

Hyperparameter Tuning for the *RouteNet* Model



Gradient Ascent

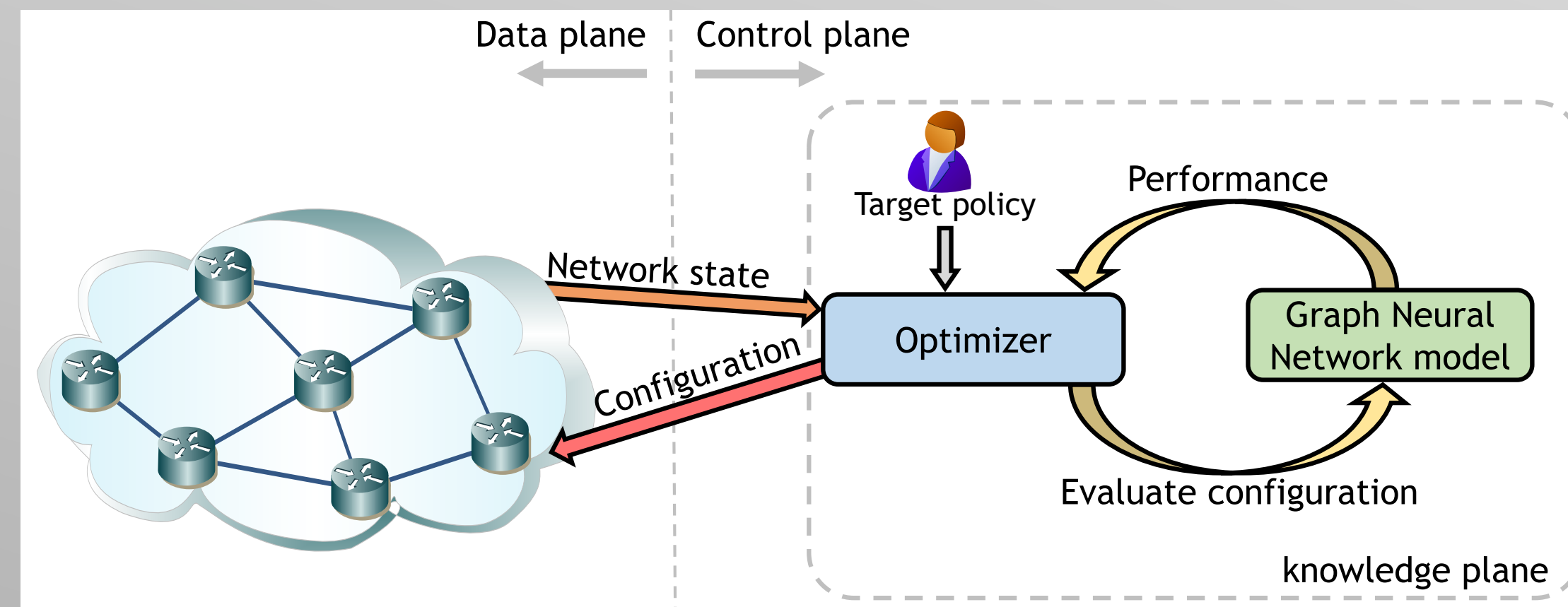
December, 16 2020

Nick Vincent Hainke, Stefan Venz, Johannes Wegener, Henrike Wissing

Motivation : ML-based QoS/QoE Optimisation

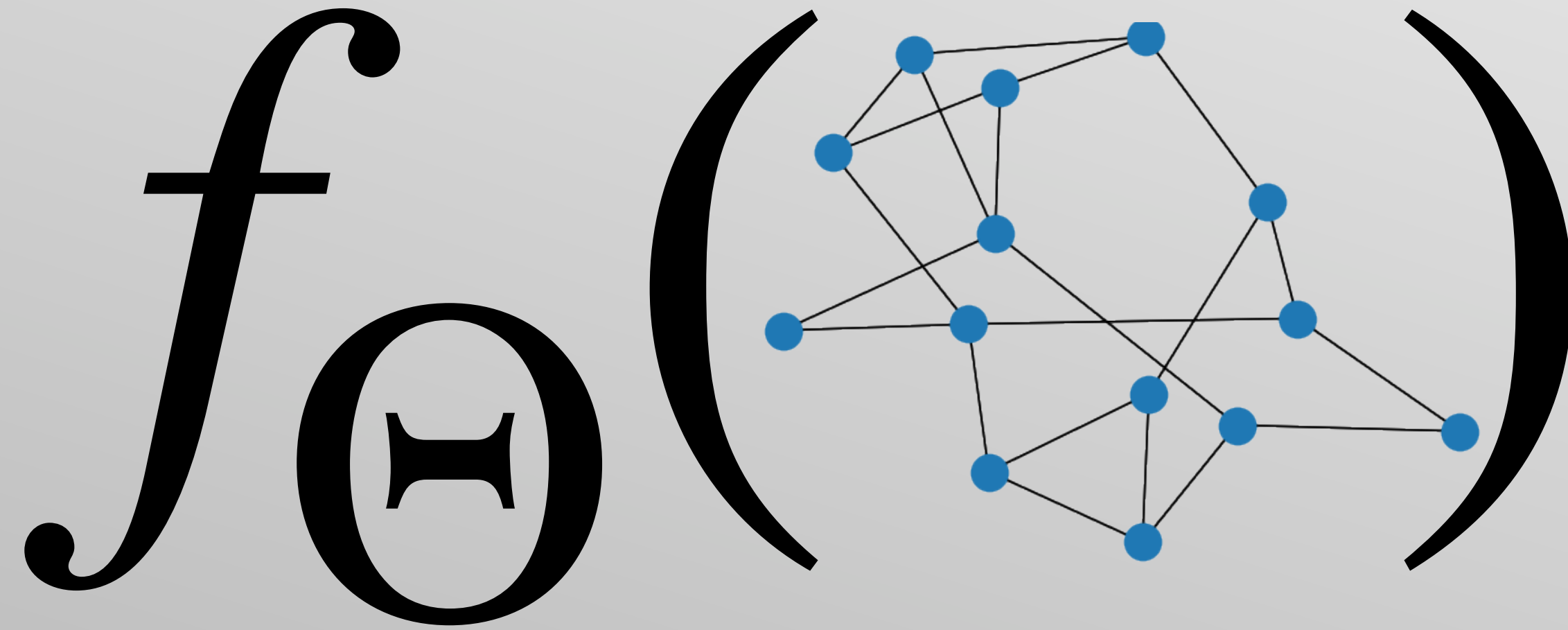
- Future Networks increasingly complex due to scale, heterogeneity, density, dynamics,
- Analytical models / heuristics no longer adequate
- Predictive / prescriptive QoS schemes (*e.g., what-if-scenarios*) based on AI / ML

Telemetry

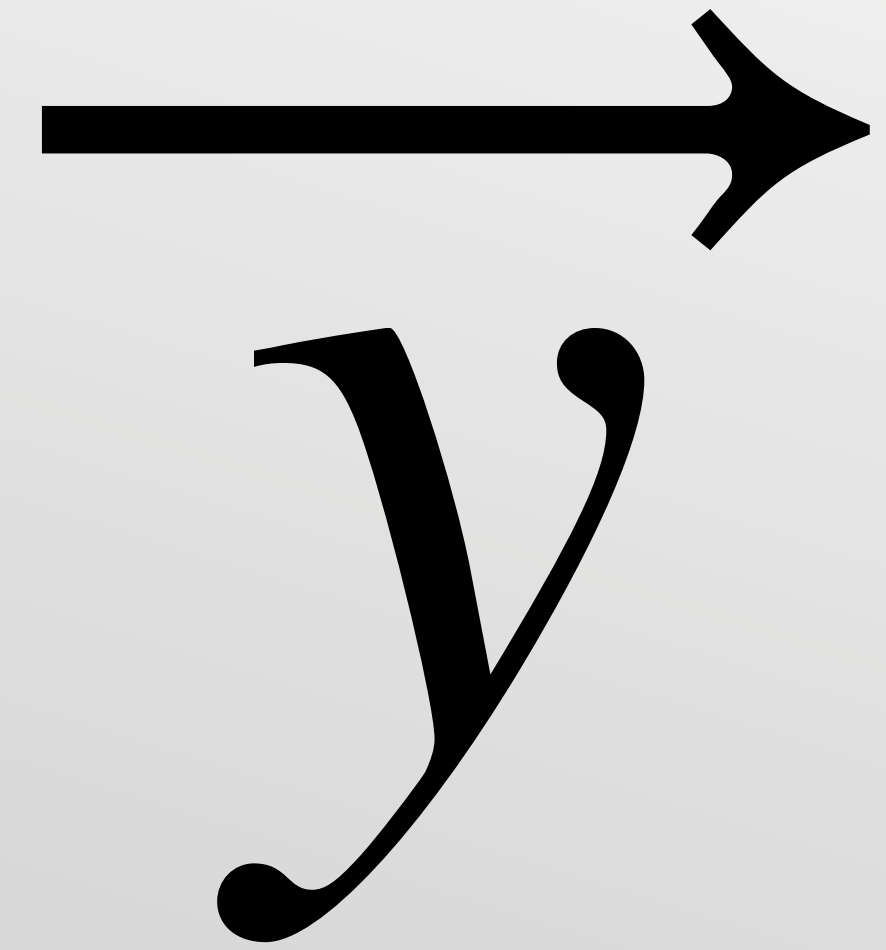


AI / ML

This Challenge: Predictive Analytics with GNN



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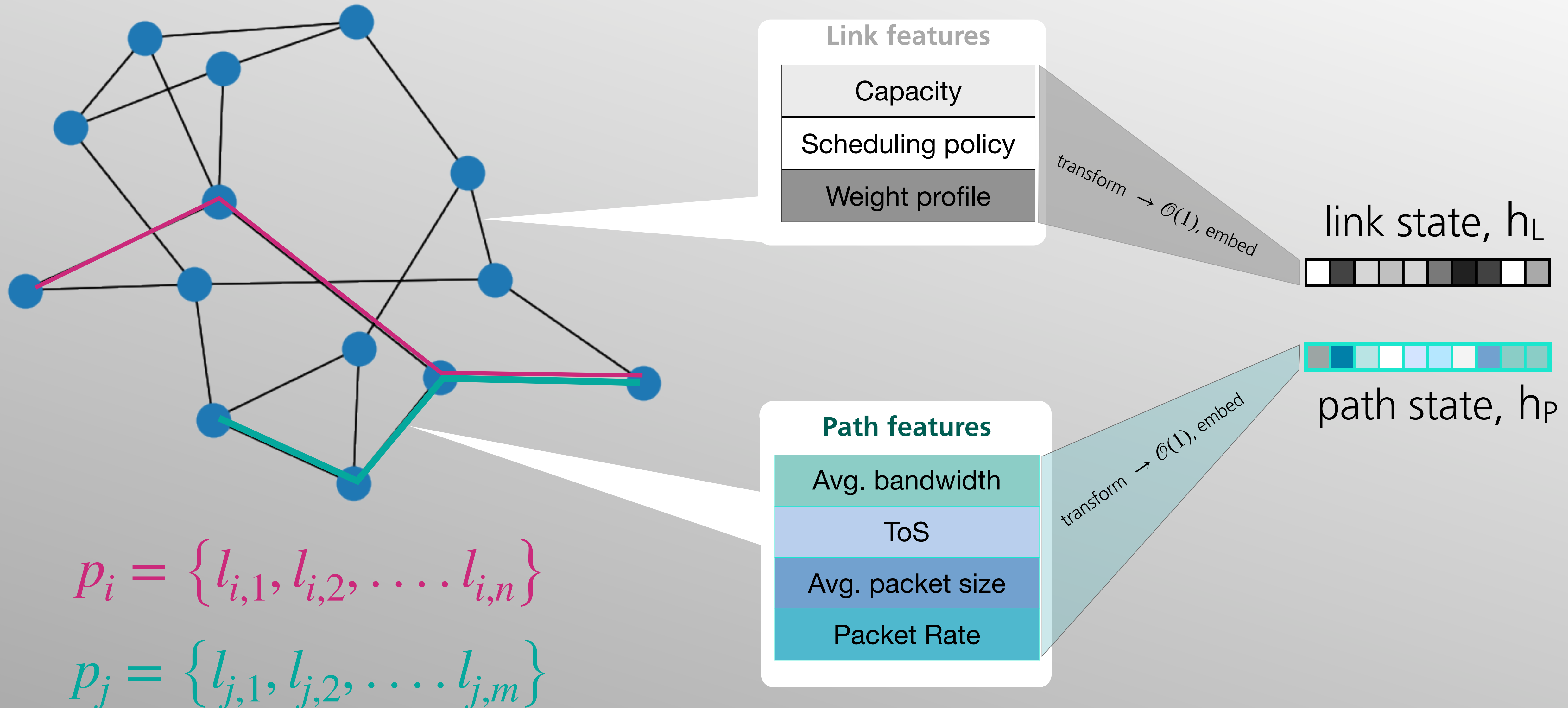


GNN
Target objective

Topology
Routing scheme
Traffic features
Link/Node features

Latency
Jitter
Throughput
Packet Loss

Network State

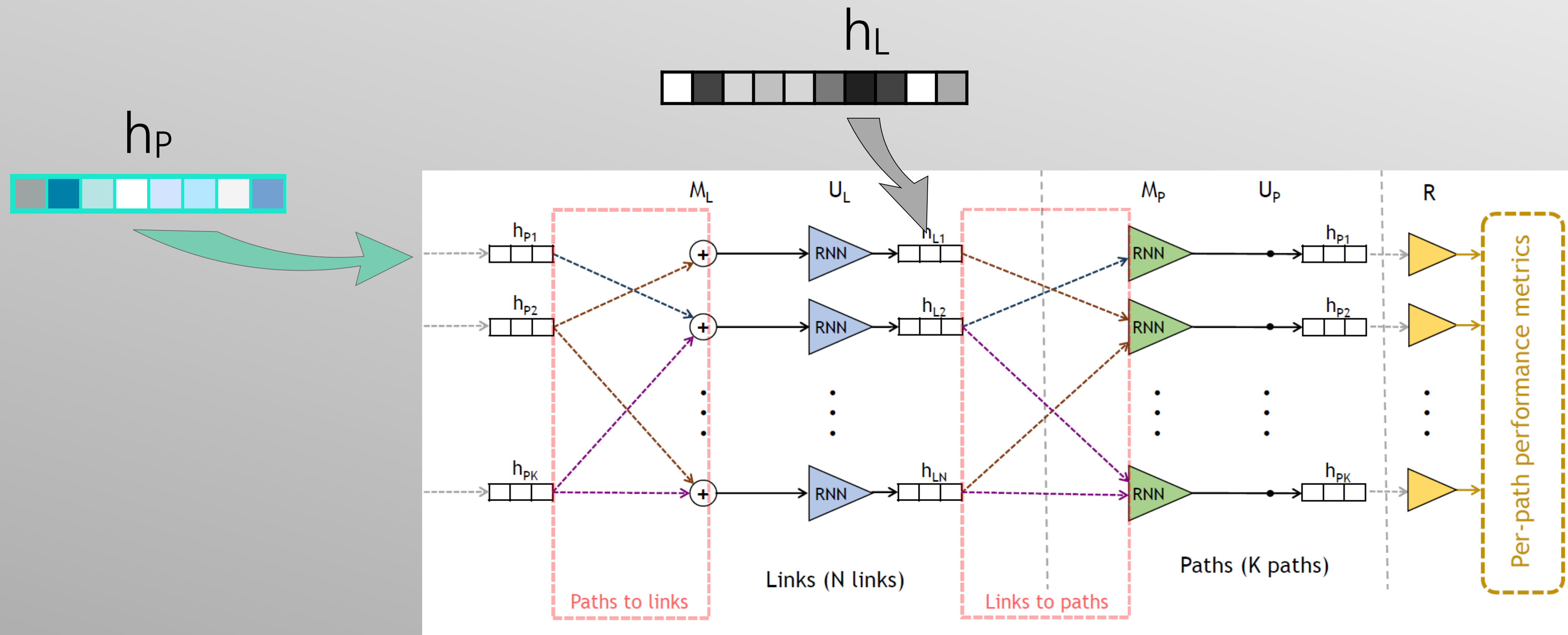


The RouteNet Model

K. Rusek, J. Suárez-Varela, A. Mestres, P. Barlet-Ros, A. Cabellos-Aparicio.

Unveiling the potential of Graph Neural Networks for network modeling and optimization in SDN

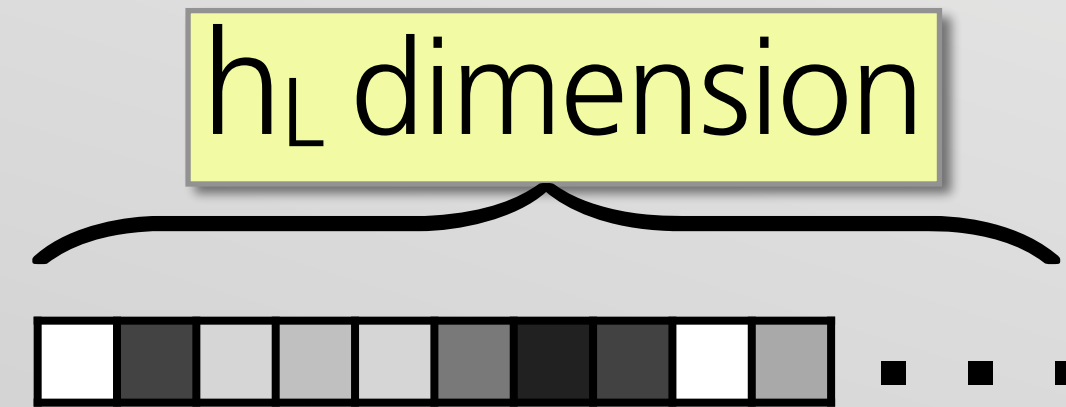
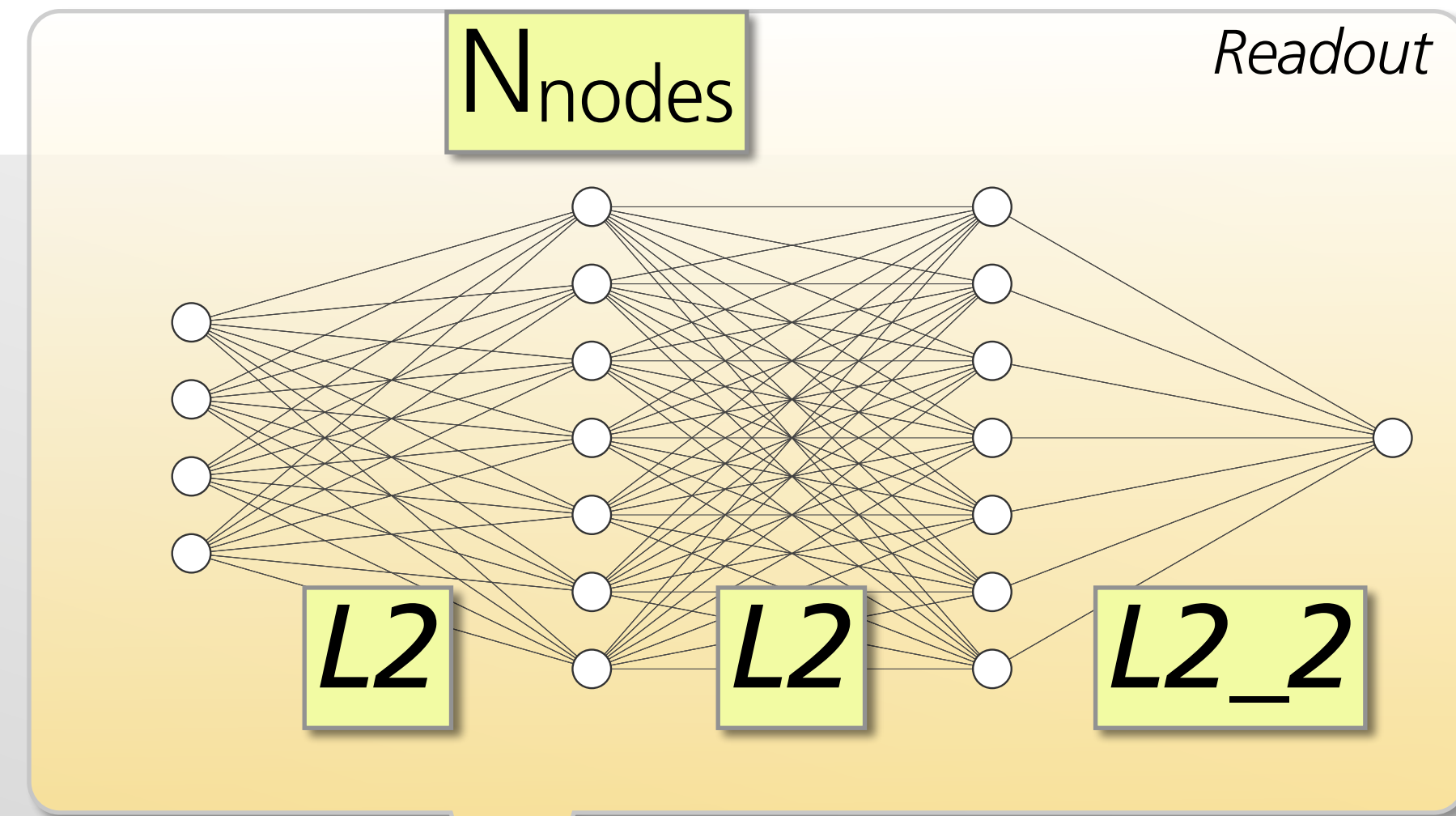
Proceedings of the 2019 ACM Symposium on SDN Research (SOSR), pp. 140-151, San Jose, USA, April 2019.



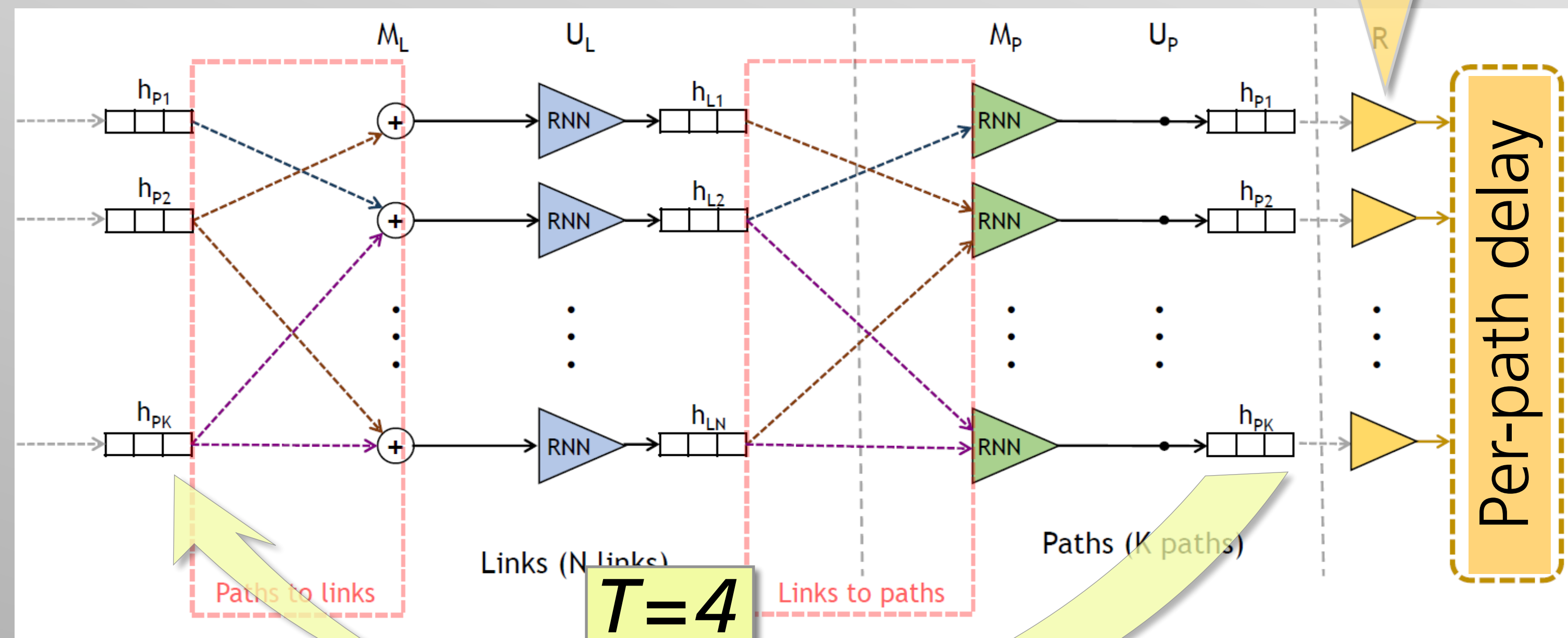
<https://github.com/knowledgedefinednetworking/demo-routenet>

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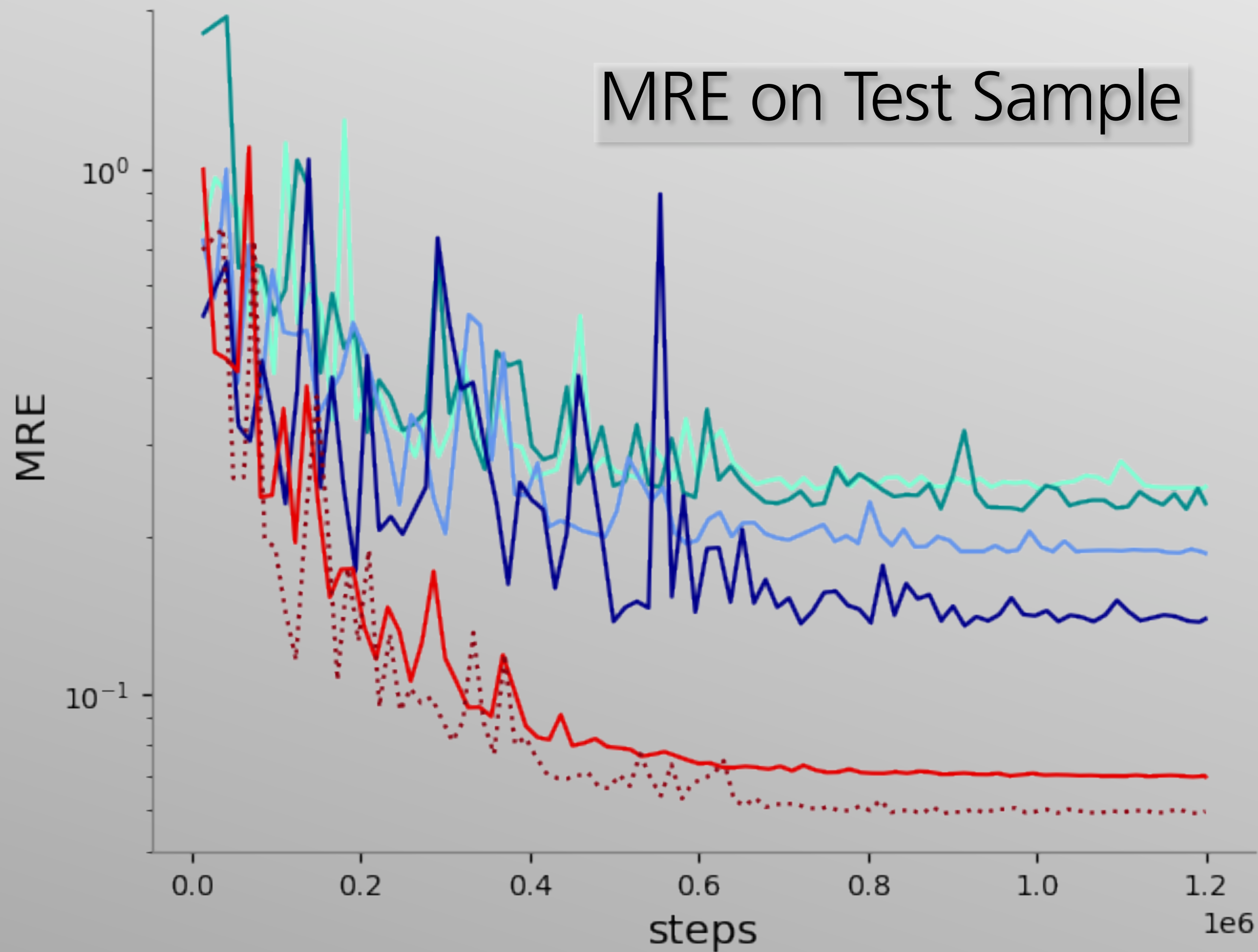


h_P dimension



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Hyperparameter Tuning



h_L dimension	h_P dimension	Readout NNodes	Regularisation $L2$	Regularisation $L2_2$
32	32	256	0.1	0.01
32	32	★ 512	0.1	0.01
★ 64	★ 64	512	0.1	0.01
★ 128	★ 128	512	0.1	0.01
128	128	512	★ N.A.	0.01
★ 256	★ 256	512	N.A.	0.01

25 %
22 %
19 %
12 %
7 %
6 %

← Submitted solution