Deep Learning for Automatic Speech Recognition

CSCI/LING-5832: Natural Language Processing

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Outline

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Context-Dependent Pre-Trained Deep Neural Networks for Large-Vocabulary Speech Recognition

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Problem Formulation

Noisy channel model: maximize the likelihood of a decoded word sequence, $\hat{w}$, given our observed audio input, x:

$$\hat{w} = \underset{w \in \mathscr{L}}{\operatorname{argmax}} \underbrace{\mathbb{P}(x|w)}_{\text{Accoustic Model}} \underbrace{\mathbb{P}(w)}_{\text{Language Model}}$$

Use N-gram language model, CD-DNN-HMM for acoustic model

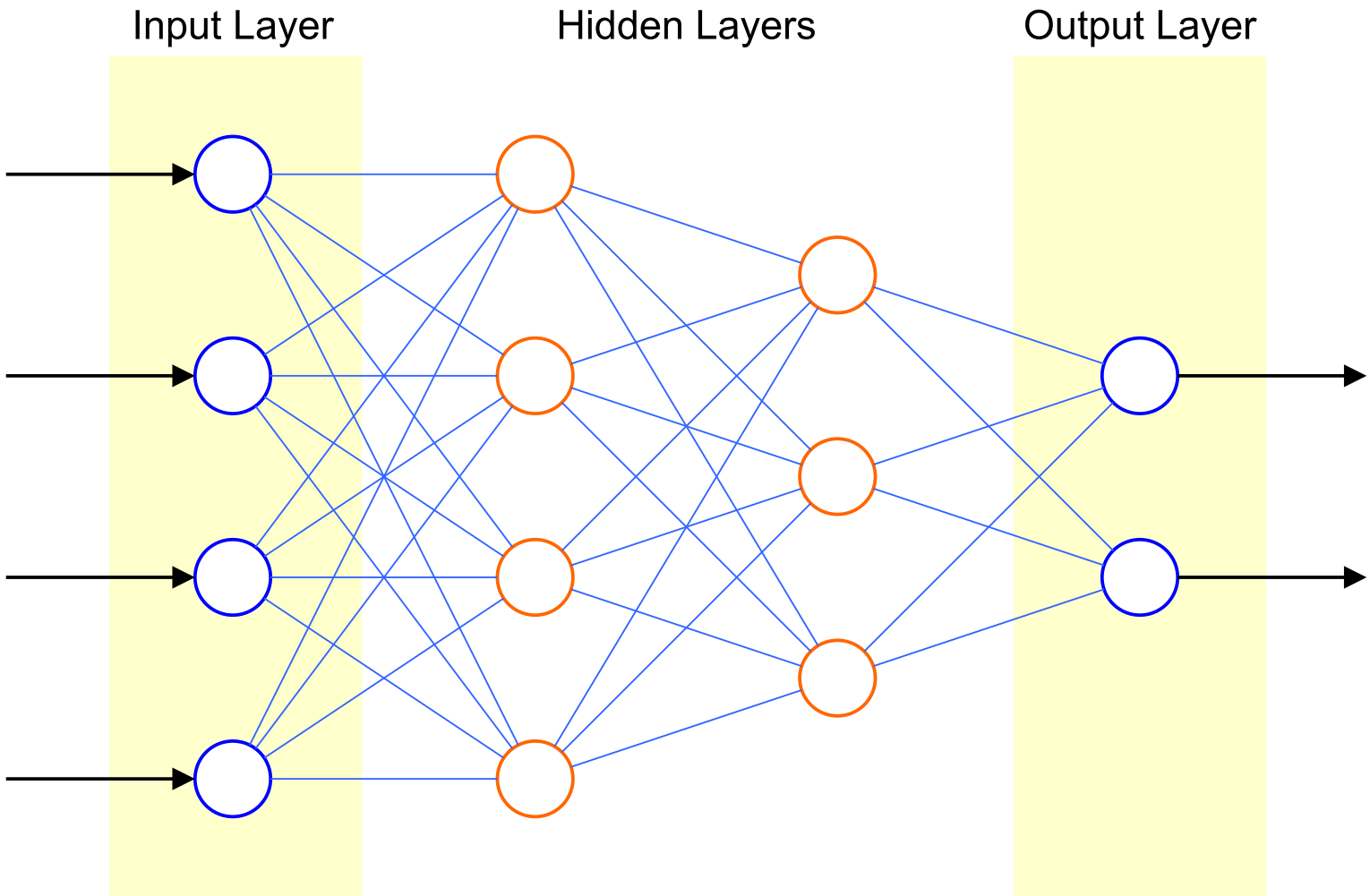
Problem Formulation (Cont)

Here the acoustic model is viewed as a sequence of transitions between states of tied-state triphones referred to as **senones**.

$$\underbrace{\mathbb{P}(x|w)}_{\text{Accoustic Model}} \approxeq \max \underbrace{\pi(q_0)}_{\text{Init State}} \prod_{t=1}^{T} \underbrace{a_{q_{t-1}q_t}}_{\text{Transistion}} \prod_{t=0}^{T} \underbrace{\mathbb{P}(x_t|q_t)}_{\text{Senone posterior}}$$

Where $\mathbb{P}(x_t|q_t)$ models the tied triphone senone posterior given mel-frequency cepstral coefficients (**MFCCs**) based on 11 sampled frames of audio.

Deep Neural Networks



Training

Training is complicated and time intensive! At a very high level two steps: initialization and DNN training.

Initialization:

- Find the best tying of triphone states
- Deal with some book keeping
- Train a CD-GMM-HMM using those states.
- Convert CD-GMM-HMM into CD-DNN-HMM keeping senone structure
- Apply pre-training algorithm on CD-DNN-HMM

Training

DNN Training:

- Generate raw alignment of states to senones
- Use alignment to refine by backpropagation
- Re-estimate prior senone probability given frames
- Refine HMM transitions probabilities
- Goto first step if no improvement against development set

Just enough time to talk about one of these steps in detail. Let's look at pre-training...

Pre-Training In-Depth

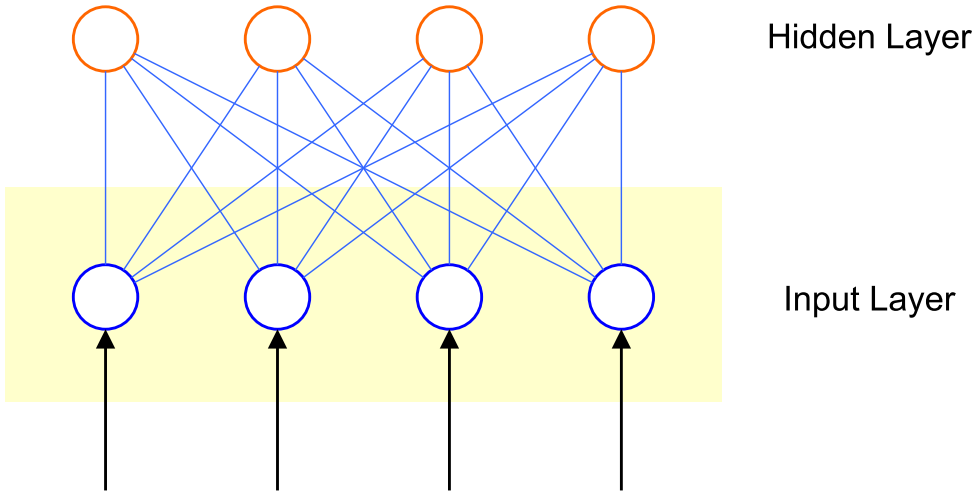
DNN training computationally intractable until Hinton et al. come to the rescue with *A Fast Learning Algorithm for Deep Belief Nets*.

Big idea: Use an approximate method, **contrastive divergence**, to get near an optimal solution, then use traditional methods, **backpropagation**, to finish the job.

Need to understand Restricted Boltzman Machines (RMBs) and Deep Belief Networks (DBNs)

Pre-Training: RBMs and DBNs

Bipartite arrangement of weights is assigned an energy:



$$E(v, h) = -b^T v - c^T h - v^T W h$$

For purpose of this talk, stack RBMs on top of one another to get a DBN

Pre-Training: Contrastive Divergence

Want to do vanilla Stochastic Gradient Descent, however, our model term takes **exponential** time to compute correctly.

$$-\frac{\partial \ell(\theta)}{\partial w_{ij}} = \left\langle \frac{\partial E}{\partial \theta} \right\rangle_{\text{data}} - \left\langle \frac{\partial E}{\partial \theta} \right\rangle_{\text{model}}$$

Instead, **approximate** it (essentially minimizing Kullback-Leibler divergence) with one step Gibbs sampling:

$$-\frac{\partial \ell(\theta)}{\partial w_{ij}} \approx \langle v_i h_j \rangle_{\text{data}} - \langle v_i h_j \rangle_1$$

Pre-Training: Bringing it all together

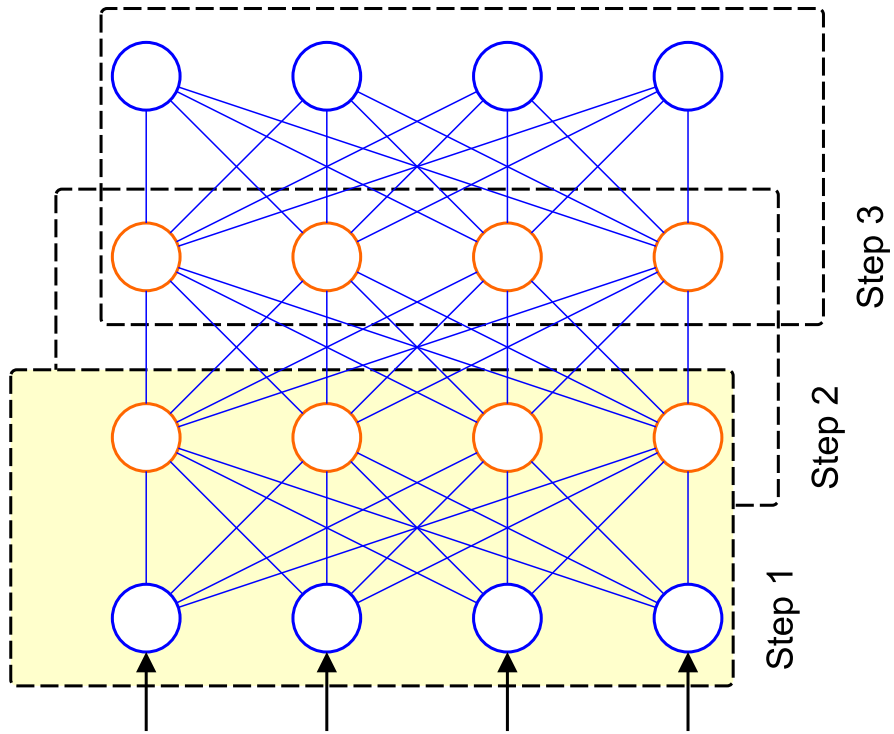
Hinton's Greedy Algorithm:

1) Train RBM consisting of first two layers

2) Move RBM frame up a layer and train

3) When out of layers, you have trained DBN

4) Refine with backpropagation



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Experimental Results

Papers report different metrics (sentence accuracy, phone error rate) on different datasets (Bing, TIMIT)

	Bing Mobile		TIMIT	
Architecture	Dev.	Test	Dev.	Test
CD-GMM-HMMM	70.3%	68.4%		
CD-DNN-HMM	71.8%	69.6%		
CNN-HMM				20.07%

Take away: Both demonstrate significant improvement over GMM approach, with CNN approach giving the best performance.

Outline

Conclusions

TODO: Garrett

Conclusions (Cont)

TODO: Garrett

Questions?