

E9 205 Machine Learning for Signal Processing

Deep Neural Networks

30-10-2019

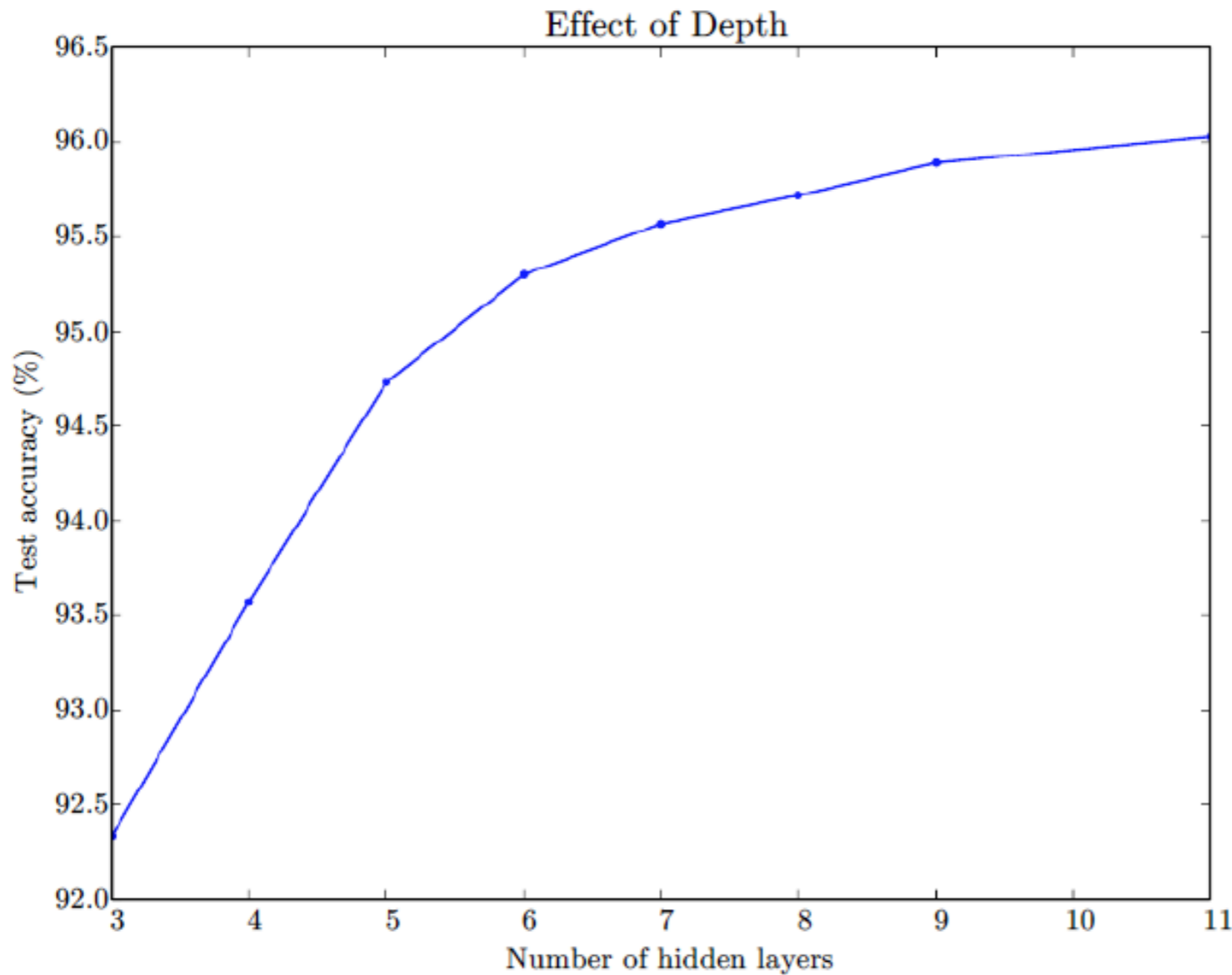
Instructor - Sriram Ganapathy (sriramg@iisc.ac.in)



Summary so far...

- **Neural networks** as discriminative classifiers
- Need for **hidden layer**
- Choice of non-linearities and target functions
- Estimating **posterior probabilities** with NNs
- Parameter learning with **back propagation**.

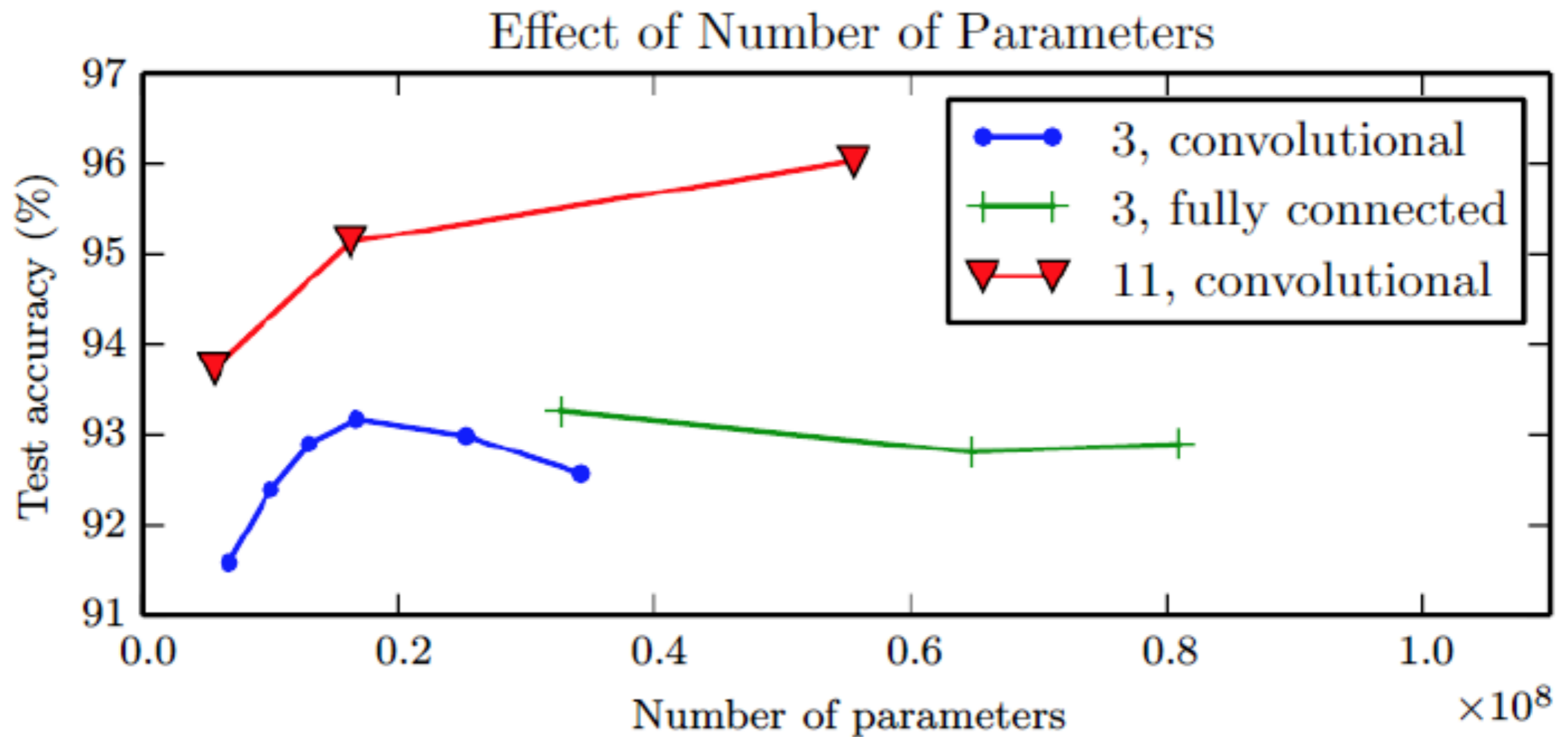
Need for Depth



$$\mathbf{h}^{(1)} = g^{(1)} \left(\mathbf{W}^{(1)\top} \mathbf{x} + \mathbf{b}^{(1)} \right)$$

$$\mathbf{h}^{(2)} = g^{(2)} \left(\mathbf{W}^{(2)\top} \mathbf{h}^{(1)} + \mathbf{b}^{(2)} \right)$$

Need for Depth



Need For Deep Networks

Modeling complex real world data like **speech, image, text**

- Single hidden layer networks are **too restrictive**.
- Needs large number of units in the hidden layer and trained with large amounts of data.
- Not generalizable enough.

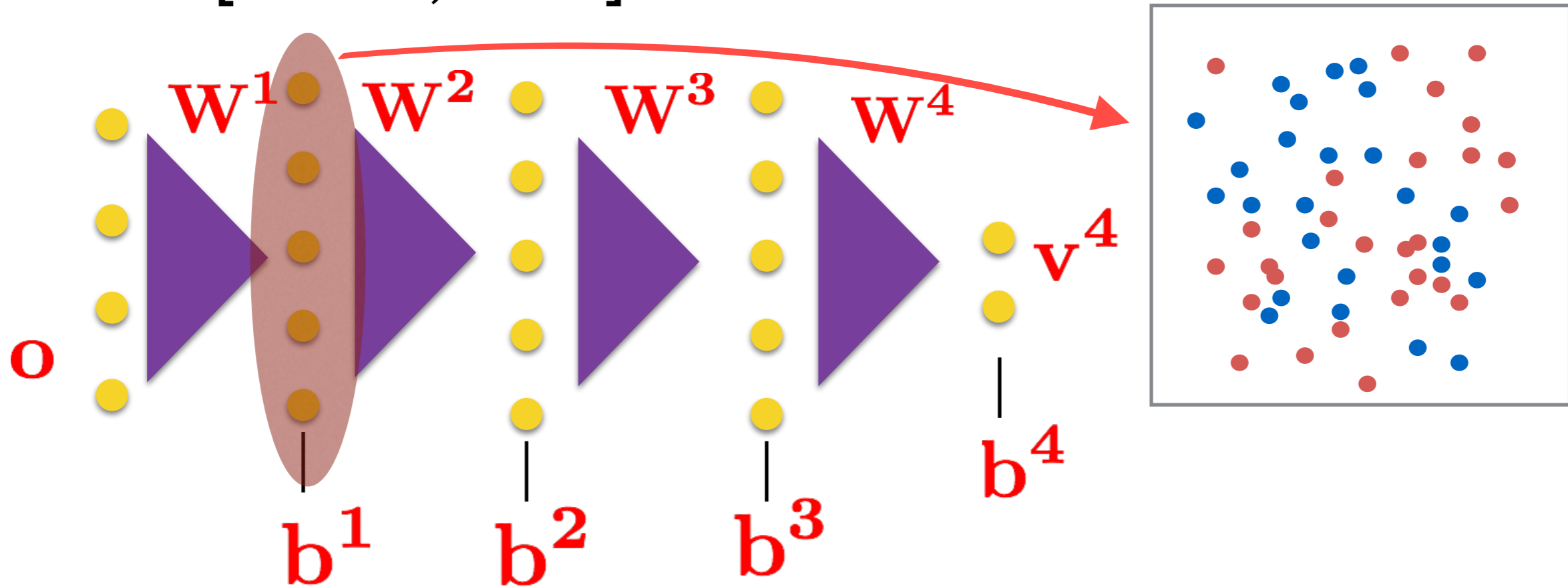
Networks with **multiple hidden layers - deep networks**

(Open questions till 2005)

- Are these networks trainable ?
- How can we initialize such networks ?
- Will these generalize well or over train ?

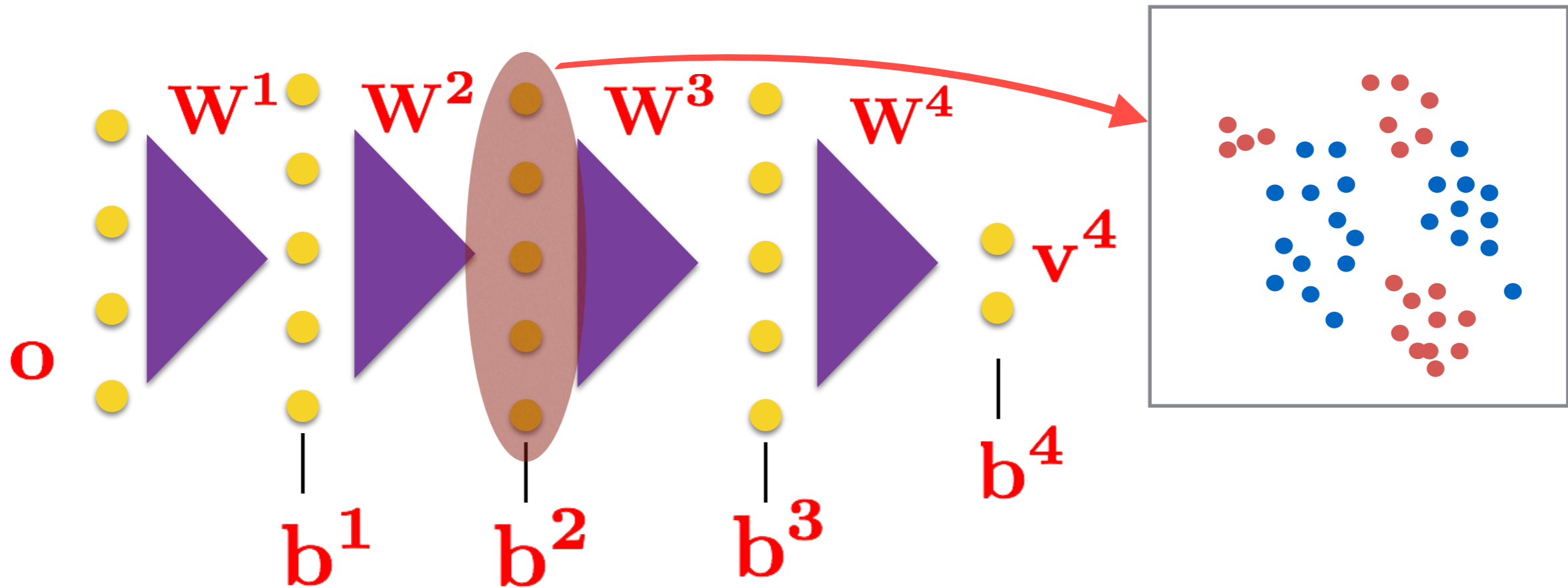
Deep Networks Intuition

Neural networks with multiple hidden layers - Deep networks [Hinton, 2006]



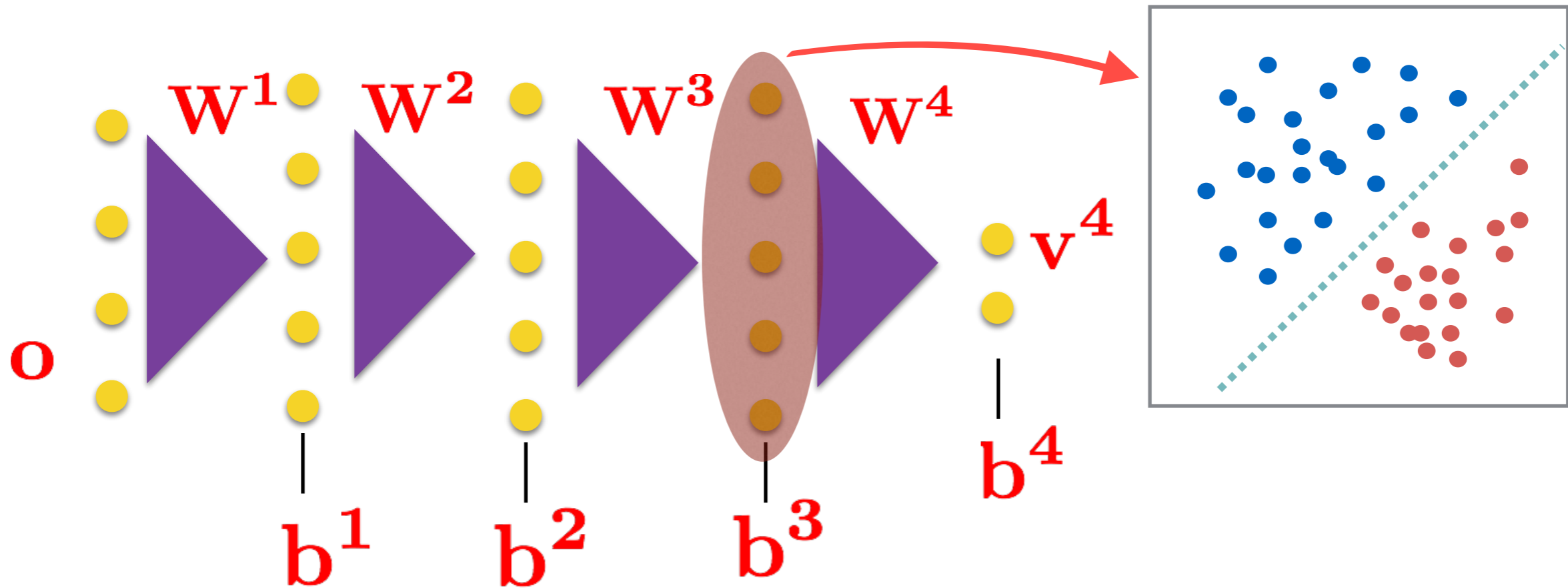
Deep Networks Intuition

Neural networks with multiple hidden layers - Deep networks



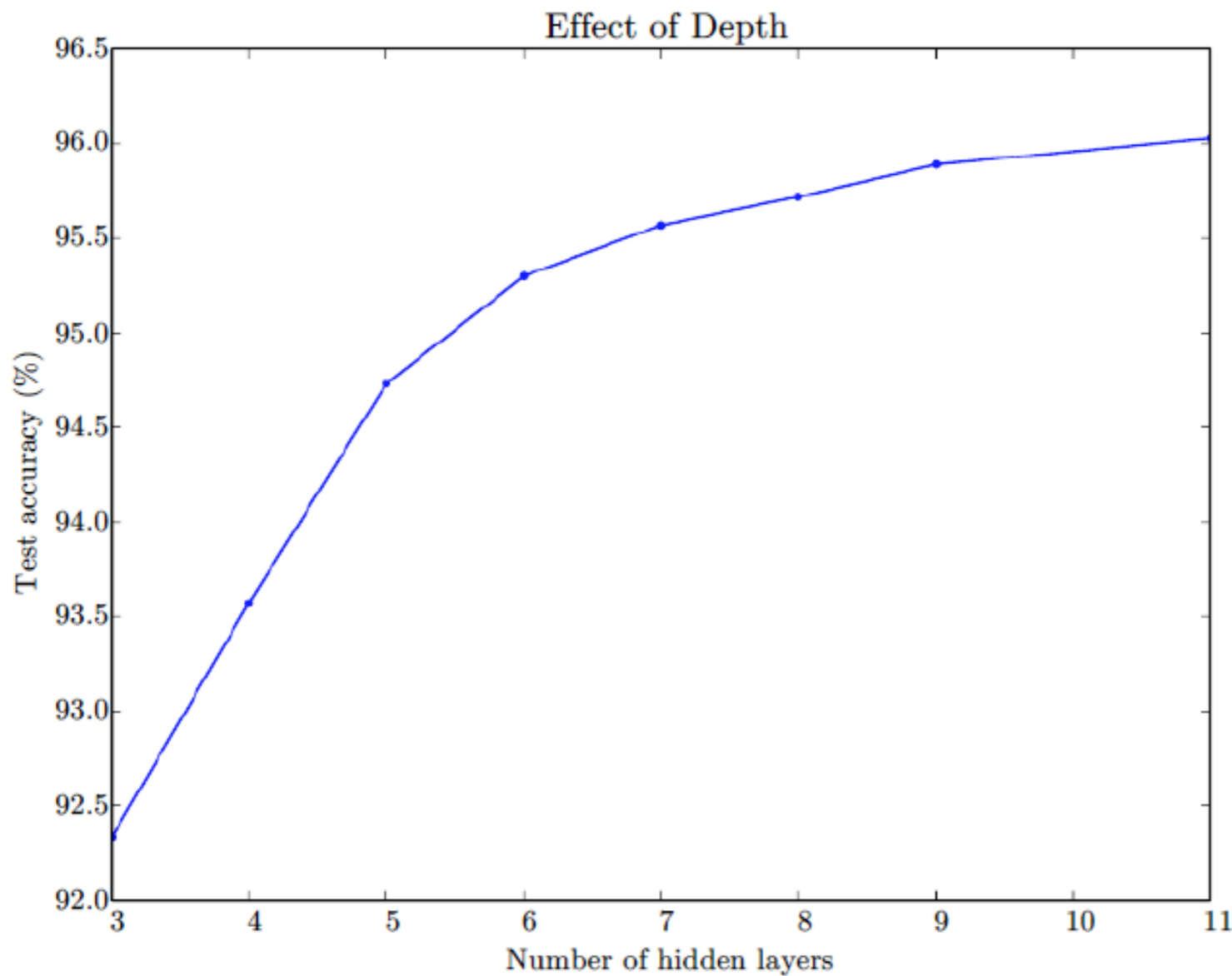
Deep Networks Intuition

Neural networks with multiple hidden layers - Deep networks



Deep networks perform **hierarchical data abstractions** which enable the non-linear separation of complex data samples.

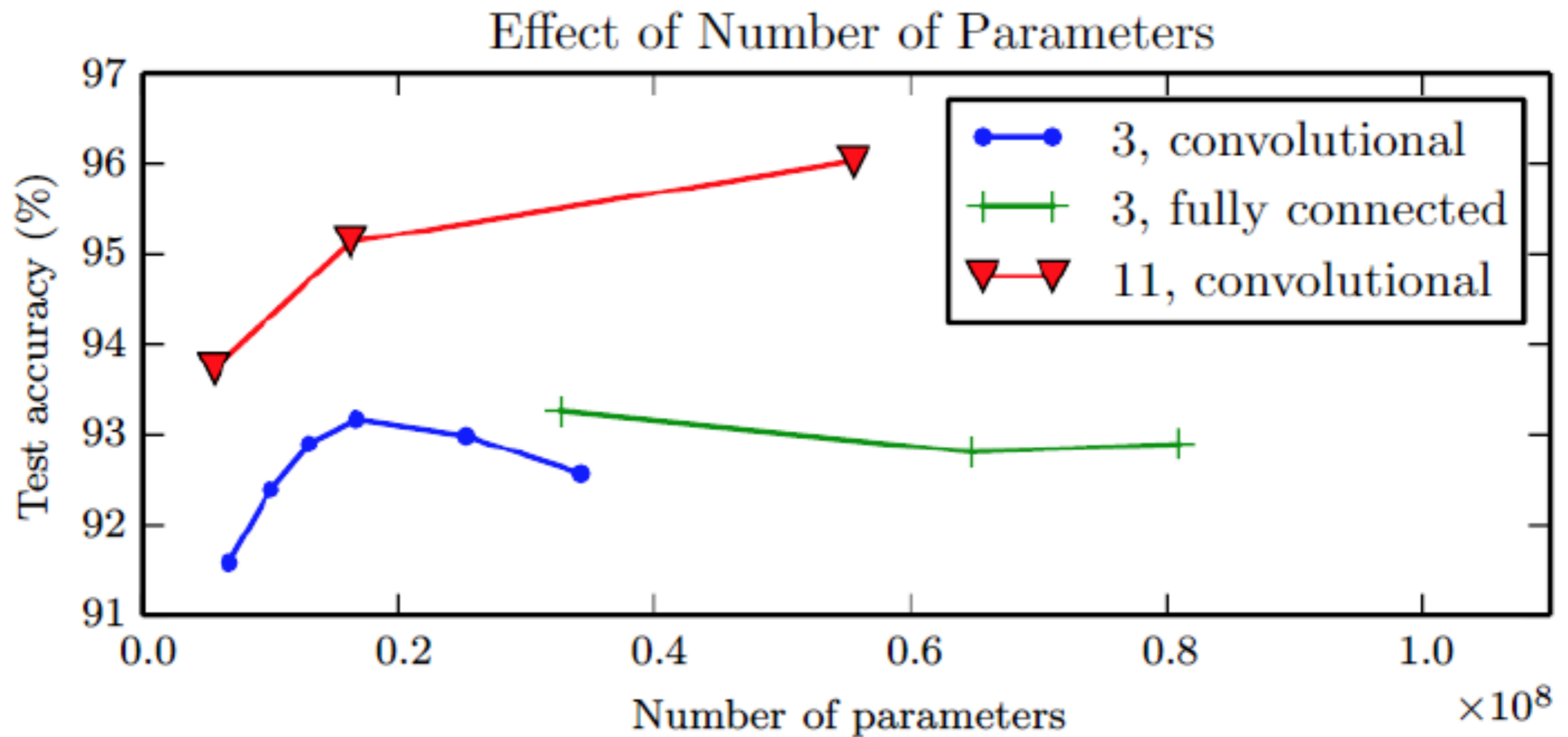
Need for Depth



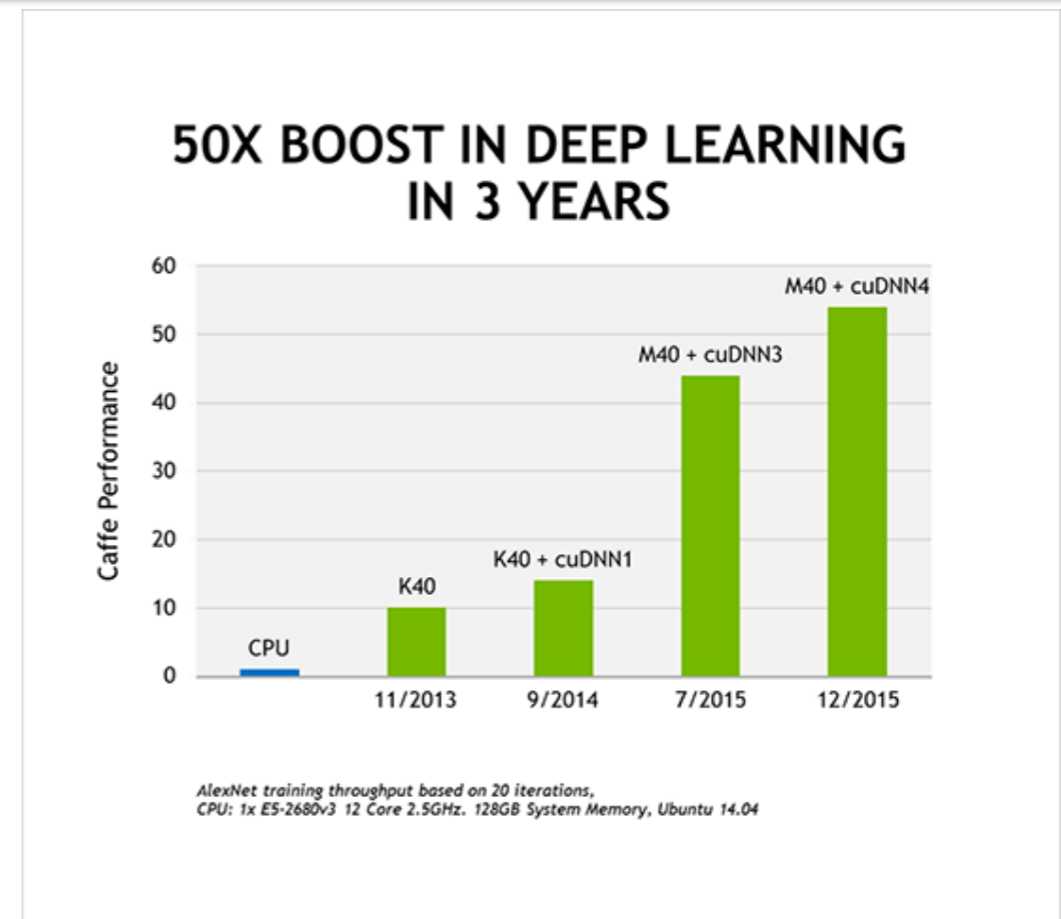
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Need for Depth



Deep Networks



- Are these networks trainable ?
 - Advances in computation and processing
 - **Graphical processing units** (GPUs) performing multiple parallel multiply accumulate operations.
 - Large amounts of supervised data sets

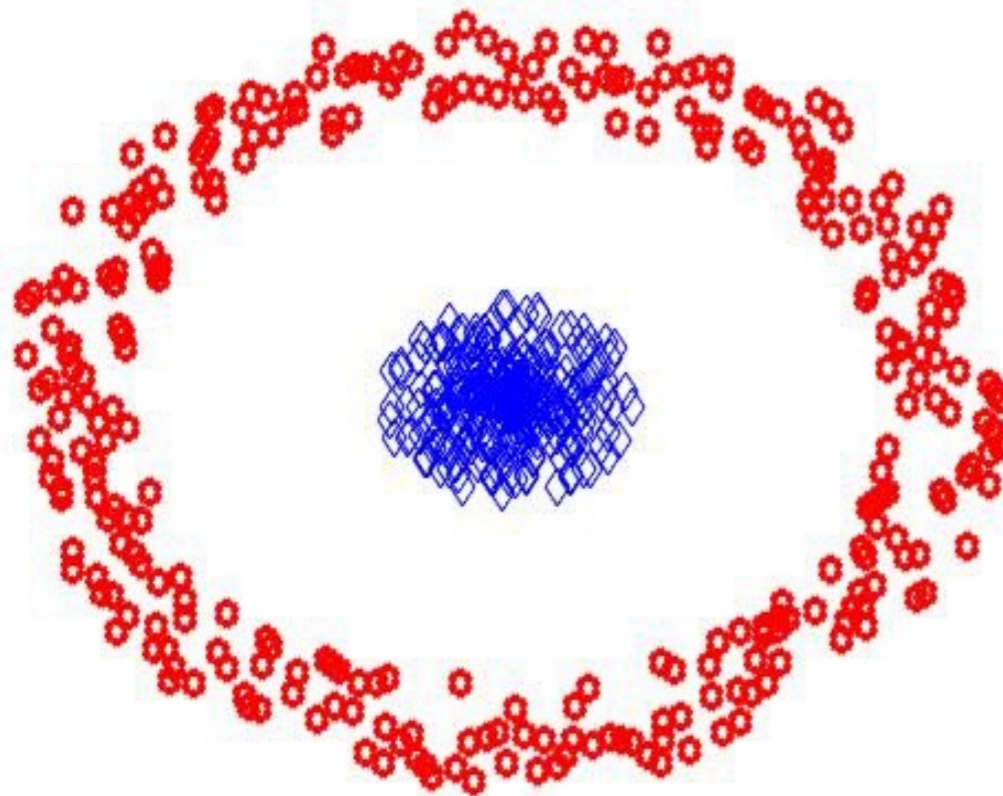
Deep Networks

- Will the networks **generalize** with deep networks
 - DNNs are **quite data hungry** and performance improves by increasing the data.
 - Generalization problem is tackled by **providing training data from all possible conditions.**
 - Many artificial data augmentation methods have been successfully deployed
 - Providing the **state-of-art performance in several real world applications.**

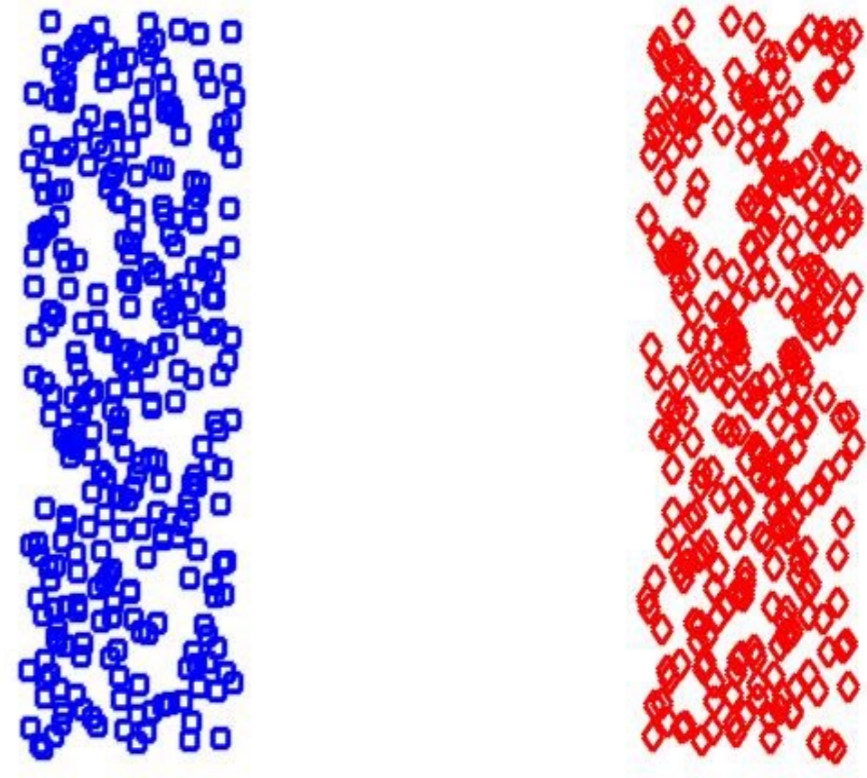
Representation Learning in Deep Networks

- The input data representation is one of most important components of any machine learning system.

Cartesian Coordinates



Polar Coordinates

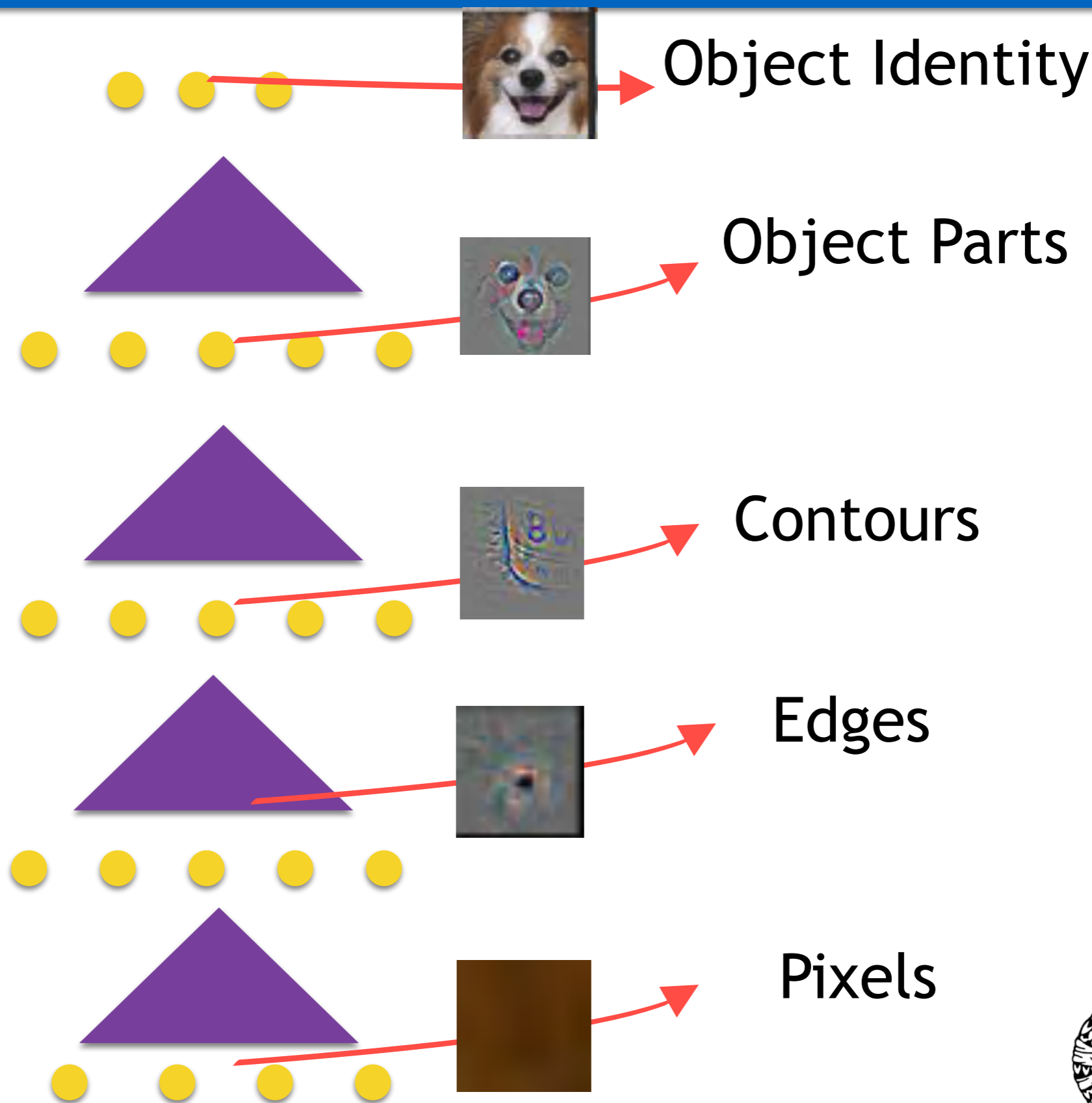


Representation Learning in Deep Networks

- The input data representation is one of most important components of any machine learning system.
 - Extract factors that enable classification while suppressing factors which are susceptible to noise.
- Finding the right representation for real world applications - substantially challenging.
 - Deep learning solution - **build complex representations from simpler representations.**
 - The dependencies between these hierarchical representations are refined by the target.

Representation Learning in Deep Networks

[Zeiler, 2014]



On the Number of Linear Regions of Deep Neural Networks

Guido Montúfar

Max Planck Institute for Mathematics in the Sciences
montufar@mis.mpg.de

Razvan Pascanu

Université de Montréal
pascanur@iro.umontreal.ca

Kyunghyun Cho

Université de Montréal
kyunghyun.cho@umontreal.ca

Yoshua Bengio

Université de Montréal, CIFAR Fellow
yoshua.bengio@umontreal.ca

Deep Learning

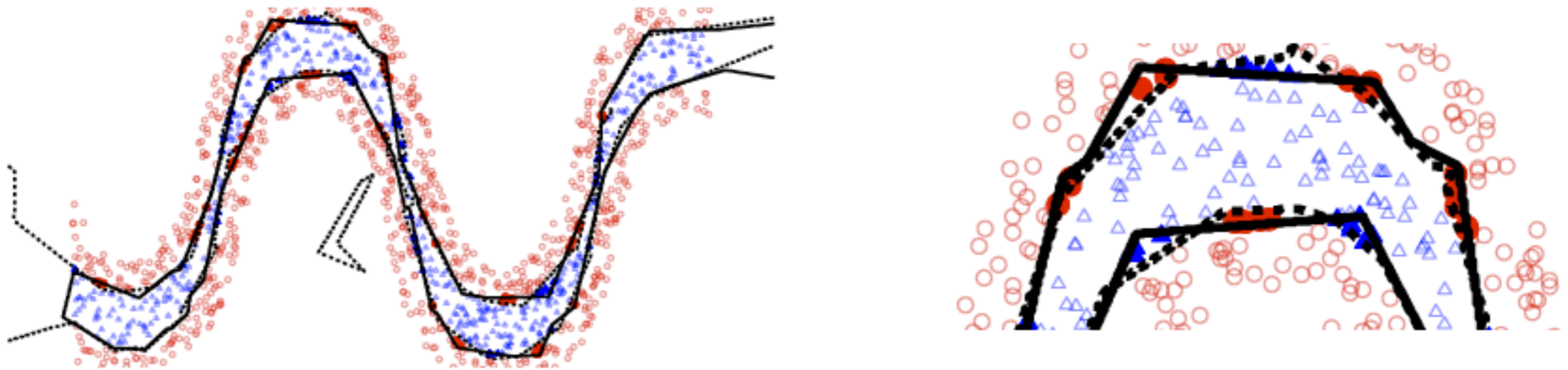
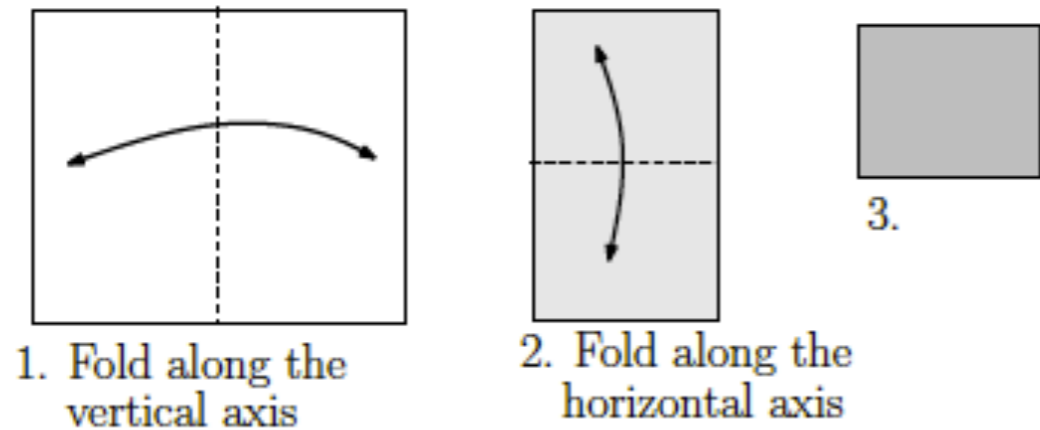
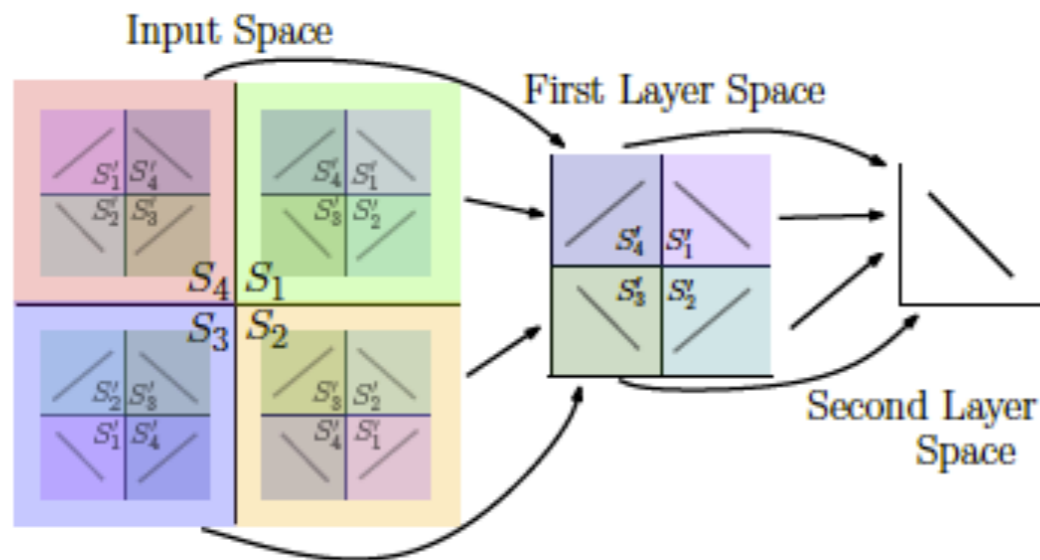


Figure 1: Binary classification using a shallow model with 20 hidden units (solid line) and a deep model with two layers of 10 units each (dashed line). The right panel shows a close-up of the left panel. Filled markers indicate errors made by the shallow model.

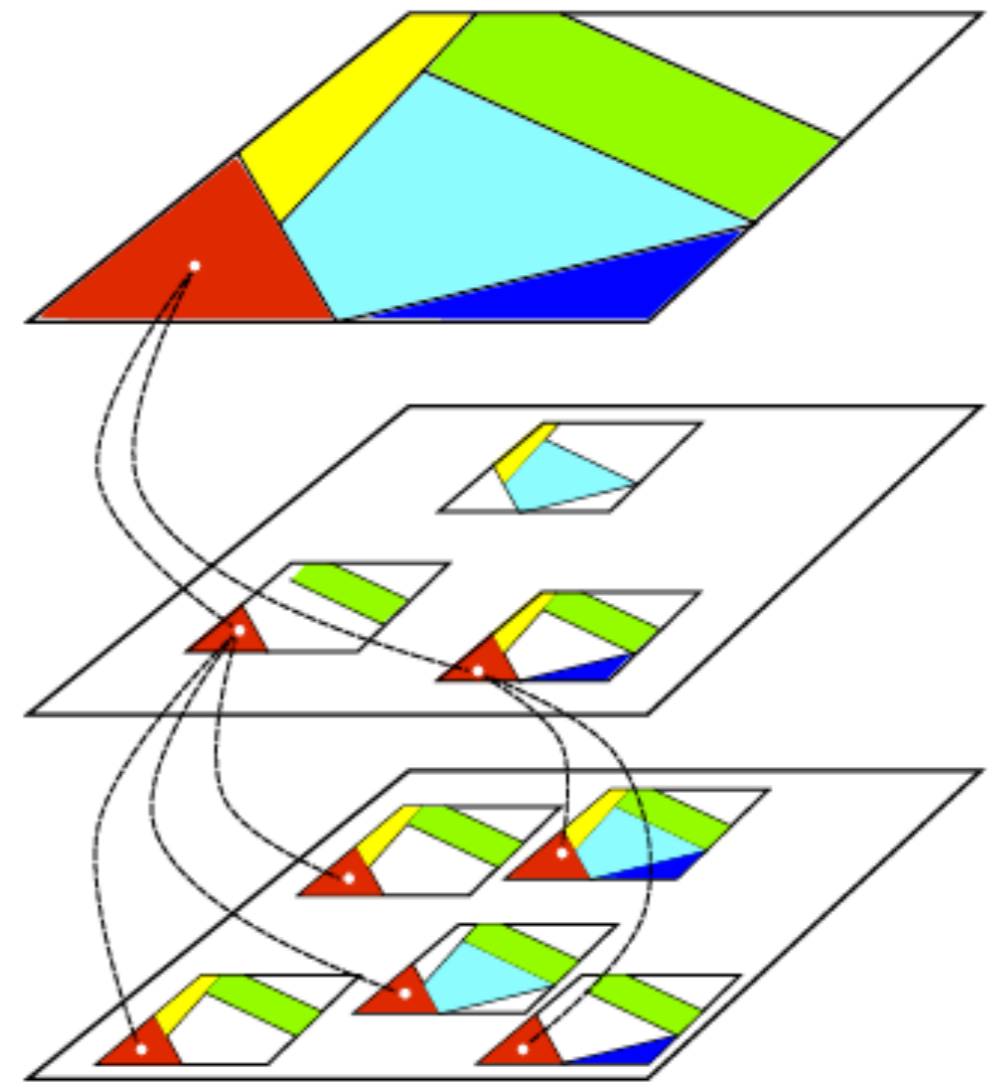
Deep Learning



(a)



(b)



(c)

Figure 2: (a) Space folding of 2-D Euclidean space along the two axes. (b) An illustration of how the top-level partitioning (on the right) is replicated to the original input space (left). (c) Identification of regions across the layers of a deep model.

Deep Learning

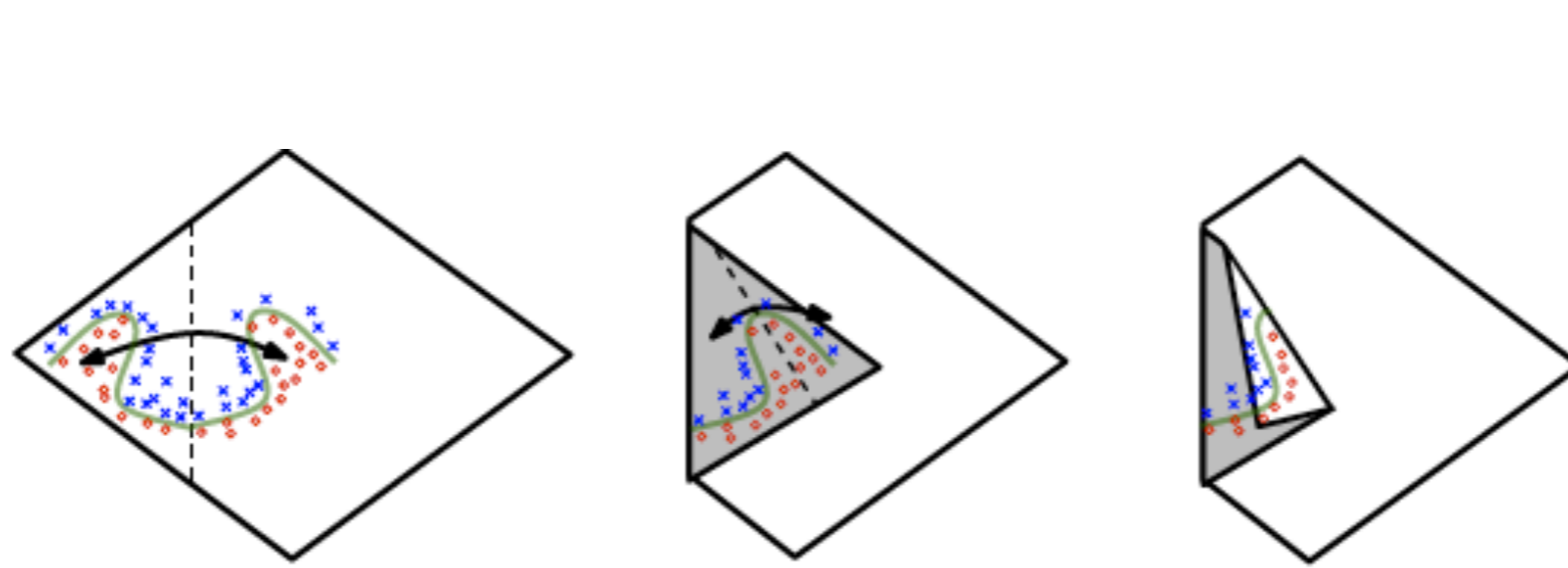


Figure 3: Space folding of 2-D space in a non-trivial way. Note how the folding can potentially identify symmetries in the boundary that it needs to learn.