Experience-driven Networking: A Deep Reinforcement Learning based Approach

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This paper gives a brief overview of an experience-driven approach in communication networking to counter a predicament of traffic engineering. The approach is self-sufficient to manage a fully modern communication network with a higher level of complexities and dynamicity. This approach outcasts all the other currently used methods in terms of efficiency.

1 Introduction

- Enhancing the efficiency of modern communication network.
- Development of DRL-TE Approach.
- Pros of DRL-TE Approach.

2 Problem Statement

- Describing Traffic Engineering (TE) Problem.
- Objective to maximize the utility function.

3 Network Utility Maximization (NUM)

- A solution to an optimization problem [3]
- Drawbacks associated with NUM.
- Algorithm combined with SDN (Software Defined Networking).

4 DEEP REINFORCEMENT LEARNING (DRL)

- Brief Overview about DRL[1].
- Key concepts of Deep Q-Network.
- Actor-critic method - Deep Deterministic Policy Gradient[4]

5 Proposed DRL Based Framework

- Design of State space, Action space and reward.
- Extending DDPG approach.
- Key points like Temporal Difference and Q gradients were defined.
- Prioritized experience replay[2]
- The working of DRL-TE algorithm is discussed in brief.

5.1 Algorithm DRL-TE

- Initialization of all weights of actor and critic network.
- Computation of various key elements - gradients, priority, weight change etc.
- Network updating.

6 PERFORMANCE EVALUATION

- ns-3 used for simulation.
- Simulation on NSFNET and ARPANET topologies
- Results were compared with other methods.
- Performance DDPG and DRL-TE was evaluated for each network topologies.

6.1 Factors for comparisons

- End to end delay
- End to end throughput.
- Total Utility.

7 Conclusion

In the end , authors provided an experience-driven DRL-TE with actor and critic networks approach to counter TE problem. The performance of this approach when evaluated using NSFNET, APRANET topologies and a random topologies outperforms all the current baselines methods.

References

[1] V. M. et al. *Human-level control through deep reinforcement learning*. Vol. 518. 7540. 2015, pp. 529–533.

[2] T. Schaul and D. Silver. "Prioritized experience replay". In: *arXiv* 1511.05952 (2015).

[3] S. H. Low and D. E. Lapsley. *Optimization flow control. I. Basic algorithm and convergence*. Vol. 518. 6. 1999, pp. 861–874.

[4] M.-C. van Leuwen. *A Handbook for Scholars*. Oxford University Press, 1900.