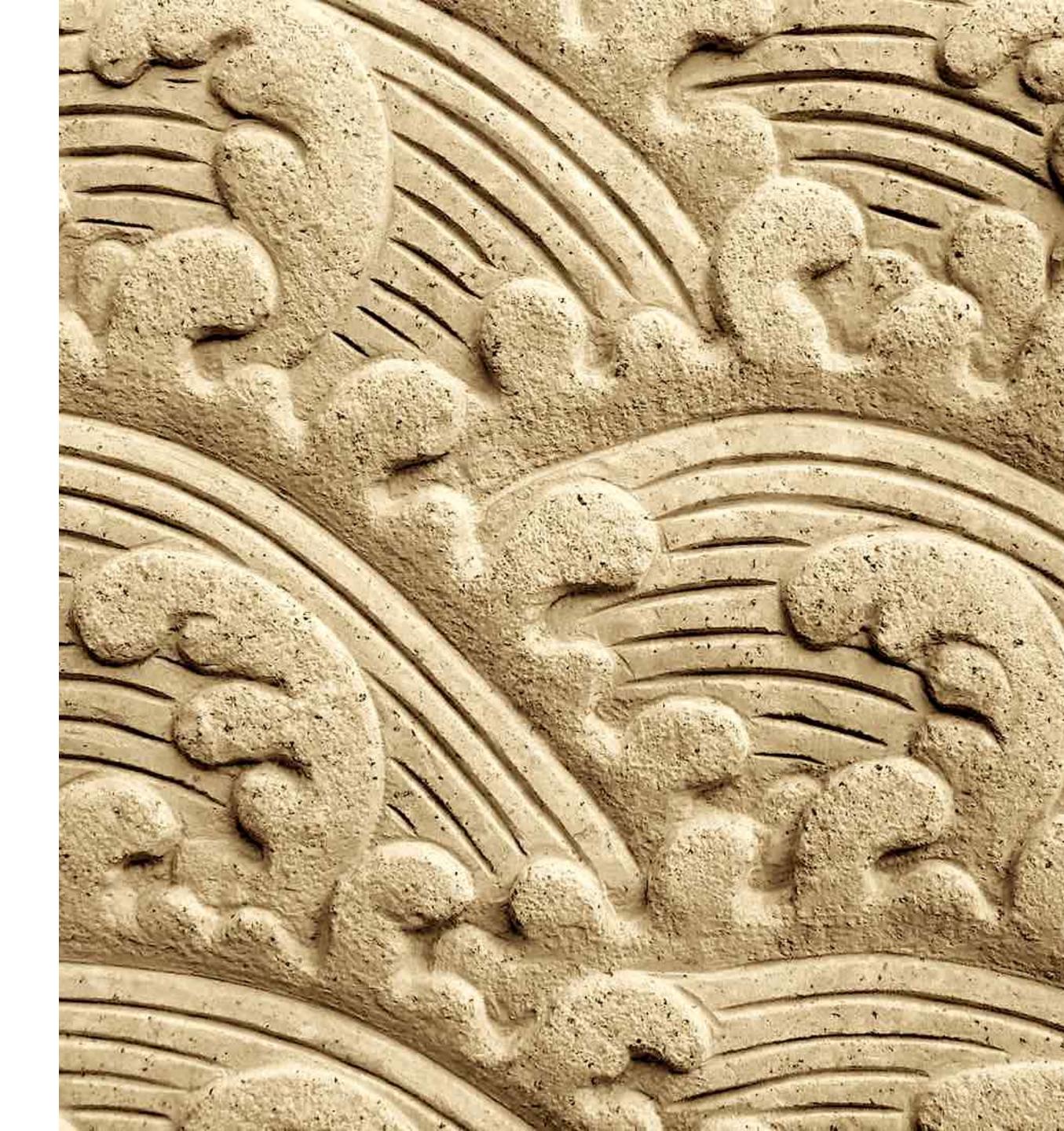
Speech Processing

Simon King University of Edinburgh

additional class slides for 2020-21



Module 8

The Hidden Markov Model



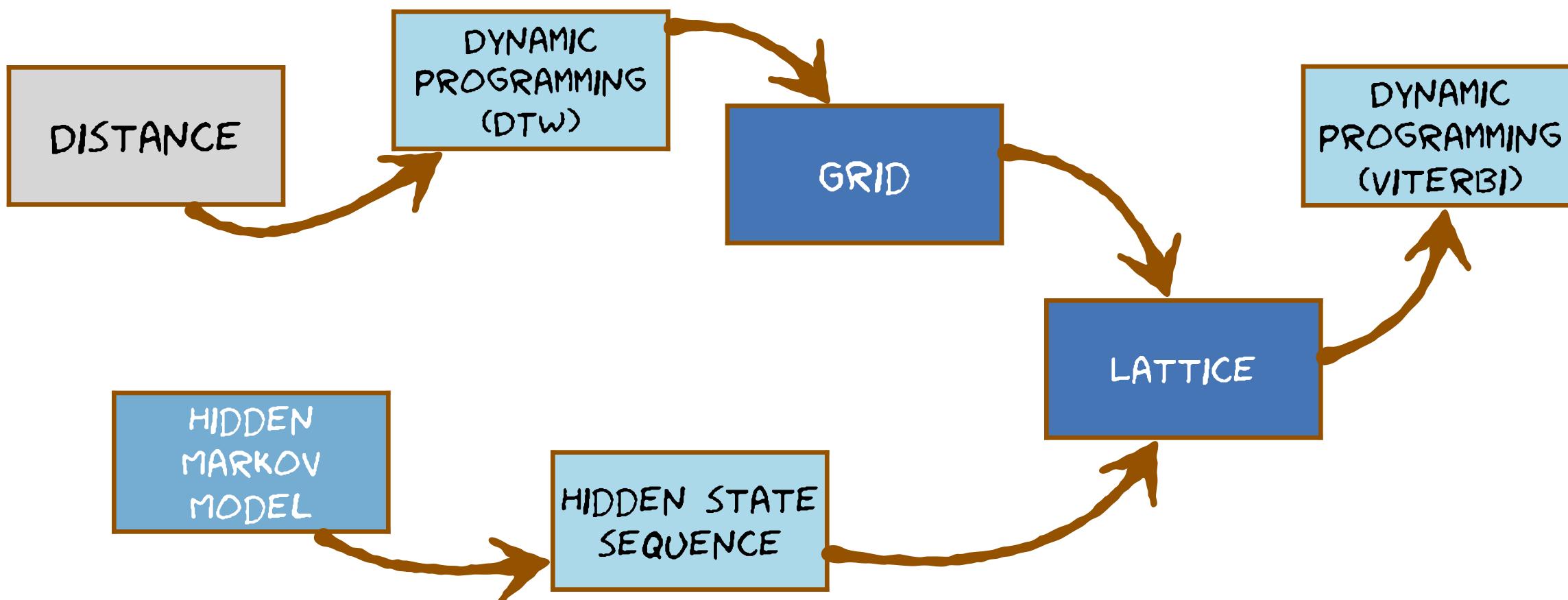
Orientation

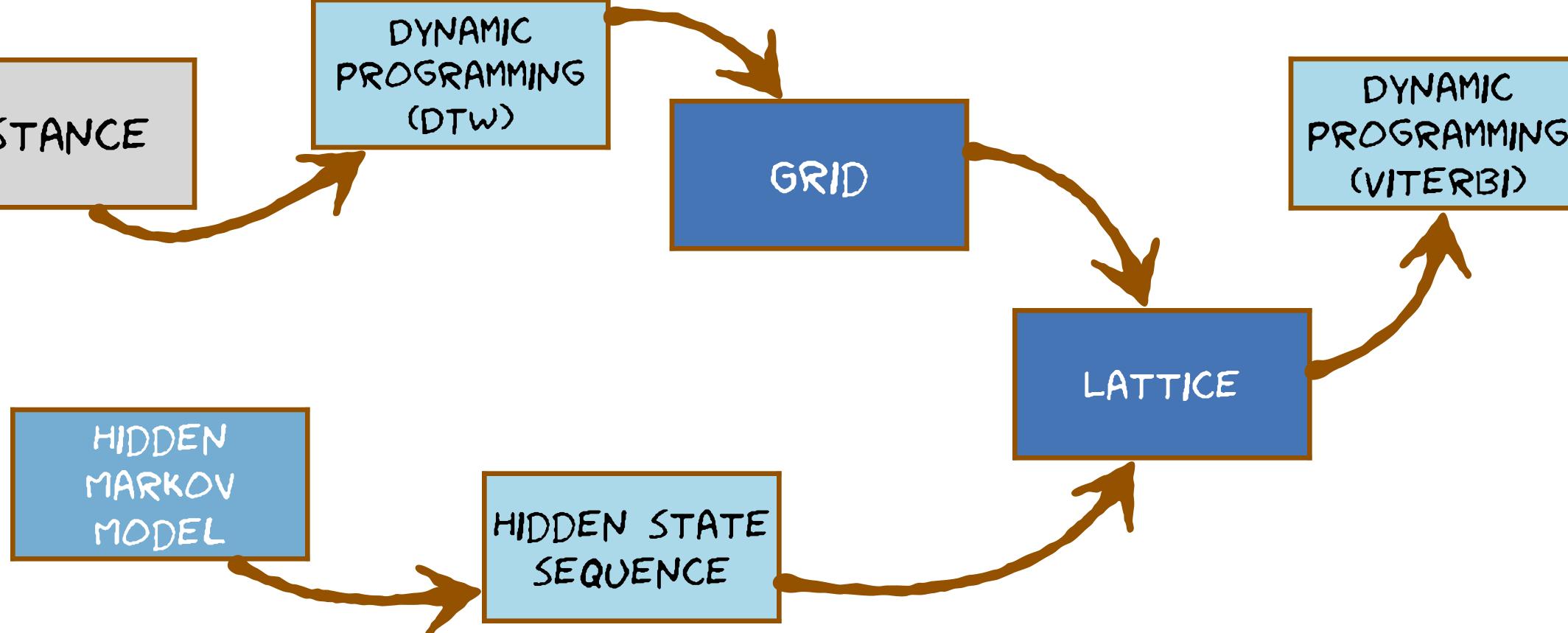
- <u>We've arrived at HMMs</u>
- Pattern matching

• Extracting **features** from speech

Probabilistic generative modelling

Orientation: from Dynamic Time Warping to the Hidden Markov Model



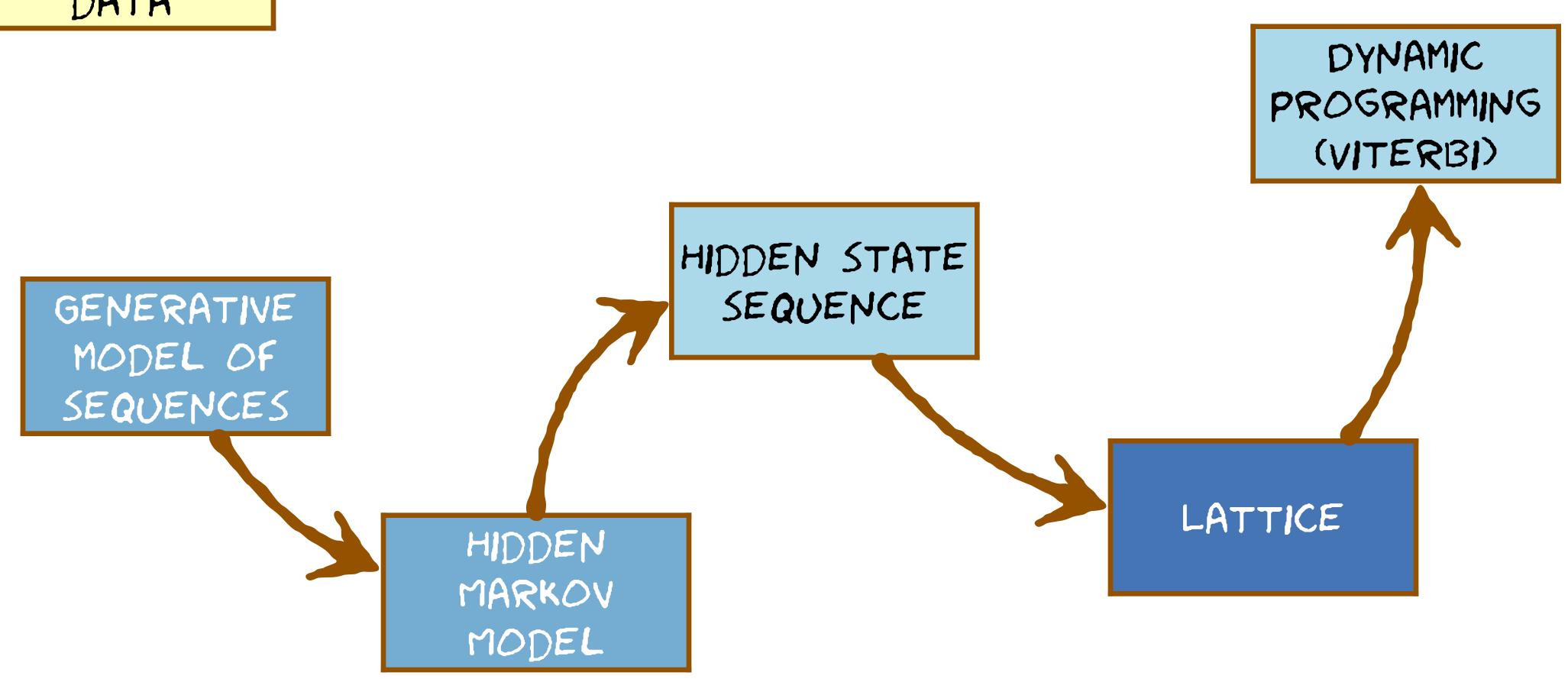




What you should already know

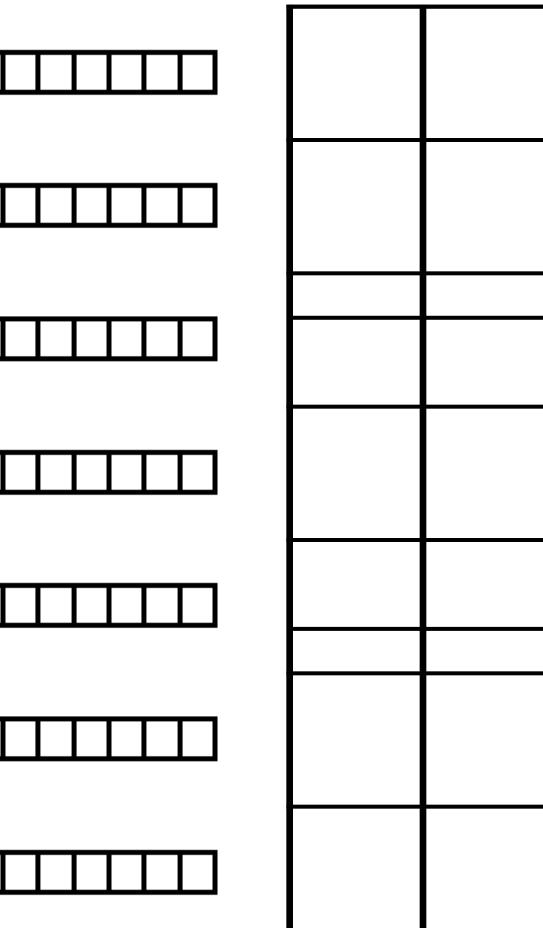
- a single template (as in DTW) cannot capture the natural variability of speech
 - an old-fashioned solution was to store multiple templates
- a much better solution is to capture variability using **statistics**
 - essentially: mean & variance

FITTING A GAUSSIAN TO DATA



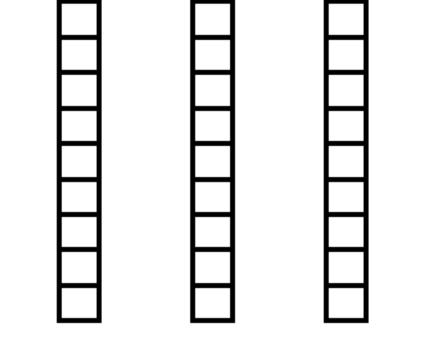
GENERATIVE MODEL OF SEQUENCES

Recap: the multivariate Gaussian as a generative model







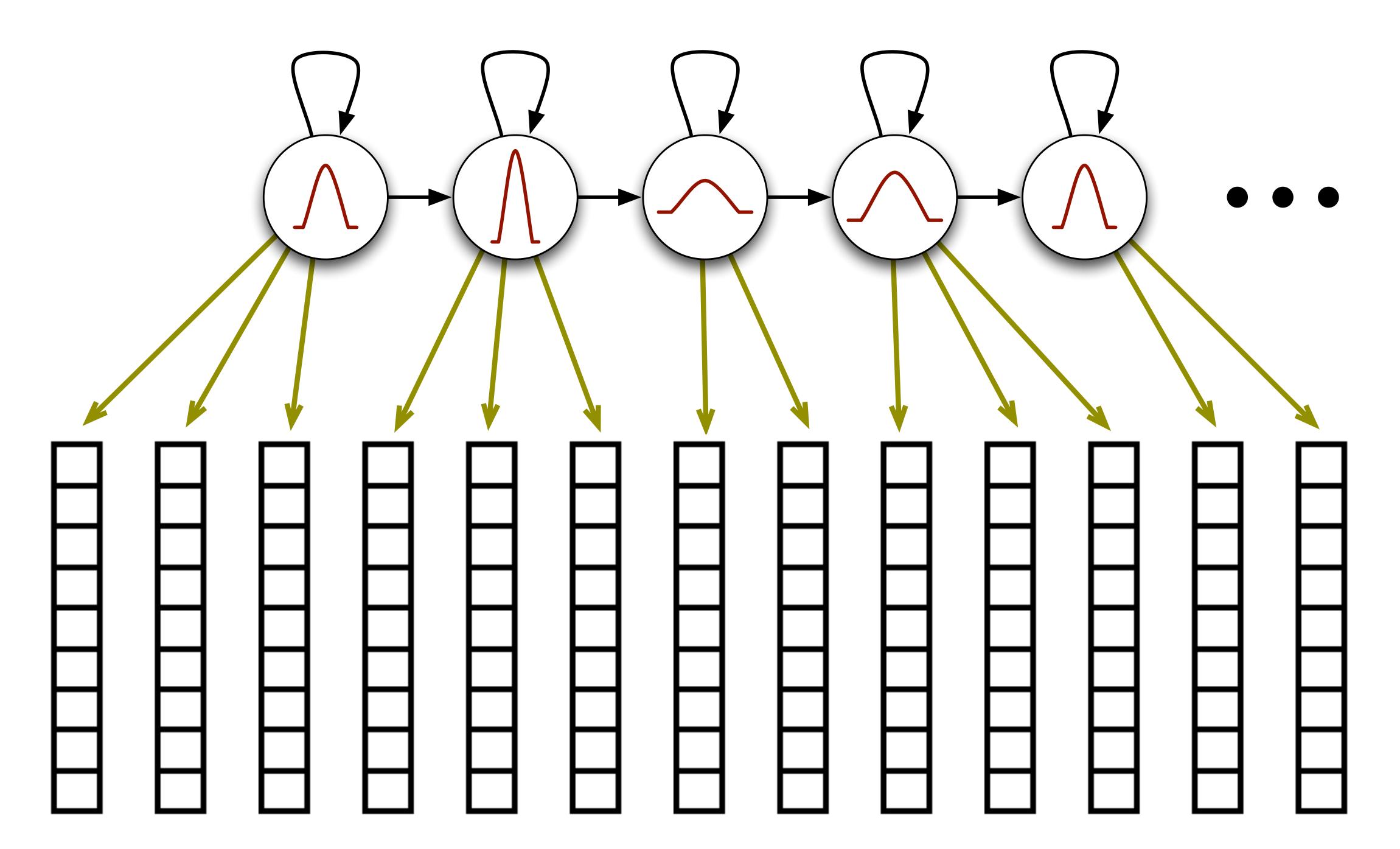


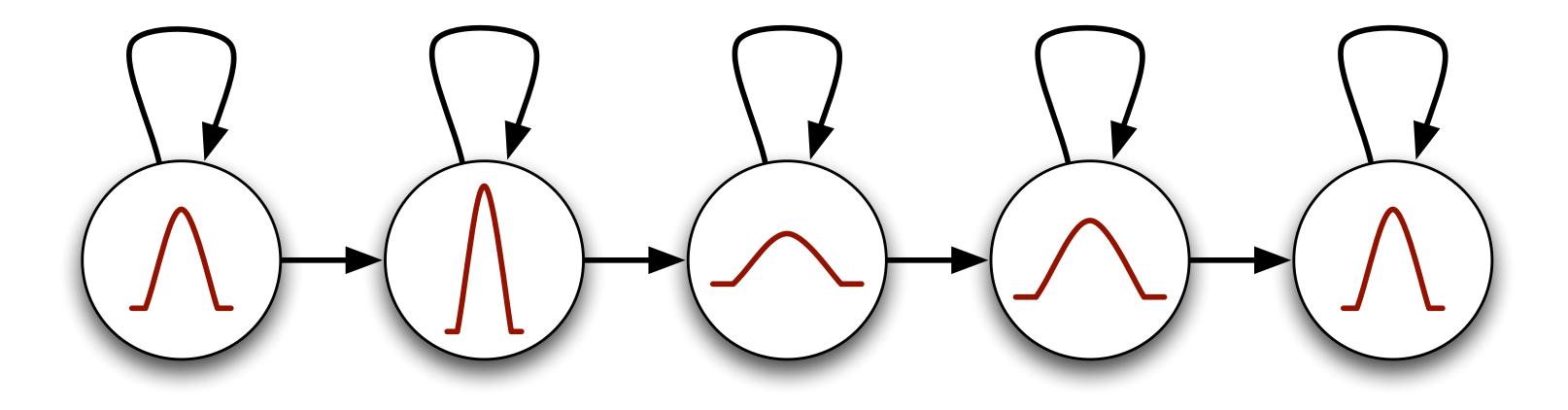
DYNAMIC PROGRAMMING (DTW)

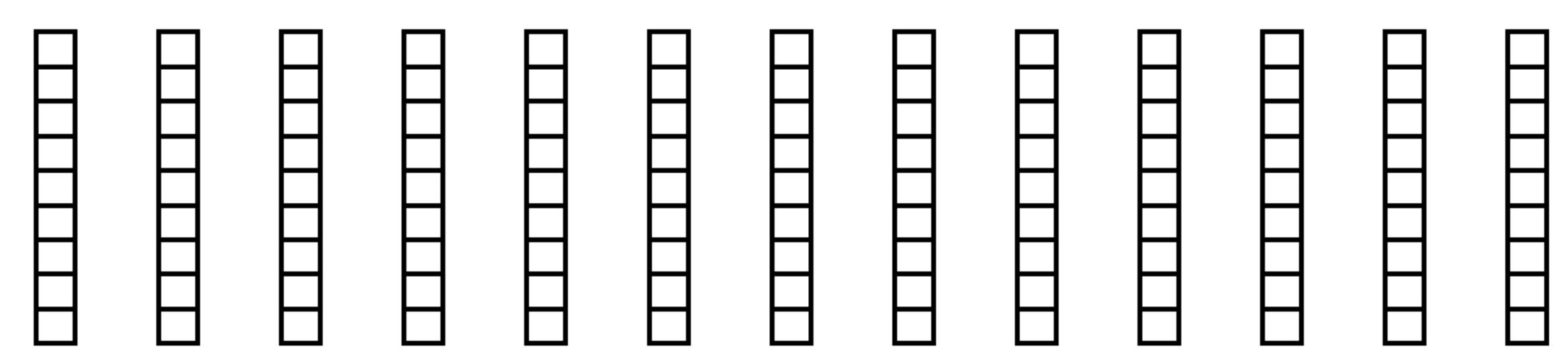


HIDDEN Markov Model

GENERATIVE MODEL OF SEQUENCES



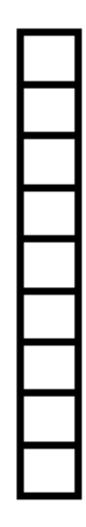


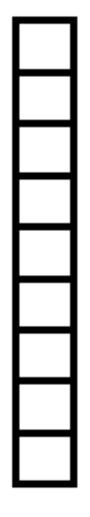


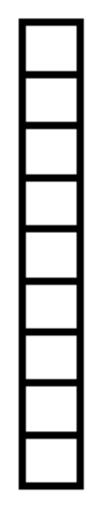












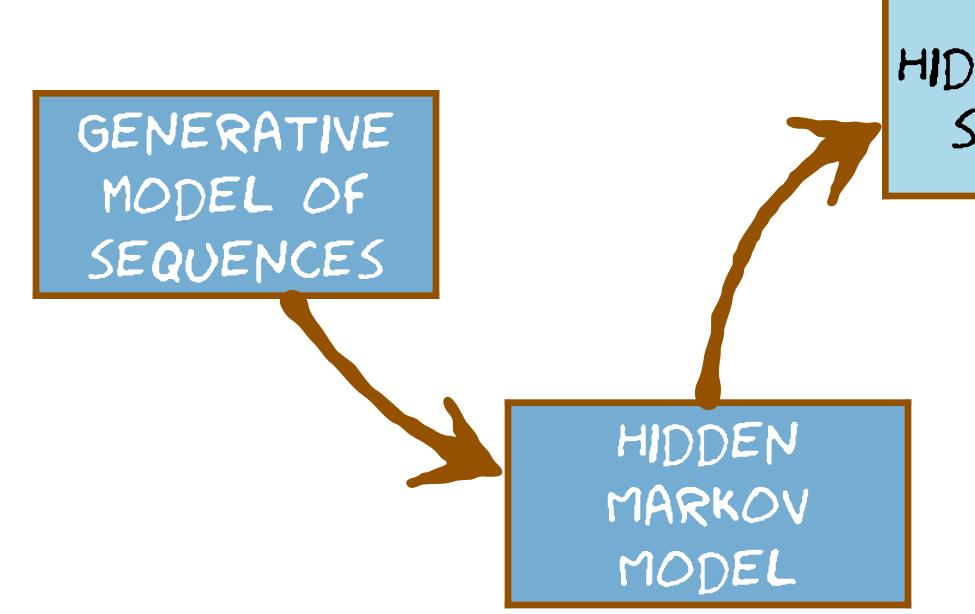




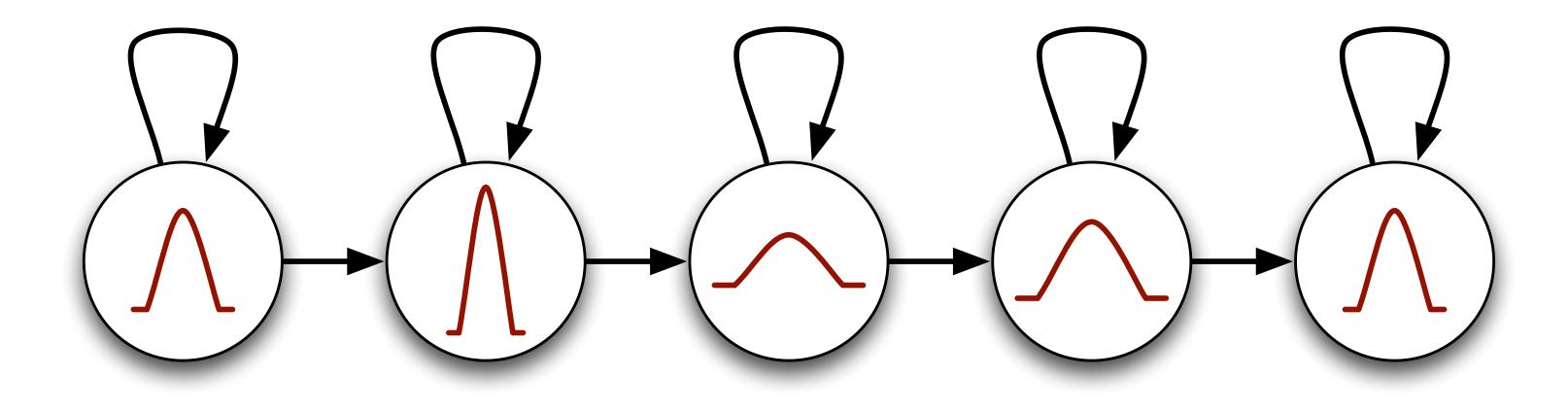


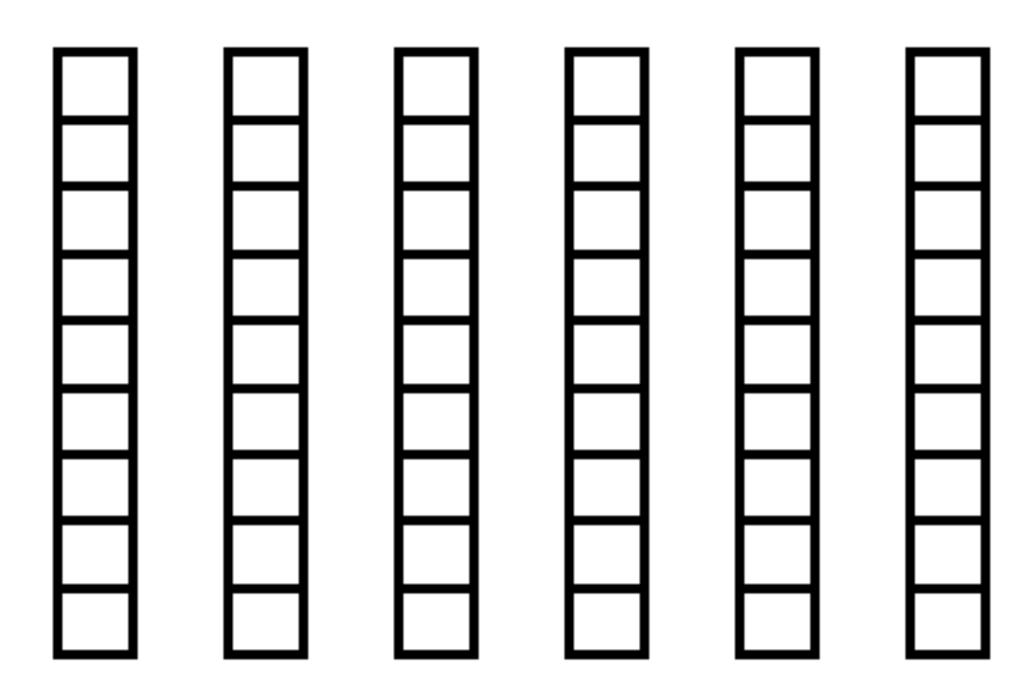
OOOOOOOOOOOOOOOOOOO

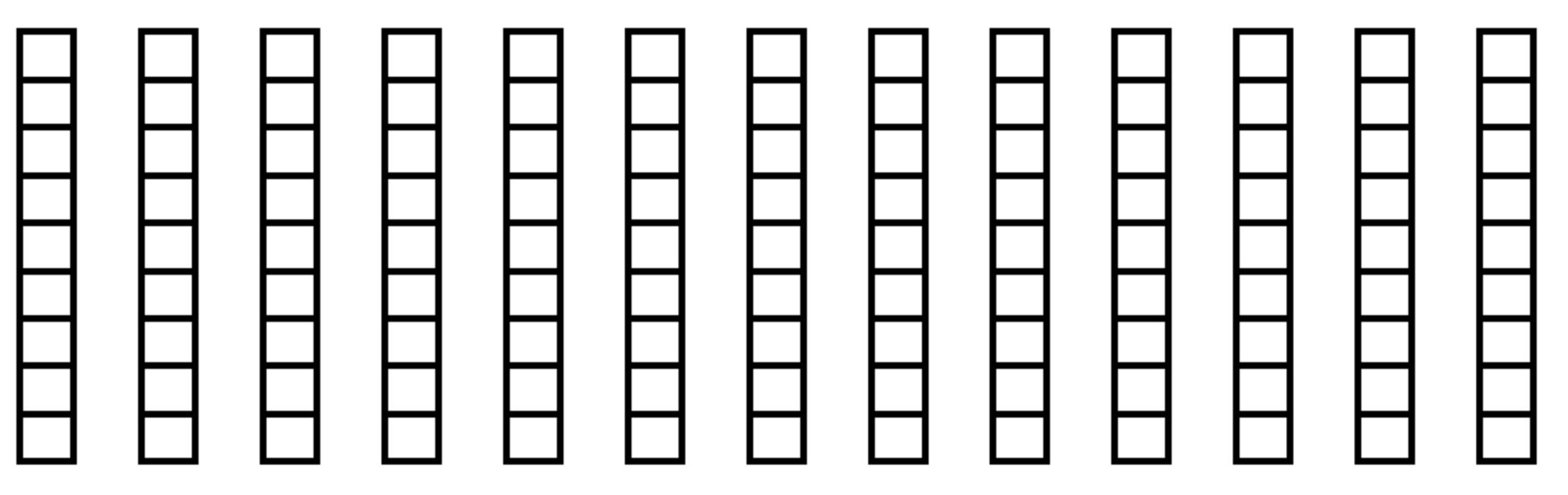
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HIDDEN STATE SEQUENCE



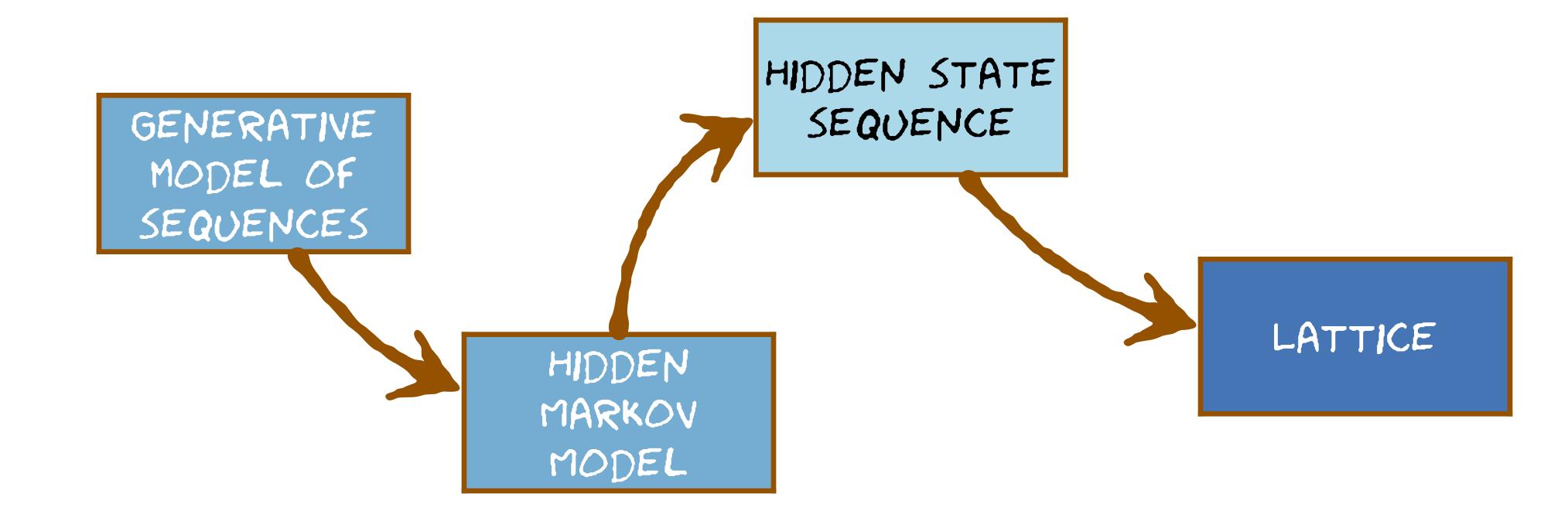


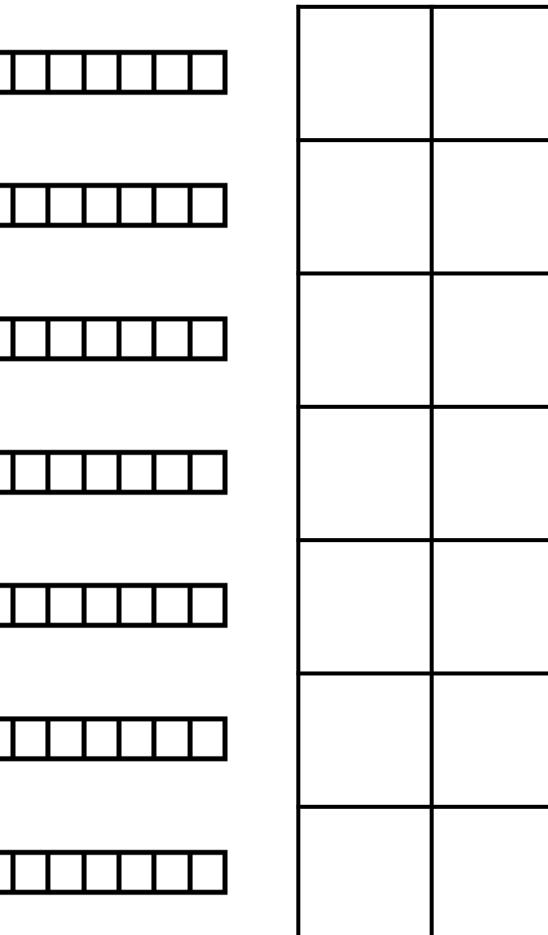


Hidden state sequence

P(O|model)

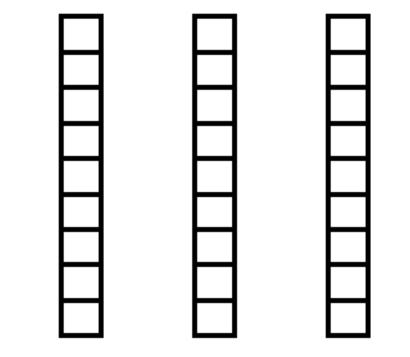
$P(\mathbf{O}, Q | \text{model})$





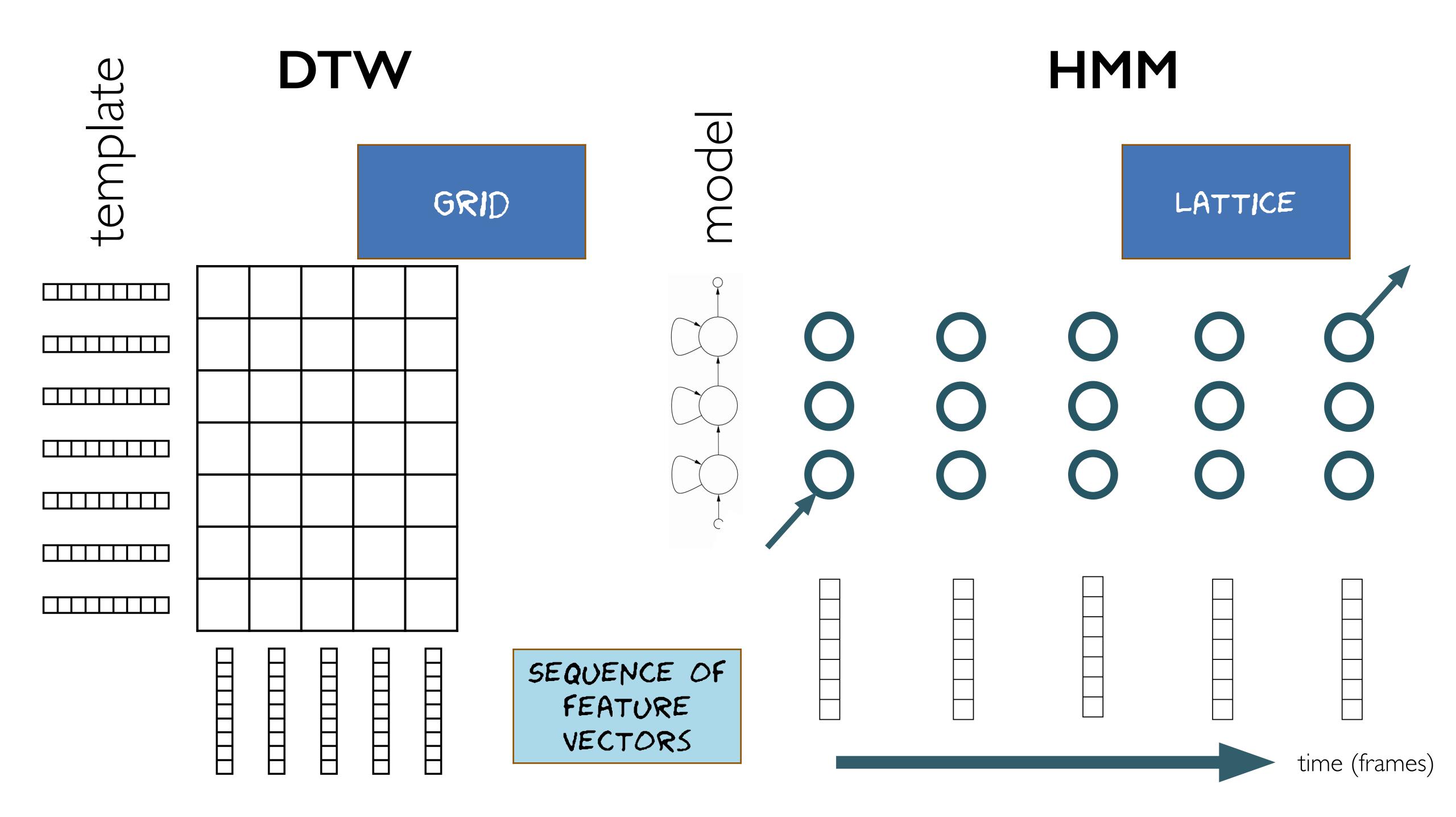


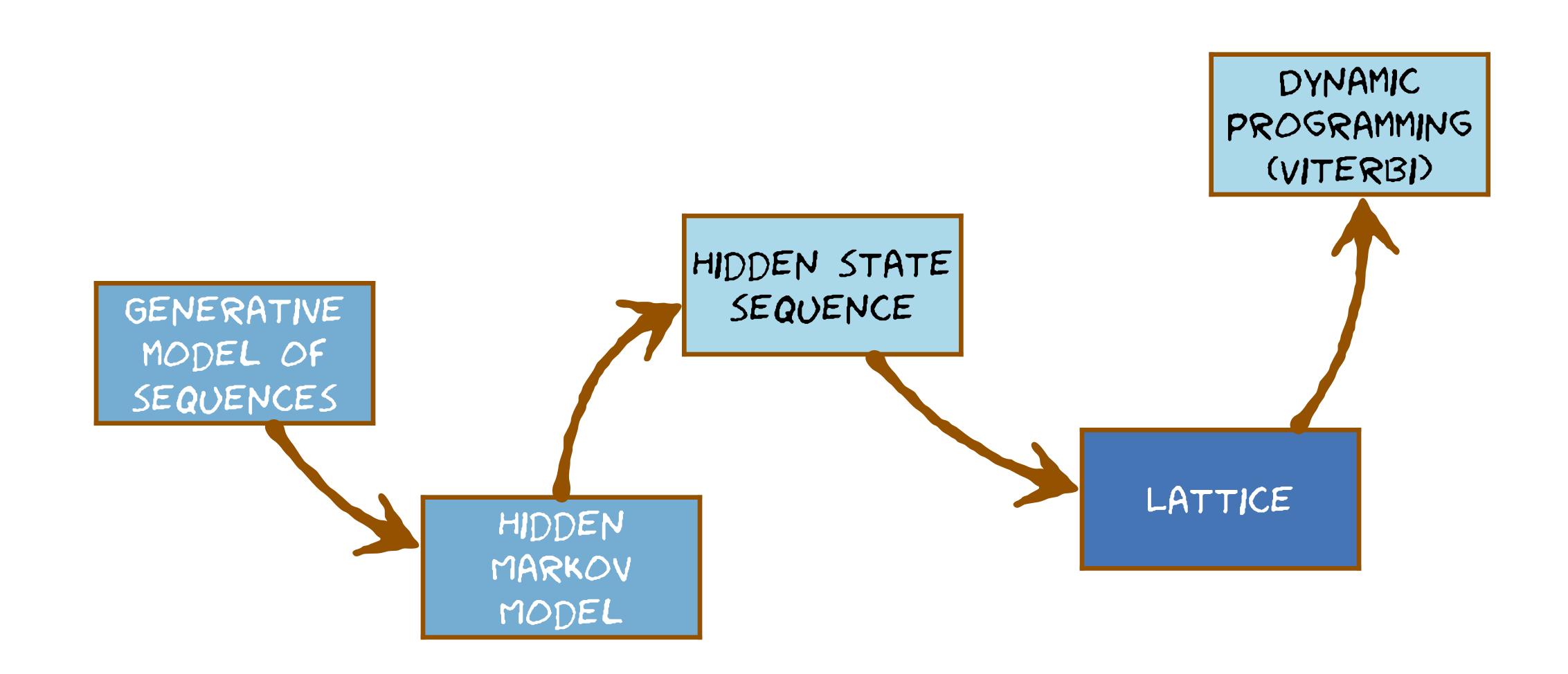




DYNAMIC PROGRAMMING (DTW)

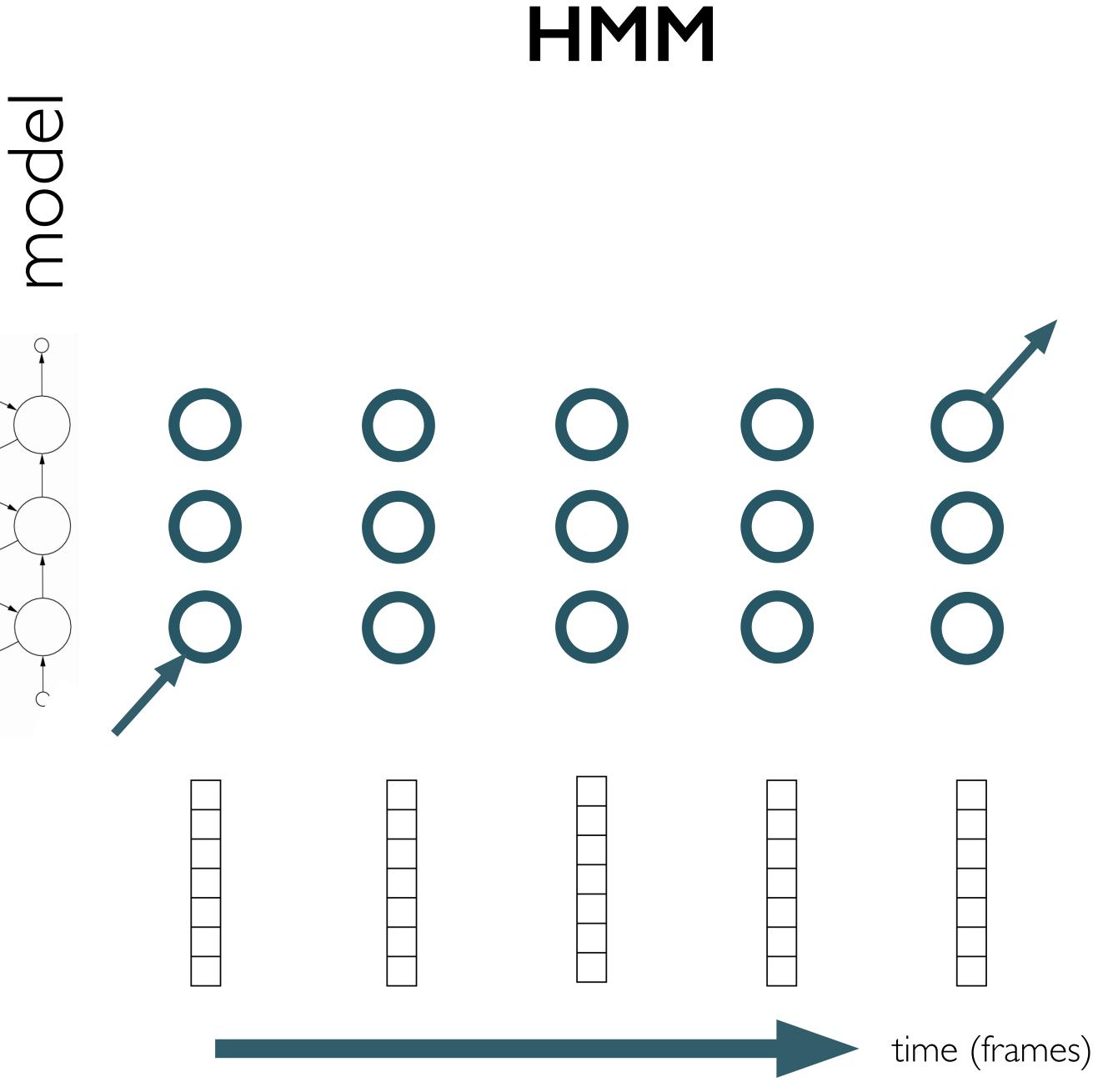






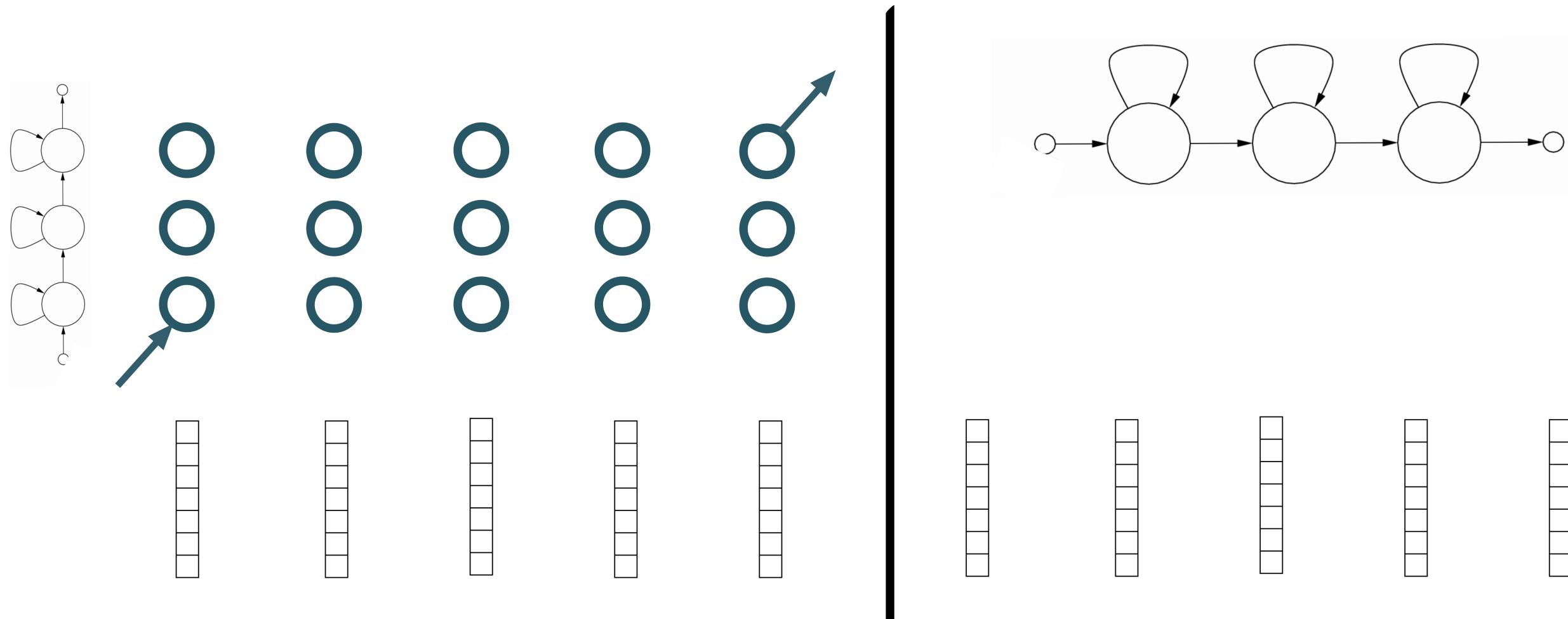
template

DTW



time	(f
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Two ways to implement the Viterbi algorithm



What next?

connected speech

• training the model from data

this extension will turn out to be quite easy we just need to add a language model

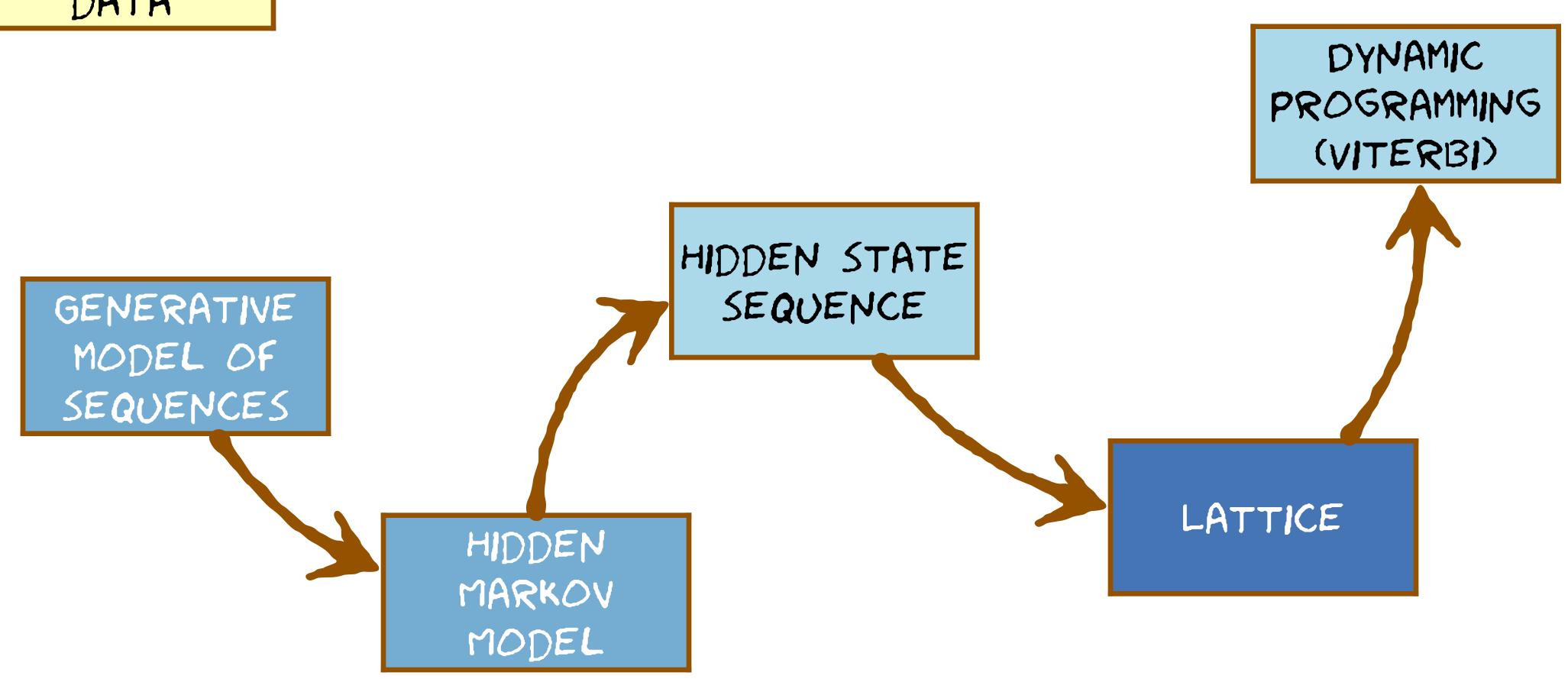
computationally, this is straightforward

but you may find it conceptually challenging

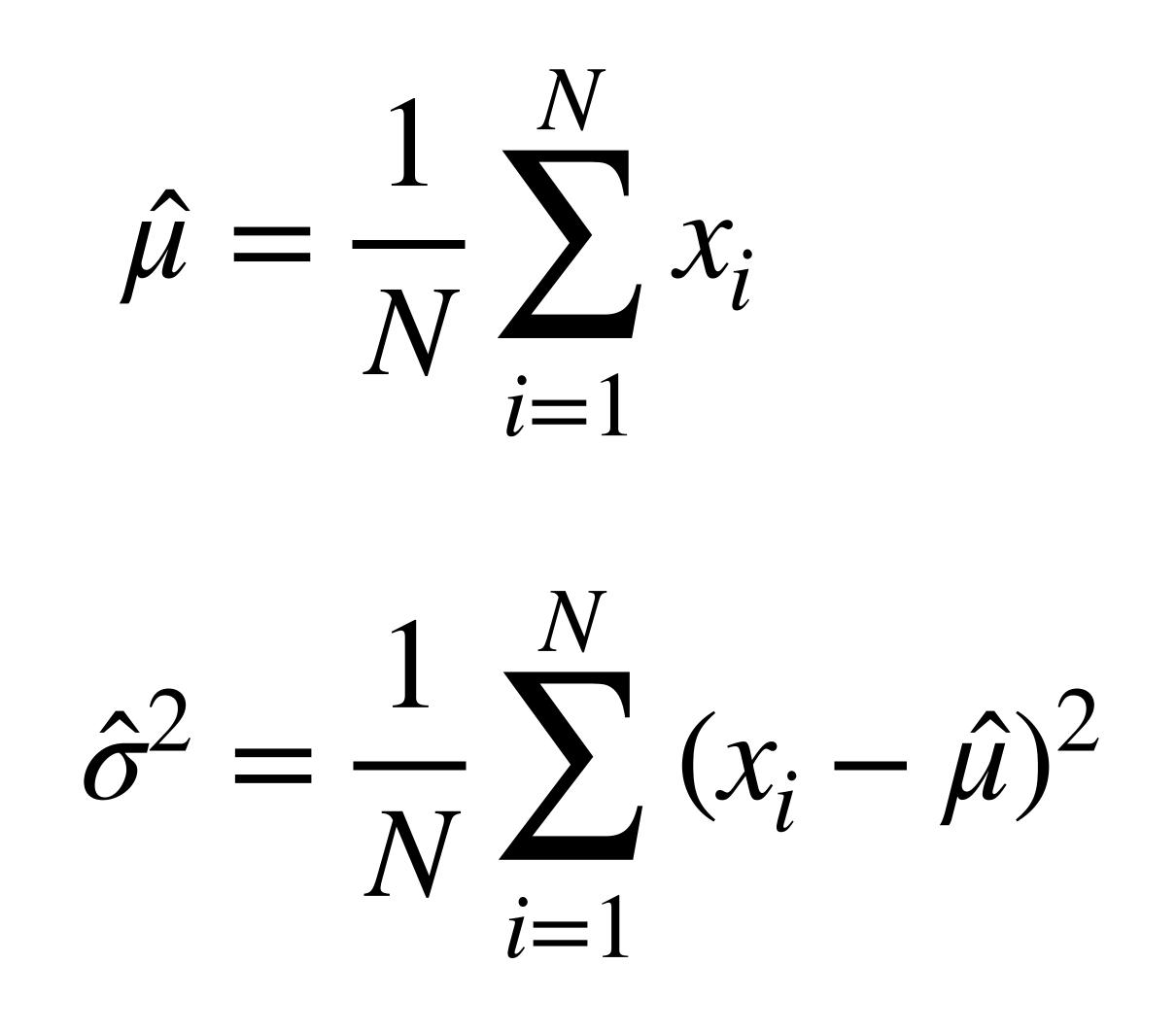




FITTING A GAUSSIAN TO DATA

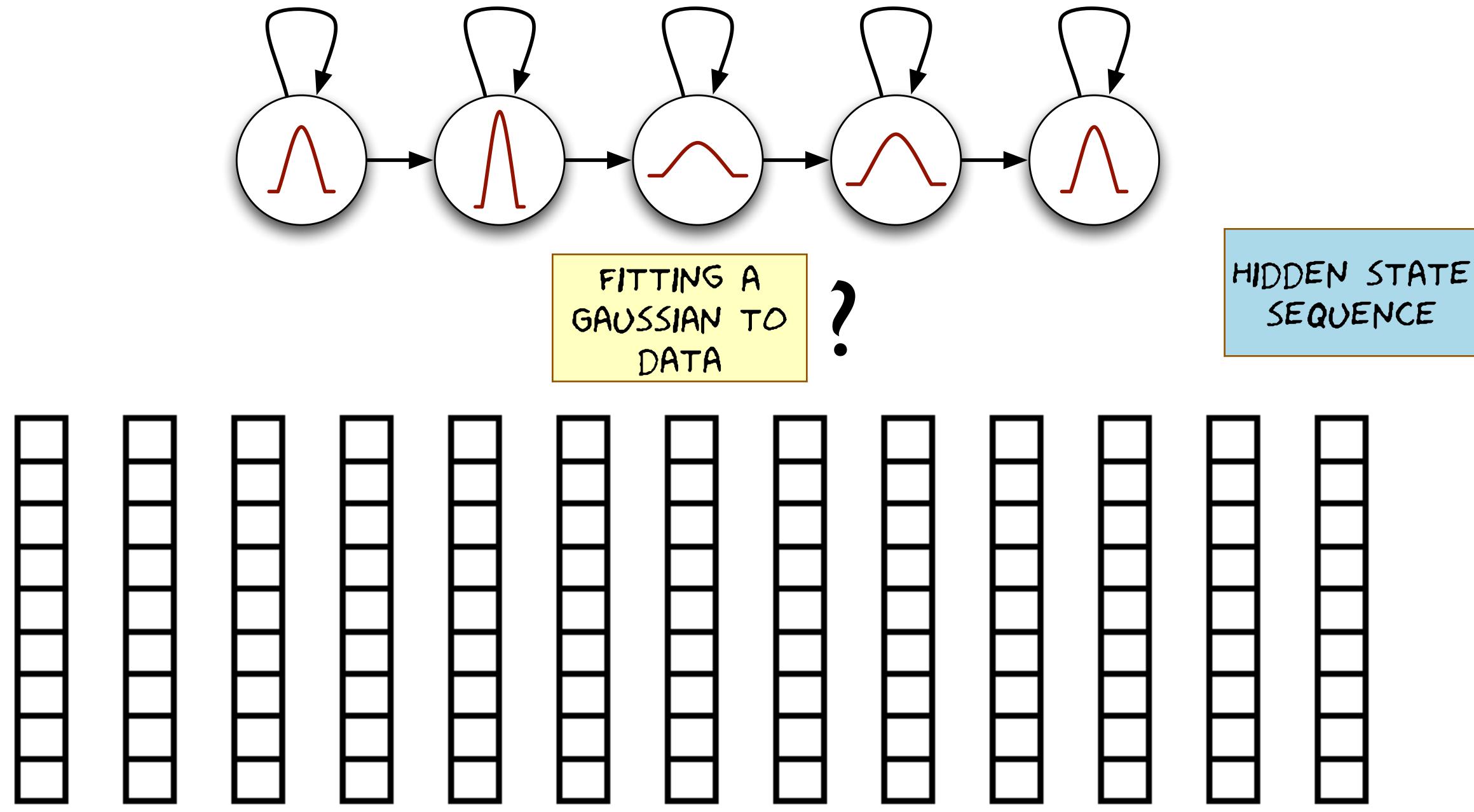


Fitting the Gaussian to data



 $(x-\mu)^2$ p(x) $-e^{-2\sigma^2}$





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