Neural Maximum Independent Set

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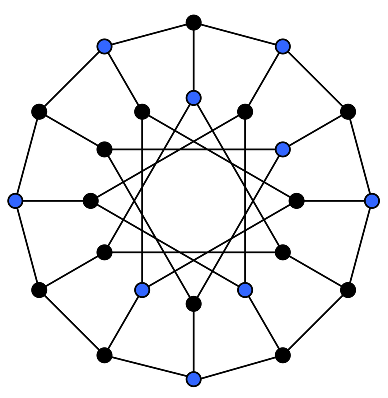
Maximum Independent Set

Given a graph, the MAXIMUM INDEPENDENT SET problem consists in finding a set of nodes of maximum size that are pairwise non-adjacent.



This problem is one of the most classical hard algorithmic graph problem and finds natural applications to non overlapping problems like automatic label placement.

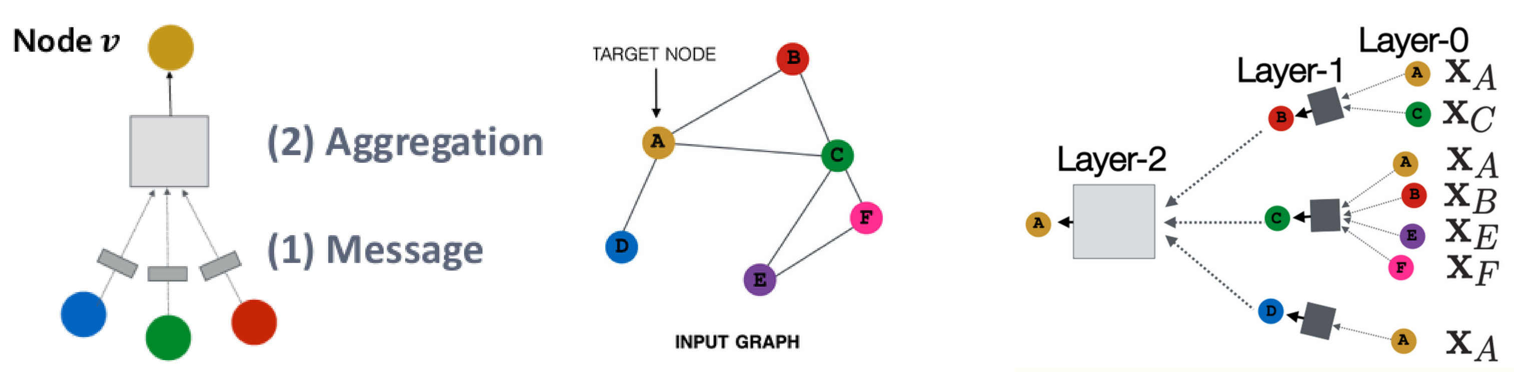
Imitation Learning

We suggest to solve MAX INDEPENDENT SET by training a neural network that, given a partial solution, predicts the next vertices to include in a good solution. We generate a training set with a Monte Carlo method that provide a set with partial solutions and a set of nodes to activate to complete the partial solutions as a target.

Graph Neural Networks

In our neural network, we use graph convolutional layers that rely on message passing.

For each node, we transform the set of features of all neighbors and the node itself, and then aggregate them to form the new features of the node.



Tuning node features

Each node is characterized by the following features:

- a $0-1$ feature *state* indicating if the node belongs to the current state or not and a $0-1$ feature *legal_moves* indicating if the node is a legal future move considering the current state.
- two random features *footprints* belonging to $[0, 1]$.
- two learned random features *embeddings*.

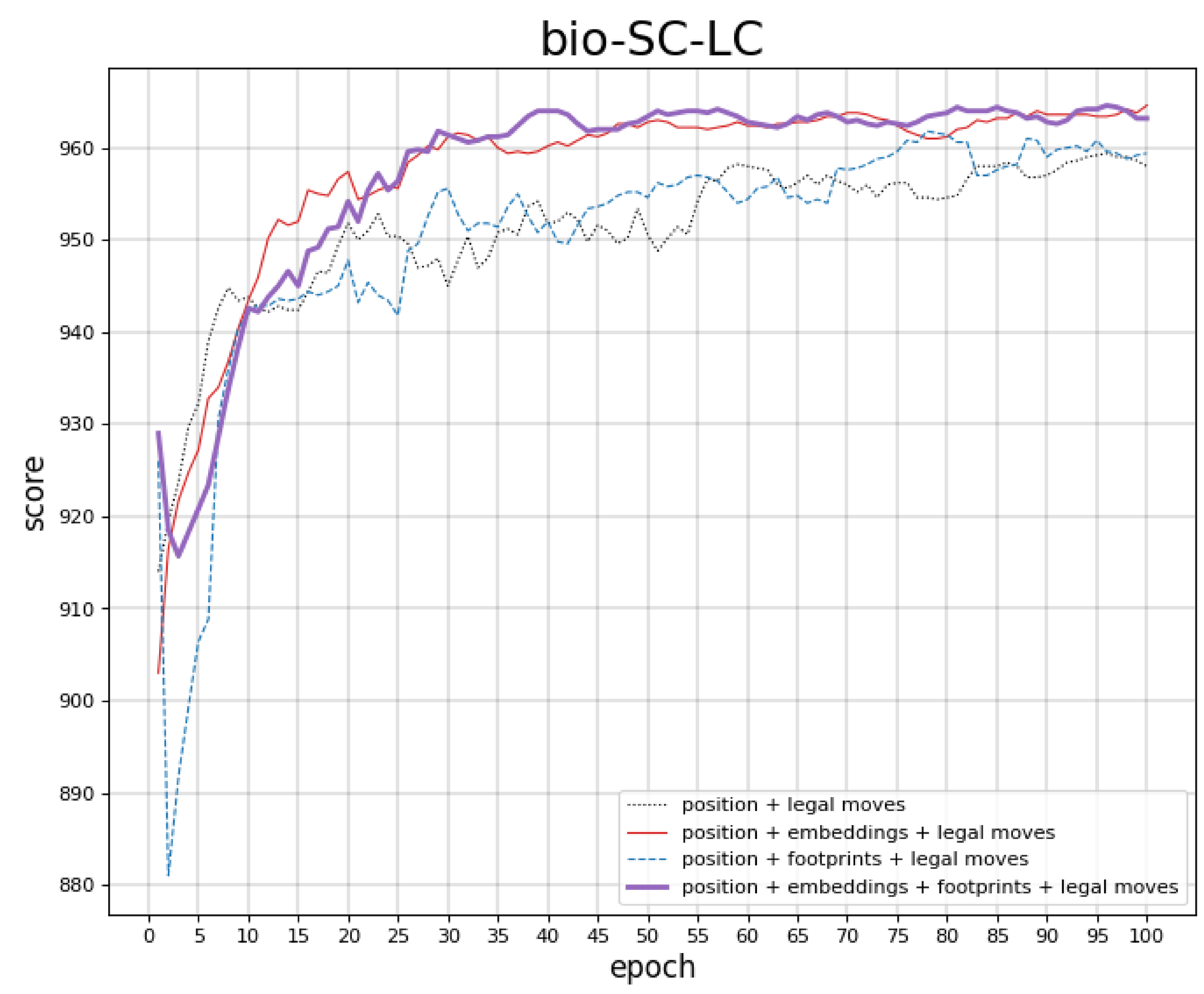


Figure 1: The score of the argmax playout (by iteratively choosing the vertex with the highest activation given in output by the neural network) for each epoch of the learning on the real-world instance `bio-SC-LC` (2004 nodes). Learning curves with embeddings are highlighted by a plain curve. The curve with all features is thicker than the other curves.

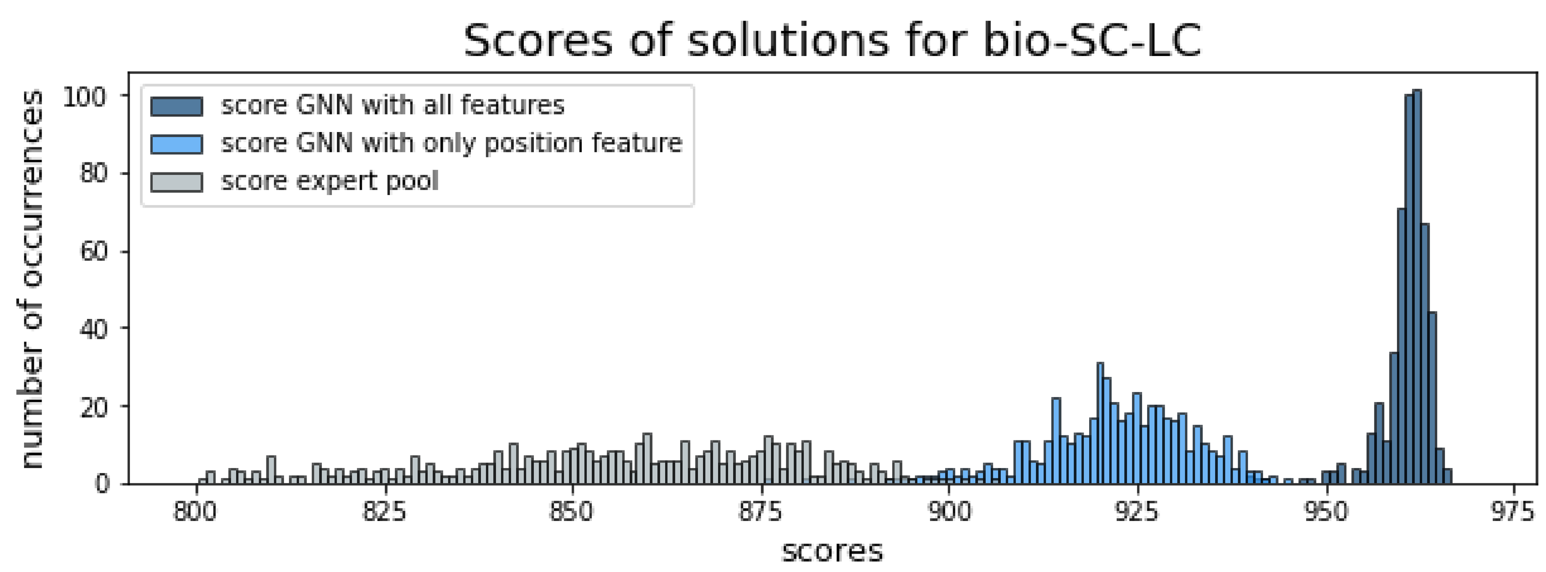


Figure 2: Distribution of scores of 500 solutions from the training set and an exploration of 500 rollouts with the GNN on `bio-SC-LC`, first with only the state, and then with all the features.

References

- Kenshin Abe and Zijian Xu and Issei Sato and Masashi Sugiyama, *Solving NP-Hard Problems on Graphs with Extended AlphaGo Zero, arXiv, 2020*
- Thomas Anthony and Zheng Tian and David Barber, *Thinking fast and slow with deep learning and tree search, Advances in Neural Information Processing Systems, 2017*
- Ryoma Sato and Makoto Yamada and Hisashi Kashima, *Random Features Strengthen Graph Neural Networks, arXiv, 2020*