
The StarCraft Multi-Agent Challenge

Mikayel Samvelyan^{*1} Tabish Rashid^{*2} Christian Schroeder de Witt² Gregory Farquhar²
Nantas Nardelli² Tim G. J. Rudner² Chia-Man Hung² Philip H. S. Torr² Jakob Foerster³
Shimon Whiteson²

¹Russian-Armenian University ²University of Oxford ³Facebook AI Research

Abstract

In the last few years, deep multi-agent reinforcement learning (RL) has become a highly active area of research. A particularly challenging class of problems in this area is partially observable, cooperative, multi-agent learning, in which teams of agents must learn to coordinate their behaviour while conditioning only on their private observations. This is an attractive research area since such problems are relevant to a large number of real-world systems and are also more amenable to evaluation than general-sum problems.

Standardised environments such as the ALE and MuJoCo have allowed single-agent RL to move beyond toy domains, such as grid worlds. However, there is no comparable benchmark for cooperative multi-agent RL. As a result, most papers in this field use one-off toy problems, making it difficult to measure real progress. In this paper, we propose the StarCraft Multi-Agent Challenge (SMAC) as a benchmark problem to fill this gap.¹ SMAC is based on the popular real-time strategy game StarCraft II and focuses on micromanagement challenges where each unit is controlled by an independent agent that must act based on local observations. We offer a diverse set of challenge scenarios and recommendations for best practices in benchmarking and evaluations. We also open-source a deep multi-agent RL learning framework including state-of-the-art algorithms.² We believe that SMAC can provide a standard benchmark environment for years to come. Videos of our best agents for several SMAC scenarios are available at: https://youtu.be/VZ7zmQ_obZ0.

1 Introduction

Deep reinforcement learning (RL) promises a scalable approach to solving arbitrary sequential decision-making problems, demanding only that a user must specify a reward function that expresses the desired behaviour. However, many real-world problems that might be tackled by RL are inherently multi-agent in nature. For example, the coordination of self-driving cars, autonomous drones, and other multi-robot systems are becoming increasingly critical. Network traffic routing, distributed sensing, energy distribution, and other logistical problems are also inherently multi-agent. As such, it is essential to develop multi-agent RL (MARL) solutions that can handle decentralisation constraints and deal with the exponentially growing joint action space of many agents.

Partially observable, cooperative, multi-agent learning problems are of particular interest. Cooperative problems avoid difficulties in evaluation inherent with general-sum games (e.g., which opponents are evaluated against). Cooperative problems also map well to a large class of critical problems where a single user that manages a distributed system can specify the overall goal, e.g., minimising

^{*}Equal contribution. Correspondence to <mikayel@samvelyan.com> or <tabish.rashid@cs.ox.ac.uk>.

¹Code is available at <https://github.com/oxwhirl/smac>

²Code is available at <https://github.com/oxwhirl/pymarl>

traffic or other inefficiencies. Most real-world problems depend on inputs from noisy or limited sensors, so partial observability must also be dealt with effectively. This often includes limitations on communication that result in a need for decentralised execution of learned policies. However, there commonly is access to additional information during training, which may be carried out in controlled conditions or simulation.

A growing number of recent works (Foerster et al., 2018a; Rashid et al., 2018; Sunehag et al., 2017; Lowe et al., 2017) have begun to address the problems in this space. However, there is a clear lack of standardised benchmarks for research and evaluation. Instead, researchers often propose one-off environments which can be overly simple or tuned to the proposed algorithms. In single-agent RL, standard environments such as the Arcade Learning Environment (Bellemare et al., 2013), or MuJoCo for continuous control (Plappert et al., 2018), have enabled great progress. In this paper, we aim to follow this successful model by offering challenging standard benchmarks for deep MARL and to facilitate more rigorous experimental methodology across the field.

Some testbeds have emerged for other multi-agent regimes, such as Poker (Heinrich & Silver, 2016), Pong (Tampuu et al., 2015), Keepaway Soccer (Stone et al., 2005), or simple gridworld-like environments (Lowe et al., 2017; Leibo et al., 2017; Yang et al., 2018; Zheng et al., 2017). Nonetheless, we identify a clear gap in challenging and standardised testbeds for the important set of domains described above.

To fill this gap, we introduce the StarCraft Multi-Agent Challenge (SMAC). SMAC is built on the popular real-time strategy game StarCraft II³ and makes use of the SC2LE environment (Vinyals et al., 2017). Instead of tackling the full game of StarCraft with centralised control, we focus on decentralised micromanagement challenges (Figure 1). In these challenges, each of our units is controlled by an independent, learning agent that has to act based only on local observations, while the opponent’s units are controlled by the hand-coded built-in StarCraft II AI. We offer a diverse set of scenarios that challenge algorithms to handle high-dimensional inputs and partial observability, and to learn coordinated behaviour even when restricted to fully decentralised execution.

The full games of StarCraft: BroodWar and StarCraft II have already been used as RL environments, due to the many interesting challenges inherent to the games (Synnaeve et al., 2016; Vinyals et al., 2017). DeepMind’s AlphaStar (DeepMind, 2019) has recently shown an impressive level of play on a StarCraft II matchup using a centralised controller. In contrast, SMAC is not intended as an environment to train agents for use in full StarCraft II gameplay. Instead, by introducing strict decentralisation and local partial observability, we use the StarCraft II game engine to build a new set of rich cooperative multi-agent problems that bring unique challenges, such as the nonstationarity of learning (Foerster et al., 2017), multi-agent credit assignment (Foerster et al., 2018a), and the difficulty of representing the value of joint actions (Rashid et al., 2018).

To further facilitate research in this field, we also open-source PyMARL, a learning framework that can serve as a starting point for other researchers and includes implementations of several key MARL algorithms. PyMARL is modular, extensible, built on PyTorch, and serves as a template for dealing with some of the unique challenges of deep MARL in practice. We include results on our full set of SMAC environments using QMIX (Rashid et al., 2018) and several baseline algorithms, and challenge the community to make progress on difficult environments in which good performance has remained out of reach so far. We also offer a set of guidelines for best practices in evaluations using our benchmark, including the reporting of standardised performance metrics, sample efficiency, and computational requirements (see Appendix B).

We hope SMAC will serve as a valuable standard benchmark, enabling systematic and robust progress in deep MARL for years to come.

2 Related Work

Much work has gone into designing environments to test and develop MARL agents. However, not many of these focused on providing a qualitatively challenging environment that would provide together elements of partial observability, challenging dynamics, and high-dimensional observation spaces.

³StarCraft II is the sequel to the game StarCraft and its expansion set Brood War. StarCraft and StarCraft II are trademarks of Blizzard Entertainment™.

Stone et al. (2005) presented Keepaway soccer, a domain built on the RoboCup soccer simulator (Kitano et al., 1997), a 2D simulation of a football environment with simplified physics, where the main task consists of keeping a ball within a pre-defined area where agents in teams can reach, steal, and pass the ball, providing a simplified setup for studying cooperative MARL. This domain was later extended to the Half Field Offense task (Kalyanakrishnan et al., 2006; Hausknecht et al., 2016), which increases the difficulty of the problem by requiring the agents to not only keep the ball within bounds but also to score a goal. Neither task scales well in difficulty with the number of agents, as most agents need to do little coordination. There is also a lack of interesting environment dynamics beyond the simple 2D physics nor good reward signals, thus reducing the impact of the environment as a testbed.

Multiple gridworld-like environments have also been explored. Lowe et al. (2017) released a set of simple grid-world like environments for multi-agent RL alongside an implementation of MADDPG, featuring a mix of competitive and cooperative tasks focused on shared communication and low level continuous control. Leibo et al. (2017) show several mixed-cooperative Markov environment focused on testing social dilemmas, however, they did not release an implementation to further explore the tasks. Yang et al. (2018); Zheng et al. (2017) present a framework for creating gridworlds focuses on many-agents tasks, where the number of agents ranges from the hundreds to the millions. This work, however, focuses on testing for emergent behaviour, since environment dynamics and control space need to remain relatively simple for the tasks to be tractable. Resnick et al. (2018) propose a multi-agent environment based on the game *Bomberman*, encompassing a series of cooperative and adversarial tasks meant to provide a more challenging set of tasks with a relatively straightforward 2D state observation and simple grid-world-like action spaces.

Learning to play StarCraft games also has been investigated in several communities: work ranging from evolutionary algorithms to tabular RL applied has shown that the game is an excellent testbed for both modelling and planning (Ontonón et al., 2013), however, most have focused on single-agent settings with multiple controllers and classical algorithms. More recently, progress has been made on developing frameworks that enable researchers working with deep neural networks to test recent algorithms on these games; work on applying deep RL algorithms to single-agent and multi-agent versions of the micromanagement tasks has thus been steadily appearing (Usunier et al., 2016; Foerster et al., 2017, 2018a; Rashid et al., 2018; Nardelli et al., 2018; Hu et al., 2018; Shao et al., 2018; Foerster et al., 2018b) with the release of TorchCraft (Synnaeve et al., 2016) and SC2LE (Vinyals et al., 2017), interfaces to respectively *StarCraft: BroodWar* and *StarCraft II*. Our work presents the first standardised testbed for decentralised control in this space.

Other work focuses on playing the full game of StarCraft, including macromanagement and tactics (Pang et al., 2018; Sun et al., 2018; DeepMind, 2019). By introducing decentralisation and local observability, our agents are excessively restricted compared to normal full gameplay. SMAC is therefore not intended as an environment to train agents for use in full gameplay. Instead, we use the StarCraft II game engine to build rich and interesting multi-agent problems.

3 Multi-Agent Reinforcement Learning

In SMAC, we focus on tasks where a team of agents needs to work together to achieve a common goal. We briefly review the formalism of such *fully cooperative multi-agent tasks* as *Dec-POMDPs* but refer readers to Oliehoek & Amato (2016) for a more complete picture.

Dec-POMDPs Formally, a Dec-POMDP G is given by a tuple $G = \langle S, U, P, r, Z, O, n, \gamma \rangle$, where $s \in S$ is the true state of the environment. At each time step, each agent $a \in A \equiv \{1, \dots, n\}$ chooses an action $u^a \in U$, forming a joint action $\mathbf{u} \in \mathbf{U} \equiv U^n$. This causes a transition of the environment according to the state transition function $P(s'|s, \mathbf{u}) : S \times \mathbf{U} \times S \rightarrow [0, 1]$.

In contrast to partially-observable stochastic games, all agents in a Dec-POMDP share the same team reward function $r(s, \mathbf{u}) : S \times \mathbf{U} \rightarrow \mathbb{R}$, where $\gamma \in [0, 1)$ is the discount factor. Dec-POMDPs consider *partially observable* scenarios in which an observation function $O(s, a) : S \times A \rightarrow Z$ determines the observations $z^a \in Z$ that each agent draws individually at each time step. Each agent has an action-observation history $\tau^a \in T \equiv (Z \times U)^*$, on which it conditions a stochastic policy $\pi^a(u^a|\tau^a) : T \times U \rightarrow [0, 1]$. The joint policy π admits a joint action-value function: $Q^\pi(s_t, \mathbf{u}_t) = \mathbb{E}_{s_{t+1:\infty}, \mathbf{u}_{t+1:\infty}} [R_t|s_t, \mathbf{u}_t]$, where $R_t = \sum_{i=0}^{\infty} \gamma^i r_{t+i}$ is the discounted return.

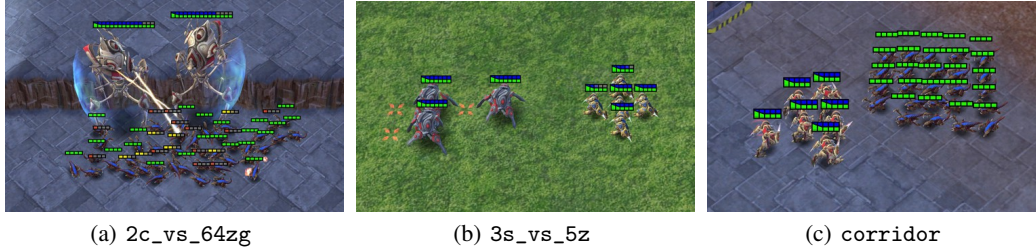


Figure 1: Screenshots of three SMAC scenarios.

Centralised training with decentralised execution If learning proceeds in simulation, as is done in StarCraft II, or in a laboratory, then it can usually be conducted in a centralised fashion. This gives rise to the paradigm of *centralised training with decentralised execution*, which has been well-studied in the planning community (Oliehoek et al., 2008; Kraemer & Banerjee, 2016). Although training is centralised, execution is decentralised, i.e., the learning algorithm has access to all local action-observation histories τ and global state s , but each agent’s learnt policy can condition only on its own action-observation history τ^a .

A number of recent state-of-the-art algorithms use extra state information available in centralised training to speed up the learning of decentralised policies. Among these, COMA (Foerster et al., 2018a) is an actor-critic algorithm with a special multi-agent critic baseline, and QMIX (Rashid et al., 2018) belongs to the Q -learning family.

4 SMAC

SMAC is based on the popular real-time strategy (RTS) game StarCraft II. In a regular full game of StarCraft II, one or more humans compete against each other or against a built-in game AI to gather resources, construct buildings, and build armies of units to defeat their opponents.

Akin to most RTSs, StarCraft has two main gameplay components: macromanagement and micromanagement. *Macromanagement* refers to high-level strategic considerations, such as economy and resource management. *Micromanagement* (micro), on the other hand, refers to fine-grained control of individual units.

StarCraft has been used as a research platform for AI, and more recently, RL. Typically, the game is framed as a competitive problem: an agent takes the role of a human player, making macromanagement decisions and performing micromanagement as a puppeteer that issues orders to individual units from a centralised controller.

In order to build a rich multi-agent testbed, we instead focus solely on micromanagement. Micro is a vital aspect of StarCraft gameplay with a high skill ceiling, and is practiced in isolation by amateur and professional players. For SMAC, we leverage the natural multi-agent structure of micromanagement by proposing a modified version of the problem designed specifically for decentralised control. In particular, we require that each unit be controlled by an independent agent that conditions only on local observations restricted to a limited field of view centred on that unit (see Figure 2). Groups of these agents must be trained to solve challenging combat scenarios, battling an opposing army under the centralised control of the game’s built-in scripted AI.

Proper micro of units during battles maximises the damage dealt to enemy units while minimising damage received, and requires a range of skills. For example, one important technique is *focus fire*, i.e., ordering units to jointly attack and kill enemy units one after another. When focusing fire, it is important to avoid *overkill*: inflicting more damage to units than is necessary to kill them.

Other common micro techniques include: assembling units into formations based on their armour types, making enemy units give chase while maintaining enough distance so that little or no damage is incurred (*kiting*), coordinating the positioning of units to attack from different directions or taking advantage of the terrain to defeat the enemy. Figure 1b illustrates how three Stalker units kite five enemy Zealots units.

Table 1: SMAC challenges.

Name	Ally Units	Enemy Units
2s3z	2 Stalkers & 3 Zealots	2 Stalkers & 3 Zealots
3s5z	3 Stalkers & 5 Zealots	3 Stalkers & 5 Zealots
1c3s5z	1 Colossus, 3 Stalkers & 5 Zealots	1 Colossus, 3 Stalkers & 5 Zealots
5m_vs_6m	5 Marines	6 Marines
10m_vs_11m	10 Marines	11 Marines
27m_vs_30m	27 Marines	30 Marines
3s5z_vs_3s6z	3 Stalkers & 5 Zealots	3 Stalkers & 6 Zealots
MMM2	1 Medivac, 2 Marauders & 7 Marines	1 Medivac, 3 Marauders & 8 Marines
2s_vs_1sc	2 Stalkers	1 Spine Crawler
3s_vs_5z	3 Stalkers	5 Zealots
6h_vs_8z	6 Hydralisks	8 Zealots
bane_vs_bane	20 Zerglings & 4 Banelings	20 Zerglings & 4 Banelings
2c_vs_64zg	2 Colossi	64 Zerglings
corridor	6 Zealots	24 Zerglings

SMAC thus provides a convenient environment for evaluating the effectiveness of MARL algorithms. The simulated StarCraft II environment and carefully designed scenarios require learning rich cooperative behaviours under partial observability, which is a challenging task. The simulated environment also provides an additional state information during training, such as information on all the units on the entire map. This is crucial for facilitating algorithms to take full advantage of the centralised training regime and assessing all aspects of MARL methods. SMAC is a qualitatively challenging environment that provides together elements of partial observability, challenging dynamics, and high-dimensional observation spaces.

Scenarios

SMAC consists of a set of StarCraft II micro scenarios which aim to evaluate how well independent agents are able to learn coordination to solve complex tasks. These scenarios are carefully designed to necessitate the learning of one or more micromanagement techniques to defeat the enemy. Each scenario is a confrontation between two armies of units. The initial position, number, and type of units in each army varies from scenario to scenario, as does the presence or absence of elevated or impassable terrain. Figures 1 include screenshots of several SMAC micro scenarios.

The first army is controlled by the learned allied agents. The second army consists of enemy units controlled by the built-in game AI, which uses carefully handcrafted non-learned heuristics. At the beginning of each episode, the game AI instructs its units to attack the allied agents using its scripted strategies. An episode ends when all units of either army have died or when a pre-specified time limit is reached (in which case the game is counted as a defeat for the allied agents). The goal is to maximise the win rate, i.e., the ratio of games won to games played.

The complete list of challenges is presented in Table 1⁴. More specifics on the SMAC scenarios and environment settings can be found in Appendices A.1 and A.2 respectively.

State and Observations

At each timestep, agents receive local observations drawn within their field of view. This encompasses information about the map within a circular area around each unit and with a radius equal to the *sight range* (Figure 2). The sight range makes the environment partially observable from the standpoint of each agent. Agents can only observe other agents if they are both alive and located within the sight range. Hence, there is no way for agents to distinguish between teammates that are far away from those that are dead.

The feature vector observed by each agent contains the following attributes for both allied and enemy units within the sight range: distance, relative x, relative y, health, shield, and unit_type. Shields serve as an additional source of protection that needs to be removed before any damage can be done to the health of units. All Protos units have shields, which can regenerate if

⁴The list of SMAC scenarios has been updated from the earlier version. All scenarios, however, are still available in the repository.

no new damage is dealt. In addition, agents have access to the last actions of allied units that are in the field of view. Lastly, agents can observe the terrain features surrounding them, in particular, the values of eight points at a fixed radius indicating height and walkability.

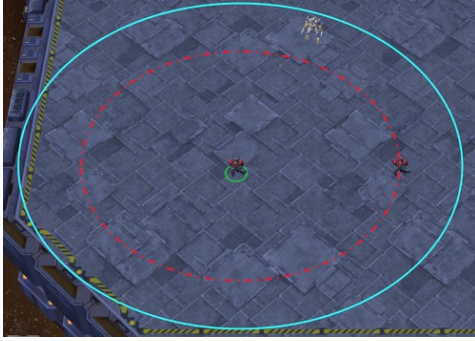


Figure 2: The cyan and red circles respectively border the sight and shooting range of the agent.

The global state, which is only available to agents during centralised training, contains information about all units on the map. Specifically, the state vector includes the coordinates of all agents relative to the centre of the map, together with unit features present in the observations. Additionally, the state stores the energy of Medivacs and cooldown of the rest of the allied units, which represents the minimum delay between attacks. Finally, the last actions of all agents are attached to the central state.

All features, both in the state as well as in the observations of individual agents, are normalised by their maximum values. The sight range is set to nine for all agents.

Action Space

The discrete set of actions that agents are allowed to take consists of move[direction]⁵, attack[enemy_id], stop and no-op.⁶ As healer units, Medivacs use heal[agent_id] actions instead of attack[enemy_id]. The maximum number of actions an agent can take ranges between 7 and 70, depending on the scenario.

To ensure decentralisation of the task, agents can use the attack[enemy_id] action only on enemies in their shooting range (Figure 2). This additionally constrains the ability of the units to use the built-in *attack-move* macro-actions on the enemies that are far away. We set the shooting range equal to 6 for all agents. Having a larger sight range than a shooting range forces agents to make use of the move commands before starting to fire.

Rewards

The overall goal is to maximise the win rate for each battle scenario. The default setting is to use the shaped reward, which produces a reward based on the hit-point damage dealt and enemy units killed, together with a special bonus for winning the battle. The exact values and scales for each of these events can be configured using a range of flags. To produce fair comparisons we encourage using this default reward function for all scenarios. We also provide another sparse reward option, in which the reward is +1 for winning and -1 for losing an episode.

5 PyMARL

To make it easier to develop algorithms for SMAC, we have also open-sourced our software engineering framework PyMARL. PyMARL has been designed explicitly with deep MARL in mind and allows for out-of-the-box experimentation and development.

PyMARL’s codebase is organized in a modular fashion in order to enable the rapid development of new algorithms, as well as providing implementations of current deep MARL algorithms to benchmark against. It is built on top of PyTorch to facilitate the fast execution and training of deep neural networks, and take advantage of the rich ecosystem built around it. PyMARL’s modularity makes it easy to extend, and components can be readily isolated for testing purposes.

Since the implementation and development of deep MARL algorithms come with a number of additional challenges beyond those posed by single-agent deep RL, it is crucial to have simple and understandable code. In order to improve the readability of code and simplify the handling of data between components, PyMARL encapsulates all data stored in the buffer within an easy to use data

⁵Four directions: north, south, east, or west.

⁶Dead agents can only take no-op action while live agents cannot.

structure. This encapsulation provides a cleaner interface for the necessary handling of data in deep MARL algorithms, whilst not obstructing the manipulation of the underlying PyTorch Tensors. In addition, PyMARL aims to maximise the batching of data when performing inference or learning so as to provide significant speed-ups over more naive implementations.

PyMARL features implementations of the following algorithms: QMIX (Rashid et al., 2018), QTRAN (Son et al., 2019) and COMA (Foerster et al., 2018a) as state-of-the-art methods, and VDN (Sunehag et al., 2017) and IQL (Tan, 1993) as baselines.

6 Results

In this section, we present results for scenarios included as part of SMAC. The purpose of these results is to demonstrate the performance of the current state-of-the-art methods in our chosen MARL paradigm.

The evaluation procedure is similar to the one in (Rashid et al., 2018). The training is paused after every 10000 timesteps during which 32 test episodes are run with agents performing action selection greedily in a decentralised fashion. The percentage of episodes where the agents defeat all enemy units within the permitted time limit is referred to as the *test win rate*.

The architectures and training details are presented in Appendix C. A table of the results is included in Appendix D. Data from the individual runs are available at the SMAC repo (<https://github.com/oxwhirl/smac>).

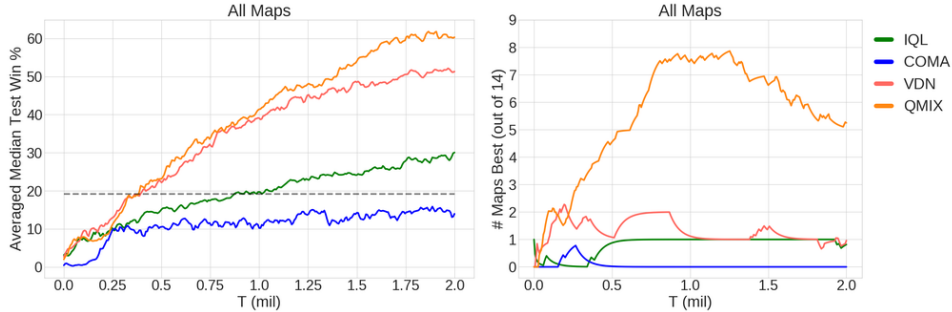


Figure 3: Left: The median test win %, averaged across all 14 scenarios. Heuristic’s performance is shown as a dotted line. Right: The number of scenarios in which the algorithm’s median test win % is the highest by at least $1/32$ (smoothed).

Figure 3 plots the median test win percentage averaged across all scenarios to compare the algorithms across the entire SMAC suite. We also plot the performance of a simple heuristic AI that selects the closest enemy unit (ignoring partial observability) and attacks it with the entire team until it is dead, upon which the next closest enemy unit is selected. This is a basic form of *focus-firing*, which is a crucial tactic for achieving good performance in micromanagement scenarios. The relatively poor performance of the heuristic AI shows that the suite of SMAC scenarios requires more complex behaviour than naively focus-firing the closest enemy, making it an interesting and challenging benchmark.

Overall QMIX achieves the highest test win percentage and is the best performer on up to eight scenarios during training. Additionally, IQL, VDN, and QMIX all significantly outperform COMA, demonstrating the sample efficiency of off-policy value-based methods over on-policy policy gradient methods.

Based on the results, we broadly group the scenarios into 3 categories: *Easy*, *Hard*, and *Super-Hard* based on the performance of the algorithms.

Figure 4 shows that IQL and COMA struggle even on the *Easy* scenarios, performing poorly on four of the five scenarios in this category. This shows the advantage of learning a centralised but factored centralised Q_{tot} . Even though QMIX exceeds 95% test win rate on all of five *Easy* scenarios, they serve an important role in the benchmark as sanity checks when implementing and testing new algorithms.

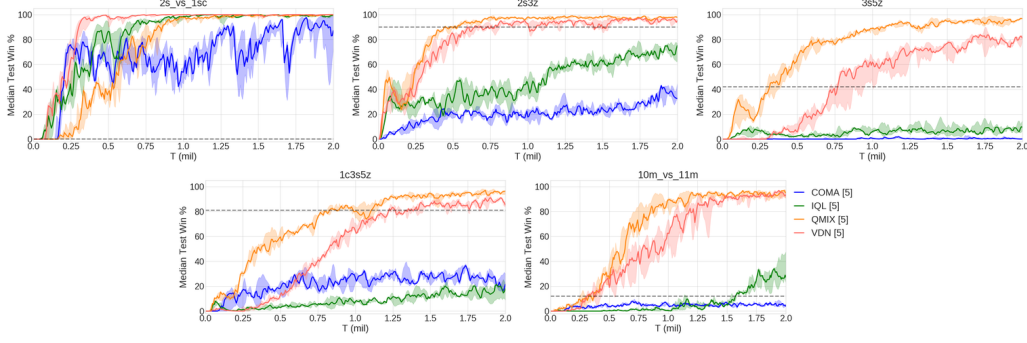


Figure 4: Easy scenarios. The heuristic AI’s performance shown as a dotted black line.

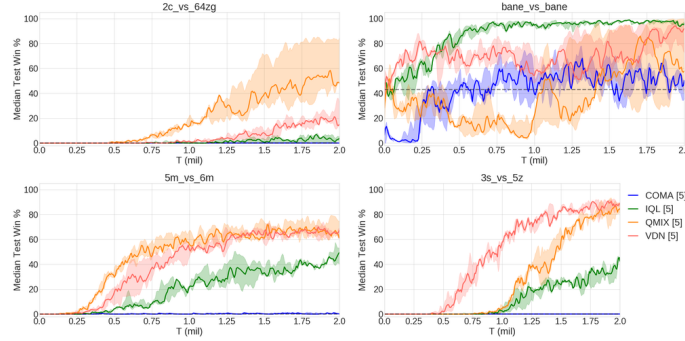


Figure 5: Hard scenarios. The heuristic AI’s performance shown as a dotted black line.

The *Hard* scenarios in Figure 5 each present their own unique problems. *2c_vs_64zg* only contains 2 allied agents, but 64 enemy units (the largest in the SMAC benchmark) making the action space of the agents much larger than the other scenarios. *bane_vs_bane* contains a large number of allied and enemy units, but the results show that IQL easily finds a winning strategy whereas all other methods struggle and exhibit large variance. *5m_vs_6m* is an asymmetric scenario that requires precise control to win consistently, and in which the best performers (QMIX and VDN) have plateaued in performance. Finally, *3s_vs_5z* requires the three allied stalkers to *kite* the enemy zealots for the majority of the episode (at least 100 timesteps), which leads to a delayed reward problem.

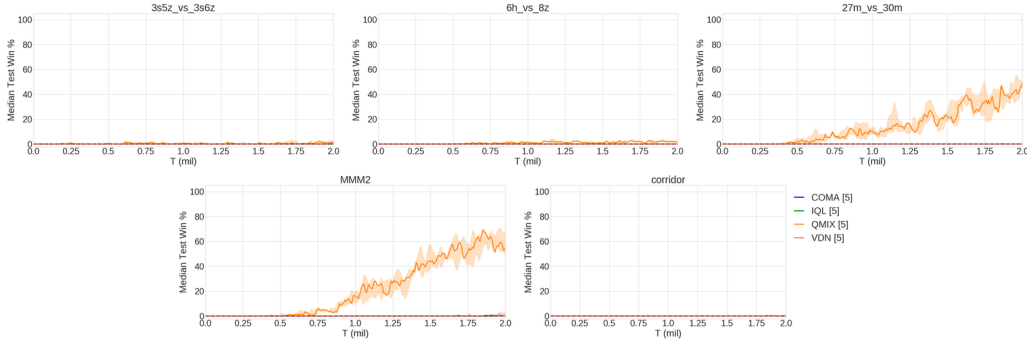


Figure 6: Super Hard scenarios. The heuristic AI’s performance shown as a dotted black line.

The scenarios shown in Figure 6 are categorised as *Super Hard* because of the poor performance of all algorithms, with only QMIX making meaningful progress on two of the five. We hypothesise that exploration is a bottleneck in many of these scenarios, providing a nice test-bed for future research in this domain.

We also test QTRAN (Son et al., 2019) on three of the easiest scenarios, as shown in Figure 7. QTRAN fails to achieve good performance on *3s5z* and takes far longer to reach the performance of

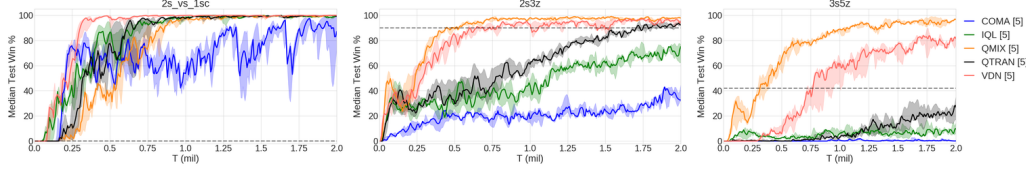


Figure 7: 3 scenarios including QTRAN.

VDN and QMIX on $2s3z$. In preliminary experiments, we found the QTRAN-Base algorithm slightly more performant and more stable than QTRAN-Alt. For more details on the hyperparameters and architectures considered, please see the Appendix.

Additionally, we compare the necessity of using an agent’s action-observation history by comparing the performance of an agent network with and without an RNN in Figure 8. On the easy scenario of $3s5z$ we can see that an RNN is not required to use action-observation information from previous timesteps, but on the harder scenarios of $3s_vs_5z$ it is crucial to being able to learn how to kite effectively.

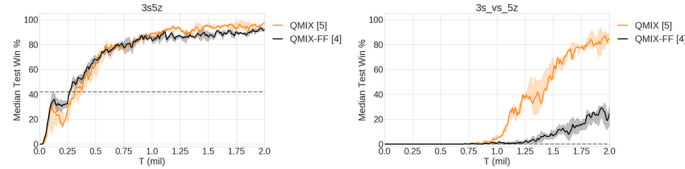


Figure 8: Comparing agent networks with and without RNNs (QMIX-FF) on 2 scenarios.

7 Conclusion and Future Work

This paper presented SMAC as a set of benchmark problems for cooperative MARL. Based on the real-time strategy game StarCraft II, SMAC focuses on decentralised micromanagement tasks and features 14 diverse combat scenarios which challenge MARL methods to handle partial observability and high-dimensional inputs. We offer recommendations for reporting evaluations using standardised performance metrics and provide a thorough report and discussion for several state-of-the-art MARL algorithms, such as QMIX and COMA. Additionally, we are open-sourcing PyMARL - our framework for design and analysis of deep MARL algorithms.

In the near future, we aim to extend SMAC with new challenging scenarios that feature a more diverse set of units and require a higher level of coordination amongst agents. Particularly, we plan to make use of the rich skill set of StarCraft II units, and host scenarios that require the agents to utilise the features of the terrain. With harder multi-agent coordination problems, we aim to explore the gaps in existing MARL approaches and motivate further research in this domain, particularly in areas such as multi-agent exploration and coordination.

We look forward to accepting contributions from the community to SMAC and hope that it will become a standard benchmark for measuring progress in cooperative MARL.

Acknowledgements

The authors would like to thank Davit Hayrapetyan for his helpful suggestions about the StarCraft II scenarios. We also thank Phil Bates and Jon Russell (Oracle Corporation) for guidance deploying and executing SMAC on Oracle’s public Cloud Infrastructure and the SC2LE teams at DeepMind and Blizzard for their work on the interface.

The work is supported by the European Union’s Horizon 2020 research and innovation programme (grant agreement number 637713), the National Institutes of Health (grant agreement number R01GM114311) and EPSRC/MURI grant EP/N019474/1. It is also supported by the an EPSRC grant (EP/M508111/1, EP/N509711/1), the Oxford-Google DeepMind Graduate Scholarship, Microsoft and Free the Drones (FreeD) project under the Innovation Fund Denmark. The experiments were made possible by generous cloud credit grants from Oracle’s Cloud Innovation Accelerator and NVIDIA.

References

- Bellemare, M. G., Naddaf, Y., Veness, J., and Bowling, M. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47:253–279, jun 2013.
- DeepMind. Alphastar: Mastering the real-time strategy game starcraft ii, 2019. URL <https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/>.
- Foerster, J., Nardelli, N., Farquhar, G., Afouras, T., Torr, P. H. S., Kohli, P., and Whiteson, S. Stabilising Experience Replay for Deep Multi-Agent Reinforcement Learning. In *Proceedings of the 34th International Conference on Machine Learning*, pp. 1146–1155, 2017.
- Foerster, J., Farquhar, G., Afouras, T., Nardelli, N., and Whiteson, S. Counterfactual multi-agent policy gradients. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence*, 2018a.
- Foerster, J. N., de Witt, C. A. S., Farquhar, G., Torr, P. H., Boehmer, W., and Whiteson, S. Multi-agent common knowledge reinforcement learning. *arXiv preprint arXiv:1810.11702*, 2018b.
- Hausknecht, M. and Stone, P. Deep Recurrent Q-Learning for Partially Observable MDPs. In *AAAI Fall Symposium on Sequential Decision Making for Intelligent Agents*, 2015.
- Hausknecht, M., Mupparaju, P., Subramanian, S., Kalyanakrishnan, S., and Stone, P. Half field offense: an environment for multiagent learning and ad hoc teamwork. In *AAMAS Adaptive Learning Agents (ALA) Workshop*, 2016.
- Heinrich, J. and Silver, D. Deep reinforcement learning from self-play in imperfect-information games. *CoRR*, abs/1603.01121, 2016. URL <http://arxiv.org/abs/1603.01121>.
- Hu, Y., Li, J., Li, X., Pan, G., and Xu, M. Knowledge-guided agent-tactic-aware learning for starcraft micromanagement. In *IJCAI*, pp. 1471–1477, 2018.
- Kalyanakrishnan, S., Liu, Y., and Stone, P. Half field offense in robocup soccer: A multiagent reinforcement learning case study. In *Robot Soccer World Cup*, pp. 72–85. Springer, 2006.
- Kitano, H., Asada, M., Kuniyoshi, Y., Noda, I., and Osawa, E. Robocup: The robot world cup initiative. In *Proceedings of the first international conference on Autonomous agents*, pp. 340–347. ACM, 1997.
- Kraemer, L. and Banerjee, B. Multi-agent reinforcement learning as a rehearsal for decentralized planning. *Neurocomputing*, 190:82–94, 2016.
- Leibo, J. Z., Zambaldi, V., Lanctot, M., Marecki, J., and Graepel, T. Multi-agent Reinforcement Learning in Sequential Social Dilemmas. February 2017. URL <http://arxiv.org/abs/1702.03037>. arXiv: 1702.03037.
- Lowe, R., Wu, Y., Tamar, A., Harb, J., Abbeel, P., and Mordatch, I. Multi-Agent Actor-Critic for Mixed Cooperative-Competitive Environments. June 2017. URL <http://arxiv.org/abs/1706.02275>. arXiv: 1706.02275.
- Nardelli, N., Synnaeve, G., Lin, Z., Kohli, P., Torr, P. H., and Usunier, N. Value propagation networks. *arXiv preprint arXiv:1805.11199*, 2018.
- Oliehoek, F. A. and Amato, C. *A Concise Introduction to Decentralized POMDPs*. Springer-Briefs in Intelligent Systems. Springer, 2016. URL <http://www.springer.com/us/book/9783319289274>.
- Oliehoek, F. A., Spaan, M. T. J., and Nikos Vlassis. Optimal and Approximate Q-value Functions for Decentralized POMDPs. *JAIR*, 32:289–353, 2008.
- Ontanón, S., Synnaeve, G., Uriarte, A., Richoux, F., Churchill, D., and Preuss, M. A survey of real-time strategy game ai research and competition in starcraft. *IEEE Transactions on Computational Intelligence and AI in games*, 5(4):293–311, 2013.

- Pang, Z.-J., Liu, R.-Z., Meng, Z.-Y., Zhang, Y., Yu, Y., and Lu, T. On reinforcement learning for full-length game of starcraft. *arXiv preprint arXiv:1809.09095*, 2018.
- Plappert, M., Andrychowicz, M., Ray, A., McGrew, B., Baker, B., Powell, G., Schneider, J., Tobin, J., Chociej, M., Welinder, P., Kumar, V., and Zaremba, W. Multi-goal reinforcement learning: Challenging robotics environments and request for research, 2018.
- Rashid, T., Samvelyan, M., Schroeder, C., Farquhar, G., Foerster, J., and Whiteson, S. QMIX: Monotonic Value Function Factorisation for Deep Multi-Agent Reinforcement Learning. In *Proceedings of the 35th International Conference on Machine Learning*, pp. 4295–4304, 2018.
- Resnick, C., Eldridge, W., Ha, D., Britz, D., Foerster, J., Togelius, J., Cho, K., and Bruna, J. Pommerman: A multi-agent playground. *arXiv preprint arXiv:1809.07124*, 2018.
- Shao, K., Zhu, Y., and Zhao, D. Starcraft micromanagement with reinforcement learning and curriculum transfer learning. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 2018.
- Son, K., Kim, D., Kang, W. J., Hostallero, D. E., and Yi, Y. QTRAN: Learning to factorize with transformation for cooperative multi-agent reinforcement learning. In *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pp. 5887–5896. PMLR, 2019.
- Stone, P., Kuhlmann, G., Taylor, M. E., and Liu, Y. Keepaway soccer: From machine learning testbed to benchmark. In *Robot Soccer World Cup*, pp. 93–105. Springer, 2005.
- Sun, P., Sun, X., Han, L., Xiong, J., Wang, Q., Li, B., Zheng, Y., Liu, J., Liu, Y., Liu, H., et al. Tstarbots: Defeating the cheating level builtin ai in starcraft ii in the full game. *arXiv preprint arXiv:1809.07193*, 2018.
- Sunehag, P., Lever, G., Gruslys, A., Czarnecki, W. M., Zambaldi, V., Jaderberg, M., Lanctot, M., Sonnerat, N., Leibo, J. Z., Tuyls, K., and Graepel, T. Value-Decomposition Networks For Cooperative Multi-Agent Learning. *arXiv:1706.05296 [cs]*, June 2017. URL <http://arxiv.org/abs/1706.05296>. arXiv: 1706.05296.
- Synnaeve, G., Nardelli, N., Auvolet, A., Chintala, S., Lacroix, T., Lin, Z., Richoux, F., and Usunier, N. TorchCraft: a Library for Machine Learning Research on Real-Time Strategy Games. *arXiv preprint arXiv:1611.00625*, 2016.
- Tampuu, A., Matisen, T., Kodelja, D., Kuzovkin, I., Korjus, K., Aru, J., Aru, J., and Vicente, R. Multiagent Cooperation and Competition with Deep Reinforcement Learning. November 2015. URL <http://arxiv.org/abs/1511.08779>. arXiv: 1511.08779.
- Tan, M. Multi-agent reinforcement learning: Independent vs. cooperative agents. In *Proceedings of the tenth international conference on machine learning*, pp. 330–337, 1993.
- Blizzard Entertainment. New blizzard custom game: Starcraft master. <http://us.battle.net/sc2/en/blog/4544189/new-blizzard-custom-game-starcraft-master-3-1-2012>, 2012. Accessed: 2018-11-16.
- Usunier, N., Synnaeve, G., Lin, Z., and Chintala, S. Episodic exploration for deep deterministic policies: An application to starcraft micromanagement tasks. *arXiv preprint arXiv:1609.02993*, 2016.
- Vinyals, O., Ewalds, T., Bartunov, S., Georgiev, P., Vezhnevets, A. S., Yeo, M., Makhzani, A., Küttler, H., Agapiou, J., Schrittwieser, J., Quan, J., Gaffney, S., Petersen, S., Simonyan, K., Schaul, T., van Hasselt, H., Silver, D., Lillicrap, T., Calderone, K., Keet, P., Brunasso, A., Lawrence, D., Ekermo, A., Repp, J., and Tsing, R. StarCraft II: A New Challenge for Reinforcement Learning. *arXiv:1708.04782 [cs]*, August 2017. URL <http://arxiv.org/abs/1708.04782>. arXiv: 1708.04782.
- Yang, Y., Luo, R., Li, M., Zhou, M., Zhang, W., and Wang, J. Mean field multi-agent reinforcement learning. *arXiv preprint arXiv:1802.05438*, 2018.
- Zheng, L., Yang, J., Cai, H., Zhang, W., Wang, J., and Yu, Y. Magent: A many-agent reinforcement learning platform for artificial collective intelligence. *arXiv preprint arXiv:1712.00600*, 2017.

A SMAC

A.1 Scenarios

Perhaps the simplest scenarios are **symmetric** battle scenarios, where the two armies are composed of the same units. Such challenges are particularly interesting when some of the units are extremely effective against others (this is known as *countering*), for example, by dealing bonus damage to a particular armour type. In such a setting, allied agents must deduce this property of the game and design an intelligent strategy to protect teammates vulnerable to certain enemy attacks.

SMAC also includes more challenging scenarios, for example, in which the enemy army outnumbers the allied army by one or more units. In such **asymmetric** scenarios it is essential to consider the health of enemy units in order to effectively target the desired opponent.

Lastly, SMAC offers a set of interesting **micro-trick** challenges that require a higher-level of cooperation and a specific micro trick to defeat the enemy. An example of such scenario is the *corridor* scenario (Figure 1c). Here, six friendly Zealots face 24 enemy Zerglings, which requires agents to make effective use of the terrain features. Specifically, agents should collectively wall off the choke point (the narrow region of the map) to block enemy attacks from different directions. The *3s_vs_5z* scenario features three allied Stalkers against five enemy Zealots (Figure 1b). Since Zealots counter Stalkers, the only winning strategy for the allied units is to kite the enemy around the map and kill them one after another. Some of the micro-trick challenges are inspired by *StarCraft Master* challenge missions released by Blizzard (Blizzard Entertainment, 2012).

A.2 Environment Setting

SMAC makes use of the StarCraft II Learning Environment (*SC2LE*) (Vinyals et al., 2017) to communicate with the StarCraft II engine. SC2LE provides full control of the game by making it possible to send commands and receive observations from the game. However, SMAC is conceptually different from the RL environment of SC2LE. The goal of SC2LE is to learn to play the full game of StarCraft II. This is a competitive task where a centralised RL agent receives RGB pixels as input and performs both macro and micro with the player-level control similar to human players. SMAC, on the other hand, represents a set of cooperative multi-agent micro challenges where each learning agent controls a single military unit.

SMAC uses the *raw API* of SC2LE. Raw API observations do not have any graphical component and include information about the units on the map such as health, location coordinates, etc. The raw API also allows sending action commands to individual units using their unit IDs. This setting differs from how humans play the actual game, but is convenient for designing decentralised multi-agent learning tasks.

Furthermore, to encourage agents to explore interesting micro strategies themselves, we limit the influence of the StarCraft AI on our agents. In the game of StarCraft II, whenever an idle unit is under attack, it automatically starts a reply attack towards the attacking enemy units without being explicitly ordered. We disable such automatic replies towards the enemy attacks or enemy units that are located closely by creating new units that are the exact copies of existing ones with two attributes modified: *Combat: Default Acquire Level* is set to *Passive* (default *Offensive*) and *Behaviour: Response* is set to *No Response* (default *Acquire*). These fields are only modified for allied units; enemy units are unchanged.

The sight and shooting range values might differ from the built-in *sight* or *range* attribute of some StarCraft II units. Our goal is not to master the original full StarCraft II game, but rather to benchmark MARL methods for decentralised control.

The game AI is set to level 7, *very difficult*. Our experiments, however, suggest that this setting does significantly impact the unit micromanagement of the built-in heuristics.

B Evaluation Methodology

We propose the following methodology for evaluating MARL methods using SMAC.

To ensure the fairness of the challenge and comparability of results, performances should be evaluated under standardised conditions. One should not undertake any changes to the environment used for evaluating the policies. This includes the observation and state spaces, action space, the game mechanics, and settings of the environment (e.g., frame-skipping rate). One should not modify the StarCraft II map files in any way or change the difficulty of the game AI. Episode limits of each scenario should also remain unchanged.

SMAC restricts the execution of the trained models to be decentralised, i.e., during testing each agent must base its policy solely on its own action-observation history and cannot use the global state or the observations of other agents. It is, however, acceptable to train the decentralised policies in centralised fashion. Specifically, agents can exchange individual observations, model parameters and gradients during training as well as make use of the global state.

B.1 Evaluation Metrics

Our main evaluation metric is the mean win percentage of evaluation episodes as a function of environment steps observed, over the course of training. Such progress can be estimated by periodically running a fixed number of evaluation episodes (in practice, 32) with any exploratory behaviours disabled. Each experiment is repeated using a number of independent training runs and the resulting plots include the median performance as well as the 25-75% percentiles. We use five independent runs for this purpose in order to strike a balance between statistical significance and the computational requirements. We recommend using the median instead of the mean in order to avoid the effect of any outliers. We report the number of independent runs, as well as environment steps used in training. Each independent run takes between 8 to 16 hours, depending on the exact scenario, using Nvidia Geforce GTX 1080 Ti graphics cards.

It can prove helpful to other researchers to include the computational resources used, and the wall clock time for running each experiment. SMAC provides functionality for saving StarCraft II replays, which can be viewed using a freely available client. The resulting videos can be used to comment on interesting behaviours observed.

C Experimental Setup

C.1 Architecture and Training

The architecture of all agent networks is a DRQN(Hausknecht & Stone, 2015) with a recurrent layer comprised of a GRU with a 64-dimensional hidden state, with a fully-connected layer before and after. Exploration is performed during training using independent ϵ -greedy action selection, where each agent a performs ϵ -greedy action selection over its own Q_a . Throughout the training, we anneal ϵ linearly from 1.0 to 0.05 over 50k time steps and keep it constant for the rest of the learning. We set $\gamma = 0.99$ for all experiments. The replay buffer contains the most recent 5000 episodes. We sample batches of 32 episodes uniformly from the replay buffer, and train on fully unrolled episodes, performing a single gradient descent step after every episode. **Note:** This differs from the earlier an earlier beta release of SMAC, which trained once after every 8 episodes. The target networks are updated after every 200 training episodes.

To speed up the learning, we share the parameters of the agent networks across all agents. Because of this, a one-hot encoding of the `agent_id` is concatenated onto each agent’s observations. All neural networks are trained using RMSprop⁷ with learning rate 5×10^{-4} .

The mixing network consists of a single hidden layer of 32 units, utilising an ELU non-linearity. The hypernetworks consist of a feedforward network with a single hidden layer of 64 units with a ReLU non-linearity⁸. The output of the hypernetwork is passed through an absolute function (to achieve non-negativity) and then resized into a matrix of appropriate size.

The architecture of the COMA critic is a feedforward fully-connected neural network with the first 2 layers having 128 units, followed by a final layer of $|U|$ units. We set $\lambda = 0.8$. We utilise the same

⁷We set $\alpha = 0.99$ and do not use weight decay or momentum.

⁸This differs from the architecture used in (Rashid et al., 2018) and in an earlier beta release of SMAC, in which a single linear layer was used for the hypernetworks.

ϵ -floor scheme as in (Foerster et al., 2018a) for the agents’ policies, linearly annealing ϵ from 0.5 to 0.01 over 100k timesteps. For COMA we roll-out 8 episodes and train on those episodes. The critic is first updated, performing a gradient descent step for each timestep in the episode, starting with the final timestep. Then the agent policies are updated by a single gradient descent step on the data from all 8 episodes.

The architecture of the centralised Q for QTran is similar to the one used in (?). The agent’s hidden states (64 units) are concatenated with their chosen action ($|U|$ units) and passed through a feedforward network with a single hidden layer and a ReLU non-linearity to produce an agent-action embedding ($64 + |U|$ units). The network is shared across all agents. The embeddings are summed across all agents. The concatenation of the state and the sum of the embeddings is then passed into the Q network. The Q network consists of 2 hidden layers with ReLU non-linearities with 64 units each. The V network takes the state as input and consists of 2 hidden layers with ReLU non-linearities with 64 units each. We set $\lambda_{opt} = 1$ and $\lambda_{nopt_min} = 0.1$.

We also compared a COMA style architecture in which the input to Q is the state and the joint-actions encoded as one-hot vectors. For both architectural variants we also tested having 3 hidden layers. For both network sizes and architectural variants we performed a hyperparameter search over $\lambda_{opt} = 1$ and $\lambda_{nopt_min} \in \{0.1, 1, 10\}$ on all 3 of the maps we tested QTran on and picked the best performer out of all configs.

C.2 Reward and Observation

All experiments use the default shaped rewards throughout all scenarios. At each timestep, agents receive positive rewards, equal to the hit-point damage dealt, and bonuses of 10 and 200 points for killing each enemy unit and winning the scenario, respectively. The rewards are scaled so that the maximum cumulative reward achievable in each scenario is around 20.

The agent observations used in the experiments include all features from Section 4, except for the he last actions of the allied units (within the sight range), terrain height and walkability.

D Table of Results

Table 2 shows the final median performance (maximum median across the testing intervals within the last 250k of training) of the algorithms tested. The mean test win %, across 1000 episodes, for the heuristic-based ai is also shown.

Table 2: The Test Win Rate % of IQL, COMA, VDN, QMIX and the heuristic-based algorithm.

	IQL	COMA	VDN	QMIX	Heuristic
2s_vs_1sc	100	98	100	100	0
2s3z	75	43	97	99	90
3s5z	10	1	84	97	42
1c3s5z	21	31	91	97	81
10m_vs_11m	34	7	97	97	12
2c_vs_64zg	7	0	21	58	0
bane_vs_bane	99	64	94	85	43
5m_vs_6m	49	1	70	70	0
3s_vs_5z	45	0	91	87	0
3s5z_vs_3s6z	0	0	2	2	0
6h_vs_8z	0	0	0	3	0
27m_vs_30m	0	0	0	49	0
MMM2	0	0	1	69	0
corridor	0	0	0	1	0