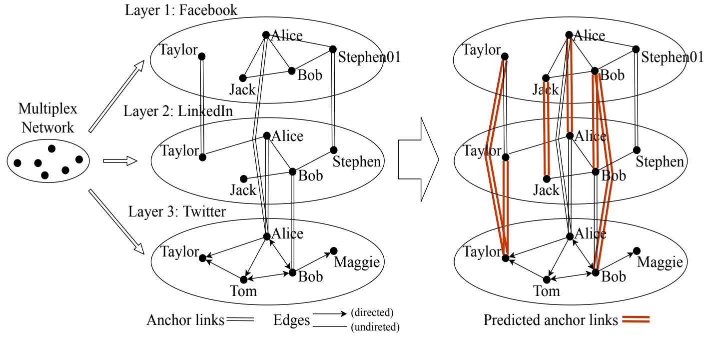
Contrastive Multi-View Multiplex Network Embedding with Applications to Robust Network Alignment

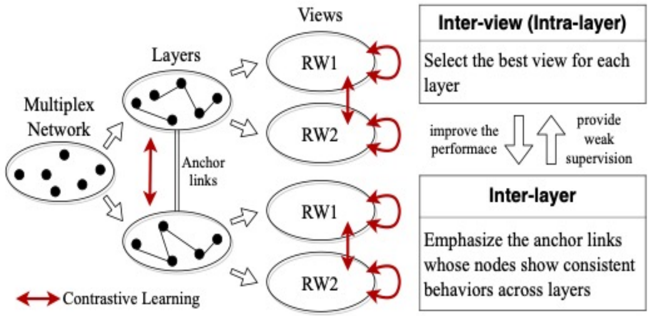
Hao Xiong[1], Junchi Yan[1*], Li Pan[1*]
{taxuexh, yanjunchi, panli}@sjtu.edu.cn, [1] Shanghai Jiao Tong University, [*] corresponding authors

Problem Formulation

Network alignment in multiplex network:



Motivation



Challenge 1 (intra-layer learning): Edges are missing to different extent on the layers. For example, some are dense (rich of structural information) while some are sparse (in a lack of structural information).

- **Solution 1:** We generate multiple structural views for each layer and adopt layer-view-specific attention to select the best views for each layer.

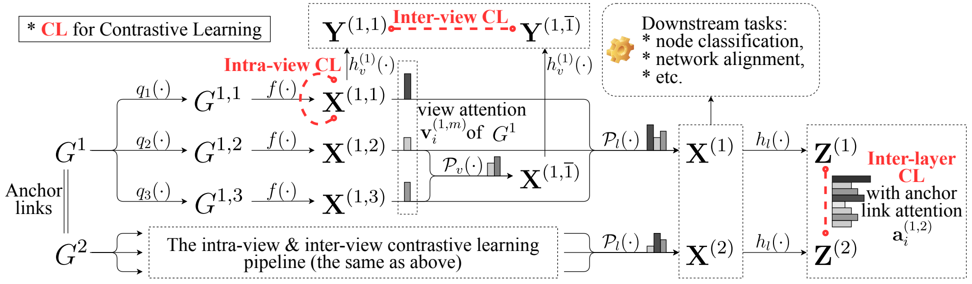
Challenge 2 (inter-layer learning): The known alignment anchor links between layers can be misleading since the behaviors of nodes on different layers are not always consistent. Treating the inter-layer anchor links equally is not reasonable.

- **Solution 2:** We use an attention tensor to measure the agreement value of anchor links. Hence, informative anchor links are emphasized and the misleading ones are de-emphasized.

Intra/inter-layer learning will promote each other. For example, determining whether an anchor link behaves in agreement/disagreement would be easier with layers' views selected properly. And intra-layer learning will also be weakly supervised by the properly learned attention over anchor links.

Method

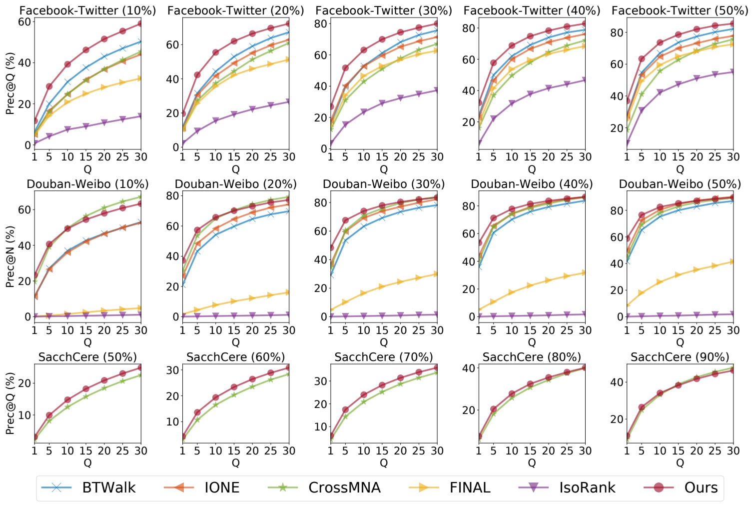
The pipeline of the proposed framework cM²NE:



The **cM²NE** framework with multiplex network $\mathcal{G} = \{G^g\}_{g=1}^N$ as input and embeddings $\{\mathbf{X}^{(g)}\}_{g=1}^N$ as output. For layer G^1, M multi-view augmentations $\{G^{1,m}\}_{m=1}^M$ are generated given functions $\{q_m(\cdot)\}_{m=1}^M$. Then by $f(\cdot)$, nodes in view $G^{1,m}$ are embedded into a low-dimensional space, where the embeddings are denoted as $\mathbf{X}^{(1,m)}$. Then contrastive learning (CL) is performed on three levels: i) Intra-view CL is conducted directly on $\mathbf{X}^{(1,m)}$ to preserve intra-view information. ii) For inter-view CL on layer G^1 between the m-th view and the others, first $\{\mathbf{X}^{(1,k)}\}_{k=1,k\neq m}^M$ are aggregated together by inter-view *readout function* $\mathcal{P}_v(\cdot)$ whose results are denoted as $\mathbf{X}^{(1,\overline{m})}$, then inter-view CL is performed after mapping $\mathbf{X}^{(1,m)}$ and $\mathbf{X}^{(1,\overline{m})}$ to $\mathbf{Y}^{(1,m)}$ and $\mathbf{Y}^{(1,\overline{m})}$ by *projection heads* $h_v^{(1)}(\cdot)$. iii) For inter-layer CL between G^1 and G^2, embeddings of multiple views are aggregated by inter-layer *readout function* $\mathcal{P}_l(\cdot)$ and we get embedding $\mathbf{X}^{(1)}$, $\mathbf{X}^{(2)}$, then they are mapped to $\mathbf{Z}^{(1)}$, $\mathbf{Z}^{(2)}$ for inter-layer CL.

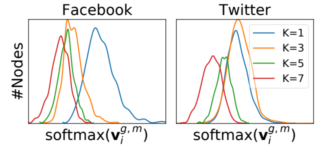
Experimental Results

Network alignment on 3 multiplex networks: Facebook-Twitter (social), Douban-Weibo (social), and SacchCere (biological).

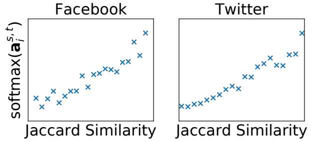


Case Study

We perform case study over the dataset Facebook-Twitter.



a) Distribution of multi-view attention (views are generated by K-hop random walk). We can see that different layers show different preferences on structural views.



b) Distribution of the learned anchor link attention, which we can see is usually positively related with the Jaccard Sim. of the neighborhoods of the two anchored nodes.