GEEM : An algorithm for Active Learning on Attributed Graphs

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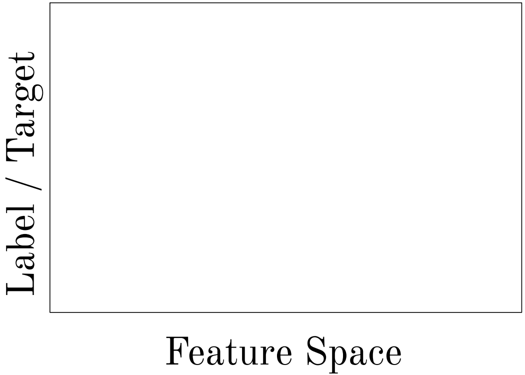
What is active learning?



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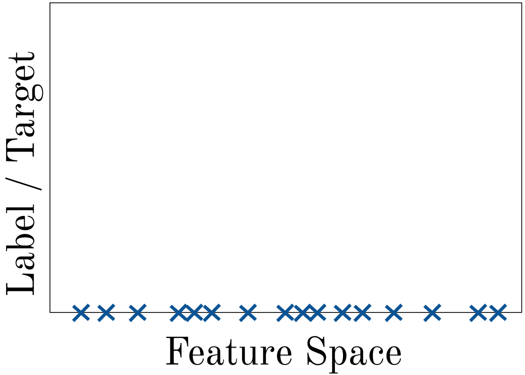

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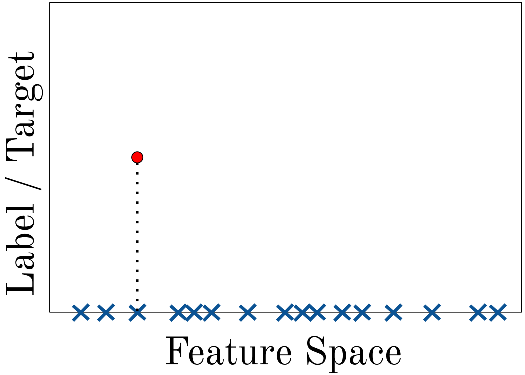

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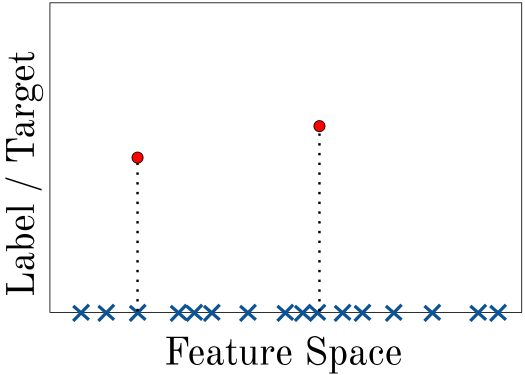

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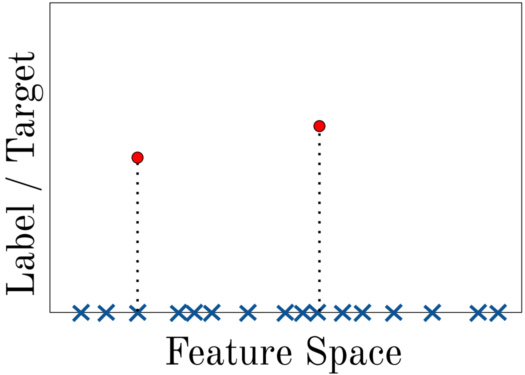

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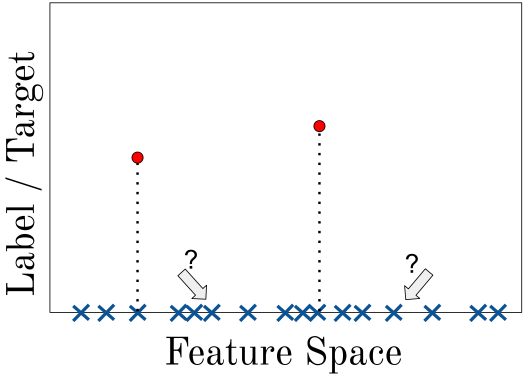
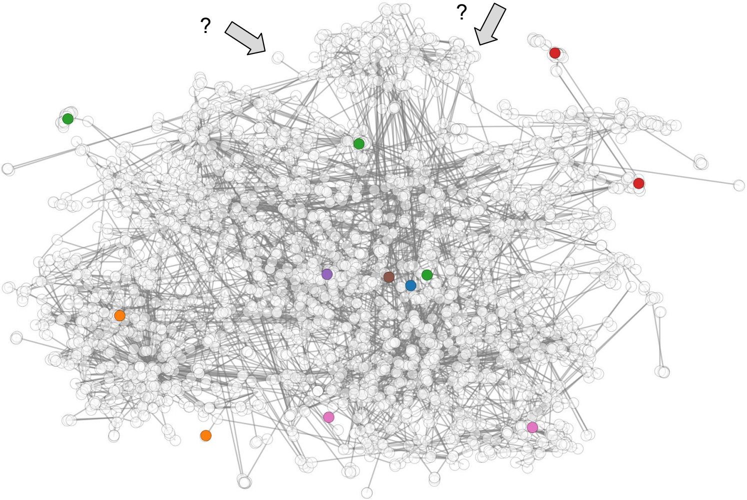


Goal: Choose optimal queries to maximize performance.

Active Learning for Node Classification



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Repeat until the query budget $\mathcal{B}$ has been reached.

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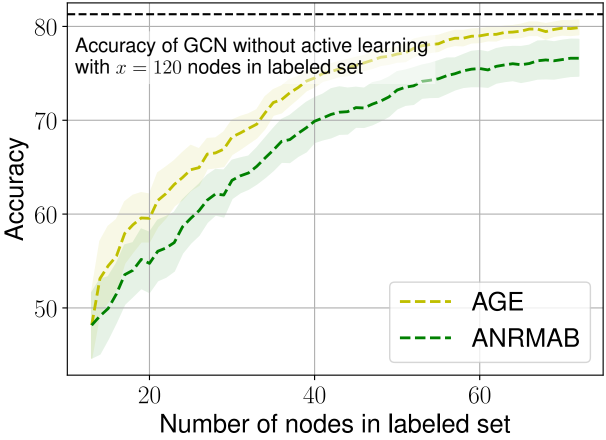
[1] Cai et al. "Active learning for graph embedding" arXiv 2017
[2] Gao et al. "Active discriminative network representation learning" IJCAI 2018

Existing work - Results

GCN-based algorithms on Cora.



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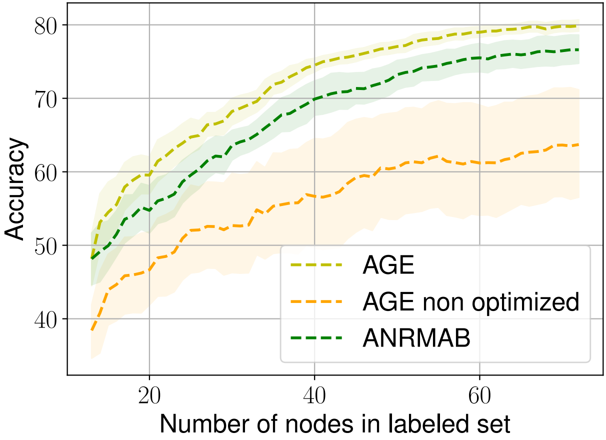
Results with **non-optimized GCN hyperparameter** **highlight this dependence**.

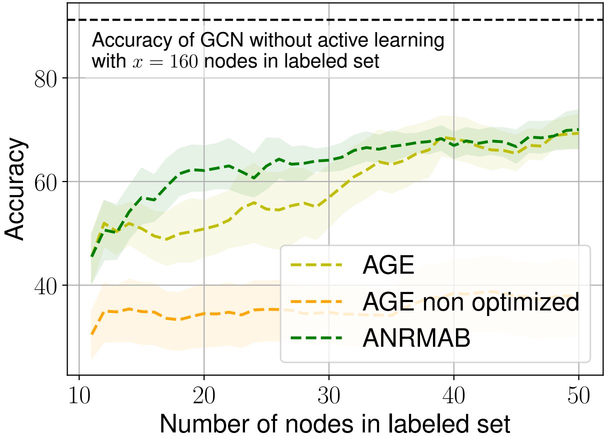
Existing work - Non optimized model

Cora with non-optimized version of **AGE**.



Existing work - Unseen dataset

Amazon-photo. Hyperparameters not fine-tuned to the dataset.



Proposed Algorithm :
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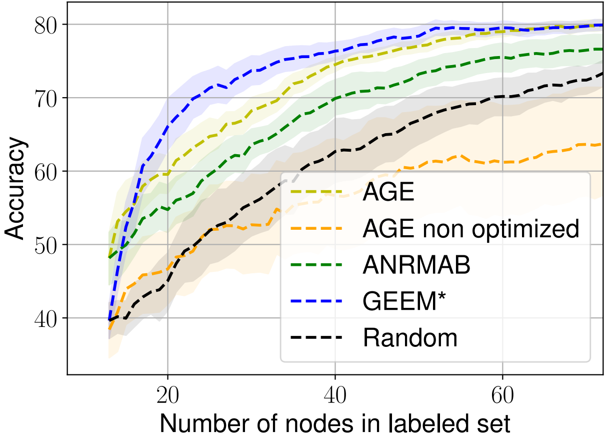
Results

Results - GEEM

Cora. GEEM outperforms GCN-based methods even when GCN hyperparameters are fine-tuned.



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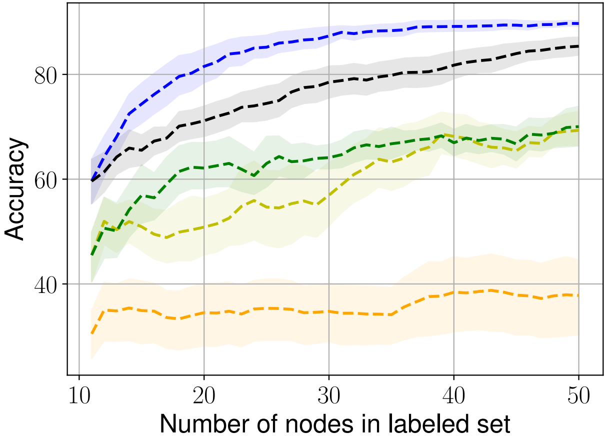

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References

[1] H. Cai, V. W. Zheng, and K. C. Chang, "Active learning for graph embedding," *arXiv preprint arXiv:1705.05085*, 2017.

[2] L. Gao, H. Yang, C. Zhou, J. Wu, S. Pan, and Y. Hu, "Active discriminative network representation learning," in *Proc. Int. Joint Conf. Artificial Intell.*, 2018, pp. 2142–2148.

[3] F. Wu, A. Souza, T. Zhang, C. Fifty, T. Yu, and K. Weinberger, "Simplifying graph convolutional networks," in *Proc. Int. Conf. Machine Learning*, Long Beach, California, USA, Jun. 2019, pp. 6861–6871.