# Dynamic Weights in Multi-Objective Deep Reinforcement Learning

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  - Try to maximize weighted return:

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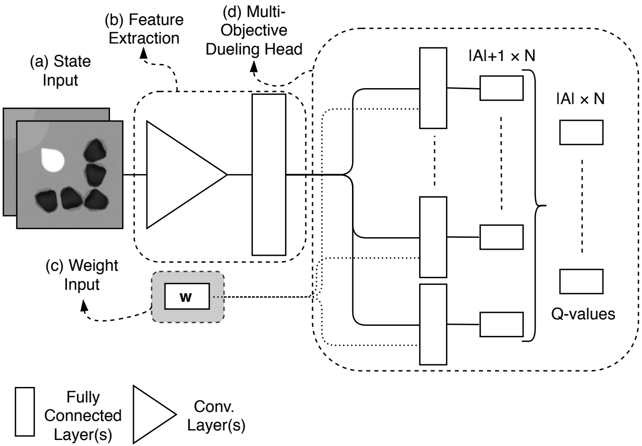
- Focus on high-dimensional problems

# Conditioned Network (CN)



# Updating the Conditioned Network

Considered loss functions

1. Train on current weight vector $\mathbf{w}_t$

$$LOSS_{CN-ACTIVE} = |\mathbf{y}^{(j)}_{\mathbf{w}_t} - \mathbf{Q}_{CN}(a_j, s_j; \mathbf{w}_t)|$$

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3. Train on both

$$LOSS_{CN} = \frac{1}{2}[|\mathbf{y}^{(j)}_{\mathbf{w}_t} - \mathbf{Q}_{CN}(a_j, s_j; \mathbf{w}_t)| + |\mathbf{y}^{(j)}_{\mathbf{w}_j} - \mathbf{Q}_{CN}(a_j, s_j; \mathbf{w}_j)|]$$

# Diverse Experience Replay (DER)

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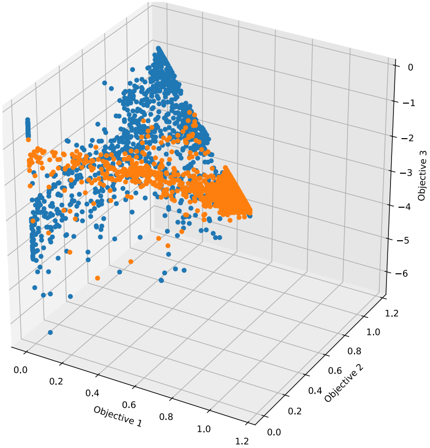
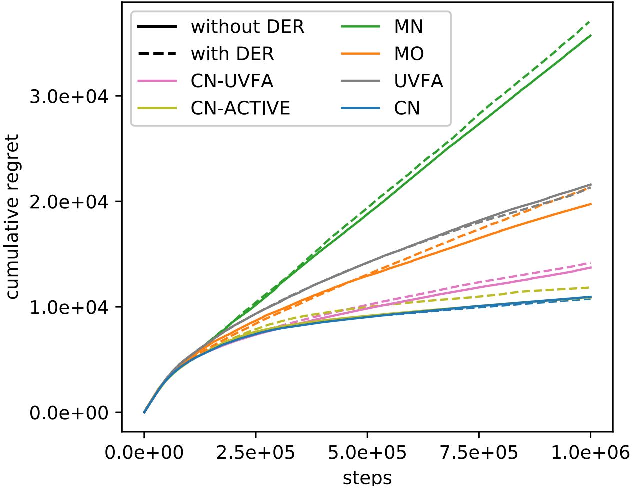
- Replay buffer bias: how can we counter it?
- By preserving diverse experiences



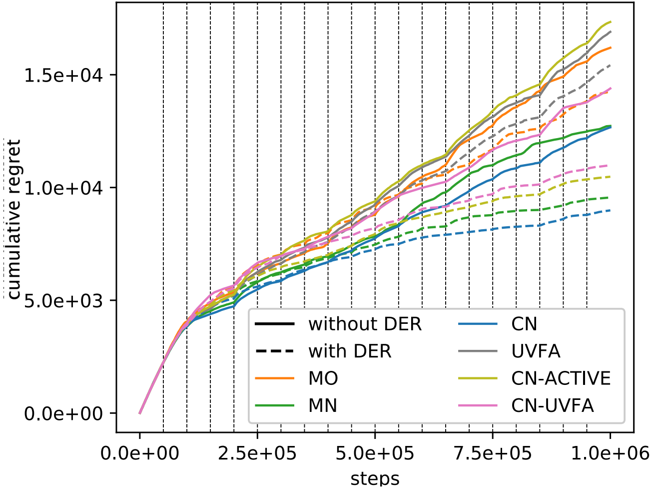

**Replay buffer diversity with and without DER.** Each dot marks a stored trajectory's 3-dimensional return.

# Our CN algorithm converges to near-optimality




Total regret when weights change regularly (lower is better)

# Diversity is crucial for large but sparse weight changes




Total regret when weights change occasionally (lower is better)

# Thank you!

- Poster #49
- 6:30pm to 9pm