ONLY GOD

1402-2023



Neural Network & Deep Learning

Deep Learning

CSE & IT Department
School of ECE
Shiraz University

Traditional Learning



Traditional model of pattern recognition (PR) (since late 50's)

Fixed/engineered features + trainable classifier



Traditional vs Deep Learning



Traditional PR: Fixed/Handcrafted feature extractor



Modern PR: Unsupervised mid-level features



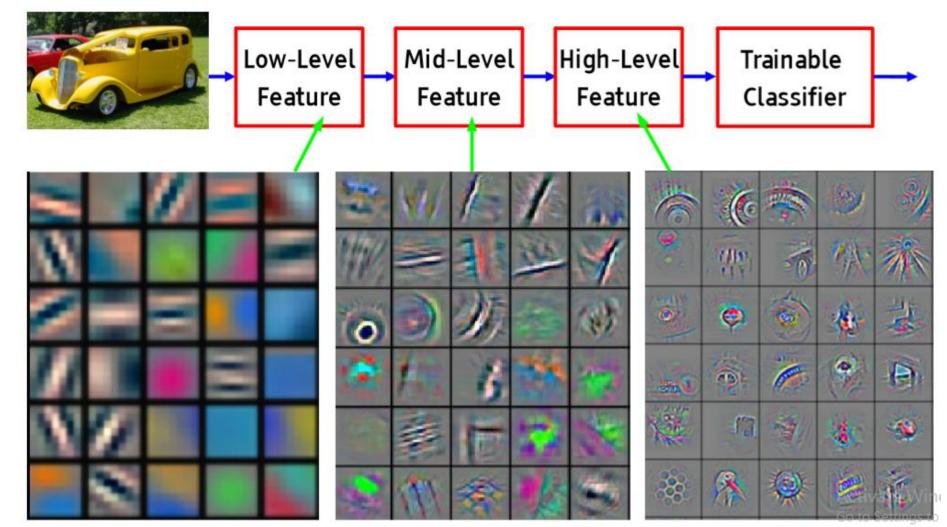
Deep learning PR: Representations are hierarchical and



Deep Learning



Learns hierarchical representations



Trainable Feature Hierarchy



Hierarchy of representations with increasing abstraction level

- Each stage is a kind of trainable feature transform
- Image recognition

```
pixel --> edge --> texton --> motif --> part --> object
```

Text

```
character --> word --> word group --> clause --> sentence
--> story
```

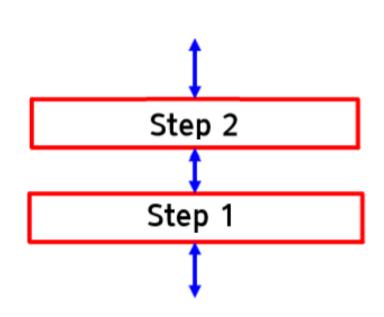
Speech

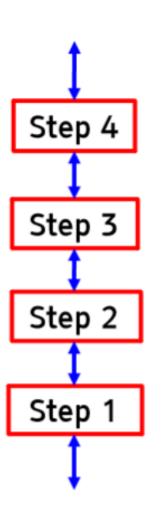
```
sample --> spectral band --> sound --> ... --> phone --> phoneme --> word
```

Shallow vs Deep



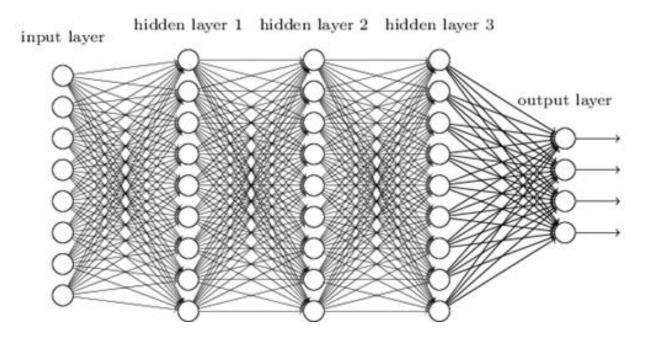
- shallow and wide vs deep and narrow
- more memory vs more time

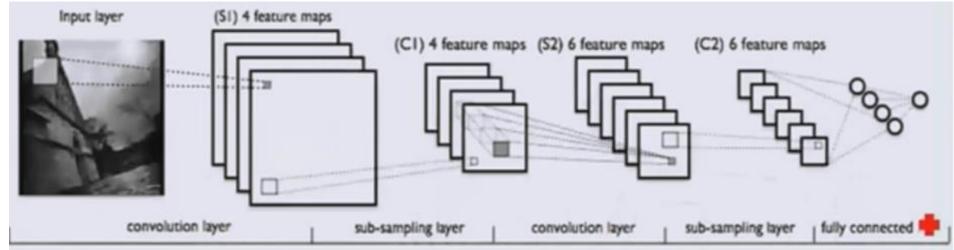




Deep Networks







DL difficulties (Unavailability of Data

- Labeled data is often scarce
- Training on insufficient data would result in over-fitting
- Unlabeled data is cheap and plentiful
- Unlabeled data is used to learn good initials for weights in all layers (except final layer)
- Labeled data is used to fine-tune weights in all layers
- Often results in much better classifiers being learned

DL difficulties (Local Optima)

- Training a shallow network using supervised learning, results in weights converging to reasonable outputs
- Training a network using supervised learning involves solving a highly non-convex optimization problem
- In deep networks, this problem turns out to be rife with bad local optima
- So, training with gradient descent (conjugate gradient, ...) no longer works well
- New optimization methods like adadelta, adagrad, ...
 are popularly used for training deep networks

DL difficulties (Vanishing Gradient Problem

- Using back-propagation to compute derivatives, gradients propagated backwards rapidly diminish in magnitude as depth of network increases
- Derivative of overall cost w.r.t weights in earlier layers is very small
- Weights of earlier layers change slowly and these layers fail to learn much



- This vanishing gradient problem occurs in gradient-based learning methods with certain activation functions
- New activation functions are proposed for solving this problem