## 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

NYC Ops Day 2024

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

∈ decision-making under uncertainty

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#### **Applications:**

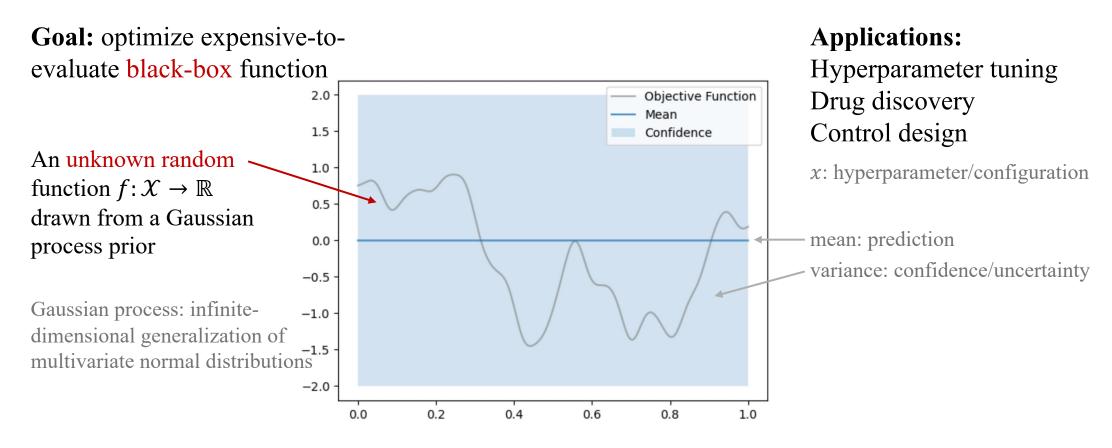
Hyperparameter tuning
Drug discovery
Control design

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

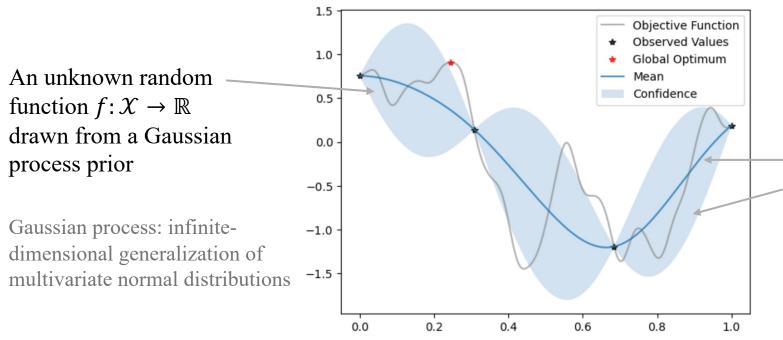
∈ decision-making under uncertainty

#### **Applications:**

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



#### **Applications:**

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x: hyperparameter/configuration

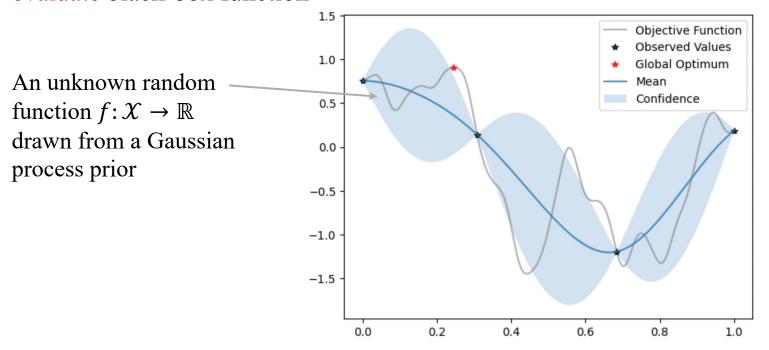
mean: prediction

variance: confidence/uncertainty

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

**Decision:** evaluate a set of points

Goal: optimize expensive-toevaluate black-box function



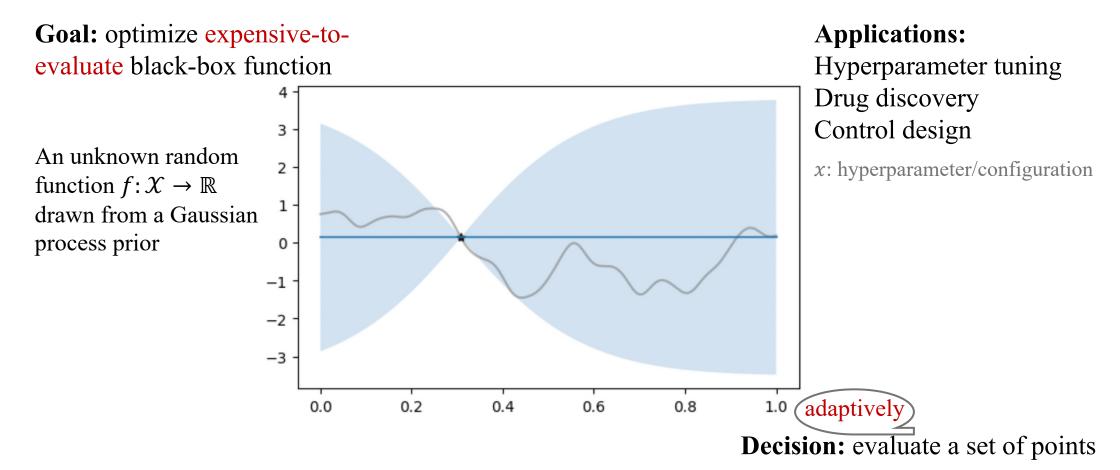
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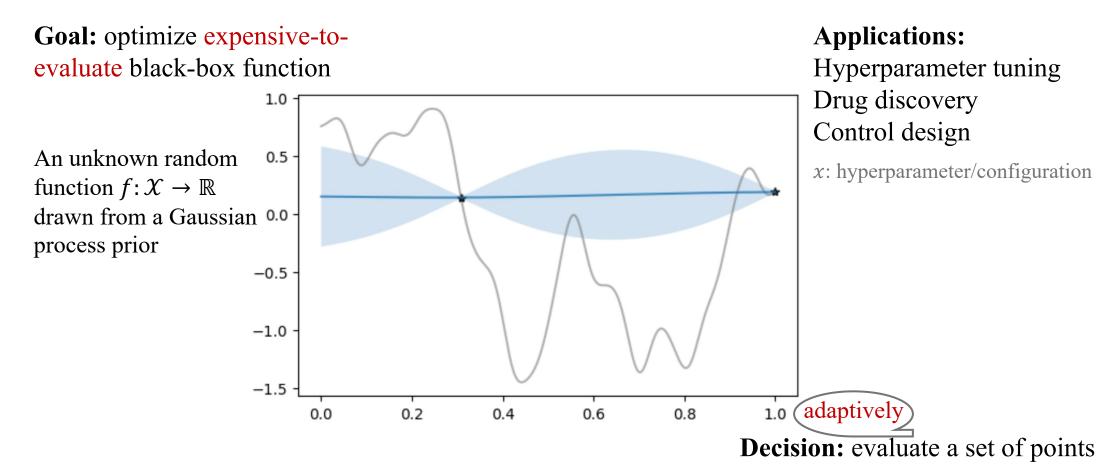
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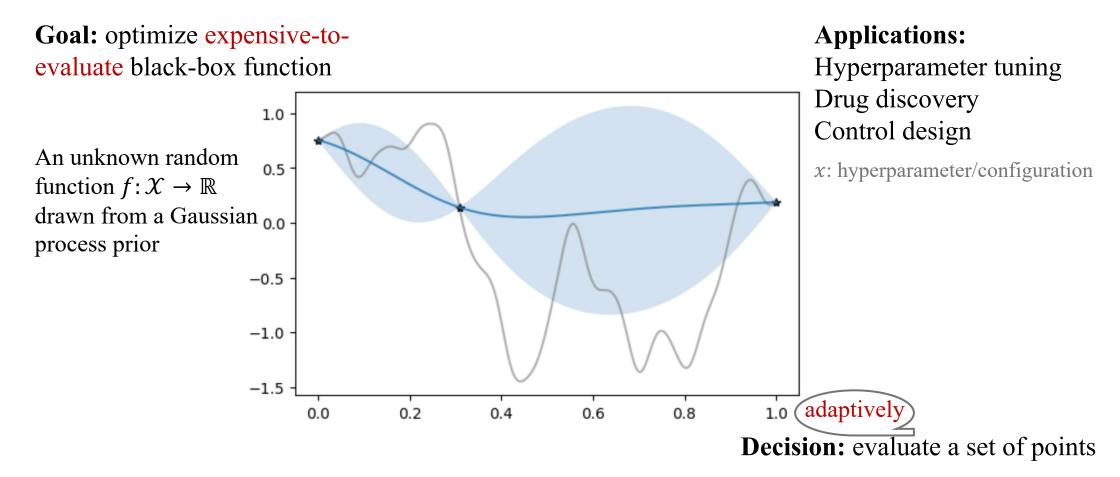
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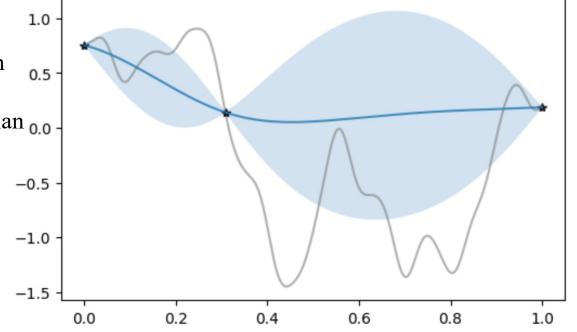






Goal: optimize expensive-toevaluate black-box function

An unknown random o.5 function  $f: \mathcal{X} \to \mathbb{R}$  drawn from a Gaussian o.0 process prior



#### **Applications:**

Hyperparameter tuning Drug discovery Control design

*x*: hyperparameter/configuration

**Decision:** adaptively evaluate a set of points

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

*T*: time budget

Goal: optimize expensive-toevaluate black-box function

An unknown random function  $f: \mathcal{X} \to \mathbb{R}$  drawn from a Gaussian 0.0 process prior  $\begin{array}{c} 1.0 \\ 0.5 \\ -0.5 \\ -1.0 \end{array}$ 

0.2

0.4

0.6

0.8

#### **Applications:**

Hyperparameter tuning
Drug discovery
Control design

*x*: hyperparameter/configuration

**Objective:** optimize best observed value at time *T* 

0.0

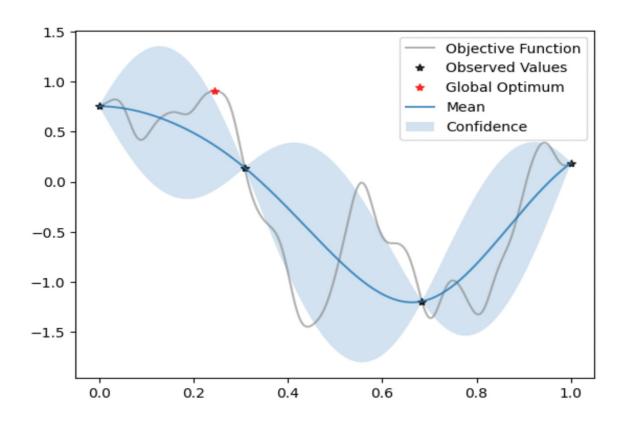
$$\max_{\text{policy}} \mathbb{E} \max_{t=1,2,\dots,T} f(x_t)$$

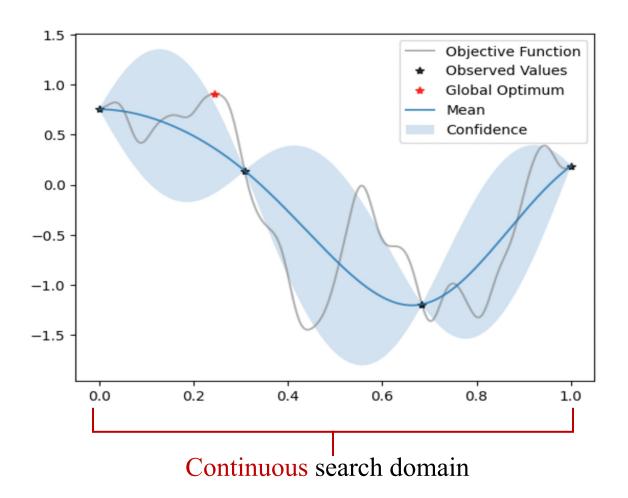
**Decision:** adaptively evaluate a set of points

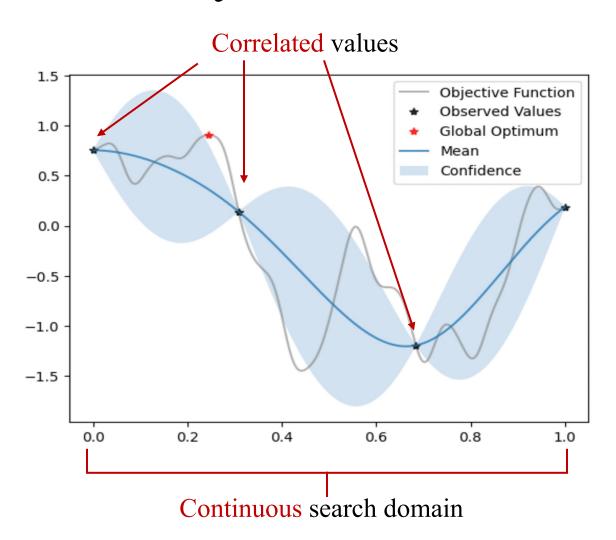
1.0

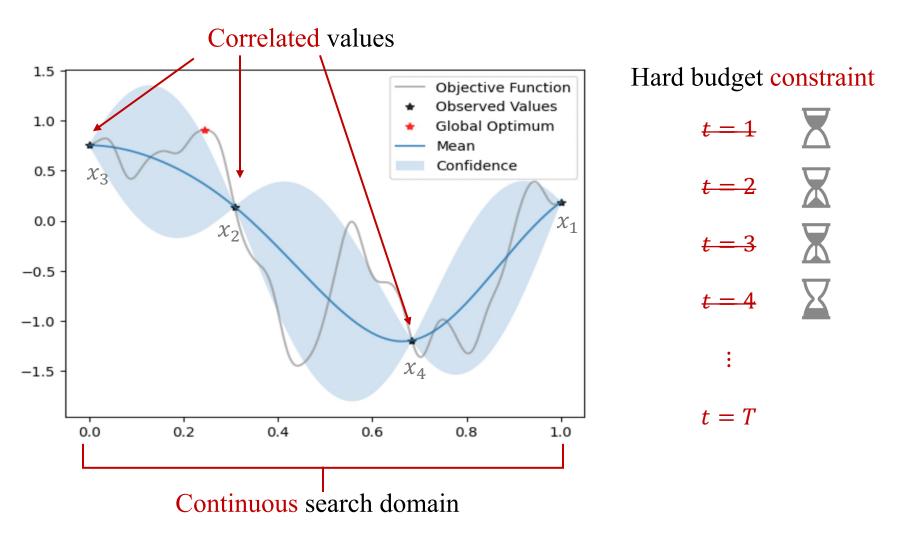
$$x_1, x_2, \dots, x_T \in \mathcal{X}$$

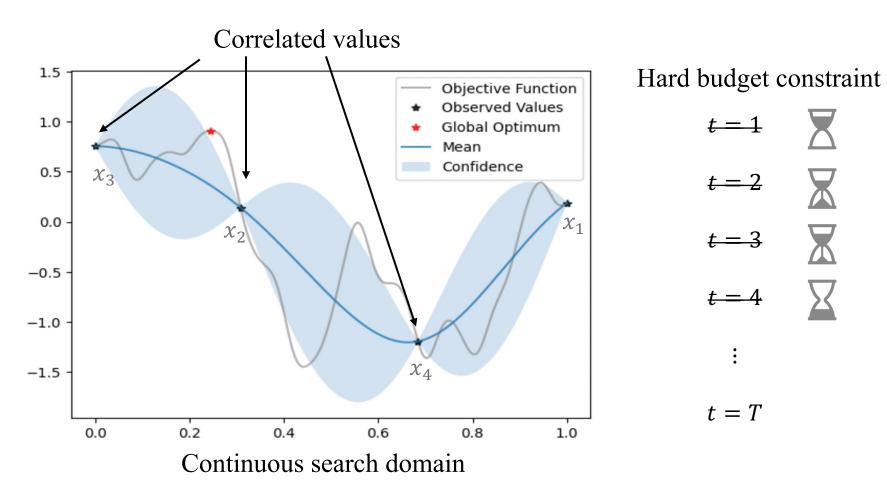
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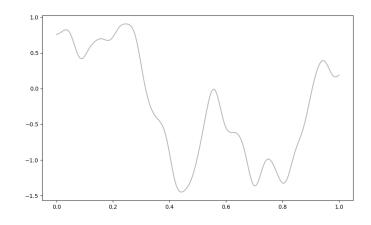








⇒ Optimal policy unknown!

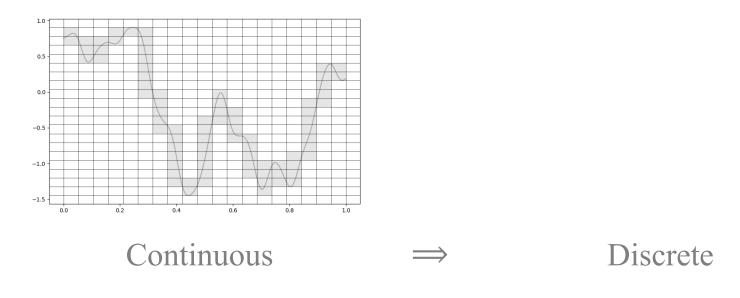


Continuous

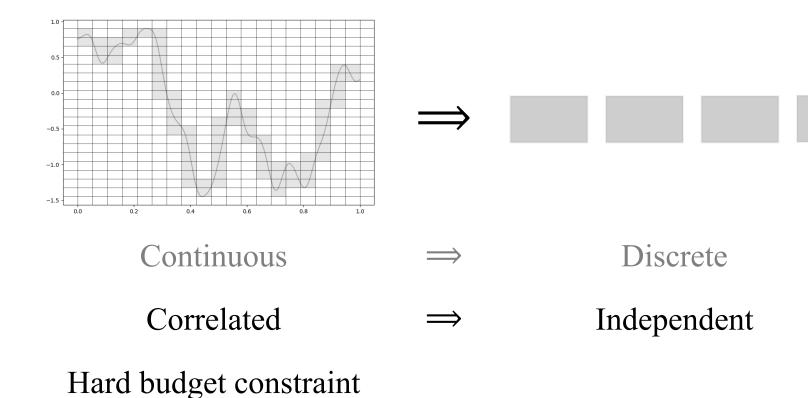
Correlated



Correlated

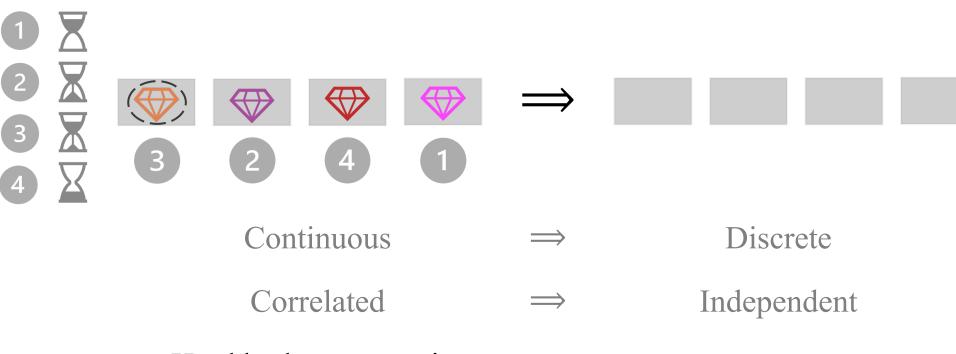


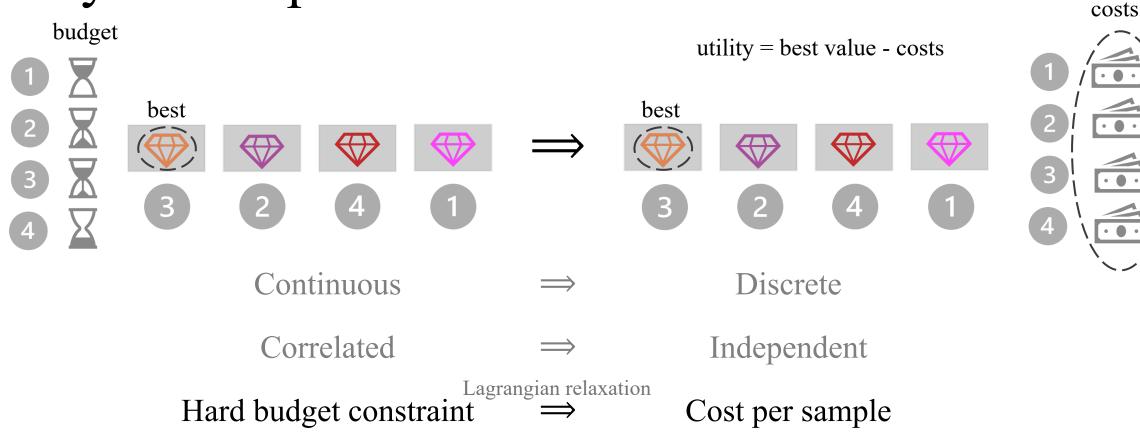
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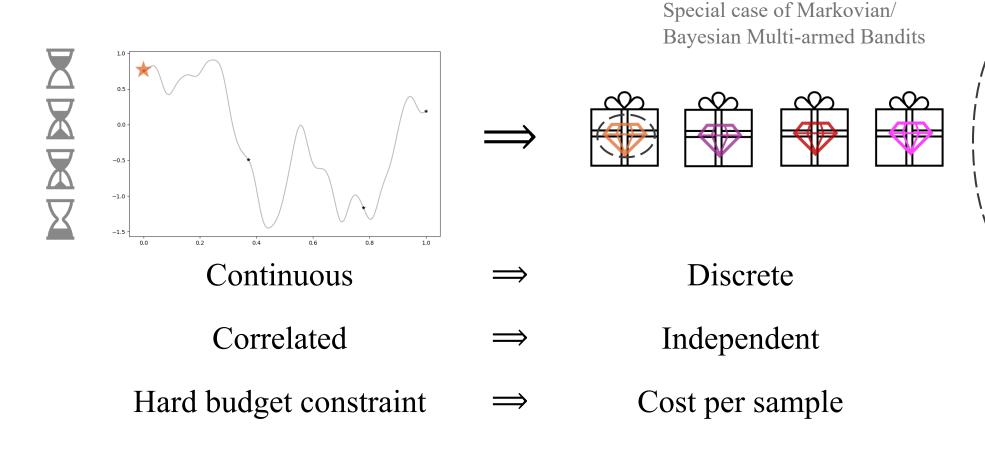


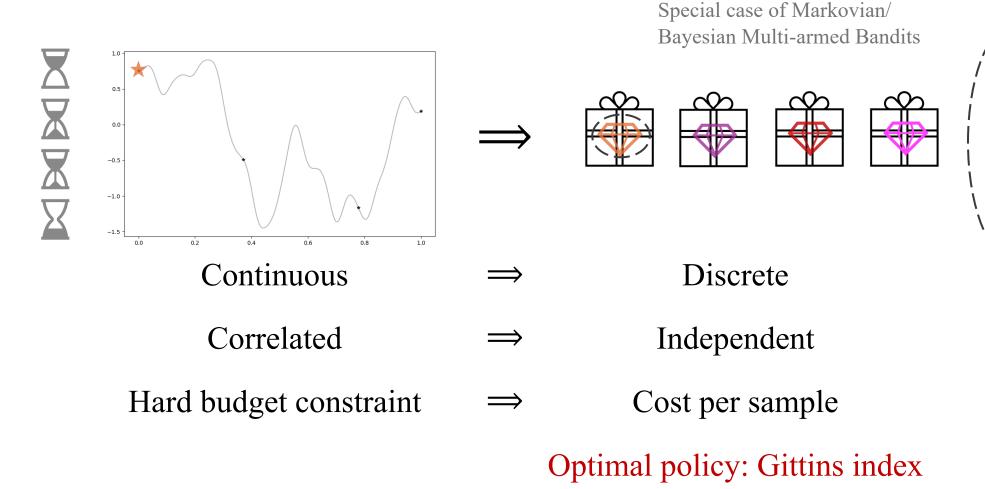
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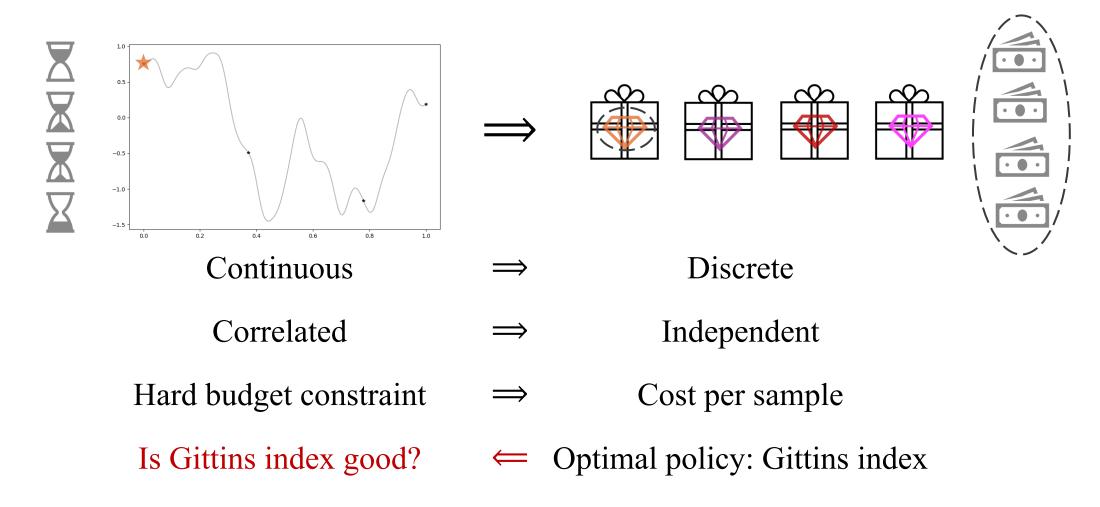
budget

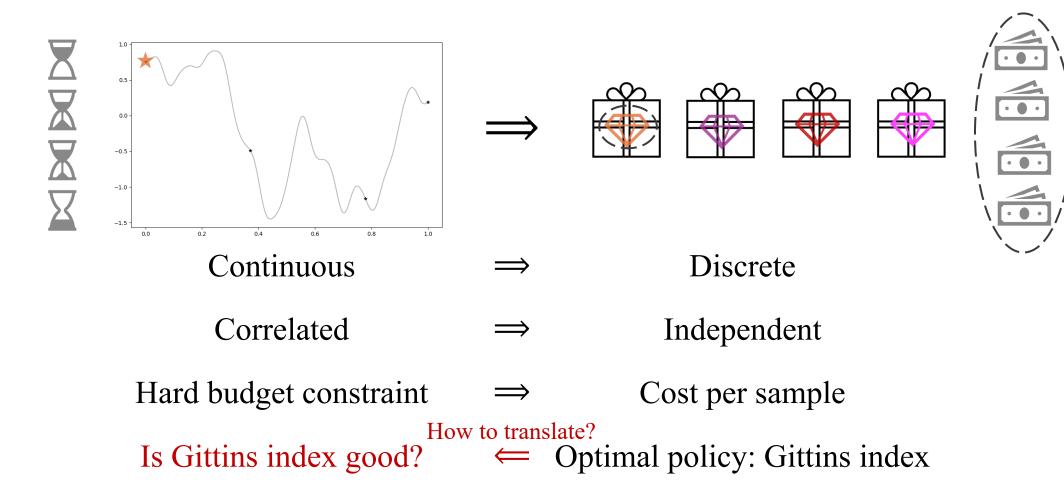


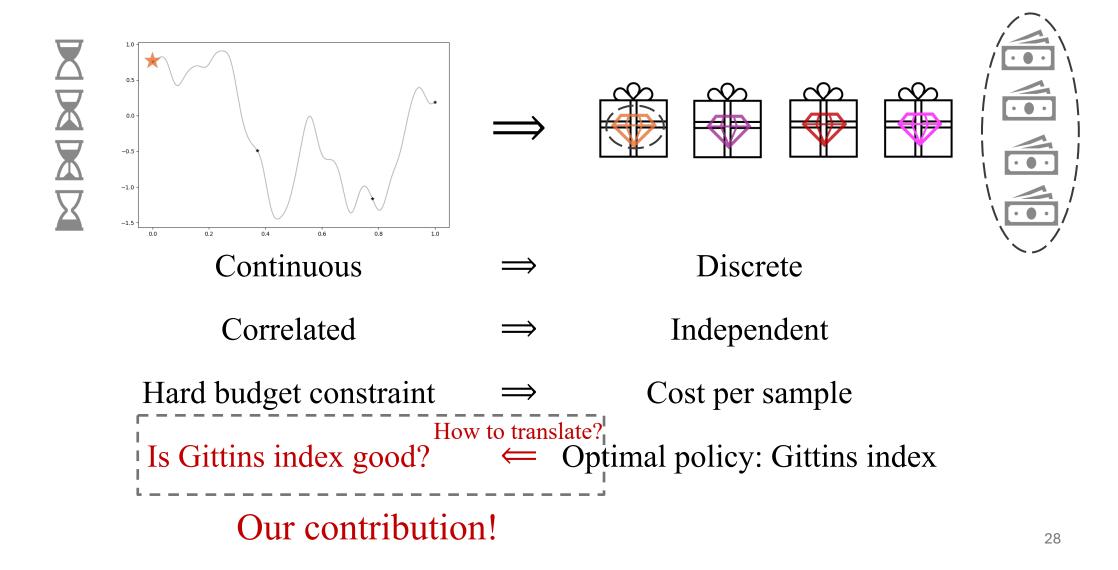






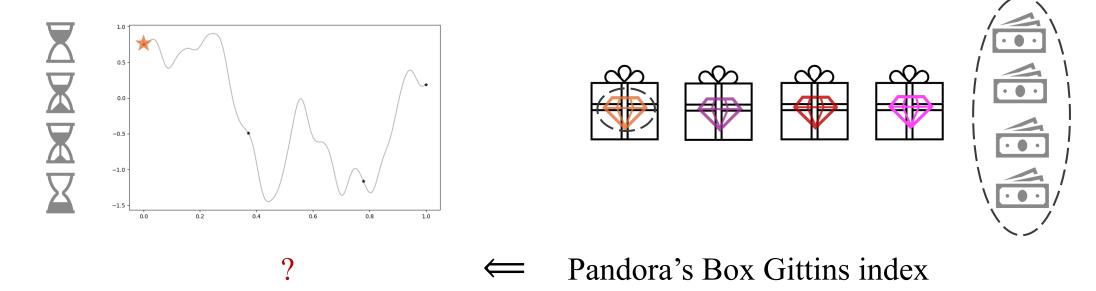






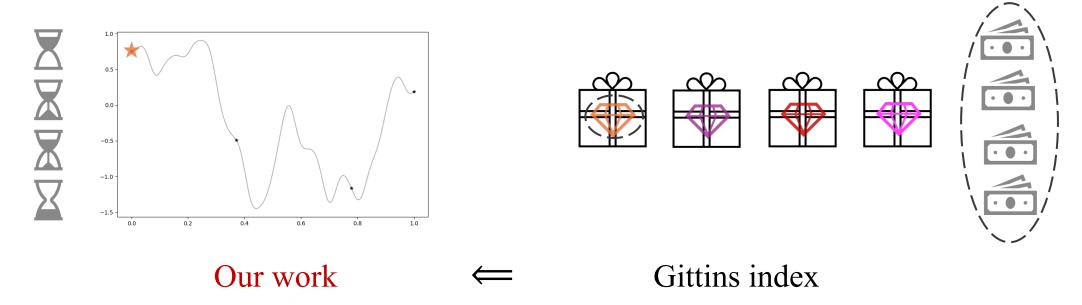
### Our Contributions

- How to translate?
- Is Pandora's Box Gittins index (PBGI) good?



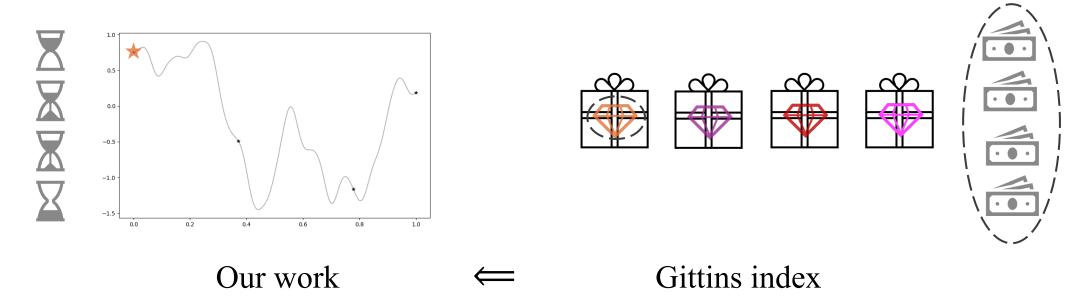
#### Our Contributions

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

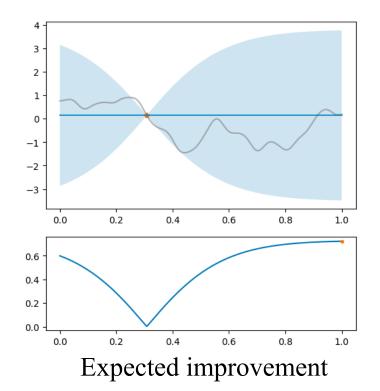


#### Our Contributions

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



How is our Gittins index function different from baselines?



mean: prediction

variance: confidence/uncertainty

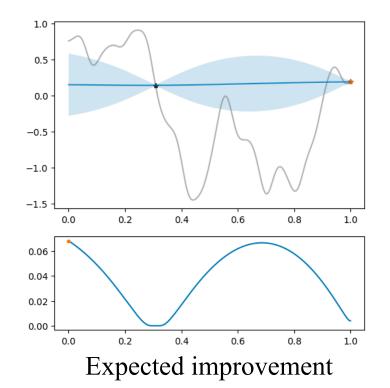
Trade-off between

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

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

y<sub>best</sub>: current best observed value

EI policy: evaluate  $argmax_x EI(x; y_{best})$ 



mean: prediction

variance: confidence/uncertainty

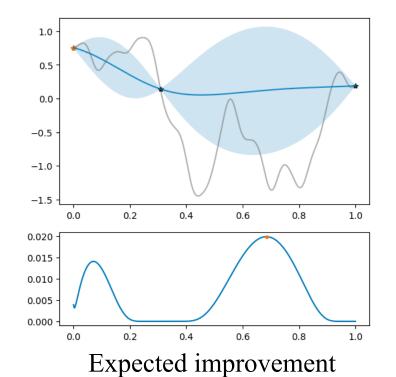
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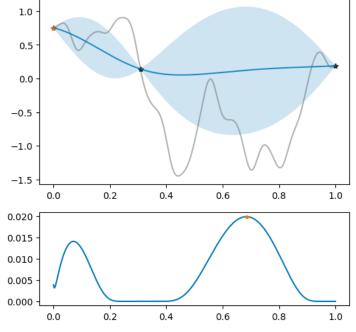
#### **Other heuristics:**

simple

- Upper Confidence Bound
- Thompson Sampling (TS)
- Predictive Entropy Search

slow

- Knowledge Gradient
- Multi-step Lookahead EI



Expected improvement

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

mean: prediction

variance: confidence/uncertainty

Trade-off between

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- exploration (high uncertainty)

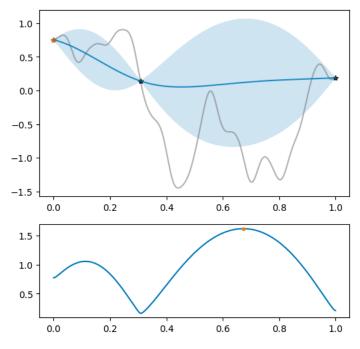
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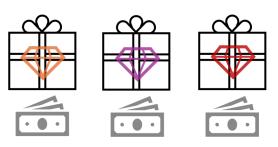
# New One-step Heuristic: PBGI

#### **Other heuristics:**

- Upper Confidence Bound
- Thompson Sampling (TS)
- Knowledge Gradient
- Predictive Entropy Search
- Multi-step Lookahead EI



Pandora's box



Pandora's box Gittins index

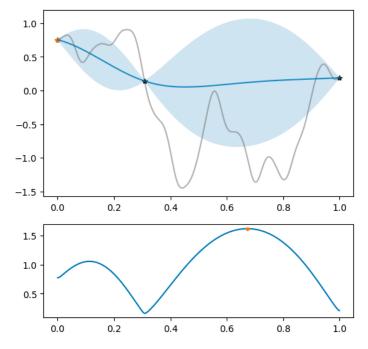
g(x): Gittins index function

PBGI policy: evaluate  $\operatorname{argmax}_{x} g(x)$ 

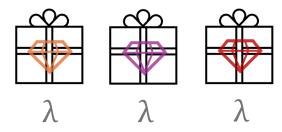
# New One-step Heuristic: PBGI

#### **Other heuristics:**

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Pandora's box



λ: cost per sample

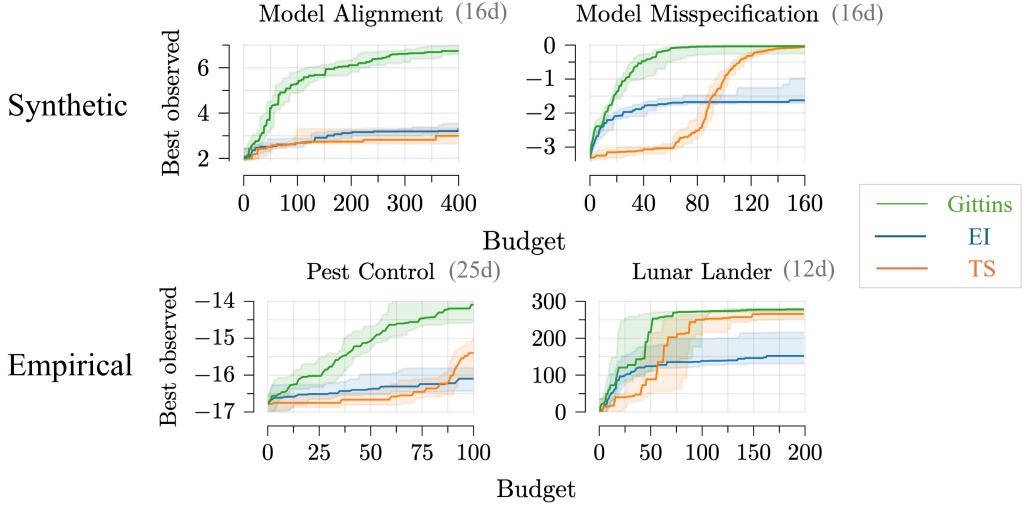
Pandora's box Gittins index

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

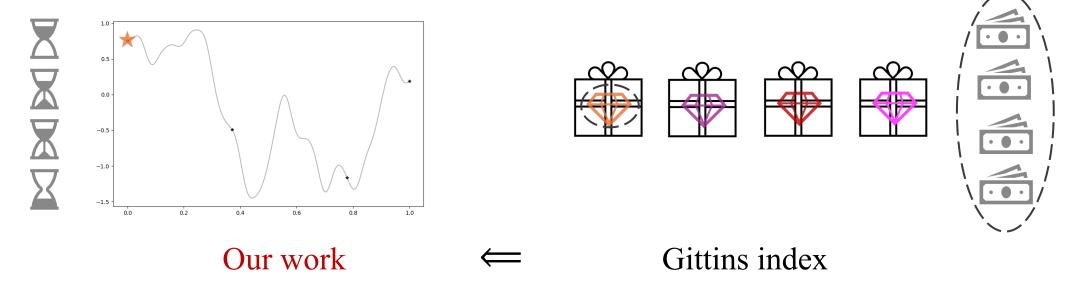
g(x): solution to  $EI(x; g(x)) = \lambda$ 

PBGI policy: evaluate  $argmax_x g(x)$ 

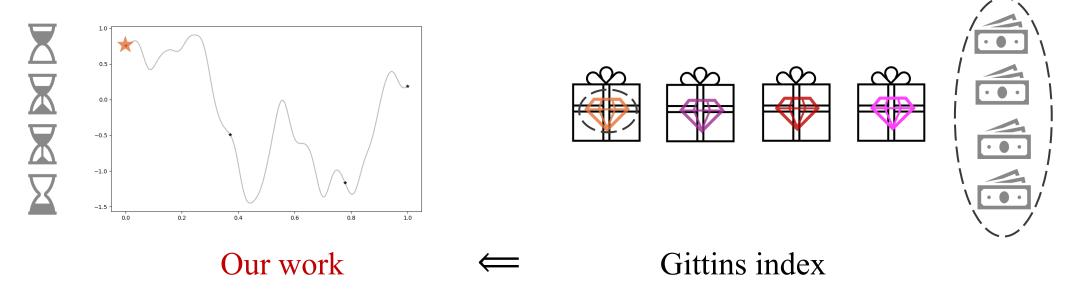
## Experiment Results: Gittins vs EI vs TS



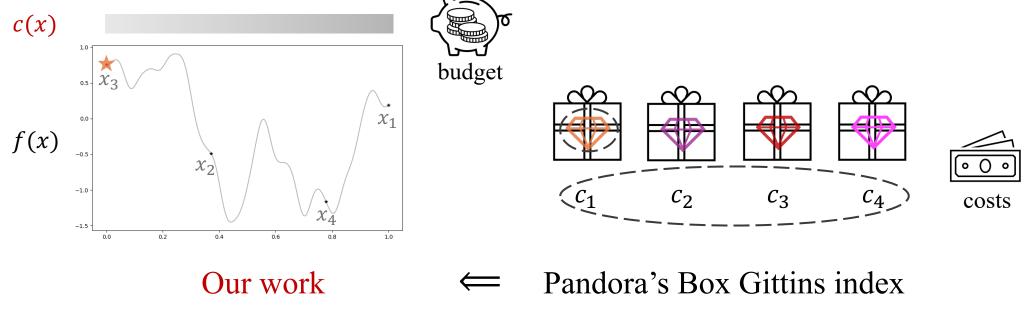
• Propose easy-to-compute Gittins index function for Bayesian optimization



- 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!

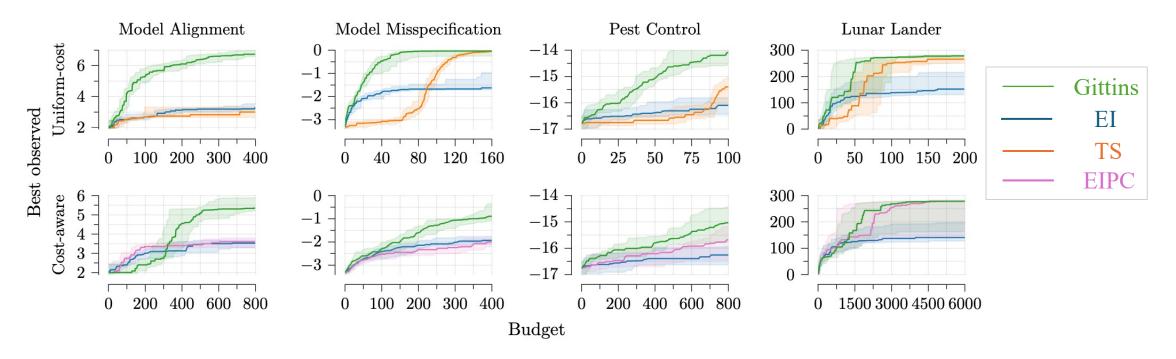


- Propose easy-to-compute Gittins index function for Bayesian optimization
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- Extend to Bayesian optimization with heterogeneous evaluation costs



# Heterogeneous-cost Experiment Results

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



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

