A Retrieve and Read Framework for Knowledge Graph Reasoning

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CIKM 2023

Knowledge Graphs

- Multi-relational graphs
- Provides **structured representation** for semantic relationships between real-world entities.

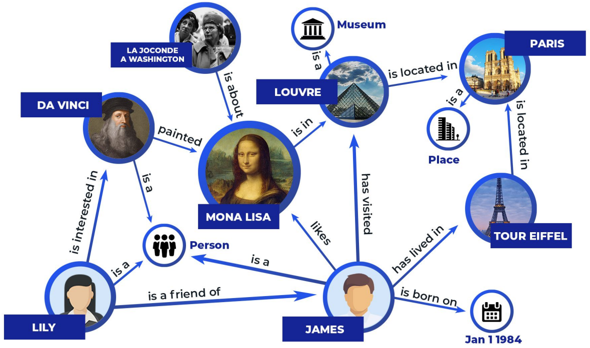
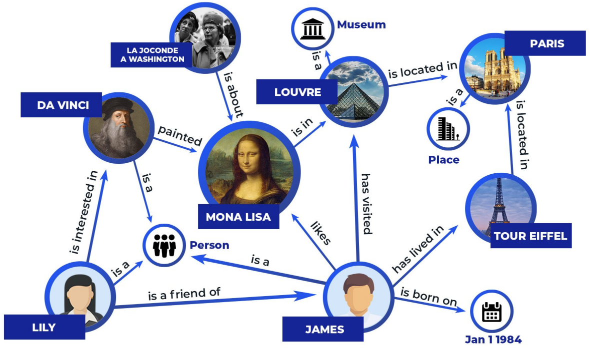
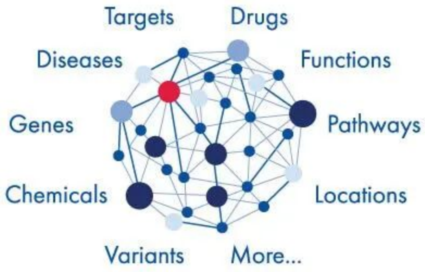


Figure credit: Hsiang-Yun Wu

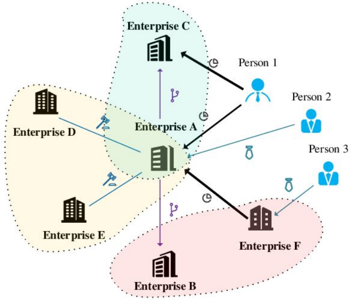
Knowledge Graphs

- Multi-relational graphs
- Provides **structured representation** for semantic relationships between real-world entities.
- Ideal knowledge representation for many domains

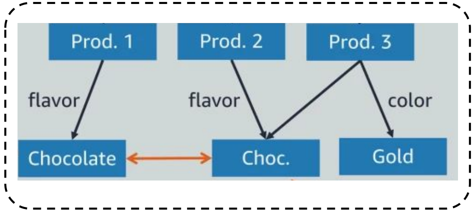




Bio/health informatics



Business



E-commerce

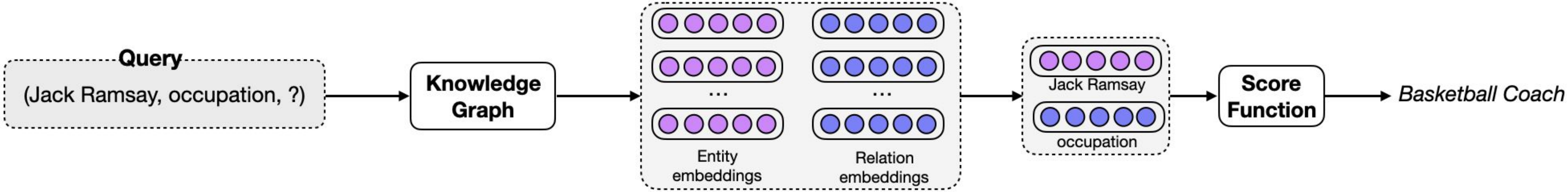
Figure credit: Hsiang-Yun Wu

Knowledge Graph Embedding

- **Distributional representation**:
  - Vector representations -> **Symbolic knowledge**
- **Downstream applications**:
  - Link prediction, question answering, relation extraction, …

Motivation

- **Shallow Embedding approaches** (TransE, DistMult, RotatE, etc.)



  - Vector embeddings do not capture rich structural and semantic information of KGs

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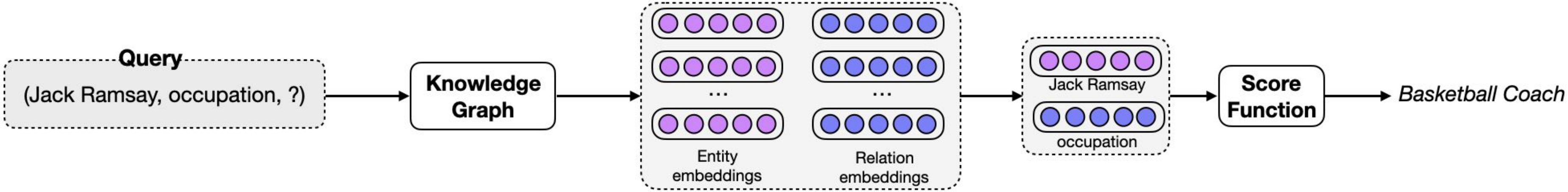

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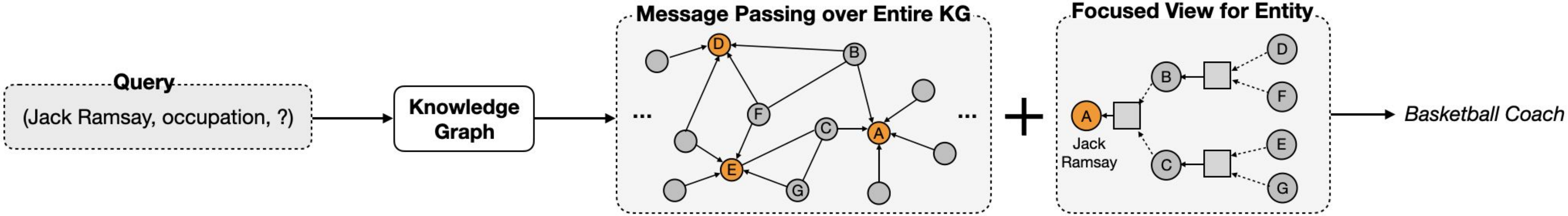
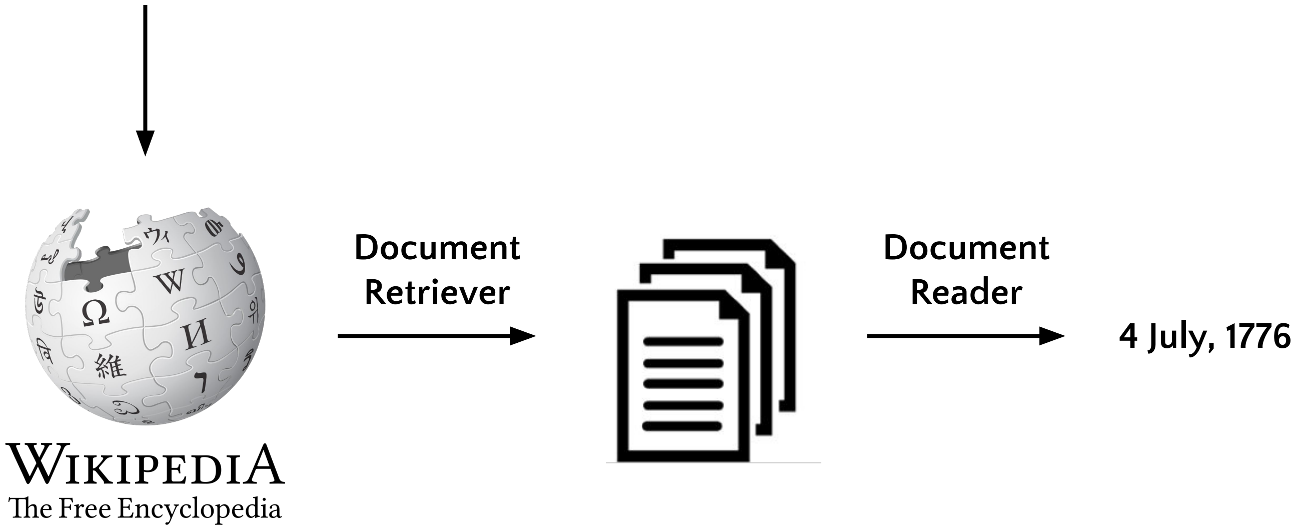
- **Message-passing based GNN approaches** (R-GCN, CompGCN, etc.)



  - Message-passing over the entire KG leads to superfluous computation.
  - Limited scalability on large-scale KGs.

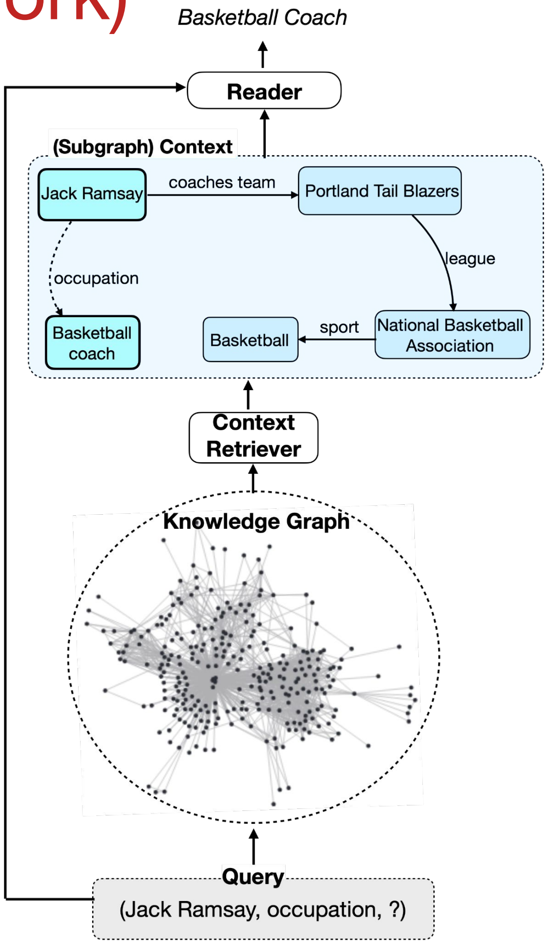
Retriever-Reader (Open-domain QA)

When did United States achieve independence?



Retrieve and Read Framework (This Work)

- ❖ More flexibility to independently develop **retriever** and **reader**.



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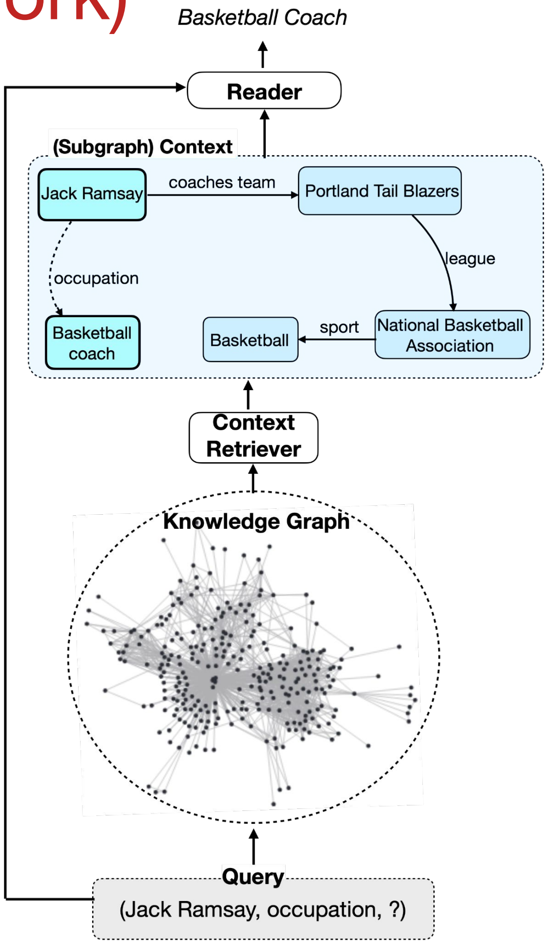
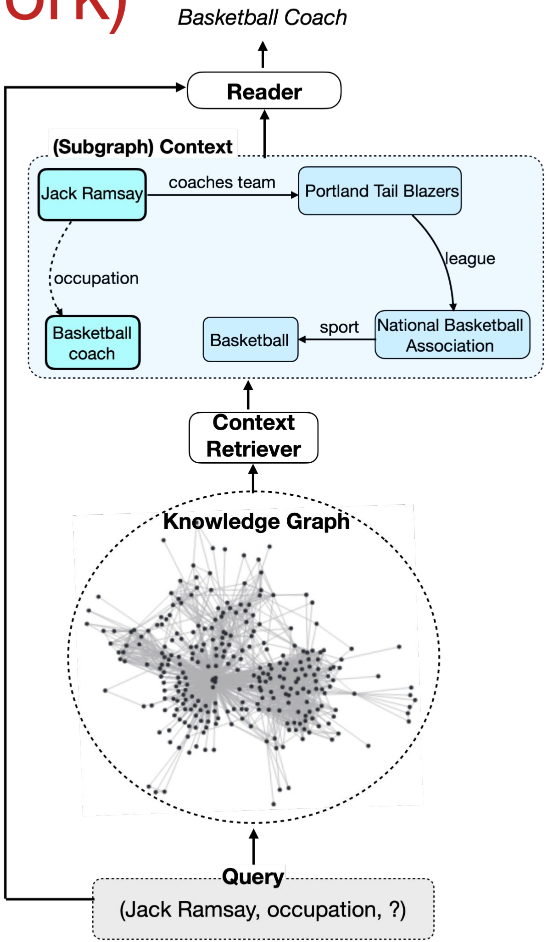


Retrieve and Read Framework (This Work)

- More flexibility to independently develop **retriever** and **reader**.
- Enables **higher capacity** reader models.
- Potential for **better scalability** to large-scale KGs.



Outline

- Retriever
- Reader Architecture
- Task Setup
- Experiments

Retriever

- **Uninformed search strategies**
  - Breadth-first search
  - One-hop neighborhood

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- **Uninformed search strategies**
  - Breadth-first search
  - One-hop neighborhood
- **Informed search strategies**
  - MINERVA [Das et al. 2017]
  - RL agent that learns to traverse the KG to reach the target entity.
  - Subgraph is union of multi-hop paths.

Das, Rajarshi, et al. "Go for a walk and arrive at the answer: Reasoning over paths in knowledge bases using reinforcement learning.", ICLR 2018

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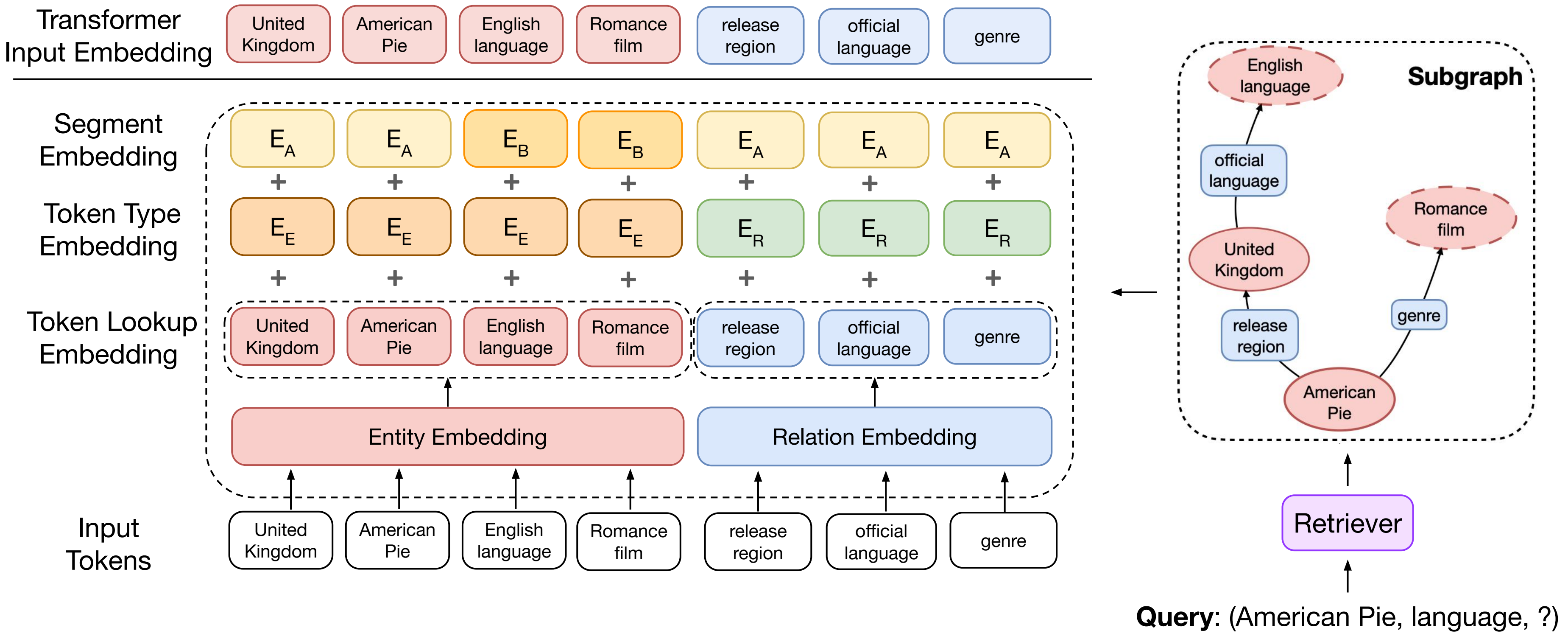
Embedding Layer Design



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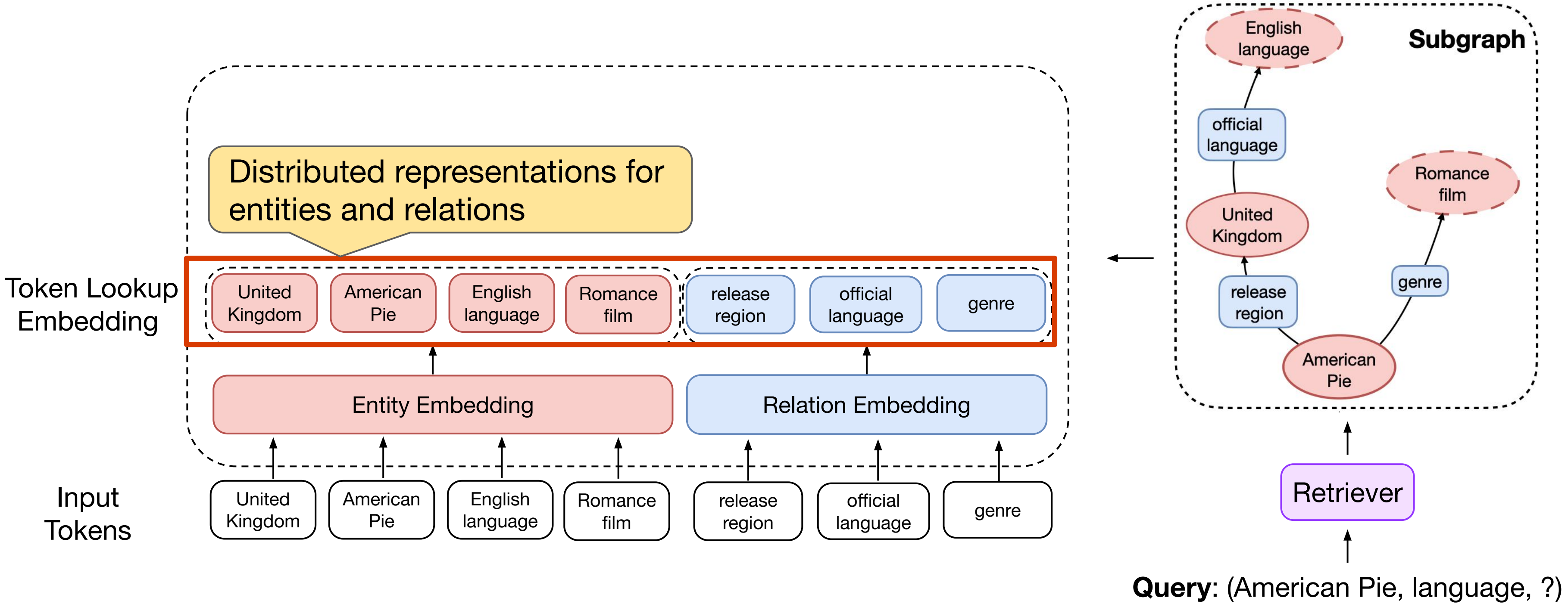

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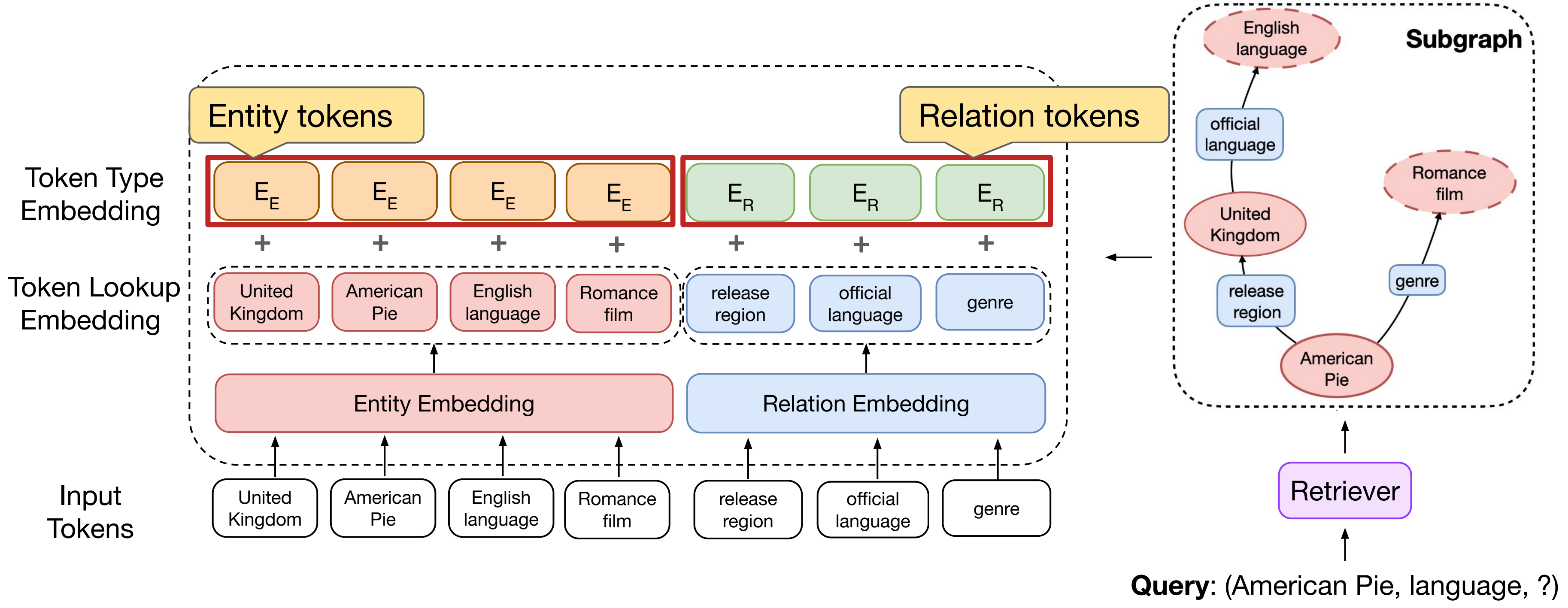

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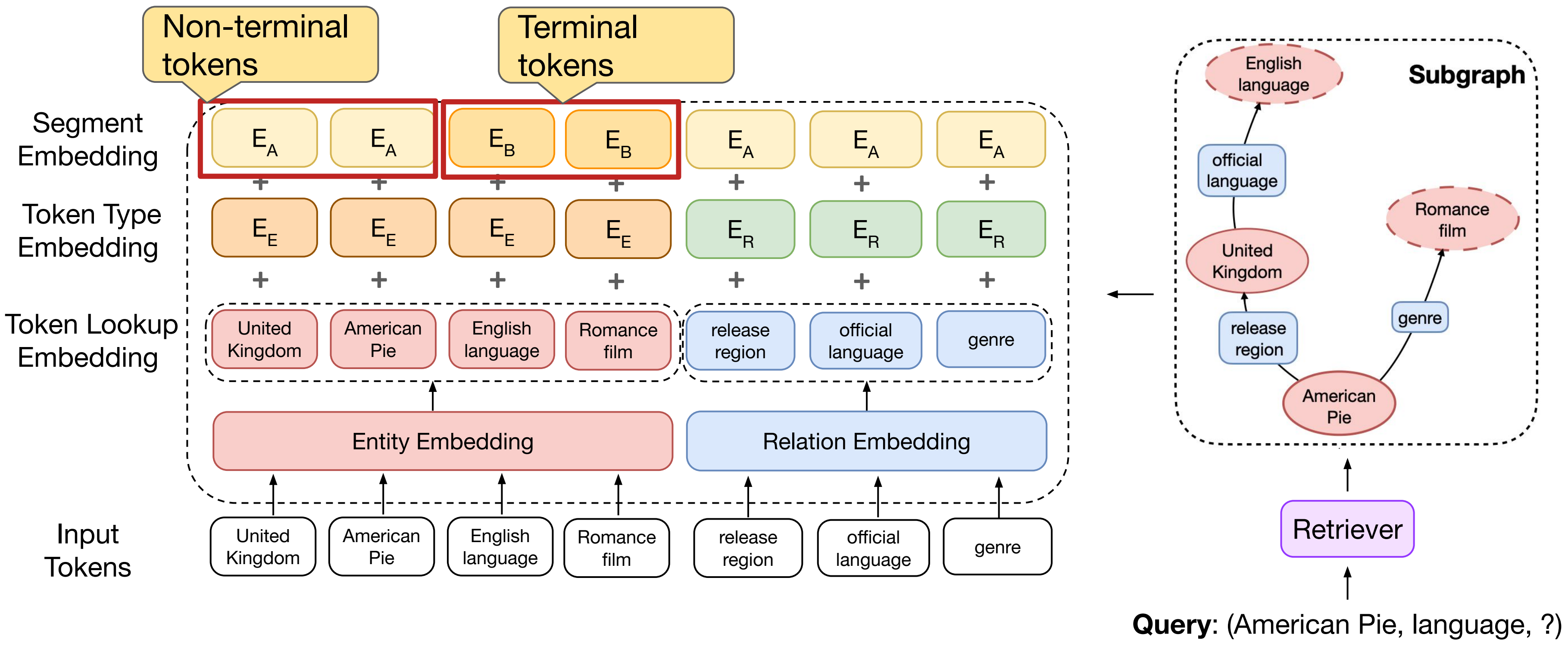
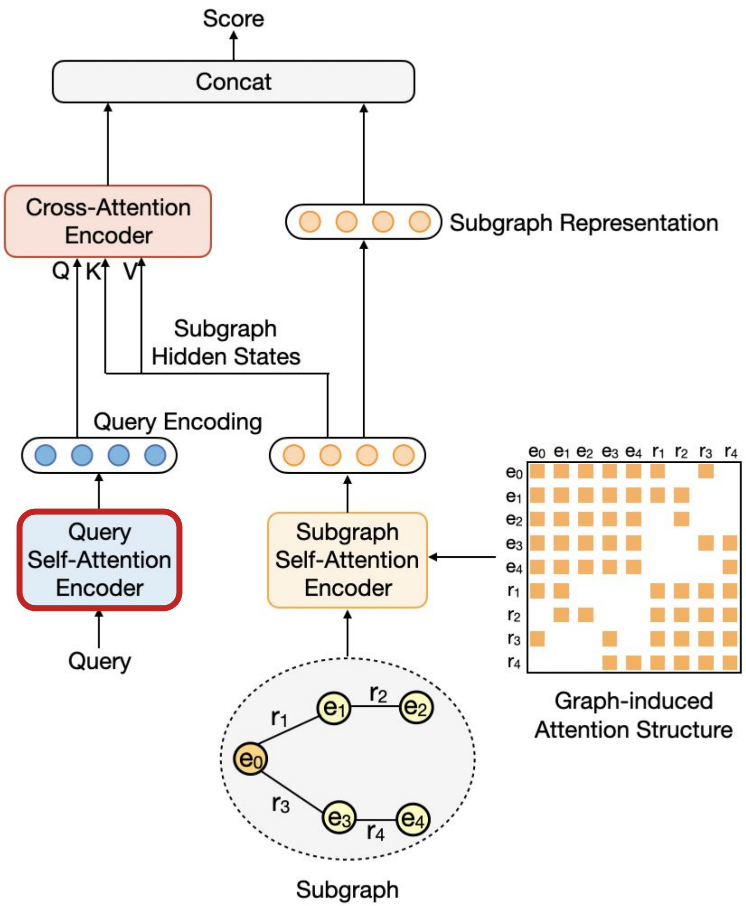


Reader Architecture

Compute query representation



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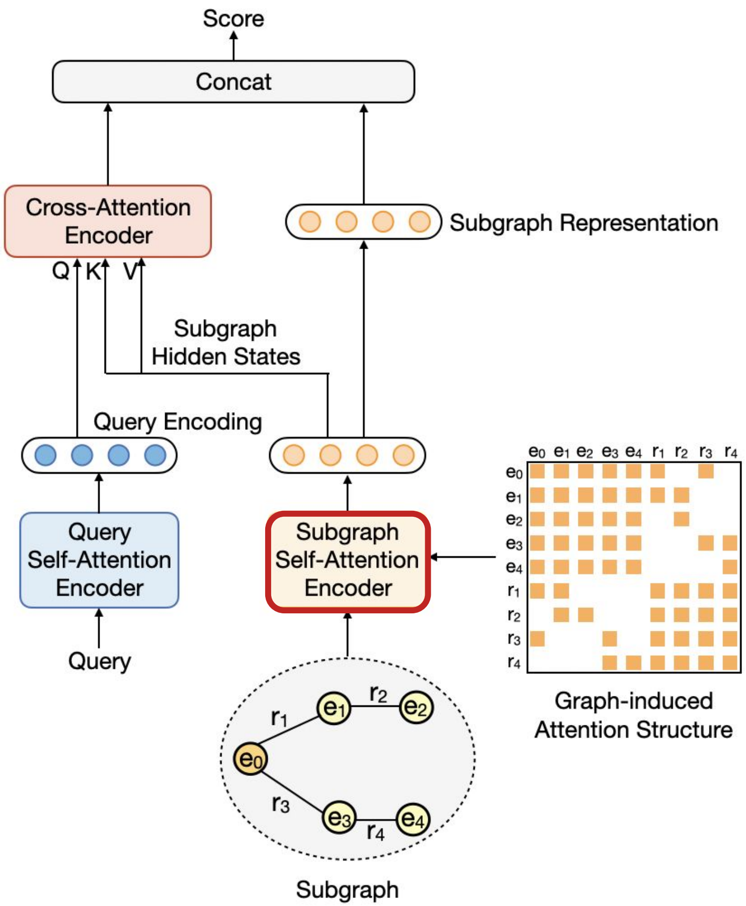
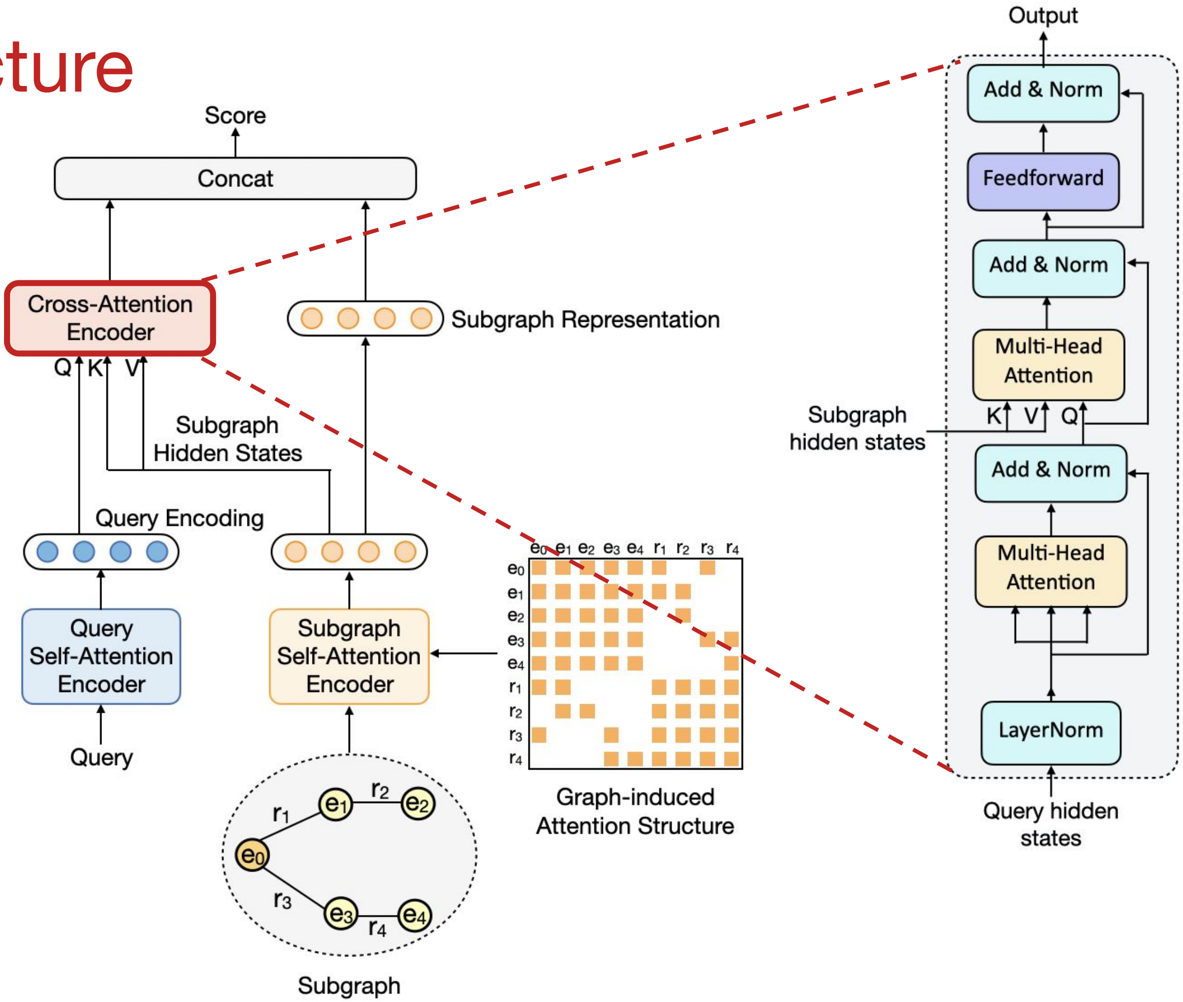


Compute subgraph representation

Reader Architecture

Fusion using Cross-attention



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- **Knowledge Graph Completion (KGC):** Given an incomplete RDF triple, infer the missing entity.
- E.g. (Statue of Liberty, located in, ?)

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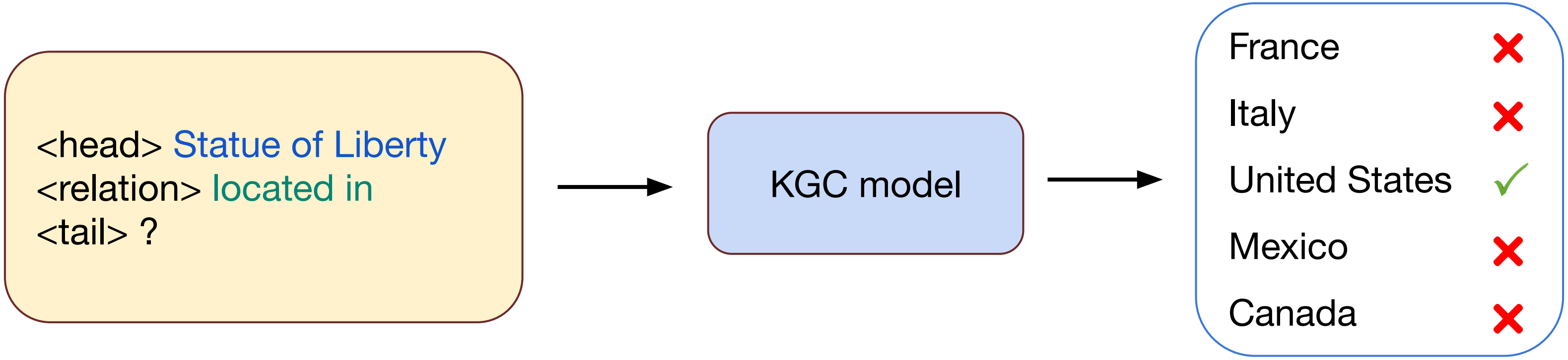

Input: Structured Query

Output: Ranked candidate entities

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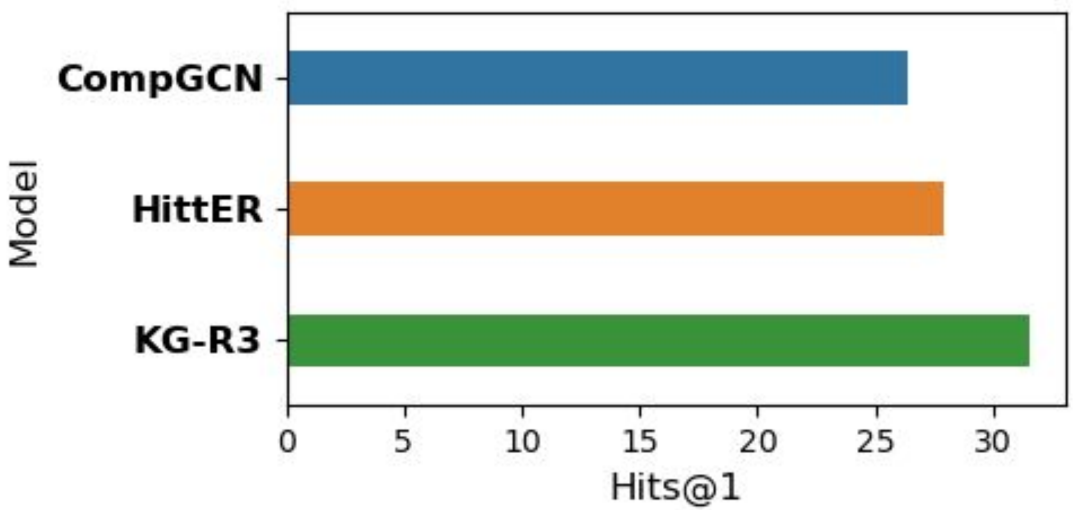
Experiments

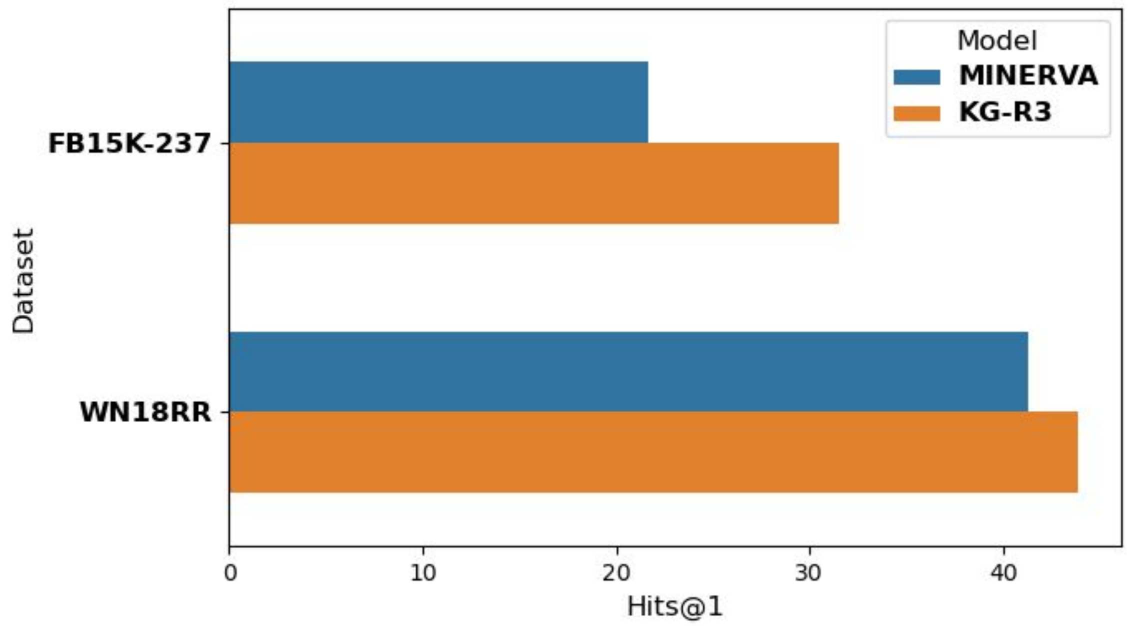
Link Prediction Performance (FB15K-237)



KG-R3 outperforms existing baselines on FB15K-237.

Experiments

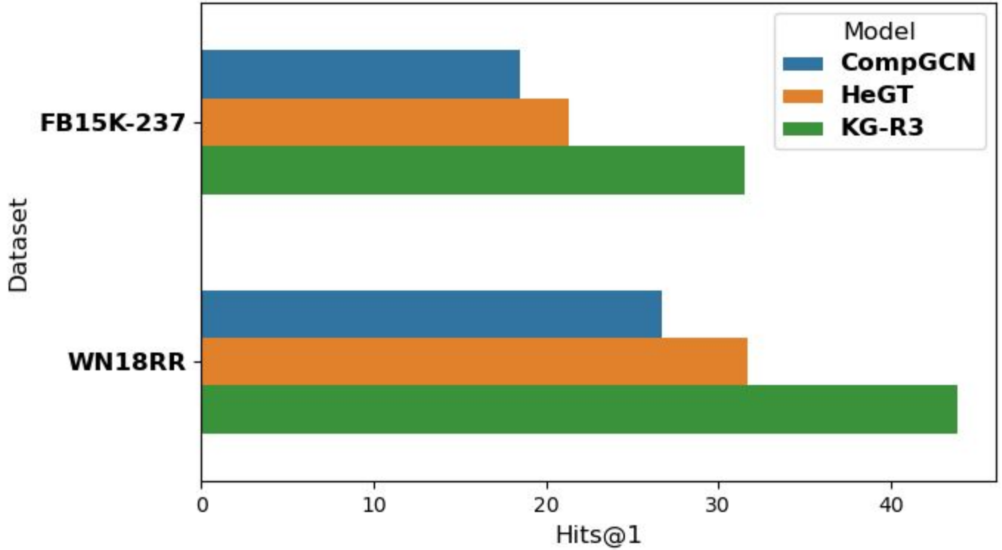
Link Prediction Performance



KG-R3 improves over MINERVA by **9.8%** and **2.6%** for FB15K-237 and WN18RR respectively

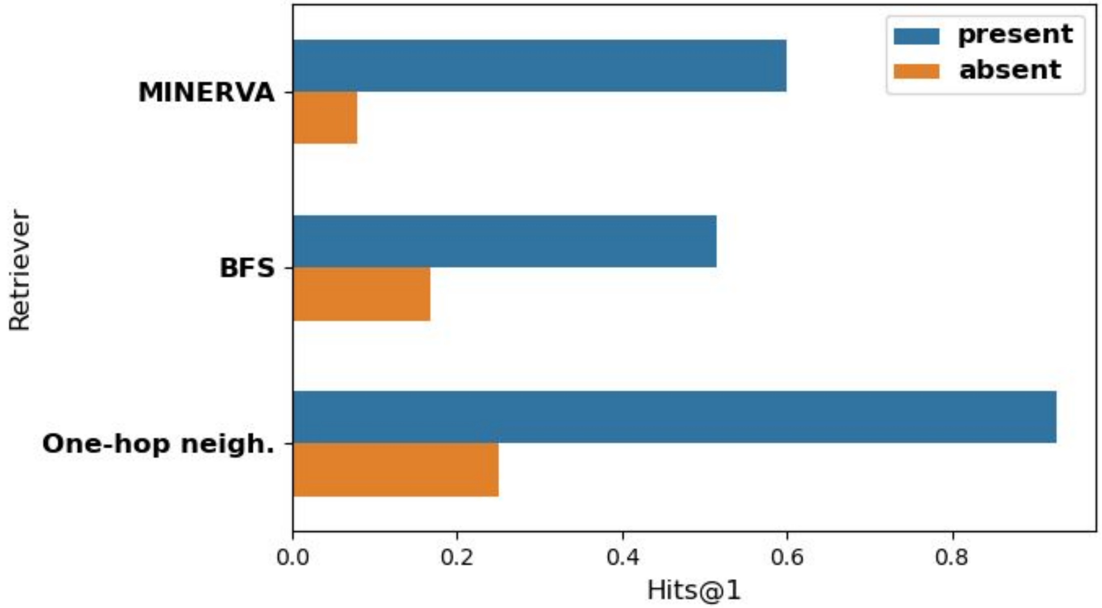
Performance comparison (Reader module)

- Baselines
  - **CompGCN** (Message-passing based GNN)
  - **HeGT** (Transformer-based GNN)



Transformer-based GNN reader vastly outperforms both baselines

Error Analysis



Higher target entity coverage in the subgraph leads to better performance.

Key Takeaways

- The Retrieve-and-Read framework for KG link prediction enables **higher capacity** and **scalable** GNNs with greater flexibility.
- Our instantiation (KG-R3) uses a **Transformer-based GNN** for KG reasoning.
- Achieves competitive performance on standard link prediction datasets.

A Retrieve and Read Framework for Knowledge Graph Reasoning

Contact: pahuja.9@osu.edu

Code: https://github.com/OSU-NLP-Group/KG-R3

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Thank You!

Backup

Experiments

		FB15K-237				WN18RR			
Framework	**Model**	**MRR**	**Hits@1**	**Hits@3**	**Hits@10**	**MRR**	**Hits@1**	**Hits@3**	**Hits@10**
Embedding-based	RESCAL [43]	.356	.263	.393	.541	.467	.439	.480	.517
	TransE [2]	.313	.221	.347	.497	.228	.053	.368	.520
	DistMult [66]	.343	.250	.378	.531	.452	.413	.466	.530
	ComplEx [55]	.348	.253	.384	.536	.475	.438	.490	.547
	ComplEx-N3 [35]	.37	–	–	.56	.48	–	–	.57
	RotatE [52]	.338	.241	.375	.533	.476	.428	.492	.571
CNN-based	ConvKB [42]	.243	.155	.371	.421	.249	.057	.417	.524
	ConvE [15]	.339	.248	.369	.521	.442	.411	.451	.504
Path-based	MINERVA [12]	.293	.217	.329	.456	.448	.413	.456	.513
	Neural LP [67]	.237	.173	.259	.361	.381	.368	.386	.408
	DRUM [47]	.238	.174	.261	.364	.382	.369	.388	.410
GNN-based	R-GCN [49]	.248	.151	–	.417	–	–	–	–
	CompGCN [56]	.355	.264	.390	.535	.479	.443	.494	.546
Transformer-based	HittER [9]	.373	.279	.409	**.558**	**.503**	**.462**	**.516**	**.584**
	KG-R3 (this work)	**.390**	**.315**	**.413**	.539	.472	.439	.481	.537

Graph Context aids KG Reasoning