本期Contributors: AI Time

北京智源人工智能研究院

大数据文摘、 数据派

新华社

AI Time PhD是AI Time的系列活动之一，邀请众多AI领域优秀的PhD来分享最前沿的研究成果，并与所有AI Timer对相关学术议题进行交流探讨，促进多个研究方向的交叉融合。AI Time PhD，既可以获得一个展示学术成果的舞台，拓展新的科研方向、提升科研能力，又可以认识更多优秀的AI研究者。

AITime PhD--1

报告题目：《Emoji赋能的用户理解》

陈震鹏，北京大学计算机软件与理论专业二年级博士生

报告题目：《认知与结构化知识》

丁铭，清华大学计算机系二年级博士生

现场观众提问请扫码！

Decoding the Ubiquitous Language for User Understanding

Zhenpeng Chen (陈震鹏) / Peking University

AI TIME PhD第一期

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Understanding Users

Users

Sentiments

Age

Gender

Preferences

...

Negative feedback identification

Personalized content delivery

Recommender systems

Online advertising

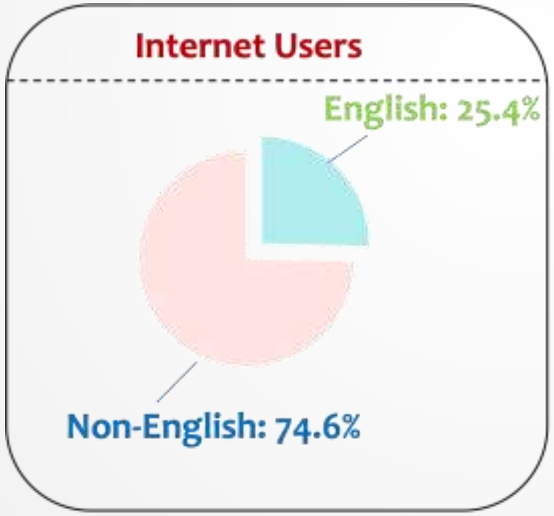
Various application scenarios

Understanding Users through Text

Sentiment analysis Gender inference

Age inference …

Mainly based on user-generated **text**



Limitation 1: Language inequality

numbers http
names $ dates
@yahoo.com time

Limitation 2: Privacy risk of accessing sensitive information

Emojis: New Ubiquitous Language of the World

✓ Popular around the world
✓ No language barriers
✓ In different apps and platforms

- Alleviate language inequality

✓ Text supplements

- Proxy of text
- Alleviate privacy risk

✓ Express emotions

- Surrogate labels of sentiments/emotions
- Avoid manual labeling

Research Idea

Sentiments

Age

Gender

Preferences

...

WWW'19

Emoji-Powered "Sensor"

Spark Big Data Techniques

Deep Learning

Data Visualization

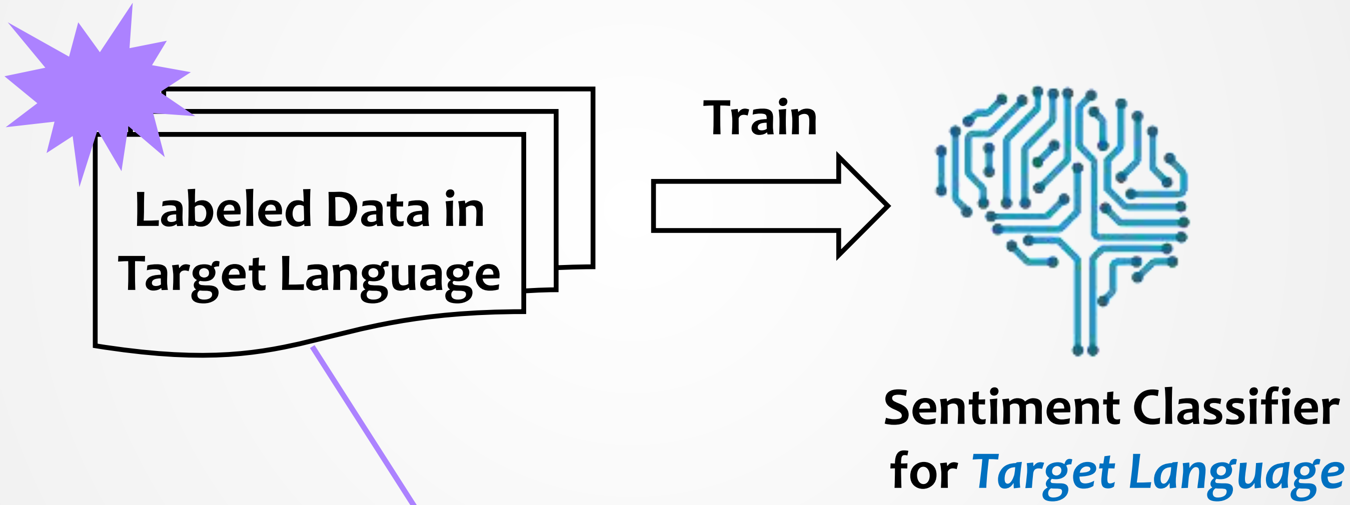
Data Mining

Technology Pillars

User-generated Content

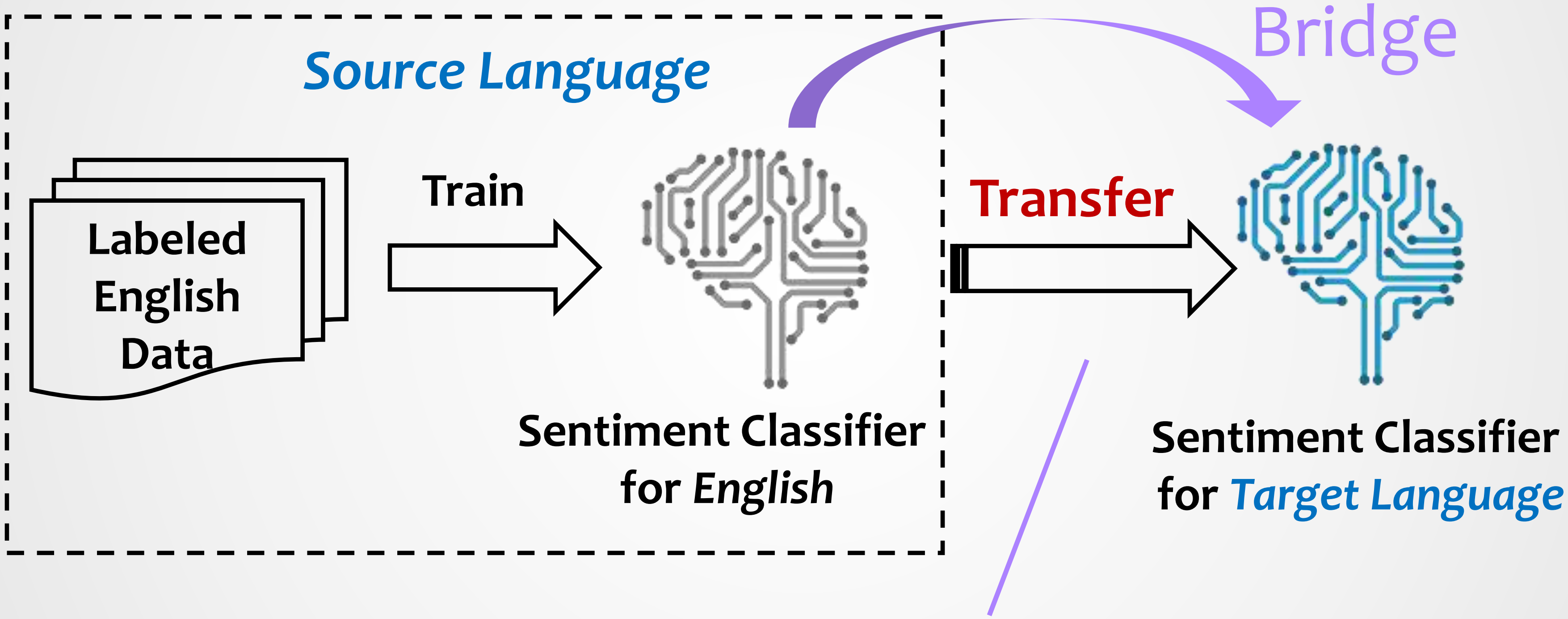
How to Alleviate Language Inequality

For each non-English language (*target language*),



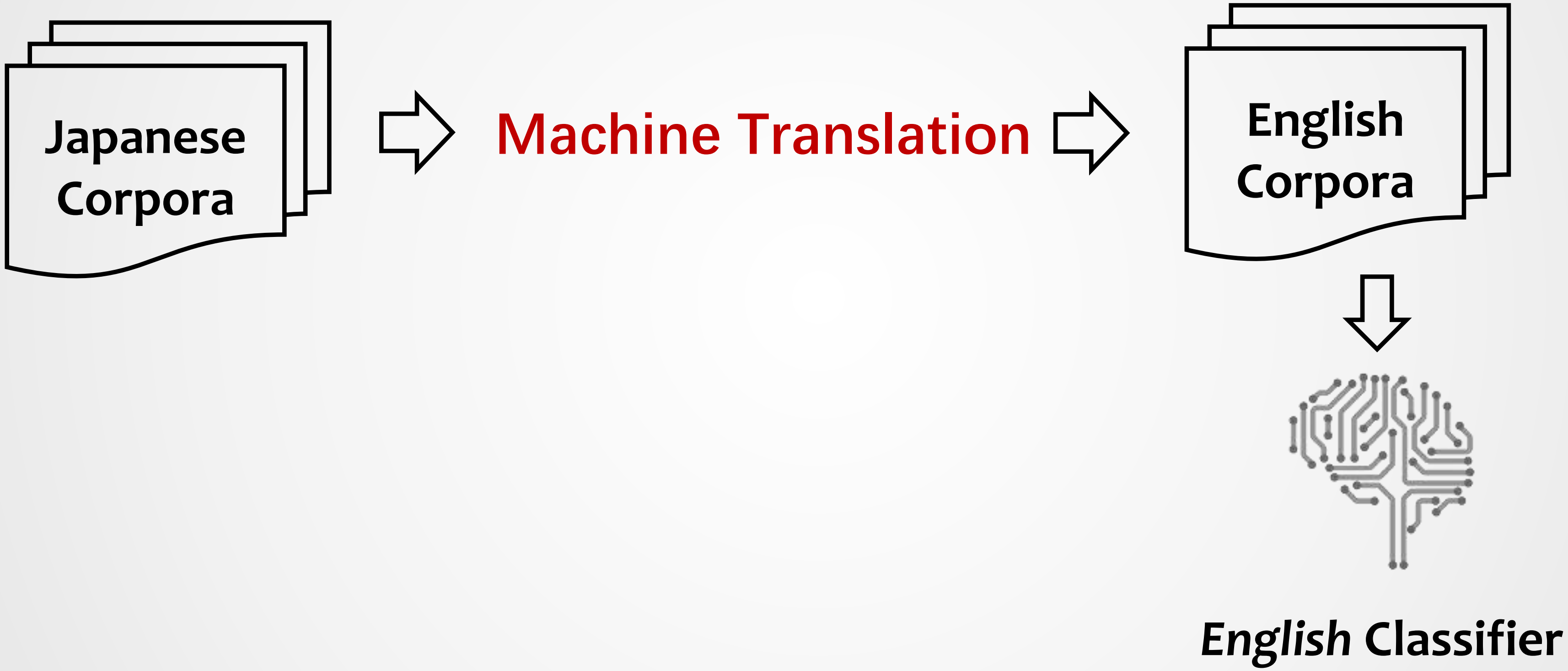
Challenge: Labels are scarce in non-English languages

Cross-Lingual Sentiment Analysis

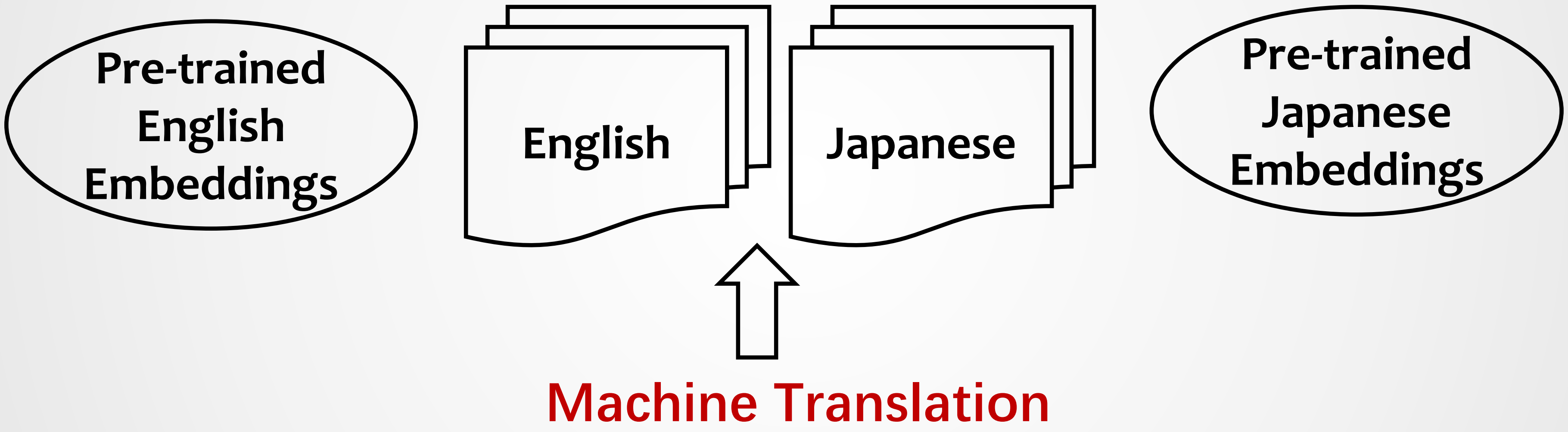


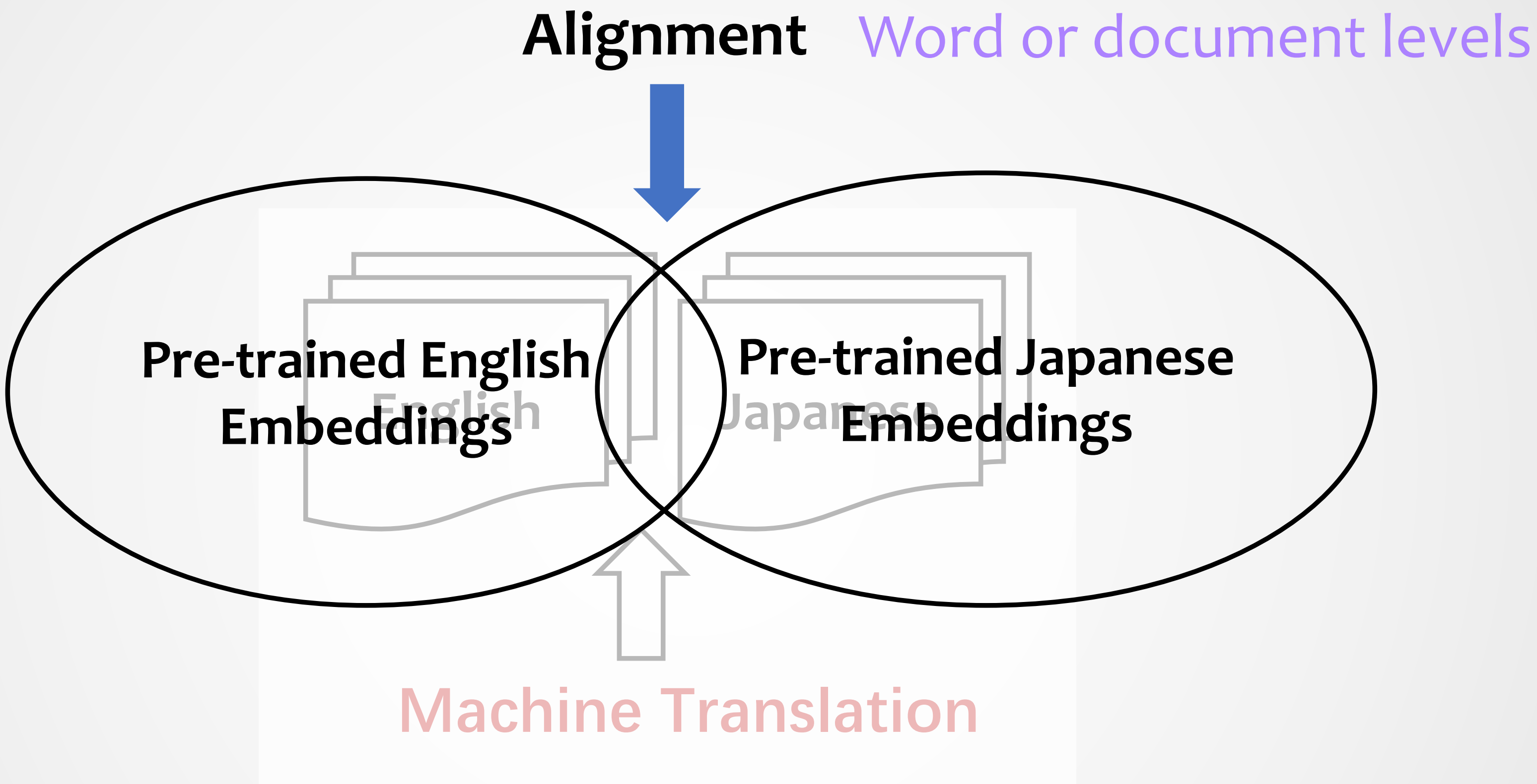
Challenge: Hard to transfer general knowledge while preserving language-specific knowledge

How the Bridge is Built Now



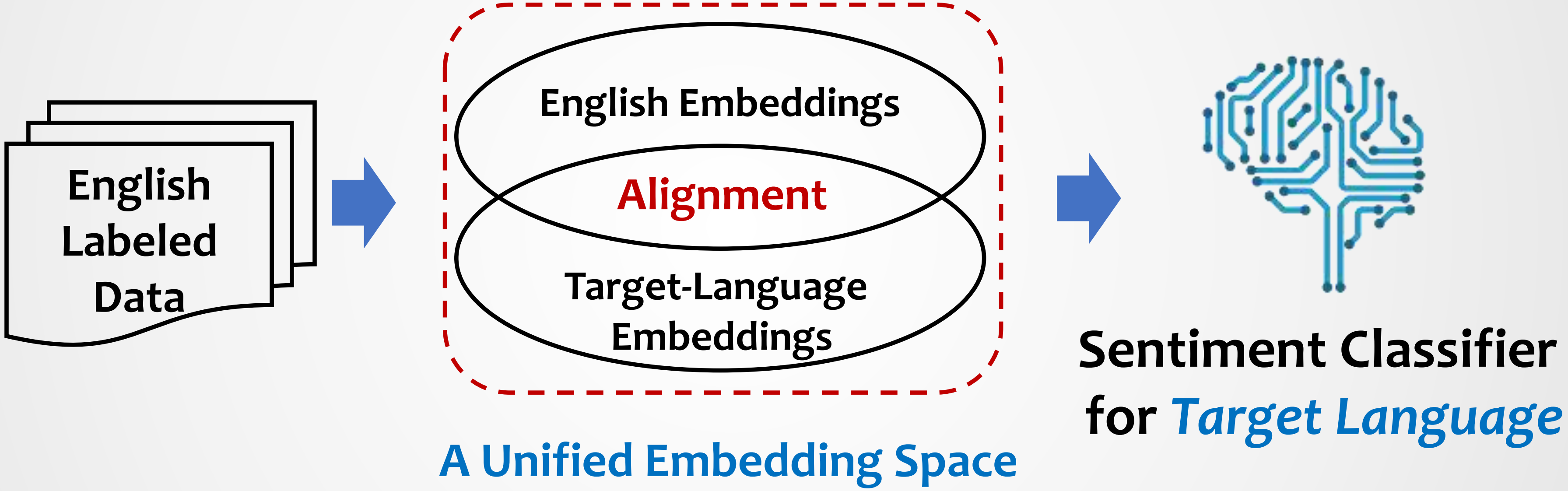
How the Bridge is Built Now





[Xiao and Guo, EMNLP'13]
[Zhou *et al.*, ACL'16]

How the Bridge is Built Now



Machine Translation as Bridge

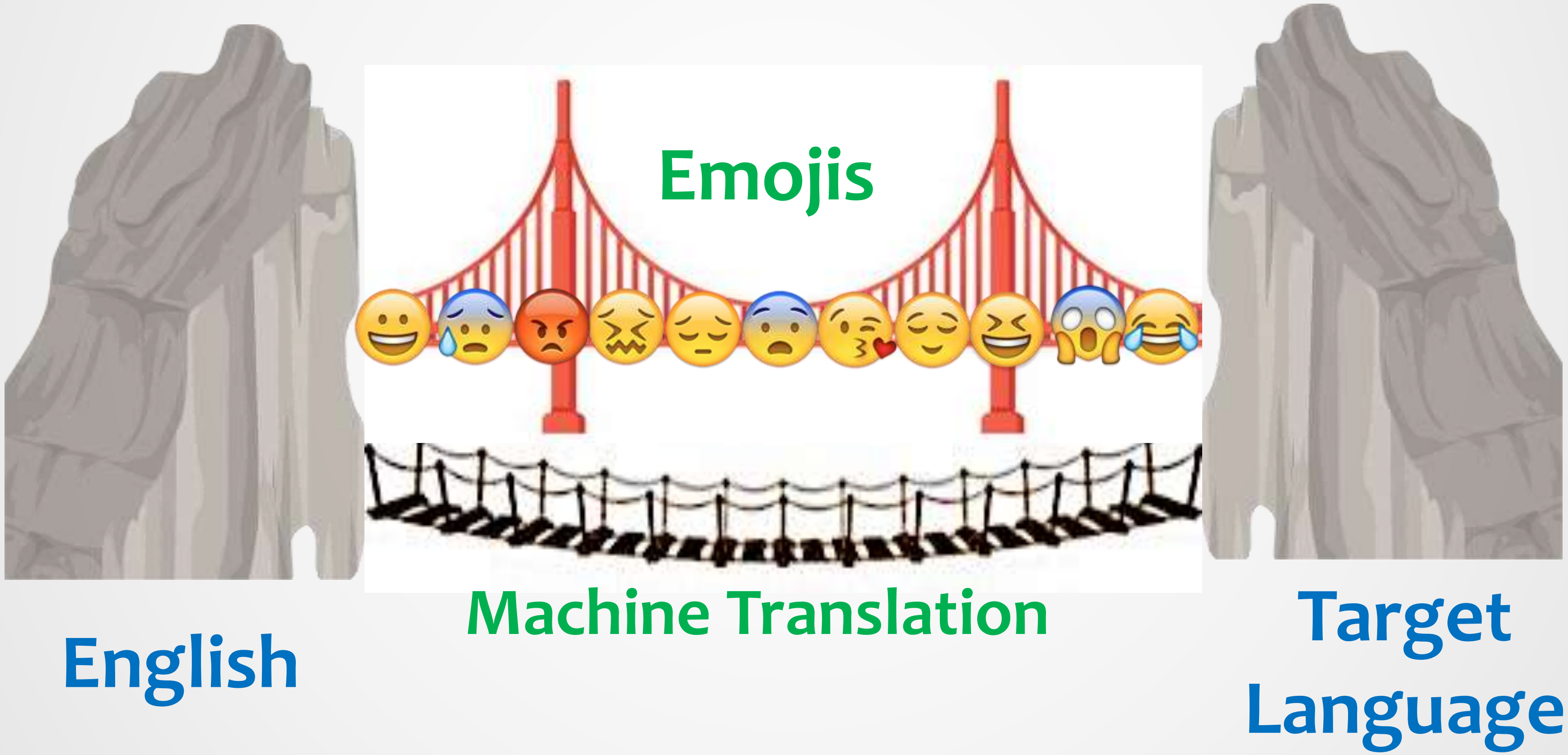
- Able to transfer general sentiment knowledge
- Fail to capture language-specific sentiment knowledge

English

Machine Translation

Target Language

Emojis as a New Bridge



Two Roles of Emojis

- As surrogate labels of sentiments

I am happy😊 ✓ **Widely available sentiment signal**

- As bridge between languages

I am happy😊
私は幸せです😊

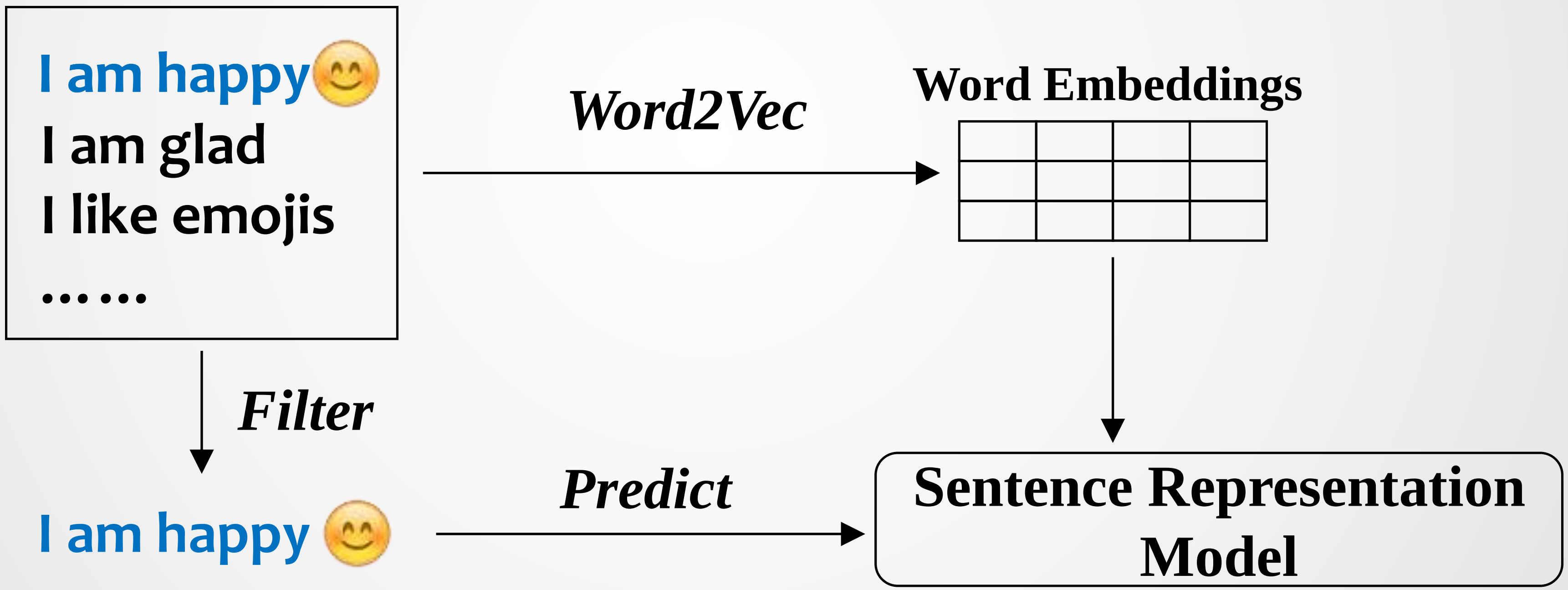
✓ **Carrying common sentiment knowledge**

I am sad😪
私は眠い😪

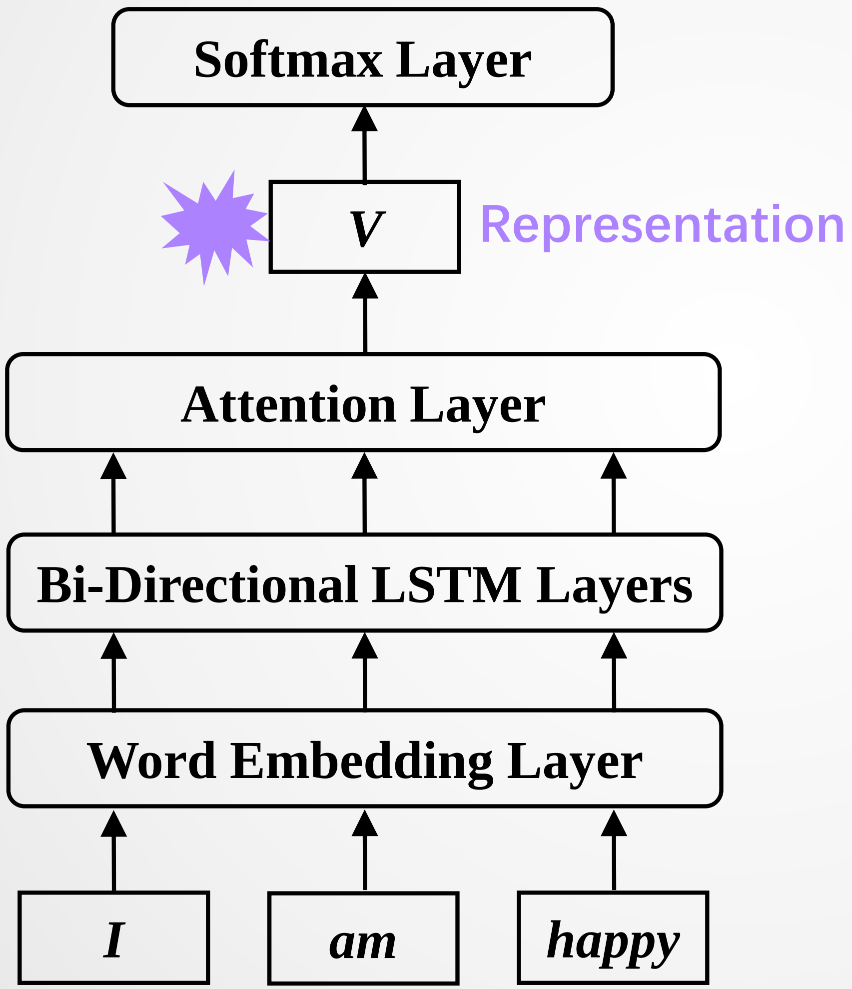
✓ **Carrying language-specific sentiment knowledge**

How to Capture Language-Specific Knowledge

- For each language, learn its specific representations through emoji prediction



Sentence Representation through Emoji Prediction



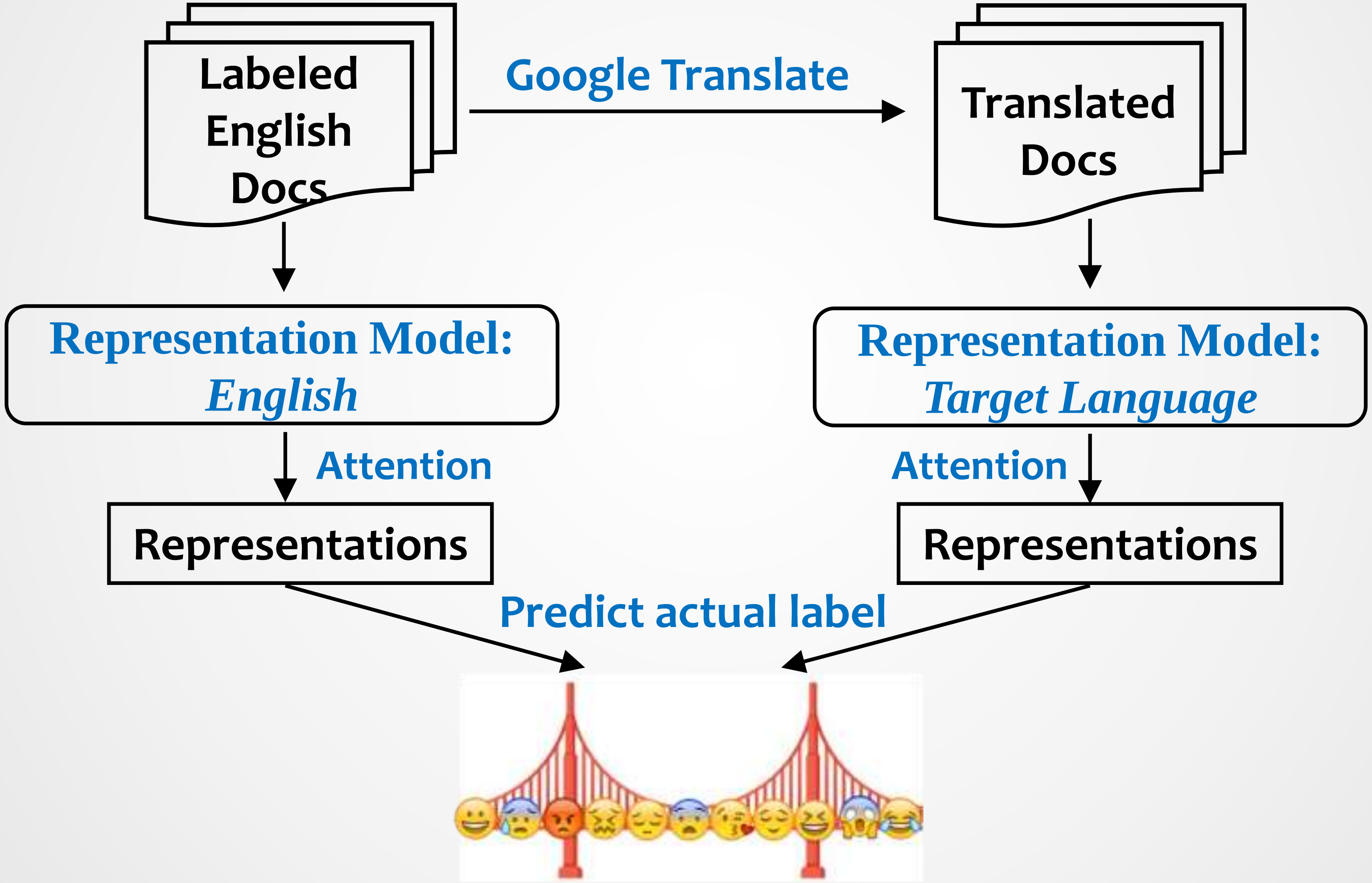
Step 4: Predict 😊

Step 3: Determine the importance (attention score) of each word

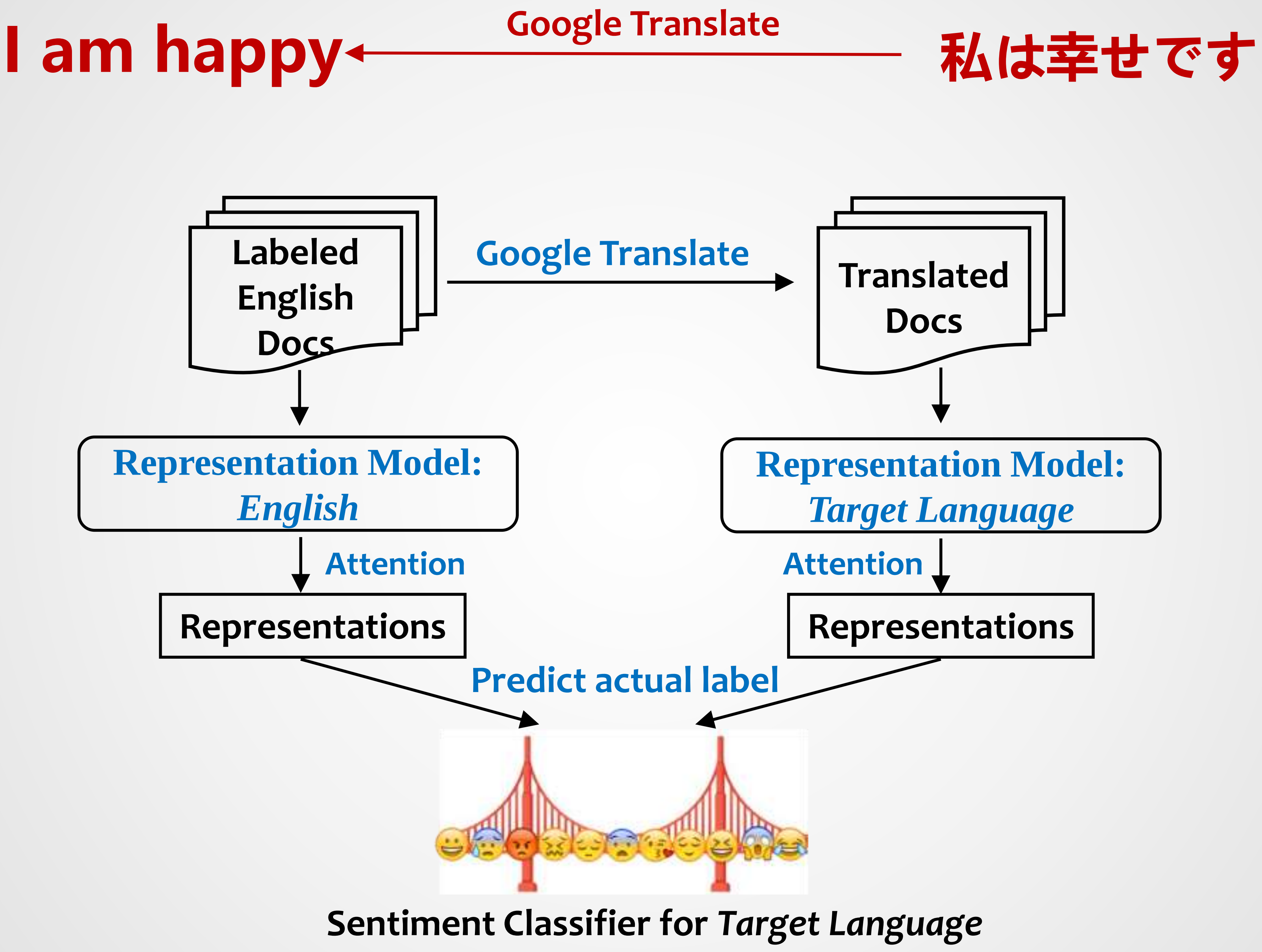
Step 2: Capture the context information of each word

Step 1: Represent every single word as a unique vector

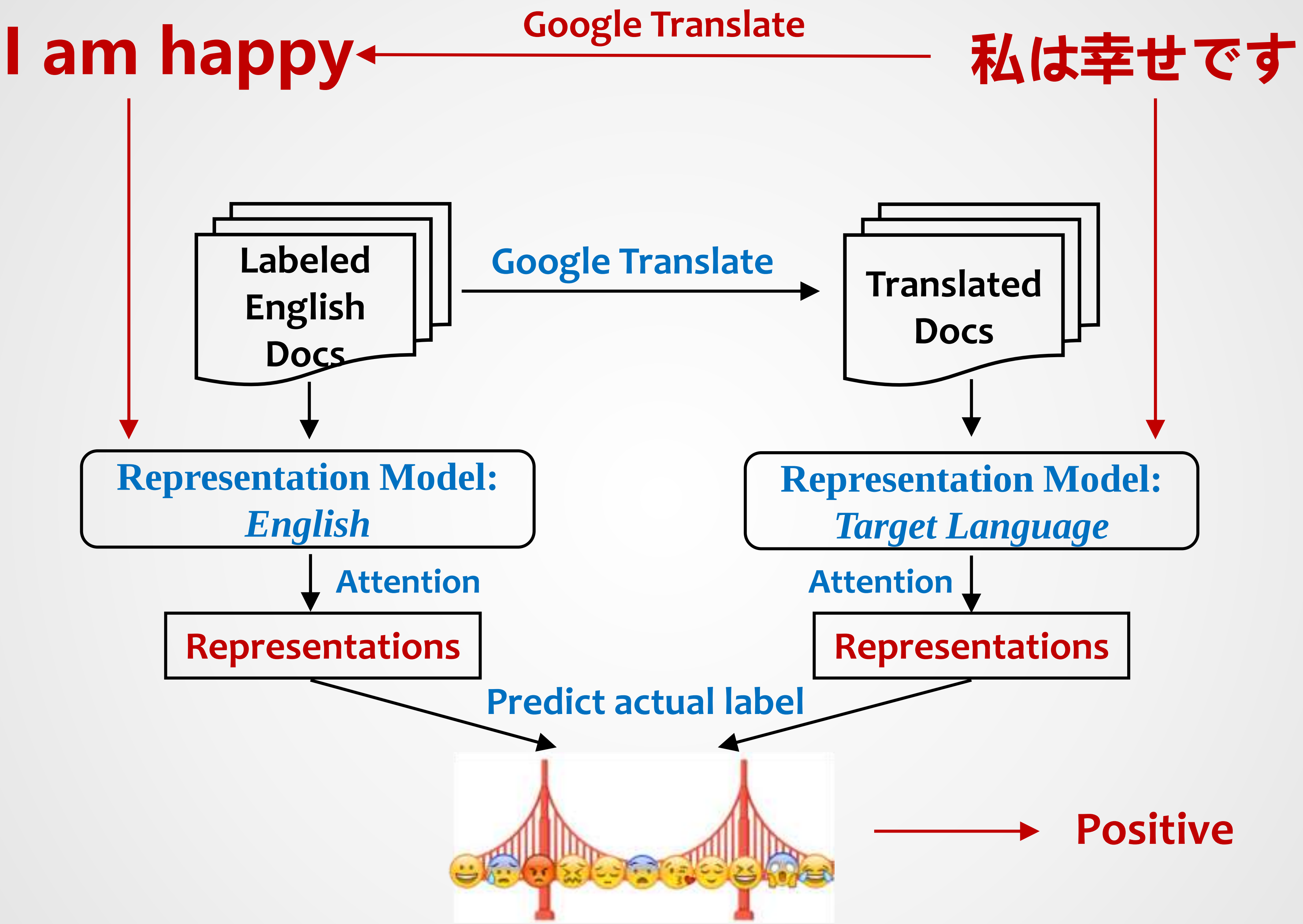
ELSA for Cross-Lingual Sentiment Classification



Sentiment Classifier for *Target Language*



I am happy
Google Translate
私は幸せです
Labeled English Docs
Google Translate
Translated Docs
Representation Model: *English*
Representation Model: *Target Language*
Attention
Attention
Representations
Representations
Predict actual label
Sentiment Classifier for *Target Language*



Sentiment Classifier for *Target Language*

Evaluation Setup

- **Benchmark:** Amazon Review Dataset

4 languages × 3 domains = 12 combinations

	Languages
Source	English
Target	Japanese
Target	French
Target	German

Domains
Book
DVD
Music

(English, Book)	1,000 pos; 1,000 neg
(English, DVD)	1,000 pos; 1,000 neg
(English, Music)	1,000 pos; 1,000 neg
……	……

- 9 tasks in total

Japanese	Book
French	DVD
German	Music

Japanese, French, German × Book, DVD, Music

Text for Representation Learning

- For each language
  - Tweets: train word embeddings
  - Tweets containing emojis: predict emoji

I love you ❤️❤️💋 ⇨

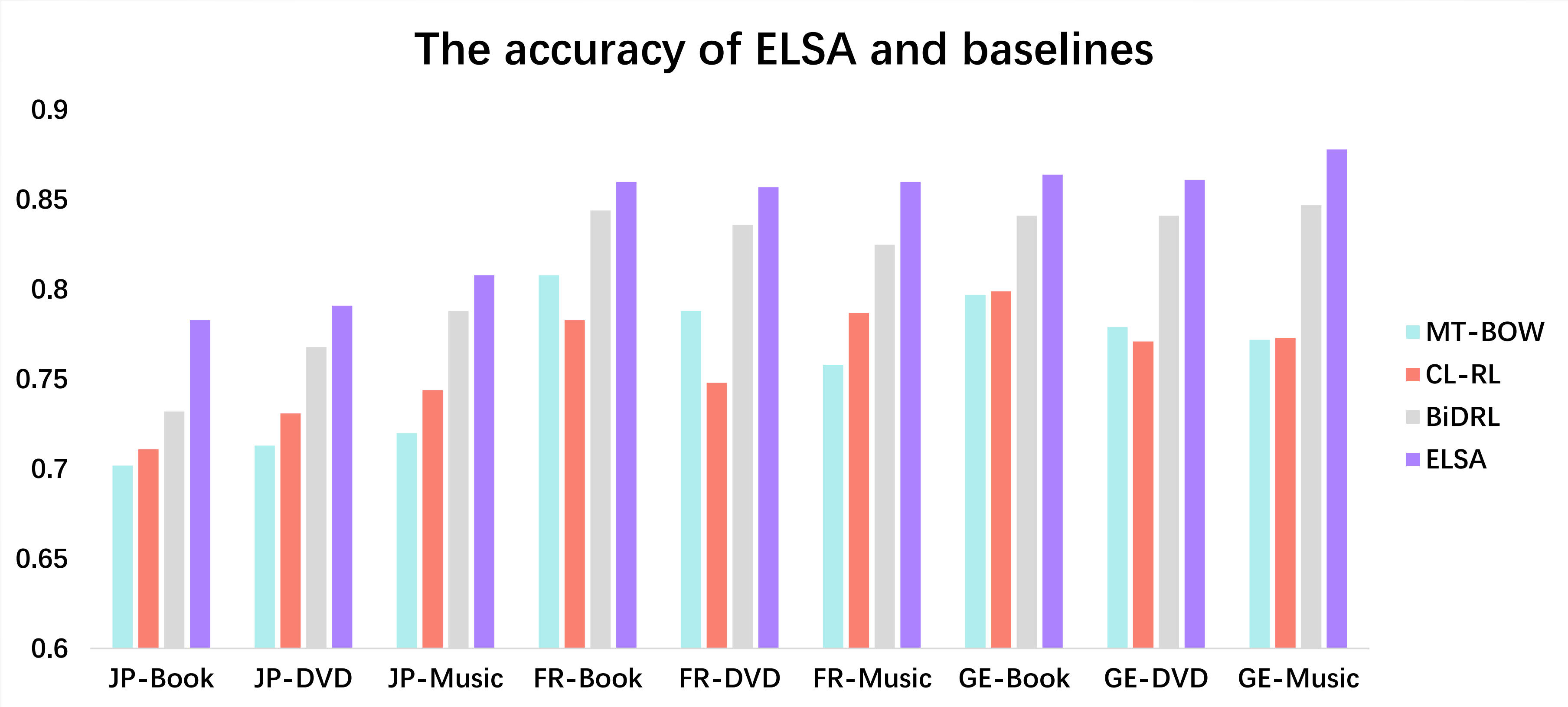
	Sentence	*Label*
1	I love you	❤️
2	I love you	💋

	English	Japanese	French	German
Raw Tweets	39.4M	19.5M	29.2M	12.4M
Emoji Tweets	6.6M	2.9M	4.4M	2.7M

Baseline Methods

- **MT-BOW** [Prettenhofer and Stein, ACL'10]
  - English classifier: bag-of-words
  - Classify translated documents
- **CL-RL** [Xiao and Guo, EMNLP'13]
  - A unified embedding space: word-level aligned
- **BiDRL** [Zhou *et al.*, ACL'16]
  - A unified embedding space: document-level aligned

Results



- ELSA outperforms all three baselines on all nine tasks

An Illustrating Example

- The translation of a Japanese sample that expresses dissatisfaction with an album

It was not interesting at all until I saw them at samasonon last year

the first song I listened live after sumasoni did not leave my head so it was my first

I bought an album and asked, but it was a very good one **Seems to be positive**

however, this album does not come with an honest pin

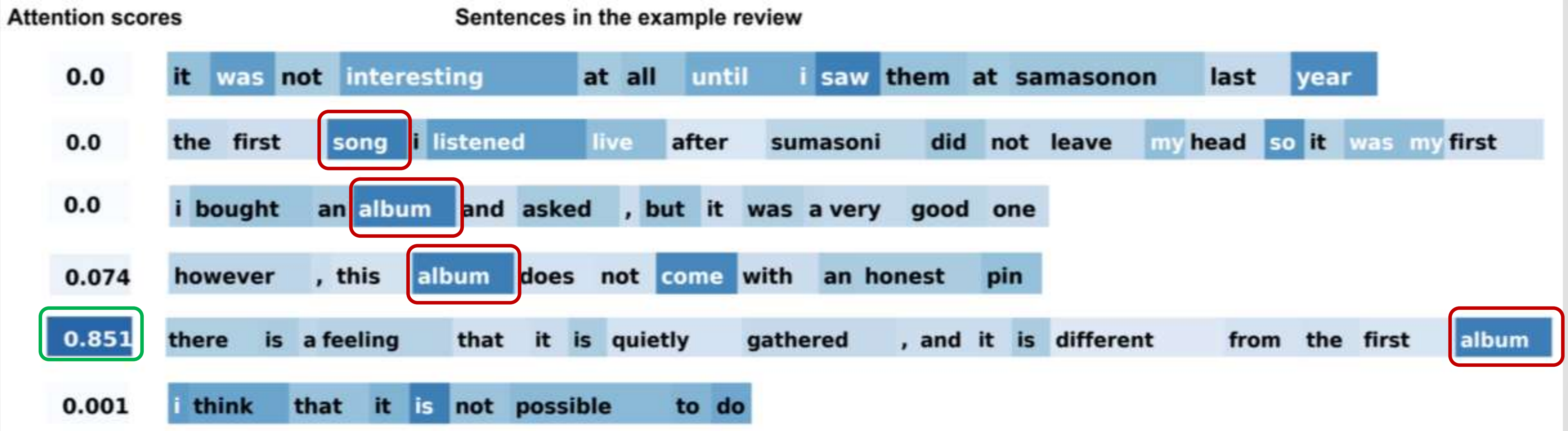
there is a feeling that it is quietly gathered, and it is different from the first album

i think that it is not possible to do

In fact, a negative example

An Illustrating Example

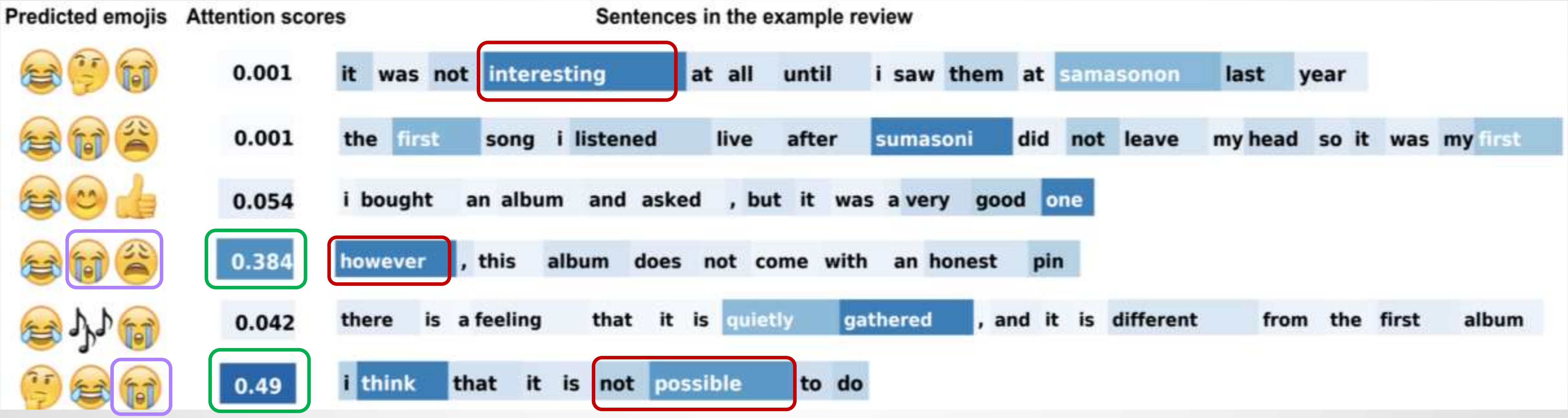
Without Emoji Incorporation



- **Neutral words:** “song”, “album”
- **The 5th sentence**

Emojis Benefit Text Comprehension

With Emoji Incorporation



- **Adjectives:** “not interesting”, “not possible”
- **Disjunctives:** “however”
- **The 4th and 6th sentence**

Research Idea

Sentiments

Age

Gender

Preferences

...

Emoji-Powered "Sensor"

User-generated Content

WWW'18

Big Data Techniques

Deep Learning

Data Visualization

Data Mining

Technology Pillars

Gender Inference Purely Based on Emoji Usage

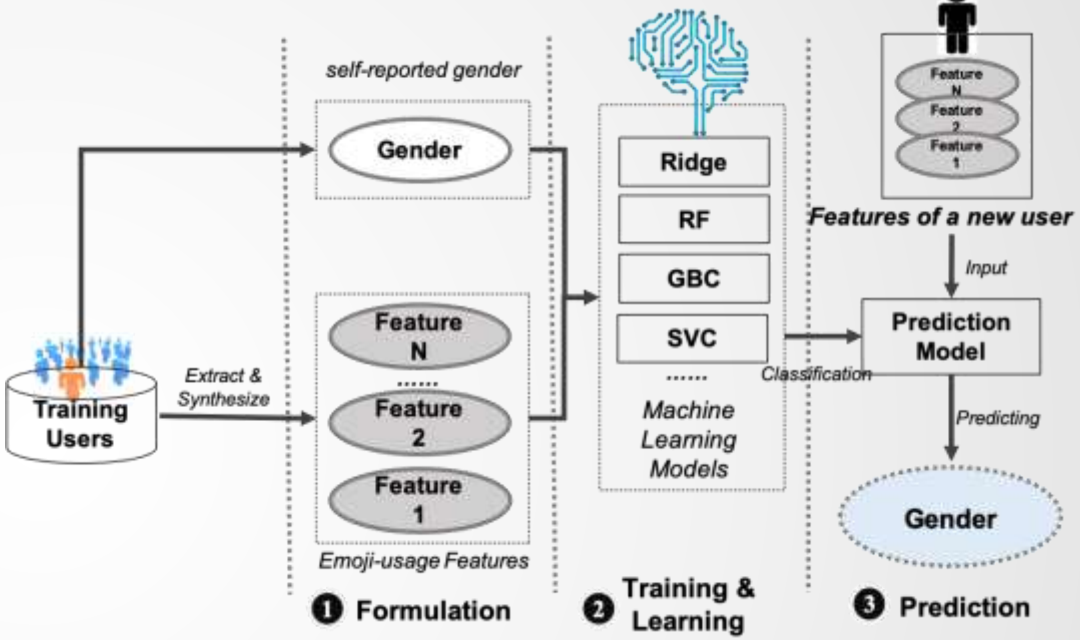
Dataset: 134,419 users, 401 million messages, 183 countries, 58 languages

Emoji Frequency

Emoji Preference

Sentiment Expression

1,370 features from 3 dimensions



Gender inference **purely** based on emoji usage

Model	Metrics		
	Accuracy	Precision_M	Precision_F
Ridge	0.718	0.702	0.721
RF	0.758	0.838	0.743
GBC	0.811	0.775	0.826
SVC	0.741	0.717	0.747
Baseline	0.653	0.347	0.653

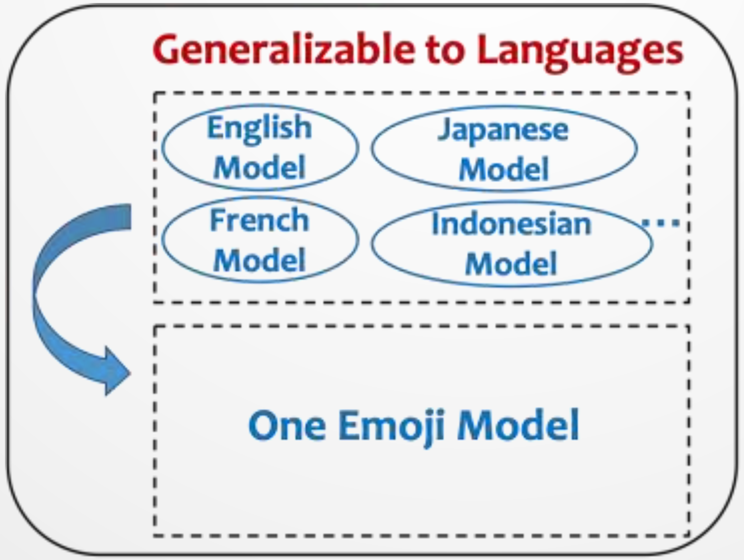
Performance of emoji-based models

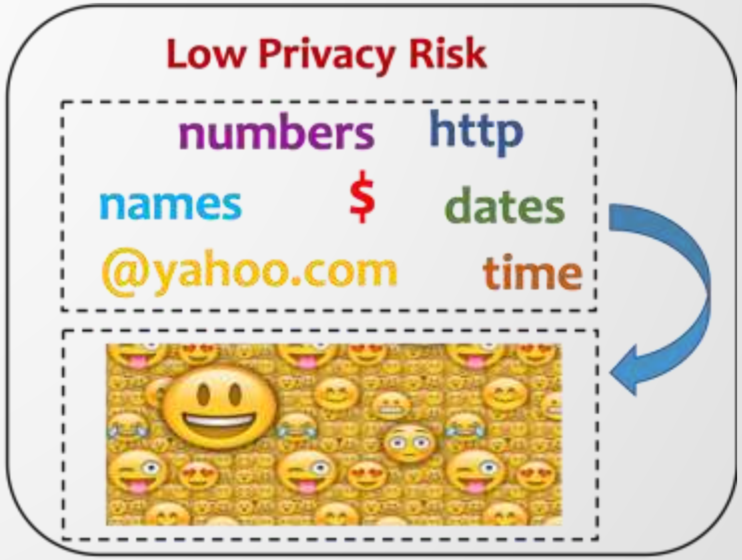
Gender Inference Purely Based on Emoji Usage

Afro-Asiatic	Indo-European	Austronesian	Tai-Kadai
Arabic	Spanish, Portuguese, French, Italian, German	Tagalog, Indonesian, Malay	Thai

Good performance on 10 non-English languages, covering four language families

Two advantages compared to text-based approaches:





Conclusion

- Emojis as a new instrument to understand users
  - Cross-lingual sentiment analysis
  - Gender inference
- Actionable insights for other Web mining applications that also suffer from inequality among languages

Thank you for attention!

现场观众提问请扫码!

认知与结构化知识

丁铭

清华大学

AI TIME PhD第一期

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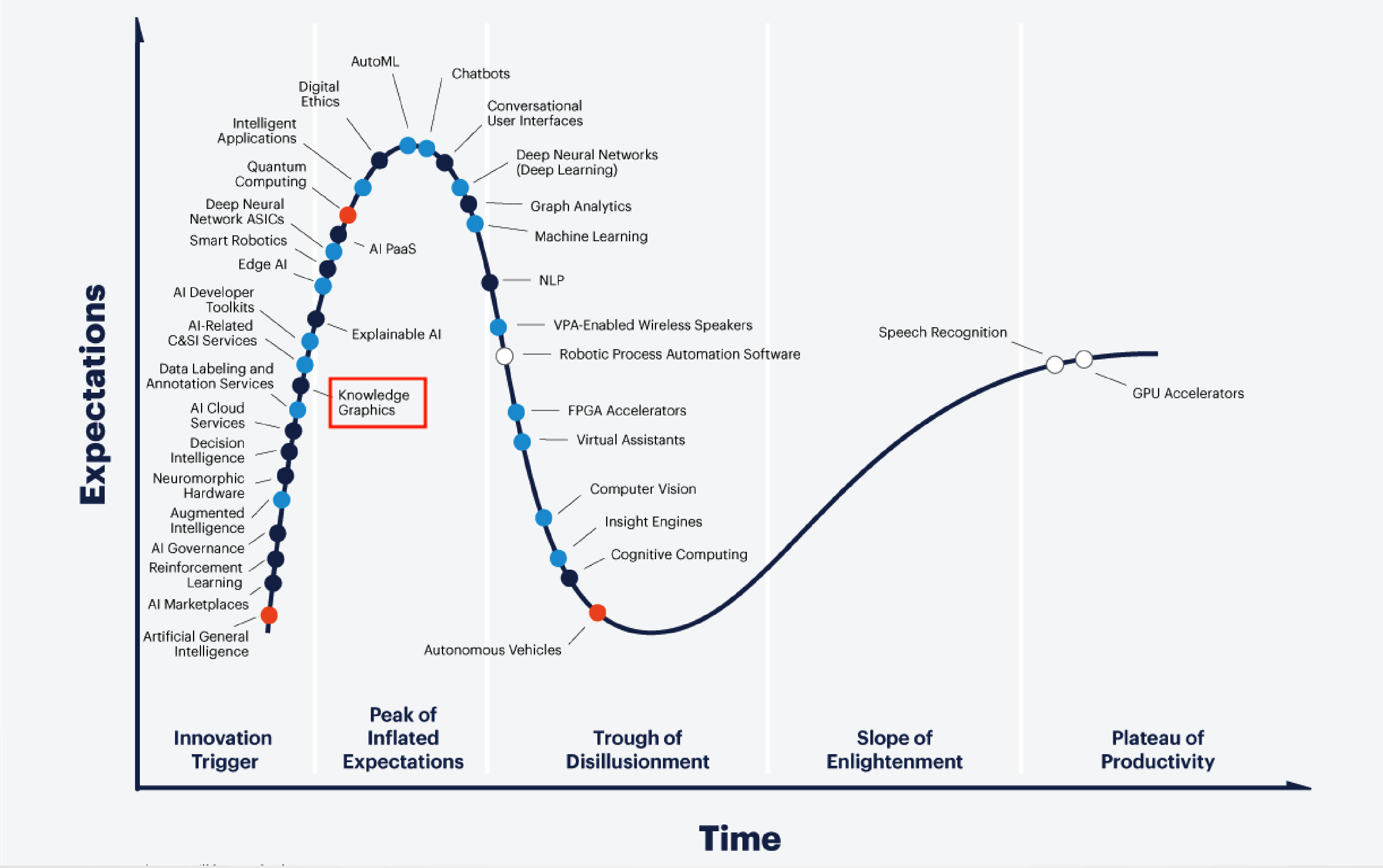
从知识图谱开始

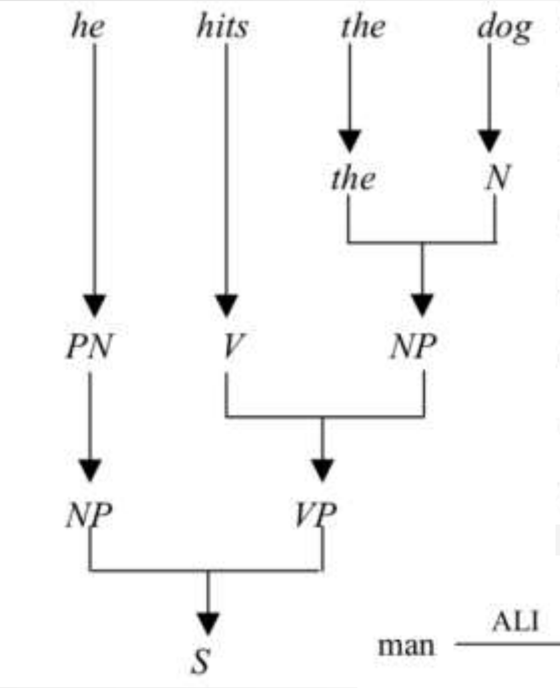
- 结构化知识是实现智能的直观想法
- 1972年，Harary 等人提出conceptual graphs，图中的节点表示概念，边表示其中的关系。
- 1982年，Stokman等人提出类似的概念knowledge graph。
- 大量逻辑推理与专家系统
- ……
- NELL、Google Knowledge Graph、Dbpedia、YAGO……

知识图谱已经发展40年，为什么还是一项新兴技术？

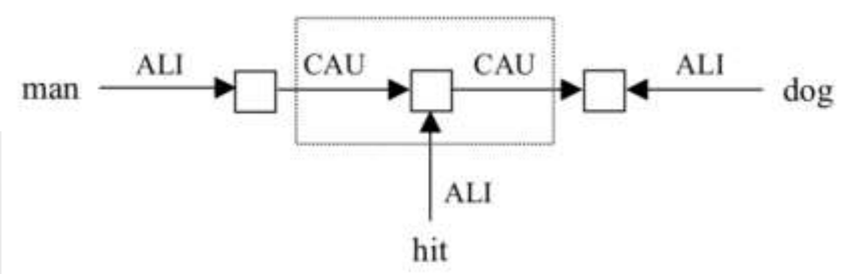


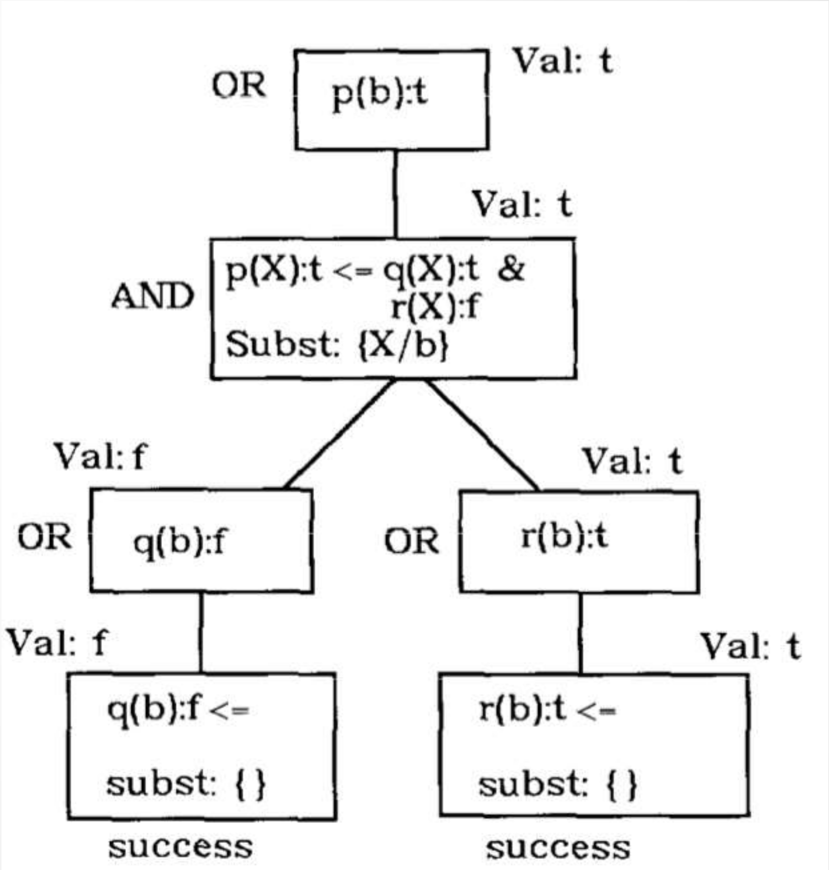
20年前典型的知识图谱研究流程

语义解析 => 正则形式 => 逻辑推理



- Equality : EQU
- Subset relationship : SUB
- Similarity of sets, alikeness : ALI
- Disparateness : DIS
- Causality : CAU
- Ordering : ORD
- Attribution : PAR
- Informational dependency : SKO.





知识表示的进步

- TransE

$$f_r(h,t) = \|\mathbf{h} + \mathbf{r} - \mathbf{t}\|_2^2$$

- 为什么如此简洁的知识嵌入方法是一种进步?
- h与t之间的关系是？h-t紧邻搜索
- 30年前的方法未能意识到机器学习和数据的力量

Dual process theory

- 人的思维由两种不同的系统控制[1][2][3]

- System 1：隐式（自动），无意识的过程
  - 例如阅读时，注意力可以聚焦到关联的相关语段
- System 2：显示（可控），有意识的过程
  - 在工作记忆中进行显式的逻辑推理

[1] Chaiken, Shelly, and Yaacov Trope, eds. *Dual-process theories in social psychology*. Guilford Press, 1999.
[2] Evans, Jonathan St BT. "In two minds: dual-process accounts of reasoning." *Trends in cognitive sciences* 7.10 (2003): 454-459.
[3] Kahneman, Daniel. Thinking, fast and slow. Macmillan, 2011.

- 30年前人们企图通过定义元规则与逻辑推理实现智能
    - 然而……
    - 吾生也有涯，而知也无涯！
    - 缺乏可扩展性
- 现在人们通过机器学习进行模式匹配
    - 非常容易受到对抗样本的影响，鲁棒性差
    - 缺乏可解释性
    - 无法进行复杂推理
- 把这两者结合起来就可以吗？

Yoshua Bengio
October 11 at 3:35 AM

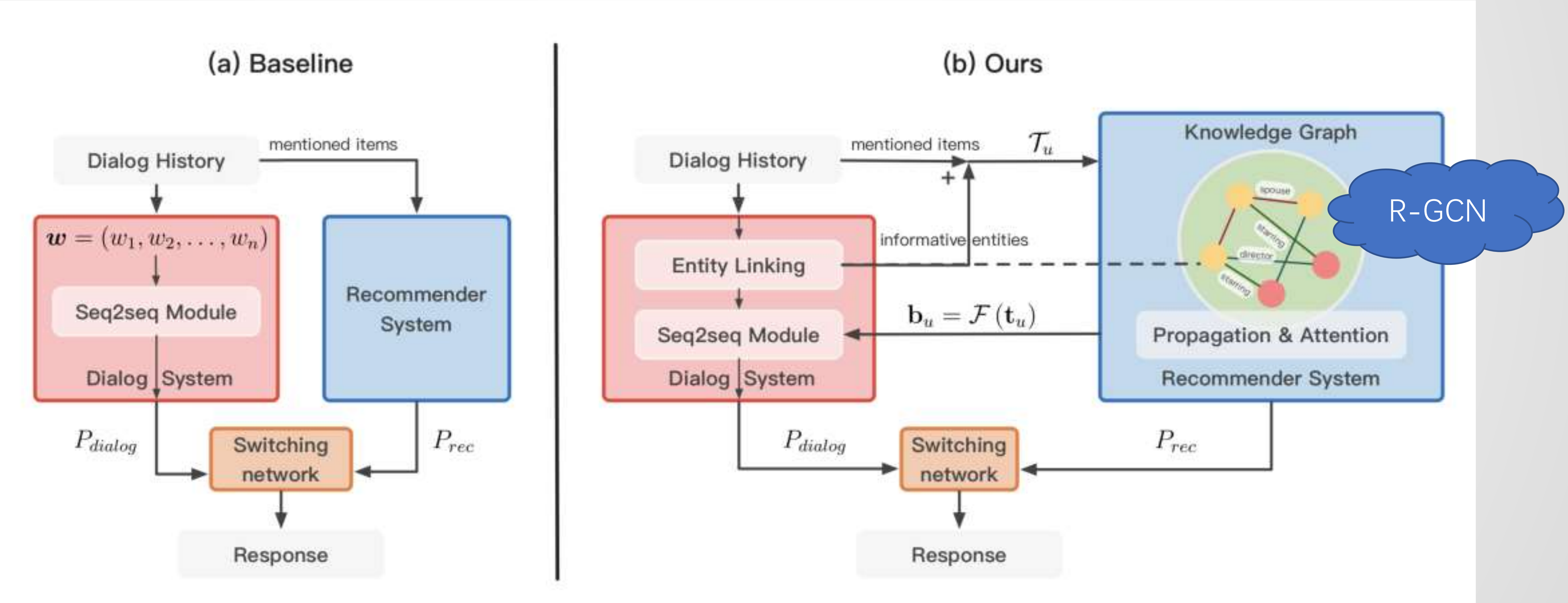
Gary Marcus likes to cite me when I talk about my current research program which studies the weaknesses of current deep learning systems in order to devise systems stronger in higher-level cognition and greater combinatorial (and systematic) generalization, including handling of causality and reasoning. He disagrees with the view that Yann LeCun, Geoff Hinton and I have expressed that neural nets can indeed be a "universal solvent" for incorporating further cognitive abilities in computers. He prefers to think of deep learning as limited to perception and needing to be combined in a hybrid with symbolic processing. I disagree in a subtle way with this view. I agree that the goals of GOFAI (like the ability to perform sequential reasoning characteristic of system 2 cognition) are important, but I believe that they can be performed while staying in a deep learning framework, albeit one which makes heavy use of attention mechanisms (hence my 'consciousness prior' research program) and the injection of new architectural (e.g. modularity) and training framework (e.g. meta-learning and an agent-based view). What I bet is that a simple hybrid in which the output of the deep net are discretized and then passed to a GOFAI symbolic processing system will not work. Why? Many reasons: (1) you need learning in the system 2 component as well as in the system 1 part, (2) you need to represent uncertainty there as well (3) brute-force search (the main inference tool of symbol-processing systems) does not scale, instead humans use unconscious (system 1) processing to guide the search involved in reasoning, so system 1 and system 2 are very tightly integrated and (4) your brain is a neural net all the way ;-)

如何从深度学习角度利用知识图谱

- 以对话推荐任务为例
- Towards Knowledge-Based Recommender Dialog System
- EMNLP 2019

USER:	Hello!
RECOMMENDER:	What kind of movies do you like?
USER:	I am looking for a movie recommendation. When I was younger I really enjoyed the *A Nightmare on Elm Street (1984)*.
BASELINE:	Have you seen *It (2017)*?
OURS:	I like horror movies too! Have your seen *Halloween (1978)* ?
HUMAN:	Oh, you like scary movies? I recently watched *Happy Death Day (2017)*.

KBRD



(a) Baseline
Dialog History
mentioned items
$\boldsymbol{w} = (w_1, w_2, \ldots, w_n)$
Seq2seq Module
Dialog System
Recommender System
P_{dialog}
P_{rec}
Switching network
Response
(b) Ours
Dialog History
mentioned items
$\mathcal{T}_u$
+
informative entities
Entity Linking
Seq2seq Module
Dialog System
$\mathbf{b}_u = \mathcal{F}(\mathbf{t}_u)$
Knowledge Graph
Propagation & Attention
Recommender System
P_{dialog}
P_{rec}
Switching network
Response
R-GCN

从知识图谱中获取的知识会导致怎样的文本生成?

Movie	1	2	3	4	5	6	7	8
Star Wars	space	alien	sci-fi	star	sci	robot	smith	harry
The Shining	creepy	stephen	gory	horror	scary	psychological	haunted	thriller
The Avengers (2012)	marvel	superhero	super	dc	wait	batman	thor	take
Beauty and the Beast	cute	disney	animated	live	music	child	robin	kids

Model	R@1	R@10	R@50
REDIAL	2.3±0.2	12.9±0.7	28.7±0.9
KBRD (D)	2.7±0.2	14.0±0.6	30.6±0.7
KBRD (K)	2.6±0.2	14.4±0.9	31.0±1.2
KBRD	**3.0**±0.2	**16.3**±0.3	**33.8**±0.7

Model	PPL	Dist-3	Dist-4	CSTC
REDIAL	28.1	0.11	0.13	1.73
Transformer	18.0	0.27	0.39	-
KBRD	**17.9**	**0.30**	**0.45**	**1.99**

反思知识图谱的融合

- 作为外部信息，知识图谱无疑提供了许多知识，但是对于抽取知识图谱的源数据，许多信息被遗漏了，许多与当前目标无关的信息被保留了。

- Data processing inequality
- 如果X->Y->Z是马尔科夫链，那么I(Y;X)>=I(Z;X)
- 对于“语义->文本->知识图谱”，要推测语义可以回到文本

- 现在我们对于语言建模能力大大增强，显式关系提取也许不再那么重要。

开领域多跳（阅读理解）问答

Question: Who is the director of the 2003 film which has scenes in it filmed at the Quality Cafe in Los Angeles?

Quality Café

The Quality Cafe is a now-defunct diner in Los Angeles, California. The restaurant has appeared as a location featured in a number of Hollywood films, including Old School, Gone in 60 Seconds, ...

Los Angeles

Los Angeles is the most populous city in California, the second most populous city in the United States, after New York City, and the third most populous city in North America.

Alessandro Moschitti

Alessandro Moschitti is a professor of the CS Department of the University of Trento, Italy. He is currently a Principal Research Scientist of the Qatar Computing Research Institute (QCRI)

WIKIPEDIA
The Free Encyclopedia

Old School

Old School is a 2003 American comedy film released by Dream Works Pictures and The Montecito Picture Company and directed by Todd Phillips.

Todd Phillips

Todd Phillips is an American director, producer, screenwriter, and actor. He is best known for writing and directing films, including Road Trip (2000), Old School (2003), Starsky & Hutch (2004), and The Hangover Trilogy.

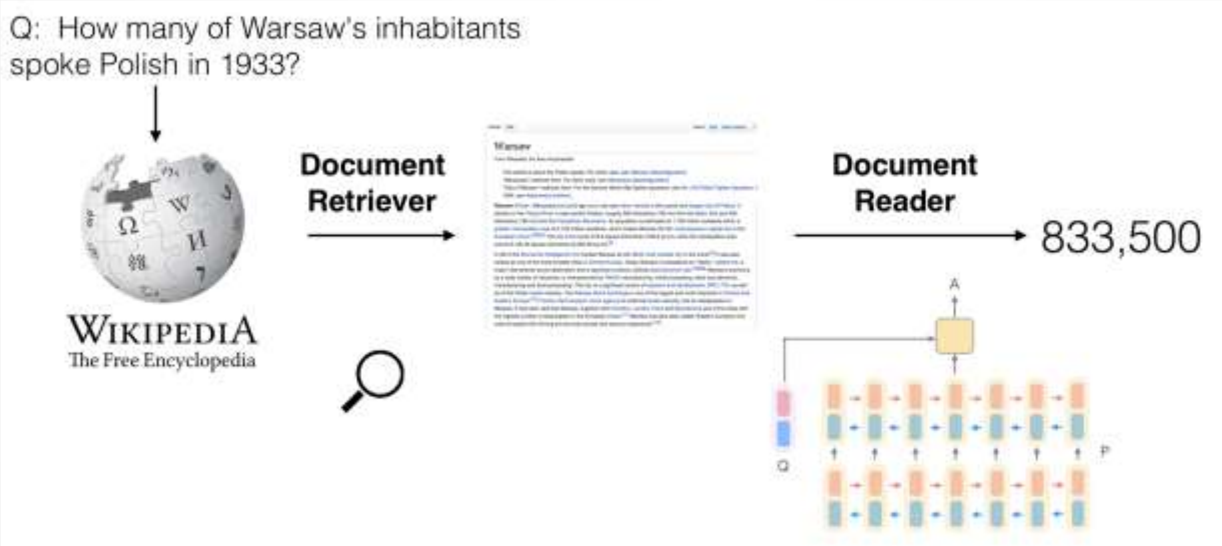
Tsinghua University

Tsinghua University is a major research university in Beijing and dedicated to academic excellence and global development. Tsinghua is perennially ranked as one of the top academic institutions in China, Asia, and worldwide...

DrQA框架

DrQA [1]提出了一种两阶段的方法。以维基百科为文本库为例:

- 文档检索:
  - 给定任意问题，检索出5个最相关的文档。
  - 这里可以使用倒排列表和tf-idf排序等传统技术。
- 阅读理解:
  - 使用深度学习的手段从文本段中抽取问题的答案，通常是文中连续的一段。



当对于复杂的多跳问题，使用知识图谱可以容易解决，但是使用阅读理解的方法有诸多障碍。

[1] Chen, Danqi, et al. "Reading wikipedia to answer open-domain questions." *arXiv preprint arXiv:1704.00051* (2017).

短视检索

Question: Who is the director of the 2003 film which has scenes in it filmed at the Quality Cafe in Los Angeles?

Document A

Old School is a 2003 American comedy film released by DreamWorks Pictures and The Montecito Picture Company…

Document B

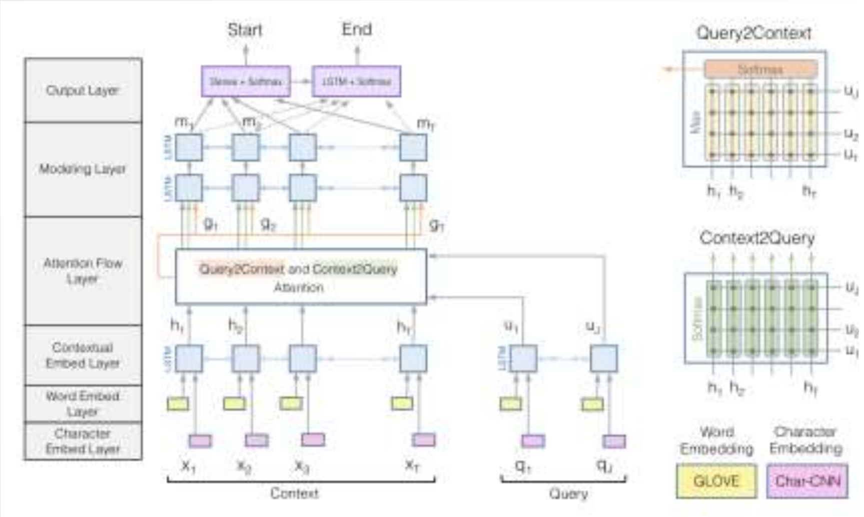
Many directors shoot scenes in Hollywood, Los Angeles, which is notable as the home of the U.S. film industry.

可是，在多跳问答中，若干跳之外的文档可能与问题有很少的共同字词——甚至意思也相去甚远；一旦第一步的检索失败，第二步的阅读理解再好也无力回天。

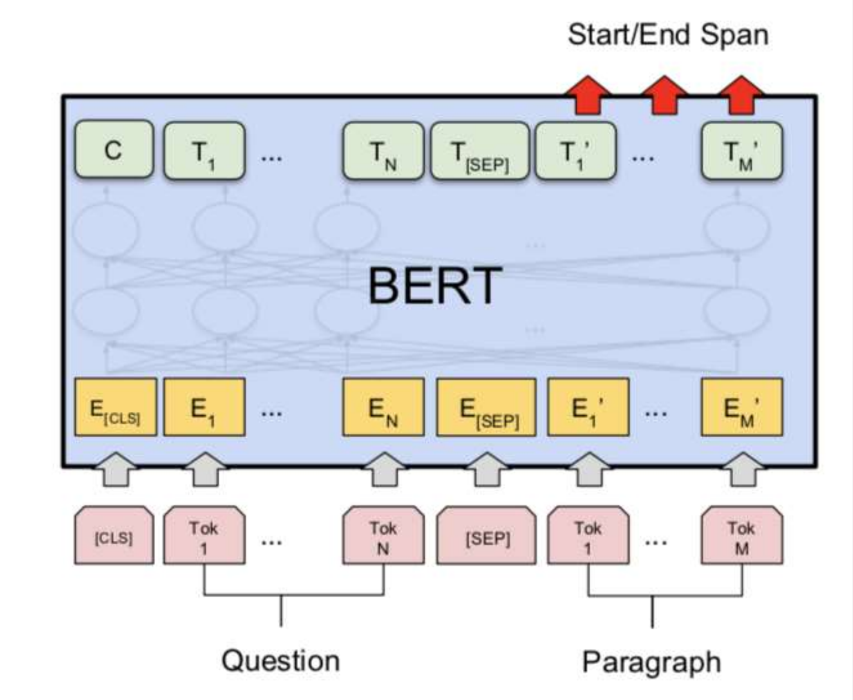
传统的阅读理解模型

- 单文档的阅读理解模型（如SQuAD上）

BiDAF



BERT



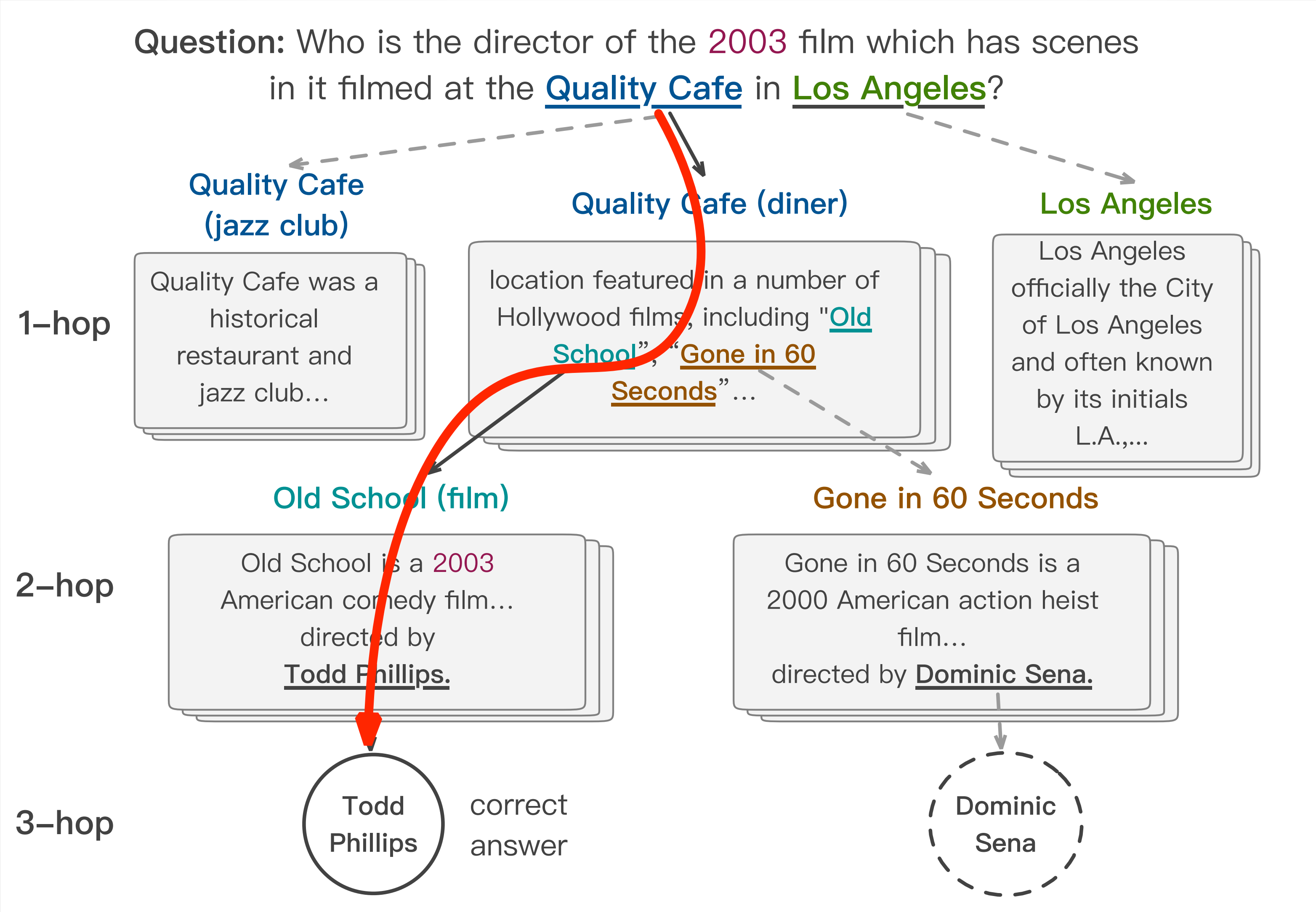
[1] Rajpurkar, Pranav, et al. "SQuAD: 100,000+ Questions for Machine Comprehension of Text." *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*. 2016.

Challenge 2: Explainability

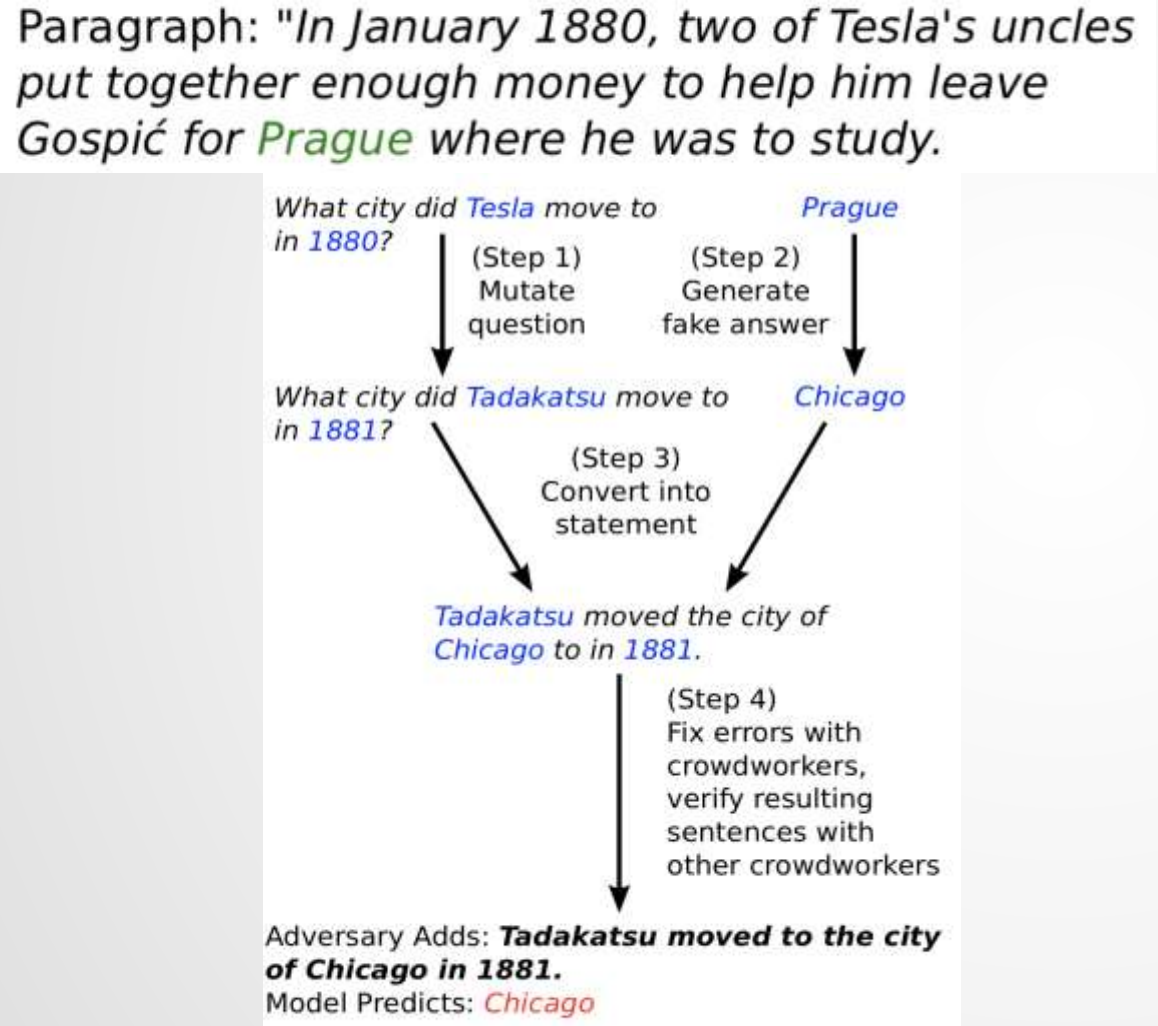
- 大多数阅读理解模型是黑盒的:
  - 输入：文本段和问题
  - 输出：答案的在文本中的（起始和结束）位置
- We 对于机器的回答，我们通常需要能够验证对错:
  - 推理的路径（或子图）
  - 每一跳的证据句子
  - 推理路径的其他可能答案以用来比较

- 最直观的方法是模仿人类解决问题的过程构建认知图谱!

Cognitive Graph



Related work: Adversarial Questions

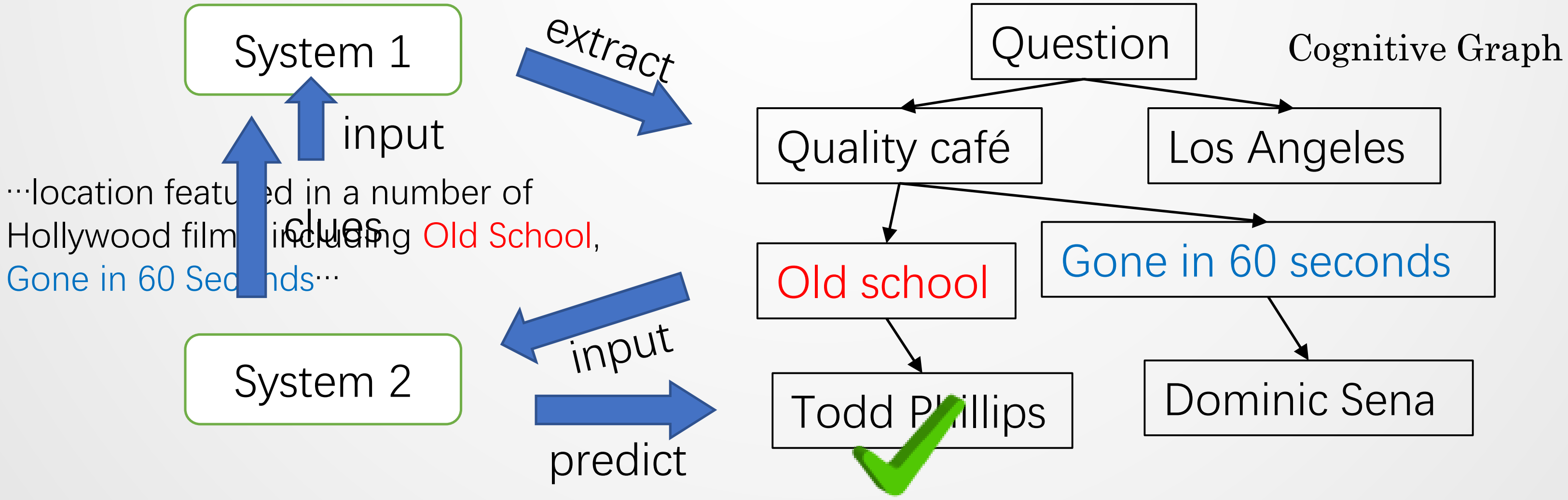


- 对抗样本测试[1]揭示了现有的阅读理解模型更多的是一种高级的匹配，缺乏鲁棒性。稍加干扰就会犯错。
- 缺乏鲁棒性的关键在于缺少System 2中的显式推理。

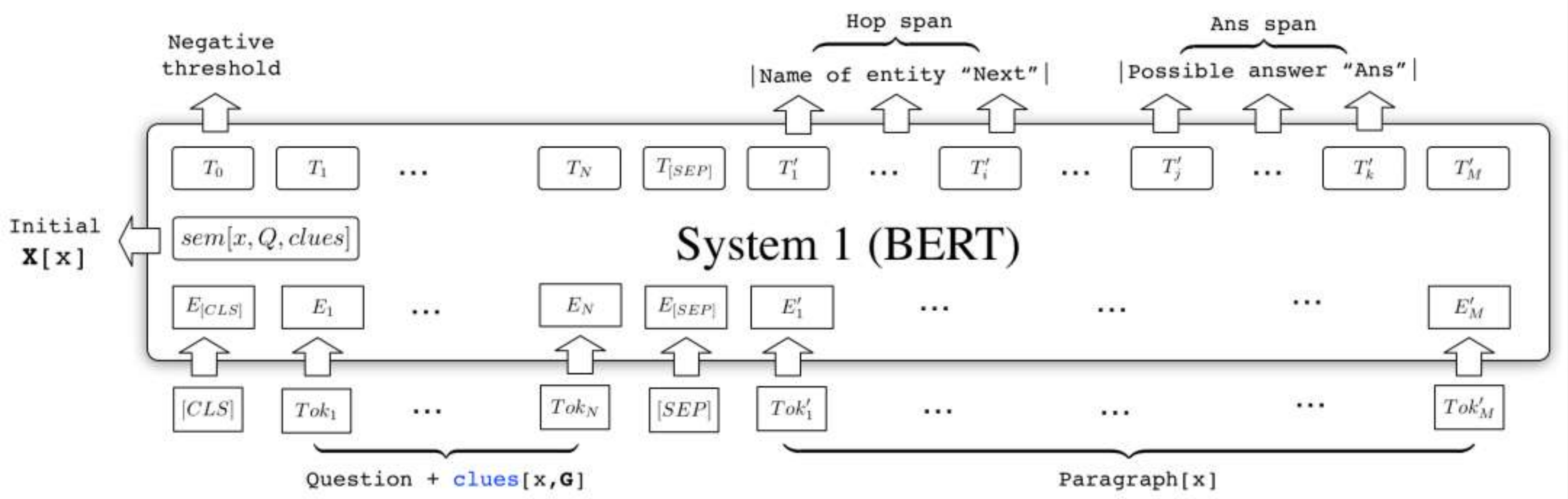
[1] Jia, Robin, and Percy Liang. "Adversarial examples for evaluating reading comprehension systems." *arXiv preprint arXiv:1707.07328* (2017).

CogQA 框架

- 基于dual process theory 的迭代式框架
- System 1 模型
  - 抽取有用的实体构建认知图谱
  - 为每个节点根据上下文生成语义向量
- System 2 模型
  - 基于语义向量和图结构进行推理（计算隐表示）
  - 计算有用的线索，来指导System 1抽取下一跳实体

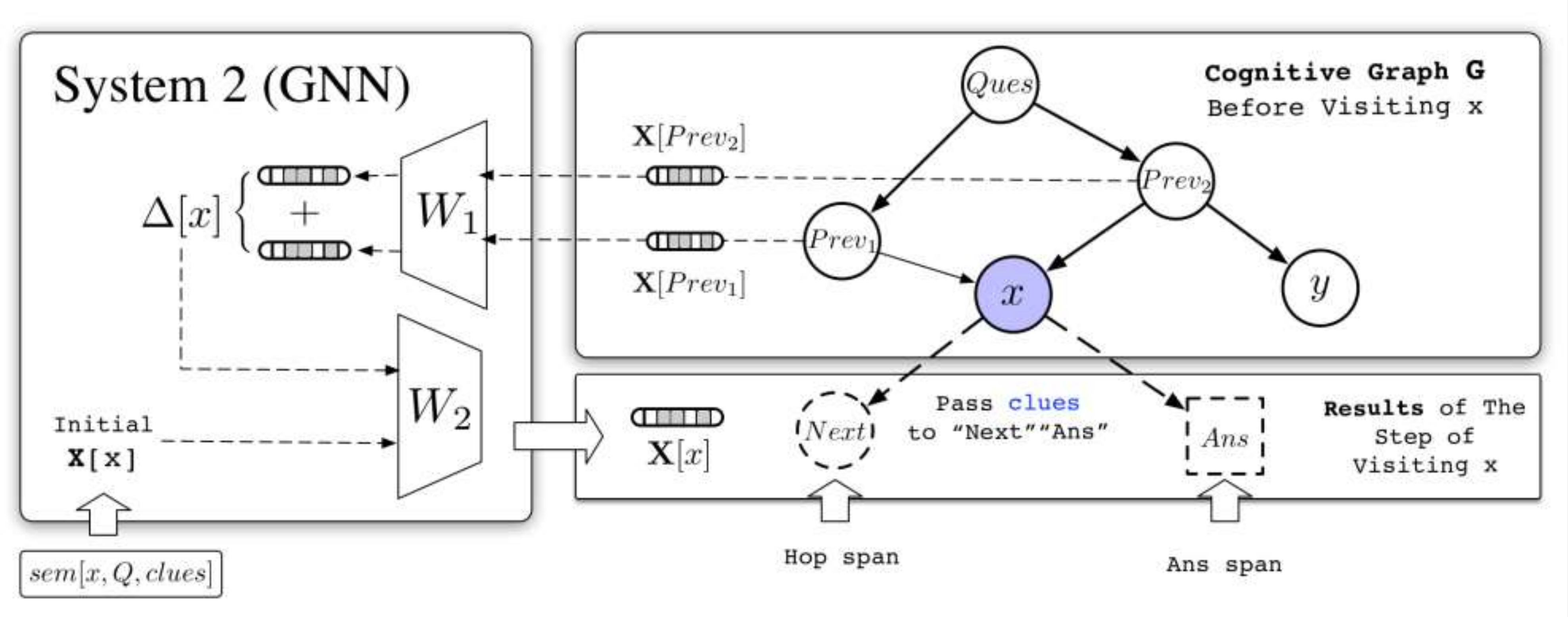


System 1: the BERT Implementation



- 分别抽取top-k 的下一跳实体和答案候选
  - 预测每个位置是下一跳实体或者答案候选的开头或结尾的概率
- 基于文本对每个实体生成语义向量
- 将第0位置的开头概率视为负阈值
  - 忽略所有开头概率小于负阈值的文本段（span）
  - 这是为了识别不相关的语段来停止迭代

System 2: the GNN implementation



每一步，节点的隐表示$\mathbf{X}$ 根据如下的GNN传播公式更新：

$$\Delta = \sigma((AD^{-1})^T \sigma(\mathbf{X}W_1))$$
$$\mathbf{X}' = \sigma(\mathbf{X}W_2 + \Delta)$$

预测器 $\mathcal{F}$ is是一个两层的全连接，它根据隐表示$\mathbf{X}$ 来预测最终结果：

$$answer = \underset{\text{answer node } x}{\arg\max} \ \mathcal{F}(\mathbf{X}[x])$$

CogQA 算法与训练

Algorithm 1: Cognitive Graph QA

Input:
System 1 model $\mathcal{S}_1$, System 2 model $\mathcal{S}_2$,
Question Q, Predictor $\mathcal{F}$,Wiki Database $\mathcal{W}$

Initialize cognitive graph $\mathcal{G}$ with entities mentioned in Q and mark them *frontier nodes*
repeat
  pop a node x from frontier nodes
  collect $clues[x, \mathcal{G}]$ from predecessor nodes of x
  // eg. $clues$ can be sentences where x is mentioned
  fetch $para[x]$ in $\mathcal{W}$ if any
  generate $sem[x, Q, clues]$ with $\mathcal{S}_1$ // initial $\mathbf{X}[x]$
  if *x is a hop node* **then**
    find hop and answer spans in $para[x]$ with $\mathcal{S}_1$
    for *y in hop spans* **do**
      if *$y \notin \mathcal{G}$ and $y \in \mathcal{W}$* **then**
        create a new hop node for y
      if *$y \in \mathcal{G}$ and $edge(x, y) \notin \mathcal{G}$* **then**
        add edge (x, y) to $\mathcal{G}$
        mark node y as a frontier node
    end
    for *y in answer spans* **do**
      add new answer node y and edge (x, y) to $\mathcal{G}$
    end
  end
  update hidden representation $\mathbf{X}$ with $\mathcal{S}_2$
until *there is no frontier node in $\mathcal{G}$ or $\mathcal{G}$ is large enough*;
Return $\underset{\text{answer node } x}{\arg\max}\ \mathcal{F}(\mathbf{X}[x])$

- 预处理
  - 通过模糊匹配找到训练集中下一跳实体的标准位置
  - 真正的认知图+ 负（下一跳或者答案候选）节点，并训练模型区分它们。
- 训练任务#1 (System 1):
  - 下一跳和答案文段的抽取
- 训练任务#2 (System 1 & 2):
  - 图卷积和答案预测

实验效果

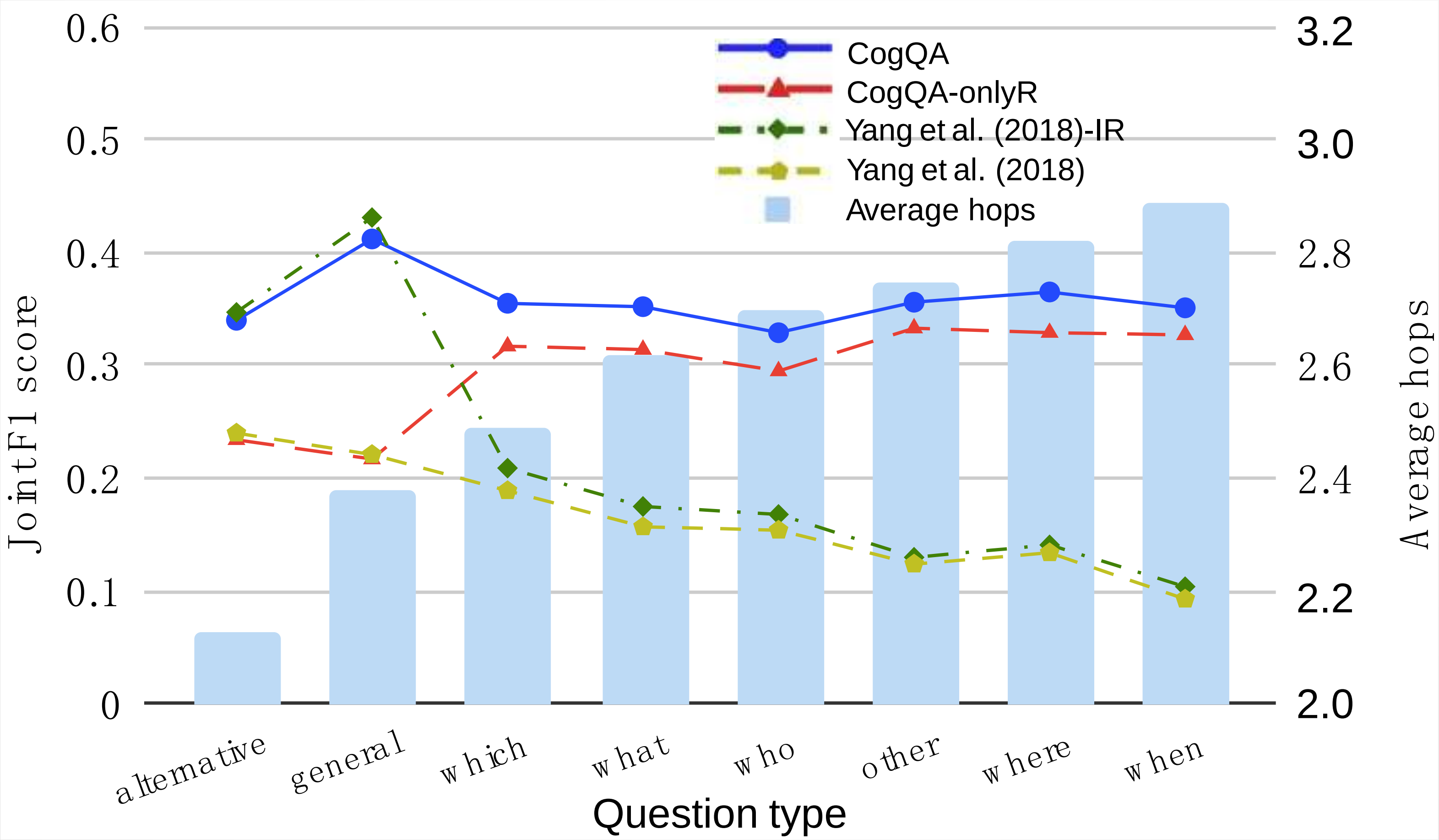
- HotpotQA 是一个类似于SQuAD的拥有leaderboard的数据集
- CogQA ranked 1st from 21, Feb to 15, May (nearly 3 months)
- Joint F_1 from 16.2 (previous work) to 34.9 (CogQA)!

	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**	-	-

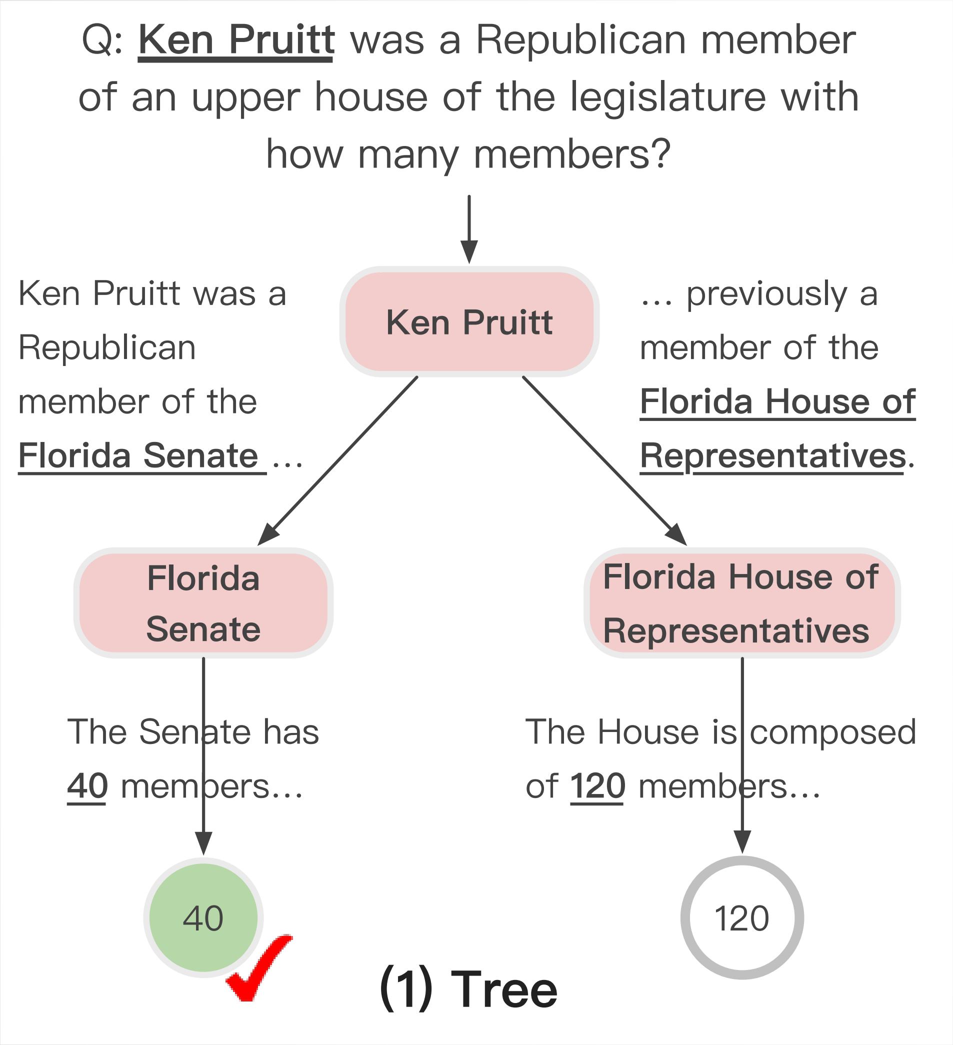
Table 1: Results on HotpotQA (fullwiki setting). The test set is not public. The maintainer of HotpotQA only offers EM and F_1 for every submission. N/A means the model cannot find supporting facts.

Analysis

CogQA 在跳数更多的问题上表现更好!

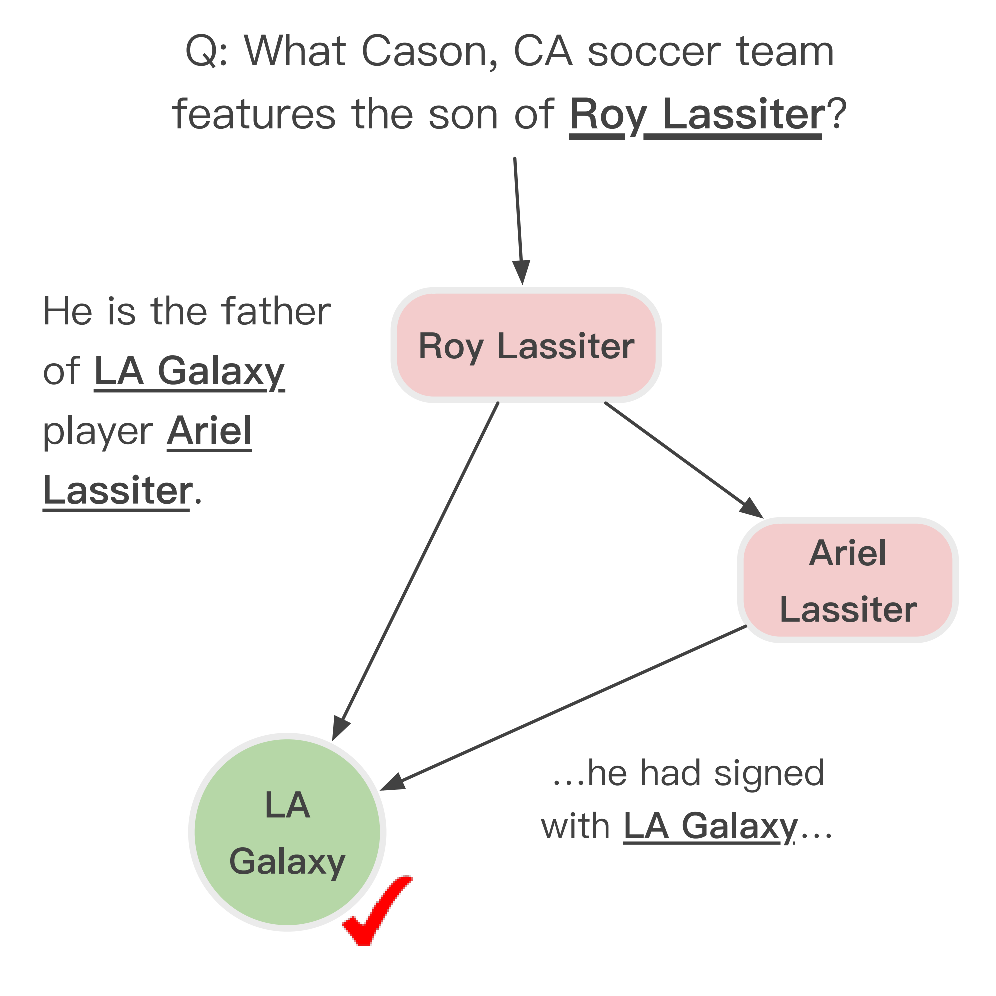


Case Study



- 树状认知图
- 用户可以通过比较推理链条上的其他
- 问题中Ken任职的“*Upper House*”（上院）类似于“*Senate*”（参议院）而不是“*House of Representative*”（众议院，下院）

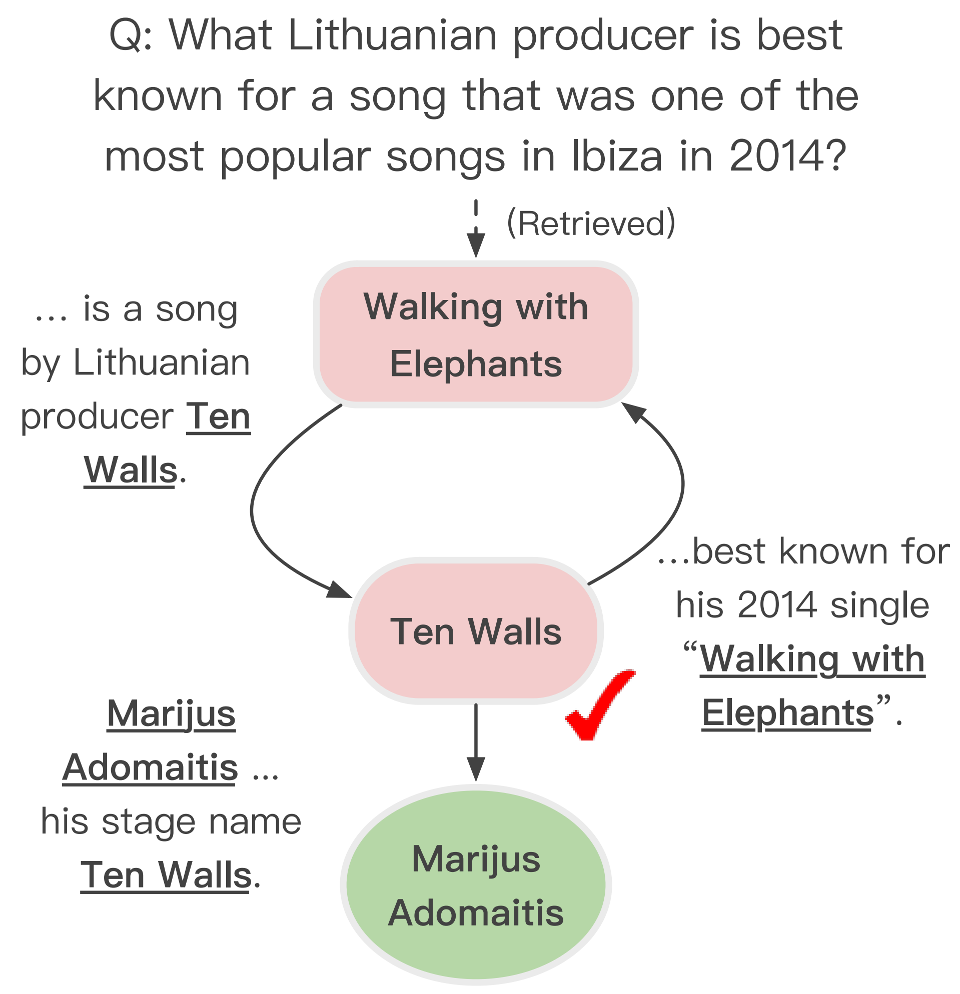
Case Study



(2) DAG

- 有向无环图
- 当多跳路径指向同一答案的时候，提供了更多信息，增强了答案的可信度。

Case Study



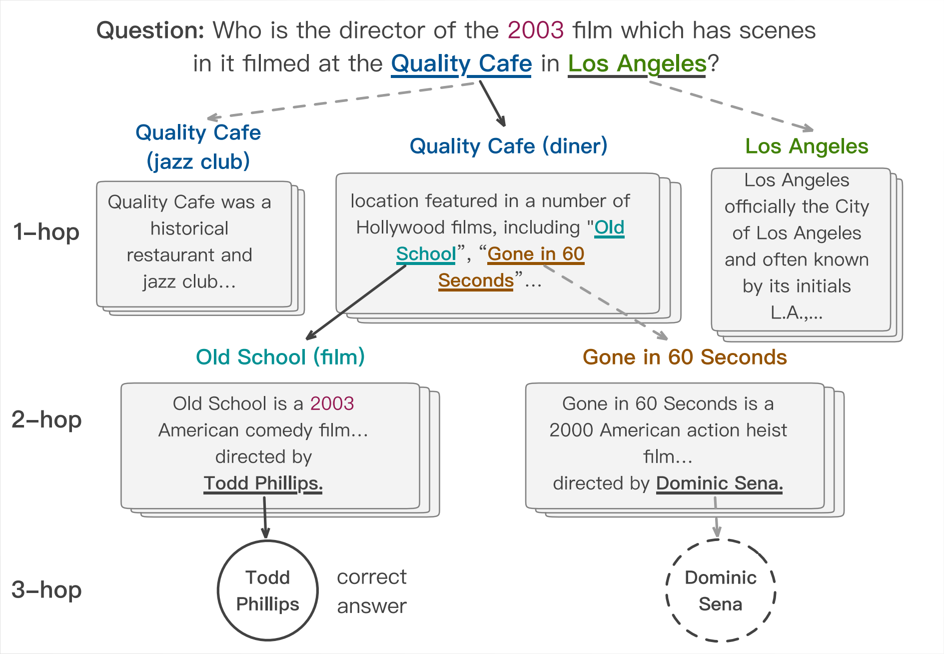
(3) Cyclic Graph

- 这个例子中，我们的算法给出答案“Marijus Adomaitis”，然而标准答案是“Ten Walls”。
- 通过我们检查认知图，我们发现Ten Walls只是Adomaitis的艺名!
- 以前的黑盒模型不允许我们回溯寻找出错原因。

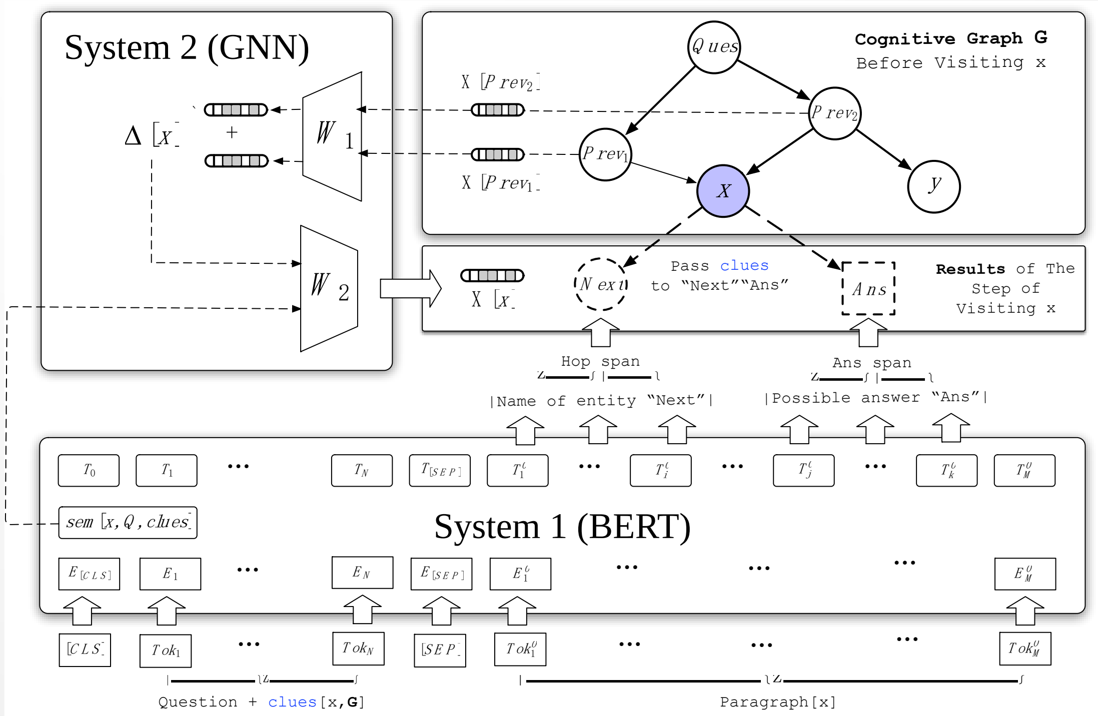
Summary of CogQA

- Iterative Framework --> Myopic Retrieval
- Cognitive Graph --> Explainability
- Dual process theory --> System 2 Reasoning

Cognitive graph



CogQA framework



讨论与未来

- 任何知识图谱的边A->Relation->B，都可由QA实例 [what is the xxx of A?] [the document about A&B] 和阅读理解模型代替。
- 弱点：如何对进行检索和跳转?
- 潜力：实际上文本更有检索的潜力，并且不损失信息。同时像CogQA中通过上下文预测跳转更加有效。

- 弱点：难以建立严密逻辑
  - 阅读过程中的理解，对检索的支持，端到端优化
  - 关系和概念的隐式表示
  - 更高层次的结构化推理

Q&A

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