

EFFICIENTLY TRAINING NEURAL NETWORKS FOR IMPERFECT INFORMATION GAMES BY SAMPLING INFORMATION SETS

Timo Bertram, Johannes Fürnkranz, Martin Müller
Johannes Kepler University Linz, University of Alberta

KI 2024



**RECONNAISSANCE
BLIND CHESS**

The background is a dark blue gradient. On the left side, there are several abstract, colorful shapes. At the top left, there is a large, thick ring with a gradient from bright cyan to orange. Below it, there are several thick, wavy lines that also follow the cyan-to-orange gradient, creating a sense of movement and depth. The text is centered in the middle of the frame.

IMPERFECT INFORMATION GAMES



The background is a dark blue gradient. On the left side, there are several abstract, colorful shapes. At the top left, there is a large, thick ring with a gradient from bright cyan to orange. Below it, there are several thick, wavy, ribbon-like shapes that also follow the cyan-to-orange gradient, curving and overlapping each other. The text is centered in the middle of the image.

RECONNAISSANCE BLIND CHESS







Opponent: Trout

Color: White

Sense ---- :

No capture

Sense c7 :



No capture

Sense f5 :



No capture

Sense d6 :



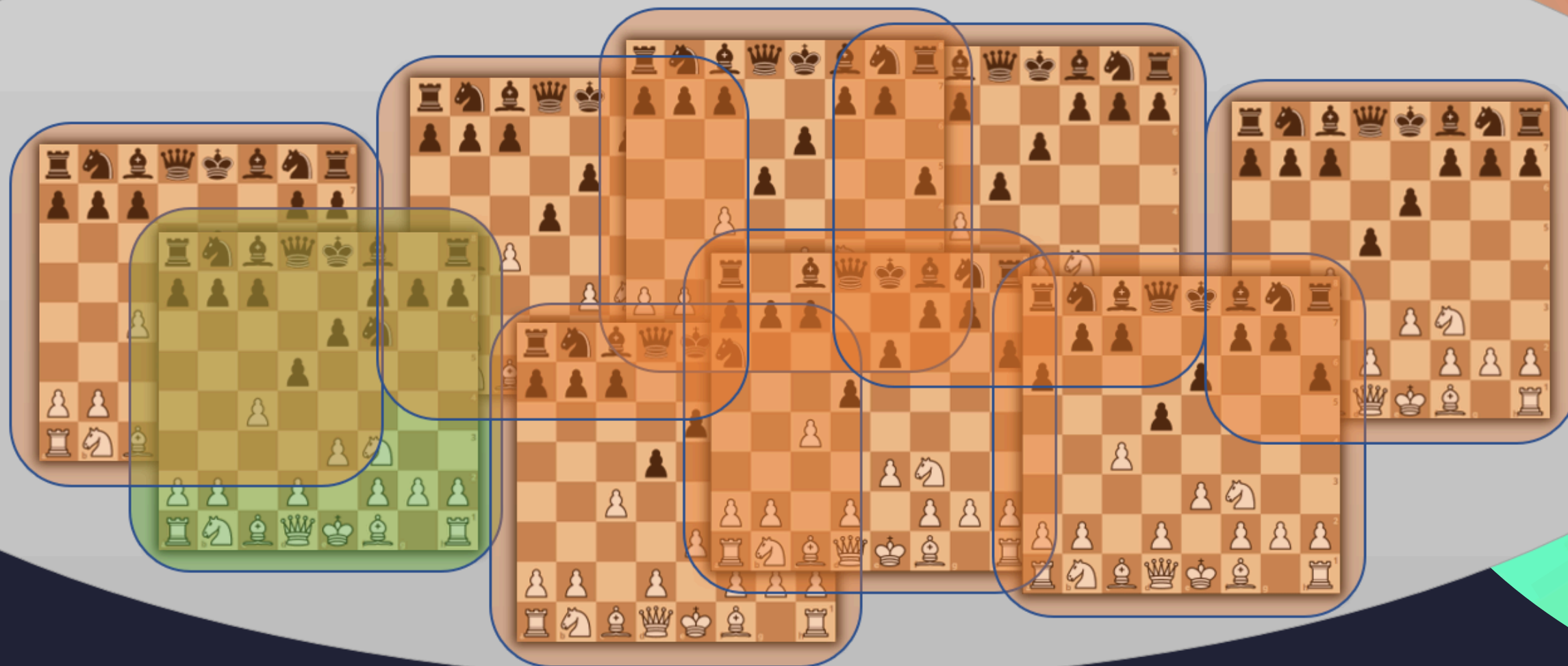
Move e3 : ✓

Move c4 : ✓

Move Nf3: ✓



Information Set



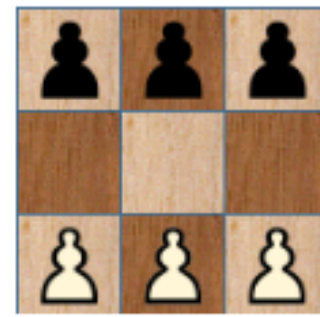


APPROXIMATING INFORMATION SETS

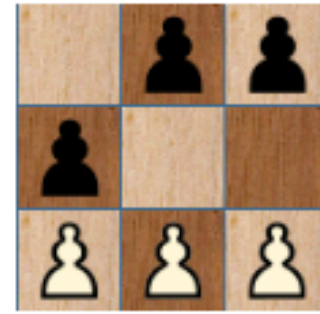
Information
Set $\mathcal{I} = \{ (\mathbf{x}, \mathbf{h}^{(i)}) \}$

Perfect Information
Evaluations $f(\mathbf{x}, \mathbf{h}^{(i)})$

Imperfect
Information
Position \mathbf{x}



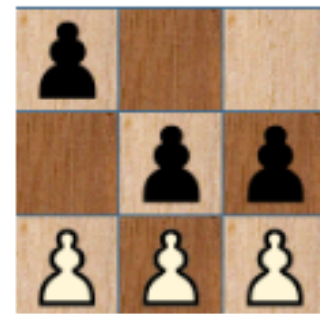
0.5



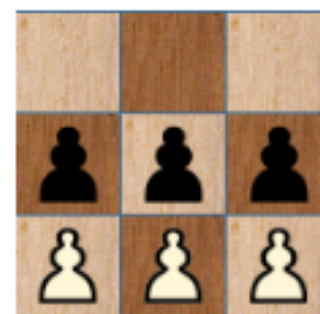
0.33

...

...



0.17



0.0

Aggregated Imperfect
Information Evaluation


$$\hat{y} = \frac{1}{n} \sum_{i=1}^n f(\mathbf{x}, \mathbf{h}^{(i)})$$

$$\hat{y} = 0.25$$

n training positions


k samples each

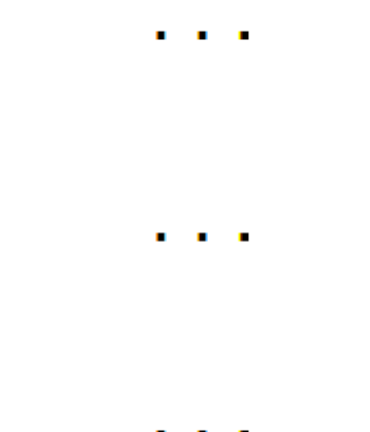
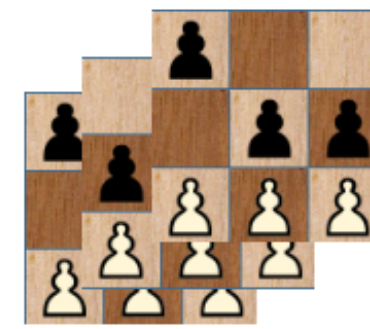
$(\mathbf{x}_1, \hat{y}_1)$

	0.28
--	------

...	...
...	...
...	...

$(\mathbf{x}_n, \hat{y}_n)$

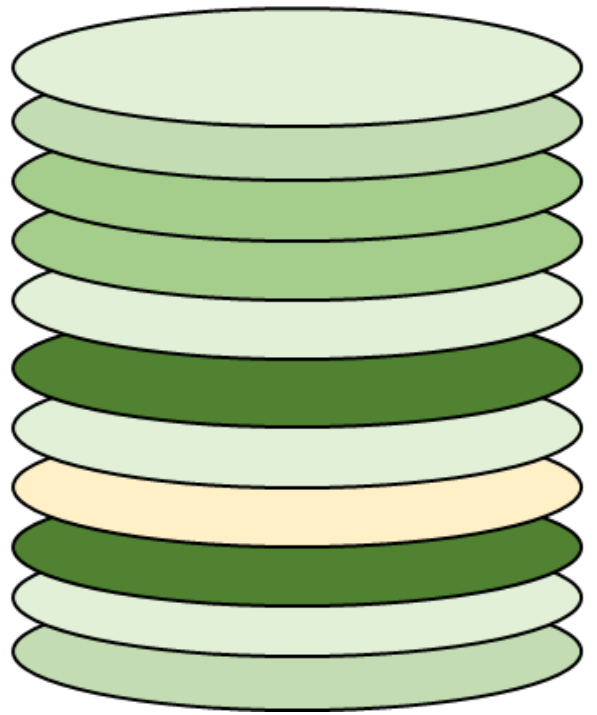
	0.46
--	------



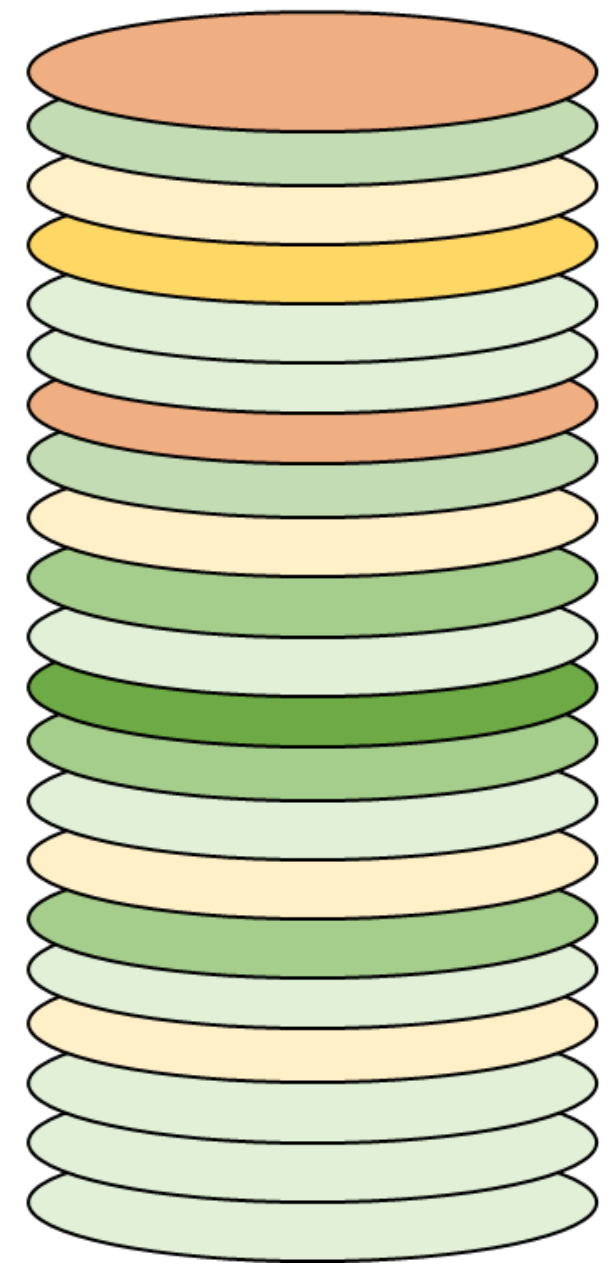
Budget of
 $N = n \cdot k$
Perfect
Information
Evaluations

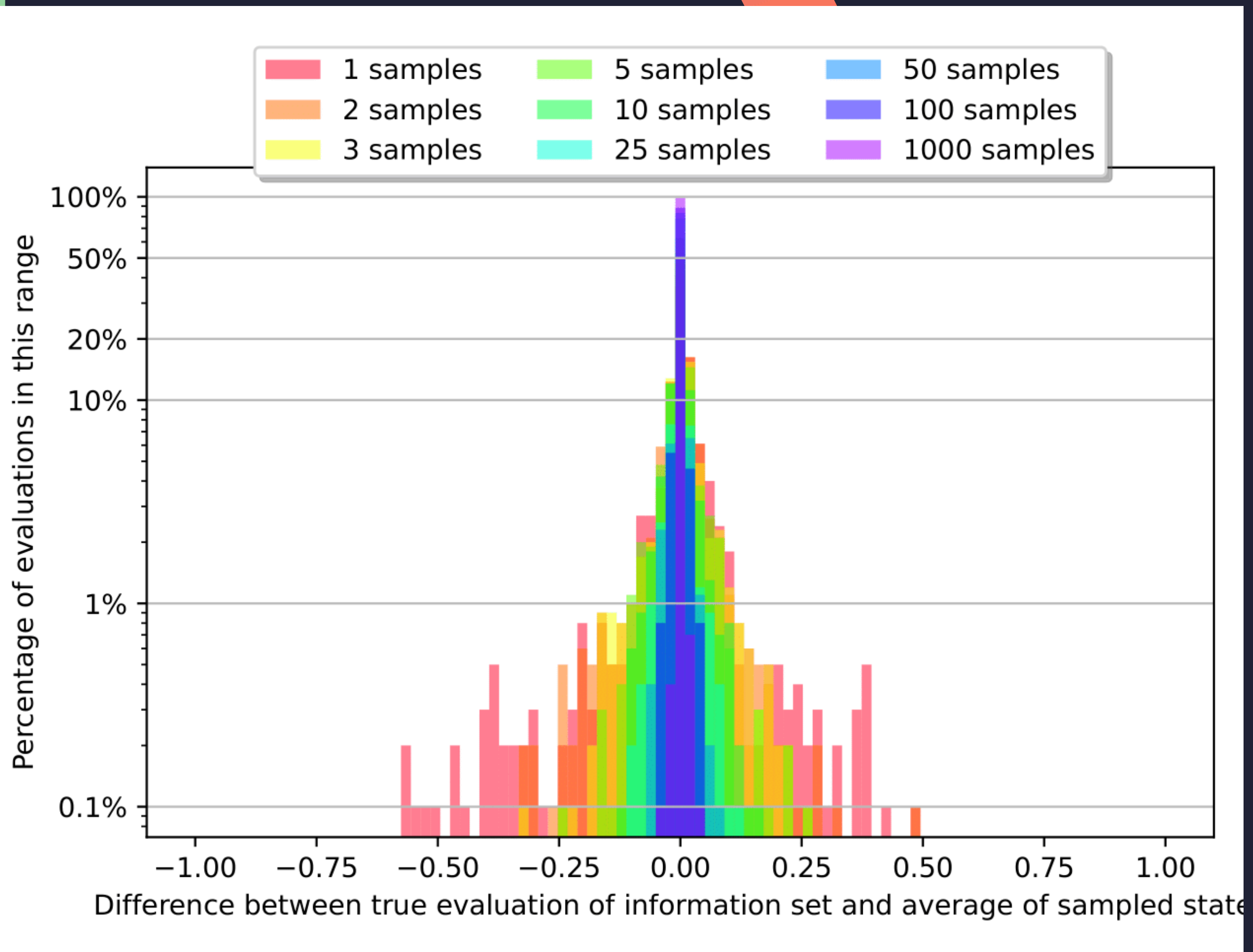
Learn function $g(\cdot)$ such that
 $g(\mathbf{x}) \approx \hat{y}$

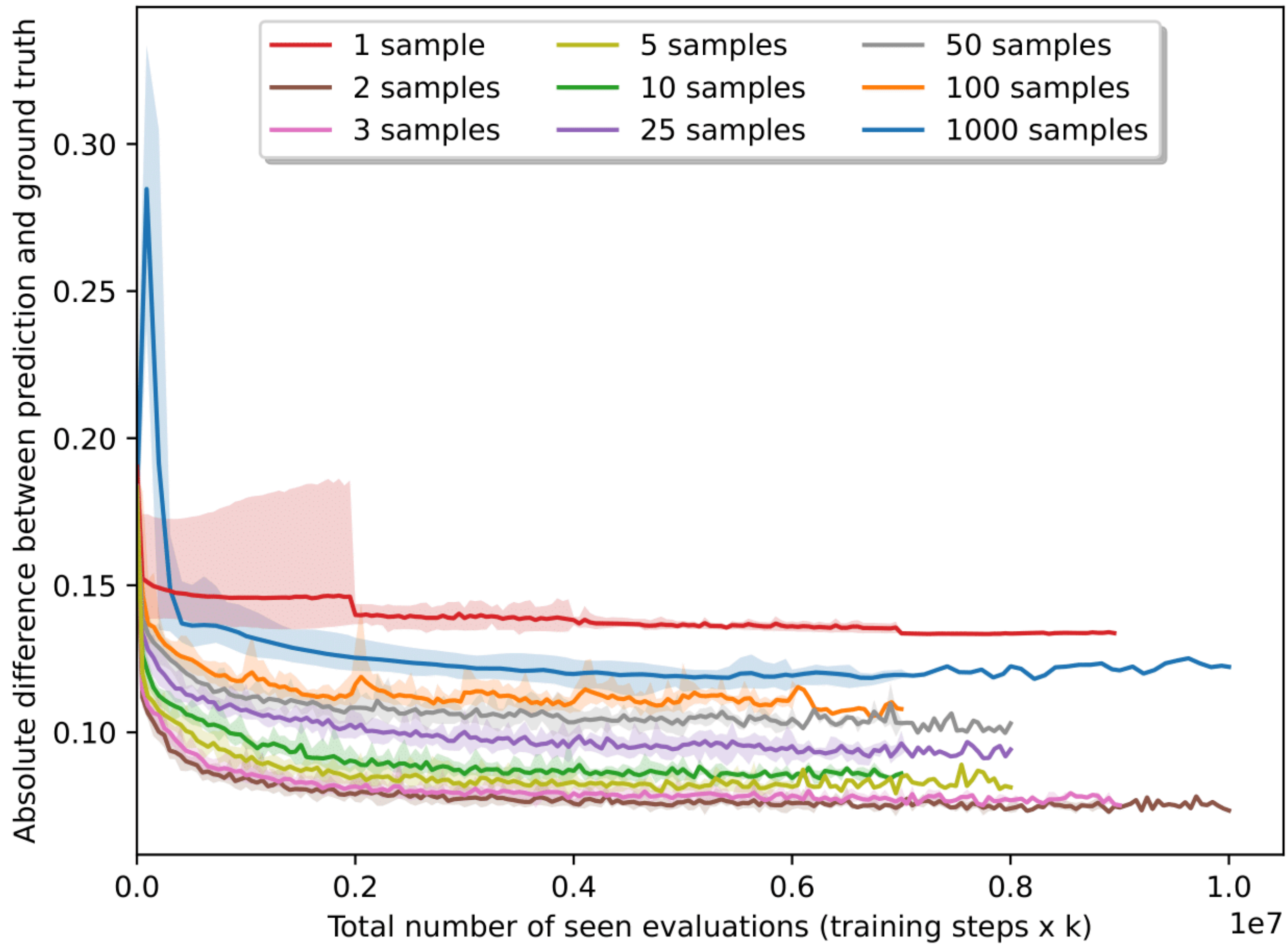
Larger k
Smaller n

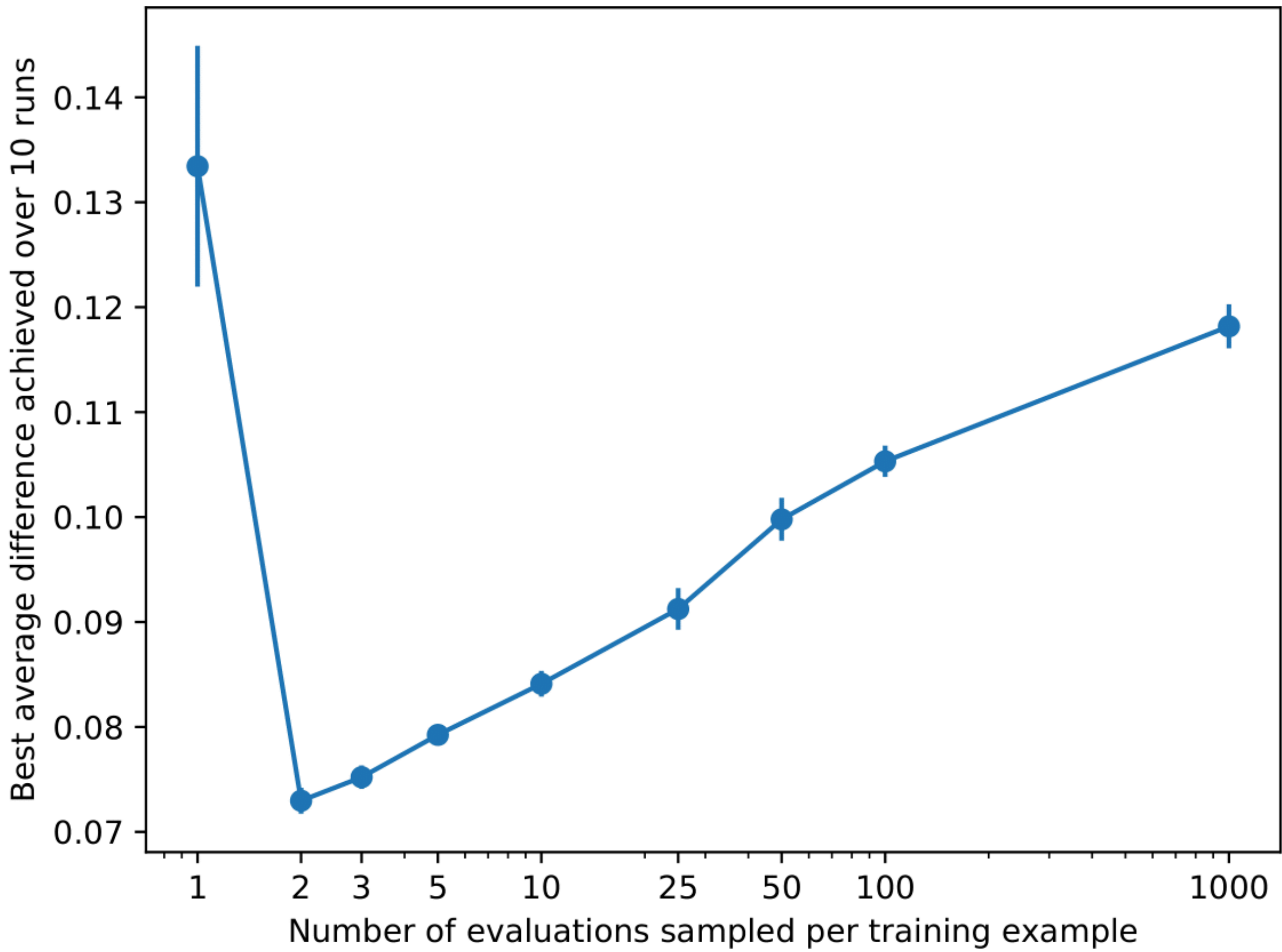


Smaller k
Larger n

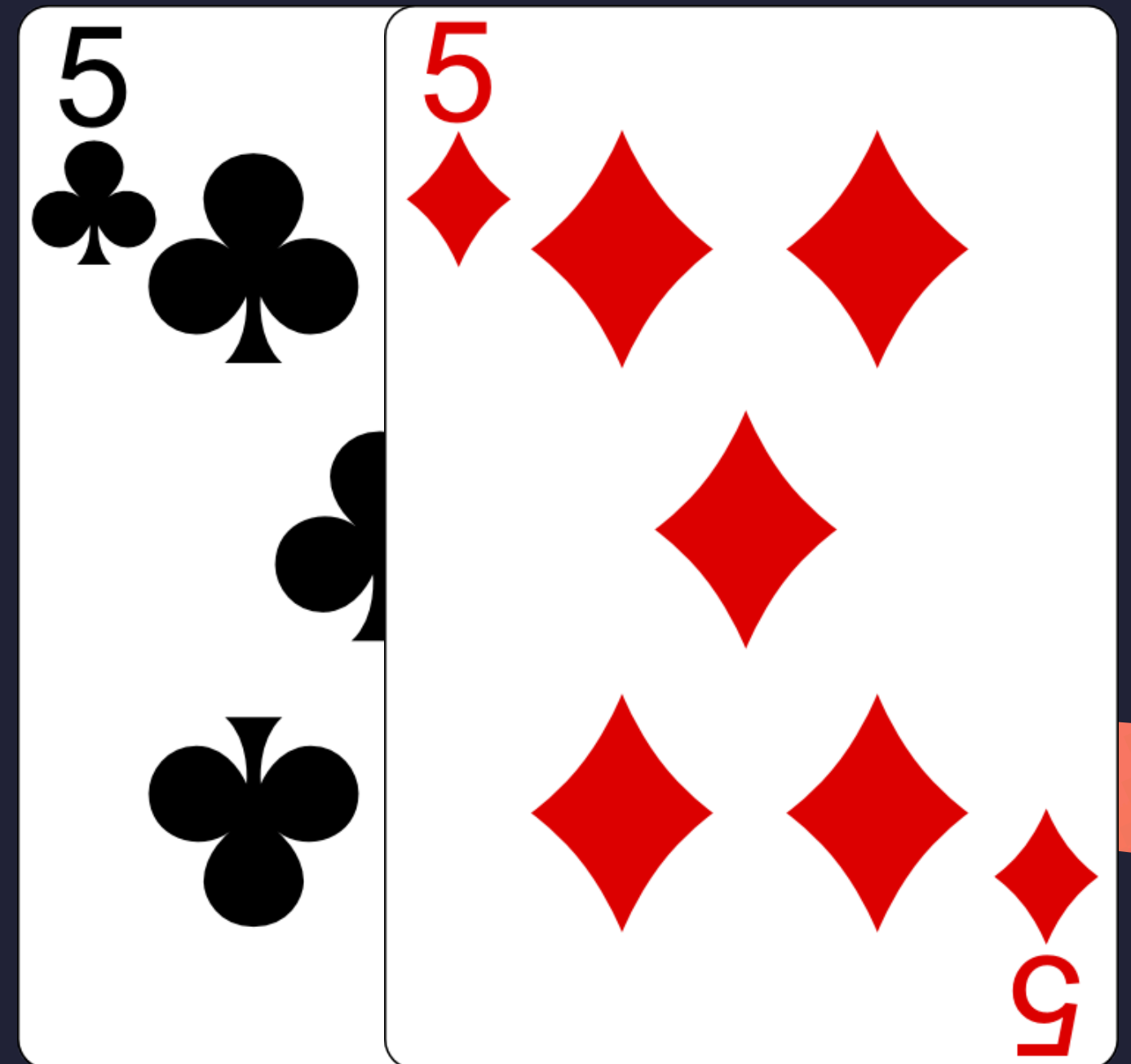
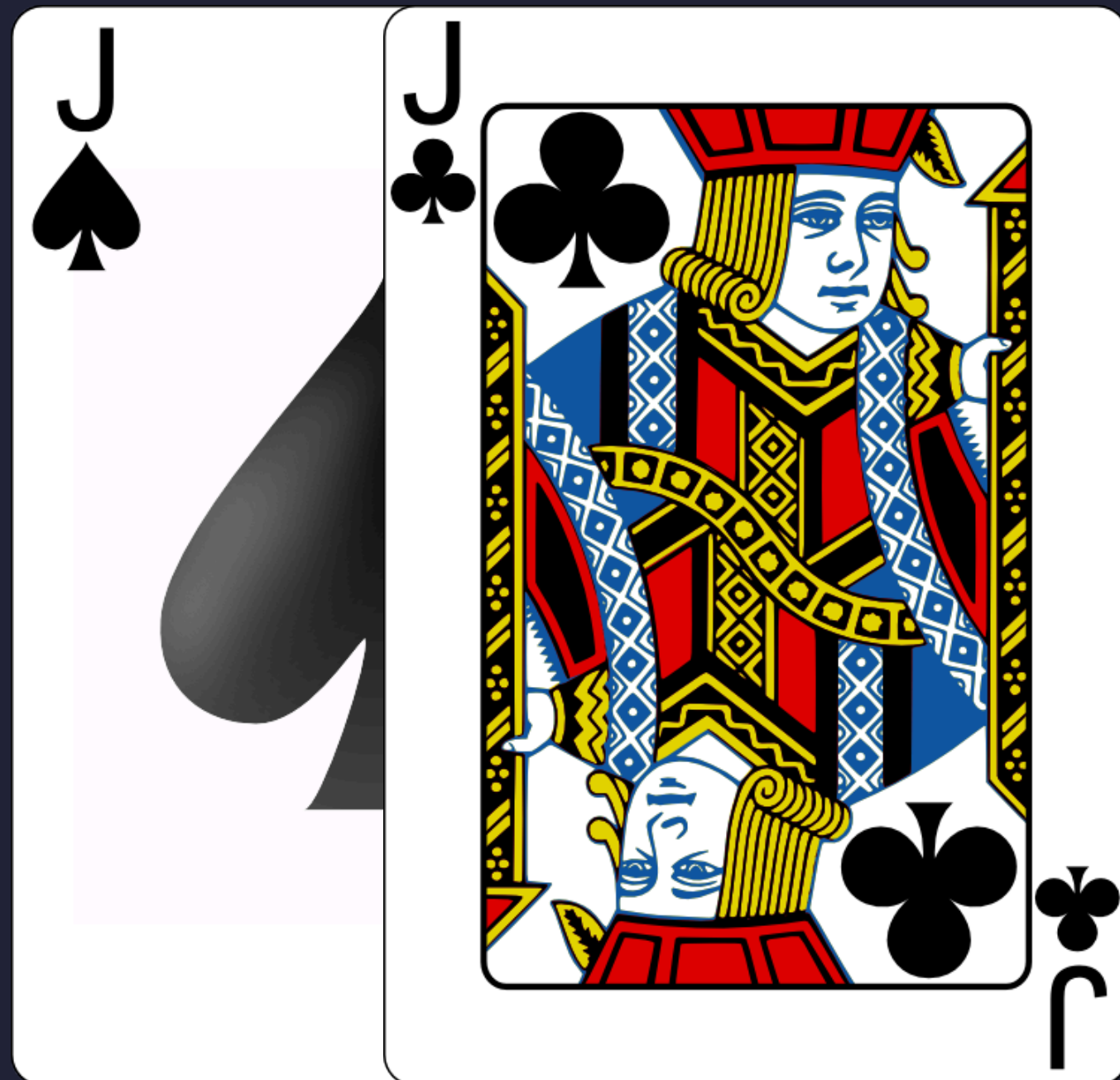




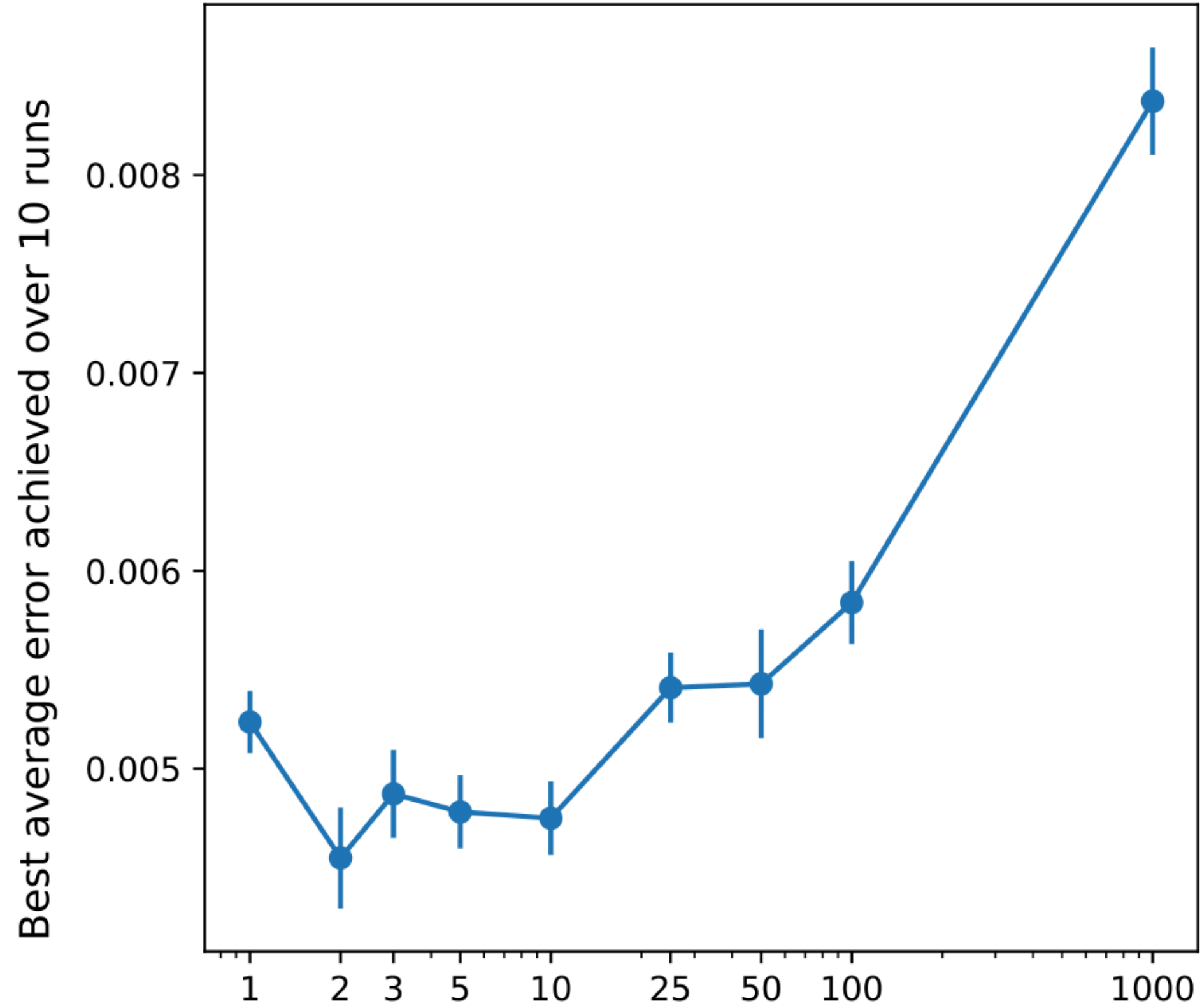




What is better?



Given 100 million evaluations



Takeaways

We want to build training datasets based on subsets of information sets

There is a clear trade-off between approximating more sets and receiving better estimates

Using 2 samples per information set empirically worked best



THANK YOU!

TBERTRAM@FAW.JKU.AT

@BERTRAMTIMO