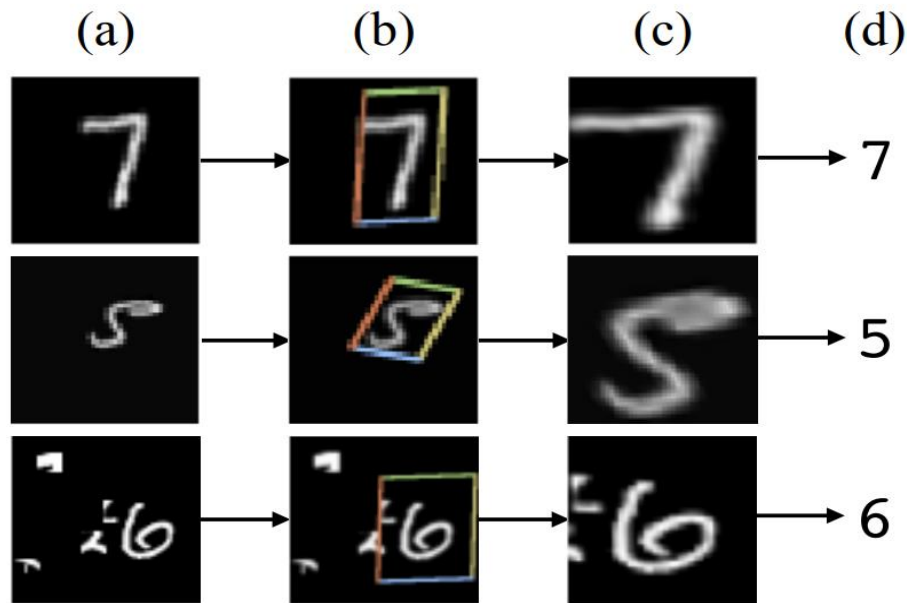


Graph Transformer Networks (NeurIPS 2019)

Seongjun Yun, Minbyul Jeong, Raehyun Kim, Jaewoo Kang, Hyunwoo J. Kim

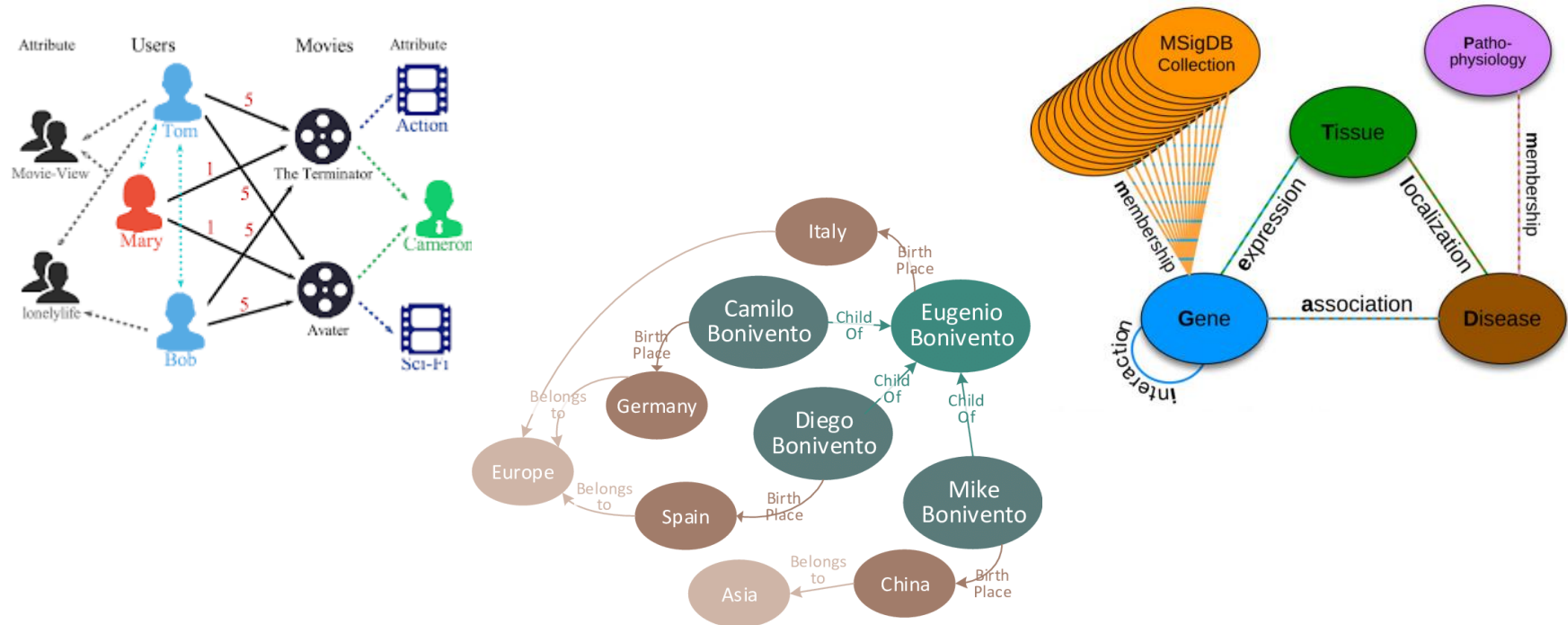
Spatial Transformer Networks



A spatial transformer that crops out and scale-normalizes the appropriate region can simplify the subsequent classification task, and lead to superior classification performance

Heterogeneous Graph

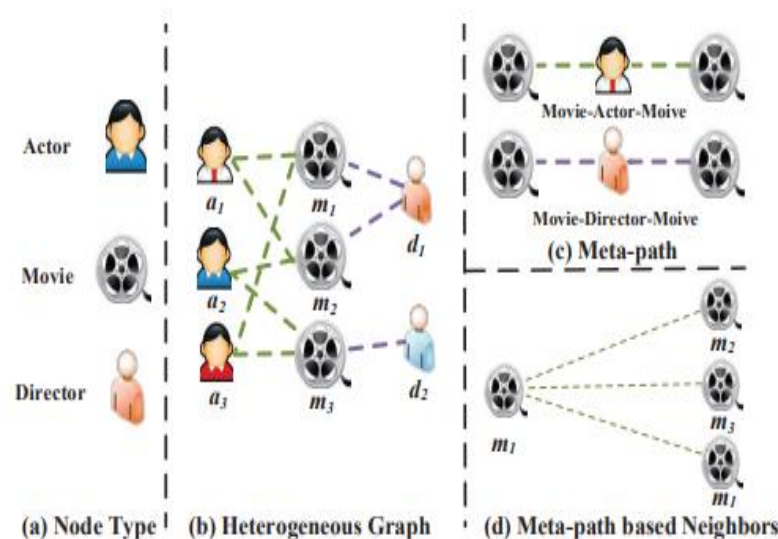
Heterogeneous graph is a graph which contains different types of nodes and edges



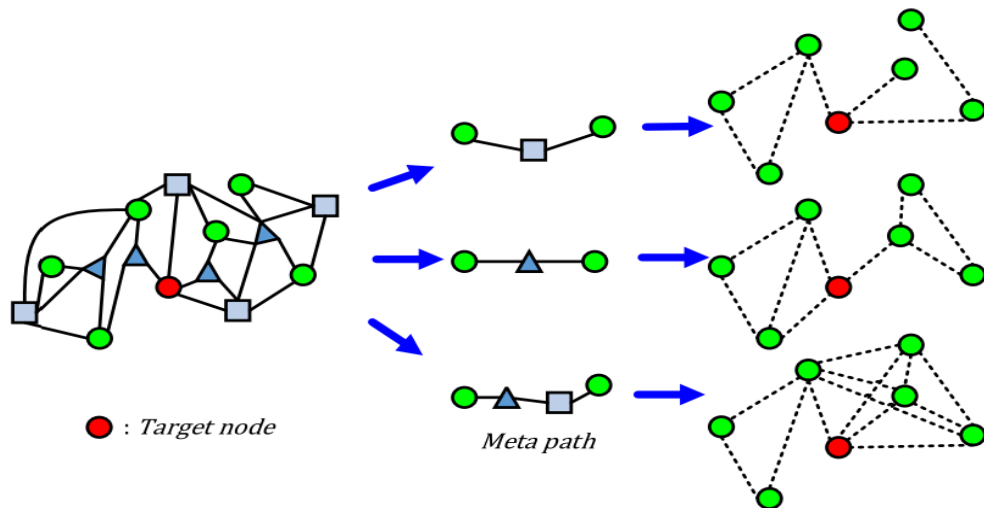
Meta-path

A meta-path is a path consisting of a sequence of relations defined between different object types

| Datasets | Examples of meta-path |
|-------------------|---|
| BlogCatalog | $\text{Blog} \xrightarrow{\text{has}} \text{Tag} \xrightarrow{\text{has}^{-1}} \text{Blog}$ $\text{Blog} \xrightarrow{\text{written.by}} \text{User} \xrightarrow{\text{written.by}^{-1}} \text{Blog}$ $\text{Blog} \xrightarrow{\text{written.by}} \text{User} \xrightarrow{\text{friend}} \text{User} \xrightarrow{\text{written.by}^{-1}} \text{Blog}$ |
| DBLP | $\text{Paper} \xrightarrow{\text{has}} \text{Term} \xrightarrow{\text{has}^{-1}} \text{Paper}$ $\text{Paper} \xrightarrow{\text{written.by}} \text{Author} \xrightarrow{\text{written.by}^{-1}} \text{Paper}$ $\text{Paper} \xrightarrow{\text{written.by}} \text{Author} \xrightarrow{\text{written.by}^{-1}} \text{Paper} \xrightarrow{\text{has}} \text{Term} \xrightarrow{\text{has}^{-1}} \text{Paper}$ |
| Chemical Compound | $\text{Compound} \xrightarrow{\text{bind}} \text{Gene} \xrightarrow{\text{PPI}} \text{Gene} \xrightarrow{\text{bind}^{-1}} \text{Compound}$ $\text{Compound} \xrightarrow{\text{treat}} \text{Disease} \xrightarrow{\text{cause}^{-1}} \text{Gene} \xrightarrow{\text{bind}^{-1}} \text{Compound}$ $\text{Compound} \xrightarrow{\text{bind}} \text{Gene} \xrightarrow{\text{has}} \text{Pathway} \xrightarrow{\text{has}^{-1}} \text{Gene} \xrightarrow{\text{bind}^{-1}} \text{Compound}$ |

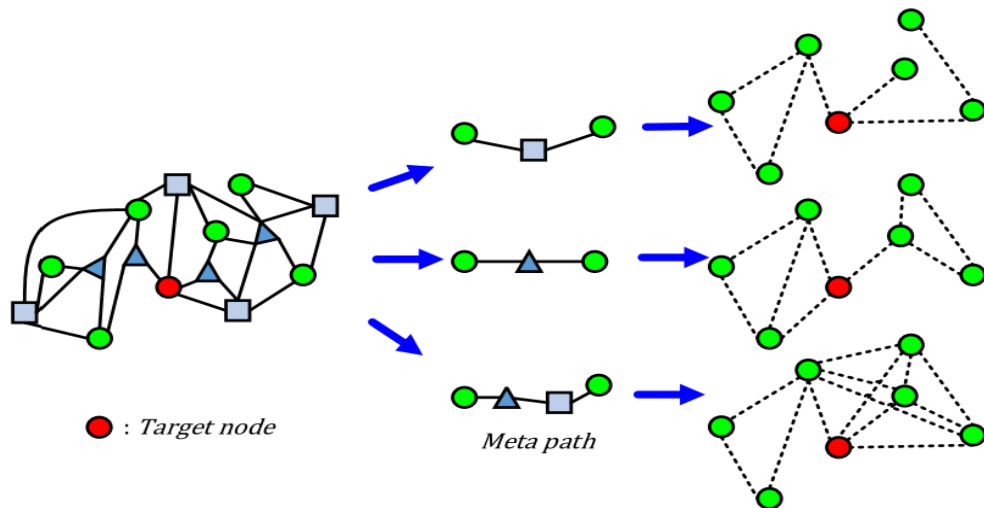


Transform a Graph into new Graphs using Meta-Paths



Previous works about graph neural networks leveraged useful meta-path which selected **manually** by domain experts.

Transform a Graph into new Graphs using Meta-Paths



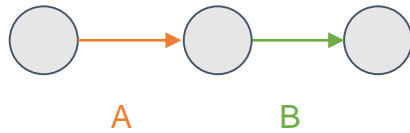
Previous works about graph neural networks leveraged useful meta-path which selected **manually by domain experts**.

Can model **learn to transform** an original graph into a new graph which involves only useful connections for task?

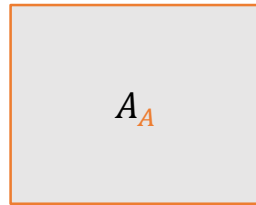
Multiplication of Adjacency Matrices for Generating Meta-Paths

Edge Type: A,B

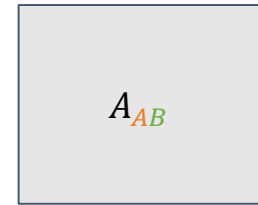
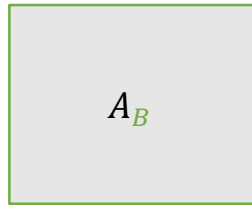
Graph



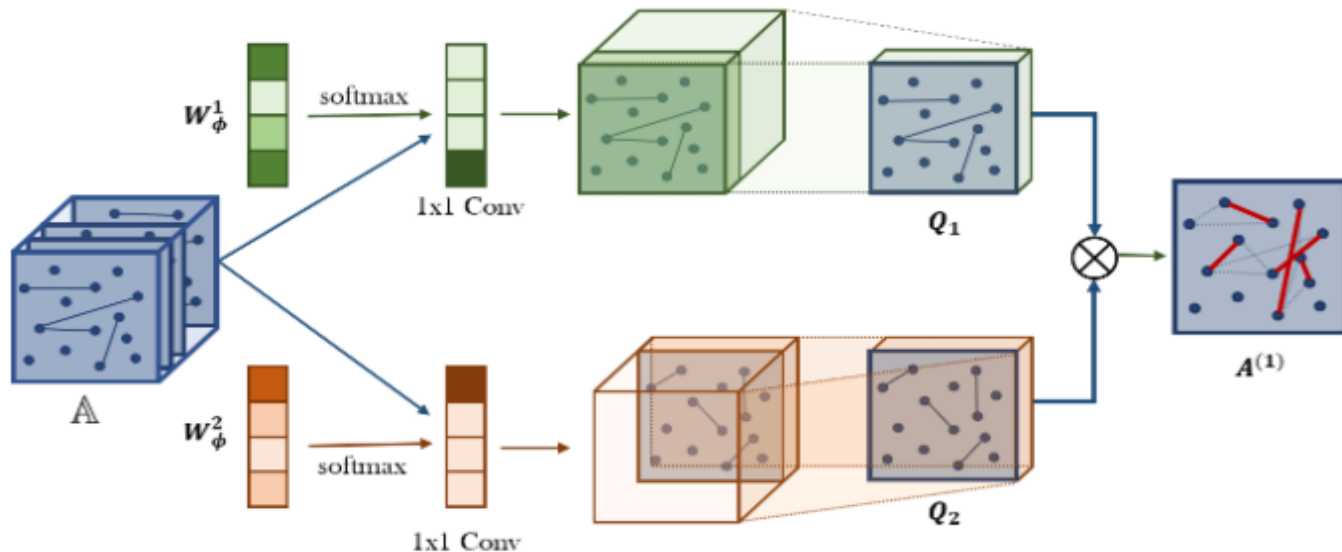
Adjacency
Matrix



X

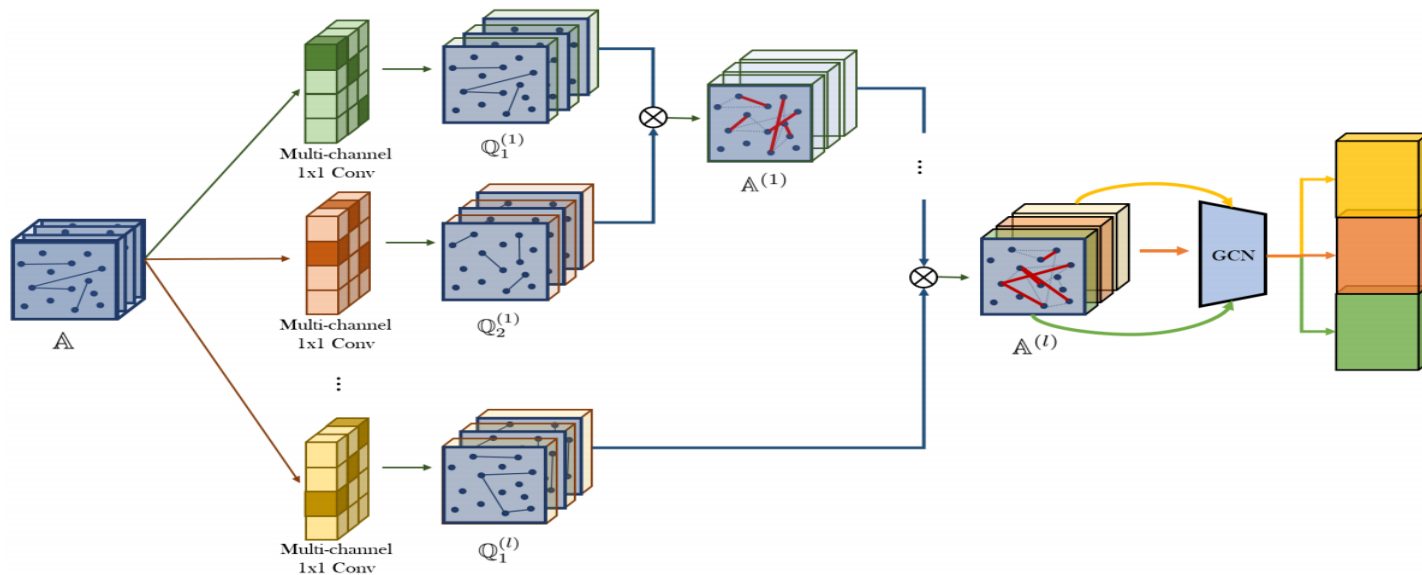


Graph Transformer Layer



Graph Transformer Layer (GTL) softly **selects adjacency matrices** (edge types) from the set of adjacency matrices and **generate** a new meta-path graph via the **matrix multiplication** of two selected adjacency matrices.

Graph Transformer Networks



Graph Transformer Networks (GTNs) learn to **generate a set of new meta-path adjacency matrices** using GT layers and perform graph convolution as in GCNs on the new graph structures.

Q1) Are the new graph structures generated by GTN effective for learning node representation?

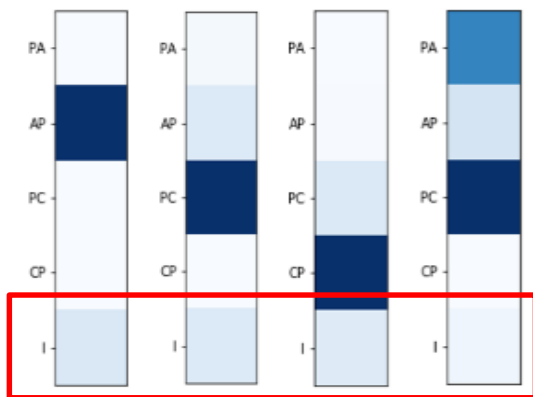
| Dataset | # Nodes | # Edges | # Edge type | # Features | # Training | # Validation | # Test |
|---------|---------|---------|-------------|------------|------------|--------------|--------|
| DBLP | 18405 | 67946 | 4 | 334 | 800 | 400 | 2857 |
| ACM | 8994 | 25922 | 4 | 1902 | 600 | 300 | 2125 |
| IMDB | 12624 | 37288 | 4 | 1256 | 300 | 300 | 2339 |

| | DeepWalk | metapath2vec | GCN | GAT | HAN | GTN _{-I} | GTN (proposed) |
|------|----------|--------------|-------|-------|-------|-------------------|----------------|
| DBLP | 63.18 | 85.53 | 87.30 | 93.71 | 92.83 | 93.91 | 94.18 |
| ACM | 67.42 | 87.61 | 91.60 | 92.33 | 90.96 | 91.13 | 92.68 |
| IMDB | 32.08 | 35.21 | 56.89 | 58.14 | 56.77 | 52.33 | 60.92 |

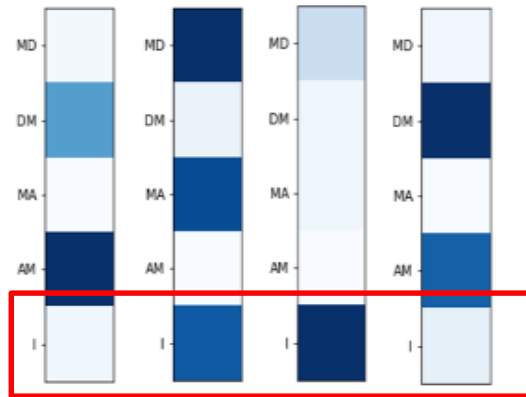
- Graph Transformer Networks (GTNs) achieves the **highest performance** on all the datasets against all network embedding methods and graph neural network methods
- GTNs performs **better** than HAN which uses the **pre-defined meta paths**.

Q2) Can GTN adaptively produce a variable length of meta-paths depending on datasets?

The attention score of adjacency matrix (edge type) from each Graph Transformer Layer



(a)
DBLP



(b)
IMDB

- By assigning **higher** attention scores to **the identity matrix (I)**, GTN tries to stick to the shorter meta-paths even in the deeper layer.
- GTN has ability to **adaptively learn most effective meta-path length** depending on the dataset

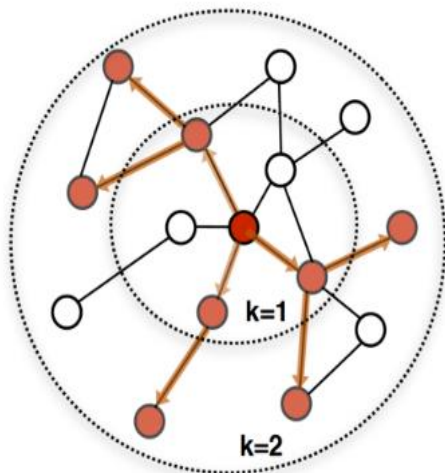
Q3) How can we interpret the importance of each meta-path from the adjacency matrix generated by GTNs?

Comparison with predefined paths and top-ranked meta-paths by GTNs

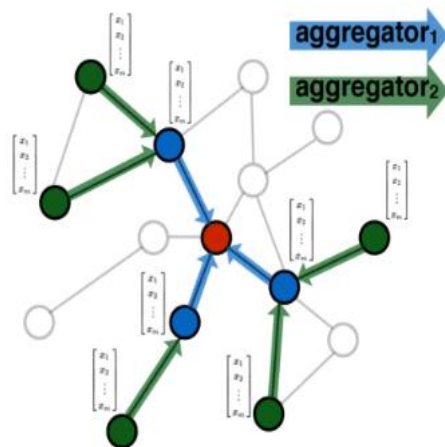
| Dataset | Predefined Meta-path | Meta-path learnt by GTNs | |
|---------|-------------------------|------------------------------|------------------|
| | | Top 3 (between target nodes) | Top 3 (all) |
| DBLP | APCPA, APA | APCPA, APAPA, APA | APCPC, APCPA, PC |
| ACM | PAP, PSP | PAP, PSP | PAPA, APA, PAPS |
| IMDB | MAM, MDM | MDM, MAM, MDMDM | DM, AM, MDM |

- The predefined meta-paths by domain knowledge are consistently top-ranked by GTNs as well.
- Our GTNs are capable to learn the importance of meta-paths for tasks

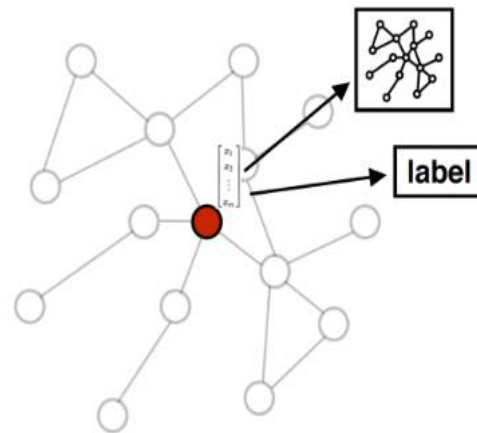
Scalability



1. Sample neighborhood



2. Aggregate feature information from neighbors



3. Predict graph context and label using aggregated information