

# Practical Course on Molecular Dynamics and Trajectory Analysis

## Episode 6: Markov models with PyEMMA

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MD Course and Trajectory Analysis  
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# Notation used throughout the notes

- Phase-space point:  $z = (q, p) \in \mathbb{R}^{3N} \times \mathbb{R}^{3N}$ , with positions  $q$  and momenta  $p$ .
- Potential energy (force field):  $U(q)$ ; forces  $\mathbf{F}(q) = -\nabla_q U(q)$ .
- Hamiltonian:  $H(q, p) = K(p) + U(q)$  with  $K(p) = \sum_i \frac{\|p_i\|^2}{2m_i}$ .
- Temperature  $T$ , Boltzmann constant  $k_B$ , inverse temperature  $\beta = (k_B T)^{-1}$ .
- Time step  $\Delta t$ ; lag time for kinetic models  $\tau$ .

## Markov state models: from trajectories to a transition matrix

Choose a state discretization (clustering)  $S(q) \in \{1, \dots, n\}$  and a lag time  $\tau$ . The MSM estimates a transition matrix  $P(\tau)$  with entries

$$P_{ij}(\tau) = \mathbb{P}(S(q_{t+\tau}) = j \mid S(q_t) = i).$$

For reversible dynamics (detailed balance) one often enforces

$$\pi_i P_{ij} = \pi_j P_{ji},$$

which improves statistical efficiency and yields real eigenvalues. Implied timescales:  $t_k = -\tau / \ln |\lambda_k|$  for eigenvalues  $1 = \lambda_1 > \lambda_2 \geq \dots$ .

## Suggested figure: Markov chain / HMM trellis diagram

**Figure:** A trellis diagram is a compact way to visualize a Markov process with observations (HMM), closely related to state discretization in MSMs. Source: Wikipedia article on Hidden Markov model.

## Transform data

- `simulateAmber.py` and `simulateCharmm.py` produce DCD trajectories that feed into PyEMMA.
- Align, trim solvent, and save to HDF5 for storage efficiency.
- Energy and RMSD reports serve as checks before discretization.

# Feature extraction

- Distances, dihedrals, and ligand–protein contacts form the vector  $\mathbf{x}$ .
- The covariance matrix  $C = \langle (\mathbf{x} - \bar{\mathbf{x}})(\mathbf{x} - \bar{\mathbf{x}})^T \rangle$  gets projected.
- All guide scripts (simulateGromacs, simulateTinker) share this output to feed PyEMMA.

# tICA and time-lagged reduction

$$C_\tau \mathbf{w} = \lambda C_0 \mathbf{w}.$$

- Choose  $\tau$  by comparing plateaus in implicit times  $t_i = -\frac{\tau}{\ln \lambda_i}$ .
- tICA captures the slow modes relevant for MSM and Deeptime.

# Microstate clustering

- k-means/minibatch create microstates; silhouette helps choose  $k$ .
- Favor dense states to avoid empty microstates (OpenMM User Guide §3.7).

# State map

## BioBridge

Miguel Angel Hernandez Sanchez

Menu

Simulation

**Graphs**

Administration

/ link 1 / link 2 / Logout

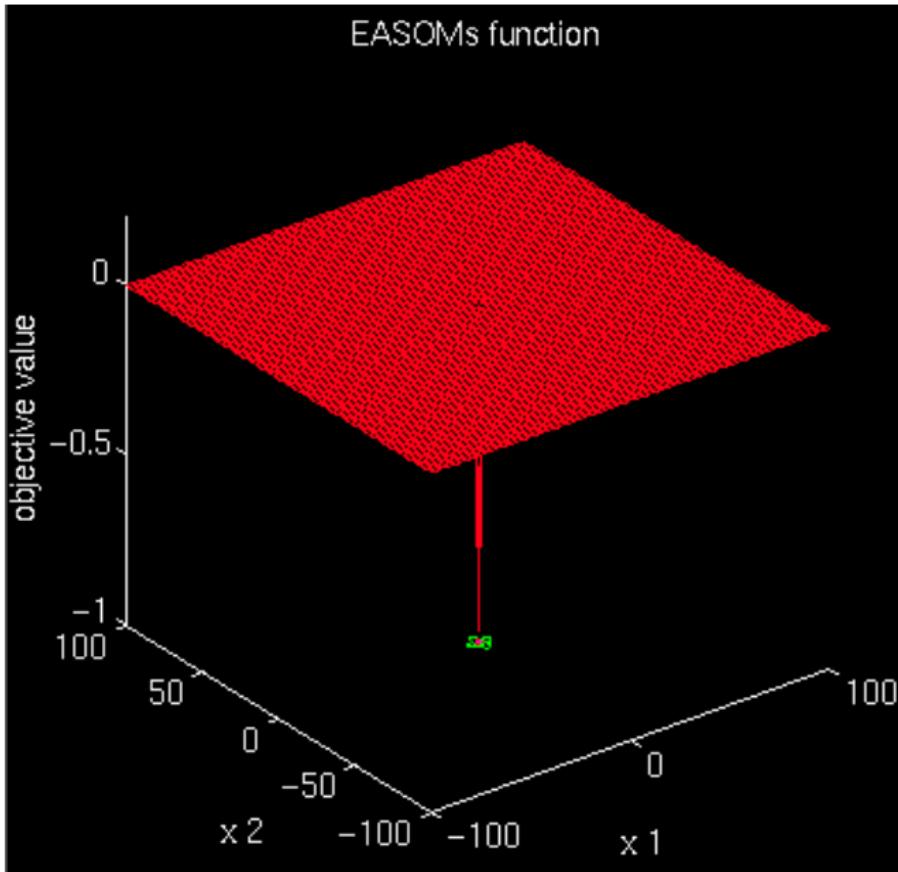
Graph View

Reactants

Pathways		
Start	End	formula
Protein 1	Protein 2	X[K]
Protein 1	Protein 3	X[K]
Protein 2	Protein 4	X[K]
Protein 2	Protein 5	X[K]
Protein 3	Protein 6	X[K]
Protein 3	Protein 7	X[K]
Protein 4	Protein 8	X[K]

Transition graph influenced by the REST tutorial results. [1]

# Energy landscape and partitions



# Transition matrix

$$T_{ij}(\tau) = \frac{C_{ij}(\tau)}{\sum_k C_{ik}(\tau)}.$$

- Rows sum to 1 and the matrix becomes reversible stochastic when detailed balance is enforced.
- Use Bayesian estimators with pseudocounts to avoid zeros.

# Markov property

$$P(X_{t+\tau} | X_t, \dots) = P(X_{t+\tau} | X_t).$$

- Chapman-Kolmogorov tests and pseudo-time diagnostics (PyEMMA) validate Markovianity.

# Stationarity

$$\pi^T T = \pi^T.$$

- The stationary distribution  $\pi$  defines relative populations.
- Relate to free energies  $F_i = -k_B T \ln \pi_i$  and compare with alchemical  $\Delta G$ .

## Implied times

$$t_i = -\frac{\tau}{\ln \lambda_i}.$$

- Eigenvalues near 1 represent slow processes (Markovianity).
- Large gaps between  $t_i$  support scale separation.

# Uncertainty and regularization

- Resample discretized trajectories to obtain reliable intervals.
- PyEMMA stores weights and allows reruns with a different seed.
- Enforce reversibility to reduce noise.
- Tune priors using forces detected in `simulateAmber.py`.

# TPT, committor, and fluxes

- Flows  $f_{ij} = \pi_i T_{ij} q_i (1 - q_j)$  identify reactive pathways.
- The committor  $q_i = P(\text{reaching B before A} \mid X_0 = i)$  gauges progress.
- A transition graph colored by flux highlights kinetic bottlenecks.
- `simulateGromacs.py` provides the reference trajectories.

# MSM checklist

- Informative features.
- Validated  $\tau$  and eigenvalues with a clear gap.
- Error bootstrap and referenced reporting.

# References I

- [1] OpenMM Cookbook. *Grafos de estados en Replica Exchange Solute Tempering*. CC BY-SA 4.0. URL:  
[https://openmm.github.io/openmm-cookbook/latest/notebooks/tutorials/Running\\_a\\_REST\\_simulation.html](https://openmm.github.io/openmm-cookbook/latest/notebooks/tutorials/Running_a_REST_simulation.html)  
(visited on 01/12/2026).
- [2] Visualización interna del curso. *Embudo energético de muestreo*. Figura adaptada del archivo function\_funnel.png del repositorio. 2024.