

Tackling the Traveling Salesman Problem with RL and Genetic Algorithms

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Students:

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Project Objective:

- Develop and implement hybrid algorithms that combine reinforcement learning (RL) with genetic algorithms (GA) to solve the Asymmetric Traveling Salesman Problem (ATSP)
- Evaluate the performance of these approaches on benchmark datasets, analyze their effectiveness, and identify the best-performing algorithm(s) through comparative results.

Motivation:

The Traveling Salesman Problem presents a classic challenge in combinatorial optimization, with wide-ranging applications where finding the shortest or most efficient route is critical. Given the complexity and asymmetry of many real-world instances, reinforcement learning shows strong potential to learn effective routing policies that adaptively optimize the path, especially when combined with the global search capabilities of genetic algorithms. Comparing different combinations of RL algorithms with different parameters of GA can be useful for both practical applications and guiding future research.

Project Plan:

- Use the methodology from Ruan et al.'s 2024 paper "Combining reinforcement learning algorithm and genetic algorithm to solve the traveling salesman problem" (<https://doi.org/10.1049/tje2.12393>) as a starting point. We are planning to -
 - Attempt to recreate the findings from the paper for a number of ASTPs
 - Expand the research by enhancing the original design:
 - In the genetic algorithm, in addition to the roulette wheel selection method used by Ruan *et al.*, we will also use the elitist selection method where the best-performing individuals are selected.
 - Experiment with the lower and higher numbers of optimal routes used as the initial population for the genetic algorithm, specifically 20 and 600, and compare the results with Ryan *et al.*'s 40 routes.
 - Experimenting with the mutation probability higher than 0.01 in Ruan *et al.*
- Utilize the [TSPLIB database](#) for the TSP instances and their optimal solutions, to set up the experimental environment for standardized evaluation and as a benchmark.
 - We are planning to use the instances utilized by Ruan *et al.* plus two more instances: one with the number of cities <60 and another - with a number of cities >99
- Leverage Ray RLlib for RL algorithm implementation, training, and evaluation pipelines.
- Conduct thorough performance comparisons across developed algorithms based on the following metrics like route length, computation time, and convergence behavior.
- Present detailed results and insights, discussing trade-offs and practical implications.