Cost-aware Bayesian Optimization via the Pandora's Box Gittins Index

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

INFORMS'24 Data Mining Best General Paper Competition

Coauthors

Raul Astudillo

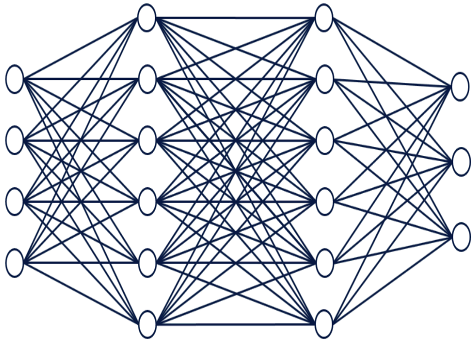
Peter Frazier

Ziv Scully

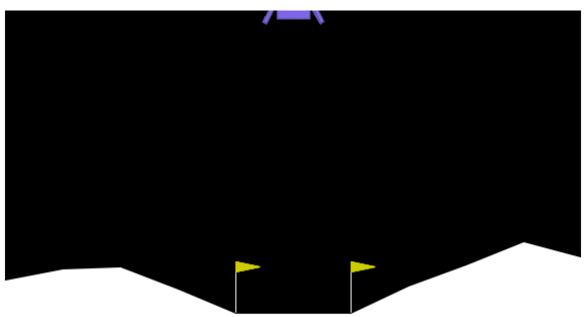
Alexander Terenin

World of Parameter Optimization

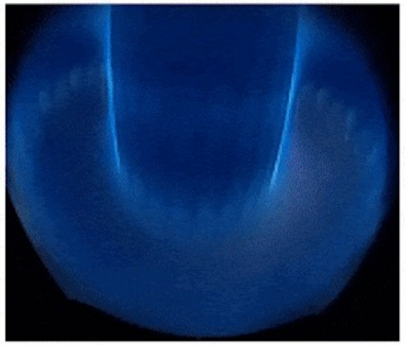
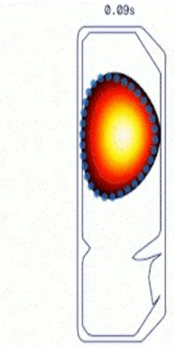
Hyperparameter tuning:

Training parameters →  → Accuracy

Control optimization:

Control parameters →  → Reward

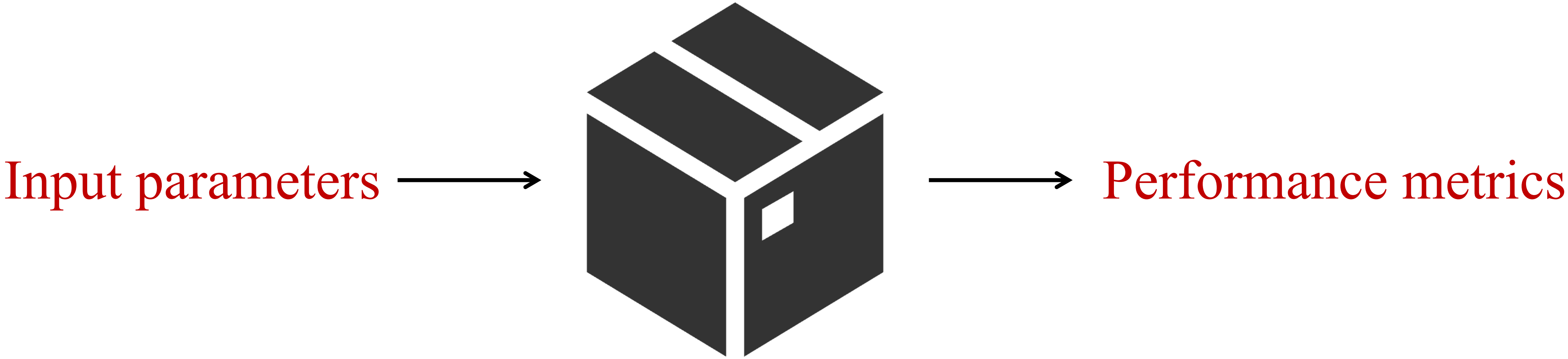
Plasma physics:

Reactor parameters →  

→ Stability

World of Parameter Optimization

Black-box optimization:



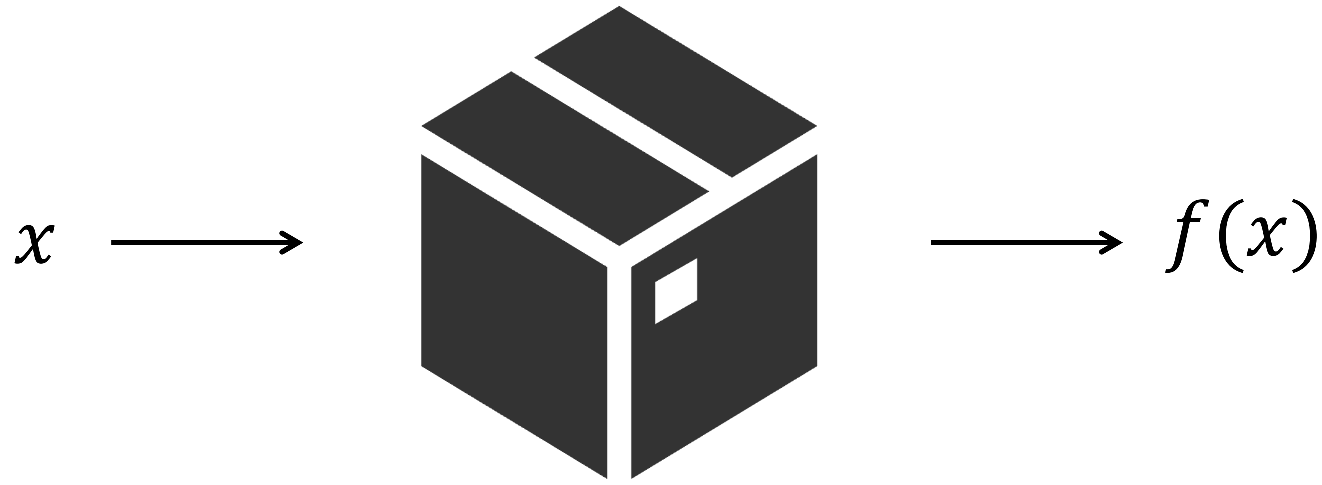
World of Parameter Optimization

Black-box optimization:

$x \longrightarrow$

$\longrightarrow f(x)$

Optimizing Black-box Functions



Goal: $\mathbf{max}_{x \in \mathcal{X}} f(x)$

Optimizing Black-box Functions

$x \longrightarrow$  $\longrightarrow f(x)$

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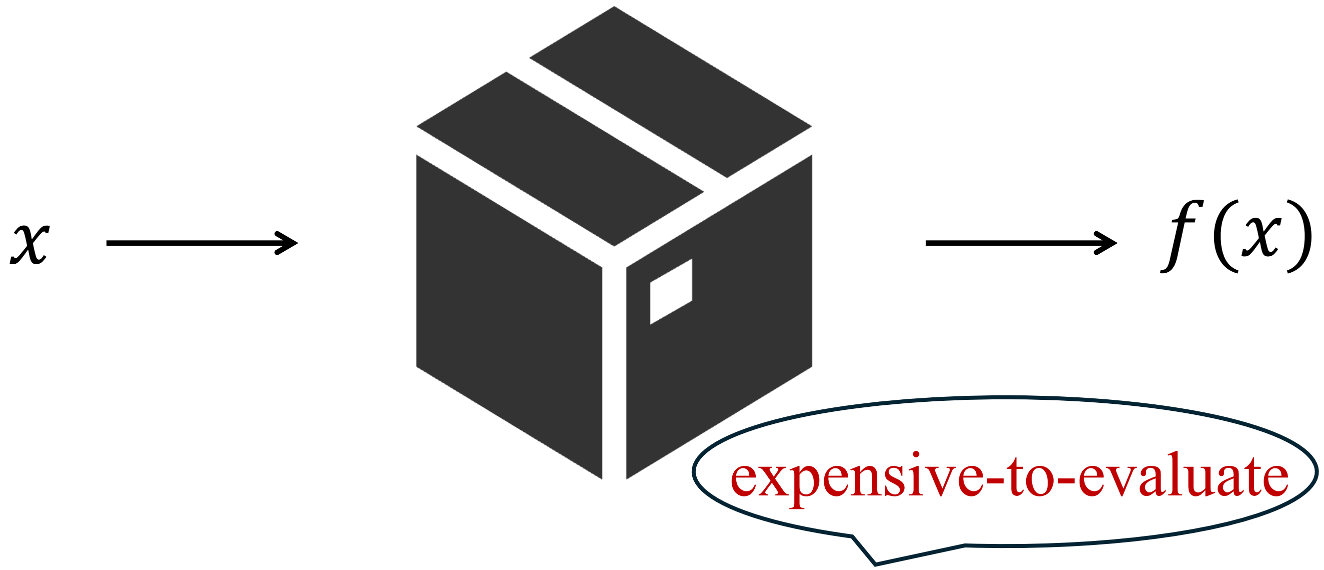
$f \sim$Stochastic Process

Optimizing Black-box Functions



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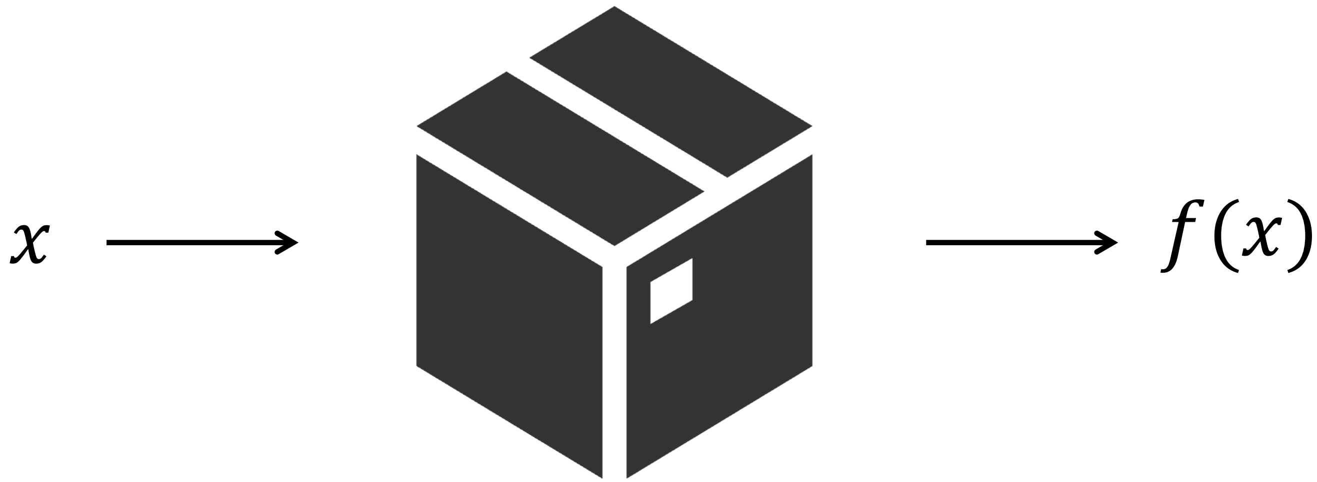
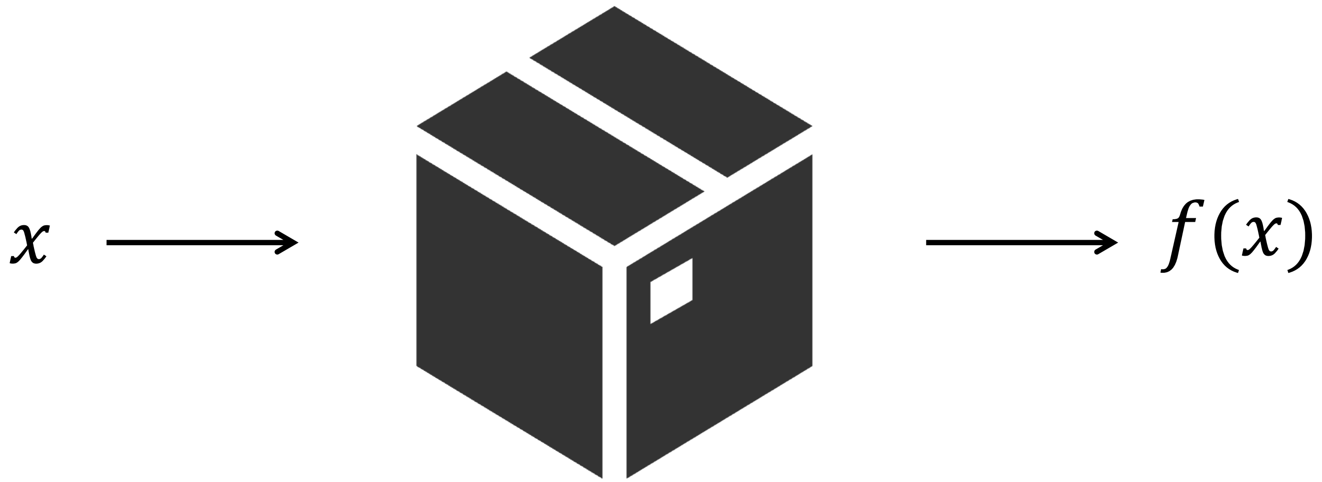


Goal: **max** $\mathbb{E} \max_{t=1,2,\ldots,T} f(x_t)$

Optimizing Black-box Functions



Goal: $\mathbf{max}\ \mathbb{E} \max_{t=1,2,\ldots,T} f(x_t)$

$f\sim$Gaussian Process

Bayesian Optimization

$x \longrightarrow$  $\longrightarrow f(x)$

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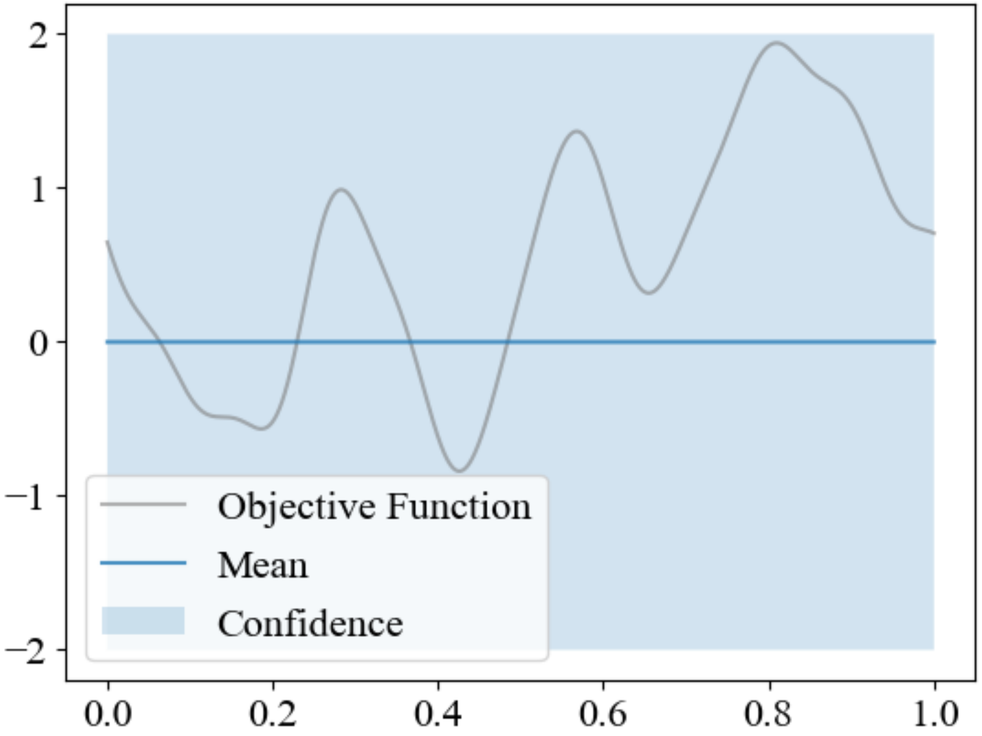

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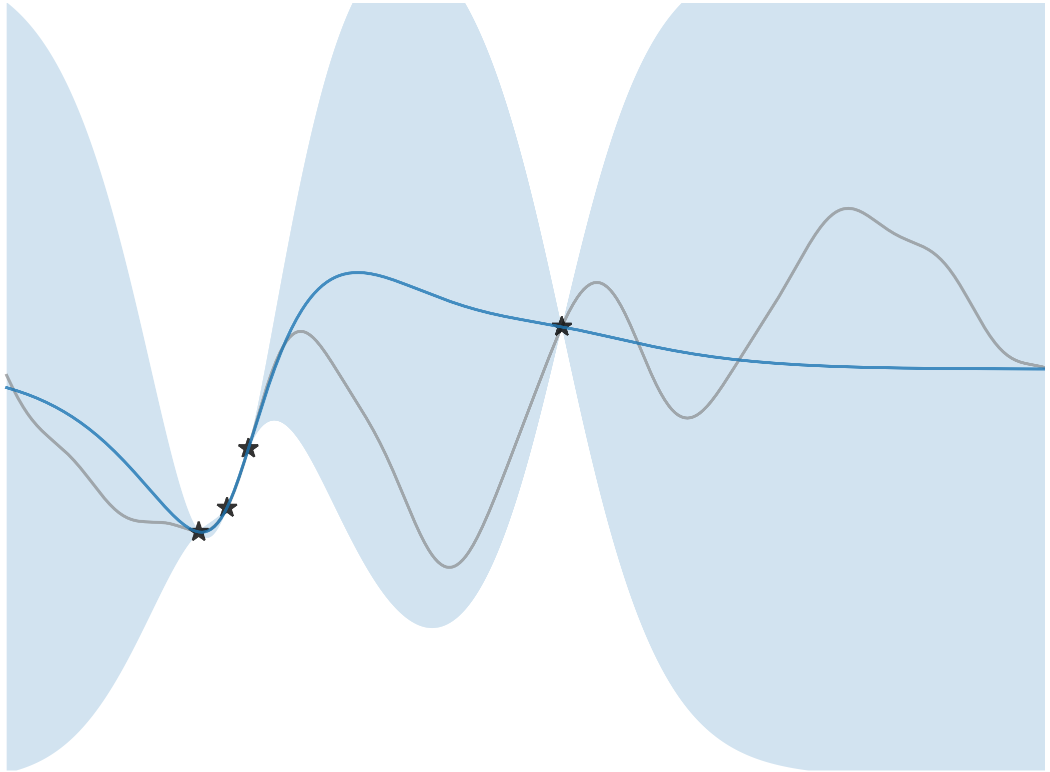

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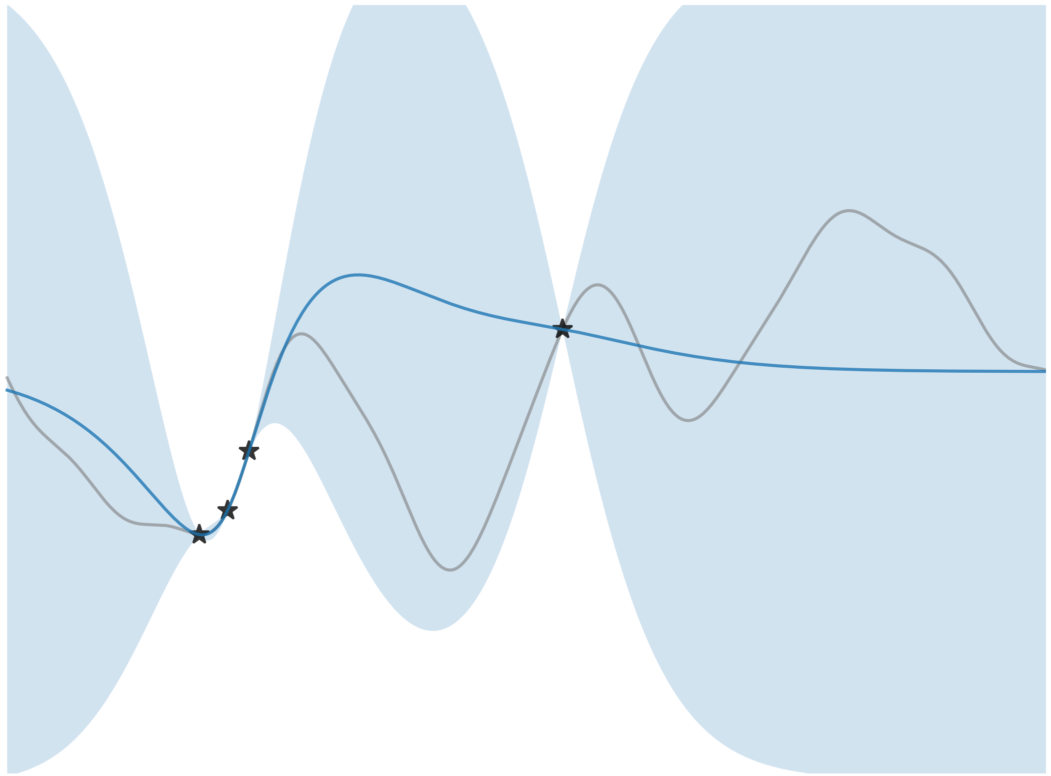
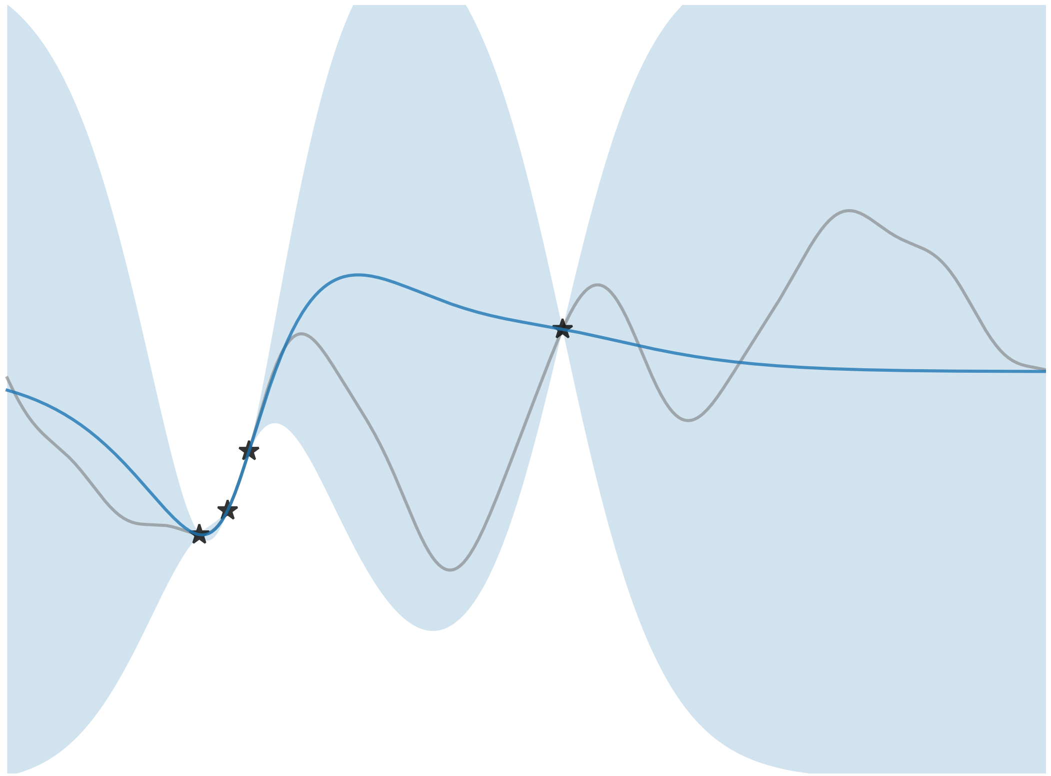


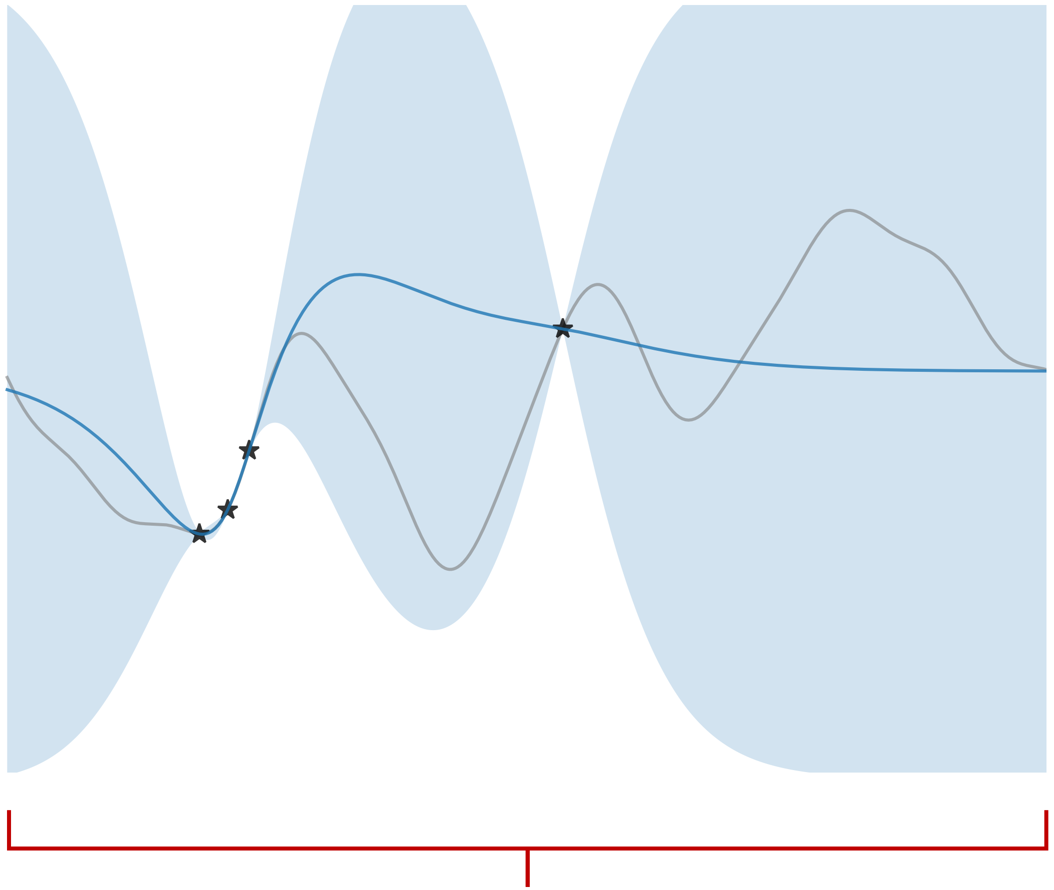
What to evaluate next?

Bayesian Optimization



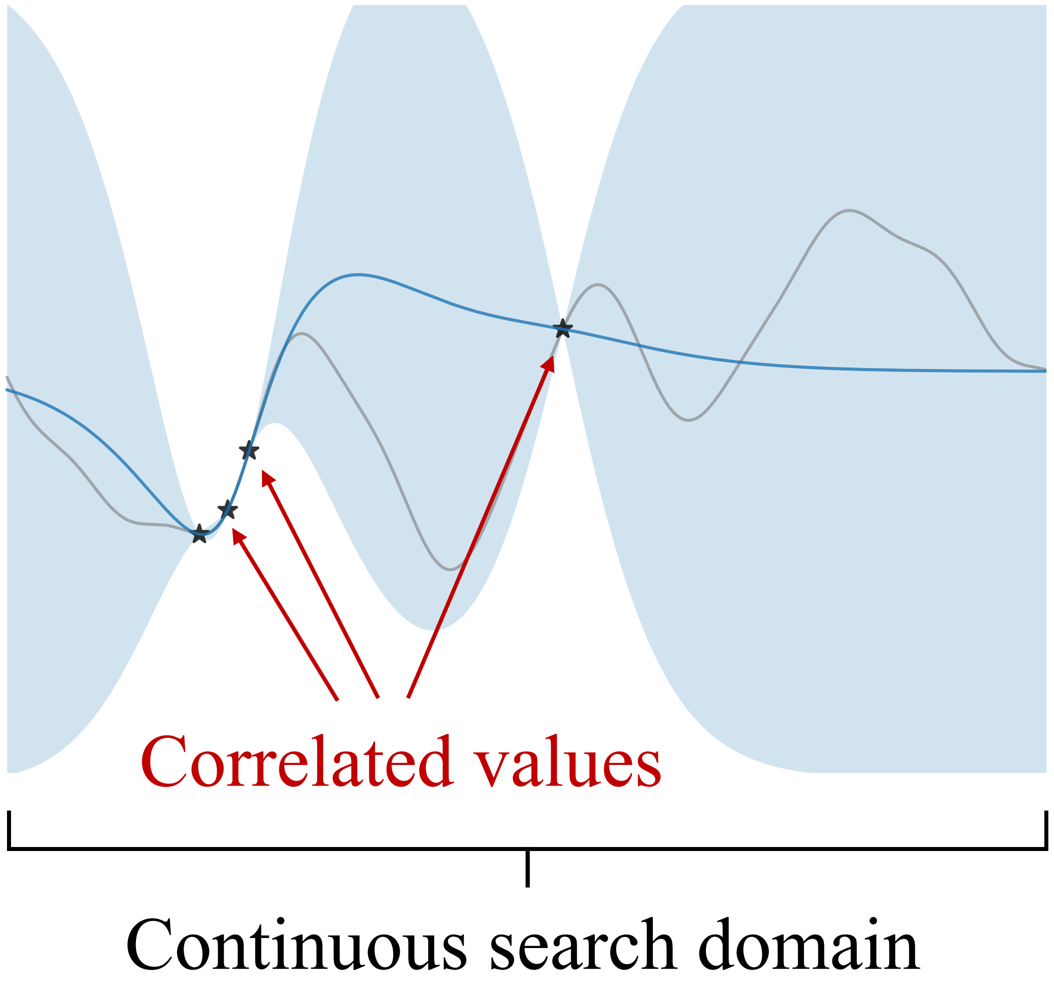
Optimal policy?

Challenges of Bayesian Optimization



Continuous search domain

Challenges of Bayesian Optimization



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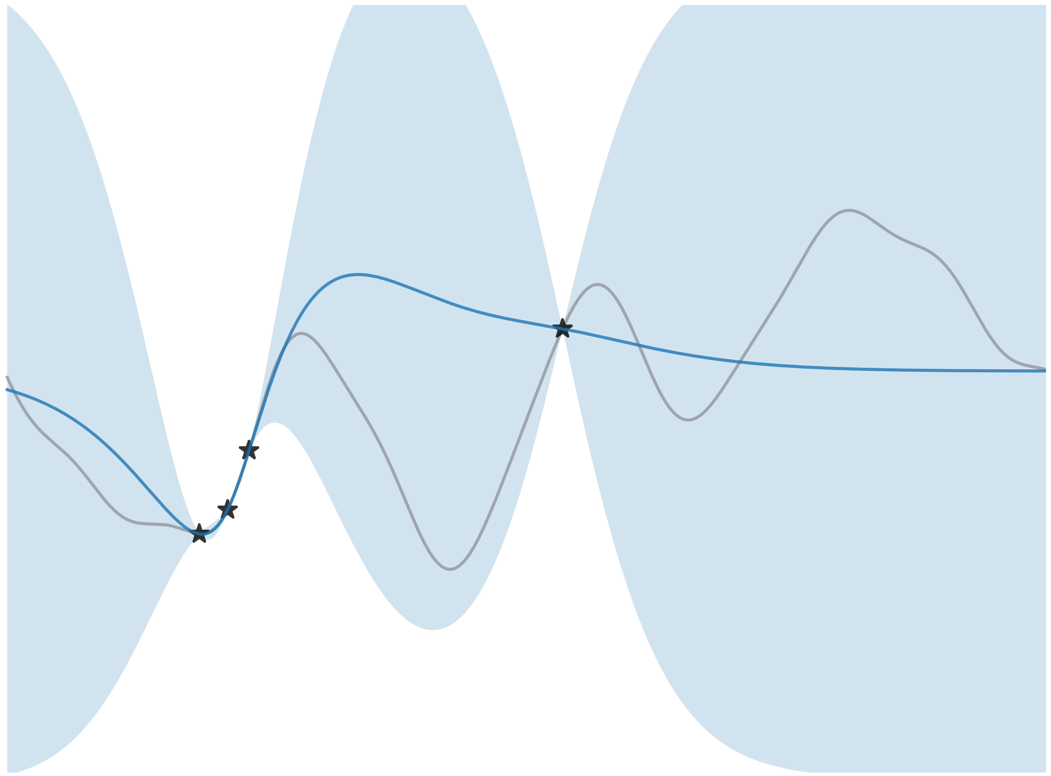
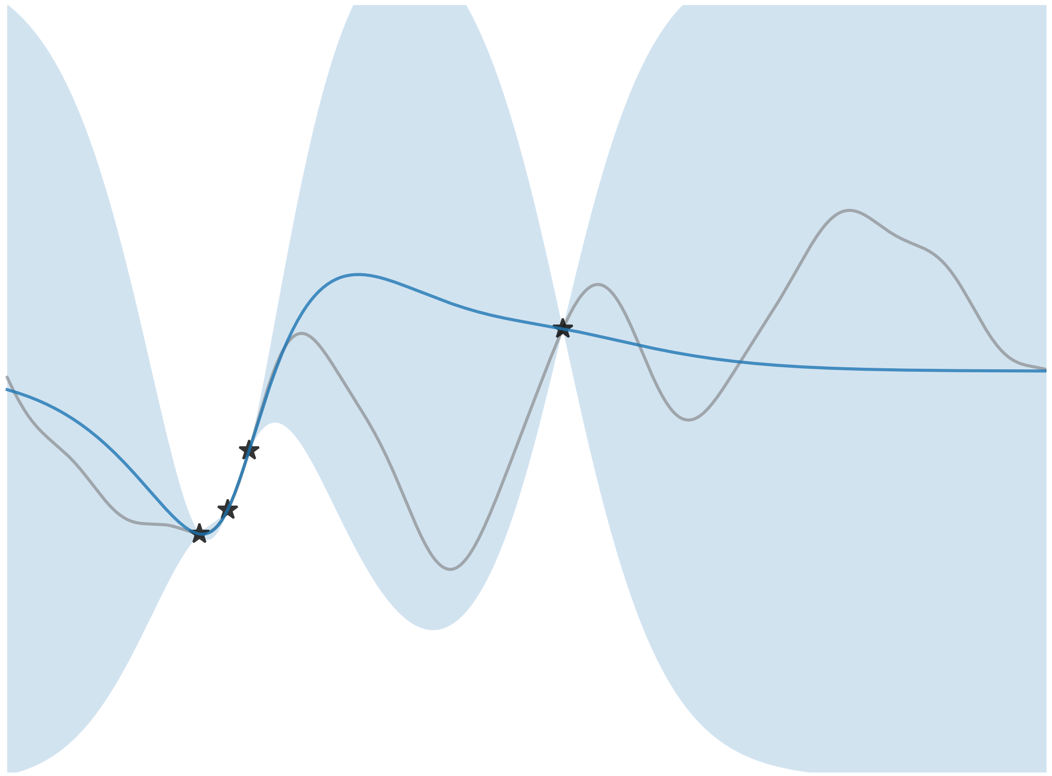


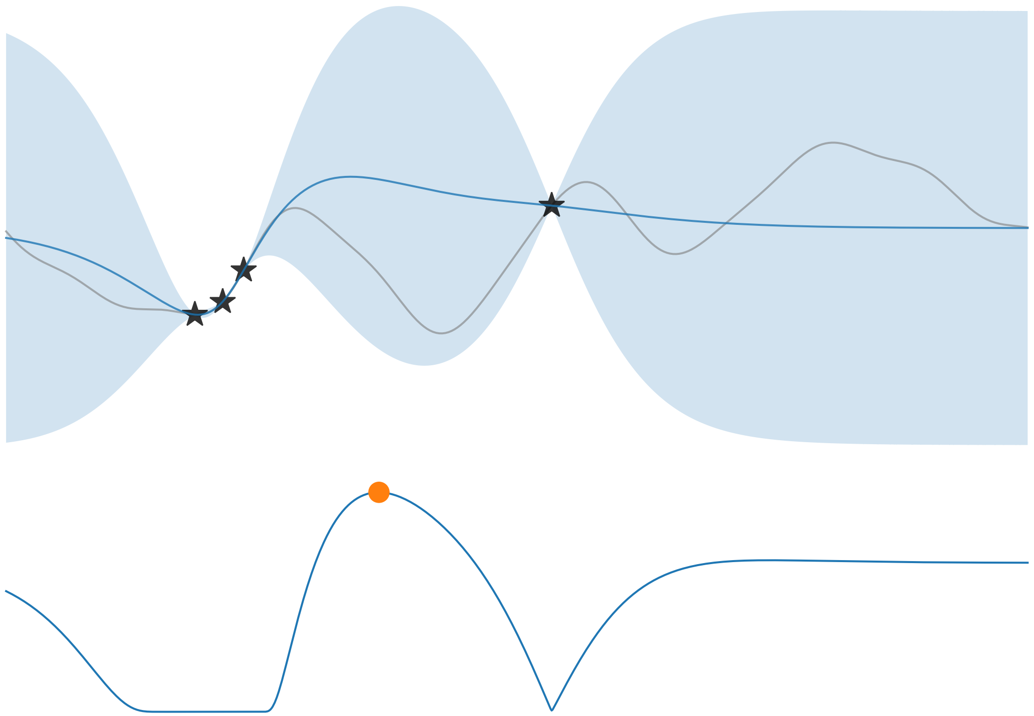
Correlation & continuity $\Longrightarrow$ Intractable MDP

Challenges of Bayesian Optimization



Intractable MDP $\Longrightarrow$ Optimal policy unknown

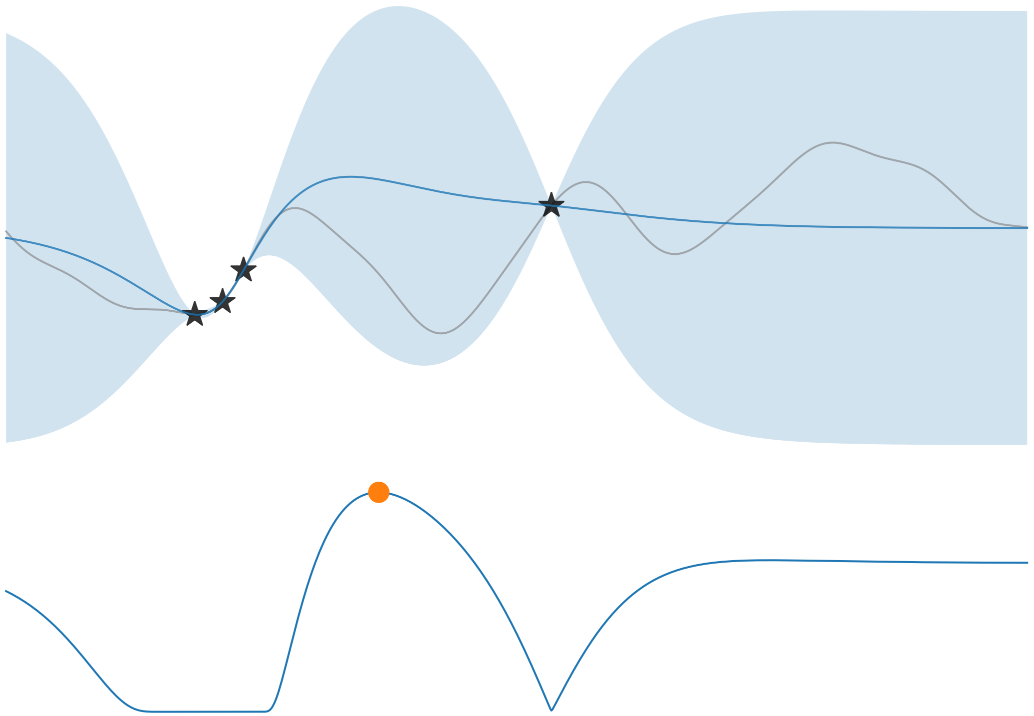
Popular Policy: Expected Improvement



current best observed
data

$$\mathrm{EI}(x) = \mathbb{E}[\underbrace{\max(f(x) - y_{\text{best}}, 0)}_{\text{“improvement”}} \mid D]$$

Popular Policy: Expected Improvement



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$$\max_x \mathrm{EI}_{f|D}(x; y_{\text{best}})$$

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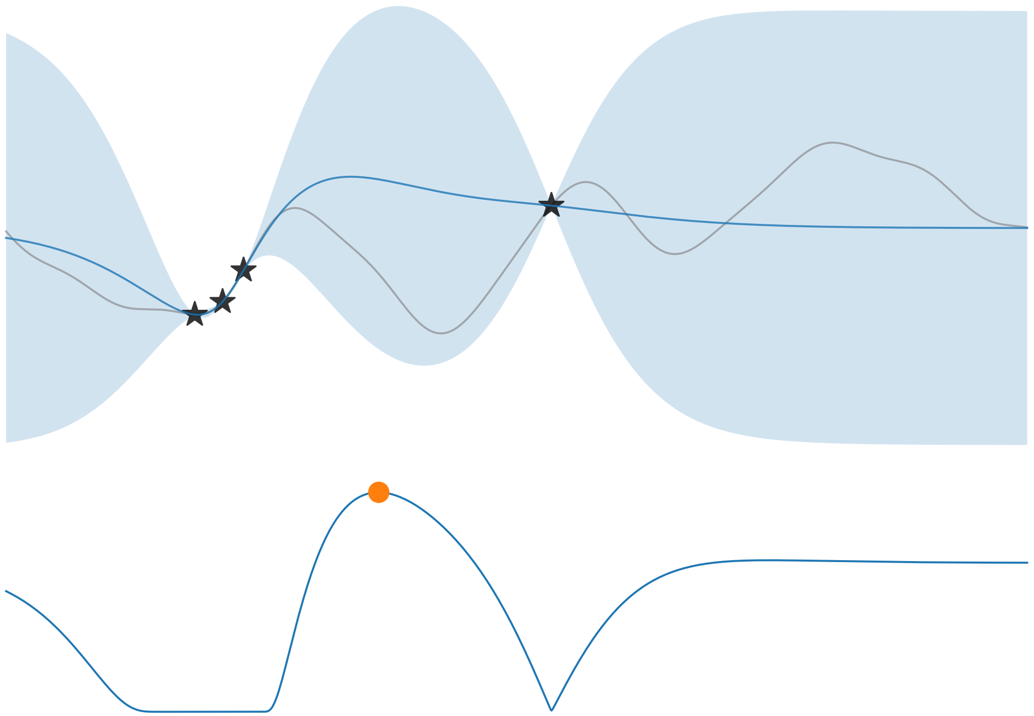

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One-step approximation to MDP

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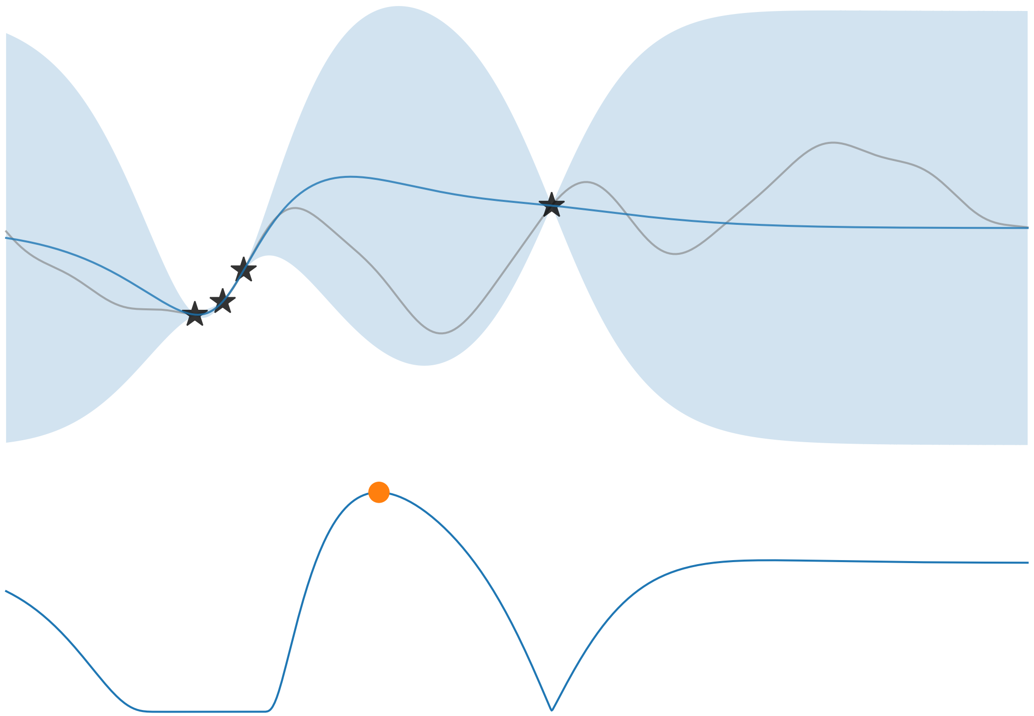

Other improvement-based policy:

- Probability of Improvement
- Knowledge Gradient
- Multi-step Lookahead EI
- …

Approaches to Bayesian Optimization

- Improvement-based:
  - Expected Improvement
  - Probability of Improvement
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- Our work: Gittins Index

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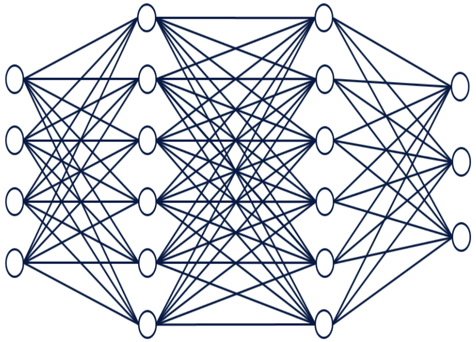
Why another approach?

Challenge: Varying Evaluation Costs

Hyperparameter tuning:

Training parameters →  → Accuracy

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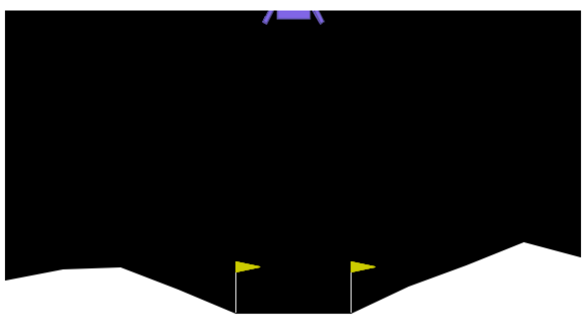
Control parameters →  → Reward

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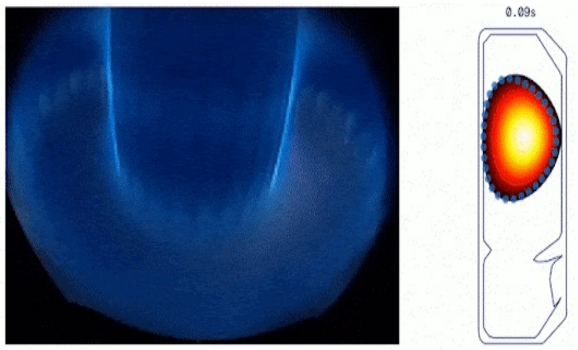
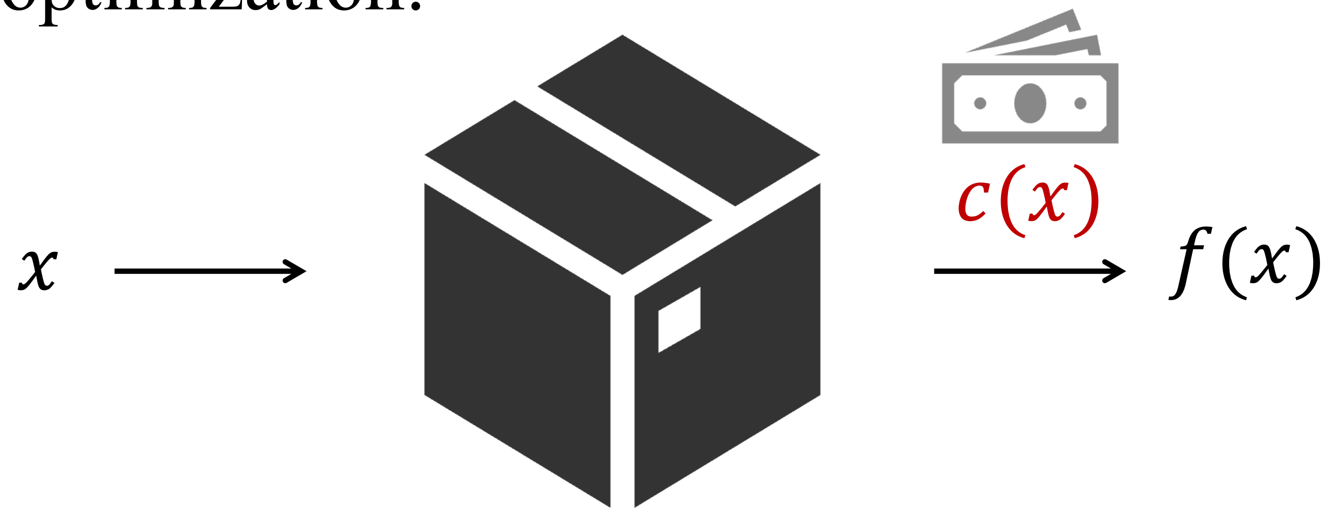
Reactor parameters → 

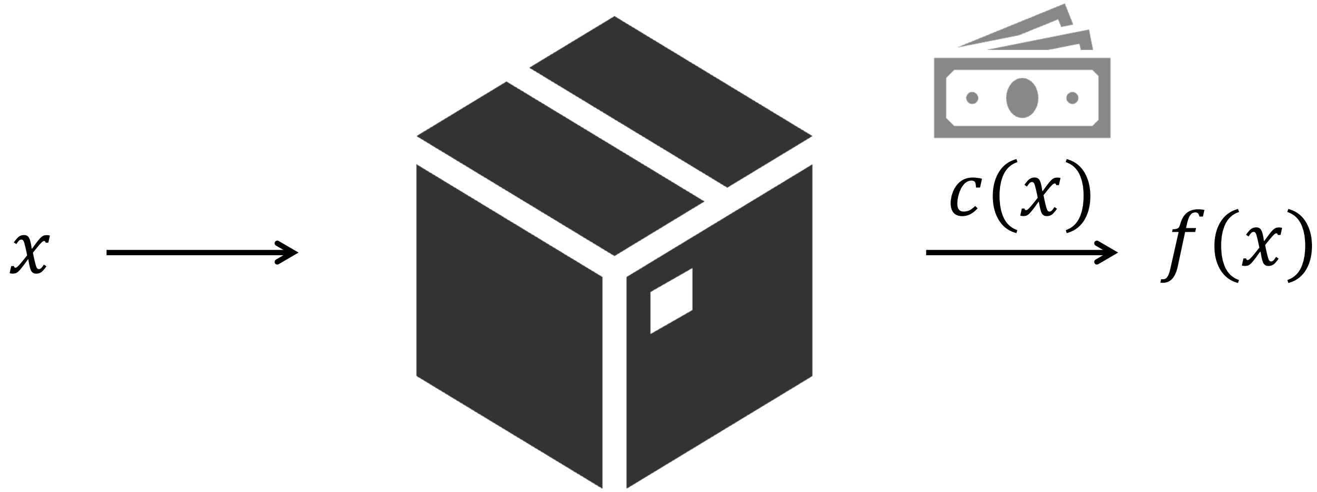
→ Stability

Challenge: Varying Evaluation Costs

Black-box optimization:



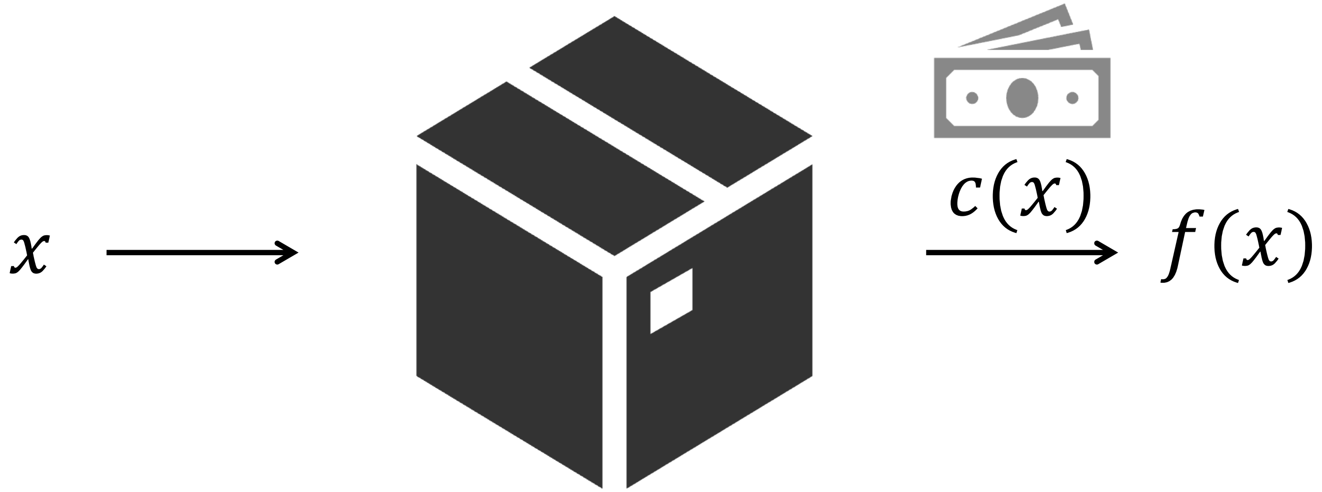
Challenge: Varying Evaluation Costs



Goal: $\mathbf{max}\ \mathbb{E} \max_{t=1,2,\ldots,T} f(x_t)$

s.t. $\mathbb{E} \sum_{t=1}^{T} c(x_t) \leq B$

Cost-aware Bayesian Optimization



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[Lee, Perrone, Archambeau, Seeger’21]

[Astudillo, Jiang, Balandat, Bakshy, Frazier’21]

Cost-aware Bayesian Optimization

Uniform costs

Expected improvement

$\max_x \mathrm{EI}_{f|D}(x; y_{\mathrm{best}})$

Varying costs

Cost-aware Bayesian Optimization

Uniform costs

Expected improvement

$\max_x \mathrm{EI}_{f|D}(x; y_{\text{best}})$

Varying costs

Expected improvement per cost

$\max_x \mathrm{EI}_{f|D}(x; y_{\text{best}})/c(x)$

Cost-aware Bayesian Optimization

Uniform costs

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Why divide?

Cost-aware Bayesian Optimization

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Why divide?

Our view: lack of a guidance to incorporate costs

Cost-aware Bayesian Optimization

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EI and EIPC policy can be arbitrarily bad under varying costs!

[Astudillo, Jiang, Balandat, Bakshy, Frazier'21]

Cost-aware Bayesian Optimization

Uniform costs	Varying costs
Expected improvement	Expected improvement per cost
Multi-step Lookahead EI	Budgeted Multi-step Lookahead EI

slow

Cost-aware Bayesian Optimization

Uniform costs	Varying costs
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Upper Confidence Bound	?
Thompson Sampling	?

Cost-aware Bayesian Optimization

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⋮	⋮

New design principle: Gittins Index

Cost-aware Bayesian Optimization

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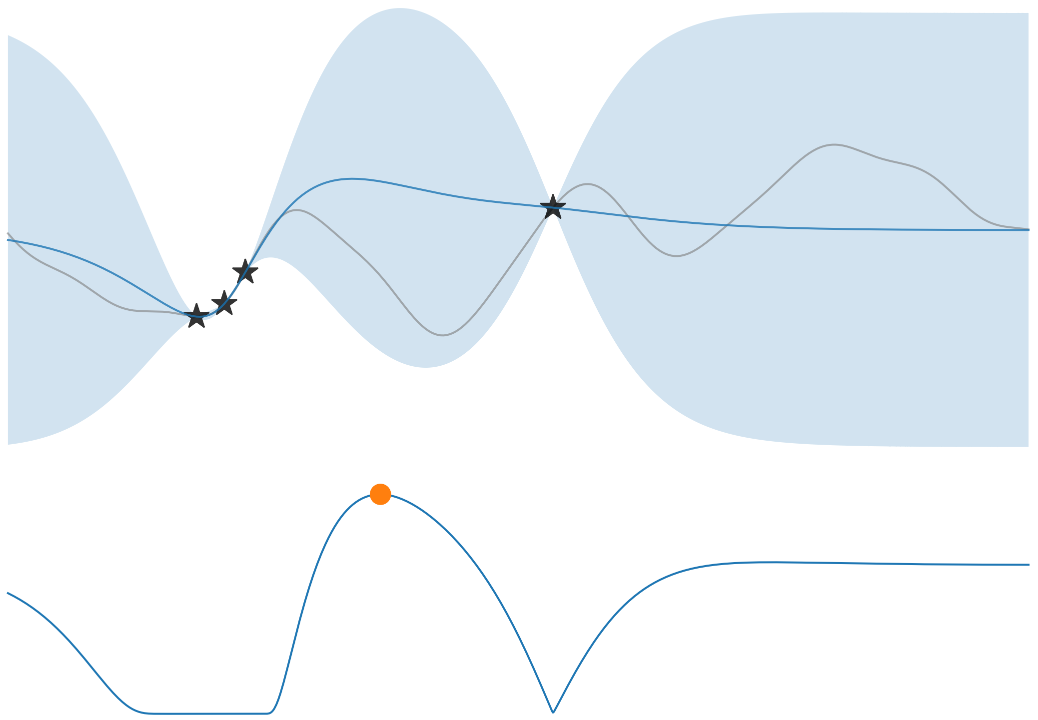
⋮	⋮

New design principle: Gittins Index

Cost-aware

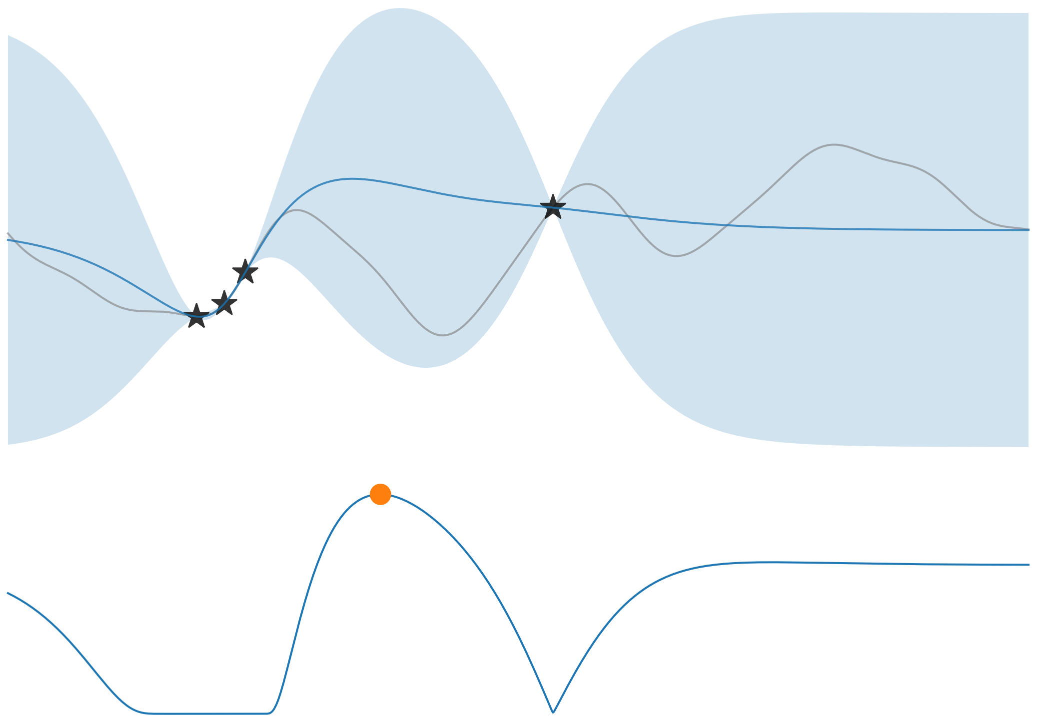
Expected Improvement



$$\mathrm{EI}(x) = \mathbb{E}[\max(f(x) - y_{\text{best}}, 0) \mid D]$$

$$\max_x \mathrm{EI}_{f|D}(x; y_{\text{best}})$$

Expected Improvement



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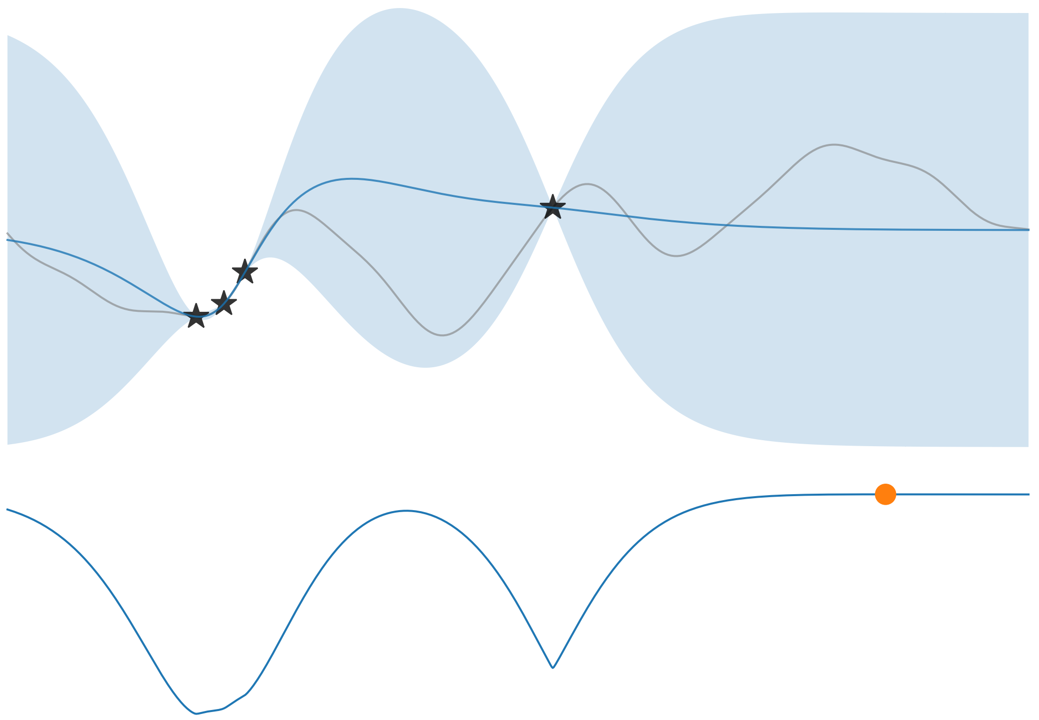
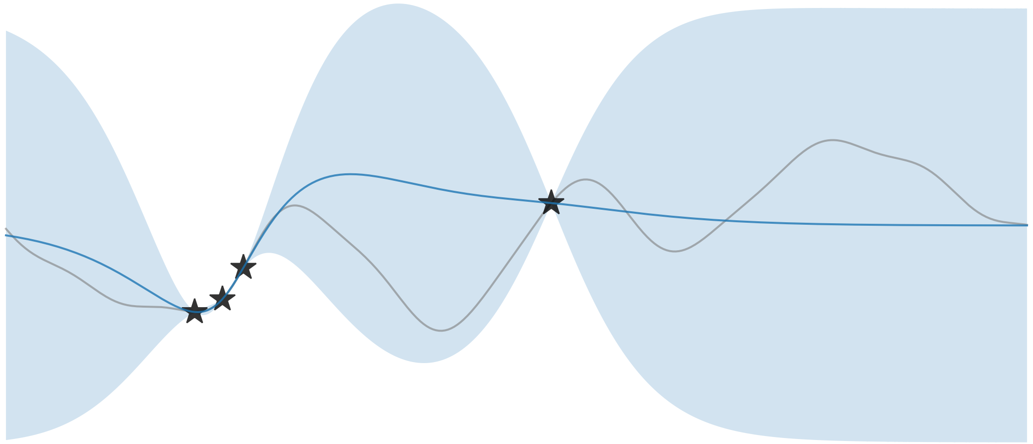
Gittins Index

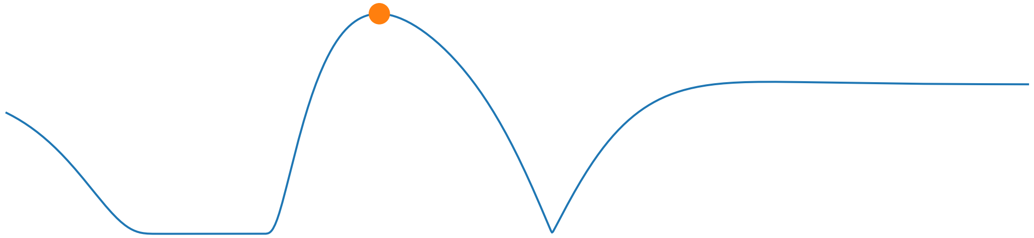


$$\color{red}{\mathrm{GI}_{f|D}(x)} = g \text{ s.t. } \mathrm{EI}_{f|D}(x; \color{red}{g}) = c(x)$$

$$\max_x \mathrm{GI}_{f|D}(x)$$

Expected Improvement





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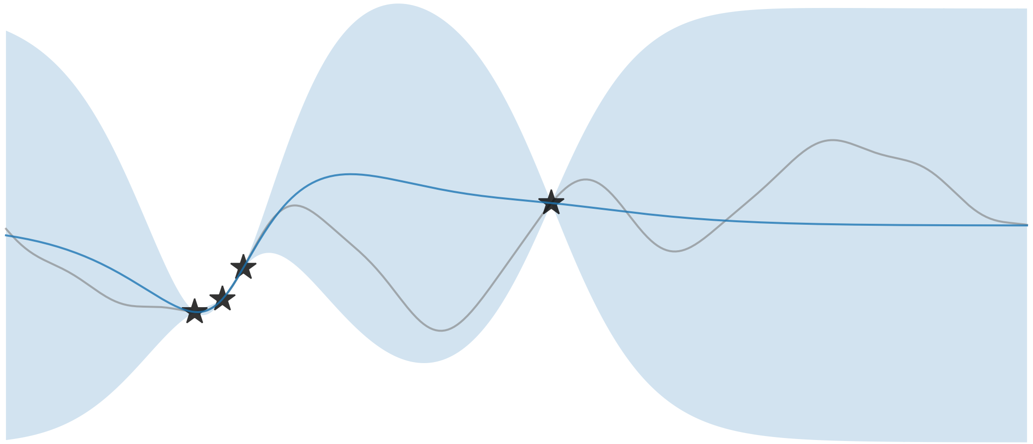
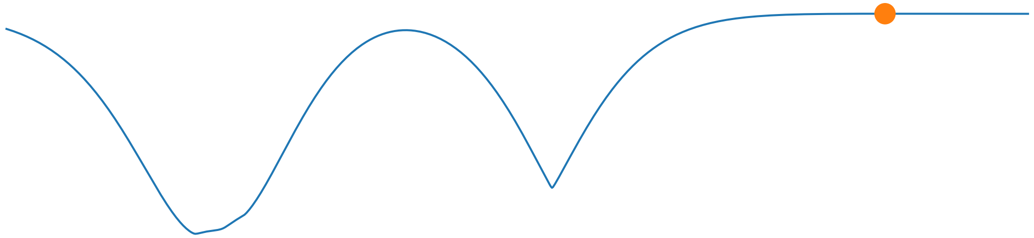
One-step approximation to MDP

Gittins Index





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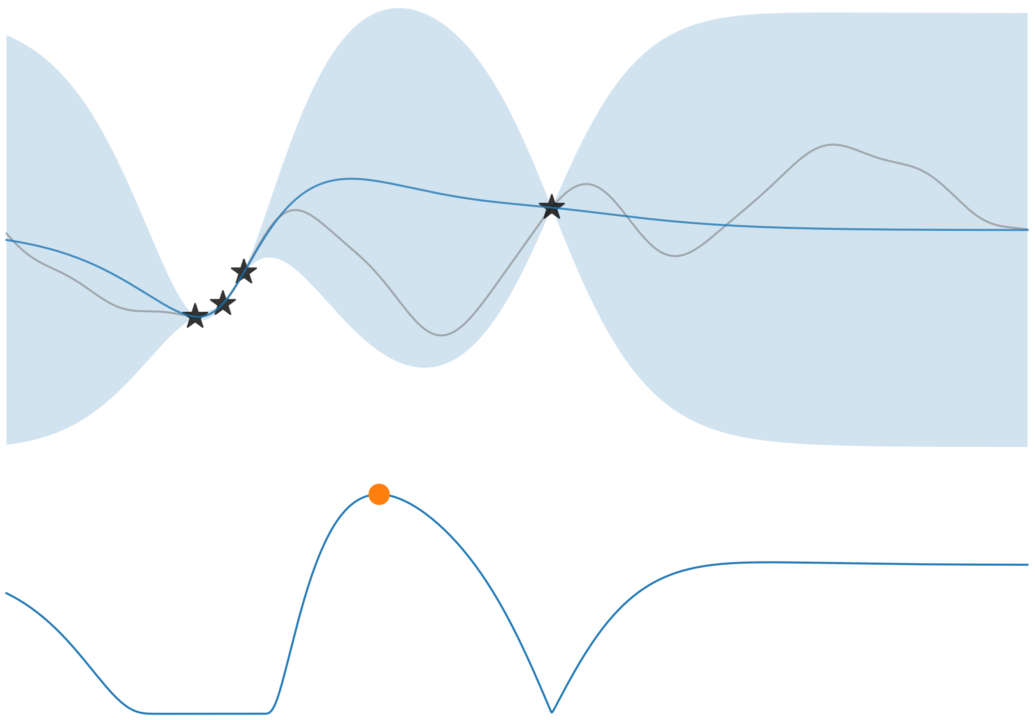

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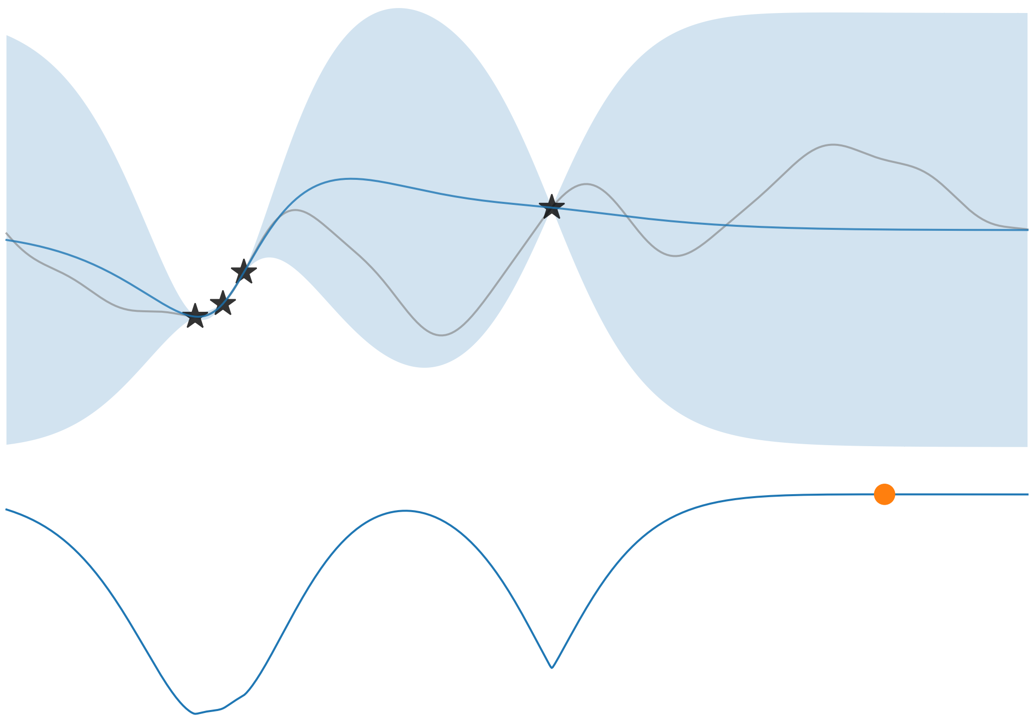
Temporal simplification to MDP

Gittins Index



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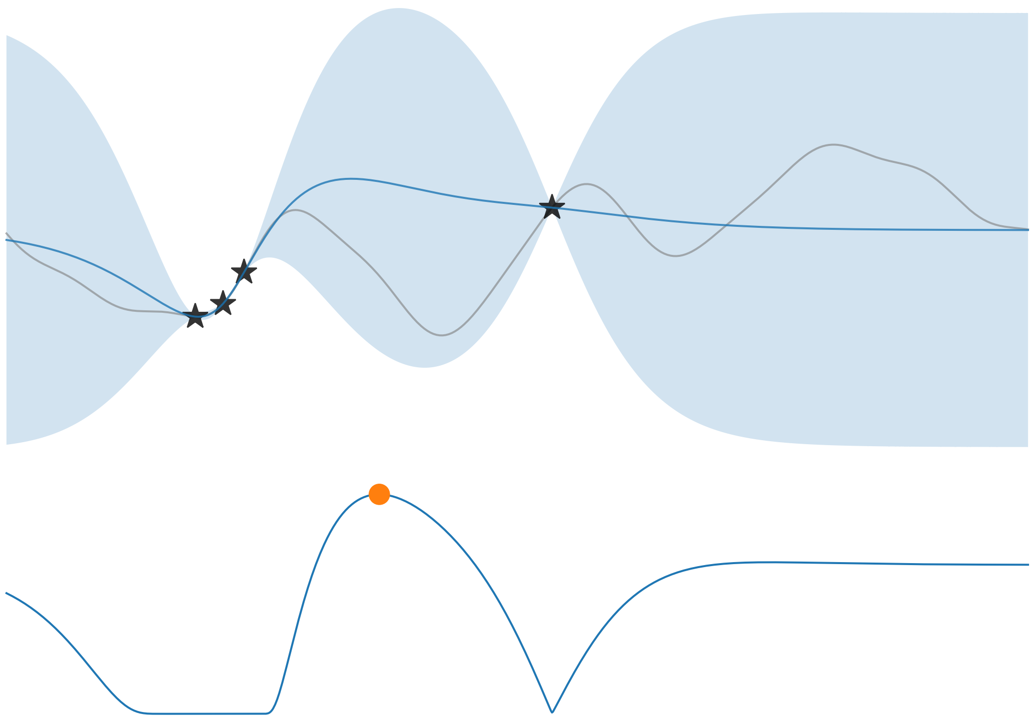

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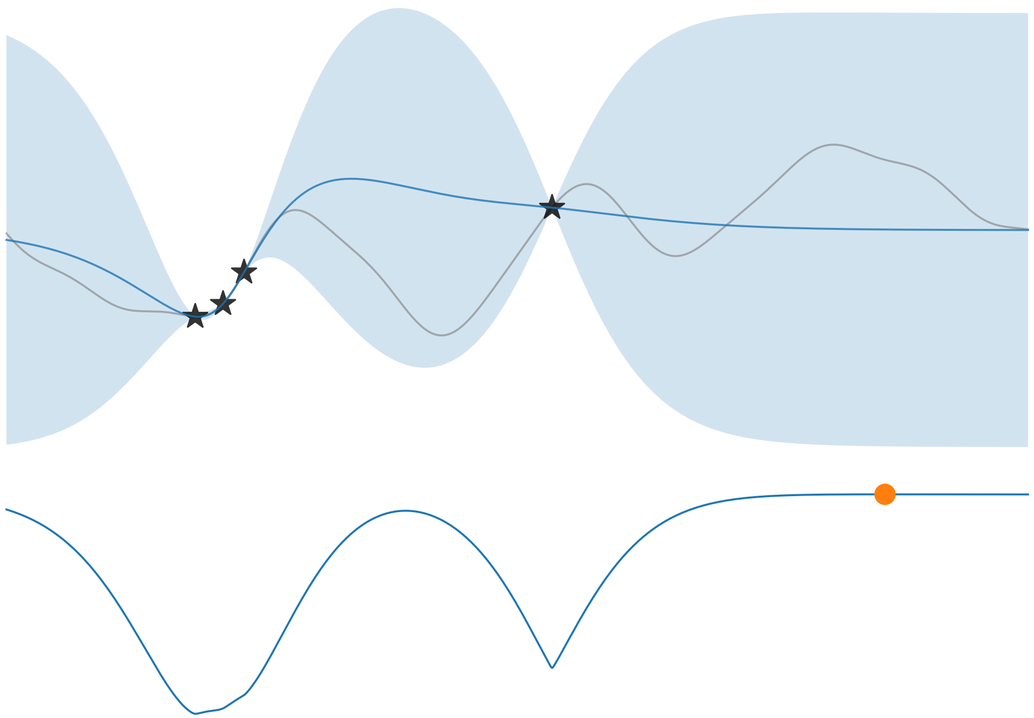

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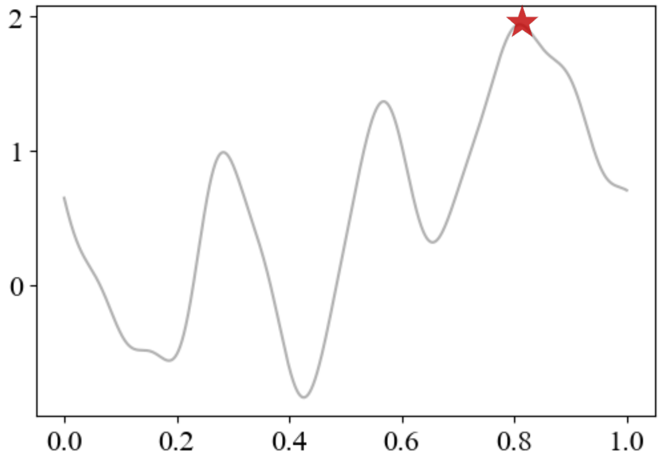
$$\max_x \mathrm{GI}_{f|D}(x)$$

Spatial simplification to MDP

Our Approach: Spatial Simplification

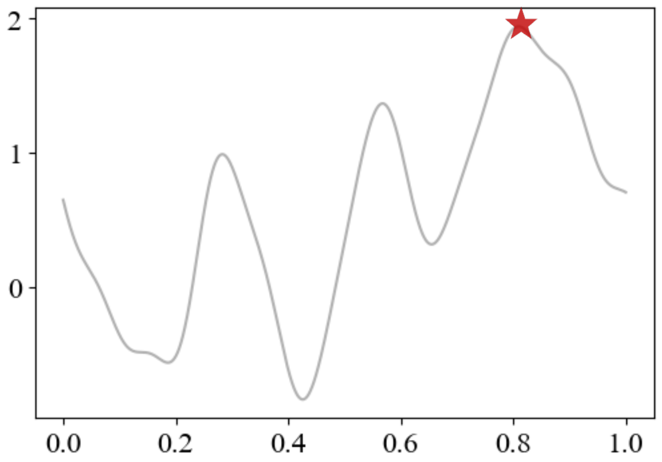


Bayesian Optimization

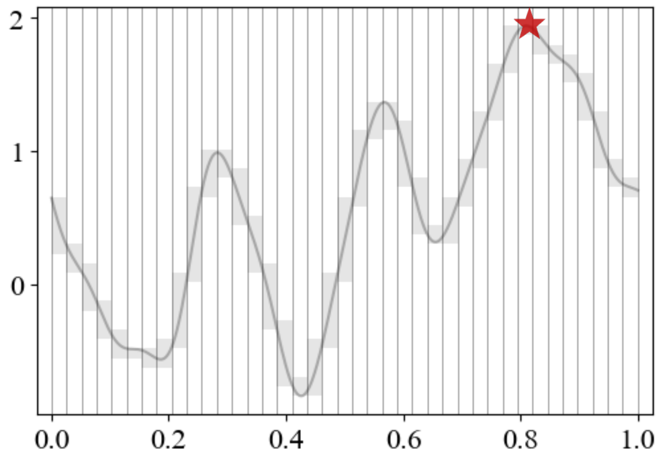
Continuous

Correlated

Our Approach: Spatial Simplification



$\Longrightarrow$



Bayesian Optimization

Continuous $\Longrightarrow$ Discrete

Correlated

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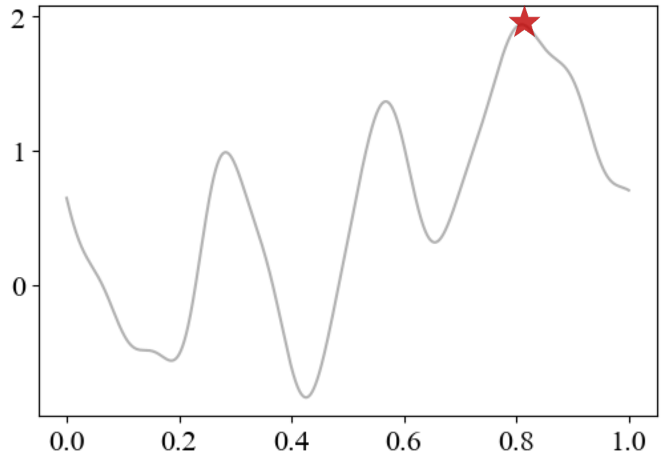

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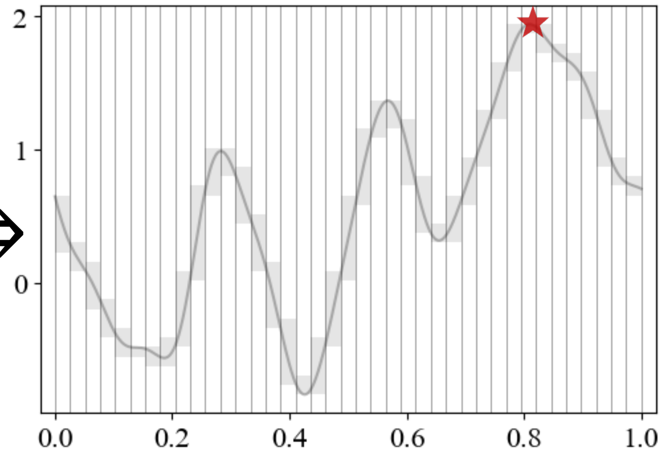

Bayesian Optimization

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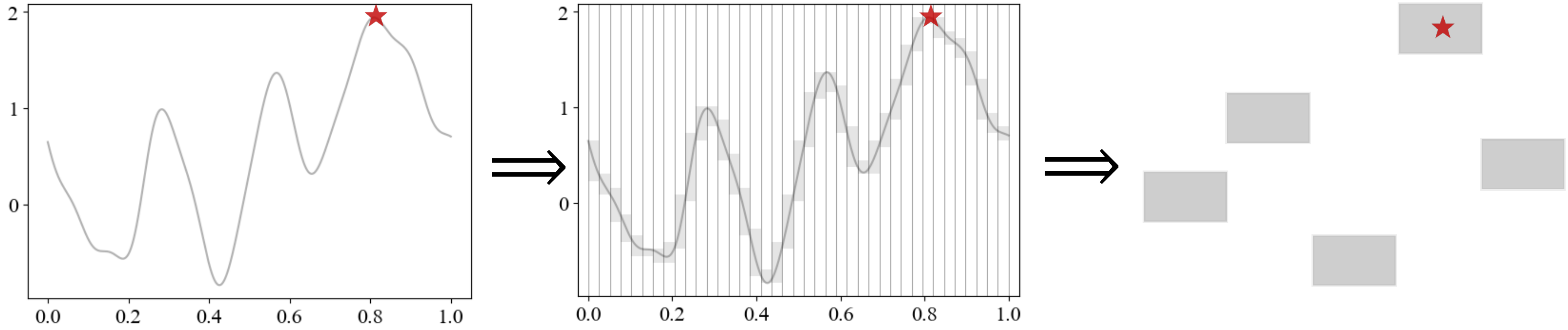
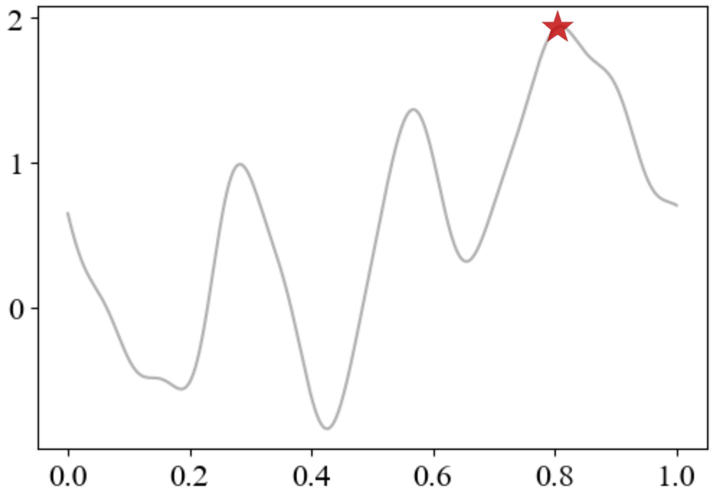


Bayesian Optimization

Continuous $\Longrightarrow$ Discrete

Correlated $\Longrightarrow$ Independent

Our Approach: Spatial Simplification



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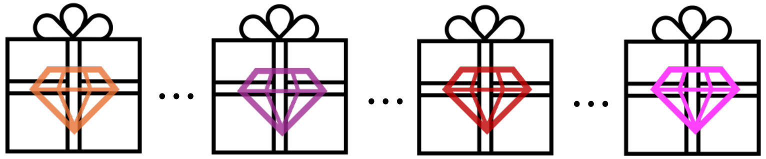


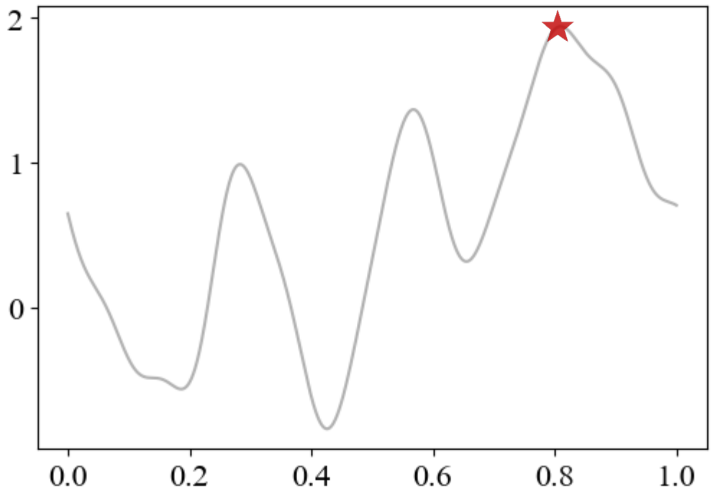
Bayesian Optimization

Pandora's Box [Weitzman'79]

Continuous $\Longrightarrow$ Discrete

Correlated $\Longrightarrow$ Independent

Our Approach: Spatial Simplification



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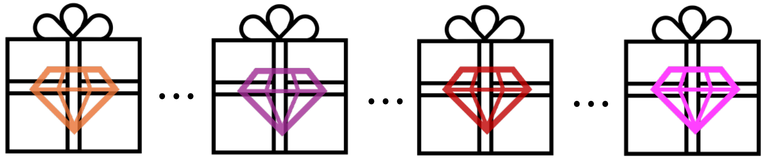


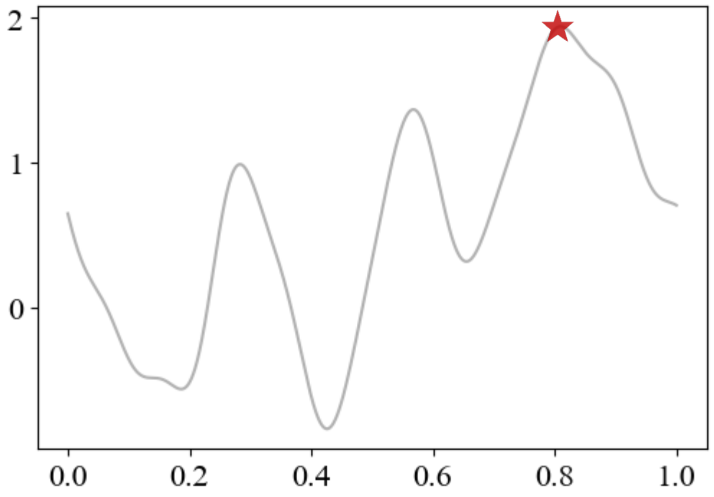
Bayesian Optimization | Pandora's Box [Weitzman'79]

Continuous $\Longrightarrow$ Discrete

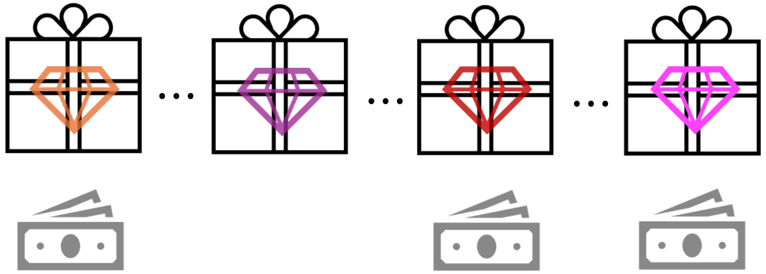
Correlated $\Longrightarrow$ Independent

Optimal policy: Gittins index

Our Approach: Spatial Simplification



$\Longrightarrow$



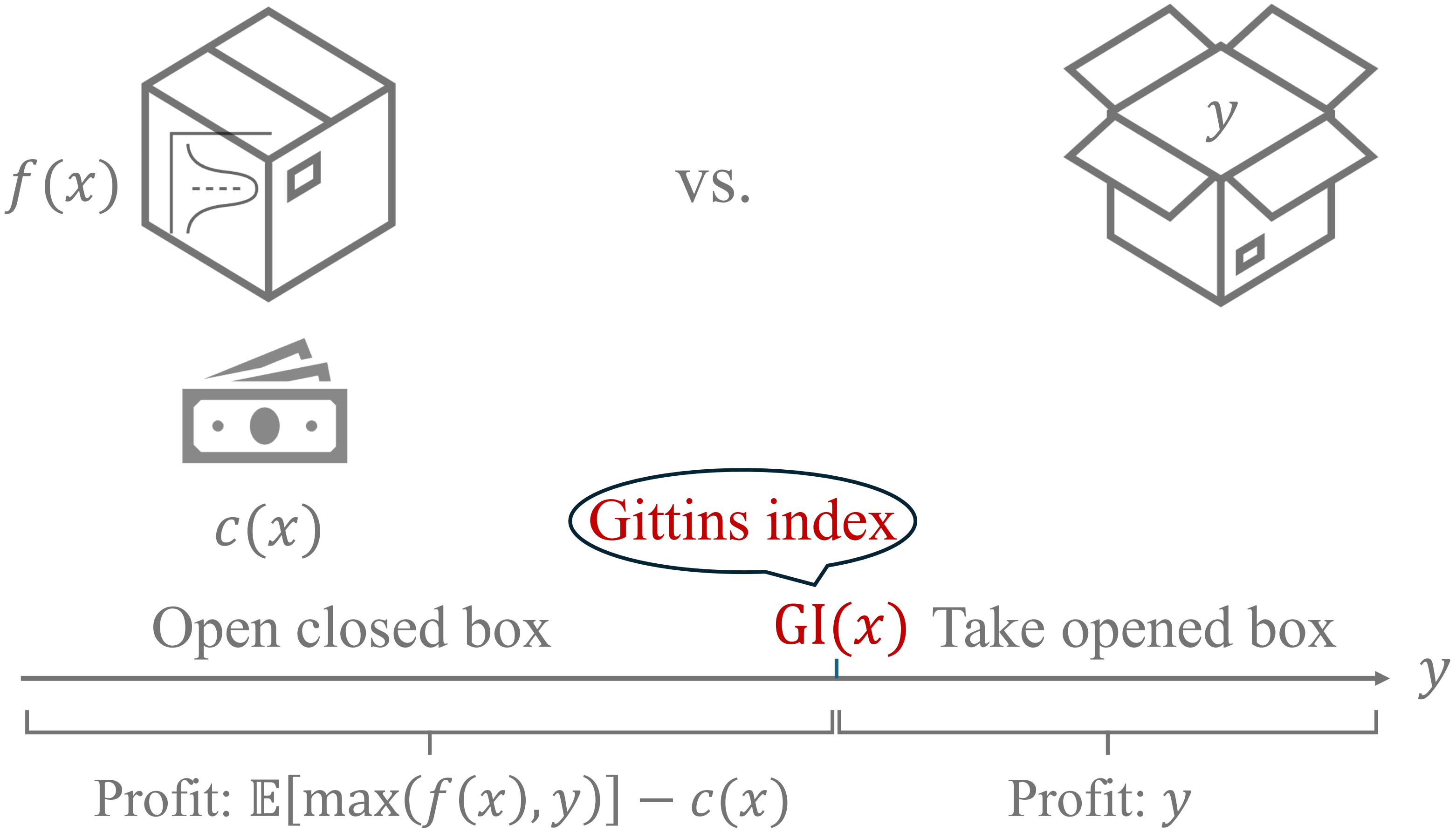
Bayesian Optimization		Pandora's Box
Continuous	$\Longrightarrow$	Discrete
Correlated	$\Longrightarrow$	Independent

allow varying costs

Optimal policy: Gittins index

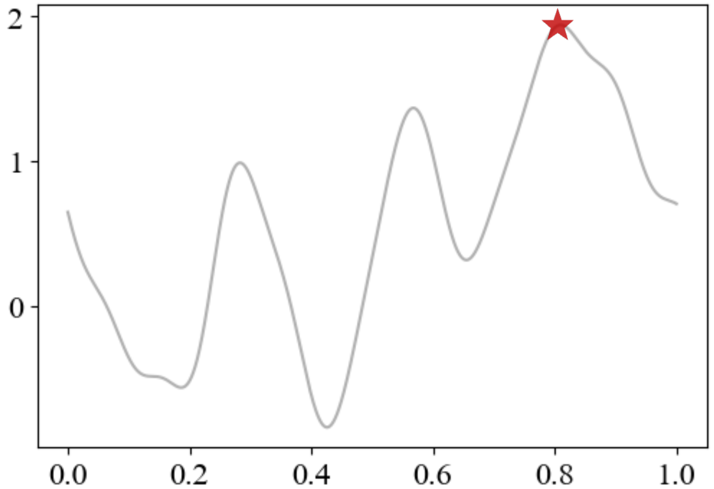
Intuition Behind Pandora's Box Gittins Index

1.5-box problem:

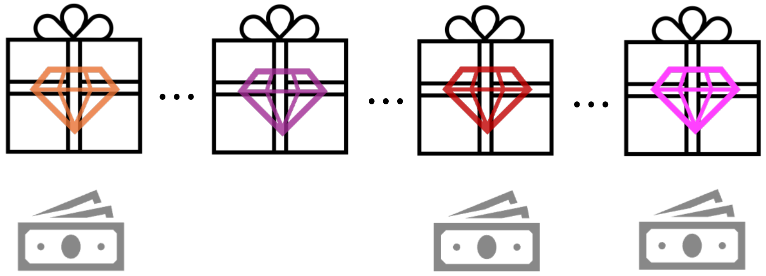


$\mathrm{GI}(x)$: solution y to $\mathbb{E}[\max(f(x), y)] - c(x) = y$

How to translate Gittins index?



$\Longrightarrow$



Bayesian Optimization

Pandora's Box

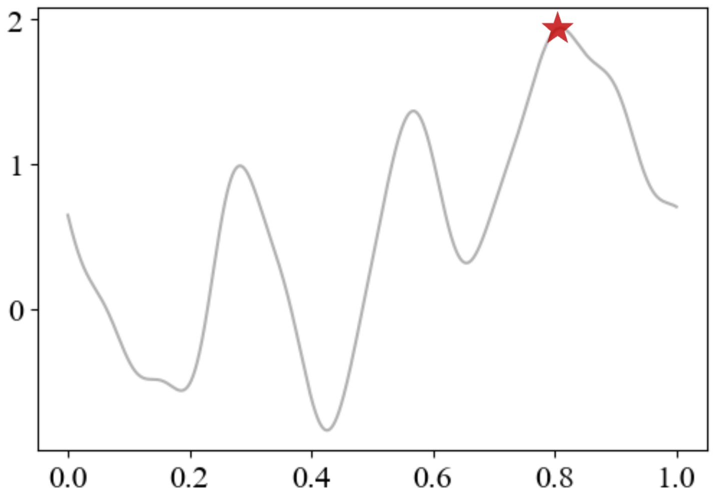
Continuous $\Longrightarrow$ Discrete

Correlated $\Longrightarrow$ Independent

How to translate?

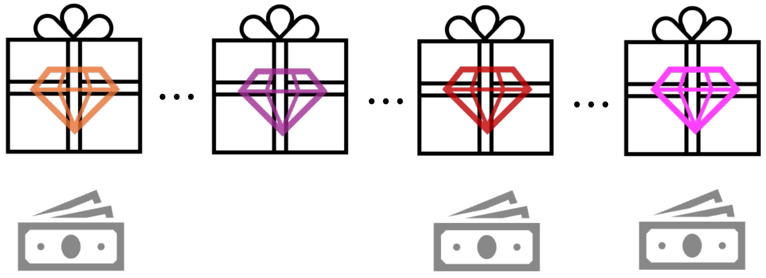
$\Longleftarrow$ Optimal policy: Gittins index

How to translate Gittins index?



Bayesian Optimization

$\Longrightarrow$



Pandora's Box

Continuous $\Longrightarrow$ Discrete

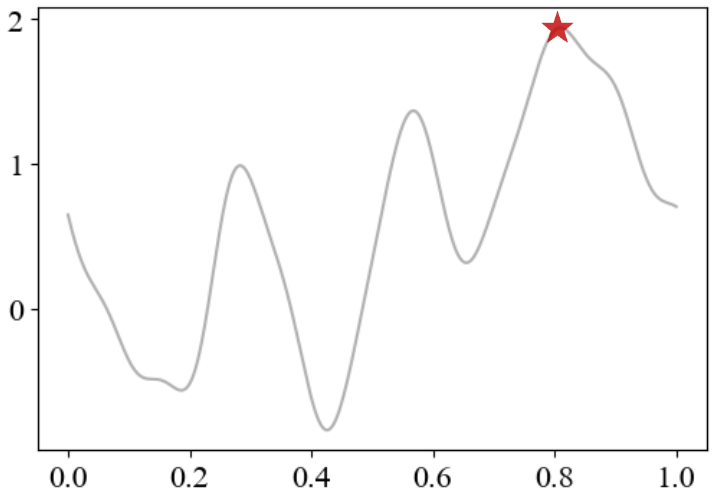
Correlated $\Longrightarrow$ Independent

incorporate posterior

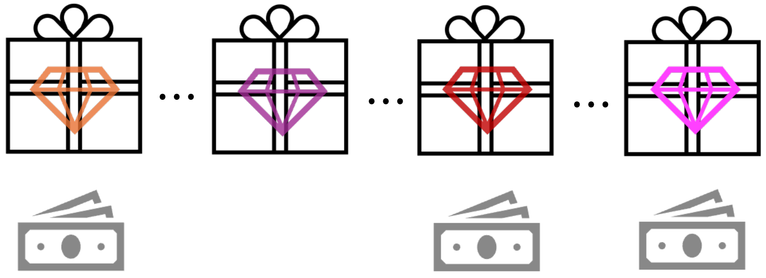
Our policy $\Longleftarrow$ Optimal policy: Gittins index

$\max_x \mathrm{GI}_{f|D}(x)$ $\qquad$ $\max_x \mathrm{GI}(x)$

Is Gittins good in Bayesian Optimization?



$\Longrightarrow$



Bayesian Optimization | Pandora's Box [Weitzman'79]

Continuous $\Longrightarrow$ Discrete

Correlated $\Longrightarrow$ Independent

Is Gittins index good? $\Longleftarrow$ Gittins index is optimal

$\max_x \mathrm{GI}_{f|D}(x)$ | $\max_x \mathrm{GI}(x)$

Experiment Setup: Objective Functions

Samples from prior

Synthetic

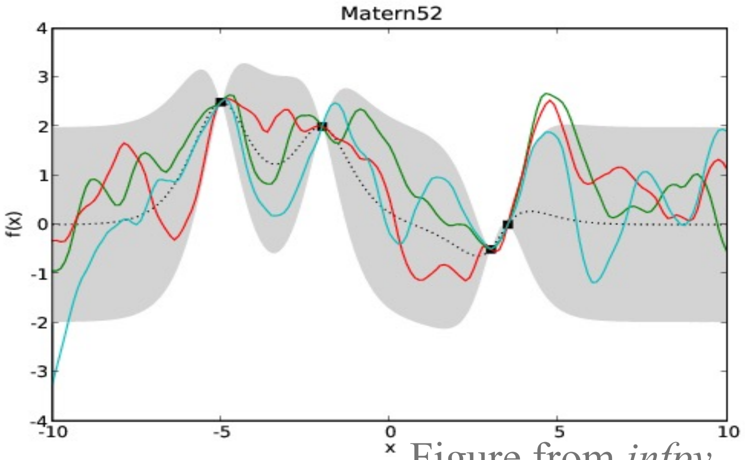


Figure from *infpy*

Ackley function

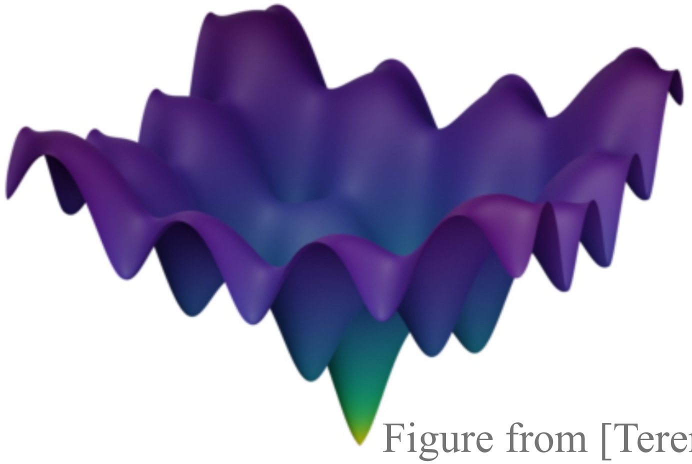


Figure from [Terenin'22]

Pest Control

Empirical

Figure from ChatGPT

Lunar Lander

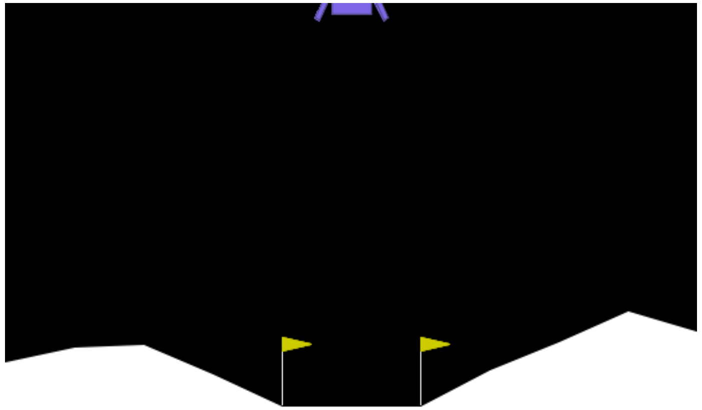
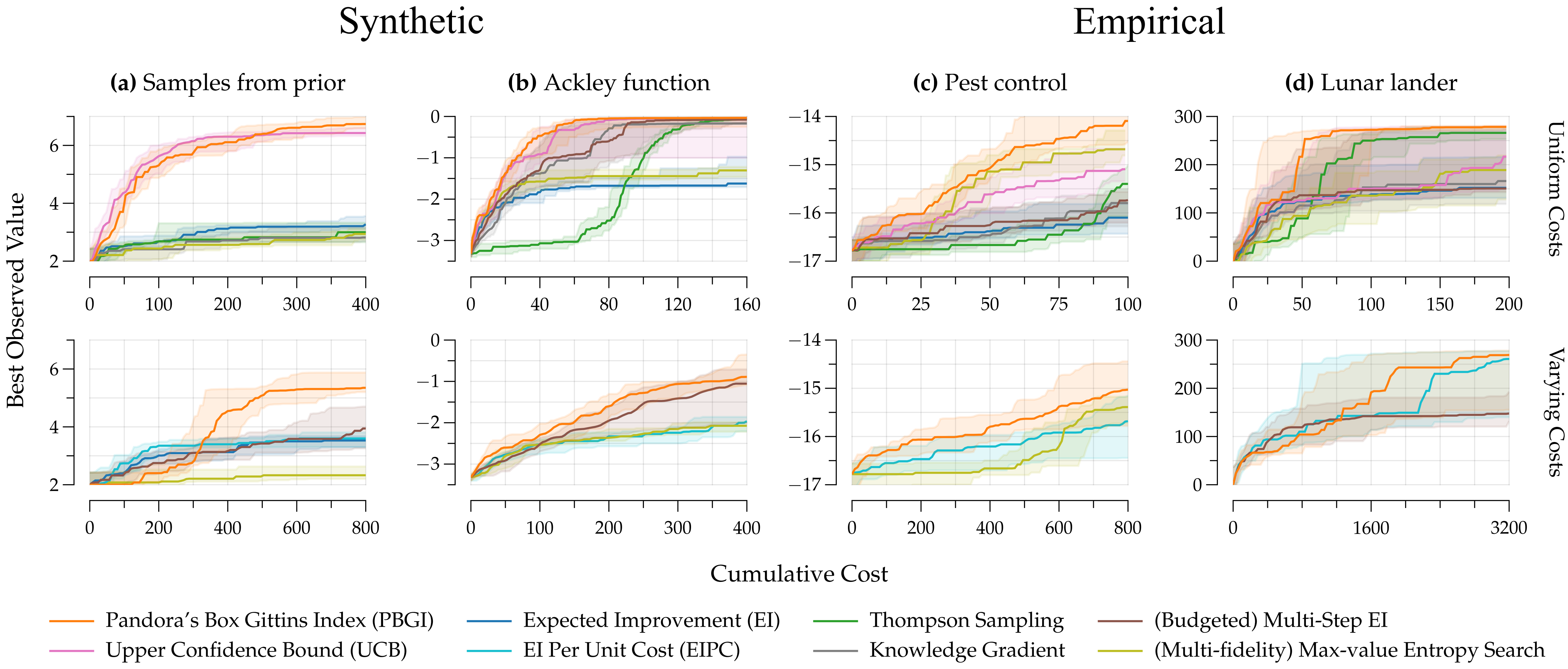


Figure from OpenAI Gym

Experiment Results



FAQ

- Easy-to-compute?

FAQ

- Easy-to-compute?

  Yes, EI + bisection

FAQ

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  Yes, EI + bisection
- Any theoretical results?

FAQ

- Easy-to-compute?

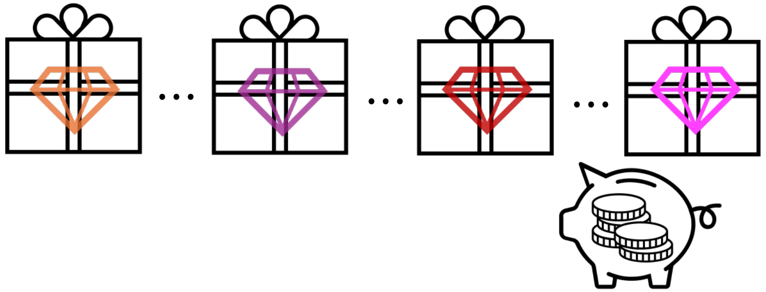
  Yes, EI + bisection

- Any theoretical results?

  Yes, expected-budget-constrained ≅ cost-per-sample

Theoretical Result

max best observed under budget

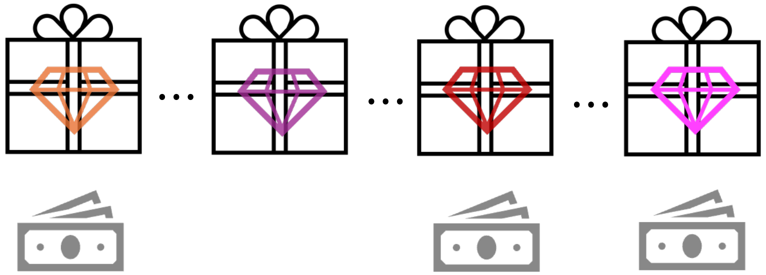


Budgeted Pandora's Box

Expected budget constraint

Optimal policy?

max (best observed – costs)



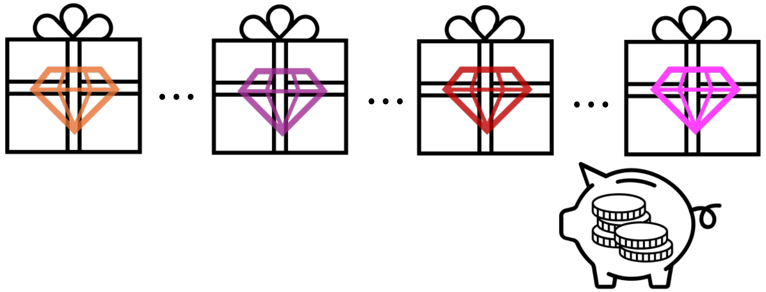
Pandora's Box

Cost per sample

Optimal policy: Gittins index

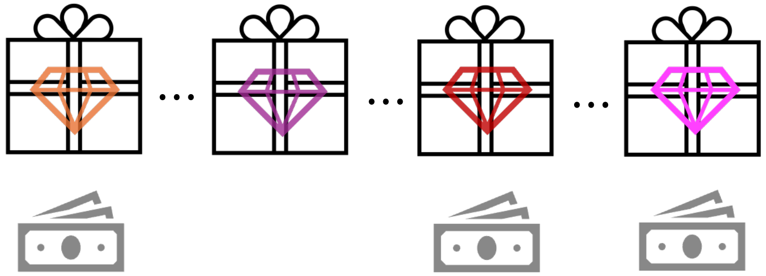
Theoretical Result

max best observed under budget



$\Longleftarrow$

max (best observed – scaled costs)



Budgeted Pandora's Box

Expected budget constraint

Optimal policy

extension to [Aminian, Manshadi, Niazadeh'24]

Pandora's Box

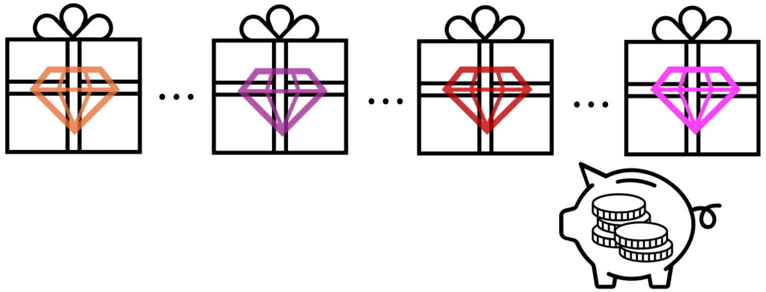
Cost per sample

Optimal policy: Gittins index

Theoretical Result

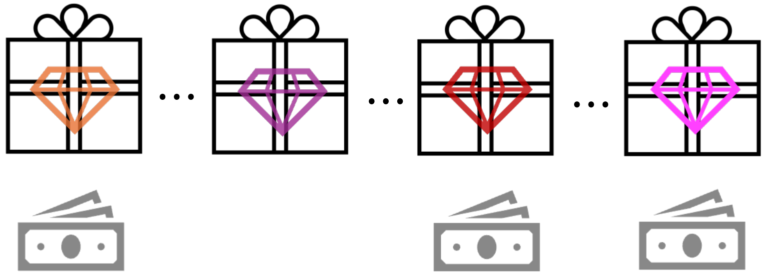
budget-dependent

max best observed under budget



$\Longleftarrow$

max (best observed – scaled costs)



Budgeted Pandora’s Box

Expected budget constraint

Optimal policy ✓

extension to [Aminian, Manshadi, Niazadeh’24]

Pandora’s Box

Cost per sample

Optimal policy: Gittins index

FAQ

- Easy-to-compute?

  Yes, EI + bisection
- Any theoretical results?

  Yes, expected-budget-constrained $\cong$ cost-per-sample
- Tuning parameters?

FAQ

- Easy-to-compute?

  Yes, EI + bisection

- Any theoretical results?

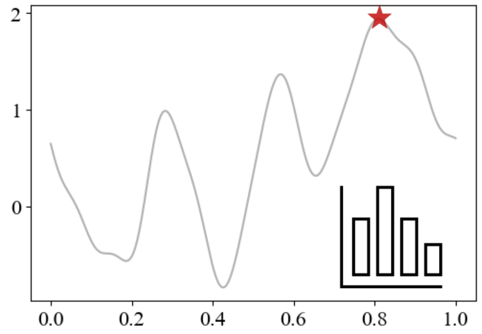
  Yes, expected-budget-constrained ≅ cost-per-sample

- Tuning parameters?

  Yes, control unit conversion

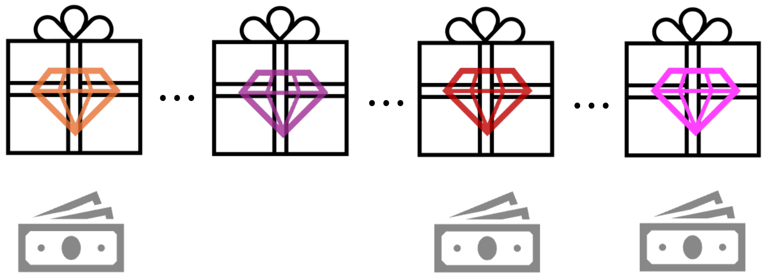
New Design Principle: Gittins Index

Problem



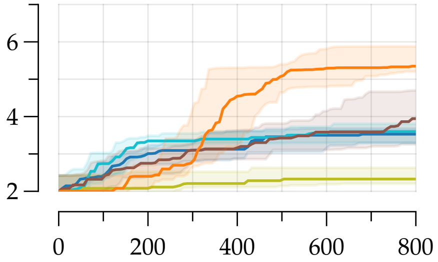
Bayesian optimization
with varying costs

Key idea



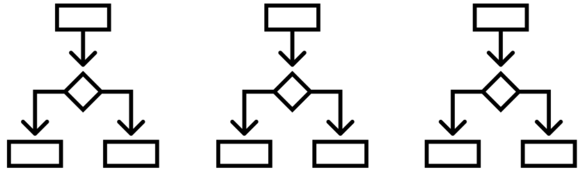
link to Pandora's box
and Gittins index theory

Impact



competitive performance

Future potential



black-box processes
with partial feedback