



## ARCHITECTURE DESIGN

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# ARCHITECTURE

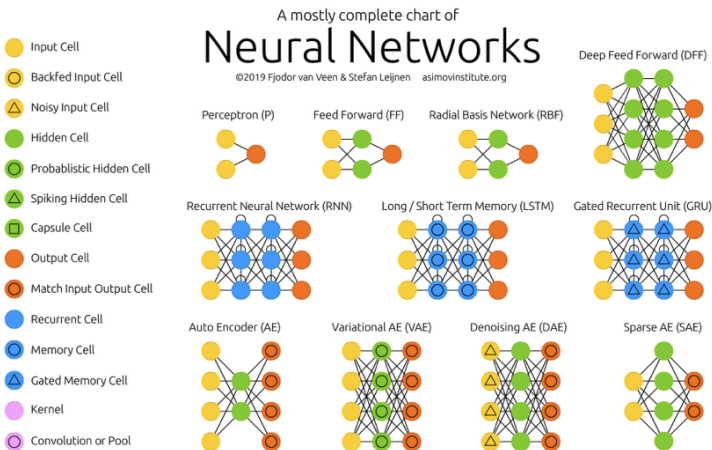
## Architecture

- ▶ Number of layers (depth)
- ▶ Number of neurons per layer
- ▶ Type of neurons
- ▶ Type of connections between neurons / layers

## Classical Network architectures

- ▶ Most networks are organized into groups of layers, arranged in a chain structure
- ▶ Each layer is a function of the previous one

# A (MOSTLY) COMPLETE ZOO<sup>1</sup>



## A (MOSTLY) COMPLETE ZOO

### Markov Chain (MC)



Hopfield Network (HN)



Boltzmann Machine (BM)



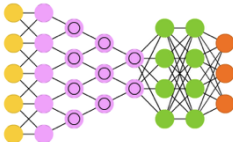
Restricted BM (RBM)



### Deep Belief Network (DBN)



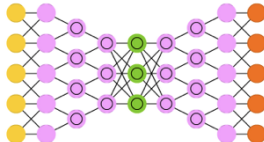
### Deep Convolutional Network (DCN)



### Deconvolutional Network (DN)



Deep Convolutional Inverse Graphics Network (DCIGN)



### Generative Adversarial Network (GAN)



Liquid State Machine (LSM)



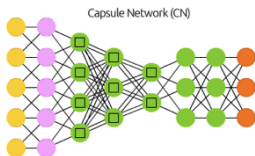
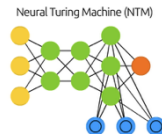
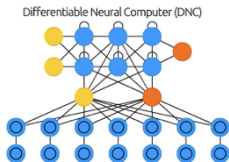
Extreme Learning Machine (ELM)



### Echo State Network (ESN)



# A (MOSTLY) COMPLETE ZOO



# UNIVERSAL APPROXIMATION

Theorem (Cybenko 1989; Hornik et al, 1991)

$\sigma$ : bounded, non-constant continuous function, -  $I_d$ :  $d$ -dimensional hypercube -  $C(I_d)$  space of continuous functions on  $I_d$ .  
( $\forall f \in C(I_d)$ )( $\forall \epsilon > 0$ )( $\exists q > 0, v_i, \mathbf{w}_i, b_i, i \in \llbracket 1 \dots q \rrbracket$ ) such that

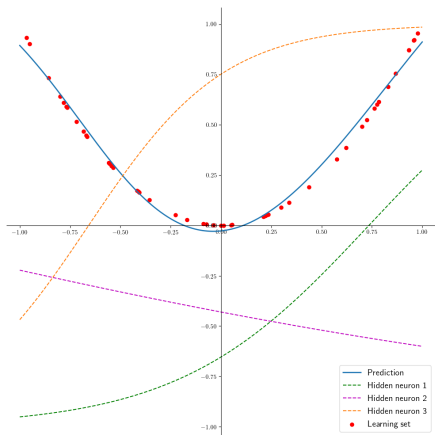
$$F(\mathbf{x}) = \sum_{i=1}^q v_i \sigma(\mathbf{w}_i^T \mathbf{x} + b_i)$$

satisfies  $\sup_{\mathbf{x} \in I_d} |f(\mathbf{x}) - F(\mathbf{x})| < \epsilon$

And so..

A feed-forward network with a single hidden layer containing a finite number of neurons can approximate continuous functions on compact subsets of  $\mathbb{R}^d$ , under mild assumptions on the activation function

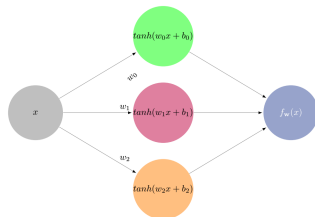
# UNIVERSAL APPROXIMATION



$$f(x) = x^2, |Z| = 50$$

## A simple example

- ▶  $|Z|$  points uniformly sampled (red) over the definition set
- ▶ 1 hidden layer MLP, 3 neurons.
- ▶  $\tanh$  activation function, and linear output neurons
- ▶ network output : blue curve
- ▶ hidden neurons outputs: dashed curves



# UNIVERSAL APPROXIMATION

## Good news but...

- ▶ Does not inform about good/bad architectures, the number of neurons  $q$  nor how they relate to the optimization procedure
- ▶ Bounds on size of the single-layer network exist for a broad class of functions....
- ▶ But worst case is exponential /  $q$

## Bad news :-): No Free Lunch theorem

There is no universal procedure for examining a training set of samples and choosing a function that will generalize to points not in training set



## EFFECT OF DEPTH

### Up to now

- ▶ A feedforward network with a single layer is sufficient to represent “any” function
- ▶ But the layer may be infeasibly large and may fail to generalize well
- ▶ Using deeper models can reduce number of units required and reduce generalization error

### Theorem (Montúfar et al, 2014)

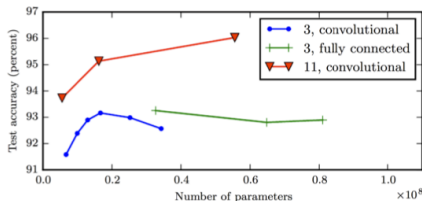
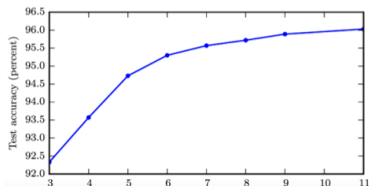
A MLP with ReLU as activation functions,  $p$  inputs,  $L$  hidden layers with  $q \geq p$  neurons can compute functions having  $\Omega\left(\left(\frac{q}{p}\right)^{(L-1)p} q^p\right)$  linear regions.

### Properties

- ▶ The number of linear regions of deep models grows exponentially in  $L$  and polynomially in  $q$ .
- ▶ Even for small values of  $L$  and  $q$ , deep rectifier models are able to produce substantially more linear regions than shallow models.

# EFFECT OF DEPTH

- ▶ Test accuracy consistently increases with depth
- ▶ Increasing parameters without increasing depth is not as effective



Deep architectures express a useful prior over the space of functions the model learns

Specialized architectures

CNN, RNN,...Discussed in future lectures