Neural Combinatorial Optimization with Deep Learning Approaches

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Abstract:

In the recent years, deep learning has exhibited immense success in various tasks, encompassing images, videos and speech, which are essentially based on Euclidean data. The concept of the graph convolutional network (GCN), however, proposed an extension to neural network capabilities by exploring the non-Euclidean space, comprising of complex graphical relationships. In the session, we intend to introduce several NP-Hard optimization problems namely Satisfiability (SAT), Maximal Independent Set (MIS), Minimum Vertex Cover (MVC), Maximal Clique (MC), Traveling Salesman (TSP) and Knapsack. Furthermore, we plan to provide an overview of existing neural network approaches, such as Graph Convolutional Networks (GCNs), Reinforcement Learning (RL) and Recurrent Neural Network (RNNs), that are used to address these problems. Additionally, we seek to provide a thorough analysis of the various experiments conducted as well as challenges encountered and conclude by proposing future research avenues. Our goal is to highlight the power of deep learning to provide optimal solutions to problems in NP-Hard, which are traditionally difficult to solve.

Papers:

Combinatorial Optimization with Graph Convolutional Networks and Guided Tree Search
https://arxiv.org/pdf/1810.10659.pdf

Neural Combinatorial Optimization with Reinforcement Learning
https://arxiv.org/pdf/1611.09940.pdf