知识图谱与低资源学习

Knowledge Graph meets Low Resource Learning

耿玉霞 浙江大学计算机科学与技术学院 博士生在读

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01

知识图谱与低资源学习

Knowledge Graph & Low Resource Learning

01 什么是知识图谱？

姚明女儿的妈妈是谁

全部 图片 新闻 视频 地图 更多 设置 工具

找到约 2,250,000 条结果 （用时 0.46 秒）

姚沁蕾 / 母亲

叶莉

叶莉是上海人，中国女子篮球运动员，曾经效力上海东方八爪鱼队，位置是中锋，她身高1.93米。 叶莉1996年进入上海体育运动技术学院，1998年入选国家青年队，1999年底进国家集训队。生涯最好的成绩是2004年代表中国国家女子篮球队夺得亚洲锦标赛冠军。 维基百科

出生信息： 1981 年 11 月 20 日（39 岁），中国上海市

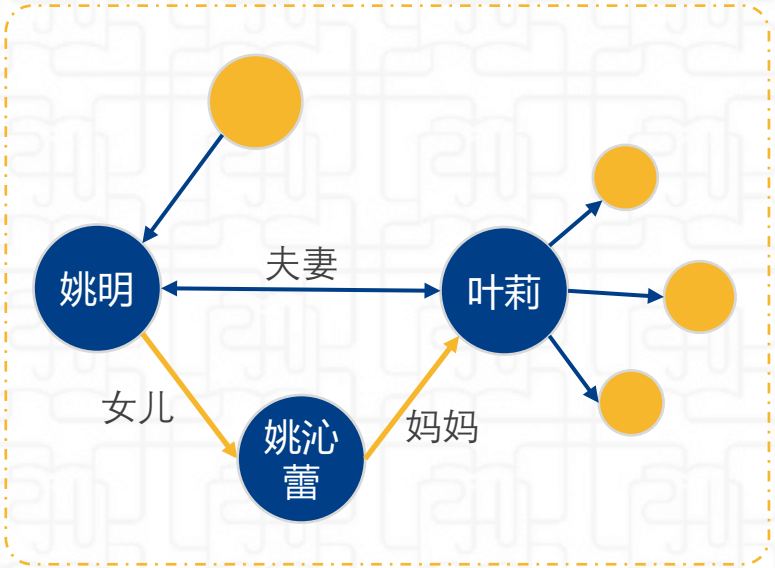
身高： 190 厘米

国籍： 中国

配偶： 姚明 (结婚时间：2007 年)

排名： 中锋

子女： 姚沁蕾



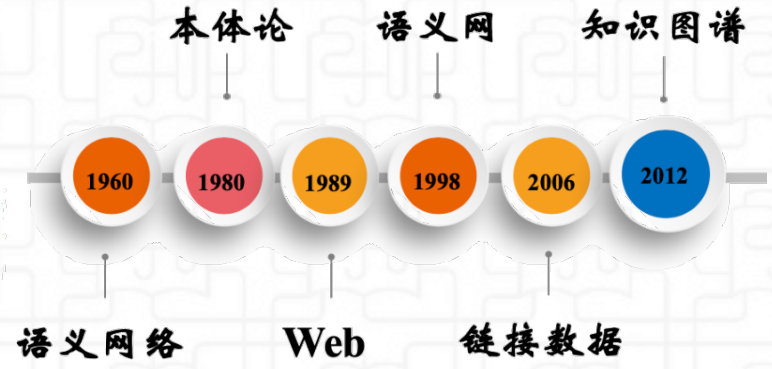
- 知识图谱
- 知识库
- 多关系图
- 。。。

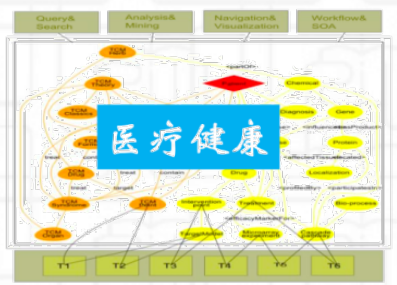
- <姚明，女儿，姚沁蕾>
- <姚沁蕾，妈妈，叶莉>
- <姚明，夫妻，叶莉>

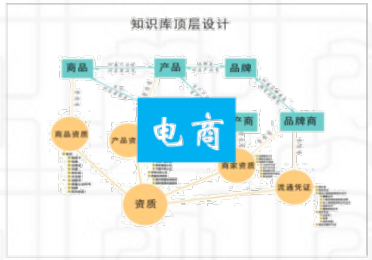
01 知识图谱：刻画事物关系、沉淀领域知识

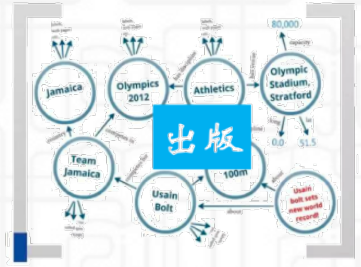
“知识图谱旨在利用图结构建模、识别和推断事物之间的复杂关联关系和沉淀领域知识，是实现认知智能的重要基石，已经被广泛应用于搜索引擎、智能问答、语言语义理解、大数据决策分析、智能物联等众多领域。”

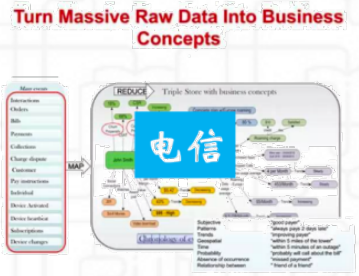
01 知识图谱的前世今生





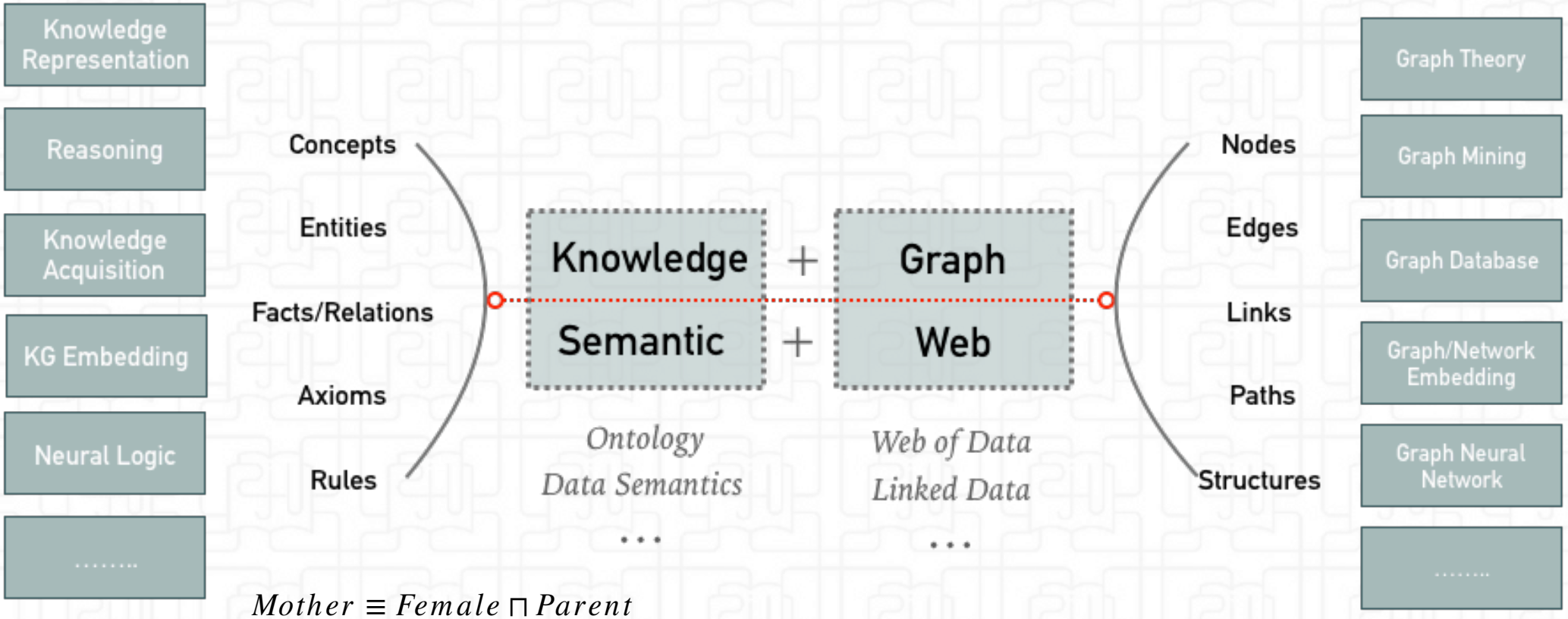






01 知识+图谱：两个互补的技术维度

Knowledge Graph is more expressive than pure Graph but less complex than formal logic.

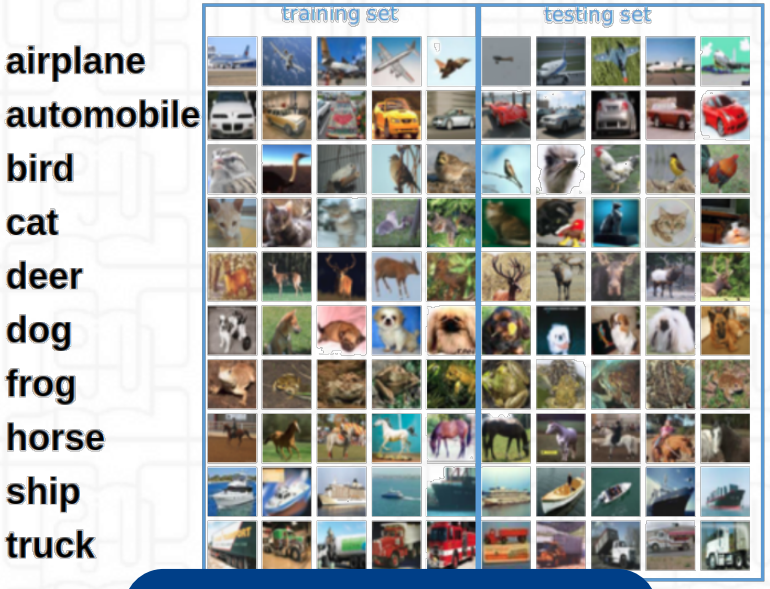


$$Mother \equiv Female \sqcap Parent$$

$$hasSon \sqsubseteq hasChild$$

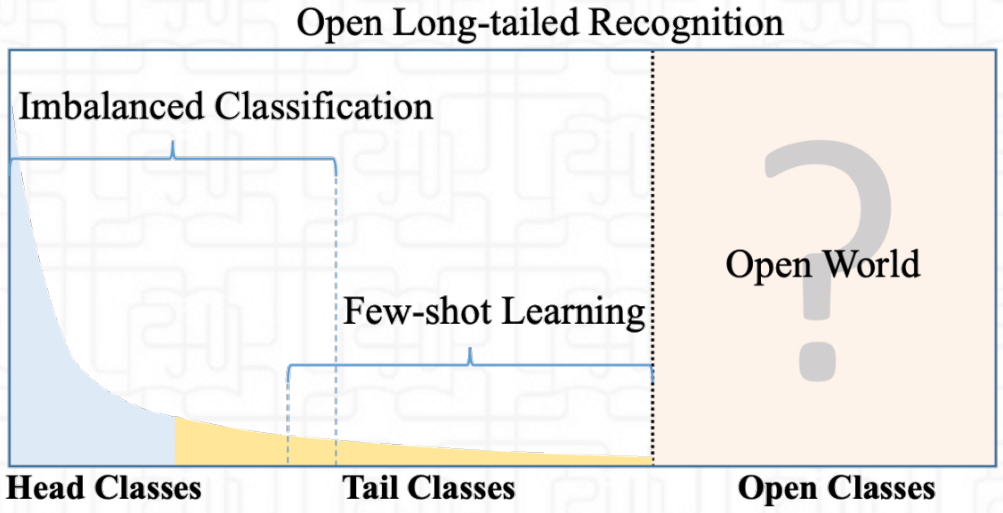
$$parentOf \equiv childOf^{-}$$

01 低资源学习



典型的机器学习/深度学习

- 需大量标记数据
- 只能在训练过的类别/概念上进行测试

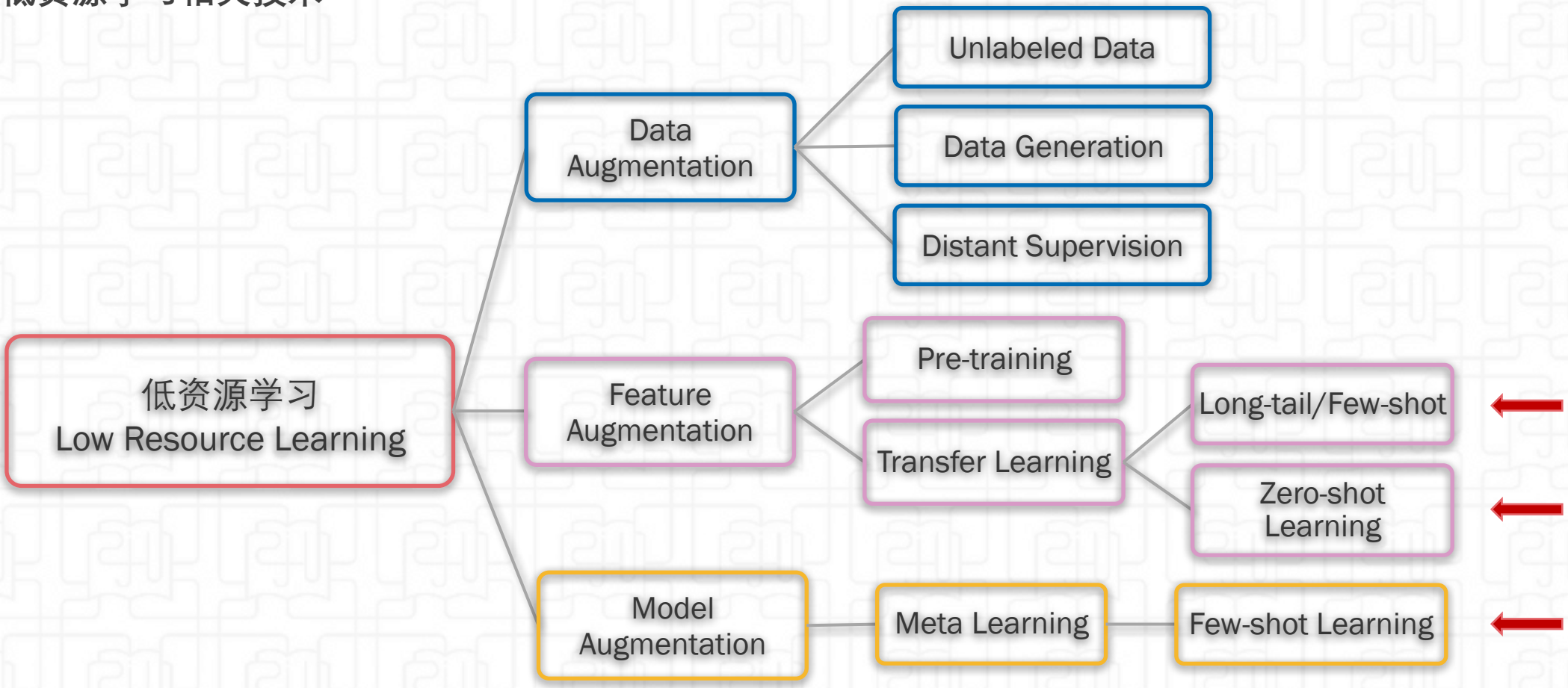


低资源学习

- 少样本 (Few-shot Learning)：如何在**样本量极少**的情况下训练模型并预测
- 零样本 (Zero-shot Learning)：如何在**没有样本**的情况下训练模型并进行预测

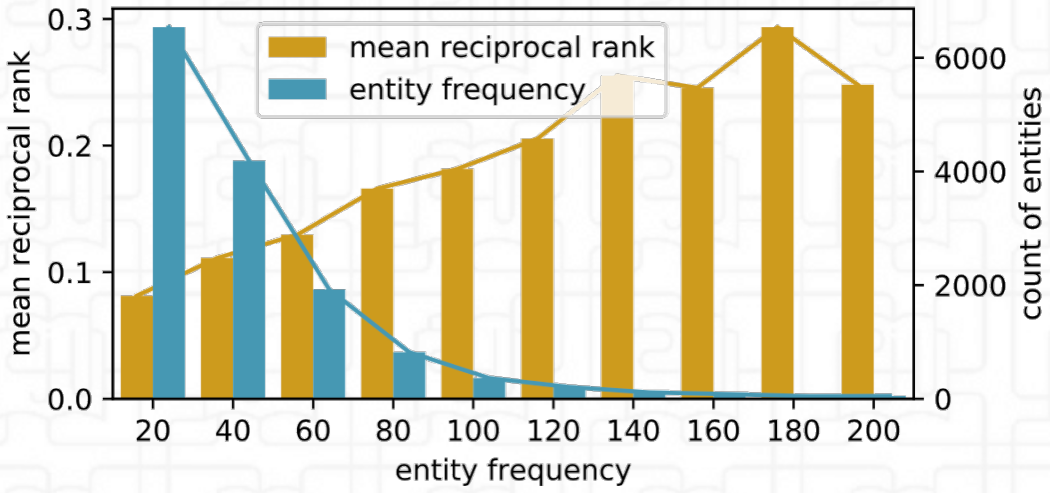
01 低资源学习

- 低资源学习相关技术

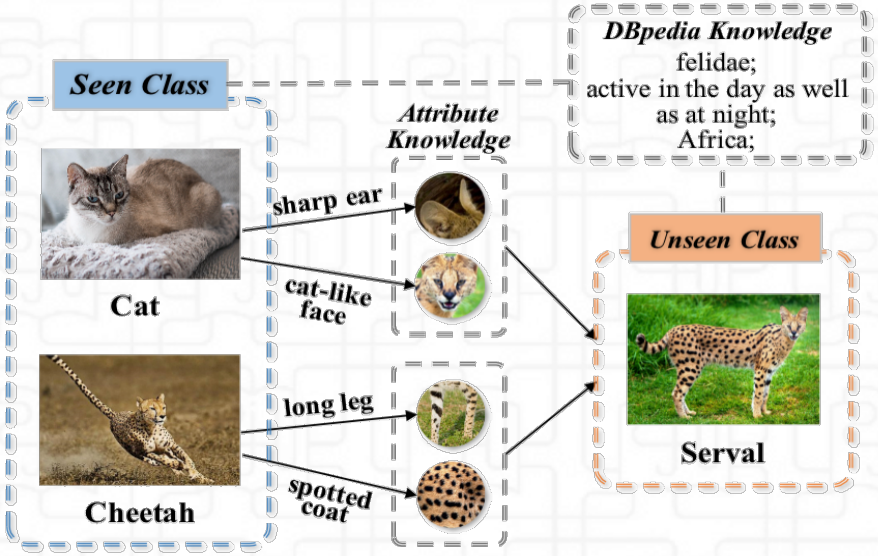


知识图谱 (Knowledge Graph, KG) & 低资源学习 (Low Resource Learning, LRL)

LRL4KG: 知识图谱中的低资源问题



KG4LRL: Knowledge as Supervision

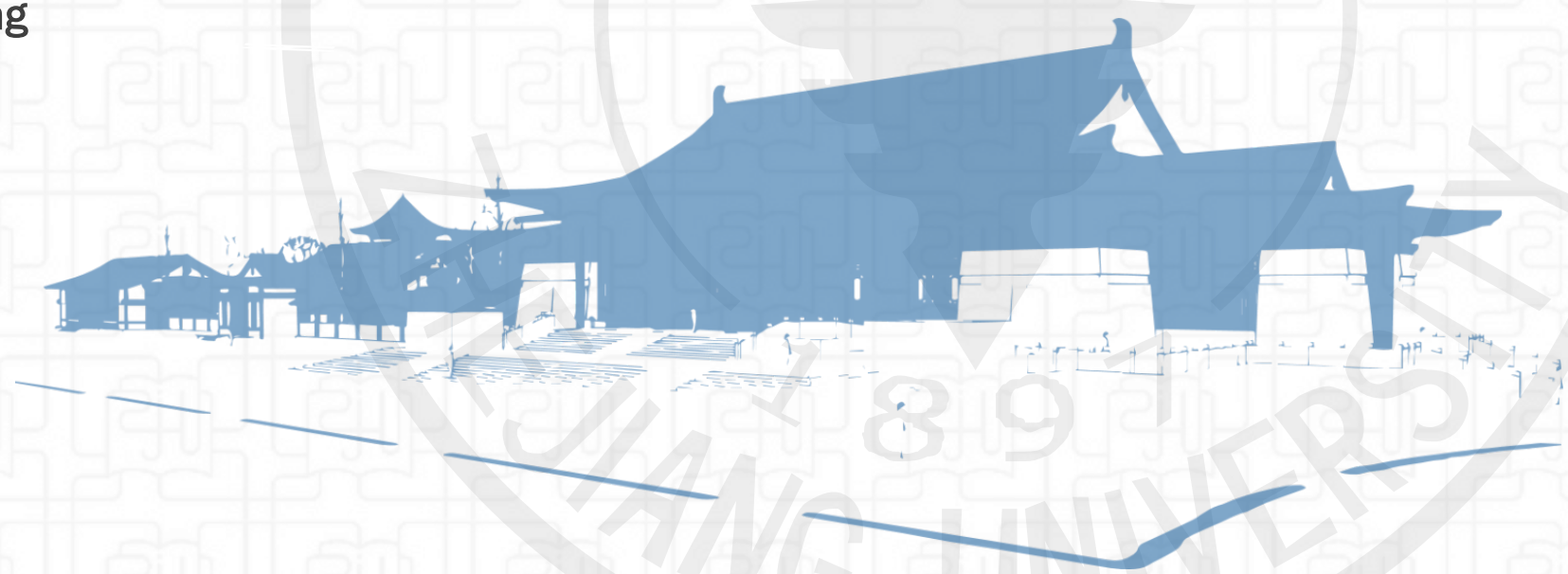


Knowledge can help reduce training !

02

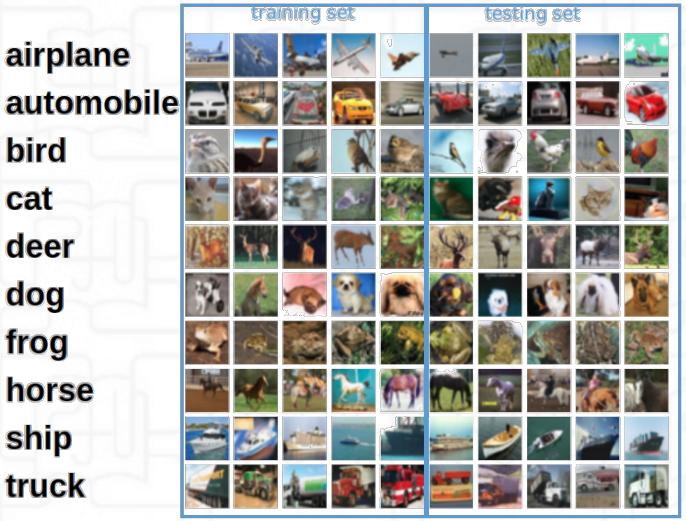
基于知识图谱的低资源学习

KG-based Low Resource Learning

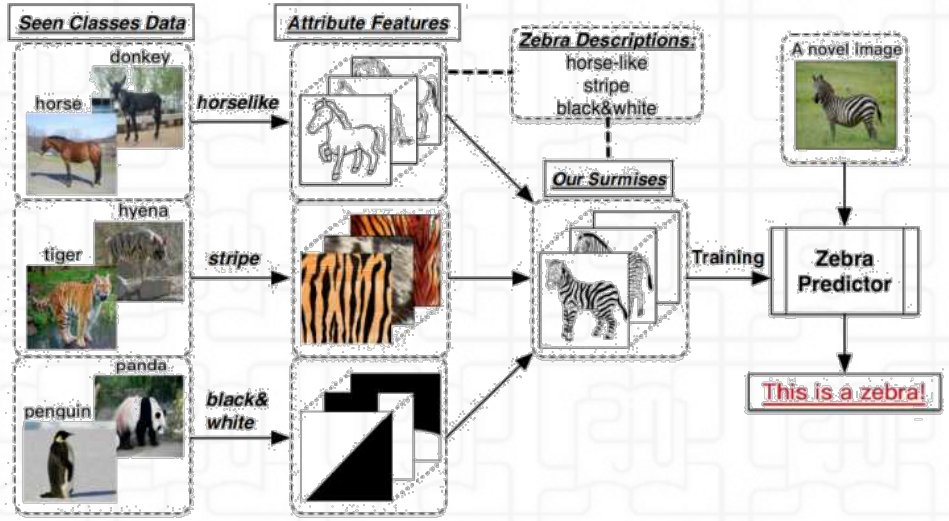


02 低资源学习之零样本学习

- 零样本学习



传统的机器学习/深度学习



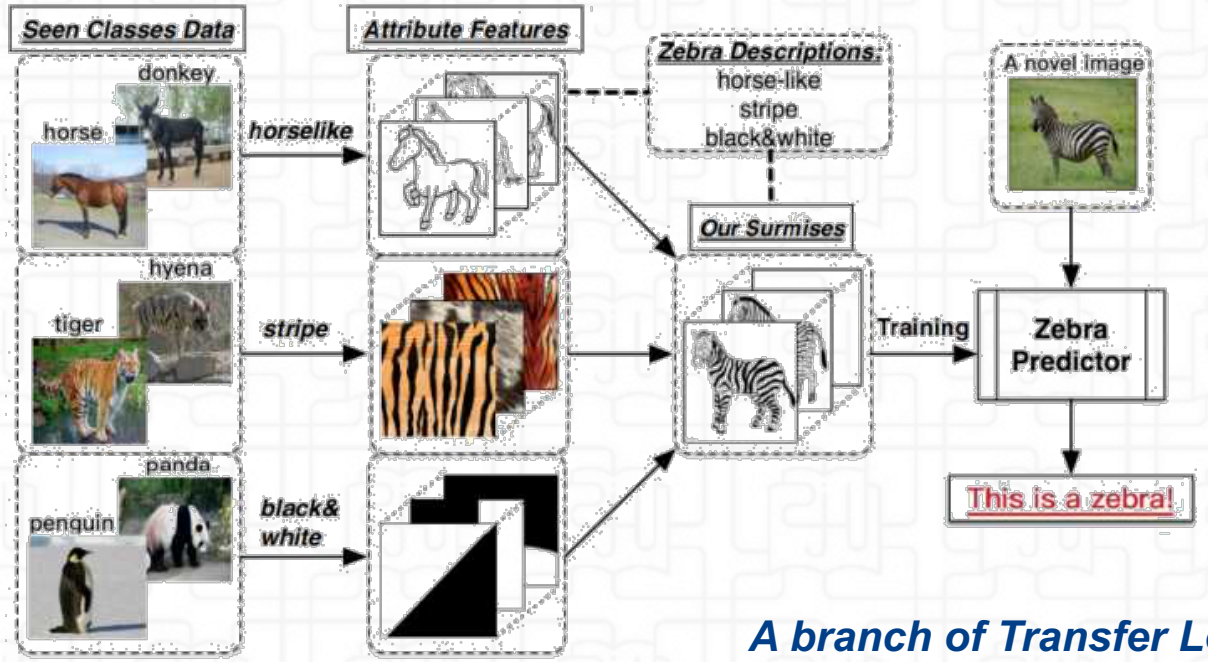
零样本学习

- 需大量标记数据
- 只能在训练过 (Seen) 的类别/概念上进行测试

- 测试时新出现 (Unseen) 的类别/概念，无训练样本

02 低资源学习之零样本学习

- 零样本学习关键技术
  - modeling the **semantic relationship** between seen and unseen classes, based on which the sample features of seen classes can be transferred to unseen classes.



A branch of Transfer Learning !

“ The *Zebra* has a *horse*’s outline, and there is a *tiger*-like stripe on it, and it is black and white like a *panda*. ”

02 低资源学习之零样本学习

- 零样本学习关键技术
  - modeling the **semantic relationship** between seen and unseen classes, based on which the sample features of seen classes can be transferred to unseen classes.

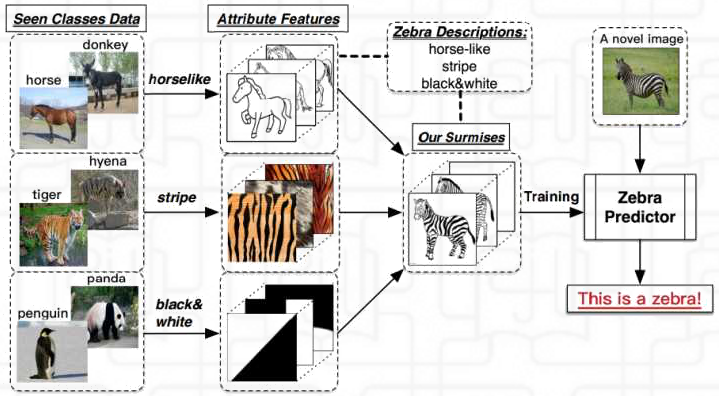
zebra

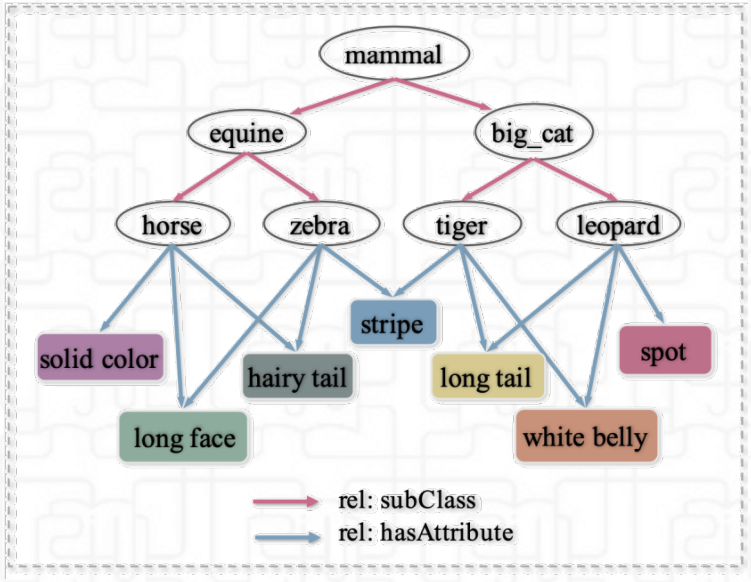
black: yes
white : yes
brown: no
stripes: yes
water: no
eats fish: no

tiger

black: yes
white : yes
brown: no
stripes: yes
water: no
eats fish: no

02 基于知识图谱的零样本学习





Knowledge Graph

KG as Bridge for Transfer

利用知识图谱建立Unseen Class与Seen Class之间关系

Knowledge as Reasoning

零样本问题本质是利用知识完成推理的过程

Knowledge as Explanation

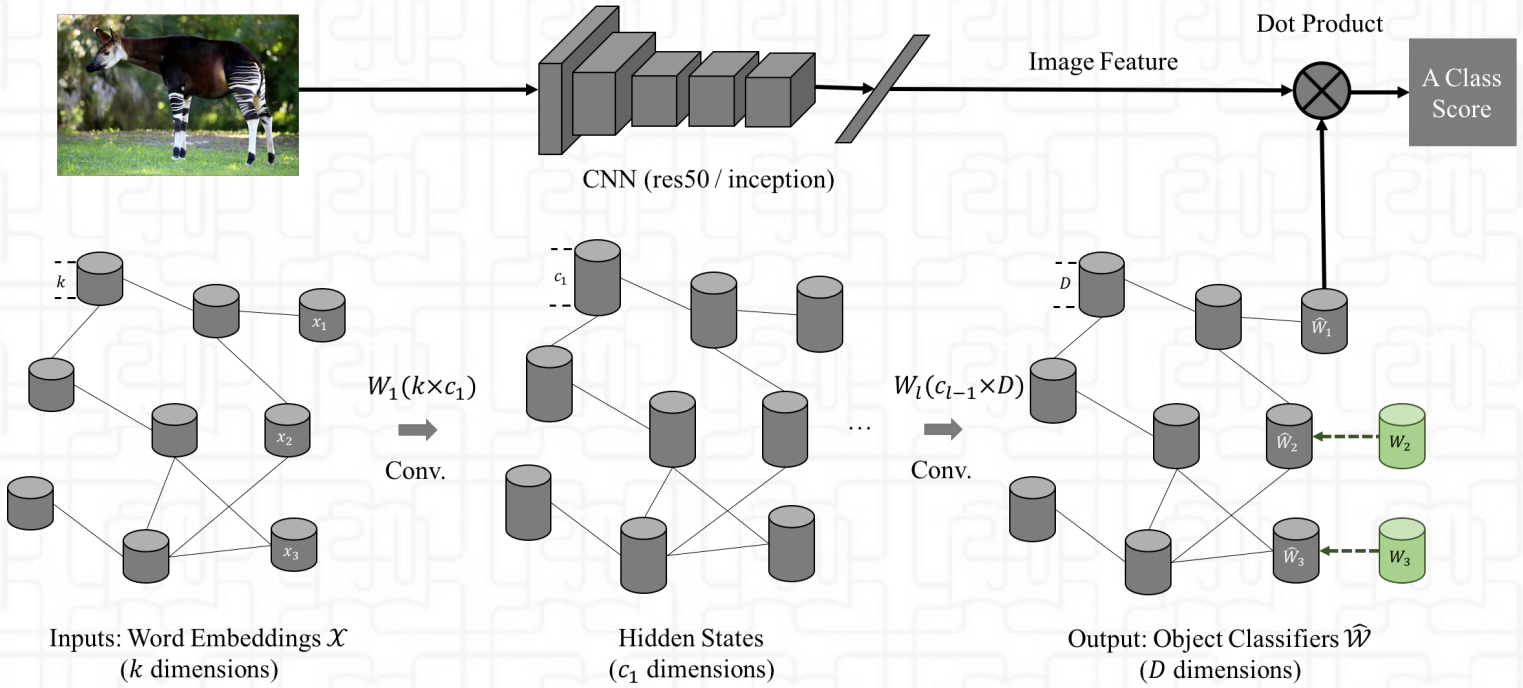
知识图谱中蕴含Seen Class与Unseen Class之间丰富的内在联系

02 基于知识图谱的零样本学习

- **Computer Vision: Image Classification**
  - GCNZ: Zero-shot Recognition via Semantic Embeddings and Knowledge Graphs. CVPR 2018.
  - Multi-Label Zero-Shot Learning with Structured Knowledge Graphs. CVPR 2018.
  - OntoZSL: Ontology-enhanced Zero-shot Learning. Under Review.
  - Ontology-guided Semantic Composition for Zero-shot Learning. KR2020.
- **Natural Language Processing: Text Classification**
  - Integrating Semantic Knowledge to Tackle Zero-shot Text Classification. NAACL 2019.
- **Natural Language Processing: Relation Extraction/Classification**
  - Logic-guided Semantic Representation Learning for Zero-Shot Relation Classification. COLING2020.
- **Explainable ZSL**
  - Explainable Zero-shot Learning via Attentive Graph Convolutional Network and Knowledge Graph. Semantic Web Journal.

- **Natural Language Processing: Relation Extraction/Classification**
  - Long-tail Relation Extraction via Knowledge Graph Embeddings and Graph Convolution Networks. NAACL 2019.

02 基于知识图谱（图）的零样本图片分类



$$\frac{1}{m}\sum_{i=1}^{m} L_{\text{mse}}(\hat{w}_i, w_i)$$

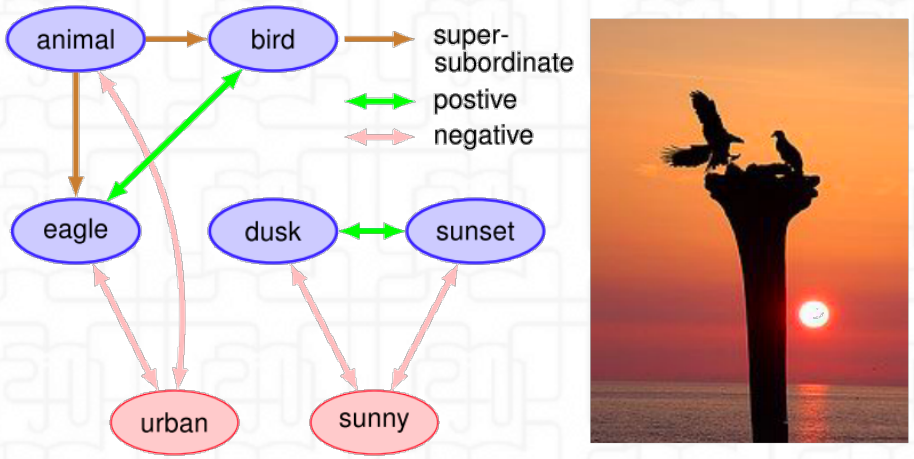
MSE损失函数

CNN模块（上）：抽取图片特征，得到一个D维的特征分类器

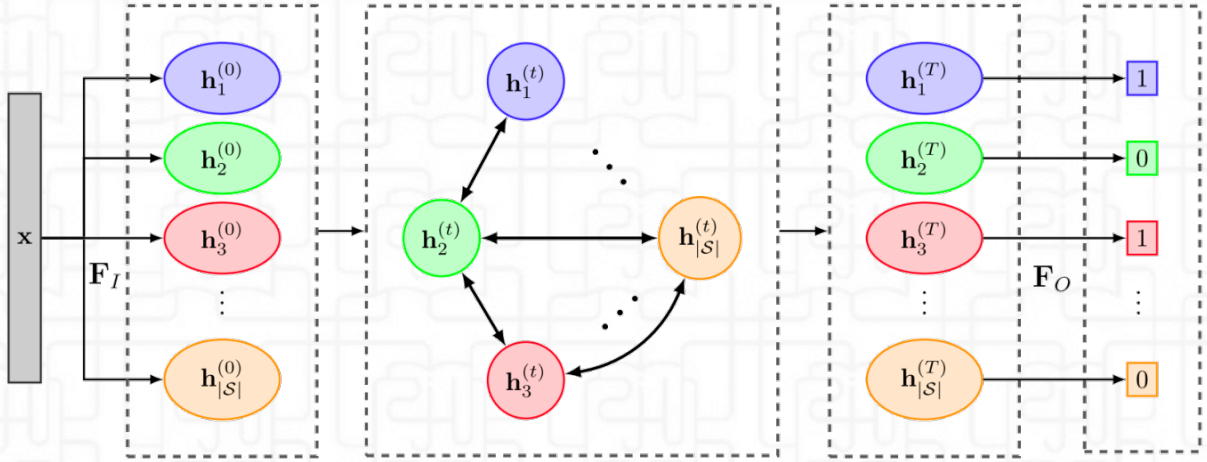
GCN模块（下）：以图片类别的词向量及类别间的层次结构（图）作为输入，为每个类别预测D维的特征分类器，用于分类该类别的测试样本。

GCNZ: Zero-shot Recognition via Semantic Embeddings and Knowledge Graphs. CVPR 2018.

02 基于知识图谱的多标签零样本图片分类

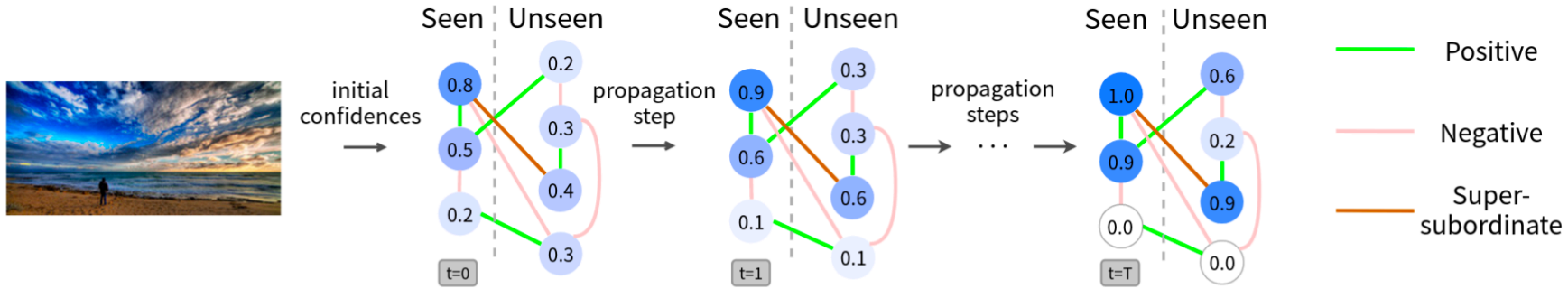


图片标签之间的结构图谱



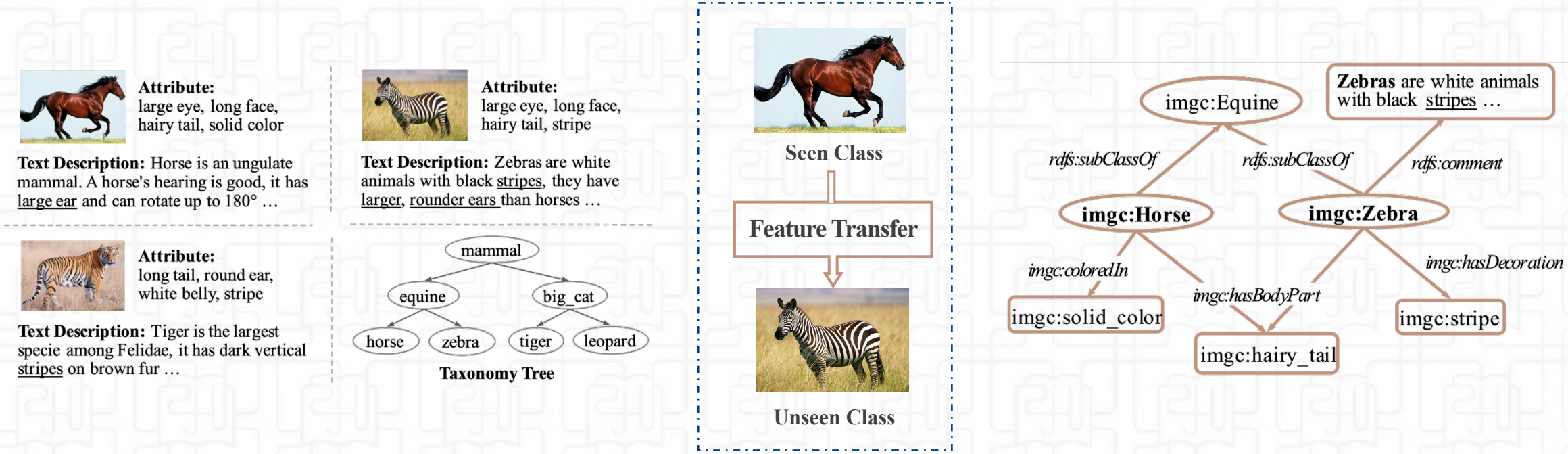
$$\mathbf{h}_v^{(0)} = \mathbf{F}_I(\mathbf{x}, \mathbf{w}_v)$$

借助门控图神经网络的信息传播模型将图片信息和标签信息进行融合并推理



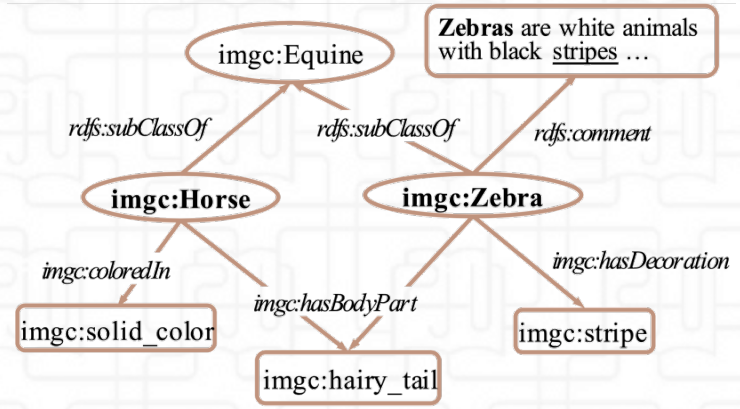
Multi-Label Zero-Shot Learning with Structured Knowledge Graphs. CVPR 2018.

02 基于知识图谱的零样本图片分类



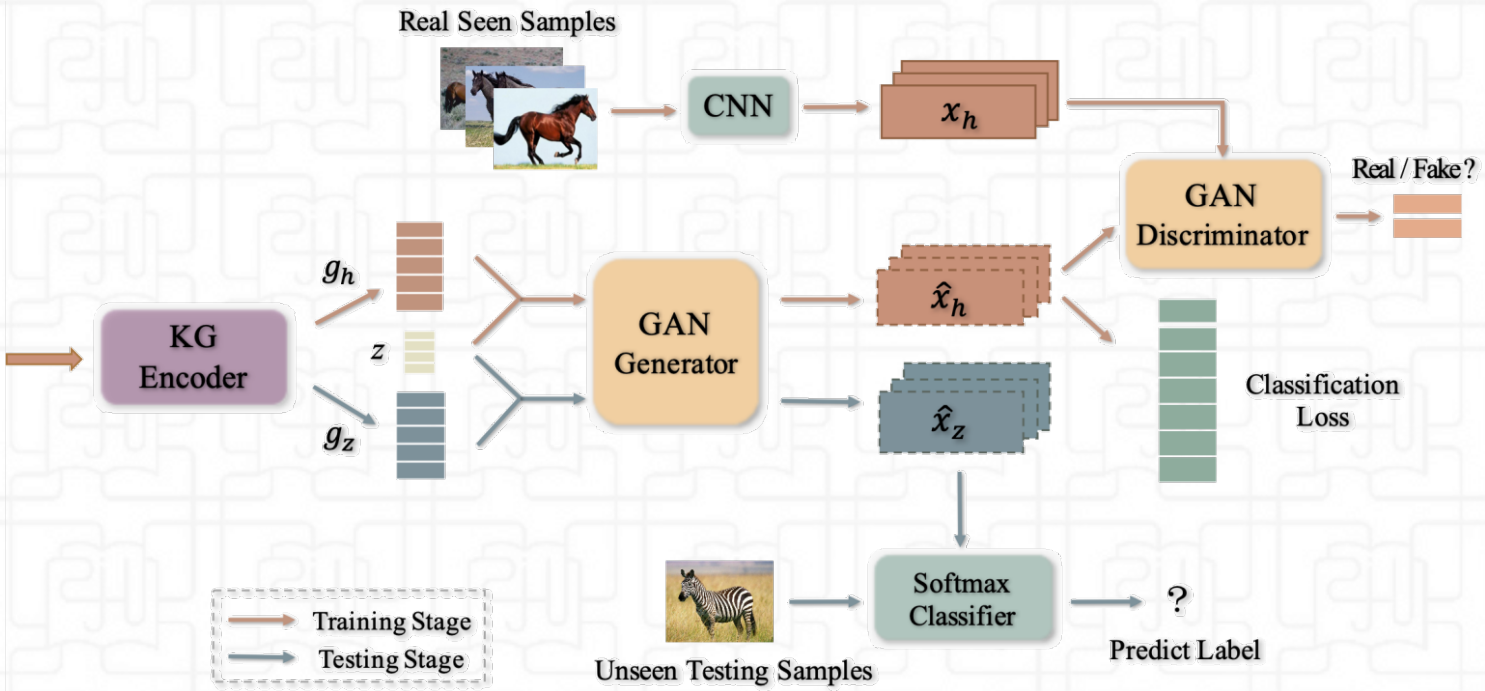
Yuxia Geng, Jiaoyan Chen, Huajun Chen, et al. OntoZSL: Ontology-enhanced Zero-shot Learning. WWW 2021 Under Review.

02 基于知识图谱的零样本图片分类



Knowledge Graph

encoder like Relational GCN, TransE …



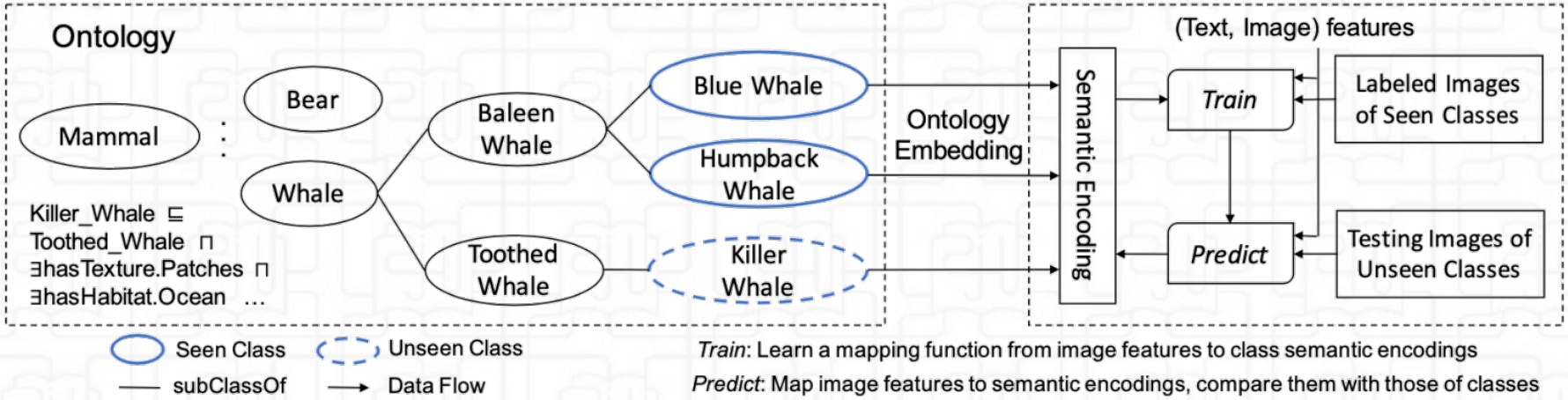
Methods	Standard ZSL			Generalized ZSL								
	AwA	ImNet-A	ImNet-O	AwA			ImNet-A			ImNet-O		
	acc	acc	acc	acc_s	acc_u	H	acc_s	acc_u	H	acc_s	acc_u	H
GCNZ	–	31.62	30.05	–	–	–	49.52	15.68	23.81	44.60	14.48	21.87
DGP	58.99	33.07	31.23	86.19	16.59	27.82	44.72	17.92	25.59	47.40	19.00	27.13
OntoZSL	**63.31**	**38.72**	**34.24**	64.90	**49.35**	**56.06**	37.92	**26.65**	**31.30**	43.40	**21.50**	**28.76**

Yuxia Geng, Jiaoyan Chen, Huajun Chen, et al. OntoZSL: Ontology-enhanced Zero-shot Learning. WWW 2021 Under Review.

02 基于本体的零样本图片分类

- More Expressive Knowledge: Ontology(Logic)-based Semantic Composition

"Killer_Whale ⊑ Toothed_Whale ⊓ ∃ hasTexture.Patches ⊓ ∃hasHabitat.Ocean …"

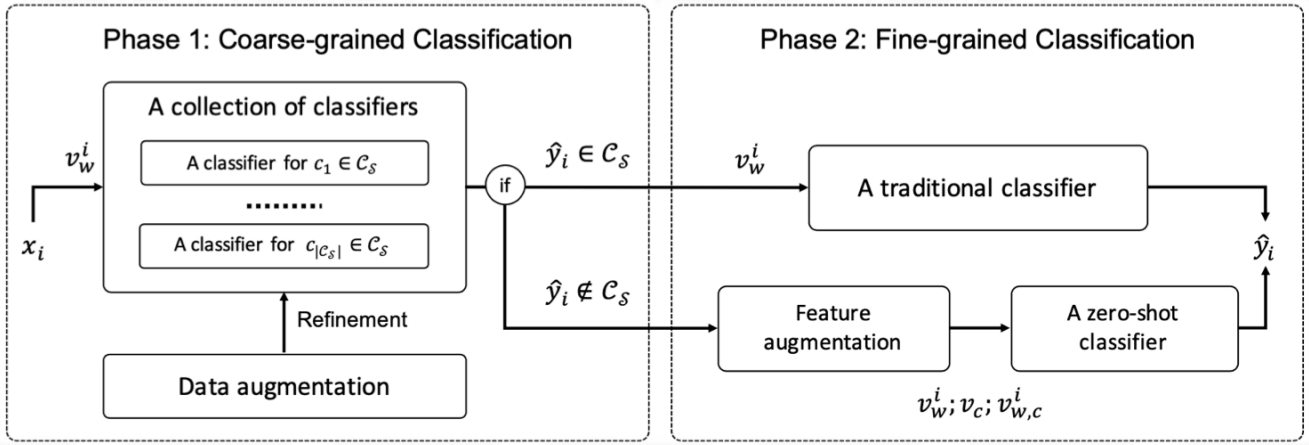


Ontology Embedding
- Embedding of Logical Axioms e.g., by geometric learning (Kulmanov et al. 2019)
- Embedding of text and paths e.g., by neural language model (Holter et al. 2019)

Jiaoyan Chen, **Yuxia Geng**, Huajun Chen, et al. Ontology-guided Semantic Composition for Zero-Shot Learning. KR2020.

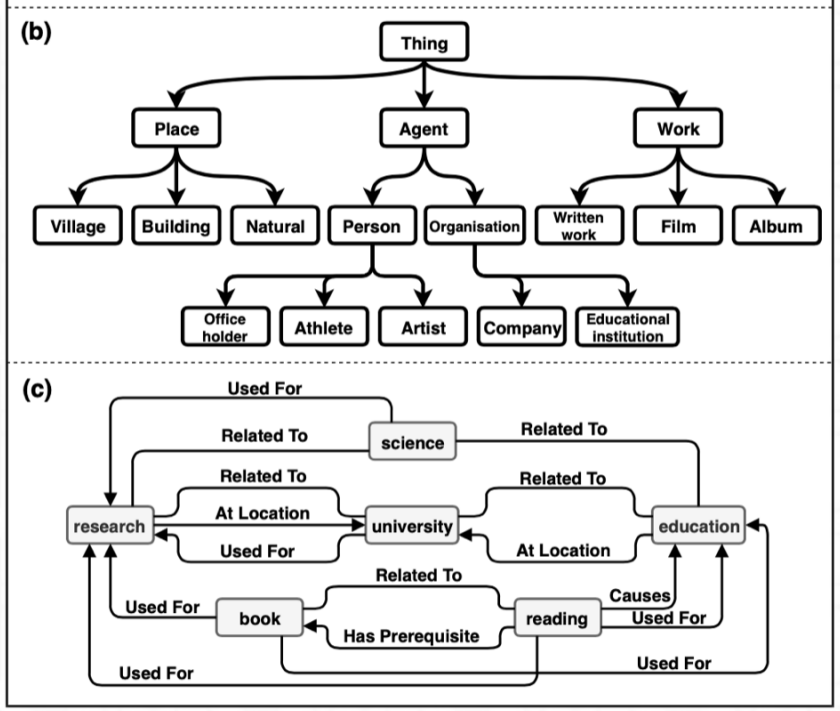
02 基于知识图谱的零样本文本分类

- Knowledge of Text Labels



(a)

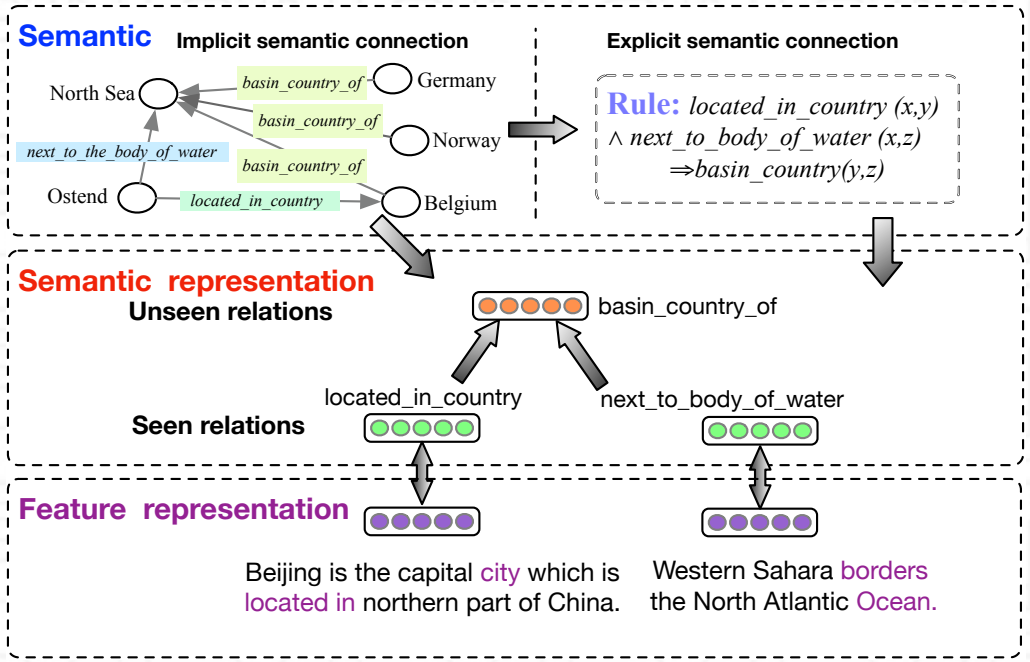
Class labels	Class descriptions
Company	an organization that provides services, or that makes or sells goods for money
Educational Institution	a place where people of different ages gain an education.
Artist	someone who makes paintings, sculptures etc

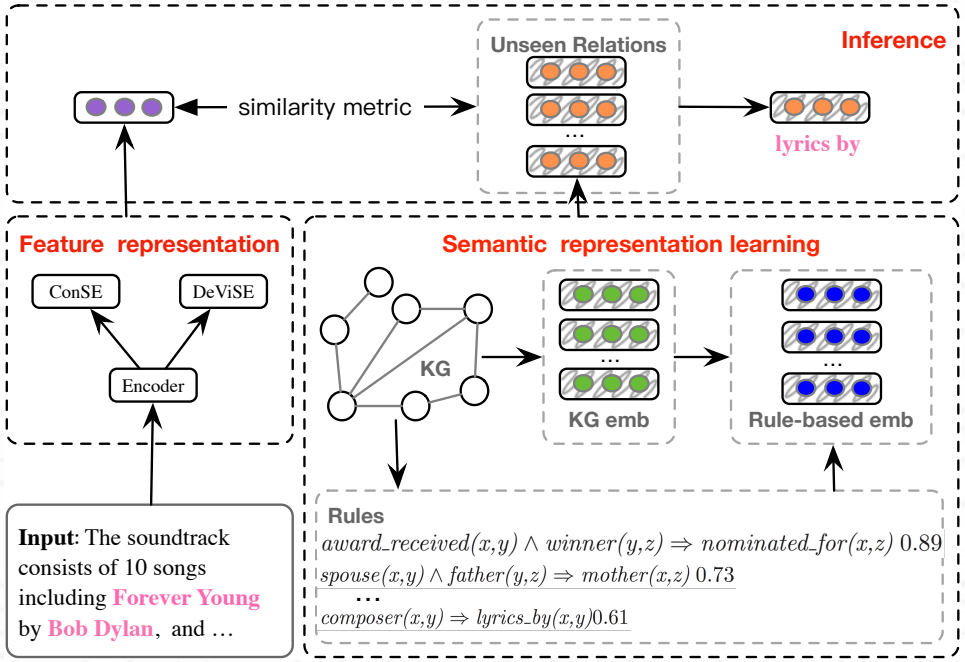


Integrating Semantic Knowledge to Tackle Zero-shot Text Classification. NAACL 2019.

02 基于知识图谱的零样本关系抽取/分类

- Logic Rules and Semantic Connections of Relation Labels

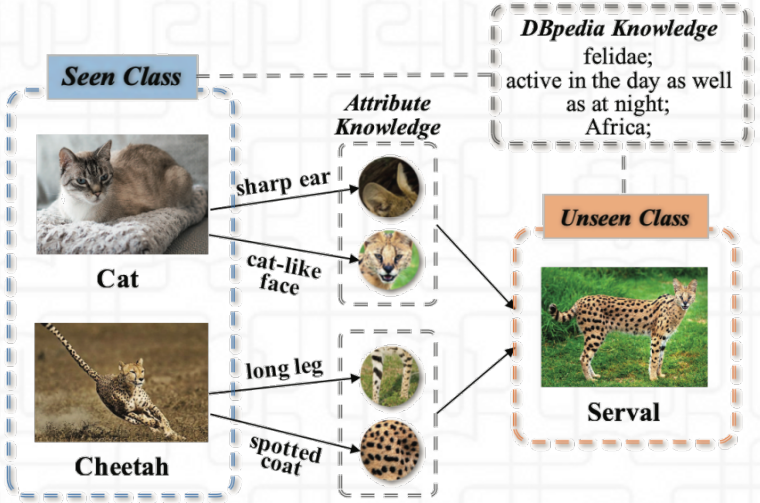




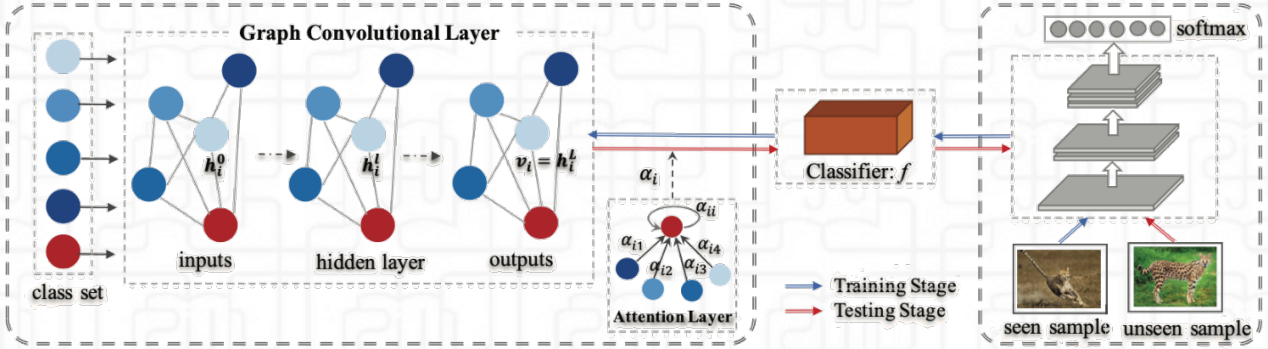
Juan Li, Ruoxu Wang, **Huajun Chen**, et al. Logic-guided Semantic Representation Learning for Zero-Shot Relation Classification. COLING2020.

02 基于知识图谱的可解释零样本学习

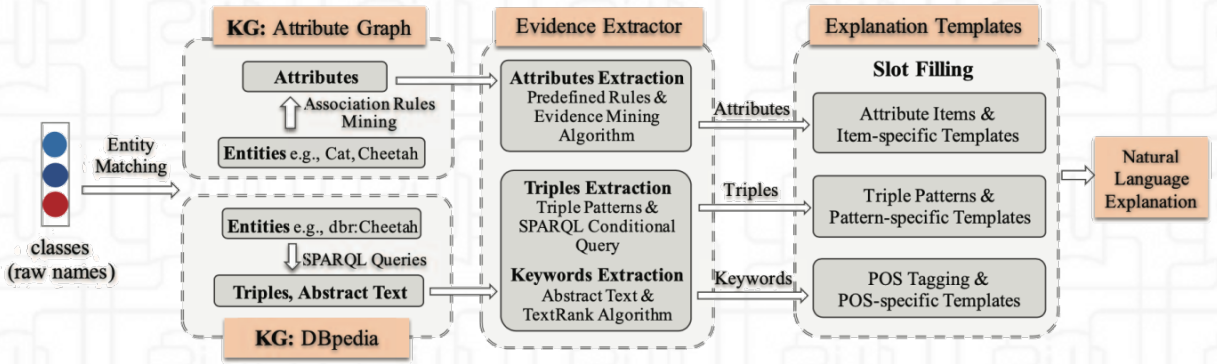
- The transferability of deep features in ZSL



“ Why *Cat* and *Cheetah* transfer their features to Serval? ”



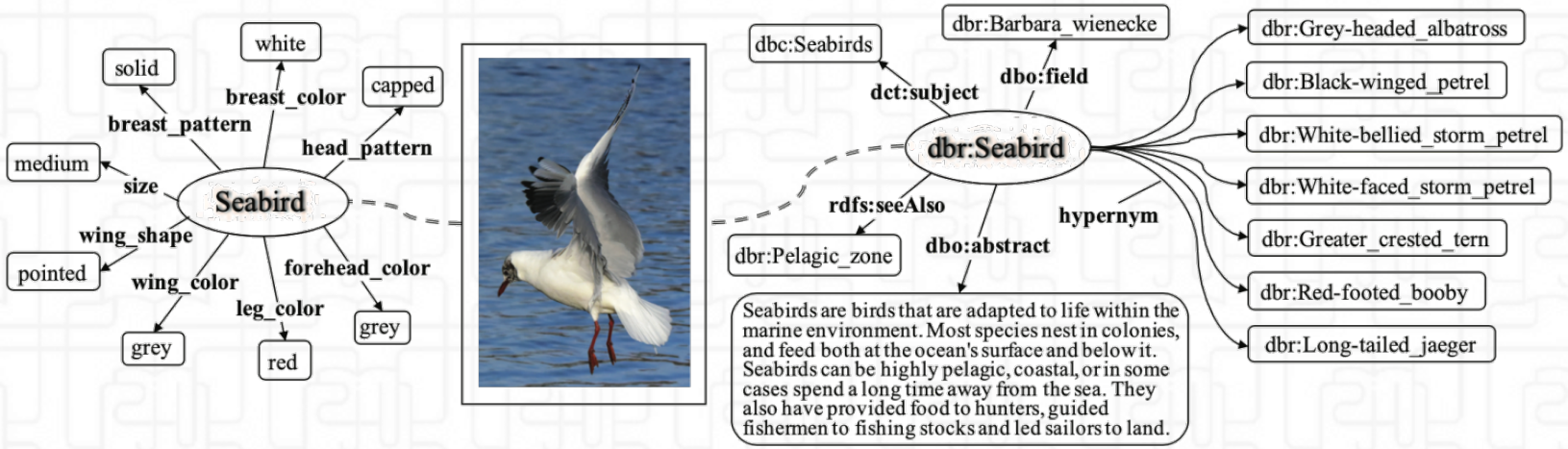
ZSL Learner: WordNet & Attentive Graph Convolutional Network



Explanation Generator: Attribute Graph & DBpedia

Yuxia Geng, Jiaoyan Chen, et al. Explainable Zero-shot Learning via Attentive Graph Convolutional Network and Knowledge Graphs. Semantic Web Journal.
Yuxia Geng, Jiaoyan Chen, et al. Human-centric Transfer Learning Explanation via Knowledge Graph. AAAI 2019 Workshop on Network Interpretability for Deep Learning.

02 基于知识图谱的可解释零样本学习



	Horse (Unseen Class)	IMSCs of Horse
		Zebra (*w*: 1.0)
Image		
Generated Explanation & Score	The prediction for samples of **horse** is supported by **zebra**. *They are both grazer, grouped, quadrupedal, both have hooves, muscle, longneck, chewteeth, both live in plains, and behave timid.* They are both species of **equus**, and are both a member of **herbivorous animals**. They are both **ungulate** animal, and are similar in **night vision** and **large ears**.	
	Readability [G/M/B]: M **Rationality [G/M/B]: G**	

Stork (Unseen Class)	IMSCs of Stork	
	White stork (*w*: 0.51)	Black stork (*w*: 0.49)
The prediction for samples of **stork** is supported by **white stork** and **black stork**. *They are both white, black, wild, both live in water and eat fish.* **White stork** and **black stork** both belong to **stork** biologically. They are both **large wadding birds**, and are similar in **long legs**.		
Readability [G/M/B]: G **Rationality [G/M/B]: G**		

Yuxia Geng, Jiaoyan Chen, et al. Explainable Zero-shot Learning via Attentive Graph Convolutional Network and Knowledge Graphs. Semantic Web Journal.
Yuxia Geng, Jiaoyan Chen, et al. Human-centric Transfer Learning Explanation via Knowledge Graph. AAAI 2019 Workshop on Network Interpretability for Deep Learning.

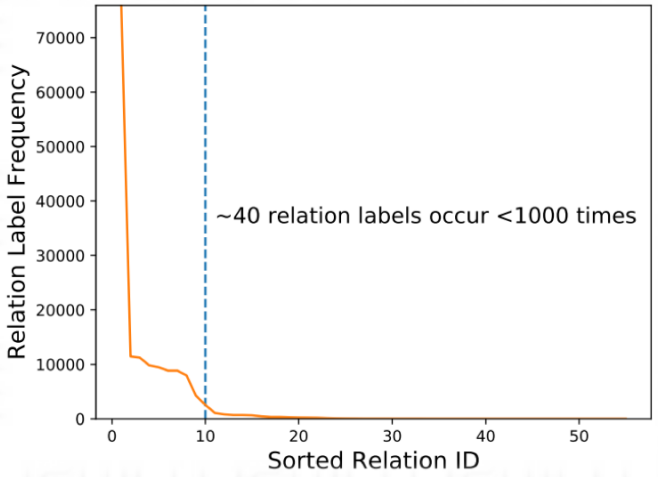
02 基于知识图谱的少样本（长尾）学习

- 关系抽取：从自然语言句子中抽取三元组如<贾玲，师生关系，冯巩>

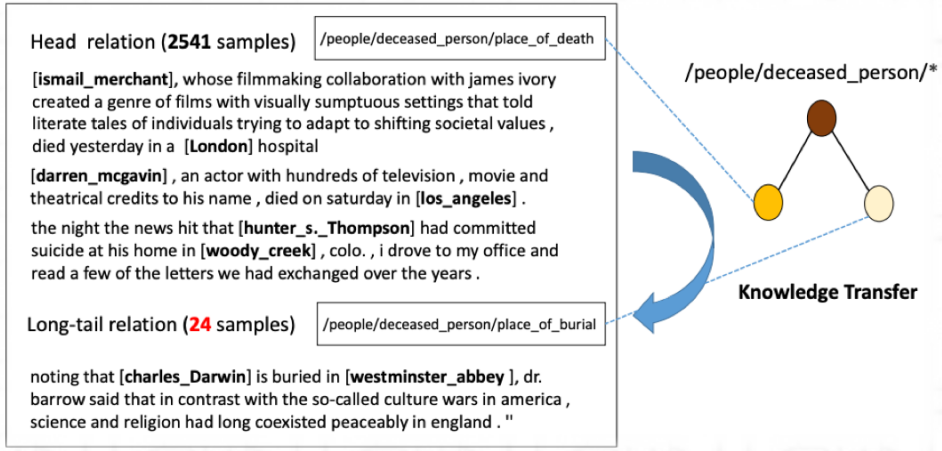
师生关系

贾玲，80后相声新秀，师承中国著名相声表演艺术家冯巩。

实体对



关系抽取中的长尾问题

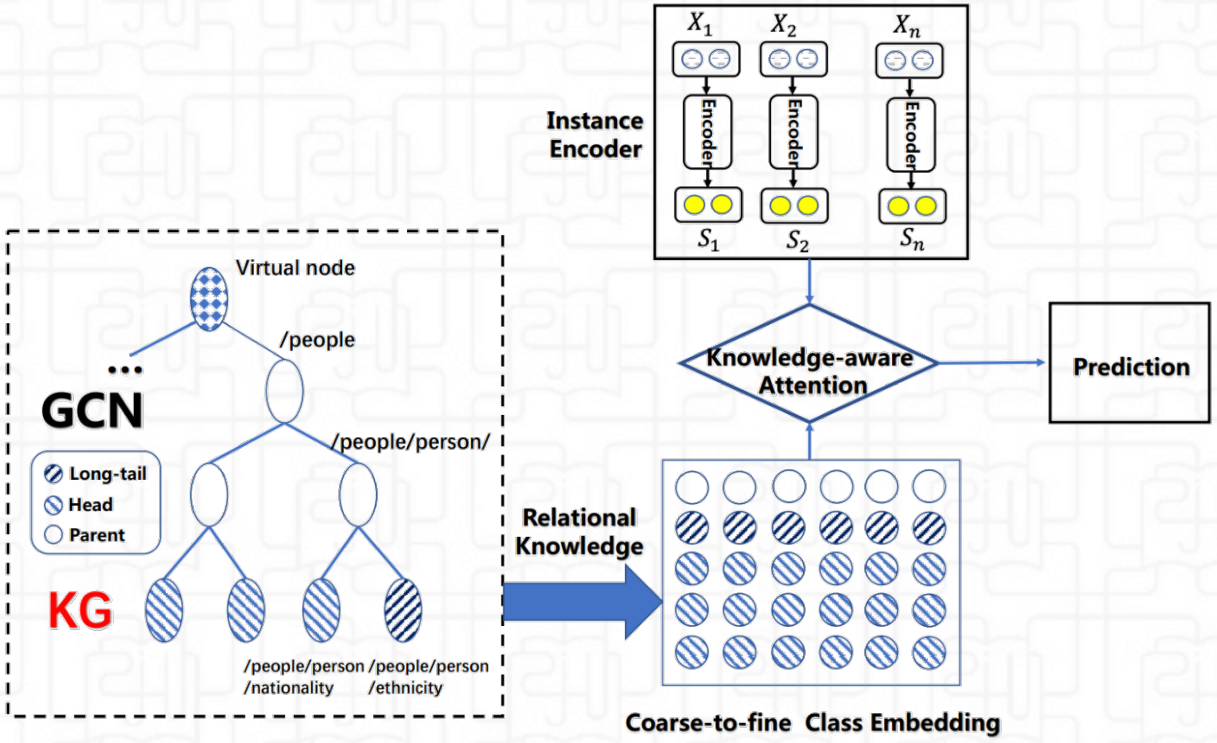


借助关系之间的“关系”进行特征迁移

Ningyu Zhang, **Huajun Chen**, et al. Long-tail Relation Extraction via Knowledge Graph Embeddings and Graph Convolution Networks. NAACL 2019.

02 基于知识图谱的少样本（长尾）学习

- 模型细节



Training Instances		<100			<200		
Hits@K (Macro)		10	15	20	10	15	20
CNN	+ATT	<5.0	<5.0	18.5	<5.0	16.2	33.3
	+HATT	5.6	31.5	57.4	22.7	43.9	65.1
	+KATT	**9.1**	**41.3**	**58.5**	**23.3**	**44.1**	**65.4**
PCNN	+ATT	<5.0	7.4	40.7	17.2	24.2	51.5
	+HATT	29.6	51.9	61.1	41.4	60.6	68.2
	+KATT	**35.3**	**62.4**	**65.1**	**43.2**	**61.3**	**69.2**

少样本“关系”预测结果

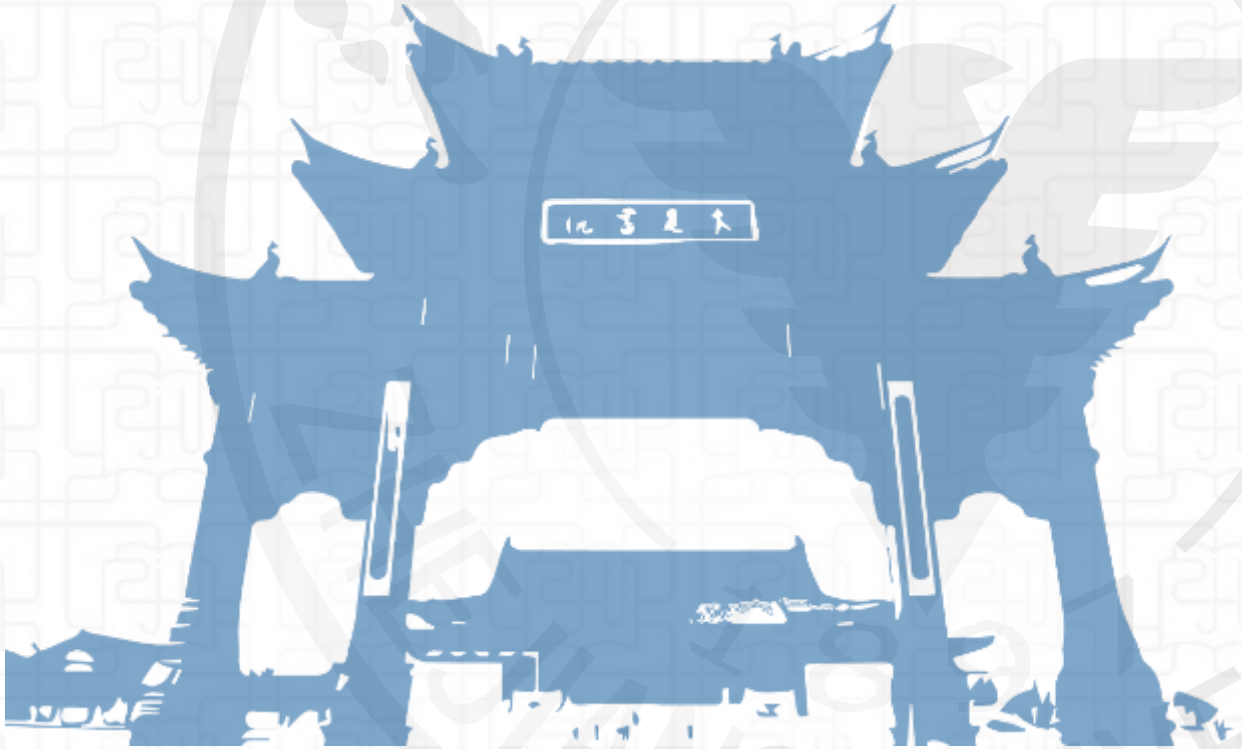
$$v_i^1 = f(W^1 v_i + \sum_{j \in \mathcal{N}_p} \frac{W_p^1 v_j}{|\mathcal{N}_p|} + \sum_{j \in \mathcal{N}_c} \frac{W_c^1 v_j}{|\mathcal{N}_c|} + b_g^1)$$

Ningyu Zhang, **Huajun Chen**, et al. Long-tail Relation Extraction via Knowledge Graph Embeddings and Graph Convolution Networks. NAACL 2019.

03

知识图谱中的低资源问题

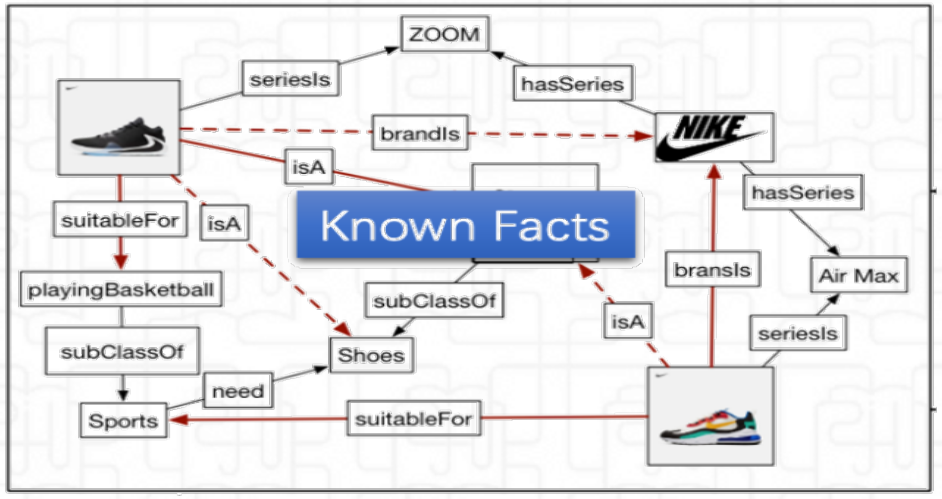
Low Resource Learning in KGs



03 知识图谱表示学习

- **基于向量表示的知识图谱推理技术**
  - 为知识图谱中的每个实体和关系都学习一个向量表示，同时保留图谱中的结构信息和语义信息；
  - 将离散的符号表示转换为连续的向量表示；
  - 将推理转换为向量或矩阵之间的计算过程。

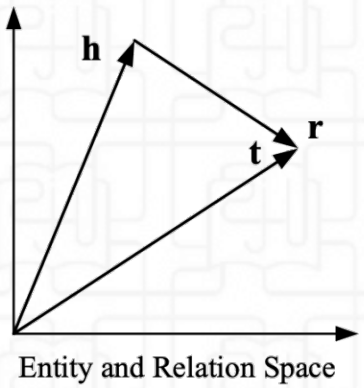
KG Embedding = Entity Vector & Relation Vectors = Distributed Representations of Knowledge Graph



已知：<姚明，女儿，姚沁蕾>，<姚沁蕾，妈妈，叶莉>

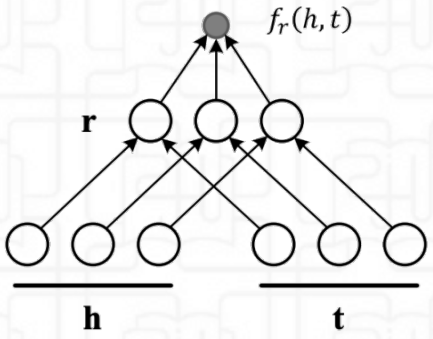
推理出：<姚明，夫妻，叶莉>

- 典型的知识图谱表示学习算法



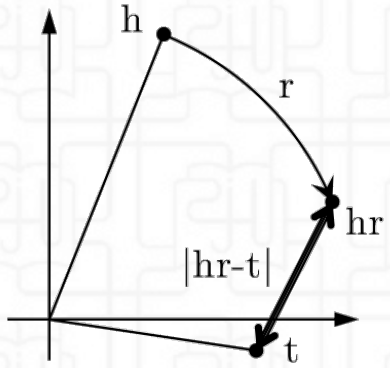
TransE

$$\boldsymbol{h} + \boldsymbol{r} = \boldsymbol{t}$$



DistMult

$$\boldsymbol{h} * \boldsymbol{M}_r = \boldsymbol{t}$$



RotatE

$$\boldsymbol{h} \circ \boldsymbol{r} = \boldsymbol{t}$$

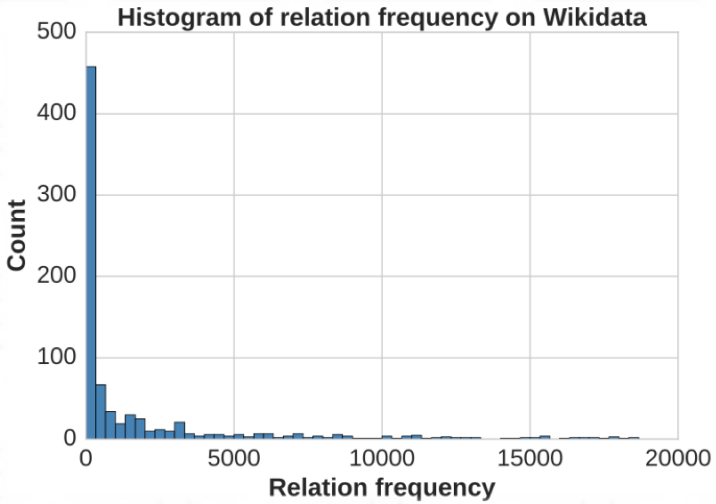
Knowledge Graph Embedding: A Survey of Approaches and Applications. TKDE2017.

03 表示学习的限制

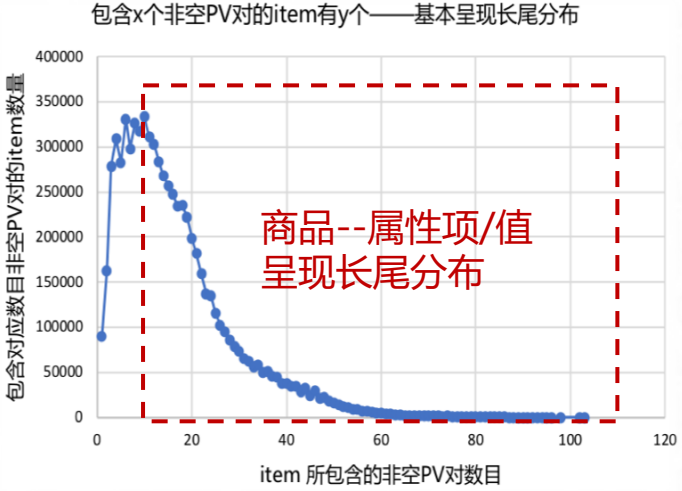
- **知识图谱的两个重要问题**
  - 稀疏性：部分实体/关系相关的三元组（样本较少）
  - 动态性：随时会有新实体/新关系加入，对于新加入的数据重新训练模型并不现实

少样本

零样本



Wikidata 中的长尾问题



商品知识图谱中的长尾问题

in the 6 months between DBPedia's October 2015 release and its April 2016 release 36, 340 new English entities were added – a rate of 200 new entities per day.

—— Open-World Knowledge Graph Completion, AAAI 2018

03 低资源下的知识图谱表示学习

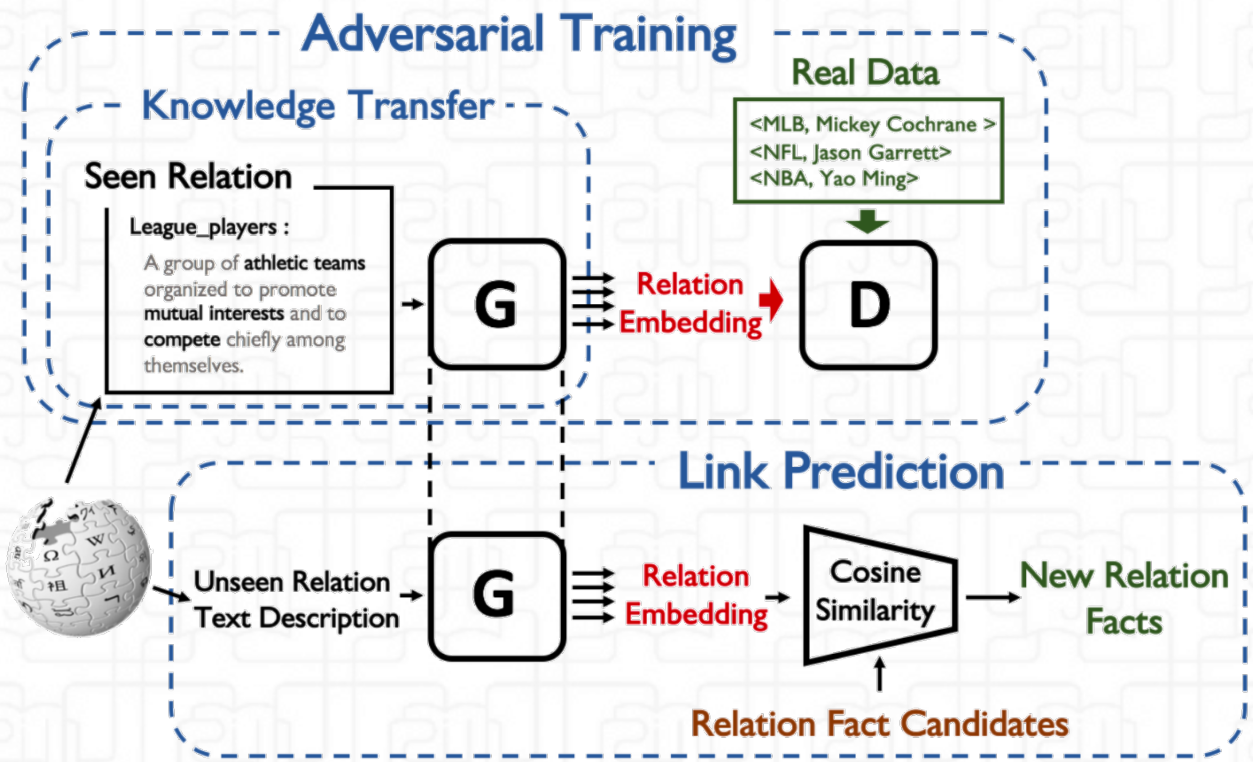
- Zero-shot Relations in KG
  - ZSGAN: Generative Adversarial Zero-Shot Relational Learning for Knowledge Graphs. AAAI 2020.
  - OntoZSL: Ontology-enhanced Zero-shot Learning. Under Review.
- Zero-shot Entities in KG
  - Knowledge transfer for out-of-knowledge-base entities: a graph neural network approach. IJCAI 2017.
  - LAN: Logic Attention Based Neighborhood Aggregation for Inductive Knowledge Graph Embedding. AAAI 2019.

- Transfer-based Few-shot Relations in KG
  - wRAN: Relation Adversarial Network for Low Resource Knowledge Graph Completion. WWW2020.

- Meta-Learning based Few-shot Relations in KG
  - GMatching: One-Shot Relational Learning for Knowledge Graphs. EMNLP 2018.
  - MetaR: Meta Relational Learning for Few-Shot Link Prediction in Knowledge Graphs. EMNLP2019.

03 零样本关系表示学习

- **知识迁移**
  - 在无训练样本的情况下实现知识推理（关系）



ZSGAN: Generative Adversarial Zero-Shot Relational Learning for Knowledge Graphs. AAAI 2020.

- **知识迁移**
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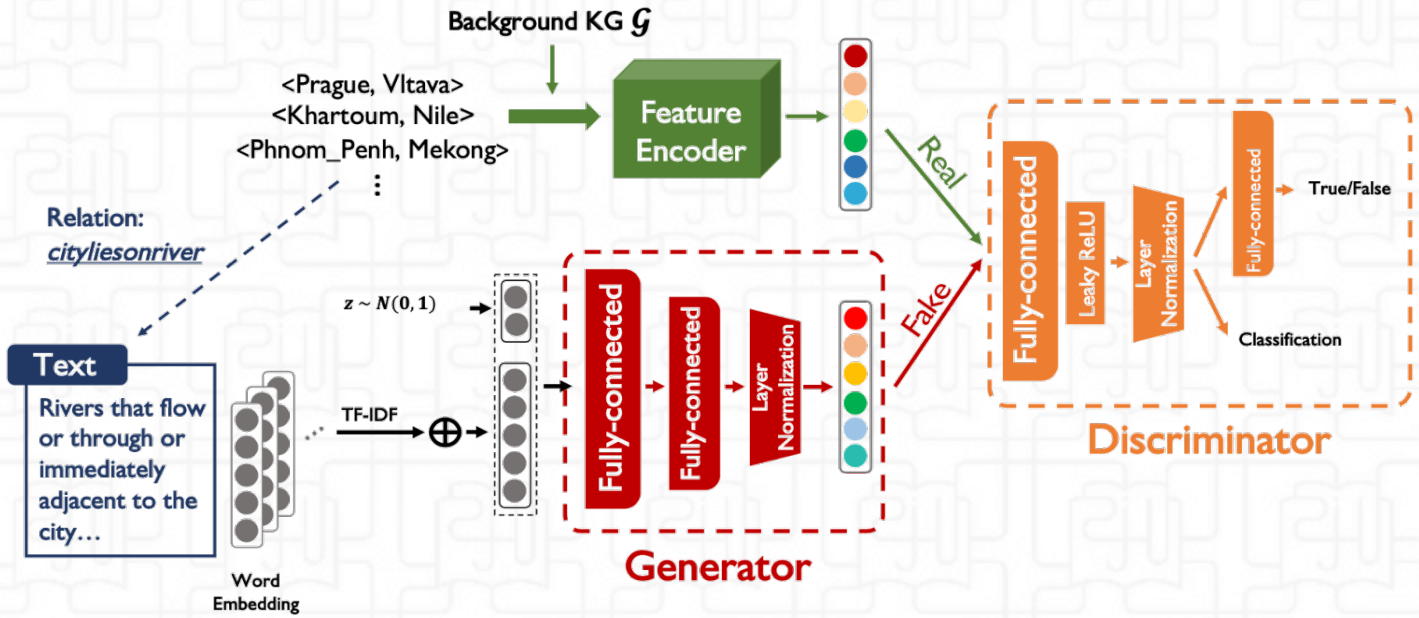
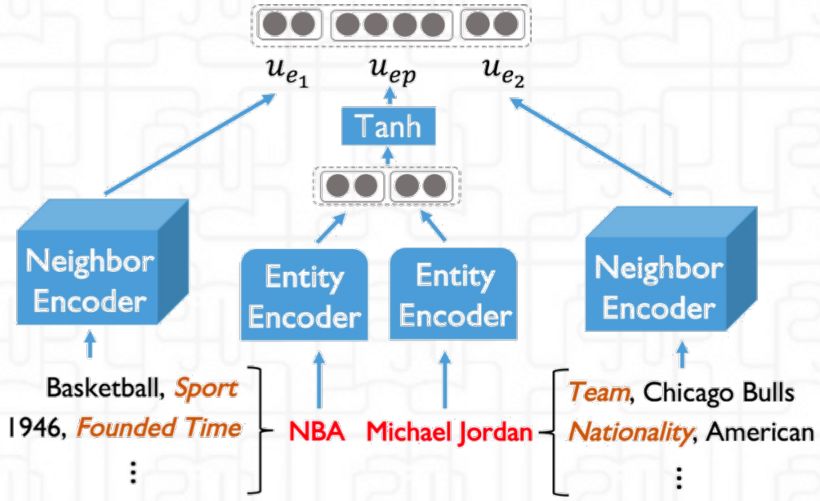


Framework

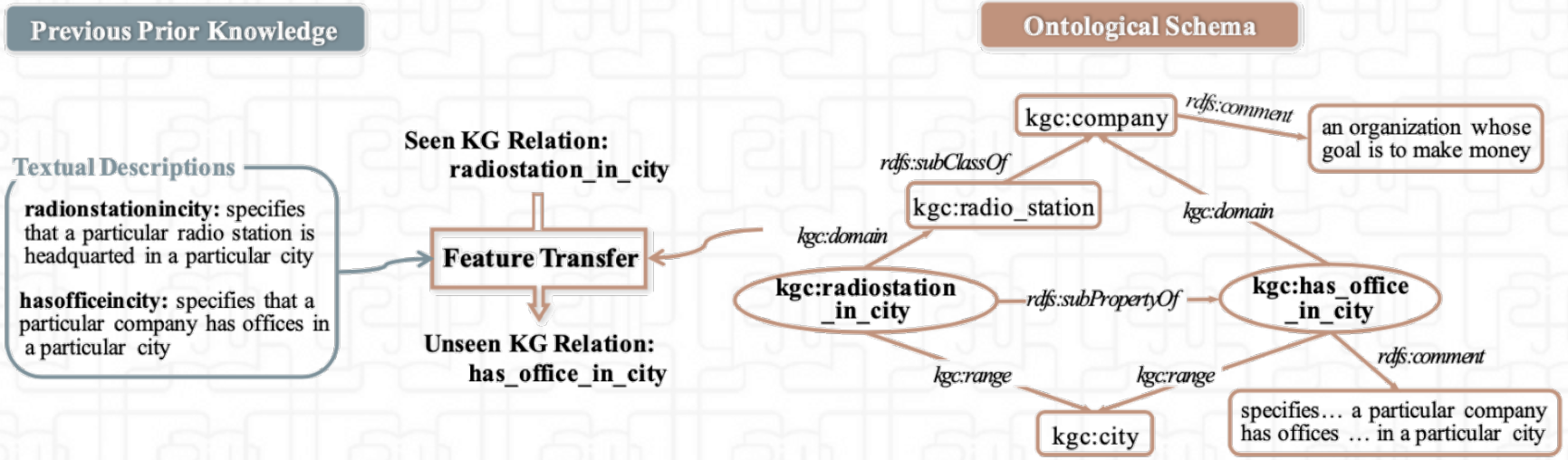


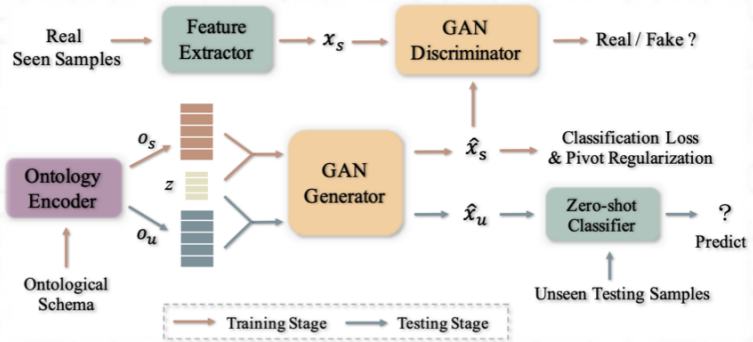
Feature Encoder

ZSGAN: Generative Adversarial Zero-Shot Relational Learning for Knowledge Graphs. AAAI 2020.

03 零样本关系表示学习

- 基于本体的知识迁移

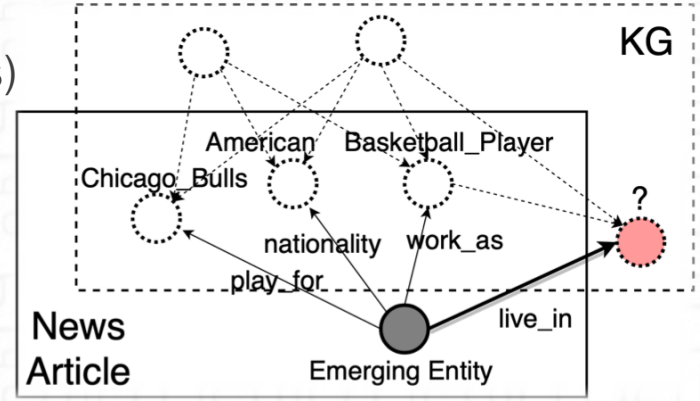


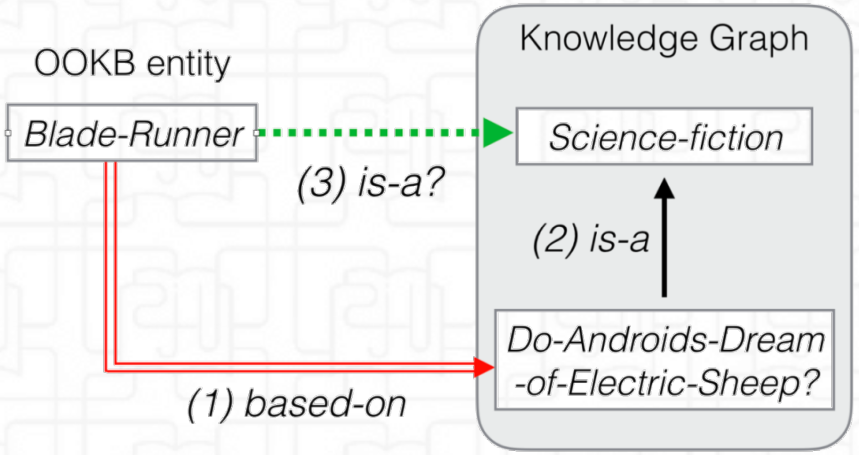


Pre-trained KG Embedding	Methods	NELL-ZS				Wikidata-ZS			
		MRR	*Hit@10*	*Hit@5*	*Hit@1*	*MRR*	*Hit@10*	*Hit@5*	*Hit@1*
TransE	ZS-TransE (Paper)	0.097	20.3	14.7	4.3	0.053	11.9	8.1	1.8
	ZSGAN	0.234	37.3	30.4	16.0	0.177	25.8	20.7	13.1
	OntoZSL	**0.250**	**39.9**	**32.7**	**17.2**	**0.184**	**26.5**	**21.5**	**13.8**
DistMult	ZS-DistMult (Paper)	0.235	32.6	28.4	18.5	0.189	23.6	21.0	16.1
	ZSGAN	0.249	37.6	30.6	18.3	0.207	28.4	23.5	16.4
	OntoZSL	**0.256**	**38.5**	**31.8**	**18.8**	**0.211**	**28.9**	**23.8**	**16.7**

Yuxia Geng, Jiaoyan Chen, Huajun Chen, et al. OntoZSL: Ontology-enhanced Zero-shot Learning. WWW 2021 Under Review.

- **借助辅助信息对新实体进行表示**
  - 未出现在训练集中的实体 (Out-of-Knowledge-Base entities, OOKB entities)





已有/训练三元组

辅助三元组

测试三元组

n: time step

$$\mathbf{v}_e^{(n)} = \begin{cases} \mathbf{v}_e, & \text{if } n = 0, \\ P(S_{\text{head}}^{(n-1)}(e) \cup S_{\text{tail}}^{(n-1)}(e)), & \text{otherwise,} \end{cases}$$

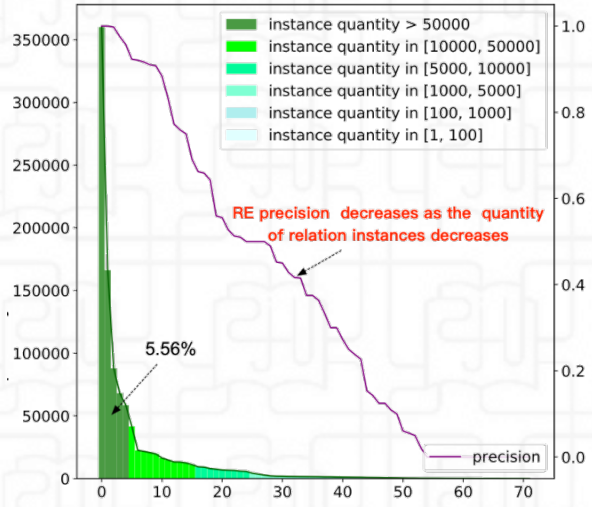
$$S_{\text{head}}(e) = \{T_{\text{head}}(\mathbf{v}_h; h, r, e) \mid (h, r, e) \in \mathcal{N}_h(e)\},$$
$$S_{\text{tail}}(e) = \{T_{\text{tail}}(\mathbf{v}_t; e, r, t) \mid (e, r, t) \in \mathcal{N}_t(e)\},$$

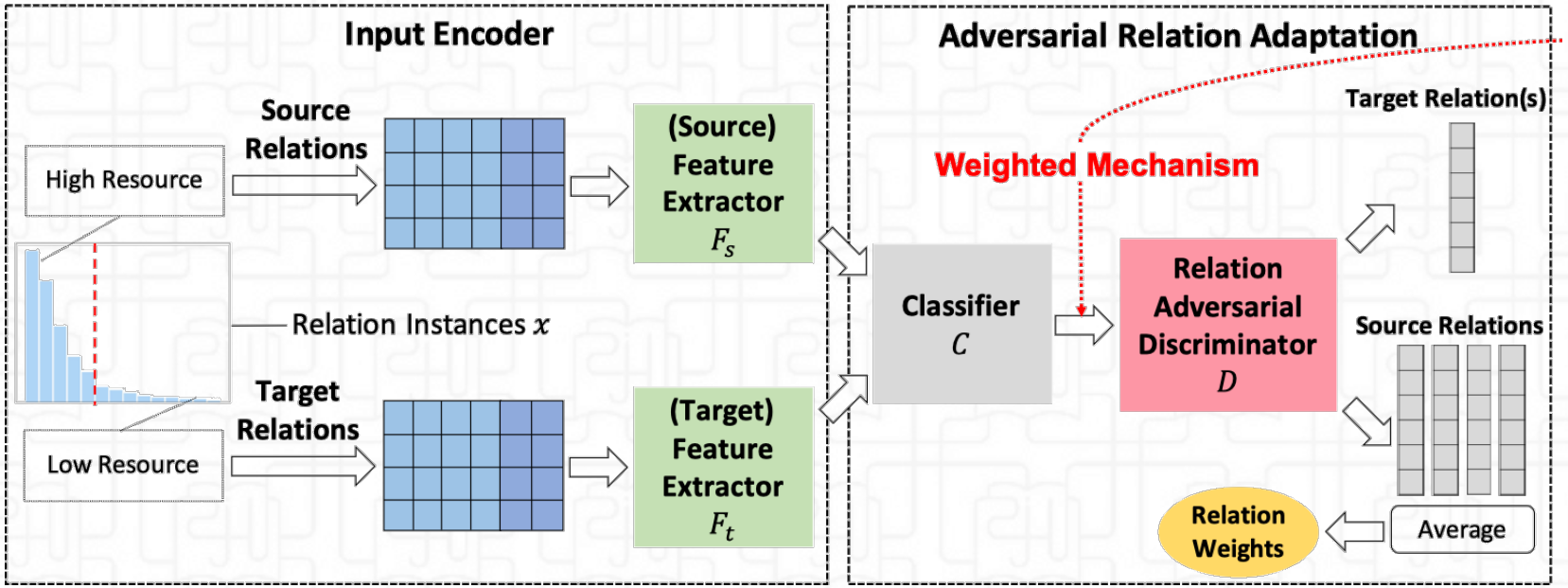
$$T_{\text{head}}(\mathbf{v}_h; h, r, e) = \text{ReLU}(\text{BN}(\boldsymbol{A}_r^{\text{head}} \mathbf{v}_h)),$$
$$T_{\text{tail}}(\mathbf{v}_t; e, r, t) = \text{ReLU}(\text{BN}(\boldsymbol{A}_r^{\text{tail}} \mathbf{v}_t)),$$

Knowledge transfer for out-of-knowledge-base entities: a graph neural network approach. IJCAI 2017.

03 长尾关系表示学习

- 利用对抗迁移学习提升长尾部分关系的学习能力，进而提升推理和补全性能





source relations => target relations

Ningyu Zhang, **Huajun Chen**, et al. wRAN: Relation Adversarial Network for Low Resource Knowledge Graph Completion. WWW2020.

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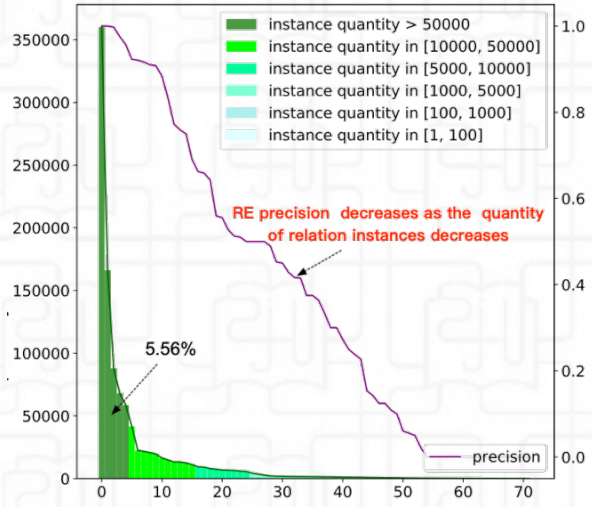

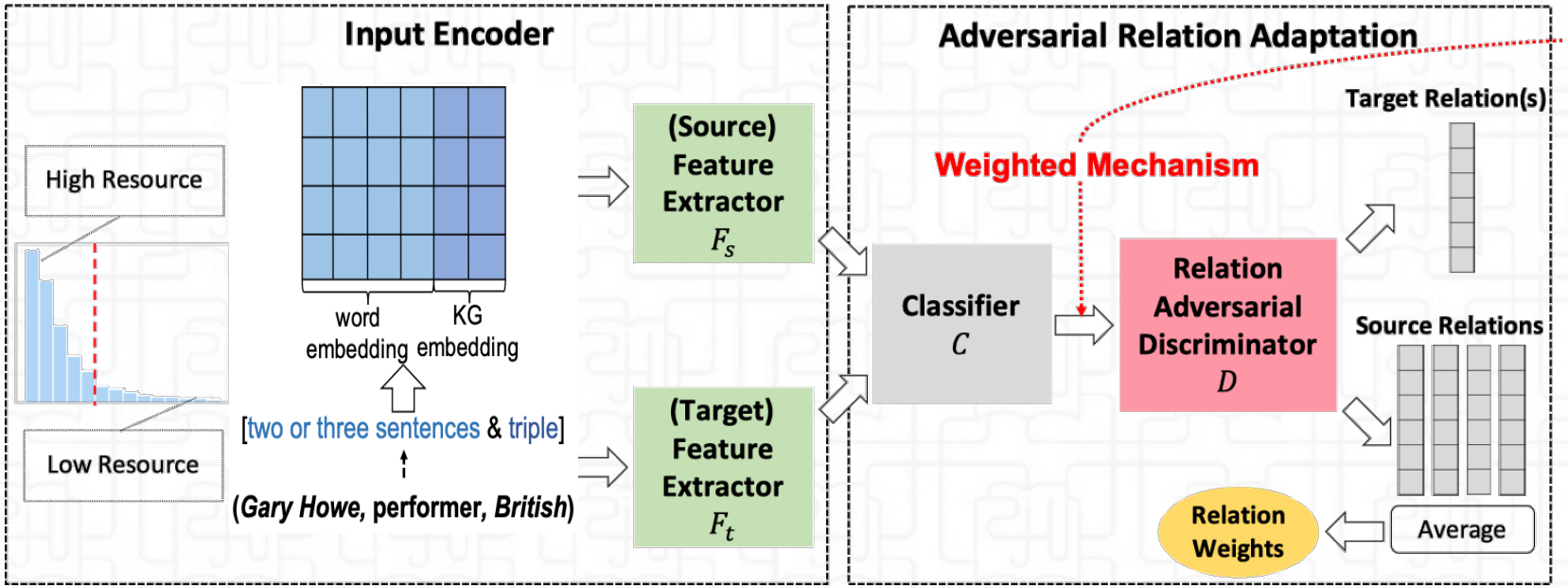

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Ningyu Zhang, **Huajun Chen**, et al. wRAN: Relation Adversarial Network for Low Resource Knowledge Graph Completion. WWW2020.

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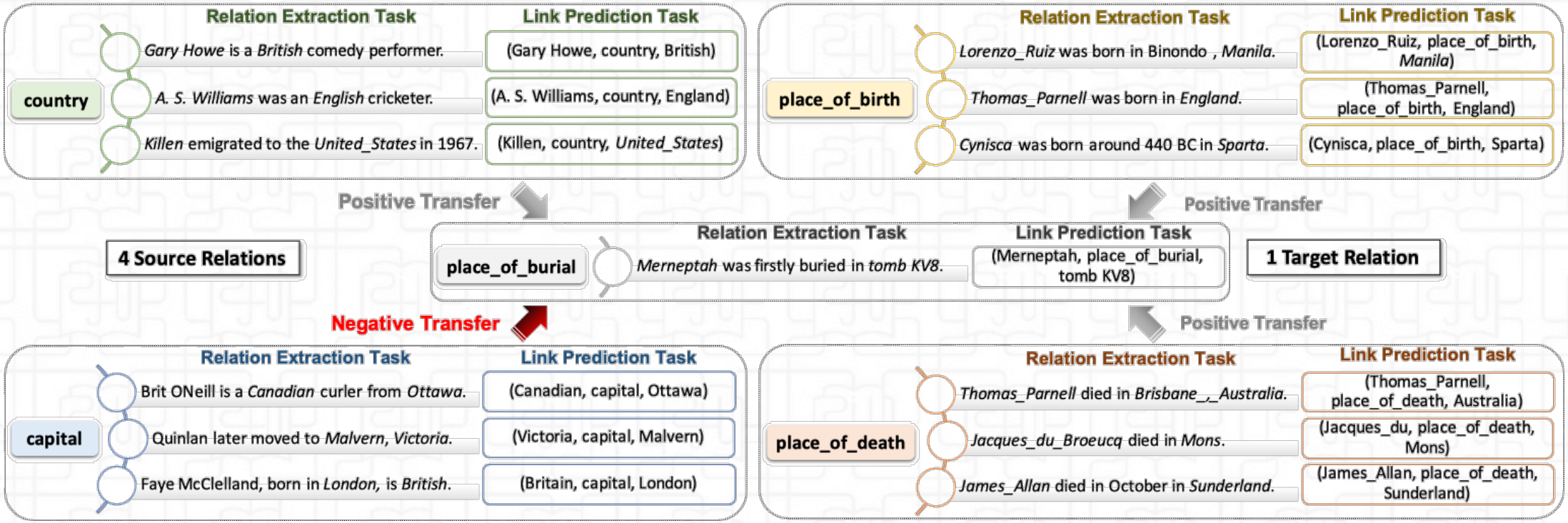

Ningyu Zhang, **Huajun Chen**, et al. wRAN: Relation Adversarial Network for Low Resource Knowledge Graph Completion. WWW2020.

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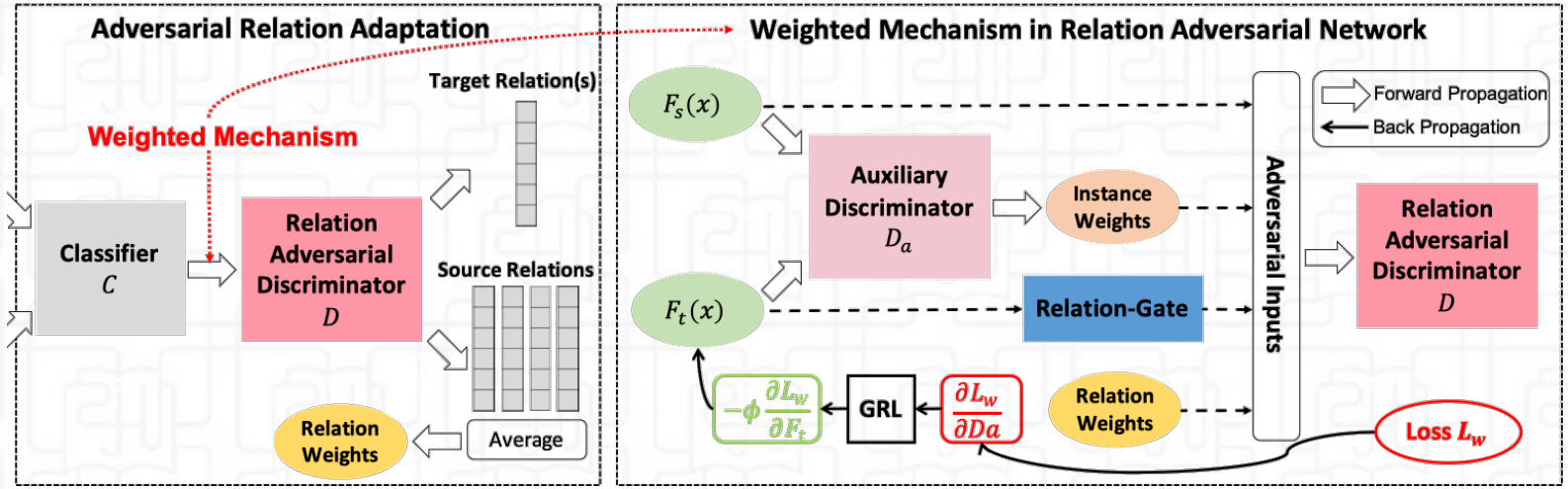


Model Architecture

$$\min_{F_s,F_t}\max_{D}\mathbb{L}(D,F_s,F_t)=\mathbb{E}_{x\sim p_s(x)}[\log D(F_s(x))]+\mathbb{E}_{x\sim p_t(x)}[1-\log D(F_t(x))]$$

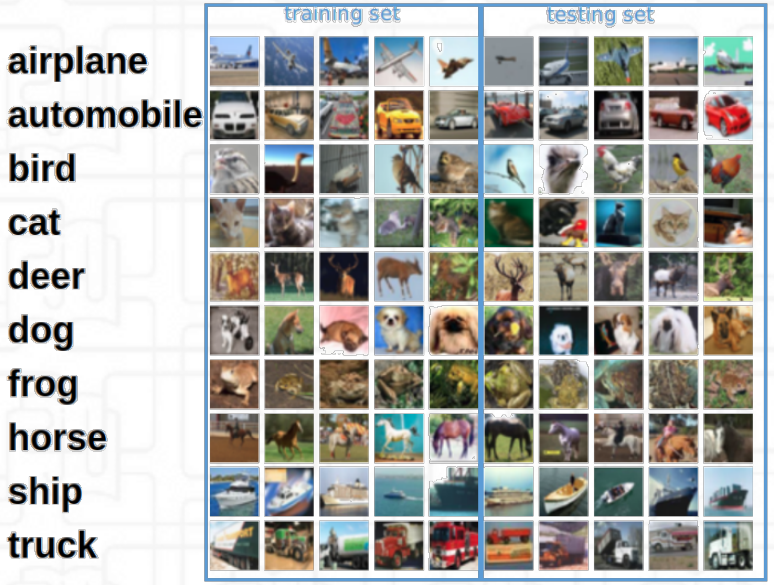
$$\min_{F_t}\max_{D_r}\mathbb{L}_w(C,D_r,F_s,F_t)=\mathbb{E}_{x\sim p_s(x)}[w^{total}\log D_r(F_s(x))]+\mathbb{E}_{x\sim p_t(x)}[1-\log D_r(F_t(x))]$$

Model	FB1.5M				
	MRR	MR	HIT@1	HIT@3	HIT@10
TransE [2]	0.075	15932	0.046	0.087	0.128
TransH [43]	0.079	15233	0.049	0.089	0.130
TransR [17]	0.081	15140	0.050	0.090	0.135
TransD [15]	0.085	15152	0.048	0.089	0.139
DistMult [45]	0.065	21502	0.036	0.076	0.102
ComplEx [38]	0.072	16121	0.041	0.090	0.115
ConvE [8]	-	-	-	-	-
Analogy [19]	0.116	13793	0.102	0.145	0.205
KBGAN [3]	-	-	-	-	-
RotatE [36]	0.125	10205	0.135	0.253	0.281
KG-BERT [46]	0.119	13549	0.093	0.195	0.206
IterE [59]	0.109	14169	0.073	0.175	0.186
wRAN	**0.141**	**9998**	**0.199**	**0.284**	**0.302**

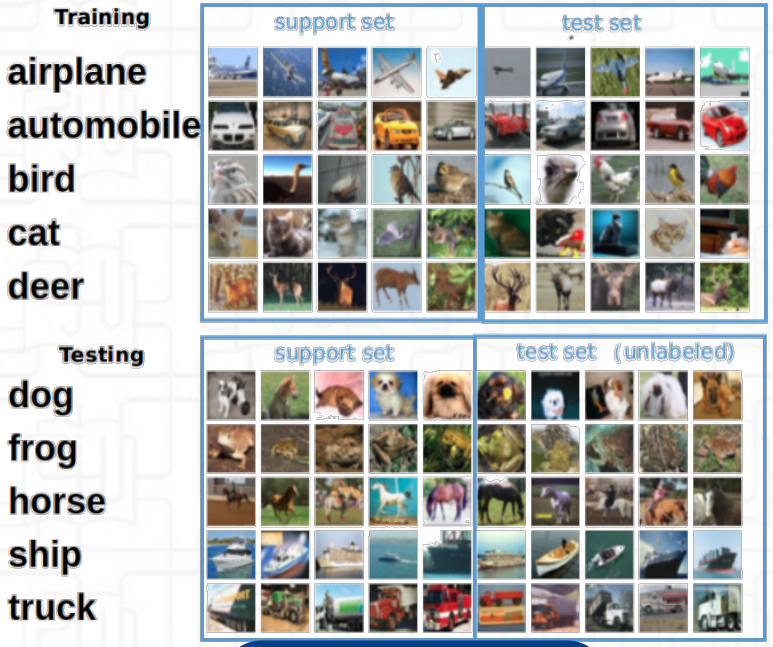
Ningyu Zhang, **Huajun Chen**, et al. wRAN: Relation Adversarial Network for Low Resource Knowledge Graph Completion. WWW2020.

03 少样本学习 & 元学习

- 少样本学习+元学习 (meta learning)



传统的机器学习/深度学习



元学习

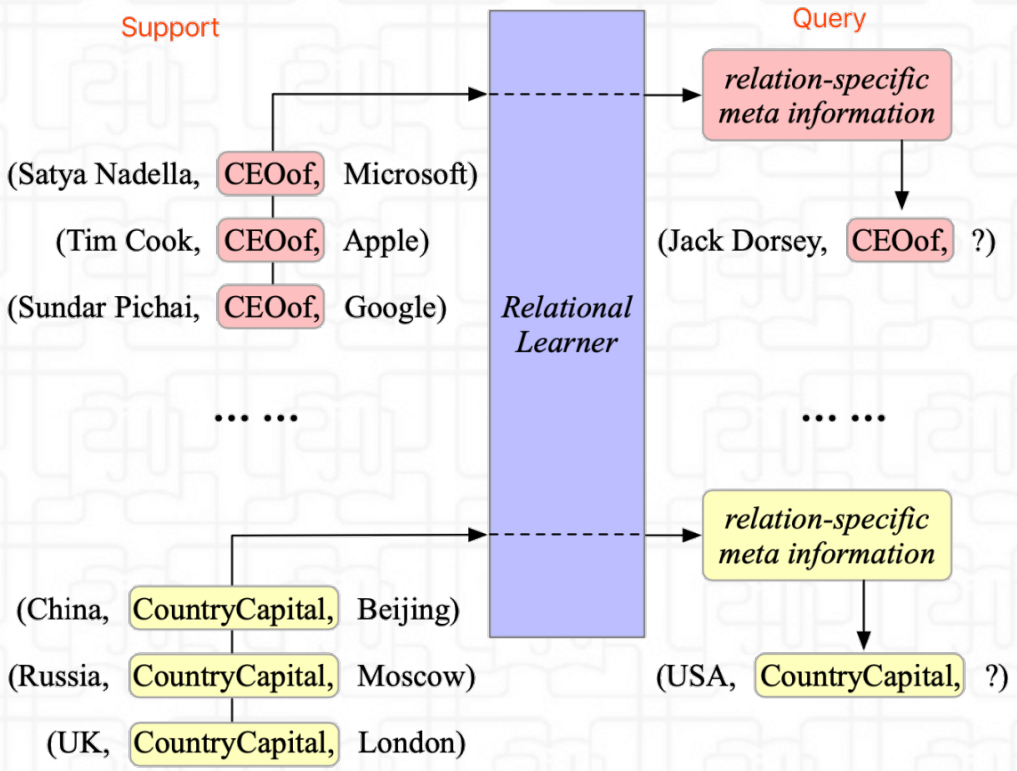
- 需大量标记数据
- 只能在训练过 (Seen) 的类别/概念上进行测试

- Learn to Learn: training tasks (models) with few examples
- Generalize to new tasks with few examples

- 元关系学习：在只有少量关系样本的情况下实现知识图谱推理

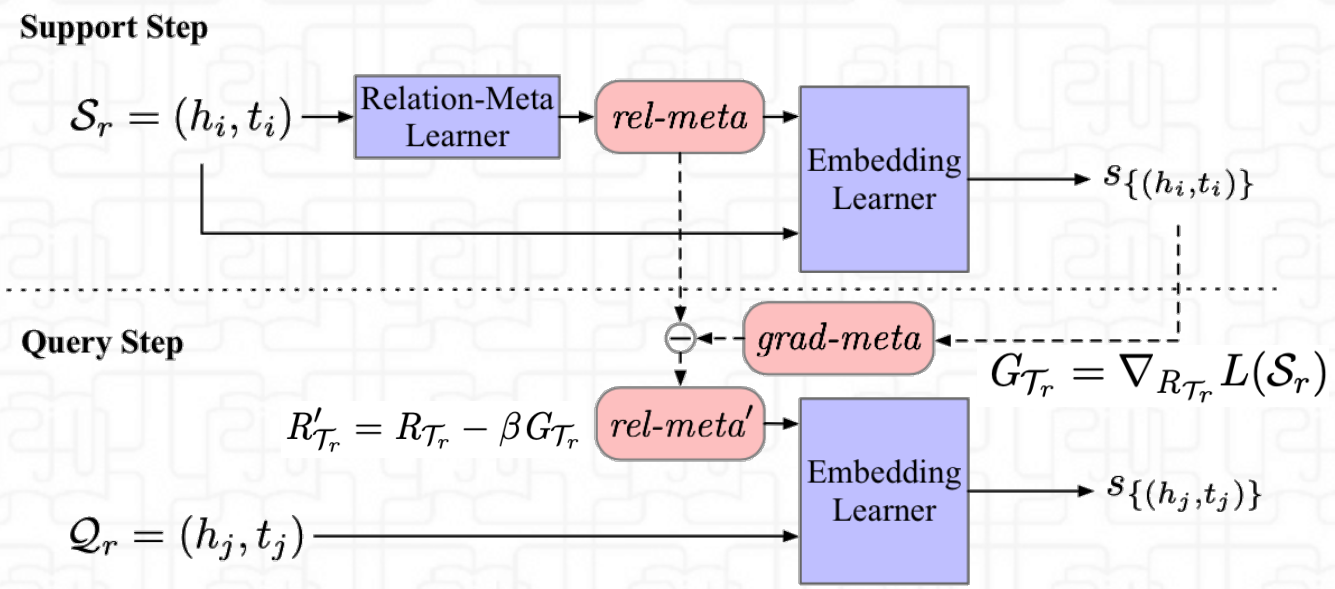
Training	
Task #1 (CountryCapital)	
Support	(China, CountryCapital, Beijing)
Query	(France, CountryCapital, Paris)
Task #2 (CEOof)	
Support	(Satya Nadella, CEOof, Microsoft)
Query	(Jack Dorsey, CEOof, Twitter)
Testing	
Task #1 (OfficialLanguage)	
Support	(Japan, OfficialLanguage, Japanese)
Query	(Spain, OfficialLanguage, Spanish)

Table 1: The training and testing examples of 1-shot link prediction in KGs.



Mingyang Chen, **Huajun Chen**, et al. MetaR: Meta Relational Learning for Few-Shot Link Prediction in Knowledge Graphs. EMNLP2019.

- **元关系学习：在只有少量关系样本的情况下实现知识图谱推理**
  - 基本思想：在Support阶段根据Support集中的头尾实体得到关系元（rel-meta）作为关系的表示，然后利用Support集中的三元组计算损失更新关系元，并把更新后的关系元作为关系的表示用到Query阶段的链接预测中。



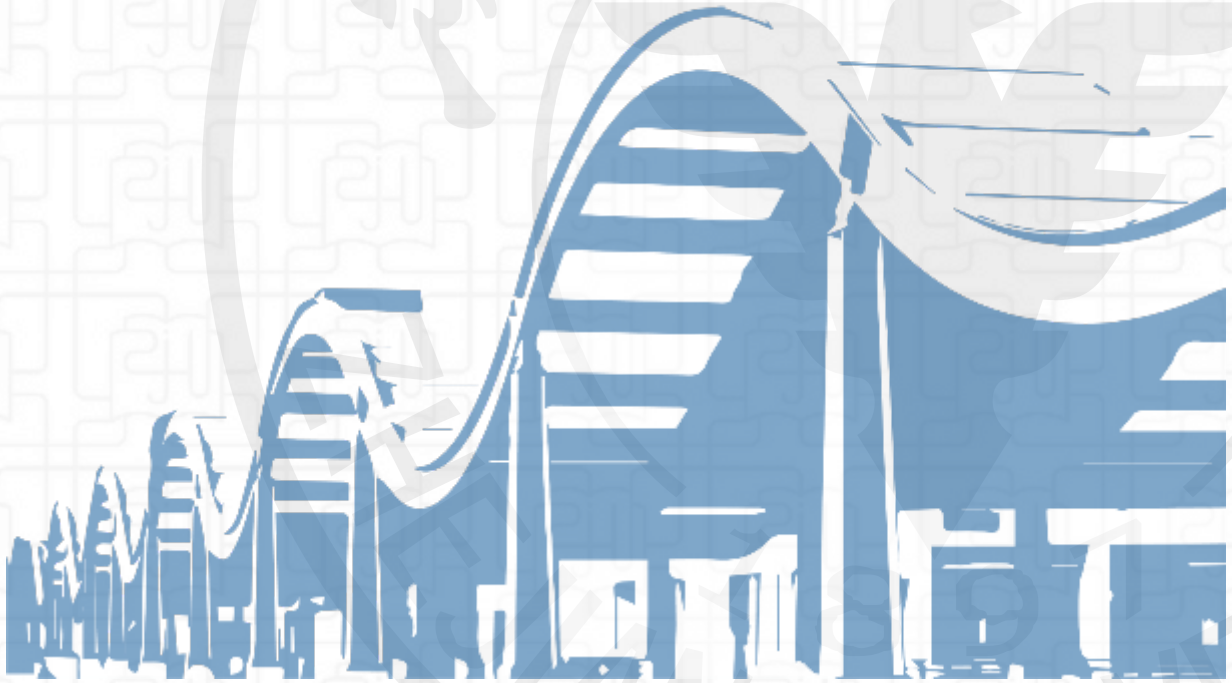
	MRR		Hits@10		Hits@5		Hits@1	
NELL-One	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
GMatching_RESCAL	.188	–	.305	–	.243	–	.133	–
GMatching_TransE	.171	–	.255	–	.210	–	.122	–
GMatching_DistMult	.171	–	.301	–	.221	–	.114	–
GMatching_ComplEx	.185	.201	.313	.311	.260	.264	.119	.143
GMatching_Random	.151	–	.252	–	.186	–	.103	–
MetaR (BG:Pre-Train)	.164	.209	.331	.355	.238	.280	.093	.141
MetaR (BG:In-Train)	**.250**	**.261**	**.401**	**.437**	**.336**	**.350**	**.170**	**.168**
Wiki-One	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
GMatching_RESCAL	.139	–	.305	–	.228	–	.061	–
GMatching_TransE	.219	–	.328	–	.269	–	.163	–
GMatching_DistMult	.222	–	.340	–	.271	–	.164	–
GMatching_ComplEx	.200	–	.336	–	.272	–	.120	–
GMatching_Random	.198	–	.299	–	.260	–	.133	–
MetaR (BG:Pre-Train)	**.314**	**.323**	**.404**	**.418**	**.375**	**.385**	**.266**	**.270**
MetaR (BG:In-Train)	.193	.221	.280	.302	.233	.264	.152	.178

Mingyang Chen, **Huajun Chen**, et al. MetaR: Meta Relational Learning for Few-Shot Link Prediction in Knowledge Graphs. EMNLP2019.

04

总结与展望

Summary & Future Directions



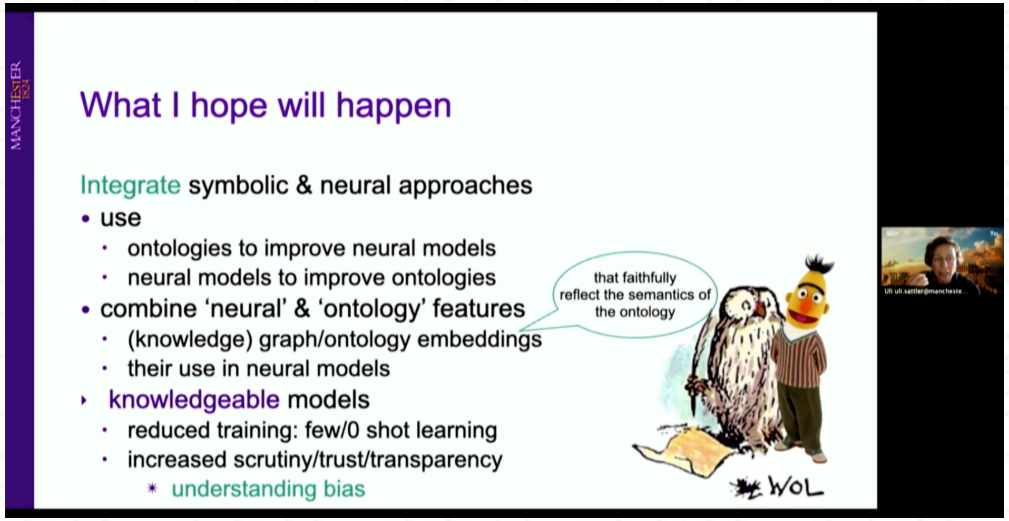
04 总结

知识的知识
Graph & Semantic Knowledge Graph & Logic
CV
TextC, RE
NLP
Explanation
ZSL
Long-tail Relation Extraction
FSL
KG & LRL
KG4LRL
LRL4KG
ZSL in KG
FSL in KG
Zero-shot Relations
Zero-shot Entities
Relation Transfer Learning
Meta Relation Learning

04 机遇与挑战

Low Resource is Everywhere!

- 人工智能 = 人工的智能？
- 数据难题（长尾分布、特殊领域）；
- 层出不穷的新概念；
- 各个领域（CV, NLP, KG, ...）；
- 模型的低成本和快速部署的诉求



Knowledge is Power!

- **数据模型 or 机器学习模型**；
- 知识提供的语义信息和关联关系可以帮助更好地建模Label空间，解决Label低资源的问题；
- 知识可以看作是质量更好、表示更规范的数据，或者是融入更多先验的数据。

Challenge

- 如何将知识与模型进行更深入的融合，将感知和认知更好地结合？
- 更丰富的知识以及更好的知识表示手段

Uli Sattler @ ISWC2020

感谢聆听

THANKS FOR YOU LISTENING

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