BenchMARL

Benchmarking Multi-Agent Reinforcement Learning

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University of Cambridge · PROROKLAB · PyTorch · Meta

Mix & match your *model*, *algorithm*, and *task* and start to BenchMARL!

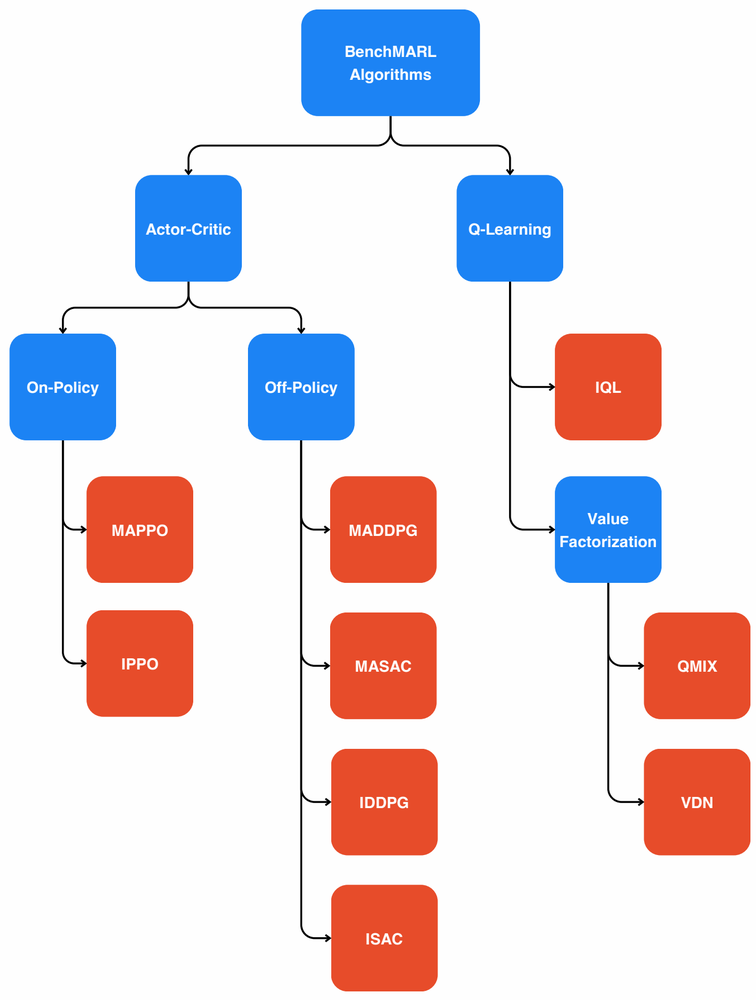
Models

Models are neural network blueprints that can be chained to make actors and critics with or without parameter sharing.

Model	Policy	Critic: Local input	Critic: Global input
MLP	✔	✔	✔
CNN	✔	✔	✔
GNN	✔	✔	✘
Deep Sets	✔	✔	✔

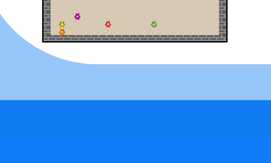
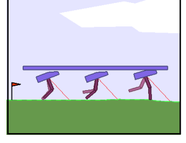
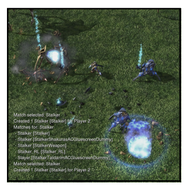
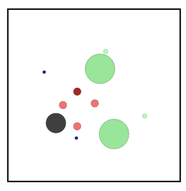
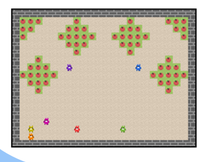
Algorithms

Algorithms are an ensemble of components (e.g., loss, replay buffer, exploration strategy) that determine the training strategy.



Tasks

Tasks are scenarios from a simulated environment which constitute the MARL challenge to solve.

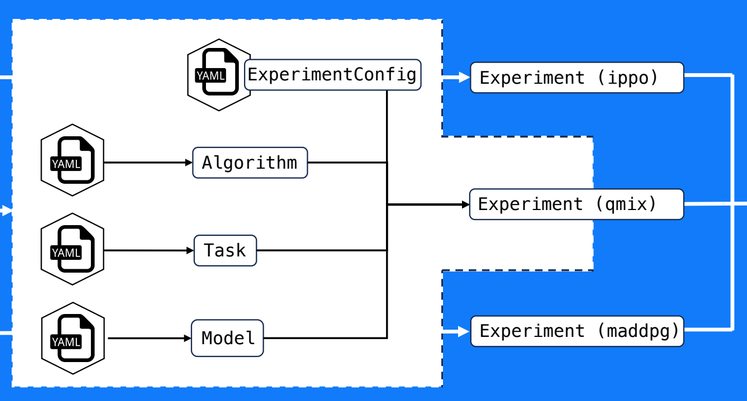
	Environment	# Tasks
	*VMAS*	27
	*SISL*	3
	*SMACv2*	15
	*MPE*	8
	*Melting Pot*	49

BenchMARL

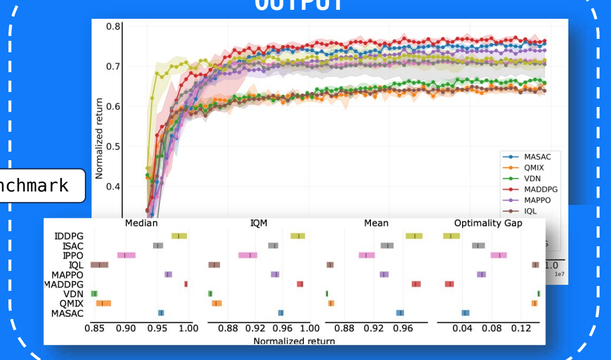
INPUT

Run a benchmark with 3 experiments

```
python benchmarl/run.py -m
seed=0
task=vmas/balance
model=layers/mlp
algorithm=ippo,qmix,maddpg
```



OUTPUT



Code

Docs

Reporting and plotting

Automatically report and plot your BenchMARL results using statistically-strong integrated tools [1,2].

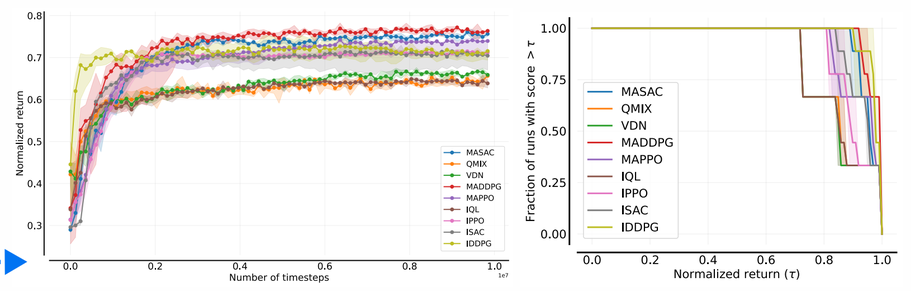
Interactively log your results on Wandb and compare with the publicly available benchmarks:

We are benchmarking and releasing results for BenchMARL tasks.

Check out the results in the VMAS environment:

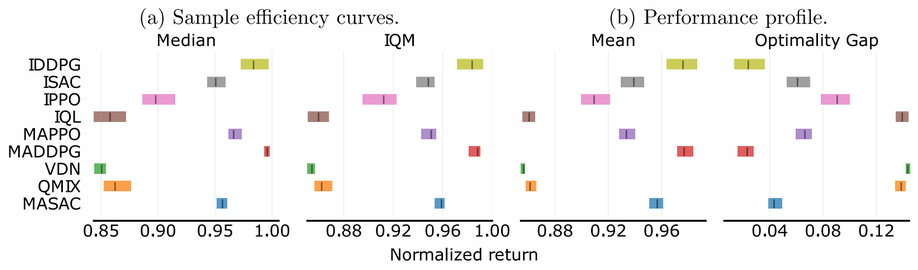
[1] Agarwal, Rishabh, et al. "Deep reinforcement learning at the edge of the statistical precipice." Advances in neural information processing systems 34 (2021): 29304-29320.
[2] Gorsane, Rihab, et al. "Towards a standardised performance evaluation protocol for cooperative marl." Advances in Neural Information Processing Systems 35 (2022): 5510-5521.

Vmas results - aggregated over tasks



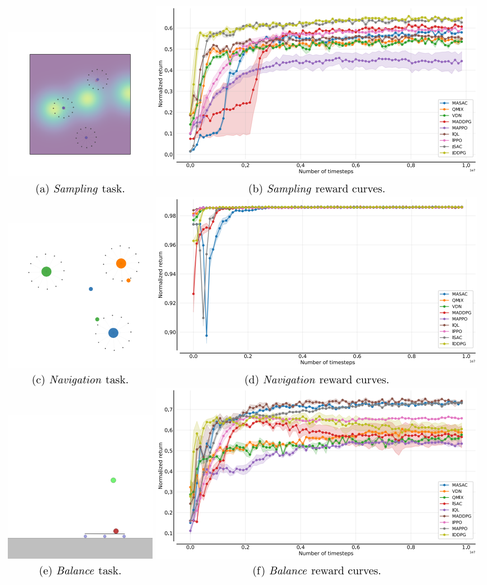
(a) Sample efficiency curves.

(b) Performance profile.



(c) Aggregate scores.

Vmas results - per task



(a) *Sampling* task. (b) *Sampling* reward curves. (c) *Navigation* task. (d) *Navigation* reward curves. (e) *Balance* task. (f) *Balance* reward curves.

Configuring

BenchMARL uses **Hydra** to load configurations from YAML files into Python dataclasses. This allows to easily override and sweep parameters while decoupling them from the codebase.

Extending

Each component in the library has an associated abstract class. This makes it easy to integrate **custom algorithms, models, and tasks**, allowing to compare them against the wide repository of already implemented ones.

Callbacks and checkpointing

We support custom callbacks in various phases of training. Experiments can also be checkpointed and reloaded for evaluation or deployment on robotic platforms.

Documentation and tests

Component documentation is available online and full training integration tests are run for each task-algorithm combination.

`masac.yaml`

```yaml
defaults:
  - masac_config
  - _self_

share_param_critic: True
num_qvalue_nets: 2
loss_function: "l2"
delay_qvalue: True
target_entropy: "auto"
discrete_target_entropy_weight: 0.2
alpha_init: 1.0
min_alpha: null
max_alpha: null
fixed_alpha: False
scale_mapping: "biased_softplus_1.0"
```

YAML configuration file for the MASAC algorithm

Loaded and type-checked lazily

Python dataclass for the MASAC algorithm

`masac.py`

```python
@dataclass
class MasacConfig(AlgorithmConfig):
    share_param_critic: bool = MISSING
    num_qvalue_nets: int = MISSING
    loss_function: str = MISSING
    delay_qvalue: bool = MISSING
    target_entropy: Union[float, str] = MISSING
    discrete_target_entropy_weight: float = MISSING
    alpha_init: float = MISSING
    min_alpha: Optional[float] = MISSING
    max_alpha: Optional[float] = MISSING
    fixed_alpha: bool = MISSING
    scale_mapping: str = MISSING
```

Features

BenchMARL's features fucus on enabling its core tenets: standardization and reproducibility.

BenchMARL core design guidelines:

- **Reproducibility**
- **Standardized reporting**
- **TorchRL backend**
- **Experiment independence**
- **Easy integration of new solutions**

The TorchRL backend allows BenchMARL to **re-use** extensively-benchmarked **single-agent implementations.**