

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

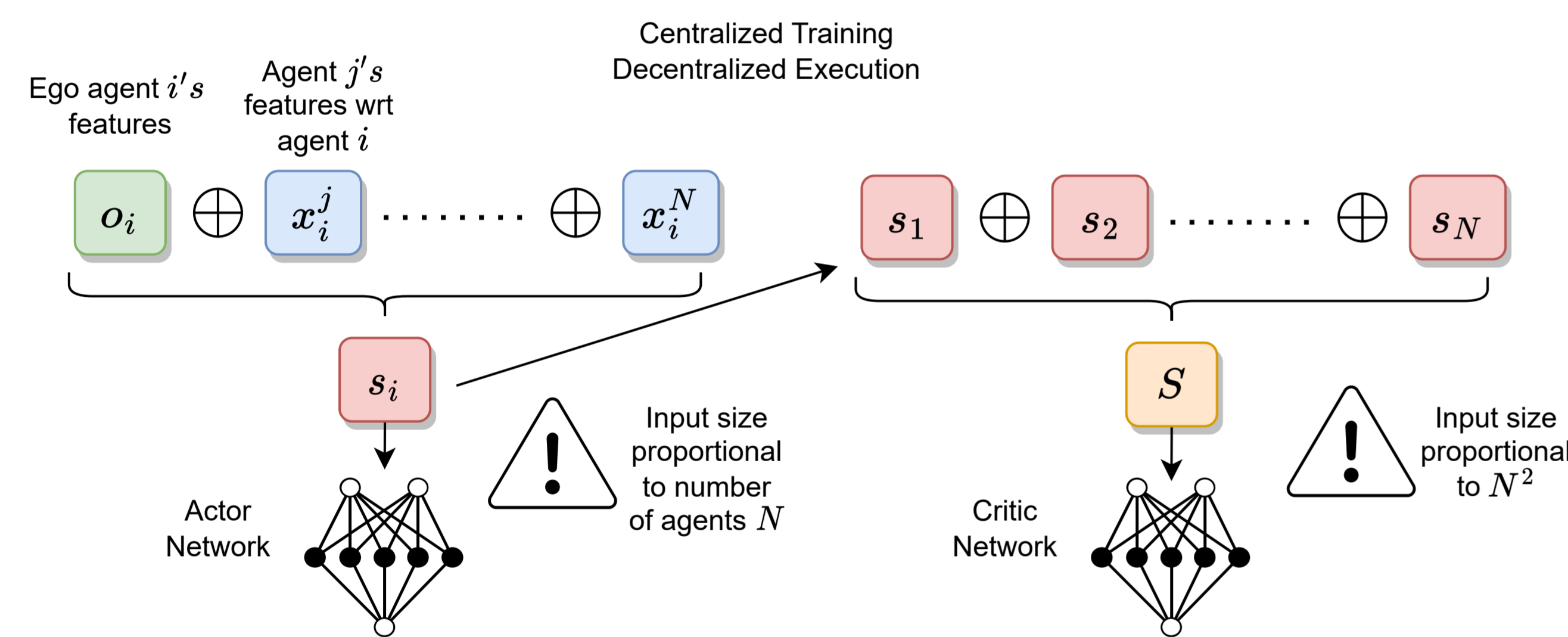
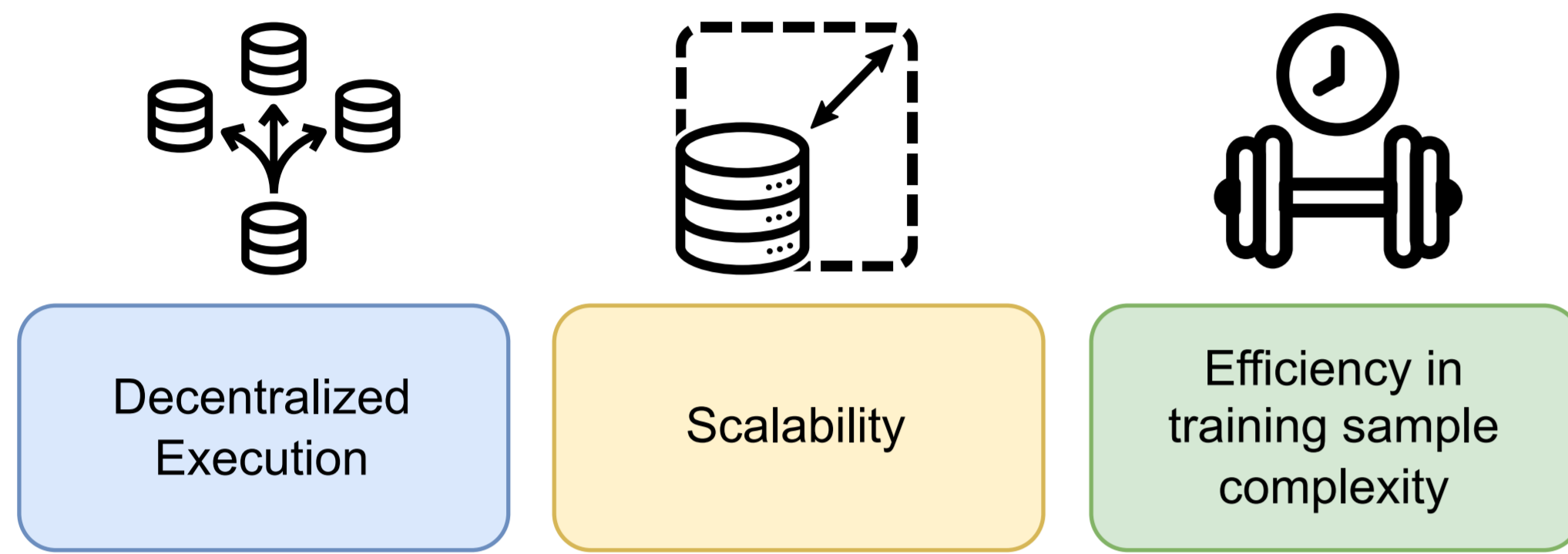
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Standard MARL Recipe

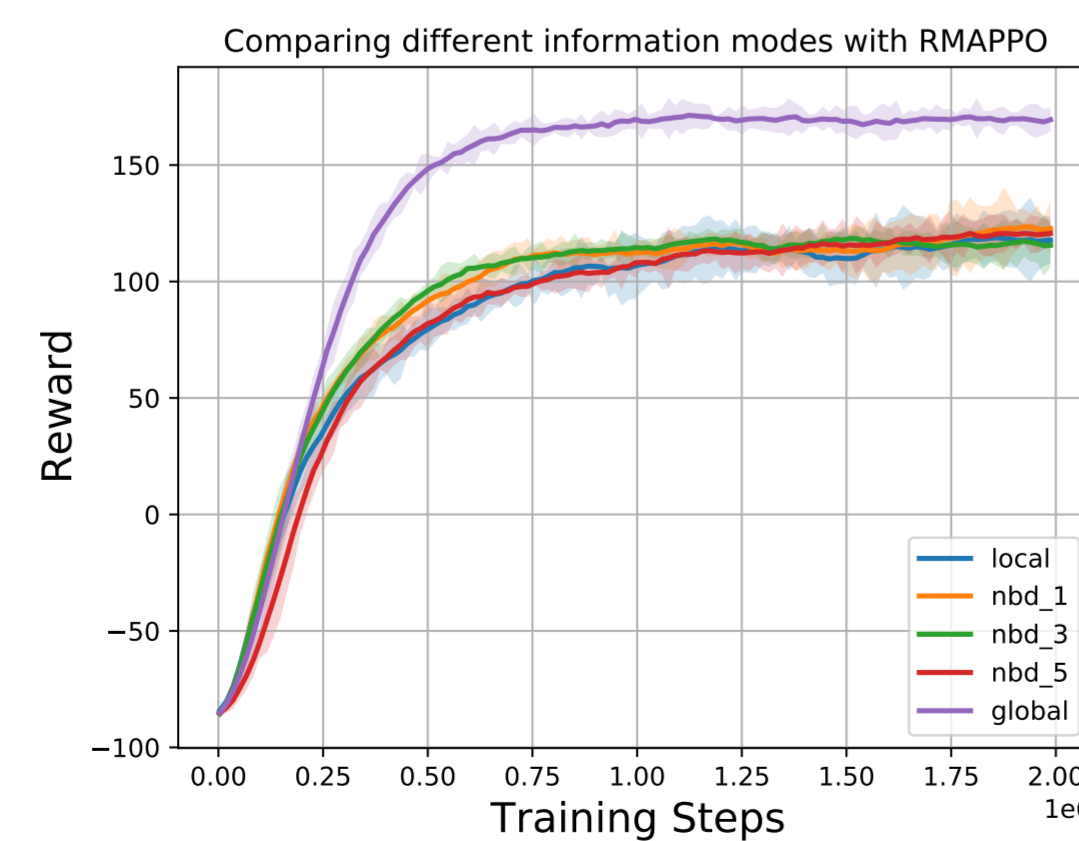
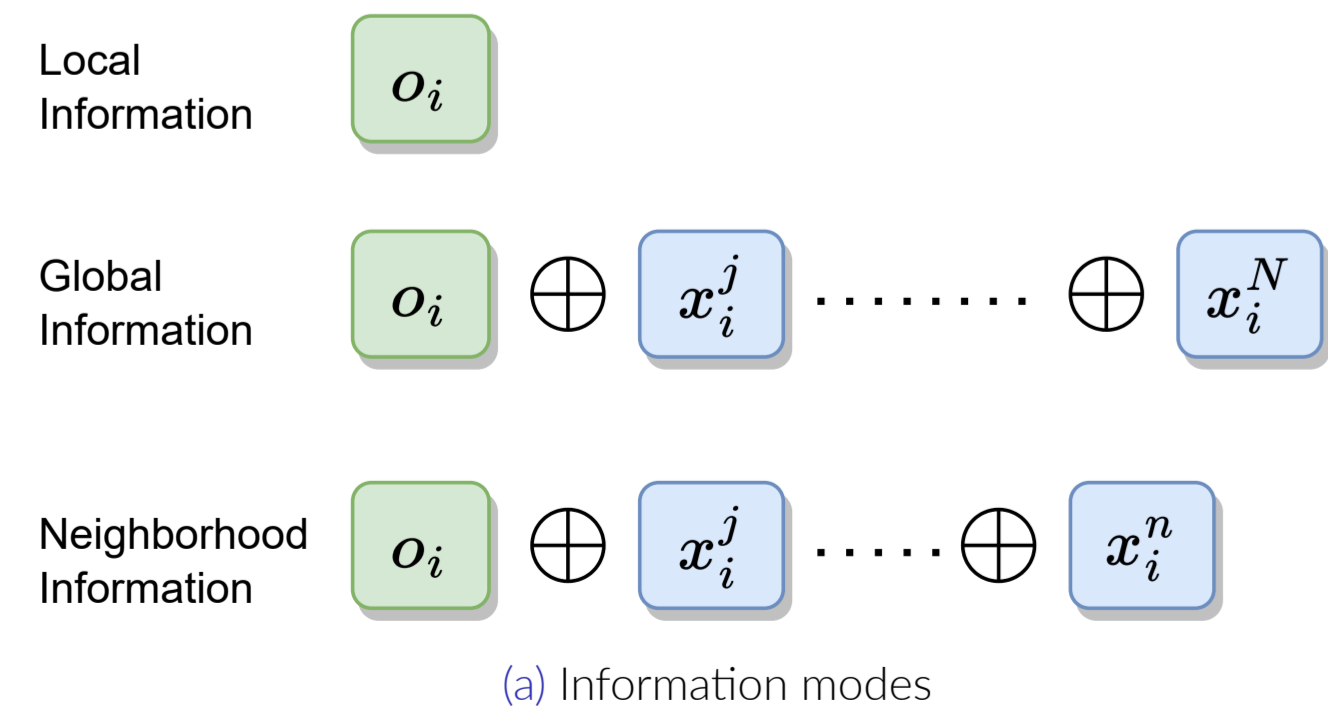
Key Features Expected from MARL algorithms:



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

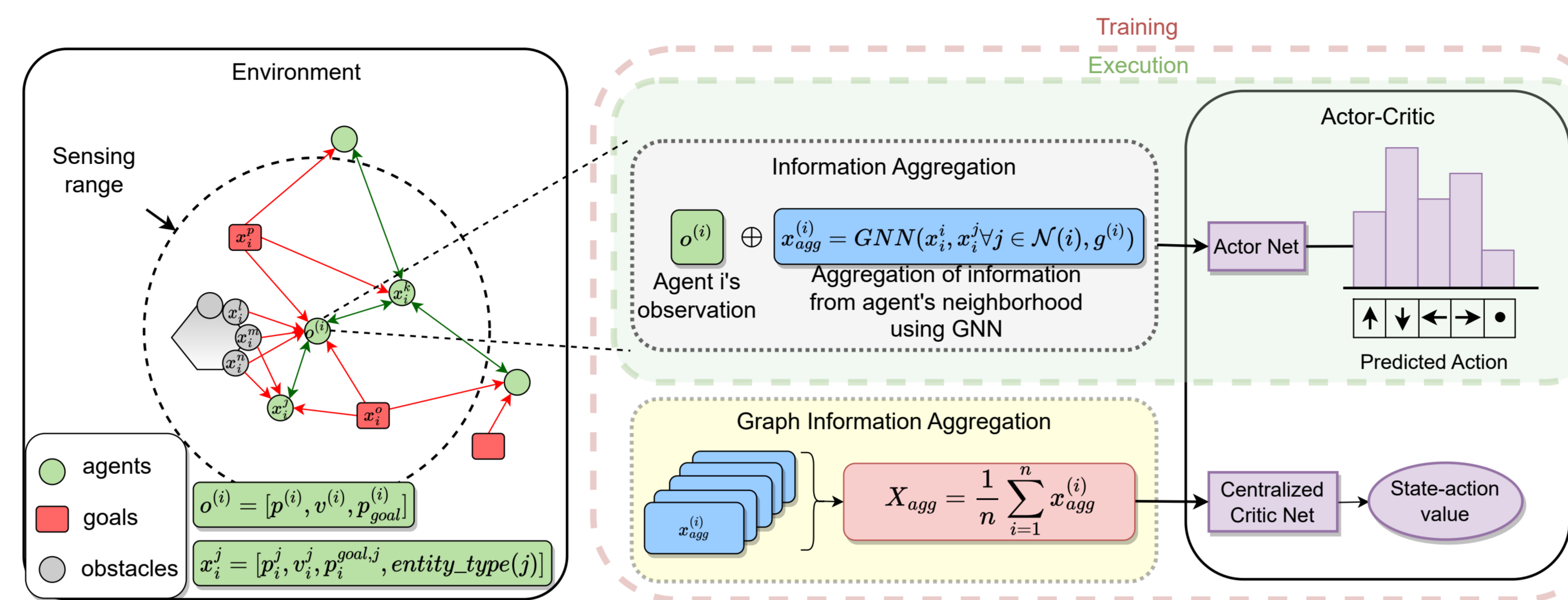
Motivation

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



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

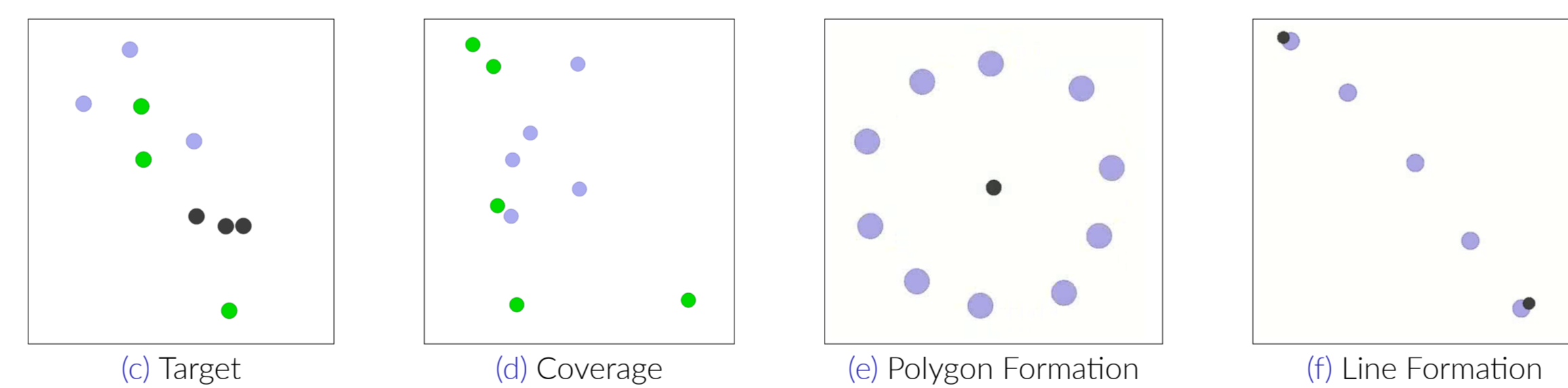
InforMARL



- 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.
- 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 $x_{agg}^{(i)}$.
- Graph Information Aggregation:** The $x_{agg}^{(i)}$ from all the agents is averaged to get X_{agg} .
- Actor-Critic:** The concatenated vector $[o^{(i)}, x_{agg}^{(i)}]$ 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.

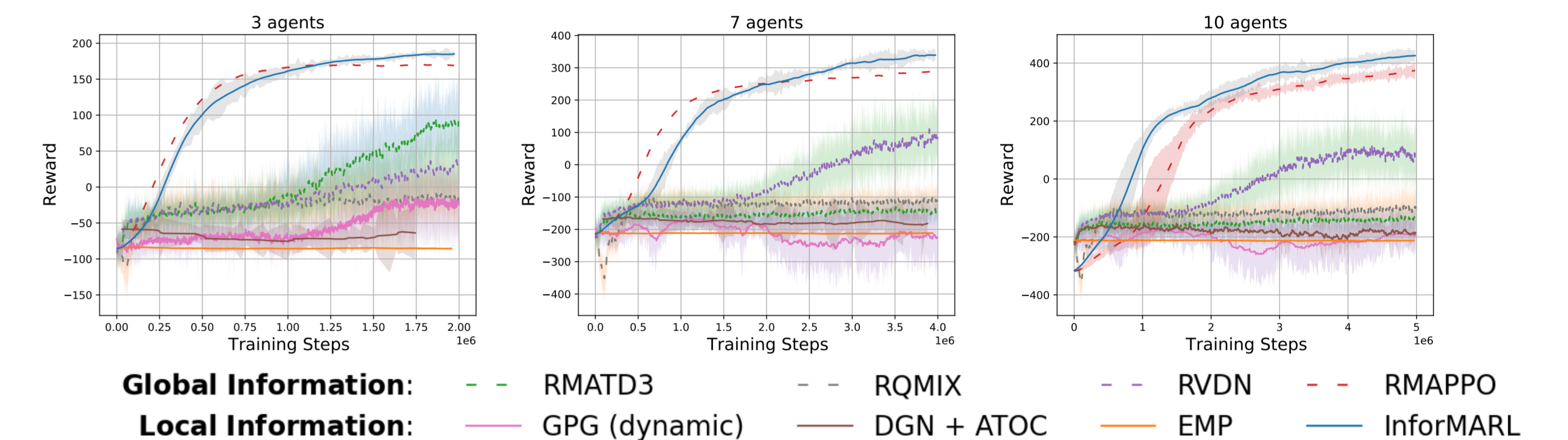


Conclusions

- 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	Algorithm	
			RMAPPO	InforMARL
m = 7	Reward/m	n = 3	61.16	61.32
		n = 7	62.23	61.32
		n = 10	61.32	61.32
		(# col)/m	0.74	0.70
m = 10	Reward/m	n = 3	58.59	58.67
		n = 7	58.23	58.67
		n = 10	58.67	58.67
		(# col)/m	0.95	0.87
m = 15	Reward/m	n = 3	53.19	54.21
		n = 7	53.46	54.21
		n = 10	54.21	54.21
		(# col)/m	1.28	1.20

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

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.