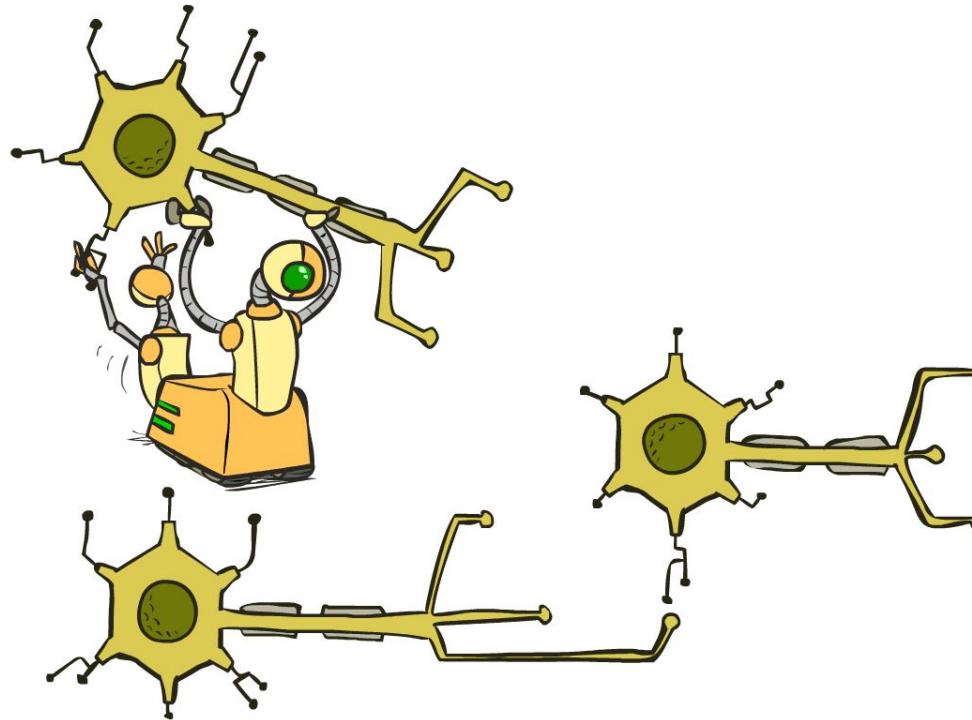


# CS 188: Artificial Intelligence

## Optimization and Neural Nets

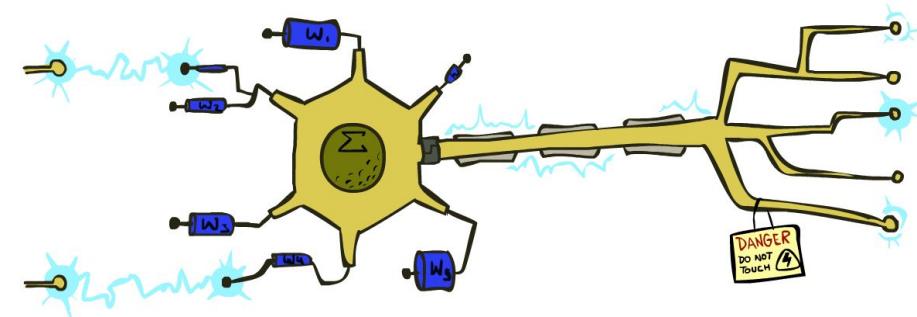


Instructors: Peyrin Kao and Emma Pierson --- University of California, Berkeley

[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All CS188 materials are available at <http://ai.berkeley.edu>.]

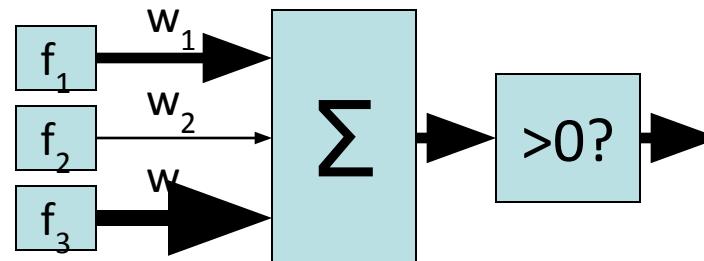
# Reminder: Linear Classifiers

- Inputs are **feature values**
- Each feature has a **weight**
- Sum is the **activation**



$$\text{activation}_w(x) = \sum_i w_i \cdot f_i(x) = w \cdot f(x)$$

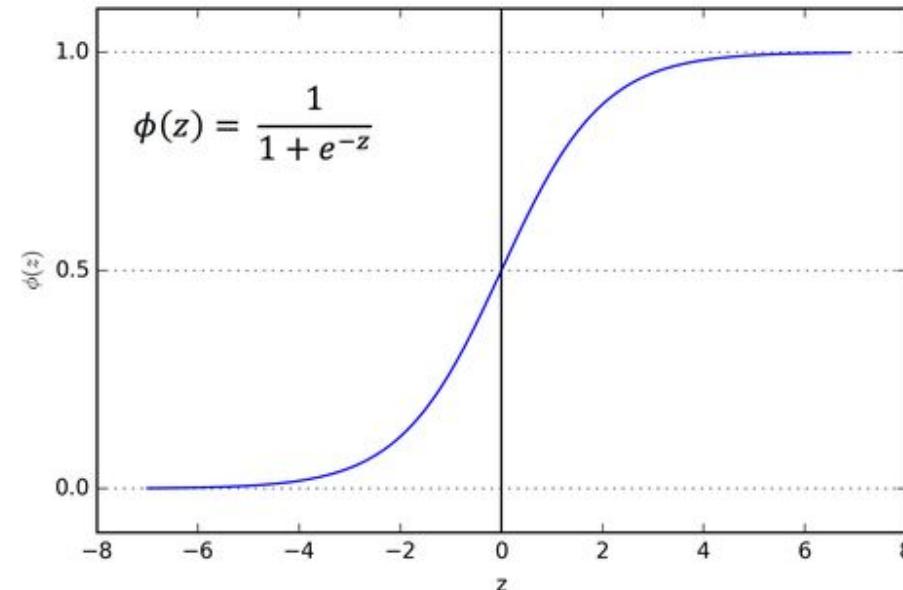
- If the activation is:
  - Positive, output +1
  - Negative, output -1



# How to get probabilistic decisions?

- Activation:  $z = w \cdot f(x)$
- If  $z = w \cdot f(x)$  very positive  want probability going to 1
- If  $z = w \cdot f(x)$  very negative  want probability going to 0
- Sigmoid function

$$\phi(z) = \frac{1}{1 + e^{-z}}$$



# Best w?

---

- Maximum likelihood estimation:

$$\max_w \text{ll}(w) = \max_w \sum_i \log P(y^{(i)} | x^{(i)}; w)$$

with:

$$P(y^{(i)} = +1 | x^{(i)}; w) = \frac{1}{1 + e^{-w \cdot f(x^{(i)})}}$$
$$P(y^{(i)} = -1 | x^{(i)}; w) = 1 - \frac{1}{1 + e^{-w \cdot f(x^{(i)})}}$$

= Logistic Regression

# Multiclass Logistic Regression

- Multi-class linear classification

- A weight vector for each class:  $w_y$

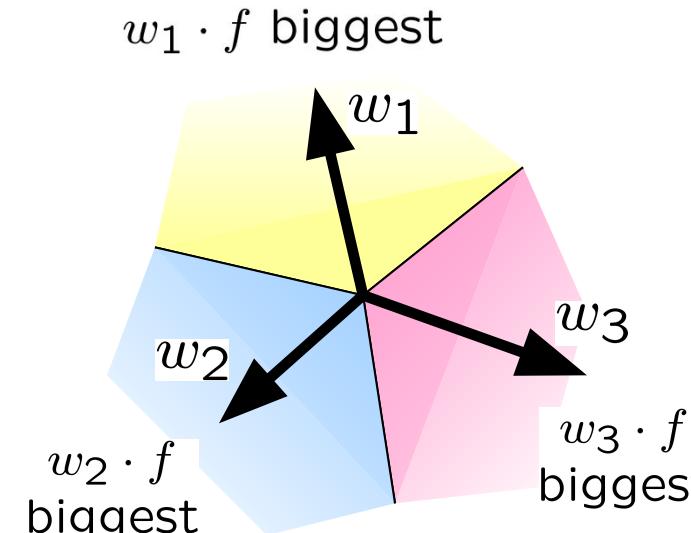
- Score (activation) of a class  $y$ :  $w_y \cdot f(x)$

- Prediction w/highest score wins:  $y = \arg \max_y w_y \cdot f(x)$

- How to make the scores into probabilities?

$$z_1, z_2, z_3 \rightarrow \underbrace{\frac{e^{z_1}}{e^{z_1} + e^{z_2} + e^{z_3}}, \frac{e^{z_2}}{e^{z_1} + e^{z_2} + e^{z_3}}, \frac{e^{z_3}}{e^{z_1} + e^{z_2} + e^{z_3}}}_{\text{softmax activations}}$$

original activations



# Best w?

---

- Maximum likelihood estimation:

$$\max_w \text{ll}(w) = \max_w \sum_i \log P(y^{(i)} | x^{(i)}; w)$$

with:

$$P(y^{(i)} | x^{(i)}; w) = \frac{e^{w_{y^{(i)}} \cdot f(x^{(i)})}}{\sum_y e^{w_y \cdot f(x^{(i)})}}$$

= Multi-Class Logistic Regression

# This Lecture

---

- Optimization
  - i.e., how do we solve:

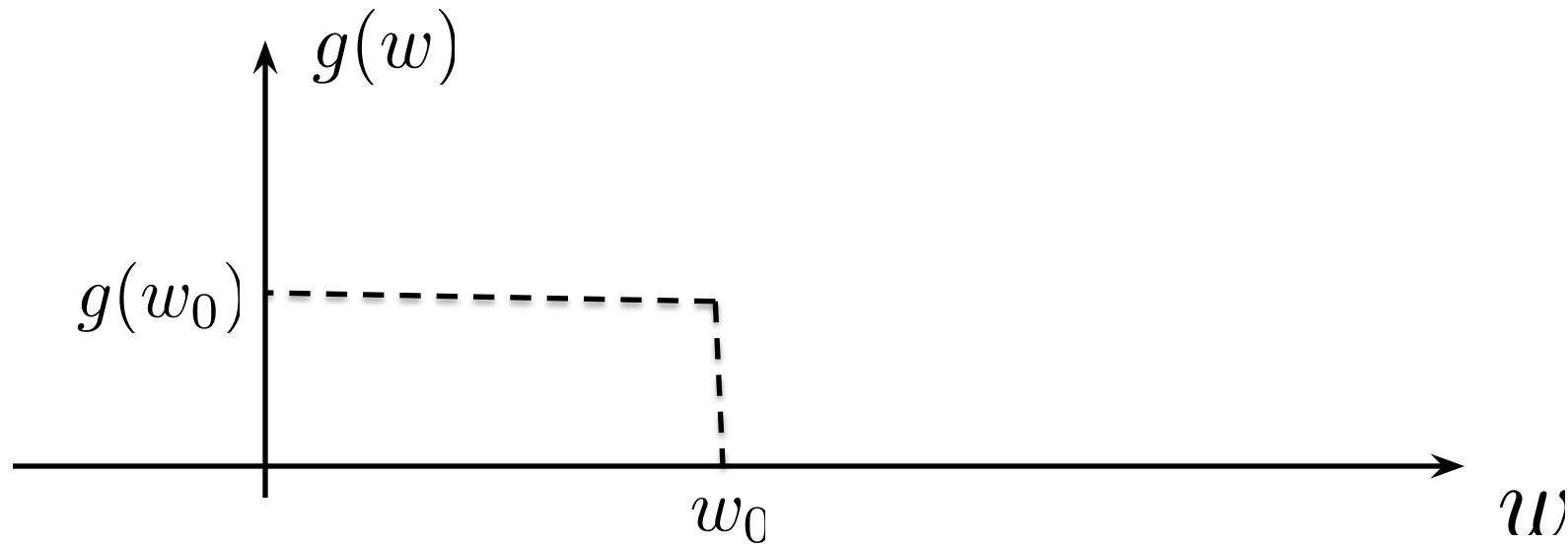
$$\max_w \text{ll}(w) = \max_w \sum_i \log P(y^{(i)} | x^{(i)}; w)$$

# Hill Climbing

- Recall from CSPs lecture: simple, general
  - Start wherever
  - Repeat: move to the best neighboring state
  - If no neighbors better than current, quit
- What's particularly tricky when hill-climbing for multiclass logistic regression?
  - Optimization over a continuous space
    - Infinitely many neighbors!
    - How to do this efficiently?

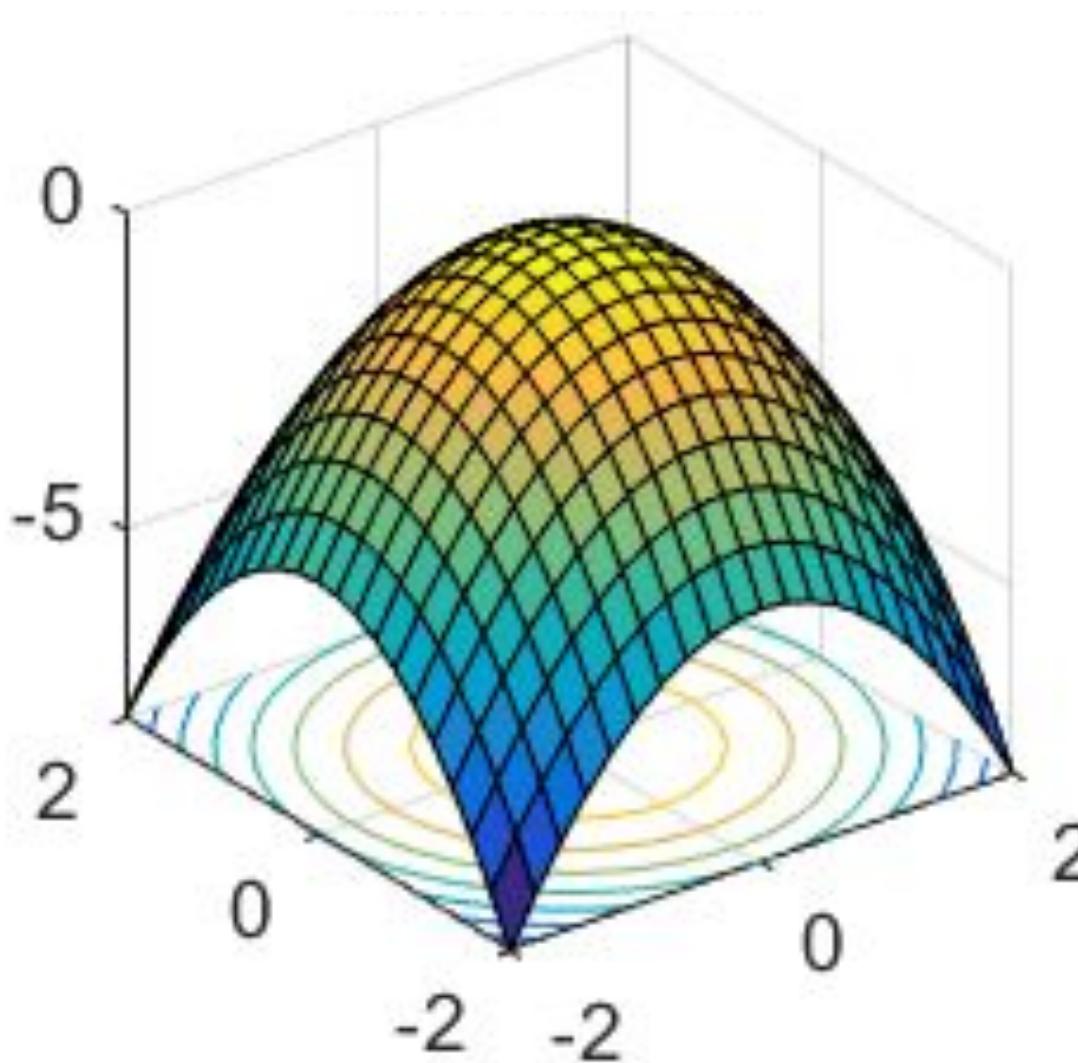


# 1-D Optimization



- Could evaluate  $g(w_0 + h)$        $g(w_0 - h)$ 
  - Then step in best direction
- Or, evaluate derivative: 
$$\frac{\partial g(w_0)}{\partial w} = \lim_{h \rightarrow 0} \frac{g(w_0 + h) - g(w_0 - h)}{2h}$$
  - Tells which direction to step into

# 2-D Optimization



# Gradient Ascent

- Perform update in uphill direction for each coordinate
- The steeper the slope (i.e. the higher the derivative) the bigger the step for that coordinate
- E.g., consider the function  $g(w_1, w_2)$

- Updates:

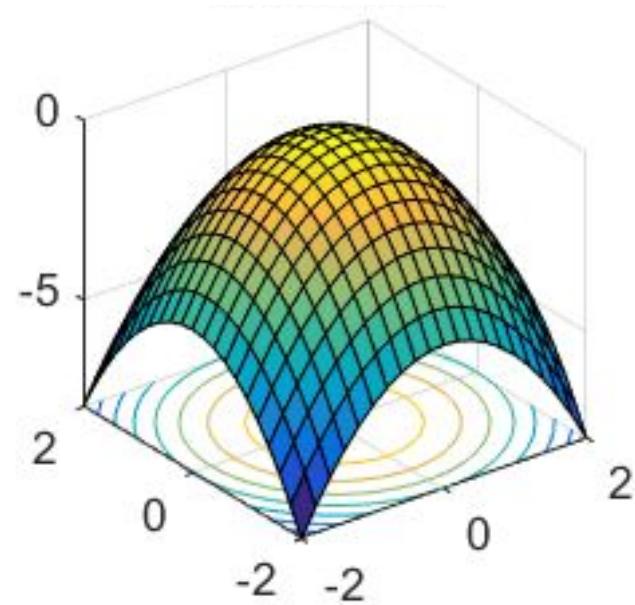
$$w_1 \leftarrow w_1 + \alpha * \frac{\partial g}{\partial w_1}(w_1, w_2)$$

$$w_2 \leftarrow w_2 + \alpha * \frac{\partial g}{\partial w_2}(w_1, w_2)$$

- Updates in vector notation:

$$w \leftarrow w + \alpha * \nabla_w g(w)$$

with:  $\nabla_w g(w) = \begin{bmatrix} \frac{\partial g}{\partial w_1}(w) \\ \frac{\partial g}{\partial w_2}(w) \end{bmatrix}$  = **gradient**



# Gradient Ascent

- Idea:
  - Start somewhere
  - Repeat: Take a step in the gradient direction

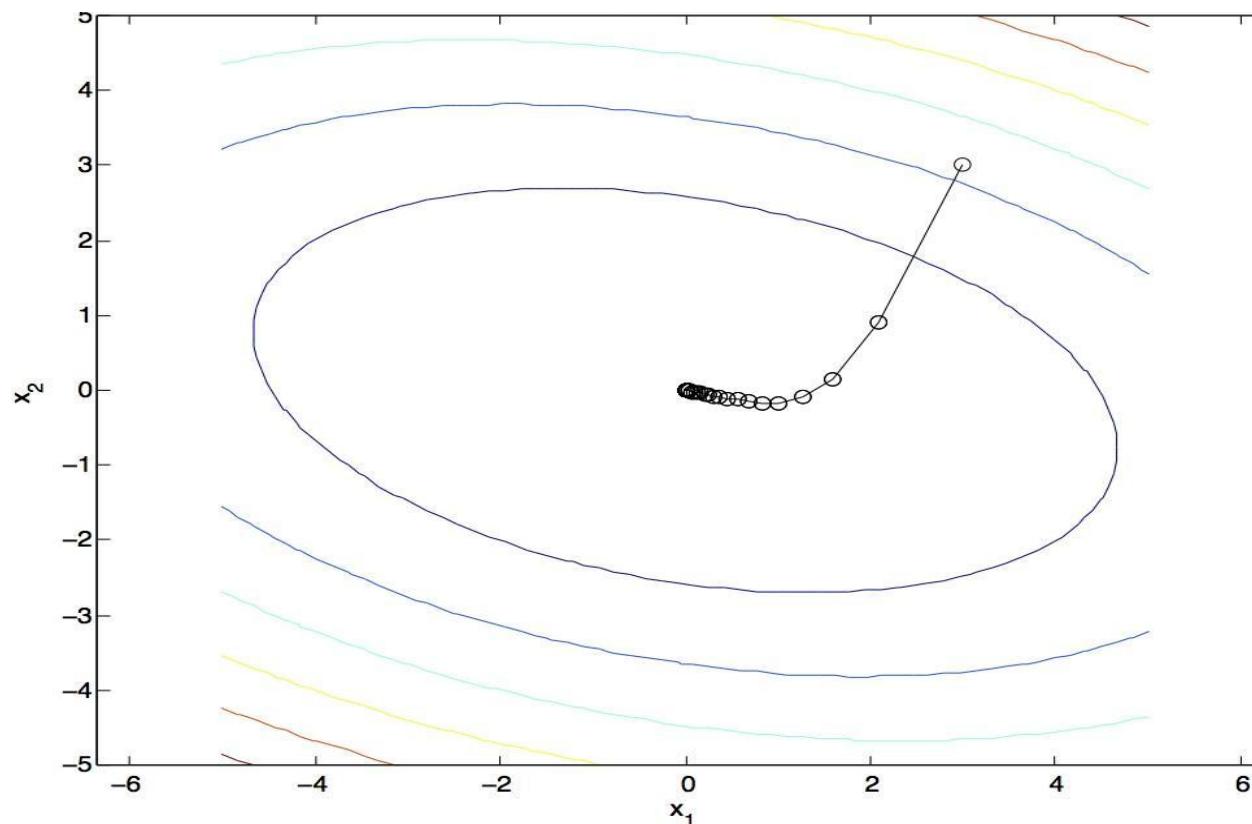
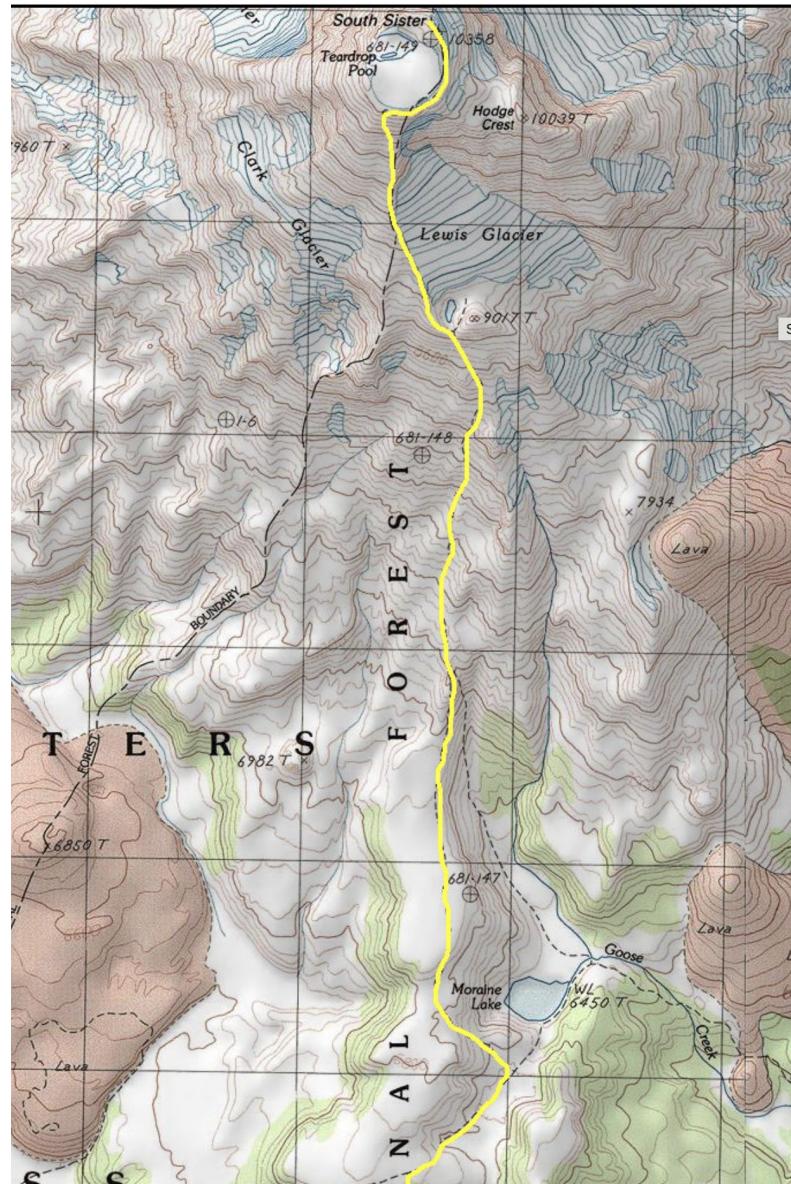


Figure source: Mathworks

# What is the Steepest Direction? Hiker's intuition



Source: <https://www.willhiteweb.com>

# What is the Steepest Direction? With actual math

$$\max_{\Delta: \Delta_1^2 + \Delta_2^2 \leq \varepsilon} g(w + \Delta)$$



- First-Order Taylor Expansion:

$$g(w + \Delta) \approx g(w) + \frac{\partial g}{\partial w_1} \Delta_1 + \frac{\partial g}{\partial w_2} \Delta_2$$

- Steepest Descent Direction:

$$\max_{\Delta: \Delta_1^2 + \Delta_2^2 \leq \varepsilon} g(w) + \frac{\partial g}{\partial w_1} \Delta_1 + \frac{\partial g}{\partial w_2} \Delta_2$$

- Recall:

$$\max_{\Delta: \|\Delta\| \leq \varepsilon} \Delta^\top a$$

$$\Delta = \varepsilon \frac{a}{\|a\|}$$

- Hence, solution:

$$\Delta = \varepsilon \frac{\nabla g}{\|\nabla g\|}$$

**Gradient direction = steepest direction!**

$$\nabla g = \begin{bmatrix} \frac{\partial g}{\partial w_1} \\ \frac{\partial g}{\partial w_2} \end{bmatrix}$$

# Gradient in n dimensions

---

$$\nabla g = \begin{bmatrix} \frac{\partial g}{\partial w_1} \\ \frac{\partial g}{\partial w_2} \\ \vdots \\ \frac{\partial g}{\partial w_n} \end{bmatrix}$$

# Example: Derivatives and Gradients

---

- What is the derivative of the function  $g(x) = x^2 + 3$

$$\frac{dg}{dx} = 2x$$

- What is the derivative of  $g(x)$  at  $x=5$ ?

$$\frac{dg}{dx}|_{x=5} = 10$$

# Example: Derivatives and Gradients

---

- What is the gradient of the function  $g(x, y) = x^2y$ 
  - Recall: Gradient is a vector of partial derivatives with respect to each variable

$$\nabla g = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = \begin{bmatrix} 2xy \\ x^2 \end{bmatrix}$$

- What is the derivative of  $g(x, y)$  at  $x=0.5, y=0.5$ ?

$$\nabla g|_{x=0.5, y=0.5} = \begin{bmatrix} 2(0.5)(0.5) \\ (0.5^2) \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.25 \end{bmatrix}$$

# Optimization Procedure: Gradient Ascent

---

- init  $w$
- for iter = 1, 2, ...

$$w \leftarrow w + \alpha * \nabla g(w)$$

- $\alpha$ : learning rate --- tweaking parameter that needs to be chosen carefully
- How? Try multiple choices
  - Crude rule of thumb: update changes  $w$  about 0.1 – 1 %

# Batch Gradient Ascent on the Log Likelihood Objective

$$\max_w \text{ll}(w) = \max_w \underbrace{\sum_i \log P(y^{(i)}|x^{(i)}; w)}_{g(w)}$$

- init  $w$
- for iter = 1, 2, ...

$$w \leftarrow w + \alpha * \sum_i \nabla \log P(y^{(i)}|x^{(i)}; w)$$

# Stochastic Gradient Ascent on the Log Likelihood Objective

$$\max_w \text{ll}(w) = \max_w \sum_i \log P(y^{(i)} | x^{(i)}; w)$$

**Observation:** once gradient on one training example has been computed, might as well incorporate before computing next one

- `init w`
- `for iter = 1, 2, ...`
  - pick random j

$$w \leftarrow w + \alpha * \nabla \log P(y^{(j)} | x^{(j)}; w)$$

# Mini-Batch Gradient Ascent on the Log Likelihood Objective

$$\max_w \text{ll}(w) = \max_w \sum_i \log P(y^{(i)} | x^{(i)}; w)$$

**Observation:** gradient over small set of training examples (=mini-batch) can be computed in parallel, might as well do that instead of a single one

- `init w`
- `for iter = 1, 2, ...`
  - pick random subset of training examples  $J$

$$w \leftarrow w + \alpha * \sum_{j \in J} \nabla \log P(y^{(j)} | x^{(j)}; w)$$

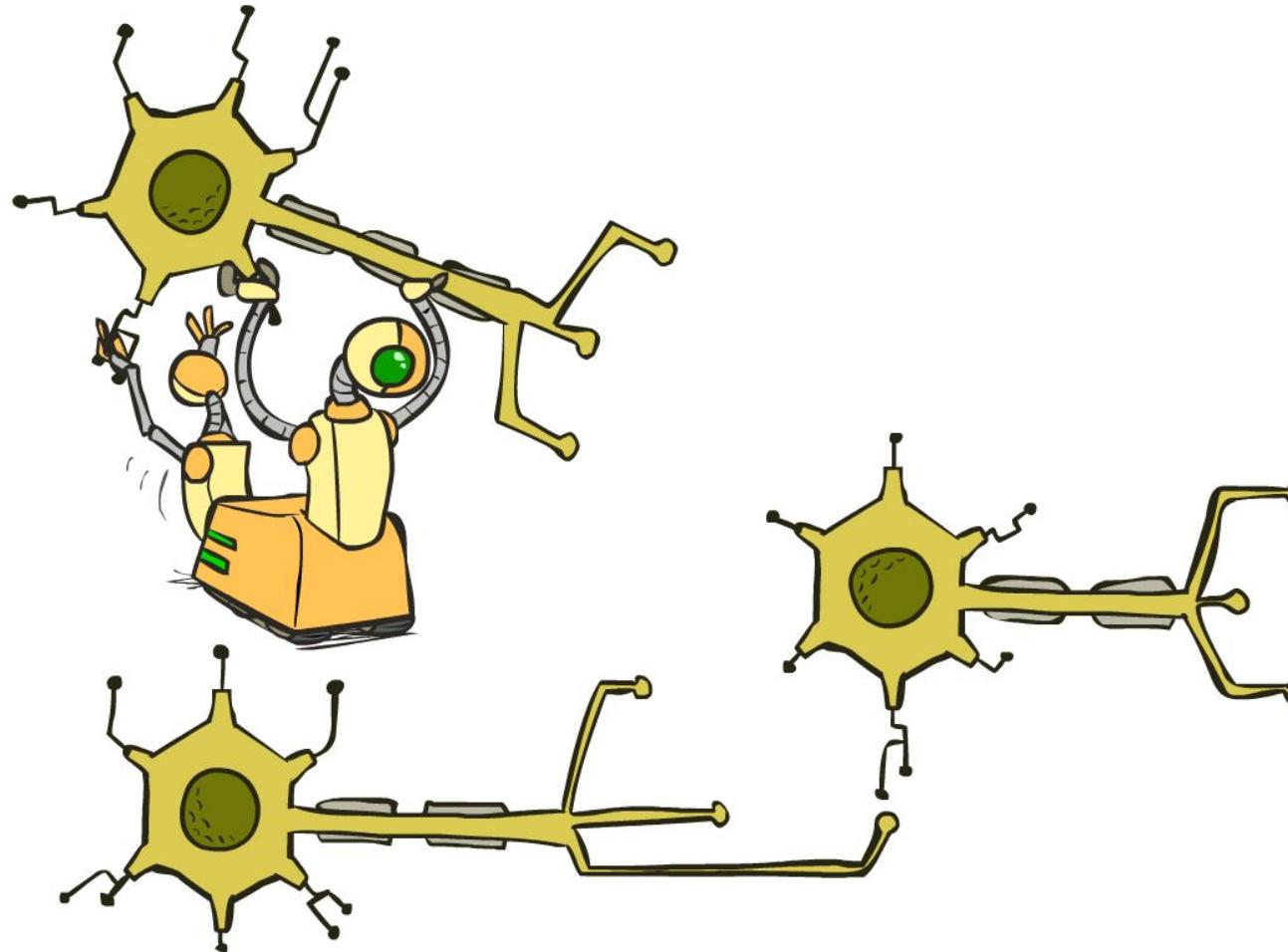
# How about computing all the derivatives?

---

- We'll talk about that once we covered neural networks, which are a generalization of logistic regression

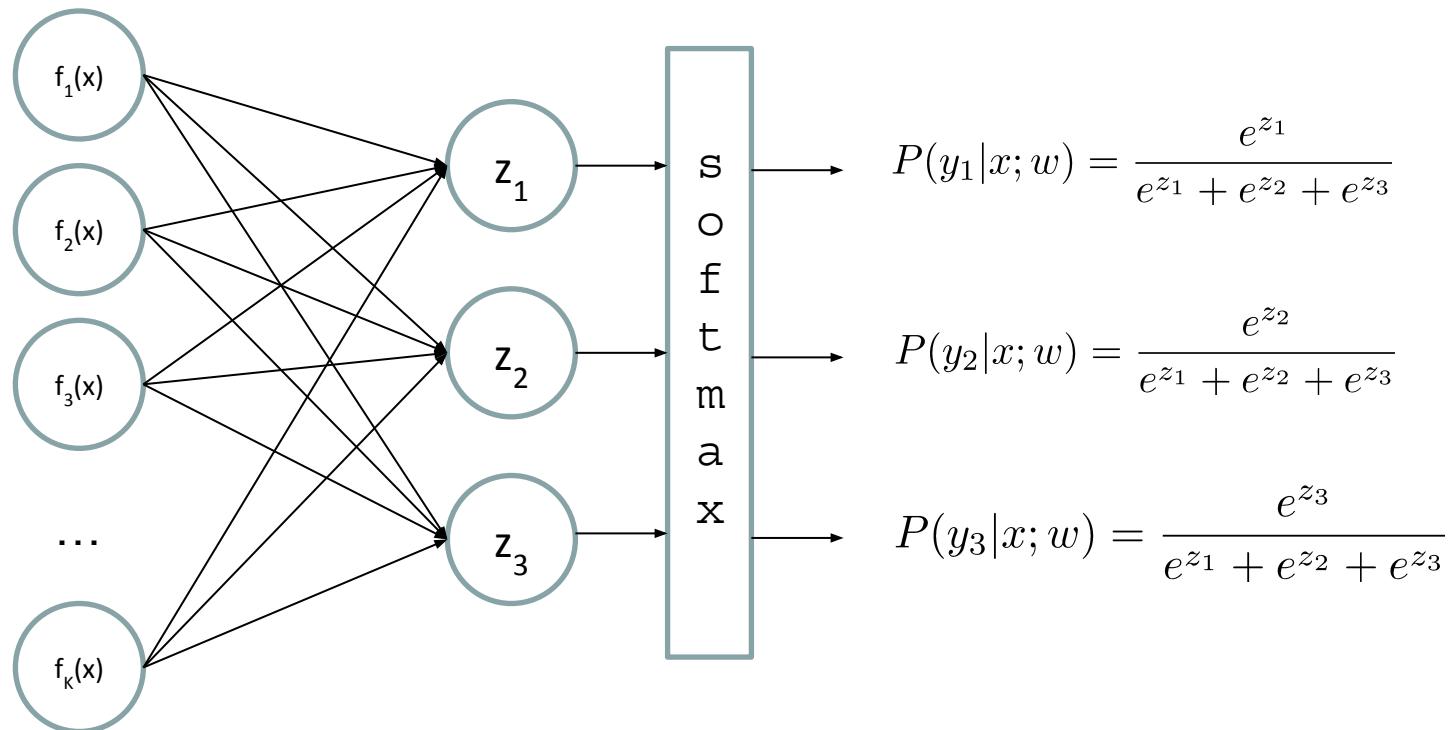
# Neural Networks

---



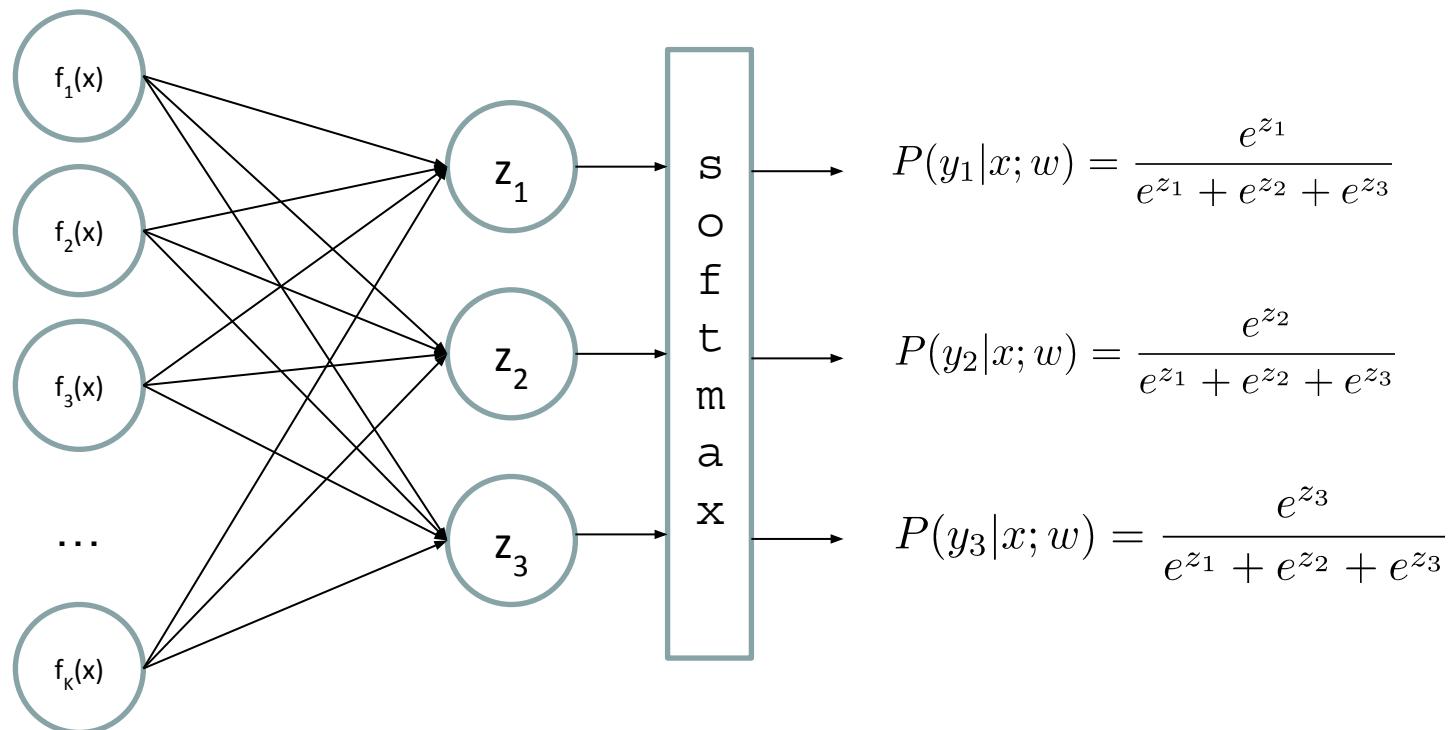
# Multi-class Logistic Regression

- = special case of neural network



# But how do we get the features?

- = special case of neural network



# Classical ML: lots of engineering

- = special case of neural network

kaggle feature engineering

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Kaggle https://www.kaggle.com/learn/feature-engineering ...

**Learn Feature Engineering**  
5 hours to go Begin Course Courses Discussions What Is Feature Engineering Learn the str and principles of creating better features.

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Learn Feature Engineering ...  
Better features make better models. Discover how to get the most ...

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Kaggle https://www.kaggle.com/code/ryanholbrook/what-... ...

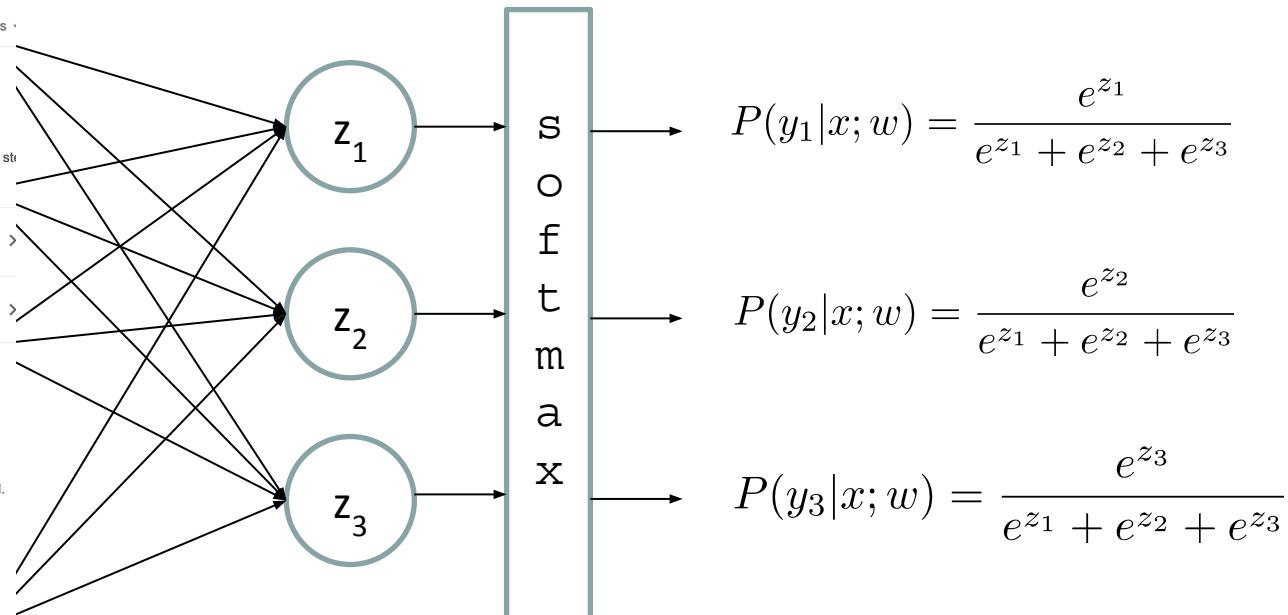
**What Is Feature Engineering**  
The goal of feature engineering is simply to make your data better suited to the problem at hand. Consider "apparent temperature" measures like the heat index ...

Kaggle https://www.kaggle.com/code/prashant111/a-refer... ...

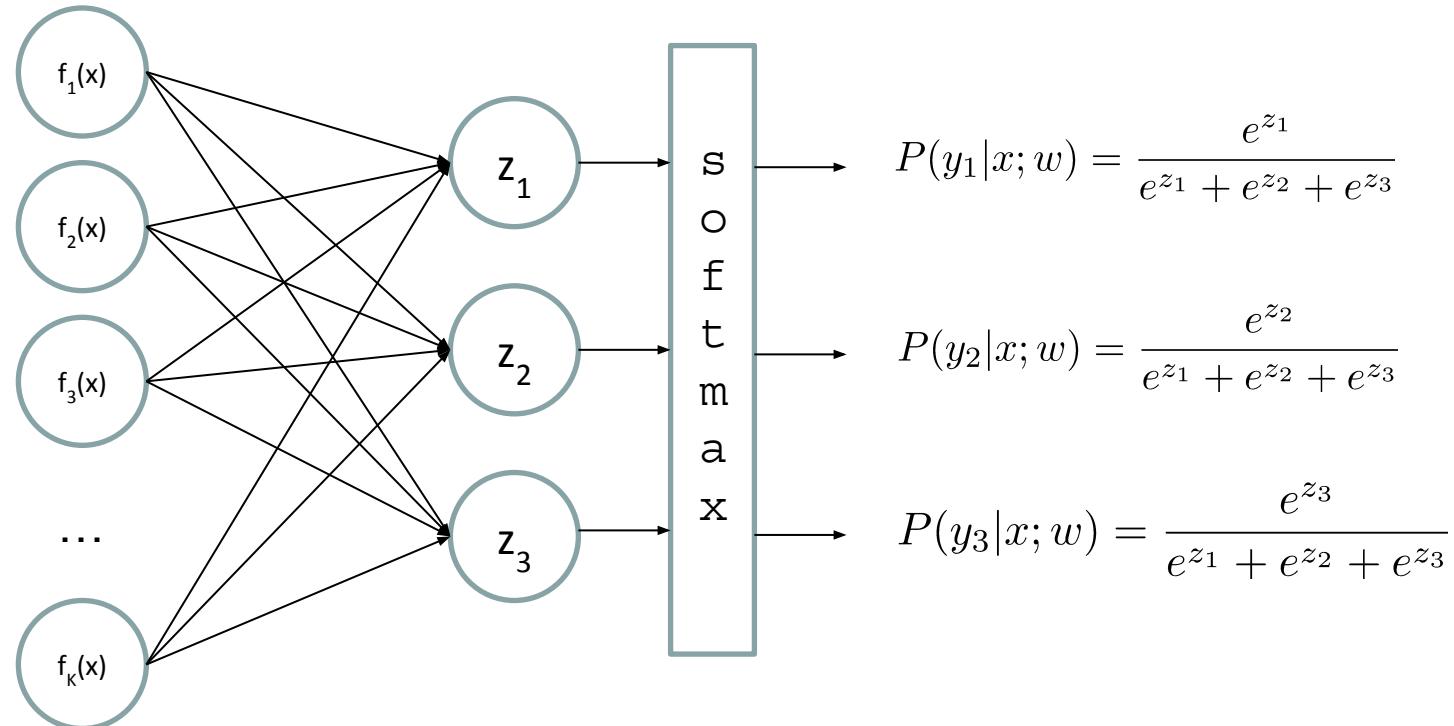
**A Reference Guide to Feature Engineering Methods**  
In this kernel, I will discuss various Feature Engineering techniques that will help us to properly extract, prepare and engineer features from our dataset.

Kaggle https://www.kaggle.com/code/seneralkan/advance... ...

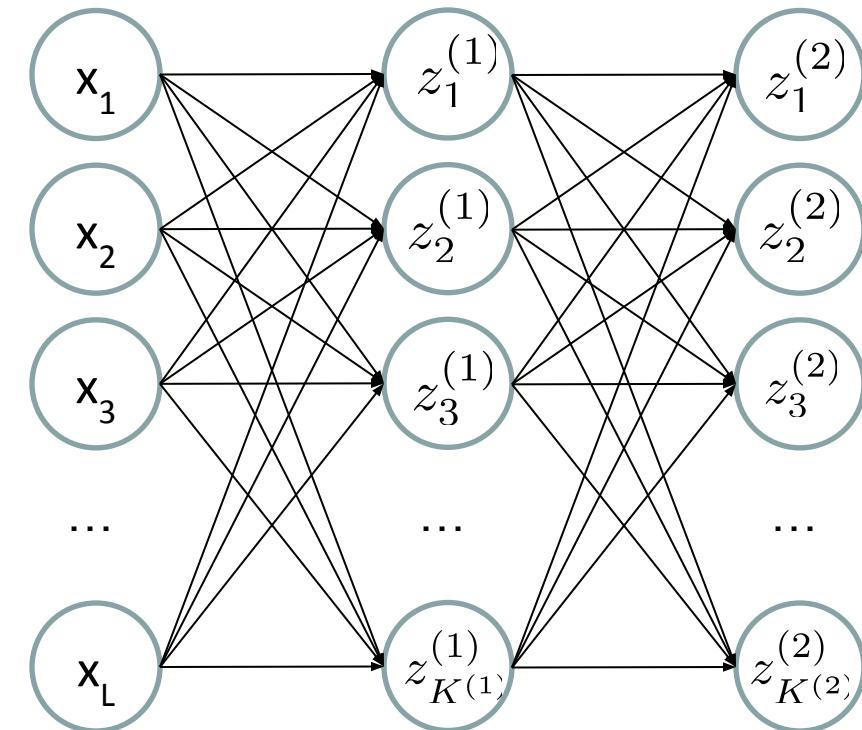
**Advanced Feature Engineering**  
Explore and run machine learning code with Kaggle Notebooks | Using data from multiple data sources.



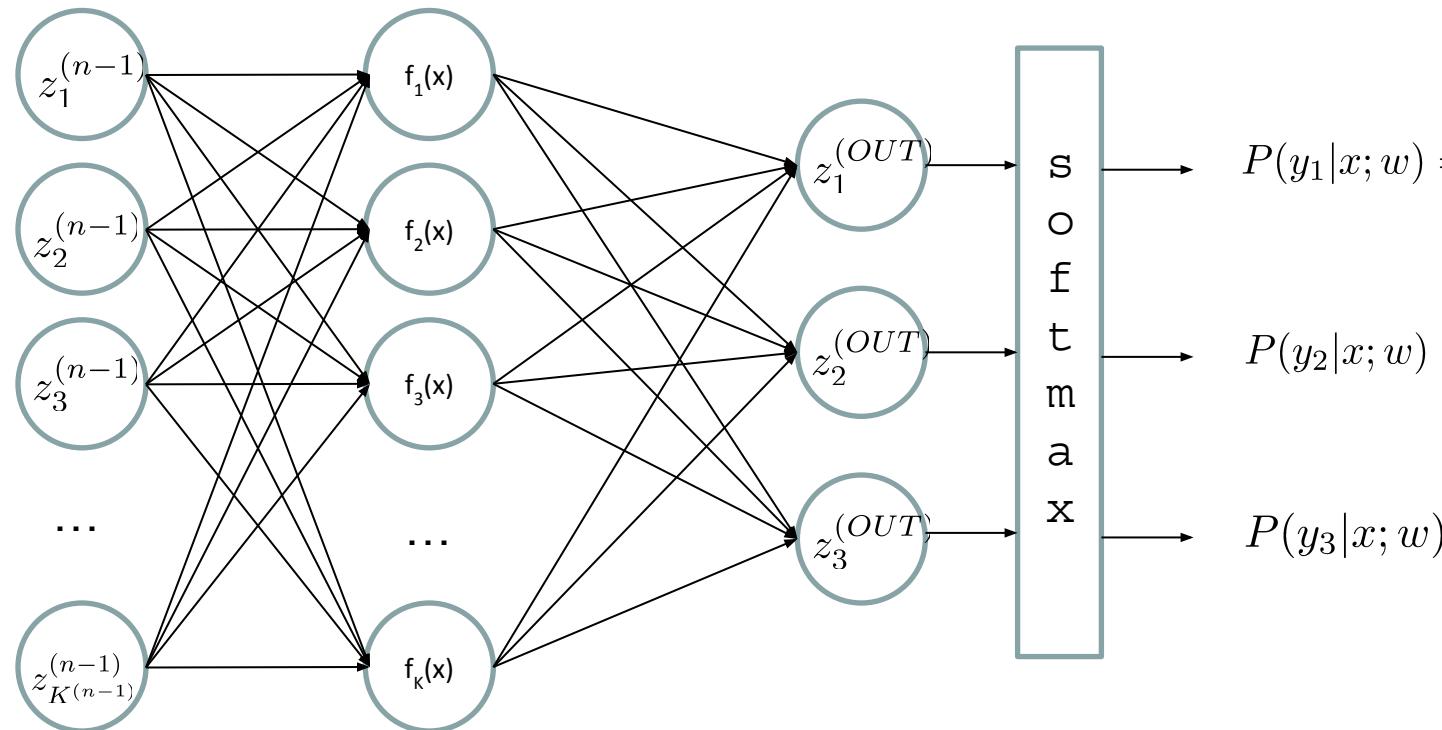
# Deep Neural Network = Also learn the features!



# Deep Neural Network = Also learn the features!

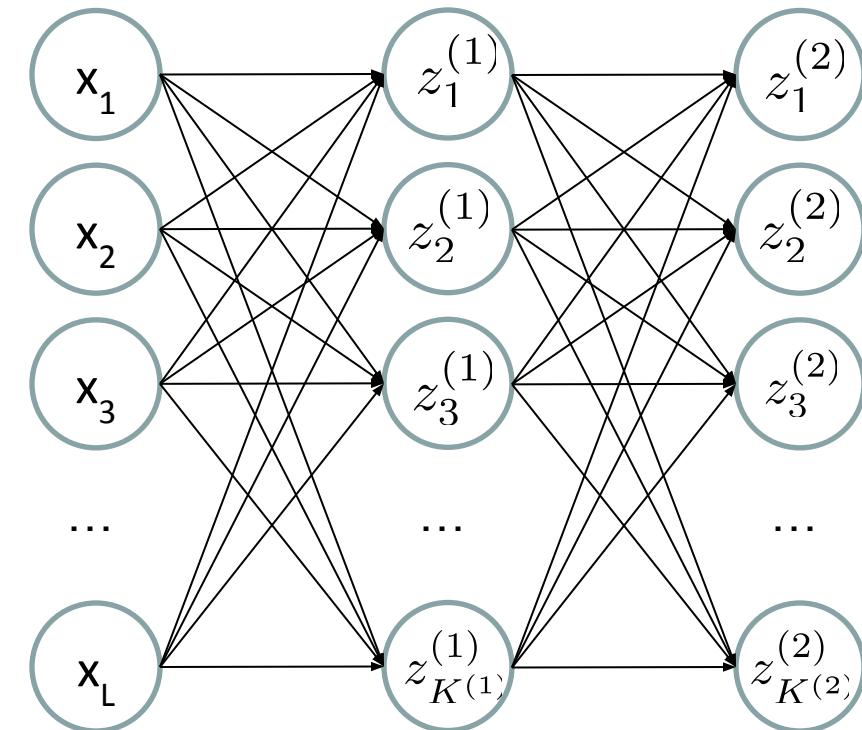


$$z_i^{(k)} = g\left(\sum_j W_{i,j}^{(k-1,k)} z_j^{(k-1)}\right)$$

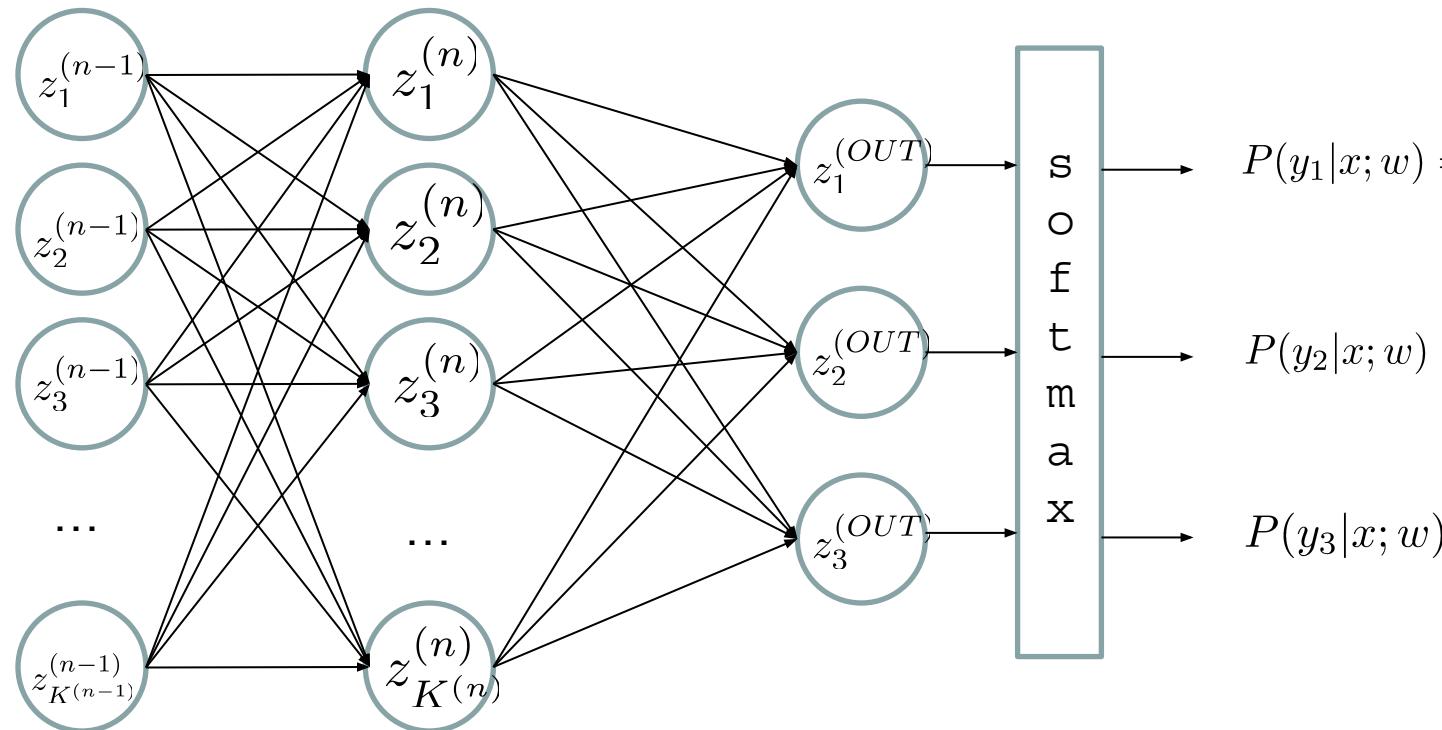


**g = nonlinear activation function  
(non-linearity is important! Otherwise you're just learning linear functions)**

# Deep Neural Network = Also learn the features!



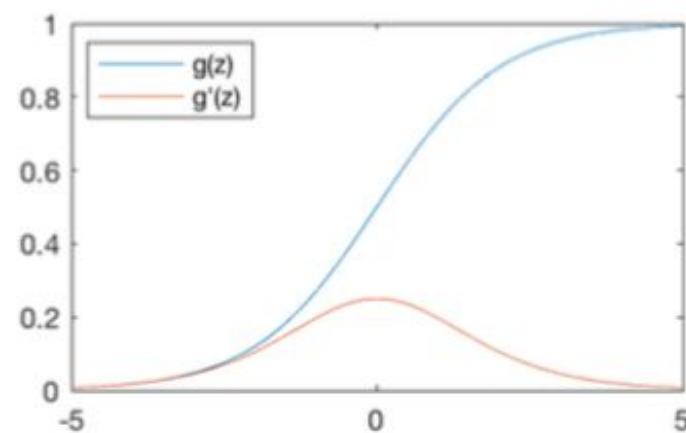
$$z_i^{(k)} = g\left(\sum_j W_{i,j}^{(k-1,k)} z_j^{(k-1)}\right)$$



**g = nonlinear activation function  
(non-linearity is important! Otherwise you're just learning linear functions)**

# Common Activation Functions

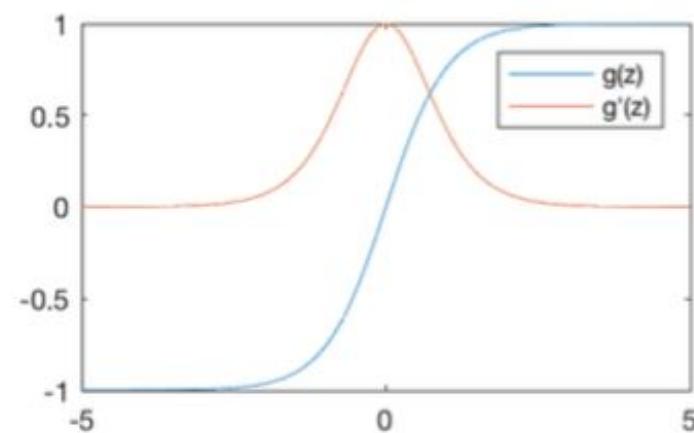
Sigmoid Function



$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

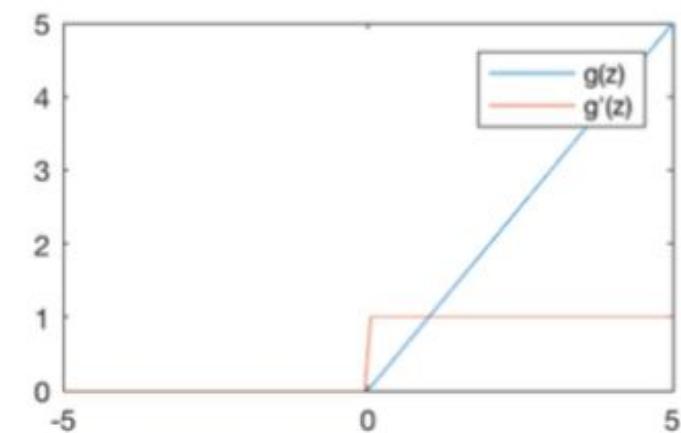
Hyperbolic Tangent



$$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

Rectified Linear Unit (ReLU)



$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

# Deep Neural Network: Also Learn the Features!

---

- Training the deep neural network is just like logistic regression:

$$\max_w \text{ll}(w) = \max_w \sum_i \log P(y^{(i)} | x^{(i)}; w)$$

just  $w$  tends to be a much, much larger vector 😊

- just run gradient ascent (or some slightly more sophisticated optimizers)  
+ stop when log likelihood of hold-out data starts to decrease

# Neural Networks Properties

---

- Theorem (Universal Function Approximators). A two-layer neural network with a sufficient number of neurons can approximate any continuous function to any desired accuracy.
- Practical considerations
  - Can be seen as learning the features
  - Large number of neurons
    - Danger for overfitting
    - (hence early stopping!)

# Universal Function Approximation Theorem\*

Hornik theorem 1: Whenever the activation function is *bounded and nonconstant*, then, for any finite measure  $\mu$ , standard multilayer feedforward networks can approximate any function in  $L^p(\mu)$  (the space of all functions on  $R^k$  such that  $\int_{R^k} |f(x)|^p d\mu(x) < \infty$ ) arbitrarily well, provided that sufficiently many hidden units are available.

Hornik theorem 2: Whenever the activation function is *continuous, bounded and non-constant*, then, for arbitrary compact subsets  $X \subseteq R^k$ , standard multilayer feedforward networks can approximate any continuous function on  $X$  arbitrarily well with respect to uniform distance, provided that sufficiently many hidden units are available.

- In words: Given any continuous function  $f(x)$ , if a 2-layer neural network has enough hidden units, then there is a choice of weights that allow it to closely approximate  $f(x)$ .

Cybenko (1989) "Approximations by superpositions of sigmoidal functions"

Hornik (1991) "Approximation Capabilities of Multilayer Feedforward Networks"

Leshno and Schocken (1991) "Multilayer Feedforward Networks with Non-Polynomial Activation Functions Can Approximate Any Function"

# Universal Function Approximation Theorem\*

Math. Control Signals Systems (1989) 2: 303–314

Mathematics of Control,  
Signals, and Systems  
© 1989 Springer-Verlag New York Inc.

## Approximation by Superpositions of a Sigmoidal Function\*

G. Cybenko

**Abstract.** In this paper we demonstrate that finite linear combinations of compositions of a fixed, univariate function and a set of affine functionals can uniformly approximate any continuous function of  $n$  real variables with support in the unit hypercube; only mild conditions are imposed on the univariate function. Our results settle an open question about representability in the class of single hidden layer neural networks. In particular, we show that arbitrary decision regions can be arbitrarily well approximated by continuous feedforward neural networks with only a single internal, hidden layer and any continuous sigmoidal nonlinearity. The paper discusses approximation properties of other possible types of nonlinearities that might be implemented by artificial neural networks.

**Key words.** Neural networks, Approximation, Completeness.

### 1. Introduction

A number of diverse application areas are concerned with the representation of general functions of an  $n$ -dimensional real variable,  $x \in \mathbb{R}^n$ , by finite linear combinations of the form

$$\sum_{j=1}^N \alpha_j \sigma(y_j^T x + \theta_j), \quad (1)$$

where  $y_j \in \mathbb{R}^n$  and  $\alpha_j, \theta \in \mathbb{R}$  are fixed. ( $y^T$  is the transpose of  $y$  so that  $y^T x$  is the inner product of  $y$  and  $x$ ). Here the univariate function  $\sigma$  depends heavily on the context of the application. Our major concern is with so-called sigmoidal  $\sigma$ 's:

$$\sigma(t) \rightarrow \begin{cases} 1 & \text{as } t \rightarrow +\infty, \\ 0 & \text{as } t \rightarrow -\infty. \end{cases}$$

Such functions arise naturally in neural network theory as the activation function of a neural node (or *unit* as is becoming the preferred term) [L1], [RHM]. The main result of this paper is a demonstration of the fact that sums of the form (1) are dense in the space of continuous functions on the unit cube if  $\sigma$  is any continuous sigmoidal

\* Date received: October 21, 1988. Date revised: February 17, 1989. This research was supported in part by NSF Grant DCR-8619103, ONR Contract N000-86-G-0202 and DOE Grant DE-FG02-85ER25001.

† Center for Supercomputing Research and Development and Department of Electrical and Computer Engineering, University of Illinois, Urbana, Illinois 61801, U.S.A.

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(893-6080/91) \$3.00 + .00  
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### ORIGINAL CONTRIBUTION

## Approximation Capabilities of Multilayer Feedforward Networks

KURT HORNIK

Technische Universität Wien, Vienna, Austria

(Received 30 January 1990; revised and accepted 25 October 1990)

**Abstract**—We show that standard multilayer feedforward networks with as few as a single hidden layer and arbitrary bounded and nonconstant activation function are universal approximators with respect to  $L^p(\mu)$  performance criteria, for arbitrary finite input environment measures  $\mu$ , provided only that sufficiently many hidden units are available. If the activation function is continuous, bounded and nonconstant, then continuous mappings can be learned uniformly over compact input sets. We also give very general conditions ensuring that networks with sufficiently smooth activation functions are capable of arbitrarily accurate approximation to a function and its derivatives.

**Keywords**—Multilayer feedforward networks, Activation function, Universal approximation capabilities, Input environment measure,  $L^p(\mu)$  approximation, Uniform approximation, Sobolev spaces, Smooth approximation.

### 1. INTRODUCTION

The approximation capabilities of neural network architectures have recently been investigated by many authors, including Carroll and Dickinson (1989), Cybenko (1989), Funahashi (1989), Gallant and White (1988), Hecht-Nielsen (1989), Hornik, Stinchcombe, and White (1989, 1990), Itoh and Miyake (1988), Lapedes and Farber (1988), Stinchcombe and White (1989, 1990). (This list is by no means complete.)

If we think of the network architecture as a rule for computing values at  $l$  output units given values at  $k$  input units, hence implementing a class of mappings from  $R^k$  to  $R^l$ , we can ask how well arbitrary mappings from  $R^k$  to  $R^l$  can be approximated by the network, in particular, if as many hidden units as required for internal representation and computation may be employed.

How to measure the accuracy of approximation depends on how we measure closeness between functions, which in turn varies significantly with the specific problem to be dealt with. In many applications, it is necessary to have the network perform simultaneously well on all input samples taken from some compact input set  $X$  in  $R^k$ . In this case, closeness is measured by the uniform distance between functions on  $X$ , that is,

$$\rho_{\sigma,X}(f, g) = \sup_{x \in X} |f(x) - g(x)|.$$

In other applications, we think of the inputs as random variables and are interested in the *average performance* where the average is taken with respect to the input environment measure  $\mu$ , where  $\mu(R^k) < \infty$ . In this case, closeness is measured by the  $L^p(\mu)$  distances

$$\rho_{\sigma,\mu}(f, g) = \left[ \int_{R^k} |f(x) - g(x)|^p d\mu(x) \right]^{1/p}.$$

$1 \leq p < \infty$ , the most popular choice being  $p = 2$ , corresponding to mean square error.

Of course, there are many more ways of measuring closeness of functions. In particular, in many applications, it is also necessary that the *derivatives* of the approximating function implemented by the network closely resemble those of the function to be approximated, up to some order. This issue was first taken up in Hornik et al. (1990), who discuss the sources of need of smooth functional approximation in more detail. Typical examples arise in robotics (learning of smooth movements) and signal processing (analysis of chaotic time series); for a recent application to problems of nonparametric inference in statistics and econometrics, see Gallant and White (1989).

All papers establishing certain approximation ca-

Requests for reprints should be sent to Kurt Hornik, Institut für Statistik und Wahrscheinlichkeitstheorie, Technische Universität Wien, Wiedner Hauptstraße 8-10/107, A-1040 Wien, Austria.

MULTILAYER FEEDFORWARD NETWORKS  
WITH NON-POLYNOMIAL ACTIVATION  
FUNCTIONS CAN APPROXIMATE ANY FUNCTION

by

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September 1991

Center for Research on Information Systems  
Information Systems Department  
Leonard N. Stern School of Business  
New York University

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# Fun Neural Net Demo Site

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- Demo-site:
  - <http://playground.tensorflow.org/>

# How about computing all the derivatives?

---

## ■ Derivatives tables:

$$\frac{d}{dx}(a) = 0$$

$$\frac{d}{dx}(x) = 1$$

$$\frac{d}{dx}(au) = a \frac{du}{dx}$$

$$\frac{d}{dx}(u+v-w) = \frac{du}{dx} + \frac{dv}{dx} - \frac{dw}{dx}$$

$$\frac{d}{dx}(uv) = u \frac{dv}{dx} + v \frac{du}{dx}$$

$$\frac{d}{dx}\left(\frac{u}{v}\right) = \frac{1}{v} \frac{du}{dx} - \frac{u}{v^2} \frac{dv}{dx}$$

$$\frac{d}{dx}(u^n) = nu^{n-1} \frac{du}{dx}$$

$$\frac{d}{dx}(\sqrt{u}) = \frac{1}{2\sqrt{u}} \frac{du}{dx}$$

$$\frac{d}{dx}\left(\frac{1}{u}\right) = -\frac{1}{u^2} \frac{du}{dx}$$

$$\frac{d}{dx}\left(\frac{1}{u^n}\right) = -\frac{n}{u^{n+1}} \frac{du}{dx}$$

$$\frac{d}{dx}[f(u)] = \frac{d}{du}[f(u)] \frac{du}{dx}$$

$$\frac{d}{dx}[\ln u] = \frac{d}{dx}[\log_e u] = \frac{1}{u} \frac{du}{dx}$$

$$\frac{d}{dx}[\log_a u] = \log_a e \frac{1}{u} \frac{du}{dx}$$

$$\frac{d}{dx}e^u = e^u \frac{du}{dx}$$

$$\frac{d}{dx}a^u = a^u \ln a \frac{du}{dx}$$

$$\frac{d}{dx}(u^v) = vu^{v-1} \frac{du}{dx} + \ln u \cdot u^v \frac{dv}{dx}$$

$$\frac{d}{dx}\sin u = \cos u \frac{du}{dx}$$

$$\frac{d}{dx}\cos u = -\sin u \frac{du}{dx}$$

$$\frac{d}{dx}\tan u = \sec^2 u \frac{du}{dx}$$

$$\frac{d}{dx}\cot u = -\csc^2 u \frac{du}{dx}$$

$$\frac{d}{dx}\sec u = \sec u \tan u \frac{du}{dx}$$

$$\frac{d}{dx}\csc u = -\csc u \cot u \frac{du}{dx}$$

# How about computing all the derivatives?

---

- But neural net  $f$  is never one of those?
  - No problem: CHAIN RULE:

If 
$$f(x) = g(h(x))$$

Then 
$$f'(x) = g'(h(x))h'(x)$$

- Derivatives can be computed by following well-defined procedures

# Automatic Differentiation

---

- Automatic differentiation software
  - e.g. Theano, TensorFlow, PyTorch, Chainer
  - Only need to program the function  $g(x,y,w)$
  - Can automatically compute all derivatives w.r.t. all entries in  $w$
  - This is typically done by caching info during forward computation pass of  $f$ , and then doing a backward pass = “backpropagation”
  - Autodiff / Backpropagation can often be done at computational cost comparable to the forward pass
- Need to know this exists
- How this is done? -- outside of scope of CS188

# PyTorch is Amazing

```
✓  [1] 1 import torch  
✓ 0s  [2] 1 # Create tensors  
      2 x = torch.tensor(2.0, requires_grad=True)  
      3 y = torch.tensor(3.0, requires_grad=True)  
      4  
      5 # Perform operations  
      6 z = x * y + x**2  
      7  
      8 # Compute gradients  
      9 z.backward()  
     10  
     11 # Print gradients  
     12 print("Gradient of z with respect to x:", x.grad)  
     13 print("Gradient of z with respect to y:", y.grad)
```

Gradient of z with respect to x: tensor(7.)  
Gradient of z with respect to y: tensor(2.)

# PyTorch is Amazing

✓  
0s

```
1 x = torch.tensor([1., 2., 3., 4.], requires_grad=True)
2 y = torch.tensor([4., 3., 2., 1.], requires_grad=True)
3 M = torch.tensor([[2., 0., 0., 1.],
4                 [1., 2., 0., 0.],
5                 [0., 0., 2., 0.],
6                 [1., 0., 0., 2.]], requires_grad=True)
7 M_inv = torch.linalg.inv(M)
8 z = y @ (M_inv @ x) # ``@`` means matrix multiplication
9
10 z.backward()
11 print("Gradient of z with respect to x:", x.grad)
12 print("Gradient of z with respect to y:", y.grad)
13 print("Gradient of z with respect to M:", M.grad)
```

→ Gradient of z with respect to x: tensor([ 1.3333, 1.5000, 1.0000, -0.1667])
Gradient of z with respect to y: tensor([-0.6667, 1.3333, 1.5000, 2.3333])
Gradient of z with respect to M: tensor([[ 0.8889, -1.7778, -2.0000, -3.1111],
[ 1.0000, -2.0000, -2.2500, -3.5000],
[ 0.6667, -1.3333, -1.5000, -2.3333],
[-0.1111, 0.2222, 0.2500, 0.3889]])

# Summary of Key Ideas

- Optimize probability of label given input

$$\max_w ll(w) = \max_w \sum_i \log P(y^{(i)}|x^{(i)}; w)$$

- Continuous optimization

- Gradient ascent:

- Compute steepest uphill direction = gradient (= just vector of partial derivatives)
    - Take step in the gradient direction
    - Repeat (until held-out data accuracy starts to drop = “early stopping”)

- Deep neural nets

- Last layer = still logistic regression
  - Now also many more layers before this last layer

- = computing the features
    - □ the features are learned rather than hand-designed

- Universal function approximation theorem

- If neural net is large enough
    - Then neural net can represent any continuous mapping from input to output with arbitrary accuracy
    - But remember: need to avoid overfitting / memorizing the training data □ early stopping!

- Automatic differentiation gives the derivatives efficiently (how? = outside of scope of 188)