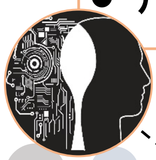
从知识图谱到认知图谱

Jie Tang

Tsinghua University

PPT可以在主页下载: http://keg.cs.tsinghua.edu.cn/jietang/   或者： Google “Jie Tang”

追溯历史：知识工程60年



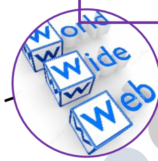
1950-1970年代

- 符号逻辑
- 神经网络
- LISP
- 产生式规则

MYCIN
PROSPECTOR
PROLOG
ExSys

1970-1990年代

- 专家系统
- 限定领域
- 知识库+推理
- 脚本、框架等

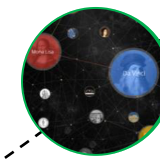


1990-2000年代

- 万维网
- 大规模知识库
- 本体概念
- 智能体/机器人

2000-2006年代

- 互联网高峰
- 语义Web
- 群体智能



2006年至今

- 维基结构化
- 领域知识图谱
- 知识获取
- 工业应用

追溯历史：知识工程60年

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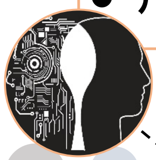

1990-2000年代

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●群体智能

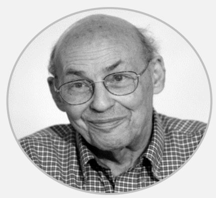
1950-1970年代

符号主义：物理符号系统是智能行为的充要条件

连结主义：大脑（大脑神经元以及连接机制）是一切智能活动的基础

通用问题求解程序（GPS）：问题形式化表示+搜索

知识表示：数理逻辑、基于逻辑的知识表示、产生式规则、语义网络



Minsky（1969图灵奖）
感知机，框架知识表示

Mccarthy（1971图灵奖）
LISP语言

Newell & Simon（1975图灵奖）
通用问题求解，形式化语言

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- 限定领域
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- 脚本、框架等

1970-1990年代 专家系统

- 确立了知识工程在人工智能中的核心地位
- 专家系统=知识库+推理
  - MYCIN，PROSPECTOR, PROLOG等
  - 日本第五代机计划
- 知识表示：框架、脚本、概念依存、面向对象
- 连结主义：神经网络复苏，BP算法

Feigenbaum（1994年图灵奖）：专家系统与知识工程

- 语义Web
- 群体智能

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- 产生式规则

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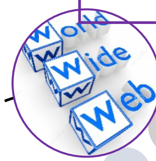

MYCIN
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- 限定领域
- 知识库+推理
- 脚本、框架等

1990-2000年代 Web1.0 万维网

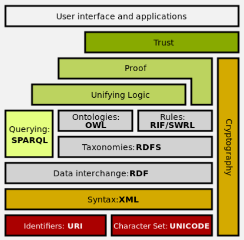
- 人工知识库：CYC，WordNet，HowNet等
- 知识表示：本体（Gruber@93）
- 万维网Web 1.0
  - W3C：互联网标记语言：HTML、XML等
  - 搜索引擎：PageRank
- 行为主义：AI是表现出一定智能行为的主体
  - Agent，机器人，多agent系统

Tim Berners Lee（2016年图灵奖）
万维网发明人

追溯历史：知识工程60年

2000-2006年代 Web2.0 群体智能

- 互联网知识表示方法：封闭 →开放，集中 →分布
- 互联网知识表示：RDF，OWL
- 群体智能知识工程：Wikipedia
- 语义Web：互联网内容的结构化表示，实现计算机理解和智能化服务
- 工业界：Google，Facebook，Yahoo，Microsoft



年代

库

器人

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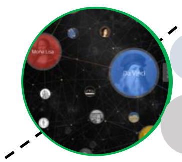
2006年至今 Web 3.0 知识图谱

- 知识获取途径的丰富及维基类知识的结构化
  - Linked Data（2006），Dbpedia（2007），YAGO，Freebase，Knowitall，NELL， Probase
- 知识图谱从通用领域扩展到限定领域
- 知识图谱在工业界大规模应用
  - 语义搜索（Google Knowledge Graph 2012）
  - 问答系统与聊天
  - 大数据语义分析
  - 智能知识服务

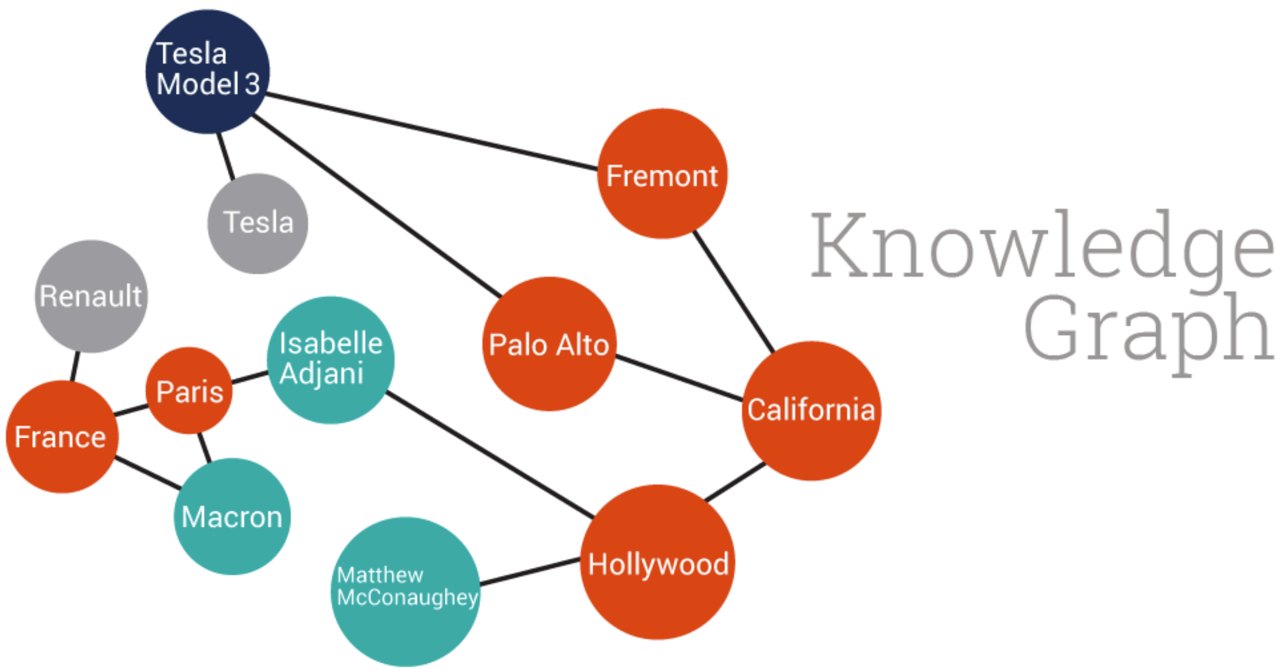


2006年至今

- 维基结构化
- 领域知识图谱
- 知识获取
- 工业应用

知识图谱 (Knowledge Graph)

- “Knowledge graph” was used by Google 2012
- Knowledge engineering, expert system
- CYC: the world's longest-lived AI project (1985)



知识驱动的AI系统

语义空间

知识图谱

底层特征空间

知识图谱以结构化的形式描述客观世界的概念、实体及其之间的关系，将互联网信息表达成更接近人类认知世界的形式，以更好地组织、管理和互联网海量信息

知识图谱近几年杀手锏应用

- IBM Watson
  - 2011年在美国Jeopardy知识比赛中战胜人类选手
  - 目前向医疗、教育、金融等行业进行应用
  - 核心：知识的关联、推理和服务
- 谷歌Knowledge Graph
  - 目标：将互联网上的信息资源转化为结构化的知识图谱
  - 信息服务的方式：关键词搜索→实体关系搜索
- DAPRA: Machine Reading
  - 目标：让机器代替人自动的阅读文本、理解语义
  - 核心：将数据转化为知识

IBM Watson

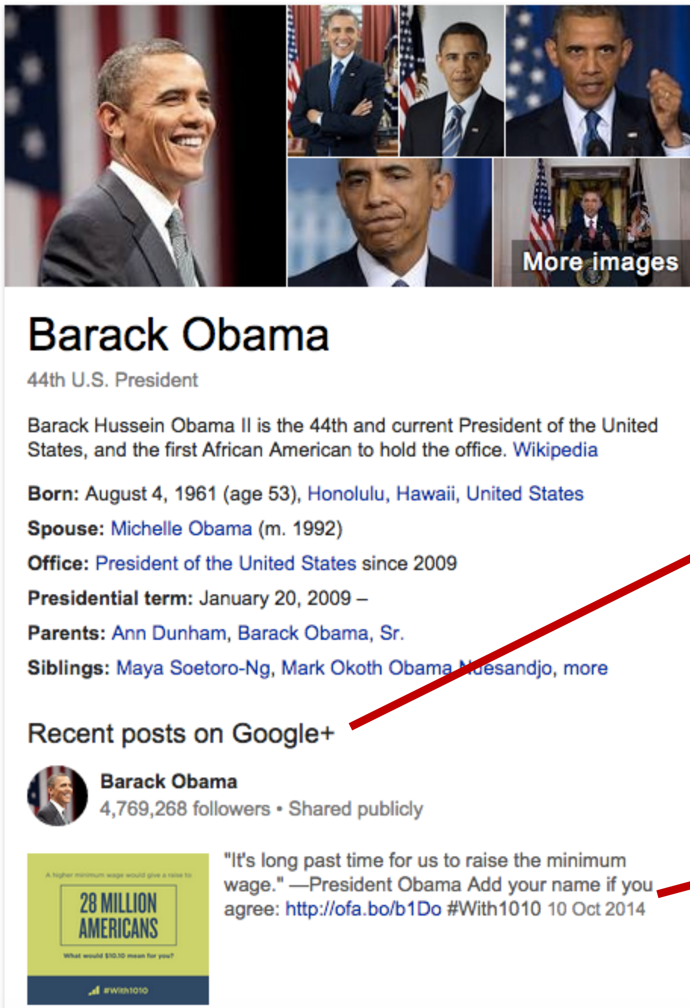
In 2011, as a test of its abilities, Watson competed on the quiz show Jeopardy!, in the show's only human-versus-machine match-up to date

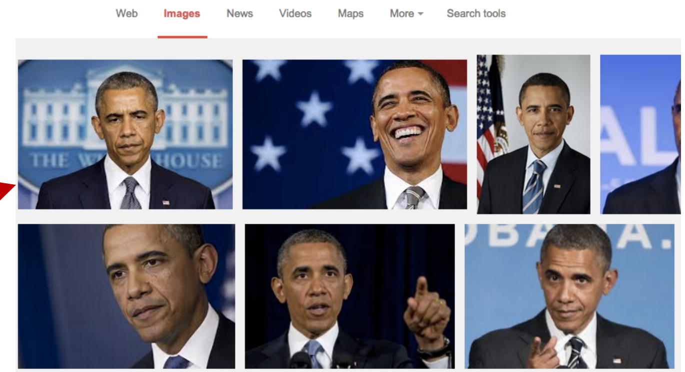
Watson is a Question answering (QA) computing system built by IBM. IBM describes it as "an application of advanced Natural Language Processing, Information Retrieval, Knowledge Representation and Reasoning, and Machine Learning technologies to the field of open domain question answering" which is "built on IBM's DeepQA technology for hypothesis generation, massive evidence gathering, analysis, and scoring

Watson had access to 200 million pages of structured and unstructured content consuming four terabytes of disk storage including the full text of Wikipedia, but was not connected to the Internet during the game. For each clue, Watson's three most probable responses were displayed on the television screen. Watson consistently outperformed its human opponents on the game's signaling device.

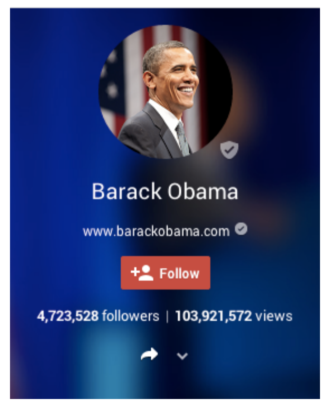
语义集成

- 基于知识图谱的语义标注



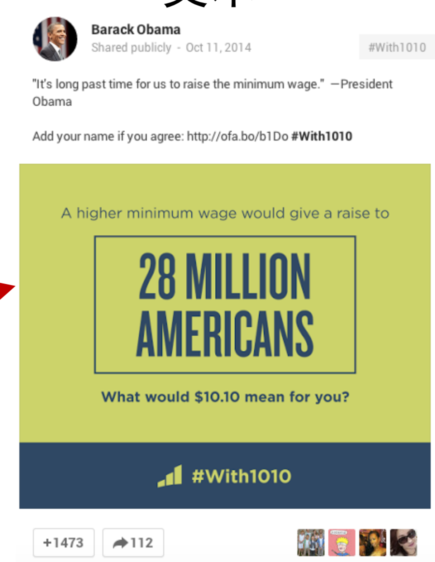


图像



社交主页

文本



语义搜索：关系搜索

刘德华的妻子是谁

All Videos News Images Maps More Settings Tools

About 4,590,000 results (0.73 seconds)

Andy Lau / **Spouse**

Carol Chu

m. 2008

More about Carol Chu

Feedback

Images for 刘德华的妻子是谁

从知识图谱到认知图谱

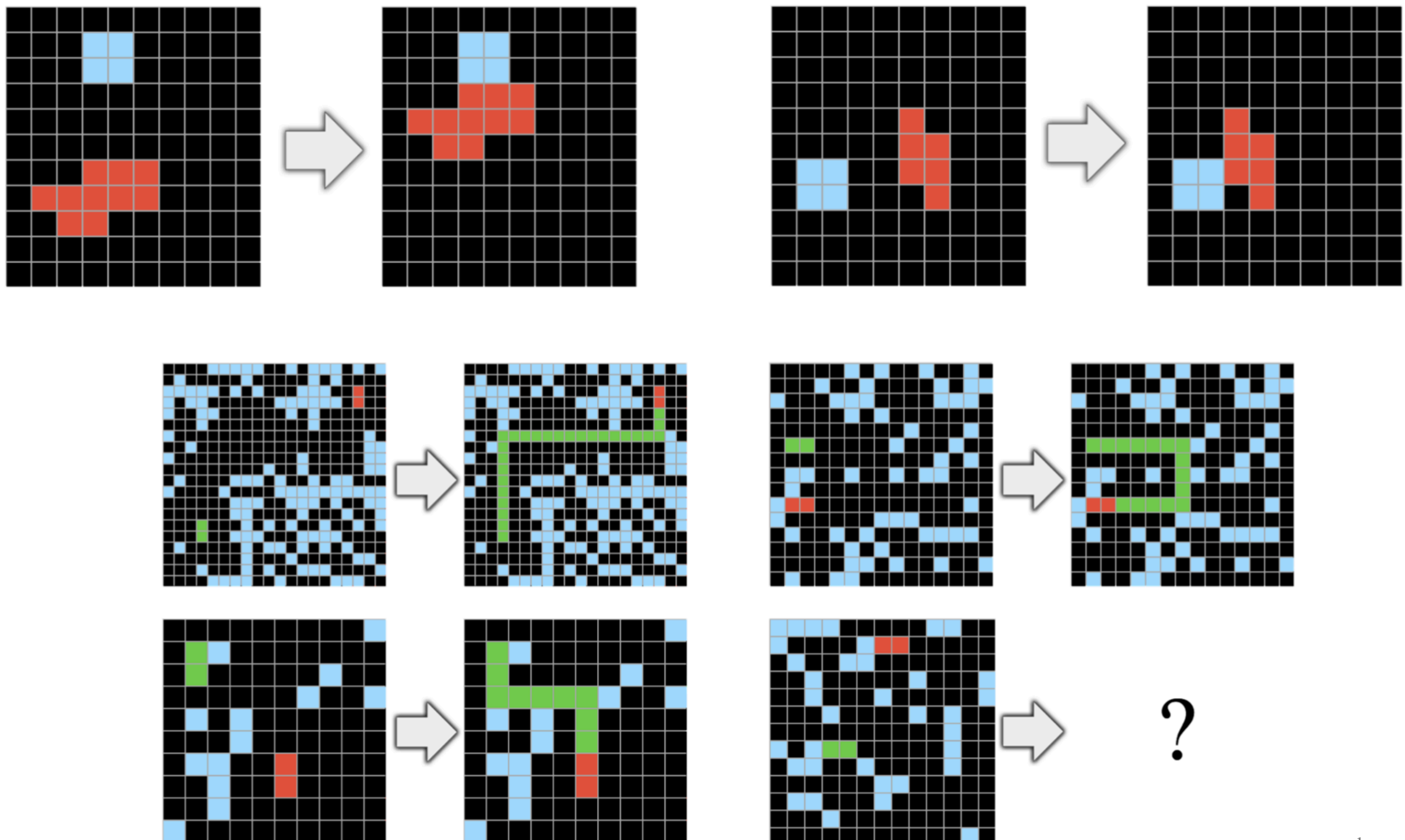
However, real AI is still far away…

AI系统

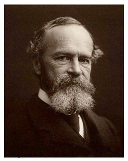
知识图谱

人类认知

抽象与推理



认知图谱[1]



认知心理

提出认知的双通道理论，
美国心理学之父

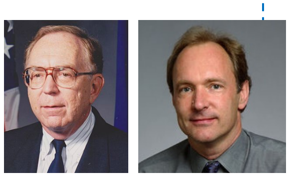
William James等人

深度学习

以深度学习为代表的机器
学习算法

Hinton等人

1842年　1979、1990年　1957、1988、2006年



知识图谱

知识库之父、知识库问答，
语义网、知识推理

E. Feigenbaum、
T. Berners Lee

**融合知识、学习与推理的
新一代认知引擎**

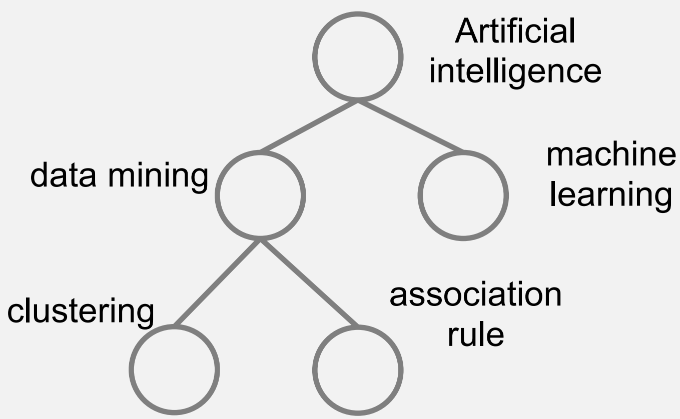
1. 团队2018首次提出

认知图谱

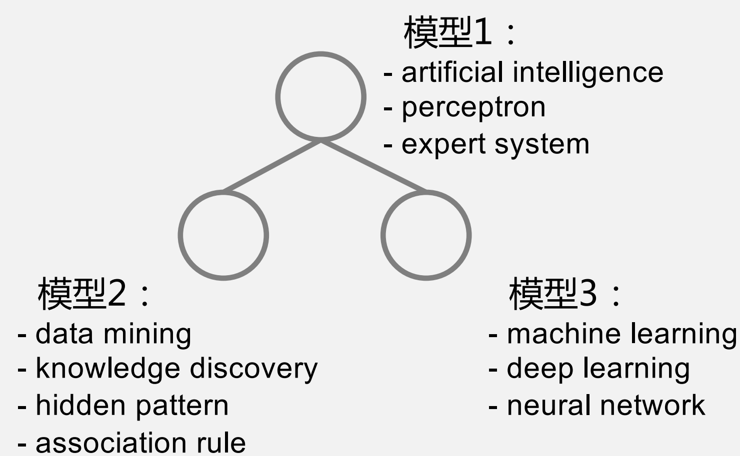
数据 → 知识图谱 → 认知图谱

知识图谱
知识概念的图谱结构

认知图谱
生成模型的图谱结构



数据处理的自动化

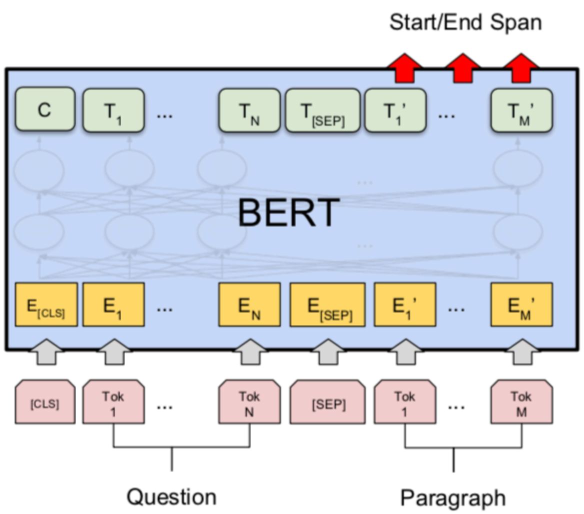


数据处理的自治性

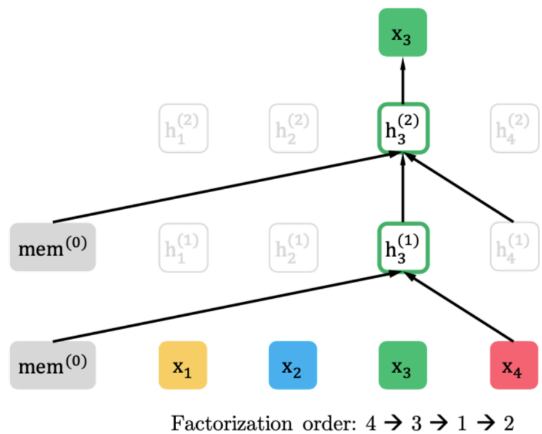
学习模型：BERT, XLNet, GPT-3

- 目标：理解整个文档，而不仅仅是局部片段
- 但仍然缺乏在知识层面上的推理能力

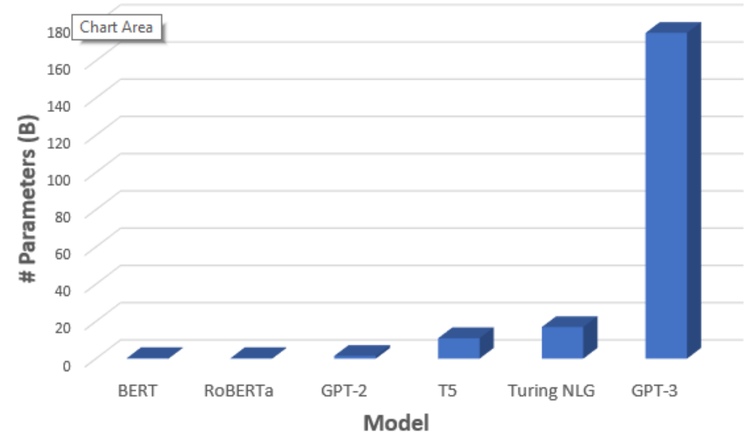
BERT



XLNet

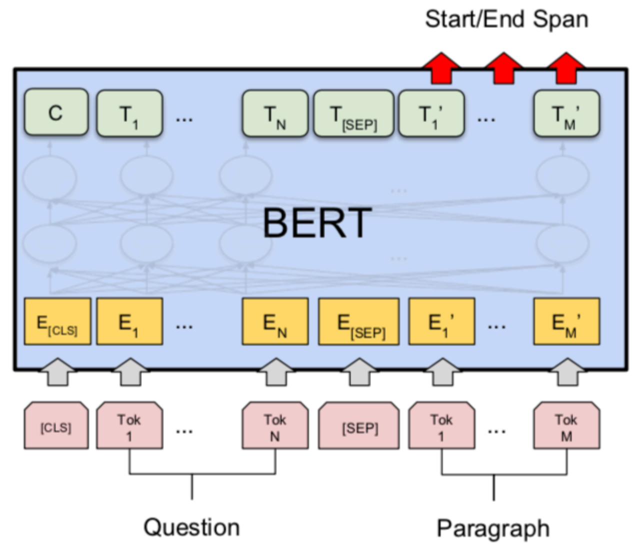


GPT-3 >1700亿参数



端到端模型的困境：以BERT为例

- 端到端的黑盒模型缺乏解释性和鲁棒性
  - 不知道推理的逻辑链条
  - 易受无关信息的“对抗攻击”

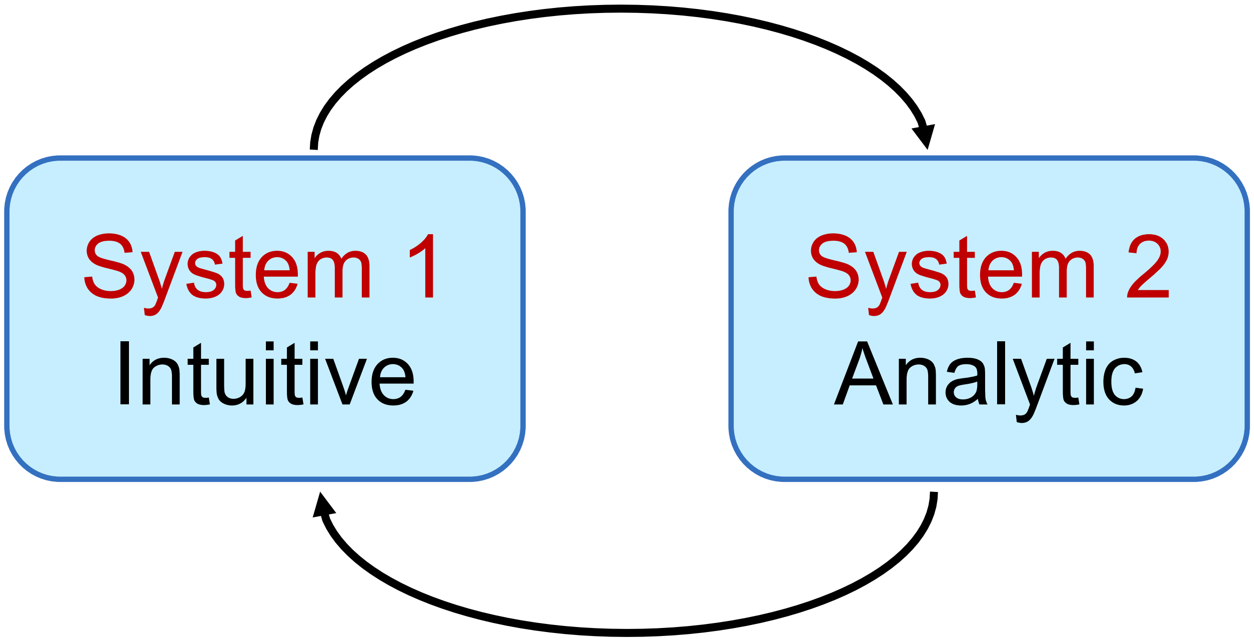


- 无法平衡信息处理精度和规模
  - BERT对于长文本时间空间消耗巨大
  - 直接检索无法考虑多步推理后的相关性

- 为什么人类可以依照逻辑推理，且能利用海量记忆？

1. Devlin Jacob et. al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. NAACL. 2019.

脑认知的双系统



Dual Process Theory (Cognitive Science)

脑认知的双系统

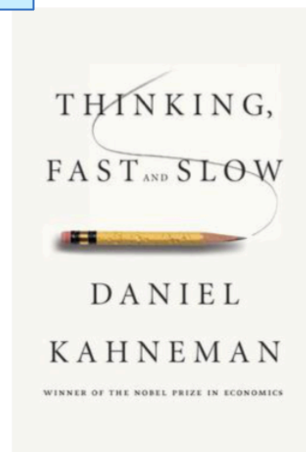
SYSTEM 1 VS. SYSTEM 2 COGNITION

当前深度学习仅解决了认知系统1的问题

Manipulates high-level / semantic concepts, which can be recombined combinatorially

System 1

- Intuitive, fast, **UNCONSCIOUS**, non-linguistic, habitual
- Current DL



System 2

- Slow, logical, sequential, **CONSCIOUS**, linguistic, algorithmic, planning, reasoning
- Future DL

Mila

3

1. From Bengio's NIPS'2019 Keynote

认知图谱(Cognitive Graph)

常识图谱

Knowledge Graph

逻辑生成

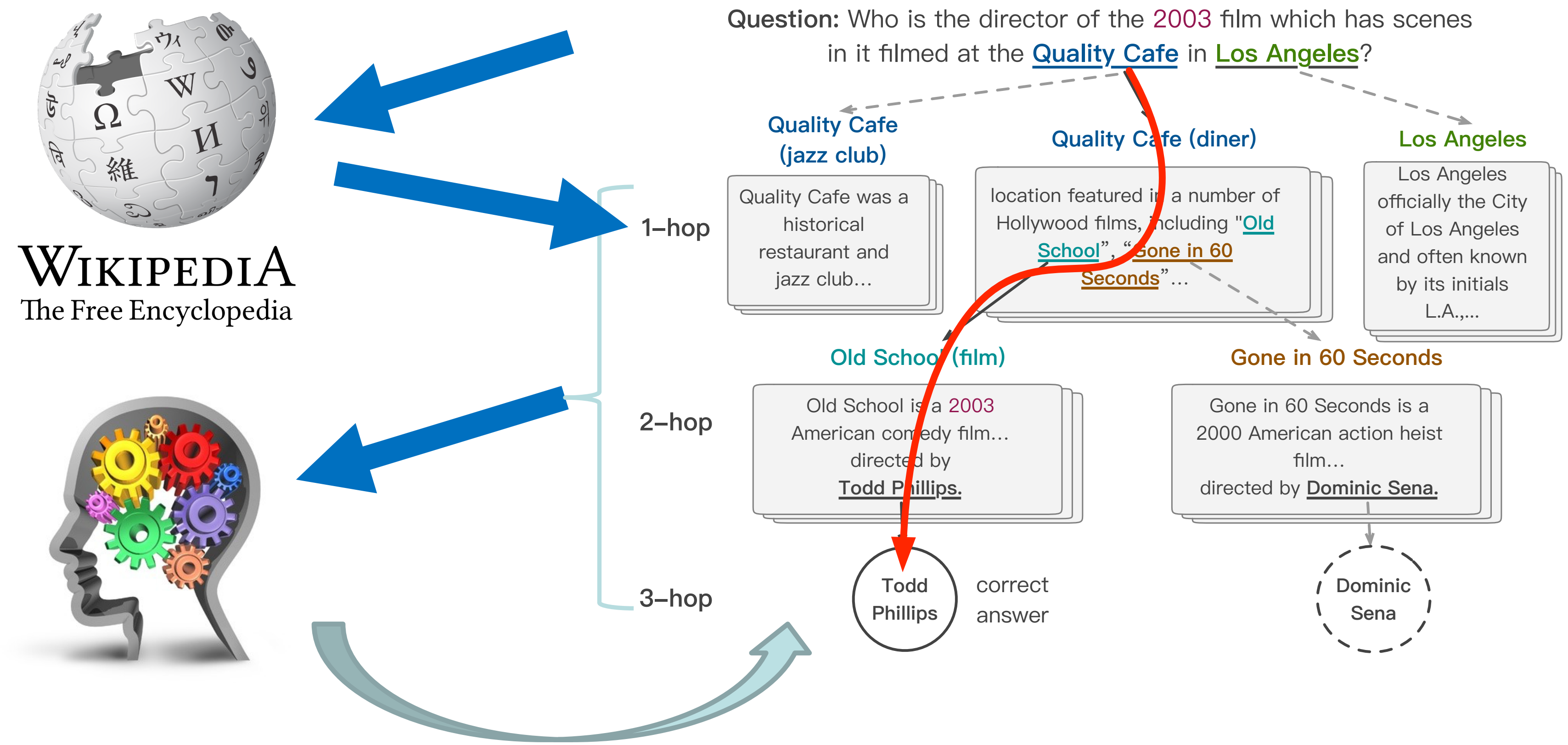
Logic Generation

认知推理

Cognitive Reasoning

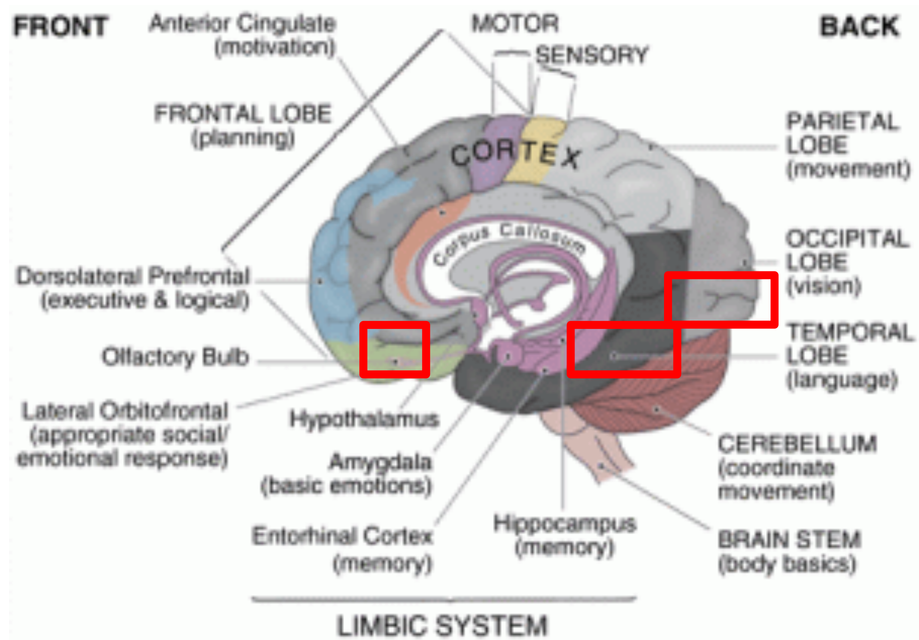
*为AI赋予认知能力

例：复杂阅读理解问答


WIKIPEDIA
The Free Encyclopedia
1–hop
2–hop
3–hop
Question: Who is the director of the 2003 film which has scenes in it filmed at the Quality Cafe in Los Angeles?
Quality Cafe (jazz club)
Quality Cafe was a historical restaurant and jazz club…
Quality Cafe (diner)
location featured in a number of Hollywood films, including "Old School", "Gone in 60 Seconds"…
Los Angeles
Los Angeles officially the City of Los Angeles and often known by its initials L.A.,…
Old School (film)
Old School is a 2003 American comedy film… directed by Todd Phillips.
Gone in 60 Seconds
Gone in 60 Seconds is a 2000 American action heist film… directed by Dominic Sena.
Todd Phillips
correct answer
Dominic Sena

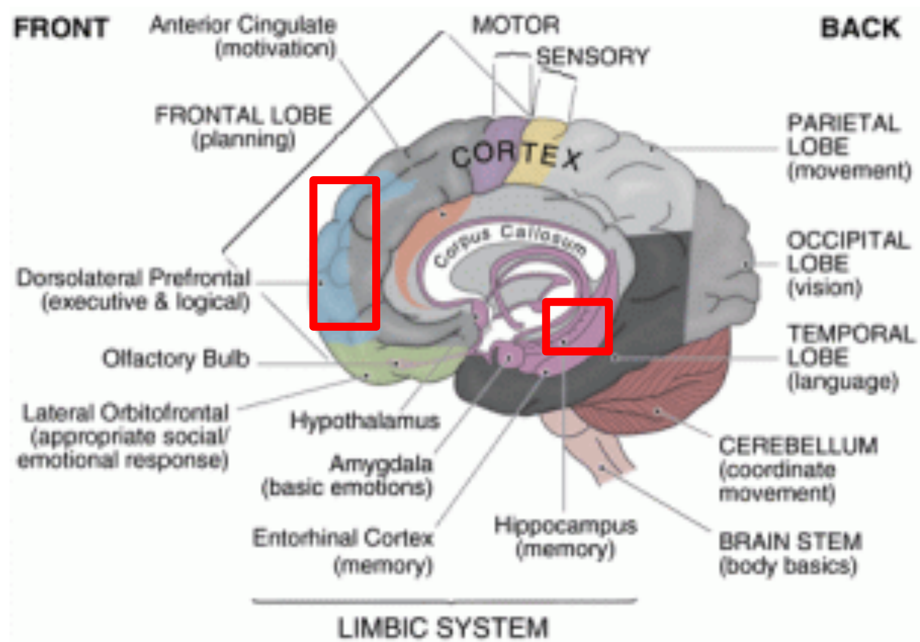
脑科学与感知智能

- 视觉脑区：
  - 主要位于枕叶（V1），通过腹（what）背（where）两条通路进行信息加工。
- 视觉性语言脑区：
  - 顶下小叶的角回（书写与口语转换）
- 听觉性语言脑区：
  - 颞叶的Wernicke’s area
- 语言脑区：
  - Broca’s area（协调发音与语法结构）
- 嗅觉脑区：
  - 嗅球、部分杏仁核
  - ……



脑科学与认知智能

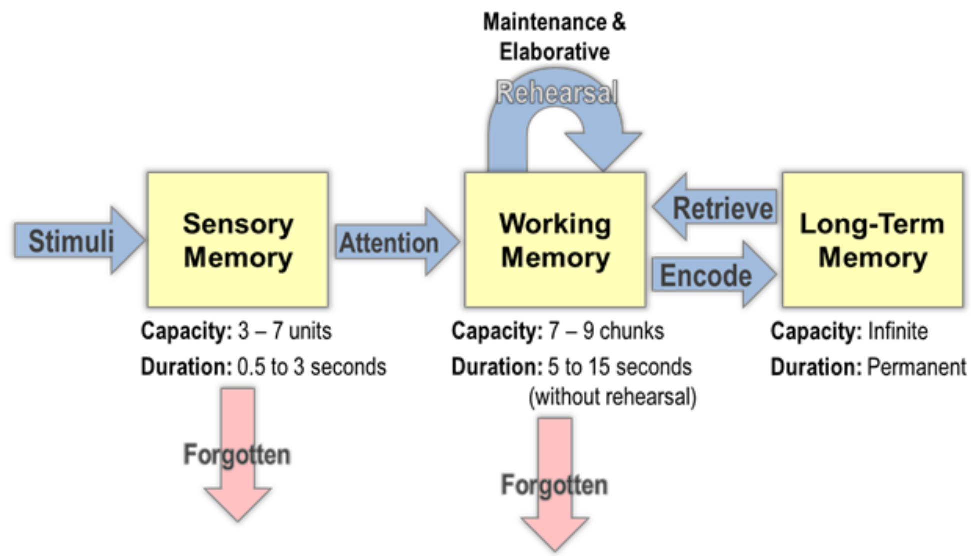
- 记忆
  - 短期记忆在海马体转化为长期（陈述性）记忆
  - 蛋白质磷酸化修饰（中期）
  - 长时程增强、新蛋白产生（长期记忆）
- 推理
  - 主要在前额叶中进行推理
  - 语言脑区参与
  - 对应工作记忆



（睡眠时前额叶兴奋可以做*能推断出自己在做梦*的“清醒梦”）

记忆：工作记忆理论

- 尽管对于认知的微观机理尚未研究清楚，我们仍可以探究宏观框架
- 巴德利的工作记忆（Working Memory）机制是里程碑式的工作，探究工作记忆调用多模态信息与长短期记忆转化（科万的分层注意力理论）



- 全局工作空间理论（Global Workspace Theory）是巴斯等人对工作记忆模型的发展，认为“意识”是不同进程争夺全局空间传播信息的结果

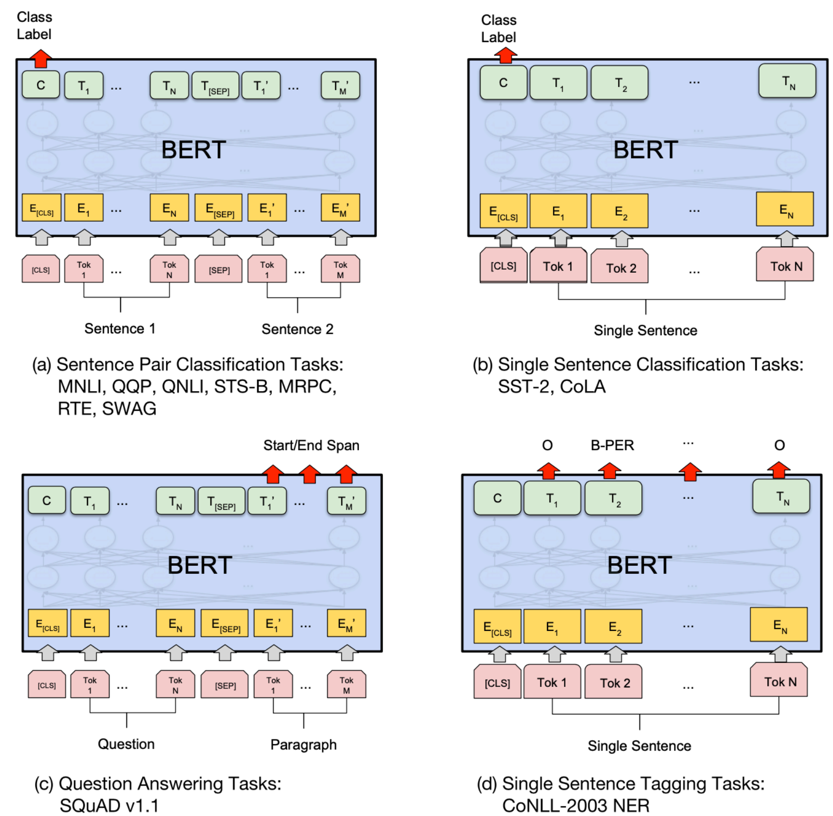
基于记忆机制的相关工作

- 神经网络经典工作LSTM通过门控机制，模拟长期记忆的遗忘与存储，与经典的RNN相比能记住更多步之前的信息。
- Memory Network的一系列工作，提出使用离散的记忆槽位（Memory slots）记录之前计算的隐向量，再通过向量相似度去索引。
- End-to-End Memory Network提出如何端到端学习如何使用记忆槽位记录和检索，并以问答作为例子。
- Dynamic Memory Networks连续通过句子的隐表示来更新目前的"工作记忆向量"。

1. Weston, Jason, Sumit Chopra, and Antoine Bordes. "Memory networks." *arXiv preprint arXiv:1410.3916* (2014).
2. Sukhbaatar, Sainbayar, Jason Weston, and Rob Fergus. "End-to-end memory networks." NIPS. 2015.
3. Kumar, Ankit, et al. "Ask me anything: Dynamic memory networks for natural language processing." ICML. 2016.

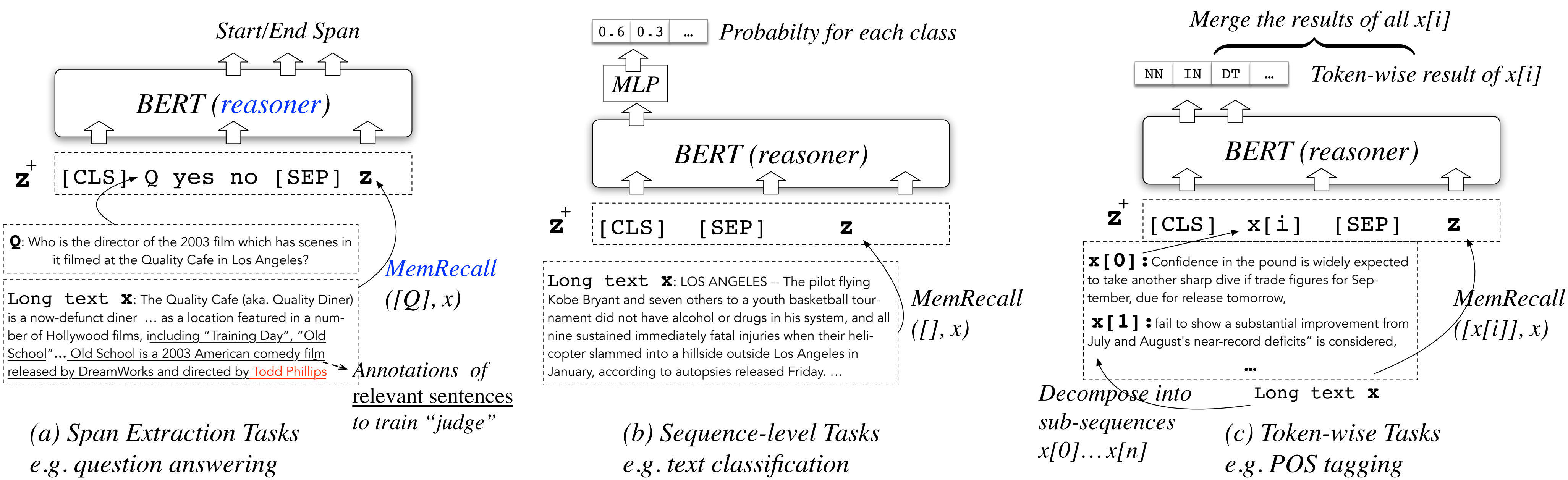
BERT时代新的挑战

- BERT是预训练的Transformer（多层自注意力模型），目前NLP领域最流行的模型之一。
- 训练时内存消耗巨大，并且关于文本长度呈$O(L^2)$增长。
- 简单的分段计算则难以实现长距离的注意力。
- 而人类的工作记忆内存有限，却可以理解长文本，为什么？



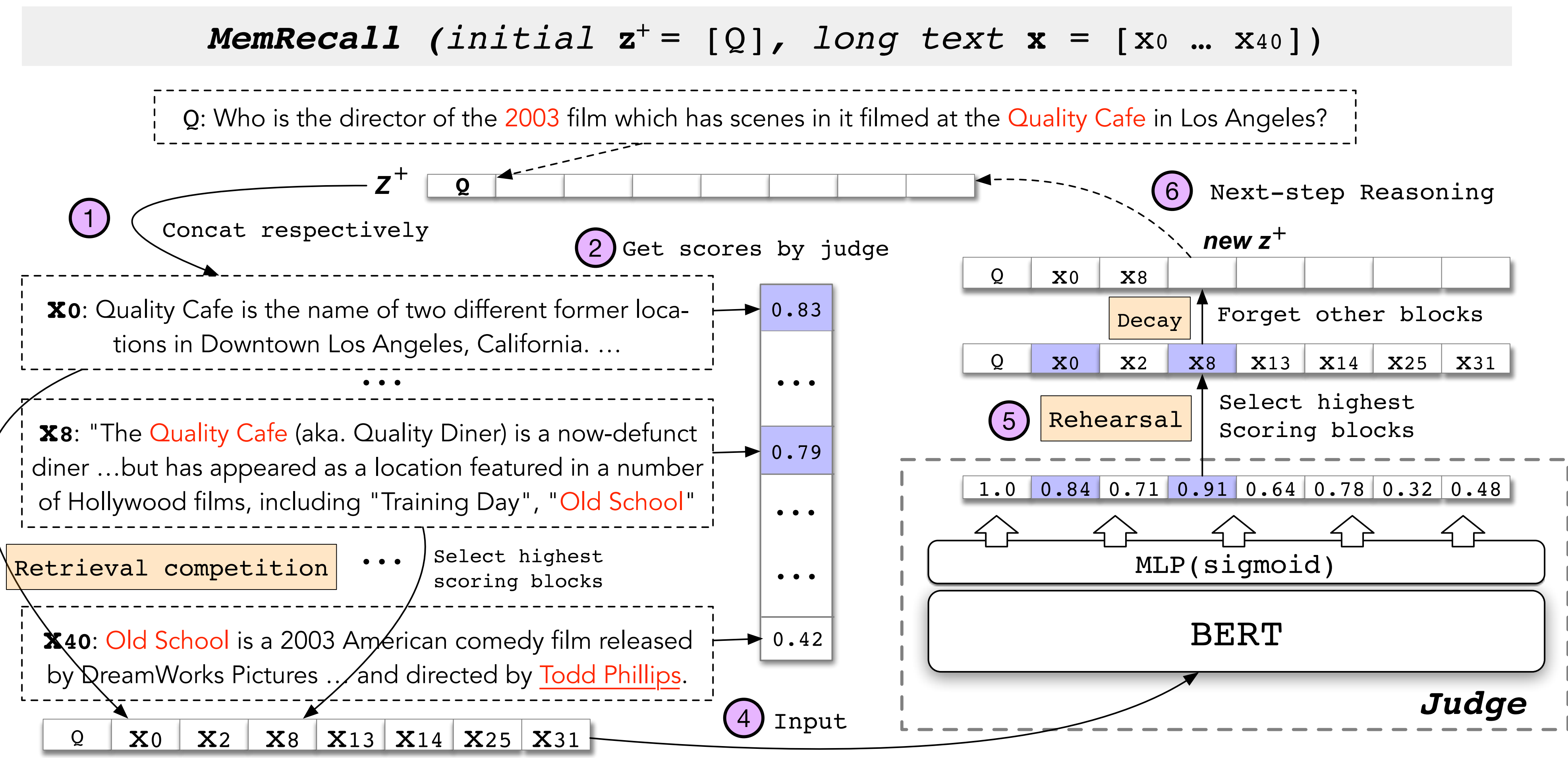
CogLTX: Applying BERT to long texts

- 通过长期记忆到工作记忆的转换，降低BERT处理文本量



1. Ming Ding, Chang Zhou, Hongxia Yang, and Jie Tang. CogLTX: Applying BERT to Long Texts. NeurIPS'20.

MemRecall操作



实验效果

Table 1: NewsQA results (%).

Model	EM	F_1
Match-LSTM [44]	34.9	50.0
BiDAF [37]	37.1	52.3
FastQAExt [47]	42.8	56.1
AMANDA [20]	48.4	63.7
MINIMAL [24]	50.1	63.2
DECAPROP [39]	53.1	66.3
RoBERTa-large [22] (sliding window)	49.6	66.3
CogLTX	**55.2**	**70.1**

Table 2: Results on HotpotQA distractor (dev). (+hyperlink) means usage of extra hyperlink data in Wikipedia. Models beginning with "–" are ablation studies without the corresponding design.

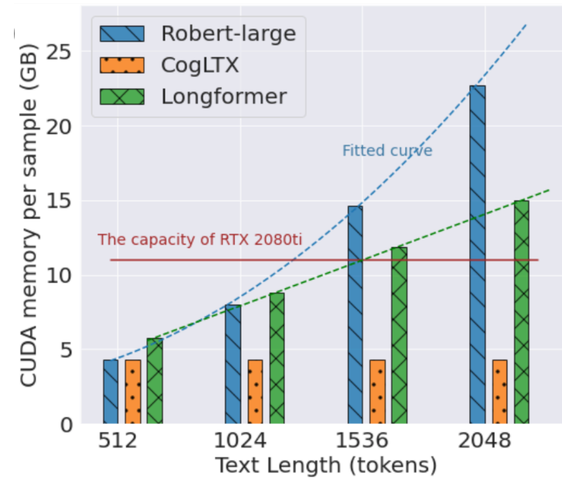
Model	Ans EM	Ans F_1	Sup EM	Sup F_1	Joint EM	Joint F_1
Baseline [49]	45.60	59.02	20.32	64.49	10.83	40.16
DecompRC [25]	55.20	69.63	N/A	N/A	N/A	N/A
QFE [26]	53.86	68.06	57.75	84.49	34.63	59.61
DFGN [32]	56.31	69.69	51.50	81.62	33.62	59.82
SAE [41]	60.36	73.58	56.93	84.63	38.81	64.96
SAE-large	66.92	79.62	61.53	86.86	45.36	**71.45**
HGN [13] (+hyperlink)	66.07	79.36	60.33	87.33	43.57	71.03
HGN-large (+hyperlink)	69.22	82.19	62.76	88.47	47.11	**74.21**
BERT (sliding window) variants						
BERT Plus	55.84	69.76	42.88	80.74	27.13	58.23
LQR-net + BERT	57.20	70.66	50.20	82.42	31.18	59.99
GRN + BERT	55.12	68.98	52.55	84.06	32.88	60.31
EPS + BERT	60.13	73.31	52.55	83.20	35.40	63.41
LQR-net 2 + BERT	60.20	73.78	56.21	84.09	36.56	63.68
P-BERT	61.18	74.16	51.38	82.76	35.42	63.79
EPS + BERT(large)	63.29	76.36	58.25	85.60	41.39	67.92
CogLTX	65.09	78.72	56.15	85.78	39.12	69.21
– multi-step reasoning	62.00	75.39	51.74	83.10	35.85	65.35
– rehearsal & decay	61.44	74.99	7.74	47.37	5.36	37.74
– train-test matching	63.20	77.21	52.57	84.21	36.11	66.90

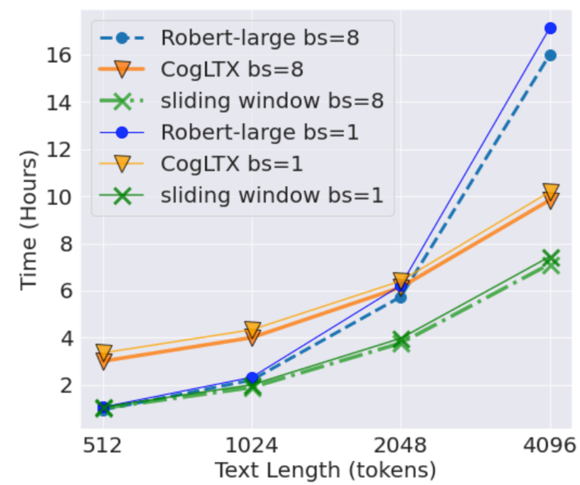
Table 3: 20NewsGroups results (%).

Model	Accuracy
BoW + SVM	63.0
Bi-LSTM	73.2
fastText [15]	79.4
MS-CNN [28]	86.1
Text GCN [50]	86.3
MLP over BERT [29]	85.5
LSTM over BERT [29]	84.7
CogLTX (Glove init)	**87.0**
only long texts	87.4
– intervention (Glove init)	84.8
Bm25 init	86.1

Table 4: A+ result (%).

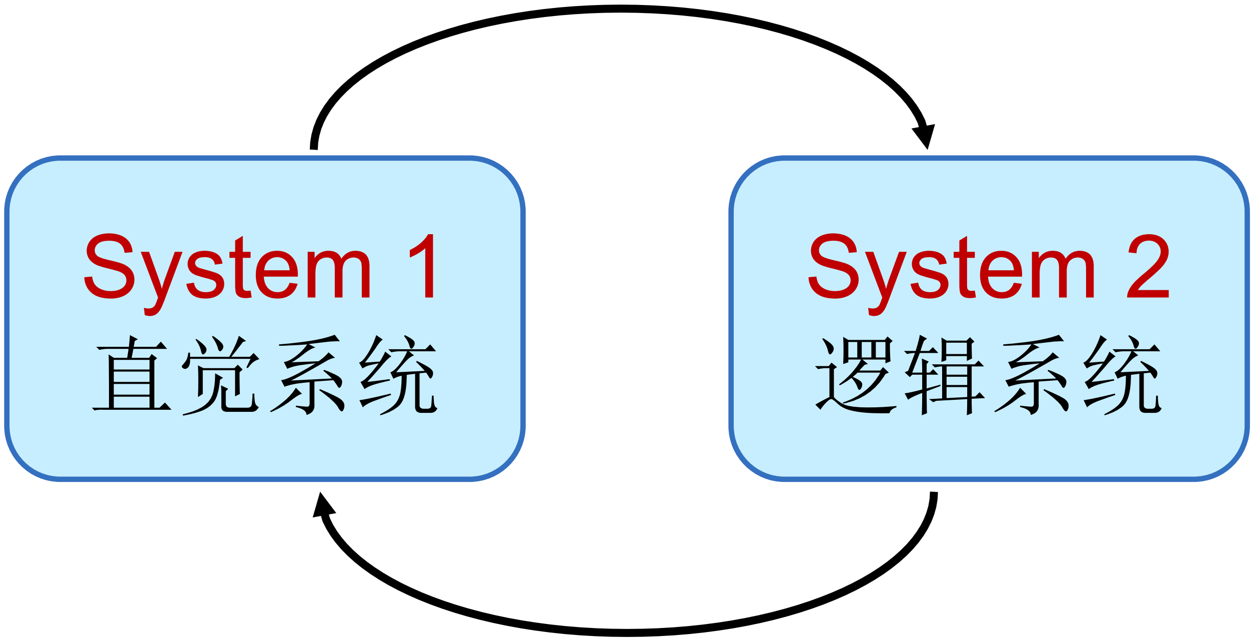
Model	Accuracy	Micro-F_1	Macro-F_1
BoW+SVM	89.9	85.8	55.3
Bi-LSTM	70.7	62.1	48.2
TextCNN	95.3	94.1	91.3
sliding window	94.5	92.7	89.9
CogLTX(tiny)	95.5	94.4	92.4
CogLTX(large)	**98.2**	**97.8**	**97.2**





1. Ming Ding, Chang Zhou, Hongxia Yang, and Jie Tang. CogLTX: Applying BERT to Long Texts. NeurIPS'20.

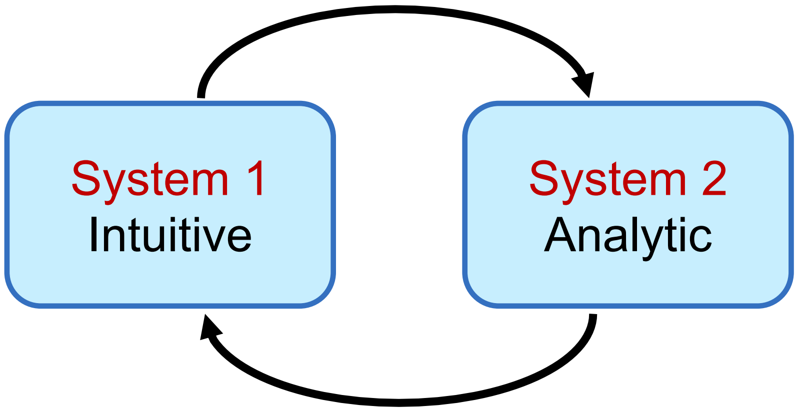
和认知科学的结合



Dual Process Theory (Cognitive Science)

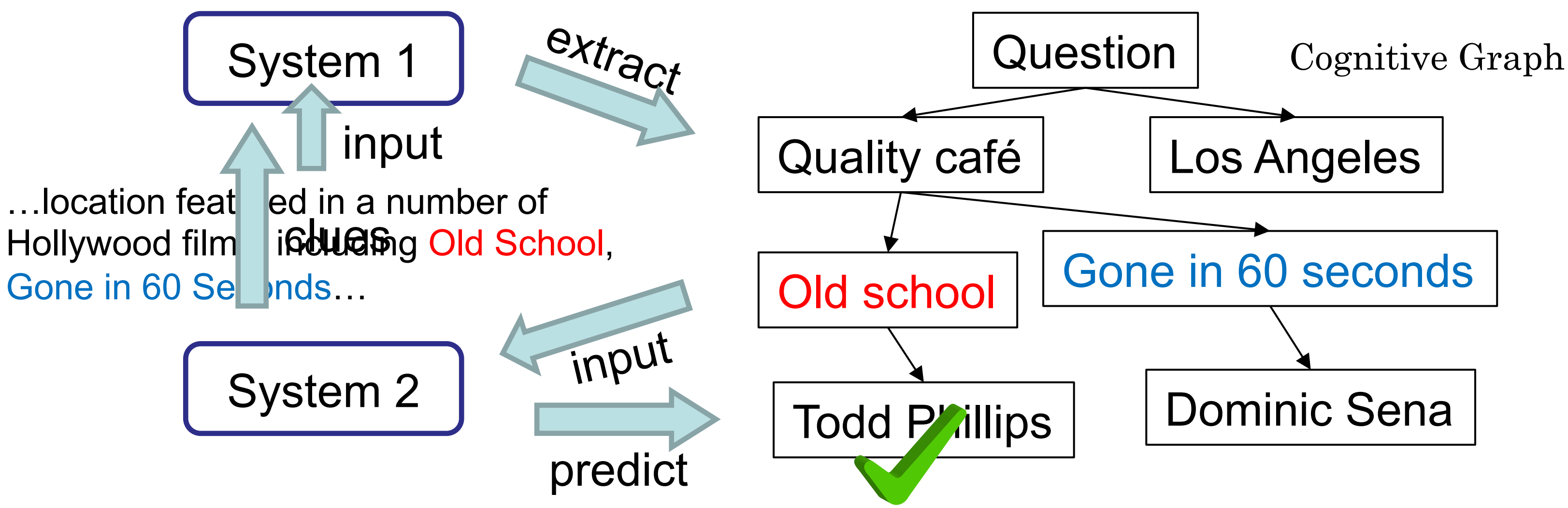
认知图谱的推理模型

- System 1:
  - Knowledge expansion by association in text when reading
- System 2:
  - Decision making w/ all the information

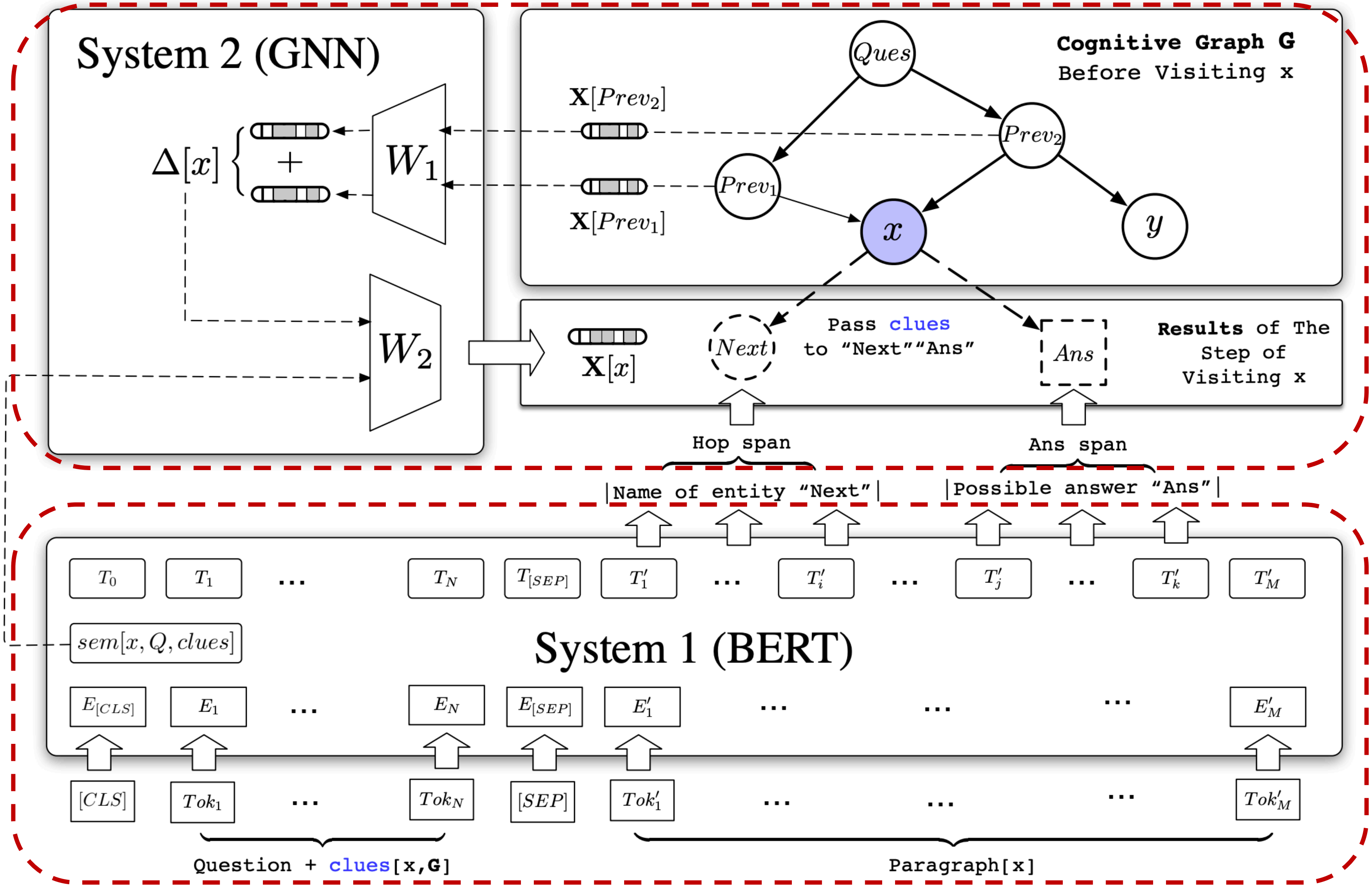


认知图谱的推理模型

- 基于认知双通道理论的迭代模型
- 系统 1
  - extract entities to build the cognitive graph
  - generate semantic vectors for each node
- 系统 2
  - Do reasoning based on semantic vectors and graph
  - Feed clues to System 1 to extract next-hop entities



认知图谱的推理模型



系统 2:
explicit
decision

系统 1:
implicit
knowledge
expansion

1. M. Ding, C. Zhou, Q. Chen, H. Yang, and J. Tang. Cognitive Graph for Multi-Hop Reading Comprehension at Scale. ACL'19.

认知图谱的推理效果

- HotpotQA is a dataset with leaderboard similar to SQuAD
- CogQA ranked 1st from 21, Feb to 15, May (nearly 3 month)

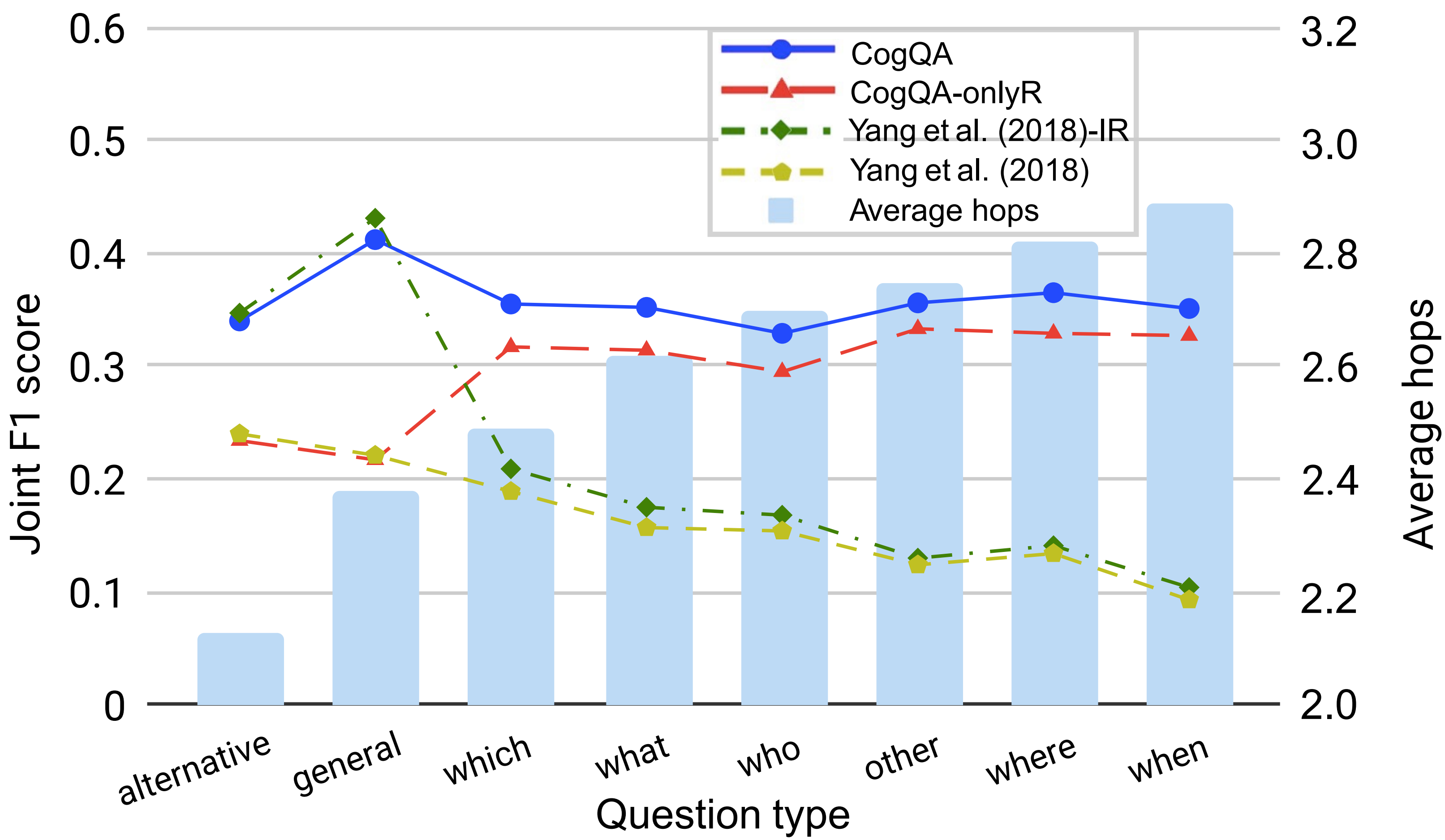
	Model	Ans				Sup				Joint			
		EM	F_1	Prec	Recall	EM	F_1	Prec	Recall	EM	F_1	Prec	Recall
Dev	Yang et al. (2018)	23.9	32.9	34.9	33.9	5.1	40.9	47.2	40.8	2.5	17.2	20.4	17.8
	Yang et al. (2018)-IR	24.6	34.0	35.7	34.8	10.9	49.3	52.5	52.1	5.2	21.1	22.7	23.2
	BERT	22.7	31.6	33.4	31.9	6.5	42.4	54.6	38.7	3.1	17.8	24.3	16.2
	CogQA-sys1	33.6	45.0	47.6	45.4	**23.7**	58.3	**67.3**	56.2	12.3	32.5	39.0	31.8
	CogQA-onlyR	34.6	46.2	48.8	46.7	14.7	48.2	56.4	47.7	8.3	29.9	36.2	30.1
	CogQA-onlyQ	30.7	40.4	42.9	40.7	23.4	49.9	56.5	48.5	**12.4**	30.1	35.2	29.9
	CogQA	**37.6**	**49.4**	**52.2**	**49.9**	23.1	**58.5**	64.3	**59.7**	12.2	**35.3**	**40.3**	**36.5**
Test	Yang et al. (2018)	24.0	32.9	-	-	3.86	37.7	-	-	1.9	16.2	-	-
	QFE	28.7	38.1	-	-	14.2	44.4	-	-	8.7	23.1	-	-
	DecompRC	30.0	40.7	-	-	N/A	N/A	-	-	N/A	N/A	-	-
	MultiQA	30.7	40.2	-	-	N/A	N/A	-	-	N/A	N/A	-	-
	GRN	27.3	36.5	-	-	12.2	48.8	-	-	7.4	23.6	-	-
	CogQA	**37.1**	**48.9**	-	-	**22.8**	**57.7**	-	-	**12.4**	**34.9**	-	-

Table 1: Results on HotpotQA (fullwiki setting). The test set is not public. The maintainer of HotpotQA only offers EM and F_1 for every submission. N/A means the model cannot find supporting facts.

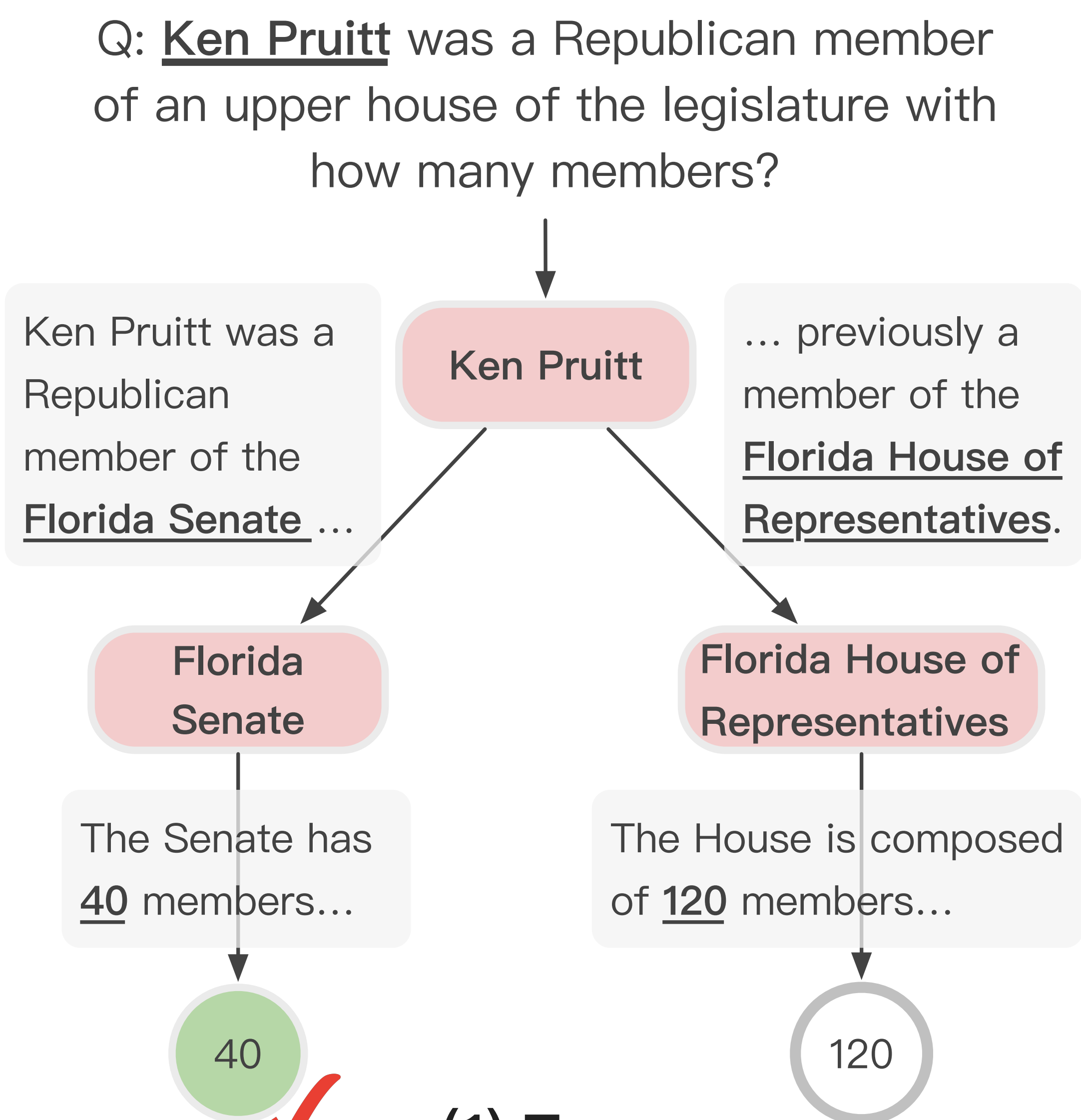
** Code available at https://github.com/THUDM/CogQA

认知图谱的推理效果

CogQA Performs much better on question with more hops !



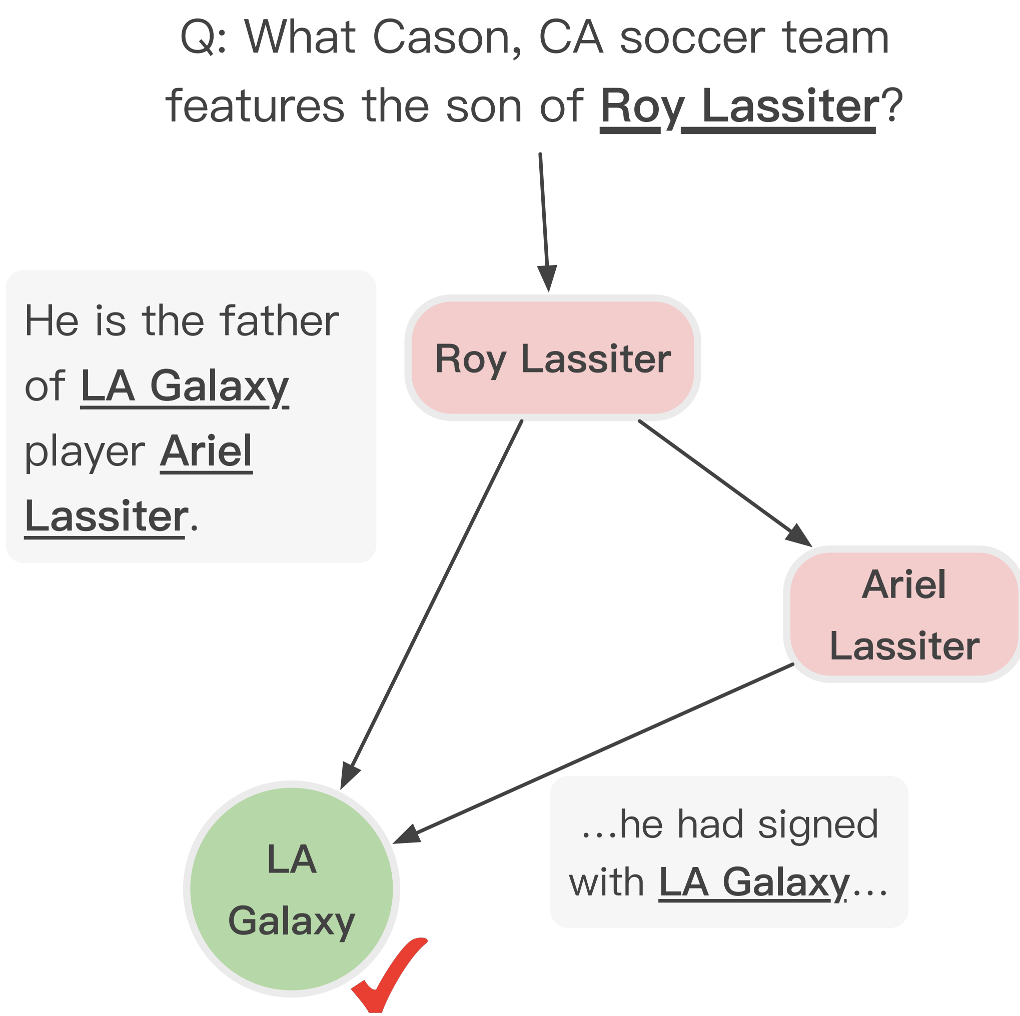
认知图谱的推理效果



(1) Tree

- Tree-shape Cognitive Graph
- Users can verify the answer by comparing it with another possible reasoning chain.
- "*Upper House*" in the question is similar to "*Senate*" not "*House of Representative*"

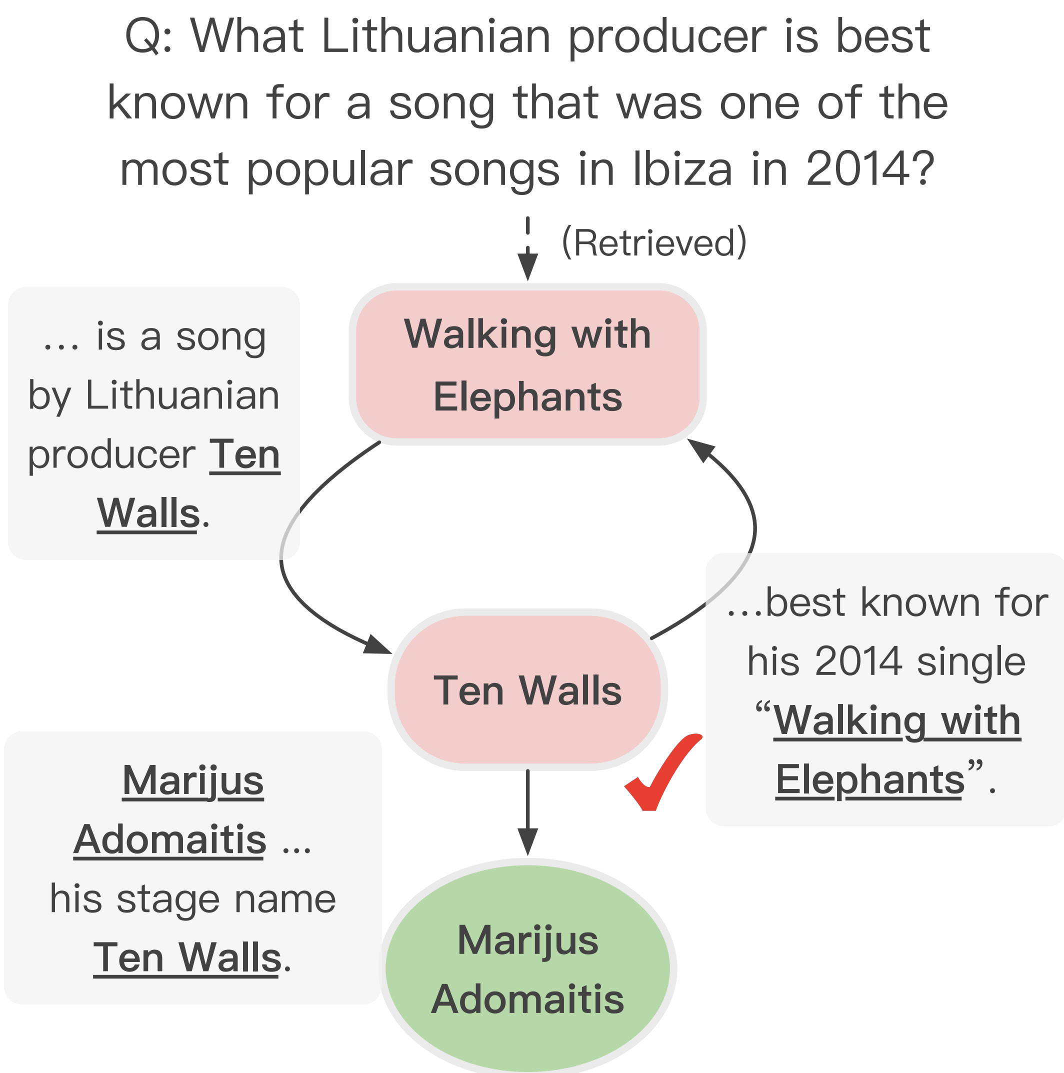
认知图谱的推理效果



(2) DAG

- DAG-shape Cognitive Graph
- Multiple supporting facts provides richer information, increasing the credibility of the answer.

认知图谱的推理效果



(3) Cyclic Graph

- CogQA gives the answer "Marijus Adomaitis" while the ground truth is "Ten Walls".
- By examining, Ten Walls is just the stage name of Marijus Adomaitis!
- Without cognitive graphs, black-box models cannot achieve it.

认知图谱(Cognitive Graph)

常识图谱

Knowledge Graph

逻辑生成

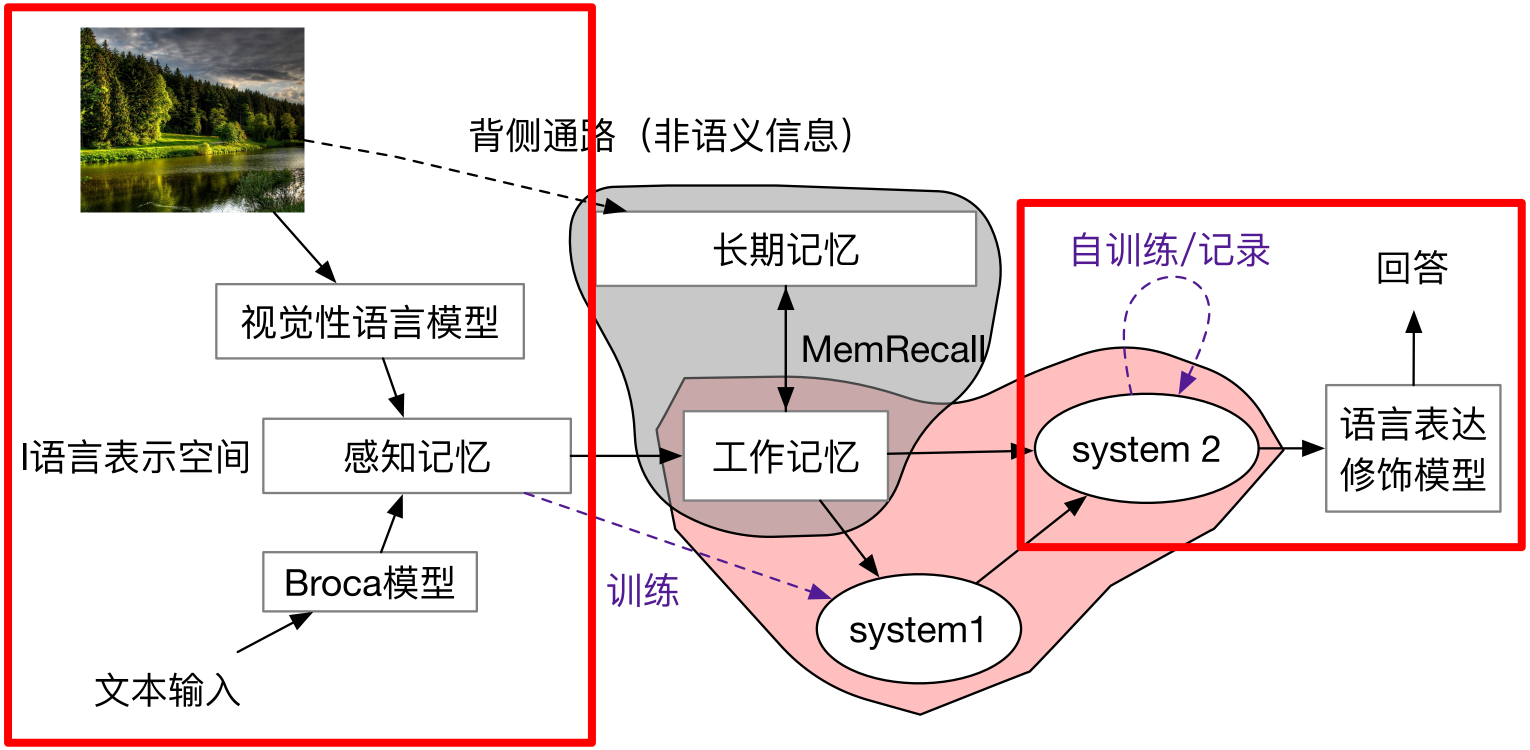
Logic Generation

认知推理

Cognitive Reasoning

*为AI赋予认知能力

认知图谱蓝图



背侧通路（非语义信息）
长期记忆
视觉性语言模型
MemRecall
自训练/记录
回答
l语言表示空间
感知记忆
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system 2
语言表达
修饰模型
Broca模型
训练
system1
文本输入

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- Ming Ding, Chang Zhou, Hongxia Yang, and Jie Tang. CogLTX: Applying BERT to Long Texts. NeurIPS'20.
- Jiezhong Qiu, Chi Wang, Ben Liao, Richard Peng, and Jie Tang. Concentration Bounds for Co-occurrence Matrices of Markov Chains. NeurIPS'20.
- Xiao Liu, Fanjin Zhang, Zhenyu Hou, Li Mian, Zhaoyu Wang, Jing Zhang, and Jie Tang. Self-supervised Learning: Generative or Contrastive. https://arxiv.org/pdf/2006.08218.pdf
- Jiezhong Qiu, Qibin Chen, Yuxiao Dong, Jing Zhang, Hongxia Yang, Ming Ding, Kuansan Wang, and Jie Tang. GCC: Graph Contrastive Coding for Structural Graph Representation Pre-Training. KDD'20.
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- Yuxiao Dong, Ziniu Hu, Kuansan Wang, Yizhou Sun and Jie Tang. Heterogeneous Network Representation Learning. IJCAI'20.
- Ming Ding, Chang Zhou, Qibin Chen, Hongxia Yang, and Jie Tang. Cognitive Graph for Multi-Hop Reading Comprehension at Scale. ACL'19.
- Jie Zhang, Yuxiao Dong, Yan Wang, Jie Tang, and Ming Ding. ProNE: Fast and Scalable Network Representation Learning. IJCAI'19.
- Yukuo Cen, Xu Zou, Jianwei Zhang, Hongxia Yang, Jingren Zhou and Jie Tang. Representation Learning for Attributed Multiplex Heterogeneous Network. KDD'19.
- Fanjin Zhang, Xiao Liu, Jie Tang, Yuxiao Dong, Peiran Yao, Jie Zhang, Xiaotao Gu, Yan Wang, Bin Shao, Rui Li, and Kuansan Wang. OAG: Toward Linking Large-scale Heterogeneous Entity Graphs. KDD'19.
- Qibin Chen, Junyang Lin, Yichang Zhang, Hongxia Yang, Jingren Zhou and Jie Tang. Towards Knowledge-Based Personalized Product Description Generation in E-commerce. KDD'19.
- Yifeng Zhao, Xiangwei Wang, Hongxia Yang, Le Song, and Jie Tang. Large Scale Evolving Graphs with Burst Detection. IJCAI'19.
- Yu Han, Jie Tang, and Qian Chen. Network Embedding under Partial Monitoring for Evolving Networks. IJCAI'19.
- Jiezhong Qiu, Yuxiao Dong, Hao Ma, Jian Li, Chi Wang, Kuansan Wang, and Jie Tang. NetSMF: Large-Scale Network Embedding as Sparse Matrix Factorization. WWW'19.
- Jiezhong Qiu, Jian Tang, Hao Ma, Yuxiao Dong, Kuansan Wang, and Jie Tang. DeepInf: Modeling Influence Locality in Large Social Networks. KDD'18.
- Jiezhong Qiu, Yuxiao Dong, Hao Ma, Jian Li, Kuansan Wang, and Jie Tang. Network Embedding as Matrix Factorization: Unifying DeepWalk, LINE, PTE, and node2vec. WSDM'18.
- Jie Tang, Jing Zhang, Limin Yao, Juanzi Li, Li Zhang, and Zhong Su. ArnetMiner: Extraction and Mining of Academic Social Networks. KDD'08.

Thank you!

Collaborators:

Jie Zhang, Ming Ding, Jiezhong Qiu, Qibin Chen, Yifeng Zhao, Yukuo Cen, Yu Han, Fanjin Zhang, Xu Zou, Yan Wang, et al. (**THU**)

Hongxiao Yang, Chang Zhou, Le Song, Jingren Zhou, et al. (**Alibaba**)

Yuxiao Dong, Chi Wang, Hao Ma, Kuansan Wang (**Microsoft**)

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