the refined node embeddings to further mitigate the effect of data imbalance. Evaluation through extensive experiments demonstrates that our model achieves state-of-the-art perfor-mance, which affirms its effectiveness in class-imbalanced

node classification, superiority over baselines, and practical significance in handling fraud detection tasks on graphs.

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