STEVENS
INSTITUTE of TECHNOLOGY
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CS584 Natural Language Processing

Deep feedforward networks

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Late Submission Policy

- **10%** penalty for late submission within **24 hours**.
- **40%** penalty for late submissions within **24-48 hours**.
- After 48 hours, you get **NO** points on the assignment.

Plan for today

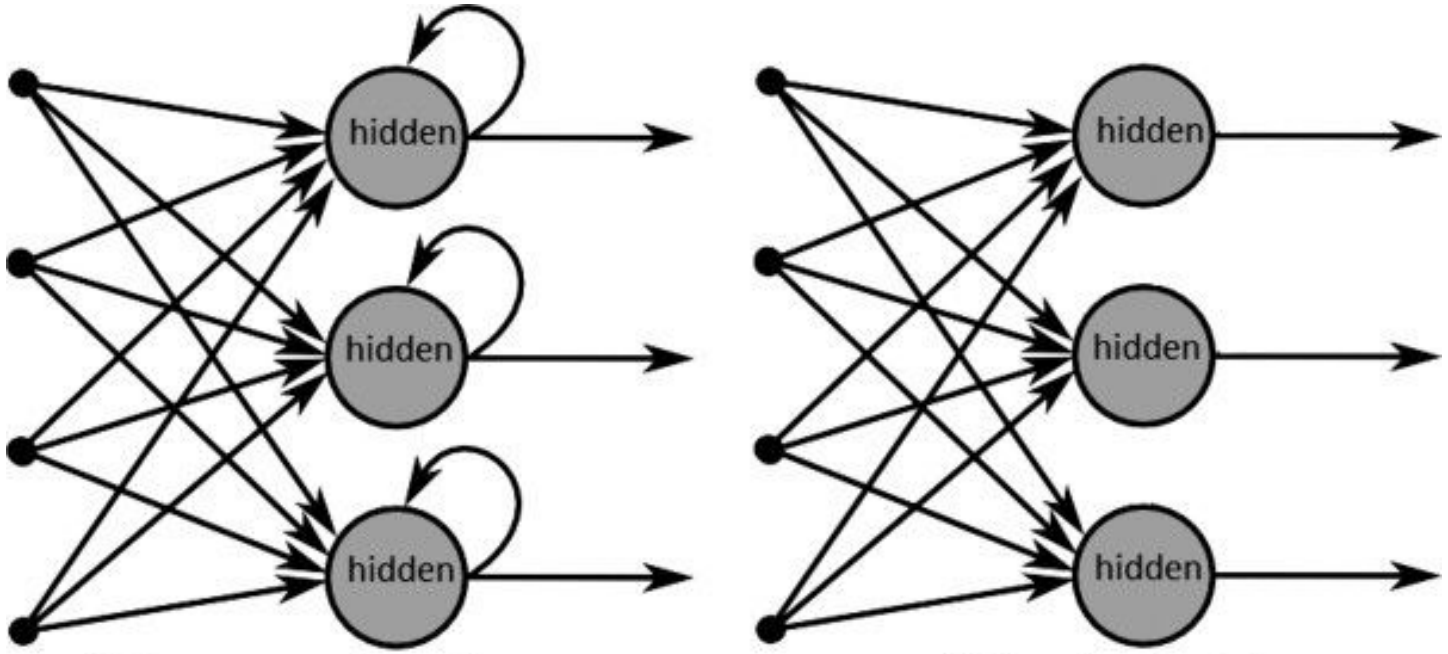
- Deep Feedforward Networks
- Regularization for Deep Learning
- Optimization for Training Deep Models

Deep Feedforward Networks

- Also called feedforward neural networks, or multilayer perceptrons (MLPs)
- Goal: approximate some function f* (target function)
  - for a classifier, y=f*(x) maps an input **x** to a category **y**. It defines a mapping y=f(x;θ) and learns the parameters θ that result in the best function approximation.
- Information x flows through the function f, and finally to the output y.
- No feedback connections in which outputs of the model are fed back into itself.

Deep Feedforward Networks

- w/o feedback connections



(a) Recurrent neural network

(b) Forward neural network

Feedforward neural networks

- They are typically represented by composing together many different functions.
- Given three functions $f^{(1)}$, $f^{(2)}$, and $f^{(3)}$ connected in a chain, to form

$$f(\boldsymbol{x}) = f^{(3)}(f^{(2)}(f^{(1)}(\boldsymbol{x})))$$

  - $f^{(1)}$ **first layer**
  - $f^{(2)}$ **second layer**
  - $f^{(3)}$ **output layer**
  - **depth** = 3

hidden layers

- Hidden layers
  - the training data does not show the desired output for each of these layers.

Example: Learning XOR

- XOR function y=f*(x)
  - When exactly one of these binary values is equal to 1, the XOR function returns 1. Otherwise, it returns 0.
- Data set:
  - $\mathbb{X} = \{[0,0]^\top, [0,1]^\top, [1,0]^\top, \text{and } [1,1]^\top\}$
  - y = { [0], [1], [1], [0] }

A B	O
0 0	0
0 1	1
1 0	1
1 1	0

- Our model learns a function y=f(x;θ), and our learning algorithm will adapt the parameters θ to make f as similar as possible to f*.

Example: Learning XOR

- We can treat this problem as a regression problem and use a mean squared error (MSE) loss function.
- Evaluated on our whole training set, the MSE loss function:

$$J(\boldsymbol{\theta}) = \frac{1}{4} \sum_{\boldsymbol{x} \in \mathbb{X}} (f^*(\boldsymbol{x}) - f(\boldsymbol{x}; \boldsymbol{\theta}))^2$$

- Suppose that we choose a linear model

$$f(\boldsymbol{x}; \boldsymbol{w}, b) = \boldsymbol{x}^\top \boldsymbol{w} + b$$

- We can minimize J(θ) in closed form with respect to w and b using the normal equations
  - w=0 and b=½
- The linear model simply outputs 0.5 everywhere. Why?

Example: Learning XOR

- We can treat this problem as a regression problem and use a mean squared error (MSE) loss function.
- Evaluated on our whole training set, the MSE loss function:

$$\boldsymbol{\theta}))^2$$

An analytical solution to the linear regression problem with a least-squares cost function.
see least squares approximation

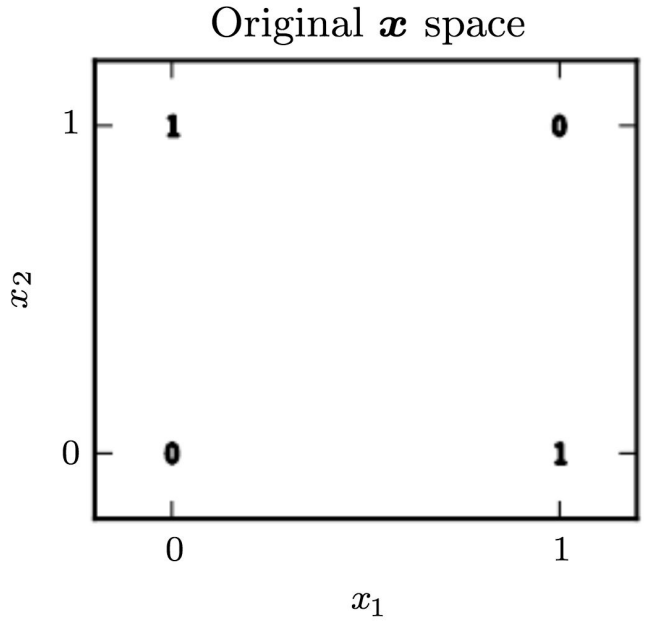
- Su

$$b$$

- We can minimize J(θ) in closed form with respect to w and b using the normal equations
  - w=0 and b=½
- The linear model simply outputs 0.5 everywhere. Why?

Example: Learning XOR

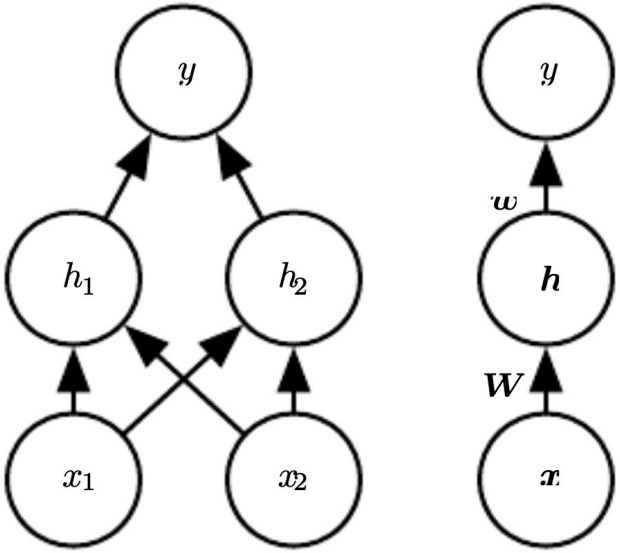
- Cannot be separated with a single line



- Let's use a simple feedforward network

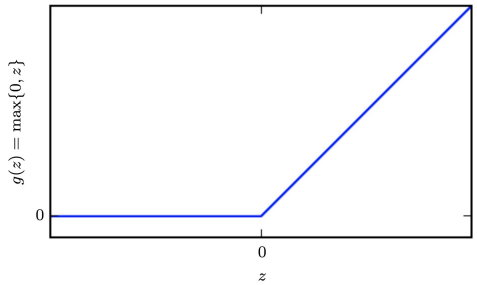
Example: Learning XOR

- Use a simple feedforward network with one hidden layer containing two hidden units.
- Use a nonlinear function as activation function in hidden units.



Example: Learning XOR

- The network now contains two functions chained together
  - $\boldsymbol{h} = f^{(1)}(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}) = g(\boldsymbol{W}^\top \boldsymbol{x} + \boldsymbol{c})$
  - $y = f^{(2)}(\boldsymbol{h}; \boldsymbol{w}, b) = \boldsymbol{h}^\top \boldsymbol{w} + b$
  - $f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = f^{(2)}(f^{(1)}(\boldsymbol{x}))$
- In modern neural networks,the default recommendation is to use the rectified linear unit, or ReLU
  - g(z) = max{0, z}



- Our complete network is

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = \boldsymbol{w}^\top \max\{0, \boldsymbol{W}^\top \boldsymbol{x} + \boldsymbol{c}\} + b$$

Example: Learning XOR

- Our complete network is

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = \boldsymbol{w}^\top \max\{0, \boldsymbol{W}^\top \boldsymbol{x} + \boldsymbol{c}\} + b$$

- We can then specify a solution to the XOR

$$\boldsymbol{W} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix},$$

$$\boldsymbol{c} = \begin{bmatrix} 0 \\ -1 \end{bmatrix},$$

$$\boldsymbol{w} = \begin{bmatrix} 1 \\ -2 \end{bmatrix},$$

$$b = 0$$

Example: Learning XOR

- Our complete network is

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = \boldsymbol{w}^\top \max\{0, \boldsymbol{W}^\top \boldsymbol{x} + \boldsymbol{c}\} + b$$

- (1) Given input matrix X $\boldsymbol{X} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix}$
- (2) multiply the input matrix by the first layer's weight matrix

$$\boldsymbol{W} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \qquad \boldsymbol{X}\boldsymbol{W} = \begin{bmatrix} 0 & 0 \\ 1 & 1 \\ 1 & 1 \\ 2 & 2 \end{bmatrix}$$

- (3) add the bias vector c, to obtain $\begin{bmatrix} 0 & -1 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix}$

$$\boldsymbol{c} = \begin{bmatrix} 0 \\ -1 \end{bmatrix}$$

Example: Learning XOR

- Our complete network is

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = \boldsymbol{w}^\top \max\{0, \boldsymbol{W}^\top \boldsymbol{x} + \boldsymbol{c}\} + b$$

- (4) apply the rectified linear transformation, computing h

$$\begin{bmatrix} 0 & -1 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix}$$

- (5) finish with multiplying by the weight vector w (b=0)

$$\boldsymbol{w} = \begin{bmatrix} 1 \\ -2 \end{bmatrix} \qquad \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} \Leftrightarrow \boldsymbol{X} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix}$$

Example: Learning XOR

- Our complete network is

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = \boldsymbol{w}^\top \max\{0, \boldsymbol{W}^\top \boldsymbol{x} + \boldsymbol{c}\} + b$$

- (4) apply the rectified linear transformation, computing h

$$\begin{bmatrix} 0 & -1 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix}$$

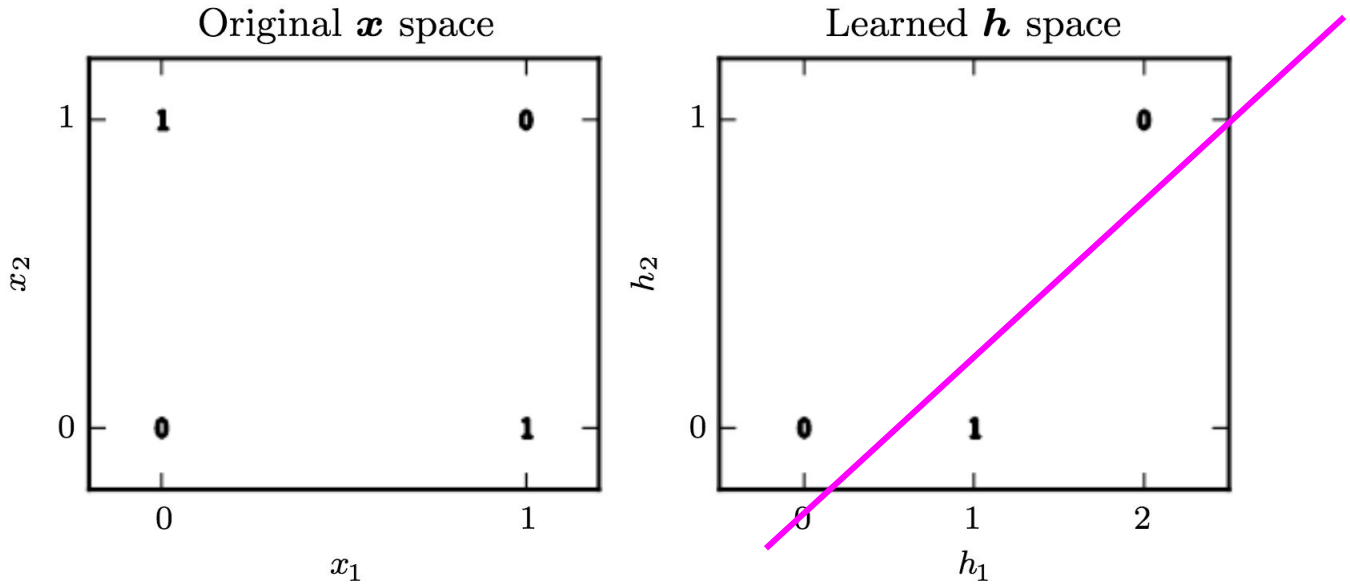
plot this!

- (5) finish with multiplying by the weight vector w (b=0)

$$\boldsymbol{w} = \begin{bmatrix} 1 \\ -2 \end{bmatrix} \qquad \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} \Leftrightarrow \boldsymbol{X} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix}$$

Example: Learning XOR

- (Right) In the transformed space represented by the features extracted by a neural network, a linear model can now solve the problem.



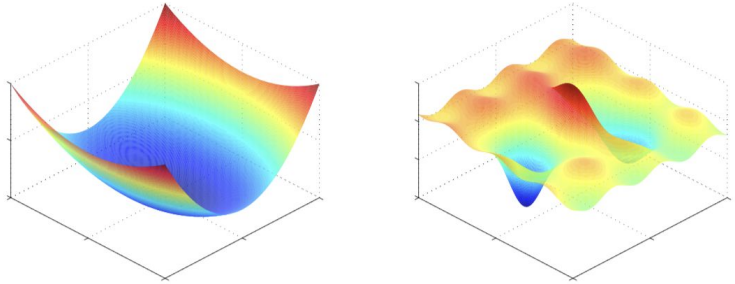
Building a Machine Learning Algorithm

- Nearly all deep learning algorithms can be described as particular instances of a fairly simple recipe: combine
  - a specification of a dataset,
  - a cost function,
  - an optimization procedure
  - and a model.

- **Optimization**
  - For linear models, we could use normal equations, closed form optimization
  - For nonlinear models, it requires us to choose an iterative numerical optimization procedure, such as gradient descent.

Gradient-Based Learning

- The largest difference between the linear models and neural networks
  - the **nonlinearity** of a neural network causes most interesting loss functions to become **nonconvex**.



- Thus, neural networks are usually trained by using iterative, gradient-based optimizers that merely drive the cost function to a very low value

➔ Cost Functions and Output Units

Cost Functions

- Learning Conditional Distributions with Maximum Likelihood
- Negative log-likelihood, equivalently, cross-entropy between the training data and the model distribution

$$J(\boldsymbol{\theta}) = -\mathbb{E}_{\mathbf{x},\mathbf{y}\sim\hat{p}_{\text{data}}} \log p_{\text{model}}(\boldsymbol{y} \mid \boldsymbol{x})$$

The specific form of the cost function changes from model to model, depending on the specific form of $\log p_{\text{model}}$.

- if $p_{\text{model}}(\boldsymbol{y} \mid \boldsymbol{x}) = \mathcal{N}(\boldsymbol{y}; f(\boldsymbol{x};\boldsymbol{\theta}), \boldsymbol{I})$, then we recover the mean squared error cost: proof: chapter 3.1.1 PRML

$$J(\theta) = \frac{1}{2}\mathbb{E}_{\mathbf{x},\mathbf{y}\sim\hat{p}_{\text{data}}} ||\boldsymbol{y} - f(\boldsymbol{x};\boldsymbol{\theta})||^2 + \text{const}$$

Cost Functions

- Learning Conditional Statistics
- Instead $p(\boldsymbol{y} \mid \boldsymbol{x}; \boldsymbol{\theta})$, we want to learn just one conditional statistic of **y** given **x**
- Design the cost function to have its minimum lie on the function that maps **x** to the expected value of **y** given **x**
- To optimize the problem

$$f^* = \arg\min_f \mathbb{E}_{\mathbf{x},\mathbf{y}\sim p_{\text{data}}} ||\boldsymbol{y} - f(\boldsymbol{x})||^2$$

Different cost functions give different statistics.
Mean Absolute Error:

$$f^* = \arg\min_f \mathbb{E}_{\mathbf{x},\mathbf{y}\sim p_{\text{data}}} ||\boldsymbol{y} - f(\boldsymbol{x})||_1$$

Output Units

- **Linear** Units
  - Based on an affine transformation with no nonlinearity.
  - Given feature $\boldsymbol{h}$, a layer of linear output units produces a vector

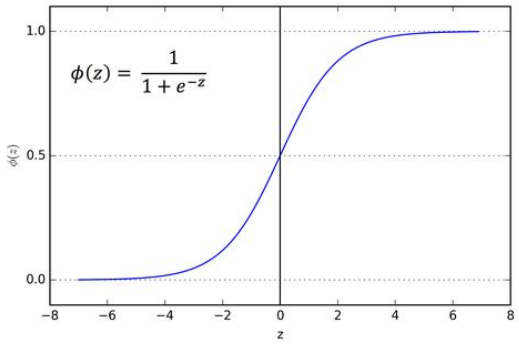
$$\hat{\boldsymbol{y}} = \boldsymbol{W}^\top \boldsymbol{h} + \boldsymbol{b}$$

- An example problem
  - Suppose we seek to predict increment (either positive or negative) of a stock's price based on its prices in the past.

Output Units

- **Sigmoid** Units
  - Many tasks require predicting the value of a binary variable y.
  - Classification problems with two classes.

$$\hat{y} = \sigma\left(\boldsymbol{w}^\top \boldsymbol{h} + b\right)$$



- An example problem
  - Provide historical weather data and predict the chance of rain for the next day

Output Units

- **Softmax** Units
  - Represent a probability distribution over a discrete variable with *n* possible values
  - a generalization of the sigmoid function, which was used to represent a probability distribution over a binary variable.

$$\boldsymbol{z} = \boldsymbol{W}^\top \boldsymbol{h} + \boldsymbol{b}$$

The softmax function can then exponentiate and normalize z to obtain the desired ˆy

$$\text{softmax}(\boldsymbol{z})_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

- An example problem
  - Handwritten digit classification

Hidden Units

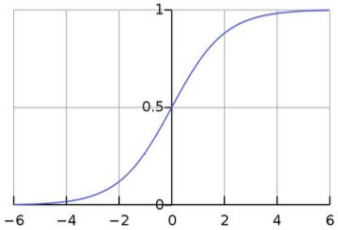
- An issue that is unique to feedforward neural nets
  - how to choose the type of hidden unit to use in the hidden layers of the model.
  - an extremely active research area and does not yet have many definitive guiding theoretical principles.

- Hidden units use the **activation functions**
  - they are typically used on top of an affine transformation:

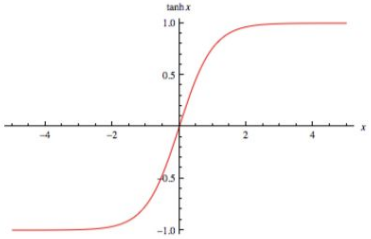
$$\boldsymbol{h} = g(\boldsymbol{W}^\top \boldsymbol{x} + \boldsymbol{b})$$

Activation Functions

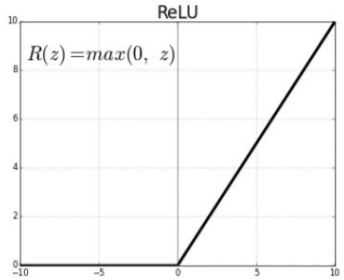
Sigmoid: $f(x) = \sigma(x) = \frac{1}{1+e^{-x}}$



tanh: $f(x) = 2\sigma(2x) - 1$

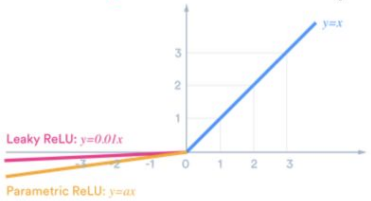


ReLU: $f(x) = \max(0, x)$



*** good default choice**

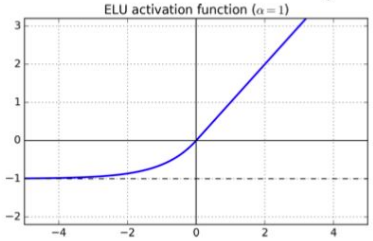
Leaky ReLU: $f(x) = \max(\alpha x, x)$



Maxout

$$\max(\mathbf{w}_1^T \mathbf{x} + b_1, \mathbf{w}_2^T \mathbf{x} + b_2)$$

ELU: $f(x) = \begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$



Architecture Design

- **Architecture** refers to the overall structure of the network:
  - how many units it should have and how these units should be connected to each other
- Most neural networks
  - are organized into groups of units called layers
  - arrange these layers in a chain structure
  - each layer being a function of the layer that preceded it

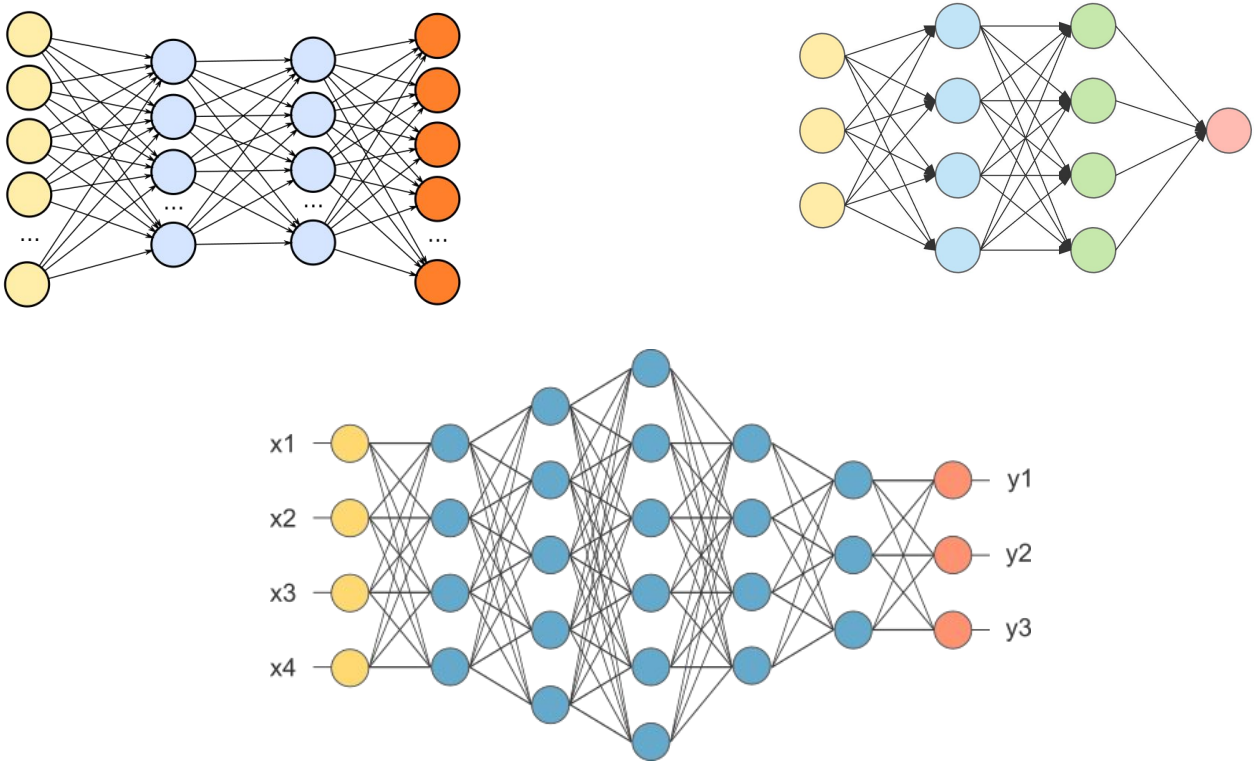
$$\boldsymbol{h}^{(1)} = g^{(1)}\left(\boldsymbol{W}^{(1)\top}\boldsymbol{x} + \boldsymbol{b}^{(1)}\right)$$

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

- main architectural considerations
  - choosing the depth and width of each layer

Architecture Design

Different neural networks



The depth and width of hidden layers are hyper-parameters!

Before Regularization and Optimization

- Basics of Convex Optimization
  - Convex Sets
  - Convex Functions
  - Convex Optimization

Convex Set

- **line segment**: between x_1 and x_2 : all points

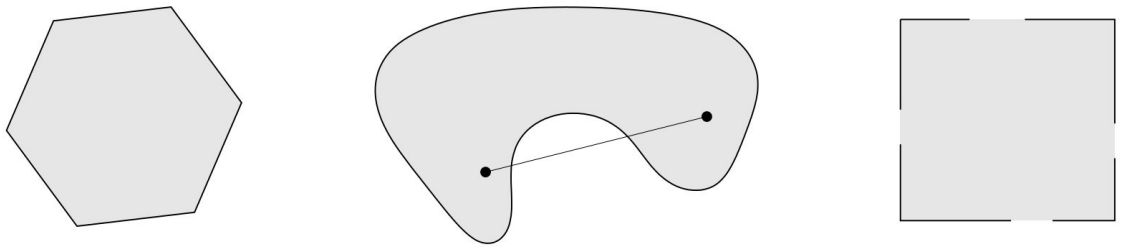
$$x = \theta x_1 + (1 - \theta)x_2$$

with $0 \leq \theta \leq 1$

- **convex set**: contains line segment between any two points in the set

$$x_1, x_2 \in C, \quad 0 \leq \theta \leq 1 \quad \Longrightarrow \quad \theta x_1 + (1 - \theta)x_2 \in C$$

- **examples** (one convex, two nonconvex sets)



Convex Function

Definition 1. *A function $f : \mathbb{R}^n \to \mathbb{R}$ is convex if its domain is a convex set and for all x, y in its domain, and all $\lambda \in [0, 1]$, we have*

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y).$$

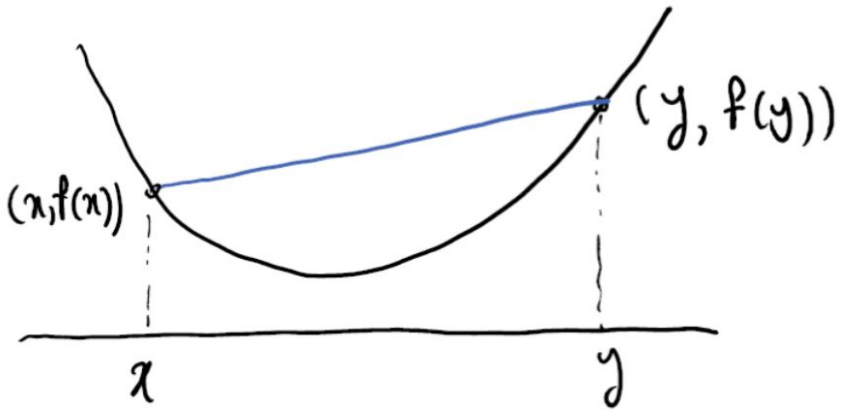


Figure 1: An illustration of the definition of a convex function

Convex Function

- Examples on $\mathbb{R}$
  - Affine: $ax + b$ over $\mathbb{R}$ for any $a, b \in \mathbb{R}$
  - Exponential: e^{ax} over $\mathbb{R}$ for any $a \in \mathbb{R}$
  - Power: x^p over $(0, +\infty)$ for $p \geq 1$ or $p \leq 0$
  - Powers of absolute value: $|x|^p$ over $\mathbb{R}$ for $p \geq 1$
  - Negative entropy: $x \ln x$ over $(0, +\infty)$
- Examples on $\mathbb{R}^n$
  - Affine function $f(x) = a'x + b$ with $a \in \mathbb{R}^n$ and $b \in \mathbb{R}$
  - Euclidean, l_1, and l_∞ norms
  - General l_p norms

$$\|x\|_p = \left(\sum_{i=1}^{n} |x_i|^p \right)^{1/p} \quad \text{for } p \geq 1$$

Convex Function

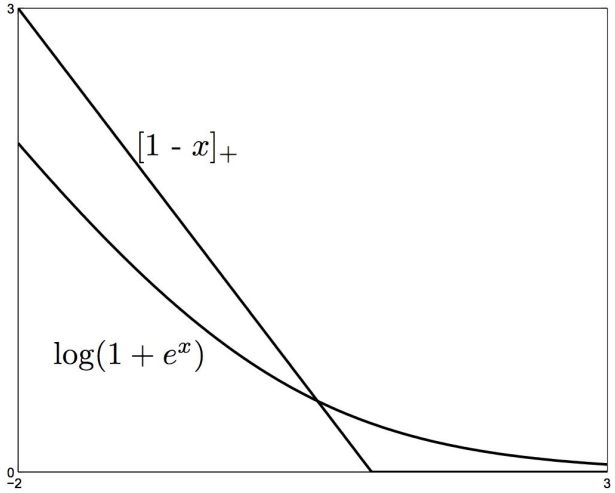
Important examples in Machine Learning

- SVM loss (hinge loss):

$$f(w) = \left[1 - y_i x_i^T w\right]_+$$

- Binary logistic loss:

$$f(w) = \log\left(1 + \exp(-y_i x_i^T w)\right)$$



Convex Optimization

Definition

- An optimization problem is **convex** if its objective is a convex function, the inequality constraints f_j are convex, and the equality constraints h_j are affine

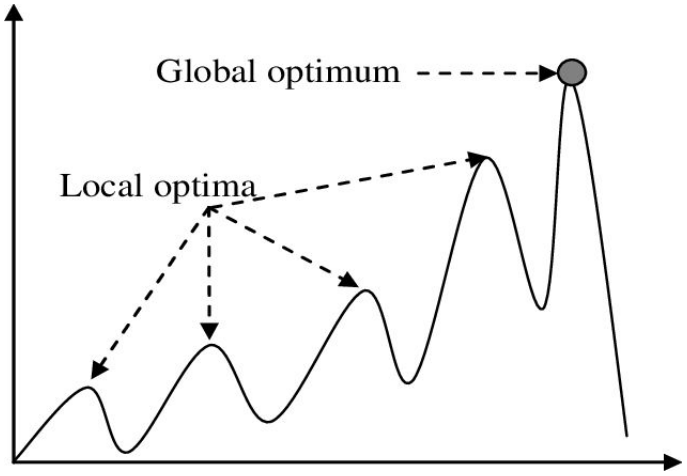
$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f_0(x) && \text{(Convex function)} \\ \text{s.t.} \quad & f_i(x) \leq 0 && \text{(Convex sets)} \\ & h_j(x) = 0 && \text{(Affine)} \end{aligned}$$

Convex Optimization

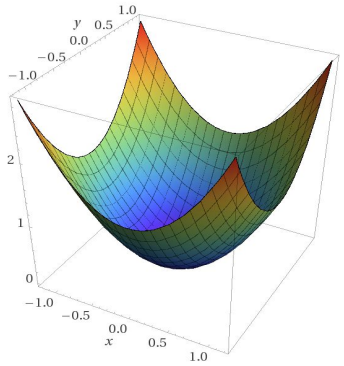
- Examples
  - Least squares regression: $\min_{\mathbf{w}} \left|\left|\mathbf{X}\mathbf{w} - \mathbf{y}\right|\right|_2^2$.
  - Logistic regression: $\min_{\mathbf{w}} \sum_j \log\left(1 + \exp\left(-y_j \mathbf{w}^T \mathbf{x}_j\right)\right)$.
  - SVM: $\min_{\mathbf{w},b} \left|\left|\mathbf{w}\right|\right|_2^2 + \lambda \sum_j \left[1 - y_j\left(\mathbf{w}^T \mathbf{x}_j + b\right)\right]_+$.
  - LASSO: $\min_{\mathbf{w}} \left|\left|\mathbf{X}\mathbf{w} - \mathbf{y}\right|\right|_2^2$; $s.t.\ \left|\left|\mathbf{w}\right|\right|_1 \leq t$.

Local and Global Optima

- Return local optimum is very common in optimization

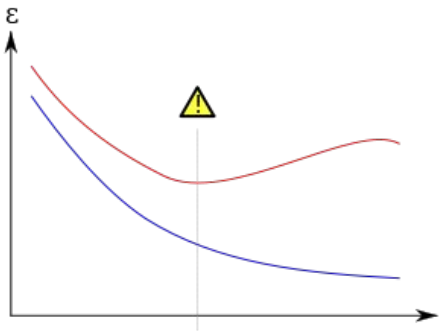


- Property of convex optimization
  - Every local optimum is global optimum.



Regularization for Deep Learning

- A central problem in machine learning
  - Neural networks are prone to overfitting
  - How to make an algorithm that perform well on **new** inputs



- Developing more effective regularization strategies has been one of the major research efforts in the field.

- Several strategies for how to create such a large, deep regularized model.

Parameter Norm Penalties

- Limiting the capacity of models,such as neural networks, linear regression, or logistic regression, by adding a parameter norm penalty $\Omega(\boldsymbol{\theta})$ to the objective function *J.* the regularized objective function $\tilde{J}$

$$\tilde{J}(\boldsymbol{\theta}; \boldsymbol{X}, \boldsymbol{y}) = J(\boldsymbol{\theta}; \boldsymbol{X}, \boldsymbol{y}) + \alpha\Omega(\boldsymbol{\theta})$$

where $\alpha \in [0, \infty)$ is a hyperparameter that weights the relative contribution of the norm penalty term Ω relative to *J*.

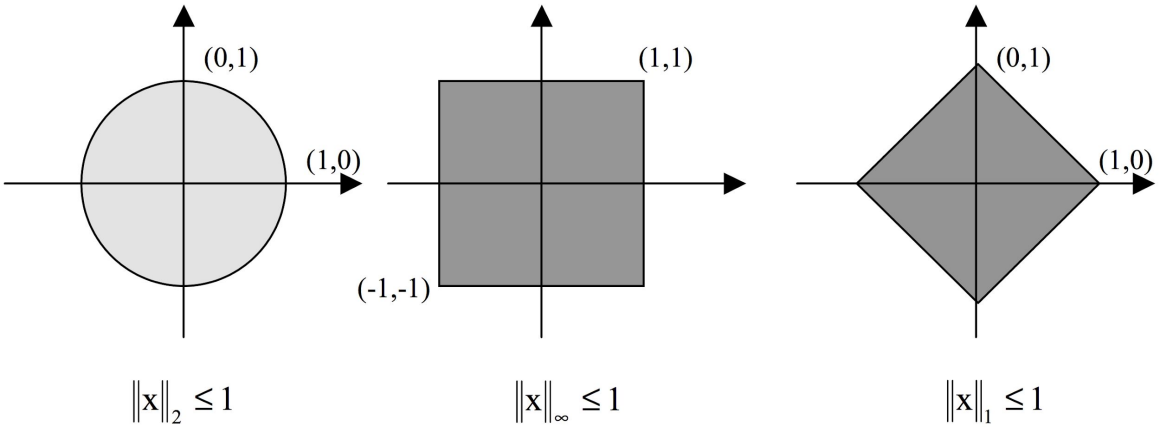
α = 0: no regularization

large α: more regularization

△ leave the biases unregularized of the affine transformation at each layer. The biases require less data than the weights to fit accurately.

Vector Norms

- The ℓ_p norm: $\|\mathbf{x}\|_p := \left(\sum_i |x_i|^p\right)^{1/p}$.
- The ℓ_2 norm: $\|\mathbf{x}\|_2 = \left(\sum_i x_i^2\right)^{1/2}$ (the Euclidean norm).
- The ℓ_1 norm $\|\mathbf{x}\|_1 = \sum_i |x_i|$.
- The ℓ_∞ norm is defined by $\|\mathbf{x}\|_\infty = \max_i |x_i|$.



Matrix Norm

- Matrix norm corresponding to given vector norm defined by

$$\|A\| = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|}$$

- **Matrix Condition Number**
  - Condition number of square nonsingular matrix A

$$\kappa(A) = \|A\| \|A^{-1}\|$$

  - By convention, k(A) = ∞ if A singular
  - ill-conditioned matrix - large condition number
    - A small change in the input results in a surprisingly large change in the computed solution.

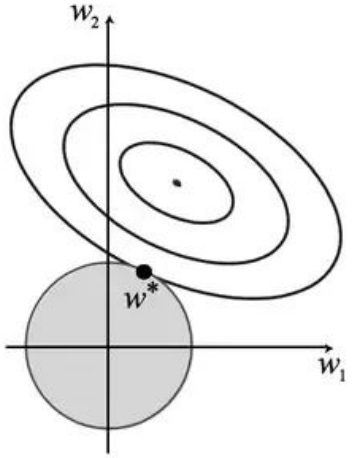
L2 Parameter Regularization

- Commonly known as **weight decay**, **ridge regression** or **Tikhonov regularization**.

$$\Omega(\boldsymbol{\theta}) = \frac{1}{2}\|\boldsymbol{w}\|_2^2$$

- We assume no bias parameter, so θ is just w. A model has the following total objective function

$$\tilde{J}(\boldsymbol{w}; \boldsymbol{X}, \boldsymbol{y}) = \frac{\alpha}{2}\boldsymbol{w}^\top \boldsymbol{w} + J(\boldsymbol{w}; \boldsymbol{X}, \boldsymbol{y})$$



L1 Parameter Regularization

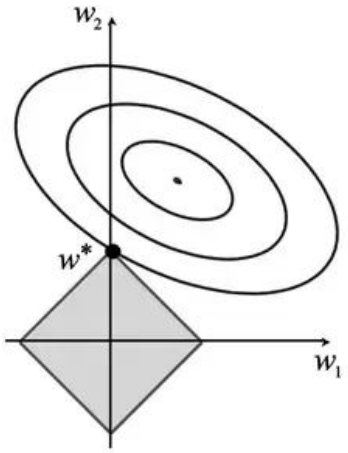
- L1 regularization on the model parameter w is defined as

$$\Omega(\boldsymbol{\theta}) = ||\boldsymbol{w}||_1 = \sum_i |w_i|$$

  as the sum of absolute values of the individual parameters.

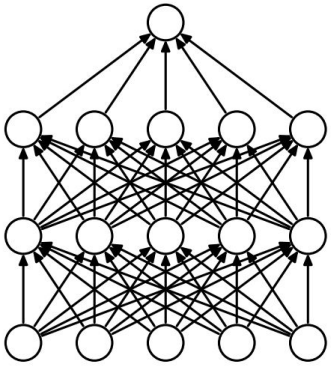
- the regularized objective function is given by

$$\tilde{J}(\boldsymbol{w}; \boldsymbol{X}, \boldsymbol{y}) = \alpha||\boldsymbol{w}||_1 + J(\boldsymbol{w}; \boldsymbol{X}, \boldsymbol{y})$$

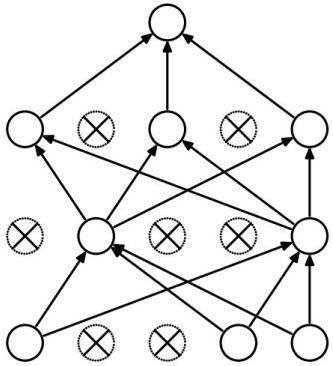


Dropout

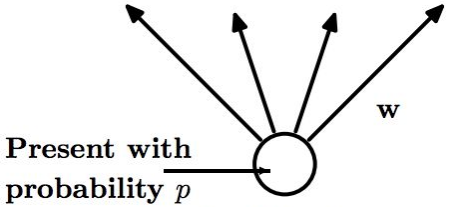
- Dropout (Srivastava et al.,2014) provides a computationally inexpensive but powerful method of regularizing a broad family of models.
- At training (each iteration)
  - each unit is retained with a probability p. (randomly)
- At test (prediction)
  - the network is used as a whole.
  - the weights are scaled-down by a factor of p.



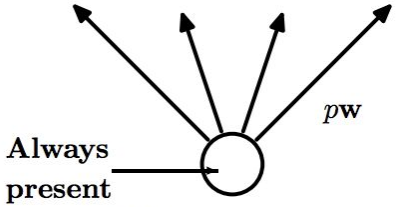
(a) Standard Neural Net



(b) After applying dropout.



(a) At training time



(b) At test time

Dropout

- Randomly dropping (setting to 0) half of the neurons in the network in each training example in the stochastic-gradient training.
- For example, a two hidden layer multi-layer perceptron:
  - $h^{[1]} = g(W^{[1]}x+b^{[1]})$
  - $h^{[2]} = g(W^{[2]}h^{[1]}+b^{[2]})$
  - $y = W^{[3]}h^{[2]}$
- Applying dropout:
  - $m^{[1]} \sim$ Bernouli $(p^{[1]})$
  - $h'^{[1]} = m^{[1]} \odot h^{[1]}$
  - $h^{[2]} = g(W^{[2]}h'^{[1]}+b^{[2]})$
  - $m^{[2]} \sim$ Bernouli $(p^{[2]})$
  - $h'^{[2]} = m^{[2]} \odot h^{[2]}$
  - $y = W^{[3]}h'^{[2]}$

Why Does Dropout Work?

- In training, dropout forces the network to make decision based on part of the features.

- Dropout is a regularization[1]
  - Alleviate overfitting.
  - Like the L1 and L2 norm regularizations.
  - But dropout is empirically better.

[1]. Wager, Wang, & Liang. Dropout Training as Adaptive Regularization. In NIPS, 2013.

Optimization for Training Deep Models

- Deep learning algorithms involve optimization in many contexts
  - performing inference in models such as PCA involves solving an optimization problem.

- Of all the many optimization problems involved in deep learning, the most difficultis is **neural network training**.

Challenges in Neural Network Optimization

- When training neural networks, we must confront the general non convex case.

- Several of the most prominent challenges involved in optimization for training deep models.
  - Ill-Conditioning
  - Local Minima
  - Saddle Points
  - Etc.

Ill-Conditioning

- The most prominent is ill-conditioning of the Hessian matrix

- **Hessian matrix** is a square matrix of second-order partial derivatives of a scalar-valued function.
  - Suppose f : ℝ^n → ℝ
    - input: a vector x ∈ ℝ^n
    - output: a scalar f(x) ∈ ℝ
  - If all second partial derivatives of f exist and are continuous over the domain of the function.

$$\mathbf{H}_{i,j} = \frac{\partial^2 f}{\partial x_i \partial x_j}$$

Ill-Conditioning

- The most prominent is ill-conditioning of the Hessian matrix

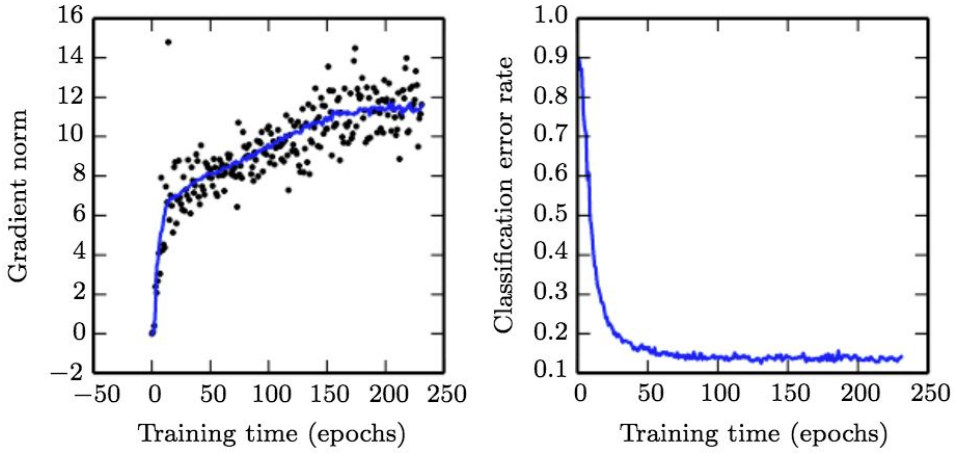
- **Hessian matrix**

$$\mathbf{H} = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \, \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \, \partial x_n} \\ \frac{\partial^2 f}{\partial x_2 \, \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2 \, \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \, \partial x_1} & \frac{\partial^2 f}{\partial x_n \, \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}$$

Ill-Conditioning

- Gradient descent often does not arrive at a critical point of any kind

$g^\top g$

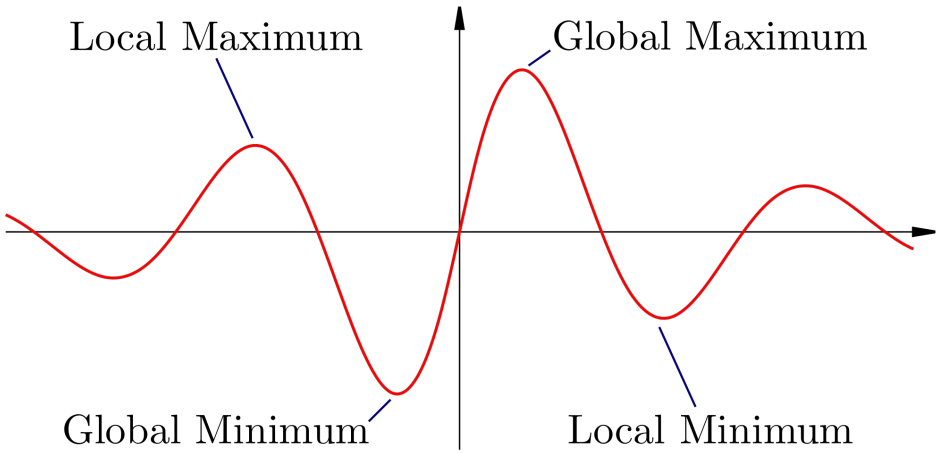


- (Left) The solid curve: running average of all gradient norms. The gradient norm clearly increases over time, rather than decreasing as we would expect.
- (Right) Despite the increasing gradient, the training process is reasonably successful. The validation set classification error decreases to a low level.
- learning becomes very slow despite the presence of a strong gradient

more: https://www.deeplearningbook.org/contents/numerical.html
https://www.deeplearningbook.org/contents/optimization.html

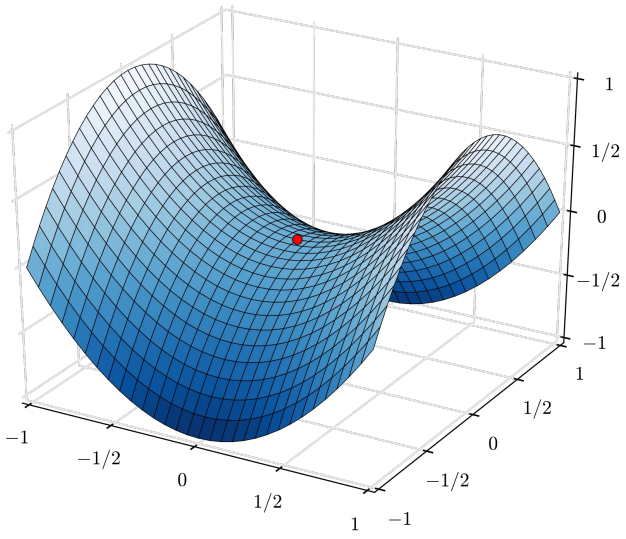
Local Minima

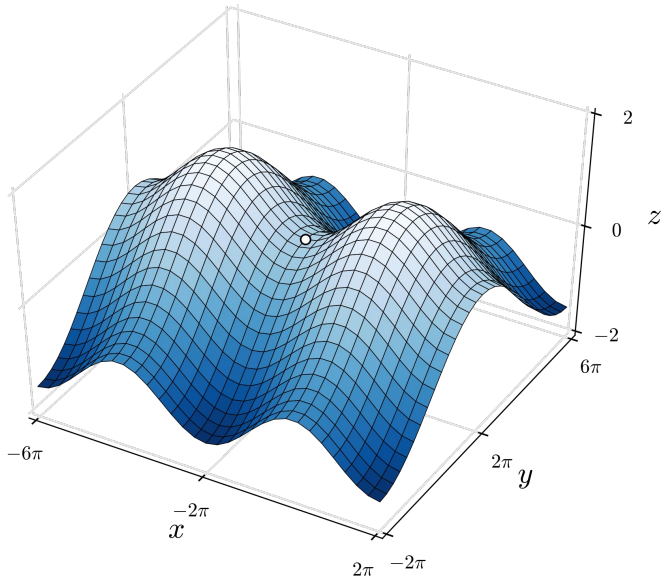
- With nonconvex functions, such as neural nets, it is possible to have many local minima.
- Nearly any deep model is essentially guaranteed to have an extremely large number of local minima.



Saddle Points

- In low-dimensional spaces
  - local minima are common
- In higher-dimensional spaces
  - local minima are rare, and saddle points are more common. (# saddle points > local minima/maxima)





Basic Algorithms

- **Gradient descent** algorithm that follows the gradient of an entire training set downhill.

- Accelerated Algorithms
  - Stochastic Gradient Descent
  - Momentum
  - Nesterov Momentum
  - Etc.

An overview of gradient descent optimization algorithms: https://arxiv.org/pdf/1609.04747.pdf

Stochastic Gradient Descent

- the most used optimization algorithms
- To estimate the gradient by taking the average gradient on a **minibatch** of *m* examples drawn i.i.d from the data-generating distribution.
  - the learning rate is crucial.

Algorithm 8.1 Stochastic gradient descent (SGD) update

Require: Learning rate schedule $\epsilon_1, \epsilon_2, \ldots$

Require: Initial parameter $\boldsymbol{\theta}$

$k \leftarrow 1$

while stopping criterion not met **do**

Sample a minibatch of m examples from the training set $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ with corresponding targets $\boldsymbol{y}^{(i)}$.

Compute gradient estimate: $\hat{\boldsymbol{g}} \leftarrow \frac{1}{m} \nabla_{\boldsymbol{\theta}} \sum_i L(f(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}), \boldsymbol{y}^{(i)})$

Apply update: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \epsilon_k \hat{\boldsymbol{g}}$

$k \leftarrow k + 1$

end while

Momentum

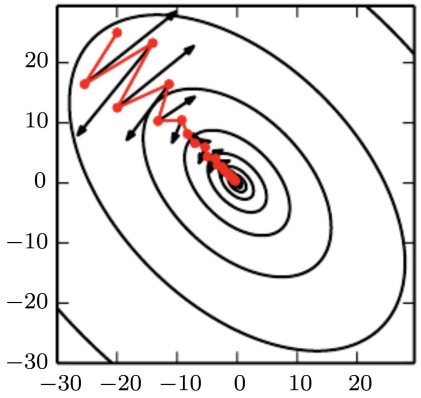
- SGD can sometimes be slow
- **Momentum** (Polyak, 1964) is designed to accelerate learning.
- **Momentum** derives from a physical analogy, in which the negative gradient is a force moving a particle through parameter space,according to Newton's laws of motion.

Momentum

- It accumulates an exponentially decaying moving average of past gradients and continues to move in their direction
  - velocity vector **v** may be regarded as the momentum of the particle
  - A hyperparameter $\alpha \in [0,1)$ determines how quickly the contributions of previous gradients exponentially decay.

$$\boldsymbol{v} \leftarrow \alpha \boldsymbol{v} - \epsilon \nabla_{\boldsymbol{\theta}} \left(\frac{1}{m} \sum_{i=1}^{m} L(\boldsymbol{f}(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}), \boldsymbol{y}^{(i)}) \right)$$

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \boldsymbol{v}.$$



http://www.columbia.edu/~nq6/publications/momentum.pdf (1999)

Momentum

Algorithm 8.2 Stochastic gradient descent (SGD) with momentum

Require: Learning rate ϵ, momentum parameter α

Require: Initial parameter $\boldsymbol{\theta}$, initial velocity $\boldsymbol{v}$

while stopping criterion not met **do**

Sample a minibatch of m examples from the training set $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ with corresponding targets $\boldsymbol{y}^{(i)}$.

Compute gradient estimate: $\boldsymbol{g} \leftarrow \frac{1}{m} \nabla_{\boldsymbol{\theta}} \sum_i L(f(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}), \boldsymbol{y}^{(i)})$.

Compute velocity update: $\boldsymbol{v} \leftarrow \alpha \boldsymbol{v} - \epsilon \boldsymbol{g}$.

Apply update: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \boldsymbol{v}$.

end while

Parameter Initialization Strategies

- Deep learning models are iterative and require the user to specify some **initial point** from which to begin the iterations.
- The initial point can determine whether the algorithm converges at all

1. initialize the weights of a fully connected layer with *m* inputs and *n* outputs by sampling each weight from

$$W_{i,j} \sim U\left(-\frac{1}{\sqrt{m}}, \frac{1}{\sqrt{m}}\right)$$

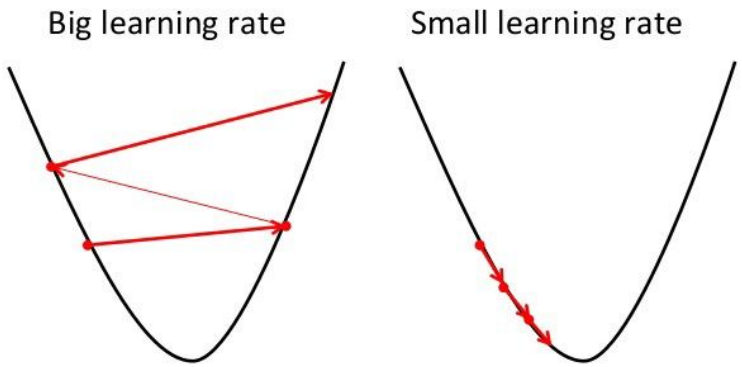
2. normalized initialization [Glorot and Bengio(2010)]

$$W_{i,j} \sim U\left(-\sqrt{\frac{6}{m+n}}, \sqrt{\frac{6}{m+n}}\right)$$

Algorithms with Adaptive Learning Rates

- The cost is often highly sensitive to some directions in parameter space
- Momentum algorithm can mitigate these issues, but it introduces another hyperparameter.

- Some algorithms
  - AdaGrad (Duchi et al.,2011)
  - RMSProp (Hinton, 2012)
  - Adam(Kingma and Ba, 2014)
  - etc.



Adaptive learning rates

- Popular and simple idea: reduce the learning rate by some factor every few epochs.
  - At the beginning, we are far from the destination, so we use larger learning rate
  - After several epochs, we are close to the destination, so we reduce the learning rate
  - E.g. 1/t decay: $\eta^t = \frac{\eta}{\sqrt{t+1}}$

- Learning rate cannot be one-size-fits-all
  - Giving different parameters different learning rates

Adaptive learning rates

- Divide the learning rate of each parameter by the root mean square of its previous derivatives.

$$\eta^t = \frac{\eta}{\sqrt{t+1}}, g^t = \frac{\partial L(w^t)}{\partial w}$$

- Vanilla gradient descent:

$$w^{t+1} \leftarrow w^t - \eta^t g^t$$

- Adagrad:

$$w^{t+1} \leftarrow w^t - \frac{\eta^t}{\sigma^t} g^t$$

σ^t : root mean square of the previous derivatives of parameter w

AdaGrad

$$
\begin{aligned}
w^{(1)} &\leftarrow w^{(0)} - \frac{\eta^{(0)}}{\sigma^{(0)}} g^{(0)} & \sigma^{(0)} &= \sqrt{(g^{(0)})^2 + \epsilon} \\
w^{(2)} &\leftarrow w^{(1)} - \frac{\eta^{(1)}}{\sigma^{(1)}} g^{(1)} & \sigma^{(1)} &= \sqrt{\tfrac{1}{2}[(g^{(0)})^2 + (g^{(1)})^2] + \epsilon} \\
w^{(3)} &\leftarrow w^{(2)} - \frac{\eta^{(2)}}{\sigma^{(2)}} g^{(2)} & \sigma^{(2)} &= \sqrt{\tfrac{1}{3}[(g^{(0)})^2 + (g^{(1)})^2 + (g^{(2)})^2] + \epsilon} \\
&\dots & &\dots \\
w^{(t+1)} &\leftarrow w^{(t)} - \frac{\eta^{(t)}}{\sigma^{(t)}} g^{(t)} & \sigma^{(t)} &= \sqrt{\tfrac{1}{t+1} \textstyle\sum_{i=1}^{t} (g^{(i)})^2 + \epsilon}
\end{aligned}
$$

ε is a smoothing term that avoids division by zero (usually on the order of 1e − 8)

AdaGrad

- Divide the learning rate of each parameter by the root mean square of its previous derivatives

$$w^{t+1} \leftarrow w^t - \frac{\eta^t}{\sigma^t} g^t$$

where $\eta^t = \frac{\eta}{\sqrt{t+1}}$ and $\sigma^{(t)} = \sqrt{\frac{1}{t+1}\sum_{i=1}^{t}(g^{(i)})^2 + \epsilon}$.

$$w^{t+1} \leftarrow w^t - \frac{\eta}{\sqrt{\sum_{i=0}^{t}(g^i)^2}} g^t$$

Contradiction?

- Vanilla gradient descent:

$$w^{t+1} \leftarrow w^t - \eta^t g^t$$

Larger gradient, larger step

- Adagrad:

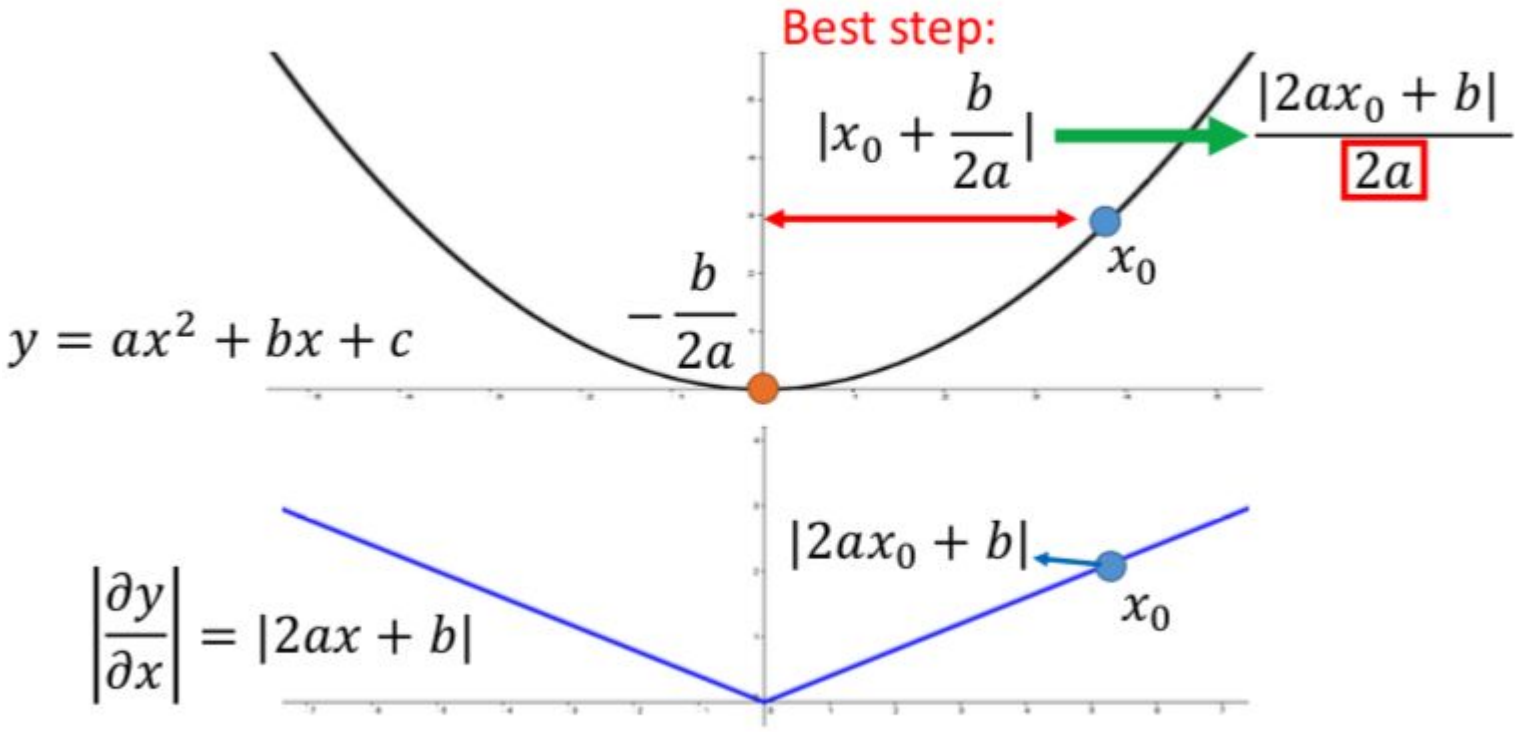
$$w^{t+1} \leftarrow w^t - \frac{\eta}{\underbrace{\sqrt{\sum_{i=0}^{t} (g^i)^2}}_{\text{larger gradient smaller step}}} \underbrace{g^t}_{\text{larger gradient larger step}}$$

Intuitive Reason

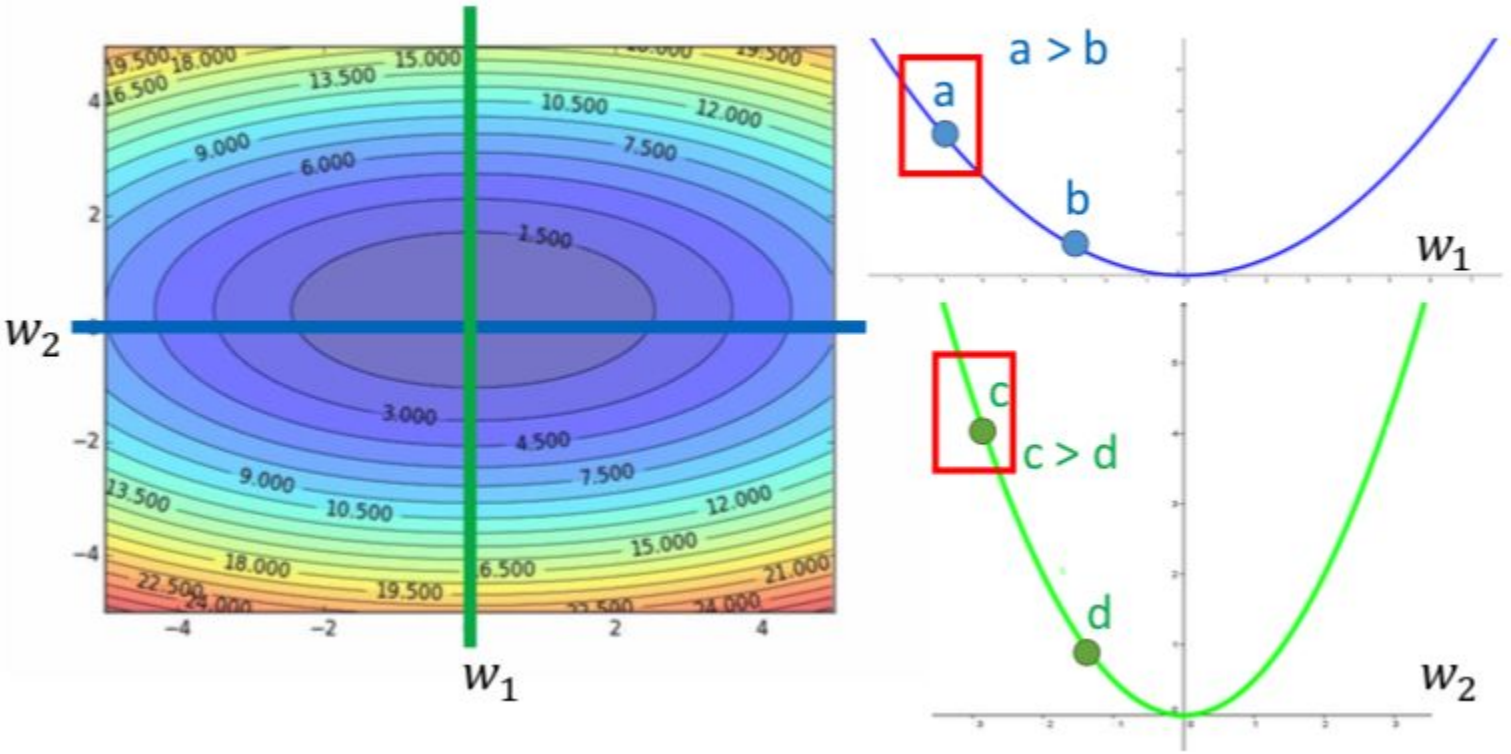
- How surprise it is

g^0	g^1	g^2	g^3	g^4	...
0.001	0.001	0.003	0.002	0.1	...
g^0	g^1	g^2	g^3	g^4	...
10.8	20.9	31.7	12.1	0.1	...

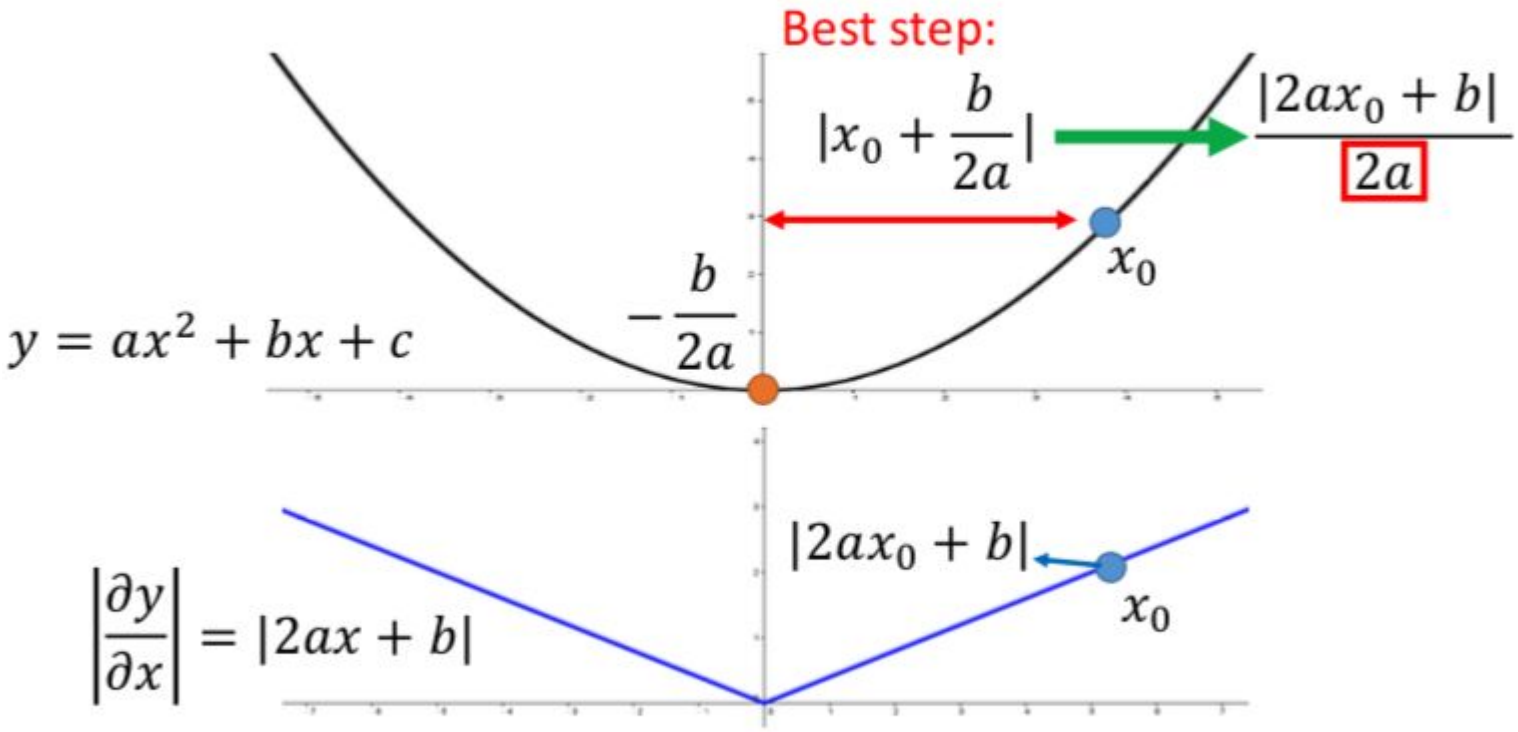
Larger gradient, larger steps?



Comparison between different parameters

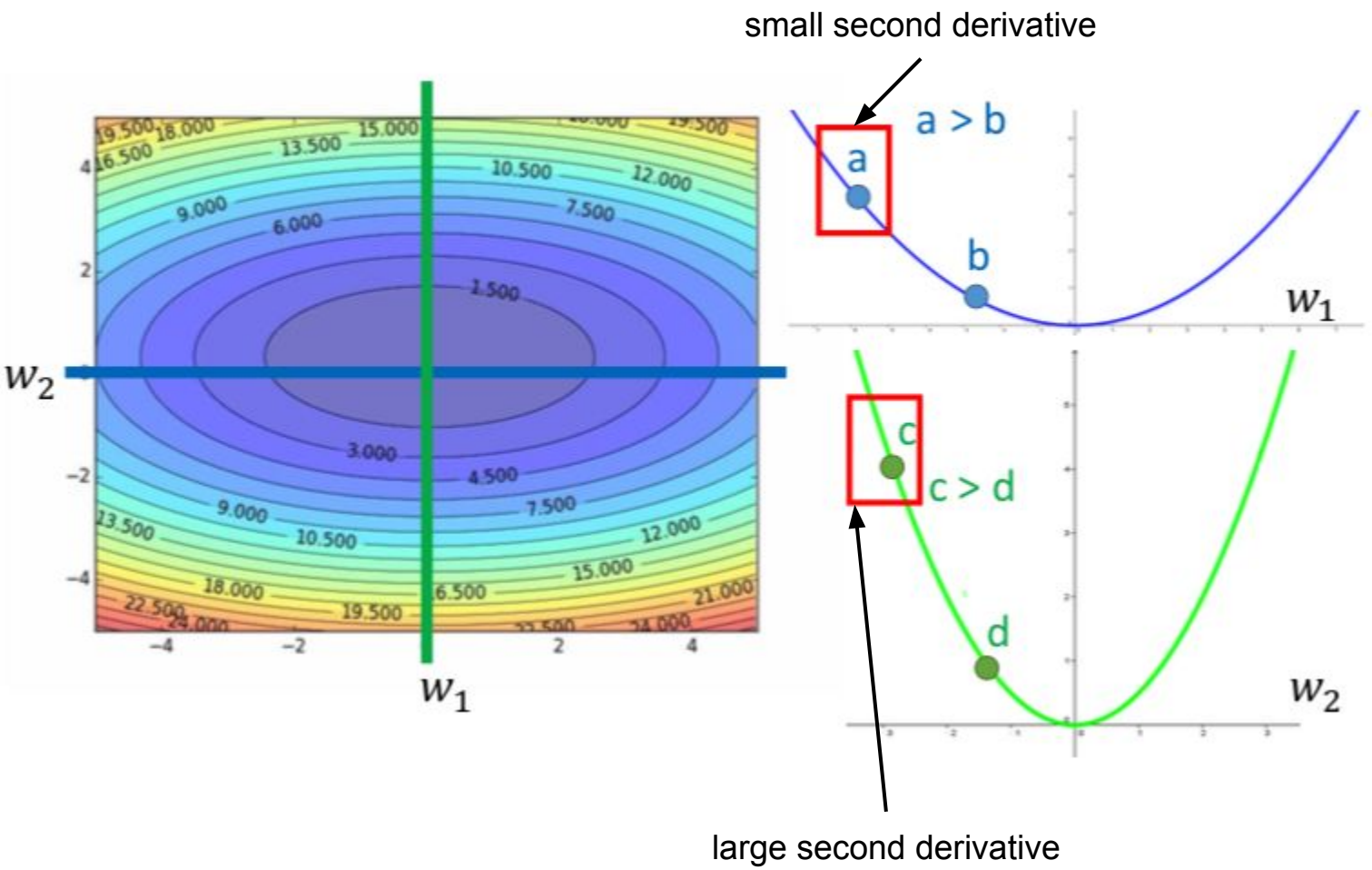


Second Derivative



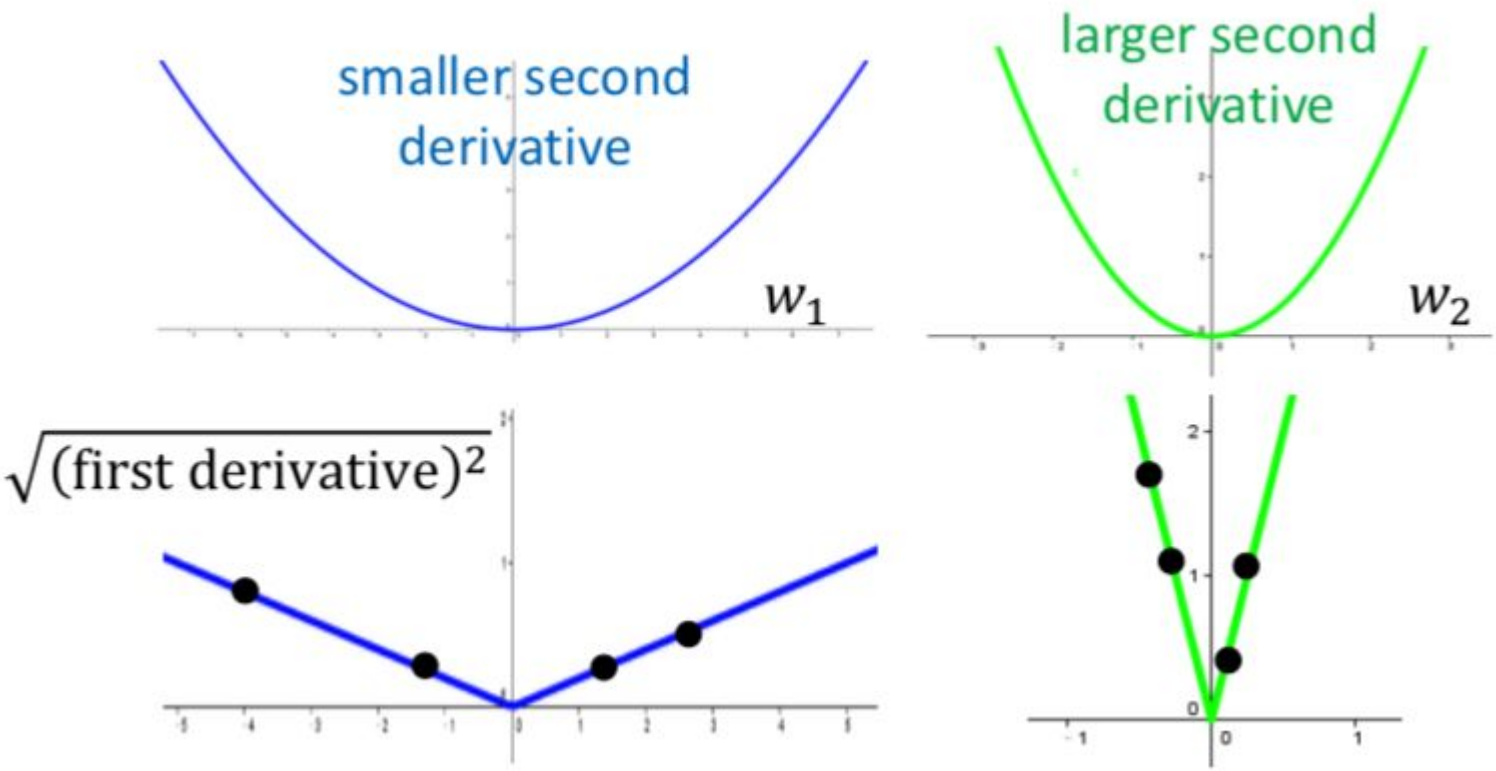
Note that $\frac{\partial^2 y}{\partial x^2} = 2a$. The best step is $\frac{|\text{first derivative}|}{\text{second derivative}}$

Comparison between different parameters



Second Derivative

- Use first derivative to estimate second derivative



Optimization Strategies

- Feature scaling
- Batch normalization
- Supervised pretraining

Feature Scaling

- Assume the samples $x_i, \ldots, x_n$ are one-dimensional.
- **Min-max normalization**

$$x_i' = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}$$

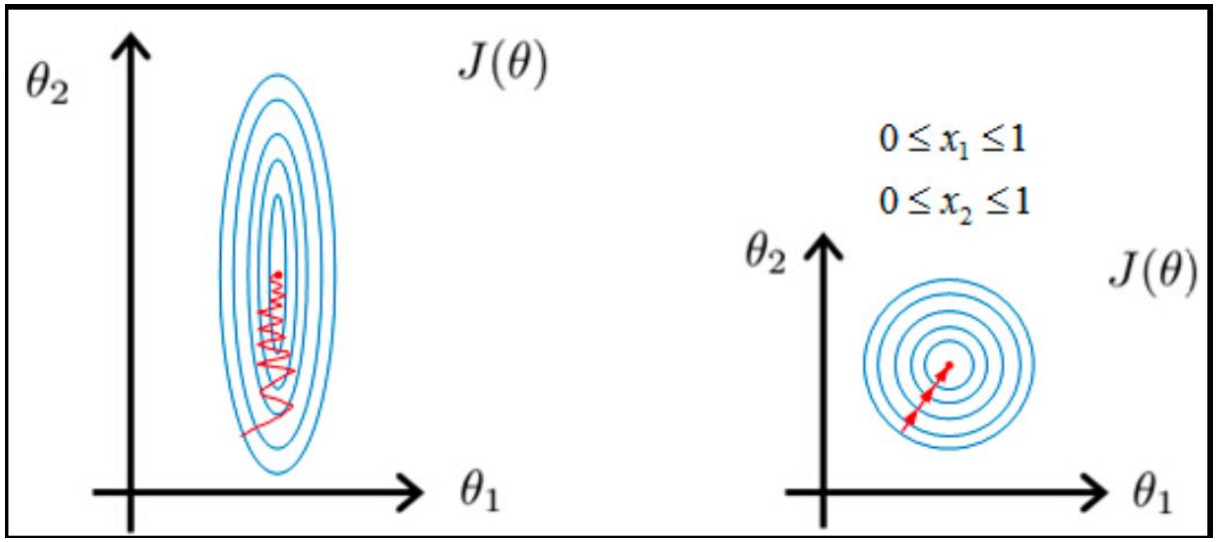
After the scaling, the samples $x_1', \cdots, x_n'$ are in [0,1]

- **Standardization** $x_i' = \frac{x_i - \hat{\mu}}{\hat{\sigma}}$
  - $\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} x_i$ is the sample mean
  - $\hat{\sigma}^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \hat{\mu})^2$ is the sample variance

After the scaling, the samples $x_1', \cdots, x_n'$ have zero mean and unit variance

Why Feature Scaling

- Make the scales of all the features comparable.
- Faster convergence



Batch Normalization

- Batch normalization (Ioffe and Szegedy, 2015) is one of the most exciting recent innovations in optimizing deep neural networks.

- Feature standardization of hidden layers

Batch Normalization

- Let $\mathbf{x}^{(k)} \in \mathbb{R}^d$ be the output of k-th hidden layer
- $\hat{\boldsymbol{\mu}} \in \mathbb{R}^d$ sample mean of $\mathbf{x}^{(k)}$ evaluated on a batch of samples
- $\hat{\boldsymbol{\sigma}} \in \mathbb{R}^d$ sample std of $\mathbf{x}^{(k)}$ evaluated on a batch of samples

- Standardization $z_j^{(k)} = \frac{x_j^{(k)} - \hat{\mu}_j}{\hat{\sigma}_j + 0.001}$, for $j = 1, \cdots, d$.

Batch Normalization

- Let $\mathbf{x}^{(k)} \in \mathbb{R}^d$ be the output of k-th hidden layer
- $\hat{\boldsymbol{\mu}} \in \mathbb{R}^d$ sample mean of $\mathbf{x}^{(k)}$ evaluated on a batch of samples
- $\hat{\boldsymbol{\sigma}} \in \mathbb{R}^d$ sample std of $\mathbf{x}^{(k)}$ evaluated on a batch of samples
- $\boldsymbol{\gamma} \in \mathbb{R}^d$ scaling parameter (**trainable**)
- $\boldsymbol{\beta} \in \mathbb{R}^d$ shifting parameter (**trainable**)

- Standardization $z_j^{(k)} = \frac{x_j^{(k)} - \hat{\mu}_j}{\hat{\sigma}_j + 0.001}$, for $j = 1, \cdots, d$.
- Scale and shift $x_j^{(k+1)} = z_j^{(k)} \circ \gamma_j + \beta_j$, for $j = 1, \cdots, d$.

- use backpropagation to update γ_j and β_j

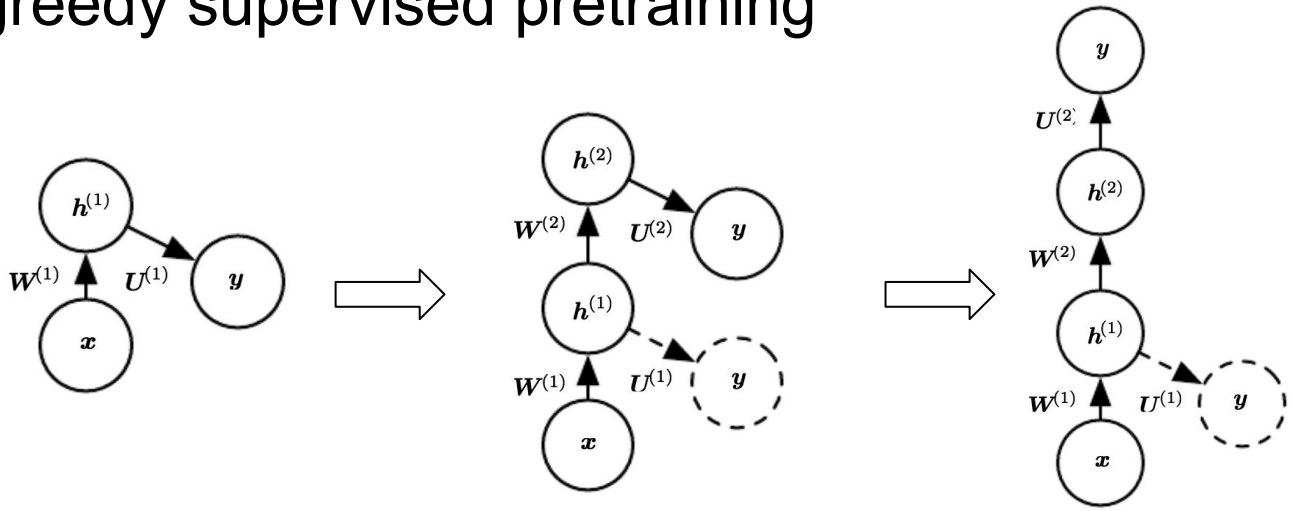
Why Batch Normalization

- Faster convergence
- Why it works?
  - weights change values after each backprop so will the input to each layer.
  - Batch norm is a way to make the range of the inputs to each layer more consistent and thus making it easier for optimize the weights in that layer.

paper: How Does Batch Normalization Help Optimization?

Supervised Pretraining

- Sometimes, directly training a model to solve a specific task can be too ambitious if
  - the model is complex and hard to optimize
  - or the task is very difficult
- It is more effective to train a simpler model to solve the task, then make the model more complex.
- **Pretraining**
  - greedy supervised pretraining



Summary

- Deep Feedforward Networks
  - Gradient-based learning
    - Cost functions
    - Output Units
  - Hidden units
- Basics of convex optimization
- Regularization for Deep Learning
  - Parameter norm penalties (l1,l2 regularization)
  - Dropout
- Optimization for Training Deep Models
  - Challenges in neural optimization
  - Accelerated algorithms
  - Algorithms with adaptive learning rates
  - Batch normalization

Practice: Sentiment analysis

- Data Set: labeled reviews from Yelp

- # samples 1000
- # positive 500
- # negative 500

	sentence	label
0	Wow... Loved this place.	1
1	Crust is not good.	0
2	Not tasty and the texture was just nasty.	0
3	Stopped by during the late May bank holiday of...	1
4	The selection on the menu was great and so wer...	1
5	Now I am getting angry and I want my damn pho.	0
6	Honeslty it didn't taste THAT fresh.)	0
7	The potatoes were like rubber and you could te...	0
8	The fries were great too.	1
9	A great touch.	1
10	Service was very prompt.	1
11	Would not go back.	0
12	The cashier had no care what so ever on what I...	0
13	I tried the Cape Cod ravoli, chicken,with cran...	1
14	I was disgusted because I was pretty sure that...	0

Practice: Sentiment analysis

- Word count as feature - Bag-of-words (BOW)

```
1  sentences = ['Would not go back', 'Crust is not good']
```

```
1  from sklearn.feature_extraction.text import CountVectorizer
2
3  vectorizer = CountVectorizer(min_df=0, lowercase=False)
4  vectorizer.fit(sentences)
5  vectorizer.vocabulary_
```

```
{'Would': 1, 'not': 6, 'go': 3, 'back': 2, 'Crust': 0, 'is': 5, 'good': 4}
```

```
1  vectorizer.transform(sentences).toarray()
```

```
array([[0, 1, 1, 1, 0, 0, 1],
       [1, 0, 0, 0, 1, 1, 1]])
```

Practice: Sentiment analysis

Load data

```
1  import pandas as pd
2  filepath ='data/sentiment_analysis/yelp_labelled.txt'
3  df = pd.read_csv(filepath, names=['sentence', 'label'], sep='\t')
4  print(df.iloc[0])
```

```
sentence    Wow... Loved this place.
label                               1
Name: 0, dtype: object
```

Split data

```
1  from sklearn.model_selection import train_test_split
2
3  sentences = df['sentence'].values
4  y = df['label'].values
5  sentences_train, sentences_test, y_train, y_test = train_test_split(
6     sentences, y, test_size=0.25, random_state=1000)
```

Vectorizer

```
1  from sklearn.feature_extraction.text import CountVectorizer
2
3  vectorizer = CountVectorizer()
4  vectorizer.fit(sentences_train)
5
6  X_train = vectorizer.transform(sentences_train)
7  X_test  = vectorizer.transform(sentences_test)
8  X_train
```

```
<750x1714 sparse matrix of type '<class 'numpy.int64'>'
        with 7368 stored elements in Compressed Sparse Row format>
```

Practice: Sentiment analysis

Deep feedforward model

```
1  from keras.models import Sequential
2  from keras import layers
3
4  input_dim = X_train.shape[1]  # Number of features
5  print('input_dim',input_dim)
6
7  model = Sequential()
8  model.add(layers.Dense(10, input_dim=input_dim, activation='relu'))
9  model.add(layers.Dropout(0.5))
10 model.add(layers.Dense(10, activation='relu'))
11 model.add(layers.Dense(1, activation='sigmoid'))
12
13 model.compile(loss='binary_crossentropy',
14               optimizer='adam',
15               metrics=['accuracy'])
16 model.summary()
```

```
input_dim 1714
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_75 (Dense)             (None, 10)                17150
_________________________________________________________________
dropout_28 (Dropout)         (None, 10)                0
_________________________________________________________________
dense_76 (Dense)             (None, 10)                110
_________________________________________________________________
dense_77 (Dense)             (None, 1)                 11
=================================================================
Total params: 17,271
Trainable params: 17,271
Non-trainable params: 0
```

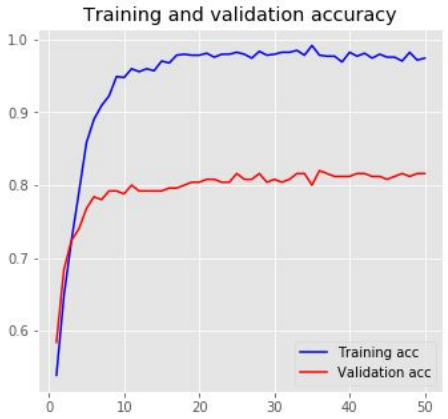
Practice: Sentiment analysis

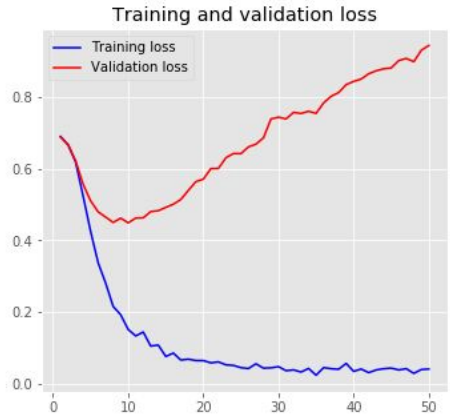
Training

```
history = model.fit(X_train, y_train,
                    epochs=50,
                    verbose=False,
                    validation_data=(X_test, y_test),
                    batch_size=10)
```

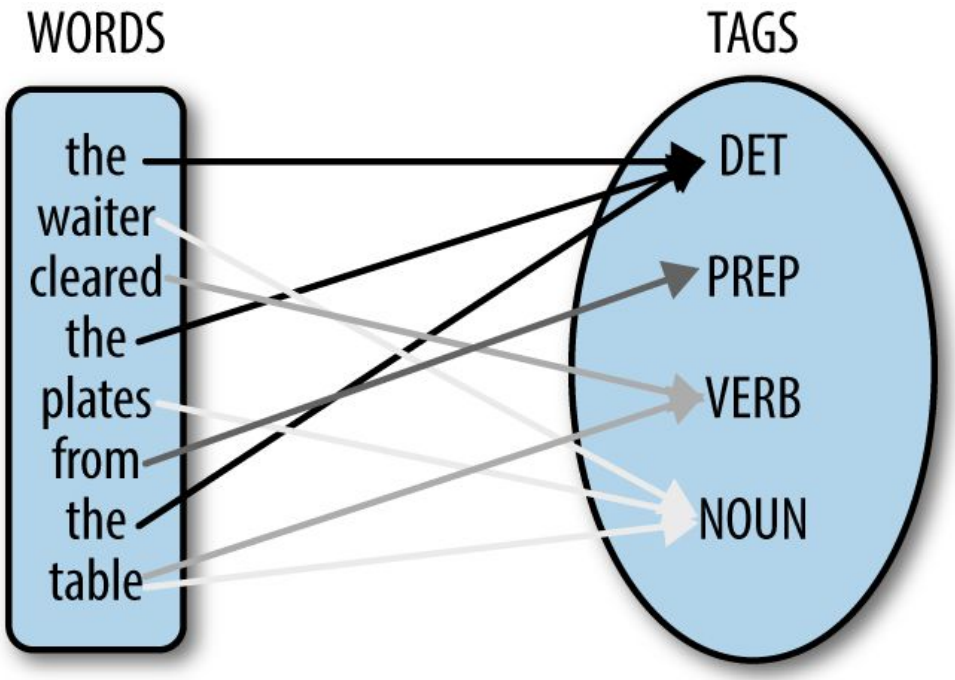
```
loss, accuracy = model.evaluate(X_train, y_train, verbose=False)
print("Training Accuracy: {:.4f}".format(accuracy))
loss, accuracy = model.evaluate(X_test, y_test, verbose=False)
print("Testing Accuracy:  {:.4f}".format(accuracy))
```

```
Training Accuracy: 1.0000
Testing Accuracy:  0.8160
```





Part of speech (POS) tagging



Data

The Penn Treebank is an annotated corpus of POS tags.

```
1  import numpy as np
2  import nltk
3  from nltk.corpus import treebank
4  # nltk.download('treebank')
5  # nltk.download('universal_tagset')
6  sentences = treebank.tagged_sents(tagset='universal')
```

```
1  print(sentences[0]) # a list of tuples (term, tag)
```

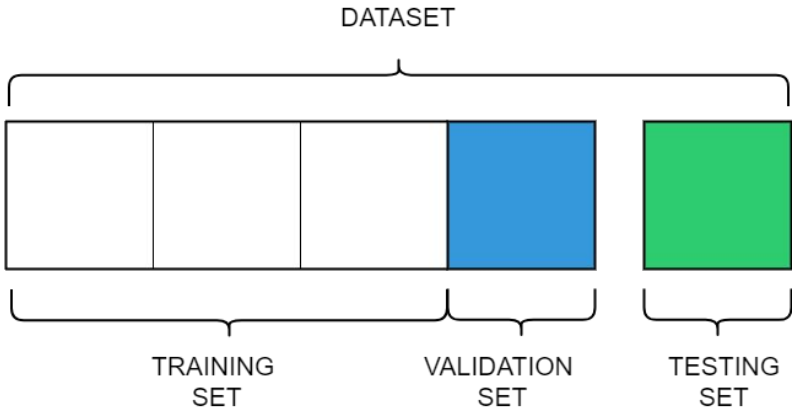
```
[('Pierre', 'NOUN'), ('Vinken', 'NOUN'), (',', '.'), ('61', 'NUM'), ('years', 'NOUN'), ('old', 'ADJ'), (',', '.'),
('will', 'VERB'), ('join', 'VERB'), ('the', 'DET'), ('board', 'NOUN'), ('as', 'ADP'), ('a', 'DET'), ('nonexecutive',
'ADJ'), ('director', 'NOUN'), ('Nov.', 'NOUN'), ('29', 'NUM'), ('.', '.')]
```

```
1  print('#sentences: %s' % (len(sentences)))
2  tags = set([tag for sentence in treebank.tagged_sents() for _, tag in sentence])
3  print('#tags: %s  %s' % (len(tags), tags))
```

```
#sentences: 3914
#tags: 46  {"''", 'DT', 'VBN', 'EX', 'RBS', '$', ',', 'VB', 'POS', 'TO', 'SYM', 'VBD', 'RBR', 'NNPS', 'PDT', '-RRB-',
'CC', 'VBZ', 'WP', 'FW', 'JJ', 'NNS', 'IN', '``', ':', '-NONE-', 'CD', 'UH', 'VBG', '-LRB-', '#', 'WRB', 'NNP', '.',
'LS', 'MD', 'RP', 'RB', 'PRP$', 'JJS', 'JJR', 'VBP', 'NN', 'WP$', 'PRP', 'WDT'}
```

Data preprocessing

- split the tagged sentences into 3 datasets
  - training
  - validation
  - test




```
1  training_sentences = sentences[: int(.8 * len(sentences)) ]
2  testing_sentences = sentences[int(.8 * len(sentences)) :]
3
4  training_sentences = training_sentences[:int(.75 * len(training_sentences))]
5  validation_sentences = training_sentences[int(.75 * len(training_sentences)):]
6
```

Feature engineering

map the list of sentences to a list of dict features.

```python
def add_basic_features(sentence_terms, index):
    term = sentence_terms[index]
    return {
        'nb_terms': len(sentence_terms),
        'term': term,
        'is_first': index == 0,
        'is_last': index == len(sentence_terms) - 1,
        'is_capitalized': term[0].upper() == term[0],
        'is_all_caps': term.upper() == term,
        'is_all_lower': term.lower() == term,
        'prefix-1': term[0],
        'prefix-2': term[:2],
        'prefix-3': term[:3],
        'suffix-1': term[-1],
        'suffix-2': term[-2:],
        'suffix-3': term[-3:],
        'prev_word': '' if index == 0 else sentence_terms[index - 1],
        'next_word': '' if index == len(sentence_terms) - 1
                        else sentence_terms[index + 1]
    }

def untag(tagged_sentence):
    return [w for w, _ in tagged_sentence]

def transform_to_dataset(tagged_sentences):
    X, y = [], []
    for pos_tags in tagged_sentences:
        for index, (term, class_) in enumerate(pos_tags):
            # Add basic NLP features for each sentence term
            X.append(add_basic_features(untag(pos_tags), index))
            y.append(class_)
    return X, y
```

Feature engineering

For training, validation and testing sentences, we split the attributes into X (input variables) and y (output variables).

```
1 X_train, y_train = transform_to_dataset(training_sentences)
2 X_test, y_test = transform_to_dataset(testing_sentences)
3 X_val, y_val = transform_to_dataset(validation_sentences)
```

```
1 len(X_train),len(X_val),len(X_test)
```

```
(61014, 16016, 20039)
```

Feature engineering

example

```
1 print(sentences[0])
```

```
[('Pierre', 'NOUN'), ('Vinken', 'NOUN'), (',', '.'), ('61', 'NUM'), ('years',
'NOUN'), ('old', 'ADJ'), (',', '.'), ('will', 'VERB'), ('join', 'VERB'), ('th
e', 'DET'), ('board', 'NOUN'), ('as', 'ADP'), ('a', 'DET'), ('nonexecutive',
'ADJ'), ('director', 'NOUN'), ('Nov.', 'NOUN'), ('29', 'NUM'), ('.', '.')]
```

```
1 X_train[0]
```

```
{'nb_terms': 18,
 'term': 'Pierre',
 'is_first': True,
 'is_last': False,
 'is_capitalized': True,
 'is_all_caps': False,
 'is_all_lower': False,
 'prefix-1': 'P',
 'prefix-2': 'Pi',
 'prefix-3': 'Pie',
 'suffix-1': 'e',
 'suffix-2': 're',
 'suffix-3': 'rre',
 'prev_word': '',
 'next_word': 'Vinken'}
```

```
1 y_train[0]
```

```
'NOUN'
```

Features encoding

- convert our dict features to vectors

```
from sklearn.feature_extraction import DictVectorizer
# Fit our DictVectorizer with our set of features
dict_vectorizer = DictVectorizer(sparse=False)
dict_vectorizer.fit(X_train + X_test + X_val)
# Convert dict features to vectors
X_train = dict_vectorizer.transform(X_train)
X_test = dict_vectorizer.transform(X_test)
X_val = dict_vectorizer.transform(X_val)
```

- encode y as integers

```
from sklearn.preprocessing import LabelEncoder
# Fit LabelEncoder with our list of classes
label_encoder = LabelEncoder()
label_encoder.fit(y_train + y_test + y_val)
# Encode class values as integers
y_train = label_encoder.transform(y_train)
y_test = label_encoder.transform(y_test)
y_val = label_encoder.transform(y_val)
```

- convert integers (y) to one-hot encoding

```
# Convert integers to dummy variables (one hot encoded)
from keras.utils import np_utils
y_train = np_utils.to_categorical(y_train)
y_test = np_utils.to_categorical(y_test)
y_val = np_utils.to_categorical(y_val)
```

```
X_train.shape
```

```
(61014, 39684)
```

Building a DNN model using Keras

```
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation

model = Sequential([
    Dense(512, input_dim=X_train.shape[1]),
    Activation('relu'),
    Dropout(0.5),
    Dense(512),
    Activation('relu'),
    Dropout(0.5),
    Dense(256),
    Activation('relu'),
    Dense(y_train.shape[1], activation='softmax')
])
model.compile(loss='categorical_crossentropy',
              optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

Building a DNN model using Keras

Model summary

Layer (type)	Output Shape	Param #
dense_12 (Dense)	(None, 512)	22647296
activation_9 (Activation)	(None, 512)	0
dropout_7 (Dropout)	(None, 512)	0
dense_13 (Dense)	(None, 512)	262656
activation_10 (Activation)	(None, 512)	0
dropout_8 (Dropout)	(None, 512)	0
dense_14 (Dense)	(None, 256)	131328
activation_11 (Activation)	(None, 256)	0
dense_15 (Dense)	(None, 12)	3084

Total params: 23,044,364
Trainable params: 23,044,364
Non-trainable params: 0

Training

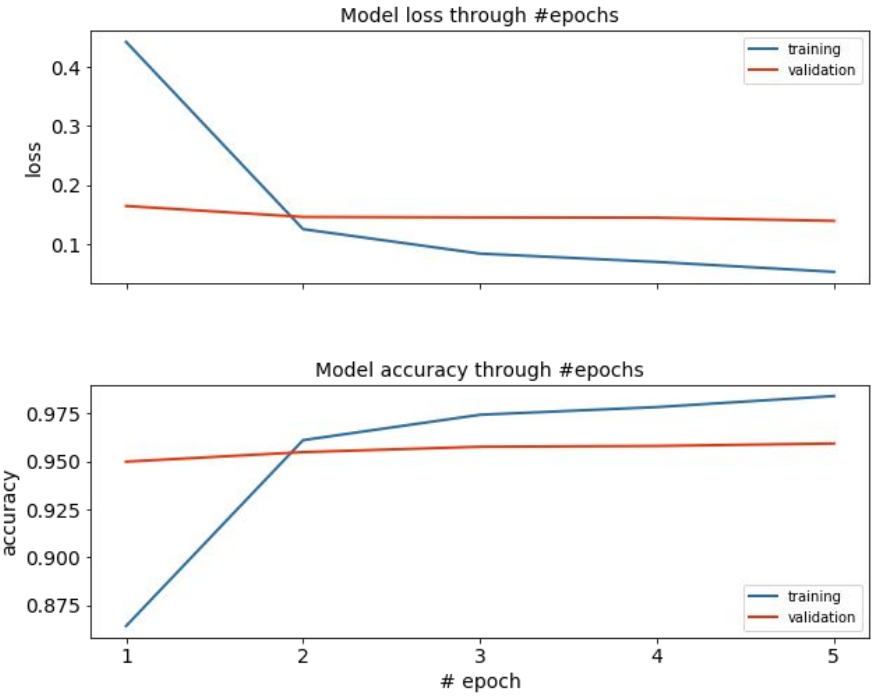
```
1  hist = model.fit(X_train, y_train, epochs=5, batch_size=128,verbose=1,
2                   shuffle=True, validation_data=(X_val, y_val))
3
```

```
Train on 61107 samples, validate on 19530 samples
Epoch 1/5
61107/61107 [==============================] - 120s 2ms/step - loss: 0.4426 - acc: 0.8641 - val_loss:
0.1642 - val_acc: 0.9499
Epoch 2/5
61107/61107 [==============================] - 117s 2ms/step - loss: 0.1250 - acc: 0.9611 - val_loss:
0.1457 - val_acc: 0.9548
Epoch 3/5
61107/61107 [==============================] - 116s 2ms/step - loss: 0.0835 - acc: 0.9743 - val_loss:
0.1449 - val_acc: 0.9577
Epoch 4/5
61107/61107 [==============================] - 115s 2ms/step - loss: 0.0694 - acc: 0.9783 - val_loss:
0.1445 - val_acc: 0.9581
Epoch 5/5
61107/61107 [==============================] - 115s 2ms/step - loss: 0.0525 - acc: 0.9841 - val_loss:
0.1390 - val_acc: 0.9593
```

Results

```
1 score = model.evaluate(X_test, y_test)
2 print(score)
```

```
20039/20039 [==============================] - 4s 178us/step
[0.1017228750231013, 0.9656170467588203]
```



reference: https://becominghuman.ai/part-of-speech-tagging-tutorial-with-the-keras-deep-learning-library-d7f93fa05537

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