Deep Neural Networks for Speech and Image Processing

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Agenda

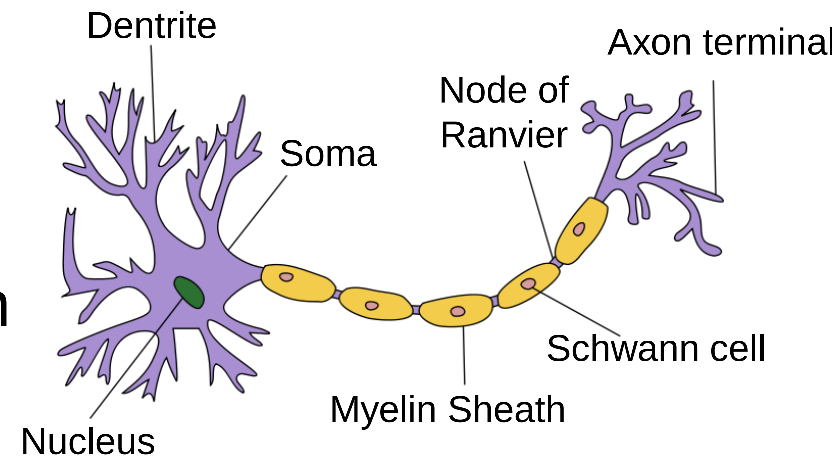
- Intro to neuroscience
- Artificial Neural Networks
- Deep Neural Networks
- Application to Speech Recognition

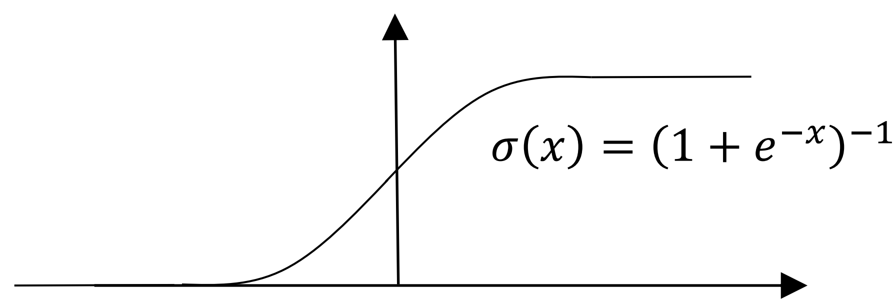
Carnegie Mellon 1990

Neurons

- Human brain:
  - 100 billion neurons (10^{11})
  - ~7000 synapses per neuron
- Neurons are
  - Non-deterministic
  - slow: 1ms
- Sigmoid nonlinearity

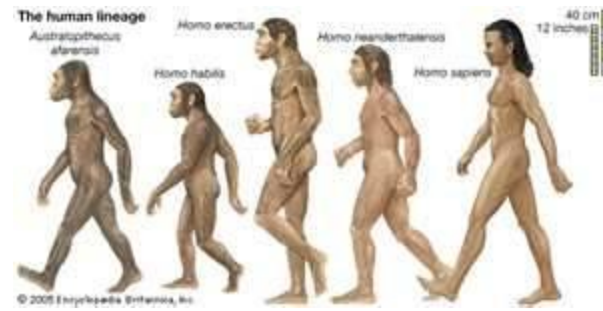
$$\sigma\left(\sum w_i v_i - b\right)$$



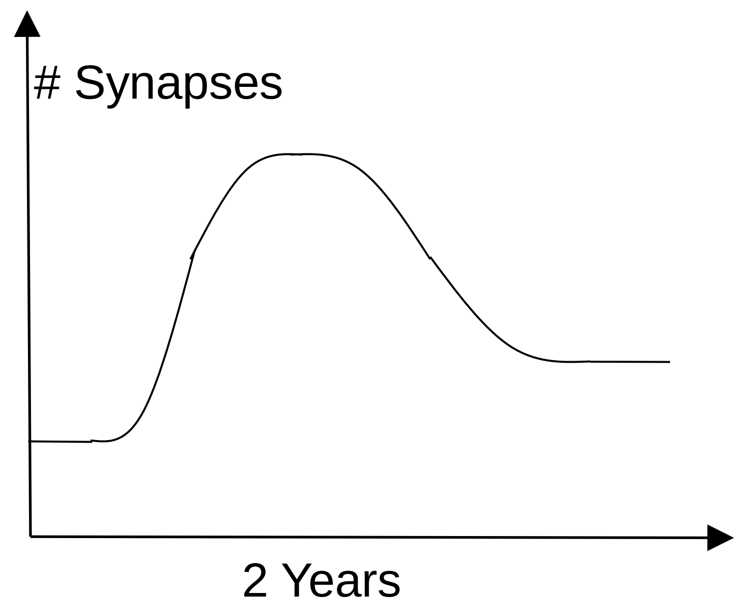


Neuroscience

- Mysteries in neuroscience
  - What's the difference between a human brain and that of a monkey?
  - Can we cure Alzheimer?

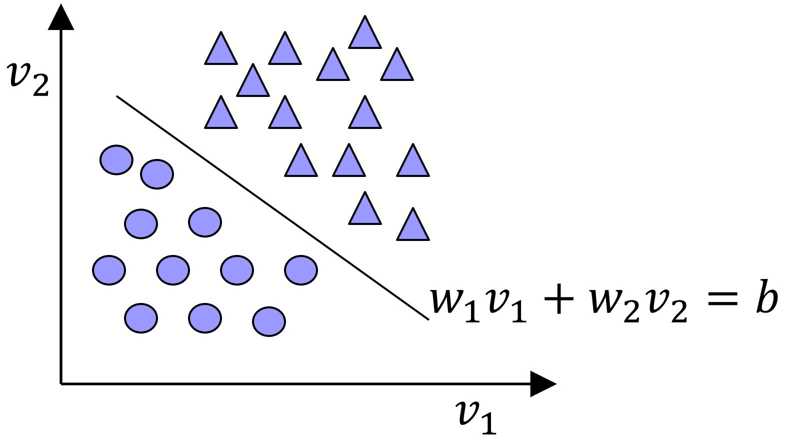


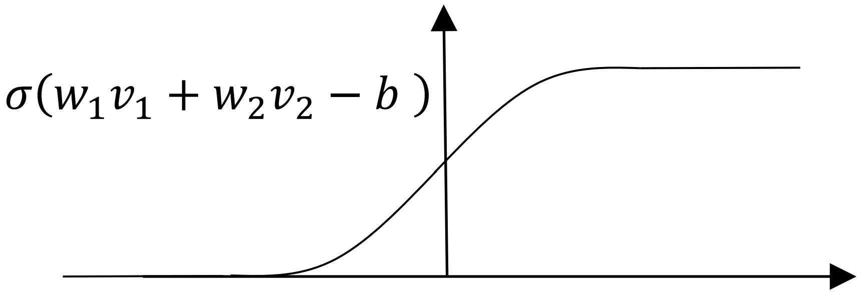
- Neurons pick up patterns
  - Hebbian rule: "Neurons that fire together, wire together"



Perceptron: the birth of ANN

- Rosenblatt (1958)
- Linear classifier





Perceptron learning

- Minimize errors

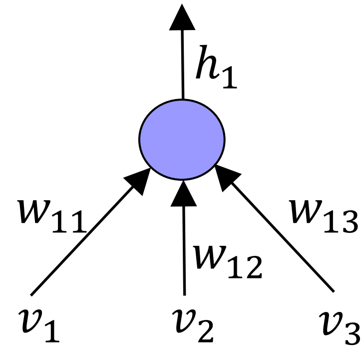
$$E = \sum_t e_1^2(t)$$

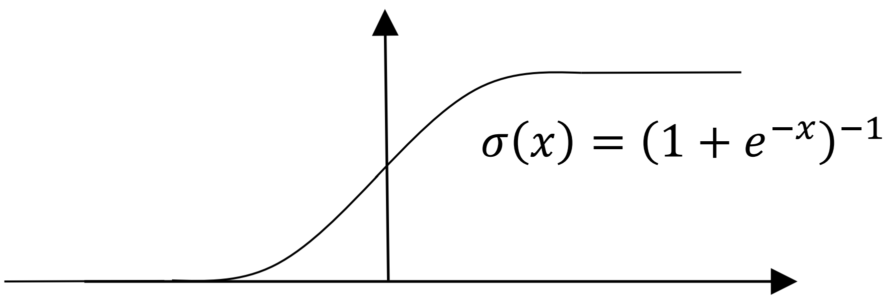
$$e_1 = h_1 - l_1$$

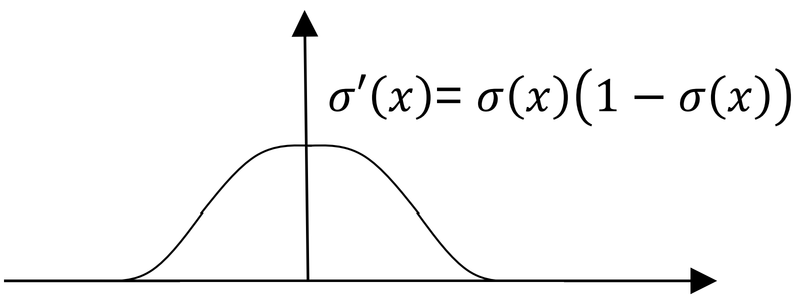
$$h_1 = \sigma\left(\sum_{i=1}^{3} w_{1i} v_i\right)$$

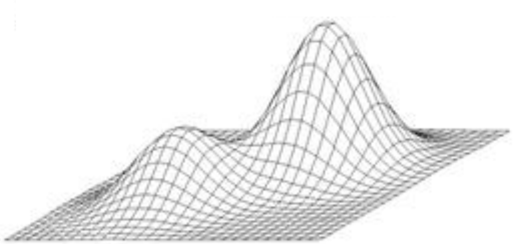
$$w_{1j}^{k+1} = w_{1j}^{k} - \alpha \frac{\partial E}{\partial w_{1j}}$$

$$\frac{\partial E}{\partial w_i} = 2 \sum_t e_1(t) h_1(t)[1 - h_1(t)] v_i(t)$$



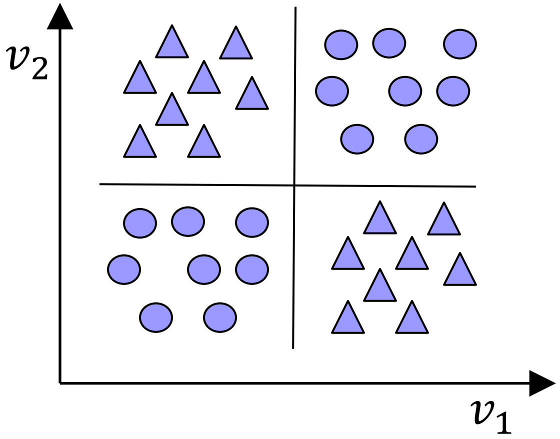




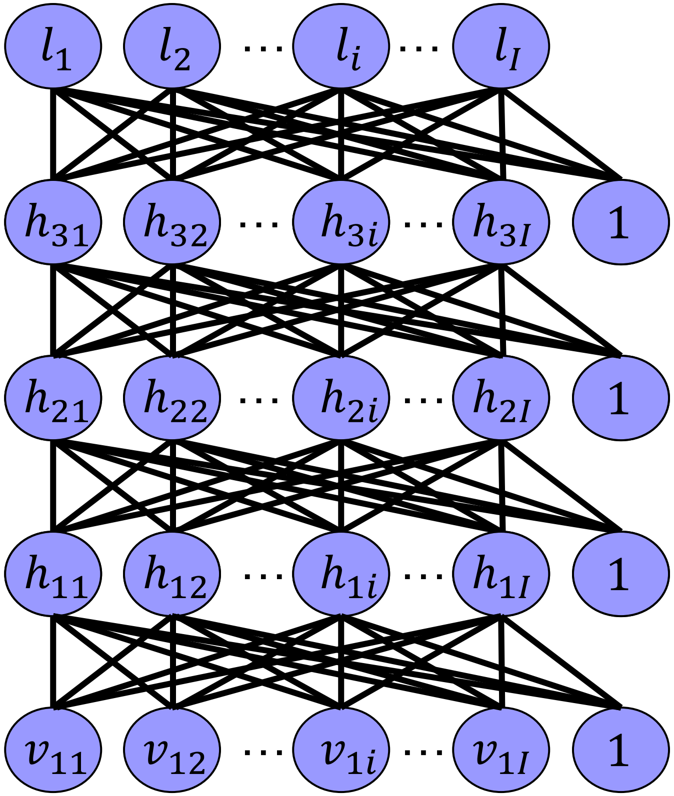


Neural Networks Winter starts

- Minsky and Papert (1969)
  - XOR cannot be modeled with a perceptron



Artificial Neural Networks



1948: Alan Turing proposes artificial neural networks (ANN)

Back propagation

- Bryson and Hoback (1969) invent it
- Hinton (1974) rediscovers it

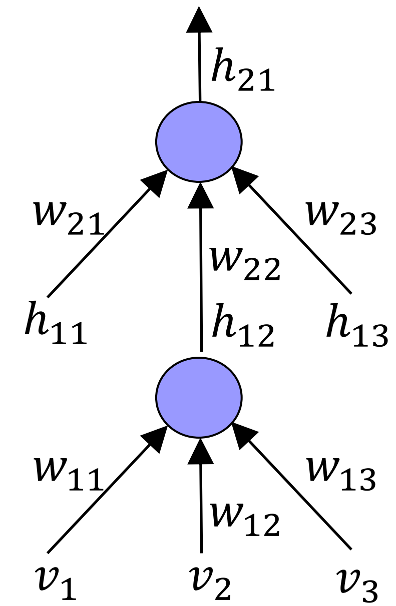
$$E = \sum_t e_1^2(t) \qquad e_1 = h_{21} - l_1$$

$$h_{21} = \sigma\left(\sum_{i=1}^{3} w_{2i} h_{1i}\right) \qquad h_{12} = \sigma\left(\sum_{i=1}^{3} w_{1i} v_i\right)$$

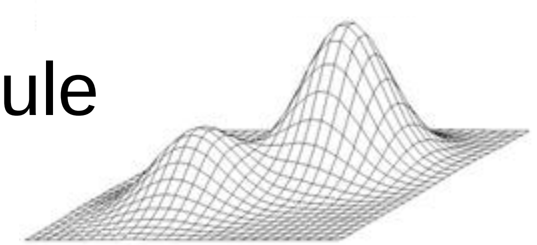
$$w_{1i}^{k+1} = w_{1i}^{k} - \alpha \frac{\partial E}{\partial w_{1i}}$$

$$\frac{\partial E}{\partial w_{1i}} = 2 \sum_t e_1(t) h_{21}(t)[1 - h_{21}(t)] w_{22} \frac{\partial h_{12}(t)}{\partial w_{1i}}$$

$$\frac{\partial h_{12}(t)}{\partial w_{1i}} = h_{12}(t)[1 - h_{12}(t)] v_i(t)$$



Chain rule



ANN in Speech Recognition: The classic period

- 1988 Morgan & Bourlard use NN for ASR
- 1989 Waibel et al. propose TDNN
- 1990: Robinson et al propose Recurrent NN

…

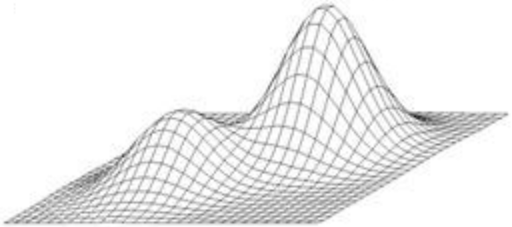
The second winter of ANN

- HMMs became dominant technology for ASR in 1990s because:
- It performed as well or better than ANN
- But it was a lot faster to train so HMMs could benefit from large training corpora whereas ANN could not

A renaissance of Neural Networks

- 2006: Hinton invents Deep Belief Networks (DBN):
  - Pre-train each layer from bottom up
  - Each pair of layers is an Restricted Boltzmann Machine (RBM), 1983
  - Jointly fine-tune all layers using back-propagation
- MNIST: handwritten digit recognition

- Great results due to good initialization



Restricted Boltzmann Machines I

Given $\mathbf{v}$ and $\mathbf{h}$ binary valued vectors

$$p(\mathbf{v},\mathbf{h}) = \frac{e^{-E(\mathbf{v},\mathbf{h})}}{Z} \qquad E(\mathbf{v},\mathbf{h}) = -\mathbf{b}^{\mathbf{T}}\mathbf{v} - \mathbf{c}^{\mathbf{T}}\mathbf{h} - \mathbf{v}^{\mathbf{T}}\mathbf{W}\mathbf{h} \qquad Z = \sum_{\mathbf{v},\mathbf{h}} e^{-E(\mathbf{v},\mathbf{h})}$$

$$p(\mathbf{h}|\mathbf{v}) = \frac{e^{-E(\mathbf{v},\mathbf{h})}}{\sum_{\tilde{\mathbf{h}}} e^{-E(\mathbf{v},\tilde{\mathbf{h}})}} = \frac{e^{\mathbf{b}^{\mathbf{T}}\mathbf{v}+\mathbf{c}^{\mathbf{T}}\mathbf{h}+\mathbf{v}^{\mathbf{T}}\mathbf{W}\mathbf{h}}}{\sum_{\tilde{\mathbf{h}}} e^{\mathbf{b}^{\mathbf{T}}\mathbf{v}+\mathbf{c}^{\mathbf{T}}\tilde{\mathbf{h}}+\mathbf{v}^{\mathbf{T}}\mathbf{W}\tilde{\mathbf{h}}}} = \frac{e^{\mathbf{c}^{\mathbf{T}}\mathbf{h}+\mathbf{v}^{\mathbf{T}}\mathbf{W}\mathbf{h}}}{\sum_{\tilde{\mathbf{h}}} e^{\mathbf{c}^{\mathbf{T}}\tilde{\mathbf{h}}+\mathbf{v}^{\mathbf{T}}\mathbf{W}\tilde{\mathbf{h}}}} = \prod_{\boldsymbol{i}} p(h_i|\mathbf{v})$$

$$p(h_i = 1|\mathbf{v}) = \sigma\left(c_i + \mathbf{v}^{\mathbf{T}}\mathbf{W}_{\boldsymbol{i}}\right)$$

Restricted Boltzmann Machines II

- Posterior of binary visible units

$$p(v_i = 1|\mathbf{h}) = \sigma(b_i + \mathbf{W}_{\boldsymbol{i}}\mathbf{h})$$

- When visible units are Gaussian

$$E(\mathbf{v},\mathbf{h}) = \frac{1}{2}(\mathbf{v}-\mathbf{b})^T(\mathbf{v}-\mathbf{b}) - \mathbf{c}^{\mathbf{T}}\mathbf{h} - \mathbf{v}^{\mathbf{T}}\mathbf{W}\mathbf{h}$$

- still

$$p(h_i = 1|\mathbf{v}) = \sigma\left(c_i + \mathbf{v}^{\mathbf{T}}\mathbf{W}_{\boldsymbol{i}}\right)$$

- Posteriors of visible units are Gaussian

$$p(\mathbf{v}|\mathbf{h}) = \mathrm{N}(\mathbf{v}, \mathbf{b} + \mathbf{h}\mathbf{W}^T, I)$$

RBM estimation

- ML parameter estimation

$$\hat{\mathbf{c}}, \hat{\mathbf{b}}, \widehat{\mathbf{W}} = \underset{\mathbf{c},\mathbf{b},\mathbf{W}}{\operatorname{argmax}}\, p(\mathbf{v}|\mathbf{c}, \mathbf{b}, \mathbf{W}) = \underset{\mathbf{c},\mathbf{b},\mathbf{W}}{\operatorname{argmax}} \sum_{\mathbf{h}} p(\mathbf{v}, \mathbf{h}|\mathbf{c}, \mathbf{b}, \mathbf{W})$$

- is highly non-linear ☹

Contrastive Divergence

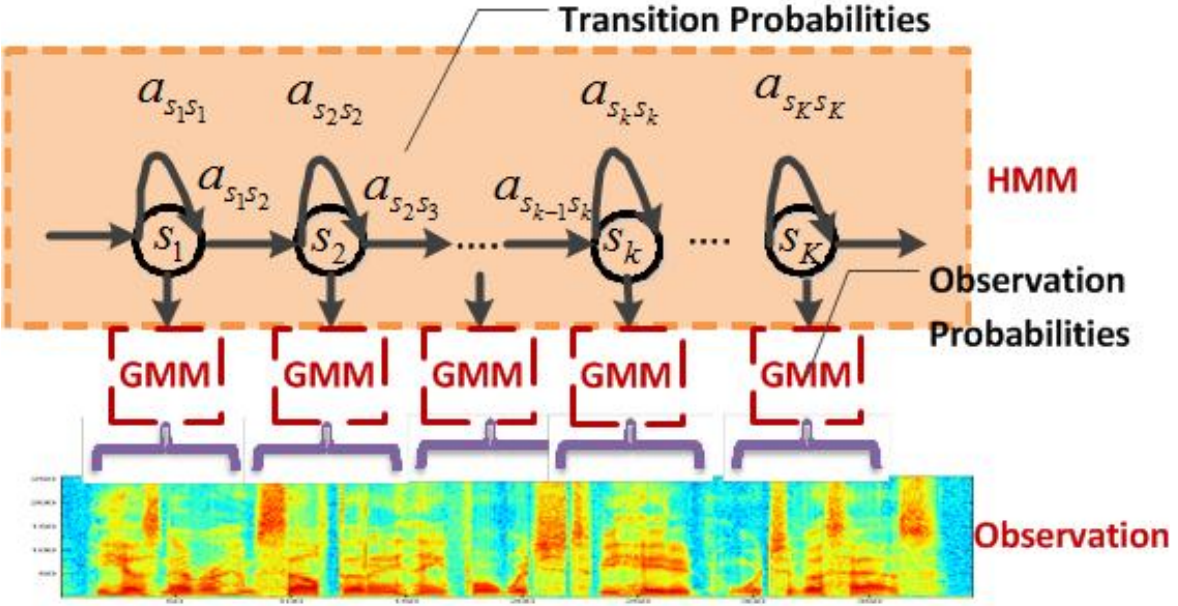
- $\Delta w_{ij} = \langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{model}$
- Approximate $\langle v_i h_j \rangle_{model}$
  i. Initialize $\mathbf{v_0}$ at data
  ii. Sample $\mathbf{h_0} \sim \boldsymbol{p}(\mathbf{h}|\mathbf{v_0})$
  iii. Sample $\mathbf{v_1} \sim \boldsymbol{p}(\mathbf{v}|\mathbf{h_0})$
  iv. Sample $\mathbf{h_1} \sim \boldsymbol{p}(\mathbf{h}|\mathbf{v_1})$
  v. Call $(\mathbf{v_1}, \mathbf{h_1})$ a sample from the model.
- $(\mathbf{v}_\infty, \mathbf{h}_\infty)$ is a true sample from the model. $(\mathbf{v_1}, \mathbf{h_1})$ is a very rough estimate but works

Neural Network training

- RBM pre-training (contrastive divergence)
- Back-propagation

State-of-the-art: GMM-HMM

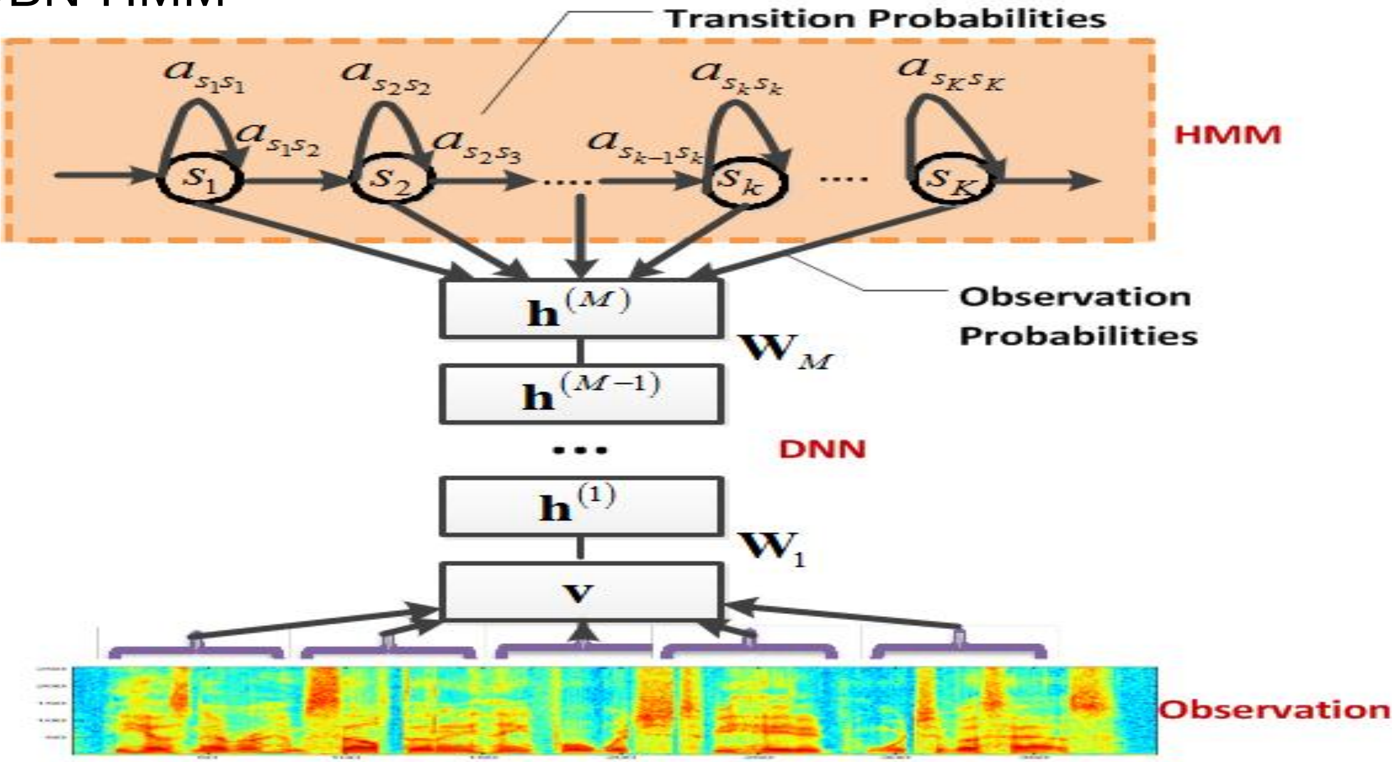
- Generatively model frames of acoustic data with two stochastic processes:
  - A hidden Markov process to model state transition
  - A Gaussian mixture model to generate observations
- Trained with maximum likelihood (ML) criterion using EM followed by discriminative training (e.g. MPE)



Context Dependent DNN-HMM

Dong Yu & Li Deng

- Extend from phoneme recognition (Mohamed et al. 2009) to LVCSR
- Extend from using CI phone state to using senones as DBN output
- Introduced priors, transition prob tuning, and DBN labels in the DBN-HMM



Context Dependent DNN-HMM

- Convert state posterior to state likelihood [Renals et al., 1994]

$$p_{o|s}(o|s) = \frac{p_{s|o}(s|o)}{p_s(s)} p_o(o)$$

- $p_o(o)$ is constant with input
- o = feature vector augmented with neighbors (5+5) [Renals *et al.*, 1994]
- ***new***: classes s are *conventional model's senones* directly [Yu *et al.* 2010]
  - in our system: ~9000
  - long-standing assumption: too many to be accurately modeled by MLP
  - the key ingredient for large WER reduction

→ hence name: **CD-DNN-HMMs**

Switchboard Experiments
Frank Seide, Dong Yu, Gang Li

- training:
  - SWBD-I corpus (309h)
  - PLP with derivatives, windowed MVN, HLDA → 39 dim
  - usual left-to-right HMMs, 9304 senones
  - GMM baseline: 40 Gaussians/state; BMMI discriminative training
- recognition:
  - speaker-independent single-pass
  - dev set: Hub5'00-SWB NOTE: speaker overlap!
  - eval sets: RT03S & internal STT corpora
  - LM and dict from Fisher transcripts, PP=84
- for comparison: our "best-ever" multi-pass baseline
  - trained on 2000 hours (SWBD-I + Fisher)
  - VTLN, GD, multi-pass MLLR, ROVER

Experimental Results



- 300h Switchboard phone conversations (cf. our best: 1700h)

acoustic model & training	recognition mode	RT03S FSH	RT03S SW	Hub5'00 SWB
GMM 40-mix, ML, SWB 309h	single-pass SI	30.2		26.5
GMM 40-mix, BMMI, SWB 309h	single-pass SI	27.4		23.6
CD-DNN 7 layers x 2048, SWB 309h, this paper	single-pass SI			
(rel. change GMM BMMI → CD-DNN)				
GMM 72-mix, BMMI, Fisher 2000h	multi-pass adaptive	18.6		17.1

Experimental Results



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GMM 40-mix, BMMI, SWB 309h	single-pass SI	27.4		23.6
CD-DNN 7 layers x 2048, SWB 309h, this paper	single-pass SI	18.5		16.1
(rel. change GMM BMMI → CD-DNN)		(-33%)		(-32%)
GMM 72-mix, BMMI, Fisher 2000h	multi-pass adaptive	18.6		17.1

Experimental Results



- 300h Switchboard phone conversations (cf. our best: 1700h)

acoustic model & training	recognition mode	RT03S FSH	RT03S SW	Hub5'00 SWB
GMM 40-mix, ML, SWB 309h	single-pass SI	30.2	40.9	26.5
GMM 40-mix, BMMI, SWB 309h	single-pass SI	27.4	37.6	23.6
CD-DNN 7 layers x 2048, SWB 309h, this paper	single-pass SI	18.5	27.5	16.1
(rel. change GMM BMMI → CD-DNN)		(-33%)	(-27%)	(-32%)
GMM 72-mix, BMMI, Fisher 2000h	multi-pass adaptive	18.6	25.2	17.1

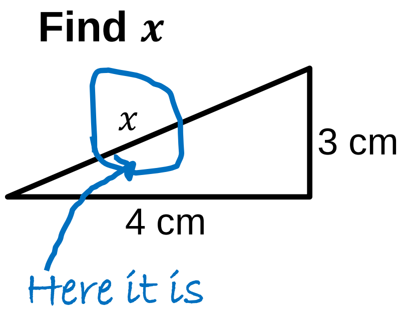
acoustic model & training	recognition mode	voicemails MS	voicemails LDC	tele-conf
GMM 40-mix, ML, SWB 309h	single-pass SI	45.0	33.5	35.2
GMM 40-mix, BMMI, SWB 309h	single-pass SI	42.4	30.8	33.9
CD-DNN 7 layers x 2048, SWB 309h, this paper	single-pass SI	32.9	22.9	24.4
(rel. change GMM BMMI → CD-DNN)		(-22%)	(-26%)	(-28%)

Summary

- CD-DNN-HMM scales to “benchmark” data
  - 9000 senones, 300h, STT task
  - unusual 33% relative error reduction
    (historically, not many technologies achieved this)
- Key factors
  - **Increase in computing power** allows more experiments:
    - direct modeling of tied triphone states [Yu et al., 2010]
    - effective use of neighbor frames (-14%) [Renals et al., 1994]
    - modeling ability of deep networks (-24%) [Yu et al., 2010]
- Training still a problem:
  - Still slow: need GPUs
  - Can get stuck in local optimum

Natural or Artificial?

- Artificial neural networks better than natural?



What is the language spoken in Latin America?

Latin

- In human intelligence tasks, ANN might do better than natural ones … one day
- But for now, ANN have a lot to learn from nature
  - Randomness, an accident or Darwin at his best?
  - Local learning instead of backprop?

Thank you