

# Self introduction and future plans

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## ① Basic information

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## ⑤ Future plans

## 1 Basic information

## 2 Honors

## 3 Publications

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## Basic information

- I'm from Suzhou, Jiangsu.
- I got my bachelor's degree at Nanjing University of Information Science & Technology and currently a master degree candidate of science in Zhejiang Gongshang University.
- My github page is <https://github.com/LEOXC1571> and my personal blog is <https://leoxc1571.github.io/>

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# Honors

- 2018 National English Competition for College Students - First Prize
- The 18th China Post-graduate Mathematical Contest in Modeling - Third Prize.
- The 5th National Post-graduate Case Competition for Applied Statistics - Third Prize
- Zhejiang Gongshang University Graduate Academic Scholarship - First Prize

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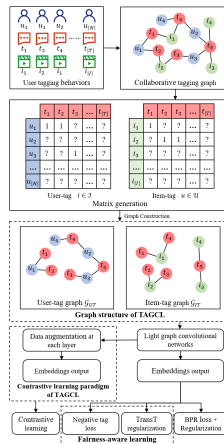
## 5 Future plans

# A fairness-aware graph contrastive learning recommender framework for social tagging systems

- The proposed method integrates contrastive learning into tag-aware recommender systems. By perturbing features with normalized noises, different perspectives on features are generated. They help the model learn high quality features via contrastive learning tasks.
- In order to promote fairness of recommendations, we introduce fairness-aware learning, which jointly optimizes TAGCL through negative tag loss and TransT regularization. Negative tag loss leverages the distribution difference between items and tags in the training data.
- TransT regularization is also proposed to promote consistency between two bipartite graphs. The differences between tag embeddings in separate graphs are regarded as relations between users and items.



# A fairness-aware graph contrastive learning recommender framework for social tagging systems



1: Overall structure of TAGCL

# A fairness-aware graph contrastive learning recommender framework for social tagging systems

**Table 3**

Performance Comparison.

| Dataset | Metric | General       |               | Tag-aware |        |               | TAGCL         | imp. SOTA | imp. TRS |
|---------|--------|---------------|---------------|-----------|--------|---------------|---------------|-----------|----------|
|         |        | LGCN          | SimGCL        | BPR-T     | TGCN   | LFGCF         |               |           |          |
| ML      | Rec.   | 0.2788        | 0.2857        | 0.2826    | 0.2774 | <u>0.2929</u> | <b>0.3180</b> | 8.57%     | 8.57%    |
|         | Pre.   | 0.0349        | <u>0.0385</u> | 0.0365    | 0.0351 | 0.0365        | <b>0.0405</b> | 5.19%     | 10.96%   |
|         | NDCG   | 0.2015        | <u>0.2279</u> | 0.2209    | 0.2147 | 0.2140        | <b>0.2338</b> | 2.59%     | 5.84%    |
|         | MRR    | 0.2101        | <b>0.2372</b> | 0.2273    | 0.2202 | 0.2183        | <u>0.2356</u> | -0.67%    | 3.65%    |
|         | ARP    | 26.78         | <u>17.87</u>  | 22.76     | 19.87  | 18.10         | <b>14.96</b>  | 16.26%    | 17.29%   |
| LFM     | Rec.   | 0.4742        | 0.5055        | 0.4759    | 0.4663 | <u>0.5057</u> | <b>0.5199</b> | 2.81%     | 2.81%    |
|         | Pre.   | 0.1350        | <u>0.1534</u> | 0.1374    | 0.1313 | 0.1465        | <b>0.1611</b> | 5.02%     | 9.97%    |
|         | NDCG   | 0.4015        | <u>0.4680</u> | 0.4358    | 0.4149 | 0.4482        | <b>0.4949</b> | 5.75%     | 10.42%   |
|         | MRR    | 0.4598        | <u>0.5263</u> | 0.5132    | 0.4727 | 0.5033        | <b>0.5541</b> | 5.28%     | 7.97%    |
|         | ARP    | 114.46        | <u>51.67</u>  | 102.84    | 80.76  | 80.65         | <b>42.99</b>  | 16.79%    | 46.70%   |
| DE      | Rec.   | 0.3337        | <u>0.3351</u> | 0.3150    | 0.3158 | 0.3300        | <b>0.3432</b> | 2.42%     | 4.00%    |
|         | Pre.   | 0.3525        | <u>0.3554</u> | 0.3409    | 0.3407 | 0.3498        | <b>0.3705</b> | 4.25%     | 5.92%    |
|         | NDCG   | <u>0.4213</u> | 0.4177        | 0.3984    | 0.4044 | 0.4080        | <b>0.4385</b> | 4.08%     | 7.48%    |
|         | MRR    | <u>0.5786</u> | 0.5529        | 0.5373    | 0.5577 | 0.5395        | <b>0.5828</b> | 0.73%     | 4.45%    |
|         | ARP    | <b>3.11</b>   | <u>4.67</u>   | 6.32      | 7.25   | 4.69          | 5.61          | -79.99%   | -19.62%  |

# Pursuit and Evasion Strategy of a Differential Game Based on Deep Reinforcement Learning

- For the kinematic solve of dog sheep game, by finding the equilibrium point in the game, this study successfully establishes the kinematic pursuit and evasion policies.
- Leverage DQN and DDPG models to train the escaping strategy for intelligent agents.
- Propose a refined reward mechanism and an attenuation mechanism to minimize the defect of DQN.

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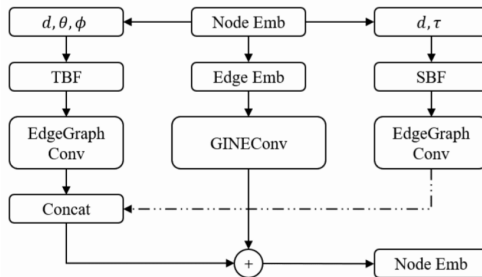
## ⑤ Future plans

# Internship at Zhejiang Lab

- Working at the research center of graph computing, leading by Hongyang Chen.
- Investigate, survey, and reproduce some state-of-the-art large-scale molecular pretraining methods, including MPG, Grover, GEM, MolCLR, and etc.
- Compete in OGB-LSC NeurIPS 22, and achieve 11th place at PCQM4M-V2 track.
- Write a survey on diffusion-based graph generative methods.
- Propose a diffusion-based 3D molecule generation method.

# OGB-LSC NeurIPS 22

- Propose HFAGNN for large-scale (over 3M) molecular property predictions.
- Build up the hybrid block that combines topology and geometry information together. Bessel function is adopted to extract pair-wise and triplet-wise geometric information.
- Use multi-gpu training and achieve 11th place of the leaderboard.



# Diffusion-based molecule generation

- Build up a framework for de novo molecule generation.
- Design the  $E(n)$  dual-track denoising kernel for effective molecular learning.
- The atom-pair track predicts the influence of inter-atomic forces on atom coordinates and atomic numbers via global Transformer. Then the pair-wise features get updated by the same structure, which incorporates triplet angle information into pair-wise features.
- Build up a loss function that facilitate correct valencies of atoms.

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## Future plans

- Graph generative methods: There are some challenges of diffusion-based graph generation, such as difficulties caused by the discrete nature of graphs, efficient training objective and evaluation metrics, relatively limited application fields, and out-of-distribution generation.
- Graph generation combined with large pretrained models, graph learning in other application fields, conditioned or out-of-distribution learning, and etc.

*Thanks!*