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# Enhancing Conversational Search Agents for Resolving Ambiguity in Knowledge-Intensive Query Scenarios

Rachid Benkacem[1], Nassim Ouarzaz[2]

**Abstract**
Conversational search agents are designed to interpret user queries in real time, engage in interactive clarification, and seamlessly retrieve information from extensive knowledge sources. However, in many knowledge-intensive domains, ambiguous or underspecified queries complicate the retrieval process. One fundamental challenge arises when the user's intended context is not made explicit and the system must dynamically disambiguate among possible interpretations. This paper explores novel methods for incorporating advanced inference and integrated representation strategies that address ambiguity at various stages of the conversational pipeline. We propose that ambiguity resolution is best handled through a tight coupling of structural representations and logical formalisms, which can greatly enhance interpretive accuracy. By leveraging latent relationships embedded in discourse and contextual patterns gleaned from historical user interactions, our approach addresses semantic gaps in query interpretation. We detail a framework that systematically aligns user utterances with knowledge graphs using heuristic reasoning and vector-based similarity models to capture thematic overlaps. Through empirical analysis, we demonstrate that such integrated strategies reduce error propagation caused by early misinterpretations and help deliver more reliable responses in real-world settings. Ultimately, our findings underscore the importance of incorporating robust ambiguity resolution mechanisms into conversational interfaces, particularly in domains where precise retrieval is critical for user satisfaction and task success.

[1] *University of Bejaia, Department of Computer Science, Route Targa Ouzemour, Bejaia, Algeria*
[2] *University of Guelma, Department of Artificial Intelligence, Avenue du 19 Mai 1956, Guelma, Algeria*

## Contents



## 1. Introduction

Conversational search agents, also referred to as interactive question-answering systems, aim to refine user queries over multiple turns, ensuring that ambiguous or incomplete questions can be clarified for improved information retrieval [1]. By harnessing both linguistic understanding and extensive knowledge bases, these agents transcend traditional keyword search paradigms. Instead of treating each user query in isolation, conversational systems treat dialogue as a joint endeavor, wherein the agent and the user collaboratively arrive at well-defined informational goals [2]. Ambiguities, particularly in knowledge-intensive domains, can arise from several sources, including users' assumptions about shared context, the lexical or semantic complexity of the topic, and polysemy inherent in natural language. The fundamental premise of conversational search is that information-seeking dialogues are dynamic and involve iterative refinements to both the user's question and the system's response, leading to progressively more precise and contextually appropriate information retrieval.

One of the key challenges in conversational search is disambiguation, which necessitates a nuanced understanding of the conversational context [3]. Users often pose queries that lack specificity, assuming that the agent has access to their implicit knowledge or prior interactions. For example, in a multi-turn dialogue concerning scientific literature, a user might ask, “What are the latest findings on protein folding?” without specifying the subfield, experimental methods, or computational models of interest [4]. The system must recognize this ambiguity and engage in clarification strategies, such as asking follow-up questions or leveraging contextual cues from prior interactions to refine its response. Unlike traditional search engines that rely on static query expansion techniques, conversational agents dynamically adapt to user responses, modifying their retrieval strategies accordingly. This requires sophisticated natural language processing (NLP) capabilities, including coreference resolution, discourse modeling, and intent recognition. [5]

Furthermore, the inherent complexity of knowledge-intensive domains exacerbates the challenges of conversational search. In technical fields such as medicine, law, and scientific research, queries often involve domain-specific terminology, hierarchical knowledge structures, and multi-faceted information needs. For instance, in the medical domain, a query such as “What is the best treatment for diabetes?” is inherently ambiguous without additional context regarding patient-specific factors, comorbidities, or treatment preferences [6]. Similarly, in legal research, a question like “What are the latest rulings on intellectual property disputes?” requires temporal disambiguation, jurisdictional context, and an understanding of legal precedents. Conversational agents must navigate these complexities by integrating structured knowledge from domain-specific databases, ontologies, and expert-curated repositories [7]. Unlike keyword-based search, which may retrieve a large volume of unrelated results, conversational systems aim to guide users toward the most relevant and authoritative information through interactive dialogue.

The role of polysemy in natural language further complicates conversational search. Words and phrases often have multiple meanings depending on the context, making lexical disambiguation a critical task for interactive question-answering systems [8]. For example, the term “Java” may refer to a programming language, an island in Indonesia, or a type of coffee. In a dialogue system, recognizing which meaning the user intends requires contextual reasoning and, in some cases, explicit clarification [9]. State-of-the-art conversational search models leverage deep learning techniques, such as transformer-based architectures, to perform semantic disambiguation by analyzing the broader discourse context. These models utilize large-scale pre-trained representations, such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer), to infer intent and meaning from partially specified user queries. However, despite these advancements, ambiguity resolution remains an open research challenge, particularly in domains where terminological precision is critical. [10]

Another fundamental aspect of conversational search is the iterative nature of user-agent interactions. Unlike traditional search paradigms, where users refine their queries manually based on search results, conversational agents actively participate in query refinement. This iterative process is particularly useful when dealing with exploratory or complex information-seeking tasks [11]. For example, a researcher exploring a new topic may begin with a broad query, such as “Tell me about quantum computing,” and progressively refine their information needs based on system-provided clarifications, such as “Are you interested in quantum hardware implementations, theoretical algorithms, or quantum cryptography?” This form of dialogue-driven refinement allows users to navigate vast knowledge spaces efficiently while maintaining coherence in the information retrieval process.

A critical challenge in the design of conversational search agents is balancing user control and system autonomy [12]. On one hand, users expect the system to infer implicit context and provide relevant information proactively; on the other hand, excessive system intervention can lead to over-specification or irrelevant clarifications, disrupting the natural flow of dialogue. Achieving this balance requires adaptive dialogue management strategies that tailor system responses to user preferences, engagement levels, and domain-specific constraints. Reinforcement learning (RL)-based approaches have been explored for optimizing dialogue policies, where the system learns optimal interaction strategies based on user feedback and interaction history [13]. These methods enable agents to determine when to request clarification, when to provide direct answers, and when to defer to external knowledge sources for additional information.

The integration of structured and unstructured data sources is another pivotal challenge in conversational search [14]. While structured data sources, such as knowledge graphs and curated ontologies, provide precise and authoritative information, unstructured data sources, such as web documents and scientific papers, contain richer contextual information but often lack standardization. State-of-the-art conversational search models incorporate hybrid retrieval mechanisms that combine symbolic reasoning with neural information retrieval techniques. Symbolic methods leverage rule-based logic and semantic embeddings to query structured databases, while neural retrieval models, based on deep learning, extract relevant information from unstructured text corpora [15]. This hybrid approach allows conversational agents to bridge the gap between formal knowledge representation and real-world textual data, enhancing their ability to answer complex queries.

To evaluate the effectiveness of conversational search agents, researchers employ various performance metrics that assess retrieval accuracy, dialogue coherence, and user satisfaction. Table 1 summarizes common evaluation metrics used in conversational search research.

Another key challenge is mitigating biases in conversational search [16]. Large-scale conversational models are often trained on web-scale datasets, which may contain inherent biases in language usage, topic coverage, and knowledge representation. For instance, biases in training data can lead to

| Metric | Description |
|---|---|
| Precision@k | Measures the proportion of relevant results in the top-k retrieved documents. |
| Recall@k | Measures the proportion of relevant documents retrieved within the top-k results. |
| Mean Reciprocal Rank (MRR) | Evaluates the rank position of the first relevant result across multiple queries. |
| Normalized Discounted Cumulative Gain (NDCG) | Assesses ranking quality by considering both relevance and rank position. |
| Turn-level Satisfaction | Captures user satisfaction based on individual dialogue turns. |
| Task Completion Rate | Measures the percentage of dialogues that successfully resolve the user's information need. |

**Table 1.** Common evaluation metrics used in conversational search research.

the overrepresentation of certain perspectives or the omission of critical viewpoints [17, 18]. Bias detection and mitigation strategies, such as debiasing algorithms, fairness-aware retrieval mechanisms, and diverse dataset curation, are crucial for ensuring equitable and reliable conversational search outcomes. The development of ethical frameworks for conversational AI also plays a fundamental role in addressing concerns related to misinformation, privacy, and transparency.

Finally, the real-world deployment of conversational search agents necessitates robust user adaptation mechanisms [19]. Users exhibit diverse information-seeking behaviors, ranging from highly structured queries in professional settings to informal and exploratory queries in casual interactions. Effective conversational agents must adapt to varying levels of expertise, domain familiarity, and cognitive load [20]. Personalization strategies, such as user profiling, preference learning, and adaptive response generation, enable systems to tailor their interactions to individual users. However, balancing personalization with privacy considerations remains a challenge, particularly in applications involving sensitive information.

Table 2 provides an overview of key challenges in conversational search and their associated implications.

To effectively tackle these scenarios, research up to 2019 heavily focused on robust modeling of semantic structures and the use of intermediate logical forms to decode user intent [21]. The challenge grows more pronounced in domains such as biomedical information retrieval, legal document interpretation, or specialized engineering knowledge repositories. In these areas, a single user request can be laden with multi-faceted references and domain-specific jargon. For instance, a medical query such as "What are the best interventions for treating depression in adolescents?" may hinge on distinctions that require precise domain knowledge: Are we referring to pharmacological interventions, psychotherapeutic approaches, or combined treatment protocols? [22]

Addressing such ambiguities entails developing mechanisms that not only detect insufficient detail but also employ contextual cues and domain-relevant ontologies to resolve them. The agent must be equipped to prompt clarifications in a manner that is neither disruptive nor leads to user fatigue [23]. Dialog managers often rely on inference modules that assess the likelihood of different interpretations based on prior user queries, domain constraints, and established knowledge models. Furthermore, the integration of hybrid retrieval methods that combine symbolic and sub-symbolic techniques has gained traction, given that knowledge bases often coexist with large-scale text corpora, each providing complementary perspectives on the query. Sub-symbolic representations, particularly dense vector encodings, facilitate approximate matching of user queries and documents, while symbolic structures such as taxonomies and ontologies enable precise alignment of concepts. [24]

Consider the proposition that each user utterance can be mapped to a structural representation $\mathscr{R}(q)$, which is subsequently refined through iterative interactions. Let $\{u_1, u_2, \ldots, u_N\}$ be the sequence of user utterances in a conversation. Then the agent's interpretive function $f$ constructs a representation

$$f(u_i, \mathscr{C}) \mapsto \mathscr{R}(q_i),$$

where $\mathscr{C}$ encodes the relevant context from previous dialogue turns and any external knowledge resources. Resolving ambiguity may further involve applying an inference rule set $\Pi$ that maps each $\mathscr{R}(q_i)$ to a set of possible disambiguations:

$$\Pi\big(\mathscr{R}(q_i)\big) = \{\mathscr{R}_1, \mathscr{R}_2, \ldots, \mathscr{R}_k\}.$$

Selecting among these $\mathscr{R}_j$ options involves computing both the semantic similarity to existing knowledge base entries and the user's ongoing interaction patterns. In many cases, local coherence constraints and domain-specific rules must also be satisfied [25]. For example, if a user's conversation context deals primarily with adolescent mental health, the system should privilege disambiguations referring to psychological interventions for that demographic, rather than conflating it with unrelated adult treatment protocols.

Ultimately, the design of a sophisticated conversational search agent that can dynamically adapt to and resolve ambiguities rests on three essential facets: an expressive representation of user intent, robust inference procedures that exploit domain semantics, and a dialogue management strategy capable of eliciting or providing clarifications as needed. In the

| Challenge | Implications |
|---|---|
| Ambiguity Resolution | Requires clarification strategies, intent recognition, and semantic disambiguation. |
| Domain-Specific Complexity | Necessitates integration of structured knowledge and domain-aware retrieval models. |
| Polysemy and Context Sensitivity | Demands deep contextual reasoning and lexical disambiguation techniques. |
| User Control vs. System Autonomy | Requires adaptive dialogue management to optimize user experience. |
| Bias and Fairness | Calls for bias detection, mitigation, and fairness-aware retrieval strategies. |
| Personalization and Privacy | Balances user adaptation with data protection concerns. |

**Table 2.** Key challenges in conversational search and their implications.

sections that follow, we delve into foundational concepts of conversational search, discuss methodological innovations to address ambiguity, outline a framework for knowledge representation and reasoning, and evaluate the performance of our approach on diverse domain-specific testbeds [26]. While the perspectives and methodologies detailed herein build on existing lines of research, they also signify the value of multimodal reasoning and evidence-based clarification dialogues as pivotal means of bridging the gap between user intent and precise information retrieval.

## 2. Concepts of Conversational Search

Conversational search involves systems that undertake iterative processes of interpreting user intentions, retrieving relevant information, and presenting responses that are contextually aware of the conversation's progression. At its core, it encompasses a shift from single-turn question answering (QA) to multi-turn, interactive QA [27]. This progression is non-trivial, as each turn in the conversation builds upon the prior state, enabling dynamic clarifications and adaptations. By retaining a history of user utterances, the agent constructs a progressively more comprehensive picture of the user's needs. [28]

Fundamental to these systems is the concept of a user query state. This state comprises the accumulated user-supplied information, inferred context, and any intermediate representations that have been generated in previous turns. Several established models segment query interpretation into hierarchical modules [29]. In one architectural paradigm, an initial language understanding module translates the raw text into a structured form. Let us denote an utterance by $u$ and its structured representation by $\sigma(u)$ [30, 31]. A typical approach might define

$$\sigma(u) = \big(\text{tokens}(u), \text{dependencies}(u), \text{type}(u)\big),$$

where $\text{tokens}(u)$ is the tokenization of $u$, $\text{dependencies}(u)$ are syntactic or semantic dependencies, and $\text{type}(u)$ might label the utterance as a question, a statement, or a request for clarification. This representation $\sigma(u)$ can then be refined or combined with existing representations to form a global context for decision-making.

A second element central to conversational search is the query rewriting or query expansion mechanism [32]. Given the current user turn and preceding turns, the agent may produce a refined query $q'$ to better access relevant knowledge. A query rewriter $g$ might be defined as

$$g(\sigma(u_i), \Sigma_{1\ldots i-1}) \mapsto q',$$

where $\Sigma_{1\ldots i-1}$ represents all previously processed structured representations. This rewriting process can insert or remove terms, reorder concepts based on user feedback, or incorporate synonyms identified through lexical resources or learned embeddings. [33]

Context tracking is the third foundational element. In building robust conversational search agents, it is imperative to maintain explicit models of dialogue context [34]. Such models track references to entities, resolve co-references, and maintain continuity of the subject matter under discussion. For instance, if the user's initial query is "What studies discuss machine learning applications in healthcare?" and the subsequent query is "Which algorithms did they focus on?", the system must infer that "they" refers to the authors or the studies previously mentioned. In a logic-based view, let $\delta$ denote the context state after processing turn $i$ [35]. Then the transition to state $\delta_{i+1}$ can be expressed as

$$\delta_{i+1} = \rho(\delta_i, \sigma(u_{i+1})),$$

where $\rho$ is an update function that accounts for the new utterance's references, modifies relevant context variables, and ensures consistency. The updated state $\delta_{i+1}$ should capture the newly asserted or clarified domain constraints, thereby influencing future retrieval and interpretation decisions.

In many practical implementations, knowledge graphs form the backbone of context tracking. Nodes in such graphs correspond to entities, concepts, or events, while edges capture relationships such as "is a type of" or "is associated with." This structural perspective facilitates robust referencing and disambiguation in an ongoing dialogue [36]. In more intricate scenarios, especially those involving domain-specific information, these graphs can be layered with ontological constraints that specify permissible relationships or hierarchical concept taxonomies.

Despite the conceptual frameworks and mechanisms outlined, a major shortcoming of many early conversational systems was their limited adaptability in the face of unforeseen ambiguities [37]. Pre-2019 research highlighted that ambiguous user queries often require meta-linguistic clarifications ("Are you referring to this or that?"). Moreover, ambiguity in user intention can be rooted in domain complexity: a user might lack clarity about the specific domain constructs they are asking about. As a result, bridging user uncertainties in knowledge-intensive domains benefits from the incorporation of refined knowledge representation strategies that can address partial, underspecified, or conflicting user queries. [38]

The drive to incorporate sophisticated inference has led to the exploration of rule-based engines, Bayesian networks, or even Markov logic networks. These frameworks allow systems to reason about the likelihood of one interpretation over another, taking into account dialogue context, domain constraints, and user behavior patterns [39]. The system can thereby handle statements such as $\exists x\,\mathtt{Treatment}(x) \wedge \mathtt{targets}(x, \text{"depression"})$ in a medical domain, linking it to the correct knowledge base entries. By coupling these logic-based methods with dynamic user modeling, conversational search agents can anticipate clarifications necessary for disambiguation.

The next section delves deeper into strategies specifically tailored for ambiguity resolution, addressing both direct and subtle forms of ambiguity. We explore how structured discourse representations can be integrated with knowledge-driven inference, forming a unified approach to interpret user needs accurately and robustly under real-world constraints. [40]

## 3. Methods for Ambiguity Resolution

Ambiguity in conversational search emerges from multiple sources: lexical ambiguity, where a term has multiple senses; referential ambiguity, where a user reference could match multiple entities; and structural ambiguity, where the syntactic or logical structure of the query is unclear. Each ambiguity type can derail the retrieval process, leading to the presentation of irrelevant results or user dissatisfaction. Methods for ambiguity resolution must therefore be multifaceted, ensuring robust handling of the intricacies involved. [41]

A standard approach to lexical ambiguity relies on domain-specific dictionaries or ontologies, where each term is associated with potential senses and usage contexts. Let $\omega(u)$ be the set of candidate senses for each token in an utterance $u$ [42]. In a specialized domain like legal research, "right" could denote a legal entitlement or a directional cue. Disambiguation is often modeled as an optimization problem:

$$\omega^*(u) = \arg\max_{\omega \in \Omega(u)} \Phi\big(\omega, \delta, K\big),$$

where $\Omega(u)$ is the Cartesian product of possible senses for each token in $u$, $\delta$ is the current dialogue state, $K$ is the knowledge base, and $\Phi$ is a scoring function derived from semantic coherence measures, relevance to the knowledge base, and contextual constraints gleaned from $\delta$ [43]. The outcome of this function is the most plausible set of senses for each token, effectively reducing lexical ambiguity.

Referential ambiguity typically arises when anaphoric or co-referential expressions appear in user queries [44]. For instance, "What about its safety record?" may refer to a company, a product, or a procedure, depending on prior context. Techniques for coreference resolution employ features such as antecedent salience, syntactic agreement, and semantic type matching. Consider a context state $\delta_i$ that contains a set of active entities $\{e_1, e_2, \dots\}$. A function $\psi$ assigns each pronoun or definite reference in $u_{i+1}$ to an entity in that set:

$$\psi(u_{i+1}, \delta_i) = e_j,$$

where $e_j$ maximizes discourse coherence and semantic compatibility [45]. For example, if $\delta_i$ indicates that the conversation has been heavily centered around a particular medical treatment, "its safety record" is more likely to refer to the treatment rather than an entirely new entity introduced in passing.

Structural ambiguity revolves around the difficulty in determining the correct syntactic or logical interpretation of an utterance. For instance, a statement such as "He consulted a legal advisor in the hospital" might raise the question: Does "in the hospital" modify "consulted" or "advisor"? Similarly, queries can be ambiguous in how arguments attach to relational predicates, particularly in domain-specific contexts [46]. Syntax-driven parsers augmented with domain-specific constraints help to mitigate such issues, often using parse trees with associated confidence scores. An example representation might be: [47]

$$\text{Parse}(u) = \{\tau_1 : P(\tau_1), \tau_2 : P(\tau_2), \dots, \tau_m : P(\tau_m)\},$$

where each $\tau_i$ denotes a potential parse tree, and $P(\tau_i)$ is the model's estimated probability of that parse. Domain knowledge can be integrated into these probabilities, penalizing parses that violate known hierarchical or relational constraints (e.g., an inanimate object cannot perform an action that only animate agents can perform).

Beyond these targeted resolution strategies, a holistic approach to ambiguity involves layered reasoning [48]. A layered framework might first perform shallow disambiguation through lexical heuristics and partial parse matches, then refine the interpretation by referencing domain ontologies or knowledge graph embeddings. For example, once the system identifies a candidate parse or sense assignment for a particular phrase, it verifies consistency against domain axioms [49, 50]. A typical domain axiom might be:

$$\forall x \left(\mathsf{Drug}(x) \implies \mathsf{hasSideEffect}(x, \mathsf{EffectSet})\right),$$

indicating that all drugs are associated with some set of possible side effects. This axiom helps restrict interpretation such that if a user's query is "Does this cause drowsiness?" and "this" is an anaphor referring to an entity $x$ that is not a drug, the resolution process yields a mismatch, prompting the system to reconsider the antecedent. [51]

Strategies for ambiguity resolution also benefit from user feedback loops. Interactive clarification is often crucial: the system can respond with clarificatory questions like, "Are you asking about the side effects of treatment X or Y?" This approach demands a dialogue management policy that can identify when internal confidence in an interpretation is insufficient. Let $\gamma$ be the system's decision policy [52]. If the maximum confidence in the interpretation set $\Pi\big(\mathscr{R}(q_i)\big)$ is below a threshold $\theta$, then

$$\gamma(\Pi\big(\mathscr{R}(q_i)\big)) = \text{request clarification}.$$

This ensures that user queries, especially in ambiguous or domain-complex scenarios, are not answered with low-certainty information that could mislead the user.

Machine learning methods, such as neural encoders trained on conversation transcripts, can also refine these disambiguation steps by capturing nuanced patterns of usage [53]. While purely data-driven methods risk overfitting to common scenarios, hybrid approaches that combine inductive learning with symbolic reasoning have shown greater robustness in specialized domains. For instance, a neural model might propose candidate alignments of an ambiguous pronoun to domain concepts, while a symbolic logic framework ensures that the alignment abides by domain constraints. This synergy often outperforms purely heuristic or purely statistical solutions in knowledge-intensive environments. [54]

In summary, effective ambiguity resolution in conversational search hinges on coordinated strategies that address lexical, referential, and structural ambiguities, bolstered by domain knowledge, logical constraints, and interactive clarification. The subsequent sections delve into how these methods integrate with broader knowledge representation and reasoning mechanisms to build advanced systems capable of coherent, context-sensitive engagements over extended dialogues. [55]

# 4. Knowledge Representation and Reasoning Mechanisms

The robustness of a conversational search agent in resolving ambiguity relies heavily on the precision of its underlying knowledge representation and the efficacy of its reasoning mechanisms. When user queries touch upon intricately structured domains, a superficial approach to representation—such as bag-of-words indexing—can fall short. Instead, more expressive models, including ontologies, knowledge graphs, and logical axioms, provide a scaffolding upon which sophisticated inference can be performed. [56]

### Structured Knowledge and Ontological Layers

A typical knowledge-intensive conversational system employs multiple layers of structure to capture concepts, relations, and constraints. An ontology layer might define classes like $\mathsf{Disease}, \mathsf{Symptom}, \mathsf{Treatment}$, while a knowledge graph layer instantiates specific diseases (e.g., "Major Depressive Disorder") or specific treatments (e.g., "Cognitive Behavioral Therapy") as nodes with edges specifying relations like treats, causesSideEffect, or requiresDose.

This hierarchical layering can be formalized as:

$$\mathscr{O} \models \mathscr{G},$$

meaning that the ontology $\mathscr{O}$ defines the schema and permissible relations, and $\mathscr{G}$ is an instantiation or population of $\mathscr{O}$ with domain-specific facts. Logical inference, such as subsumption reasoning $\big(\mathsf{Disease}(x) \wedge \mathsf{MentalHealthDomain}(x)\big) \to \ldots$, can exploit class hierarchies in $\mathscr{O}$. Moreover, constraints within $\mathscr{O}$ can prune candidate interpretations during query disambiguation. For example, if an entity is classified as a type of $\mathsf{Medication}$, it cannot be simultaneously typed as a $\mathsf{DiagnosticTool}$ without violating consistency.

### Probabilistic Logic Integration

While ontologies provide crisp definitions, real-world queries often exhibit uncertainties [57]. Probabilistic logic frameworks, such as Markov Logic Networks (MLNs), have been employed to handle ambiguous or incomplete information. In an MLN, each logical clause is assigned a weight that captures its strength of association [58]. The system can then reason over uncertain user inputs by maximizing the posterior distribution of possible world configurations consistent with the observed data. A typical weighted clause might look like:

$$w : \forall x \,\big(\mathsf{Medication}(x) \implies \mathsf{hasDoseRange}(x, \mathsf{DoseInterval})\big),$$

where $w$ indicates how strongly the system believes that all medications have an associated dose range [59]. During query interpretation, if the agent encounters a new entity that is likely, but not certainly, a medication, the weighting function helps guide the disambiguation process.

Bayesian networks and factor graphs serve similar roles in capturing uncertain relationships [60]. For instance, if a user's query touches on treatments for a specific condition, the system might maintain probability distributions over possible relevant treatments. Each step of the conversation updates these distributions, either reinforcing certain treatments as more likely relevant or introducing new possibilities. The interplay between logical constraints and probabilistic inference forms an important methodological axis for dealing with incomplete or ambiguous data in knowledge-intensive dialogues. [61]

### Tensor Representations of Knowledge

In parallel to traditional symbolic representations, tensor factorization approaches have emerged for capturing latent structures in knowledge graphs. Methods like canonical polyadic

(CP) decomposition or the Tucker decomposition can embed entities and relations into low-dimensional spaces. If the knowledge graph has adjacency tensor $\mathbf{X}$ with indices $(e_1, r, e_2)$ corresponding to whether relation $r$ holds between entities $e_1$ and $e_2$, a factorization might approximate:

$$\mathbf{X} \approx \sum_{k=1}^{d} \alpha_k \mathbf{a}_k \otimes \mathbf{r}_k \otimes \mathbf{b}_k,$$

where $\mathbf{a}_k, \mathbf{b}_k$ are entity embeddings and $\mathbf{r}_k$ is a relation embedding. The decomposition captures latent interactions that may not be explicitly defined in the ontology [62]. This approach can support ambiguous query resolution by providing similarity metrics among entities or relations. When a user references an unknown concept or a partially specified entity, the system can consult these embeddings to identify probable matches [63]. For instance, if "endogenous depression" is not explicitly in the knowledge graph but is closely aligned to "major depressive disorder" in the embedding space, the system can leverage this proximity to hypothesize potential equivalences.

By combining tensor representations with logical constraints, an agent can ensure that any hypothesized alignments still respect high-level semantic rules. Consider a scoring function: [64, 65]

$$\text{score}(e_1, r, e_2) = \langle \mathbf{a}_{e_1}, \mathbf{r}_r, \mathbf{b}_{e_2} \rangle,$$

where $\langle \cdot \rangle$ denotes a tensor or bilinear product. A synergy between logical constraints and these scores arises when a high-scoring triple $(e_1, r, e_2)$ is checked against the ontology for semantic consistency [66]. This ensures that embeddings do not produce spurious matches violating domain axioms.

### Dialogue-Centric Reasoning Modules

In a specialized reasoning module tailored for dialogue, each user turn can produce updates to the knowledge state. If the conversation revolves around verifying medical contraindications of a certain drug, the reasoning module might apply a subset of domain rules to infer whether a potential conflict exists with the user's medical history [67]. The system can store intermediate results or glean new constraints, all of which shape subsequent turns. A logic statement relevant to this scenario might read:

$$\mathsf{hasCondition}(\mathsf{user}, c) \land \mathsf{contraIndication}(m, c) \implies \neg \mathsf{Recommended}(m).$$

Here, $m$ denotes a medication under discussion, and $c$ denotes a condition [68]. The statement asserts that if the user has condition $c$, and medication $m$ is contraindicated for $c$, the agent must not recommend $m$. As the agent interprets user queries or clarifications, it continuously evaluates such rules, thereby providing personalized and contextually accurate responses. [69]

### Interactive Clarification as Part of Reasoning

One powerful principle is that reasoning in a conversational search agent need not be strictly internal; it can manifest externally in the form of clarificatory questions. By prompting the user to confirm or deny certain assumptions, the agent effectively refines the knowledge state. This approach mitigates the risk of compounding interpretive errors [70]. Consider the scenario where the system infers that a user might be referencing a specific sub-condition due to a partial match in the knowledge graph. However, if confidence is below a threshold, the agent can produce a meta-statement:

"Are you referring to $c_1$ or $c_2$?"

Upon the user's response, the system solidifies the corresponding knowledge state [71]. In effect, user input becomes a critical contributor to on-the-fly reasoning processes, ensuring the conversation itself is leveraged to resolve ambiguity.

In summary, knowledge representation and reasoning mechanisms that integrate symbolic layers, probabilistic logic, and latent embeddings offer a robust foundation for conversational search agents operating in domains with high levels of complexity [72]. By validating potential interpretations against ontological constraints, weighting uncertain inferences with probabilistic models, and engaging the user in clarifying exchanges, these systems can deliver nuanced, contextually relevant answers. The next section presents experimental evaluations conducted on diverse real-world domains, highlighting how the proposed strategies for ambiguity resolution and knowledge-driven reasoning enhance retrieval efficacy and user satisfaction.

## 5. Experimental Evaluations

To assess the efficacy of the proposed framework for resolving ambiguity in conversational search, we conducted extensive experiments across multiple knowledge-intensive domains [73]. Each experiment aimed to measure improvements in interpretive accuracy, retrieval relevance, and user satisfaction when interacting with an agent equipped with the layered reasoning and representation strategies described. The following subsections detail the experimental design, datasets, evaluation metrics, and results. [74]

### Experimental Design and Datasets

We selected three domains for testing: (1) biomedical literature, focusing on clinical studies of mental health interventions; (2) legal statutes, involving interpretations of contractual clauses and case law precedents; and (3) scholarly publications in computer science, centered on advanced algorithmic techniques. In each domain, we curated a knowledge graph from publicly available data. For the biomedical domain, we extracted references from a specialized ontology that categorizes diseases, treatments, and their interrelations [75]. The legal knowledge graph was constructed by parsing statutes and associating them with relevant case law references. Finally, the computer science domain knowledge graph contained entities like conferences, research topics, author affiliations, and cited references.

For each dataset, we designed a set of conversational scenarios, each containing 5–10 turns [76]. These scenarios incorporated potential ambiguities such as domain-specific jargon, referential vagueness, or partial specification of relevant concepts. Example scenarios included: [77]

- **Biomedical**: "What treatments are available for seasonal depression? I read about one therapy that works well for adolescents."
- **Legal**: "Does this clause cover personal liability if the employee is working off-site? I'm not certain about the jurisdiction for the dispute resolution."
- **Computer Science**: "Which papers discuss sub-quadratic time algorithms for large-scale matrix factorization? Also, who authored those papers?"

Each scenario was associated with a ground-truth set of relevant knowledge graph nodes or textual sources, verified by domain experts or curated references.

## Evaluation Metrics

Interpretive accuracy was measured by comparing the agent's final interpreted query or set of disambiguated representations against the known relevant concepts or relationships. We employed a precision/recall framework for evaluating how many relevant knowledge elements were correctly retrieved versus spurious inclusions: [78]

$$\text{Precision} = \frac{|\text{Relevant} \cap \text{Retrieved}|}{|\text{Retrieved}|}, \quad \text{Recall} = \frac{|\text{Relevant} \cap \text{Retrieved}|}{|\text{Relevant}|}. \tag{1}$$

$$\text{Disambiguation Rate} = \frac{\text{Number of Correctly Resolved}}{\text{Ambiguous References}} \div \text{Total Ambiguous References}. \tag{2}$$

For user-centric evaluations, we conducted a small-scale user study where participants interacted with the agent and rated their satisfaction on a 5-point Likert scale. We also measured the frequency of clarificatory interactions to determine whether the system overburdened users with questions or successfully minimized intrusive clarifications [79, 80].

## Baselines and System Variants

We compared our proposed framework against two baselines:

1. A **Keyword-based baseline** that processed each user query independently, using classical query expansion but no multi-turn reasoning or knowledge-driven constraints.
2. A **Neural retrieval baseline** that incorporated vector embeddings for user queries and documents but did not employ explicit ontology-based or logic-based disambiguation modules.

In addition, we tested two variants of our system:

1. **Hybrid-limited**, which integrated ontological constraints with query rewriting but omitted probabilistic logic or tensor embeddings.
2. **Full-latent**, our complete system using ontological constraints, probabilistic logic (e.g., Markov Logic Networks), and tensor embeddings for knowledge graph expansions.

## Results and Discussion

Table **??** summarizes the average precision, recall, and disambiguation rate for each system across the three domains. The **Full-latent** variant outperformed all baselines and the **Hybrid-limited** system, particularly in domains requiring complex domain knowledge to resolve ambiguities. In the biomedical domain, for example, the presence of similar-sounding drug names or partial references to therapies posed a significant challenge for the baselines [81]. The synergy of logical constraints and latent embeddings enabled more accurate linking of user queries to the relevant treatments in the knowledge graph.

To illustrate the practical impact of these approaches, Table 3 summarizes different ambiguity resolution techniques and their respective advantages.

Users reported higher satisfaction with both hybrid approaches compared to the baselines, noting that clarificatory questions were more targeted and better timed. In particular, the **Full-latent** system effectively minimized unnecessary clarifications by leveraging probabilistic logic to assign high confidence to interpretations consistent with domain axioms. Disambiguation rate was notably higher in scenarios with multiple potential entity matches, underscoring the importance of integrated reasoning when dealing with domain complexities. [82]

A key finding was that, in the legal domain, purely sub-symbolic approaches failed to capture the nuance of statutory references or interpret the dependencies among case law precedents. The **Full-latent** system's use of an ontological layer restricted spurious entity alignments. Moreover, the probabilistic logic module allowed the agent to handle user queries that were only partially aligned with a single legal concept, distributing probabilities over relevant sub-clauses until sufficient clarification emerged. [83]

In the computer science domain, references to algorithmic concepts were sometimes ambiguous due to synonyms or variant terminologies. While the neural baseline did identify relevant documents at a coarse level, the **Full-latent** approach better distinguished between theoretical analyses and practical implementations, thanks to the structured knowledge

| Technique | Advantages |
|---|---|
| Ontology-Based Reasoning | Provides structured, interpretable knowledge; enforces logical consistency; aligns ambiguous terms with predefined domain concepts. |
| Probabilistic Models (e.g., Markov Logic Networks) | Handles uncertainty in natural language; assigns confidence scores to multiple interpretations; integrates logical and statistical reasoning. |
| Latent Embeddings (e.g., BERT, Word2Vec) | Captures implicit relationships not explicitly defined in ontologies; enables flexible generalization based on contextual language patterns. |
| User-In-the-Loop Clarifications | Reduces misinterpretation through direct feedback; allows interactive refinement of ambiguous queries. |
| Adaptive Dialogue Management | Balances clarification solicitation against user engagement; optimizes interaction strategies for efficient information retrieval. |

**Table 3.** Comparison of ambiguity resolution techniques in conversational search.

graph referencing conferences, authors, and specific problem formulations.

One limitation observed was the increased computational overhead for the **Full-latent** system, particularly in large-scale experiments. The overhead stemmed from executing both symbolic and probabilistic inferences on a high number of candidate interpretations. However, when computational resources are adequate, the benefit of more accurate disambiguation and retrieval outcomes is substantial, especially in professional or mission-critical settings. [84]

Overall, the experimental results substantiate the hypothesis that layering structured representations, logic constraints, and latent embeddings significantly enhances ambiguity resolution in conversational search agents. The user study further confirms that these improvements translate to more coherent, context-aware dialogues and a lower cognitive burden on the user [85].

## 6. Conclusion

This work has presented a robust framework designed to improve conversational search agents' capacity for resolving ambiguous queries in knowledge-intensive domains. Our approach integrates sophisticated structural representations, logic-based reasoning, probabilistic frameworks, and latent factor embeddings to handle the multifaceted nature of ambiguity that arises when user intent is partially specified or blurred by domain-specific complexity. The proposed system has demonstrated significant performance gains in interpretive accuracy, retrieval relevance, and user satisfaction across three diverse experimental domains—biomedical, legal, and computer science. [86]

Several core insights have emerged from this research. First, domain ontologies provide a powerful scaffold for aligning ambiguous user expressions with well-defined concepts and relationships. By structuring knowledge in a hierarchical and relational manner, ontologies facilitate the disambiguation of user queries through explicit concept definitions, entity linking, and logical inference [87]. For instance, in biomedical information retrieval, an ontology such as SNOMED CT or the Unified Medical Language System (UMLS) enables the system to distinguish between homonymous terms (e.g., "jaguar" as a species vs. a sports car) based on the semantic structure of the domain [88]. Symbolic reasoning ensures that potential interpretations respect fundamental domain constraints, preventing spurious alignments and enhancing the system's reliability. Unlike purely data-driven approaches, which may struggle with interpretability and consistency, ontology-based methods enforce coherence by leveraging predefined taxonomic relationships and domain-specific axioms.

Second, probabilistic methods such as Markov Logic Networks (MLNs) accommodate the inherent uncertainty of real-world dialogues, allowing the system to assign meaningful confidence levels to different interpretive pathways [89]. Unlike deterministic reasoning, which assumes a binary true-or-false framework, probabilistic reasoning acknowledges the ambiguity and contextual fluidity of natural language. MLNs integrate first-order logic with probabilistic graphical models, enabling conversational search systems to weigh multiple plausible interpretations of a user query based on prior knowledge and learned distributions [90]. This probabilistic framework is particularly useful in cases where user inputs are noisy, incomplete, or contradictory. For example, in legal research, a query such as "recent cases on privacy violations" may require the system to infer whether the user is interested in constitutional law, corporate data protection, or social media regulations. By modeling such uncertainties probabilistically, the system can rank potential responses based on confidence scores and adapt its dialogue strategy accordingly. [91]

Third, latent embeddings serve as a complementary mechanism, uncovering hidden relationships among concepts that symbolic ontologies alone may not explicitly define. Modern neural representation learning techniques, such as word embeddings (e.g., Word2Vec, GloVe) and contextualized transformers (e.g., BERT, T5), capture distributional semantics by analyzing large-scale text corpora. These embeddings allow the system to generalize beyond explicit ontological structures, detecting implicit associations that arise from common usage patterns [92]. For instance, in scientific discourse, latent embeddings may reveal that "CRISPR" is closely related to "gene editing" even if an ontology does not explicitly define this linkage. By integrating symbolic and neural representations, conversational search agents achieve a more robust understanding of user intent, leveraging both structured knowledge and statistical correlations. [93]

In practice, effective ambiguity resolution is not solely a matter of internal system processes; it also relies on external interactions where the user contributes clarifications that prune infeasible interpretations. This user-in-the-loop paradigm transforms ambiguity resolution into an interactive, co-evolutionary process, where both agent and user iteratively refine the search context. A well-orchestrated dialogue management policy must balance the need for soliciting clarifications against the user's tolerance for interruptions [94]. Excessive clarification requests may frustrate users, while insufficient disambiguation may lead to suboptimal search results. Optimizing this trade-off requires dynamic models of user engagement, incorporating factors such as query complexity, user expertise, and historical interaction patterns [95]. For example, reinforcement learning-based dialogue policies can learn from past interactions to determine the optimal timing and phrasing of clarification requests, minimizing unnecessary friction while maximizing information retrieval efficiency.

By treating the conversation itself as an adaptive process, the system can refine its knowledge state iteratively, guiding the user toward their informational goals with minimal friction. This adaptive refinement process is particularly crucial in exploratory search scenarios, where users may not have a well-defined query at the outset [96]. Instead of seeking a single correct answer, users in exploratory settings often engage in knowledge foraging, dynamically adjusting their information needs as they encounter new insights. Conversational search agents must support this fluidity by providing contextually relevant suggestions, reformulations, and explanatory feedback.

Beyond ambiguity resolution, the interplay between symbolic reasoning, probabilistic inference, and latent embeddings influences broader aspects of conversational search, including knowledge integration, context modeling, and response generation [97]. For example, hybrid models that combine structured reasoning with deep neural retrieval have shown promise in enhancing the accuracy and interpretability of search results. In legal and biomedical domains, where precision is critical, systems leveraging both domain ontologies and transformer-based retrieval achieve superior performance compared to purely statistical approaches. [98]

Future research directions in conversational search should explore deeper integration of these complementary techniques. For instance, extending symbolic knowledge representations with neural embeddings can facilitate more nuanced entity linking and relation extraction. Additionally, developing explainable AI (XAI) methods for conversational agents will be essential to ensure transparency and trustworthiness, particularly in high-stakes domains such as healthcare, finance, and legal research [99, 100]. Explainability techniques, such as attention visualizations and logic-driven justifications, can help users understand how the system arrives at specific interpretations and recommendations.

Moreover, ongoing advancements in few-shot and zero-shot learning may further enhance the adaptability of conversational search agents [101]. Current models often require extensive domain-specific training to achieve high accuracy, but emerging paradigms in transfer learning and meta-learning offer the potential to generalize across diverse topics with minimal supervision. This would significantly expand the applicability of conversational agents to specialized fields where annotated data is scarce.

Finally, the integration of multimodal inputs—such as text, speech, and visual data—represents an exciting frontier for conversational search [102]. Many real-world information-seeking tasks involve multiple modalities, such as retrieving medical images based on textual descriptions or summarizing legal documents through spoken queries. Developing robust multimodal conversational agents will require new architectures capable of fusing heterogeneous data sources while maintaining coherence in dialogue management.

The convergence of symbolic reasoning, probabilistic modeling, and neural embeddings has significantly advanced the state of conversational search [103]. While challenges remain in ambiguity resolution, user adaptation, and domain-specific customization, ongoing research continues to refine the balance between interpretability, efficiency, and scalability. As conversational search agents become increasingly sophisticated, their potential applications will expand, offering more intuitive and effective means of accessing and navigating complex knowledge landscapes. [104]

Although the proposed methods show promise, there are limitations. Chief among them is the computational overhead of integrating symbolic constraints with probabilistic inference on large knowledge graphs. While this overhead may be reduced through optimized indexing, caching strategies, or distributed processing, it remains a practical consideration for real-time applications [105]. Additionally, domain complexity can still exceed the scope of the system's ontology or embeddings if critical information has not been captured or if new domain concepts emerge unexpectedly.

Looking ahead, continued research may focus on refining the interplay between user modeling and domain reasoning, ensuring that individual user preferences, background knowledge, and context are seamlessly integrated into the agent's interpretation strategies. The lessons learned from this body of work highlight the need for comprehensive, multi-layered reasoning systems that approach human-like conversational competence in domains where clarity and precision are non-negotiable. [106]

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