# Multi-Graph Based Hierarchical Semantic Fusion For Cross-Modal Representation

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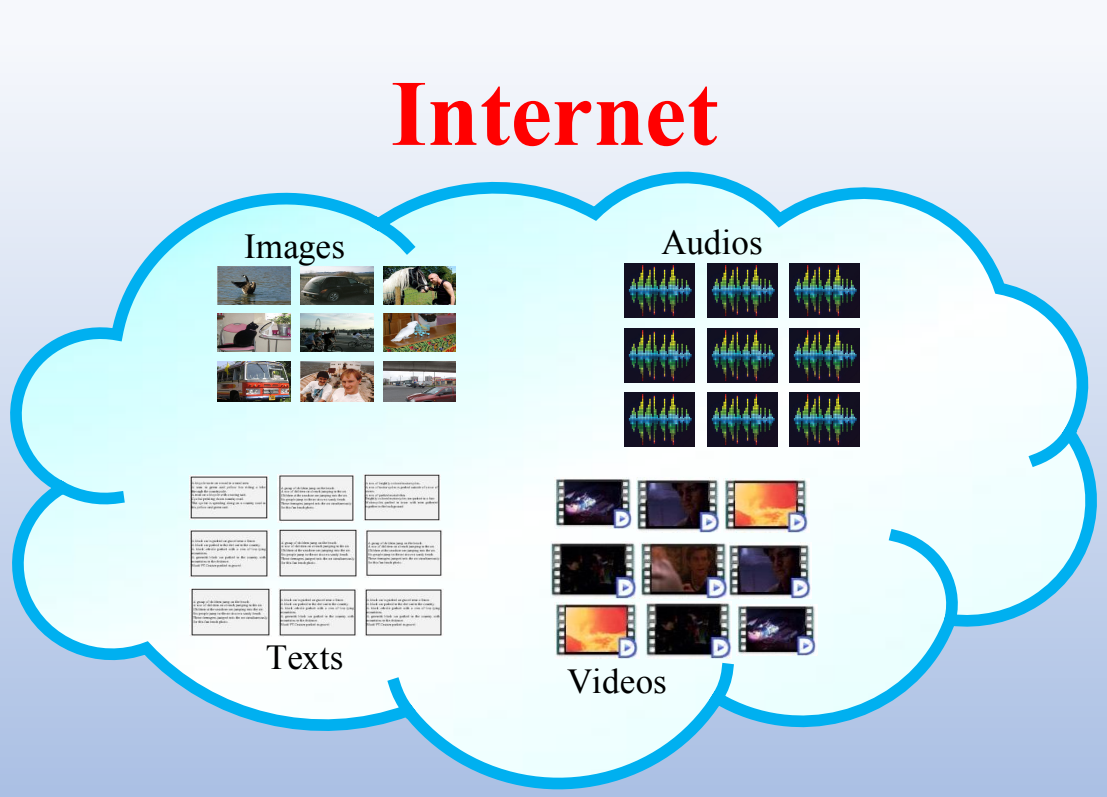
# Background

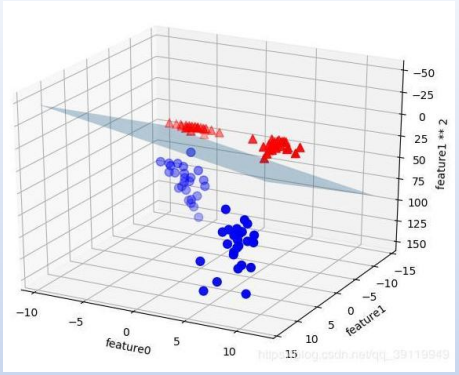




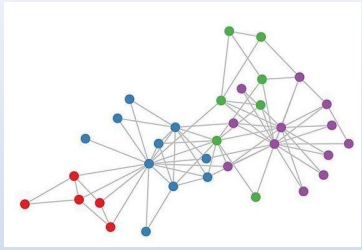
The main challenge of cross-modal retrieval task is how to efficiently realize semantic alignment and reduce the heterogeneity gap between different modalities.

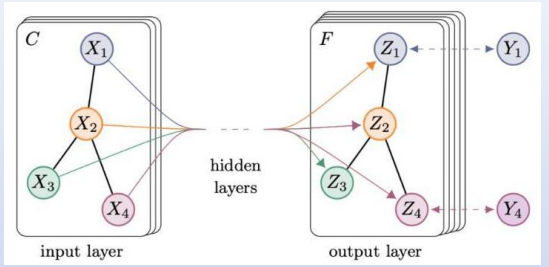
# Related Work

## Shallow Models

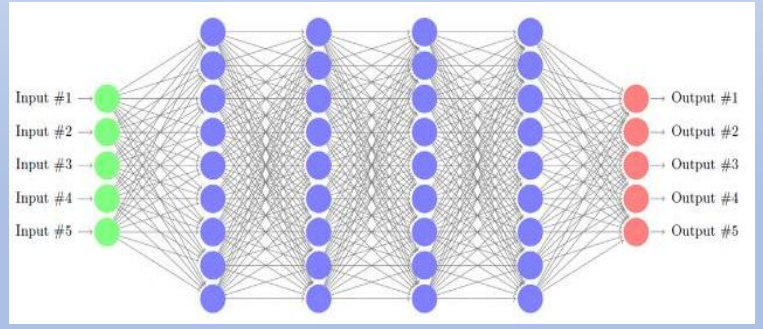



## Graph Models

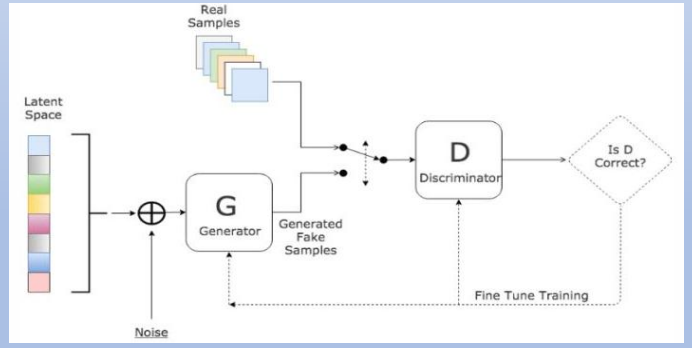





## Deep Models

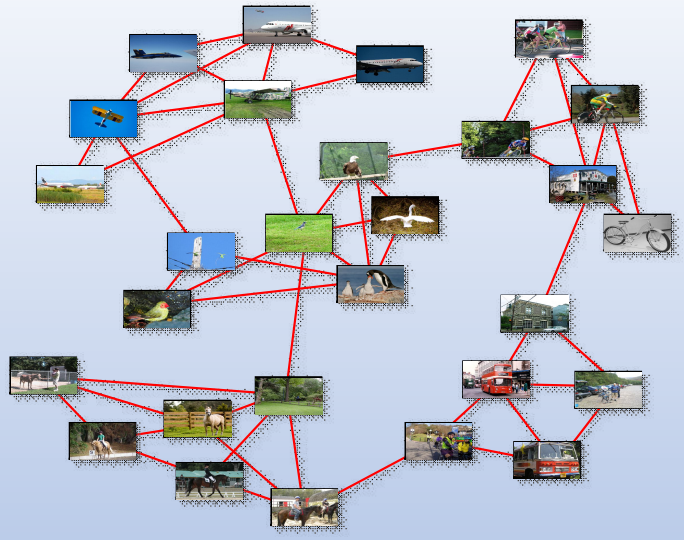



## Adversarial Models

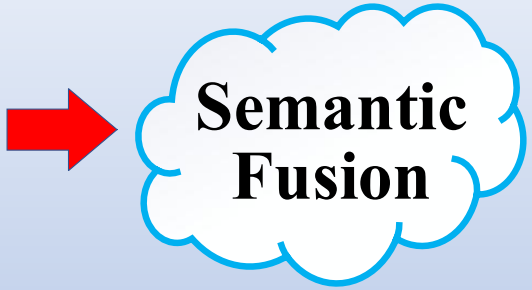


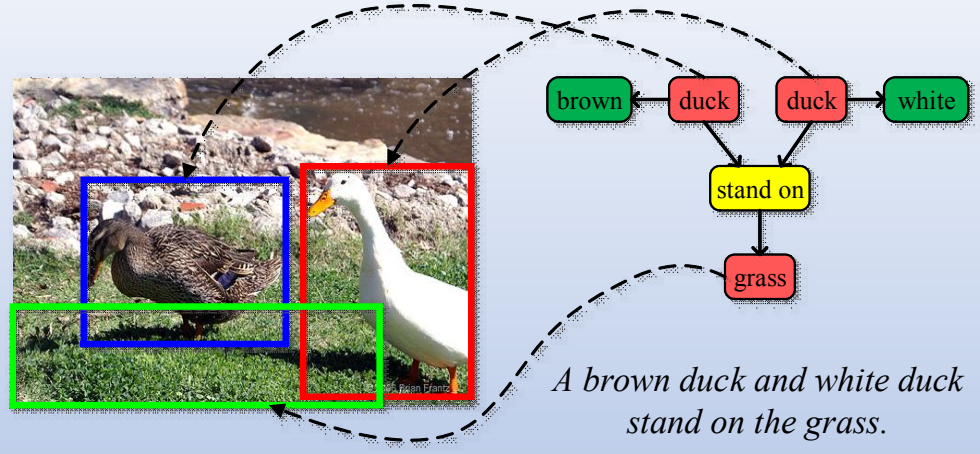

Although the existing researches have strikingly enhanced the performance of cross-modal retrieval, the semantic gap and heterogeneous gap have not been narrowed efficiently.

# Motivation



(1) Coarse-grained Semantic Knowledge




(2) Fine-grained Semantic Knowledge

The latest approaches focused on capturing high-level semantics, but ignored the hierarchical multi-grained knowledge discovery and semantic fusion. this paper investigates how to find multi-grained semantic knowledge from multi-modal objects, and realize the semantic fusion efficaciously to support cross-modal representation learning.

# Contributions

I. A novel end-to-end cross-modal representation method, named **MG-HSF**.

II. A scene graph based model to learn hierarchical semantic representation to capture the fine-grained knowledge; An intra-model semantic graph based representation model is developed to capture coarse-grained knowledge.

III. A semantic fusion model integrated with intra-modal and inter-modal adversarial learning to reduce the cross-modal heterogeneity.

# Problem Definition

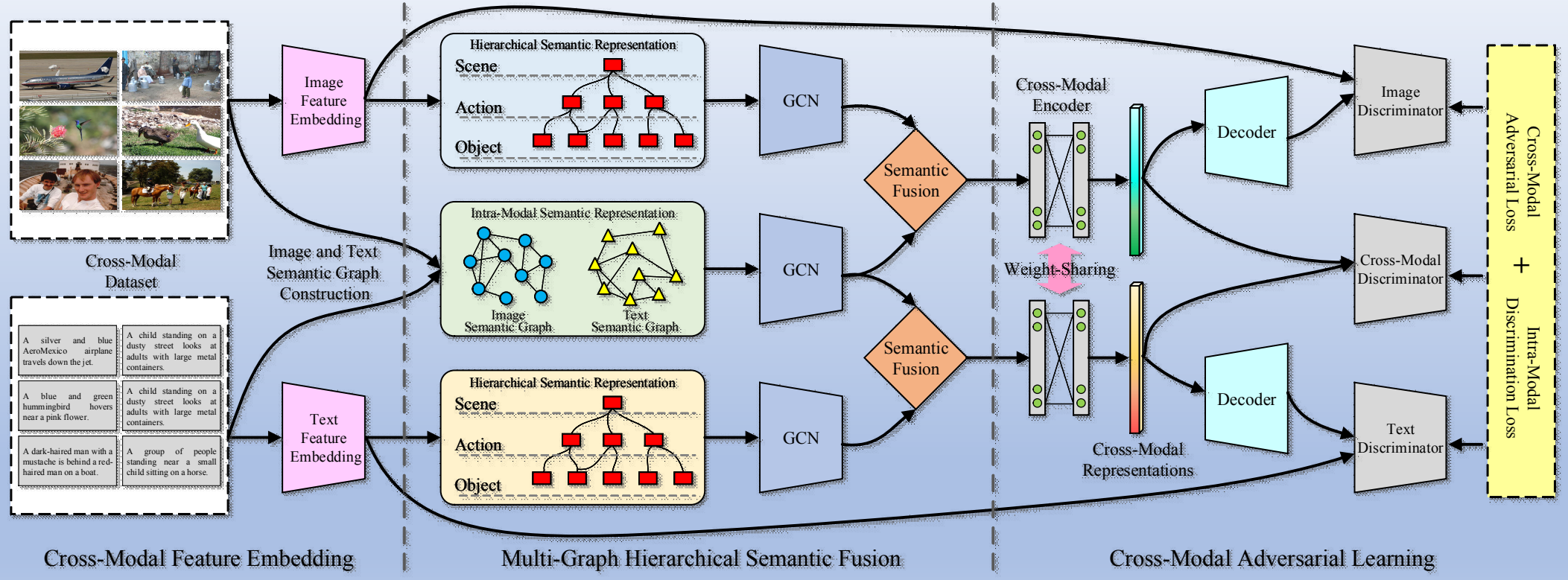
- Let $\mathcal{D}=\{\langle I_i,T_i,L_i\rangle\}_{i=1}^{N}$ be a multimedia dataset containing $N$ triplets, where $I_i$ and $T_i$ are the $i$-th image and text, $L_i$ is the label of them. Take image query$Q_I \in \mathcal{D}$ as an example, an image-to-text (Img2Txt) retrieval can be formulated as follows:

$$\mathcal{R}=\{T|Sim\left(\Phi_I(Q_I;\boldsymbol{\theta}_I),\Phi_T(T;\boldsymbol{\theta}_T)\right)\geq Sim\left(\Phi_I(Q_I;\boldsymbol{\theta}_I),\Phi_T(T';\boldsymbol{\theta}_T)\right),T\in\mathcal{D},T'\in\mathcal{D}\setminus\mathcal{R}\},$$

where $\mathcal{R}$ is the result set, $\boldsymbol{\theta}_I$ and $\boldsymbol{\theta}_T$ are the parameter vectors. $Sim\left(\right)$is the similarity function To realize the projections $\Phi_I(\cdot;\boldsymbol{\theta}_I)$ and $\Phi_T(\cdot;\boldsymbol{\theta}_T)$, we propose a novel cross-modal representation model, named MG-HSF, which is an integration of multi-graph knowledge fusion and adversarial learning technique.

# The Method

- **The Framework**

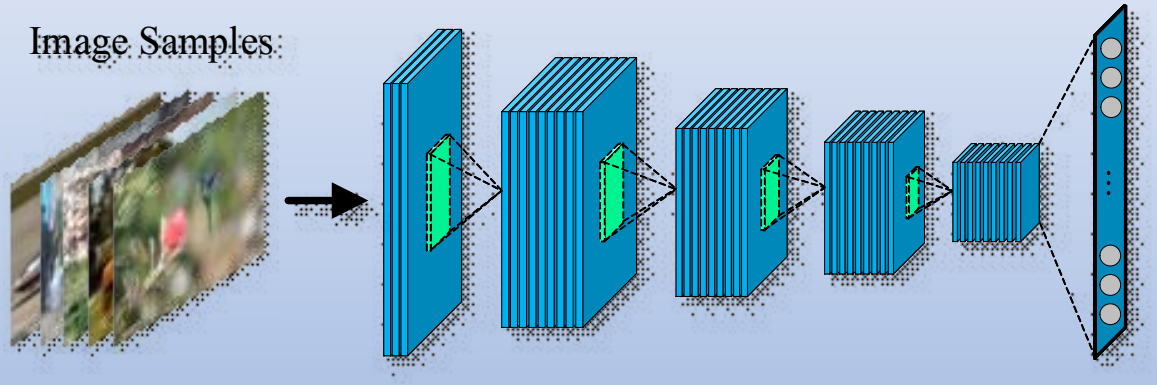



This model consists of three components: (1) cross-modal feature embedding; (2) multi-graph hierarchical semantic fusion; (3) cross-modal adversarial learning.

# The Method

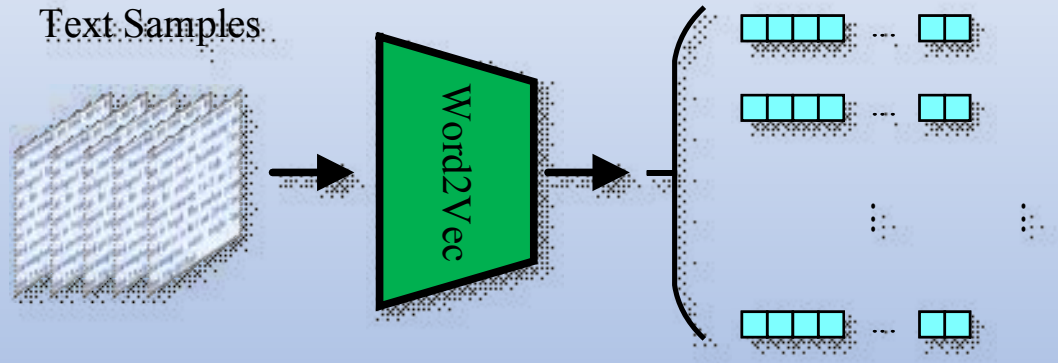
- **Cross-Model Feature Embedding**

Image Feature Embedding




For images, we employ deep CNN to learn visual features

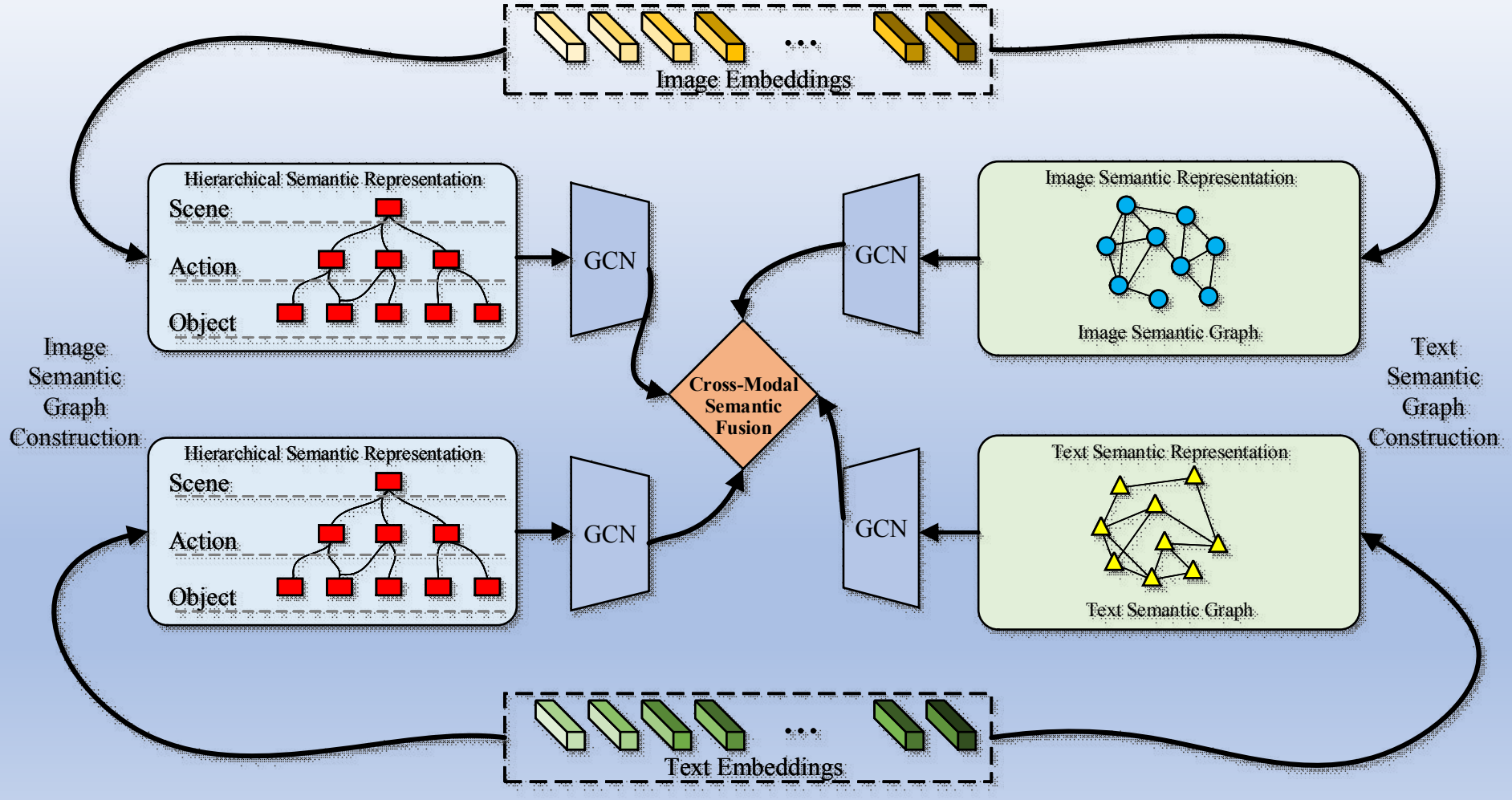
Text Feature Embedding




For texts, we embed each word by a word2vec model

# The Method

- **Multi-Graph Hierarchical Semantic Fusion**



# The Method

For image and text, we construct the hierarchical semantic graph with three levels: scene, action and object

**For text**: vertices can be learned via bi-LSTM from the word embeddings:

$$\boldsymbol{\varpi}_j = \frac{1}{2}(L_1(\boldsymbol{\omega}_j, \boldsymbol{\omega}_{j-1}; \boldsymbol{\theta}_{L1}) + L_2(\boldsymbol{\omega}_j, \boldsymbol{\omega}_{j+1}; \boldsymbol{\theta}_{L2})),$$

where $L_1(\cdot, \cdot; \boldsymbol{\theta}_{L1})$ and $L_2(\cdot, \cdot; \boldsymbol{\theta}_{L2})$ are LSTM models of two direction. a text attention mechanism is used to capture important information:

$$\boldsymbol{\varphi}^s = \sum_{j=1}^{K}\left(\frac{exp\left(\boldsymbol{A}_s \boldsymbol{\varpi}_j\right)\boldsymbol{\varpi}_j}{\sum_{k=1}^{K} exp\left(\boldsymbol{A}_s \boldsymbol{\varpi}_k\right)}\right)$$

# The Method

For image and text, we construct the hierarchical semantic graph with three levels: scene, action and object

**For image**: three matrices are adopted to encode scene vertex, action vertex and object vertex representations:

$$\boldsymbol{h}_i^s = \boldsymbol{M}_s C_i \qquad \boldsymbol{h}_i^a = \boldsymbol{M}_a \boldsymbol{C}_i \qquad \boldsymbol{h}_i^o = \boldsymbol{M}_o \boldsymbol{C}_i$$

Each element of $\boldsymbol{h}_i^a$ or $\boldsymbol{h}_i^o$ corresponds to an action vertex or an object vertex.

We propose to utilize the text semantic representation to train this model.

# The Method

For the intra-modal semantic graph construction, $k$NN algorithm is used on image set and text set to produce two graphs: $\mathcal{G}_I$ and $\mathcal{G}_T$,

$$\mathcal{G}_I = \langle \{\boldsymbol{C}_i\}, \mathcal{E}_I \rangle \qquad \mathcal{G}_T = \langle \{\boldsymbol{W}_j\}, \mathcal{E}_T \rangle$$

where $\mathcal{E}_I = \{E_{I:ij}\}$ and $\mathcal{E}_T = \{E_{T:ij}\}$ denote the edge sets that represent the connection of nearest neighbors for image or text. The weight of each edges is calculated by Euclidean distance:

$$E_{I:ij} = EucDst(\boldsymbol{C}_i, \boldsymbol{C}_j)$$

$$E_{T:ij} = EucDst(\boldsymbol{W}_i, \boldsymbol{W}_j)$$

where $\boldsymbol{C}_i \in \mathcal{N}_{knn}(\boldsymbol{C}_j)$ $\boldsymbol{C}_j \in \mathcal{N}_{knn}(\boldsymbol{C}_i)$ $\boldsymbol{W}_i \in \mathcal{N}_{knn}(\boldsymbol{W}_j)$ $\boldsymbol{W}_j \in \mathcal{N}_{knn}(\boldsymbol{W}_i)$

# The Method

## • Cross-Modal Adversarial Learning

A cross-modal encoder that is implemented by fully connected networks with weight-sharing is used to generate modality invariant representation: $\bar{\boldsymbol{\xi}}_i = Enc_I(\boldsymbol{\xi}_i; \boldsymbol{\theta}_{Ei})$ and $\bar{\boldsymbol{\zeta}}_i = Enc_T(\boldsymbol{\zeta}_i; \boldsymbol{\theta}_{Et})$. Besides, two decoders are integrated, and then re-construct the feature embeddings of image and text: $\hat{\boldsymbol{C}}_i$ and $\hat{\boldsymbol{W}}_i$. To realize intra-modal and inter-modal adversarial learning, three discriminators: $D_I(\cdot,\cdot;\boldsymbol{\theta}_{Di})$, $D_T(\cdot,\cdot;\boldsymbol{\theta}_{Dt})$ and cross-modal discriminator $D_{CI}(\cdot;\boldsymbol{\theta}_{Dci})$ and $D_{CT}(\cdot;\boldsymbol{\theta}_{Dct})$. The loss functions:

$$\mathcal{L}_{g1} = \mathbb{E}_{\boldsymbol{C}}[logD_I(\boldsymbol{C})] + \mathbb{E}_{\boldsymbol{C}}[log(1 - D_I(\hat{\boldsymbol{C}}))],$$

$$\mathcal{L}_{g2} = \mathbb{E}_{\boldsymbol{W}}[logD_I(\boldsymbol{W})] + \mathbb{E}_{\boldsymbol{W}}[log(1 - D_I(\hat{\boldsymbol{W}}))],$$

$$\mathcal{L}_{g3} = \mathbb{E}_{\boldsymbol{C},\boldsymbol{W}}[logD_{CI}(\bar{\boldsymbol{\xi}}) - logD_{CI}(\bar{\boldsymbol{\zeta}}) + logD_{CT}(\bar{\boldsymbol{\xi}}) - logD_{CT}(\bar{\boldsymbol{\zeta}})].$$

# Experiments

- **Data sets**
  - I. Wikipedia
  - II. NUS-WIDE
  - III. NUS-WIDE
- **Competitors**

  Shallow: CCA and SM

  Deep: Deep-SM and DSCMR

  Adversarial: ACMR and MHTN

Wikipedia

NUS-WIDE

Pascal Sentence

# Experiments

- The results (mAP) on Wikipedia

**Table 1**. The results (mAP@50 in %) with 6 competitors on Wikipedia dataset.

| Method | Img2Txt | Txt2Img | Average |
|---|---|---|---|
| CCA | 21.01 | 17.84 | 19.43 |
| SM | 23.34 | 28.51 | 25.93 |
| Deep-SM | 39.90 | 35.43 | 37.67 |
| DSCMR | 52.13 | 47.82 | 49.97 |
| ACMR | 47.74 | 43.42 | 45.58 |
| MHTN | 51.41 | 44.45 | 47.93 |
| MG-HSF | **52.85** | **53.21** | **53.03** |

# Experiments

- The results (mAP) on NUS-WIDE

**Table 2.** The results (mAP@50 in %) with 6 competitors on NUS-WIDE dataset.

| Method | Img2Txt | Txt2Img | Average |
|---|---|---|---|
| CCA | 38.17 | 36.80 | 37.49 |
| SM | 39.16 | 42.37 | 40.77 |
| Deep-SM | 57.80 | 62.55 | 60.18 |
| DSCMR | 61.10 | 61.54 | 61.32 |
| ACMR | 58.41 | 57.85 | 58.13 |
| MHTN | 52.03 | 53.41 | 52.72 |
| MG-HSF | **62.06** | **64.88** | **63.47** |

# Experiments

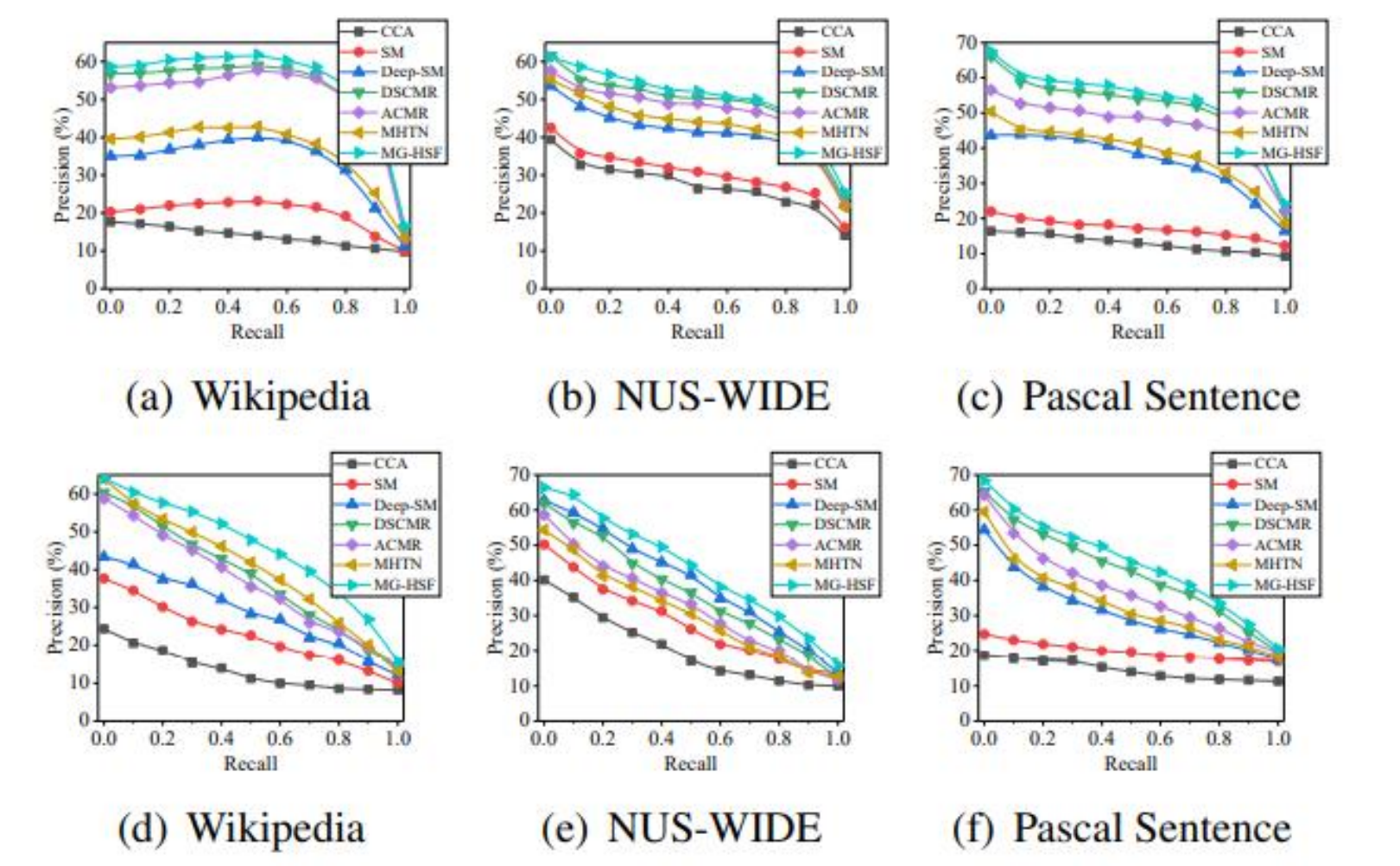
- The results (mAP) on Pascal Sentence

**Table 3**. The results (mAP@50 in %) with 6 competitors on Pascal Sentence dataset.

| Method | Img2Txt | Txt2Img | Average |
|---|---|---|---|
| CCA | 11.21 | 12.06 | 11.64 |
| SM | 18.74 | 21.12 | 20.14 |
| Deep-SM | 44.63 | 48.05 | 46.34 |
| DSCMR | 69.10 | 71.08 | 70.09 |
| ACMR | 60.48 | 59.75 | 60.12 |
| MHTN | 49.61 | 50.04 | 49.83 |
| MG-HSF | **69.62** | **71.55** | **70.59** |

# Experiments

- The PR-Curves on Wikipedia, NUS-WIDE and Pascal Sentence



# Conclusion

- This paper proposes a novel cross-modal representation method, called Multi-Graph based Hierarchical Semantic Fusion (MG-HSF).
- A multi-graph based hierarchical semantic fusion method is developed to learn fine-grained and coarse-grained knowledge.
- Intra-modal and inter-modal adversarial learning networks are utilized to reduce the cross-modal heterogeneity.

# Acknowledgments

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# Thank You !