New Applications

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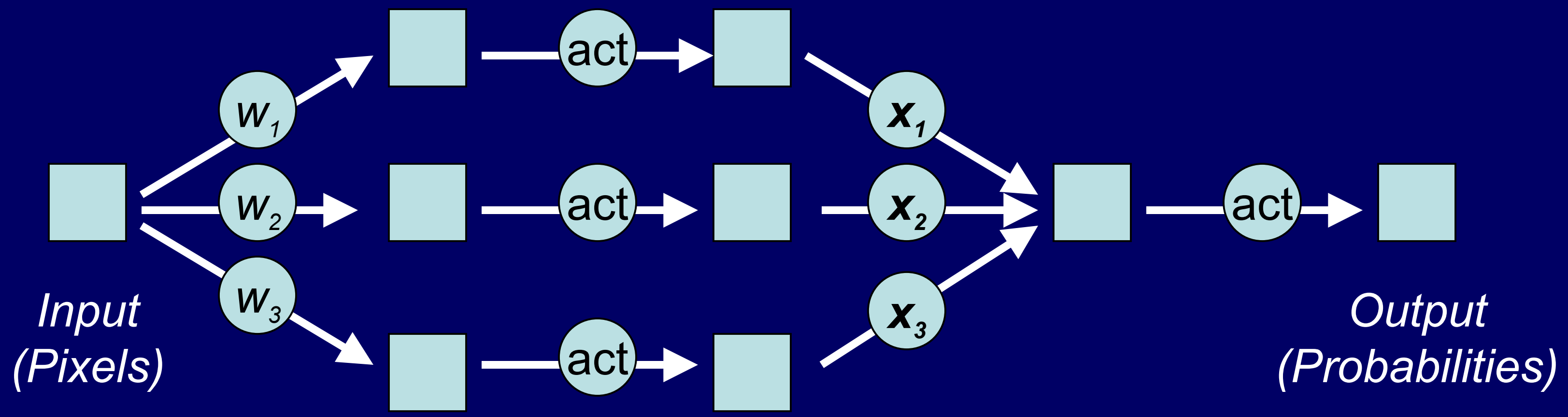
Neural Networks

- Commercial Use
  - Handwriting recognition
    - Mail Sorting
    - User Interface
- Research Use
  - Network Design (Compute Heavy)
    - Training on large datasets
    - Parameter search

Neural Networks

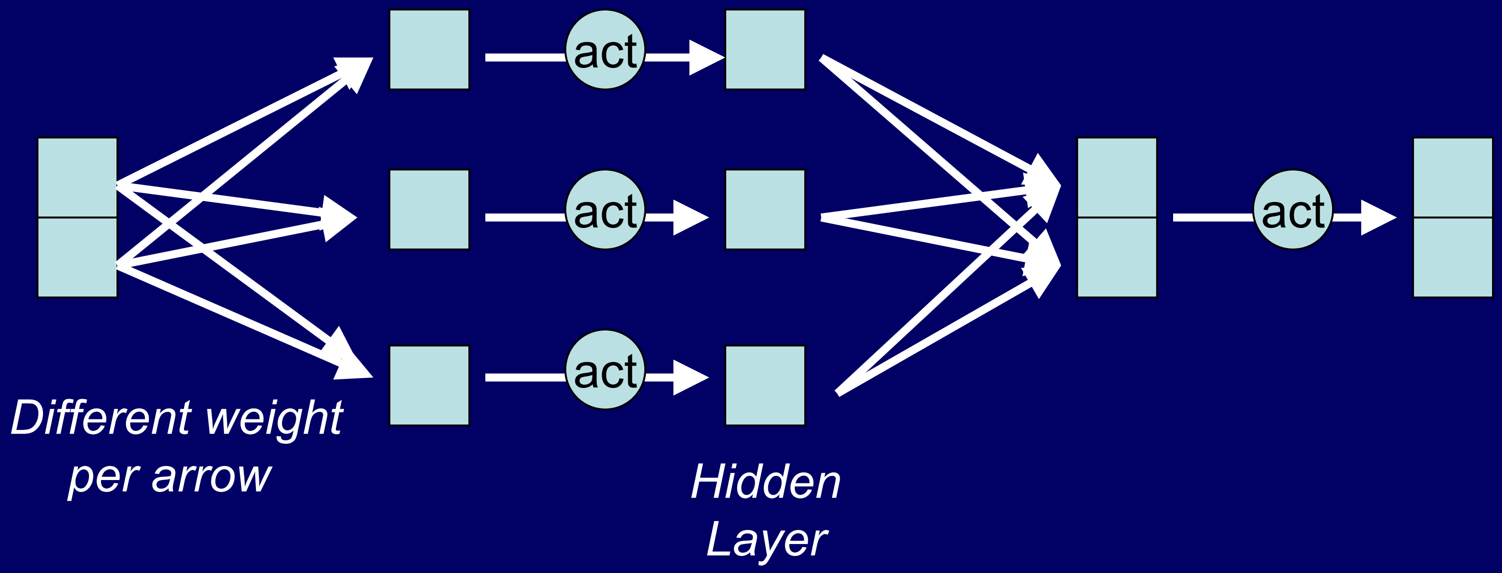


Hidden
Layer

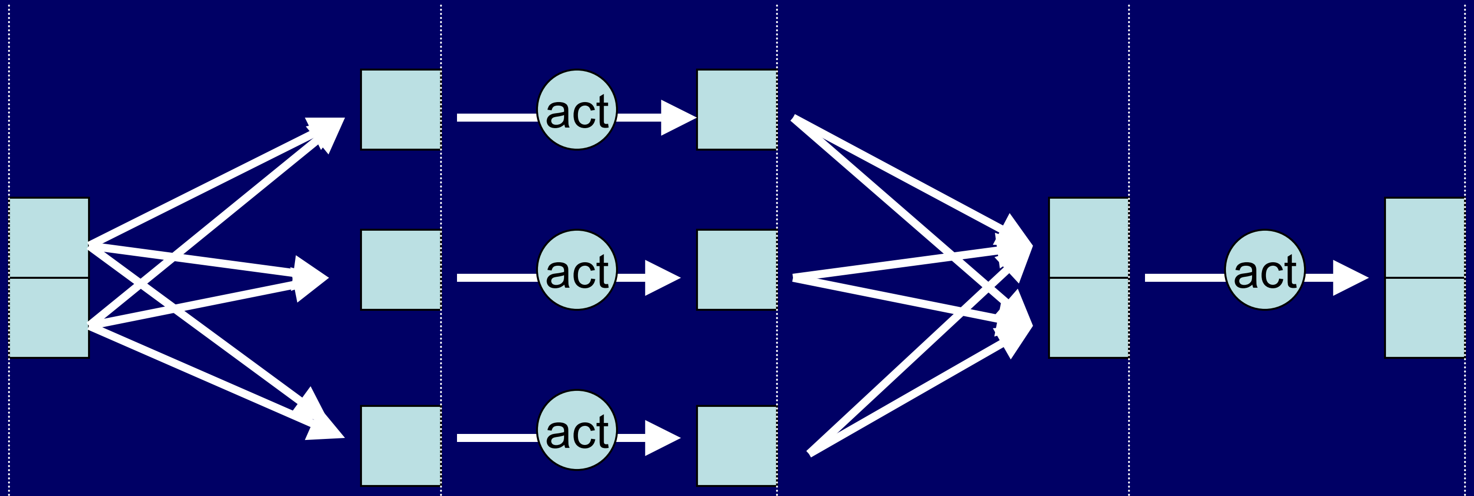
Any non-linear mapping function tanh(), sigmoid()

Chapter 20, Russel, Norvig

Neural Networks



Neural Networks



*Matrix * Vector*

a = W in

Function Map

*Matrix * Vector*

Function Map

Backward Propagation Learning

- Iterative process over learning samples
- Weight Matrix Update

  $W_{i,j} \mathrel{+}= \alpha * a_j * \Delta_i$

- Error Propagation

  $\Delta_j = act'(in_j)\, W^T \Delta_i$

Brook

- Efficient linear algebra implementation
  - Matrix * vector

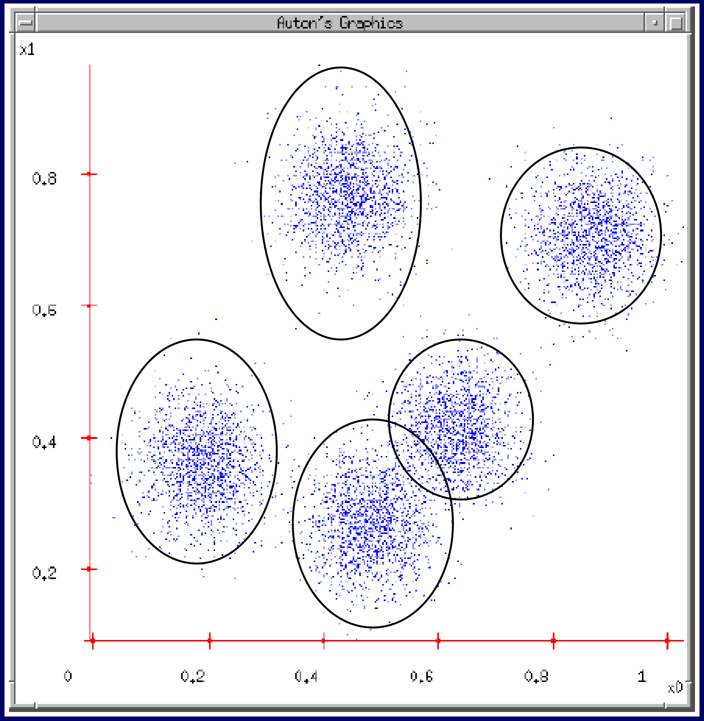
```
for (i=0; i<rows; i++)
  … dot product reduce …
```

  - Need for multi-dimensional reductions
    - Reduce to stream

`float a<100,200>` **`float b<100,1>`**

Gaussian Mixture Models

- Given a set of nD data
- Fit m nD gaussians



$$p(\mathbf{x}|\Theta) = \sum_{i=1}^{M} \alpha_i p_i(\mathbf{x}|\theta_i)$$

$$\theta = (\mu, \Sigma)$$

Gaussian Mixture Models

- Applications
  - Speech
    - Phoneme detector
    - Speaker identification
  - Vision
    - Skin detection
  - Sales and Marketing
    - Searching for sales trends

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Big Data Problems

Algorithm

- Expectation Maximization (EM) Algorithm

$$p(\mathcal{X}|\Theta) = \prod_{i=1}^{N} p(\mathbf{x}_i|\Theta) = \mathcal{L}(\Theta|\mathcal{X}).$$

$$\Theta^* = \underset{\Theta}{\operatorname{argmax}} \; \mathcal{L}(\Theta|\mathcal{X}).$$

$$\Theta = (\mu, \sigma^2 \; \alpha)$$

Blimes, *A Gentle Tutorial of the EM algorithm and its Application to Parameter Estimation for Gaussian Mixture and Hidden Markov Models*

EM Algorithm

Iterative Algorithm

$$p_\ell(x|\mu_\ell, \Sigma_\ell) = \frac{1}{(2\pi)^{d/2}|\Sigma_\ell|^{1/2}} e^{-\frac{1}{2}(x-\mu_\ell)^T \Sigma_\ell^{-1}(x-\mu_\ell)}.$$

$$\alpha_\ell^{new} = \frac{1}{N}\sum_{i=1}^{N} p(\ell|x_i, \Theta^g)$$

$$\mu_\ell^{new} = \frac{\sum_{i=1}^{N} x_i p(\ell|x_i, \Theta^g)}{\sum_{i=1}^{N} p(\ell|x_i, \Theta^g)}$$

$$\Sigma_\ell^{new} = \frac{\sum_{i=1}^{N} p(\ell|x_i, \Theta^g)(x_i - \mu_\ell^{new})(x_i - \mu_\ell^{new})^T}{\sum_{i=1}^{N} p(\ell|x_i, \Theta^g)}$$

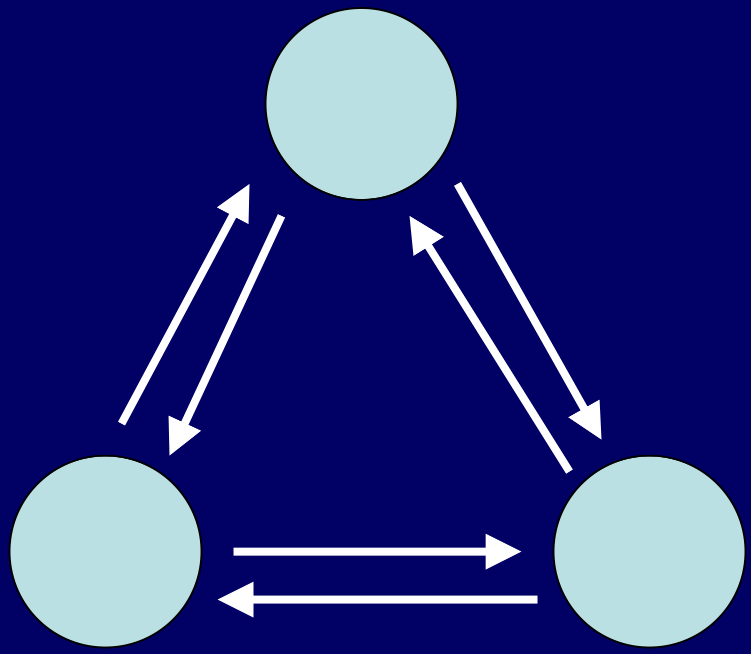
Use Bayes Rule to compute $p(\ell|x_i, \Theta^g)$

EM Algorithm

- Gaussian Evaluation
  - Lots of ops
- Series computation
  - Sum reduction
  - Bandwidth
- Iterative
  - Lots of work

Hidden Markov Models (HMM)

- State machine producing outputs
  - Each state contains different prob. dist. for output



$$\pi_i = p(Q_1 = i)$$

$$A = \{a_{i,j}\} = p(Q_t = j | Q_{t-1} = i).$$

$$b_j(o_t) = p(O_t = o_t | Q_t = j).$$

$$B = \{b_j(\cdot)\}$$

HMM Applications

- Speech
  - Recognition
    - Combine with GMM
    - Training and evaluation
- Vision
  - Handwriting
  - Gesture & lip reading
- Text
  - Translation

EM Algorithm for HMM

- Training HMM with EM

$$\tilde{\pi}_i = \gamma_i(1)$$

$$\tilde{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_{ij}(t)}{\sum_{t=1}^{T-1} \gamma_i(t)}$$

$$\tilde{b}_i(k) = \frac{\sum_{t=1}^{T} \delta_{o_t, v_k} \gamma_i(t)}{\sum_{t=1}^{T} \gamma_i(t)}$$

$$\gamma_i(t) = \frac{\alpha_i(t)\beta_i(t)}{\sum_{j=1}^{N} \alpha_j(t)\beta_j(t)}$$

$$\xi_{ij}(t) = \frac{\gamma_i(t) a_{ij} b_j(o_{t+1}) \beta_j(t+1)}{\beta_i(t)}$$

1. $\beta_i(T) = 1$
2. $\beta_i(t) = \sum_{j=1}^{N} a_{ij} b_j(o_{t+1}) \beta_j(t+1)$

1. $\alpha_i(1) = \pi_i b_i(o_1)$
2. $\alpha_j(t+1) = \left[\sum_{i=1}^{N} \alpha_i(t) a_{ij}\right] b_j(o_{t+1})$

HMM

- Series Computations
  - Reductions
  - Bandwidth wins
- Iterative
  - Lots of Work
- Combine with GMM
  - Lots of ops