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Graph Domain Adaptation via Theory-Grounded Spectral Regularization



Gap: Competitive Transfer Performance with Theoretical Guarantee

- Graph self-supervised learning: Potential "negative transfer" [1]
- Transfer algorithms for specific scenarios: Restricted to designated scenarios (e.g. size transfer) [2]
- Applying domain adaptation methods to graphs: Not specific for graph data, with room to improve [3]
- Question: How to design algorithms to boost transfer performance across different graph domains, with the grounded theoretical foundation?

Yuning You¹, Tianlong Chen², Zhangyang Wang², Yang Shen¹ ¹Texas A&M University, ²University of Texas at Austin

Solution: A theoretical guaranteed, generic, and graph-specific algorithm

Analysis: We identify important GNN properties related to the bound: • Spectral smoothness (SS) and maximum frequency response (MFR) • More importantly, SS relates to **node transfer** and MFR relates to **link transfer** (see Sec. 4.2)

We accordingly propose to regularize SS and MFR to confine the bound

| Methods | Co-expression: Link transfer \Rightarrow MFRReg | | | | | | 14 M 1 M 1 M 1 M 1 M 1 M 1 M 1 M 1 M 1 M | ~ | | | $\neg \gamma$ | ~ |
|--|---|---|--|---|---------------------------|---------------------|--|---|---|---|--|-----------------|
| | Mouse | Zebrafish | Fruit fly | Yeast | Mean↑ | Rank↓ | | ~()) | | ectral - | | |
| Mashup | 48.98±2.34 (5.49±0.32) | 51.63±1.81 (5.37±0.33) | 50.28±2.20 (5.51±0.17) | 46.31±0.63 (4.96±0.05) | 43.90 (5.33) | 9.0 | | $x(\lambda)$ | | gnals | \uparrow \checkmark | |
| D-SCRIPT | 54.48 ± 3.27 (6.01 ± 0.63) | 61.18 ± 1.05 (8.12 \pm 1.77) | 66.63 ± 1.41 (9.78 ± 0.25) | 58.88 ± 0.80 (7.53 ± 0.11) | 60.29 (7.86) | 7.5 | | - | | | | |
| GraphCL | 73.09±1.56 (14.98±2.18) | $74.19 \pm 0.50 \\ (18.76 \pm 2.11)$ | 66.80±2.55 (12.12±2.00) | $\begin{array}{c} 62.41 \pm 1.12 \\ (11.32 \pm 2.86) \end{array}$ | 69.12 (14.29) | 5.2 | | | | -) | | |
| Transformer | 69.55±0.41 (18.06±0.13) | 69.63±0.84 (27.44±1.21) | 57.38±1.77 (10.13±1.02) | 63.01±1.45 (11.25±1.58) | 64.89 (16.72) | 5.8 | | $\lambda_1 \ \lambda_2 \ \lambda_1 \ \lambda_2$ | | | | |
| Transformer +GIN | 76.35±0.38 (21.91±1.60) | 79.29±2.78 (28.07±4.71) | 66.54±1.11 (13.48±0.71) | 63.91 ±1.55 (11.15±1.11) | 71.52 (18.65) | 4.0 | | SSRe | g: Regulariz | ze | MFRReg: 1 | Regula |
| Transformer +GIN+DA-C | 78.56 ±1.55 (22.76±4.42) | 79.46 ±2.97 (27.10±3.10) | 64.78±1.23 (11.61±2.08) | 60.65 ± 3.85 (10.72 ± 2.44) | 70.86 (18.04) | 4.8 | - Cart | $ \tilde{z}(\lambda$ | $\lambda_2) - 	ilde{z}(\lambda_1)$ | m | $\sum_{i=1}^{\infty} \frac{\tilde{z}(\lambda_2)}{i}$ | $\tilde{z}($ |
| Transformer +GIN+DA-W | 77.38 ± 2.54 (23.03 ± 2.98) | $\begin{array}{c} 79.22 \pm 0.89 \\ (26.90 \pm 2.03) \end{array}$ | 67.78 ±0.40 (13.78 ±0.94) | 62.43 ± 2.62 (11.59 ± 1.98) | 71.70 (18.82) | 3.6 | | $ \lambda_2 	ilde{x}(\lambda_2) $ | $\lambda_2) - \lambda_1 	ilde{x} (\lambda_2)$ | $\lambda_1)$ | $\tilde{x}(\lambda_2)$ | $\tilde{x}($ |
| ransformer+GIN +DA-W+SSReg | 77.57±1.14 (23.13 ±0.64) | 79.44±1.21 (28.97 ±2.22) | 65.27±1.49 (11.88±0.89) | 62.28±1.71 (13.24 ±2.49) | 71.14 (19.30) | 3.6 | Methods | Mouse | Physica Zebrafish | I: Node transfer \Rightarrow SSReg Fruit fly Yeast Mean [↑] | | |
| ransformer+GIN DA-W+MFRReg | 77.63 ±1.00 (23.83 ±2.75) | 80.81±1.27 (29.04±0.62) | 68.56±0.88 (13.94±0.47) | 63.74 ±0.27 (16.80 ±2.34) | 72.68 (20.90) | 1.2 | Mashup | 51.54±3.82 (5.58±0.35) | 37.82±3.43 (3.98±0.12) | 46.88±6.87 (7.19±3.93) | 57.99 ± 2.28 (6.78 \pm 0.92) | 48.55 (5.88) |
| 1000 C | | | | 1.8. C. C. C. C. K. | 19.5 | 17 (A 1 (A | D-SCRIPT | 58.22 ± 6.97 (7.03±1.09) | 49.58 ± 1.12 (5.02±0.76) | 62.97 ± 0.78 (9.61 \pm 0.21) | 62.43 ± 0.59 (8.56 \pm 0.15) | 58.30 (7.55) |
| | | | 1 | | | | GraphCL | 76.88 ± 0.42 (31.16 \pm 1.43) | $79.11 \pm 1.14 \\ (41.80 \pm 3.20)$ | 81.02 ± 0.98 (38.63 ± 2.30) | 71.03 ± 0.30 (14.58 ± 1.16) | 77.01 (31.54) |
| PI link prediction | | | | | | Transformer | 77.65±0.84 (35.05 ±0.92) | 75.61±1.86 (45.13 ±3.15) | 76.90±1.64 (32.72±2.34) | 67.86±0.61 (12.46±1.08) | 74.50 (31.34) | |
| Please refer to the paper for more numerical results | | | | | | Transformer +GIN | 79.77 ± 0.92 (31.23+1.94) | 80.85 ± 2.41 (34.29+12.42) | 82.38 ± 1.13 (42.40+2.04) | 71.54 ± 0.36 (15.73 \pm 0.79) | 78.63 | |
| is a second to the paper for more numerical results | | | | | | | Transformer | 80.14±1.86 | 83.58±1.15 | 81.49±1.27 | 71.30 ± 0.61 | 79.12 |
| o citatio | n networ | k node c | assificat | ion) | | | +GIN+DA-C | (34.29 ± 4.12) | (44.01 ± 4.00) | (38.94 ± 2.36) | (16.80 ± 0.65) | (33.51) |

[1] You et al., "Graph Contrastive Learning with Augmentations", NeurIPS'20. [2] Yehudai et al, "From local structures to size References generalization in graph neural networks", ICML'21. [3] Wu et al, "Unsupervised domain adaptive graph convolutional networks", WWW'20

Contact: {yuning.you, yshen}@tamu.edu, {tianlong.chen,atlaswang}@utexas.edu



Theoretically charactering graph transfer risk bound (by combining Eqs. (4-6)) Tools: Domain adaptation and spectral graph theory

$$\begin{aligned} \epsilon_{\mathrm{T}}(h,\hat{h}) &\leq \hat{\epsilon}_{\mathrm{S}}(h,\hat{h}) + \sqrt{\frac{4d}{N_{\mathrm{S}}}\log(\frac{eN_{\mathrm{S}}}{d}) + \frac{1}{N_{\mathrm{S}}}\log(\frac{1}{\delta})} + 2C_{f}C_{g}W_{1}\left(\mathbb{P}_{\mathrm{S}}(G),\mathbb{P}_{\mathrm{T}}(G)\right) + \omega, \quad (4) \\ & \|f(G_{1}) - f(G_{2})\|_{2} \leq C_{\lambda}(1 + \tau\sqrt{N_{G}})\|A_{1} - P^{*}A_{2}P^{*\mathsf{T}}\|_{\mathsf{F}} \\ & + \mathcal{O}(\|A_{1} - P^{*}A_{2}P^{*\mathsf{T}}\|_{\mathsf{F}}^{2}) + \max\left\{|\mathcal{S}(\Lambda_{2})|\right\}\|X_{1} - P^{*}X_{2}\|_{\mathsf{F}}, \quad (5) \\ & \mathcal{C}_{f} = \max\left\{C_{\lambda}K_{1} + \varepsilon K_{2}, |\mathcal{S}(\lambda^{*})|\right\}, \quad (6) \end{aligned}$$