



Neural Prioritized Planning: Flatland

Task 2.1 Beta release - UvA

Context



Definition

Multi-Agent Path Finding (MAPF) involves finding collision-free paths for multiple agents in a shared environment.

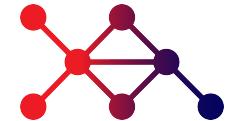
Motivation

Efficiently scheduling agents in congested networks (e.g., railway systems) is crucial for minimizing delays and optimizing flow. While optimal solvers do exist, they **fail to scale** to problems with more than a few dozen agents. More scalable solvers are needed.

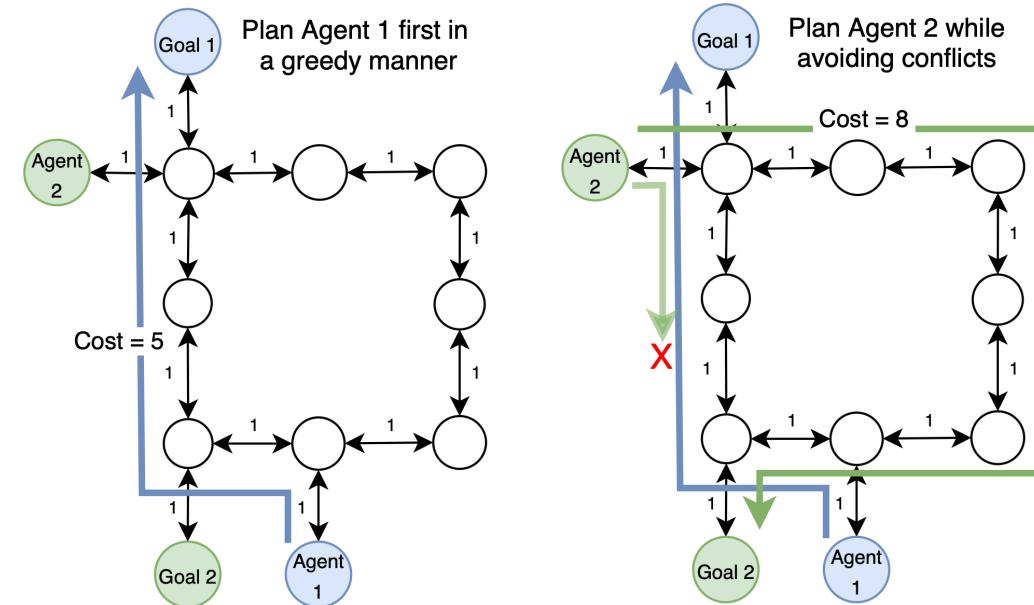
Use cases

Railway networks: Scheduling and routing trains. Ability to quickly replan on case of train breakdowns.

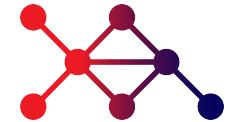
Motivation: small scale example



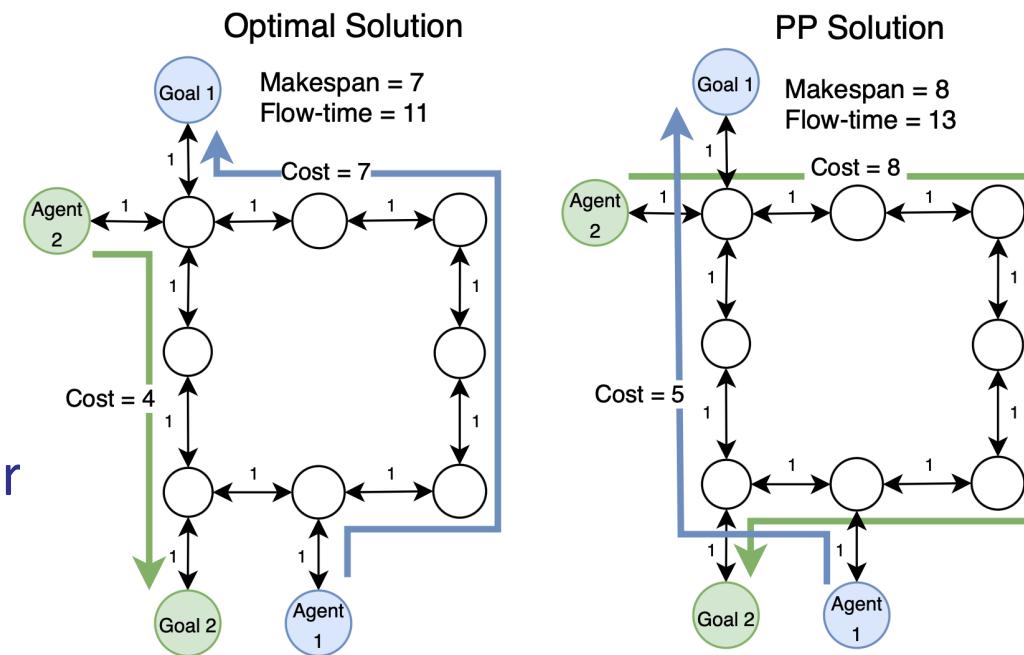
- Plan Agent 1 **greedily**, by using shortest distance to goal
- Agent 2 has to **avoid collision** with Agent 1
- **Prioritized Planning (PP)** is such an algorithm, that plans agents in sequence, based on the assigned priorities.
- Often times, PP it is **not** optimal.



Motivation: small scale example



- In this example the optimal path is for Agent 1 to take the slightly longer route, while Agent 2 takes the much shorter one.
- **Makespan** = max length of all paths
- **Flow-time** = sum of length of all paths
- However, computing such optimal solutions for large scale environments is **not scalable**.



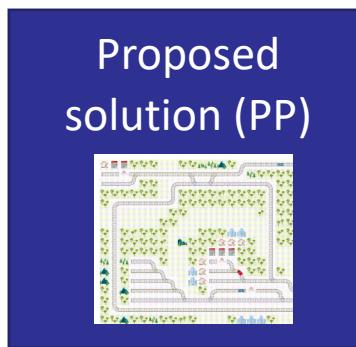
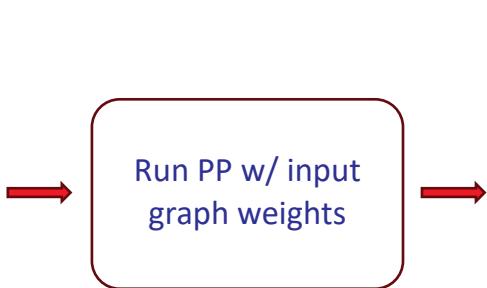
Methodology



- Main idea = learn **graph edge weights** representation such that Prioritized Planning (PP) finds solutions that are closer to optimal, while still planning in a greedy way.



Flatland input instance.
Graph weights set to **1** at
the beginning.



Proposed
solution (PP)

Differentiable loss
calculation between
the 2 solutions



Expert (optimal)
solution

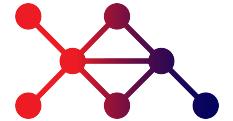
Back-propagate loss to
update the graph **edge
weights**, making PP paths
more similar to optimal.



Set **updated weights**
for PP

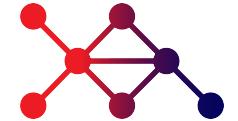
Use Conflict Based
Search (CBS) to
generate optimal
paths.

Methodology

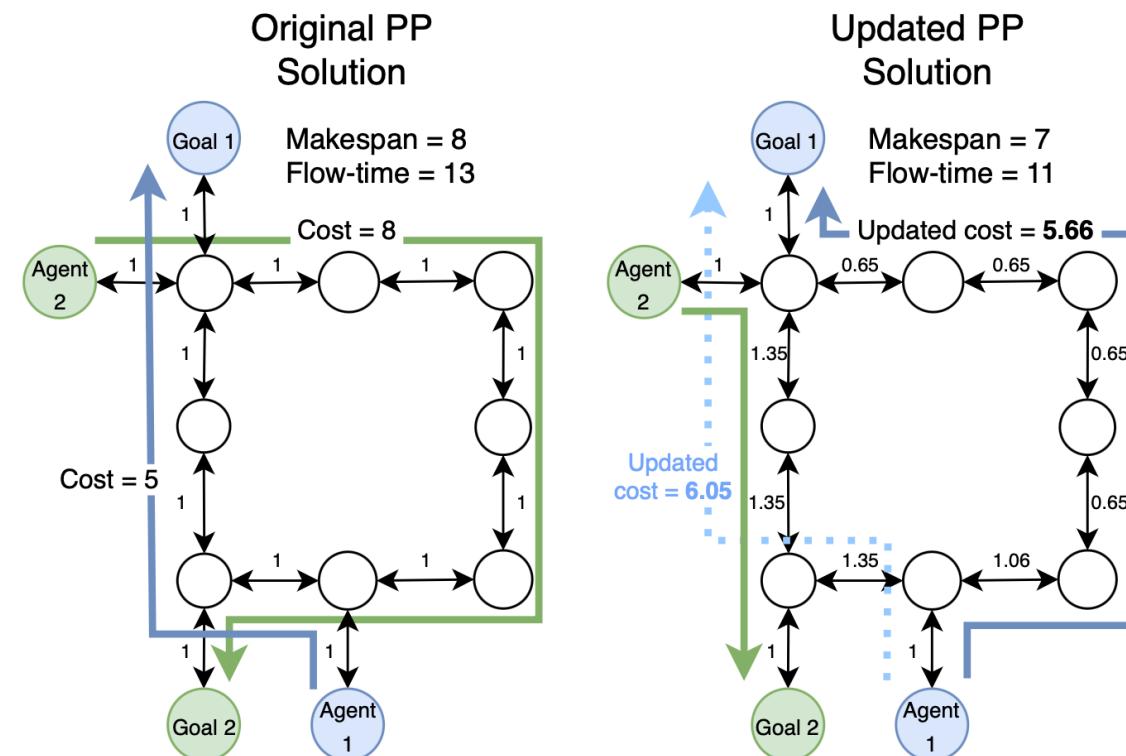


- **Conflict Based Search (CBS)** (Sharon, Guni, et al. 2015) is used to generate optimal paths.
- In order to get a meaningful gradient based on the computed loss, we use the method proposed in Vlastelica et al., 2019 which allows for the **Differentiation of Blackbox Combinatorial Solvers**.
- The main training loop is as follows:
 1. Generate optimal CBS paths.
 2. Compute initial PP paths on cost 1 graph.
 3. Calculate usage discrepancy using Hamming distance or similar metric.
 4. Update edge weights using the differentiable solver.
 5. Re-run PP with updated weights.
 6. Iterate until convergence or a fixed number of iterations.

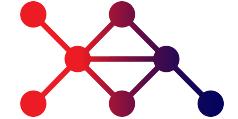
Methodology: back to the small scale example



- Using the proposed methodology, we can learn to assign updated weights to edges in our first example.
- This way the **updated input graph** allows PP to find the optimal path, given this fixed set of priorities.
- PP still plans **greedily** in a fast way, since the input is the only change.

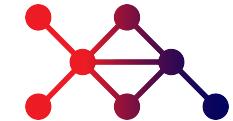


Preliminary experiments on Flatland

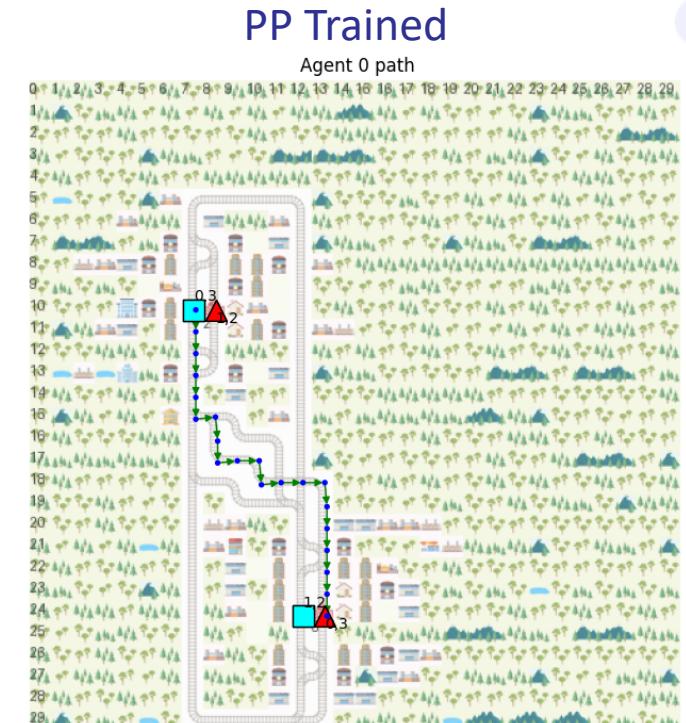
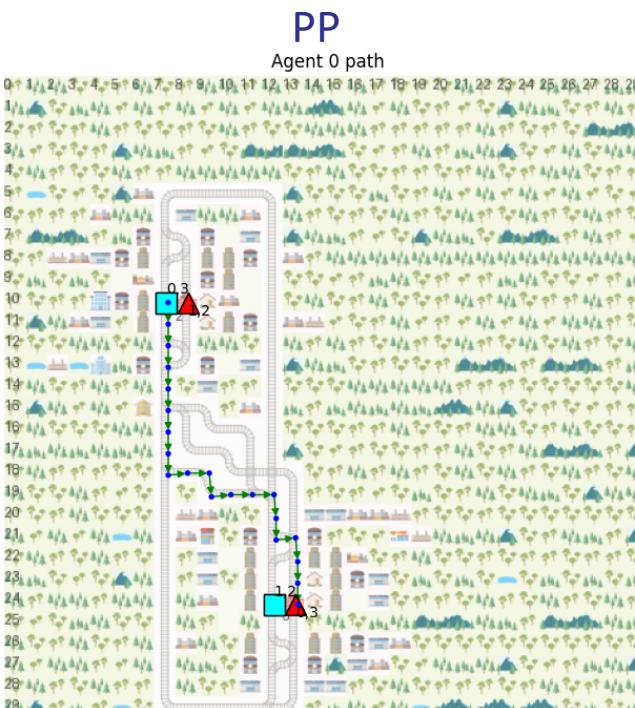
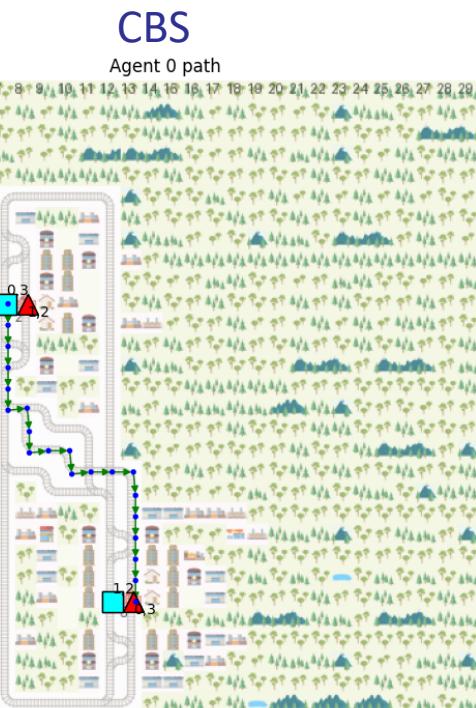


- On 30x30 Flatland maps.
- Over 50 seeds with different layouts and train departure schedules:
 - 7 total agents:
 - **PP** avg flow-time: 143.06
 - **CBS** avg flow-time: 139.39
 - **Trained PP** avg flow-time: 141.85

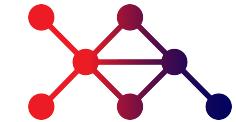
Preliminary experiments on Flatland



- Example on 30x30 map with 4 agents, PP with the **updated weights** plans new paths for each agent, reducing flow-time from 82 to the optimal 80:

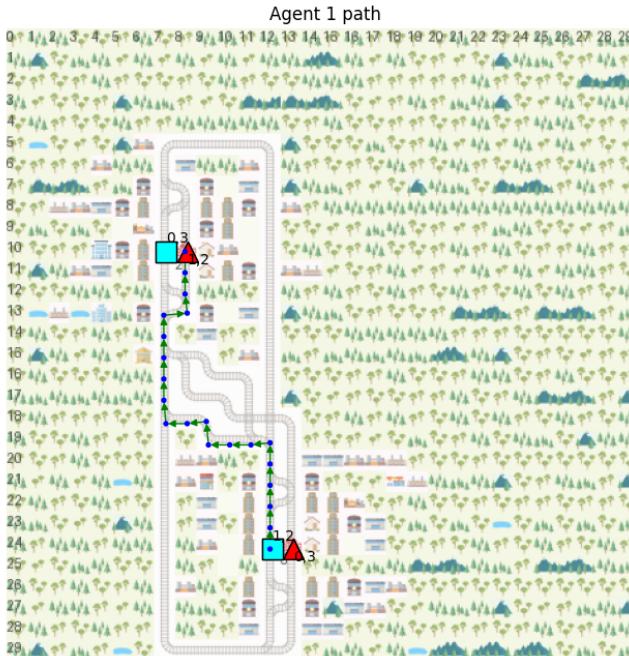


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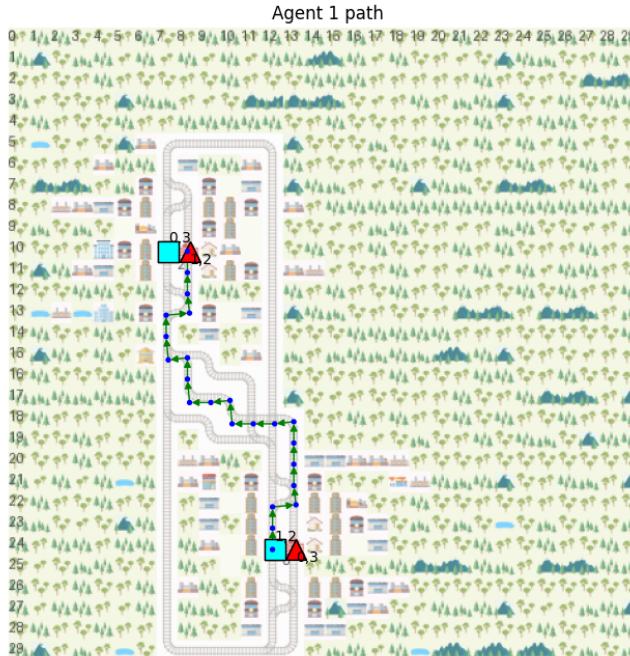


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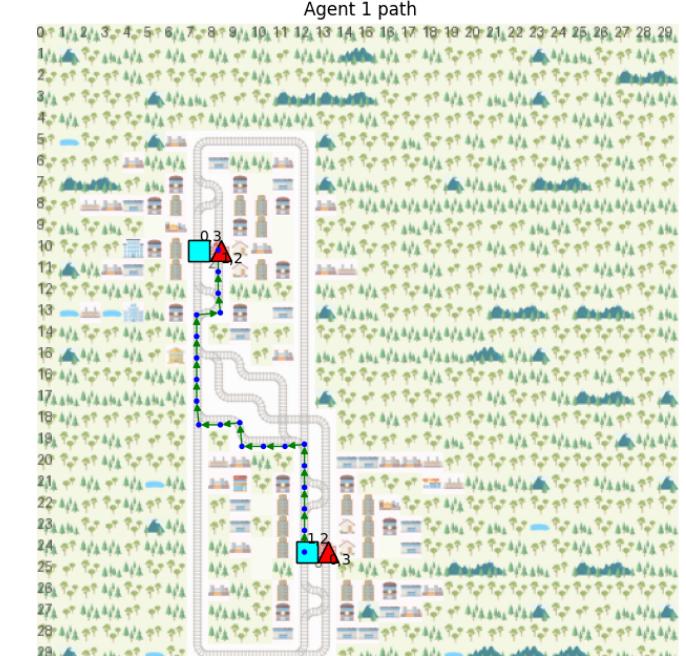
CBS



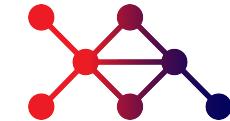
PP



PP Trained



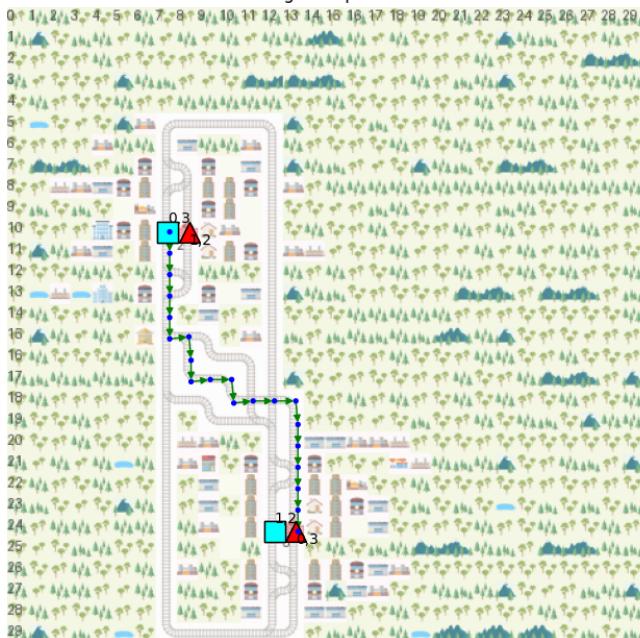
Preliminary experiments on Flatland



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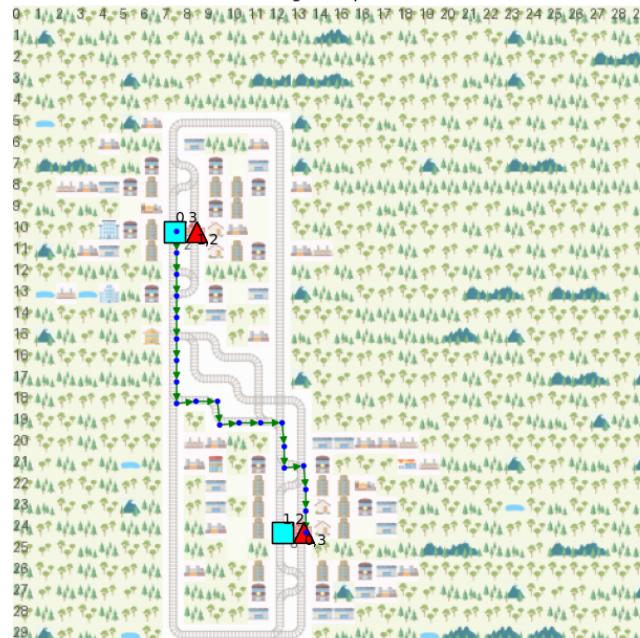
CBS

Agent 3 path



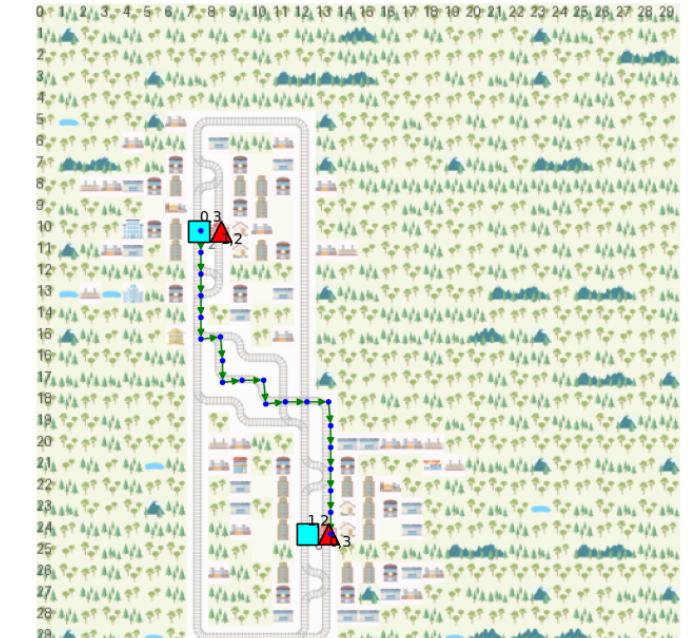
PP

Agent 3 path

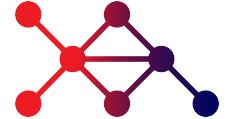


PP Trained

Agent 3 path



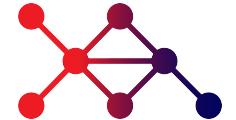
Overview of code structure



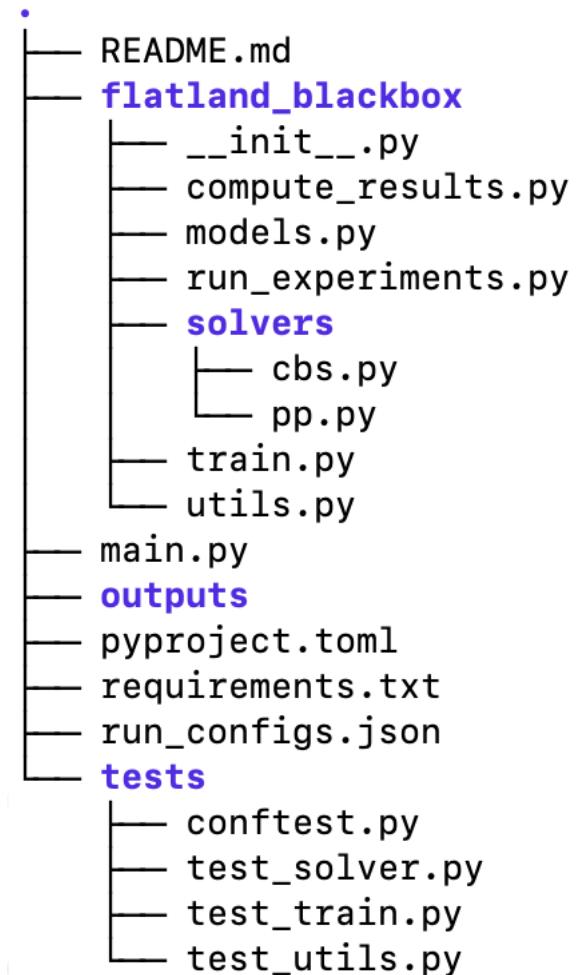
- main.py is the entry point for running experiments
- CBS and PP implementation can be found under **/solvers**
- **utils.py** provides utility functions related to graph and instance processing
- **/outputs** stores outputs:
 - For single experiments: as **images** of the agent's paths overlaid over the flatland environment
 - For multiple experiments: a **two csv files** with path length statistics for each seeded run
- **/tests** includes all tests which can all be run using:
 - python -m pytest

```
. └── README.md
    └── flatland_blackbox
        ├── __init__.py
        ├── compute_results.py
        ├── models.py
        ├── run_experiments.py
        └── solvers
            ├── cbs.py
            └── pp.py
        └── train.py
        └── utils.py
    └── main.py
    └── outputs
        ├── pyproject.toml
        ├── requirements.txt
        └── run_configs.json
    └── tests
        ├── conftest.py
        ├── test_solver.py
        ├── test_train.py
        └── test_utils.py
```

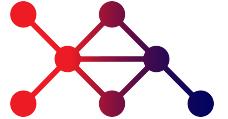
Installation and running experiments



- The installation instructions can be found on the README.md
- Run single experiments using command line arguments:
 - `python main.py —mode —solver [pp or cbs]`
- To run a single training instance :
 - `python main.py —mode train`
- To run a set of experiments across multiple instances, over a set amount of seeds:
 - `python main.py —mode experiments`
 - The experiments parameters can be altered inside `run_configs.json`
- `python main.py —help` to get a list of all possible commands



Perspectives



- Next steps:
 - Working in Flatland simulation:
 - Learn based on **dynamic start/current positions** of agents.
 - Edge weights as a function of the current agent positions
 - If breakdowns happen, **replan** using updated positions/weights.
 - Learned weights should reflect possibility of **breakdowns**.
 - Learn to assign **priorities** (learn to rank approach).
 - Future work:
 - Optimal solvers such as CBS dont scale into more realistic scenarios with tens/hundreds of agents at the same time.
 - Have an **Reinforcement Learning loss** instead of relying on expert optimal trajectories.



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