we propose Hybrid Contrastive Learning (HCL) for graph-based recommendation that integrates unsupervised and supervised contrastive learning. To summarize, the contributions of this work are three-folds:

- We identify the limitation of existing contrastive learning methods for recommendation and propose Hybrid Contrastive Learning.
- We generalize a permutational approach that performs hybrid contrastive learning across multiple views which are generated to convey incomplete and noisy information with respect to node embeddings and topology.
- Extensive experiments show the superiority of HCL regarding to model generalization and robustness over SOTA baselines on two public and one internal dataset.

In general, the proposed HCL has three steps:

- We propose novel bipartite graph augmentation strategies by taking node embeddings and topology into consideration to generate different incomplete and noisy views for the input user-item graph.
- The proposed hybrid contrastive learning performs unsupervised and supervised contrastive learning on homogeneous nodes and observed user-item interactions, respectively.
- We conduct the hybrid contrastive learning among multiple views permutationally.

Bipartite Graph Augmentation
we propose four bipartite graph augmentation strategies to generate different graph views that contain incomplete and noisy information about node embedding and node topology to boost downstream contrastive learning, including node embedding dropout, edge dropout, edge moving and connecting similar homogeneous nodes.

Hybrid Contrastive Learning

Unsupervised Contrastive Learning: We pull together the different views of the same node and push apart those of different nodes.

\[
\ell_{uc}(\theta, \theta') = \frac{1}{2m} \sum_{i=1}^{m} \log \frac{\exp\left(\frac{s_{io}(\theta, \theta')}{T}\right)}{\sum_{j=1}^{m} \exp\left(\frac{s_{jo}(\theta, \theta')}{T}\right)}
\]

Supervised Contrastive Learning: We propose to encourage the consistency of the embeddings of the users and the interacted items by computing supervised contrastive learning (SCL) loss given the observed user-item interactions. We maximize agreement between user representation and item representation generated from different views.

Multi-view Permutation
The total multi-view HCL loss is the summation of the HCL loss terms computed on every pair of graph views permutationally, and each HCL loss term is the summation of unsupervised contrastive learning losses on user and item nodes and supervised contrastive learning losses.

\[
\ell_{HCL} = \sum_{u \in U} \ell_{uc}(\theta, \theta') + \sum_{i \in I} \ell_{uc}(\theta, \theta') + \sum_{u \in U} \ell_{sup}(\theta, \theta') + \sum_{i \in I} \ell_{sup}(\theta, \theta')
\]

We trained the model in the multi-task learning fashion with the final loss

Effect of probability for bipartite graph augmentation

Time (seconds) of training models for one epoch.

Model performance with noise ratios. The bar represents the results in terms of Recall@20 and NDCG@20, respectively.

Visualization of users and items embeddings learnt by SGL and the proposed HCL.