Gittins Indices for Bayesian Optimization: Insights from Pandora's Box

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Joint work with Raul Astudillo, Peter Frazier, Ziv Scully, and Alexander Terenin

Joint PhD Colloquium @ NYC Ops Day

Bayesian Optimization

Goal: optimize expensive-to-evaluate black-box function

$\in$ decision-making under uncertainty

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Applications:
Hyperparameter tuning
Drug discovery
Control design

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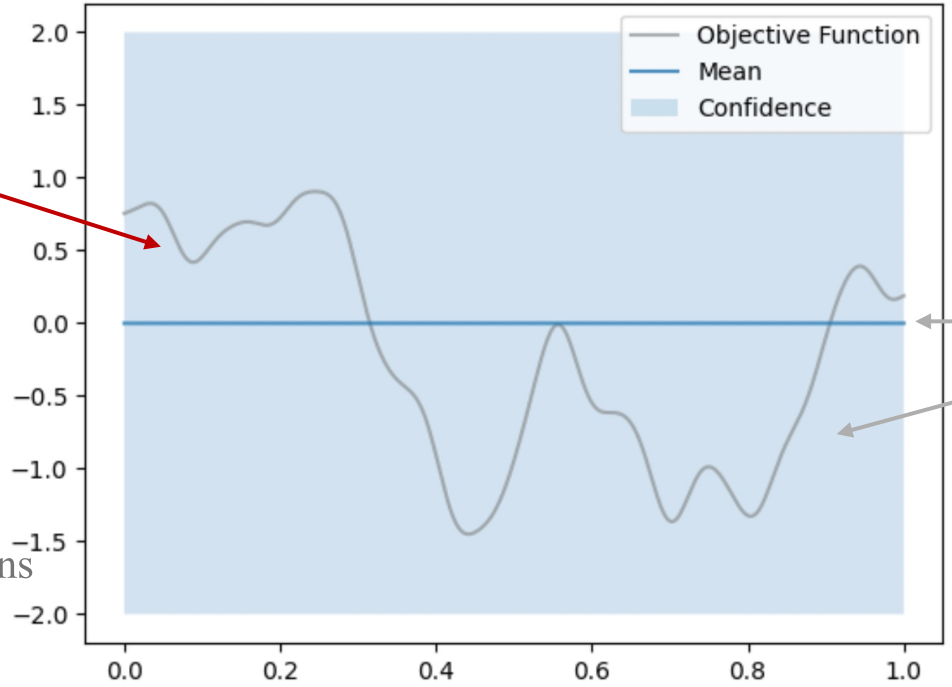
An unknown random function $f: \mathcal{X} \to \mathbb{R}$ drawn from a Gaussian process prior

Gaussian process: infinite-dimensional generalization of multivariate normal distributions



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x: hyperparameter/configuration

mean: prediction

variance: confidence/uncertainty

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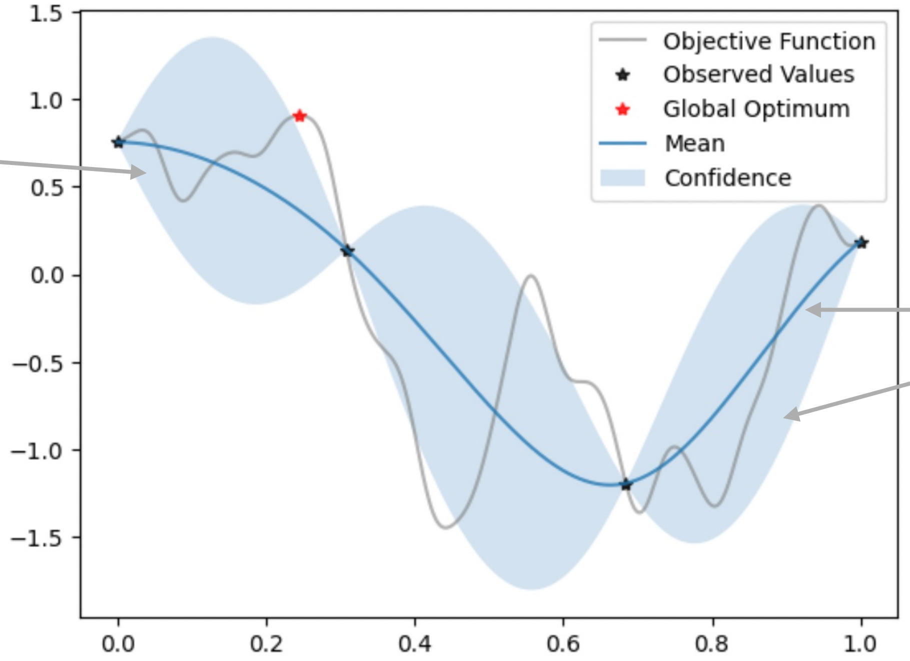

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Objective: find global optimum $x^* = \text{argmax}_{x \in \mathcal{X}} f(x)$

Decision: evaluate a set of points

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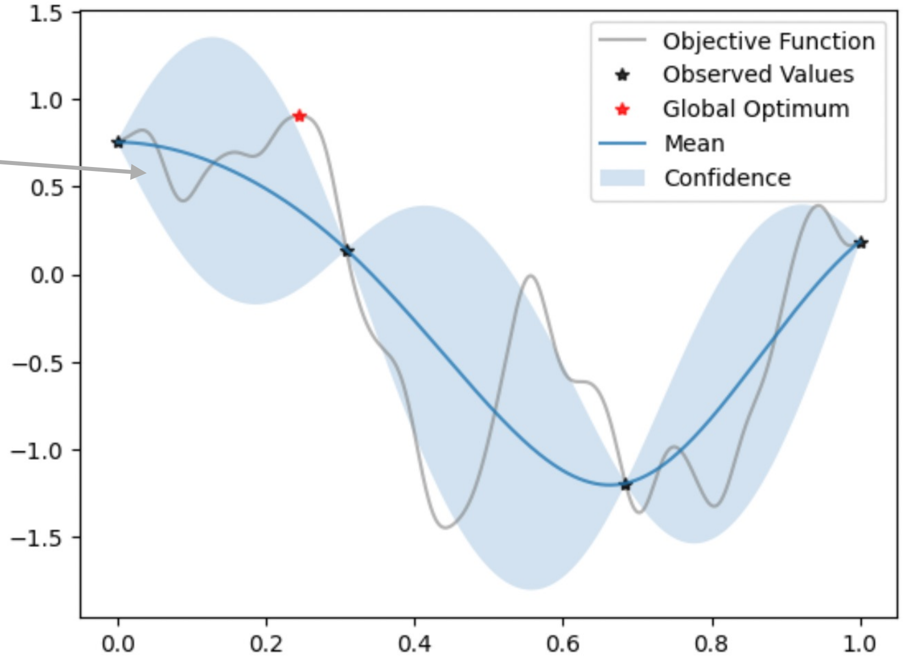

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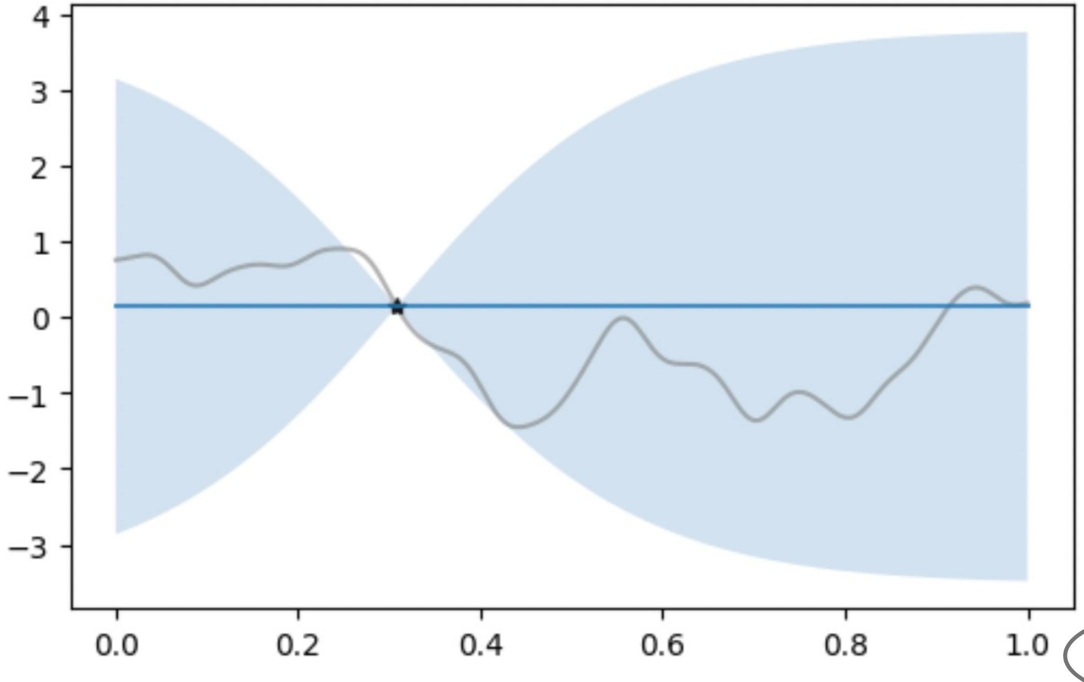

adaptively

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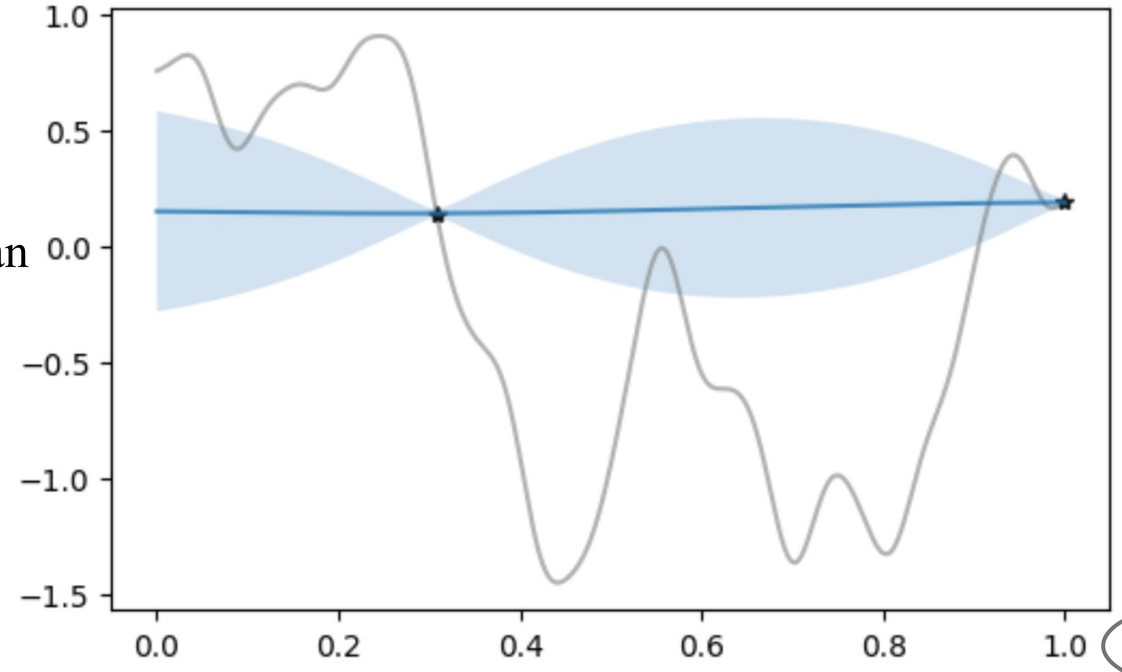

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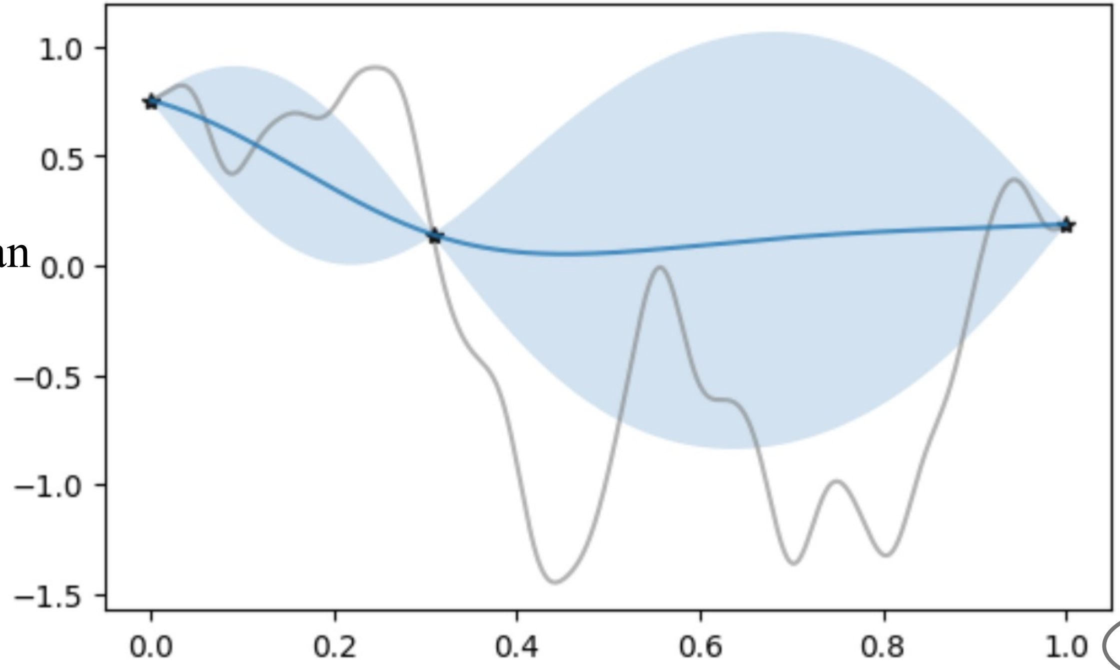

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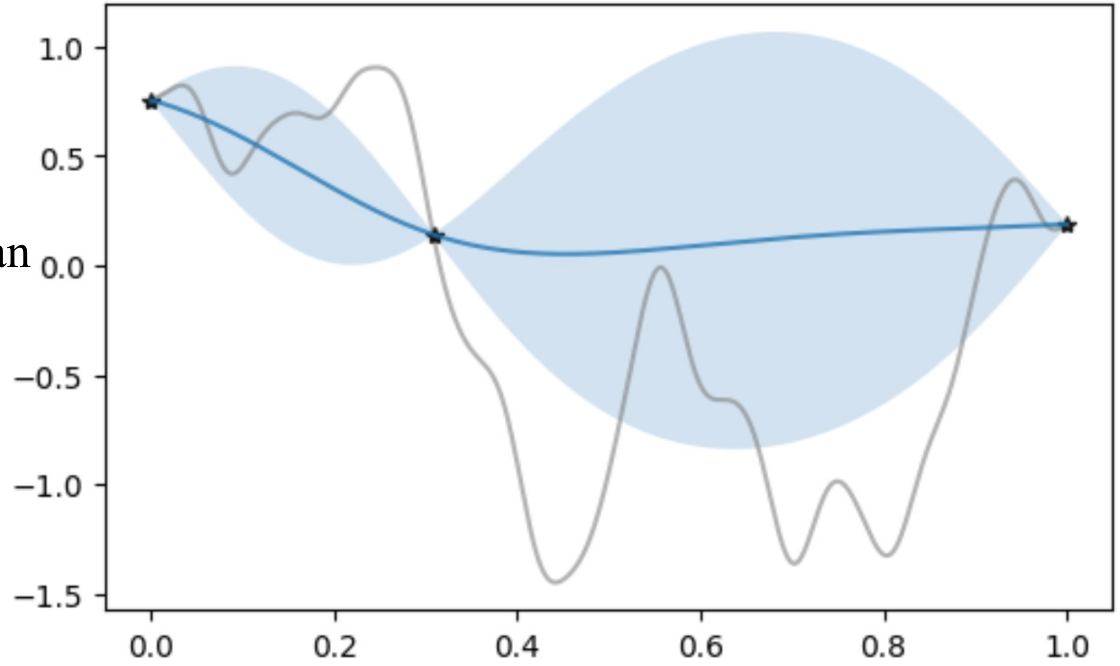

Applications:
Hyperparameter tuning
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x: hyperparameter/configuration

Decision: adaptively evaluate a set of points

$$x_1, x_2, \dots, x_T \in \mathcal{X}$$

T: time budget

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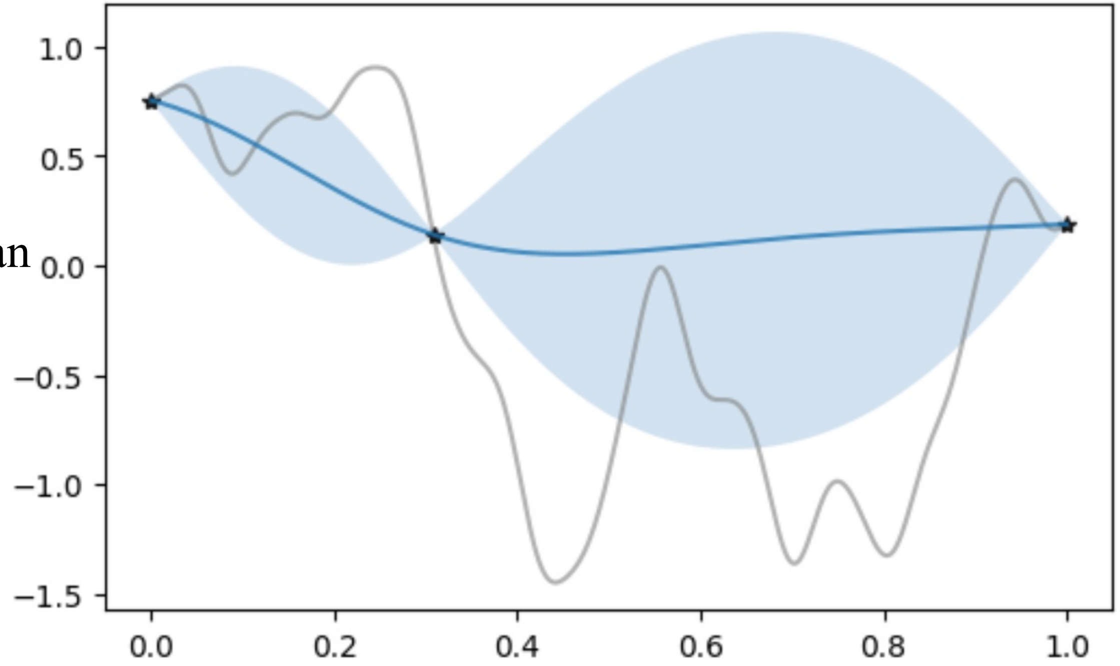


Objective: optimize best observed value at time T

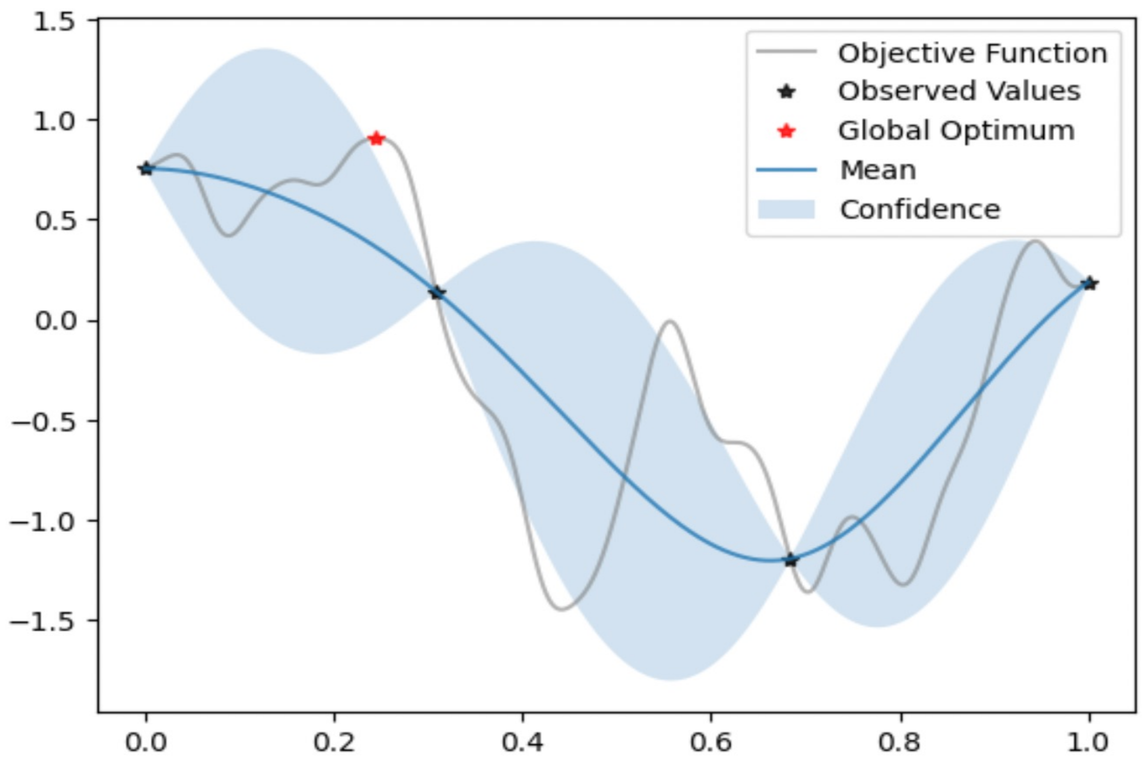
$$\max_{\text{policy}} \mathbb{E} \max_{t=1,2,\ldots,T} f(x_t)$$

Decision: adaptively evaluate a set of points

$$x_1, x_2, \ldots, x_T \in \mathcal{X}$$

T: time budget

Why is it hard?



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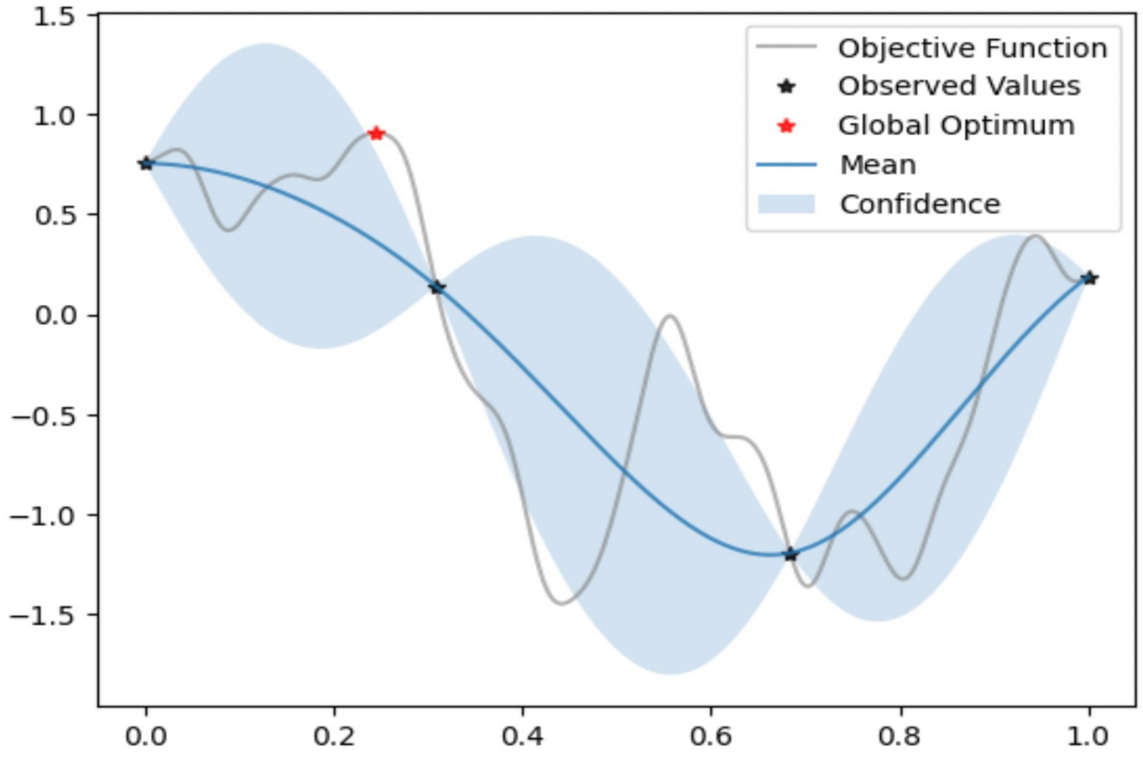
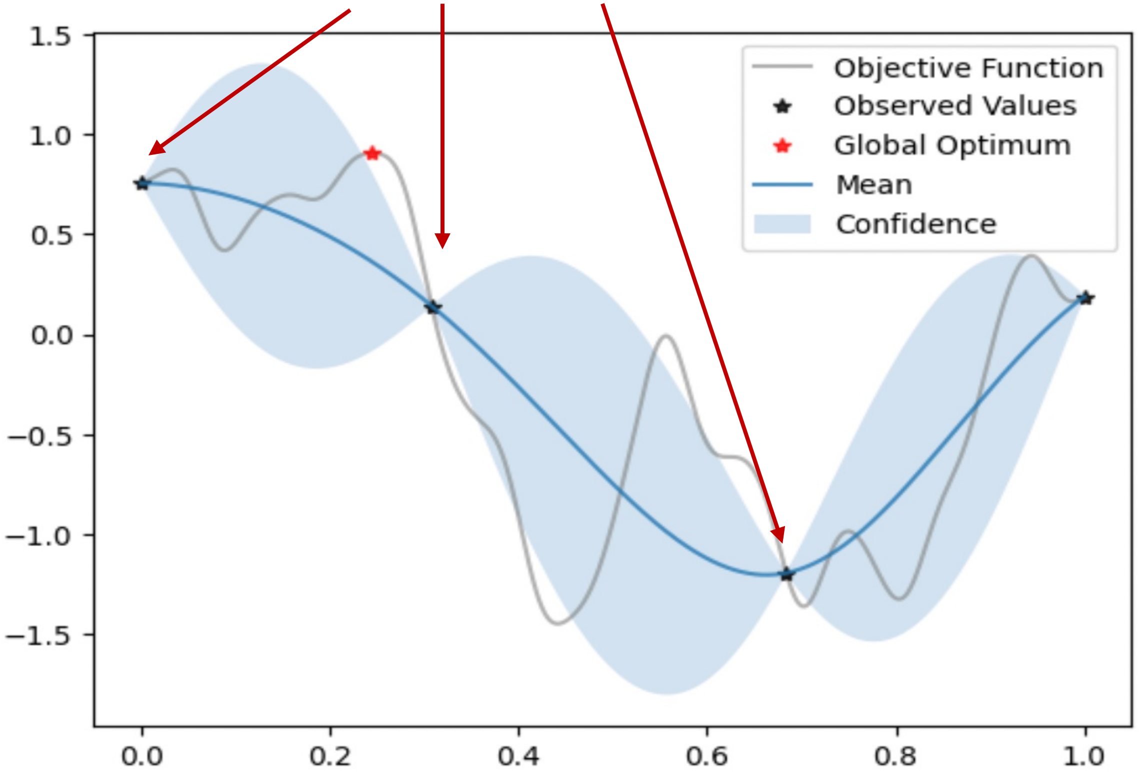


Continuous search domain

Why is it hard?

Correlated values



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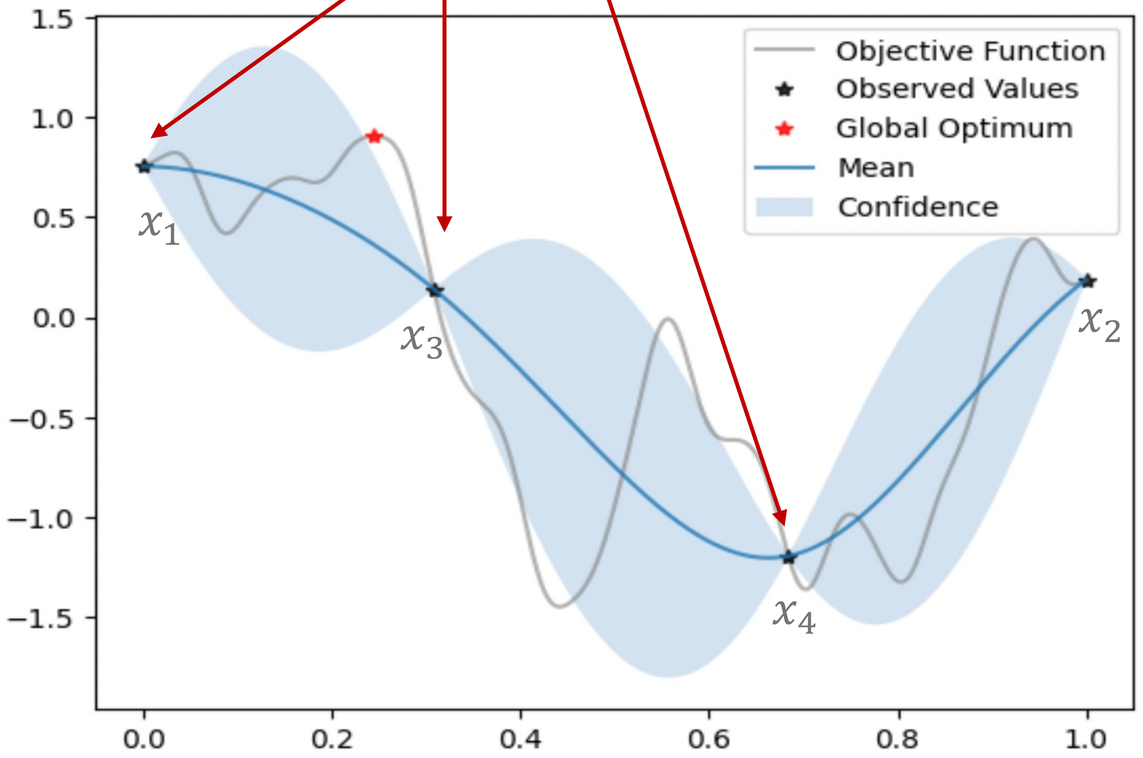

Continuous search domain

Hard budget constraint

~~$t = 1$~~

~~$t = 2$~~

~~$t = 3$~~

~~$t = 4$~~

$\vdots$

$t = T$

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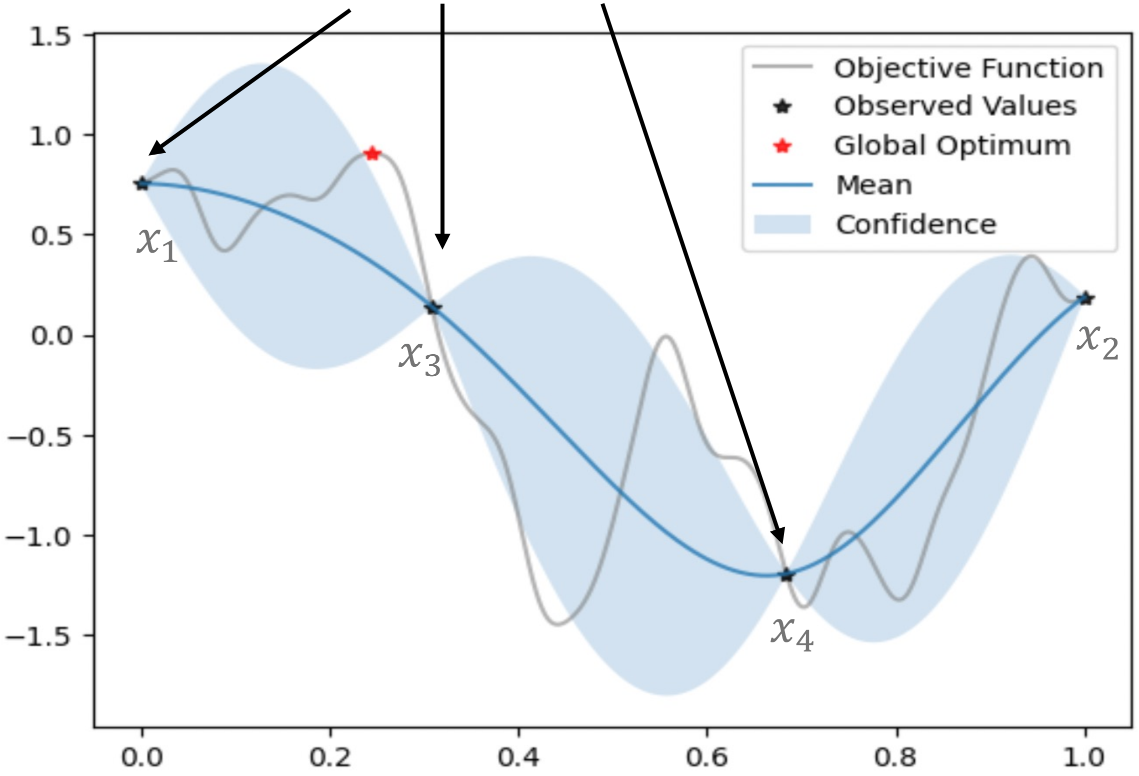
Correlated values



Continuous search domain

Hard budget constraint

$\cancel{t = 1}$

$\cancel{t = 2}$

$\cancel{t = 3}$

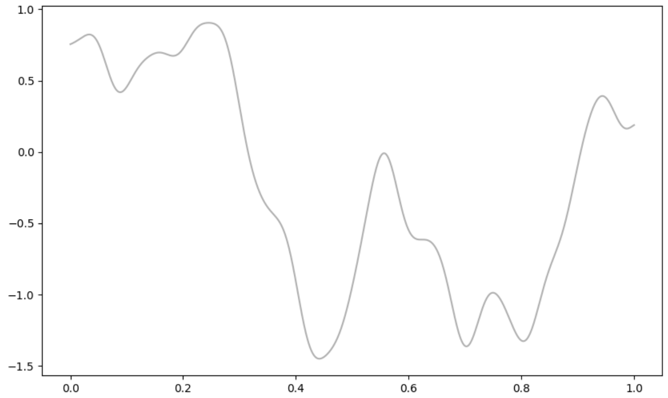
$\cancel{t = 4}$

$\vdots$

$t = T$

$\Longrightarrow$ Optimal policy unknown!

Bayesian Optimization

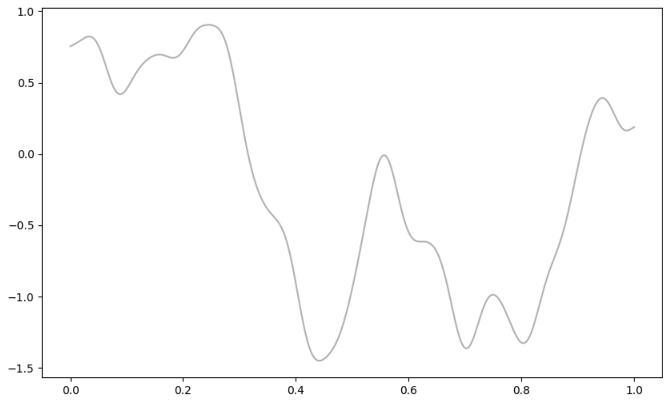


Continuous

Correlated

Hard budget constraint

Bayesian Optimization



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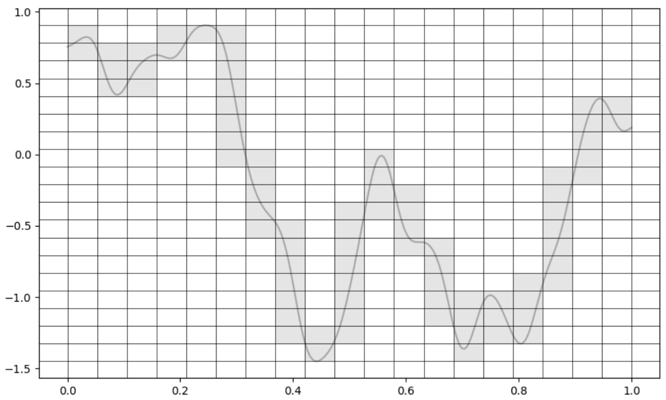
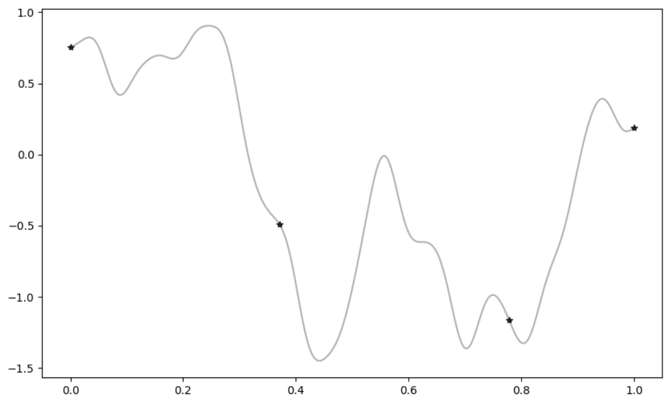


Continuous $\Rightarrow$ Discrete

Correlated

Hard budget constraint

Bayesian Optimization



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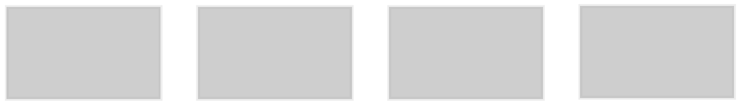
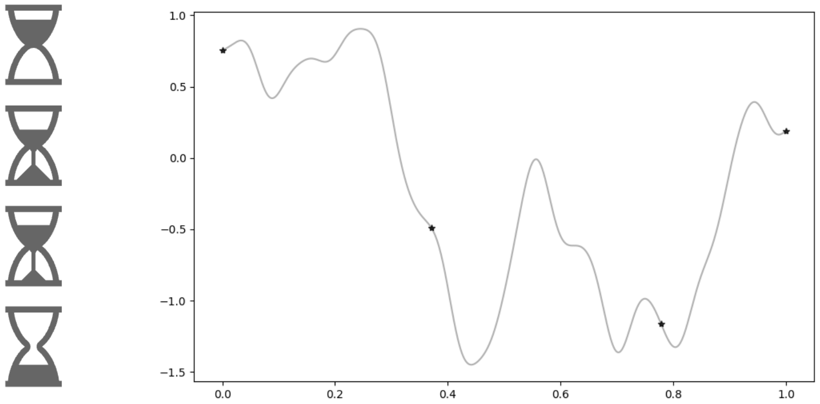


Continuous	$\Longrightarrow$	Discrete
Correlated	$\Longrightarrow$	Independent
Hard budget constraint		

Bayesian Optimization



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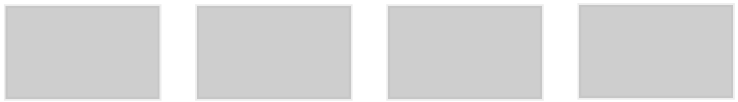
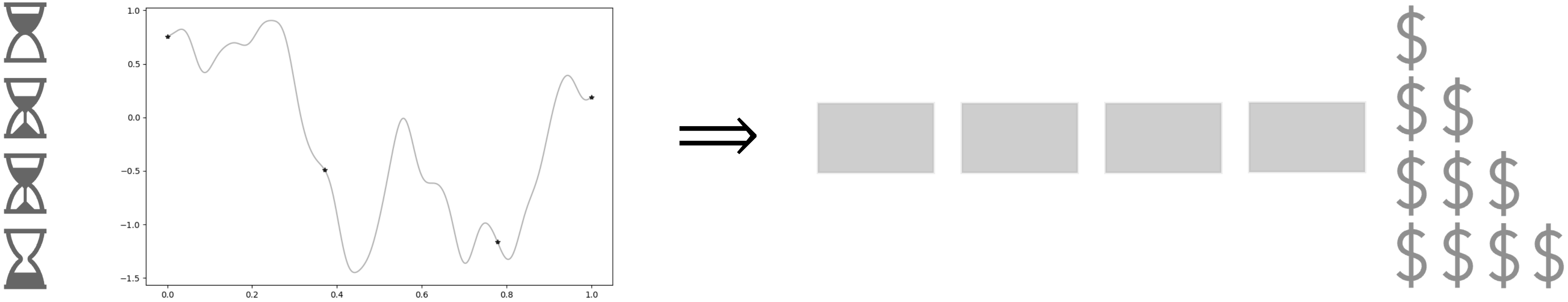


Continuous $\Longrightarrow$ Discrete

Correlated $\Longrightarrow$ Independent

Hard budget constraint

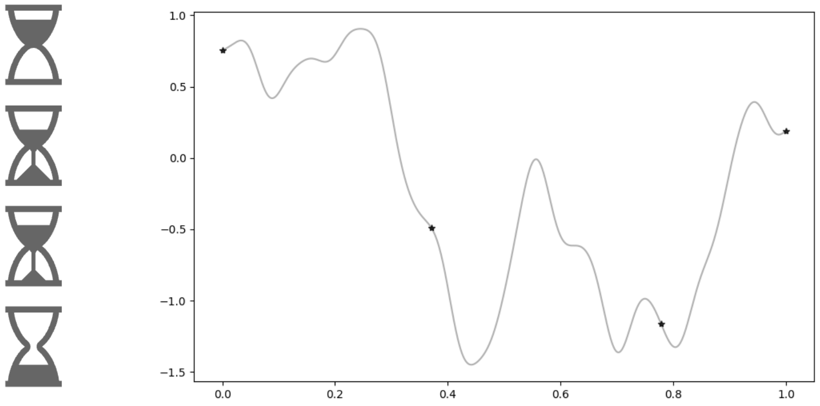
Bayesian Optimization



Continuous	$\Longrightarrow$	Discrete
Correlated	$\Longrightarrow$	Independent
Hard budget constraint	Lagrangian relaxation $\Longrightarrow$	Cost per sample

Bayesian Optimization ⟹ Pandora's Box

Special case of Markovian/
Bayesian Multi-armed Bandits



⟹

Continuous	⟹	Discrete
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Hard budget constraint	⟹	Cost per sample

Bayesian Optimization $\Longrightarrow$ Pandora's Box

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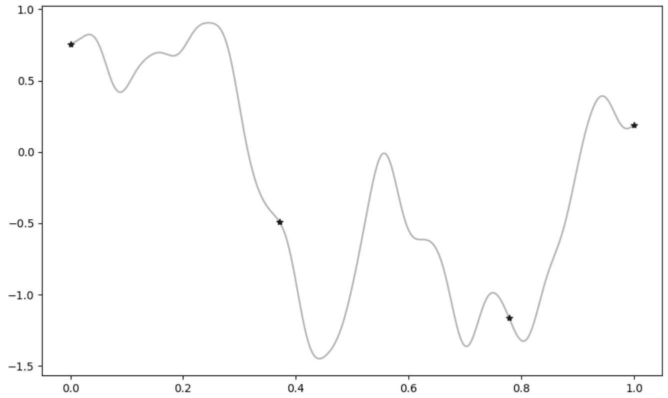

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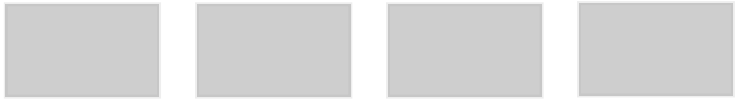

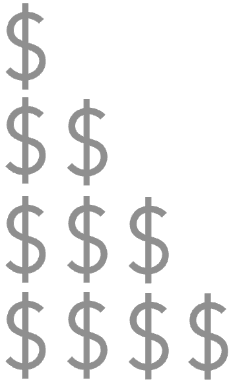

Continuous	$\Longrightarrow$	Discrete
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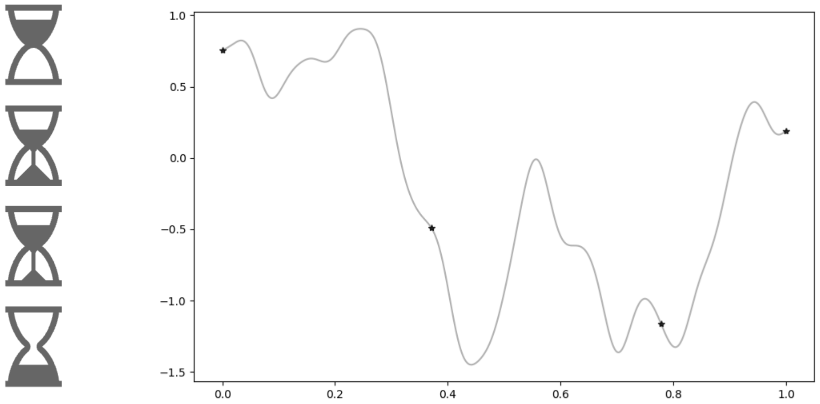
Hard budget constraint	$\Longrightarrow$	Cost per sample

Optimal policy: Gittins index

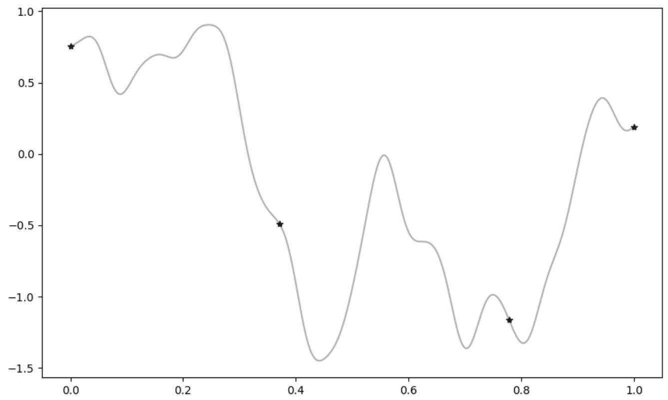
Bayesian Optimization ⟹ Pandora’s Box



⟹

Continuous	⟹	Discrete
Correlated	⟹	Independent
Hard budget constraint	⟹	Cost per sample
Is Gittins index good?	⟸	Optimal policy: Gittins index

Bayesian Optimization $\Longrightarrow$ Pandora's Box



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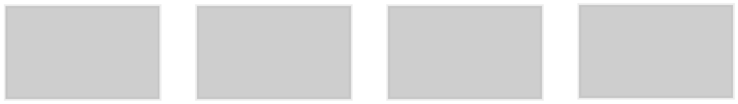

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Continuous $\Longrightarrow$ Discrete

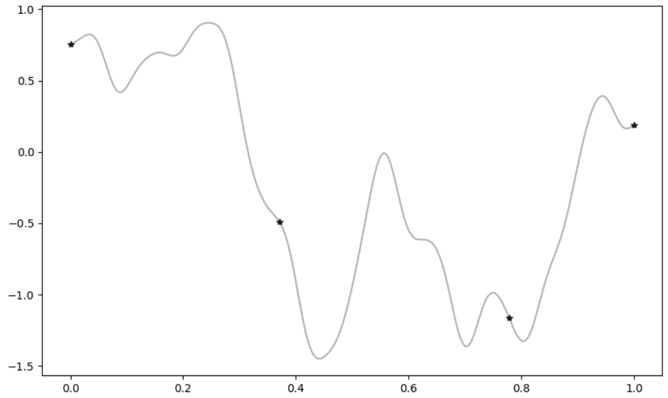
Correlated $\Longrightarrow$ Independent

Hard budget constraint $\Longrightarrow$ Cost per sample

How to translate?

Is Gittins index good? $\Longleftarrow$ Optimal policy: Gittins index

Bayesian Optimization $\Longrightarrow$ Pandora's Box



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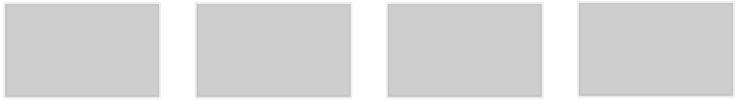

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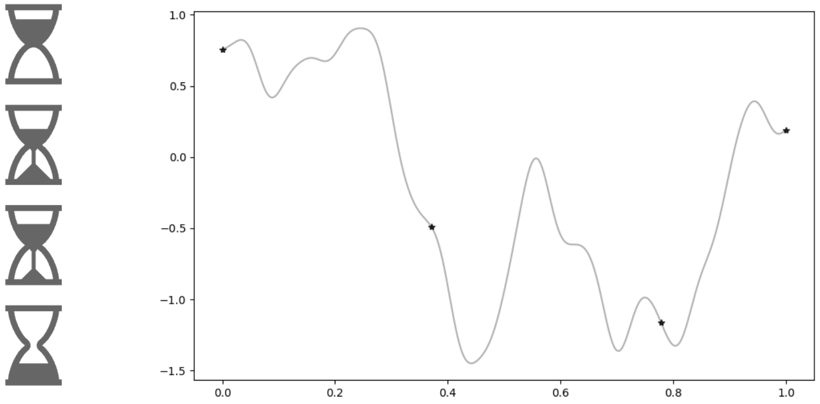
Continuous	$\Longrightarrow$	Discrete
Correlated	$\Longrightarrow$	Independent
Hard budget constraint	$\Longrightarrow$	Cost per sample
Is Gittins index good?	How to translate? $\Longleftarrow$	Optimal policy: Gittins index

Our contribution!

Our Contributions

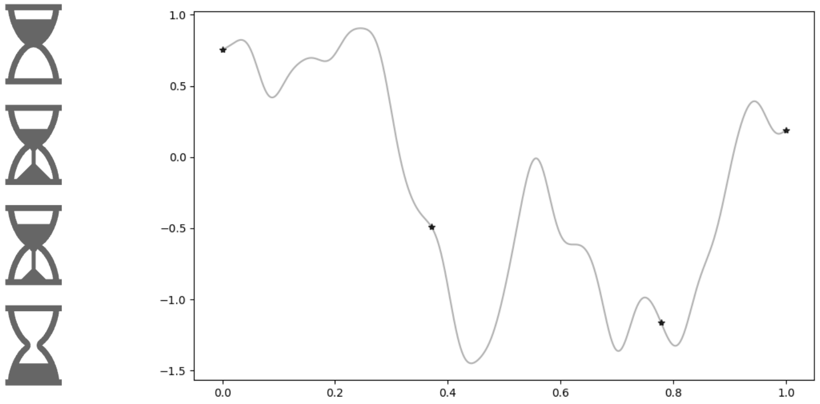
- How to translate?
- Is Gittins index good?



? $\Longleftarrow$ Gittins index

Our Contributions

- Develop Gittins index function for Bayesian optimization
- Show performance against baselines on synthetic & empirical experiments



Our work $\Longleftarrow$ Gittins index

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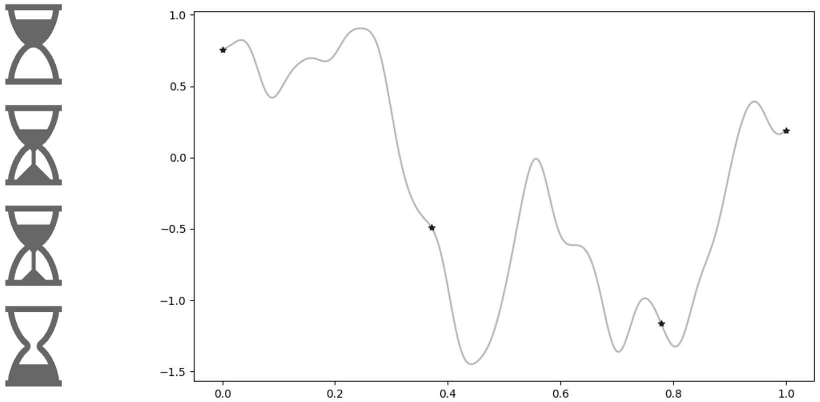
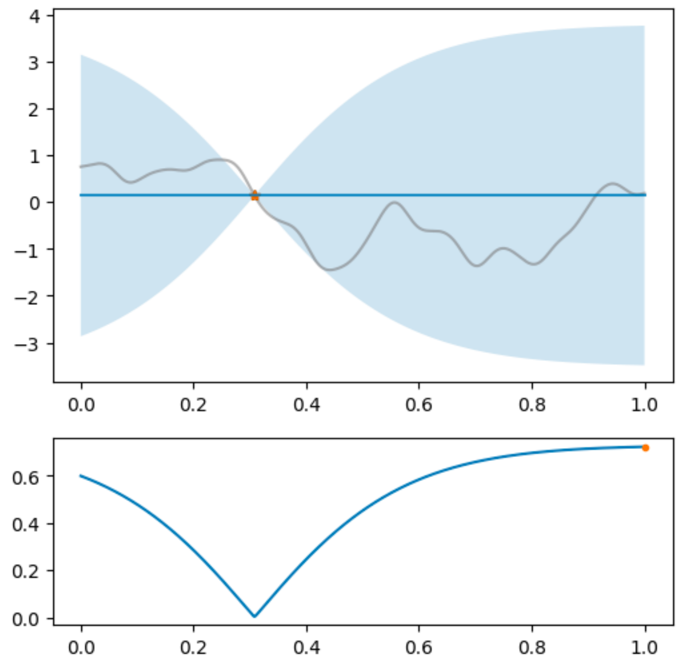


Our work $\Longleftarrow$ Gittins index

How is our Gittins index function different from baselines?

Popular One-step Heuristic: EI



mean: prediction

variance: confidence/uncertainty

Trade-off between

- exploitation (high mean) and
- exploration (high uncertainty)

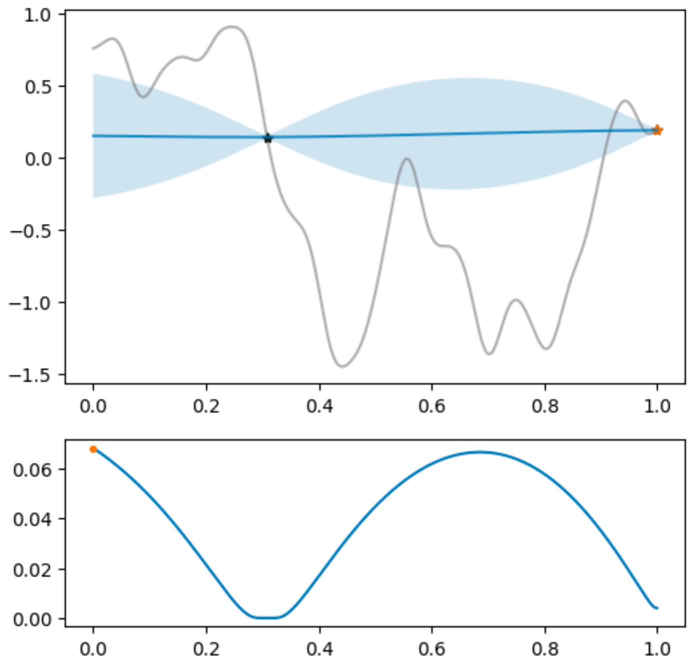
Expected improvement

$$\mathrm{EI}(x; y) = \mathbb{E}[(f(x) - y)^+]$$

y_{best}: current best observed value

EI policy: evaluate $\mathrm{argmax}_x\ \mathrm{EI}(x; y_{\mathrm{best}})$

Popular One-step Heuristic: EI



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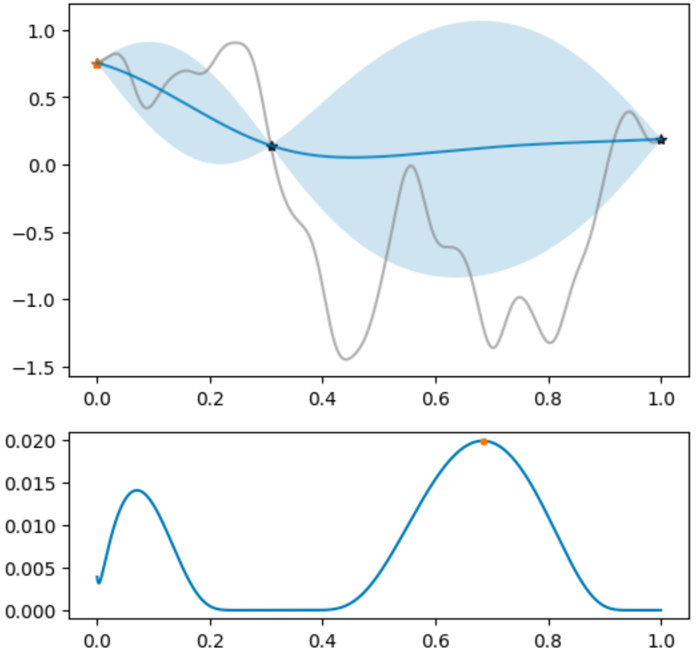

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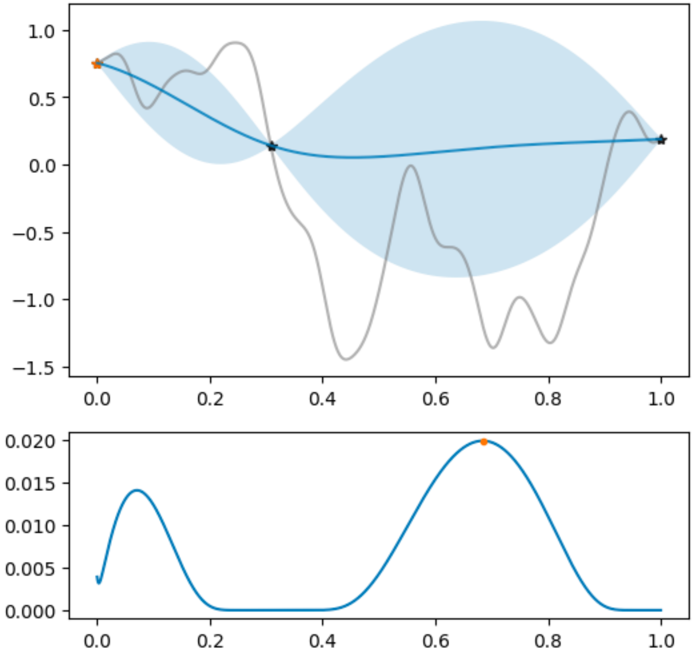
Popular One-step Heuristic: EI

Other heuristics:

simple
- Upper Confidence Bound
- Thompson Sampling (TS)
- Knowledge Gradient

slow
- Predictive Entropy Search
- Multi-step Lookahead EI



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New One-step Heuristic: Gittins

Other heuristics:
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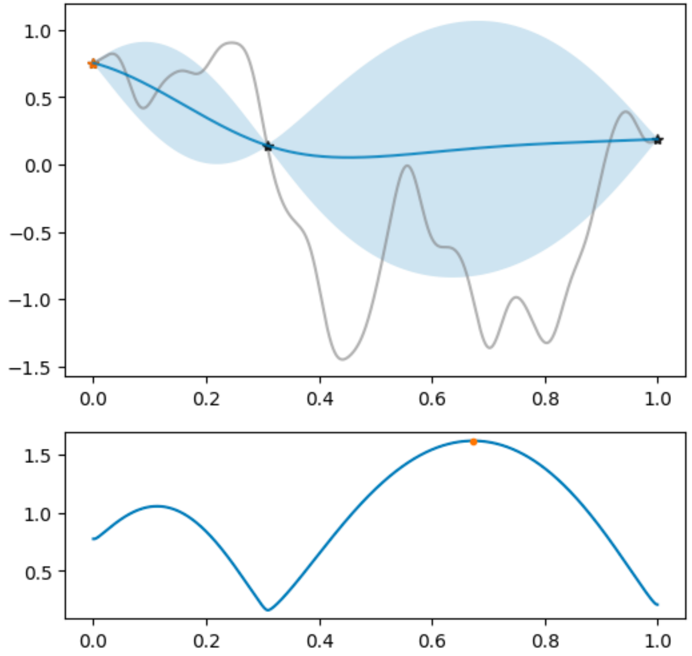
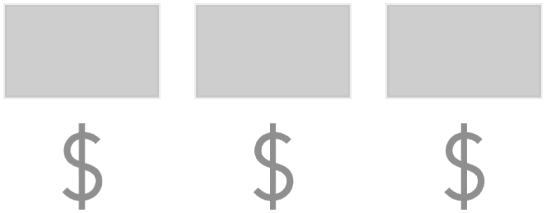
- Thompson Sampling (TS)
- Knowledge Gradient
- Predictive Entropy Search
- Multi-step Lookahead EI



Gittins index

Pandora’s box



$g(x)$: Gittins index function

Gittins policy: evaluate $\mathrm{argmax}_x\, g(x)$

New One-step Heuristic: Gittins

Other heuristics:

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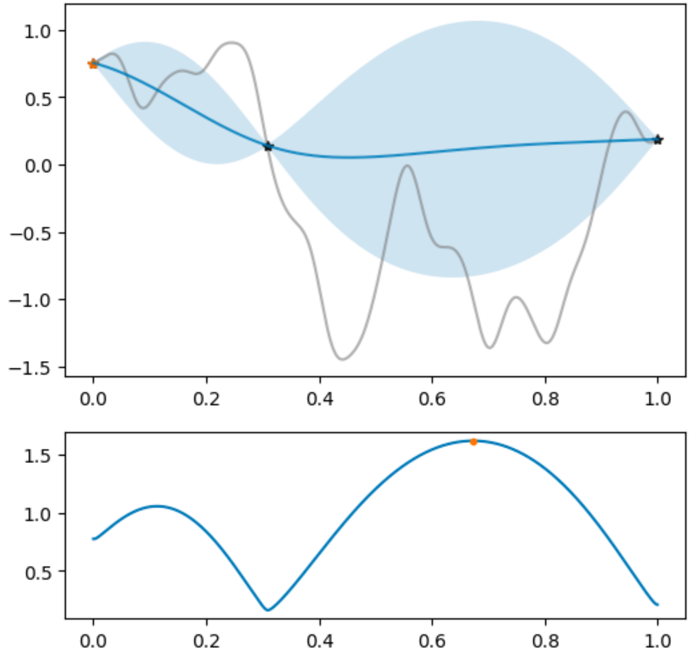


Gittins index

Pandora's box

λ λ λ

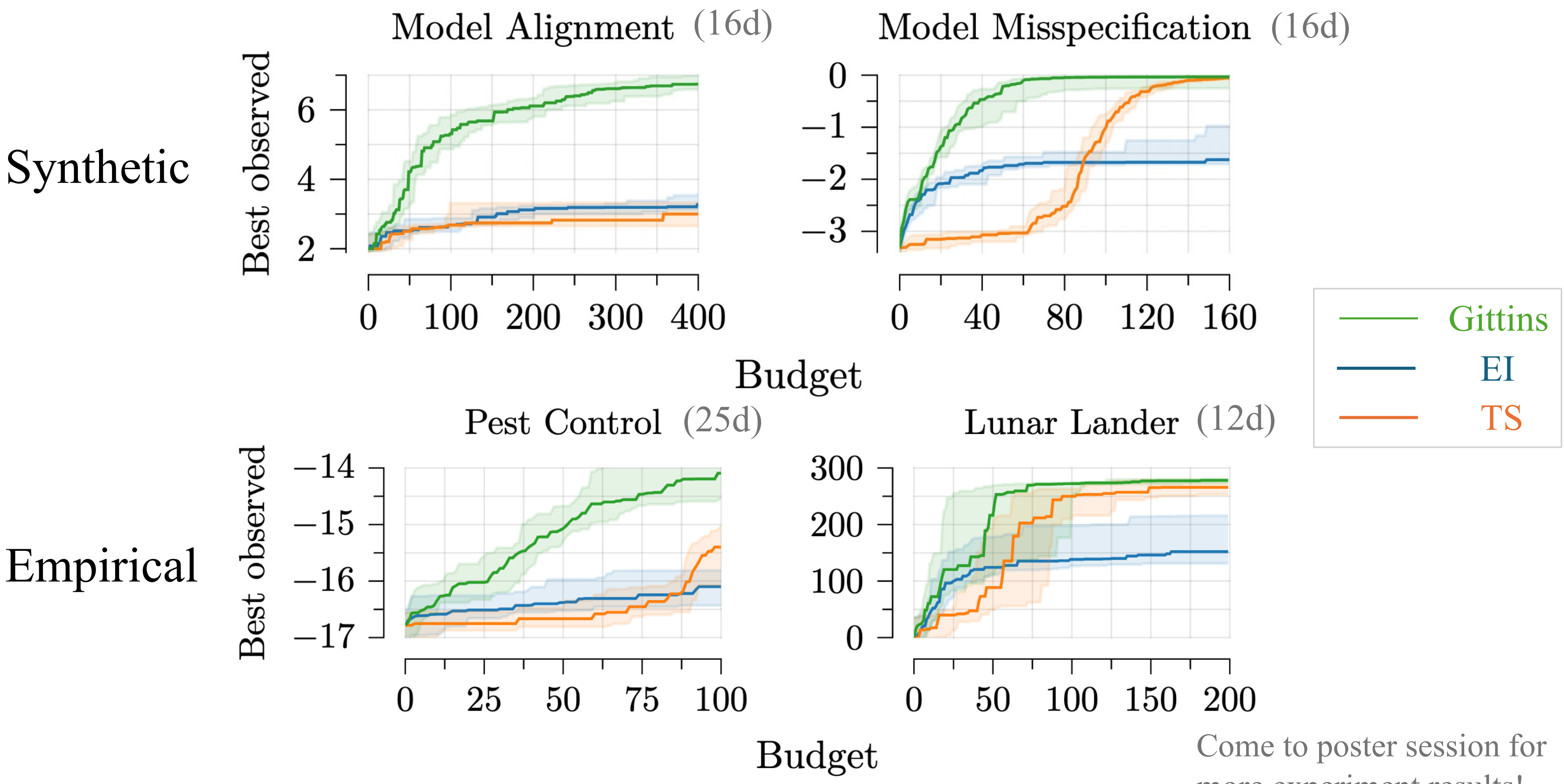
λ: cost per sample

$$\mathrm{EI}(x; y) = \mathbb{E}[(f(x) - y)^+]$$

$g(x)$: solution to $\mathrm{EI}(x; g(x)) = \lambda$

Gittins policy: evaluate $\mathrm{argmax}_x\, g(x)$

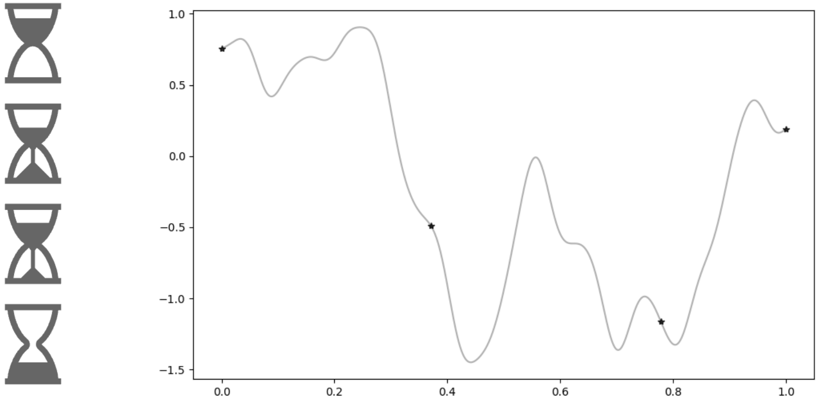
Experiment Results: Gittins vs EI vs TS

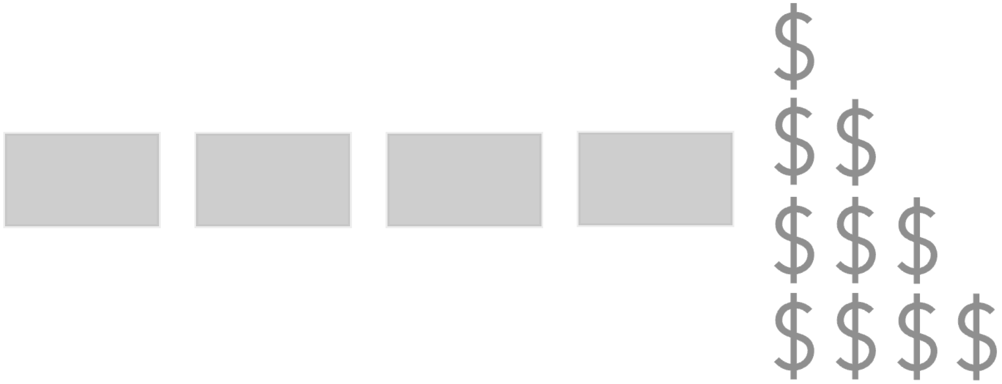


Come to poster session for more experiment results!

Conclusions

- Propose easy-to-compute Gittins index function for Bayesian optimization





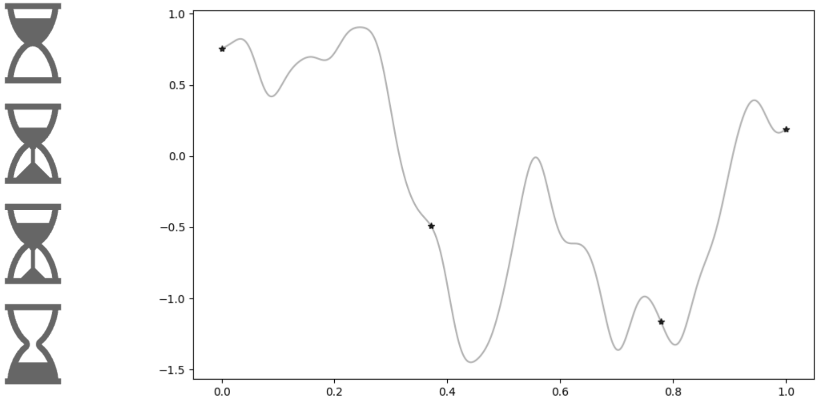
Our work ⟸ Gittins index

Preprint coming in two weeks!

Conclusions

- Propose easy-to-compute Gittins index function for Bayesian optimization
- Show Gittins mostly outperforms baselines on synthetic & empirical experiments

  particularly higher dimensions and larger domains!



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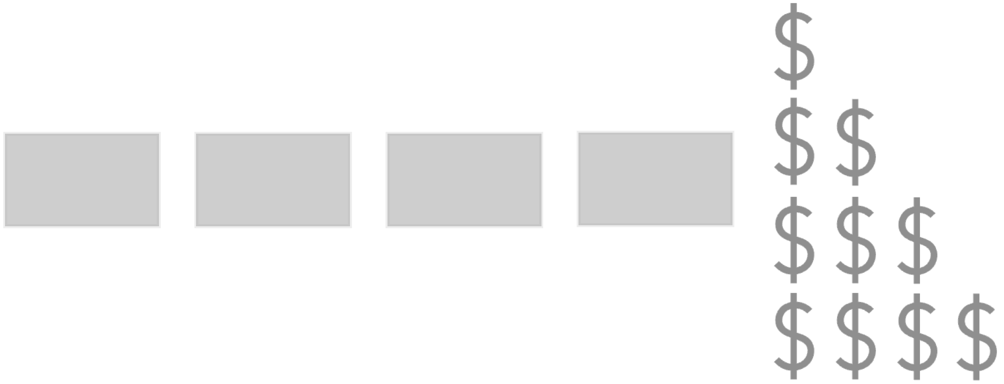

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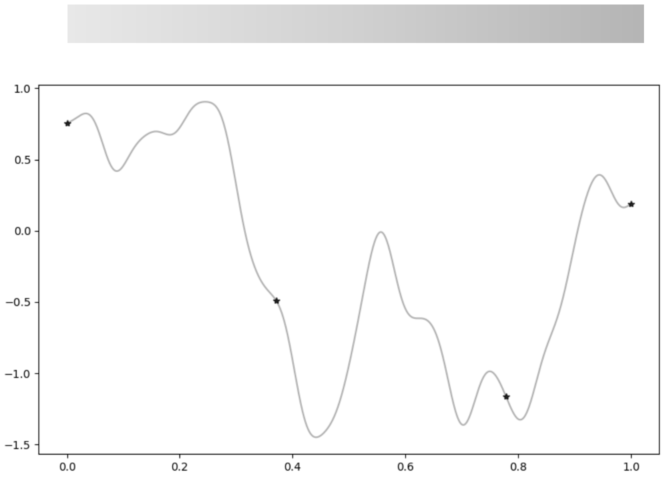
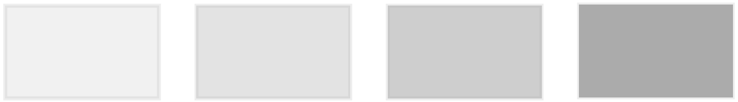
- Extend to Bayesian optimization with heterogeneous evaluation costs

$c(x)$

$f(x)$





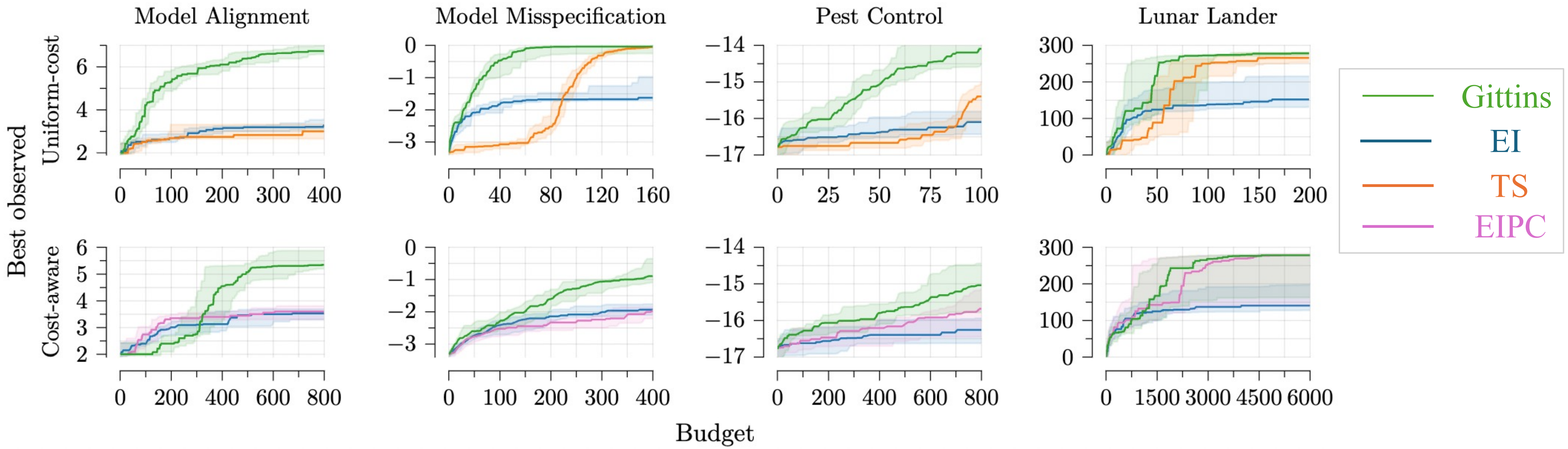
c_1 c_2 c_3 c_4

Our work $\Longleftarrow$ Gittins index

Preprint coming in two weeks!

Heterogeneous-cost Experiment Results

- Show Gittins mostly outperforms baselines on synthetic & empirical experiments
- Extend to Bayesian optimization with heterogeneous evaluation costs



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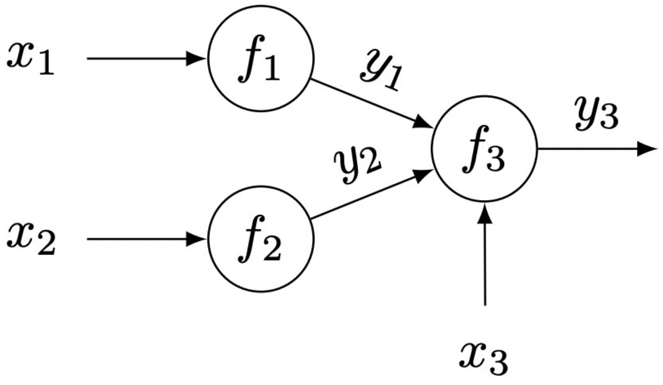
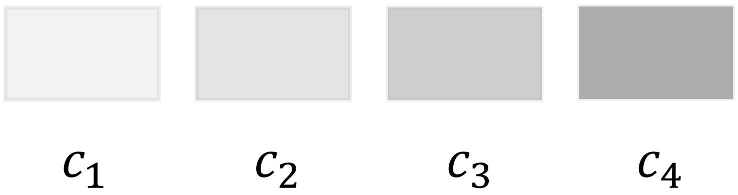
- Show Gittins mostly outperforms baselines on synthetic & empirical experiments
- Extend to Bayesian optimization with heterogeneous evaluation costs
- Open door for exotic BO (freeze-thaw, multi-fidelity, function network, etc.)





? $\Longleftarrow$ Gittins index

Preprint coming in two weeks!