



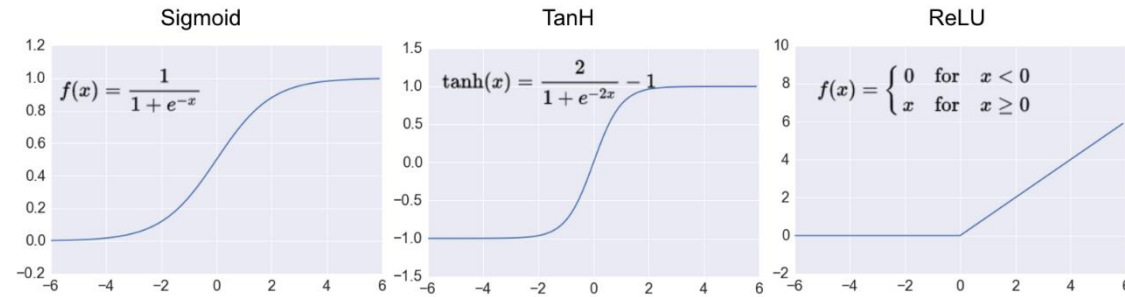
---

# Artificial Neural Networks: On Order and Time

---

Alexander G. Ororbia II  
Introduction to Machine Learning  
CSCI-635  
12/1/2023

# Non-Standard Activations

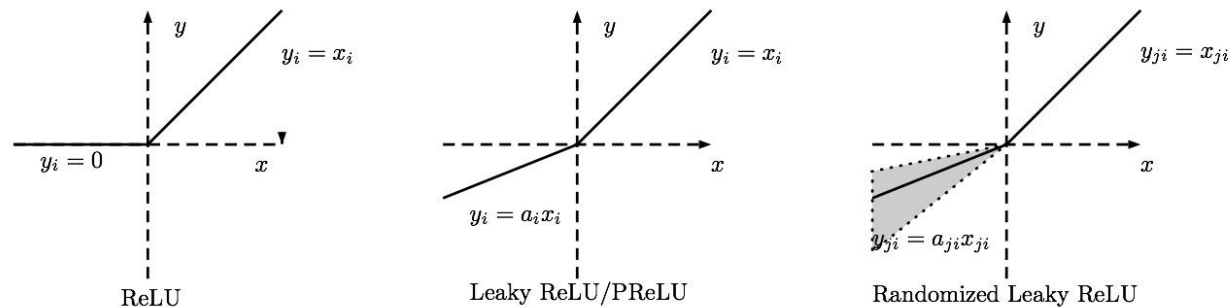


## Linear Rectified Unit (Relu)

Not smooth / not differentiable everywhere, **Benefit:** Hard sparsity

**Issues:** Dead units, explosive weight updates

Parametric Relu (PReLU), leaky Relu: “Learn” slope of activation function



The magic behind deep learning

# **THE HUMAN-IN-THE-LOOP**

# Manual, Exhaustive Search

## Manual Search

- Fast if you know what you are doing!
- Explore a few configurations, based on literature/heuristics
- Select lowest validation loss configuration



Deep tuning!

## Grid Search

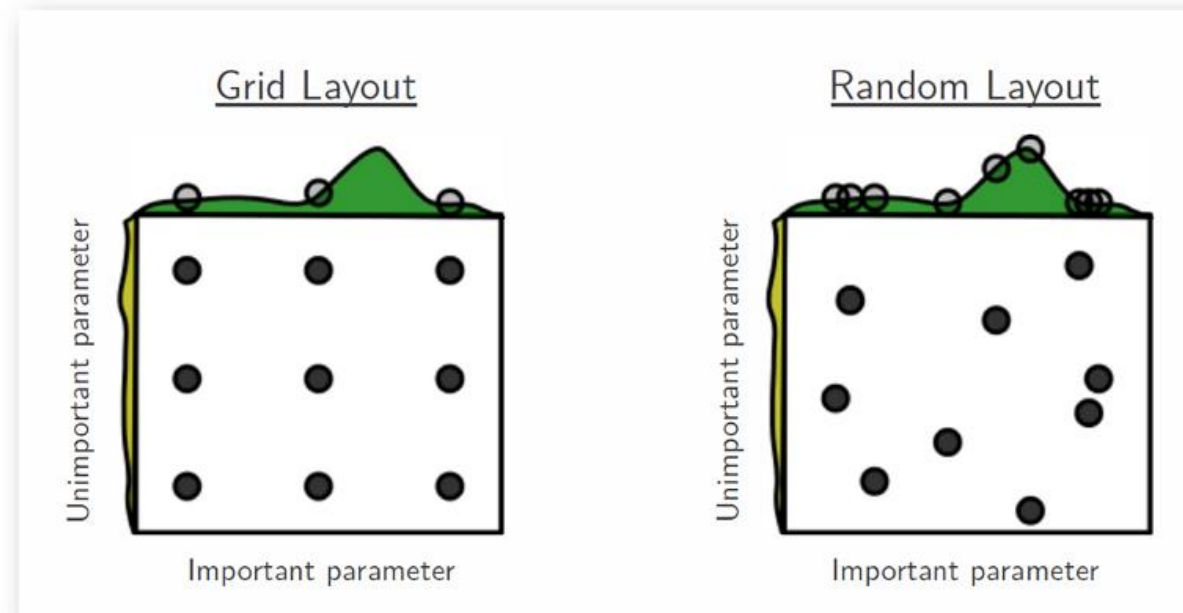
- Compose an n-dimensional hypercube, where along each axis is a hyper-parameter (length determined by max & min values to explore)
- Exhaustively calculate loss/error for each configuration (or combination of meta-parameter values) in hypercube
  - Choose lowest error/minimal loss configuration as optimal model
  - Loss/error is calculated on a held-out validation/development set (or in held-out set in cross-fold validation schemes)
- Will ultimately find optimal model (given coarseness of grid-search)
- Takes long time!

# Random Search

Draw  $k$  sample configurations from hypercube & calculate validation loss for each (w/o replacement)

Repeat  $T$  trials, can use optimal of each trial to inform subsequent trials  
Could “guide” or “target” next set of random samples based on best last found point (a guided stochastic search)

Surprisingly effective (over manual search) & faster than grid search



# Bayesian Optimization: Meta Machine Learning

Use machine learning to do your research for you...

Sequential Model Optimization (*SMO*)

Gaussian Processes for surface-response modeling

Gradient-based: Use another ANN

How do we tune this higher-level  
parametric model?

*Meta-meta-meta-....-machine learning??*

High-level idea:

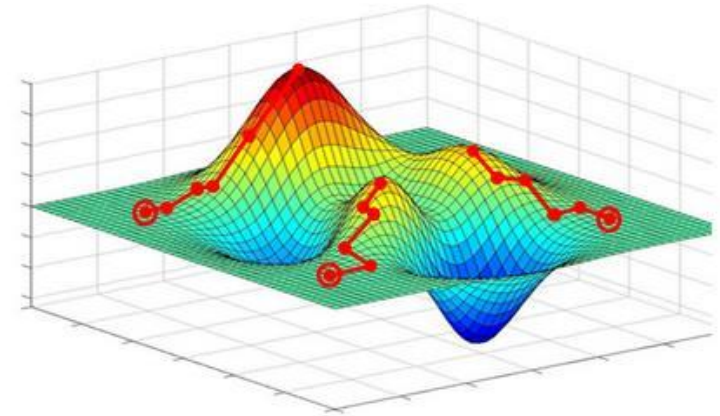
Build a meta-model (w/ some prior that  
encodes intuition about hyper-parameter space)

Draw samples from space (i.e., run few model configurations)

Update meta-model using these samples

Meta-model selects next best point to evaluate

Balancing criterion, i.e., minimal error & minimal compute time



# Bayesian Optimization: Meta Meta Learning

Use machine learning to do

Sequential Model Based

Gaussian

Gradient-based

How do we  
parametric

*Meta-meta-*

High-level idea

Build a meta-model

encodes intuition

Draw samples from

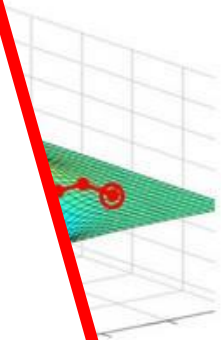
Update meta-model

Meta-model selected

erion,

compute time

Now all we need is for our models to write our papers for us, submit them to the conferences on our behalf, and...  
...then go to class for us too! Neat!



# Deep Thinking!

## It is a matter of posing the problem

What is the low-level representation of your sample?

(i.e., low-level features, inputs, or sensors)

Is there an output we are interested in?

Regression: a real-valued target

Categorization: a discrete target

## How much data do you have?

More data is better! (MNIST is 60K)

Only a small sample?

Go Bayesian Neural Networks!

## What kind of hardware do you have?

Multi-CPU settings

GPUs

Specialized hardware?

FPGAs, TPUs?















Deep digit recognition!



# Neural Networks

©2016 Hjordor van Veen - asimovinstitute.org

-  Backfed Input Cell
-  Input Cell
-  Noisy Input Cell
-  Hidden Cell
-  Probablistic Hidden Cell
-  Spiking Hidden Cell
-  Output Cell
-  Match Input Output Cell
-  Recurrent Cell
-  Memory Cell
-  Different Memory Cell
-  Kernel
-  Convolution or Pool

Deep Feed Forward (DFF)



Perceptron (P)



Feed Forward (FF)



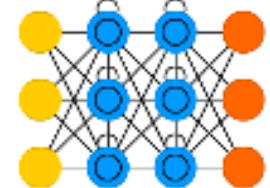
Radial Basis Network (RBF)



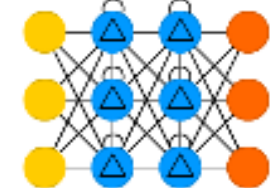
Recurrent Neural Network (RNN)



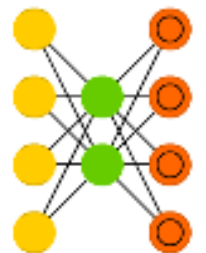
Long / Short Term Memory (LSTM)



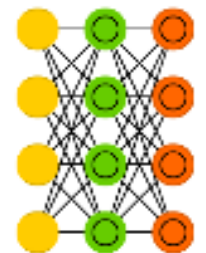
Gated Recurrent Unit (GRU)



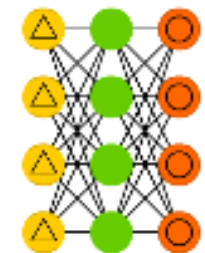
Auto Encoder (AE)



Variational AE (VAE)



Denising AE (DAE)



Sparse AE (SAE)



Markov Chain (MC)



Hopfield Network (HN)



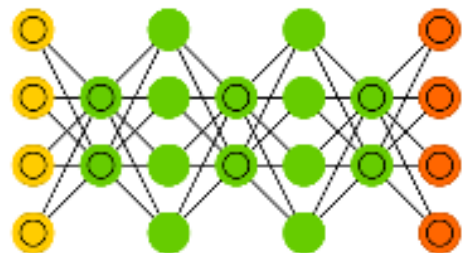
Boltzmann Machine (BM)

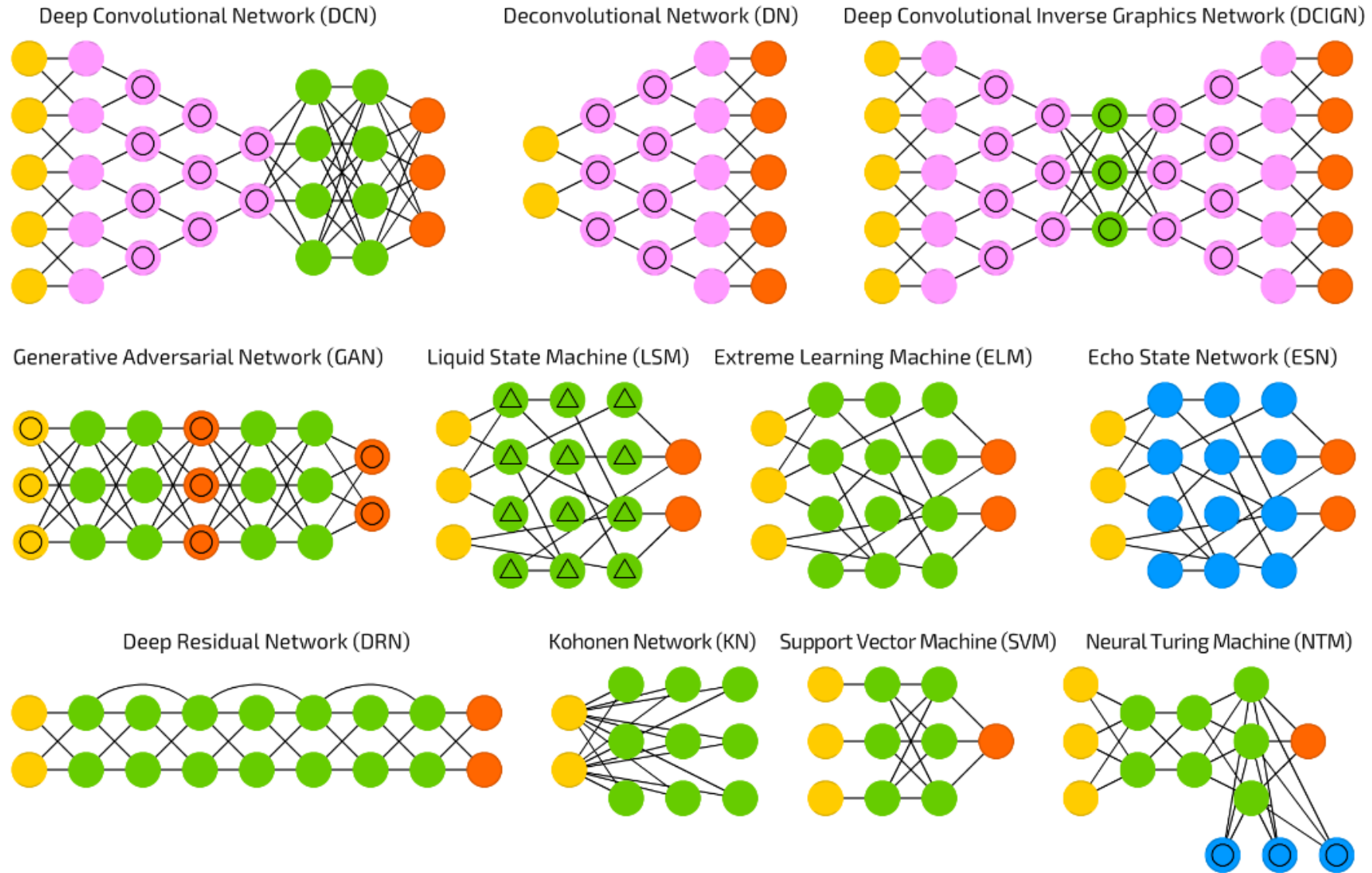


Restricted BM (RBM)



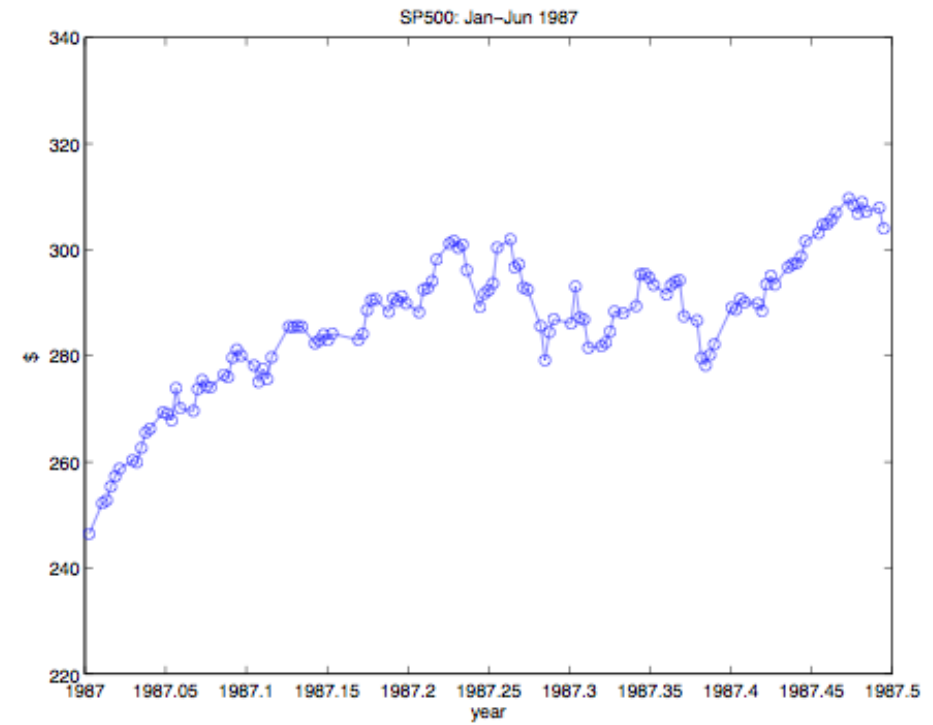
Deep Belief Network (DBN)





Violating the first ‘i’ in i.i.d....

# RECURRENT NEURAL NETWORKS



# RNNs process sequential data

- Recurrent Neural Networks are a family of neural networks for processing sequential data
- RNN and CNN are both specialized architectures
  - RNN is specialized for processing a sequence of values  $x^{(1)}, \dots, x^{(\tau)}$ 
    - Just as CNN is specialized for processing a grid of values such as an image
  - RNNs can scale to much longer sequences than would be impractical for networks without sequence-based specialization
  - RNNs can also process variable-length sequences
    - Just as a CNN can scale to images with large width/height and process variable size images

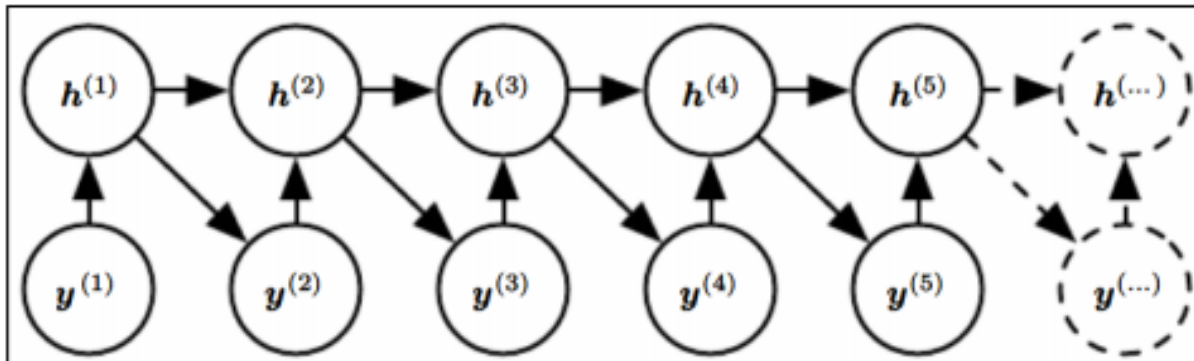


# White Board Time!

(Turning MLPs into RNNs)



Efficient parameterization based on  $h^{(t)} = f(h^{(t-1)}, x^{(t)}; \theta)$



# QUESTIONS?

