

# Sample-efficient Bayesian optimisation using known invariances

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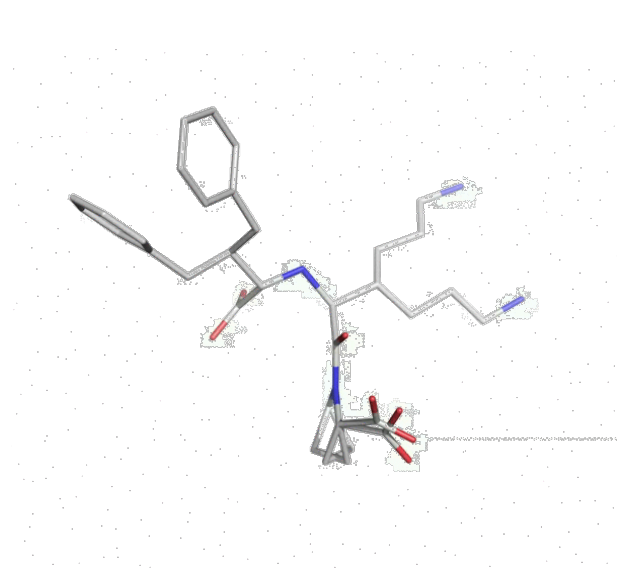
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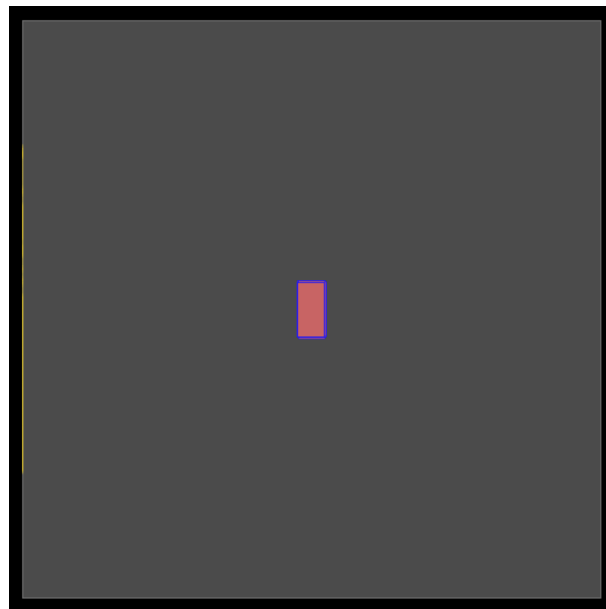
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# Bayesian optimisation

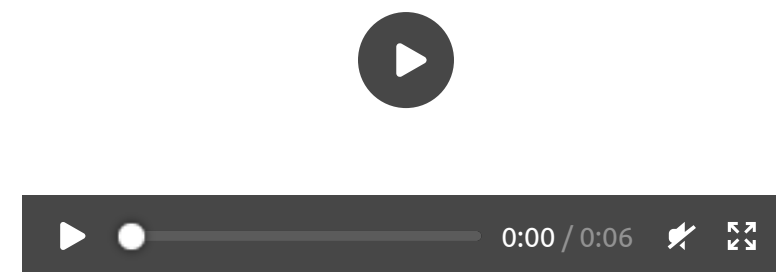
*Wide range of applications*



Drug discovery [C4XD]



Chip design [NVIDIA]



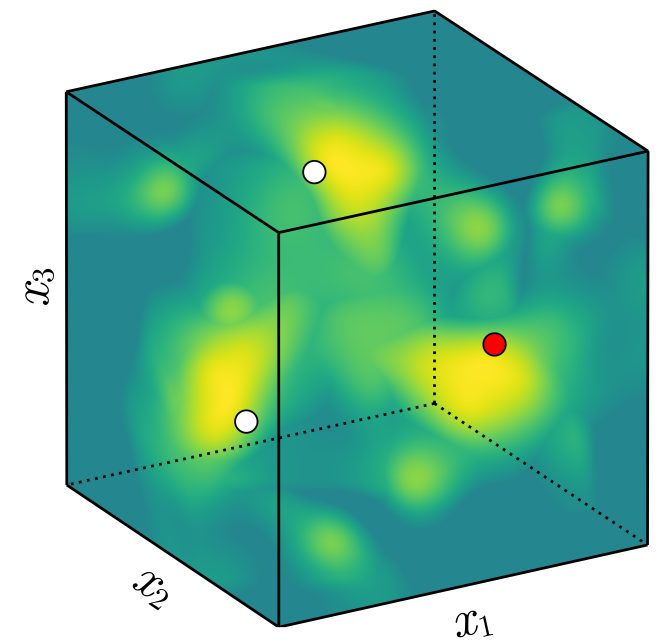
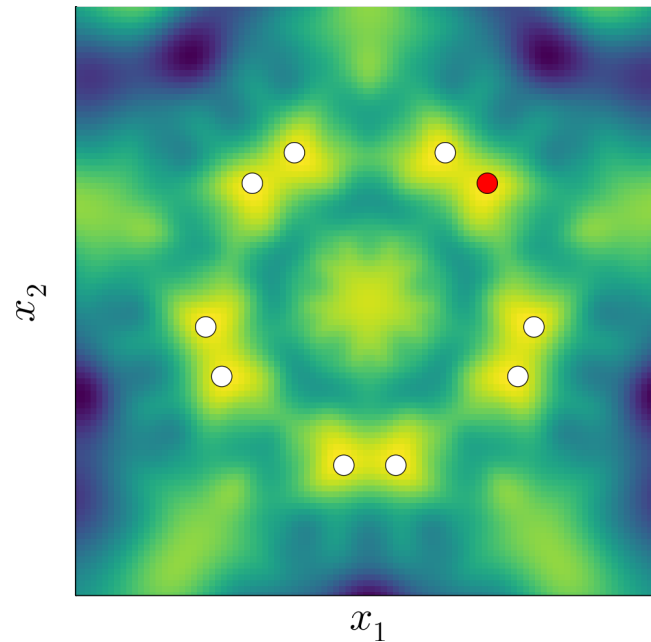
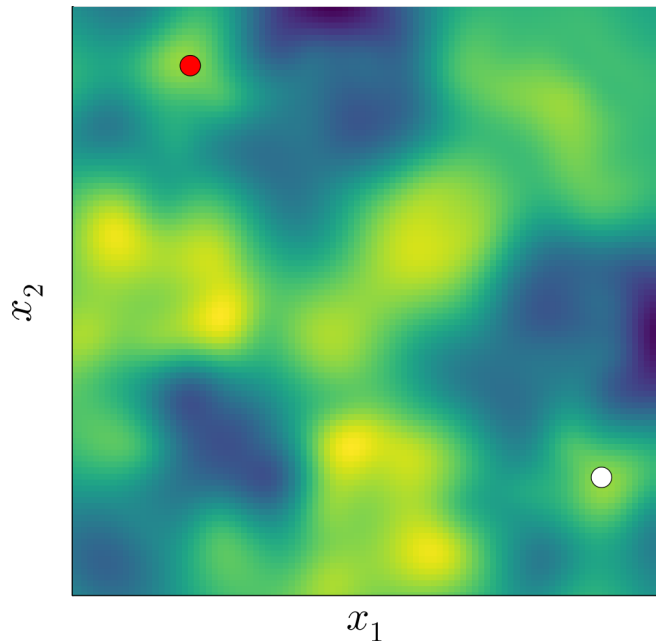
Nuclear fusion reactors  
[Proxima Fusion]

Goal: sample efficiency

# Symmetry and invariance

*How can we exploit symmetry in BO?*

- Objective function is known to be symmetric
- Key insight: **making one observation gives additional information**
- In the noiseless case, this is perfect information



# Invariant Gaussian processes

*Naive method: data augmentation*

- Key insight: **making one observation gives additional information**
- Data augmentation: add transformed data to dataset

$$\mathcal{D} \leftarrow \mathcal{D} \cup \{(\sigma(x), f(x)) \mid \forall \sigma \in G, x \in \mathcal{D}\}$$

- **Problem:** computational cost of GP scales with  $\mathcal{O}(|G|^3 n^3)$

**Can we do better?**

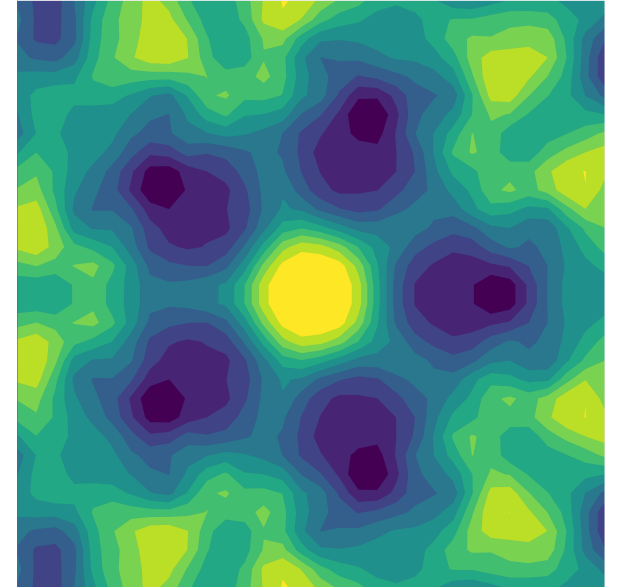


# Invariant Gaussian processes

*Our method: invariant kernel*

- Construct an invariant kernel:

$$k_G(x, x') = \frac{1}{|G|} \sum_{\sigma \in G} k(x, \sigma(x'))$$



- GPs with this kernel are distributions over **invariant functions!**

Compute cost reduced from  $\mathcal{O}(|G|^3 n^3)$  to  $\mathcal{O}(|G| n^3)$

# Sample complexity for invariant kernel BO

*Number of samples  $T$  for precision  $\epsilon$*

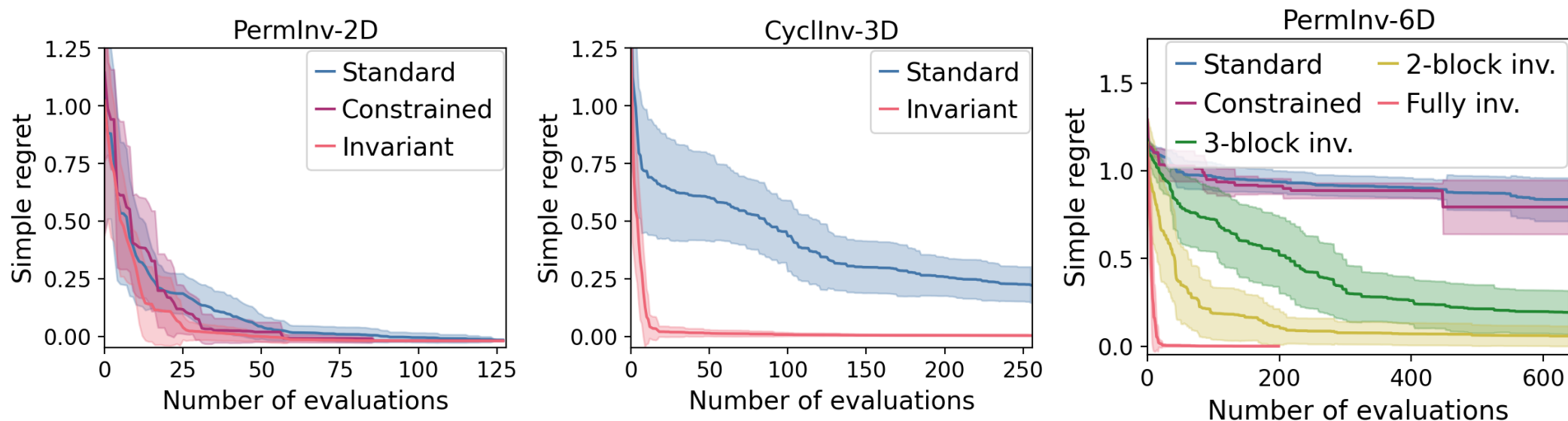
- Our upper bound:

$$T = \tilde{O} \left( \left( \frac{1}{|G|} \right)^{\frac{2\nu+d-1}{2\nu}} \epsilon^{-\frac{2\nu+d-1}{\nu}} \right)$$

- Large  $|G|$  → **large reduction in number of samples**
- Lower bound in our paper

# Synthetic experiments

## *Invariant GP-MVR*

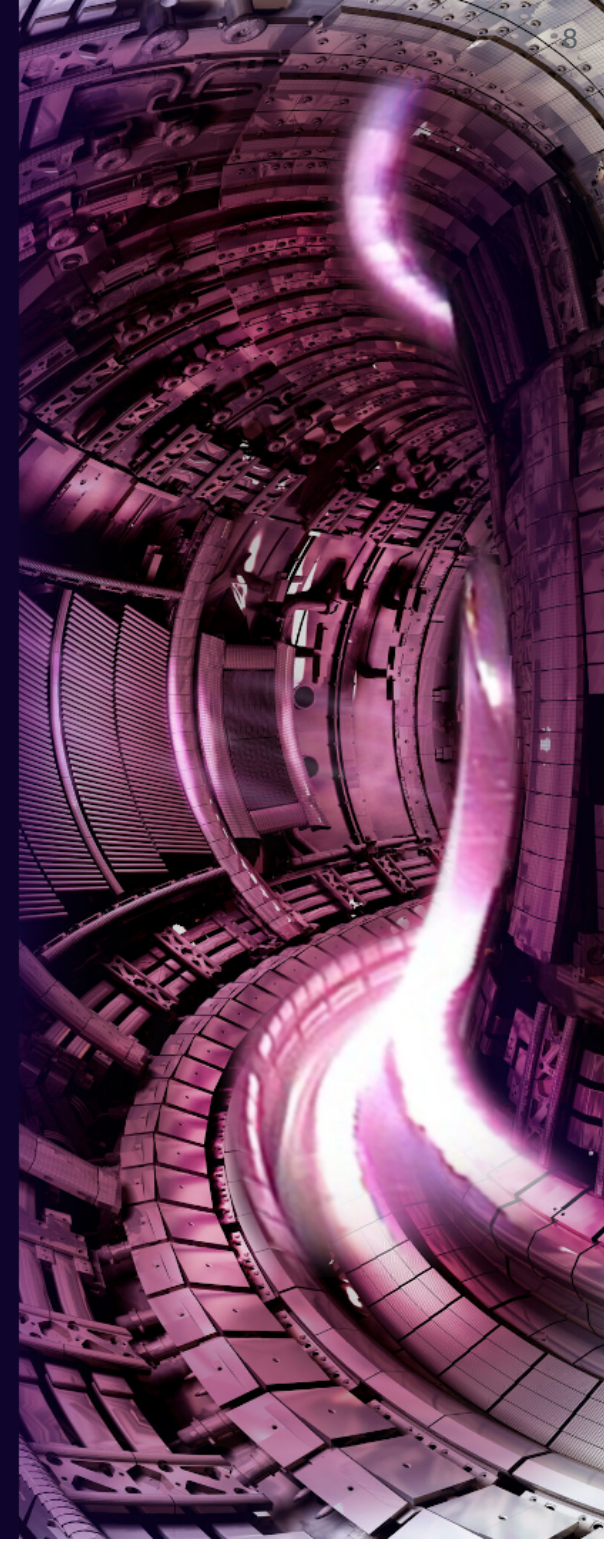
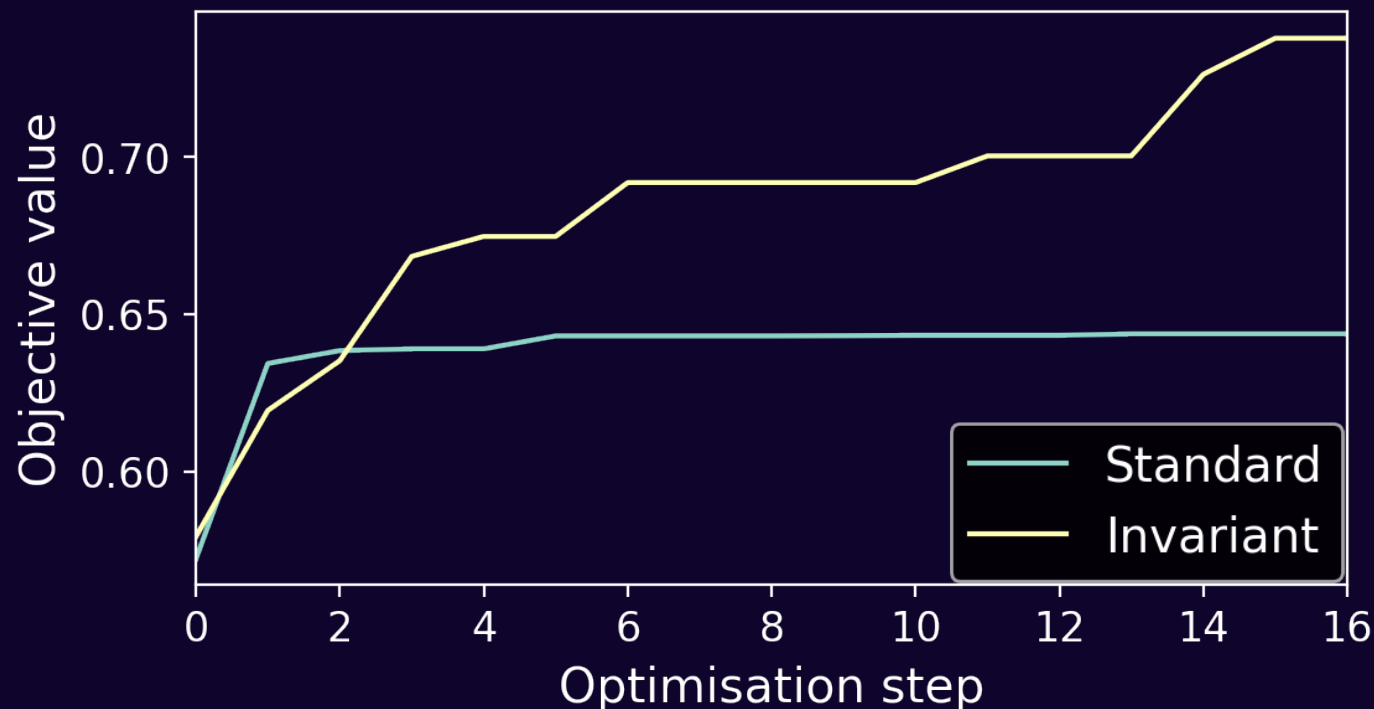


- **Invariant** beats **standard**
- **Invariant** beats **constrained**
- Use **subgroups** for low-cost approximation (**2-** and **3-** block invariance)

# Application: fusion reactor design

*High-temperature plasma* → zero-carbon, low-waste energy

- **Task:** find an operating point with high stability
- Actuators are **permutation invariant**
- Using an invariant kernel achieves better results!



# Sample-efficient Bayesian optimisation using known invariances

 Check out our [poster](#)

 Read the paper on [arXiv](#)

 See our [blog](#) for more info

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