The problem

- Create a generative model and a learning algorithm that can learn high-dimensional complex sequence data
- There are many applications where the HMM and the LDS are not nearly powerful enough

Tractable sequence models

- HMM – has N^2 parameters and when generating data the hidden state only carries log N bits of information
- LDS – assumptions too unrealistic, data can rarely be explained linearly, seldom gaussian

Less tractable sequence models

- More powerful models with distributed hidden states need approximate inference for learning:
  - Particle filtering
  - Assumed density filtering
  - MCMC

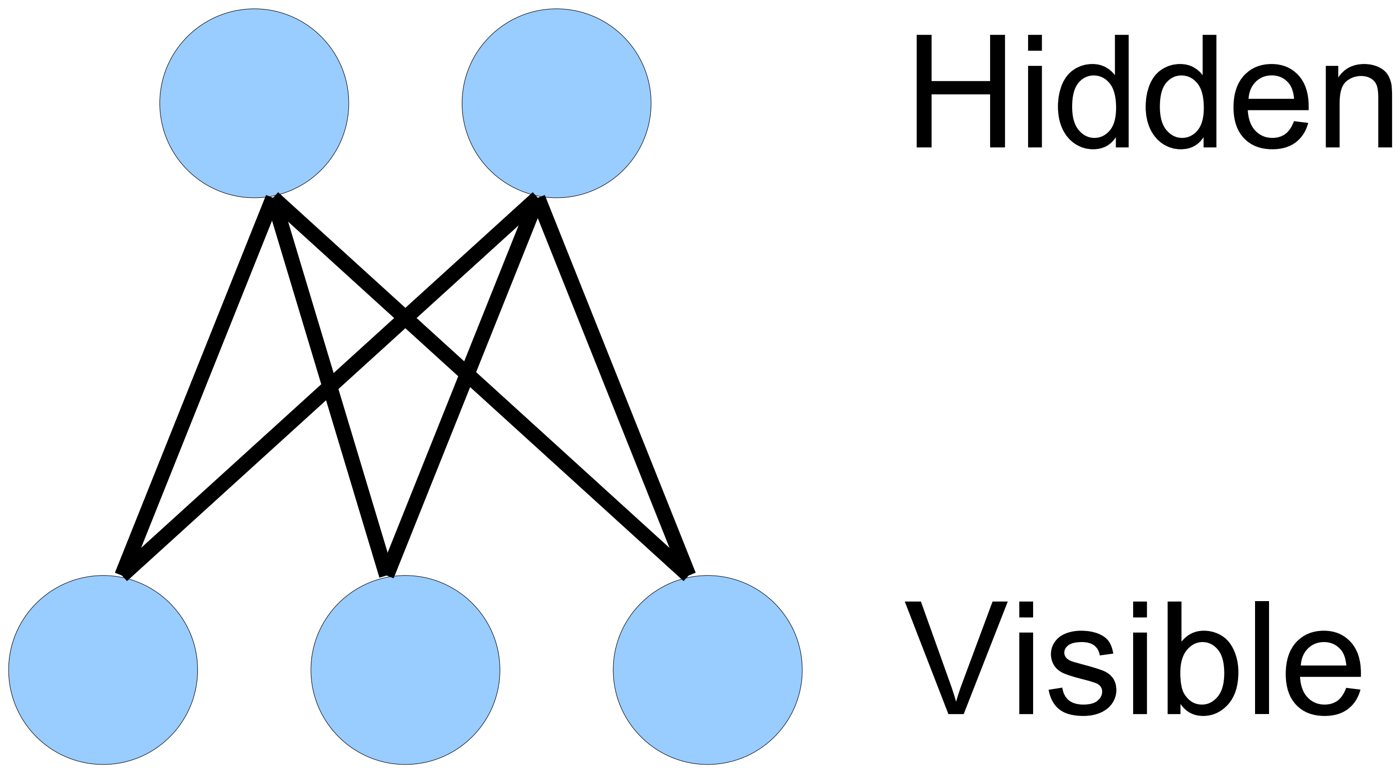
Our new model

- Built from the Restricted Boltzmann Machine (RBM)
- A casual sequence of RBMs
- Highly intractable, lost of approximations

The Restricted Boltzmann Machine

- Powerful model of binary data useful properties:
- Has an easy *exact* inference algorithm
- Has an efficient learning algorithm
- Has a natural hierarchical multilayered extension
  - This is a big win over other models

The Restricted Boltzmann Machine



- An undirected model
- Given V, H is factorial

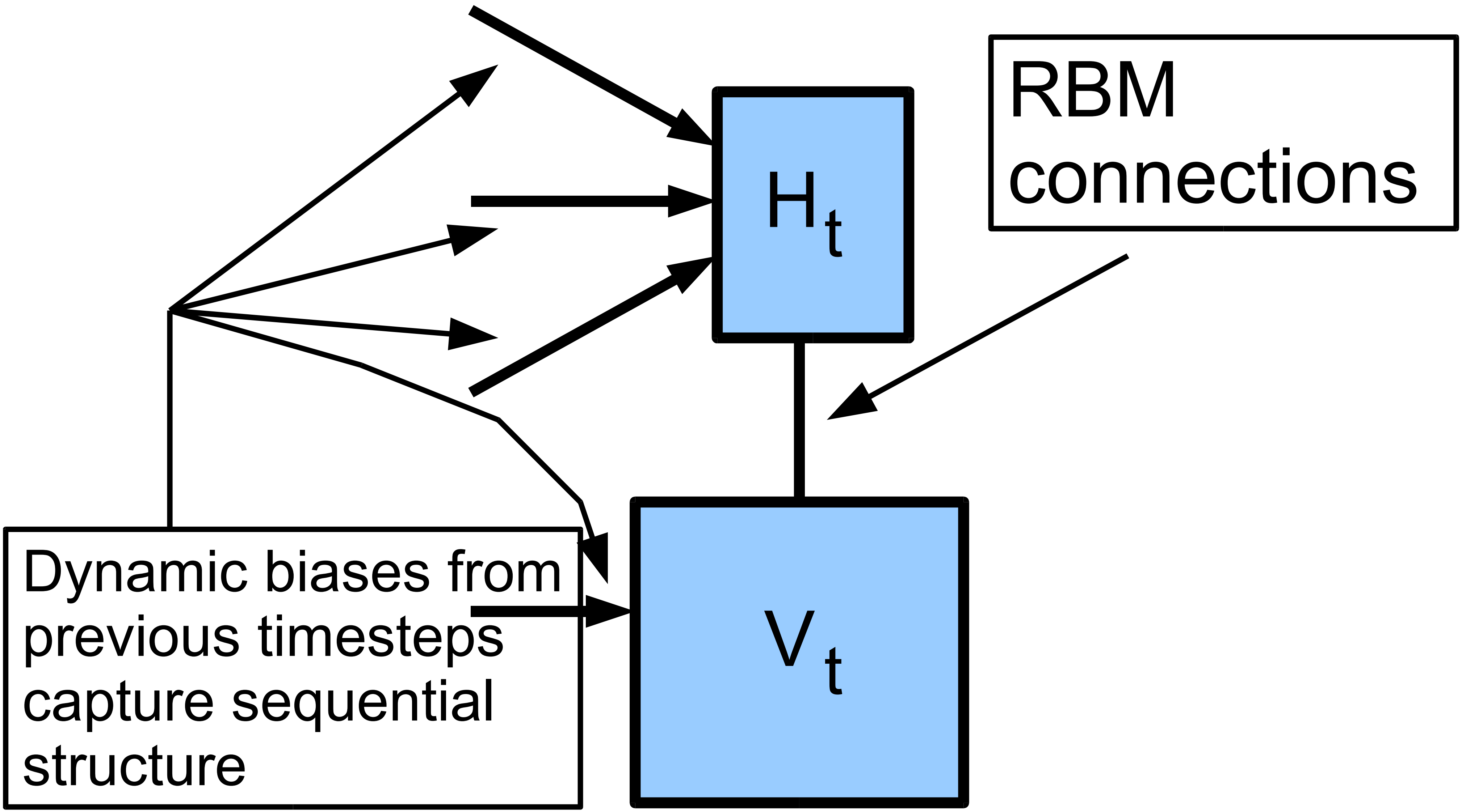
Goals:

- Construct a sequence model using RBM's
- The model should inherit some good qualities of the RBM

The Temporal Restricted Boltzmann Machine

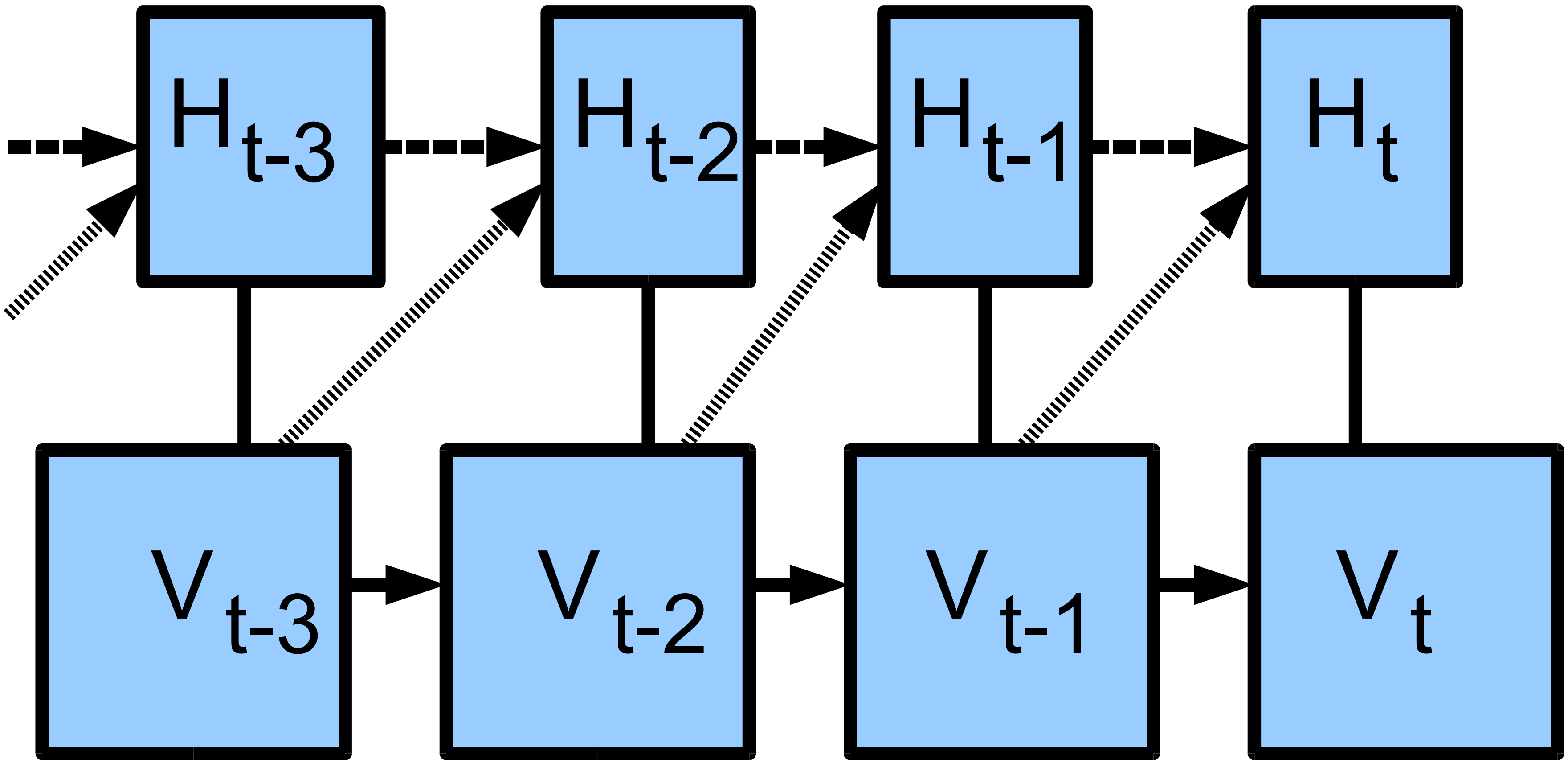
- Use an RBM to model each item in the sequence
- Connect the RBM's with directed connections
- The result: a hybrid directed/undirected model

The Temporal Restricted Boltzmann Machine



The Temporal Restricted Boltzmann Machine

- Each RBM has the same parameters



The Temporal Restricted Boltzmann Machine

- With the past fixed, the undirected observation model makes exact inference easy

Approximate filtering

- The distribution $P(H_T|V_1,\ldots,V_{T,}H_1,\ldots,H_{T-1})$ is factorial by definition
- This suggests: compute a factorial approximation to the filtering distribution
- Like a very simple form of Assumed Density Filtering

Approximate filtering

- Variables are binary in $\{0,1\}^N$
- A factorial distribution is in $[0,1]^N$
- $P(H_T|V_1,\ldots,V_{T,}H_1,\ldots,H_{T-1})$ is factorial, thus in $[0,1]^N$
- Use approx (μ_t is H_t's distribution): $\mu_T=P(H_T|V_1,\ldots,V_{T,}\mu_1,\ldots,\mu_{T-1})$ using mean-field equations

Learning

- Select a random training vector
- Sample from the approximate *filtering* distribution (no smoothing)
- Slightly increase the log likelihood of each RBM given the fully visible data (this is easy for the RBM's)
- Not variational because learning ignores change in approximate posterior

Multilayered Models

- We can introduce additional hidden layers to get a better representation
- The result: a slightly better generative model

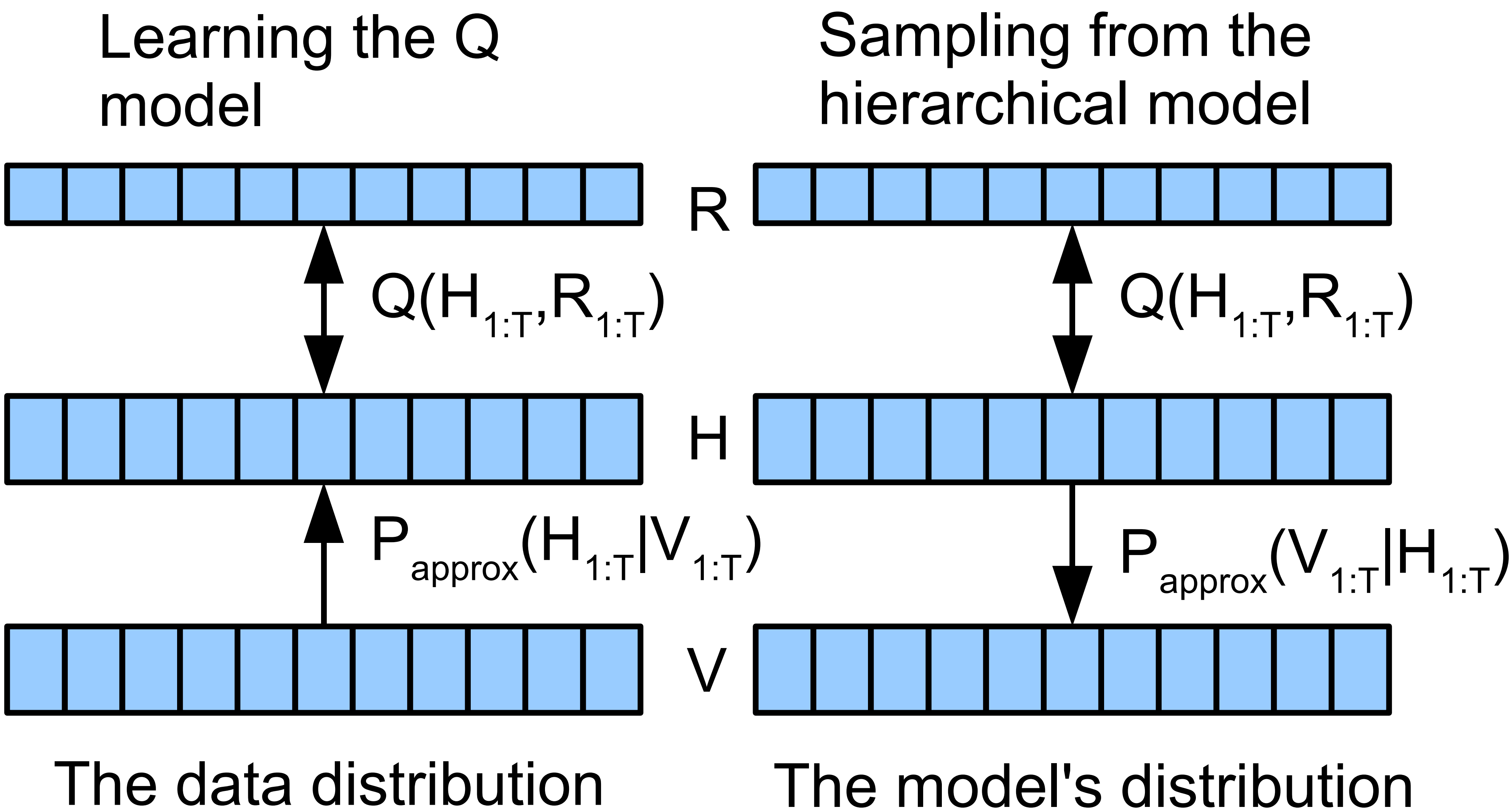
Multilayered TRBM's

- Using the idea of a multilayered RBM it is possible to add hidden layers to the TRBM model one layer at a time
- Has natural approximate inference
- Improves generative model

Multilayered TRBM's

- Use another TRBM Q to learn the aggregated approximate posterior: $P_{agg}(H_{1:T})=\Sigma_V P_{approx}(H_{1:T}|V_{1:T})D(V_{1:T})$
  - D is the data distribution
- To generate, sample $Q(H_{1:T})$, then sample $P(V_{1:T}|H_{1:T})$, approximately
- Can recurse for Q to make very deep models
- Has some variational justification

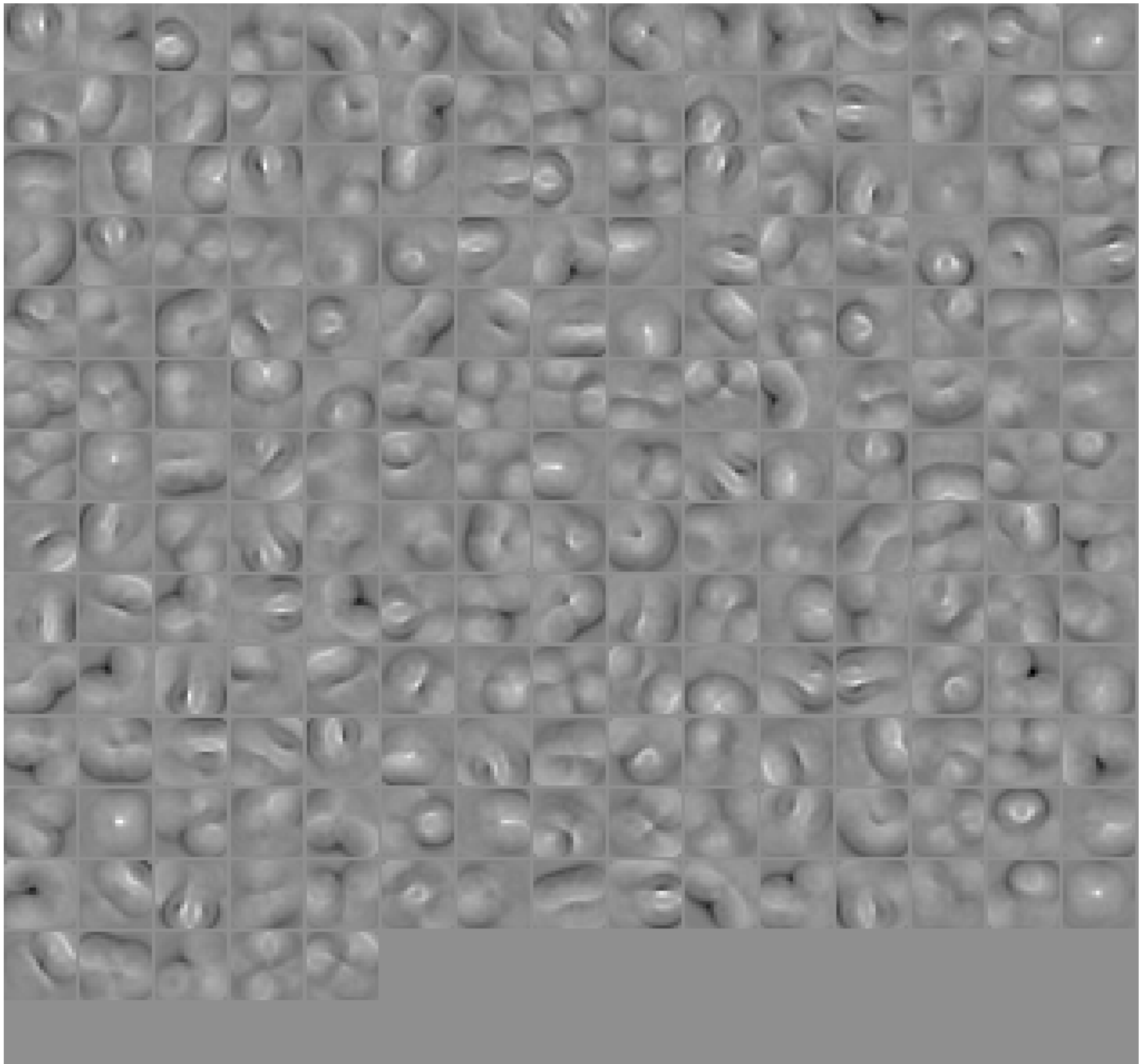
Multilayered TRBM's



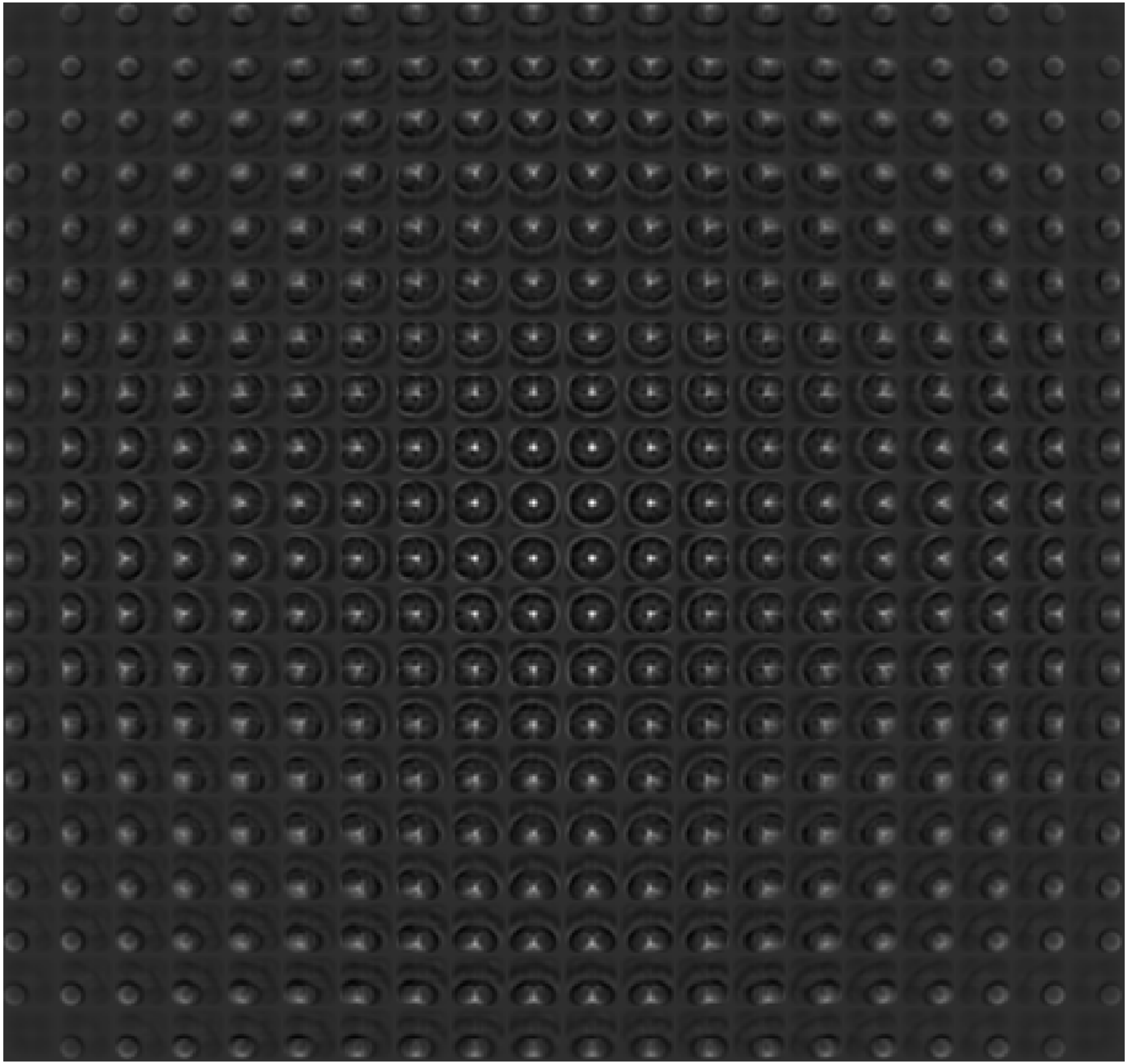
Finetuning

- The learned weights can be further finetuned by the Wake-Sleep algorithm (and doesn't hurt performance)

Visible-Hidden Connections



Visible-Visible Connections

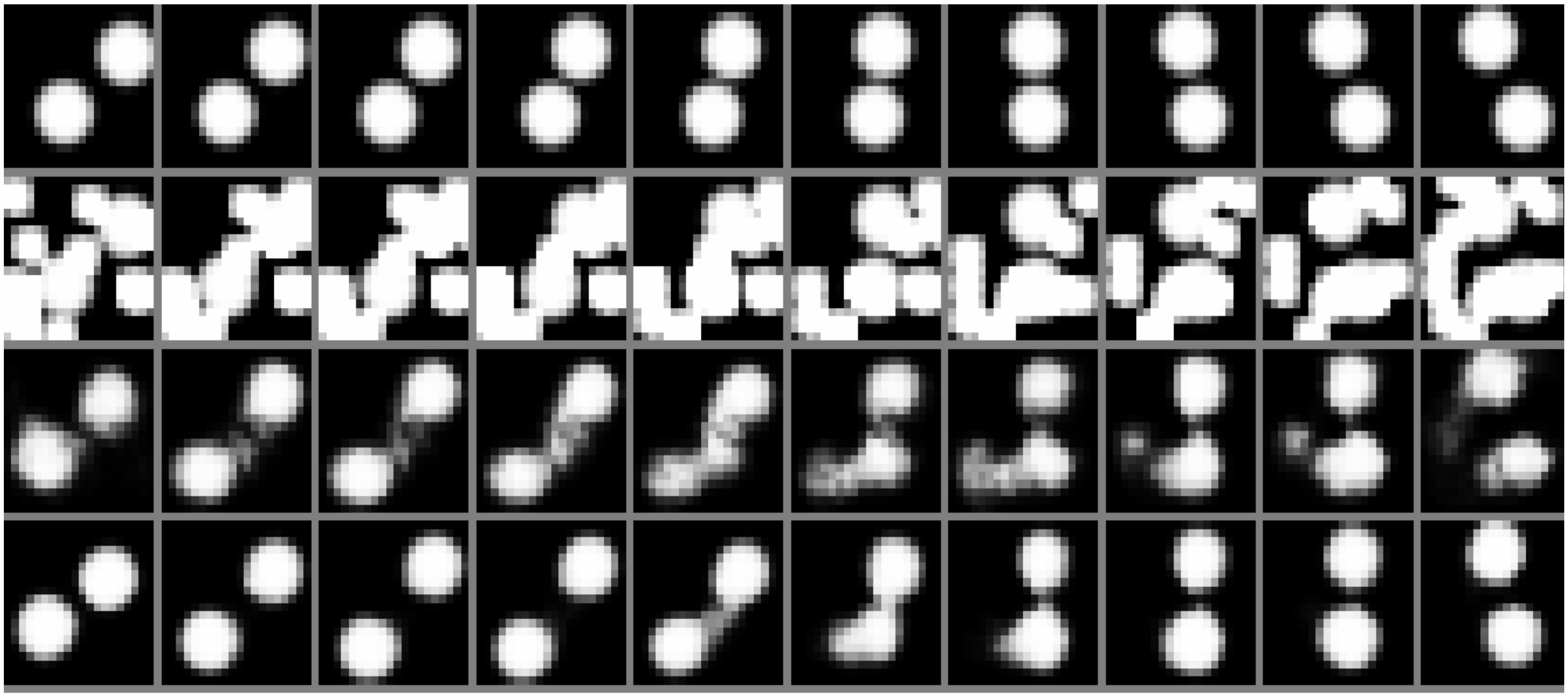


Questions?

Denoising using the TRBM

- The TRBM can be used to denoise:
  Reconstruct the noisy data from the hidden variables
- The TRBM denoises well, even though it was not “meant” for this task

Denoising Results



- Data
- Noise
- 1 hid
- 2 hid