Training Neural Networks

DEEP LEARNING FUNDAMENTALS PART 2

databricks

Logistics

- We can’t hear you…
- Recording will be available…
- Slides will be available…
- Code samples and notebooks will be available…
- Queue up Questions…

About our speaker

Denny Lee

Developer Advocate, Databricks

Former:

- Senior Director of Data Sciences Engineering at SAP Concur
- Principal Program Manager at Microsoft
    - Azure Cosmos DB Engineering Spark and Graph Initiatives
    - Isotope Incubation Team (currently known as HDInsight)
    - Bing's Audience Insights Team
    - Yahoo!'s 24TB Analysis Services cube

databricks

VISION Accelerate innovation by unifying data science, engineering and business

PRODUCT Unified Analytics Platform powered by Apache Spark™

WHO WE ARE

- Founded by the original creators of Apache Spark
- Contributes 75% of the open source code, 10x more than any other company
- Trained 100k+ Spark users on the Databricks platform

Deep Learning Fundamentals Series

This is a three-part series:

- Introduction to Neural Networks
- Training Neural Networks
- Applying your Neural Networks

This series will be make use of Keras (TensorFlow backend) but as it is a fundamentals series, we are focusing primarily on the concepts.

Previous Session: Introduction to Neural Networks

- What is Deep Learning?
- What can Deep Learning do for you?
- What are artificial neural networks?
- Let’s start with a perceptron…
- Understanding the effect of activation functions

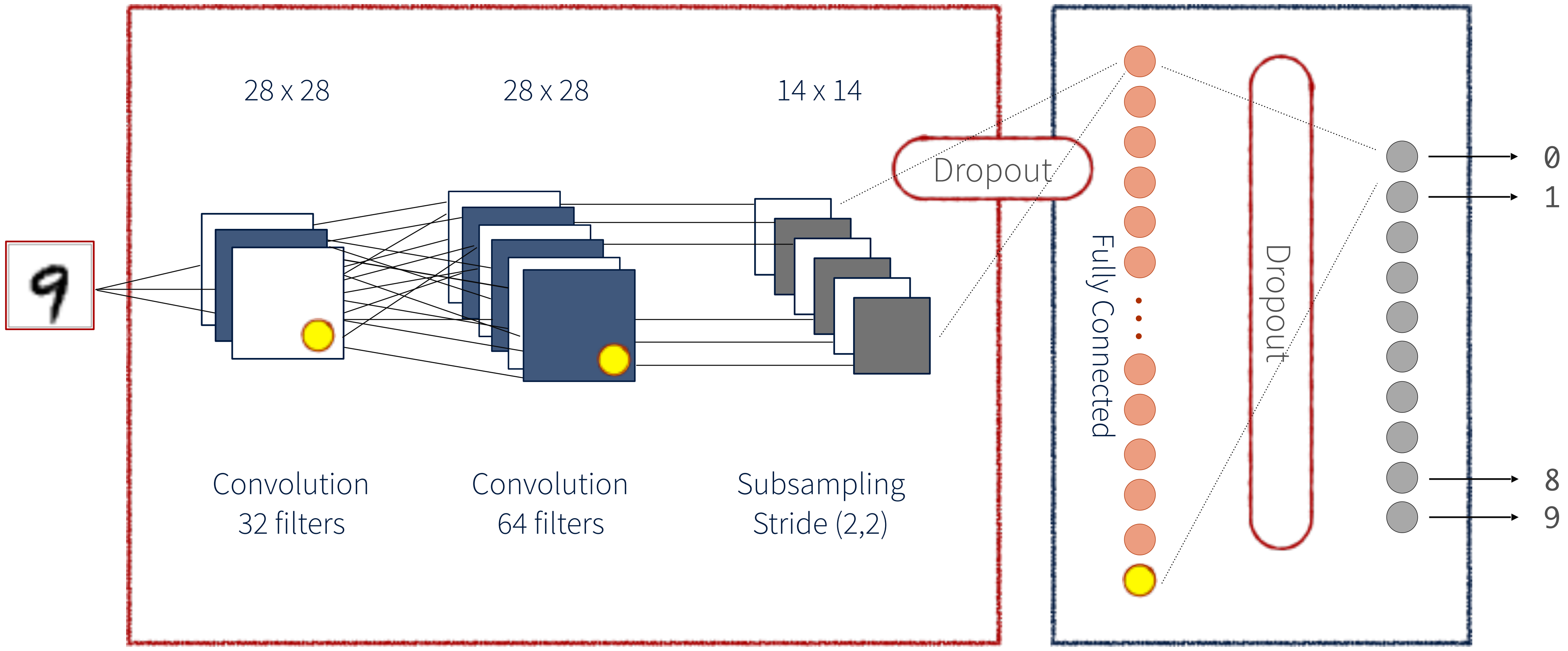
Current Session: Training Neural Networks

- Tuning training
- Training Algorithms
- Optimization (including Adam)
- Convolutional Neural Networks

Upcoming Session: Applying Neural Networks

- Diving further into CNNs
- CNN Architectures
- Convolutions at Work!

Convolutional Neural Networks



Feature Extraction

Classification

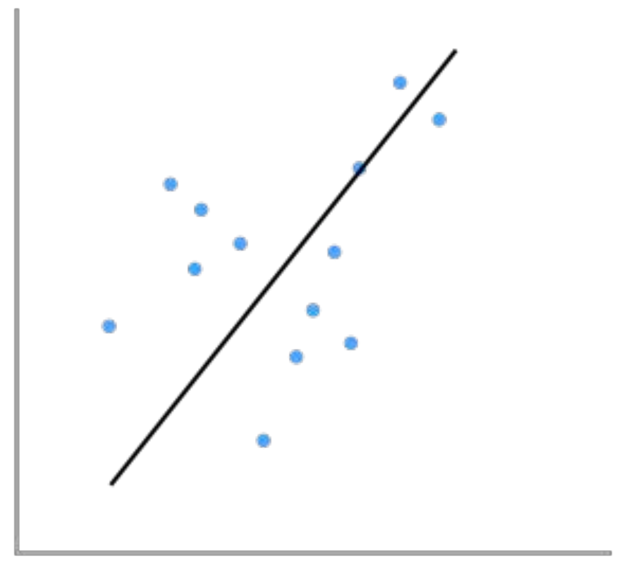
Tuning Training

Hyperparameters

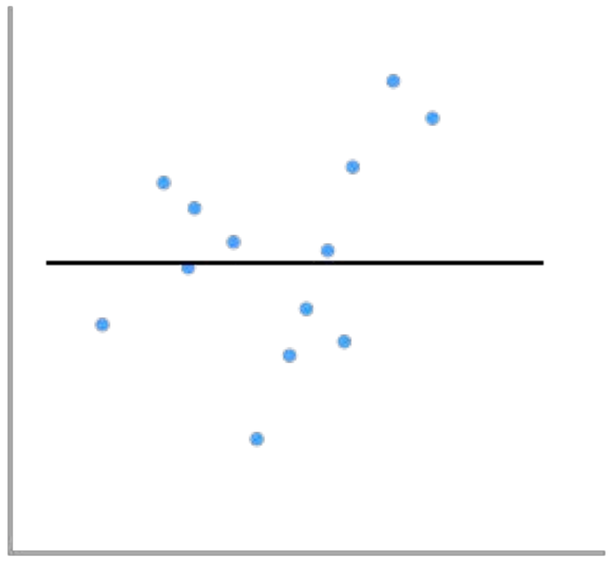
- Network
  - How many layers?
  - How many neurons in each layer?
  - What activation functions to use?

- Learning algorithm
  - What’s the best value of the learning rate?
  - How quickly decay the learning rate? Momentum?
  - What type of loss function should I use?
  - What batch size?
  - How many iterations is enough?

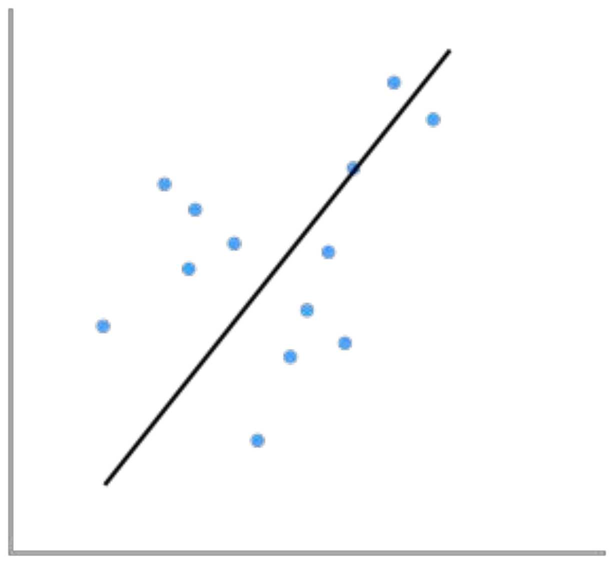
Overfitting and underfitting


balanced

Overfitting and underfitting

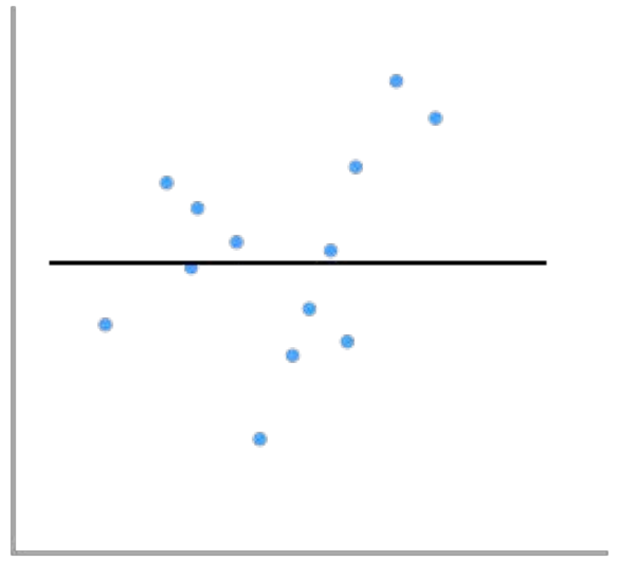


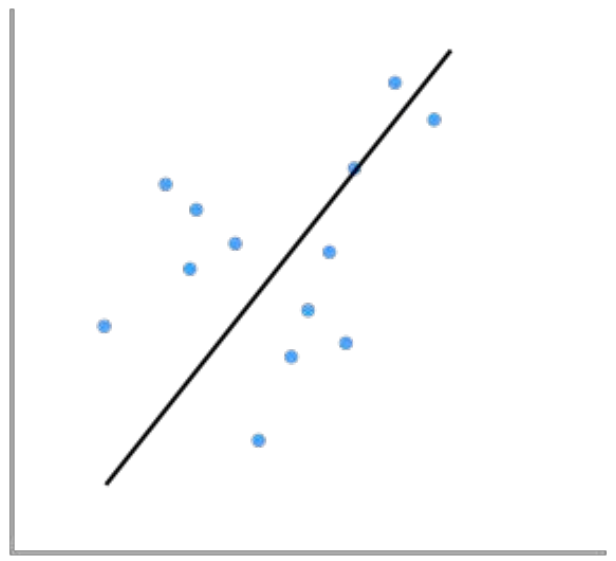
under fitting

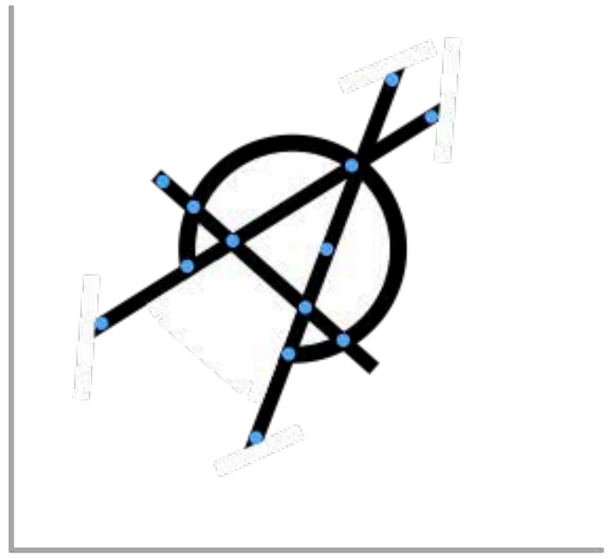


balanced

Overfitting and underfitting


under fitting


balanced


over fitting

(or OPA-fitting)

Hyperparameters: Network

Generally, the more layers and the number of units in each layer:

- The greater the capacity of the artificial neural network
- The risk is **overfitting** when your goal is to build a generalized model.

From a practical perspective, a good starting point is:

- The number of input units equals the dimension of features
- The number of output units equals the number of classes (e.g. in the MNIST dataset, there are 10 possible values represents digits (0…9) hence there are 10 output units
- Start with one hidden layer that is 2x the number of input units
- A good reference is Andrew Ng's Coursera Machine Learning course.

Hyperparameters: Activation Functions?

- Good starting point: ReLU
  - Note many neural networks samples: Keras MNIST, TensorFlow CIFAR10 Pruning, etc.
  - Note that each activation function has its own strengths and weaknesses. A good quote on activation functions from CS231N summarizes the choice well:

"What neuron type should I use?" Use the ReLU non-linearity, be careful with your learning rates and possibly monitor the fraction of "dead" units in a network. If this concerns you, give Leaky ReLU or Maxout a try. Never use sigmoid. Try tanh, but expect it to work worse than ReLU/Maxout.

DEMO

Neurons … Activate!

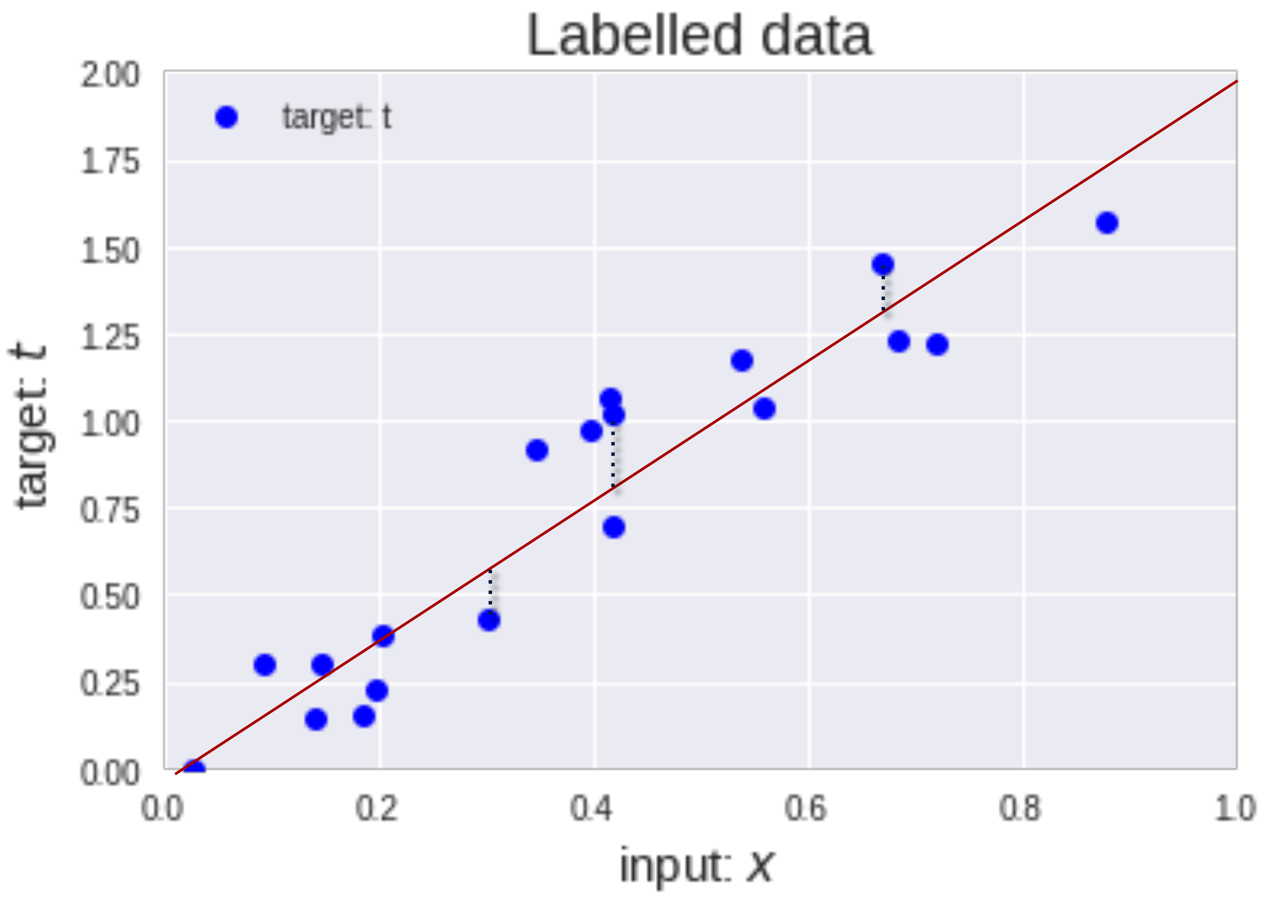
Hyperparameters

Learning algorithm

- What’s the best value of the learning rate?
- How quickly decay the learning rate? Momentum?
- What type of loss function should I use?
- What batch size?
- How many iterations is enough?

Training Algorithms

Cost function



Source: https://bit.ly/2IoAGzL

For this linear regression example, to determine the best p (slope of the line) for

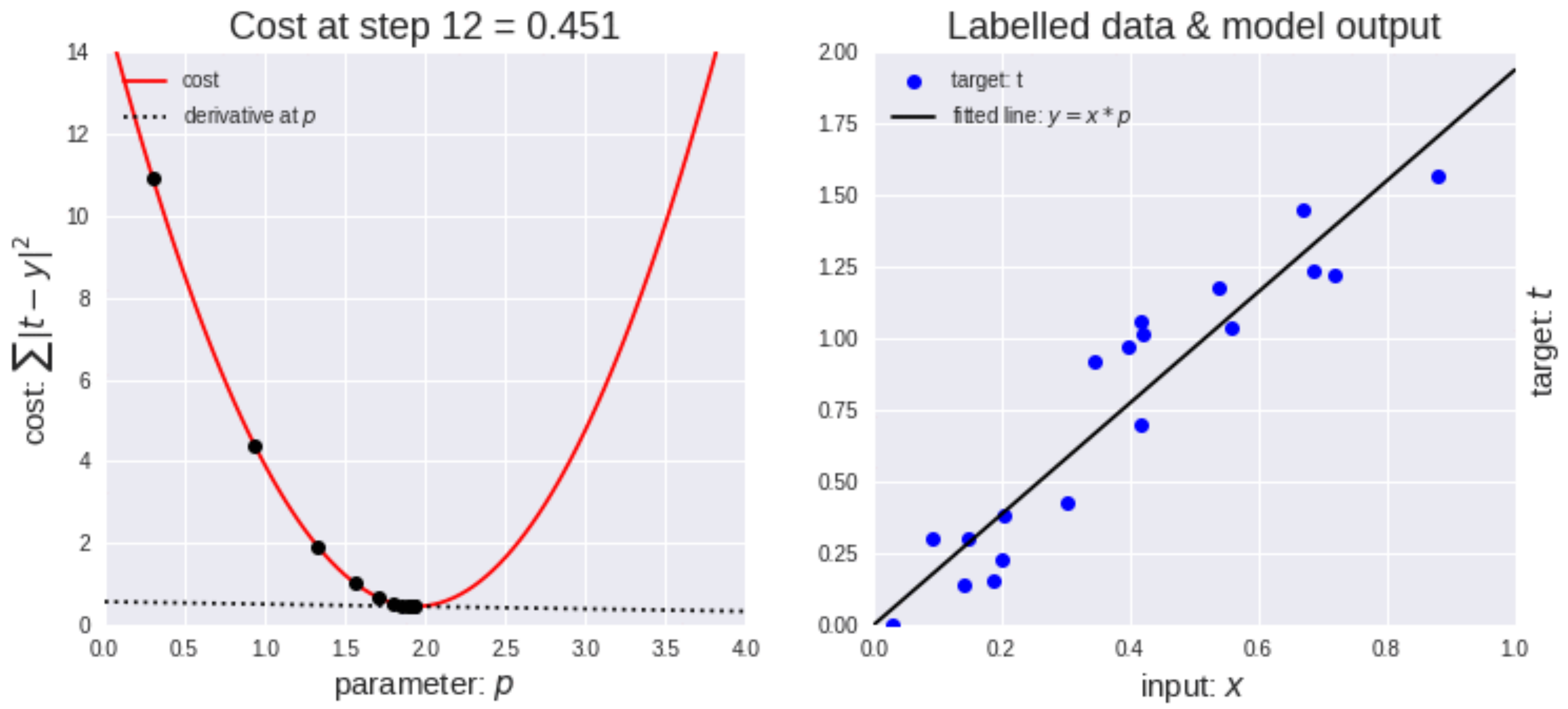
$$y = x \cdot p$$

we can calculate the <u>cost function</u>, such as Mean Square Error, Mean absolute error, Mean bias error, SVM Loss, etc.

For this example, we'll use sum of squared absolute differences

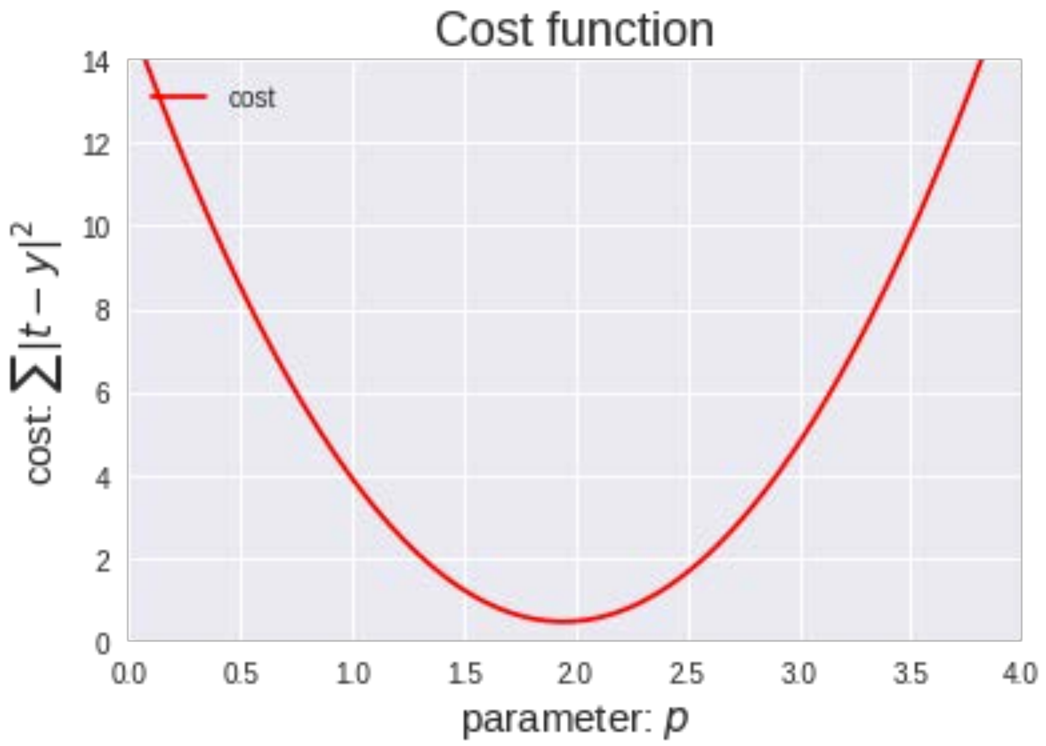
$$cost = \sum |t - y|^2$$

Gradient Descent Optimization



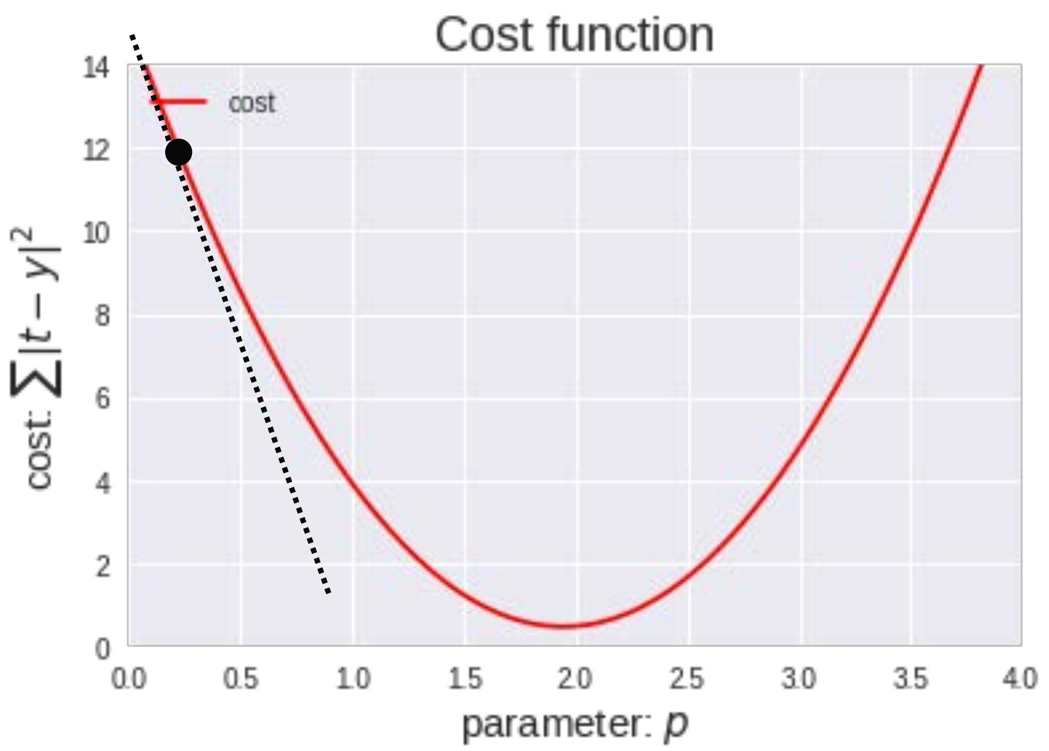
Source: https://bit.ly/2IoAGzL

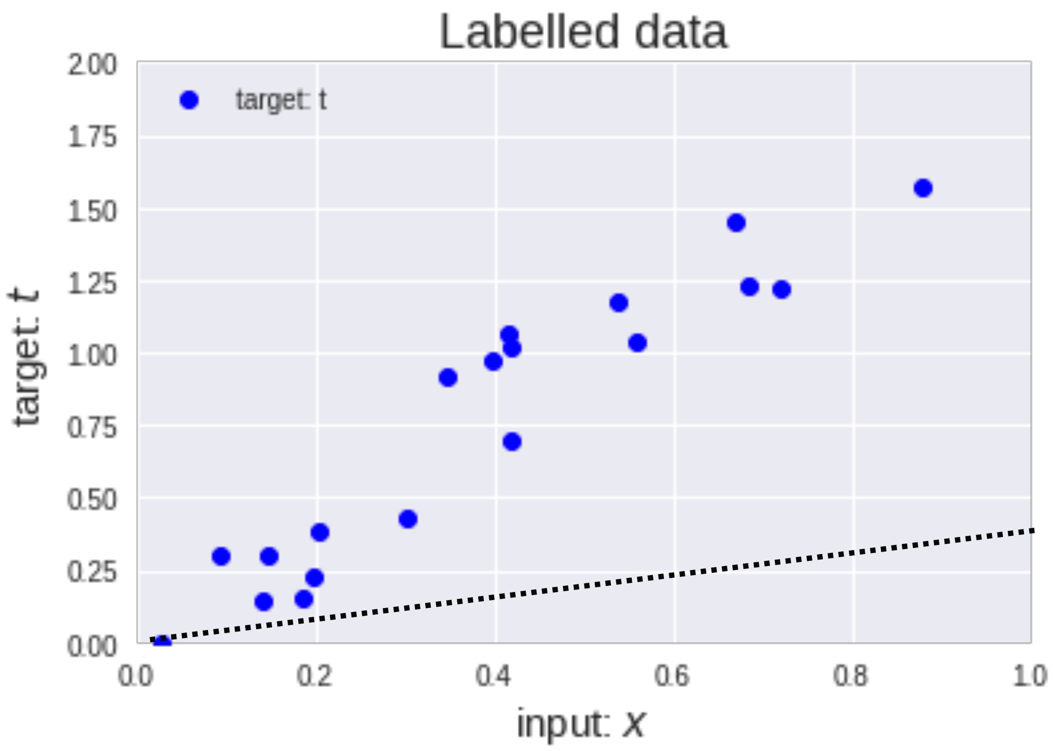
Small Learning Rate



Source: https://bit.ly/2IoAGzL

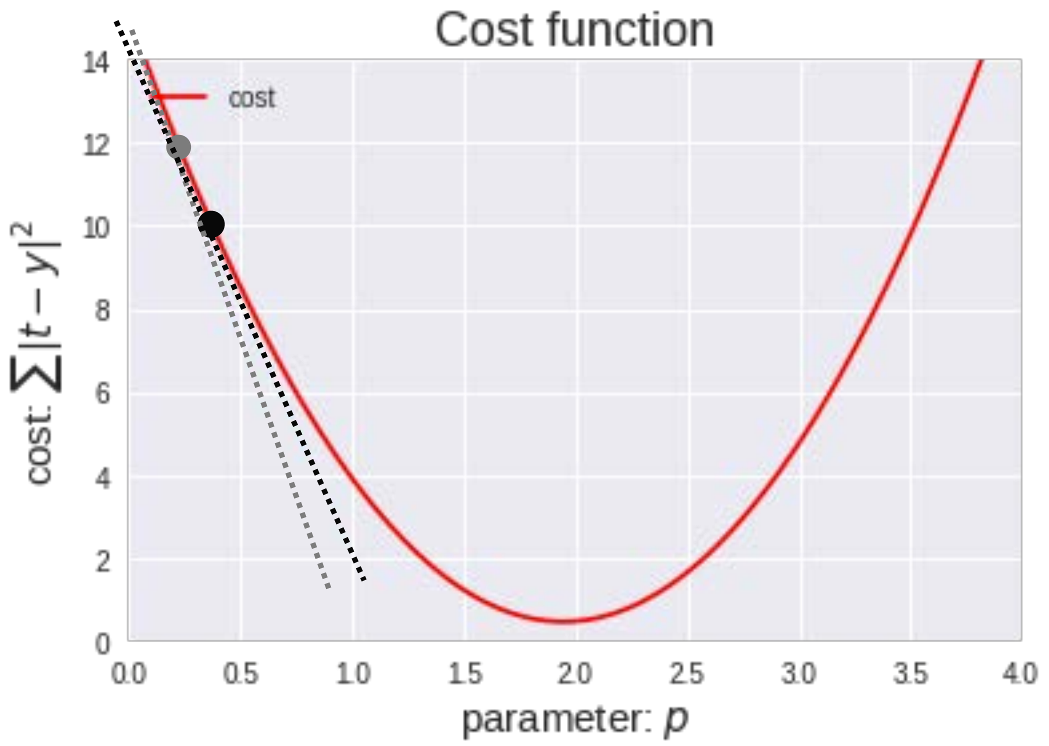
Small Learning Rate

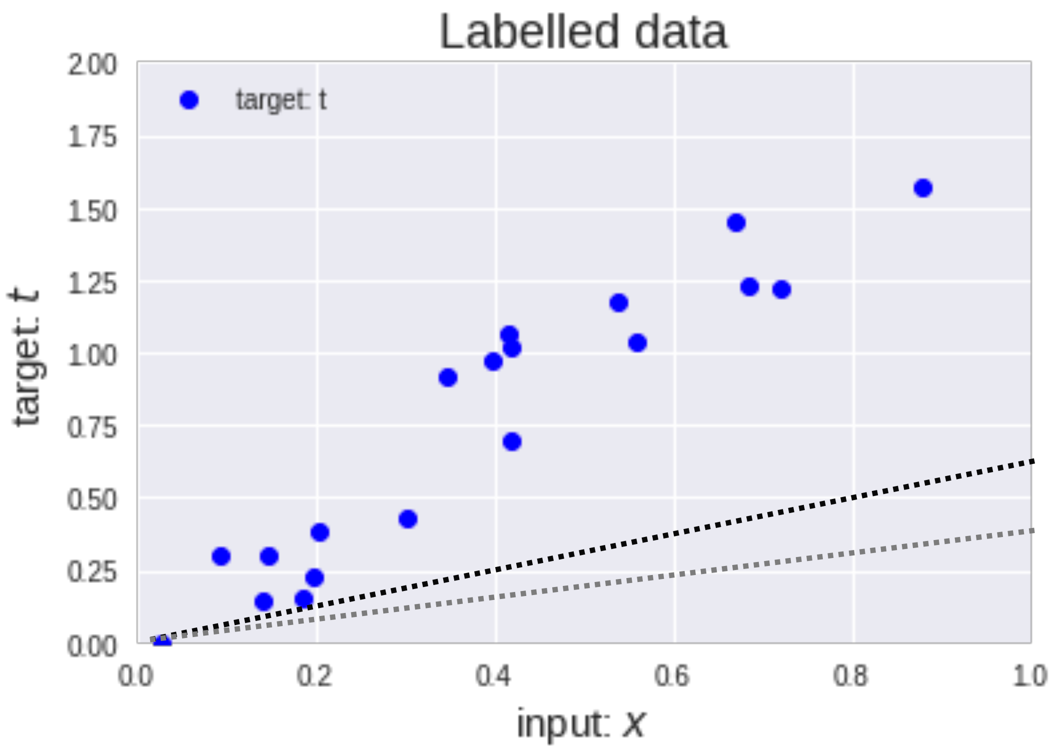




Source: https://bit.ly/2IoAGzL

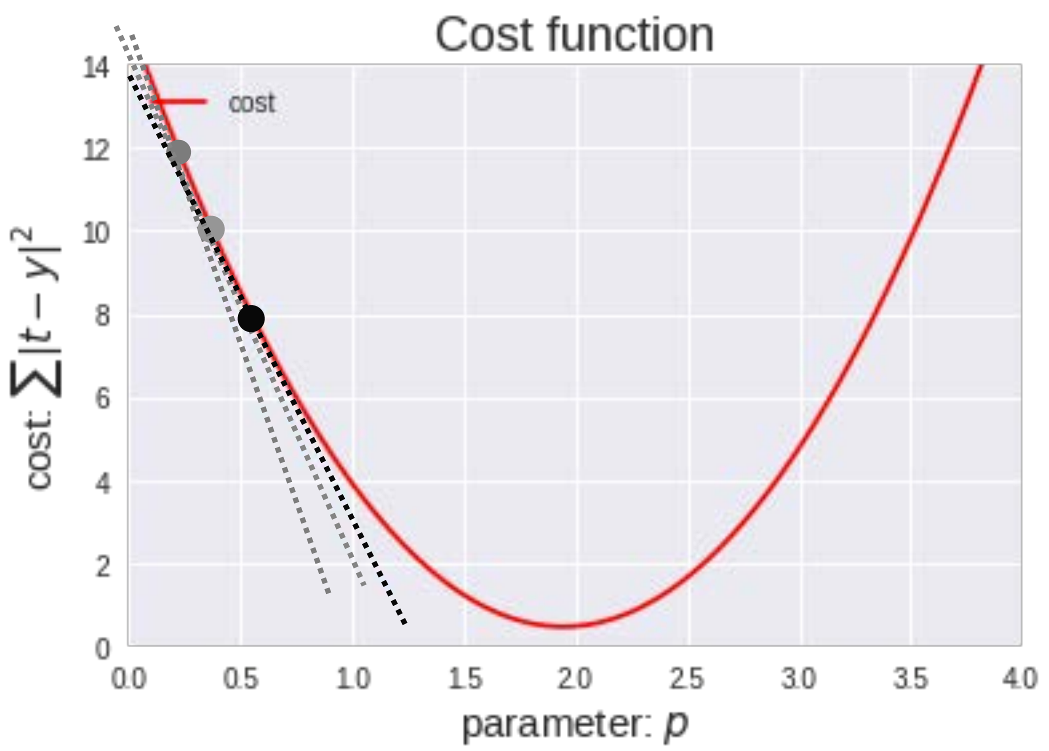
Small Learning Rate

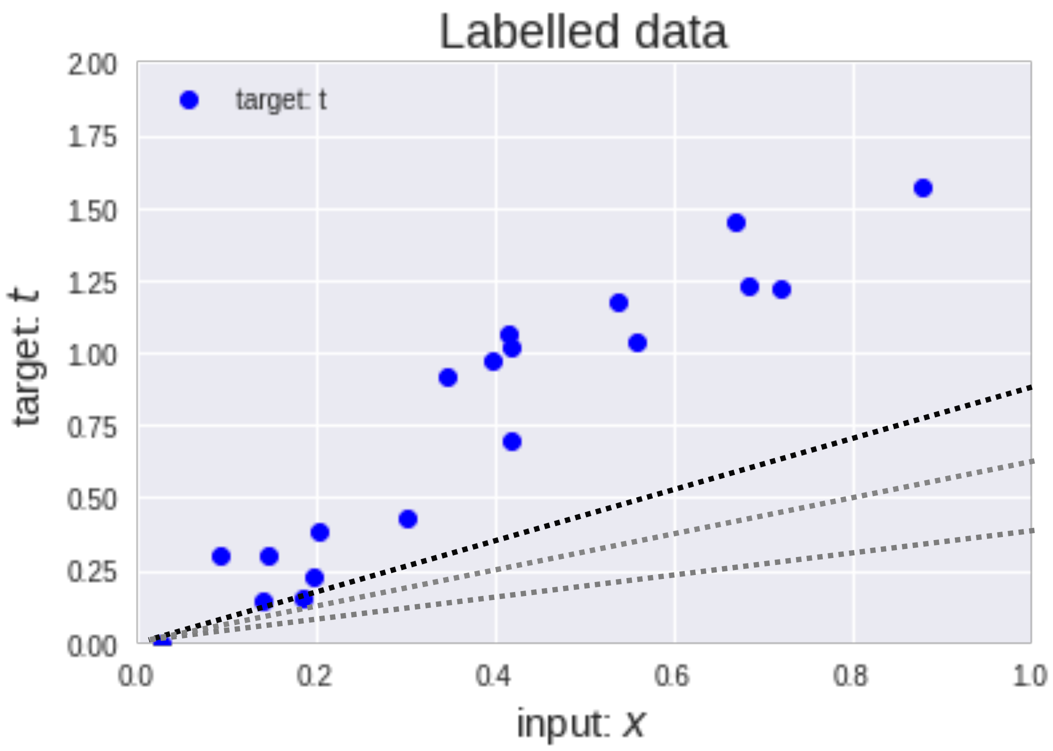




Source: https://bit.ly/2IoAGzL

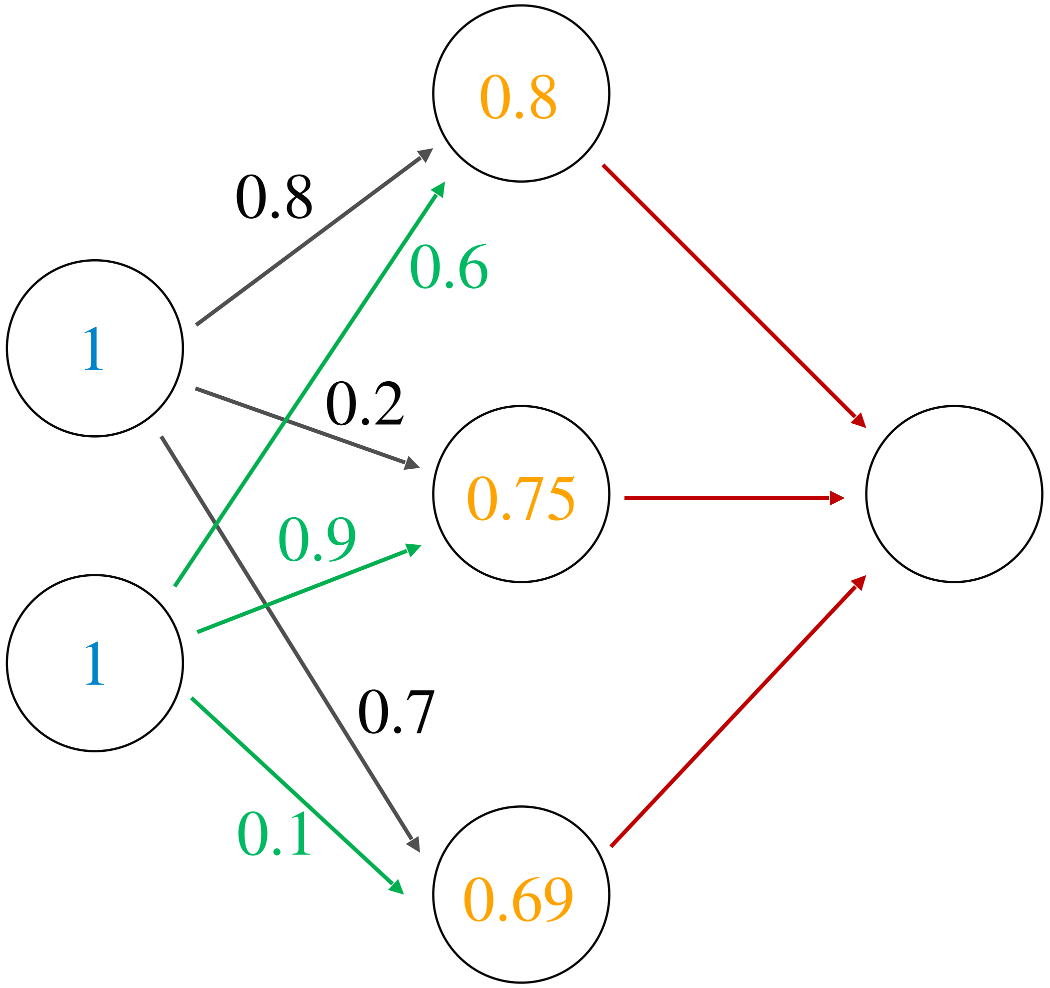
Small Learning Rate





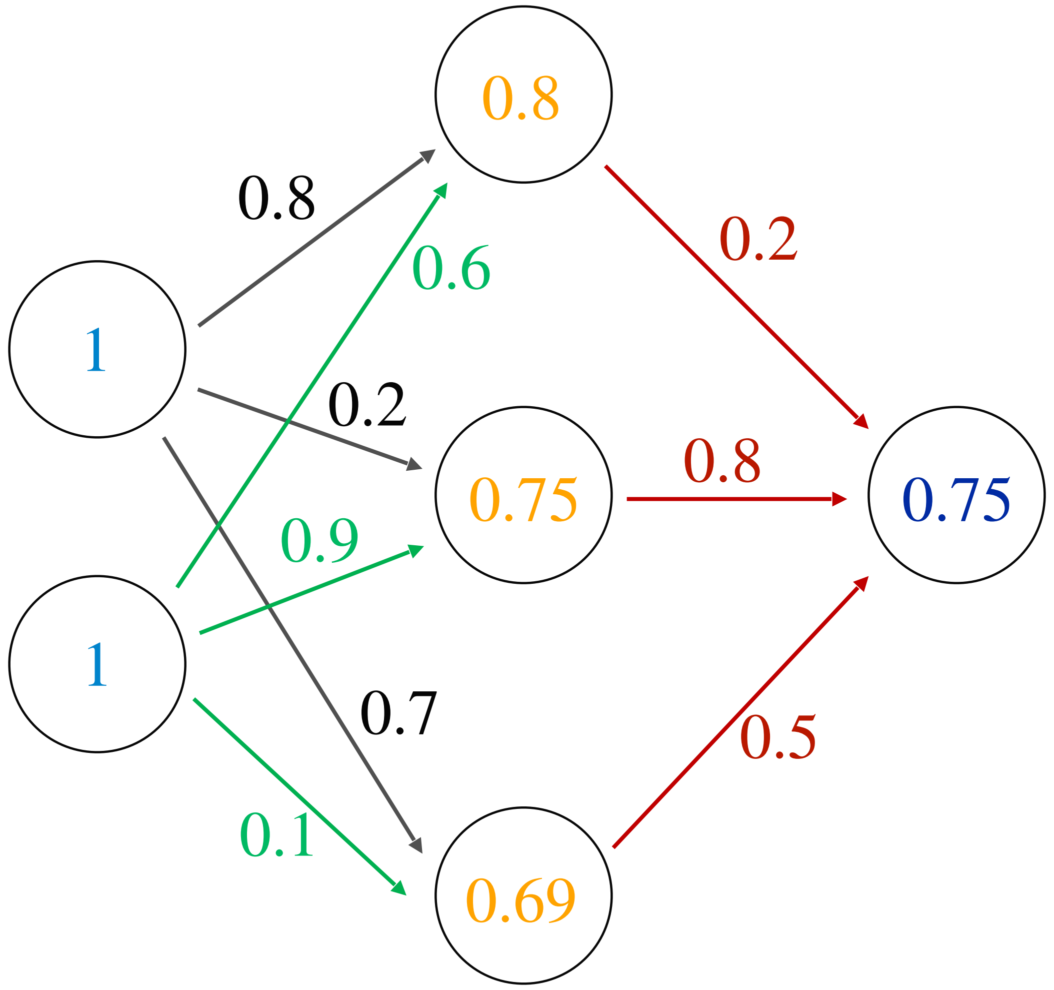
Source: https://bit.ly/2IoAGzL

Simplified Two-Layer ANN



$$h_1 = \sigma(1x0.8 + 1x0.6) = 0.80$$
$$h_2 = \sigma(1x0.2 + 1x0.9) = 0.75$$
$$h_3 = \sigma(1x0.7 + 1x0.1) = 0.69$$

Simplified Two-Layer ANN

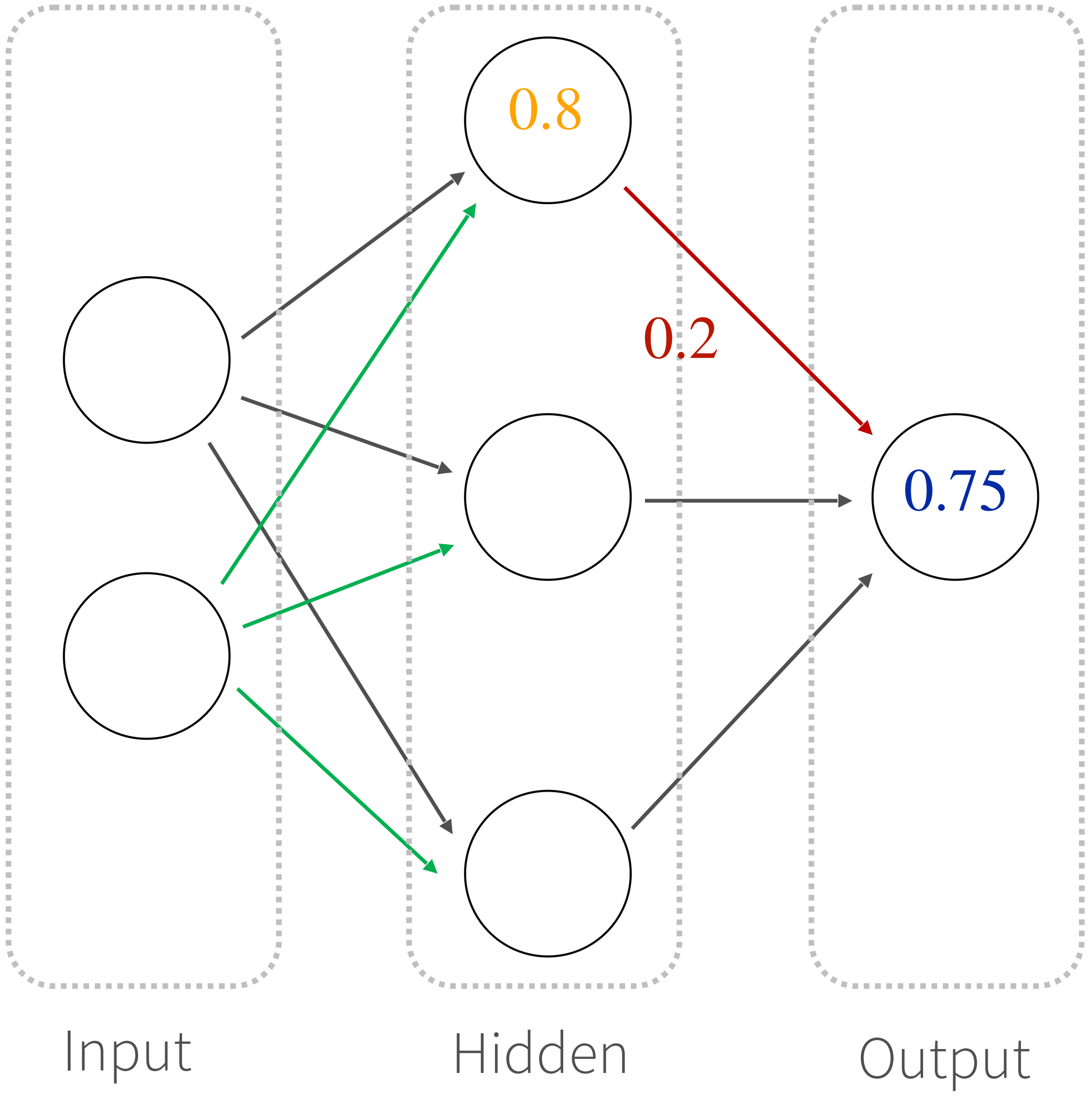


$$out = \sigma(0.2x0.8 + 0.8x0.75 + 0.5x0.69)$$

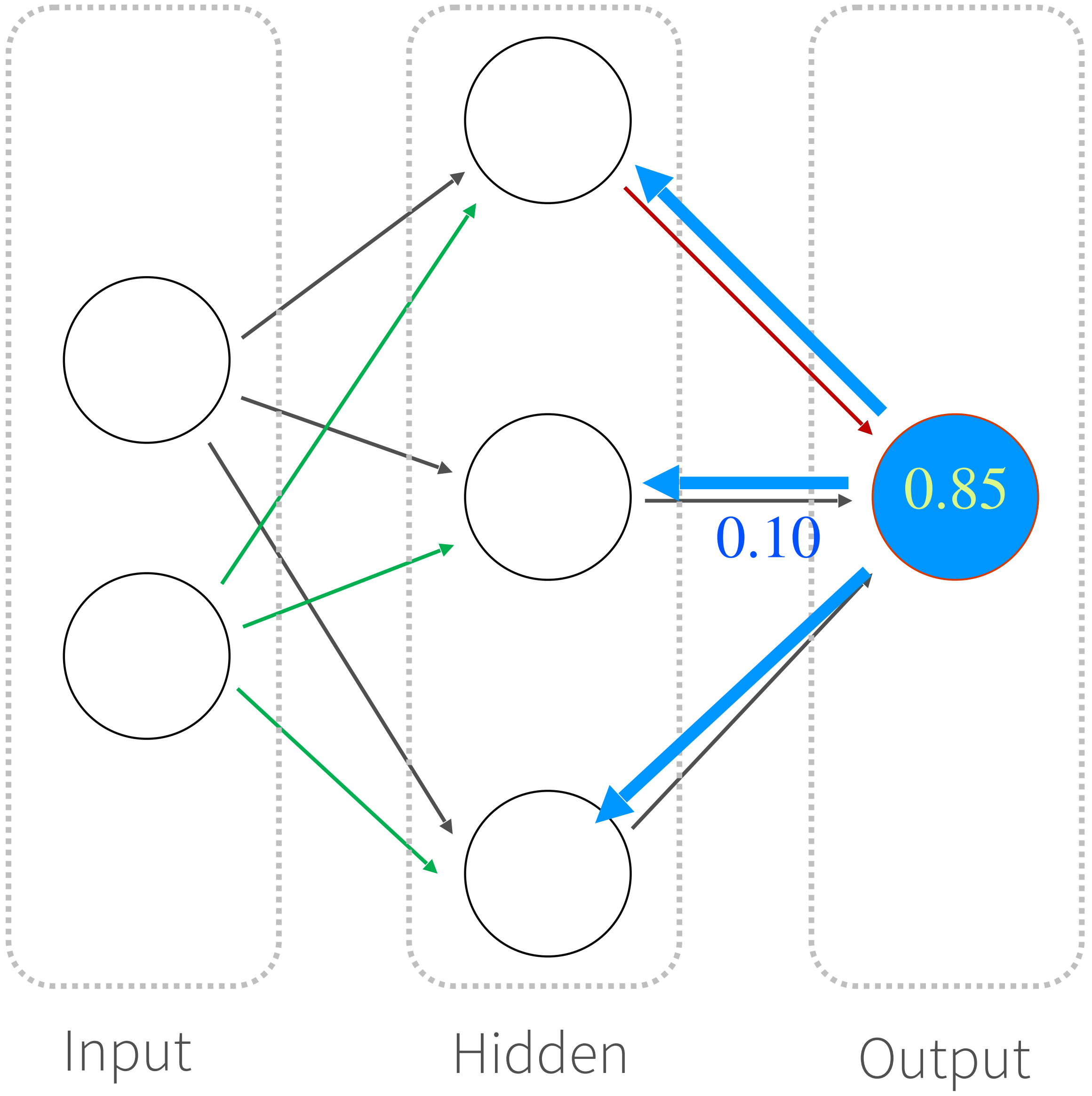
$$= \sigma(1.105)$$

$$= 0.75$$

Backpropagation

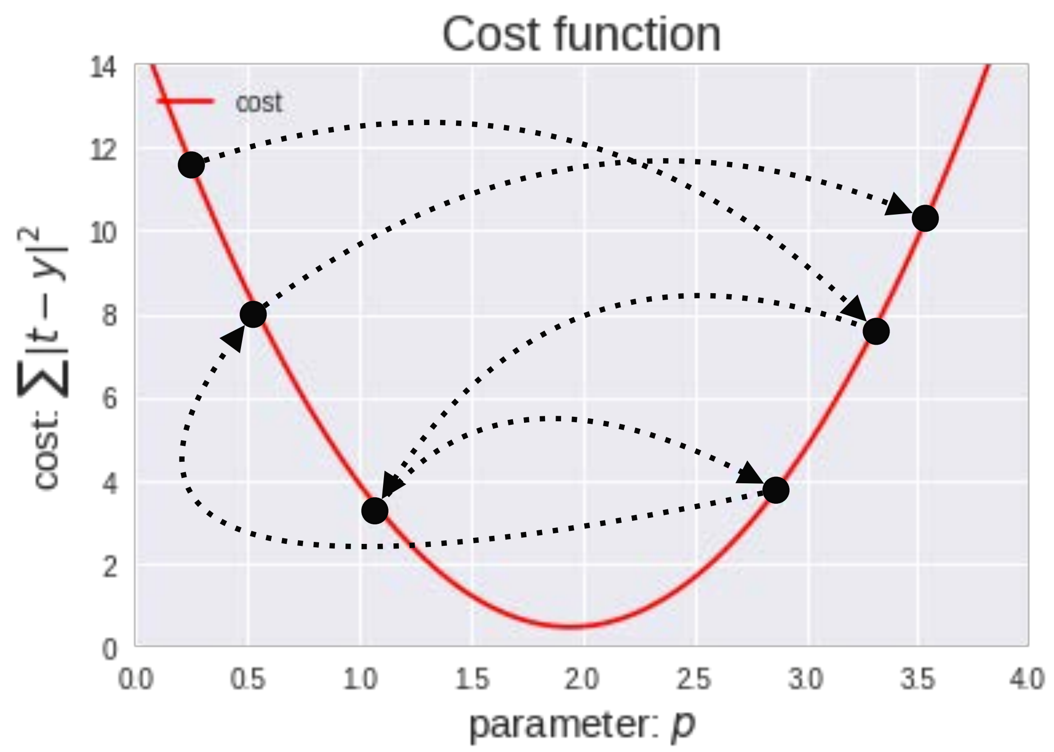


Backpropagation



- Backpropagation: calculate the gradient of the cost function in a neural network
- Used by gradient descent optimization algorithm to adjust weight of neurons
- Also known as backward propagation of errors **as the error is calculated and distributed back through the network of layers**

Sigmoid function (continued)



Source: https://bit.ly/2IoAGzL

Output is not zero-centered: During gradient descent, if all values are positive then during backpropagation the weights will become all positive or all negative creating zig zagging dynamics.

Learning Rate Callouts

- Too small, it may take too long to get minima
- Too large, it may skip the minima altogether

Optimization

Optimization Overview

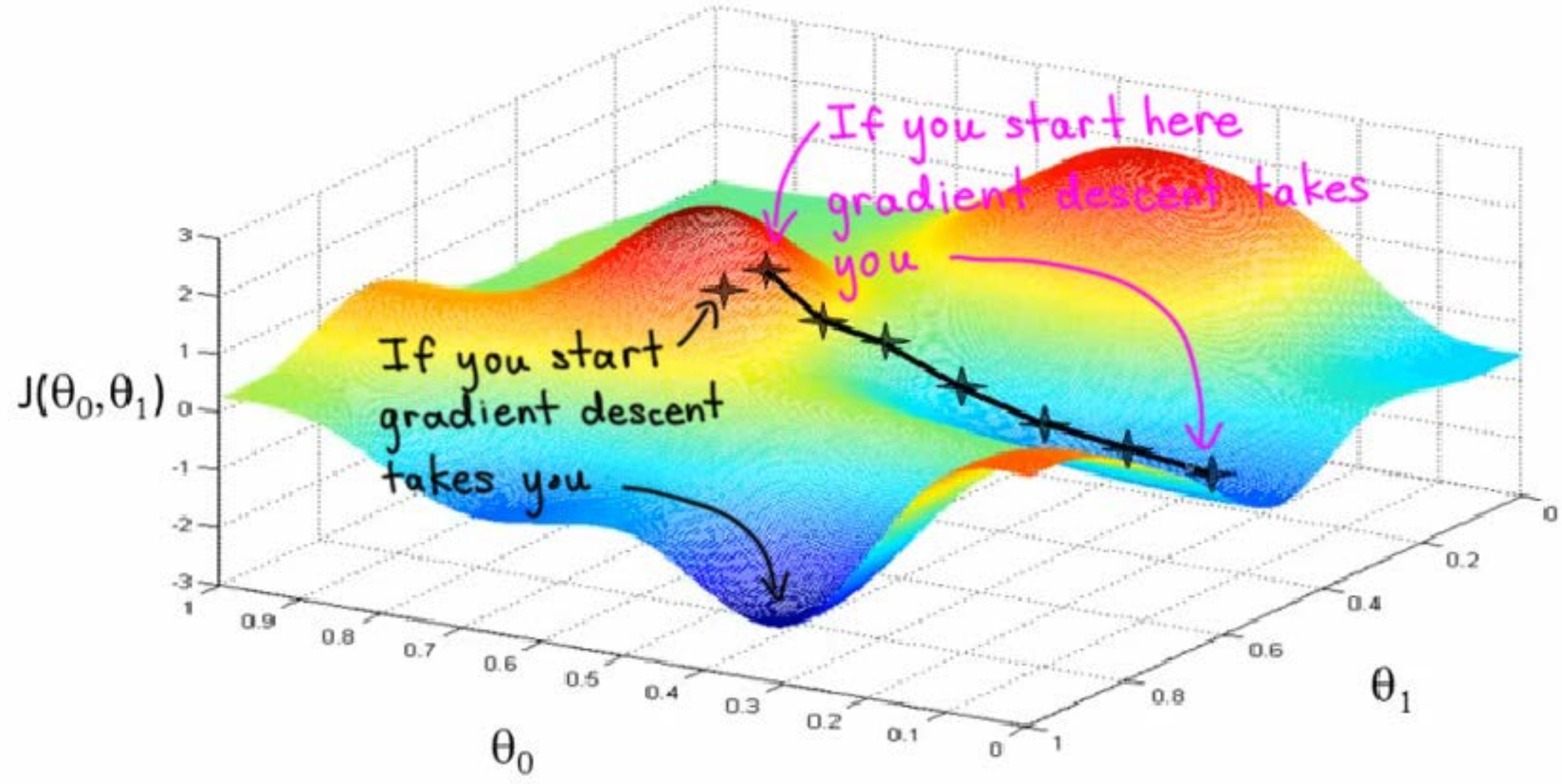
- After backpropagation, the <u>parameters are updated</u> based on the gradients calculated
- There are several approaches in this area of active research; we will focus on:
  - Stochastic Gradient Descent
  - Momentum, NAG
  - Per-parameter adaptive learning rate methods

Stochastic Gradient Descent

- (Batch) Gradient Descent is computed on the full dataset (not efficient for large scale models and datasets).
- Often converges faster because it performs updates more frequently
- But due to frequent updates, this may complicate convergence to the exact minima
- For more information, refer to:
  - Andrew Ng's 2. Stochastic Gradient (https://goo.gl/bNrJbx)
  - Types of Optimization Algorithms used in Neural Networks and Ways to Optimize Gradient Descent (https://goo.gl/tB2e7S)

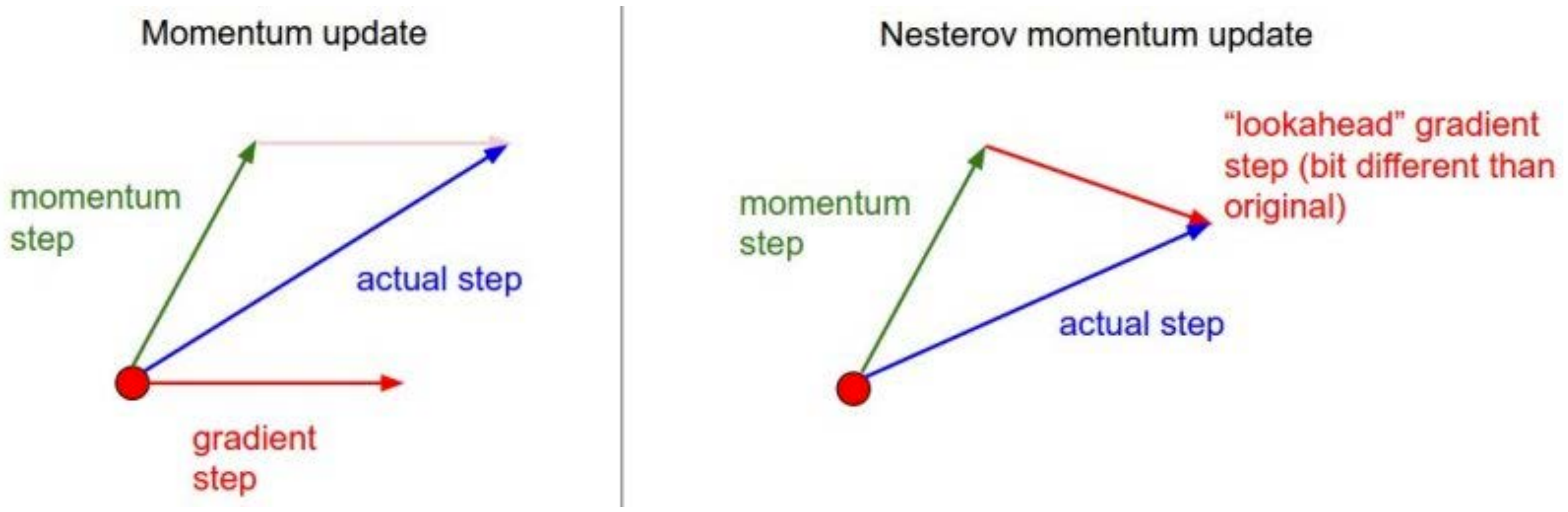
Gradient Descent

Source: https://goo.gl/VUX2ZS



Momentum and NAG

- Obtain faster convergence by helping parameter vector build up velocity
  - i.e. use the momentum of the gradient to converge faster
- Nesterov Accelerated Gradient (NAG): optimized version of Momentum
  - Typically works better in practice than Momentum



Source: http://cs231n.github.io/neural-networks-3

Annealing the learning rate

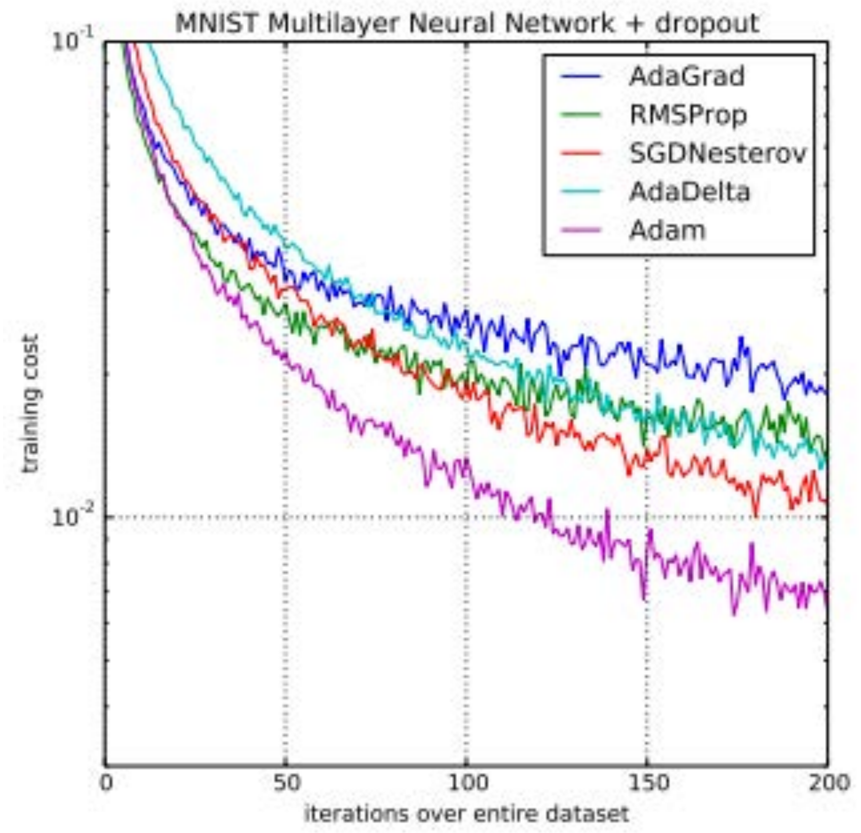
- i.e. slow down the learning rate to prevent it from bouncing around too much
- Referred as the **decay** parameter (i.e., the learning rate decay over each update) to reduce kinetic energy
- Note, this is different from **rho** (i.e. exponentially weighted average or exponentially weighted decay of past gradients) to smooth the descent path trajectory

Per-parameter adaptive learning rate methods

- Adaptively tune learning rates at the parameter level
- Popular methods include:
  - **Adaptive Gradient Algorithm (AdaGrad)** improves performance on problems with sparse gradients (e.g. natural language and computer vision problems).
  - **Root Mean Square Propagation (RMSProp)** maintains per-parameter learning rates based on the average of recent magnitudes of the gradients for the weight (e.g. how quickly it is changing). This means the algorithm does well on online and non-stationary problems (e.g. noisy).
  - **AdaDelta**: Per dimension learning rate method for gradient descent with minimal computational overhead, requires no manual tuning, and quite robust

Which Optimizer?

Source: https://goo.gl/2da4WY



"In practice Adam is currently recommended as the default algorithm to use, and often works slightly better than RMSProp. However, it is often also worth trying SGD+Nesterov Momentum as an alternative.."

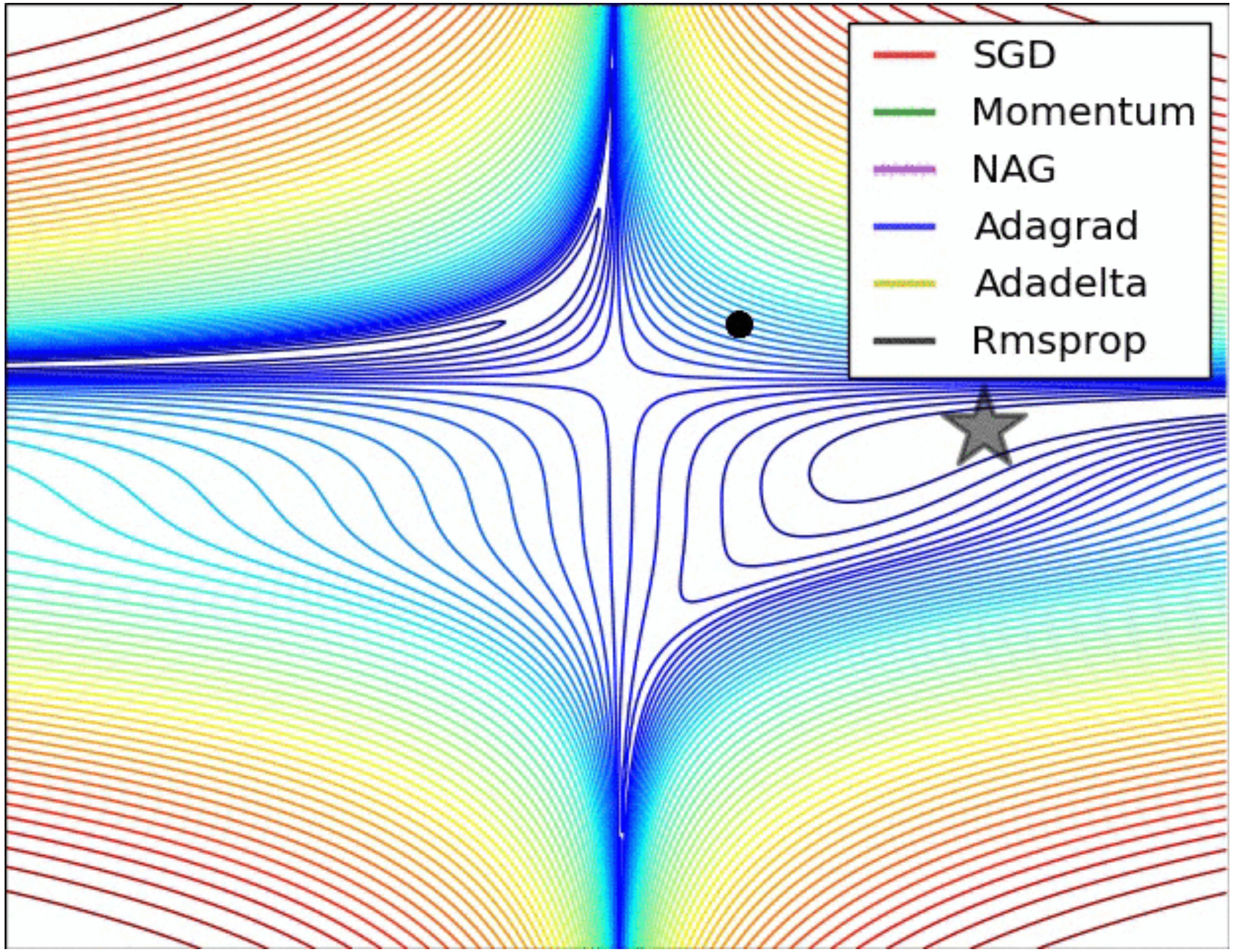
Andrej Karpathy, et al, CS231n

Comparison of Adam to Other Optimization Algorithms Training a Multilayer Perceptron
Taken from Adam: A Method for Stochastic Optimization, 2015.

Optimization on loss surface contours

Source: http://cs231n.github.io/neural-networks-3/#hyper

Image credit: [Alec Radford](#)



Adaptive algorithms converge quickly and find the right direction for the parameters.

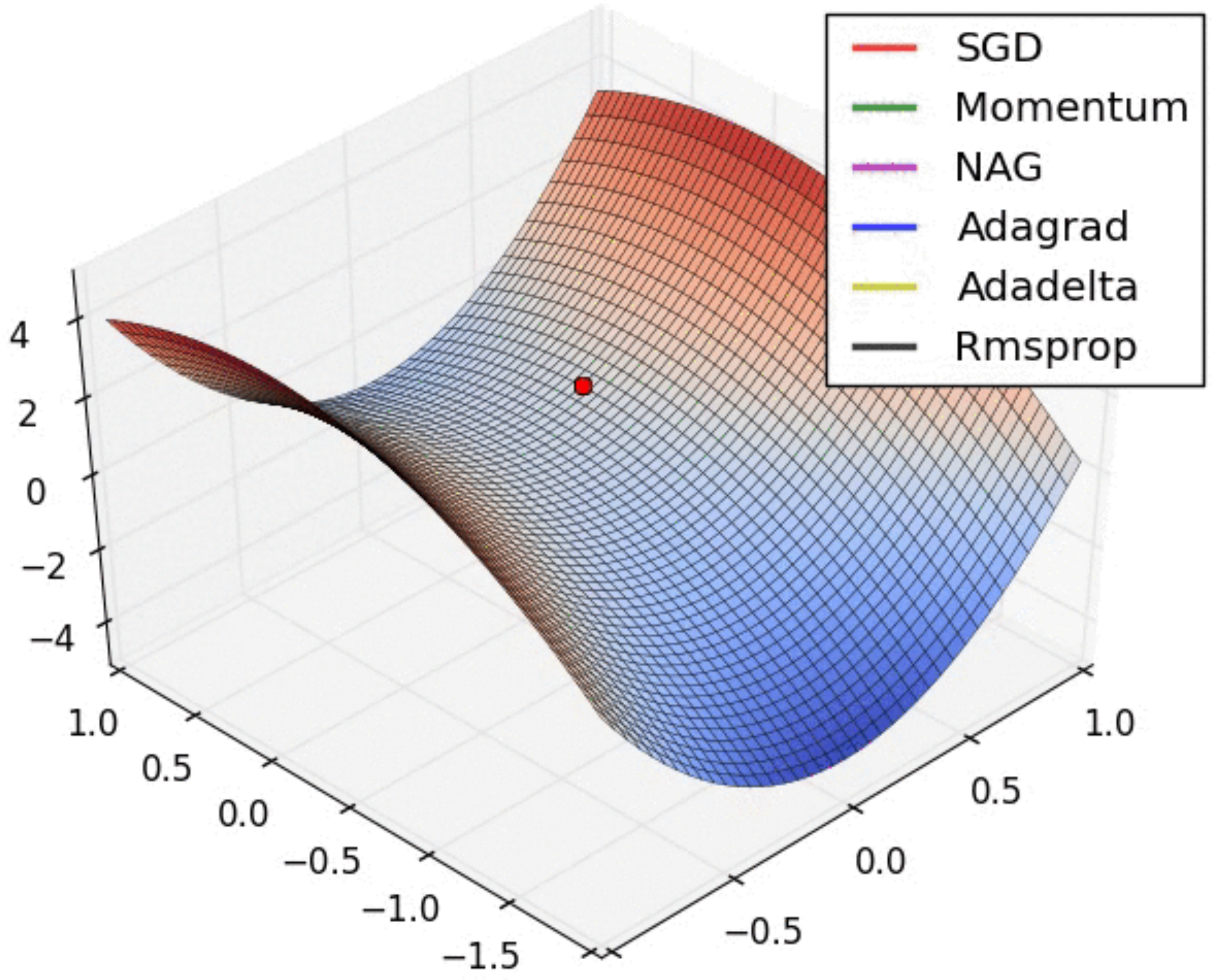
In comparison, SGD is slow

Momentum-based methods overshoot

Optimization on saddle point

Source: http://cs231n.github.io/neural-networks-3/#hyper

Image credit: Alec Radford



Notice how SGD gets stuck near the top

Meanwhile adaptive techniques optimize the fastest

Good References

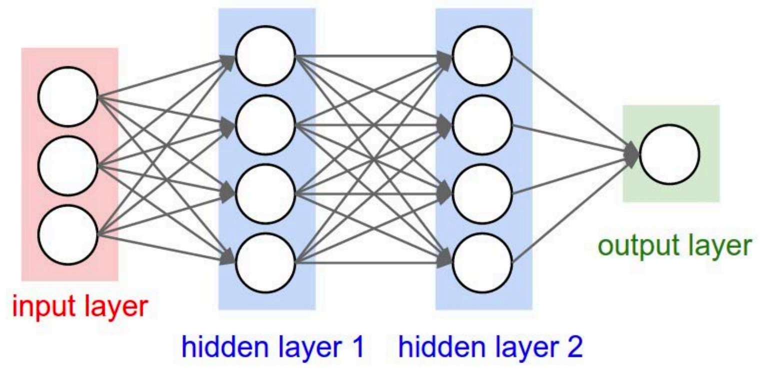
- Suki Lau's Learning Rate Schedules and Adaptive Learning Rate Methods for Deep Learning
- CS23n Convolutional Neural Networks for Visual Recognition
- Fundamentals of Deep Learning
- ADADELTA: An Adaptive Learning Rate Method
- Gentle Introduction to the Adam Optimization Algorithm for Deep Learning

Convolutional Networks

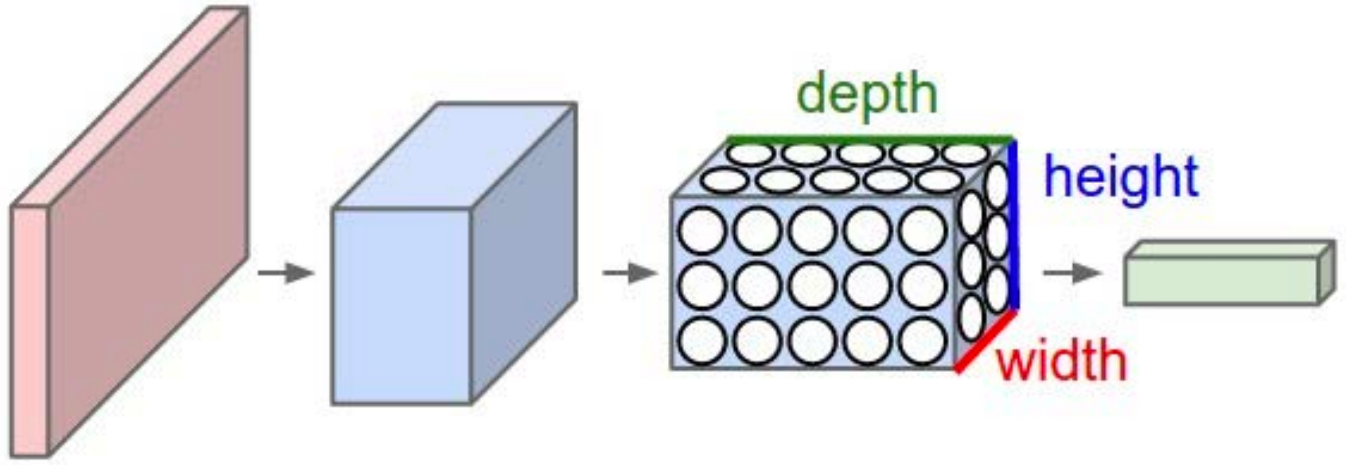
Convolutional Neural Networks

- Similar to Artificial Neural Networks but CNNs (or ConvNets) make explicit assumptions that the input are images
- Regular neural networks do not scale well against images
  - E.g. CIFAR-10 images are 32x32x3 (32 width, 32 height, 3 color channels) = 3072 weights – somewhat manageable
  - A larger image of 200x200x3 = 120,000 weights
- CNNs have neurons arranged in 3D: width, height, depth.
  - Neurons in a layer will only be connected to a small region of the layer before it, i.e. **NOT all of the neurons in a fully-connected manner**.
  - Final output layer for CIFAR-10 is 1x1x10 as we will reduce the full image into a single vector of class scores, arranged along the depth dimension

CNNs / ConvNets



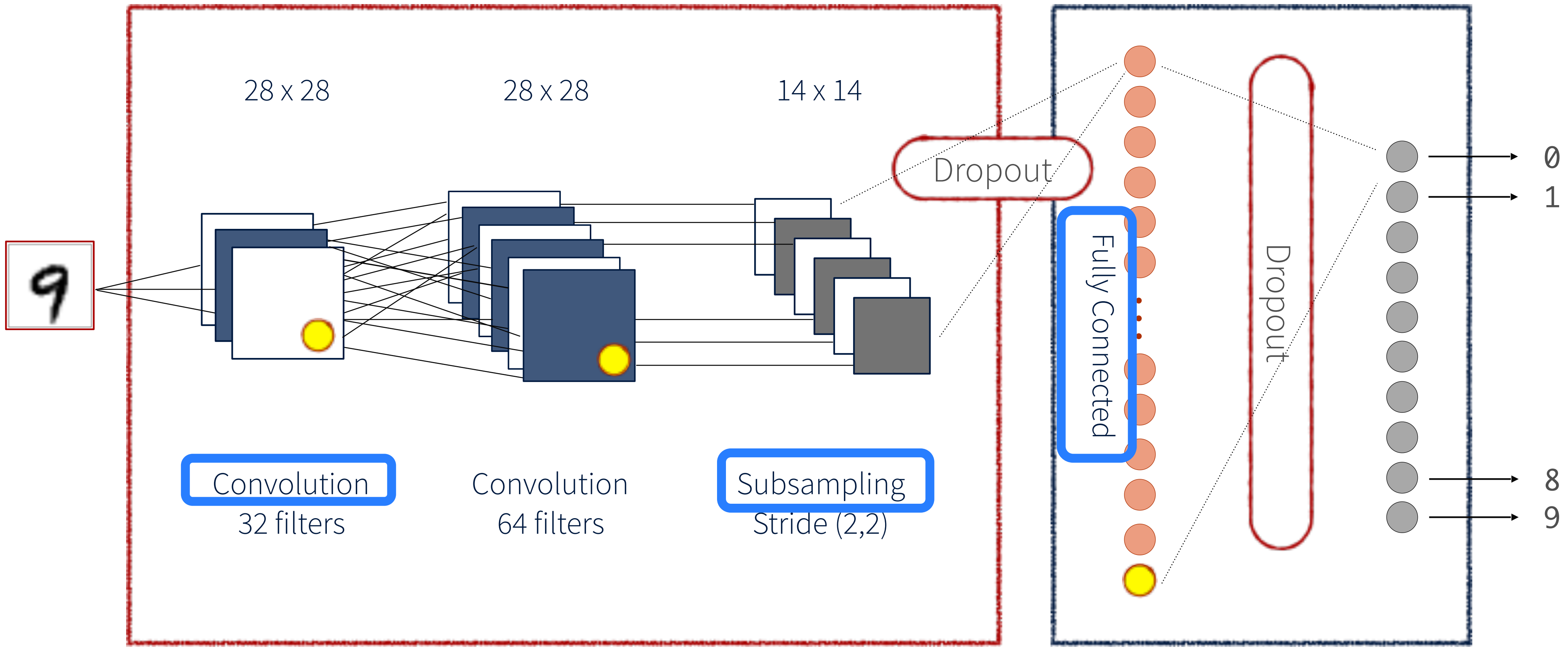
Regular 3-layer neural network



- ConvNet arranges neurons in 3 dimensions
- 3D input results in 3D output

Source: https://cs231n.github.io/convolutional-networks/

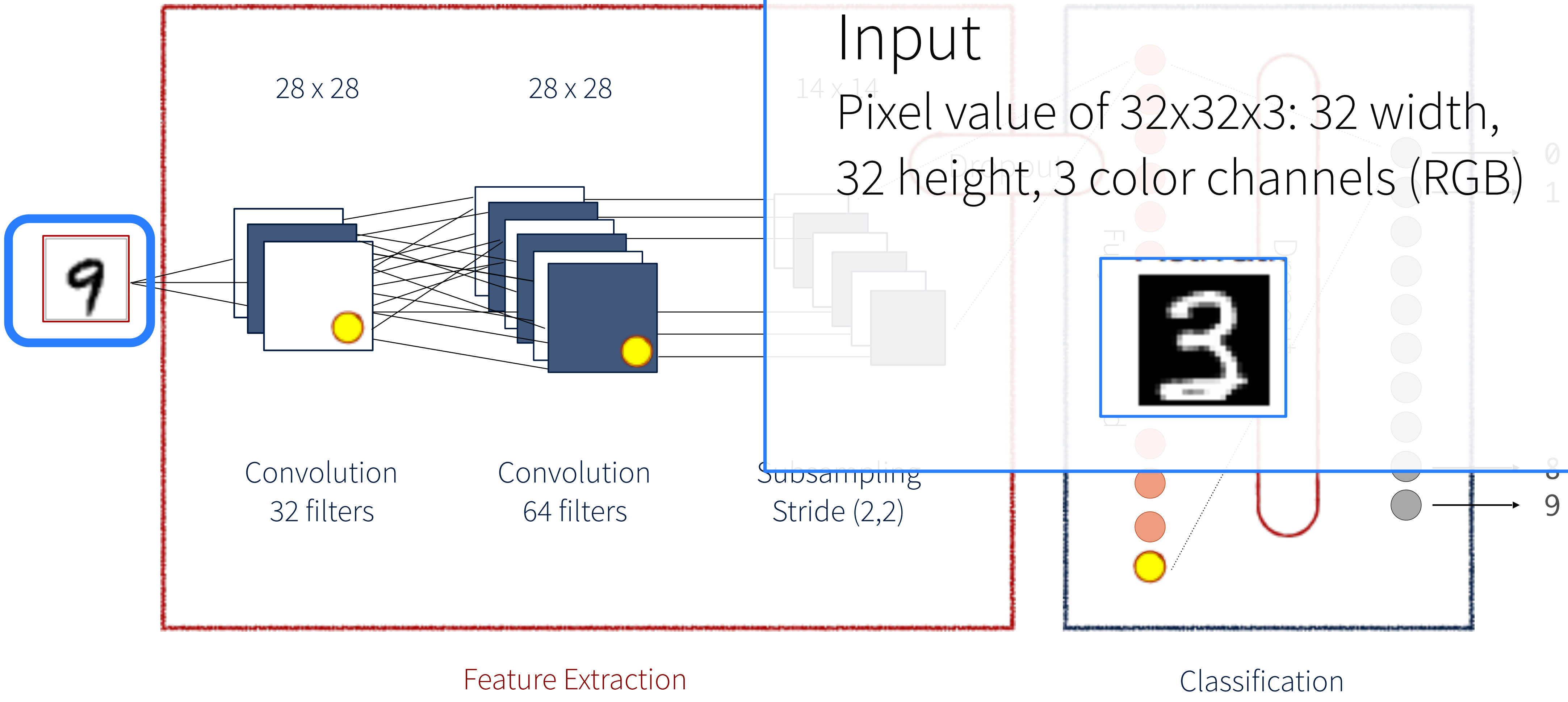
Convolutional Neural Networks



Feature Extraction

Classification

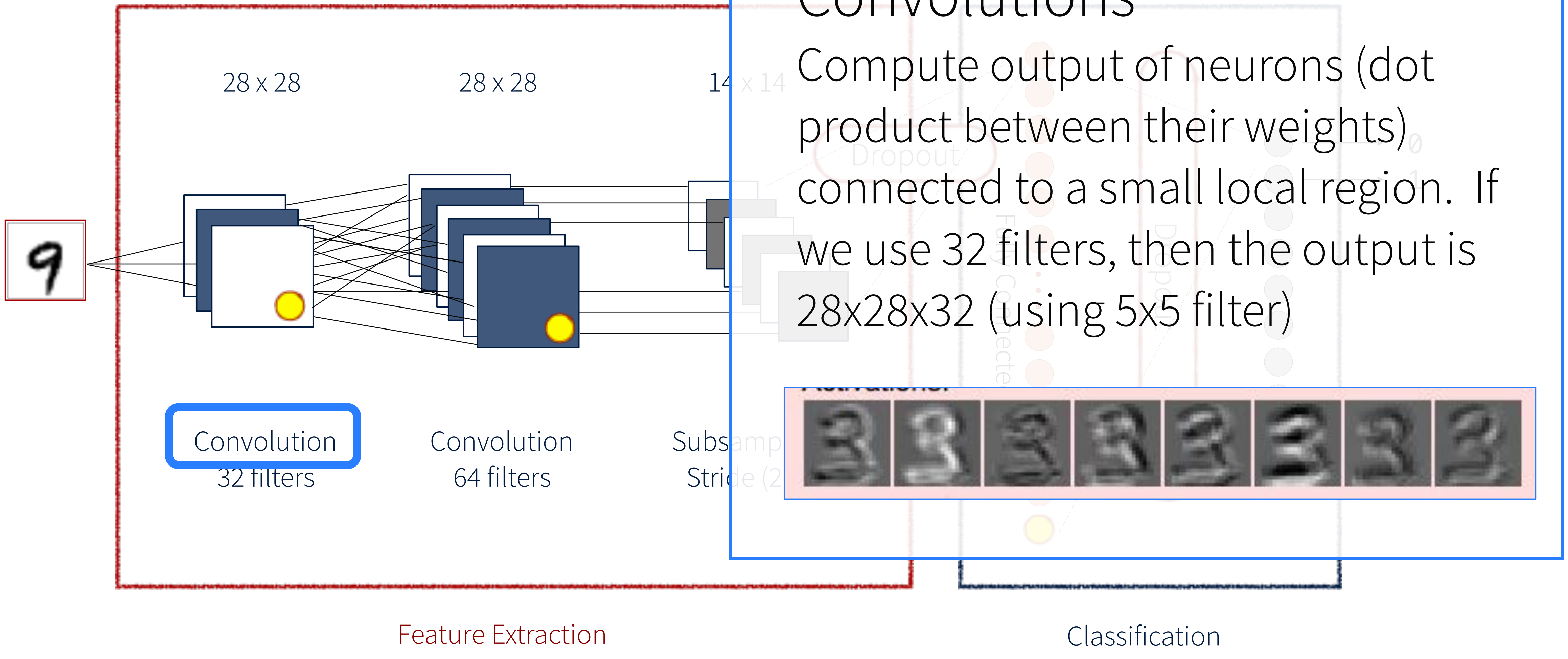
Convolutional Neural Networks



Input

Pixel value of 32x32x3: 32 width, 32 height, 3 color channels (RGB)

Convolutional Neural Networks



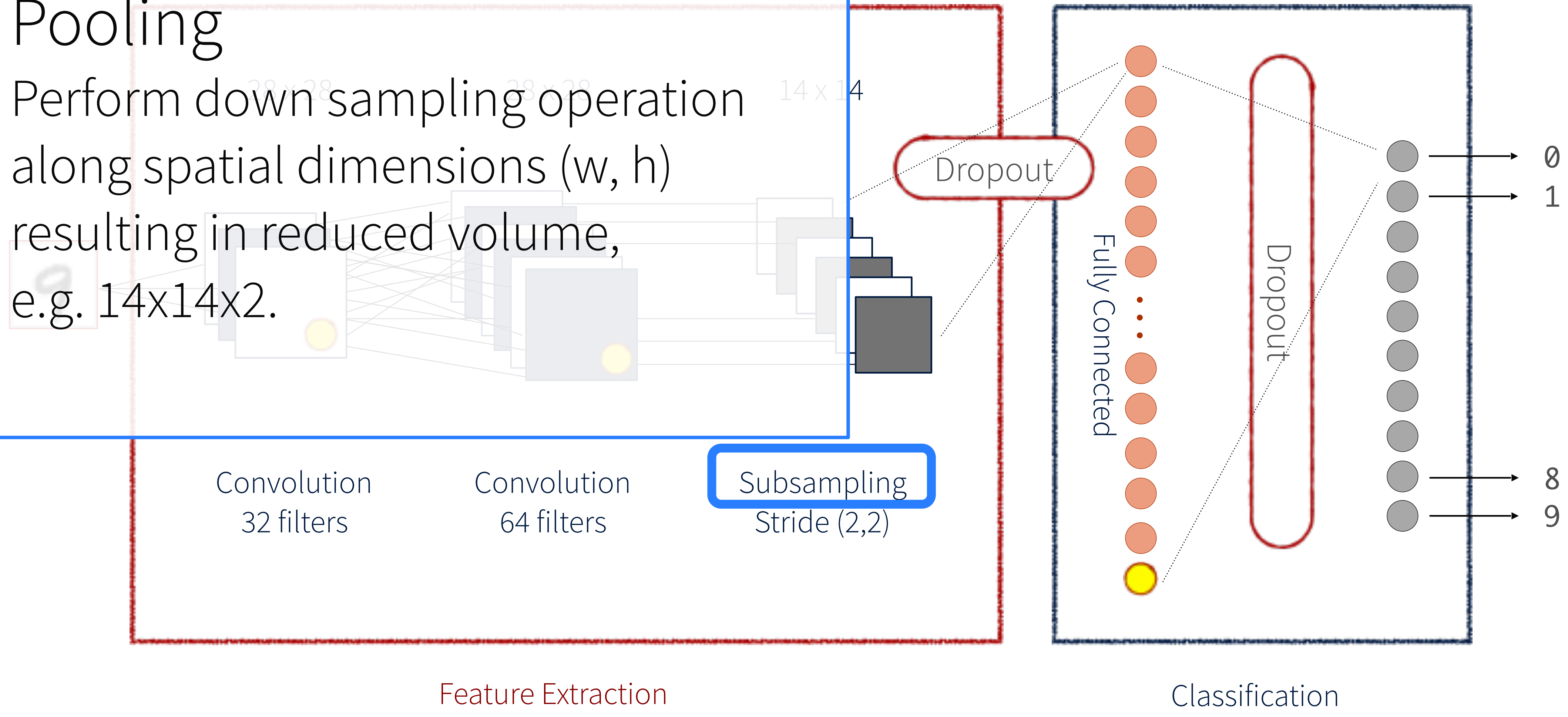
Convolutions

Compute output of neurons (dot product between their weights) connected to a small local region. If we use 32 filters, then the output is 28x28x32 (using 5x5 filter)

Convolutional Neural Networks

Pooling

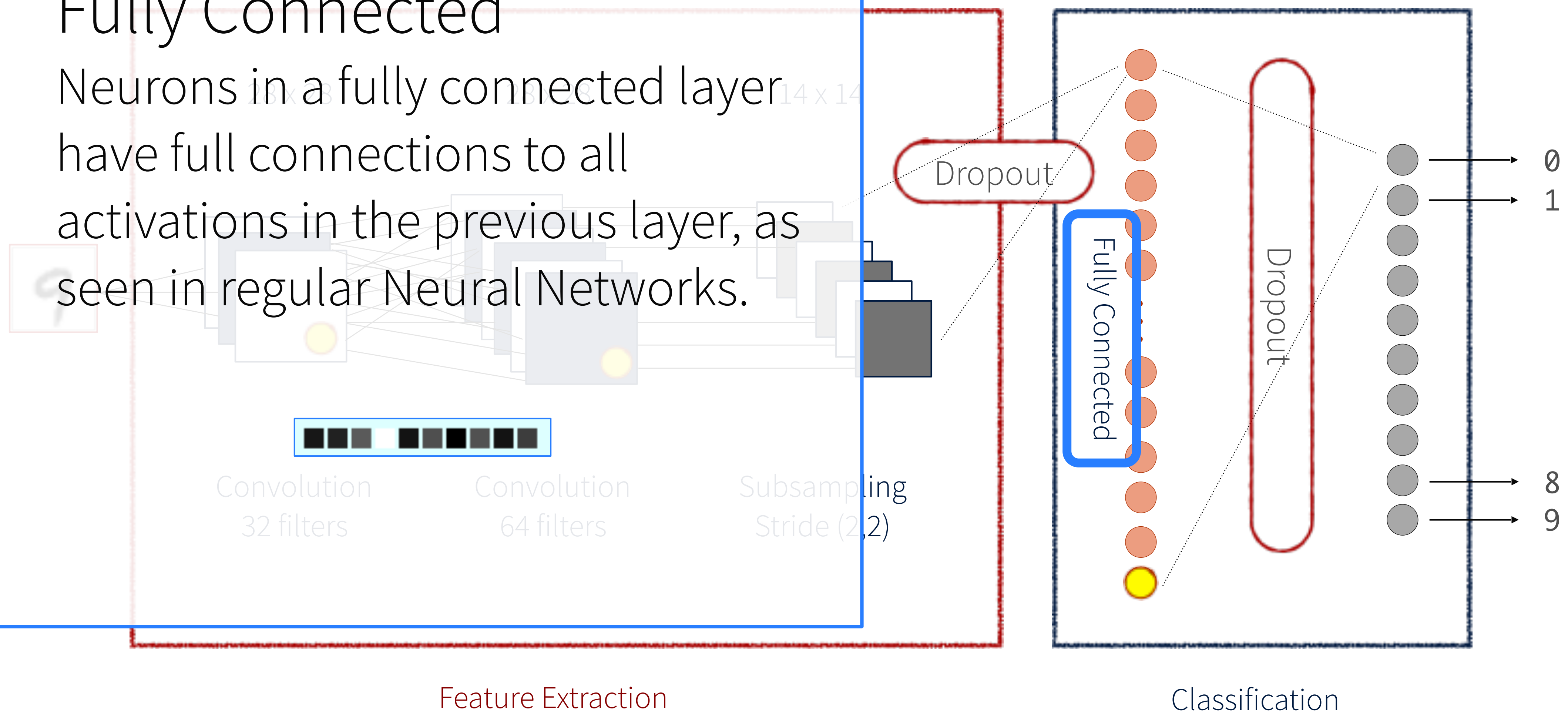
Perform down sampling operation along spatial dimensions (w, h) resulting in reduced volume, e.g. 14x14x2.



Convolutional Neural Networks

Fully Connected

Neurons in a fully connected layer have full connections to all activations in the previous layer, as seen in regular Neural Networks.



ConvNetJS MNIST Demo

https://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html

DEMO

Neurons . . . Activate!

I’d like to thank…

Great References

- Andrej Karparthy's ConvNetJS MNIST Demo
- What is back propagation in neural networks?
- CS231n: Convolutional Neural Networks for Visual Recognition
    - Syllabus and Slides | Course Notes | YouTube
    - With particular focus on CS231n: Lecture 7: Convolution Neural Networks
- Neural Networks and Deep Learning
- TensorFlow

Great References

- Deep Visualization Toolbox
- Back Propagation with TensorFlow
- TensorFrames: Google TensorFlow with Apache Spark
- Integrating deep learning libraries with Apache Spark
- Build, Scale, and Deploy Deep Learning Pipelines with Ease

Attribution

Tomek Drabas

Brooke Wenig

Timothee Hunter

Cyrielle Simeone

Q&A

What's next?

Applying your Convolutional Neural Networks

October 24th, 2019

3pm Sydney | 12pm Singapore | 9.30am Mumbai

https://databricks.com/tensorflow/deep-learning-event