Advanced Data Visualization

CS 6965

Fall 2019

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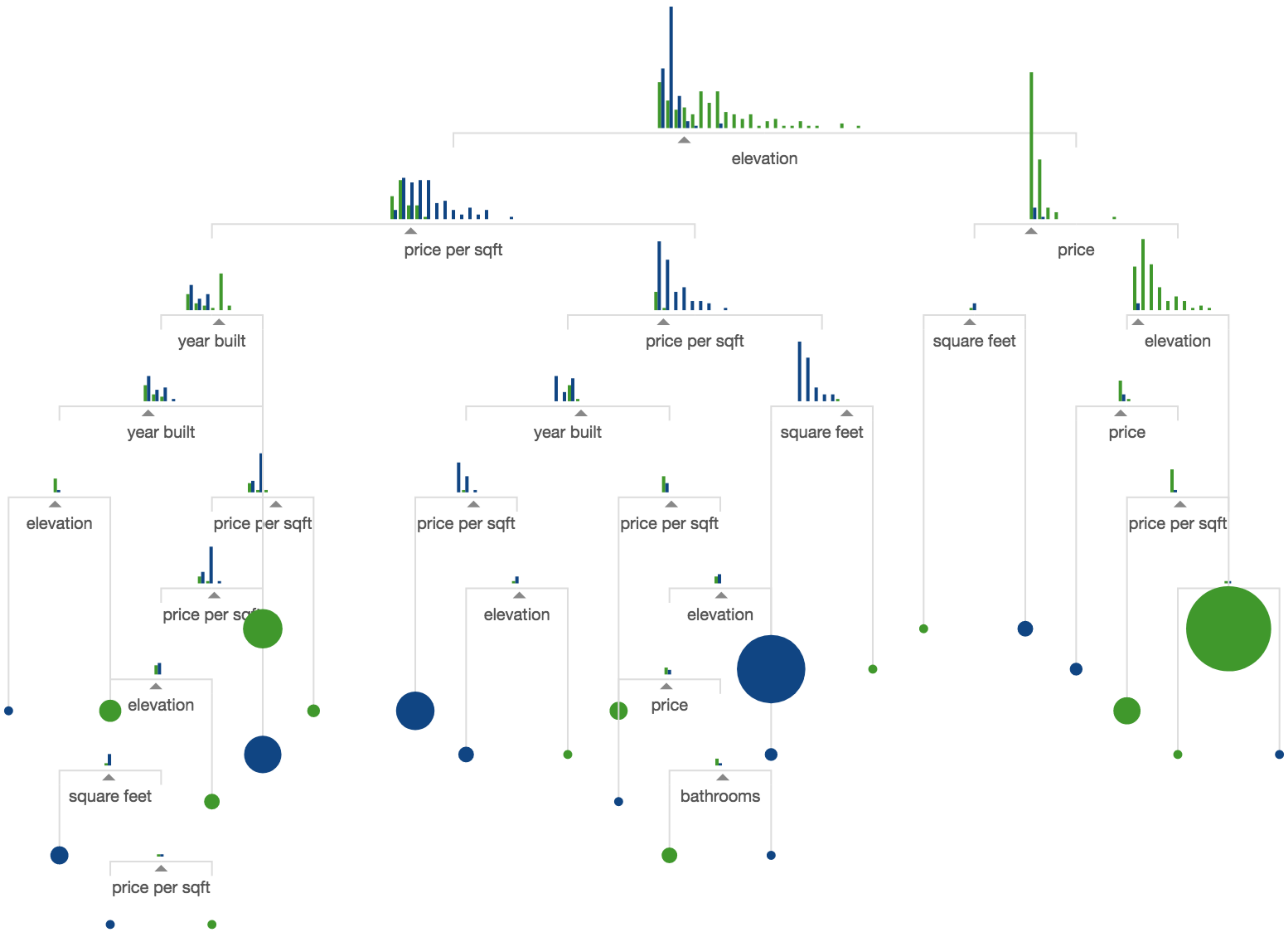
University of Utah

Lecture 12

Decision Tree, Deep Learning and Vis

HD

Decision Tree
in a nutshell



By Tony Chu at noodle.io

http://www.r2d3.us/visual-intro-to-machine-learning-part-1/

Decision tree on a high-level

- The notion of a contingency table: like 1D, 2D and 3D histograms

age	employme	education	edun	marital	...	job	relation	race	gender	hour	country	wealth
					...							
39	State_gov	Bachelors	13	Never_mar	...	Adm_cleric	Not_in_fam	White	Male	40	United_Sta	poor
51	Self_emp_	Bachelors	13	Married	...	Exec_man	Husband	White	Male	13	United_Sta	poor
39	Private	HS_grad	9	Divorced	...	Handlers_c	Not_in_fam	White	Male	40	United_Sta	poor
54	Private	11th	7	Married	...	Handlers_c	Husband	Black	Male	40	United_Sta	poor
28	Private	Bachelors	13	Married	...	Prof_speci	Wife	Black	Female	40	Cuba	poor
38	Private	Masters	14	Married	...	Exec_man	Wife	White	Female	40	United_Sta	poor
50	Private	9th	5	Married_sp	...	Other_serv	Not_in_fam	Black	Female	16	Jamaica	poor
52	Self_emp_	HS_grad	9	Married	...	Exec_man	Husband	White	Male	45	United_Sta	rich
31	Private	Masters	14	Never_mar	...	Prof_speci	Not_in_fam	White	Female	50	United_Sta	rich
42	Private	Bachelors	13	Married	...	Exec_man	Husband	White	Male	40	United_Sta	rich
37	Private	Some_coll	10	Married	...	Exec_man	Husband	Black	Male	80	United_Sta	rich
30	State_gov	Bachelors	13	Married	...	Prof_speci	Husband	Asian	Male	40	India	rich
24	Private	Bachelors	13	Never_mar	...	Adm_cleric	Own_child	White	Female	30	United_Sta	poor
33	Private	Assoc_acc	12	Never_mar	...	Sales	Not_in_fam	Black	Male	50	United_Sta	poor
41	Private	Assoc_voc	11	Married	...	Craft_repai	Husband	Asian	Male	40	*MissingVa	rich
34	Private	7th_8th	4	Married	...	Transport_	Husband	Amer_India	Male	45	Mexico	poor
26	Self_emp_	HS_grad	9	Never_mar	...	Farming_fi	Own_child	White	Male	35	United_Sta	poor
33	Private	HS_grad	9	Never_mar	...	Machine_o	Unmarried	White	Male	40	United_Sta	poor
38	Private	11th	7	Married	...	Sales	Husband	White	Male	50	United_Sta	poor
44	Self_emp_	Masters	14	Divorced	...	Exec_man	Unmarried	White	Female	45	United_Sta	rich
41	Private	Doctorate	16	Married	...	Prof_speci	Husband	White	Male	60	United_Sta	rich
:	:	:	:	:	:	:	:	:	:	:	:	:

(agegroup,wealth)

wealth values: poor rich

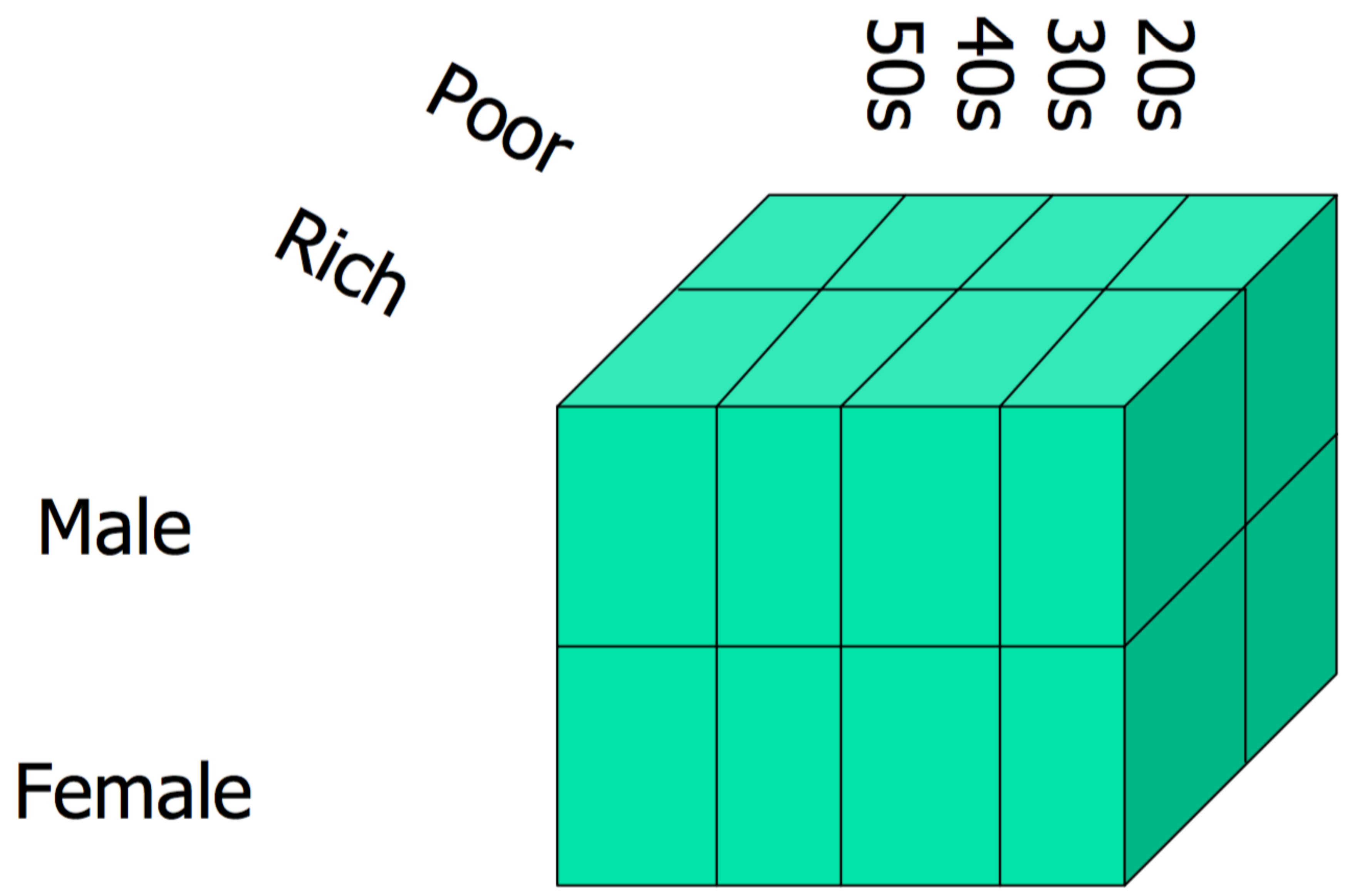
agegroup	poor	rich
10s	2507	3
20s	11262	743
30s	9468	3461
40s	6738	3986
50s	4110	2509
60s	2245	809
70s	668	147
80s	115	16
90s	42	13

2D contingency table

http://www.cs.cmu.edu/~./awm/tutorials/dtree.html

3D contingency table

- Goal: avoid manually looking at contingency tables
- For example, 100 variables, 161700 tables…
- Instead, using information theory to decide whether a pattern is interesting, such as entropy or information gain



http://www.cs.cmu.edu/~./awm/tutorials/dtree.html

Is a pattern interesting?

- Finding the attribute with the highest information gain

wealth values: poor rich

		poor	rich	
relation	Husband	10870	8846	H(wealth | relation = Husband) = 0.992385
	Not_in_family	11307	1276	H(wealth | relation = Not_in_family) = 0.473439
	Other_relative	1454	52	H(wealth | relation = Other_relative) = 0.216617
	Own_child	7470	111	H(wealth | relation = Own_child) = 0.110192
	Unmarried	4816	309	H(wealth | relation = Unmarried) = 0.328606
	Wife	1238	1093	H(wealth | relation = Wife) = 0.997207

H(wealth) = 0.793844 H(wealth|relation) = 0.628421

IG(wealth|relation) = 0.165423

Information Gain

What is Information Gain used for?

Suppose you are trying to predict whether someone is going live past 80 years. From historical data you might find…

- IG(LongLife | HairColor) = 0.01
- IG(LongLife | Smoker) = 0.2
- IG(LongLife | Gender) = 0.25
- IG(LongLife | LastDigitOfSSN) = 0.00001

IG tells you how interesting a 2-d contingency table is going to be.

http://www.cs.cmu.edu/~./awm/tutorials/infogain11.pdf

Entropy

General Case

Suppose X can have one of *m* values... $V_1, V_2, \ldots V_m$

$P(X=V_1) = p_1$	$P(X=V_2) = p_2$	....	$P(X=V_m) = p_m$

What's the smallest possible number of bits, on average, per symbol, needed to transmit a stream of symbols drawn from X's distribution? It's

$$H(X) = -p_1 \log_2 p_1 - p_2 \log_2 p_2 - \ldots - p_m \log_2 p_m$$

$$= -\sum_{j=1}^{m} p_j \log_2 p_j$$

H(X) = The entropy of X

- "High Entropy" means X is from a uniform (boring) distribution
- "Low Entropy" means X is from varied (peaks and valleys) distribution

http://www.cs.cmu.edu/~./awm/tutorials/infogain11.pdf

Conditional entropy

Specific Conditional Entropy H(Y|X=v)

X = College Major

Y = Likes "Gladiator"

X	Y
Math	Yes
History	No
CS	Yes
Math	No
Math	No
CS	Yes
History	No
Math	Yes

Definition of Specific Conditional Entropy:

H(Y |X=v) = The entropy of *Y* among only those records in which *X* has value *v*

Example:

- $H(Y|X=Math) = 1$
- $H(Y|X=History) = 0$
- $H(Y|X=CS) = 0$

Conditional Entropy

X = College Major

Y = Likes "Gladiator"

X	Y
Math	Yes
History	No
CS	Yes
Math	No
Math	No
CS	Yes
History	No
Math	Yes

Definition of Conditional Entropy:

H(Y|X) = The average conditional entropy of *Y*

$= \Sigma_j Prob(X=v_j)\ H(Y \mid X = v_j)$

Example:

v_j	$Prob(X=v_j)$	$H(Y \mid X = v_j)$
Math	0.5	1
History	0.25	0
CS	0.25	0

$H(Y|X) = 0.5 * 1 + 0.25 * 0 + 0.25 * 0 = 0.5$

http://www.cs.cmu.edu/~./awm/tutorials/infogain11.pdf

Information Gain

Information Gain

X = College Major

Y = Likes "Gladiator"

X	Y
Math	Yes
History	No
CS	Yes
Math	No
Math	No
CS	Yes
History	No
Math	Yes

Definition of Information Gain:

$IG(Y|X)$ = I must transmit Y. How many bits on average would it save me if both ends of the line knew X?

$$IG(Y|X) = H(Y) - H(Y \mid X)$$

Example:

- $H(Y) = 1$
- $H(Y|X) = 0.5$
- Thus $IG(Y|X) = 1 - 0.5 = 0.5$

http://www.cs.cmu.edu/~./awm/tutorials/infogain11.pdf

Learning a decision tree

- A Decision Tree is a tree-structured plan of a set of attributes to test in order to predict the output.
- To decide which attribute should be tested first, simply find the one with the highest information gain.
- Then recurse…

http://www.cs.cmu.edu/~./awm/tutorials/dtree.html

Decision tree on a high-level

- Tree structure
- Using the notion of entropy or information gain to choose which dimension to split
- Recurse

http://www.cs.cmu.edu/~./awm/tutorials/dtree.html

Learn more on decision tree

- Youtube, e.g. https://www.youtube.com/watch?v=eKD5gxPPeY0
- Decision tree tutorials
  - By Avinash Kak: https://engineering.purdue.edu/kak/Tutorials/DecisionTreeClassifiers.pdf
  - By Andrew Moore:
    - http://www.cs.cmu.edu/~./awm/tutorials/dtree.html
    - http://www.cs.cmu.edu/~./awm/tutorials/infogain11.pdf

Deep Learning & Vis

The goal of this lecture

- Not a complete overview of neural networks or deep learning
- But rather a high level view of the technique and its connection to visualization

Deep learning tutorial

- http://neuralnetworksanddeeplearning.com/
- http://deeplearning.stanford.edu/tutorial/
- http://www.deeplearningbook.org/
- And many more…

TensorFlow

- TensorFlow programming environment:
  - https://www.tensorflow.org/get_started/get_started_for_beginners
  - https://www.tensorflow.org/get_started/premade_estimators

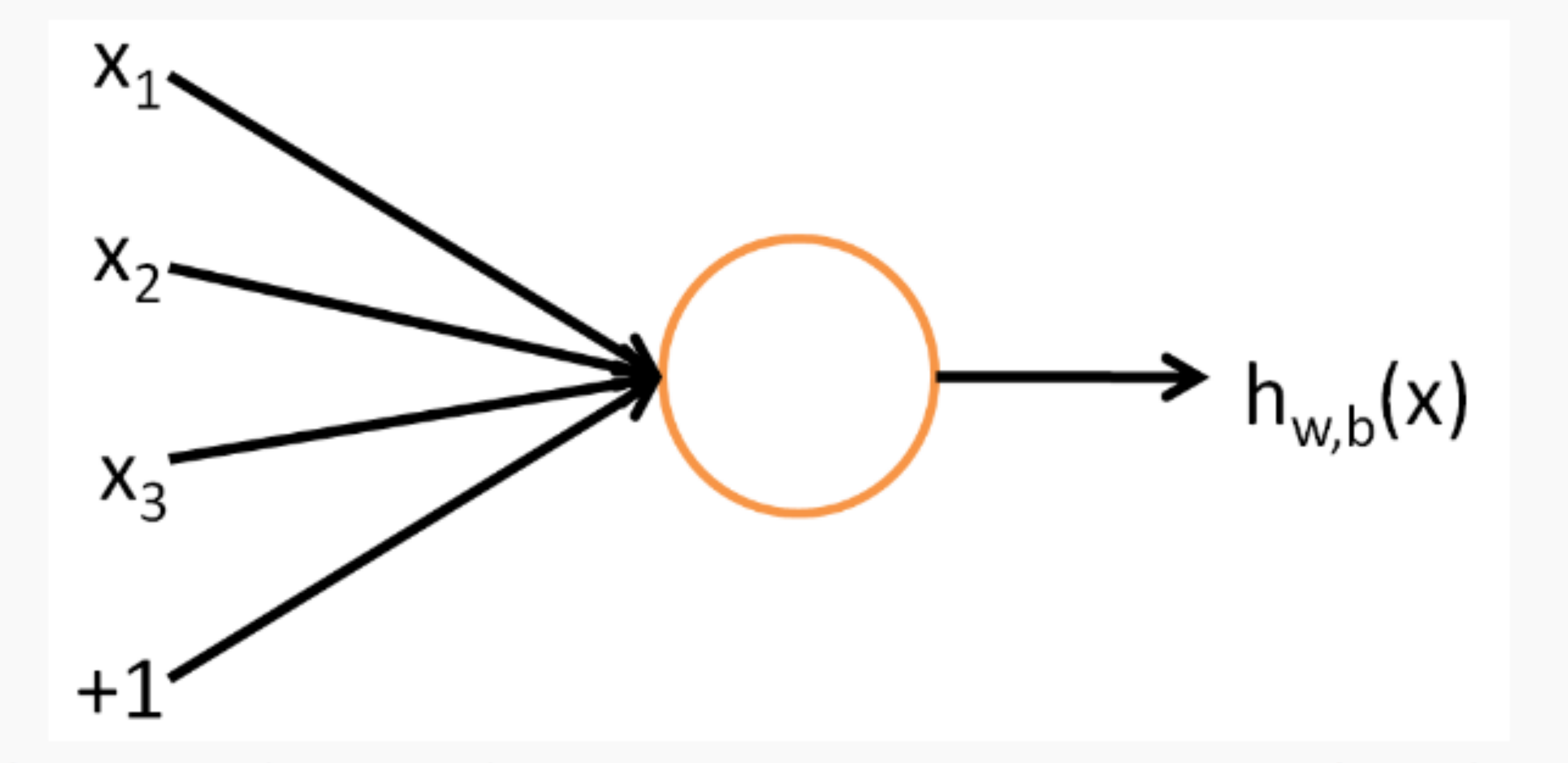
Multi-Layer Neural Network in a nutshell

A review based on materials from UFLDL Tutorial and Michael Nielsen

http://neuralnetworksanddeeplearning.com/

http://ufldl.stanford.edu/tutorial/

A single neuron



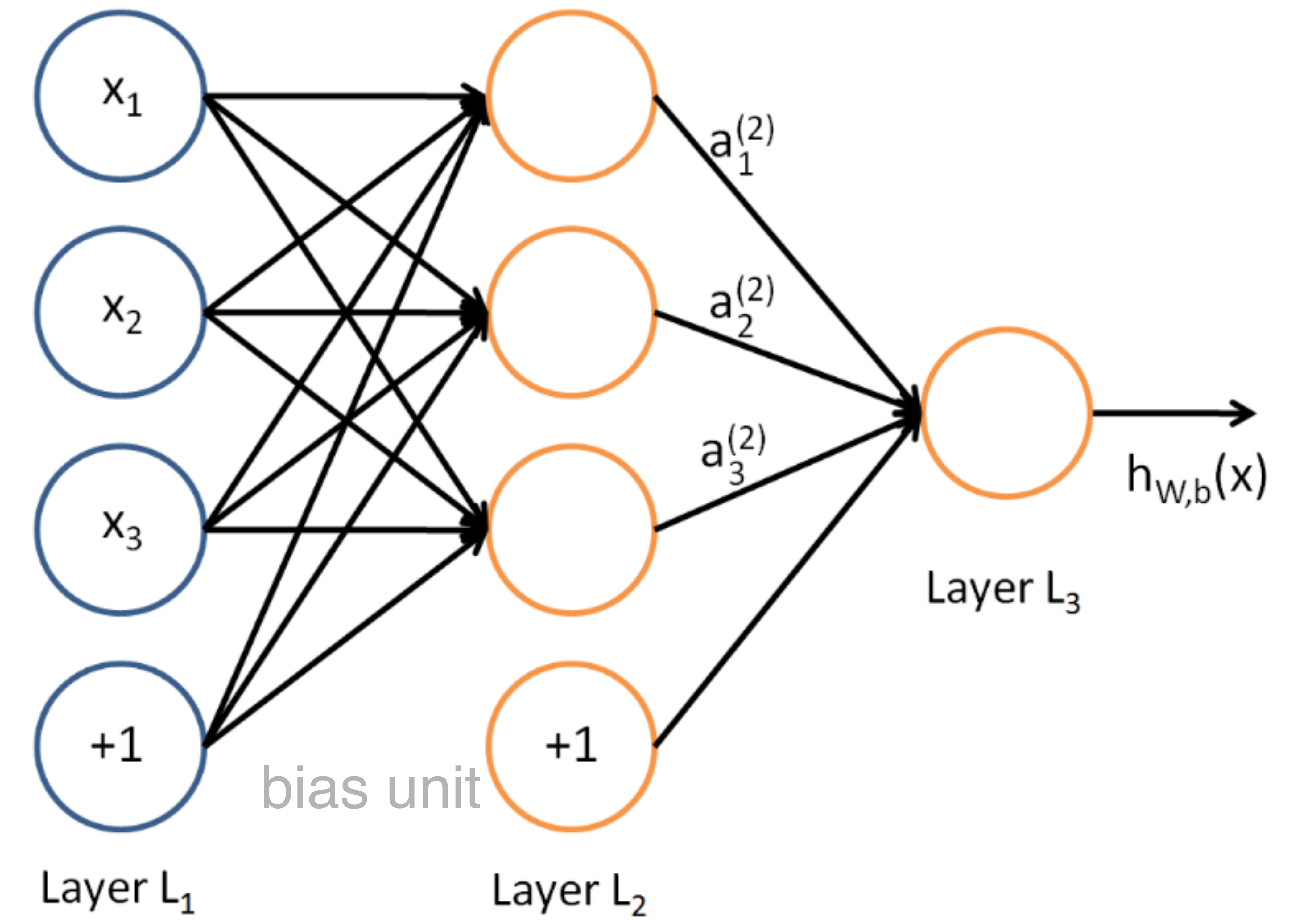
This "neuron" is a computational unit that takes as input x_1, x_2, x_3 (and a +1 intercept term), and outputs $h_{W,b}(x) = f(W^T x) = f(\sum_{i=1}^{3} W_i x_i + b)$, where $f : \Re \mapsto \Re$ is called the **activation function**. In these notes, we will choose $f(\cdot)$ to be the sigmoid function:

$$f(z) = \frac{1}{1 + \exp(-z)}.$$

http://ufldl.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/

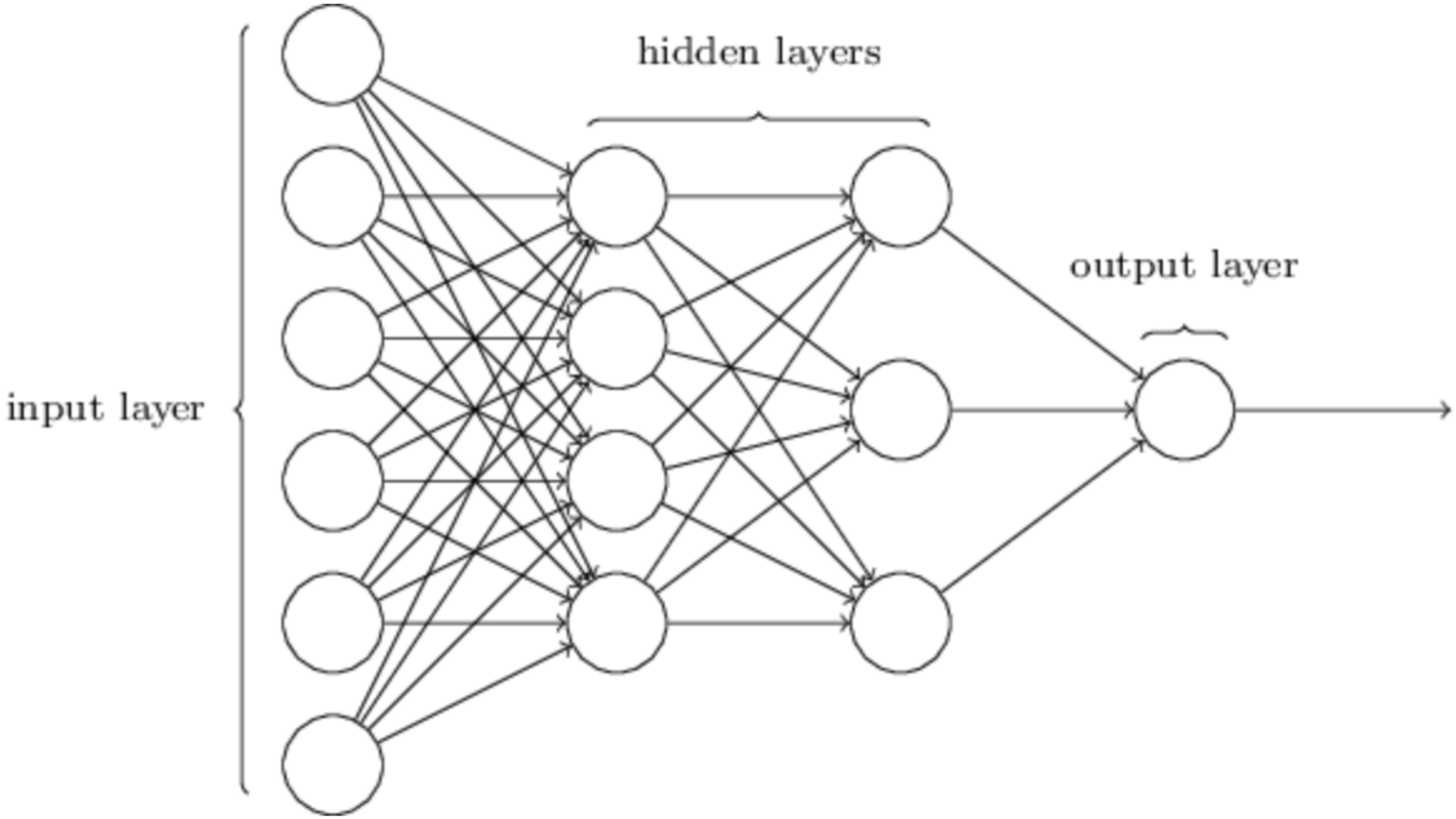
A Neural Network

A neural network is put together by hooking together many of our simple "neurons," so that the output of a neuron can be the input of another. For example, here is a small neural network:



http://ufldl.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/

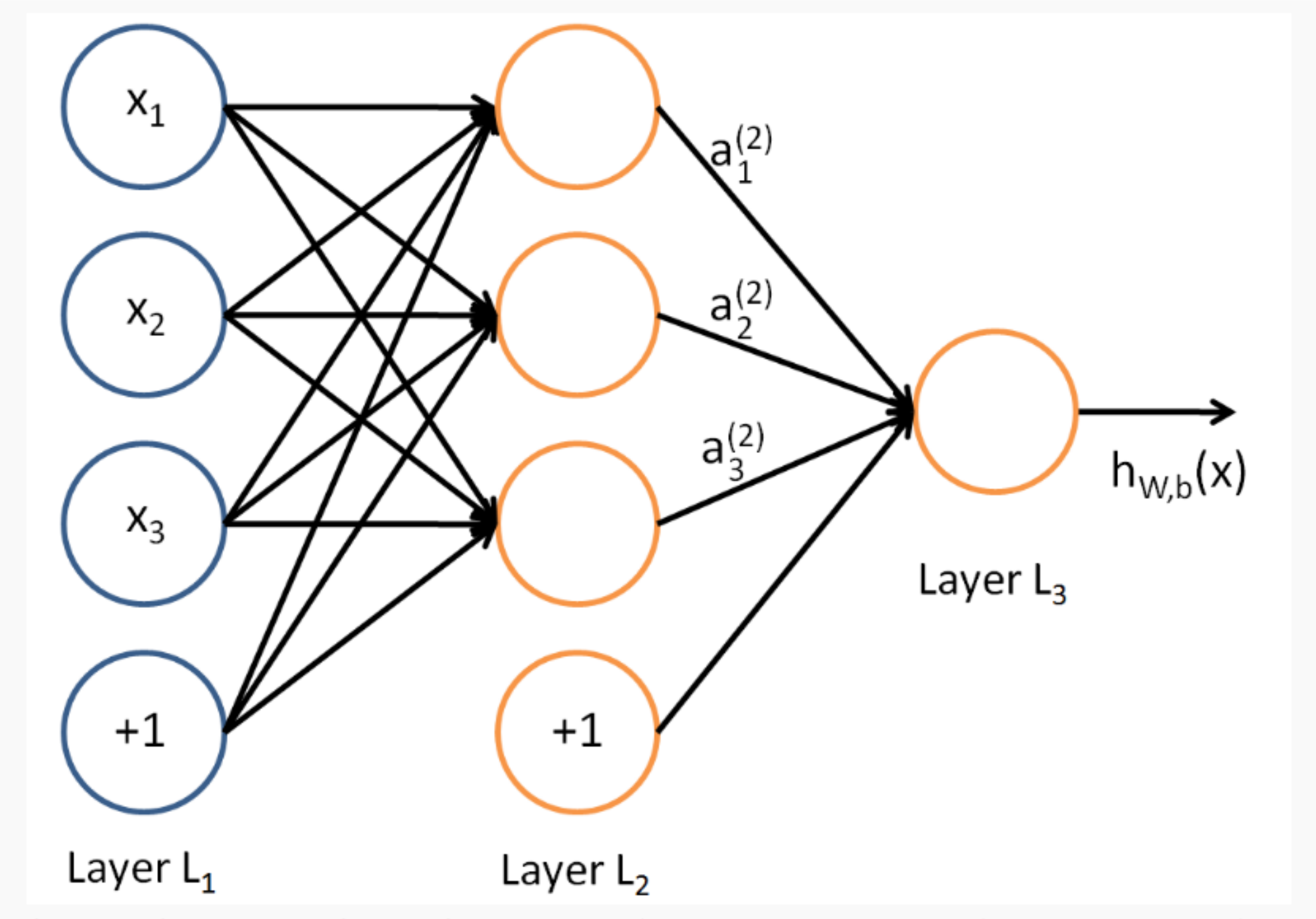
A Neural Network



http://neuralnetworksanddeeplearning.com/chap1.html

Forward propagation

- Multiplying input with weights and add bias before applying activation function at each node



$$a_1^{(2)} = f(W_{11}^{(1)}x_1 + W_{12}^{(1)}x_2 + W_{13}^{(1)}x_3 + b_1^{(1)})$$
$$a_2^{(2)} = f(W_{21}^{(1)}x_1 + W_{22}^{(1)}x_2 + W_{23}^{(1)}x_3 + b_2^{(1)})$$
$$a_3^{(2)} = f(W_{31}^{(1)}x_1 + W_{32}^{(1)}x_2 + W_{33}^{(1)}x_3 + b_3^{(1)})$$
$$h_{W,b}(x) = a_1^{(3)} = f(W_{11}^{(2)}a_1^{(2)} + W_{12}^{(2)}a_2^{(2)} + W_{13}^{(2)}a_3^{(2)} + b_1^{(2)})$$

$$z^{(2)} = W^{(1)}x + b^{(1)}$$
$$a^{(2)} = f(z^{(2)})$$
$$z^{(3)} = W^{(2)}a^{(2)} + b^{(2)}$$
$$h_{W,b}(x) = a^{(3)} = f(z^{(3)})$$

$$z^{(l+1)} = W^{(l)}a^{(l)} + b^{(l)}$$
$$a^{(l+1)} = f(z^{(l+1)})$$

http://ufldl.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/

Learning with gradient descent

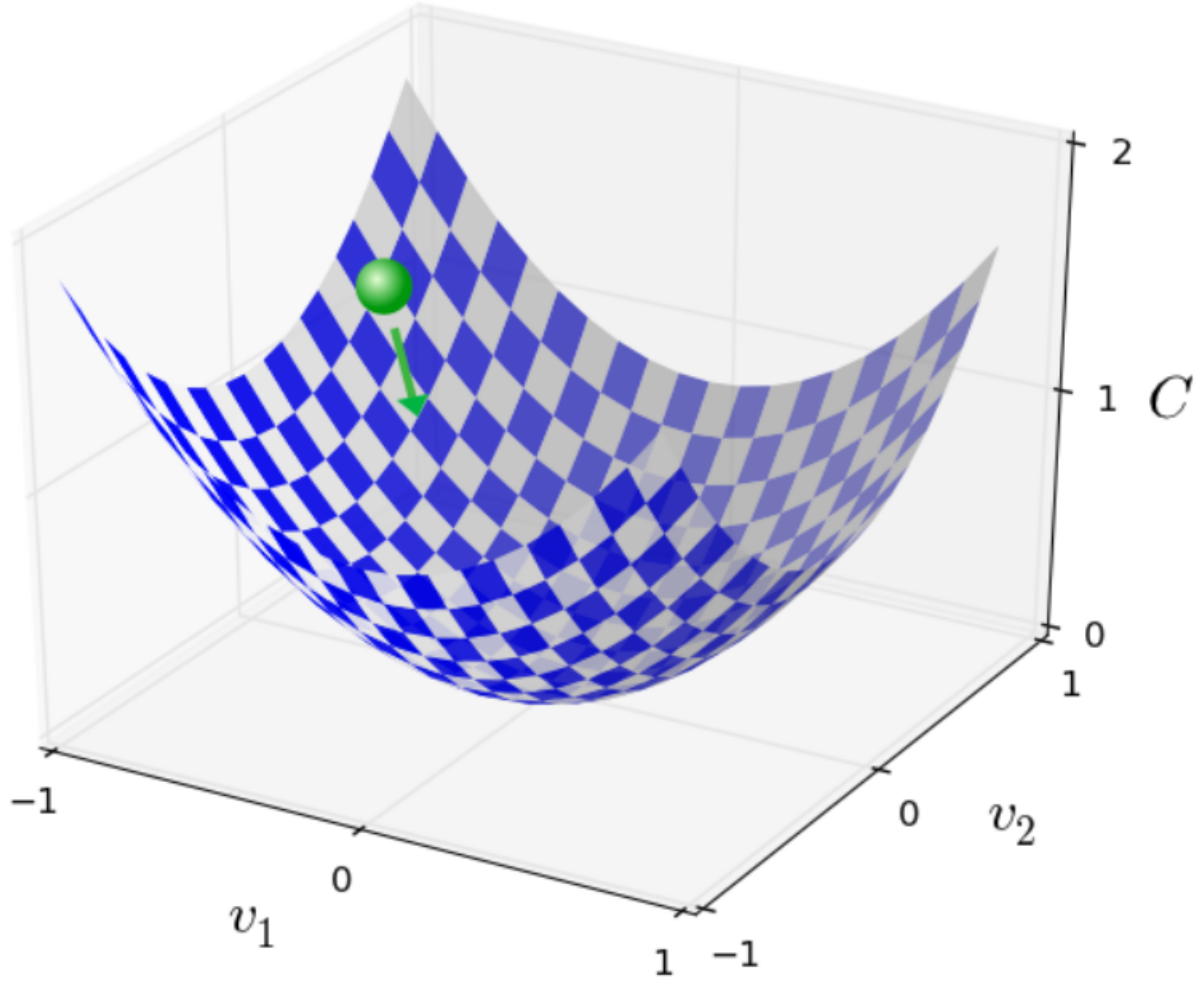
$$C(w, b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2.$$

- Cost function
  - x: input
  - y(x): approximate
  - w: collection of all weights
  - b: all the biases
  - n: total number of training inputs
  - a: the vector of outputs from the network when x is input

http://neuralnetworksanddeeplearning.com/chap1.html

Learning with gradient descent

Summing up, the way the gradient descent algorithm works is to repeatedly compute the gradient ∇C, and then to move in the *opposite* direction, "falling down" the slope of the valley. We can visualize it like this:



http://neuralnetworksanddeeplearning.com/chap1.html

Back propagation Algorithm

Cost function with a single training example:

$$J(W,b;x,y) = \frac{1}{2}\left\|h_{W,b}(x) - y\right\|^2.$$

Cost function with m training examples:

$$\begin{aligned} J(W,b) &= \left[\frac{1}{m}\sum_{i=1}^{m} J(W,b;x^{(i)},y^{(i)})\right] + \frac{\lambda}{2}\sum_{l=1}^{n_l-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}\left(W_{ji}^{(l)}\right)^2 \\ &= \left[\frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{2}\left\|h_{W,b}(x^{(i)}) - y^{(i)}\right\|^2\right)\right] + \frac{\lambda}{2}\sum_{l=1}^{n_l-1}\sum_{i=1}^{s_l}\sum_{i=1}^{s_{l+1}}\left(W_{ji}^{(l)}\right)^2 \end{aligned}$$

One iteration of gradient descent updates the parameters W, b as follows:

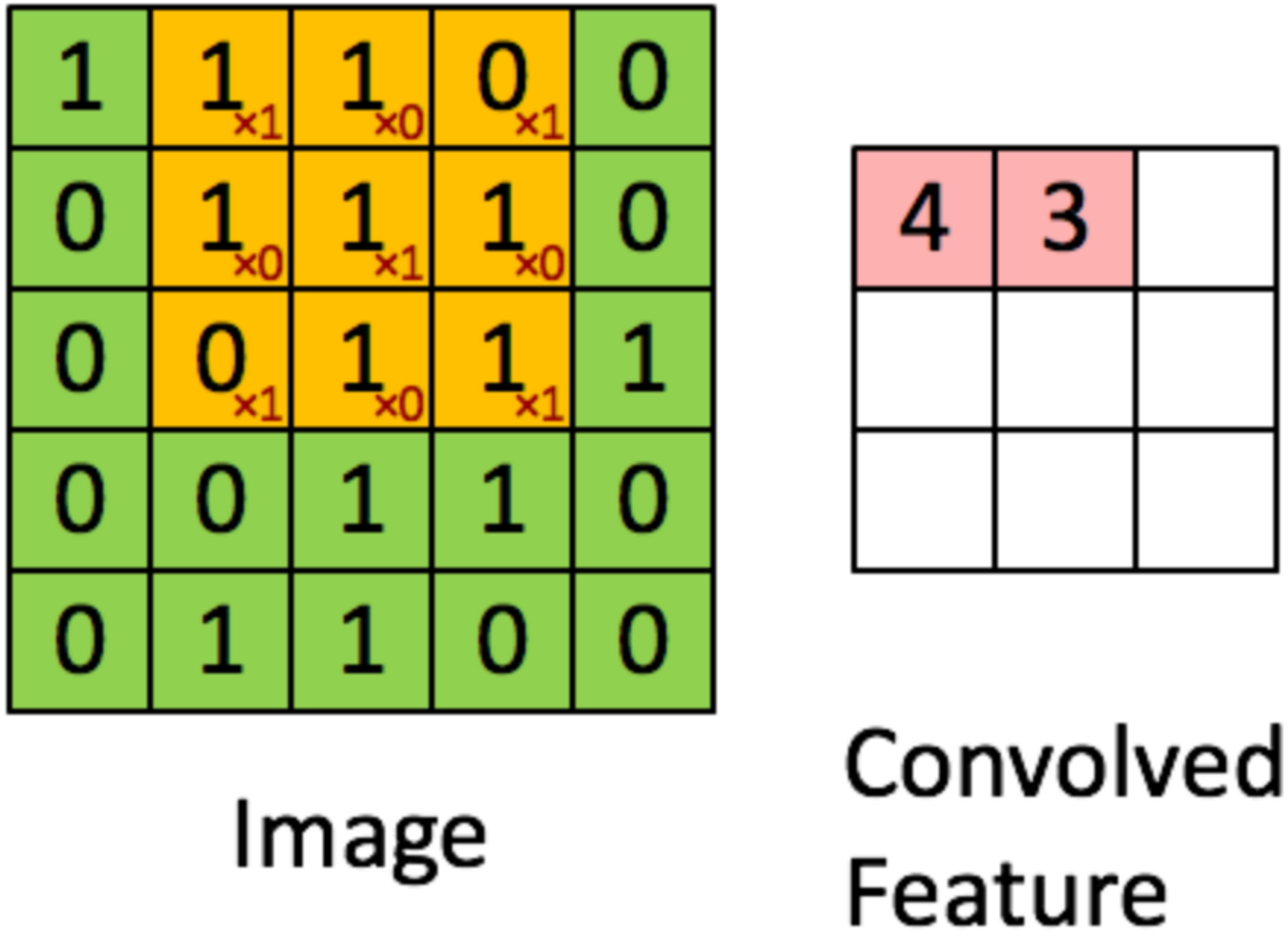
$$W_{ij}^{(l)} = W_{ij}^{(l)} - \alpha\frac{\partial}{\partial W_{ij}^{(l)}}J(W,b)$$

$$b_{i}^{(l)} = b_{i}^{(l)} - \alpha\frac{\partial}{\partial b_{i}^{(l)}}J(W,b)$$

Back propagation algorithm: gives an efficient way to compute these partial derivatives.

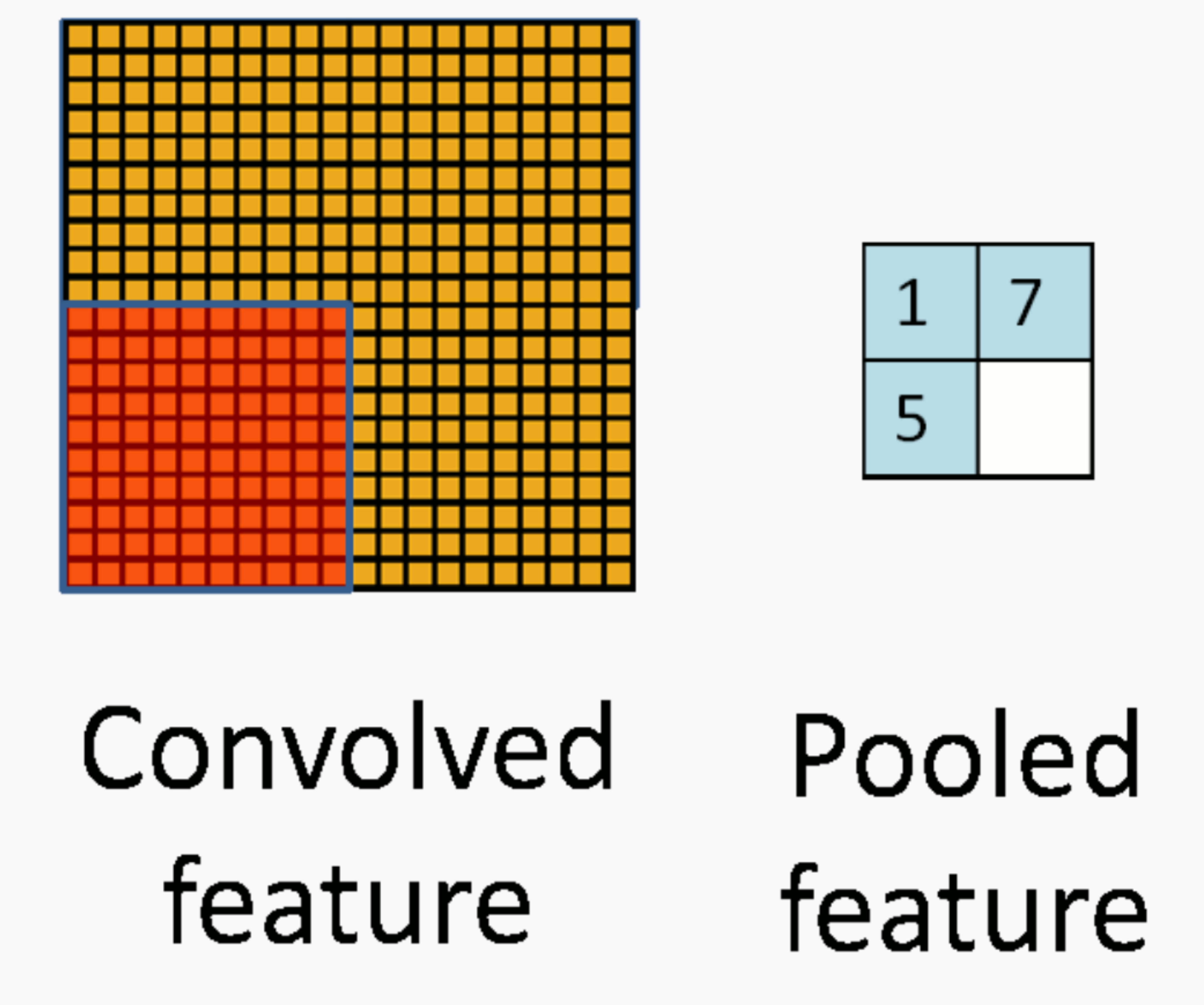
http://ufldl.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/

Feature convolution



http://ufldl.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/

Pooling



Aggregate statistics of convolved features at various locations

http://ufldl.stanford.edu/tutorial/supervised/Pooling/

Pooling

Formally, after obtaining our convolved features as described earlier, we decide the size of the region, say $m \times n$ to pool our convolved features over. Then, we divide our convolved features into disjoint $m \times n$ regions, and take the mean (or maximum) feature activation over these regions to obtain the pooled convolved features. These pooled features can then be used for classification.

Aggregate statistics of convolved features at various locations

http://ufldl.stanford.edu/tutorial/supervised/Pooling/

Convolutional Neural Network

- A CNN consists of an input and an output layer, as well as multiple hidden layers.
- The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers

Stochastic Gradient Descent

The standard gradient descent algorithm updates the parameters θ of the objective $J(\theta)$ as,

$$\theta = \theta - \alpha \nabla_\theta E[J(\theta)]$$

where the expectation in the above equation is approximated by evaluating the cost and gradient over the full training set. Stochastic Gradient Descent (SGD) simply does away with the expectation in the update and computes the gradient of the parameters using only a single or a few training examples. The new update is given by,

$$\theta = \theta - \alpha \nabla_\theta J(\theta; x^{(i)}, y^{(i)})$$

with a pair $(x^{(i)}, y^{(i)})$ from the training set.

http://ufldl.stanford.edu/tutorial/supervised/OptimizationStochasticGradientDescent/

Visualization for Deep Learning

Topics

- Directly visualizing the activations and parameters in intuitive aggregates
- Visualizing weights as features
- Visualizing gradient aggregates during training
- Improving interpretability of networks
- Localizing “responsibility” in the network for particular outputs
- Sensitivity/stability of network behavior
- Visualizing loss function geometry and the trajectory of the gradient descent process
- Visual representation of the input-output mapping of the network
- Visualizing alternative structures and their performance
- Monitoring/debugging the training process, i.e to detect saddle points or local optima, saturation units
- Visualizing distributed training methods across a cluster
- Using animation in network visualization
- Interactive visualizations for exploration or parameter tuning
- Software architectures for effective visualization
- Visualization and interaction user interfaces

https://icmlviz.github.io/icmlviz2016/

Visualizing the inner workings of neurons

Epoch
000,000
Learning rate
0.03
Activation
Tanh
Regularization
None
Regularization rate
0
Problem type
Classification
DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10
REGENERATE
FEATURES
Which properties do you want to feed in?
X_1
X_2
X_1^2
X_2^2
X_1X_2
$\sin(X_1)$
$\sin(X_2)$
2 HIDDEN LAYERS
4 neurons
2 neurons
This is the output from one **neuron**. Hover to see it larger.
The outputs are mixed with varying **weights**, shown by the thickness of the lines.
OUTPUT
Test loss 0.509
Training loss 0.503
Colors shows data, neuron and weight values.
-1
0
1
Show test data
Discretize output
http://playground.tensorflow.org/

Deep Vis

http://yosinski.com/deepvis#toolbox

Multifaceted Feature Vis

Uncovering the Different Types of Features Learned By Each Neuron in Deep Neural Networks

Figure 1. **Top:** Visualizations of 8 types of images (feature facets) that activate the same “grocery store” class neuron. **Bottom:** Example training set images that activate the same neuron, and resemble the corresponding synthetic image in the top panel.

NguyenYosinskiClune2016

(a) *Movie theater*: outside (day & night) and inside views.

(b) *Convertible*: with different colors and both front & rear views.

(c) *Pool table*: Up close & from afar, with different backgrounds.

Figure 4. Multifaceted visualization of fc8 units uncovers interesting facets. We show 4 different facets for each neuron. In each pair of images, the bottom is the facet visualization that represents a cluster of images from the training set, and the top is the closest image to the visualization from the same cluster.

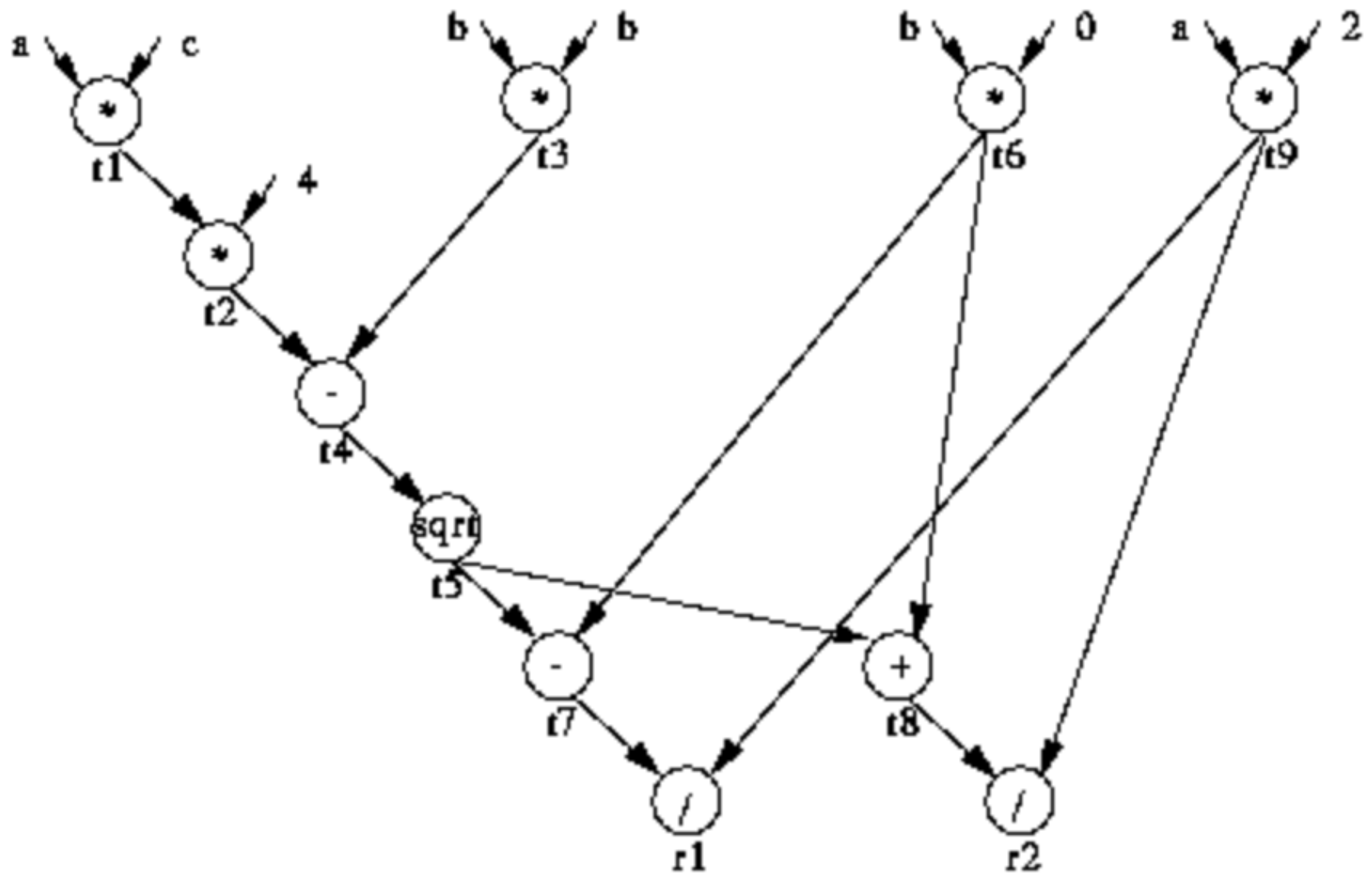
NguyenYosinskiClune2016

Visualizing the Data flow of DL algorithms

Data flow graph

- A data flow graph (DFG) is a graph which represents a data dependancies between a number of operations.

```
quad( a, b, c)
t1 = a*c;
t2 = 4*t1;
t3 = b*b;
t4 = t3 - t2;
t5 = sqrt( t4);
t6 = -b;
t7 = t6 - t5;
t8 = t7 + t5;
t9 = 2*a;
r1 = t7/t9;
r2 = t8/t9;
```



http://bears.ece.ucsb.edu/research-info/DP/dfg.html

Dataflow graph in TensorFlow

- A TensorFlow model is a data flow graph that represents a computation.
- Nodes in the graph represent various operations: addition, matrix multiplication, summary variable operations for storing model parameters, etc.
- Edges in TensorFlow:
  - Data dependency edges represent tensors, or multidimensional arrays, that are input and output data of the operations.
  - Reference edges, or outputs of variable operations, represent pointers to the variable rather than its value
  - Control dependency edges do not represent any data but indicate that their source operations must execute before their tail operations can start.

Simplifying data flow graph

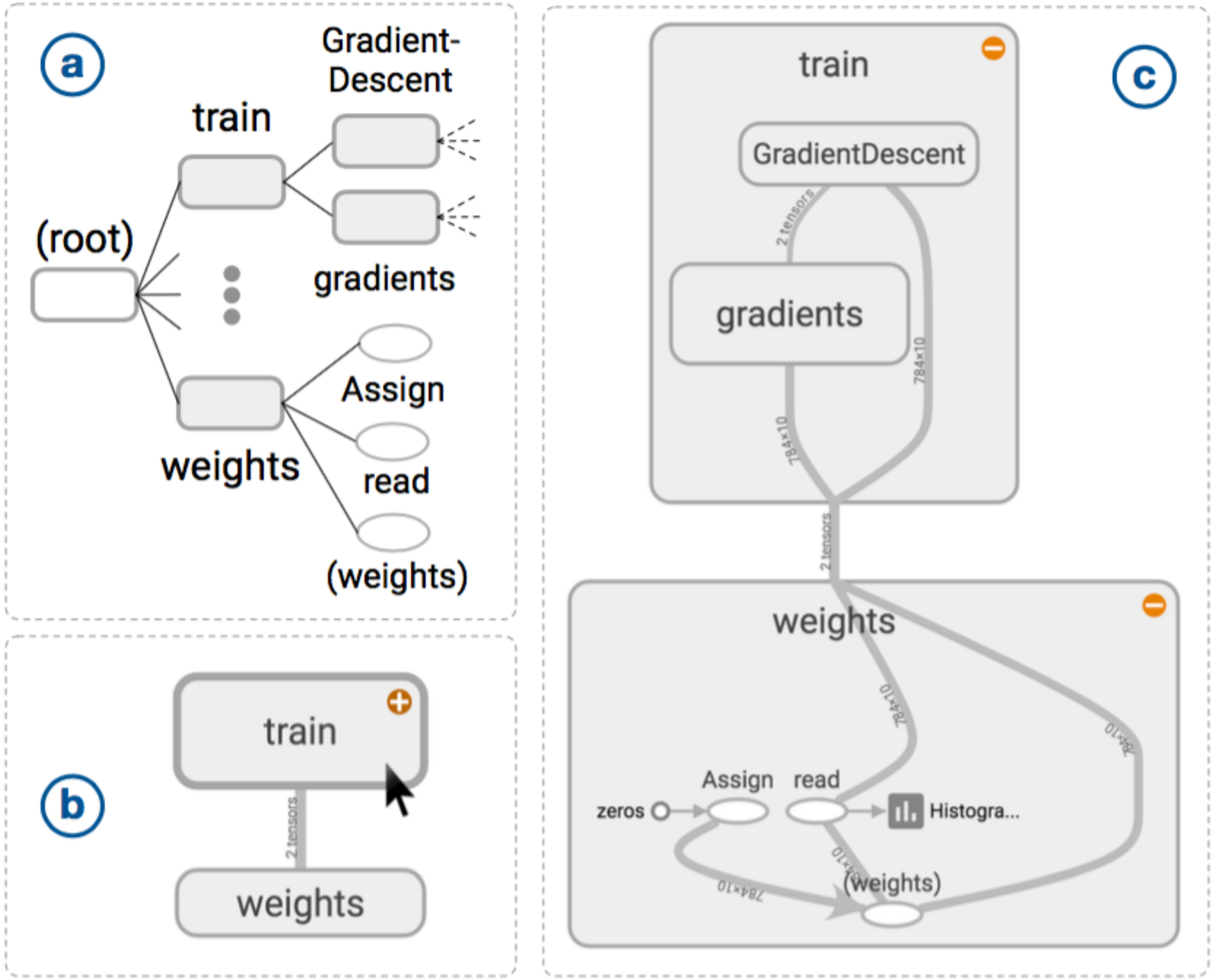
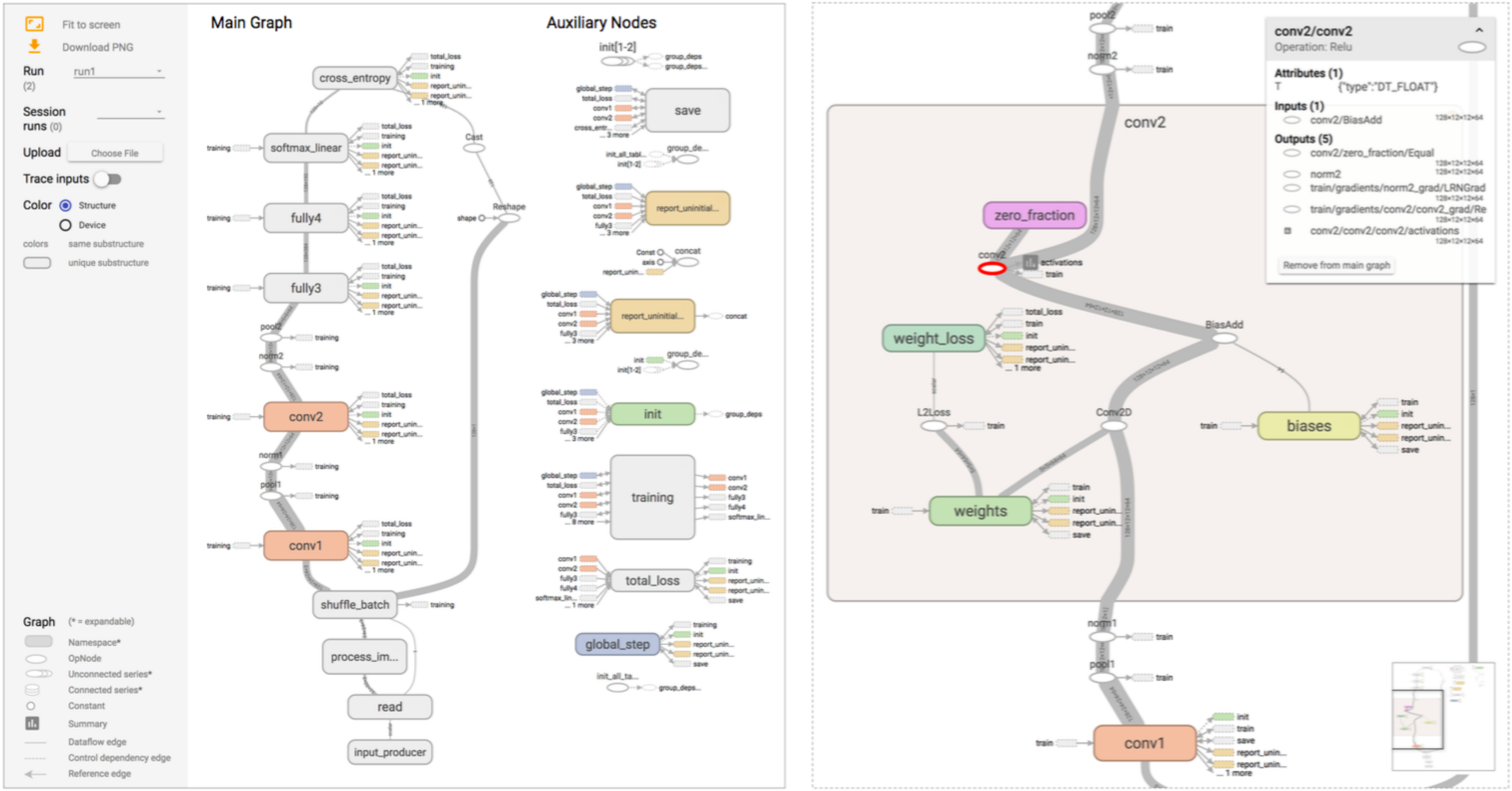


Fig. 5. Build a hierarchical clustered graph. (a) A hierarchy showing only `train` and `weights` namespaces from **`tf_mnist_simple`** in Figure 4. (b) A high-level diagram showing dependency between `train` and `weights`. Hovering over the `train` namespace shows a button for expansion. (c) A diagram with `train` and `weights` expanded.

- Given a low-level directed data flow graph of a model as input, produce an interactive visualization that shows the high-level structure of the model.
- Enables user to explore its nested structure on demand.

WongsuphasawatSmilkovWexler2018



(a) (b)

Fig. 1. The TensorFlow Graph Visualizer shows a convolutional network for classifying images (**tf_cifar**) . (a) An overview displays a dataflow between groups of operations, with *auxiliary nodes* extracted to the side. (b) Expanding a group shows its nested structure.

WongsuphasawatSmilkovWexler2018

Techniques employed

- Overview: a clustered graph by grouping nodes based on their hierarchical namespaces
- Exploration: edge bundling that supports expansion of clusters
- Declutter: heuristics to extract non-critical nodes
- Detect and highlight repeated structures
- Overlay the graph with additional quantitative information to help developers inspect their models.

Learn more on deep learning

- Stanford deep learning tutorial:
  - http://deeplearning.stanford.edu/tutorial/
  - http://neuralnetworksanddeeplearning.com/

Further Reading

- Workshop on Visualization for Deep Learning
  - http://icmlviz.github.io/
  - https://icmlviz.github.io/icmlviz2016/

Thanks!

Any questions?

You can find me at: beiwang@sci.utah.edu

CREDITS

Special thanks to all people who made and share these awesome resources for free:

- Presentation template designed by Slidesmash
- Photographs by unsplash.com and pexels.com
- Vector Icons by Matthew Skiles

Presentation Design

This presentation uses the following typographies and colors:

Free Fonts used:

http://www.1001fonts.com/oswald-font.html

https://www.fontsquirrel.com/fonts/open-sans

Colors used