

Pathfinding and Routing

NAIL137

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Centralized approach

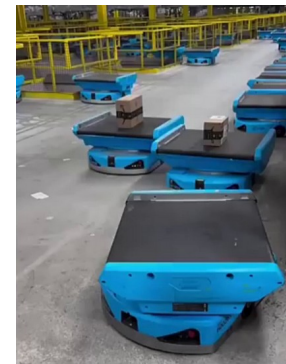
- So far...
 - There is a central coordination agent
 - All moving agents obey
- Challenges
 - Communication
 - Synchronization
 - Computation resources
 - No outside influence

Decentralized approach

- Each agent acts with its own interest
- Challenges
 - Requires sensing
 - Can not be optimal
 - Needs to avoid deadlocks/livelocks

Decentralized approach

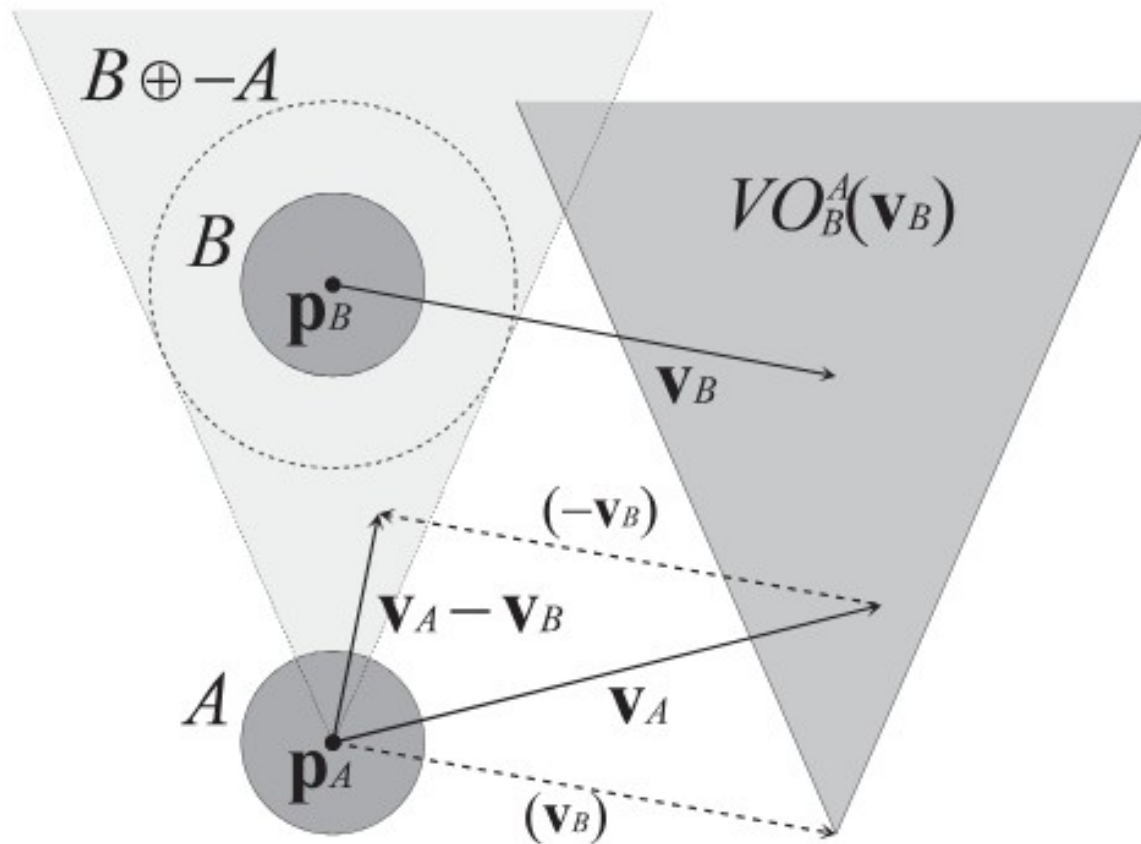
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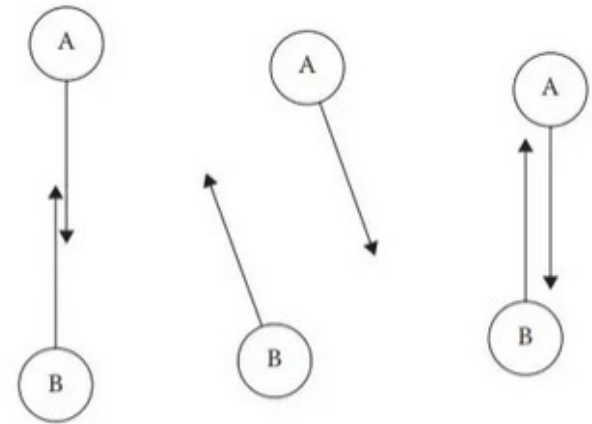
General approach

- A greedy path is known
- Each agent has a policy (i.e. set of rules)
 - Current state \rightarrow action
- Actions aim to avoid collisions and navigate towards goal
- Rules can be hand-made or learned

- Velocity Obstacle (VO)

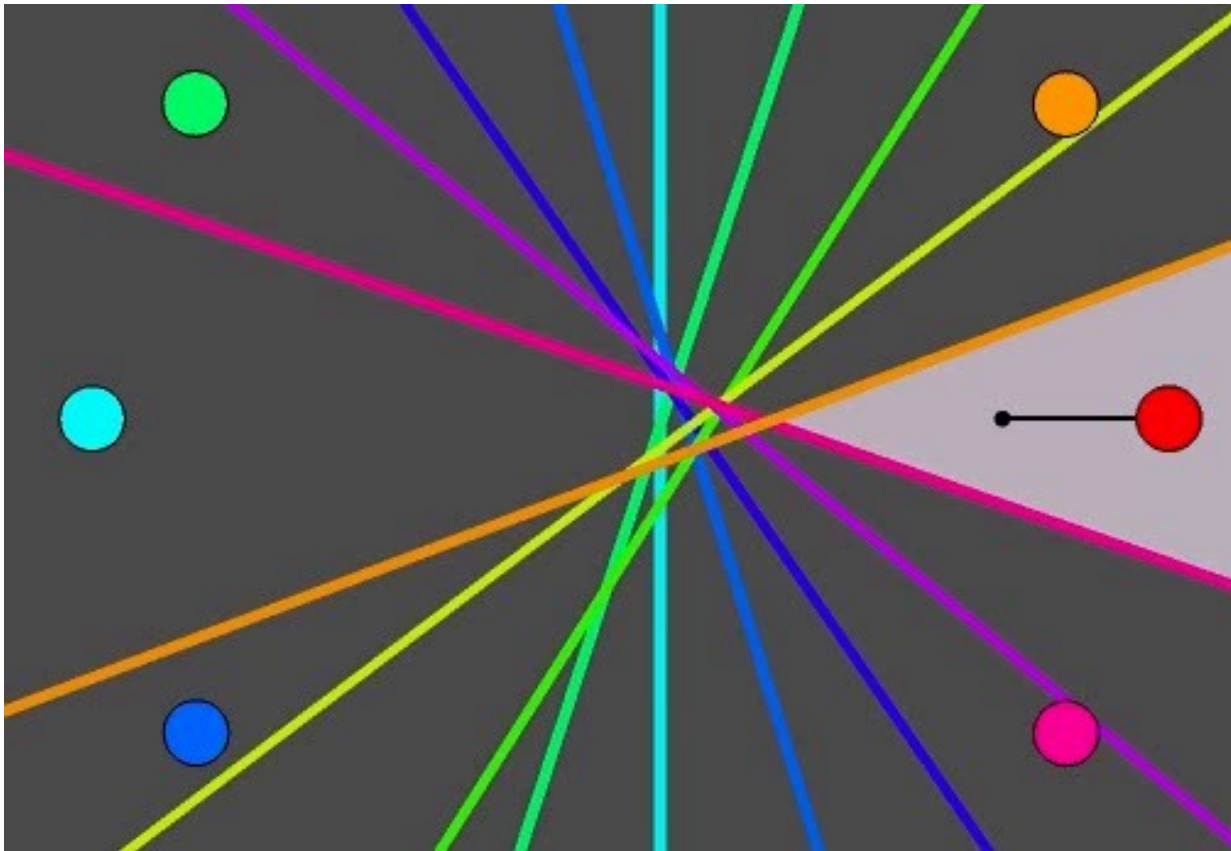


- Problem with VO is jitter



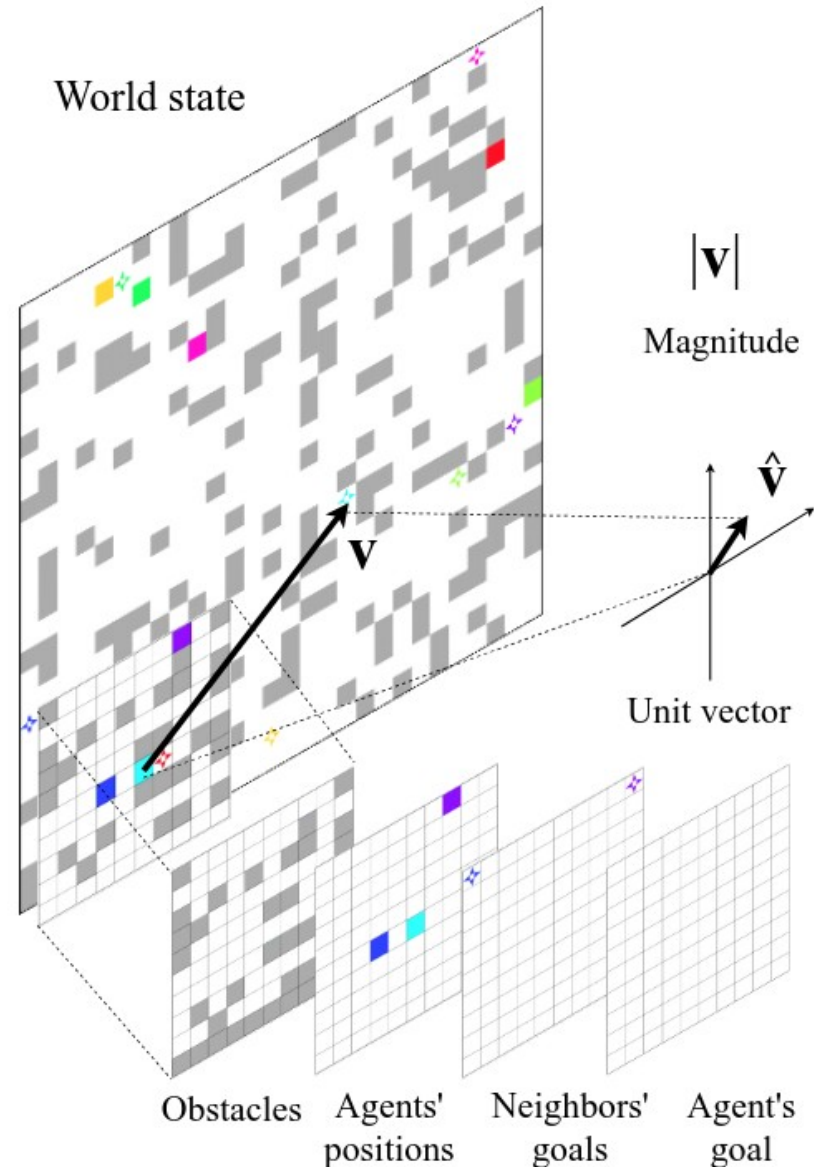
- Reciprocal Velocity Obstacle (RVO)
 - Both agents take responsibility
 - Both agents know they follow the same rules

- Optimal Reciprocal Collision Avoidance
 - Can deal with multiple agents at once



Primal

- ML approach
- Decentralized
- Local observation



Primal - NN structure

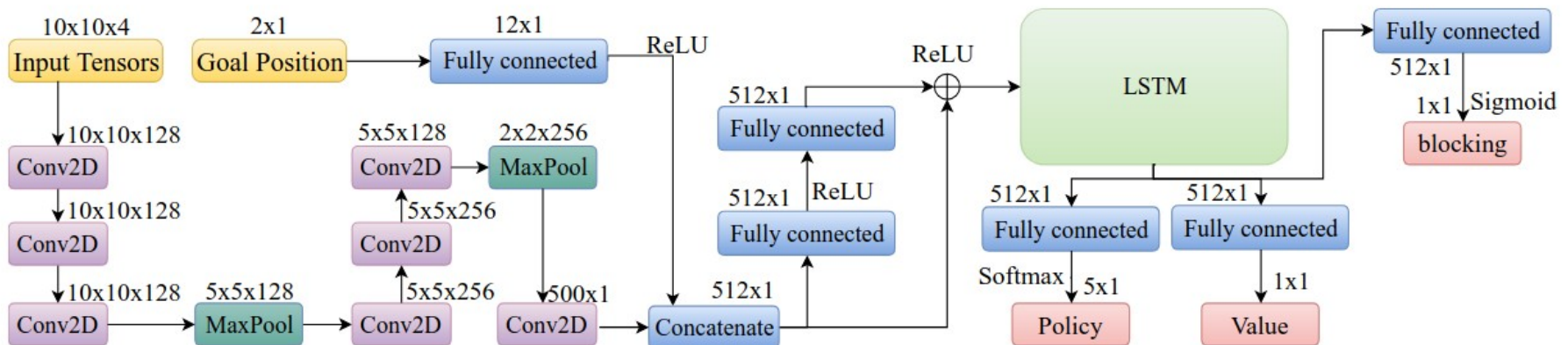



Fig. 3. The neural network consists of 7 convolutional layers interleaved with maxpooling layers, followed by an LSTM.

Primal - learning

- Initial approach

SIMPLE REWARD STRUCTURE.

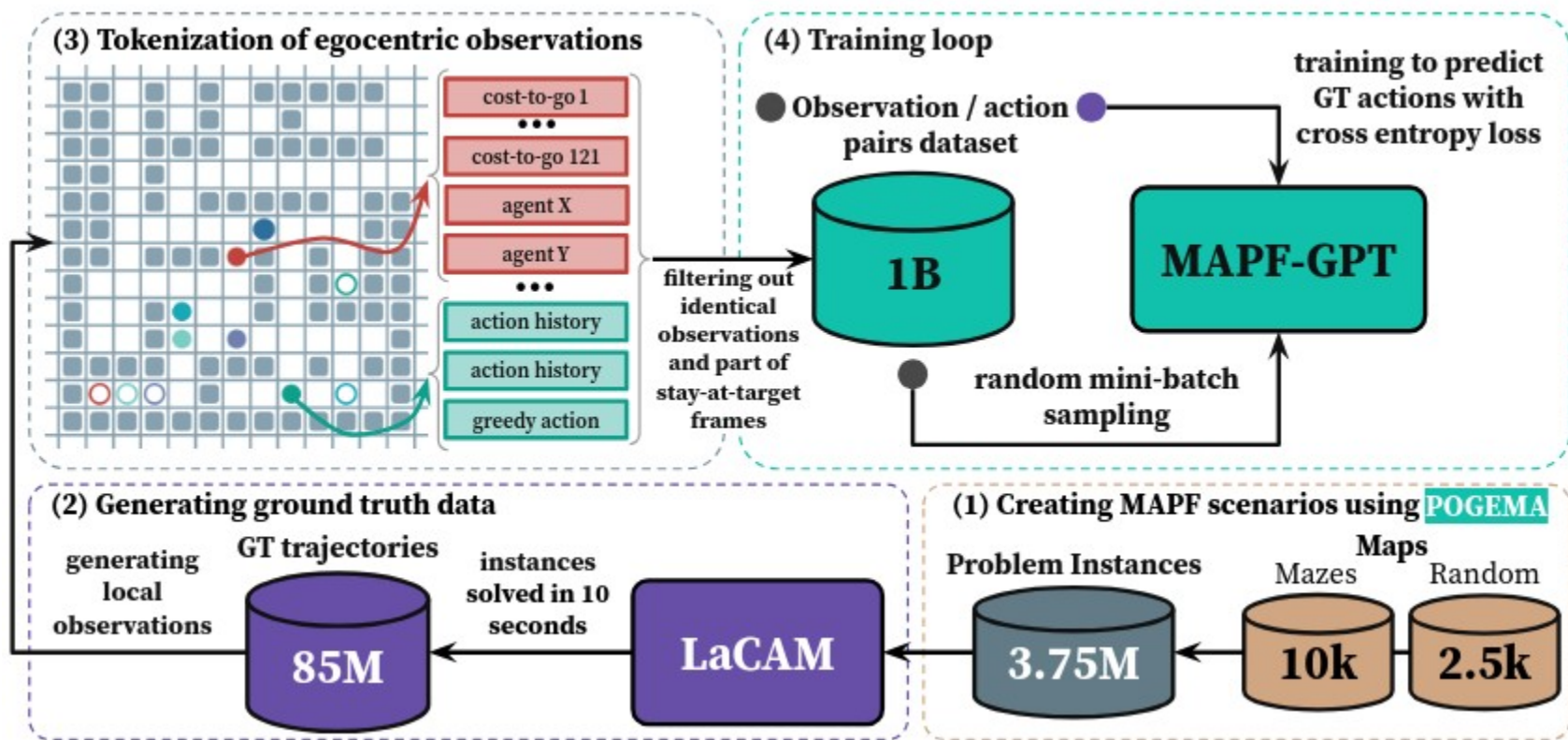
Action	Reward
Move [N/E/S/W] 	-0.3
Agent Collision	-2.0
No Movement (on/off goal)	0.0 / -0.5
Finish Episode	+20.0

- Make decentralized agents act selflessly
 - Blocking penalty
 - Imitation learning
 - Custom cluttered scenarios

Imitation learning

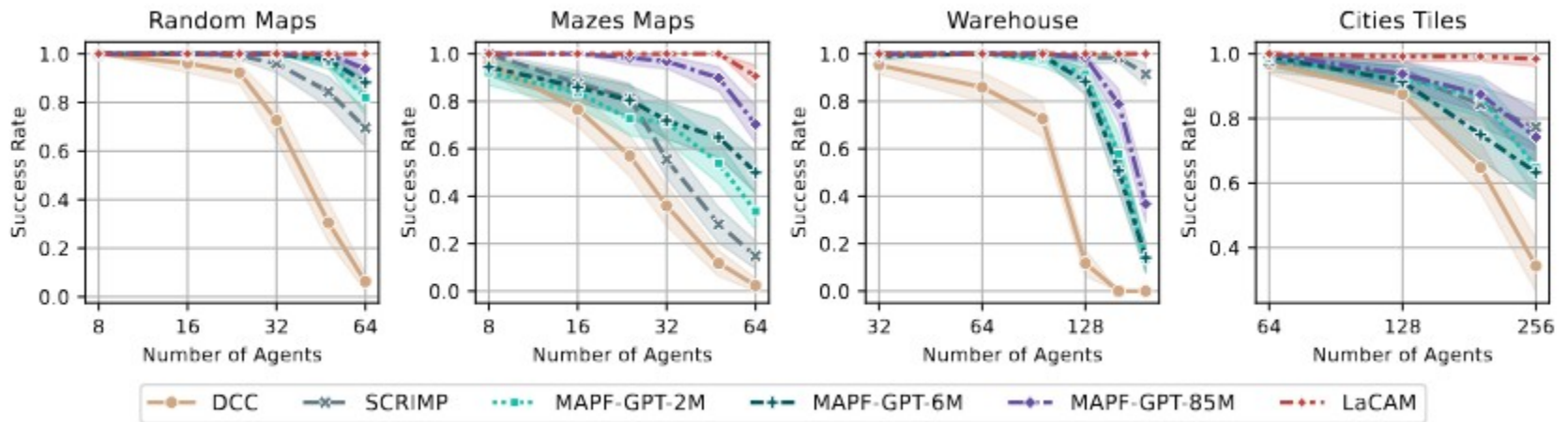
- 1) Collect ground truth from expert solver
 - 2) Supervised learning aiming to mimic expert
- Aim is to improve scalability
 - Combined with reinforcement learning and curriculum learning might outperform expert

MAPF-GPT



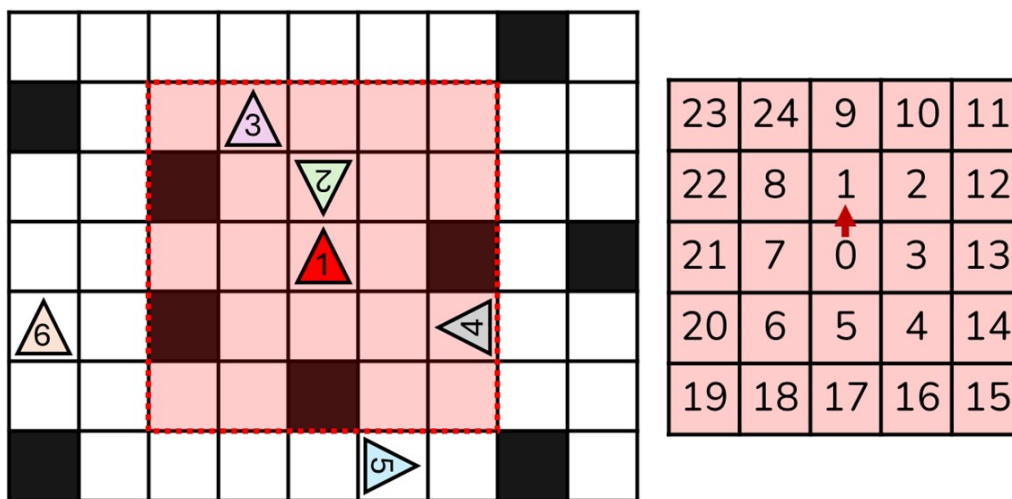
MAPF-GPT

- Does not work well yet!



Social rules

- Like traffic rules when there are no signs
- Hand made
 - Deterministic
 - Stochastic
- Learned?

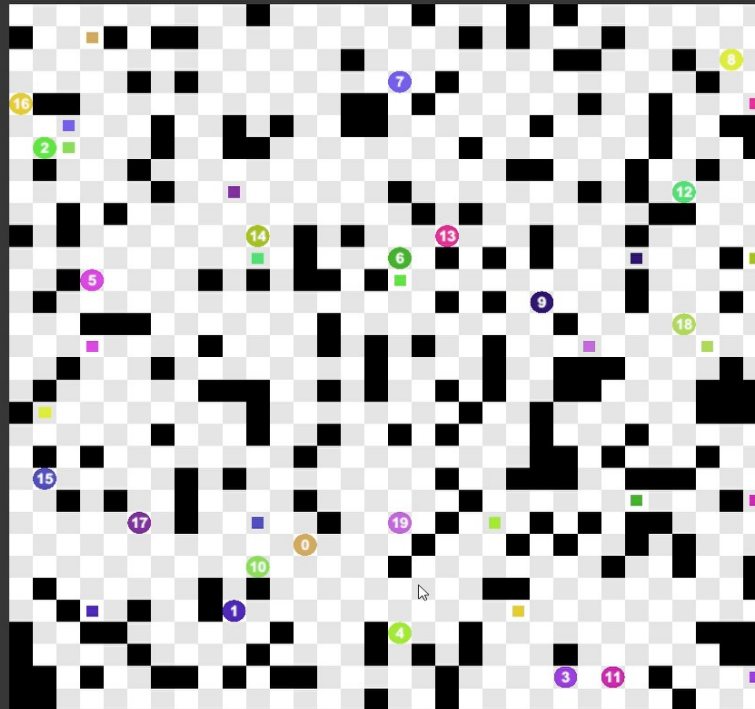


(A1) (N3) (P3) (N4) (N13) -> (R100)

Social rules

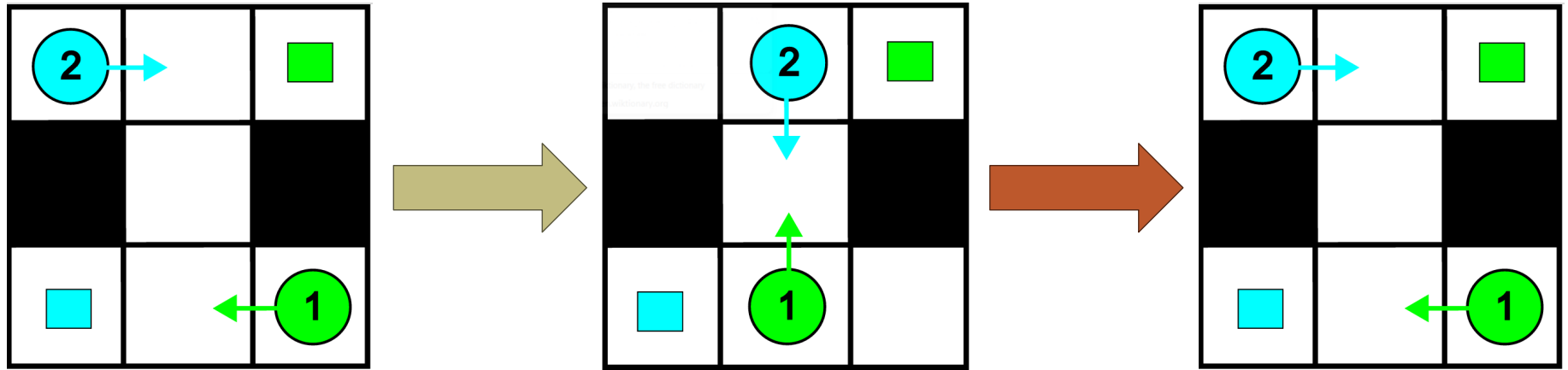
Time: 0

[Log] : Starting simulation.



Finished agents: 0/20

Social rules - resolve deadlocks

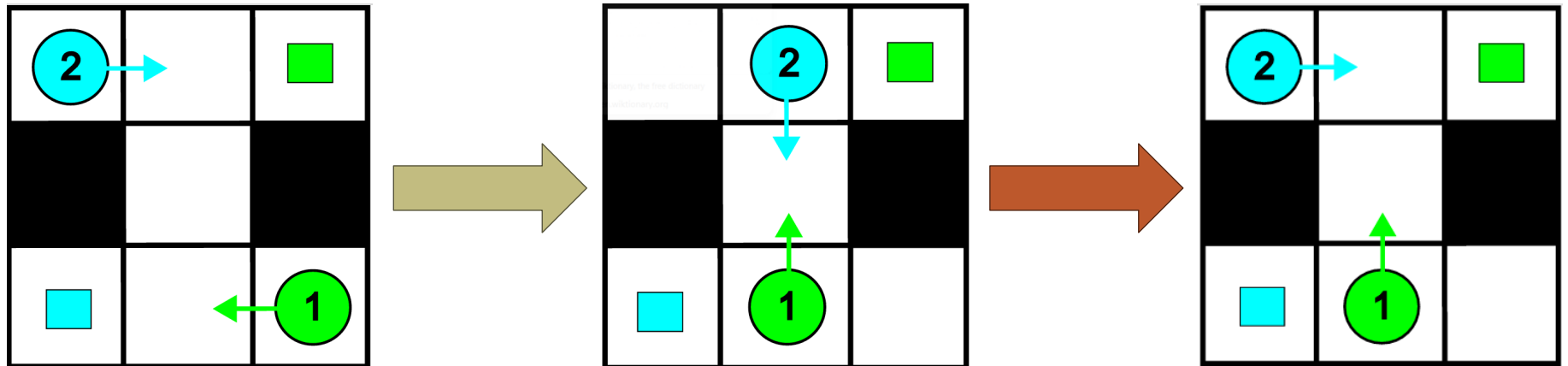


Stochastic social law:

1: (A1) (N3) (P3) (N4) (N13) > (R50) (S50)

2: (A1) (N5) (P5) (N6) (N17) > (B50) (S50)

3: (A1) (N7) (P7) (N8) (N21) > (L50) (S50)



MAPF simulator for social laws

General Settings:

20 agents

Select file with map

Selected file: random-32-32-20.map

Select file with
scenario

Selected file: random-32-32-20-random-2.scen

Optional Settings:

Select output file

No file selected

Select file with paths

No file selected

Select file with social
laws

Selected file: Stochastická sociální

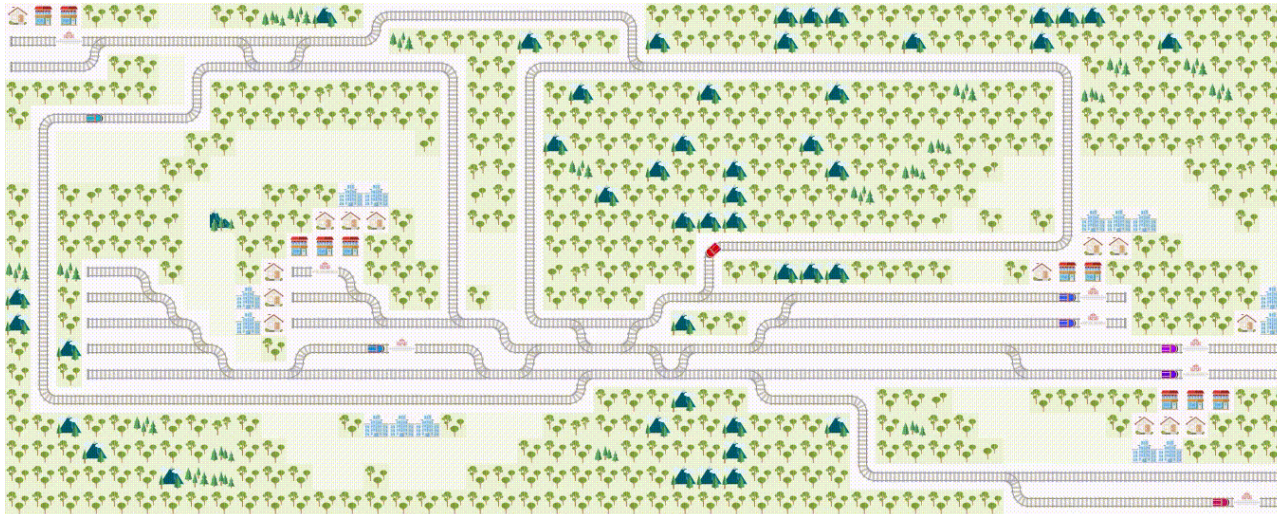
Delay of agent probability:

0.0

Start simulation

Comparing ML and classic approach

- So far, ML techniques fall behind
 - Expensive training
 - Poor scaling
 - Can not handle complicated situations
- Was seen in Flatland challenge

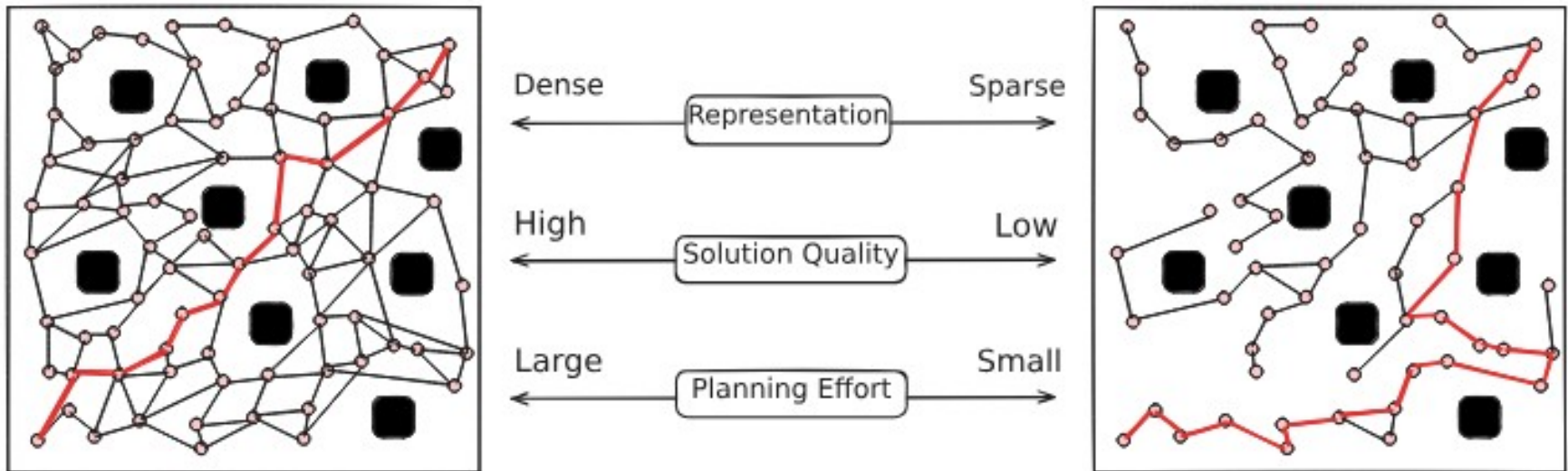


Other ML applications in MAPF

- Environment representation
- Algorithm selection
- Augment existing solver

Environment representation

- General optimization scheme
 - 1) Sample vertices
 - 2) Create edges
 - 3) Minimize custom cost function



Environment representation

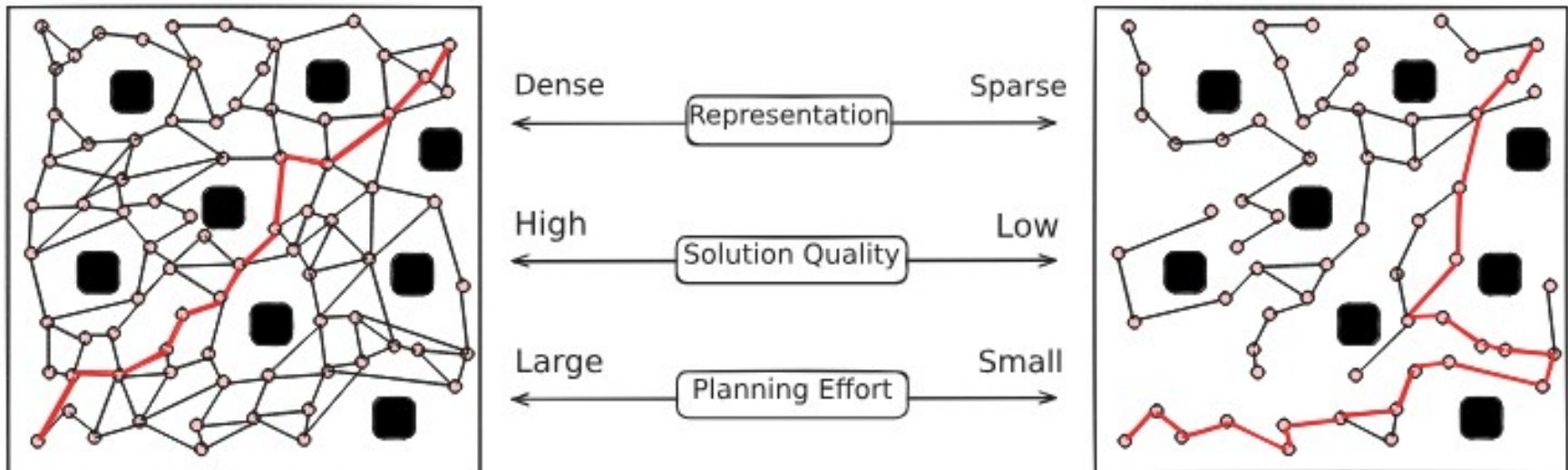
- General optimization scheme

- 1) Sample vertices

Identify critical locations for collision avoidance

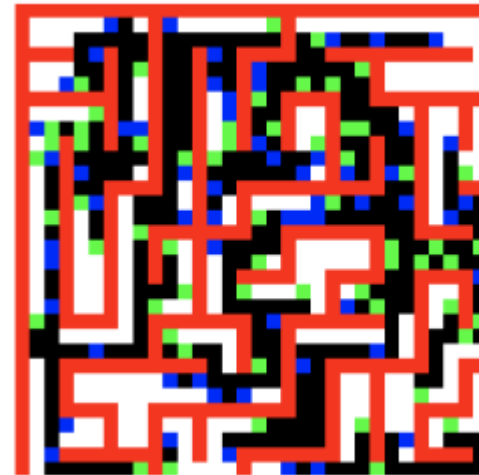
- 2) Create edges

- 3) Minimize custom cost function



Algorithm selection

- Decide what algorithm to use on given instance
- The hard part is to decide what makes the instance hard
 - Map size
 - Obstacle density
 - Agent density
 - Agent placement
 - ...



Augment solvers with ML

- CBS
 - Conflict selection
- EECBS
 - Heuristic functions for top level
- PP
 - Priority selection
- LNS
 - Select neighborhoods