

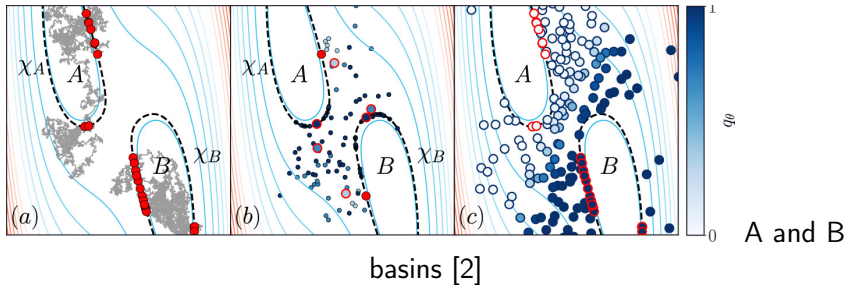
Committer guided estimates of molecular transition rates

Andrew R. Mitchell, Grant M. Rotskoff (Stanford)

Connor Blake

Motivation

- Committors are the “ideal reaction coordinate”
- Rare event sampling is hard, important
- ML has seen good results recently [1]



$$x \in \Omega \subset \mathbb{R}^d$$

$$C_k \subset \Omega \quad C_k \cap C_{k'} = \emptyset \quad \forall k, k' \in [K]$$

$$\Omega^C = \Omega \setminus (\cup_k C_k)$$

$$x \in \Omega \subset \mathbb{R}^d$$

$$C_k \subset \Omega \quad C_k \cap C_{k'} = \emptyset \quad \forall k, k' \in [K]$$

$$\Omega^C = \Omega \setminus (\cup_k C_k)$$

$$dx_t = -\nabla U(x_t) dt + \sqrt{2\beta^{-1}} dW_t$$

Committer Properties

$$p_k(x) = P(\text{trajectory hits basin } k \text{ before any other basin})$$

$$q_k(x) = 1 - p_k(x)$$

Committer Properties

$$p_k(x) = P(\text{trajectory hits basin } k \text{ before any other basin})$$

$$q_k(x) = 1 - p_k(x)$$

$$\sum_k p_k(x) = 1 \quad \forall x \in \Omega$$

Committer Properties

$$p_k(x) = P(\text{trajectory hits basin } k \text{ before any other basin})$$

$$q_k(x) = 1 - p_k(x)$$

$$\sum_k p_k(x) = 1 \quad \forall x \in \Omega$$

$$p_k(x) = 1 \quad x \in C_k$$

$$p_k(x) = 0 \quad x \in \bigcup_{k' \neq k} C_{k'}$$

Committer Properties

$$p_k(x) = P(\text{trajectory hits basin } k \text{ before any other basin})$$

$$q_k(x) = 1 - p_k(x)$$

$$\sum_k p_k(x) = 1 \quad \forall x \in \Omega$$

$$p_k(x) = 1 \quad x \in C_k$$

$$p_k(x) = 0 \quad x \in \bigcup_{k' \neq k} C_{k'}$$

$$p_k(x_0) = E[p_k(x_\tau^{x_0})] \quad x \in \Omega^C$$

$$\approx \frac{1}{n} \sum_{i=1}^n p_k(x_\tau^{x_0, i})$$

Log Committed Algorithm, $A \rightarrow B$

Hill Relation: $r_{AB} = j_A - \int_{\partial A} q_A(x) dx$

Log Committor Algorithm, $A \rightarrow B$

Hill Relation: $r_{AB} = j_{A-} \int_{\partial A} q_A(x) dx$

Their Goal: $q_{\theta,A} : \Omega \rightarrow \mathbb{R} \xrightarrow{\text{sigmoid}} [0, 1]$

$$q_A(x) + q_B(x) = 1 \quad \{A, B\} = [K]$$

Log Committor Algorithm, $A \rightarrow B$

Hill Relation: $r_{AB} = j_{A-} \int_{\partial A} q_A(x) dx$

Their Goal: $q_{\theta,A} : \Omega \rightarrow \mathbb{R} \xrightarrow{\text{sigmoid}} [0, 1]$

$$q_A(x) + q_B(x) = 1 \quad \{A, B\} = [K]$$

$$q_A(x_0) \approx \frac{1}{n} \sum_{i=1}^n q_A(x_{\tau}^{x_0,i})$$

Log Committor Algorithm, $A \rightarrow B$

Hill Relation: $r_{AB} = j_{A-} \int_{\partial A} q_A(x) dx$

Their Goal: $q_{\theta,A} : \Omega \rightarrow \mathbb{R} \xrightarrow{\text{sigmoid}} [0, 1]$

$$q_A(x) + q_B(x) = 1 \quad \{A, B\} = [K]$$

$$q_A(x_0) \approx \frac{1}{n} \sum_{i=1}^n q_A(x_\tau^{x_0,i})$$

$$\log(q_A(x_0)) \approx \log \left(\frac{1}{n} \sum_{i=1}^n q_A(x_\tau^{x_0,i}) \right) \quad (\text{biased})$$

Log Committor Algorithm, $A \rightarrow B$

Hill Relation: $r_{AB} = j_{A-} \int_{\partial A} q_A(x) dx$

Their Goal: $q_{\theta,A} : \Omega \rightarrow \mathbb{R} \xrightarrow{\text{sigmoid}} [0, 1]$

$$q_A(x) + q_B(x) = 1 \quad \{A, B\} = [K]$$

$$q_A(x_0) \approx \frac{1}{n} \sum_{i=1}^n q_A(x_{\tau}^{x_0, i})$$

$$\log(q_A(x_0)) \approx \log \left(\frac{1}{n} \sum_{i=1}^n q_A(x_{\tau}^{x_0, i}) \right) \quad (\text{biased})$$

Loss: $L_{nk\tau}(\theta) = \frac{1}{|[K]|} \sum_{k \in [K]} \frac{1}{2n} \sum_{i=1}^n \log \left(\frac{q_{\theta,k}(x_i)}{\frac{1}{M} \sum_{m=1}^M q_{\theta,k}(x_{\tau}^{x_i, m})} \right)^2$

Base Algorithm Results

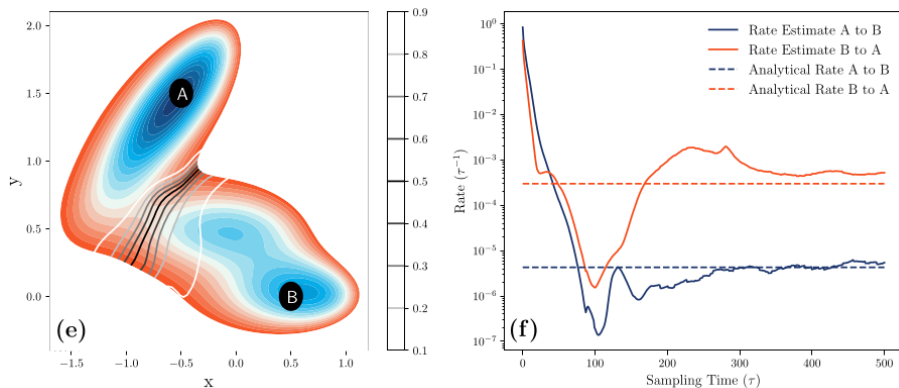


Figure: Muller-Brown Potential e) MLSE Committor f) Rate estimates [2]

Base Algorithm Results (cont.)

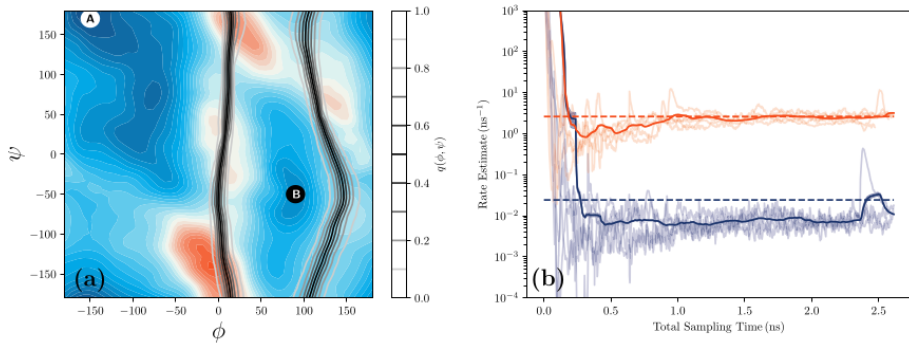


Figure: Dialanine peptide a) MLSE Committor on ϕ, ψ b) Rate estimates [2]

Base Algorithm Problems

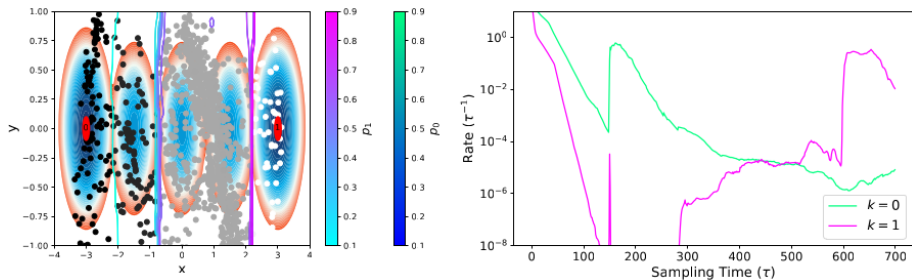


Figure: 5 Linear Wells a) MLSE Committor b) “Rate estimates”

Fixing the Base Algorithm

- 1 Run a short sample from base algorithm
- 2 Run DBSCAN on q_A committor values into K clusters (including originals 2)

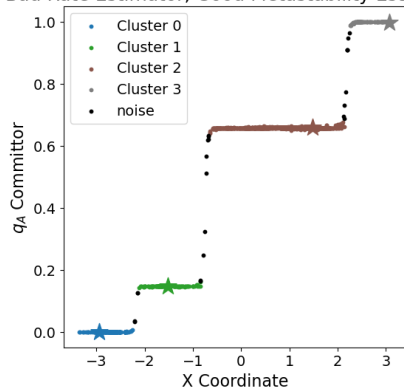
3

$$x_{k,c} = \arg \min_{x_{k,i}} \{U(x_{k,i})\}$$

- 4 Rerun simulation with K basins to sample from starting from $x_{k,c}$ to train

$$q_{\theta,k} : \Omega \rightarrow \mathbb{R}^K \xrightarrow{\text{softargmax}} [0, 1]^K$$

Bad Rate Estimator, Good Metastability Estimator



DBSCAN on q_A committor

Improved Algorithm Results

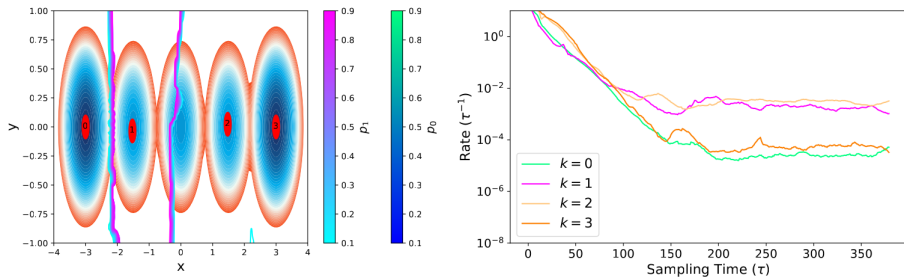


Figure: 5 Linear Wells a) MLSE Committor b) Rate estimates

Composite Rates from Continuous Time Markov Chains

$$Q_{ij} = k_{i \rightarrow j}, \quad Q_{ii} = - \sum_{j \neq i} k_{i \rightarrow j} = -j_{k-} \int_{\partial C_k} q_k(x) dx \quad (\text{Hill Relation})$$

$$\sum_k Q_{ik} m_{kj} = -1, \quad i \neq j; \quad m_{jj} = 0$$

$$T_{ij} \sim \text{Exp}(k_{ij}) \implies \mathbb{E}[T_{ij}] = \frac{1}{k_{ij}} \implies k_{ij} = \frac{1}{m_{ij}}$$

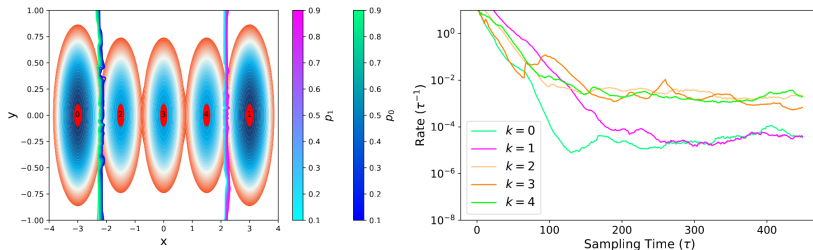


Figure: Rates from 0 to 1 can now be computed with a CTMC

References I



John Strahan, Chatipat Lorpaiboon, Jonathan Weare, and Aaron R. Dinner.

Bad-neus: Rapidly converging trajectory stratification, 2024.



Andrew R. Mitchell and Grant M. Rotskoff.

Committer guided estimates of molecular transition rates.

arXiv preprint arXiv:2408.05879, 2024.