A Survey on Sentence Relevance, Recommendation Systems, Information Retrieval, Query Optimization, and Semantic Matching

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Abstract

This survey explores the interconnected fields of sentence relevance, recommendation systems, information retrieval, query optimization, and semantic matching, emphasizing their collective role in advancing computational linguistics and data science. The integration of neural matching models has shown significant improvements over traditional methods in question retrieval and prediction tasks, underscoring the importance of continuous innovation. Service-enhanced retrieval systems have demonstrated the potential to improve search result relevance by integrating diverse strategies, highlighting the need for future advancements in algorithms that better interpret context and relevance. Explainability remains a critical focus, necessitating robust evaluation methods. The Qlarify method exemplifies significant improvements in user experience and understanding of scientific papers, while LaSER addresses language-specific event recommendation challenges. The survey underscores the necessity for further research into formal query languages, metadata quality, and user-centric design to enhance dataset search usability. Additionally, advancements in clustering tags indicate potential progress in information retrieval and recommendation systems. The Multi-Perspective Sentence Relevance system's application in clinical settings showcases its practical utility. Overall, the survey emphasizes the importance of integrating advancements across these fields to enhance the precision, efficiency, and user experience of information retrieval systems, driving future innovations in computational linguistics and data science.

1 Introduction

1.1 Interconnected Fields Overview

The interplay among sentence relevance, recommendation systems, information retrieval, query optimization, and semantic matching constitutes a vital network for advancing computational linguistics and data science. These domains collectively enhance information retrieval precision by refining the expression and understanding of information needs, ultimately improving user experience [1]. Harbaoui et al. highlight the symbiotic relationship between these areas, underscoring the importance of their integration for optimizing query performance and ensuring content relevance [2].

At the core of these interconnected fields are intelligent information retrieval systems that rely heavily on contextual understanding. Kurtz et al. emphasize the importance of this contextual intelligence in accurately interpreting and responding to user queries [3]. Semantic matching plays a critical role in aligning user preferences with relevant content in recommendation systems, thus enhancing recommendation efficiency [4]. Piyadigama's survey further illustrates the limitations of baseline recommendation systems and the need for integrating opinion mining and information retrieval techniques to improve recommendation relevance [5].

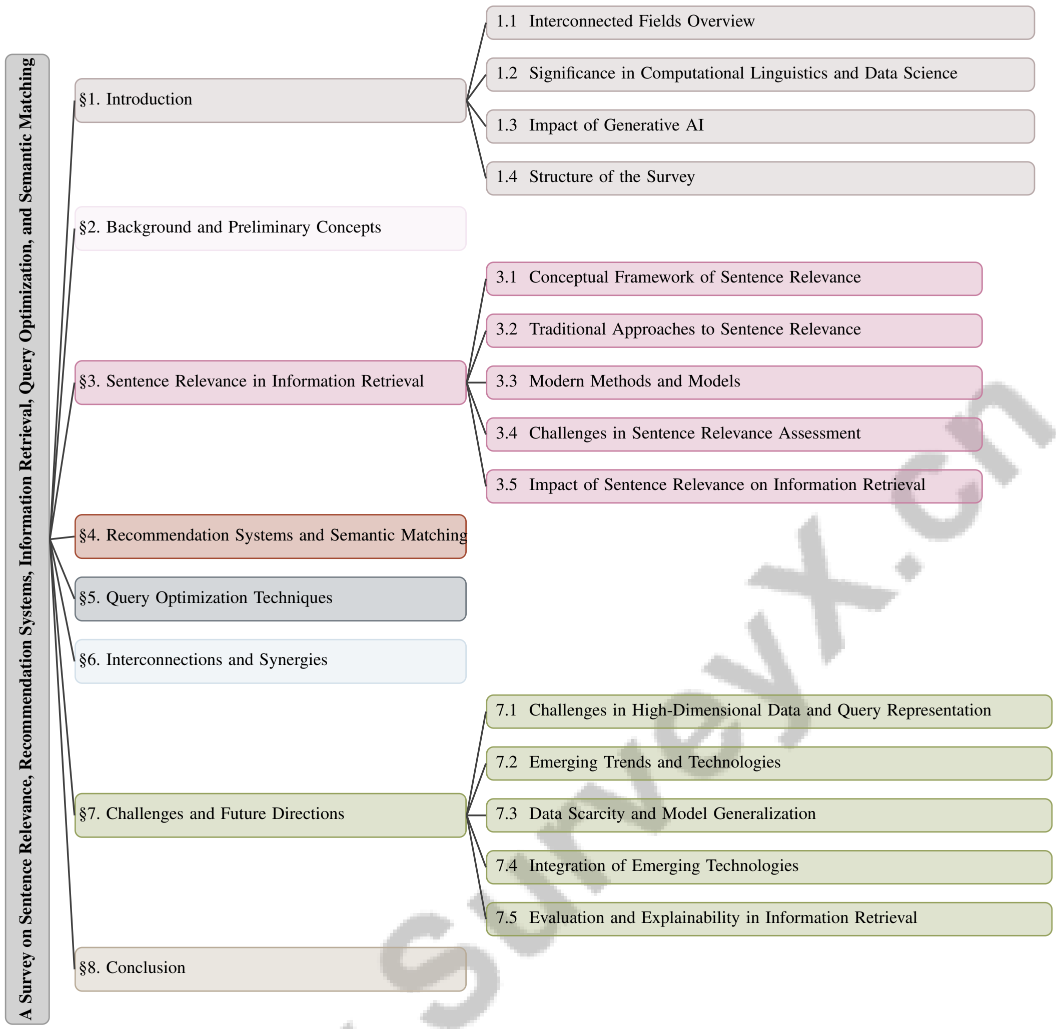

Figure 1: chapter structure

Innovative interaction paradigms, such as recursively expandable abstracts, exemplify the dynamic interaction among these fields, providing novel ways for users to engage with information retrieval systems and better access and interpret information [6]. Yu et al. address the challenges of detecting and supporting everyday learning in web search, highlighting the intersections of information retrieval, human-computer interaction, and learning sciences [7]. As these fields evolve, their interconnectedness remains crucial in addressing ongoing challenges and advancing computational linguistics and data science [8]. Lamart discusses the necessity for sophisticated techniques to manage large multimodal datasets, focusing on semantic-aware methods for data embedding [9].

Moreover, Sachin et al. emphasize the importance of query optimization in generating relevant query suggestions, particularly in online news contexts, which is essential for enhancing information retrieval systems [10]. Wang et al. highlight challenges users encounter when interacting with large language models like ChatGPT, pointing to the significance of user experience in computational linguistics [11]. Strukova et al. tackle the issue of expert identification in QA portals, which is relevant for improving information retrieval and recommendation systems through expert knowledge [12]. Rawal's work in the biomedical domain illustrates the need for innovative approaches in information retrieval due to the growing volume of scientific literature and domain-specific challenges [13].

1.2 Significance in Computational Linguistics and Data Science

The domains of sentence relevance, recommendation systems, information retrieval, query optimization, and semantic matching are fundamentally transforming computational linguistics and data

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science. These fields are crucial for enhancing data processing, understanding, and utilization across various applications. The emergence of generative AI exemplifies the importance of integrating sophisticated systems that can dynamically adapt to user queries, refining information retrieval frameworks and optimizing data processing efficiency [14].

Large language models (LLMs) significantly enhance user interactions with information retrieval systems. Caramancion et al. explore user preferences between traditional search engines and LLMs, emphasizing the need to understand user interactions with these technologies [15]. Recent research has focused on integrating LLMs into existing information retrieval systems, improving accuracy and reliability in data processing tasks [16]. This integration is vital for advancing information retrieval efficiency, particularly in complex domains like healthcare, where precise medical information retrieval is critical [17].

Conversational search is essential for addressing ambiguities in user queries, thereby improving user experience and ensuring the relevance of retrieved content [18]. The challenges posed by vast datasets on platforms like Twitter further emphasize the significance of optimizing query retrieval methods, especially for applications in traffic prediction [19].

In AI-assisted writing, tools like Generative Language Models (GLMs) such as Google Smart Compose and GPT-3 provide innovative solutions for content creation and information retrieval, marking significant advancements in computational linguistics [20]. Effective information representation alongside retrieval is crucial, particularly in exploratory search tasks that require a nuanced understanding of the information landscape [21].

Understanding user query intent is essential for enhancing search experiences, particularly in e-commerce, with innovative methods addressing the challenges of natural language queries [22]. Abdollahi et al. highlight the importance of language-specific relevance in recommendation systems, noting that existing methods often overlook this aspect, leading to suboptimal results [23].

Lastly, accurately identifying experts, non-experts, and out-of-scope comments in data science discussions is a critical challenge in computational linguistics and data science [12]. This is especially pertinent in platforms like Reddit, where expert identification can significantly enhance discourse quality and information retrieval. These advancements collectively improve data processing and retrieval capabilities, contributing to the broader development of computational linguistics and data science by facilitating more intelligent and efficient data interaction paradigms.

1.3 Impact of Generative AI

Generative AI is revolutionizing sentence relevance, recommendation systems, information retrieval, query optimization, and semantic matching by introducing advanced capabilities and presenting new challenges. The integration of multilingual large language models (LLMs) enhances interpretability and predictive power, reflecting the transformative impact of generative AI across these fields [24]. These models enable more nuanced understanding and processing of complex queries, thereby increasing the precision and relevance of information retrieval systems.

The rapid evolution of information retrieval tools and the complexity of LLMs present challenges for students, necessitating adaptation in their search skills [25]. This highlights the need for educational strategies that incorporate generative AI to support exploratory learning and enhance user competencies in navigating sophisticated search environments.

AI-assisted writing tools exemplify the practical applications of generative AI, significantly improving writing quality, efficiency, and user enjoyment through push and pull paradigms [20]. These tools streamline content creation and enhance user engagement by providing personalized writing assistance.

Additionally, the integration of supportive functions in LLM interactions offers new opportunities to enhance user experience, tailoring responses to individual user needs and contexts [11]. This personalization is crucial for optimizing user interactions, ensuring that information retrieval systems are both effective and user-friendly.

Recent advancements in generative AI, particularly in Natural Language Generation and interactive information retrieval, underscore its significant influence on computational linguistics and data science. These innovations pave the way for enhanced AI-assisted writing tools that facilitate seamless user collaboration and diverse idea generation, transforming user interactions with information retrieval systems through more expressive, natural language communication and multi-modal inputs. However, these developments necessitate adaptive strategies to address potential challenges, including user concerns regarding AI bias and ensuring effective feedback mechanisms in generative systems [1, 20].

1.4 Structure of the Survey

This survey is meticulously structured to provide a comprehensive exploration of the interconnected fields of sentence relevance, recommendation systems, information retrieval, query optimization, and semantic matching. The paper begins with an introduction that underscores the critical roles of computational linguistics and data science in enhancing machine understanding of human language, particularly in the context of generative AI. It offers a thorough overview of the interconnections among these fields, emphasizing the importance of semantic processing tools and neural network approaches in advancing information retrieval and AI-assisted writing. The introduction also discusses the implications of these advancements for future research, addressing challenges and potential solutions in automating tasks such as paper-reviewer matching and relevance assessments using large language models [26, 27, 28, 29, 20]. The introduction concludes with an outline of the survey's structure.

The second section delves into background and preliminary concepts, providing definitions and explanations of core ideas such as sentence relevance and semantic matching. This foundational section sets the stage for a deeper understanding of subsequent discussions.

The third section focuses on sentence relevance in information retrieval, examining both traditional and modern approaches while identifying challenges associated with sentence relevance assessment. This section highlights the impact of sentence relevance on the efficiency and accuracy of information retrieval systems.

The fourth section explores the role of semantic matching in recommendation systems, emphasizing the integration of user feedback and the application of deep learning and neural networks. It addresses the challenges faced in implementing semantic matching within these systems.

The fifth section discusses various query optimization techniques, including semantic matching and query affinity models, query reformulation and expansion techniques, and advanced parsing and entity recognition. This section underscores the role of semantic matching in enhancing query performance.

The sixth section analyzes the interconnections among the surveyed fields, discussing domain-specific applications and the synergies that enhance system performance. It also examines the complexity and adaptability of information retrieval systems in light of these interconnections.

The penultimate section identifies current challenges and proposes future research directions, emphasizing the need for integrated approaches. It discusses issues related to high-dimensional data, emerging trends and technologies, data scarcity, and the integration of new technologies.

The survey concludes by synthesizing key insights discussed throughout the analysis, emphasizing the critical interconnections among the various fields explored and outlining potential advancements arising from this interdisciplinary approach. This underscores the importance of context-sensitive methodologies in information retrieval and user satisfaction [26, 30, 31, 32, 12]. This structured approach ensures a coherent narrative that guides readers through the complexities of these interrelated domains.The following sections are organized as shown in Figure 1.

2 Background and Preliminary Concepts

2.1 Core Concepts in Information Retrieval

Information retrieval (IR) serves as a cornerstone in computational linguistics and data science, focusing on extracting relevant data from extensive datasets. Traditional approaches like Term Frequency-Inverse Document Frequency (TF-IDF) and BM25 rely on term-matching algorithms to rank documents based on term frequency and significance. However, these methods often face challenges such as vocabulary mismatches, where relevant documents might not contain the exact terms used in queries, highlighting the need for enhanced semantic understanding [33].

The integration of neural information retrieval systems introduces interpretability challenges, as these systems must explain document relevance in response to user queries, compounded by advanced model integration [13]. Personalization in IR necessitates a thorough understanding of search sessions and user engagement, with query performance prediction (QPP) being pivotal in estimating retrieval quality without relevance judgments.

Recent developments emphasize neural networks and semantic-aware retrieval processes to improve accuracy and relevance. Dense retrieval models using semantic embeddings show promise in overcoming traditional limitations, although effective domain adaptation strategies are necessary for diverse datasets [33]. The use of large language models (LLMs) for generating synthetic data has facilitated comparisons among retrieval models, advancing the field further.

Conversational passage retrieval (ConvPR) systems underscore the importance of addressing ambiguities in user queries from natural language dialogues. This is crucial when users are uncertain about their search intent, necessitating clarification questions to disambiguate queries. Prompt engineering enhances IR personalization by integrating task context and user perceptions, tackling challenges like prompt initialization and cognitive barriers. Supportive functions such as perception articulation and conversation explanations foster interactivity, allowing users to express information needs and receive tailored feedback, thus improving engagement in generative IR systems [11, 1].

Evaluating IR systems, particularly regarding benchmarks for relevance judgments generated by LLMs, is crucial. Recent studies suggest that LLMs can efficiently and cost-effectively label document relevance, potentially enhancing retrieval test collections. While LLM-generated relevance judgments correlate well with human assessments, maintaining statistical significance in evaluations is essential. Findings indicate that LLM-generated judgments can identify significant differences while controlling false positives. However, discrepancies in system evaluations under LLM-generated labels suggest a need for further research to ensure fairness and reliability in automatic relevance assessments [28, 34]. This approach provides a means to evaluate LLMs' reliability in creating test collections, ensuring systems are both accurate and user-friendly.

The principles of information retrieval integrate traditional and modern methods to tackle challenges like vocabulary mismatches from polysemy and synonymy. Traditional systems rely on keyword-based indexing, which can yield incomplete results when different terms describe similar concepts. Modern approaches use semantic indexing techniques, such as those utilizing resources like WordNet, to enhance document retrieval accuracy by focusing on words' meanings rather than their lexical forms. Advancements in word sense disambiguation and ontologies further enhance IR systems' capabilities to bridge vocabulary gaps, leading to more relevant search outcomes [35, 36, 37]. These advancements are integral to the field's development, improving IR systems' accuracy and efficiency and enhancing user experience by meeting diverse information needs.

2.2 Sentence Relevance and Semantic Matching

Sentence relevance and semantic matching are crucial in evolving IR systems, ensuring retrieved content aligns with user queries in pertinence and contextual understanding. Evaluating sentence relevance involves assessing text segments' pertinence to specific queries, requiring nuanced understanding of contextual and semantic nuances. This is especially important in specialized domains, like biomedical literature, where conventional models struggle with term mismatches and underspecified queries [13]. Integrating neural networks into IR systems significantly enhances the ability to address these challenges, allowing for more effective matching of user queries to relevant documents [33].

Semantic matching transcends keyword matching by employing advanced techniques to comprehend words' meanings and contexts, addressing traditional systems' limitations in bridging vocabulary gaps [38]. This gap is evident when relevant documents lack the exact terms present in user queries, underscoring the need for systems capable of matching concepts rather than exact word occurrences [39]. Ontology-driven query interpretation and synonym-based query expansion enhance sentence relevance, especially in complex domains where terminological heterogeneity complicates retrieval processes.

Integrating semantic sentence matching is vital for natural language tasks such as inference, paraphrase identification, and question answering, benefiting from semantic similarity, shared topics, and citation connections. These tasks are essential for applications like paper-reviewer matching, where semantic understanding can significantly improve recommendation relevance [12]. The limitations

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of existing probabilistic indexing models, which often rely on unwarranted assumptions about data distribution, highlight the need for improved semantic matching techniques.

Challenges in sentence relevance and semantic matching also stem from biases in text embedding models, which may favor specific writing styles, impacting information retrieval fairness [40]. The complexity of relevance in IR is further emphasized by concepts of partial relevance and domain-specific definitions, necessitating more sophisticated approaches to capture relevance's nuanced nature [28].

Evaluating semantic embedding APIs in realistic retrieval scenarios focuses on domain generalization and multilingual retrieval, addressing diverse information needs. A significant challenge remains the time-consuming nature of query development, often requiring users to sift through large document collections to refine search terms, making it inaccessible for non-expert users. The benchmark introduced by Bonifacio et al. addresses the challenge of retrieving relevant passages from large datasets based on user queries, specifically evaluating the relevance between queries and passages encoded into embeddings [39]. Furthermore, integrating entity embeddings into models like BERT, as proposed by Gerritse et al., enhances the retrieval of relevant entities, refining the semantic matching process. These advancements are critical for the field's development, improving IR systems' accuracy and efficiency and enhancing user experience by meeting diverse information needs.

2.3 Recommendation Systems and Query Optimization

Recommendation systems and query optimization are pivotal in enhancing IR by predicting user preferences and refining search queries to improve efficiency and accuracy. These systems leverage user data and interactions to suggest relevant content, addressing traditional search methodologies' limitations in capturing user intent, particularly when users lack a specific target [41]. The integration of sophisticated frameworks, such as personalized conversational recommendation agents combining dialogue systems with recommender systems using deep reinforcement learning, exemplifies advancements in user engagement and recommendation precision [42].

Hybrid recommendation systems, blending content-based filtering, collaborative filtering, and deep learning, have significantly advanced the field by comprehensively understanding user preferences through diverse data sources and methodologies [10]. These systems are crucial in domains like news, where event-centric query suggestions enhance recommendation relevance and timeliness by utilizing news metadata [10].

Query optimization, a critical component of IR, aims to improve retrieval outcomes by refining user queries. Traditional methods, such as relevance feedback and pseudo-relevance feedback, often struggle with vocabulary mismatch issues, necessitating innovative approaches like query expansion techniques [43]. The Zero-shot Query Reformulation (ZeQR) framework proactively addresses query ambiguities, demonstrating the potential of advanced query reformulation techniques [44]. Additionally, integrating genetic algorithms for query optimization, which evolve Boolean queries to minimize false negatives and positives, highlights ongoing efforts to refine retrieval strategies [19].

The application of LLMs in IR systems represents a significant advancement, offering improved performance and addressing challenges like data scarcity and interpretability [45]. Developing classifiers to select appropriate retrieval strategies for each query further enhances query latency and resource utilization, underscoring the importance of adaptive retrieval strategies [46].

Recent advancements in personalized retrieval frameworks, such as those employing bi-encoder architectures, efficiently manage multiple information access functionalities, emphasizing the importance of focusing on informative terms to enhance retrieval accuracy [18]. These innovations underscore the continuous need for advancement in recommendation systems and query optimization techniques to meet users' evolving needs in diverse IR contexts, ensuring systems are both effective and user-friendly.

In exploring the complexities of information retrieval, it is essential to understand the underlying frameworks that guide the development of retrieval systems. As illustrated in Figure 2, this figure depicts the hierarchical structure of sentence relevance in information retrieval. It categorizes the conceptual framework into traditional and modern approaches, while also addressing the challenges and impacts these methodologies have on retrieval systems. Each category is meticulously divided into specific techniques and applications, thereby highlighting the evolution and integration of semantic understanding. This progression is crucial for enhancing both retrieval accuracy and user experience, underscoring the importance of a nuanced approach to information retrieval in contemporary research.

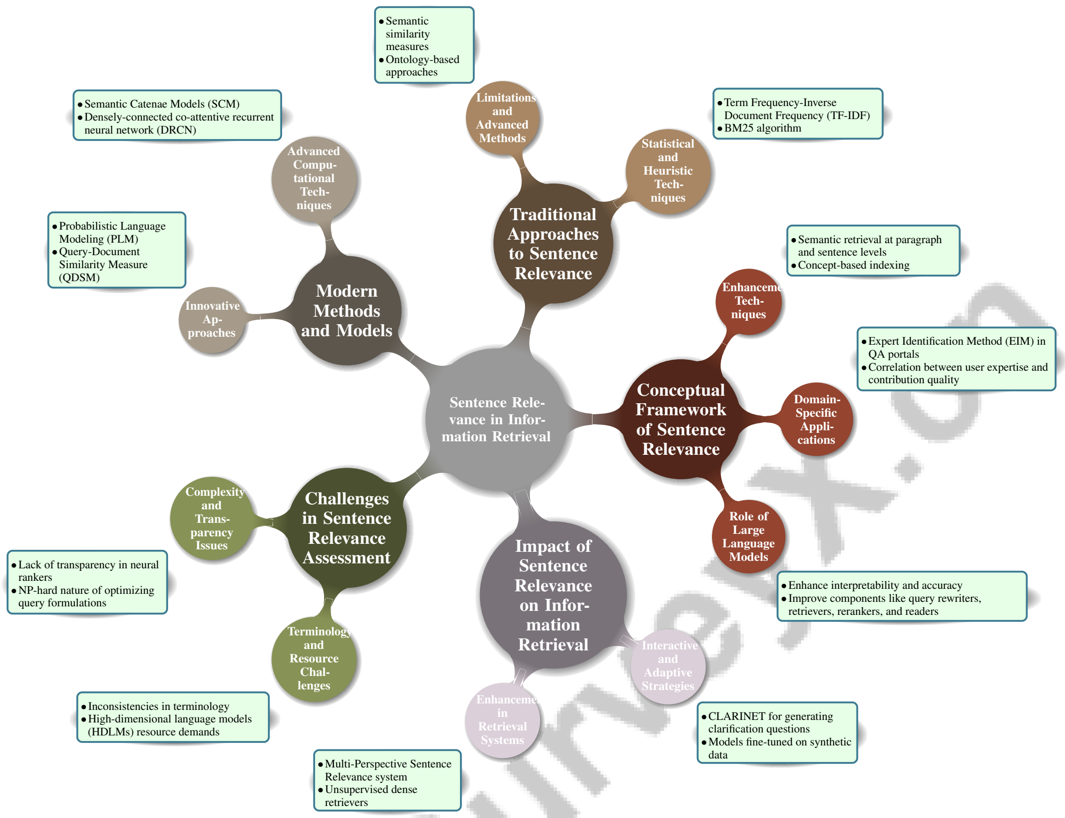

Figure 2: This figure illustrates the hierarchical structure of sentence relevance in information retrieval, categorizing the conceptual framework, traditional and modern approaches, challenges, and impact on retrieval systems. Each category is further divided into specific techniques, applications, and methodologies, highlighting the evolution and integration of semantic understanding in enhancing retrieval accuracy and user experience.

3 Sentence Relevance in Information Retrieval

3.1 Conceptual Framework of Sentence Relevance

The conceptual framework of sentence relevance is pivotal for enhancing precision and contextual understanding in information retrieval, aiming to replicate human judgment by capturing semantic relationships and contextual nuances. Large language models (LLMs) significantly contribute to this framework by improving interpretability and accuracy in human-machine collaborative relevance judgments [11]. These models refine various retrieval system components, including query rewriters, retrievers, rerankers, and readers, thereby enhancing sentence relevance [38].

Benchmarks for complex answer retrieval, as discussed by Nanni et al., highlight the need for frameworks that effectively address challenges posed by intricate queries, often inadequately managed by traditional methods [47]. Hashemi's framework further advocates adapting retrieval models to new domains using high-level textual descriptions that encapsulate essential characteristics for effective adaptation [38].

In domain-specific applications like expert identification in QA portals, the effectiveness of the Expert Identification Method (EIM) is predicated on the correlation between user expertise and contribution quality, inferred from behavioral metrics and comment content, underscoring the importance of domain-specific adaptations in sentence relevance frameworks [12].

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This framework incorporates advanced semantic understanding, dynamic user interaction, and domain-specific adaptations to enhance retrieval precision. It emphasizes semantic retrieval at multiple levels, including paragraph and sentence granularity, to improve document relevance ranking. By utilizing salient context and concept-based indexing, the framework prioritizes semantically relevant content, leading to improved user outcomes and efficient information processing [48, 49, 35]. Collectively, these methodologies address traditional challenges while accommodating modern retrieval demands, ultimately enhancing user experience and retrieval effectiveness.

3.2 Traditional Approaches to Sentence Relevance

Traditional approaches to sentence relevance in information retrieval primarily rely on statistical and heuristic techniques, quantifying text segment pertinence to user queries. A foundational method is Term Frequency-Inverse Document Frequency (TF-IDF), which evaluates term significance within documents relative to a broader collection, aiding in identifying term relevance and enhancing sentence ranking [50, 51]. The BM25 algorithm extends this by integrating probabilistic models for refined term weighting and relevance assessment.

Despite widespread use, traditional models often struggle with capturing semantic nuances and contextual relevance due to reliance on exact term matching. This limitation is evident in complex retrieval tasks where sentence relevance cannot be inferred solely from term frequency [52]. Consequently, more sophisticated methodologies, including semantic similarity measures and ontology-based approaches, are being explored.

Semantic similarity measures quantify likeness between text segments based on meaning rather than lexical similarity, employing resources like WordNet to identify synonyms and related concepts, thus enhancing retrieval of relevant sentences that may lack exact keyword matches. By utilizing word sense disambiguation techniques, these systems address challenges posed by polysemy and synonymy, allowing for a nuanced understanding of information retrieval [53, 36].

Ontology-based approaches further enhance traditional models by leveraging structured knowledge representations to infer semantic relationships between terms, improving understanding of domain-specific terminology and contextual dependencies. Advanced semantic matching techniques and context-aware term weighting frameworks lead to improved relevance assessments in specialized fields [48, 27, 54, 55, 51].

While traditional approaches have established foundational principles for information retrieval, their limitations in semantic comprehension necessitate the development of more sophisticated techniques. These advanced methods incorporate deeper linguistic insights and contextual awareness, enhancing relevance ranking accuracy and retrieval effectiveness across diverse contexts [54, 48].

3.3 Modern Methods and Models

Contemporary methods for assessing sentence relevance have evolved significantly, employing advanced computational techniques to enhance semantic comprehension and retrieval accuracy. Notable developments include the Semantic Catenae Models (SCM), which formalize semantic dependencies among words, sentences, and concepts, improving semantic inference in information retrieval [27]. This structured approach facilitates a deeper understanding of semantic relationships, essential for capturing nuanced text meanings.

The densely-connected co-attentive recurrent neural network (DRCN) represents a significant advancement in neural architectures, integrating recurrent and attentive features across multiple layers to capture complex sentence relationships [56]. This model's capacity to integrate diverse features enhances its ability to discern intricate semantic connections, improving sentence relevance assessments. Neural methods that learn representations of queries and documents further demonstrate the efficacy of deep learning in modern information retrieval [57].

Probabilistic Language Modeling (PLM) has also become pivotal, estimating the probability of generating a query from a document's language model to rank documents effectively based on query relevance [58]. This probabilistic approach aligns with semantic understanding principles, facilitating more accurate relevance assessments. The Query-Document Similarity Measure (QDSM) innovatively combines semantic measures with traditional ranking methods like BM25, highlighting the potential of hybrid models to enhance document retrieval performance [53].

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The integration of semantic information is exemplified by the Post-processing-based Universal Approach (PP-UA), which aligns extracted keywords more closely with the input text context, improving retrieval outcome relevance [59]. Additionally, the SC method selects terms based on cumulative similarity to the original document, ensuring a specified percentage of similarity, thereby enhancing term selection precision [60].

Incorporating part-of-speech information, the POS-based Term Weighting (POTW) method computes term weights from frequency statistics of POS n-grams, providing a refined approach to term weighting that captures both syntactic and semantic nuances [61]. The novel re-ranking method introduced by Bradfordizing utilizes bibliometric principles to enhance relevance distributions in search results, offering an alternative to traditional text-based ranking techniques [62].

CodeMatcher exemplifies the integration of information retrieval techniques with deep learning insights, enhancing query understanding and retrieval speed, significantly outperforming existing models [63]. These advancements underscore the ongoing evolution of methods for assessing sentence relevance, emphasizing the importance of integrating semantic understanding and computational innovation to improve retrieval accuracy and user experience.

3.4 Challenges in Sentence Relevance Assessment

Assessing sentence relevance in information retrieval systems presents numerous challenges due to the complexity of natural language and existing methodologies' limitations in capturing semantic nuances. A core obstacle is the lack of transparency in neural rankers, complicating bias identification and understanding the intent behind rankings for specific queries [64]. This opacity hinders fairness and accuracy in relevance assessments, as tracing decision-making processes within these models becomes difficult.

Another significant challenge is the NP-hard nature of optimizing query formulations to minimize false negatives and positives, which traditional methods often struggle to address effectively [19]. This complexity is compounded by balancing precision and recall, especially when determining optimal query phrases amidst vast combinations.

Inconsistencies in terminology and conceptual frameworks across fields complicate classification and identification of semantic changes, leading to challenges in accurately assessing sentence relevance [65]. These inconsistencies are exacerbated by high-dimensional language models (HDLMs) requiring substantial resources for training on large datasets, posing practical barriers to widespread application [66].

In entity type recognition, the lack of contextual information in short search queries presents a key obstacle, complicating accurate recognition of entity types and sentence relevance assessment [67]. This issue is further compounded by existing query expansion methods, which often assume the relevance of top-ranked documents in initial searches, an assumption frequently failing in microblog contexts where queries may contain proper nouns or informal language [68].

Bias in text embedding models is another critical challenge, influenced by diverse writing styles and training data, which can skew relevance assessments [69]. Additionally, outdated experimental practices inadequately addressing modern information access complexities can lead to validity and applicability issues in research findings [70]. The lack of user involvement in evaluation processes further detracts from accuracy, as evaluations fail to reflect real-world user experiences and needs [71].

Zero-shot query reformulation methods face challenges in universality, struggling with explainability and ambiguity resolution, crucial for accurately assessing sentence relevance [44]. In conversational search contexts, inherent ambiguity in queries due to coreference and omission complicates relevance assessments [18]. Furthermore, integrating fluctuating user perceptions and task context into static search systems remains a significant obstacle, emphasizing the need for dynamic and adaptive approaches [11].

The challenges highlighted in the current landscape of information retrieval and machine reading underscore the critical need for developing sophisticated methodologies that seamlessly integrate advanced semantic understanding, contextual awareness, and robust evaluation frameworks. These improvements are essential for enhancing the accuracy and reliability of sentence relevance assessments, particularly as systems increasingly rely on hierarchical semantic retrieval at both paragraph and sentence levels. Leveraging techniques such as salient-context-based semantic matching and deep contextualized term weighting can significantly refine relevance ranking processes and optimize downstream tasks like fact verification and open-domain multihop question answering [54, 48, 49, 51].

3.5 Impact of Sentence Relevance on Information Retrieval

The impact of sentence relevance on information retrieval is profound, significantly enhancing retrieval systems' efficiency and accuracy by aligning retrieved content more closely with user queries through advanced semantic understanding and contextual analysis. The integration of sentence-based semantic methods, such as the Multi-Perspective Sentence Relevance system, has demonstrated substantial improvements in capturing contextual relationships and nuances, particularly in specialized domains like medical language, where traditional methods often fall short [13]. This underscores the importance of nuanced sentence-level analysis in improving retrieval outcomes.

Advancements in retrieval models, like unsupervised dense retrievers, have shown competitive performance against traditional methods such as BM25, indicating a paradigm shift in retrieval approaches [33]. These models leverage semantic embeddings to enhance relevance, showcasing the potential for improved precision and recall in information retrieval tasks.

Systems like CLARINET, which significantly outperform traditional methods in retrieval accuracy, highlight the effectiveness of generating clarification questions that enhance user interactions and improve retrieval outcomes [72]. This approach emphasizes the role of interactive and adaptive retrieval strategies in addressing user needs more effectively.

Experiments with models fine-tuned on synthetic data have shown significant performance improvements over traditional models, achieving state-of-the-art results on multiple information retrieval datasets [39]. This illustrates the potential of augmented data to enhance retrieval model training, thereby improving sentence relevance assessment accuracy.

The challenges of query performance prediction (QPP) in ad-hoc search, which do not generalize well to conversational search, highlight the necessity for improvements in query rewriting and the development of QPP methods that understand conversational context [40]. This underscores the need for sophisticated approaches that integrate advanced semantic understanding and contextual awareness to enhance the accuracy of sentence relevance assessments.

The relevance of sentences is integral to the efficiency and accuracy of information retrieval systems. By incorporating advanced semantic techniques, contextual analysis, and domain-specific adaptations, these systems can more effectively align retrieved content with user queries, ultimately improving user satisfaction and retrieval outcomes. Ongoing advancements in retrieval methodologies significantly enhance information retrieval system performance by integrating diverse techniques such as automatic query expansion, contextual learning, and innovative re-ranking methods like Bradfordizing. These developments address critical challenges, including improving generalizability and maintaining effectiveness across various conditions, enabling systems to retrieve more relevant information through a combination of probabilistic and co-occurrence approaches, as well as iterative refinements based on user interactions and bibliometric analyses [73, 54, 62, 74].

4 Recommendation Systems and Semantic Matching

4.1 Semantic Matching in Recommendation Systems

Semantic matching is crucial in recommendation systems, enhancing alignment between user preferences and relevant content through advanced contextual analysis. Techniques like Dense Retrieval Adaptation using Target Domain Description (DRD-TDD) generate synthetic data from domain descriptions, improving recommendation systems' performance in understanding user intent, particularly in low-resource environments [38, 39]. The Task Supportive and Personalized Human-Large Language Model Interaction (TSPLM) method integrates user perceptions into large language model (LLM) interactions, personalizing recommendations based on specific user contexts [11]. This personalization aligns with the idea that information retrieval should accommodate diverse user intents throughout search sessions, not just the final outcome [75].

Frameworks that categorize research in document retrieval elucidate algorithmic relationships between retrieval challenges and fundamental issues in trees, strings, and discrete geometry, providing a structured understanding of semantic complexities in recommendation systems [76]. Systems like CLARINET enhance user interactions by generating clarification questions, improving the rank of true candidates in retrieval tasks and increasing recommendation precision [72]. This underscores the importance of interactive retrieval strategies in addressing user needs effectively.

Incorporating semantic matching into recommendation systems is vital for developing frameworks that enhance recommendation accuracy and reliability. Sophisticated techniques and contextual analysis align user preferences with pertinent content by identifying salient contexts and refining thematic descriptions, leading to improved relevance ranking and greater user satisfaction [54, 48, 71]. Ongoing advancements in semantic matching methodologies ensure that recommendation systems meet evolving user needs across diverse contexts.

4.2 Integration of User Feedback and Semantic Understanding

Integrating user feedback and semantic understanding is essential for refining recommendation systems, making them responsive to user needs and delivering personalized content. This involves using user interactions and contextual information to enhance semantic matching and improve recommendation relevance. Aliannejadi et al. demonstrate this approach with an Android application that collects data on users' contexts and interactions during search tasks, offering insights into user preferences [77]. Addressing click bias in user engagement, Zamani et al. show that integrating user feedback into semantic understanding enhances search results [4].

Deep learning-based recommender systems have advanced significantly, offering improved recommendation accuracy and managing large datasets. These systems leverage user feedback to refine semantic matching processes [78]. The combination of implicit session feedback with explicit questioning, as proposed by Li et al., exemplifies the potential of merging user feedback with semantic understanding to enhance product search [41]. User involvement in evaluation processes is crucial for aligning recommendation systems with user expectations, as emphasized by Bouramoul et al. [71].

The integration of user feedback and semantic understanding is pivotal for developing effective recommendation systems. By utilizing user interactions and contextual information, these systems provide tailored content that enhances user satisfaction and engagement, achieved through advanced evaluation methods and intelligent algorithms [54, 30, 71]. Ongoing advancements continue to refine recommendation systems, ensuring they meet users' evolving needs across various contexts.

4.3 Deep Learning and Neural Networks in Semantic Matching

Deep learning and neural networks have transformed semantic matching in recommendation systems, enhancing their ability to align user preferences with relevant content through advanced pattern recognition and contextual understanding. Dual-encoder architectures like Poly-DPR utilize multiple context representations to improve query-document matching, particularly in specialized domains such as biomedical information retrieval [79]. Recent research has made significant strides in modality interactions and retrieval performance through pretrained models that leverage large datasets [80]. Entity-aware transformers like EM-BERT, which incorporate entity embeddings from knowledge graphs, further illustrate how neural networks can enhance entity retrieval tasks [81].

Siamese neural network architectures eliminate the need for manual feature design by learning to classify terms through deep neural networks, improving traditional similarity functions [82]. Large language models (LLMs) enhance query performance prediction and improve information retrieval evaluation measures [83]. The Ogmios platform, which utilizes existing NLP modules, exemplifies the integration of deep learning techniques to handle domain-specific linguistic tasks [84].

Deep learning and neural networks have markedly improved recommendation systems' performance, enabling them to analyze user preferences effectively and deliver accurate, contextually relevant content. This advancement is largely due to deep learning models' ability to learn intricate feature representations, enhancing systems' capabilities to manage information overload and improve user experience [29, 78]. These advancements ensure that recommendation systems are efficient and responsive to users' evolving needs across diverse contexts.

4.4 Challenges in Semantic Matching for Recommendation Systems

Implementing semantic matching in recommendation systems presents challenges due to language complexities and user context variability. A significant limitation is the reliance on the quality of training data for large language models (LLMs), which may not align with specific dataset contexts, resulting in variable imputation quality [85]. Current neural information retrieval (IR) models often struggle to generalize across diverse scenarios [86]. The absence of hyperlinks in datasets poses challenges for methods like PageRank, which rely on structural relationships for reranking [87]. These methods may not fully account for language and context nuances, particularly in ambiguous queries [61].

The interpretability of deep learning-based recommender systems remains a critical challenge, with limitations in understanding these models' mechanisms. Extensive data requirements and hyperparameter tuning complicate practical applications [78]. Query type variability presents challenges for classifiers, which may not generalize well to unseen queries [46]. Cao's analysis shows that universal text embedding models prefer clear writing styles, undervaluing informal styles, impacting semantic matching effectiveness [69]. Saxena et al.'s intelligent recommendation system highlights the need for adaptive solutions that respond to dynamic user contexts [88].

These challenges underscore the need for advancements in methodologies that improve data alignment, enhance model interpretability, and develop adaptive systems. These systems must address users' diverse and evolving needs across various contexts, emphasizing the importance of salient context in relevance ranking, neural text matching models in natural language processing tasks, and domain adaptation techniques for enhanced retrieval performance. Integrating hierarchical semantic retrieval strategies significantly improves machine reading tasks by optimizing information filtering and data distribution [48, 54, 38, 49, 89].

5 Query Optimization Techniques

5.1 Semantic Matching and Query Affinity Models

Semantic matching is essential for improving query affinity and retrieval outcomes by aligning user queries with relevant content through advanced indexing and disambiguation methods. The Proximity Full-Text Search (PFTS) method exemplifies this by utilizing additional indexes to maintain stable query response times and efficiently process proximity searches, thereby enhancing the retrieval of semantically relevant documents [90]. This highlights the importance of indexing strategies in optimizing query performance.

Concept-based indexing enhances semantic matching by identifying and weighting document concepts, moving beyond traditional keyword reliance to capture deeper semantic relationships [35]. This ensures that retrieved documents reflect the underlying concepts relevant to user queries. Similarly, the CFO framework uses Protocol Buffers to ensure data type correctness, improving query affinity and retrieval results [91].

Advanced parsing techniques, such as the Fast Statistical Noun Phrase Parser, analyze word modification structures to disambiguate and accurately index documents [92]. This statistical approach enhances query understanding and retrieval precision by focusing on syntactic and semantic nuances.

The Topic Level Disambiguation (TLD) method leverages Wikipedia's structural knowledge to identify relevant topics, improving retrieval accuracy and demonstrating the potential of external knowledge bases for semantic matching [93]. Additionally, the Network of Natural Hierarchies of Terms (NNHT) incorporates significant and frequent terms, reflecting their natural usage and relationships within the text [94].

The WKQE method enhances query expansion by utilizing pseudo-relevant documents from web search engines and employing three distinct weighting models: tf-idf, kNN-based cosine similarity, and correlation score [43]. This broadens the semantic scope of user queries, addressing vocabulary gaps and enhancing query affinity. Furthermore, DIRAS effectively distills knowledge from state-of-the-art LLMs, allowing smaller models to understand complex relevance definitions, thus improving semantic matching [95].

Incorporating diverse retrieval strategies, as demonstrated by Schaer et al., enhances semantic matching by addressing various aspects of document relevance, thereby improving search result quality [73]. These strategies emphasize a multifaceted approach to query affinity, integrating various semantic matching techniques to optimize retrieval performance. The conversational browsing method reduces cognitive load by engaging users in a dialogue that clarifies their information needs, serving as an effective query optimization strategy [96].

Semantic matching and query affinity models are integral to improving retrieval outcomes by aligning user queries with semantically relevant content through advanced indexing, disambiguation, and expansion techniques. Methodologies such as intelligent context characterization and automatic query expansion enhance information retrieval systems' capabilities, allowing them to learn and adapt to user needs more effectively. Incremental methods refine vocabulary based on user interactions and document relevance, while various query expansion approaches leverage term co-occurrence and probabilistic distributions to improve search results. Additionally, user-driven reindexing enriches content by aligning system outputs with actual user requirements, ensuring that systems can dynamically address the diverse and evolving information needs of users [54, 2, 74].

5.2 Query Reformulation and Expansion Techniques

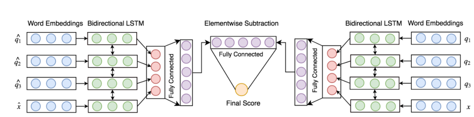
Query reformulation and expansion techniques are crucial for enhancing retrieval outcomes by refining user queries to better align with relevant content. The Deep Reinforced Query Reformulation (DRQR) model exemplifies advanced approaches by integrating query performance prediction into the reformulation process, thereby improving precision and relevance [97]. This model highlights the potential of reinforcement learning to dynamically adjust queries based on predicted performance metrics.

The iterative QueryBuilder approach, incorporating continuous user feedback, emphasizes the importance of human-in-the-loop systems in query development. By iteratively refining queries, QueryBuilder enhances retrieval performance, demonstrating the value of user interaction in the query reformulation process [98]. This aligns with broader trends in interactive query expansion, where varying levels of user participation improve retrieval outcomes [99].

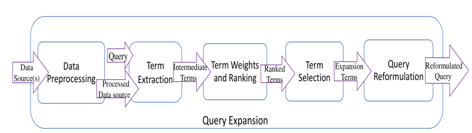
The Zero-shot Query Reformulation (ZeQR) framework reinterprets query reformulation tasks as machine reading comprehension exercises, addressing coreference and omission ambiguities to clarify user queries and enhance retrieval accuracy [44]. Additionally, the multi-stage conversational passage retrieval method reformulates conversational queries into clearer standalone queries, aligning with the objectives of query reformulation techniques to improve clarity and relevance [18].

The Proximity Full-Text Search (PFTS) method addresses excessive query response times by utilizing additional indexes that store proximity information about frequently occurring words, enhancing full-text search capabilities and ensuring more efficient retrieval of relevant documents [90]. The Parallel Relevance Vertical Framework (PRVF) accelerates query expansion by selecting relevant verticals from an external corpus and processing them in parallel, thus improving retrieval outcomes through efficient resource utilization [100].

Query reformulation and expansion techniques are integral to optimizing information retrieval systems, ensuring effective alignment of user queries with relevant content. By integrating advanced computational models, such as neural representations addressing vocabulary mismatches, interactive frameworks facilitating hybrid search schemes, and efficient processing methods like query expansion through co-occurrence and probabilistic approaches, these techniques significantly enhance both precision and recall of information retrieval outcomes [101, 74].



(a) Deep Learning Model for Sentence Classification[82]



(b) Query Expansion Process Flowchart[99]

Figure 3: Examples of Query Reformulation and Expansion Techniques

As shown in Figure 3, query optimization significantly enhances the efficiency and accuracy of search results in information retrieval and database management. The example presented delves into two pivotal techniques: Query Reformulation and Expansion Techniques. The first visual, "Deep Learning Model for Sentence Classification," showcases a deep learning architecture that categorizes sentences using a bidirectional LSTM layer for word embedding, followed by a fully connected layer for classification. This model illustrates how advanced neural networks can optimize query responses through accurate sentence structure classification. The second visual, "Query Expansion Process Flowchart," outlines a systematic approach to query expansion, detailing a multi-step process that includes data preprocessing, term extraction, and query reformulation. This emphasizes the iterative nature of query expansion, where each phase builds upon the previous one to refine the search query, enhancing the retrieval of pertinent information. Collectively, these examples underscore the sophisticated methodologies employed in query optimization, highlighting the integration of deep learning models and structured expansion processes to improve search efficacy [82, 99].

5.3 Advanced Parsing and Entity Recognition

Advanced parsing and entity recognition are critical in query optimization, enhancing information retrieval systems' ability to accurately interpret and process user queries. Techniques like the Fast Statistical Noun Phrase Parser play a pivotal role in disambiguating and accurately indexing documents by analyzing word modification structures [92]. This statistical approach facilitates a nuanced understanding of syntactic and semantic relationships within text, improving retrieval precision.

Entity recognition techniques further augment query optimization by identifying and categorizing key entities within user queries, enabling more precise search results. The integration of entity-aware models, such as EM-BERT, exemplifies advancements in this area by incorporating entity embeddings from knowledge graphs to enhance entity retrieval tasks [81]. This provides a richer semantic context, improving the alignment of user queries with relevant content.

These techniques are particularly beneficial for handling complex queries involving multiple entities or ambiguous language, enabling systems to disambiguate and accurately interpret user intent, ensuring that retrieved content is relevant and contextually appropriate. By utilizing structured knowledge representations alongside advanced linguistic analysis, these methods significantly enhance the efficiency and accuracy of query optimization processes, allowing for precise semantic querying and indexing tailored to specific domains. The integration of Natural Language Processing (NLP) enables effective processing of large document collections, enriching them with semantic annotations that enhance information retrieval and extraction capabilities. Moreover, the development of intelligent systems that learn context-specific vocabulary further refines query construction, resulting in more relevant material retrieval compared to traditional methods [84, 54, 58].

Advanced parsing and entity recognition techniques are integral to the ongoing development of information retrieval systems, ensuring they effectively meet diverse and evolving user needs. By enhancing the accuracy of query interpretation and retrieval results, these techniques play a crucial role in refining information retrieval methodologies. This refinement is achieved through clarifying questions that directly influence user satisfaction by addressing common issues such as vocabulary mismatch and poorly formulated queries. Empirical studies indicate that specific, emotionally aware, and concise clarifying questions significantly improve user engagement and overall system performance. Additionally, the integration of neural representations and hybrid search schemes further boosts the recall of relevant documents during the initial retrieval stage, ensuring users receive more pertinent results. These innovations collectively contribute to a more effective information retrieval process, ultimately leading to greater user satisfaction and engagement [54, 30, 101].

6 Interconnections and Synergies

6.1 Domain-Specific Applications and Synergies

Domain-specific applications in information retrieval (IR) and recommendation systems (RS) highlight the impact of tailored methodologies on system performance. In legal domains, specialized strategies improve document retrieval accuracy by incorporating domain-specific knowledge [102].

Similarly, platforms like CareerBuilder utilize entity type recognition to enhance semantic search, benefiting millions of users [67].

The use of scale-free networks with exponential distributions shows promise in ontology building and information retrieval by providing structured frameworks for efficient organization and retrieval [94]. These networks use natural term hierarchies to enhance retrieval accuracy, especially in complex contexts requiring contextual understanding.

Conversational search (ConvSearch) addresses challenges related to user intent and system responses, necessitating integrated methodologies for effective solutions [103]. Integrating large language models (LLMs) with traditional search engines is a promising direction for improving user experience, as research merges the strengths of both approaches [15]. This integration is crucial for advancing IR capabilities, ensuring systems respond to evolving user needs across diverse fields.

Leveraging historical experimental evaluations in IR, RS, and natural language processing (NLP) provides a foundation for future innovations, emphasizing the importance of past research in developing integrated systems that enhance performance across applications [70]. By building on this foundation, researchers can devise sophisticated methodologies to address unique challenges across different domains, improving the effectiveness and efficiency of information retrieval and recommendation systems.

Synergies between domain-specific applications and information retrieval methodologies enhance system performance by merging specialized knowledge and techniques. Innovations in IR and RS, like query expansion, Bradfordizing, and author centrality, bridge the gap between user relevance and system relevance, offering nuanced insights into user needs. By utilizing user-generated content and advanced re-ranking methods, these systems deliver tailored search results across domains, effectively adapting to dynamic user demands [73, 2, 99, 62].

6.2 Complexity and Adaptability in Information Retrieval Systems

The complexity and adaptability of information retrieval (IR) systems are vital for managing and retrieving information across diverse domains. The integration of natural language processing (NLP) components into IR systems exemplifies this complexity, as shown by the CFO framework's incorporation of multiple NLP elements to enhance retrieval efficiency and accuracy [91]. This synergy between NLP and IR leads to more robust retrieval systems.

Adaptability is further demonstrated by dense retrieval models maintaining high performance across contexts without accessing sensitive data, ensuring privacy and security [38]. Compressed indexes in Learning to Retrieve (LTRe) methods improve retrieval effectiveness and training efficiency while conserving computational resources [104].

Neural networks enhance IR systems' adaptability by enabling the comparison of queries and candidate expansion terms within a shared embedding space, as evidenced by siamese networks [82]. However, integrating neural methods with traditional IR systems presents challenges, as many studies lack comprehensive real-world evaluations, limiting the understanding of their full potential [57].

The EXS framework exemplifies explainable search results by providing clear explanations for document relevance and ranking decisions, enhancing user trust in neural ranking systems [64].

Interdisciplinary collaboration between computational and historical linguistics emphasizes IR systems' adaptability, as insights from these fields can improve retrieval methodologies [65]. Categorizing research into Language Model (LM) and Vector Space Model (VSM) approaches offers valuable insights into adaptable IR systems' methodologies and performance metrics [17].

The complexity and adaptability of information retrieval systems (IRS) are crucial for their development and effectiveness across applications. These systems must bridge the gap between user relevance and system relevance, address challenges in natural language understanding, and incorporate user-driven content enrichment through reindexing and intelligent context characterizations. Employing advanced evaluation techniques, such as active sampling, enhances the quality of retrieved documents and improves user experience in obtaining pertinent information [54, 2, 105]. By integrating advanced computational techniques and fostering interdisciplinary collaboration, IR systems can adapt to the changing landscape of information needs, ensuring they remain efficient and reliable tools for information retrieval.

7 Challenges and Future Directions

The landscape of information retrieval (IR) is characterized by increasing data volume and complexity, presenting challenges that necessitate innovative approaches. This section delves into the specific challenges associated with high-dimensional datasets and query representation, highlighting the limitations of traditional methodologies and the need for advanced solutions.

7.1 Challenges in High-Dimensional Data and Query Representation

High-dimensional data management and query representation in IR systems are challenging due to semantic heterogeneity, which often leads to irrelevant document retrieval or omission of relevant ones [106]. Achieving high precision and recall is particularly difficult when positive instances are sparse [107]. The complexity of multi-dimensional data further complicates efficient retrieval, underscoring the need for optimized real-time models [9]. A significant challenge is the scarcity of detailed user behavior data, which is crucial for evaluating personalized IR support [75]. Additionally, user query ambiguity and traditional models' limitations in exploiting tag correlations affect accurate query interpretation [89]. Modeling long-term dependencies and semantic relationships is essential, especially in conversational contexts, where existing benchmarks fall short [40]. Despite their success, deep neural networks face challenges in IR due to dataset reliance and variability in learning efficacy [106]. Erratic user behavior complicates feedback mechanisms, and the lack of diverse user demographic understanding further challenges query representation [41, 71]. Addressing these issues requires advanced computational models and robust data generation techniques to improve high-dimensional data handling and query representation, especially in critical areas like medical and legal information retrieval [64].

7.2 Emerging Trends and Technologies

Emerging trends in IR, recommendation systems, and semantic matching are driven by advanced methodologies and novel applications. Enhancing large language models (LLMs) within IR systems is a significant trend, with future research focusing on developing efficient architectures incorporating retrieval-augmented techniques to improve scalability and adaptability [108, 95, 109]. Addressing source bias is crucial for maintaining information integrity. In query optimization, refining pseudo-relevant document selection and exploring weighting models are key areas of interest [101]. Advanced semantic analysis techniques are being integrated to improve performance, particularly in multilingual contexts [53]. Exploring biases in ranking methods and developing sophisticated models integrating social and textual data are promising areas for future research [62, 110]. In recommendation systems, extending benchmarks to include diverse datasets and tasks is crucial [111]. Future research should focus on improving LLM-generated judgments and scaling synthetic dataset generation [28, 39]. These advancements will enhance query expansion techniques, improve query performance prediction, and refine recommendation systems, addressing challenges posed by the increasing volume of online information [40, 99].

7.3 Data Scarcity and Model Generalization

Data scarcity and model generalization are significant challenges in IR, recommendation systems, and semantic matching. The construction of synthetic data provides a solution to data scarcity, enhancing model adaptability [38]. The computational complexity of advanced models highlights the trade-offs between sophistication and demands [44]. Future research should explore the impact of datasets on performance and develop strategies to mitigate computational overheads. Evaluating entity-aware models across tasks can enhance generalizability [81]. Addressing data scarcity and enhancing model generalization require innovative techniques such as Bradfordizing and co-word analysis for query expansion [73, 62].

7.4 Integration of Emerging Technologies

Integrating emerging technologies into IR and recommendation systems enhances performance and user satisfaction. Developing hybrid models that integrate neural and non-neural methods is crucial [38]. Adaptive query expansion techniques and structural adaptations can enhance system adaptability [19]. Addressing model biases and promoting equitable retrieval outcomes require developing balanced text embedding models [112, 69]. Improving information extraction methods and exploring hierarchical knowledge graphs' resilience can significantly enhance information systems [40]. Incorporating LLMs into collaborative evaluation processes can improve information access research quality [109, 28]. Future research should focus on improving robustness, employing stable improvement strategies, and enhancing user-centered retrieval systems [75, 54, 71]. The integration of emerging technologies promises significant improvements in IR and recommendation outcomes, addressing diverse and evolving user needs [73, 20, 113].

7.5 Evaluation and Explainability in Information Retrieval

Benchmark	Size	Domain	Task Format	Metric
IRSE[114]	5,000	Software Engineering	Binary Classification	F1 Score, Accuracy
Sy-SE-PQA[115]	100,000	Community Question Answering	Answer Generation	P@1, NDCG@10
MS-Shift[86]	8,800,000	Information Retrieval	Zero-shot Retrieval	MRR@10, ASL
UTS/UTSB[116]	12,000	Information Retrieval	Relevance Estimation	RBP
MSLR-WEB[117]	30,000	Information Retrieval	Ranking	Precision, NDCG
CAILMD-23[118]	10,000	Semantic Textual Relatedness	Sentence Pair Similarity	F1, Accuracy
SSE[119]	500	Information Retrieval	Search Evaluation	SSE
InPars-v2[120]	20,000	Information Retrieval	Query-Document Pair Generation	BM25, monoT5-3B

Table 1: The table presents a comprehensive overview of various benchmarks utilized in the evaluation of information retrieval (IR) systems, detailing their size, domain, task format, and performance metrics. These benchmarks encompass a range of applications from software engineering to semantic textual relatedness, highlighting the diversity and scope of current IR evaluation methodologies.

Evaluation and explainability are crucial for developing effective and transparent IR systems. Metrics such as precision, recall, and F-Score are essential for assessing performance [121]. Concept-based indexing approaches outperform traditional methods, necessitating innovative evaluation techniques [35]. Explainability enhances user trust and understanding of retrieval processes, as demonstrated by the WeKnow-RAG experiments [16]. Future research should focus on expanding datasets and exploring novel modeling approaches to improve comment relevance classification [114]. Developing methods for generating clarifying questions can enhance user satisfaction and system reliability [30]. Table 1 provides a detailed enumeration of representative benchmarks critical for the evaluation and explainability of information retrieval systems. Emphasizing evaluation and explainability ensures IR systems meet evolving user needs, enhancing effectiveness and fostering trust [119, 2, 80].

8 Conclusion

The survey highlights significant advancements in sentence relevance, recommendation systems, information retrieval, query optimization, and semantic matching, illustrating their interrelated nature and collective importance in enhancing computational linguistics and data science. Neural matching models have consistently outperformed traditional methods in question retrieval and prediction tasks, underscoring the necessity for ongoing innovation in these domains [122]. The effectiveness of service-enhanced retrieval systems in improving search result relevance further demonstrates the potential of integrating diverse retrieval strategies to enhance scholarly information systems [73].

Future advancements must focus on algorithms that better interpret context and relevance, aligning with the overarching themes of the survey [3]. Explainability remains a crucial area, necessitating robust evaluation methods for explanations [123]. The Qlarify method illustrates significant improvements in user experience and comprehension of scientific papers, emphasizing the value of innovative approaches in enhancing information access [6].

Moreover, the survey points to the nascent stage of dataset search and the need for further research into formal query languages, metadata quality enhancements, and user-centric design to improve usability [31]. The potential of conversational browsing systems to enhance users' ability to locate relevant information compared to traditional search interfaces is also acknowledged, reinforcing its value as a tool for exploratory search [96].

Additionally, LaSER's effectiveness in addressing language-specific event recommendation challenges underscores the importance of considering language context in recommendation systems [23]. Advances in clustering tags indicate promising progress in information retrieval and recommendation systems, as evidenced by the proposed method's performance [124]. The Multi-Perspective Sentence Relevance system has shown significant improvements in retrieving relevant biomedical information, demonstrating practical applications in clinical settings [13].

This conclusion reiterates the importance of integrating advancements across the surveyed fields, highlighting the potential for future innovations to enhance the precision, efficiency, and user experience of information retrieval systems [2]. As these fields continue to evolve, the ongoing development of sophisticated techniques and methodologies will be essential in addressing emerging challenges and driving progress in computational linguistics and data science.

AI-generated, for reference only.

References

[1] Mohammad Aliannejadi, Jacek Gwizdka, and Hamed Zamani. Interactions with generative information retrieval systems, 2024.

[2] Azza Harbaoui, Malek Ghenima, and Sahbi Sidhom. Enrichissement des contenus par la réindexation des usagers : un état de l'art sur la problématique, 2009.

[3] Michael J. Kurtz. Advice from the oracle: Really intelligent information retrieval, 2018.

[4] Hamed Zamani, Bhaskar Mitra, Everest Chen, Gord Lueck, Fernando Diaz, Paul N. Bennett, Nick Craswell, and Susan T. Dumais. Analyzing and learning from user interactions for search clarification, 2020.

[5] Dinuka Ravijaya Piyadigama and Guhanathan Poravi. A review on pushing the limits of baseline recommendation systems with the integration of opinion mining information retrieval techniques, 2022.

[6] Raymond Fok, Joseph Chee Chang, Tal August, Amy X. Zhang, and Daniel S. Weld. Qlarify: Recursively expandable abstracts for directed information retrieval over scientific papers, 2024.

[7] Ran Yu, Ujwal Gadiraju, and Stefan Dietze. Detecting, understanding and supporting everyday learning in web search, 2018.

[8] Daniel Locke and Guido Zuccon. Case law retrieval: problems, methods, challenges and evaluations in the last 20 years, 2022.

[9] Pierre Lamart, Yinan Yu, and Christian Berger. Semantic-aware representation of multi-modal data for data ingress: A literature review, 2024.

[10] Sachin and Dhaval Patel. Event-centric query suggestion for online news, 2022.

[11] Ben Wang, Jiqun Liu, Jamshed Karimnazarov, and Nicolas Thompson. Task supportive and personalized human-large language model interaction: A user study, 2024.

[12] Sofia Strukova, José A. Ruipérez-Valiente, and Félix Gómez Mármol. Identifying experts in question answer portals: A case study on data science competencies in reddit, 2022.

[13] Samarth Rawal. Multi-perspective semantic information retrieval in the biomedical domain, 2020.

[14] Martin Semmann and Mahei Manhei Li. New kids on the block: On the impact of information retrieval on contextual resource integration patterns, 2023.

[15] Kevin Matthe Caramancion. Large language models vs. search engines: Evaluating user preferences across varied information retrieval scenarios, 2024.

[16] Weijian Xie, Xuefeng Liang, Yuhui Liu, Kaihua Ni, Hong Cheng, and Zetian Hu. Weknow-rag: An adaptive approach for retrieval-augmented generation integrating web search and knowledge graphs, 2024.

[17] Harsh Thakkar, Ganesh Iyer, and Prasenjit Majumder. A comparative study of approaches in user-centered health information retrieval, 2015.

[18] Sheng-Chieh Lin, Jheng-Hong Yang, Rodrigo Nogueira, Ming-Feng Tsai, Chuan-Ju Wang, and Jimmy Lin. Multi-stage conversational passage retrieval: An approach to fusing term importance estimation and neural query rewriting, 2021.

[19] Emory Hufbauer and Hana Khamfroush. Automatic query optimization for retrieving traffic tweets, 2020.

[20] Carlos Alves Pereira, Tanay Komarlu, and Wael Mobeirek. The future of ai-assisted writing, 2023.

[21] Bahareh Sarrafzadeh, Adam Roegiest, and Edward Lank. Hierarchical knowledge graphs: A novel information representation for exploratory search tasks, 2020.

[22] Andrea Papenmeier, Dagmar Kern, Daniel Hienert, Alfred Sliwa, Ahmet Aker, and Norbert Fuhr. Dataset of natural language queries for e-commerce, 2023.

[23] Sara Abdollahi, Simon Gottschalk, and Elena Demidova. Laser: Language-specific event recommendation, 2023.

[24] Kun Sun and Rong Wang. Computational sentence-level metrics predicting human sentence comprehension, 2024.

[25] Yiming Luo, Patrick Cheong-Iao Pang, and Shanton Chang. Enhancing exploratory learning through exploratory search with the emergence of large language models, 2025.

[26] Yu Zhang, Yanzhen Shen, SeongKu Kang, Xiusi Chen, Bowen Jin, and Jiawei Han. Chain-of-factors paper-reviewer matching, 2025.

[27] Christina Lioma. Dependencies: Formalising semantic catenae for information retrieval, 2017.

[28] David Otero, Javier Parapar, and Álvaro Barreiro. On the statistical significance with relevance assessments of large language models, 2024.

[29] Ye Zhang, Md Mustafizur Rahman, Alex Braylan, Brandon Dang, Heng-Lu Chang, Henna Kim, Quinten McNamara, Aaron Angert, Edward Banner, Vivek Khetan, Tyler McDonnell, An Thanh Nguyen, Dan Xu, Byron C. Wallace, and Matthew Lease. Neural information retrieval: A literature review, 2017.

[30] Hossein A. Rahmani, Xi Wang, Mohammad Aliannejadi, Mohammadmehdi Naghiaei, and Emine Yilmaz. Clarifying the path to user satisfaction: An investigation into clarification usefulness, 2024.

[31] Adriane Chapman, Elena Simperl, Laura Koesten, George Konstantinidis, Luis-Daniel Ibáñez-Gonzalez, Emilia Kacprzak, and Paul Groth. Dataset search: a survey, 2019.

[32] Metin Doslu and Haluk O. Bingol. Context sensitive article ranking with citation context analysis, 2016.

[33] Gautier Izacard, Mathilde Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. Unsupervised dense information retrieval with contrastive learning. *arXiv preprint arXiv:2112.09118*, 2021.

[34] Christina Lioma, Birger Larsen, Wei Lu, and Yong Huang. A study of factuality, objectivity and relevance: Three desiderata in large-scale information retrieval?, 2016.

[35] Fatiha Boubekeur and Wassila Azzoug. Concept-based indexing in text information retrieval, 2013.

[36] Vuong M. Ngo, Tru H. Cao, and Tuan M. V. Le. Wordnet-based information retrieval using common hypernyms and combined features, 2018.

[37] Christophe Van Gysel. Remedies against the vocabulary gap in information retrieval, 2017.

[38] Helia Hashemi, Yong Zhuang, Sachith Sri Ram Kothur, Srivas Prasad, Edgar Meij, and W. Bruce Croft. Dense retrieval adaptation using target domain description, 2023.

[39] Luiz Bonifacio, Hugo Abonizio, Marzieh Fadaee, and Rodrigo Nogueira. Inpars: Data augmentation for information retrieval using large language models, 2022.

[40] Chuan Meng, Negar Arabzadeh, Mohammad Aliannejadi, and Maarten de Rijke. Query performance prediction: From ad-hoc to conversational search, 2023.

[41] Zixuan Li, Lizi Liao, and Tat-Seng Chua. Learning to ask critical questions for assisting product search, 2024.

[42] Yueming Sun and Yi Zhang. Conversational recommender system. In *The 41st international acm sigir conference on research & development in information retrieval*, pages 235–244, 2018.

[43] Hiteshwar Kumar Azad and Akshay Deepak. A novel model for query expansion using pseudo-relevant web knowledge, 2019.

[44] Dayu Yang, Yue Zhang, and Hui Fang. Zeqr: Zero-shot query reformulation for conversational search, 2024.

[45] Yutao Zhu, Huaying Yuan, Shuting Wang, Jiongnan Liu, Wenhan Liu, Chenlong Deng, Haonan Chen, Zheng Liu, Zhicheng Dou, and Ji-Rong Wen. Large language models for information retrieval: A survey, 2024.

[46] Negar Arabzadeh, Xinyi Yan, and Charles L. A. Clarke. Predicting efficiency/effectiveness trade-offs for dense vs. sparse retrieval strategy selection, 2021.

[47] Federico Nanni, Bhaskar Mitra, Matt Magnusson, and Laura Dietz. Benchmark for complex answer retrieval, 2017.

[48] Yuanyuan Qi, Jiayue Zhang, Weiran Xu, and Jun Guo. Finding salient context based on semantic matching for relevance ranking, 2019.

[49] Yixin Nie, Songhe Wang, and Mohit Bansal. Revealing the importance of semantic retrieval for machine reading at scale, 2019.

[50] Ivan Boban, Alen Doko, and Sven Gotovac. Sentence retrieval using stemming and lemmatization with different length of the queries. *Advances in Science, Technology and Engineering Systems*, 5(3):349–354, 2020.

[51] Zhuyun Dai and Jamie Callan. Context-aware sentence/passage term importance estimation for first stage retrieval. *arXiv preprint arXiv:1910.10687*, 2019.

[52] Liang Pang, Yanyan Lan, Jiafeng Guo, Jun Xu, Jingfang Xu, and Xueqi Cheng. Deeprank: A new deep architecture for relevance ranking in information retrieval, 2019.

[53] Sun Kim, Nicolas Fiorini, W. John Wilbur, and Zhiyong Lu. Bridging the gap: Incorporating a semantic similarity measure for effectively mapping pubmed queries to documents, 2017.

[54] Carlos M. Lorenzetti and Ana G. Maguitman. Learning better context characterizations: An intelligent information retrieval approach, 2010.

[55] Zeynep Akkalyoncu Yilmaz, Wei Yang, Haotian Zhang, and Jimmy Lin. Cross-domain modeling of sentence-level evidence for document retrieval. In *Proceedings of the 2019 conference on empirical methods in natural language processing and the 9th international joint conference on natural language processing (EMNLP-IJCNLP)*, pages 3490–3496, 2019.

[56] Seonhoon Kim, Inho Kang, and Nojun Kwak. Semantic sentence matching with densely-connected recurrent and co-attentive information. In *Proceedings of the AAAI conference on artificial intelligence*, volume 33, pages 6586–6593, 2019.

[57] Tom Kenter, Alexey Borisov, Christophe Van Gysel, Mostafa Dehghani, Maarten de Rijke, and Bhaskar Mitra. Neural networks for information retrieval, 2018.

[58] Jay M Ponte and W Bruce Croft. A language modeling approach to information retrieval. In *ACM SIGIR Forum*, volume 51, pages 202–208. ACM New York, NY, USA, 2017.

[59] Enes Altuncu, Jason R. C. Nurse, Yang Xu, Jie Guo, and Shujun Li. Improving performance of automatic keyword extraction (ake) methods using pos-tagging and enhanced semantic-awareness, 2025.

[60] Luis M. de Campos, Juan M. Fernández-Luna, and Juan F. Huete. On the selection of the correct number of terms for profile construction: theoretical and empirical analysis, 2024.

[61] Christina Lioma and Roi Blanco. Part of speech based term weighting for information retrieval, 2017.

[62] Philipp Mayr. Relevance distributions across bradford zones: Can bradfordizing improve search?, 2013.

[63] Chao Liu, Xin Xia, David Lo, Zhiwei Liu, Ahmed E. Hassan, and Shanping Li. Codematcher: Searching code based on sequential semantics of important query words, 2022.

[64] Jaspreet Singh and Avishek Anand. Exs: Explainable search using local model agnostic interpretability, 2018.

[65] Nina Tahmasebi, Lars Borin, and Adam Jatowt. Survey of computational approaches to lexical semantic change, 2019.

[66] Benjamin Piwowarski, Ingo Frommholz, Mounia Lalmas, and Keith van Rijsbergen. Exploring a multidimensional representation of documents and queries (extended version), 2010.

[67] Walid Shalaby, Khalifeh Al Jadda, Mohammed Korayem, and Trey Grainger. Entity type recognition using an ensemble of distributional semantic models to enhance query understanding, 2016.

[68] Runwei Qiang, Feifan Fan, Chao Lv, and Jianwu Yang. Knowledge-based query expansion in real-time microblog search, 2015.

[69] Hongliu Cao. Writing style matters: An examination of bias and fairness in information retrieval systems, 2024.

[70] Christine Bauer, Ben Carterette, Nicola Ferro, and Norbert Fuhr. Report from dagstuhl seminar 23031: Frontiers of information access experimentation for research and education, 2023.

[71] Abdelkrim Bouramoul, Mohamed-Khireddine Kholladi, and Bich-Lien Doan. Using context to improve the evaluation of information retrieval systems, 2011.

[72] Yizhou Chi, Jessy Lin, Kevin Lin, and Dan Klein. Clarinet: Augmenting language models to ask clarification questions for retrieval, 2024.

[73] Philipp Schaer, Philipp Mayr, and Peter Mutschke. Demonstrating a service-enhanced retrieval system, 2010.

[74] José R. Pérez-Agüera and Lourdes Araujo. Comparing and combining methods for automatic query expansion, 2008.

[75] Nicholas J. Belkin, Daniel Hienert, Philipp Mayr, and Chirag Shah. Data requirements for evaluation of personalization of information retrieval - a position paper, 2018.

[76] Gonzalo Navarro. Spaces, trees and colors: The algorithmic landscape of document retrieval on sequences, 2013.

[77] Mohammad Aliannejadi, Morgan Harvey, Luca Costa, Matthew Pointon, and Fabio Crestani. Understanding mobile search task relevance and user behaviour in context, 2019.

[78] Shuai Zhang, Lina Yao, Aixin Sun, and Yi Tay. Deep learning based recommender system: A survey and new perspectives, 2019.

[79] Man Luo, Arindam Mitra, Tejas Gokhale, and Chitta Baral. Improving biomedical information retrieval with neural retrievers, 2022.

[80] Jun Rao, Fei Wang, Liang Ding, Shuhan Qi, Yibing Zhan, Weifeng Liu, and Dacheng Tao. Where does the performance improvement come from? – a reproducibility concern about image-text retrieval, 2022.

[81] Emma J. Gerritse, Faegheh Hasibi, and Arjen P. de Vries. Entity-aware transformers for entity search, 2022.

[82] Ayyoob Imani, Amir Vakili, Ali Montazer, and Azadeh Shakery. Deep neural networks for query expansion using word embeddings, 2018.

[83] Chuan Meng, Negar Arabzadeh, Arian Askari, Mohammad Aliannejadi, and Maarten de Rijke. Query performance prediction using relevance judgments generated by large language models, 2024.

[84] Thierry Hamon, Adeline Nazarenko, Thierry Poibeau, Sophie Aubin, and Julien Derivière. A robust linguistic platform for efficient and domain specific web content analysis, 2007.

[85] David Selby, Kai Spriestersbach, Yuichiro Iwashita, Mohammad Saad, Dennis Bappert, Archana Warrier, Sumantrak Mukherjee, Koichi Kise, and Sebastian Vollmer. Had enough of experts? quantitative knowledge retrieval from large language models, 2025.

[86] Simon Lupart, Thibault Formal, and Stéphane Clinchant. Ms-shift: An analysis of ms marco distribution shifts on neural retrieval, 2023.

[87] Oren Kurland and Lillian Lee. Pagerank without hyperlinks: Structural re-ranking using links induced by language models, 2006.

[88] Rohan Saxena, Maheep Chaudhary, Chandresh Kumar Maurya, and Shitala Prasad. An intelligent recommendation-cum-reminder system, 2021.

[89] Jiafeng Guo, Yixing Fan, Xiang Ji, and Xueqi Cheng. Matchzoo: A learning, practicing, and developing system for neural text matching, 2019.

[90] Alexander B. Veretennikov. Proximity full-text search with a response time guarantee by means of additional indexes, 2018.

[91] Rishav Chakravarti, Cezar Pendus, Andrzej Sakrajda, Anthony Ferritto, Lin Pan, Michael Glass, Vittorio Castelli, J. William Murdock, Radu Florian, Salim Roukos, and Avirup Sil. Cfo: A framework for building production nlp systems, 2020.

[92] Chengxiang Zhai. Fast statistical parsing of noun phrases for document indexing, 1997.

[93] Hui Zhang, Kiduk Yang, and Elin Jacob. Topic level disambiguation for weak queries, 2015.

[94] Dmitry Lande. Building of networks of natural hierarchies of terms based on analysis of texts corpora, 2014.

[95] Jingwei Ni, Tobias Schimanski, Meihong Lin, Mrinmaya Sachan, Elliott Ash, and Markus Leippold. Diras: Efficient llm annotation of document relevance in retrieval augmented generation, 2025.

[96] Svitlana Vakulenko, Vadim Savenkov, and Maarten de Rijke. Conversational browsing, 2020.

[97] Xiao Wang, Craig Macdonald, and Iadh Ounis. Deep reinforced query reformulation for information retrieval, 2020.

[98] Hemanth Kandula, Damianos Karakos, Haoling Qiu, Benjamin Rozonoyer, Ian Soboroff, Lee Tarlin, and Bonan Min. Querybuilder: Human-in-the-loop query development for information retrieval, 2024.

[99] Hiteshwar Kumar Azad and Akshay Deepak. Query expansion techniques for information retrieval: A survey, 2019.

[100] Flávio Martins, João Magalhães, and Jamie Callan. A vertical prf architecture for microblog search, 2018.

[101] Yan Xiao, Jiafeng Guo, Yixing Fan, Yanyan Lan, Jun Xu, and Xueqi Cheng. Beyond precision: A study on recall of initial retrieval with neural representations, 2018.

[102] Keet Sugathadasa, Buddhi Ayesha, Nisansa de Silva, Amal Shehan Perera, Vindula Jayawardana, Dimuthu Lakmal, and Madhavi Perera. Legal document retrieval using document vector embeddings and deep learning, 2018.

[103] Naga Sai Krishna Adatrao, Gowtham Reddy Gadireddy, and Jiho Noh. A survey on conversational search and applications in biomedicine, 2022.

[104] Jingtao Zhan, Jiaxin Mao, Yiqun Liu, Min Zhang, and Shaoping Ma. Learning to retrieve: How to train a dense retrieval model effectively and efficiently, 2020.

[105] Dan Li and Evangelos Kanoulas. Active sampling for large-scale information retrieval evaluation, 2017.

[106] Gowri Shankar Ramaswamy and F Sagayaraj Francis. Concept driven framework for latent table discovery, 2012.

[107] Dirk Tasche. A plug-in approach to maximising precision at the top and recall at the top, 2018.

[108] Tiziano Labruna, Jon Ander Campos, and Gorka Azkune. When to retrieve: Teaching llms to utilize information retrieval effectively, 2024.

[109] Jiongnan Liu, Jiajie Jin, Zihan Wang, Jiehan Cheng, Zhicheng Dou, and Ji-Rong Wen. Reta-llm: A retrieval-augmented large language model toolkit, 2023.

[110] Ted Underwood. The historical significance of textual distances, 2018.

[111] Hanqi Zhang, Chong Chen, Lang Mei, Qi Liu, and Jiaxin Mao. Mamba retriever: Utilizing mamba for effective and efficient dense retrieval, 2024.

[112] Sunhao Dai, Yuqi Zhou, Liang Pang, Weihao Liu, Xiaolin Hu, Yong Liu, Xiao Zhang, Gang Wang, and Jun Xu. Neural retrievers are biased towards llm-generated content, 2024.

[113] Corinna Breitinger, Kay Herklotz, Tim Flegelskamp, and Norman Meuschke. Recommending research papers to chemists: A specialized interface for chemical entity exploration, 2022.

[114] Sruthi S and Tanmay Basu. Identification of the relevance of comments in codes using bag of words and transformer based models, 2023.

[115] Marco Braga, Pranav Kasela, Alessandro Raganato, and Gabriella Pasi. Synthetic data generation with large language models for personalized community question answering, 2024.

[116] Gabriella Kazai, Bhaskar Mitra, Anlei Dong, Nick Craswell, and Linjun Yang. Less is less: When are snippets insufficient for human vs machine relevance estimation?, 2022.

[117] Xinzhi Han and Sen Lei. Feature selection and model comparison on microsoft learning-to-rank data sets, 2018.

[118] Sharvi Endait, Srushti Sonavane, Ridhima Sinare, Pritika Rohera, Advait Naik, and Dipali Kadam. Multilingual evaluation of semantic textual relatedness, 2024.

[119] Catherine Chen and Carsten Eickhoff. Sse: A metric for evaluating search system explainability, 2023.

[120] Vitor Jeronymo, Luiz Bonifacio, Hugo Abonizio, Marzieh Fadaee, Roberto Lotufo, Jakub Zavrel, and Rodrigo Nogueira. Inpars-v2: Large language models as efficient dataset generators for information retrieval, 2023.

[121] Delroy Cameron, Amit Sheth, Nishita Jaykumar, Krishnaprasad Thirunarayan, Gaurish Anand, and Gary A. Smith. A hybrid approach to finding relevant social media content for complex domain specific information needs, 2014.

[122] Liu Yang, Hamed Zamani, Yongfeng Zhang, Jiafeng Guo, and W. Bruce Croft. Neural matching models for question retrieval and next question prediction in conversation, 2017.

[123] Avishek Anand, Lijun Lyu, Maximilian Idahl, Yumeng Wang, Jonas Wallat, and Zijian Zhang. Explainable information retrieval: A survey, 2022.

[124] Gaëlle Candel and David Naccache. Tagged documents co-clustering, 2021.

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