

Solving Combinatorial Optimization Problems with Machine Learning and LLMs

Project Description

Combinatorial Optimization (CO) includes a variety of important NP-hard problems. Many such problems surface in practically useful domains like scheduling, vehicle route planning and bin packing, making efficient and effective algorithms highly desirable. Typically, finding exact, optimal solutions becomes computationally infeasible with growing instance size and, as an alternative, heuristics are used that can find solutions of good-enough quality fast.

In the last years, Neural Combinatorial Optimization (NCO) has emerged as a promising line of research that investigates how machine learning methods can be used to build such heuristics [2], [3], [7]. Compared to traditional heuristics, machine-learning-based methods are usually faster during inference, but require substantial resources for the training. Traditional heuristics to solve CO problems usually fall into the category of “metaheuristics” such as adaptive large neighborhood search (ALNS, [5], [6]). Since developing, adapting and fine-tuning can be tedious and often requires domain-knowledge, Large Language Models (LLMs) have become a popular tool to automate the process of finding metaheuristics to solve a specific problem [1], [4], [8], [9].

In this thesis, we want to bridge the gap between LLM-based automation of metaheuristic development and NCO by using LLMs to build the training pipelines of reinforcement learning-based methods for CO. The ultimate goal is to obtain generalizable methods that are fast when deployed, produce near-optimal solutions and require minimal manual tuning.

Tasks

Concretely, you will:

- Familiarize yourself with the state-of-the-art in neural combinatorial optimization and LLM-based heuristic generation.
- Investigate principled and systematic approaches to LLM-based environment, reward and curriculum design for reinforcement learning for CO.
- Implement your approach across a wide benchmark suite of combinatorial problems, including the Traveling Salesperson Problem (TSP), scheduling problems and Vehicle Routing Problems (VRPs).

Depending on your interests, you could also deepen your analysis along the following axes:

- Solving novel problem types where traditional heuristics and/or exact methods severely underperform.
- Applying your approach to real-life problems in areas such as logistics, last-mile delivery and emergency evacuation.

- Investigating theoretical perspectives, e.g., performance guarantees.

Who should apply?

We are looking for one or two students with a background in machine learning and optimization. In particular, you should be familiar with the following concepts:

- Programming in Python and, ideally, PyTorch.
- Machine learning concepts such as supervised learning and different neural network types (e.g., transformers, graph neural networks) but most importantly reinforcement learning.
- Some experience in optimization and concepts such as (I)LPs.

What we offer

- Supervision by researchers in transportation systems and graph machine learning.
- Access to computing resources.
- A scientifically exciting project with high publication potential (conference or journal).
- A chance to contribute to next-generation tools for mobility planning.

Practical Information

The start date is flexible. Supervisors are Filip Rydin and Attila Lischka at the department of Electrical Engineering, Chalmers.

To apply, send an email to filipry@chalmers.se and lischka@chalmers.se with a short CV and grades transcript. Applications will be reviewed on a rolling basis.

References

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