Neural networks

Deep learning - unsupervised pre-training

DEEP LEARNING

Topics: why training is hard

- Depending on the problem, one or the other situation will tend to prevail

- If first hypothesis (underfitting): use better optimization
  - this is an active area of research

- If second hypothesis (overfitting): use better regularization
  - unsupervised learning
  - stochastic «dropout» training

UNSUPERVISED PRE-TRAINING

Topics: unsupervised pre-training

- Solution: initialize hidden layers using unsupervised learning
  - force network to represent latent structure of input distribution

character image

random image

  - encourage hidden layers to encode that structure

UNSUPERVISED PRE-TRAINING

Topics: unsupervised pre-training

- Solution: initialize hidden layers using unsupervised learning
  - force network to represent latent structure of input distribution

Why is one a character and the other is not ?

character image

random image

  - encourage hidden layers to encode that structure

UNSUPERVISED PRE-TRAINING

Topics: unsupervised pre-training

- Solution: initialize hidden layers using unsupervised learning
  - this is a harder task than supervised learning (classification)

Why is one a character and the other is not ?

character image

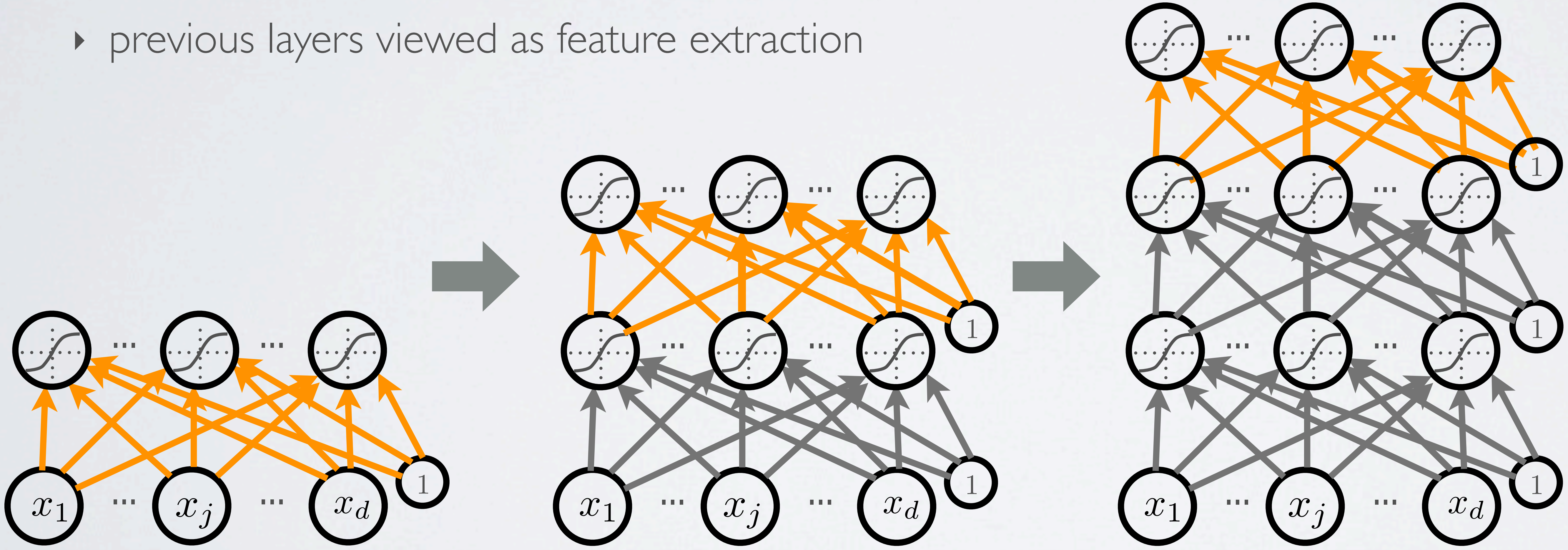
random image

  - hence we expect less overfitting

UNSUPERVISED PRE-TRAINING

Topics: unsupervised pre-training

- We will use a greedy, layer-wise procedure
  - train one layer at a time, from first to last, with unsupervised criterion
  - fix the parameters of previous hidden layers
  - previous layers viewed as feature extraction



UNSUPERVISED PRE-TRAINING

Topics: unsupervised pre-training

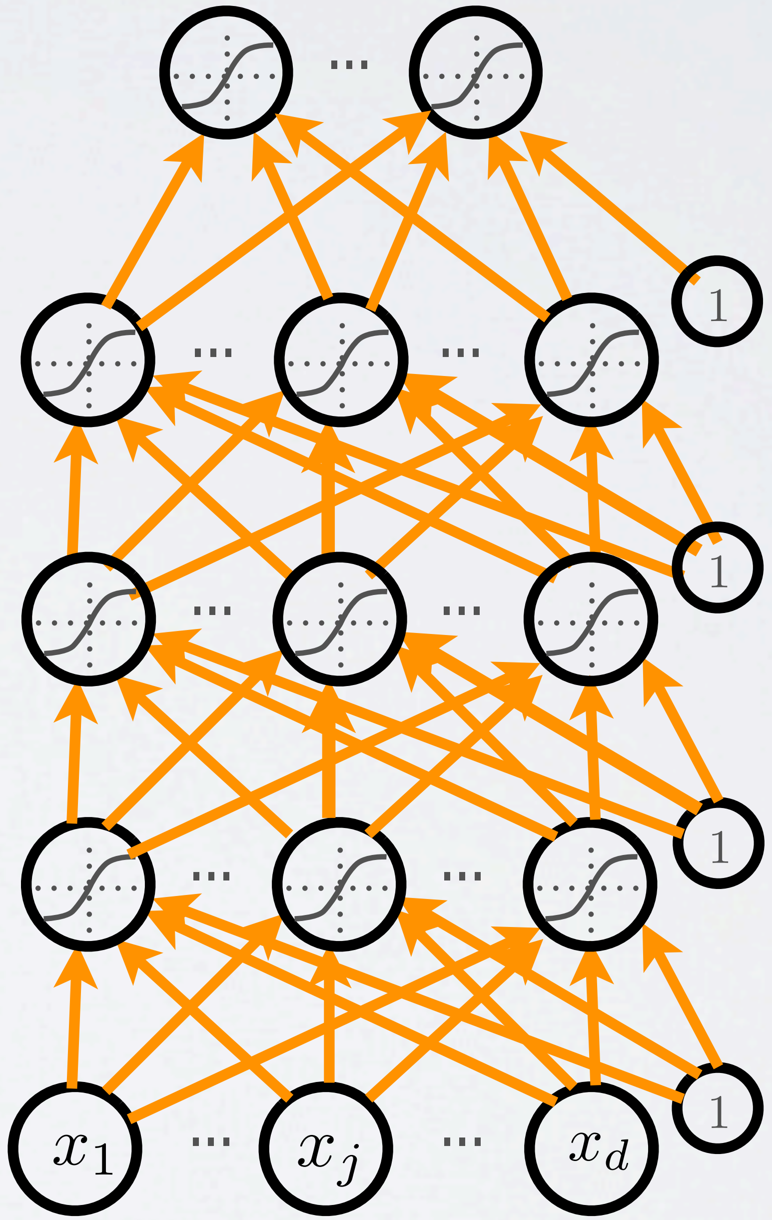
- We call this procedure unsupervised pre-training
  - **first layer:** find hidden unit features that are more common in training inputs than in random inputs
  - **second layer:** find *combinations* of hidden unit features that are more common than random hidden unit features
  - **third layer:** find *combinations of combinations* of ...
  - etc.

- Pre-training initializes the parameters in a region such that the near local optima overfit less the data

FINE-TUNING

Topics: fine-tuning

- Once all layers are pre-trained
  - add output layer
  - train the whole network using supervised learning
- Supervised learning is performed as in a regular feed-forward network
  - forward propagation, backpropagation and update
- We call this last phase fine-tuning
  - all parameters are "tuned" for the supervised task at hand
  - representation is adjusted to be more discriminative



DEEP LEARNING

Topics: pseudocode

- for l=1 to L
  - build unsupervised training set (with $\mathbf{h}^{(0)}(\mathbf{x}) = \mathbf{x}$):

$$\mathcal{D} = \left\{\mathbf{h}^{(l-1)}(\mathbf{x}^{(t)})\right\}_{t=1}^{T}$$

  - train "greedy module" (RBM, autoencoder) on $\mathcal{D}$
  - use hidden layer weights and biases of greedy module to initialize the deep network parameters $\mathbf{W}^{(l)}$, $\mathbf{b}^{(l)}$
- Initialize $\mathbf{W}^{(L+1)}$, $\mathbf{b}^{(L+1)}$ randomly (as usual)
- Train the whole neural network using (supervised) stochastic gradient descent (with backprop)

DEEP LEARNING

Topics: pseudocode

- for l=1 to L
  - build unsupervised training set (with $\mathbf{h}^{(0)}(\mathbf{x}) = \mathbf{x}$):

$$\mathcal{D} = \left\{\mathbf{h}^{(l-1)}(\mathbf{x}^{(t)})\right\}_{t=1}^{T}$$

  - train "greedy module" (RBM, autoencoder) on $\mathcal{D}$
  - use hidden layer weights and biases of greedy module to initialize the deep network parameters $\mathbf{W}^{(l)}$, $\mathbf{b}^{(l)}$

pre-training

- Initialize $\mathbf{W}^{(L+1)}$, $\mathbf{b}^{(L+1)}$ randomly (as usual)
- Train the whole neural network using (supervised) stochastic gradient descent (with backprop)

DEEP LEARNING

Topics: pseudocode

- for l=1 to L
  - build unsupervised training set (with $\mathbf{h}^{(0)}(\mathbf{x}) = \mathbf{x}$):

    $$\mathcal{D} = \left\{\mathbf{h}^{(l-1)}(\mathbf{x}^{(t)})\right\}_{t=1}^{T}$$

  - train "greedy module" (RBM, autoencoder) on $\mathcal{D}$
  - use hidden layer weights and biases of greedy module to initialize the deep network parameters $\mathbf{W}^{(l)}$, $\mathbf{b}^{(l)}$

pre-training

- Initialize $\mathbf{W}^{(L+1)}$, $\mathbf{b}^{(L+1)}$ randomly (as usual)
- Train the whole neural network using (supervised) stochastic gradient descent (with backprop)

fine-tuning

WHAT KIND OF UNSUPERVISED LEARNING ?

Topics: stacked RBMs, stacked autoencoders

- Stacked restricted Boltzmann machines:
  - Hinton, Teh and Osindero suggested this procedure with RBMs
    - A fast learning algorithm for deep belief nets.
      Hinton, Teh, Osindero., 2006.
    - To recognize shapes, first learn to generate images.
      Hinton, 2006.
- Stacked autoencoders:
  - Bengio, Lamblin, Popovici and Larochelle studied and generalized the procedure to autoencoders
    - Greedy Layer-Wise Training of Deep Networks.
      Bengio, Lamblin, Popovici and Larochelle, 2007.
  - Ranzato, Poultney, Chopra and LeCun also generalized it to sparse autoencoders
    - Efficient Learning of Sparse Representations with an Energy-Based Model.
      Ranzato, Poultney, Chopra and LeCun, 2007.

WHAT KIND OF UNSUPERVISED LEARNING ?

Topics: stacked RBMs, stacked autoencoders

- Stacked denoising autoencoders:
  - proposed by Vincent, Larochelle, Bengio and Manzagol
    - Extracting and Composing Robust Features with Denoising Autoencoders, Vincent, Larochelle, Bengio and Manzagol, 2008.
- And more:
  - stacked semi-supervised embeddings
    - Deep Learning via Semi-Supervised Embedding. Weston, Ratle and Collobert, 2008.
  - stacked kernel PCA
    - Kernel Methods for Deep Learning.
      Cho and Saul, 2009.
  - stacked independent subspace analysis
    - Learning hierarchical invariant spatio-temporal features for action recognition with independent subspace analysis.
      Le, Zou, Yeung and Ng, 2011.