KLE Society's
KLE Technological University, Hubballi.

A Minor Project -2 Report

On

Search Engine Anatomy

Crawler and Recommendations

submitted in partial fulfillment of the requirement for the degree of

Bachelor of Engineering

In

School of Computer Science and Engineering

Submitted By

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SCHOOL OF COMPUTER SCIENCE & ENGINEERING

CERTIFICATE

This is to certify that Minor Project -2 entitled "Search Engine Anatomy –Crawler and Recommendations" is a bonafied work carried out by Abhijna Ravindra Kalbhag (01FE21BCS107), Shreya M. Pai (01FE21BCS089), Anushika Kothari (01FE21BCS062), and Nandan Date (01FE21BCI034) in partial fulfillment of completion of Sixth semester B.E. in School of Computer Science and Engineering duringthe year 2023-2024. The project report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above said program.

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1.	
2.	

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Project Completion Letter

This letter is to certify that the project titled "Search Engine Anatomy – Crawler and Recommendations" from Knit Space was successfully completed by the student team mentioned below from KLE Technological University as a part of VI semester five credit minor project. The project work was carried out under the guidance of Mr. Prakash Hegade. The team performance was graded excellent and has positively contributed towards the industry segment growth.

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ABSTRACT

In the digital age, search engines are vital for retrieving relevant information from vast datasets. The project "Search Engine Anatomy – Crawler and Recommendations" aims to improve search engine efficiency and accuracy through a domain-specific web crawler and a heuristic-based recommendation system. Traditional search mechanisms often struggle with delivering specificity and relevance in niche domains, leading to information overload or irrelevant results. This project addresses this challenge by developing a crawling mechanism that indexes content within designated domains, refining search precision.The initial phase involves implementing a domain-specific, keyword-centric web crawler. Unlike traditional crawlers that navigate hyperlinks indiscriminately, this crawler prioritizes exact keyword searches. It employs advanced parsing and search algorithms to quickly identify and index relevant web pages, focusing on user-defined keywords. This approach streamlines information retrieval by excluding irrelevant content, thereby improving search relevance.In the second phase, the project applies the A* search algorithm to generate heuristic-based product recommendations within an e-commerce platform. The product dataset is structured as a grid, with products positioned based on category encoding, normalized rating features, and semantic similarity derived from context aware textual embeddings. The A* search algorithm navigates this grid using a heuristic that combines cosine similarity of product descriptions, rating similarity, and rating count similarity. This method efficiently identifies paths through the grid, representing sequences of highly relevant products.Results show that the A* search-based approach significantly enhances the relevance and precision of product recommendations, providing users with coherent and context-aware suggestions. This innovative application of A* search in a grid-based product space offers a robust framework for improving recommendation systems in e-commerce.

Keywords : *Domain-Specific, Keyword-Centric , Web crawler, A* search, Heuristic recommendations, Product recommendation*

CONTENTS

LIST OF FIGURES

Chapter 1

INTRODUCTION

The title "Search Engine Anatomy – Crawler and Recommendations" encapsulates the dual focus of this project: designing a system that efficiently crawls and indexes web content while providing precise, heuristic-based product recommendations. While traditional search engines employ broad indexing and generalized recommendation techniques, this project zeroes in on optimizing the recommendation process using a domain-specific approach.

In today's digital landscape, the overwhelming volume of online information makes it difficult for traditional hyperlink-driven crawlers to quickly locate specific material. This necessitates a domain-specific keyword-centric crawler. Our crawler prioritizes exact keyword searches over random hyperlink traversal, focusing on user-defined keywords to efficiently sort through web pages and exclude irrelevant content. Utilizing advanced parsing and search algorithms, it delivers highly targeted results swiftly, streamlines information retrieval, enhances recommendations, and simplifies data indexing. This innovative approach significantly improves search precision and relevance, making it essential for effective web exploration in specialized domains.

The project involves creating a structured representation of the product dataset as a grid. Products are positioned in this grid based on a combination of categorical encoding, normalized rating features and semantic similarity .The A* search algorithm, traditionally used in pathfinding, is adapted to traverse this grid. It employs a heuristic function that considers cosine similarity of product descriptions, rating similarity, and rating count similarity to guide the search. This enables the identification of optimal paths through the grid, representing sequences of products that are highly relevant to the user's preferences.

1.1 Motivation

In the current digital age, where the volume of online information is exponentially increasing, traditional search engines struggle to efficiently index and retrieve relevant content. This project addresses the critical need for precision and relevance in search engine operations, particularly in specialized domains. By developing a domain-specific keyword-centric crawler, we aim to overcome the limitations of conventional hyperlink-driven approaches, which often result in irrelevant and generalized content retrieval.

Our crawler prioritizes exact keyword searches, significantly enhancing the efficiency and accuracy of information retrieval. Furthermore, the integration of a heuristic-based

recommendation system, using advanced parsing, search algorithms, and A* pathfinding, ensures highly relevant product suggestions tailored to user preferences. This dual-focus approach not only refines the indexing process but also revolutionizes user interaction with digital content, providing precise, context-aware recommendations. In today's information-saturated environment, such innovations are essential for improving search precision, enhancing user satisfaction, and maintaining competitiveness in the search engine industry.

1.2 Literature Survey

Search engines have been researched to optimize the components that contribute to the holistic working. Storage of data, representation, query processing, data handling, analysis, results presentation, etc. each of its components has been worked on to meet the state-of-art needs. If we refer back to the history of search engines, from processing the data in links, to managing indices, search engine has been enabled with optimizations [1]. Search engines have been evaluated on various parameters to measure the effectiveness [2]. Search engines have been seen as a medium of information retrieval and processing [3]. They have been a means to understand the web dynamics [4]. They have also been viewed from political perspective to understand how they shape the generational dynamics [5]. From optimizations to presentations, they have been researched on several fronts.

The domain-specific keyword-centric crawler is a sophisticated tool designed to enhance the efficiency and relevance of information retrieval in specialized fields. Unlike general-purpose crawlers, this crawler focuses on identifying and aggregating keywords pertinent to a specific domain, ensuring that the indexed content is highly relevant to the user's area of interest[6]. By utilizing advanced techniques such as semantic similarity clustering and Named Entity Recognition (NER)[7], the crawler can intelligently filter and prioritize information, leading to more precise search results and improved user experience. This targeted approach not only optimizes search engine performance but also significantly enhances recommendation systems, as it ensures that the data used for generating recommendations is contextually appropriate and highly pertinent to the user's needs[8].

Simple heuristics, as introduced by Gigerenzer, Todd, and The ABC Research Group (1999), embody principles for information search, stopping, and decision-making. These heuristics suggest that such processes are straightforward. For instance, an analysis of general practitioners' (GPs) information search and decision-making behavior when prescribing lipid-lowering drugs demonstrated that information search can be simple, and heuristics predicting a straightforward decision-making process can accurately describe information search [9]. Understanding how people process information and make decisions while searching the World Wide Web has become increasingly important. Dual-process

theories and decision theory, which distinguish between systematic and heuristic processing, provide a useful framework for analyzing this decision-making process [10]. Search is a universal problem-solving mechanism in artificial intelligence (AI). In AI, the sequence of steps required to solve a problem is often unknown a priori and must be determined through systematic trial-and-error exploration of alternatives. AI search algorithms address problems falling into three general classes: those that require systematic exploration of alternatives, those that require efficient data processing, and those that optimize the representation and retrieval of information [11].

1.3 Problem Statement

To design and implement domain specific crawler and platform for heuristic recommendations for a search engine

1.4 Applications

- To optimize product search capabilities by focusing on specific product categories, attributes, or customer preferences to enhance user experience and increase sales.
- For curating and aggregating content from diverse sources such as news websites, blogs, and forums to provide comprehensive coverage on specific topics of interest.
- Aggregating reviews, news, and content related to movies, music, books, and other forms of entertainment for enthusiasts and consumers.
- In a larger domain, this project can be applied to optimize recommendation systems across various industries such as e-commerce, streaming services, and content platforms.
- The project can be applied to improve user engagement and deliver personalized experiences across diverse applications such as personalized content curation and efficient information retrieval.

1.5 Objectives and Scope of the project

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1.5.1 Objectives

- To design and implement a domain-specific web crawler to enhance precision in targeted search result by leveraging initial keyword extraction from web content

- To design and implement product mapping to a relevant grid data structure and application of A* algorithm for recommendations.

1.5.2 Scope of the project

Following are the boundaries under which method works correctly:

1. The project operates under the condition that the user-provided keyword exists and its corresponding Wikipedia URL is present in the database.
2. The project is exclusively designed for the English language.
3. The project accepts only textual input based on the user-provided keyword.
4. The project is console based.

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Chapter 2

REQUIREMENT ANALYSIS

Effective requirement analysis is crucial in ensuring that software development projects meet user expectations and operational needs. It serves as the foundation for defining project scope, identifying functionalities, and aligning development efforts with business objectives. By systematically gathering and documenting requirements, stakeholders can mitigate risks, clarify project goals, and optimize resource allocation. Ultimately, thorough requirement analysis fosters transparency and enhances the likelihood of delivering a solution that meets both technical specifications and user demands.

2.1 Functional Requirements

Functional requirements are essential for a project as they provide a clear and precise description of what the system should do, ensuring all stakeholders have a common understanding of the objectives. They guide developers in designing and implementing the system, form the basis for testing to verify performance, and help define the project scope to prevent scope creep. Additionally, they enhance communication among team members and stakeholders, ensure the system aligns with user needs and business goals, and assist in efficient resource allocation. Following are the Functional Requirements for the project :

- The system should fetch and store keywords along with their associated WikiURLs and Google URLs in the database.
- The system should rank the results based on relevance and display them to the user.
- The system should construct a structured grid representation of the product dataset.
- The system should implement a heuristic-based recommendation system utilizing the A* search algorithm adapted for grid navigation.

2.2 Non Functional Requirements

Non-functional requirements are crucial as they define the quality attributes and operational standards of a system, ensuring it performs effectively under various conditions. They address aspects such as performance, security, usability, reliability, and scalability, which are vital for user satisfaction and system stability. By setting benchmarks for these

attributes, non-functional requirements help in assessing system efficiency and robustness, ensuring it meets user expectations beyond basic functionality. Following are the Non-Functional Requirements for the project :

- Availability of the system = 0.99
- Mean time of Failure (MTTF) = 100 hours
- Mean time of Repair (MTTR) = 1 hour
- Mean time Between Failure (MTTR) = 100 + 1 = 101 hours
- Availability = MTTF / MTTR = 100/101

2.3 Hardware Requirements

- Core i5 Processor
- 8GB RAM

2.4 Software Requirements

The following packages, third-party APIs, and visualization libraries are used in the project:

2.4.1 Packages

- **requests**:Making HTTP requests to fetch web pages and API data.
- **beautifulSoup**:Parsing HTML content fetched from web pages.
- **NLTK**: For tokenizing , parts of speech tagging, removing stopwords and named-entity recognition.
- **sqlite3**: To provide an interface for SQLite databases.
- **textstat**:To provide statistical analysis of text complexity, including readability scores.
- **spacy**:Used for advanced natural language processing tasks like Named Entity Recognition (NER).
- **vaderSentiment**: To provide sentiment analysis capabilities.
- **datetime**:Standard Python library for handling date and time.
- **csv**: For reading CSV files.

- **numpy**: For numerical operations and array manipulation.
- **scikit-learn (sklearn)**
  - **TfidfVectorizer**:To convert raw documents into a matrix of TF-IDF features.
  - **AgglomerativeClustering**: To perform hierarchical clustering to cluster the keywords.
  - **MinMaxScaler**: For normalizing data.
  - **OneHotEncoder**: For encoding categorical variables.
  - **cosine_similarity**: For calculating cosine similarity between vectors.
- **matplotlib**: For creating visualizations and plotting the grid and paths.
- **gensim**
  - **Word2Vec**: For generating word embeddings.
- **transformers**: For using pre-trained BERT models.
- **torch**: For handling tensor operations with the BERT model.
- **heapq**: For managing priority queues used in the A* search algorithm.

2.4.2 Third-party APIs

- **Wikipedia API** : To fetch search results and extract article URLs based on user-provided topics.
- **Google Search** : To fetch additional URLs related to a given topic.
- **BERT (Bidirectional Encoder Representations from Transformers):**
  - **BertTokenizer**: For tokenizing text input.
  - **BertModel**: For generating BERT embeddings.
  - These are provided by the **transformers** library from Hugging Face.

2.4.3 Visualization Libraries

- **matplotlib**: Used for plotting the grid, highlighting recommended products, and visualizing the A* search path.
- **matplotlib.patches (mpatches)**: For creating legend patches with category colors.

Chapter 3

SYSTEM DESIGN

3.1 Architecture Design

The architecture design for the domain-specific web crawler involves a modular structure where the crawler extracts and processes initial keywords from web content to enhance precision in targeted search results. The system integrates a product mapping module that organizes data into a grid structure, applying the A* algorithm for generating heuristic recommendations, thereby improving search engine performance and relevance.

3.1.1 Crawler Module

The system architecture diagram outlines the entire workflow for the Crawler Module which is designed to enhance search efficiency and relevance through a structured sequence of steps involving user interaction, content extraction, analysis, and recommendation generation, leveraging both Wikipedia and Google search results.

The process begins by prompting the user to specify the topic and category of interest, which tailors the content extraction and analysis to the user's needs. Based on this input, a Wikipedia URL is constructed to serve as a seed URL, acting as the primary source of high-quality information. A category filter is then applied to ensure that the URL falls within the desired scope, narrowing down the results to the most relevant articles. Following this, the system compiles a list of top Wikipedia URLs that match the user's criteria.

The next step involves fetching and parsing the content from the selected URLs, using advanced parsing techniques to extract text and other relevant data from the web pages. A summary of the fetched content is generated by extracting the first three paragraphs from each Wikipedia page. Simultaneously, the system fetches the top URLs from Google search results for the same topic to expand the pool of data sources.

The extracted content is then tokenized and tagged with Part-of-Speech (POS) labels, preparing it for further analysis. A Named Entity Recognition (NER) model is used to identify and classify entities within the text, such as names of people, organizations, and locations. The identified entities and other significant terms are aggregated to form a comprehensive list of keywords.

These keywords are used to construct additional Wikipedia URLs, which are stored in a SQLite database along with the corresponding keywords to ensure a record of the URLs being worked with. The system fetches and parses the content of these stored URLs

using BeautifulSoup, generating summaries and constructing queries to search Google for additional URLs. The top five Google URLs are fetched, and these URLs are ranked based on relevance. Finally, the database is updated with the fetched Google URLs, and the top URLs are displayed to the user for review.

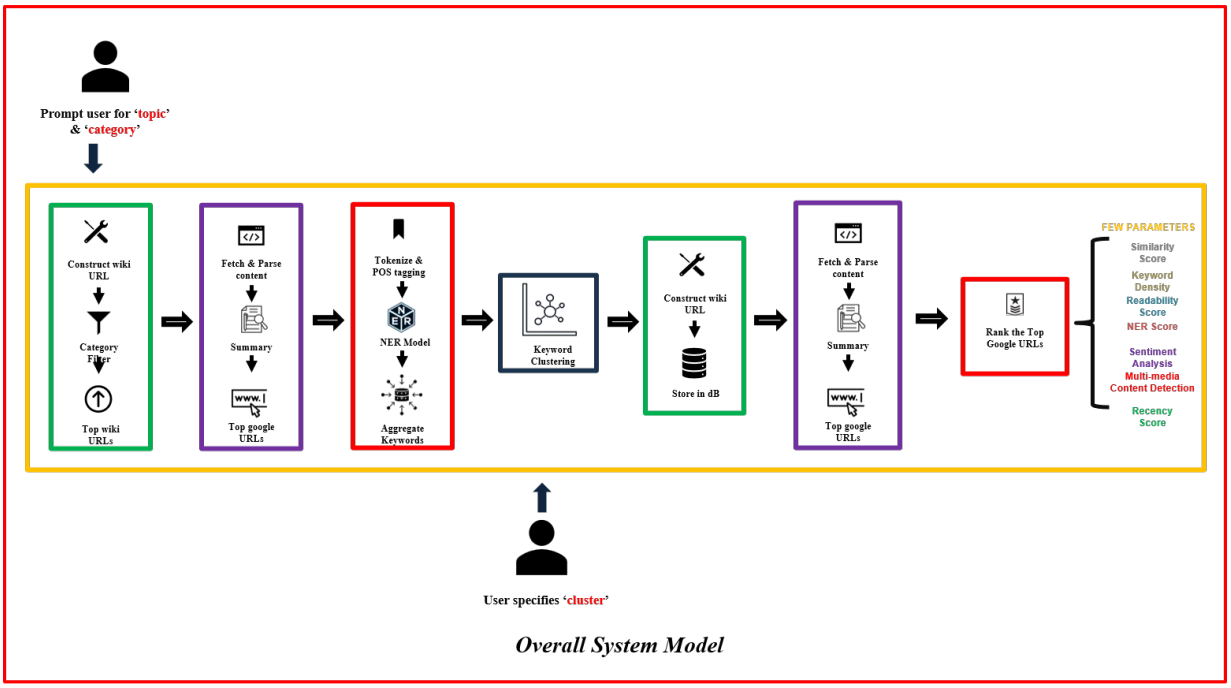


Figure 3.1: System Architecture of the Crawling Module

3.1.2 Reccomendation module

The architecture in figure 3.2 outlines a product recommendation module. The diagram illustrates a sophisticated approach to building a product recommendation system by integrating data preprocessing, feature extraction, and advanced search algorithms. Initially, raw data from a CSV file is cleaned to handle missing values, remove duplicates, and standardize formats, ensuring a consistent and reliable dataset. This cleaned data is then structured into a product dictionary, where each product entry includes key attributes such as 'product_id', 'product_name', 'category', 'rating', 'rating_count', and 'about_product'. Feature encoding and normalization are performed next: categorical data is converted into binary vectors using OneHotEncoding, and ratings along with rating counts are normalized through logarithmic transformation. The product descriptions are transformed into vector embeddings using the Word2Vec model, capturing semantic similarities between products. These encoded features are used to calculate row and column indices for placing products in a grid, where rows represent normalized ratings and columns represent similarity embeddings. The recommendation system leverages cosine similarity between product description vectors, rating similarity, and rating count similarity to compute a comprehensive similarity score. A* search algorithm is employed to find the optimal path

from the source to the destination product IDs within this grid, using a cost function and a heuristic function that consider absolute distances between grid cells. The output is a sequence of recommended products along the traversed path, visualized within the grid, highlighting the most relevant products based on the defined metrics.

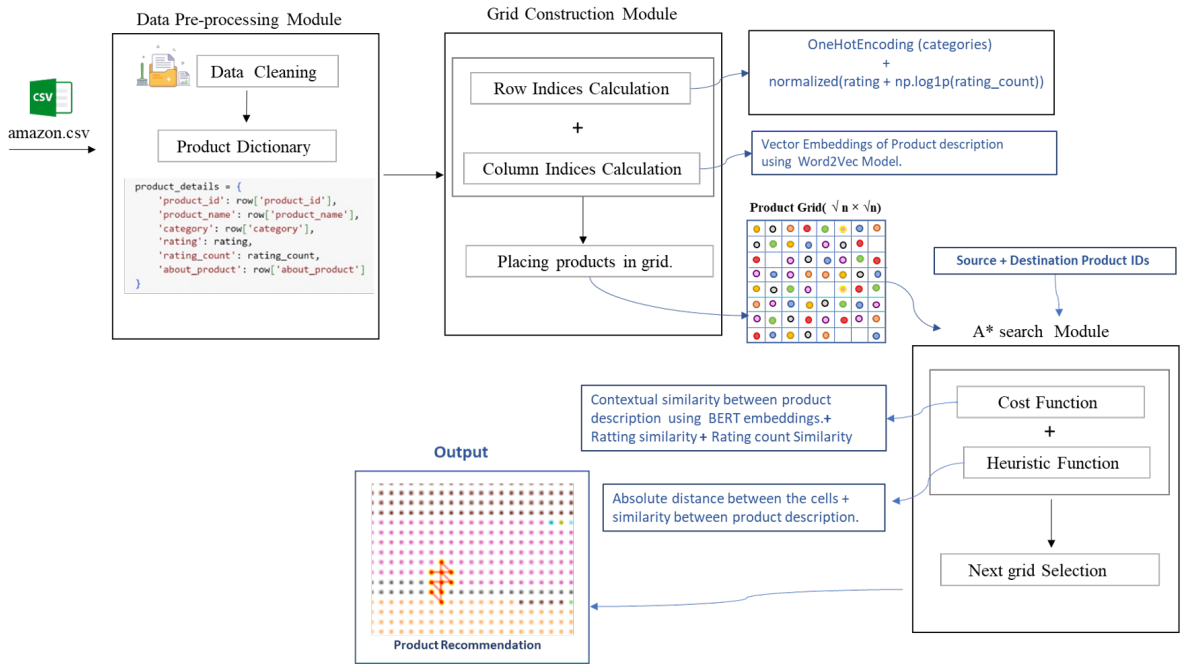


Figure 3.2: System Architecture of the Recommendation Module

3.2 Data Design

The data design for the project focuses on structuring and organizing the data to support both the domain-specific web crawler and the recommendation system.

3.2.1 Database Design for Crawler Module

Database 1:

This database is meticulously designed to store clusters and their respective keywords, ensuring that the data is organized and easily accessible. Each cluster is represented as a separate table within the database, creating a clear and structured format that enhances data management and retrieval efficiency.

Cluster Tables : Each cluster is designated its own table, making it straightforward to manage and query keywords associated with a specific cluster. The design of these tables allows for an organized approach where each table corresponds to a unique cluster, encapsulating all keywords that are relevant to that cluster within a singular, coherent dataset.

Keywords Storage : The keywords stored in each cluster table are carefully curated to represent the core topics and concepts associated with the cluster. This design ensures that the keywords are not only related but also contribute to a comprehensive understanding of the cluster's theme or subject matter.

Benefits of Separate Tables for Clusters : By using separate tables for each cluster, the database maintains a high level of organization and avoids the complexity that might arise from storing all keywords in a single table. This separation facilitates easier updates, queries, and maintenance operations. Additionally, it enhances performance by reducing the size of individual tables, which can be queried more efficiently than a massive, monolithic table.

This database design follows a modular and scalable approach, where each cluster's table is autonomous and focused, allowing for the easy addition of new clusters and their corresponding tables without disrupting the existing structure. This flexibility is crucial for growing datasets and evolving keyword clusters over time.

In summary, the database's architecture, with separate tables for each cluster, not only enhances clarity and manageability but also optimizes performance and scalability, making it a robust solution for storing and managing keyword clusters.

For instance, if there is a cluster dedicated to "Bollywood Hungama Cinema," a corresponding table named "Cluster Bollywood Hungama Cinema" will be created. This table would then store all keywords pertinent to Bollywood Hungama Cinema, such as "Planet Bollywood," "Bollywood Hit Beats," "Bollywood Saga," and so on.

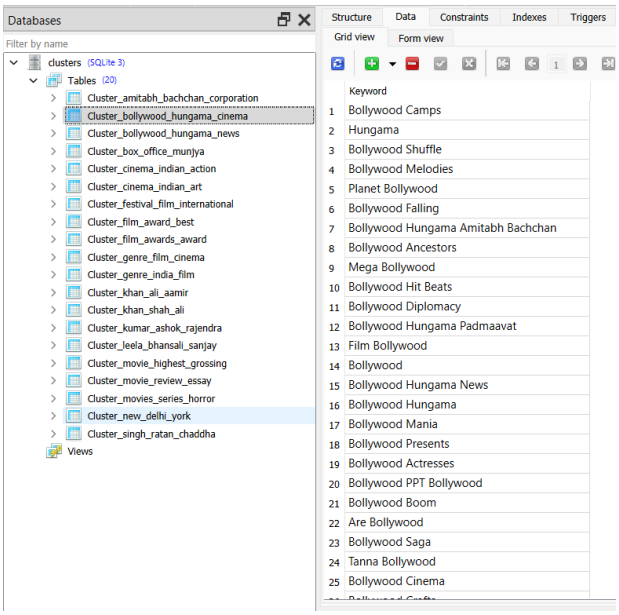


Figure 3.3: Table storing keywords related to Cluster 1

Database 2:

This database serves as a comprehensive repository for storing essential information about keywords, encompassing their respective Wikipedia URLs (Wiki URL), Google search re-

sult URLs (Google URL), and a synthesized measure of their relevance encapsulated in the Combined Score attribute.

Ranked URLs Table Details

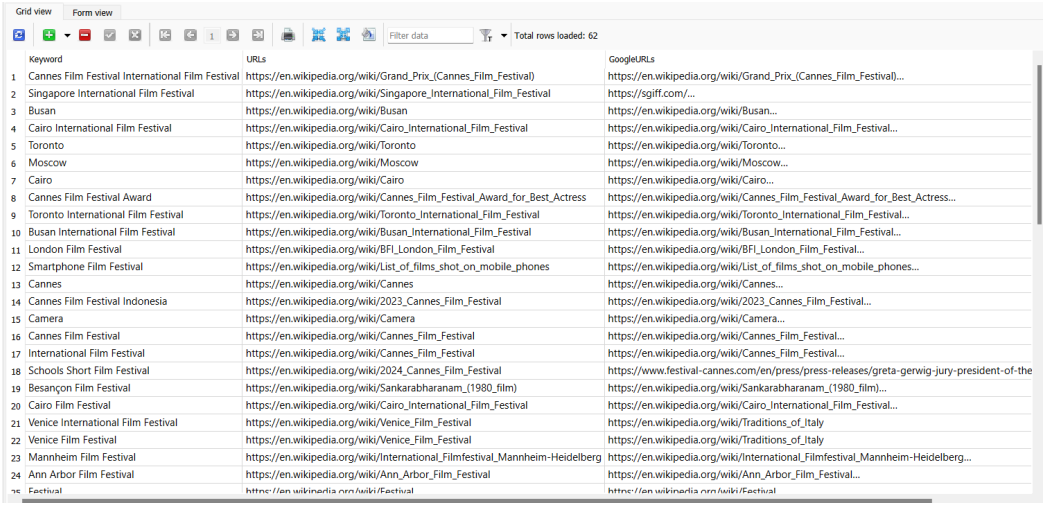
The Ranked URLs table plays a pivotal role in organizing and managing metadata linked to each keyword. This structured approach facilitates efficient data retrieval and supports analytical processes critical for applications such as information retrieval systems and data analytics tools.

Table Structure

The Ranked URLs table is meticulously designed with the following fields:

- keyword (VARCHAR): Represents the specific keyword or term of interest.
- Wiki URL (VARCHAR): Stores the URL leading directly to the corresponding Wikipedia page associated with the keyword.
- Google URL (VARCHAR): Contains the URL pointing to the top Google search result relevant to the keyword.
- Combined Score (FLOAT): Represents a consolidated score that integrates multiple criteria to assess the importance and relevance of the keyword within its context.

Purpose and Utility : Each row in the Ranked URLs table is dedicated to a specific keyword, enabling straightforward retrieval and management of associated URLs and scores.The Combined Score amalgamates diverse metrics (e.g., relevance, popularity) to provide a holistic measure of the keyword's significance, facilitating informed decision-making and analysis.



Grid view | Form view

Filter data | Total rows loaded: 62

	Keyword	URLs	GoogleURLs
1	Cannes Film Festival International Film Festival	https://en.wikipedia.org/wiki/Grand_Prix_(Cannes_Film_Festival)	https://en.wikipedia.org/wiki/Grand_Prix_(Cannes_Film_Festival)...
2	Singapore International Film Festival	https://en.wikipedia.org/wiki/Singapore_International_Film_Festival	https://sgiff.com/...
3	Busan	https://en.wikipedia.org/wiki/Busan	https://en.wikipedia.org/wiki/Busan...
4	Cairo International Film Festival	https://en.wikipedia.org/wiki/Cairo_International_Film_Festival	https://en.wikipedia.org/wiki/Cairo_International_Film_Festival...
5	Toronto	https://en.wikipedia.org/wiki/Toronto	https://en.wikipedia.org/wiki/Toronto...
6	Moscow	https://en.wikipedia.org/wiki/Moscow	https://en.wikipedia.org/wiki/Moscow...
7	Cairo	https://en.wikipedia.org/wiki/Cairo	https://en.wikipedia.org/wiki/Cairo...
8	Cannes Film Festival Award	https://en.wikipedia.org/wiki/Cannes_Film_Festival_Award_for_Best_Actress	https://en.wikipedia.org/wiki/Cannes_Film_Festival_Award_for_Best_Actress...
9	Toronto International Film Festival	https://en.wikipedia.org/wiki/Toronto_International_Film_Festival	https://en.wikipedia.org/wiki/Toronto_International_Film_Festival...
10	Busan International Film Festival	https://en.wikipedia.org/wiki/Busan_International_Film_Festival	https://en.wikipedia.org/wiki/Busan_International_Film_Festival...
11	London Film Festival	https://en.wikipedia.org/wiki/BFI_London_Film_Festival	https://en.wikipedia.org/wiki/BFI_London_Film_Festival...
12	Smartphone Film Festival	https://en.wikipedia.org/wiki/List_of_films_shot_on_mobile_phones	https://en.wikipedia.org/wiki/List_of_films_shot_on_mobile_phones...
13	Cannes	https://en.wikipedia.org/wiki/Cannes	https://en.wikipedia.org/wiki/Cannes...
14	Cannes Film Festival Indonesia	https://en.wikipedia.org/wiki/2023_Cannes_Film_Festival	https://en.wikipedia.org/wiki/2023_Cannes_Film_Festival...
15	Camera	https://en.wikipedia.org/wiki/Camera	https://en.wikipedia.org/wiki/Camera...
16	Cannes Film Festival	https://en.wikipedia.org/wiki/Cannes_Film_Festival	https://en.wikipedia.org/wiki/Cannes_Film_Festival...
17	International Film Festival	https://en.wikipedia.org/wiki/Cannes_Film_Festival	https://en.wikipedia.org/wiki/Cannes_Film_Festival...
18	Schools Short Film Festival	https://en.wikipedia.org/wiki/2024_Cannes_Film_Festival	https://www.festival-cannes.com/en/press/press-releases/greta-gerwig-jury-president-of-the
19	Besançon Film Festival	https://en.wikipedia.org/wiki/Sankarabharanam_(1980_film)	https://en.wikipedia.org/wiki/Sankarabharanam_(1980_film)...
20	Cairo Film Festival	https://en.wikipedia.org/wiki/Cairo_International_Film_Festival	https://en.wikipedia.org/wiki/Cairo_International_Film_Festival...
21	Venice International Film Festival	https://en.wikipedia.org/wiki/Venice_Film_Festival	https://en.wikipedia.org/wiki/Traditions_of_Italy
22	Venice Film Festival	https://en.wikipedia.org/wiki/Venice_Film_Festival	https://en.wikipedia.org/wiki/Traditions_of_Italy
23	Mannheim Film Festival	https://en.wikipedia.org/wiki/International_Filmfestival_Mannheim-Heidelberg	https://en.wikipedia.org/wiki/International_Filmfestival_Mannheim-Heidelberg...
24	Ann Arbor Film Festival	https://en.wikipedia.org/wiki/Ann_Arbor_Film_Festival	https://en.wikipedia.org/wiki/Ann_Arbor_Film_Festival...
25	Festival	https://en.wikipedia.org/wiki/Festival	https://en.wikipedia.org/wiki/Festival

Figure 3.4: Table storing ranked URLs and associated metadata for each keyword.

For instance, a keyword such as "Cannes Film Festival Indonesia" would have its corresponding Wiki URL pointing to https://en.wikipedia.org/wiki/2023-Cannes-Film-Festival

and its primary Google URL pointing to https://www.festival-cannes.com/en/press/press-releases/the-76th-festival-de-cannes-winners-list/". The Combined Score would reflect the synthesized assessment of its importance based on criteria like relevance, popularity, and contextual significance.

3.2.2 Data Structure Design for Recommendation Module

Product Dictionary

The product dictionary serves as a fundamental data structure that stores detailed information about each product in the dataset. Each product is represented by a unique product ID, which acts as the key in the dictionary. The value associated with each key is another dictionary containing various attributes of the product, such as product name, category, rating, rating count, and a brief description.The product dictionary is constructed by iterating over the dataset and extracting the relevant attributes for each product.

```
# We Create a dictionary for each product
        product_details = {
            'product_id': row['parent_asin'],
            'product_name': row['title'],
            'category': row['main_category'],
            'rating': average_rating,
            'rating_count': rating_number,
            'about_product': row['description'],
            'bought_together': row['bought_together']
        }
 # We use parent_asin as the key for the products dictionary
 products_dict[row['parent_asin']] = product_details
```

Figure 3.5: Product Dictionary

Grid Data Structure

The grid data structure used in this project is designed as a 2D array where each cell represents a product. The grid supports efficient traversal using the A* search algorithm, enabling rapid identification of optimal paths for product recommendations. By organizing products in this manner, the structure facilitates easy access and manipulation of product data.

Figure 3.6: Product Grid

Chapter 4

IMPLEMENTATION

4.1 Domain Specific Keyword-Centric Crawler

4.1.1 Algorithm of Crawler Module

Algorithm – Domain-Specific Keyword-Centric Crawler

Step 1 : Prompt User for Topic
Prompt the user to specify the topic T and category C of interest.
Step 2 : Construct Wikipedia URL
Construct a Wikipedia URL : $URL \leftarrow https://en.wikipedia.org/wiki/+T$
Filter by category : $URL \leftarrow FilterByCategory(T,C)$
Compile top URLs: $Top\ URLs \leftarrow CompileTopURLs(Filtered\ URLs)$
Step 3 : Fetch, Parse, and Summarize Content
Fetch and Parse : $Content \leftarrow FetchAndParse(Top\ URLs)$
Generate Summary : $Summary \leftarrow GenerateSummary(Content)$
Step 4 : Fetch and Rank Google URLs
Construct query : $Google\ Query \leftarrow ConstructQuery(Summary)$
Fetch top URLs : $Google\ URLs \leftarrow FetchTopGoogleURLs(Google\ Query)$
Rank URLs : Ranked URLs $\leftarrow RankingAlgorithm(Google\ URLs)$
Step 5 : Tokenize, POS Tag, and NER
Tokenize Content : $Tokenized\ Content \leftarrow Tokenize\ (Content)$
Apply NER : Entities $\leftarrow NERModel(Tokenized\ Content)$
Step 6 : Keyword Aggregation and Clustering
Aggregate Keywords : $Keywords \leftarrow E\ UT$
Cluster Keywords : Clusters $\leftarrow Cluster(Keywords)$
Present clusters and analyze selected cluster : $Analyze(c_i)$
Step 7 : Store, Fetch, and Display URLs
Construct URLs for keywords : $URL_j \leftarrow https://en.wikipedia.org/wiki/+k_j$
Store URLs in database : $DB\ Insert : (URL_j\ , k_j)$
Fetch and parse content : $Content_j \leftarrow FetchAndParse(URL_j)$
Generate Summary : $Summary_j \leftarrow ExtractSummary(Content_j)$
Fetch and rank Google URLs: $Google\ Query_j \leftarrow ConstructQuery\ (Summary_j)$
Update database with ranked URLs : $DB\ Update: UpdateGoogleURLs(URL_j\ ,\ Ranked\ URLs_j)$
Display top URLs : Display :$PrintTopURLs\ (\ .\ Ranked\ URLs_j)$

Figure 4.1: Algorithm Design for Keyword-Centric Crawler

4.1.2 Keyword Extraction - NER Model

In our approach to keyword extraction, we leverage a Named Entity Recognition (NER) model as a powerful tool to enhance the precision and relevance of identified keywords. NER models are instrumental in automatically identifying and classifying entities within text, such as names of people, organizations, locations, dates, and other significant terms. By utilizing an NER model, we can systematically extract keywords that not only capture the core themes and entities within a given text corpus but also provide contextually relevant terms that may otherwise be overlooked. This process involves parsing through textual data, applying sophisticated algorithms to detect and categorize entities, and subsequently aggregating these recognized terms into a comprehensive list of keywords. The application of NER ensures that our keyword extraction methodology is robust, efficient, and capable of adapting to varying domains and datasets, thereby enhancing the effectiveness of downstream tasks such as information retrieval, content analysis, and data categorization.

4.1.3 Data Cleaning - Removal of Stop Words

In our keyword processing pipeline, we employ the NLTK (Natural Language Toolkit) library to effectively remove stopwords, a critical preprocessing step that refines the quality of our extracted keywords. Stopwords are common words in a language (e.g., "the", "is", "and") that often carry little semantic meaning and can skew the analysis if included. By leveraging NLTK's predefined list of stopwords for various languages, we systematically filter out these irrelevant terms from our keyword datasets. This cleansing process helps streamline subsequent text analysis tasks by focusing on meaningful content words that carry substantive information. After removing stopwords, the remaining keywords retain their contextual relevance and semantic significance, making them more suitable for applications such as text summarization, sentiment analysis, and information retrieval. This approach not only enhances the accuracy of our keyword extraction process but also optimizes the efficiency of downstream natural language processing (NLP) tasks, ensuring that our analyses are based on meaningful and actionable insights derived from cleaned and refined data.

4.1.4 Scores Normalization

To normalize scores for ranking results effectively, it's essential to ensure that each score across different metrics or features is on a comparable scale. This normalization process harmonizes disparate measurements, facilitating a fair and balanced evaluation of each item in the dataset. A common approach is to rescale scores to a common range, such as between 0 and 1, where 0 represents the lowest possible score and 1 signifies the highest. This normalization prevents any single metric from disproportionately influencing the final ranking. Techniques like min-max scaling or z-score normalization can be employed

based on the distribution of scores and the specific requirements of the ranking algorithm. By normalizing scores, we achieve a standardized basis for comparison, enabling robust decision-making and insightful analysis in applications ranging from search engine optimization to content recommendation systems.

4.2 Product Grid Placement and A* Search Recommendations

4.2.1 Algorithm of Reccomendation Module

Algorithm 1 Product Grid Placement and A* Search Recommendations

Step 1: Read data from the CSV file.
For each row in the CSV:
Create a dictionary called *product_details* with the product ID as the key
Step 2: Construct Grid
Calculate Grid Size:
$grid\_size \leftarrow \lceil \sqrt{\text{number\_of\_products}} \rceil$
Calculate Row Indices:
Concatenate encoded categories with features (e.g., ratings and logarithm of rating counts)
Normalize row indices
Calculate Column Indices:
Convert product descriptions into word vectors
Normalize column indices
Place Products in the Grid:
Sort product IDs by category
For each product, find an empty spot in the grid based on row and column indices
Step 3: A* Search Recommendations
Compute BERT Embeddings for product descriptions
Calculate Similarity between two products based on BERT embeddings of features
A* Search Algorithm:
Define a heuristic function combining grid distance and similarity scores
Find a path of recommendations from a start product to a destination product
Step 4: Visualization
Visualize the Grid and Recommendations:
Plot grid cells colored by product categories
Highlight recommended products and visualize the path found by the A* search algorithm

Figure 4.2: Product Grid Placement and A* Search Recommendations

4.2.2 Data Pre-Processing

In the data preprocessing module, datasets from various Amazon reviews categories are loaded using the Hugging Face datasets library. From each dataset, products are extracted and merged into a single DataFrame, which is then converted to a CSV file. This CSV is read into a DataFrame, where key fields such as product_id, product_name, category, rating, rating_count, and about_product are extracted. The rating_count is cleaned by removing commas and handling missing values, converting them to zero, and the rating field is converted to float, defaulting to 0.0 in case of errors. Normalization is applied: the rating_count is log-transformed to reduce skewness, and both rating and log-transformed rating_count are scaled to a [0, 1] range using MinMaxScaler, ensuring all features contribute equally in the analysis. Additionally, the category data is one-hot encoded for machine learning compatibility. The cleaned and normalized data is then structured into a dictionary of products, keyed by product_id, for further analysis and visualization.

4.2.3 Data Normalization

Normalization is a crucial pre-processing step that ensures consistency and comparability across various features of the product data. The 'rating_count' is first log-transformed using 'np.log1p' to handle its typically wide range and skewed distribution, making it more comparable across products by reducing skewness. Both the 'rating' and the log-transformed 'rating_count' are then normalized to a [0, 1] range using 'MinMaxScaler'. This scaling ensures that these features contribute equally when determining product placement in the grid, avoiding any single feature dominating due to its scale. Furthermore, categorical data like 'category' is one-hot encoded, converting it into a numerical format suitable for machine learning models. This combined normalization and encoding process ensures that the data is uniformly formatted and ready for the embedding-based similarity calculations that follow.

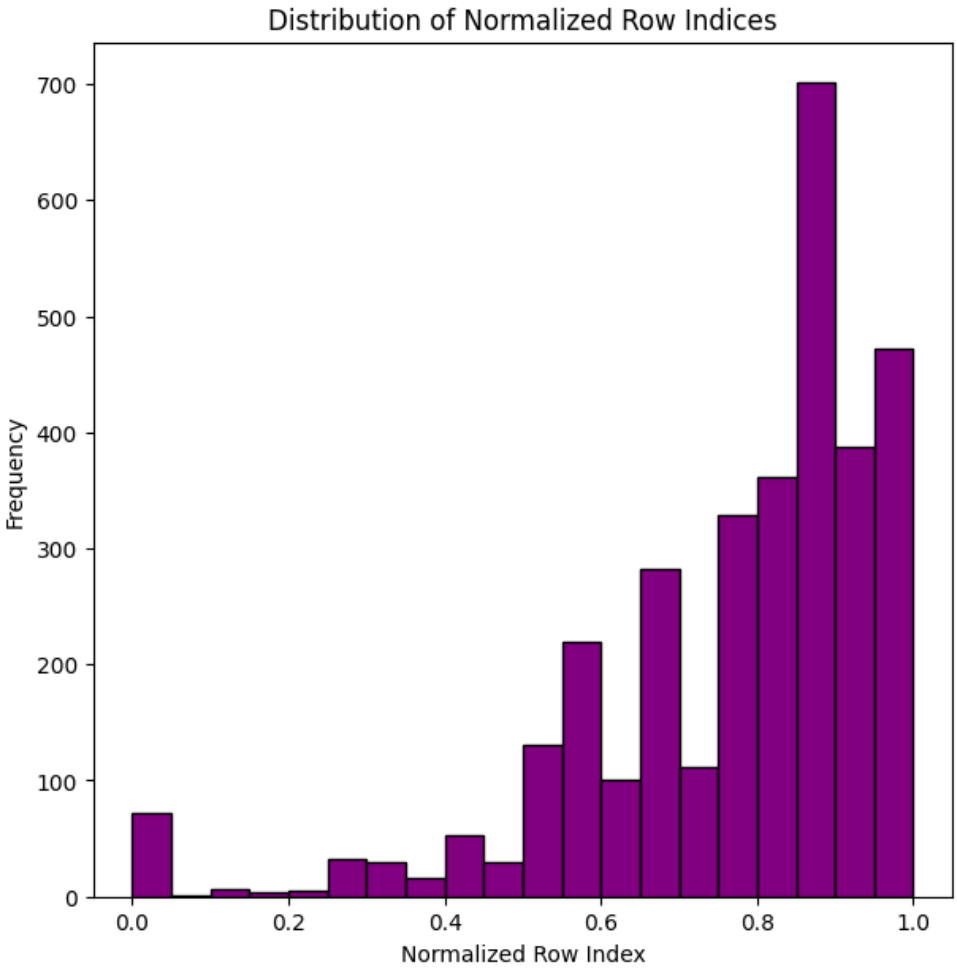


Figure 4.3: Distribution of Normalized Indices

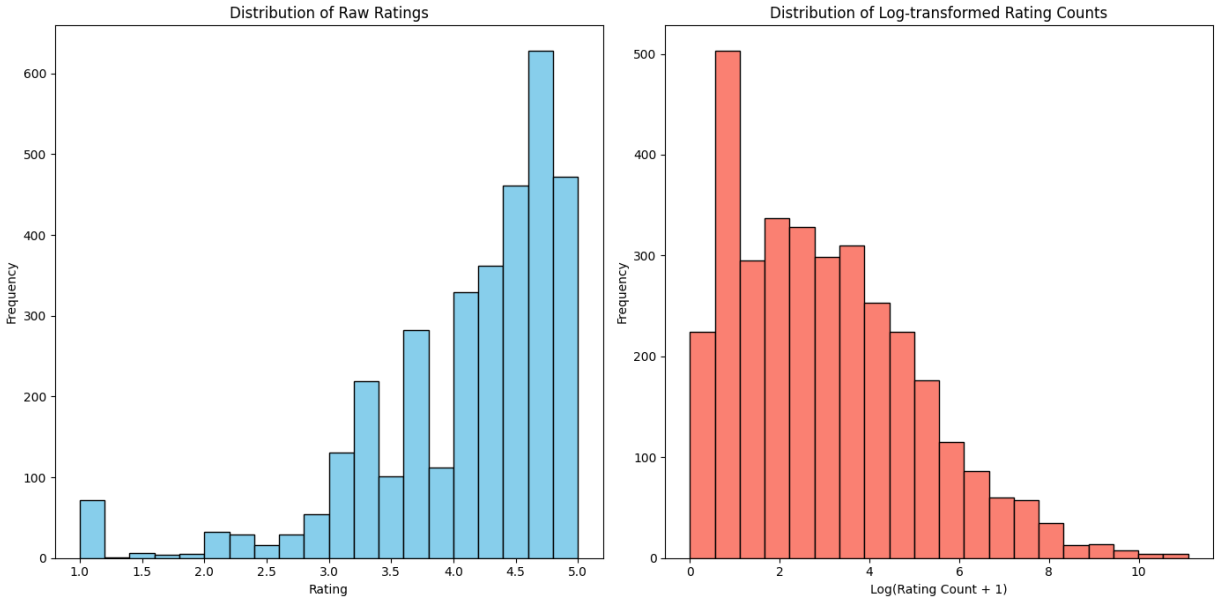


Figure 4.4: Distribution of Raw Ratings and Ratingn Counts

4.2.4 Product placement in the grid

The grid is constructed by employing hybrid filtering and Word2Vec embeddings to place products based on their similarity in both categorical and textual attributes. Initially, we preprocess the product data, extracting key attributes such as product ID, name, category, rating, rating count, and a descriptive text (about the product). Using one-hot encoding, we encode the product categories, and with MinMaxScaler, we normalize the ratings and logarithmically transformed rating counts to handle skewness. This results in a combined feature set that captures both categorical and numeric attributes. For the textual description, we utilize Word2Vec embeddings to capture semantic similarities, creating a dense vector representation of each product description. These embeddings are normalized and used to determine the column indices in the grid, while the combined category and rating features determine the row indices. Products are then placed into the grid based on these normalized indices, ensuring that similar products are positioned close to each other. If a grid cell is already occupied, we employ a simple collision resolution strategy by shifting to the next available cell. This placement method effectively clusters similar products together, making it easier to identify related items. The grid serves as the basis for our A* search algorithm, which navigates through the grid to recommend products based on their similarities.

4.2.5 A* search and Product recomendations

The model implements an A* search algorithm for recommending products based on their attributes and similarities. The algorithm takes into account the grid-based layout of products, where each product is placed at a specific row and column index based on its attributes. The goal is to find a path between a start product and a destination product, while recommending products along the way that are similar to those in the path.

The ‘a_star_search_recommendations‘ function is the core of the recommendation system. It uses a heuristic function to estimate the cost of reaching the destination from a given position, taking into account both the grid distance (Manhattan distance) and the product similarity using BERT embeddings. The function uses a priority queue to explore the grid cells efficiently, considering the cost of reaching each cell from the start. Once the destination is reached, the function reconstructs the path from the start to the destination, considering the products in each cell along the way.

The visualization part of the code uses matplotlib to plot the grid cells, highlighting the recommended products and the A* path. Each product is represented by a square marker colored according to its category. The recommended products are highlighted with circular markers, and the A* path is shown as a series of red lines connecting the products in the path. The legend provides a color key for the different product categories, making it easier to interpret the visualization. Overall, this code demonstrates how A* search can be used for efficient and context-aware product recommendations in a grid-based layout.

Chapter 5

RESULTS AND DISCUSSIONS

5.1 Domain Specific Keyword-Centric Crawler

The process starts by prompting the user to specify a topic and category.To follow a structured approach - First, when prompting the user, we capture their specified topic of interest and the category within which they want information. This input is crucial as it guides us in constructing relevant URLs for both Wikipedia and Google sources.

For Wikipedia URLs, upon receiving the user's topic and category preferences, we construct a specific Wikipedia URL tailored to their input. This URL acts as a seed URL, ensuring that the content extraction and analysis are focused on the user's specified area of interest. Additionally, we apply a category filter to this URL to ensure it falls within the desired scope, narrowing down the results to the most relevant articles. This step is essential for retrieving high-quality, topic-specific information directly from Wikipedia, which serves as a primary source for our content extraction.

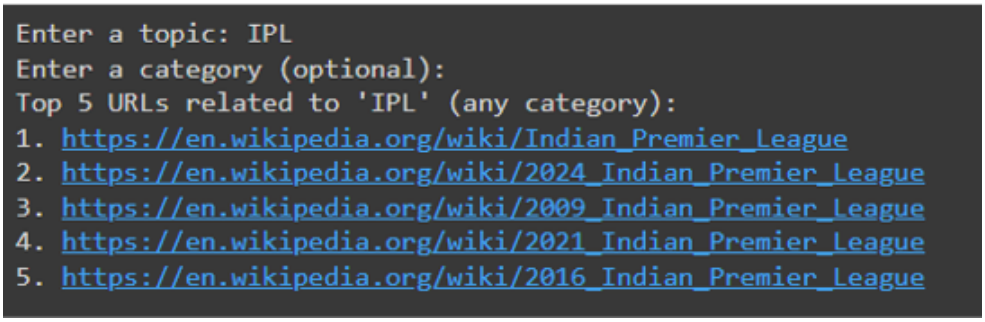


Figure 5.1: Extraction of Wikipedia Seed URLs

Simultaneously, for Google URLs, we utilize the same user-provided topic and category to conduct a search query. This query fetches the top URLs from Google search results related to the user's topic, thereby expanding our pool of data sources beyond Wikipedia. These URLs are gathered to complement the information obtained from Wikipedia, providing a broader perspective and ensuring comprehensive coverage of the chosen topic. By integrating both Wikipedia and Google URLs into our data collection process, we enhance the depth and diversity of information available for further analysis and summarization.

Continuing from the previous steps of fetching and summarizing content from Wikipedia and Google URLs, the next stage involves tokenization and Part-of-Speech (POS) tagging

Figure 5.2: Extraction of GoogleURLs for broader perspective

of the extracted text. Tokenization breaks down the text into individual words or tokens, while POS tagging assigns grammatical labels such as nouns, verbs, and adjectives to each token. This preprocessing step prepares the text for deeper linguistic analysis and facilitates the identification of key elements within the content.

Following tokenization and POS tagging, we integrate a Named Entity Recognition (NER) model into our pipeline. This advanced natural language processing technique identifies and classifies named entities within the text, including names of people, organizations, locations, dates, and more. By leveraging NER, we extract specific entities of interest, enriching our understanding of the information retrieved from Wikipedia and Google sources. This comprehensive approach ensures that we not only summarize content effectively but also identify and categorize crucial entities relevant to the user's topic of interest, enhancing the depth and usability of the extracted information.

Figure 5.3: Keyword Extraction using NER Model

The identified entities and significant terms are aggregated to form a comprehensive list of keywords. These keywords are then clustered based on their semantic similarity, organizing them into meaningful groups. The user selects the cluster they are most inter-

ested in, allowing for personalized content delivery and ensuring relevance to their specific interests. Each cluster represents a different aspect or subtopic related to the main keyword. By analyzing these clusters, users can gain a deeper understanding of various facets of their topic.

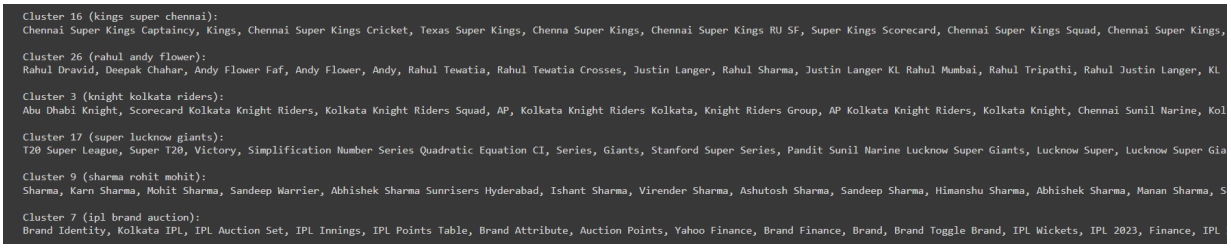


Figure 5.4: Keywords Clustering for personalized content delivery

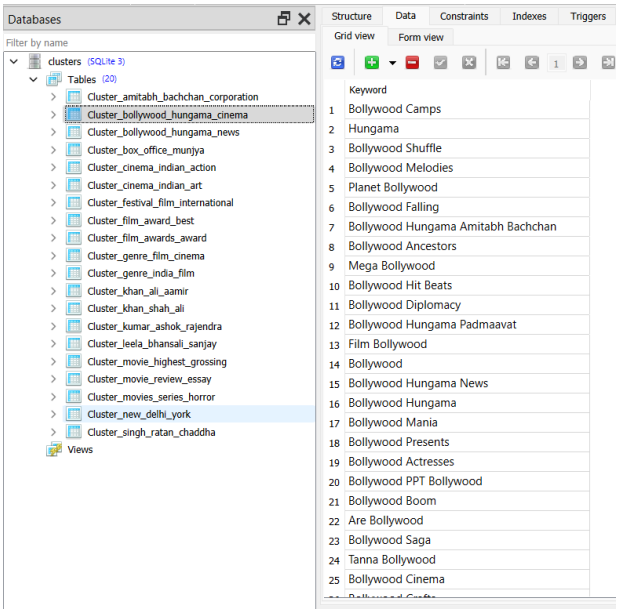
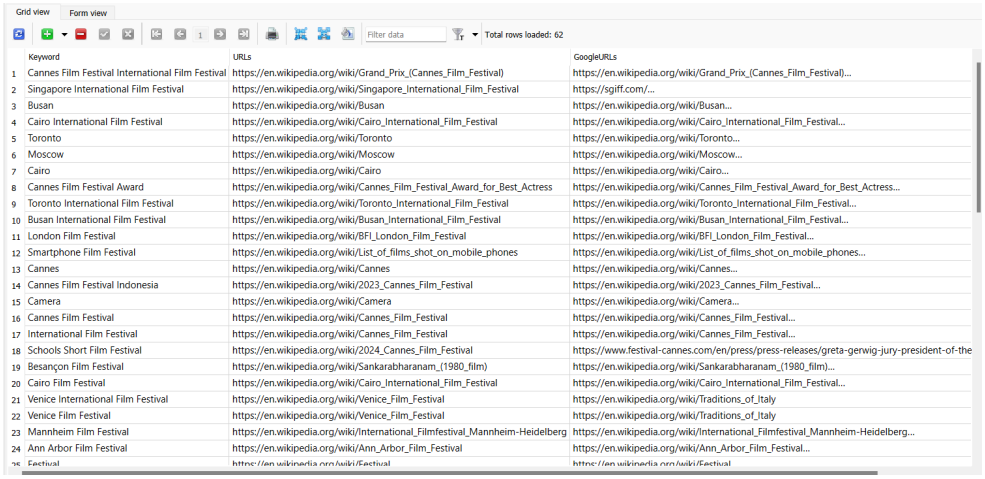


Figure 5.5: Clusters stored in SQ-Lite Database

The system then begins by allowing users to select clusters of keywords. For each keyword in the chosen cluster, specific Wikipedia URLs are constructed and stored in a SQLite database alongside their respective keywords. These URLs serve as primary sources of information. Next, the system retrieves content from these Wikipedia URLs, parses it using BeautifulSoup to extract text, and generates summaries by condensing the first three paragraphs of each page.

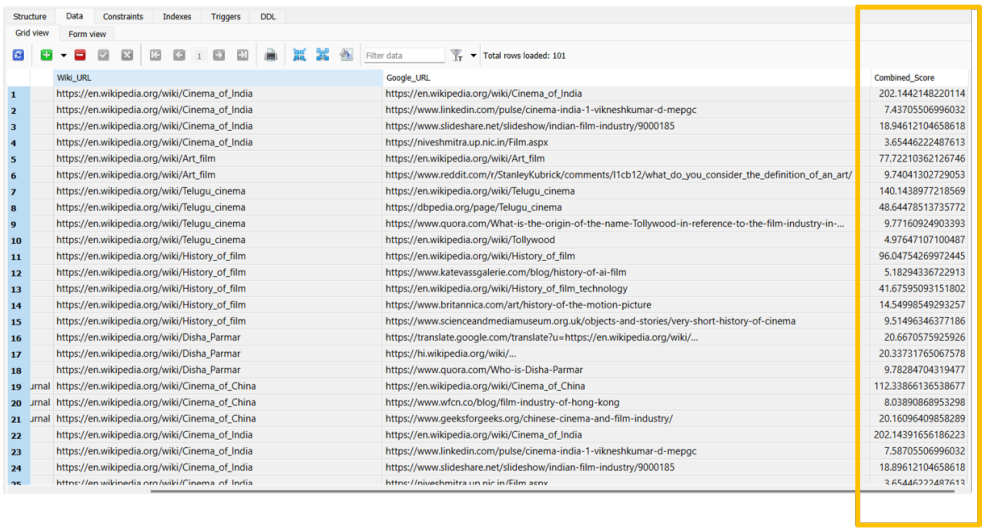
Additionally, summaries are used to query Google for further relevant URLs, with the top 5 results fetched and stored. This approach ensures comprehensive coverage of the chosen topics by leveraging both Wikipedia and Google sources effectively.



	Keyword	URLs	GoogleURLs
1	Cannes Film Festival International Film Festival	https://en.wikipedia.org/wiki/Grand_Prix_(Cannes_Film_Festival)	https://en.wikipedia.org/wiki/Grand_Prix_(Cannes_Film_Festival)...
2	Singapore International Film Festival	https://en.wikipedia.org/wiki/Singapore_International_Film_Festival	https://sgiff.com/...
3	Busan	https://en.wikipedia.org/wiki/Busan	https://en.wikipedia.org/wiki/Busan...
4	Cairo International Film Festival	https://en.wikipedia.org/wiki/Cairo_International_Film_Festival	https://en.wikipedia.org/wiki/Cairo_International_Film_Festival...
5	Toronto	https://en.wikipedia.org/wiki/Toronto	https://en.wikipedia.org/wiki/Toronto...
6	Moscow	https://en.wikipedia.org/wiki/Moscow	https://en.wikipedia.org/wiki/Moscow...
7	Cairo	https://en.wikipedia.org/wiki/Cairo	https://en.wikipedia.org/wiki/Cairo...
8	Cannes Film Festival Award	https://en.wikipedia.org/wiki/Cannes_Film_Festival_Award_for_Best_Actress	https://en.wikipedia.org/wiki/Cannes_Film_Festival_Award_for_Best_Actress...
9	Toronto International Film Festival	https://en.wikipedia.org/wiki/Toronto_International_Film_Festival	https://en.wikipedia.org/wiki/Toronto_International_Film_Festival...
10	Busan International Film Festival	https://en.wikipedia.org/wiki/Busan_International_Film_Festival	https://en.wikipedia.org/wiki/Busan_International_Film_Festival...
11	London Film Festival	https://en.wikipedia.org/wiki/BFI_London_Film_Festival	https://en.wikipedia.org/wiki/BFI_London_Film_Festival...
12	Smartphone Film Festival	https://en.wikipedia.org/wiki/List_of_films_shot_on_mobile_phones	https://en.wikipedia.org/wiki/List_of_films_shot_on_mobile_phones...
13	Cannes	https://en.wikipedia.org/wiki/Cannes	https://en.wikipedia.org/wiki/Cannes...
14	Cannes Film Festival Indonesia	https://en.wikipedia.org/wiki/2023_Cannes_Film_Festival	https://en.wikipedia.org/wiki/2023_Cannes_Film_Festival...
15	Camera	https://en.wikipedia.org/wiki/Camera	https://en.wikipedia.org/wiki/Camera...
16	Cannes Film Festival	https://en.wikipedia.org/wiki/Cannes_Film_Festival	https://en.wikipedia.org/wiki/Cannes_Film_Festival...
17	International Film Festival	https://en.wikipedia.org/wiki/Cannes_Film_Festival	https://en.wikipedia.org/wiki/Cannes_Film_Festival...
18	Schools Short Film Festival	https://en.wikipedia.org/wiki/2024_Cannes_Film_Festival	https://www.festival-cannes.com/en/press/press-releases/greta-gerwig-jury-president-of-the
19	Besançon Film Festival	https://en.wikipedia.org/wiki/Sankarabharanam_(1980_film)	https://en.wikipedia.org/wiki/Sankarabharanam_(1980_film)...
20	Cairo Film Festival	https://en.wikipedia.org/wiki/Cairo_International_Film_Festival	https://en.wikipedia.org/wiki/Cairo_International_Film_Festival...
21	Venice International Film Festival	https://en.wikipedia.org/wiki/Venice_Film_Festival	https://en.wikipedia.org/wiki/Traditions_of_Italy
22	Venice Film Festival	https://en.wikipedia.org/wiki/Venice_Film_Festival	https://en.wikipedia.org/wiki/Traditions_of_Italy
23	Mannheim Film Festival	https://en.wikipedia.org/wiki/International_Filmfestival_Mannheim-Heidelberg	https://en.wikipedia.org/wiki/International_Filmfestival_Mannheim-Heidelberg...
24	Ann Arbor Film Festival	https://en.wikipedia.org/wiki/Ann_Arbor_Film_Festival	https://en.wikipedia.org/wiki/Ann_Arbor_Film_Festival...

Figure 5.6: Wikipedia and Google URLs stored alongside keywords for a cluster

After fetching the top Google search results based on relevance, the script implements a custom ranking algorithm to further refine the order of URLs. This algorithm evaluates parameters such as recency score, sentiment score, similarity score, keyword density, and Named Entity Recognition (NER) score to prioritize the most pertinent results. Once ranked, the script updates its database with these URLs and presents the top-ranked URLs to the user via the console interface. This ensures that the user receives the most relevant and comprehensive information available from the web on their selected topic clusters.



	Wiki_URL	Google_URL	Combined_Score
1	https://en.wikipedia.org/wiki/Cinema_of_India	https://en.wikipedia.org/wiki/Cinema_of_India	202.1442148220114
2	https://en.wikipedia.org/wiki/Cinema_of_India	https://www.linkedin.com/pulse/cinema-india-1-vikneshkumar-d-mepgc	7.43705506996032
3	https://en.wikipedia.org/wiki/Cinema_of_India	https://www.slideshare.net/slideshow/indian-film-industry/9000185	18.94612104658618
4	https://en.wikipedia.org/wiki/Cinema_of_India	https://niveshmitra.up.nic.in/Film.aspx	3.65446222487613
5	https://en.wikipedia.org/wiki/Art_film	https://en.wikipedia.org/wiki/Art_film	77.72210362126746
6	https://en.wikipedia.org/wiki/Art_film	https://www.reddit.com/r/StanleyKubrick/comments/l1cb12/what_do_you_consider_the_definition_of_an_art/	9.74041302729053
7	https://en.wikipedia.org/wiki/Telugu_cinema	https://en.wikipedia.org/wiki/Telugu_cinema	140.1438977218569
8	https://en.wikipedia.org/wiki/Telugu_cinema	https://dbpedia.org/page/Telugu_cinema	48.64478513735772
9	https://en.wikipedia.org/wiki/Telugu_cinema	https://www.quora.com/What-is-the-origin-of-the-name-Tollywood-in-reference-to-the-film-industry-in-...	9.77160924903393
10	https://en.wikipedia.org/wiki/Telugu_cinema	https://en.wikipedia.org/wiki/Tollywood	4.97647107100487
11	https://en.wikipedia.org/wiki/History_of_film	https://en.wikipedia.org/wiki/History_of_film	96.04754269972445
12	https://en.wikipedia.org/wiki/History_of_film	https://www.katevassgalerie.com/blog/history-of-ai-film	5.18294336722913
13	https://en.wikipedia.org/wiki/History_of_film	https://en.wikipedia.org/wiki/History_of_film_technology	41.67595093151802
14	https://en.wikipedia.org/wiki/History_of_film	https://www.britannica.com/art/history-of-the-motion-picture	14.54998549293257
15	https://en.wikipedia.org/wiki/History_of_film	https://www.scienceandmediamuseum.org.uk/objects-and-stories/very-short-history-of-cinema	9.51496346377186
16	https://en.wikipedia.org/wiki/Disha_Parmar	https://translate.google.com/translate?u=https://en.wikipedia.org/wiki/...	20.6670575925926
17	https://en.wikipedia.org/wiki/Disha_Parmar	https://hi.wikipedia.org/wiki/...	20.33731765067578
18	https://en.wikipedia.org/wiki/Disha_Parmar	https://www.quora.com/Who-is-Disha-Parmar	9.78284704319477
19	https://en.wikipedia.org/wiki/Cinema_of_China	https://en.wikipedia.org/wiki/Cinema_of_China	112.33866136538677
20	https://en.wikipedia.org/wiki/Cinema_of_China	https://www.wfcn.co/blog/film-industry-of-hong-kong	8.03890868953298
21	https://en.wikipedia.org/wiki/Cinema_of_China	https://www.geeksforgeeks.org/chinese-cinema-and-film-industry/	20.16096409858289
22	https://en.wikipedia.org/wiki/Cinema_of_India	https://en.wikipedia.org/wiki/Cinema_of_India	202.14391656186223
23	https://en.wikipedia.org/wiki/Cinema_of_India	https://www.linkedin.com/pulse/cinema-india-1-vikneshkumar-d-mepgc	7.58705506996032
24	https://en.wikipedia.org/wiki/Cinema_of_India	https://www.slideshare.net/slideshow/indian-film-industry/9000185	18.89612104658618

Figure 5.7: Raking URLs based on Custom Ranking Algorithm

```
(mp2) C:\Users\Dell\Downloads>python top10_final.py
Top 10 URLs based on ranking:
Rank 1:
Keyword: Indian Cinema
Wikipedia URL: https://en.wikipedia.org/wiki/Cinema_of_India
Google URL: https://en.wikipedia.org/wiki/Cinema_of_India
Combined Score: 202.16058322852888

Rank 2:
Keyword: Indian Films
Wikipedia URL: https://en.wikipedia.org/wiki/Cinema_of_India
Google URL: https://en.wikipedia.org/wiki/Cinema_of_India
Combined Score: 202.1563081663914

Rank 3:
Keyword: Indian Popular Cinema
Wikipedia URL: https://en.wikipedia.org/wiki/Cinema_of_India
Google URL: https://en.wikipedia.org/wiki/Cinema_of_India
Combined Score: 202.14421482201l4

Rank 4:
Keyword: Popular Indian Cinema
Wikipedia URL: https://en.wikipedia.org/wiki/Cinema_of_India
Google URL: https://en.wikipedia.org/wiki/Cinema_of_India
Combined Score: 202.14421482201l4

Rank 5:
Keyword: Revolutionized Indian Cinema
```

Figure 5.8: Displaying Top-ranked URLs to User

5.2 Mapping Recommendations to A* search

The products are organized into a 2D grid where each cell represents a unique product. The rows and columns of the grid are structured based on the derived values from the dataset.

In our implementation, we have identified two types of product grids: one where similar categories are grouped together and another where categories are scattered randomly. For both grid types, we utilize product details including product ID, name, category, rating, rating count, description, and bought-together information. This data is read from a CSV file and stored in a dictionary with the product ID as the key.

For the category-grouped grid, we encode product categories and normalize their ratings and rating counts to calculate row indices. Word2Vec embeddings of product descriptions are used to compute column indices. Products are sorted by category and placed in the grid based on these indices, ensuring similar categories are placed together.

In the randomly scattered grid, we follow a similar process but shuffle product IDs before placing them in the grid. This results in a random distribution of products.

To recommend products, we initally applied an A* algorithm with a single-source traversal. The heuristic function combines grid distance and product similarity, encouraging recommendations that are both spatially close and similar in terms of content. We start the search from a given product's position, and explore its neighbors to generate a list of recommendations based on their similarity scores and heuristic values. This ensures that our recommendations are both relevant and efficiently found within the grid.

For calculating product similarity, we use BERT embeddings of product descriptions along with their ratings and rating counts. The BERT embeddings provide a nuanced understanding of product descriptions, while the ratings and rating counts add additional layers of similarity.In The final A* search, we consider both the starting product and the destination product to ensure the recommendations follow a meaningful path from the

source to the destination. The pathfinding algorithm adjusts based on the heuristic, which accounts for both the grid distance and the semantic similarity of the products, providing a balanced and effective recommendation system.

Figure 5.9: Visualization of the Product Grid Placement

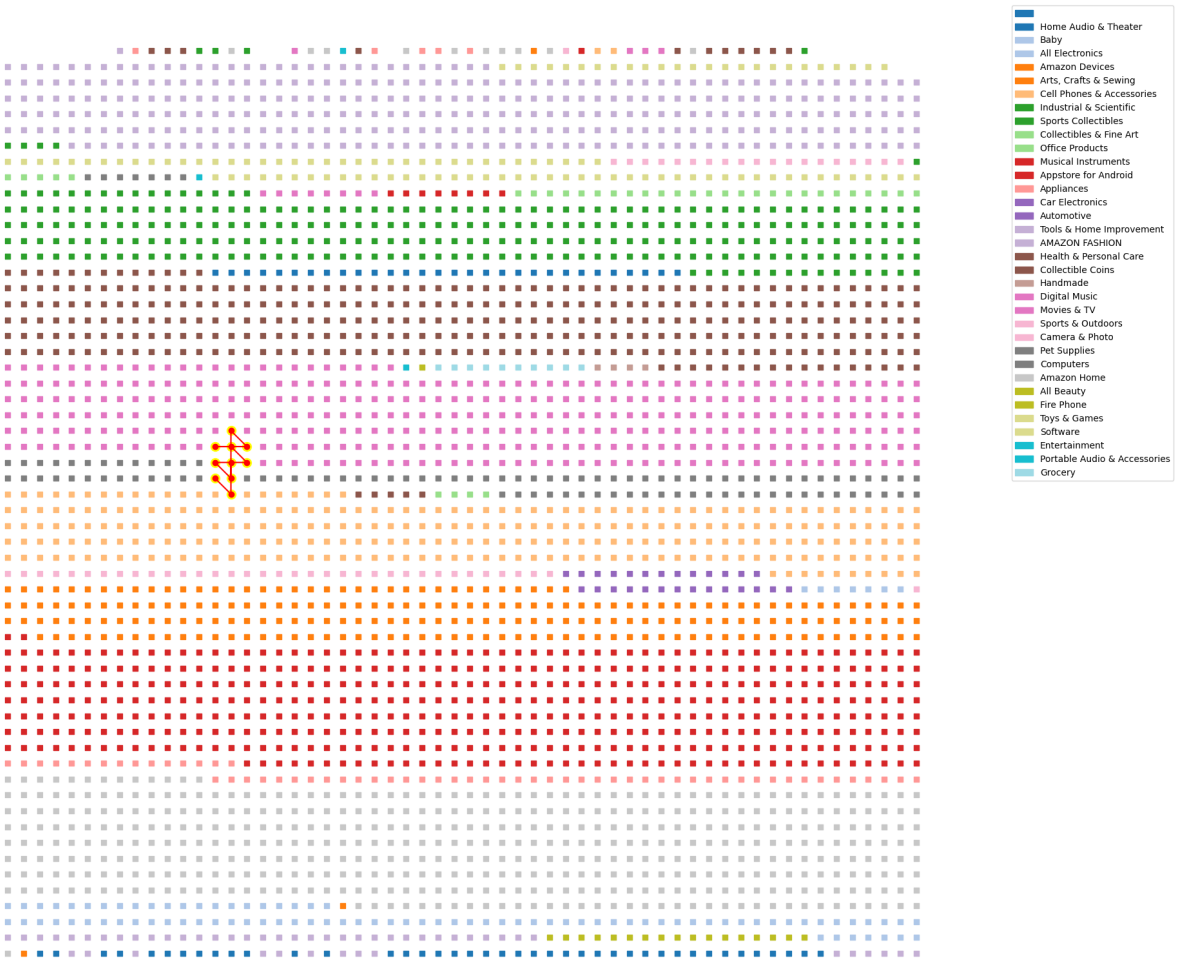


Figure 5.10: A* Algorithm with only source product given

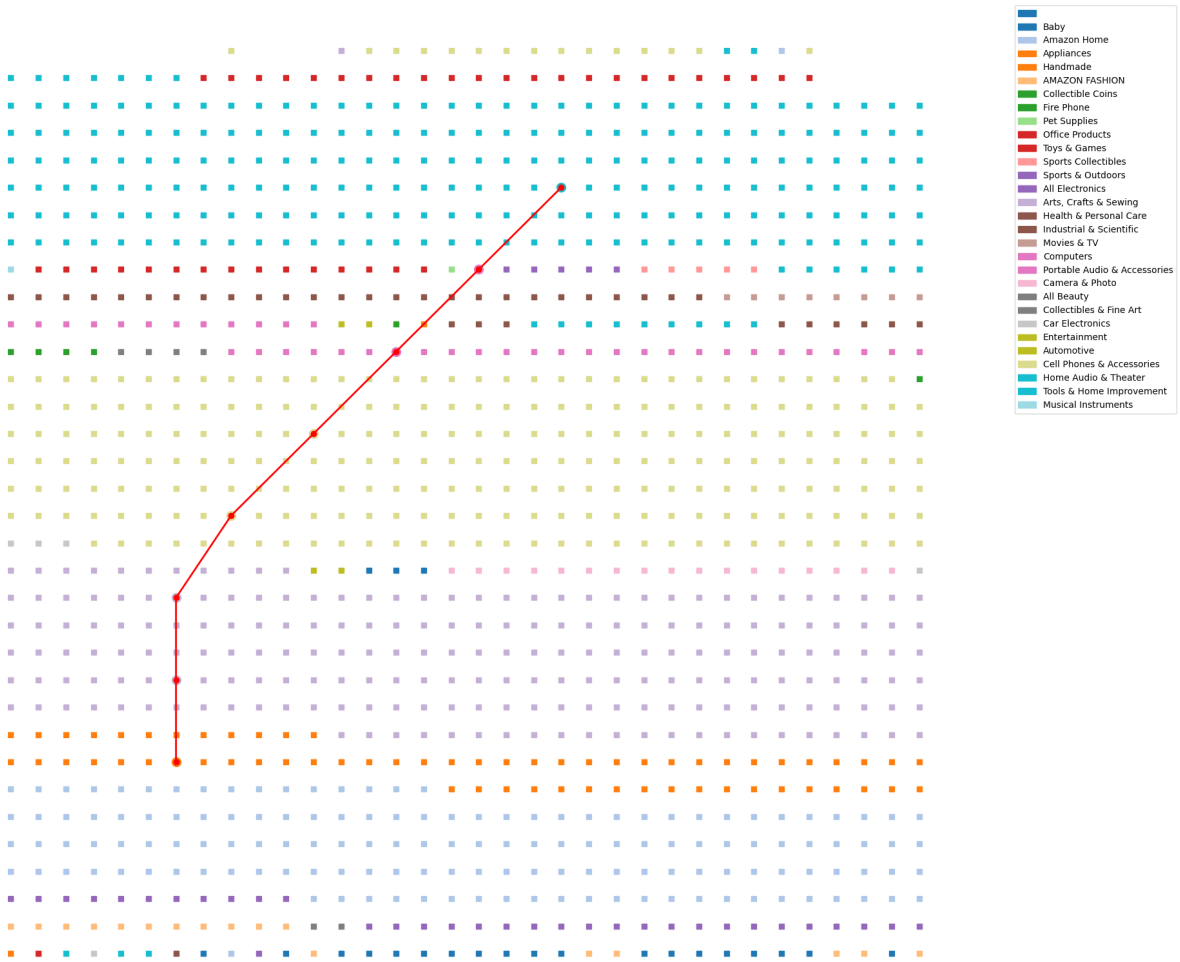


Figure 5.11: A* Algorithm with source and destination product ID's

The A* search traversal over a grid representation of products, showcases a diverse range of items recommended based on their attributes and similarities. The recommended products include items from various categories such as Sports and Outdoors, Digital Music, Amazon Home, Tools and Home Improvement, Industrial and Scientific, Computers, Appliances, Camera and Photo, Appstore for Android, and All Beauty. Each product is detailed with its ID, name, category, rating, rating count, and a description. This detailed presentation allows users to understand the attributes contributing to each recommendation. The traversal path highlights how the A* algorithm effectively navigates through the product attributes to identify the most relevant items.

1. Product ID: B09CQGV36R
   Product Name: Ushaker 2 Pack x 27 Oz Sublimation Blanks Shaker - Stainless Steel Protein Shakers with Shrink Wrap Sleeves for Heat Press Sport Water Bottles w/h White Polymer Coating Gym Cups Blank GB27-101
   Category: Sports & Outdoors
   Rating: 3.2
   Rating Count: 5
   Description: Ushaker 27oz 750ml Sublimation Protein Shaker Cups Blank will add colors and uniqueness to your sport and daily life. Realize your design ideas and create the best gift for your friends, family, colleagues, teammates and other athletes who like sports, fitness, running etc.

2. Product ID: B0007SMD1Y
   Product Name: Book of Invasions: A Celtic Symphony
   Category: Digital Music
   Rating: 4.7
   Rating Count: 68
   Description: Reissue of 1976 album from Irish folk/progressive rock band.

3. Product ID: B07MTRZ9WF
   Product Name: 3dRose Garden Flag, White
   Category: Amazon Home
   Rating: 1.0
   Rating Count: 1
   Description: Vintage Patchwork Pattern Distressed Style in Teal Turquoise And Pink Towel is great to use in the kitchen, bathroom or gym. This 15 by 22 inch, hand/sports towel allows you to customize your room with a special design or color. Great for drying dishes, hands and faces. Suitable to put in any sports bag. Image will not fade after washing. Machine wash, tumble dry low, do not bleach.

4. Product ID: B0B4FQ5P28
   Product Name: CPU&GPU Cooling Fan for Lenovo Yoga
   Category: Industrial & Scientific
   Rating: 5.0
   Rating Count: 2
   Description: Package include: 1x CPU&GPU Cooling Fan Comaptible with models: FOR Lenovo Yoga

5. Product ID: B00NGFW8L0
   Product Name: 100Pcs/lot ERASER CLEANER MELAMINE SPONGE CLEANING 10x6x2CM
   Category: All Beauty
   Rating: 4.5
   Rating Count: 5
   Description: 100% Brand New. Usage: Cleaning Feature: Eco-Friendly/ Stocked
   Package Content: 1x100pcs (100x60x20mm/1pcs) Sponge Eraser

Figure 5.12: List 1 of recommended products

```
1. Product ID: B07QFGZ2MF
   Product Name: Royale Best Game Battle New Action Adventure Run Game
   Category: Appstore for Android
   Rating: 3.5
   Rating Count: 0
   Description: Royale Best Game Battle New Action Adventure Run Game is a
   platform adventure gamewhere you run for the gold .In a jungle full with hidden
   dangers, beautifully crafted levels and hidden traps turn this side-running game to
   an epic objects adventure
2. Product ID: B00YD3IHUA
   Product Name: Replacement for Whirlpool GD5YHAXNL00 Refrigerator Water Filter -
   Compatible with Whirlpool 4396508, 4396510 Fridge Water Filter Cartridge
   Category: Amazon Home
   Rating: 5.0
   Rating Count: 2
   Description: This is a Denali Pure Brand replacement part, NOT an OEM product.
   All mentions of brand names or model descriptions are made strictly to illustrate compatibility.
   All brand names and logos are registered trademarks of their respective owners.
3. Product ID: B076QF5SQ4
   Product Name: NOWA Shaper Hybrid Smart Watch Waterproof Stainless Steel Sapphire Glass Activity
   Fitness Tracker (Steps, Distance, Calories, Sleep Quality) and Smartphone Notifications, Black
   Category: Cell Phones & Accessories
   Rating: 2.6
   Rating Count: 4
   Description: Designed for the modern traveler, the NOWA smart watch looks like a beautiful analog
   watch with a sleek and modern design. But it's also a powerful activity tracker with hidden
   smartwatch capabilities. The NOWA is a minimalist connected watch that gives you the exact time
   anywhere you go, keeps you motivated to move, and remarkably fits any styles.
4. Product ID: B00JGGF1M6
   Product Name: Traitonline Blue Stars Quicksand Shell, Protective Skin Case Cover for Samsung Note
   4 + 3 Screen Protector
   Category: Cell Phones & Accessories
   Rating: 3.0
   Rating Count: 2
   Description: This Case easy to install and take off.Easy to place inside a pocket, purse or
   briefcase or carry alone . Precise cut-outs for all controls, buttons and ports of your cell phone,
   you do not need to take it off when receive calls, charging or listen to music with the earphone plug
   in, ultra convenient!
5. Product ID: B09QD5JBKL
   Product Name: Bluetone Liquid Iron Supplement; Vegetarian Friendly Iron Supplement for Adults and Kids,
   Natural Iron in Mixed Fruit Flavor - 500 ml, 15 ml dose per Day, 33 doses
   Category: Health & Personal Care
   Rating: 4.0
   Rating Count: 3
   Description: Our liquid iron supplement is formulated to suit for adults. It is gentle on the stomach
   and does not cause digestive problems often associated with taking iron supplements. It is easily absorbed
   by the body. It supports healthy red blood cells function.
```

Figure 5.13: List 2 of recommended products

Through mapping products in the dataset to a grid and application of the A* search algorithm , we have successfully mapped a path of product recommendations, with the traversal from source product to the destination product. This path not only demonstrates the algorithm's capability to efficiently navigate through a complex grid of products but also highlights its effectiveness in providing relevant recommendations. The algorithm

showed a high degree of relevance in its traversal, connecting diverse categories through shared attributes and user preferences. The results suggest that this approach is scalable and could be further refined to accommodate larger datasets or more nuanced recommendation systems.

Chapter 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

The "Search Engine Anatomy – Crawler and Recommendations" project exemplifies the transformative impact of a domain-specific, keyword-centric crawler on search engine functionality and e-commerce recommendation systems. By meticulously targeting domain-relevant keywords, the crawler efficiently gathers and indexes precise, high-quality data, enhancing the search engine's ability to deliver highly relevant results and elevate user satisfaction.

Moreover, the project showcases innovation in e-commerce through advanced recommendation techniques. The implementation of a heuristic-based recommendation engine addresses significant challenges in navigating extensive product catalogs. Integrating grid-based representation, semantic similarity using Word2Vec embeddings, and the A* search algorithm optimizes the recommendation process. This comprehensive approach not only enhances the accuracy and relevance of product recommendations but also ensures scalability and performance, effectively meeting the evolving demands of modern e-commerce platforms.

6.2 Future Scope

Creating an interactive and user-friendly interface that integrates advanced NLP techniques for keyword extraction, content summarization, and user feedback is crucial for enhancing information retrieval systems. Future scopes include optimizing query input and improving keyword extraction methods, refining summarization techniques, and implementing a feedback mechanism for enhanced user interaction and satisfaction.

Looking ahead, the project offers numerous opportunities for enhancement and expansion. Developing real-time data processing capabilities would allow the system to dynamically adapt to user interactions and current trends, thereby enhancing the immediacy and relevance of recommendations. Additionally, expanding the system's reach to global markets through multilingual support, regional preferences, and cultural nuances can significantly increase inclusivity and effectiveness for diverse user bases.

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