Multiplex Heterogeneous Graph Convolutional Networks

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What’s Multiplex Heterogeneous Network?

Heterogeneous Network

\[ \mathcal{G} = \{ \mathcal{V}, \mathcal{E} \}, \text{ with } \phi: \mathcal{V} \rightarrow \mathcal{O}, \ \psi: \mathcal{E} \rightarrow \mathcal{R} \]\n
If \(|\mathcal{O}| + |\mathcal{R}| > 2\), and existing different types of edges between same node pairs.

Multiplex Heterogeneous Network

E-commerce Network

User (U) → Item (I)

- buy
- click
- add-to-cart
- add-to-collect
Challenges

• **Heterogeneity vs. Multiplexity**
  - Diverse types of nodes and edges.
  - Multiple interactions between the same node pairs.
Challenges

• **Heterogeneity vs. Multiplexity**
  - Multiple types of nodes and edges.
  - Multiple interactions between the same node pairs.

• Accurate Meta-path design (MAGNN, etc.)
  - Different length.
  - Different interaction order.

• Embedding efficiency
  - Unable to handle large-scale network data
Architecture of Proposed MHGCN

Distinguish the **importance** of the relations

Automatically capture **meta-path information**
Multiplex Relation Aggregation

- Decoupling multiplex networks
- Weighted aggregate sub-networks.
- Extracting node attribute features

Adaptively adjust the relation-aware weights during training.

User & Item Attributes

E-commerce Network

Click, Buy, Add-to-cart, Collect

User & Item Attributes

Multiplicity Relation Aggregation

$A = \sum_{r=1}^{[R]} \beta_r A_r$
How to Automatically Capture Heterogeneous Meta-paths?

- Distinguish the importance of different relations.
- Automatically capture the meta-path information.
Multilayer Graph Convolution Module

One layer convolution:
\[ H^{(1)} = A \cdot X \cdot W^{(1)} \]

Two layer convolution:
\[ H^{(2)} = A \cdot H^{(1)} \cdot W^{(2)} = A \cdot (A \cdot X \cdot W^{(1)}) \cdot W^{(2)} = A^2 \cdot X \cdot W^{(1)} \cdot W^{(2)} \]

L-layer convolution:
\[ H^{(l)} = A \cdot H^{(l-1)} \cdot W^{(l)} = A \cdot (A \cdot H^{(l-2)} \cdot W^{(l-1)}) \cdot W^{(l)} = A \cdots (A \cdot X \cdot W^{(1)}) \cdots W^{(l)} \]
\[ = A^l \cdot X \cdot W^{(1)} \cdots W^{(l)} \]

Adjust the influence of meta-paths with different lengths
Multilayer Graph Convolution Module

\[ H(l) = A \cdot H^{(l-1)} \cdot W^{(l)} \]

\[ H = \frac{1}{l} \sum_{i=1}^{l} H^{(i)} = \frac{1}{l} \sum_{i=1}^{l} A \cdot H^{(i-1)} \cdot W^{(i)} \]
\[ \mathcal{L} = - \sum_{(u,v) \in \Omega} \log \sigma(<H_{u}^{T}, H_{v}>)
- \sum_{(u',v') \in \Omega^{-}} \log \sigma(<H_{u'}^{T}, H_{v'}>)
\]

\[ \mathcal{L} = - \sum_{i \in \mathcal{V}_{ids}} Y_{i} \ln(C \cdot H_{i}) \]
Experiments: Datasets and Baselines

- **Two** multiplex heterogeneous networks.
- **Three** heterogeneous networks.

- **Five** homogeneous network embedding methods.
- **Five** heterogeneous network embedding methods.
- **Eight** multiplex heterogeneous network embedding methods.

| Dataset   | #nodes | #edges  | #n-type | #e-type | #feat. | Mult. |
|-----------|--------|---------|---------|---------|--------|-------|
| Alibaba   | 21,318 | 41,676  | 2       | 4       | 19     | ✓     |
| Amazon    | 10,166 | 148,865 | 1       | 2       | 1,156  | ✓     |
| AMiner    | 58,068 | 118,939 | 3       | 3       | 4      | ✗     |
| IMDB      | 12,772 | 18,644  | 3       | 2       | 1,256  | ✗     |
| DBLP      | 26,128 | 119,783 | 4       | 3       | 4,635  | ✗     |

| Method     | Heter. Node | Edge | Multi. | Attr. | Unsup. | Auto. |
|------------|-------------|------|--------|-------|--------|-------|
| node2vec   | ✗           | ✗    | ✗      | ✗     | ✓      | ✗     |
| RandNE     | ✗           | ✗    | ✗      | ✗     | ✓      | ✗     |
| FastRP     | ✗           | ✗    | ✗      | ✗     | ✓      | ✗     |
| SGC        | ✗           | ✗    | ✓      | ✓     | ✓/✗    | ✗     |
| AM-GCN     | ✗           | ✗    | ✓      | ✓     | ✓/✗    | ✗     |
| R-GCN      | ✓           | ✓    | ✓      | ✓     | ✓/✗    | ✗     |
| HAN        | ✓           | ✓    | ✓      | ✓     | ✗      | ✗     |
| NARS       | ✓           | ✓    | ✓      | ✓     | ✗      | ✗     |
| MAGNN      | ✓           | ✓    | ✓      | ✓     | ✓/✗    | ✗     |
| HPN        | ✓           | ✓    | ✓      | ✓     | ✓/✗    | ✗     |
| PMNE       | ✗           | ✓    | ✓      | ✓     | ✗      | ✗     |
| MNE        | ✗           | ✓    | ✓      | ✓     | ✗      | ✗     |
| GATNE      | ✓           | ✓    | ✓      | ✓     | ✓      | ✓     |
| GTN        | ✓           | ✓    | ✓      | ✓     | ✓      | ✓     |
| DKGI       | ✓           | ✓    | ✓      | ✓     | ✓      | ✓     |
| FAME       | ✓           | ✓    | ✓      | ✓     | ✓      | ✓     |
| HGSN       | ✓           | ✓    | ✓      | ✓     | ✓      | ✓     |
| DualHGNN   | ✓           | ✗    | ✓      | ✓     | ✓      | ✗     |
| MHGCN      | ✓           | ✓    | ✓      | ✓     | ✓/✗    | ✓     |
Experiments: Overview

• Two downstream tasks
  ➢ Link Prediction: vs. 15 baselines
  ➢ Node Classification: vs. 17 baselines

• Ablation Study
  ➢ Verify the effectiveness of each component of our MHGCN.

• Parameter Sensitivity
  ➢ Verify the sensitivity of three important parameters?

• Model Efficiency Analysis
  ➢ Evaluate the efficiency of our proposed MHGCN?
MHGCN achieves average gains of 5.68% F1 score in comparison to the best performed GNN baselines across all datasets.

| Method     | AMiner R-AUC | PR-AUC | F1  | Alibaba R-AUC | PR-AUC | F1  | IMDB R-AUC | PR-AUC | F1  | Amazon R-AUC | PR-AUC | F1  | DBLP R-AUC | PR-AUC | F1  |
|------------|--------------|--------|-----|---------------|--------|-----|------------|--------|-----|-------------|--------|-----|-----------|--------|-----|
| node2vec   | 0.594        | 0.663  | 0.602 | 0.614         | 0.580  | 0.593 | 0.479      | 0.568  | 0.474 | 0.946       | 0.944  | 0.880 | 0.449      | 0.452  | 0.478 |
| RandNE     | 0.607        | 0.630  | 0.608 | 0.877         | 0.888  | 0.826 | 0.901      | 0.933  | 0.839 | 0.950       | 0.941  | 0.903 | 0.492      | 0.491  | 0.493 |
| FastRP     | 0.620        | 0.634  | 0.600 | 0.927         | 0.900  | 0.926 | 0.869      | 0.893  | 0.811 | 0.954       | 0.945  | 0.893 | 0.515      | 0.528  | 0.506 |
| SGC        | 0.589        | 0.585  | 0.567 | 0.686         | 0.708  | 0.623 | 0.826      | 0.889  | 0.769 | 0.791       | 0.802  | 0.760 | 0.601      | 0.606  | 0.587 |
| R-GCN      | 0.599        | 0.601  | 0.610 | 0.674         | 0.710  | 0.629 | 0.826      | 0.878  | 0.790 | 0.811       | 0.820  | 0.783 | 0.589      | 0.592  | 0.566 |
| MAGNN      | 0.663        | 0.681  | 0.666 | 0.961         | 0.963  | 0.948 | 0.912      | 0.923  | 0.887 | 0.958       | 0.949  | 0.915 | 0.690      | 0.699  | 0.684 |
| HPN        | 0.658        | 0.664  | 0.660 | 0.958         | 0.961  | 0.950 | 0.900      | 0.903  | 0.892 | 0.949       | 0.949  | 0.904 | 0.692      | 0.710  | 0.687 |
| PMNE-n     | 0.651        | 0.669  | 0.677 | 0.966         | 0.973  | 0.891 | 0.674      | 0.683  | 0.646 | 0.956       | 0.945  | 0.893 | 0.672      | 0.679  | 0.663 |
| PMNE-r     | 0.615        | 0.653  | 0.662 | 0.859         | 0.915  | 0.824 | 0.646      | 0.646  | 0.613 | 0.884       | 0.890  | 0.796 | 0.637      | 0.640  | 0.629 |
| PMNE-c     | 0.613        | 0.635  | 0.657 | 0.597         | 0.591  | 0.664 | 0.651      | 0.634  | 0.630 | 0.934       | 0.934  | 0.868 | 0.622      | 0.625  | 0.609 |
| MNE        | 0.660        | 0.672  | 0.681 | 0.944         | 0.946  | 0.901 | 0.688      | 0.701  | 0.681 | 0.941       | 0.943  | 0.912 | 0.657      | 0.660  | 0.635 |
| GATNE      | OOT          | OOT    | OOT  | 0.981         | 0.986  | 0.952 | 0.872      | 0.878  | 0.791 | 0.963       | 0.948  | 0.914 | OOT        | OOT    | OOT  |
| DMGI       | OOM          | OOM    | OOM  | 0.857         | 0.781  | 0.784 | 0.926      | 0.935  | 0.873 | 0.905       | 0.878  | 0.847 | 0.905      | 0.878  | 0.847 |
| FAME       | 0.687        | 0.747  | 0.726 | 0.993         | 0.996  | 0.979 | 0.944      | 0.959  | 0.897 | 0.959       | 0.950  | 0.900 | 0.959      | 0.963  | 0.633 |
| DualHGN     | /            | /      | /    | 0.974         | 0.977  | 0.966 | /          | /      | /    | /           | /      | /    | /          | /      | /    |
| MHGCN      | 0.711        | 0.753  | 0.730 | 0.997         | 0.997  | 0.992 | 0.967      | 0.966  | 0.959 | 0.972       | 0.974  | 0.961 | 0.718      | 0.722  | 0.703 |
## Node Classification

| Method  | AMiner   | Alibaba  | IMDB     | DBLP     |
|---------|----------|----------|----------|----------|
|         | Macro-F1 | Micro-F1 | Macro-F1 | Micro-F1 |
| node2vec| 0.522 (0.0032) | 0.532 (0.0051) | 0.238 (0.0125) | 0.347 (0.0093) | 0.363 (0.0237) | 0.382 (0.0703) | 0.352 (0.0103) | 0.351 (0.0112) |
| RandNE  | 0.641 (0.0074) | 0.672 (0.0064) | 0.319 (0.0170) | 0.358 (0.0093) | 0.373 (0.0143) | 0.392 (0.0185) | 0.351 (0.0153) | 0.372 (0.0150) |
| FastRP  | 0.650 (0.0086) | 0.690 (0.0074) | 0.301 (0.0180) | 0.392 (0.0119) | 0.363 (0.0236) | 0.381 (0.0140) | 0.343 (0.0201) | 0.375 (0.0199) |
| MNE     | 0.643 (0.0069) | 0.686 (0.0045) | 0.289 (0.0155) | 0.390 (0.0021) | 0.374 (0.0153) | 0.382 (0.0680) | 0.366 (0.0117) | 0.384 (0.0109) |
| GATNE   | OOT      | OOT      | 0.291 (0.0086) | 0.390 (0.0014) | 0.369 (0.0132) | 0.333 (0.0005) |               | OOT      |
| DMGI    | 0.473 (0.0155) | 0.626 (0.0093) | 0.220 (0.0214) | 0.392 (0.0026) | 0.548 (0.0190) | 0.544 (0.0189) | 0.781 (0.0303) | 0.787 (0.0235) |
| FAME    | 0.722 (0.0114) | 0.727 (0.0091) | 0.323 (0.0154) | 0.393 (0.0060) | 0.593 (0.0135) | 0.594 (0.0143) | 0.842 (0.0183) | 0.868 (0.0127) |
| DualHGNN|          |          | 0.347 (0.0114) | 0.402 (0.0127) |          |          |               |          |
| SGC     | 0.516 (0.0047) | 0.587 (0.0157) | 0.286 (0.0231) | 0.361 (0.0175) | 0.489 (0.0106) | 0.563 (0.0133) | 0.622 (0.0009) | 0.623 (0.0009) |
| AM-GCN  | 0.702 (0.0175) | 0.713 (0.0223) | 0.307 (0.0232) | 0.399 (0.0156) | 0.610 (0.0021) | 0.640 (0.0013) | 0.867 (0.0105) | 0.878 (0.0112) |
| R-GCN   | 0.690 (0.0078) | 0.692 (0.0106) | 0.265 (0.0326) | 0.381 (0.0125) | 0.544 (0.0172) | 0.572 (0.0145) | 0.862 (0.0053) | 0.870 (0.0070) |
| HAN     | 0.690 (0.0149) | 0.726 (0.0086) | 0.275 (0.0327) | 0.392 (0.0081) | 0.552 (0.0112) | 0.568 (0.0078) | 0.806 (0.0078) | 0.813 (0.0100) |
| NARS    | 0.722 (0.0103) | 0.721 (0.0097) | 0.297 (0.0097) |               |               |               | 0.794 (0.0255) | 0.804 (0.0320) |
| MAGNN   | 0.755 (0.0105) | 0.757 (0.0133) | 0.348 (0.0089) |               |               |               | 0.881 (0.0284) | 0.895 (0.0396) |
| HPN     | 0.710 (0.0612) | 0.732 (0.0490) | 0.263 (0.0081) |               |               |               | 0.822 (0.0201) | 0.830 (0.0201) |
| GTN     | OOM      | OOM      | 0.255 (0.0420) | 0.392 (0.0071) | 0.615 (0.0108) | 0.616 (0.0093) | 0.852 (0.0137) | 0.868 (0.0125) |
| HGLS    | 0.754 (0.0100) | 0.758 (0.0103) | 0.338 (0.0121) | 0.398 (0.0238) | 0.620 (0.0048) | 0.638 (0.0030) | 0.893 (0.0284) | 0.902 (0.0396) |
| MHGCN   | 0.868 (0.0160) | 0.875 (0.0200) | 0.351 (0.0204) | 0.458 (0.0160) | 0.764 (0.0145) | 0.782 (0.0138) | 0.945 (0.0221) | 0.952 (0.0203) |

**Improvement:**

- 23.23% improvement on Macro-F1
- 22.19% improvement on Micro-F1
Ablation Study

• **MHGCN-R** does not consider the importance of different relations.
  ➢ Demonstrate the crucial role of our designed **multiplex relation aggregation module**.

• **MHGCN-L** uses only a two-layer GCN to obtain the embedding
  ➢ Reflect the importance of our **multilayer graph convolution module**.
**Parameter Sensitivity**

- 1-length and 2-length meta-path already effectively capture the topological structures of network.
- Achieve the best performance when embedding dimension $d = 128$.
- Achieve the stable performance within 80 rounds on all tested datasets.
# Model Efficiency Analysis

| Method   | AMiner   | Alibaba  | IMDB     | DBLP     |
|----------|----------|----------|----------|----------|
| AM-GCN   | 8703.71  | 2519.82  | 24280.12 | 2786.73  |
| R-GCN    | **153.04** | 301.25   | 155.40   | 192.85   |
| HAN      | 87105.55 | 4226.95  | 70510    | 22315.36 |
| NARS     | 172.21   | **211.54** | **75.81** | **108.54** |
| MAGNN    | 10361.20 | 2320.62  | 731.03   | 2125.33  |
| HPN      | 172.82   | 249.47   | 176.64   | 109.49   |
| GTN      | OOM      | 21166.83 | 4287.20  | 18233.64 |
| HGSL     | 1684.03  | 2120.93  | 1758.21  | 2037.10  |
| DualHGN  | /        | 11295.92 | /        | /        |
| **MHGCN** | **645.20** | **996.52** | **677.23** | **970.29** |

- Adopt the idea of simplifying graph convolutional networks
- Ensure efficiency with high performance
  - **135 times** faster than HAN on AMiner.
  - **21 times** faster than GTN on Alibaba.

* Speedup of MHGCN over HAN.
** Speedup of MHGCN over GTN.
OOM: Out Of Memory.
Conclusion

• We propose an effective graph convolution network model for attributed multiplex heterogeneous networks.

• Our model can well deal with the multilayered nature of multiplex networks and distinguish the importance of different relations in heterogeneous networks.

• Our model can automatically capture the useful relation-aware meta-path information in multiplex heterogeneous networks.

• Experiments on five real-word datasets demonstrate the effectiveness and efficiency of the proposed model.
Thanks for Listening
Q & A

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