Satellite Navigation and Coordination with Limited Information Sharing

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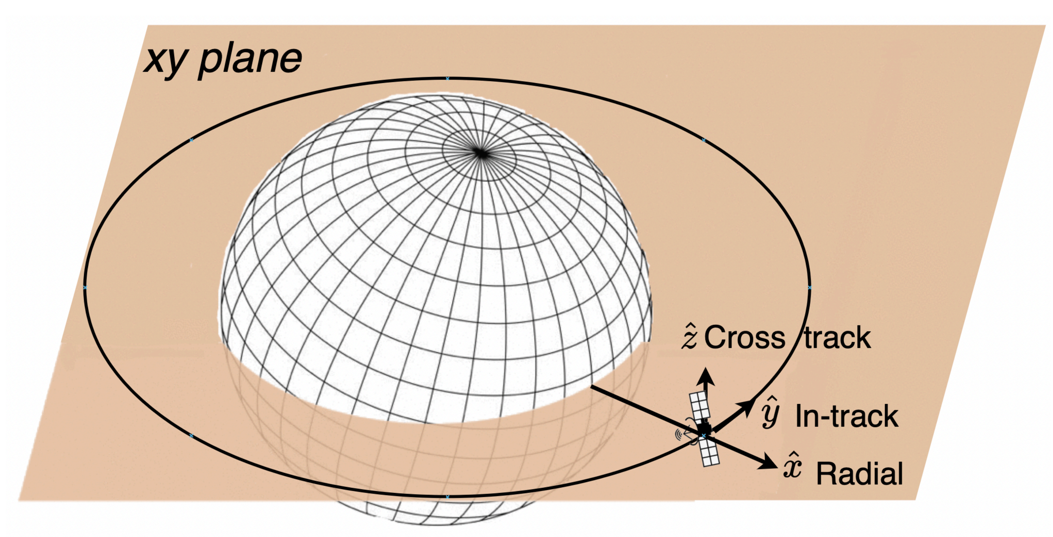
Overview

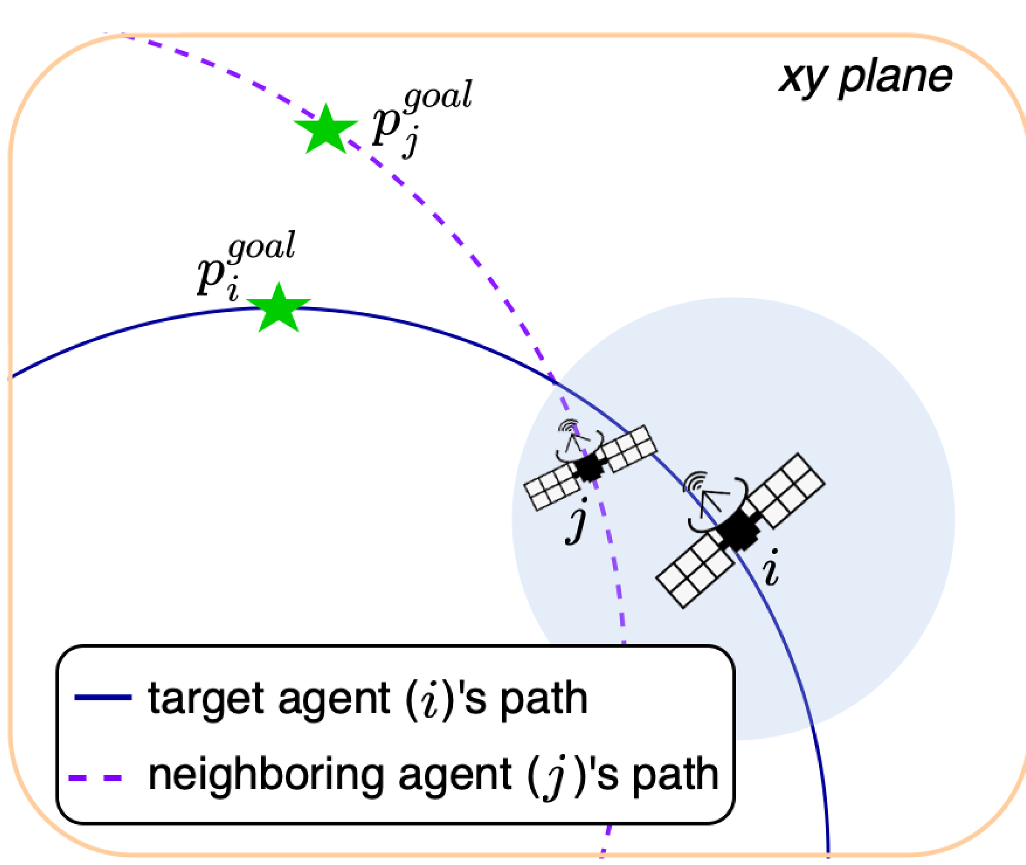
- We consider the problem of proximity operation satellite navigation, where satellites exist in an uncertain local environment observations are limited to the local neighborhood of each agent.
- We show that (1) through transfer learning, training can be accelerated and in fact out-perform models trained solely on the satellite environment, and (2) in testing, it scales well to environments with arbitrary numbers of agents and obstacles.

Background and Motivation

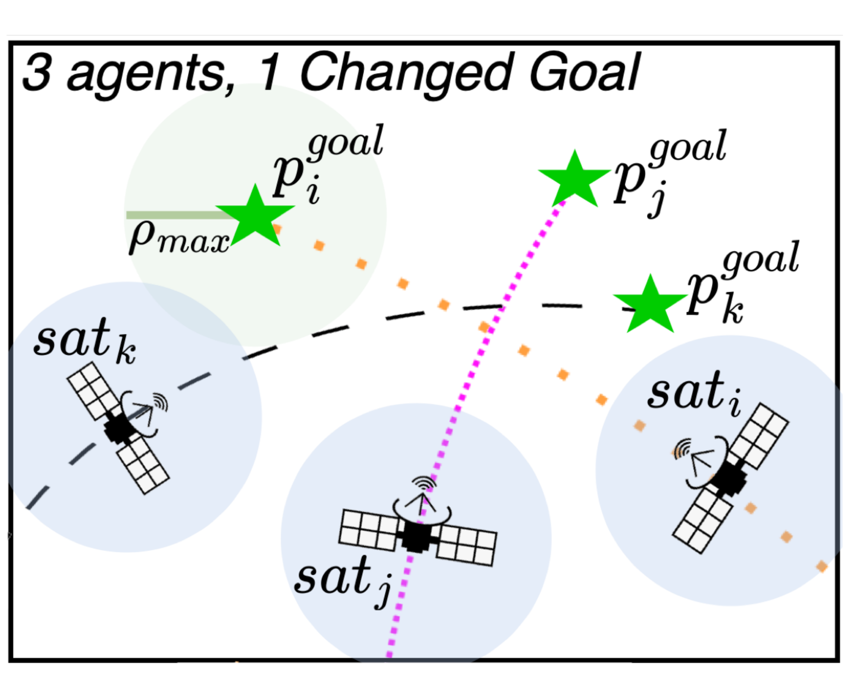
- There are more objects in orbit than ever before, motivating the need for autonomous collision avoidance mechanisms.
- Transfer learning has achieved extensive success by leveraging prior knowledge of past learned policies of relevant tasks.
- We consider two different environments, whose scale differs vastly (m/s vs km/s) but whose numerical values are quite similar

Ground Environment	Space Environment
$\ddot{x} = -\frac{\gamma}{m}\dot{x} + \frac{f_x}{m}$	$\ddot{x} = 3\omega_n^2 x + 2\omega_n \dot{y}$
$\ddot{y} = -\frac{\gamma}{m}\dot{y} + \frac{f_y}{m}$	$\ddot{y} = -2\omega_n \dot{x}$

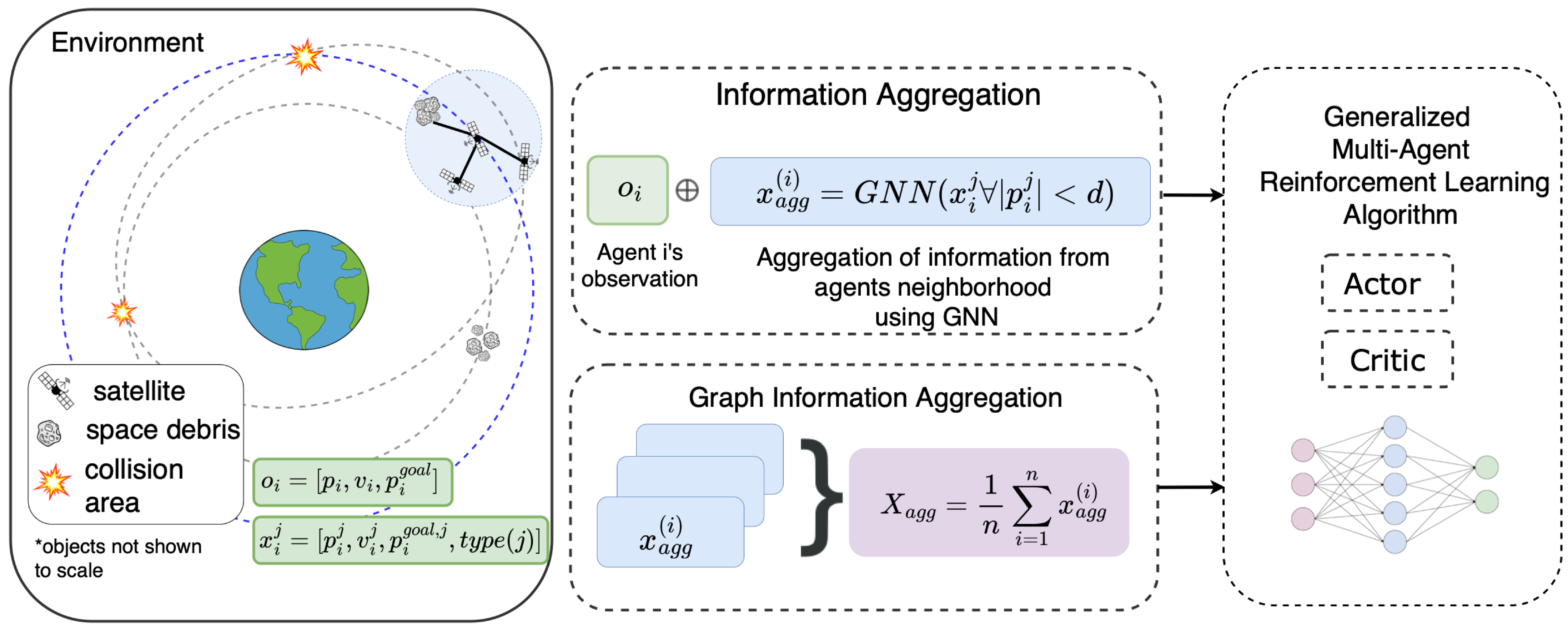




Special Case: Goal Sharing Scenarios

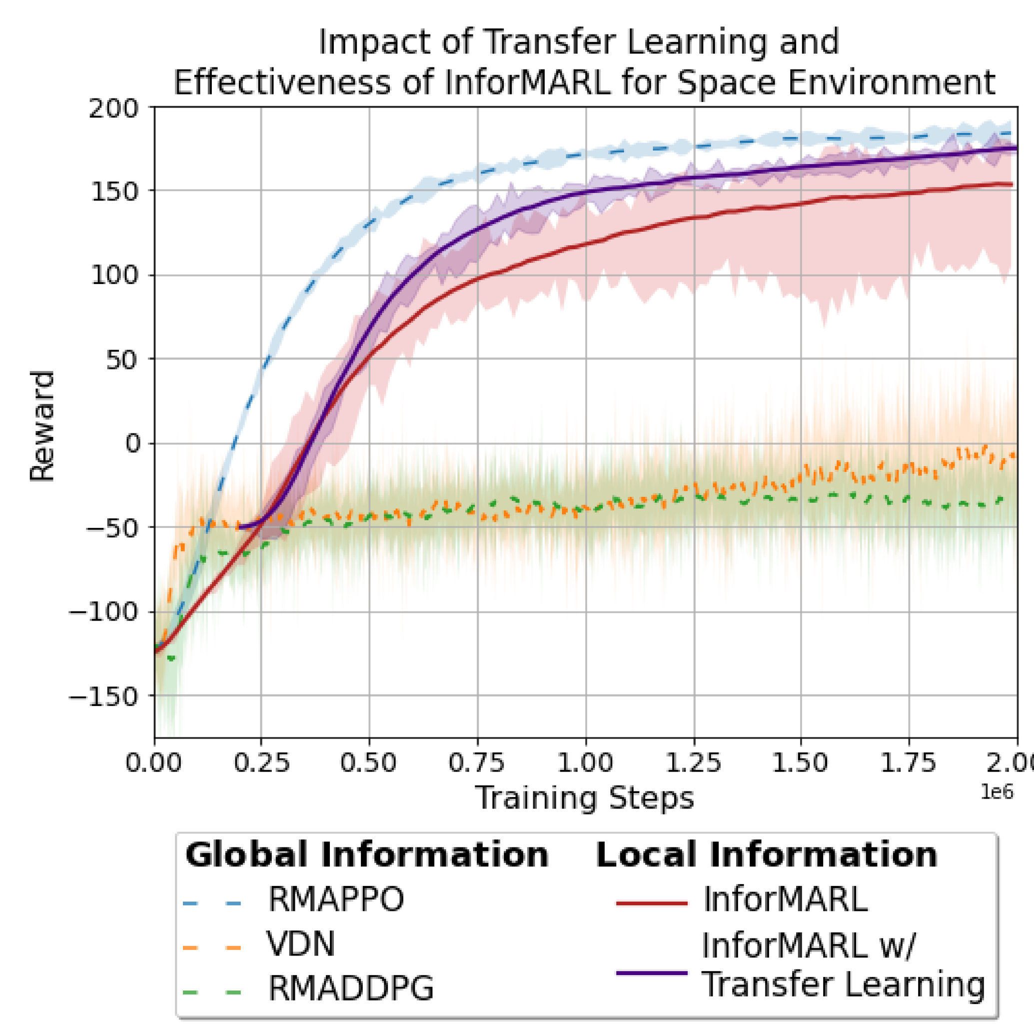


InforMARL Model Architecture



1. **Environment**: The agents are depicted by green circles, the goals by red rectangles, and the unknown obstacles by gray circles. $x_{agg}^{(i)}$ represents the aggregated information from the neighborhood, which is the output of a GNN. A graph is created by connecting entities within the sensing-radius of the agents. The inter-agent edges are bidirectional, while the edges between agents and non-agent entities are unidirectional.
2. **Information Aggregation**: Each agent's observation is concatenated with $x_{\text{agg}}^{(i)}$.
3. **Graph Information Aggregation**: The $x_{\text{agg}}^{(i)}$ from all the agents is averaged to get X_{agg}.
4. **Actor-Critic**: The concatenated vector $[o^{(i)}, x_{\text{agg}}^{(i)}]$ is fed into the actor network to get the action, and X_{agg} is fed into the critic network to get the state-action values.

Results



Key Takeaway: Transfer learning from the ground environment to the space environment accelerates training and improves performance

Train \ Test		$m=3$	$m=5$	$m=10$
$n=3$	Reward/m	61.57	60.21	57.78
	T	0.44	0.44	0.43
	(# col)/m	0.36	0.77	1.41
	$S\%$	98	94	96
$n=5$	Reward/m	60.52	60.52	57.07
	T	0.44	0.44	0.44
	(# col)/m	0.78	1.28	1.41
	$S\%$	98	98	91

Table 1: Performance metrics obtained by training InforMARL on a space environment with n satellites and testing it on one with m satellites: (a) Total reward obtained in an episode per agent, Reward/m. (b) Fraction of episode taken on average by agents to reach their goal, T (lower is better). (c) Average number of collisions per agent in an episode, #col/m (lower is better). (d) Success rate, $S\%$: percentage of episodes in which all agents are able to get to their goals (higher is better)

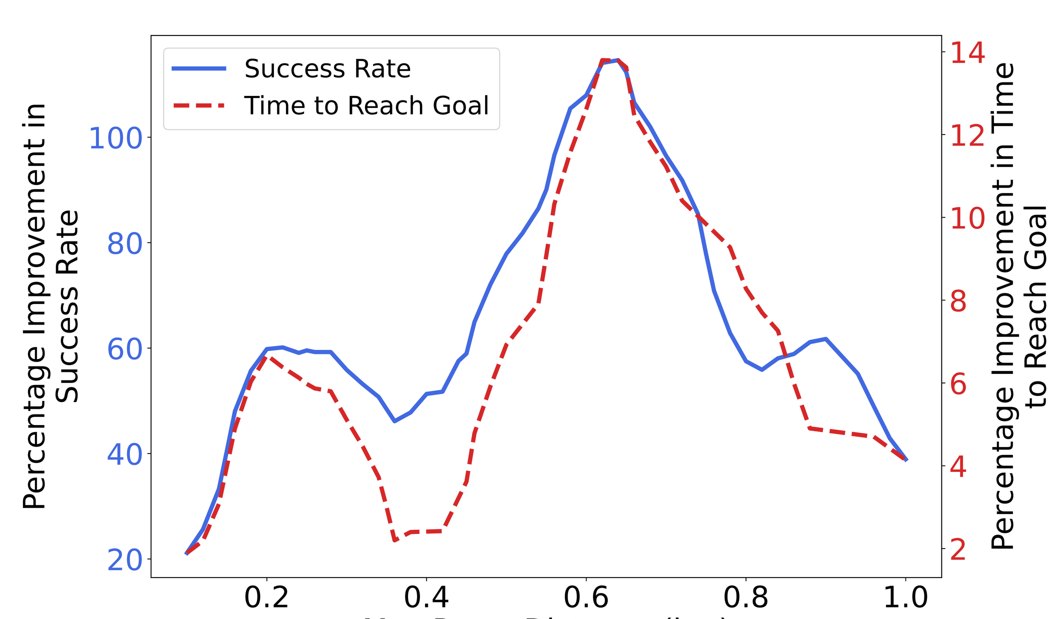


Figure 2: Percentage improvement achieved through goal-sharing for (1) the success rates, S (in blue; left-axis), and (2) the fraction of episode (or time) taken on average by agents to reach their goal, T (in red; right-axis). Moving averages over 0.2 km increases in $\rho_{\max}$ are shown.

Discussion and Future Work

Figure 2 demonstrates the performance improvement (relative to the performance without goal sharing) that is achieved through goal sharing, as the maximum goal reset distance increases. Positive values in Figure 2 indicate that the success rates *increase* with goal-sharing and the times taken by agents to reach their goals *decrease*, illustrating the benefits of goal-sharing for all values of $\rho_{\max}$.

Future work will include:

- Developing a more realistic space traffic simulation environment
- Accounting for communication delays and losses
- Adding mechanisms to provide safety guarantees

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