

# On the Existence of Double-Descent in Reinforcement Learning

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# Outline

Double Descent Background

Experimental Setup

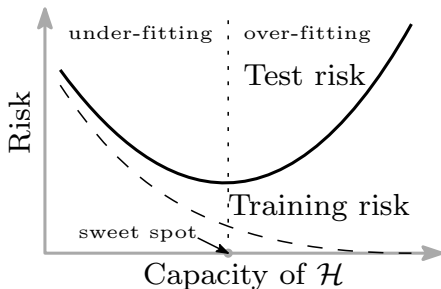
Results & Discussion

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# What is Double Descent?

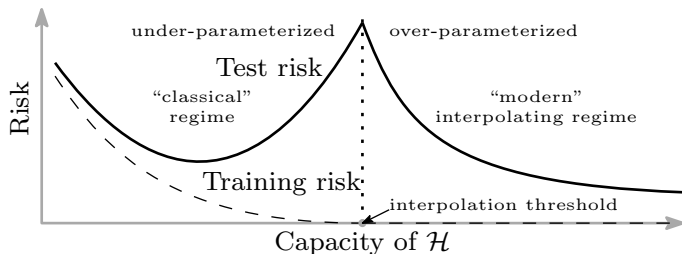
- ▶ **Double Descent (DD)** is a phenomenon of models recovering generalization capacity after surpassing the interpolation threshold (Nakkiran et al. 2019).
- ▶ Classically, increasing model capacity leads to a U-shaped risk curve:



**Figure:** Classical U-shaped risk curve arising from the bias-variance trade-off. Belkin et al. (2019).

# Double Descent Risk Curve

- ▶ However, modern machine learning models often operate in regimes where they can perfectly fit (interpolate) the training data.
- ▶ This can occur in both model size and training time regimens as well as multiple problem types in supervised learning (Belkin et al. 2019; Nakkiran et al. 2019).



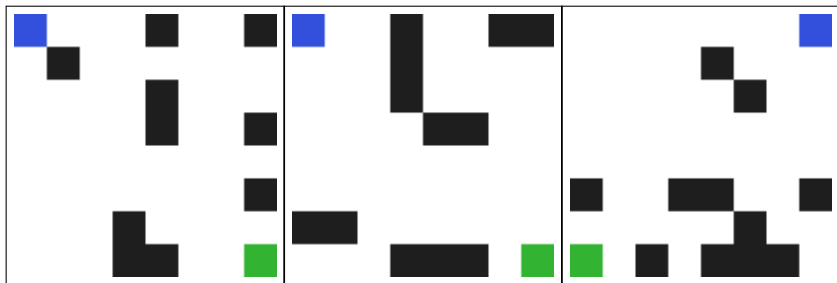
**Figure:** Double Descent risk curve exhibiting a second descent. Belkin et al. (2019).

# DD in Reinforcement Learning

- ▶ Double Descent has not been studied much in Reinforcement Learning (RL) settings.
- ▶ There is some research on theoretical aspects of overparameterization in RL with regard to visited states (Brellmann et al. 2024).
- ▶ There is also an approach of using information theoretic metrics to analyze generalization in RL (Veselý, Todorov, and Sabatelli 2025).

# Methods

- ▶ We are trying to emulate the supervised learning setup in RL: Train/test split, and plotting a “risk” curve.
- ▶ To mimick train and test sets, we use a family of seeded randomly generated maps, training on a subset of these maps and testing on a disjoint subset.



**Figure:** Examples of randomly generated training and validation environments, with agent (blue) and goal (green) tiles.

# Metrics

- ▶ To plot risk curves, we need something to plot on the y-axis since we don't have a loss function in RL.
- ▶ We use the **average return** over the test maps as our metric.
- ▶ Further, we compute the trace of the **Fisher Information Matrix (FIM)** of the policy network.
- ▶ The FIM is defined as:

$$F = \mathbb{E}_{a,s \sim \pi_\theta} \left[ \nabla_\theta \log \pi_\theta(a|s) \nabla_\theta \log \pi_\theta(a|s)^T \right]$$

where  $s, a$  are sampled from trajectories under the policy  $\pi_\theta$ , collected on the training maps.

- ▶ Thus the FIM is the expected outer product of the score function (the gradient of the log-likelihood).
- ▶ The trace of the FIM gives a measure of the sensitivity of the policy to parameter changes, which can be related to generalization.

# Agents & Training Setup

- ▶ We train two agent types: A DQN (Mnih et al. 2013) agent and a TRPO agent (Schulman et al. 2017), both using feedforward neural networks.
- ▶ DQNs implement Q-learning with experience replay using a neural network to estimate Q-values.
- ▶ TRPO is a policy gradient method that optimizes the policy directly while constraining updates using a trust region defined by the Kullback-Leibler (KL) divergence.
- ▶ We vary the model capacity by changing the depth and width of the networks.
- ▶ Training is performed on a fixed set of training maps, with evaluation held-out test maps.
- ▶ We record the average return and trace of the FIM at various points during training to analyze the presence of Double Descent.



# Results in Parametric Regime

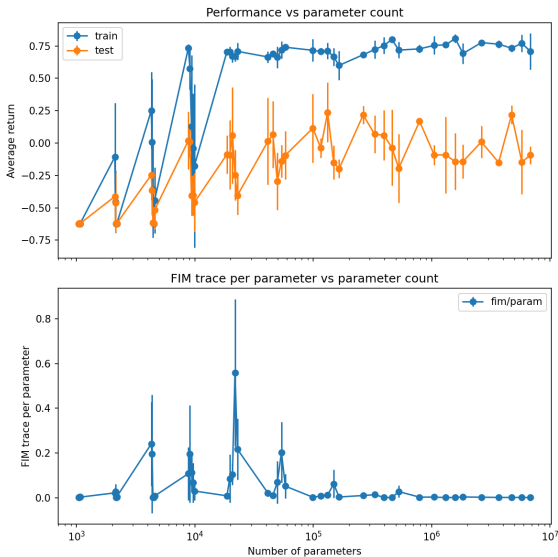


Figure: Results from TRPO agents trained on 100 maps for 50k episodes.

# Results in Episodic Regime

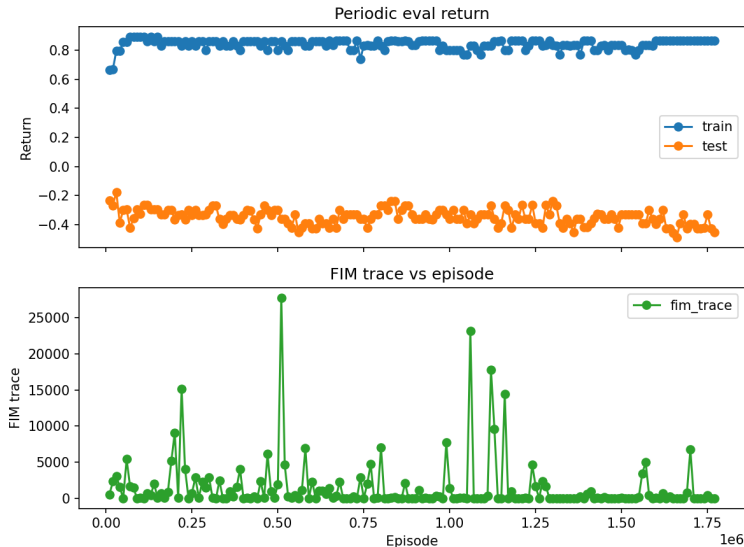


Figure: Results of a TRPO agent trained on 100 maps for 1.8M episodes.

# Discussion

- ▶ Unfortunately, we are unable to observe a clear Double Descent phenomenon in our experiments.
- ▶ There may be several reasons for this, including the complexity of reinforcement learning environments and the computational constraints limiting the scale of our experiments.
- ▶ We observe a spike in the FIM trace around the interpolation threshold. This indicates that the model is unstable in the parameter space, but stabilizes later.
- ▶ However, this does not translate to a clear second ascent in average return.

# Limitations & Future Work

- ▶ We are constrained by limited access to compute, with training runs taking multiple days and wait times for available GPUs.
- ▶ One avenue for further work is exploring the transition between lacking generalization and perfect generalization—we observe no emerging generalization gap when training on 1,000 maps.
- ▶ Additionally, we could explore why the FIM trace's spike around the interpolation threshold comes back down despite the test return not moving.
- ▶ Further, training on larger maps as well as different algorithms could be explored, as well as stochastic transitions.

# References I



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-  Veselý, Viktor, Aleksandar Todorov, and Matthia Sabatelli (2025). *On The Presence of Double-Descent in Deep Reinforcement Learning*. arXiv: 2511.06895 [cs.LG]. URL: <https://arxiv.org/abs/2511.06895>.

# Thank You!

Questions?



# Environment Details

- ▶ Each map is  $8 \times 8$  tiles, with the agent in the top left and the goal in the bottom right unless randomized.
- ▶ Every other tile has a 20% chance of being a wall, with a possible path being guaranteed.
- ▶ At each timestep, the agent receives a reward given by:

$$r_t = \begin{cases} 1, & \text{if goal reached at time } t \\ \Phi(s_{t+1}) - \Phi(s_t) - 0.01, & \text{otherwise} \end{cases}$$

where  $\Phi(s) = \frac{\text{Euclidean distance to goal}}{100}$  is the potential function.

- ▶ Episodes are truncated at 64 timesteps and terminated when the goal is reached.
- ▶ Action space: up, right, down, left, deterministic transitions.
- ▶ Observation space:  $8 \times 8$  grid with one-hot encoded tiles, frame stacking of 2 frames ( $8 \times 8 \times 4 \times 2 = 512$  bits).

# Training Configurations

- ▶ On the following configurations, we trained agents of varying widths between 3 and 8 and depths between 4 and 1024:

Type	Train Maps	Training Episodes	Start & Goal Position
TRPO	10	10,000	Standard <sup>1</sup>
DQN	50	20,000	Standard
DQN	100	50,000	Standard
TRPO	50	20,000	Randomized
TRPO	100	50,000	Randomized
TRPO	500	1,000,000	Standard

- ▶ On the following configurations, we trained agents of depth 3 and widths 4, 16, 64, 256, and 1024 for unlimited time:

Type	Train Maps	Start & Goal Position
TRPO	50	Standard
TRPO	100	Standard

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<sup>1</sup>Agent starts in top left, goal in bottom right

# The Fisher Information Matrix

- ▶ The **Fisher Information Matrix** (FIM) (originally in Fisher 1922, in this form in Kakade 2001) is defined as:

$$F(\theta) = \mathbb{E}_{a,s \sim \pi_\theta} \left[ \nabla_\theta \log \pi_\theta(a|s) \nabla_\theta \log \pi_\theta(a|s)^T \right]$$

- ▶  $s, a$  are sampled under the stochastic policy  $\pi_\theta$  defined by parameters  $\theta$ .
- ▶  $\nabla_\theta \log \pi_\theta(a|s)$  is the gradient of the log-probability of the action given the state with respect to the policy parameters
- ▶ A FIM where  $\theta = [\theta_1, \theta_2]^T$  is therefore a  $2 \times 2$  matrix given by

$$\mathbb{E} \begin{bmatrix} \left( \frac{\partial}{\partial \theta_1} \log \pi_\theta(a|s) \right)^2 & \frac{\partial}{\partial \theta_1} \log \pi_\theta(a|s) \frac{\partial}{\partial \theta_2} \log \pi_\theta(a|s) \\ \frac{\partial}{\partial \theta_2} \log \pi_\theta(a|s) \frac{\partial}{\partial \theta_1} \log \pi_\theta(a|s) & \left( \frac{\partial}{\partial \theta_2} \log \pi_\theta(a|s) \right)^2 \end{bmatrix}$$

## Computing the FIM's Trace

- ▶ We do not need to form the full  $|\theta| \times |\theta|$  matrix!
- ▶ Recall  $F = \mathbb{E}_{a,s \sim \pi_\theta} [\nabla_\theta \log \pi_\theta(a|s) \nabla_\theta \log \pi_\theta(a|s)^T]$ , and let  $g = \nabla_\theta \log \pi_\theta(a|s)$ . Then  $F = \mathbb{E}[gg^T]$ .
- ▶ Since the trace of a matrix is the sum of its diagonal entries  $\sum_i F_{ii}$ , we have (see Petersen and Pedersen 2008):

$$\text{tr}(F) = \sum_i \mathbb{E}[g_i^2] = \mathbb{E} \left[ \sum_i g_i^2 \right] = \mathbb{E}[g^T g] = \mathbb{E}[\|g\|_2^2].$$

- ▶ We can thus form a Monte Carlo estimate of the trace of the FIM by sampling states from collected trajectories and actions from the policy in that state:

$$\text{tr}(F) \approx \frac{1}{N} \sum_{i=1}^N \|\nabla_\theta \log \pi_\theta(a_i|s_i)\|_2^2$$

# Algorithms: DQN and TRPO

- ▶ **Deep Q-Networks (DQN)** (Mnih et al. 2013) are value-based and approximate the optimal action-value function  $Q^*(s, a)$  using a neural network. The agent selects actions based on an  $\epsilon$ -greedy policy derived from the Q-values.
- ▶ **Trust Region Policy Optimization (TRPO)** (Schulman et al. 2017) is a policy gradient method that optimizes the policy directly.
- ▶ TRPO uses a surrogate objective function given by the expected advantage  $\mathbb{E}_{s, a \sim \pi_{\theta_{\text{old}}}} \left[ \frac{\pi_{\theta}(a|s)}{\pi_{\theta_{\text{old}}}(a|s)} A^{\pi_{\theta_{\text{old}}}}(s, a) \right]$ .
- ▶ TRPO constrains the policy updates using a trust region defined by the Kullback-Leibler (KL) divergence to ensure stable learning by  $D_{KL}(\pi_{\theta_{\text{old}}} || \pi_{\theta}) \leq \delta$  for some small  $\delta$ .