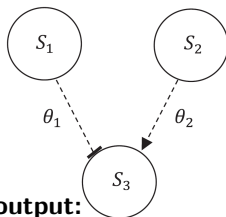


# MOCU: motivating example



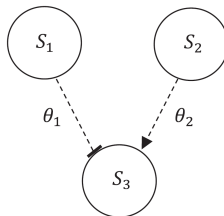
- **System dynamics and output:**

$$R(S, \psi) = \psi_1 \theta_1 S_1 + \psi_2 \theta_2 S_2 \quad , \quad (S_1, S_2) \sim \rho(S_1, S_2)$$

$$S_3 = \begin{cases} 1 & \text{if } R(S, \psi) > 0 \\ 0 & \text{if } R(S, \psi) < 0 \\ 1(\text{prob } 0.5) & \text{if } R(S, \psi) = 0 \end{cases}$$

- **Uncertainty:**  $\theta_i \in \{-1, 1\}$  ,  $\theta_i \sim \rho(\theta_i)$
- **Intervention:**  $\Psi = \{(1, 0), (0, 1)\}$
- **Cost:**  $C(\theta, \psi) = S_3$  (we don't want  $S_3$  activated)
- **Experiment:** “probe”  $x_i$  measures  $y_j$  probability  $\rho(y_j | x_i, \theta_k)$

# MOCU: motivating example, informal discussion



- **Given:**

- Uncertain system dynamics
- User-specified control/intervention
- Cost of intervention under uncertainty
- Experimental measurement (assumed to be expensive)

- **Question:** what experiment should be made next that (1) reduces uncertainty and (2) is optimal across all uncertainty w.r.t. the cost?

# MOCU: Algorithm and Pseudocode

**inputs** : set of  $\Theta = \{\theta_1 \dots \theta_k\}$  with  $\rho(\Theta)$ , computer model  $\hat{y} = f_m(x, \theta)$ , set of experimental choices  $X = \{x_1 \dots x_n\}$  with possible outcomes  $Y = \{y_1 \dots y_m\}$

Monte Carlo sample the computer model over  $X \times Y \times \Theta$  and approximate  $\rho(Y|X, \Theta)$

for all  $x_i$  in  $X$ :

for all  $y_j$  in  $Y$ :

Compute  $\rho(\theta|x_i = y_j)$  via Bayes with priors  $\rho(\theta)$ ,  $\rho(y_j|x_i, \theta)$

Compute  $\psi(\Theta|x_i = y_j) = \operatorname{argmin}_{\psi} \mathbb{E}_{\theta|x_i=y_j}[C(\theta, \psi)]$

Compute  $\omega(x_i = y_j) = \mathbb{E}_{\theta|x_i=y_j}[C(\theta, \psi(\Theta|x_i = y_j))]$

Compute  $\mathbb{E}_{y|x_i}[\omega(x_i)]$  (i.e., averaged over the  $m$  outcomes in  $Y$ )

Compute  $x^* = \operatorname{argmin}_X \mathbb{E}_{y|x}[\omega(x)]$  (i.e., minimization over the  $n$  experiments in  $X$ )

**outputs** :  $x^*$

# Application: BCPs

How does this map to BCPs and materials discovery?

- **Uncertain system dynamics:** Cahn-Hilliard with uncertain RHS terms added (“model inadequacies”, closures)

$$\delta_t c = f_{ch}(c; \epsilon^2(T, \theta), \sigma(T, \theta), m)$$

- Example:  $\epsilon^2(T, \theta) = \epsilon_{scft}^2(T) + \theta \epsilon^2(T^2) + \theta^2 \epsilon^2(T^3) + \dots$
- Example:  $\epsilon^2(T, \theta) = \epsilon_{scft}^2(T) + \theta g(x_{micro})$ ,  $x_{micro}$  are microstate variables, perhaps computed locally with MD
- **Intervention:**  $\Psi = \{T, m, c(\mathbf{x}, t_0), c(\mathbf{x} \in d\Omega, t)\}$
- **Cost:**  $C(\theta, \psi) = d(c(\mathbf{x}, t_f; \theta, \psi) - c^*(\mathbf{x}))$  (distance from target structure)
- **Experiment:**  $X = \{c(\mathbf{x}, t_0), c(\mathbf{x} \in d\Omega, t)\}$ ,  
 $Y = \{\text{close-packed spheres, cylinders, lamellae, gyroids}\}$ ,  $\psi = \{T^*, m^*\}$   
(fixed operating conditions)

# Test problem: Toy SDE

Let's start simple...

- **Uncertain system dynamics:**

$$dc = \lambda c(c-1) (c - (a|\psi - \theta|^2 + b)) dt + \sigma dW$$

$$dW, dW \sim \mathcal{N}(0, 1^2), \theta \in \Theta = \{0, 0.5, 1\}, \rho(\Theta)$$

- **Intervention**

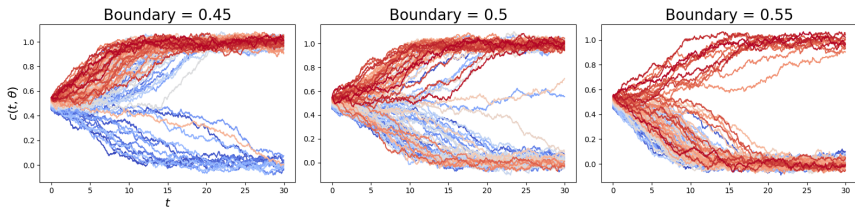
- $\psi \in \Psi = \{0, 0.5, 1\}$
- Material design option that affects the final “phase” of a given IC

- **Cost:**  $C(\theta, \psi) = \|c(t_f; \theta, \psi) - 1\|$  (distance from desired final “phase”)

- **Experiment**

- $c(t_0) \in X = \{a, 0.5(a+b), a+b\}$  (initial condition)
- $c(t_f) \in Y = \{0, 1\}$  (final phase)
- $\psi^* = 0$  (fixed operating conditions)
- $\theta^* = 0.5$  (true, “unknown” value of  $\theta$  in the “real” system)

# Test problem: Toy SDE



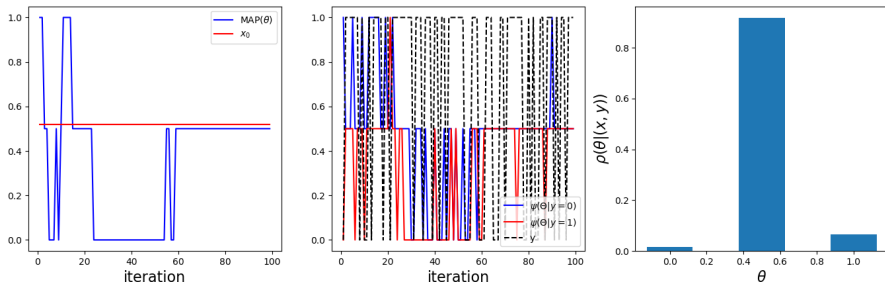
- Small  $|\psi - \theta| \mapsto$  low boundary, best for getting phase 1
- Large  $|\psi - \theta| \mapsto$  high boundary, best for getting phase 0

# Test problem: Toy SDE

Use some intuition...

- Our goal is to design materials that get to phase 1
- Optimal experiment
  - The bigger the quantity  $(c(t_0) - [\text{boundary}])$ , the more certain we can be that  $c(t_f) = 1$ , regardless of the value of  $\theta$
  - Pick the highest IC value  $c(t_0)$
- Optimal intervention
  - Small  $|\psi - \theta| \mapsto$  low boundary, best for getting phase 1
  - Pick  $\psi$  to minimize  $|\psi - \theta|$  over average weighted by  $\rho(\theta)$

# Test problem: Toy SDE



- Plot 1

- MAP estimate correctly converges to true value  $\theta^* = 0.5$
- Optimal experiment always correct (highest possible IC value)

- Plot 2

- Dash-black: experimental observations
- Blue/Red: optimal interventions conditioned on an observation

- Plot 3: Posterior distribution for  $\theta$  (centered around correct value)