Deep Learning

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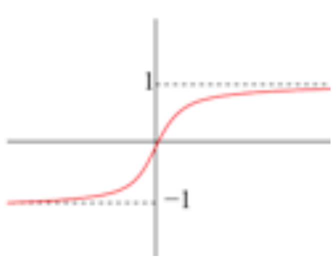
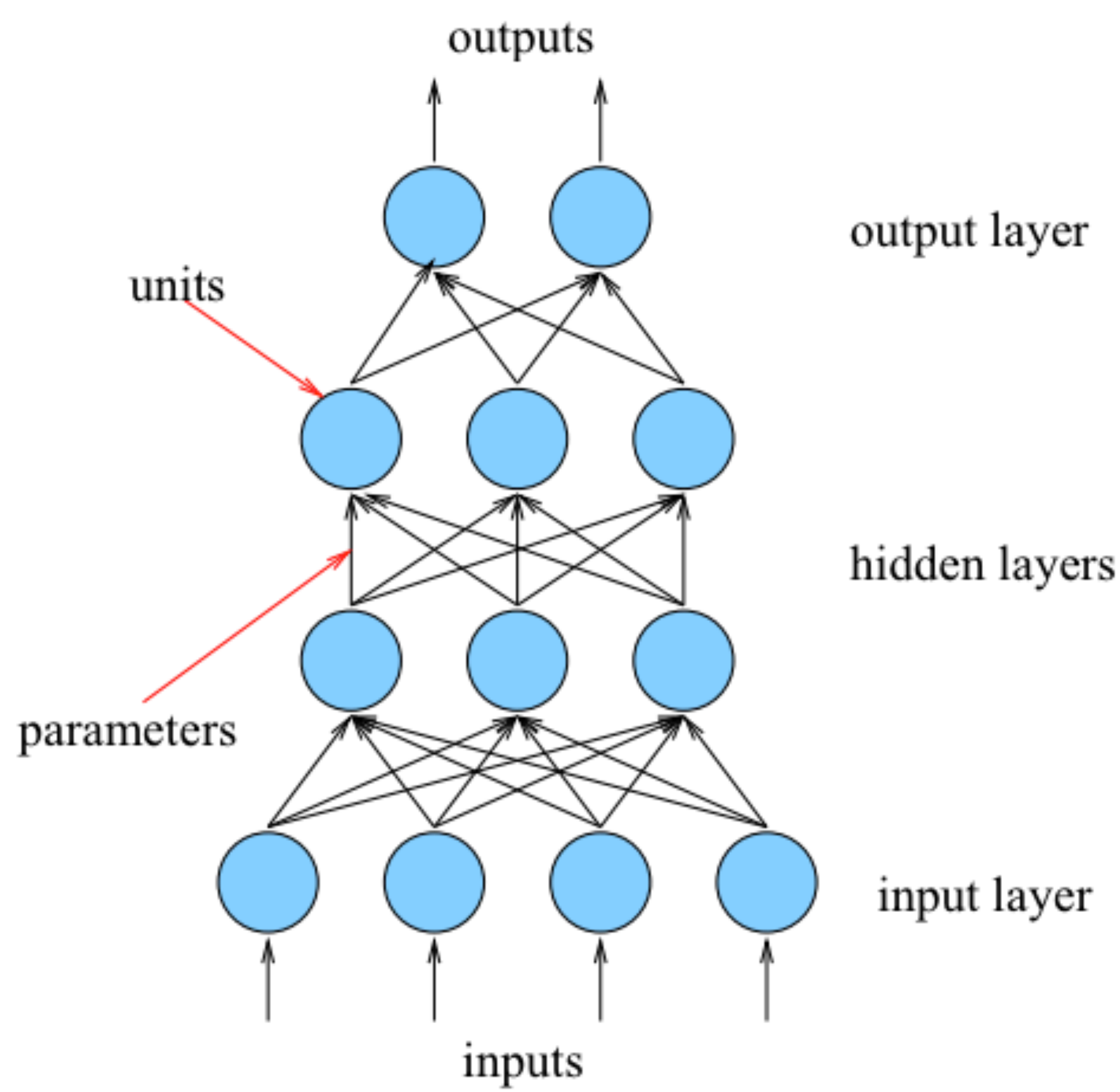
Machine Learning Course @ OHSU

2015-06-01

Recap: ANNs

- ANN is composed of multiple layers
- Layers perform non-linear transformations
    - `y=g(Wx+b)`





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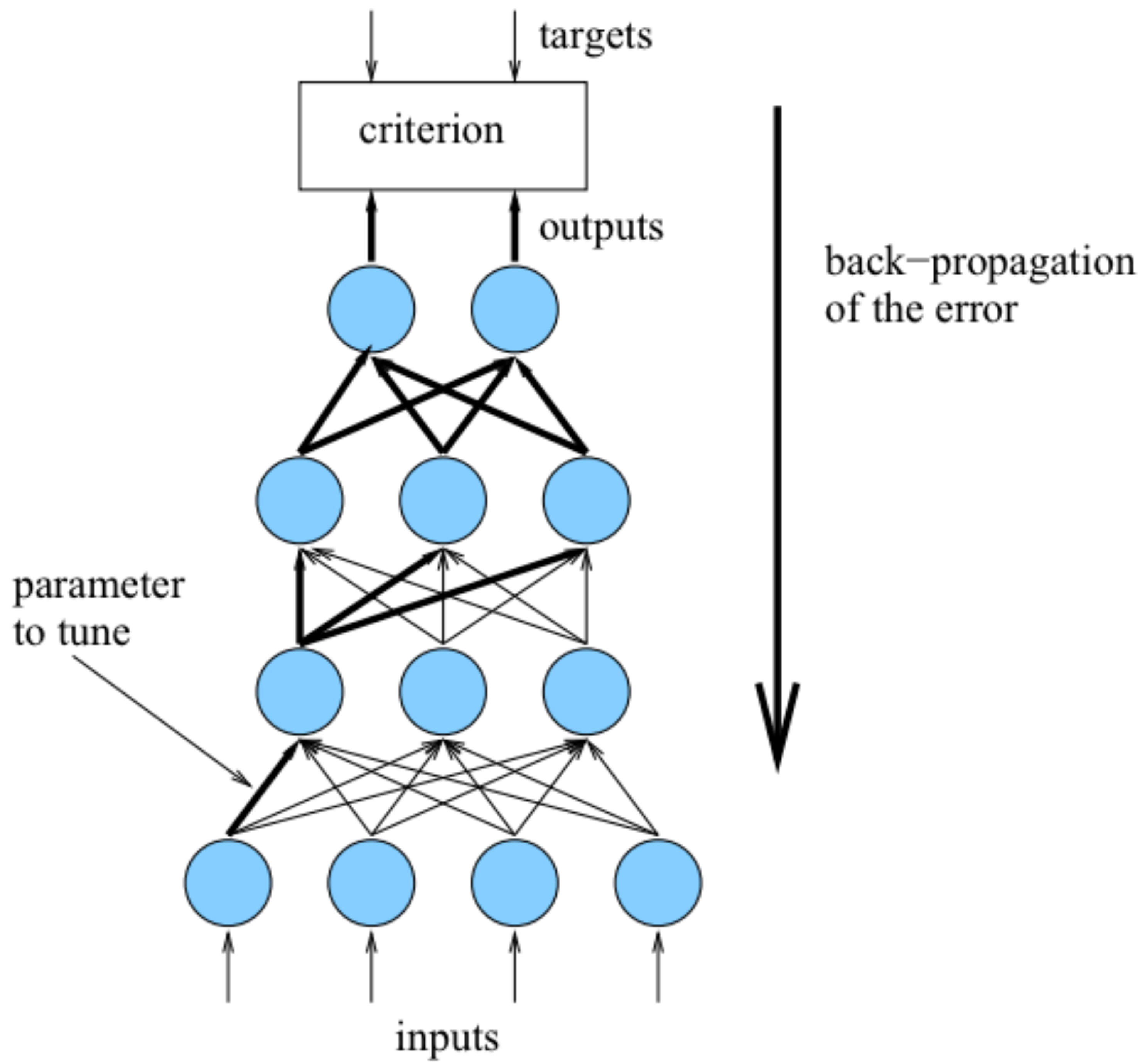
Backpropagation

- Estimating model Parameters `Ws` and `bs`



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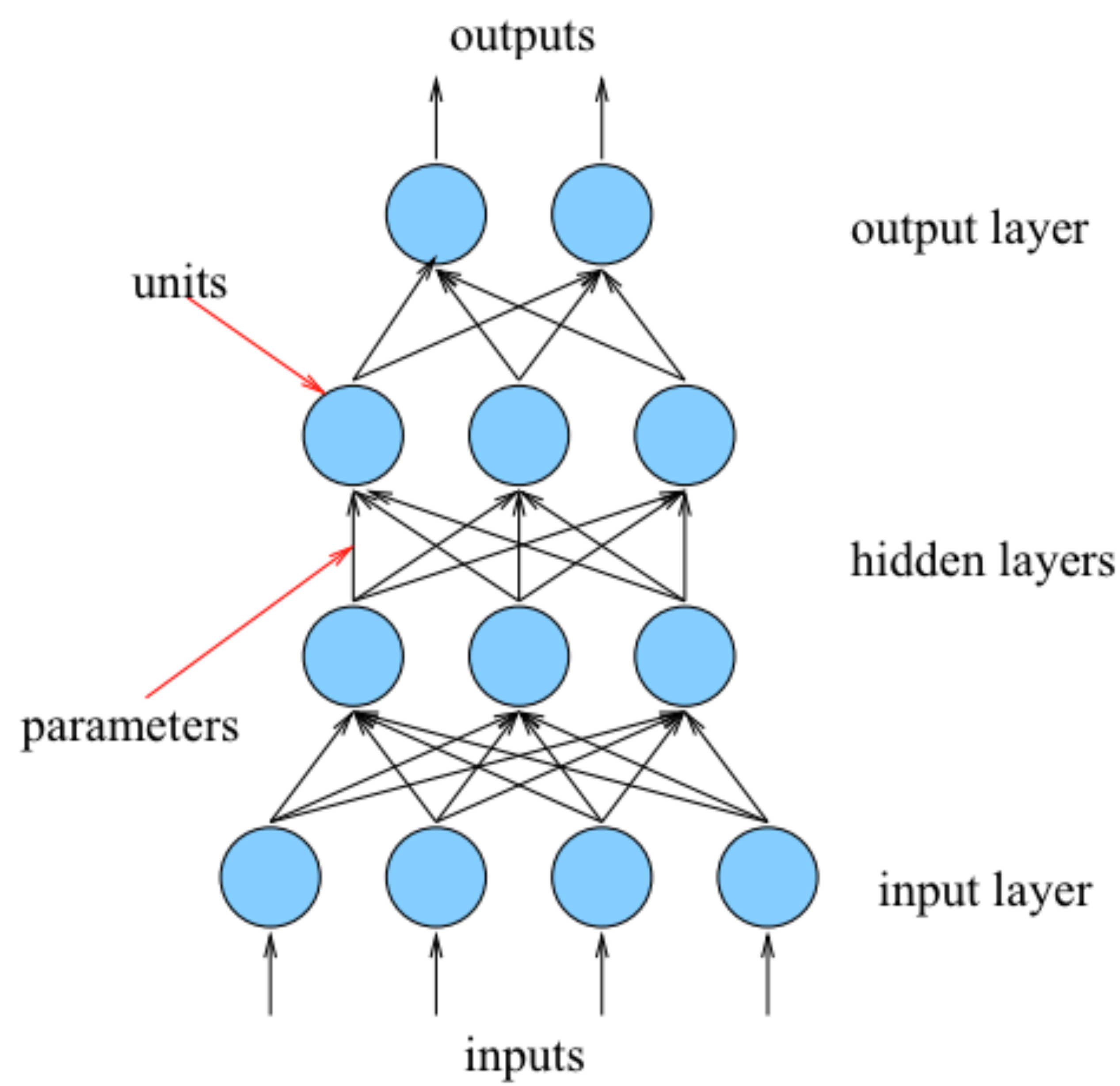
Backpropagation

- Criterion for ANN
  - Mean Squared Error:
    - `Error=(ŷ-y)^2`
  - Cross-entropy
    - `Error=-sum(ŷlog(y)+ (1-ŷ)log(1-y))`

Deep ANNs

- ANN is called
  - Shallow if only # layers=2
  - Deep if #layers>2



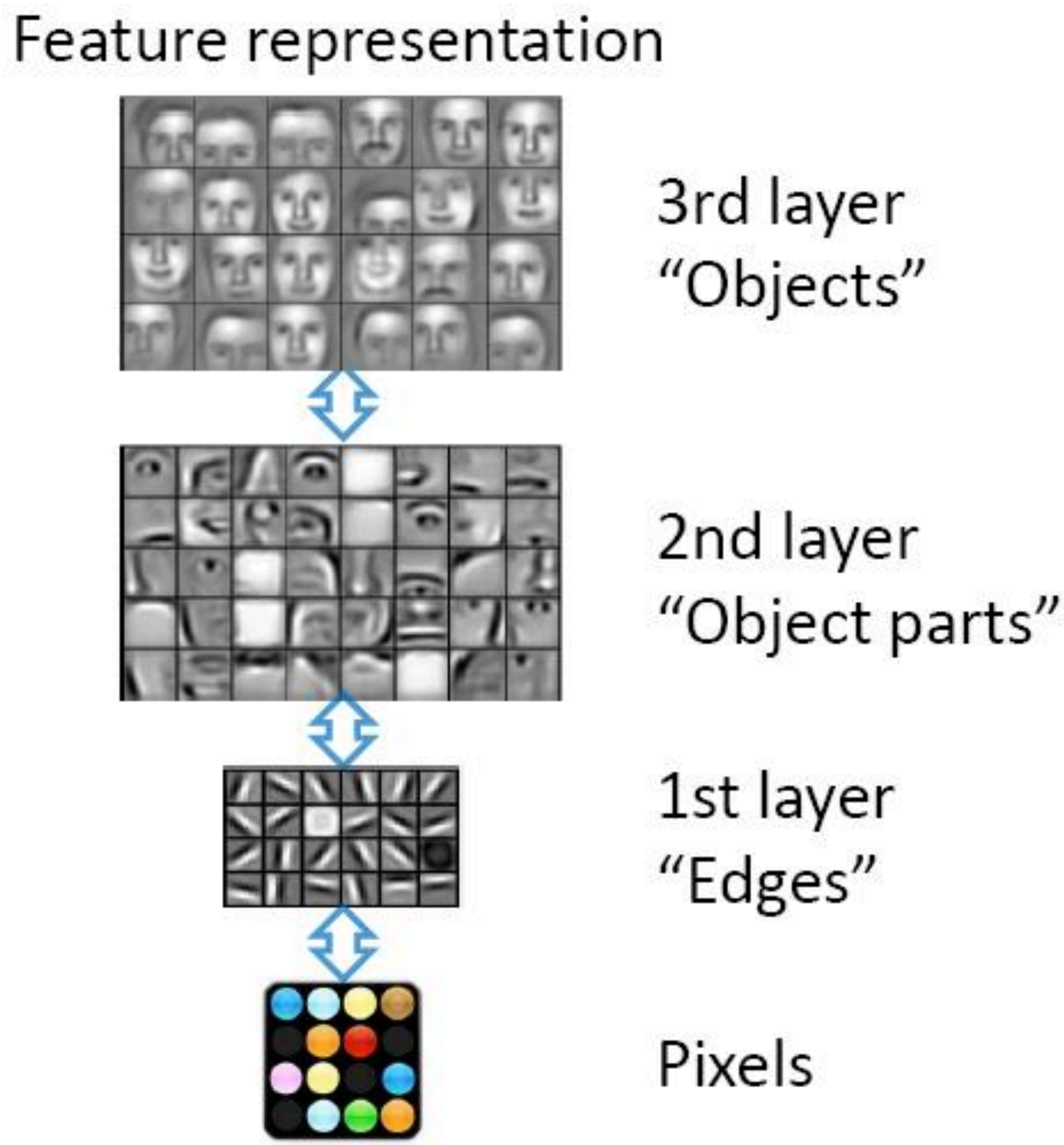
Why deep architecture?

- Isn't a two-layer ANN a universal approximator?
- Why deep architectures are needed?
  - The brain has a deep architecture
  - Cognitive processes seem deep
  - Insufficient depth can hurt

Why deep architecture?

- The brain has a deep architecture:
  - visual cortex has a sequence of levels
  - Each level represents the input at a different level of abstraction,
  - more abstract features further up in the hierarchy, defined in terms of the lower-level ones.
- Cognitive processes seem deep
- Insufficient depth can hurt

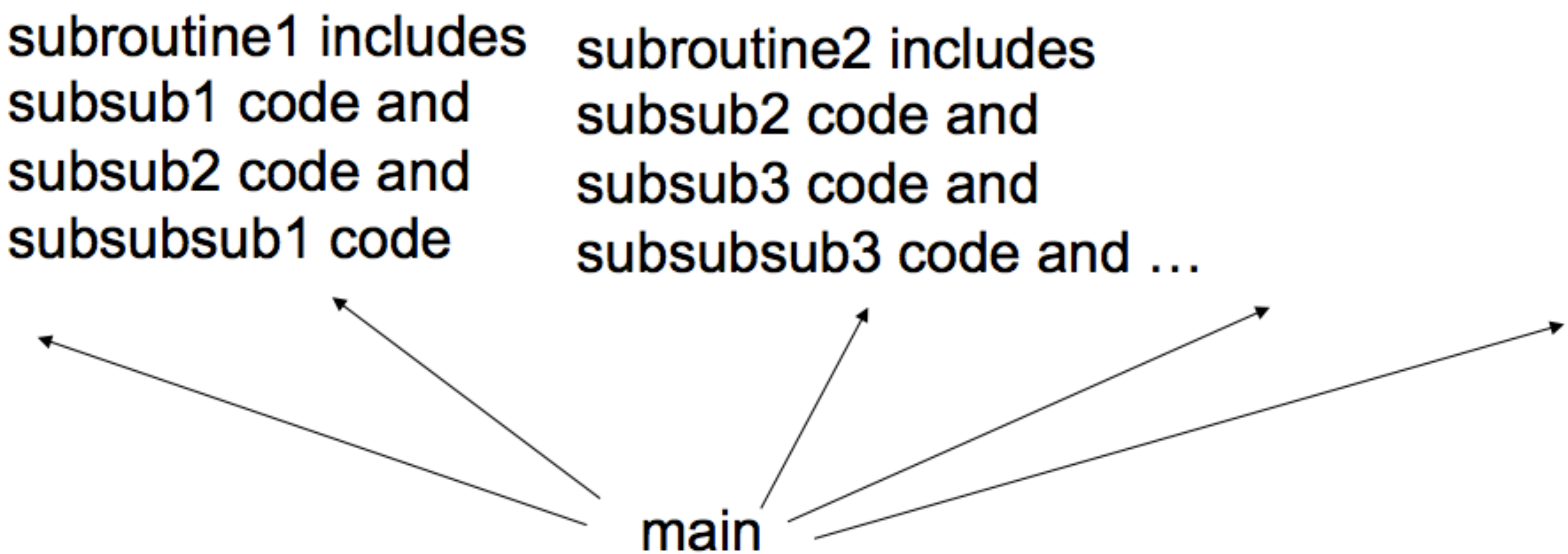
Why deep architecture?



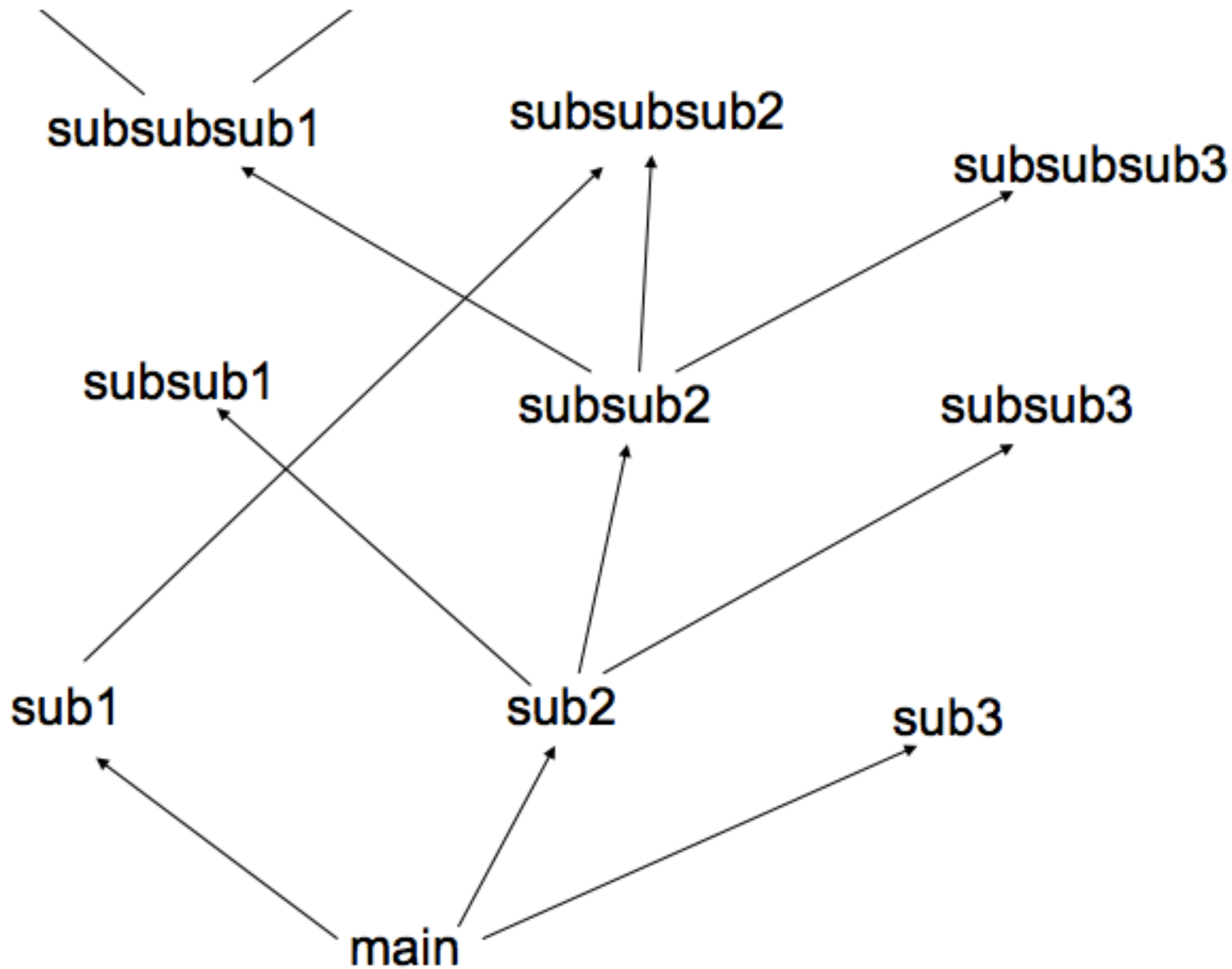
Why deep architecture?

- The brain has a deep architecture:
- Cognitive processes seem deep
  - Humans organize their ideas and concepts hierarchically.
  - Humans first learn simpler concepts and then compose them to represent more abstract ones.
  - Engineers break-up solutions into multiple levels of abstraction and processing
- Cognitive processes seem deep

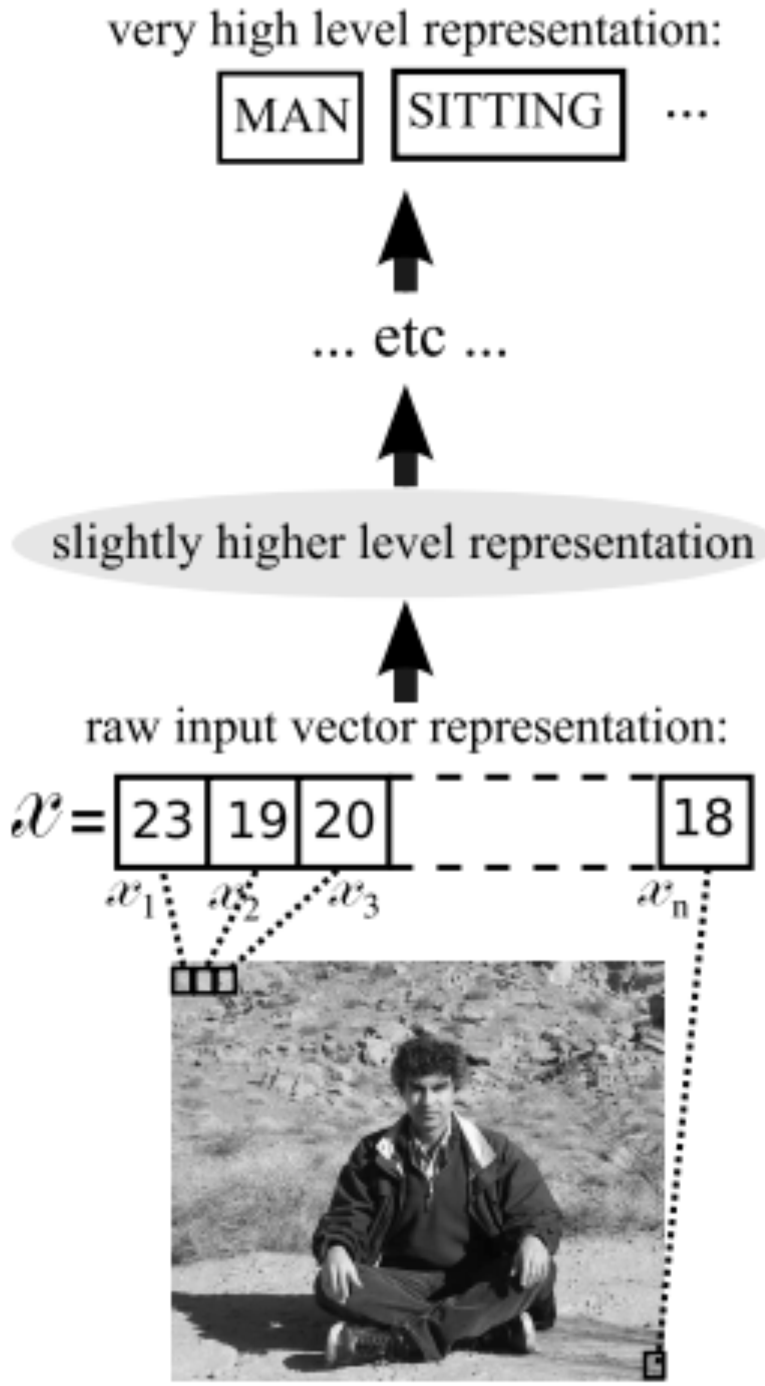
Why deep architecture?



Why deep architecture?



Why deep architecture?



Why deep architecture?

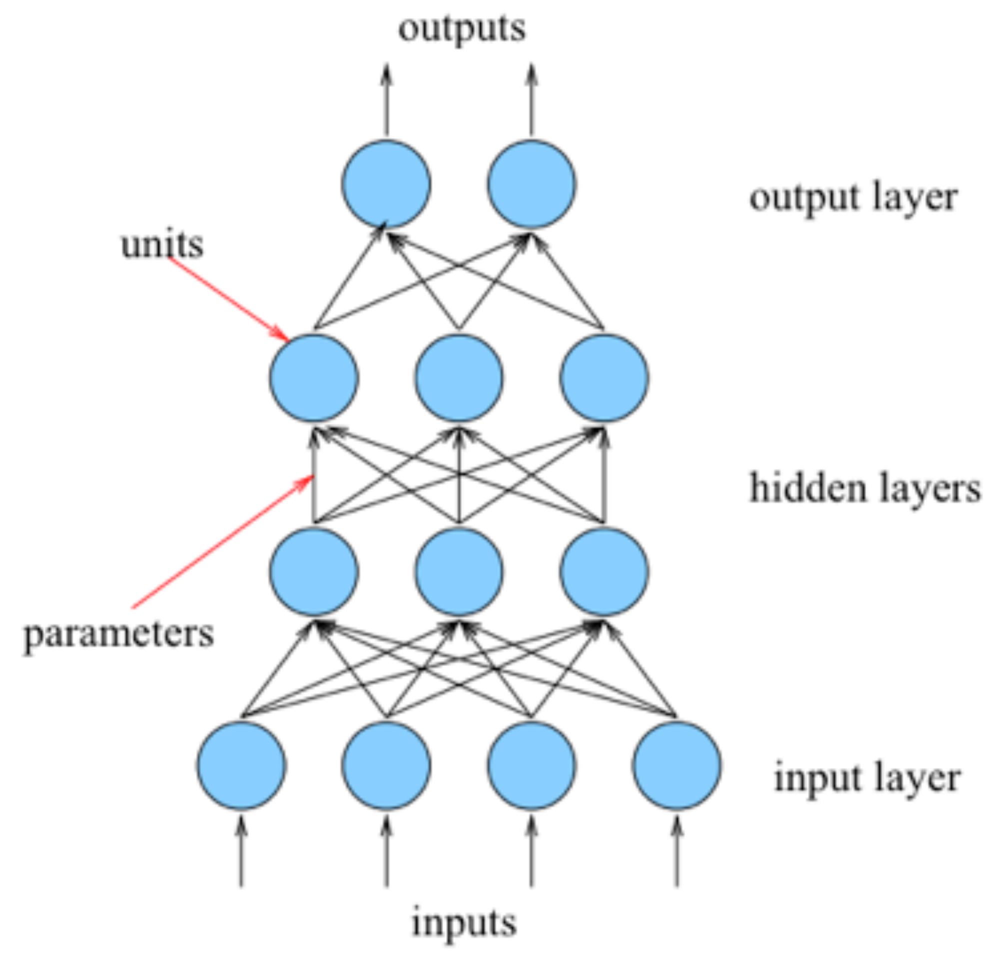
- The brain has a deep architecture:
- Cognitive processes seem deep
- Insufficient depth can hurt
  - there exist function families which the required number of nodes may grow exponentially with the input size [Hastad 1986]

Why deep architecture?

- Some families of functions which can be efficiently (compactly) represented with O(n) nodes (for n inputs) for **depth d**
- but for which an exponential number (O(2^n)) of nodes is needed if **depth is restricted to d-1**

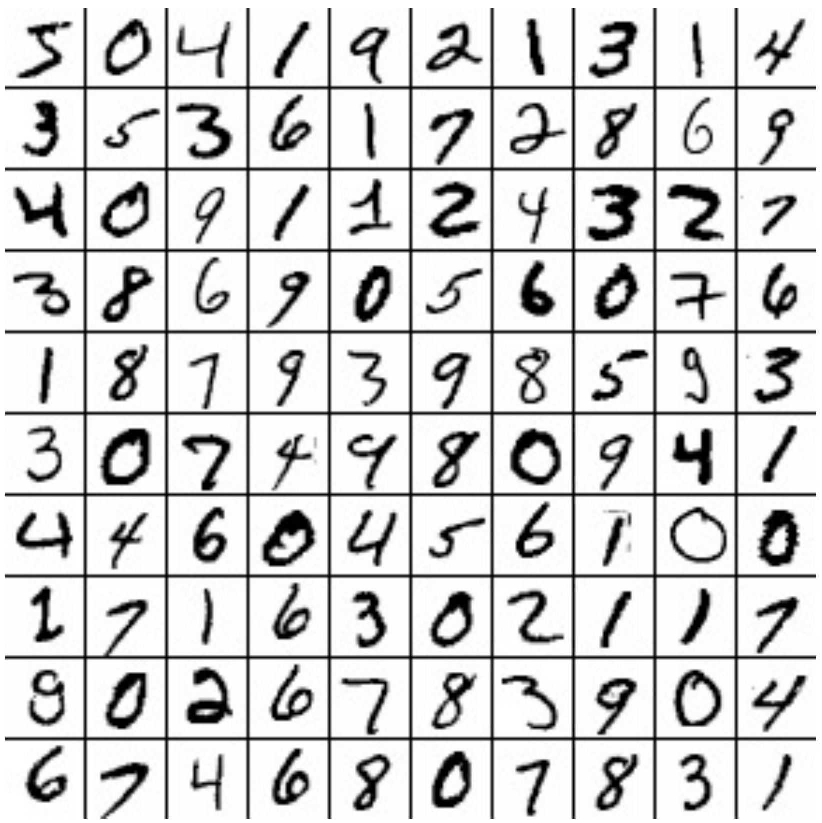
DNN

- It is hard to effectively train a deep ANN



MNIST Corpus

- 28x28 pixels, pixel values range from 0 to 1
- Contains 70,000 images
  - 50,000 training set
  - 10,000 validation set
  - 10,000 test set
- Task: Classify 10 digit classes

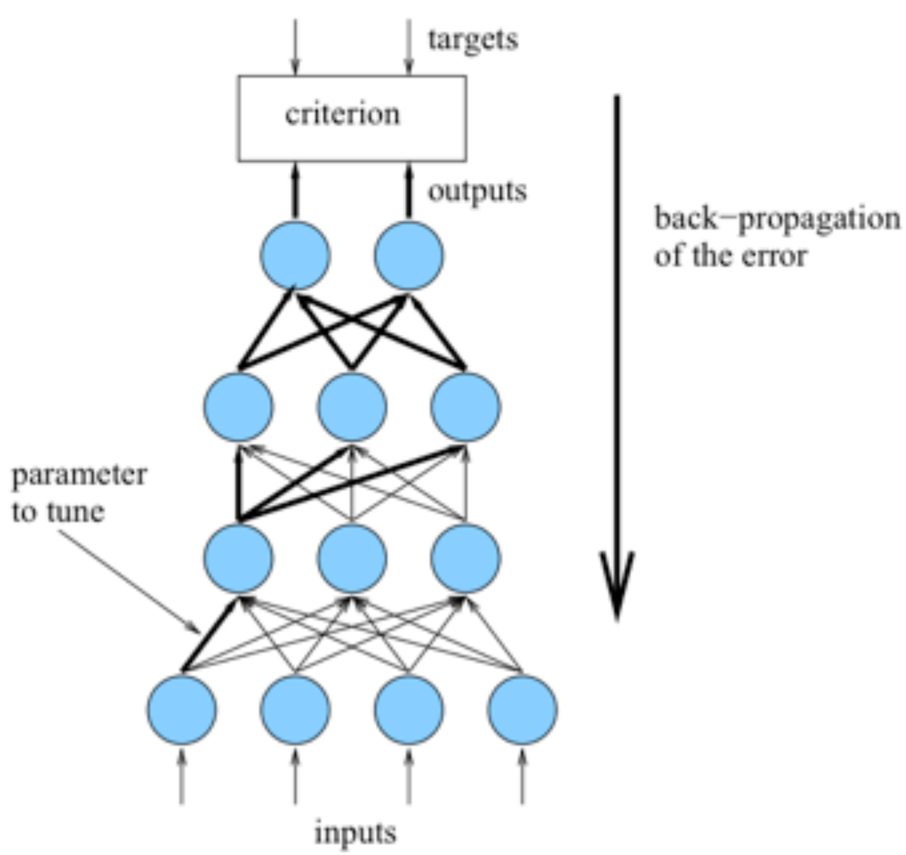


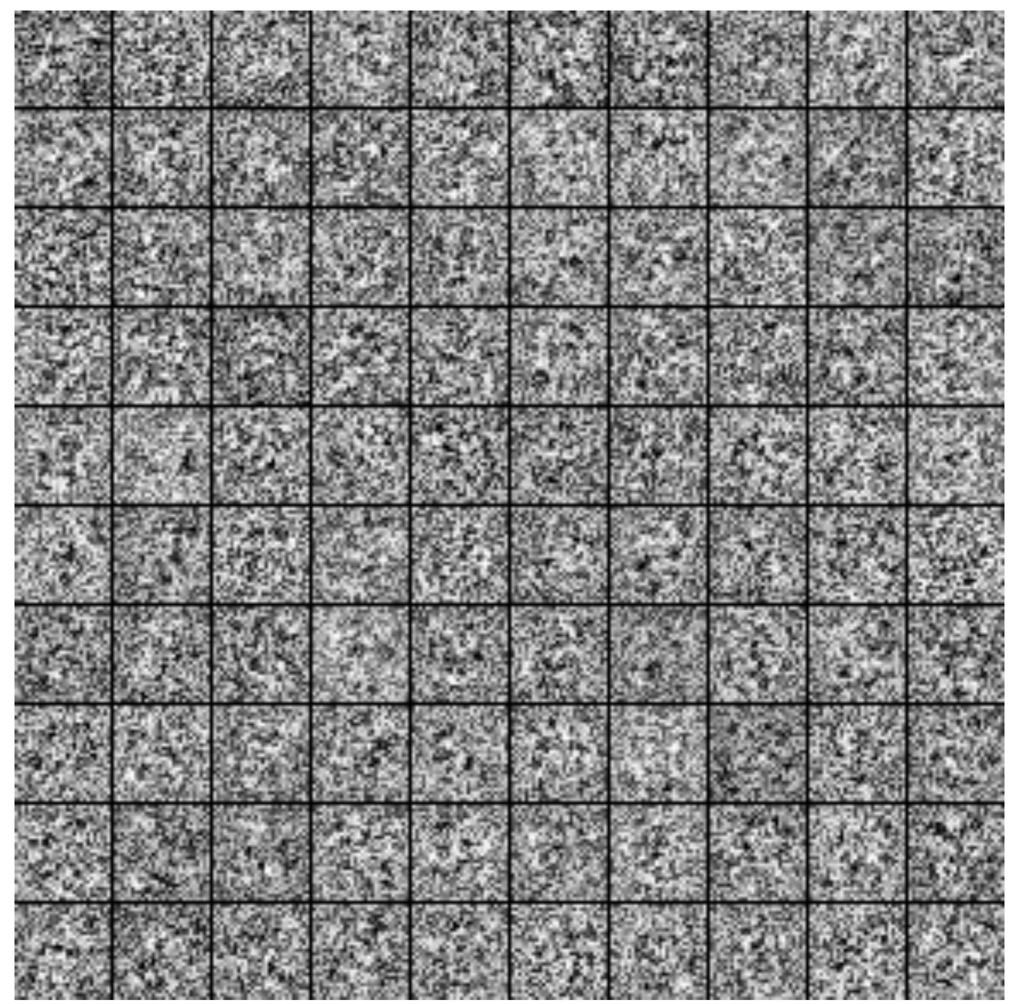
MNIST Corpus

Convolutional net Boosted LeNet-4, [distortions]	none	0.7
Trainable feature extractor + SVMs [no distortions]	none	0.83
Trainable feature extractor + SVMs [elastic distortions]	none	0.56
Trainable feature extractor + SVMs [affine distortions]	none	0.54
unsupervised sparse features + SVM, [no distortions]	none	0.59
Convolutional net, cross-entropy [affine distortions]	none	0.6
Convolutional net, cross-entropy [elastic distortions]	none	0.4
large conv. net, random features [no distortions]	none	0.89
large conv. net, unsup features [no distortions]	none	0.62
large conv. net, unsup pretraining [no distortions]	none	0.60
large conv. net, unsup pretraining [elastic distortions]	none	0.39
large conv. net, unsup pretraining [no distortions]	none	0.53
large/deep conv. net, 1-20-40-60-80-100-120-120-10 [elastic distortions]	none	0.35
committee of 7 conv. net, 1-20-P-40-P-150-10 [elastic distortions]	width normalization	0.27 +-0.02
committee of 35 conv. net, 1-20-P-40-P-150-10 [elastic distortions]	width normalization	0.23

Weight decay

- What weights might look like this if DNN is trained using simple back-propagation





ANN

- The simple backprop would either
  - get stuck in local minima and give bad results or
  - it might give better results but the weights are hard to describe (how does it work?)

DNN training

- How to train a DNN effectively?

DNN training

- How to train a DNN effectively?
  - First breakthrough: Unsupervised pre-training
  - Huge amounts of data: requires high computation power. Lots of work on GPUs
  - New structures: activation functions like ReLU and maxout, other structures like CNNs and RNNS
  - Clever training: dropout

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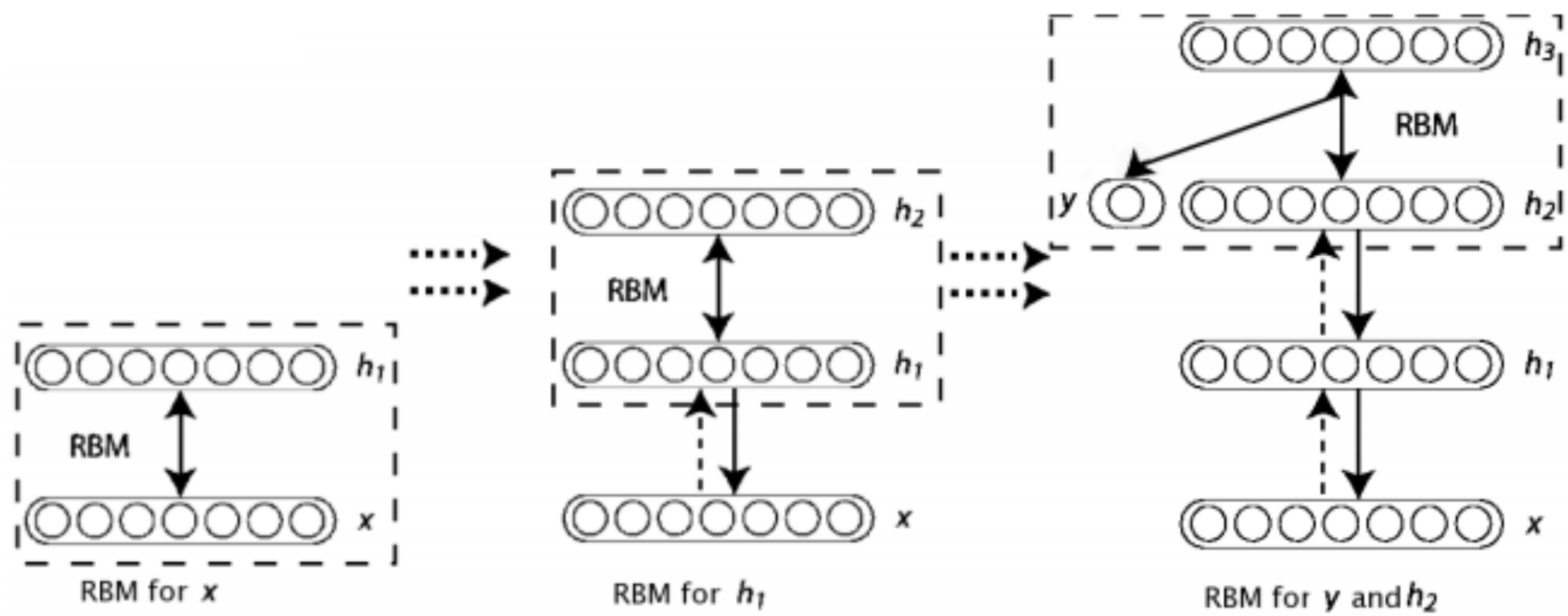
Unsupervised Pre-training

- previous purely supervised attempt failed
- Unsupervised feature learners:
    - Restricted Boltzmann Machines
    - Auto-encoder variants
    - Sparse coding variants

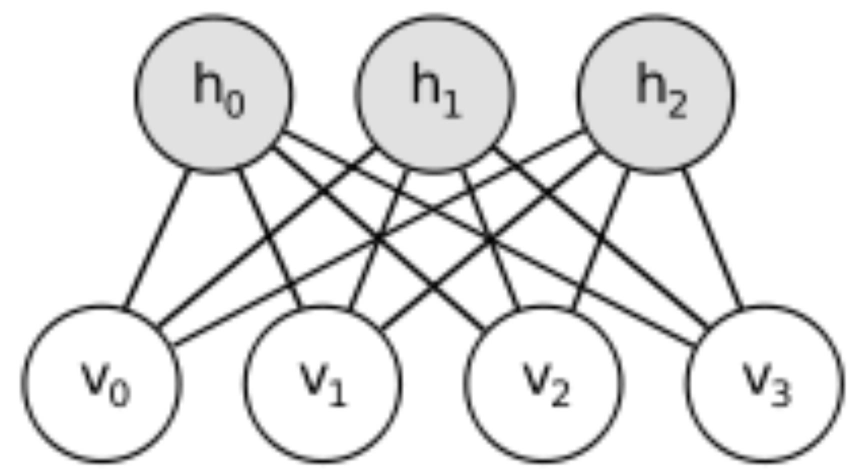
Unsupervised Pre-training

- One of the big ideas from 2006: **layer-wise** unsupervised ore-training



Unsupervised Pre-training

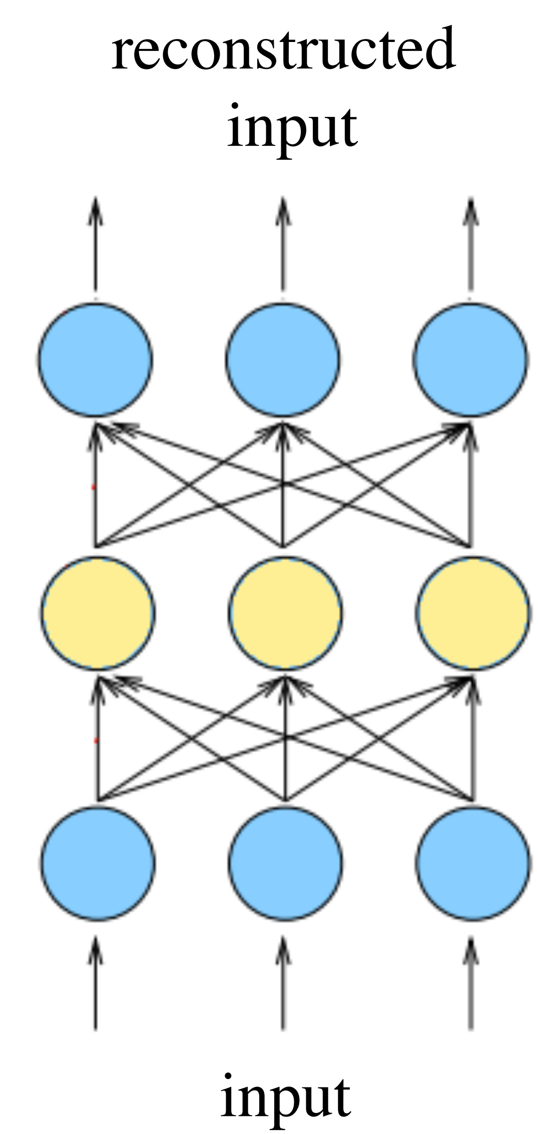
- RBMs
- `h=g(Wv+b)`
- `v=g(W'h+c)`



- RBMs are Energy-based models trained to maximize the energy

Autoencoders

- These networks try to reconstruct the input
- `h=g(Wx+b1)`
- `x_rec=g(W'h+b2)`
- where the first and second layer weights are tied `W'=transpose(W)`



Autoencoders vs RBMs

- RBMs and denoising autoencoders (DAE) have shown to converge to the same solution under certain conditions

Unsupervised Pre-training

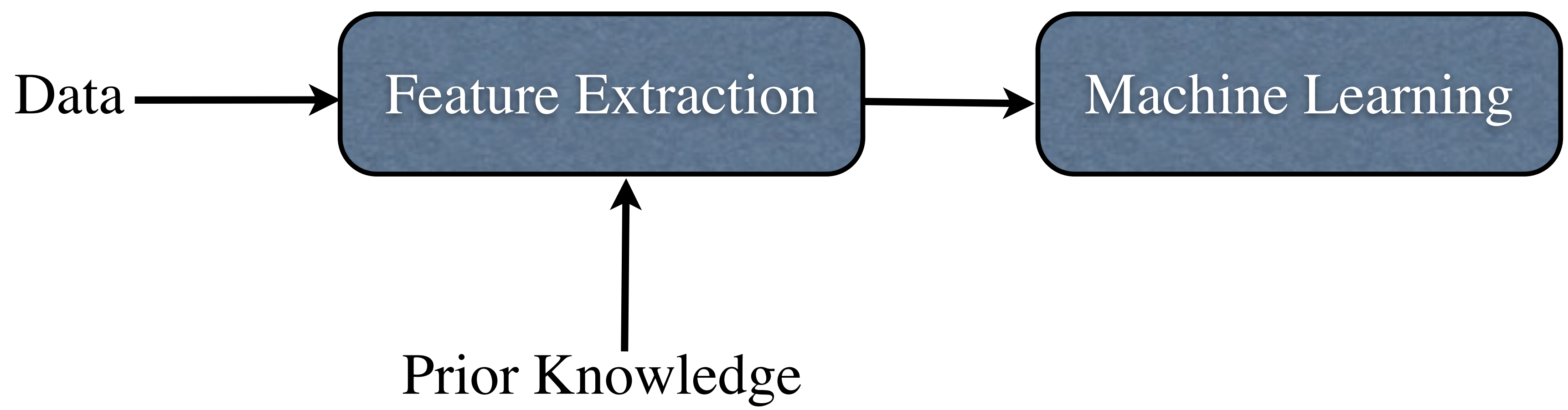
- Start training the network using backprop from the RBM or DAE weights and not initial randomization.
- Why does unsupervised pre-training work?
  - It is a form of feature learning.

Unsupervised Pre-training

- The goal of unsupervised pre-training is
  - to see a lot of unlabeled examples
  - learn features from it

Feature Learning

- Usual Machine Learning applications have two steps



Feature Learning

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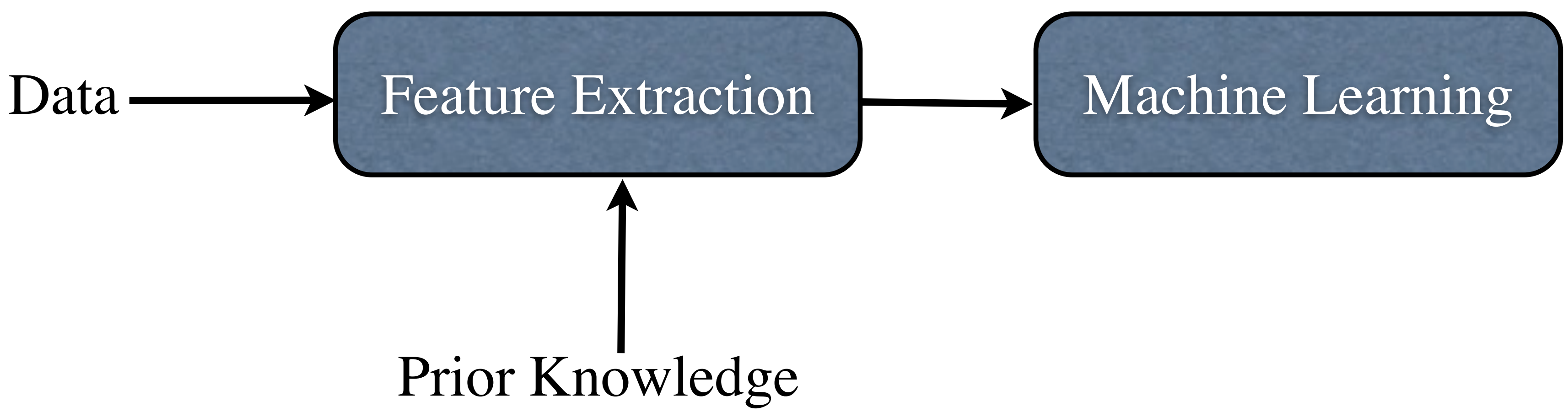
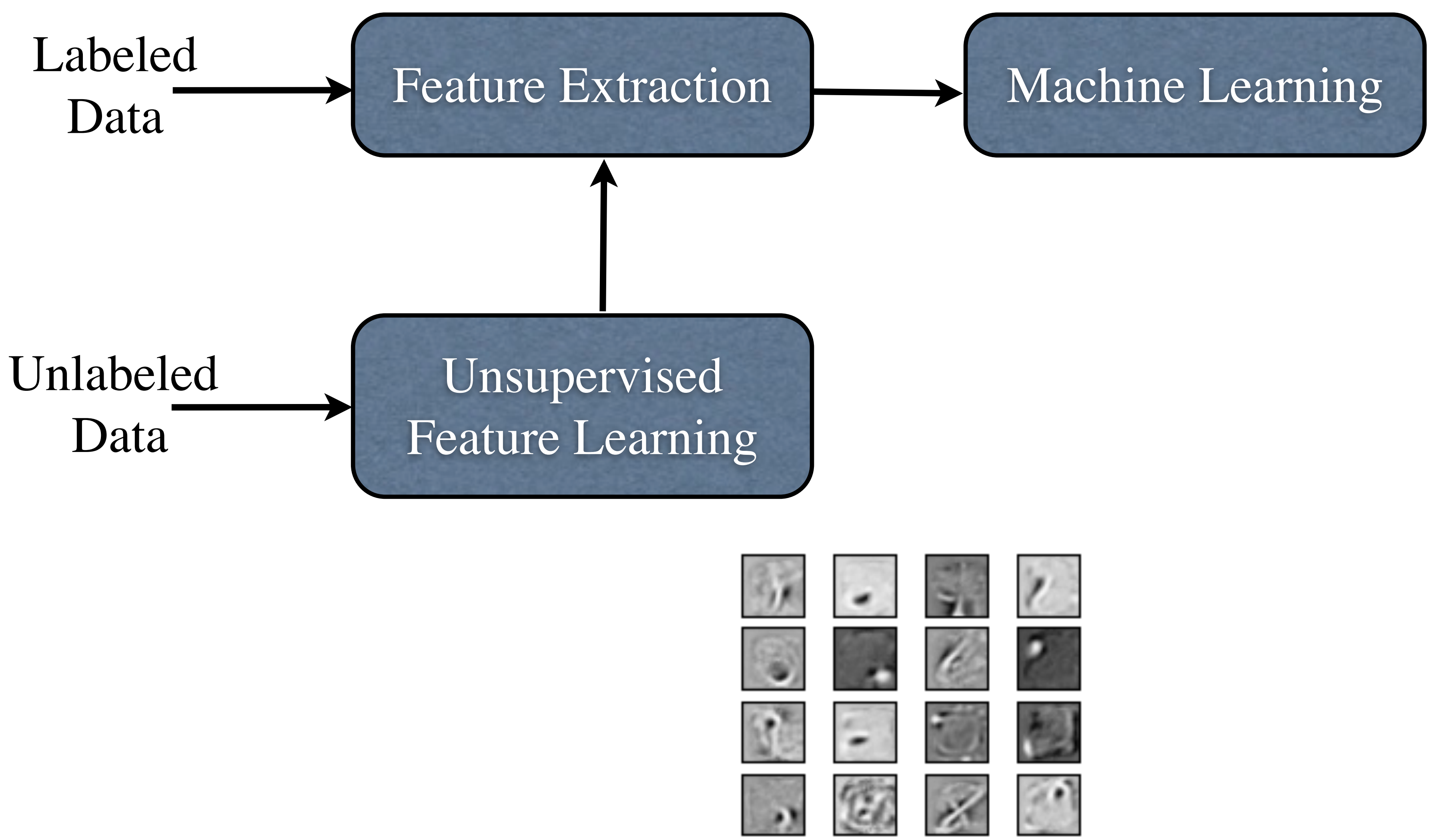


how many straight vertical lines? how long?

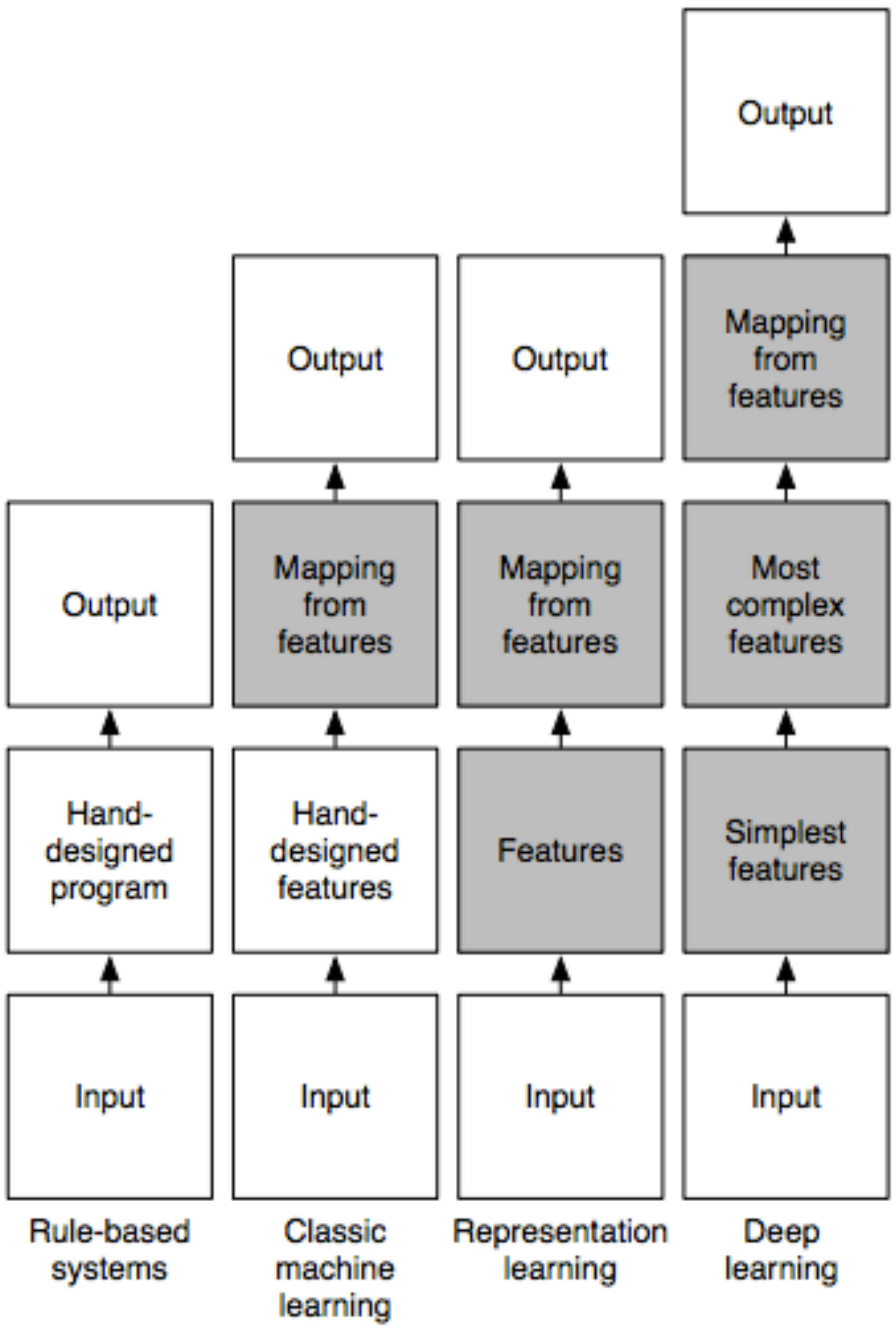
how many circles?

how many straight horizontal lines? how long?

Feature Learning

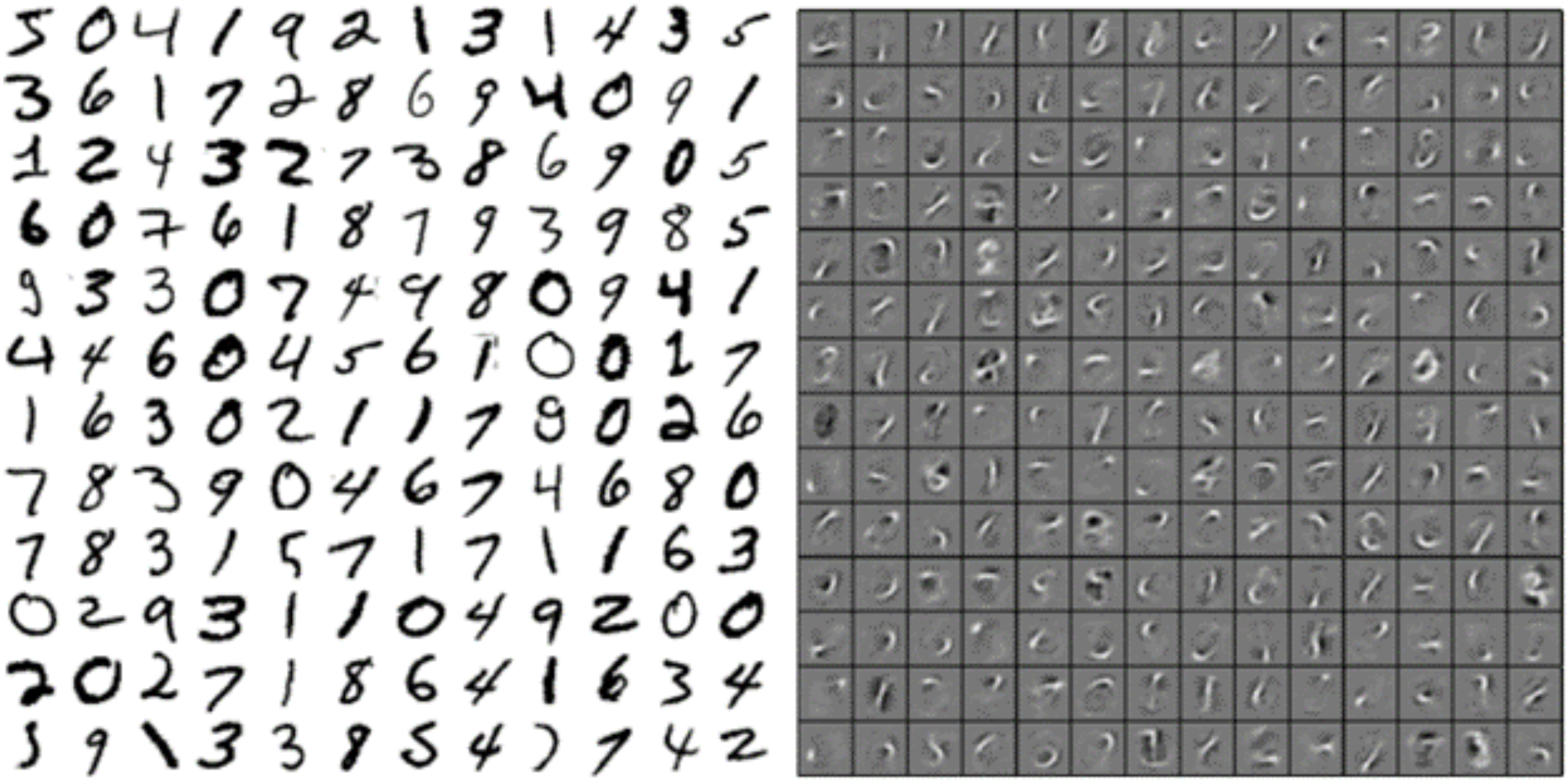


Feature learning

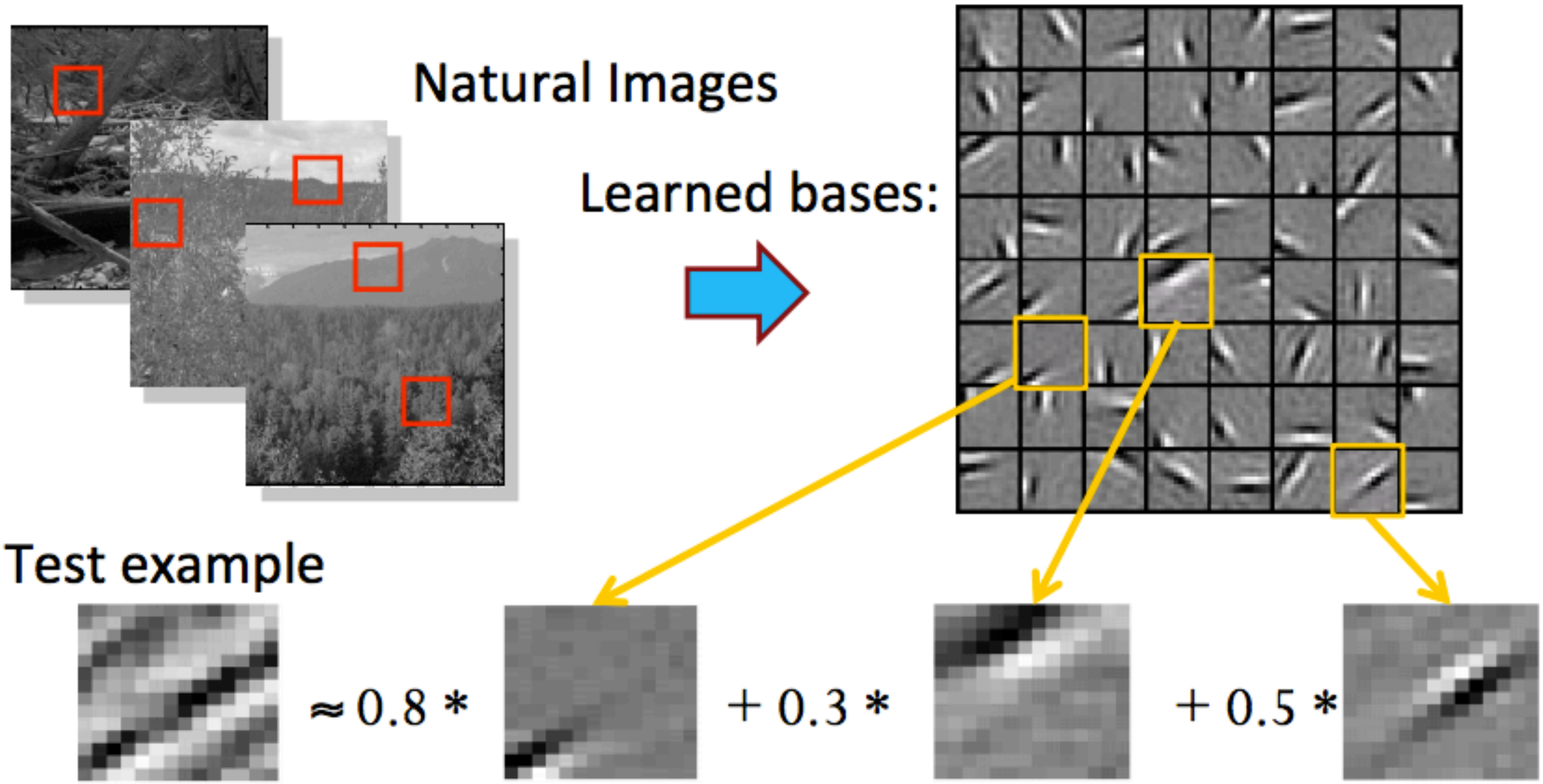


Edge detection

Unsupervised Feature Learning



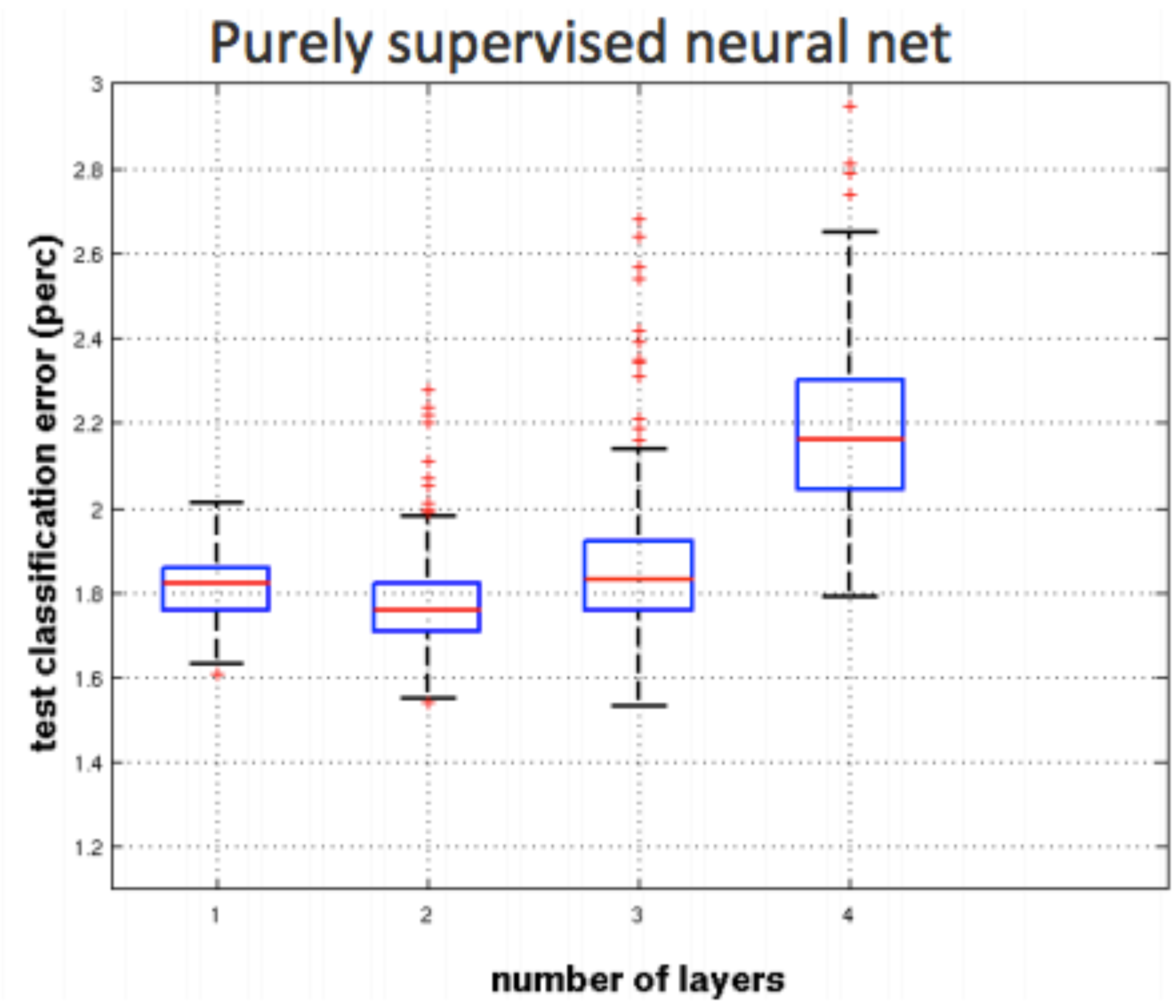
Sparse Coding

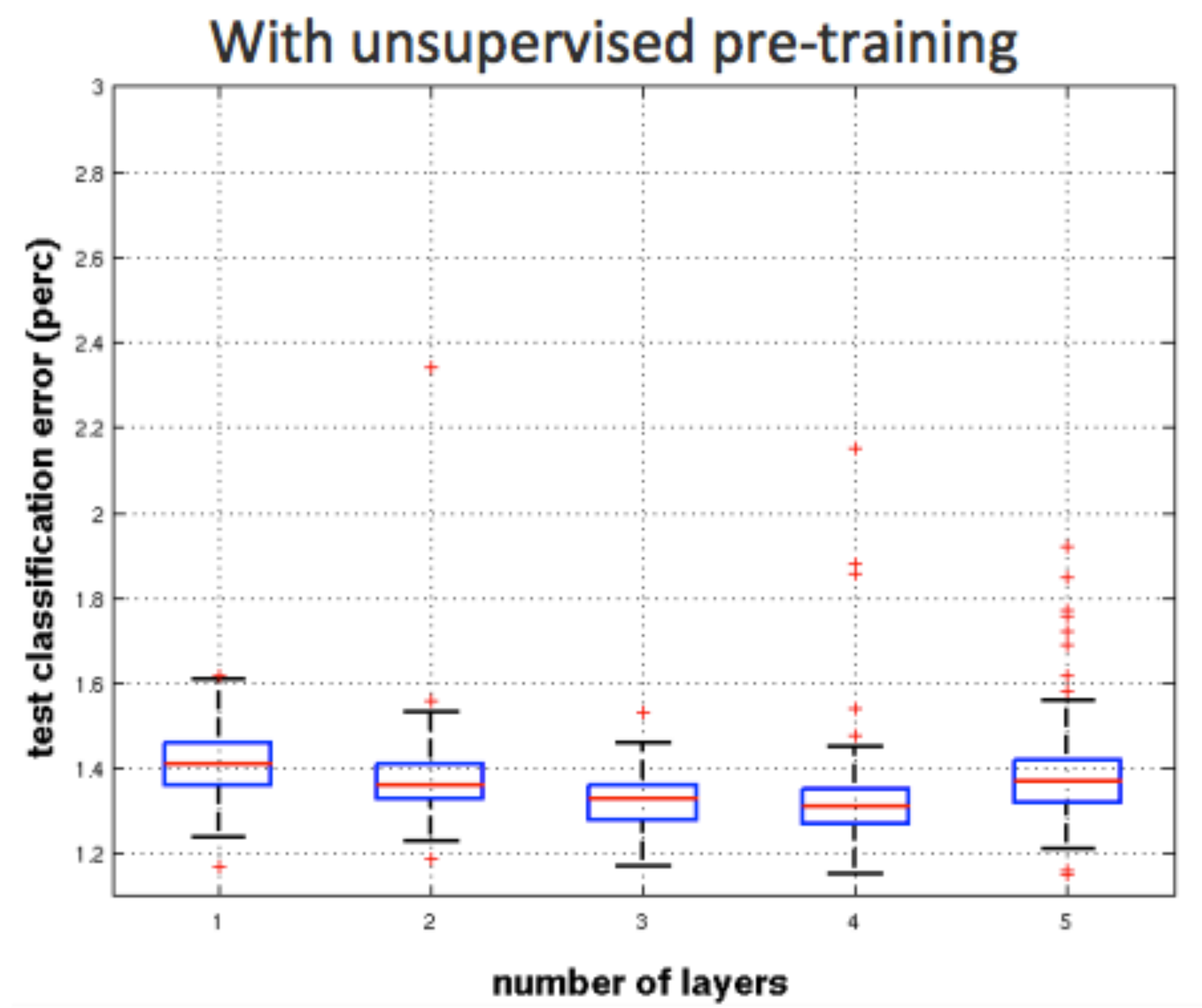


$[h_1, \ldots, h_{64}]$ = [0, 0, ..., 0, **0.8**, 0, ..., 0, **0.3**, 0, ..., 0, **0.5**, 0]
(feature representation)

Results

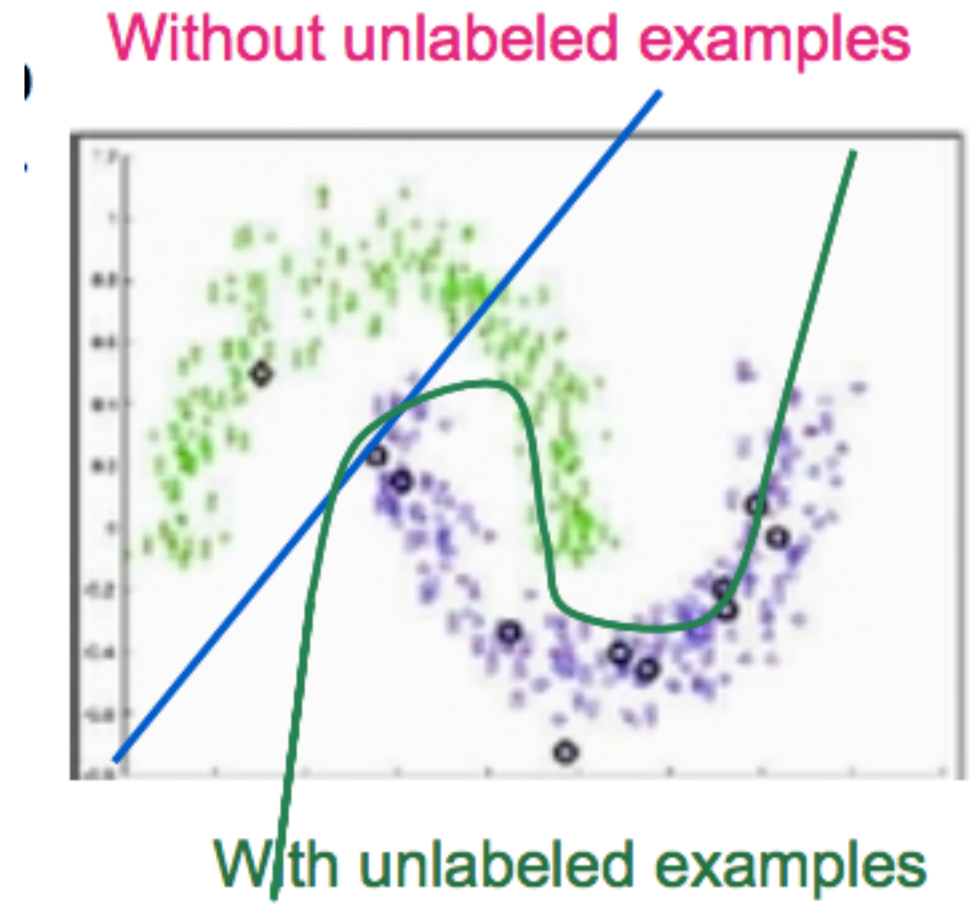
- MNIST results





Unsupervised

- Recently, with enough data, and advances in the field, it has been shown that unsupervised learning is not always necessary
- but helps if:
    - data size is small
    - low computation power



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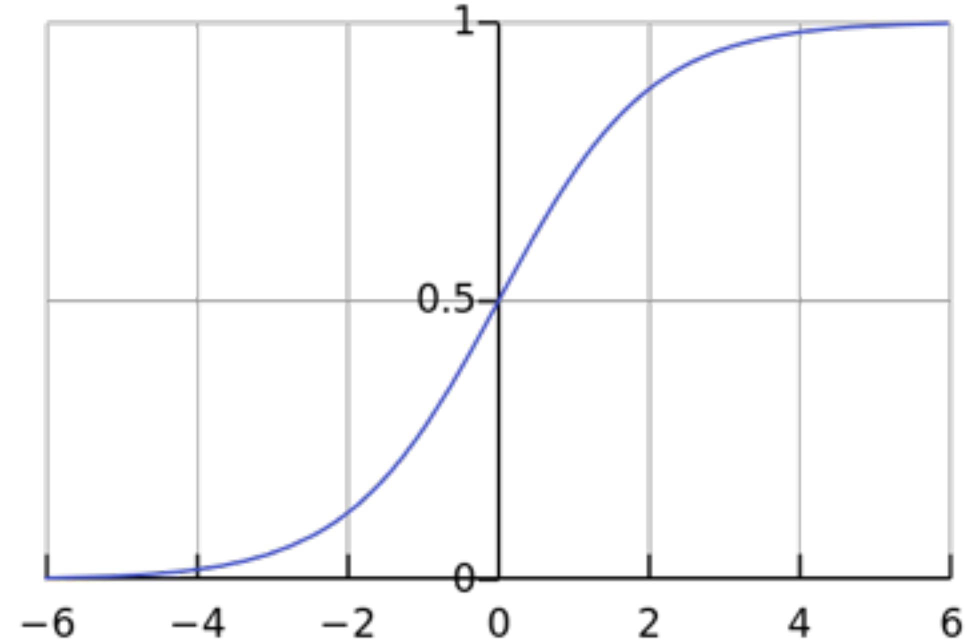
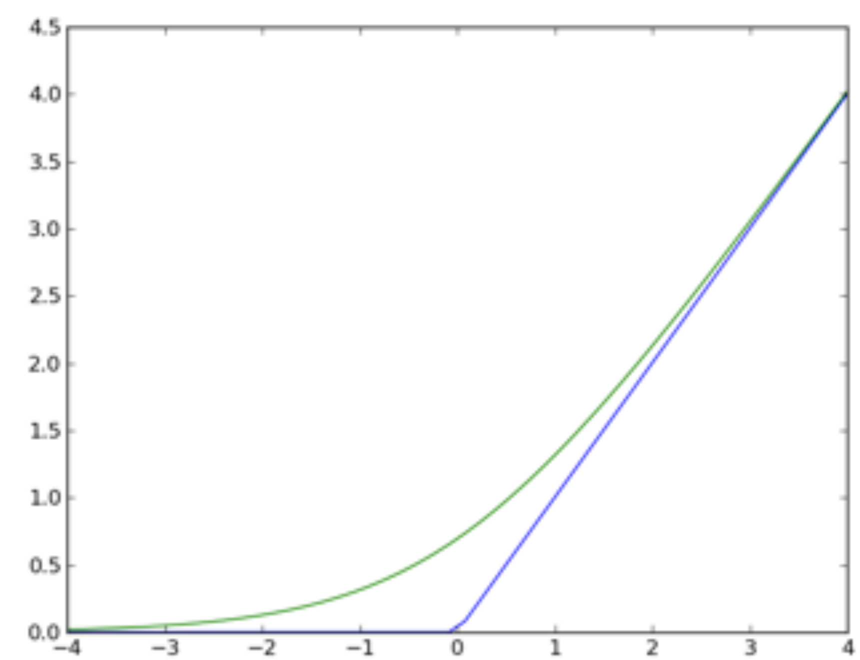
Activation functions

- Old style ones:
  - Sigmoid
  - Tanh



- Rectifier f(x) = max(0, x)
- Softplus f(x) = ln(1 + e^x)

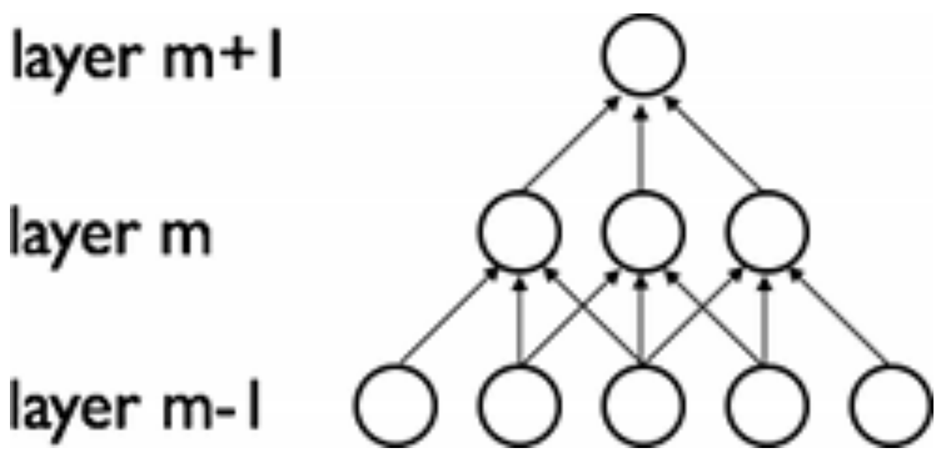


Convolutional NN

- Convolutional Neural Networks (CNN) are biologically-inspired variants of MLPs.
- Mimic visual cortex cell arrangemens
- exploit the strong spatially local correlation present in natural images

Convolutional NN

- Sparse Connectivity



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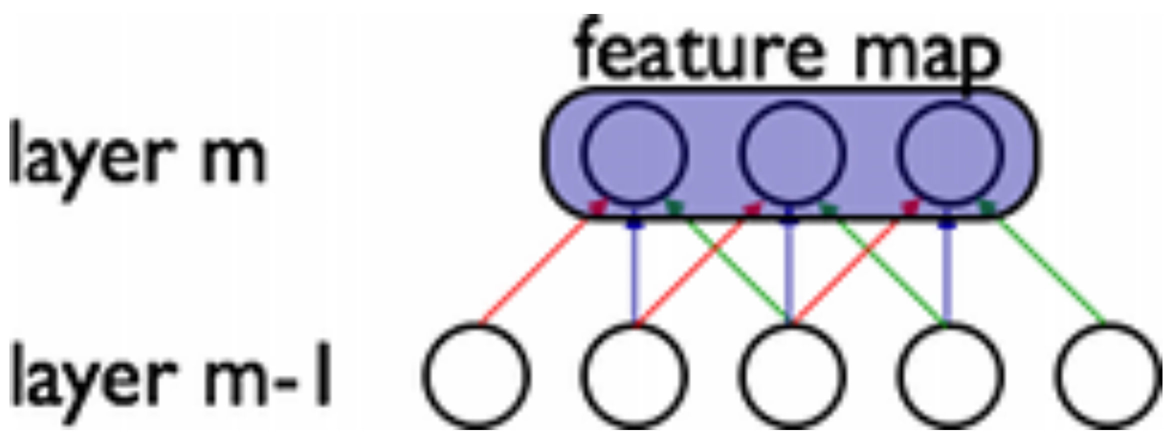
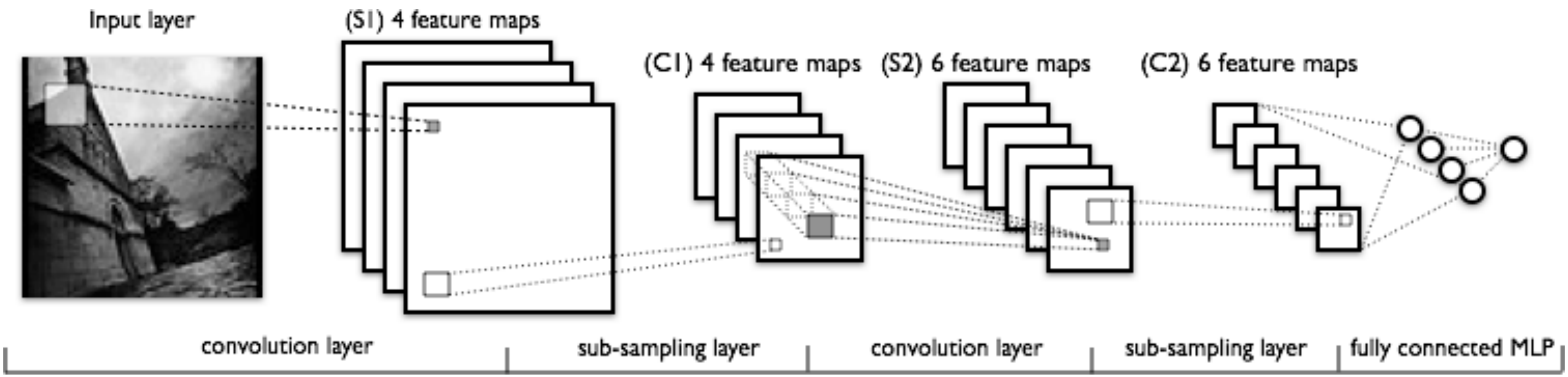
Convolutional NN

- Weight sharing

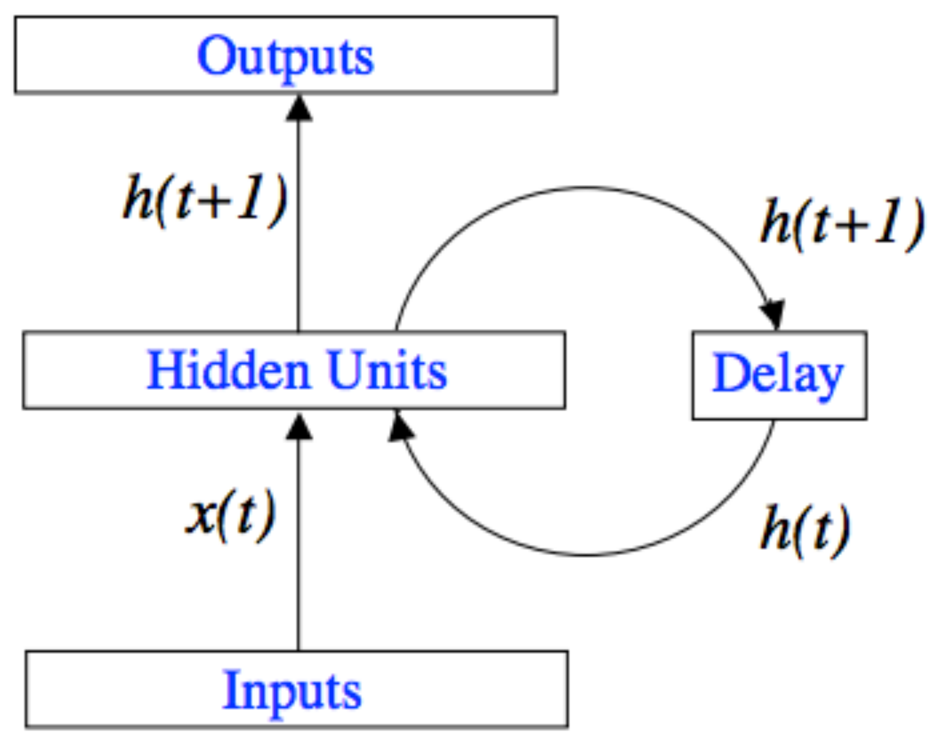


Deep CNNs



Input layer
(S1) 4 feature maps
(C1) 4 feature maps
(S2) 6 feature maps
(C2) 6 feature maps
convolution layer
sub-sampling layer
convolution layer
sub-sampling layer
fully connected MLP

Recurrent NNs



Application specific

- CNNs have shown significant improvements for vision field
- RNNs have shown significant improvements for speech field
- New machine learning: less signal processing (feature engineering) and more model engineering

DNN training

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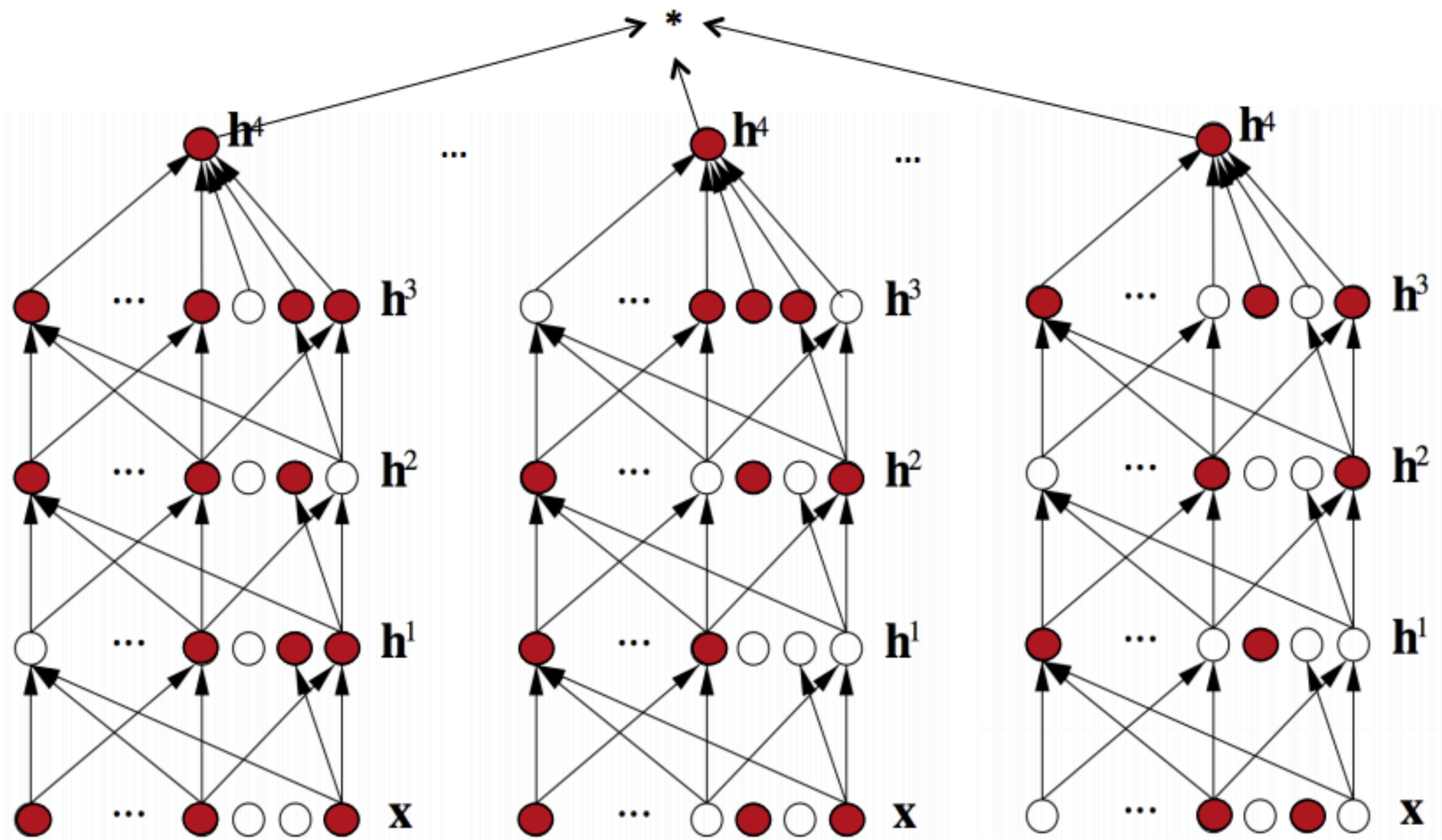
Dropout

- during training multiply neuron output by random 0/1 bit (p=0.5),
- during test weight by 0.5 to adjust
- works very good with ReLU and maxout

Dropout



Dropout

- New Machine Learning:
  - set the number of your parameters to more than it is actually needed
  - use clever regularizations such as dropout to avoid over-fitting

Conclusion

- How to train a DNN effectively?
  - First: Unsupervised pre-training
  - Huge amounts of data, high computation power
  - Activation functions like ReLU
  - Clever training: dropout
- The last three innovations have made unsupervised learning less necessary

Conclusion

- Designing models rather than feature engineering -> is signal processing going to be extinct?!

- Huge number of parameters (more than needed) but use regularization

References

- [1] Y. Bengio, Learning Deep Architectures for AI, 2009
- [2] Y. Bengio, Deep Learning, MLSS, 2015
- [3] http://www.iro.umontreal.ca/~pift6266/H10/notes/deepintro.html
- [4] deeplearning.net
- [5] http://www.cs.bham.ac.uk/~jxb/INC/