Multi-Label Image Recognition with Graph Convolutional Network

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Introduction

Multi-Label Image Recognition

- Predict a set of object labels that present in an image

- A Naïve way -a set of binary classification problems to predict whether each object

- Ignoring the complex topology structure between objects

→ Inter-dependent object classifiers from prior label representations

→ Utilize GCN to propagate information between multiple labels and consequently learn inter-dependent classifiers for each of image labels

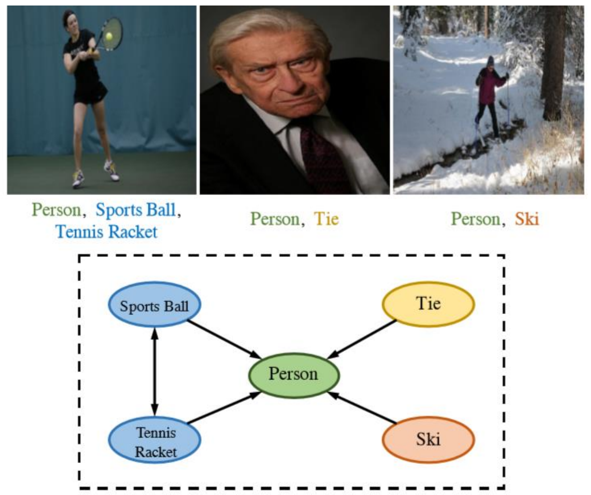


Figure 1. We build a directed graph over the object labels to model label dependencies in multi-label image recognition. In this figure, "$\text{Label}_\text{A} \rightarrow \text{Label}_\text{B}$", means when Label_A appears, Label_B is likely to appear, but the reverse may not be true.

Approach

Overall Architecture

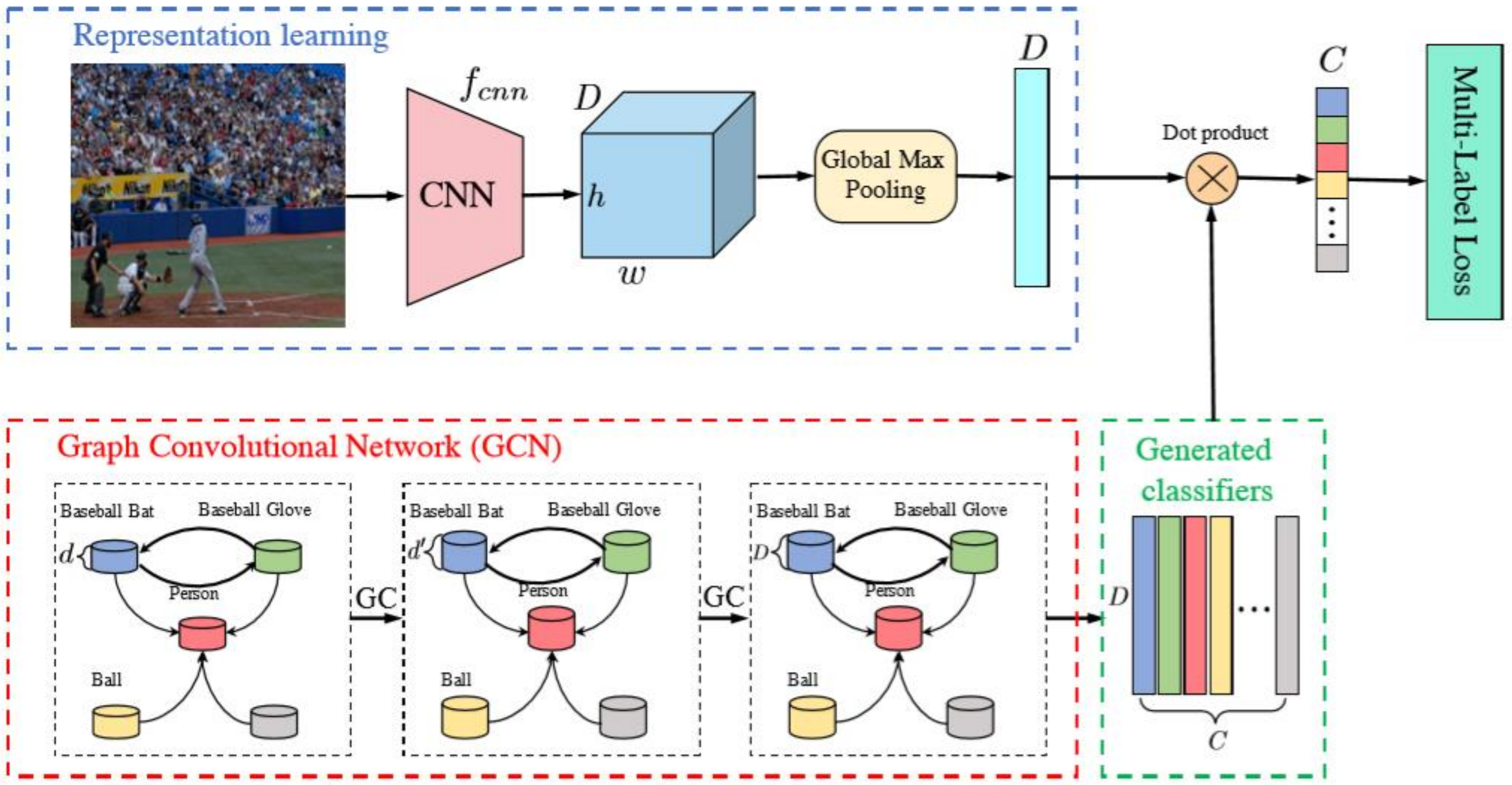
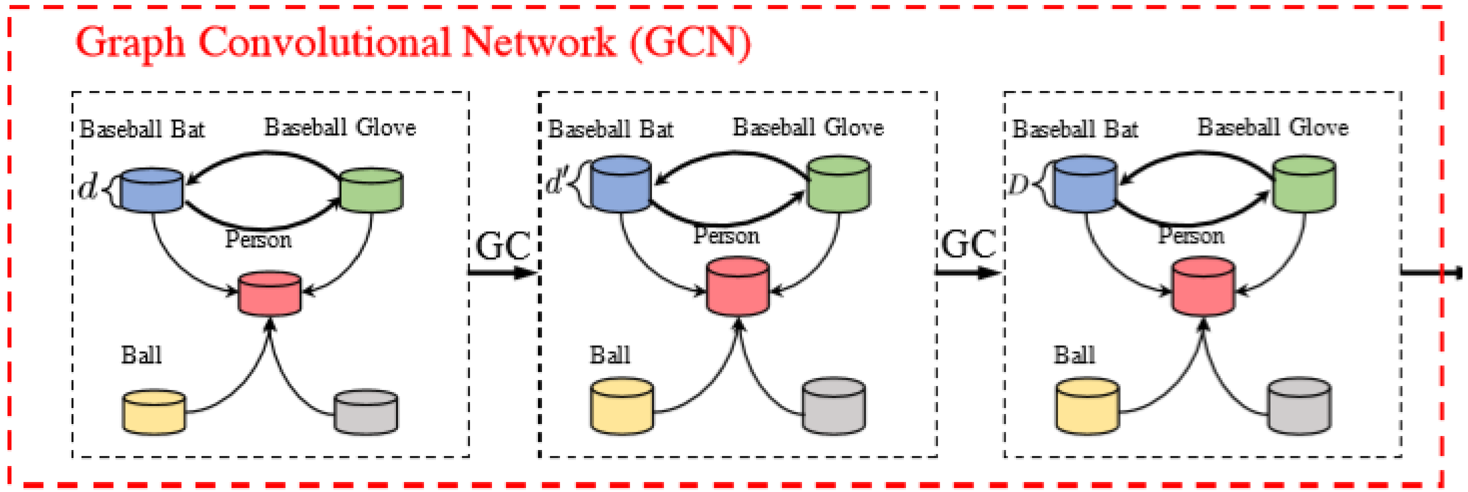


Figure 2. Overall framework of our ML-GCN model for multi-label image recognition. The object labels are represented by word embeddings $\boldsymbol{Z} \in \mathbb{R}^{C \times d}$ (C is the number of categories and d is the dimensionality of word-embedding vector). A directed graph is built over these label representations, where each node denotes a label. Stacked GCNs are learned over the label graph to map these label representations into a set of inter-dependent object classifiers, *i.e.*, $\boldsymbol{W} \in \mathbb{R}^{C \times D}$, which are applied to the image representation extracted from the input image via a convolutional network for multi-label image recognition.

Approach

Motivations



Use a graph to model the inter dependencies between labels, which is a flexible way to capture the topological structure in the label space

1. the learned classifiers can retain the weak semantic structures in the word embedding space, where semantic related concepts are close to each other
2. Design a novel label correlation matrix based on their co-occurrence patterns to explicitly model the label dependencies by GCN, with which the update of node features will absorb information from correlated nodes (labels)

Approach

Graph Convolutional Network Recap

Graph Convolutional Network (GCN) was introduced in[14] to perform semi-supervised classification. The goal of GCN is to learn a function $f(\cdot,\cdot)$ on a graph $\mathcal{G}$.

$$\boldsymbol{H^{l+1} = f(H^{l}, A)}$$

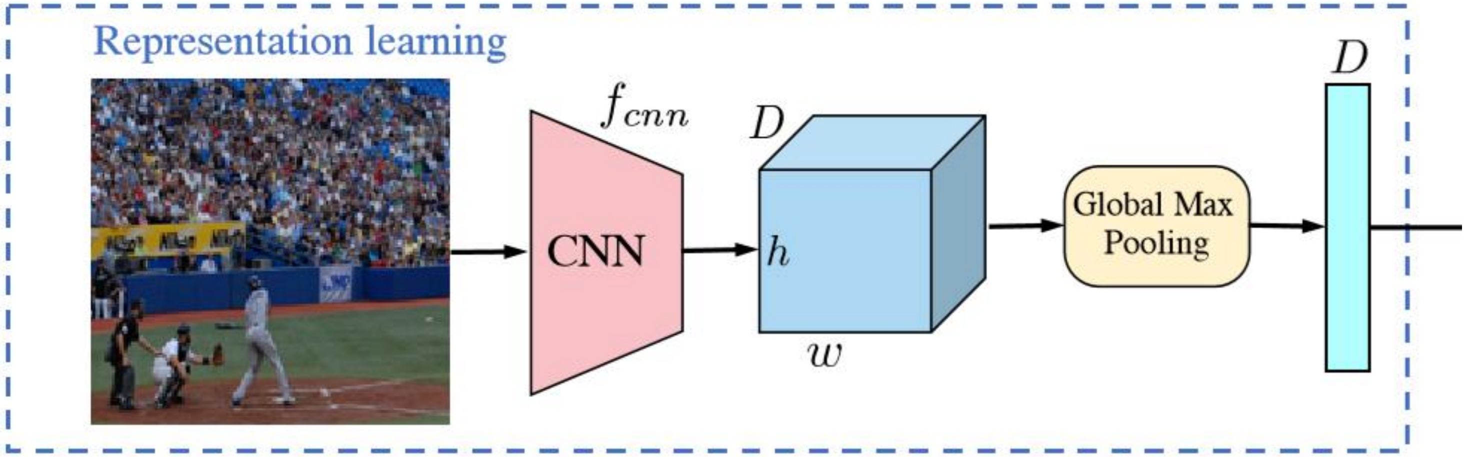
$$\boldsymbol{H^{l+1} = h(\widehat{A}H^{l}W^{l})}$$

Feature description: $\boldsymbol{H^{l}} \in \boldsymbol{R^{n\times d}}$
Input: $\boldsymbol{A} \in \boldsymbol{R^{n\times n}}$
Transformation Matrix: $\boldsymbol{W^{l}} \in \boldsymbol{R^{d\times d'}}$
Normalized version of correlation matrix: $\boldsymbol{\widehat{A}} \in \boldsymbol{R^{n\times n}}$
Non-linear function: $\boldsymbol{h}(\cdot)$

Approach

GCN for Multi-label Recognition

Image representation learning



ResNet-101 → global max-pooling

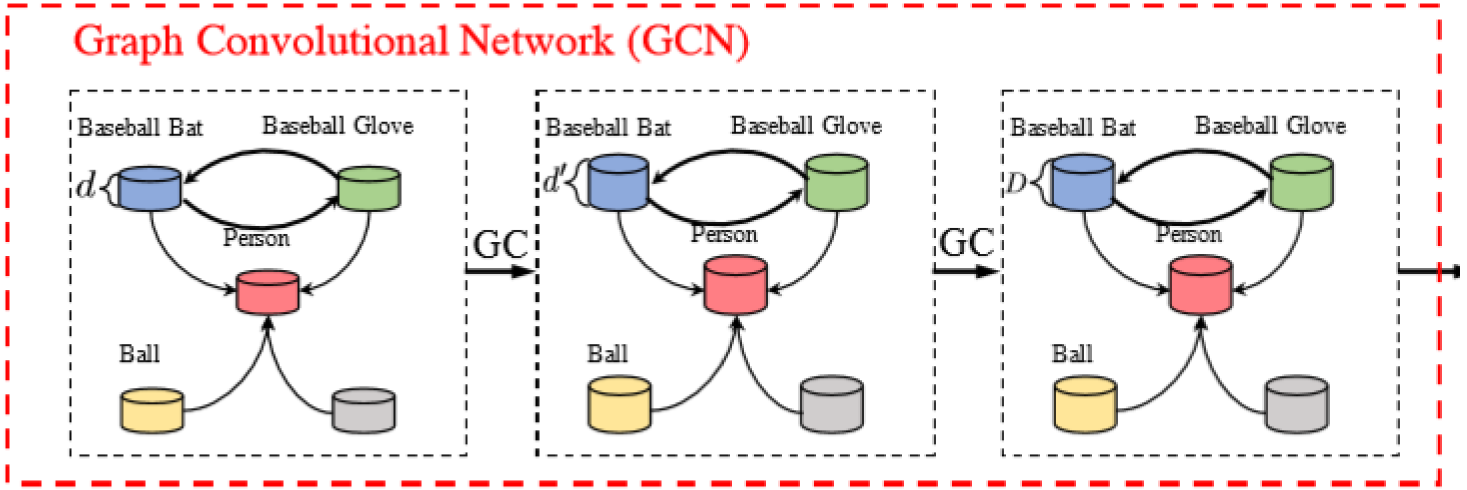
$$x = f_{GMP}(f_{cnn}(I; \theta_{cnn})) \in R^D$$

I is with the 448×448 resolution
θ_{cnn} indicates model parameters and D = 2048.

Approach

GCN for Multi-label Recognition

GCN based classifier learning



We use stacked GCNs where each GCN layer l takes the node representations from previous layer H^l as inputs and outputs new node representations, i.e., H^{l+1}

Approach

GCN for Multi-label Recognition

GCN based classifier learning

For the first layer, the input is the $Z \in R^{C \times d}$ matrix, where d is the dimensionality of the label-level word embedding

For the last layer, the output is $W \in R^{C \times D}$ with D denoting the dimensionality of the image representation

$$\hat{y} = Wx$$

Loss function

$$\mathcal{L} = \sum_{c=1}^{C} y^c \log(\sigma(\hat{y}^c)) + (1 - y^c) \log(1 - \sigma(\hat{y}^c))$$

ground truth: $y \in R^C \ where \ y^i = \{0, 1\}$

Approach

GCN for Multi-label Recognition

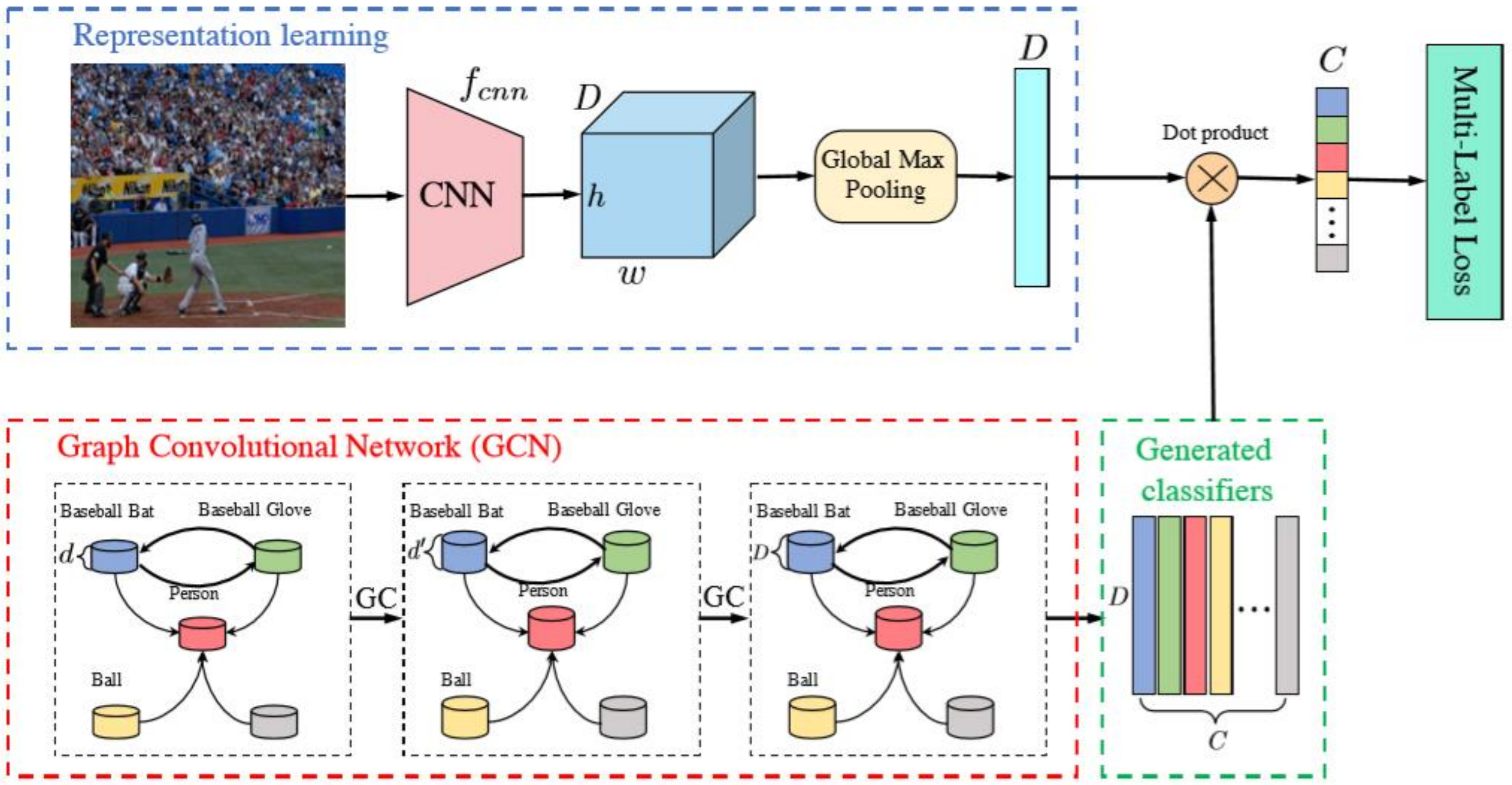


Figure 2. Overall framework of our ML-GCN model for multi-label image recognition. The object labels are represented by word embeddings $\boldsymbol{Z} \in \mathbb{R}^{C \times d}$ (C is the number of categories and d is the dimensionality of word-embedding vector). A directed graph is built over these label representations, where each node denotes a label. Stacked GCNs are learned over the label graph to map these label representations into a set of inter-dependent object classifiers, *i.e.*, $\boldsymbol{W} \in \mathbb{R}^{C \times D}$, which are applied to the image representation extracted from the input image via a convolutional network for multi-label image recognition.

Approach

Correlation Matrix of ML-GCN

We model the label correlation dependency in the form of conditional probability, i.e., $P(L_i|L_j)$

* $P(L_i|L_j) \neq P(L_i|L_j)$

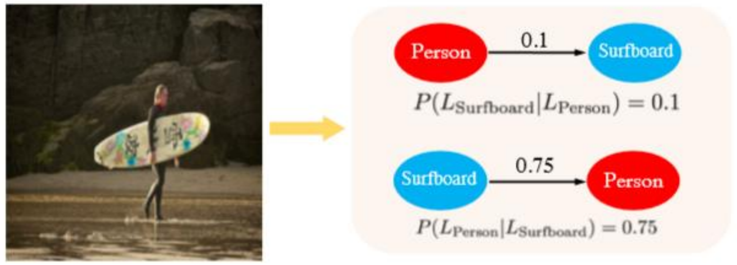

Person
0.1
Surfboard
$P(L_{\text{Surfboard}}|L_{\text{Person}}) = 0.1$
Surfboard
0.75
Person
$P(L_{\text{Person}}|L_{\text{Surfboard}}) = 0.75$

Figure 3. Illustration of conditional probability between two labels. As usual, when "`surfboard`" appears in the image, "`person`" will also occur with a high probability. However, in the condition of "`person`" appearing, "`surfboard`" will not necessarily occur.

Make matrix

1. $M \in R^{C \times D}$ where M_{ij} denotes the concurring times of L_i and L_j
2. $P_i = M_i / N_i$

Introduction

Correlation Matrix of ML-GCN

Two drawbacks

1. May exhibit a long-tail distribution
2. the absolute number of co-occurrences from training and test may not be completely consistent
   → Overfitting

Solution

The threshold τ

$$\boldsymbol{A}_{ij} = \begin{cases} 0, & \text{if } \boldsymbol{P}_{ij} < \tau \\ 1, & \text{if } \boldsymbol{P}_{ij} \geq \tau \end{cases}$$

A is the binary correlation matrix

Approach

Over-smoothing problem

From Eq.(2), we can conclude that after GCN, the feature of a node will be the weighted sum of its own feature and the adjacent nodes' features. → Oversmooth

$$\boldsymbol{H}^{l+1} = \boldsymbol{h}(\hat{\boldsymbol{A}}\boldsymbol{H}^{l}\boldsymbol{W}^{l}) \qquad (2)$$

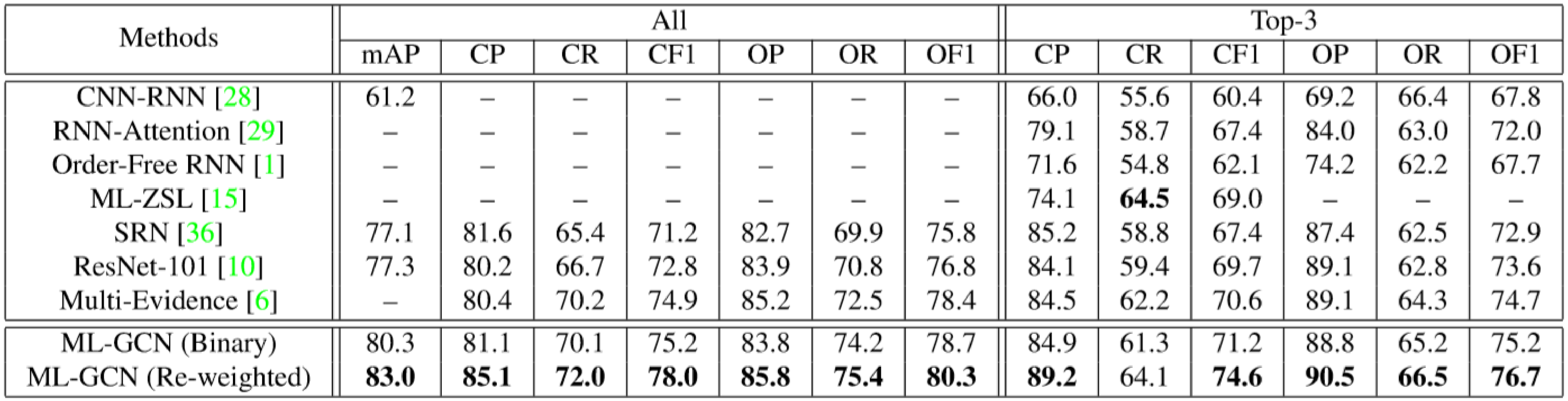
→ Propose the following re-weighted scheme,

$$\boldsymbol{A}'_{ij} = \begin{cases} p / \sum_{\substack{j=1 \\ i \neq j}}^{C} \boldsymbol{A}_{ij}, & \text{if } i \neq j \\ 1 - p, & \text{if } i = j \end{cases}, \qquad (8)$$

where A' is the re-weighted correlation matrix, and p determines the weights assigned to a node itself and other correlated nodes.

Experimental Results

Results on MS-COCO



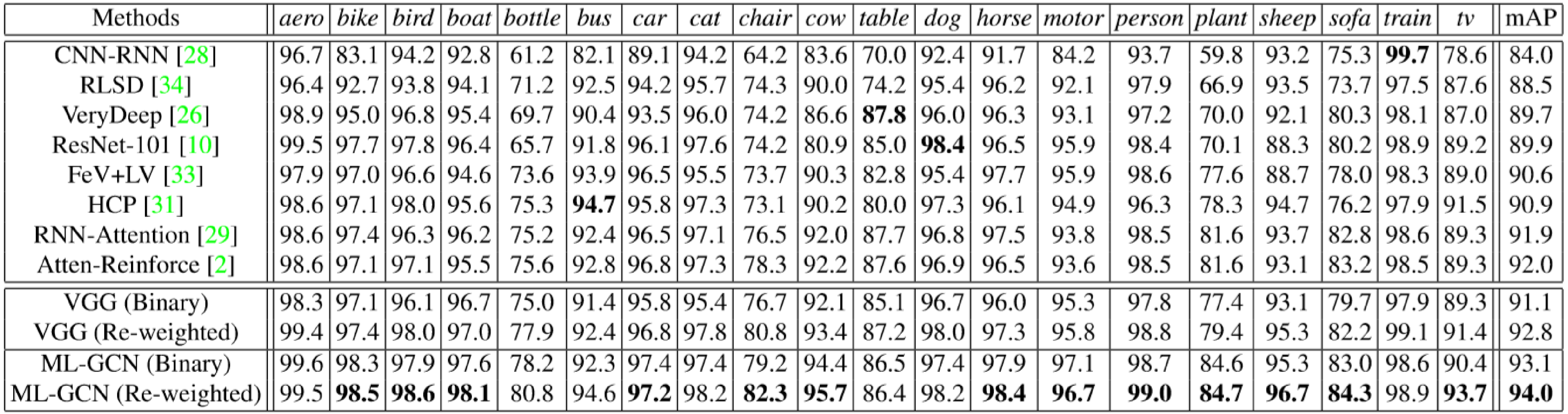
Methods	All							Top-3					
	mAP	CP	CR	CF1	OP	OR	OF1	CP	CR	CF1	OP	OR	OF1
CNN-RNN [28]	61.2	–	–	–	–	–	–	66.0	55.6	60.4	69.2	66.4	67.8
RNN-Attention [29]	–	–	–	–	–	–	–	79.1	58.7	67.4	84.0	63.0	72.0
Order-Free RNN [1]	–	–	–	–	–	–	–	71.6	54.8	62.1	74.2	62.2	67.7
ML-ZSL [15]	–	–	–	–	–	–	–	74.1	**64.5**	69.0	–	–	–
SRN [36]	77.1	81.6	65.4	71.2	82.7	69.9	75.8	85.2	58.8	67.4	87.4	62.5	72.9
ResNet-101 [10]	77.3	80.2	66.7	72.8	83.9	70.8	76.8	84.1	59.4	69.7	89.1	62.8	73.6
Multi-Evidence [6]	–	80.4	70.2	74.9	85.2	72.5	78.4	84.5	62.2	70.6	89.1	64.3	74.7
ML-GCN (Binary)	80.3	81.1	70.1	75.2	83.8	74.2	78.7	84.9	61.3	71.2	88.8	65.2	75.2
ML-GCN (Re-weighted)	**83.0**	**85.1**	**72.0**	**78.0**	**85.8**	**75.4**	**80.3**	**89.2**	64.1	**74.6**	**90.5**	**66.5**	**76.7**

Table 2. Comparisons of AP and mAP with state-of-the-art methods on the VOC 2007 dataset. The meanings of "Binary" and "Re-weighted" are the same as Table 1.

Experimental Results

Results on VOC 2007

Table 2. Comparisons of AP and mAP with state-of-the-art methods on the VOC 2007 dataset. The meanings of "Binary" and "Re-weighted" are the same as Table 1.



Methods	*aero*	*bike*	*bird*	*boat*	*bottle*	*bus*	*car*	*cat*	*chair*	*cow*	*table*	*dog*	*horse*	*motor*	*person*	*plant*	*sheep*	*sofa*	*train*	*tv*	mAP
CNN-RNN [28]	96.7	83.1	94.2	92.8	61.2	82.1	89.1	94.2	64.2	83.6	70.0	92.4	91.7	84.2	93.7	59.8	93.2	75.3	**99.7**	78.6	84.0
RLSD [34]	96.4	92.7	93.8	94.1	71.2	92.5	94.2	95.7	74.3	90.0	74.2	95.4	96.2	92.1	97.9	66.9	93.5	73.7	97.5	87.6	88.5
VeryDeep [26]	98.9	95.0	96.8	95.4	69.7	90.4	93.5	96.0	74.2	86.6	**87.8**	96.0	96.3	93.1	97.2	70.0	92.1	80.3	98.1	87.0	89.7
ResNet-101 [10]	99.5	97.7	97.8	96.4	65.7	91.8	96.1	97.6	74.2	80.9	85.0	**98.4**	96.5	95.9	98.4	70.1	88.3	80.2	98.9	89.2	89.9
FeV+LV [33]	97.9	97.0	96.6	94.6	73.6	93.9	96.5	95.5	73.7	90.3	82.8	95.4	97.7	95.9	98.6	77.6	88.7	78.0	98.3	89.0	90.6
HCP [31]	98.6	97.1	98.0	95.6	75.3	**94.7**	95.8	97.3	73.1	90.2	80.0	97.3	96.1	94.9	96.3	78.3	94.7	76.2	97.9	91.5	90.9
RNN-Attention [29]	98.6	97.4	96.3	96.2	75.2	92.4	96.5	97.1	76.5	92.0	87.7	96.8	97.5	93.8	98.5	81.6	93.7	82.8	98.6	89.3	91.9
Atten-Reinforce [2]	98.6	97.1	97.1	95.5	75.6	92.8	96.8	97.3	78.3	92.2	87.6	96.9	96.5	93.6	98.5	81.6	93.1	83.2	98.5	89.3	92.0
VGG (Binary)	98.3	97.1	96.1	96.7	75.0	91.4	95.8	95.4	76.7	92.1	85.1	96.7	96.0	95.3	97.8	77.4	93.1	79.7	97.9	89.3	91.1
VGG (Re-weighted)	99.4	97.4	98.0	97.0	77.9	92.4	96.8	97.8	80.8	93.4	87.2	98.0	97.3	95.8	98.8	79.4	95.3	82.2	99.1	91.4	92.8
ML-GCN (Binary)	99.6	98.3	97.9	97.6	78.2	92.3	97.4	97.4	79.2	94.4	86.5	97.4	97.9	97.1	98.7	84.6	95.3	83.0	98.6	90.4	93.1
ML-GCN (Re-weighted)	99.5	**98.5**	**98.6**	**98.1**	80.8	94.6	**97.2**	98.2	**82.3**	**95.7**	86.4	98.2	**98.4**	**96.7**	**99.0**	**84.7**	**96.7**	**84.3**	98.9	**93.7**	**94.0**

Experimental Results

ML-GCN under different types of word embeddings

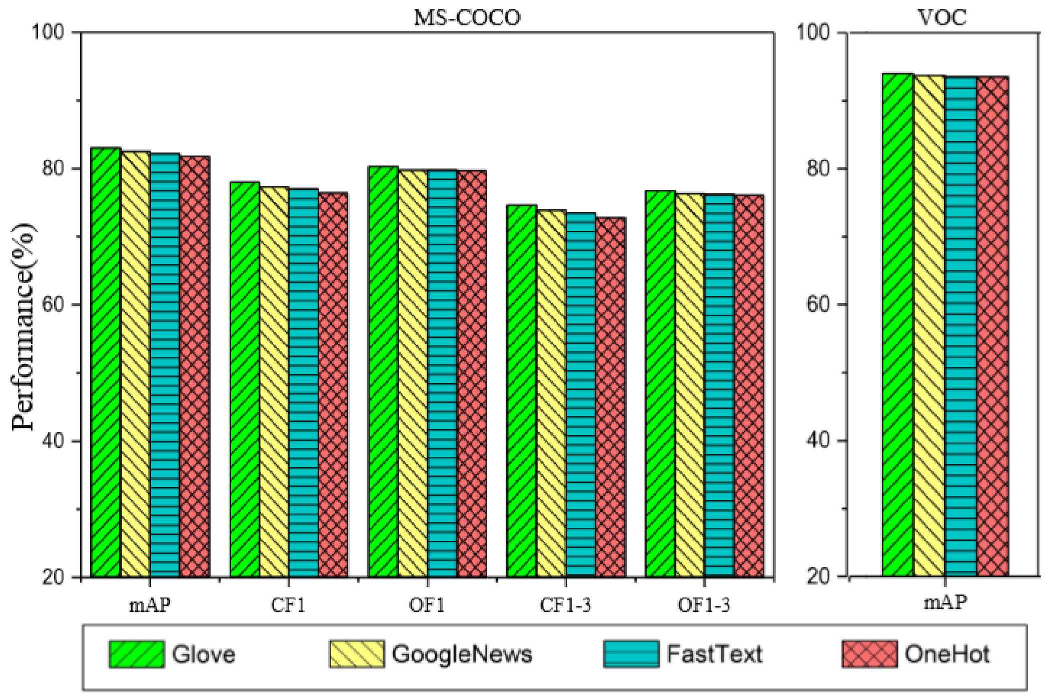
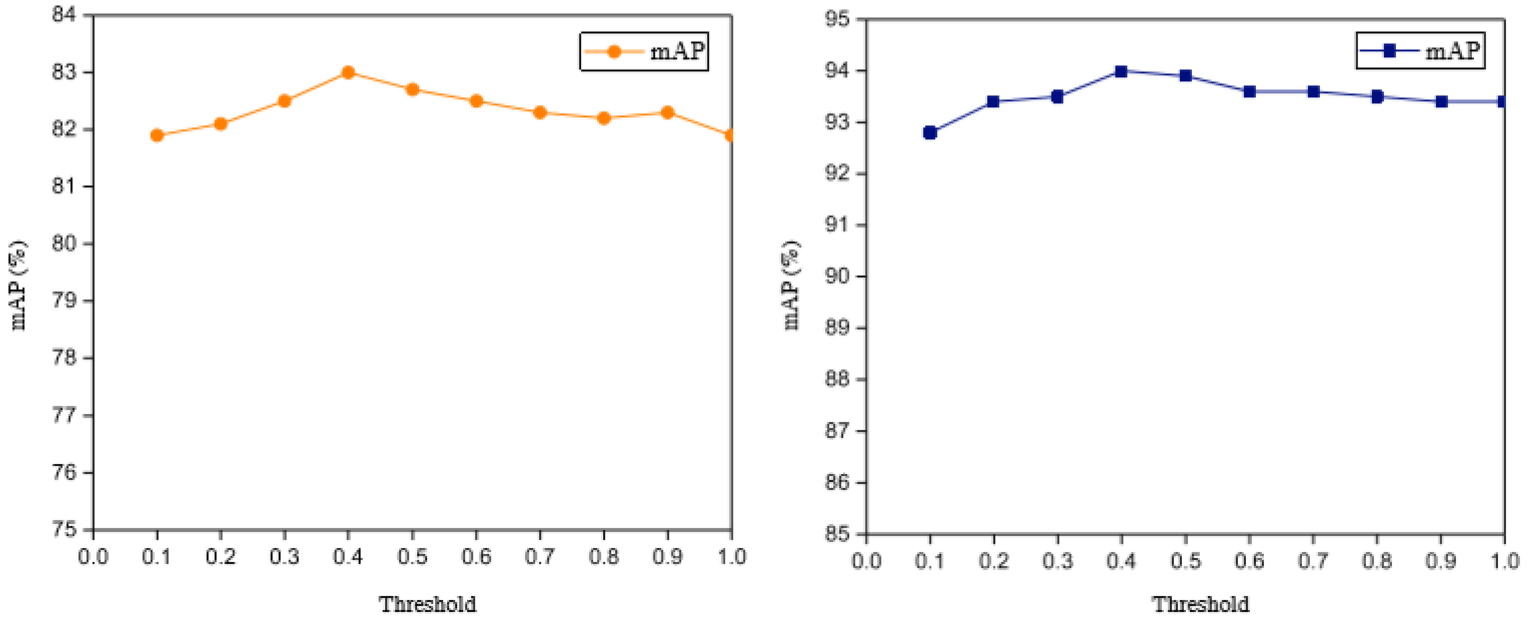


Figure 4. Effects of different word embedding approaches. It is clear to see that, different word embeddings will hardly affect the accuracy, which reveals our improvements do not absolutely come from the semantic meanings derived from word embeddings, rather than our ML-GCN.

Experimental Results

Effects of different threshold values τ

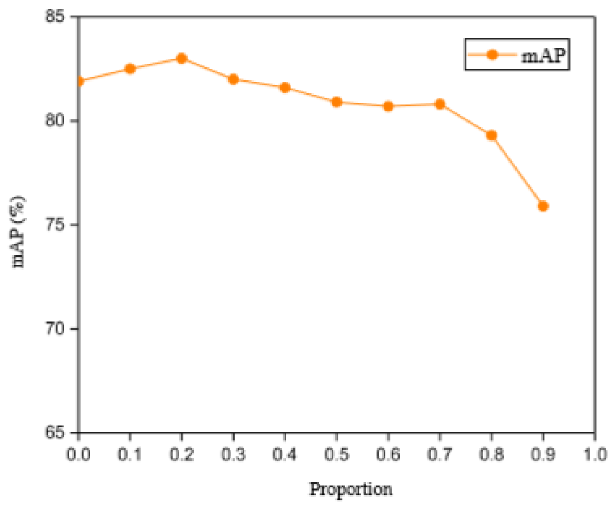


(a) Comparisons on MS-COCO. (b) Comparisons on VOC 2007.

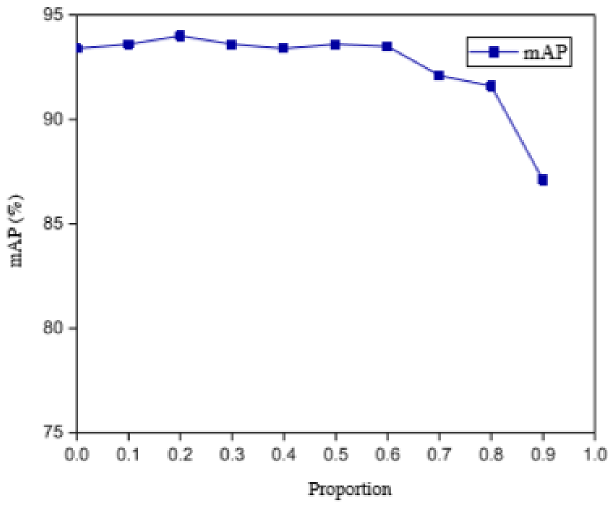
Figure 5. Accuracy comparisons with different values of τ.

Experimental Results

Effects of different *p* for correlation matrix re-weighting



(a) Comparisons on MS-COCO.



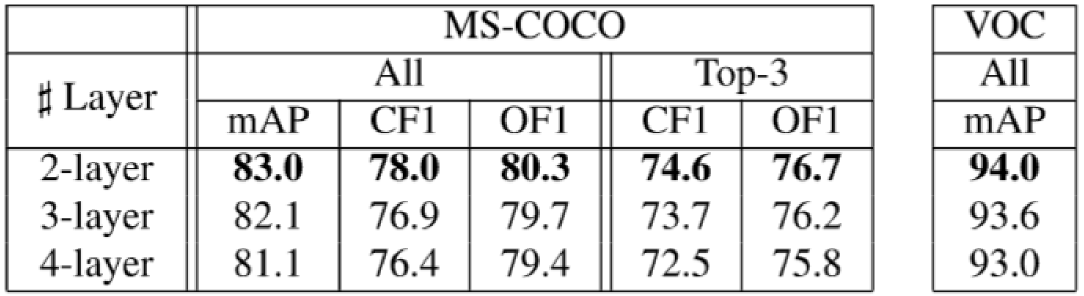
(b) Comparisons on VOC 2007.

Figure 6. Accuracy comparisons with different values of p. Note that, when $p = 1$, the model does not converge.

Experimental Results

The deeper, the better?

Table 3. Comparisons with different depths of GCN in our model.



	MS-COCO					VOC
♯ Layer	All			Top-3		All
	mAP	CF1	OF1	CF1	OF1	mAP
2-layer	**83.0**	**78.0**	**80.3**	**74.6**	**76.7**	**94.0**
3-layer	82.1	76.9	79.7	73.7	76.2	93.6
4-layer	81.1	76.4	79.4	72.5	75.8	93.0

The possible reasonfor the performance drop may be that when using more GCN layers, the propagation between nodes will be accumulated, which can result in over-smoothing.

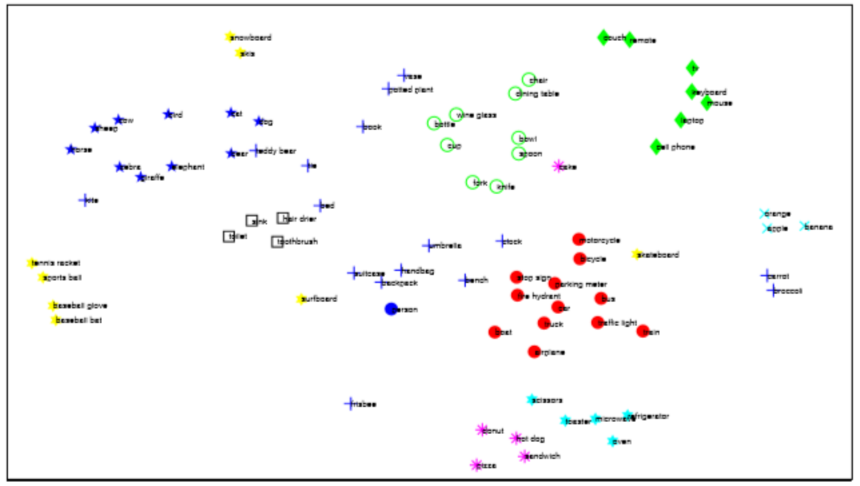
Experimental Results

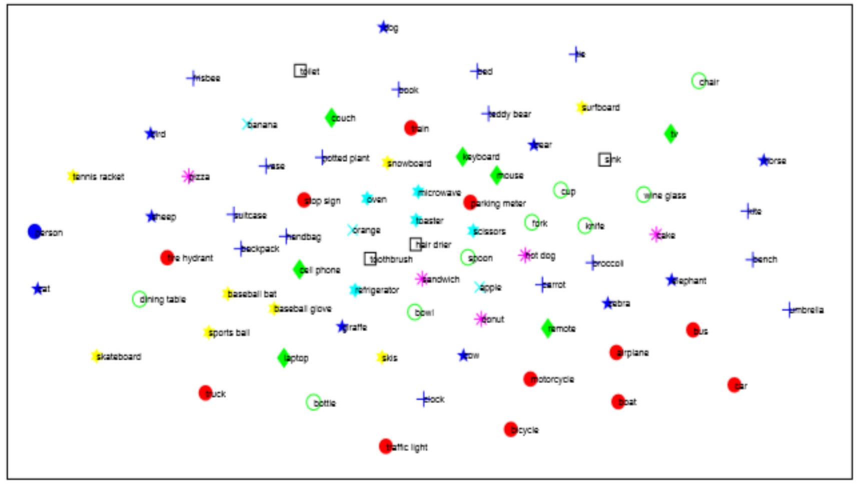
Classifier Visualization

In this section, we visualize the learned inter-dependent classifiers to show if meaningful semantic topology can be maintained.
→ t-SNE

It is clear to see that, the classifiers learned by our method maintain meaningful semantic topology.

The classifiers learned through vanilla ResNet uniformly distribute in the space and do not shown any meaningful topology.


(a) t-SNE on the learned inter-dependent classifiers by our model.


(b) t-SNE on the classifiers by the vanilla ResNet.

Experimental Results

Performance on image retrieval

Evaluate if our model can learn better image representations.

We use the k-NN algorithm.
→ Better than the vanilla ResNet base line.

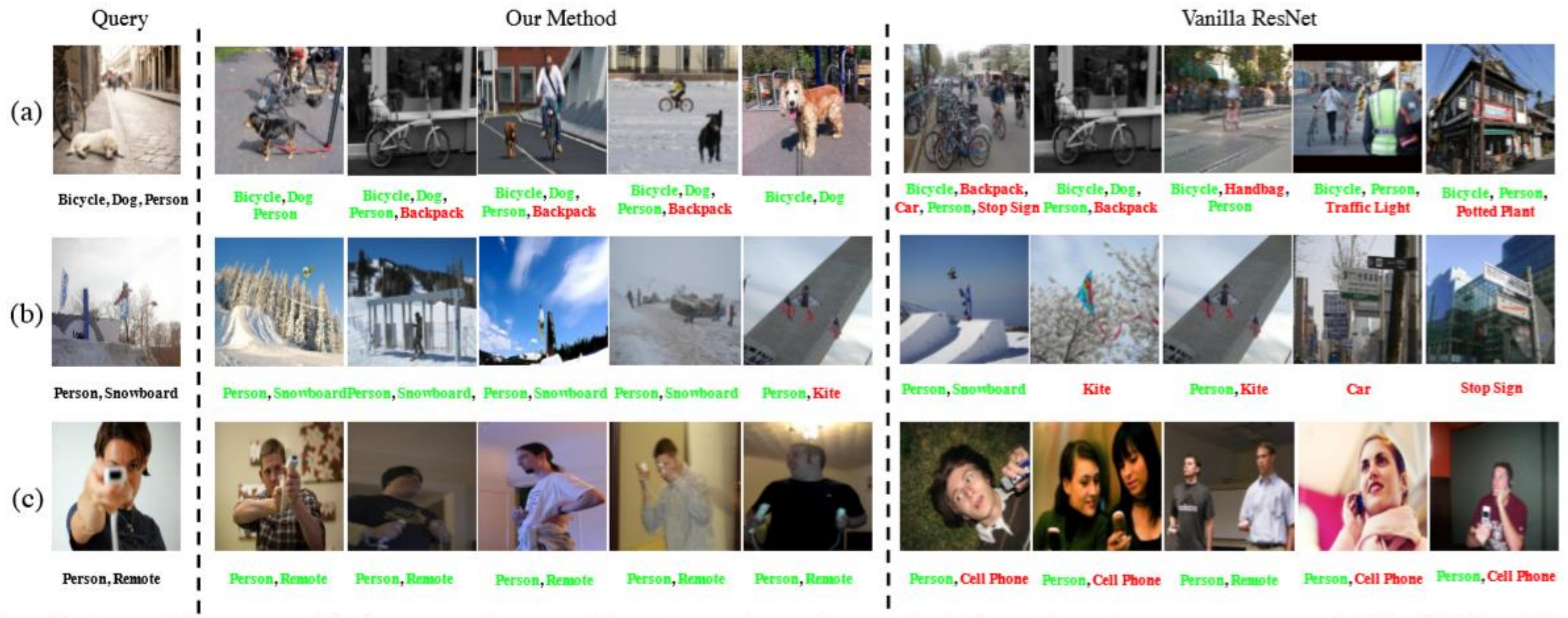


Figure 7. Top-5 returned images with the query image. The returned results on the left are based on our proposed ML-GCN, while the results on the right are vanilla ResNet. All results are sorted in the ascending order according to the distance from the query image.