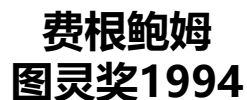


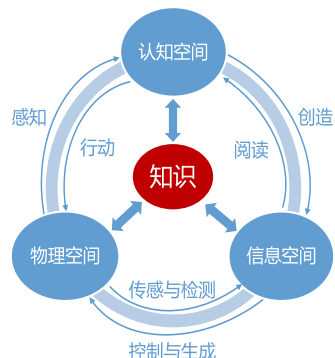
大模型与知识图谱前沿综述

陈玉博

中国科学院自动化研究所



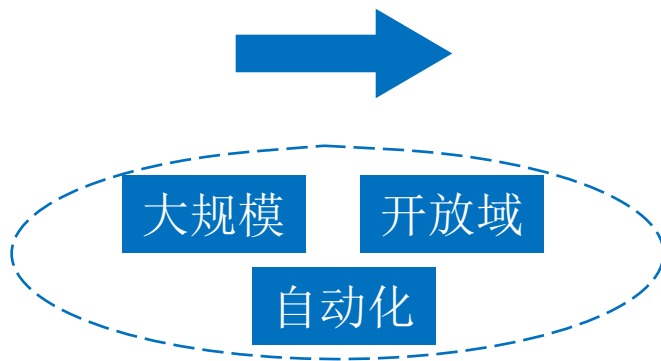
1977年，在第五届国际人工智能会议上，图灵奖获得者费根鲍姆提出了**知识工程**的概念，确立了知识工程在人工智能中的重要地位。



人工智能的基石

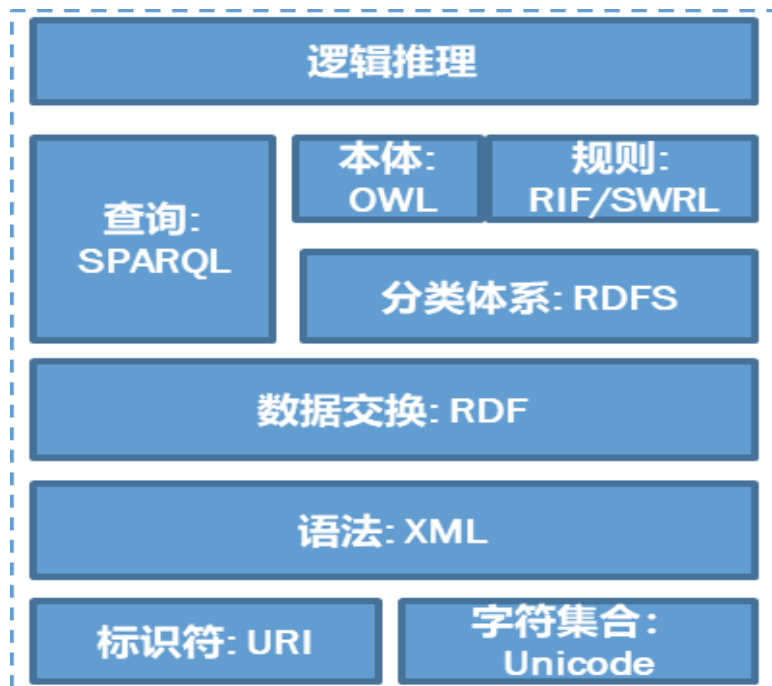


大数据知识工程

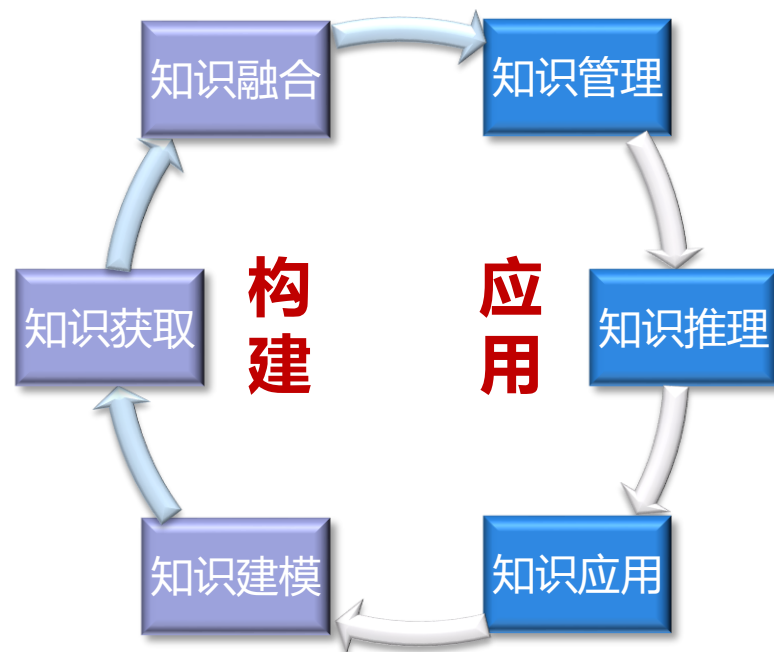


知识图谱

- 知识图谱是以三元组为基本语义单元，以有向标签图为数据结构，从知识本体和知识实例两个层次，对世界万物进行体系化、规范化描述，并支持高效知识推理和语义计算的大规模知识系统。



描述体系



生命周期

知识图谱 VS 大模型

■ 知识图谱（符号化表示）

□ 优点：

- 语义明确
- 准确度高
- 可解释性好
- 规范的存储与更新机制

□ 不足：

- 知识类型有限
- 知识规模有限

■ 大模型（参数化表示）

□ 优点：

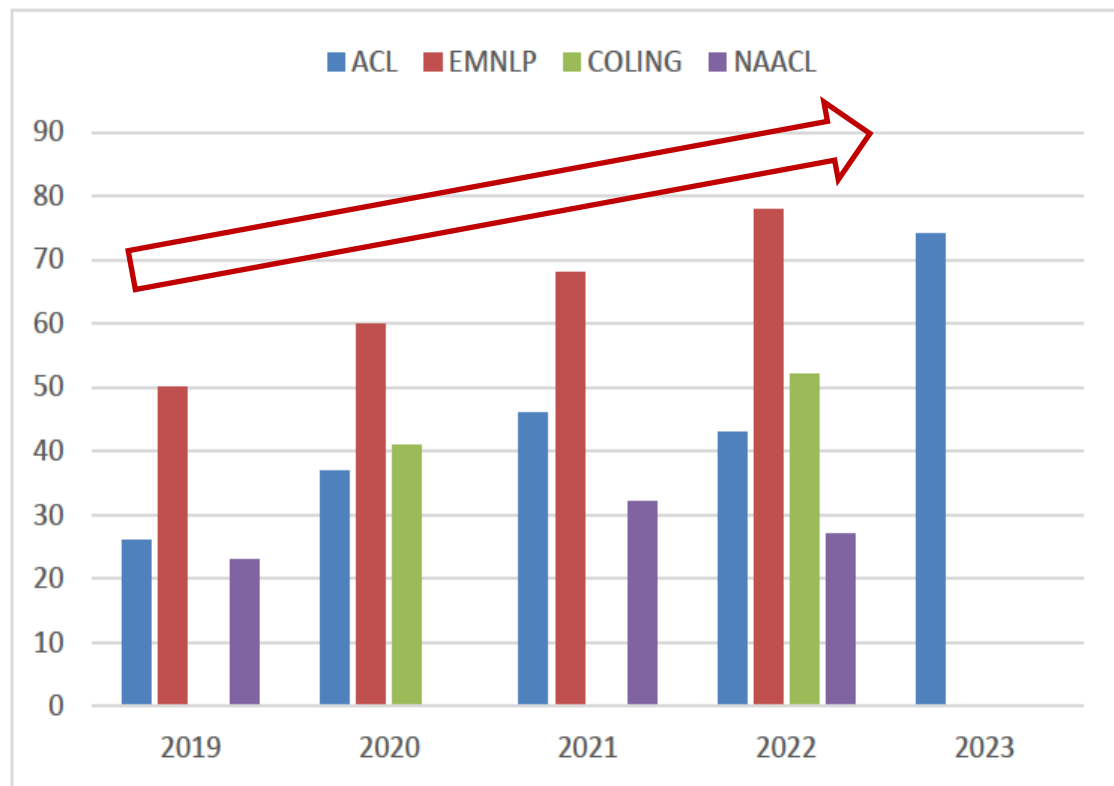
- 知识类型开放
- 知识规模庞大
- 自然语言形式的访问

□ 不足：

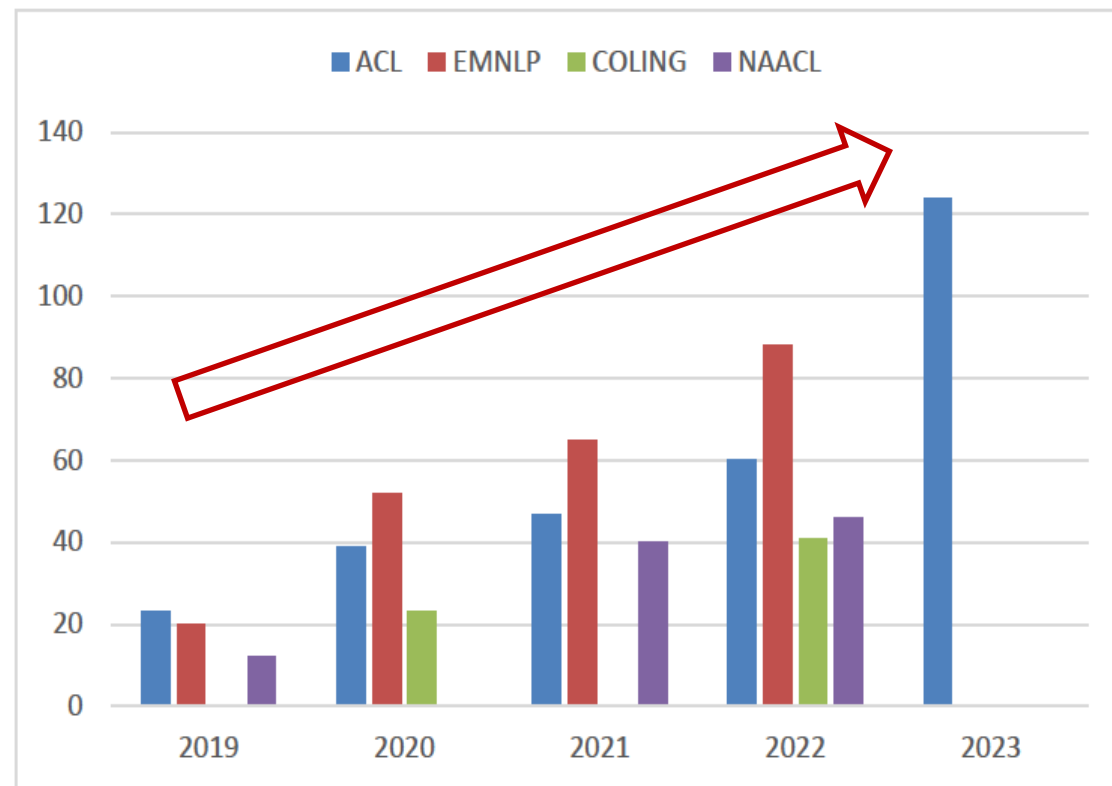
- 幻象
- 黑盒、可解释差
- 缺乏领域/最新知识

大规模预训练语言模型从语料中自动学到了大量知识，常被看作“参数化知识图谱”

NLP会议论文分布

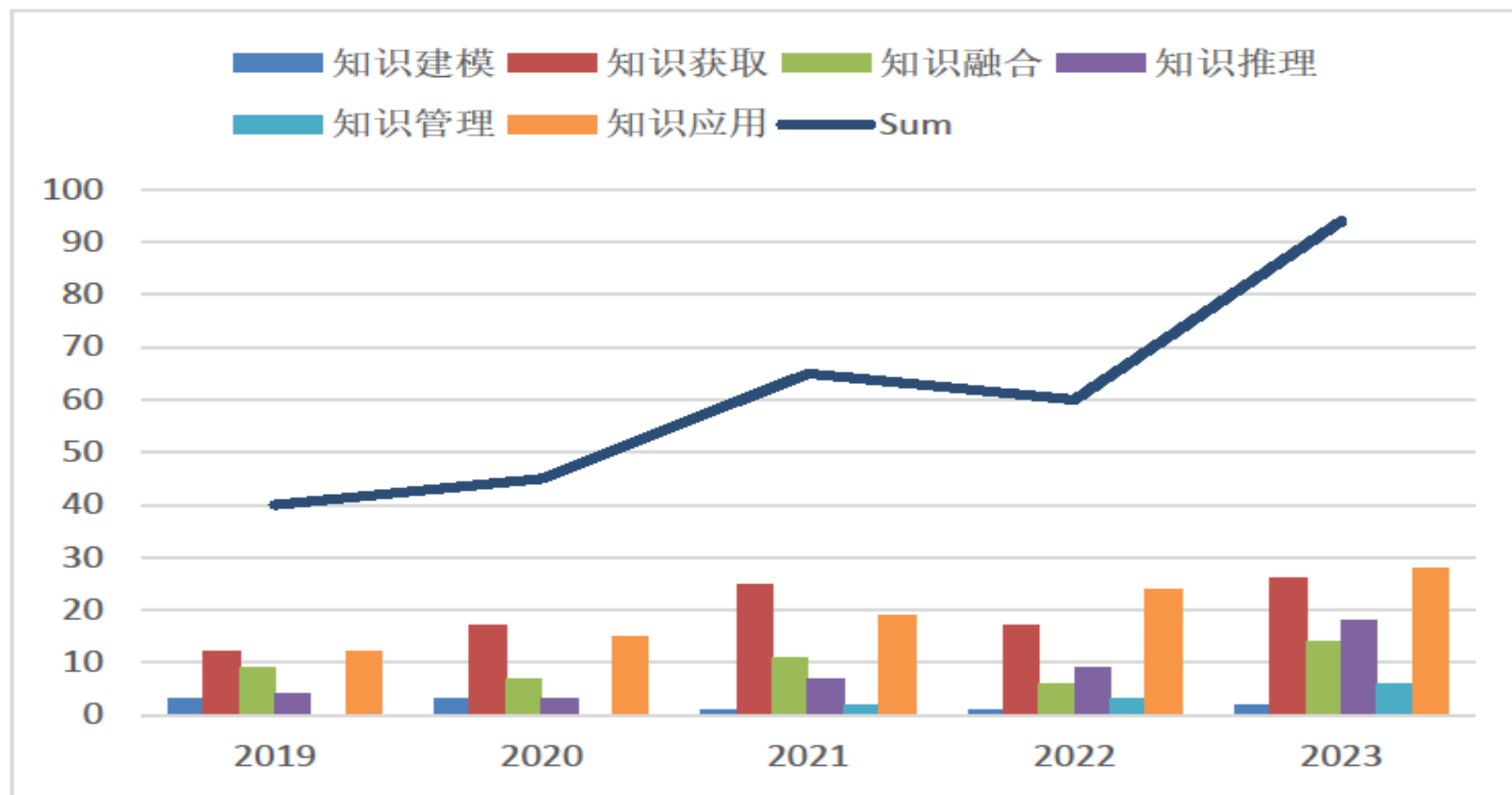


知识图谱论文粗略统计



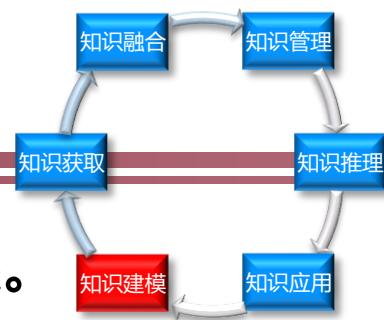
语言模型论文粗略统计

NLP会议论文分布



知识获取与知识应用相关的研究最多，知识推理逐渐成为研究的热点

知识建模



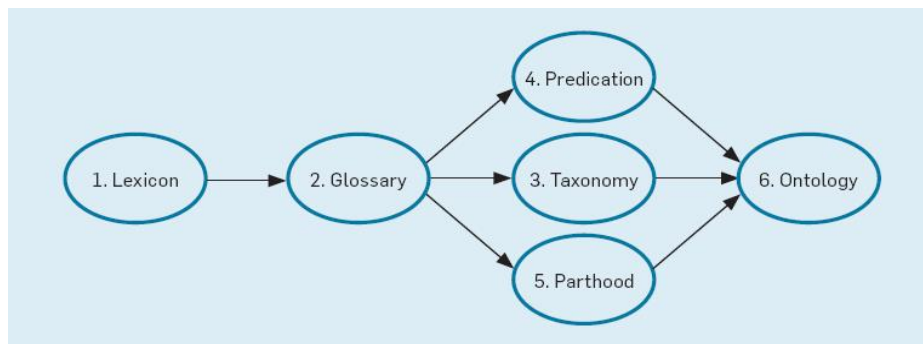
■ 知识建模，或知识体系构建，旨在构建一个本体对目标知识进行描述。

■ 输入：

- 领域 (医疗、金融...)
- 应用场景
- 数据/大模型

■ 输出：领域知识本体

- 领域实体类别体系
- 实体类别的属性
- 类别之间的语义关系
- 语义关系之间的关系

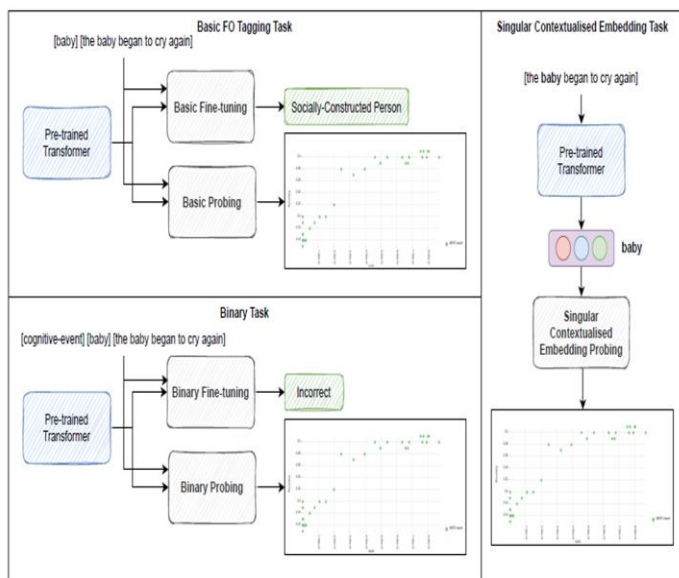


Ontology engineering				
File Edit View Insert Format Data Tools Add-ons Help All changes saved in Drive				
fx				
	A	B	C	D
1	Term	Synonyms	Kind	Description [source]
2	Delivery address	Shipping address	Complex property	Location to which goods are to be sent [1].
3	Invoice	Bill	Object	Itemized list of goods shipped, usually specifying the price and the terms of sale [2].
4	Postal address	Address	Complex property	Information that locates and identifies a specific address, as defined by the postal service [3].
5	Purchasing conditions	Purchase terms and conditions	Object	Conditions related to the transaction and the trade [4].
6	Purchase order	PO	Object	Commercial document issued by a buyer to a seller, indicating types, quantities, and agreed prices for products or services the seller will provide to the buyer [5].
7	Customer	Client	Actor	One who purchases a commodity or service [2].
8	Invoicing	Issuing invoice	Process	Making or issuing an invoice for goods or services [6].
9	Purchasing	Buying	Process	Acquisition of something for payment [6].
+ ≡ 1. Lexicon 2. Glossary 3. Taxonomy 4. Predication 5. Parthood				

知识建模

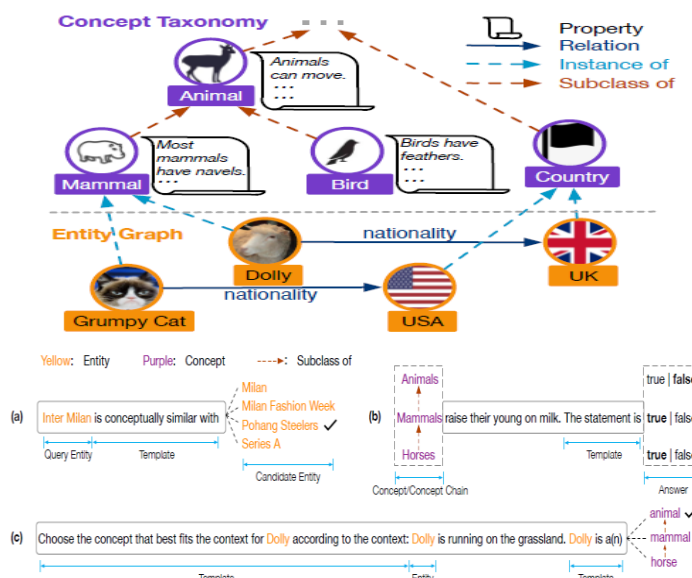
■ 实体本体建模

- 通过描述实体、属性以及关系来刻画客观世界中事物的静态规律。
- 采用微调→提示学习等方法探测/激发大模型中的实体本体知识。



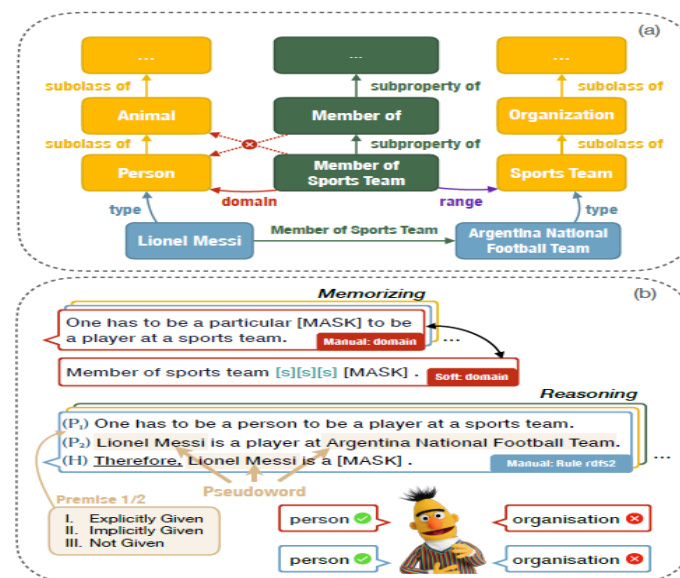
实体

Jullien et al. Do Transformers Encode a Foundational Ontology? (2022)



实体、属性及实体之间语义关系

Peng et al. COPEN: Probing Conceptual Knowledge in Pre-trained Language Models (EMNLP 2022)



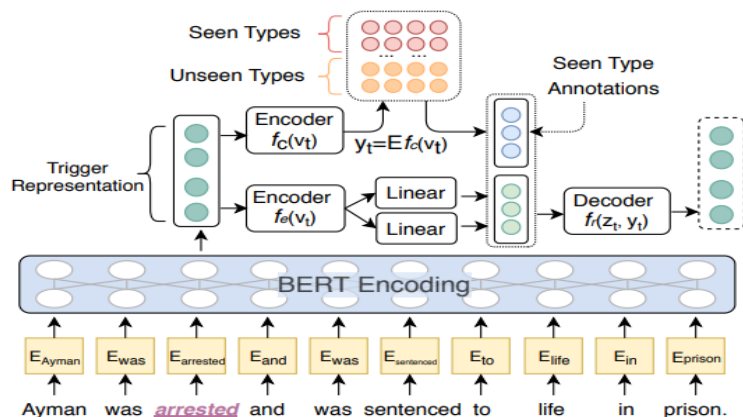
实体、属性、实体之间及属性之间语义关系

Wu et al. Do PLMs Know and Understand Ontological Knowledge? (ACL 2023)

知识建模

事件本体建模

- 通过描述事件类型、论元及关系来刻画现实世界中事物的动态变化规律。
- 微调 → 提示学习。



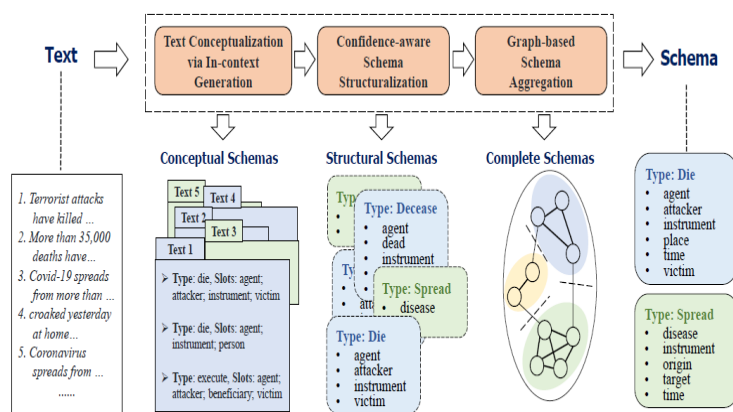
事件类型归纳

Huang et al. Semi-supervised New Event Type Induction and Event Detection (EMNLP 2020)

Xu et al. CEO: Corpus-based Open-Domain Event Ontology Induction (2023)

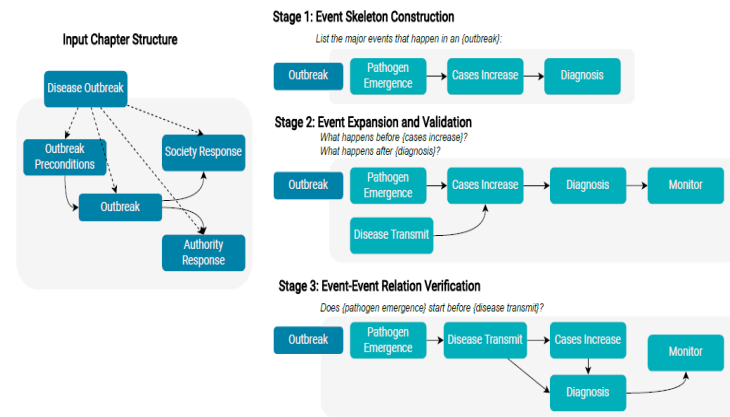
Dror et al. Zero-Shot On-the-Fly Event Schema Induction (EACL 2023)

Edwards et al. Semi-supervised New Event Type Induction and Description via Contrastive Loss-Enforced Batch Attention (EACL 2023)



原子事件模式归纳

Tang et al. Harvesting Event Schemas from Large Language Models (2023)



事件图模式归纳

Li et al. Open-Domain Hierarchical Event Schema Induction by Incremental Prompting and Verification (ACL 2023)

知识建模

脚本建模

利用大模型创建脚本数据集，为专业化小型模型赋约束语言规划能力。

Language Planning

 **How to Make a Cake?**

1. Gather your ingredients.
2. Preheat the oven to 325 °F (163 °C) and grease and flour a cake pan.
3. Cream the butter and sugar.
4. Add the eggs.
5. Stir in the cake flour.
6. Pour the batter into the pan.
7. Bake the cake for 1 hour 15 minutes.

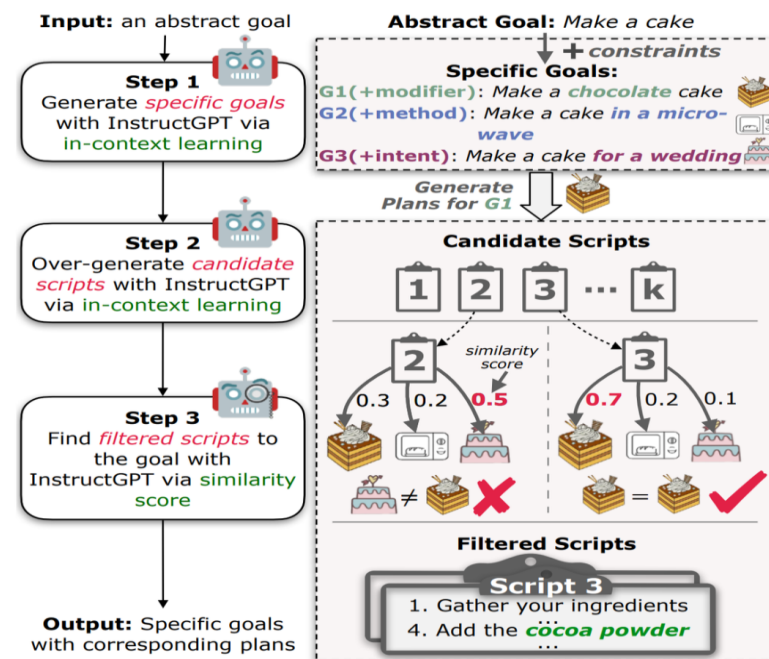


Constrained Language Planning

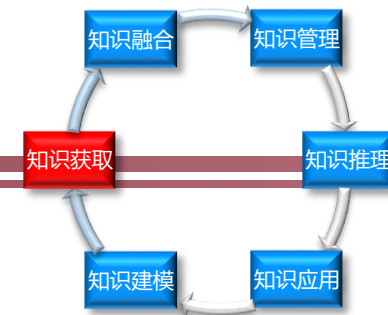
 **How to Make a Strawberry Cake?**
...Add strawberry jams into the flour...

 **How to Make a Chocolate Cake?**
...Add the cocoa powder into the flour...

Abstract goal can be inherited by different real-life **specific goals** with multi-faceted **constraints**



知识获取



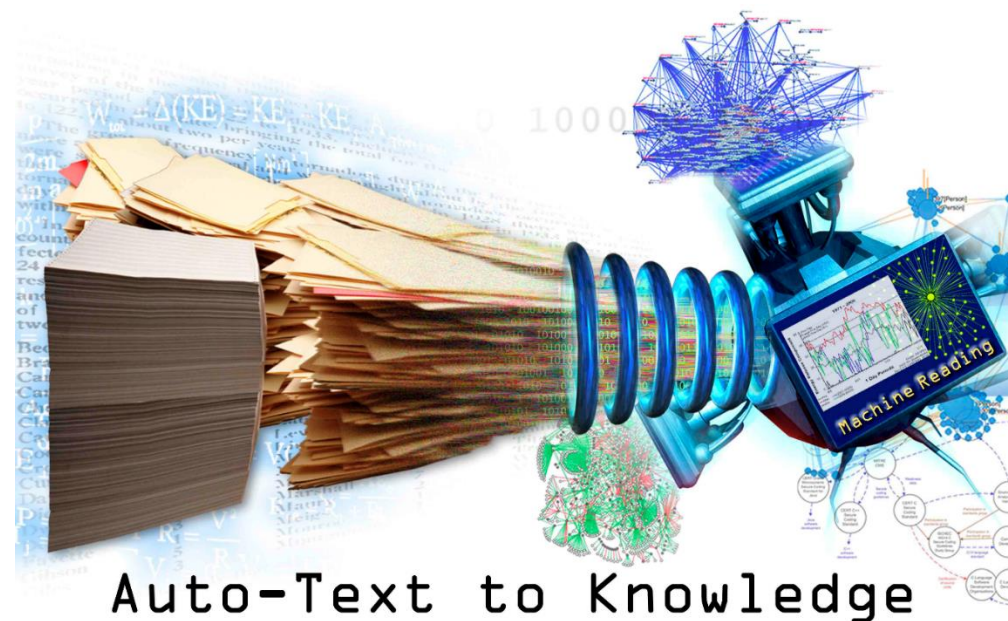
■ 知识获取，旨在从非结构化数据中抽取结构化知识。

■ 输入：

- 领域知识本体
- 海量数据：文本、垂直站点、百科
- 大模型

■ 输出：实例知识

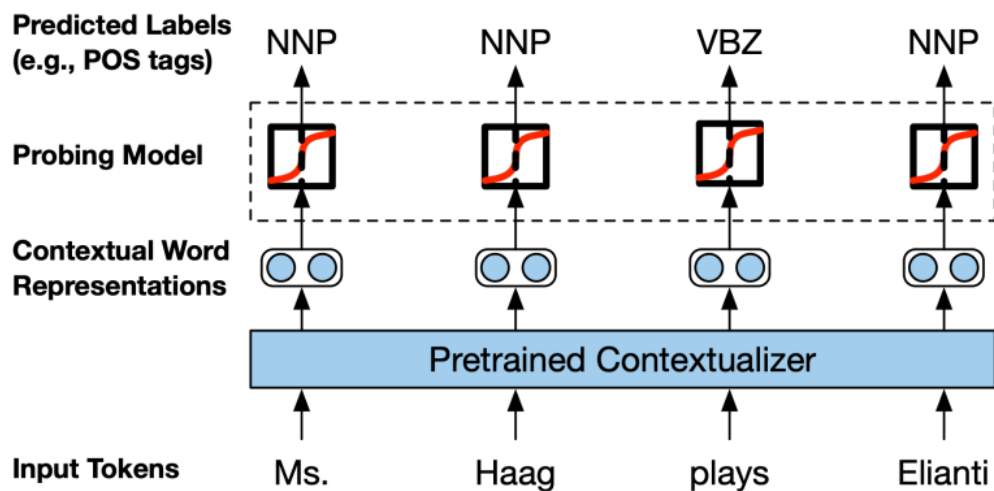
- 实体集合
- 实体关系/属性



知识获取

语言学知识

- 词性、句法结构、词语关系等知识。
- 微调→提示学习。



语言结构知识

Liu et al. Linguistic Knowledge and Transferability of Contextual Representations (NAACL 2019)

Prompt	<i>avg F</i>	Frequency
is a type of	25.5	14,503
is the type of	24.2	809
is a kind of	23.6	2,934
is a form of	22.1	9,518
is one form of	17.9	124
is a	7.4	9,328,426
is a type	1.0	15,085

词语关系知识

Jain et al. Distilling Hypernymy Relations from Language Models: On the Effectiveness of Zero-Shot Taxonomy Induction (*SEM 2022)

知识获取

世界知识

- 有关特定实体的事实知识。
- 通过构造自然语言提示获取世界知识，手动→自动→连续向量。

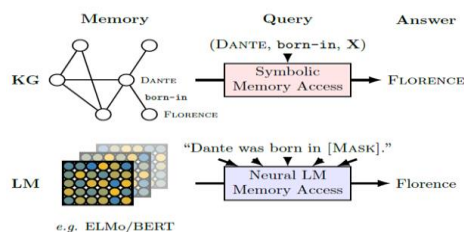
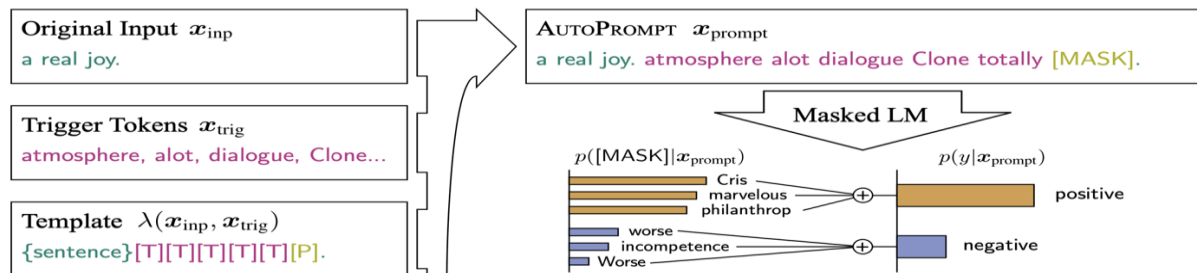
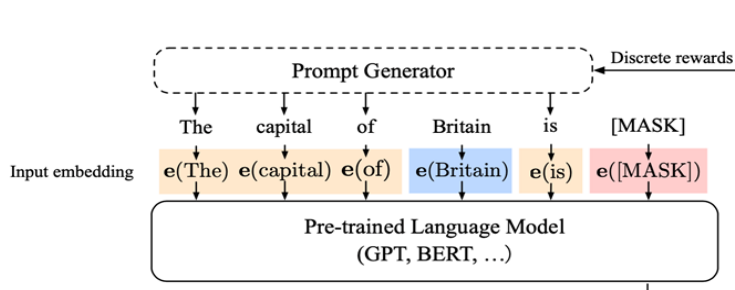


Figure 1: Querying knowledge bases (KB) and language models (LM) for factual knowledge.

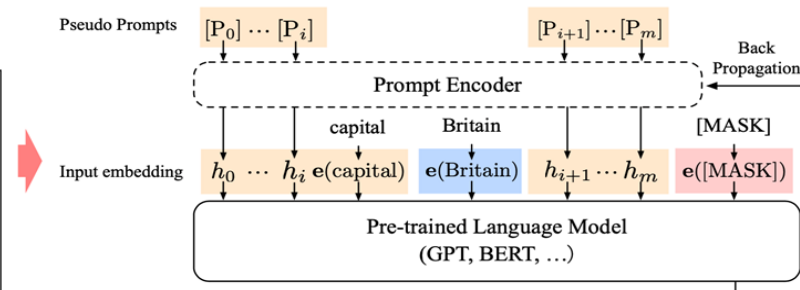
LAMA: Petroni et al. Language Models as Knowledge Bases? (EMNLP 2019)



AutoPrompt: Shin et al. AutoPrompt: Eliciting Knowledge from Language Models with Automatically Generated Prompts (EMNLP 2020)



(a) Discrete Prompt Search



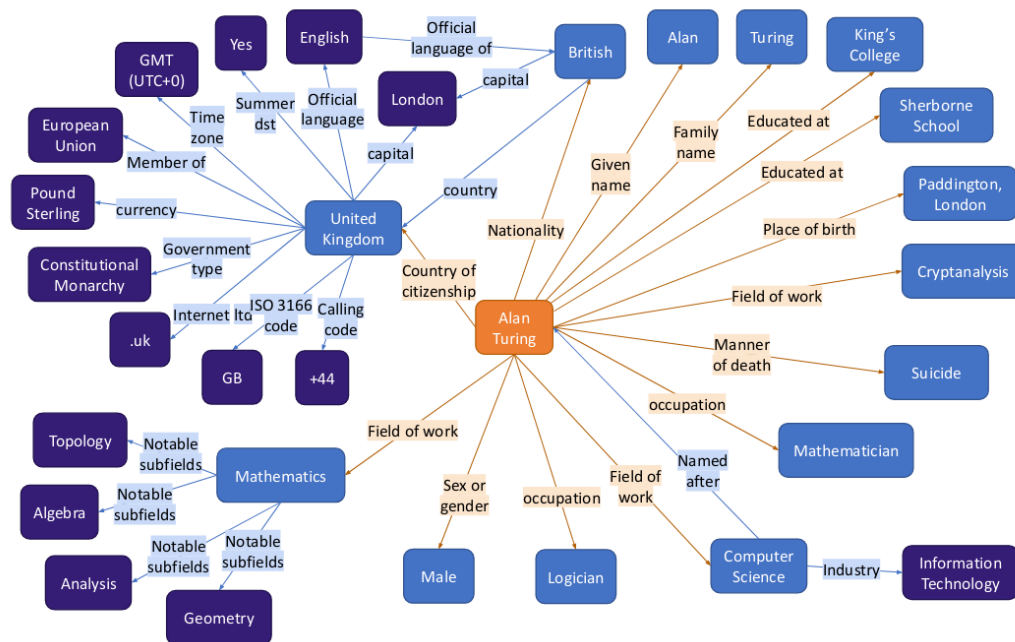
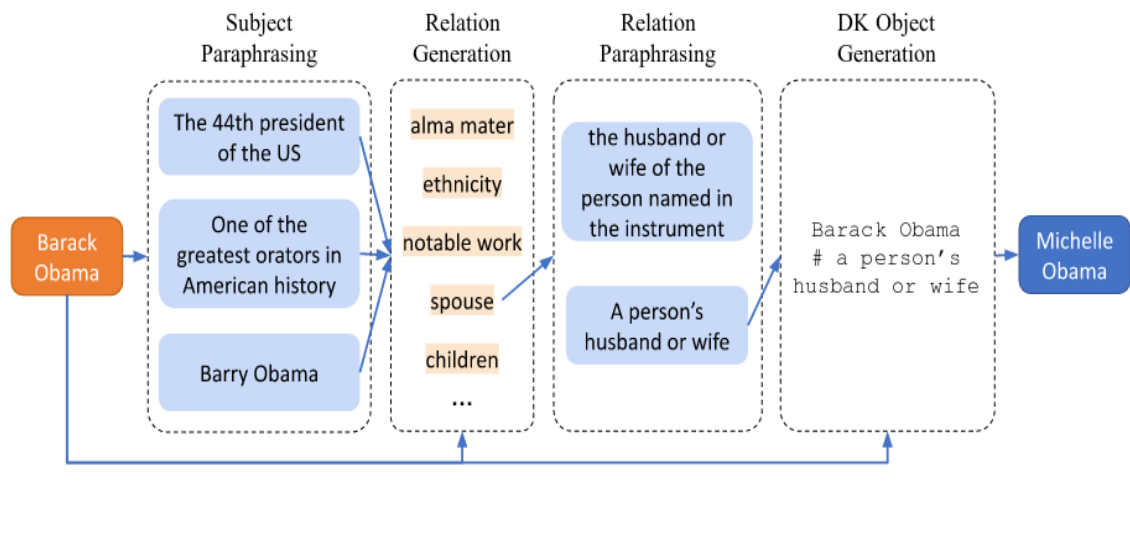
(b) P-tuning

ContinualPrompt: Liu et al. GPT Understands, Too (2021)

知识获取

世界知识

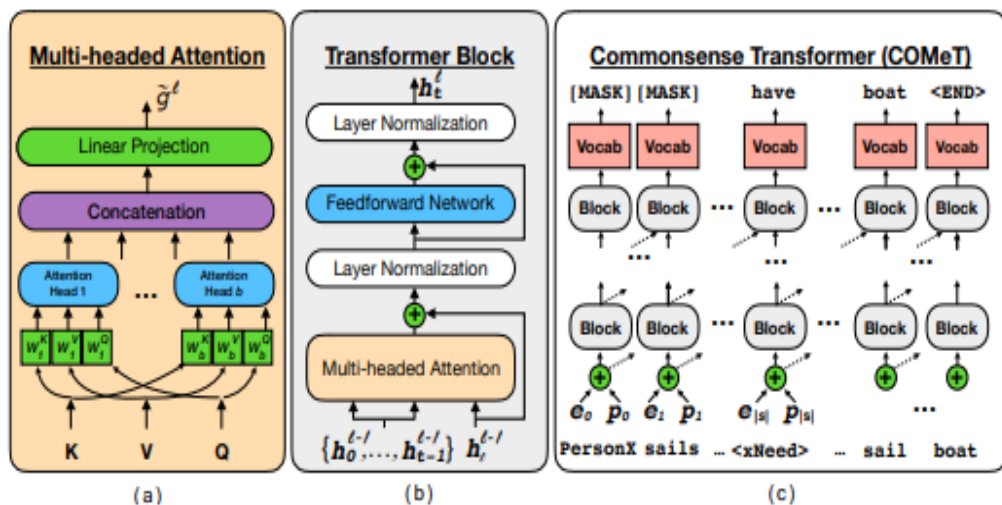
- 有关特定实体的事实知识。
- 提示中添加“答案未知”例子，引导模型在结果不确定时输出“答案未知”。



知识获取

■ 常识知识

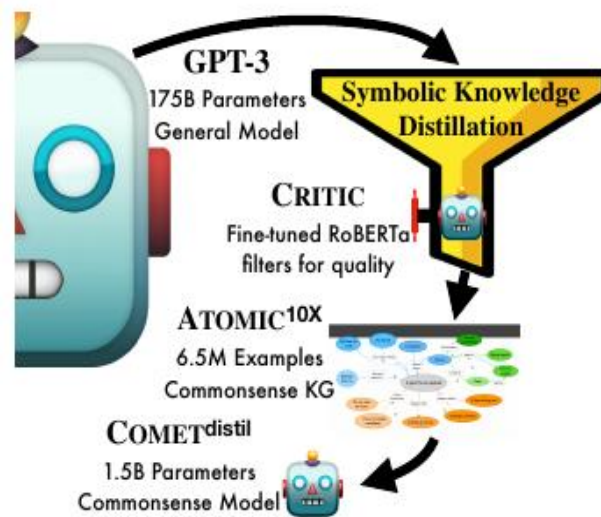
- 人们默认掌握的有关物理世界和人类社会的概括性知识。
- 大规模英语语言模型 → 小规模语言模型。



微调LLMs生成常识知识

Bosselut et al. COMET: Commonsense Transformers for Automatic Knowledge Graph Construction (EMNLP 2019)

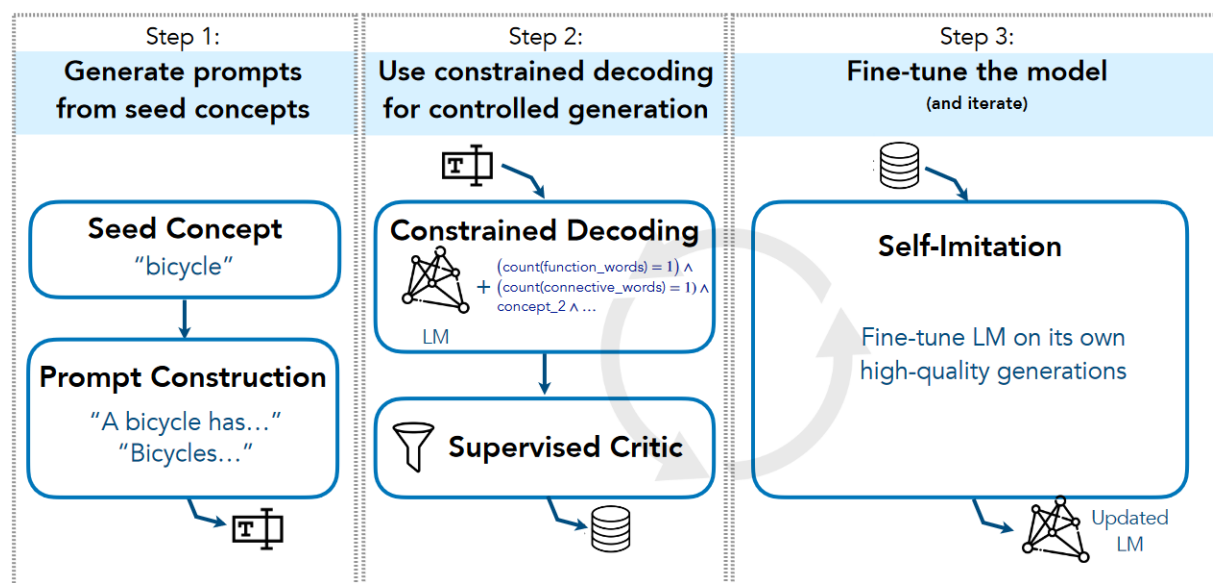
1. Event: X overcomes evil with good
2. Event: X does not learn from Y
- ...
10. Event: X looks at flowers
- 11.



提示LLMs生成常识知识

West et al. Symbolic Knowledge Distillation: from General Language Models to Commonsense Models (NAACL 2022)

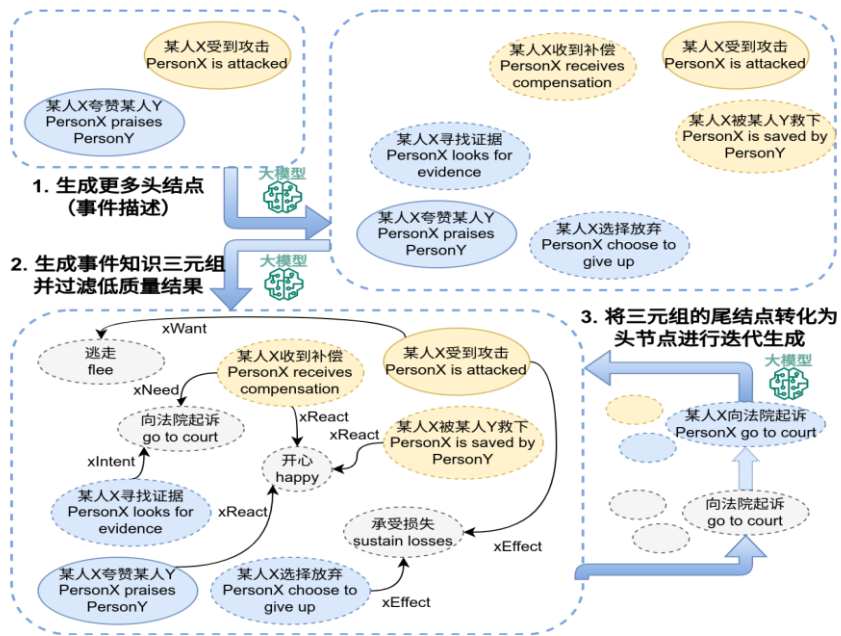
- 人们默认掌握的有关物理世界和人类社会的概括性知识。
- 大规模英语语言模型→小规模语言模型



Bhagavatula et al. I2D2: Inductive Knowledge Distillation with NeuroLogic and Self-Imitation (ACL 2023)

常识知识

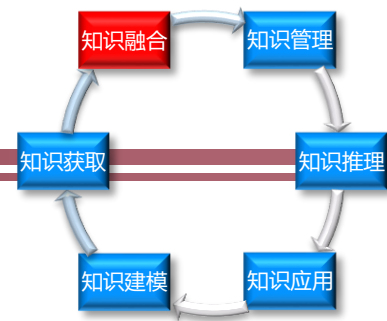
- 人们默认掌握的有关物理世界和人类社会的概括性知识。
- 大规模语言模型→小规模语言模型（中文）。



	Knowledge Graph	Construction	Unique Head Items	Unique Tail Items	Triples	Human Acceptance
English CKGs	ATOMIC ₂₀ ²⁰ (Hwang et al., 2021)	Human	25,807	354,777	760,034	86.8*
	ATOMIC _{10X} ^{10X} (Unfiltered) (West et al., 2021)	Generation	165,783	874,417	6,456,300	78.5*
	ATOMIC _{10X} ^{10X} (High-Quality)	Generation	164,553	357,761	2,512,720	96.4*
Chinese CKGs	ATOMIC-zh (Li et al., 2022)	Translation	20,949	276,446	712,970	38.7
	(ours) CN-AutoMIC (Unfiltered)	Generation	114,364	1,101,556	6,868,766	47.6
	(ours) CN-AutoMIC _{low}	Generation	99,817	385,333	2,764,465	75.2
	(ours) CN-AutoMIC _{mid}	Generation	97,329	269,655	1,812,175	80.5
	(ours) CN-AutoMIC _{high}	Generation	89,738	182,893	1,140,840	87.2
Festival	某人X和某人Y共度中秋 → xNeed → 做月饼 PersonX spends the Mid-Autumn Festival with PersonY → xNeed → make moon cakes					
Traditional Practice	某人X坐月子 → xIntent → 把身体照顾好好 PersonX is in postpartum confinement → xIntent → take good care of (her) health					
Game	某人X歇一整天 → xWant → 打麻将 PersonX takes a day off → xWant → play mahjong					
App	某人X看视频 → xNeed → 打开优酷 PersonX watches videos → xNeed → open the Youku app.					

提示LLMs生成中文常识知识

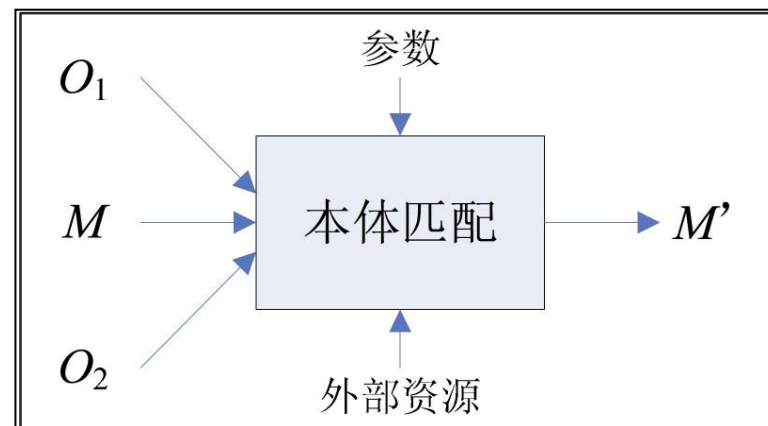
知识融合



■ 知识融合，旨在对不同来源、不同语言和不同结构的知识进行融合。

■ 输入：

- 抽取出来的知识实例
- 知识本体
- 现有知识库



■ 输出：

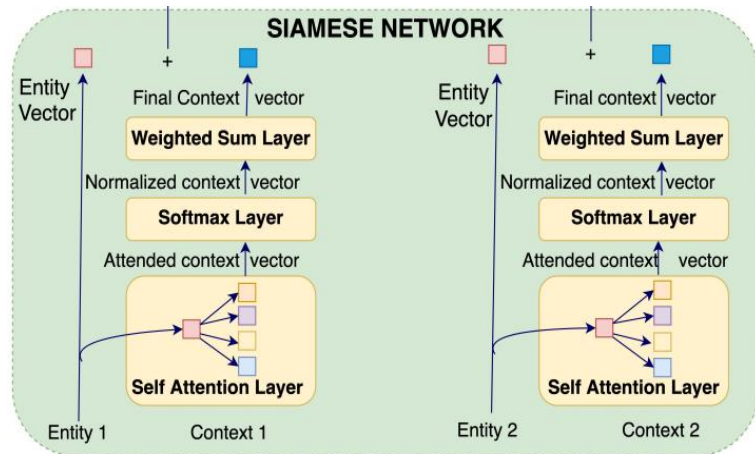
- 统一知识库
- 知识置信度



知识融合

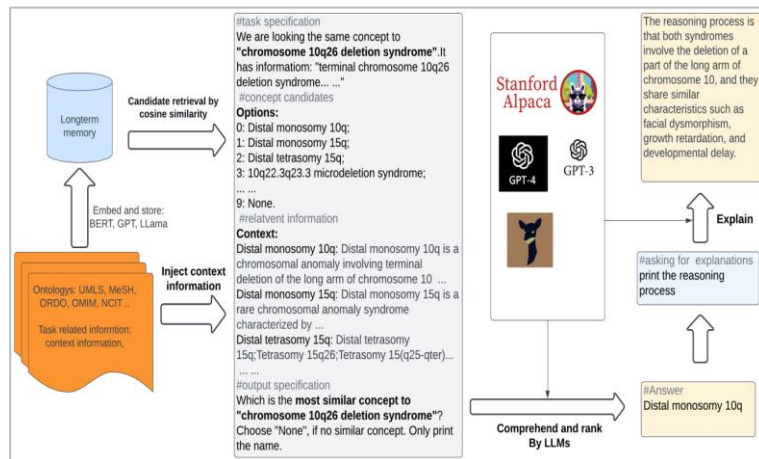
■ 本体知识融合

- 将两个或多个异构知识本体中相同的概念、属性和关系进行对齐。
- 微调→ 提示学习。



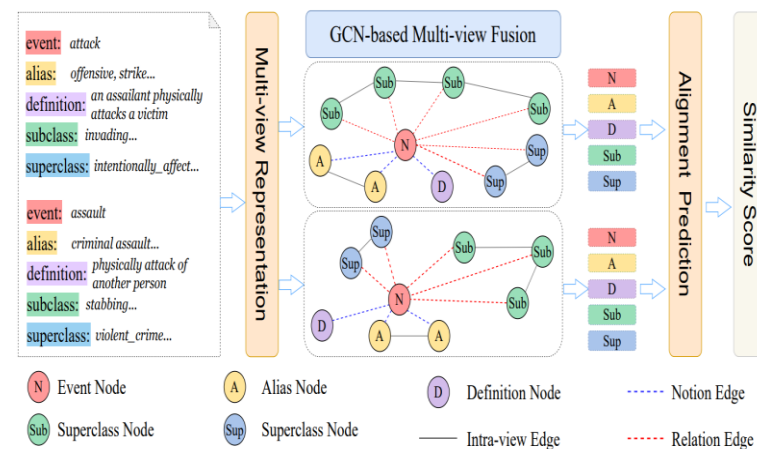
实体本体融合

Iyer et al. VeeAlign: Multifaceted Context Representation Using Dual Attention for Ontology Alignment (EMNLP 2021)



实体本体融合

Wang et al. Exploring the In-context Learning Ability of Large Language Model for Biomedical Concept Linking (arxiv 2023)

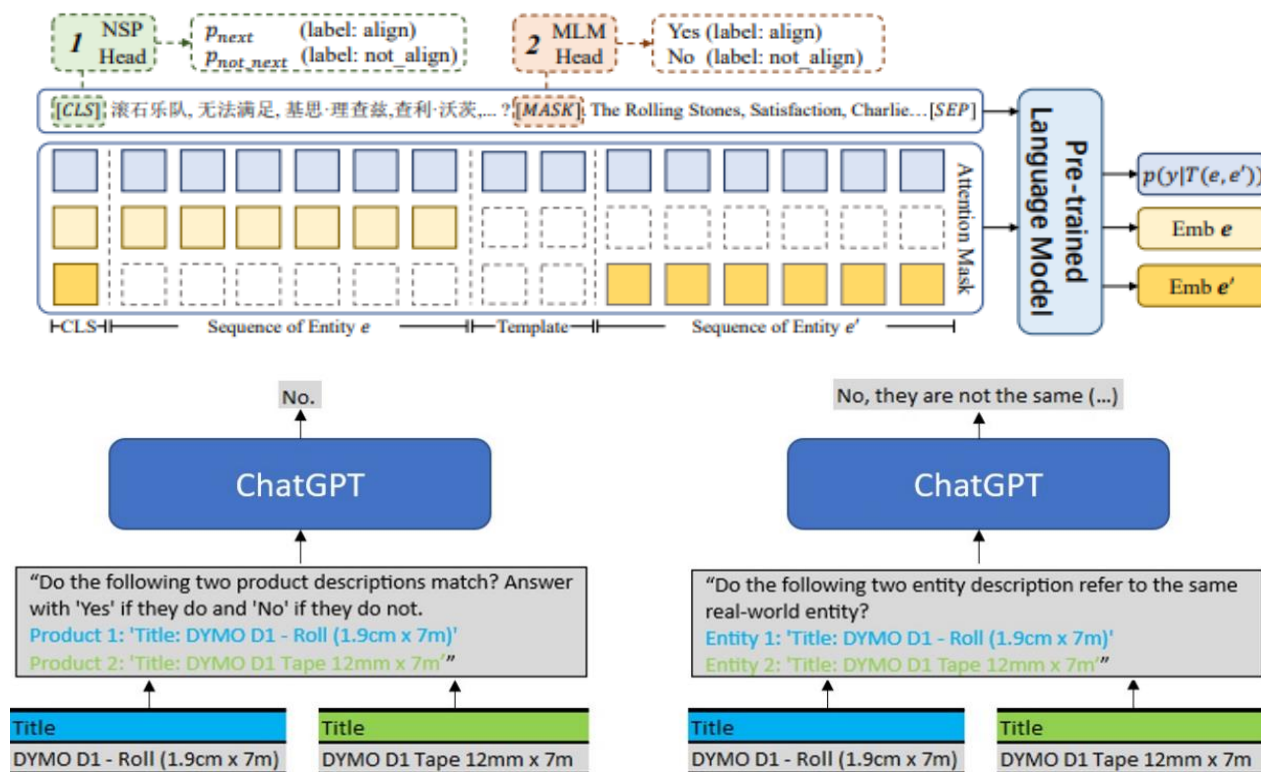


事件本体融合

Guo et al. EventOA: An Event Ontology Alignment Benchmark Based on FrameNet and Wikidata (ACL2023)

实例知识融合

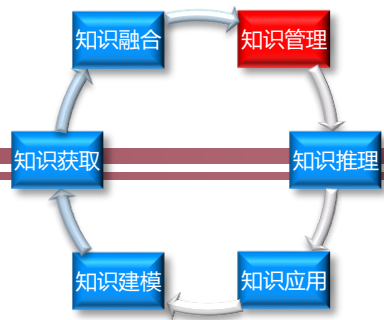
- 对两个不同知识实例进行对齐。
- 微调 → 提示学习。



From Alignment to Entailment: A Unified Textual Entailment Framework for Entity Alignment (ACL 2023)

Peeters et al. Using ChatGPT for Entity Matching (arxiv ,2023)

知识管理



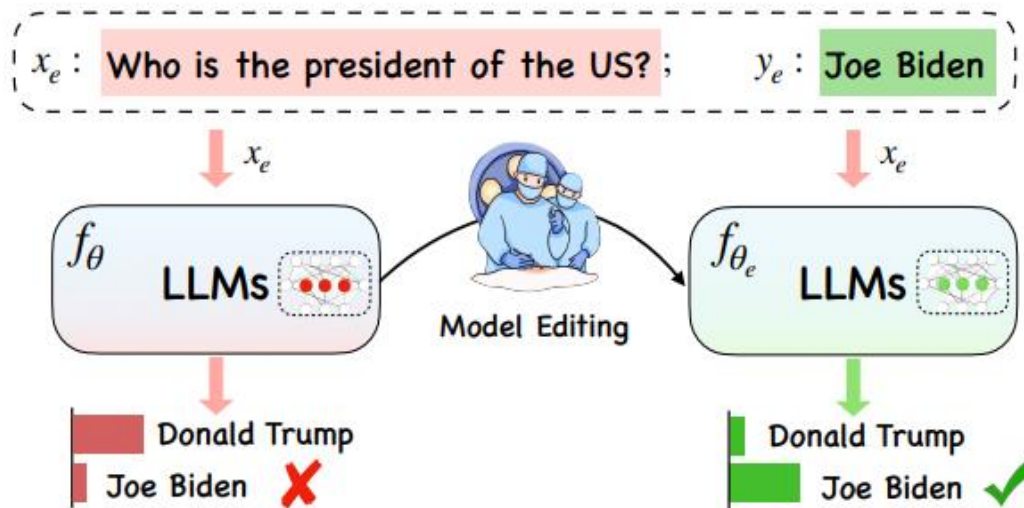
■ 知识管理，旨在实现对知识图谱的持久化存储，以及对目标知识的高效检索和更新。

■ 输入：

- 大规模知识图谱
- 大模型

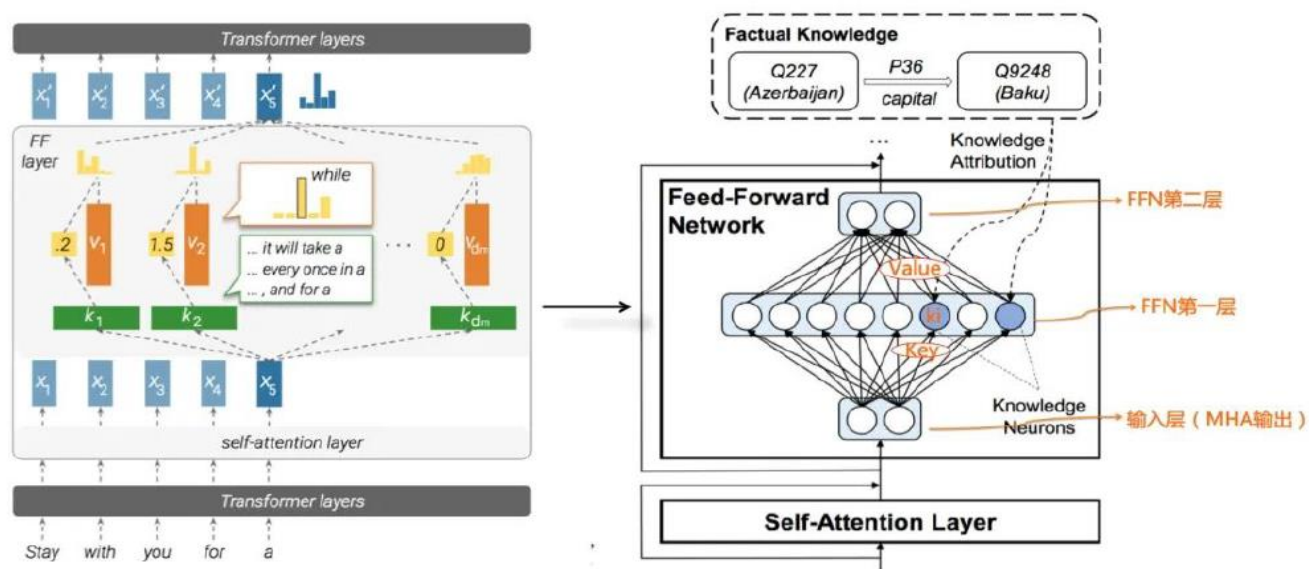
■ 输出：

- 知识库存储结构
- 查询、更新、插入、删除等服务



知识定位

- 探索大模型中“知识”的存储位置和访问机制。
- 一个流行的观点是：PLM的FFN模块存储了大量知识。

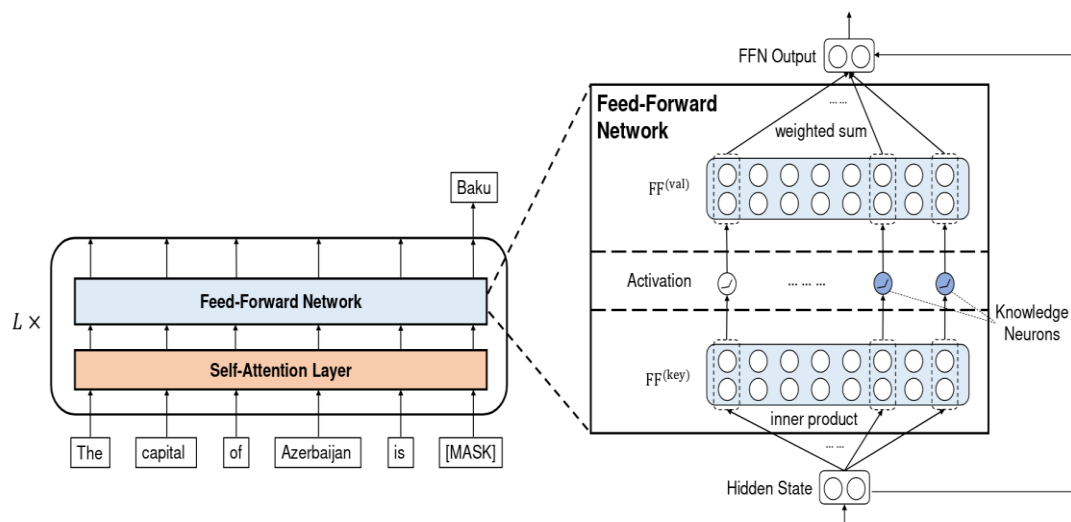


Geva et al. Transformer Feed-Forward Layers Are Key-Value Memories (EMNLP 2021)

知识管理

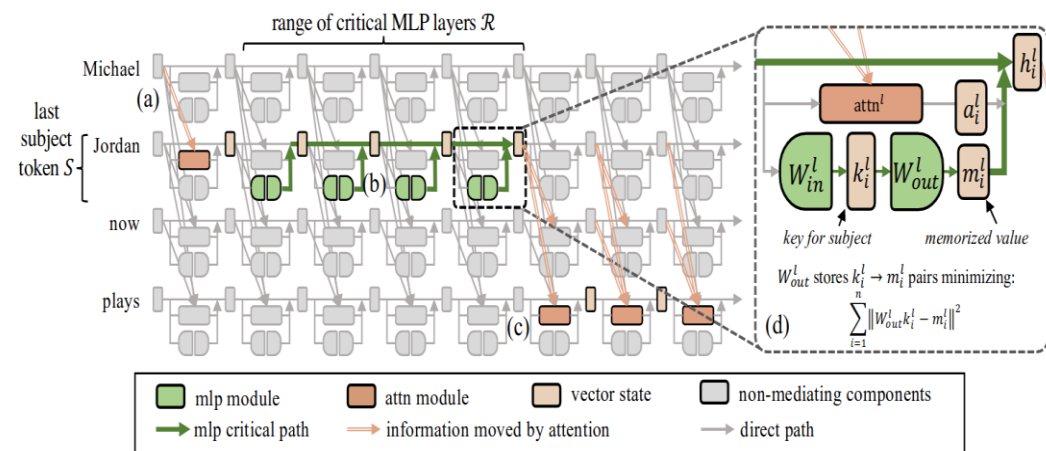
知识定位

- 探索大模型中“知识”的存储位置和访问机制。
- 一个流行的观点是：PLM的FFN模块存储了大量知识。



梯度归因法

Dai et al. Knowledge Neurons in Pretrained Transformers (ACL 2022)



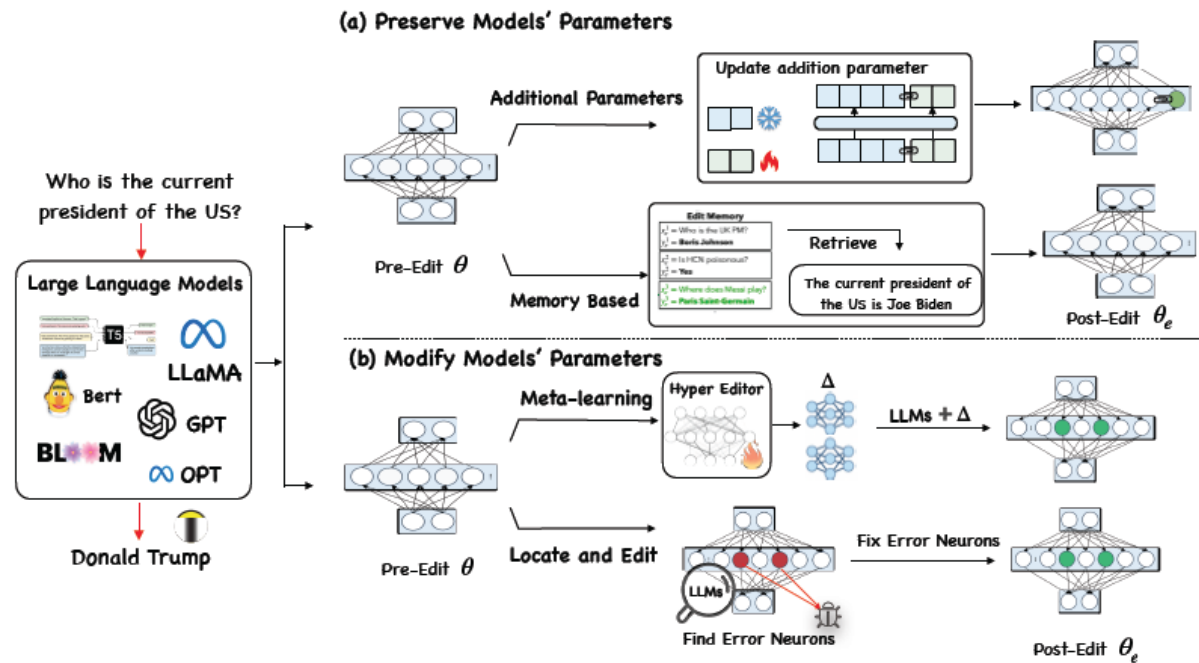
因果推断法

Meng et al. Mass-Editing Memory in a Transformer. (ICLR 2023)

知识管理

知识编辑

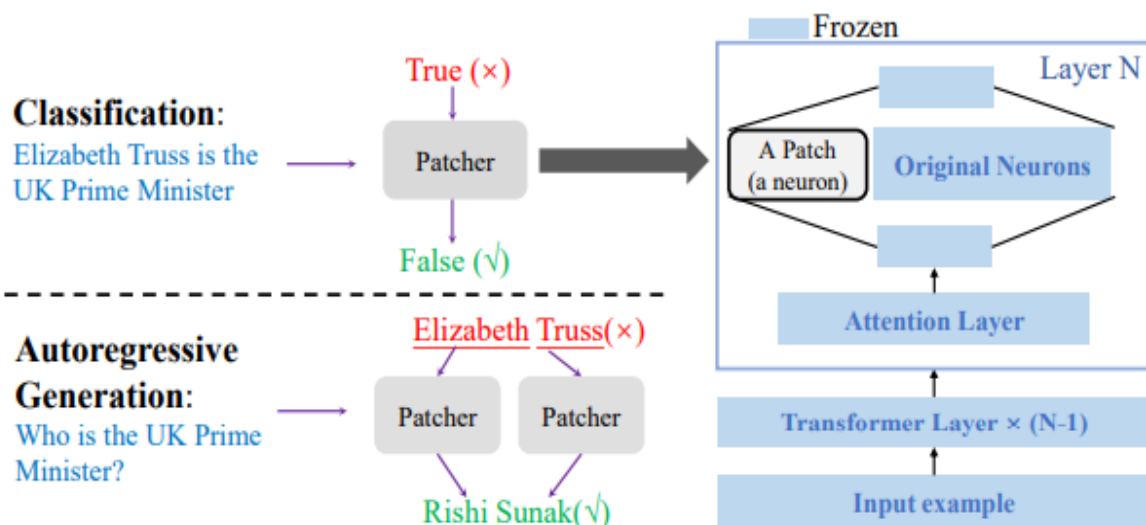
- 对语言模型中参数知识进行编辑，在编辑特定知识的时候，减少对其他知识的破坏。
- 保持模型参数不变 VS. 修改模型内部参数



知识管理

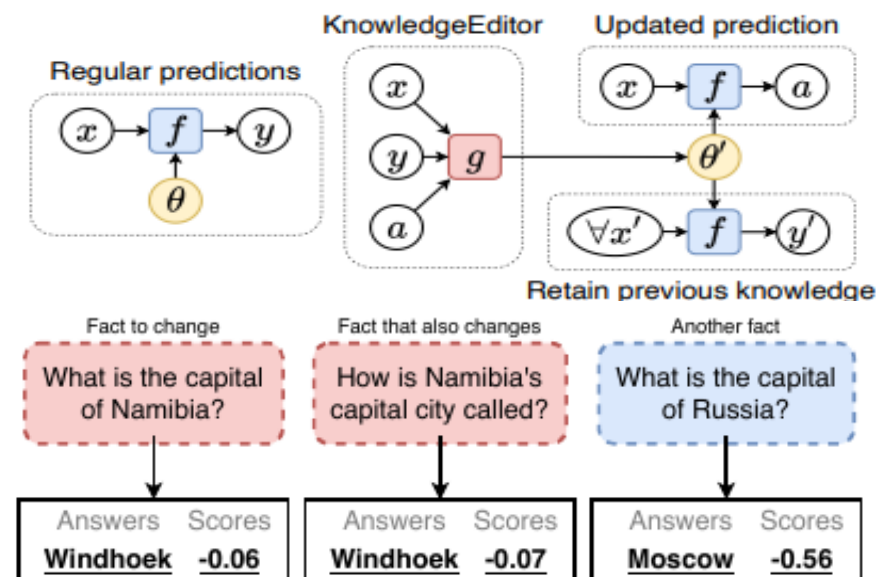
知识编辑

- 对语言模型中参数知识进行编辑，在编辑特定知识的时，减少对其他知识的破坏。
- 保持模型参数不变 VS. 修改模型内部参数



基于记忆的方法

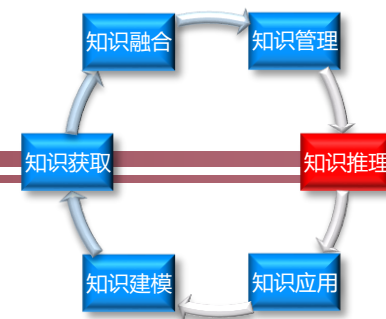
Huang et al. Transformer-Patcher: One Mistake worth One Neuron (ICLR 2023)



超网络方法

De Cao et al. Editing Factual Knowledge in Language Models. (EMNLP 2021)

知识推理



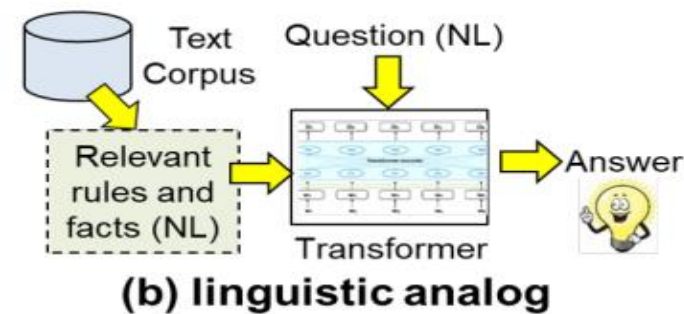
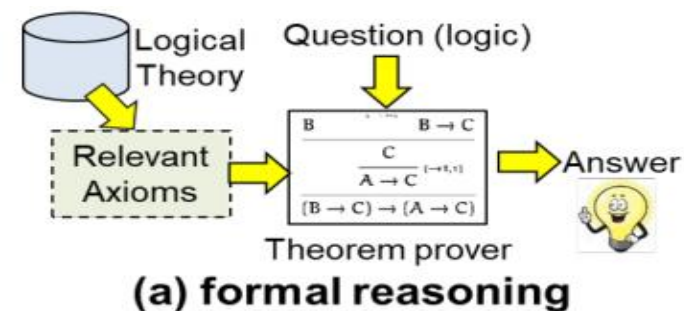
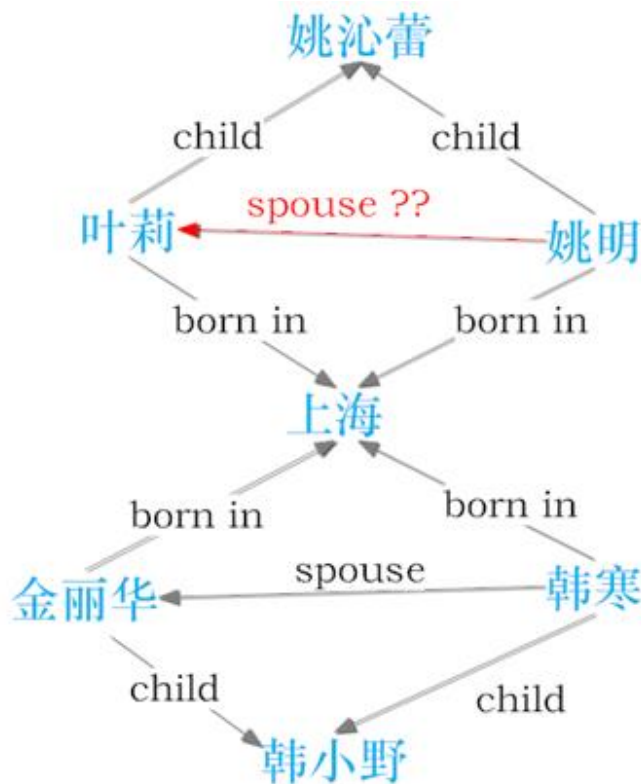
■ 知识推理，旨在采用推理手段发现已有知识中隐含的知识。

■ 输入：

- 大规模知识图谱
- 大模型

■ 输出：

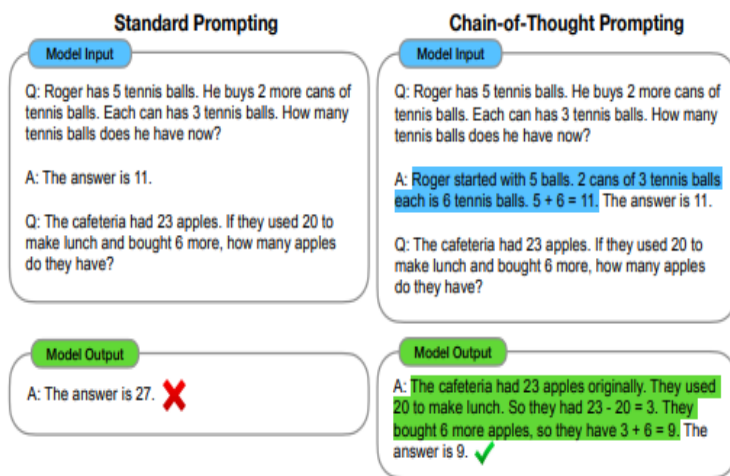
- 隐含知识
- 思维链



知识推理

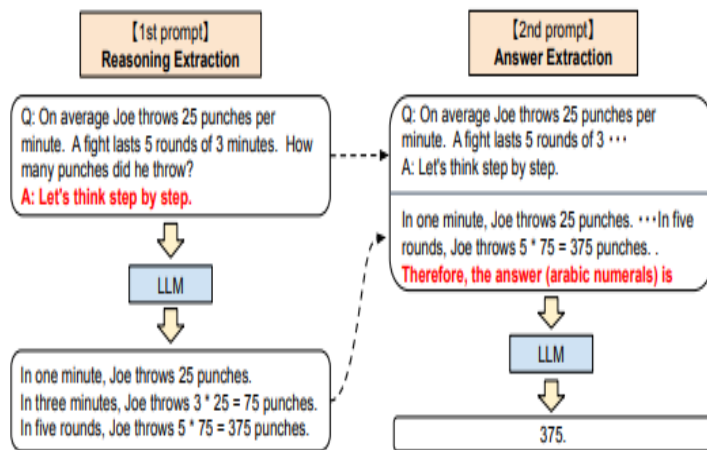
思维链技术

- 思维链可以增强大语言模型的推理能力。
- 参考人类解决复杂问题推理方式，将问题分解为中间问题，逐步解决问题以获得最终结果。



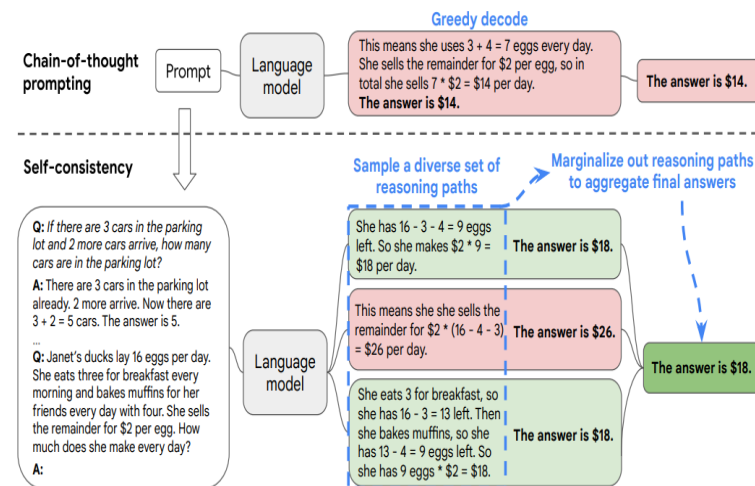
思维链

Wei et al. Chain-of-Thought Prompting Elicits Reasoning in Large Language Mode (NeurIPS 2022)



零样本思维链

Kojima et al. Large Language Models are Zero-Shot Reasoners (NeurIPS 2022)



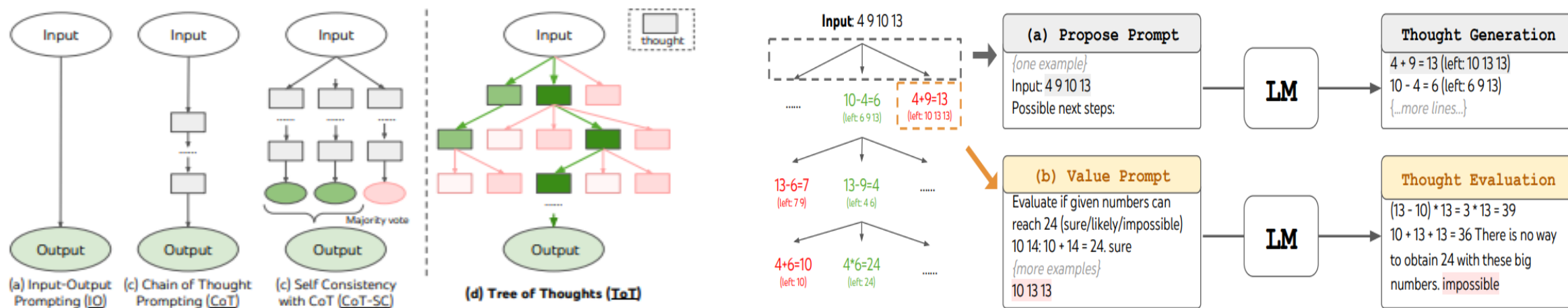
自洽性思维链

Wang et al. Self-Consistency Improves Chain of Thought Reasoning in Language Models (ICLR 2023)

知识推理

思维链技术

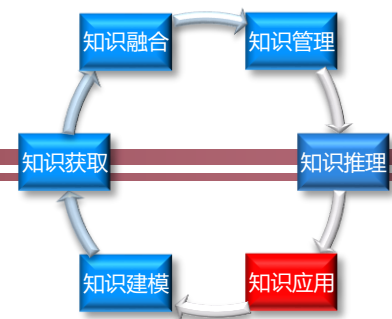
- 思维链可以增强大语言模型的推理能力。
- 参考人类解决复杂问题推理方式，将问题分解为中间问题，逐步解决问题以获得最终结果。



思维树

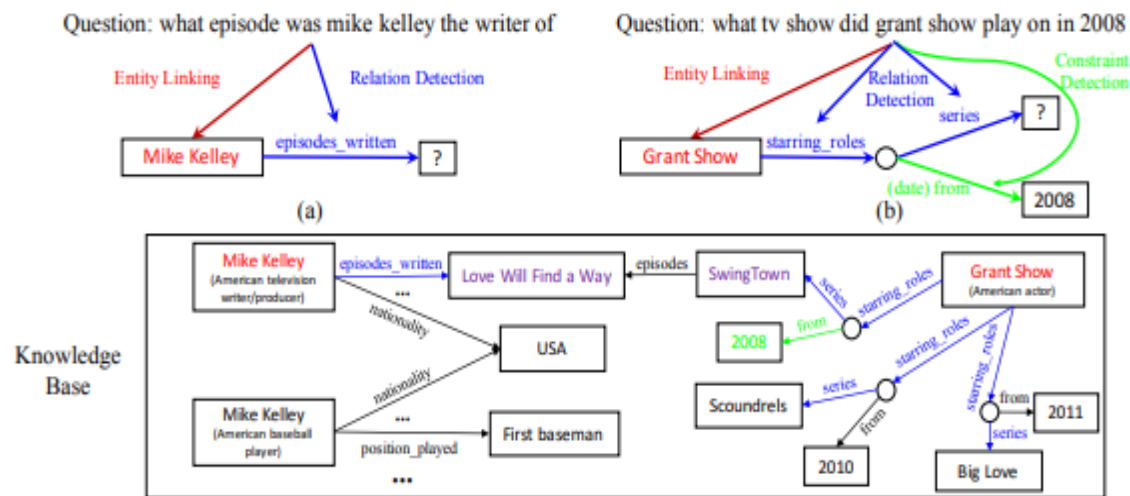
Yao et al. Tree of Thoughts: Deliberate Problem Solving with Large Language Models (2023)

知识应用



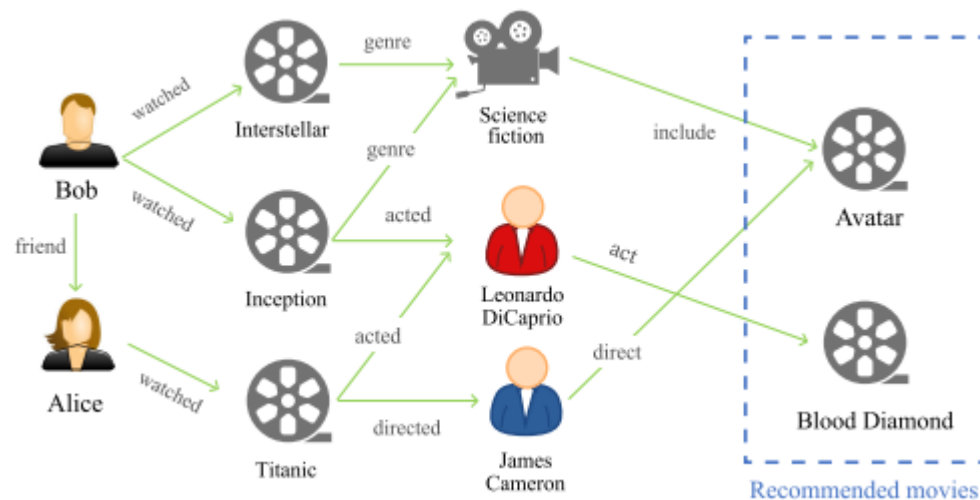
■ 知识应用，是指将知识应用于具体任务和应用场景的过程。

□ 知识图谱 → 大模型 → 知识图谱 + 大模型



基于知识图谱问答

Yu et al. Improved Neural Relation Detection for Knowledge Base Question Answering (ACL 2017)



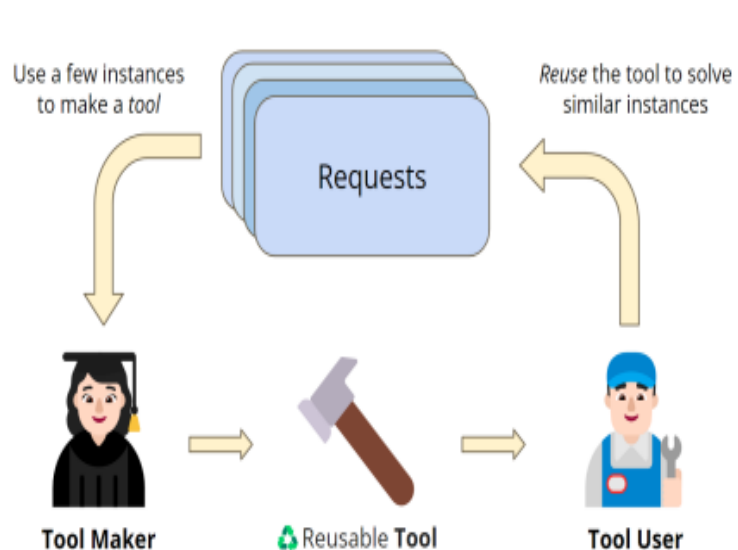
基于知识图谱推荐

Guo et al. A Survey on Knowledge Graph-Based Recommender Systems (TKDE 2020)

知识应用

■ 知识应用，是指将知识应用于具体任务和应用场景的过程。

□ 知识图谱 → **大模型** → 知识图谱 + 大模型



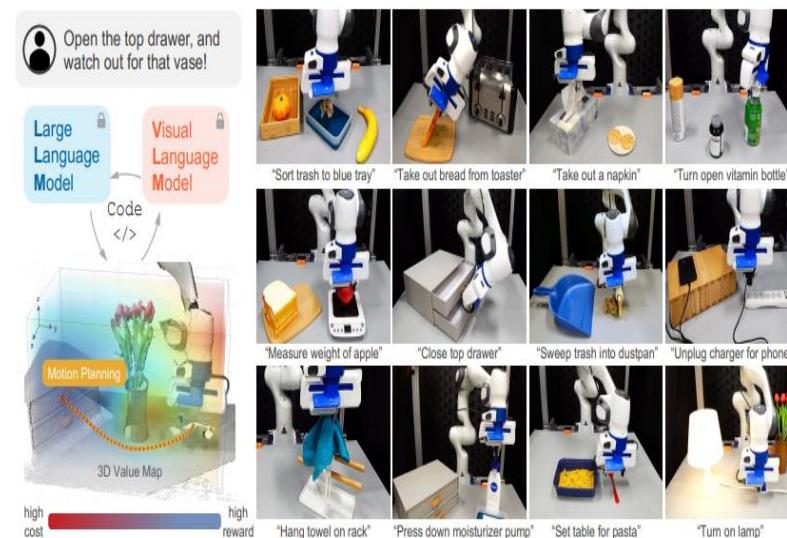
工具生成器

Cai et al. Large Language Models as Tool Makers (2023)



软件开发

Chen et al. Communicative Agents for Software Development (2023)



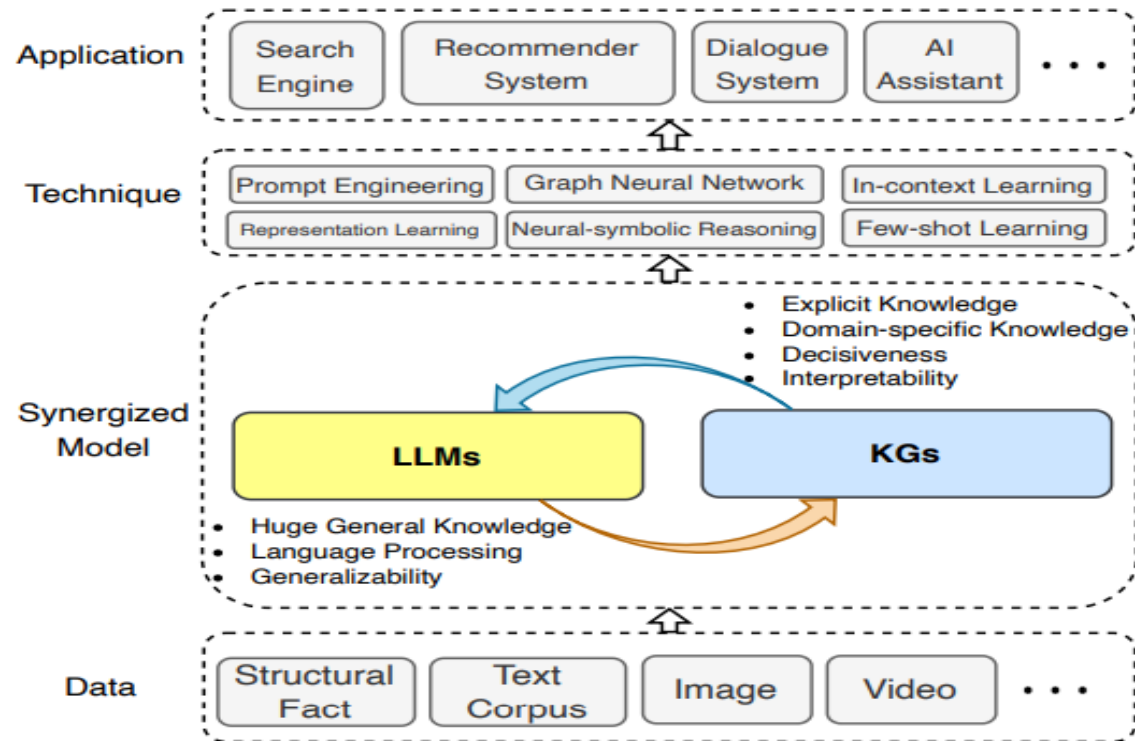
零样本控制机器人

Huang et al. VoxPoser: Composable 3D Value Maps for Robotic Manipulation with Language Models (2023)

知识应用

■ 知识应用，是指将知识应用于具体任务和应用场景的过程。

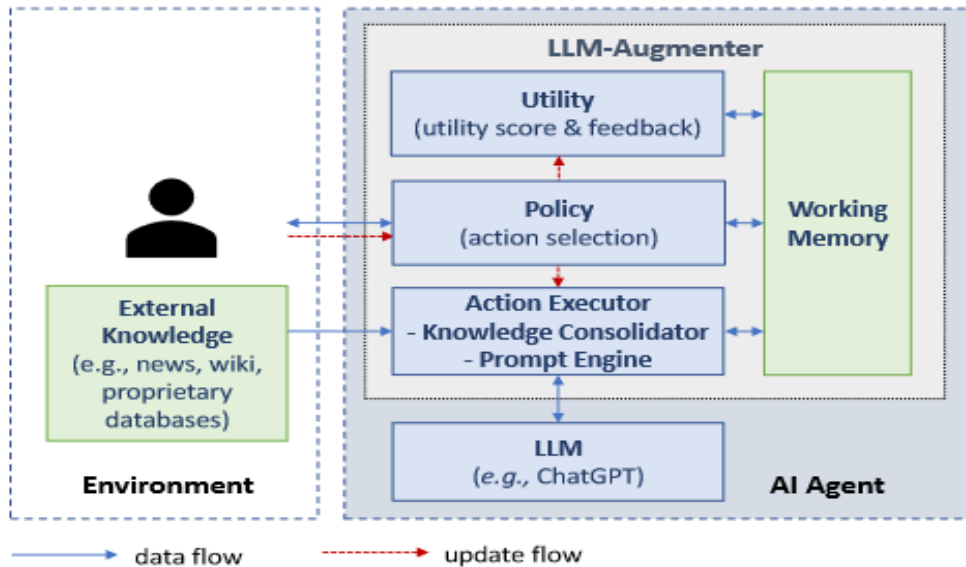
□ 知识图谱 → 大模型 → **知识图谱 + 大模型**



知识应用

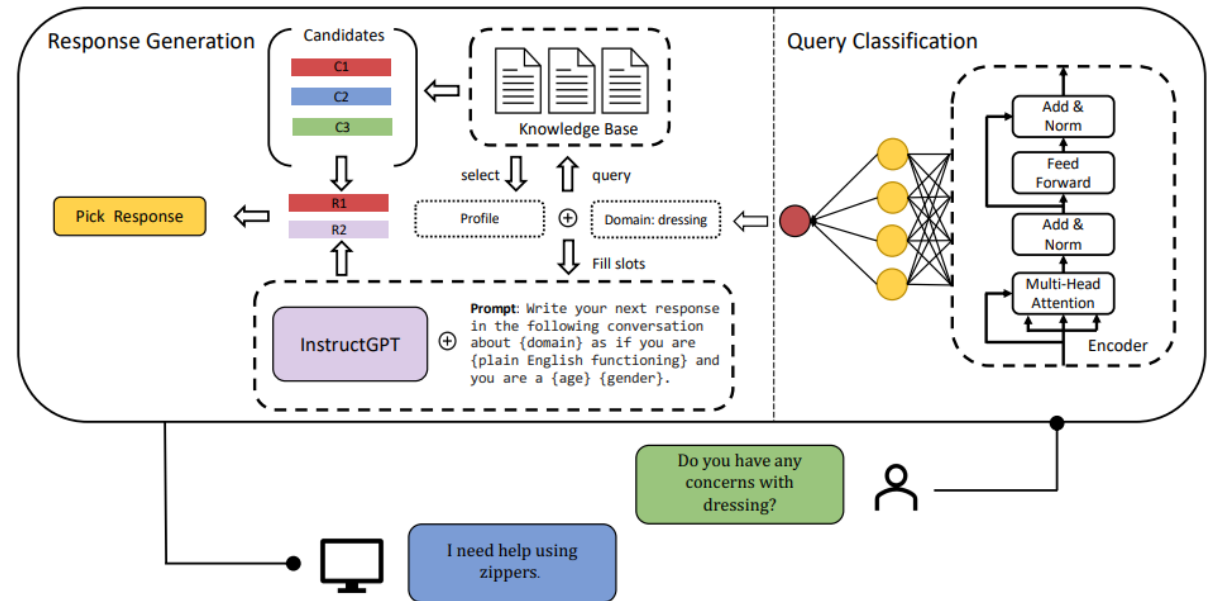
■ 知识应用，是指将知识应用于具体任务和应用场景的过程。

□ 知识图谱 → 大模型 → 知识图谱 + 大模型



缓解幻觉

Peng et al. Check Your Facts and Try Again: Improving Large Language Models with External Knowledge and Automated Feedback (2023)

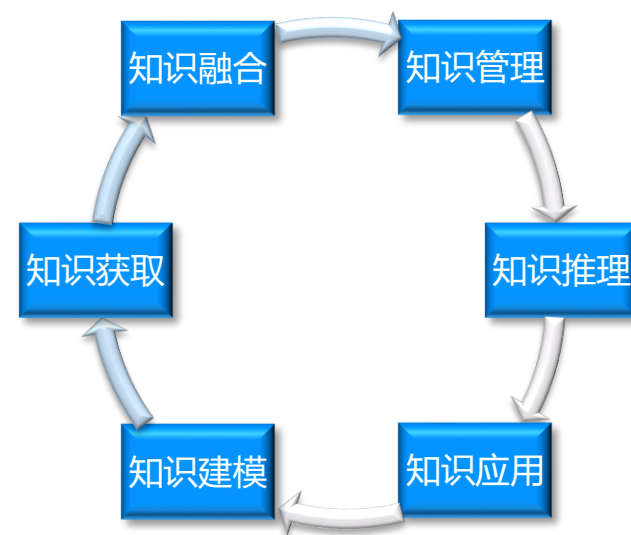


对话一致性

Sheng et al. A Dialogue System for Assessing Activities of Daily Living: Improving Consistency with Grounded Knowledge (2023)

总结

- ❑ 知识建模：实体本体建模，事件本体建模，脚本建模
- ❑ 知识获取：语言知识，世界知识，常识知识
- ❑ 知识融合：本体融合，实例融合
- ❑ 知识管理：知识定位，知识编辑
- ❑ 知识推理：Cot, Zot, Tot
- ❑ 知识应用：知识图谱，大模型，知识图谱+大模型



未来展望

■ 大模型助力知识图谱构建

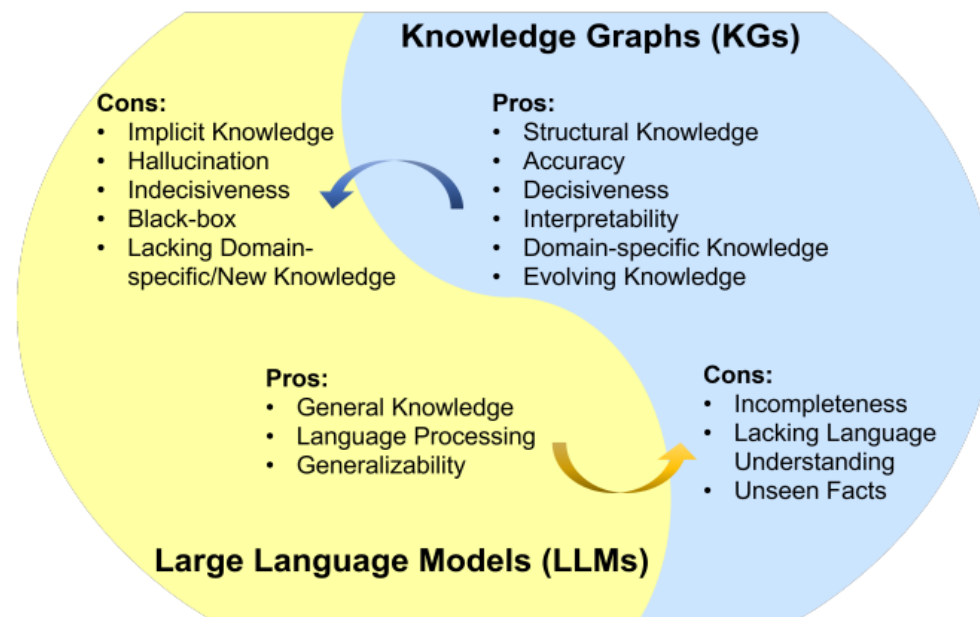
- 提高知识抽取和融合效率
- 增强知识图谱的覆盖度和泛化性

■ 知识图谱辅助大模型进行知识校准

- 缓解大模型幻觉性问题
- 增强大模型知识编辑能力

■ 大模型与知识图谱协同工作

- 数据和知识双驱的人工智能应用



Pan et al. Unifying Large Language Models and Knowledge Graphs: A Roadmap (2023)

谢谢！