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

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4. The University of Edinburgh, UK

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

Tutorial of The 32nd International Joint Conference on Artificial Intelligence (19th August, 2023, Macao, S.A.R)

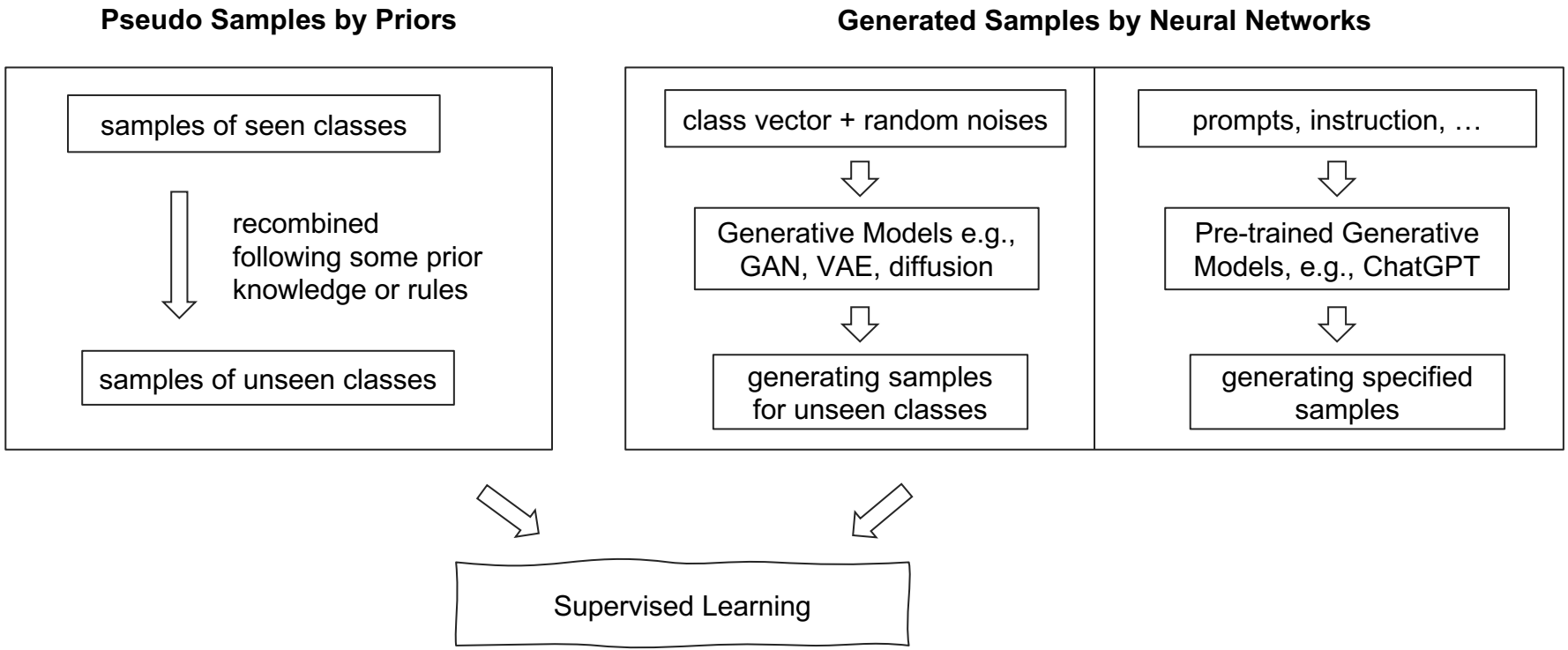
IJCAI/2023 MACAO

Part II – Knowledge-aware ZSL Methods

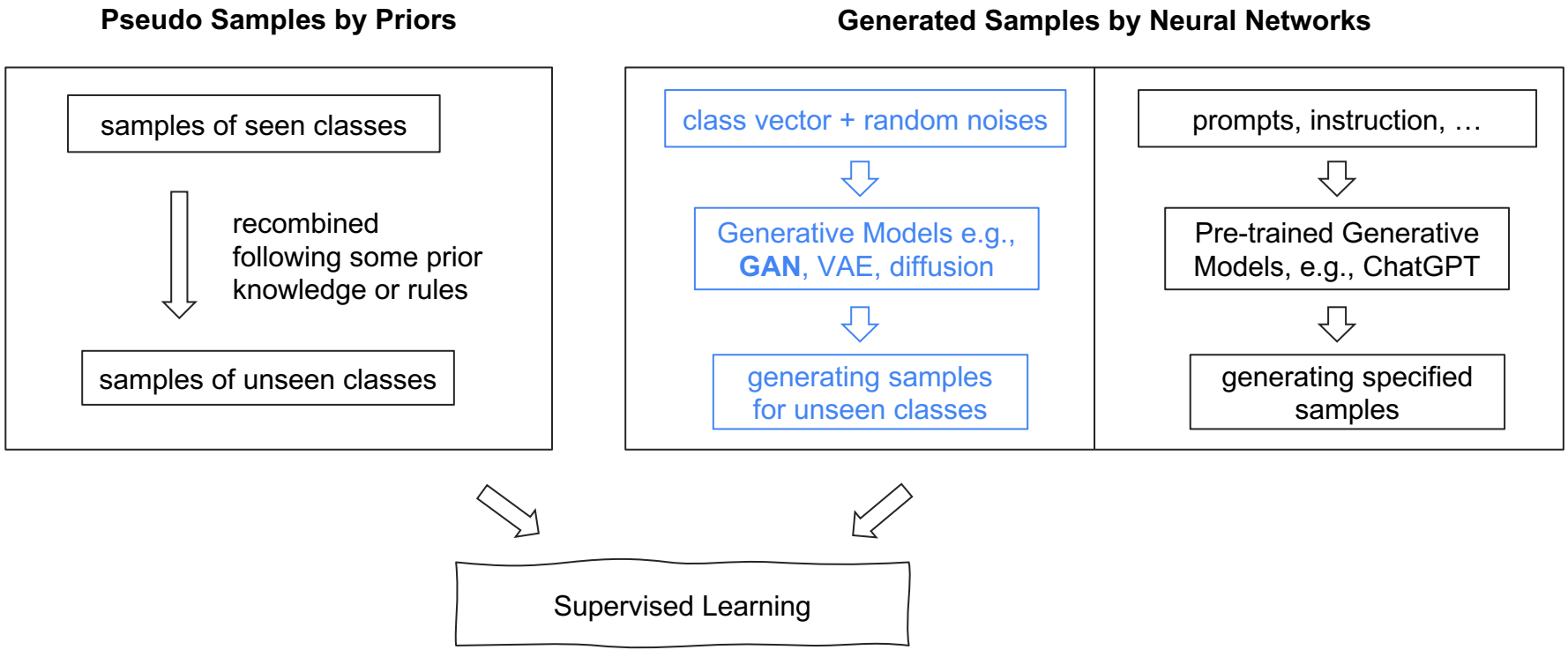
T3

KGZSL: Knowledge Graph-based Sample Generation and ZSL Enhancement

Data Augmentation Strategy



Data Augmentation Strategy

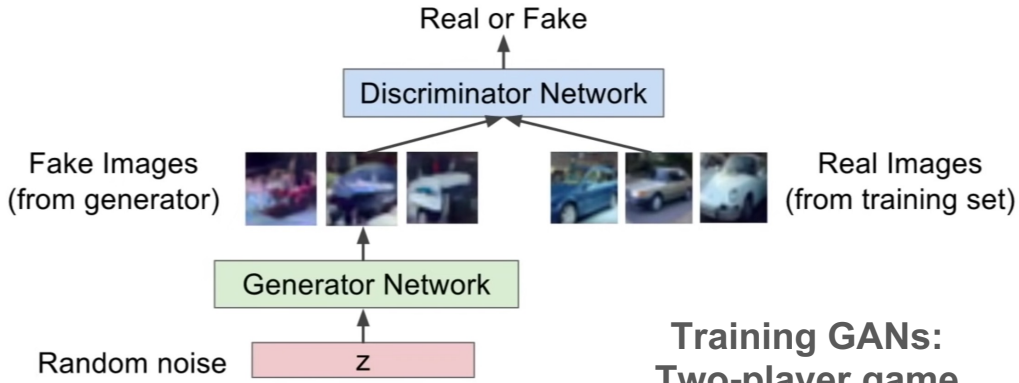


Generative Adversarial Networks (GANs)

- Generative models: Generative Adversarial Networks (GANs)

A human face synthesized by Deepfake

Generator Network: try to fool the discriminator by generating real-looking images;
Discriminator Network: try to distinguish between real and fake images

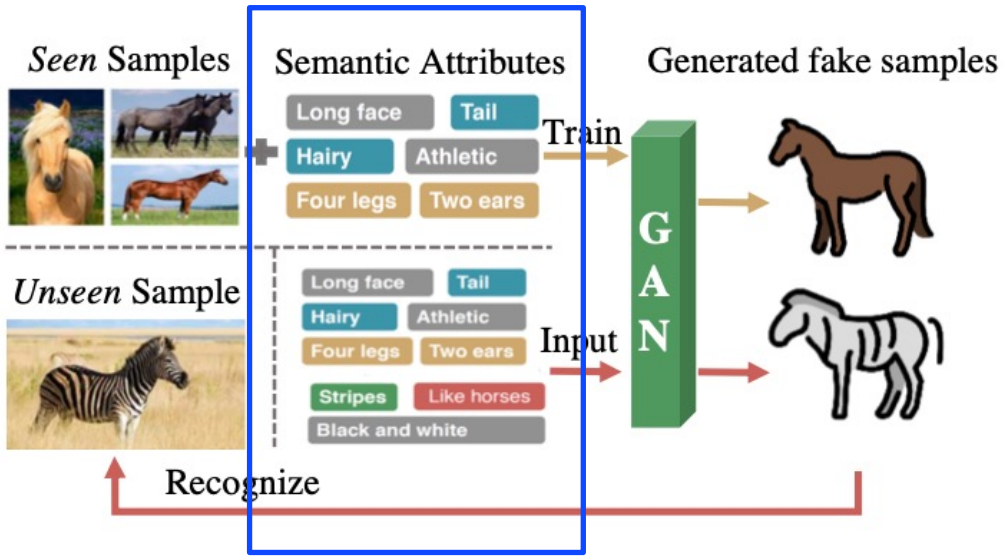


Training GANs:
Two-player game

Ian Goodfellow et al., Generative Adversarial Nets, NIPS 2014

GANs for ZSL

- Generative Adversarial Networks (GANs) & Zero-shot Learning

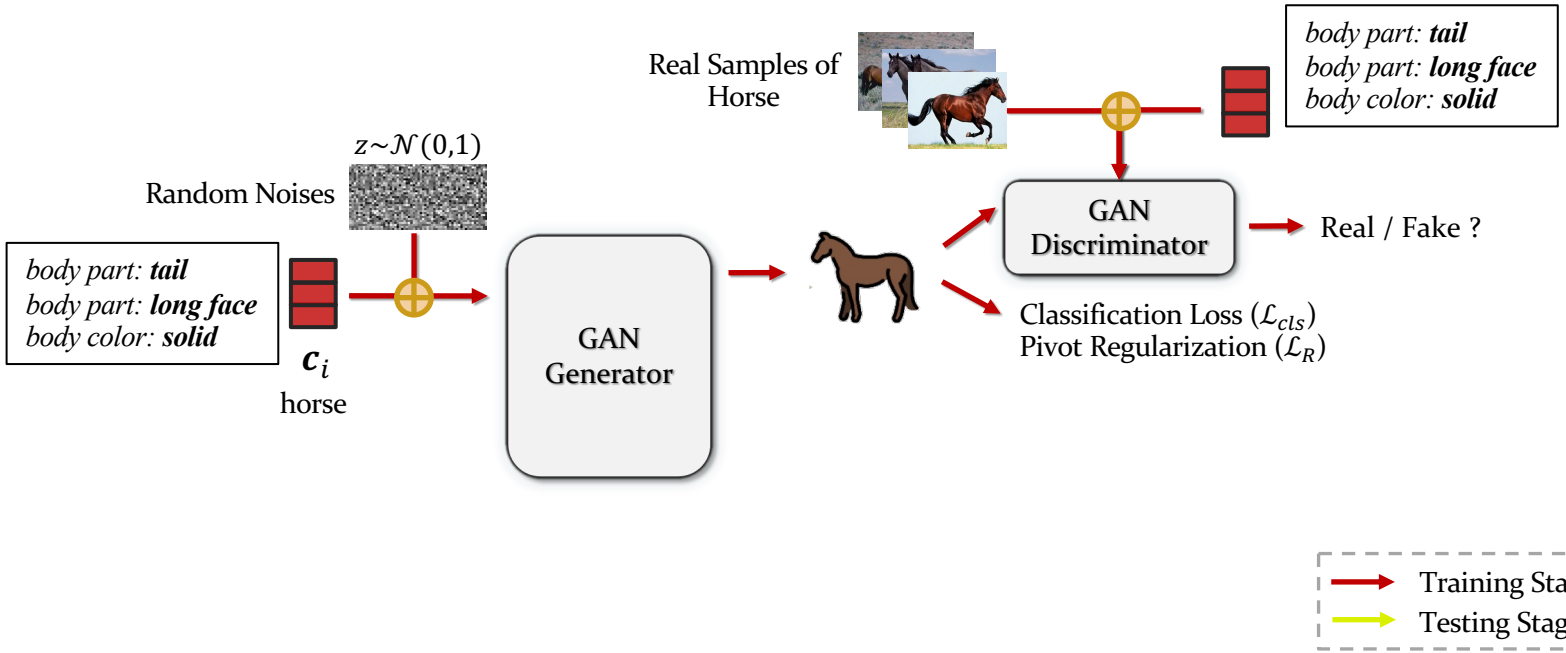


Conditional GANs

Xian, Yongqin, et al. "Feature generating networks for zero-shot learning." CVPR 2018.
Li, Jingjing, et al. "Leveraging the invariant side of generative zero-shot learning." CVPR 2019.

GANs for ZSL

- A running example with zero-shot animal classification



GANs for ZSL

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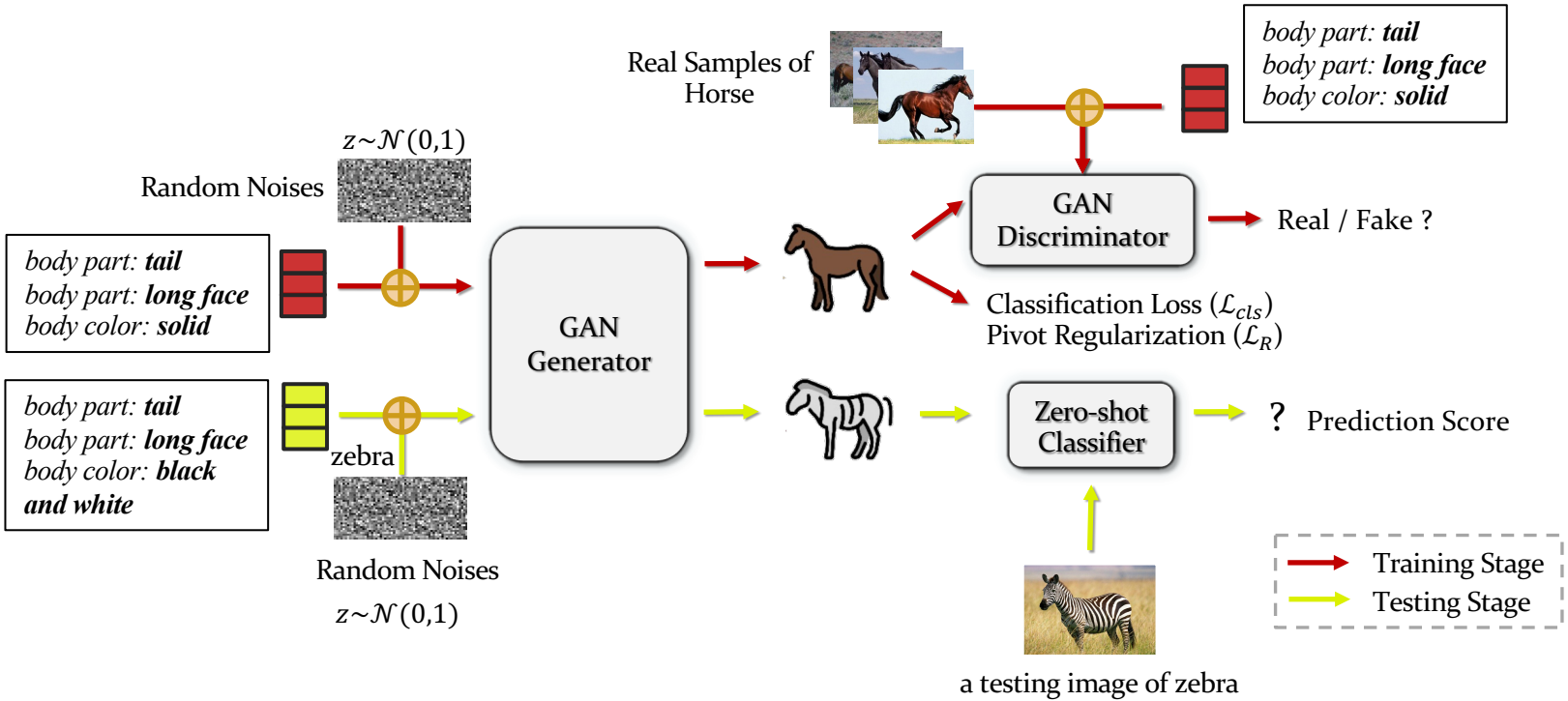
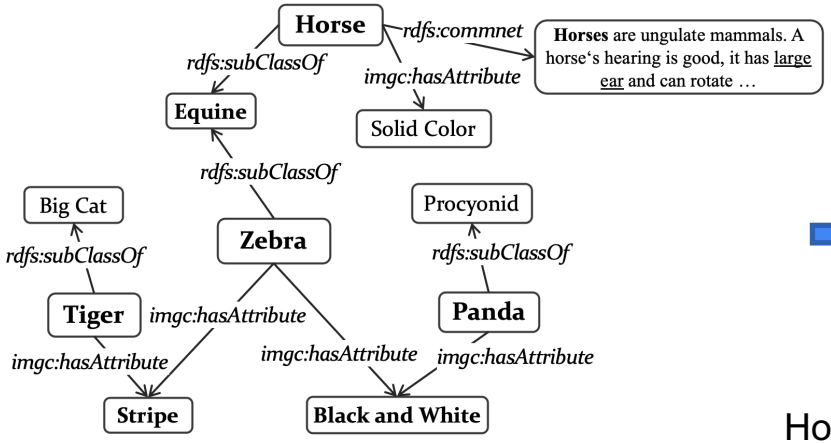


GANs for ZSL

- Knowledge Graphs have high compatibility in representing and integrating diverse and discriminative knowledge about seen and unseen classes



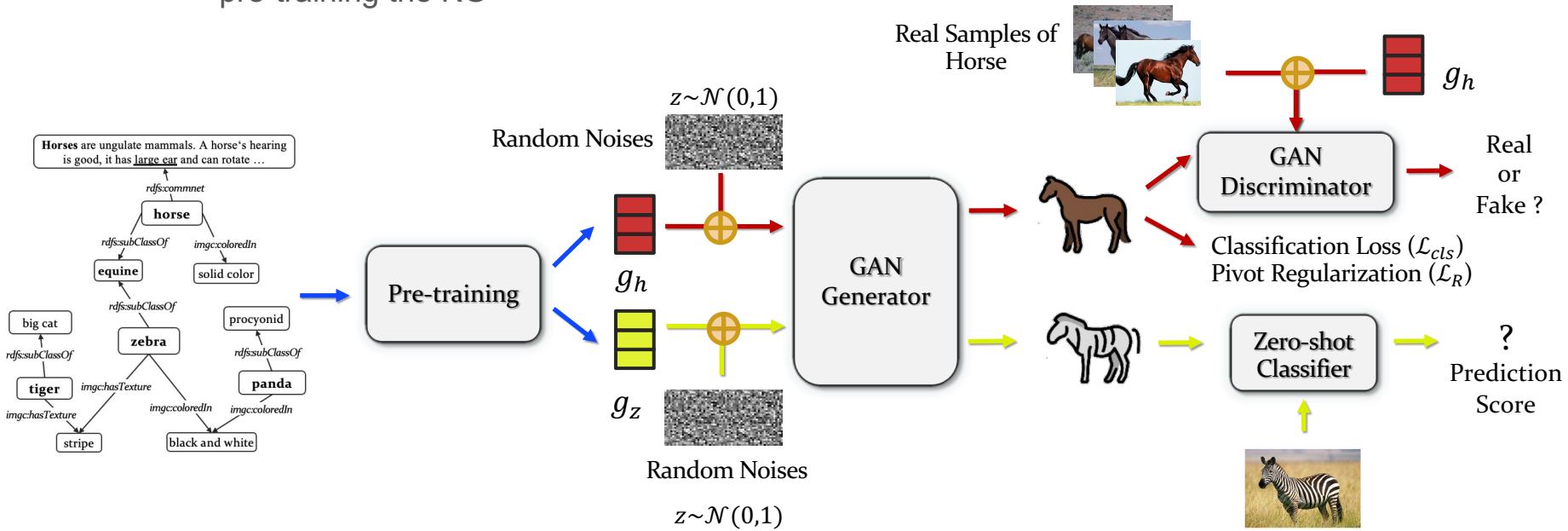
a fragment of Knowledge Graph (KG)

GAN

How do we incorporate a symbolic KG with GAN for ZSL problem?

KGZSL: KG-enhanced Zero-shot Learning

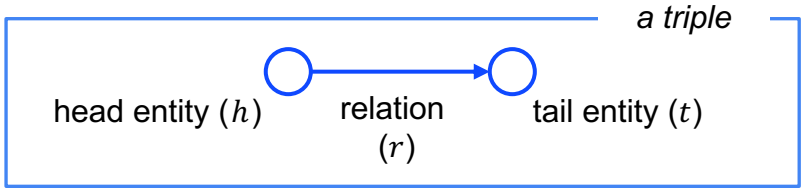
- How do we incorporate a KG with GAN for ZSL problem?
  - pre-training the KG



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

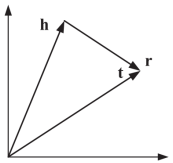
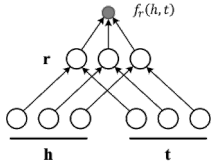
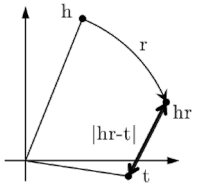
KGZSL: KG-enhanced Zero-shot Learning

- How to pre-train a KG?
  - self-supervised training with triple supervision
  - scoring a triple under different assumptions



$$\min_{\Theta} \sum_{\tau^+ \in \mathbb{D}^+} \sum_{\tau^- \in \mathbb{D}^-} \max(0, \gamma - f_r(h,t) + f_{r'}(h',t'))$$

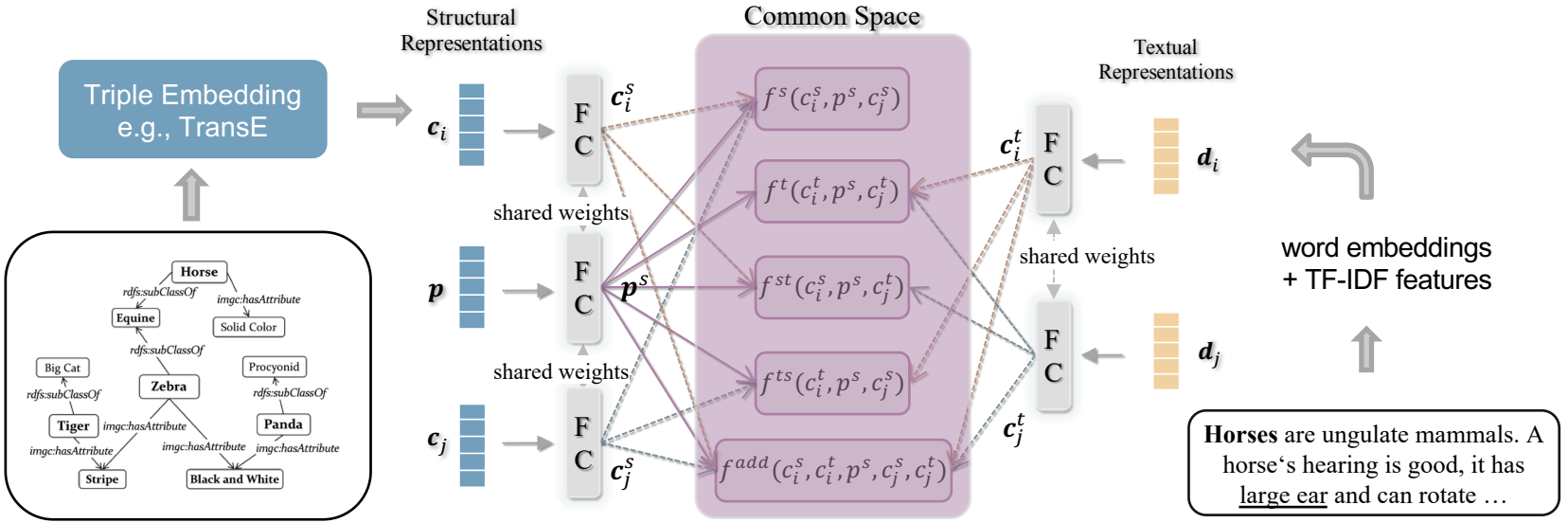
positive triples are expected to receive higher score than negative ones

vector space			
method	TransE	DistMult	RotatE
assumption	$h + r = t$	$h * M_r = t$	$h \circ r = t$
triple score	$f_r(h,t) = -\|\|h + r - t\|\|$	$f_r(h,t) = -(h^T \cdot diag(r) \cdot t)$	$f_{r(h,t)} = -\|\|h \circ r - t\|\|$

Wang, Quan, et al. “Knowledge Graph Embedding: A Survey of Approaches and Applications”. TKDE2017.

KGZSL: KG-enhanced Zero-shot Learning

- text-aware pre-training



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KGZSL: KG-enhanced Zero-shot Learning

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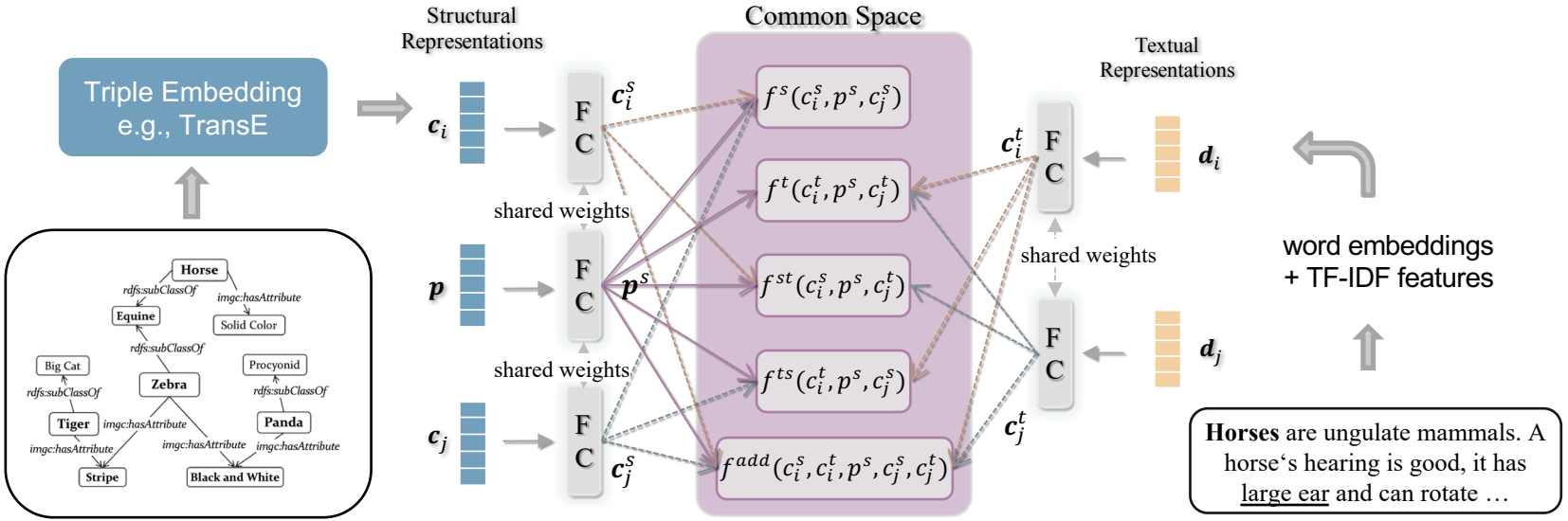
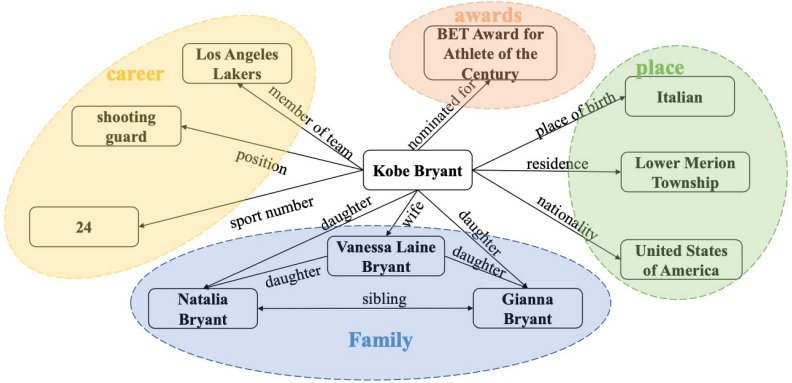
$$c_i = [c_i^s; c_i^t]$$

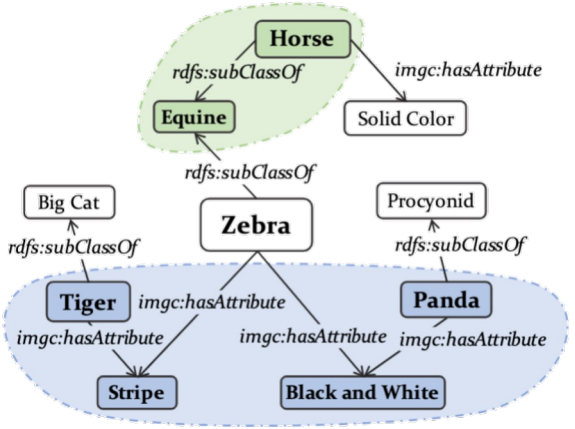


Geng, Yuxia, et al. "OntoZSL: Ontology-enhanced zero-shot learning." WWW 2021.

DKZSL: KGZSL with Disentangled KG Embedding

- different kinds of neighbors for a center entity
- disentanglement-aware pre-training

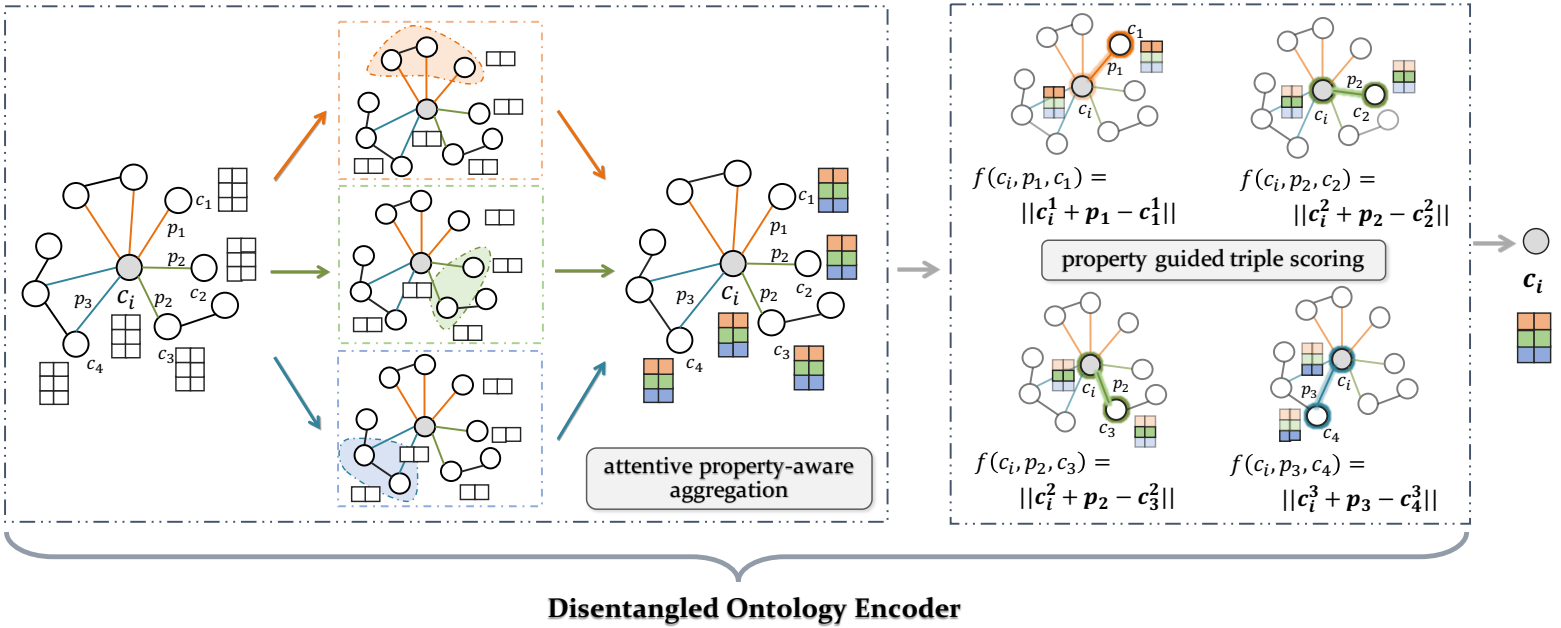




The entanglement characteristics of KGs: a class (entity) is often related to other classes (entities) in different semantic aspects.

DKZSL: KGZSL with Disentangled KG Embedding

- disentanglement-aware pre-training



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

DKZSL: KGZSL with Disentangled KG Embedding

- Learning disentangled embeddings for each class according to its semantics of different aspects
  a) split the initial embedding of class i into K components, $\boldsymbol{c}_i = [\boldsymbol{c}_i^1, \boldsymbol{c}_i^2, \ldots, \boldsymbol{c}_i^K]$;

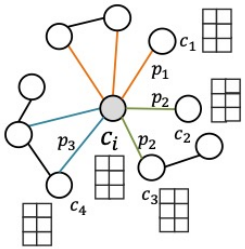


Illustration of DOZSL with K = 3, d = 6.

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

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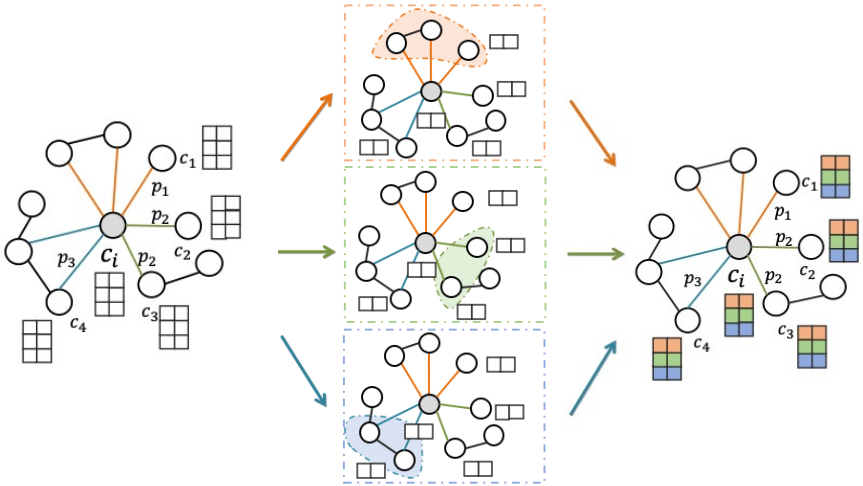
  b) attentively aggregate the graph neighborhood information for each component;



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  b) attentively aggregate the graph neighborhood information for each component;
  c) extract relation-specific components to compute the triple scores to further refine the semantics of each component

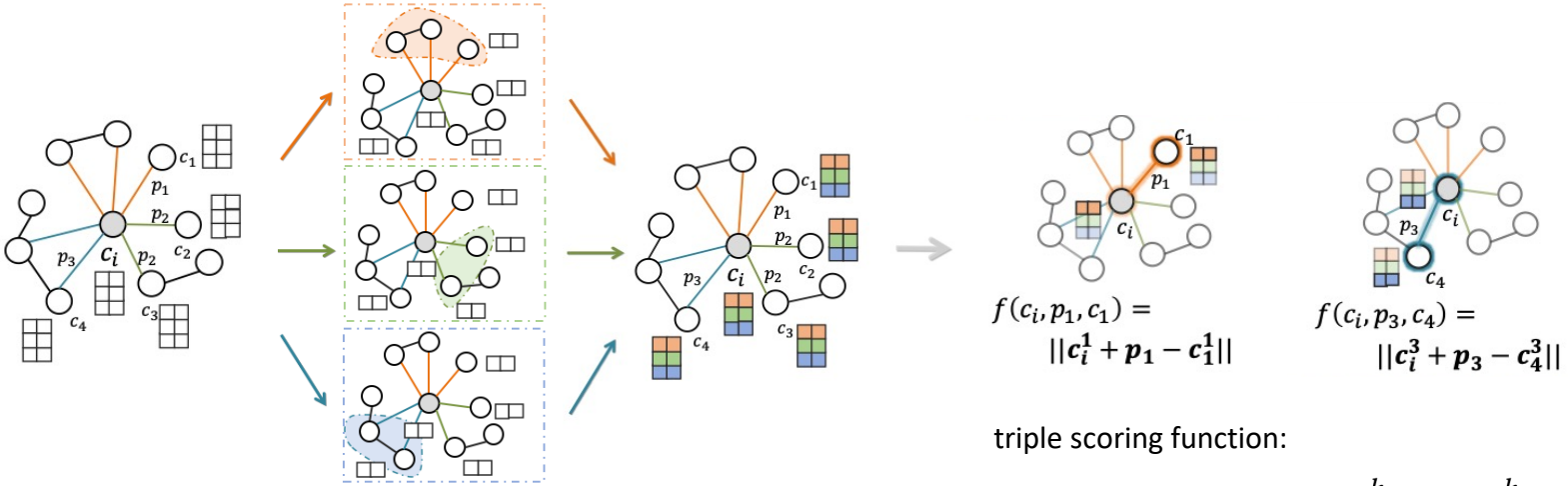


Illustration of DOZSL with K = 3, d = 6.

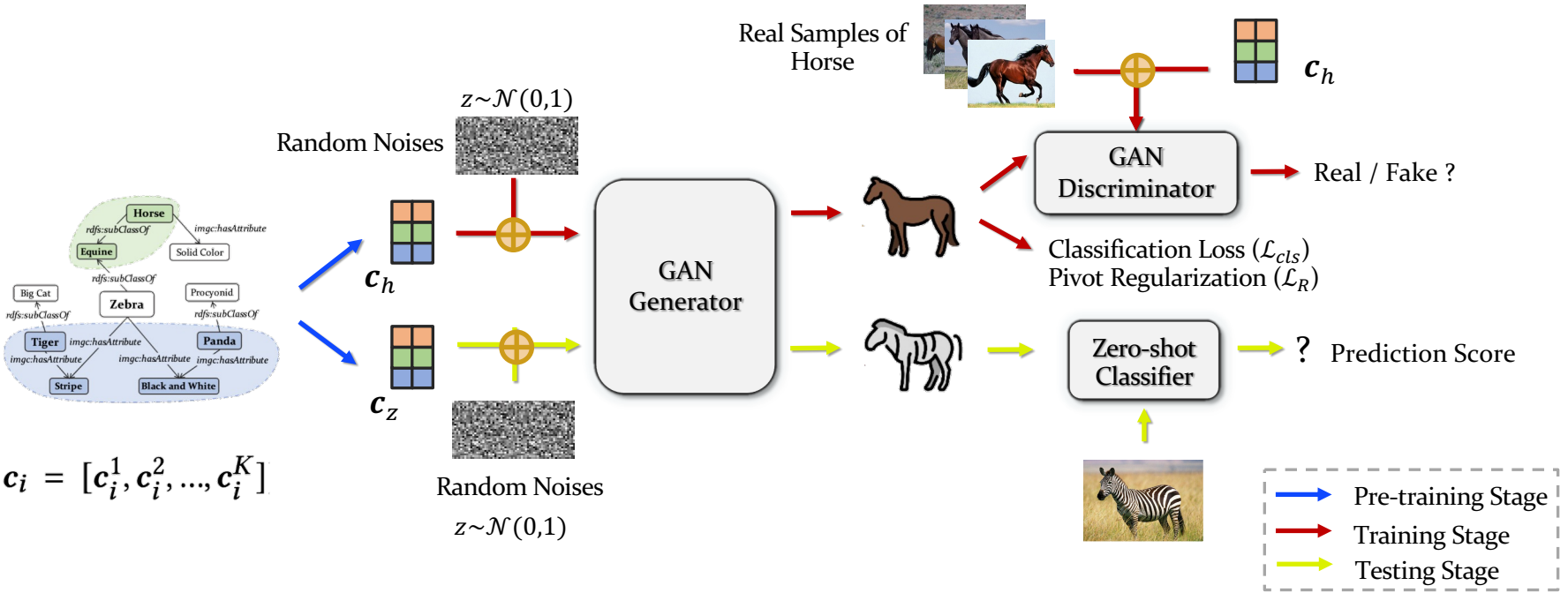
triple scoring function:

$$q_{(c_i, p_k, c_j)} = f(-||\boldsymbol{c}_i^k + \boldsymbol{p}_k - \boldsymbol{c}_j^k||)$$

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

DKZSL: KGZSL with Disentangled KG Embedding

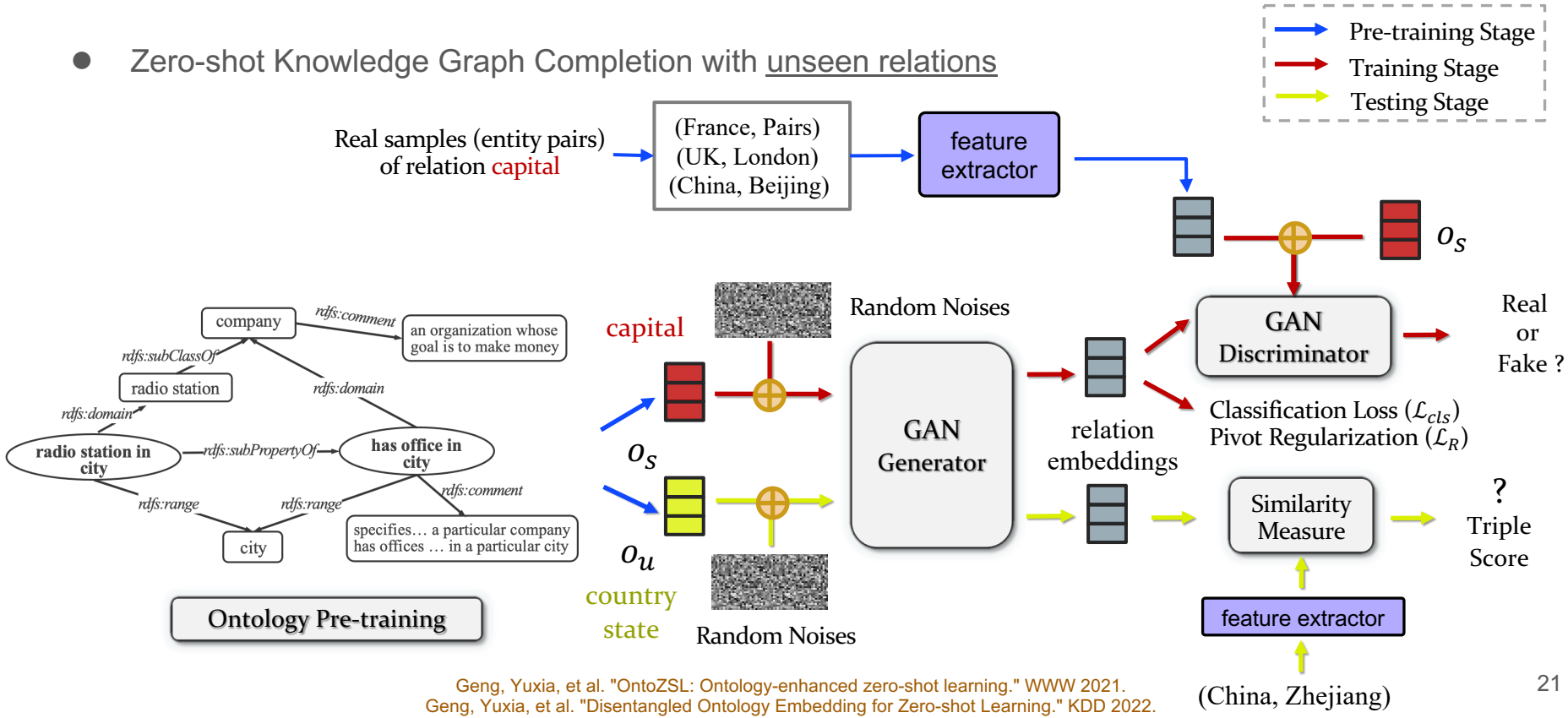
- disentanglement-aware pre-training



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

OntoZSL & DOZSL

- Zero-shot Knowledge Graph Completion with unseen relations



Geng, Yuxia, et al. "OntoZSL: Ontology-enhanced zero-shot learning." WWW 2021.
Geng, Yuxia, et al. "Disentangled Ontology Embedding for Zero-shot Learning." KDD 2022.

More Reading

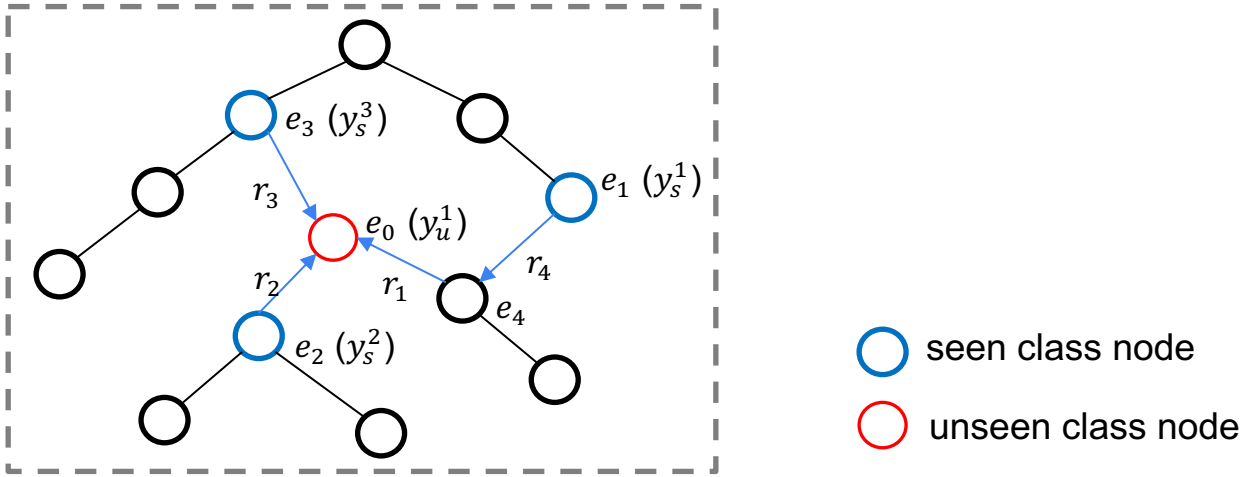
- Prior-based
  - Zero and Few Shot Learning with Semantic Feature Synthesis and Competitive Learning. TPAMI 2020
  - Iteratively learning embeddings and rules for knowledge graph reasoning. WWW 2019
  - Injecting Logical Background Knowledge into Embeddings for Relation Extraction. NAACL 2015
- VAE-based
  - Mishra et al., A Generative Model For Zero Shot Learning Using Conditional Variational Autoencoders, CVPR 2018
  - Wang et al., Zero-Shot Learning via Class-Conditioned Deep Generative Models, AAAI 2018
- Large Generative Model-based
  - Is synthetic data from generative models ready for image recognition? ICLR 2023

T4

Feature Propagation-based Methods for KG-aware ZSL

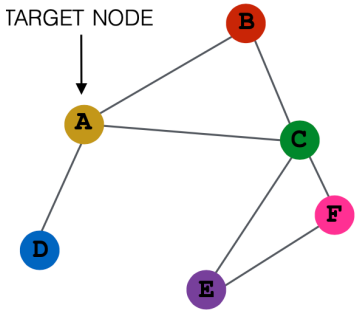
Feature Propagation Strategy

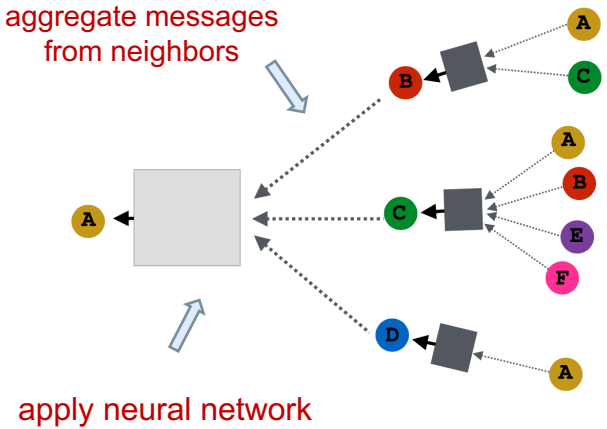
- Regarding the structural class knowledge contained in KGs or ontologies, how about directly preforming computation (feature transfer) on graph to tackle ZSL problems?
- For example, propagate model parameters or features from seen class nodes to unseen class nodes

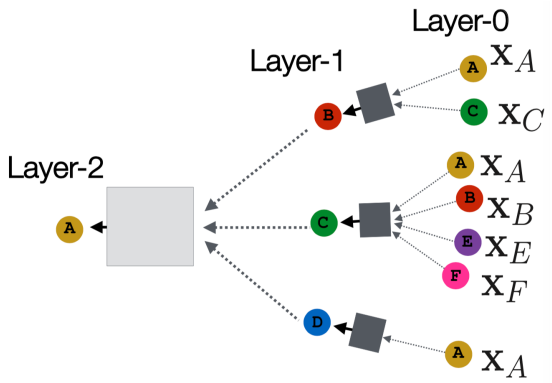


Graph Neural Networks (GNNs)

- Objective
  - learn and output a meaningful embeddings for each node u, given the input graph $\mathrm{G} = (V, E)$
- Important Steps
  - neighbourhood aggregation: aggregating neighbour information and pass into a neural network
  - self updating: update the node's hidden states using another network



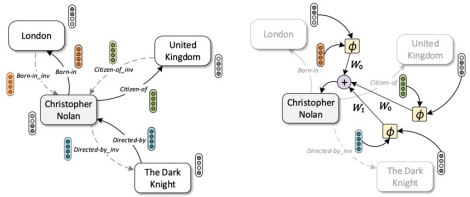




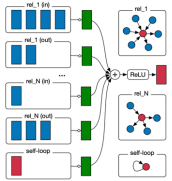
Graph Neural Networks (GNNs)

- Representative GNNs

Composition-based Multi-Relational Graph Convolutional Networks (CompGCN)	Vashishth et al., ICLR'20
Modeling Relational Data with Graph Convolutional Networks (RGCN)	Schlichtkrull et al., ESWC'18
Graph Attention Networks (GAT)	Velickovic et al., ICLR'18
Inductive Representation Learning on Large Graphs (GraphSAGE)	Hamilton et al., NIPS'17
Semi-Supervised Classification with Graph Convolutional Networks (GCN)	Kipf and Welling, ICLR'17

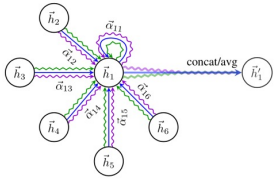


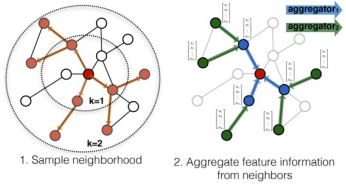
CompGCN



RGCN

GAT





GraphSAGE

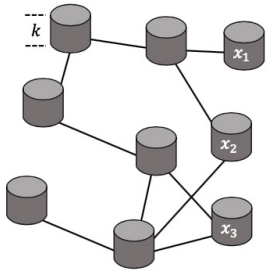
Zhou, Jie, et al. "Graph neural networks: A review of methods and applications." AI Open 1 (2020): 57-81.

Propagate Classifiers on Graph: GCNZ

- Input: a graph $G = (V, E)$ with $|V|$ class nodes and hierarchical relationship edges from WordNet
  - Adjacency matrix

$$A_{i,j} = \begin{cases} a_{i,j} = 1 & (i,j) \in E \\ 0 & (i,j) \notin E \end{cases}$$

  - Node feature matrix: $X \in \mathbb{R}^{n \times k}$ for k-dim word embeddings of n class nodes



Inputs: Word Embeddings $\mathcal{X}$
(k dimensions)

Wang, Xiaolong, Yufei Ye, and Abhinav Gupta. "GCNZ: Zero-shot recognition via semantic embeddings and knowledge graphs." CVPR 2018.

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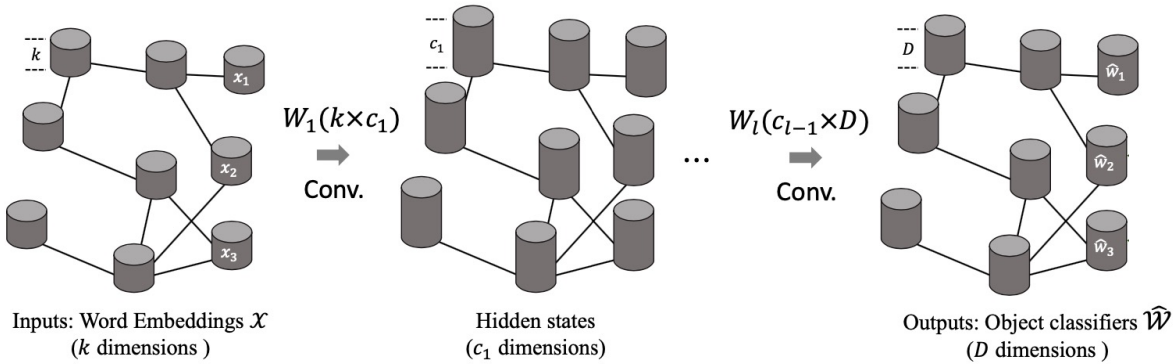
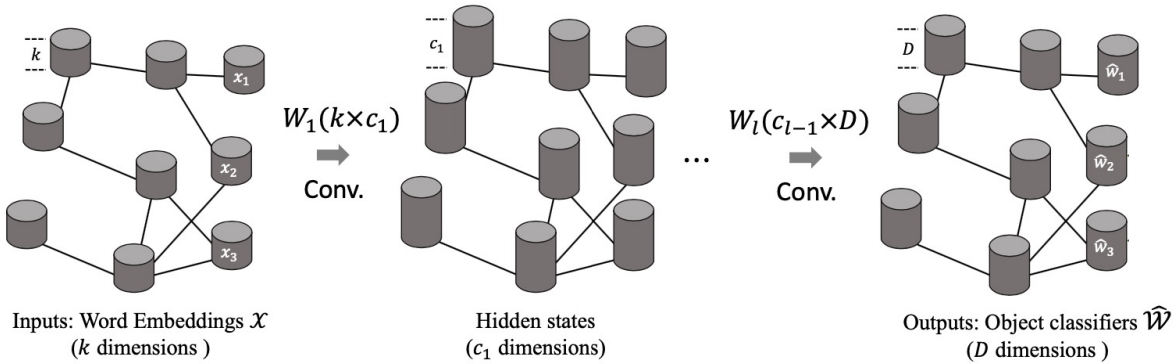


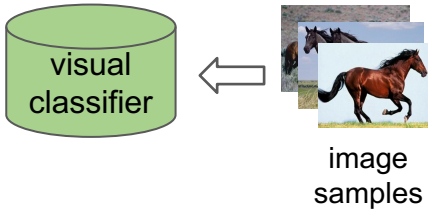
GCN: propagate features among class nodes and output classifiers

Wang, Xiaolong, Yufei Ye, and Abhinav Gupta. "GCNZ: Zero-shot recognition via semantic embeddings and knowledge graphs." CVPR 2018.

Propagate Classifiers on Graph: GCNZ

- Output: sample classifiers
  - each seen class node is supervised by a classifier, which is often a D-dim vector for class-specific sample features
  - each unseen class node is inferred to output its corresponding classifier for classification





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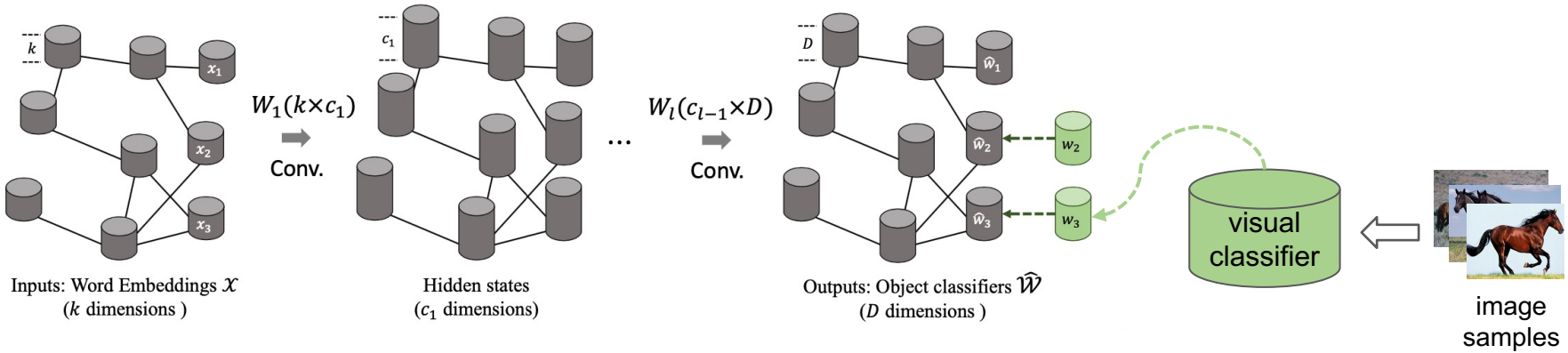

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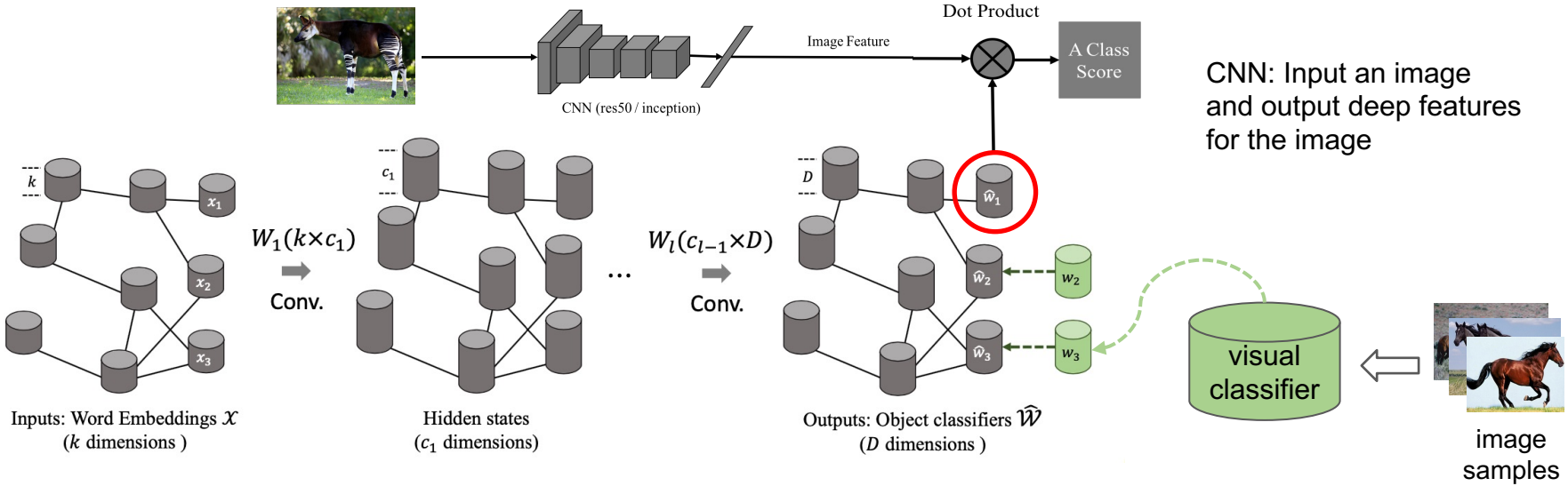
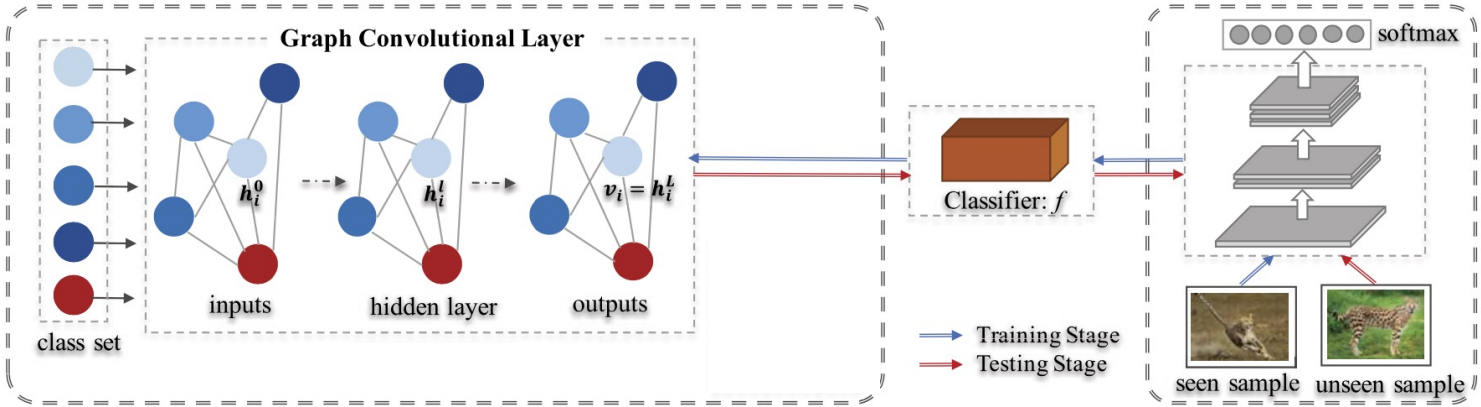
- Output: sample classifiers
  - each seen class node is supervised by a classifier, which is often a D-dim vector for class-specific sample features
  - each unseen class node is inferred to output its corresponding classifier for classification



Wang, Xiaolong, Yufei Ye, and Abhinav Gupta. "GCNZ: Zero-shot recognition via semantic embeddings and knowledge graphs." CVPR 2018.

Propagate Classifiers on Graph: Attentive GCN

- Optimized Graph Propagation with **attention, to highlight significant neighbors**



Geng, Yuxia, et al. "Explainable zero-shot learning via attentive graph convolutional network and knowledge graphs." Semantic Web Journal 2021.

Propagate Classifiers on Graph: Attentive GCN

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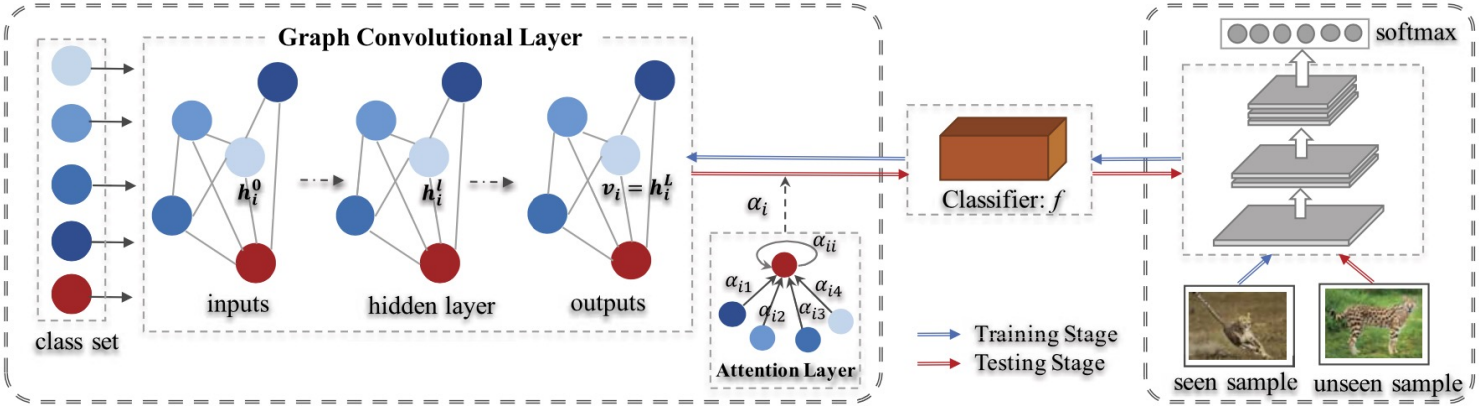
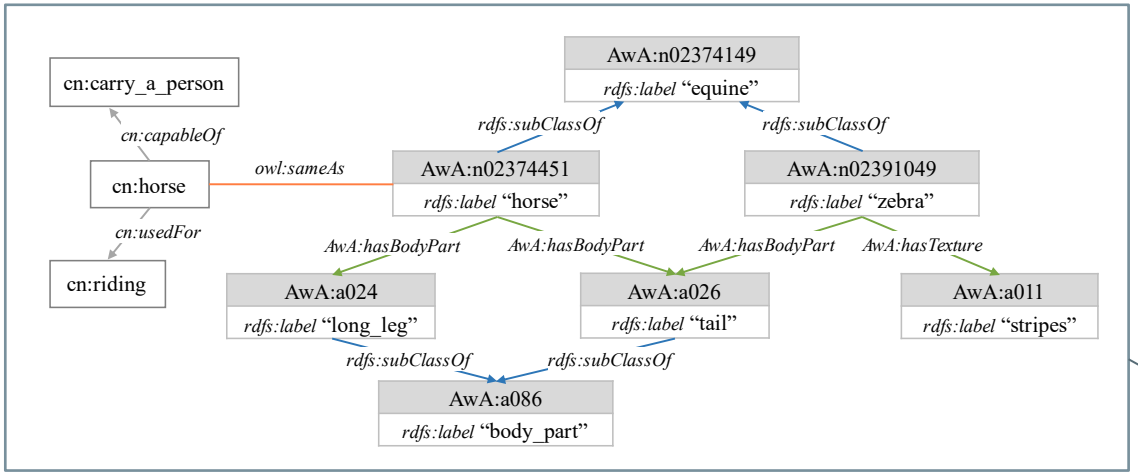


$$\alpha_{ij} = \frac{\exp(\cos(v_i, v_j))}{\sum_{k \in \mathcal{N}_i} \exp(\cos(v_i, v_k))} \qquad \bar{v}_i = \sum_{j \in \mathcal{N}_i} \alpha_{ij} \cdot v_j$$

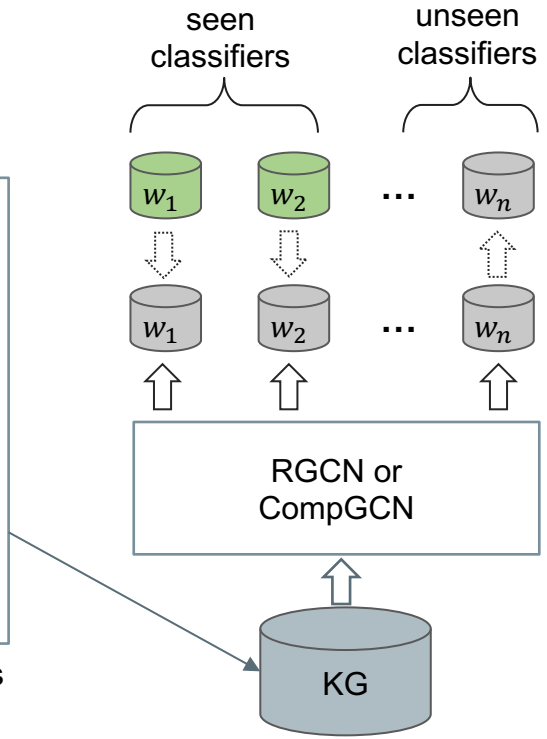
Geng, Yuxia, et al. "Explainable zero-shot learning via attentive graph convolutional network and knowledge graphs." Semantic Web Journal 2021.

Propagate Classifiers on Graph: RGCN-ZSL, CompGCN-ZSL

- Optimized Graph Propagation with **relation-aware GCN**



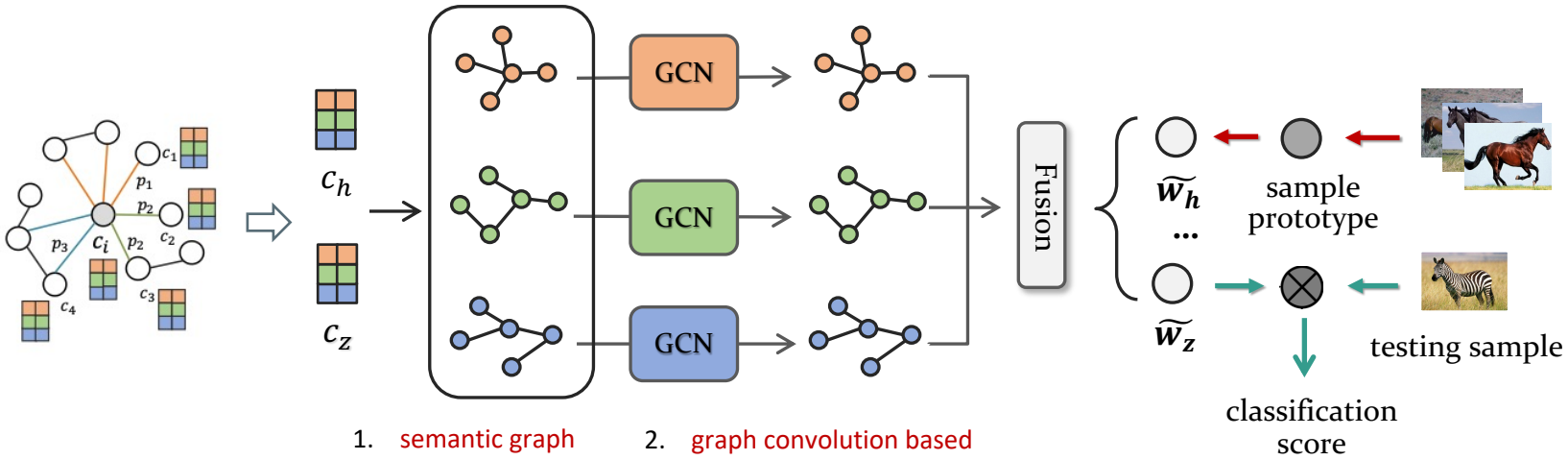
A KG fragment for animal classes, including 6 relations for different semantics



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

Propagate Classifiers on Graph: DKZSL

- Relational Graph Propagation with **disentangled semantic graphs**



1. semantic graph construction

$$A_k(i,j) = \begin{cases} 1 & \text{if } sim(\boldsymbol{c}_i^k, \boldsymbol{c}_j^k) > \tau \\ 0 & \text{otherwise} \end{cases}$$

2. graph convolution based feature propagation

$$H_k^{l+1} = \sigma(\widehat{A}_k H_k^l \Phi_k^l)$$

3. classifier fusion

$$\widetilde{W} = \frac{1}{K} \sum_k Z_k$$

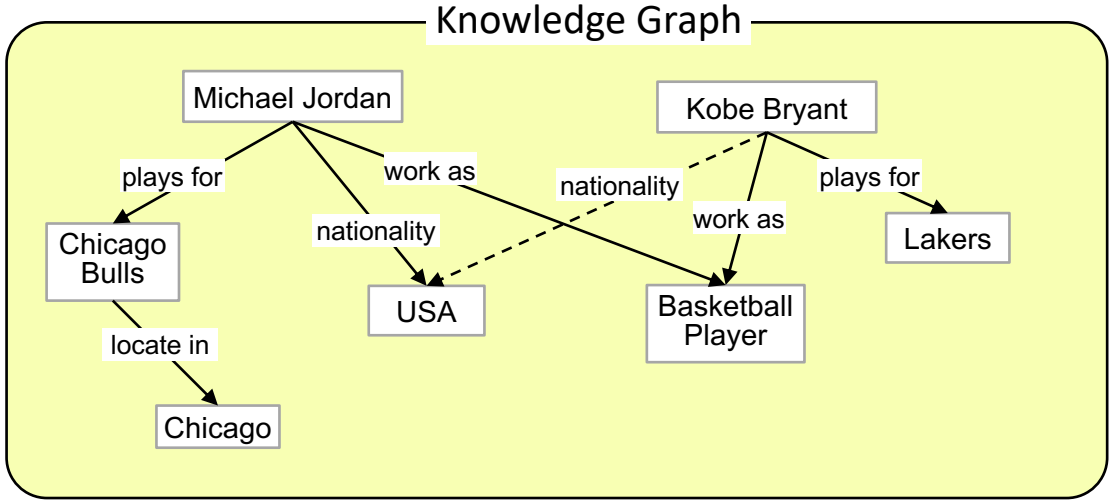
$$\widetilde{W} = W_1([Z_1; Z_2; ...; Z_K])$$

Training Stage
Testing Stage

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

Propagate Embeddings on Graph

- Knowledge Graph Completion



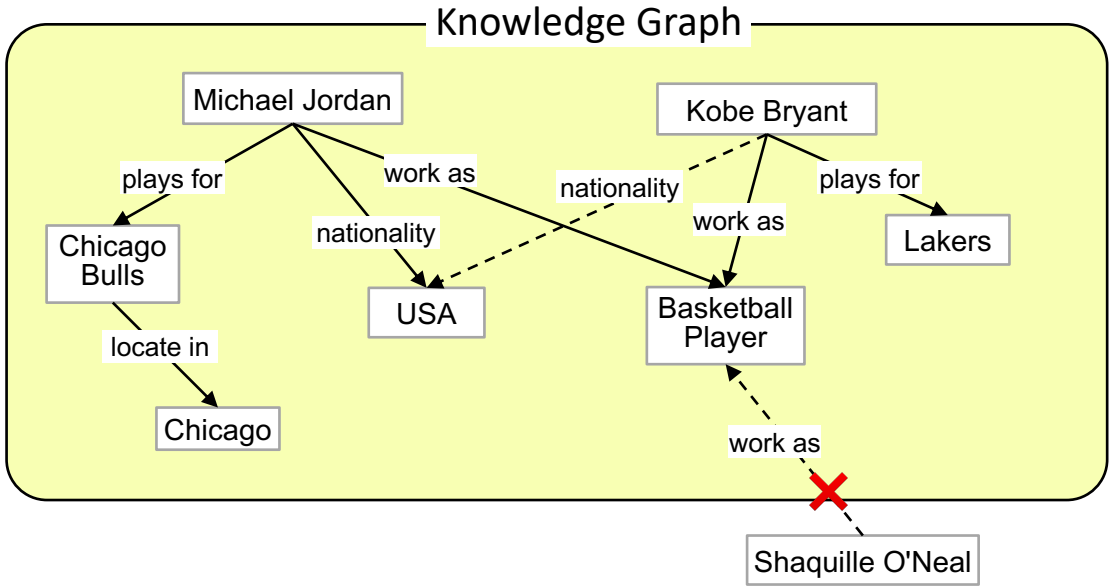
(a) Training: learn embeddings for entities and relations

(b) Traditional Completion: perform vector computation on the learned embeddings

👍 *TransE, DistMult, RotatE, …*

Propagate Embeddings on Graph

- Zero-shot Knowledge Graph Completion



(a) Training: learn embeddings for entities and relations

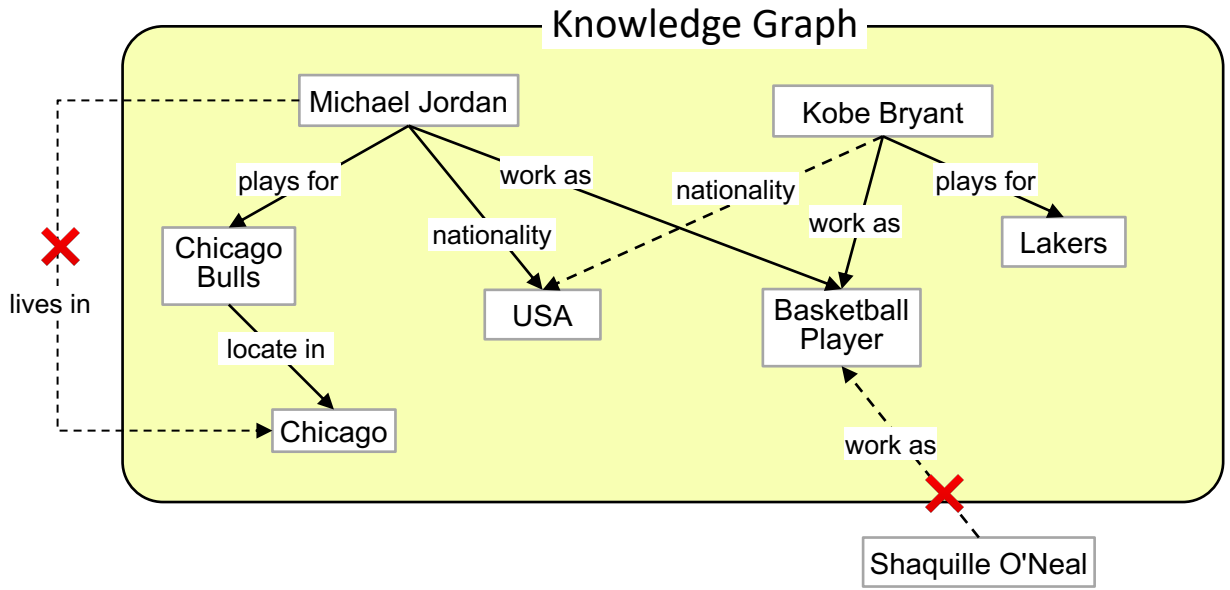
(b) Traditional Completion: perform vector computation on the learned embeddings

(c) Completion with new entity

✗ *TransE, DistMult, RotatE, …*

Propagate Embeddings on Graph

- Zero-shot Knowledge Graph Completion



(a) Training: learn embeddings for entities and relations

(b) Traditional Completion: perform vector computation on the learned embeddings

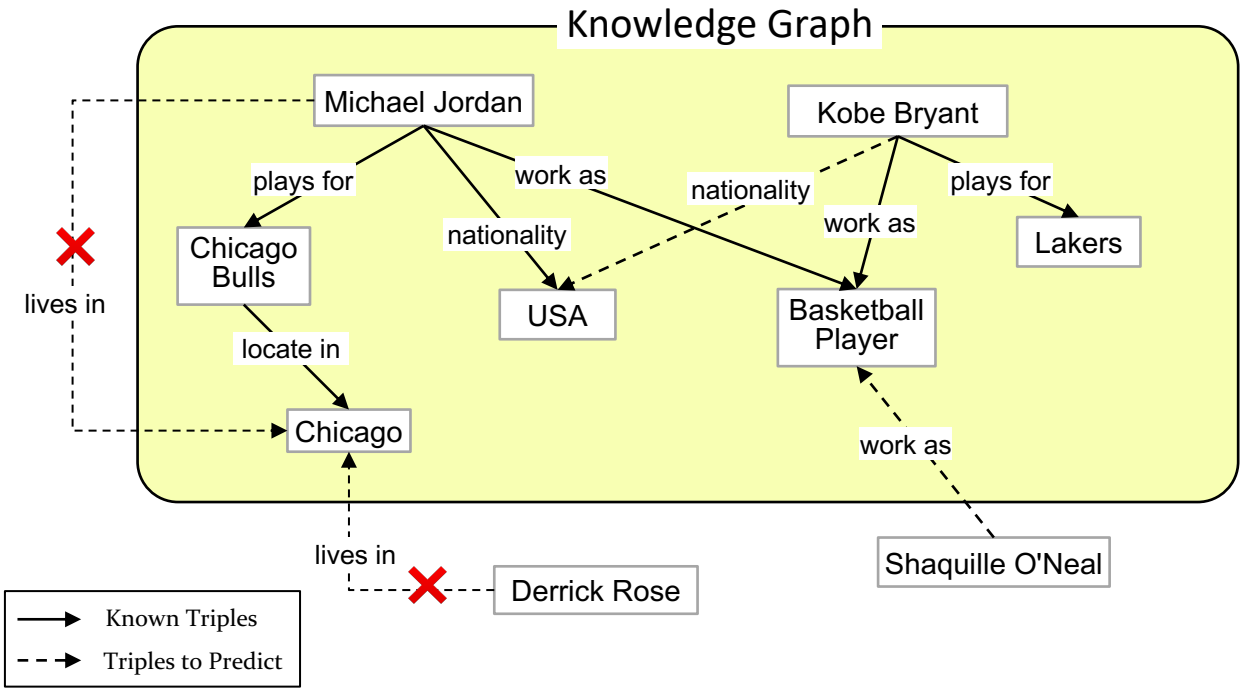
(c) Completion with new entity

(d) Completion with new relation

✗ *TransE, DistMult, RotatE, …*

Propagate Embeddings on Graph

- Zero-shot Knowledge Graph Completion



(a) Training: learn embeddings for entities and relations

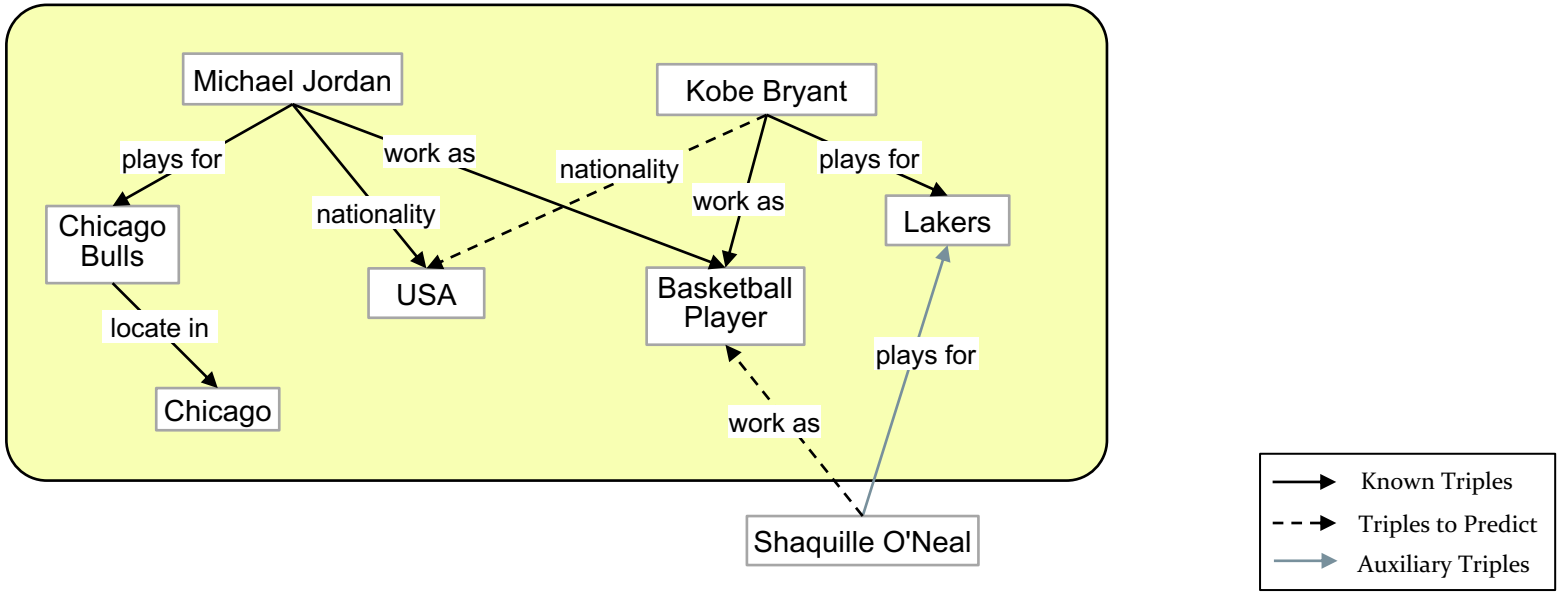
(b) Traditional Completion: perform vector computation on the learned embeddings

(c) Completion with new entity
(d) Completion with new relation
(e) Completion with new entity and new relation

✗ *TransE, DistMult, RotatE, …*

Propagate Entity Embeddings on Graph

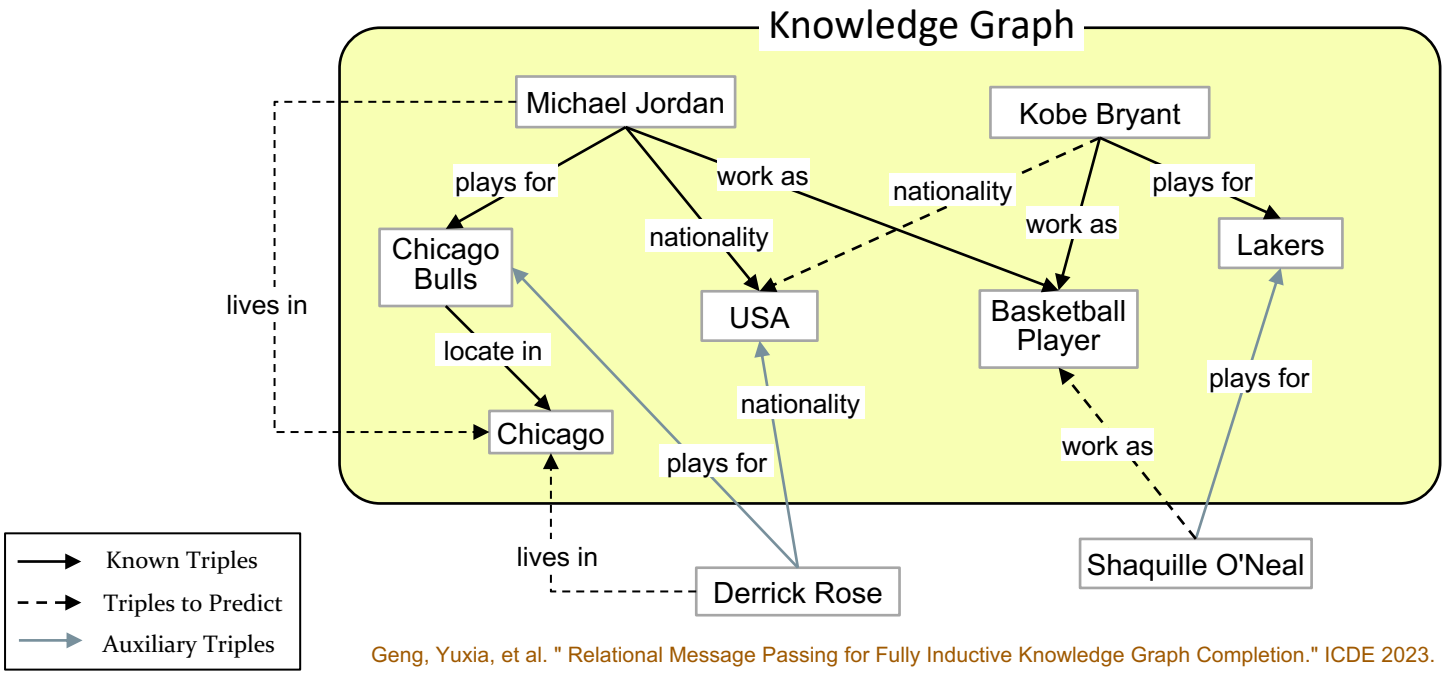
- New (unseen) entities are represented by aggregating neighboring trained entities and relations



Hamaguchi, Takuo, et al. "Knowledge transfer for out-of-knowledge-base entities: A graph neural network approach." IJCAI 2017.

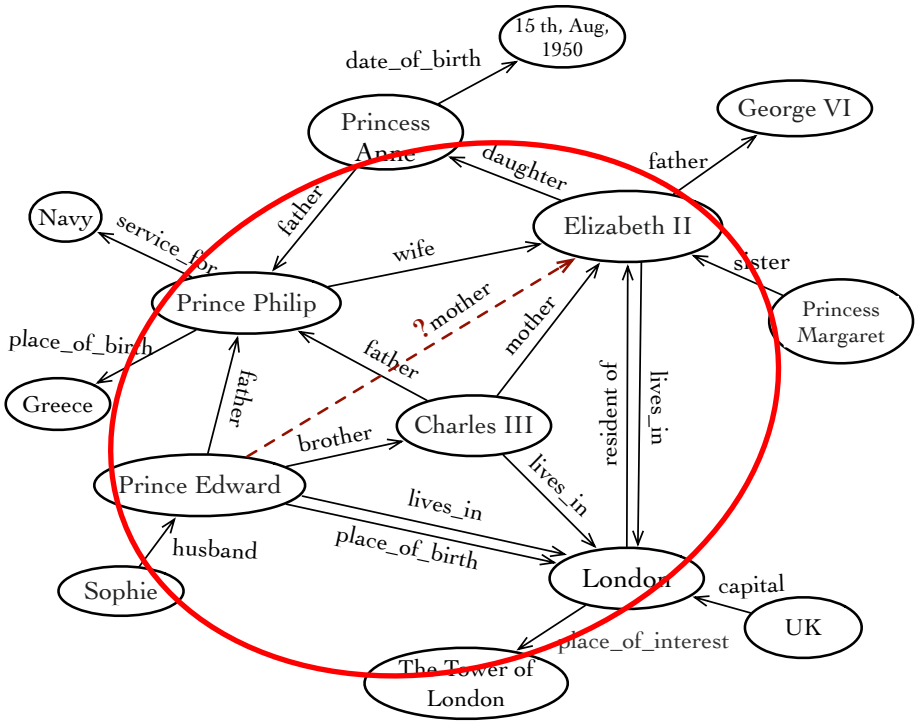
Propagate Relation Embeddings on Graph: RMPI

- generalize to unseen relations and unseen entities simultaneously



Geng, Yuxia, et al. " Relational Message Passing for Fully Inductive Knowledge Graph Completion." ICDE 2023.

Propagate Relation Embeddings on Graph: RMPI

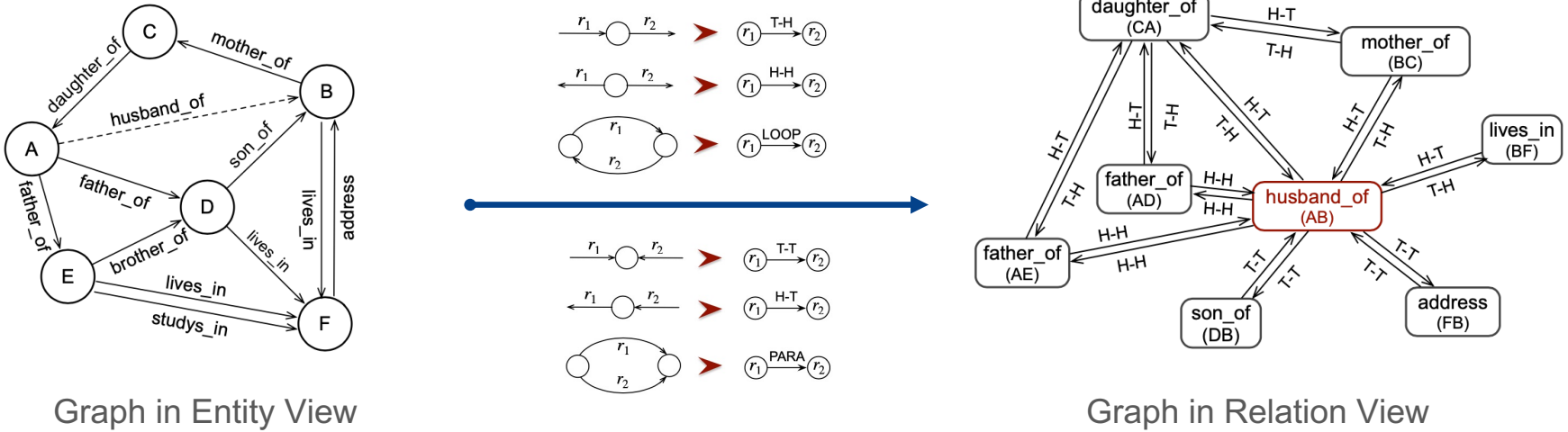


- New (unseen) relations are represented by aggregating neighboring trained relations, can generalize to unseen relations
- RMPI infers the plausibility of a triple without knowing entities, can generalize to unseen entities

Geng, Yuxia, et al. " Relational Message Passing for Fully Inductive Knowledge Graph Completion." ICDE 2023.

Propagate Relation Embeddings on Graph: RMPI

- Subgraph Extraction and Transformation (by 6 meta-relations)



Graph in Entity View

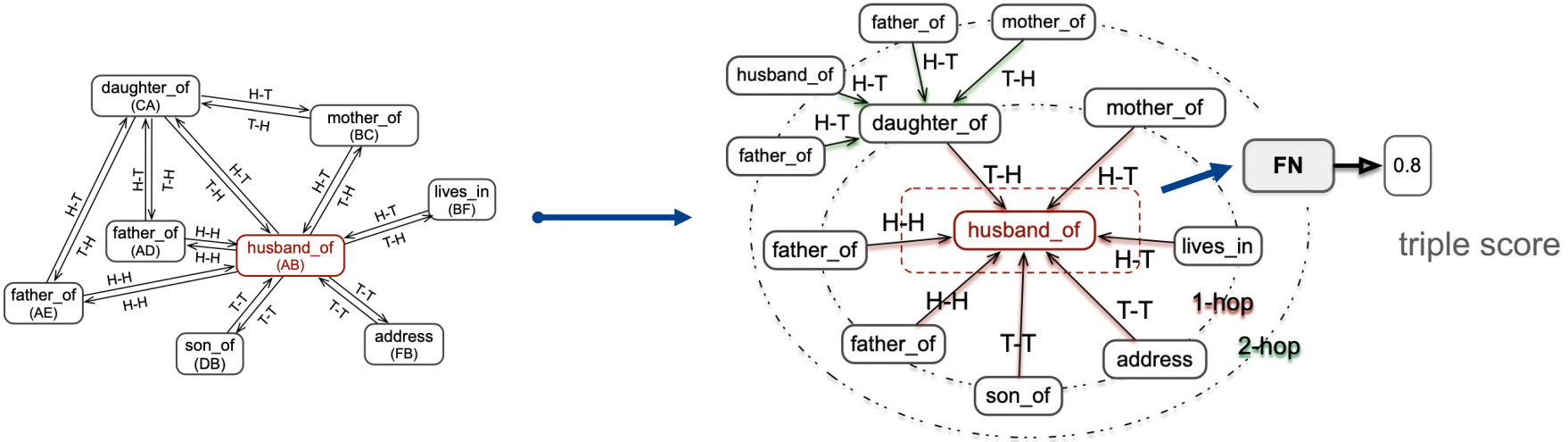
Graph in Relation View

Meta Relations
connection patterns of relations in the original graph

Geng, Yuxia, et al. " Relational Message Passing for Fully Inductive Knowledge Graph Completion." ICDE 2023.

Propagate Relation Embeddings on Graph: RMPI

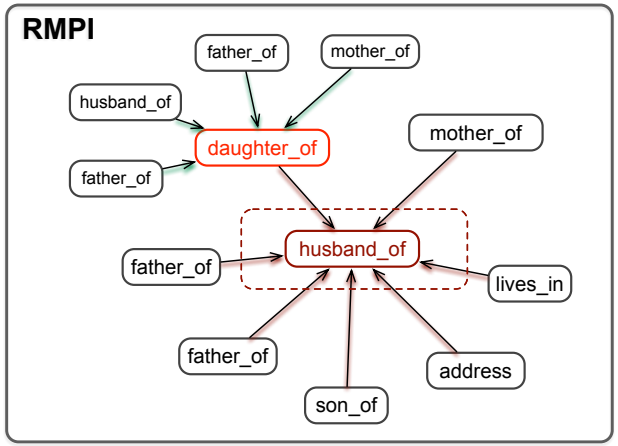
- **R**elational **M**essage **P**assing (Feature Propagation) Network for directly propagating features between relations
  - a target relation-guided graph pruning strategy
  - a target relation-aware neighborhood aggregation mechanism



Geng, Yuxia, et al. " Relational Message Passing for Fully Inductive Knowledge Graph Completion." ICDE 2023.

Propagate Relation Embeddings on Graph: RMPI

- Infer embeddings for unseen relations

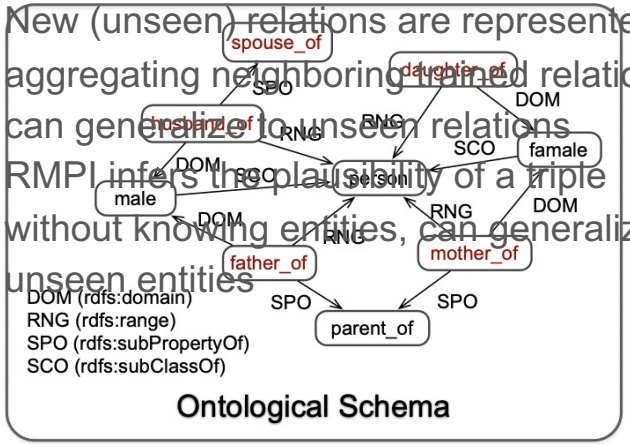


① aggregate features of their neighboring trained seen relations

② explore more relation correlations from KG's Ontology

1) pretrain the ontology and initialize relation embeddings used for relation message passing

- New (unseen) relations are represented by aggregating neighboring trained relations, can generalize to unseen relations
- RMPI infers the plausibility of a triple without knowing entities, can generalize to unseen entities



Geng, Yuxia, et al. " Relational Message Passing for Fully Inductive Knowledge Graph Completion." ICDE 2023.

More Reading

- Propagate Classifiers
  - Kampffmeyer, Michael, et al. "Rethinking knowledge graph propagation for zero-shot learning." CVPR 2019.
  - Geng, Yuxia, et al. "Explainable zero-shot learning via attentive graph convolutional network and knowledge graphs." Semantic Web Journal 2021.
  - Wang et al., Zero-Shot Learning via Contrastive Learning on Dual Knowledge Graphs, ICCV 2021
  - Chen et al., Zero-shot Ingredient Recognition by Multi-Relational Graph Convolutional Network, AAAI 2020
- Propagate Embeddings (entity or image)
  - Lee, Chung-Wei, et al. "Multi-label zero-shot learning with structured knowledge graphs." CVPR 2018.
  - Wang, Peifeng, et al. "Logic attention based neighborhood aggregation for inductive knowledge graph embedding." AAAI 2019.
- Subgraph Reasoning
  - Teru, Komal, et al. “Inductive Relation Prediction by Subgraph Reasoning”. ICML 2020.
  - Chen, Jiajun, et al. "Topology-aware correlations between relations for inductive link prediction in knowledge graphs." AAAI 2021.

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

Yuxia Geng[1], Zhuo Chen[2], Jiaoyan Chen[3], Wen Zhang[2] and Jeff Z. Pan[4]

1. Hangzhou Dianzi University, China
2. Zhejiang University, China
3. The University of Manchester & University of Oxford, UK
4. The University of Edinburgh, UK

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

Tutorial of The 32nd International Joint Conference on Artificial Intelligence (19th August, 2023, Macao, S.A.R)

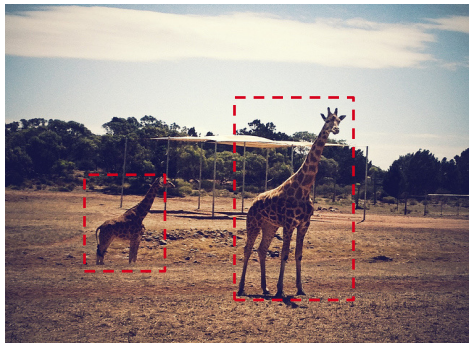
IJCAI/2023 MACAO

T5

KG Augmented Zero-shot Visual Question Answering

Knowledge-aware Visual Question Answering (K-VQA)

- Traditional VQA (E.g., VQA 2.0)
  - Multi-modal feature fusion

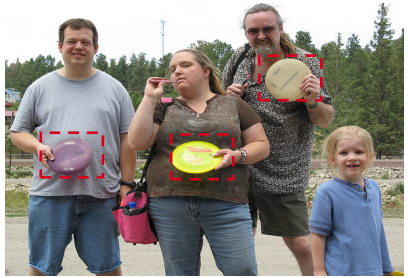


\+ **Q1: How many giraffes are there?** = **Ans: two**

Chen, Zhuo, et al. “Zero-shot Visual Question Answering using Knowledge Graph.” ISWC 2021.

Knowledge-aware Visual Question Answering (K-VQA)

- Knowledge-based VQA (E.g., F-VQA)
  - Querying constructed sub-KG through SPARQL
  - Get unstructured knowledge via using search engine
  - Large-scale language model



\+ Q2: What object in this image is a toy? + Knowledge Base / Search Engine / Language Model = Ans: toy

Chen, Zhuo, et al. “Zero-shot Visual Question Answering using Knowledge Graph.” ISWC 2021.

Zero-shot Visual Question Answering (ZS-VQA)

- Zero-shot multiple-choice VQA: **unseen words**

What color are the *barricades* ?

✓ pink
black
red
orange

What animal is in the picture ?

puppy
bulldog
✓ dog
pitbull

Seen

Unseen

Chen, Zhuo, et al. “Zero-shot Visual Question Answering using Knowledge Graph.” ISWC 2021.

Zero-shot Visual Question Answering (ZS-VQA)

- Zero-shot open-ended (Top-K) VQA: **unseen answers**

What object in this image is a toy?

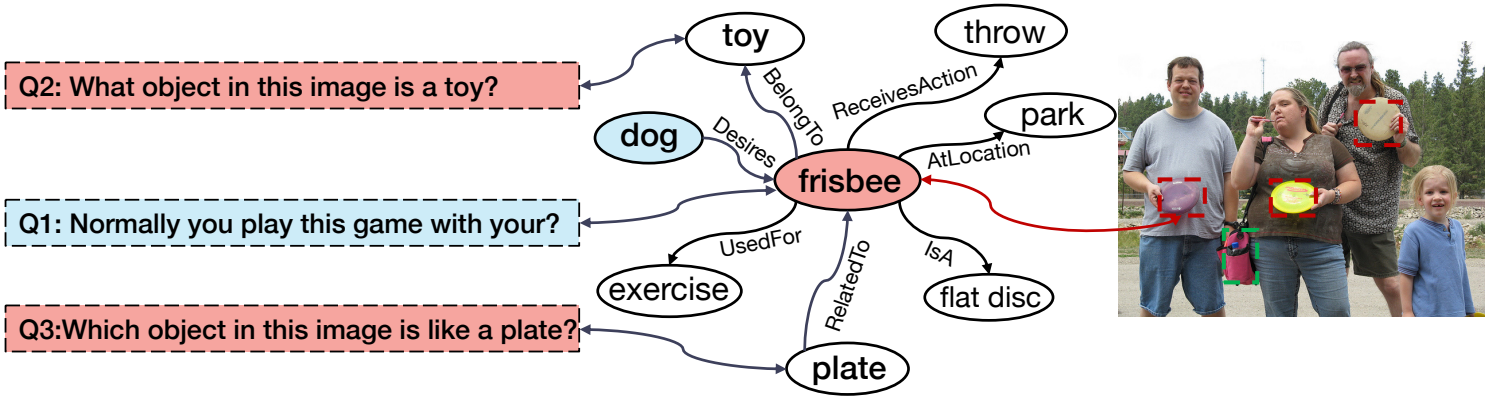
What object has engine?

- Candidate Answer Pool:

person, bus, wall, desk, water, bicycle, tree, street, chair ..... *frisbee, luggage, hotdog, motorcycle .....*

Chen, Zhuo, et al. "Zero-shot Visual Question Answering using Knowledge Graph." ISWC 2021.

KG Augmented Zero-shot Visual Question Answering



- A Zero-shot VQA algorithm using knowledge graphs and a mask-based learning mechanism for better incorporating external knowledge.
- A new answer-based Zero-shot VQA split for the F-VQA dataset.

Chen, Zhuo, et al. “Zero-shot Visual Question Answering using Knowledge Graph.” ISWC 2021.

KG Augmented Zero-shot Visual Question Answering

Q: Which object in this image is like a plate?

ResNet

GRUs

Fusion Module

Fusion Module

Fusion Module

Object Space

match

Semantic Space

match

Knowledge Space

B N

F C

Support Entity Representation

B N

F C

Relation Representation

B N

F C

Answer Representation

Fact KG

Entities: { plate, wheel box, … }
Relations: { IsA, RelatedTo, … }

match

park
frisbee
plate
dog
IsA
AtLocation
RelatedTo
Desires

{ frisbee, waffle iron, … }

Target Set

add mask (hard / soft)

Similarity

max

{ frisbee }

Answer

Seen Answers

Unseen Answers

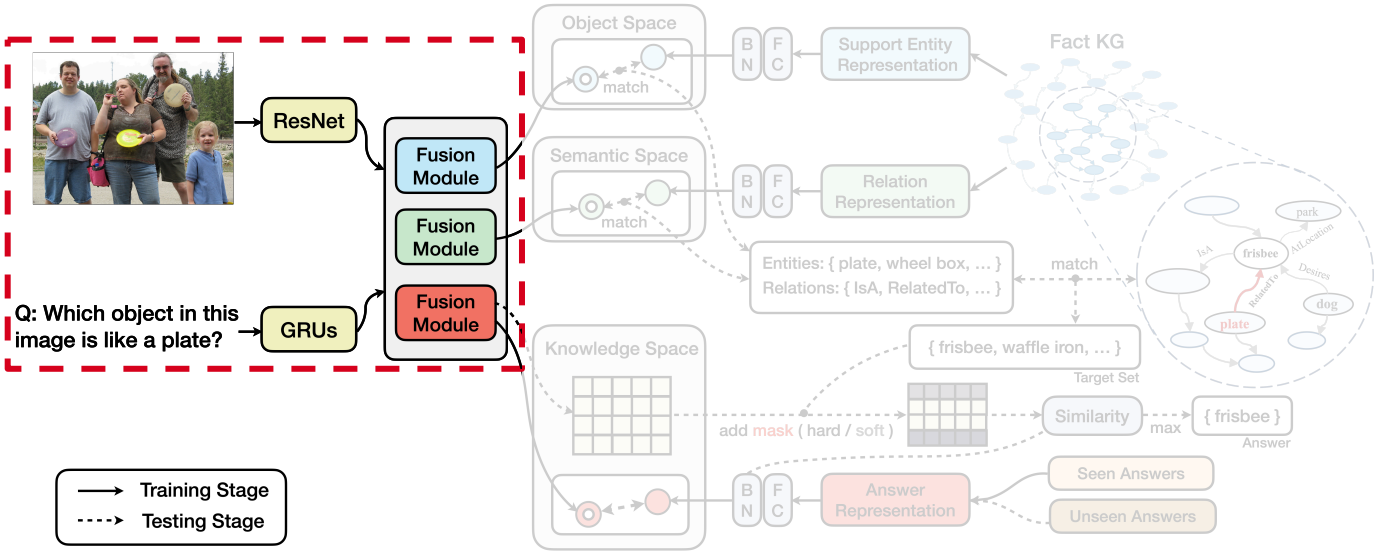
Training Stage

Testing Stage

Chen, Zhuo, et al. “Zero-shot Visual Question Answering using Knowledge Graph.” ISWC 2021.

KG Augmented Zero-shot Visual Question Answering

- Multiple Feature Spaces :
  - Convert VQA from a classification task to a mapping task



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KG Augmented Zero-shot Visual Question Answering

- Multiple Feature Spaces :
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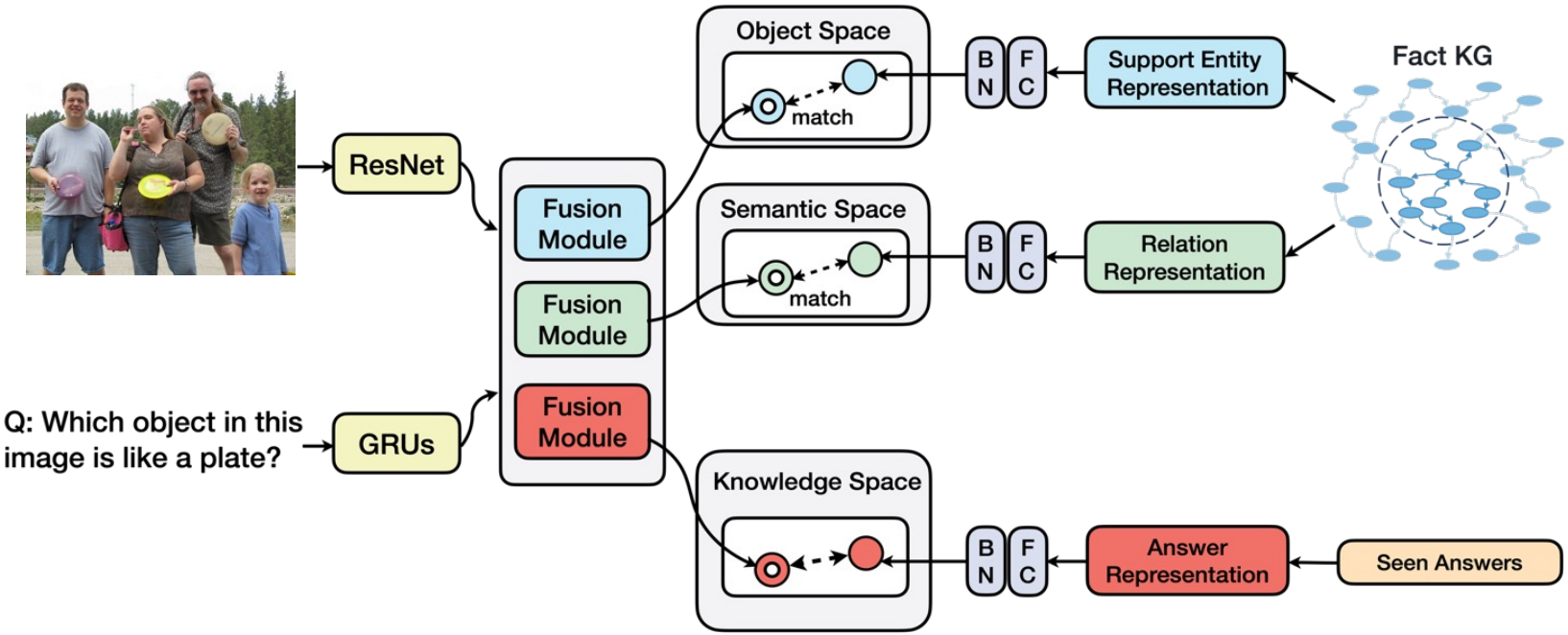
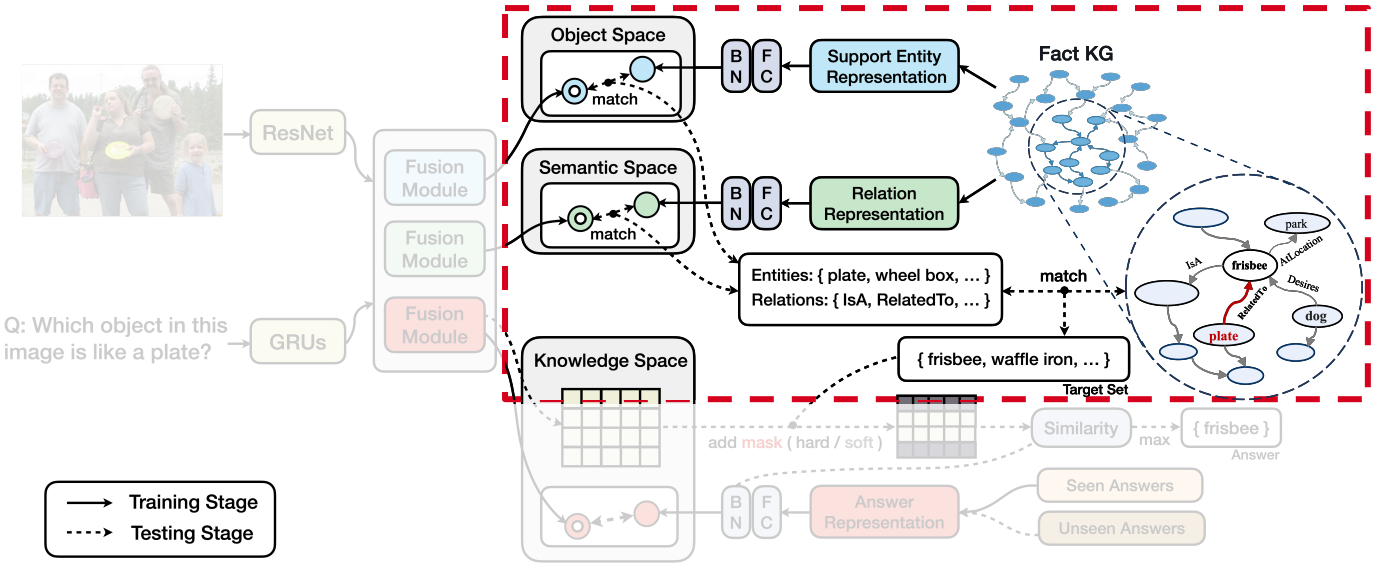


Chen, Zhuo, et al. “Zero-shot Visual Question Answering using Knowledge Graph.” ISWC 2021.

KG Augmented Zero-shot Visual Question Answering

- Answer Mask via Knowledge
  - Enhance alignment process meanwhile alleviating error cascading



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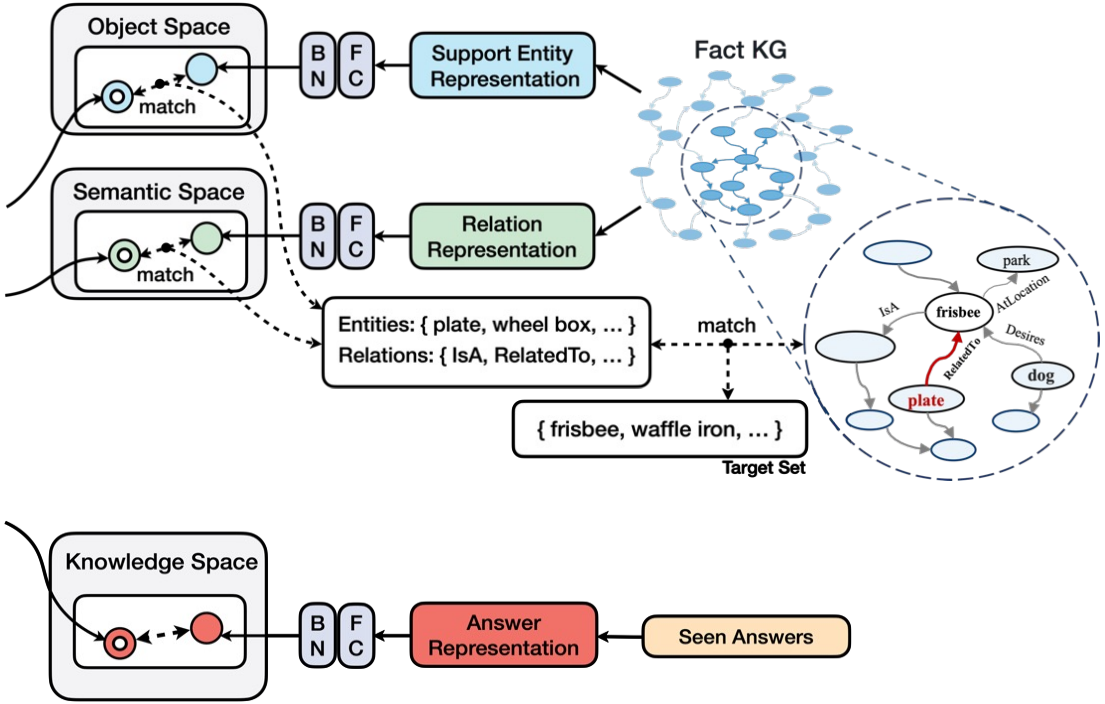
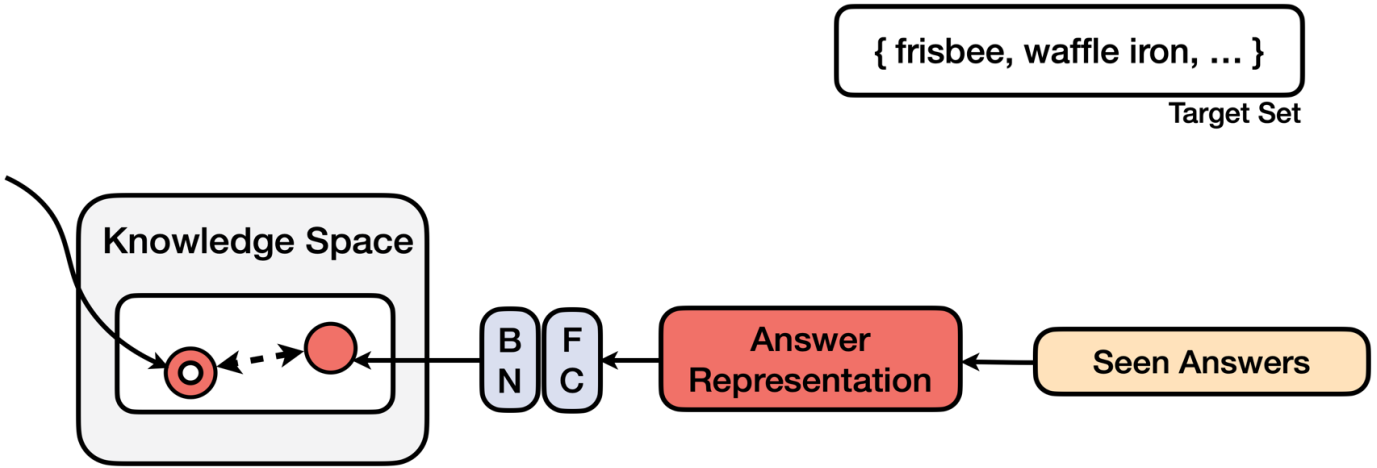


Chen, Zhuo, et al. "Zero-shot Visual Question Answering using Knowledge Graph." ISWC 2021.

KG Augmented Zero-shot Visual Question Answering

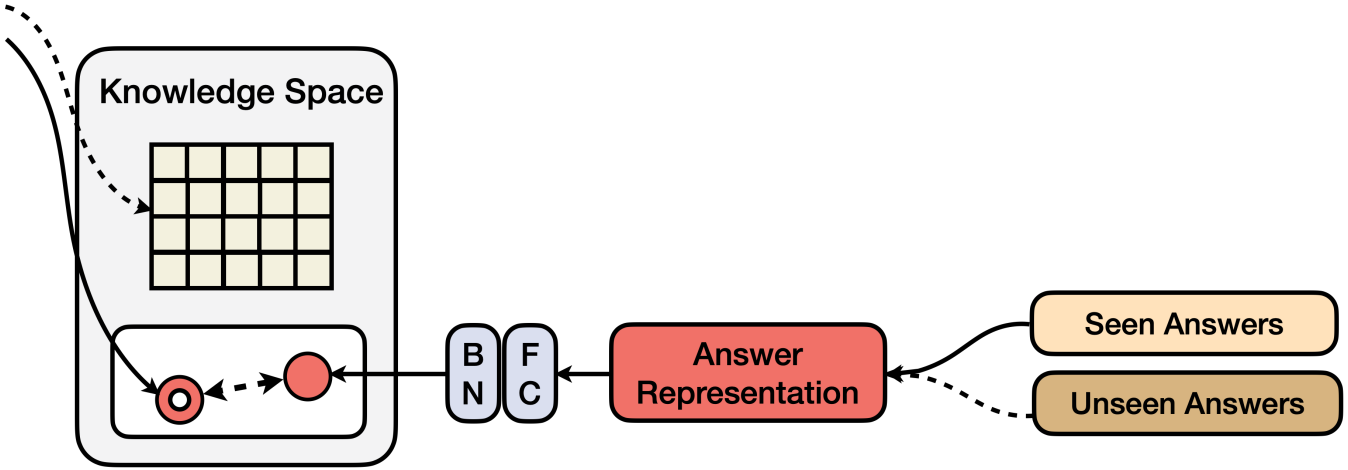
- Answer Mask via Knowledge
  - Filter a candidate target set



Chen, Zhuo, et al. “Zero-shot Visual Question Answering using Knowledge Graph.” ISWC 2021.

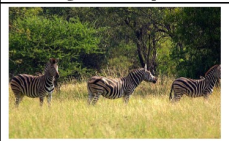
KG Augmented Zero-shot Visual Question Answering

- Answer Mask via Knowledge
  - soft mask score
  - hard mask score



Chen, Zhuo, et al. “Zero-shot Visual Question Answering using Knowledge Graph.” ISWC 2021.

KG Augmented Zero-shot Visual Question Answering

Question		What thing does the animal in this image have as a part?	Which object in this image could perform a screen	which object in this image is faster than bike?	Which object in this image is related to fly?
Image					
Our Model	Support Entity	zebra, elephant, zoo, giraffe	screen capture, screen, computer display, display image	fast than bicycle, bike, ride, fast than car	fly, catch fly, attempt to fly, learn to fly
	Relation	has a, part of, is a	capable of, used for, related to	slow, expensive, efficient	related to, belong to, specific
	Answer	stripe, horse, string ✓	computer, tv, keyboard ✓	car, bicycle, traffic light ✓	dragonfly, bird, airplane ✓
SAN†	Answer	string, water, ocean ✗	mouse, hand, lamp ✗	bicycle, traffic light, airplane ✗	airplane, kite, fly ✗
Ground Truth		stripe	computer	car	dragonfly

Question		Which object in this image is a cartilaginous fish?	Which object in this image is related to drive?	What is the place in this image used for?
Image				
Our Model	Support Entity	fish, eat fish, fish tank, carp, crab	drive, disk drive, drive on, drive lorry, drive only on track	ocean, sandy, lake, ocean beach, sand
	Relation	is a, belong to, related to	related to, specific, used for	used for, related to, capable of
	Answer	ray, jellyfish, lobster, turtle, sea, fish ✓	horse, cattle, car, cart, train, bicycle ✓	store boat, sail boat, swim, ski, swimming, life preserver ✓
SAN†	Answer	ray, turtle, fish, frog, jellyfish, lobster ✓	horse, cart, cow, sheep, cattle, camel ✓	life preserver, travel across water, sea, desert, ocean , store boat ✗
Ground Truth		grass	cattle	swim

Chen, Zhuo, et al. “Zero-shot Visual Question Answering using Knowledge Graph.” ISWC 2021.

More Reading

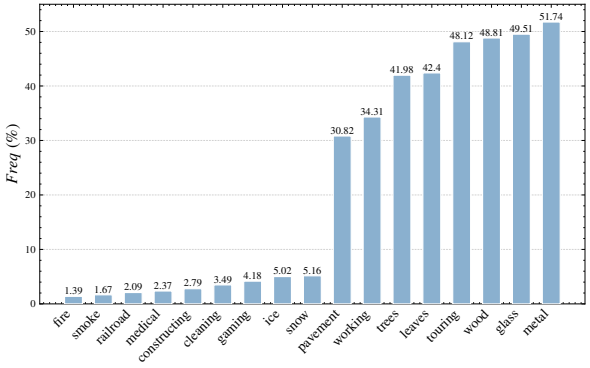
- Fvqa: Fact-based visual question answering. TPAMI 2018
- Out of the Box: Reasoning with Graph Convolution Nets for Factual Visual Question Answering. NeurIPS 2018
- Straight to the facts: Learning knowledge base retrieval for factual visual question answering. ECCV 2018
- OK-VQA: A visual question answering benchmark requiring external knowledge. CVPR 2019
- KVQA: Knowledge-aware visual question answering. AAAI 2019
- Mucko: Multi-Layer Cross-Modal Knowledge Reasoning for Fact-based Visual Question Answering. IJCAI 2020
- Conceptbert: Concept-aware representation for visual question answering. EMNLP 2020
- Krisp: Integrating implicit and symbolic knowledge for open-domain knowledge-based vqa. CVPR 2021
- Retrieval augmented visual question answering with outside knowledge. EMNLP 2022
- LaKo: Knowledge-driven Visual Question Answering via Late Knowledge-to-Text Injection. IJCKG 2022
- K-lite: Learning transferable visual models with external knowledge. NeurIPS 2022
- Multi-modal answer validation for knowledge-based vqa. AAAI 2022

T7

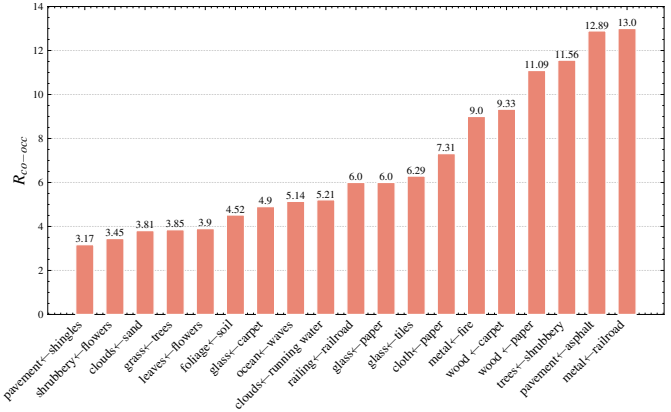
Cross-modal Semantic Grounding for Contrastive ZSL

Cross-modal Semantic Grounding for ZSL

(a) Imbalance distribution of attributes

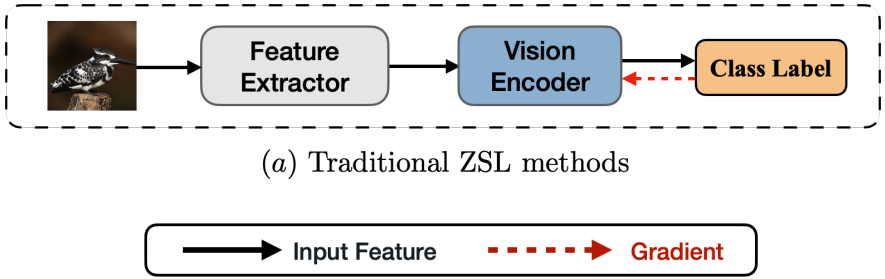


(b) Attribute co-occurrence

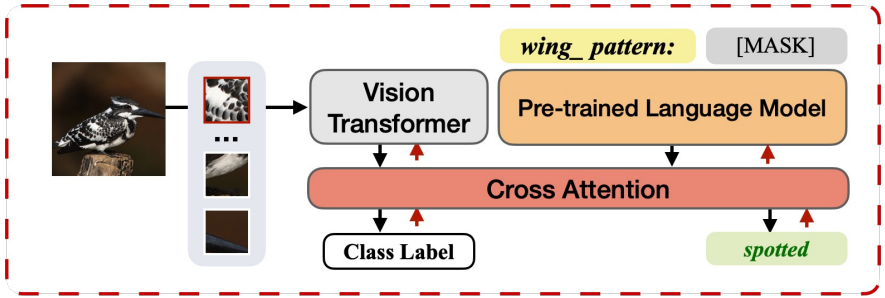


Chen, Zhuo, et al. “DUET: Cross-modal Semantic Grounding for Contrastive Zero-shot Learning.” AAAI 2023.

Cross-modal Semantic Grounding for ZSL



(a) Traditional ZSL methods



(b) Cross-modal semantic grounding

(a) The paradigm of previous ZSL methods.

(b) The paradigm of our method DUET which exploits the semantics of PLMs to augment the transformer-based vision encoder via reconstructing masked attributes with a cross-model attention mechanism.

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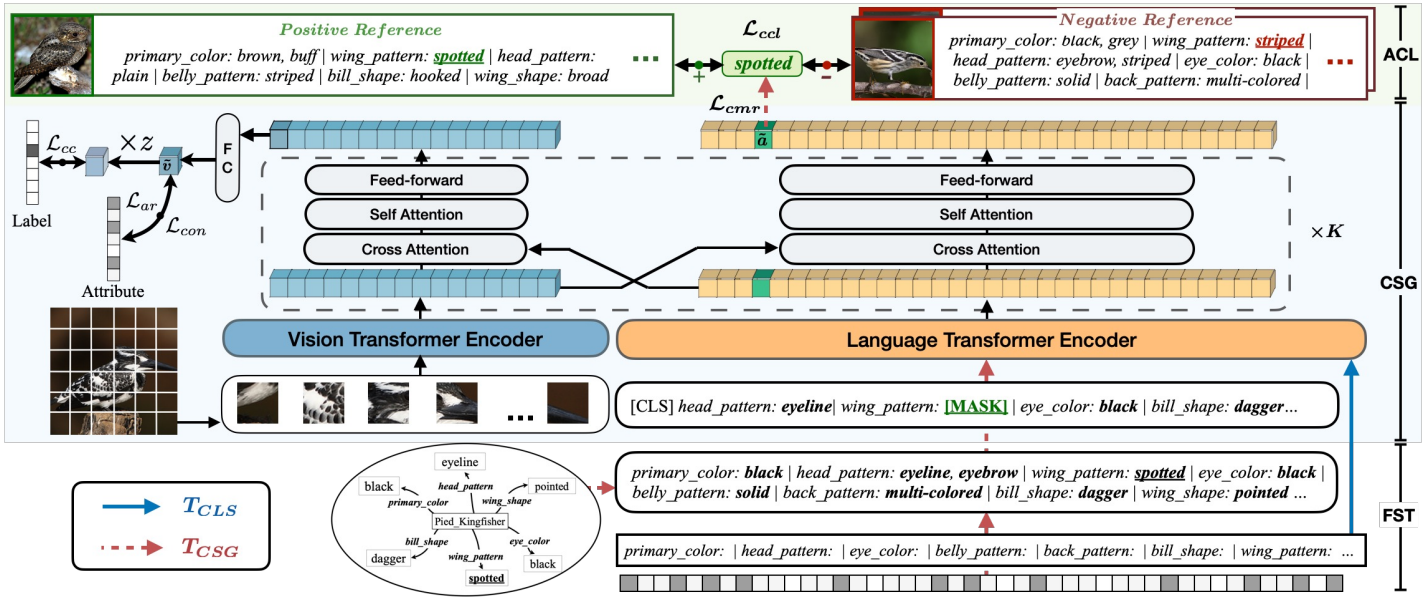
Cross-modal Semantic Grounding for ZSL

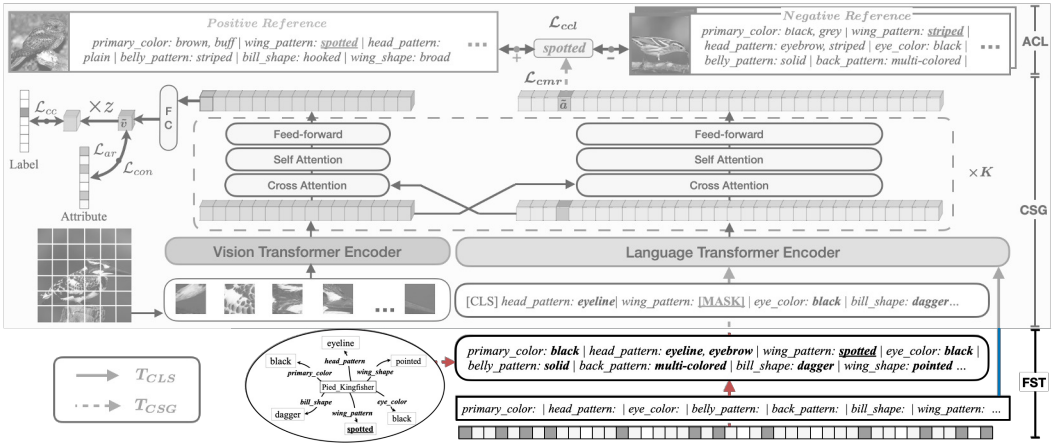


- Attribute-level Contrastive Learning (ACL)
- Cross-modal Semantic Grounding (CSG)
- Feature-to-Sequence Transformation (FST)

Chen, Zhuo, et al. "DUET: Cross-modal Semantic Grounding for Contrastive Zero-shot Learning." AAAI 2023.

Cross-modal Semantic Grounding for ZSL

1. Transform different types of attributes into a textual sequence
2. Make our model compatible to multiple ZSL tasks with different side information



$$\mathcal{D}_s = \{(x^s, y^s) | x^s \in \mathcal{X}^s, y^s \in \mathcal{Y}^s\}$$
$$\mathcal{D}_u = \{(x^u, y^u) | x^u \in \mathcal{X}^u, y^u \in \mathcal{Y}^u\}$$

unseen classes ($\mathcal{C}^u$)
seen classes ($\mathcal{C}^s$)
$$c \in \mathcal{C} = \mathcal{C}^s \cup \mathcal{C}^u$$

$$\mathcal{A} = \{a_1, \ldots, a_{|\mathcal{A}|}\}$$
$$z^c = \left[z_1^c, \ldots, z_{|\mathcal{A}|}^c\right]^\top$$

..| color : brown | haspart : tail, flippers, ... |...

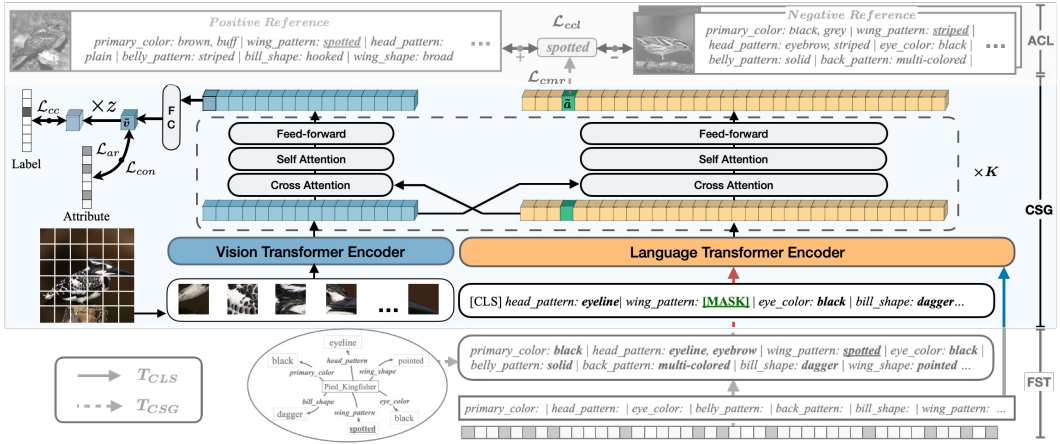
Prompt | Attribute | Prompt | Attributes

Chen, Zhuo, et al. “DUET: Cross-modal Semantic Grounding for Contrastive Zero-shot Learning.” AAAI 2023.

Cross-modal Semantic Grounding for ZSL

- Attribute Phrase Masking (APM)
  - Linear weighted random sampling (LWRS)
  - Random attributes pruning (RAP)

$$a_t = LWRS(\mathcal{A})$$
$$\mathcal{A}_{rap} = RAP(r_{rap}, \mathcal{A})$$



- Cross-modal Mask Reconstruction (CMR)

$$\mathcal{L}_{cmr} = \mathbb{E}_{x\sim\mathcal{X}^s}[-\boldsymbol{z_{a_t}}\sum_{i=1}^{Len(w)}\log P(w_i \mid \widehat{\mathcal{A}}_{rap\setminus t}, x)]$$

- Basic ZSL Classification Objective
  - Attribute regression ($\mathcal{L}_{ac}$)
  - Class cross-entropy ($\mathcal{L}_{cr}$)
  - class-level supervised contrastive ($\mathcal{L}_{con}$)

$$\mathcal{L}_{ar} = \mathbb{E}_{x\sim\mathcal{X}^s}\|\tilde{v} - z\|_2^2$$
$$\mathcal{L}_{cc} = \mathbb{E}_{x\sim\mathcal{X}^s}[-\log\frac{\exp(\tilde{v}\cdot z)}{\sum_{\hat{c}\in\mathcal{C}^s}\exp(\tilde{v}\cdot z^{\hat{c}})}]$$
$$\mathcal{L}_{con} = \mathbb{E}_{x\sim\mathcal{X}^s}[-\log f_\theta(\tilde{v}\mid s, x)]$$

$$f_\theta = \frac{\exp(D(\tilde{v},\tilde{v}^+)/\tau)}{\exp(D(\tilde{v},\tilde{v}^+)/\tau) + \sum_{\tilde{v}'\in\mathcal{N}(\tilde{v})}\exp(D(\tilde{v},\tilde{v}')/\tau)}$$

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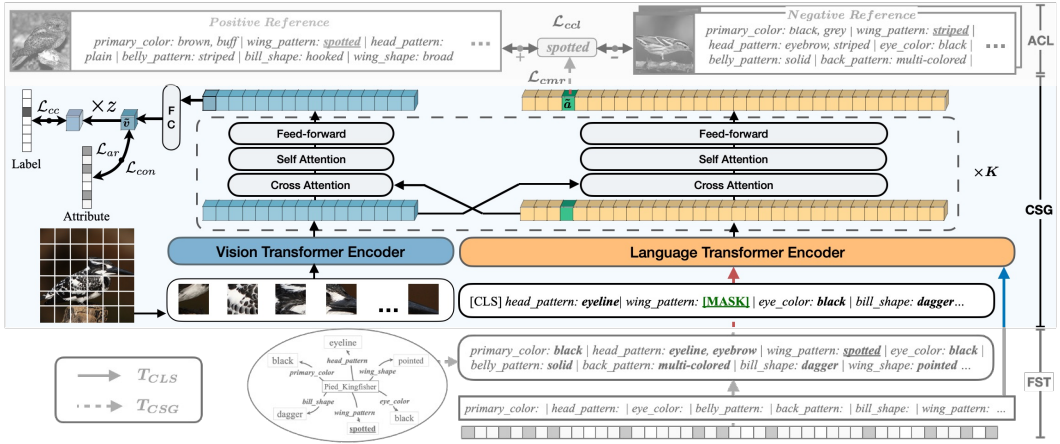
Cross-modal Semantic Grounding for ZSL

- Two Stage
  - T_{CSG} : cross-modal semantic grounding
  - T_{CLS} : simple image classification without textual attributes

..| color : | haspart : | pattern : | shape : |...

Prompt Prompt Prompt Prompt



- Multi-task Learning

$$L_{CLS} = \mathcal{L}_{zsl} + \lambda_{con}\mathcal{L}_{con}$$
$$L_{CSG} = \mathcal{L}_{zsl} + \lambda_{cmr}\mathcal{L}_{cmr}$$

$$\mathcal{L}_{zsl} = \mathcal{L}_{cc} + \lambda_{ar}\mathcal{L}_{ar}$$

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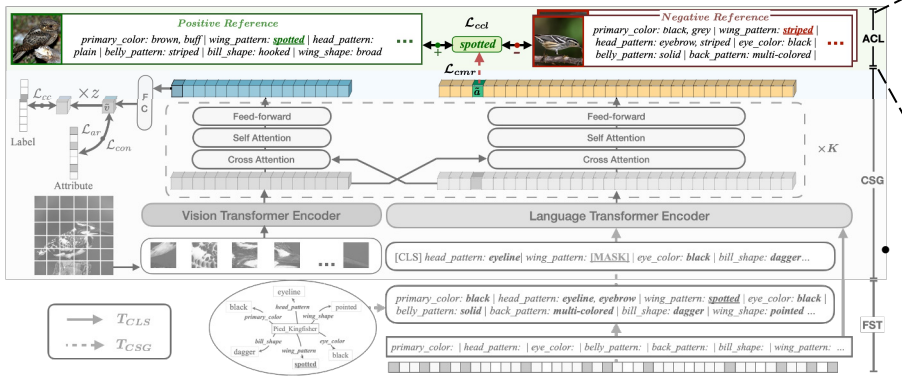
Cross-modal Semantic Grounding for ZSL

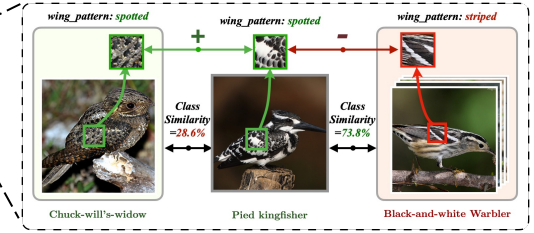
$$\mathcal{L}_{acl} = \mathbb{E}_{x\sim\mathcal{X}^s}[-Min(z_a, z_{a^+}) \log f_\phi(\tilde{a} \mid s, x)]$$

$$f_\phi = \frac{\exp(D(\tilde{a}, \tilde{a}^+)/\tau)}{\exp(D(\tilde{a}, \tilde{a}^+)/\tau) + \sum_{\tilde{a}'\in\mathcal{N}(\tilde{a})} \exp(D(\tilde{a}, \tilde{a}')/\tau)}$$

- Attribute-based (negative) sampling strategy:

$$L_{CSG} \longleftarrow L_{CSG} + \mathcal{L}_{acl}$$





- Select
  - those distinctive classes as positive references when they are associated with at least one common attribute (e.g., "spotted")
  - those similar classes as negative references when they have mutually exclusive attributes (e.g., "striped") toward the same aspect (e.g., "wing pattern")

Chen, Zhuo, et al. "DUET: Cross-modal Semantic Grounding for Contrastive Zero-shot Learning." AAAI 2023.

Cross-modal Semantic Grounding for ZSL

..| color : [MASK] | haspart : [MASK] |..
Prompt Prompt

Image Case	Prompt	Attribute
oilrig (S) 	transportation function	DUET : boating (46.60%) swimming (34.39%) digging (19.01%)
		GT : boating (51.99%) swimming (12.71%)
	coarse meterial	DUET : metal (39.91%) ocean (37.55%) wire (22.54%)
		GT : ocean (48.52%) metal (43.90%) wire (6.93%)
	specific meterial	DUET : fire (40.75%) waves (37.78%) smoke (21.47%)
		GT : still water (24.26%) waves (16.17%) fire (15.08%)
living room (S) 	environment function	DUET : reading (55.42%) eating (31.13%) working (13.45%)
		GT : reading (46.60%) eating (12.33%) socializing (6.85%)
	specific meterial	DUET : cloth (39.55%) flowers (38.47%) tiles (21.98%)
		GT : carpet (28.78%) cloth (23.30%) flowers (10.96%)
	feeling	DUET : soothing (59.97%) symmetrical (32.92%) cluttered (7.11%)
		GT : soothing (49.33%)
basketball arena (U) 	environment function	DUET : sports (49.15%) playing (32.78%) socializing (18.07%)
		GT : congregating (47.31%) sports (43.48%) playing (11.51%)
	technical function	DUET : competing (40.00%) audience (36.19%) exercise (23.81%)
		GT : competing (52.43%) audience (52.43%) exercise (17.90%)
	surface	DUET : glossy (41.56%) rusty (32.74%) sterile (25.70%)
		GT : glossy (17.90%) dry (15.34%)
bus depot (U) 	transportation function	DUET : driving (42.95%) biking (37.98%) climbing (19.07%)
		GT : driving (41.53%) biking (17.96%)
	coarse meterial	DUET : asphalt (34.28%) metal (33.71%) concrete (32.01%)
		GT : asphalt (38.94%) metal (22.06%) pavement (20.77%)
	light	DUET : natural (57.30%) indoor (33.55%) direct sun/sunny (9.15%)
		GT : natural (54.51%) direct sun/sunny (20.36%)

Figure 6: Attribute prediction for interpretation.

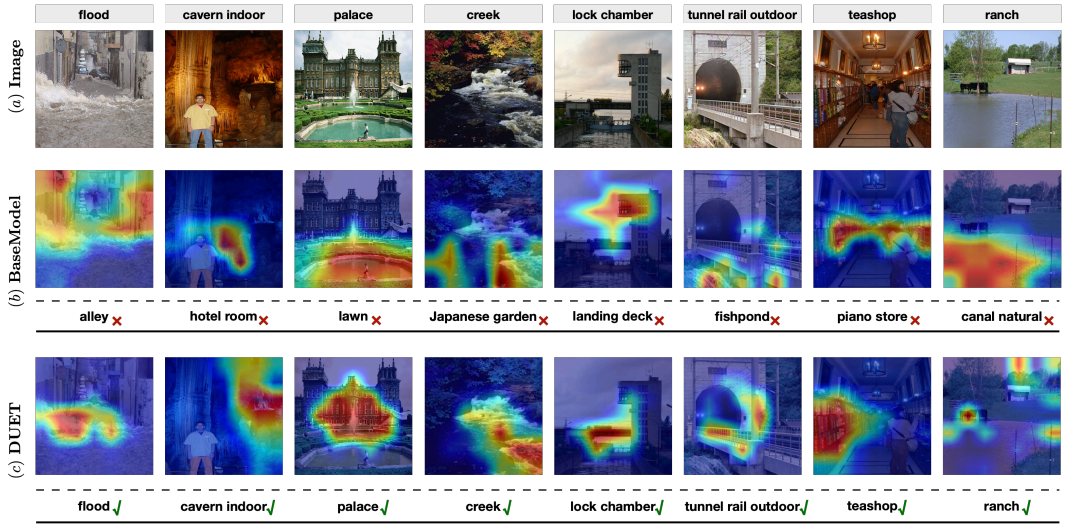


Figure 8: Visualization of attention maps together with attribute grounding results. (a) Original images. (b) BaseModel: Only using ENC_{vis} without cross-modal semantic grounding (CSG) and attribute-level contrastive learning (ACL). (c)DUET.

Chen, Zhuo, et al. “DUET: Cross-modal Semantic Grounding for Contrastive Zero-shot Learning.” AAAI 2023.

More Reading

- Adaptive and Generative Zero-Shot Learning. ICLR 2021
- TransZero: Attribute-guided Transformer for Zero-Shot Learning. AAAI 2022
- MSDN: Mutually Semantic Distillation Network for Zero-Shot Learning. CVPR 2022
- Progressive Semantic-Visual Mutual Adaption for Generalized Zero-Shot Learning. CVPR 2023
- Decomposed soft prompt guided fusion enhancing for compositional zero-shot learning . CVPR 2023

T7

KG Structure Pretraining for KG-aware ZSL

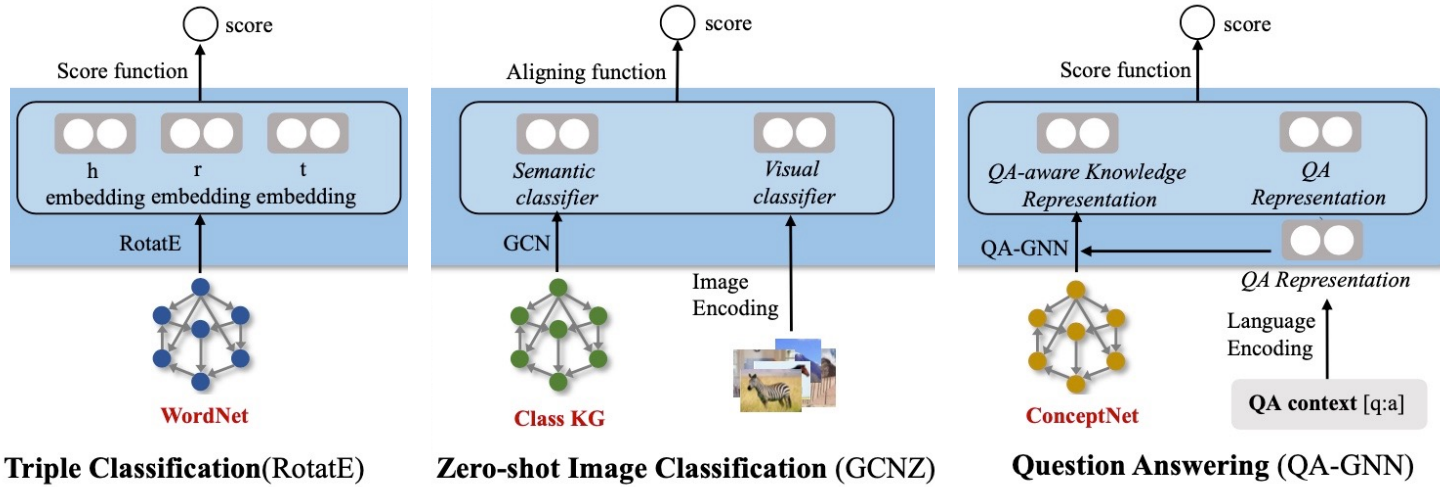
KGTransformer

- Knowledge graphs are useful resource for many tasks
  - Knowledge management
  - Natural Language Understanding
  - Zero-shot Learning (of course ;))
  - …
- Question:
  - How is knowledge graph used into those task models?

Zhang, Wen et al. “Structure Pretraining and Prompt Tuning for Knowledge Graph Transfer.” WWW 2023.

KGTransformer

- Examples:

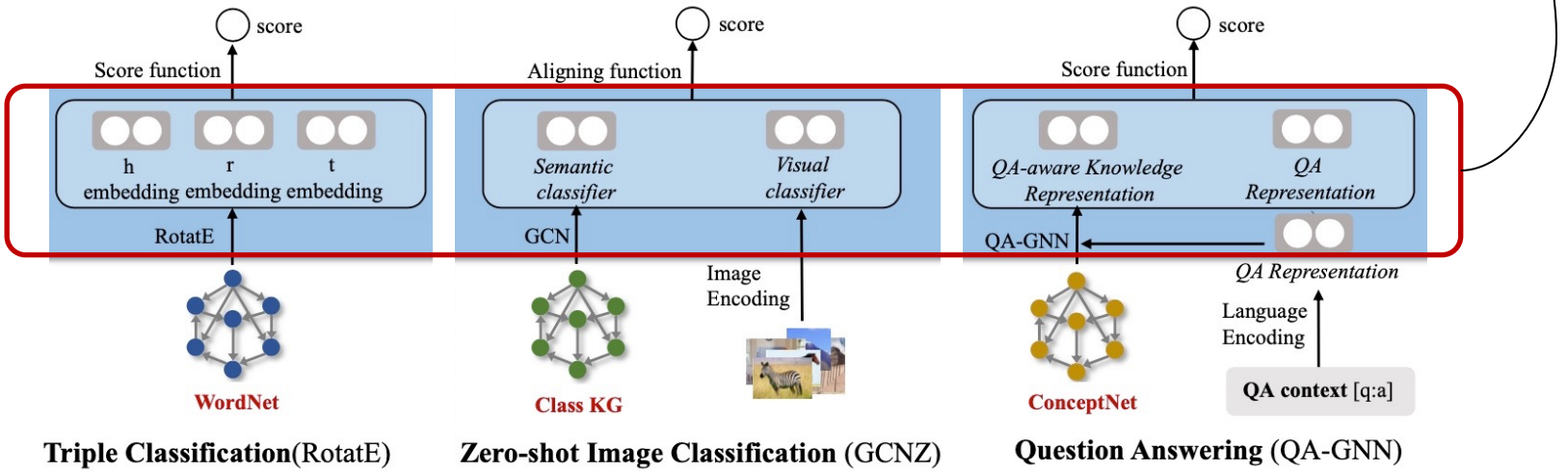


Zhang, Wen et al. “Structure Pretraining and Prompt Tuning for Knowledge Graph Transfer.” WWW 2023.

KGTransformer

- Examples:

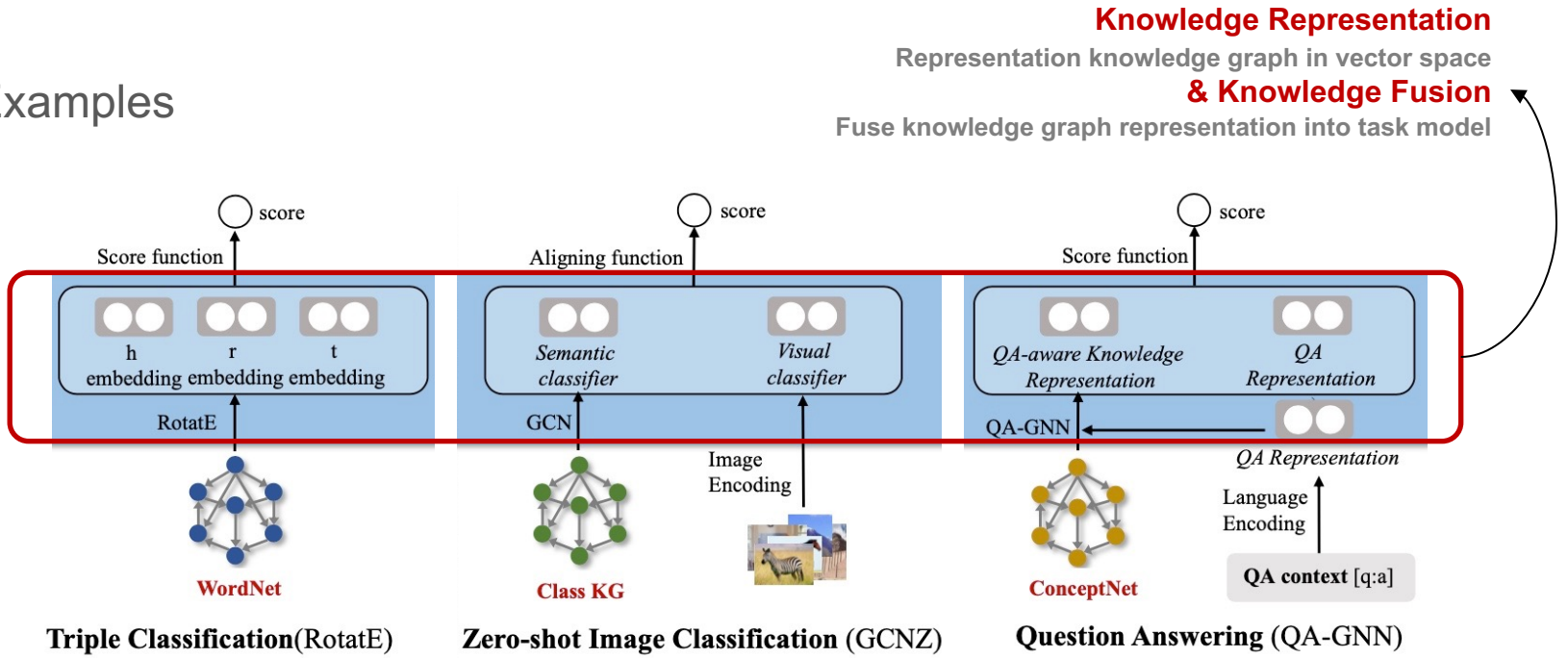
Knowledge Representation
Representation knowledge graph in vector space
& Knowledge Fusion
Fuse knowledge graph representation into task model



Zhang, Wen et al. “Structure Pretraining and Prompt Tuning for Knowledge Graph Transfer.” WWW 2023.

KGTransformer

- Examples



  - They all have knowledge representation and fusion module
  - The knowledge graphs used in the task are different

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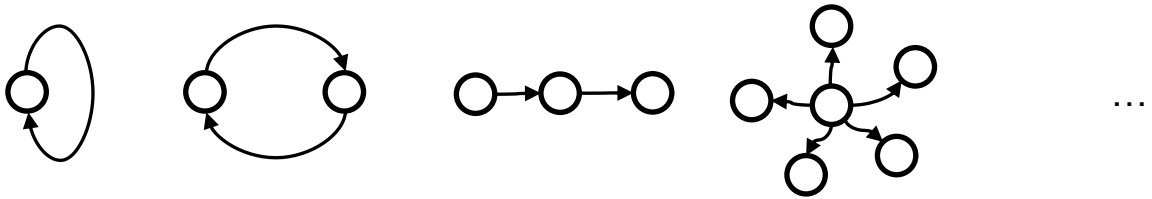
KGTransformer

- Knowledge graphs
  - YAGO, Wikidata, ConceptNet, …
  - They have common structures
    - Circles
    - Paths
    - Star shapes
    - …



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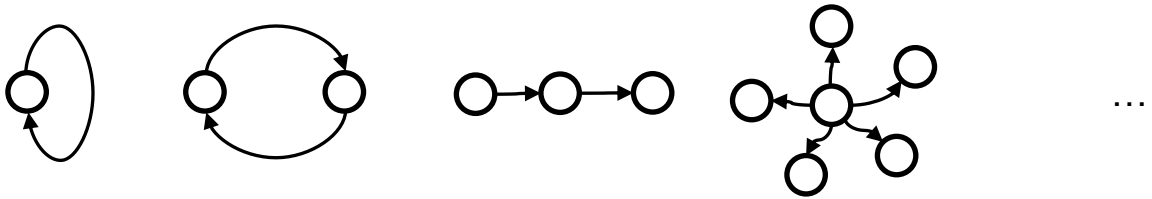
KGTransformer

- Knowledge graphs
  - YAGO, Wikidata, ConceptNet, …
  - They have common structures
    - Circles
    - Paths
    - Star shapes
    - …

Pre-train KG ?!
(Structure Pre-train)



…

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KGTransformer

- Pre-trained knowledge graph model (PKGM)
  - Learn universal embeddings of entities and relations that could be applied in many tasks
  - These embeddings are supposed to contain
    - Entity similarity
    - Hierarchies
    - Relationships
    - …
  - Challenges
    1. What if the task KG and the pre-trained KG have different entities and relations?
    2. Essential interaction and fusion between KG and the task data is missing.
       - designing a fusion module as part of the work for downstream task model devising

Zhang, Wen et al. “Structure Pretraining and Prompt Tuning for Knowledge Graph Transfer.” WWW 2023.

KGTransformer

- Pre-trained knowledge graph model (PKGM)
  - Learn universal embeddings of entities and relations that could be applied in many tasks
  - These embeddings are supposed to contain
    - Entity similarity
    - Hierarchies
    - Relationships
    - …
  - Challenges
    1. What if the task KG and the pre-trained KG have different entities and relations?
       - ➢ Be unrelated to specific entities and relations
    2. Essential interaction and fusion between KG and the task data is missing.
       - ➢ Prompt tuning to enable uniform and flexible fusion

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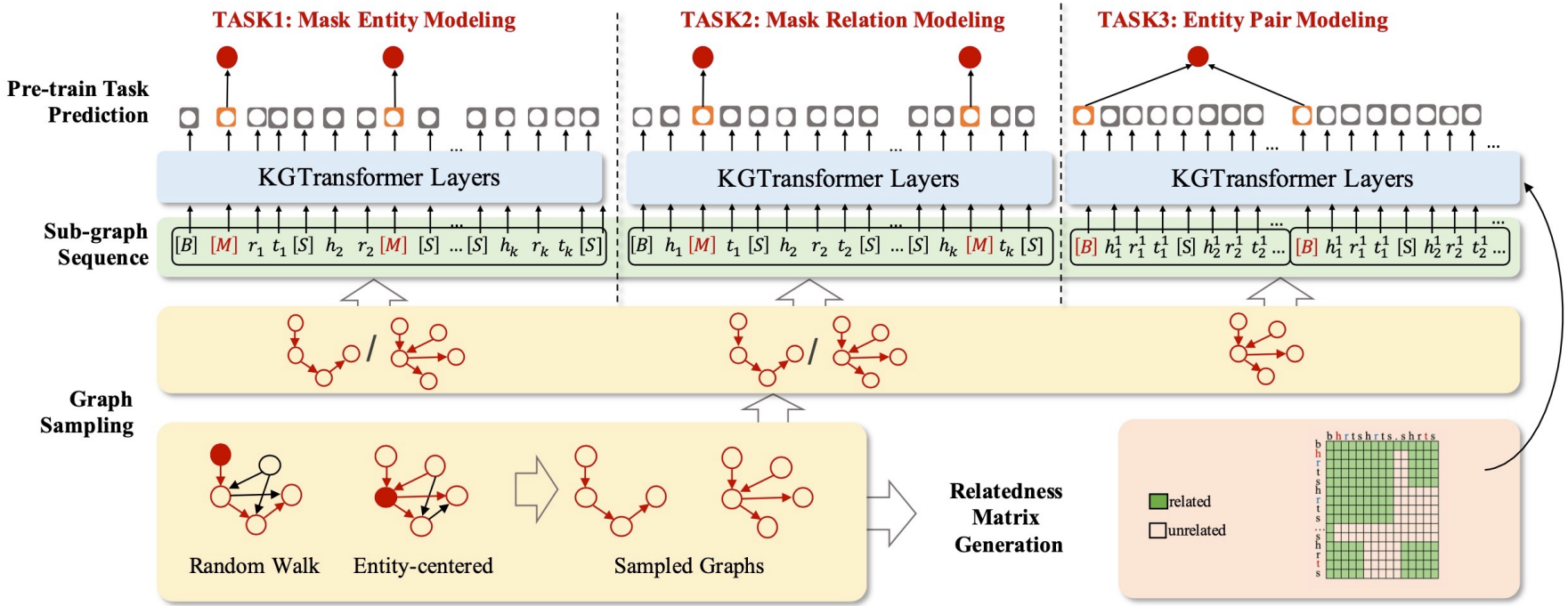
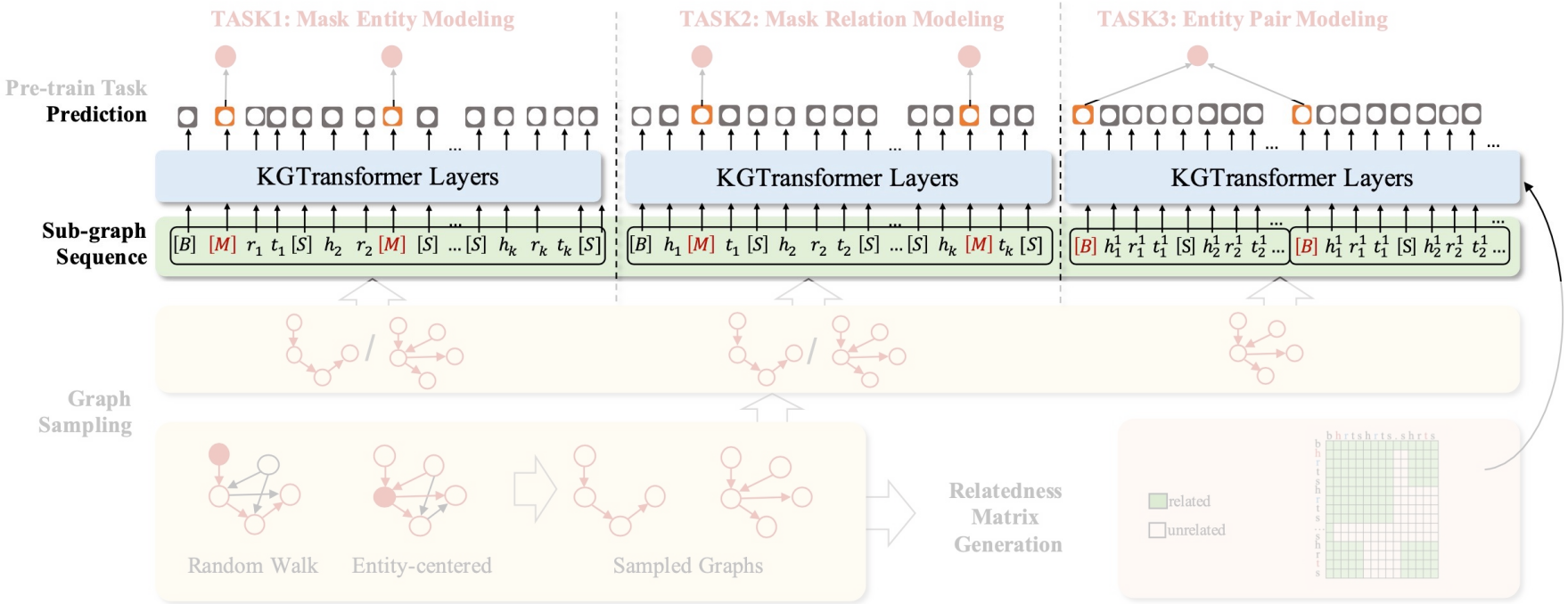
KGTransformer



KGTransformer



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KGTransformer

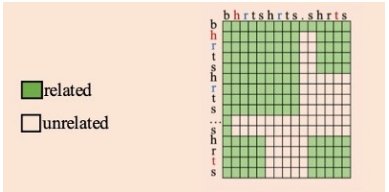
- KGTransformer layer
  - Subgraph sequence as input

$$s_{in} = [[B], h_1, r_1, t_1, [S], h_2, r_2, t_2, [S], ..., h_k, r_k, t_k, [S]]$$

  - Modified transformer layer with relatedness matrix

$$M_{ij} = \begin{cases} 1 \text{ if } i = 1 \text{ or } j = 1 \\ 1 \text{ if } trp(i) \cap trp(j) \neq \emptyset \\ 0 \text{ otherwise} \end{cases},$$

$$trp(n) = \{h_p, r_p, t_p\} \text{ where } p = \lfloor (n-2)/4 \rfloor + 1$$



  - Attention

$$Q = HW_Q,\ K = HW_K,\ V = HW_V,$$

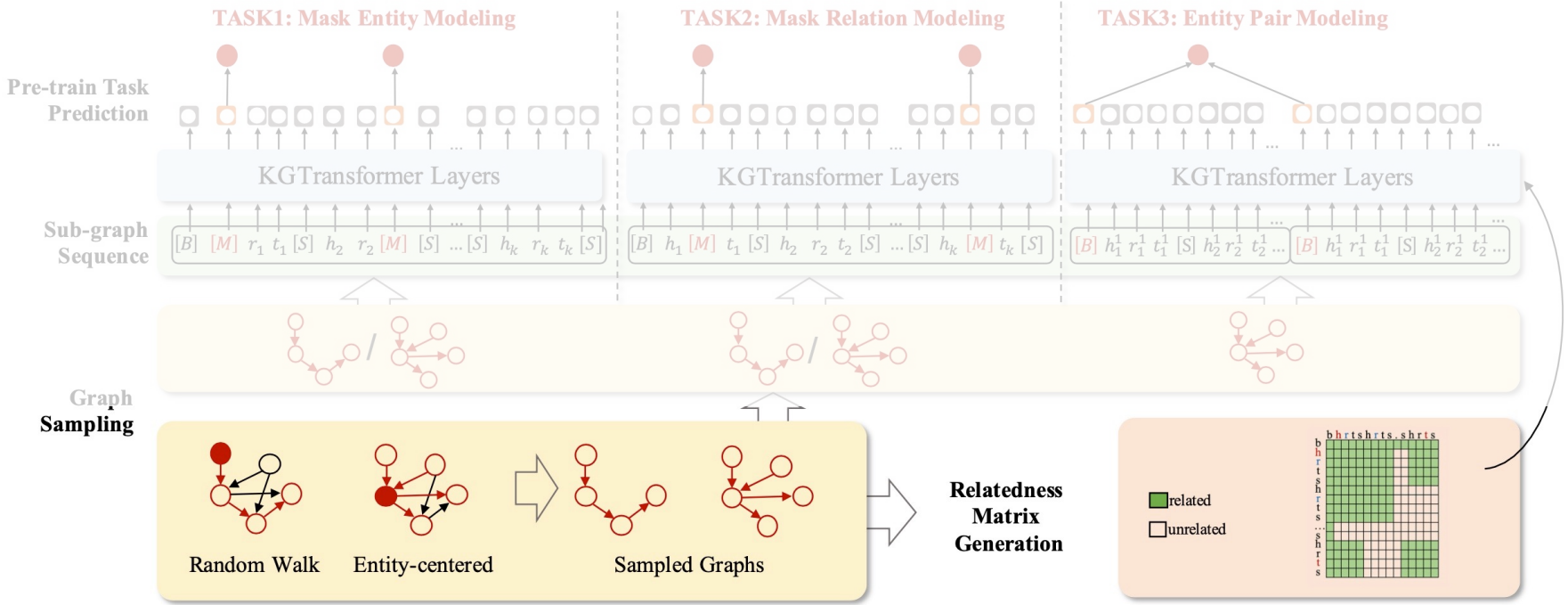
$$A = \frac{QK^\top \odot M}{\sqrt{d_K}} + (1 - M) * \delta,$$

$$Attn(H) = softmax(A)V,$$

Compare to GNN & Conventional Transformer:
- (William Shakespeare, field of work, Fiction)
- (France, capital, Paris)
- (William Shakespeare, notable book, Hamlet)

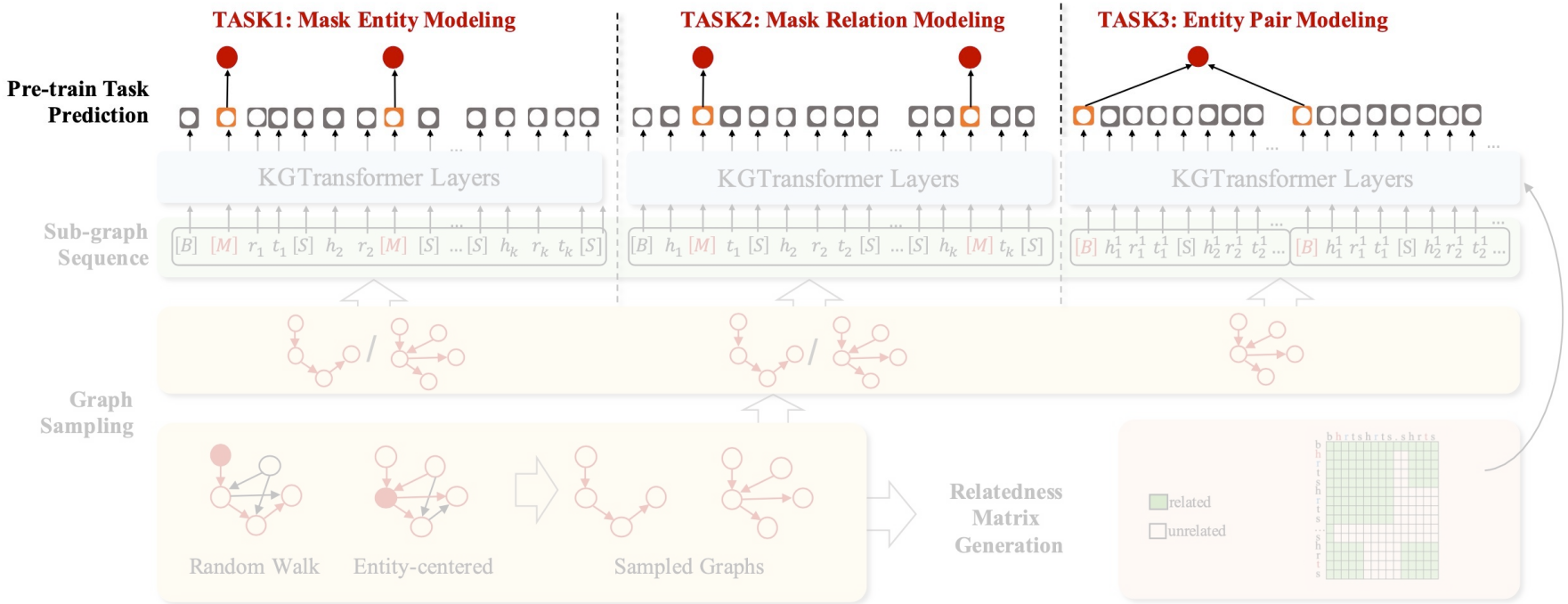
KGTransformer

- Graph Sampling



KGTransformer

- Pre-training Task



KGTransformer

- Masked Entity Modeling (MEM)

$$L_{MEM}(\mathcal{G}_e) = \sum_{e \in \mathcal{M}_e} CE(s_e^m W_{MEM} \mathbf{E}(e)^\top, 1) + \sum_{e' \in \Delta} CE(s_e^m W_{MEM} \mathbf{E}(e')^\top, 0),$$

- Masked Relation Modeling (MRM)

$$L_{MRM}(\mathcal{G}_e) = \sum_{r \in \mathcal{M}_r} CE(MLP(s_r^m W_{MRM}), l_r), \; W_{MRM} \in \mathbb{R}^{d \times d}$$

- Entity Pair Modeling(EPM)

$$L_{EPM}(\mathcal{G}_{e_i}, \mathcal{G}_{e_j}) = CE(MLP([s^m_{[B]_{e_i}} || s^m_{[B]_{e_j}}]), l_{(e_i,e_j)})$$

- Training objective

$$L(\mathcal{G}) = \sum_{e \in \mathcal{E}} (L_{MEM}(\mathcal{G}_e^1) + L_{MRM}(\mathcal{G}_e^2) + L_{EPM}(\mathcal{G}_e^3, \mathcal{G}_{e'}))$$

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- Prompt Tuning

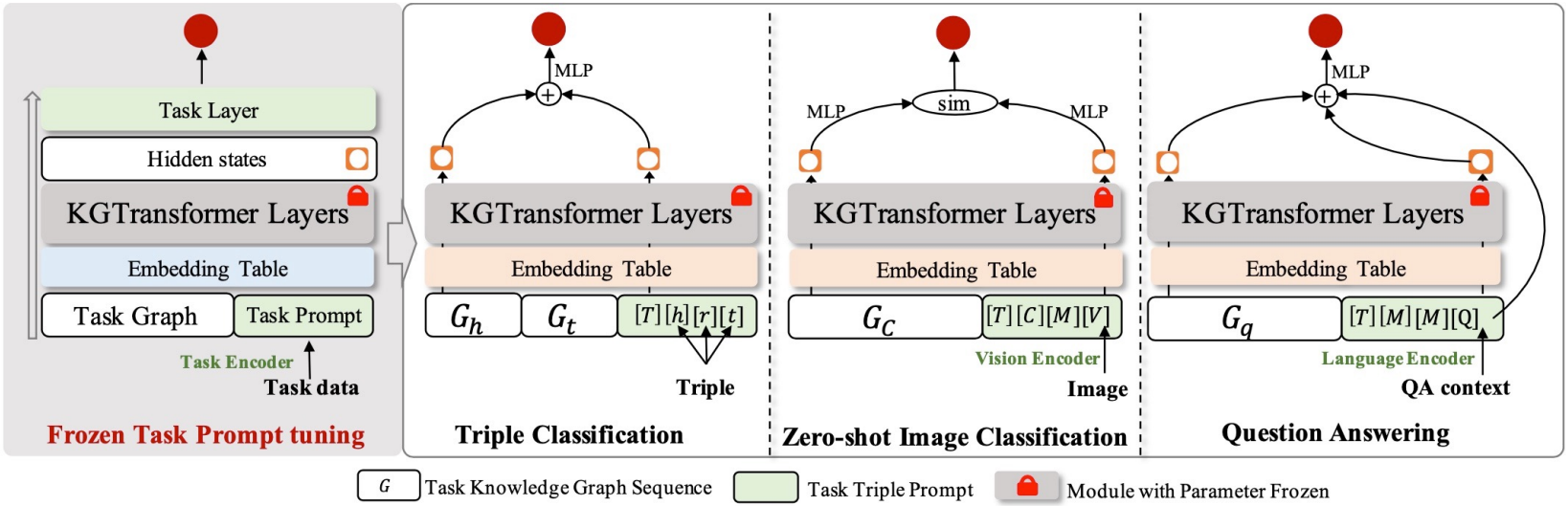

Figure 3: Overview of task prompt tuning (left) and examples of three specific tasks (right).

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KGTransformer

- Experiment
  - Pre-training dataset

	#R	#E	# T	Std_{rel}	Std_{ent}	Density($\times 10^{-6}$)
WFC	317	133435	1015556	13230	134	0.18
wn18rr	11	40943	93003	12540	9	5.04
$fb15k-237$	237	14541	310115	2467	128	6.19
codex	69	77951	612437	24664	159	1.46

  - Task datasets

	Task KG				**Task Data**				**Properties**		
	KG	#E	#R	#T	Task Sample	# Train	#Valid	#Test	Task Type	Modality	Overlap to WFC
T1: Triple Classification	WN18RR	40943	11	-	Triple	86835	6068	6268	in-KG	KG	Yes
T2: ZSL Image Classification	AwA-KG	146	16	1595	Image	23527	-	13795	out-of-KG	Image+KG	No
T3: Question Answering	CommonsenQA	64388	16	309444	QA pair	8500	1221	1241	out-of-KG	Language+KG	No

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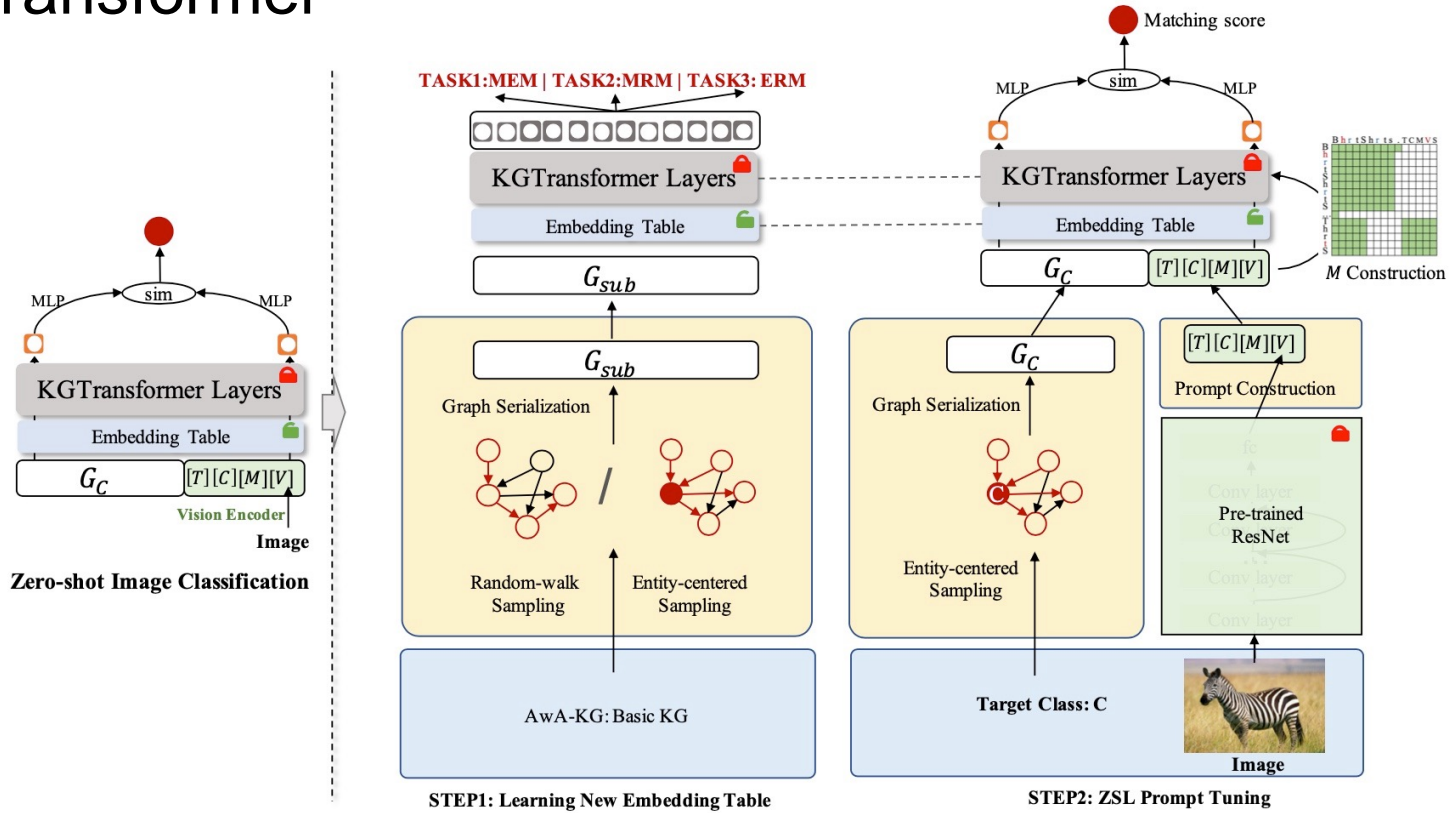

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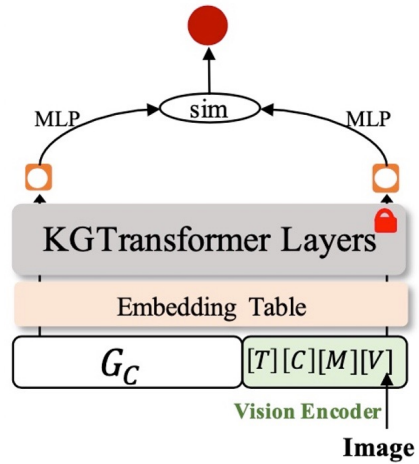
KGTransformer

- Zero-shot image classification results on AwA-KG



Zero-shot Image Classification

	T1	S	U	H
DeViSE[10]	43.24	**86.44**	6.40	11.91
GCNZ[60]	62.98	75.59	20.28	31.98
OntoZSL[14]	62.65	59.59	50.58	54.71
KGTransformer	**66.26**	61.13	**55.14**	**57.98**
KGT-finetune	63.59	63.61	50.08	56.04
KGT-scratch	58.96	56.48	47.93	51.85

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KGTransformer

- Triple classification on WN18RR

	Acc.	Precision	Recall	F1
TransE [3]	88.35	93.45	82.48	87.62
RotatE [46]	88.26	93.03	82.71	87.57
ComplEx [50]	85.07	**96.73**	72.59	82.94
KGTransformer	**89.21**	85.56	**94.32**	**89.73**
KGT-finetune	87.48	83.02	94.22	88.27
KGT-scratch	67.02	67.91	64.55	66.19

- QA Accuracy on CommonsenceQA

	IHdev	IHtest
RoBERTa-Large [34]	73.07	68.69
RoBERTa-Large [34](ours)	72.24	68.49
+ GconAttn [59]	72.61	68.59
+ KagNet [28]	73.47	69.01
+ MHGRN [9]	74.45	71.11
+ QA-GNN [67]	76.54	73.41
+ ***KGTransformer***	77.64	74.13
+ *KGT-finetune*	**78.05**	**74.21**
+ *KGT-scratch*	72.32	69.22

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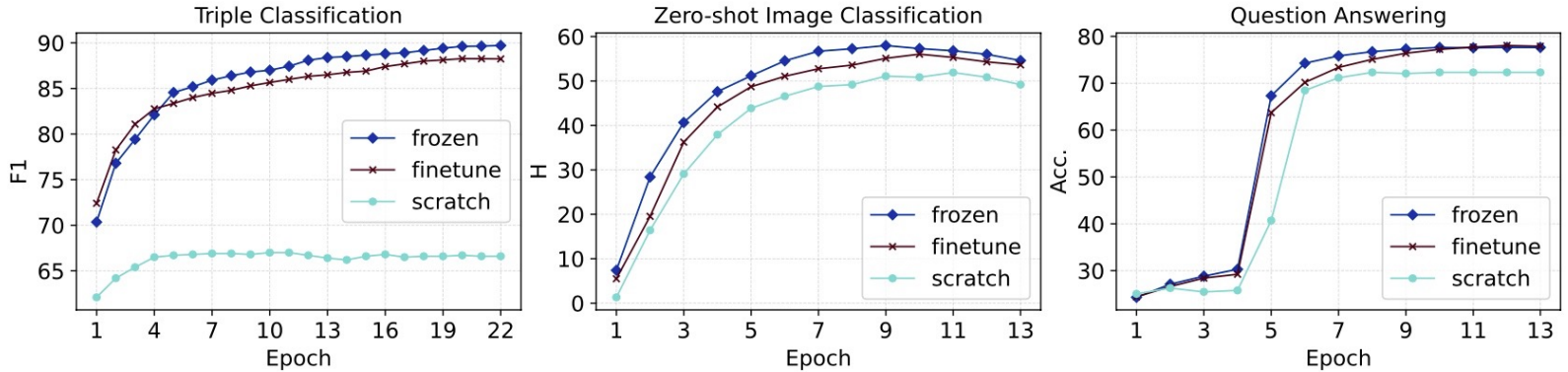
KGTransformer

	Triple Classification				Zero-shot Image Classification				Question Answering	
	Acc.	Precision	Recall	F1	T1	S	U	H	IHdev	IHtest
KGTransformer	89.20	85.56	94.32	89.73	66.26	61.13	55.14	57.98	77.64	74.13
- MEM	86.85	82.15	94.16	87.74	63.44	61.49	52.77	56.80	75.84	72.60
- MRM	84.91	79.42	94.22	86.19	62.36	66.41	47.97	55.70	74.45	71.47
- EPM	87.78	83.54	94.10	88.51	65.73	64.13	52.50	57.74	76.33	72.84
-*M*	74.15	67.43	93.42	78.33	61.47	59.98	36.33	45.25	74.12	69.70



Zhang, Wen et al. “Structure Pretraining and Prompt Tuning for Knowledge Graph Transfer.” WWW 2023.

Conclusion

- Data augmentation
  - OntoZSL [Geng et al. WWW'21], DOZSL [Geng et al. KDD'22]
- Feature Propagation
  - GCNZ [Wang et al. CVPR'18], X-ZSL [Geng et al. SWJ'21], DOZSL [Geng et al. KDD'22], RMPI [Geng et al. ICDE'23]
- KG for VQA
  - ZS-F-VQA [Chen et al. ISWC'21]
- Semantic Grounding
  - DUET [Chen et al. AAAI'23]
- Transformer
  - KGTransformer [Zhang et al. WWW'23]

See our hands-on session (Part III) for more details of experimenting with representative KG-aware ZSL methods

Thanks!

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