InforMARL: Scalable Multi-Agent Reinforcement Learning through Intelligent Information Aggregation

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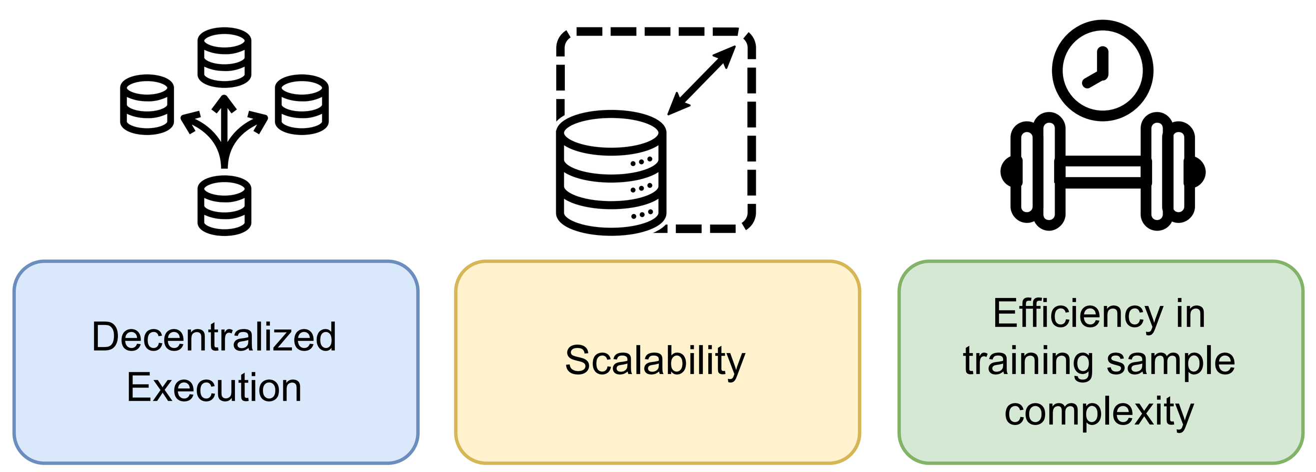
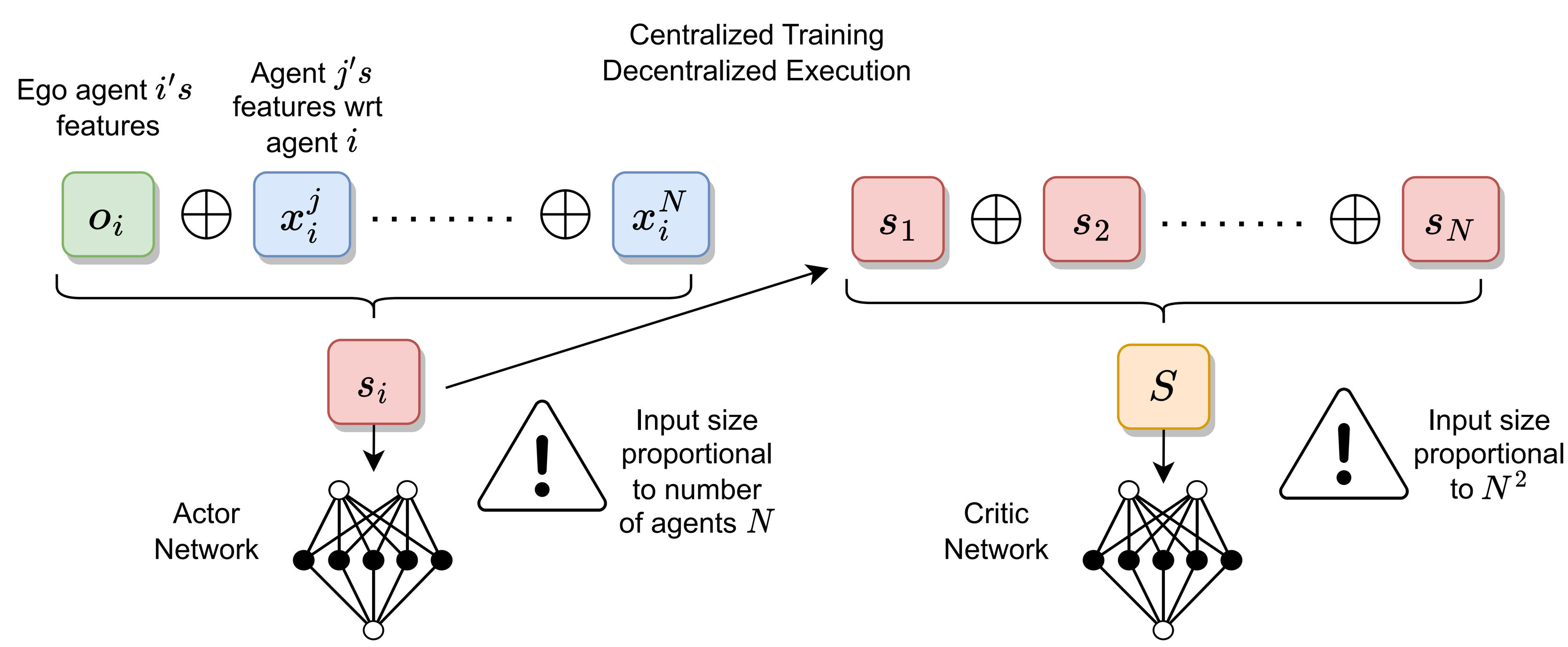
Project Website

Standard MARL Recipe

Key Features Expected from MARL algorithms:

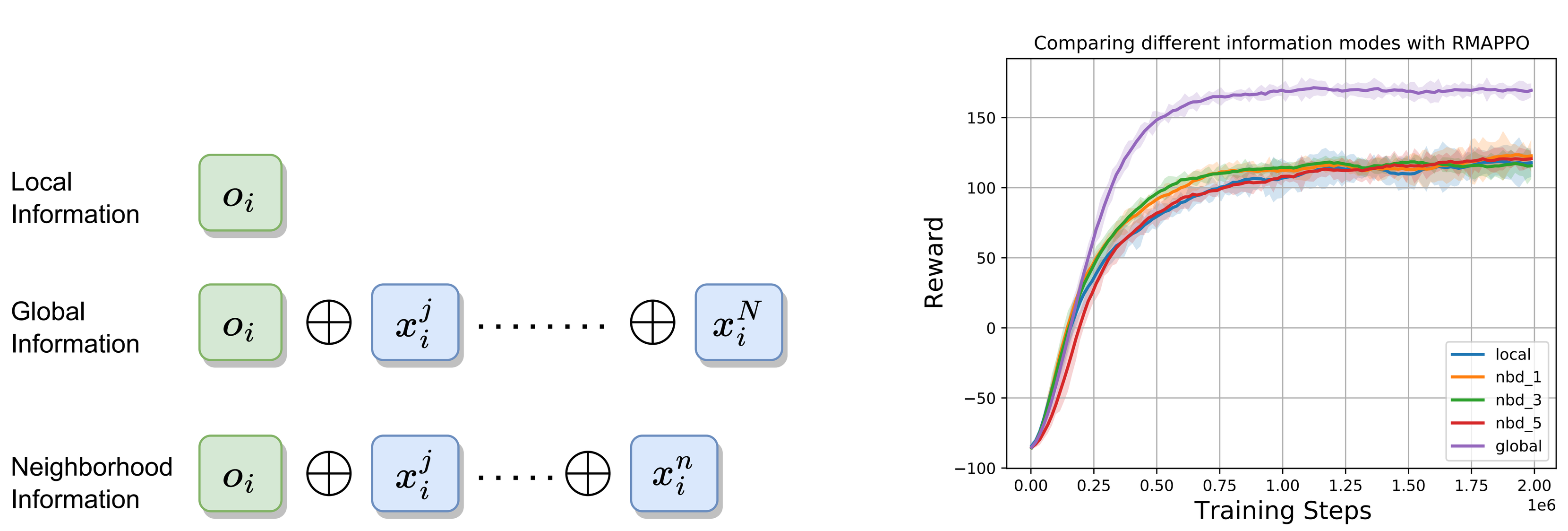




Need a method which is agnostic to number of entities in the environment

Motivation

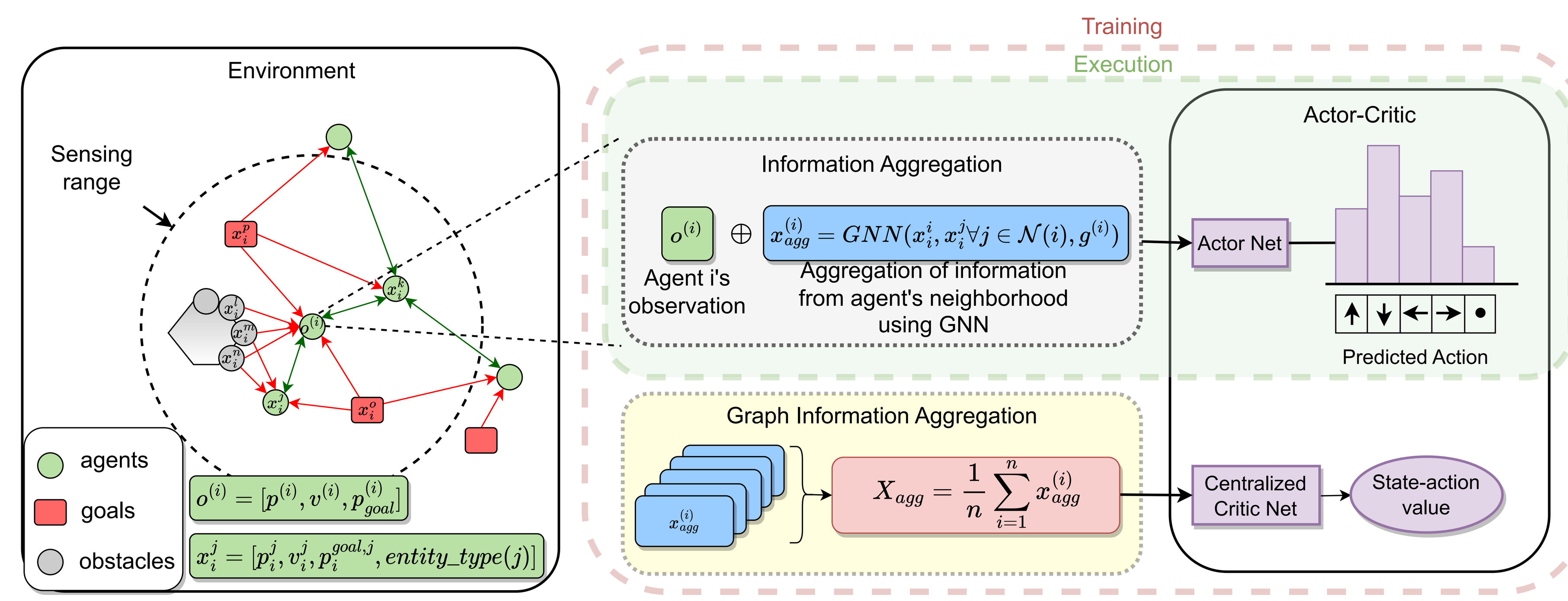
Consider MAPPO (Yu et al. 2022) with different amount of information included as inputs to the actor-critic networks.



(a) Information modes (b) Training MAPPO with different information modes

There is a significant improvement in performance when MAPPO has access to global information.

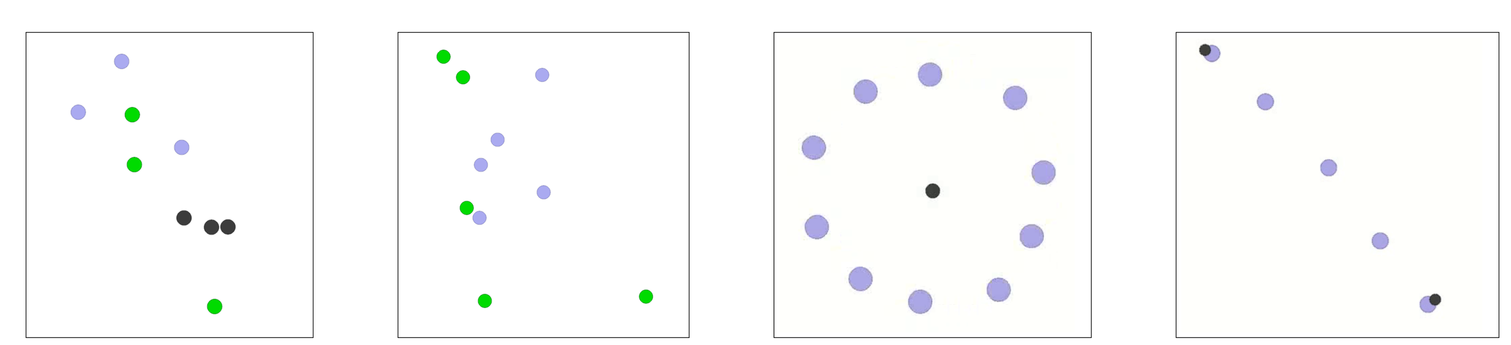
InforMARL



1. **Environment**: The agents are depicted by green circles, the goals by red rectangles, and the unknown obstacles by gray circles. 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**: $x_{agg}^{(i)}$ represents the aggregated information from the neighborhood, which is the output of a GNN. 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.

Task Environments

We perform experiments in 4 different environments: target, coverage, polygon-formation and line-formation environments.



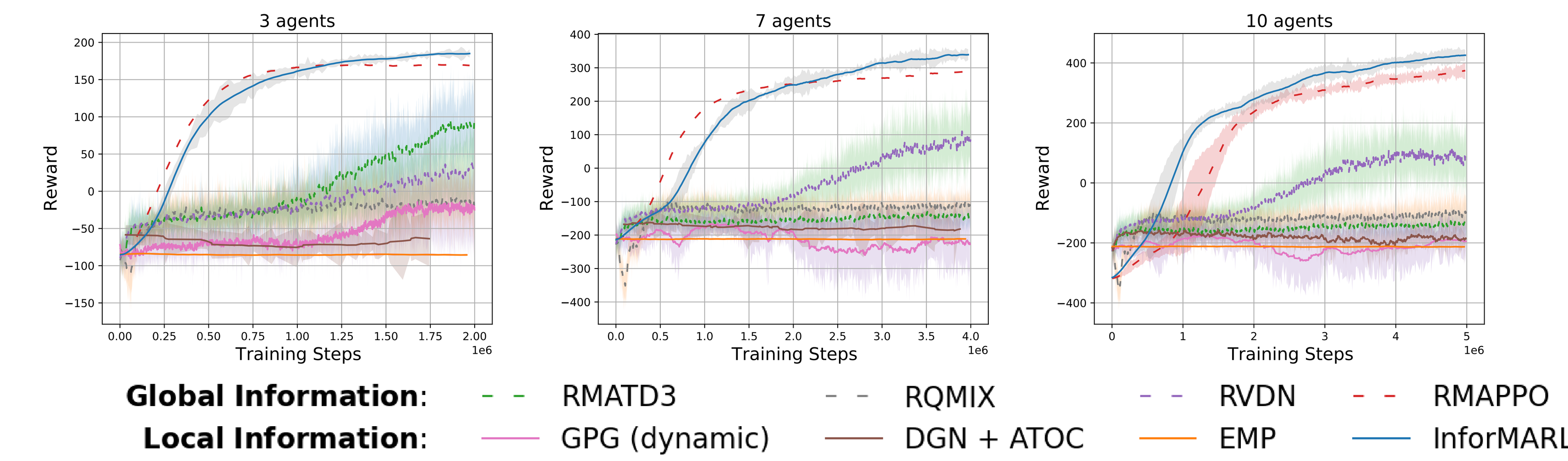
(c) Target (d) Coverage (e) Polygon Formation (f) Line Formation

Conclusions

- InforMARL uses a graph neural network (GNN)-based architecture for scalable multi-agent RL in a decentralized fashion.
- InforMARL is transferable to scenarios with a different number of entities in the environment than what it was trained on.
- InforMARL has better sample complexity than most other standard MARL algorithms with global observations.

Results

Comparison to Baselines



Algorithm	Information mode	$N=3$				$N=10$			
		R	T	# col	$S\%$	R	T	# col	$S\%$
RMATD3	Global	105.49	0.51	3.07	67	-131.72	0.99	11.14	1
RQMIX	Global	19.21	0.77	1.42	28	-76.98	0.96	17.04	2
RVDN	Global	64.04	0.62	1.05	45	157.63	0.64	10.00	43
GPG (dynamic)	Local	−46.27	0.87	0.43	8	-173.53	1.00	4.68	0
DGN + ATOC	Local	67.70	0.66	1.49	35	-201.01	1.00	4.06	0
RMAPPO	Global	173.13	0.41	1.47	96	366.81	0.44	13.21	79
InforMARL	Local	**205.24**	**0.38**	**1.45**	**100**	**429.14**	**0.39**	**10.50**	**100**

InforMARL significantly outperforms most baseline algorithms. Although RMAPPO has similar performance, it requires global information.

Scalability and Performance in different task environments

Test \ Train		$n=3$	$n=7$	$n=10$
$m=7$	Reward/m	61.16	62.23	61.32
	T	0.38	0.40	0.40
	(# col)/m	0.74	0.66	0.70
	$S\%$	100	100	100
$m=10$	Reward/m	58.59	58.23	58.67
	T	0.38	0.40	0.39
	(# col)/m	0.95	0.88	0.87
	$S\%$	100	99	100
$m=15$	Reward/m	53.19	53.46	54.21
	T	0.39	0.40	0.40
	(# col)/m	1.28	1.21	1.20
	$S\%$	100	99	99

Table 1. InforMARL trained and tested in the target environment when then no. of agents is varied.

Environment	m	Metric	Algorithm	
			RMAPPO	InforMARL
Coverage	3	T	0.34	0.36
		$S\%$	100	100
	7	T	0.42	0.43
		$S\%$	100	99
Formation	3	T	0.31	0.30
		$S\%$	100	100
	7	T	0.47	0.43
		$S\%$	100	100
Line	3	T	0.24	0.21
		$S\%$	100	100
	7	T	0.38	0.36
		$S\%$	100	100

Table 2. InforMARL was trained with 3 agents in the environment whereas MAPPO was trained in environments with 3 and 7 agents.

InforMARL is able to achieve a success rate of almost 100% across all scenarios in different environments whilst also being transferable.

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