AI KNOWLEDGE RETRIEVAL SYSTEM

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Abstract : This study has been undertaken to investigate the process of retrieving relevant information from large document collections using an AI-based Knowledge Retrieval System. The system utilizes advanced techniques including semantic embeddings, vector databases, and hybrid search methods to improve the accuracy of information retrieval. To implement the system, text data from documents such as PDFs and datasets is processed, and semantic embeddings are generated using transformer-based models.

IndexTerms **- Artificial Intelligence, Knowledge Retrieval, NLP, Semantic Search, FAISS, Information Retrieval.**

INTRODUCTION

In the modern digital era, a vast amount of information is stored in the form of documents such as research papers, reports, datasets, and online content. Retrieving relevant information from these large document collections efficiently has become a significant challenge for individuals and organizations. Traditional information retrieval systems primarily rely on keyword-based search techniques, which often fail to capture the actual meaning and context of user queries. As a result, users may receive irrelevant or incomplete results.

With the advancement of Artificial Intelligence (AI) and Natural Language Processing (NLP), more intelligent approaches have been developed to improve information retrieval systems. These technologies enable systems to understand the semantic meaning of text and provide more accurate and relevant results. Techniques such as semantic embeddings, vector databases, and hybrid retrieval methods have significantly enhanced the performance of modern search systems.

NEED OF THE STUDY.

The rapid growth of digital information in the form of documents such as research papers, reports, and datasets has created a significant challenge in retrieving relevant information efficiently. Traditional search systems mainly rely on keyword-based techniques, which often fail to understand the semantic meaning of user queries. As a result, users may receive irrelevant results or may not be able to locate important information hidden within large document collections. With the increasing volume of data, manual searching becomes time-consuming and inefficient. Users such as students, researchers, and professionals require intelligent systems that can quickly analyze large datasets and provide accurate results. The limitations of existing systems highlight the need for a more advanced solution that can understand context and meaning rather than relying solely on keyword matching.

3.1Population and Sample

In this study, the population consists of large document collections including research papers, reports, and structured datasets such as CSV and text files. These documents represent diverse domains and contain substantial textual information for analysis.

The sample for this study includes selected datasets and document files used to test the performance of the AI Knowledge Retrieval System. The documents are chosen based on relevance, size, and diversity to evaluate the system's ability to handle different types of data. A subset of these documents is processed and indexed to simulate real-world information retrieval scenarios.

3.2 Data and Sources of Data

For this study, both structured and unstructured data are used. The data includes text datasets, CSV files, and document-based content such as PDFs. These datasets are either publicly available or manually created for testing purposes.

The system processes the uploaded data by extracting textual content, cleaning it through preprocessing techniques, and converting it into machine-readable format. The processed data is then used to generate semantic embeddings.

The data collection and processing are carried out within the system environment, where the datasets are analyzed in real-time to retrieve relevant information based on user queries.

3.3 Theoretical framework

The theoretical framework of the study is based on Artificial Intelligence and Natural Language Processing techniques used for information retrieval. The system operates on the concept of converting textual data into semantic embeddings that capture the contextual meaning of the content.

RESEARCH METHODOLOGY

The methodology section outlines the plan and approach used to conduct the study. It includes the universe of the study, sample selection, data sources, and the theoretical framework used for information retrieval. The details are as follows;

3.1Population and Sample

n this study, the population consists of large collections of documents such as research papers, reports, PDFs, and structured datasets like CSV and text files. These documents represent various domains and contain significant textual information used for retrieval.

The sample for this study includes selected document datasets that are used to test and evaluate the AI Knowledge Retrieval System. These datasets are chosen based on relevance, diversity, and size to simulate real-world scenarios. A subset of these documents is processed and indexed to analyze the system's ability to retrieve accurate and meaningful information.

3.2 Data and Sources of Data

For this study, secondary data is used in the form of document files such as PDFs, CSV datasets, and text-based data. The data is either publicly available or manually prepared for testing purposes.

The system processes the uploaded documents by extracting textual content using preprocessing techniques. The extracted text is cleaned, structured, and divided into smaller meaningful chunks. These chunks are then converted into semantic embeddings using transformer-based models.

3.3 Theoretical framework

Variables of the study consist of input and output variables. The study uses a predefined method for the selection of variables. In this study, the user query is considered as the independent variable, while the retrieved relevant information from the document collection is treated as the dependent variable. The system processes textual data and retrieves information based on similarity between the query and document content.

Semantic embeddings are the primary independent component of the system, as they represent textual data in numerical vector form. These embeddings are generated using transformer-based models such as Sentence-BERT. The embeddings capture the contextual meaning of text, enabling the system to understand semantic relationships between queries and documents. It is assumed that higher similarity between query embeddings and document embeddings results in more accurate retrieval of relevant information.Vector similarity search is used as a core mechanism for retrieval. The FAISS (Facebook AI Similarity Search) vector database is used to store and search embeddings efficiently. It enables fast comparison between high-dimensional vectors and retrieves the closest matching results. The similarity score between vectors determines the relevance of retrieved documents, where higher similarity indicates stronger relevance.

Keyword-based retrieval techniques such as BM25 are also incorporated in the system. BM25 evaluates the relevance of documents based on term frequency and document length. It is assumed that keyword matching complements semantic search by improving precision in cases where exact term matching is required. The combination of semantic search and keyword-based search forms a hybrid retrieval model, which enhances overall system performance. The preprocessing of textual data plays an important role in the framework. Text cleaning, tokenization, and chunking are performed before generating embeddings. This ensures that the data is structured and meaningful for processing. The system assumes that better preprocessing leads to improved embedding quality and, consequently, better retrieval accuracy.

The system architecture acts as the operational framework, where documents are processed, embeddings are generated and stored, and queries are matched against stored data. The relationship between input (query) and output (retrieved information) is determined through similarity computation and ranking mechanisms.

Overall, the theoretical framework is based on Artificial Intelligence, Natural Language Processing, and Information Retrieval techniques. It assumes that combining semantic understanding with efficient search algorithms improves the accuracy, speed, and relevance of information retrieval compared to traditional keyword-based systems.

3.4 Statistical tools and models

This section explains the statistical and computational techniques used to analyze the performance of the AI Knowledge Retrieval System and derive meaningful conclusions from the data. The methodology focuses on evaluating retrieval accuracy, similarity measures, and system efficiency. The details are as follows.

3.4.1 Descriptive Statistics

Descriptive statistics are used to analyze the characteristics of the textual data and embedding vectors generated in the system. Measures such as mean, minimum, maximum, and standard deviation are used to understand the distribution and variation of embedding values and similarity scores. Additionally, evaluation metrics such as precision and relevance scoring are used to measure the accuracy of retrieved results. These metrics help determine how many of the retrieved results are actually relevant to the user query.

3.4.2 Retrieval Model and Similarity Computation

After descriptive analysis, the methodology proceeds to the implementation of the retrieval model in order to evaluate the performance of the AI Knowledge Retrieval System. The primary objective of the model is to determine how effectively the system retrieves relevant information based on the similarity between user queries and document content. The key question of interest is whether the semantic similarity between embeddings accurately represents the relevance of retrieved results. The study follows a two-stage retrieval process. In the first stage, documents are processed and converted into semantic embeddings using transformer-based models such as Sentence-BERT. These embeddings represent the contextual meaning of textual data in high-dimensional vector space. In the second stage, user queries are also converted into embeddings, and similarity is computed between query vectors and stored document vectors to retrieve the most relevant results.

The system performance is further evaluated using relevance-based metrics such as precision and ranking quality. These measures help in analyzing how accurately the system retrieves useful information and ranks it according to relevance.

The model assumes that higher similarity scores correspond to more relevant results and that combining semantic and keyword-based approaches improves overall system efficiency. This methodology ensures that the retrieval system is both accurate and scalable for large document collections.

3.4.2.1 Model for Semantic Retrieval (Vector Model)

The similarity between query and document embeddings is calculated using cosine similarity.

$$S(Q, D) = (Q \cdot D) / (||Q|| \times ||D||) \quad (3.1)$$

Where Q = Query embedding vector , D = Document embedding vector, S(Q, D) = Similarity score between query and document.

The similarity score is computed for all document embeddings stored in the vector database (FAISS). Based on this score, the top relevant documents are retrieved.

In the second stage, ranking is applied on the retrieved documents based on similarity scores:

$$R\_i = \alpha + \beta\, S(Q, D\_i) + \varepsilon \quad (3.2)$$

Where Ri = Relevance score of document i, S(Q, Di) = Similarity score, α = Intercept, β = Weight coefficient, Є is error term.

3.4.2.2 Model For Hybrid Retrieval

In the first stage, multiple relevance components are computed instead of regression-based betas. The system calculates semantic similarity and keyword-based relevance scores for each document. These components act as independent factors influencing the final retrieval score.

$$R\_i = w1\, S(Q, D\_i) + w2\, BM25(Q, D\_i) + w3\, TF(Q, D\_i) + w4\, IDF(D\_i) + \epsilon \quad (3.3)$$

Where Ri = Final relevance score of document I, S(Q, Di) = Semantic similarity score, IDF(Di) = Inverse document frequency ϵ is the error term.

n the second stage, ranking is performed based on the combined relevance scores:

$$\bar{R} = \gamma 0 + \gamma 1\, S(Q, D) + \gamma 2\, BM25(Q, D) + \gamma 3\, TF(Q, D) + \gamma 4\, IDF(D) + \epsilon\_i \quad (3.4)$$

Where $\bar{R}$ = Average relevance score, γ0 = Intercept, γ1 to γ4 = Coefficients of different retrieval factors and ε_i is the error term.

3.4.3 Comparison of the Models

The next step of the study is to compare the retrieval models to evaluate which model performs better in terms of accuracy and relevance. The comparison is made between the **Semantic Retrieval Model** and the **Hybrid Retrieval Model**. The evaluation is based on performance metrics such as precision, relevance score, and ranking efficiency. These metrics help determine which model provides more accurate and meaningful results for user queries.

3.4.3.1 Model Comparison Equation

The Semantic Model can be considered a special case of the Hybrid Model, where only semantic similarity is used. However, both models differ in their approach, as the Hybrid Model incorporates multiple retrieval factors.

To compare these models, a combined evaluation equation is used:

$$R\_i = \alpha\, R\_Hybrid + (1 - \alpha)\, R\_Semantic + e\_i \quad (3.5)$$

Where Ri = Final relevance score of document i, RHybrid = Relevance score from Hybrid Model, RSemantic = Relevance score from Semantic Model and α measure the effectiveness of the models.

3.4.3.2 Posterior Odds Ratio

In information retrieval systems, it is generally assumed that relevance scores and similarity measures follow a consistent distribution across different queries and datasets. Under this assumption, it is possible to compare different retrieval models based on their error measures and performance consistency.

Given that the residual errors between predicted relevance scores and actual relevant results follow an independent and identically distributed (IID) assumption, a comparative evaluation between the **Semantic Retrieval Model** and the **Hybrid Retrieval Model** can be performed. The posterior odds ratio provides a formal statistical approach to compare the effectiveness of two competing models.

The posterior odds ratio is used to evaluate which model better fits the observed data based on error measures. The formula is adapted as follows:

$$R = [ESS\_S / ESS\_H]\text{^}(N/2) \times N\text{^}((K\_S - K\_H)/2) \quad (3.6)$$

Where ESSS = Error Sum of Squares of Semantic Model, ESSH = Error Sum of Squares of Hybrid Model, N = Number of queries/observations, KS = Number of parameters in Semantic Model, KH = Number of parameters in Hybrid Model.

IV. RESULTS AND DISCUSSION

4.1 Performance Analysis of AI Knowledge Retrieval System

Table 4.1: System Performance Metrics

Variable	Minimum	Maximum	Mean	Std. Deviation
Query Response Time (sec)	0.8	2.5	1.6	0.5
Retrieval Accuracy (%)	78	95	88.5	5.2
Precision (%)	75	93	86.2	4.8
Recall (%)	70	90	82.4	6.1
F1-Score (%)	72	91	84.1	5.0

Table 4.1 presents the performance evaluation of the AI Knowledge Retrieval System based on different metrics such as response time, retrieval accuracy, precision, recall, and F1-score.

The average query response time of the system is **1.6 seconds**, indicating that the system provides fast results within an acceptable time range. The retrieval accuracy has a mean value of **88.5%**, which shows that the system is able to correctly identify relevant information for most user queries.

Precision and recall values are **86.2%** and **82.4%**, respectively. This indicates that the system retrieves relevant results with good accuracy while maintaining a balance between correctness and completeness. The F1-score, which is the harmonic mean of precision and recall, is **84.1%**, demonstrating overall effective performance.

The standard deviation values indicate that the system performance is consistent with moderate variation across different queries. The results show that the system performs efficiently in retrieving relevant information from datasets.

Table 1 Table Type Styles

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