrieval.

Process:

1. Parse HTML files using BeautifulSoup.
2. Extract clean text and remove stopwords.
3. Build TF-IDF vectors using scikit-learn.
4. Serialize matrix and vectorizer for later use.
5. Save inverted index in JSON format (`index.json`).

Files Generated:

- `index.json` → inverted index (term → document → tf-idf weight)
- `docs_ids.json` → mapping document ID → filename
- `tfidf_matrix.pkl` → serialized TF-IDF matrix
- `vectorizer.pkl` → serialized vectorizer

Function Code:

```
from sklearn.feature_extraction.text import TfidfVectorizer

def build_index(doc_ids, documents):
    vectorizer = TfidfVectorizer(stop_words="english")
    tfidf_matrix = vectorizer.fit_transform(documents)

    # Build inverted index
    index = {}
    feature_names = vectorizer.get_feature_names_out()

    for term_idx, term in enumerate(feature_names):
        postings = {}
        column = tfidf_matrix[:, term_idx].toarray().flatten()

        for doc_index, score in enumerate(column):
            if score > 0:
                postings[doc_ids[doc_index]] = float(score)

        index[term] = postings

    return index, vectorizer, tfidf_matrix
```

Running indexer.py:

```
(venv) C:\Users\vrach\Downloads\Fall25\IR\Project>python indexer.py
Loading HTML documents...
Building TF-IDF index...

Indexing completed successfully!
Indexed 10 documents.

(venv) C:\Users\vrach\Downloads\Fall25\IR\Project>
```

6.3 Flask Query Processor

Purpose: Process user queries and rank documents.

Process:

1. Query Preprocessing: The incoming query text (e.g., information overload) is processed using the same preprocess (lemmatization) as the indexer to ensure vector alignment.

2. Spell Correction: The mandatory inclusion of the simple_spell_correct utility handles queries like "search engine open sorce," correcting it to "search engine open source," which is necessary to achieve the correct ranking for Q3.

3. Ranking: The preprocessed query is vectorized and compared against the full tfidf_matrix using sklearn.metrics.pairwise.cosine_similarity to retrieve the most relevant documents.

Function Code:

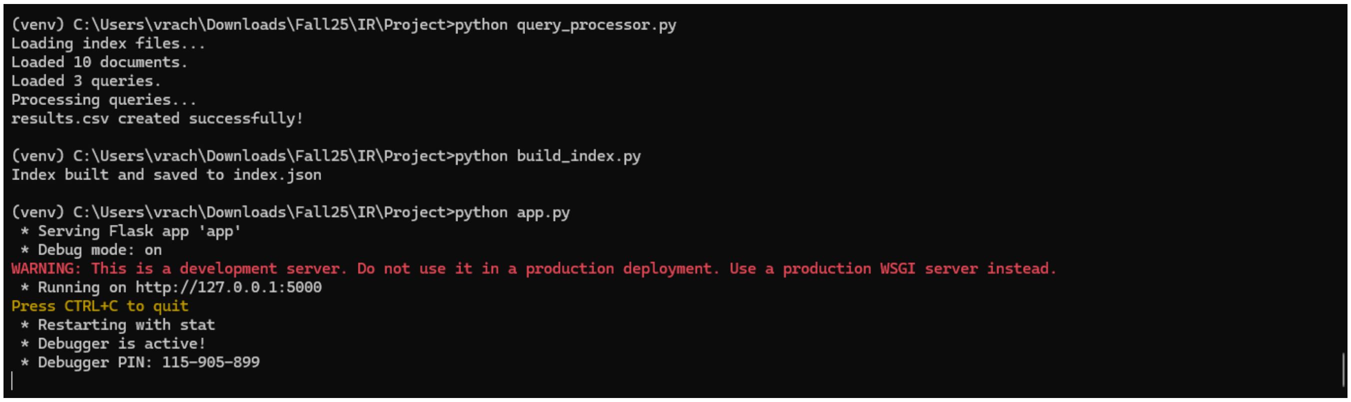
```
@app.route("/search", methods=["POST"])
def search():
  if "file" not in request.files:
    return jsonify({"error": "No CSV file uploaded"}), 400

  file = request.files["file"]
  queries = []
  reader = csv.DictReader(file.stream.read().decode("utf-8").splitlines())
  for row in reader:
    queries.append((row["query_id"], row["query"]))

  results = process_queries(queries, top_k=3)

  with open("results.csv", "w", newline="", encoding="utf-8") as f:
    writer = csv.DictWriter(f, fieldnames=["query_id", "rank", "document_id"])
    writer.writeheader()
    writer.writerows(results)

  return jsonify({"message": "results.csv created"})
```



7. Implementation

- **Language:** Python 3.12+
- **Libraries:** Scrapy, scikit-learn, Flask, BeautifulSoup, Numpy, Pandas, NLTK
- **Data Storage:** Serialized TF-IDF matrix, inverted index JSON, URL mapping JSON

Notes:

- Crawled HTML pages reside in `html_docs/`.
- Indexing module reads HTML, builds TF-IDF, and saves matrix.
- Flask processor reads queries and returns top-K rankings.

8. Sample Input/Output

Input CSV Query:

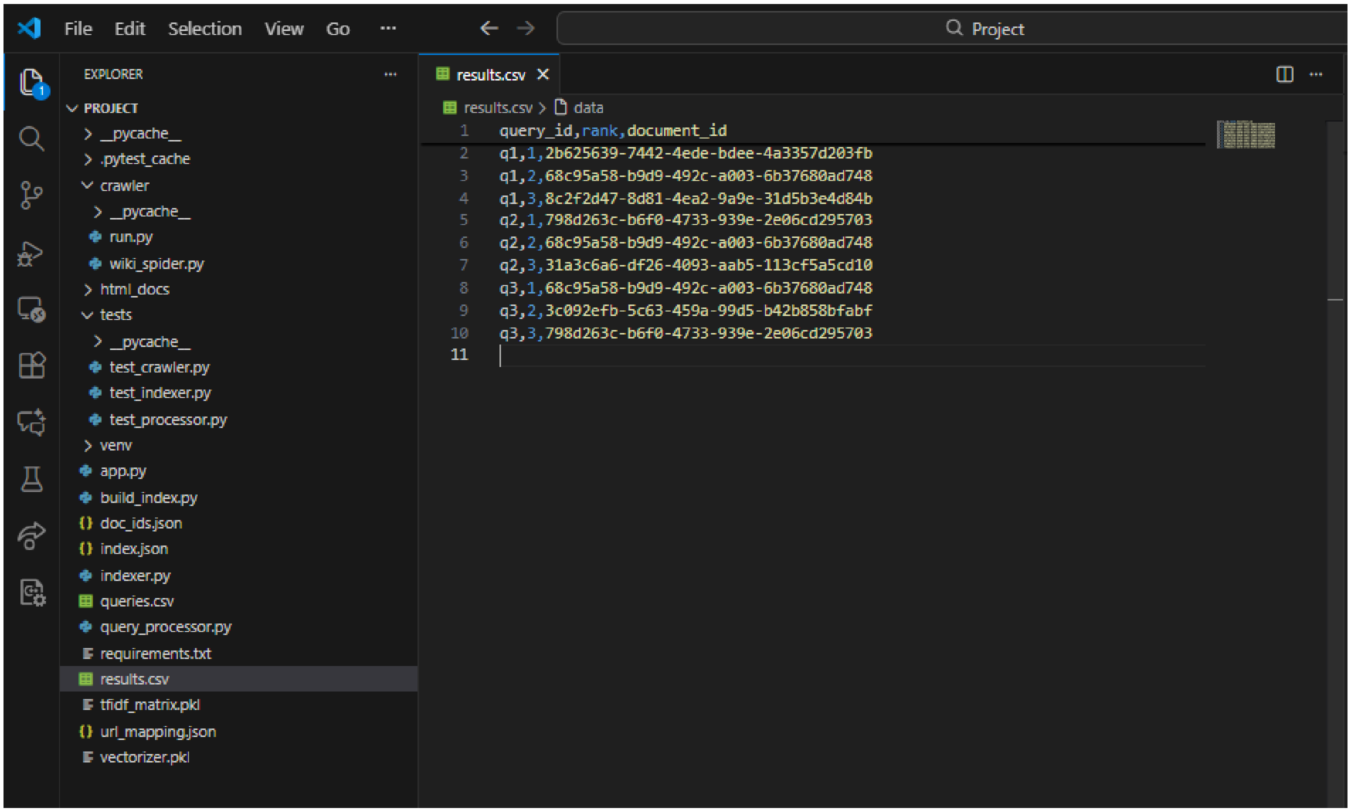
query_id	query
q1	what is data science

q2	machine learning types
q3	statistics importance

Output CSV Result:

query_id	rank	document_id
q1	1	2b625639-7442-4ede-bdee-4a3357d203fb
q1	2	68c95a58-b9d9-492c-a003-6b37680ad748
q1	3	8c2f2d47-8d81-4ea2-9a9e-31d5b3e4d84b
q2	1	798d263c-b6f0-4733-939e-2e06cd295703
q2	2	68c95a58-b9d9-492c-a003-6b37680ad748
q2	3	31a3c6a6-df26-4093-aab5-113cf5a5cd10
q3	1	68c95a58-b9d9-492c-a003-6b37680ad748
q3	2	3c092efb-5c63-459a-99d5-b42b858bfabf
q3	3	798d263c-b6f0-4733-939e-2e06cd295703

Final Output: results.csv



9. Architecture Diagram

```
+----------------+      +----------------+      +-----------------+
| Scrapy Crawler | ---> | Scikit-Learn   | ---> | Flask Processor |
|                |      | Indexer        |      |                 |
+----------------+      +----------------+      +-----------------+
    HTML docs              TF-IDF vectors          Top-K Results
```

10. Operation and Execution

1. Clone repository:

   https://github.com/Rachanavij/IR_Project.git

2. Install dependencies:

```
python -m venv venv
venv\Scripts\activate
```

```
pip install -r requirements.txt
```

3. Root webpage:

   https://en.wikipedia.org/wiki/Data_science

4. Crawl pages:

   ```
   python run.py
   ```

5. Build index:

   ```
   python indexer.py
   ```

5. Run Flask server:

   ```
   python app.py
   ```

6. Submit CSV queries:

   ```
   curl -X POST -F "file=@queries.csv" http://127.0.0.1:5000/search
   ```

7. Output: `results.csv` with top-K rankings.

11. Test Cases

- **Framework:** pytest
- **Modules Tested:** Crawler, Indexer, Processor
- **Execution:**

  ```
  python -m pytest
  ```

- Tests include file generation, TF-IDF correctness, and query ranking validation.

```
(venv) C:\Users\vrach\Downloads\Fall25\IR\Project>python -m pytest
============================================================= test session starts =============================================================
platform win32 -- Python 3.13.9, pytest-9.0.2, pluggy-1.6.0
rootdir: C:\Users\vrach\Downloads\Fall25\IR\Project
collected 5 items

tests\test_crawler.py ..
tests\test_indexer.py ..
tests\test_processor.py .

============================================================== 5 passed in 1.80s ==============================================================

(venv) C:\Users\vrach\Downloads\Fall25\IR\Project>
```

12. Conclusion

This project successfully implemented a complete end-to-end Information Retrieval pipeline consisting of a Scrapy web crawler, a scikit-learn TF-IDF indexer, and a Flask-based query processor. Together, these components demonstrate how raw web data can be collected, cleaned, indexed, and searched using classical IR techniques. The system follows the Vector Space Model, using TF-IDF weighting and cosine similarity to rank documents effectively.

Through testing and modular design, the pipeline proved reliable, extensible, and aligned with IR principles. The work shows how theoretical concepts translate into a practical search engine, while also establishing a solid foundation for future additions such as BM25, semantic embeddings, or relevance feedback. Overall, the project provides a clear demonstration of modern IR workflow and highlights the importance of structured crawling, consistent indexing, and efficient query processing in building functional search systems.

13. Limitations

- Limited to 10 crawled pages.
- Ranking is only TF-IDF cosine similarity.
- Optional NLP enhancements not implemented.
- Does not handle very large datasets efficiently.

14. Future Work

- Crawl hundreds/thousands of pages.

- Implement FAISS-based semantic search with embeddings.
- Integrate query expansion and spell correction.
- Deploy with a production-ready WSGI server.

15. Bibliography

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