Attribute Propagation Network for Graph Zero-shot Learning

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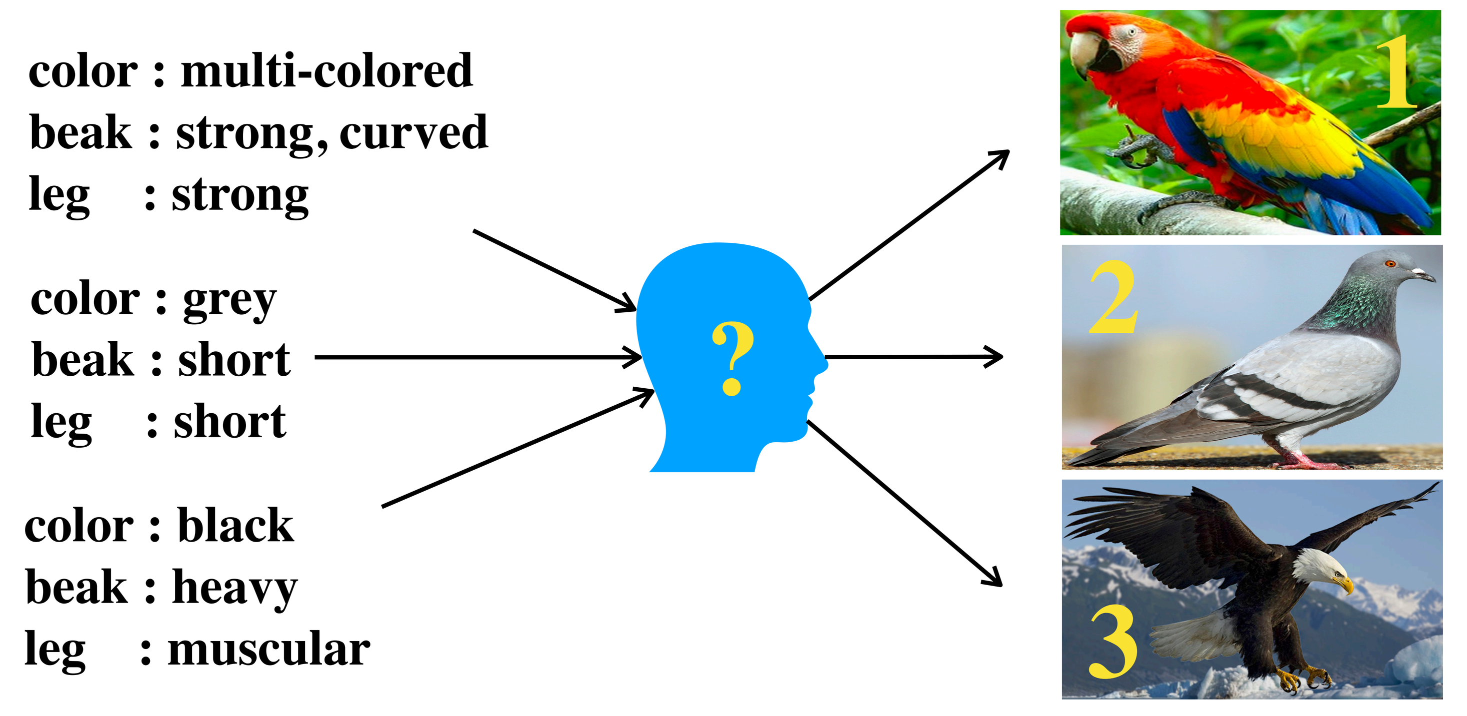
Instructions for reading this poster

Are you familiar with zero-shot learning?

Yes → Go to 2. for pipeline of our method and 3. for more details → Go to 4. & 5. for experiment results → Thank you for reading our poster !

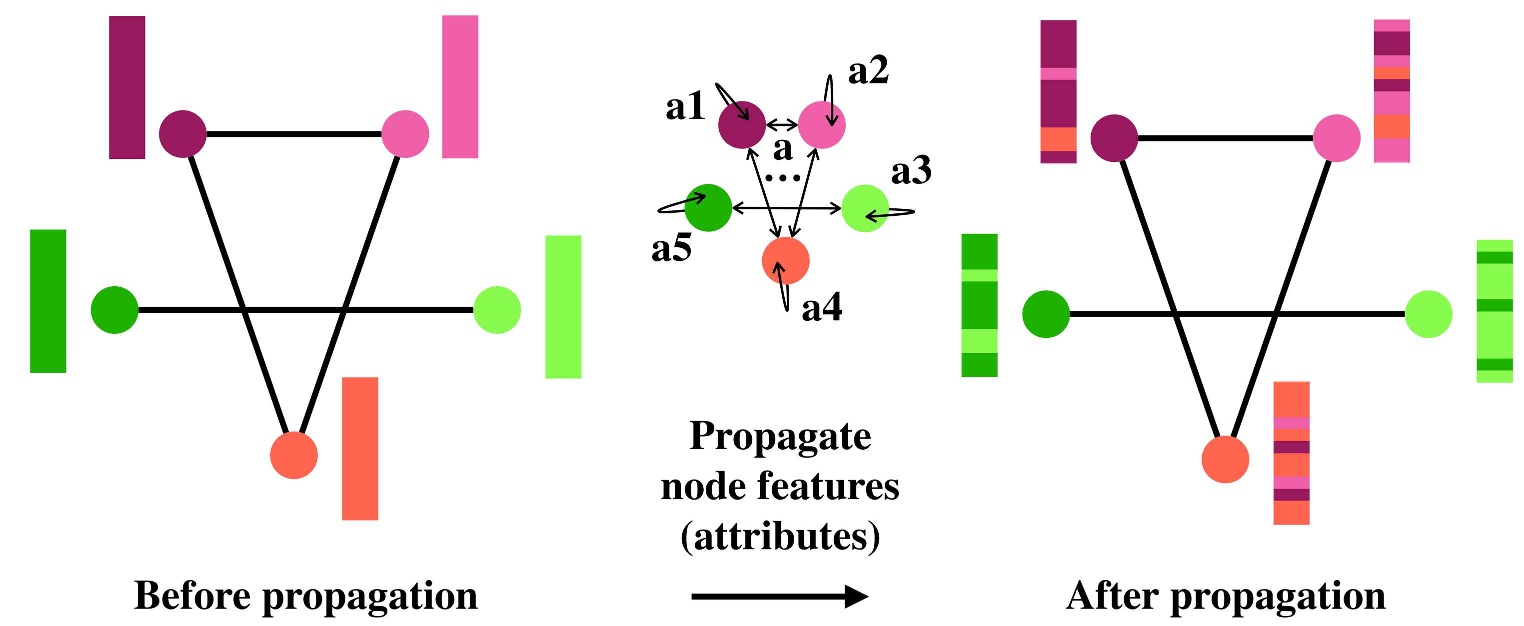
No → Go to 1. for problem introduction → Go to 2. for pipeline of our method and 3. for more details

1. Zero-shot Learning



Formally, we assume that a training set $\mathcal{X}^{tr}$ and a test set $\mathcal{X}^{te}$ are sampled from a data space $\mathcal{X}$. Each training data $\boldsymbol{x} \in \mathcal{X}^{tr}$ is annotated with a label $y \in \mathcal{Y}^{seen}$. The model is tested over $\mathcal{X}^{te}$, which are not only from the seen classes $\mathcal{Y}^{seen}$ but also the unseen classes $\mathcal{Y}^{unseen}$. The challenge is that the seen and unseen classes have no overlaps: $\mathcal{Y}^{seen} \cap \mathcal{Y}^{unseen} = \emptyset$. Hence, the semantic attributes $\boldsymbol{S}$ for each class is made available during both training and testing to act as a bridge between training classes and test classes. Specifically, every class $y \in \mathcal{Y}^{seen} \cup \mathcal{Y}^{unseen}$ is associated with a semantic embedding vector $\boldsymbol{s}_y \in \boldsymbol{S}$.

3. Attribute Propagation on the Graph

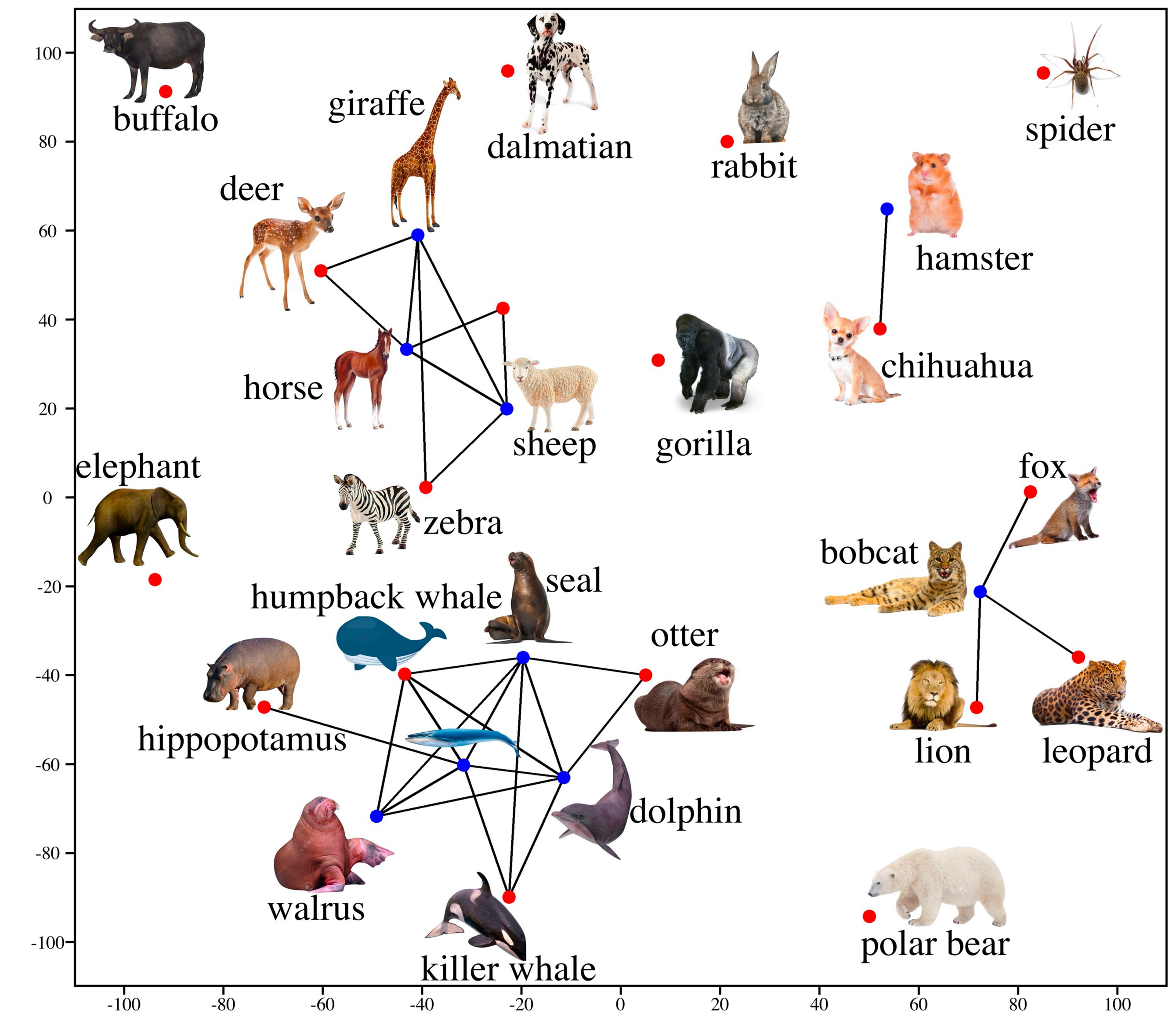


Before propagation: The nodes with different colors represent different classes and the node features are the attribute features X of the associated class. Propagating the node features (attributes): Propagation computes a weighted sum of its neighbors' node features, where the weights are produced by an attention module.

propagation $$\boldsymbol{X}_y^{t+1} \leftarrow \sum_{z \in \mathcal{N}_y} a'(\boldsymbol{X}_y^t, \boldsymbol{X}_z^t) \times \boldsymbol{X}_z^t$$

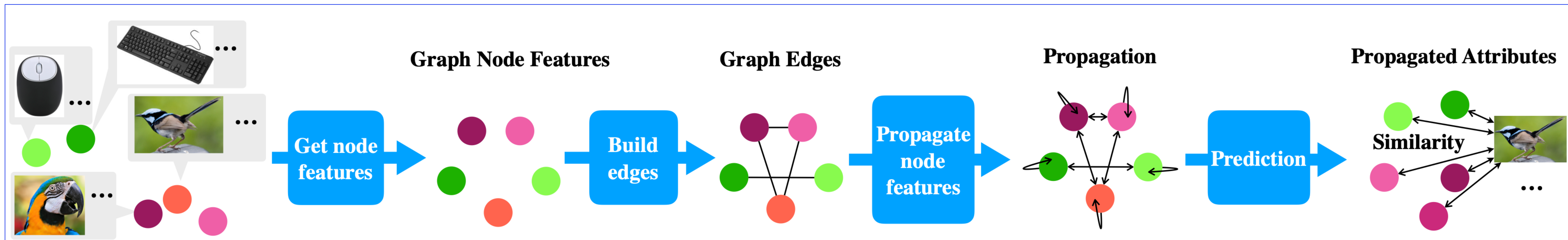
attention $$a'(\boldsymbol{X}_y^t, \boldsymbol{X}_z^t) = \frac{\exp[\gamma_1 a(\boldsymbol{X}_y^t, \boldsymbol{X}_z^t)]}{\sum_{z \in \mathcal{N}_y} \exp[\gamma_1 a(\boldsymbol{X}_y^t, \boldsymbol{X}_z^t)]}$$

5. T-SNE Visualization



Visualization of the *refined attribute vector* per class produced by APNet using t-SNE and the *graph of classes* generated based on given semantic embedding per class. The red nodes and blue nodes are the propagated attribute vectors for training classes and test classes, respectively.

2. Pipeline



We train a propagation scheme and a similarity metric on a set of training tasks. For a new task:

1. **Initialize the nodes features**: the attribute vectors of different classes are represented by different-colored dots. Each attribute vector is associated with some images from the corresponding class.
2. **Determine the graph edges**: Two nodes on the propagation graph are connected by an edge if the similarity between their feature vectors exceeds a pre-determined threshold.
3. **Propagation on the graph**: The node features are propagated by an attention mechanism for steps.
4. **Zero-shot prediction**: After propagation, we achieve an attribute representation for each class. Given a query image's representation, we compute its similarity to all the candidate classes' attribute representations by using a meta-trained similarity metric and predict its class as the one with the largest similarity.

4. Main Result

Methods	SUN			CUB			AWA1			AWA2			aPY		
	S	U	H	S	U	H	S	U	H	S	U	H	S	U	H
DEVISE (Frome et al. 2013)	27.4	16.9	20.9	53.0	23.8	32.8	68.7	13.4	22.4	74.7	17.1	27.8	76.9	4.9	9.2
CONSE (Norouzi et al. 2013)	39.9	6.8	11.6	**72.2**	1.6	3.1	88.6	0.4	0.8	90.6	0.5	1.0	**91.2**	0.0	0.0
SYNC (Changpinyo et al. 2016)	**43.3**	7.9	13.4	70.9	11.5	19.8	87.3	8.9	16.2	90.5	10.00	18.0	66.3	7.4	13.3
SAE (Kodirov, Xiang, and Gong 2017)	18.0	8.8	11.8	54.0	7.8	13.6	77.1	1.8	3.5	82.2	1.1	2.2	80.9	0.4	0.9
DEM (Zhang, Xiang, and Gong 2017)	34.3	20.5	25.6	57.9	19.6	29.2	84.7	32.8	47.3	86.4	30.5	45.1	75.1	11.1	19.4
RN (Sung et al. 2018)	-	-	-	61.1	38.1	47.0	**91.3**	31.4	56.7	**93.4**	30.0	45.3	-	-	-
PQZSL (Li et al. 2019)	35.3	35.1	35.2	51.4	43.2	46.9	70.9	31.7	43.8	-	-	-	64.1	27.9	38.8
CRNet (Zhang and Shi 2019)	36.5	34.1	35.3	56.8	45.5	50.5	74.7	58.1	65.4	78.8	52.6	63.1	68.4	32.4	44.0
APNet(ours)	40.6	**35.4**	**37.8**	55.9	**48.1**	**51.7**	76.6	**59.7**	**67.1**	83.9	**54.8**	**66.4**	74.7	**32.7**	**45.5**