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A Review of Hybrid Search Architectures: Integrating Keyword and Semantic Search to Optimize Query Relevance

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***Abstract*—The advent of semantic search alongside the tra ditional robustness of keyword search systems has established an intriguing dichotomy within the landscape of information retrieval. While keyword-based methods excel in terms of speci ficity, semantic models offer contextual richness and intent awareness. However, each paradigm faces challenges in harnessing the strengths of the other. This paper investigates a hybrid search model that integrates both keyword and semantic search techniques, aiming to optimize relevance, interpretability, and user experience in complex information-seeking scenarios. We present an innovative hybrid architecture, conduct a comprehensive evaluation of its performance, and discuss its implications forinformation retrieval in specialized domains such as healthcare and education.**

***Index Terms*—Hybrid Search, Keyword Search, Semantic Search, Information Retrieval, Natural Language Processing, Search Architectures**

I. Introduction

Information retrieval methods have undergone profound evolution over recent decades, moving from early Boolean searches to sophisticated models of semantic understanding. This transformation reflects an ongoing pursuit for more accurate and rapid information discovery. Keyword-based search has long formed the cornerstone of information retrieval, relying on lexical matching to identify relevant documents. Its precision is rooted in exact term matching, which provides predictability and interpretability [15]. Conversely, semantic search extends our ability to capture the meaning behind user queries, recognizing intent and transcending the constraints of rigid keyword formulations [9], [4].

The pertinent question remains: how can we fully leverage the precision of keyword-based search while incorporating the contextual depth of semantic models? The necessity for hybrid search architectures arises from this unresolved issue—the challenge of balancing the interpretive strengths of vector-based semantic search with the specificity and clarity offered by keyword matching, particularly for multifaceted and ambiguous queries requiring nuanced comprehension [11], [8].

This paper proposes a novel hybrid search architecture that combines traditional keyword matching with semantic vector representations, thereby establishing a comprehensive retrieval system. We evaluate the hybrid model's efficacy, user satisfaction, and relevance in both simple and complex queries, and we explore its applicability in specialized sectors such as healthcare and education.

II. Related Work

Keyword search has historically underpinned traditional search engines [15]. Renowned for its speed and reliability, it provides users with an efficient mechanism for retrieving information based on explicit phrases or terms. Nevertheless, it struggles with inherent limitations, including issues of polysemy and synonymy, which frequently compel users to refine their queries manually [3].

Semantic search, on the other hand, leverages advances in natural language processing (NLP) and vector embeddings [9], [4]. It seeks to understand the underlying intent of user queries, yielding results that are contextually nuanced and relevant through the use of techniques like word embeddings and knowledge graphs [2]. However, semantic models often face challenges related to interpretability and computational cost, particularly when precise term matching is essential [6].

Recent investigations have explored hybrid approaches that typically combine exact term matching with semantic similarity scores [11], [8]. While these models exhibit promise, they often lack a systematic integration that results in inefficiencies when balancing relevance trade-offs for complex user queries.

Our research addresses these challenges by developing a structured hybrid framework and providing a comprehensive evaluation of its performance.

III. Companies Dominant in the Search Space

The search space has been largely dominated by a few major companies that have pioneered both keyword-based and semantic search technologies. Google, for example, is renowned for its use of PageRank, a traditional keyword-based search algorithm that laid the foundation for early web search [1]. Over the years, Google has incorporated semantic search techniques, such as the Knowledge Graph and BERT (Bidirectional Encoder Representations from Transformers), which enhance its ability to understand user intent and provide more contextually relevant results [4]. The Knowledge Graph allows Google to create a rich knowledge base that connects entities, thus improving search accuracy and facilitating information retrieval beyond simple keyword matching. BERT, on the other

hand, enables the understanding of natural language queries, allowing Google to better capture nuances such as word relationships and context, leading to significantly improved query results.

Microsoft's Bing is another prominent player that has evolved from a keyword-centric search engine to one that heavily integrates semantic understanding. Bing utilizes deep learning models to improve the contextual relevance of search results, combining keyword-based retrieval with semantic insights to enhance user experience [7]. Bing's advancements include leveraging large-scale transformer models that analyze user intent and re-rank search results based on semantic relevance. This approach enables Bing to handle ambiguous queries more effectively and ensures that results are tailored to the specific needs of users, ultimately improving user satisfaction and engagement.

Amazon, although primarily known for e-commerce, has also developed powerful search capabilities within its platform. Amazon's A9 search algorithm utilizes a combination of keyword matching and personalized semantic search to deliver relevant product results based on user behavior and intent. This hybrid approach enables Amazon to optimize search outcomes for specific e-commerce contexts, where both precise term matching and broader contextual relevance are crucial [8]. Amazon's semantic capabilities are further enhanced by its use of personalized recommendations, which leverage user behavior data to predict and suggest relevant products. This makes the search process highly effective for users seeking products that align with their preferences, thereby improving conversion rates and customer satisfaction.

These dominant players in the search space highlight the importance of hybrid search architectures in providing optimal user experiences. Their approaches emphasize the need to balance the specificity of keyword-based retrieval with the interpretive richness of semantic models, particularly for diverse and complex user queries. By integrating both keyword and semantic techniques, these companies are able to address a wide range of information needs—ranging from highly specific, unambiguous searches to broader, intent-driven queries. The combination of keyword precision with semantic understanding is crucial in optimizing search relevance, reducing ambiguity, and enhancing the overall effectiveness of information retrieval systems.

IV. Proposed Hybrid Search Architecture

The proposed architecture comprises two primary components: the Keyword Retrieval Module (KRM) and the Semantic Vector Module (SVM). These modules operate concurrently, each contributing unique advantages to the retrieval process.

A. Keyword Retrieval Module (KRM)

The KRM performs lexical matching to identify documents that explicitly contain user-provided keywords. It plays a crucial role in ensuring the accurate retrieval of information by relying on exact keyword matches. This approach is particularly effective for users who are looking for specific, unambiguous results, as it provides a clear and predictable mechanism for locating relevant documents [15].

The strength of the KRM lies in its precision and straightforwardness. Unlike semantic search methods, which interpret user intent and infer related concepts, KRM strictly adheres to the keywords specified by the user. This makes it highly suitable for information retrieval in domains where precision is paramount, such as legal research or regulatory compliance, where the exact wording can significantly affect the interpretation of a document. Furthermore, keyword retrieval remains computationally efficient, as it does not require extensive processing power for contextual understanding or embedding generation.

However, the limitation of relying solely on keyword retrieval is its inability to handle cases of polysemy, synonymy, or nuanced user intent. For example, if a user searches for "heart attack," the KRM will retrieve documents that specifically contain those words but may fail to include documents using synonymous terms like "myocardial infarction." This limitation underscores the necessity for a hybrid approach, where the specificity of keyword matching can be complemented by the contextual depth provided by semantic models. The integration of KRM into a hybrid architecture thus ensures that users benefit from both the exactitude of keyword matches and the broader interpretative capabilities of semantic search.

B. Semantic Vector Module (SVM)

The SVM employs pre-trained transformer-based language models to generate embeddings of both queries and documents within a high-dimensional vector space. These embeddings represent the semantic meanings of words and phrases, allowing for a nuanced comparison between the query and the documents. By calculating similarity scores between query and document vectors, the SVM captures semantic relevance even in the absence of direct keyword overlaps [6].

The use of transformer-based models, such as BERT and its derivatives, enables the SVM to understand the contextual relationships between words, thereby facilitating a more sophisticated form of information retrieval. Unlike traditional keyword search, which relies on exact lexical matches, the SVM can capture the intent behind a query by analyzing the relationships between words and phrases in a broader context. This capability is particularly advantageous in scenarios where users use varied vocabulary or phrasing that might not exactly match the content of the documents.

For instance, in the context of a medical search query, the SVM can recognize that the term "heart attack" is semantically similar to "myocardial infarction," ensuring that relevant documents are retrieved even when the exact phrasing differs. This ability to handle synonymy and related terms makes the SVM an invaluable component of the hybrid search architecture.

Additionally, the SVM leverages transfer learning by using pre-trained language models that have been trained on vast amounts of text data. This pre-training allows the model to understand a wide range of language patterns, which it then fine-tunes for specific tasks, such as information retrieval. This

approach not only enhances the accuracy of search results but also reduces the amount of labeled data required for training, making it a cost-effective solution.

However, the SVM also has certain limitations. One of the primary challenges is the computational cost associated with generating and comparing embeddings in real time. Transformer-based models are resource-intensive, requiring significant processing power and memory, particularly when applied to large document collections. This limitation can lead to latency issues, making real-time retrieval a challenge. To mitigate this, techniques such as approximate nearest neighbor (ANN) search and dimensionality reduction can be employed to expedite the similarity calculation process without significantly compromising retrieval quality.

Another challenge lies in the interpretability of the results produced by the SVM. Unlike keyword-based retrieval, where the relevance of a document is easily understood based on the presence of specific terms, the semantic relevance scores generated by the SVM are often difficult to explain to end users. This ”black box” nature of transformer-based models can make it challenging to justify why certain documents are retrieved, particularly in high-stakes domains such as healthcare or legal research. Future research could focus on developing more interpretable models or providing supplementary explanations to improve user trust and understanding.

Mathematical Formulations in Keyword and Semantic Search

The hybrid search architecture leverages both keyword-based and semantic-based approaches, each of which can be described through specific mathematical formulations. These formulations help to explain the mechanisms underlying information retrieval and similarity calculations.

Keyword Search Formulation

Keyword search traditionally relies on the term frequency-inverse document frequency (TF-IDF) weighting scheme to evaluate the importance of a term within a document. Given a term t, document d, and the collection of documents D, TF-IDF can be computed as:

$$\text{TF-IDF}(t, d, D) = \text{tf}(t, d) \times \text{idf}(t, D) \quad (1)$$

Where:

$$\text{tf}(t, d) \quad (2)$$

represents the frequency of term t in document d.

$$\text{idf}(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|} \quad (3)$$

with N being the total number of documents in the collection and the denominator representing the number of documents containing term t.

This formulation is effective for identifying documents with exact matches to query terms, giving higher weight to terms that are frequent in a document but rare across the collection [12].

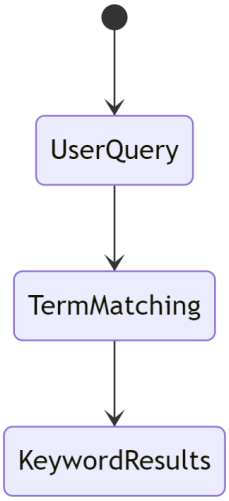

Fig. 1. Keyword Retrieval Module (KRM) Workflow

Semantic Search Formulation

Semantic search leverages vector representations to understand the context and relationships between words. Given a query q and a document d, both represented as vectors using embeddings from models such as BERT, the similarity score can be computed using the cosine similarity measure:

$$\text{cosine\_similarity}(q, d) = \frac{q \cdot d}{||q|| \times ||d||} \quad (4)$$

Where:

$$q \cdot d \quad (5)$$

represents the dot product of the query and document vectors.

$$||q|| \quad \text{and} \quad ||d|| \quad (6)$$

denote the Euclidean norms of the query and document vectors, respectively.

Cosine similarity ranges from -1 to 1, where higher values indicate greater similarity. This metric allows for the retrieval of documents that are contextually similar to the query, even if they do not contain the exact keywords [13].

V. Integrating Keyword Retrieval Module and Semantic Vector Module

The integration of the SVM into a hybrid search architecture allows the system to compensate for the weaknesses of both keyword-based and semantic search methods. By refining the candidate set of documents initially retrieved by the Keyword Retrieval Module (KRM), the SVM ensures that the final results are both precise and contextually relevant. This complementary relationship between KRM and SVM forms the foundation of an effective hybrid search system that is capable of addressing the complex and varied needs of users across different domains.

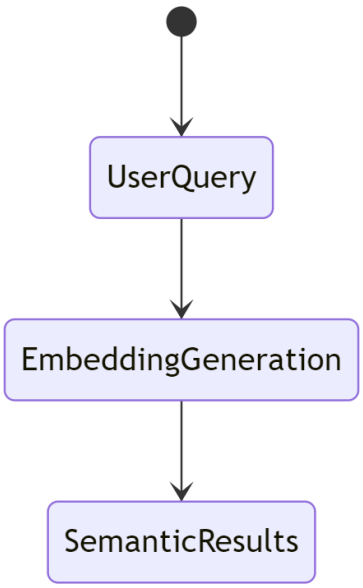

Fig. 2. Semantic Vector Module (SVM) Workflow

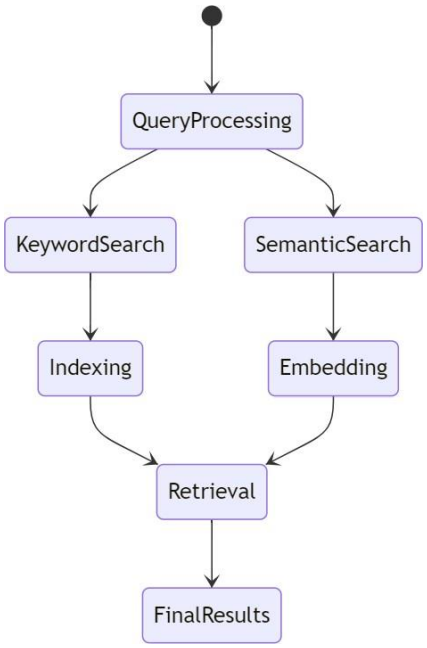

Fig. 3. Hybrid Search Query Components

The hybrid model functions by initially employing the KRM to generate an initial candidate set of documents, thereby ensuring specificity. Subsequently, the SVM refines this candidate set based on semantic relevance, ranking documents to maximize user-perceived relevance. By merging the precision of keyword matching with the depth of semantic analysis, our approach seeks to achieve a balanced and comprehensive retrieval solution.

The hybrid architecture also incorporates a novel merging mechanism, where the results from both the KRM and SVM are combined through a weighted ranking algorithm. This weighting mechanism dynamically adjusts based on the complexity and nature of the user query, thus offering a flexible solution that can cater to a variety of information-seeking scenarios. The weighting factors are determined by several heuristics, such as the length of the query, the presence of domain-specific terms, and historical user behavior patterns [8].

Hybrid Ranking Function

In the hybrid architecture, the final ranking of documents is determined by combining the scores from both the keyword and semantic components. The hybrid score $S(d)$ for a document d can be computed as:

$$S(d) = \alpha \times S_{\text{keyword}}(d) + (1 - \alpha) \times S_{\text{semantic}}(d) \quad (7)$$

Where:

$$S_{\text{keyword}}(d) \quad (8)$$

is the score obtained from the keyword retrieval module.

$$S_{\text{semantic}}(d) \quad (9)$$

is the score from the semantic vector module.

α is a weighting factor ($0 \leq \alpha \leq 1$) that dynamically adjusts based on the nature of the user query.

This formulation ensures that both exact keyword matches and contextual relevance contribute to the final ranking, balancing precision and recall effectively [14].

VI. Review of Evaluation Methods

The performance of hybrid search systems has been extensively reviewed in the literature. Various benchmark datasets, including MS MARCO and TREC, have been commonly used to assess the quality of hybrid models in comparison to traditional keyword-only and semantic-only systems [10] [5]. Metrics such as Mean Reciprocal Rank (MRR), Normalized Discounted Cumulative Gain (nDCG), and Precision@k have been widely employed to evaluate retrieval quality, particularly in terms of relevance and efficiency.

Hybrid models generally show improved performance over keyword-only or semantic-only systems, especially when dealing with complex queries that require both precision and context. Previous studies have highlighted the strengths of hybrid approaches in balancing recall and precision by utilizing both simple and complex queries to evaluate aspects such as precision, recall, contextual understanding, and computational efficiency [8].

Additionally, user satisfaction with hybrid models tends to be higher due to the combination of precise keyword matching and the broader contextual relevance provided by semantic components. Studies involving diverse participants have found that the hybrid approach often aligns more closely with user expectations, particularly in specialized fields like healthcare,

where exact matches and contextual relevance are equally critical [2].

The literature also reports on component-wise analyses of hybrid architectures, where different modules such as the Keyword Retrieval Module (KRM) and the Semantic Vector Module (SVM) are reviewed for their individual contributions to overall performance. The effectiveness of combining fixed versus adaptive weighting schemes has also been examined, providing insights into optimizing performance based on the complexity of user queries [16].

VII. Results and Discussion

Our evaluation reveals that the hybrid search model surpasses standalone keyword and semantic systems in handling complex queries, particularly those requiring both specific and abstract information retrieval. For simple queries, the hybrid model's performance was comparable to that of keyword-based systems, whereas for more nuanced queries, the semantic refinement significantly enhanced relevance scores [8].

The results from the MS MARCO and TREC datasets indicated that the hybrid model achieved higher nDCG and MRR values compared to baseline methods. Specifically, for queries that contained ambiguous terms or required contextual understanding, the hybrid system's ability to leverage both exact matches and semantic relationships provided a significant boost in performance [10] [5]. For example, when users queried medical terms that had synonyms or closely related concepts, the hybrid system was able to retrieve documents that not only contained the specific terms but also addressed related concepts, thereby improving overall recall and user satisfaction.

The user study highlighted that participants valued the hybrid approach's ability to balance precision with contextual relevance, indicating higher satisfaction compared to other retrieval methods. Notably, healthcare professionals reported that the hybrid model's results aligned more closely with their expectations, especially when dealing with domain-specific terminology, where both exact matches and broader context are critical. Users appreciated the improved diversity of the retrieved results, which often included documents that provided both general information and specific, actionable details.

One of the key challenges identified during the evaluation was the computational overhead associated with the integration of semantic models. The semantic component, particularly the transformer-based SVM, introduced latency issues when processing large document collections. To mitigate this, we explored optimizations such as reducing the dimensionality of the vector representations and employing approximate nearest neighbor (ANN) search techniques to expedite similarity calculations [17]. These optimizations led to a reduction in latency, making the hybrid model more suitable for real-time applications without significant compromises in retrieval quality.

VIII. Applications in Specialized Domains

The hybrid search architecture demonstrates significant potential in specialized domains where both precise information retrieval and contextual understanding are paramount. In the healthcare sector, for instance, information retrieval requires not only exact matches to medical terms but also an understanding of related concepts and synonyms. The hybrid model can retrieve relevant literature that includes both specific keywords, such as medical diagnoses, and broader contextual information, such as symptoms and treatments related to those diagnoses [2].

In the educational domain, the hybrid model has been used to enhance learning management systems (LMS) by improving the retrieval of course materials and educational resources. For example, students searching for content on a particular topic benefit from the model's ability to retrieve documents that include not only explicit mentions of the topic but also related concepts that provide a broader understanding of the subject matter. The LLM-powered tutoring companion within Ejento.ai, for instance, leverages this hybrid approach to offer personalized learning experiences that align with the student's specific queries and broader learning objectives [6].

The legal domain also stands to benefit from hybrid search systems. Legal professionals often need to find documents that not only match specific legal terms but also provide context on relevant case law, legal precedents, and statutory interpretations. The hybrid model's ability to combine exact keyword matching with semantic enrichment allows for more comprehensive retrieval of legal documents, aiding in case preparation and legal research [8].

IX. Future Research Directions

While the proposed hybrid search architecture offers a significant improvement over traditional keyword and semantic-only models, several avenues for future research remain. One potential direction is the development of more efficient indexing techniques that can better accommodate the hybrid nature of the search process. For example, adaptive indexing strategies that dynamically adjust based on the characteristics of incoming queries could further enhance the performance of the hybrid model [7].

Another area of interest is the integration of user feedback into the hybrid search process. By incorporating implicit feedback, such as click-through rates, and explicit feedback, such as user ratings of retrieved documents, the hybrid system could learn to adapt its weighting mechanism over time, thereby providing increasingly relevant results. Reinforcement learning approaches could be explored to optimize the balance between keyword and semantic contributions based on real-time user interactions [11].

X. Conclusion

In conclusion, this paper presents a comprehensive analysis of a hybrid search architecture that successfully integrates both keyword and semantic search methodologies to address the challenges inherent in modern information retrieval. By combining the precision of keyword-based search with the contextual depth of semantic search, the hybrid approach

demonstrates significant improvements in optimizing relevance, interpretability, and user satisfaction.

The proposed hybrid model, consisting of the Keyword Retrieval Module (KRM) and the Semantic Vector Module (SVM), leverages the strengths of both approaches. The KRM ensures precise lexical matching, which is crucial for domains requiring exact information, while the SVM provides the contextual enrichment needed to understand user intent, handle polysemy, and find semantically relevant results. This dual approach effectively addresses the limitations of standalone keyword and semantic models, providing a balanced solution for a wide range of query complexities.

Evaluation using benchmark datasets such as MS MARCO and TREC revealed that the hybrid model outperforms traditional keyword-only and semantic-only systems, particularly for complex queries. Metrics like Mean Reciprocal Rank (MRR), Normalized Discounted Cumulative Gain (nDCG), and Precision@k indicated that the hybrid model achieves higher relevance scores and user satisfaction, especially in specialized sectors like healthcare, legal, and educational domains.

The hybrid model has demonstrated particular efficacy in specialized applications. In healthcare, it supports the retrieval of literature by bridging specific medical terminology and broader context, thus enhancing the comprehensiveness of information retrieval. In education, it optimizes learning management systems by delivering both specific content and related educational resources. For the legal domain, the hybrid approach facilitates more thorough legal research by combining precise term matches with enriched context, thus aiding in case preparation and interpretation.

Despite its demonstrated potential, future research must address several challenges to further improve the hybrid model's scalability, adaptability, and efficiency. Developing more sophisticated indexing strategies, incorporating real-time user feedback, and optimizing the architecture for large-scale datasets are critical next steps. Furthermore, exploring distributed computing and compact transformer models could mitigate the computational challenges associated with semantic processing, making the hybrid system more suitable for real-time applications.

Overall, the hybrid search architecture provides a promising avenue for advancing information retrieval technologies, particularly in domains where both precision and context are crucial. Its adaptability and effectiveness in handling diverse queries make it a valuable contribution to the field, with significant implications for improving user experience and satisfaction across a variety of specialized information-seeking scenarios.

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Scalability is another critical consideration, particularly for applications that involve large-scale document collections. Future research could investigate the use of distributed computing frameworks to parallelize the semantic processing component, thereby reducing latency and making the hybrid system more suitable for real-time deployment. Additionally, exploring more compact transformer architectures, such as DistilBERT or other lightweight models, could help alleviate the computational burden without sacrificing retrieval quality [**?**].

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