On the Existence of Double-Descent in Reinforcement Learning

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Outline

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.
- 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)

Classical U-shaped Risk Curve

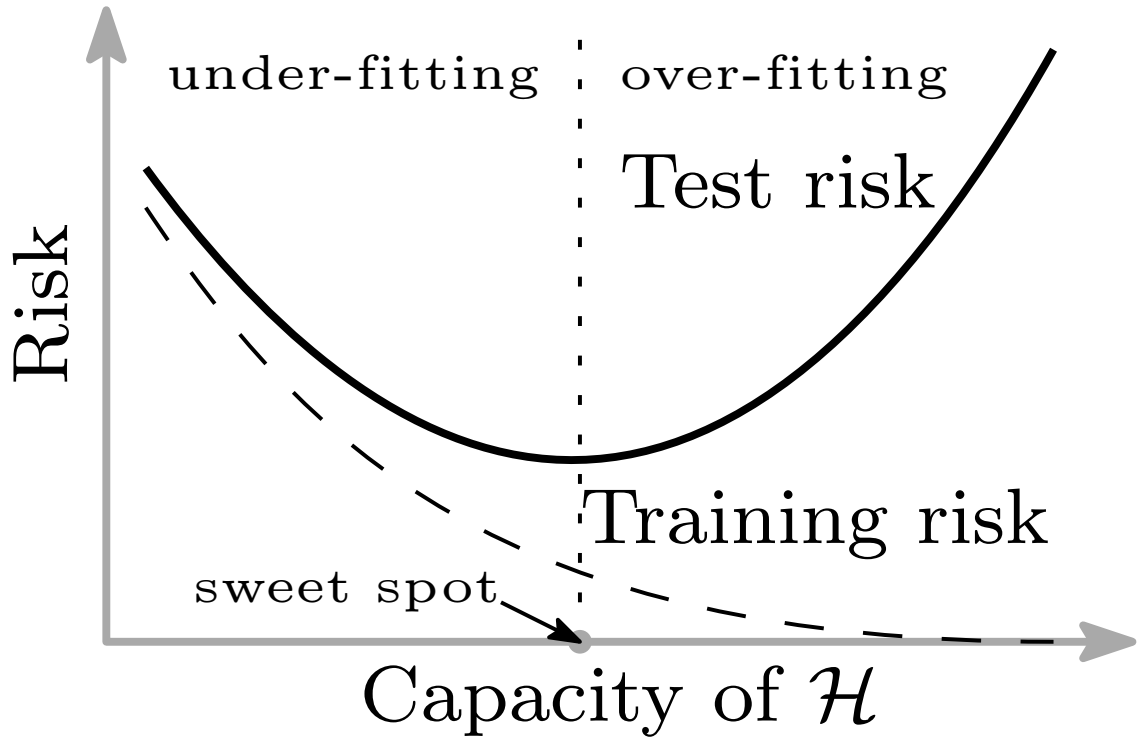

Figure: Classical U-shaped risk curve arising from the bias-variance trade-off. Belkin et al. (2019).

Double Descent Risk Curve

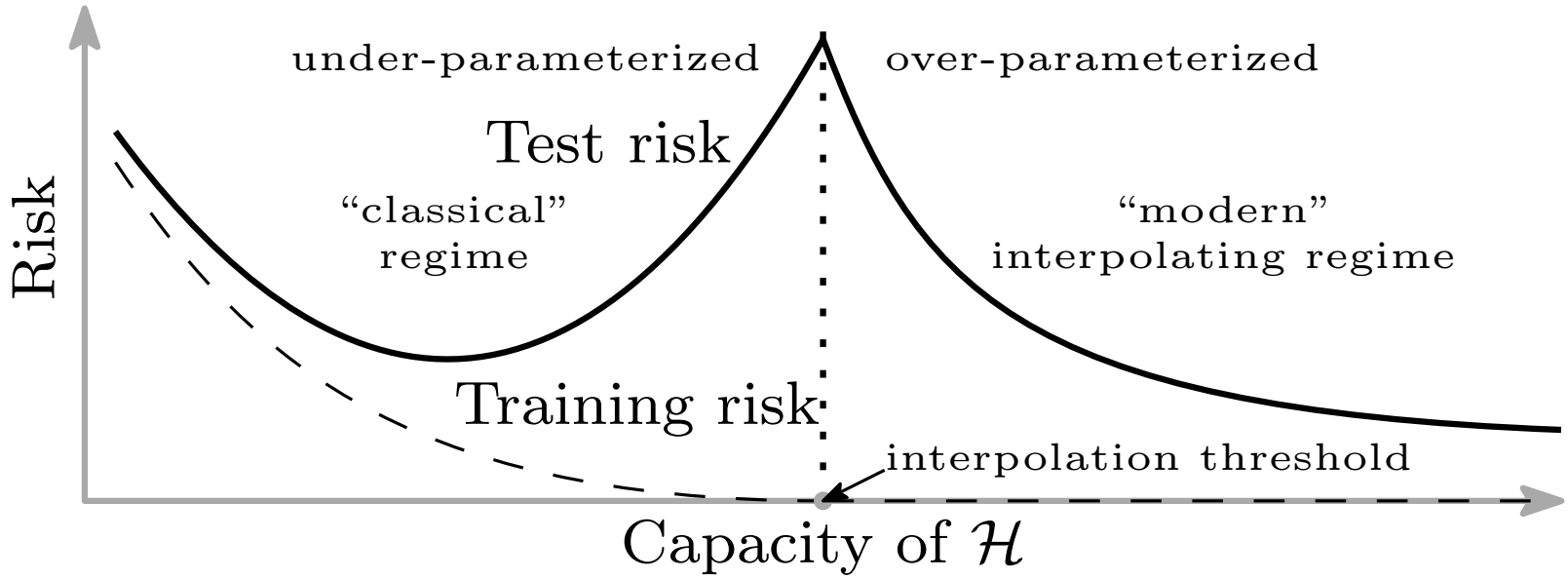

Figure: Double Descent risk curve exhibiting a second descent Belkin et al. (2019).

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.

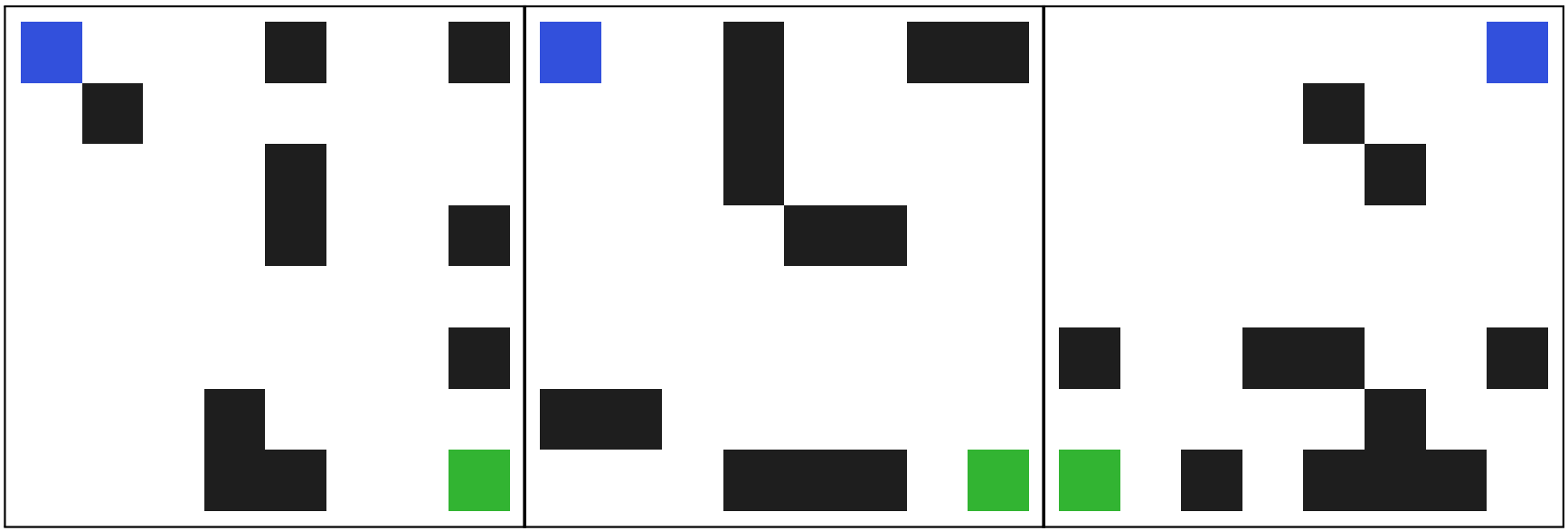

Figure: Examples of randomly generated training and validation environments, with agent (blue) and goal (green) tiles.

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 π_θ, collected on the training maps.
- 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.
- 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

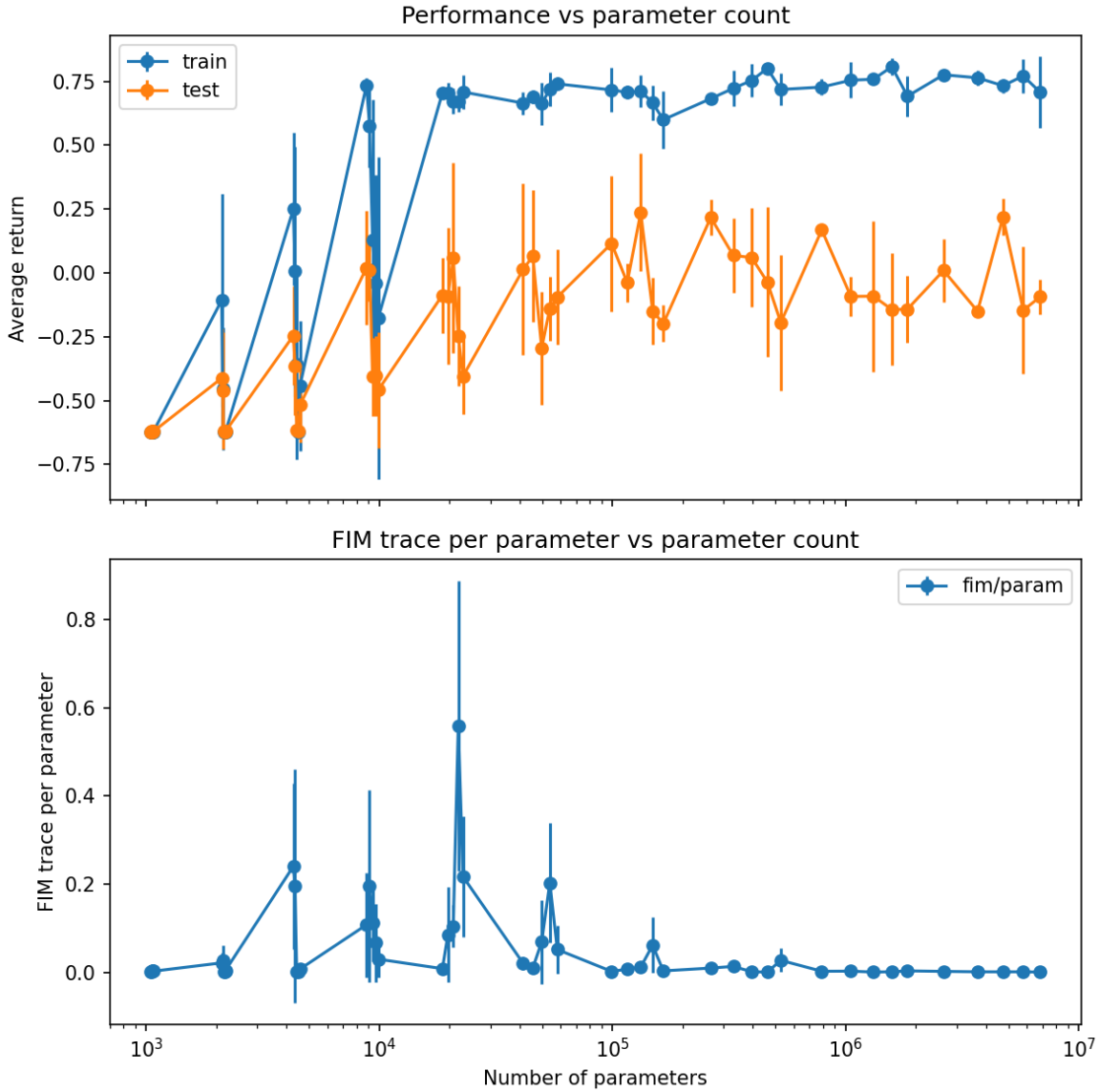

Figure: Results from TRPO agents trained on 100 maps for 50k episodes.

Results in Episodic Regime

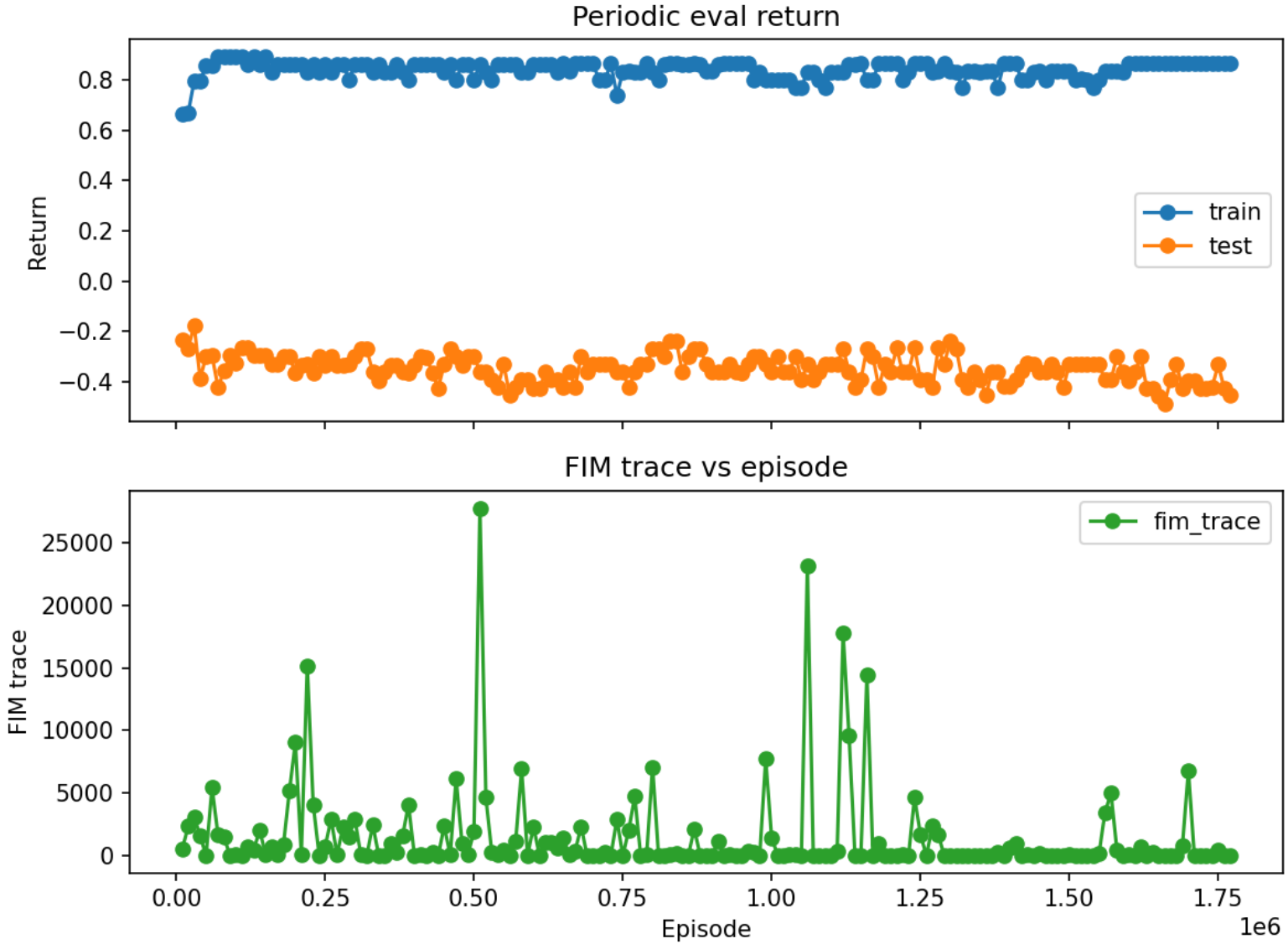

Figure: Results of a TRPO agent trained on 100 maps for 1.8M episodes.

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.
- Further, training on larger maps as well as different algorithms could be explored, as well as stochastic transitions.

References I

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Thank You!

Questions?

Environment Details

- Each map is 8×8 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 blocked, with a guaranteed path.
- 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.
- Action space: up, right, down, left, deterministic transitions.
- Observation space: 8×8 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[1]
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

[1] Agent starts in top left, goal in bottom right

The Fisher Information Matrix

- The **Fisher Information Matrix** (FIM) is defined as:

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

- s, a are sampled from trajectories under the policy π_θ, collected on the training maps.
- θ are the policy parameters
- $\nabla_\theta \log \pi_\theta(a|s)$ 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 2×2 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 use Hutchinson's estimator for the trace to avoid forming the full FIM (Hutchinson 1989):

$$\text{trace}(F) = \mathbb{E}[k^T F k]$$

  where k is a vector with entries sampled from a Rademacher distribution $\{-1, 1\}$.
- Fisher vector products are implemented as part of the TRPO algorithm, so we can compute Fk without forming F explicitly.
- Our implementation samples 50 state-action pairs and 4 random vectors k per pair to compute an empirical estimate of the trace, for 200 total samples.