

Neural networks

Deep learning - difficulty of training

NEURAL NETWORK

Topics: multilayer neural network

- Could have L hidden layers:

- ▶ layer input activation for $k > 0$ ($\mathbf{h}^{(0)}(\mathbf{x}) = \mathbf{x}$)

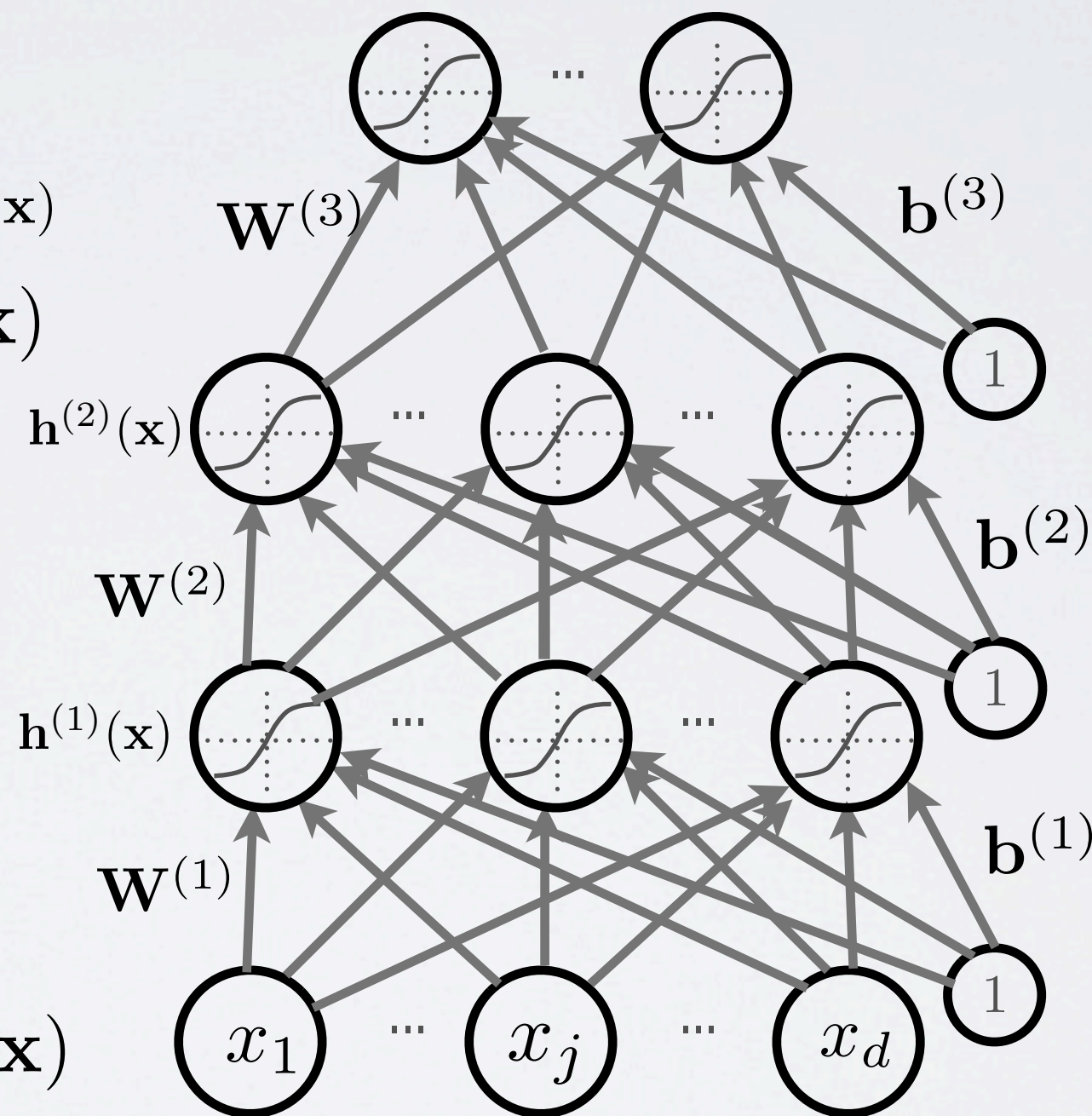
$$\mathbf{a}^{(k)}(\mathbf{x}) = \mathbf{b}^{(k)} + \mathbf{W}^{(k)} \mathbf{h}^{(k-1)}(\mathbf{x})$$

- ▶ hidden layer activation (k from 1 to L):

$$\mathbf{h}^{(k)}(\mathbf{x}) = \mathbf{g}(\mathbf{a}^{(k)}(\mathbf{x}))$$

- ▶ output layer activation ($k = L + 1$):

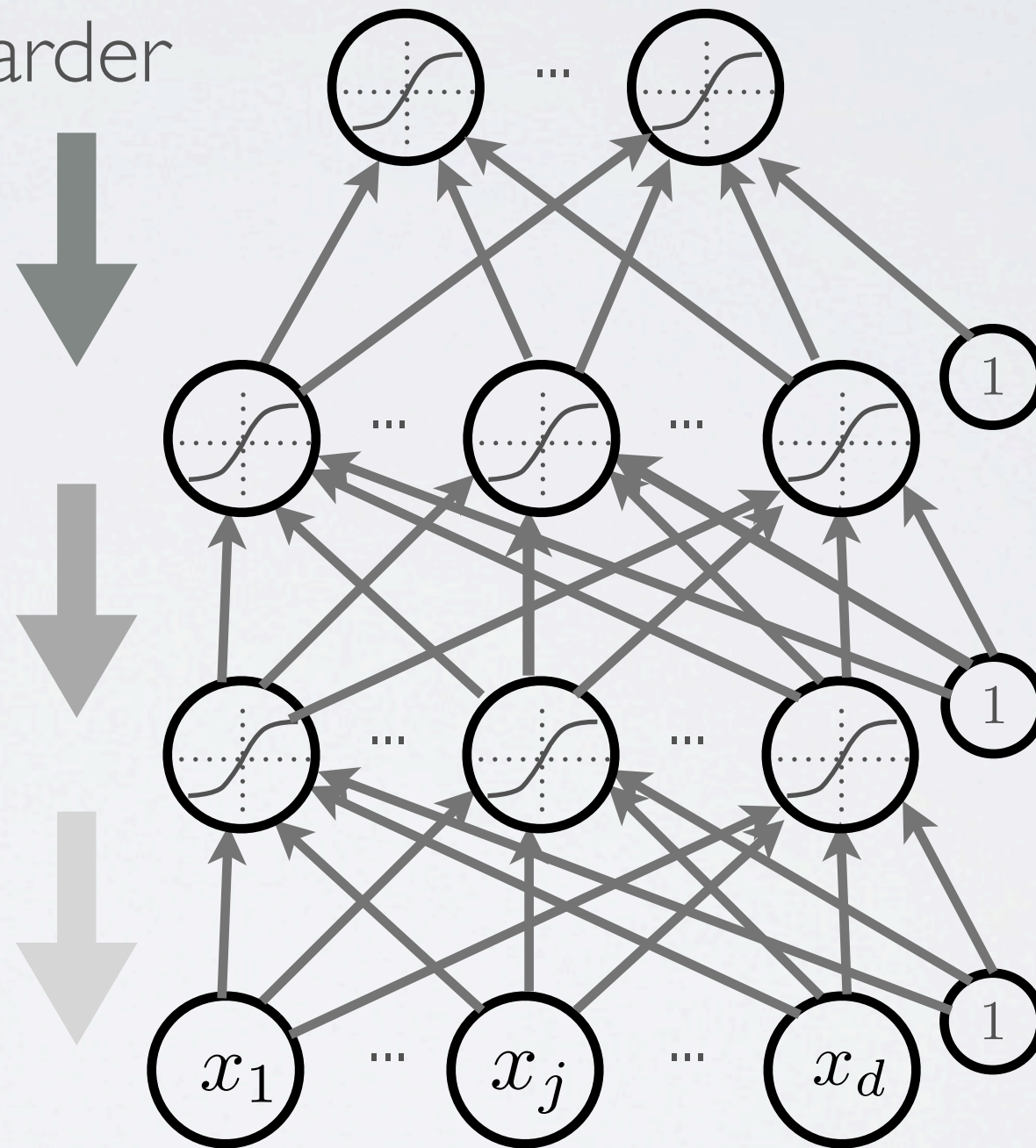
$$\mathbf{h}^{(L+1)}(\mathbf{x}) = \mathbf{o}(\mathbf{a}^{(L+1)}(\mathbf{x})) = \mathbf{f}(\mathbf{x})$$



DEEP LEARNING

Topics: why training is hard

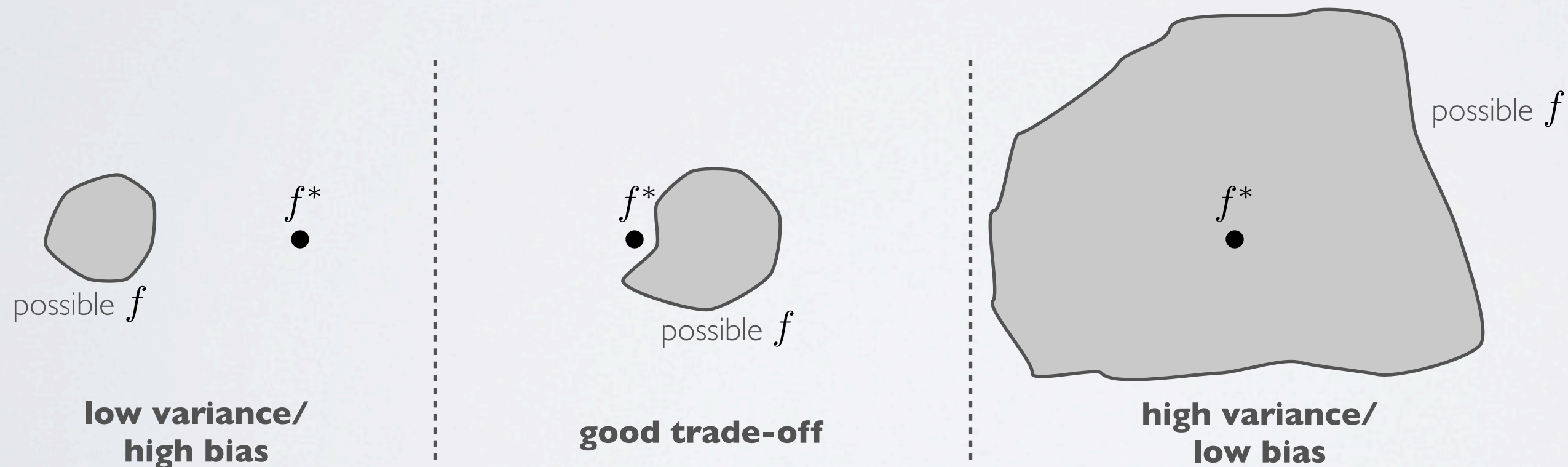
- First hypothesis: optimization is harder (underfitting)
 - vanishing gradient problem
 - saturated units block gradient propagation
- This is a well known problem in recurrent neural networks



DEEP LEARNING

Topics: why training is hard

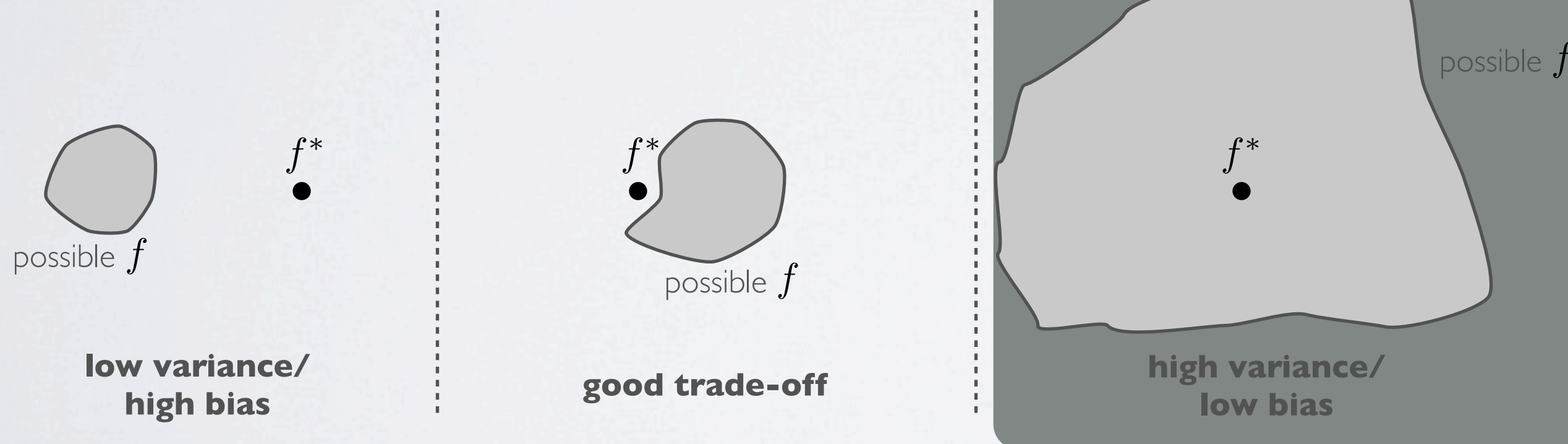
- Second hypothesis: overfitting
 - we are exploring a space of complex functions
 - deep nets usually have lots of parameters
- Might be in a high variance / low bias situation



DEEP LEARNING

Topics: why training is hard

- Second hypothesis: overfitting
 - we are exploring a space of complex functions
 - deep nets usually have lots of parameters
- Might be in a high variance / low bias situation



DEEP LEARNING

Topics: why training is hard

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