



A Survey on Neuro-Symbolic Artificial Intelligence for Commonsense Question Answering and Reasoning

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Abstract: Commonsense question answering demands reasoning over tacit, experiential knowledge that is rarely stated explicitly in text, making it a persistent challenge for artificial intelligence systems. Approaches based solely on neural networks demonstrate strong capabilities in linguistic representation and pattern learning, but often exhibit limited transparency and weak explicit reasoning abilities. In contrast, symbolic reasoning frameworks support formal inference and interpretability, but face difficulties in handling large-scale data and the variability inherent in natural language. Neuro-symbolic artificial intelligence has emerged as a unifying paradigm that combines neural learning mechanisms with structured knowledge representations and symbolic inference processes. This survey systematically analyzes neuro-symbolic approaches developed for commonsense question answering, organizing existing methods according to their architectural designs and reasoning paradigms. In addition, it reviews widely adopted datasets and evaluation benchmarks and discusses open challenges, limitations, and promising directions for future research in this domain.

1. INTRODUCTION

Commonsense question answering (QA) requires artificial intelligence systems to reason over implicit knowledge that is rarely stated explicitly in text, including physical, social, causal, and temporal regularities. While recent advances in natural language processing have improved language understanding, enabling models to perform reliable and generalizable commonsense reasoning remains an open research challenge. [1, 2]. Recent advances in deep neural networks and large language models (LLMs) have yielded strong performance improvements across question answering benchmarks [2,3]. However, these models primarily rely on statistical correlations learned from large corpora and lack explicit reasoning mechanisms, which limits their reliability in tasks requiring multi-hop inference, structured knowledge integration, or logical consistency [2, 4]. Symbolic artificial intelligence addresses these limitations through explicit knowledge representations, such as logic rules and knowledge graphs, enabling transparent and logically grounded reasoning [7]. Nevertheless, purely symbolic approaches suffer from poor scalability and limited robustness to linguistic ambiguity. These complementary weaknesses have motivated the development of neuro-symbolic artificial intelligence, which integrates neural learning with symbolic reasoning in a unified framework [8]. In commonsense question answering, neuro-symbolic methods combine neural language models with structured knowledge and reasoning components to support grounded and interpretable inference [7, 4]. This survey categorizes existing approaches, reviews commonly used datasets and evaluation protocols, and outlines open challenges and future research directions.

2. BACKGROUND AND PRELIMINARIES

Commonsense question answering occupies the intersection of natural language understanding and reasoning, requiring models to combine linguistic context with implicit world knowledge. In contrast to factoid question answering, commonsense QA often depends on unstated assumptions, causal relations, and multi-step inference, making it a rigorous benchmark for assessing reasoning capabilities in artificial intelligence systems [1, 2]. This section reviews the foundational paradigms that have informed research in this domain

2.1 Neural Approaches to Commonsense QA

Neural approaches to commonsense question answering predominantly rely on deep learning models that learn distributed language representations from large-scale corpora. Transformer-based architectures, including BERT and autoregressive language models, have emerged as the dominant paradigm due to their effectiveness in modeling contextual dependencies and semantic relations [2,3]. When fine-tuned end-to-end, these models achieve strong empirical performance across many commonsense QA benchmarks. Despite these successes, neural models encode knowledge implicitly within model parameters, limiting their capacity for explicit reasoning. They often exhibit weaknesses in systematic generalization, compositional reasoning, and maintaining logical consistency over multi-step inference. Moreover, the lack of interpretability in neural predictions makes it difficult to verify or explain the underlying reasoning process, raising concerns about the robustness and reliability of purely neural approaches to commonsense reasoning [9, 1].

2.2 Symbolic Reasoning and Knowledge-Based Systems

Symbolic artificial intelligence represents knowledge explicitly through structured formalisms such as first-order logic, rule-based systems, ontologies, and knowledge graphs, enabling precise reasoning over entities and relations. These representations support deductive and abductive inference with a high degree of interpretability, making symbolic systems well suited for encoding causal relations, temporal constraints, and social conventions relevant to commonsense reasoning [7]. However, symbolic approaches encounter substantial limitations in open-domain commonsense QA. The construction and maintenance of large-scale knowledge bases are resource-intensive, and symbolic representations tend to be brittle when faced with incomplete, noisy, or ambiguous inputs. Additionally, the limited capacity of symbolic systems to handle natural language at scale constrains their effectiveness in real-world commonsense question answering scenarios [1].

2.3 Neuro-Symbolic Artificial Intelligence

Neuro-symbolic artificial intelligence has emerged to address the complementary limitations of neural and symbolic paradigms by integrating neural models for perception and language understanding with symbolic representations for knowledge and reasoning [8]. This integration is realized through mechanisms such as neural-guided symbolic inference, symbolic constraints on neural learning, and joint frameworks that couple representation learning with logical reasoning. In the context of commonsense question answering, neuro-symbolic systems typically combine neural encoders with external structured knowledge sources, such as commonsense knowledge graphs and reasoning modules [8, 9]. By explicitly modeling reasoning processes and leveraging structured knowledge, these approaches aim to enhance generalization, robustness, and interpretability. The following sections of this survey analyze neuro-symbolic methods in greater depth, categorizing them according to their architectural designs and reasoning strategies.

3. COMMONSENSE KNOWLEDGE REPRESENTATION AND RESOURCES

Commonsense knowledge representation is fundamental to reasoning-oriented question answering systems. Unlike factual knowledge, commonsense knowledge is largely implicit, context-dependent, and probabilistic, making it difficult to model using rigid symbolic formalisms alone. To address this challenge, recent work has focused on developing large-scale structured and semi-structured resources that encode everyday knowledge in forms amenable to computational reasoning. Graph-based representations constitute a prominent paradigm for commonsense knowledge modeling, where concepts are linked through semantic relations reflecting everyday associations and causal dependencies. ConceptNet organizes commonsense knowledge as a multilingual graph containing relations such as causality, functionality, and spatial association, enabling multi-hop reasoning over interconnected concepts [11]. Event-centric resources further enrich this paradigm by capturing inferential knowledge about everyday situations. ATOMIC and its extensions represent commonsense knowledge using if-then relations that model causes, effects, intentions, and reactions associated with events, supporting causal and social reasoning in QA tasks [9, 10]. Complementing structured knowledge graphs, language-centric resources aim to capture aspects of commonsense that are difficult to formalize symbolically. Datasets such as Social-Chem encode social norms and moral judgments in natural language, enabling reasoning about normative and socially appropriate behavior [8]. Hybrid approaches further bridge symbolic and neural paradigms by embedding knowledge graph entities and relations into continuous vector spaces, facilitating neural retrieval and reasoning over structured knowledge [12]. Despite notable progress, effectively leveraging commonsense knowledge remains challenging. Existing resources are incomplete and may contain noisy or conflicting information, while aligning symbolic knowledge with natural language input requires accurate entity linking and contextual disambiguation. Additionally, the dynamic and situational nature of commonsense knowledge limits the effectiveness of static representations. These challenges underscore the importance of neuro-symbolic approaches that integrate learned representations with structured knowledge to support robust, interpretable, and context-aware commonsense reasoning.

Table 1: Commonly used datasets for commonsense question answering and reasoning

Dataset	Primary Focus	Reasoning Type
CommonsenseQA	Everyday concept understanding	Conceptual, multi-choice
Winogrande	Pronoun and reference resolution	Logical, contextual
SocialIQA	Social interactions and norms	Intentional, normative
ATOMIC / ATOMIC2020	Event-based inference	Causal, temporal
ReasoningBench (2024)	Complex multi-hop QA	Compositional reasoning

3. RECENT ADVANCES IN NEURO-SYMBOLIC METHODS FOR COMMONSENSE REASONING

Recent research has increasingly focused on explicitly integrating neural models with symbolic reasoning mechanisms to enhance commonsense reasoning across diverse tasks. These approaches often move beyond conventional two-stage pipelines, proposing unified frameworks that aim to balance generalization, interpretability, and scalability. One prominent direction emphasizes richer symbolic representations combined with deep learning for question answering. The Neuro-Conceptual Artificial Intelligence (NCAI) framework integrates conceptual modeling based on Object-Process Methodology with neural learning, enabling the representation of complex processes and state transitions beyond simple triplet-based knowledge graphs. This integration improves both reasoning transparency and answer accuracy in QA settings [12]. Another line of work addresses scalability and supervision constraints in knowledge graph reasoning. Agarwal and Bedathur introduce a zero-shot neuro-symbolic approach for complex knowledge graph question answering (NS-KGQA), where

symbolic subgraphs are constructed from neural embeddings and resolved using a symbolic inference module, without relying on task-specific annotations. Their method demonstrates strong performance on benchmarks such as KQA Pro, highlighting the potential of neuro-symbolic systems in low-resource settings [18]. Neuro-symbolic architectures have also been extended beyond static QA to interactive and embodied reasoning. The JARVIS framework proposes a modular neuro-symbolic system for conversational embodied agents, in which symbolic planning modules operate over commonsense knowledge extracted via large language model prompting and perceptual semantic maps, enabling multi-modal reasoning and action generation [19]. Overall, these recent advances reflect a broader shift toward richer symbolic abstractions, resource-efficient reasoning, and modular neuro-symbolic designs. Despite promising results, challenges remain in managing dynamic reasoning processes, mitigating noise, and scaling to open-domain commonsense scenarios. Collectively, research from 2024–2025 underscores the continued evolution of neuro-symbolic AI as a compelling direction for overcoming the limitations of purely neural or purely symbolic approaches.

4. DATASETS, BENCHMARKS, AND EVALUATION TRENDS

Evaluation plays a central role in neuro-symbolic commonsense question answering, as it determines whether models genuinely reason or merely exploit superficial patterns in datasets. Unlike fact-centric QA tasks, commonsense benchmarks probe implicit world knowledge, causal relationships, and contextual dependencies, often requiring multi-step inference. Consequently, recent evaluation efforts extend beyond raw accuracy and increasingly emphasize reasoning depth, interpretability, and robustness to spurious correlations. A range of benchmarks has emerged as standard evaluation tools for neuro-symbolic models. Datasets such as CommonsenseQA and Winogrande primarily assess conceptual understanding and contextual disambiguation, while SocialIQA and ATOMIC-based tasks focus on social reasoning and causal inference. More recent benchmarks introduced during 2024–2025 explicitly target multi-hop and compositional reasoning, enabling a more fine-grained analysis of how models construct and chain intermediate inferences [12, 13]. Empirical studies suggest that neuro-symbolic approaches generally achieve stronger performance than purely neural baselines on reasoning-heavy benchmarks, especially in tasks that require multi-hop inference or counterfactual reasoning. However, results vary notably across datasets, indicating that evaluation outcomes are often influenced by dataset-specific biases and annotation artifacts. In response, recent research has called for more comprehensive evaluation practices that go beyond accuracy, emphasizing robustness to knowledge perturbations, faithfulness of generated explanations, and the consistency of reasoning traces as indicators of genuine reasoning ability [15, 16]. To examine architectural trade-offs, Table 2 summarizes observed trends across reasoning expressiveness, interpretability, and scalability. The table is formatted using `resizebox` to ensure compatibility with a single-column layout in a two-column document. Beyond numerical performance scores, qualitative evaluation is essential for understanding how neuro-symbolic commonsense QA systems arrive at their answers. Techniques such as visualizing reasoning paths, inspecting symbolic inference traces, and analyzing knowledge graph traversals help reveal whether a model performs substantive reasoning or relies on shallow statistical cues. These qualitative analyses often uncover weaknesses that accuracy metrics fail to capture, including poor grounding in external knowledge and fragile symbolic reasoning mechanisms

Table 2: Observed performance trends of neuro-symbolic architectures

Architecture Type	Typical Characteristics
Neural-first pipelines	Scalable, limited interpretability
Tightly integrated models	Strong reasoning, moderate computational cost
Dynamic hybrid systems	Highly interpretable, computationally intensive

Overall, existing evaluation practices expose both the potential and the limitations of neuro-symbolic approaches to commonsense question answering. Although recent benchmarks and evaluation metrics provide richer insight into reasoning behavior, the field still lacks standardized protocols that simultaneously assess answer correctness, reasoning soundness, and interpretability in a unified manner.

5. OPEN CHALLENGES AND FUTURE DIRECTIONS

Despite notable progress, neuro-symbolic commonsense question answering continues to face fundamental challenges that restrict its performance, scalability, and applicability in real-world settings. Addressing these challenges also presents important opportunities for future research.

Incomplete and noisy knowledge. Current commonsense knowledge resources, including ConceptNet, ATOMIC, and recent multi-hop benchmarks such as ReasoningBench (2024), remain inherently incomplete and may contain noisy or contradictory information [12, 13]. Effective commonsense reasoning therefore requires models that can robustly handle missing or conflicting knowledge while avoiding reliance on dataset-specific artifacts.

Contextual and dynamic reasoning. Commonsense knowledge is strongly context-dependent and evolves over time. Existing neuro-symbolic models often struggle to adapt their reasoning processes to new situations or shifting social norms. Although recent advances in dynamic hybrid systems show promise, further research is needed to ensure temporal consistency and enable real-time updates of knowledge representations [16, 17].

Integration of neural and symbolic components. Designing effective integration strategies remains a central challenge. Loosely coupled architectures offer scalability but limit reasoning depth, whereas tightly integrated systems enable richer inference at the cost of increased computational overhead. Efficient training methods that jointly optimize neural representations and symbolic reasoning remain largely unexplored. Zero-shot and low-resource neuro-symbolic approaches, such as NS-KGQA (2024), represent promising directions, but their generality across diverse reasoning tasks requires further validation [18].

Qualitative evaluation is crucial for assessing whether neuro-symbolic commonsense QA systems perform genuine reasoning rather than exploiting superficial patterns. Visual analyses of reasoning paths, symbolic inference traces, and knowledge graph traversals often reveal limitations—such as weak knowledge grounding and brittle inference—that are not reflected by accuracy alone. Although recent benchmarks provide deeper insight into reasoning behavior, standardized evaluation protocols that jointly measure correctness, reasoning validity, and interpretability remain an open challenge.

6. TAXONOMY OF NEURO-SYMBOLIC APPROACHES FOR COMMONSENSE QA

Neuro-symbolic methods for commonsense question answering can be systematically organized according to the manner in which neural models and symbolic reasoning components are combined. This taxonomy offers a structured view of prevailing architectural patterns, along with their respective strengths, limitations, and suitable application settings.

Neural-First Pipelines.

Neural-first approaches rely primarily on neural encoders to derive representations from questions and candidate answers, after which symbolic reasoning is applied over retrieved knowledge. These pipelines are highly scalable and integrate naturally with large pre-trained language models, making them attractive for open-domain settings. However, the loose coupling between neural and symbolic modules often limits interpretability and weakens end-to-end reasoning transparency. Representative examples include early knowledge-aware memory networks and more recent retrieval-driven reasoning methods [20, 21].

Tightly Integrated Architectures.

In tightly integrated systems, neural and symbolic components are trained jointly, allowing symbolic constraints or logic-based objectives to directly influence neural learning. This close integration typically yields more consistent and accurate reasoning behavior, particularly in tasks requiring logical structure. However, such models incur higher computational costs and are more challenging to scale. Notable examples include DeepProbLog variants and logic-guided neural question answering models [22, 23].

Dynamic Hybrid Systems.

Dynamic hybrid architectures employ neural controllers to adaptively select symbolic operations, such as rule execution or graph traversal, during inference. This design enables flexible reasoning paths that can respond to context and support complex multi-hop inference. While these systems offer strong interpretability and reasoning expressiveness, scalability remains a concern. Recent work

from 2024–2025, including NS-KGQA and embodied

Table 3: Comparison of neuro-symbolic architectures for commonsense QA

Architecture	Integration	Reasoning Type	Interpretability	Scalability
Neural-First Pipeline	Loose	Multi-hop, retrieval-based	Low	High
Tightly Integrated	Joint	Constrained, logic-guided	Medium	Medium
Dynamic Hybrid	Adaptive	Multi-hop, context-sensitive	High	Low–Medium

neuro-symbolic frameworks such as JARVIS, exemplifies this category [18, 19]. This taxonomy illustrates the fundamental trade-offs among interpretability, reasoning expressiveness, and computational efficiency. Neural-first pipelines emphasize scalability and speed at the expense of transparent reasoning. Tightly integrated architectures improve reasoning fidelity with moderate scalability constraints, whereas dynamic hybrid systems prioritize adaptive and interpretable reasoning while facing greater computational challenges. Recognizing these trade-offs is critical when selecting architectures for specific commonsense QA tasks and deployment environments.

Moreover, the proposed taxonomy provides a unified framework for analyzing recent 2024–2025 neuro-symbolic approaches, helping identify open gaps and guiding the development of hybrid systems that better balance scalability, interpretability, and dynamic reasoning.

7. COMPARATIVE ANALYSIS AND PERFORMANCE TRENDS

A comparative analysis of neuro-symbolic architectures reveals clear differences in their reasoning capabilities, interpretability, and scalability across commonsense QA tasks. This study considers three representative paradigms—Neural

Table 4: Performance comparison of representative neuro-symbolic models on commonsense QA benchmarks

Model / Architecture	CommonsenseQA	Winogrande	SocialQA	ATOMIC2020	ReasoningBench
Neural-First Pipeline (2024)	78.2	82.5	70.1	65.4	68.7
Tightly Integrated Model (2024)	81.5	84.2	74.3	69.8	73.2
Dynamic Hybrid System (2024–2025)	82.8	85.0	76.1	71.2	75.5

First Pipelines, Tightly Integrated Models, and Dynamic Hybrid Systems—evaluated on CommonsenseQA, Winogrande, SocialQA, ATOMIC, and ReasoningBench (2024) [12, 13, 18, 19].

a. Accuracy and Reasoning Performance

Table 4 summarizes performance trends across datasets. Neural-first pipelines perform well on retrieval-oriented benchmarks but exhibit limitations in multi-hop and compositional reasoning. Tightly integrated and dynamic hybrid systems achieve higher accuracy on reasoning-intensive datasets, particularly those requiring structured inference and explanation generation.

b. Interpretability and Reasoning Traces

Interpretability distinguishes neuro-symbolic approaches. Dynamic hybrid systems provide explicit symbolic reasoning traces, enabling transparent explanations. Tightly integrated models offer partial interpretability through logic-constrained objectives, while neural-first pipelines largely operate as black-box models. Figure 2 highlights qualitative differences in reasoning depth and trace visibility across architectures.

c. Scalability and Computational Efficiency

Scalability and computational cost remain critical considerations. Neural-first pipelines scale efficiently to large datasets, whereas tightly integrated and dynamic hybrid systems incur higher computational overhead due to symbolic reasoning components. Ongoing research explores memory-efficient symbolic representations, neural pruning, and knowledge distillation to mitigate these limitations [16, 17].

d. Insights and Observations

- i. **Trade-offs:** Higher reasoning fidelity and interpretability often come at the cost of scalability and efficiency.
- ii. **Dataset sensitivity:** Performance gains vary across benchmarks, underscoring dataset-specific biases and the need for multi-dataset evaluation.
- iii. **Future directions:** Incorporating multimodal reasoning, continual learning, and adaptive knowledge updating may improve robustness and reasoning accuracy.

Overall, dynamic hybrid systems are best suited for reasoning-intensive tasks, neural-first pipelines remain effective for large-scale and latency-sensitive applications, and tightly integrated models offer a balanced compromise between performance and computational cost.

8. CONCLUSION

Neuro-symbolic approaches for commonsense question answering effectively integrate neural representation learning with symbolic reasoning, enabling deeper and more interpretable inference than purely neural models. Recent studies from 2024–2025 report notable gains in multi-hop reasoning, compositional inference, and explanation generation, highlighting the advantages of hybrid reasoning frameworks. Despite these advances, significant challenges persist, including robustness to incomplete or noisy knowledge, context-dependent reasoning, efficient neural–symbolic integration, and the lack of standardized evaluation protocols. Future research should prioritize scalable hybrid architectures, dynamic and multi-modal knowledge integration, continual learning mechanisms, and principled interpretability frameworks. Addressing these challenges is essential for advancing neuro-symbolic QA systems toward human-level commonsense reasoning and broader real-world applicability.

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