Stanford CS224W: Exam Preparation

CS224W: Machine Learning with Graphs Xuan Su & Serina Chang, Stanford University http://cs224w.stanford.edu



Exam Information

Percentage: 35% of your course grade

 Time: a consecutive, 120-minute slot from Nov 19, 10:00AM to Nov 20, 09:59AM
 The make-up exam is 2 days prior

- Exam Format: The exam is administered through Gradescope
 - You can typeset your answers in LaTeX or handwrite your answers + upload them as images
 - The exam should take around 110 minutes, and you have 10 minutes to upload images

Exam Information

There will be **11** questions

- Some questions are easy, and some are harder
- Try to spend 5-15 minutes on each question
- If stuck on a particular question for too long, please skip that question and come back later

Types of questions:

- True/False questions with explanation
- Give examples of graphs
- Comparison of approaches
- Mathematical calculations and derivations
- We feel that the exam is medium difficulty

General Advice for the Exam

- We suggest that you read through all lecture slides carefully
- **Topics** that are **important** for the exam:
 - Node centrality measures, PageRank
 - GNN model and design space (e.g., message, aggregation, update)
 - Knowledge graph embeddings, Query2Box, recommender systems (LightGCN)
- Lectures that are important for the exam: lectures 2, 4, 6, 7, 8, 10, 11, 13

General Advice for the Exam

- We suggest that you read through all lecture slides carefully
- Lectures that are relatively unimportant for the exam: lectures 1, 3, 5, 9, 12, 14
 - You can spend less time studying these lectures
 - However, you should still read through them and understand the concepts as there may be miscellaneous questions

Stanford CS224W: Homework Review

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- We use GNNs to execute the BFS algorithm
 Initially, all nodes have input features 0, except a source node with feature 1
- At every step, nodes reached by BFS have embedding 1, and nodes not reached by BFS have embedding 0
- Describe the message, aggregate, update functions
 Advice: Think from the perspective of nodes in the graph



(1) Message passing

- Imagine you are a node in the graph. What information would you tell your neighbors?
 - "I have been visited by the BFS algorithm!" or "I have not been visited!"
 - Simply pass my embedding to my neighbors

$$ext{message}_{v
ightarrow u} \left(h_v^{(k-1)}, e_{v,u}
ight) = h_v^{(k-1)}$$



(2) Aggregation

- What information should you get from your neighbors?
 - I want to know whether any of my neighbors have been visited
- Node *u* aggregates neighbors' information via:

$$ext{aggregate}\left(\{ ext{message}_{v
ightarrow u}, \, orall v \in \mathcal{N}(u)\}
ight) =$$

```
\max_{v \in \mathcal{N}(u)} \operatorname{message}_{v 
ightarrow u}
```



(3) Update

- Don't forget the self-link to the previous embedding for node u
 - BFS: I am visited if (1) I have been visited, or (2) any of my neighbors has been visited

update
$$\left(h_u^{(k-1)}, \operatorname{aggregate}(\cdots)\right) = \max\left(h_u^{(k-1)}, \operatorname{aggregate}(\cdots)\right)$$

 This is one solution to Q4.6, there are alternatives



- There are common patterns in knowledge graph embeddings
 - **Symmetry**: A is married to B, and B is married to A
 - Inverse: A is teacher of B, and B is student of A
 - Composition: A is son of B, and C is sister of B, then C is aunt of A
- **KG method:** TransE
 - Given a triplet (h, l, t), TransE trains entity and relation embeddings to follow the equation h + l ≈ t
- Can we use TransE to model each of the relation patterns?

- Given (*h*, *l*, *t*), TransE equation is: *h* + *l* ≈ *t*
- Key question: For the given relation pattern, what equations should hold true?
- Symmetry: A is married to B, and B is married to A
- Can we use TransE to model symmetry? No
 - For two triplets (*h*, *l*, *t*) and (*t*, *l*, *h*) to both hold true, we will have: *h* + *l* ≈ *t* and *t* + *l* ≈ *h*
 - The only possibility for both equations to be true is if
 I = 0 and h = t, which is a problem since two
 different entities should have different embeddings

- Given (h, l, t), TransE equation is: h + l ≈ t
- **Inverse:** A is teacher to B, and B is student to A
- Can we use TransE to model *inverse*? Yes
 - For two triplets (h, r1, t) and (t, r2, h) to both hold true, we will have: h + r1 ≈ t and t + r2 ≈ h
 - It suffices to set the inverse relation r2 = -r1



- Given (h, l, t), TransE equation is: h + l ≈ t
- Composition: A is son of B, and C is sister of B, then C is aunt of A
- Can we use TransE to model composition? Yes
 - Given three triplets, (a, r1, b), (b, r2, c), (a, r3, c), where r3 is the composition of r2 and r1
 - For all triplets to be true, we will have: $a + r1 \approx b, b + r2 \approx c, a + r3 \approx c$
 - Set r3 = r1 + r2 for composition



Stanford CS224W: Miscellaneous Topics

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Erdös-Rényi Random Graph

To produce an undirected graph G = (V, E), the ER model uses a fixed likelihood to generate edges connecting any pair of nodes:

$$\mathbb{P}\left[(u,v)\in E
ight]=r, \quad orall u,v\in V, u
eq v$$



Erdös-Rényi Random Graph

What is the expected average node degree, **E**[*d*], of a graph generated by ER?

• **Key idea**: summing the edge connectivity over nodes to compute the expected node degree

$$\begin{split} |E| &= \frac{1}{2} \sum_{u \in V} \sum_{v \in V \setminus \{u\}} 1 \cdot \mathbb{1}[(u, v) \in E] \\ \mathbb{E}[|E|] &= \frac{1}{2} \sum_{u \in V} \sum_{v \in V \setminus \{u\}} 1 \cdot \mathbb{E}[\mathbb{1}[(u, v) \in E]] \\ &= \frac{1}{2} \sum_{u \in V} \sum_{v \in V \setminus \{u\}} 1 \cdot r \\ &= \frac{|V|(|V| - 1)}{2} r \\ &= \binom{|V|}{2} r \end{split}$$
total degree in G
$$\begin{split} \mathbb{E}[d] &= \frac{2|E|}{|V|} \\ \mathbb{E}[d] &= \frac{2|E||E|}{|V|} \\ = (|V| - 1)r \end{split}$$

All the Best

All the best with your exam preparation!