

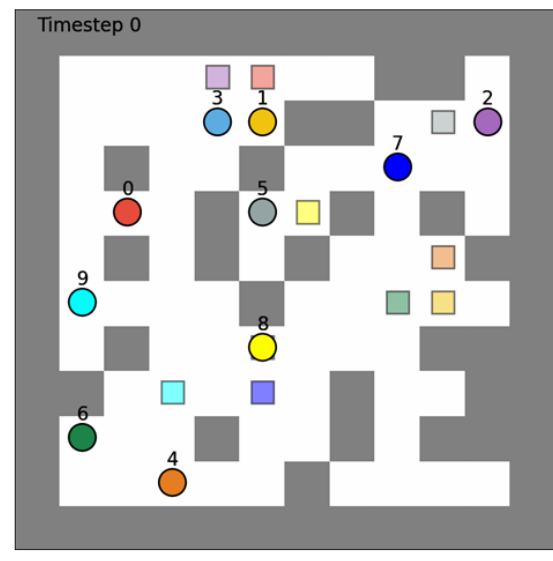
Abstract

Teams of robots must often assign locations among themselves and then plan collision-free paths to these locations. Examples include autonomous aircraft towing vehicles, automated warehouse systems, office robots, drones and game characters in video games. For example, soon, autonomous aircraft towing vehicles will tow aircraft all the way from the runways to their gates (and vice versa) to avoid the pollution and excessive energy consumption resulting from planes taxiing with their engines. Today, hundreds of robots already navigate autonomously in Amazon fulfillment centers to move inventory pods all the way from their storage locations to the inventory stations that need the products they store (and vice versa). Optimal and even some approximately optimal path planning for these robots is NP-hard, yet one must find high-quality collision-free paths for them in real-time since shorter paths result in higher throughput or lower operating costs (since fewer robots are required). Algorithms for such multi-agent path-finding problems have been studied in robotics and theoretical computer science for a longer time but are insufficient since they are either fast but of insufficient solution quality or of good solution quality but too slow (especially for highly congested environments), see my educational website mapf.info for more information.

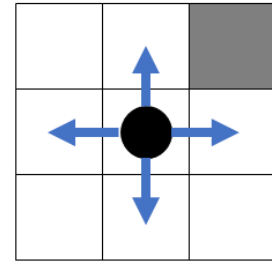
We therefore study different variants of multi-agent path finding (MAPF) problems (including "lifelong" variants), their complexities, algorithms for solving them and their applications. We proved that even approximating optimal solutions can be NP-hard in some cases but also managed to scale up bounded-suboptimal planners to hundreds of agents and high-quality planners without solution guarantees to thousands of agents via a variety of techniques, such as "highway" heuristics, symmetry-breaking techniques, better node-splitting techniques, mutex propagation, more informed heuristics and learning which collision to resolve next as well as more standard techniques, such as rapid random restarts and large neighborhood search. We also studied MAPF solving based on prioritized planning and deep reinforcement learning. Finally, we developed a hierarchical planning architecture that combines ideas from AI, optimization and robotics. It makes use of a simple temporal network to post-process the output of a MAPF algorithm in polynomial time to create a plan-execution schedule that takes the maximum translational and rotational velocities of robots into account, provides a guaranteed safety distance between them and exploits slack to absorb imperfect plan executions and avoid time-intensive re-planning in many cases.

Multi-Agent Path Finding (MAPF)

- Optimization problem with the objective to minimize the **task-completion time** (called **makespan**) or the sum of travel times (called **flowtime**)



Simplifying assumptions



Science of Making Good Decisions

- We need a science of making good decisions
 - Artificial intelligence
 - Search, planning, coordination, probabilistic reasoning, constraint reasoning, machine learning, ...
 - Decision and utility theory
 - utility theory, limited rationality, ...
 - Economics
 - auctions, ...
 - Operations research
 - Markov decision processes, ...
 - Control theory
 - Theoretical computer science and mathematics



The future of AI is in combining decision-making techniques from different disciplines.

Science of Making Good Decisions

CCC Artificial Intelligence/Operations Research Workshop II

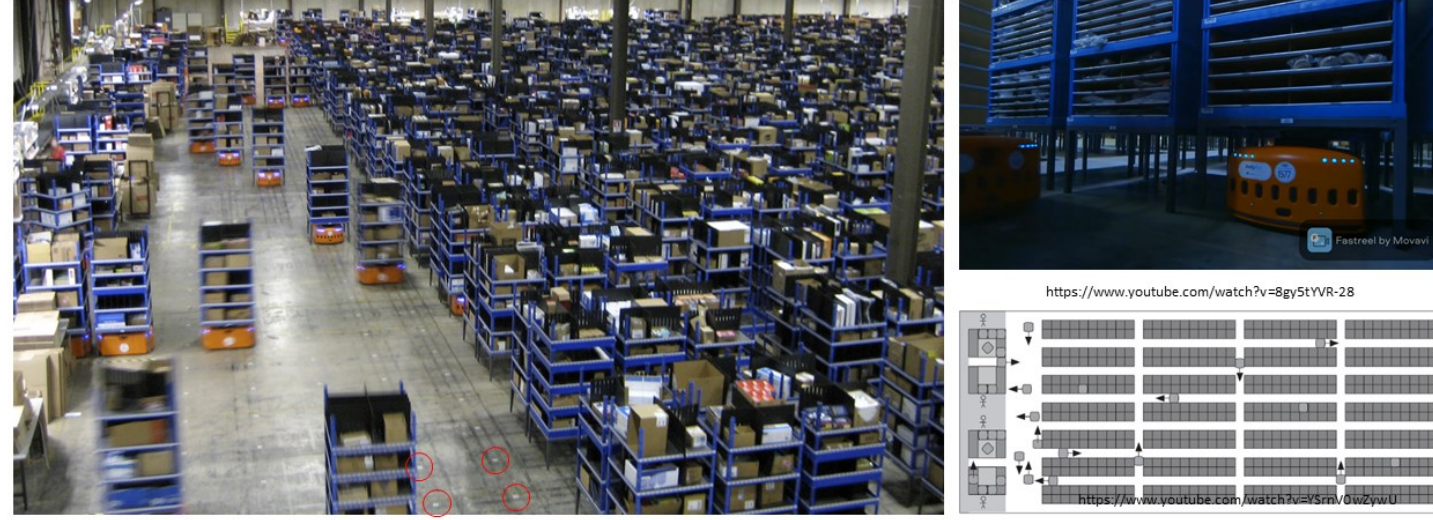
August 16, 2022 – August 17, 2022
7:30 AM-2:15 PM

Georgia Tech Hotel and Conference Center
800 Spring Street Northwest
Atlanta, GA 30308



Automated Warehousing

- Amazon fulfillment centers – warehousing part



[1] P. Wurman et al., "Coordinating Hundreds of Cooperative, Autonomous Vehicles in Warehouses", AI Magazine 29(1), 9-20, 2008.

Automated Warehousing

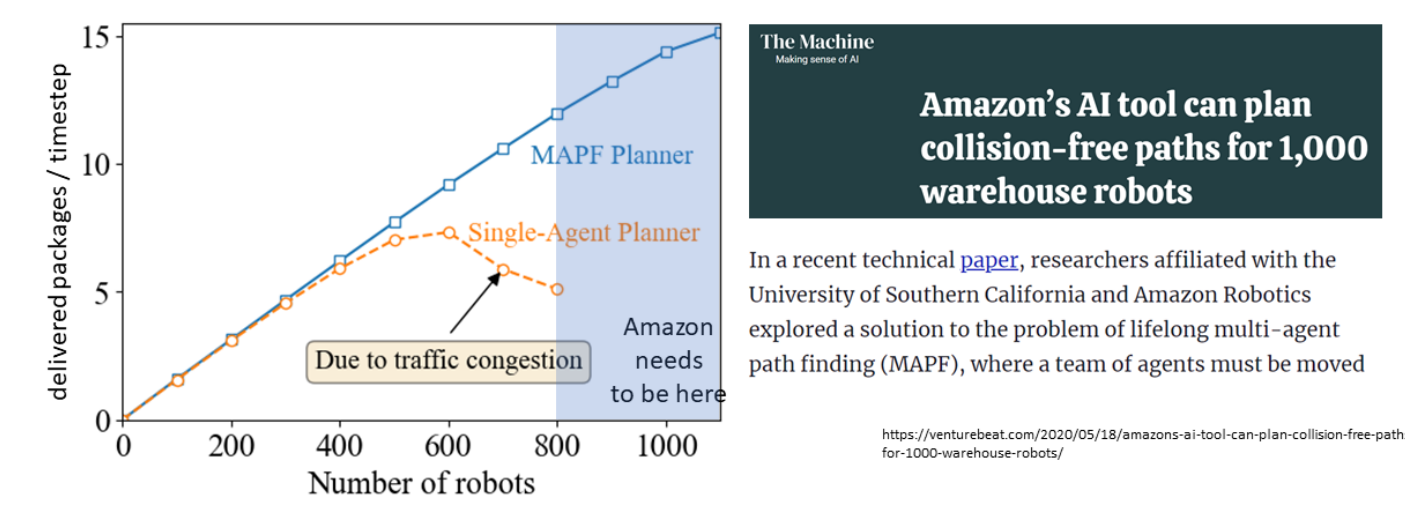
- Amazon fulfillment centers – sorting part



<https://www.wired.com/story/amazon-warehouse-robots/>

Automated Warehousing

- 800 robots (= 32% empty cells) on a 37x77 sorting-center map with 50 workstations and 275 chutes (joint project with Amazon Robotics)



[2] J. Li et al., "Lifelong Multi-Agent Path Finding in Large-Scale Warehouses", AAAI, 2021.

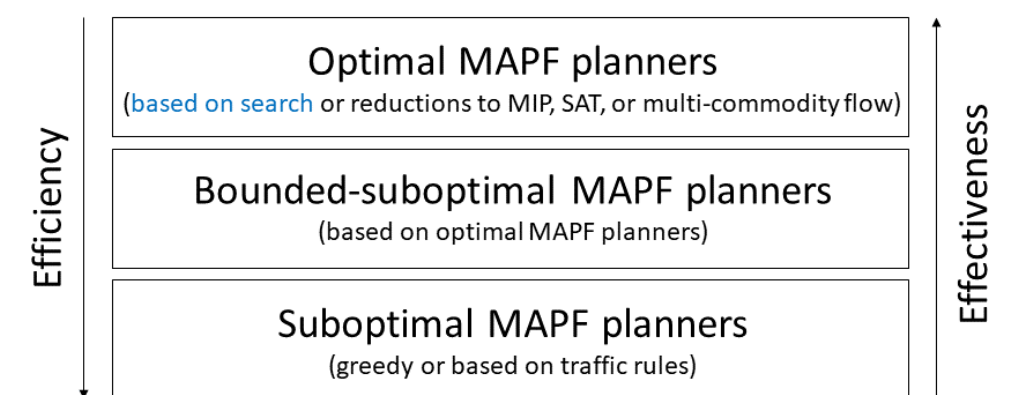
Complexity of MAPF

- Optimal or bounded-suboptimal MAPF planning
 - NP hard to find a makespan- or flow-time optimal MAPF plan [3], even on planar [4] or grid-like graphs [5]
 - NP-hard to find a makespan-bounded-suboptimal MAPF plan with suboptimality factors of less than 4/3 [6]



- [3] J. Yu and S. LaValle, "Structure and Intractability of Optimal Multi-Robot Path Planning on Graphs", AAAI, 2013.
 [4] J. Yu, "Intractability of Optimal Multi-Robot Path Planning on Planar Graphs", IEEE Robotics and Automation Letters, 2016.
 [5] J. Banfi et al., "Intractability of Time-Optimal Multi-Robot Path Planning on 2D Grid Graphs with Holes", IEEE Robotics and Automation Letters, 2017.
 [6] H. Ma et al., "Multi-Agent Path Finding with Payload Transfers and the Package-Exchange Robot-Routing Problem", AAAI, 2016.

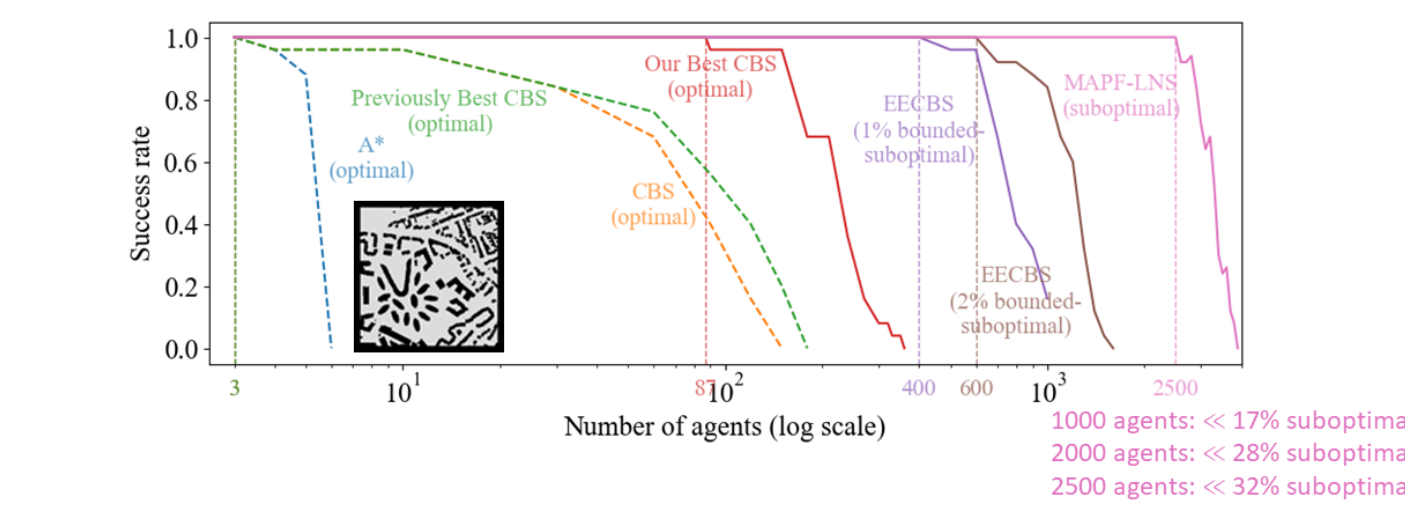
Planning-Based MAPF Algorithms



[7] E. Boyarski et al., "Iterative-Deepening Conflict-Based Search", UCAI 2020.

Planning-Based MAPF Algorithms

- Runtime limit: 1 minute



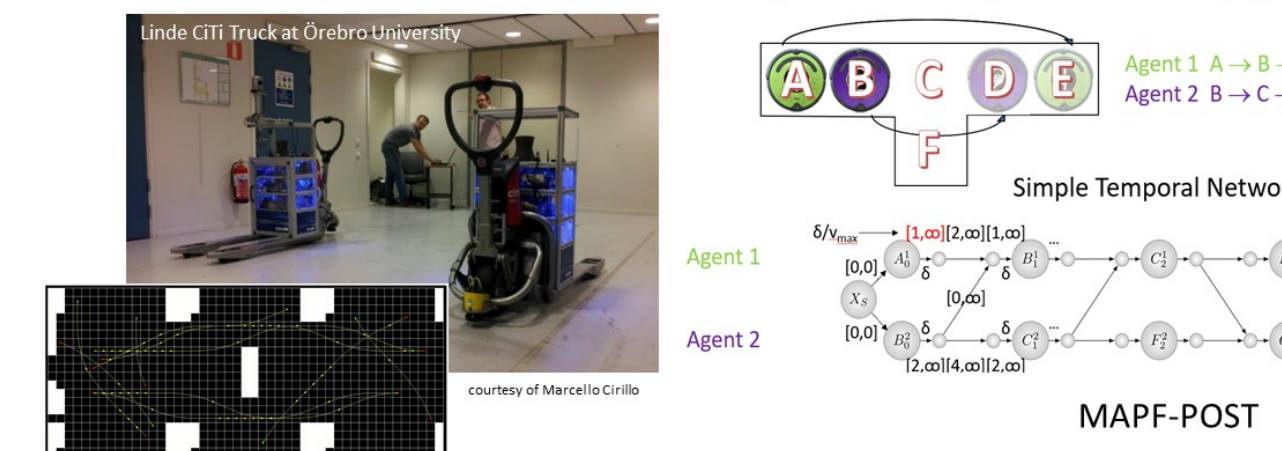
[10] V. Mnih et al., "Human Level Control through Deep Reinforcement Learning", Nature 518, 2015.

Planning-Based MAPF Algorithms

- Resolving collisions efficiently
 - Symmetry breaking with designed or discovered constraints (optimal)
 - Disjoint splitting (optimal)
 - Priority-based planning (suboptimal)
- Selecting nodes cleverly
 - Informed heuristics (optimal)
 - Explicit Estimation Search (bounded-suboptimal)
- Reducing the number of collisions in a node
 - Highways (bounded-suboptimal)
 - Rolling-horizon collision resolution (suboptimal)
- Other techniques
 - Random restarts (optimal)
 - Large neighborhood search with designed or learned neighborhoods (suboptimal)

Planning-Based MAPF Algorithms

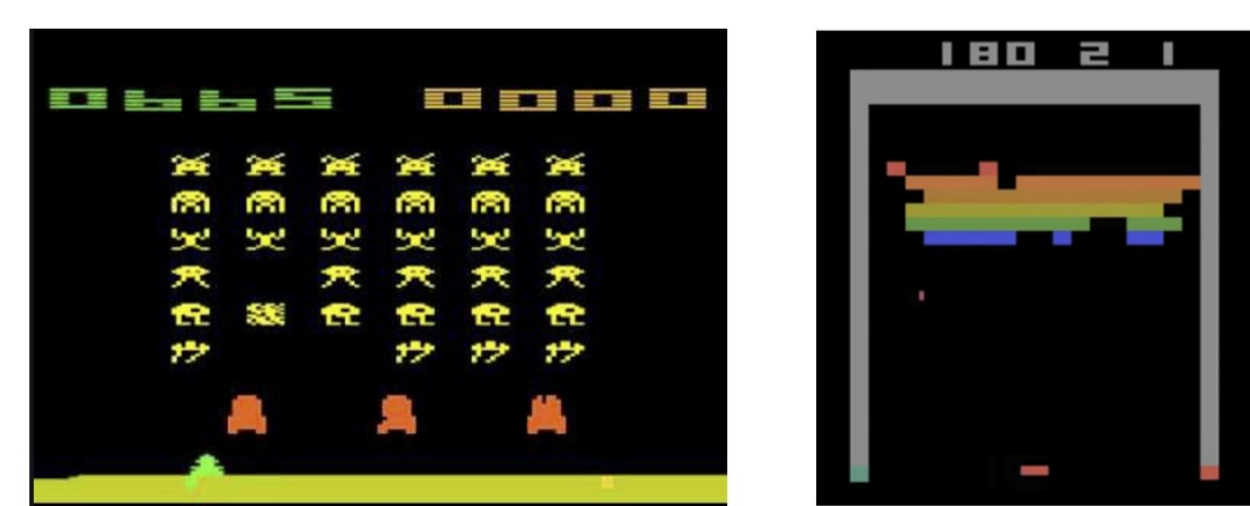
- Agents of more complicated kinodynamics (left)
- Uncertainty about the speeds of agents during execution (right)



[8] L. Cohen et al., "Optimal and Bounded-Suboptimal Multi-Agent Motion Planning", SOCS 2019.
 [9] W. Hoenig et al., "Multi-Agent Path Finding with Kinematic Constraints", ICAPS, 2016.

Learning-Based MAPF Algorithms

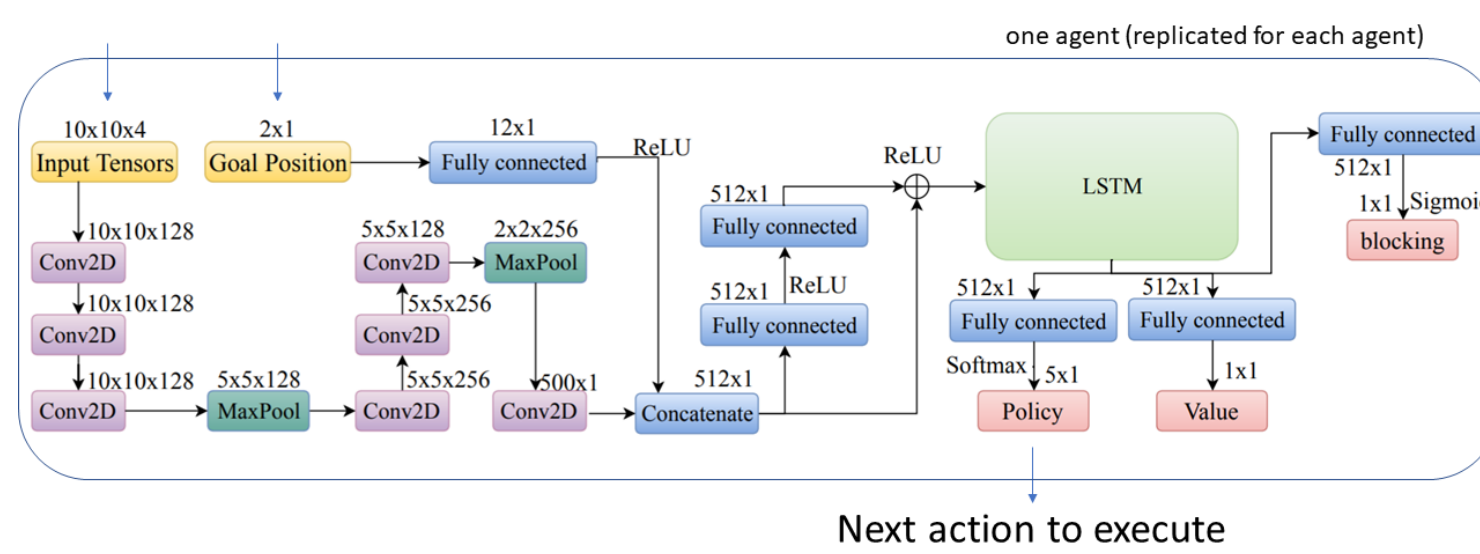
- PRIMAL: mix of deep reinforcement learning and imitation learning



[10] V. Mnih et al., "Human Level Control through Deep Reinforcement Learning", Nature 518, 2015.

Learning-Based MAPF Algorithms

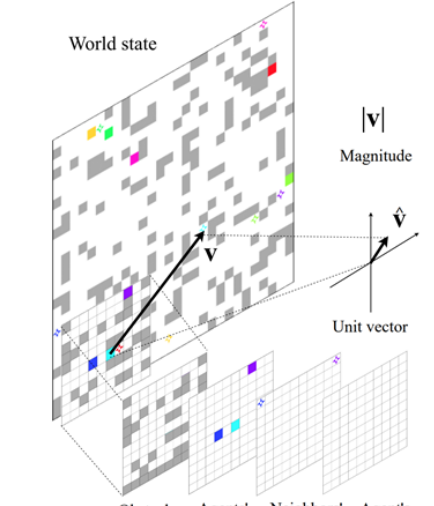
- PRIMAL: mix of deep reinforcement learning and imitation learning



[11] G. Sartoretti et al., "PRIMAL: Pathfinding via Reinforcement and Imitation Multi-Agent Learning", IEEE RAL 4(3), 2019.

Learning-Based MAPF Algorithms

- PRIMAL: mix of deep reinforcement learning and imitation learning



[12] G. Sartoretti et al., "PRIMAL: Pathfinding via Reinforcement and Imitation Multi-Agent Learning", IEEE RAL 4(3), 2019.

Learning-Based MAPF Algorithms

- Advantages
 - Learning takes time but following the resulting policy is fast during execution
 - Can yield a decentralized/distributed system while most effective planning based MAPF algorithms are centralized
- Challenge
 - End-to-end learning does not yet work sufficiently well, as also shown by the results of the NeurIPS 2020 Flatland competition

Learning-Based MAPF Algorithms

- NeurIPS 2020 Flatland Competition: 700 participants from 51 countries

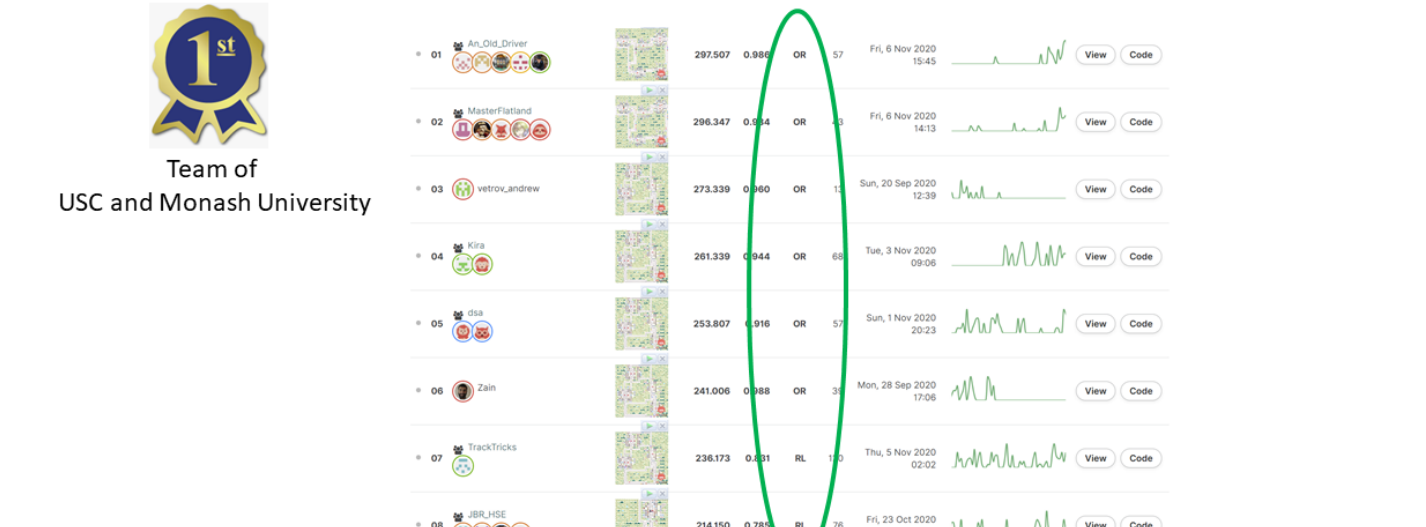


thousands of trains in large environments

[13] J. Li et al., "Scalable Rail Planning and Replanning: Winning the 2020 Flatland Challenge", ICAPS, 2021.

Learning-Based MAPF Algorithms

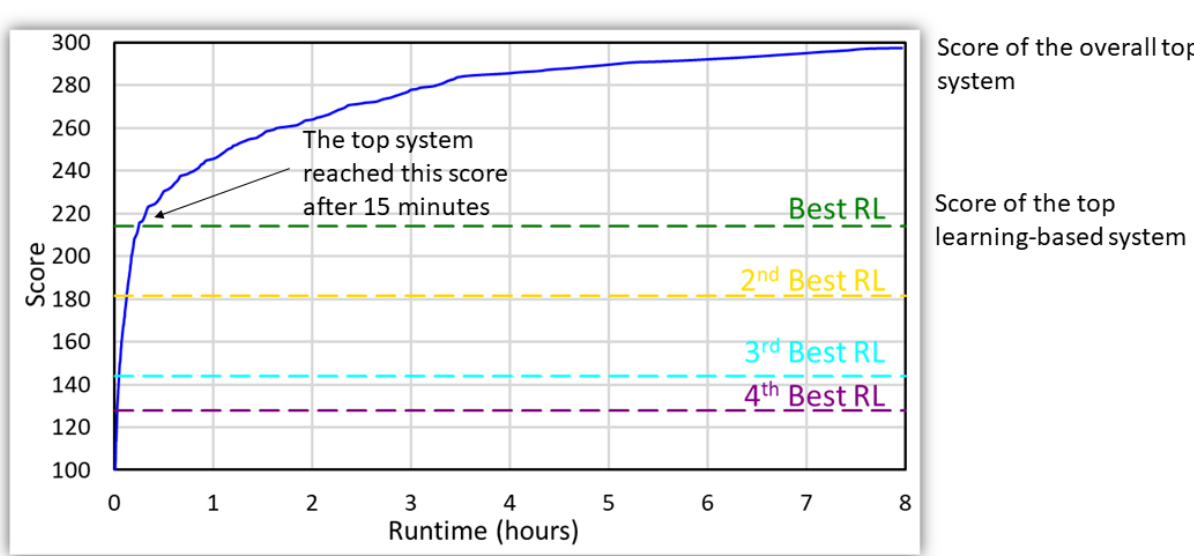
- NeurIPS 2020 Flatland Competition: 700 participants from 51 countries



[14] J. Li et al., "Scalable Rail Planning and Replanning: Winning the 2020 Flatland Challenge", ICAPS, 2021.

Learning-Based MAPF Algorithms

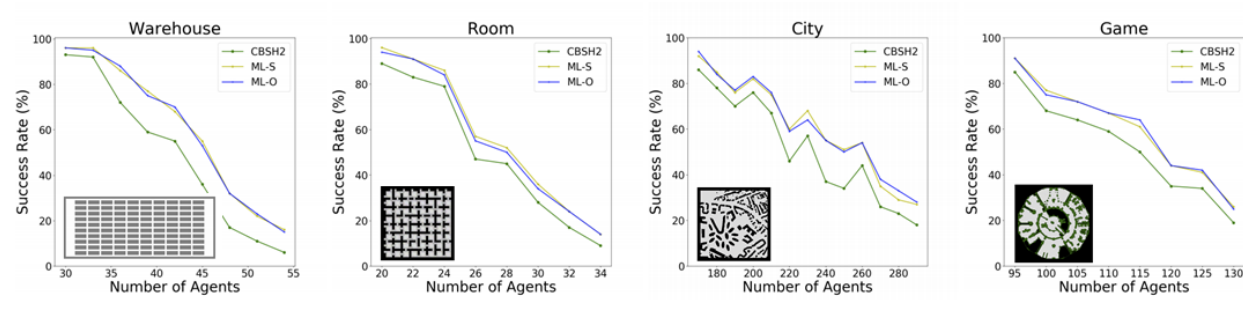
- NeurIPS 2020 Flatland Competition: 700 participants from 51 countries



[15] J. Li et al., "Scalable Rail Planning and Replanning: Winning the 2020 Flatland Challenge", ICAPS, 2021.

Learning-Based MAPF Algorithms

- Enhancing planning with machine learning
 - Planners use lots of hard-coded decision strategies
 - Machine learning can often learn to make better decisions
 - The resulting planners can be more efficient and/or effective



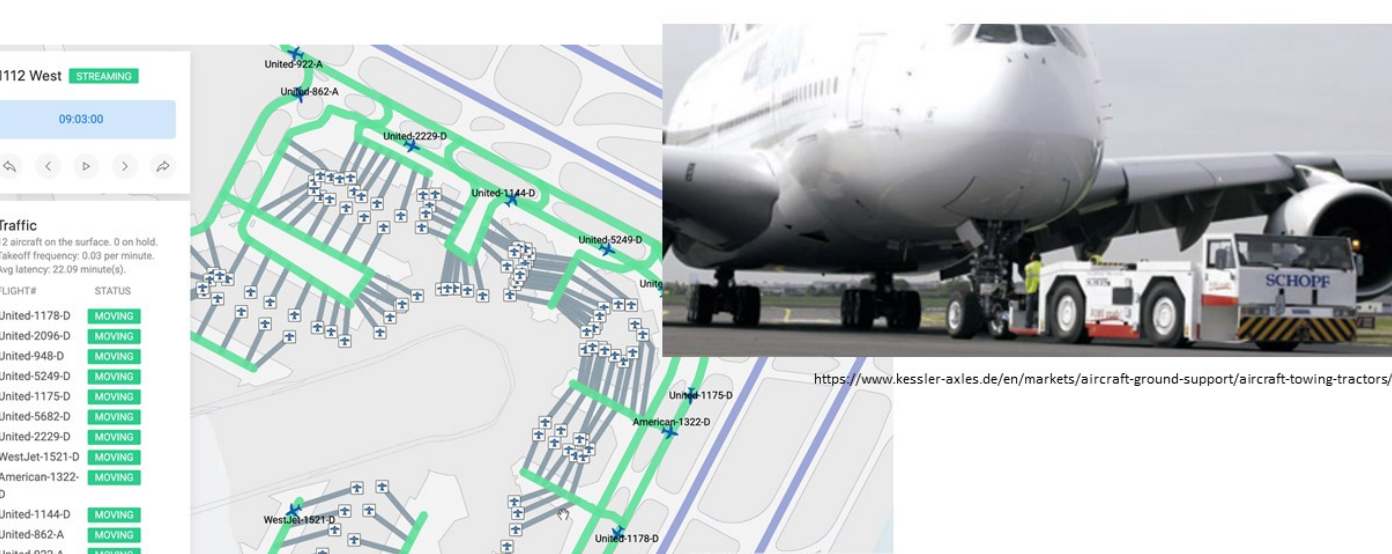
[16] T. Huang et al., "Learning to Resolve Conflicts for Multi-Agent Path Finding with Conflict-Based Search", AAAI, 2021.
 [17] T. Huang et al., "Learning Node-Selection Strategies in Bounded-Suboptimal Conflict-Based Search for Multi-Agent Path Finding", AAMAS, 2021.

Multi-Arm Assembly



[18] J. Chen et al., "Cooperative Task and Motion Planning for Multi-Arm Assembly Systems", under review for IEEE Robotics and Automation Letters and ICRA, 2022.

Airport Surface Operation



[1] J. Li et al., "Scheduling and Airport Taxiway Path Planning under Uncertainty", AAAI, 2019.
 [2] R. Morris et al., "Planning, Scheduling and Monitoring for Airport Surface Operations", AAAI-16 Workshop, 2016.

Multi-Agent Path Finding (MAPF)

- Want to learn more about multi-agent path finding?
 - Go here: <http://mapf.info/>

mapf.info

Welcome!

News: MAPF Team wins the NeurIPS-20 Flatland Competition

Multi-Agent Path Finding (MAPF) is the problem of computing collision-free paths for a team of agents from their current locations to given destinations. Application examples include autonomous aircraft towing vehicles, automated warehouse systems, office robots, and game characters in video games. Practical systems must find high-quality collision-free paths for these agents quickly.

Deserving All Credit

- H. Andreasson, D. Atzmon, N. Ayanian, J. Baier, R. Bartak, G. Belov, E. Boyarski, V. Bulitko, T. Cai, D. Chan, S.-H. Chan, J. Chen, Z. Chen, H. Choset, M. Cirillo, L. Cohen, B. Dilikina, W. Du, J. Durham, A. Felner, G. Gange, M. Garcia de la Banda, M. Gong, M. Greco, D. Harabor, C. Hernandez, W. Hoenig, T. Huang, S. Jung, J. Kerr, S. Kiesel, S. Kumar, E. Lam, P. Le Bodic, J. Li, Z. Liang, M. Liu, W. Liu, Z. Liu, H. Ma, R. Morris, W. Paivine, C. Pasareanu, F. Pecora, W. Ruml, G. Sartoretti, G. Sharon, Y. Shi, D. Sigurdson, R. Stern, P. Stuckey, N. Sturtevant, K. Sun, P. Surynek, L. Terr, A. Tinka, Z. Tong, C. Tovey, T. Uras, G. Wagner, T. Walker, J. Wang, X. Wei, B. Williams, Y. Wu, H. Xu, M. Yao, W. Yeoh, L. Yi, D. Zhang, H. Zhang, Y. Zheng and many others (my apologies that I ran out of space)

