Subgraph Pattern Matching with Deep Representations

Team Member: Joe Lou, Yue Zhang, Ziyi Yang Mentor: Rex Ying, Jiaxuan You, Jure Leskovec

Subgraph Matching





Method: Graph Convolutional Networks (GCNs)



Single Query Matching



Single Query Matching

train_AUROC_overall 1 0.98 minun 0.95 0.94 0.9 0.9 0.85 0.86 0.8 0.82 0.75 0.78 0 40 80 120 160 200 80 160 40 120 200 0

test_AUROC_

Family Classification



Family Classification



test_AUROC_





Generalizing

train_AUROC_overall



test_AUROC_

Random Training (In Progress)







Order embedding

 Query graph node embedding (Y), Test graph node embedding (X)



- Comparing embeddings directly reduces computational cost.
- Penalizing Order Violations: $E(x, y) = ||\max(0, y x)||^2$
- Max-margin loss

$$\sum_{(u,v)\in P} E(f(u), f(v)) + \sum_{(u',v')\in N} \max\{0, \alpha - E(f(u'), f(v'))\}$$

• Hyperparameters introduced: Margin *a*, dimension threshold *b*

Order embedding on multi-query experiment



test_AUROC_



Order embedding Results

• Compare the node embeddings for common subgraph



1 is subgraph of 2 and 2 is subgraph of 3.

- Node embeddings have dimension 60.
- Out of 60 elements,

0 elements in embedding 1 > 2 (expect < 12) 9 elements in embedding 2 > 3 (expect < 12) 27 elements in embedding 4 > 5 (expect > 12) 36 elements in embedding 5 > 6 (expect > 12)

Order embedding Results



Conclusions & Future Work

- Delivered a Graph Convolutional Neural Network model for subgraph matching.
- Order embedding method was used to train node embeddings that can be compared directly to reduce computational cost.