Generalisable data-driven routing using Deep RL with GNNs

Oliver Hope

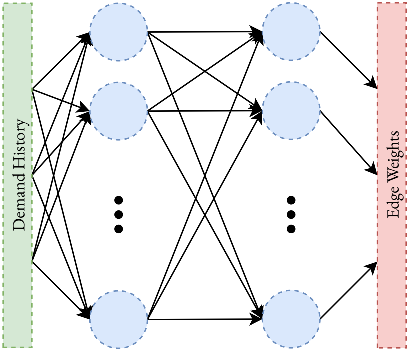
Jesus College

Context

- Recent paper: ‘Learning To Route with Deep RL’[3]
- Intradomain routing
- Minimising link congestion
- Optimal routing
- Oblivious routing[2]

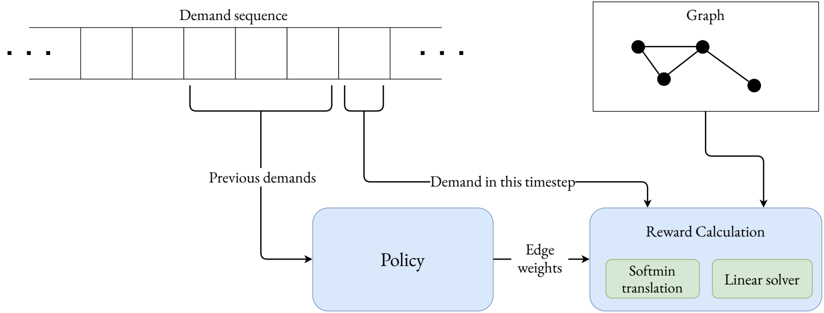
Issues

- Policy is multilayer perceptron (MLP)
- Different sized graphs
- Same graph with modifications
- This project generalises to different graphs



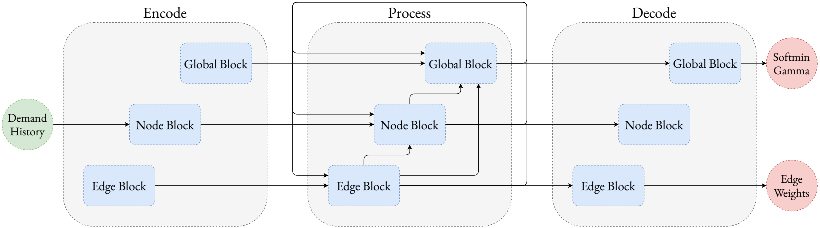
Reinforcement Learning

- State: List of previous demands
- Action: Routing strategy (well, edge weights which can be converted to one)
- Reward: Ratio between link utilisation under the strategy and optimal achievable



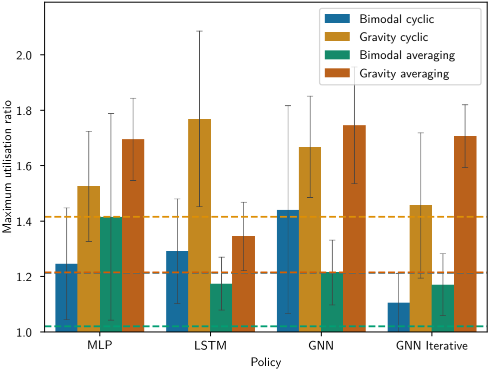
Policy

- An ‘Encode-process-decode’[1] policy
- Input is demand history on nodes
- Outputs are edge weights on edges
- Routing is derived from these edge weights



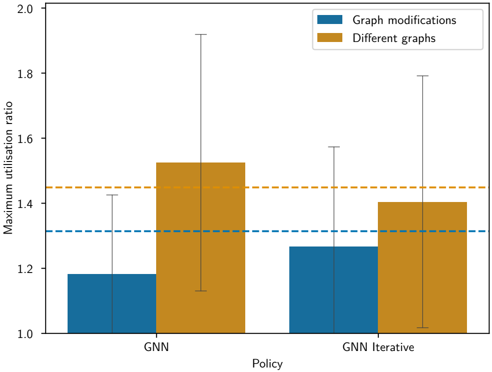
Evaluation - comparison

- Compare to previous policy
- Lower is better
- Colour indicates different experiment
- Overfitting issues



Evaluation - generalisation

- Test for generalising to different graphs
- Graphs same as before (lower is better)
- Generalisation had some level of success



Summary

Contributions:

- Shown graph generalisation works and a policy that can do it.
- Assessed the generalisation ability and learnability of policies to this problem
- Provided an environment that can be used for further experimentation

Future work:

- Devising new mapping from edge weights to a routing strategy would be advisable
- Translating onto real SDN systems for real experimentation

Questions?

References

[1] Peter W. Battaglia et al. Relational inductive biases, deep learning, and graph networks. 2018. arXiv: 1806.01261 [cs.LG].

[2] Harald Racke. "Minimizing congestion in general networks". In: The 43rd Annual IEEE Symposium on Foundations of Computer Science, 2002. Proceedings. IEEE. 2002, pp. 43–52.

[3] Asaf Valadarsky et al. "Learning to route with deep rl". In: NIPS Deep Reinforcement Learning Symposium. 2017.