AI506 Term Project
Ensemble Learning for Hyperedge Prediction using Graph Structure based on features in Hypergraph

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1. Motivation

Problem: Hyperedge prediction in large hypergraph

Challenge I. Scalability issue

- It is difficult to directly apply the methodology visiting the entire large graph such as Girvan-Newman and DeepWalk.
  >>> *We extract **graph structure based features** of hyperedge*

Challenge II. Low level representation

- It is limited to predict hyperedge using only graph structure based features of hyperedge because high level features cannot be considered.
  >>> *Abstract hyperedge through **n-order expansion** and extract graph structure based features for each abstracted hyperedge*

2. Method

Our method has the following steps:

*Step 1. Abstract hypergraph through **n-order expansion** to extract high level features*

*Step 2. Extract **graph structure based features** of n-projected graph*

*Step 3. Boost performance through **ensemble learning***

2. Method

n-order expansion

: We adopt n-order expansion which is a method of incrementally representing high-order interactions as n-projected graphs in a given hypergraph[1]. We extract high-order latent features from n-projected graphs of hypergraph.

graph structure based features

: We used 8 different features for hyperedge prediction and extracted each feature from n-projected graphs.

>> *Features* *Harmonic Mean (HM), Arithmetic Mean (AM), Common neighbors (CN), Jaccard Index (JI), Adamic Adar Index (AA), Resource Allocation (RA), Hub Promoted Index (HPI), Number of Nodes in a hyperedge(NN)*

ensemble learning

: We use following classifiers and conducted ensemble learning for hyperedge prediction

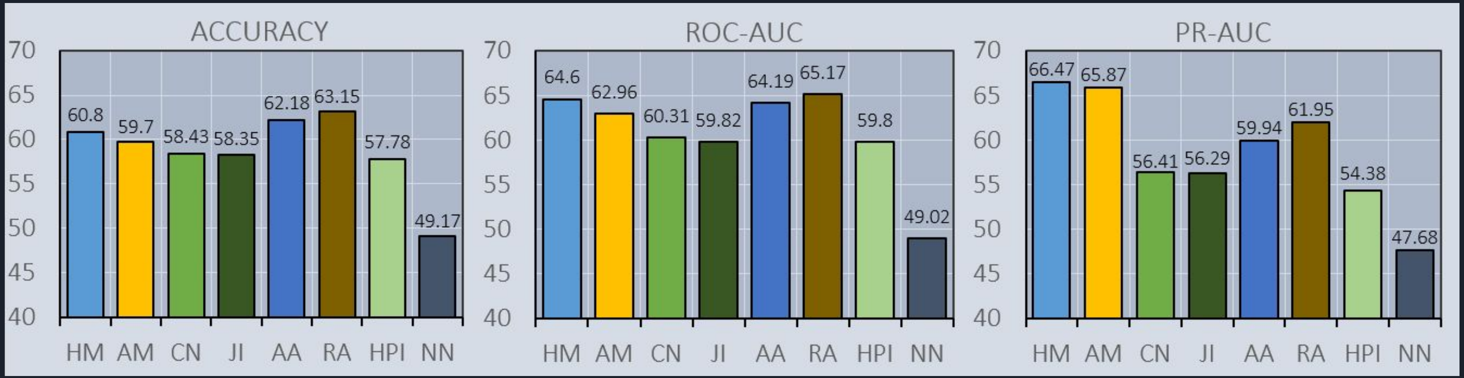
>> Classifiers *Random Forest(RF), LightGBM(LGBM)*

[1] Yoon, Se-eun, et al. "How Much and When Do We Need Higher-order Informationin Hypergraphs? A Case Study on Hyperedge Prediction." Proceedings of The Web Conference 2020. 2020.

3. Performance evaluation

We construct a graph using 58646 nodes and 137958 hyperedges. For hyperedge prediction task, we use 34479 candidate hyperedges 27583 for train, and 6896 for test.

Effectiveness of graph structure based features
: To show the performance of each feature, we ran 8 different hyperedge prediction models with each feature. The results are displayed in following chart.



>> ***Features*** *Harmonic Mean (HM), Arithmetic Mean (AM), Common neighbors (CN), Jaccard Index (JI), Adamic Adar Index (AA), Resource Allocation (RA), Hub Promoted Index (HPI), Number of Nodes in a hyperedge(NN),*

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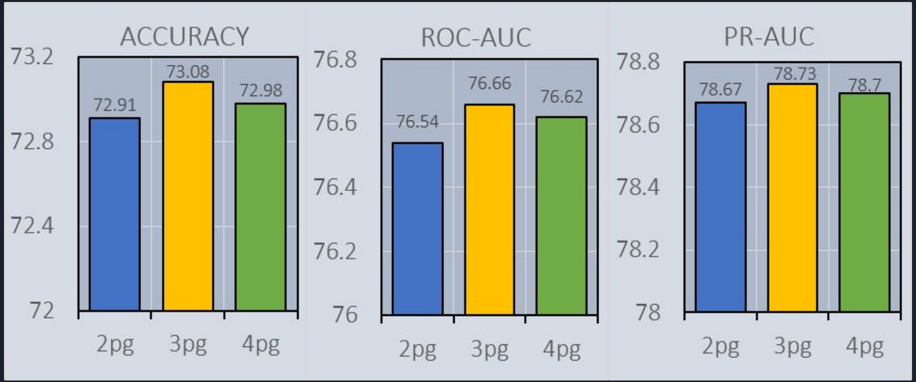
Effectiveness of n-order expansion

: To show the performance of n-order expansion, we trained models by gradually concatenating features from n-projected Graph. (i.e 3pg has total 16 features extracted from 2-projected Graph and 3-projected Graph) We extended the graph to 4-order expansion to represent the high-order interaction in hyperedge.



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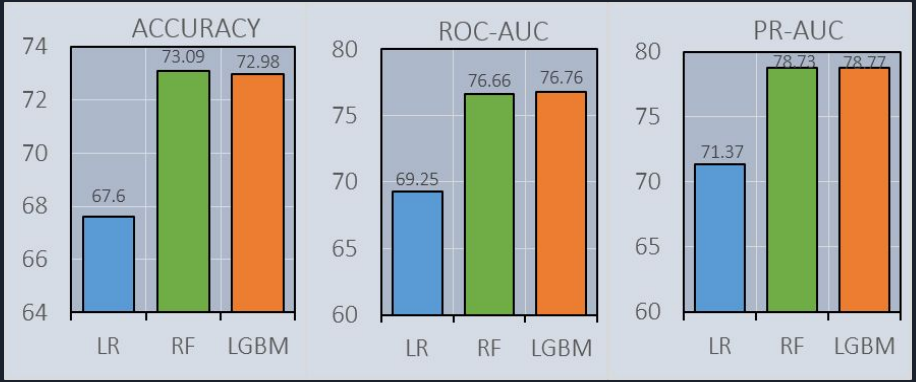
Effectiveness of ensemble learning
: To show the performance of the ensemble learning, we ran 3 models(Logistic Regression, Random Forest, LightGBM). We use 16 features extracted from 2-projected Graph and 3-projected Graph. We compare ensemble learning method(Random Forest and LightGBM) with normal linear model, Logistic Regression.



3. Performance evaluation

Effectiveness of graph structure based features. *Every features have great performance than Random Guessing except NN. But NN complements other features and shows good results.*

Effectiveness of n-order expansion. *N-order expansion gives better accuracy, ROC-AUC, PR-AUC than using 2-projected graph. Especially, model with graph extended to 3-order shows the best performance.*

Effectiveness of ensemble learning. *Ensemble learning method achieves high performance than simple linear method. Especially, Random Forest gives the best performance.*

FINAL MODEL. ***Random Forest trained with 16 features extracted from 2-pg Graph and 3-pg Graph.***

4. Conclusion

- To overcome two challenges(scalability issue, low level representation), we abstracted the graph through n-order expansion and conducted *Ensemble Learning for Hyperedge Prediction using Graph Structure based on features in Hypergraph*.

- In experiment using co-authorship network data, our method showed 73.09% accuracy, 76.66 ROC-AUC and 78.73 PR-AUC score for co-author relationship predictions.

- We showed the effectiveness of our features, n-order expansion and ensemble learning

THANK YOU!

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