Neural Prioritized Planning: Flatland

Task 2.1 Beta release - UvA

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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.

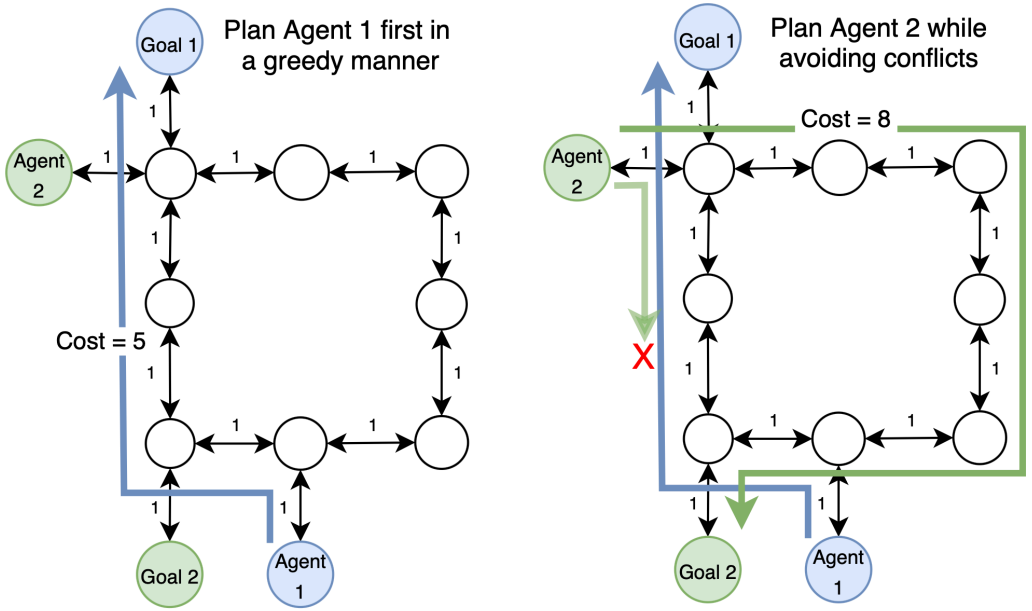
Use cases

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

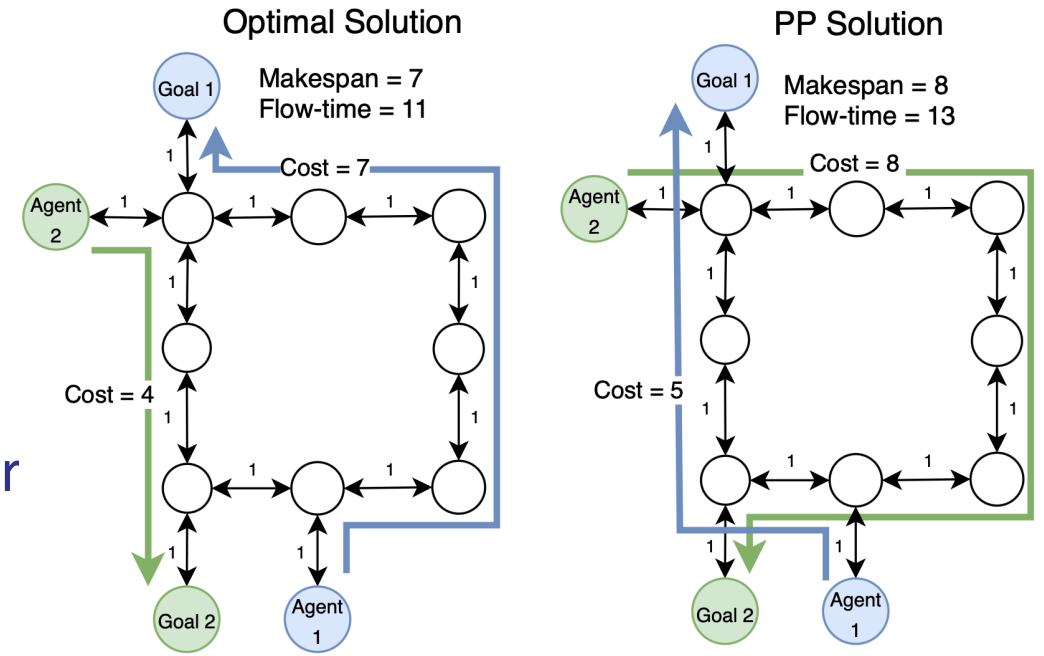
- **Prioritized Planning** (PP) is such an algorithm, that plans agents in sequence, based on the assigned priorities.
- Often times, PP it is **not** optimal.



Motivation: small scale example

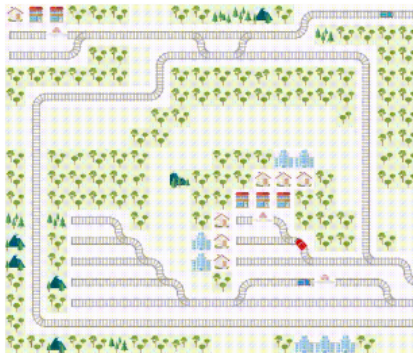
- In this example the optimal path is for Agent 1 to take the slightly longer route, while Agent 2 takes the much shorter one.
- **Makespan** = max length of all paths
- **Flow-time** = sum of length of all paths

- 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.

Run PP w/ input graph weights

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

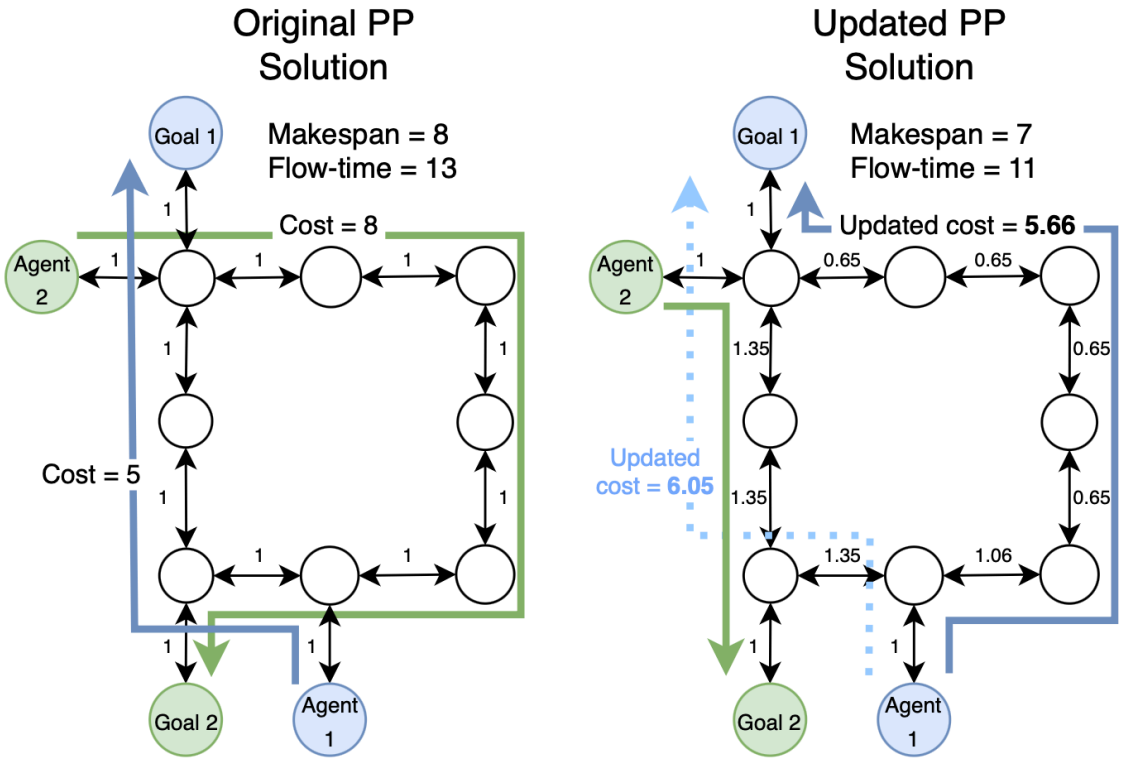
Use **Conflict Based Search** (CBS) to generate optimal paths.

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, overall **mean flow-times** over 100 seeds for each configuration:

	Mean Flow-time		
Number of agents	CBS	PP	Trained PP
3	**59.75**	60.74	60.38
7	**140.86**	144.39	143.03
11	**224.33**	230.14	227.67

Preliminary experiments on Flatland

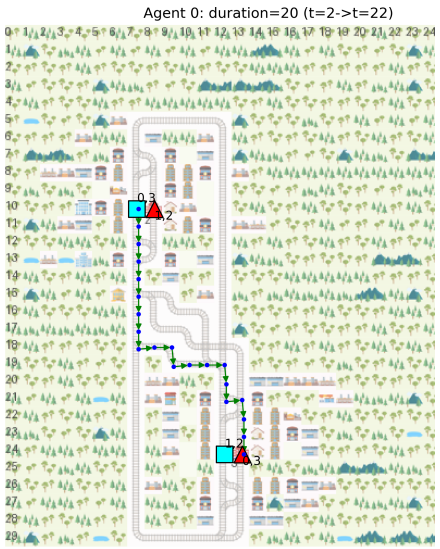
- Filtered mean flow-times (**only** cases when flow-time of **PP > CBS**):

	Mean Flow-time		
Number of agents	CBS	PP	Trained PP
3	**56.65**	60.83	59.30
7	**137.90**	145.42	142.52
11	**214.81**	224.76	220.52

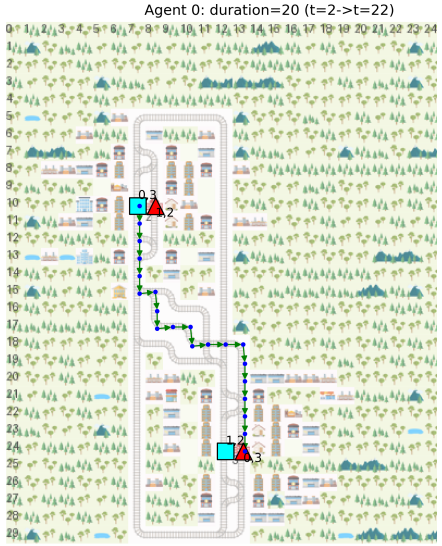
Example on 30x30 Flatland map with 4 agents

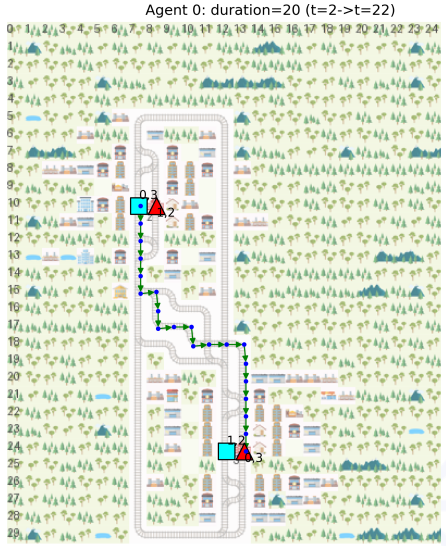
- End Stations are represented with a ▲, the numbers represents which agents has to finish there.
- Start Stations are represented with a ■, the numbers represents which agents start there.
- PP with the updated weights re-routes **Agent 0** through the middle rail, instead of the bottom one.
- **Agent 0 paths:**

Original PP → CBS → PP Trained (matches CBS Agent 0 path)



Vs

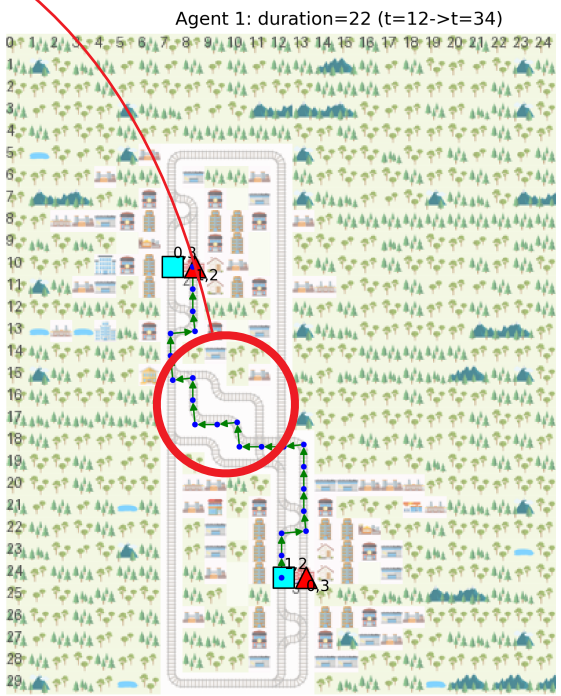




Preliminary experiments on Flatland

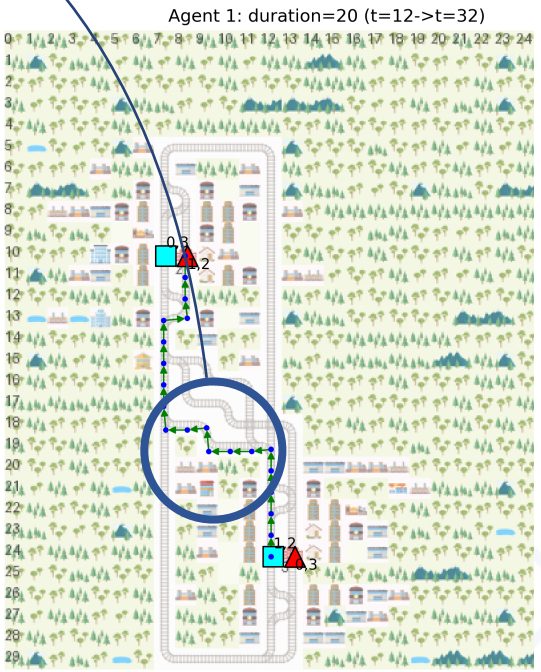
- So that Agent 1 can take the shorter route (**20 length**) using the **updated weights**, instead of the old PP route (**22 length**) to arrive at the goal, avoiding the conflict with Agent 0:

Original PP



Vs

PP Trained



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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: **3 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 are stored in **`run_configs.json`**
- **`python main.py –help`** to get a list of all possible commands

```
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Experiments input and output

- **Input**: Flatland instances, defined by the underlying graph structure and the collection of various agent's start and goal positions.
- For the experiments the specific input is given by the parameters found inside **`run_configs.json`** `on the right ->`
- **Output**: A **Plan**. A plan is a dictionary of **Agent_ID: Path** entries. A path is a list of tuples ((row, col), timestep), representing the positions of an agent at each distinct timestep.

{..} **run_configs.json** 229 B

```
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  "iters": 300,
  "lr": 0.01,
  "lam": 3.0,
  "num_seeds": 100,
  "start_seed": 0,
  "num_agents_list": [
    3,
    7,
    11
  ],
  "max_cities_list": [
    2
  ],
  "width_list": [
    30
  ],
  "height_list": [
    30
  ]
}
```

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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