知识表示与获取

——博士的成长之路：大体系与小合作

清华大学　韩 旭

庞大的科研体系——方向多

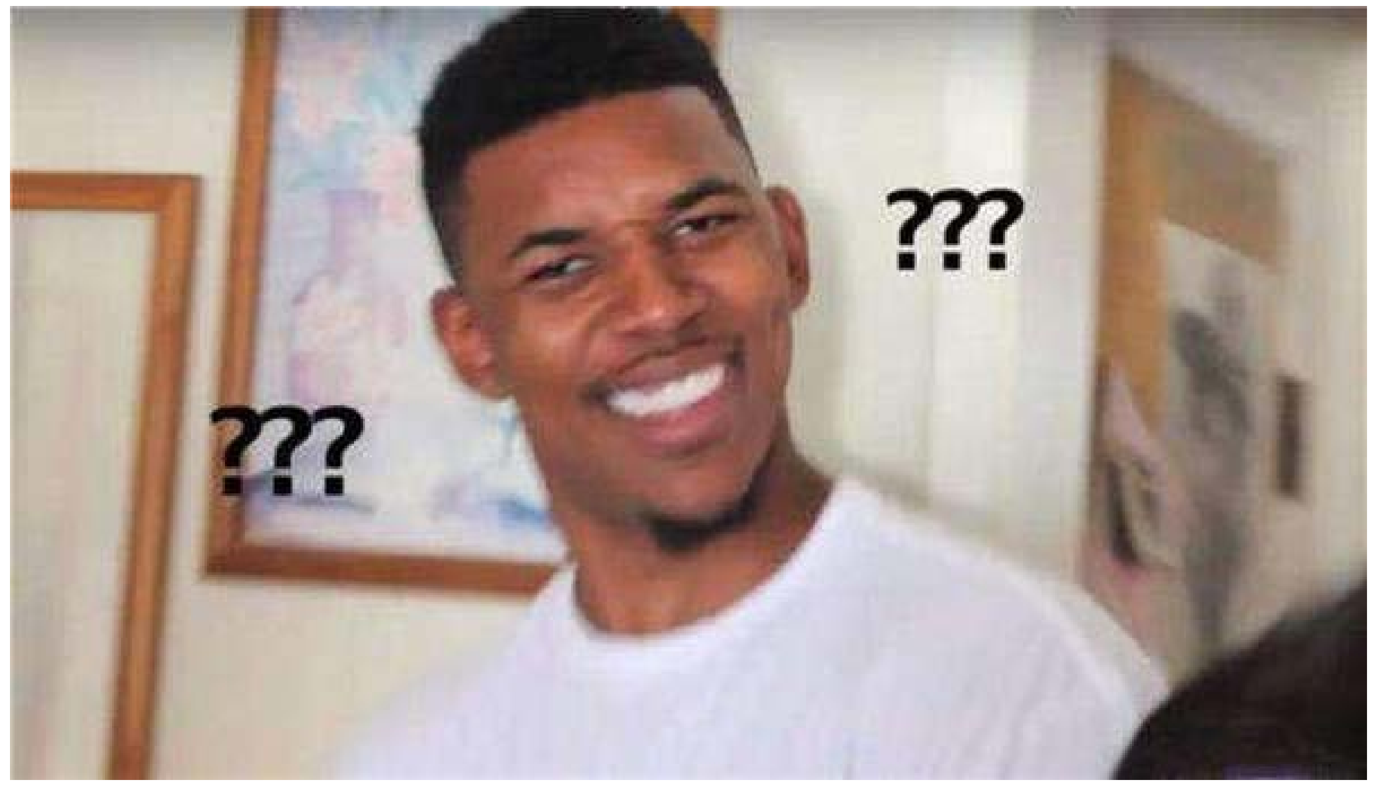
组里的各研究方向

知识计算

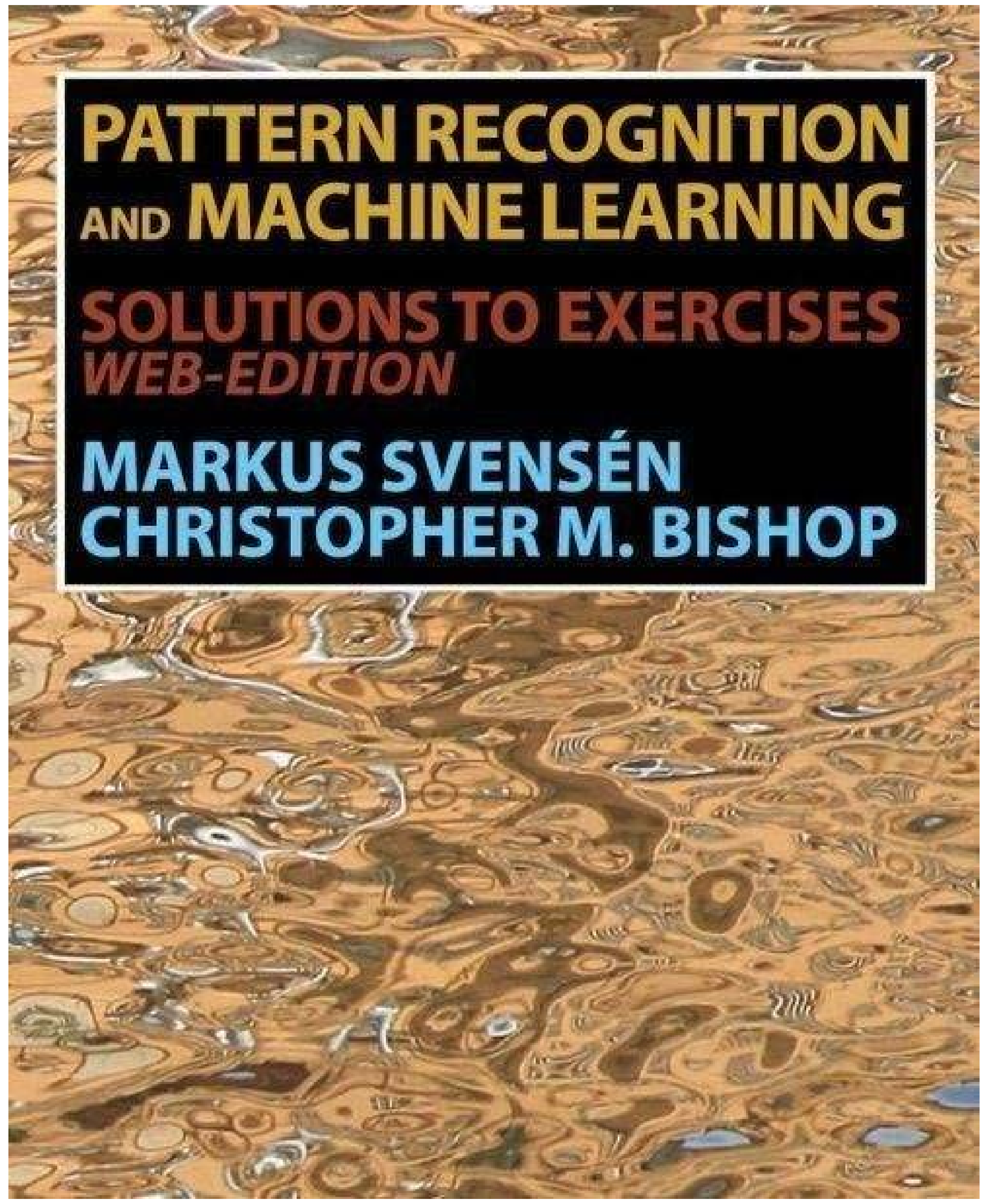
社会计算

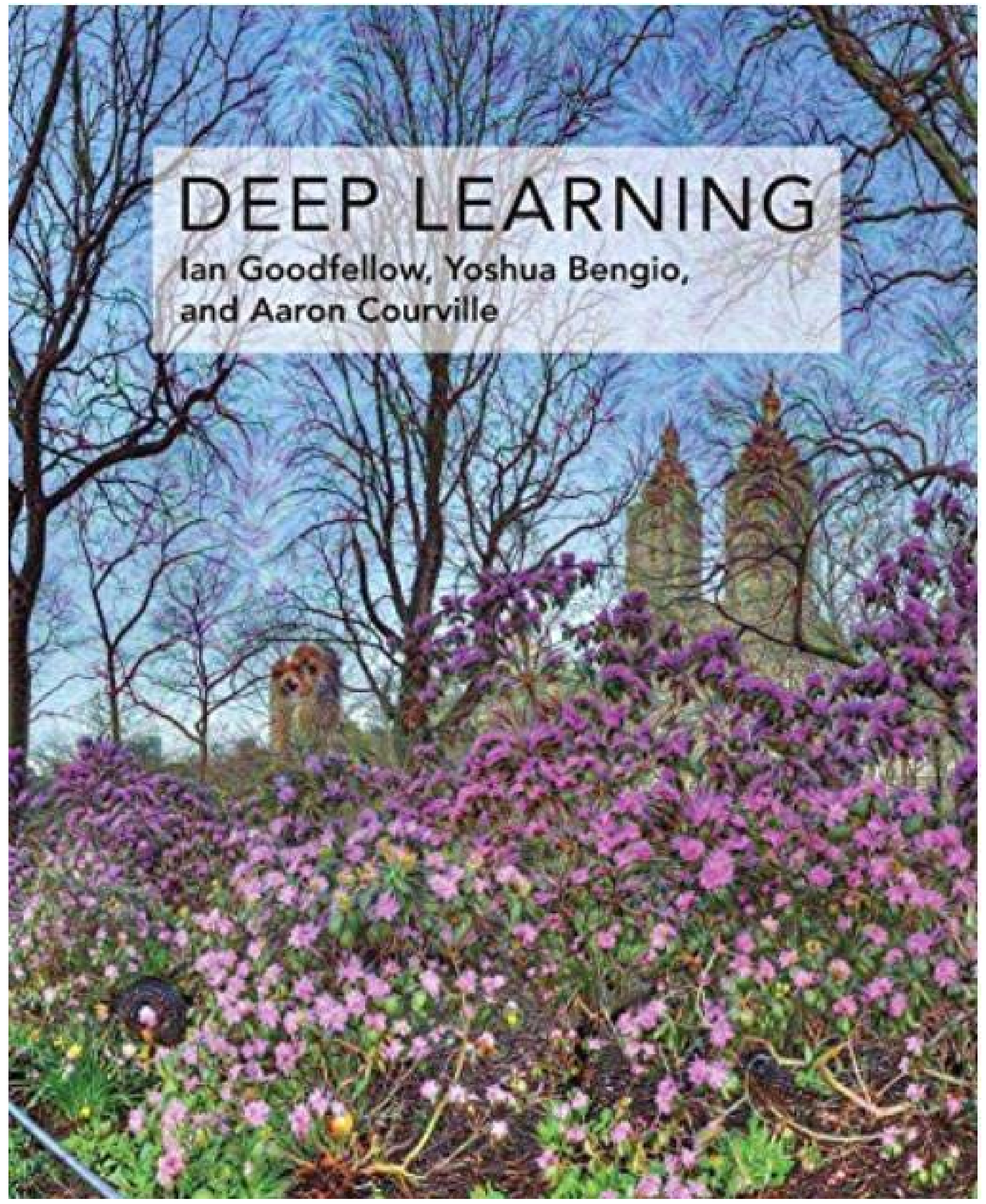
语义计算

我的认知



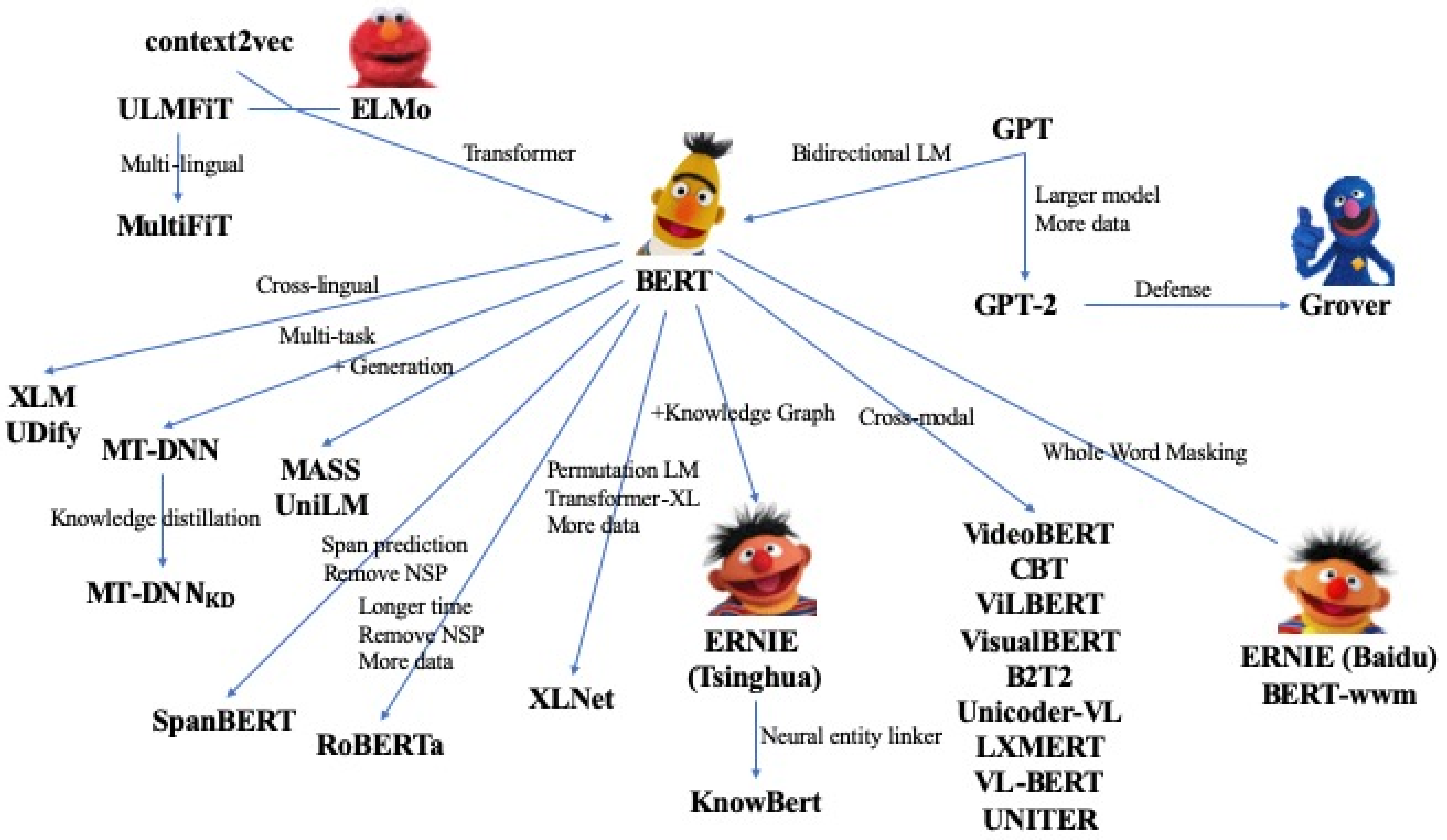
庞大的科研体系——文献厚





1. **context2vec:Learning Generic Context Embedding with Bidirectional LSTM**. *Oren Melamud, Jacob Goldberger, Ido Dagan*. CoNLL 2016. [pdf] [project] (**context2vec**)
2. **Deep contextualized word representations**. *Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee and Luke Zettlemoyer*. NAACL 2018. [pdf] [project] (**ELMo**)
3. **Universal Language Model Fine-tuning for Text Classification**. *Jeremy Howard and Sebastian Ruder*. ACL 2018. [pdf] [project] (**ULMFiT**)
4. **Improving Language Understanding by Generative Pre-Training**. *Alec Radford, Karthik Narasimhan, Tim Salimans and Ilya Sutskever*. Preprint. [pdf] [project] (**GPT**)
5. **BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**. *Jacob Devlin, Ming-Wei Chang, Kenton Lee and Kristina Toutanova*. NAACL 2019. [pdf] [code & model]
6. **Language Models are Unsupervised Multitask Learners**. *Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei and Ilya Sutskever*. Preprint. [pdf] [code] (**GPT-2**)
7. **ERNIE: Enhanced Language Representation with Informative Entities**. *Zhengyan Zhang, Xu Han, Zhiyuan Liu, Xin Jiang, Maosong Sun and Qun Liu*. ACL2019. [pdf] [code & model] (**ERNIE (Tsinghua)**)
8. **ERNIE: Enhanced Representation through Knowledge Integration**. *Yu Sun, Shuohuan Wang, Yukun Li, Shikun Feng, Xuyi Chen, Han Zhang, Xin Tian, Danxiang Zhu, Hao Tian and Hua Wu*. Preprint. [pdf] [code] (**ERNIE (Baidu)**)
9. **Defending Against Neural Fake News**. *Rowan Zellers, Ari Holtzman, Hannah Rashkin, Yonatan Bisk, Ali Farhadi, Franziska Roesner, Yejin Choi*. NeurIPS. [pdf] [project] (**Grover**)
10. **Cross-lingual Language Model Pretraining**. *Guillaume Lample, Alexis Conneau*. NeurIPS2019. [pdf] [code & model] (**XLM**)
11. **Multi-Task Deep Neural Networks for Natural Language Understanding**. *Xiaodong Liu, Pengcheng He, Weizhu Chen, Jianfeng Gao*. ACL2019. [pdf] [code & model] (**MT-DNN**)
12. **MASS: Masked Sequence to Sequence Pre-training for Language Generation**. *Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, Tie-Yan Liu*. ICML2019. [pdf] [code & model]
13. **Unified Language Model Pre-training for Natural Language Understanding and Generation**. *Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, Hsiao-Wuen Hon*. Preprint. [pdf] (**UniLM**)
14. **XLNet: Generalized Autoregressive Pretraining for Language Understanding**. *Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, Quoc V. Le*. NeurIPS2019. [pdf] [code & model]

庞大的科研体系——联系杂



By Xiaozhi Wang & Zhengyan Zhang @THUNLP

庞大的科研体系——迭代快

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Sep 18, 2019	ALBERT (ensemble model) *Google Research & TTIC* https://arxiv.org/abs/1909.11942	**89.731**	**92.215**
2 Jul 22, 2019	XLNet + DAAF + Verifier (ensemble) *PINGAN Omni-Sinitic*	88.592	90.859
2 Sep 16, 2019	ALBERT (single model) *Google Research & TTIC* https://arxiv.org/abs/1909.11942	88.107	90.902
2 Jul 26, 2019	UPM (ensemble) *Anonymous*	88.231	90.713
3 Aug 04, 2019	XLNet + SG-Net Verifier (ensemble) *Shanghai Jiao Tong University & CloudWalk* https://arxiv.org/abs/1908.05147	88.174	90.702
4 Aug 04, 2019	XLNet + SG-Net Verifier++ (single model) *Shanghai Jiao Tong University & CloudWalk* https://arxiv.org/abs/1908.05147	87.238	90.071
5 Jul 26, 2019	UPM (single model) *Anonymous*	87.193	89.934
6 Mar 20, 2019	BERT + DAE + AoA (ensemble) *Joint Laboratory of HIT and iFLYTEK Research*	87.147	89.474
6 Jul 20, 2019	RoBERTa (single model) *Facebook AI*	86.820	89.795

	Model	Code	Ans		Sup		Joint	
			EM	F_1	EM	F_1	EM	F_1
1 Sep 27, 2019	HGN (single model) *Microsoft Dynamics 365 AI Research*		66.07	79.36	**60.33**	**87.33**	**43.57**	**71.03**
2 Jul 29, 2019	TAP 2 (ensemble)		**66.64**	**79.82**	57.21	86.69	41.21	70.65
3 Oct 1, 2019	EPS + BERT(wwm) (single model) *Anonymous*		65.79	79.05	58.50	86.26	42.47	70.48
4 Jul 29, 2019	TAP 2 (single model)		64.99	78.59	55.47	85.57	39.77	69.12
5 May 31, 2019	EPS + BERT(large) (single model) *Anonymous*		63.29	76.36	58.25	85.60	41.39	67.92
6 Aug 31, 2019	SAE (single model) *Anonymous*		60.36	73.58	56.93	84.63	38.81	64.96
7 Jun 13, 2019	P-BERT (single model) *Anonymous*		61.18	74.16	51.38	82.76	35.42	63.79
8 Sep 16, 2019	LQR-net 2 + BERT-Base (single model) *Anonymous*		60.20	73.78	56.21	84.09	36.56	63.68
9 Apr 11, 2019	EPS + BERT (single model) *Anonymous*		60.13	73.31	52.55	83.20	35.40	63.41
10 May 16, 2019	PIPE (single model) *Anonymous*		59.77	72.77	52.53	82.82	35.54	62.92

Rank	Model	Test Score
1	RoBERTa *Facebook AI* 07/19/2019	Accuracy: **89.92%**
2	BigBird *Pengcheng He, Weizhu Chen from Microsoft Dynamics 365 AI Research* 05/17/2019	Accuracy: **87.06%**
3	BERT (Bidirectional Encoder Representations from Transformers) *Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova* 10/12/2018	Accuracy: **86.28%**
4	OpenAI Transformer Language Model *Original work by Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Run on SWAG by Nicholas Lourie.* 10/12/2018	Accuracy: **77.97%**
5	ESIM with ELMo *Zellers, Rowan and Bisk, Yonatan and Schwartz, Roy and Choi, Yejin* 08/31/2018	Accuracy: **59.06%**
6	ESIM with Glove *Zellers, Rowan and Bisk, Yonatan and Schwartz, Roy and Choi, Yejin* 08/30/2018	Accuracy: **52.45%**

新手上路

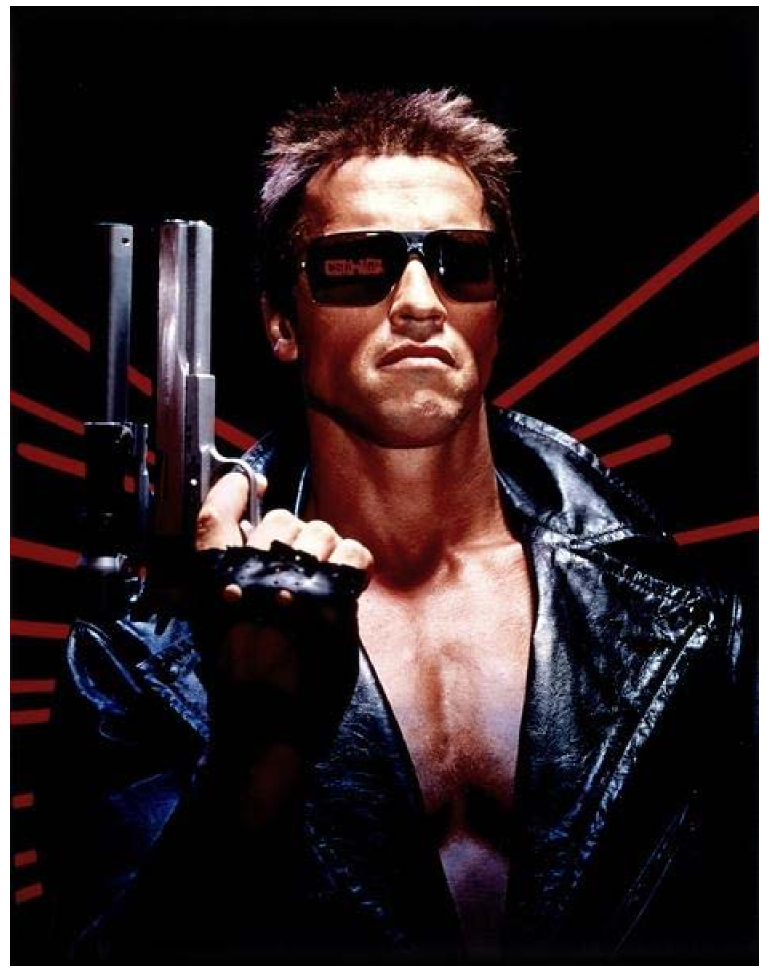
新手上路——选择方向

热门方向

冷门方向

新手上路——选择方向

与一线研究者探讨，**与高年级研究生合作**，学术社区是开放的

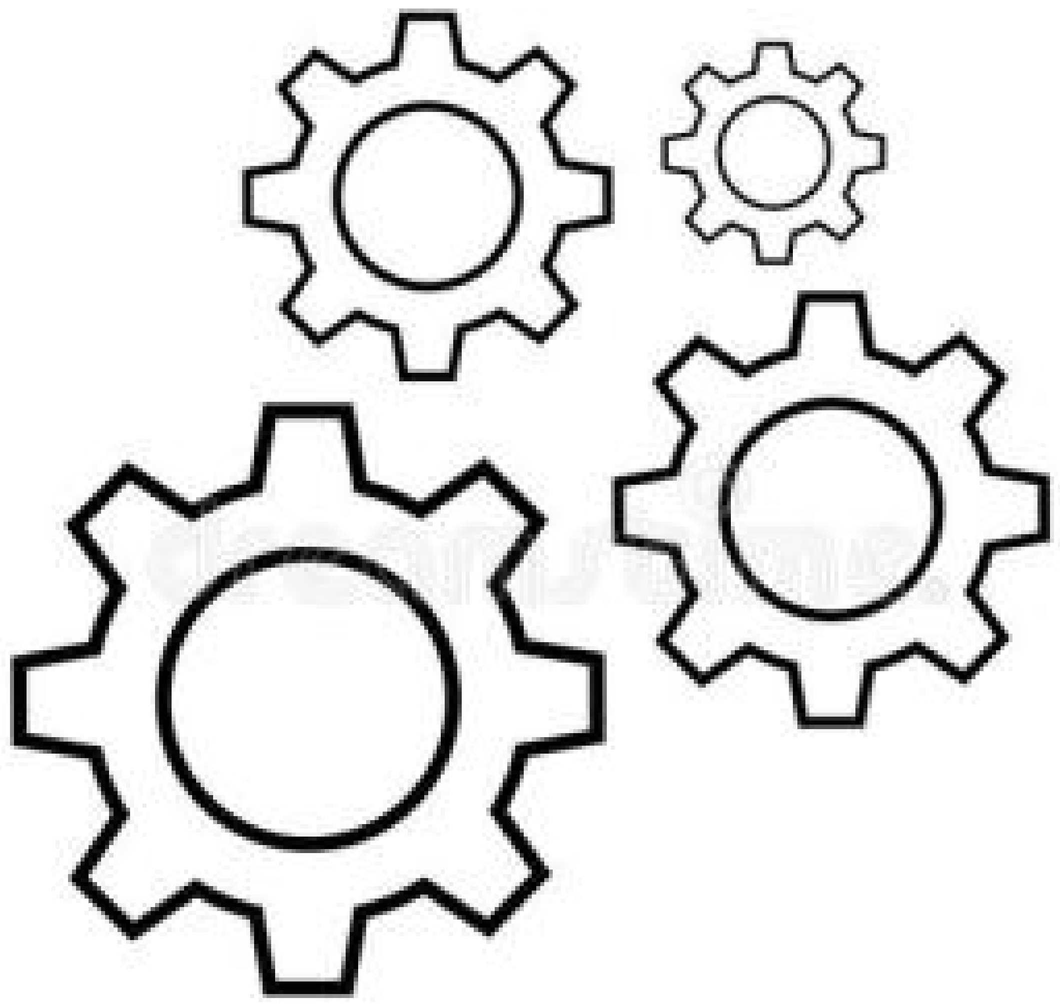


新手上路——选择方向

了解的基础上，**有自己的思考**

核心

重要问题、重大挑战
满足兴趣、充满信心
即将成熟（optional）
有自己的思考



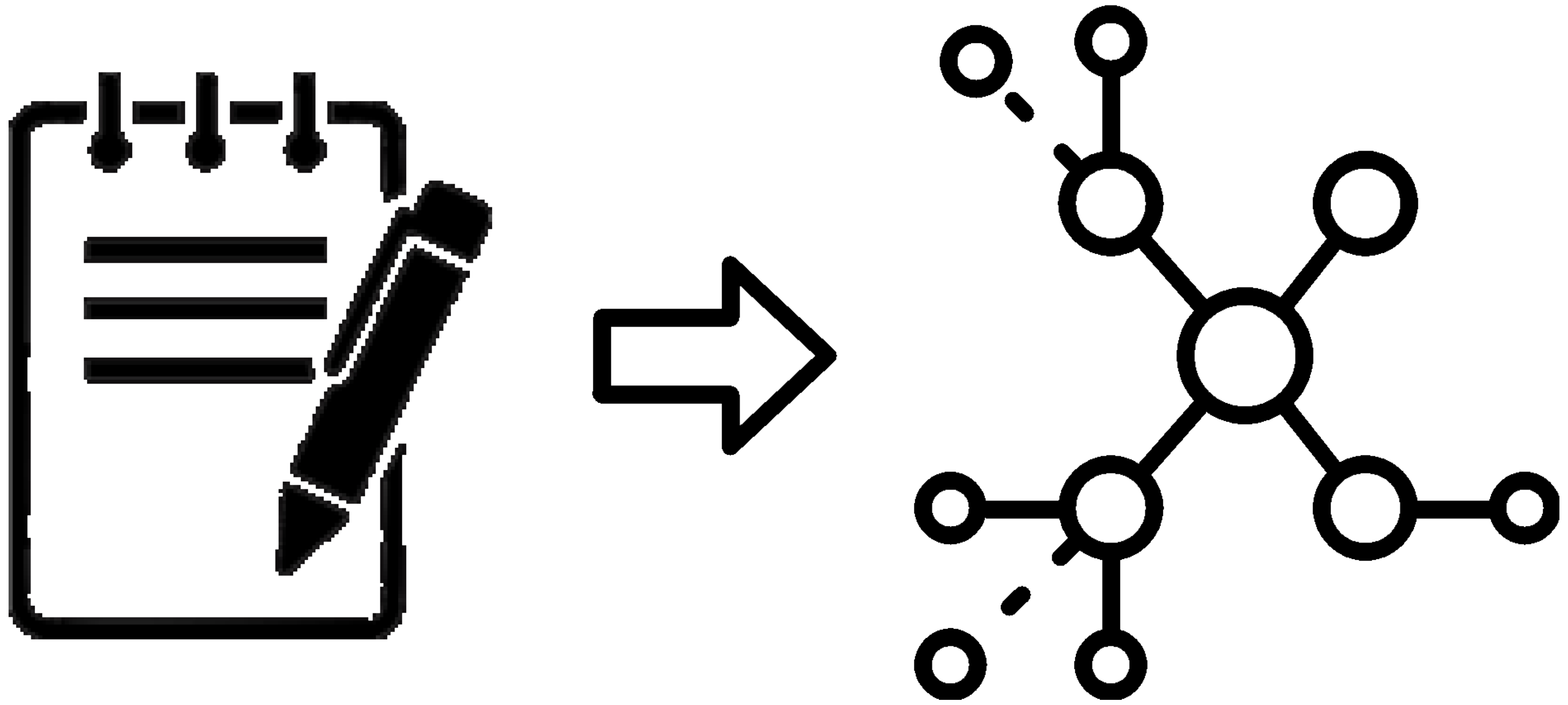
- 自主选题
- 导师指定
- 项目驱动

新手上路——选择方向

语义计算

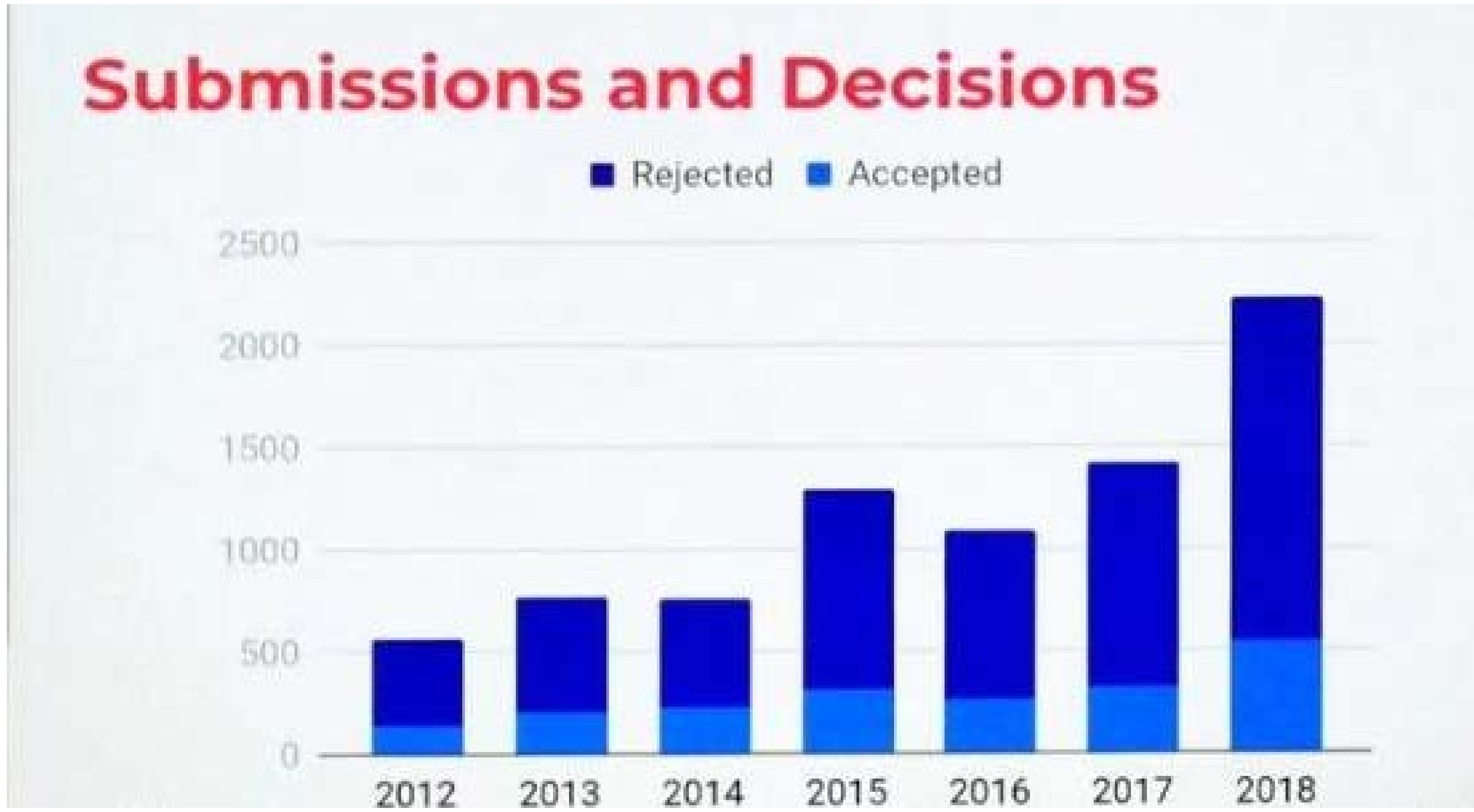
社会计算

知识计算



新手上路——文献阅读

文献增长迅速，**要有所取舍**



新手上路——文献阅读

关注领域综述、经典工作的相关工作

Distant supervision for relation extraction without labeled data
M Mintz, S Bills, R Snow, D Jurafsky - … of the Joint Conference of the 47th …, 2009 - dl.acm.org
Modern models of relation extraction for tasks like ACE are based on supervised learning of relations from small hand-labeled corpora. We investigate an alternative paradigm that does not require labeled corpora, avoiding the domain dependence of ACE-style algorithms, and allowing the use of corpora of any size. Our experiments use Freebase, a large semantic database of several thousand relations, to provide distant supervision. For each pair of entities that appears in some Freebase relation, we find all sentences containing those …
☆ 99 被引用次数：1569 相关文章 所有 25 个版本

Knowledge-based weak supervision for information extraction of overlapping relations
R Hoffmann, C Zhang, X Ling, L Zettlemoyer… - Proceedings of the 49th …, 2011 - dl.acm.org
Abstract Information extraction (IE) holds the promise of generating a large-scale knowledge base from the Web's natural language text. Knowledge-based weak supervision, using structured data to heuristically label a training corpus, works towards this goal by enabling …
☆ 99 被引用次数：550 相关文章 所有 20 个版本

Modeling relations and their mentions without labeled text
S Riedel, L Yao, A McCallum - Joint European Conference on Machine …, 2010 - Springer
Several recent works on relation extraction have been applying the distant supervision paradigm: instead of relying on annotated text to learn how to predict relations, they employ existing knowledge bases (KBs) as source of supervision. Crucially, these approaches are …
☆ 99 被引用次数：546 相关文章 所有 15 个版本

Open information extraction: The second generation
O Etzioni, A Fader, J Christensen, S Soderland - … Second International Joint …, 2011 - aaai.org
How do we scale information extraction to the massive size and unprecedented heterogeneity of the Web corpus? Beginning in 2003, our KnowItAll project has sought to extract high-quality knowledge from the Web. In 2007, we introduced the Open Information …
☆ 99 被引用次数：457 相关文章 所有 17 个版本 »

Multi-instance multi-label learning for relation extraction
M Surdeanu, J Tibshirani, R Nallapati… - Proceedings of the 2012 …, 2012 - dl.acm.org
Distant supervision for relation extraction (RE)--gathering training data by aligning a database of facts with text--is an efficient approach to scale RE to thousands of different relations. However, this introduces a challenging learning scenario where the relation …
☆ 99 被引用次数：454 相关文章 所有 15 个版本

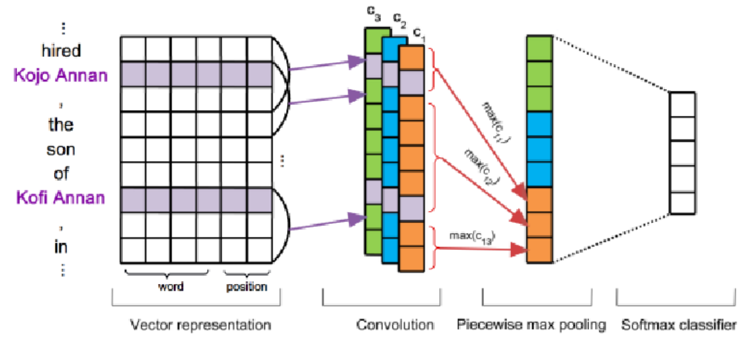
A survey of paraphrasing and textual entailment methods
I Androutsopoulos, P Malakasiotis - Journal of Artificial Intelligence …, 2010 - jair.org
Paraphrasing methods recognize, generate, or extract phrases, sentences, or longer natural language expressions that convey almost the same information. Textual entailment methods, on the other hand, recognize, generate, or extract pairs of natural language …
☆ 99 被引用次数：408 相关文章 所有 10 个版本 »

[PDF] Relation extraction with matrix factorization and universal schemas
S Riedel, L Yao, A McCallum, BM Marlin - … of the 2013 Conference of the …, 2013 - aclweb.org
Traditional relation extraction predicts relations within some fixed and finite target schema. Machine learning approaches to this task require either manual annotation or, in the case of distant supervision, existing structured sources of the same schema. The need for existing …
☆ 99 被引用次数：410 相关文章 所有 13 个版本 »

新手上路——文献阅读

关注NLP重要会议（ACL、EMNLP、NAACL、COLING ...），**重在总结**

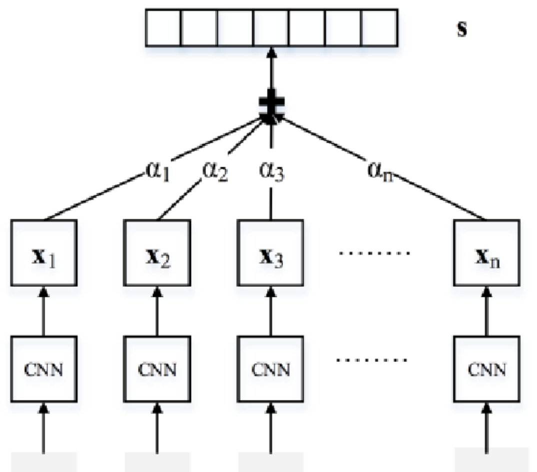
- 基于远程监督、多实例学习的神经模型
  Distant Supervision for Relation Extraction via Piecewise Convolutional Neural Networks. (Zeng et al., 2015)



- 采用了 at-least-one 的多实例学习机制，每次从包中选取最大概率的句子进行训练
- **远程监督 ＋ 多实例学习 ＋ 神经网络模型**成为近来关系抽取研究的**重要基础**

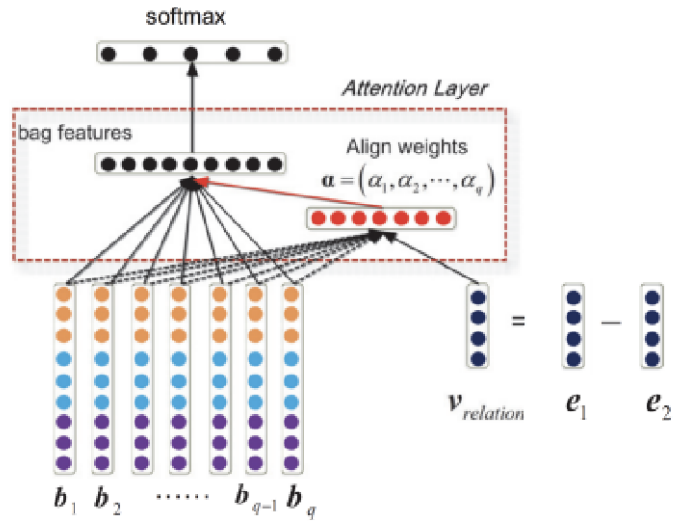
Neural Relation Extraction with Selective Attention over Instances (ACL16)

- 核心思路：为同一个包下的所有句子赋予权重，信息量高的句子权重大，反之权重小
- 对同一个包下的所有句子加权求和，以进行后续预测



Distant Supervision for RE with Sentence-Level Attention and Entity Descriptions (AAAI17)

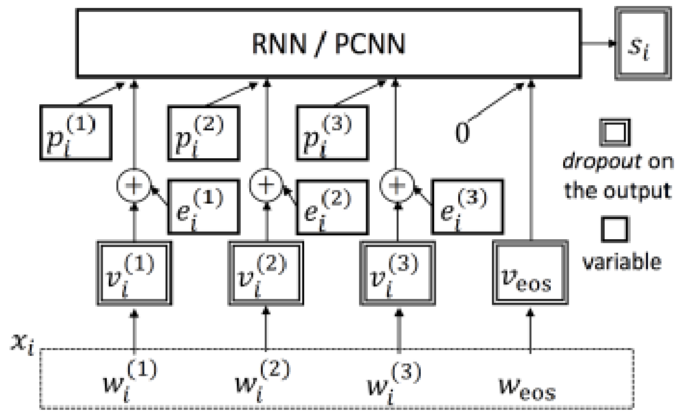
- 引入实体的描述信息来构建注意力机制



- 将文本模型与关系抽取模型一同训练，文本模型从实体的描述文本中提取信息来构建注意力机制

Adversarial Training for Relation Extraction (EMNLP17)

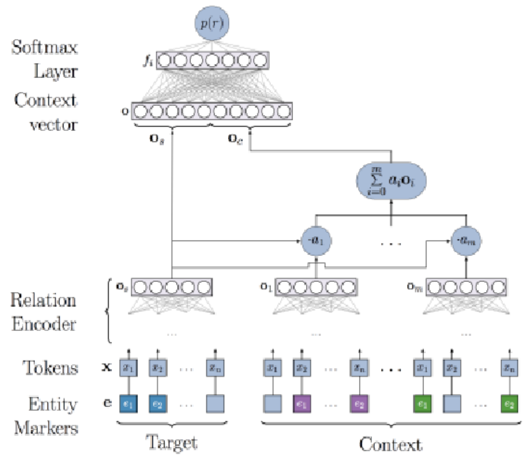
- 在原有注意力机制模型上引入对抗训练



- 在训练过程中，通过给原始数据增加扰动，增大神经网络模型的loss，提升模型的鲁棒性

Context-Aware Representations for Knowledge Base Relation Extraction (EMNLP17)

- 同时抽取文本中多个实体对之间的关系



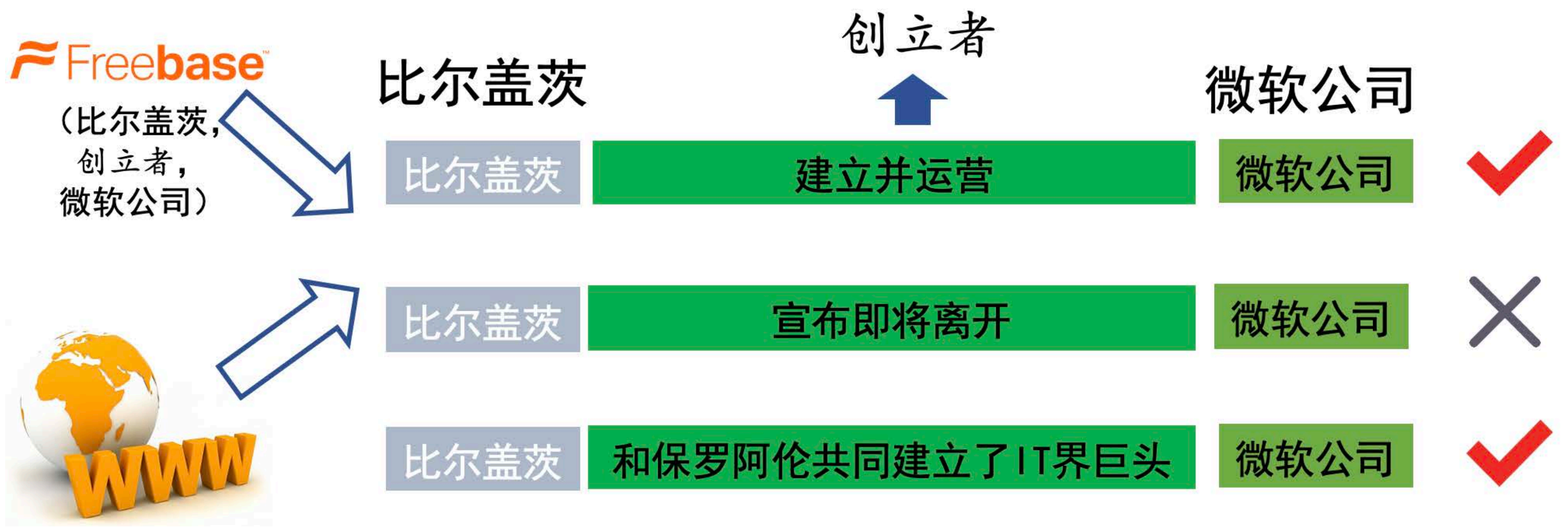
- 对任意实体对下的文本均进行编码，得到文本特征，并在不同实体对的文本特征上构建注意力机制，以获取实体对之间的相关性信息

新手上路——文献阅读

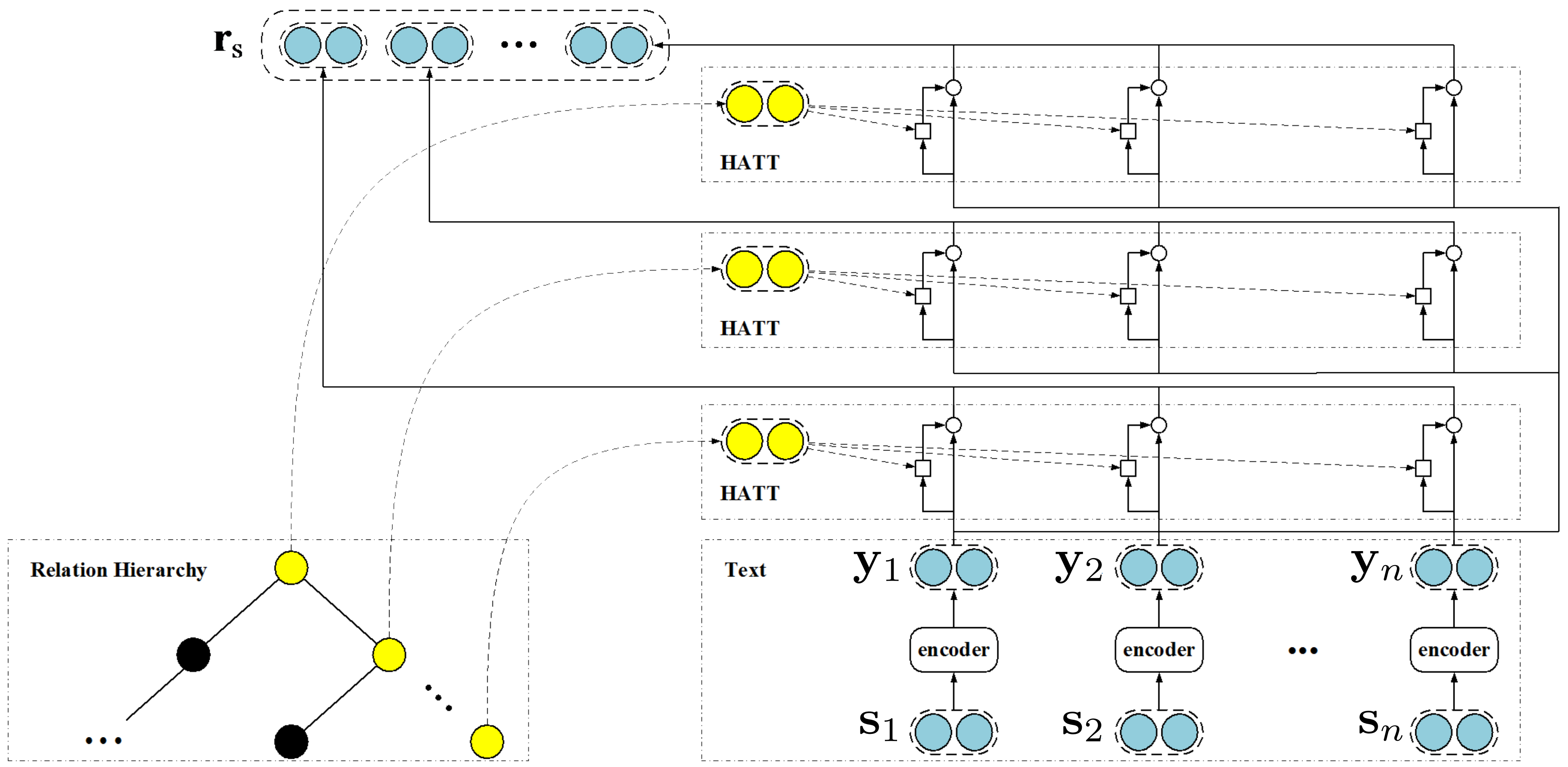
阅读arxiv论文，其他领域重要会议 (NIPS、ICLR、ICML、KDD ...)，**重在积累**

Model	Scoring Function	Parameters	Loss Function
RESCAL (Nickel et al., 2011)	$\mathbf{h}^\top \mathbf{M}_r \mathbf{t}$	$\mathbf{M}_r \in \mathbb{R}^{k\times k}, \mathbf{h} \in \mathbb{R}^k, \mathbf{t} \in \mathbb{R}^k$	margin-based loss
TransE (Bordes et al., 2013)	$-\lVert \mathbf{h}+\mathbf{r}-\mathbf{t} \rVert_{L_1/L_2}$	$\mathbf{r} \in \mathbb{R}^k, \mathbf{h} \in \mathbb{R}^k, \mathbf{t} \in \mathbb{R}^k$	margin-based loss
TransH (Wang et al., 2014)	$-\lVert(\mathbf{h}-\mathbf{w}_r^\top \mathbf{h}\mathbf{w}_r)+\mathbf{r}-(\mathbf{t}-\mathbf{w}_r^\top \mathbf{t}\mathbf{w}_r)\rVert_{L1/L2}$	$\mathbf{w}_r \in \mathbb{R}^k, \mathbf{r} \in \mathbb{R}^k, \mathbf{h} \in \mathbb{R}^k, \mathbf{t} \in \mathbb{R}^k$	margin-based loss
TransR (Lin et al., 2015)	$-\lVert \mathbf{M}_r\mathbf{h}+\mathbf{r}-\mathbf{M}_r\mathbf{t} \rVert_{L_1/L_2}$	$\mathbf{M}_r \in \mathbb{R}^{k_r\times k_e}, \mathbf{r} \in \mathbb{R}^{k_r}, \mathbf{h} \in \mathbb{R}^{k_e}, \mathbf{t} \in \mathbb{R}^{k_e}$	margin-based loss
TransD (Ji et al., 2015)	$-\lVert(\mathbf{r}_p\mathbf{h}_p^\top+\mathbf{I})\mathbf{h}+\mathbf{r}-(\mathbf{r}_p\mathbf{t}_p^\top+\mathbf{I})\mathbf{t}\rVert_{L1/L2}$	$\mathbf{r}_p \in \mathbb{R}^{k_r}, \mathbf{h}_p \in \mathbb{R}^{k_e}, \mathbf{t}_p \in \mathbb{R}^{k_e}, \mathbf{I} \in \mathbb{R}^{k_r\times k_e},$ $\mathbf{r} \in \mathbb{R}^{k_r}, \mathbf{h} \in \mathbb{R}^{k_e}, \mathbf{t} \in \mathbb{R}^{k_e}$	margin-based loss
DistMult (Yang et al., 2015)	$< \mathbf{h}, \mathbf{r}, \mathbf{t} >$	$\mathbf{r} \in \mathbb{R}^k, \mathbf{h} \in \mathbb{R}^k, \mathbf{t} \in \mathbb{R}^k$	logistic loss
HolE (Nickel et al., 2016)	$\mathbf{r}^\top\left(\mathcal{F}^{-1}(\overline{\mathcal{F}(\mathbf{h})} \odot \mathcal{F}(\mathbf{t}))\right)$	$\mathbf{r} \in \mathbb{R}^k, \mathbf{h} \in \mathbb{R}^k, \mathbf{t} \in \mathbb{R}^k$	logistic loss
ComplEx (Trouillon et al., 2016)	$\Re(< \mathbf{h}, \mathbf{r}, \bar{\mathbf{t}} >)$	$\mathbf{r} \in \mathbb{C}^k, \mathbf{h} \in \mathbb{C}^k, \mathbf{t} \in \mathbb{C}^k$	logistic loss

数据降噪



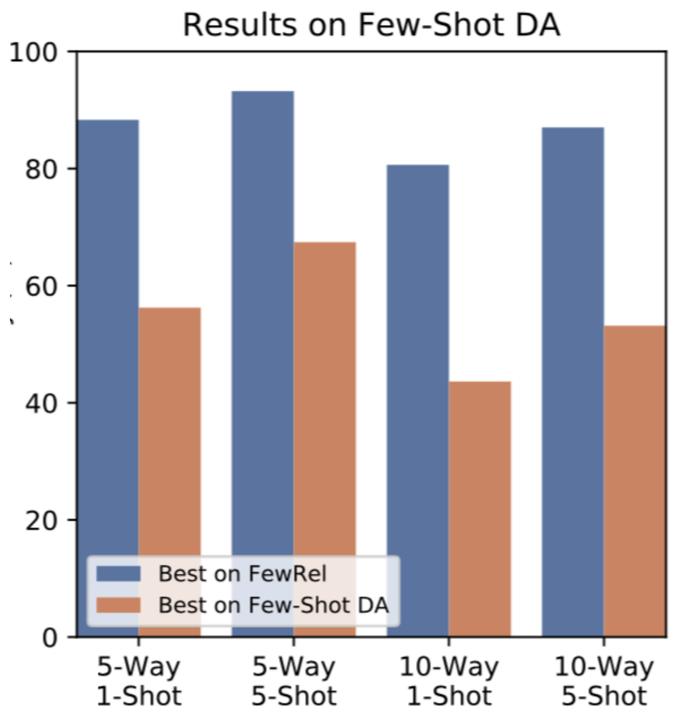
远程监督训练数据存在噪音标注问题

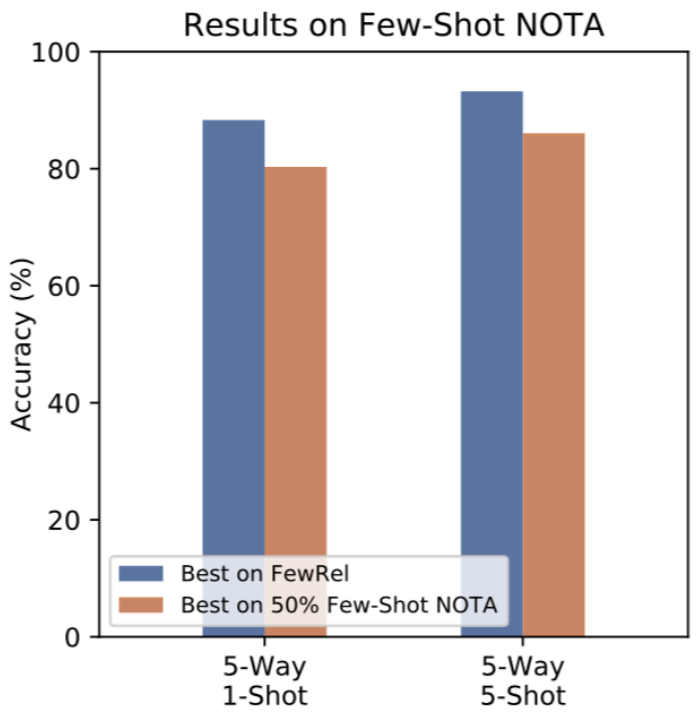


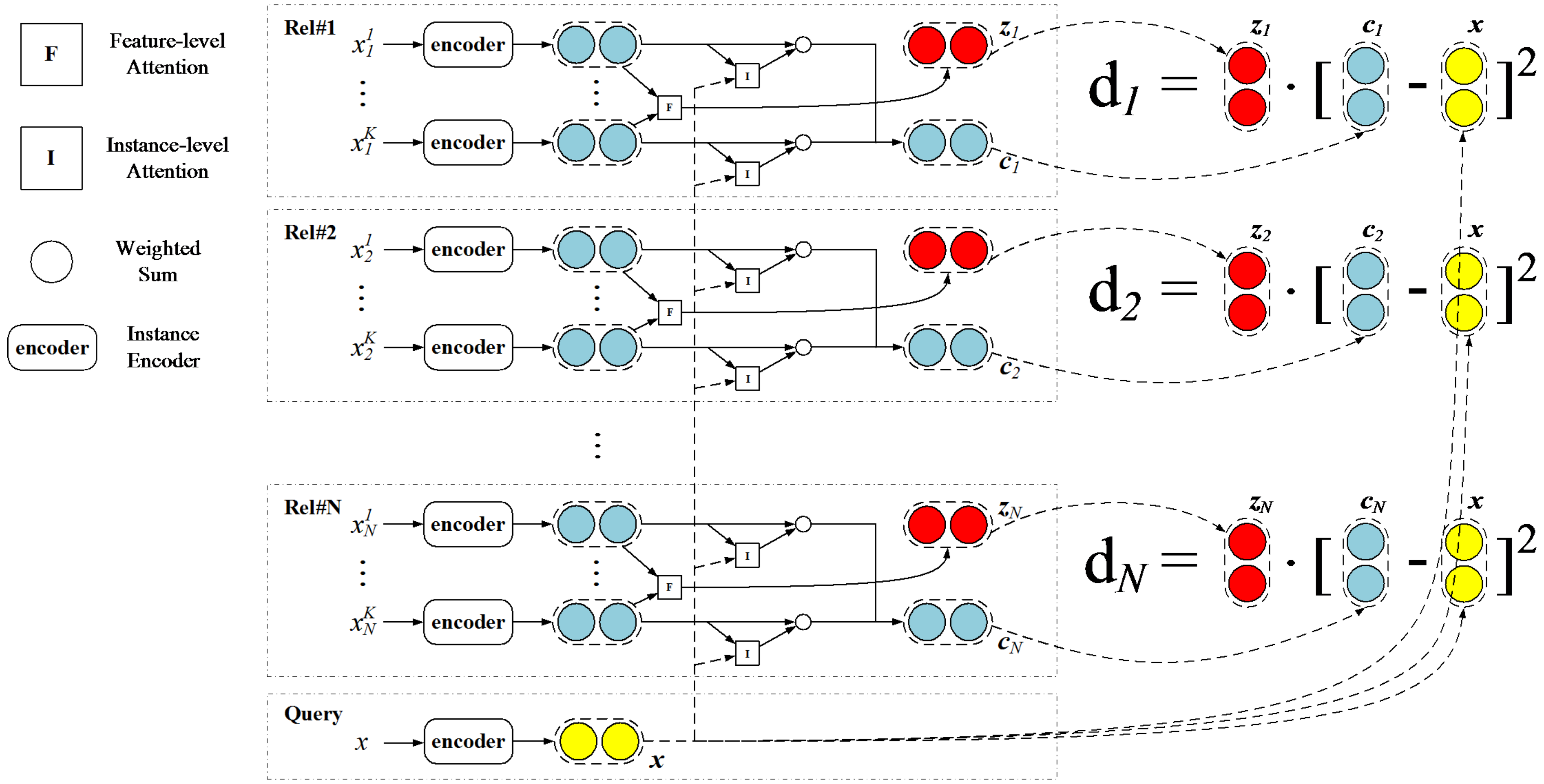
提出层次信息构建的注意力机制，自动学习句子反映标注关系的可信度，降低噪音标和长尾关系的影响（EMNLP 2018）

少次学习

Supporting Set	
(A) capital_of	(1) London is the capital of the U.K. (2) Washington is the capital of the U.S.A.
(B) member_of	(1) Newton served as the president of the Royal Society. (2) Leibniz was a member of the Prussian Academy of Sciences.
(C) birth_name	(1) Samuel Langhorne Clemens, better known by his pen name Mark Twain, was an American writer. (2) Alexei Maximovich Peshkov, primarily known as Maxim Gorky, was a Russian and Soviet writer.
Test Instance	
(A) or (B) or (C)	Euler was elected a foreign member of the Royal Swedish Academy of Sciences.





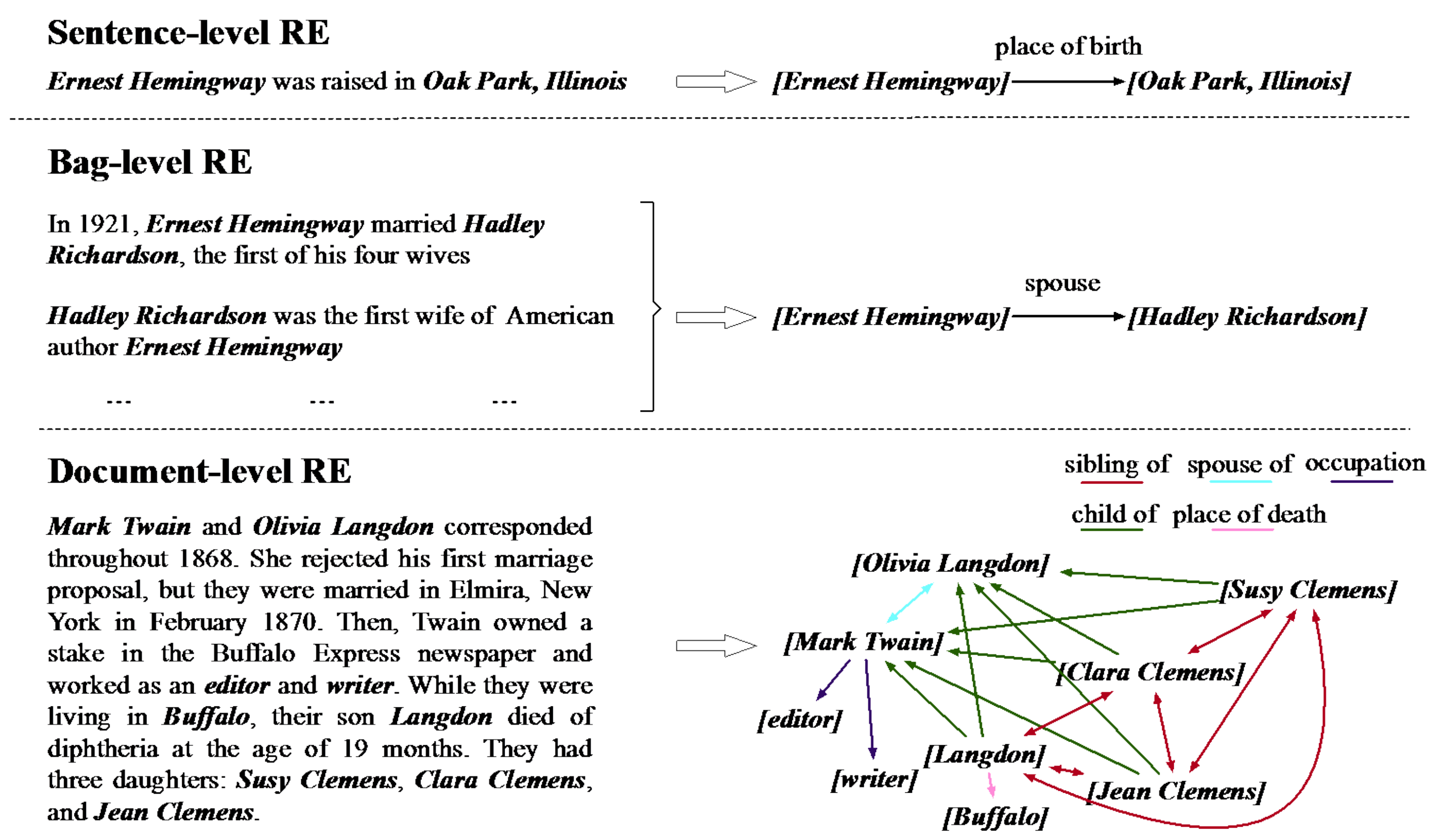


大量实体对或关系对应的训练样例少，面临少次学习、知识迁移问题，需要模型从少量样本中快速学习知识获取能力

提出基于混合注意力机制的原型网络解决噪音场景下的少次学习问题（AAAI 2019）

标注构造数据集FewRel 1.0和2.0推动相关研究（EMNLP 2018/2019）

篇章理解



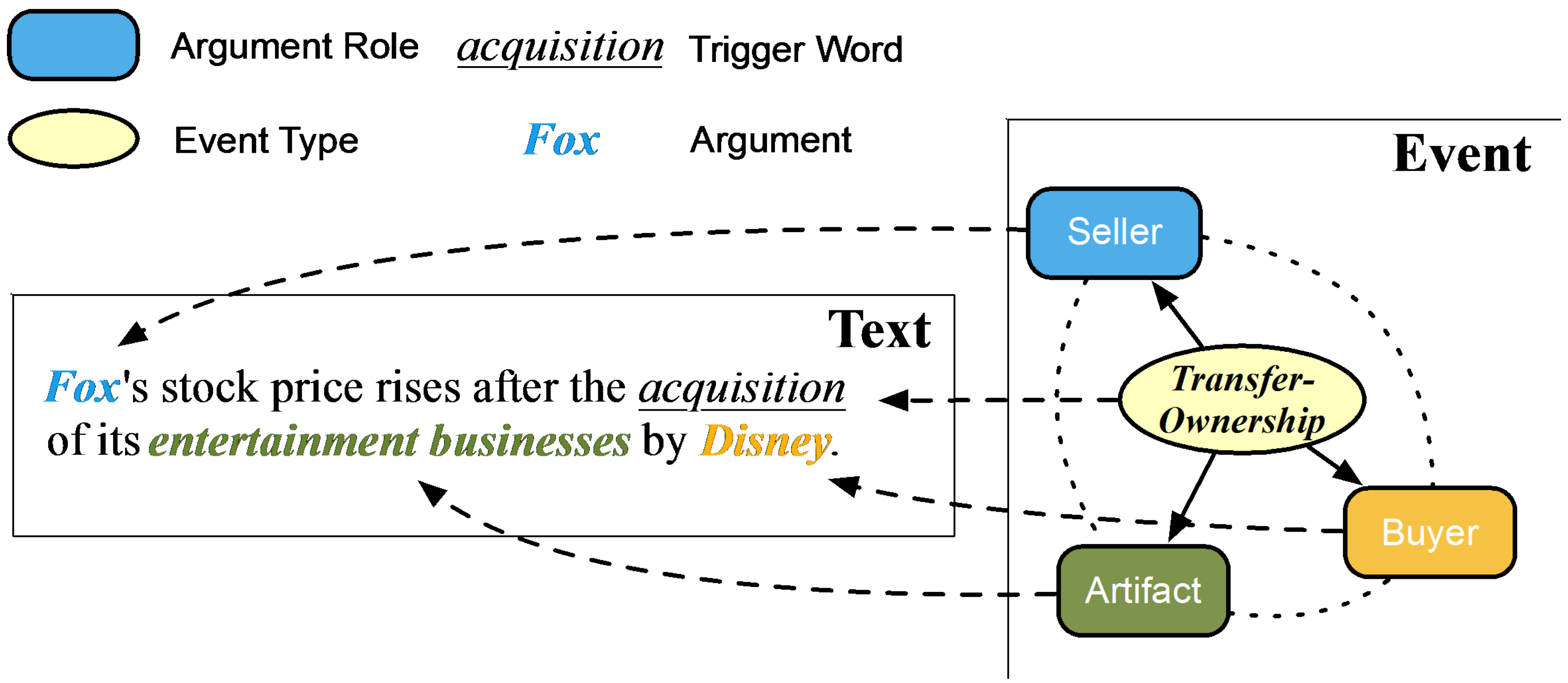
Reasoning Types	%	Examples
Pattern recognition	38.9	[1] *Me Musical Nephews* is a 1942 one-reel animated cartoon directed by Seymour Kneitel and animated by Tom Johnson and George Germanetti. [2] Jack Mercer and Jack Ward wrote the script. ... **Relation:** `publication_date` **Supporting Evidence:** 1
Logical reasoning	26.6	[1] "Nisei" is the ninth episode of the third season of the American science fiction television series The X-Files. ... [3] It was directed by David Nutter, and written by Chris Carter, Frank Spotnitz and Howard Gordon. ... [8] The show centers on FBI special agents *Fox Mulder* (David Duchovny) and Dana Scully (Gillian Anderson) who work on cases linked to the paranormal, called X-Files. ... **Relation:** `creator` **Supporting Evidence:** 1, 3, 8
Coreference reasoning	17.6	[1] *Dwight Tillery* is an American politician of the Democratic Party who is active in local politics of Cincinnati, Ohio. ... [3] He also holds a law degree from the University of Michigan Law School. [4] *Tillery* served as mayor of Cincinnati from 1991 to 1993. **Relation:** `educated_at` **Supporting Evidence:** 1, 3
Common-sense reasoning	16.6	[1] *William Busac* (1020-1076), son of William I, Count of Eu, and his wife Lesceline. ... [4] *William* appealed to King Henry I of France, who gave him in marriage Adelaide, the heiress of the county of Soissons. [5] Adelaide was daughter of Renaud I, Count of Soissons, and Grand Master of the Hotel de France. ... [7] *William* and Adelaide had four children: ... **Relation:** `spouse` **Supporting Evidence:** 4, 7

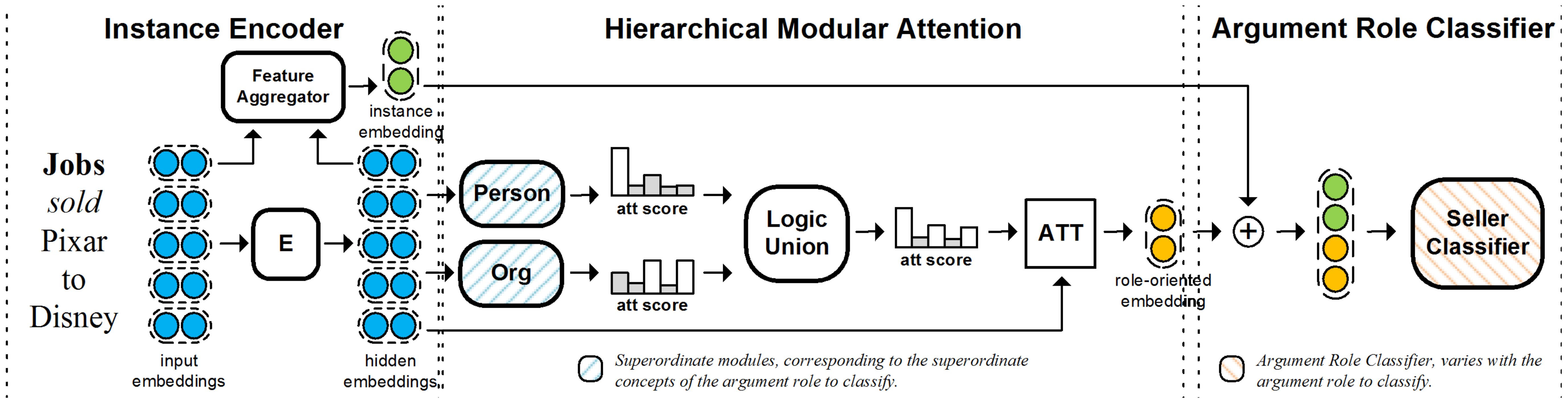
传统的关系抽取集中在单句级别，无法处理隐藏在**段落中的复杂知识结构**

标注构造数据集**DocRED**推动相关研究（ACL 2019）

解决DocRED需要模型具有**模式识别、逻辑推理、指代推理、常识推理**等多方位能力

事件抽取





进行更加复杂结构的知识获取（事件抽取）

引入大量无标注的文本数据来解决事件抽取中的数据稀疏问题，通过对抗训练来进行数据降噪与过滤（NAACL-HLT 2019）

引入事件参数的抽象概念信息，来学习事件参数之间的关联性（EMNLP 2019）

新手上路——文献阅读

和实验室同学、其他研究者合作读论文，**重在合作交流**

开会不超过一小时小组(15)

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发现你感兴趣的论文

PaperWeekly是一个推荐、解读、讨论和报道人工智能前沿论文成果的学术平台。在这里，来自人工智能领域的学习达人们，各自用精炼妙语推荐当下最新的高质量文章。

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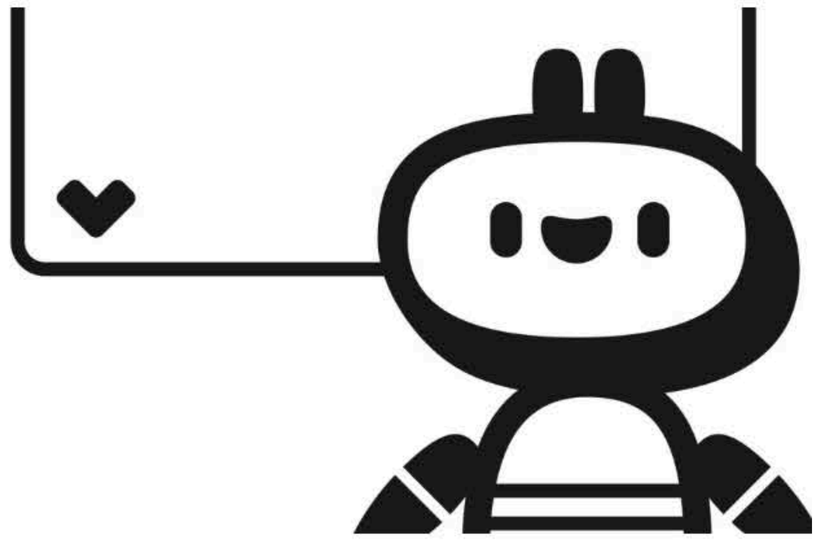

Must-read papers on GNN

GNN: graph neural network

Contributed by Jie Zhou, Ganqu Cui, Zhengyan Zhang and Yushi Bai.

Must-read papers on NRE

NRE: Neural Relation Extraction.

Contributed by Tianyu Gao and Xu Han.

Must-read papers on KRL/KE.

KRL: knowledge representation learning. KE: knowledge embedding.

Contributed by Shulin Cao and Xu Han.

PLMpapers

Contributed by Xiaozhi Wang and Zhengyan Zhang.

新手上路——代码和实验

代码和实验的核心之一是数据，数据的获取需要**拥抱开源社区！**

sebastianruder / **NLP-progress**

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Repository to track the progress in Natural Language Processing (NLP), including the datasets and the current state-of-the-art for the most common NLP tasks. https://nlpprogress.com/

natural-language-processing | machine-learning | named-entity-recognition | machine-translation | nlp-tasks | dialogue

Freebase-15K-237 (FB15K-237)

The FB15K dataset was introduced in Bordes et al., 2013. It is a subset of Freebase which contains about 14,951 entities with 1,345 different relations. This dataset was found to suffer from major test leakage through inverse relations and a large number of test triples can be obtained simply by inverting triples in the training set initially by Toutanova et al.. To create a dataset without this property, Toutanova et al. introduced FB15k-237 – a subset of FB15k where inverse relations are removed.

WordNet-18-RR (WN18RR)

The WN18 dataset was also introduced in Bordes et al., 2013. It included the full 18 relations scraped from WordNet for roughly 41,000 synsets. Similar to FB15K, This dataset was found to suffer from test leakage by Dettmers et al. (2018) introduced the WN18RR.

As a way to overcome this problem, Dettmers et al. (2018) introduced the WN18RR dataset, derived from WN18, which features 11 relations only, no pair of which is reciprocal (but still include four internally-symmetric relations like *verb_group*, allowing the rule-based system to reach 35 on all three metrics).

FewRel

The Few-Shot Relation Classification Dataset (FewRel) is a different setting from the previous datasets. This dataset consists of 70K sentences expressing 100 relations annotated by crowdworkers on Wikipedia corpus. The few-shot learning task follows the N-way K-shot meta learning setting. It is both the largest supervised relation classification dataset as well as the largest few-shot learning dataset till now.

The public leaderboard is available on the FewRel website.

New York Times Corpus

The standard corpus for distantly supervised relationship extraction is the New York Times (NYT) corpus, published in Riedel et al, 2010.

This contains text from the New York Times Annotated Corpus with named entities extracted from the text using the Stanford NER system and automatically linked to entities in the Freebase knowledge base. Pairs of named entities are labelled with relationship types by aligning them against facts in the Freebase knowledge base. (The process of using a separate database to provide label is known as 'distant supervision')

TACRED

TACRED is a large-scale relation extraction dataset with 106,264 examples built over newswire and web text from the corpus used in the yearly TAC Knowledge Base Population (TAC KBP) challenges. Examples in TACRED cover 41 relation types as used in the TAC KBP challenges (e.g., *per:schools_attended* and *org:members*) or are labeled as *no_relation* if no defined relation is held. These examples are created by combining available human annotations from the TAC KBP challenges and crowdsourcing.

新手上路——代码和实验

代码和实验的核心之二是复现，轮子的复用需要**拥抱开源社区！！**

thunlp / **KB2E**

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Knowledge Graph Embeddings including TransE, TransH, TransR and PTransE

DeepGraphLearning / **KnowledgeGraphEmbedding**

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DeepGraphLearning / **graphvite**

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GraphVite: A General and High-performance Graph Embedding System https://graphvite.io

machine-learning network-embedding knowledge-graph data-visualization representation-learning cu

thunlp / **NRE**

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Neural Relation Extraction, including CNN, PCNN, CNN+ATT, PCNN+ATT

jxwuyi / **AtNRE**

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Adversarial Training for Neural Relation Extraction

新手上路——代码和实验

代码和实验的核心之三是实现，实现的上手需要**拥抱开源社区！！！**

TensorFlow Examples

This tutorial was designed for easily diving into TensorFlow, through examples. For readability, it includes both notebooks and source codes with explanation, for both TF v1 & v2.

It is suitable for beginners who want to find clear and concise examples about TensorFlow. Besides the traditional 'raw' TensorFlow implementations, you can also find the latest TensorFlow API practices (such as `layers`, `estimator`, `dataset`, ...).

Update (08/17/2019): Added new TensorFlow 2.0 examples! (more coming soon).

If you are using older TensorFlow version (0.11 and under), please take a look here.

Tutorial index

0 - Prerequisite

- Introduction to Machine Learning.
- Introduction to MNIST Dataset.

1 - Introduction

- **Hello World** (notebook) (code). Very simple example to learn how to print "hello world" using TensorFlow.
- **Basic Operations** (notebook) (code). A simple example that cover TensorFlow basic operations.
- **TensorFlow Eager API basics** (notebook) (code). Get started with TensorFlow's Eager API.

2 - Basic Models

- **Linear Regression** (notebook) (code). Implement a Linear Regression with TensorFlow.
- **Linear Regression (eager api)** (notebook) (code). Implement a Linear Regression using TensorFlow's Eager API.
- **Logistic Regression** (notebook) (code). Implement a Logistic Regression with TensorFlow.
- **Logistic Regression (eager api)** (notebook) (code). Implement a Logistic Regression using TensorFlow's Eager API.
- **Nearest Neighbor** (notebook) (code). Implement Nearest Neighbor algorithm with TensorFlow.
- **K-Means** (notebook) (code). Build a K-Means classifier with TensorFlow.
- **Random Forest** (notebook) (code). Build a Random Forest classifier with TensorFlow.
- **Gradient Boosted Decision Tree (GBDT)** (notebook) (code). Build a Gradient Boosted Decision Tree (GBDT) with TensorFlow.
- **Word2Vec (Word Embedding)** (notebook) (code). Build a Word Embedding Model (Word2Vec) from Wikipedia data, with TensorFlow.

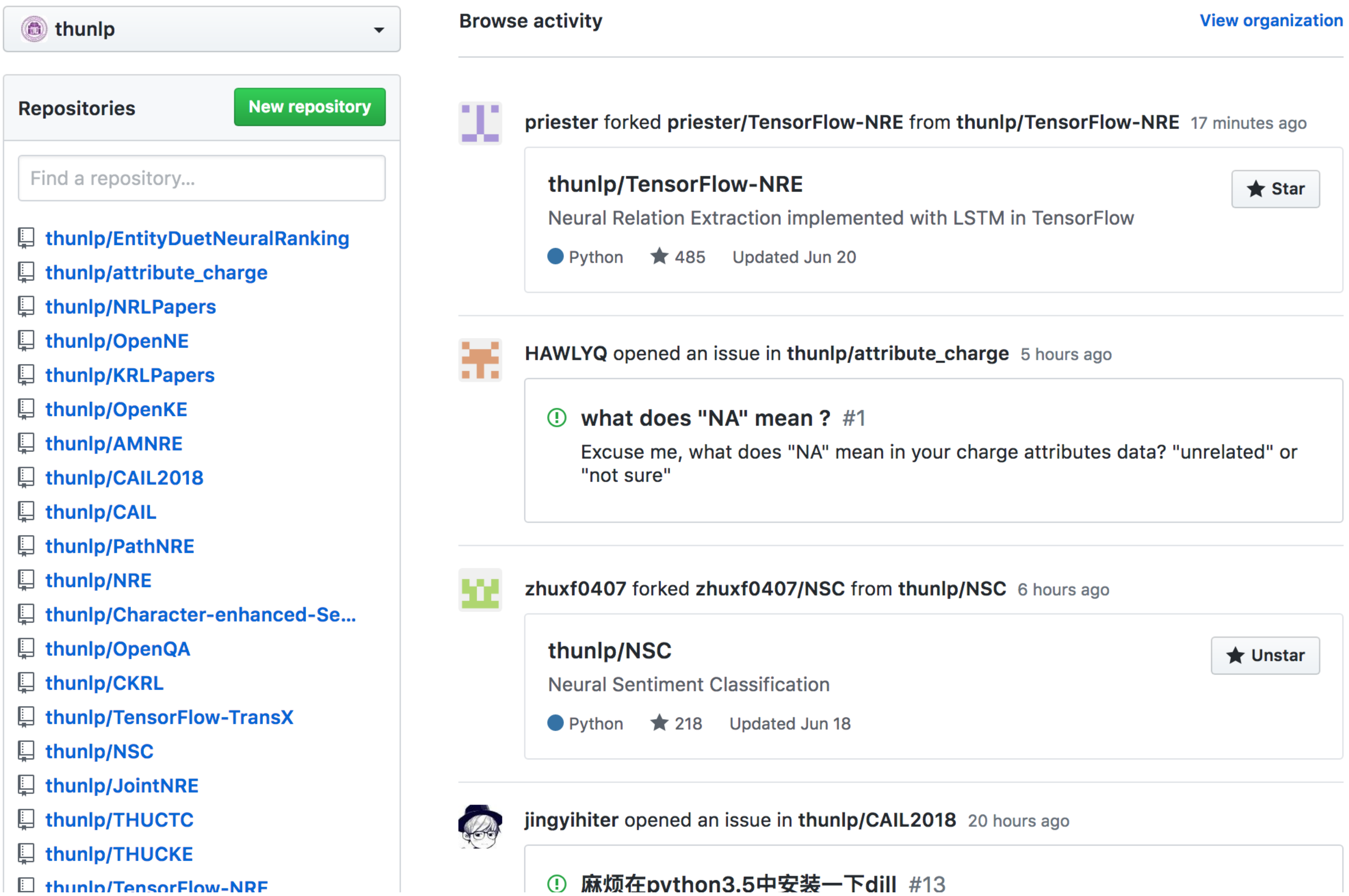
3 - Neural Networks

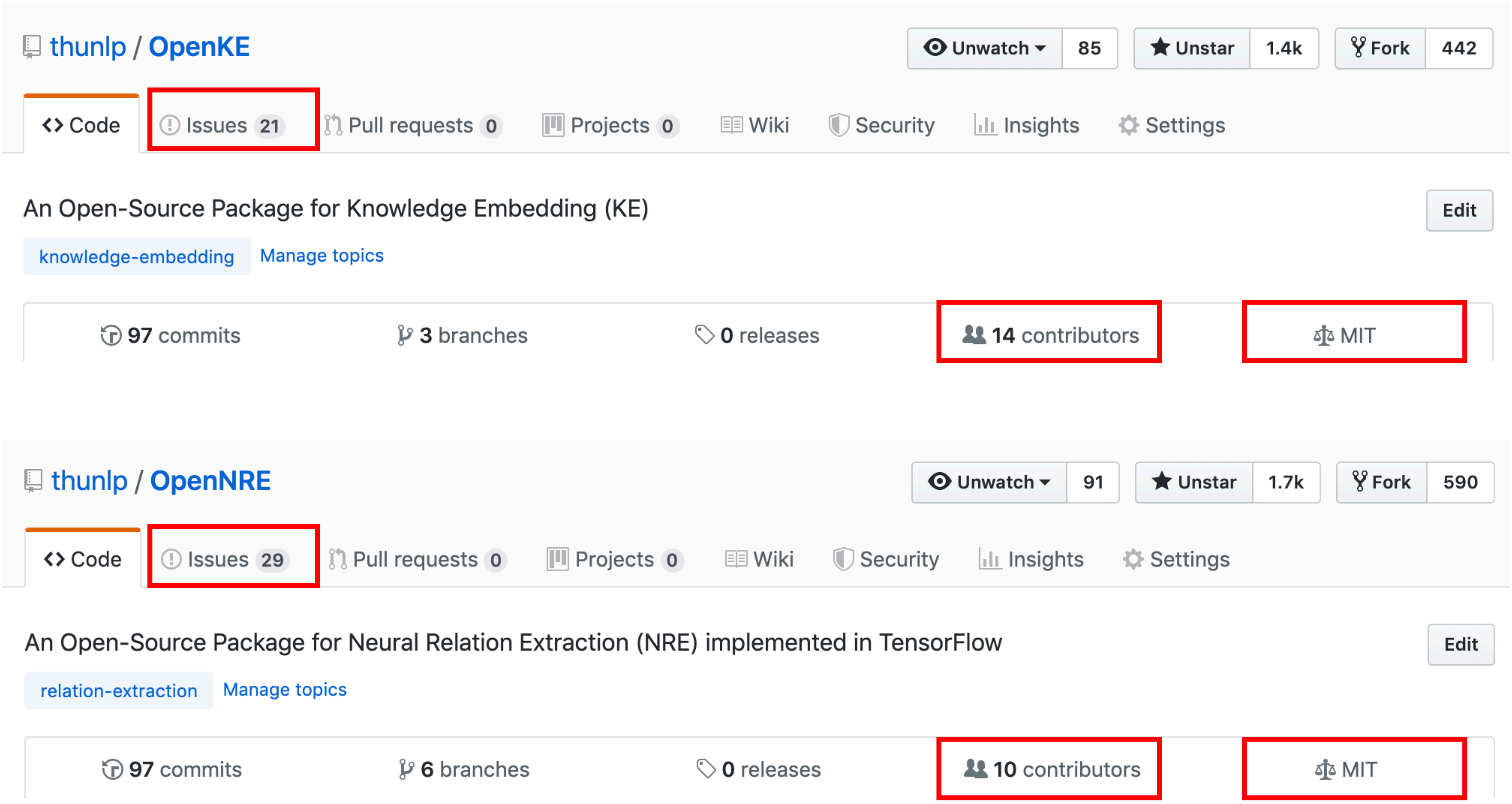
Supervised

- **Simple Neural Network** (notebook) (code). Build a simple neural network (a.k.a Multi-layer Perceptron) to classify MNIST digits dataset. Raw TensorFlow implementation.
- **Simple Neural Network (tf.layers/estimator api)** (notebook) (code). Use TensorFlow 'layers' and 'estimator' API to build a simple neural network (a.k.a Multi-layer Perceptron) to classify MNIST digits dataset.

新手上路——代码和实验

代码和实验的核心之四是维护，长期的维护需要**拥抱开源社区！！！！**





新手上路——写作和投稿

如何写出可用的文章，阅读母语者范文，仿照思路撰写摘要、介绍、方法、实验、总结；或者更简单的思路是，直接**向老师学习**

你以为审稿人应该是这样审稿的:

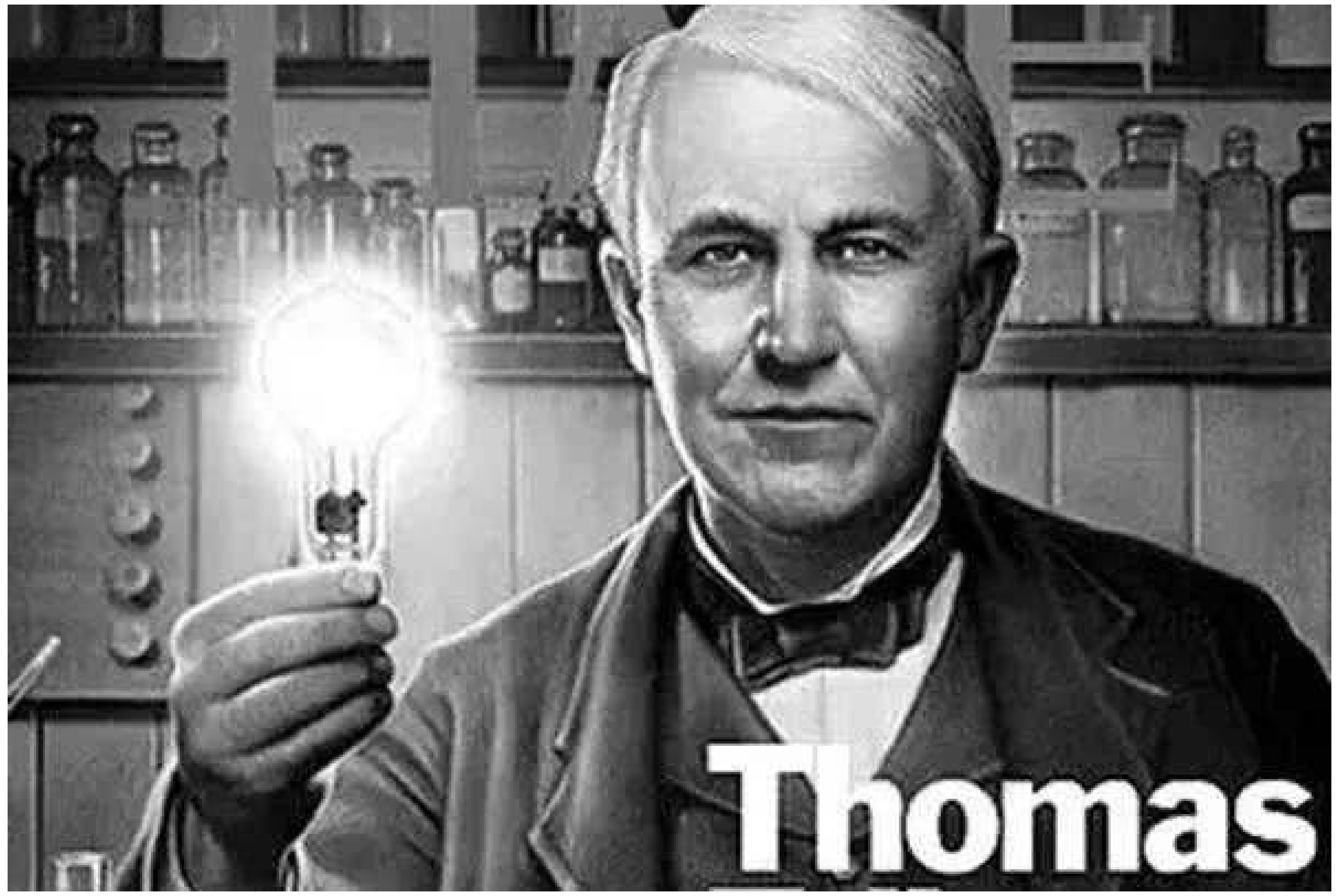
审稿人一定是专家，无所不知。打印出来，仔细研读揣摩数天，对于看不懂的地方反复推敲。即使你的英文写得极其糟糕、即使你的文章组织很混乱、即使你的表述很难看懂，审稿人花费了大量的时间后终于看懂了，他认为你的工作是有意义的，决定给你个border line或以上的分数。

审稿人实际上往往是这样审稿的:

他不一定是专家，一直忙于其他事，在deadline到来之前一天要完成n篇。审稿时他往往先看题目、摘要，扫一下introduction（知道你做什么），然后直接翻到最后找核心实验结果（做得好不好），然后基本确定录还是不录（也许只用5分钟！）。如果决定录，剩下就是写些赞美的话，指出些次要的小毛病。如果决定拒，下面的过程就是细看中间部分找理由拒了。

新手上路——写作和投稿

所有步骤都到位了，需要的就是**等待、坚持和反思**



天才就是1%的灵感加上99%的汗水

前提是你要**拥抱合作**

然后遇到靠谱的**审稿人**