Hidden Markov state models

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2019 PyEMMA Workshop FU Berlin **Tuesday, Feb 19th**

Discretization

1.0

0.8

0.6

0.4

0.2

0.0

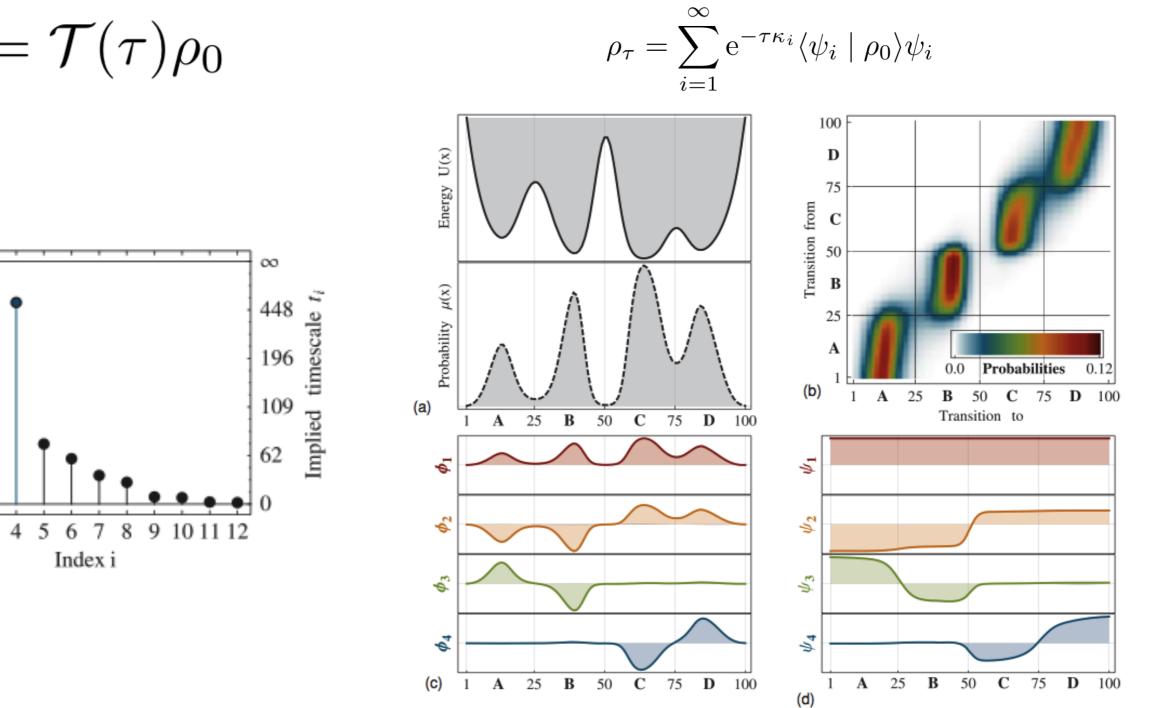
Eigenvalue λ_i

(e)

Backward propagator

$$\rho_{\tau} = \mathcal{T}(\tau)\rho_0$$

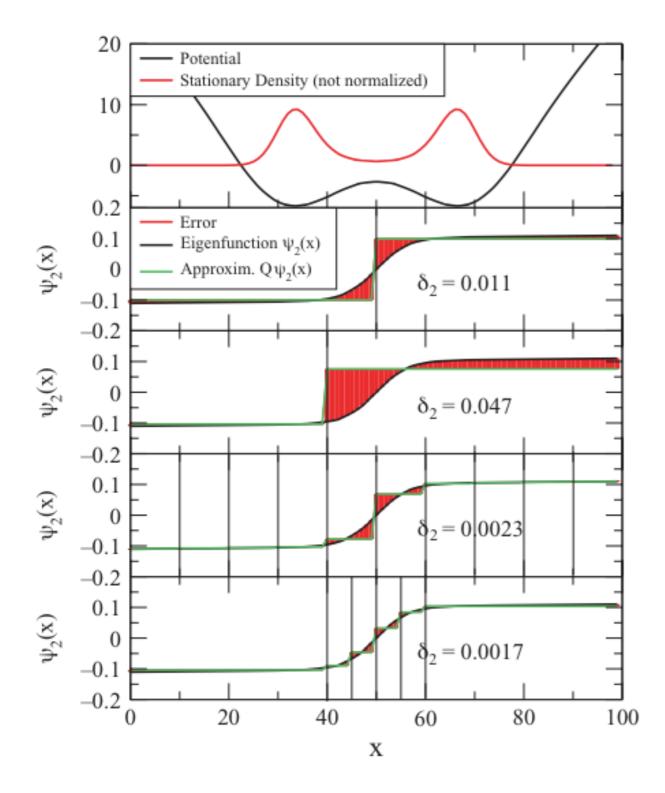
Spectral decomposition

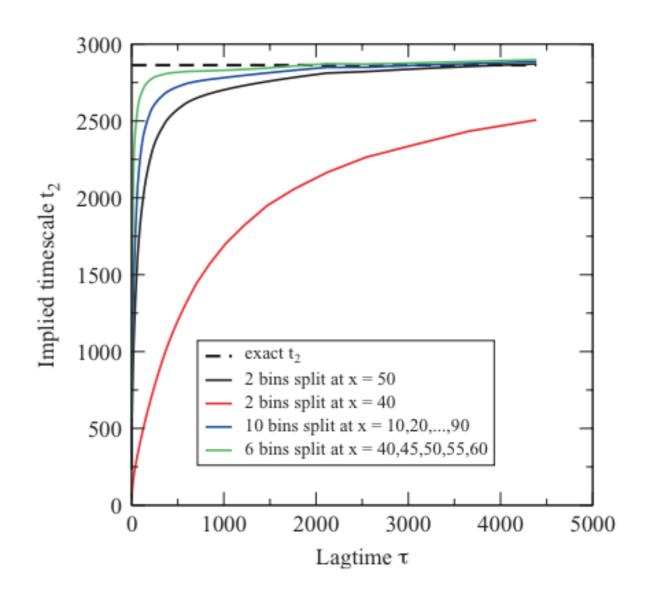


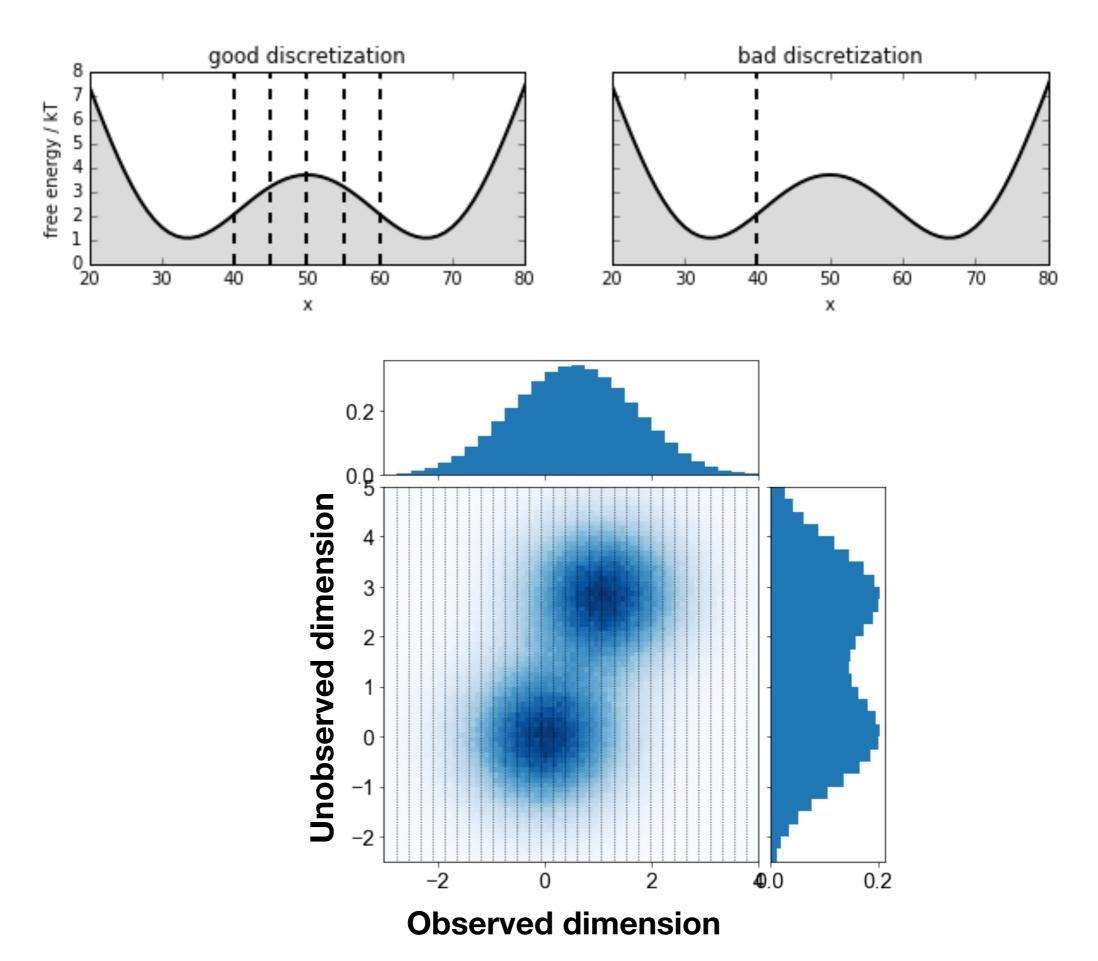
2 3

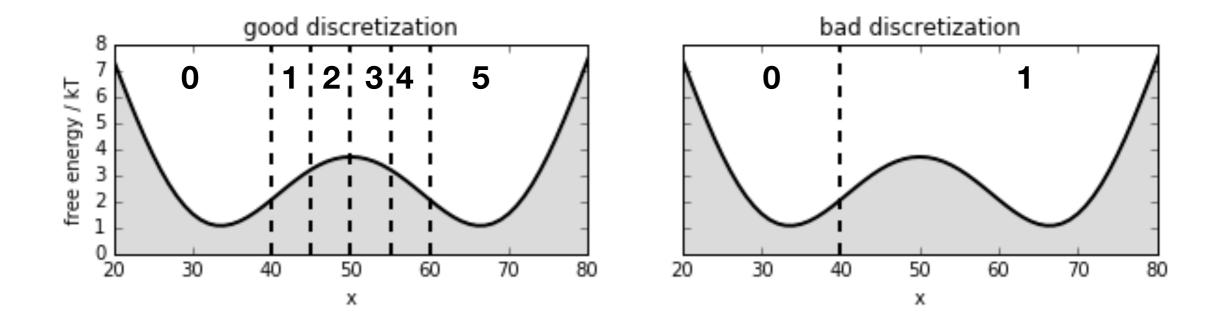
1

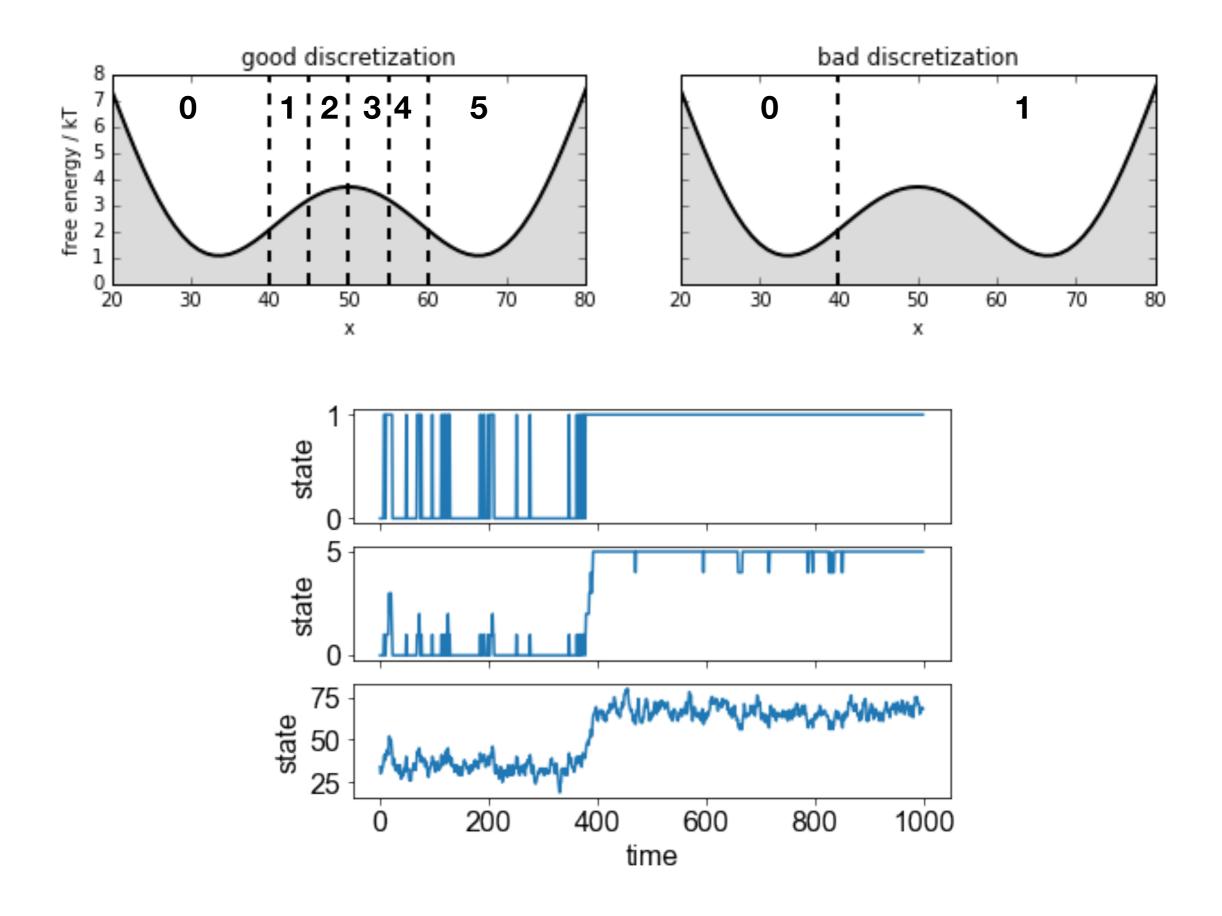
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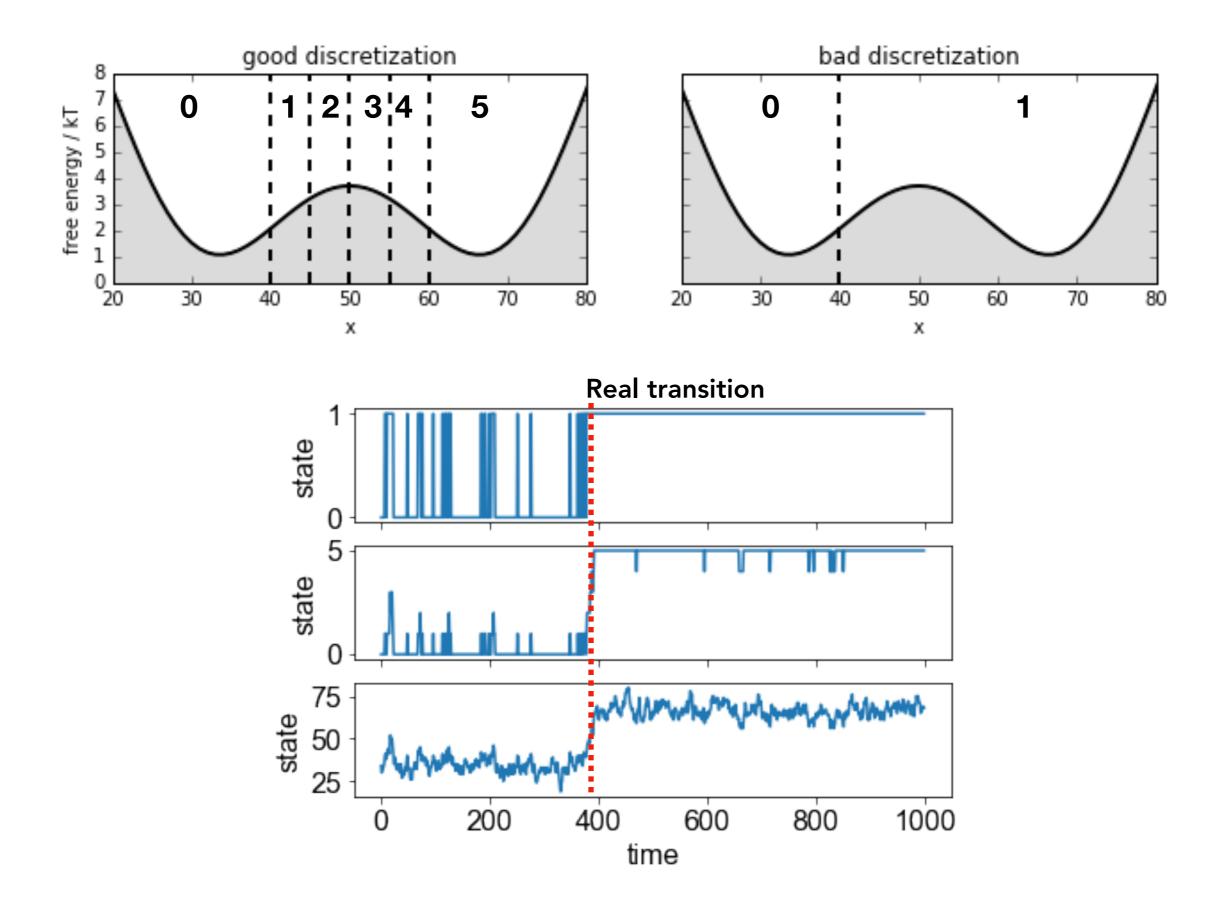


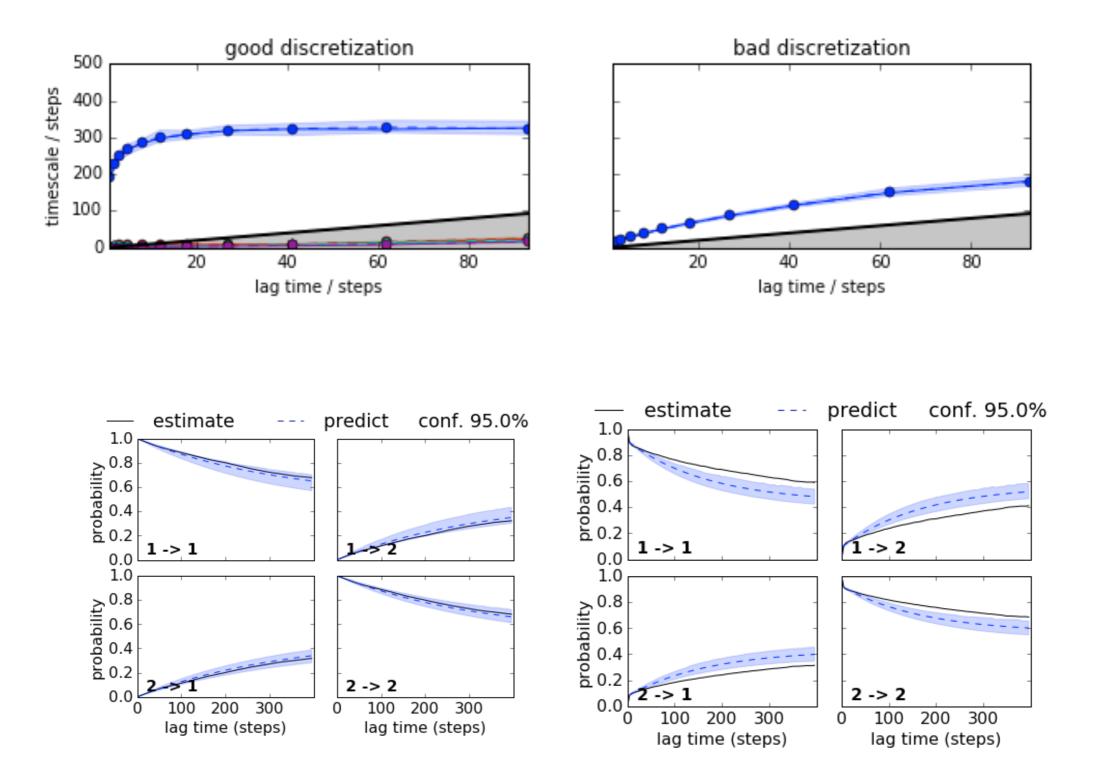












Projection/discretization error leads to systematic errors

- Discretization and projection errors hampers our ability to distinguish between meta-stable states
- Apparent non-Markovian behavior of the dynamics.

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Remedies:

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- Improve featurization and clustering

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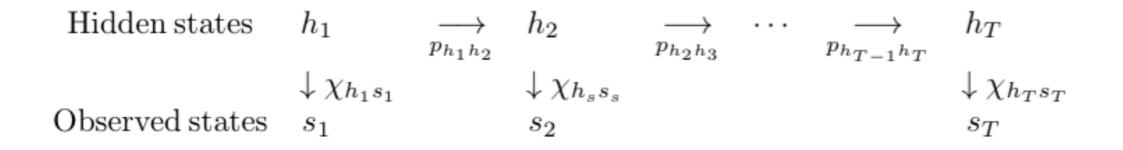
- Increase lag-time when estimating MSM
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<u>However we know that the underlying dynamics is Markovian,</u> <u>can we exploit fact in some way?</u>

Hidden Markov state models

We assume the existence of an underlying (hidden) Markovian dynamics described by the transition probabilities $\mathbf{P} = \{p_{ij}\}$

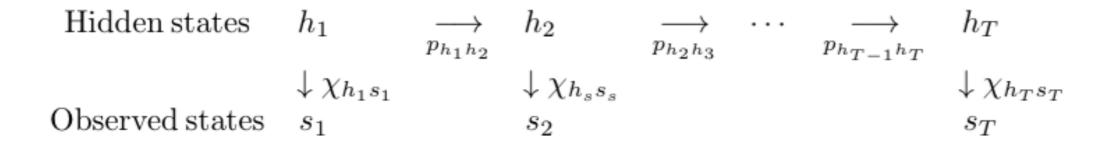
Instead of observing the state h_i directly we observe some distorted representation, s_i with a probability $\chi_{h_i s_i}$ — the emission probabilities.

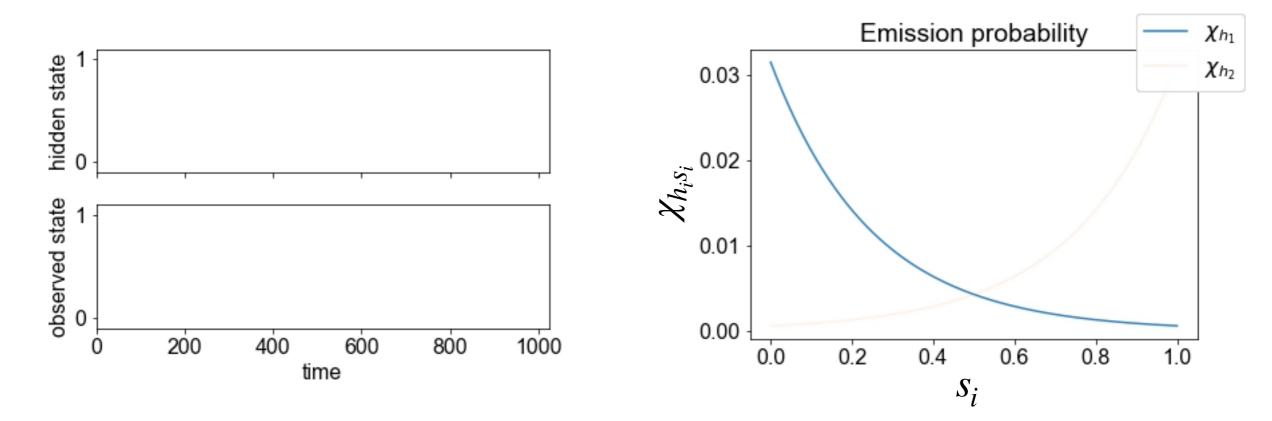


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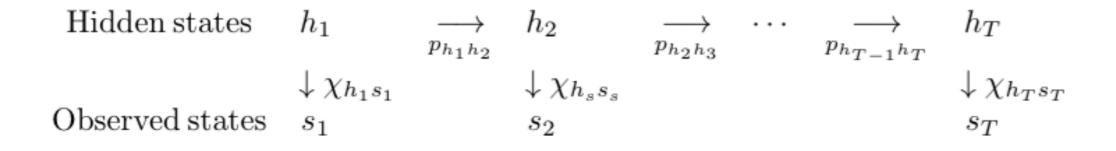


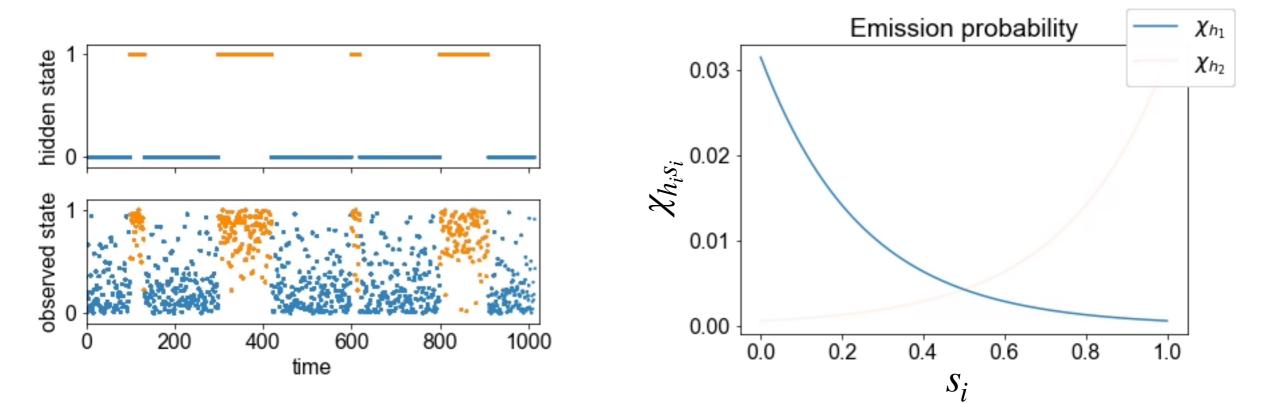


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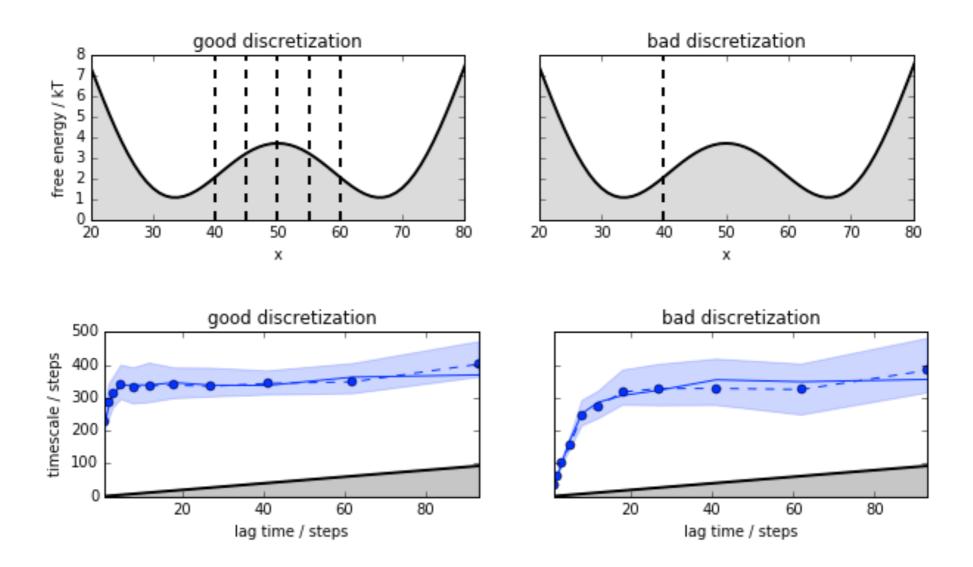
Maximum-Likelihood and Bayesian estimators are available:

Rabiner Proc IEEE (1989) 77,2, pp.257 Noé et al. JCP (2013) 139, 184114 Chodera et al. arxiv:1108:1430

- Models the system dynamics by estimation of transition probabilities of hidden Markov process, and emission probability distributions.
- We need to decide the number of states of the hidden Markov process a priori (the number of meta-stable states)

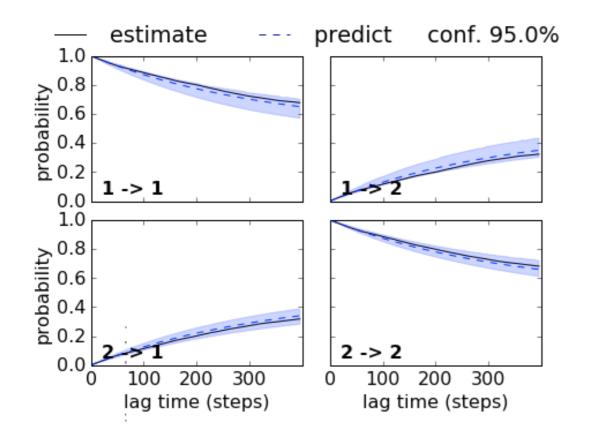
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Let's revisit our two well potential from before:

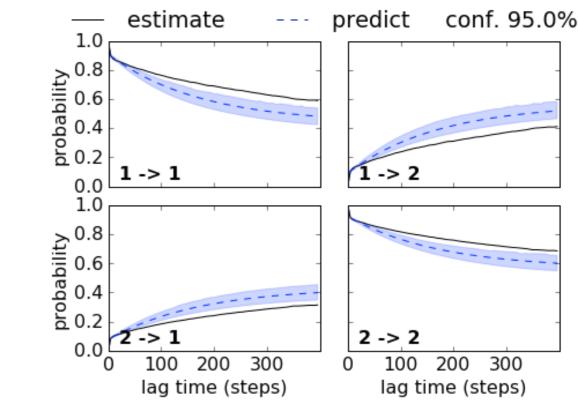


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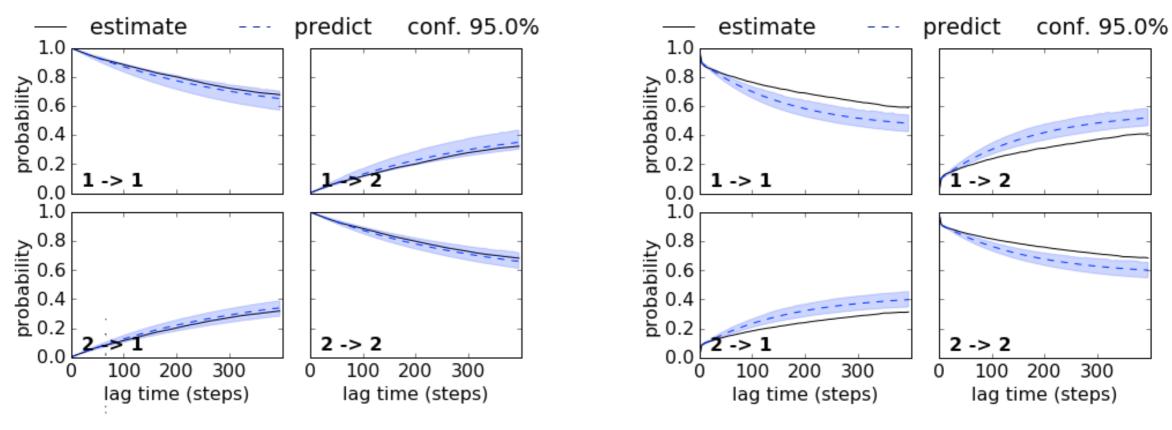


Bad discretization

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Let's revisit our two well potential from before:

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Bad discretization

We get a robust model of the dynamics which simultaneously resolves meta-stable states.

Questions?

Notebook time