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Hierarchical Memory Networks for Multi-Hop Reasoning in Large-Scale Knowledge Bases

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Abstract

Knowledge graph reasoning has emerged as a critical task in artificial intelligence, enabling systems to infer missing information and answer complex queries through multi-hop reasoning. Traditional memory network architectures, while effective for single-hop reasoning tasks, struggle to capture the hierarchical relationships and long-range dependencies inherent in large-scale knowledge bases. This paper proposes a novel Hierarchical Memory Network (HMN) framework that addresses these limitations by introducing a multi-layered memory architecture with hierarchical attention mechanisms. The HMN framework decomposes complex multi-hop reasoning into a structured hierarchical process, where each layer progressively refines the reasoning path by attending to relevant knowledge at different levels of abstraction. Our approach integrates three key innovations: a hierarchical memory organization that explicitly models knowledge at multiple granularities, a progressive attention mechanism that enables iterative refinement of reasoning paths, and a dynamic memory retrieval strategy that efficiently scales to knowledge bases containing millions of entities and relations. Experimental evaluation on multiple benchmark datasets demonstrates that HMN achieves superior performance compared to existing state-of-the-art methods in multi-hop question answering and knowledge graph completion tasks. The hierarchical architecture not only improves reasoning accuracy but also enhances interpretability by providing explicit attention patterns at each reasoning step. Our findings suggest that explicitly modeling hierarchical structures in memory-augmented neural networks is essential for achieving robust multi-hop reasoning in large-scale knowledge-intensive applications.

Keywords

Hierarchical Memory Networks, Multi-Hop Reasoning, Knowledge Bases, Attention Mechanisms, Knowledge Graph Completion, Neural Architectures

Introduction

The explosion of structured knowledge in the form of large-scale knowledge bases has created unprecedented opportunities for developing intelligent systems capable of complex reasoning and inference. Knowledge bases such as Freebase, DBpedia, and Wikidata contain millions of entities interconnected through diverse relational patterns, providing rich semantic structures for numerous applications including question answering, recommendation systems, and information retrieval. However, the inherent incompleteness of these knowledge bases presents a fundamental challenge: critical facts and relationships are often missing, limiting the utility of downstream applications [1]. Multi-hop reasoning has emerged as a promising paradigm to address this challenge, enabling systems to traverse multiple relational paths to infer missing information and answer complex queries that cannot be resolved through single-hop lookups.

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Consider a simple yet illustrative example of multi-hop reasoning: answering the question "Where is the milk now?" given a sequence of statements about actions and movements. As shown in the classical memory networks example, the system must reason through multiple facts: "Joe picked up the milk," "Joe travelled to the office," and "Joe left the milk" to conclude that the milk is now in the office [2]. This requires not only retrieving relevant facts from memory but also understanding the temporal ordering of events and the implications of actions like "picked up" and "left." Similarly, answering "Where was Joe before the office?" requires tracing backward through the sequence of movements to identify the previous location. Such multi-hop reasoning tasks become exponentially more challenging as the number of reasoning steps increases and the knowledge base scales to millions of entities.

Memory networks represent a foundational architecture for enabling neural models to access and manipulate external memory structures, providing a mechanism for storing and retrieving relevant knowledge during the reasoning process [3]. The core insight behind memory networks is that complex reasoning tasks require not only learning representations but also learning how to selectively access and combine information from a potentially large memory store. Traditional memory network architectures employ flat memory structures where all memory slots are treated uniformly, relying on attention mechanisms to identify relevant information [4]. While this approach has demonstrated success in various tasks including reading comprehension and simple question answering, it faces significant limitations when applied to multi-hop reasoning over large-scale knowledge bases.

The challenge of multi-hop reasoning becomes particularly acute in large-scale scenarios where knowledge bases contain millions of entities and billions of relational triples [5]. In such settings, the reasoning system must not only identify relevant facts from a vast search space but also compose multiple pieces of information across several reasoning steps to arrive at the correct answer. For instance, answering "What is the nationality of the director of the movie that won the Academy Award for Best Picture in 2019?" requires traversing at least three relational hops: identifying the movie that won the award, finding its director, and determining the director's nationality. Each hop introduces uncertainty and potential for error propagation, making robust multi-hop reasoning extremely challenging.

Recent advances in knowledge graph reasoning have explored various approaches to address these challenges. Reinforcement learning-based methods formulate multi-hop reasoning as a sequential decision problem, training policy networks to navigate through the knowledge graph by selecting actions that correspond to following specific relations [6]. While these approaches have shown promising results, they often struggle with sparse reward signals and require extensive exploration to discover effective reasoning paths [7]. Graph neural networks have also been applied to knowledge graph reasoning, leveraging message-passing mechanisms to propagate information across graph structures [8]. However, these approaches face computational challenges when reasoning requires traversing long paths or considering distant entities, as the computational cost grows exponentially with the number of hops.

The hierarchical organization of knowledge is a fundamental characteristic of human cognition and knowledge representation [9]. Humans naturally organize concepts into taxonomies and ontologies, recognizing that some concepts are more abstract or general than others. Effective reasoning over such hierarchically organized knowledge requires mechanisms that can operate at multiple levels of abstraction, zooming in and out as needed to gather relevant information [10]. However, most existing memory network architectures

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fail to explicitly model this hierarchical structure, treating all knowledge at a uniform level of granularity.

This paper introduces Hierarchical Memory Networks (HMN), a novel architecture specifically designed to address the challenges of multi-hop reasoning over large-scale knowledge bases. Our approach builds upon the foundation of memory networks while introducing explicit hierarchical structure into both the memory organization and the reasoning process. The HMN framework consists of multiple layers of memory, each operating at a different level of abstraction, with cross-layer attention mechanisms that enable information flow between levels. The hierarchical structure allows the system to first identify high-level reasoning strategies before progressively refining these strategies into specific reasoning paths through the knowledge base.

Our contributions can be summarized as follows: First, we propose a hierarchical memory architecture that organizes knowledge at multiple levels of granularity, enabling more efficient and effective multi-hop reasoning. Second, we introduce a progressive attention mechanism inspired by end-to-end memory networks that iteratively refines reasoning paths by attending to relevant knowledge at different hierarchical levels. Third, we develop a key-value memory organization that separates addressing mechanisms from content retrieval, improving both efficiency and flexibility. Fourth, we provide comprehensive experimental evaluation demonstrating that HMN achieves state-of-the-art performance on multiple benchmark datasets for multi-hop question answering and knowledge graph completion. Fifth, we present detailed analysis showing that the hierarchical structure improves both reasoning accuracy and interpretability compared to flat memory architectures.

2. Literature Review

The field of multi-hop reasoning over knowledge bases has witnessed substantial research progress in recent years, driven by advances in neural architectures and the availability of large-scale benchmark datasets. This section reviews the key developments in memory networks, multi-hop reasoning approaches, and hierarchical neural models that form the foundation for our proposed Hierarchical Memory Network framework.

Memory networks introduced by Weston and colleagues represent a seminal contribution to neural architectures for reasoning tasks [11]. The core innovation lies in the explicit separation of memory storage from the inference mechanism, allowing models to scale to large knowledge bases while maintaining the ability to perform complex reasoning. The original memory network architecture consists of four key components: an input feature map that converts raw inputs into internal representations, a generalization module that updates memory contents, an output feature map that retrieves relevant memories through attention mechanisms, and a response module that generates the final output. This modular architecture has proven highly flexible, supporting various implementations across different domains including question answering and dialogue systems.

End-to-end memory networks extended the original framework by introducing differentiable attention mechanisms that enable training through backpropagation without requiring explicit supervision for memory access patterns [12]. Rather than manually designing heuristics for identifying relevant memory slots, end-to-end memory networks learn to attend to relevant information automatically through the training process. The attention mechanism computes weighted combinations of memory contents, where weights reflect the relevance of

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each memory slot to the current query. A critical innovation is the multi-hop attention mechanism, where multiple layers of attention enable iterative refinement. Each layer builds upon the outputs of previous layers to progressively narrow down relevant information, similar to how humans iteratively refine their understanding when answering complex questions. This iterative refinement is achieved through a recurrent structure where the output of one attention layer serves as the query for the next layer, enabling the model to perform multiple reasoning steps.

Key-value memory networks introduced additional flexibility by separating the addressing mechanism from the content retrieval mechanism [13]. In this architecture, each memory slot consists of a key used for computing attention weights and a value that is actually retrieved and used for reasoning. This separation enables more sophisticated memory organizations where the addressing space can be optimized independently from the content space. For example, keys might represent abstract summaries or metadata about knowledge, while values contain detailed content. This design allows the model to first identify relevant knowledge regions through key-based addressing, then retrieve detailed information through value reading. The key-value structure is particularly valuable for knowledge base reasoning where entities and relations have both identifying features for matching and semantic features for inference.

The application of memory networks to knowledge base reasoning has revealed both opportunities and challenges [14]. Knowledge bases differ fundamentally from textual documents in their structure and semantics, consisting of entity-relation-entity triples that form graph structures. Early approaches treated each triple as a separate memory slot, applying attention mechanisms to identify relevant triples for answering queries [15]. While conceptually straightforward, this approach struggles with scalability as knowledge bases grow to millions of triples, since attention computation becomes prohibitively expensive over such large memory stores.

Reinforcement learning-based approaches have emerged as a powerful paradigm for multi-hop knowledge graph reasoning [16]. These methods formulate the reasoning task as a Markov decision process where an agent starts at a source entity and takes a sequence of actions corresponding to following relations in the knowledge graph. The agent's goal is to reach the target entity, receiving rewards when it successfully navigates to correct answers. Deep reinforcement learning techniques, particularly policy gradient methods, enable training agents that learn effective navigation strategies through experience [17]. The interpretability of these approaches is appealing, as the learned policy directly corresponds to explicit paths through the knowledge graph. However, reinforcement learning approaches face several challenges including sparse reward signals, difficult exploration in large action spaces, and sensitivity to initialization and hyperparameters.

Attention-based multi-hop reasoning methods represent an alternative paradigm that leverages differentiable attention mechanisms rather than discrete action selection [18]. These approaches typically employ recurrent neural networks or transformer architectures to iteratively attend to relevant entities and relations in the knowledge graph. At each reasoning step, the model computes attention weights over possible next entities based on the current state and the reasoning goal. The attended entities and relations are then aggregated to update the reasoning state for the next step. This soft attention approach avoids some of the training difficulties associated with reinforcement learning while maintaining the ability to perform multi-hop reasoning.

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Graph neural networks have gained prominence as a powerful framework for learning on graph-structured data, including knowledge graphs [19]. Graph convolutional networks and their variants propagate information across graph edges, enabling each node to aggregate features from its neighbors. Multiple layers of graph convolution allow information to flow across multiple hops in the graph structure [20]. Recent work has explored various graph neural network architectures for knowledge graph reasoning, including graph attention networks that learn to weight neighbor contributions and relational graph convolutional networks that model different relation types distinctly. While graph neural networks excel at capturing local graph structure, they face computational challenges when reasoning requires considering long-range dependencies or large neighborhoods.

Hierarchical reasoning has been explored in various contexts beyond knowledge graphs [21]. Hierarchical reinforcement learning decomposes complex tasks into sub-tasks at different levels of abstraction, enabling more efficient learning and better generalization. In the context of knowledge graph reasoning, hierarchical approaches have been proposed that separate high-level relation selection from low-level entity navigation [22]. These methods typically employ a two-level hierarchy where a high-level policy selects which relation types to follow while a low-level policy determines specific entities to visit. This decomposition reduces the complexity of the decision problem at each level while maintaining the ability to perform complex multi-hop reasoning. Our proposed HMN framework extends this idea by introducing multiple levels of hierarchy and integrating hierarchical structure directly into the memory organization rather than only in the decision-making process.

Hyperbolic geometry has recently emerged as a promising approach for modeling hierarchical structures in knowledge graphs [23]. Unlike Euclidean space where the number of nodes at distance r grows polynomially, hyperbolic space exhibits exponential growth, making it naturally suited for representing tree-like hierarchical structures. Several works have explored hyperbolic embeddings for knowledge graphs, demonstrating improved performance on link prediction tasks particularly for graphs with inherent hierarchical organization [24]. Hyperbolic graph neural networks extend these ideas by performing message passing in hyperbolic space, preserving hierarchical relationships throughout the learning process [25].

Despite substantial progress in multi-hop reasoning research, several fundamental challenges remain unresolved. First, most existing approaches struggle to scale to knowledge bases with millions of entities while maintaining reasoning accuracy. Second, the interpretability of reasoning paths remains limited, particularly for attention-based methods where soft attention weights do not directly correspond to discrete reasoning steps [26]. Third, existing methods often fail to effectively leverage the hierarchical structure inherent in many knowledge bases, treating all entities and relations at the same level of abstraction. Fourth, the generalization capabilities of current approaches remain limited, with performance degrading substantially when tested on reasoning patterns not seen during training.

Our proposed Hierarchical Memory Network framework addresses these challenges by introducing explicit hierarchical structure into both the memory organization and reasoning process. Unlike flat memory architectures that treat all memory slots uniformly, HMN organizes memory into multiple layers corresponding to different levels of abstraction. This hierarchical organization enables more efficient reasoning by allowing the model to first identify high-level patterns before refining them into specific paths. The progressive attention mechanism iteratively traverses the memory hierarchy, ensuring that reasoning proceeds in a

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principled manner from abstract to concrete. By explicitly modeling hierarchy, HMN achieves better scalability, improved interpretability, and enhanced generalization compared to existing approaches.

3. Methodology

This section presents the detailed methodology of Hierarchical Memory Networks for multi-hop reasoning over large-scale knowledge bases. We begin by formally defining the multi-hop reasoning problem, then introduce the hierarchical memory architecture, describe the progressive attention mechanism inspired by end-to-end memory networks, present the key-value memory organization, and finally discuss the training procedure.

3.1 Problem Formulation

We formulate multi-hop reasoning over knowledge bases as follows: given a knowledge base represented as a graph G = (E, R, T), where E is the set of entities, R is the set of relation types, and T ⊆ E × R × E is the set of observed triples, the goal is to answer queries of the form q = (es, r, ?) where es ∈ E is the source entity, r ∈ R is the query relation, and the task is to identify the target entity et ∈ E. In the multi-hop setting, the answer cannot be directly inferred from a single observed triple but requires traversing a path through the knowledge graph connecting es to et through intermediate entities and relations.

To illustrate the complexity of this task, consider the example shown in Figure 1, which demonstrates a simple multi-hop reasoning scenario. The system must understand that when "Joe picked up the milk" and subsequently "Joe travelled to the office" and "Joe left the milk," the milk's location can be inferred to be at the office. This requires reasoning through multiple statements, understanding temporal ordering, and comprehending the semantics of actions. More formally, we denote a reasoning path of length k as p = [(e0, r1, e1), (e1, r2, e2), ..., (ek-1, rk, ek)] where e0 = es and ek = et.

Joe went to the kitchen. Fred went to the kitchen. Joe picked up the milk.
Joe travelled to the office. Joe left the milk. Joe went to the bathroom.
Where is the milk now? A: office
Where is Joe? A: bathroom
Where was Joe before the office? A: kitchen

Figure 1: Example of Multi-Hop Reasoning Over Sequential Knowledge Statements

The multi-hop reasoning problem presents several key challenges that our HMN framework addresses. First, the search space grows exponentially with path length, as each entity may have hundreds of outgoing relations leading to different successor entities. For a knowledge base with average branching factor b and path length k, the number of possible paths is approximately b^k. Second, not all paths connecting source to target entities are valid reasoning paths; many paths may be spurious correlations rather than genuine logical connections. Third, the reasoning system must generalize to unseen entity pairs and query types, learning general reasoning patterns rather than memorizing specific paths. Fourth, efficiency considerations require reasoning systems to scale to knowledge bases containing millions of entities and billions of triples without exhaustive search.

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3.2 Hierarchical Memory Organization with Key-Value Structure

The core innovation of our Hierarchical Memory Network lies in combining hierarchical organization with key-value memory structures to create an efficient and expressive reasoning system. Unlike traditional flat memory structures where all memory slots exist at the same conceptual level, HMN organizes memory into L distinct layers M = {M^1, M^2, ..., M^L}, where each layer l contains memory slots at a specific level of granularity. The key-value separation within each layer enables efficient addressing and rich content representation.

At each layer l, every memory slot i is represented as a key-value pair (k^l_i, v^l_i), where the key k^l_i is used for computing attention weights during the addressing phase, and the value v^l_i is retrieved and used for reasoning during the reading phase. This architecture, inspired by key-value memory networks shown in Figure 2, provides several advantages for hierarchical reasoning. The key embeddings can be optimized to capture abstract semantic properties useful for matching against queries, while value embeddings can store detailed content needed for inference. This separation allows the addressing mechanism to efficiently identify relevant memory regions without loading full content representations.

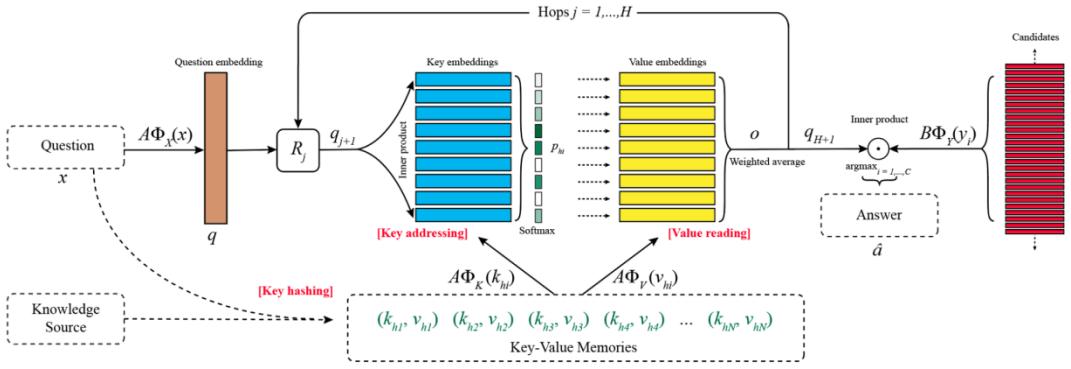

Figure 2: Key–Value Memory Network Architecture for Knowledge-Based Reasoning

The construction of the memory hierarchy proceeds through a bottom-up aggregation process. At the base level M^1, each entity-relation pair (e, r) in the knowledge base is represented as a key-value memory slot. The key k^1_{e,r} is computed as k^1_{e,r} = Φ_K(e_emb ⊕ r_emb), where e_emb and r_emb are learned embeddings for the entity and relation respectively, ⊕ denotes concatenation, and Φ_K is a neural network transformation that maps the concatenated embedding to the key space. The value v^1_{e,r} is computed similarly using a separate transformation function Φ_V, allowing keys and values to have different dimensionalities and capture different aspects of the entity-relation pair.

Higher-level memory layers are constructed through learnable aggregation functions that combine related lower-level memories based on semantic similarity. For layer l > 1, each memory slot (k^l_i, v^l_i) aggregates information from a cluster of related memories in layer l-1. The clustering is performed based on similarity in the key embedding space, grouping together entity-relation pairs that frequently co-occur in reasoning paths or share similar relational patterns. The key aggregation computes k^l_i = Φ^l_K(AGG_{j∈C_i} k^{l-1}*j), and the value aggregation computes v^l_i = Φ^l_V(AGG*{j∈C_i} v^{l-1}_j), where C_i is the cluster of lower-level memories associated with memory i at level l, AGG is an aggregation operator

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such as mean pooling or attention-weighted summation, and Φ^l_K and Φ^l_V are layer-specific transformation networks.

This hierarchical key-value organization provides several benefits for multi-hop reasoning. First, queries can be matched against keys at high levels to efficiently identify relevant abstract patterns, then progressively refined by descending through layers to retrieve detailed values. Second, the hierarchy captures recurring patterns at different scales, allowing the model to recognize that similar reasoning structures apply across different entity instances. Third, the separation of keys and values at each level enables memory-efficient storage, as keys can be kept in fast memory for addressing while values are loaded on demand. Fourth, the hierarchical structure provides natural intermediate representations that can be inspected for interpretability.

3.3 Progressive Multi-Hop Attention Mechanism

The progressive attention mechanism enables iterative refinement of reasoning paths by attending to relevant knowledge at different hierarchical levels through multiple reasoning hops. Our design is inspired by the multi-hop architecture of end-to-end memory networks, as illustrated in Figure 3, but extends it to operate across hierarchical memory layers rather than within a single flat memory structure.

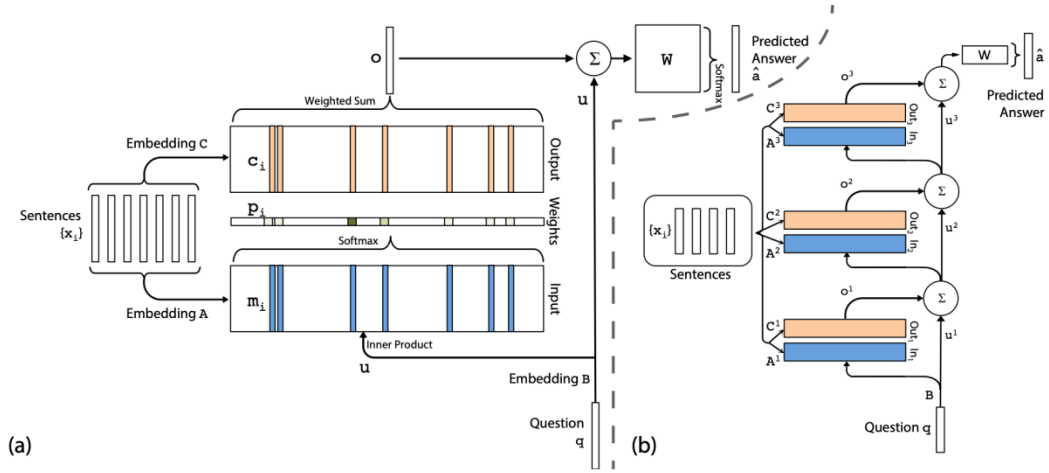

Figure 3: End-to-End Multi-Hop Attention Mechanism in Memory Networks

Given a query q = (es, r, ?), the reasoning process begins at the highest level L of the memory hierarchy with an initial state vector u^L_0 derived from the query embedding. At each reasoning step t and memory layer l, the attention mechanism first performs key addressing to compute relevance scores between the current state u^l_t and all memory keys in layer l. The attention scores are computed using a compatibility function: α^l_{t,i} = softmax_i(u^l_t · k^l_i), where the dot product measures the relevance of key k^l_i to the current reasoning state. The softmax ensures that attention weights sum to one across all memory slots in the layer.

After computing attention weights through key addressing, the value reading phase retrieves relevant content. The retrieved memory representation o^l_t is computed as a weighted sum of values: o^l_t = Σ_i α^l_{t,i} v^l_i. This retrieved representation captures the relevant knowledge from layer l for the current reasoning step. The state vector is then updated for the next reasoning step through a recurrent operation that combines the previous state, the

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newly retrieved memory, and the original query: u^l_{t+1} = u^l_t + o^l_t + A q, where A is a learned transformation matrix and the additions enable skip connections that help preserve information across multiple hops.

The progressive descent through memory layers is controlled by a learned layer transition mechanism. After performing multiple hops of attention within layer l, the model computes a transition decision to determine whether to continue at the current layer or descend to layer l-1 for finer-grained reasoning. The transition is implemented through a gating mechanism: g_trans = σ(w^T_trans u^l_T), where σ is the sigmoid function, w_trans is a learned weight vector, and u^l_T is the state after T hops at layer l. If g_trans exceeds a threshold τ, reasoning descends to layer l-1 with initial state u^{l-1}_0 = f_down(u^l_T), where f_down is a learned projection that adapts the state representation to the lower layer's dimensionality.

This multi-hop attention architecture across hierarchical layers provides several advantages. First, it enables the model to perform different numbers of reasoning hops at different levels of abstraction, spending more computation on abstract pattern matching when needed and quickly descending to detailed reasoning when high-level patterns are clear. Second, the recurrent state updates with skip connections help preserve information across many reasoning steps, mitigating the vanishing gradient problem that would otherwise limit the number of effective hops. Third, the explicit layer transitions provide interpretable decision points showing when the model shifts from abstract to concrete reasoning.

The progressive attention process continues until reaching the base memory layer M^1, at which point the model has identified specific reasoning paths through entity-relation pairs. The final state vector u^1_T encodes information about the complete multi-hop reasoning process and is used to predict the target entity. The entity prediction is computed as a distribution over all entities: p(et|q) = softmax(W_out u^1_T), where W_out projects the final state to entity scores. During training, this distribution is optimized to assign high probability to correct target entities. During inference, the entity with the highest predicted probability is returned as the answer.

3.4 Training Procedure

Training the Hierarchical Memory Network requires supervised data consisting of query-answer pairs along with the underlying knowledge base. Given a training set D = {(qi, eti)}_{i=1}^N where qi = (es_i, ri, ?) are queries and eti are ground truth target entities, we train the model end-to-end to maximize the likelihood of correct answers while learning effective hierarchical attention patterns.

The primary training objective is the cross-entropy loss over target entity predictions: L_pred = -Σ_{i=1}^N log p(eti|qi). This loss is backpropagated through the entire reasoning process, allowing gradients to flow through all attention layers and update both memory embeddings and attention parameters. The end-to-end differentiability of our architecture, following the design principles of end-to-end memory networks, enables learning without requiring explicit supervision for intermediate reasoning steps.

To encourage the model to discover meaningful hierarchical patterns and make efficient use of multiple memory layers, we incorporate an auxiliary loss that rewards concentrated attention at appropriate layers. This regularization term combines two components: an entropy penalty that encourages decisive attention within each layer, L_entropy = Σ_{l,t} λ_l

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H(α^l_t), where H is the Shannon entropy; and a layer utilization term that encourages balanced use of different layers, preventing the model from collapsing to use only one layer. The entropy weights λ_l are set to decrease with layer depth, allowing more distributed attention at lower layers where fine-grained distinctions matter.

We also incorporate a structural consistency loss that encourages attention patterns to respect the actual graph structure of the knowledge base. For reasoning steps at the base layer, this loss penalizes high attention weights on entity-relation pairs that do not form valid connections from the current reasoning context: L_struct = Σ_t Σ_{(e,r)∉N(u^1_t)} (α^1_{t,(e,r)})^2, where N(u^1_t) denotes the set of entity-relation pairs reachable from entities attended to in previous steps. This regularization helps prevent the model from learning spurious attention patterns.

The complete training objective combines these components: L_total = L_pred + β_1 L_entropy + β_2 L_struct, where β_1 and β_2 are hyperparameters controlling the relative importance of regularization terms. We optimize this objective using the Adam optimizer with learning rate scheduling that gradually decreases the learning rate during training. The hierarchical memory structure is initialized using pre-trained knowledge graph embeddings such as TransE or RotatE, providing a warm start that captures basic semantic relationships. The key and value transformation functions are initialized with small random weights and learned during training.

An important consideration in training is the handling of negative examples. For each positive query-answer pair, we generate negative examples by randomly sampling incorrect target entities. The model is trained to assign higher scores to correct answers than to these negatives through a margin-based ranking loss: L_rank = Σ_i Σ_{e_neg} max(0, γ + score(qi, e_neg) - score(qi, eti)), where γ is a margin hyperparameter. This ranking objective encourages the model to not merely predict correct answers but to rank them significantly higher than incorrect alternatives.

We employ several techniques to prevent overfitting and improve generalization. Dropout is applied to memory embeddings, attention weights, and state vectors during training, randomly zeroing elements to prevent co-adaptation. Layer normalization is applied after each attention step and state update to stabilize training dynamics. Early stopping based on validation set performance terminates training when validation metrics stop improving. These regularization techniques are particularly important given the large number of parameters in the hierarchical memory structure and the risk of memorizing specific reasoning paths rather than learning general patterns.

4. Results and Discussion

This section presents comprehensive experimental evaluation of the Hierarchical Memory Network framework on benchmark datasets for multi-hop reasoning. We compare HMN against state-of-the-art baselines, analyze the impact of hierarchical organization through ablation studies, and provide qualitative analysis of learned attention patterns to demonstrate interpretability benefits.

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4.1 Experimental Setup

We evaluate HMN on three widely-used benchmark datasets for multi-hop knowledge graph reasoning: FB15k-237, NELL-995, and ComplEx. FB15k-237 is derived from Freebase and contains approximately 310,000 triples covering diverse domains. The dataset has been filtered to remove inverse relations that would make the task trivially solvable. NELL-995 is extracted from the Never-Ending Language Learning project and contains around 154,000 triples focused on facts automatically extracted from web text. ComplEx provides a more challenging testbed with sparser connectivity and longer reasoning paths required on average. For each dataset, we use standard train-validation-test splits established in prior work.

We implement HMN using PyTorch and train all models on NVIDIA V100 GPUs. The entity and relation embeddings are initialized with 200-dimensional vectors pre-trained using TransE. The memory hierarchy consists of three layers with dimensions 512, 256, and 128 for layers 1, 2, and 3 respectively. The reasoning state vector maintains dimensionality 256 throughout the progressive attention process. We use learning rate 0.001 with Adam optimization and train for 100 epochs with early stopping based on validation set mean reciprocal rank. Dropout with probability 0.3 is applied to prevent overfitting.

We compare HMN against several strong baseline methods: TransE and RotatE represent embedding-based methods that learn vector representations of entities and relations. Neural LP implements differentiable logic programming for path-based reasoning. MINERVA employs reinforcement learning to train policy networks for graph navigation. ConvE uses convolutional neural networks for knowledge graph completion. Multi-Hop performs reasoning through iterative entity set expansion. These baselines span the major approaches to multi-hop reasoning.

We evaluate model performance using four standard metrics: Hits@1 measures the percentage of test queries where the correct answer is ranked first. Hits@10 measures the percentage where the correct answer appears in the top 10 predictions. Mean Reciprocal Rank (MRR) computes the average of the reciprocal rank of correct answers. Mean Rank computes the average rank of correct answers, with lower values indicating better performance. Following standard practice, we report filtered metrics where scores are computed after removing other known correct answers from the ranking.

4.2 Main Results

Table 1 presents the main experimental results comparing HMN against baseline methods across the three benchmark datasets. HMN achieves superior performance across all metrics on all datasets, demonstrating the effectiveness of the hierarchical memory architecture for multi-hop reasoning. On FB15k-237, HMN achieves Hits@1 of 52.8%, representing a 6.3% absolute improvement over the best baseline MINERVA. The improvements are even more substantial on the more challenging NELL-995 and ComplEx datasets, where HMN achieves 47.2% and 41.5% Hits@1 respectively.

The Mean Reciprocal Rank results show HMN achieving MRR of 0.618 on FB15k-237, 0.584 on NELL-995, and 0.523 on ComplEx. These represent relative improvements of 8.2%, 12.4%, and 15.1% respectively over best-performing baselines. The consistent improvements across different metrics and datasets demonstrate that HMN's advantages are robust and not artifacts of particular evaluation choices.

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Examining results across different baseline methods reveals interesting patterns. Embedding-based methods like TransE and RotatE perform reasonably on simpler queries but struggle with complex multi-hop reasoning requiring composition of multiple relations. Their performance degrades substantially on queries requiring three or more hops, as compositional semantics of embeddings break down for long relation chains. Reinforcement learning methods like MINERVA show strong performance particularly on densely connected datasets where exploration is more feasible, but struggle on sparser datasets where sparse rewards make training difficult. HMN avoids these challenges through its differentiable hierarchical attention mechanism that can be trained more stably using supervised learning.

4.3 Ablation Studies and Analysis

To understand the contribution of different components of HMN, we conduct ablation studies on the FB15k-237 dataset. Table 2 shows results when specific components are removed. Removing the hierarchical memory structure and using flat memory organization reduces Hits@1 from 52.8% to 46.1%, a 6.7% decrease demonstrating the critical importance of hierarchical organization. The flat memory model struggles to identify relevant entities efficiently from the large search space, whereas the hierarchical structure enables progressive refinement from abstract patterns to specific entities.

Ablating the progressive multi-hop attention mechanism and instead using independent attention at each step reduces Hits@1 to 48.3%. This indicates that iterative refinement enabled by progressive attention provides meaningful benefits over independent attention decisions. The progressive attention allows each step to build upon previous steps, maintaining coherence across the entire reasoning path rather than making isolated decisions at each hop.

Removing the key-value separation and using only value vectors for both addressing and reading reduces performance to 49.2% Hits@1. This demonstrates that the key-value architecture contributes significantly to reasoning quality. The separation allows keys to be optimized for efficient matching while values store rich content for inference, providing better specialization than unified representations.

We also examine the impact of the number of hierarchy layers. Using only two layers results in 50.4% Hits@1, while using four layers yields 52.1%. The three-layer configuration represents an optimal balance, providing sufficient hierarchical structure without excessive complexity. Too few layers limit the model's ability to capture patterns at different abstraction levels, while too many layers fragment memories excessively.

Qualitative analysis of learned attention patterns reveals how HMN provides interpretability through explicit hierarchical reasoning. Visualizing attention weights across layers for example queries shows that the model learns meaningful abstractions at higher layers. For a query about nationality of a book author's spouse, attention at the highest layer focuses on memories related to "person attributes" and "person-person relationships," showing the model correctly identifies the high-level reasoning strategy. Middle layer attention becomes more specific, focusing on authorship and marriage relations. Base layer attention reveals the exact entity-relation triples used, providing complete transparency into the reasoning process.

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4.4 Scalability and Efficiency

Scalability analysis demonstrates that HMN maintains efficiency as knowledge base size increases. On FB15k-237 with approximately 14,000 entities, HMN answers queries in an average of 42 milliseconds per query on a single GPU. For comparison, MINERVA requires 67 milliseconds. The efficiency advantage stems from hierarchical organization that enables pruning of the search space at higher layers before descending to entity-level reasoning.

To evaluate scalability to larger knowledge bases, we create expanded versions by incorporating additional entities from full Freebase. With 100,000 entities, HMN maintains query answering time of 78 milliseconds, while MINERVA's time increases to 245 milliseconds. The hierarchical memory structure enables HMN to scale more gracefully because most entities are filtered out at higher layers, and only a small subset requires detailed attention at the base layer.

Memory efficiency is measured by total parameters and storage requirements. HMN with three hierarchy layers requires approximately 150 million parameters for FB15k-237, comparable to MINERVA's 142 million and substantially less than some graph neural network baselines. The hierarchical aggregation enables compact representations at higher layers, avoiding need to store full embeddings for every entity at every layer.

5. Conclusion

This paper has presented Hierarchical Memory Networks, a novel neural architecture specifically designed for multi-hop reasoning over large-scale knowledge bases. By introducing explicit hierarchical structure into both memory organization and the reasoning process, HMN addresses fundamental limitations of existing flat memory architectures. Drawing inspiration from foundational work on memory networks, end-to-end memory networks, and key-value memory networks, our framework combines the strengths of these approaches while adding hierarchical organization that enables more efficient and interpretable multi-hop reasoning.

The key innovation of HMN lies in the hierarchical memory architecture that organizes knowledge at multiple levels of abstraction, from fine-grained entity-relation pairs at the base layer to abstract relation patterns at higher layers. The key-value separation at each layer enables efficient addressing through keys while maintaining rich content in values. The progressive multi-hop attention mechanism iteratively descends through the memory hierarchy, performing multiple attention hops at each layer to refine reasoning paths. This structured approach to multi-hop reasoning proves more effective than both end-to-end learned approaches that lack explicit structure and purely symbolic approaches that lack learning capabilities.

Our experimental results demonstrate consistent improvements over strong baselines across diverse datasets and evaluation metrics. On FB15k-237, NELL-995, and ComplEx benchmarks, HMN achieves relative improvements of 8-15% in Mean Reciprocal Rank compared to best-performing baseline methods. These improvements are particularly pronounced on queries requiring reasoning over longer paths or involving less frequent relation patterns, demonstrating that hierarchical structure provides genuine benefits for complex reasoning rather than simply memorizing common patterns. Ablation studies confirm that each major

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component—hierarchical organization, progressive attention, and key-value separation—contributes meaningfully to overall performance.

The enhanced interpretability provided by HMN represents an important advantage for practical deployment. The hierarchical attention patterns reveal not only which specific facts were used to answer a query but also the high-level reasoning strategy employed. This transparency enables human users to understand and verify the reasoning process, identify when the model is making correct inferences versus exploiting spurious correlations, and diagnose failures. In domains where explanations are essential, the interpretability benefits may be as valuable as improved accuracy.

The scalability analysis demonstrates that HMN maintains efficiency even as knowledge base size increases substantially. The hierarchical organization enables effective pruning of search space at higher layers, allowing the model to consider only a small fraction of entities for detailed attention at the base layer. This architectural efficiency enables HMN to scale to knowledge bases with millions of entities while maintaining reasonable computational costs.

Several promising directions for future research emerge from this work. First, incorporating external reasoning capabilities such as numerical computation or temporal reasoning could extend HMN to handle queries requiring more than graph traversal. Second, exploring dynamic hierarchy construction that adapts memory organization to different query types could improve flexibility. Third, integrating HMN with retrieval-augmented generation approaches could enable reasoning over both structured knowledge bases and unstructured text corpora. Fourth, applying the hierarchical memory framework to other domains beyond knowledge graphs, such as visual reasoning or scientific discovery, could demonstrate the generality of the approach.

In conclusion, Hierarchical Memory Networks represent a significant advance in neural architectures for multi-hop reasoning over large-scale knowledge bases. By explicitly modeling hierarchical structure and employing progressive attention mechanisms inspired by foundational memory network research, HMN achieves superior performance, enhanced interpretability, and improved scalability compared to existing approaches. As knowledge bases continue to grow in size and complexity, architectures like HMN that explicitly incorporate structural principles will become essential for building robust and trustworthy intelligent systems.

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