Advanced Topics in Deep Reinforcement Learning

Hyperparameters

Theresa Eimer

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- Exploration epsilon
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These are often integral to successful training

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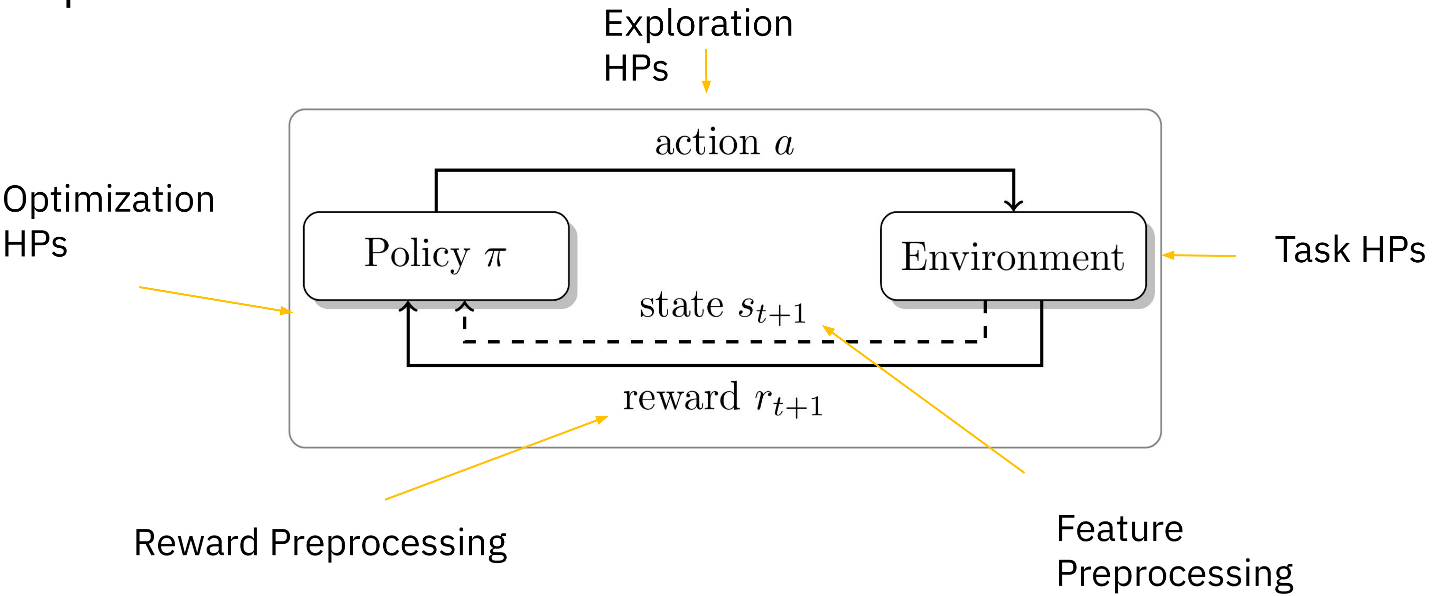

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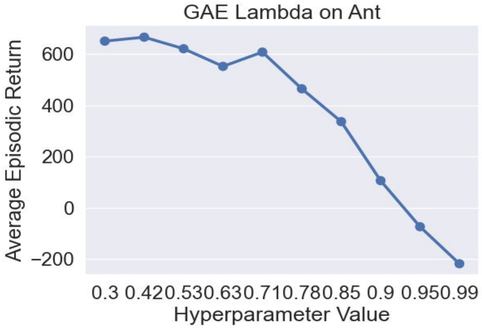

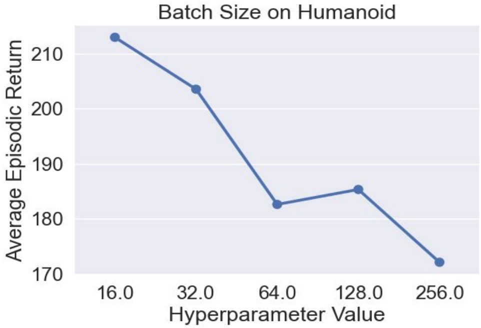

Top: Sweeps on PPO Brax.

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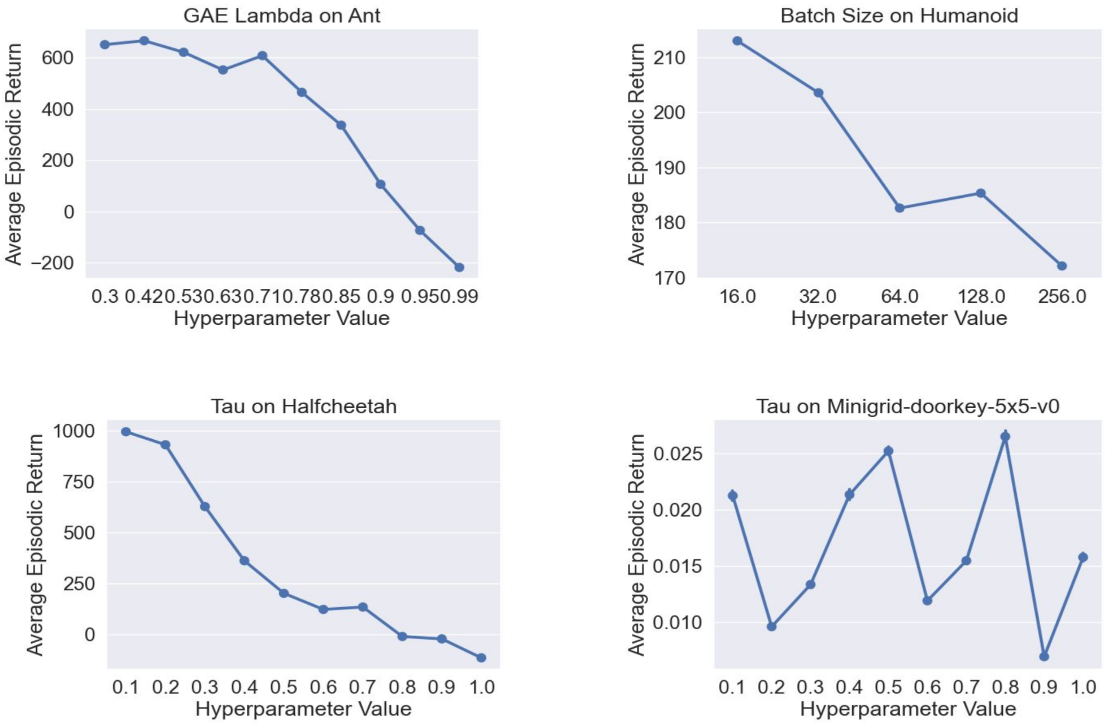

Top: Sweeps on PPO Brax.
Bottom: Sweeps on DQN.
[Eimer et al. 2023]

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- This suggests batch size is much more complex in RL than supervised learning

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- Different decay curves are possible, e.g. exponential decay
- This makes simple exploration a lot more capable

Meta-Algorithmics

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Examples:

- Hyperparameter Optimization
- Algorithm Selection
- Landscape analysis
- Meta-learning initializations, algorithms, etc.
- Task ordering
- ...

AutoRL [Parker-Holder et al. 2022]

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Hyperparameters, Algorithms, Tasks, etc.

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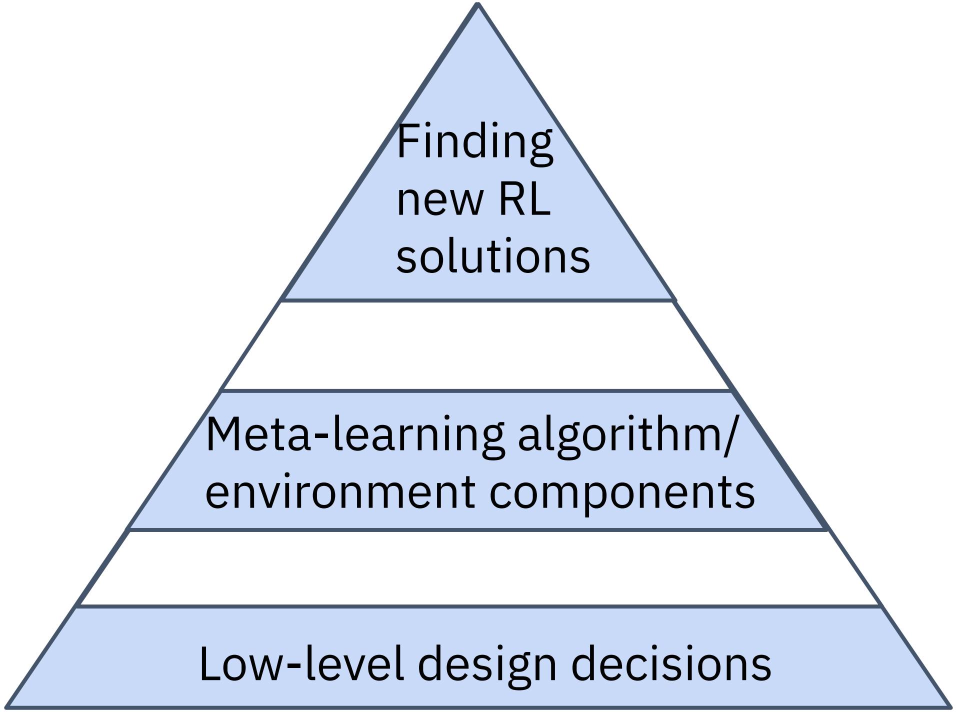
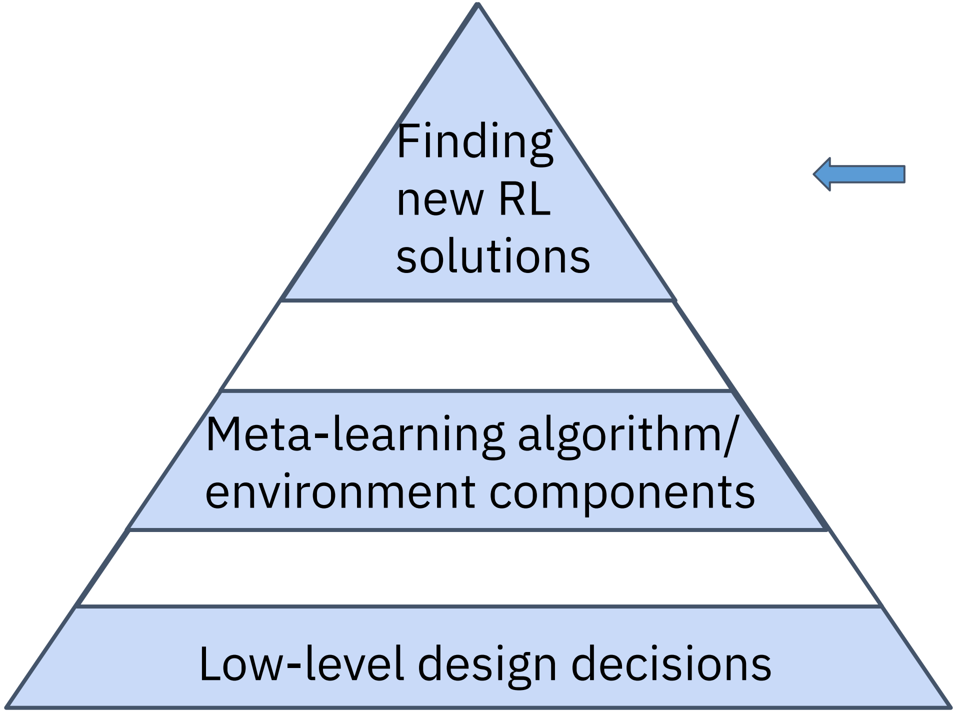

Finding new RL solutions
Meta-learning algorithm/ environment components
Low-level design decisions

AutoRL



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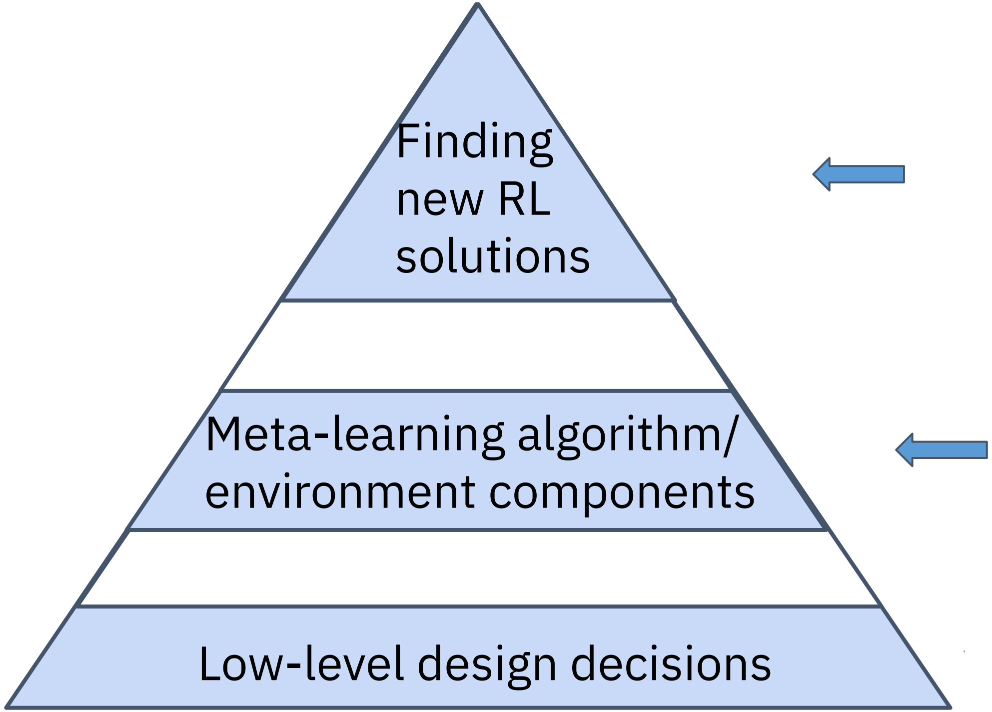

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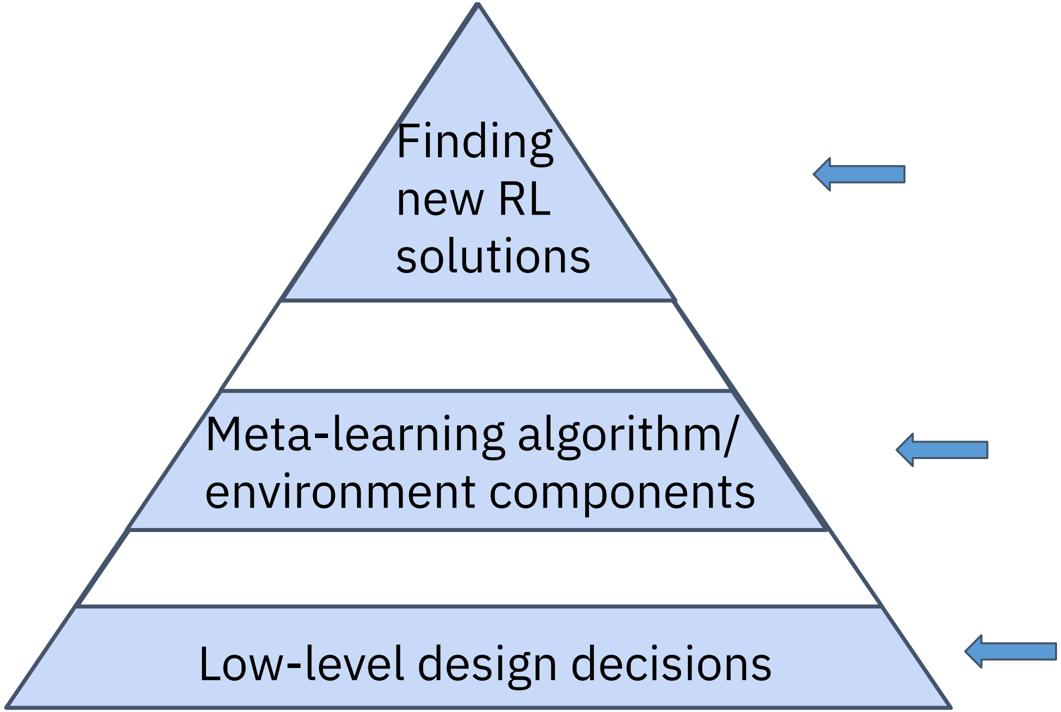

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Hyperparameters, Task Ordering, ...

Examples of AutoRL Methods

- HPO via Population-based Training
- RL pipeline configuration with ARLO
- Curriculum learning via PLR
- Online exploration adjustment with Bootstrapped Meta-Gradients
- Meta-learned objective functions
- Evolved RL algorithms
- …

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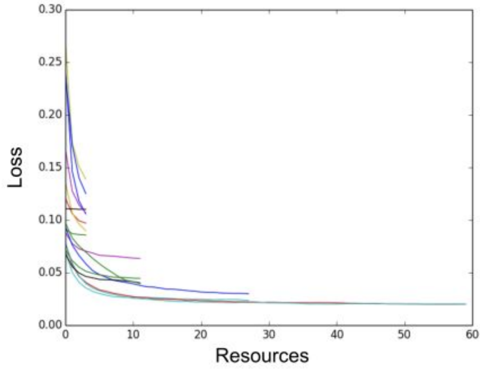

Resource allocation in Hyperband [Li et al. 2018]

Considerations For RL

Before applying HPO to RL, we have to consider a few RL-specific issues in:

- Performance estimation
- Search spaces
- Objectives
- Dynamism
- Generalization

Considerations For RL: Performance estimates

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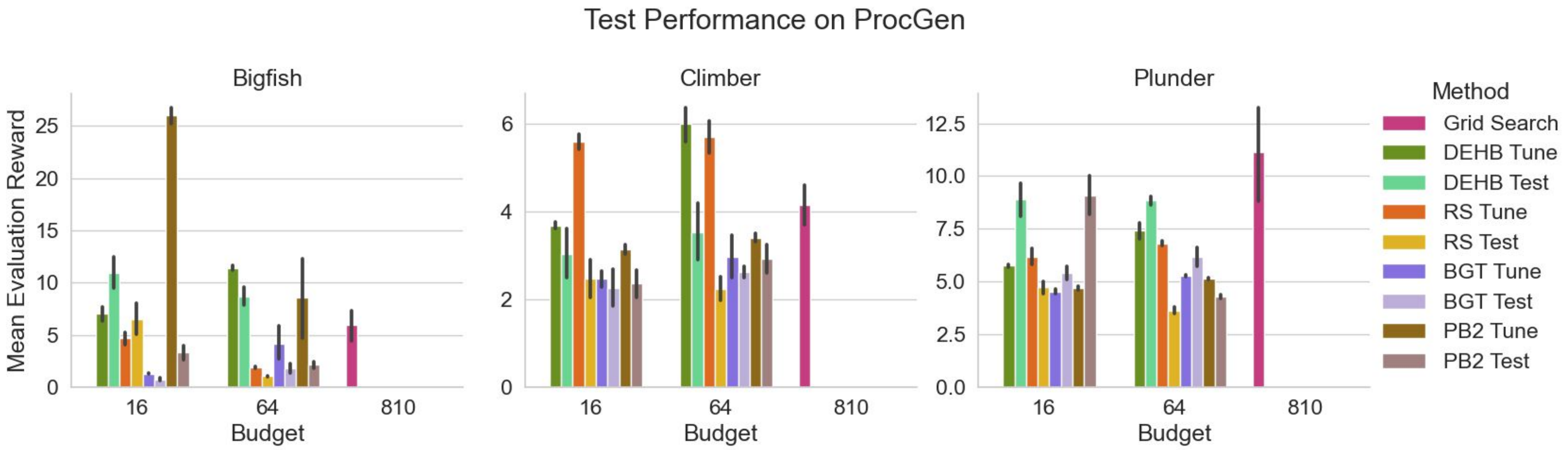

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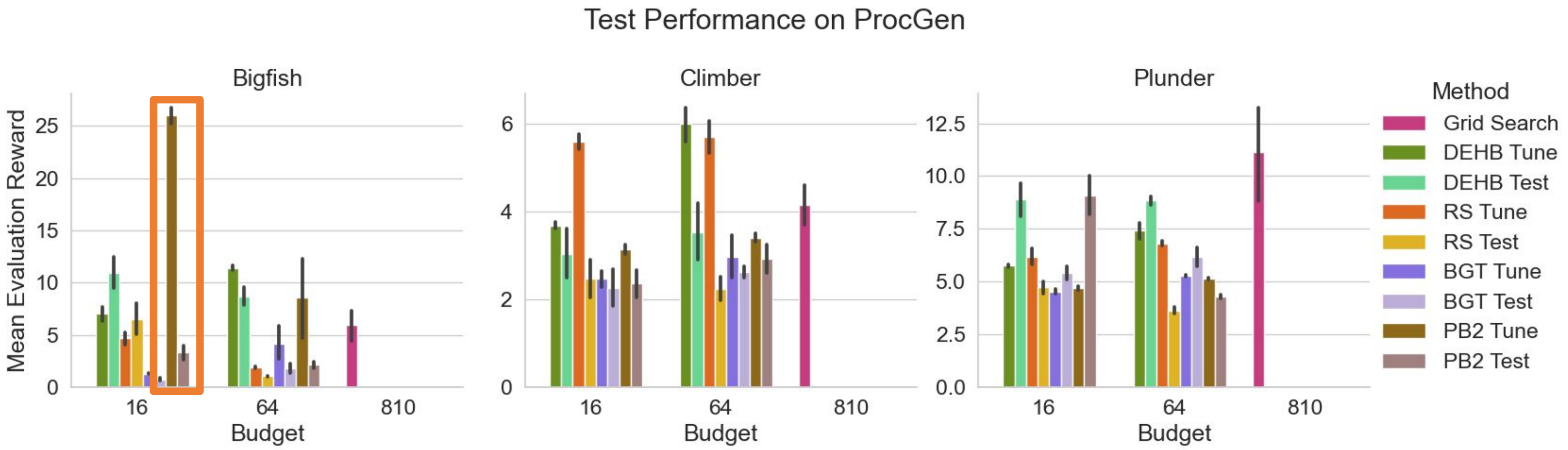

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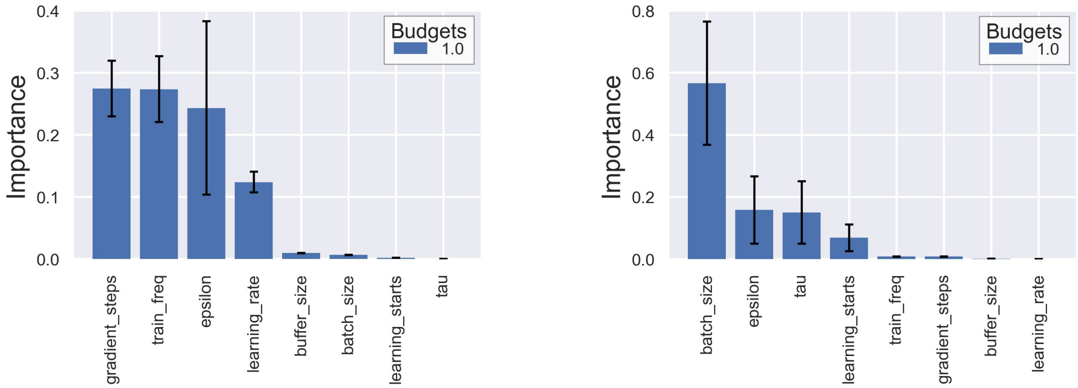

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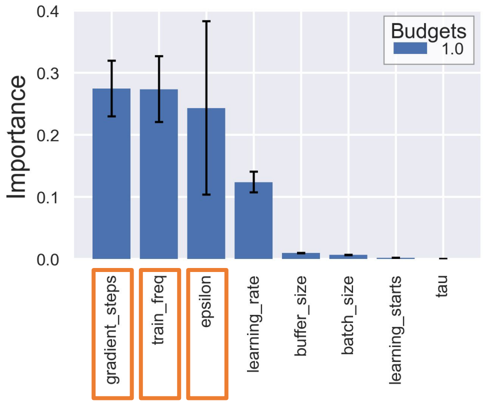

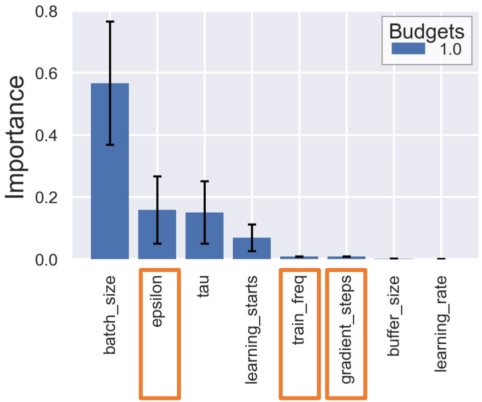

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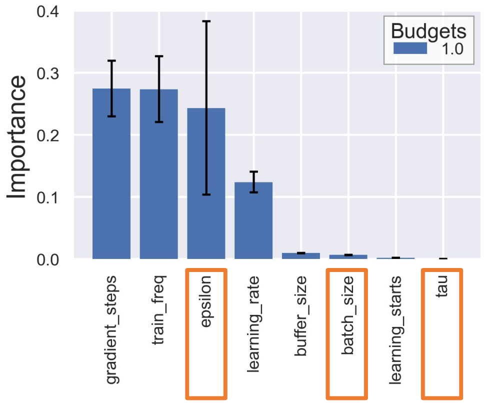

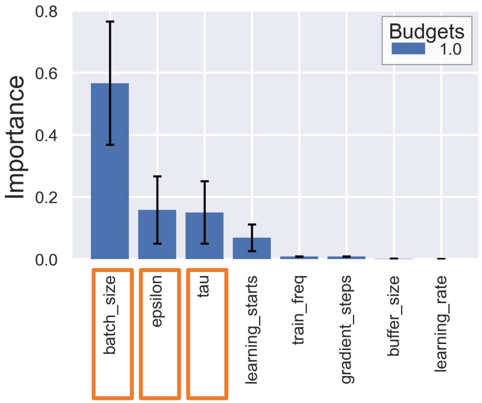

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- Final evaluation reward is by far the most common objective in RL so far

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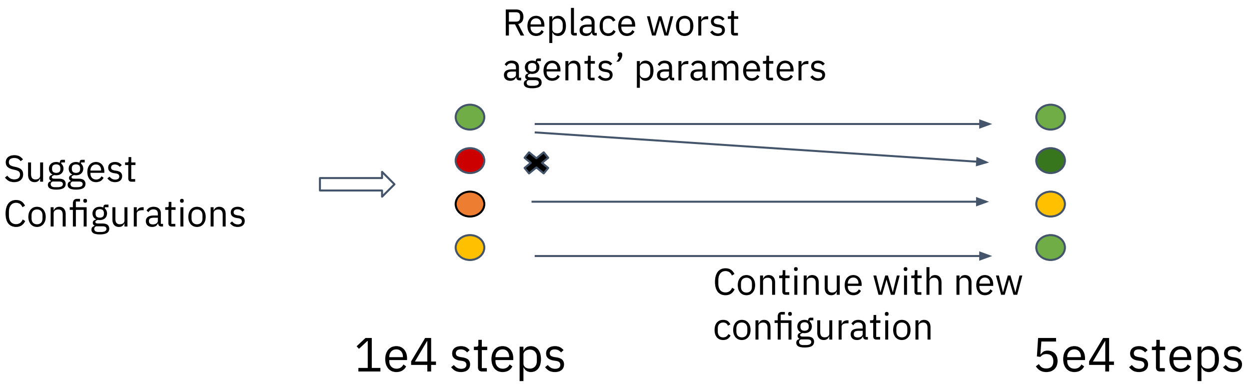

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- Best examples for RL: meta-gradient methods [Xu et al. 2018]

Meta-Gradients in RL

Hyperparameters η

Performance t

Meta-Gradients in RL

Hyperparameters η

Train

Performance t

Meta-Gradients in RL

Hyperparameters η

Train

Performance t

Performance t+1

Meta-Gradients in RL

Hyperparameters η

Update η via SGD using a differentiable meta-objective

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Meta-Gradients in RL

Hyperparameters η

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Update η via SGD using a differentiable meta-objective

=> Highly adaptive hyperparameter schedule learned during training

My Understanding of Hyperparameters in RL

- ❑ I understand what hyperparameters do
- ❑ I can name a few RL hyperparameters
- ❑ I understand the difficulties in performance estimation for RL

- ❑ I can describe AutoRL & give some examples
- ❑ I know at least 3 considerations for HPO in RL

- ❑ I can 1-2 HPO approaches for RL
- ❑ I can discuss which considerations we need for HPO in RL
- ❑ I can propose a simple HPO pipeline