

# FLATLAND CHALLENGE

## DEEP LEARNING COURSE FINAL PROJECT

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# ENVIRONMENT

#### RAILWAY ENCODING

- Standard encoding: dense, matrix-based
- Custom encoding: sparse, graph-based
  - Only stores meaningful positions: junctions and targets
  - Memory efficient



(a) Grid



(b) COJG

#### **PREDICTIONS**

- Standard predictions: shortest path only, computed on the matrix encoding
- Custom predictions: shortest and deviation paths, computed on the custom graph encoding
  - Scalable solution
  - Incremental computation
  - Time efficient

#### **IMPROVEMENTS**

- Choices: reduced action space
  - Follow the track to the left, to the right or stop
- Real decisions: only relevant calls to the policy estimator
  - On before join, at fork or in a combination of the two
- Action masking: only consider legal moves
  - Stop is legal only when there is more than one agent
- Rewards shaping
  - Incremental rewards (related to real decisions)
  - Deadlock penalty
  - Target arrival bonus
  - Consecutive stop action penalty

# ARCHITECTURES

# DQN (DEEP Q-NETWORK)

- ullet From state representation to Q-values
- Standard experience replay
- Regression framework: TD error minimization
  - MSE or Huber loss
- Double, dueling version with custom Bellman operators

# GNN (GRAPH NEURAL NETWORK)

- From graph nodes to an embedding space
- Two main uses: the input graph could be ...
  - ... railway encoding
  - ... agent communication network
- Different graph convolutional layer
  - GCN as a simple sum/mean neighborhood aggregator
  - GAT as a learnable information gatherer, with attention over features of nearby agents

# Model flows

#### **BINARY TREE**

- Binary tree observation
  - Shaped like the standard tree observation, with two branches (left and right choice)
  - Based on the graph railway encoding (nodes in the tree are linked to nodes in the graph)
  - Prior knowledge injection: only nodes corresponding to predictions (shortest/deviation) are filled with features
  - Carefully designed features (based on direction, speed and malfunction of agents)
- Per-agent flow
  - 1. Compute, linearize and normalize the binary tree
  - 2. The observation is fed to the DQN, which returns Q-values
  - 3. The action selector chooses an action

#### ENTIRE GRAPH EMBEDDINGS

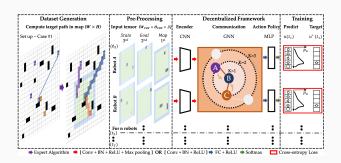
- Graph observation
  - Exploit the railway encoding graph and assign simple features to each node (cell status, target distance)
  - Does not make use of predictions
- Per-agent flow
  - The GNN computes convolutions over the input graph and extracts embeddings from pre-specified positions

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- 2. Such embeddings are given as input to the DQN, which returns *Q*-values
- 3. The action selector chooses an action

#### MULTI-AGENT GRAPH EMBEDDINGS I

- FOV observation
  - Square Field Of View centered around each agent, of dimension (c, d, d)
  - $\blacksquare$  Channel dimension c used to represent different features
  - Makes use of the shortest/deviation paths prediction



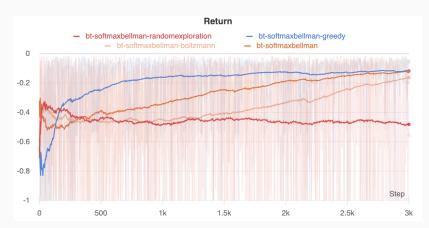
#### MULTI-AGENT GRAPH EMBEDDINGS II

- All agents flow
  - 1. The FOV observation is computed for all agents at once
  - 2. A CNN (built by blocks of Conv + BN + ReLU + MaxPool) is used to extract higher-level features from FOVs
  - 3. The CNN output is compressed into a fixed size by an MLP
  - 4. A GNN takes as input a graph where nodes are agents (features are MLP outputs) and edges encode their proximities in the environment
  - 5. The output embeddings of the GNN are used as input to the DQN, which returns *Q*-values
  - 6. The action selector chooses an action for each agent

# EXPERIMENTS

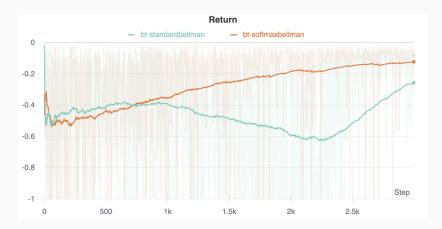
#### **ACTION SELECTORS**

- ullet  $\epsilon$ -greedy vs. Boltzmann
- Random and greedy baselines



## BELLMAN OPERATORS

• Standard vs. softmax Bellman





## **ENVIRONMENT SETTINGS**

### Environment

Parameter	Medium	Big			
width	48	64			
height	27	36			
max_cities	5	9			
<pre>max_rails_between_cities</pre>	2	5			
<pre>max_rails_in_cities</pre>	3	5			
Complications					

Parameter	Α	В
speeds	1	$\{1, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}\}$
malfunctions.rate	0	1 200
malfunctions.min_duration	-	15
${\tt malfunctions.max\_duration}$	-	50

#### MEDIUM ENVIRONMENT

- Model flow
  - Binary tree observator with DQN model
  - lacktriangleright  $\epsilon$ -greedy action selector and softmax Bellman operator

	3 agents		5 agents		7 agents	
	Α	В	Α	В	Α	В
Dones	93.07%	83.80%	89.40%	76.64%	82.51%	67.66%
Deadlocks	3.07%	5.80%	5.96%	13.40%	10.23%	12.54%
Return	-0.1404	-0.1459	-0.1581	-0.1688	-0.2057	-0.1940
Steps	142	339	187	415	250	445

## BIG ENVIRONMENT

• Model flow: the same one used in the medium setting

	5 agents		7 agents		10 agents	
	Α	В	Α	В	Α	В
Dones	86.28%	68.76%	84.17%	61.43%	76.90%	50.28%
Deadlocks	3.24%	12.88%	5.89%	20.97%	12.54%	31.82%
Return	-0.2331	-0.2081	-0.2449	-0.2260	-0.2790	-0.2615
Steps	400	637	447	650	497	675

