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: Stability Reactor parameters

World of Parameter Optimization

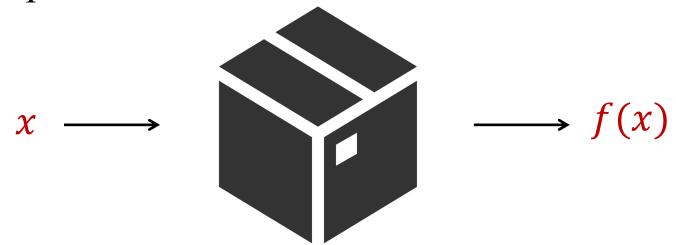
Black-box optimization:

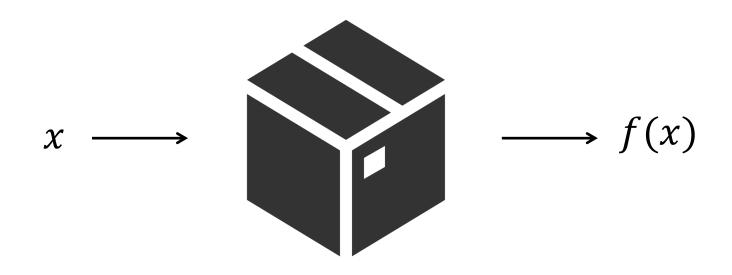
Input parameters

Performance metrics

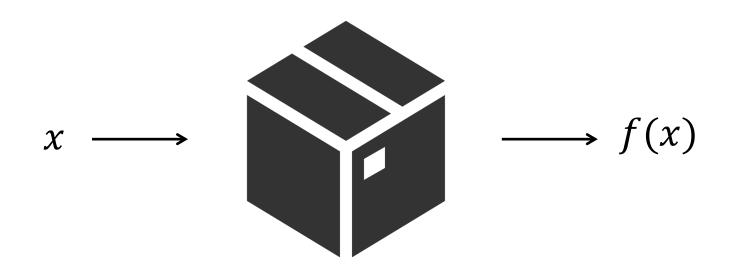
World of Parameter Optimization

Black-box optimization:



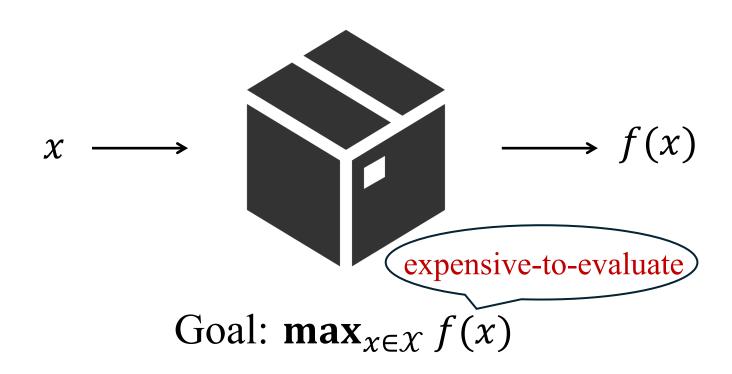


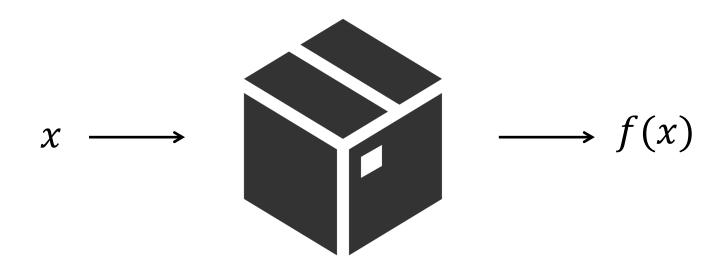
Goal: $\max_{x \in \mathcal{X}} f(x)$



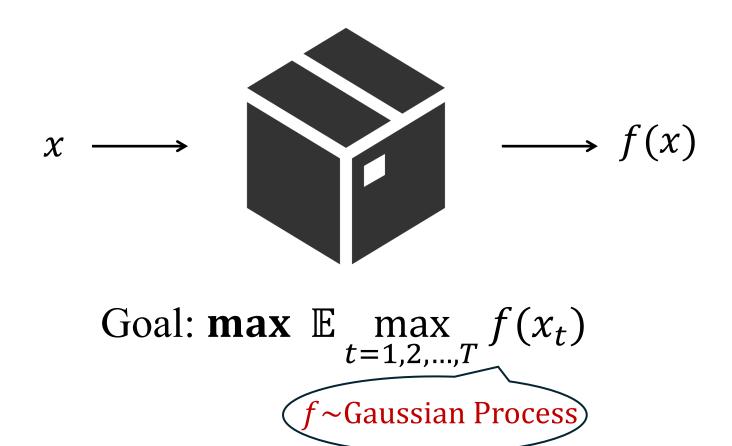
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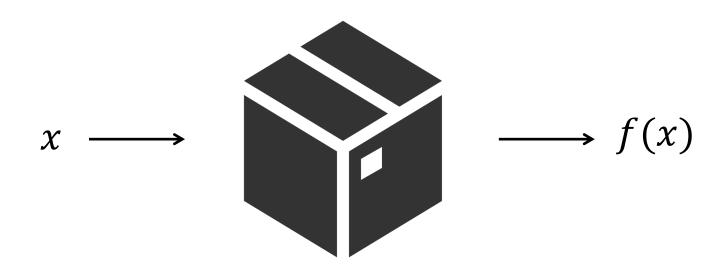
f~Stochastic Process





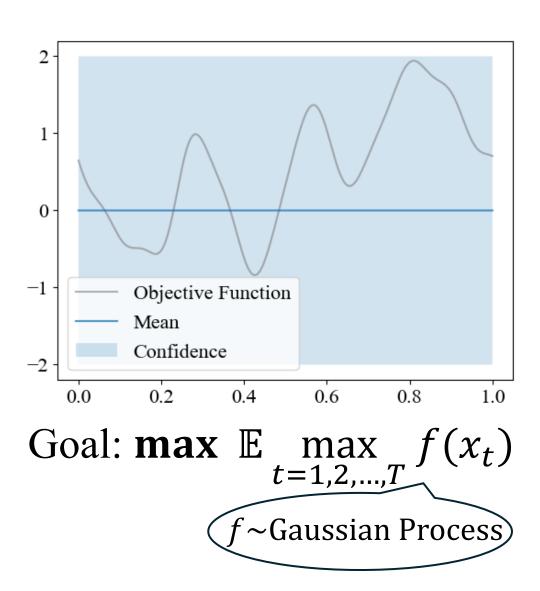
Goal:
$$\max_{t=1,2,...,T} f(x_t)$$

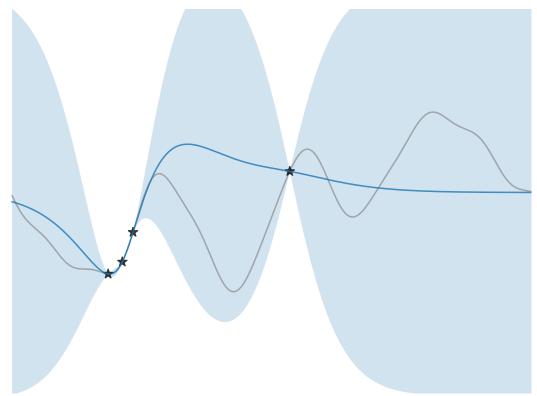




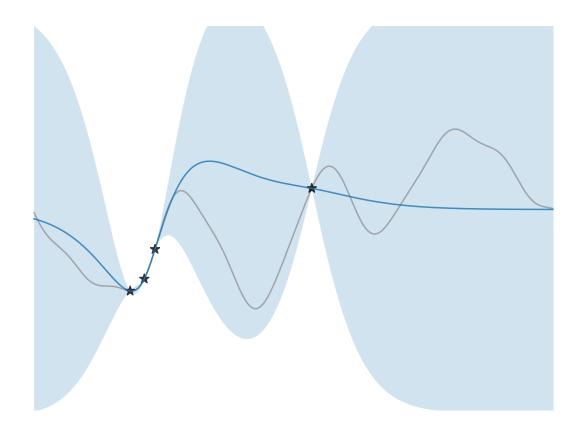
Goal: **max**
$$\mathbb{E} \max_{t=1,2,...,T} f(x_t)$$

$$f \sim \text{Gaussian Process}$$

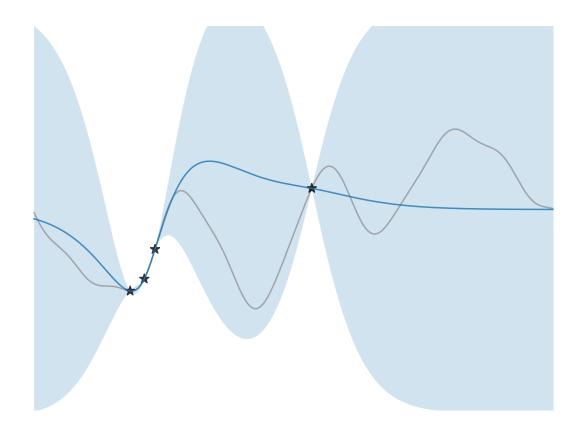




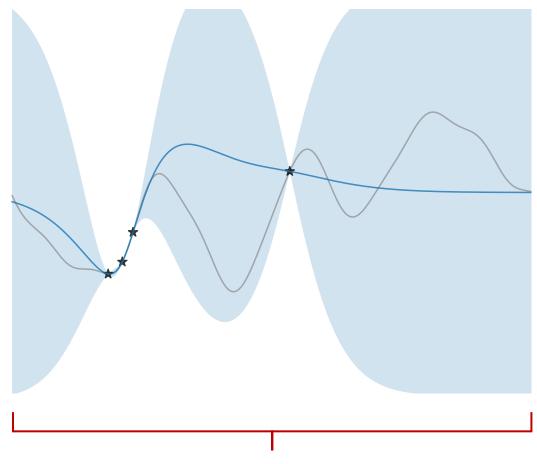
Goal: $\max_{t=1,2,...,T} f(x_t)$ f~Gaussian Process



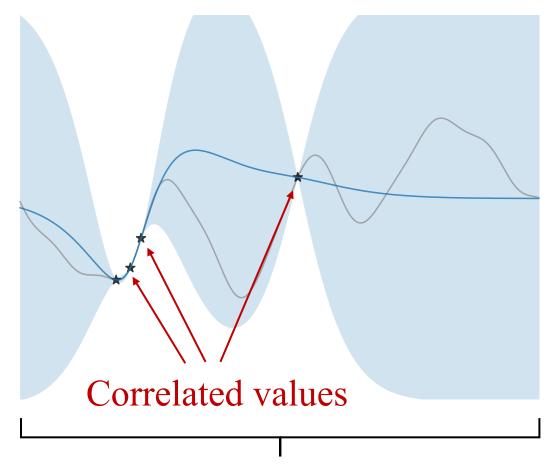
What to evaluate next?



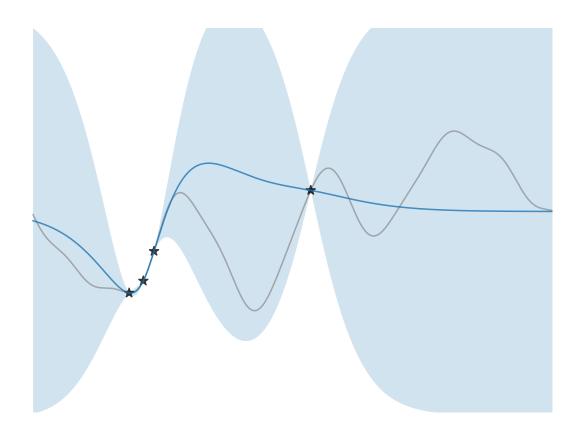
Optimal policy?



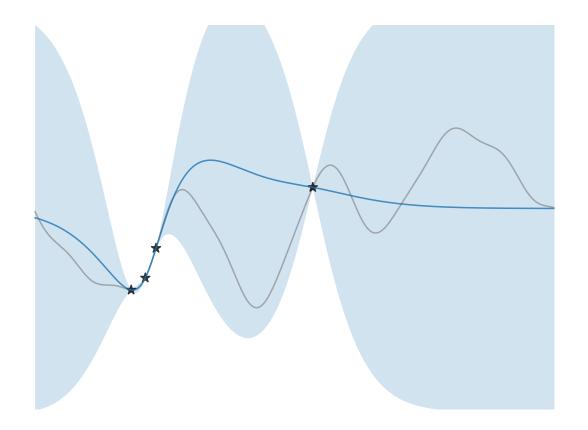
Continuous search domain



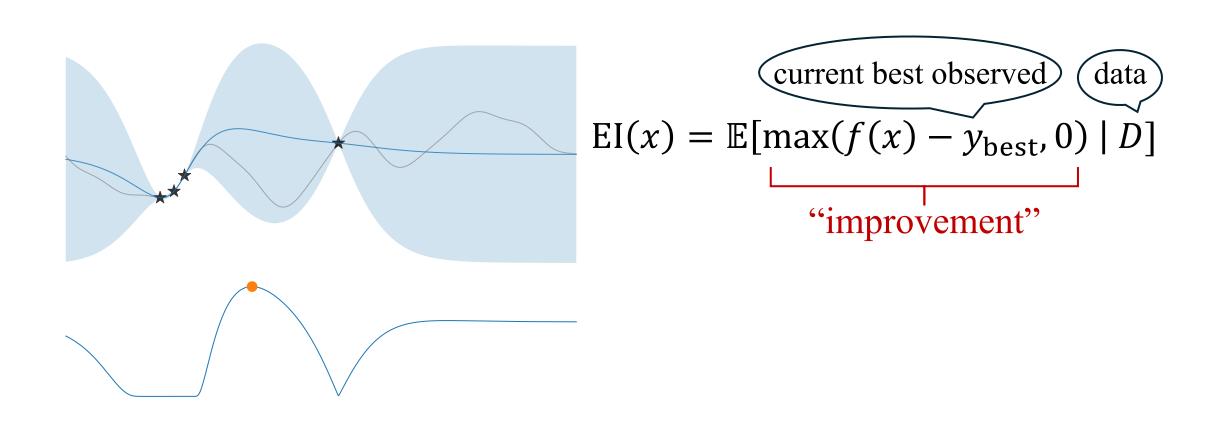
Continuous search domain

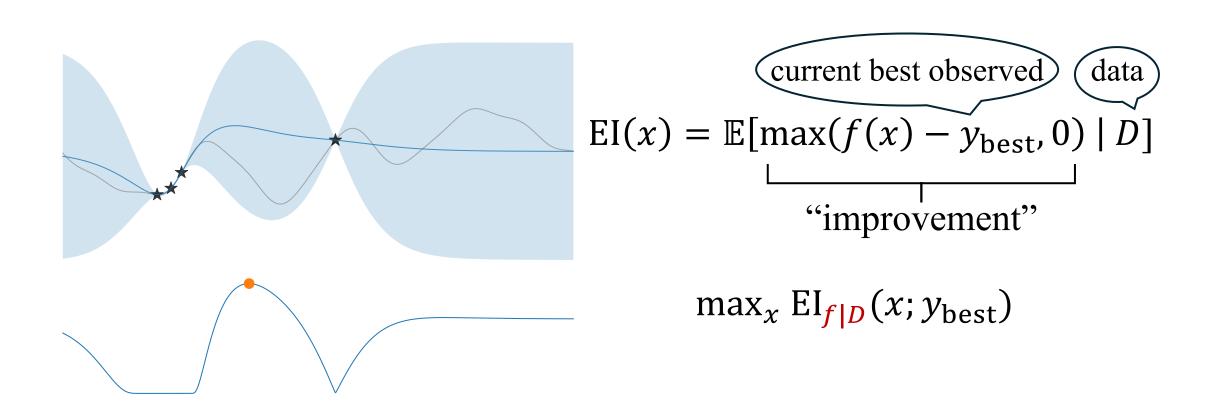


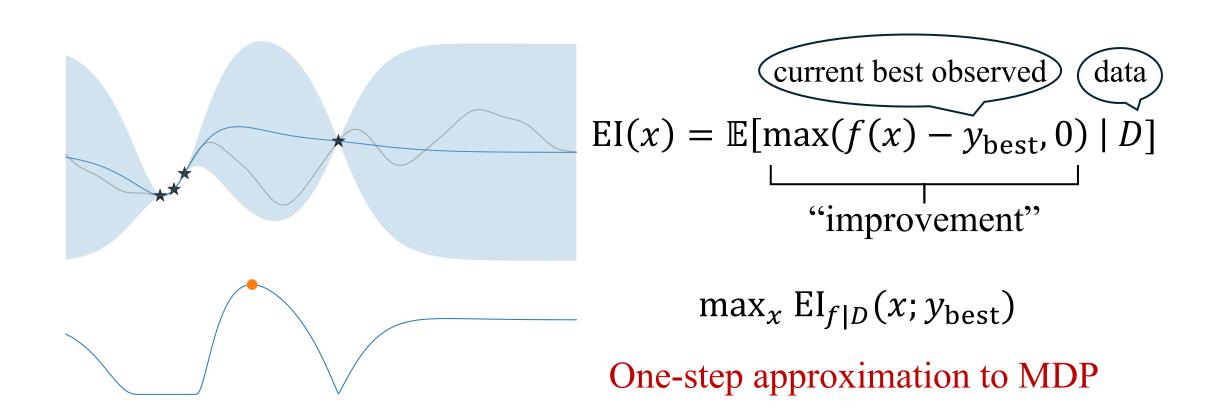
Correlation & continuity ⇒ Intractable MDP

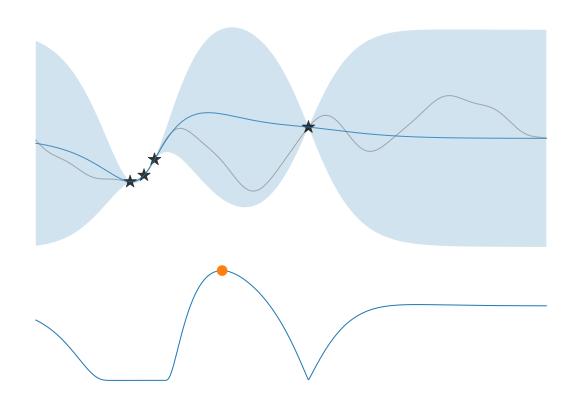


Intractable MDP \Longrightarrow Optimal policy unknown









Other improvement-based policy:

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

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- Improvement-based:
 - Expected Improvement
 - Probability of Improvement
 - Knowledge Gradient
 - Multi-step Lookahead EI

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- Entropy-based:
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 - Predictive Entropy Search

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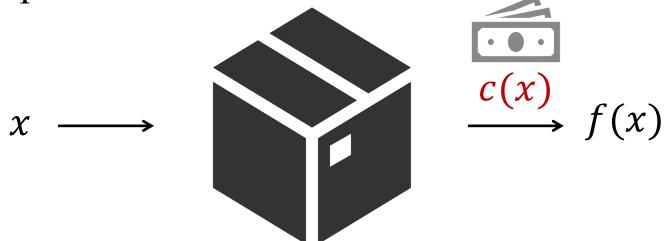
Why another approach?

Challenge: Varying Evaluation Costs

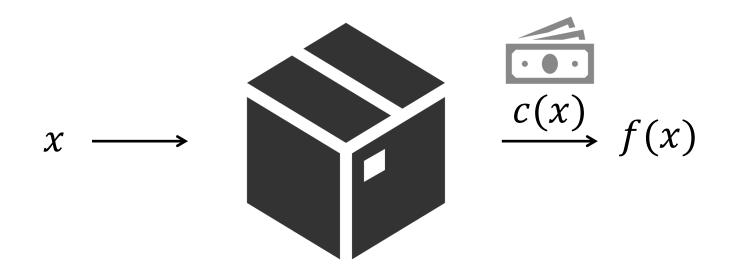
Hyperparameter tuning: Training parameters Accuracy Control optimization: Control parameters Reward Plasma physics: Stability Reactor parameters

Challenge: Varying Evaluation Costs

Black-box optimization:



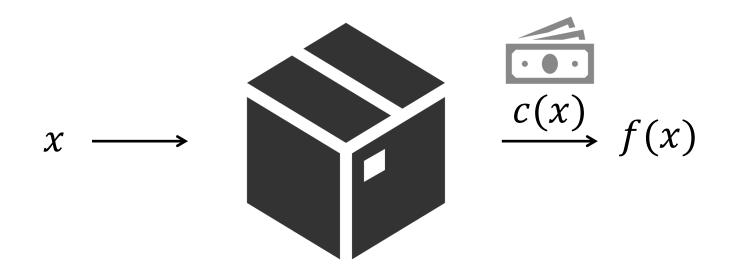
Challenge: Varying Evaluation Costs



Goal:
$$\max_{t=1,2,...,T} f(x_t)$$

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

Cost-aware Bayesian Optimization



Goal:
$$\max_{t=1,2,...,T} f(x_t)$$

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

[Lee, Perrone, Archambeau, Seeger'21] [Astudillo, Jiang, Balandat, Bakshy, Frazier'21]

Cost-aware Bayesian Optimization

Uniform costs

Varying costs

Expected improvement

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

Cost-aware Bayesian Optimization

Uniform costs

Expected improvement

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Varying costs

Expected improvement per cost

 $\max_{x} EI_{f|D}(x; y_{best})/c(x)$

Uniform costs

Expected improvement $\max_{x} \operatorname{EI}_{f|D}(x; y_{\text{best}})$

Varying costs

Expected improvement per cost $\max_{x} \operatorname{EI}_{f|D}(x; y_{\text{best}})/c(x)$ Why divide?

Uniform costs

Expected improvement

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

Varying costs

Expected improvement per cost

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

Why divide?

Our view: lack of a guidance to incorporate costs

Uniform costs

Expected improvement

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

Varying costs

Expected improvement per cost

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

EI and EIPC policy can be arbitrarily bad under varying costs! [Astudillo, Jiang, Balandat, Bakshy, Frazier'21]

Uniform costs

Expected improvement

Multi-step Lookahead EI

Varying costs

Expected improvement per cost

Budgeted Multi-step Lookahead EI



Uniform costs

Expected improvement

Multi-step Lookahead EI

Upper Confidence Bound

Thompson Sampling

Varying costs

Expected improvement per cost

Budgeted Multi-step Lookahead EI

?

?

Uniform costs	Varying costs
Expected improvement	Expected improvement per cost
Multi-step Lookahead EI	Budgeted Multi-step Lookahead EI
Upper Confidence Bound	?
Thompson Sampling	?
• •	• •

New design principle: Gittins Index

Uniform costs

Expected improvement

Multi-step Lookahead EI

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Budgeted Multi-step Lookahead EI

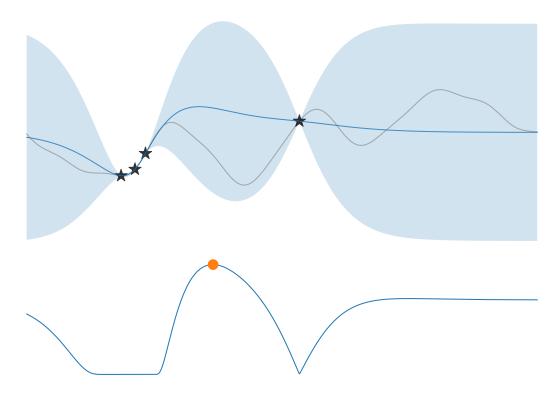
?

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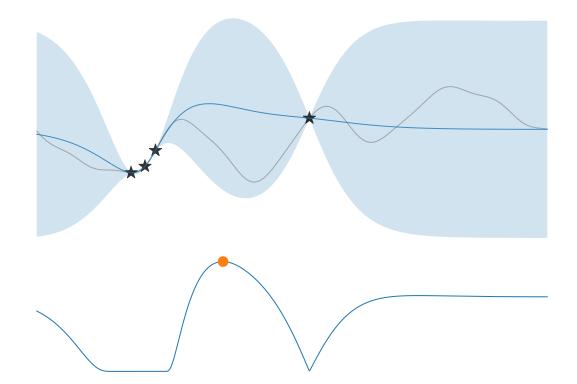
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New design principle: Gittins Index



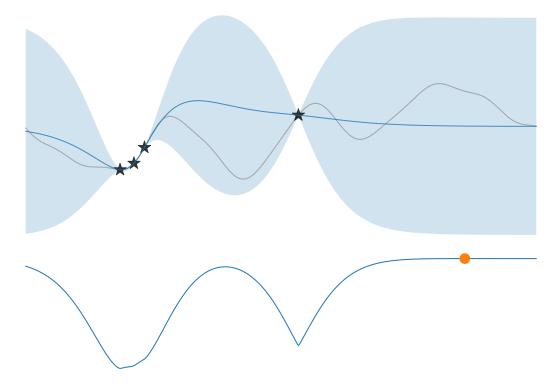


$$EI(x) = \mathbb{E}[\max(f(x) - y_{\text{best}}, 0) \mid D]$$
$$\max_{x} EI_{f|D}(x; y_{\text{best}})$$



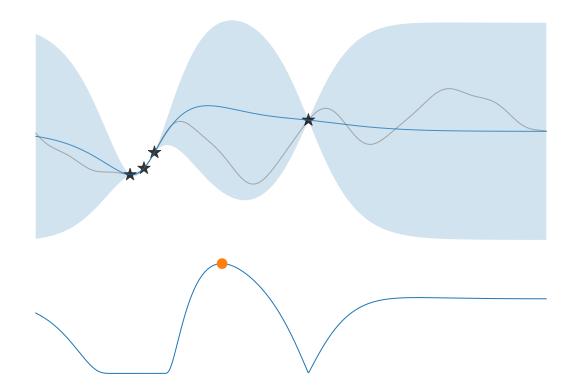
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Gittins Index



$$GI_{f|D}(x) = g \text{ s.t. } EI_{f|D}(x; g) = c(x)$$

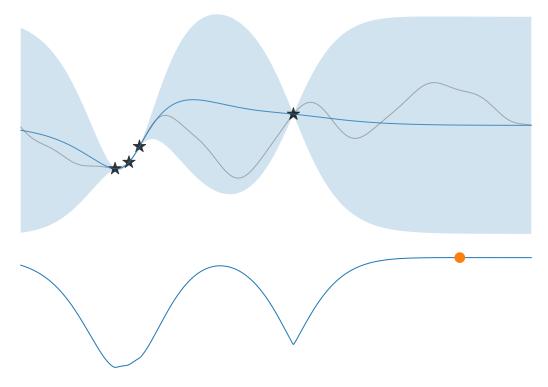
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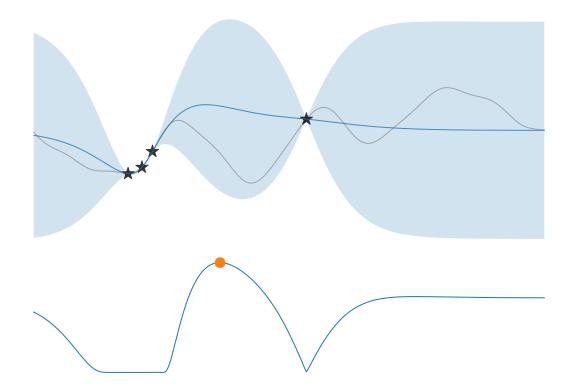
One-step approximation to MDP

Gittins Index



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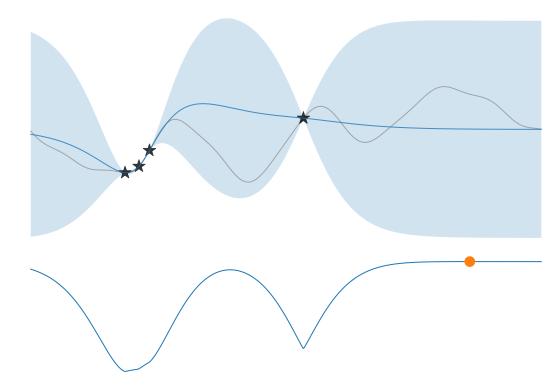
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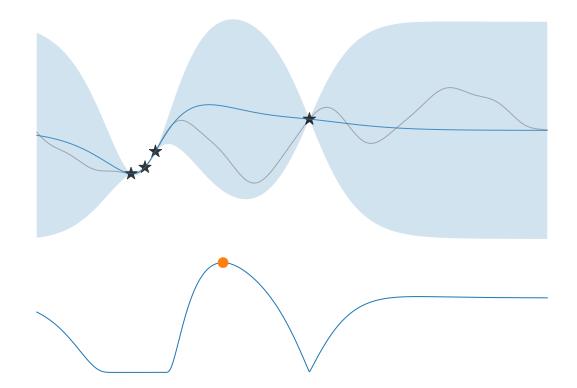
Temporal simplification to MDP

Gittins Index



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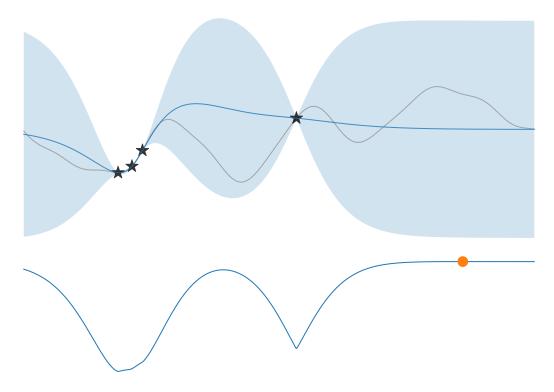
$$\max_{x} GI_{f|D}(x)$$



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Temporal simplification to MDP

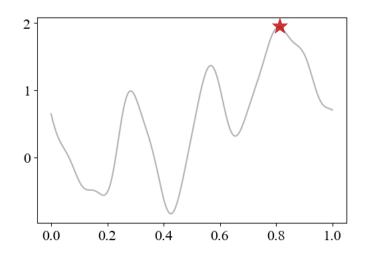
Gittins Index



$$GI_{f|D}(x) = g \text{ s.t. } EI_{f|D}(x;g) = c(x)$$

$$\max_{x} GI_{f|D}(x)$$

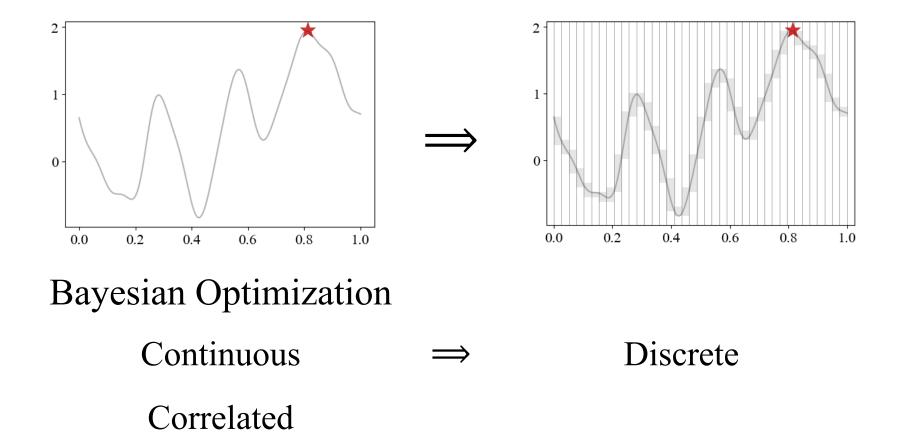
Spatial simplification to MDP

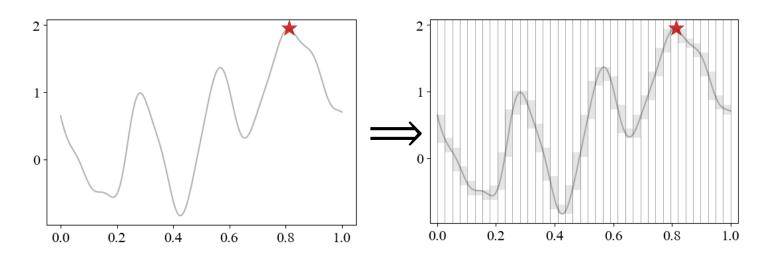


Bayesian Optimization

Continuous

Correlated

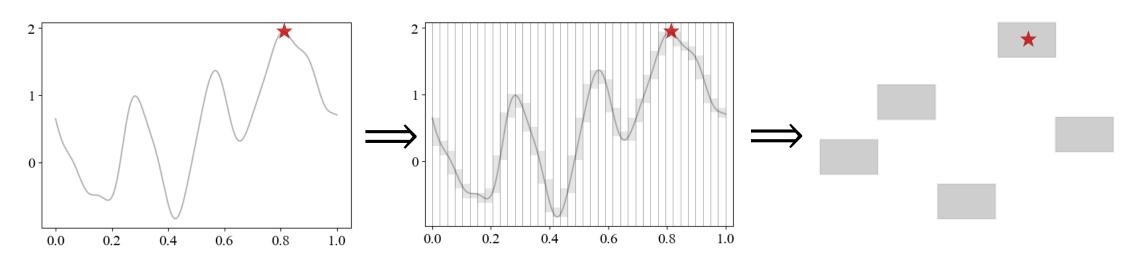




Bayesian Optimization

Continuous ⇒ Discrete

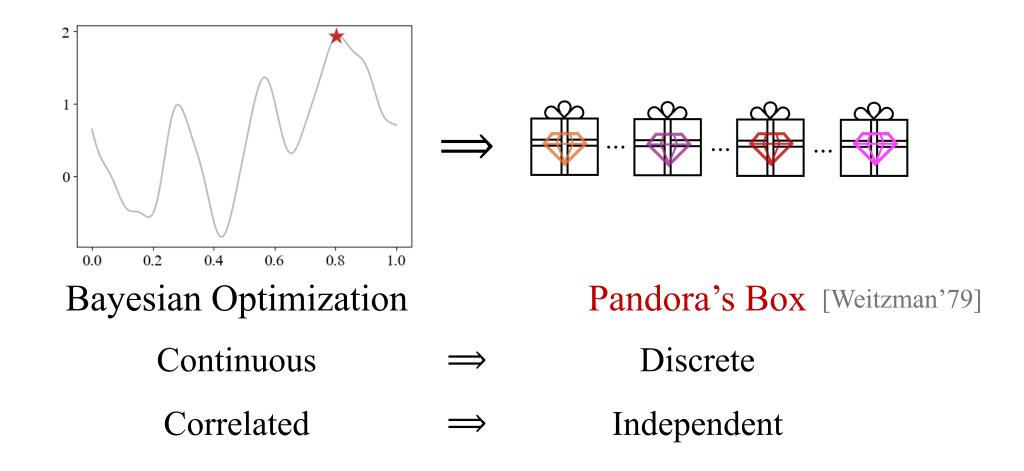
Correlated

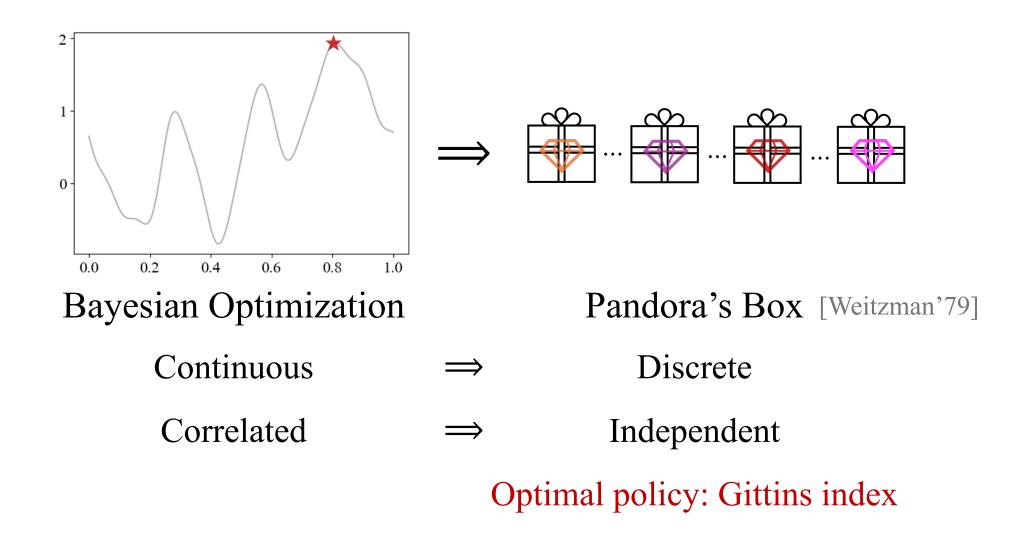


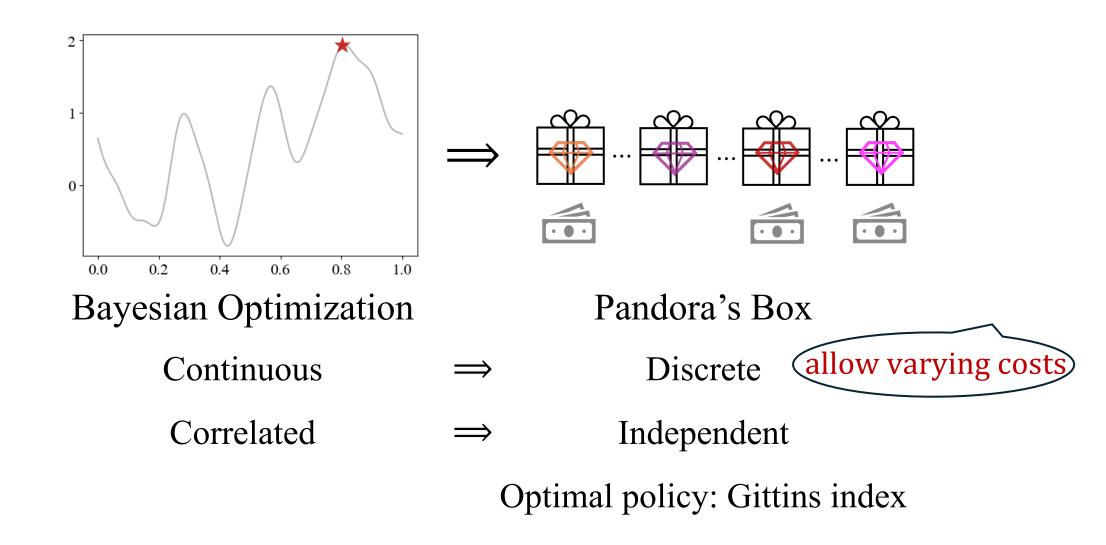
Bayesian Optimization

Continuous \Rightarrow Discrete

Correlated \Rightarrow Independent

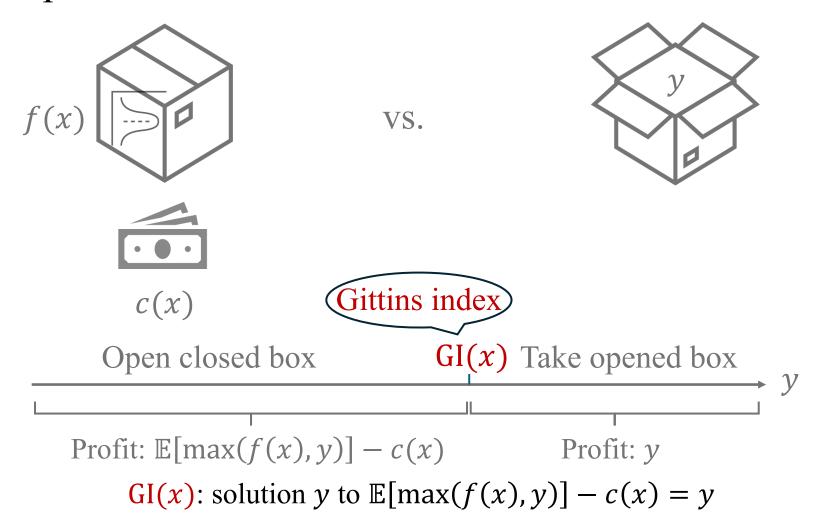




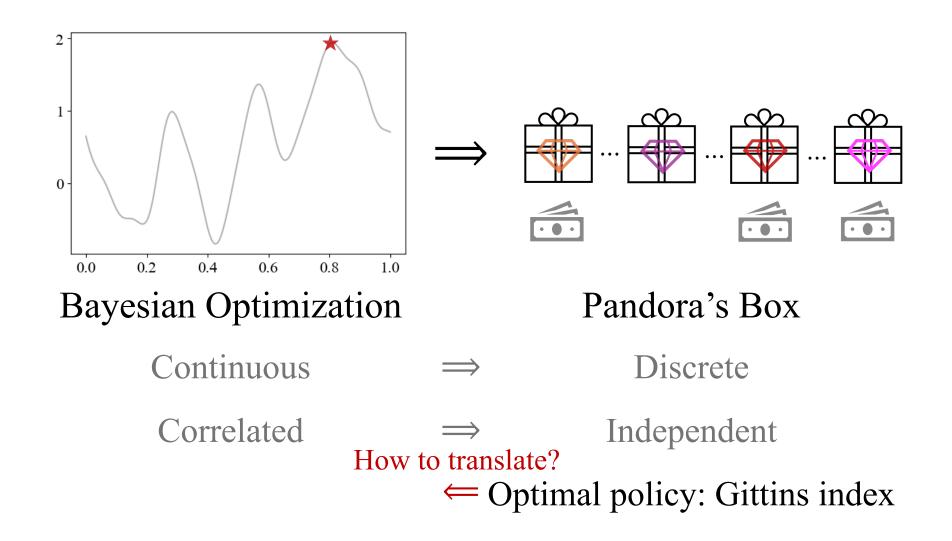


Intuition Behind Pandora's Box Gittins Index

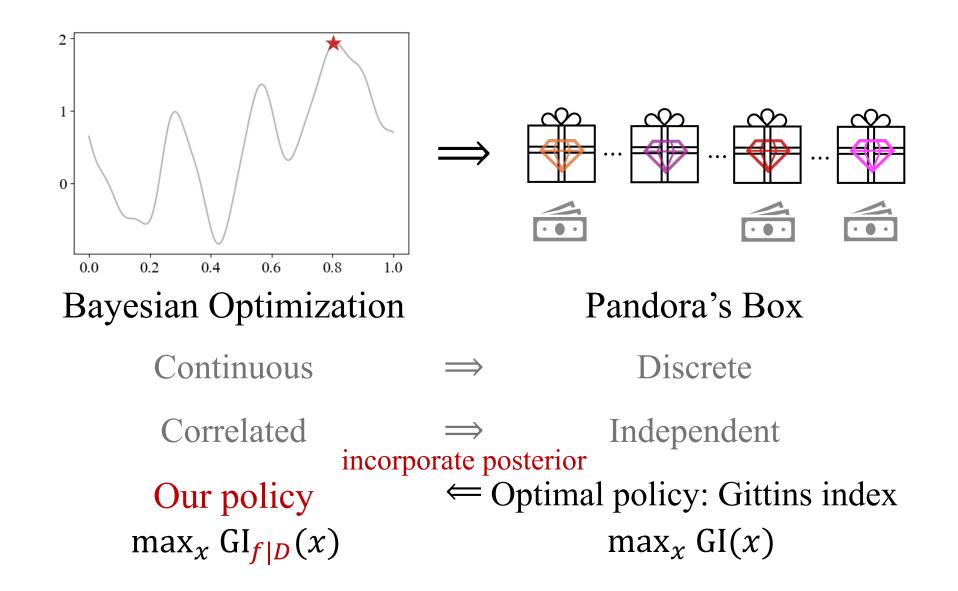
1.5-box problem:



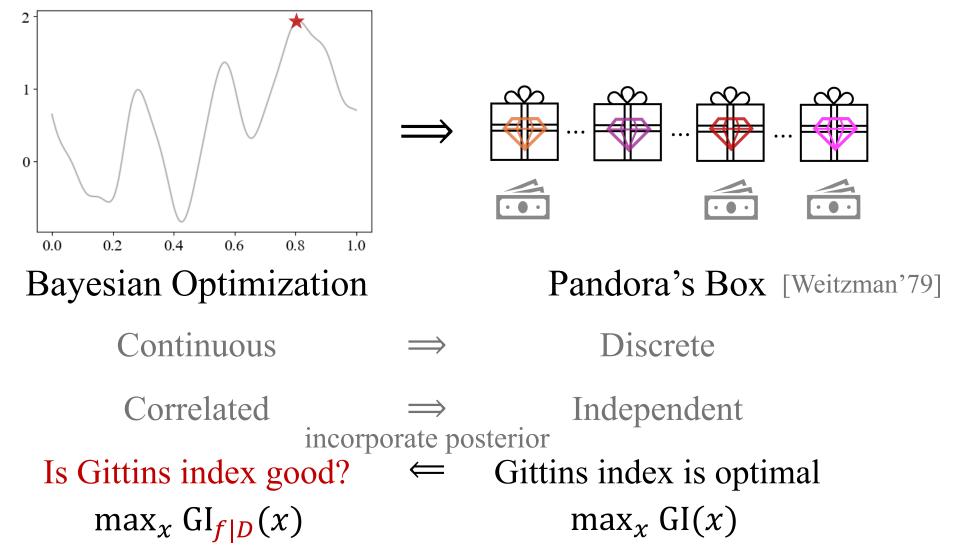
How to translate Gittins index?



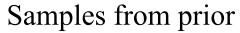
How to translate Gittins index?

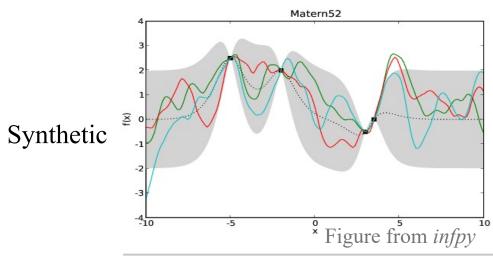


Is Gittins good in Bayesian Optimization?

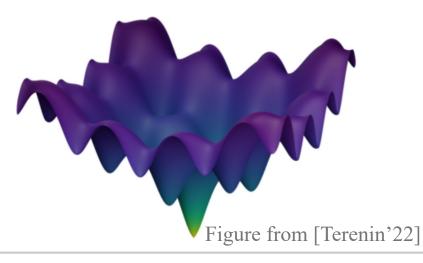


Experiment Setup: Objective Functions





Ackley function



Pest Control



Empirical

Figure from ChatGPT

Lunar Lander

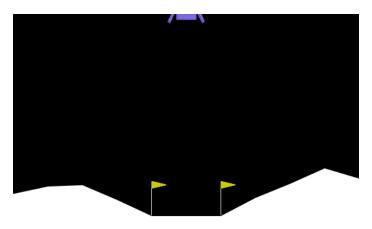
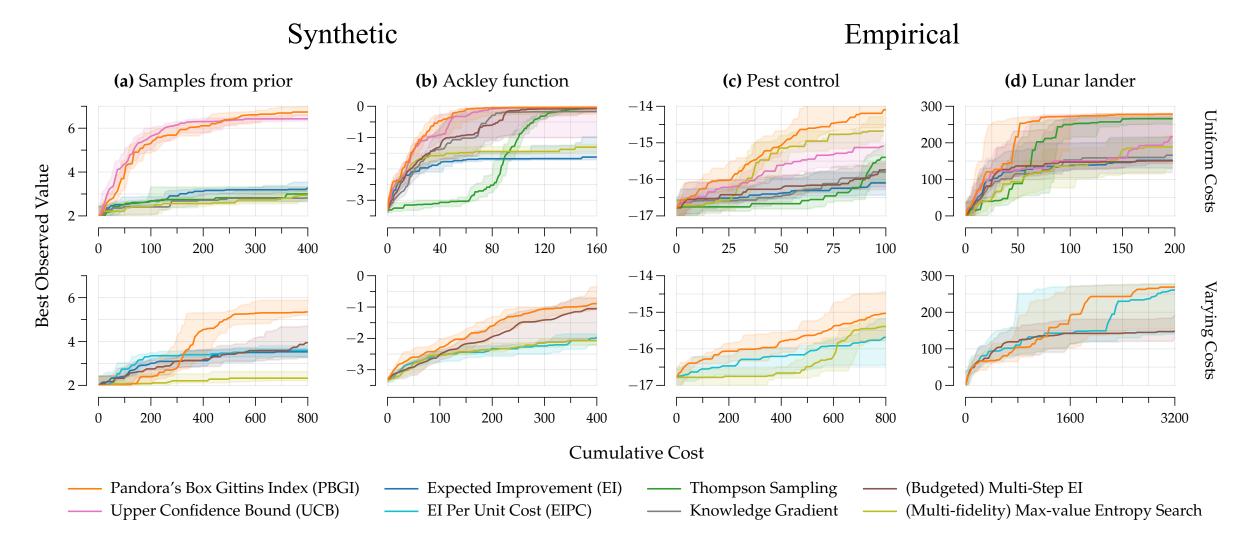


Figure from OpenAI Gym

Experiment Results



• Easy-to-compute?

• Easy-to-compute?
Yes, EI + bisection

- Easy-to-compute?

 Yes, EI + bisection
- Any theoretical results?

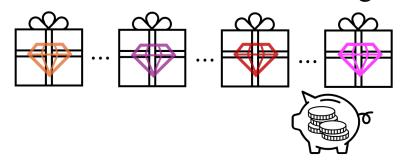
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 Yes, expected-budget-constrained ≅ cost-per-sample

Theoretical Result

max best observed under budget

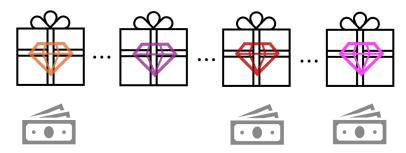


Budgeted Pandora's Box

Expected budget constraint

Optimal policy?

max (best observed – costs)



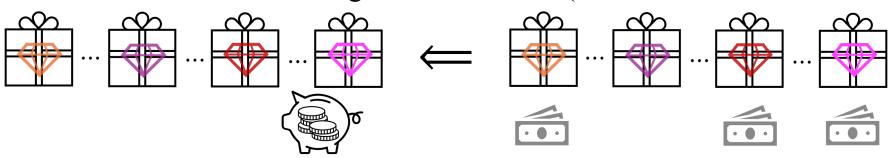
Pandora's Box

Cost per sample

Optimal policy: Gittins index

Theoretical Result

max best observed under budget



Budgeted Pandora's Box

Expected budget constraint

Optimal policy \checkmark

Pandora's Box

max (best observed – scaled costs)

Cost per sample

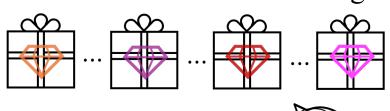
Optimal policy: Gittins index

extension to [Aminian, Manshadi, Niazadeh'24]

Theoretical Result

budget-dependent

max best observed under budget











max (best observed – scaled costs)









Budgeted Pandora's Box

Expected budget constraint

Optimal policy



Pandora's Box

Cost per sample

Optimal policy: Gittins index

extension to [Aminian, Manshadi, Niazadeh'24]

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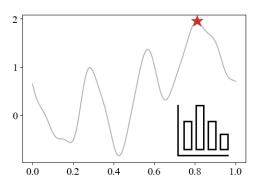
 Yes, expected-budget-constrained ≅ cost-per-sample
- Tuning parameters?

- Easy-to-compute?

 Yes, EI + bisection
- Any theoretical results?
 Yes, expected-budget-constrained ≅ cost-per-sample
- Tuning parameters?
 Yes, control unit conversion

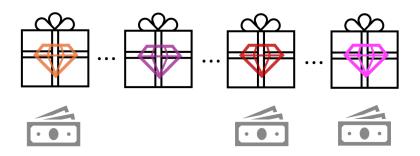
New Design Principle: Gittins Index

Problem



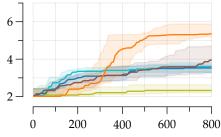
Bayesian optimization with varying costs

Key idea



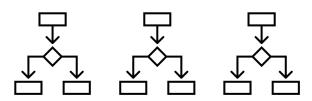
link to Pandora's box and Gittins index theory

Impact



competitive performance

Future potential



black-box processes with partial feedback

Check our paper on ArXiv!



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