Knowledge-aware Zero-shot Learning (K-ZSL): Concepts, Methods and Resources

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https://china-uk-zsl.github.io/kg-zsl-tutorial-ijcai-2023/

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IJCAI/2023 MACAO

Part III – Resources, Benchmarking and Lessons

T8

Hands-on with Resource, Benchmarking and Demo

- Zero-shot Image Classification -

- Zero-shot Knowledge Graph Completion -

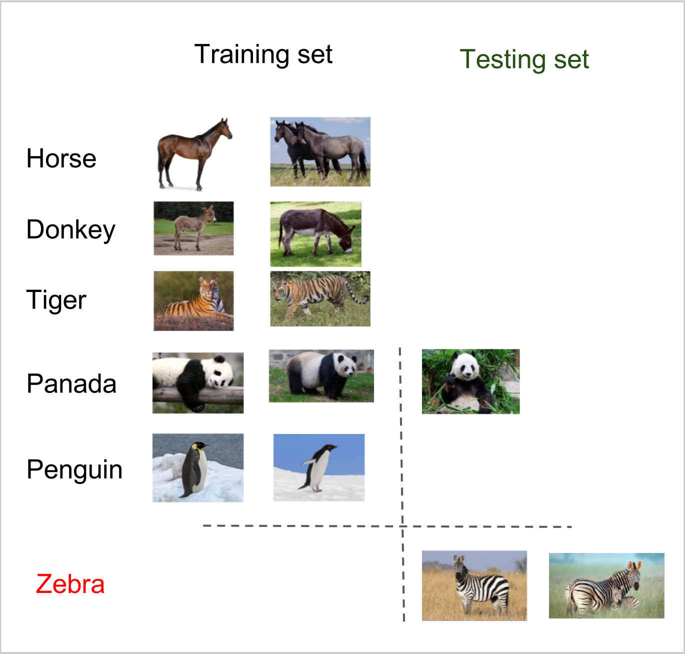
Zero-shot Image Classification (ZS-IMGC)

- Revisit Task Definition
- ZS-IMGC Benchmarks
- Existing External Knowledge vs KG
- Benchmarking Results

Task Definition

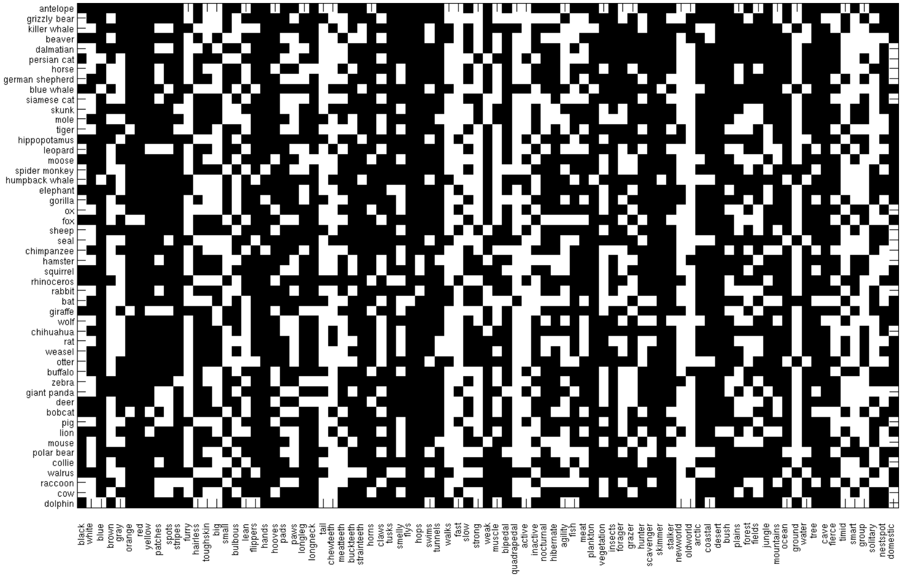
- Classifying the images of new (unseen) classes without seeing their training examples

Zero-shot Animal Image Classification



Benchmarks

- AwA2
  - A popular ZSL benchmark on animal image classification, with images from the Web, by [Xian et al. 2018]
  - 50 classes (usually 40 used as seen classes and 10 used as unseen classes), 37,322 images, 85 real-valued attributes for visual characteristics
  - Pros: high quality attributes, classes aligned with WordNet
  - Cons: small scales



AwA is an older version of AwA2, but does not have public copyright license for its images

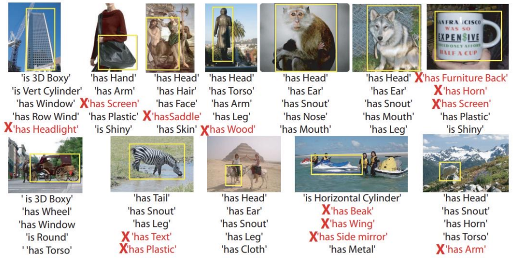
Xian, Yongqin, et al. "Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly." IEEE transactions on pattern analysis and machine intelligence 41.9 (2018): 2251-2265.

Benchmarks

- Other similar benchmarks as AwA2 with visual annotations

CUB [Wah et al. 2011]: fine-grained bird classification, 150/50 seen/unseen classes, 312 attributes

SUN [Xiao et al, 2010]: fine-grained sense classification, 645/72 seen/unseen classes, 102 attributes



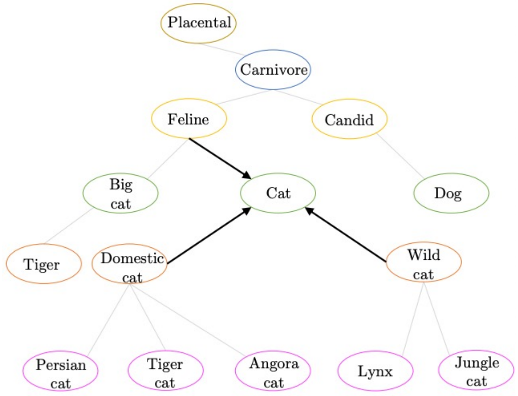
aPy [Farhadi et al. 2009]: coarse-grained classification, 20/12 seen/unseen classes, 64 attributes

Xiao, Jianxiong, et al. "Sun database: Large-scale scene recognition from abbey to zoo." CVPR 2010.
Farhadi, Ali, et al. "Describing objects by their attributes." CVPR 2009.
Wah, Catherine, et al. "The caltech-ucsd birds-200-2011 dataset." (2011).

Benchmarks

https://www.image-net.org/

- ImageNet
  - ~14 million images and ~21K classes (aligned with the WordNet hierarchy) in total
  - In ZSL studies e.g., [Wang et al. 2018] and [Kampffmeyer et al. 2019]:
    - 1K classes with balanced images as seen classes for training
    - Classes that are 2-hops or 3-hops away from the seen classes according to the class hierarchy as unseen classes
    - Pros:
      - Large image and class scales
      - Aligned with a popular KG --- WordNet
    - Cons:
      - Short of other external knowledge such as visual annotations



A segment of the class hierarchy

Wang, Xiaolong, Yufei Ye, and Abhinav Gupta. "Zero-shot recognition via semantic embeddings and knowledge graphs." CVPR 2018.
Kampffmeyer, Michael, et al. “Rethinking knowledge graph propagation for zero-shot learning.” CVPR 2019.

Summary

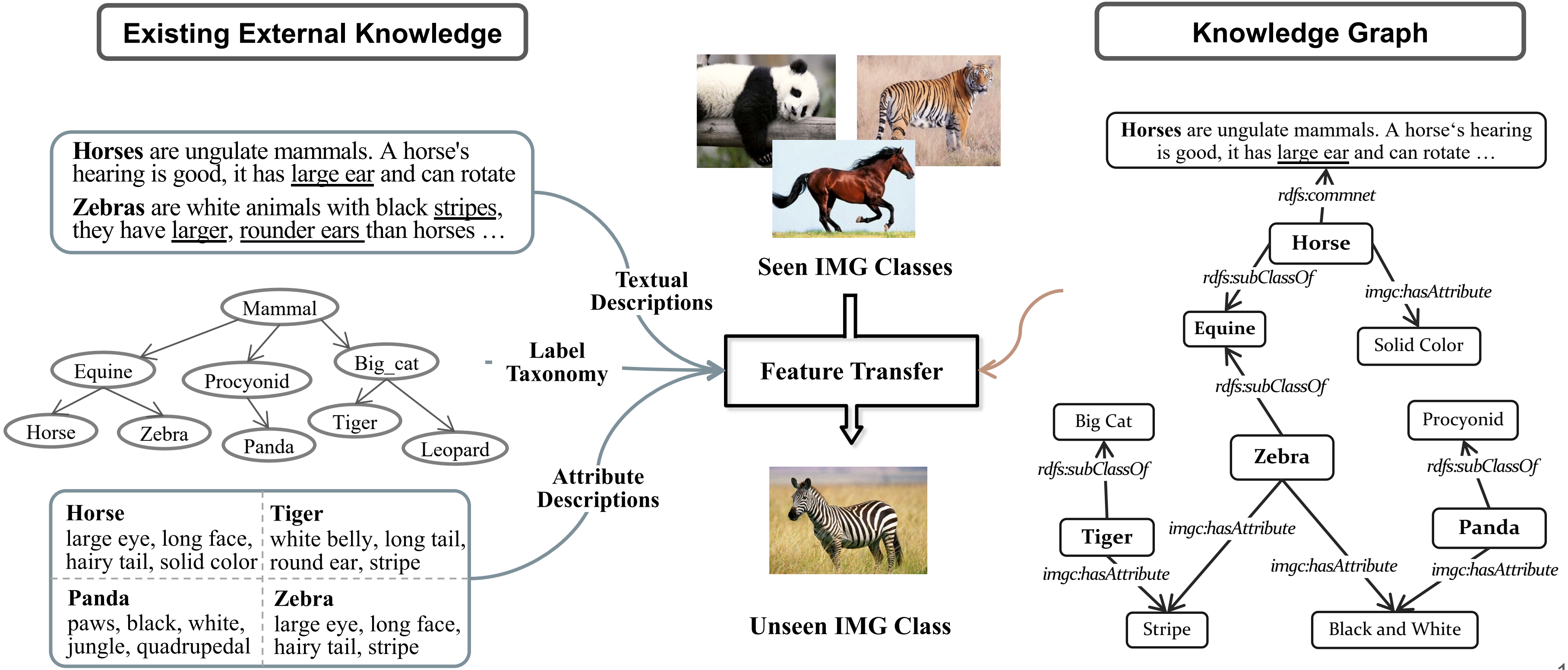
Datasets	class text e.g., names or descriptions	class attribute	class hierarchy	granularity
AwA2	√	√	√	coarse
CUB	√	√		fine
SUN	√	√		fine
aPY	√	√		coarse
ImageNet	√		√	coarse + fine

Benchmarks

- The above datasets often have only one kind or two kinds of external knowledge
- ImNet-A and ImNet-O for single-label image classification are proposed
  - two **fine-grained** subsets extracted from ImageNet by [Geng et al. 2021, 2022]
  - ImNet-A: 80 animal classes (28 seen, 52 unseen)
  - ImNet-O: 35 general object classes (10 seen, 25 unseen)
  - Equipped with different kinds of knowledge including visual annotations, textual descriptions, common sense knowledge from ConceptNet, class hierarchy from WordNet and logical relationships such as disjointness

Geng, Yuxia, et al. "OntoZSL: Ontology-enhanced zero-shot learning." WWW 2021.
Geng, Yuxia, et al. “Benchmarking knowledge-driven zero-shot learning”, Journal of Web Semantics. 2022.

Existing External Knowledge vs KG

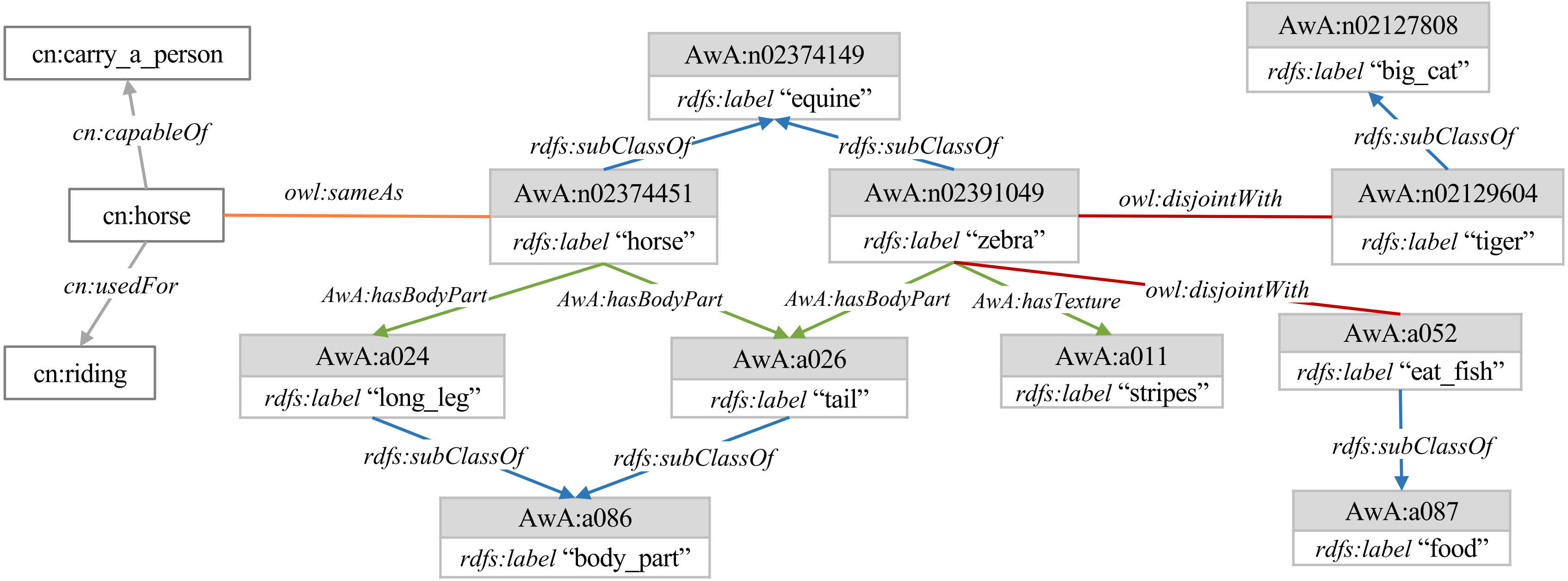


Existing External Knowledge vs KG

Datasets	class text e.g., names or descriptions	class attribute	class hierarchy	KG	granularity
AwA2	√	√	√	√	coarse
CUB	√	√			fine
SUN	√	√			fine
aPY	√	√			coarse
ImageNet	√		√		coarse + fine
ImNet-A	√	√	√	√	fine
ImNet-O	√	√	√	√	fine

The KG contains different kinds of <u>class knowledge</u> including visual annotations, textual descriptions, class hierarchy from WordNet, as well as common sense knowledge from ConceptNet, and logical relationships such as disjointness

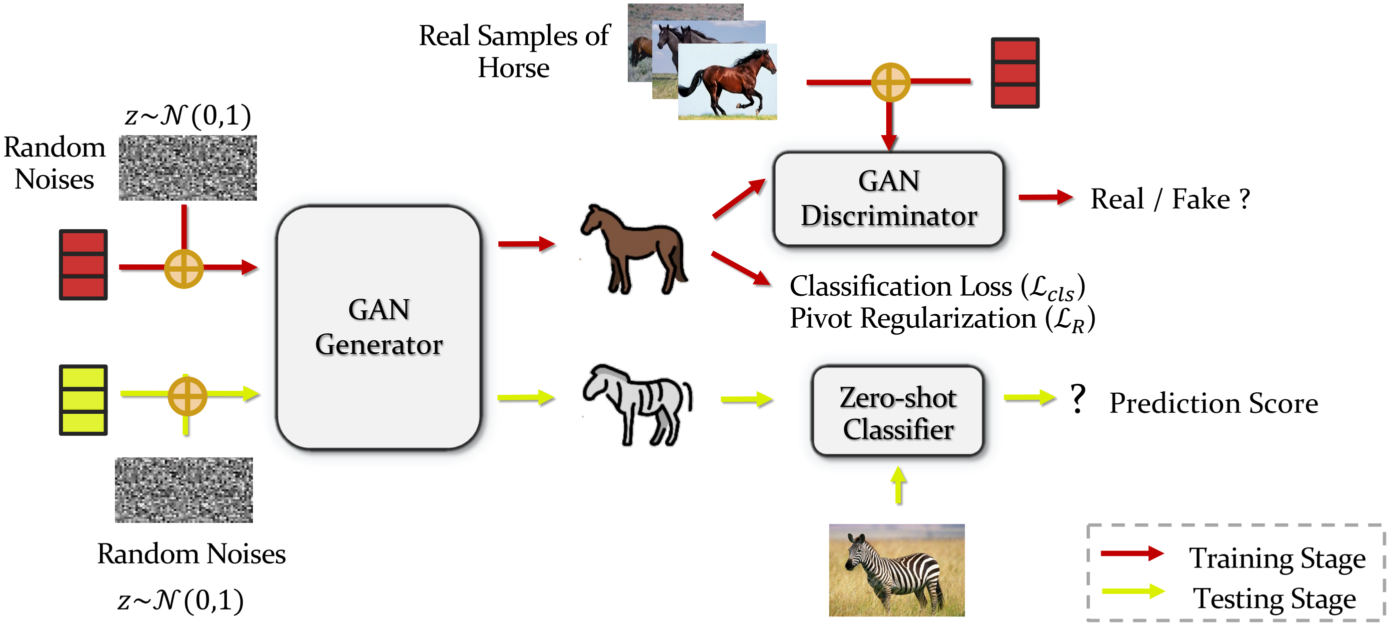
A Segment of KG for AwA2



Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning", Journal of Web Semantics. 2022.

Benchmarking GAN-based Methods KGZSL

- modifying the input class embedding

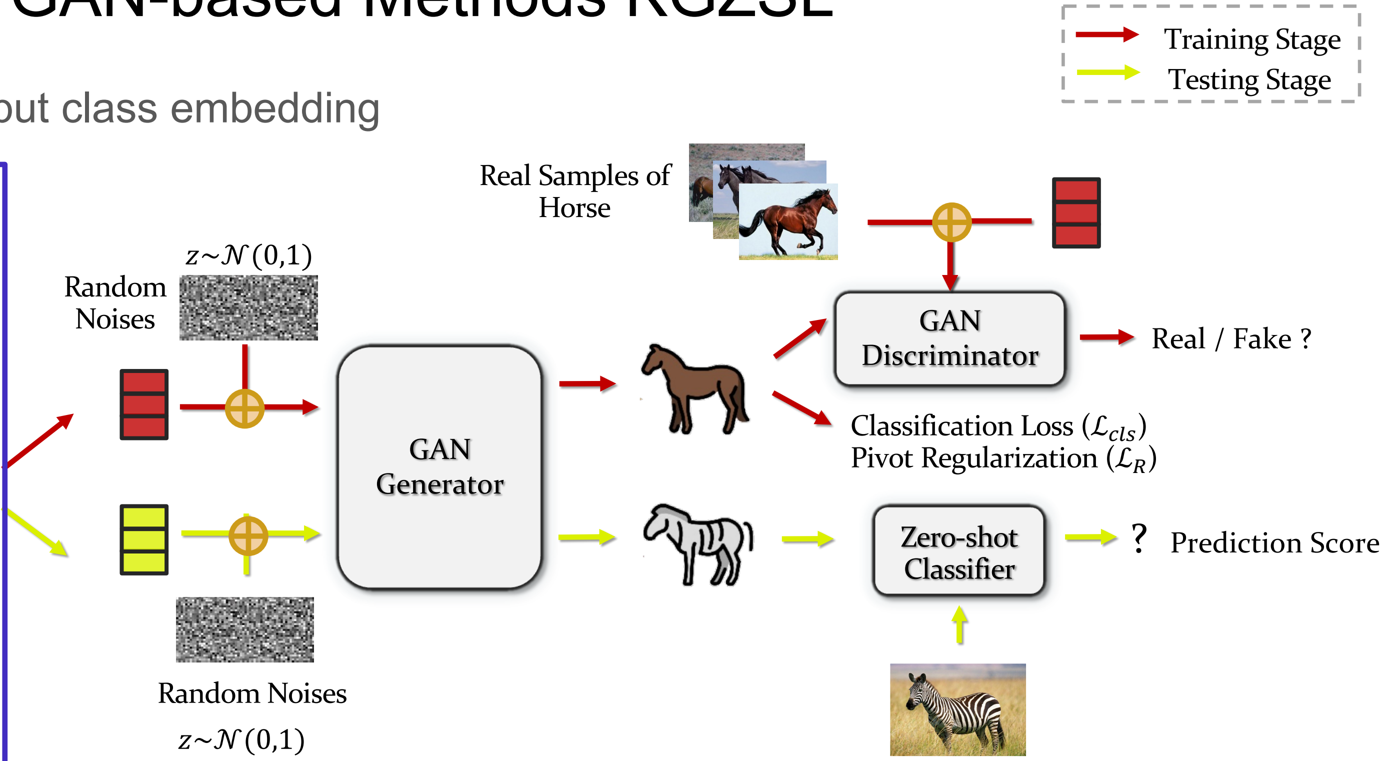


Geng, Yuxia, et al. "OntoZSL: Ontology-enhanced zero-shot learning." WWW 2021.

Benchmarking GAN-based Methods KGZSL

- modifying the input class embedding

1. **word embeddings (w2v)**
   - by [1] & Glove;
2. **multi-hot attribute vectors (att)**
3. **class hierarchy (hie)**
   - by GAE [2]
4. **Basic KG**
   - class hierarchy, class attributes, attribute hierarchy;
5. **Basic KG + literals**
   + literal names
6. **Basic KG + CN**
   + triples from ConceptNet
7. **Basic KG + logics**
   + triples of disjointness



[1] Soravit Changpinyo, et al., "Synthesized Classifiers for Zero-Shot Learning", CVPR 2016.
[2] Thomas N. Kipf et al., "Variational Graph Auto-Encoders"

Geng, Yuxia, et al. “Benchmarking knowledge-driven zero-shot learning”, Journal of Web Semantics. 2022.

Benchmarking GAN-based Methods KGZSL

- generating image features rather than raw images

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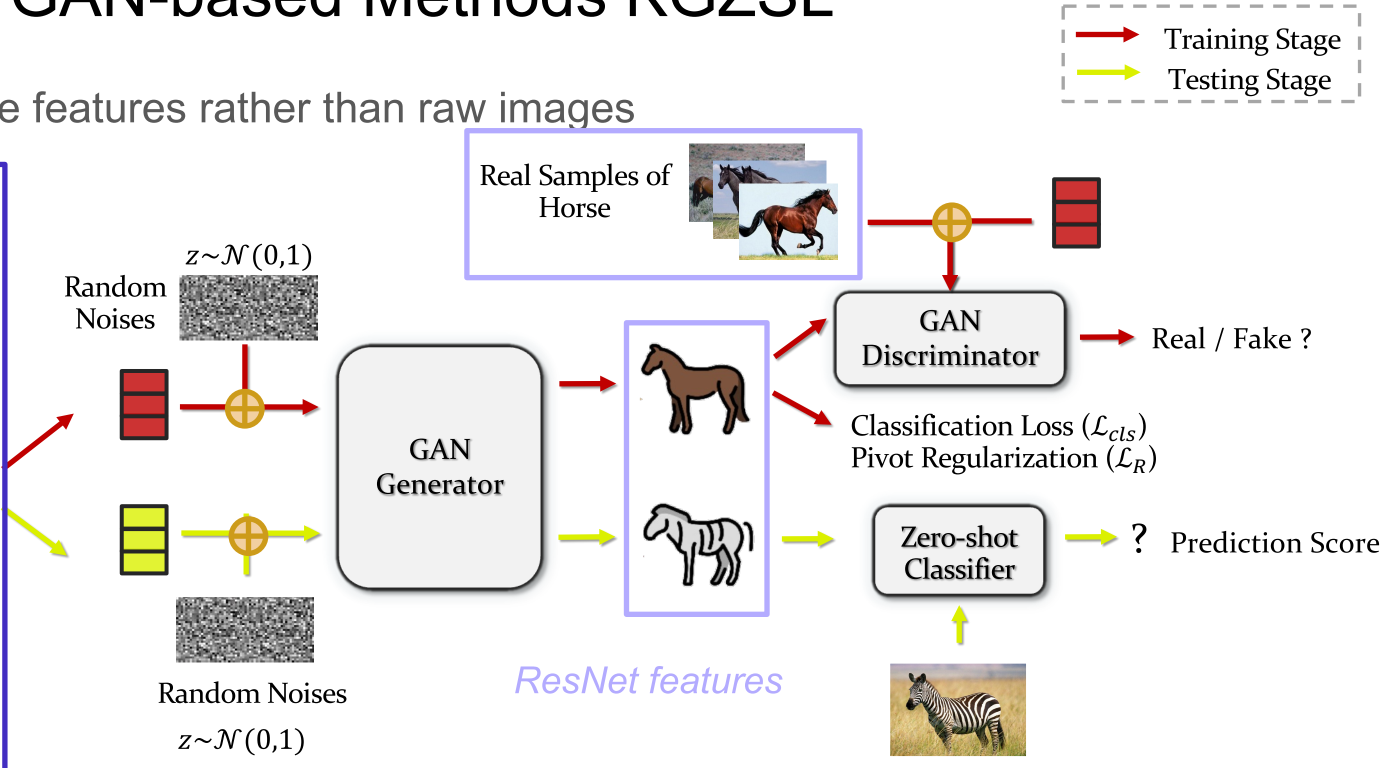

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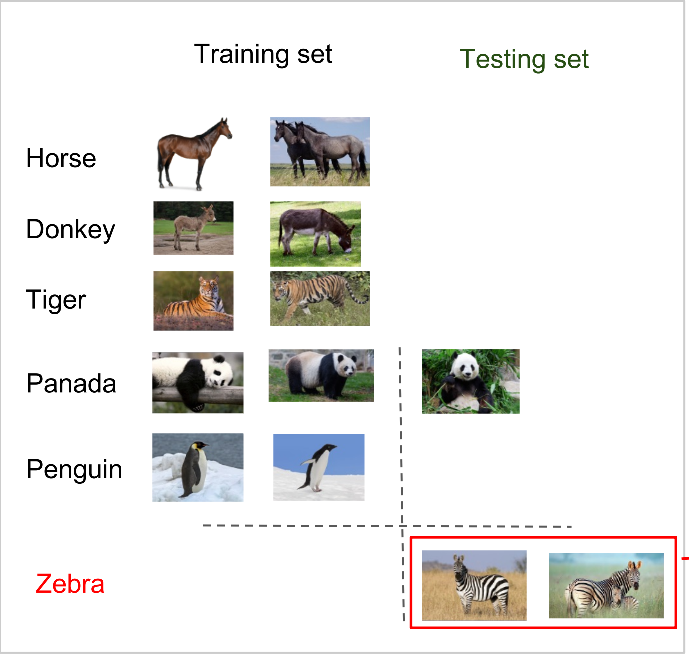
Evaluation Metrics

- Classifying the images of new (unseen) classes without seeing their training examples

Zero-shot Animal Image Classification



standard ZSL setting: classifying the testing samples of unseen classes with candidates of all unseen classes

Xian, Yongqin, et al. "Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly." TPAMI 2018.

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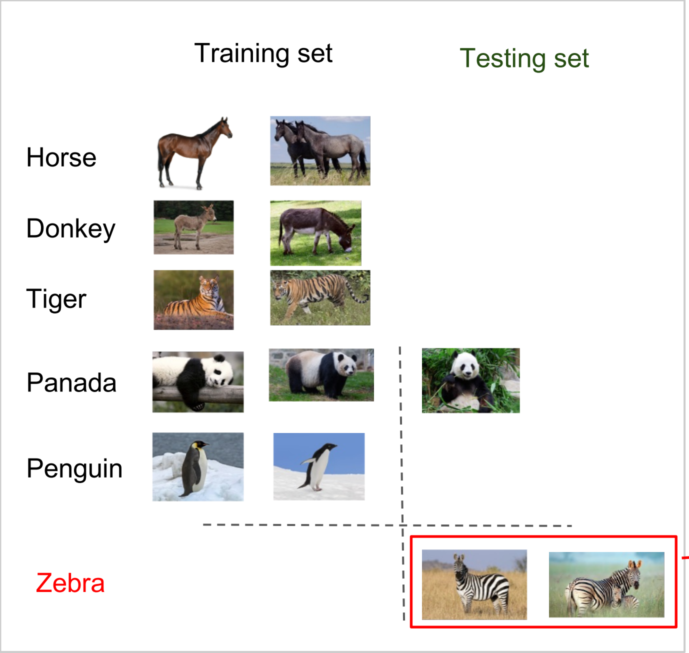
Zero-shot Animal Image Classification



macro accuracy:

$$acc = \frac{1}{||Y_u||} \sum_{c=1}^{||Y_u||} \frac{\#\ correct\ predictions\ in\ c}{\#\ samples\ in\ c}$$

standard ZSL setting: classifying the testing samples of unseen classes with candidates of all unseen classes

Xian, Yongqin, et al. "Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly." TPAMI 2018.

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- Classifying the images of new (unseen) classes without seeing their training examples

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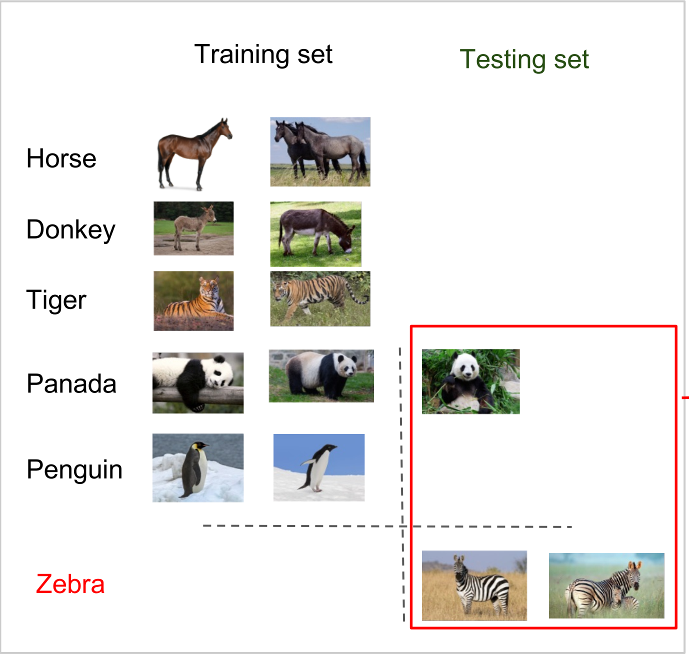


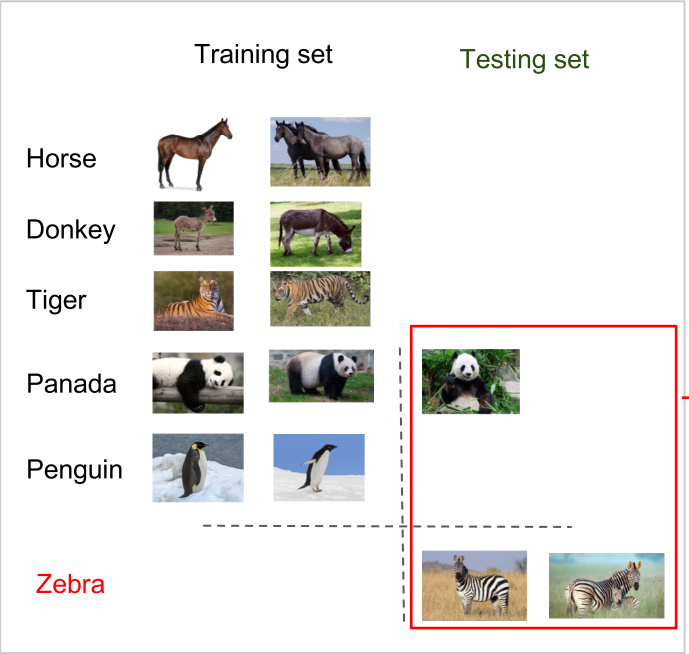
generalized ZSL setting:
classifying the testing samples of <u>seen and unseen classes</u> with candidates of <u>all classes</u>

Xian, Yongqin, et al. "Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly." TPAMI 2018.

Evaluation Metrics

- Classifying the images of new (unseen) classes without seeing their training examples

Zero-shot Animal Image Classification



generalized ZSL setting:
classifying the testing samples of <u>seen and unseen classes</u> with candidates of <u>all classes</u>

$$acc_u = \frac{1}{||Y_u||} \sum_{c=1}^{||Y_u||} \frac{\#\ correct\ predictions\ in\ c}{\#\ samples\ in\ c}$$

$$acc_s = \frac{1}{||Y_s||} \sum_{c=1}^{||Y_s||} \frac{\#\ correct\ predictions\ in\ c}{\#\ samples\ in\ c}$$

$$H = \frac{2 \times acc_s \times acc_u}{acc_s + acc_u}$$

Xian, Yongqin, et al. "Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly." TPAMI 2018.

Results

- KG-based external knowledge achieves better performance than traditional none-KG-based external knowledge in most situations.
- Although more semantics are introduced in **Basic KG+CN** and **Basic KG+logics**, their results are not better than **Basic KG** on most metrics.

External Knowledge	AwA				ImNet-A				ImNet-O			
	acc	acc_s	acc_u	H	acc	acc_s	acc_u	H	acc	acc_s	acc_u	H
w2v(500)	45.39	57.83	34.53	43.24	20.94	34.50	15.62	21.50	20.00	41.20	14.33	21.27
w2v(300)	20.80	22.67	12.88	16.43	27.76	40.50	20.40	27.13	24.73	37.20	17.52	23.83
att	58.47	59.90	44.24	50.89	37.87	33.50	27.62	30.28	32.98	42.00	20.67	27.71
hie	38.89	51.08	31.38	38.88	33.32	40.93	23.06	29.50	33.17	36.80	21.13	26.85
Basic KG	62.65	59.59	50.58	54.71	38.21	45.71	23.21	30.79	32.14	44.60	18.74	26.39
Basic KG + literals	59.21	62.39	45.55	52.66	38.58	35.64	27.64	31.13	32.57	44.80	19.35	27.03
Basic KG + CN	54.61	63.31	39.19	48.41	35.24	39.86	24.97	30.71	29.39	42.20	19.64	26.80
Basic KG + logics	54.65	65.37	40.76	50.21	–	–	–	–	–	–	–	–

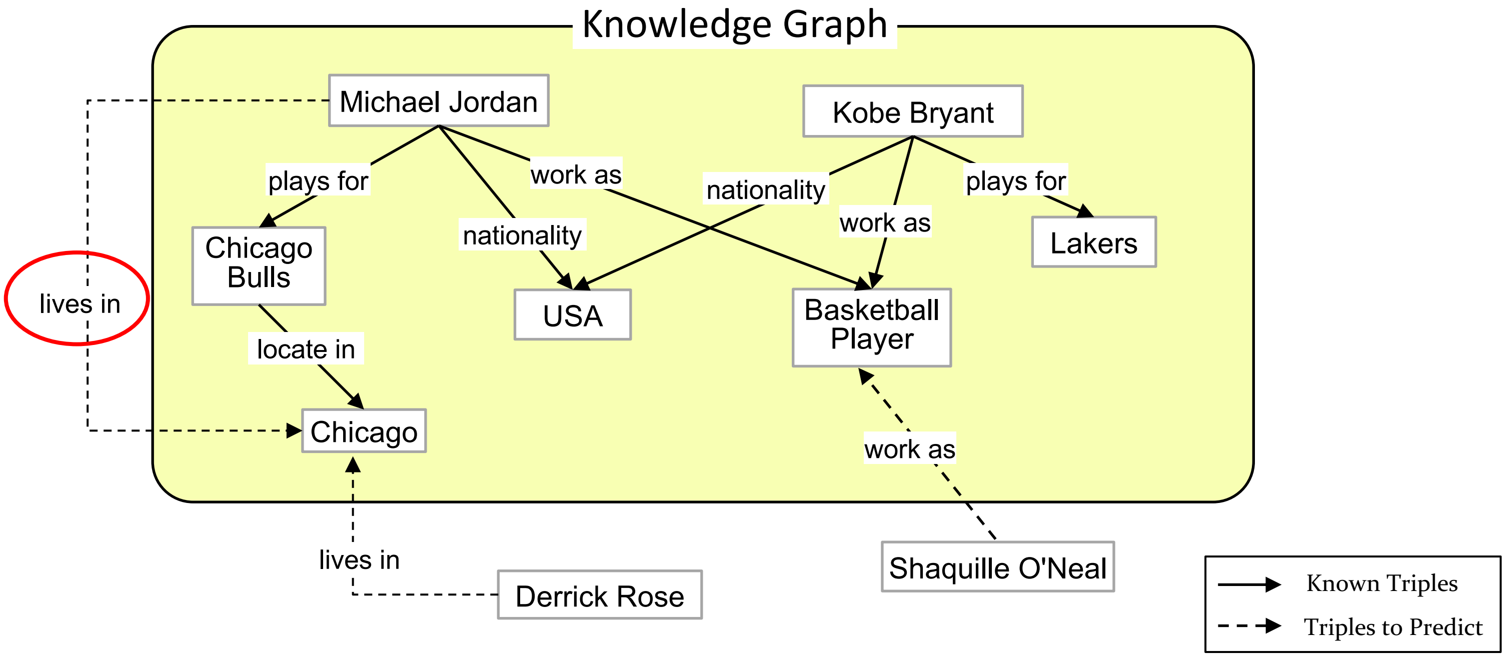
Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning", Journal of Web Semantics. 2022.

Zero-shot Knowledge Graph Completion (ZS-KGC)

- Revisit Task Definition
- ZS-KGC Benchmarks
- Existing External Knowledge vs KG's KG (**Ontological Schema**)
- Benchmarking Results

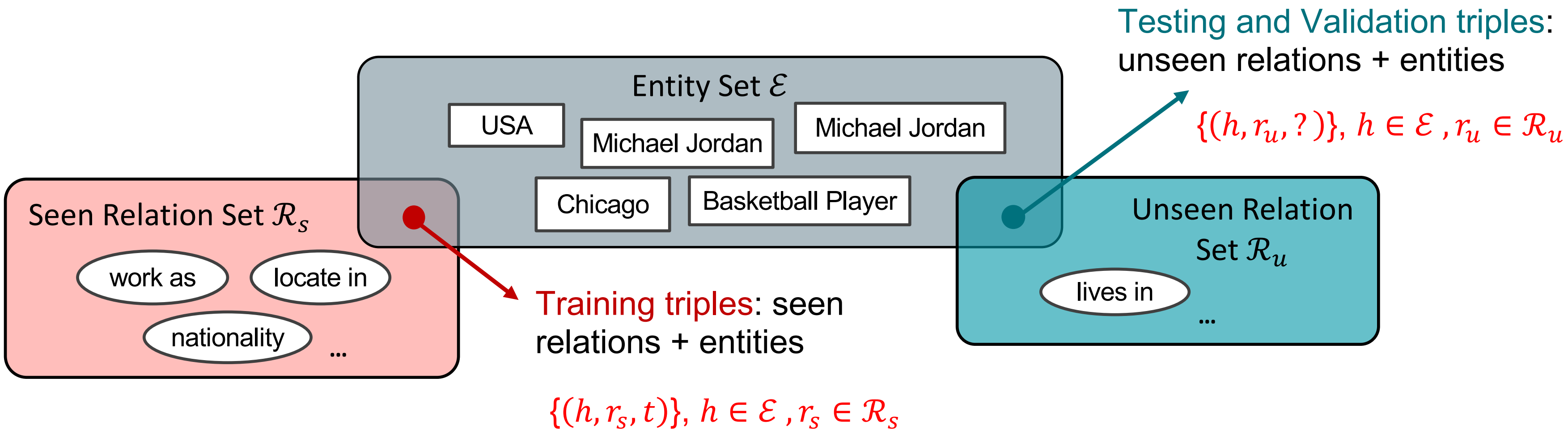
Task Definition

- Completing the KG triples with new (unseen) relations without seeing their training triples
- also known as **Inductive KGC**



ZS-KGC Benchmarks

- NELL-ZS and Wiki-ZS, two sub-KGs from NELL and Wikidata
  - relations are selected and split into two **disjoint** sets: $\mathcal{R}_s$ (seen) and $\mathcal{R}_u$ (unseen);
  - a closed set of entities shared during training and testing;
  - triples of $\mathcal{R}_s$ are collected for training, triples of $\mathcal{R}_u$ are collected for validation and testing



Qin, Pengda, et al. "Generative adversarial zero-shot relational learning for knowledge graphs." AAAI 2020.
Geng, Yuxia, et al. “OntoZSL: Ontology-enhanced zero-shot learning.” WWW 2021.

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Datasets	# Entities	# Relations				# Triples			
		Total	Training Seen	Validation Unseen	Testing Unseen	Total	Training Seen	Validation Unseen	Testing Unseen
NELL-ZS	65,567	181	139	10	32	188,392	181,053	1,856	5,483
Wiki-ZS	605,812	537	469	20	48	724,928	701,977	7,241	15,710

Qin, Pengda, et al. "Generative adversarial zero-shot relational learning for knowledge graphs." AAAI 2020.
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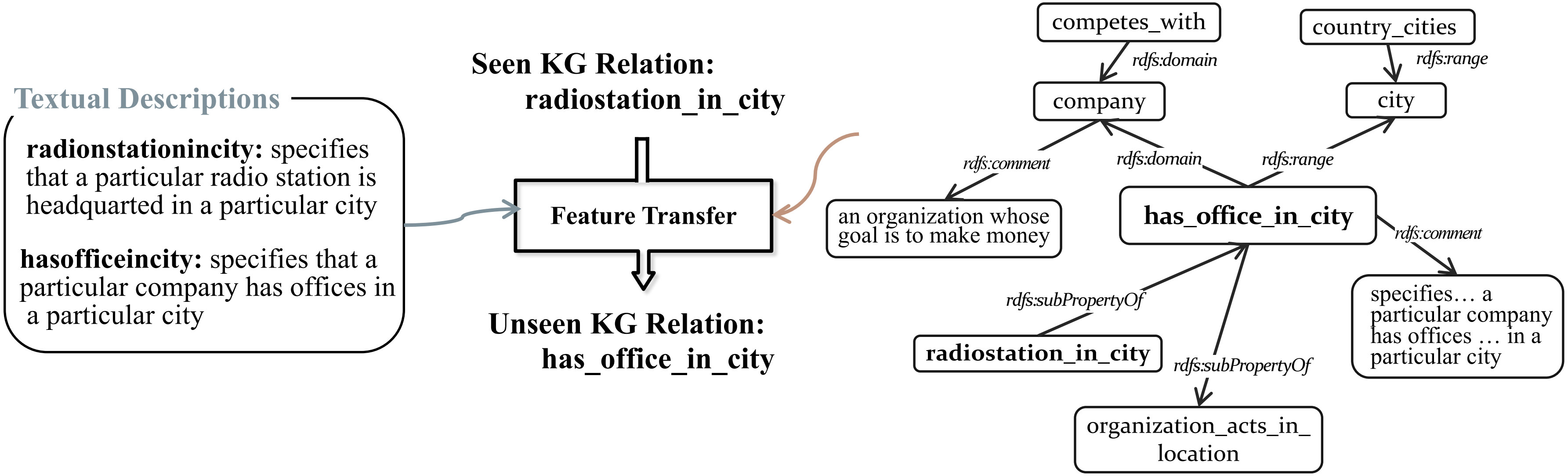
Existing External Knowledge vs Ontological Schema

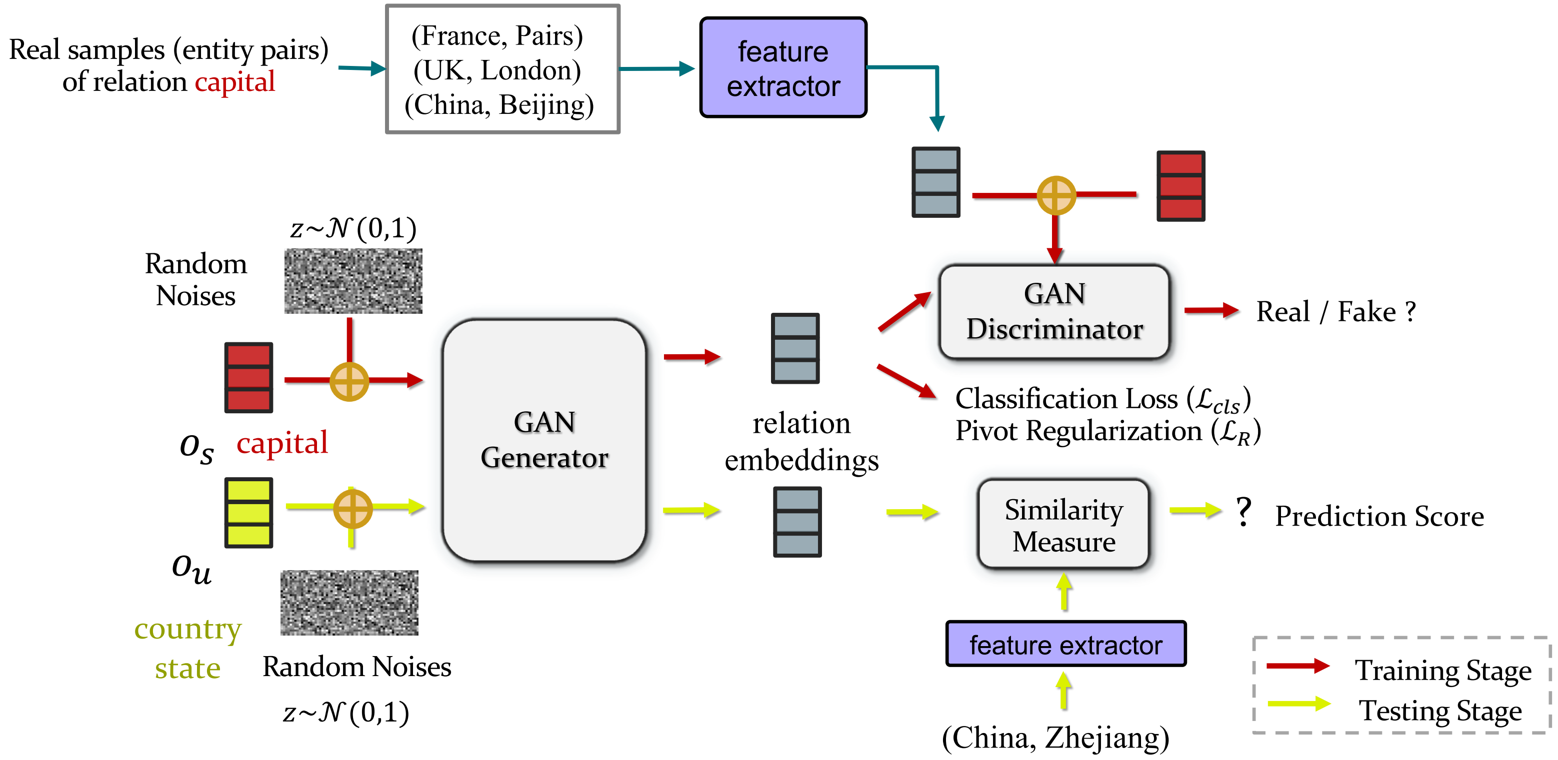
Existing External Knowledge

KG's KG: Ontological Schema



The Ontological Schemas contains different kinds of *<u>relation knowledge</u>* *including textual names and descriptions, and relation semantics from RDFS and OWL.*

Benchmarking GAN-based Methods OntoZSL



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Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning." Journal of Web Semantics 2022.

Benchmarking GAN-based Methods OntoZSL

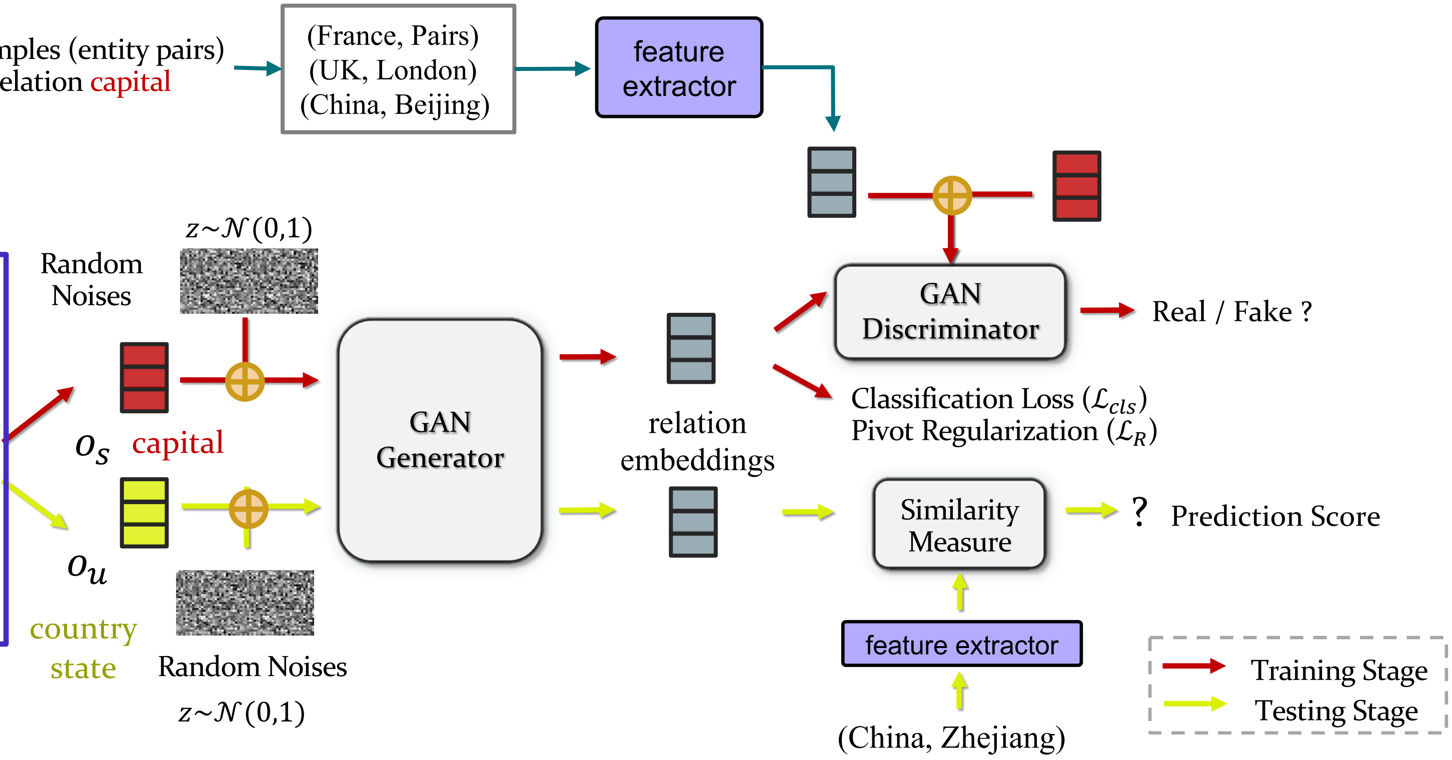
1. text description:
word embeddings + TF-IDF features

2. RDFS graph

- **RDFS-hie**
- **RDFS-cons**

3. RDFS graph+literals

+ literal information



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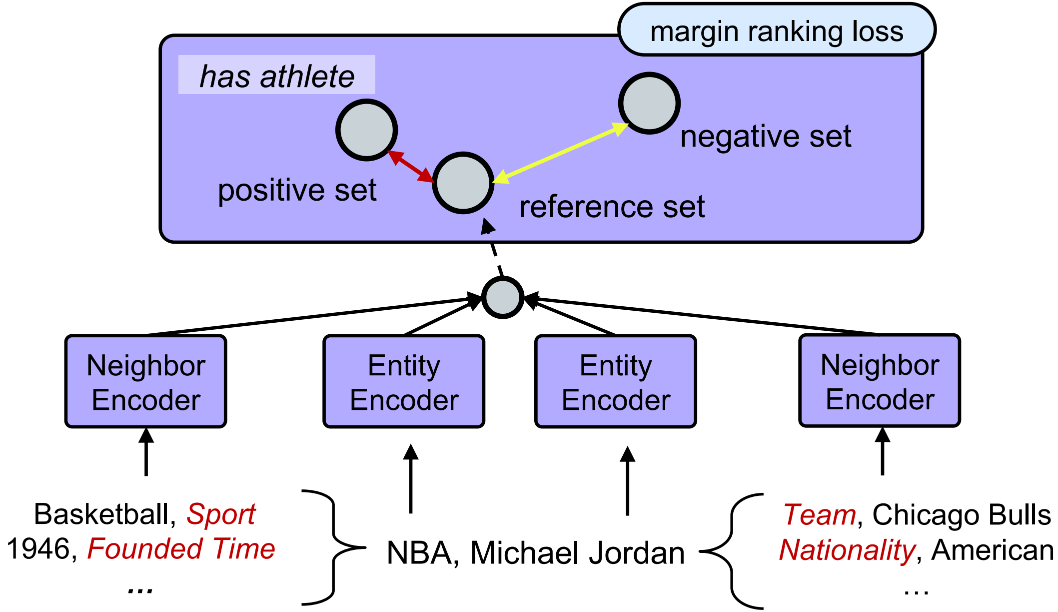
Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning." Journal of Web Semantics 2022.

Task-specific Feature Extractor

- relation sample: a pair of associated entities
- learn clustered features of KG relations



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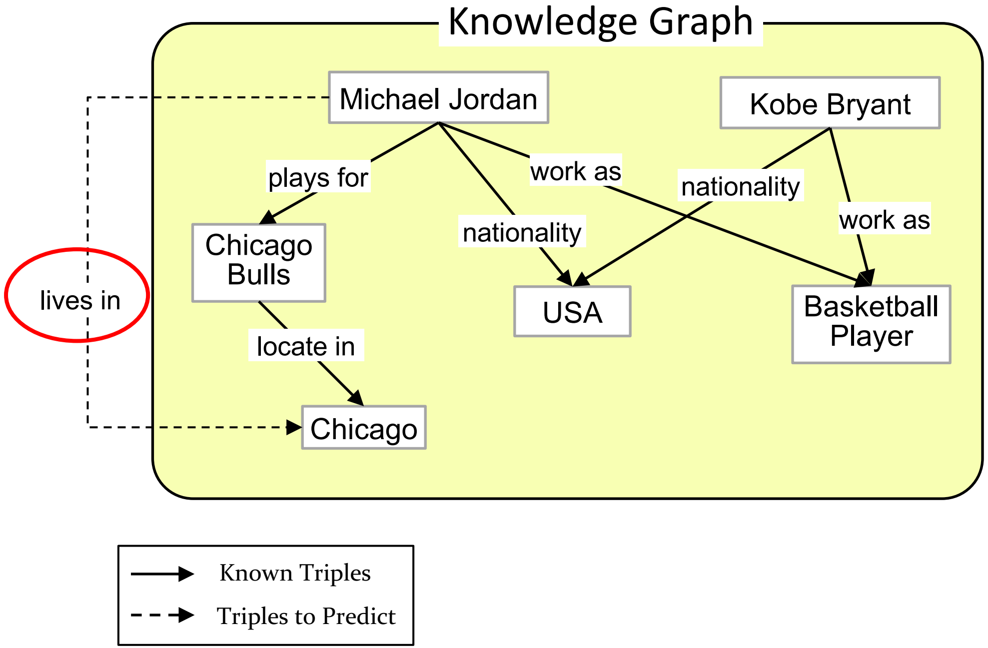
Evaluation Metrics

- Completing the KG triples with new (unseen) relations without seeing their training triples



	Training Set	Testing Set
Entity Set	$\mathcal{E}$	$\mathcal{E}$
Relation Set	$\mathcal{R}_s$	$\mathcal{R}_u$
Triple Set	$\{(h, r_s, t)\}$ $h \in \mathcal{E}, r_s \in \mathcal{R}_s$	$\{(h, r_u, ?)\}$ $h \in \mathcal{E}, r_u \in \mathcal{R}_u$

$\boldsymbol{MRR}$: the average of the reciprocal predicted ranks of all the ground truths (right tail entities)
$\boldsymbol{hit@k}$: the ratio of testing samples whose ground truths are ranked in the top-k positions (k is set to 1, 5, 10)

Results

- RDFS graphs and the text-aware RDFS graph always lead to better performance than relations' textual descriptions
- Text-aware graph combines the advantages of relation semantics in RDF schema and text.

External Knowledge	OntoZSL							
	NELL-ZS				Wiki-ZS			
	MRR	hit@10	hit@5	hit@1	MRR	hit@10	hit@5	hit@1
Text	0.215	34.5	28.3	14.5	0.185	27.3	22.3	13.5
RDFS-hie	0.225	34.8	28.9	<u>15.9</u>	0.175	25.4	20.4	13.1
RDFS-cons	0.220	34.3	28.0	15.4	0.177	25.7	21.2	13.0
RDFS graph	0.223	35.1	29.1	15.3	0.185	27.5	22.3	13.4
RDFS+literals	<u>0.227</u>	<u>35.6</u>	<u>29.4</u>	15.6	<u>0.188</u>	<u>28.1</u>	<u>22.6</u>	<u>13.5</u>

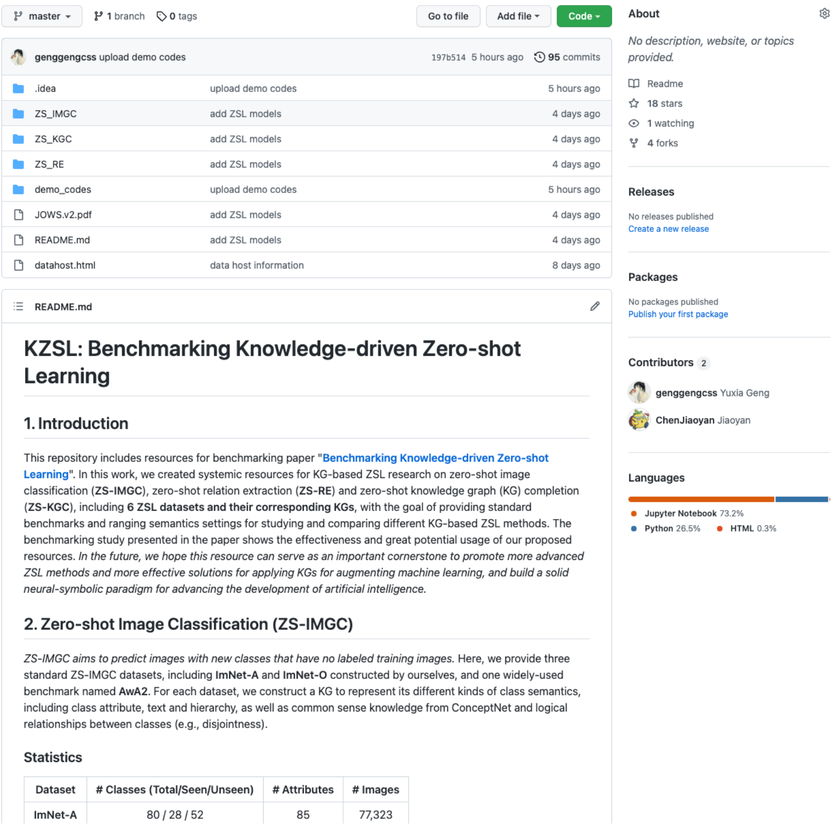
Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning." Journal of Web Semantics 2022.

Hands-on practice

- Download data and Run codes on Google Codelabs
  - ZS-IMGC and ZS-KGC with unseen relations
  - Well-experimented KGZSL and OntoZSL models
- Things you need to prepare
  - Google Drive for saving codes and data
  - Download codes from our Github repository (https://github.com/China-UK-ZSL/Resources_for_KZSL/tree/master/demo_codes)

Resources

- More resources are here
  - https://github.com/China-UK-ZSL/Resources_for_KZSL



master · 1 branch · 0 tags · Go to file · Add file · Code

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.idea	upload demo codes	5 hours ago
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ZS_KGC	add ZSL models	4 days ago
ZS_RE	add ZSL models	4 days ago
demo_codes	upload demo codes	5 hours ago
JOWS.v2.pdf	add ZSL models	4 days ago
README.md	add ZSL models	4 days ago
datahost.html	data host information	8 days ago

README.md

KZSL: Benchmarking Knowledge-driven Zero-shot Learning

1. Introduction

This repository includes resources for benchmarking paper "Benchmarking Knowledge-driven Zero-shot Learning". In this work, we created systemic resources for KG-based ZSL research on zero-shot image classification (**ZS-IMGC**), zero-shot relation extraction (**ZS-RE**) and zero-shot knowledge graph (KG) completion (**ZS-KGC**), including **6 ZSL datasets and their corresponding KGs**, with the goal of providing standard benchmarks and ranging semantics settings for studying and comparing different KG-based ZSL methods. The benchmarking study presented in the paper shows the effectiveness and great potential usage of our proposed resources. *In the future, we hope this resource can serve as an important cornerstone to promote more advanced ZSL methods and more effective solutions for applying KGs for augmenting machine learning, and build a solid neural-symbolic paradigm for advancing the development of artificial intelligence.*

2. Zero-shot Image Classification (ZS-IMGC)

ZS-IMGC aims to predict images with new classes that have no labeled training images. Here, we provide three standard ZS-IMGC datasets, including **ImNet-A** and **ImNet-O** constructed by ourselves, and one widely-used benchmark named **AwA2**. For each dataset, we construct a KG to represent its different kinds of class semantics, including class attribute, text and hierarchy, as well as common sense knowledge from ConceptNet and logical relationships between classes (e.g., disjointness).

Statistics

Dataset	# Classes (Total/Seen/Unseen)	# Attributes	# Images
ImNet-A	80 / 28 / 52	85	77,323

About

No description, website, or topics provided.

Readme
18 stars
1 watching
4 forks

Releases

No releases published
Create a new release

Packages

No packages published
Publish your first package

Contributors 2

genggengcss Yuxia Geng
ChenJiaoyan Jiaoyan

Languages

Jupyter Notebook 73.2%
Python 26.5%
HTML 0.3%

Summary

- Resource review
  - There have been diverse resources in different domains, but there is still a shortage of resources for evaluating KG/Ontology-based ZSL methods
- KG Construction for ZSL benchmarks
  - principle: a standard procedure for guidance
  - cost: semi-automatic (extract from existing open resources + human check)
- Benchmarking
  - Different Class (Relation) Semantics
    - KG/Ontology-based semantics are always superior to traditional external knowledge
    - different kinds of semantics perform differently on different datasets/tasks
    - some semantics of the KG/Ontology are not fully utilized by the current methods
- Demonstration

T9

Conclusions, Discussions, and Future Directions

Overall Conclusion

- What have we introduced?
  - ZSL definitions, concepts, background and paradigm
  - Knowledge-aware ZSL, different external knowledge and typical methods
  - Resources and benchmarking on KG-aware ZSL, demonstration
  - **Methods**:
    - OntoZSL (Data Augmentation with GAN)
    - Feature Propagation-based Methods
    - Zero-shot Visual Question Answering
    - DUET (better utilize the attributes with Transformer)
    - KG Structure Pretraining

Open Challenges

- Quality of knowledge graphs
    - Impact of low quality knowledge
    - Task oriented knowledge retrieval
    - Other forms of structured knowledge, such as databases and web tables
    - Crowd sourcing and human in the loop methods
- Learning paradigm
    - Data augmentation based methods only have few works and have good potential to help avoid data bias
    - Belief propagation has not been widely investigated, but would be a good solution for some CV tasks, such as scene graph extraction and VQA
    - With the wide adoption of LMs, class feature based methods become more popular
- ZSL in KG Construction
- Benchmarking
    - Domain specific benchmarks

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Thanks!

Please feel free to contact the presenters

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Q & A