Deep Neural Networks

DT2118 Speech and Speaker Recognition

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Outline

State-to-Output Probability Model

Artificial Neural Networks
- Perceptron
- Multi Layer Perceptron
- Error Backpropagation
- Hybrid HMM-MLP

Deep Learning (Initialization)
- Deep Neural Networks
- Restricted Boltzmann Machines
- Deep Belief Networks

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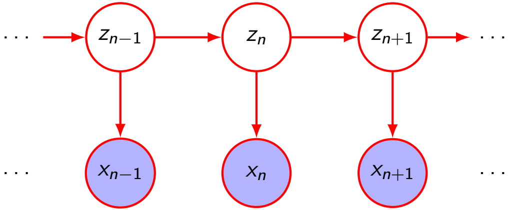
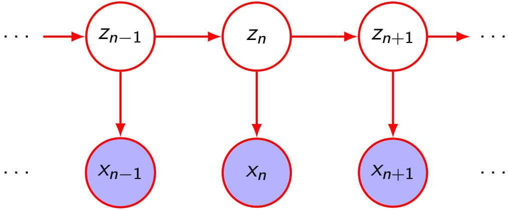
State-to-Output Probability Model



is responsible for the discriminative power of the whole model

- GMMs used because easy to train and adapt
- discriminative training can improve results

State-to-Output Probability Model



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Alternatives:

- artificial neural networks (ANNs)
- deep neural networks (DNNs)
- support vector machines (SVMs) not used for ASR

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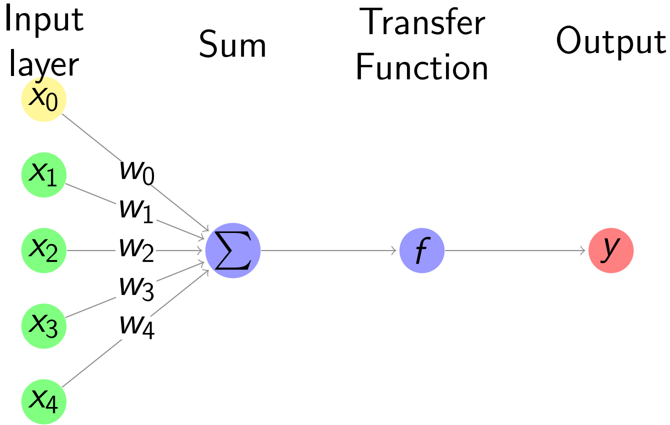
Perceptron

Known since the 1950's [4]



[4] F. Rosenblatt. *The perceptron: A perceiving and recognizing automaton*. Tech. rep. 85-460-1. Cornell Aeronautical Laboratory, 1957

Perceptron input/output

$$y = f\left(b + \sum_i w_i x_i\right)$$

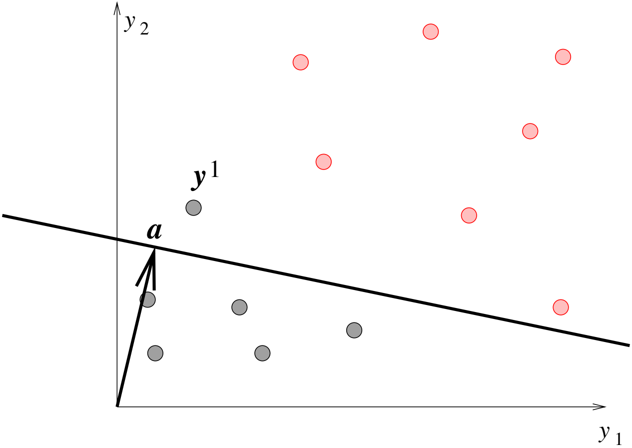
where

$$\begin{aligned} f(z) &= \frac{1}{1+e^{-z}} \quad \text{sigmoid} \\ f(z) &= \frac{e^z - e^{-z}}{e^z + e^{-z}} \quad \text{hyperbolic tangent} \\ f(z) &= \max(0, z) \quad \text{rectified linear unit} \end{aligned}$$

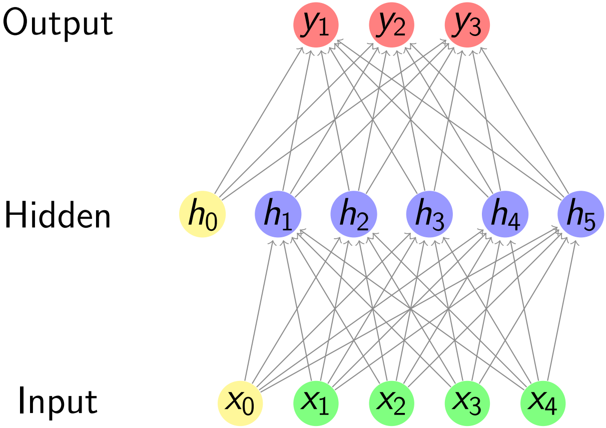
Equivalent to logistic regression ($b = w_0 x_0$ bias)

Perceptron: Linear Classification

Learning adjust weights to correct errors



Multi-layer Perceptron [3]



[3] F. Rosenblatt. *Principles of neurodynamics. perceptrons and the theory of brain mechanisms.* Tech. rep. DTIC Document, 1961

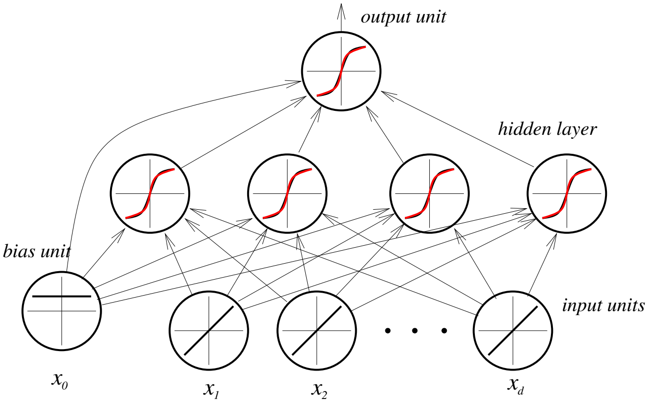
Universal Approximation Theorem

- First proposed by Gybenko [1]
- one single hidden layer and finite but appropriate number of neurons
- can approximate any function in $\mathbb{R}^N$ with mild constraints

[1] G. Gybenko. "Approximation by superposition of sigmoidal functions". In: *Mathematics of Control, Signals and Systems* 2.4 (1989), pp. 303–314

Multi-layer Perceptron: Training

Backpropagation algorithm [5]



[5] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. *Learning internal representations by error propagation*. Tech. rep. DTIC Document, 1985

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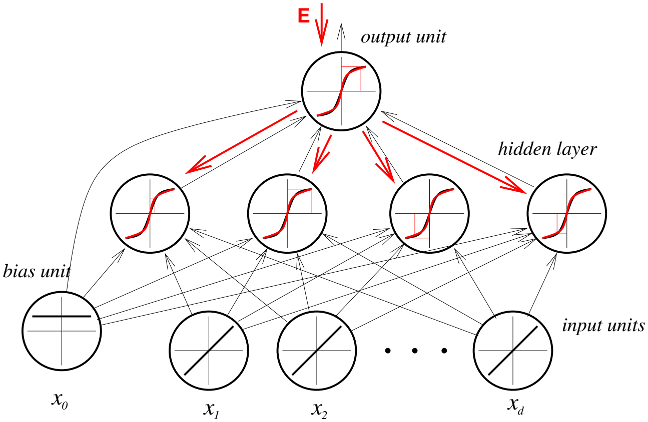
Backpropagation algorithm [5]



[5] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. *Learning internal representations by error propagation*. Tech. rep. DTIC Document, 1985

Learning Criteria

Ideally minimise Expected Loss:

$$J_{\text{EL}} = \mathbb{E}\big[J(W, B, o, y)\big] = \int_o J(W, B, o, y) p(o) do$$

where $o =$ features, $y =$ labels

but we do not know $p(o)$

Use empirical learning criteria instead:

- Mean Square Error (MSE)
- Cross Entropy (CE)

Mean Square Error Criterion

$$J_{\text{MSE}} = \frac{1}{M} \sum_{m=1}^{M} J_{\text{MSE}}(W, B, o^m, y^m)$$

$$\begin{aligned} J_{\text{MSE}}(W, B, o^m, y^m) &= \frac{1}{2} \left\| v^L - y \right\|^2 \\ &= \frac{1}{2} \left(v^L - y\right)^T \left(v^L - y\right) \end{aligned}$$

Cross Entropy Criterion

$$J_{\mathrm{CE}} = \frac{1}{M} \sum_{m=1}^{M} J_{\mathrm{CE}}(W, B, o^m, y^m)$$

$$J_{\mathrm{CE}}(W, B, o^m, y^m) = -\sum_{i=1}^{C} y_i \log v_i^L$$

Equivalent to minimising Kullback-Leibler divergence (KLD)

Update rules

$$
\begin{aligned}
W_{t+1}^{l} &\leftarrow W_t^l - \epsilon \Delta W_t^l \\
b_{t+1}^{l} &\leftarrow b_t^l - \epsilon \Delta b_t^l
\end{aligned}
$$

To compute ΔW_t^l and Δb_t^l we need the gradient of the criterion function.
Key trick: chain rule of gradients $f(g(x))$:

$$
\frac{\partial f}{\partial x} = \frac{\partial f}{\partial g}\frac{\partial g}{\partial x}
$$

Backpropagation: Properties

- weights only depend on neighbouring variables
- algorithm finds local optimum
- sensitive to initialisation

Practical Issues

- preprocessing: Cepstral Mean Normalisation
- initialisation: random (symmetry breaking), linear range of activation function
- regularisation (weight decay, dropout)
- batch size selection
- sample randomisation
- momentum
- learning rate and stopping criterion

Output Layer

Regression tasks: Linear layer

$$v^L = z^L = W^L v^{L-1} + b^L$$

Classification tasks: Softmax layer

$$v_i^L = \text{softmax}_i(z^L) = \frac{e^{z_i^L}}{\sum_{j=1}^{C} e^{z_j^L}}$$

Probabilistic Interpretation

1. $v_i^L \in [0, 1] \quad \forall i$
2. $\sum_{j=1}^{C} v_i^L = 1$

Output activations are posterior probabilities of the classes given the observations

$$v_i^L = P(i|o)$$

In speech: $P(\text{state}|\text{sounds})$

Hybrid HMM+Multi Layer Perceptron

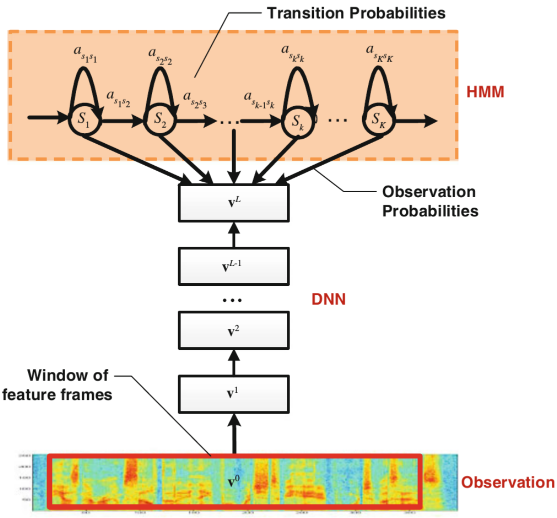


Figure from Yu and Deng

Combining probabilities

- HMMs use likelihoods $P(\text{sound}|\text{state})$
- MLPs and DNNs estimate posteriors $P(\text{state}|\text{sound})$

We can combine with Bayes:

$$P(\text{sound}|\text{state}) = \frac{P(\text{state}|\text{sound})P(\text{sound})}{P(\text{state})}$$

- $P(\text{state})$ can be estimated from the training set
- $P(\text{sound})$ is constant and can be ignored

Use scaled likelihoods:

$$\bar{P}(\text{sound}|\text{state}) = \frac{P(\text{state}|\text{sound})}{P(\text{state})}$$

Time Dependent and Recurrent ANNs

ANNs in ASR: Advantages

- discriminative in nature
- powerful time model:
- Time-Delayed Neural Networks (TDNNs)
- Recurrent Neural Networks (RNNs)

ANNs in ASR: Disadvantages

- training requires state level annotations (no EM available)
- usually annotations obtained with forced alignment
- not easy to adapt

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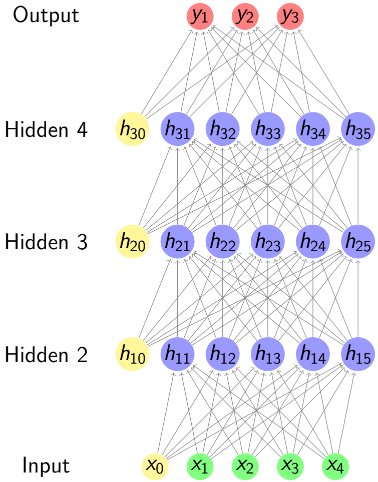
Deep Neural Network



DNN: Motivation

- depth $\sim$ abstraction
- good initialisation (see later)
- fast computers, large datasets

DNN and MLPs

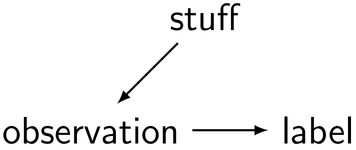
- no conceptual difference from MLPs
- Backpropagation alone not powerful enough
- local minima
- vanishing gradients

Deep Learning for Acoustic Modelling

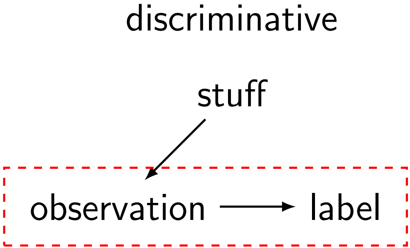
- most promising technique at the moment
- pioneered by Geoffry Hinton (Univ. Toronto)
- most of the large companies are using it (Microsoft, Google, Nuance, IBM)
- unifies properties of generative and discriminative models

Deep Learning: Idea

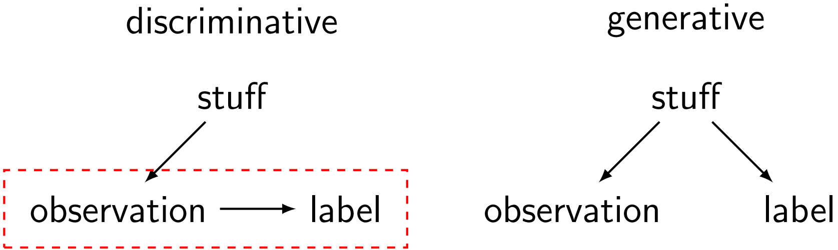
discriminative



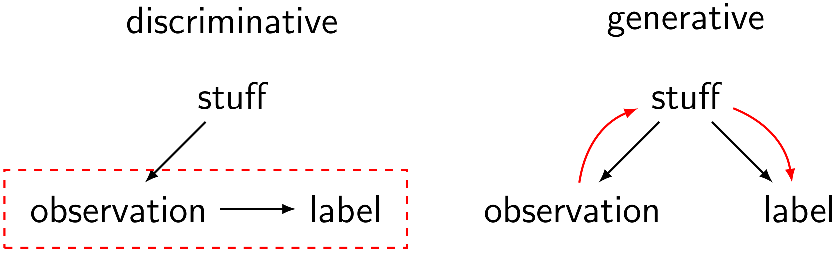
Deep Learning: Idea



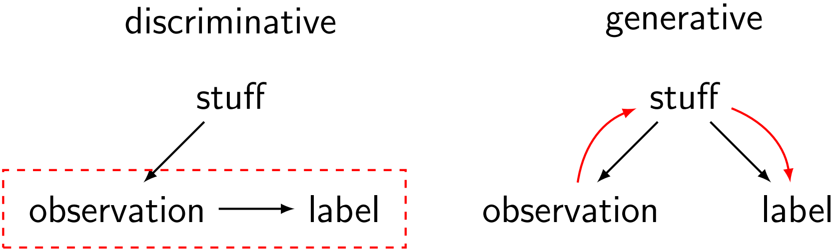
Deep Learning: Idea



Deep Learning: Idea



Deep Learning: Idea



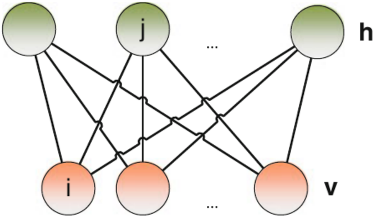
. . . but HMMs with Gaussian Mixure Models are also generative: why is this better?

Deep Learning: Idea #2

1. initialise DNN with Restricted Boltzmann Machines (RBM) that can be trained unsupervised
2. use fast learning procedure (Hinton)
3. use ridiculous amounts of unlabelled (cheap) data to train a ridiculous number of parameters in an unsupervised fashion
4. at the end, use small amounts of labelled (expensive) data and backpropagation to learn the labels

Restricted Boltzmann Machines (RBMs)

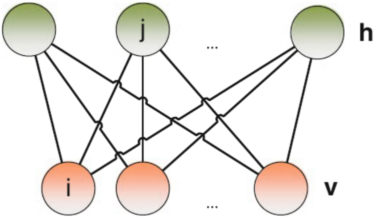
First called Harmonium [6]



- binary nodes: Bernoulli distribution
- continuous nodes: Gaussian-Benoulli

[6] P. Smolensky. "Information processing in dynamical systems: Foundations of harmony theory". In: Department of Computer Science, University of Colorado, Boulder, 1986. Chap. 6

Restricted Boltzmann Machines (RBMs)



Energy (Benoulli):

$$E(\mathbf{v}, \mathbf{h}) = -\mathbf{a}^T\mathbf{v} - \mathbf{b}^T\mathbf{h} - \mathbf{h}^T\mathbf{W}\mathbf{v}$$

Energy (Gaussian-Benoulli):

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

RBM: Probabilistic Interpretation

$$P(\mathbf{v}, \mathbf{h}) = \frac{e^{-E(\mathbf{v},\mathbf{h})}}{\sum_{\mathbf{v},\mathbf{h}} e^{-E(\mathbf{v},\mathbf{h})}}$$

Posteriors (conditional independence):

$$P(\mathbf{h}|\mathbf{v}) = \cdots = \prod_i P(h_i|\mathbf{v})$$

and

$$P(\mathbf{v}|\mathbf{h}) = \cdots = \prod_i P(v_i|\mathbf{h})$$

Binary Units: Cond Prob

Posterior equals sigmoid function!!

$$
\begin{aligned}
P(h_i = 1|\mathbf{v}) &= \frac{e^{(b_i 1 + 1\mathbf{W}_{i,*}\mathbf{v})}}{e^{(b_i 1 + 1\mathbf{W}_{i,*}\mathbf{v})} + e^{(b_i 0 + 0\mathbf{W}_{i,*}\mathbf{v})}} \\
&= \frac{e^{(b_i 1 + 1\mathbf{W}_{i,*}\mathbf{v})}}{e^{(b_i 1 + 1\mathbf{W}_{i,*}\mathbf{v})} + 1} \\
&= \sigma(b_i 1 + 1\mathbf{W}_{i,*}\mathbf{v})
\end{aligned}
$$

Same as Multi Layer Perceptron (viable for initialisation!)

Gaussian Units: Cond Prob

$$P(\mathbf{v}|\mathbf{h}) \;=\; \mathcal{N}(\mathbf{v}; \mu, \mathbf{\Sigma})$$

with

$$\mu = \mathbf{W}^T\mathbf{h} + \mathbf{a}$$
$$\mathbf{\Sigma} = \mathbf{I}$$

RBM Training

Stochastic Gradient Descend (minimise the negative log likelihood)

$$J_{\text{NLL}}(\mathbf{W}, \mathbf{a}, \mathbf{b}, \mathbf{v}) = -\log P(\mathbf{v}) = F(\mathbf{v}) + \log \sum_{\mathbf{v}} e^{-F(\mathbf{v})}$$

where

$$F(\mathbf{v}) = -\log \left(\sum_{\mathbf{h}} e^{-E(\mathbf{v},\mathbf{h})} \right)$$

is the free energy of the system.

BUT: the gradient can not be computed exactly

RBM Gradient

$$\frac{\partial J_{\text{NLL}}(\mathbf{W}, \mathbf{a}, \mathbf{b}, \mathbf{v})}{\partial \theta} = \frac{\partial F(\mathbf{v})}{\partial \theta} - \sum_{\tilde{\mathbf{v}}} p(\tilde{\mathbf{v}}) \frac{\partial F(\tilde{\mathbf{v}})}{\partial \theta}$$

- first term increases prob of training data
- second term decreases prob density defined by the model

RBM Stochastic Gradient

The general form is:

$$\nabla_\theta J_{\text{NLL}}(\mathbf{W}, \mathbf{a}, \mathbf{b}, \mathbf{v}) = -\left[\left\langle \frac{\partial E(\mathbf{v}, \mathbf{h})}{\partial \theta} \right\rangle_{\text{data}} - \left\langle \frac{\partial E(\mathbf{v}, \mathbf{h})}{\partial \theta} \right\rangle_{\text{model}}\right]$$

Example: visible layer

$$\nabla_{w_{ij}} J_{\text{NLL}}(\mathbf{W}, \mathbf{a}, \mathbf{b}, \mathbf{v}) = -\left[\langle v_i h_j \rangle_{\text{data}} - \langle v_i h_j \rangle_{\text{model}}\right]$$

Gibbs Sampling

$\langle v_i h_j \rangle_{\text{model}}$ computed with sampling

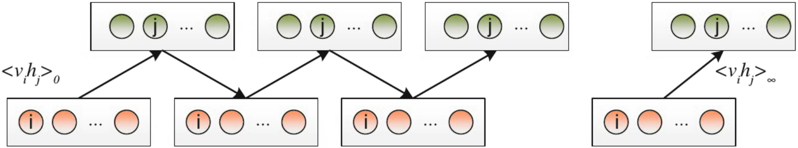
Sample joint distribution of N variables, one at a time:

$$P(X_i | X_{-i})$$

where X_{-i} are all the other variables

BUT: it takes exponential time to compute exactly

Contrastive Divergence



Two tricks:

1. initialise the chain with a training sample
2. do not wait for convergence

RBMs and Deep Belief Networks

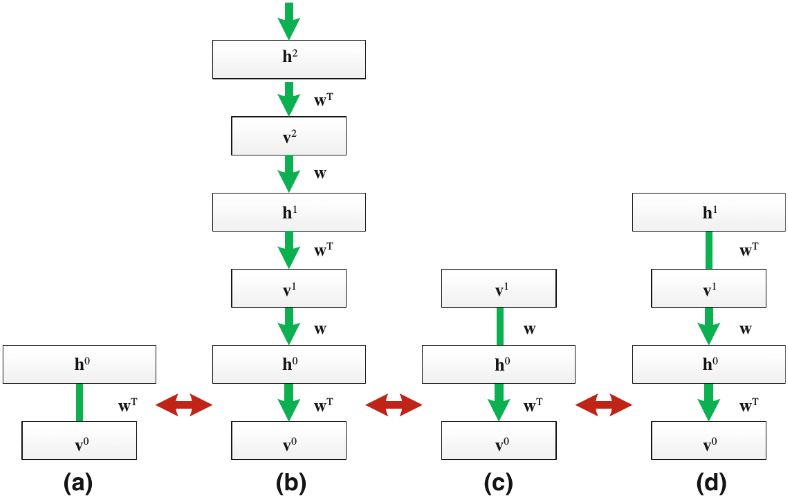


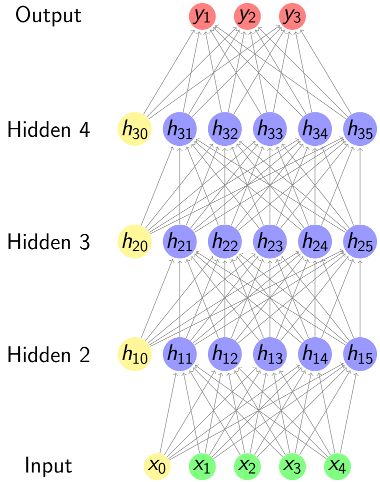
Figure from Yu and Deng

Deep Belief Networks: Training

Yee-Whye Teh (one of Hinton's students) observed that DBNs can be trained greedily
for each layer:

1. train a RBM unsupervised
2. excite the network with training data to produce outputs
3. use the outputs to train next RBM

Final Step: Supervised Training



Deep Learning: Performance

- state-of-the-art on most ASR tasks
- Made people from University of Toronto, Microsoft, Google and IBM write a paper together [2]
- experiments with learning the features from speech signal

Yu and Deng's book has many examples

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[2] G. Hinton, L. Deng, D. Yu, G. Dahl, A. Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T. Sainath, and B. Kingsbury. "Deep Neural Networks for Acoustic Modeling in Speech Recognition". In: *IEEE Signal Processing Magazine* (2012)