Deep Learning and Applications

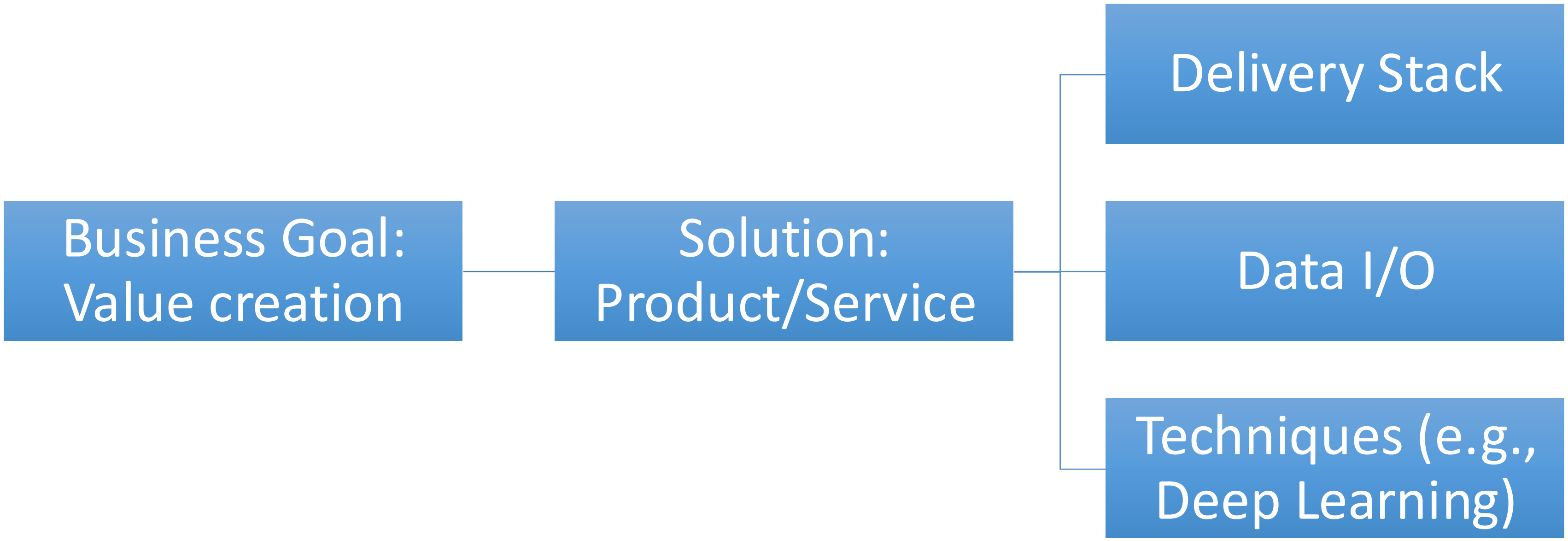
Theja Tulabandhula

Today's Outline

- Introduction to the Course
- Getting Started with Neural Nets
  - Classification
  - Backpropagation
  - Feedforward Neural Nets

Introduction to the Course

20000 Ft View



- You need a critical understanding of the domain to be successful in shipping solutions
- Before venturing into a complex technique, try a shallow/easy technique

A Business Analyst's Toolkit

- Techniques
  - Prediction
    - Decision Trees
    - Linear classifiers and logistic regression
    - Naïve Bayes classifier
    - SVMs
    - Neural networks (and deep learning)
    - Online/reinforcement learning
  - Exploration
    - Clustering
    - Market basket analysis

Two Themes of the Course

- Data Variety
  - Images and Videos/Audio
  - Text and Language
- Complex Decisions
  - Sequential Decision Making

Data Variety

- Structured data
  - Examples:
    - Medical/healthcare data, advertising data
  - Have ordinal, integer, binary or categorical fields
  - Deep learning allows embedding of categorical features
- Unstructured data
  - Examples:
    - Images (tensor, i.e., typically a 3 dimensional array) and videos (a sequence of images), text strings/documents
  - Deep learning reduces feature engineering effort here

Complex Decisions

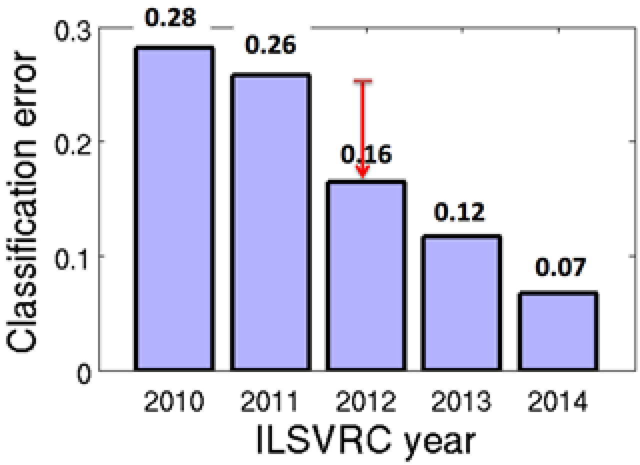
- Decisions
  - Examples:
    - which articles to show, how to price products
  - May use many predictions
  - May need to be taken repeatedly for different contexts
  - May have longer term goals
  - Online and reinforcement learning methods address this ‘learning on the go’ problem

Techniques covered in the Course

- To address data variety and complex decision problems, we will look at:
  - Deep Learning
  - Online and Reinforcement Learning + Deep Learning

Deep Learning

- One example (in vision) of its success is at the ILSVRC[1]
- ImageNet dataset has 22000 categories across 14 million images
- ILSVRC Task 1 was a classification challenge
  - Given 1000 categories and1.5 million images, predict 5 categories for a test image



[1]ImageNet Large Scale Visual Recognition Challenge

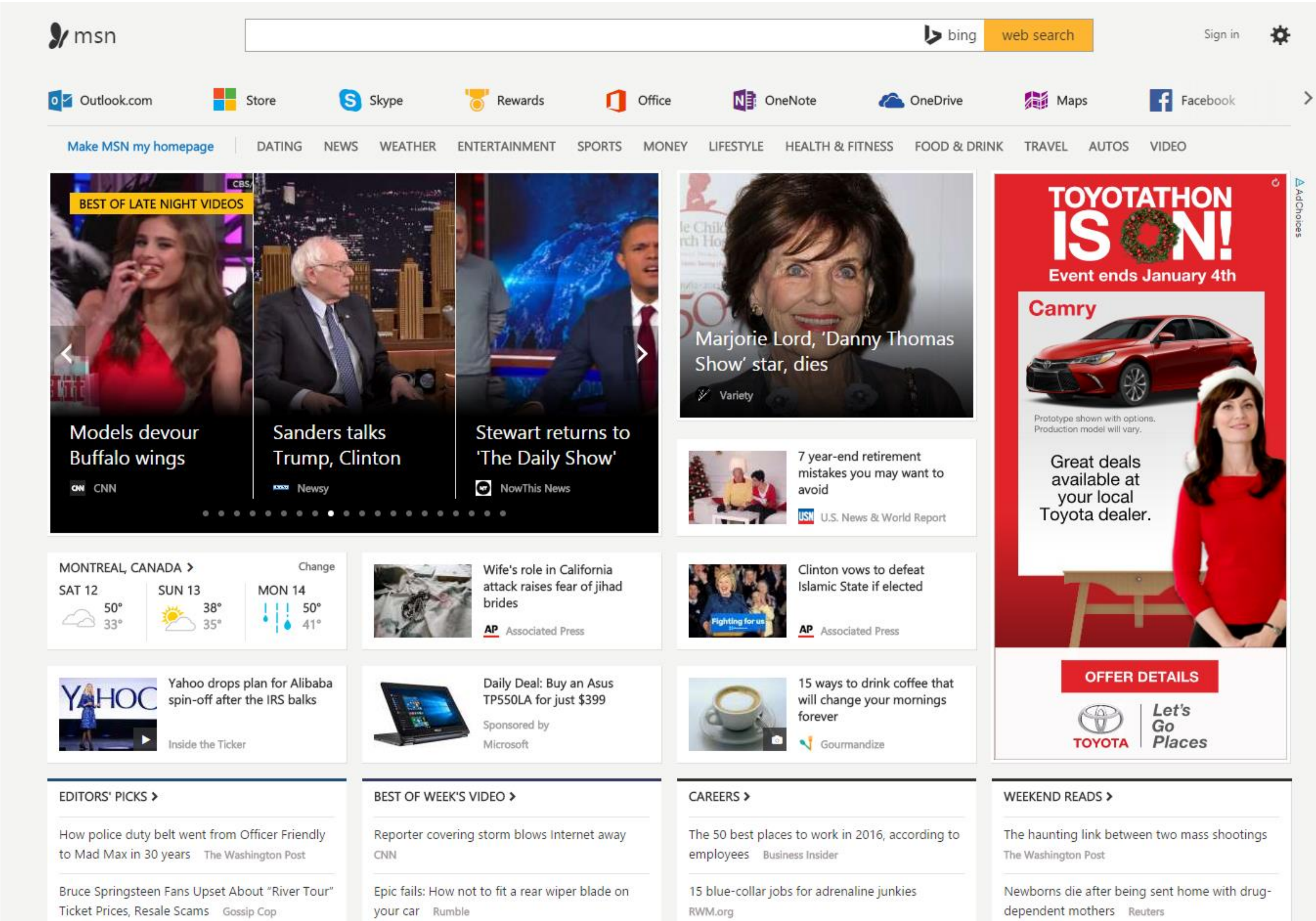
[2]Figure: Russakovsky et al. arxiv:1409.0575

Deep Learning

- Neural nets are not new (1960s). Applied to handwritten digit recognition back in 1998
- Were not mainstream till around 2010/2012*
  - What changed? Access to GPUs and Data
- Caveat:
  - Deep learning achieves good performance on some tasks
  - Typically has not worked well beyond classification…
  - There is a lot of scope for improvement, engineering, system building, model building

*Context-Dependent Pre-trained Deep Neural Networks for Large Vocabulary Speech Recognition, Dahl et al. 2010
Imagenet classification with deep convolutional neural networks, Krizhevsky et al. 2012

Online/Reinforcement Learning



[1]Reference: Alekh Agarwal et al., http://arxiv.org/abs/1606.03966

Online/Reinforcement Learning

ε-greedy exploratio
n

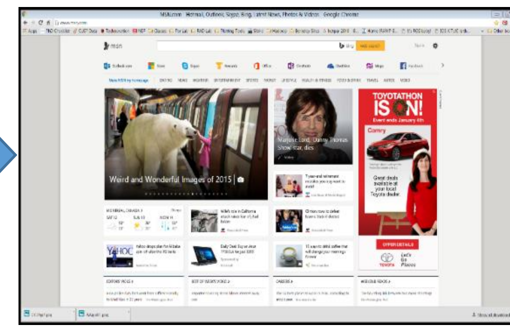
User demographics feature vector
User history feature vector
50 editorially chosen articles with feature vectors

Ranked List

⋮

Front End Server

Clicks logged as feedback



User Clicks Story

Client Brower

[1]Reference: Alekh Agarwal et al., http://arxiv.org/abs/1606.03966

Online/Reinforcement Learning


nature

THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE

At last — a computer program that can beat a champion Go player PAGE 484

ALL SYSTEMS GO

CONSERVATION
SONGBIRDS À LA CARTE
Illegal harvest of millions of Mediterranean birds

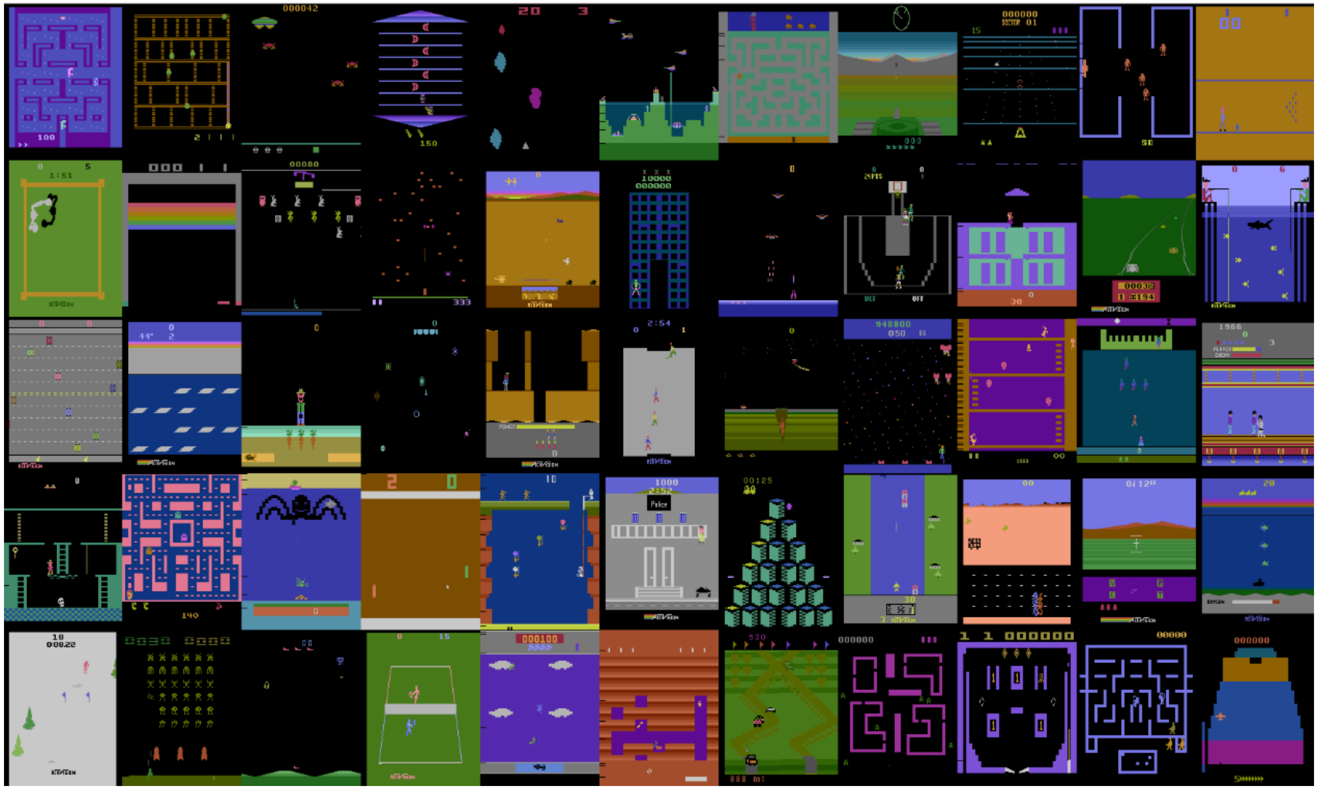
RESEARCH ETHICS
SAFEGUARD TRANSPARENCY
Don't let openness backfire on individuals

POPULAR SCIENCE
WHEN GENES GOT 'SELFISH'
Dawkins's calling card forty years on

NATURE.COM/NATURE

[1]Reference: DeepMind, March 2016

Online/Reinforcement Learning



[1]Figure: Defazio Graepel, Atari Learning Environment

Caveat with Any Technique

- Measurable metrics of business success take priority over technical success metrics
- Need to ask:
  - Does a Y% increase in classification accuracy help in X% increase in sales?
  - Does a Z% increase in classification accuracy due to using a deep learning solution help the bottom-line?
  - What is the technical debt incurred? Who will maintain?

Questions?

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Classification

- Classification
  - Data
  - Model
  - Loss
  - Optimization

Classification

- To design the classifier, we need
  - Training data
  - Model specification for the classifier
  - Loss function to define the best model
  - Optimization to get to the best model

Data (I)

- Lets pick a domain: Vision
- What is an image?
  - A bunch of numbers between 0 to 255
  - A 3 dimensional array
  - The same object can look different based on
    - Location of the camera
    - Location of the light source
    - Rigidity of the object
    - Occluding objects
    - Background
    - Variation across objects of the same category

Data (II)

- Say we have N training examples $(x_i, y_i), i = 1, \ldots, N$
  - x_i is the feature vector for the i^{th} example
  - y_i is the label for the i^{th} example

- Before deep learning
  - Carefully designed features
    - Histogram of colors
    - Histogram of Oriented Gradients (HOG)
    - Scale Invariant Feature Transform (SIFT)
    - Various types of filters

- With deep learning
  - Almost no feature engineering (for this type of data)

Model (I)

- Parametric vs non-parametric
- Example:
  - Logistic classifier is parametric
  - K-Nearest Neighbor is a non-parametric classifier
- We will focus on parametric models
- A fixed set of parameters and hyper-parameters determine a model completely

Model (II)

- Pick a concrete parametric model $f(x, W, b)$
  - x is the input ($d \times 1$ dimensional)
    - Vectorize the image or get features
  - W is a parameter ($p \times d$ dimensional)
  - b is also a parameter ($p \times 1$ dimensional)

- Let $f(x, W, b) = Wx + b$
  - This is a linear model
  - We will change this later
  - The output of the linear model is a vector of scores

Model (III)

- Given a model (i.e., a fixed W, b pair) our classifier can be
  - Pick the index with the highest 'score'
    - $\hat{l} = \text{argmax}_{\{j=1,\ldots,p\}} f(x, W, b)$
  - Pick the index with the highest 'probability'
    - Need a map/function from scores to probabilities
- We want to use the best model. How?
  - Define best: Loss function
  - Find the best: Optimization

Loss functions (I)

- Let the j^{th} coordinate of $f(x, W, b)$ be s_j
- Loss L_{data} is defined over the training data
- Is chosen to be decomposable over N terms, one per example
  - $L_{data} = \sum_{i=1}^{N} L_i$

Loss functions (I)

- Let the j^{th} coordinate of $f(x, W, b)$ be s_j
- Loss L_{data} is defined over the training data
- Is chosen to be decomposable over N terms, one per example
  - $L_{data} = \sum_{i=1}^{N} L_i$
- Logistic loss (Cross-entropy or softmax) for example i
  - $L_i = -\log P(Y = y_i | X = x_i)$ where
    - $P(Y = j | X = x_i) = \dfrac{e^{s_j}}{\sum_k e^{s_k}}$
- SVM loss (2 class, W is a row vector) for example i
  - $L_i = \max(0, 1 - y_i s_{y_i})$

Loss functions (II)

- Need for regularization
  - Unique model
  - Desired model
  - Control overfitting

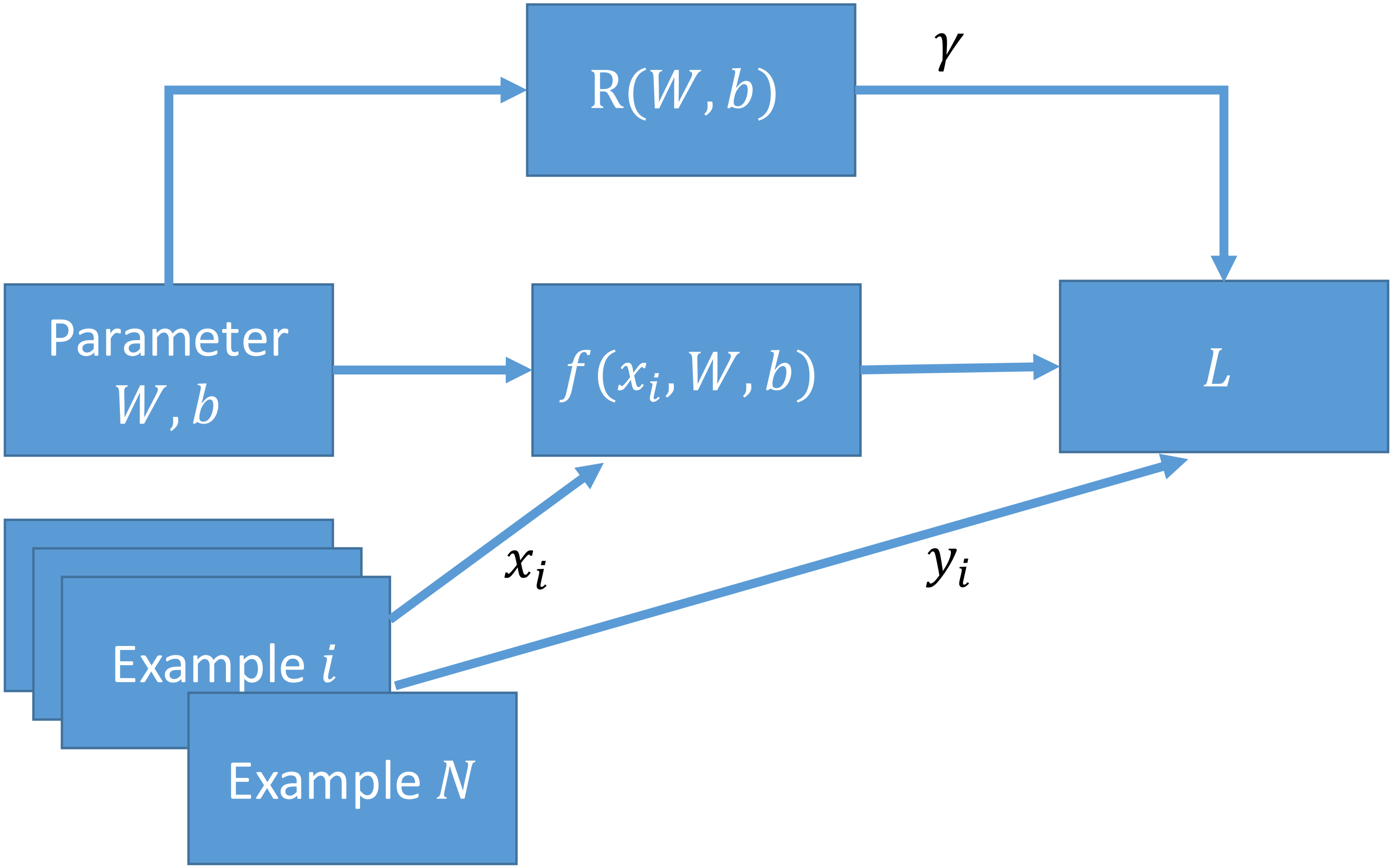
- Final loss $L = L_{data} + \lambda R(W, b)$
- $R(W, b)$ can be just a function of W or b or both

Loss functions (III)

- L2 regularization: $||W||_2^2 = \sum_i \sum_j W_{ij}^2$
- L1: $||W||_1 = \sum_i \sum_j |W_{ij}|$
- Elastic net: $\alpha \left|\left|W\right|\right|_1 + (1 - \alpha)\left|\left|W\right|\right|_2^2$

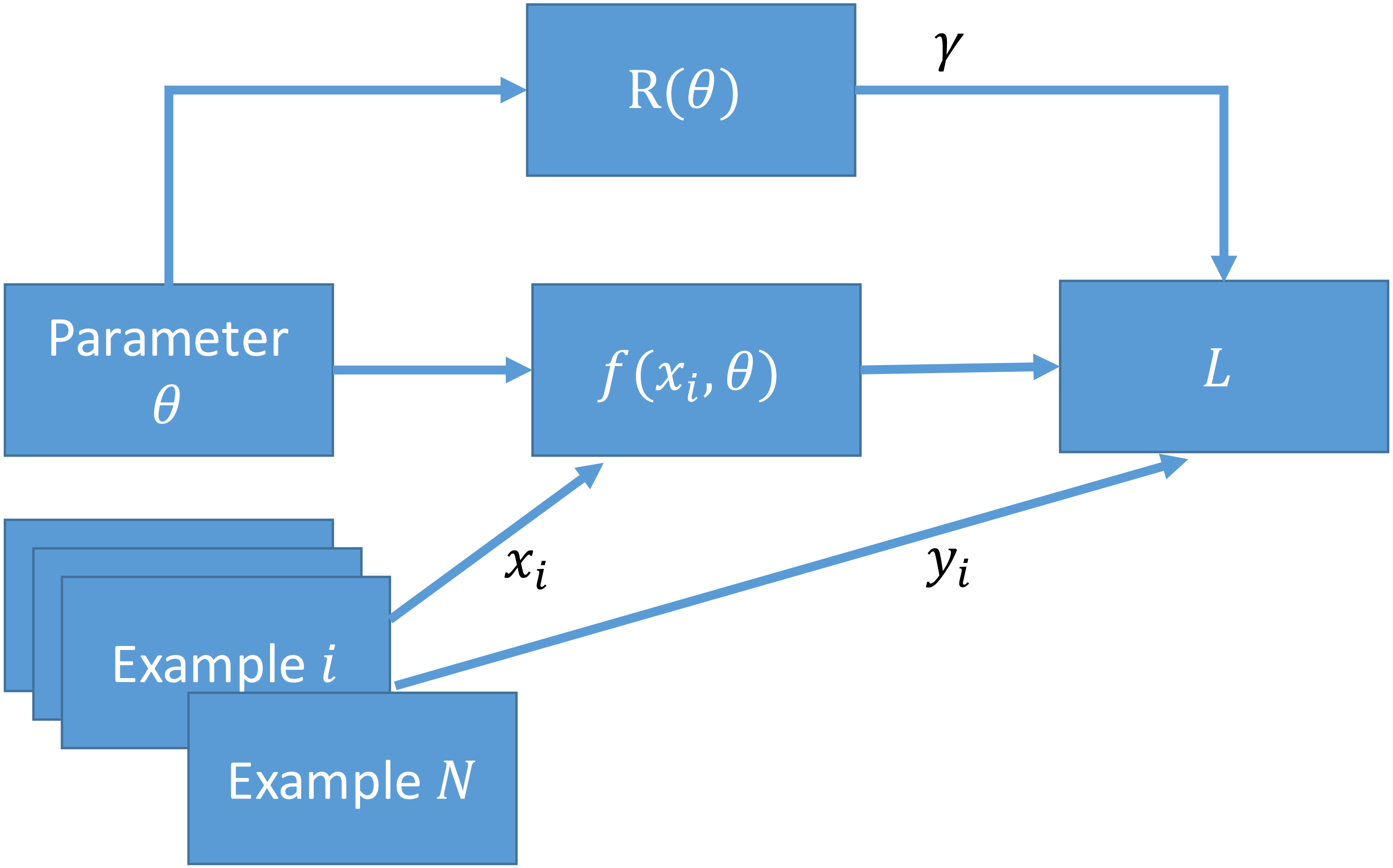
- Regularization may not always be and explicit function of the parameters
  - We will see dropout later

Optimization (I)



Need to find parameters W, b and hyper-parameter γ

Optimization (I)



Need to find parameters θ and hyper-parameter γ

Optimization (II)

- Many ways to optimize differentiable models
- We will focus on first order methods
  - Key ingredient: Gradient

- Gradient is the vector of partial derivatives of a function

- Can be computed
  - Numerically: $\lim_{h \to 0} \frac{f(z+h)-f(z)}{h}$
  - Analytically: Calculus and chain rule

Optimization (III)

- Intuition
  - Start with a model (i.e., W_0, b_0)
  - Evaluate L for this model on the training data
  - Change W_0, b_0 to W_1, b_1 such that the new L is smaller
  - Repeat

- This intuition is the essence of Gradient Descent methods
  - Gradient of L with respect to the parameters is used to change W_0, b_0 to W_1, b_1

Optimization (IV)

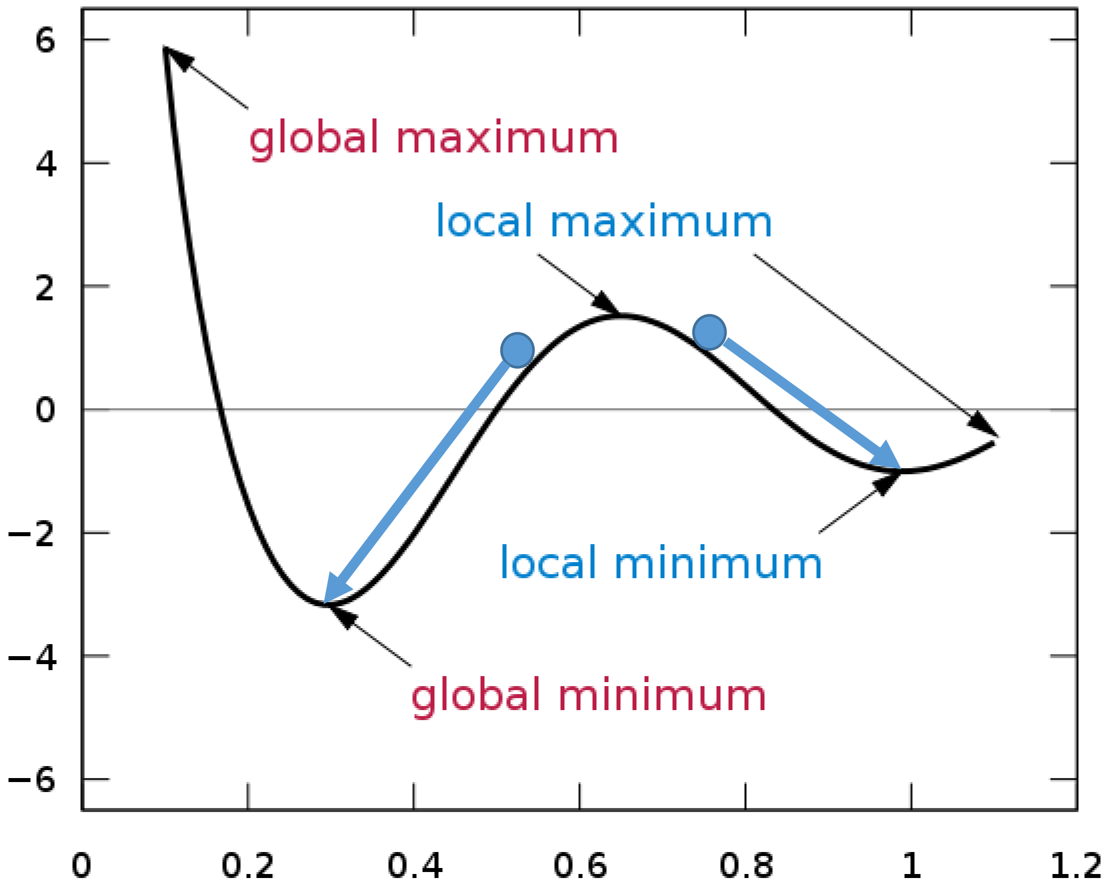
- Example method: Batched Gradient Descent
- Get a sample of training data
  - Example: AlexNet[1] used 256 examples as one batch
- Get gradient of L with respect to parameters W, b
- Update
  - $W_{k+1} \leftarrow W_k - \alpha \nabla_W L$
  - $b_{k+1} \leftarrow b_k - \beta \nabla_b L$

- Step sizes (learning rates) α, β need careful choice

[1]Krizhevsky et al. NIPS Deep Learning Workshop 2012

Optimization (IV): Gradient Descent

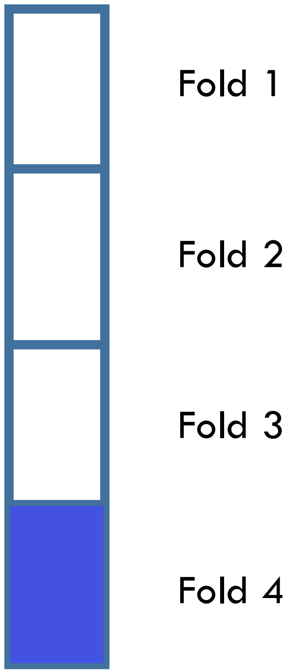
Gradient descent can only reach local optima



[1]By I, KSmrq, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=2276449

Optimization (V)

- Tuning the hyper-parameter(s)
  - Break dataset into two parts: test and train
  - Remove test data access while you are tuning the parameters of your model
  - With training data, do cross validation to tune parameters and hyper-parameters



Essentially cycle through the choice of validation fold
Optimize parameters over the remaining folds

Questions?

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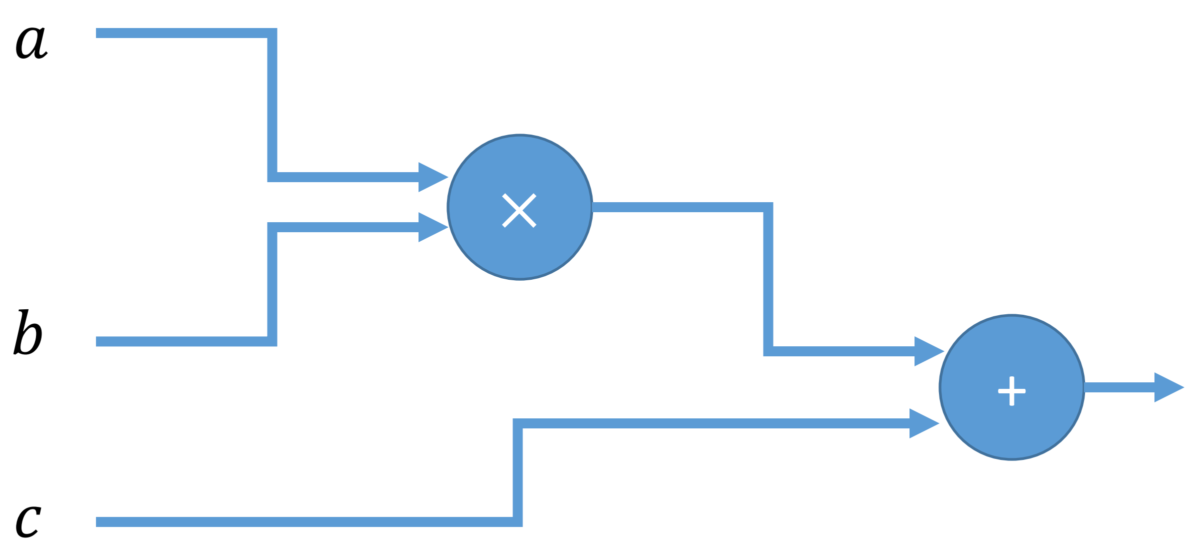
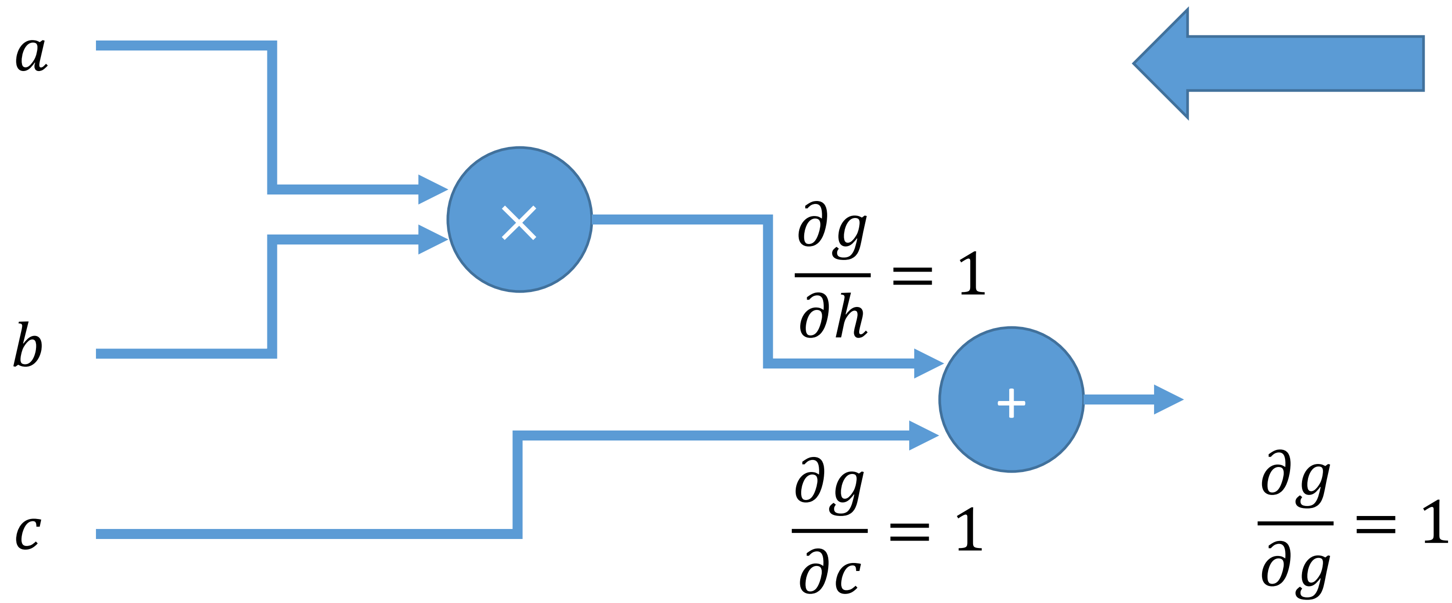
Notion of a Computational Graph

- Consider a function $g(a, b, c) = a * b + c$
- Draw a graph



Backprop Example 1

- The circles represent compute nodes
- Let $h = a * b$. Then $g = h + c$



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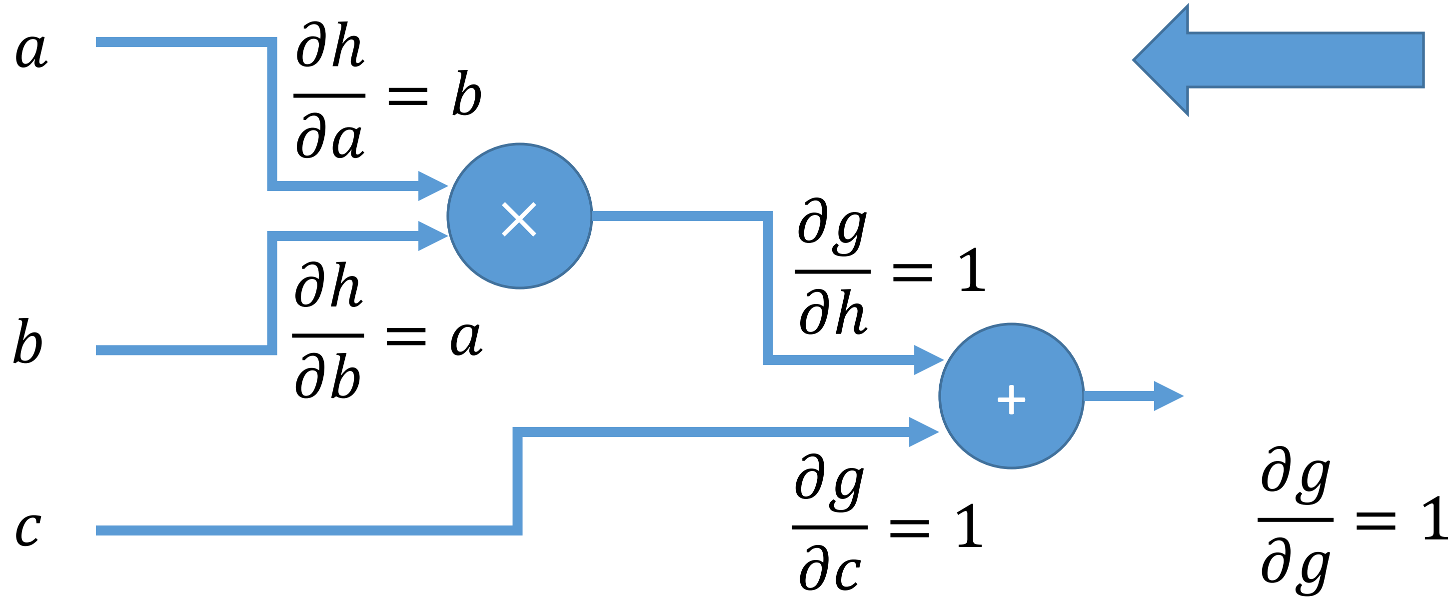
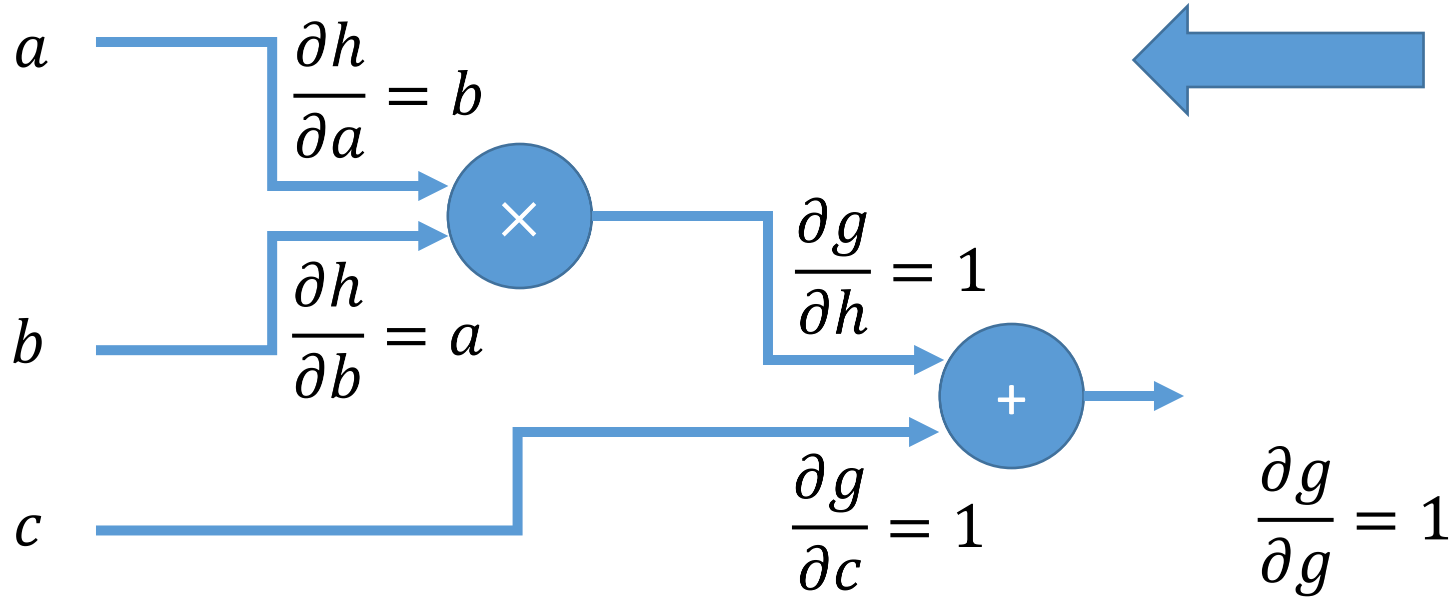


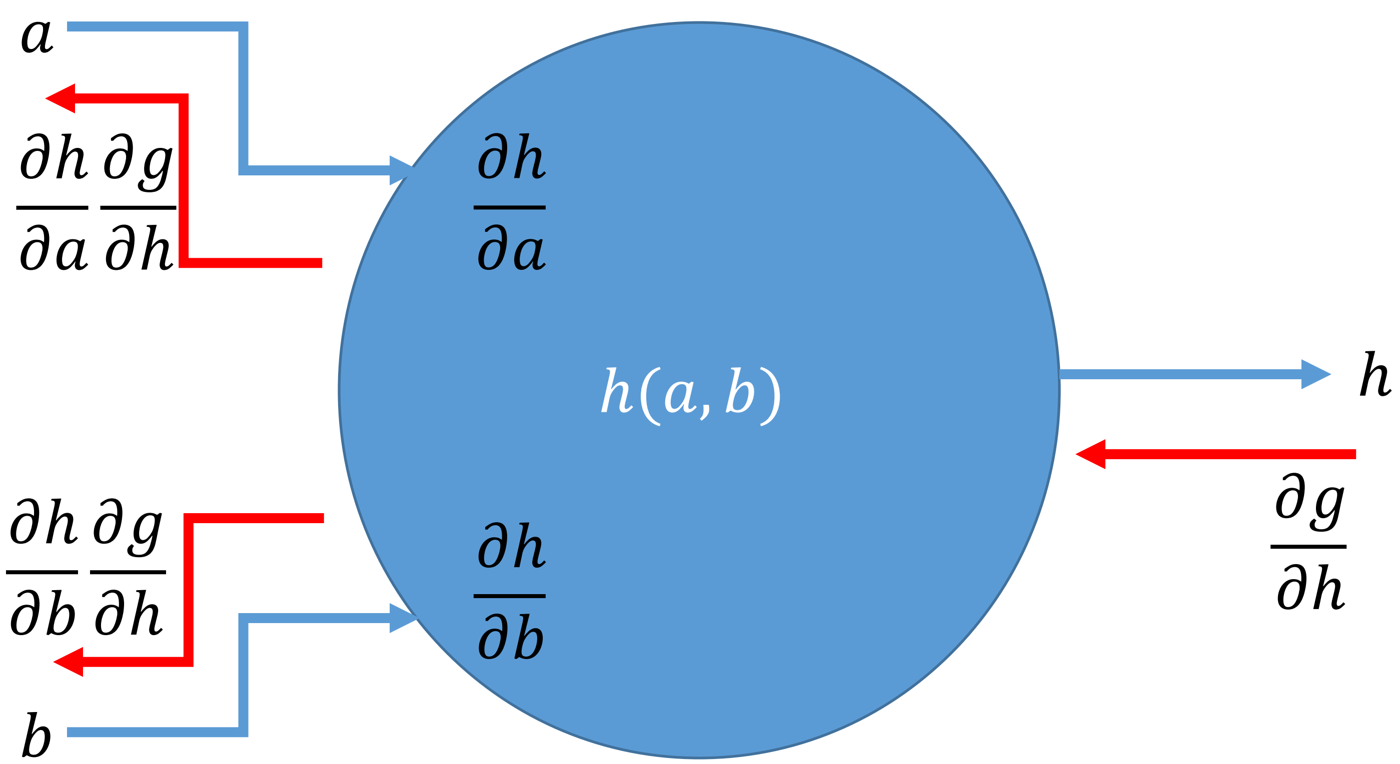
Backprop Example 1

- We can find $\frac{\partial g}{\partial a}, \frac{\partial g}{\partial b}$ and $\frac{\partial g}{\partial c}$ by chain rule!

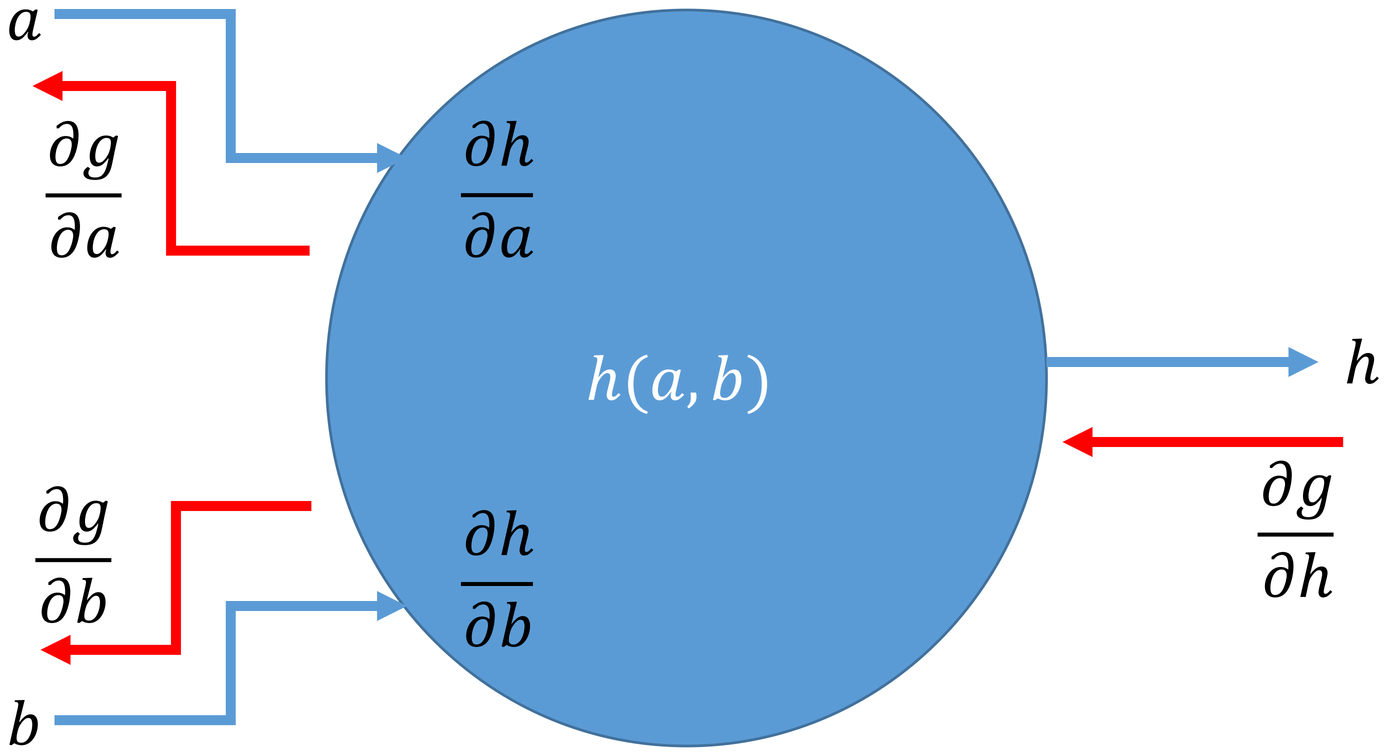


Backpropagation

- An efficient way to get the gradient needed for optimization

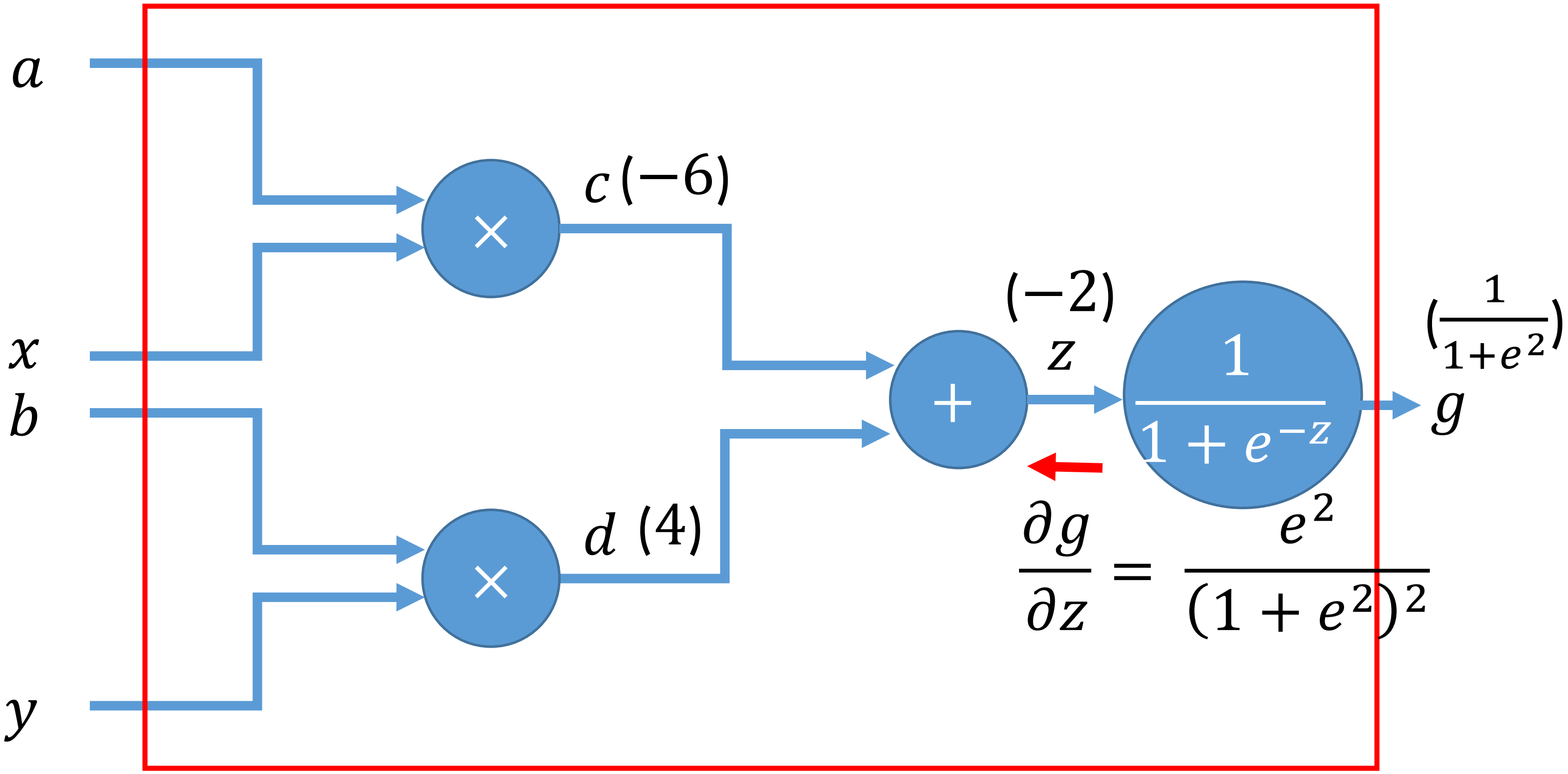


Backpropagation



Backprop Example 2

- Consider a function $g(a, b, x, y) = \frac{1}{1+e^{-(ax+by)}}$
- Let $a = 2, b = 1, x = -3$ and $y = 4$



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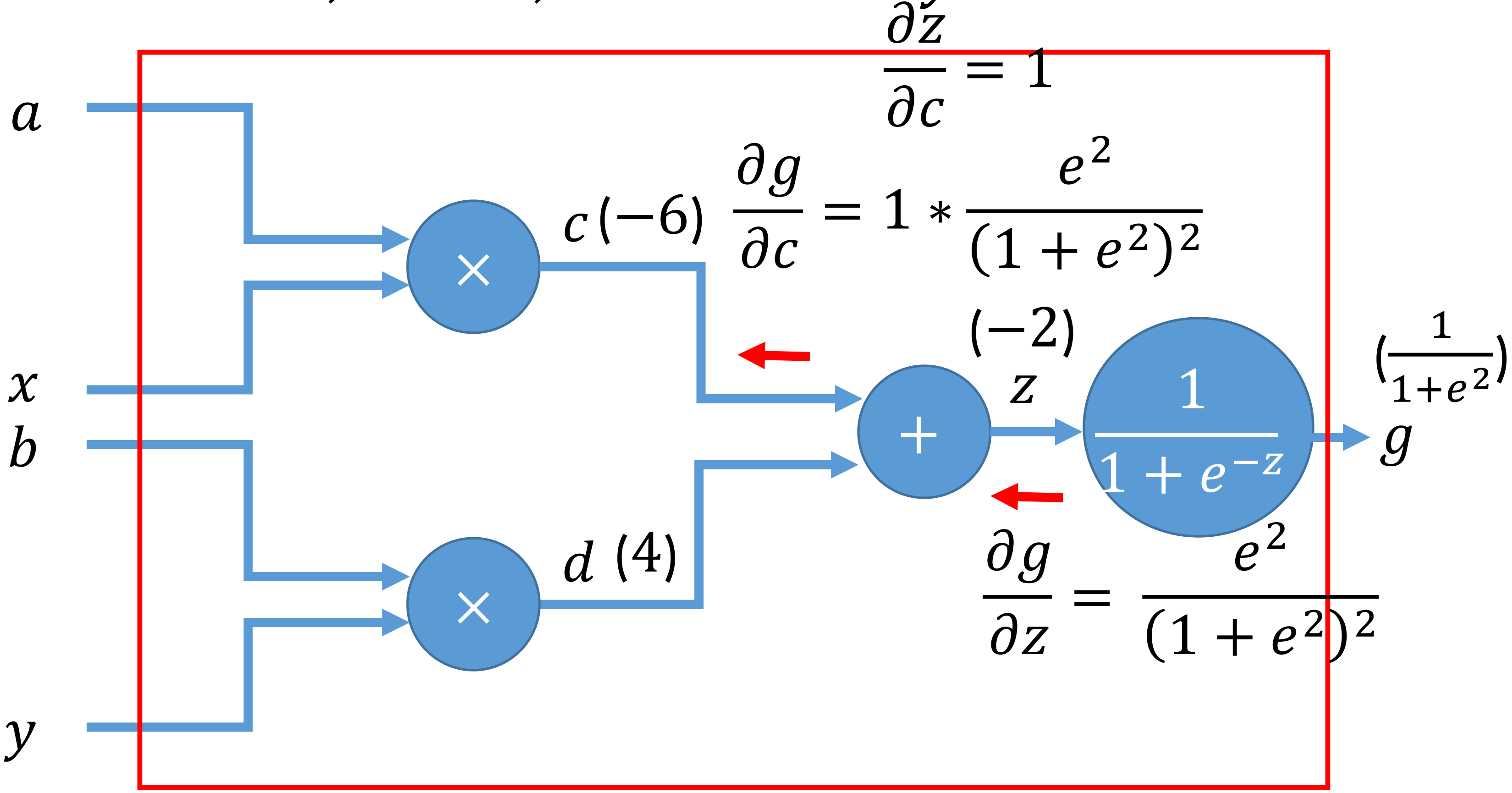

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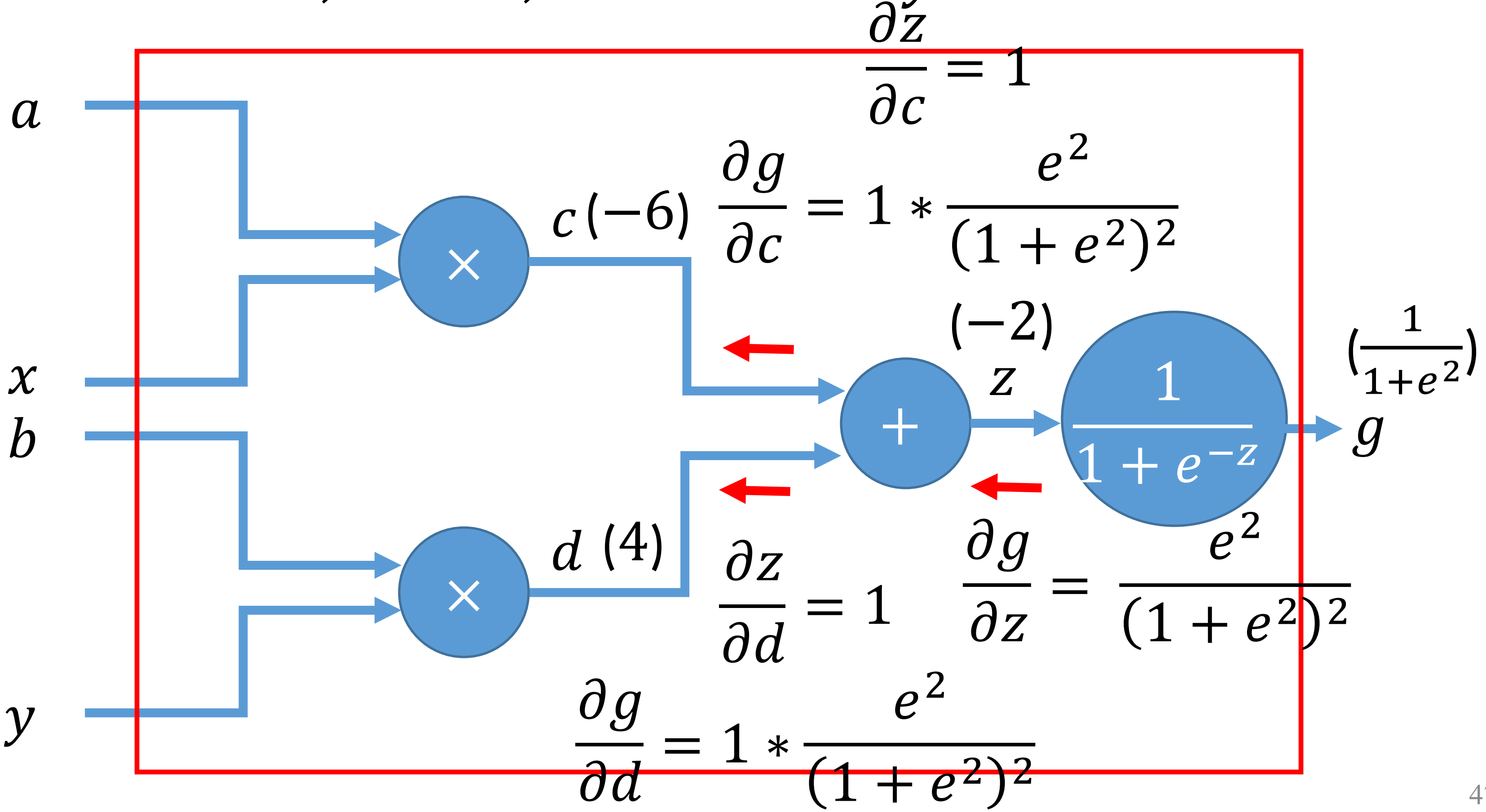

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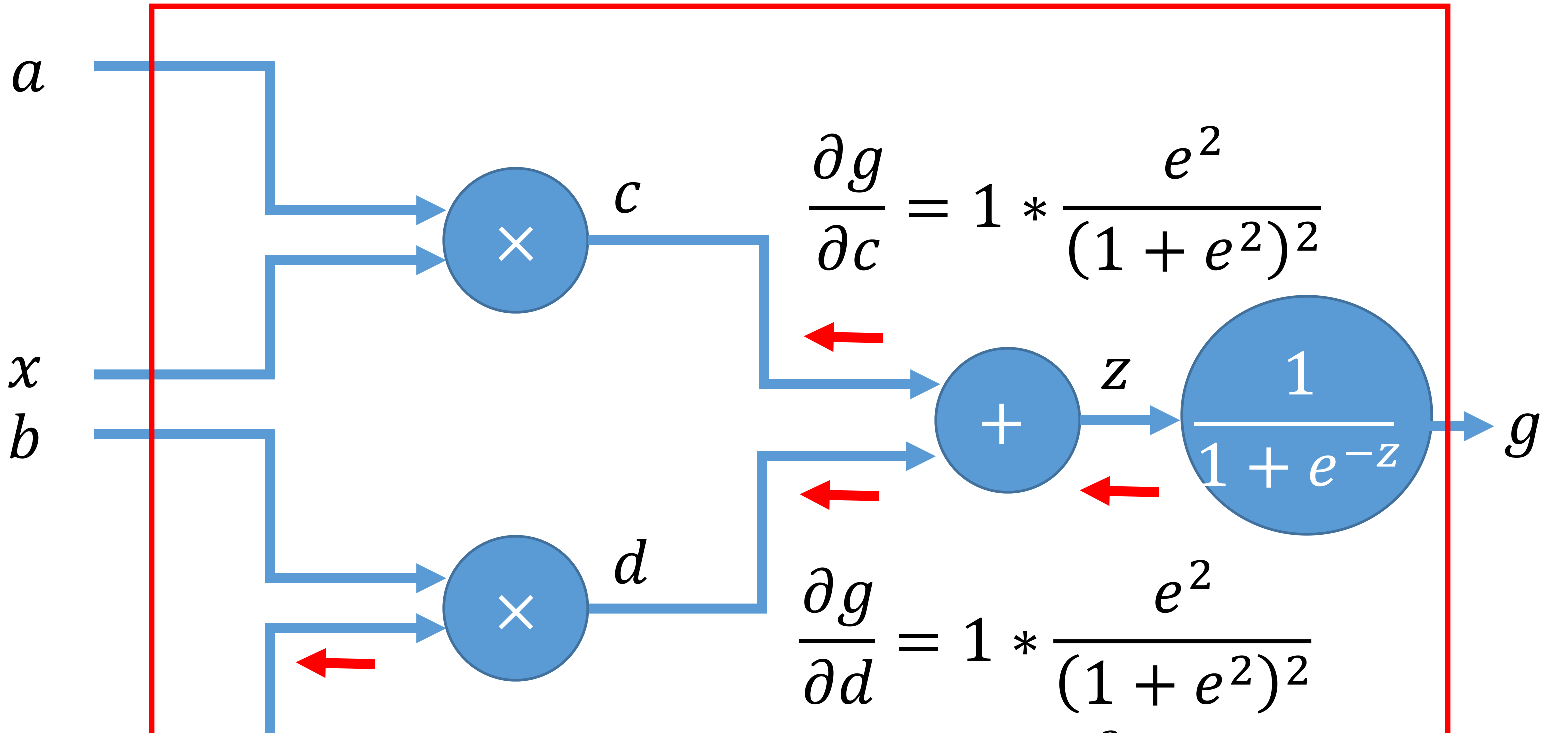
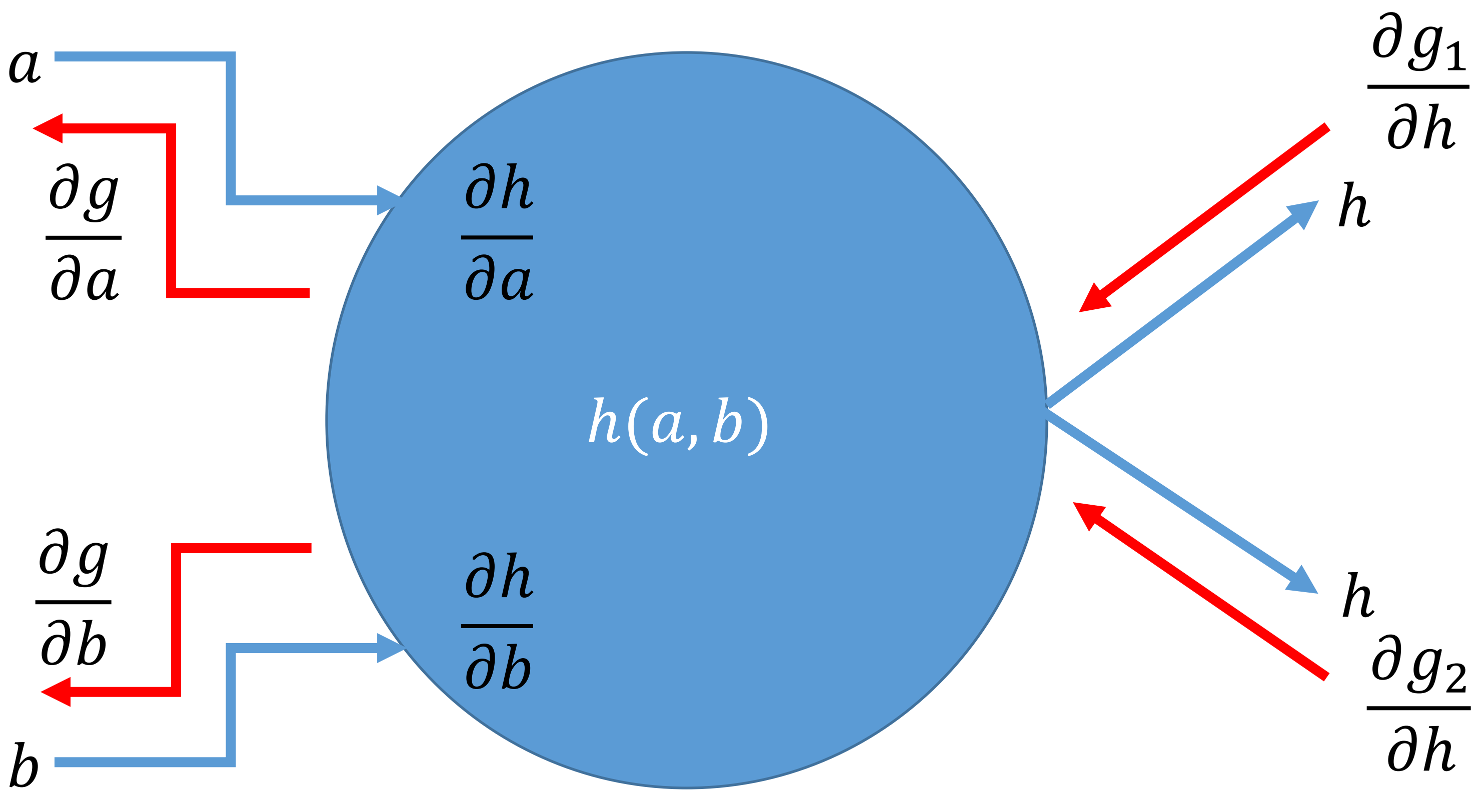


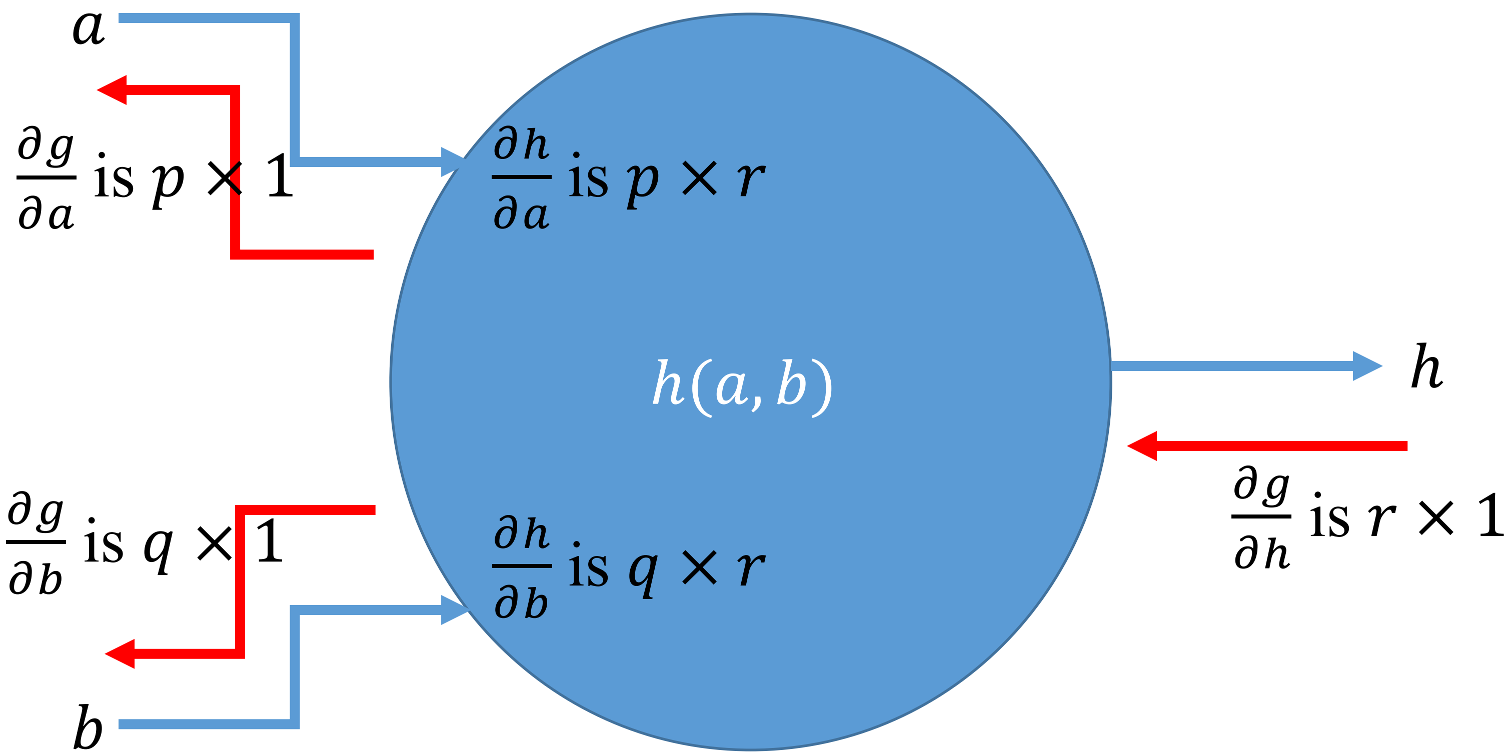
$\frac{\partial d}{\partial y} = b$. Hence, $\frac{\partial g}{\partial y} = \frac{\partial g}{\partial d}\frac{\partial d}{\partial y} = 1 * \frac{e^2}{(1+e^2)^2}$

Backprop for multiple outputs



Backprop for vectors

- Say, a is $p \times 1$ dimensional, b is $q \times 1$ dimensional and h is $r \times 1$ dimensional and g is scalar



Node tracks matrices (cleverly)

Backprop API for a Node

- Implement two functions
  - Forward
  - Backward
- Forward
  - Get input from preceding node(s)
  - Track inputs and local gradients
  - Return computation
- Backward
  - Get gradient from succeeding node(s)
  - Compute gradients (simple multiplication)
  - Return gradients to preceding node(s)

Computational Graph API

- Data structure a graph (nodes and directed edges)
- Implement two functions for it
  - Forward
  - Backward
- Forward
  - Recursively pass the inputs to the next nodes
  - Return L
- Backward
  - Recursively traverse the graph backwards
  - Return gradients

Backprop and Batched Gradient Descent

- Choose a mini-batch (sample) of size B
- Forward propagate through the computation graph
  - Compute losses $L_{i_1}, L_{i_2}, \dots L_{i_B}$ and $R(W, b)$
  - Get loss L for the batch
- Backprop to compute gradients with respect to W, b
- Update parameters W, b
  - In the direction of the negative gradient

Linear Classifier in Python

```
#Example modified from http://cs231n.github.io/neural-networks-case-study/

#Imports
import numpy as np #Represent ndarrays a.k.a. tensors
import matplotlib.pyplot as plt #For plotting
np.random.seed(0) #For repeatability of the experiment
import pickle #To read data for this experiment

#Setup
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'
```

Linear Classifier in Python

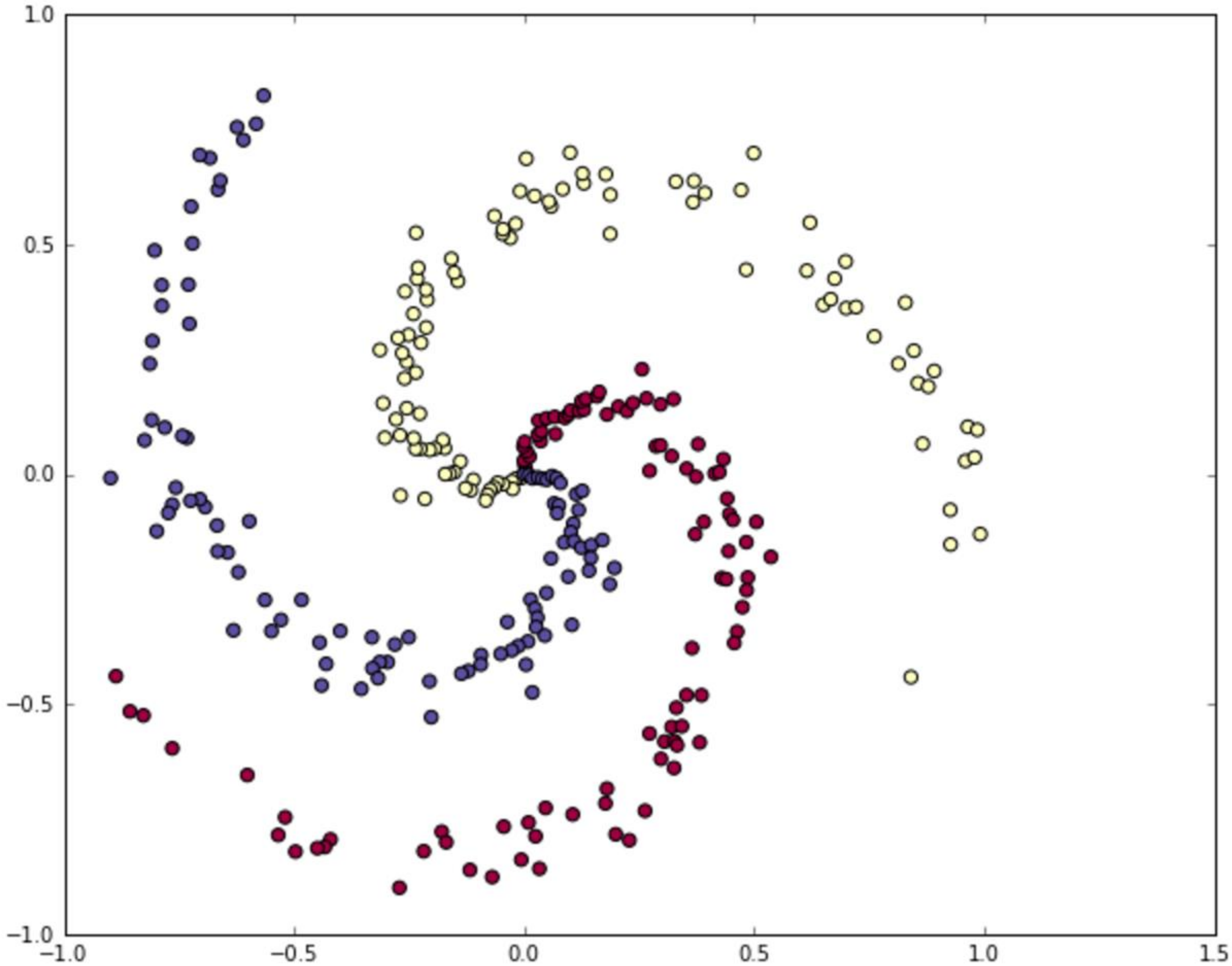
Data

```
#Read data
X = pickle.load(open('dataX.pickle','rb'))
y = pickle.load(open('dataY.pickle','rb'))

#Define some local varaibles
D = X.shape[1] #Number of features
K = max(y)+1 #Number of classes assuming class index starts from 0

#Plot the data
fig = plt.figure()
plt.scatter(X[:, 0], X[:, 1], c=y, s=40, cmap=plt.cm.Spectral)
```

Linear Classifier in Python



Linear Classifier in Python

Model

```
# Linear model

# Start with an initialize parameters randomly
W = 0.01 * np.random.randn(D,K)
b = np.zeros((1,K))

# Initial values from hyperparameter
reg = 1e-3 # regularization strength

#For simplicity, we will not optimize this using grid search here.
```

Linear Classifier in Python

```
#Perform batch SGD using backprop

#For simplicity we will take the batch size to be the same as number of examples
num_examples = X.shape[0]

#Initial value for the Gradient Descent Parameter
step_size = 1e-0 #Also called learning rate

#For simplicity, we will not hand tune this algorithm parameter as well.
```

Linear Classifier in Python

```
# gradient descent loop
for i in xrange(200):

    # evaluate class scores, [N x K]
    scores = np.dot(X, W) + b

    # compute the class probabilities
    exp_scores = np.exp(scores)
    probs = exp_scores / np.sum(exp_scores, axis=1, keepdims=True) # [N x K]

    # compute the loss: average cross-entropy loss and regularization
    corect_logprobs = -np.log(probs[range(num_examples),y])
    data_loss = np.sum(corect_logprobs)/num_examples
    reg_loss = 0.5*reg*np.sum(W*W)
    loss = data_loss + reg_loss
    if i % 10 == 0:
        print "iteration %d: loss %f" % (i, loss)

    # compute the gradient on scores
    dscores = probs
    dscores[range(num_examples),y] -= 1
    dscores /= num_examples

    # backpropate the gradient to the parameters (W,b)
    dW = np.dot(X.T, dscores)
    db = np.sum(dscores, axis=0, keepdims=True)

    dW += reg*W # regularization gradient

    # perform a parameter update
    W += -step_size * dW
    b += -step_size * db
```

Linear Classifier in Python

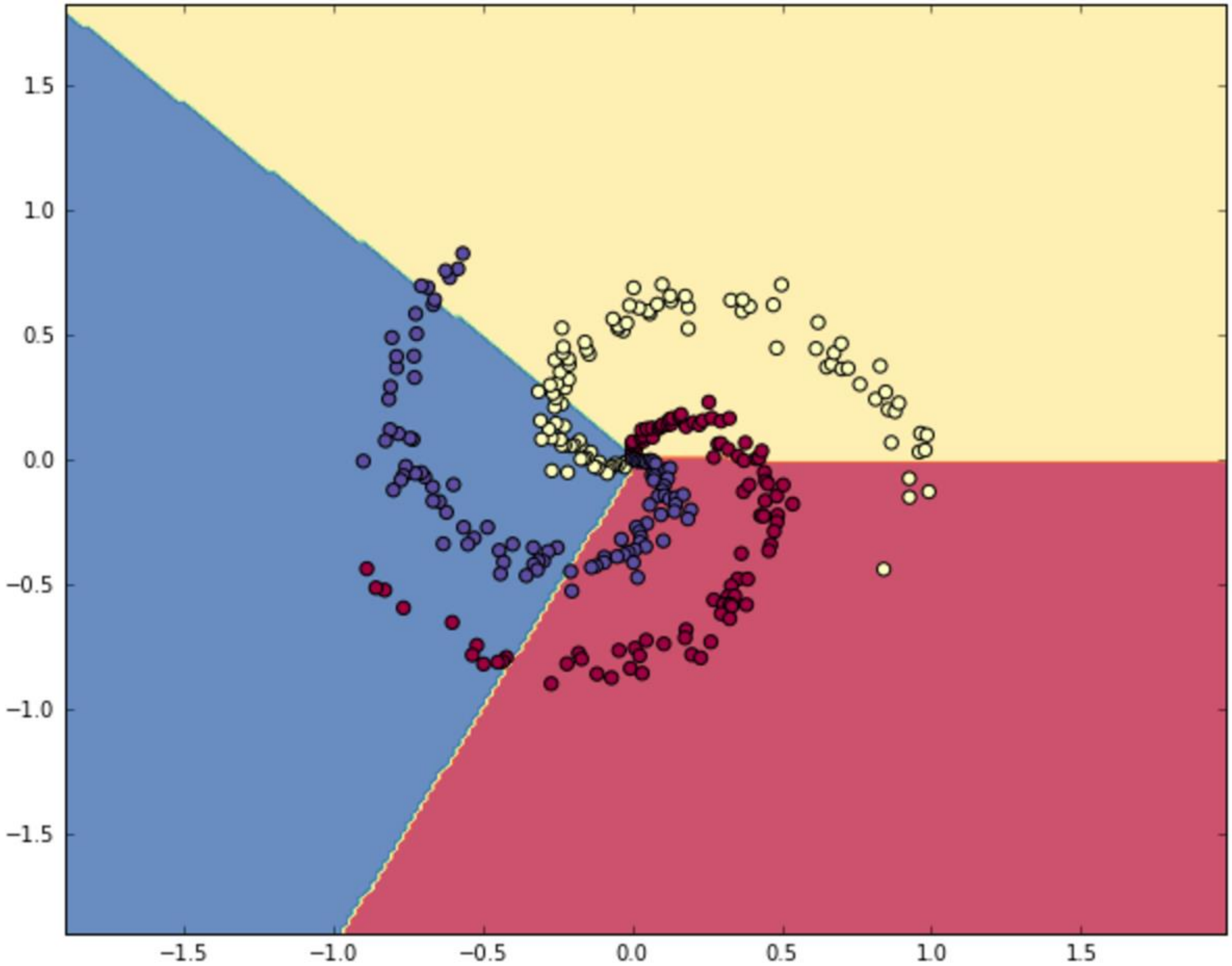
Post Training

```
# Post-training: evaluate test set accuracy

#For simplicity, we will use training data as proxy for test. Do not do this.
X_test = X
y_test = y

scores = np.dot(X_test, W) + b
predicted_class = np.argmax(scores, axis=1)
print 'test accuracy: %.2f' % (np.mean(predicted_class == y_test))
```

Linear Classifier in Python



Questions?

Summary

- Data variety poses challenges
  - Missing
  - Noisy
- Complex decisions poses challenges
  - Learning on the go
- We reviewed classification
  - Regression would have similar considerations
- Discussed backpropagation
  - A useful method for optimizing for the best model parameters