好みを学習して支援するデザイン支援システム

小山 裕己（産業技術総合研究所）

2023-07-25 | 第67回AIセミナー「HCI × AI：人工知能で進化するHCI研究の最前線」

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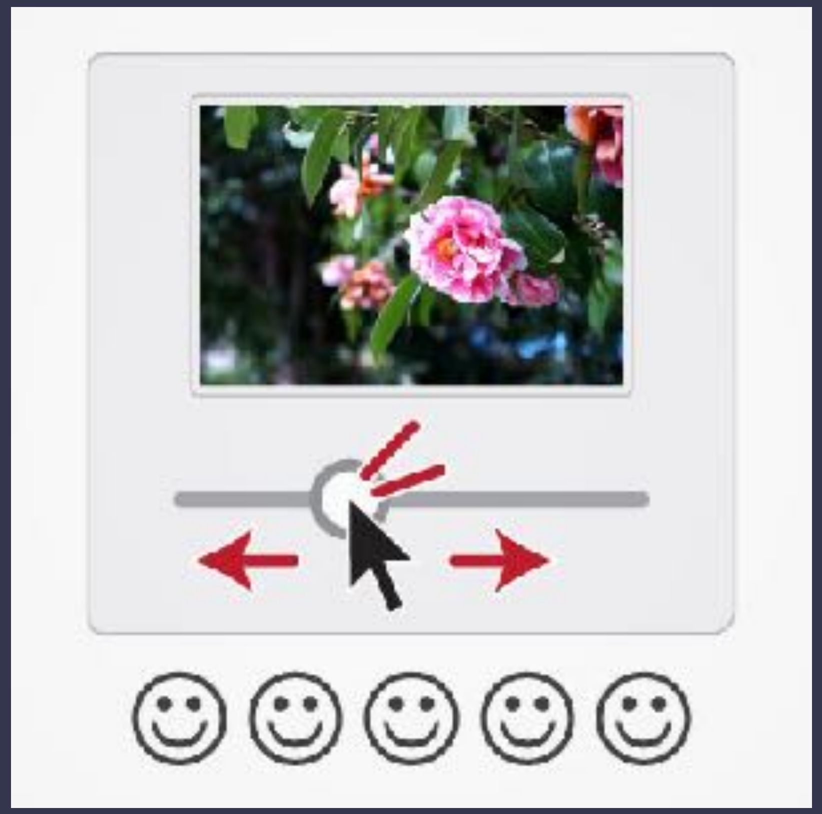
https://koyama.xyz/

自己紹介

- **専門分野**
  - **Computer Graphics (CG)**
    - 最適化計算に基づくデザイン・コンテンツ創作支援（Computational Design）
  - **Human-Computer Interaction (HCI)**
    - 数理技術に基づくインタラクション（Computational Interaction）
- **最近の研究トピック**
  - **Human-in-the-Loopベイズ最適化**

- 研究背景とアプローチ
- 研究１：Sequential Line Search [SIGGRAPH 2017]
- 研究２：Sequential Gallery [SIGGRAPH 2020]
- 研究３：BO as Assistant [UIST 2022]
- まとめと議論



Sequential Line Search
[SIGGRAPH 2017]

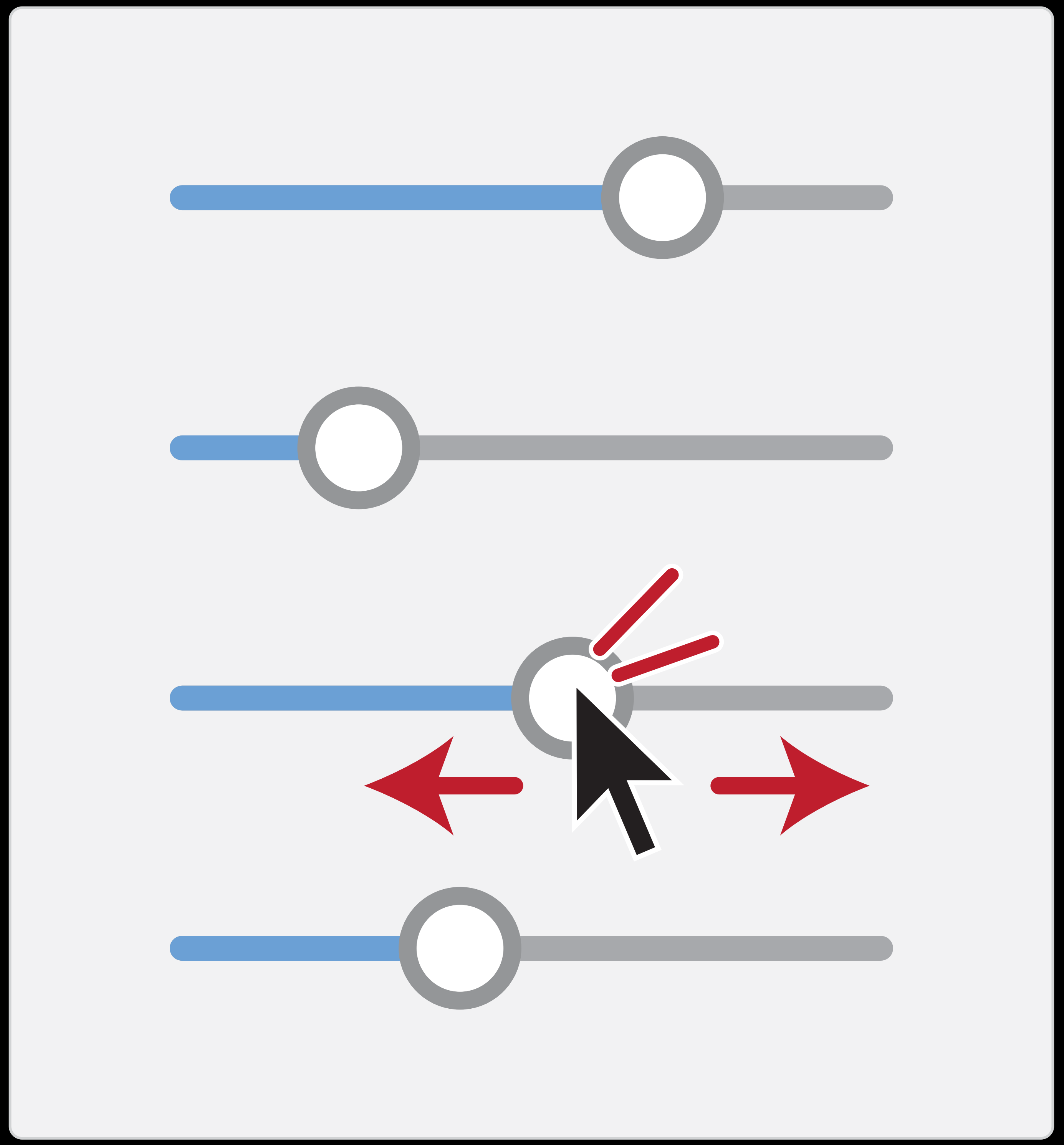
Sequential Gallery
[SIGGRAPH 2020]

BO as Assistant
[UIST 2022]

研究背景とアプローチ

Human-in-the-Loopデザイン最適化

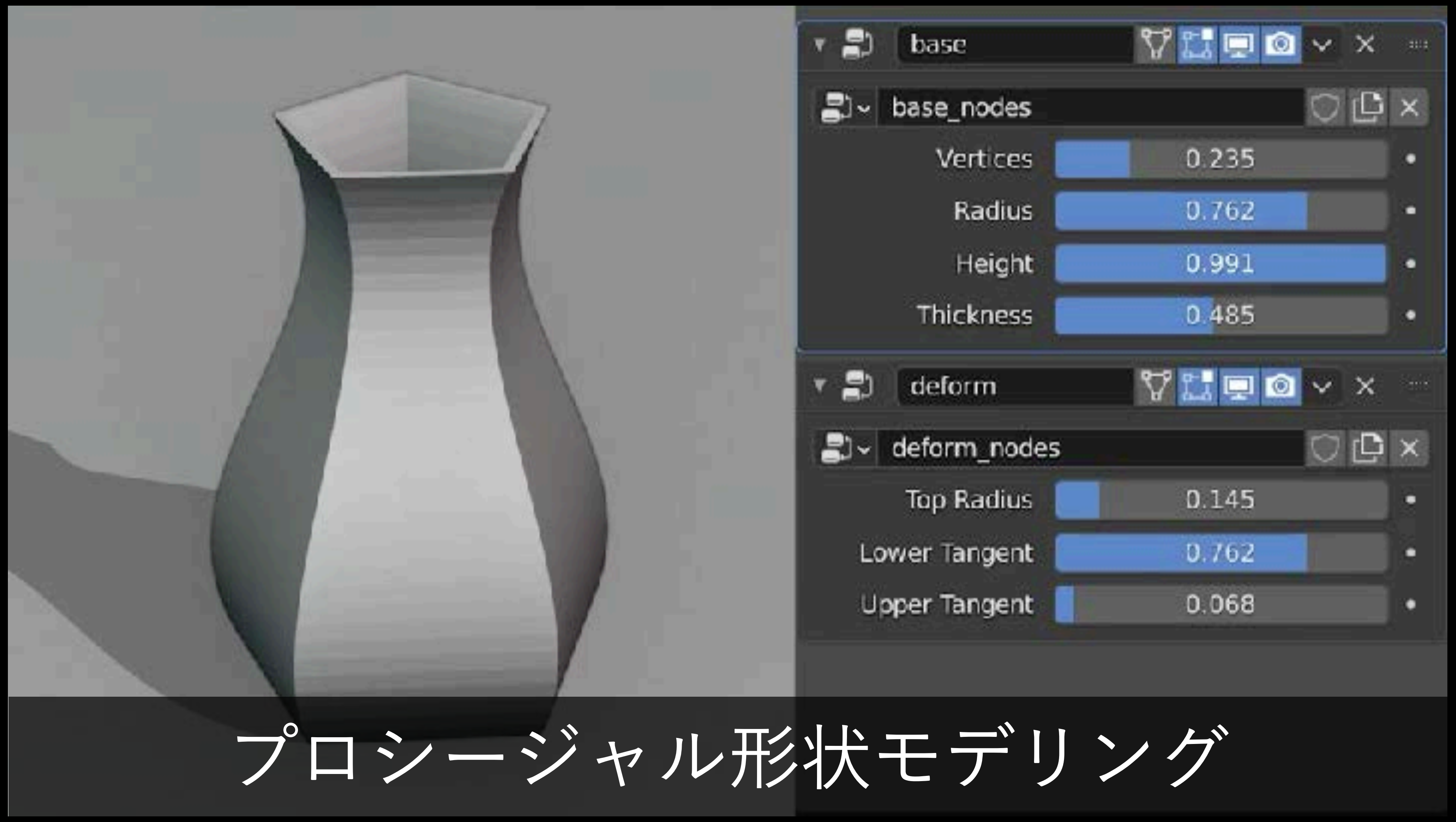
パラメタ調整タスクは様々なデザインの文脈に共通して登場する



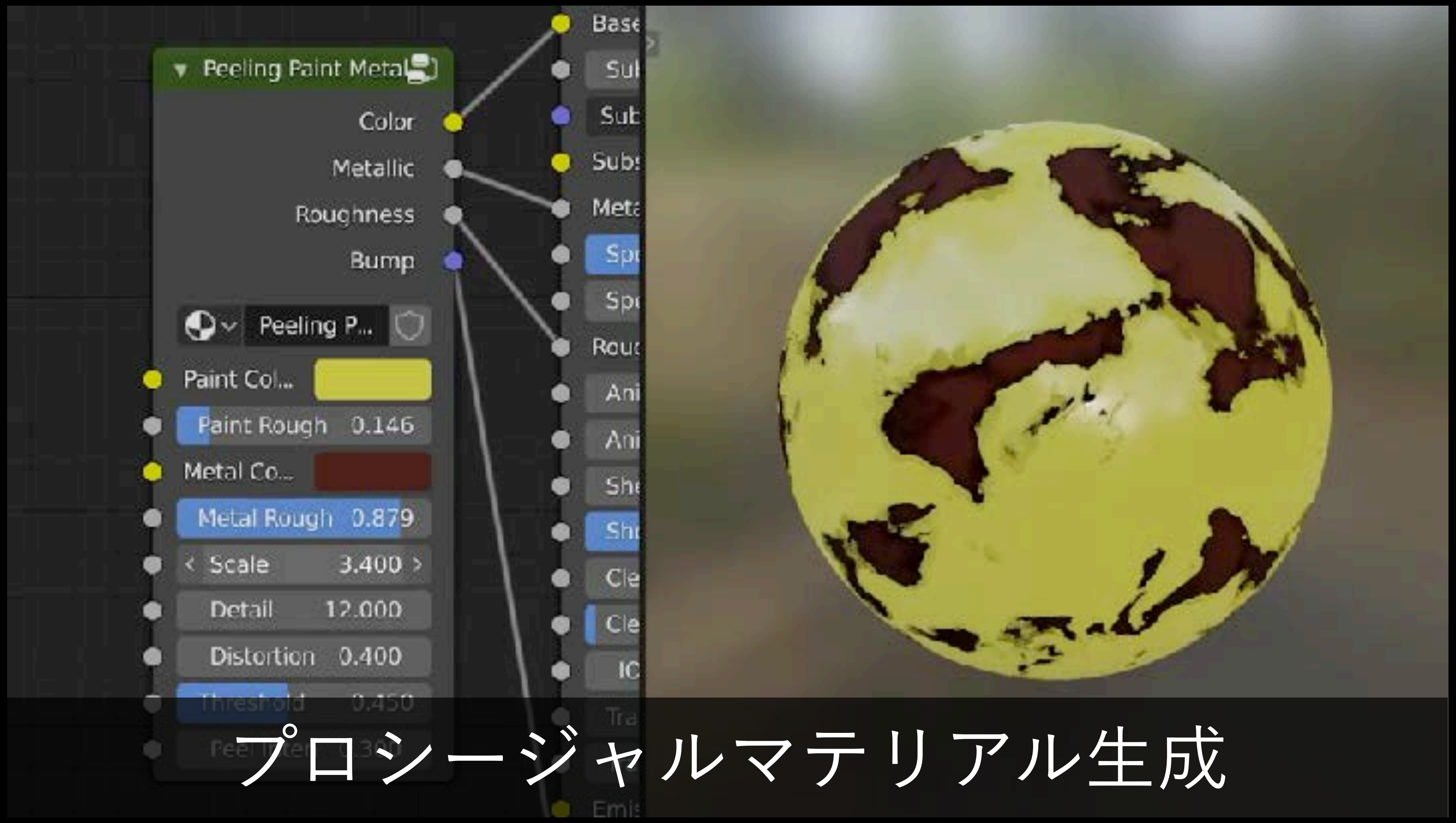
パラメタ調整タスクは様々なデザインの文脈に共通して登場する

写真の色調編集

機械学習によるコンテンツ生成

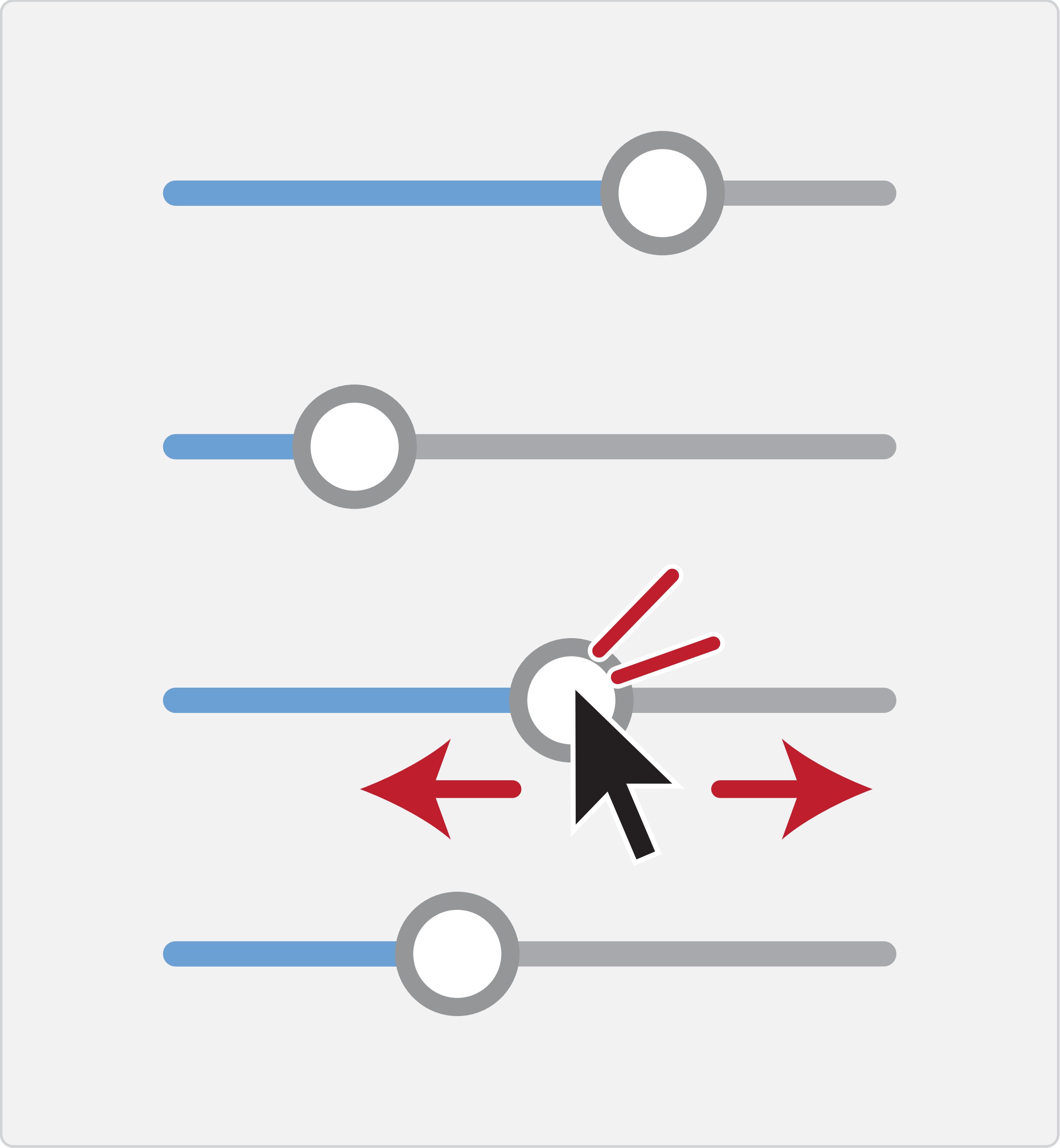


プロシージャル形状モデリング

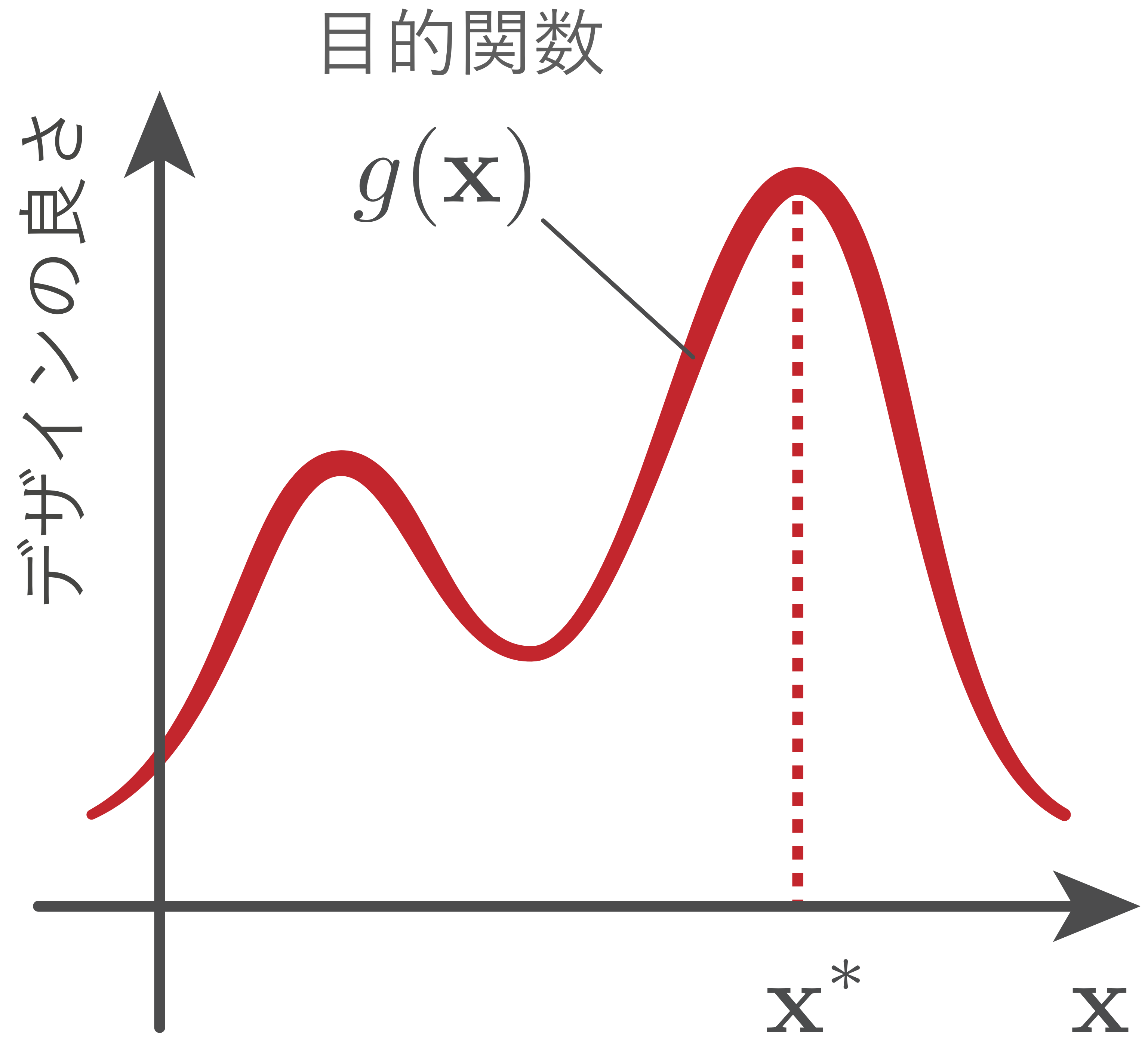


プロシージャルマテリアル生成

数学的な解釈（モデル化）[*]



デザインにおけるパラメタ調整

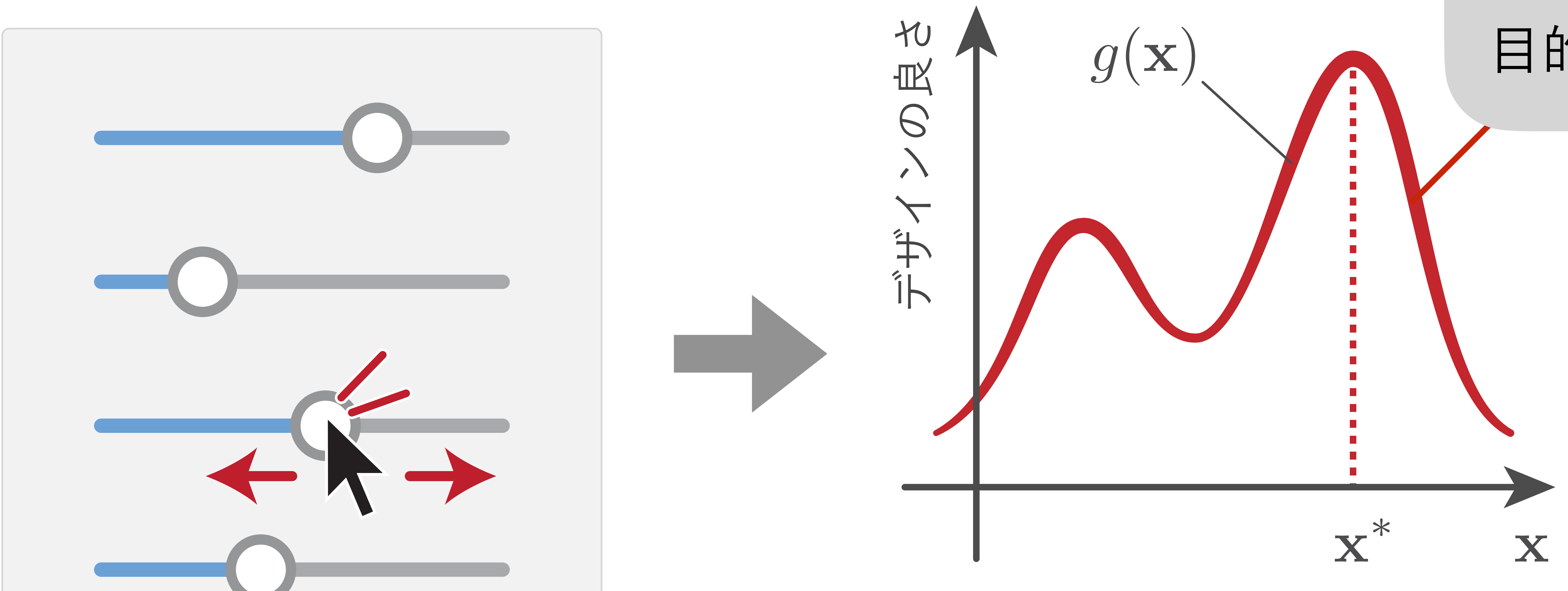


$$\mathbf{x}^* = \arg\max_{\mathbf{x}} g(\mathbf{x})$$

最適化問題

[*] Yuki Koyama. 2021. Introduction to Computational Design. In Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems (CHI EA '21—Courses), pp.136:1–136:4.

数学的な解釈（モデル化）[*]



$$\mathbf{x}^* = \underset{\mathbf{x}}{\arg\max}\, g(\mathbf{x})$$

難しさ：
人間の評価によって
目的関数が定義される

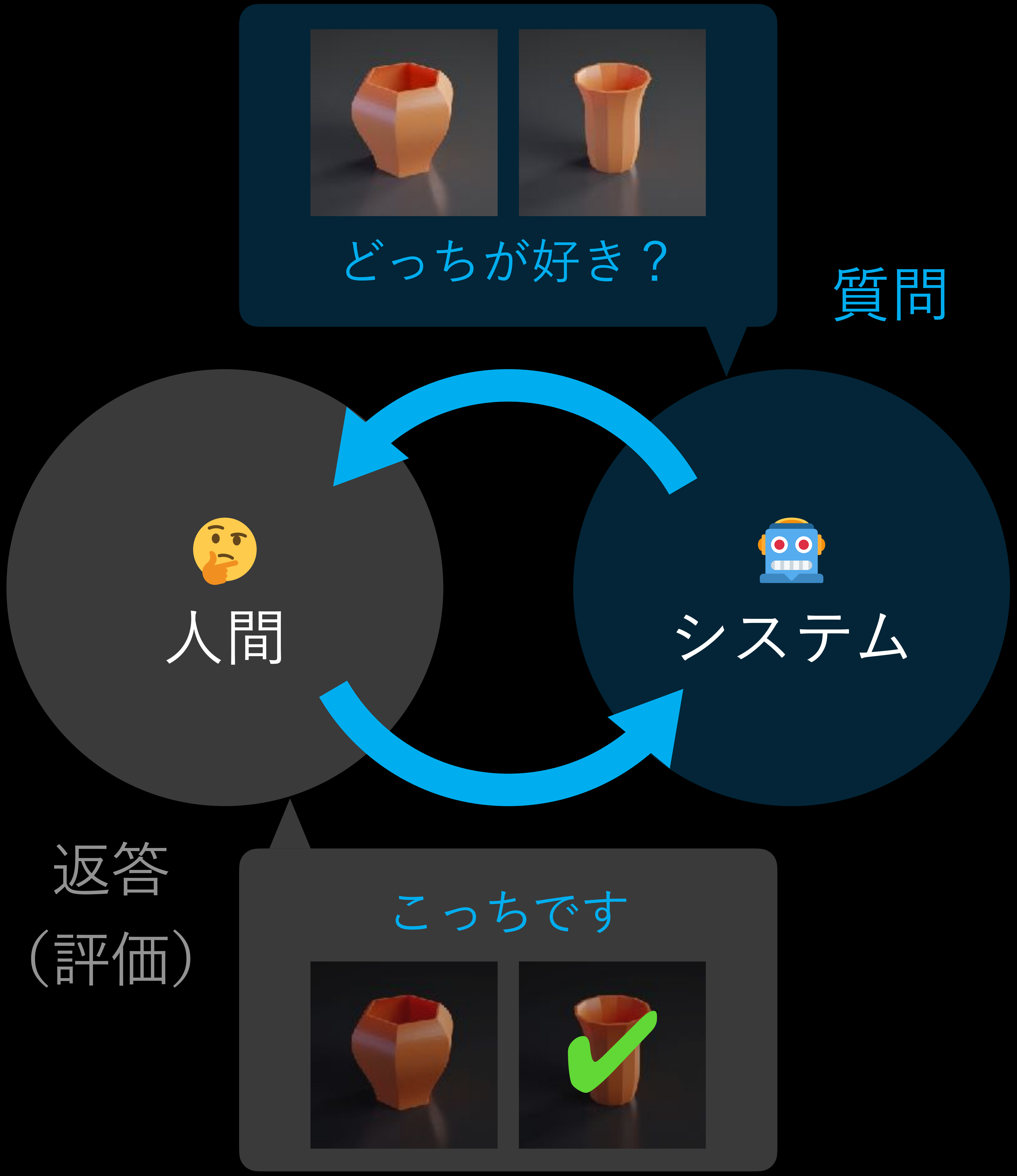
デザインにおけるパラメタ調整

最適化問題

[*] Yuki Koyama. 2021. Introduction to Computational Design. In Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems (CHI EA '21—Courses), pp.136:1–136:4.

Human-in-the-loop最適化

人間の評価が必要な目的関数を
対象とする最適化問題を解く
ためのアプローチ



Human-in-the-Loop最適化の要件 [1/2]

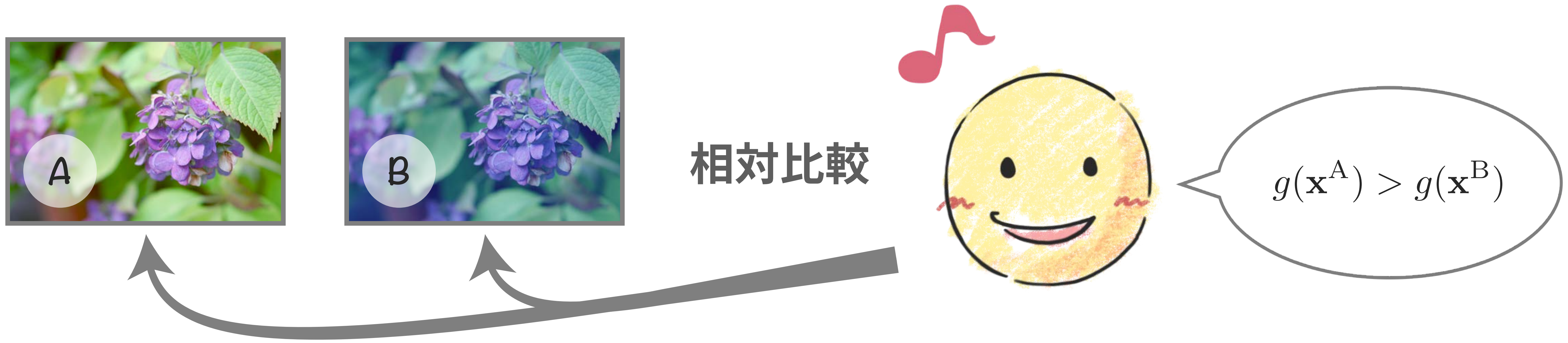
絶対評価を用いるのは好ましくない：

ユーザは関数の値を安定に答えることができない

[Brochu+10; Koyama+18]

相対評価を用いるのが好ましい：

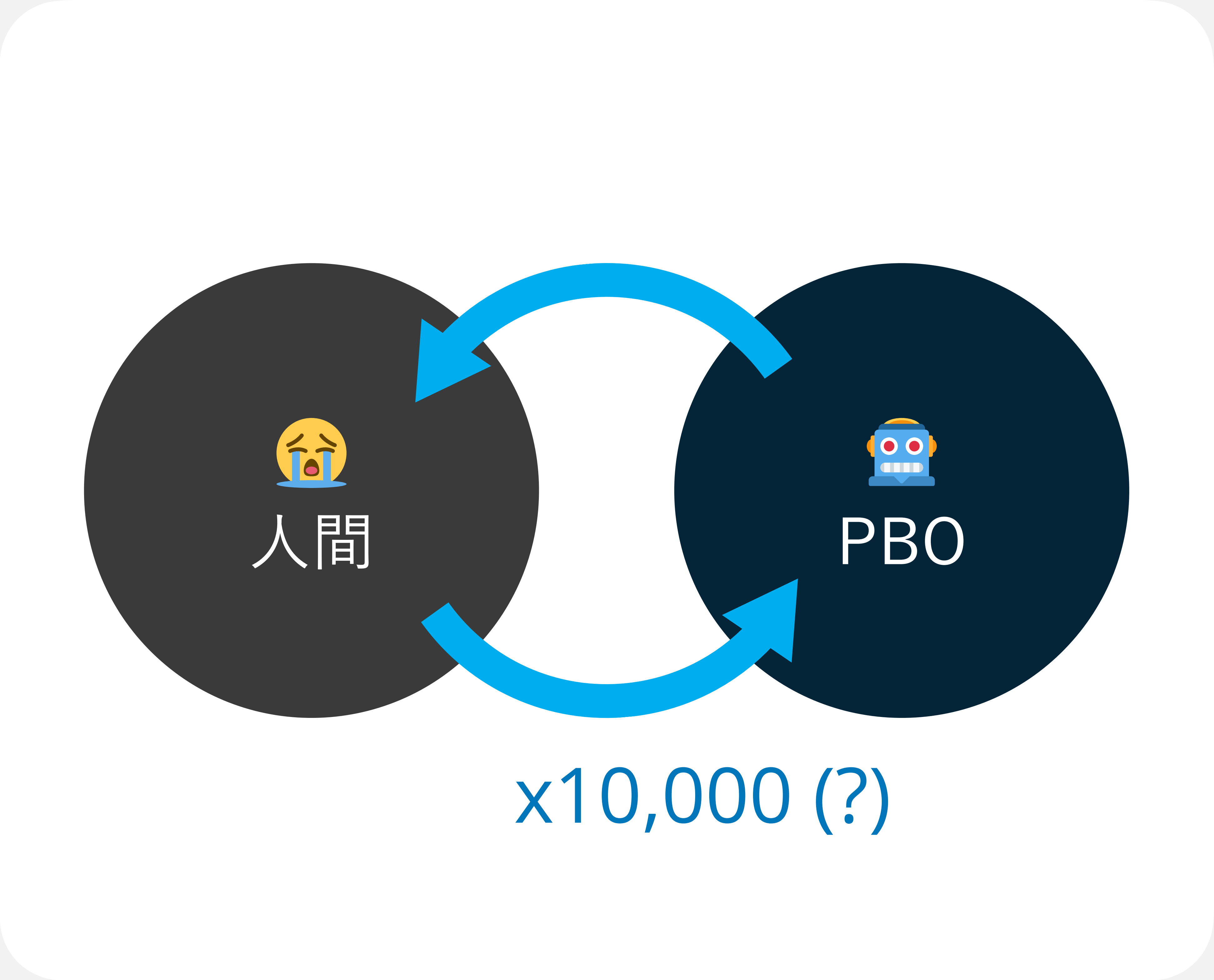
ユーザは複数の選択肢の中から相対的に良いものを安定に選ぶことができる



[Koyama+, Computational Interaction (2018)] Yuki Koyama and Takeo Igarashi. 2018. Computational Design with Crowds. In Computational Interaction (Eds. A. Oulasvirta, P. O. Kristensson, X. Bi, and A. Howes), Oxford University Press, pp.153–184. https://arxiv.org/abs/2002.08657

Human-in-the-Loop最適化の要件 [2/2]

- **全体の反復回数が十分に少ない必要がある**
  - 人間のレスポンスは遅い
  - 人間は疲れてしまう



選好ベイズ最適化 Preferential Bayesian Optimization (PBO)

ベイズ最適化 (BO) の派生手法 [Brochu+, NIPS 2007]

- 賢いサンプリング戦略で質問を生成

特徴：

- 相対比較データ（絶対評価データではなく）から好みを推定して最適化を実行
- 少ない反復回数で解を発見できる性質

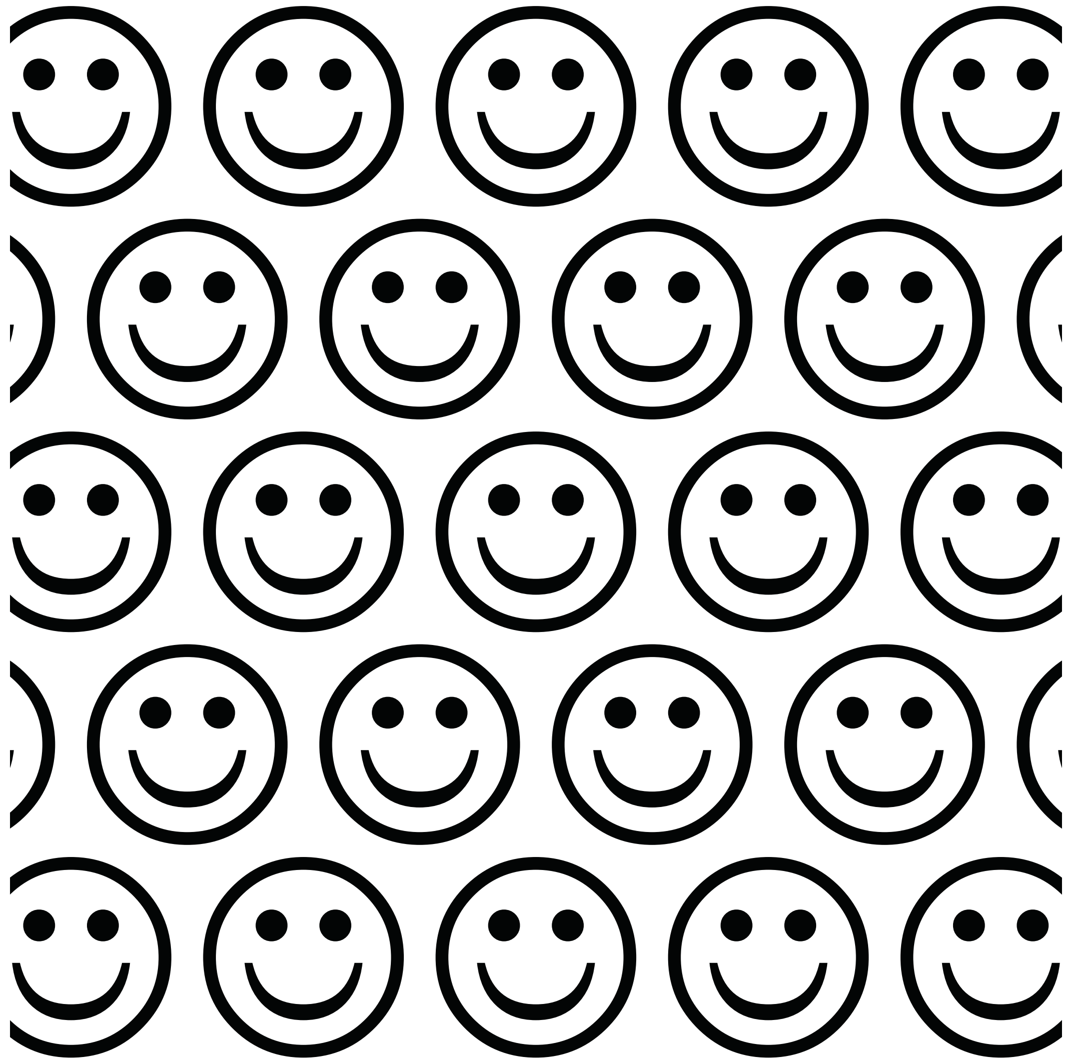
➡ Human-in-the-Loop最適化と相性が良い

Yuki Koyama, Toby Chong, and Takeo Igarashi. 2022. Preferential Bayesian Optimisation for Visual Design. In Bayesian Methods for Interaction and Design, Cambridge University Press, pp.239–258.

研究事例 1

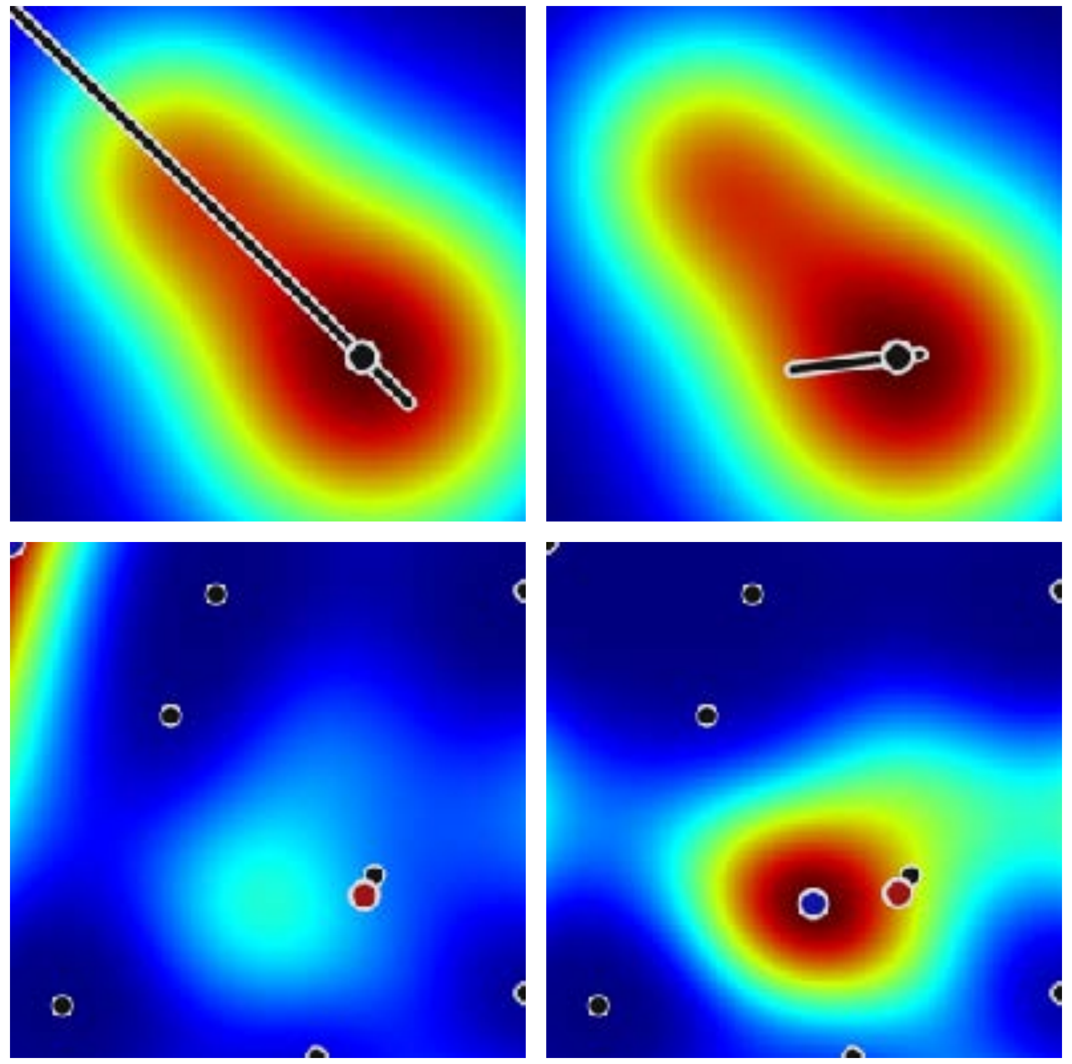
Sequential Line Search [SIGGRAPH 2017]

研究の貢献



コンセプト提案：Crowd-in-the-Loop最適化

クラウドワーカを計算資源とみなして最適化を実行する仕組み

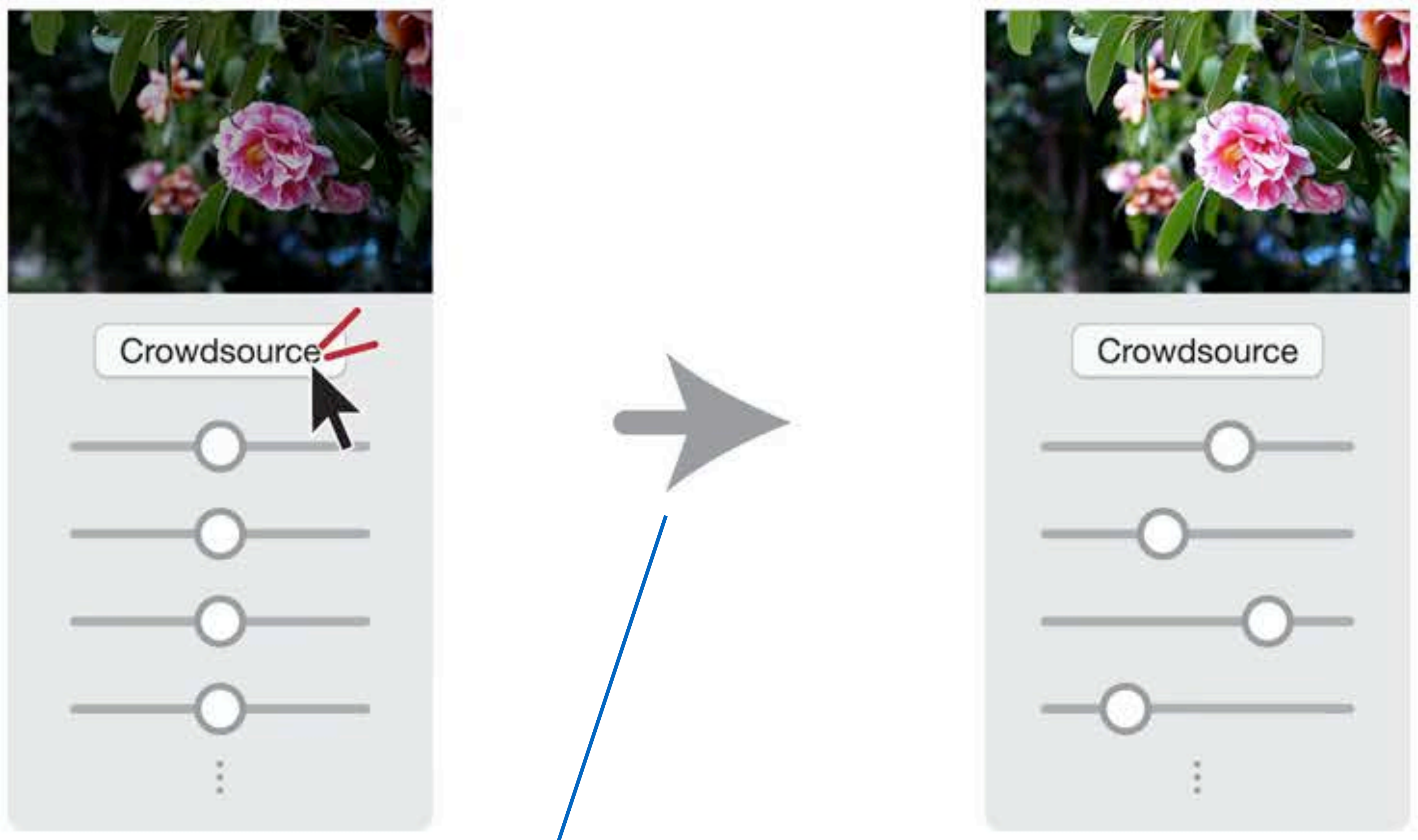


技術提案：Sequential Line Search法

選好ベイズ最適化 (PBO) を拡張して "Line Search" の質問方式を扱えるようにすることで効率性を向上

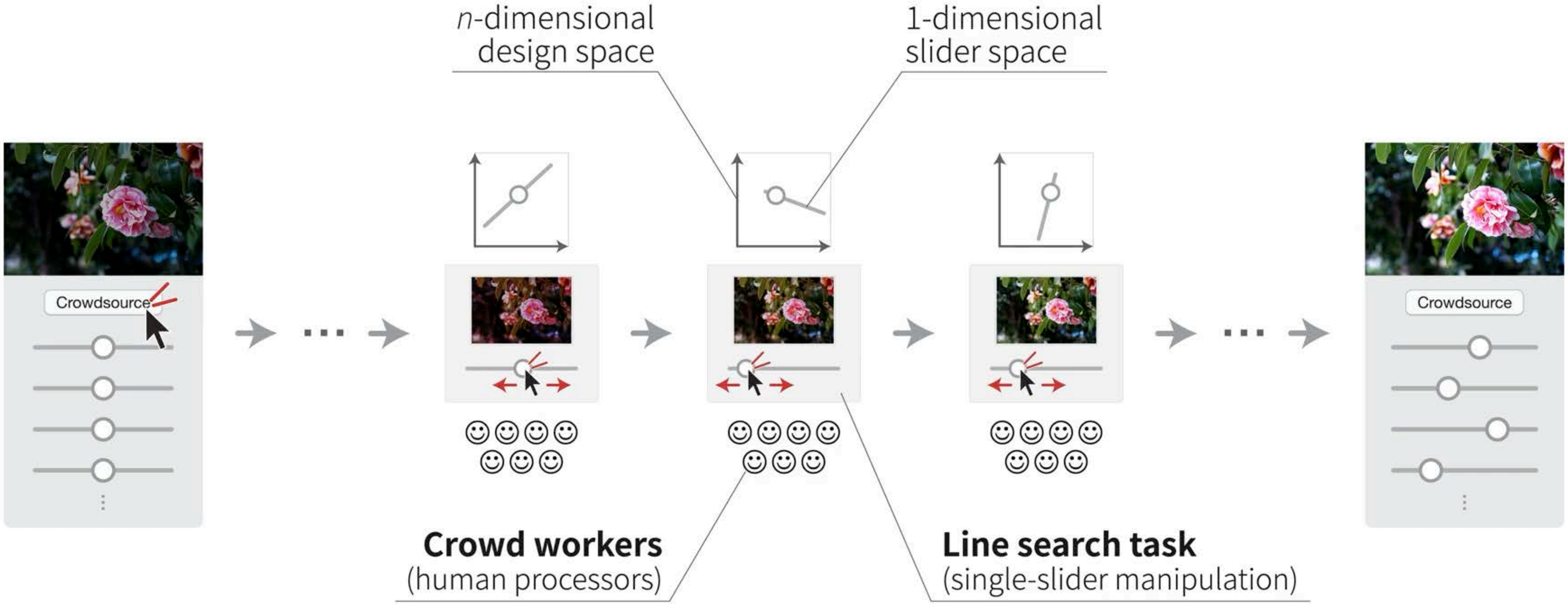
「クラウド最適化」ボタン

“People’s Choice”
最適なスライダ値



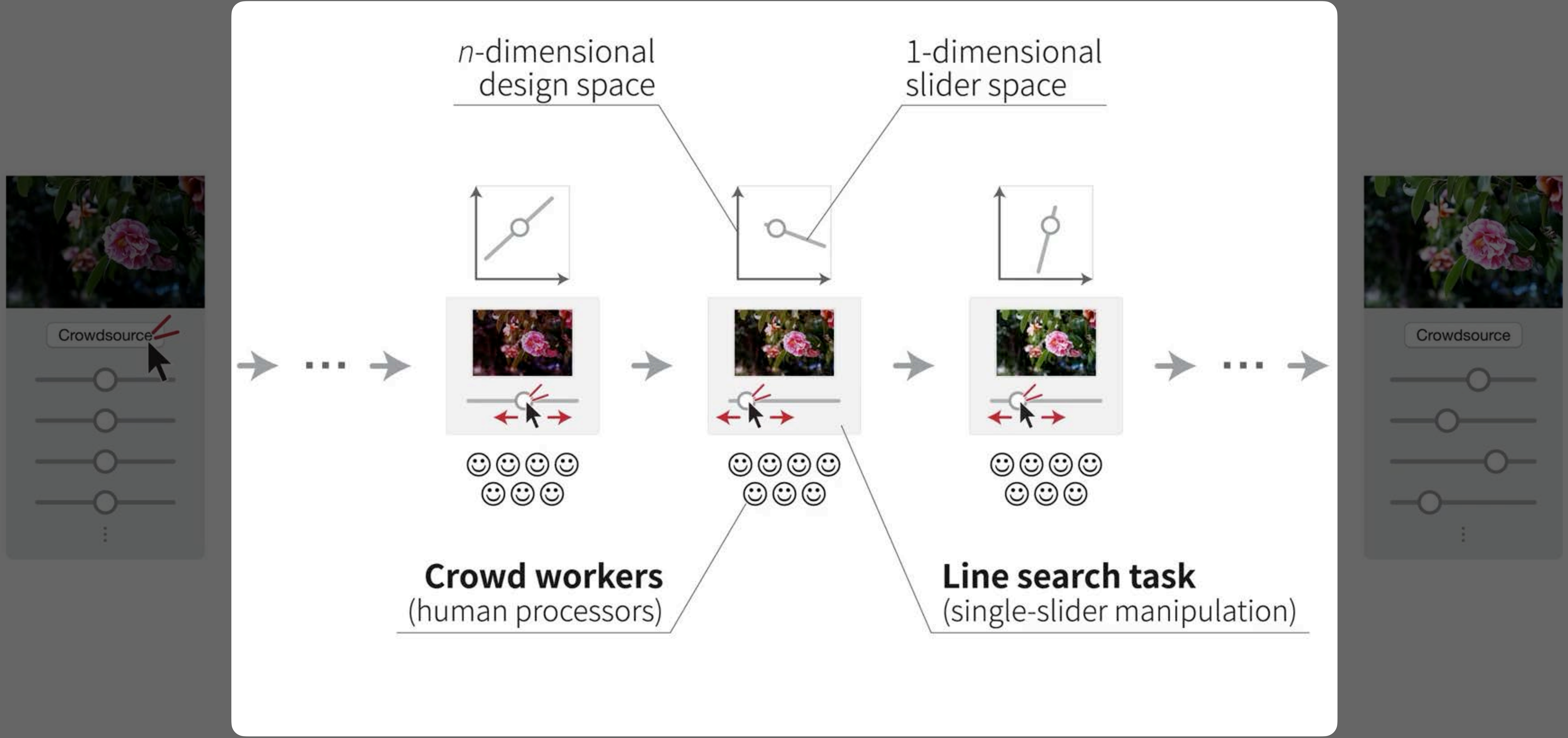
Crowd-in-the-Loop最適化

[Koyama+, SIGGRAPH 2017] Yuki Koyama, Issei Sato, Daisuke Sakamoto, and Takeo Igarashi. 2017. Sequential Line Search for Efficient Visual Design Optimization by Crowds. ACM Trans. Graph. 36, 4, pp.48:1–48:11 (2017). https://doi.org/10.1145/3072959.3073598



[Koyama+, SIGGRAPH 2017] Yuki Koyama, Issei Sato, Daisuke Sakamoto, and Takeo Igarashi. 2017. Sequential Line Search for Efficient Visual Design Optimization by Crowds. ACM Trans. Graph. 36, 4, pp.48:1–48:11 (2017). https://doi.org/10.1145/3072959.3073598

Sequential Line Search法 (本研究で提案する選好ベイズ最適化の新しい拡張)



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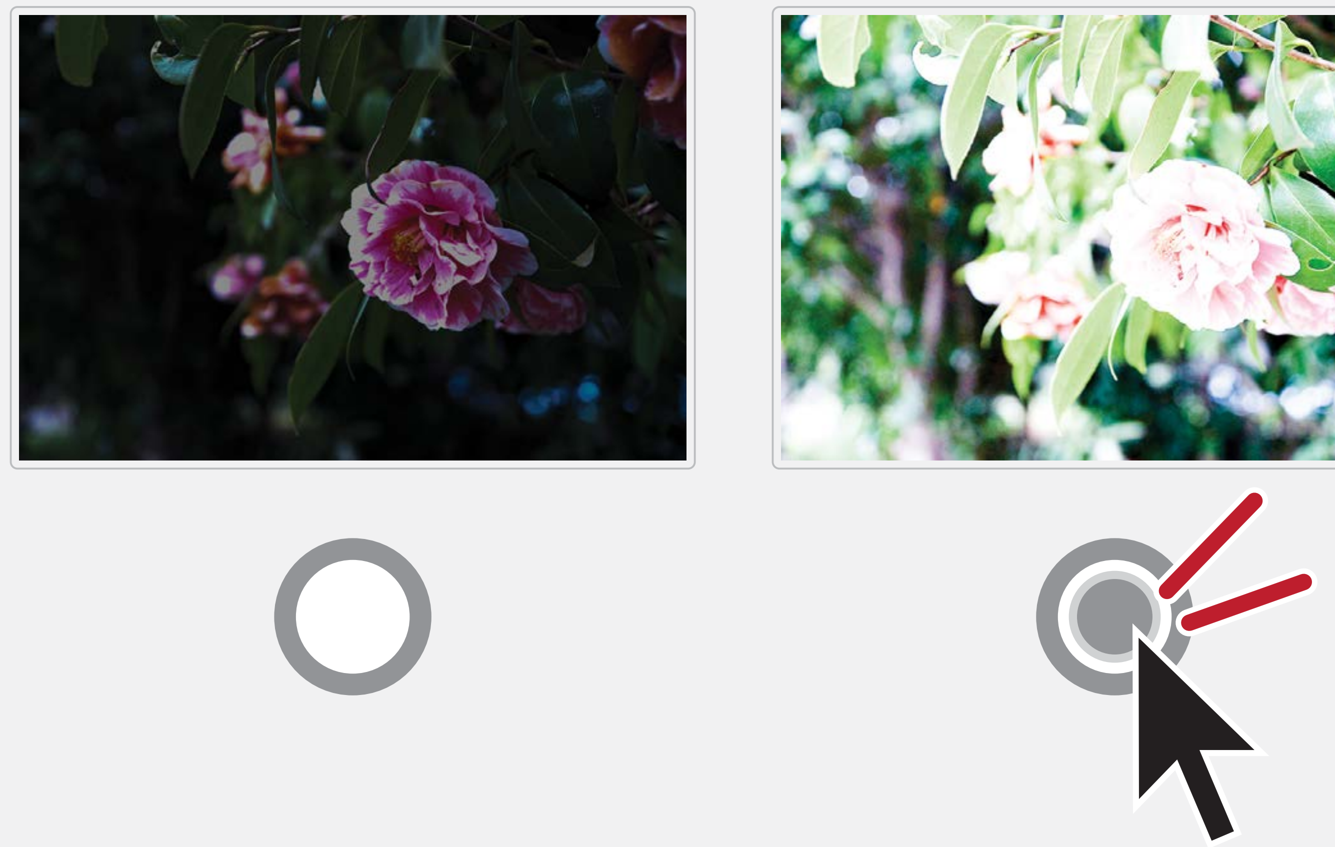
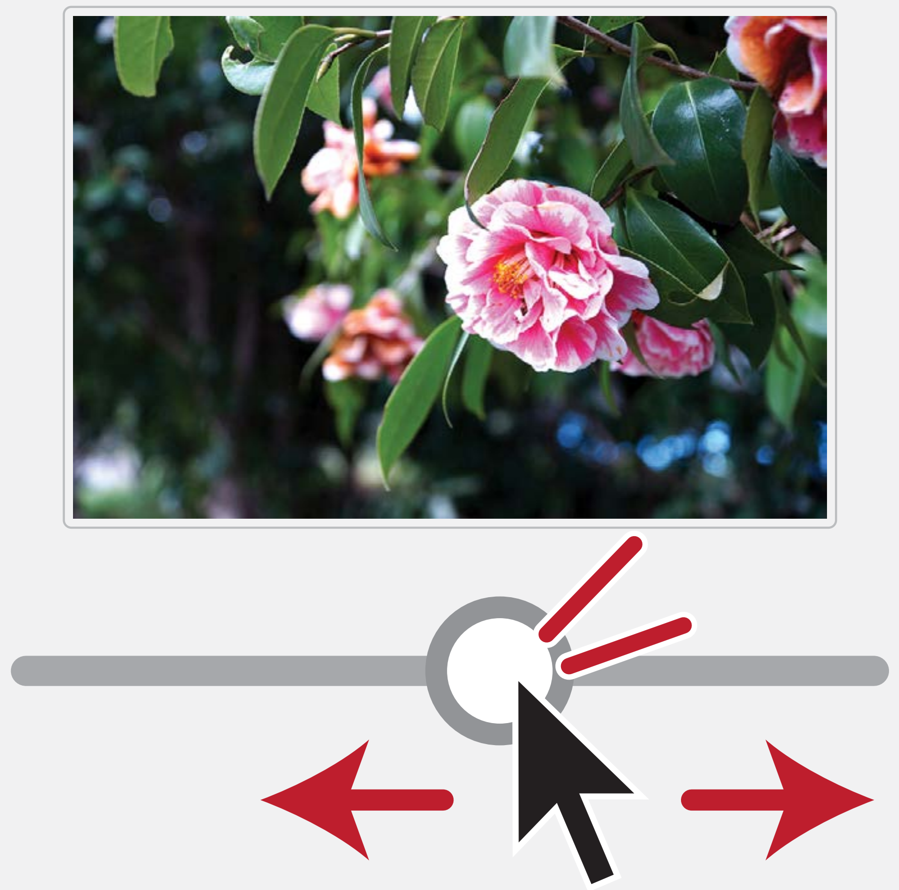
相対比較に関する質問方式の設計の工夫

Task: Choose the image that looks better



Task: Adjust the slider so that the image looks the best



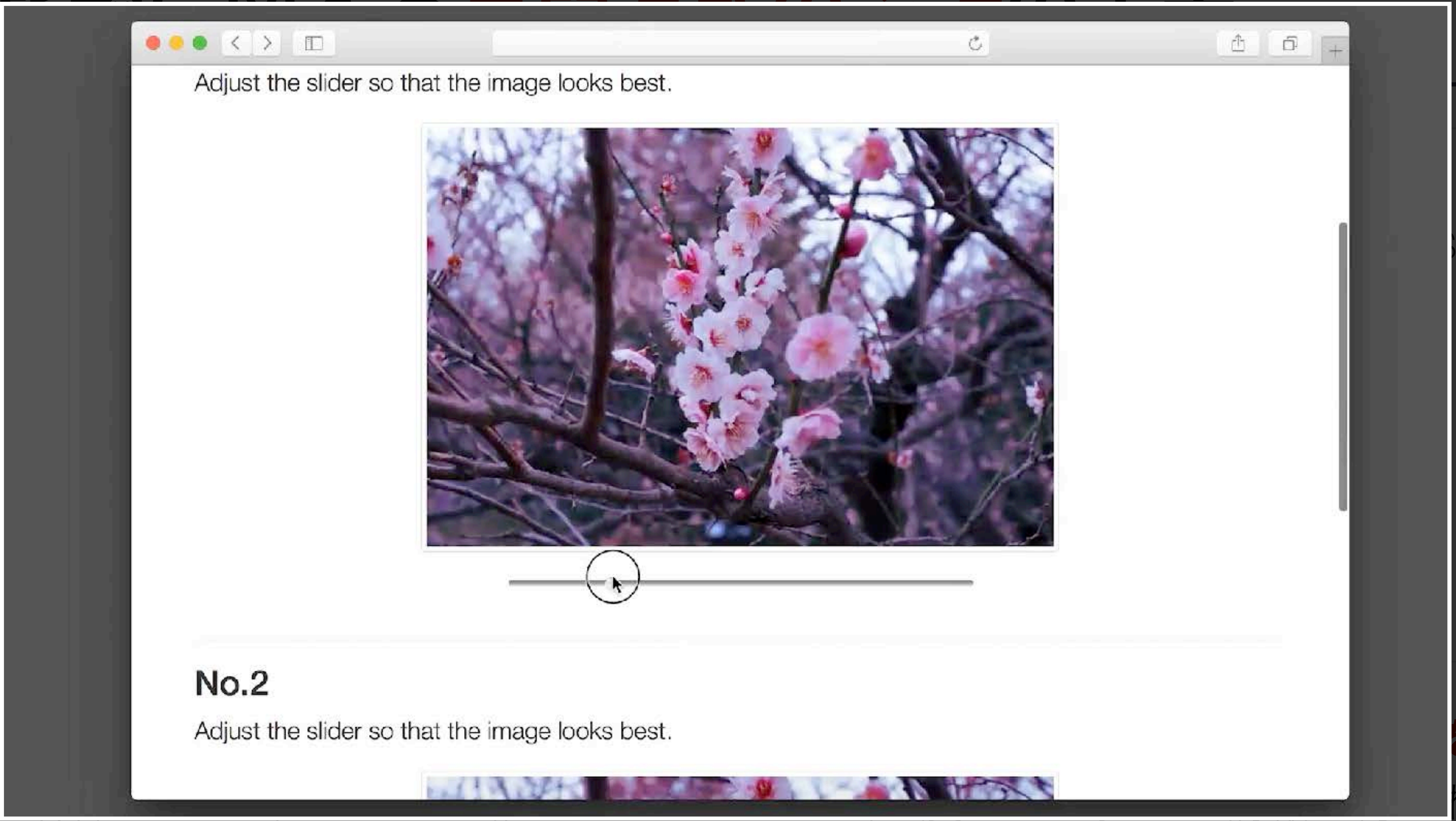
基本：一対比較
(e.g., [Brochu+, NIPS 2007])

本研究で提案：一つのスライダを操作
(一度により多くの情報を得られる)

➡ より少ない反復回数で解を発見

相対比較に関する質問方式の設計の工夫

Task:



実際の回答の様子

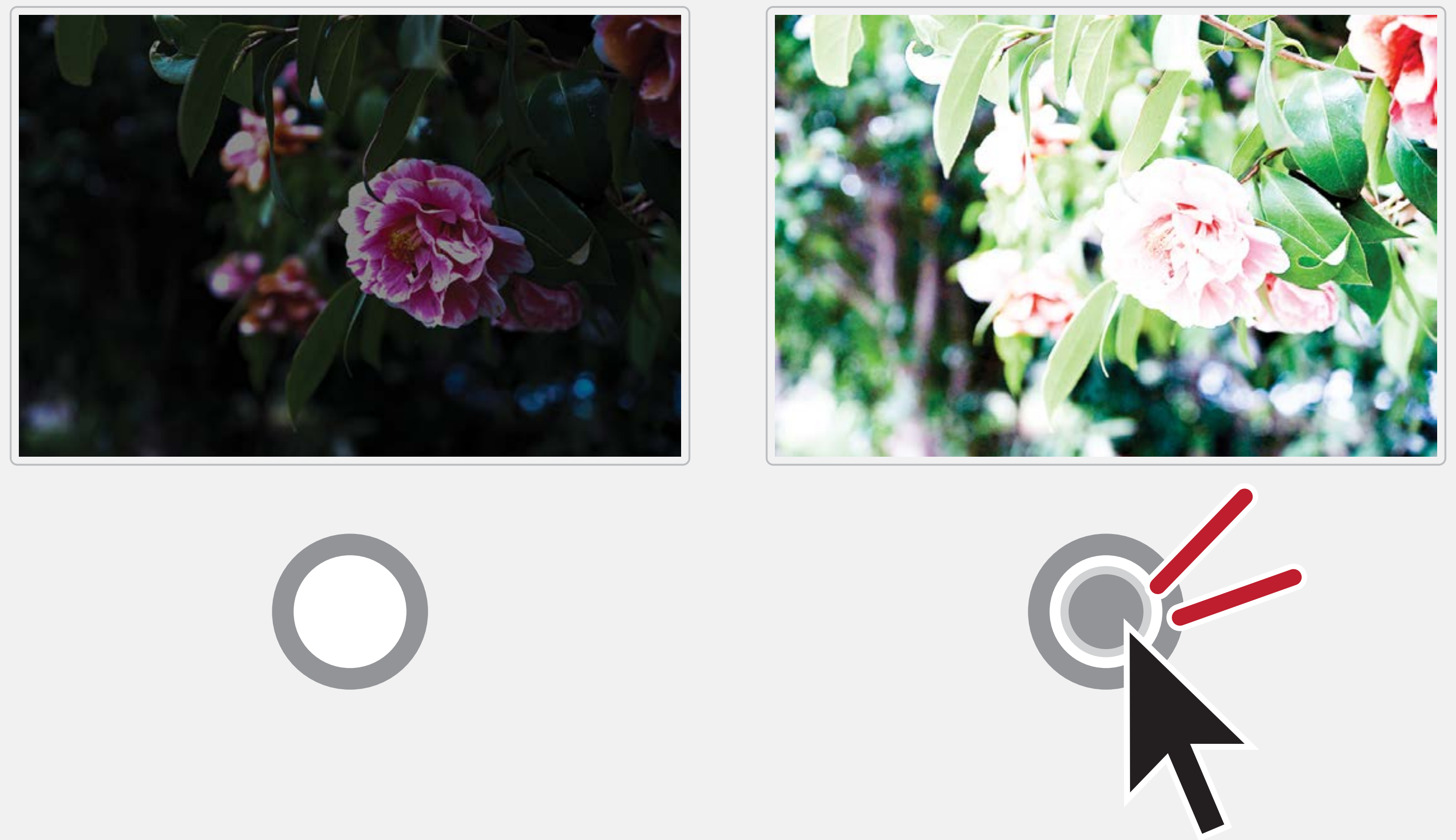
を操作

れる)

➡ より少ない反復回数で解を発見

相対比較に関する**質問方式の設計**の工夫

Task: Choose the image that looks better



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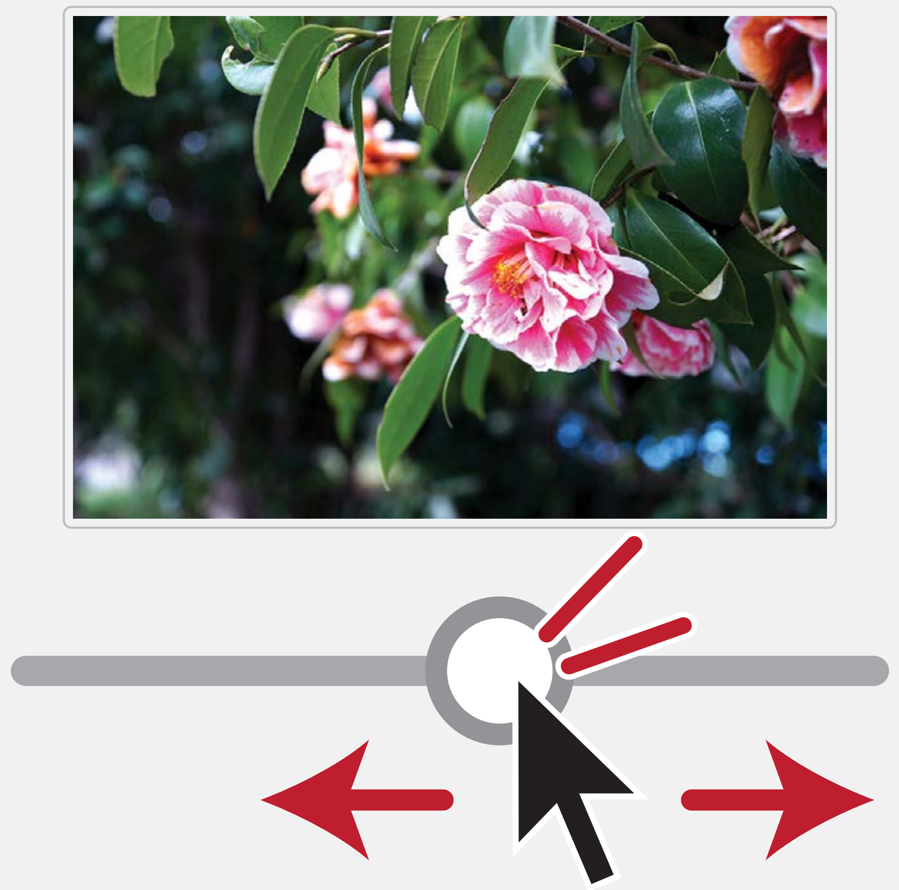

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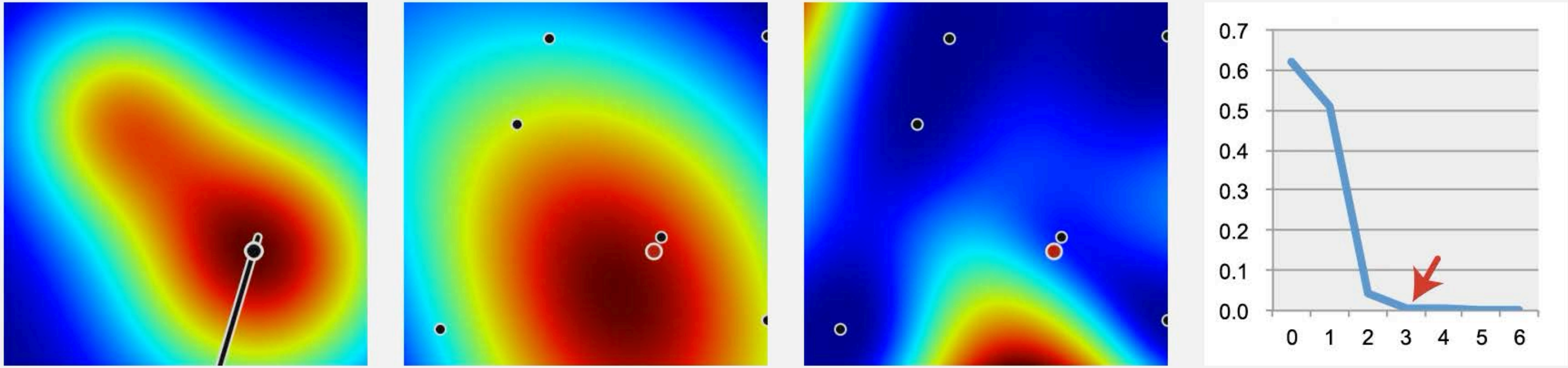
➡ より少ない反復回数で解を発見

スライダ操作に基づく相対比較を扱えるよう選好ベイズ最適化を拡張

（Sequential Line Search法）



Objective function　Estimated function　Expected improvement　Residuals over iterations

詳細は [Koyama+, SIGGRAPH 2017] を参照

[Koyama+, SIGGRAPH 2017] Yuki Koyama, Issei Sato, Daisuke Sakamoto, and Takeo Igarashi. 2017. Sequential Line Search for Efficient Visual Design Optimization by Crowds. ACM Trans. Graph. 36, 4, pp.48:1–48:11 (2017). https://doi.org/10.1145/3072959.3073598

Applications

写真の色調補正 (6D)

Original Photographs

For each photo, it runs **15 iterations**, cost **5.25 USD** in total, and took **68 min** in average

Results






For each photo, it runs **15 iterations**, cost **5.25 USD** in total, and took **68 min** in average

Replay

Original Photographs






For each photo, it runs **15 iterations**, cost **5.25 USD** in total, and took **68 min** in average

Results






For each photo, it runs **15 iterations**, cost **5.25 USD** in total, and took **68 min** in average

Evaluation: Crowdsourced Voting

Q. Which one do you like?

Original

By Crowds

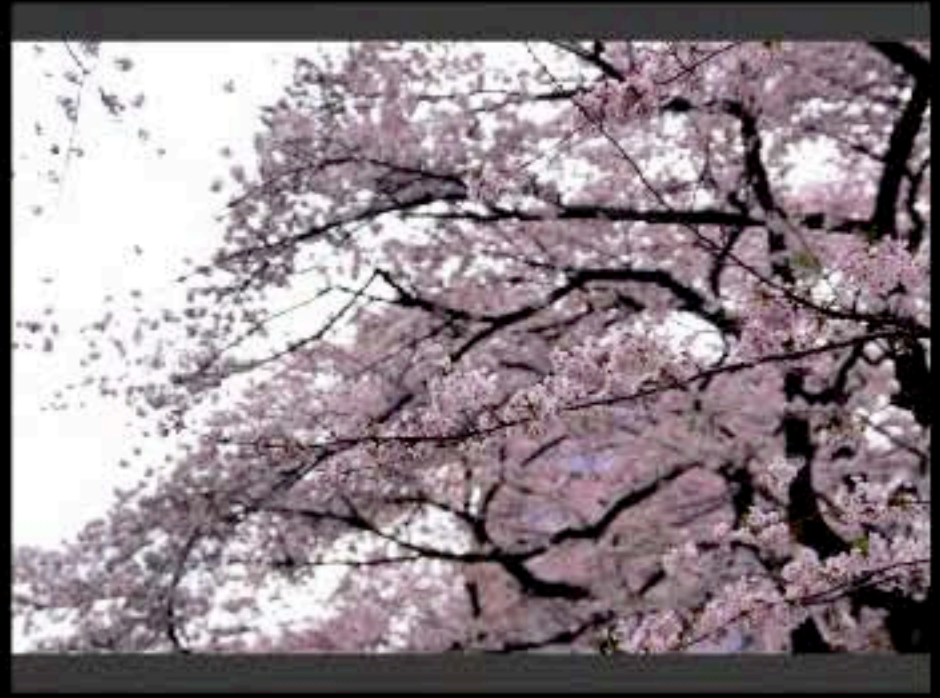
By Photoshop

By Lightroom

Baselines

	Original	Crowds	Photoshop	Lightroom
				
Preferred by:	2	26	2	3
				
Preferred by:	0	32	0	1

	Original	Crowds	Photoshop	Lightroom
				
Preferred by:	0	29	1	3
				
Preferred by:	1	23	3	6

	Original	Crowds	Photoshop	Lightroom
				
Preferred by:	0	29	3	1
				
Preferred by:	0	31	0	2

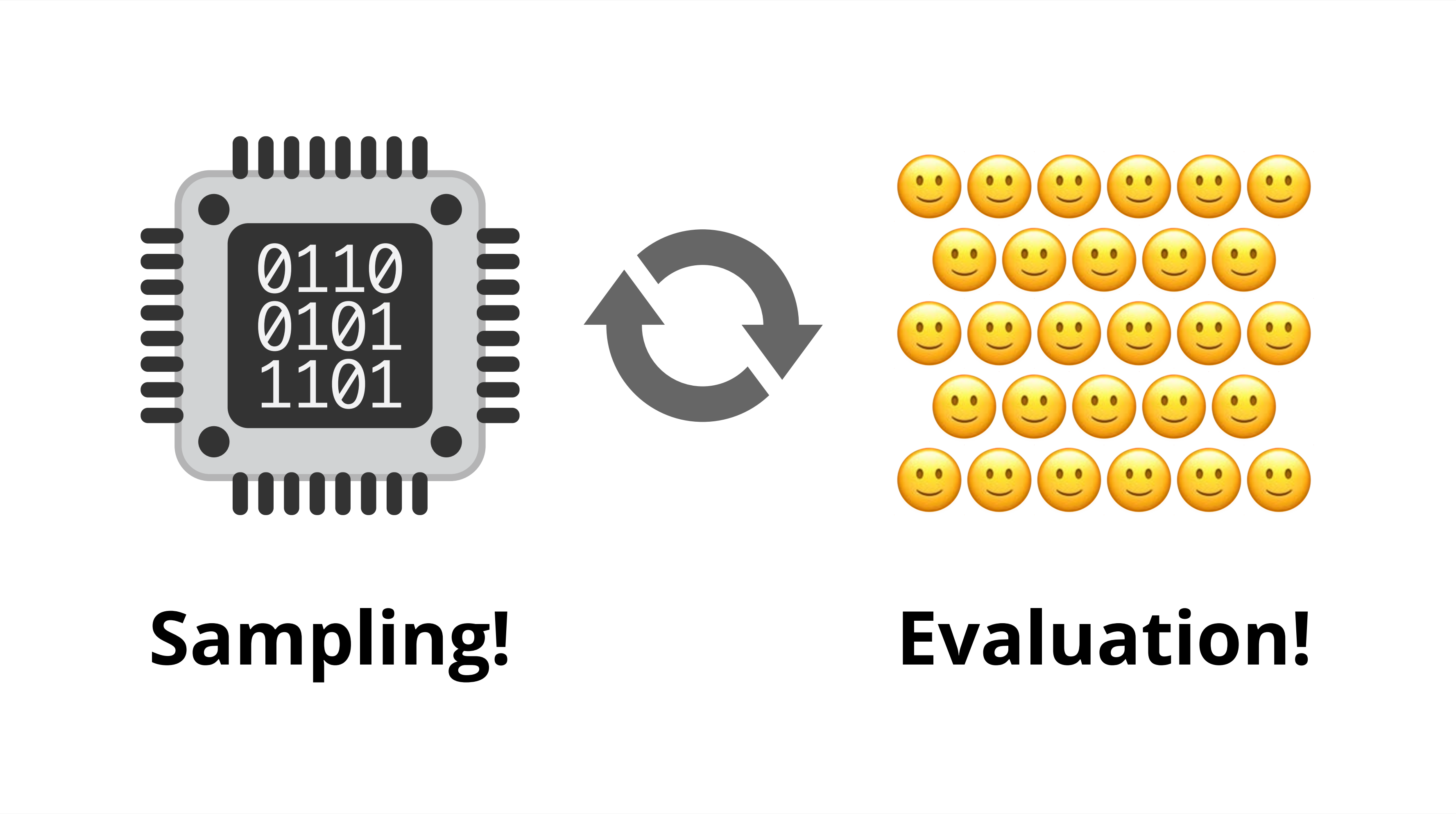
Q. Which one do you like?

Original	By Crowds	By Photoshop	By Lightroom

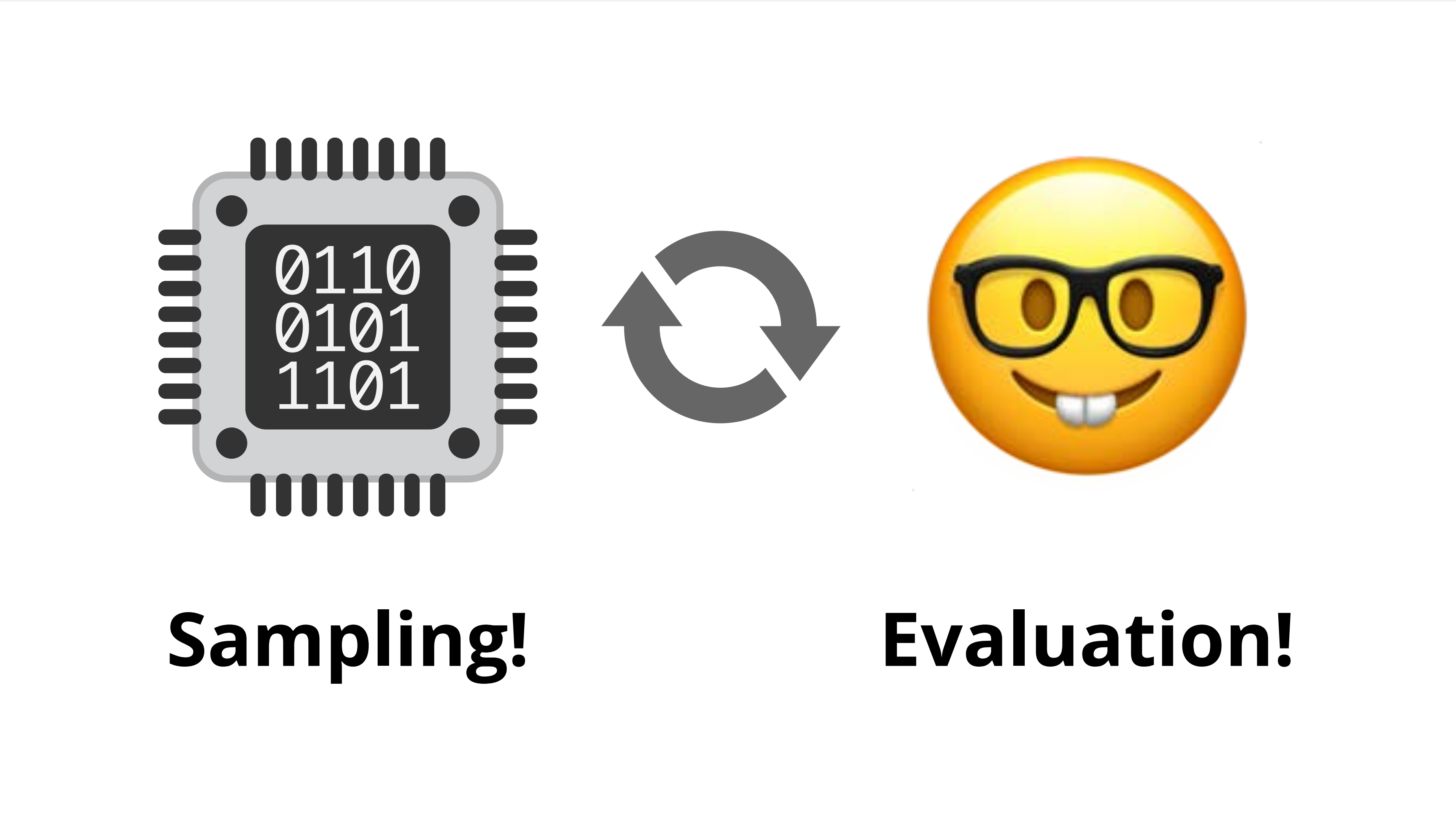
➡ 大衆の好みに基づいて最適化した (“people’s choice”) ため、大衆に好まれる

- **Crowd-in-the-Loop最適化**を実現
- 一対比較ではなく**一つのスライダを操作するタスク**を採用することで必要な反復回数を削減
- そのために**選好ベイズ最適化 (PBO) を拡張**
    - Sequential Line Search法

評価者



- Crowd-in-the-Loop最適化
- 特徴：
  - 大衆の好み
  - クラウドソーシングで自動実行が可能

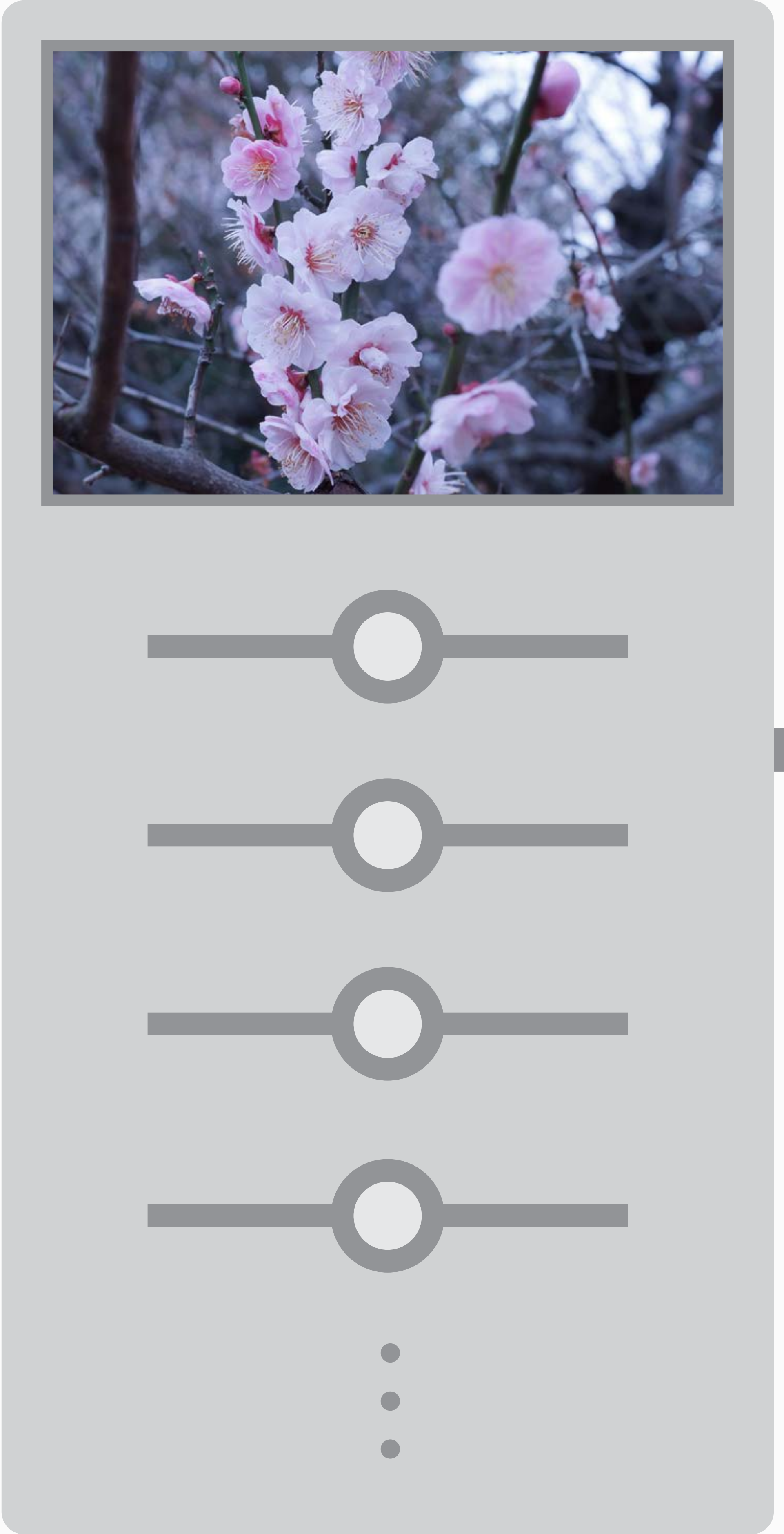


- User-in-the-Loop最適化
- 特徴：
  - 個人の好み
  - 対話的な実行

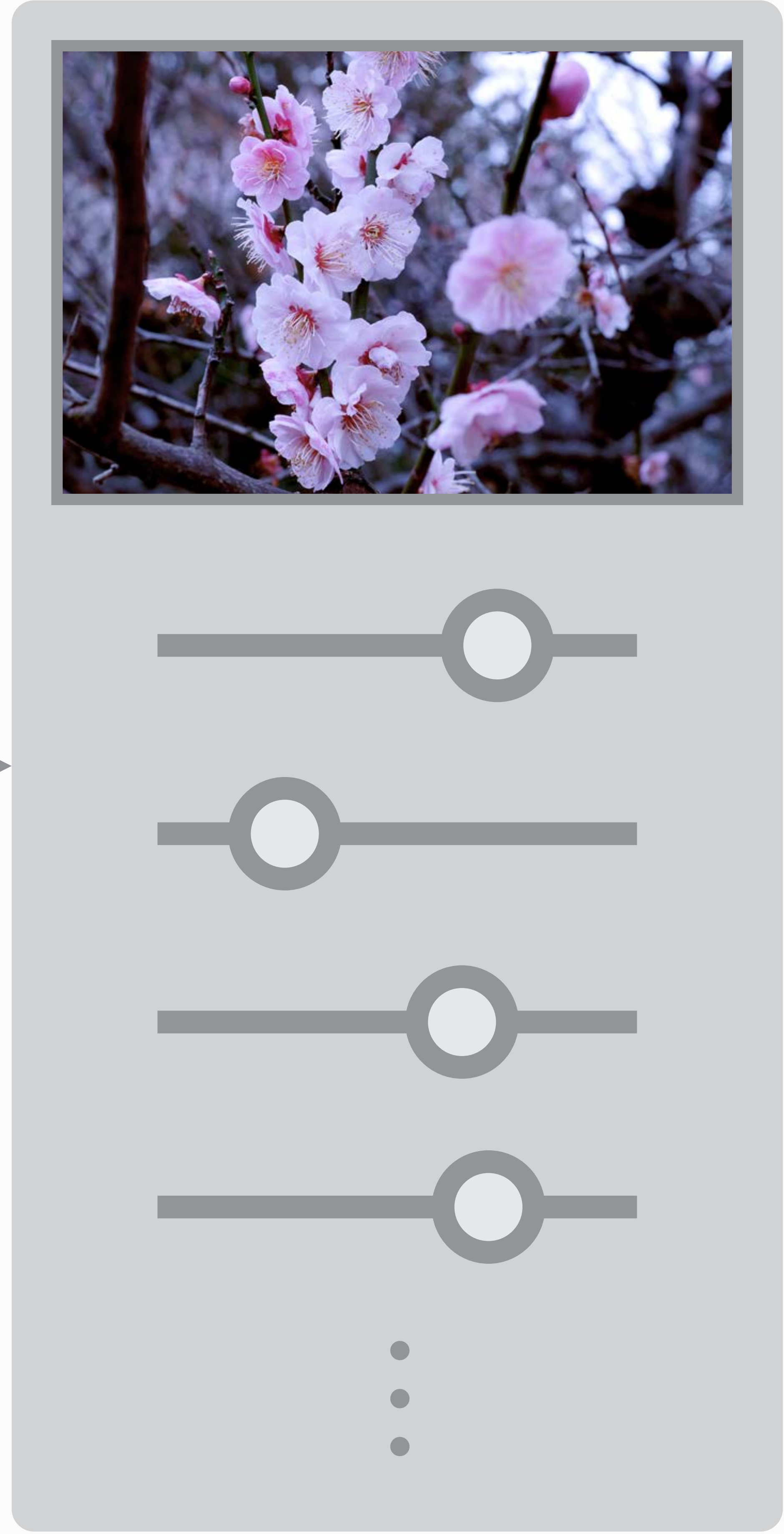
研究事例 2

Sequential Gallery [SIGGRAPH 2020]

Target:
n design parameters
(e.g., photo enhance)



Output:
An optimal
parameter set



Target:
n design parameters
(e.g., photo enhance)

Sequential Gallery:
An interactive optimization framework
where the user sequentially performs
2D search subtasks via a grid interface

Output:
An optimal
parameter set

Target:
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(e.g., photo enhance)

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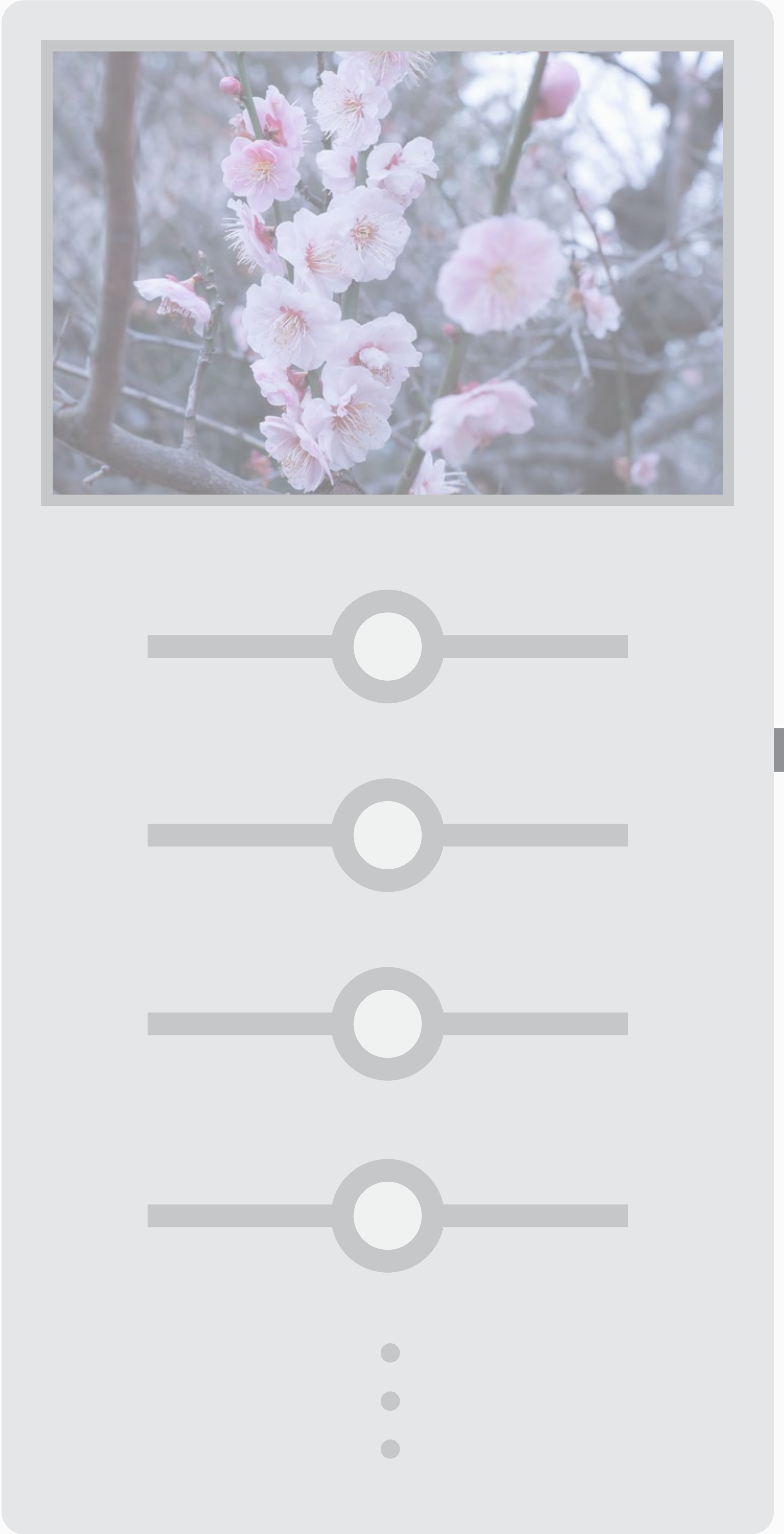
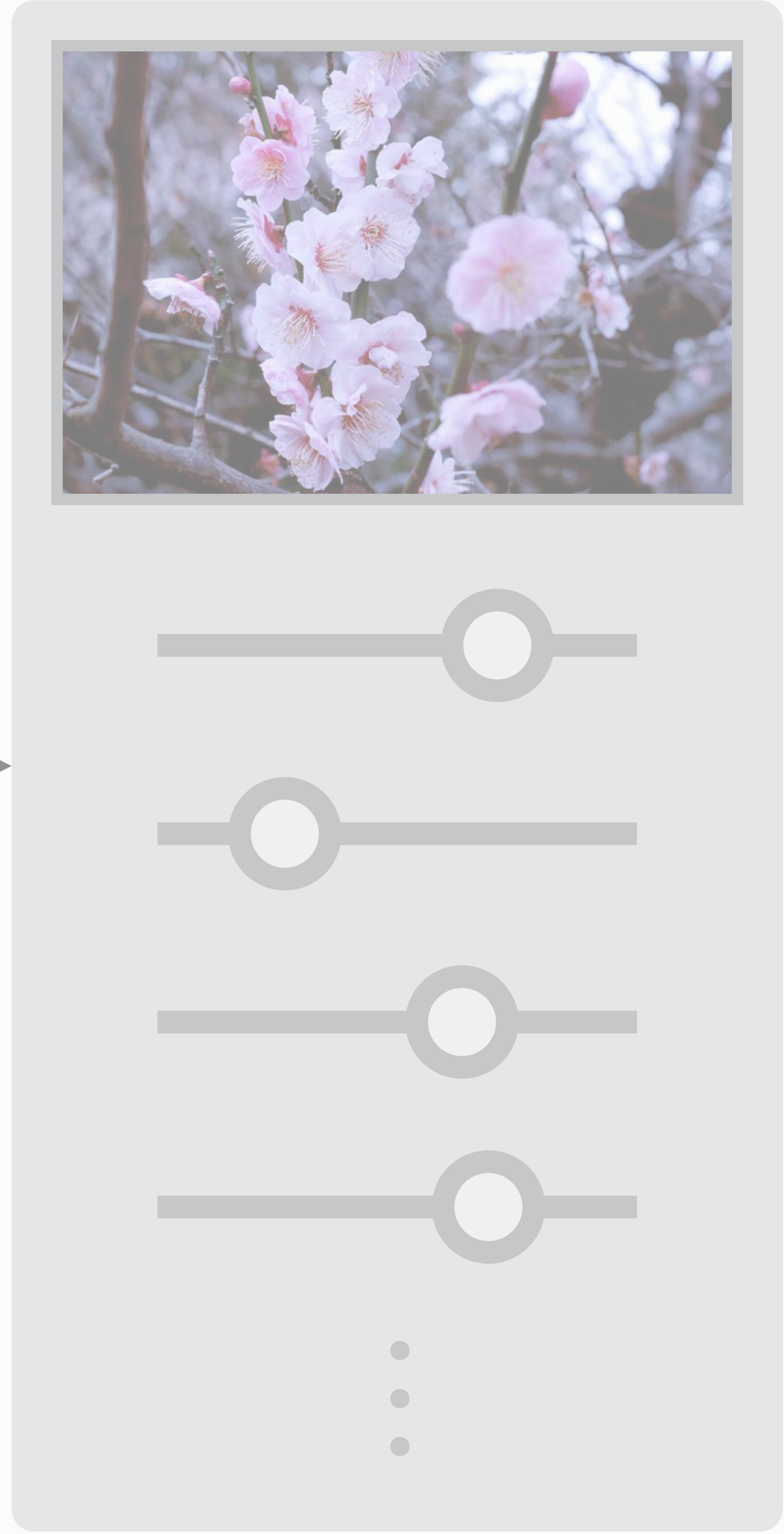


2D search subtask #1



Target:
n design parameters
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Sequential Gallery:
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Output:
An optimal
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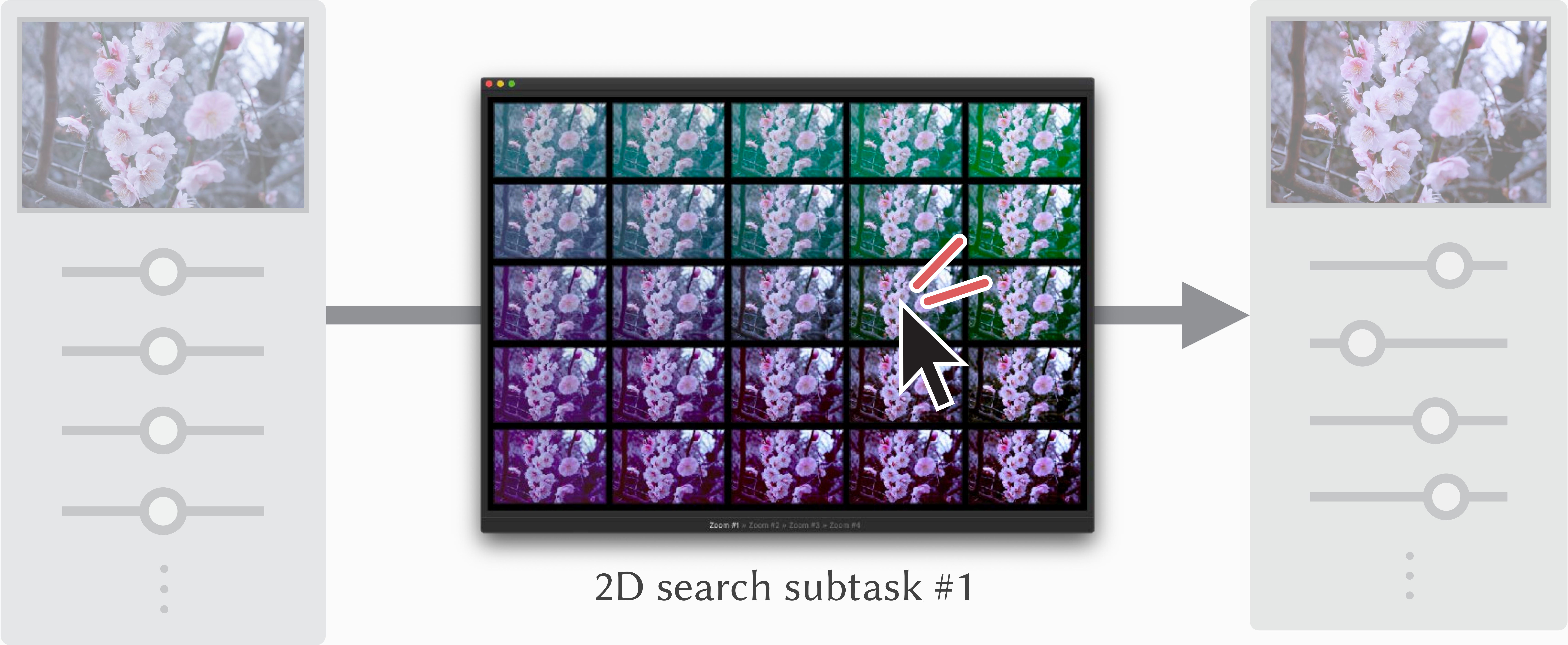

2D search subtask #1

Target:
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An interactive optimization framework where the user sequentially performs 2D search subtasks via a grid interface

Output:
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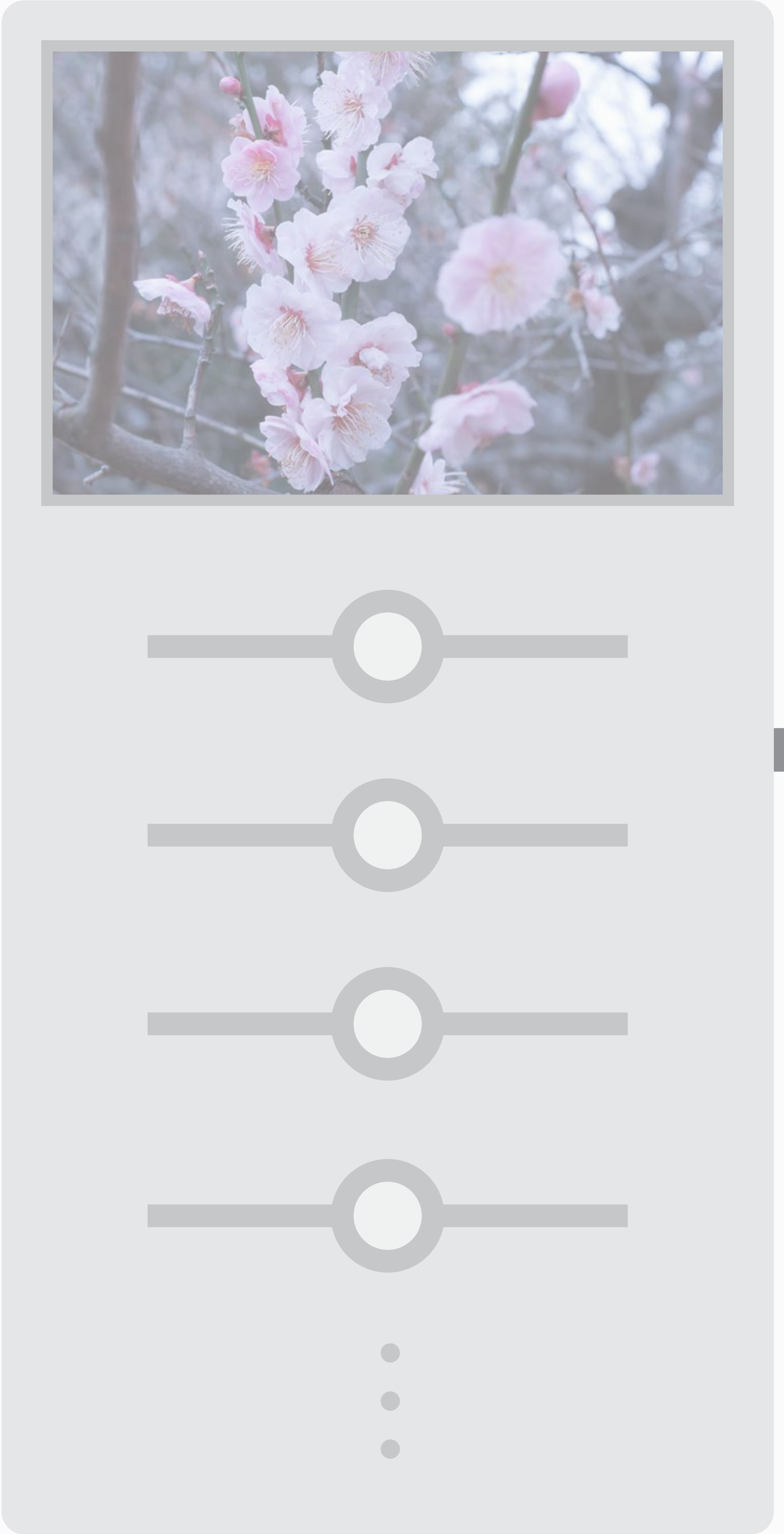
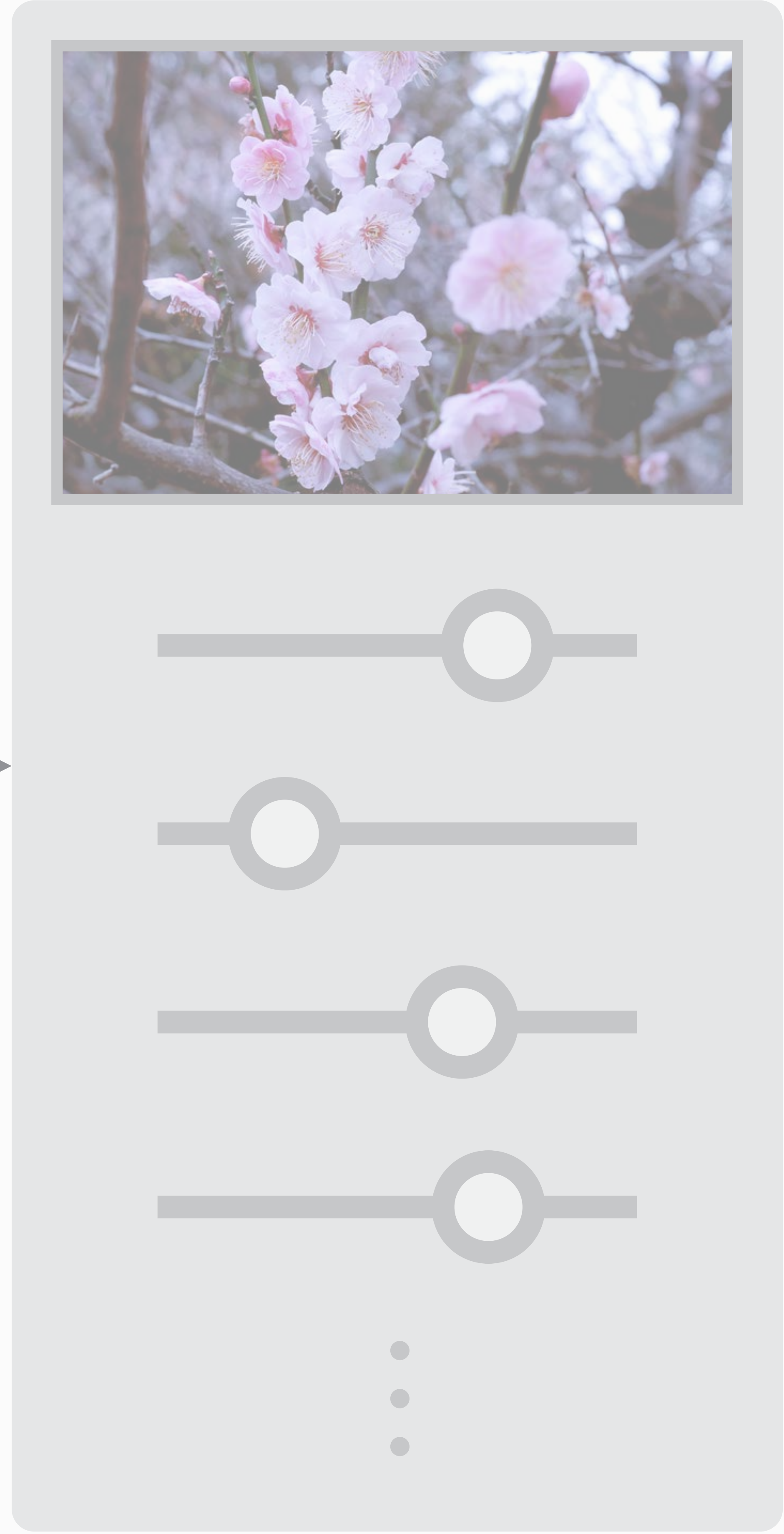


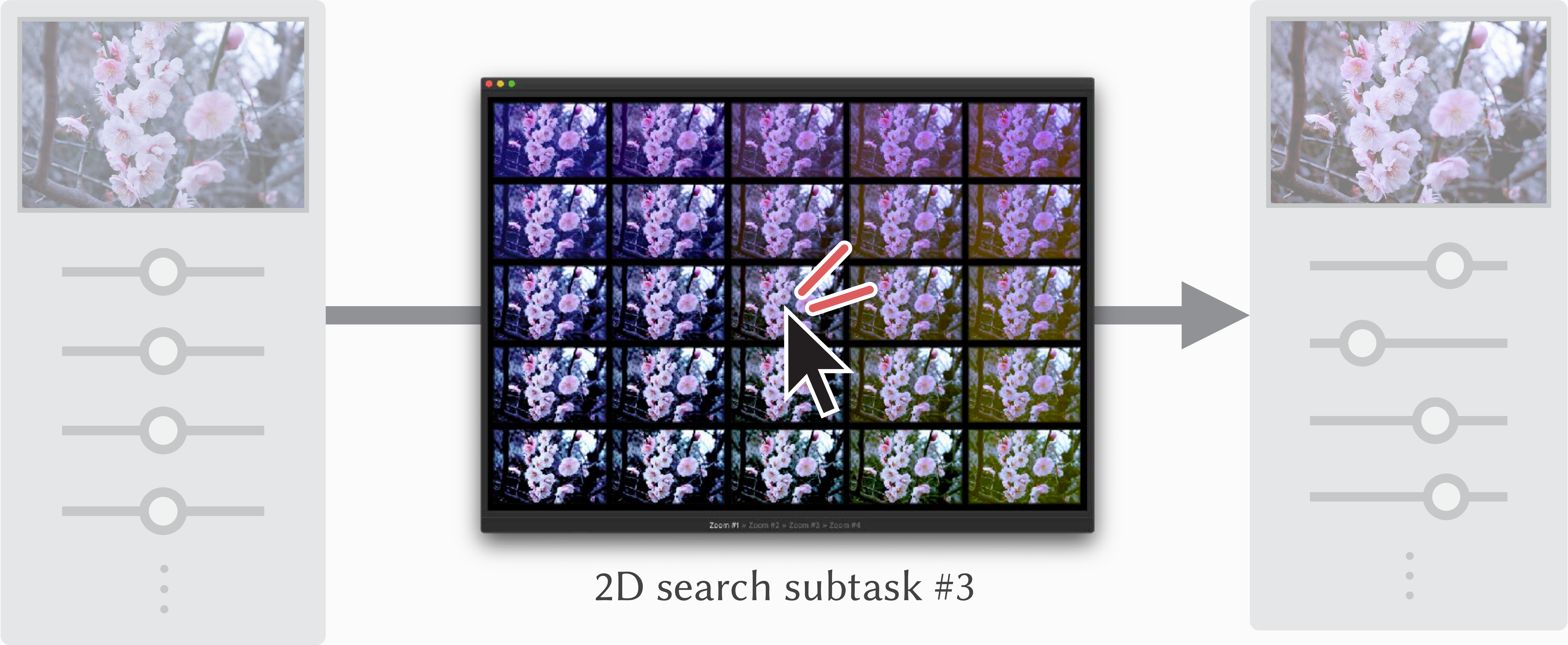
2D search subtask #2



Target:
n design parameters
(e.g., photo enhance)

Sequential Gallery:
An interactive optimization framework where the user sequentially performs 2D search subtasks via a grid interface

Output:
An optimal parameter set

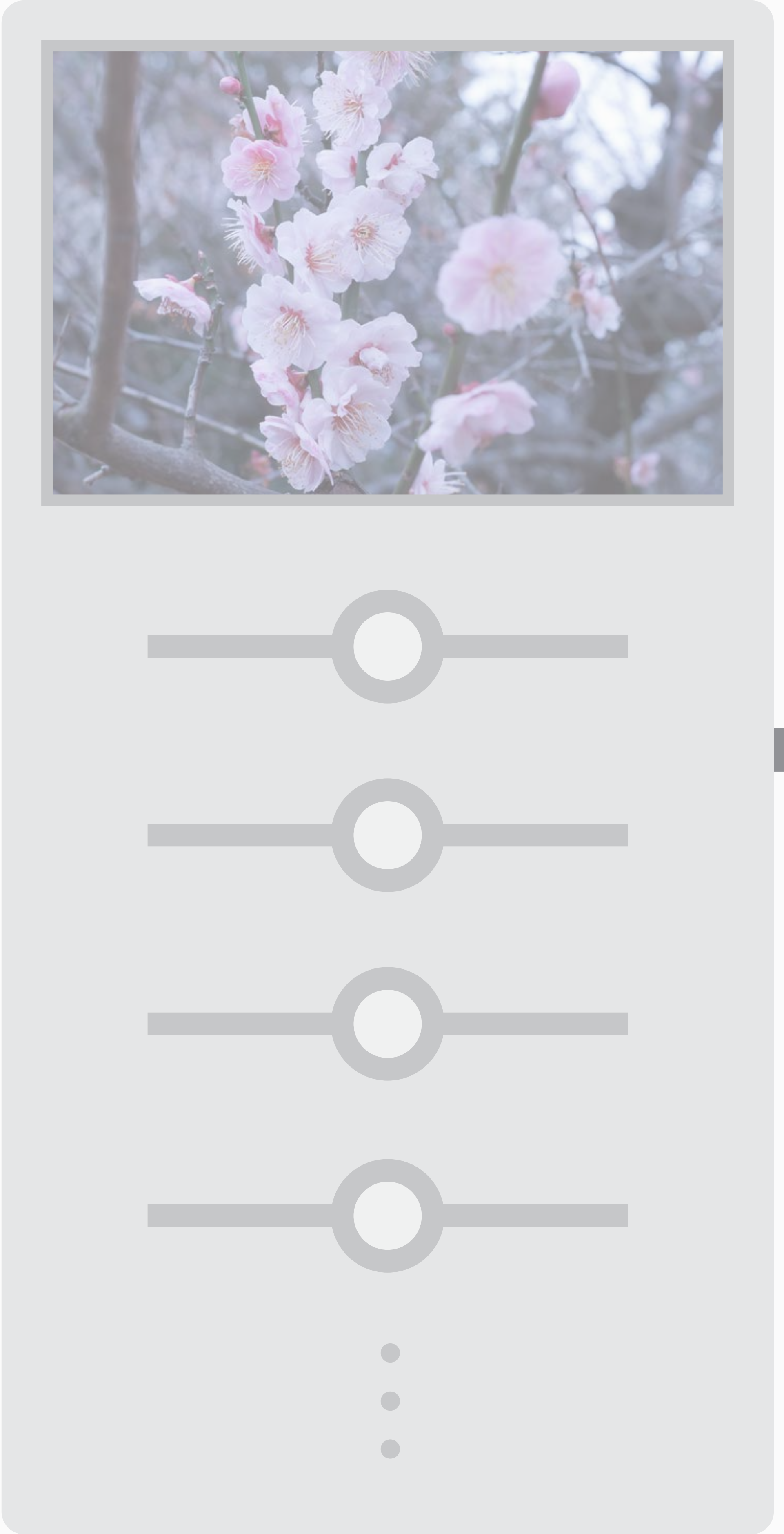


2D search subtask #3

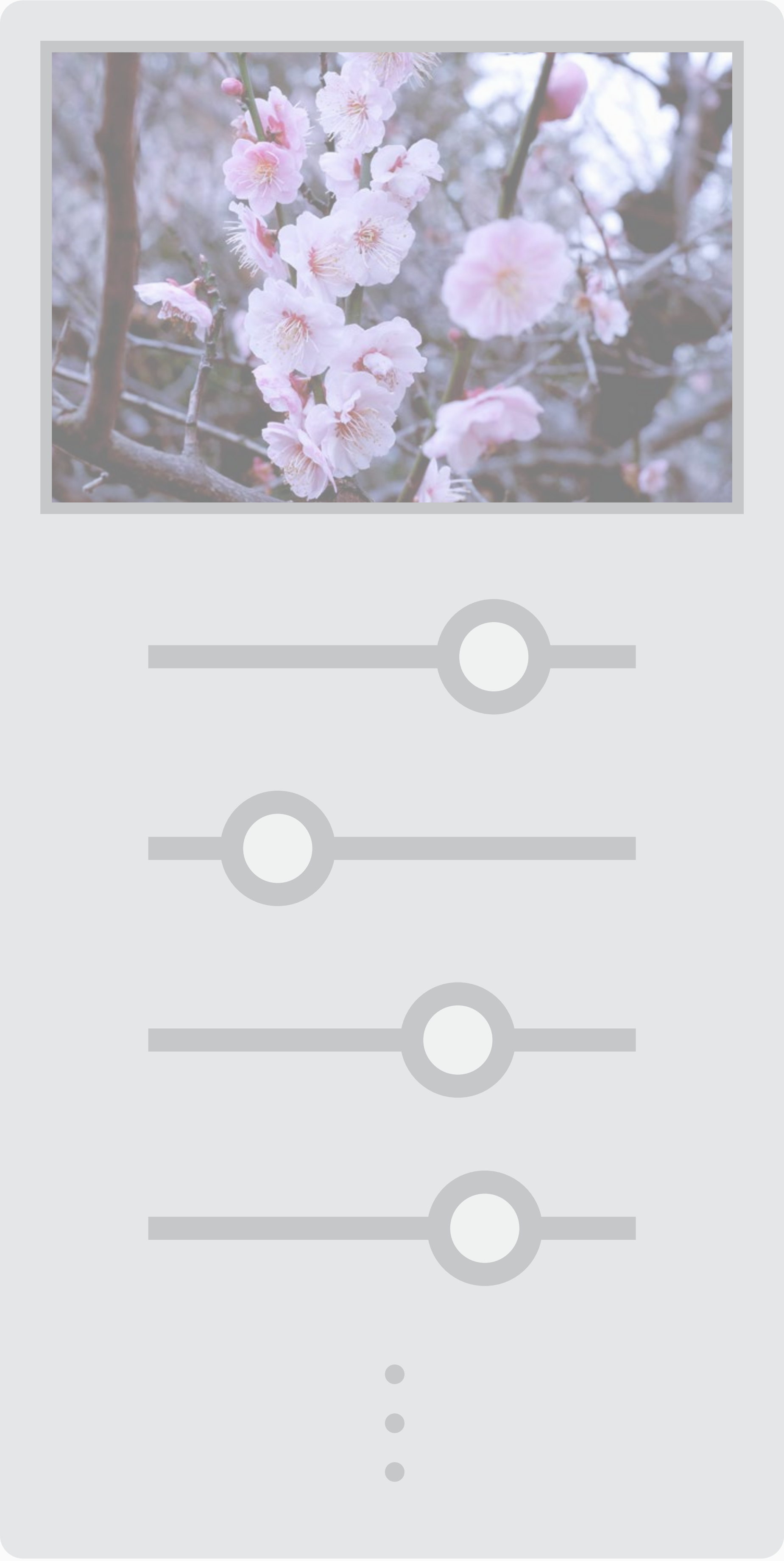
Target:
n design parameters
(e.g., photo enhance)

Sequential Gallery:
An interactive optimization framework
where the user sequentially performs
2D search subtasks via a grid interface

Output:
An optimal
parameter set



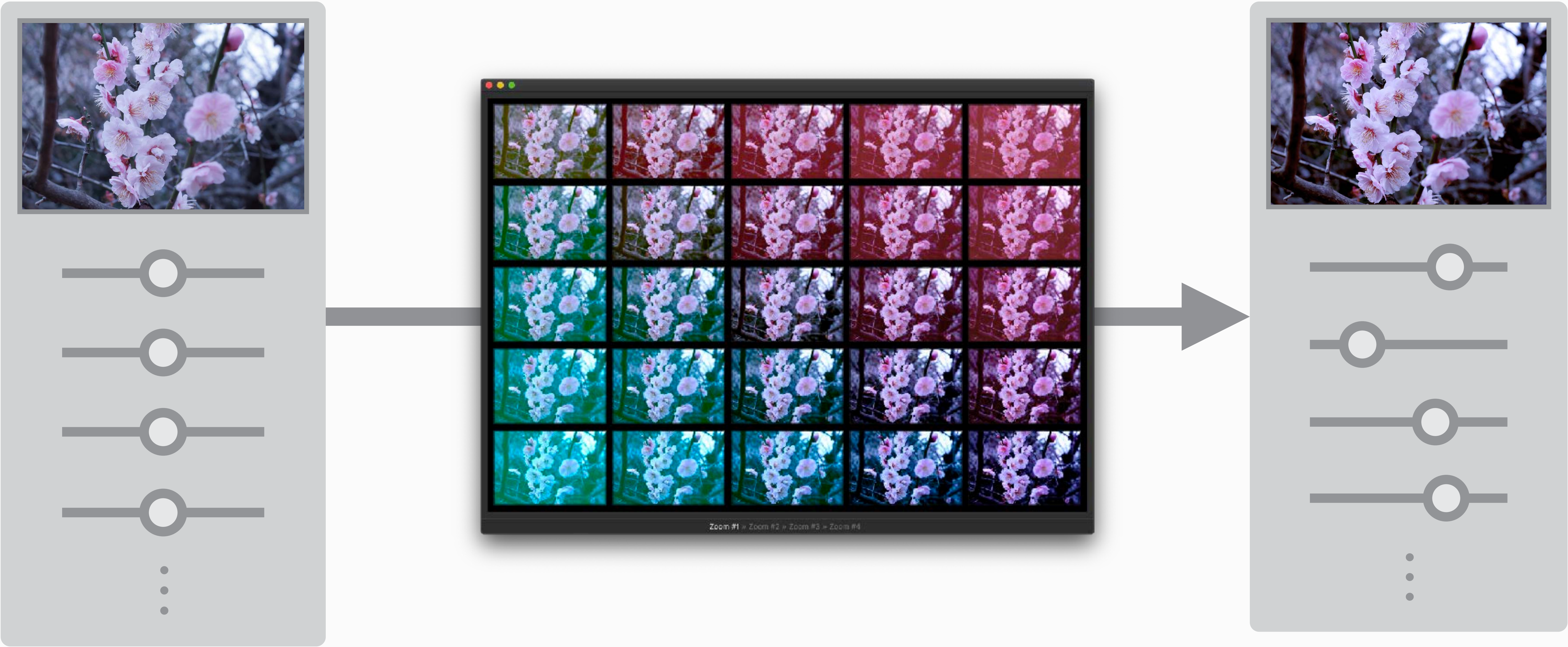
2D search subtask #4

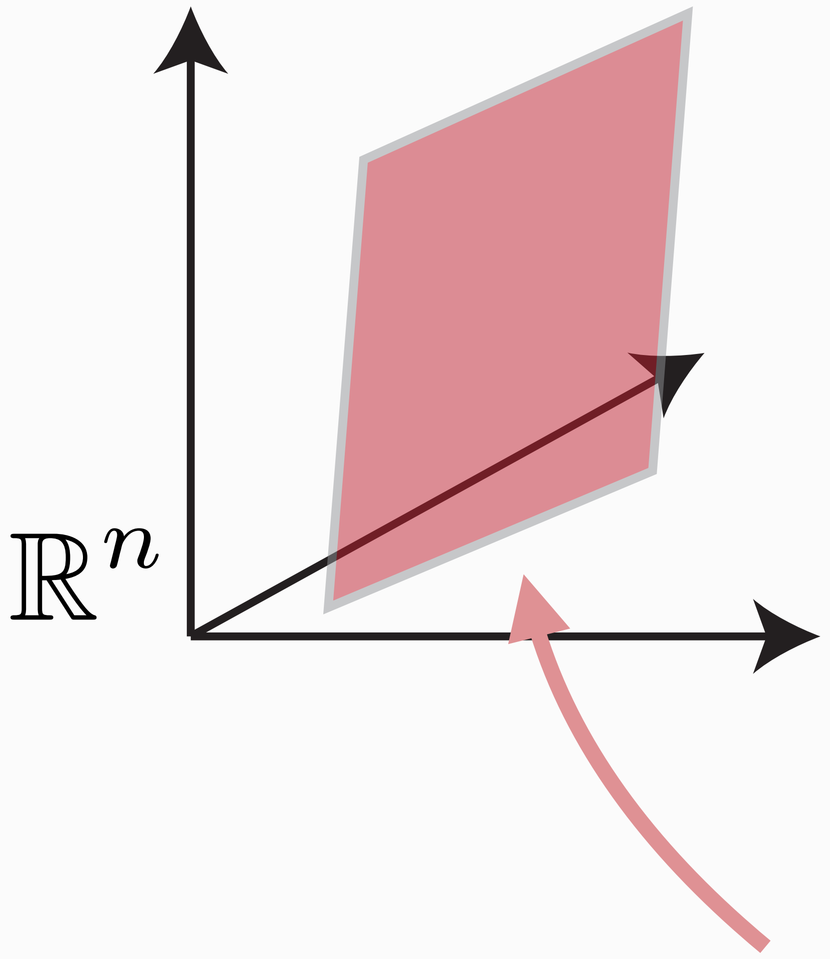


Target:
n design parameters
(e.g., photo enhance)

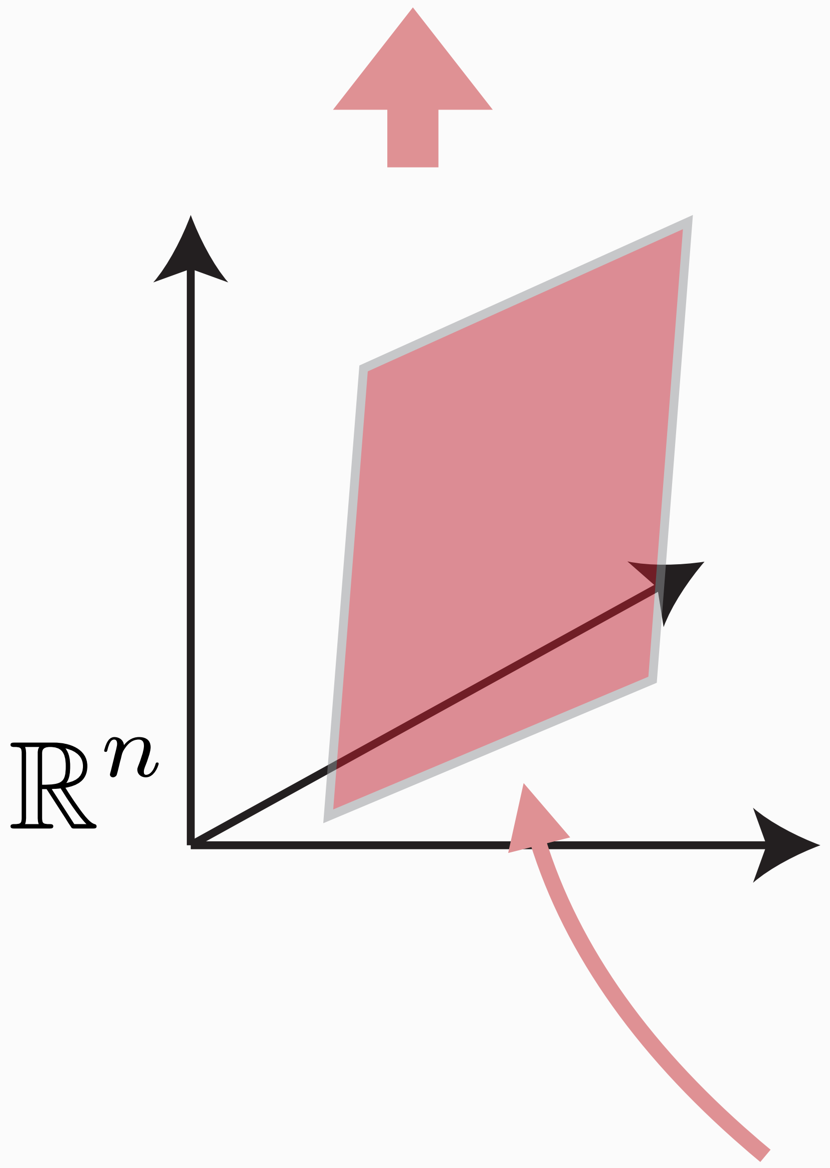
Sequential Gallery:
An interactive optimization framework where the user sequentially performs 2D search subtasks via a grid interface

Output:
An optimal parameter set





2-dimensional search subspaces (= **search planes**)
determined by **preferential Bayesian optimization** (PBO)



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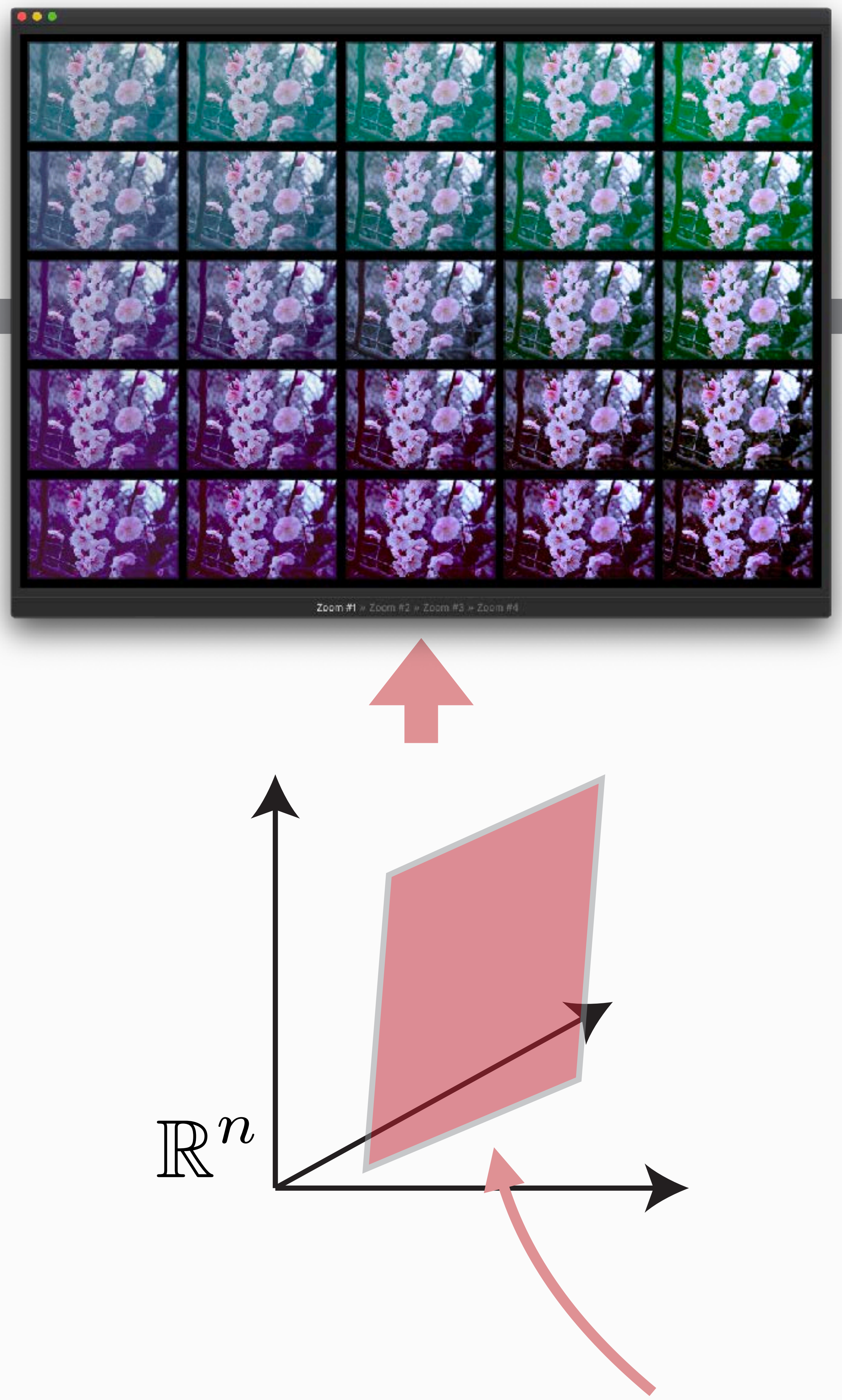
Yuki Koyama, Issei Sato, and Masataka Goto. Sequential Gallery for Interactive Visual Design Optimization. ACM Trans. Graph. (SIGGRAPH 2020)

… 2D search subtask



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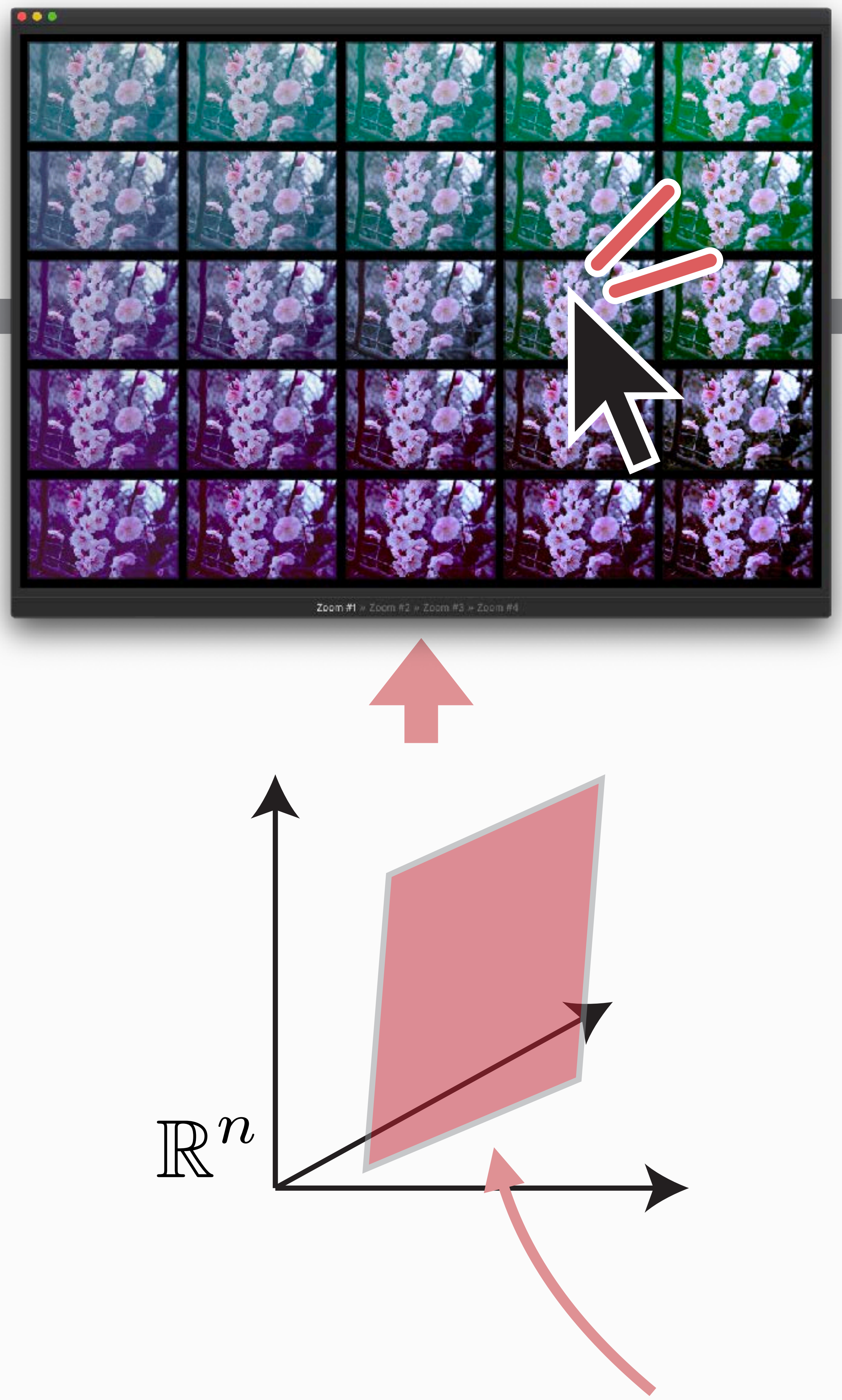

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... 2D search subtask

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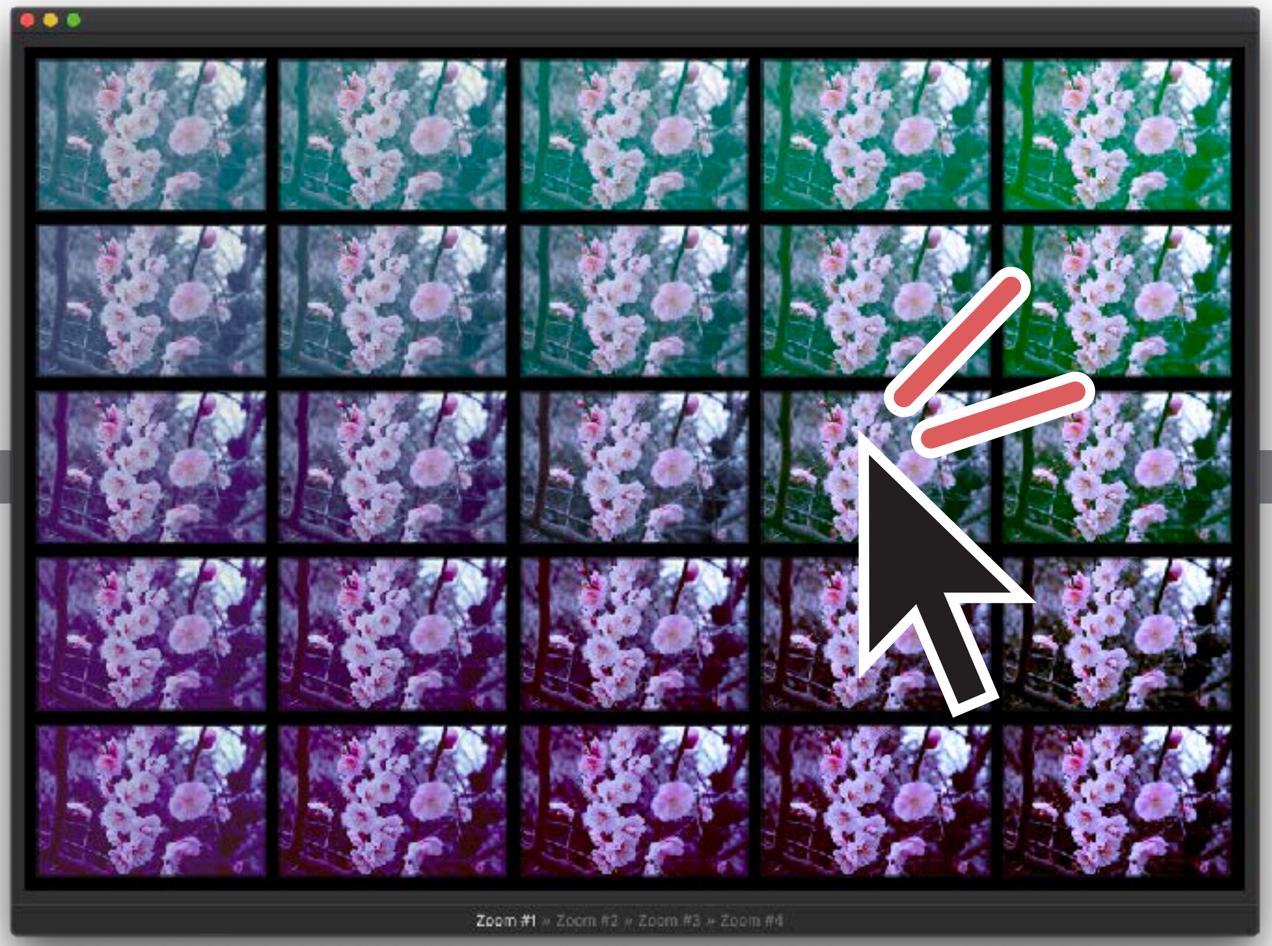
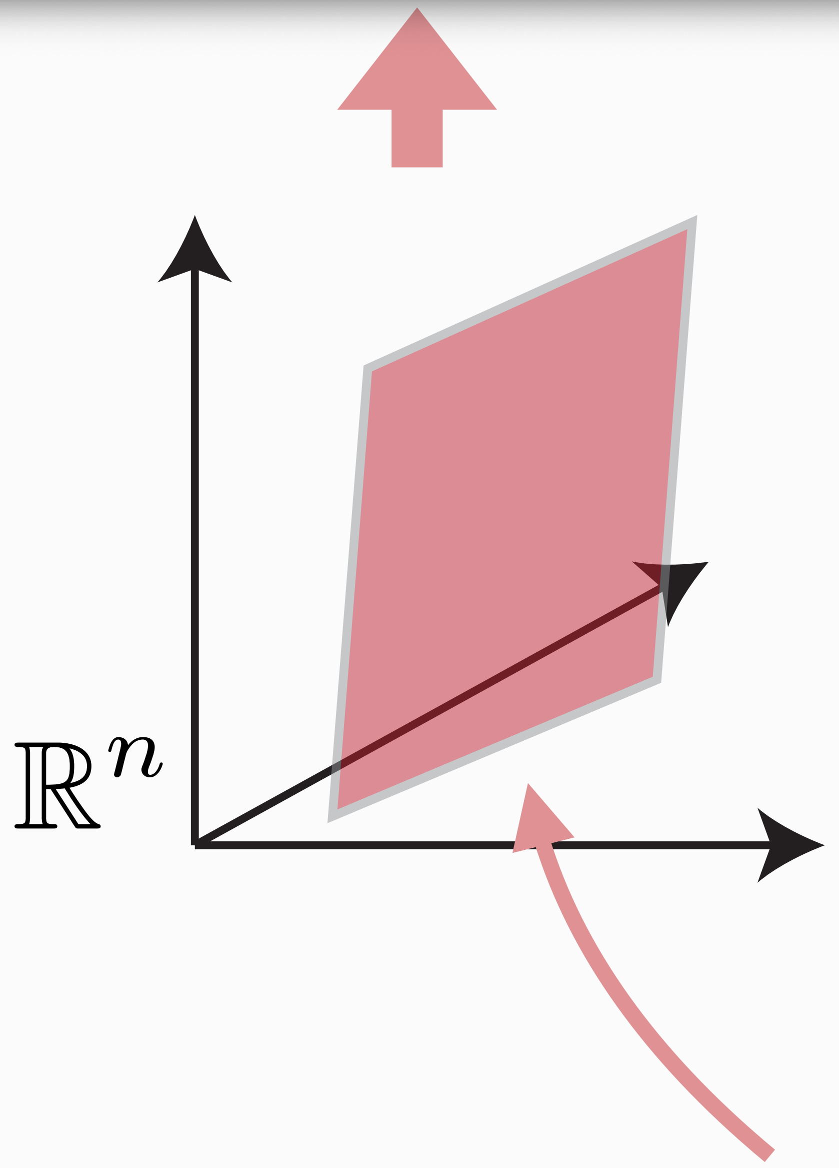
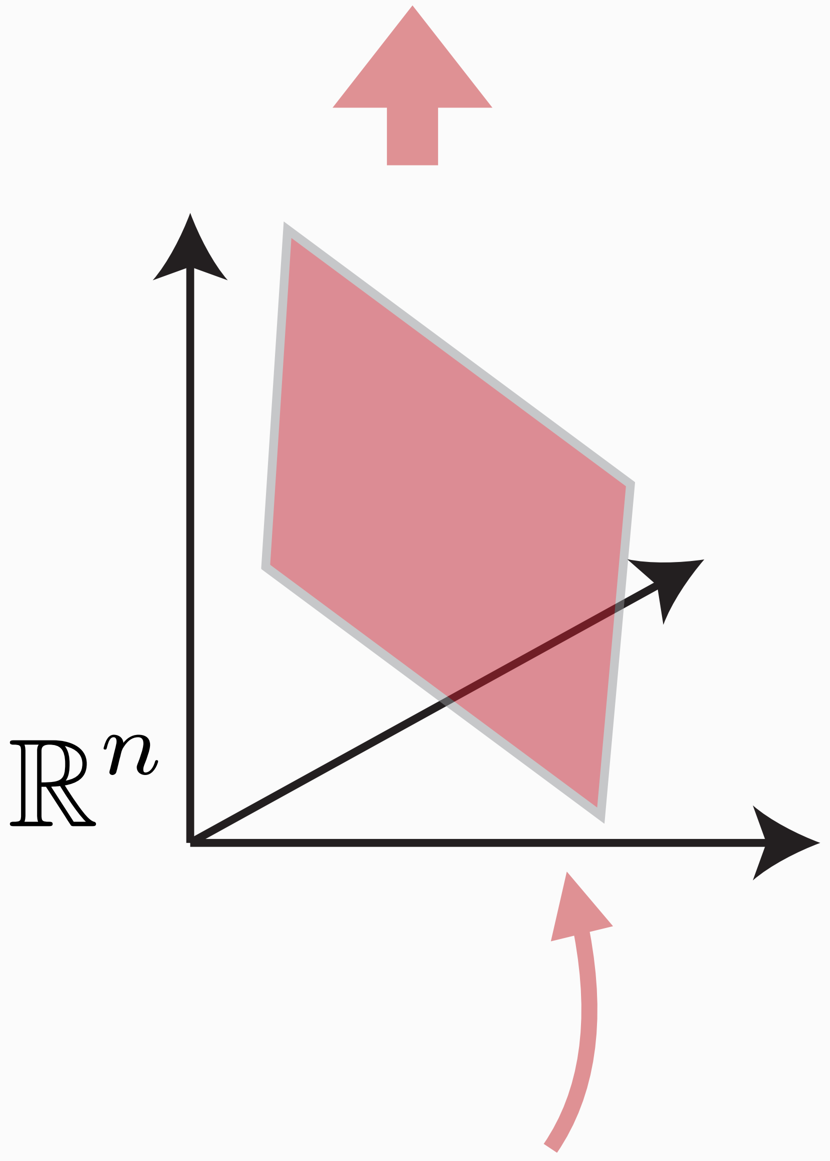






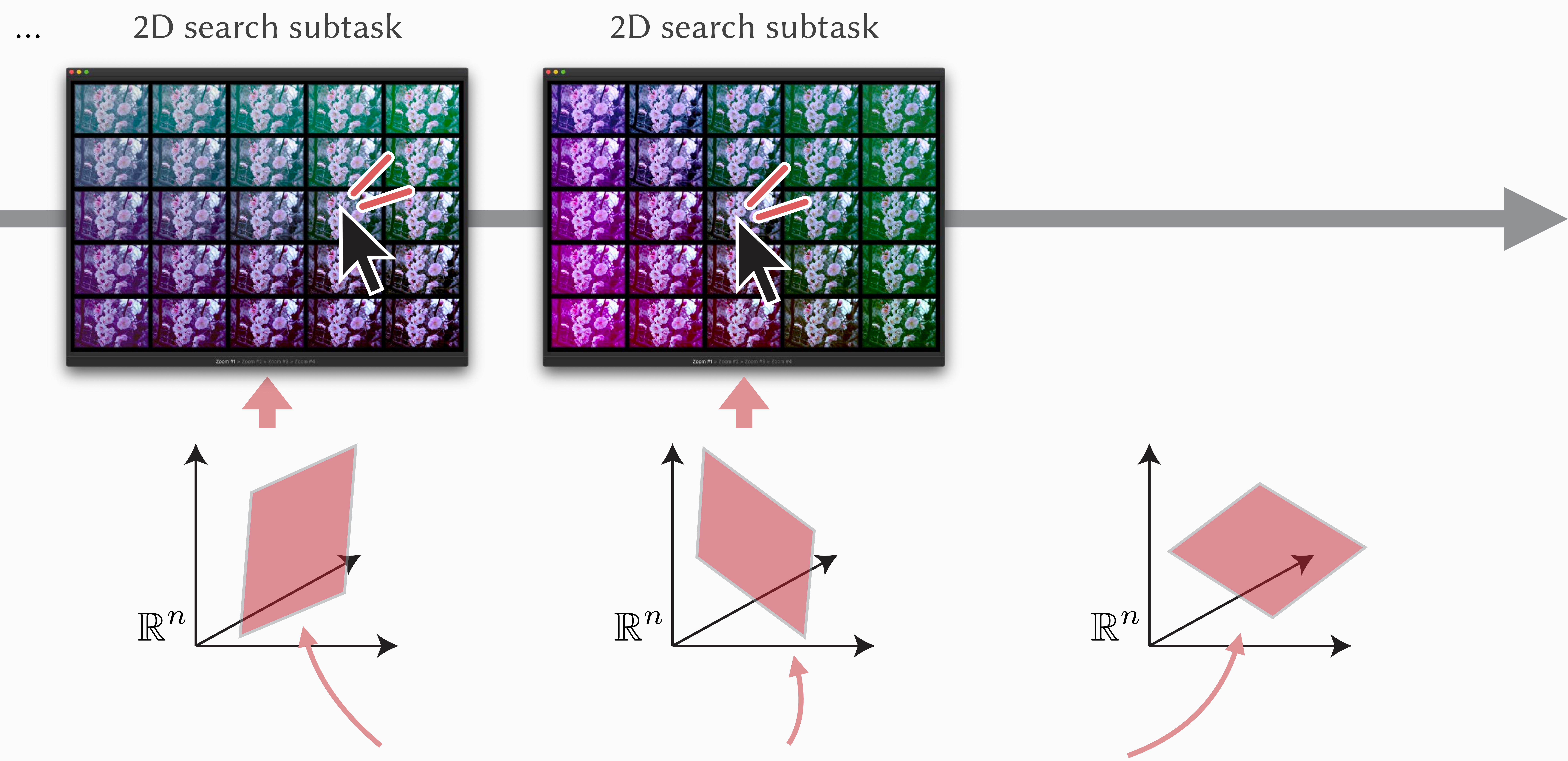
2-dimensional search subspaces (= **search planes**)
determined by **preferential Bayesian optimization** (PBO)

2-dimensional search subspaces (= **search planes**)
determined by **preferential Bayesian optimization** (PBO)

… 2D search subtask 2D search subtask

2-dimensional search subspaces (= **search planes**)
determined by **preferential Bayesian optimization** (PBO)


...
2D search subtask
2D search subtask
Next search plane
User's feedback
$\mathbb{R}^n$
$\mathbb{R}^n$
$\mathbb{R}^n$
2-dimensional search subspaces (= **search planes**)
determined by **preferential Bayesian optimization** (PBO)



2-dimensional search subspaces (= **search planes**)
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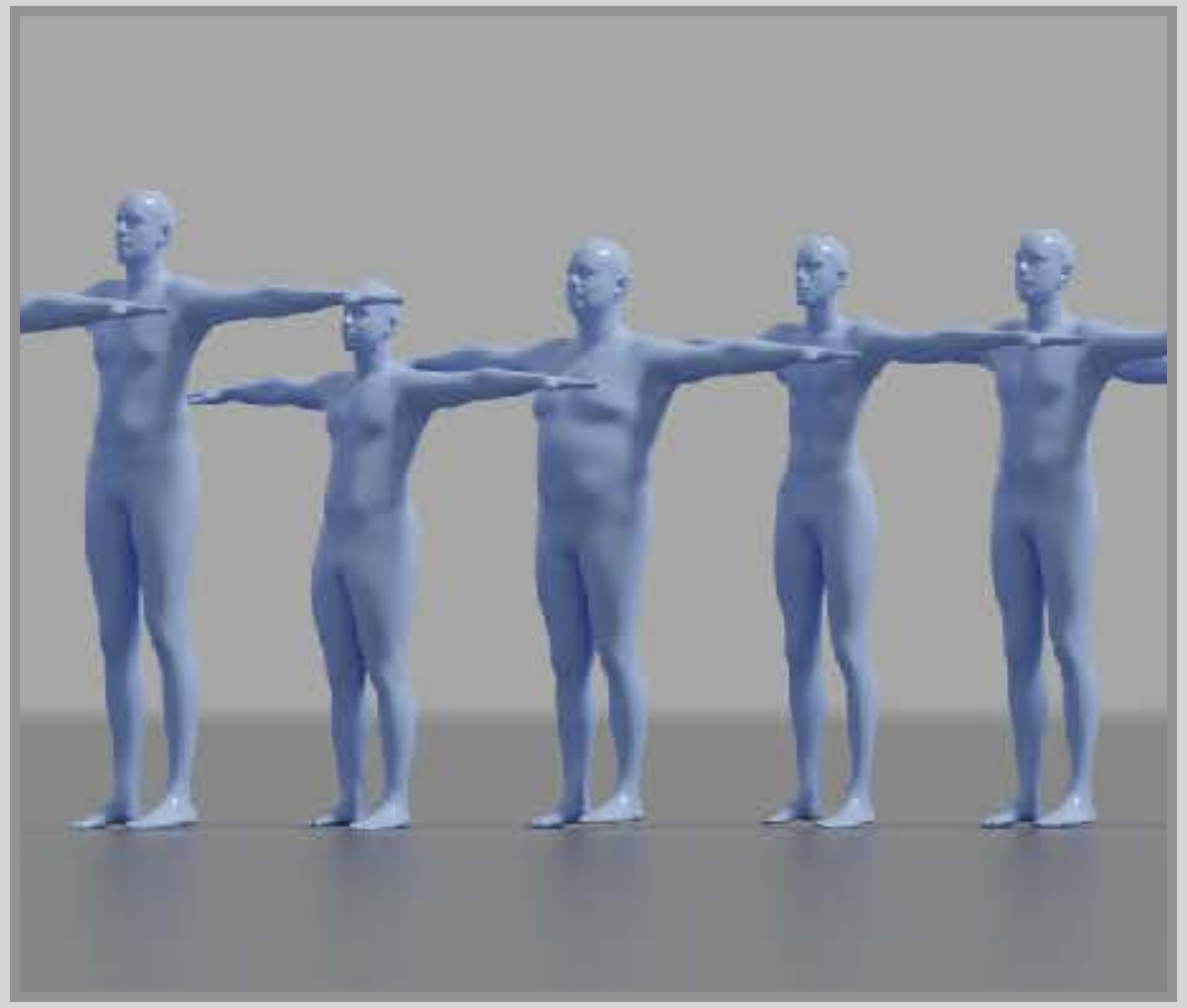
2-dimensional search subspaces (= **search planes**)
determined by **preferential Bayesian optimization** (PBO)

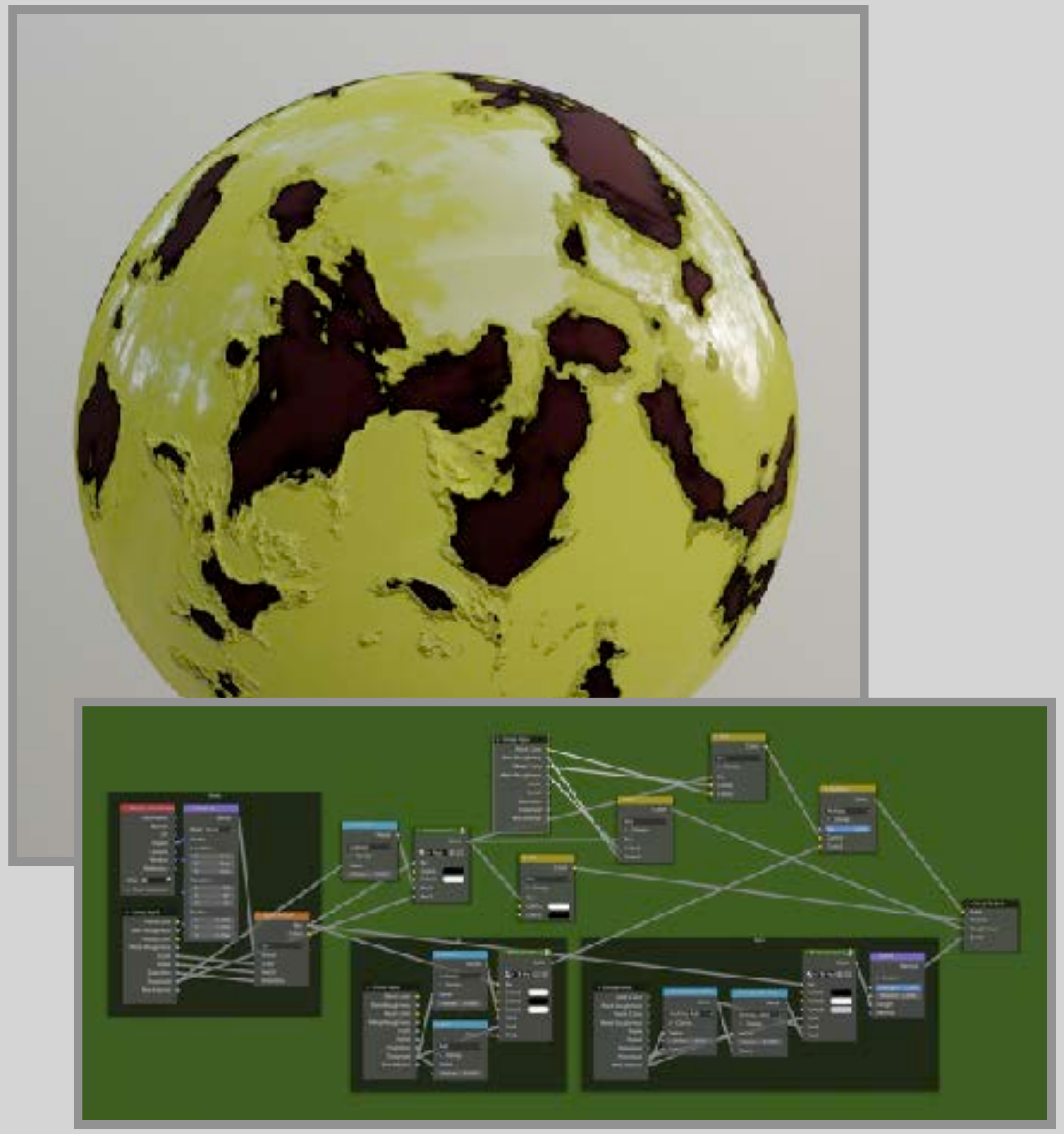
Potential Applications

Photo color enhancement

Generative modeling



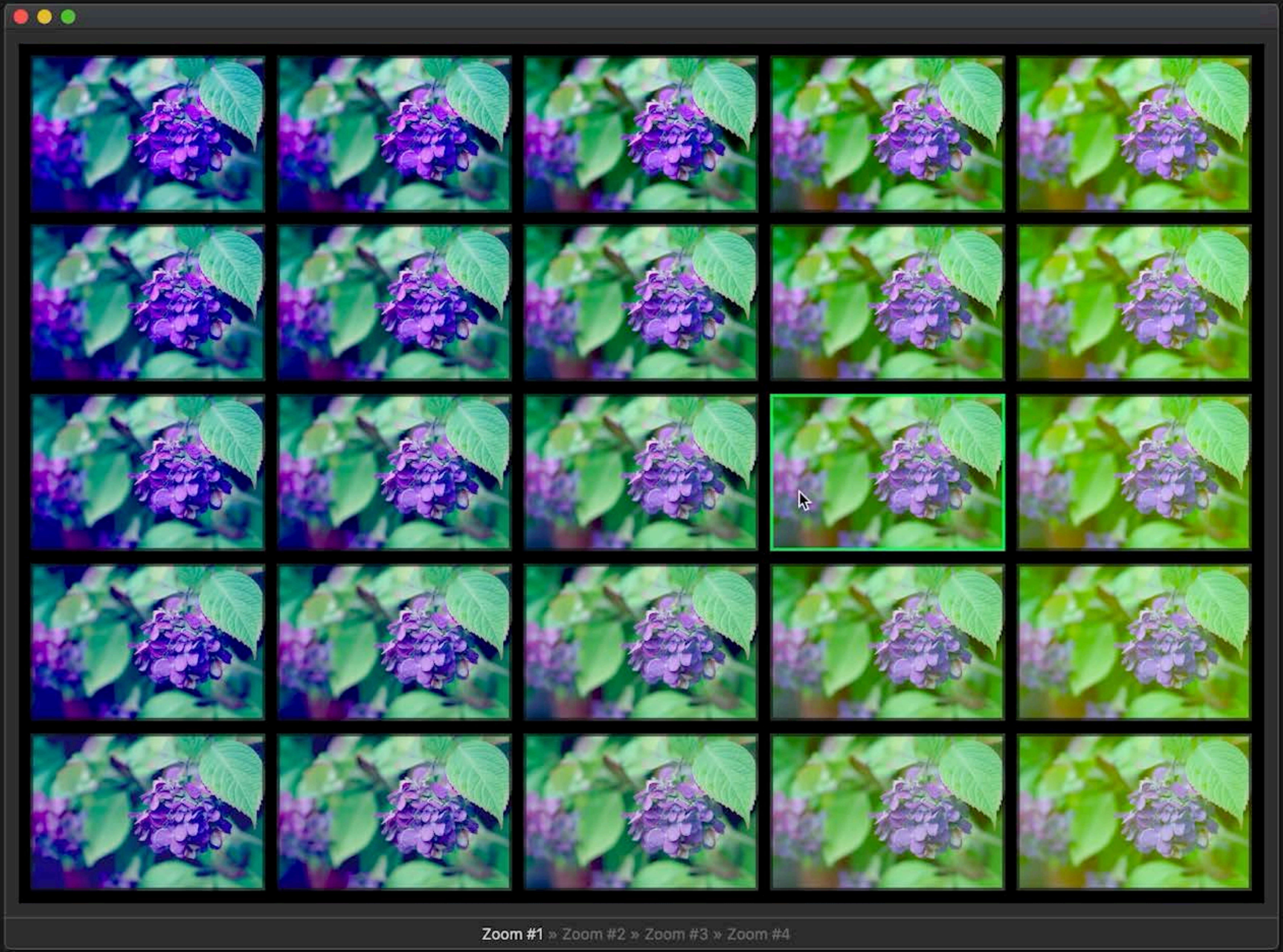
Procedural texturing



… and many other parametric design scenarios

Photo Color Enhancement (12D)

Brightness, contrast, saturation, shadows (RGB), midtones (RGB), and highlights (RGB)



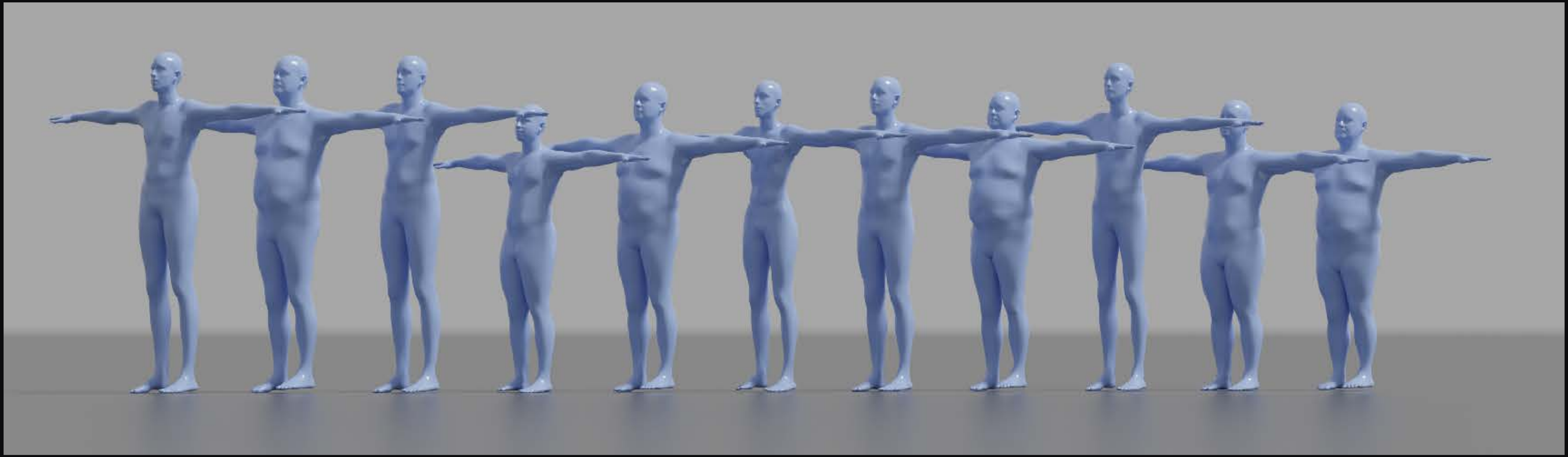
x1.5 speed

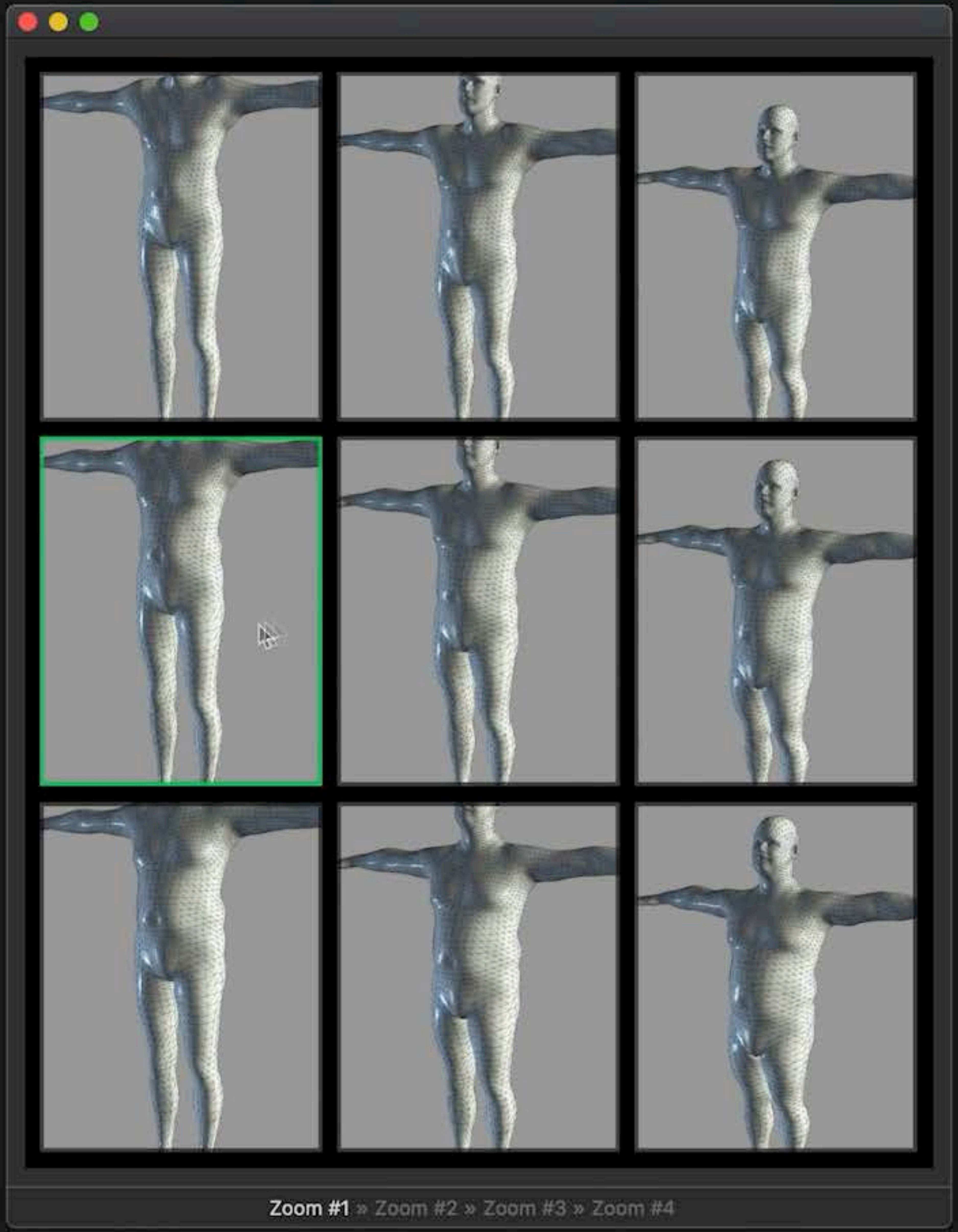
Original photograph

Enhanced photograph
(after 4 iterations)

Body Shaping (10D)

Using the SMPL model [Loper+15] (the first 10 principal components)





x1.5 speed

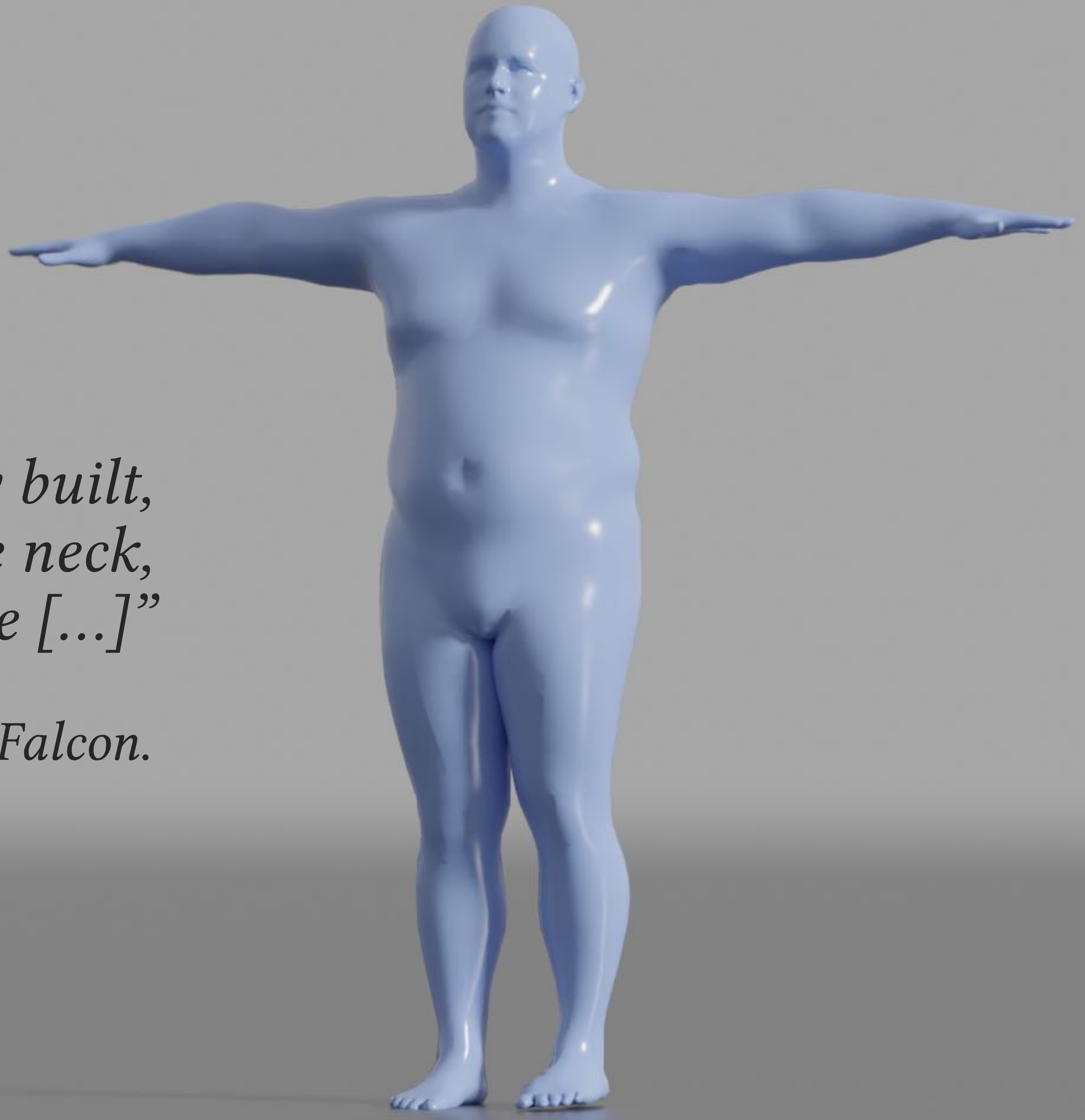
Goal: Body shaping from a character description

"He was of medium height, solidly built, wide in the shoulders, thick in the neck, with a jovial heavy-jawed red face [...]"

Dashiell Hammett. 1930. *The Maltese Falcon.*

“He was of medium height, solidly built, wide in the shoulders, thick in the neck, with a jovial heavy-jawed red face […]”

Dashiell Hammett. 1930. *The Maltese Falcon.*



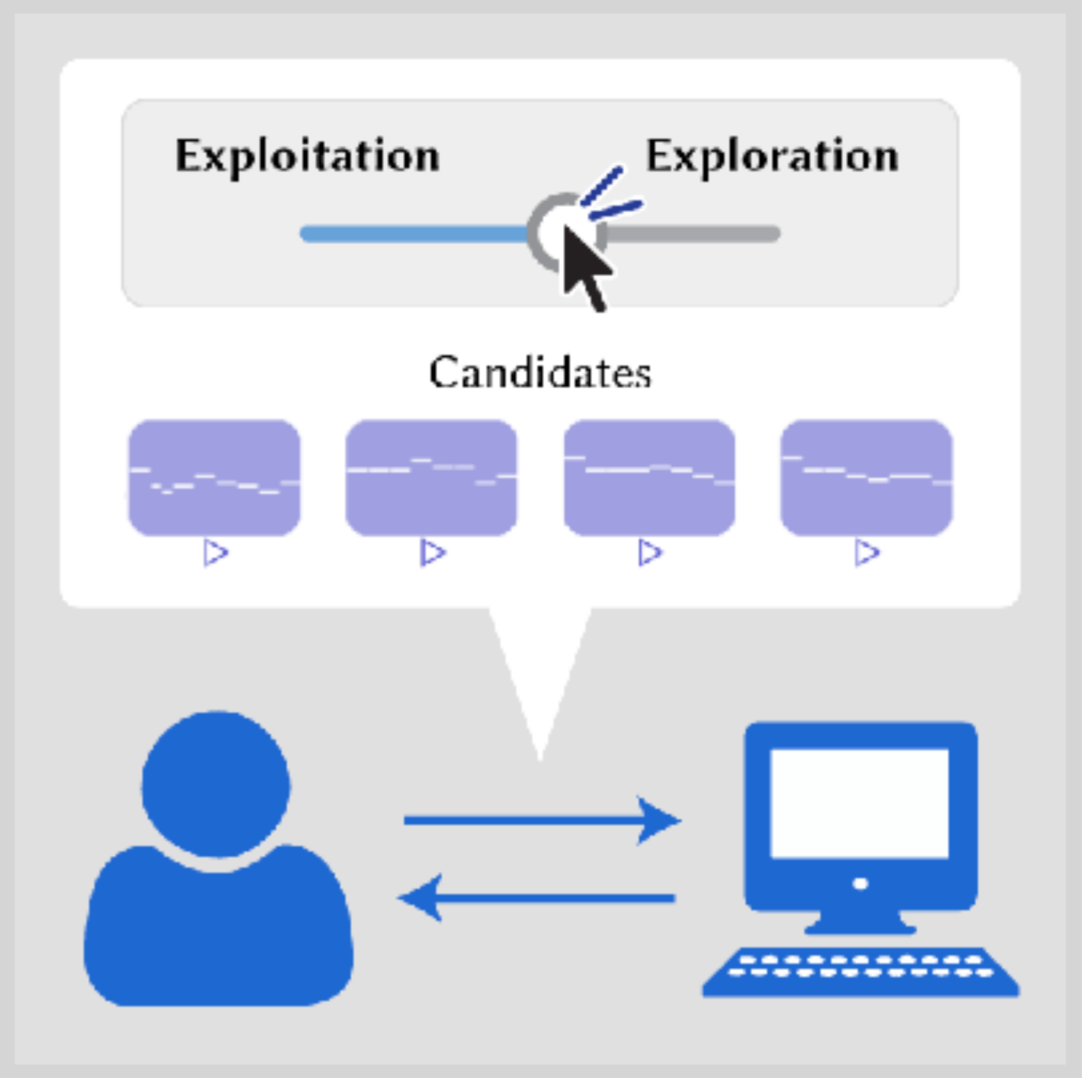
- **User-in-the-Loop最適化**を実現
- **グリッド状に選択肢を提示するインタフェース**を採用することで必要な反復回数を削減
- そのために**選好ベイズ最適化 (PBO) を拡張**

Human-in-the-Loop選好ベイズ最適化

写真の色調編集や3Dグラフィクス

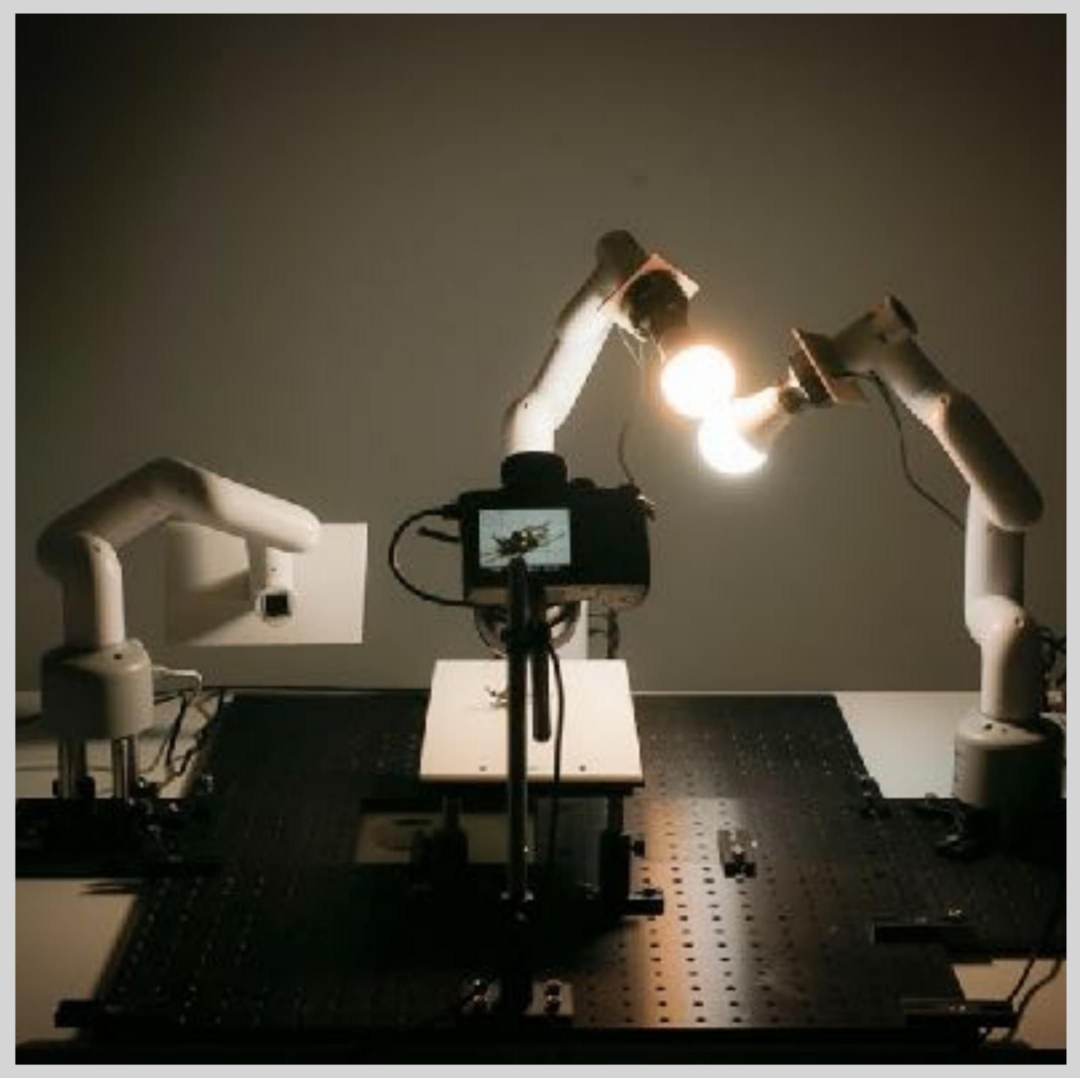
Koyama+
SIGGRAPH 2017

Koyama+
SIGGRAPH 2020



メロディー生成

Zhou+
IUI 2020



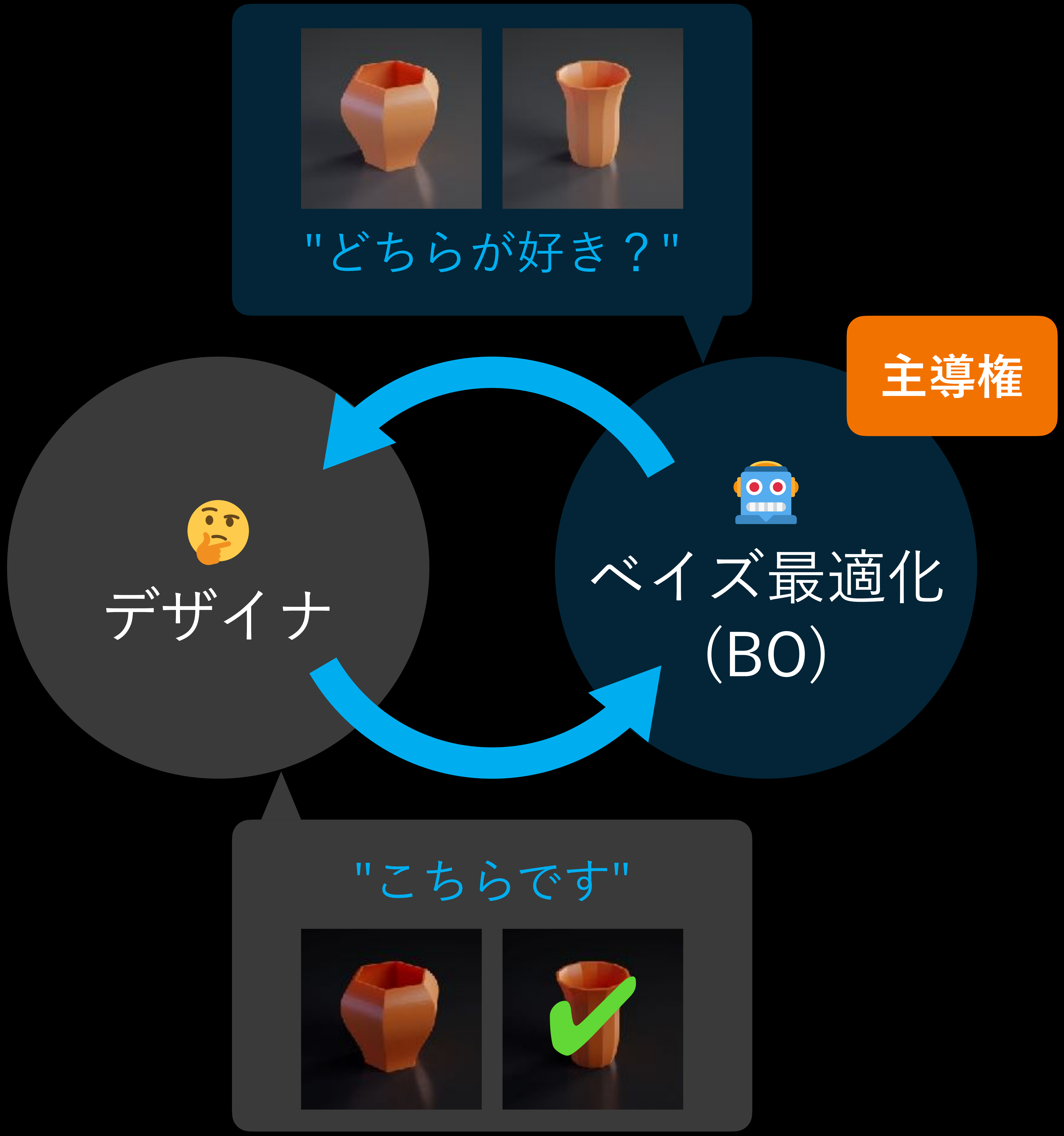
写真撮影時の照明

Yamamoto+
UIST 2022

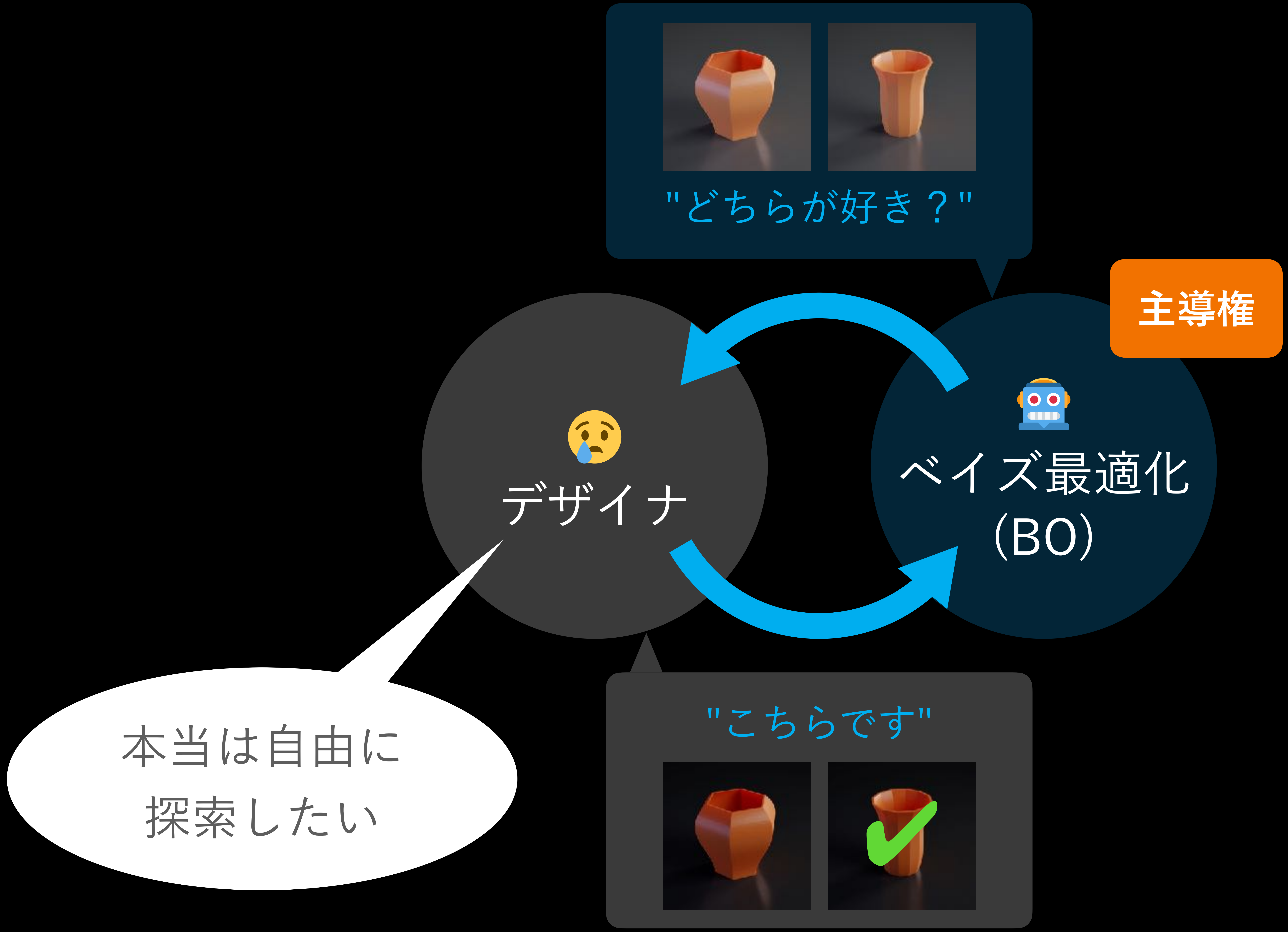
- 様々なデザインシナリオでその可能性を模索してきた
- 一方でHuman-in-the-Loopベイズ最適化には課題もある

研究事例３

BO as Assistant [UIST 2022]

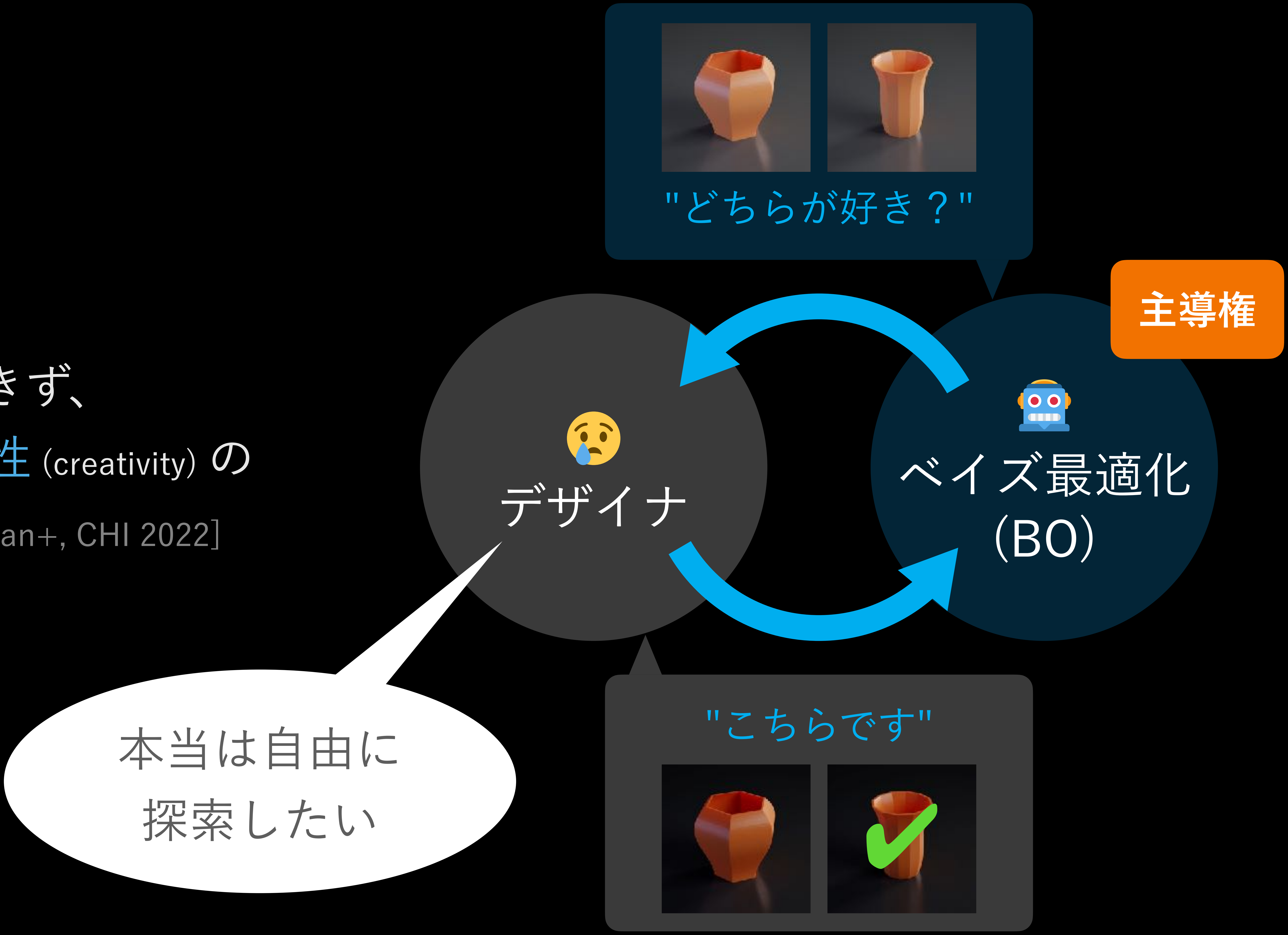


"どちらが好き？"
主導権
デザイナ
ベイズ最適化
(BO)
"こちらです"


"どちらが好き？"
主導権
ベイズ最適化
(BO)
デザイナ
本当は自由に
探索したい
"こちらです"

問題：

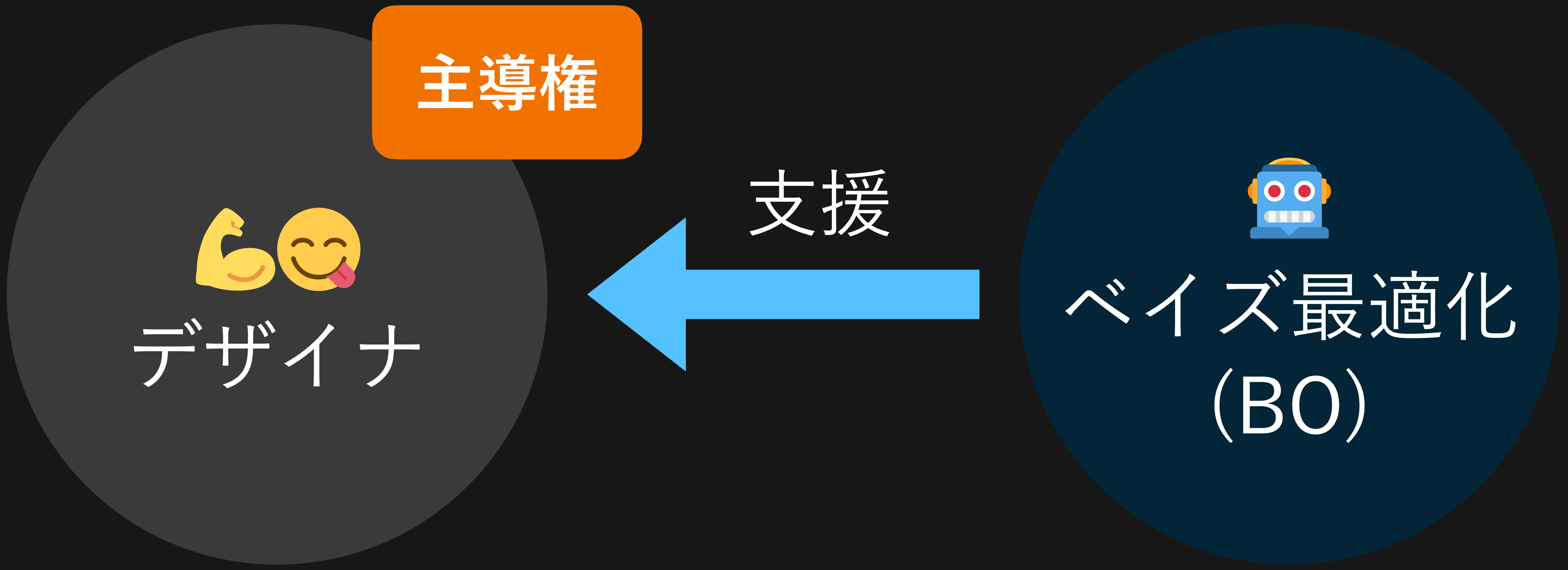
デザイナが自由に探索できず、
行為主体感 (agency) や創造性 (creativity) の
低下を招く懸念がある [Chan+, CHI 2022]



[Chan+, CHI 2022] L. Chan et al. 2022. Investigating Positive and Negative Qualities of Human-in-the-Loop Optimization for Designing Interaction Techniques. In Proc. CHI 2022.

着想：

ベイズ最適化（BO）のサンプリング戦略の賢さの恩恵を受けつつ、
デザイナが自由にデザイン探索できるようにしたい



主導権を持って探索する　　賢い "助手" に徹する

➡ ベイズ最適化（BO）を（human-in-the-loopの仕組みとしてでなく）
デザイナの "助手"（assistant）として活用するフレームワークを提案

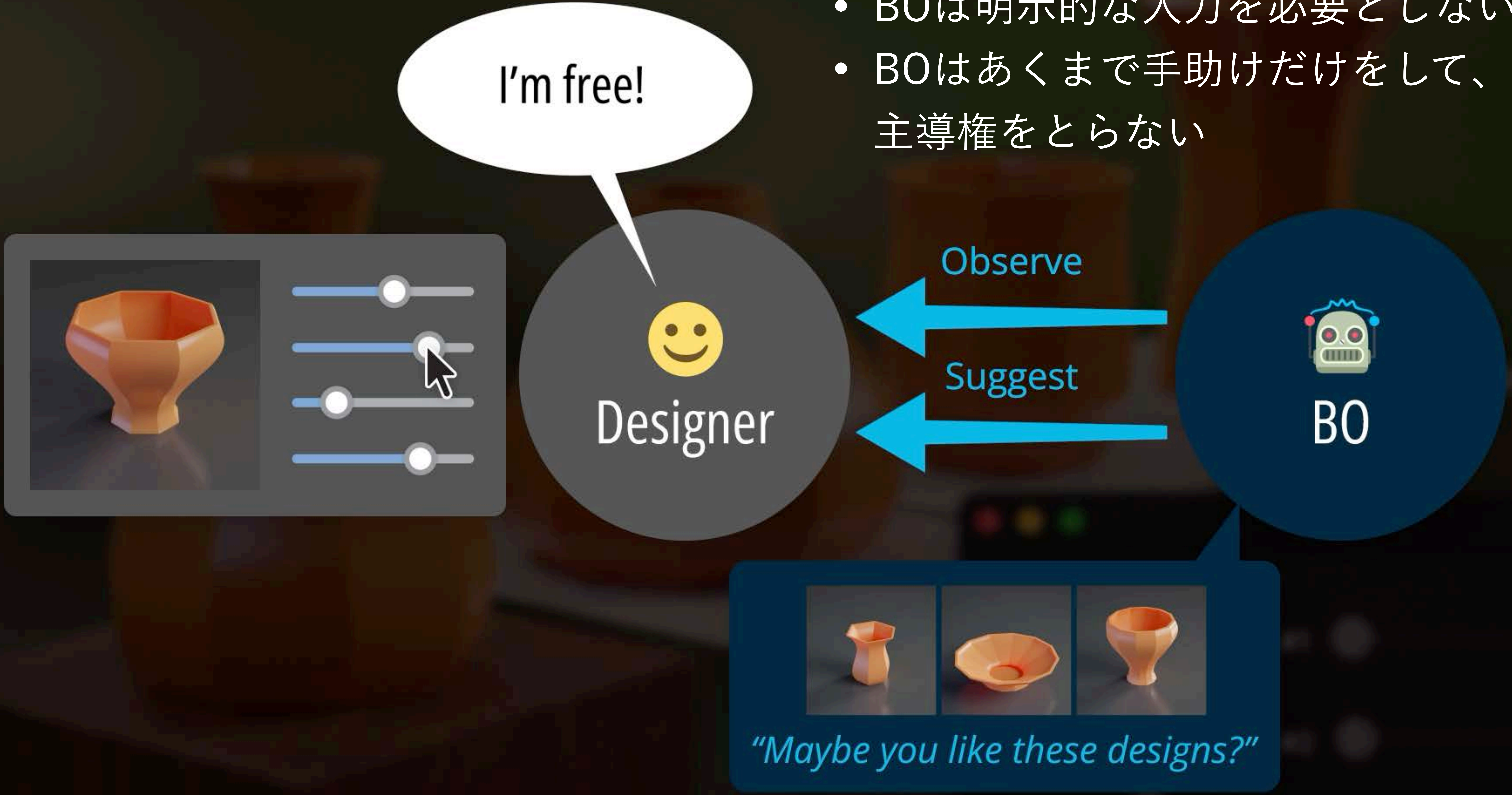
提案フレームワーク："BO as Assistant"

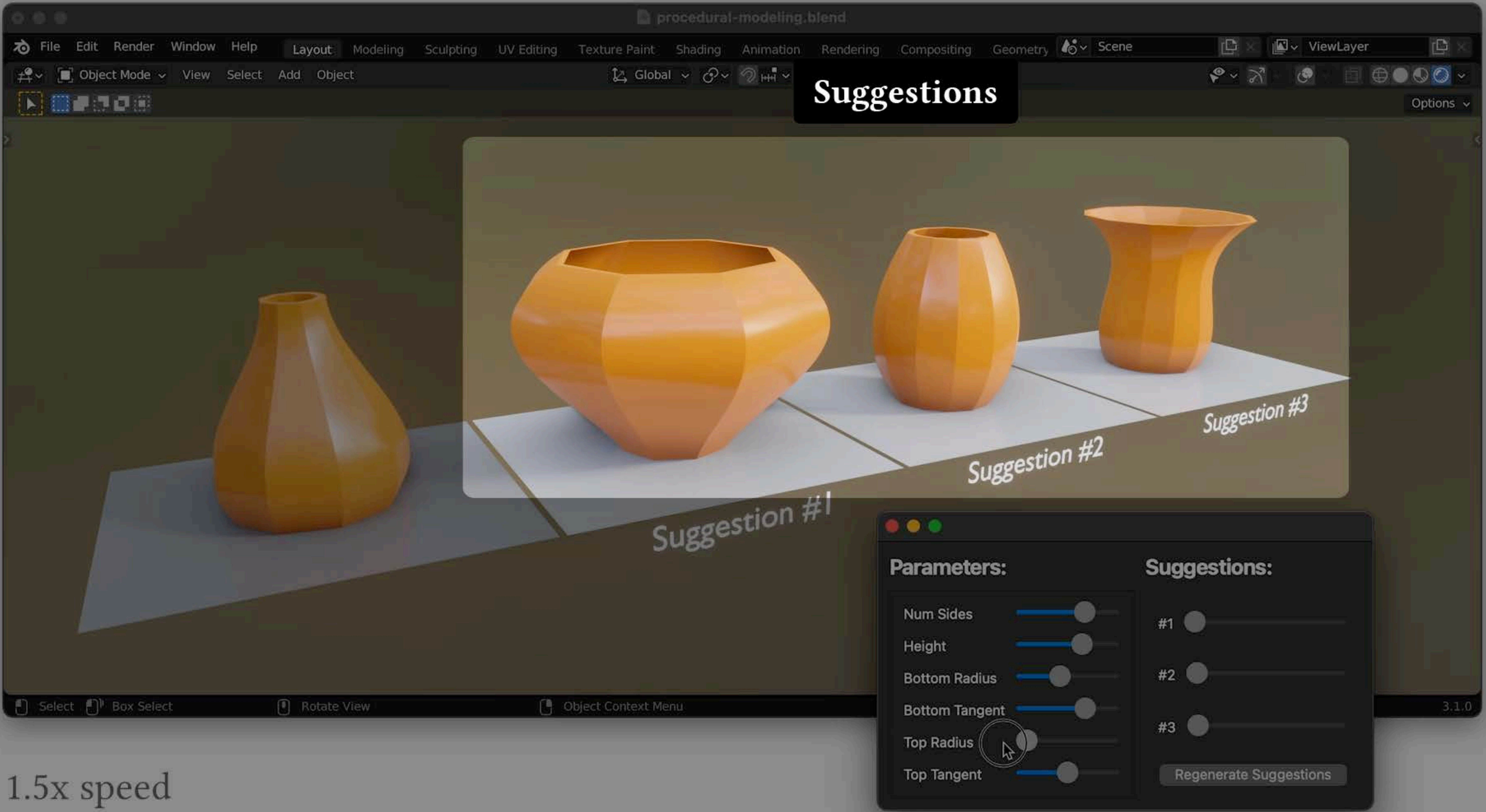
BO as Assistantの場合：

BO as Assistantの場合：

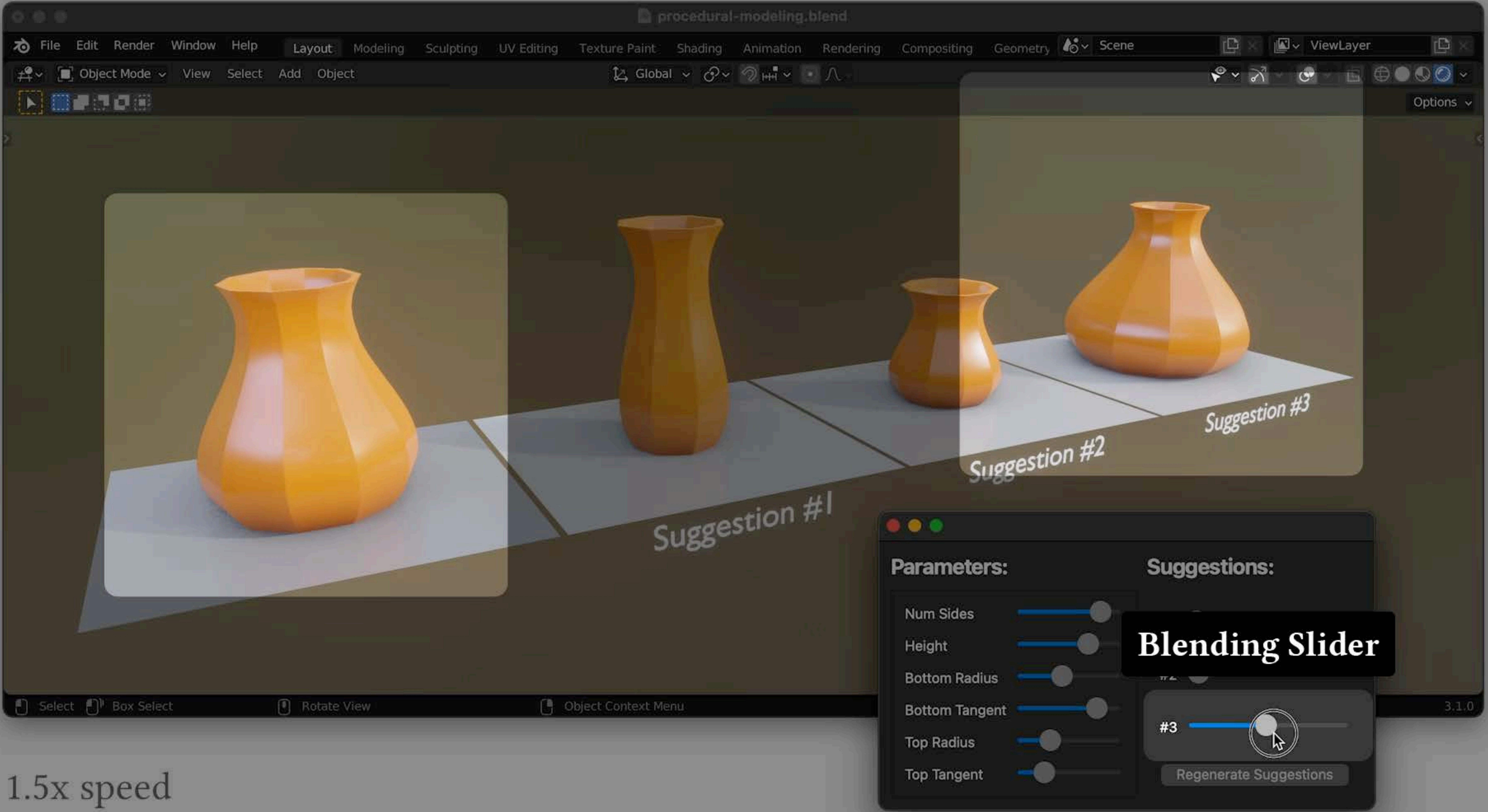
BO as Assistantの場合：

- BOは明示的な入力を必要としない
- BOはあくまで手助けだけをして、主導権をとらない




procedural-modeling.blend
File
Edit
Render
Window
Help
Layout
Modeling
Sculpting
UV Editing
Texture Paint
Shading
Animation
Rendering
Compositing
Geometry
Scene
ViewLayer
Object Mode
View
Select
Add
Object
Global
Options
Suggestions
Suggestion #1
Suggestion #2
Suggestion #3
Parameters:
Suggestions:
Num Sides
Height
Bottom Radius
Bottom Tangent
Top Radius
Top Tangent
#1
#2
#3
Regenerate Suggestions
Select
Box Select
Rotate View
Object Context Menu
3.1.0

1.5x speed


procedural-modeling.blend
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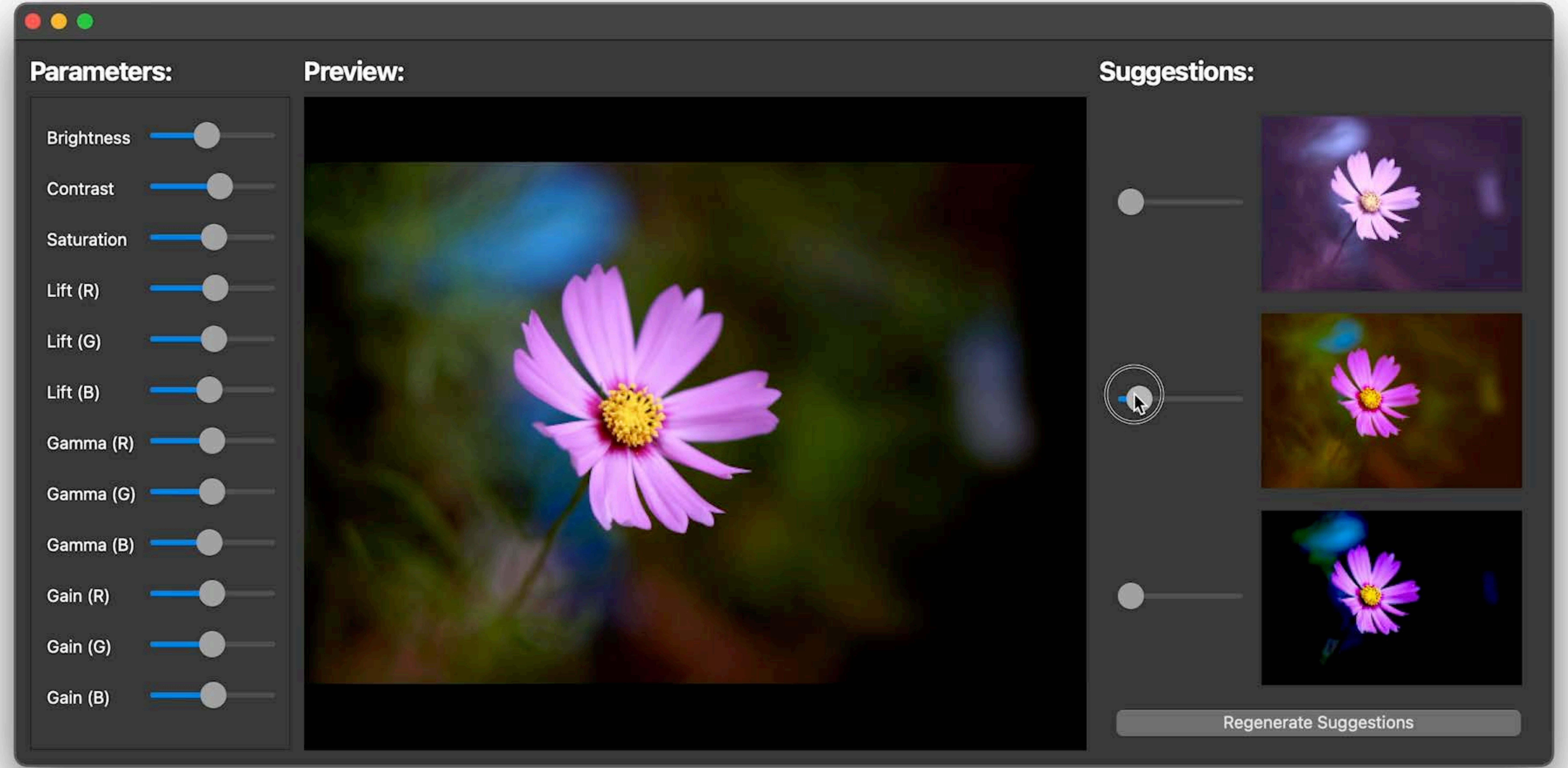
ViewLayer
Object Mode
View
Select
Add
Object
Global
Options
Suggestion #1
Suggestion #2
Suggestion #3
Parameters:
Suggestions:
Num Sides
Height
Bottom Radius
Bottom Tangent
Top Radius
Top Tangent
Blending Slider
#3
Regenerate Suggestions
Select
Box Select
Rotate View
Object Context Menu
3.1.0

1.5x speed

写真の色調編集

- パラメタ数：12
  - Brightness
  - Contrast
  - Saturation
  - Lift (RGB)
  - Gamma (RGB)
  - Gain (RGB)
- デザイン目標：
  写真の見栄えが良くなるようにする

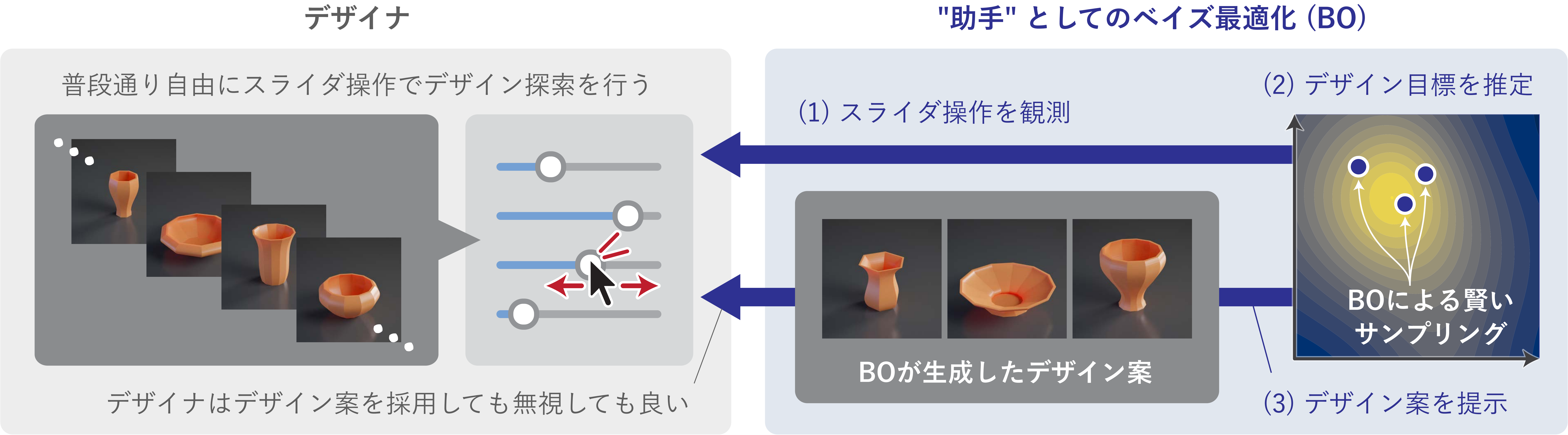

Parameters:
Brightness
Contrast
Saturation
Lift (R)
Lift (G)
Lift (B)
Gamma (R)
Gamma (G)
Gamma (B)
Gain (R)
Gain (G)
Gain (B)
Preview:
Suggestions:
Regenerate Suggestions

x5

プロシージャルマテリアル生成

- パラメタ数：8
  - Threshold
  - Noise Scale
  - Noise Detail
  - Noise Roughness
  - Noise Distortion
  - Ambient Occlusion
  - Bump Strength
  - Peel Boundary Strength
- デザイン目標：
  ペイントが剥げている錆びた金属


x5
Suggestion #1
Suggestion #2
Suggestion #3
Parameters:
Threshold
Noise Scale
Noise Detail
Noise Roughness
Noise Distortion
Ambient Occlusion
Bump Strength
Peel Boundary Strength
Suggestions:
#1
#2
#3
Regenerate Suggestions
The 3D model is provided by Bastien Genbrugge under CC BY 4.0 at https://skfb.ly/6pNQ6



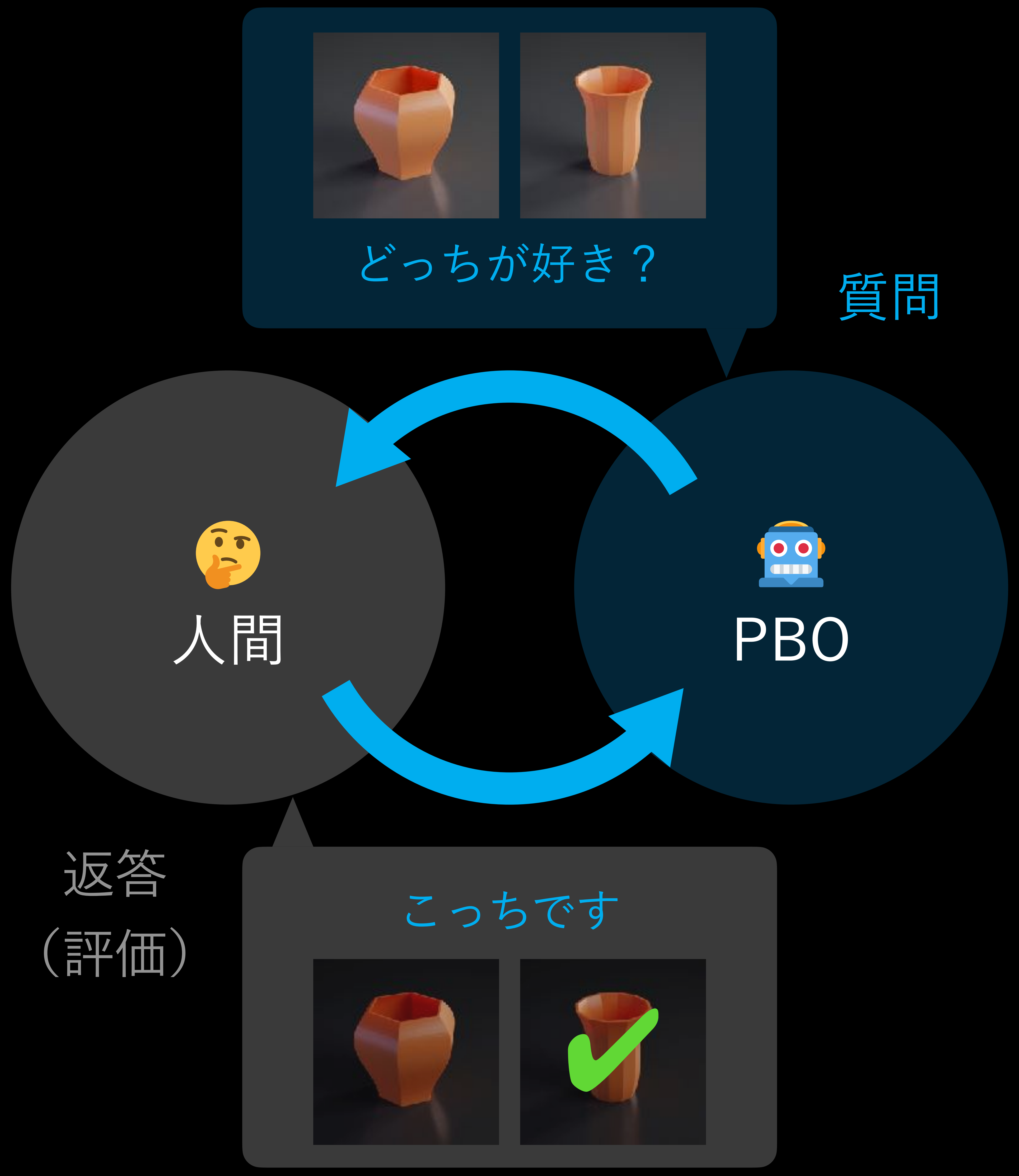
- ベイズ最適化（BO）を（human-in-the-loopでなく）デザイナの "助手"（assistant）として活用するインタラクションを提案
- スライダ操作を観測することで好みを学習し、賢くデザイン案を生成する技術を提案

終わりに

まとめと議論

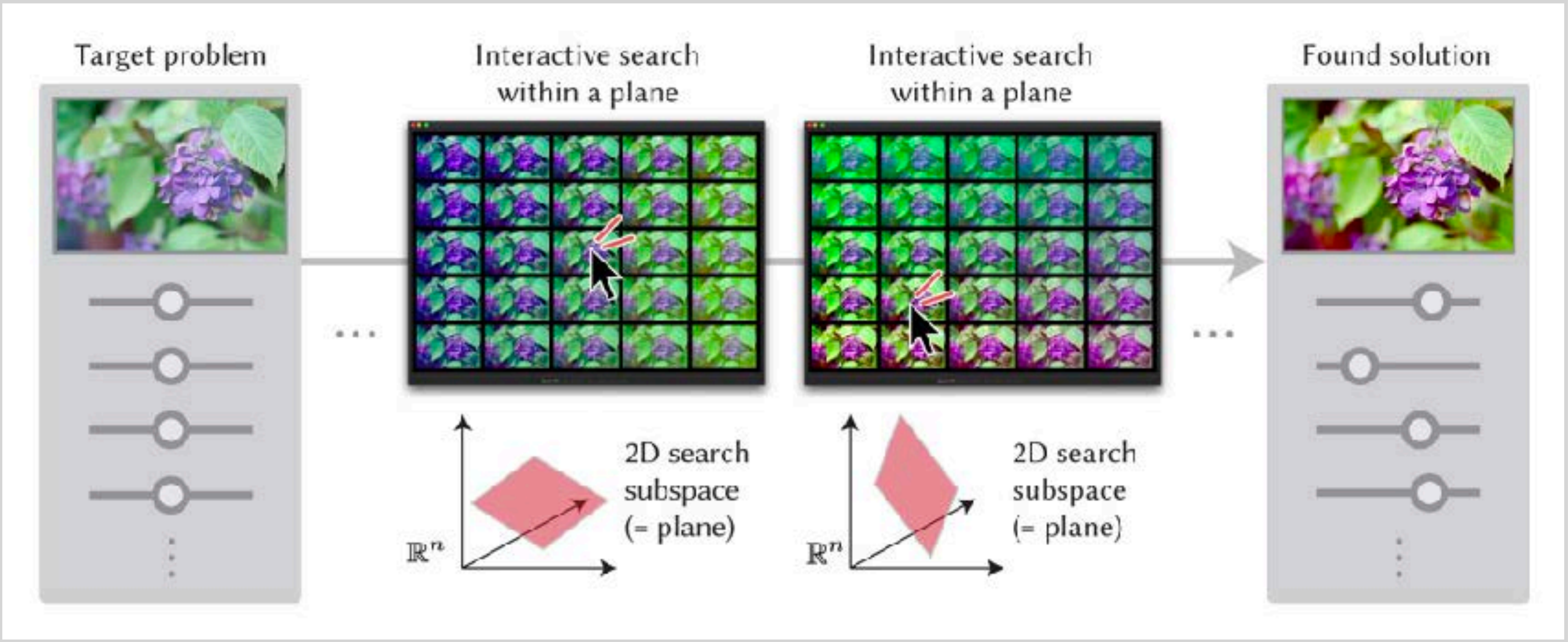
まとめ [1/2]

- **Human-in-the-Loop最適化**
  - **人間の評価が必要な目的関数（好みなど）**を対象とする最適化問題を解く上で有効なアプローチ
- **選好ベイズ最適化** **Preferential Bayesian Optimization (PBO)** が役立つ
  - **相対比較データから好みを推定**して最適化を実行
  - **少ない反復回数で解を発見**できる性質

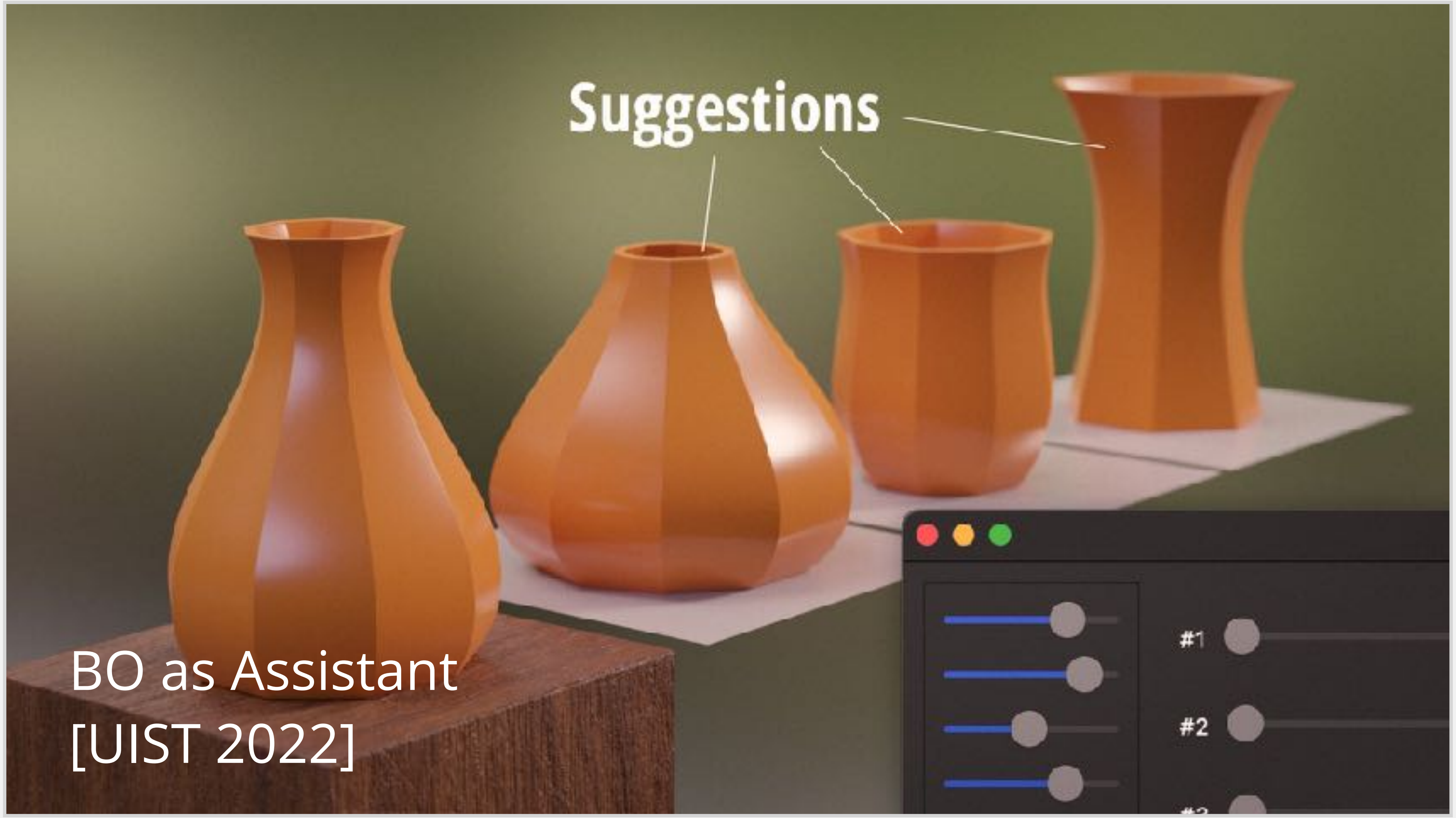


まとめ [2/2]

- **アルゴリズムとインタフェース両側面**から工夫することが、効率的なHuman-in-the-Loop最適化を実現する上で重要 [SIGGRAPH 2017; 2020]
- Human-in-the-Loop最適化でないインタラクション設計として、デザインを提案してくれる **"助手" としてベイズ最適化技術を活用**可能 [UIST 2022]



Sequential Gallery
[SIGGRAPH 2020]

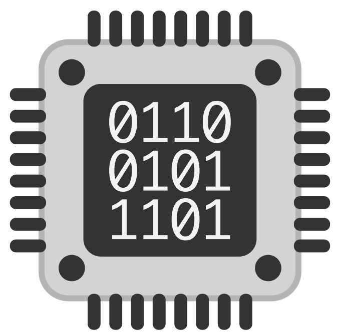


BO as Assistant
[UIST 2022]

議論：Human-AI Collaborationの観点

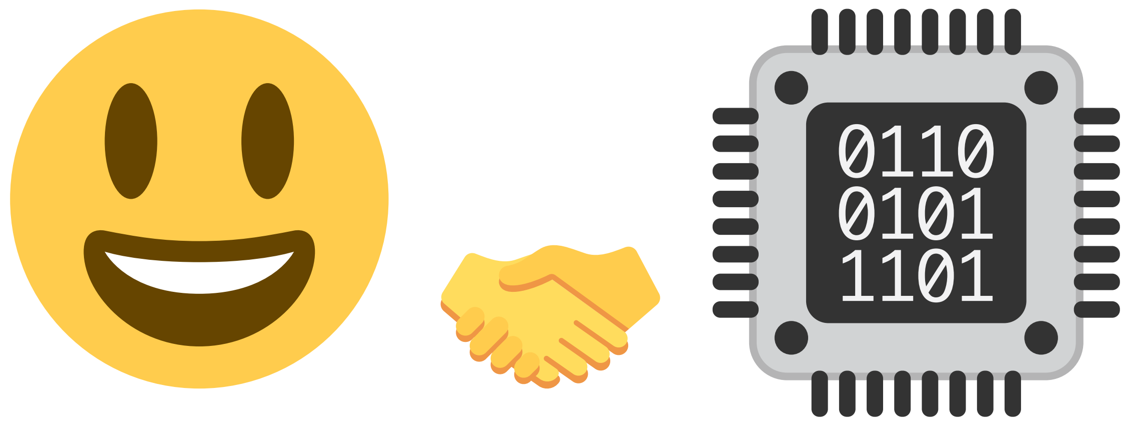
Human Only

経験と勘による属人的な戦略と思考に
依存し、計算効率も悪い



AI Only

事前に定義された問題を扱い、
人間の柔軟な判断を取り込めない



Human-AI Collaboration

数理技術の持つ合理性・効率性を活かしながら、
人間とAIとが協調して柔軟な問題解決・意思決定を行う

- 人工知能技術を実問題に対し効果的に適用するために必要な観点であり、学術的注目も高まっている
- 選好ベイズ最適化によるインタラクションは設計変数を効率的に決定するhuman-AI collaborationの汎用手法の一つとみなせる

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Takeo
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Goto