Learning frameworks

Supervised learning

- Assumes environment specifies correct output (targets) for each input

Unsupervised learning

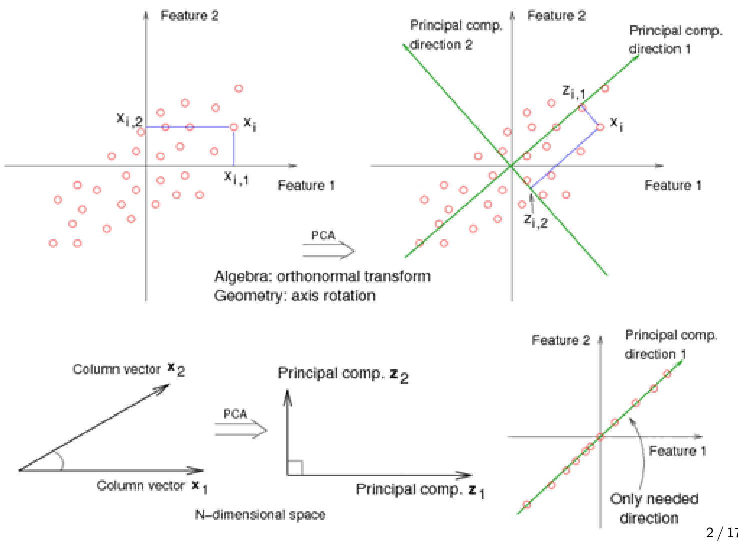
- Assumes environment only provides input; learning is based on capturing the statistical structure of that input (efficient coding)

Reinforcement learning

- Assumes environment provides evaluative feedback on actions (how good or bad was the outcome) but not what the correct/best action would have been

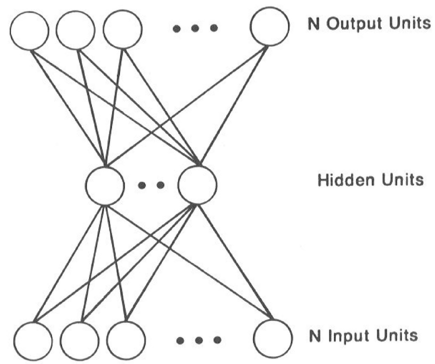
Efficient coding: Principal Components Analysis (PCA)

Recode high-dimensional data into smaller number of orthgonal dimensions that capture as much **variance** (information) as possible



Self-supervised learning: (Auto)encoder networks

- Network must copy inputs to outputs through a “bottleneck” (fewer hidden units)
- Hidden representations become a learned compressed code of the inputs/outputs
  - Capture systematic structure among full set of patterns
  - Due to bottleneck, don’t have capacity to overlearn idiosyncratic aspects of particular patterns
- For N linear hidden units, hidden representations span the same subspace as the first N principal components (≈ PCA)

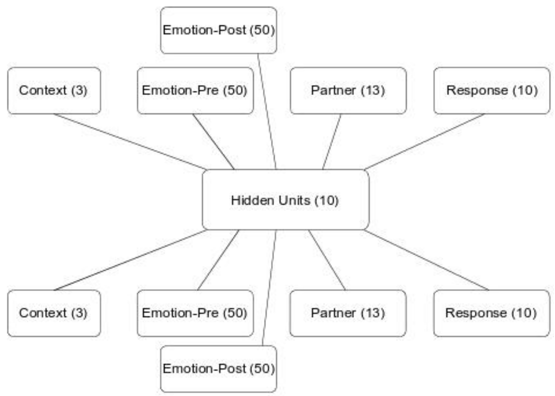


Autoencoder can approximate a recurrent network

Patterns can be multiple groups coding different types of information

- Can present all or only some of the information as input, and require network to generate all of the information as output [supervised]

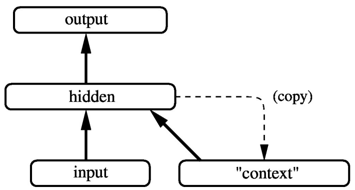
Social attachment learning
(Thrush & Plaut 2008)

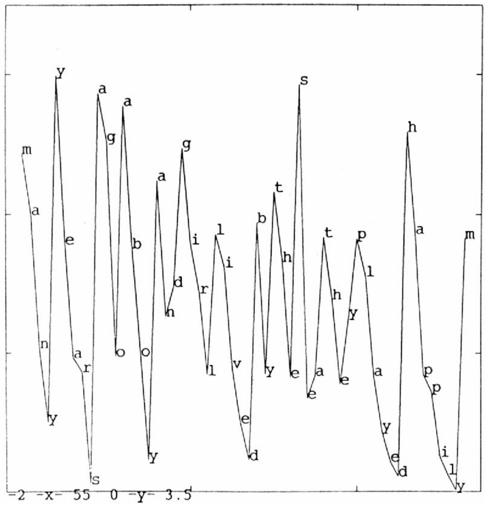


Self-supervised learning: Prediction

Simple recurrent (sequential) networks

- Target output can be prediction of next input

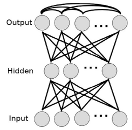




Boltzmann Machine learning: Unsupervised / generative version

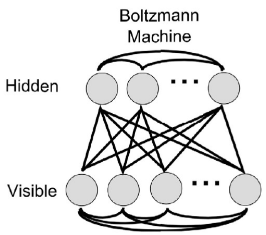
Supervised version

- **Negative phase**: Clamp inputs only; run hidden and outputs units [cf. forward pass]
- **Positive phase**: Clamp both inputs and outputs (targets); run hidden [cf. backward pass]



Unsupervised / generative version

- **Positive phase**: Visible units clamped to external input
  - analogous to *targets* in supervised version
- **Negative phase**: Network "free-runs" (nothing clamped)
- Network learns to make its free-running behavior look like its behavior when receiving input (i.e., learns to **generate** input patterns)

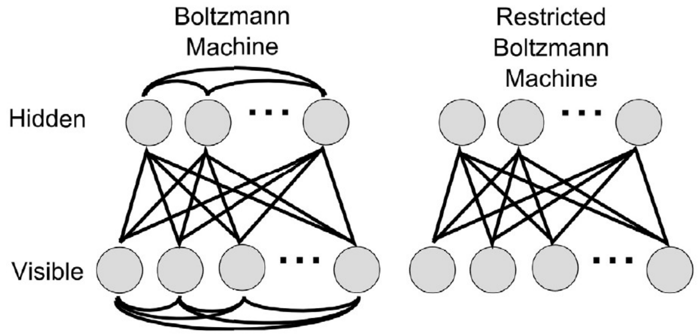


Objective function (unsupervised)

$$G = \sum_{\alpha} p^{+}(V_\alpha) \log \frac{p^{+}(V_\alpha)}{p^{-}(V_\alpha)}$$

$$\left[G = \sum_{\alpha,\beta} p^{+}(I_\alpha, O_\beta) \log \frac{p^{+}(O_\beta | I_\alpha)}{p^{-}(O_\beta | I_\alpha)} \right]$$

Restricted Boltzmann Machines



- No connections among units within a layer; allows fast settling
- Fast/efficient learning procedure
- Can be stacked; successive hidden layers can be **learned incrementally** (starting closest to the input) (Hinton)

Hinton's handwritten digit generator/recognizer

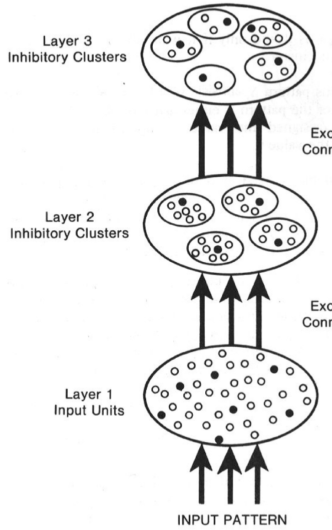
- Multilayer generative model trained on handwritten digits (generates image and label)
- Final recognition performance fine-tuned with back-propagation

Competitive learning

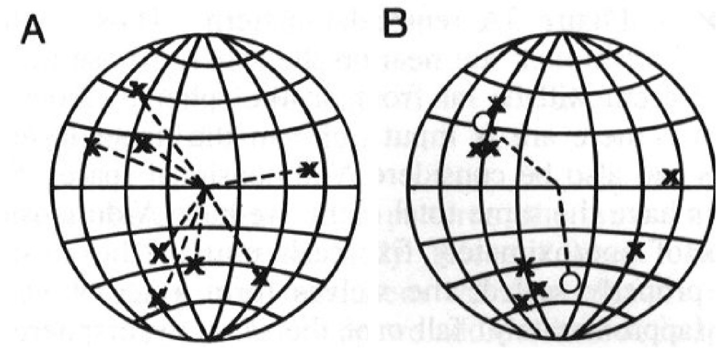
- Units in a layer are organized into non-overlapping cluster of competing units
- Each unit has a fixed amount of total weight to distribute among its input lines (usually $\sum_i w_{ij} = 1$)
- All units in a cluster receive the same input pattern
- The most active unit in a cluster shifts weight from inactive to active input lines:

$$\Delta w_{ij} = \epsilon \left(\frac{a_i}{\sum_k a_k} - w_{ij} \right)$$

- Units gradually come to respond to clusters of similar inputs



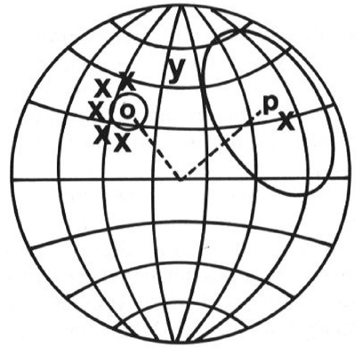
Competitive learning: Geometric interpretation



Competitive learning: Recovering “lost” units

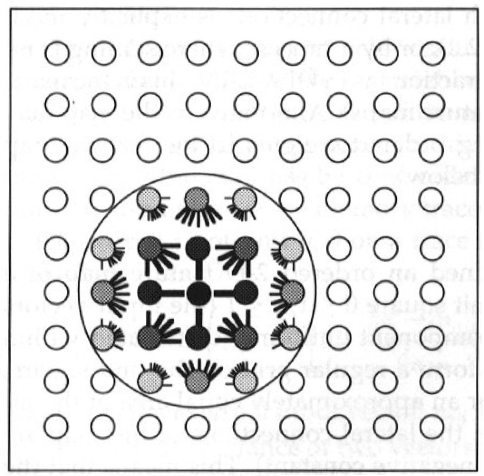
Problem: poorly initialized units (far from any input) will *never* win competition and so will never adapt

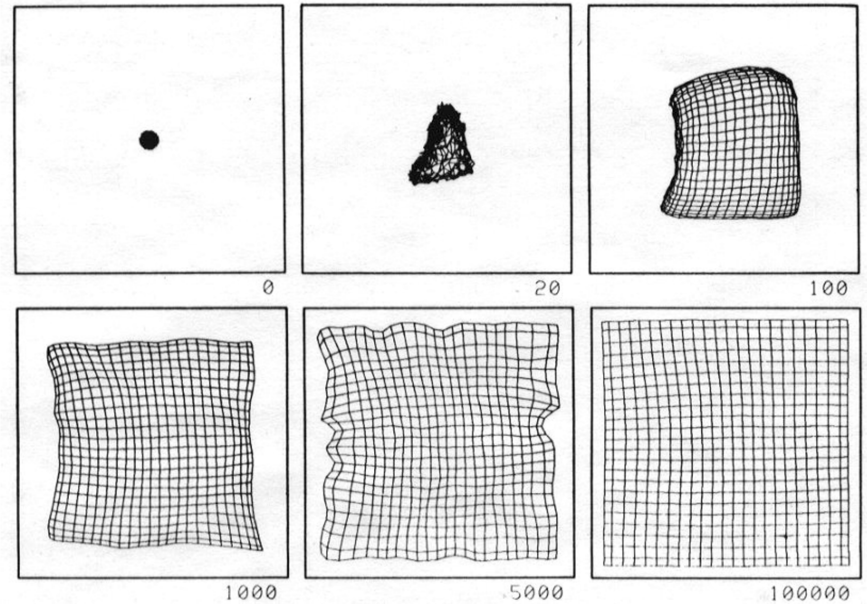
Solution: Adapt losers as well (but with much smaller learning rate); all units eventually drift towards input patterns and start to win

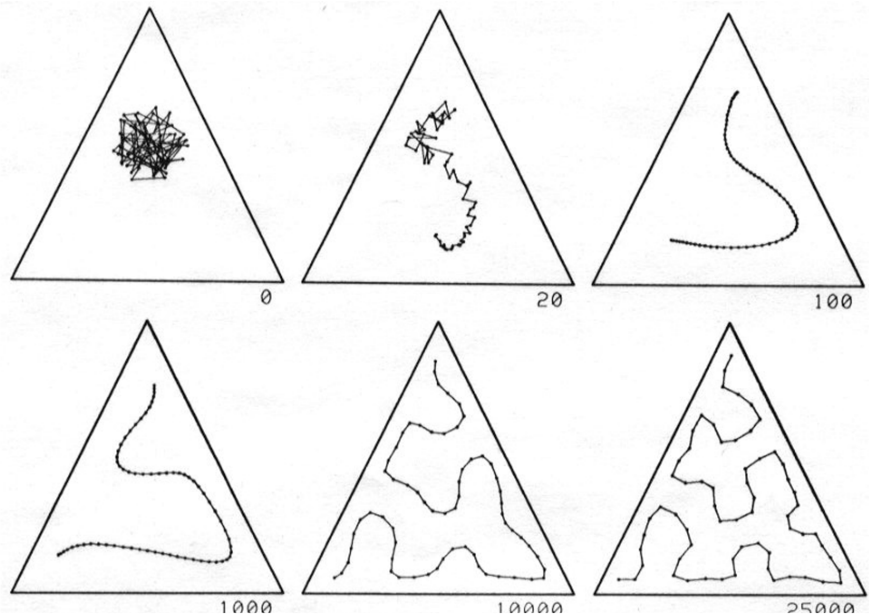


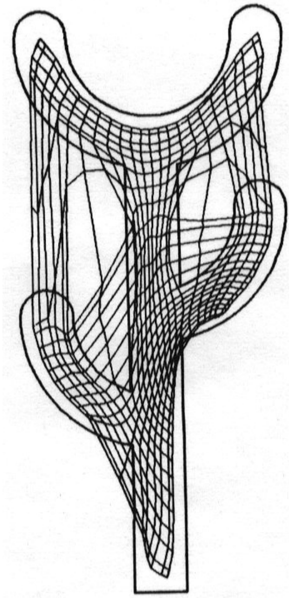
Self-Organizing Maps (SOMs)/Kohonen networks

- Extension of competitive learning in which competing units are topographically organized (usually 2D)
- Neighbors of “winner” also update their weights (usually to a lesser extent), and thereby become more likely to respond to similar inputs
- Input space similarity gets mapped onto (2D) topographic unit space

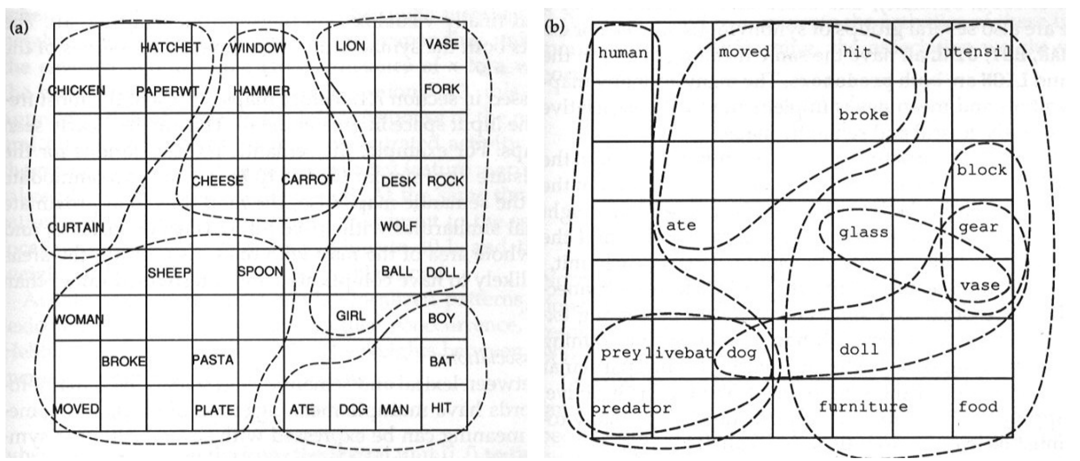








Lexical representations



World Bank poverty indicators (1992)