

Everything you wanted to know
about VAMP but were afraid to ask

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Stanford/FU Berlin
PyEMMA Workshop
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First of all

Variational Approach for Markov Processes

Key papers:

Wu & Noé 2017, arXiv:1707.04659, "Variational approach..."

Paul et al, arXiv:1811.12551, "Identification of kinetic..."

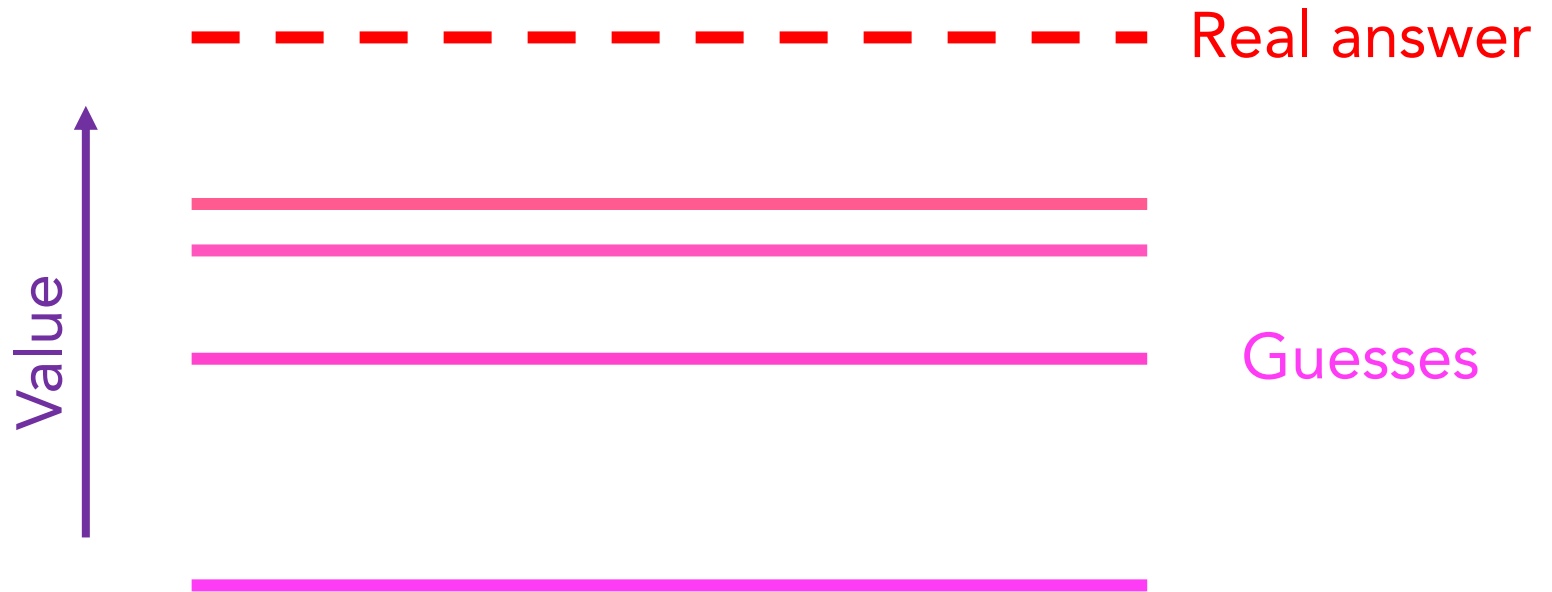
First of all

Variational

Approach for

Markov

Processes



Key papers:

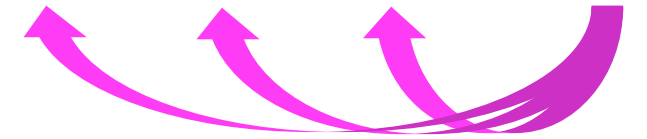
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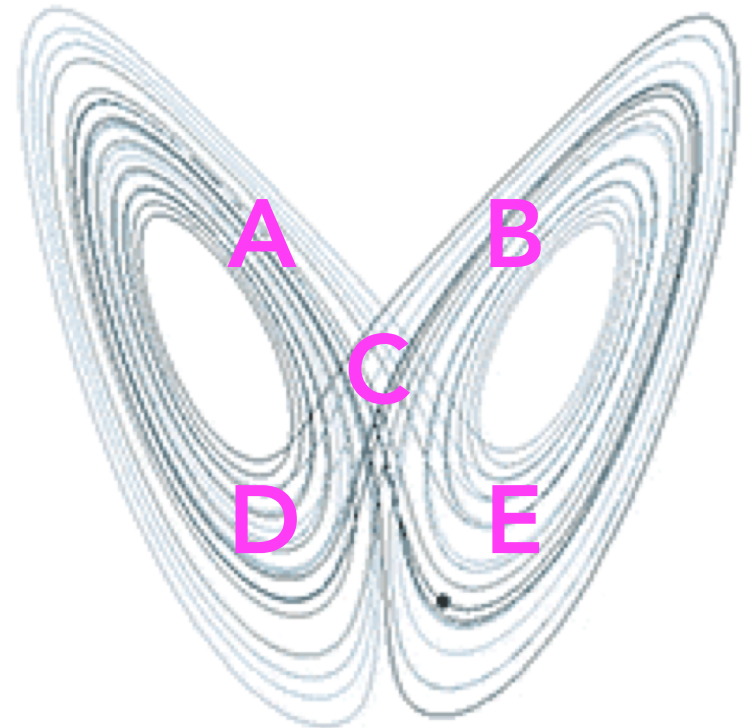
First of all

Variational Approach for Markov Processes

Our data: $z_1, z_2, \dots, z_{t-2}, z_{t-1}, z_t, z_{t+1}$



$$\begin{aligned}\frac{dx}{dt} &= \sigma(y - x), \\ \frac{dy}{dt} &= x(\rho - z) - y, \\ \frac{dz}{dt} &= xy - \beta z.\end{aligned}$$



Key papers:

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First of all

Variational Approach for Markov Processes

Our data: $z_1, z_2, \dots, z_{t-2}, z_{t-1}, z_t, z_{t+1}$

$[z_t, z_{t+1}]$

$[z_t, z_{t+\tau}]$

$X =$

$\begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \\ \dots \\ z_{t-1} \end{bmatrix}$

$Y =$

$\begin{bmatrix} z_2 \\ z_3 \\ z_4 \\ z_5 \\ \dots \\ z_t \end{bmatrix}$

Key papers:

Wu & Noé 2017, arXiv:1707.04659, "Variational approach..."
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Some history

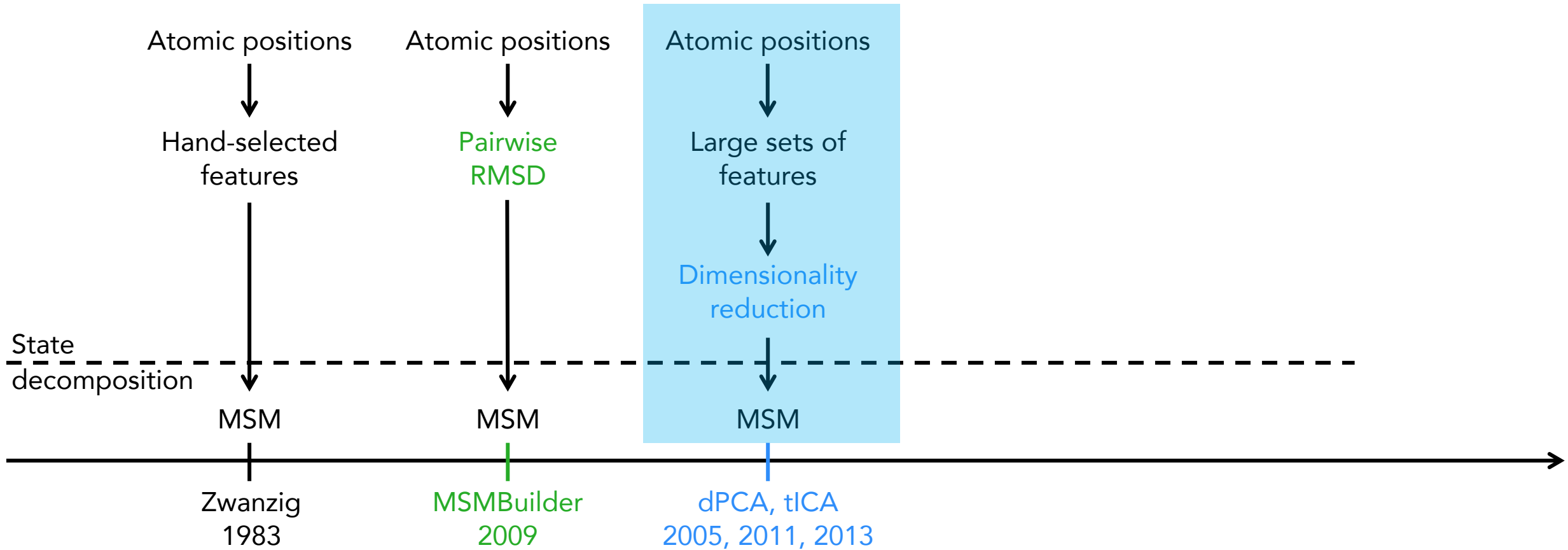
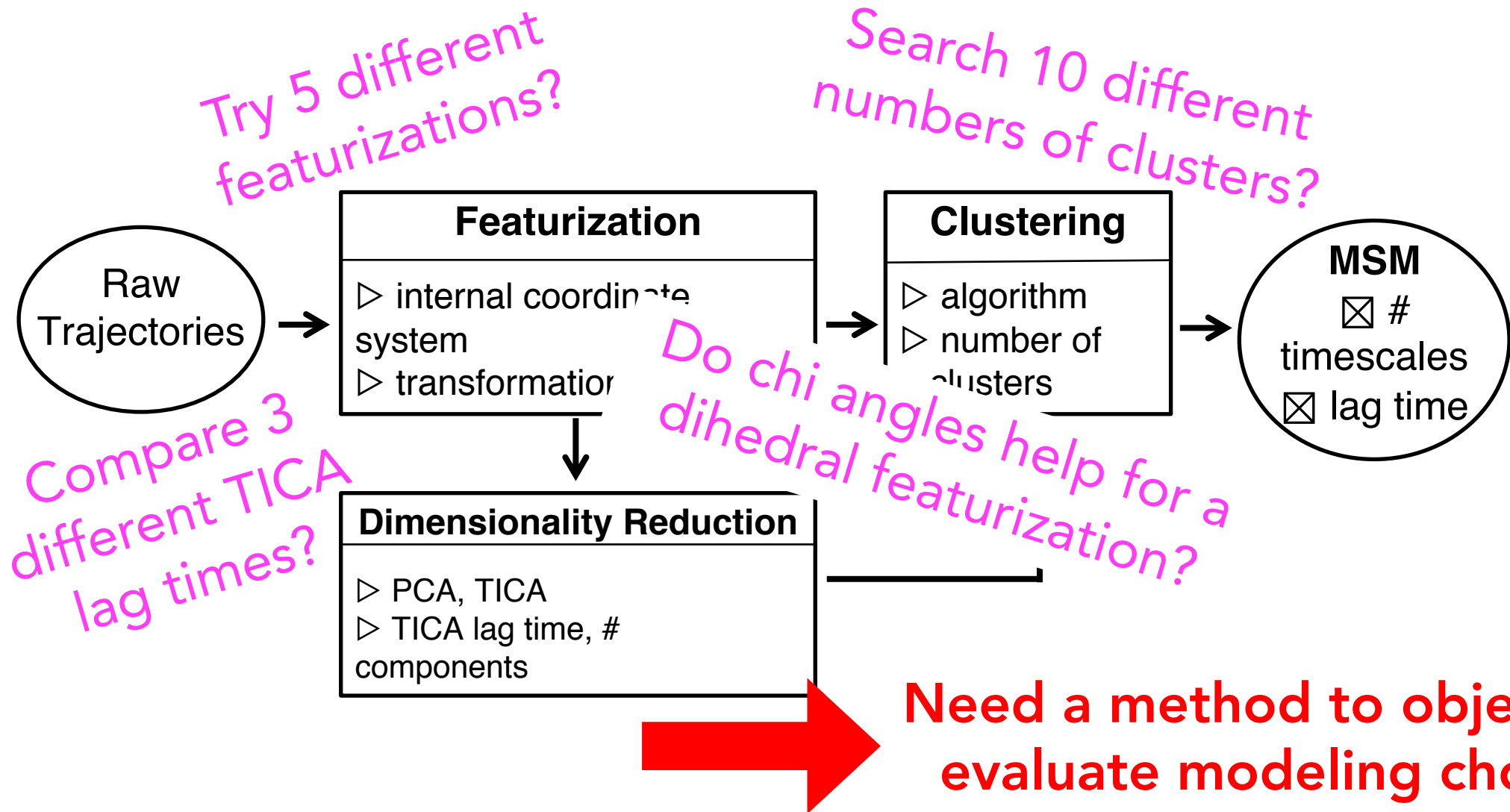


Figure from: Husic & Pande 2018, JACS, "Markov State Models: From an Art to a Science"

The problem



Back to history

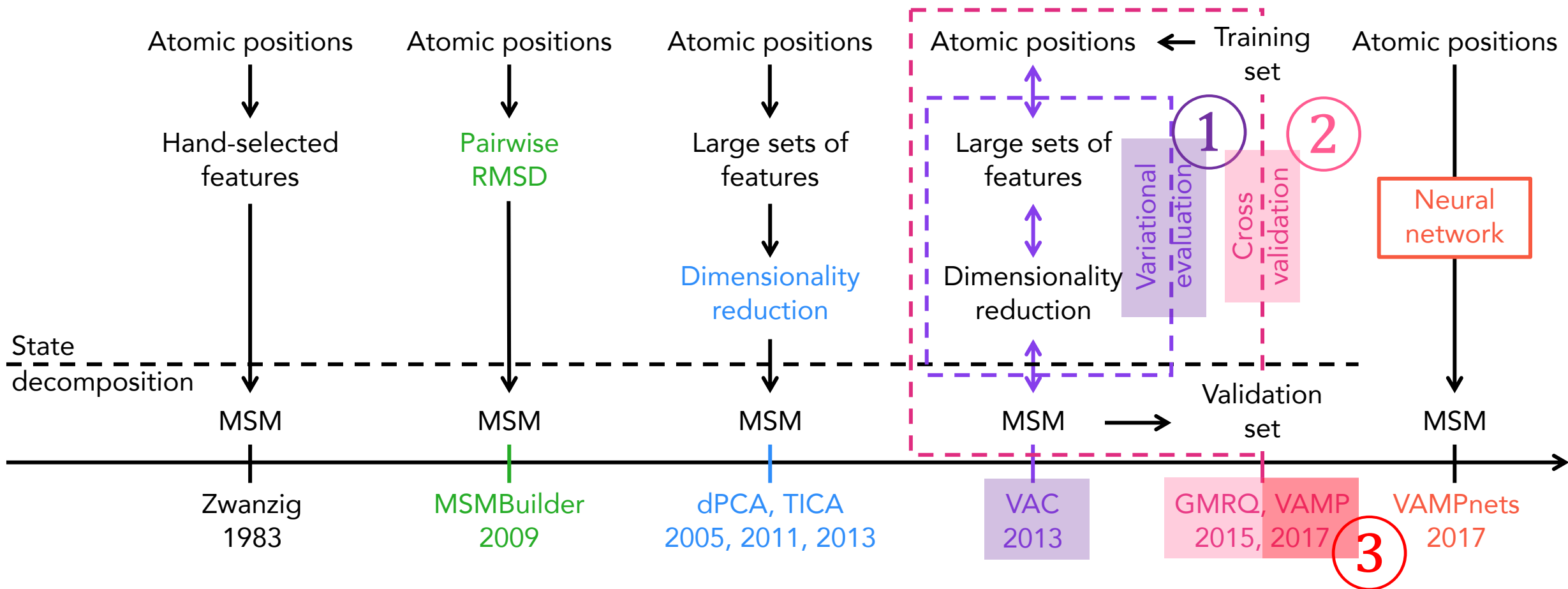
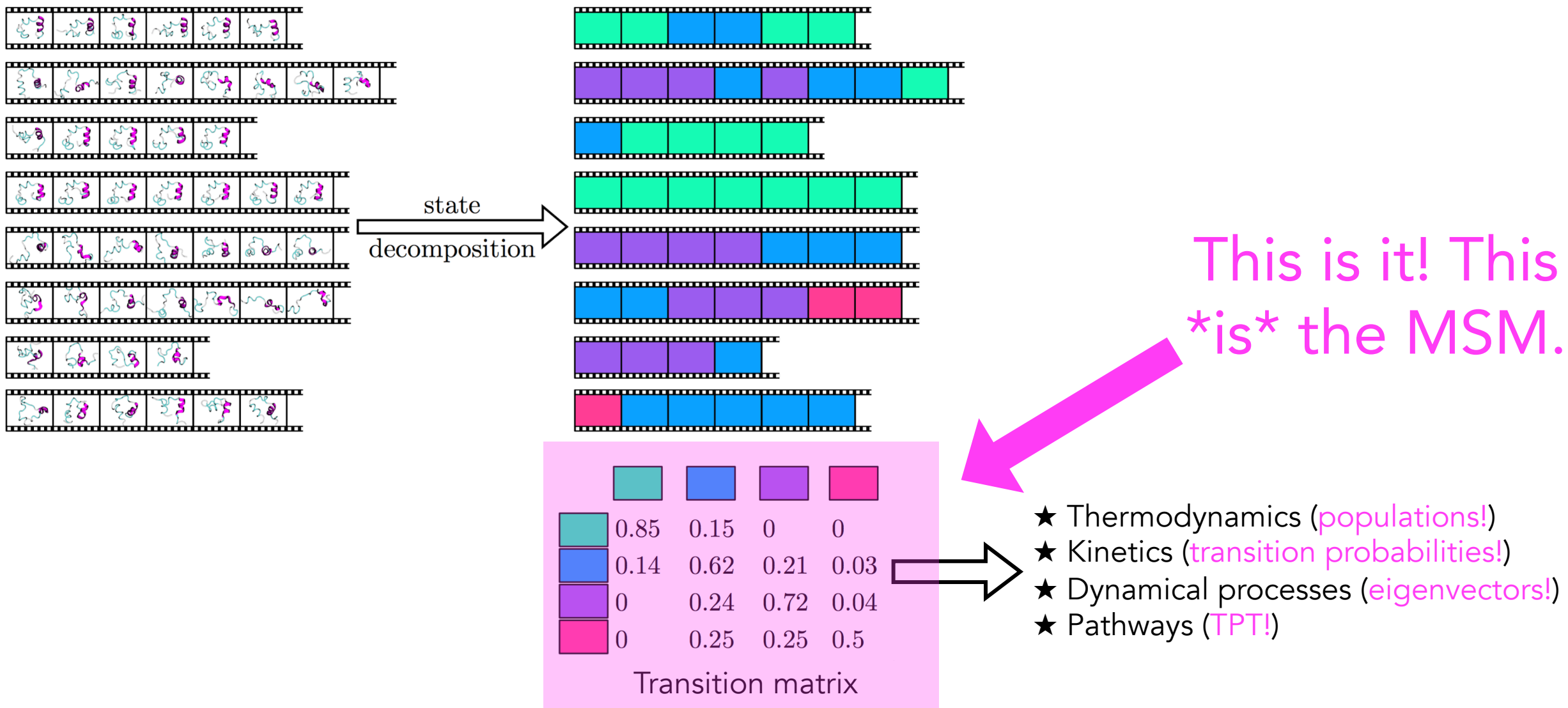
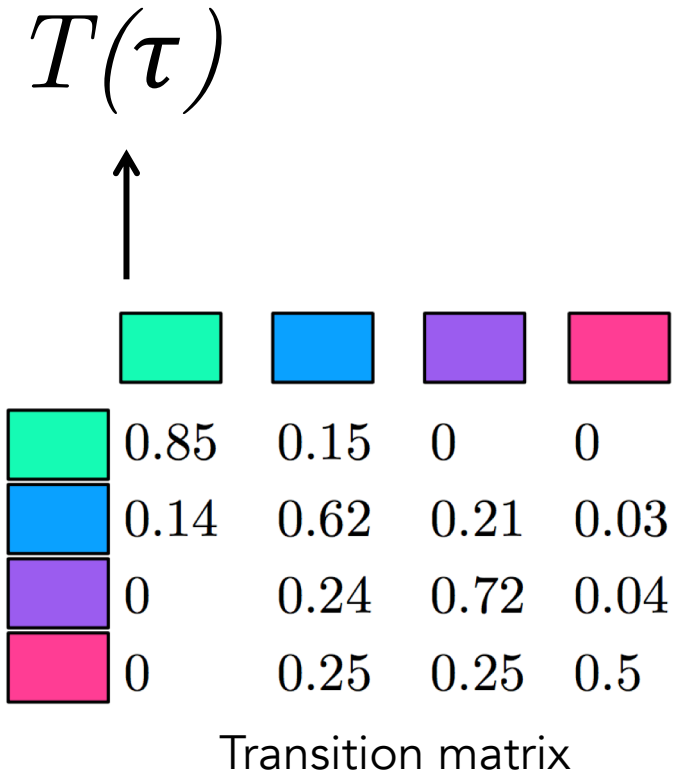


Figure from: Husic & Pande 2018, JACS, "Markov State Models: From an Art to a Science"

Let's make sure we're clear on MSMs



The VAC



Key papers:

Noé & Nüske 2013, Multiscale Model Simul, "A Variational Approach..."
Nüske et al 2014, J Chem Theory Comput, "Variational Approach..."

The VAC

$$T(\tau)\psi_i = \lambda_i\psi_i \longrightarrow t_i = -\tau / \ln |\lambda_i|$$

Eigenvectors: dynamical processes

Eigenvalues: related to timescales

The eigenvalues have special properties according to the Perron-Frobenius theorem:

- They are real
- There is a unique maximum eigenvalue of 1
- All other eigenvalues have absolute values below 1

Key papers:

Noé & Nüske 2013, Multiscale Model Simul, "A Variational Approach..."

Nüske et al 2014, J Chem Theory Comput, "Variational Approach..."

The VAC

$$T(\tau)\psi_i = \lambda_i\psi_i \longrightarrow t_i = -\tau / \ln |\lambda_i|$$

↑
The variational principle is for the **eigenvalues**

$$\sum_{i=1}^m \hat{\lambda}_i \leq \sum_{i=1}^m \lambda_i$$

Unknown true eigenvalues

↙
↘
Eigenvalue predictions from MSM

Key papers:

Noé & Nüske 2013, Multiscale Model Simul, "A Variational Approach..."
Nüske et al 2014, J Chem Theory Comput, "Variational Approach..."

The VAC

$$T(\tau)\psi_i = \lambda_i\psi_i \longrightarrow t_i = -\tau / \ln |\lambda_i|$$

IMPORTANT: This score is only for the transition matrix defined at the given lag time τ

①

$$\text{SCORE} = \sum_{i=1}^m \hat{\lambda}_i \leq \sum_{i=1}^m \lambda_i$$

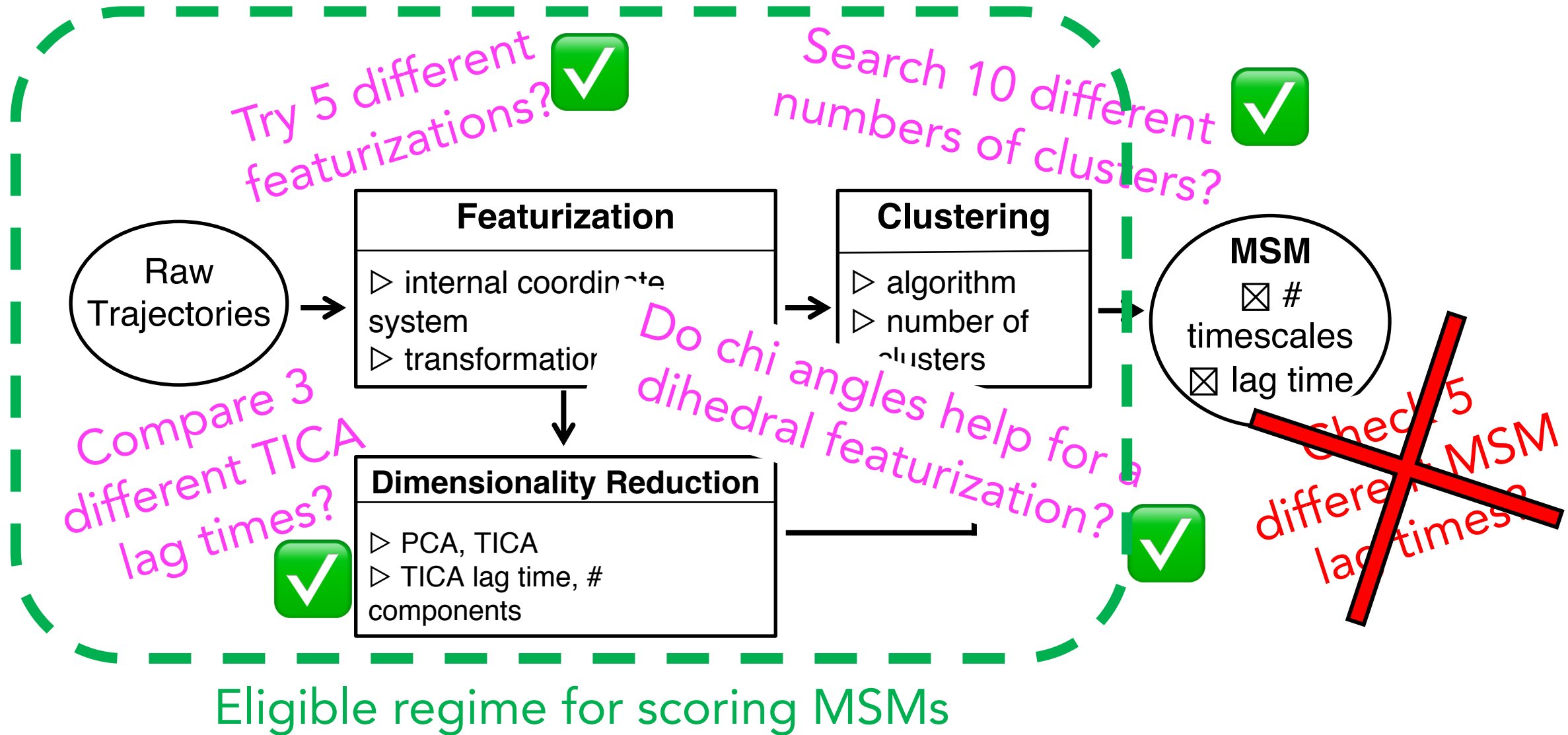
Unknown true eigenvalues

Eigenvalue predictions from MSM

Key papers:

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Reminder



Cross validation

$$\text{SCORE} = \sum_{i=1}^m \hat{\lambda}_i \leq \sum_{i=1}^m \lambda_i$$

Unknown true eigenvalues

This method will have a problem with overfitting

Eigenvalue predictions from MSM **validation set**



Make MSM

Apply MSM and score eigenvalues

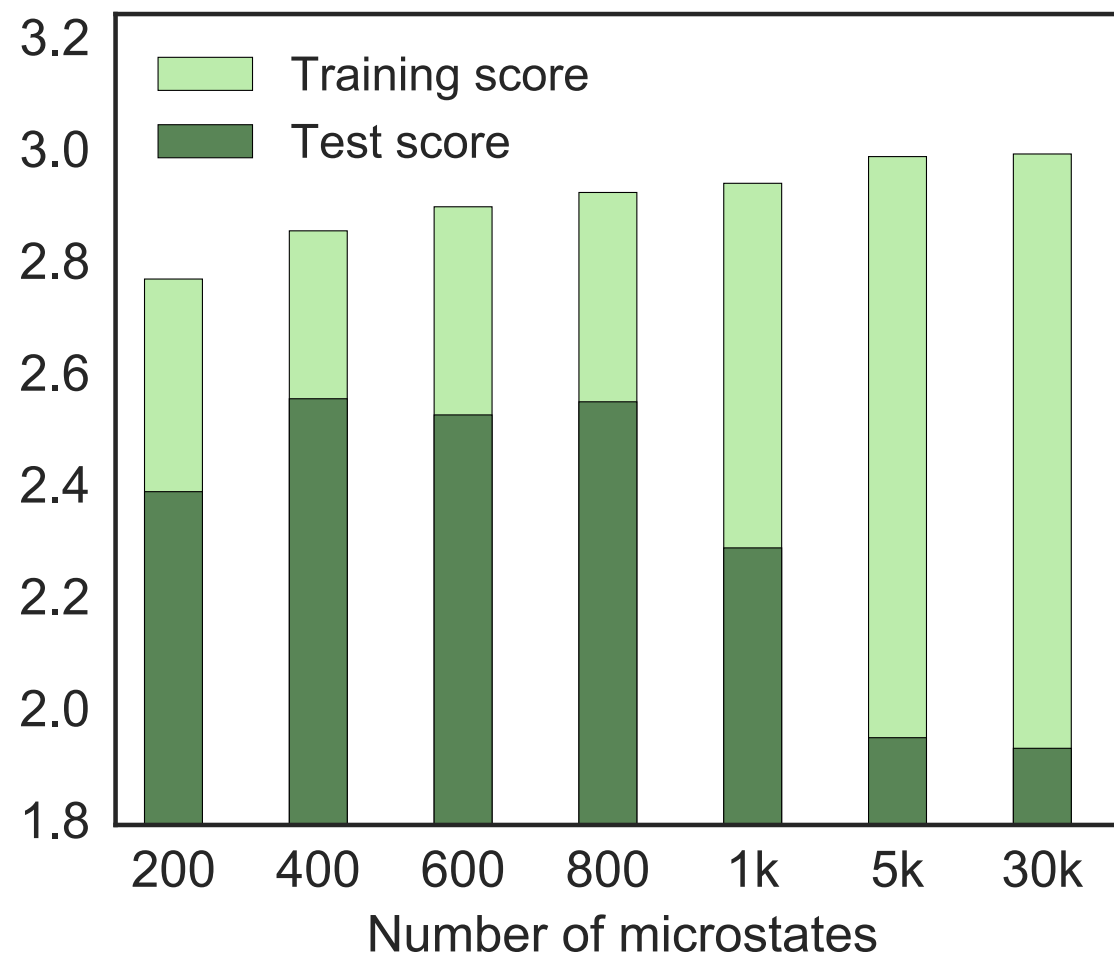
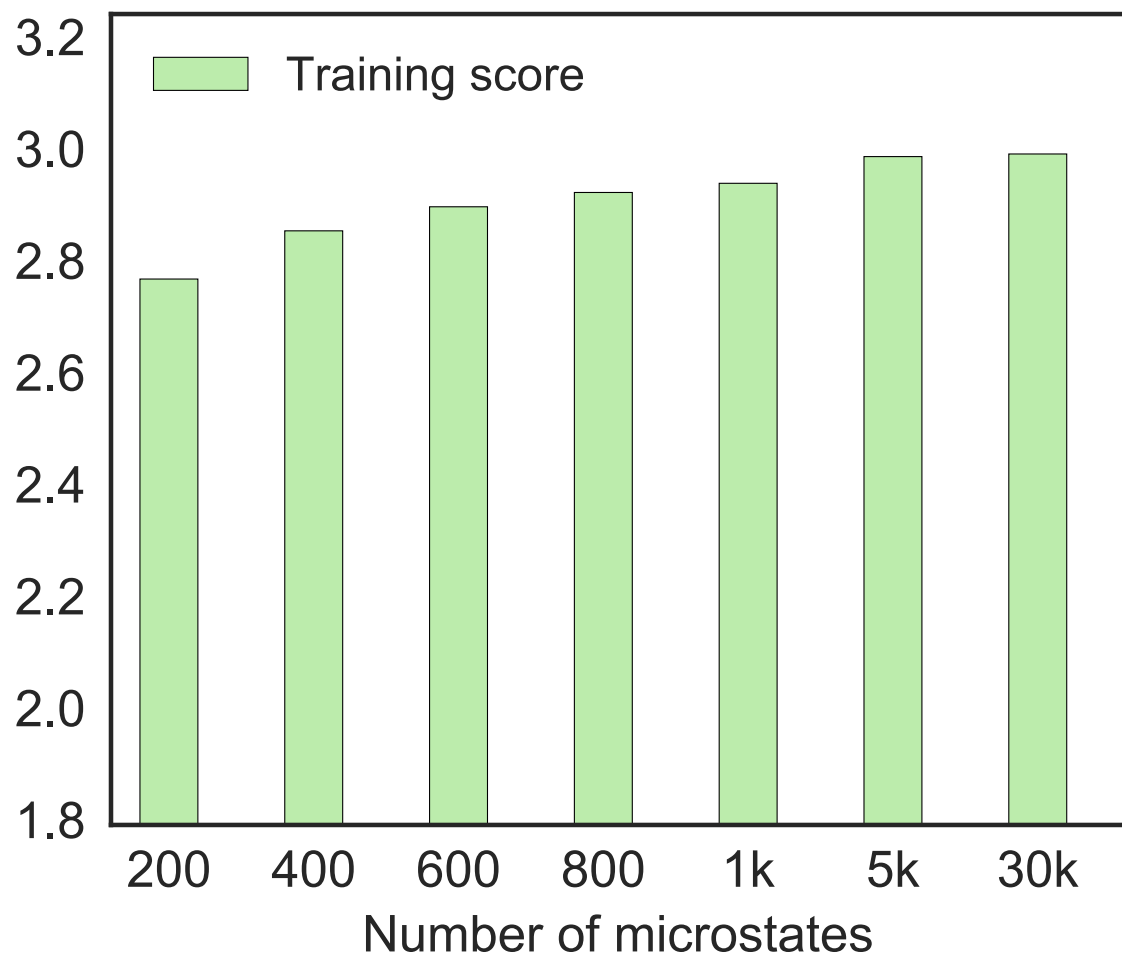
(is there enough sampling?)

Key paper:

McGibbon & Pande 2015, J Chem Phys, "Variational cross-validation..."

× some number of iterations with different sets

An example











From Husic et al 2016, J Chem Phys, "Optimized parameter selection..."

Finally: the VAMP!

$T(\tau)$



			
 0.85	0.15	0	0
 0.14	0.62	0.21	0.03
 0	0.24	0.72	0.04
 0	0.25	0.25	0.5

Transition matrix

The transition matrix has certain properties due to the reversibility assumption.

This includes having an eigendecomposition.

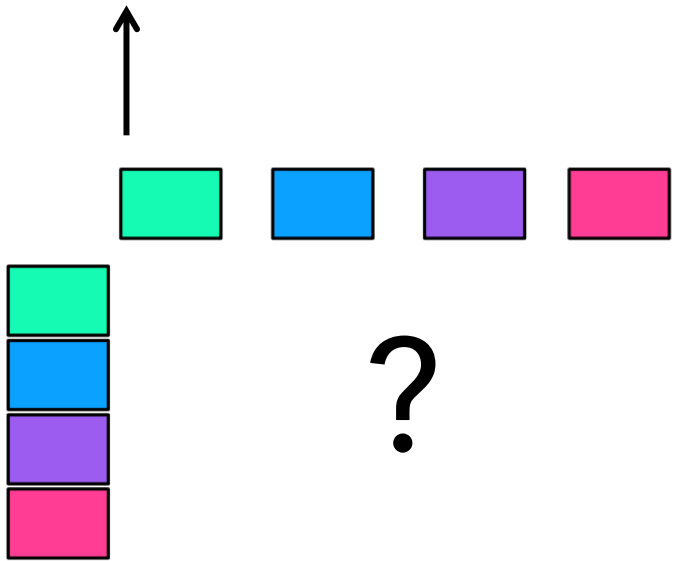
Key papers:

Wu & Noé 2017, arXiv:1707.04659, "Variational approach..."

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Finally: the VAMP!

$$K(\tau) \longrightarrow \{ \varphi_i, \sigma_i, \varphi_i \}$$



Consider now a different matrix that is not necessarily reversible.
It may not have an eigendecomposition anymore, or its eigendecomposition may not be useful.

$$\text{SCORE} = \sum_{i=1}^m \hat{\sigma}_i \leq \sum_{i=1}^m \sigma_i$$

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However, it will always have a **singular value decomposition**.

The VAMP uses more general math to score models that may not be reversible

Key papers:

Wu & Noé 2017, arXiv:1707.04659, "Variational approach..."

Paul et al, arXiv:1811.12551, "Identification of kinetic..."

What we've learned...

- We have many choices when we make Markov state models
- Luckily, we have the VAC to evaluate different choices objectively
 - *But not the MSM lag time, of course.*
- We just have to do it under cross-validation to avoid overfitting
- We can use the VAMP in the more general, nonreversible case
 - *Which is the same as the VAC when we have an MSM!*
- With an objective metric, can't we just make models automatically..?
 - *Stay tuned!*

Paper highlights

VAC theory

Noé & Nüske 2013, Multiscale Model Simul, "A Variational Approach..."

Nüske et al 2014, J Chem Theory Comput, "Variational Approach..."

Cross-validation

McGibbon & Pande 2015, J Chem Phys, "Variational cross-validation..."

VAMP theory

Wu & Noé 2017, arXiv:1707.04659, "Variational approach..."

Paul et al, arXiv:1811.12551, "Identification of kinetic..."

General overview/history of MSMs

Husic & Pande 2018, JACS, "Markov State Models: From an Art to a Science"

General overview of ML methods

Noé 2018, arXiv:1812.07669, "Machine learning..."