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

Part III – Hands-on: Resources and Benchmarking

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https://china-uk-zsl.github.io/kg-zsl-tutorial-iswc-2022/

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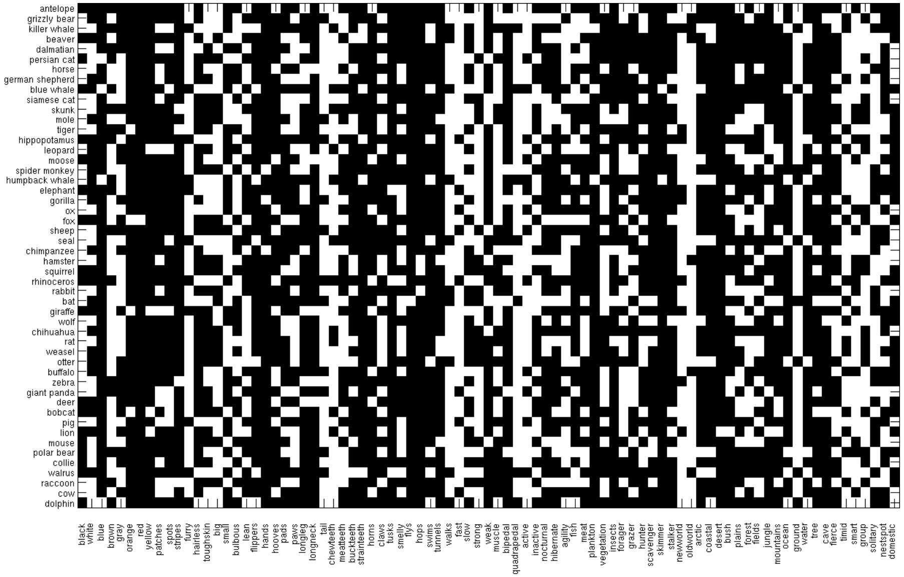
A Brief Review on Evaluation Resources

Scope

- Computer Vision
  - image classification (single-label and multi-label)
  - visual question answering
- Open Information Extraction
  - fine-grained entity typing
  - relation extraction
  - event extraction
- Knowledge Graph Completion
  - with unseen entities and/or relations
- …

Image Classification

- 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

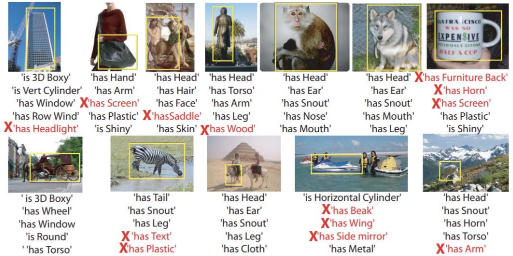
Xian, Yongqin, et al. "Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly." IEEE transactions on pattern analysis and machine intelligence 41.9 (2018): 2251-2265.

Image Classification

- 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



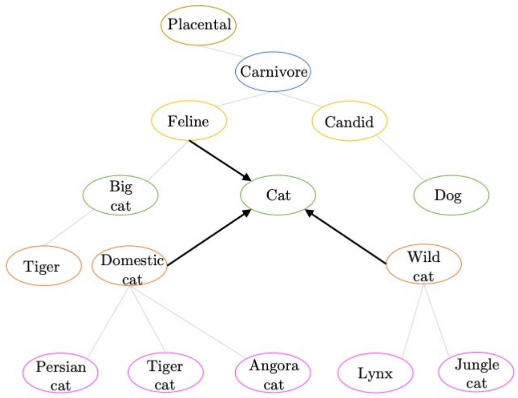
aPy [Farhadi et al. 2009]: coarse-grained classification, 20/12 seen/unseen classes, 64 attributes

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).

Image Classification

IMAGENET
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

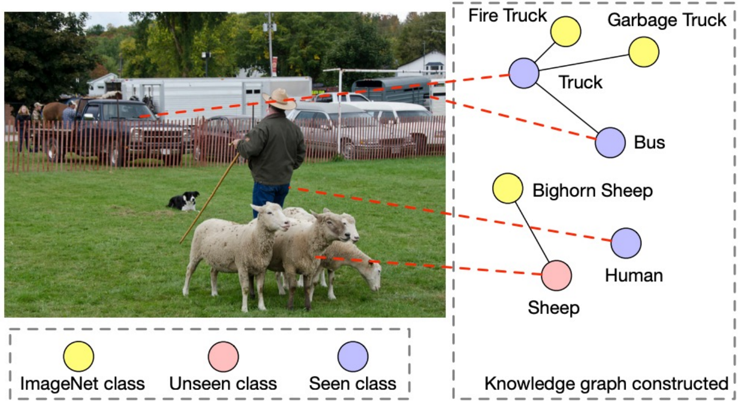


A segment of the class hierarchy

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.

Image Classification

- NUS-WIDE
  - Multi-label zero-shot image classification proposed by [Huang et al. 2020]
  - 270K images
  - Two sets of labels:
    - 925 labels from Flickr user tags, as seen classes
    - 81 human-annotated concepts, as unseen classes
  - External knowledge: subsumption relationships extracted from WordNet



Huang, He, et al. "Multi-label Zero-shot Classification by Learning to Transfer from External Knowledge." BMVC 2020.

Image Classification

- 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 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

See more details introduced in our next part

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.

Visual Question Answering

- ZS-FVQA [Chen et al. 2021]
  - Constructed by re-splitting a fact-based VQA benchmark FVQA [Wang et al. 2017]
  - 250 seen answers and 250 unseen answers
  - 2384 questions and 1297 images
  - External knowledge: facts from DBpedia, ConceptNet and WebChild

Question: What can the red object on the ground be used for ?
Answer: Firefighting
Support Fact: Fire hydrant can be used for fighting fires.

- OK-VQA [Marino et al. 2019]
  - Require external knowledge to answer the question
  - 14031 images, 14055 questions, 407 answers
  - Could be splitted into a ZSL setting as ZS-F-VQA

Chen, Zhuo, et al. "Zero-shot visual question answering using knowledge graph." International Semantic Web Conference. Springer, Cham, 2021.
Wang, Peng, et al. "Fvqa: Fact-based visual question answering." IEEE transactions on pattern analysis and machine intelligence 40.10 (2017): 2413-2427.
Marino, Kenneth, et al. "Ok-vqa: A visual question answering benchmark requiring external knowledge." CVPR 2019.

Knowledge Extraction (NLP)

- BBN, OntoNotes and Wikipedia
  - Fine-grained named **entity typing**
  - Types are hierarchical, and (partially) matched with Freebase types
  - BNN: 2311 Wall Street Journal articles, ~48K sentences and 93 types
  - OntoNotes: 13109 news document from NewsWire, Broadcast News, Broadcast Conversation and Web text, 89 types
  - Wikipedia: 780.5K Wikipedia articles, 1.15M senteces, 112 types

  - ZSL setting in [Ma et al. 2016]
    - Coarse-grained types as seen classes
    - Second-level fine-grained types as unseen classes

Ma, Yukun, Erik Cambria, and Sa Gao. "Label embedding for zero-shot fine-grained named entity typing." COLING 2016.

Knowledge Extraction (NLP)

- NYT10 and WEB19
  - **Relation (property) extraction**
  - NYT10: New York Times corpus + Freebase triples
  - WEB19: predicate paths in FB15k + Microsoft Bing search API + human evaluation
  - ZSL setting in [Imrattanatrai et al. 2019]
    - 43 relations as seen and 11 relations as unseen from NYT10
    - 217 relations as seen and 54 relations as unseen for WEB19

Huang, Lifu, et al. "Zero-shot transfer learning for event extraction." ACL 2018

Knowledge Extraction (NLP)

- ZeroRel [Geng et al. 2022] and [Li et al. 2020]
    - **Zero-shot relation extraction**
    - Training: 84000 sentences with 70 seen relations
    - Testing: 17150 sentences of 30 unseen relations, 3496 sentences of seen relations
    - External knowledge:
    - KG: Wikipedia dump (21M entities, 594 relations and 69M triples)
        - Logical rules mined from the KG by AMIE
            - 50 length-1 rules, e.g., born_in_country(x, y) => nationality(x, y)
            - 122 length-2 rules, e.g., brother(x, y)^father(y, z) => uncle(x, z)

Geng, Yuxia, et al. “Benchmarking knowledge-driven zero-shot learning”, Journal of Web Semantics. 2022.
Li, Juan, et al. "Logic-guided semantic representation learning for zero-shot relation classification." COLING 2020.

Knowledge Extraction (NLP)

- ACE05
  - **Event extraction** with 33 fine-grained sub-types under 8 coarse-grained main types
  - ZSL settings in
    - Seen classes (i.e., sub-types) are portioned according to main types

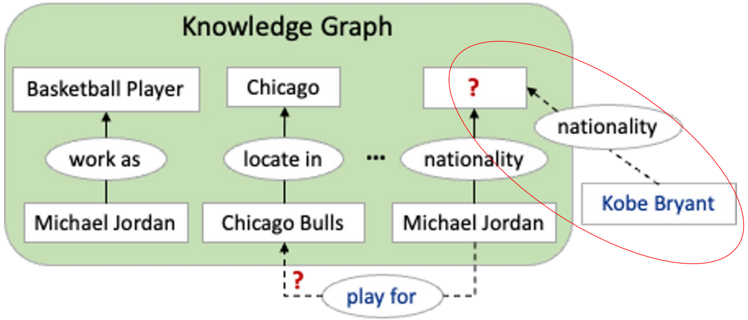
ACE event schema specification:
https://www.ldc.upenn.edu/sites/www.ldc.upenn.edu/files/english-events-guidelines-v5.4.3.pdf

Main Types	Seen Class (10)	Unseen Class (23)
Conflict	Attack	Demonstrate
Movement	Transport	
Transaction	Transfer Money, Transfer Ownership	
Business		Start Org, Merge Org, Declare Bankruptcy, End Org
Justice	Sentence, Arrest Jail	Pardon, Appeal, Acquit, Extradite, Execute, Fine, Convict, Sue, Charge Indict, Trial Hearing, Release Parole
Personnel	Elect, End Position	Start Position, Nominate
Contact	Meet	Phone Write
Life	Die	Marry, Divorce, Injure, Be born

Huang, Lifu, et al. "Zero-shot transfer learning for event extraction." ACL 2018

KG Completion with Unseen Entities

- What are unseen entities in KGC?
  - In triples to predict, the new entities that have not appeared in the KG (triples) whose embeddings have been learned
  - Sometimes known as ***inductive KGC***
  - Assumption: the original KG embeddings are fixed (with no re-training)



Two Settings

Setting I: some side information of the unseen entities, such as names, textual descriptions, images, attributes, and hyper-relational facts are given during prediction

Setting II: some additional triples of the unseen entities (graph structure information) are given during prediction

KG Completion with Unseen Entities

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Two Settings

Setting I: some auxiliary information of the unseen entities, including names, textual descriptions, images, attributes, and hyper-relational facts are given during prediction

Setting II: some additional triples of the unseen entities (graph structure information) are given during prediction

We usually regard Setting I as ZSL and Setting II as few-shot learning

KG Completion with Unseen Entities

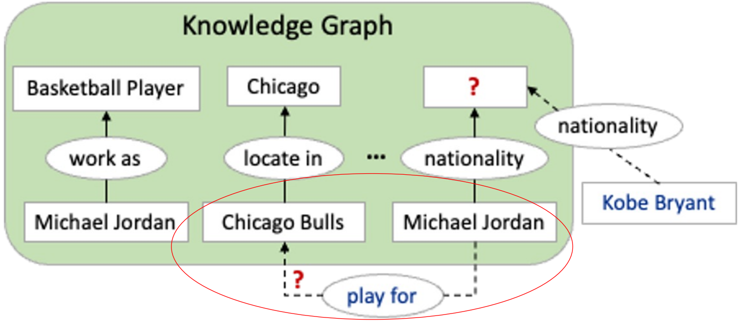
- For Setting I (ZSL), original KGC benchmarks could be re-set by
  - Deleting training triples or adding new testing triples
  - Extracting the side information from e.g., the original KGs
  - Benchmarks:
    - FB15k-237-OWE [Shah et al. 2019] and FB20k [Xie et al. 2016] from FB15k-237
      - FB15k-237-OWL: 2K unseen entities, 12K seen entities, 235 relations, 289.7K triples
      - FB12k: 19.9K entities and 88K triples added to the testing set of FB15k-237
    - DBpedia50k and DBpedia500k [Shi et al. 2018]
      - DBpedia50k: 49.9K entities, 654 relations, 43.8K triples
      - DBpedia500K: 517K entities, 654 relations, 4.2M triples
    - Wikidata5M with Wikipedia articles for side information [Wang et al. 2021]
      - Large size: 4.6M entities, 822 relations, 20.6M triples

all the relations are seen!!!

Shah, Haseeb, et al. "An open-world extension to knowledge graph completion models." AAAI 2019.
Shi, Baoxu, and Tim Weninger. "Open-world knowledge graph completion." AAAI 2018
Wang, Xiaozhi, et al. "KEPLER: A unified model for knowledge embedding and pre-trained language representation." Transactions of the Association for Computational Linguistics 9 (2021): 176-194.
Xie, Ruobing, et al. "Representation learning of knowledge graphs with entity descriptions." AAAI 2016.

KG Completion with Unseen Relations

- The two settings for unseen entities can also be applied to unseen relations. Unseen relations of **setting I** (ZSL) rely on side information such as relation names, descriptions and ontological schemas.



- "*play for* usually refers to a sporter playing game for a team …"
- *play for* is a sub-relation of *work for*
- The domain of *play for* is sporter which is a sub-class of perso
- …

KG Completion with Unseen Relations

- The two settings for unseen entities can also be applied to unseen relations. Unseen relations of **setting I** (ZSL) rely on auxiliary information such as relation names, descriptions and ontological schemas.
- NELL-ZS and Wiki-ZS [Qin et al. 2022] *all the entities are seen!!!*
  - NELL-ZS: 138 seen relations for training, 10/32 unseen relations for validation/testing, 66K entities
  - Wiki-ZS: 469 seen relations for training, 20/48 unseen relations for validation/testing, 606K entities
  - External knowledge: name and text description by [Qin et al. 2022] + ontological schemas e.g., relation subsumption, domain and range by [Geng et al. 2021, 2022]

See more details introduced in our next part

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

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Benchmarking Zero-shot Image Classification (ZS-IMGC)

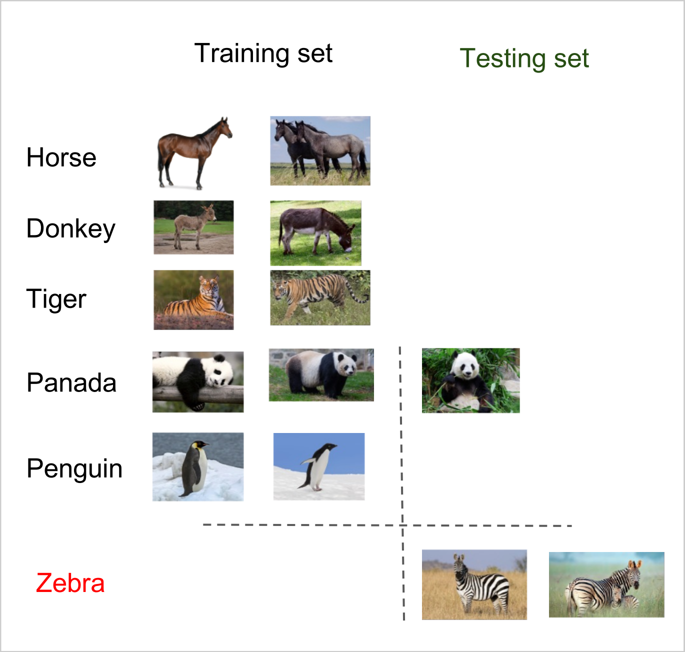
ZS-IMGC

- Revisit Task Definition
- Revisit ZSL Benchmarks
- Existing Side Information vs KG
- KG Construction and Statistics
- Benchmarking Results

Task Definition

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

Zero-shot Animal Image Classification



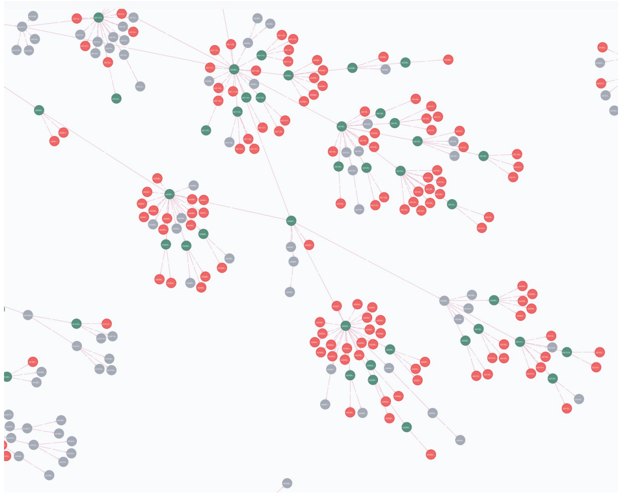
ZS-IMGC Benchmarks

Datasets	Classes			Images					Attributes
	Total	Training	Testing	Total	Training		Testing		
		Seen	Unseen		Seen	Unseen	Seen	Unseen	
AwA2	50	40	10	37,322	23,527	0	5,882	7,913	85
CUB	200	150	50	11,788	7,057	0	1,764	2,967	312
SUN	717	645	72	14,340	10,320	0	2,580	1,440	102
aPY	32	20	12	15,339	5,932	0	1,483	7,924	64
ImageNet	21,842	1,000	20,842	*	1300, 000	0	50,000	*	/
ImNet-A	80	28	52	77,323	36,400	0	1,400	39,523	85
ImNet-O	35	10	25	39,361	12,907	0	500	25,954	40

* too large to count

ZS-IMGC Benchmarks

- ImNet-A and ImNet-O
  - two subsets extracted from **ImageNet** (a set of hierarchical classes)
  - **seen classes** are classes in the ImageNet 2012 1k (a balanced subset), **unseen classes** are those 2-hops away according to the hierarchy

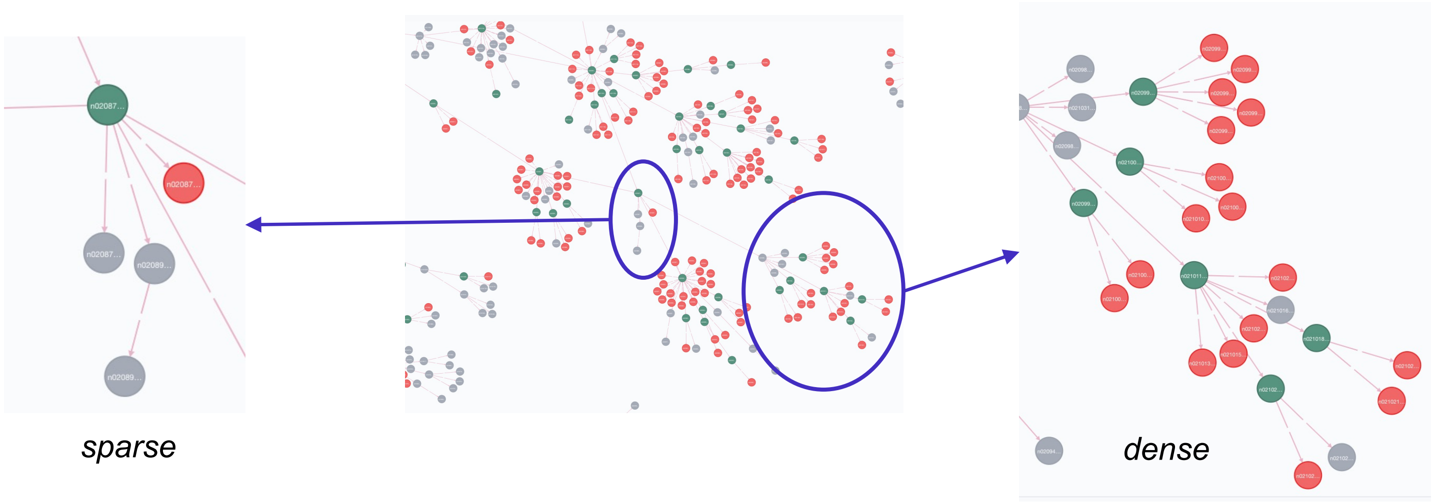


a visualization by neo4j, seen classes are colored in green, unseen classes are in red, the remaining classes colored in gray are for connection.

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.

ZS-IMGC Benchmarks

- ImNet-A and ImNet-O
  - extract the dense part of ImageNet for fine-grained classes, where the total number of seen and unseen classes in each part is at least **5**



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.

ZS-IMGC Benchmarks

- ImNet-A and ImNet-O
  - every class can be linked to a Wikipedia page to access more information

Fox

From Wikipedia, the free encyclopedia

For the U.S. television network, see Fox Broadcasting Company. For other uses, see Fox (disambiguation).
"Foxes" and "Vixen" redirect here. For other uses, see Foxes (disambiguation) and Vixen (disambiguation).

Foxes are small to medium-sized, omnivorous mammals belonging to several genera of the family Canidae. They have a flattened skull, upright triangular ears, a pointed, slightly upturned snout, and a long bushy tail (or *brush*).

Twelve species belong to the monophyletic "true foxes" group of genus *Vulpes*. Approximately another 25 current or extinct species are always or sometimes called foxes; these foxes are either part of the paraphyletic group of the South American foxes, or of the outlying group, which consists of the bat-eared fox, gray fox, and island fox.[1]

Foxes live on every continent except Antarctica. The most common and widespread species of fox is the red fox (*Vulpes vulpes*) with about 47 recognized subspecies.[2] The global distribution of foxes, together with their widespread reputation for cunning, has contributed to their prominence in popular culture and folklore in many societies around the world. The hunting of foxes with packs of hounds, long an established pursuit in Europe, especially in the British Isles, was exported by European settlers to various parts of the New World.

Foxes

A red fox in Västernorrlands Län,

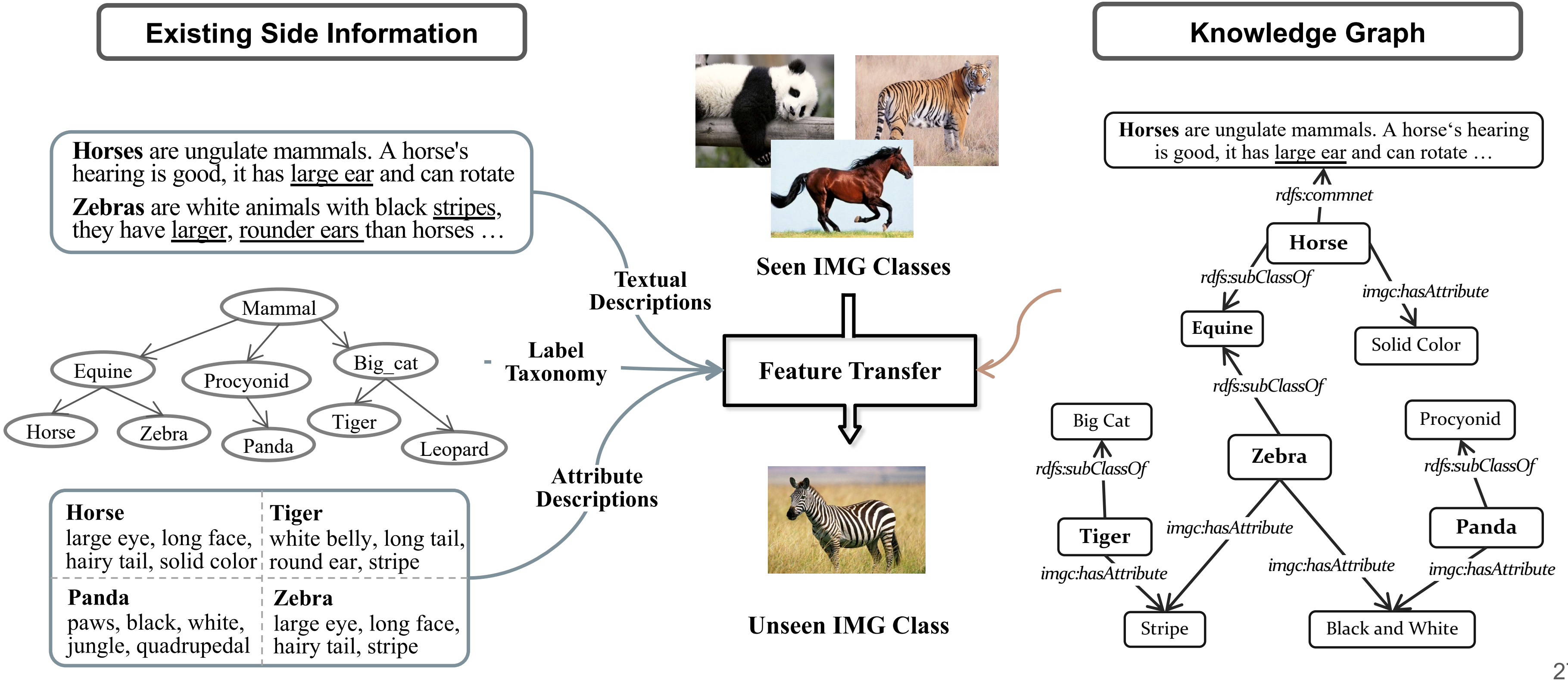
Geng, Yuxia, et al. "OntoZSL: Ontology-enhanced zero-shot learning." WWW 2021.
Geng, Yuxia, et al. “Benchmarking knowledge-driven zero-shot learning”, Journal of Web Semantics. 2022.

ZS-IMGC benchmarks

- ImNet-A and ImNet-O
  - ImNet-A: 80 **A**nimal classes
    - 28 seen, 52 unseen
    - 11 class groups
    - bees, foxes
  - ImNet-O: 35 general **O**bject classes
    - 10 seen, 25 unseen
    - 5 class families
    - fast food, fungi

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 Side Information vs KG



Existing Side Information vs KG

Datasets	class text e.g., names or descriptions	class attribute	class hierarchy	KG
AwA2	✓	✓	✓	✓
CUB	✓	✓		
SUN	✓	✓		
aPY	✓	✓		
ImageNet	✓		✓	
ImNet-A	✓	✓	✓	✓
ImNet-O	✓	✓	✓	✓

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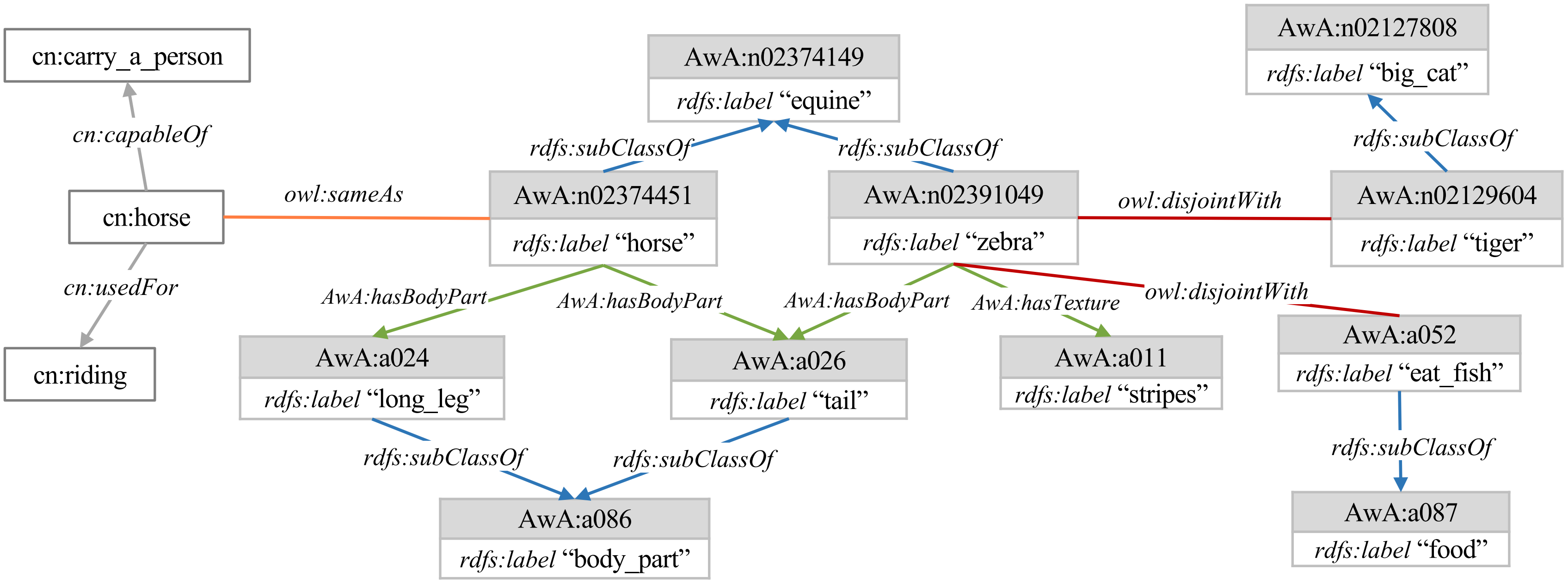
Datasets	class text e.g., names or descriptions	class attribute	class hierarchy	KG
AwA2	√	√	√	√
CUB	√	√		
SUN	√	√		
aPY	√	√		
ImageNet	√		√	
ImNet-A	√	√	√	√
ImNet-O	√	√	√	√

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

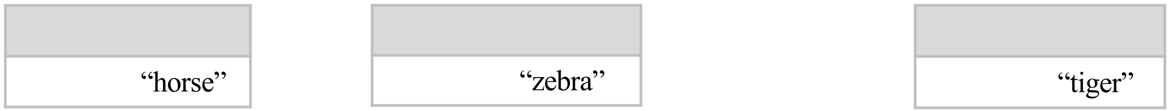
A Segment of KG for AwA2



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

KG Construction Steps

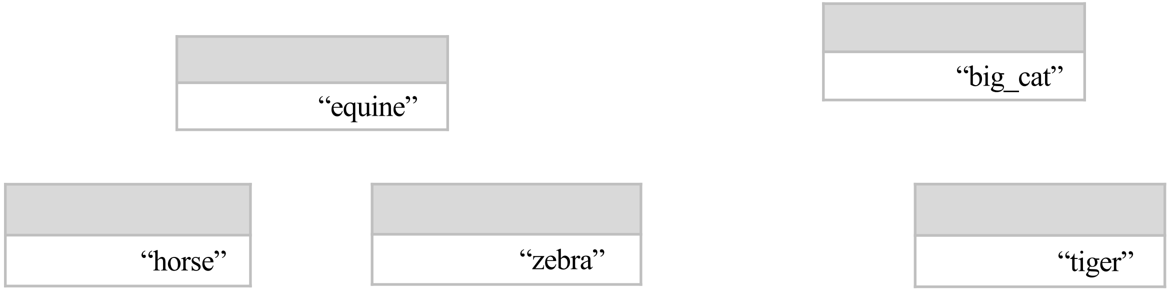
1. KG scope: describing the semantic relationships among image classes in datasets



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

KG Construction Steps

2. Class hierarchy from WordNet: WordNet ID + *rdfs:subClassOf*



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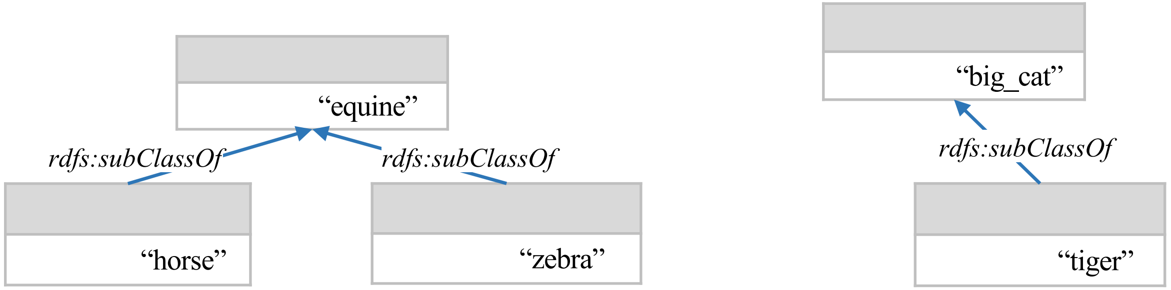

the extraction is supported by the WordNet interface packaged in ***NLTK*** *(see more at https://www.nltk.org/howto/wordnet.html).*

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

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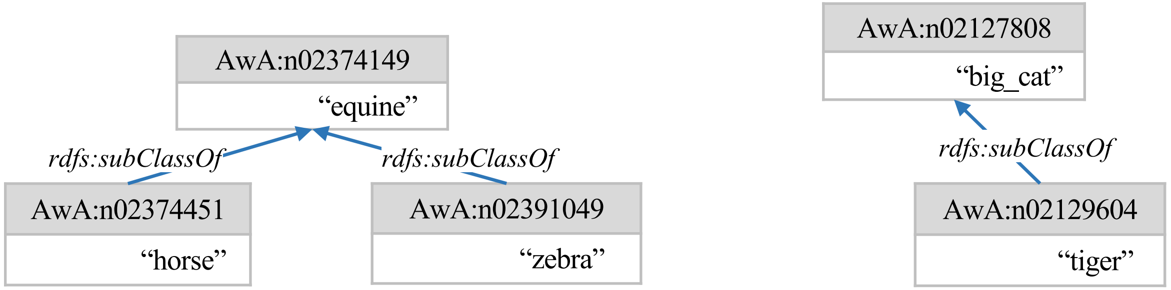

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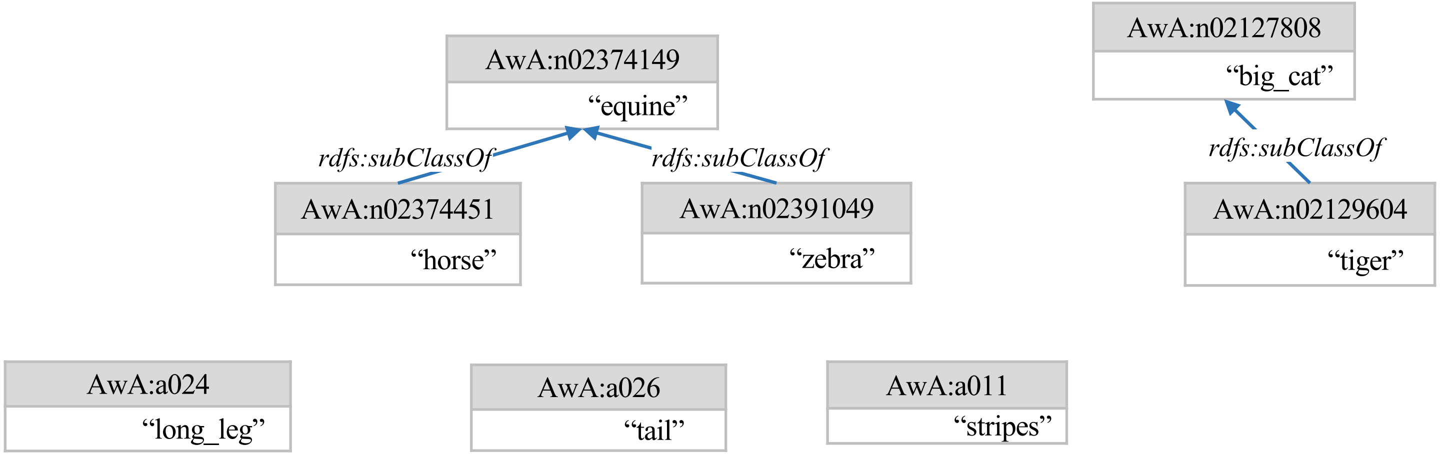
KG Construction Steps

3. Class Attribute from annotations: self-defined ID + *AwA:hasBodyPart, AwA:hasTexture*



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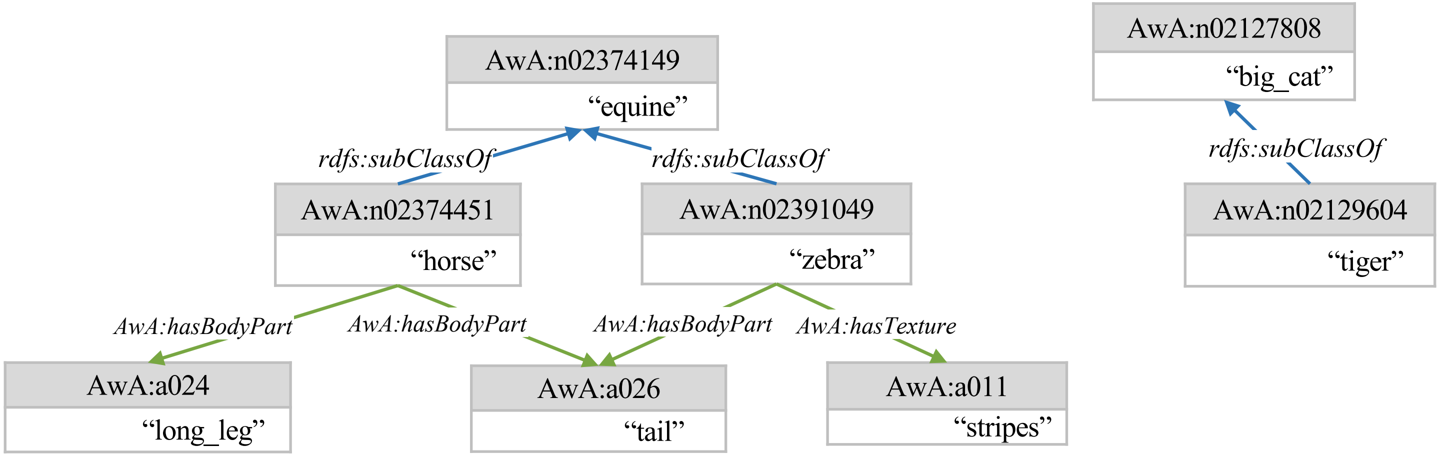

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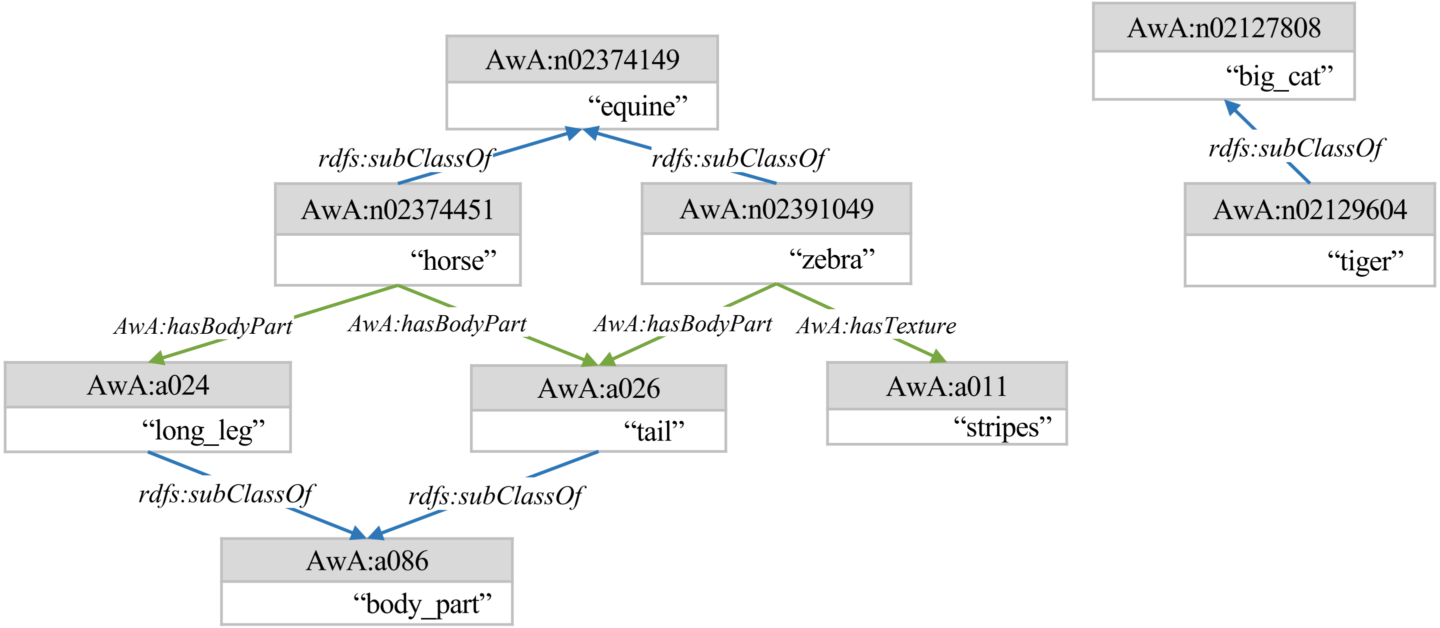
KG Construction Steps

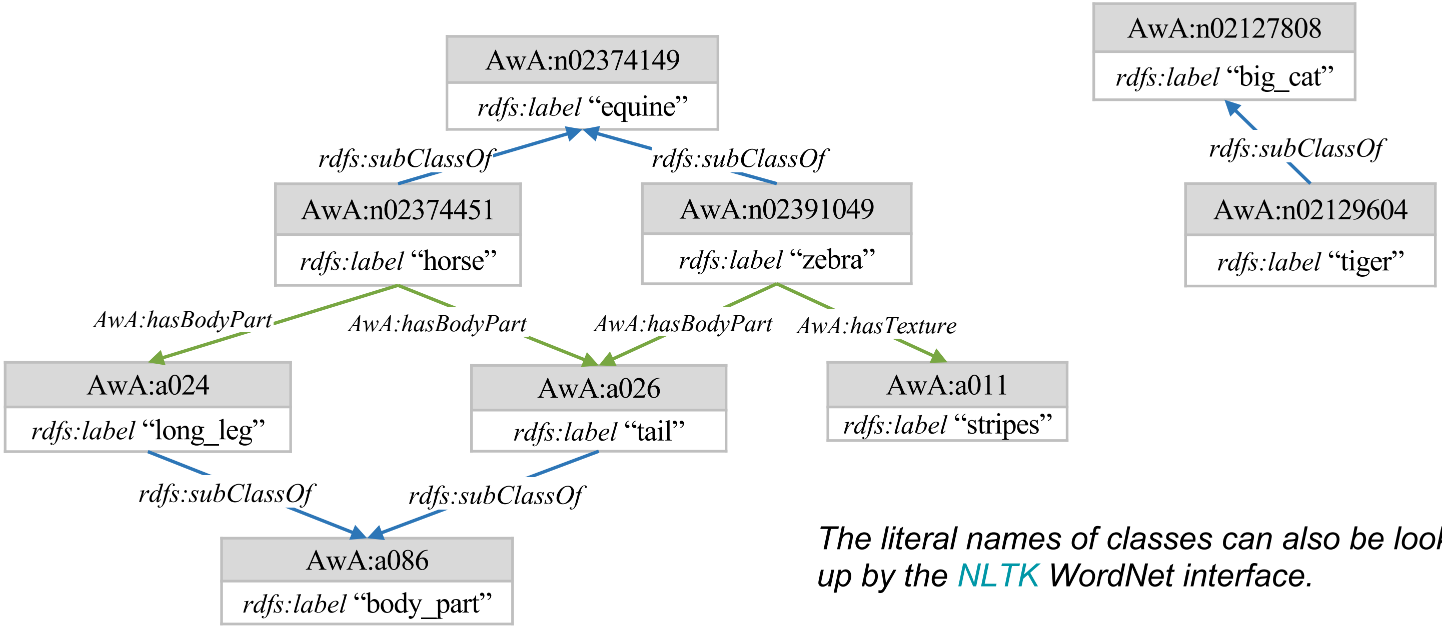
3. Class Attribute from annotations: self-defined ID + *AwA:hasBodyPart, AwA:hasTexture* + Attribute Hierarchy



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

KG Construction Steps

4. Class Text: English surface names by *rdfs:label*

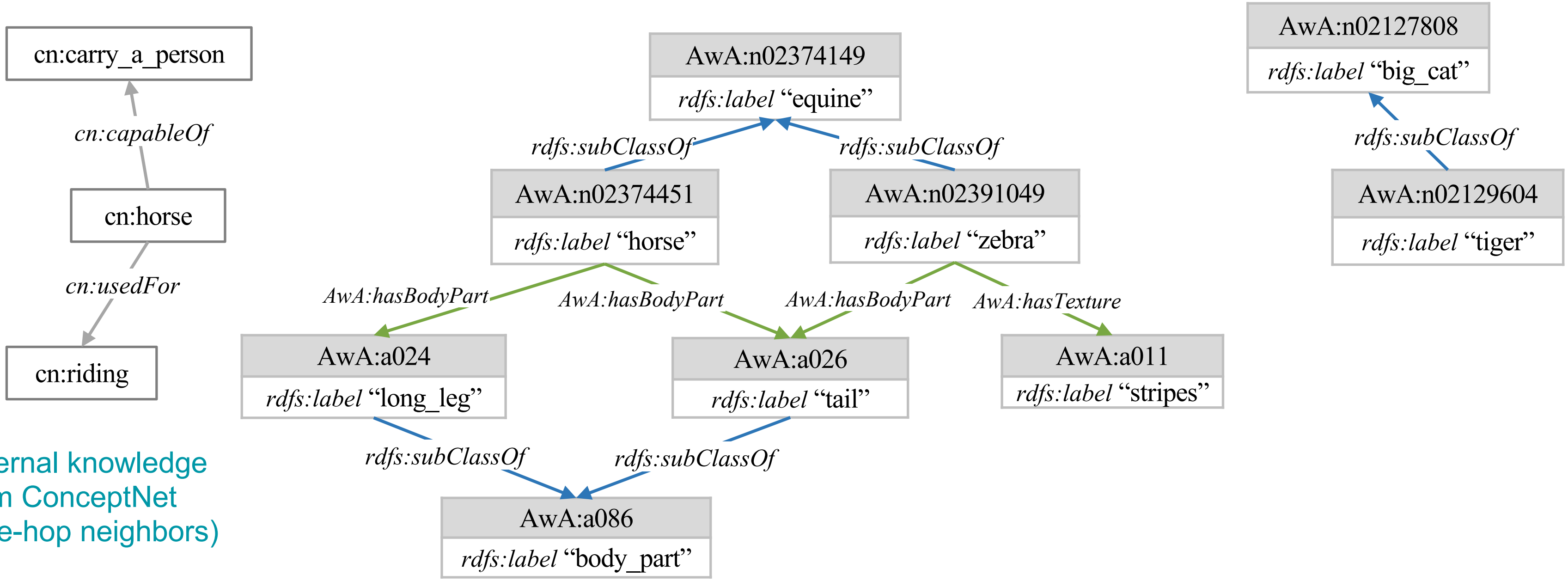


The literal names of classes can also be looked up by the NLTK WordNet interface.

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

KG Construction Steps

5. Relational Facts from External KG e.g., ConceptNet by *owl:sameAs*

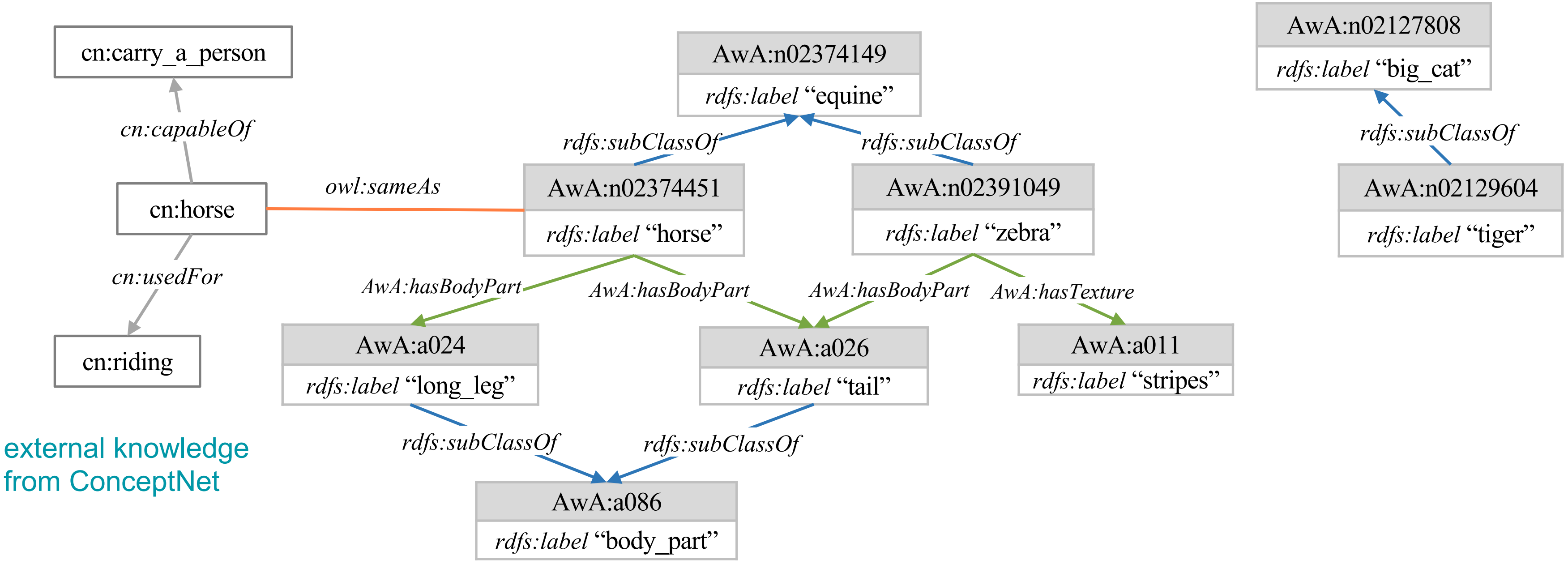


external knowledge from ConceptNet (one-hop neighbors)

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

KG Construction Steps

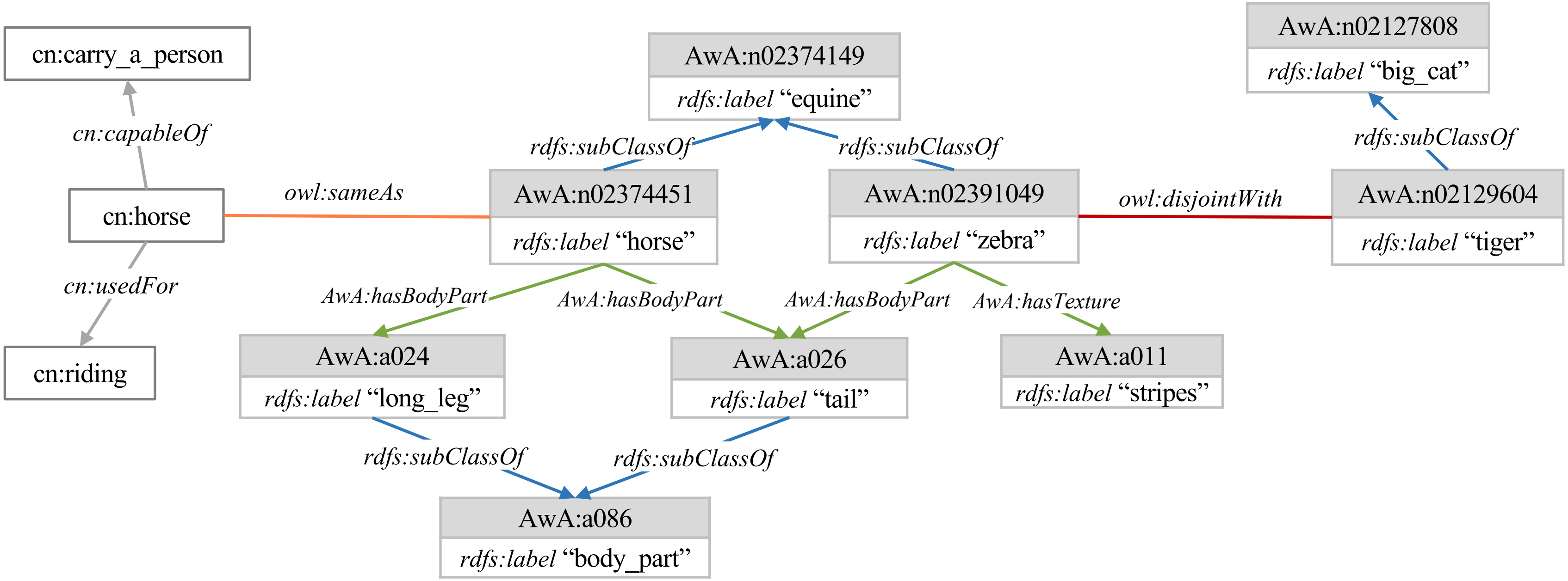
5. Relational Facts from External KG e.g., ConceptNet by *owl:sameAs*



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

KG Construction Steps

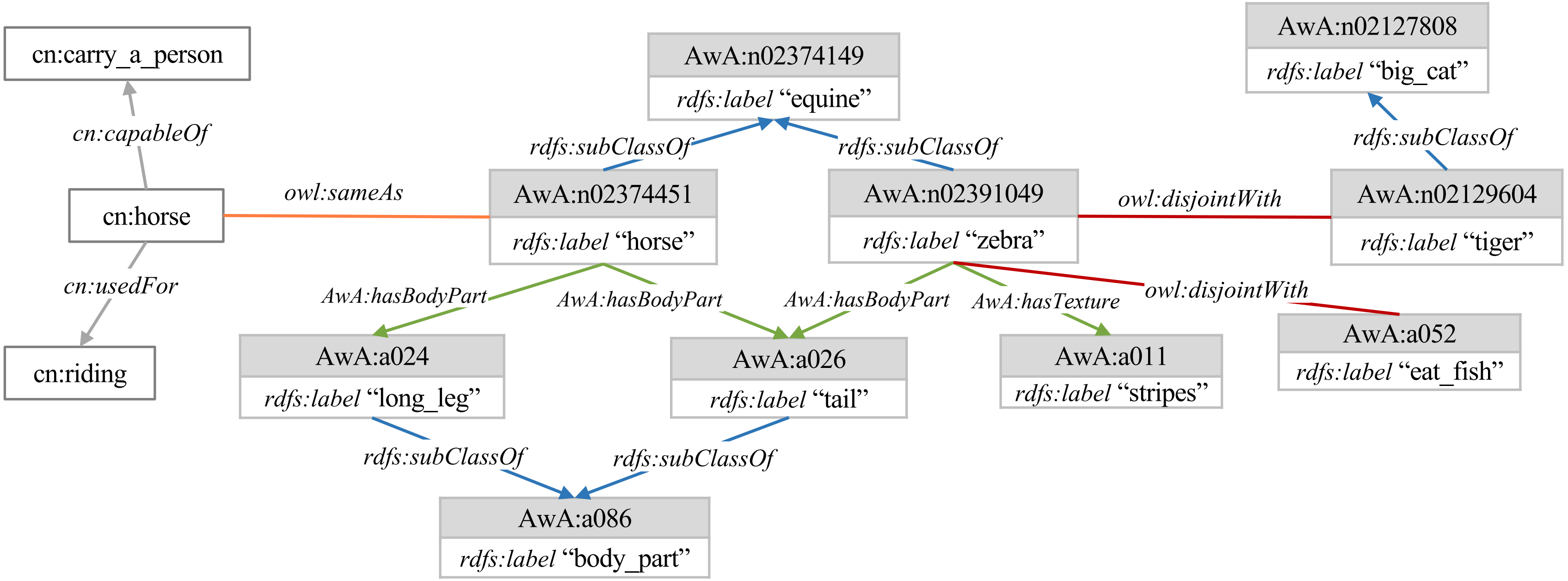
6. Logical Constraints between classes by *owl:disjointWith*



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

KG Construction Steps

6. Logical Constraints between classes by *owl:disjointWith*



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

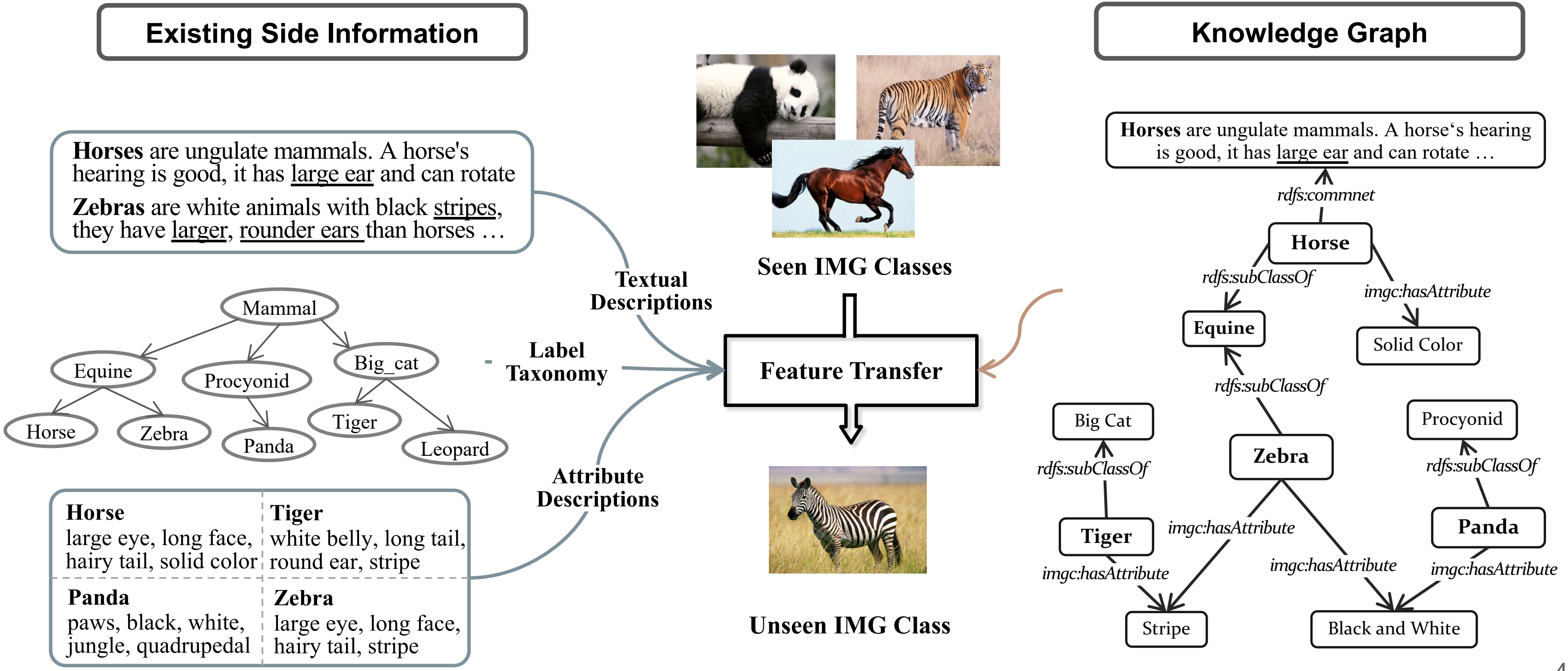
KG Statistics

	# Entities	# Relations	# Triples						
	Total (Classes/Att./CN)	Total (Att./CN)	Total	Hie	Att	Literal	sameAs	CN	disjointWith
AwA2	9,195 (100 / 102 / 8,993)	42 (15 / 23)	14, 112	197	1,562	202	182	10,546	1,423
ImNet-A	8,920 (111 / 103 / 8,706)	41 (17 / 21)	10,461	210	335	214	156	9,546	/
ImNet-O	3,148 (59 / 52 / 3,037)	31 (6 / 22)	3,990	110	110	111	93	3,566	/

"Hie": class hierarchy
"Att": class attribute
"CN": ConceptNet

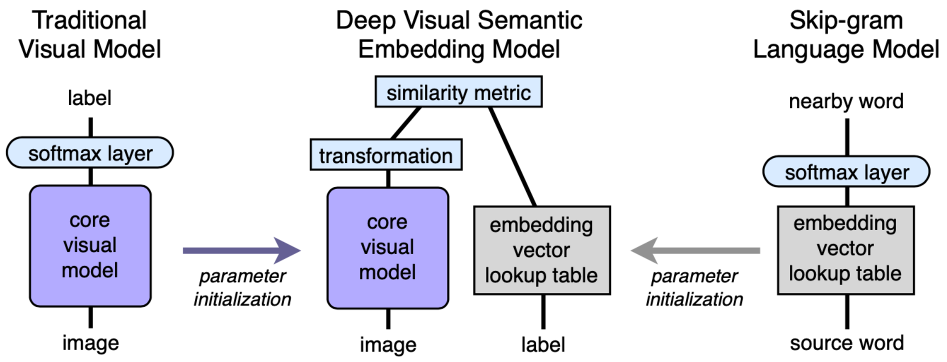
Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning", Journal of Web Semantics. 2022.

Existing Side Information vs KG



Benchmarking Mapping-based Methods

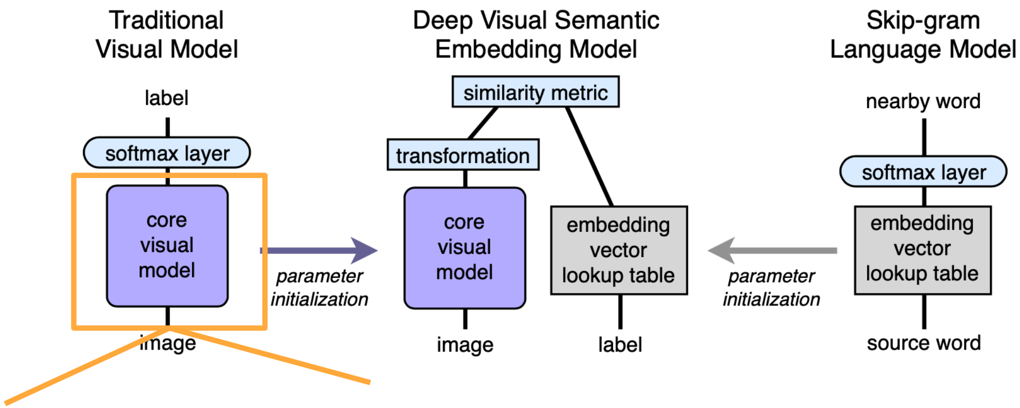
- DeViSE & traditional side information



Frome, Andrea, et al. "Devise: A deep visual-semantic embedding model." NIPS 2013.

Benchmarking Mapping-based Methods

- DeViSE & traditional side information



CNN models such as ResNet-101

a model pre-trained on ImageNet with 1K classes

[Xian et al.] published the ResNet features of images in the existing benchmarks and proposed new class splits to ensure that

i) *all the seen classes are **among** the 1K classes of ImageNet so that we do not need to fine-tune ResNet for any datasets;*

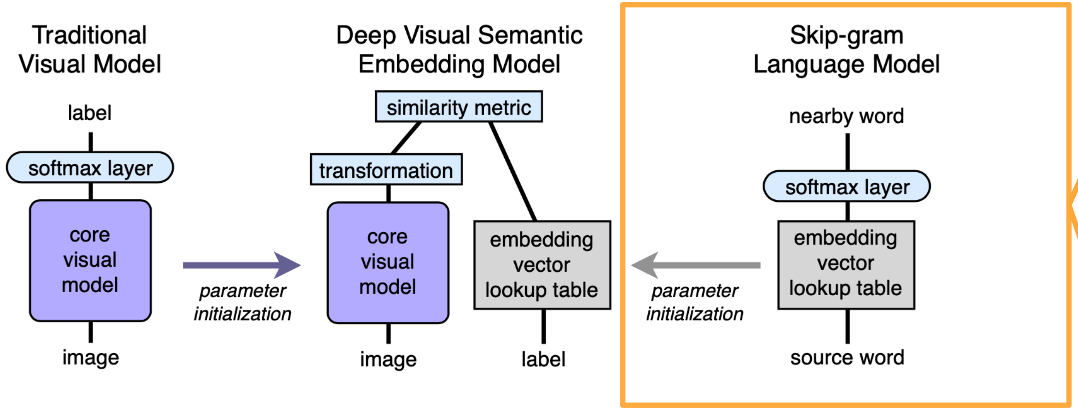
ii) *all the unseen classes are **not among** the 1K classes to avoid data leakage (i.e., images of test classes is present at training time)*

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

Frome, Andrea, et al. "Devise: A deep visual-semantic embedding model." NIPS 2013.

Benchmarking Mapping-based Methods

- DeViSE & traditional side information



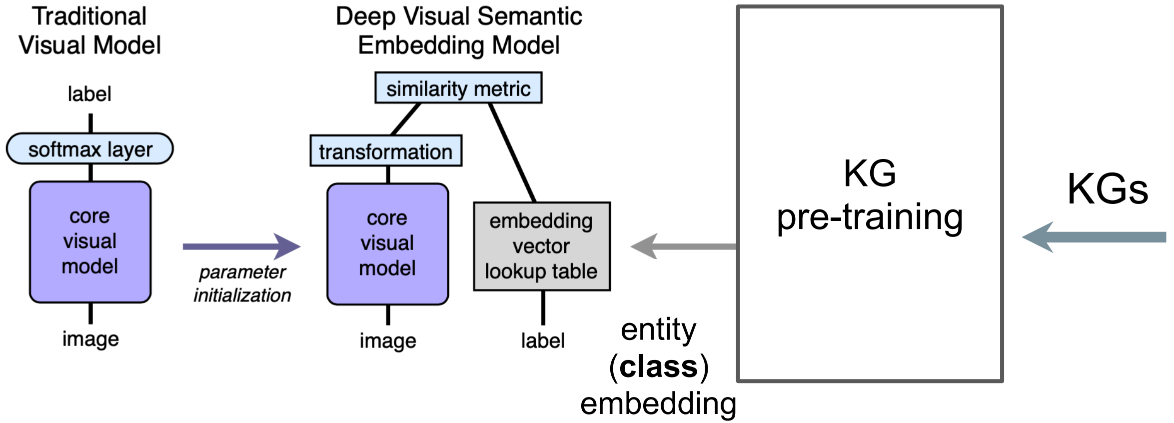
1. **word embeddings (w2v)**
   - 500-dim by [1];
   - 300-dim by Glove;
2. **multi-hot attribute vectors (att)**
   - 85-dim for AwA2;
   - 85-dim for ImNet-A;
   - 40-dim for ImNet-O;
3. **class hierarchy (hie)**
   - 100-dim by GAE [2]

[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 Mapping-based Methods

- DeViSE & KG-based side information

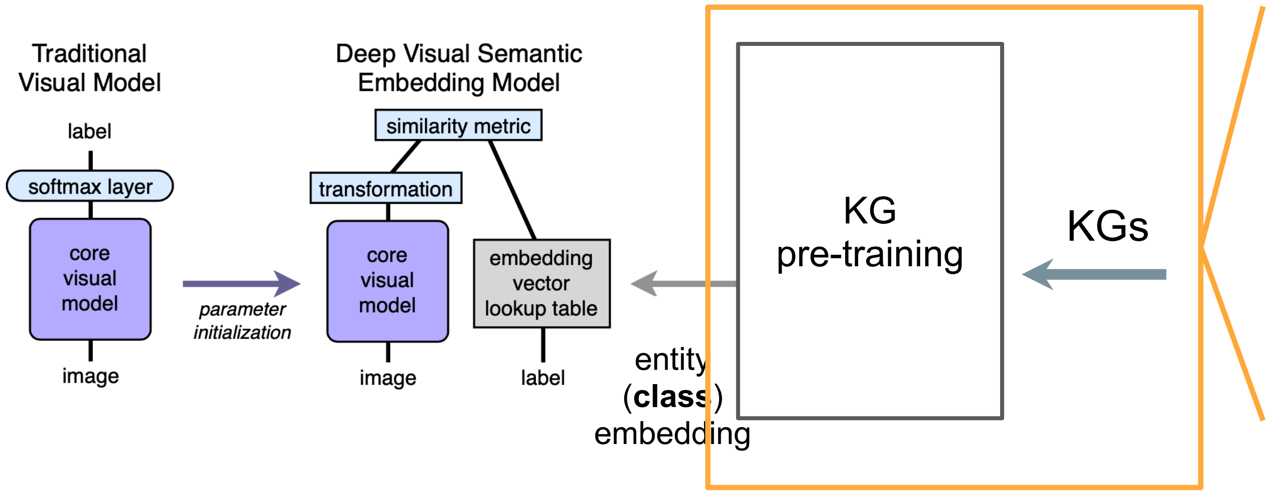


Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning", Journal of Web Semantics. 2022.

Benchmarking Mapping-based Methods

- DeViSE & KG-based side information

KG (1), (3), (4) + TransE;
KG (2) + text-aware TransE (see OntoZSL [1] for more)



1. **Basic KG**
   - class hierarchy;
   - class attributes;
   - attribute hierarchy;
2. **Basic KG + literals**
   + literal names
3. **Basic KG + CN**
   + triples from ConceptNet
4. **Basic KG + logics**
   + triples of disjointness

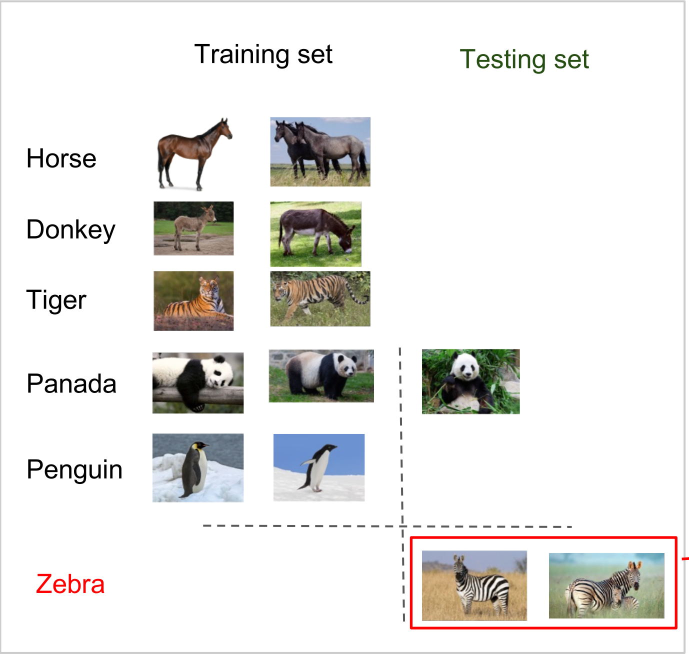
[1] Geng, Yuxia, et al. "OntoZSL: Ontology-enhanced zero-shot learning." WWW 2021.

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

Evaluation Metrics

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

Zero-shot Animal Image Classification



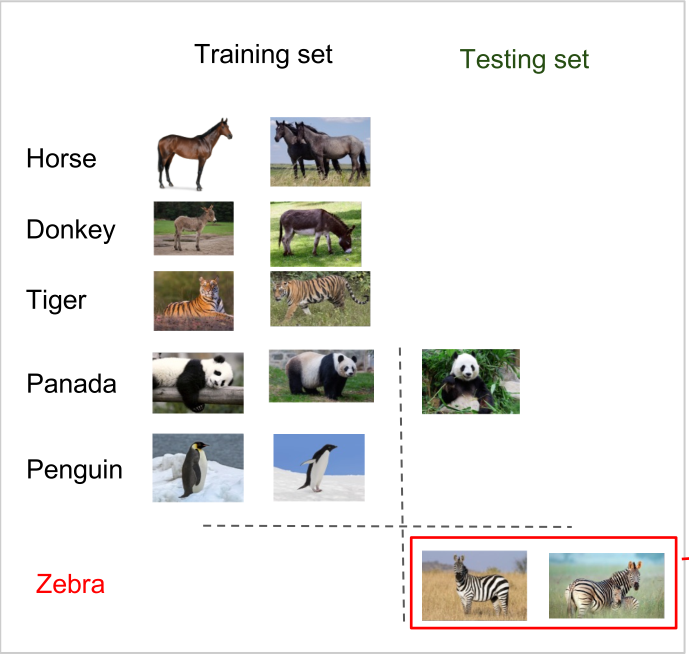
standard ZSL setting: classifying the testing samples of unseen classes with candidates of all unseen classes

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

Evaluation Metrics

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

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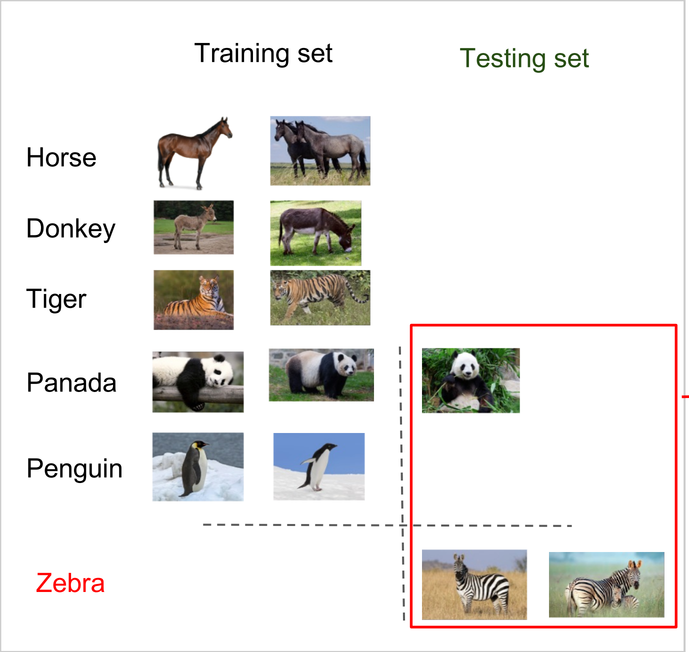
- Classifying the images of new (unseen) classes without seeing their training examples

Zero-shot Animal Image Classification



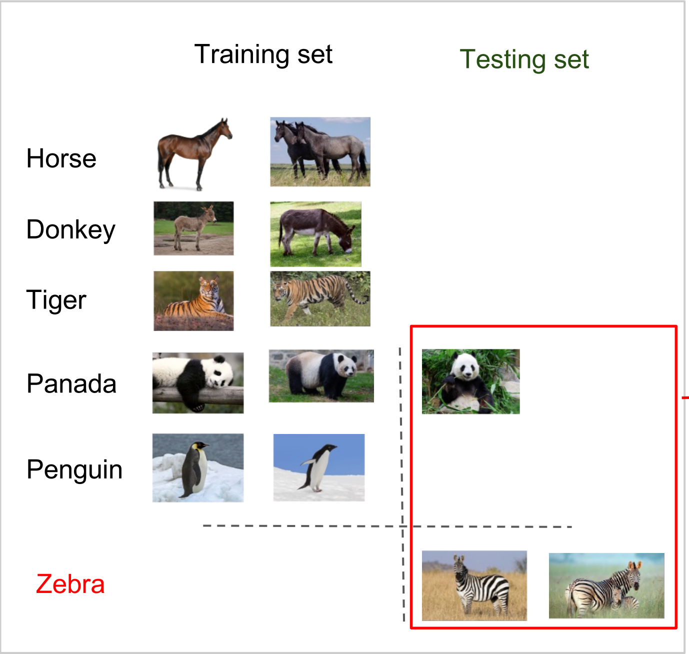
generalized ZSL setting:
classifying the testing samples of seen and unseen classes with candidates of all classes

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 seen and unseen classes with candidates of all classes

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

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

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

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.

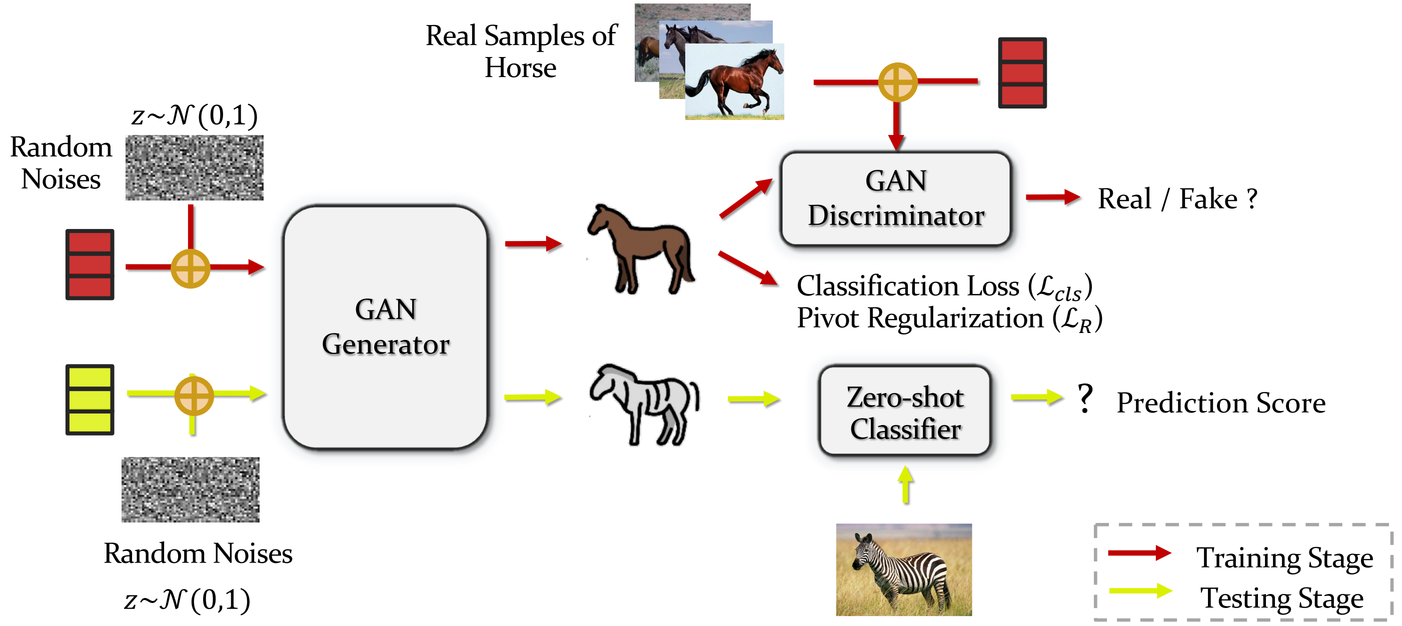
Accuracy (%) of DeViSE on AwA, ImNet-A and ImNet-O. The best result on each metric is marked with underline.

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)	24.22	78.42	1.05	2.08	13.52	59.71	0.63	1.25	14.21	66.40	3.93	7.43
w2v (300)	8.42	86.32	0.00	0.00	26.95	84.36	0.16	0.32	20.49	93.60	0.00	0.00
att	38.48	81.86	3.59	6.88	35.72	61.00	12.60	20.89	31.75	47.80	17.24	25.34
hie	43.50	65.25	5.60	10.32	30.94	62.07	1.67	3.25	29.25	54.60	10.85	18.10
Basic KG	43.24	86.44	6.40	11.91	34.38	25.50	28.13	26.75	24.77	34.20	22.49	27.14
Basic KG + literals	46.12	84.42	8.76	15.88	33.62	23.36	29.33	26.01	26.13	38.60	21.67	27.75
Basic KG + CN	45.56	88.85	0.38	0.76	35.11	67.71	7.46	13.43	26.72	70.40	7.23	13.11
Basic KG + logics	37.54	80.69	1.09	2.15	–	–	–	–	–	–	–	–

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

Benchmarking GAN-based Methods

- changing the input class embedding



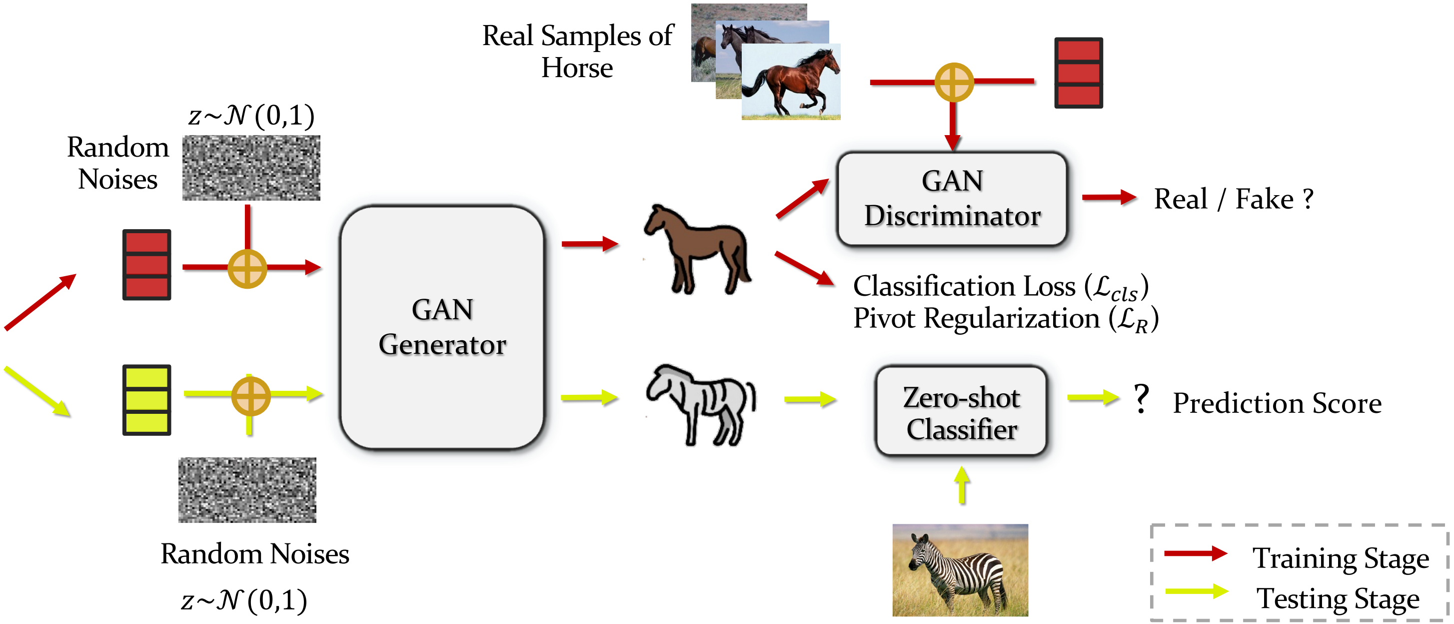
Geng, Yuxia, et al. "OntoZSL: Ontology-enhanced zero-shot learning." WWW 2021.

Benchmarking GAN-based Methods

- changing the input class embedding

non-KGs:
w2v (500), w2v (300), att, hie

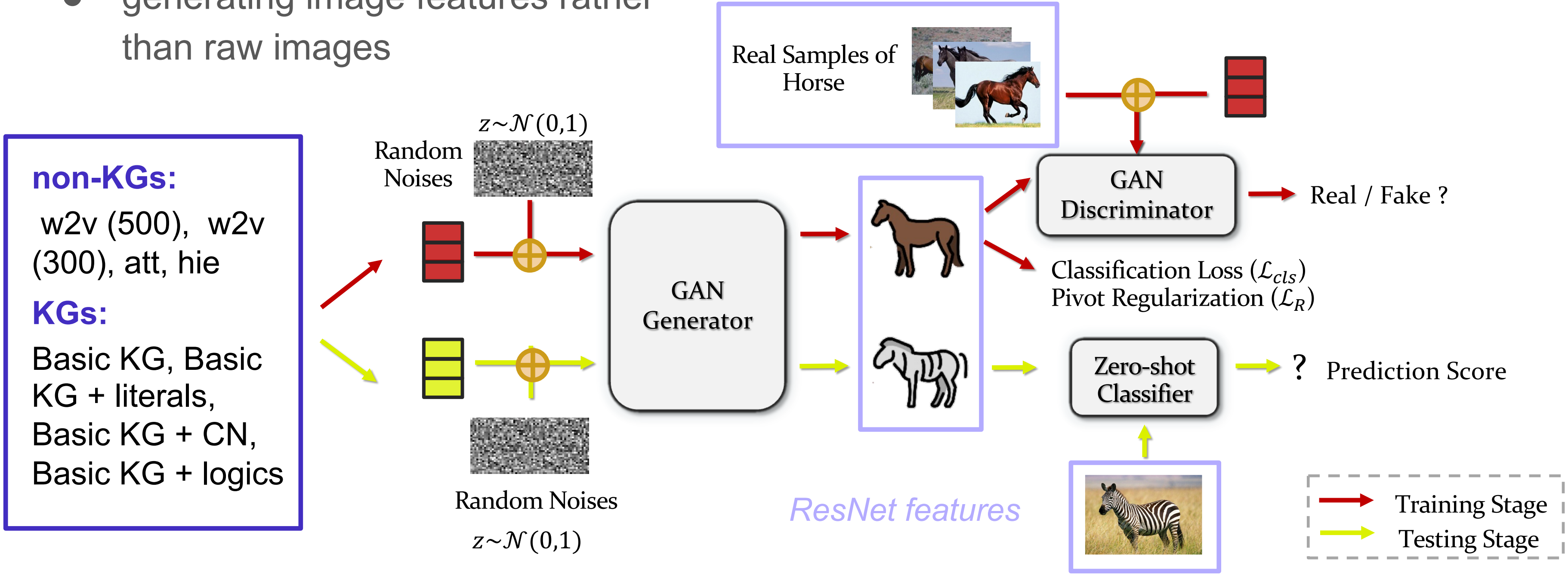
KGs:
Basic KG, Basic KG + literals, Basic KG + CN, Basic KG + logics



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

Benchmarking GAN-based Methods

- generating image features rather than raw images



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

Results

Accuracy (%) of DeViSE on AwA, ImNet-A and ImNet-O. The best result on each metric is marked with underline.

External Knowledge	AwA acc	AwA acc_s	AwA acc_u	AwA H	ImNet-A acc	ImNet-A acc_s	ImNet-A acc_u	ImNet-A H	ImNet-O acc	ImNet-O acc_s	ImNet-O acc_u	ImNet-O H
w2v (500)	24.22	78.42	1.05	2.08	13.52	59.71	0.63	1.25	14.21	66.40	3.93	7.43
w2v (300)	8.42	86.32	0.00	0.00	26.95	$\underline{84.36}$	0.16	0.32	20.49	$\underline{93.60}$	0.00	0.00
att	38.48	81.86	3.59	6.88	$\underline{35.72}$	61.00	12.60	20.89	$\underline{31.75}$	47.80	17.24	25.34
hie	43.50	65.25	5.60	10.32	30.94	62.07	1.67	3.25	29.25	54.60	10.85	18.10
Basic KG	43.24	86.44	6.40	11.91	34.38	25.50	28.13	$\underline{26.75}$	24.77	34.20	$\underline{22.49}$	27.14
Basic KG + literals	$\underline{46.12}$	84.42	$\underline{8.76}$	$\underline{15.88}$	33.62	23.36	$\underline{29.33}$	26.01	26.13	38.60	21.67	$\underline{27.75}$
Basic KG + CN	45.56	$\underline{88.85}$	0.38	0.76	35.11	67.71	7.46	13.43	26.72	70.40	7.23	13.11
Basic KG + logics	37.54	80.69	1.09	2.15	–	–	–	–	–	–	–	–

Accuracy (%) of OntoZSL on AwA, ImNet-A and ImNet-O. The best result on each metric is also underlined.

External Knowledge	AwA acc	AwA acc_s	AwA acc_u	AwA H	ImNet-A acc	ImNet-A acc_s	ImNet-A acc_u	ImNet-A H	ImNet-O acc	ImNet-O acc_s	ImNet-O acc_u	ImNet-O 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	$\underline{27.71}$
hie	38.89	51.08	31.38	38.88	33.32	40.93	23.06	29.50	$\underline{33.17}$	36.80	$\underline{21.13}$	26.85
Basic KG	$\underline{62.65}$	59.59	$\underline{50.58}$	$\underline{54.71}$	38.21	$\underline{45.71}$	23.21	30.79	32.14	44.60	18.74	26.39
Basic KG + literals	59.21	62.39	45.55	52.66	$\underline{38.58}$	35.64	$\underline{27.64}$	$\underline{31.13}$	32.57	$\underline{44.80}$	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	$\underline{65.37}$	40.76	50.21	–	–	–	–	–	–	–	–

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

&3

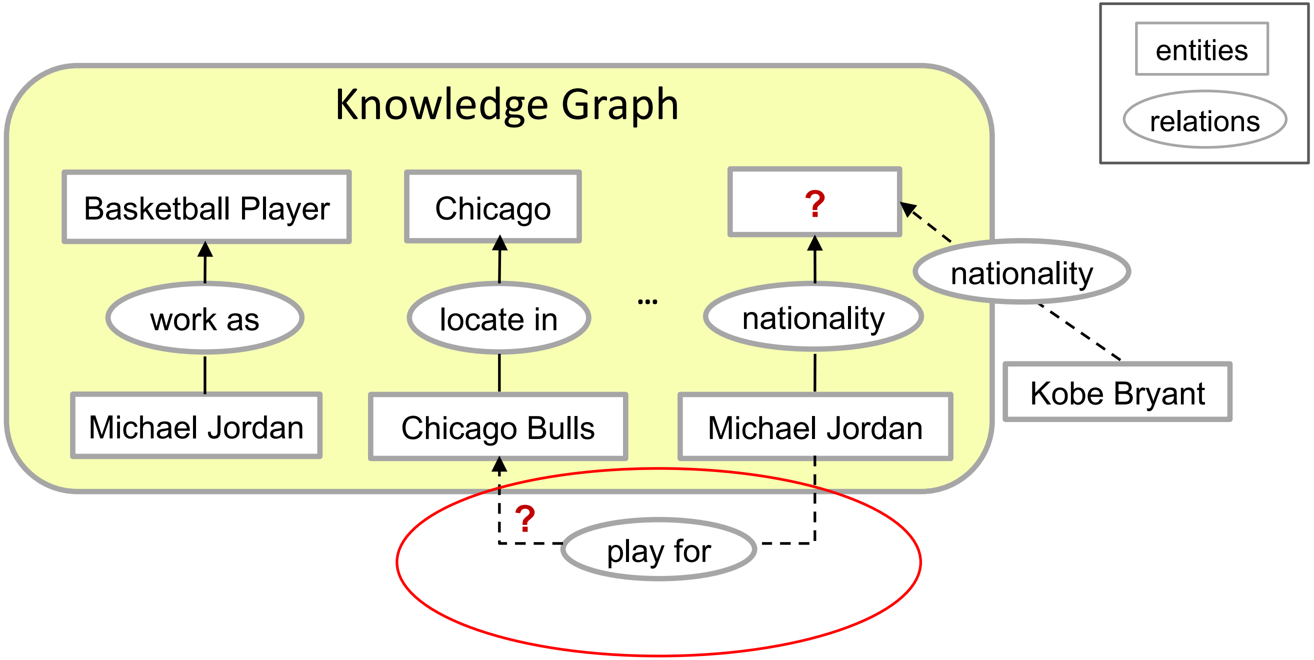
Benchmarking Zero-shot Knowledge Graph Completion (ZS-KGC) with Unseen Relations

ZS-KGC

- Revisit Task Definition
- Revisit ZSL Benchmarks
- Existing Side Information vs KG’s KG (**Ontological Schema**)
- Onto Construction and Statistics
- Benchmarking Results

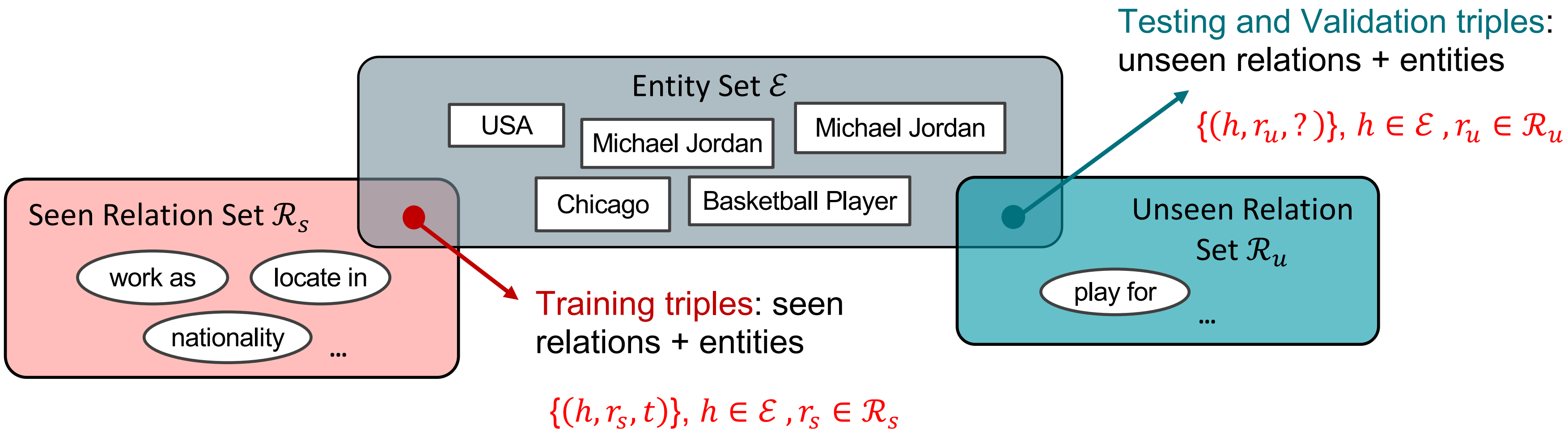
Task Definition

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



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.

ZS-KGC Benchmarks

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    - a closed set of entities shard during training and testing;
    - triples of $\mathcal{R}_s$ are collected for training, triples of $\mathcal{R}_u$ are collected for validation and testing

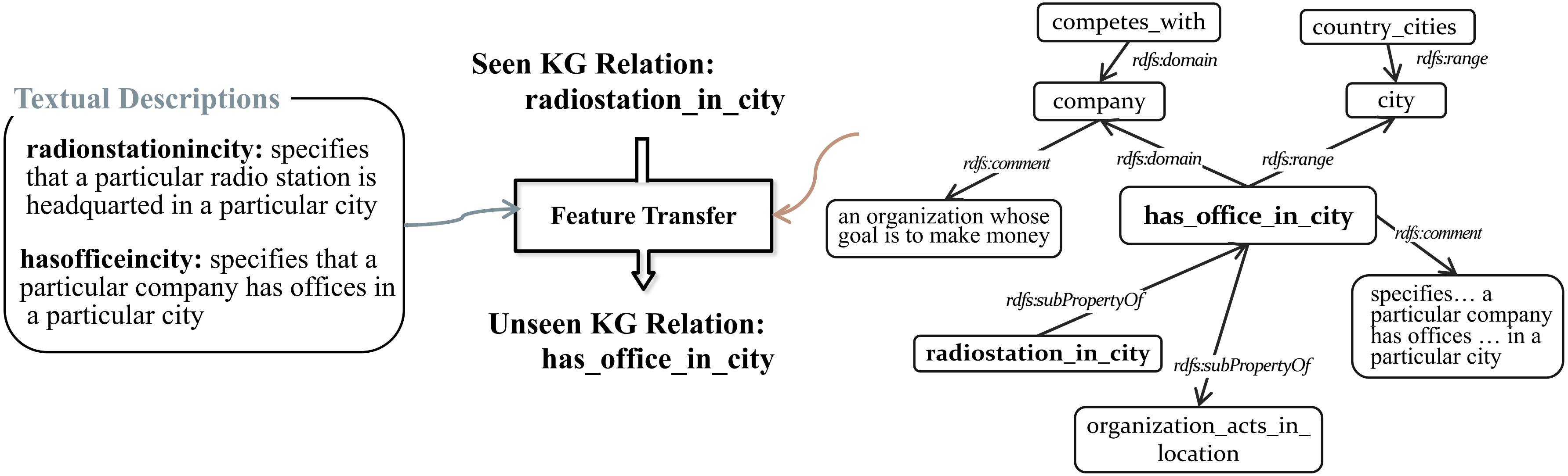
Datasets	# Entities	# Relations				# Triples			
		Total	Training Seen	Validation Unseen	Testing Unseen	Total	Training Seen	Validation Unseen	Testing Unseen
NELL-ZS	65,567	181	139	10	32	188,392	181,053	1,856	5,483
Wiki-ZS	605,812	537	469	20	48	724,928	701,977	7,241	15,710

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

Existing Side Information vs Ontological Schema

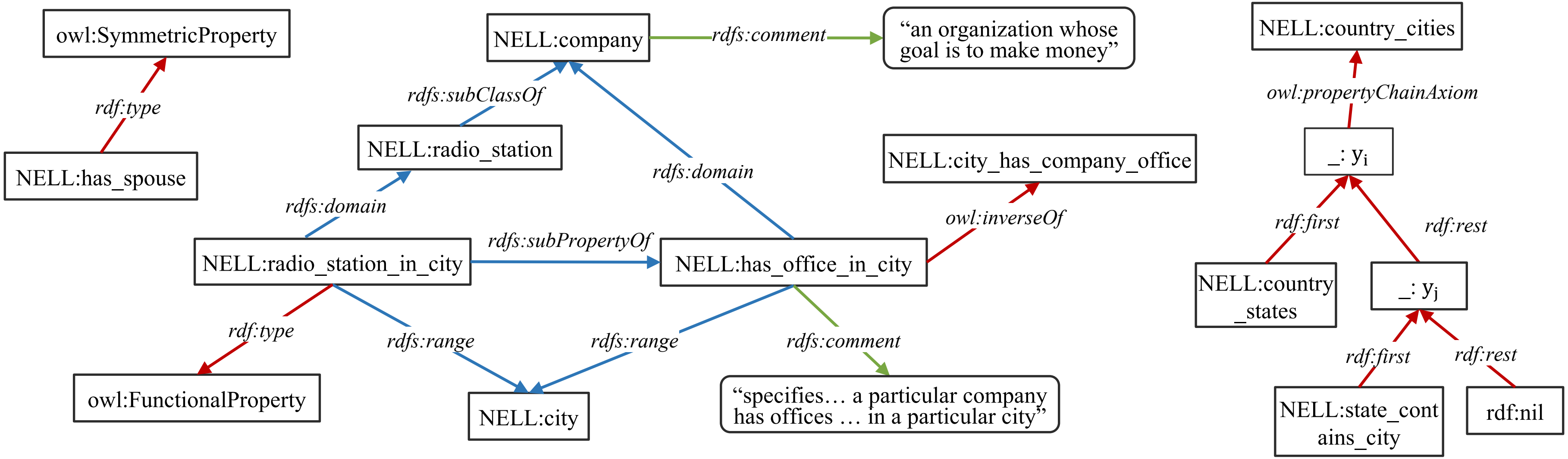
Existing Side Information

KG's KG: Ontological Schema



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

An Ontological Schema segment for NELL-ZS



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

Schema Construction Steps

1. Schema scope: describing the semantic relationships among KG relations in the datasets

NELL:radio_station_in_city

NELL:has_office_in_city

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

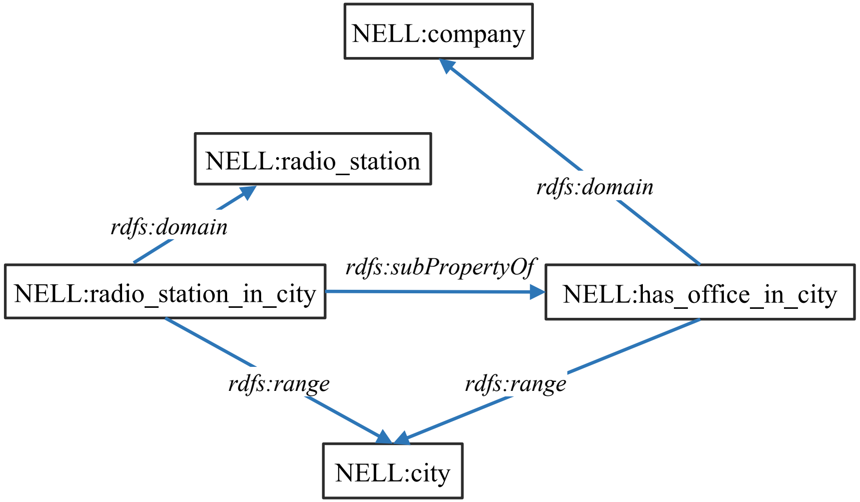
Schema Construction Steps

2. Relation hierarchy by *rdfs:subPropertyOf*

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

Schema Construction Steps

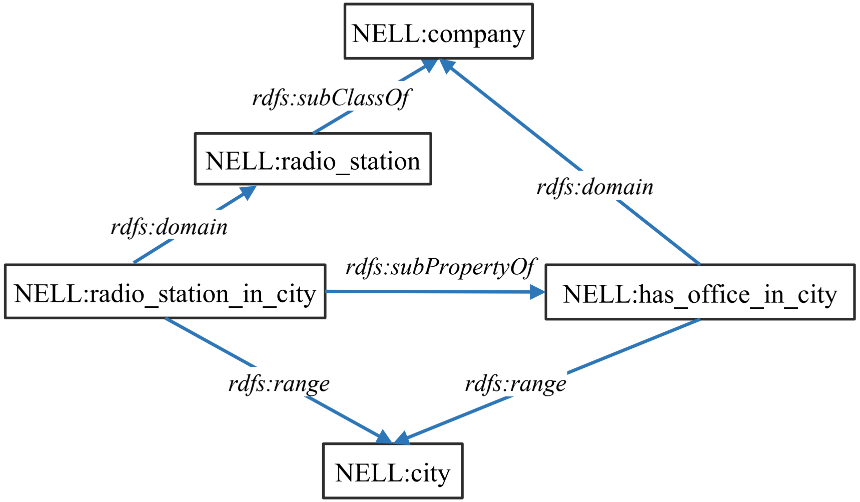
3. Relation’s domain and range constraints by *rdfs:domain* and *rdfs:range*



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

Schema Construction Steps

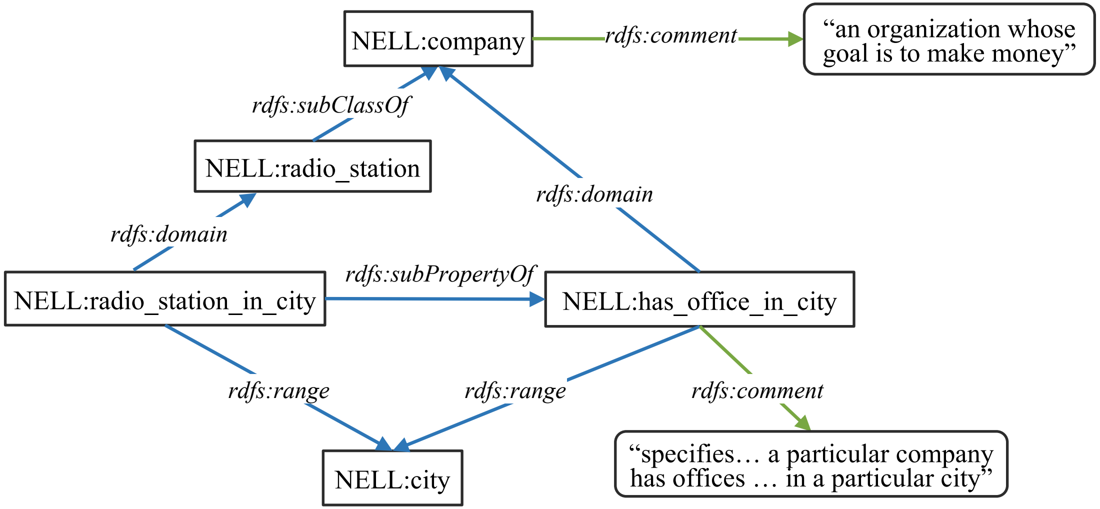
4. Entity Type hierarchy by *rdfs:subClassOf*



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

Schema Construction Steps

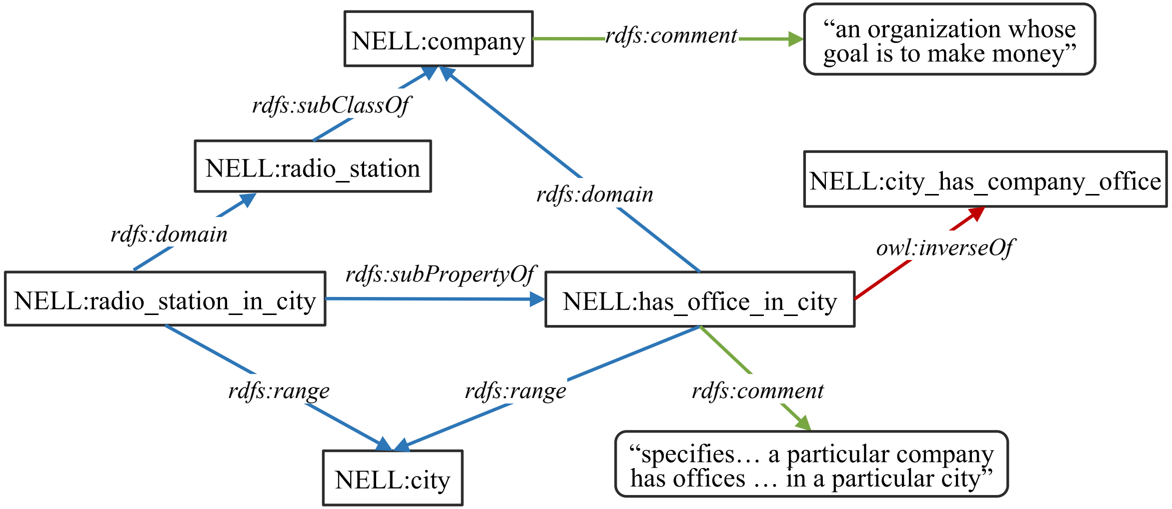
5. Text information of Relation and Entity Type by *rdfs:comment* and *rdfs:label*



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

Schema Construction Steps

6. Inverse Relationship by *owl:inverseOf*

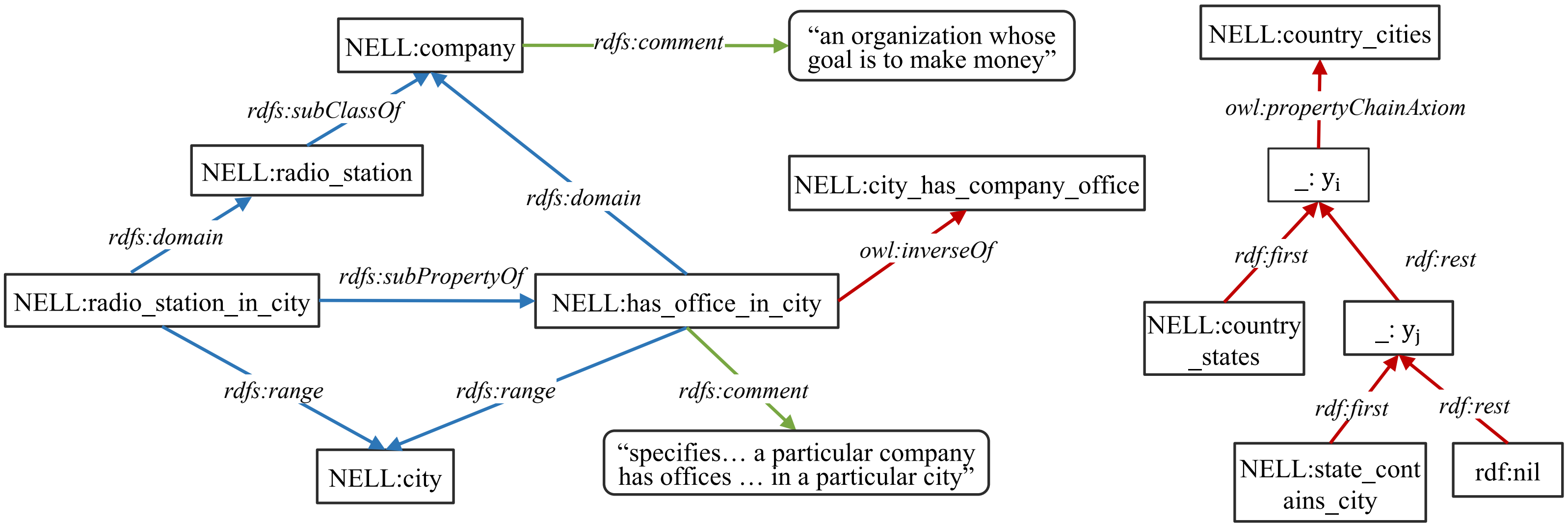


Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning", Journal of Web Semantics. 2022.

Schema Construction Steps

7. Compositional Relationship

$$\textit{country states} \wedge \textit{state contains city} \Longrightarrow \textit{country cities}$$

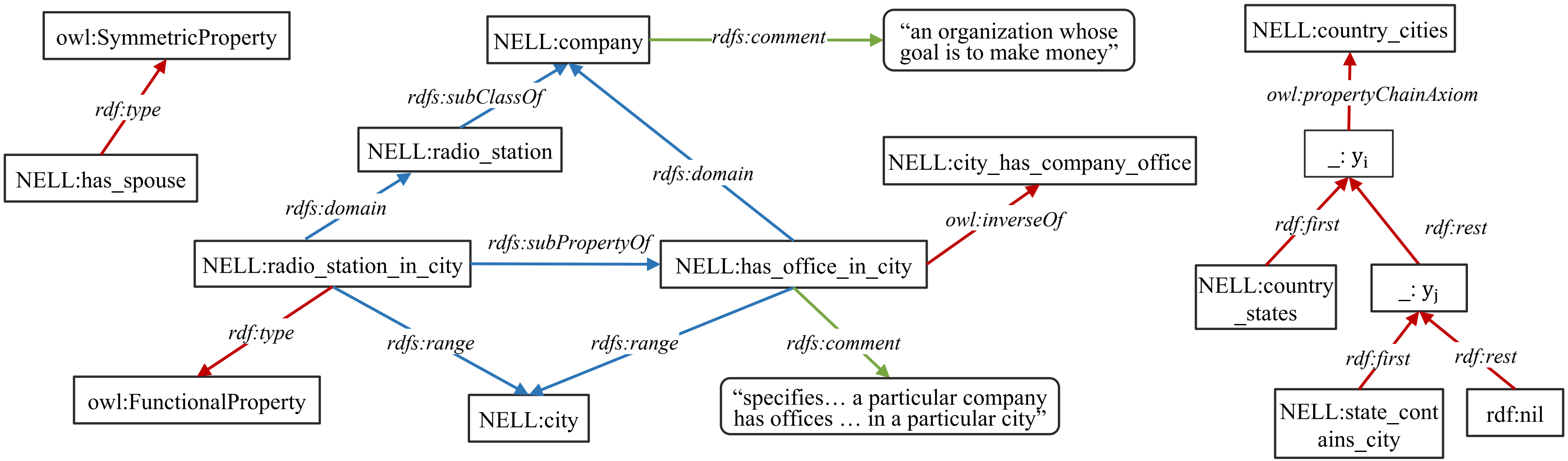


Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning", Journal of Web Semantics. 2022.

Schema Construction Steps

8. Relation Characteristics by *rdf:type* and *owl axioms*

Symmetric & Asymmetric;
Reflexive & Irreflexive;
Functionality & Inverse Functionality



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

Ontological Schema Statistics

	# Nodes			#edges	# Triples		# Others	
	#R	#C	#L	meta-relations	subproperty / domain / range / subclass	Relation Characteristics	inversion	composition
NELL-ZS	894	292	1,063	9	935 / 894 894 / 332	114	0	20
Wiki-ZS	560	1,344	3,808	11	208 / 1,843 1,378 / 1,392	67	39	7

"R": relations
"C": concepts (entity type)
"L": literals

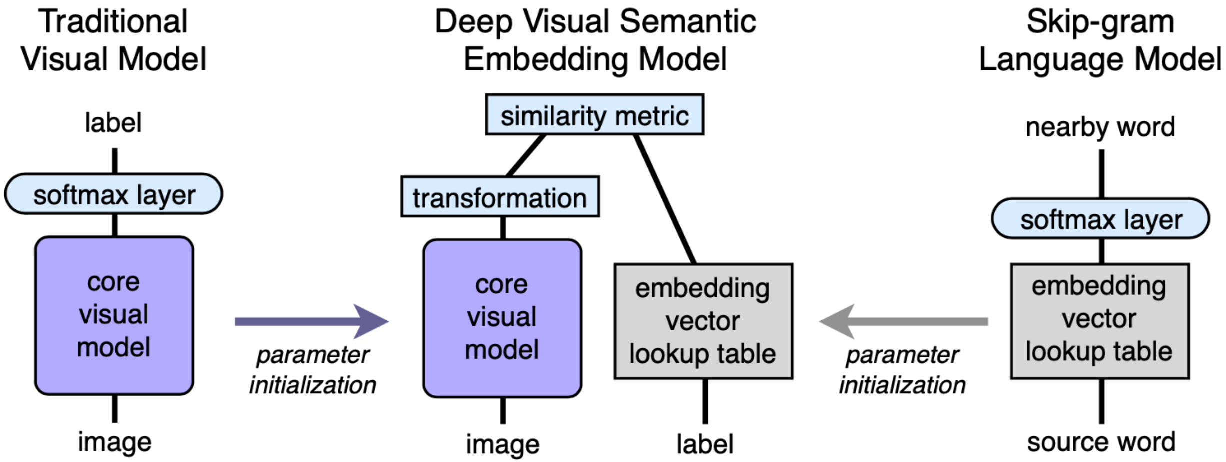
The ontology ontology of NELL is at:
[http://rtw.ml.cmu.edu/resources/results/08m/NELL.08m.1115. ontology.csv.gz](http://rtw.ml.cmu.edu/resources/results/08m/NELL.08m.1115.ontology.csv.gz)

The ontology of Wikidata can be accessed by Python package
https://pypi.org/project/Wikidata/

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

Benchmarking Mapping-based Methods

- DeViSE for ZS-IMGC

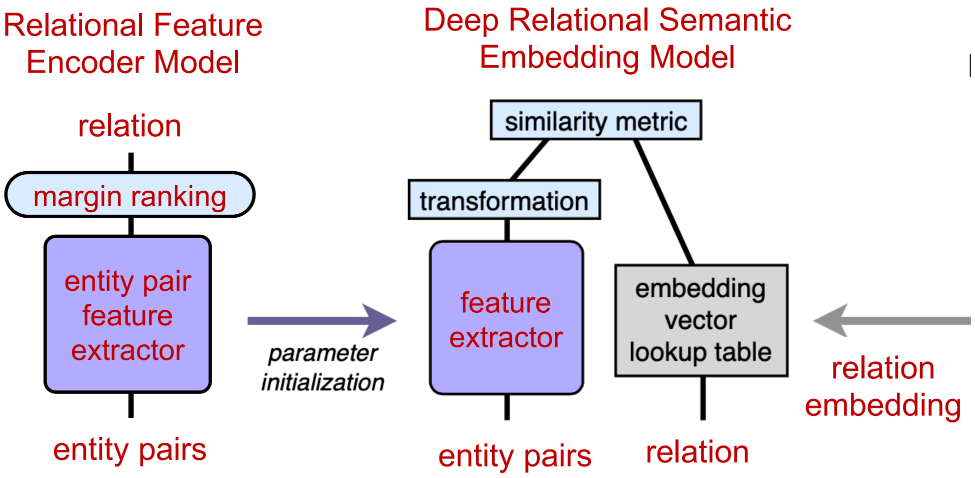


Geng et al., Benchmarking Knowledge-driven Zero-shot Learning, Journal of Web Semantics 2022.

Benchmarking Mapping-based Methods

- DeViSE for ZS-KGC with unseen relations
  - relational feature encoder
  - relation embeddings learned from side information

TransE for RDFS graphs;
text-aware TransE for RDFS+literals;
OWL can be applied in an ensemble way



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

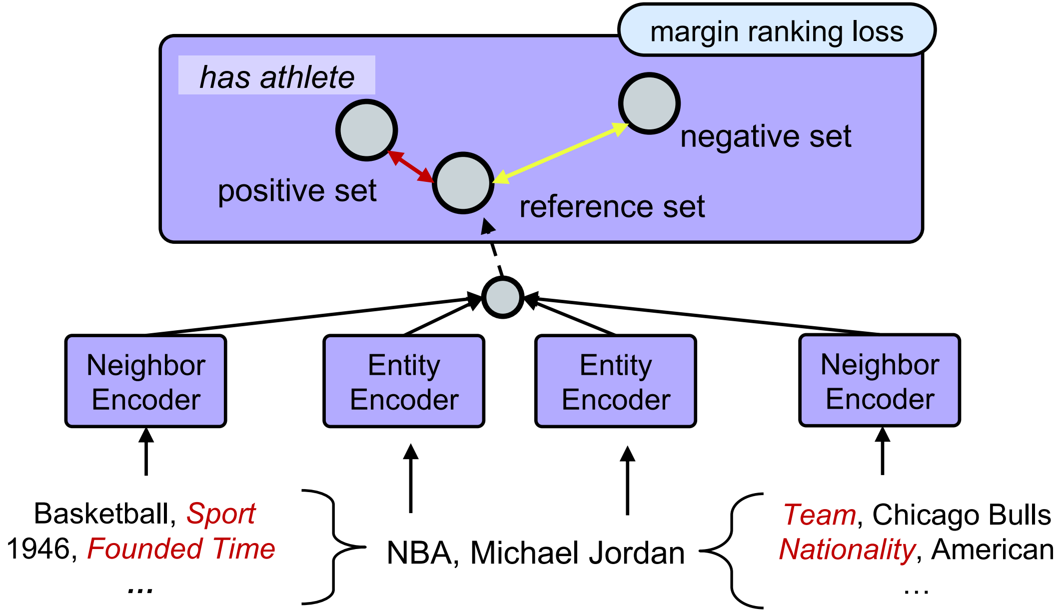
2. RDFS graph
- **RDFS-hie:** relation hierarchy, entity type hierarchy
- **RDFS-cons:** relation's domain and range

3. RDFS graph + literals
+ literal information

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

Benchmarking Mapping-based Methods

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



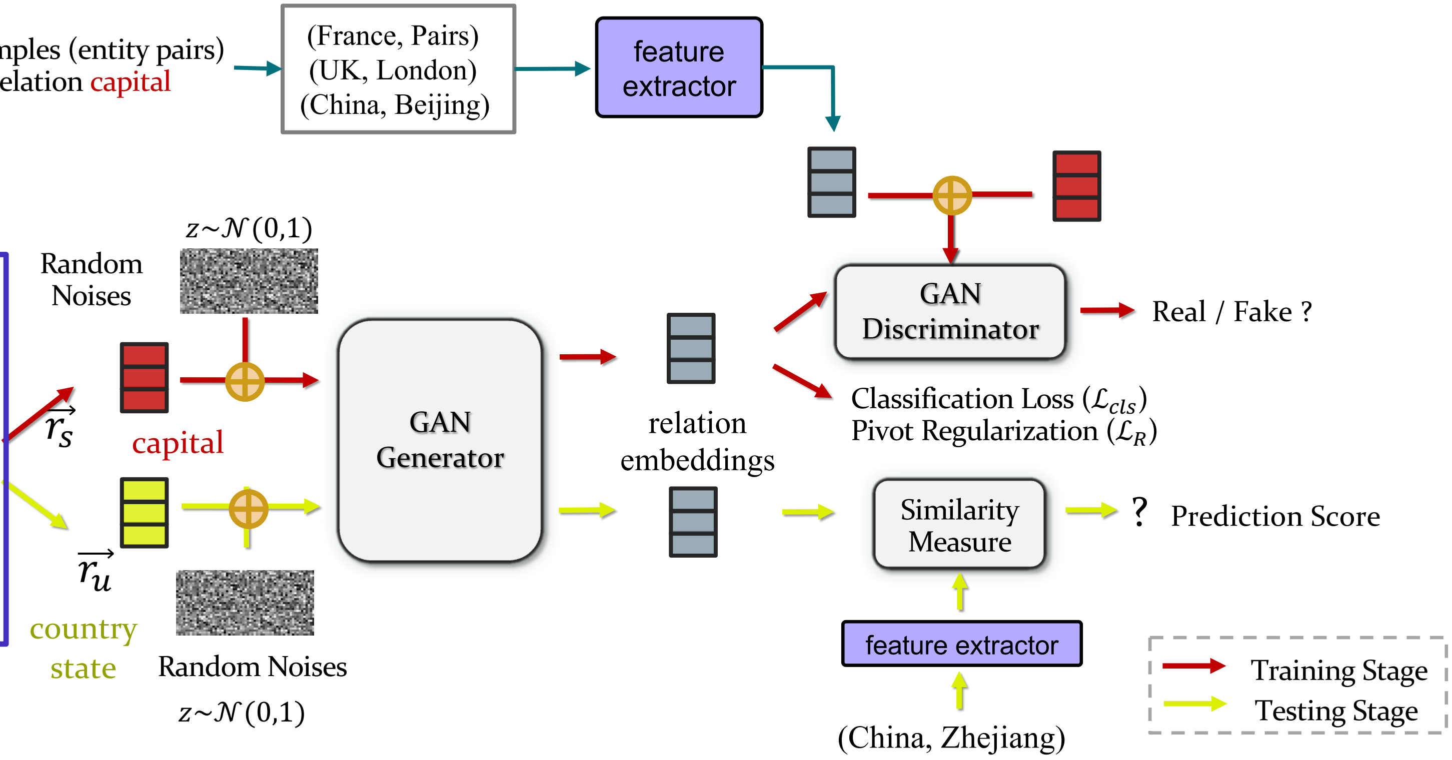
Qin, Pengda, et al. "Generative adversarial zero-shot relational learning for knowledge graphs." AAAI 2020.
Geng, Yuxia, et al. “OntoZSL: Ontology-enhanced zero-shot learning.” WWW 2021.

Benchmarking GAN-based Methods

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

2. RDFS graph
- **RDFS-hie**
- **RDFS-cons**

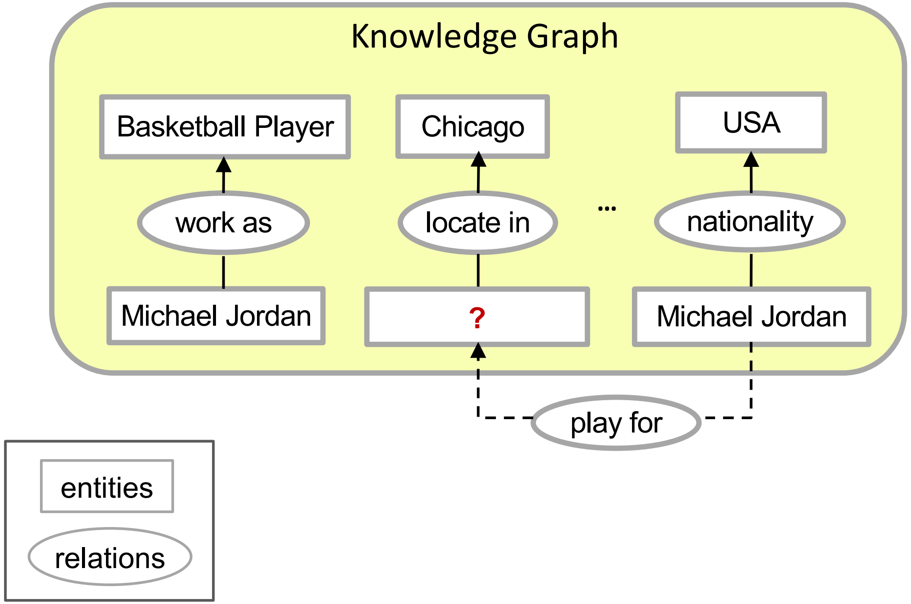
3. RDFS graph+literals
+ literal information



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.

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	$\mathcal{R}_s$ ⟵ disjoint ⟶	$\mathcal{R}_u$
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.

Results (*MRR* and *hit@k* (%)) of DeViSE and OntoZSL on NELL-ZS and Wiki-ZS. The best result on each metric is underlined.

External Knowledge	DeViSE								OntoZSL							
	NELL-ZS				Wiki-ZS				NELL-ZS				Wiki-ZS			
	MRR	hit@10	hit@5	hit@1	MRR	hit@10	hit@5	hit@1	MRR	hit@10	hit@5	hit@1	MRR	hit@10	hit@5	hit@1
Text	0.221	34.6	29.0	15.5	0.183	26.7	21.7	13.5	0.215	34.5	28.3	14.5	0.185	27.3	22.3	13.5
RDFS-hie	<u>0.229</u>	35.1	29.3	<u>16.3</u>	0.179	25.4	20.9	13.5	0.225	34.8	28.9	<u>15.9</u>	0.175	25.4	20.4	13.1
RDFS-cons	0.221	34.5	28.7	15.3	0.183	26.4	21.7	13.6	0.220	34.3	28.0	15.4	0.177	25.7	21.2	13.0
RDFS graph	0.225	<u>35.3</u>	<u>29.4</u>	15.6	0.184	27.0	21.7	13.6	0.223	35.1	29.1	15.3	0.185	27.5	22.3	13.4
RDFS+literals	0.223	35.0	29.0	15.3	<u>0.185</u>	<u>27.1</u>	<u>22.0</u>	<u>13.6</u>	<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.

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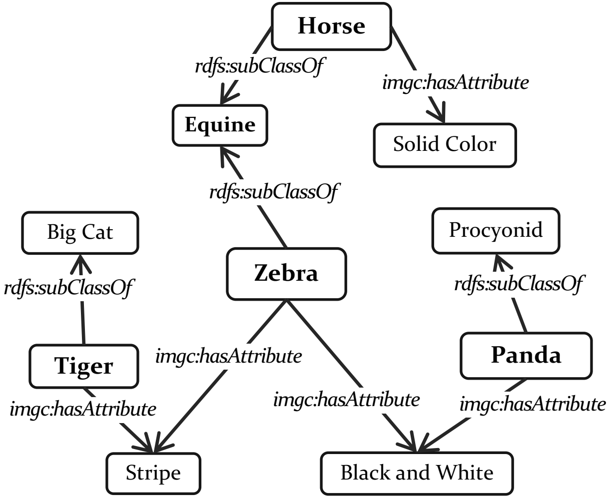
Benchmarking Propagation-based ZSL Methods

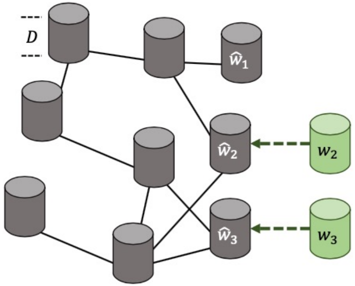
Propagation Methods for ZS-IMGC



Basic KG for AwA2

different class KGs
class hierarchy vs Basic KG

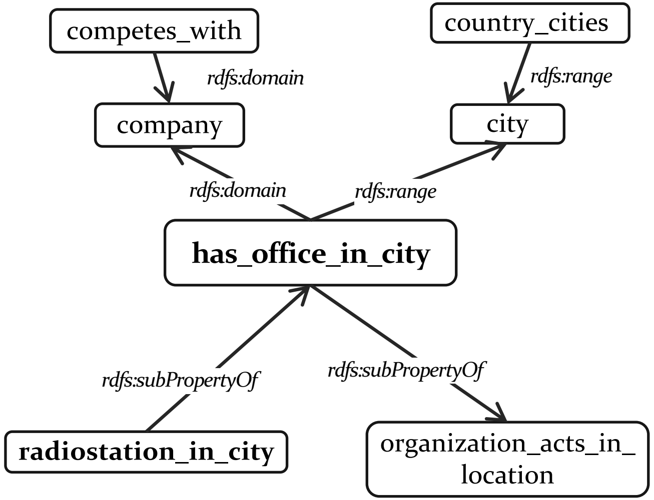
different propagation methods
GCN
RGCN-ZSL & CompGCN-ZSL
Disentangled-based Propagation



Outputs: Object classifiers $\widehat{\mathcal{W}}$
(D dimensions)

Geng, Yuxia, et al. "Benchmarking knowledge-driven zero-shot learning." Journal of Web Semantics 2022.
Geng, Yuxia, et al. "Disentangled ontology embedding for zero-shot learning." KDD 2022.

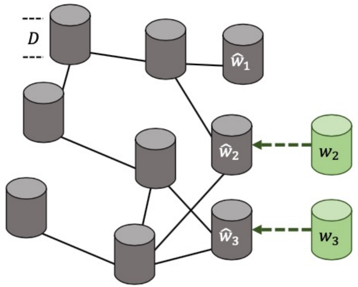
Propagation Methods for ZS-KGC



RDFS graph for NELL-ZS

relation schema graph
RDFS Graph

different propagation methods:
GCN
RGCN-ZSL & CompGCN-ZSL
Disentangled-based Propagation



Outputs: Object classifiers $\hat{\mathcal{W}}$
(D dimensions)

Geng, Yuxia, et al. "Disentangled ontology embedding for zero-shot learning." KDD 2022.

Results

Accuracy (%) of GCNZ on AwA, ImNet-A and ImNet-O. The better result on each metric is marked with underline.

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
Class Hierarchy	37.44	81.45	7.86	14.34	33.95	48.71	18.37	26.68	32.24	49.00	18.04	26.37
Basic KG	62.98	75.59	20.28	31.98	36.64	45.57	23.92	31.38	33.98	43.80	21.61	28.94

Results from "Geng et al., Benchmarking Knowledge-driven Zero-shot Learning, Journal of Web Semantics 2022."

ZS-IMGC: different class KGs w.r.t. GCN-based propagation method

Methods	AwA		ImNet-A		ImNet-O		NELL-ZS				Wiki-ZS			
	acc	H	acc	H	acc	H	$hit@10$	$hit@5$	$hit@1$	MRR	$hit@10$	$hit@5$	$hit@1$	MRR
DGP	59.03	28.97	35.72	29.98	34.89	29.76	36.2	29.5	16.1	23.0	27.7	22.7	13.3	18.6
Wang et al. [32]	43.81	42.13	34.33	21.95	32.73	26.86	35.8	29.6	15.7	22.8	26.8	21.9	13.5	18.3
RGCN-ZSL	44.90	24.95	37.36	**33.01**	31.19	23.39	37.4	30.7	**17.0**	**24.1**	**28.5**	**23.2**	13.7	**19.1**
CompGCN-ZSL	53.46	29.33	38.34	29.01	28.95	27.35	36.0	29.7	16.4	23.2	28.0	22.7	13.5	18.8
TransE+GCN	63.56	36.15	36.69	22.12	33.16	24.72	35.8	29.8	16.0	22.9	26.6	21.5	13.6	18.3
RGAT+GCN	58.83	37.35	37.53	31.27	35.47	28.49	36.1	29.8	16.0	22.9	26.6	21.6	13.7	18.3
DisenE+GCN	58.34	50.86	32.56	27.76	32.02	26.33	35.5	29.7	15.6	22.7	26.7	21.7	13.7	18.3
DisenKGAT+GCN	61.24	37.43	37.55	32.27	35.92	29.50	35.7	29.5	16.1	23.0	27.5	22.1	13.8	18.6
DOZSL(RD+GCN)	62.79	**52.74**	36.01	30.29	33.66	31.19	**38.0**	**31.2**	16.5	23.9	26.7	21.9	**13.8**	18.5
DOZSL(AGG+GCN)	**63.88**	44.52	**38.69**	32.12	**37.42**	**31.77**	36.2	29.3	16.2	23.0	27.5	22.4	13.6	18.7

Results from "Geng, Yuxia, et al., Disentangled Ontology Embedding for Zero-shot Learning, KDD 2022."

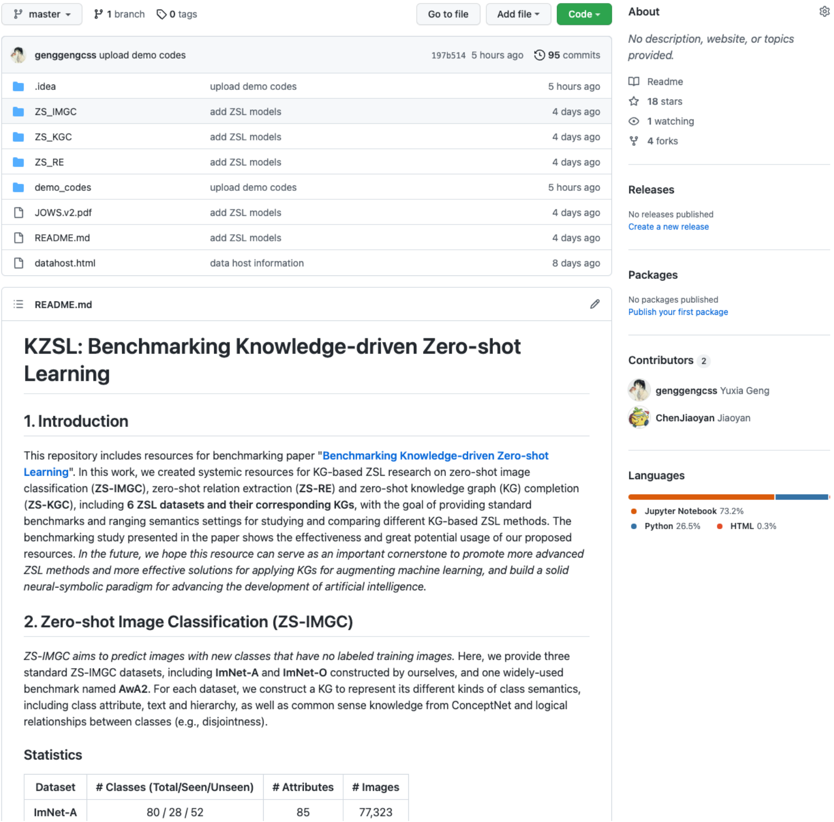
ZS-IMGC (resp. ZS-KGC): different propagation methods w.r.t. class KGs (resp. relation schema graphs)

Hands-on practice

- Download data and Run codes on Google Codelabs
  - ZS-IMGC and ZS-KGC with unseen relations
  - Well-experimented DeViSE 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

- All the resources used in Part III are here
  - https://github.com/China-UK-ZSL/Resources_for_KZSL


master 1 branch 0 tags Go to file Add file Code

genggengcss upload demo codes 197b514 5 hours ago 95 commits

.idea	upload demo codes	5 hours ago
ZS_IMGC	add ZSL models	4 days ago
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 side information
    - different kinds of semantics perform differently on different datasets/tasks
    - some semantics of the KG/Ontology are not fully utilized by the current methods
  - Different ZSL Methods (mapping-based vs GAN-based)
    - GAN-based often achieves better performance
    - mapping-based is often easy to run
- Demonstration

Overall Conclusion and Discussion

- What have we introduced?
  - ZSL concepts, background and paradigm
  - Knowledge-aware ZSL, different external knowledge and typical methods
  - Resources and benchmarking on KG-aware ZSL, demonstration

- What future directions?
  - Neural-symbolic integration with KGs
    - KGs with complex semantics (multi-modal knowledge, logical relationships, etc.)
  - KG construction for ZSL
    - Automatic, customized
  - Applications, resources and benchmarks
  - Other low-resource learning settings
    - e.g., few-shot learning, fully inductive KG completion

Acknowledgement

- We would like to thank all the researchers who participated our works or contributed comments/discussion to our tutorial, including
    - Jeff Z. Pan from The University of Edinburgh
    - Wen Zhang and Zhuo Chen from Zhejiang University
    - Ian Horrocks from University of Oxford
    - and so on.

A List of Our Works

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9. Geng, Y., Chen, J., Zhang, W., Pan, J. Z., Yang, M., Chen, H. & Jiang, S. Relational Message Passing for Fully Inductive Knowledge Graph Completion. arXiv preprint arXiv:2210.03994. (2022). (Under minor revision of ICDE'22 research track)

Q & A

Thanks!

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