GraphRAG-论文调研

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目录

1 论文调研概况

- 调研背景：
  - 检索增强生成(RAG)已被广泛应用，通过从外部来源检索相关信息来提升大语言模型(LLM)的性能，解决大语言模型上下文窗口受限的问题，提高事实准确性并减少幻觉。
  - 虽然RAG主要处理文本数据，但许多现实场景涉及图结构数据，如知识图谱(KGs)、社交图和分子图。GraphRAG旨在从各种类型的图结构数据中检索信息。图的内在结构通过捕捉相连节点之间的关系来增强检索效果。

1 论文调研概况

- 调研目录:
  - [1] Graph-R1，2025-07-29：引入了轻量级的知识超图构建，多轮智能体-环境交互端到端RL
  - [2] GNN-RAG，2025-07
  - [3] HyKGE，2025-07：假设输出(HO)+KG-RAG
  - [4] MKGF，2025-06：多模态KG-RAG，增强视觉大语言模型LVLM的医学视觉问答(MedVQA)
  - [5] Graphusion，2025-05：教育场景的应用
  - [6] StructRAG，2025-05：结构感知的RAG，（DDM：pdf->md）
  - [7] KG-Retriever，2025-05-05：文档级+实体级分层RAG，图构建+检索器 【详见9-Report.ppt】
  - [8] SuperRAG，2025-04：结构感知的多模态RAG
  - [9] From Local to Global，2025-02-19
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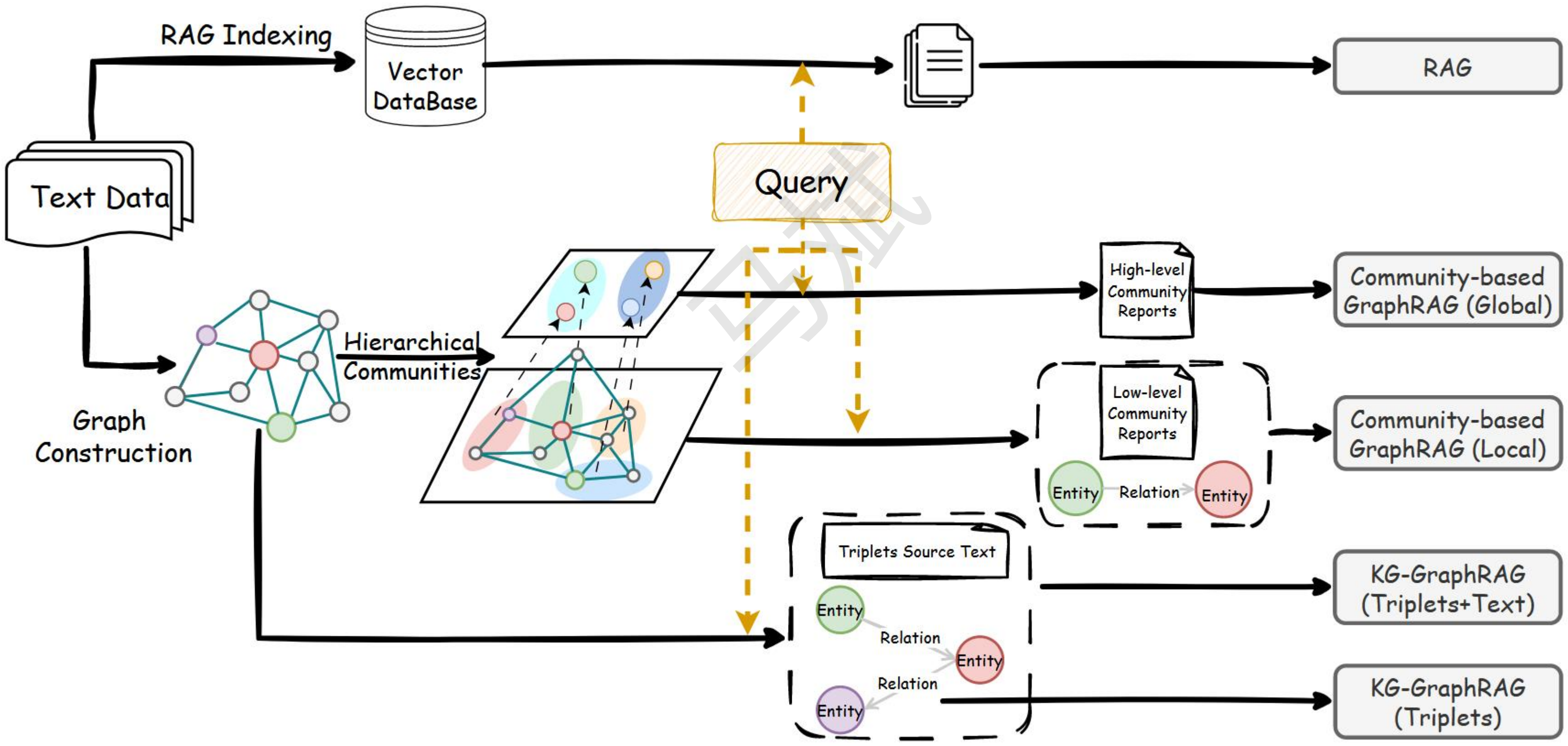
  - [18] Multilingual Word Sense Disambiguation for Semantic Annotations，2024-11
  - [19] Knowledge Graph Prompting for Multi-Document Question Answering，2024-03
  - [20] ASQA，2022

2 论文的理解与分析 --- [10] RAG vs. GraphRAG

■ 概述：

文章对比了RAG和两种GraphRAG【KG-based(Liu, 2022)、Community-based(Edge et al., 2024)】，在解决问答（单跳/多跳、单文档/多文档）、基于查询的摘要（单文档/多文档）任务的性能。



2 论文的理解与分析 --- [10] RAG vs. GraphRAG

- 实验结果：
- **QA**：只有Community-GraphRAG (Local)与RAG性能结果相当。
- **Summay**：RAG往往最优，可捕捉到文档内的详细信息。Integration(RAG+Community-GraphRAG (Local))整合策略性能次之。

问答任务：
- RAG：单跳问题、需详细信息的问题表现好
- GraphRAG（Community-GraphRAG Local）：多跳问题表现好
- Community-GraphRAG Global：QA任务表现差，易幻觉
- KG-based GraphRAG：因知识图不完整，整体表现欠佳

摘要任务：
- RAG：整体表现好，尤其多文档摘要
- KG-based GraphRAG：结合三元组和文本性能提升
- Community-based GraphRAG：Local搜索优于Global搜索
- 评估偏差：LLM-as-a-Judge存在位置偏差

表 1：NQ 和 Hotpot 数据集上的性能对比（%）。最佳结果以粗体突出显示，次佳结果以下划线标注。

Method	NQ						Hotpot					
	Llama 3.1-8B			Llama 3.1-70B			Llama 3.1-8B			Llama 3.1-70B		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
RAG	**71.7**	**63.93**	**64.78**	**74.55**	**67.82**	**68.18**	62.32	60.47	60.04	66.34	63.99	63.88
KG-GraphRAG (Triplets only)	40.09	33.56	34.28	37.84	31.22	28.50	26.88	24.81	25.02	32.59	30.63	30.73
KG-GraphRAG (Triplets+Text)	58.36	48.93	50.27	60.91	52.75	53.88	45.22	42.85	42.60	51.44	48.99	48.75
Community-GraphRAG (Local)	69.48	62.54	63.01	71.27	65.46	65.44	**64.14**	**62.08**	**61.66**	**67.20**	**64.89**	**64.60**
Community-GraphRAG (Global)	60.76	54.99	54.48	61.15	55.52	55.05	45.72	47.60	45.16	48.33	48.56	46.99

表 2：MultiHop-RAG 数据集上不同查询类型的性能对比（%）

Method	LLama 3.1-8B					Llama 3.1-70B				
	Inference	Comparison	Null	Temporal	Overall	Inference	Comparison	Null	Temporal	Overall
RAG	**92.16**	57.59	96.01	30.7	67.02	**94.85**	56.31	91.36	25.73	65.77
KG-GraphRAG (Triplets only)	55.76	22.55	**98.67**	18.7	41.24	76.96	32.36	**94.35**	19.55	50.98
KG-GraphRAG (Triplets+Text)	67.4	34.7	97.34	17.15	48.51	85.91	35.98	86.38	21.61	54.58
Community-GraphRAG (Local)	86.89	60.63	80.07	50.6	**69.01**	92.03	60.16	88.70	49.06	**71.17**
Community-GraphRAG (Global)	89.34	**64.02**	19.27	**53.34**	64.4	89.09	**66.00**	13.95	**59.18**	65.69

表 4：使用 Llama3.1-8B 进行基于查询的单文档摘要任务的性能。

Method	SQuALITY						QMSum					
	ROUGE-2			BERTScore			ROUGE-2			BERTScore		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
RAG	15.09	8.74	10.08	74.54	81.00	77.62	21.50	**3.80**	6.32	**81.03**	84.45	**82.69**
KG-GraphRAG (Triplets only)	11.99	6.16	7.41	82.46	84.30	83.17	13.71	2.55	4.15	80.16	82.96	81.52
KG-GraphRAG (Triplets+Text)	15.00	**9.48**	10.52	**84.37**	**85.88**	**84.92**	16.83	3.32	5.38	80.92	83.64	82.25
Community-GraphRAG (Local)	**15.82**	8.64	10.10	83.93	85.84	84.66	20.54	3.35	5.64	80.63	84.13	82.34
Community-GraphRAG (Global)	10.23	6.21	6.99	82.68	84.26	83.30	10.54	1.97	3.23	79.79	82.47	81.10
Integration	15.69	9.32	**10.67**	74.56	81.22	77.73	**21.97**	**3.80**	**6.34**	80.89	**84.47**	82.63

表 5：使用 Llama3.1-8B 的基于查询的多文档摘要任务的性能。

Method	ODSum-story						ODSum-meeting					
	ROUGE-2			BERTScore			ROUGE-2			BERTScore		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
RAG	**15.39**	8.44	**9.81**	**83.87**	**85.74**	**84.57**	15.50	**6.43**	**8.77**	**83.12**	**85.84**	**84.45**
KG-GraphRAG (Triplets only)	11.02	5.56	6.62	82.09	83.91	82.77	11.64	4.87	6.58	81.13	84.32	82.69
KG-GraphRAG (Triplets+Text)	9.19	5.82	6.22	79.39	83.30	81.03	11.97	4.97	6.72	81.50	84.41	82.92
Community-GraphRAG (Local)	13.84	7.19	8.49	83.19	85.07	83.90	15.65	5.66	8.02	82.44	85.54	83.96
Community-GraphRAG (Global)	9.40	4.47	5.46	81.46	83.54	82.30	11.44	3.89	5.59	81.20	84.50	82.81
Integration	14.77	**8.55**	9.53	83.73	85.56	84.40	**15.69**	6.15	8.51	82.87	85.81	84.31

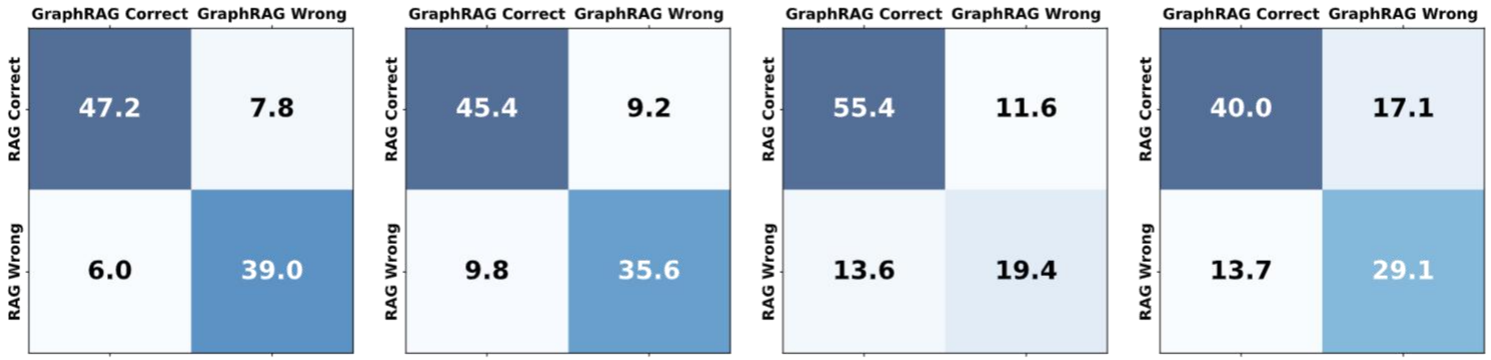
2 论文的理解与分析 --- [10] RAG vs. GraphRAG

- 本文提出QA方面解决方案：

1. RAG vs. GraphRAG Selection
2. RAG and GraphRAG Integration

- 优化结果：

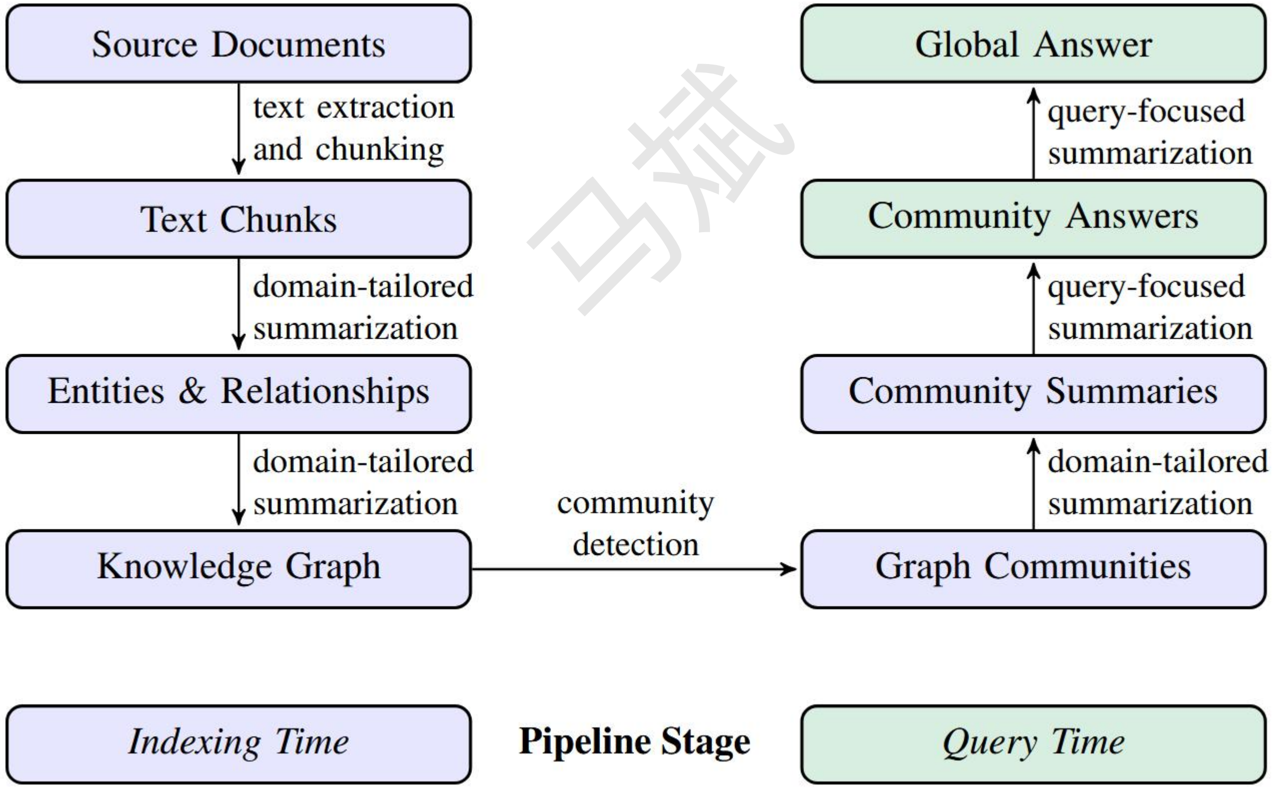
- 选择和结合方案分别将最佳方法提高了 1.1% 和 6.4%



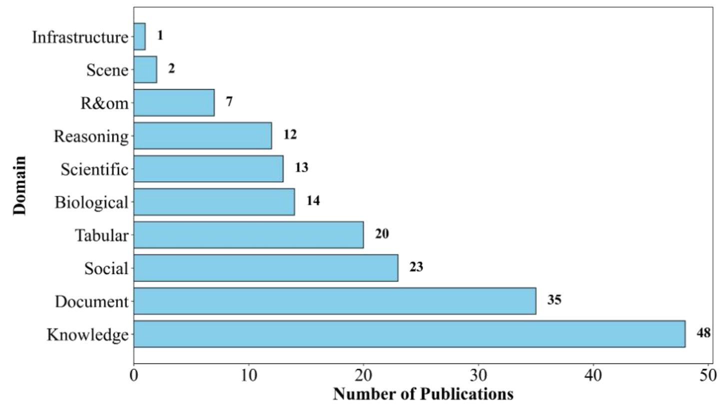
(a) NQ (b) Hotpot (c) MultiHop-RAG (d) NovelQA

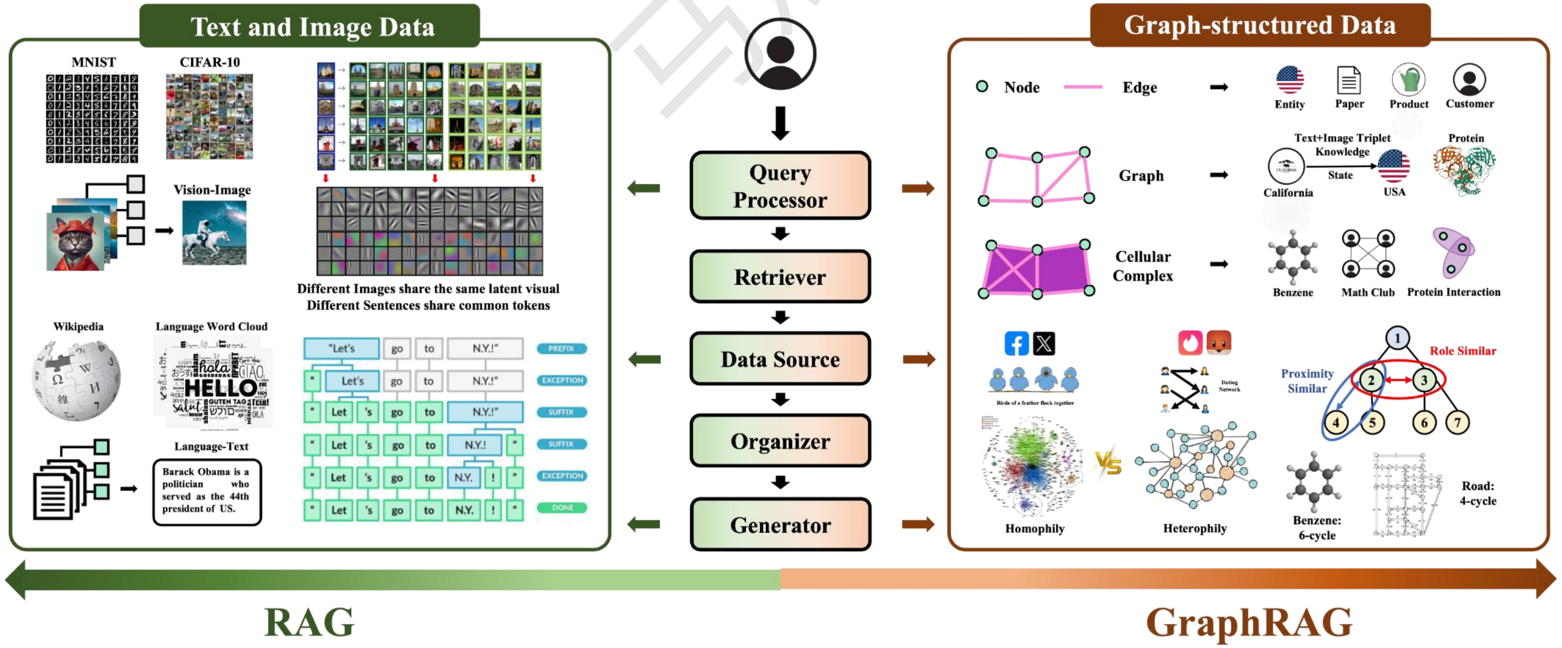
2 论文的理解与分析 --- [9] From Local to Global

- Pipline概述： 即 Community-GraphRAG
  - 源文档 -LLM> 文本块 -LLM> 实体和关系 -> 知识图谱
  - -分层方式使用莱顿社区检测算法递归> 图社区 -LLM低到高迭代> 社区摘要
  - -LLM打分> 社区答案 -LLM> 全局答案



- 概述：对GraphRAG整体框架进行了最新的定义与综述。整理先前研究中繁杂的概念、技术和数据集。
- 核心组件：
  - query processor 查询处理器
  - retriever 检索器
  - organizer 组织器
  - generator 生成器
  - data source 数据源





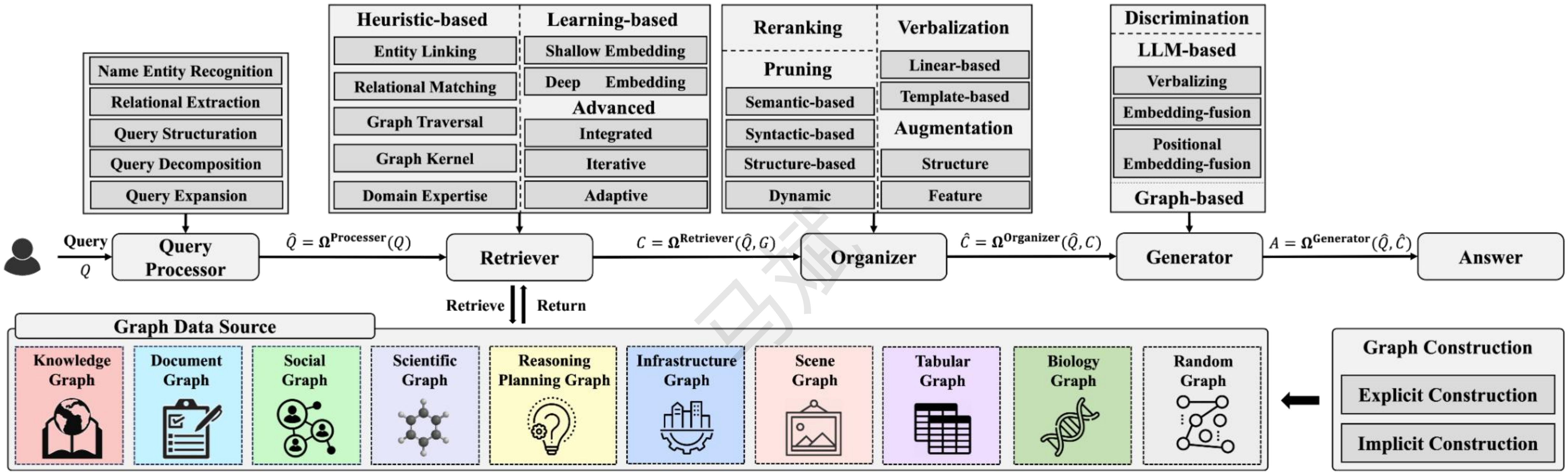
2 论文的理解与分析 --- [11] GraphRAG

- 当前应用：
  - 知识图谱：问答、事实核查、知识补全等
  - 文档图：多文档摘要、文本生成、文档检索等
  - 科学图：分子生成、分子属性预测、科学问答等
  - 社交图：实体属性预测、文本生成、推荐等
  - 规划与推理图：序列计划检索、异步规划等
  - 表格图：欺诈检测、表格问答、表格检索等
  - 其他领域：基础设施图、单细胞图、场景图等

- 相对于RAG，GraphRAG图结构数据的差异
  - 格式异构，来源异构 --- 检索器、生成器需要针对性设计
  - 信息有关联性 --- 可尝试结合检索器、生成器
  - 数据有领域特定性，常共享可迁移语义 --- 不同领域的GraphRAG难以统一，研究趋于专业化

人工智能研究最近从以<u>模型</u>为中心的角度向以<u>数据</u>为中心明显转变。

- GraphRAG结构定义：



- **Query Processor** $\Omega^{\text{Processor}}$: Preprocessing the given query $\hat{Q} = \Omega^{\text{Processor}}(Q)$.
- **Graph Data Source** G: Information organized in graph-structured format.
- **Retriever** $\Omega^{\text{Retriever}}$: Retrieve the content $C = \Omega^{\text{Retriever}}(\hat{Q}, G)$ from G based on the query $\hat{Q}$.
- **Organizer** $\Omega^{\text{Organizer}}$: Arrange and refine the retrieved content $\hat{C} = \Omega^{\text{Organizer}}(\hat{Q}, C)$.
- **Generator**: Generate answers $A = \Omega^{\text{Generator}}(\hat{Q}, \hat{C})$ to answer query Q.

- **Query processor**：--- NLP
  - 命名实体识别(NER)：深度学习、LLM
  - 关系提取(RE)：文本表示、上下文编码、三元组预测。深度学习
  - 查询结构化：图查询语言(GQL)
  - 查询分解
  - 查询扩展：查询增强(QE)，不同于基于文本相似度。

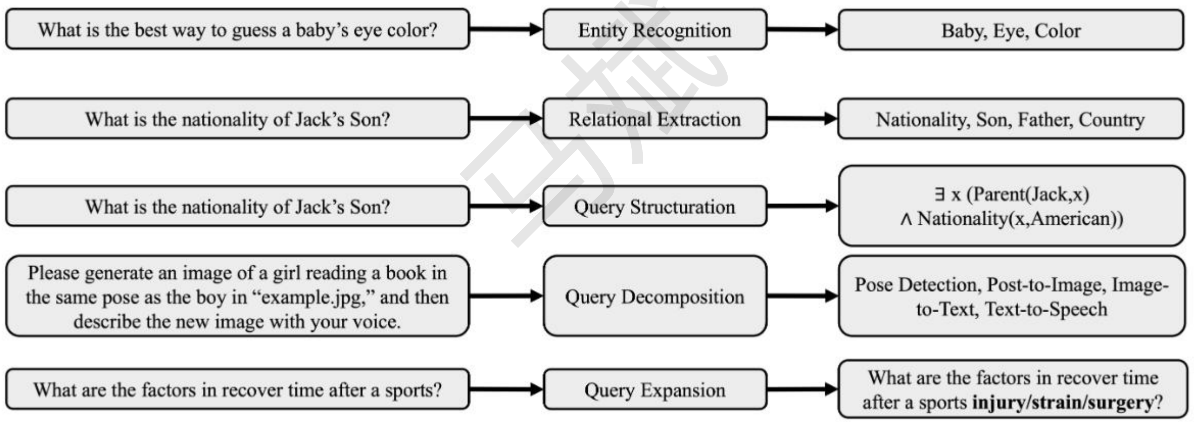


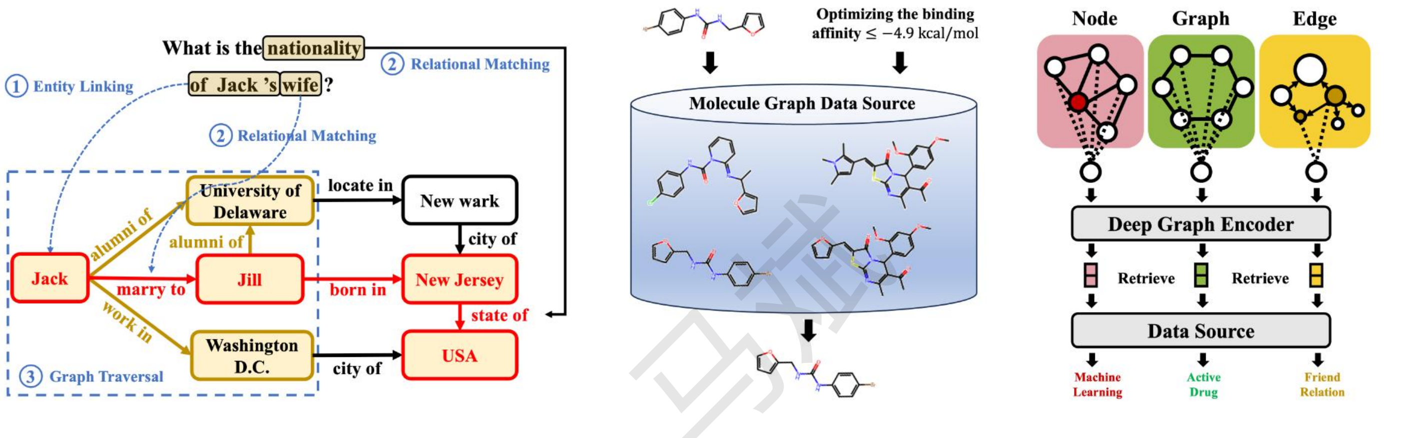
Figure 4: Existing techniques of query processor $\Omega^{\text{Processor}}$ in GraphRAG.

Table 2: Difference of query processor $\Omega^{\text{Processor}}$ between RAG and GraphRAG.

Technique	RAG	GraphRAG
Entity Recognition	Extracting mentions in knowledge bases	Extracting mentioned nodes in graphs.
Relational Extraction	Extracting textual relations	Extracting graph edge relations
Query Structuration	Structuring text query to SQL, SPARQL	Structuring text query to GQL
Query Decomposition	Decomposed queries are separate	Decomposed queries are logically related
Query Expansion	Expansion based on semantic knowledge	Expansion based on relational knowledge

2 论文的理解与分析 --- [11] GraphRAG

- **Retriever**：--- LLM
  - 信号分类： “文本/图输入，文本/图输出” ，语义信号和图结构信号。
  - 设计分类：基于启发式、基于学习、高级策略(集成、迭代、自适应)



(a) Entity Linking, Relational Matching, and Graph Traversal (b) Graph Kernal and Domain Expertise (c) Shallow and Deep Graph Embedding

Figure 5: Visualizing representative retrievers used in GraphRAG.

Table 3: Categorizing representative retrievers used in GraphRAG.

Method/Strategy	Input	Output	Description
Entity Linking	Entity Mention	Node	Match query entity and graph node
Relational Matching	Relation Mention	Edge	Match query relation and graph edge
Graph Traversal	Node/Edge	Graph	Expand seed nodes/edges into subgraphs
Graph Kernel	(Sub)Graph	(Sub)Graph	Match query graph and candidate graph
Shallow Embedding	Any	Any	Embedding similarity match query and candidate
Deep Embedding	Any	Any	Embedding similarity match query and candidate
Domain Expertise	Expertise Rule	Any	Match Domain Expertise with nodes/edges/graphs

2 论文的理解与分析 --- [11] GraphRAG

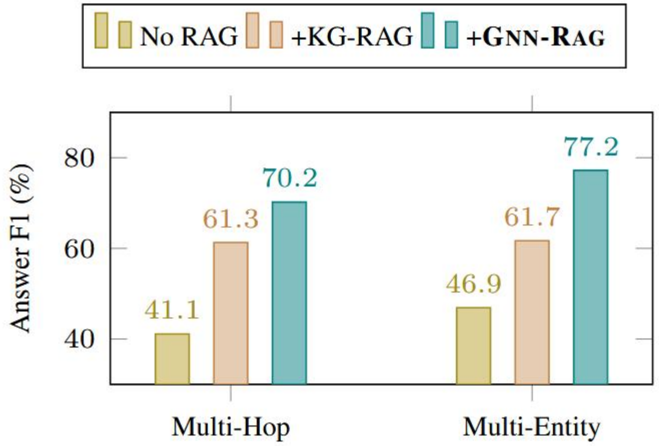
- **Organizer**：
  - 图剪枝：基于语义、基于句法、基于结构、动态剪枝。
  - 重排序：GNN或基于出现时间顺序
  - 图增强：图结构增强(新边or结点)，图特征增强(LLM作特征增强器)
  - 语言表达：线性语言表达(基于元组、模板)、基于LLMs的语言表达(图到文本、图总结)
- **Generator**：
  - 基于判别式：利用GNNs和图变换器等模型来完成分类等任务;
  - 基于LLM：利用大语言模型的能力为基于文本的任务生成答案;
  - 基于图：利用扩散模型等生成模型来生成新的图。
- **Data source**：
  - 图构建方法： 显示(根据预定义的关系)、隐式(连接可能的相关项)
  - 图表示方法：邻接矩阵、边列表、邻接表、节点序列、自然语言(LLM)

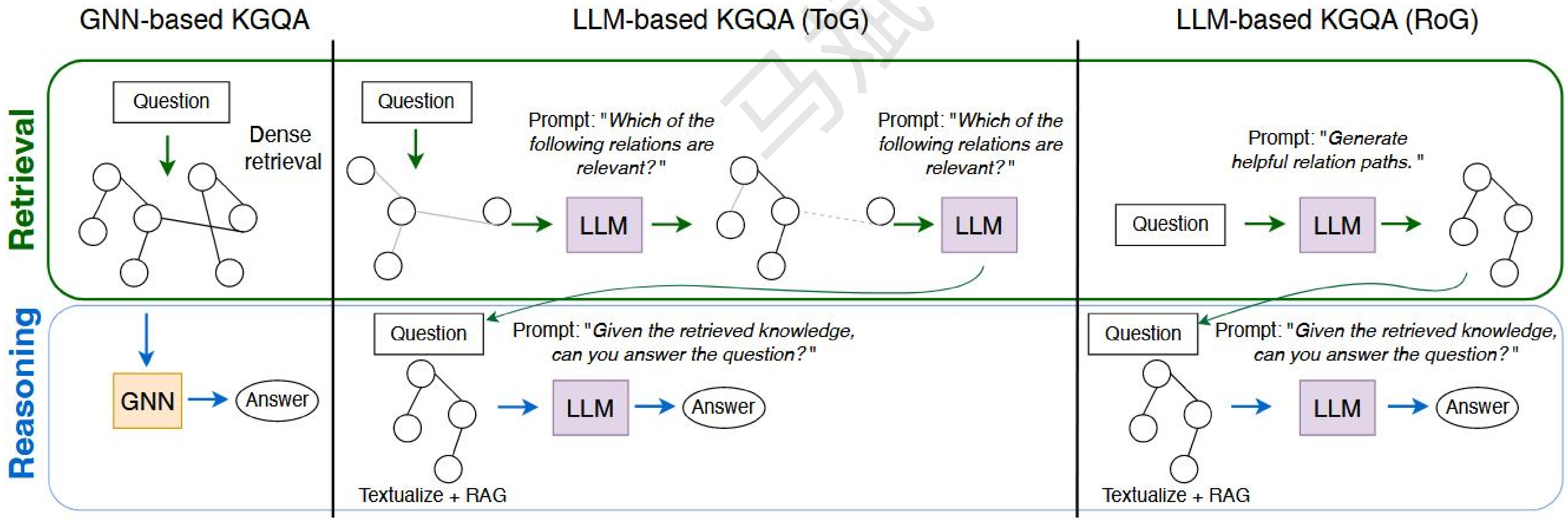
2 论文的理解与分析 --- [11] GraphRAG

- 挑战与机遇：
  - 图构建：实体关系处理、格式优劣、多模态、动态图
  - 检索器：区分神经知识与符号知识、协调内外部知识、权衡准确性多样性新颖性、自适应
  - 组织器：去噪去冗、多模态对齐组件、数据增强
  - 生成器：LLM仅文本输入
  - 整体系统：组件集成交互、可拓展性、安全与可信、
  - 性能评估：组件级最佳、端到端基准测试、多任务多领域评估、可信度基准
  - GraphRAG 新应用领域：代码生成Codexgraph[262]、健壮网络防御RAG4RCD[330]

2 论文的理解与分析 --- [2] GNN-RAG

- 概述：LLM -> GNN --- 属于IR信息检索策略
- 通过检索增强和路由技术，利用 GNN-RAG 提高整体端到端效率。

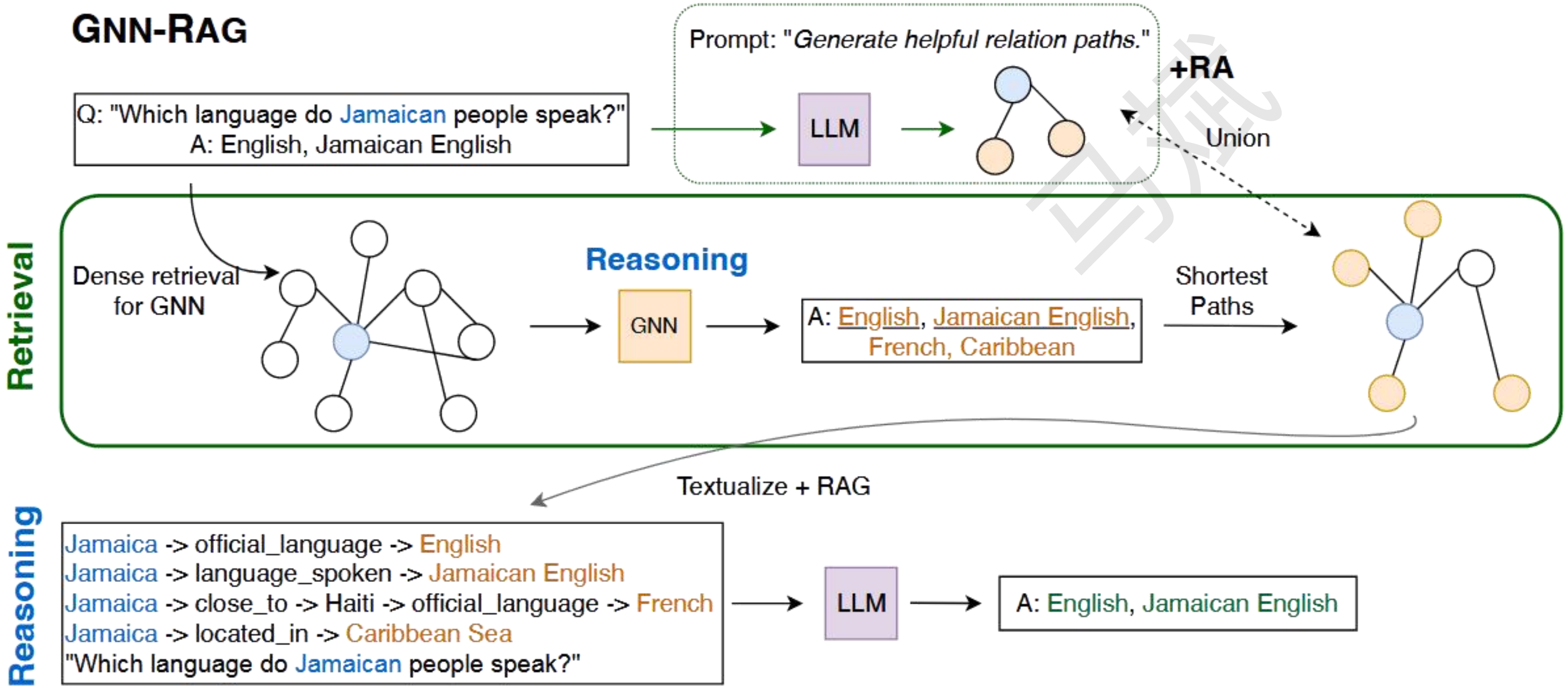




2 论文的理解与分析 --- [2] GNN-RAG

- 创新点:
  - (基于文本相似性的长文本上下文检索 or LLM检索) -> GNN 图检索

    --- 为解决GNN在KGQA中泛化能力局限性问题
  - 检索增强(RA)：GNN-RAG + (LLM_based)RoG
  - 路由技术(Route)：SubgraphRAG



Type	Method	WebQSP Hit	WebQSP F1	CWQ Hit	CWQ F1
Embedding	KV-Mem (Miller et al., 2016)	46.7	38.6	21.1	–
	EmbedKGQA (Saxena et al., 2020)	66.6	–	–	–
	TransferNet (Shi et al., 2021)	71.4	–	48.6	–
	Rigel (Sen et al., 2021)	73.3	–	48.7	–
GNN	GraftNet (Sun et al., 2018)	66.7	62.4	36.8	32.7
	PullNet (Sun et al., 2019)	68.1	–	45.9	–
	NSM (He et al., 2021)	68.7	62.8	47.6	42.4
	SR+NSM(+E2E) (Zhang et al., 2022a)	69.5	64.1	50.2	47.1
	NSM+h (He et al., 2021)	74.3	67.4	48.8	44.0
	SQALER (Atzeni et al., 2021)	76.1	–	–	–
	UniKGQA (Jiang et al., 2023b)	77.2	72.2	51.2	49.1
	ReaRev (Mavromatis and Karypis, 2022)	76.4	70.9	52.9	47.8
	ReaRev + LM_{SR}	77.5	72.8	53.3	49.7
LLM	Flan-T5-xl (Chung et al., 2024)	31.0	–	14.7	–
	Alpaca-7B (Taori et al., 2023)	51.8	–	27.4	–
	LLaMA2-Chat-7B (Touvron et al., 2023)	64.4	–	34.6	–
	ChatGPT	66.8	–	39.9	–
	ChatGPT+CoT	75.6	–	48.9	–
KG+LLM	KAPING (Baek et al., 2023)	73.9	–	–	–
	KD-CoT (Wang et al., 2023)	68.6	52.5	55.7	–
	StructGPT (Jiang et al., 2023a)	72.6	–	–	–
	KB-BINDER (Li et al., 2023)	74.4	–	–	–
	ToG+Llama2-70B (Sun et al., 2024)	68.9	–	57.6	–
	ToG+ChatGPT (Sun et al., 2024)	76.2	–	58.9	–
	ToG+GPT-4 (Sun et al., 2024)	82.6	–	**69.5**	–
	RoG-7B (Luo et al., 2024a)	85.7	70.8	62.6	56.2
GNN+LLM	G-Retriever (He et al., 2024)	70.1	–	–	–
	GNN-RAG	85.7	71.3	66.8	59.4
	GNN-RAG+RA	**90.7**	**73.5**	68.7	**60.4**
KG-LC	SubgraphRAG (Li et al., 2024b)	89.4	–	68.6	–
	GNN-RAG+Route	90.1	–	72.4	–
	GNN-RAG+RA+Route	91.0*	–	73.3*	–

We denote the **best** and second-best methods, as well as the best* method with long-context (KG-LC).
GNN-RAG, RoG, KD-CoT, and G-Retriever use 7B fine-tuned Llama2 models. KD-CoT employs ChatGPT as well. For KG-LC, methods use Llama-3.1-8B.

2 论文的理解与分析 --- [6] StructRAG

- 概述：

  结构感知的RAG框架，利用学术知识图谱来增强问答。

- 创新点：
  - 自动化KG构建：基于深度文档模型(DDM)的自动化KG构建管道，保留文档分层结构。.pdf -> .md
  - 基于多样性的检索过程：语义相关性(LLM->top-15)+源多样性(重排->top-5)
  - 上下文感知的答案生成：增加来自DDM表示的结构元数据，严格限制模型仅基于提供的段落生成答案

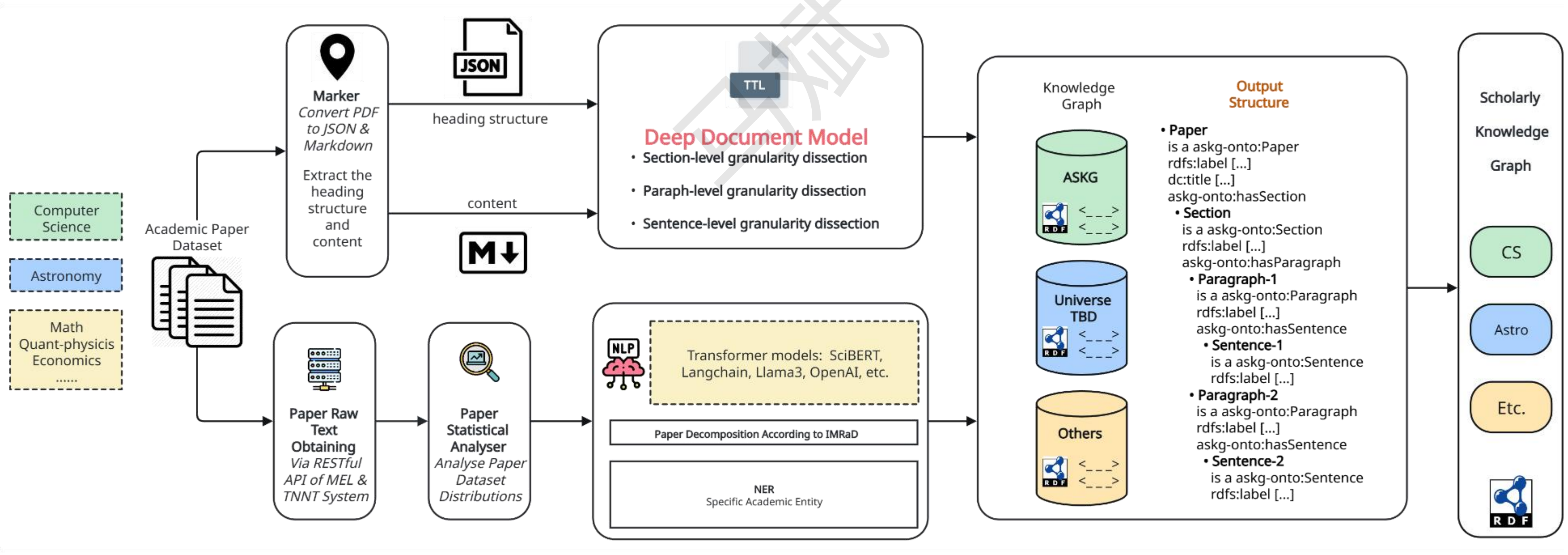


Figure 1: System architecture for academic paper processing and knowledge graph construction.

2 论文的理解与分析 --- [8] SuperRAG

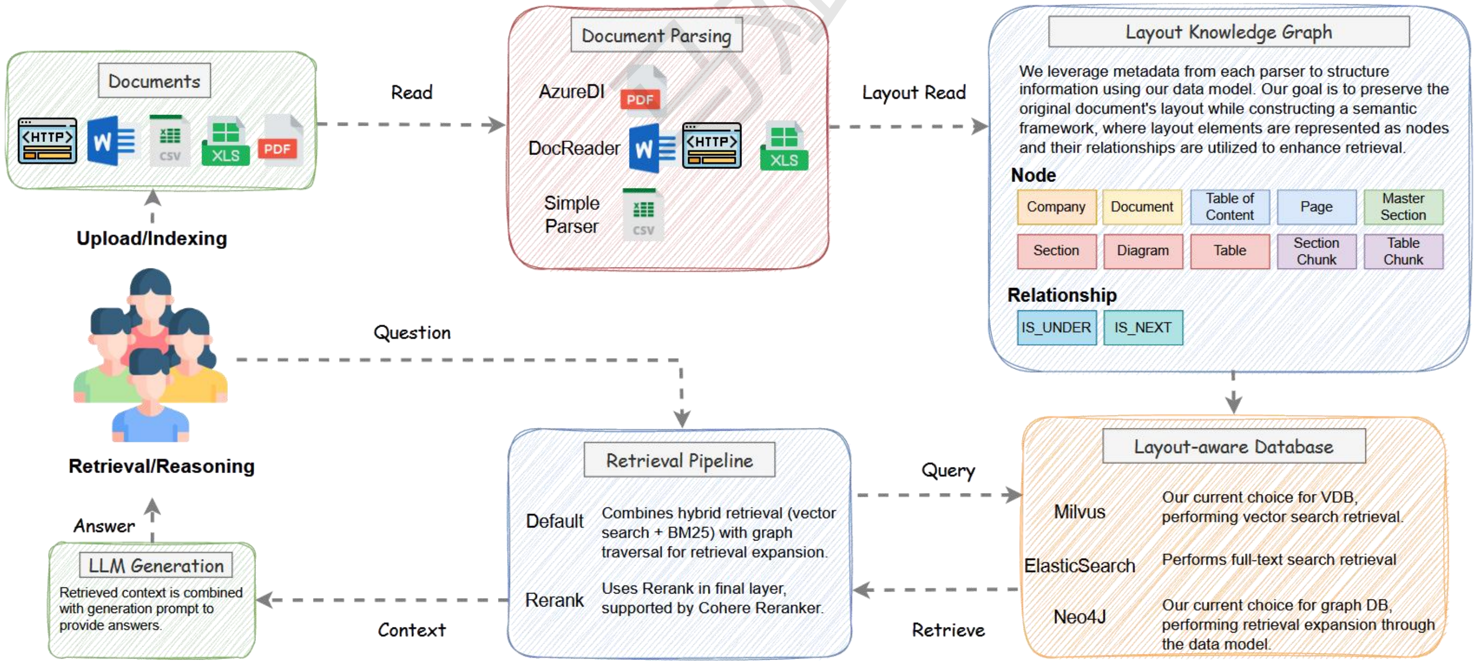
■ 概述：

结构感知的多模态RAG框架。

利用布局感知图建模(LAGM)，基于原始文档布局，构建包含文本块、表格和图形之间关系的图。

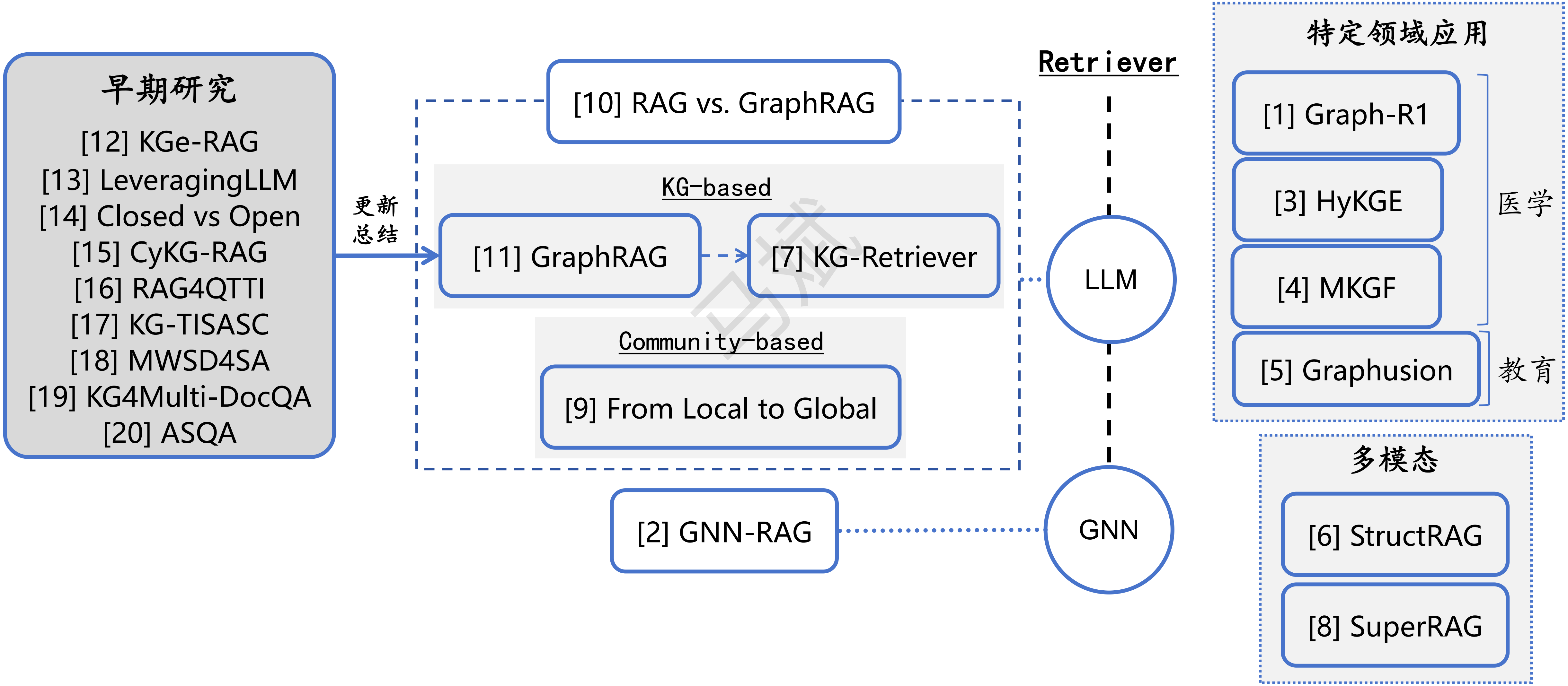
■ 创新点：

- LAGM保留了文档原始布局与结构，连接文本块、表格和图表
- 采用LLM基于图遍历和启发式检索两种方式，结合知识图谱（KG）与全文、向量搜索构建高级IR模块
- 引入自反思层，按需整合表格和图表信息，减少无关内容



3 总结

- 本次调研以 Graph RAG 为关键词调研了以下20篇文章。
  其中，对 [2, 7, 9, 10, 11] 进行了详细分析，对 [7] 尝试了实验复现。



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