

Self introduction and future plans

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① Basic information

② 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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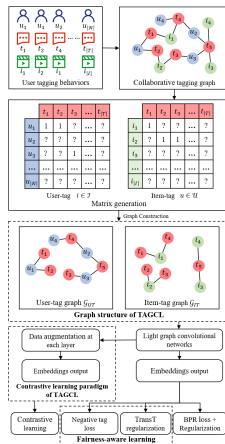
③ Experiences

④ 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>	0.3180	8.57%	8.57%
	Pre.	0.0349	<u>0.0385</u>	0.0365	0.0351	<u>0.0365</u>	0.0405	5.19%	10.96%
	NDCG	0.2015	<u>0.2279</u>	0.2209	0.2147	0.2140	0.2338	2.59%	5.84%
	MRR	0.2101	0.2372	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	14.96	16.26%	17.29%
LFM	Rec.	0.4742	0.5055	0.4759	0.4663	<u>0.5057</u>	0.5199	2.81%	2.81%
	Pre.	0.1350	<u>0.1534</u>	0.1374	0.1313	0.1465	0.1611	5.02%	9.97%
	NDCG	0.4015	<u>0.4680</u>	0.4358	0.4149	0.4482	0.4949	5.75%	10.42%
	MRR	0.4598	<u>0.5263</u>	0.5132	0.4727	0.5033	0.5541	5.28%	7.97%
	ARP	114.46	<u>51.67</u>	102.84	80.76	80.65	42.99	16.79%	46.70%
DE	Rec.	0.3337	<u>0.3351</u>	0.3150	0.3158	0.3300	0.3432	2.42%	4.00%
	Pre.	0.3525	<u>0.3554</u>	0.3409	0.3407	0.3498	0.3705	4.25%	5.92%
	NDCG	<u>0.4213</u>	0.4177	0.3984	0.4044	0.4080	0.4385	4.08%	7.48%
	MRR	<u>0.5786</u>	0.5529	0.5373	0.5577	0.5395	0.5828	0.73%	4.45%
	ARP	3.11	<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 agent.
- Propose a refined reward mechanism and an attenuation mechanism to minimize the defect of DQN.

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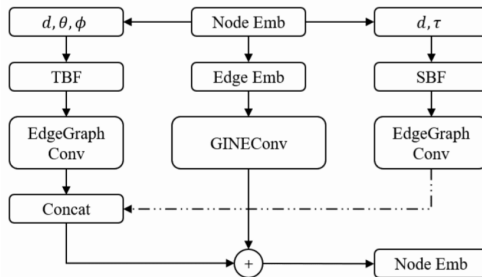
④ Future plans

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.
- Patent writing.
- 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 distances on atomic positions and numbers via global Transformer. Then the pair-wise distance features get updated by the same structure, which incorporates triplet torsion angle information into atom pair features.
- Build up a loss function that facilitate correct valencies of atoms.

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Graph learning

- From my point of view, 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.

Thanks!