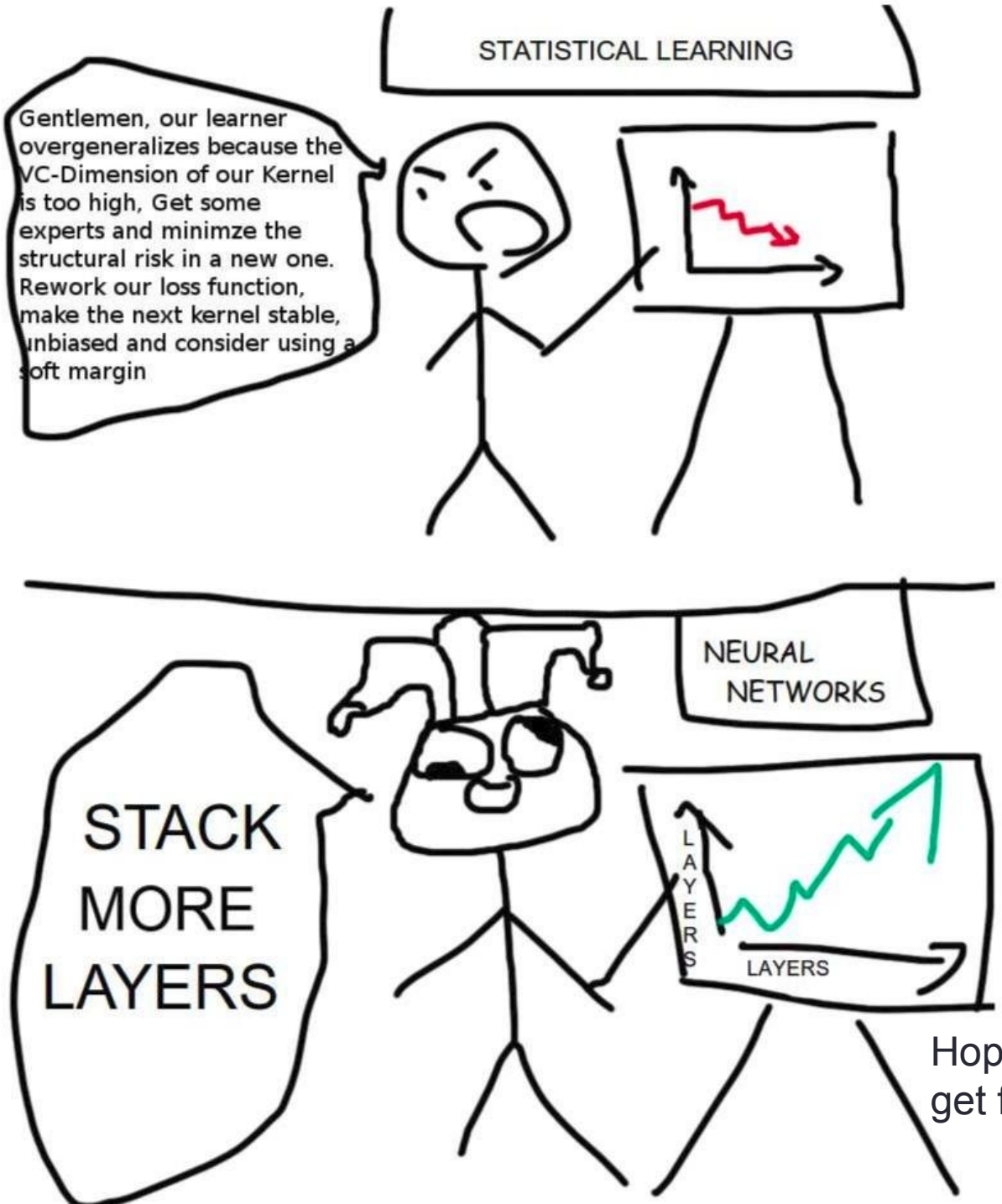
NEURAL NETWORKS

Deep learning = Deep neural networks = neural networks

https://xkcd.com/1838/



Hopefully this won't be all you get from this class

DNNs (Deep Neural Networks)

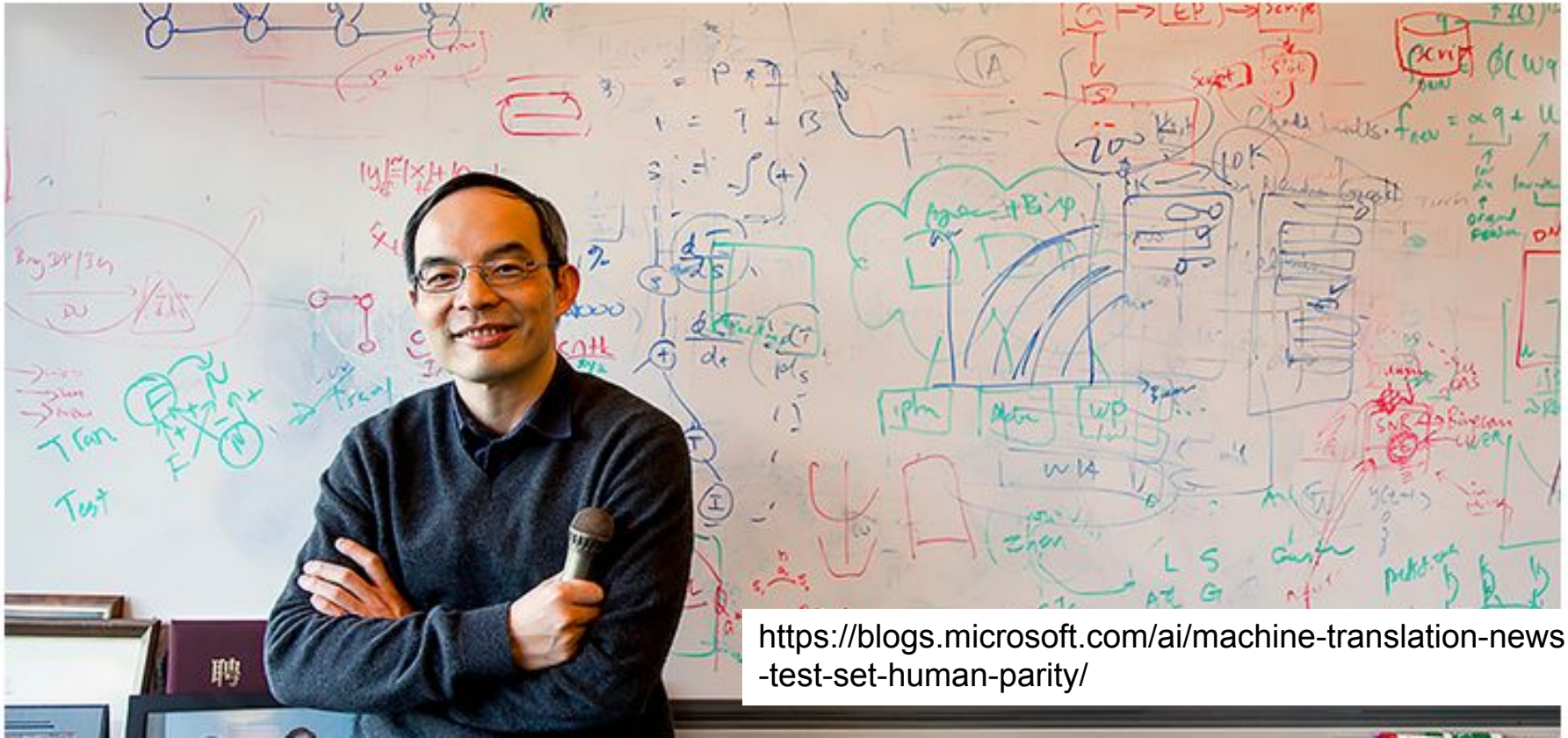
- Why deep learning?
- Greatly improved performance in ASR and other tasks (Computer Vision, Robotics, Machine Translation, NLP, etc.)
- Surpassed human performance in many tasks

Task	Previous state-of-the-art	Deep learning (2012)	Deep learning (2017)
TIMIT	24.4%	20.0%	17.0%
Switchboard	23.6%	16.1%	5.5%
Google voice search	16.0%	12.3%	4.9%

Geoffrey Hinton, Deep Neural Networks for Acoustic Modeling in Speech Recognition, 2012

Microsoft reaches a historic milestone, using AI to match human performance in translating news from Chinese to English

Mar 14, 2018 | Allison Linn



https://blogs.microsoft.com/ai/machine-translation-news-test-set-human-parity/

Google's AlphaGo Defeats Chinese Go Master in Win for A.I.

点击查看本文中文版

By PAUL MOZUR MAY 23, 2017

RELATED COVERAGE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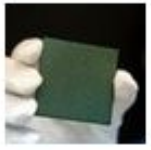
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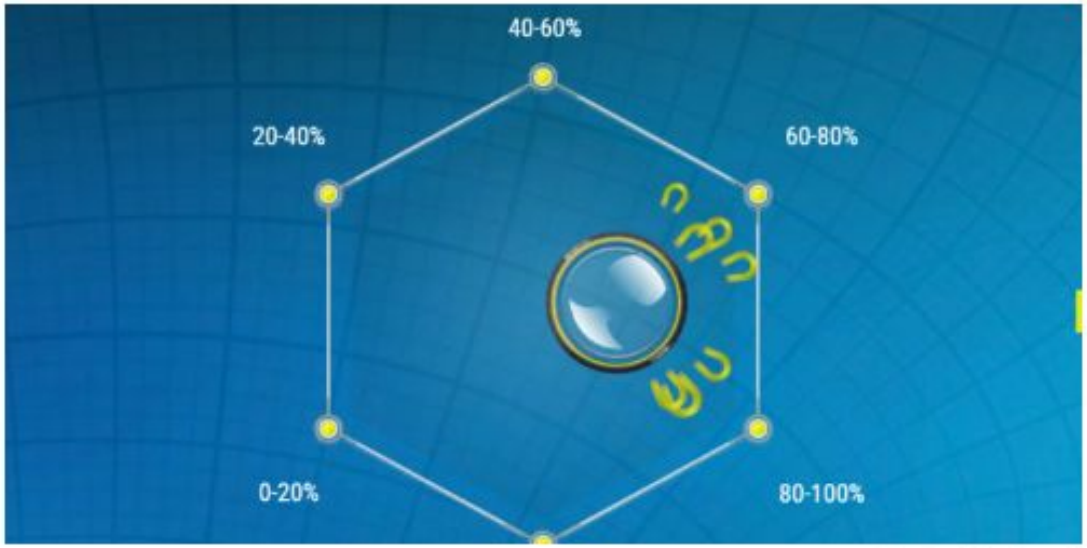
https://www.nytimes.com/2017/05/23/business/google-deepmind-alphago-go-champion-defeat.html

The Stanford Daily

Artificial swarm intelligence diagnoses pneumonia better than individual computer or doctor

by Fan Liu — September 27, 2018 0



Courtesy of Unanimous AI

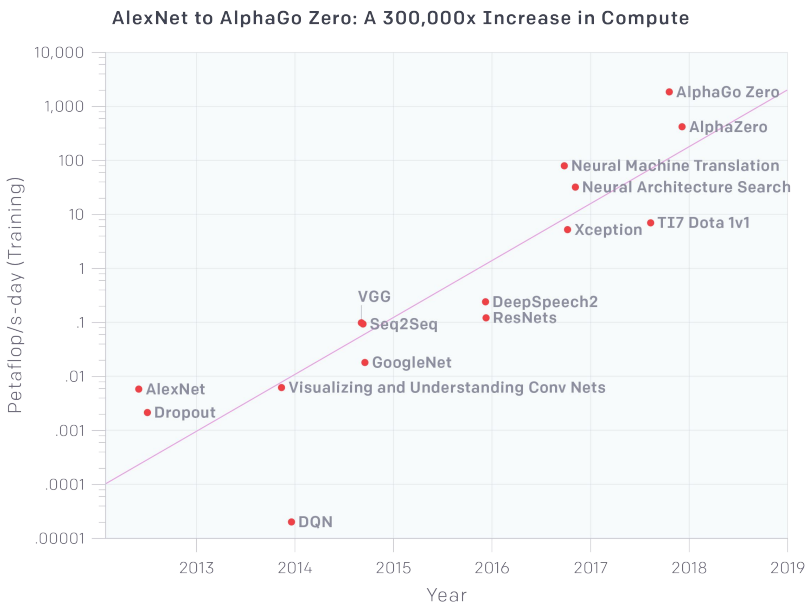
Popular Posts

Artificial swarm intelligence diagnoses pneumonia better than individual computer or

https://www.stanforddaily.com/2018/09/27/artificial-swarm-intelligence-diagnoses-pneumonia-better-than-individual-computer-or-doctor/

Why now

- Neural Networks has been around since 1990s
- Big data – DNN can take advantage of large amounts of data better than other models
- GPU – Enable training bigger models possible
- Deep – Easier to avoid bad local minima when the model is large



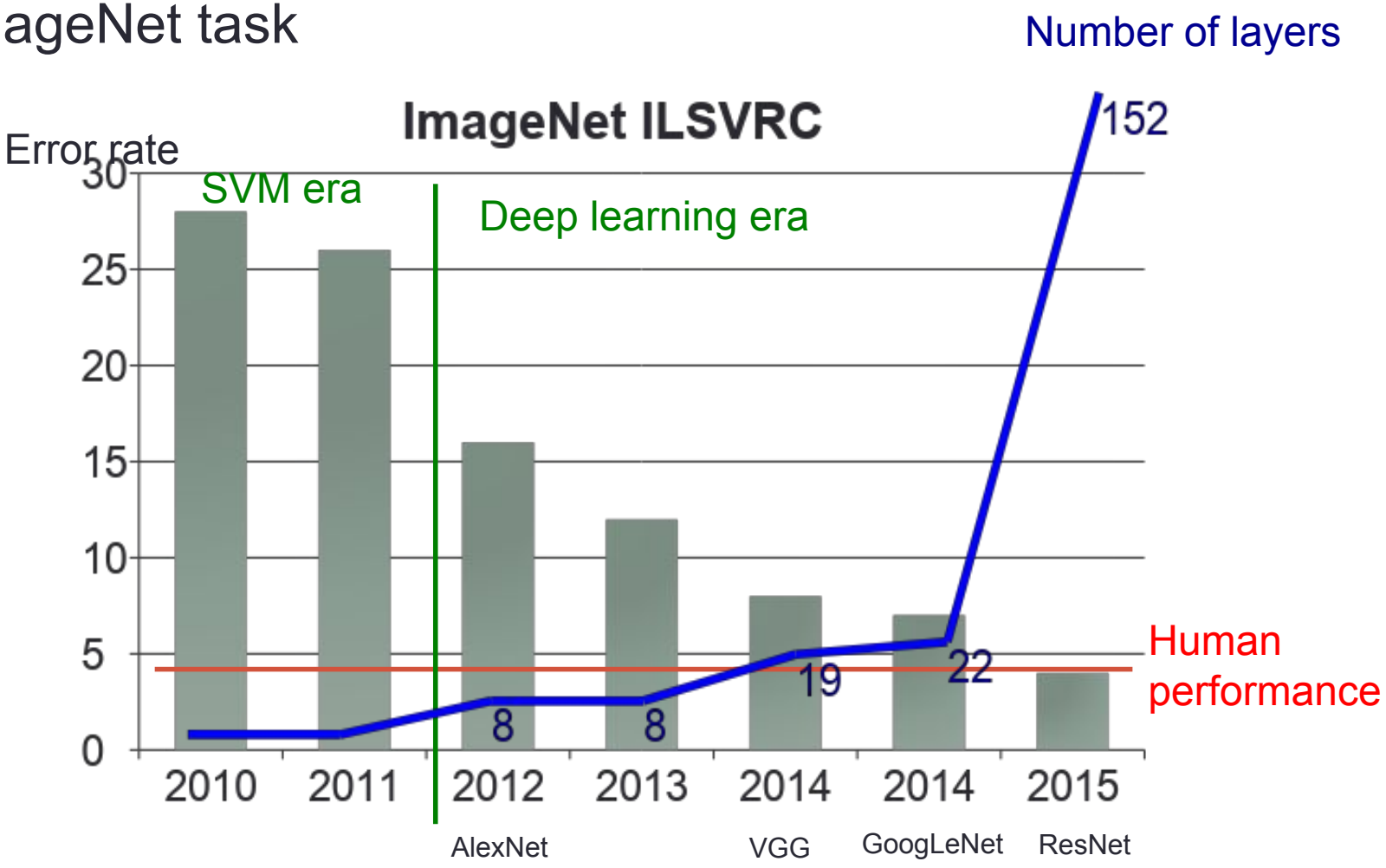
https://blog.openai.com/ai-and-compute/

ImageNet - Object classification

Alex, Krizhevsky, Imagenet classification with deep convolutional neural networks, 2012

Wider and deeper networks

- ImageNet task



Olga Russakovsky, ImageNet Large Scale Visual Recognition Challenge, 2014 https://arxiv.org/abs/1409.0575

Statistics > Machine Learning

Dynamical Isometry and a Mean Field Theory of CNNs: How to Train 10,000-Layer Vanilla Convolutional Neural Networks

Lechao Xiao, Yasaman Bahri, Jascha Sohl-Dickstein, Samuel S. Schoenholz, Jeffrey Pennington

(Submitted on 14 Jun 2018)

In recent years, state-of-the-art methods in computer vision have utilized increasingly deep convolutional neural network architectures (CNNs), with some of the most successful models employing hundreds or even thousands of layers. A variety of pathologies such as vanishing/exploding gradients make training such deep networks challenging. While residual connections and batch normalization do enable training at these depths, it has remained unclear whether such specialized architecture designs are truly necessary to train deep CNNs. In this work, we demonstrate that it is possible to train vanilla CNNs with ten thousand layers or more simply by using an appropriate initialization scheme. We derive this initialization scheme theoretically by developing a mean field theory for signal propagation and by characterizing the conditions for dynamical isometry, the equilibration of singular values of the input-output Jacobian matrix. These conditions require that the convolution operator be an orthogonal transformation in the sense that it is norm-preserving. We present an algorithm for generating such random initial orthogonal convolution kernels and demonstrate empirically that they enable efficient training of extremely deep architectures.

Comments: ICML 2018 Conference Proceedings
Subjects: **Machine Learning (stat.ML)**; Machine Learning (cs.LG)
Cite as: arXiv:1806.05393 **[stat.ML]**
(or **arXiv:1806.05393v1 [stat.ML]** for this version)

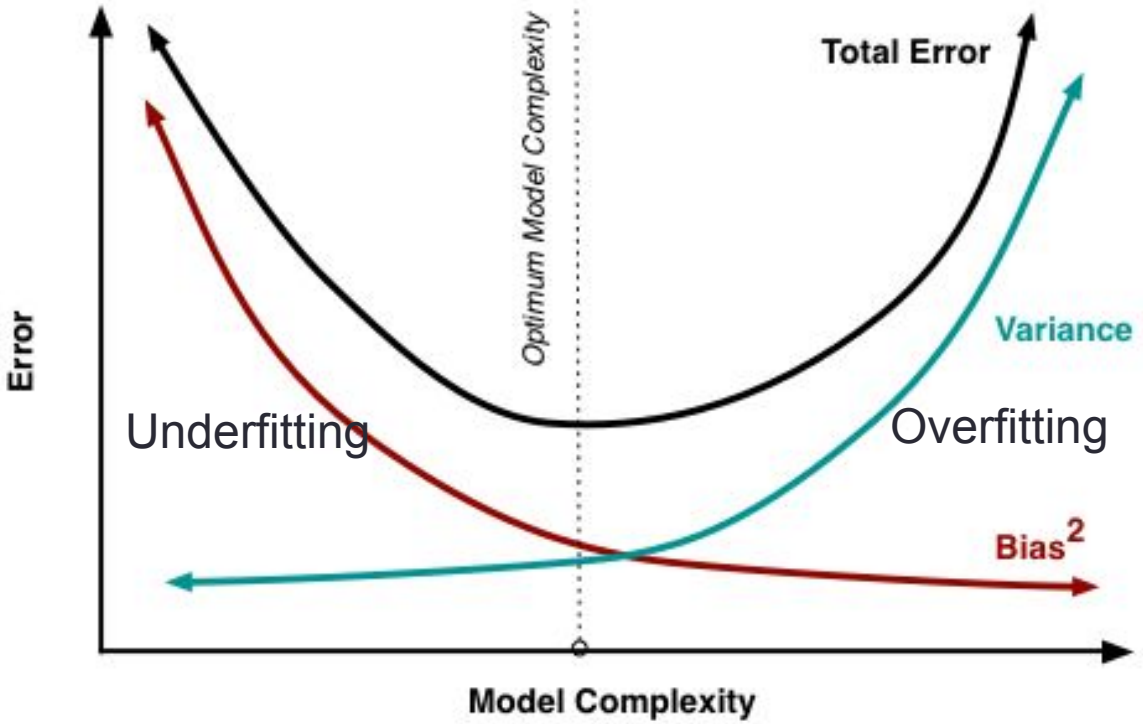
Submission history

From: Samuel Schoenholz [view email]
[v1] Thu, 14 Jun 2018 07:04:15 GMT (6734kb,D)

Which authors of this paper are endorsers? | Disable MathJax (What is MathJax?)

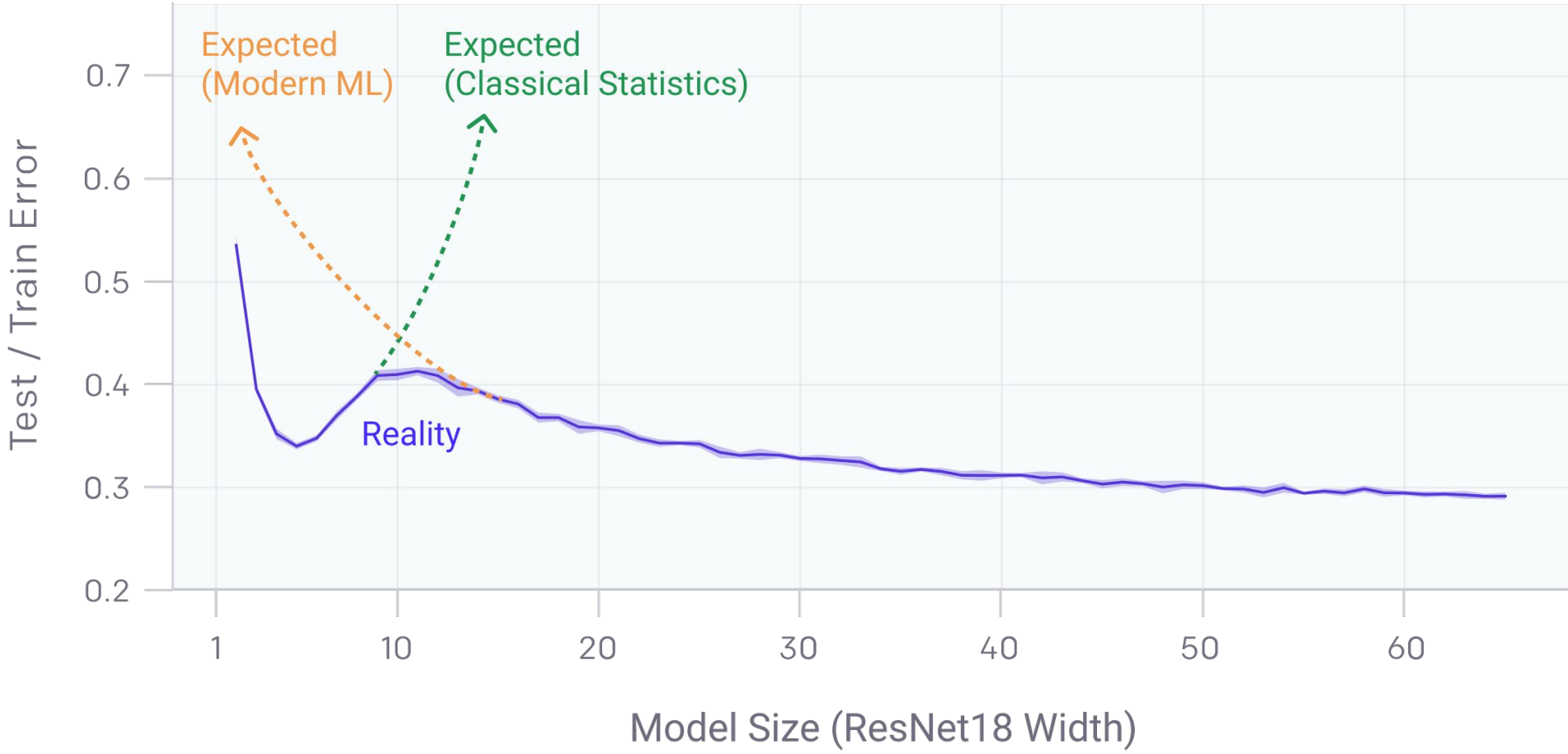
Bias-Variance Underfitting-Overfitting

- Usually if you try to reduce the bias of your model, the variance will increase, and vice versa.
- Called the bias-variance trade-off



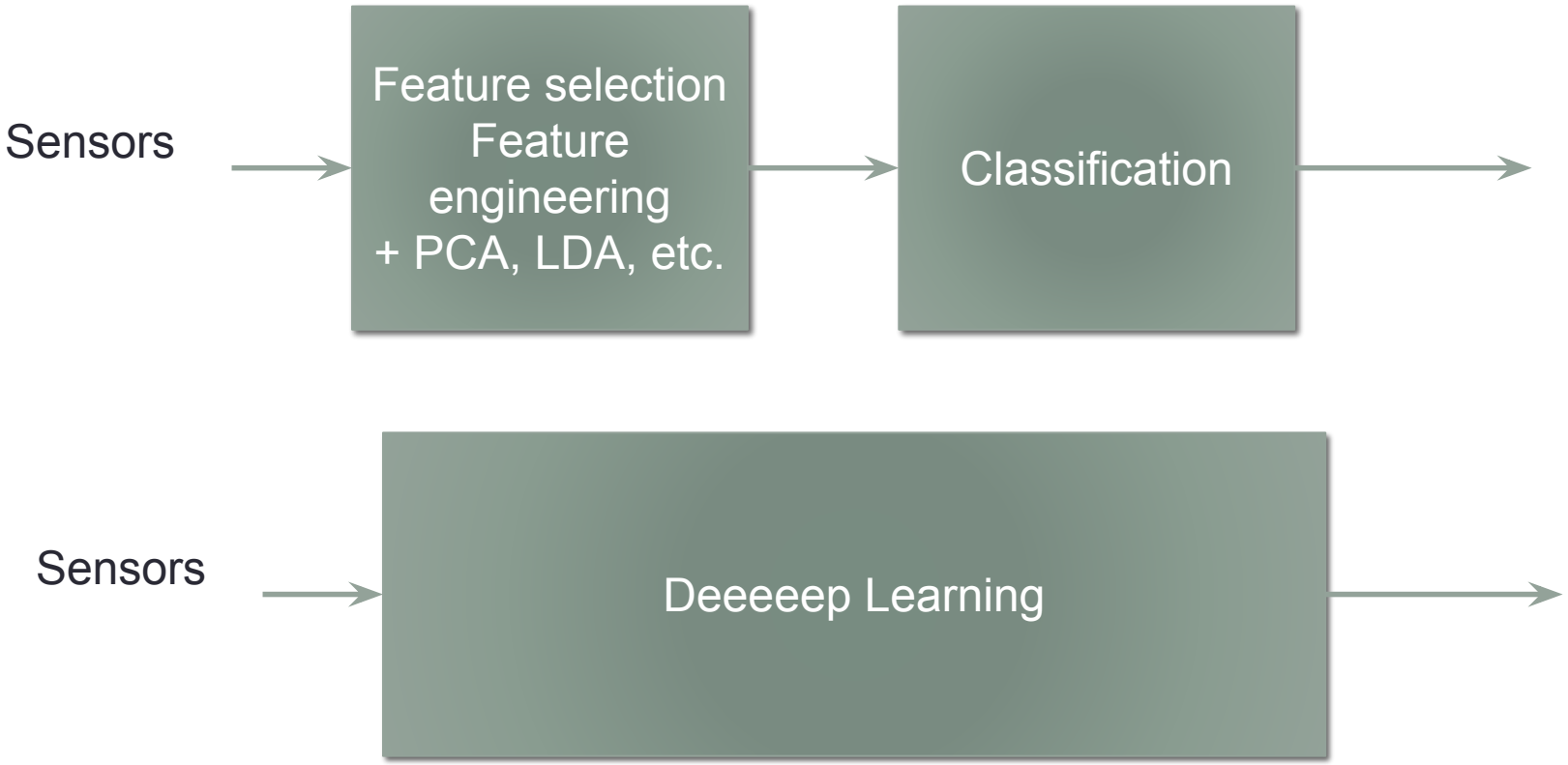
http://www.cs.cornell.edu/courses/cs4780/2017sp/lectures/lecturenote11.html

The double descent problem



https://openai.com/blog/deep-double-descent/

Traditional VS Deep learning

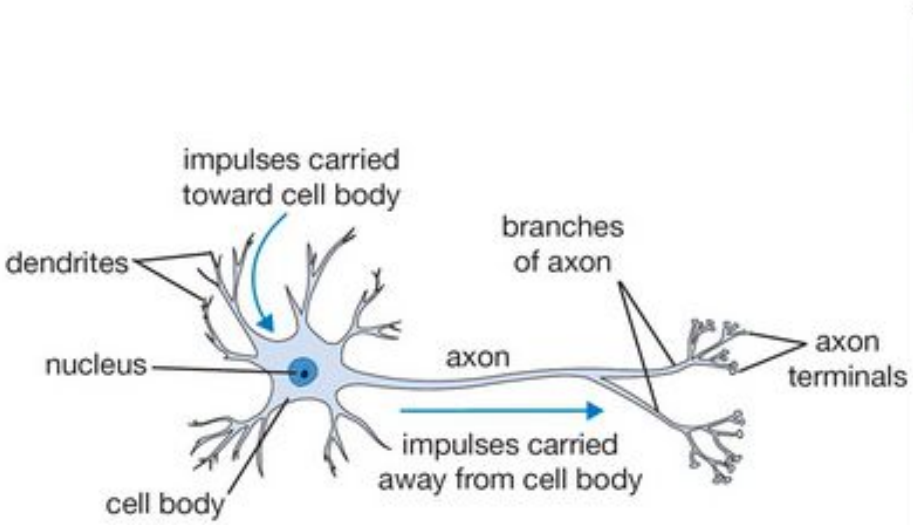


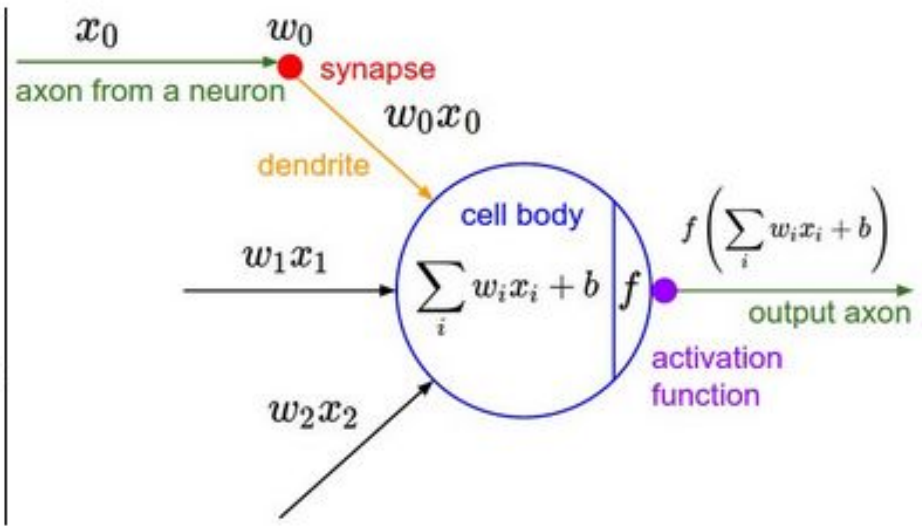
Neural networks

- Fully connected networks
  - Neuron
  - Non-linearity
  - Softmax layer
- DNN training
  - Loss function and regularization
  - SGD and backprop
  - Learning rate
  - Overfitting – dropout, batchnorm
- Demos
  - Tensorflow, Keras
- CNN, RNN, LSTM, GRU <- Next class

Fully connected networks

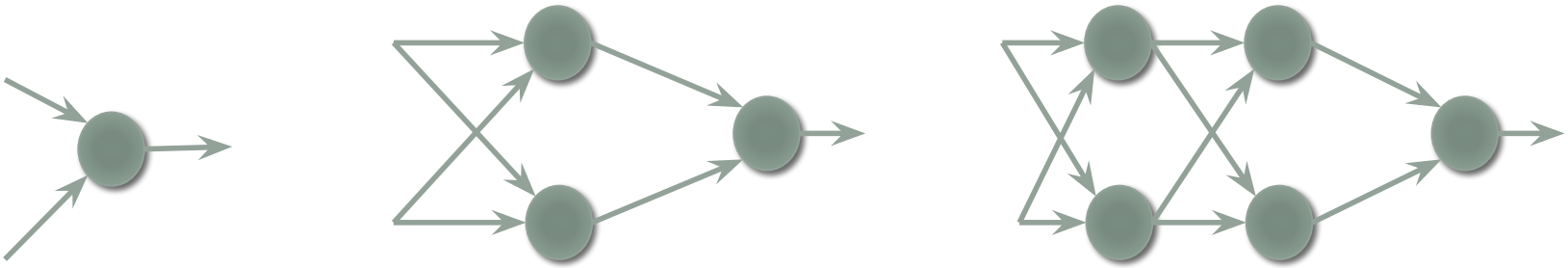
- Many names: feed forward networks or deep neural networks or multilayer perceptron or artificial neural networks
- Composed of multiple neurons

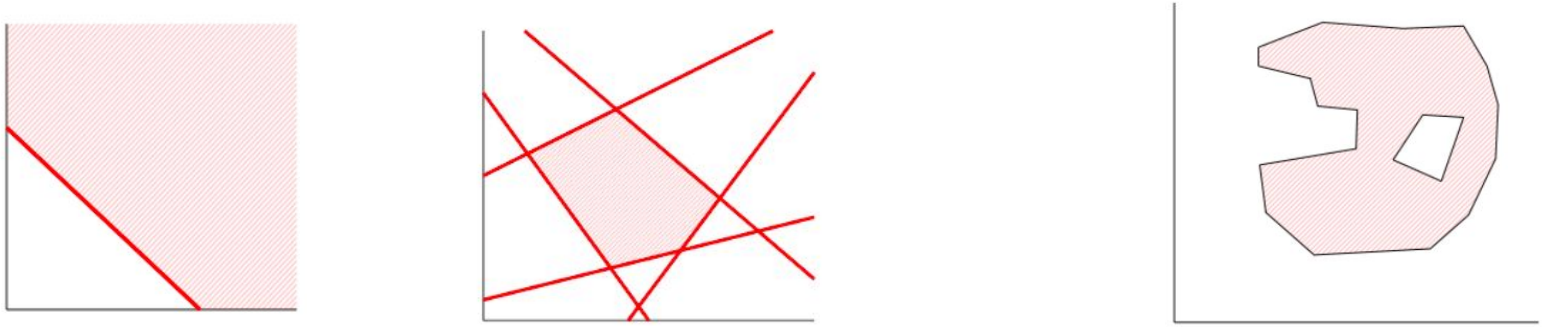




Combining neurons

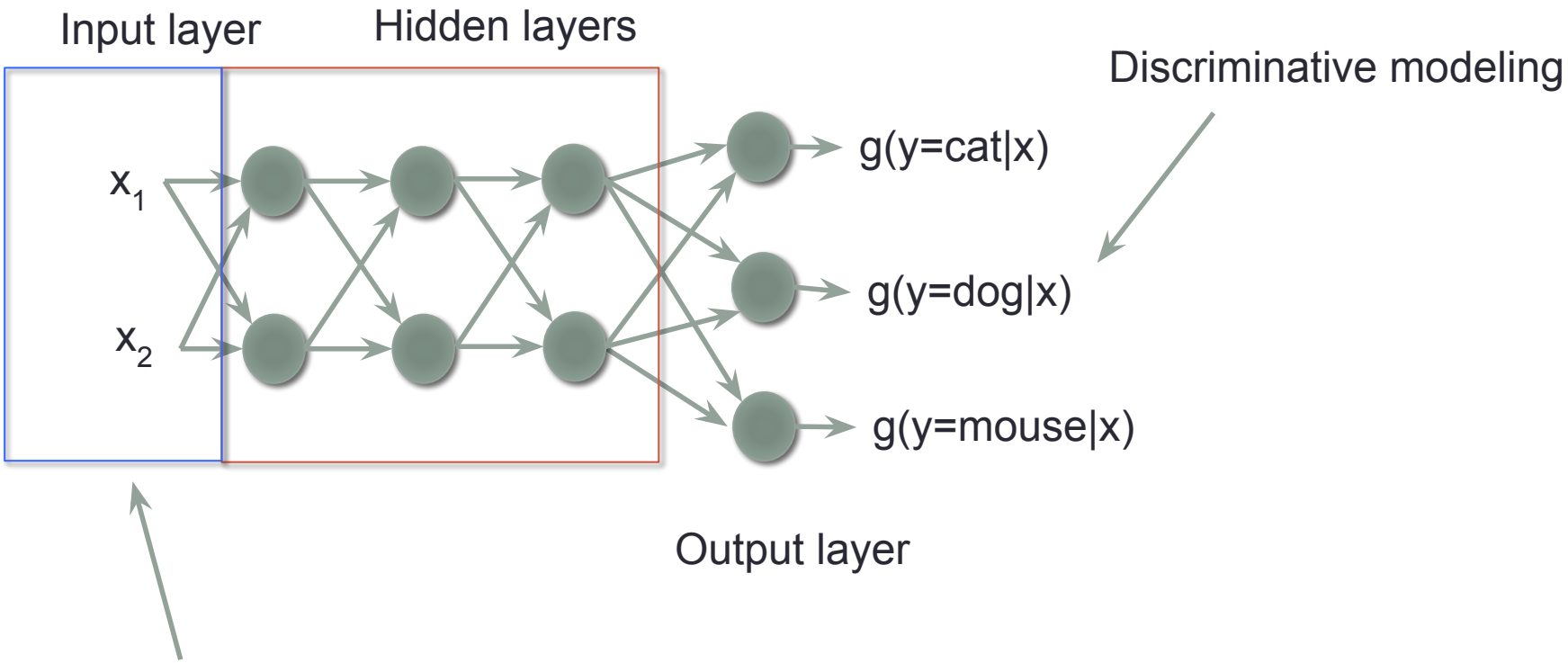
- Each neuron splits the feature space with a hyperplane
- Stacking neuron creates more complicated decision boundaries
- More powerful but prone to overfitting





Terminology

Deep in Deep neural networks means many hidden layers



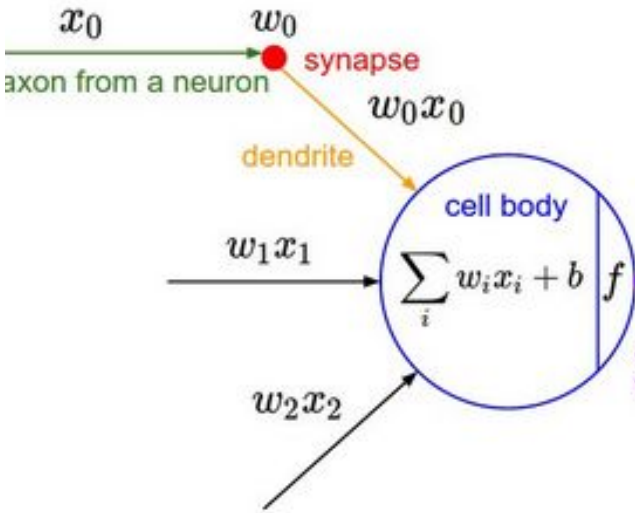
Matrices

- Inputs

features

x_1
x_2
x_3

X



W

weights

w_1
w_2
w_3

$W^T X + b$

w_1 w_2 w_3 x_1 x_2 x_3

+ b

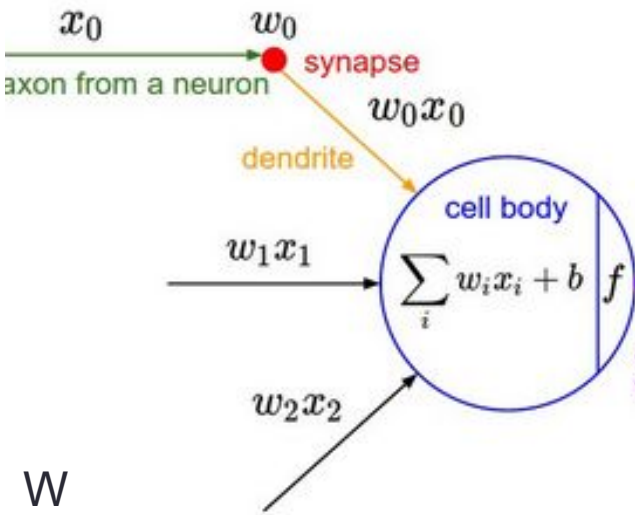
Matrices

- Inputs

samples

features

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{bmatrix}$$



W

weights

$$W = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}$$

$W^T X + b$

$$\begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{bmatrix} + \begin{bmatrix} b \end{bmatrix}$$

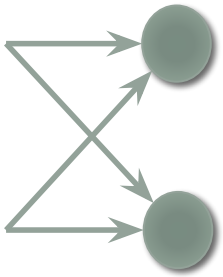
Matrices

- Inputs

samples

features

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{bmatrix}$$



neorons

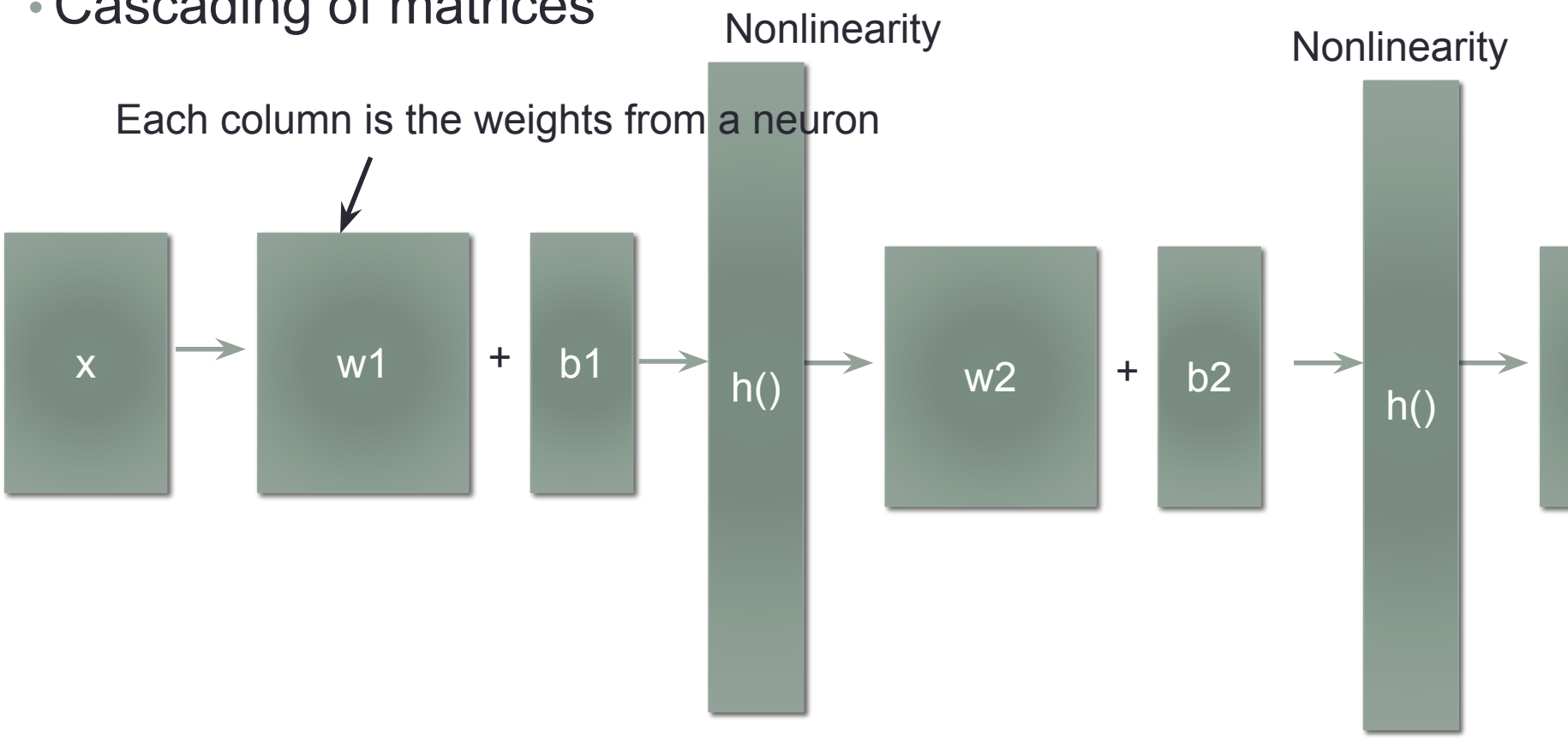
weights

$$W = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \end{bmatrix}$$

$$W^T X + b = \begin{bmatrix} w_{11} & w_{21} & w_{31} \\ w_{21} & w_{22} & w_{23} \end{bmatrix} \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

More linear algebra

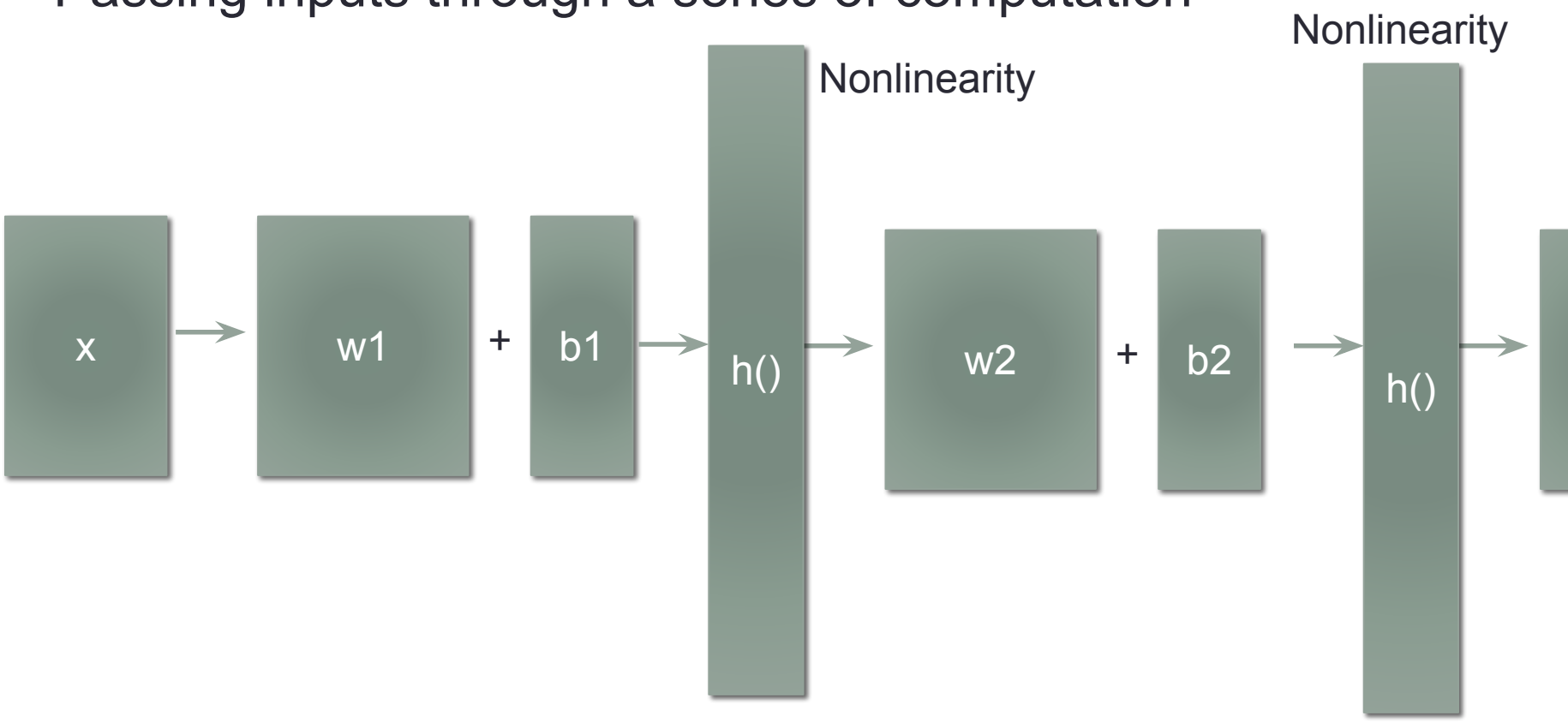
- Cascading of matrices



$h(W_2^T\, h(W_1^T X + \mathbf{b_1}) + \mathbf{b_2})$

Computation graph

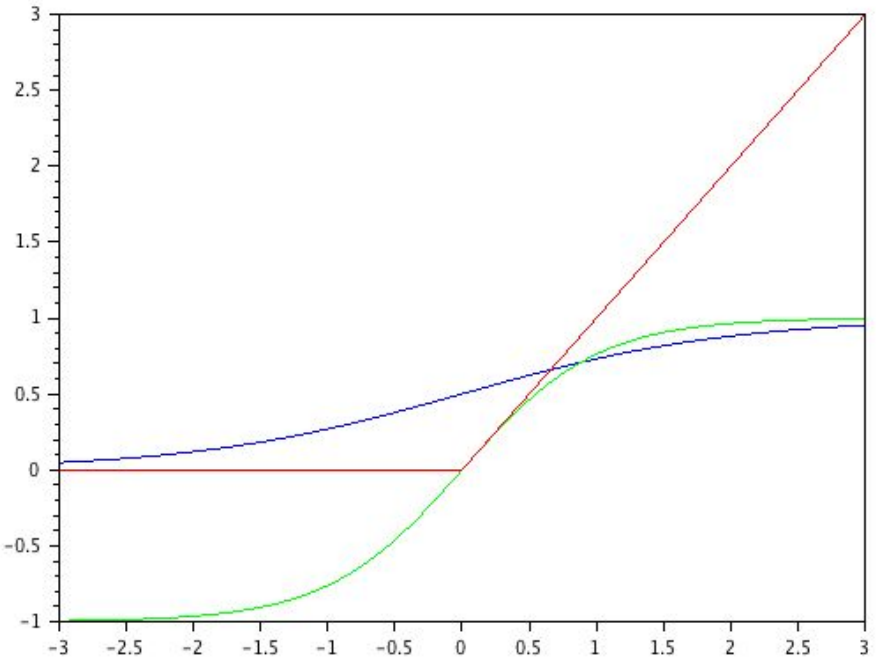
- Passing inputs through a series of computation



$h(W_2^T\, h(W_1^T X + \mathbf{b_1}) + \mathbf{b_2})$

Non-linearity

- The Non-linearity is important in order to stack neurons
- Sigmoid or logistic function
- tanh
- Rectified Linear Unit (ReLU)
- Swish
- Most popular is ReLU and its variants (Fast to train, and more stable)



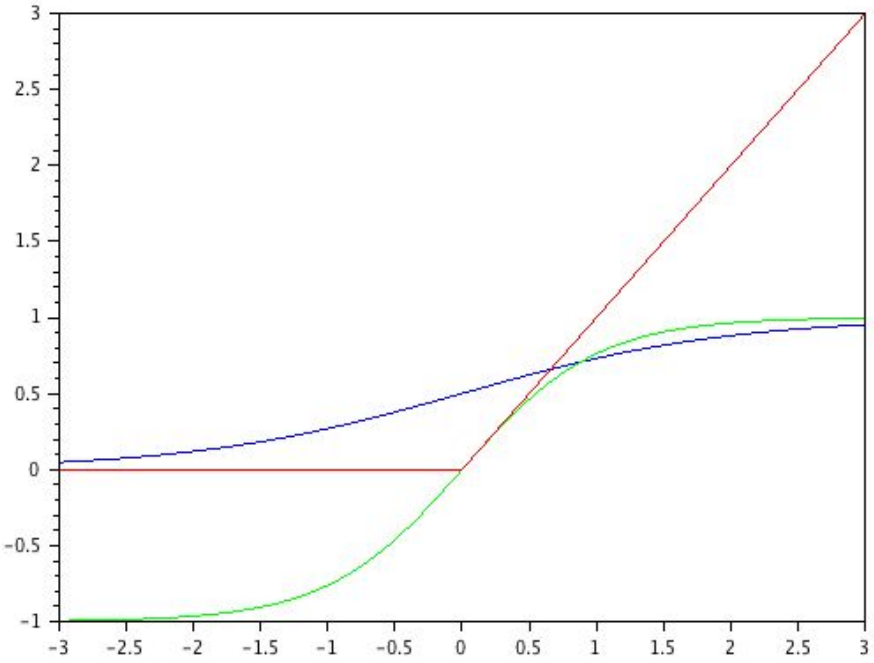
Non-linearity

- Sigmoid $\frac{1}{1+e^{-x}}$
- tanh

$$tanh(x)$$

- Rectified Linear Unit (ReLU)

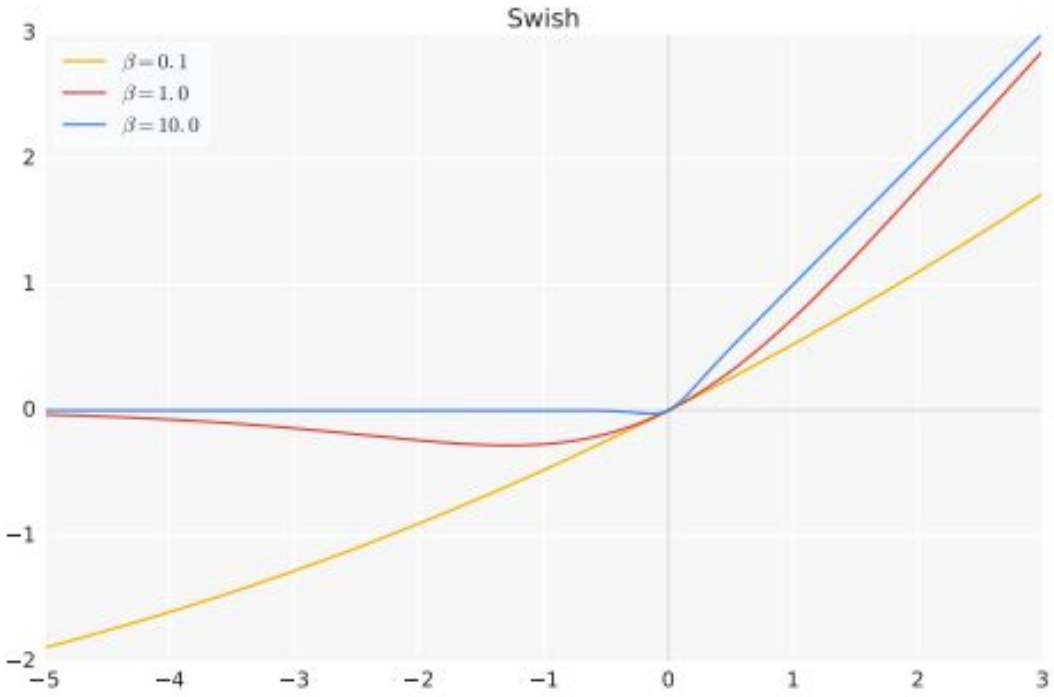
$$max(0, x)$$



Swish

Found through reinforcement learning to be the best general non-linearity

$$x \cdot sig(\beta x)$$



sig refers to a sigmoid function
Beta is a learnable parameter or can be set to 1 for slightly worse performance

Beta -> inf, then Swish -> ReLu

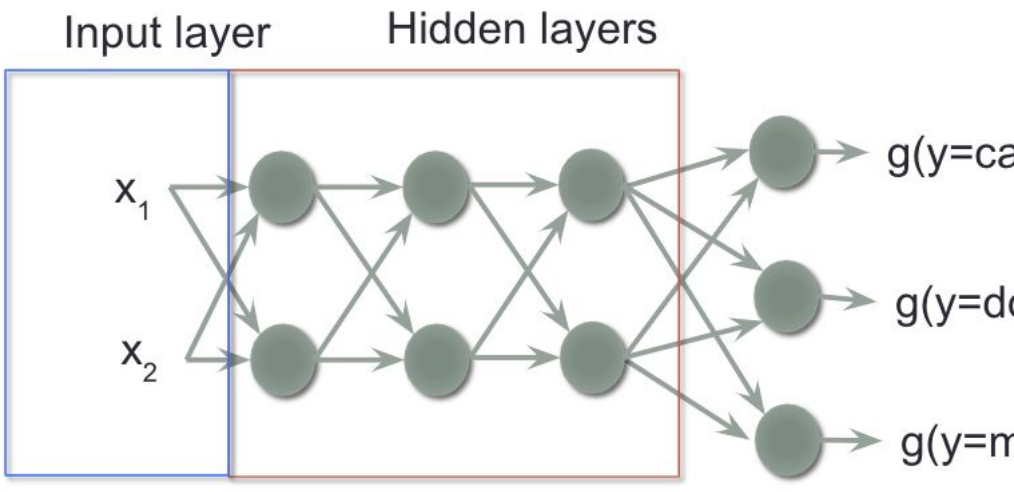
Searching for Activation Functions - arXiv

Proven theoretically to be optimal

Expectation propagation: a probabilistic view of Deep Feed Forward Networks

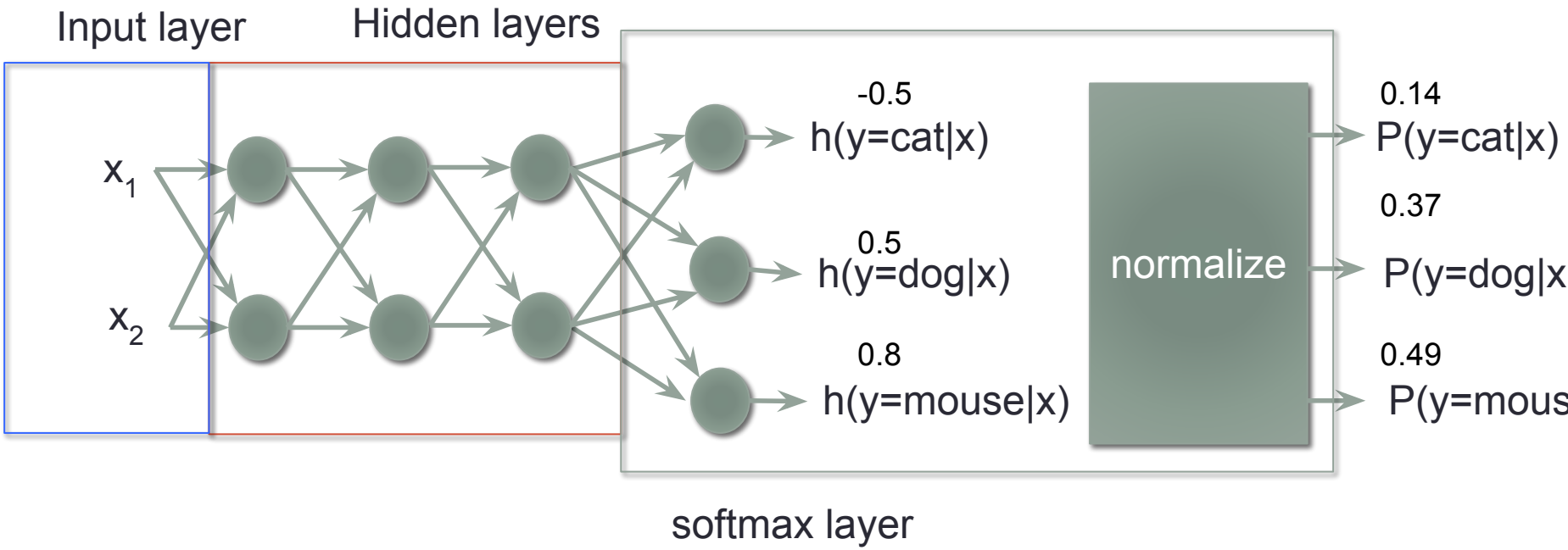
Output layer – Softmax layer

- We usually wants the output to mimic a probability function (0<=P<=1,sums to 1)
- Current setup has no such constraint
- The current output should have highest value for the correct class.
  - Value can be positive or negative number
- Takes the exponent
- Add a normalization



Softmax layer

$$P(y=j|x) = \frac{e^{h(y=j|x)}}{\sum_y e^{h(y|x)}}$$



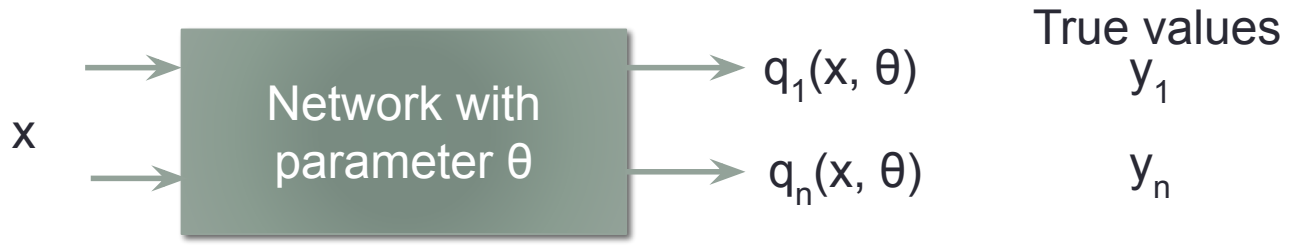
Neural networks

- Fully connected networks
  - Neuron
  - Non-linearity
  - Softmax layer
- DNN training
  - Loss function and regularization
  - SGD and backprop
  - Learning rate
  - Overfitting – dropout, batchnorm
- Demos
  - Tensorflow, Keras
- CNN
- RNN, LSTM, GRU <- Next class

Objective function (Loss function)

- Can be any function that summarizes the performance into a single number
- Cross entropy

- Sum of squared errors



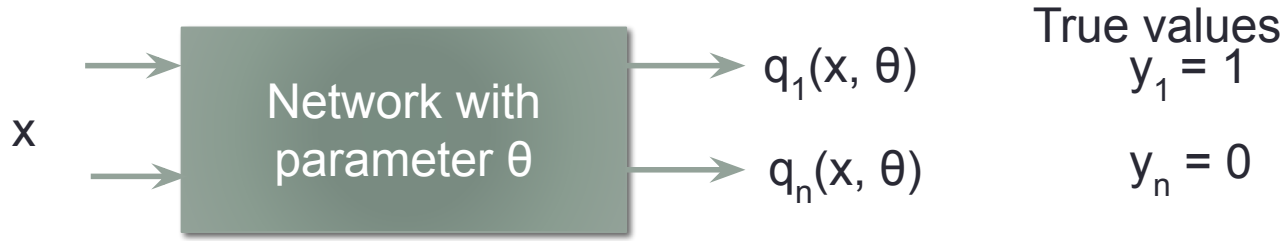
Cross entropy loss

- Used for softmax outputs (probabilities), or classification tasks

$$L = -\Sigma_n y_n log q_n(x, \theta)$$

- Where y_n is 1 if data x comes from class n
  0 otherwise

- L only has the term from the correct class
- L is non negative with highest value when the output matches the true values, a “loss” function

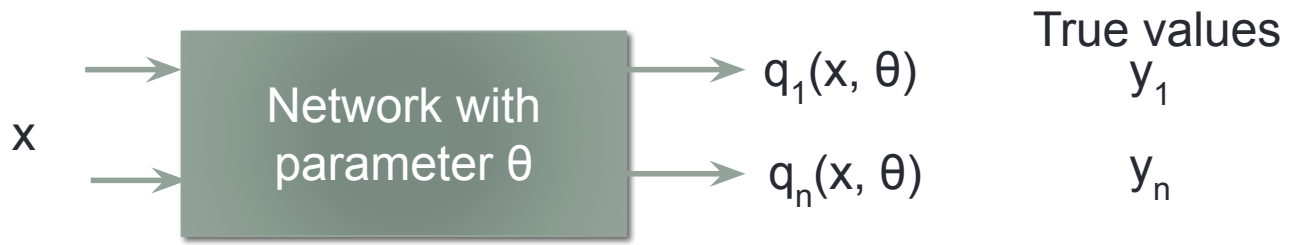


Sum of squared errors (MSE)

- Used for any real valued outputs such as regression

$$L = \frac{1}{2}\Sigma_n(y_n - q_n(x,\theta))^2$$

- Non negative, the better the lower the loss



Other losses (later)

Squared EMD loss

Classification tasks with ordering (dog -> elephant is better than dog -> car)

Adversarial loss

Learning distribution or when no single answer exist

Perceptual loss

Wants output to have certain properties (Computer vision)

Smoothed L1

L1 + L2

Regularization

There two main approaches to regularize neural networks

- Explicit regularization
  Deals with the loss function
- Implicit regularization
  Deals with the network

Regularization in one slide

- What?
  - Regularization is a method to lower the model variance (and thereby increasing the model bias)
- Why?
  - Gives more generalizability (lower variance)
  - Better for lower amounts of data (reduce overfitting)
- How?
  - Introducing regularizing terms in the original loss function

Famous types of regularization

- L1 regularization: Regularizing term is a sum
  - $\mathbf{w}^T\mathbf{w} + C\Sigma\varepsilon_i$
- L2 regularization: Regularizing term is a sum of squares
  - $\mathbf{w}^T\mathbf{w} + C\Sigma\varepsilon_i^2$

L2 regularization	L1 regularization
Computational efficient due to having analytical solutions	Computational inefficient on non-sparse cases
Non-sparse outputs	Sparse outputs
No feature selection	Built-in feature selection

http://www.chioka.in/differences-between-l1-and-l2-as-loss-function-and-regularization/

Regularization in neural networks L2

- We want to improve generalization somehow.
- Observation, models are better when the weights are spread out (no peaky weights).
  - Try to use every part of the model.
- Add a cost if we put some value to the weights

- Regularized loss = Original loss + $C\Sigma w^2$

- we sum the square of weights of the whole model
- C is a hyperparameter weighting the regularization term

Regularization in neural networks

- We want to improve generalization somehow.
- Observation, models behave better when we force the weights to be sparse.
  - Sparse means many weights are zero or close to zero
  - Force the model to focus on only important parts
  - Less prone to noise
- Add a cost if we put some value to the weights
- Regularized loss = Original loss + $C\Sigma|w|$

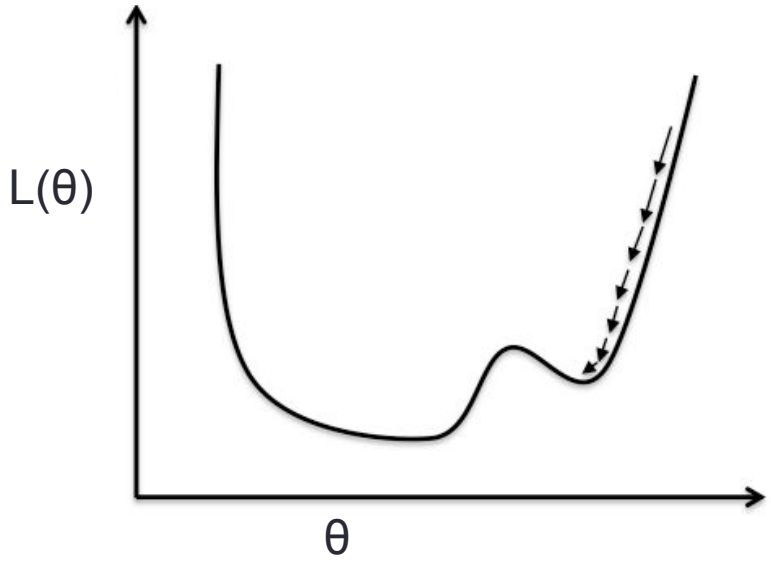
- we sum the absolute weights of the whole model
- C is a hyperparameter weighting the regularization term

L1 L2 regularization notes

- Can use both at the same time
  - People claim L2 is superior (called weight decay by some community)
- Mostly ignored nowadays
- Other regularization methods exist (we will go over these later)

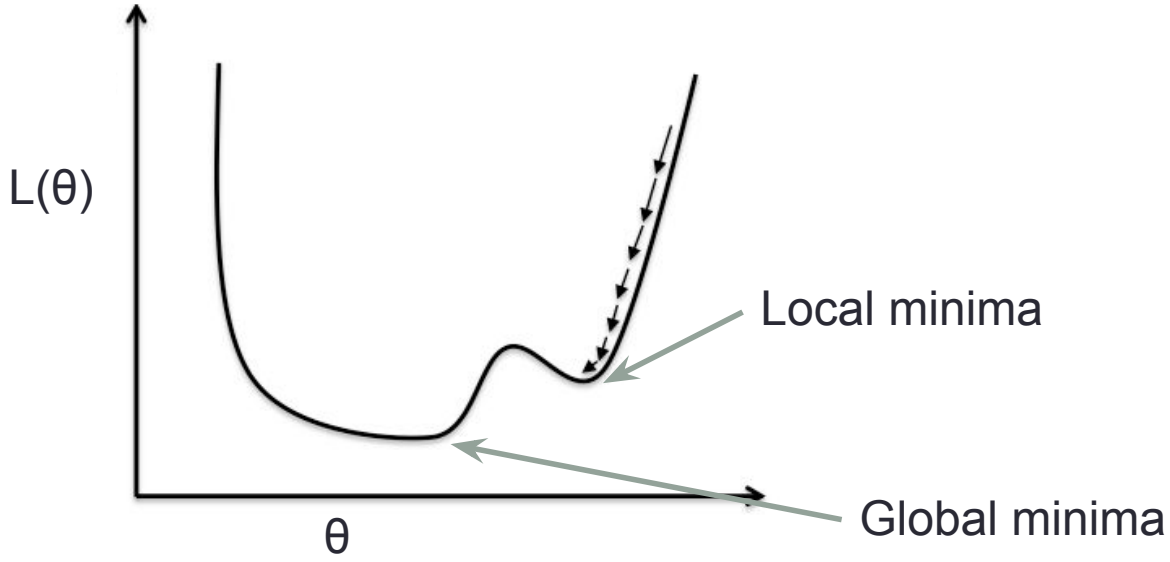
Minimization using gradient descent

- We want to minimize L with respect to θ (weights and biases)
  - Differentiate with respect to θ
  - Gradients passes through the network by Back Propagation



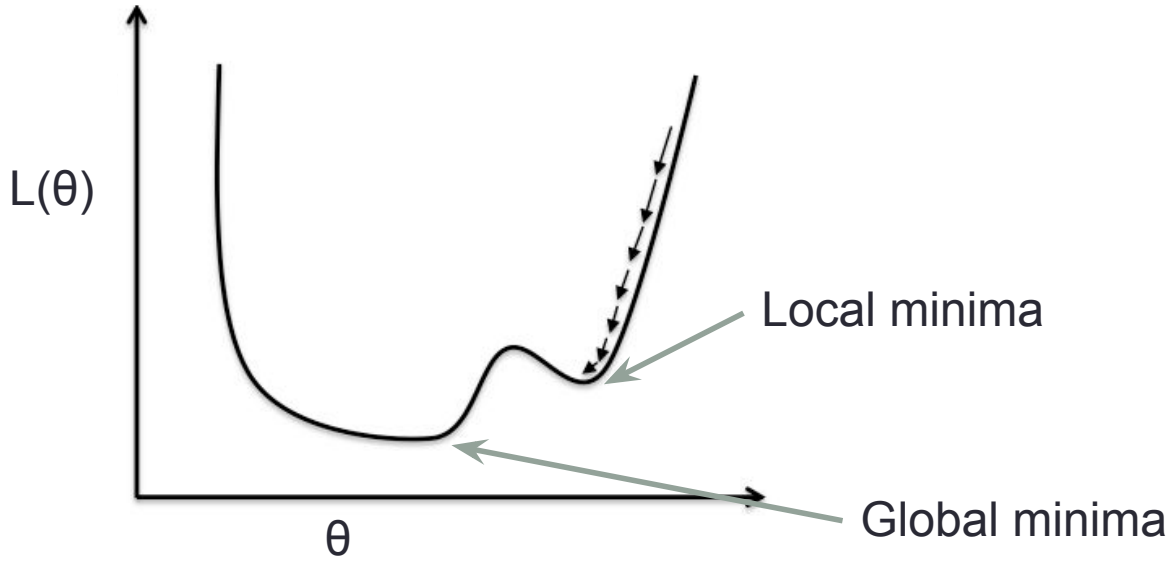
Deep vs Shallow

- The loss function of neural network is non-convex (and non-concave)
  - Local minimas can be avoided with convexity
    - Linear regression, SVM are convex optimization
  - Convexity gives easier training
    - Does not imply anything about the generalization of the model
    - The loss is optimized by the training set



Deep vs Shallow

- If deep, most local minimas are the global minima!
  - Always a way to lower the loss in the network with millions of parameters
  - Enough parameters to remember every training examples
  - Does not imply anything about generalization



Kenji Kawaguchi,Deep Learning without Poor Local Minima, 2016 https://arxiv.org/abs/1605.07110

Differentiating a neural network model

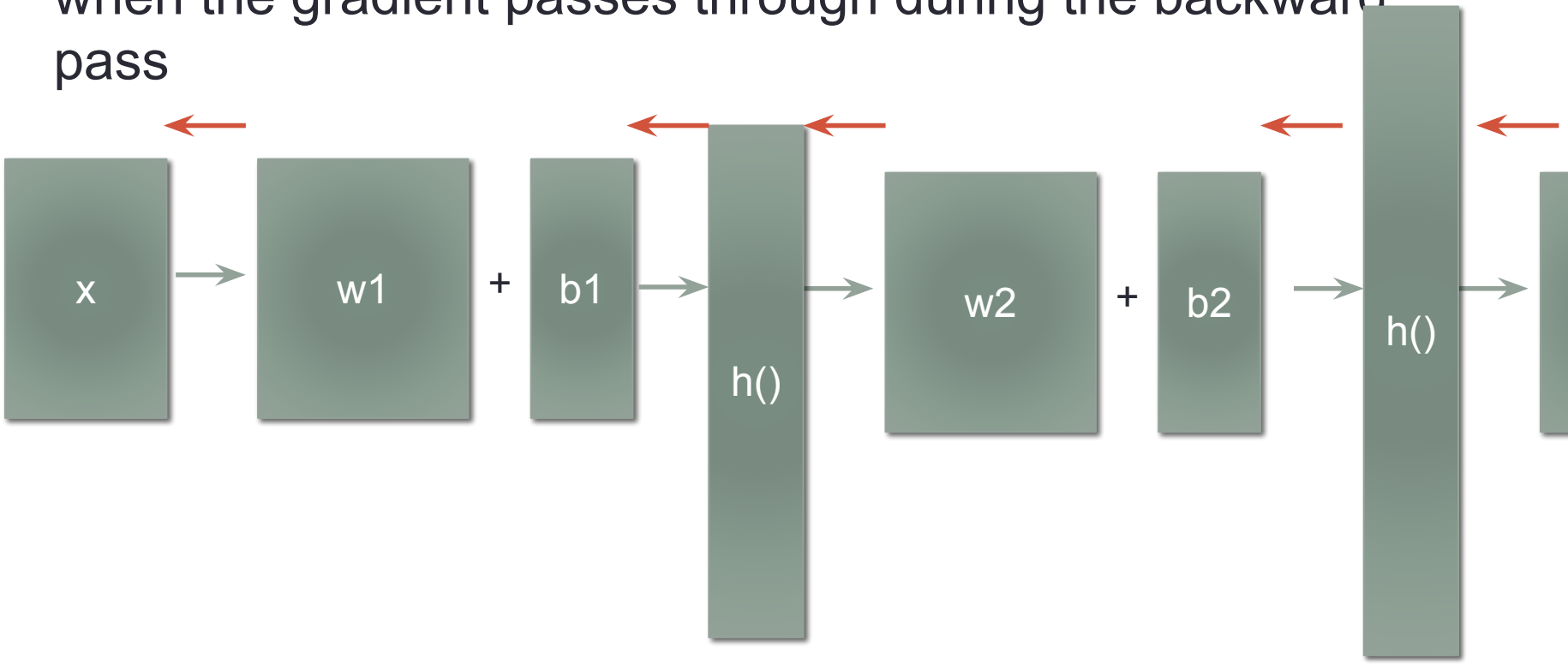
- We want to minimize loss by gradient descent
- A model is very complex and have many layers! How do we differentiate this!!?

Back propagation

- Forward pass
  - Pass the value of the input until the end of the network
- Backward pass
  - Compute the gradient starting from the end and passing down gradients using chain rule

Backprop and computation graph

- We can also define what happens to a computing graph when the gradient passes through during the backward pass

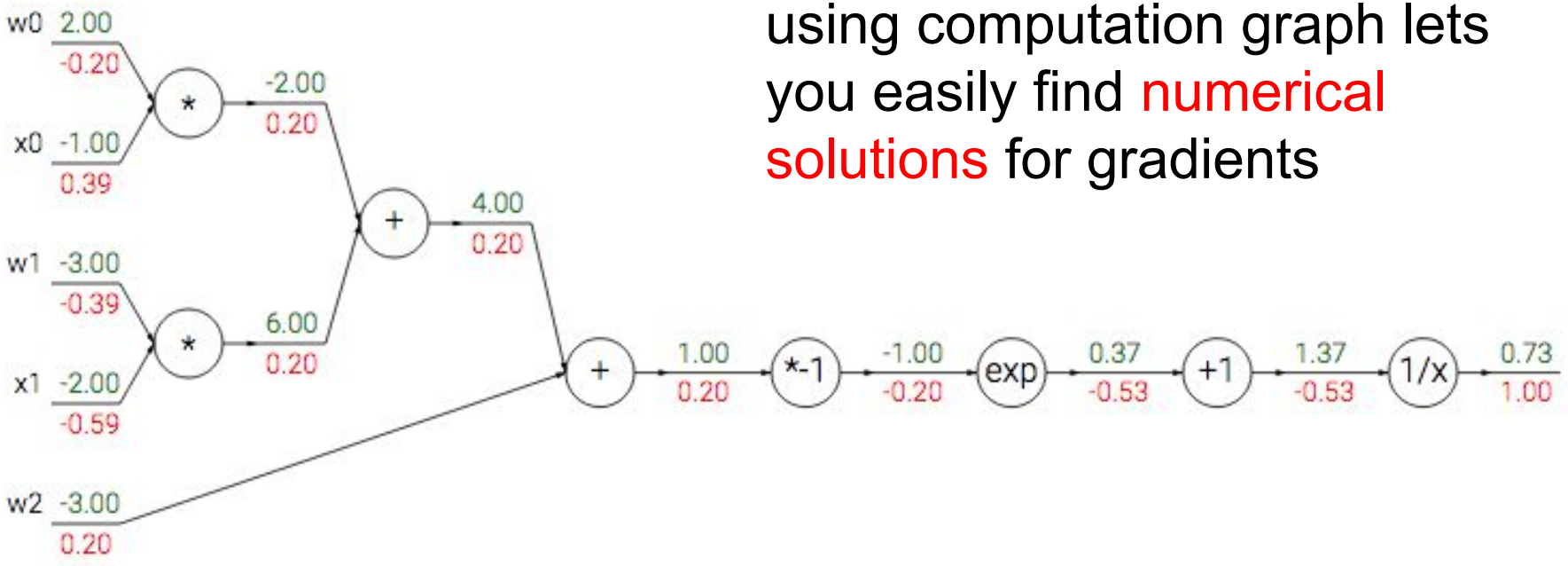


This lets us to build any neural networks without having to redo all the derivation as long as we define a forward and backward computation for the block.

Numerical gradient flow

- Let's find the gradient of $$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

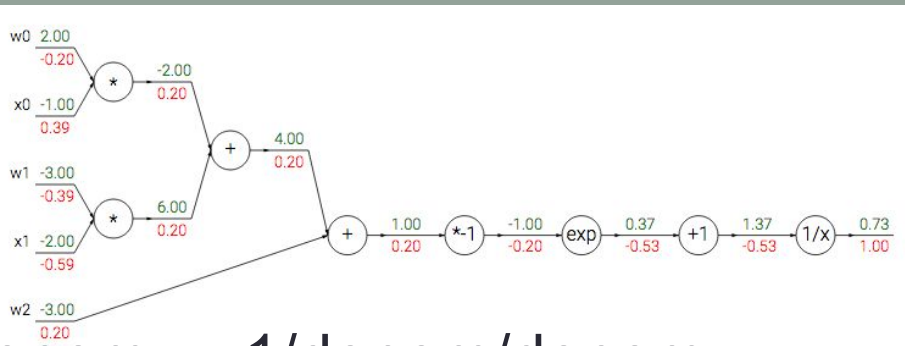
Computation graph



Doing backprop (chain rule) by using computation graph lets you easily find numerical solutions for gradients

http://cs231n.github.io/optimization-2/

$$f(w,x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$$

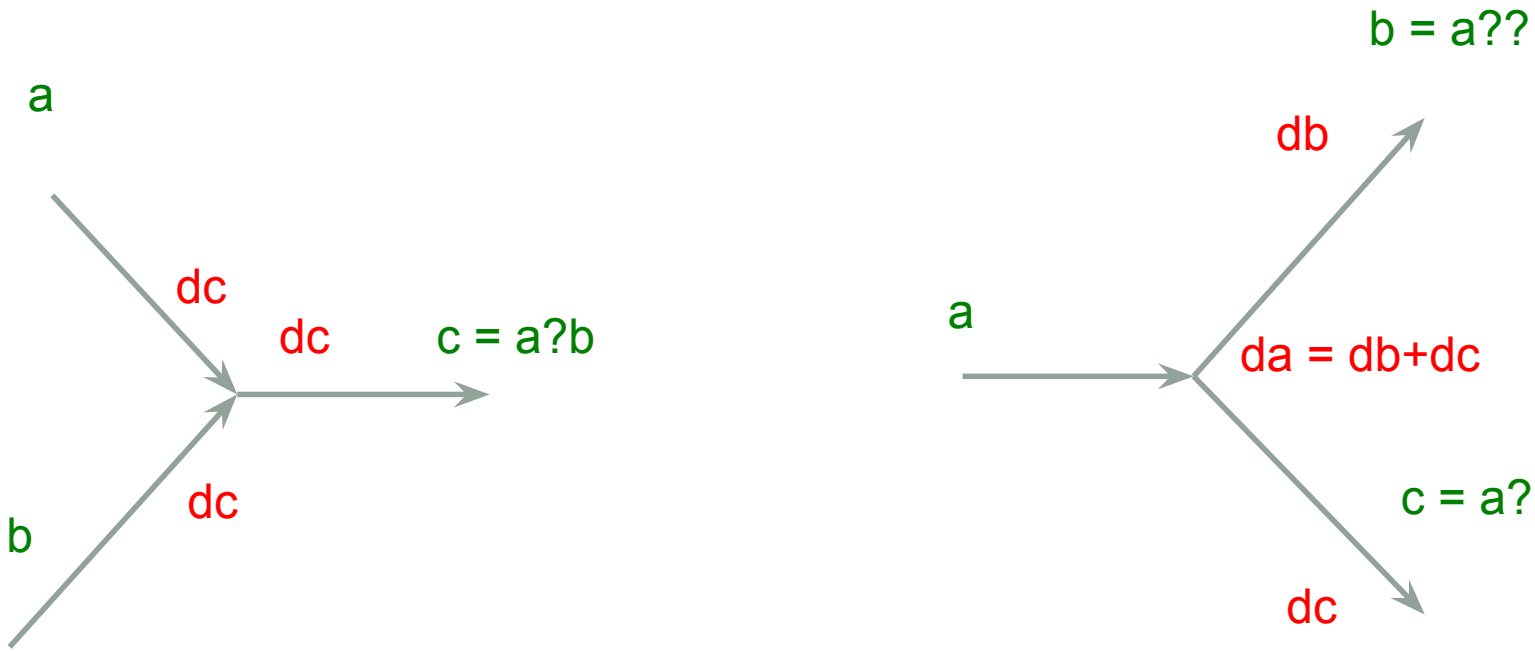


- w = [0, -3, -3]
- x = [-1, -2]
- $t_0 = w[0]*x[0]$
- $t_1 = w[1]*x[1]$
- $t_{01} = t_0+t_1$
- $t_{012} = t_{01}+w[2]$
- $n_t = -t_{012}$
- $e = \exp(n_t)$
- denom = e+1
- f = 1/denom

- $ddenom = -1/denom/denom$
- $de = 1*ddenom$
- $dn_t = \exp(n_t)*de$
- $dt_{012} = -dn_t$
- $dw_2 = 1*dt_{012}$
- $dt_{01} = 1*dt_{012}$
- $dt_0 = 1*dt_{01}$
- $dt_1 = 1*dt_{01}$
- $dw_1 = x[1]dt_1$
- $dx_1 = w[1]dt_1$
- $dw_0 = x[0]dt_0$; $dx_0 = w[0]dt_0$

Perform backward pass in reverse order. No need to explicitly find overall derivative

Gradient flow at forks



Forward and backward pass acts differently at forks

Gradient and non-linearities

We can now talk about how good a non-linearity is by looking at the gradients.

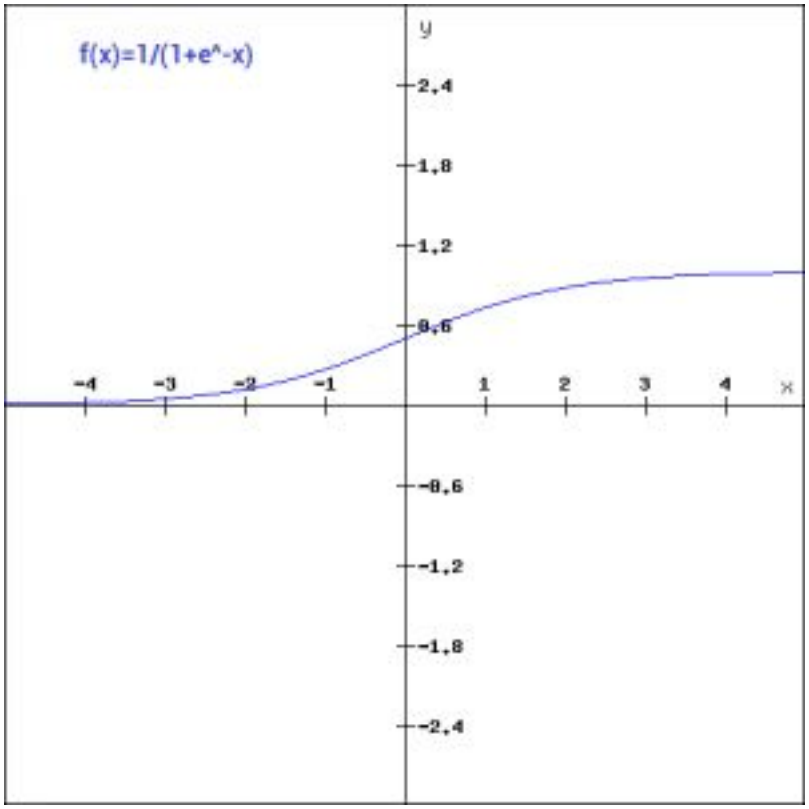
We want

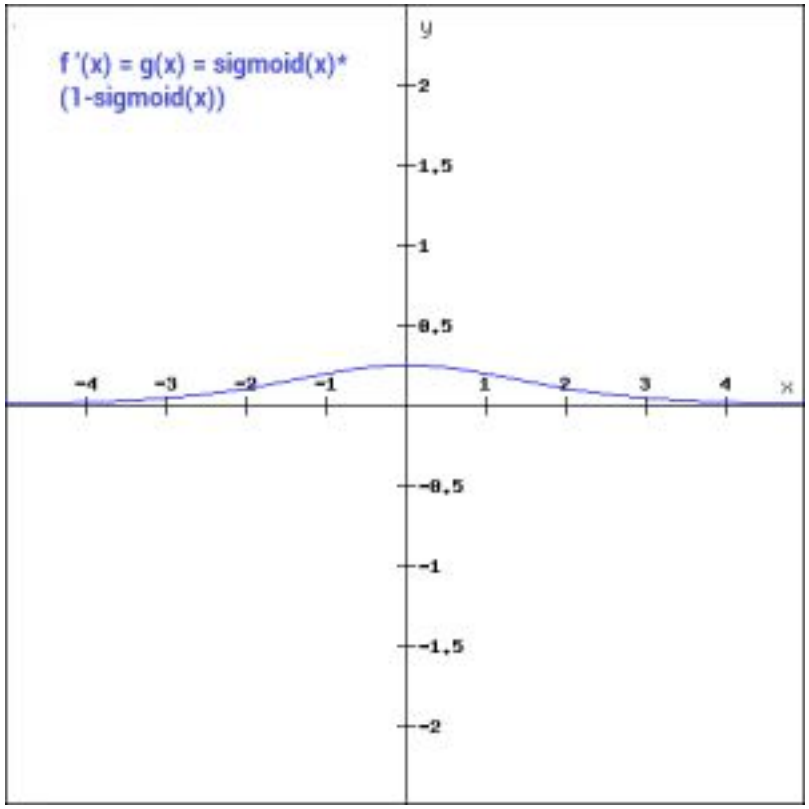
- Something that is differentiable numerically
- Cheap to compute
- Big gradients at every point

Notes on non-linearity

- Sigmoid

  Models get stuck if fall go far away from 0. Output always positive



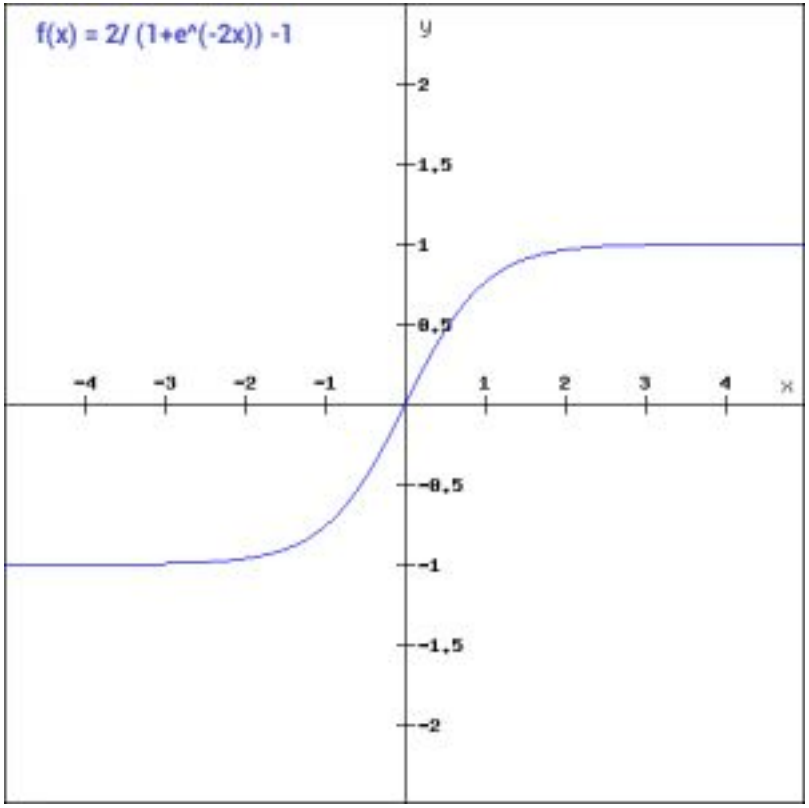


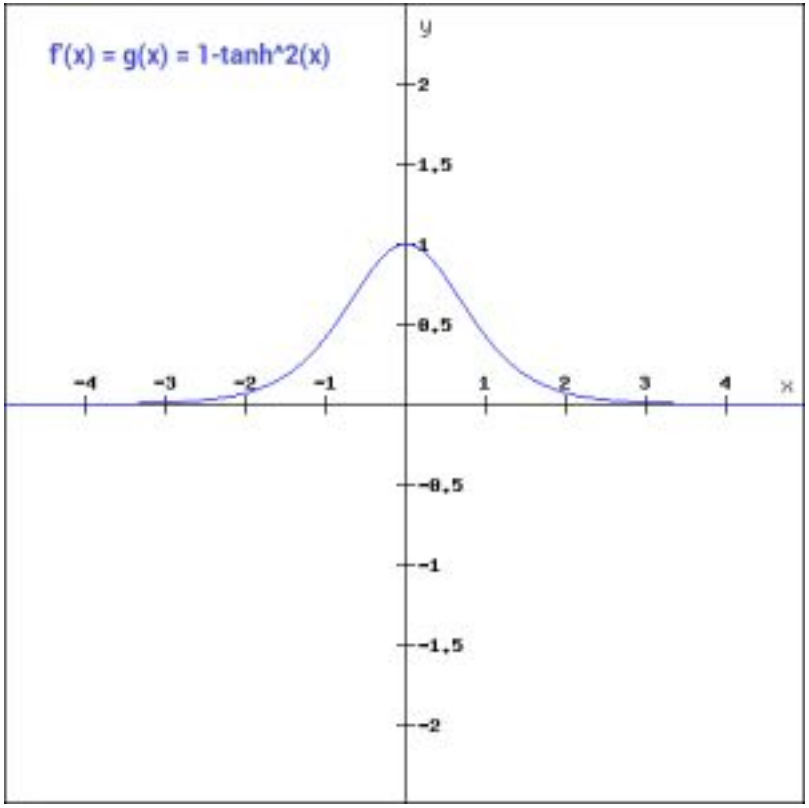
https://www.analyticsvidhya.com/blog/2017/10/fundamentals-deep-learning-activation-functions-when-to-use

Notes on non-linearity

- Tanh

Output can be +-. Models get stuck if far away from 0



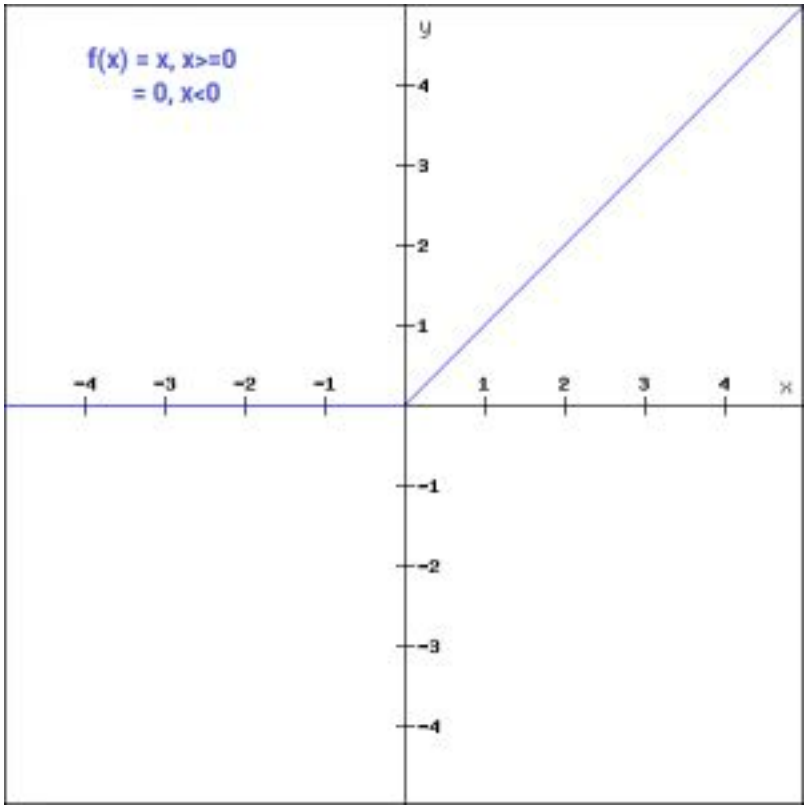


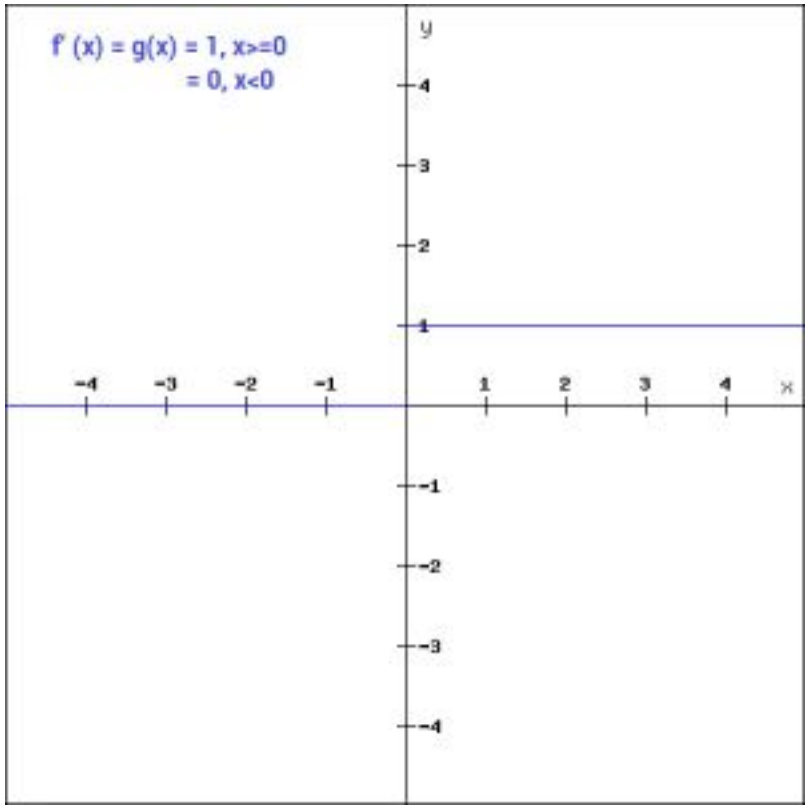
https://www.analyticsvidhya.com/blog/2017/10/fundamentals-deep-learning-activation-functions-when-to-use

Notes on non-linearity

- ReLU

  High gradient in positive. Fast compute. Gradient doesn't move in negative



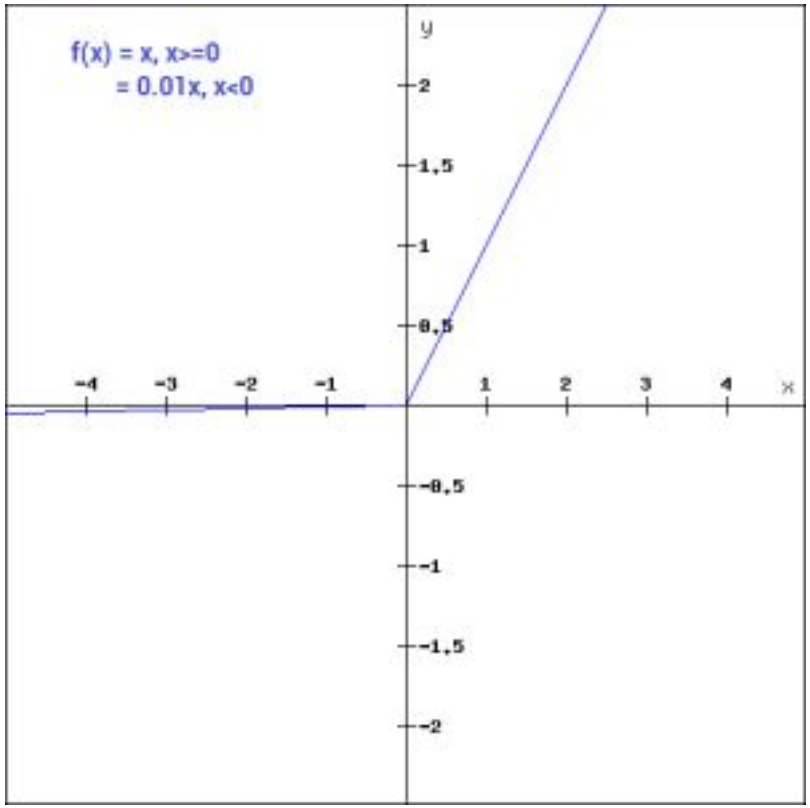


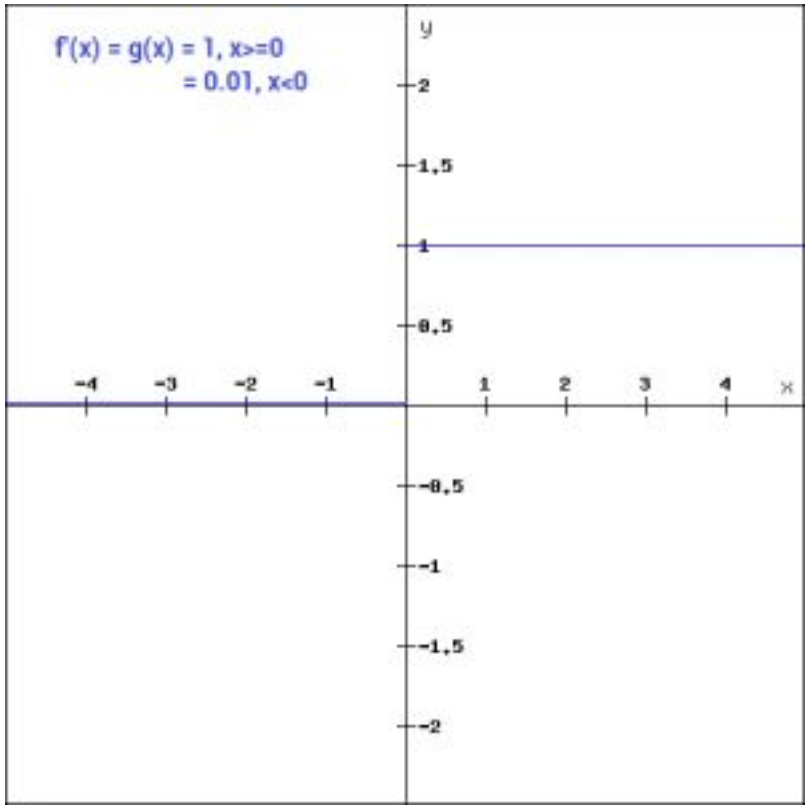
https://www.analyticsvidhya.com/blog/2017/10/fundamentals-deep-learning-activation-functions-when-to-use

Notes on non-linearity

- Leaky ReLU

  Negative part now have some gradient. Small improvements depending on tasks



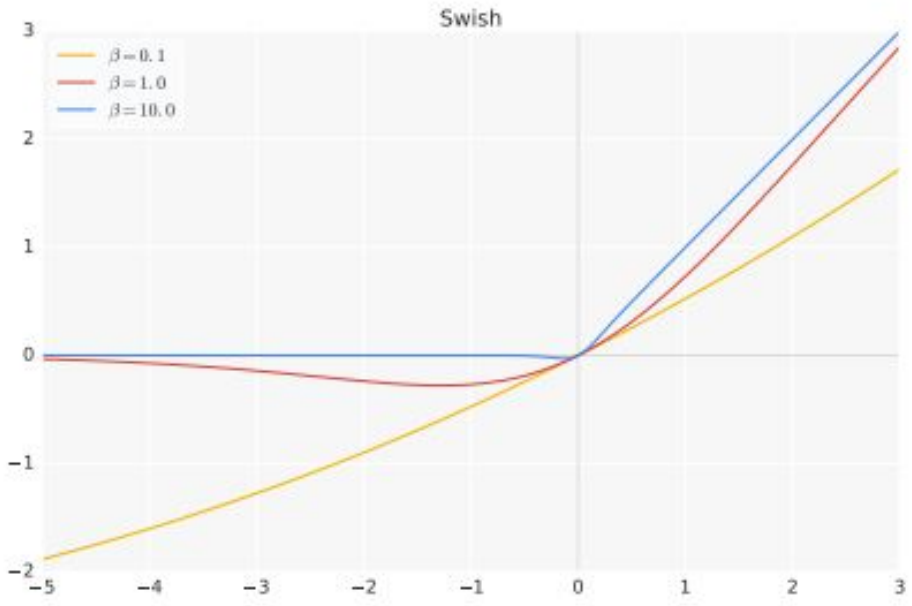


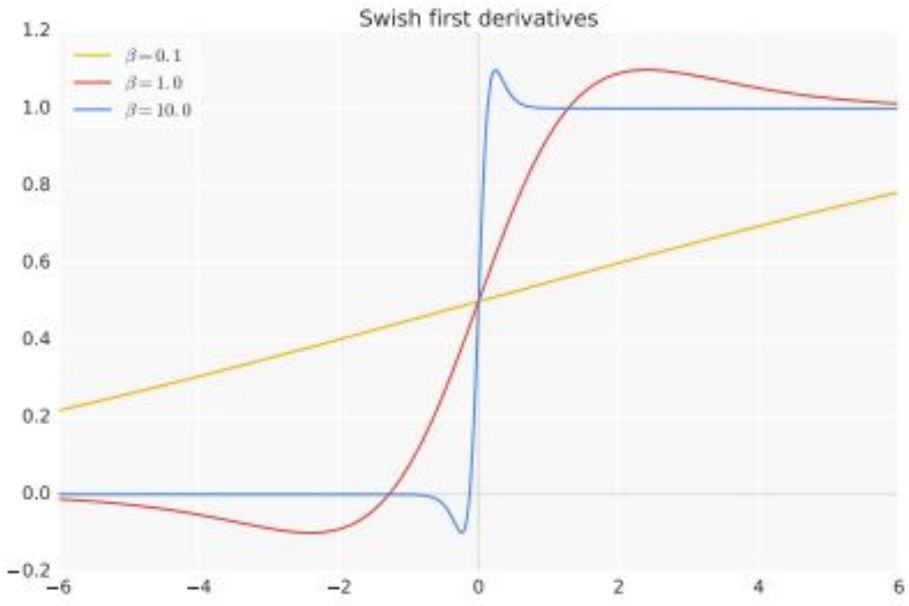
https://www.analyticsvidhya.com/blog/2017/10/fundamentals-deep-learning-activation-functions-when-to-use

Notes on non-linearity

- Swish

  Nonnegative everywhere. Not monotonic.





[Searching for Activation Functions - arXiv]

Initialization

- The starting point of your descent
- Important due to local minimas
- Not as important with large networks AND big data
- Now usually initialized randomly
  - One strategy

$$W \sim \text{Uniform}(0, \frac{1}{\sqrt{\text{FanIn} + \text{FanOut}}})$$

  - For ReLUs

```
w = np.random.randn(n) * sqrt(2.0/n)
```

  - Or use a pre-trained network as initialization

X. Glorot and Y. Bengio. Understanding the difficulty of training deep feedforward neural networks. 2010

https://paperswithcode.com/method/he-initialization

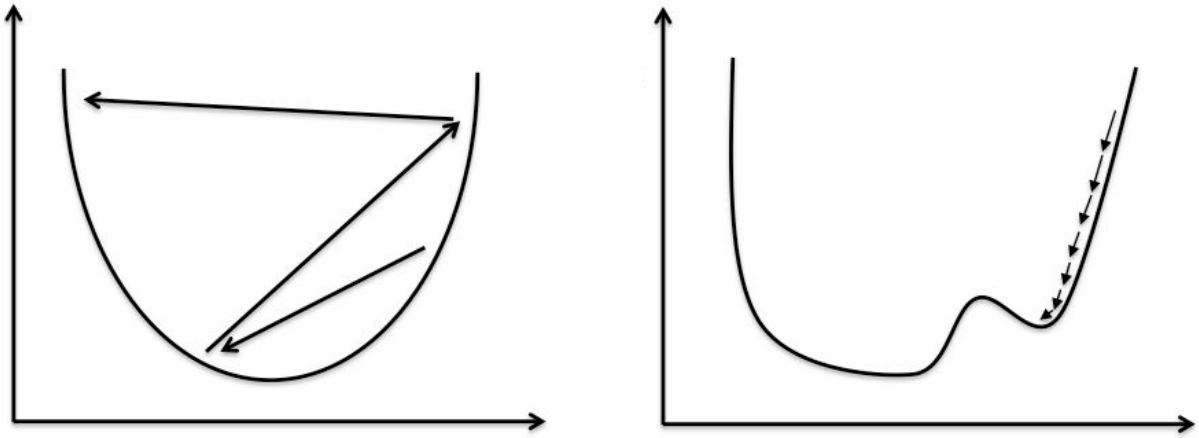
Stochastic gradient descent (SGD)

- Consider you have one million training examples
  - Gradient descent computes the objective function of all samples, then decide direction of descent
  - SGD computes the objective function on subsets of samples
    - The subset should not be biased and properly randomized to ensure no correlation between samples
- The subset is called a mini-batch
- Size of the mini-batch determines the training speed and accuracy
  - Usually somewhere between 32-1024 samples per mini-batch
- Definition: 1 batch vs 1 epoch
- SGD by its randomized nature does not overfit (as fast)
  - Considered as an implicit regularization (no change in the loss)

https://cbmm.mit.edu/sites/default/files/publications/CBMM-Memo-067-v3.pdf

Learning rate

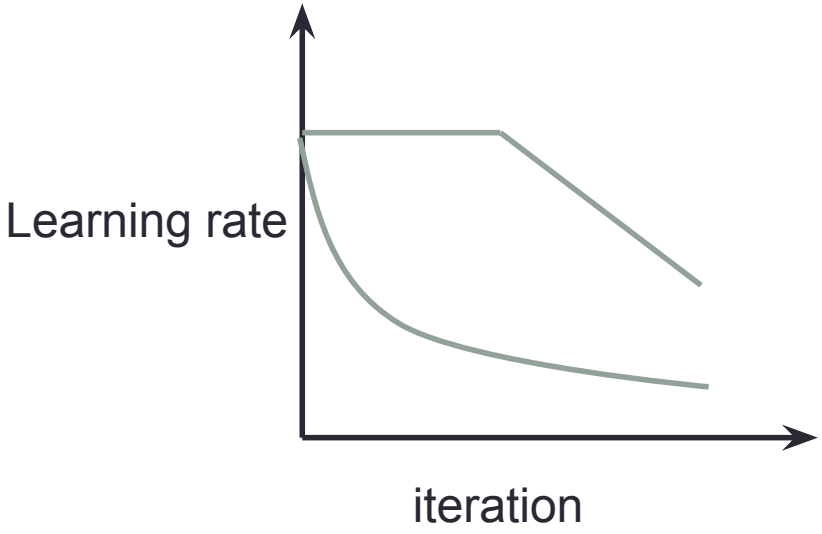
- How fast to go along the gradient direction is controlled by the learning rate
- Too large models diverge
- Too small the model get stuck in local minimas and takes too long to train



http://sebastianraschka.com/Articles/2015_singlelayer_neurons.html

Learning rate scheduling

- Usually starts with a large learning rate then gets smaller later
- Depends on your task
- Automatic ways to adjust the learning rate : Adagrad, Adam, etc. (still need scheduling still)



Learning rate strategies (annealing)

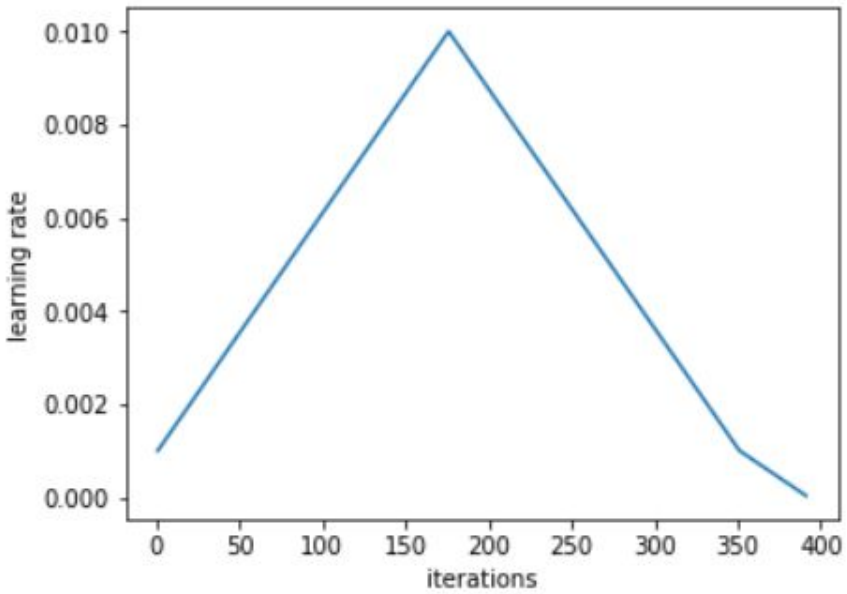
- Step decay: reduce learning rate by x after y epochs
- New bob method: half learning rate every time the validation error goes up. Only plausible in larger tasks
- Exponential decay: multiplies the learning rate by exp(-rate*epoch number)

Learning rate warm up

Initial point of the network can be at a bad spot.

Try not to go to fast - has a warm up period.

Useful for large datasets, or adaption (transfer learning)



Potentially leads to faster convergence and better accuracy

See links below for methods to select the shape of the triangle

https://sgugger.github.io/the-1cycle-policy.html#the-1cycle-policy

Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour

Cyclical Learning Rates for Training Neural Networks

Momentum

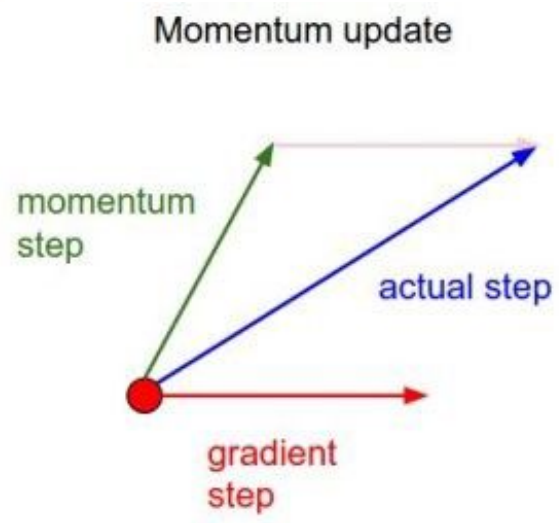
- Gradient descent can get stuck on small local minimas
  - Or slow down at saddle points
- Have concept of speed

speed Momentum rate gradient

$$V_t = \beta V_{t-1} + (1-\beta)\nabla_w L(W, X, y)$$

$$W = W - \alpha V_t$$

learning rate



https://towardsdatascience.com/stochastic-gradient-descent-with-momentum-a84097641a5d
http://cs231n.github.io/neural-networks-3/

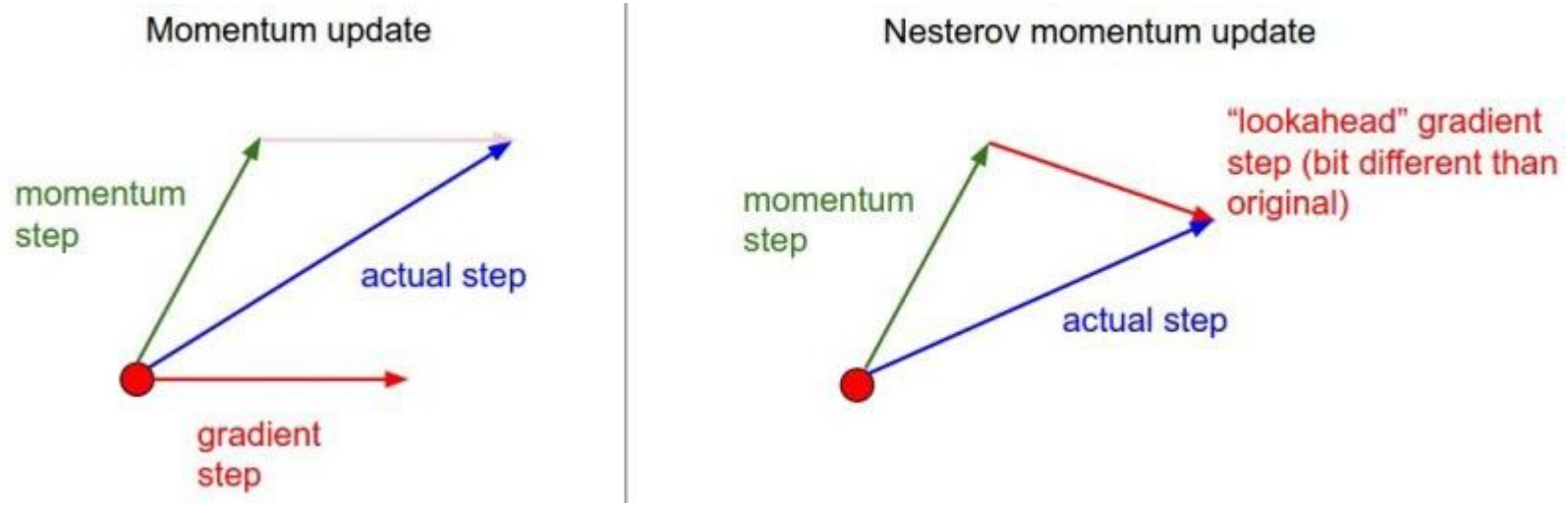
Nesterov Momentum

- Momentum with look ahead.
  - Compute gradient as if we took an additional step

$$V_t = \beta V_{t-1} + \alpha \nabla_w L(W - \beta V_{t-1}, X, y)$$

$$W = W - V_t$$

gradient is computed as if we took a step



https://towardsdatascience.com/stochastic-gradient-descent-with-momentum-a84097641a5d
http://cs231n.github.io/neural-networks-3/

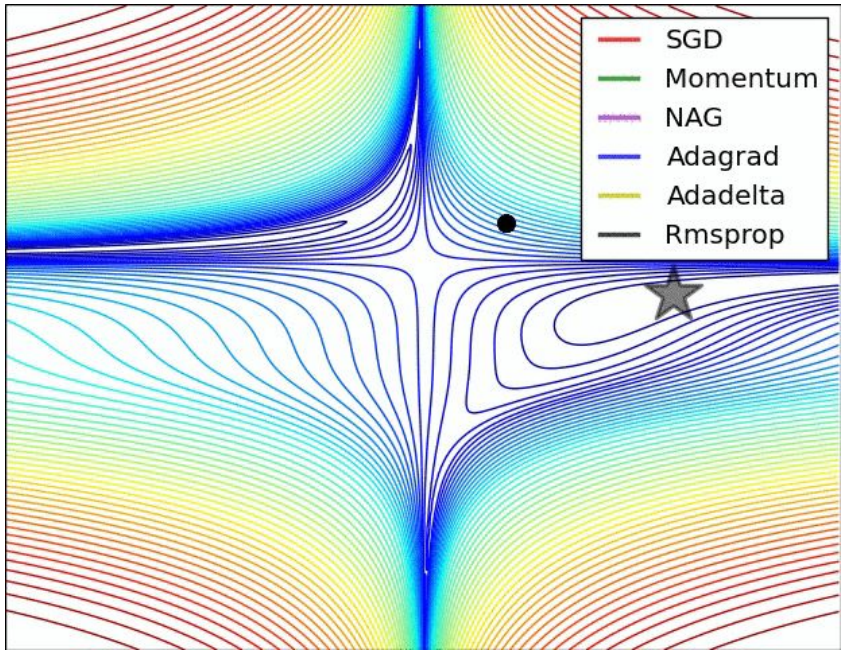
Optimizers

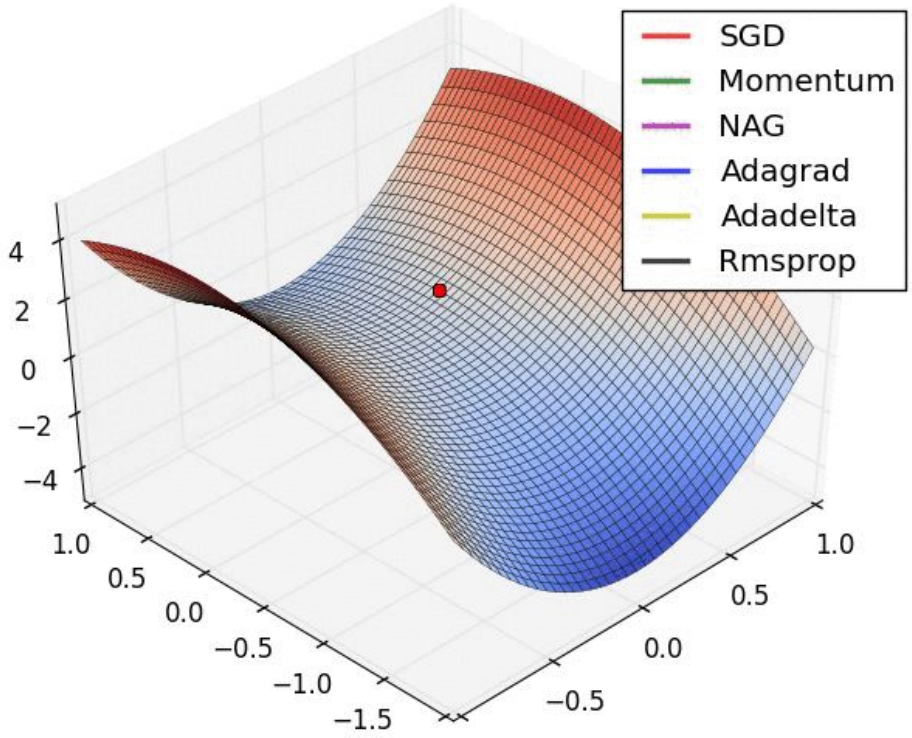
- Besides learning rate scheduling (coarse grain) we can do finer (and automatic) control of the learning rate via optimizers

- RMSprop
  - Faster than SGD but slower than ADAM
  - More stable than ADAM
- ADAM + variants
  - Most popular for its ease of use

People find simple SGD with momentum and decay to perform better (with proper tuning)

Optimization method and speed





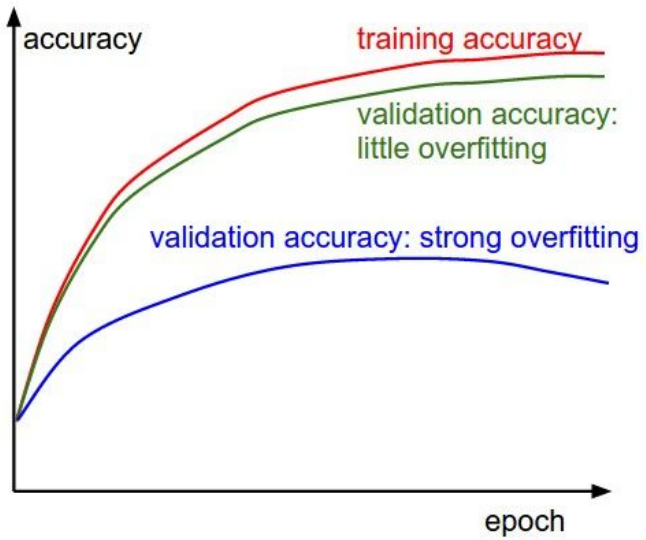
http://ruder.io/optimizing-gradient-descent/index.html#whichoptimizertochoose

Learning rate tricks

- At least decay the learning rate
  - Monitor validation set performance
- If the loss never goes down -> decrease the learning rate (by factor of 10)
- Start with ADAM. Also try RMSprop and SGD with Nesterov Momentum if you have time

Overfitting

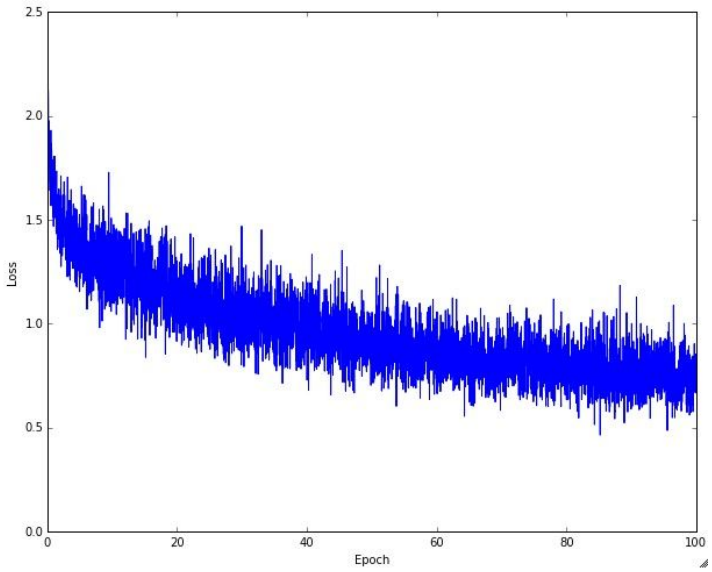
- You can keep doing back propagation forever!
- The training loss will always go down
- But it overfits
- Need to monitor performance on a held out set
- Stop or decrease learning rate when overfit happens



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

Monitoring performance

- Monitor performance on a dev/validation set
  - This is NOT the test set
- Can monitor many criterions
  - Loss function
  - Classification accuracy
- Sometimes these disagree
- Actual performance can be noisy, need to see the trend



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

Dropout

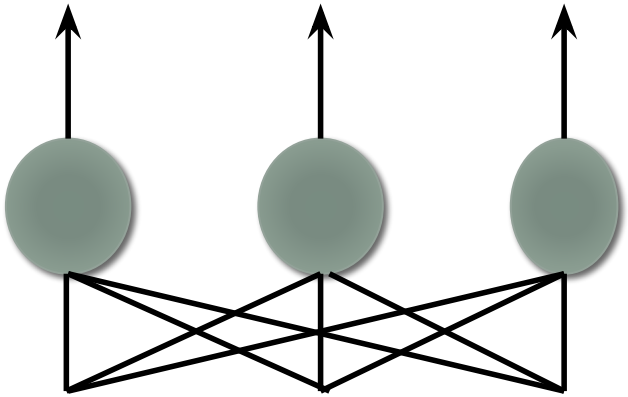
A implicit regularization technique for reducing overfitting

Randomly turn off different subset of neurons during training

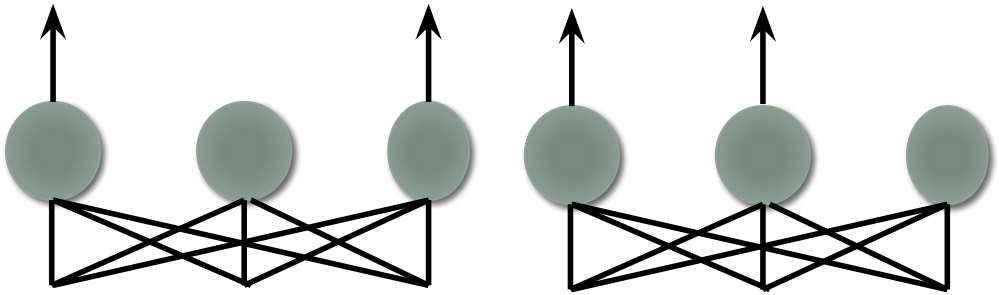
Network no longer depend on any particular neuron

Force the model to have redundancy – robust to any corruption in input data

A form of performing model averaging (ensemble of experts)



Model

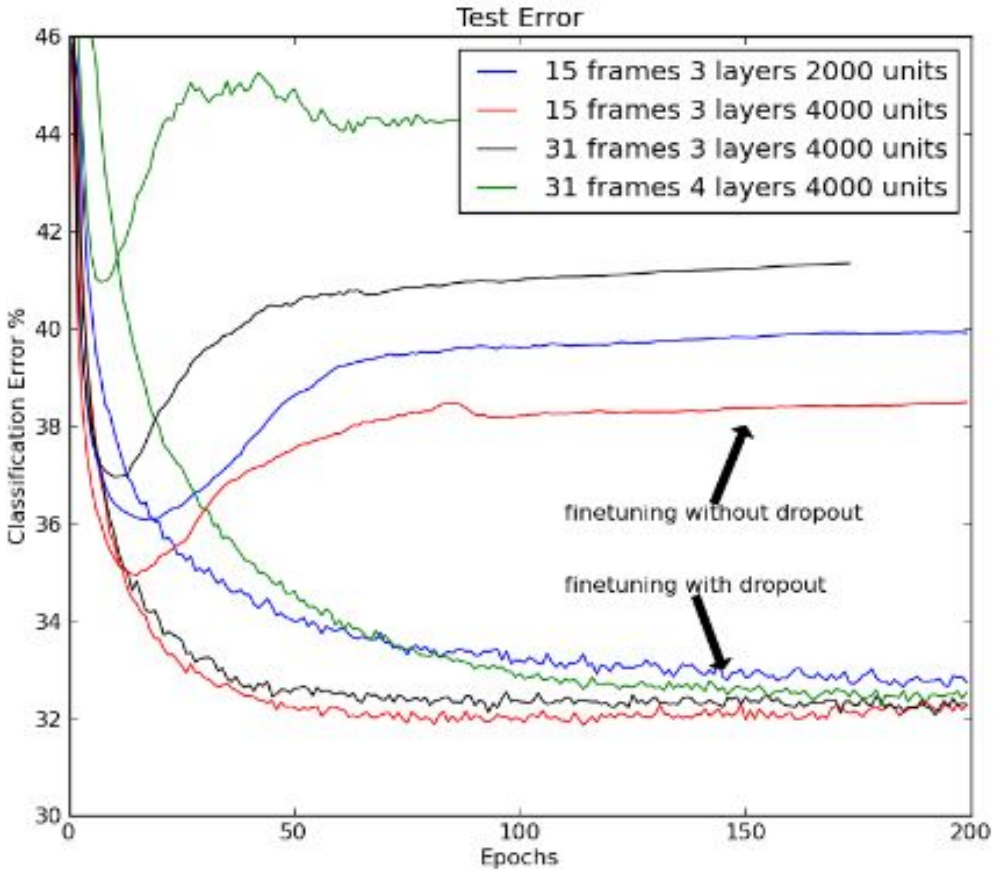


Dropout rate of 0.33

Hinton, Geoffrey "Improving neural networks by preventing co-adaptation of feature detectors" 2012

Dropout on TIMIT

- A phoneme recognition task



Hinton, Geoffrey "Improving neural networks by preventing co-adaptation of feature detectors" 2012

Batch normalization

- Recent technique for (implicit) regularization
- Normalize every mini-batch at various batch norm layers to standard Gaussian (different from global normalization of the inputs)
- Place batch norm layers before non-linearities
- Faster training and better generalizations

For each mini-batch that goes through batch norm

1. Normalize by the mean and variance of the mini-batch for each dimension
2. Shift and scale by learnable parameters

Replaces dropout in some networks

https://arxiv.org/abs/1502.03167

$$\hat{x} = \frac{x - \mu_b}{\sigma_b}$$

$$y = \alpha\hat{x} + \beta$$

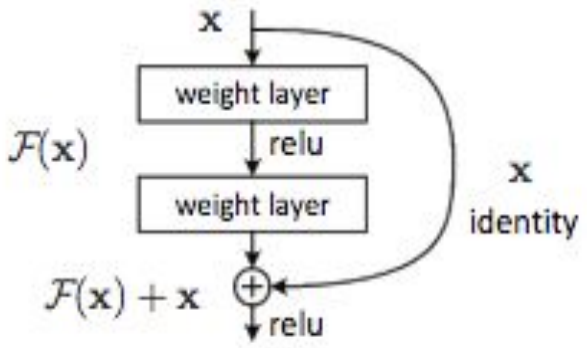
Dropout vs batchnorm

- You can add dropout in the hidden layers (0-0.5)
- Or input layers (0-0.2 is typical)
  - “Noising” the inputs, data augmentation
- Dropout in computer vision
  - use batchnorm instead (convolution layers leak output when using dropout)
- Dropout in NLP
  - Usually works better than Batchnorm for NLP in simple architectures
  - Drop full words at the embedding
  - Recurrent dropout http://arxiv.org/abs/1512.05287
  - Recent works (transformers) find batchnorm to be better than dropout
  - For seq2seq models, layer norm is popular

Vanishing/Exploding gradient

- Backprop introduces many multiplications down chain
- The gradient value gets smaller and smaller
  - The deeper the network the smaller the gradient in the lower layers
  - Lower layers changes too slowly (or not at all)
  - Hard to train very deep networks (>6 layers)
- The opposite can also be true. The gradient explodes from repeated multiplication
  - Put a maximum value for the gradient (Gradient clipping)

- How to deal with this?
  - Residual connection



https://arxiv.org/pdf/1512.03385.pdf

Neural networks

- Fully connected networks
  - Neuron
  - Non-linearity
  - Softmax layer
- DNN training
  - Loss function and regularization
  - SGD and backprop
  - Learning rate
  - Overfitting – dropout, batchnorm
- Demos
  - Tensorflow, Keras
- CNN
- RNN, LSTM, GRU <- Next class

Convolutional Neural Networks (CNNs)

- Consider an image of a cat. DNNs need different neurons to learn every possible location a cat can be

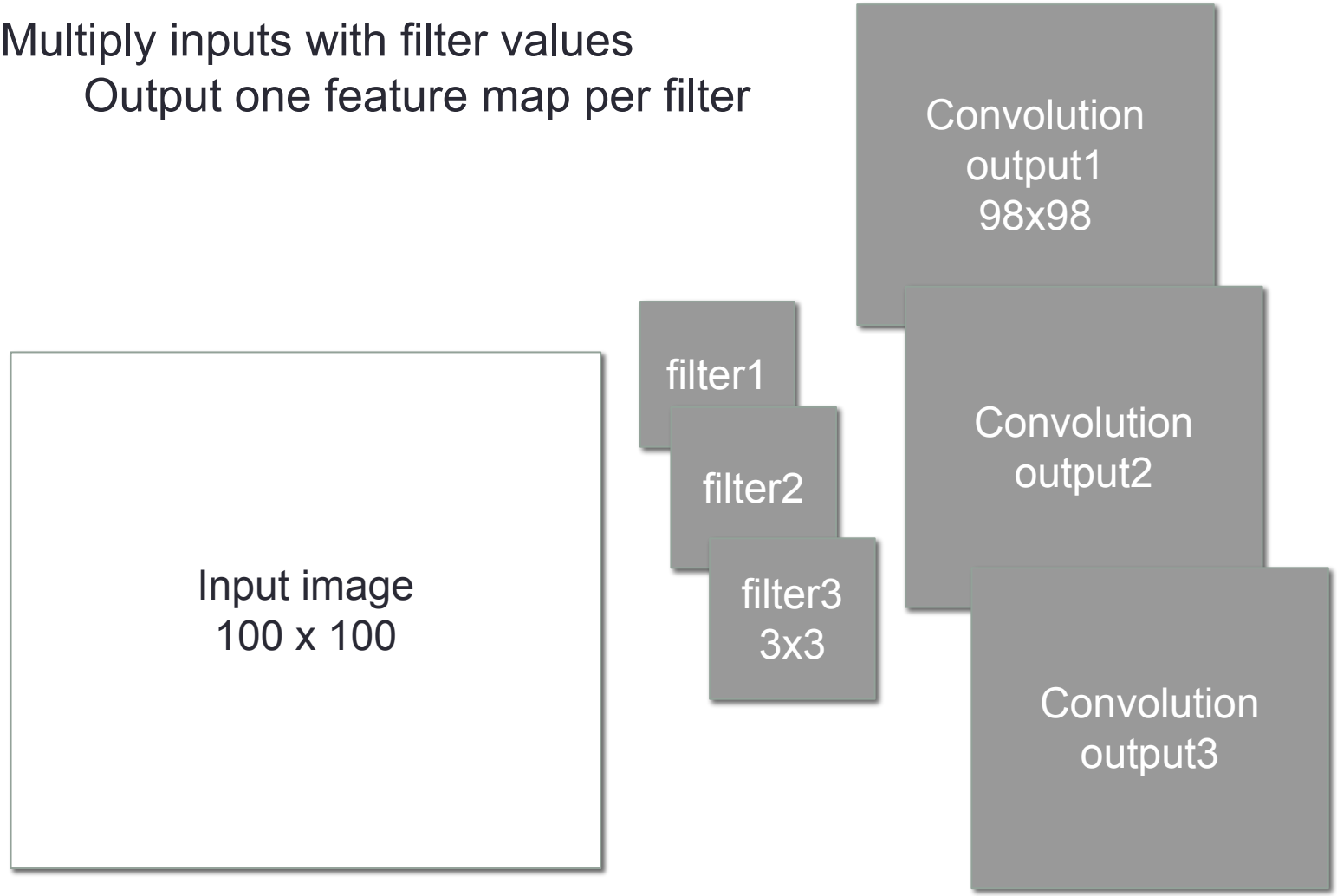
- Can we use the same parameters to learn that a cat exists regardless of location?

- 2 parts: convolutional layer and pooling layer

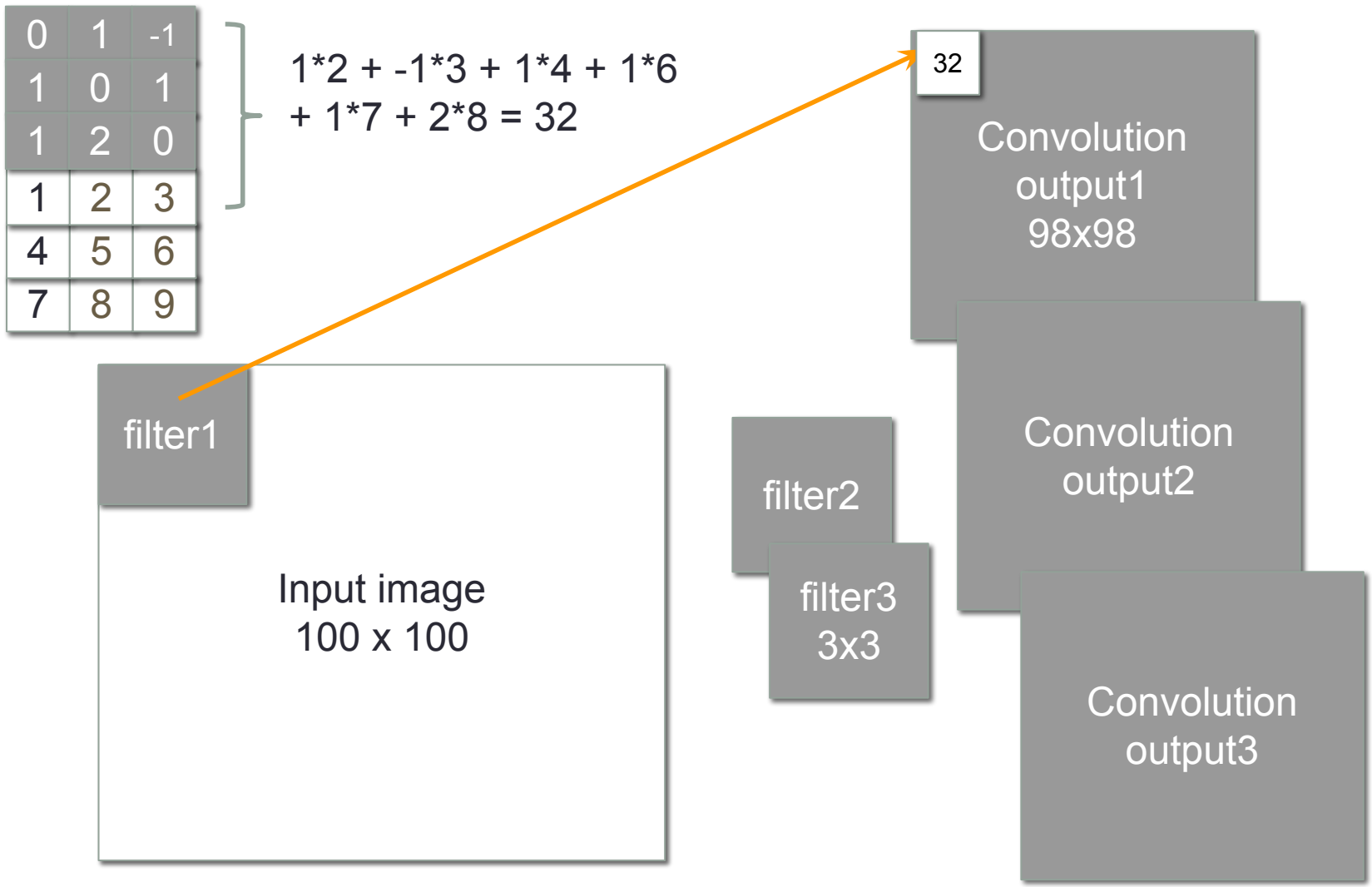
Convolutional filters

Multiply inputs with filter values

Output one feature map per filter

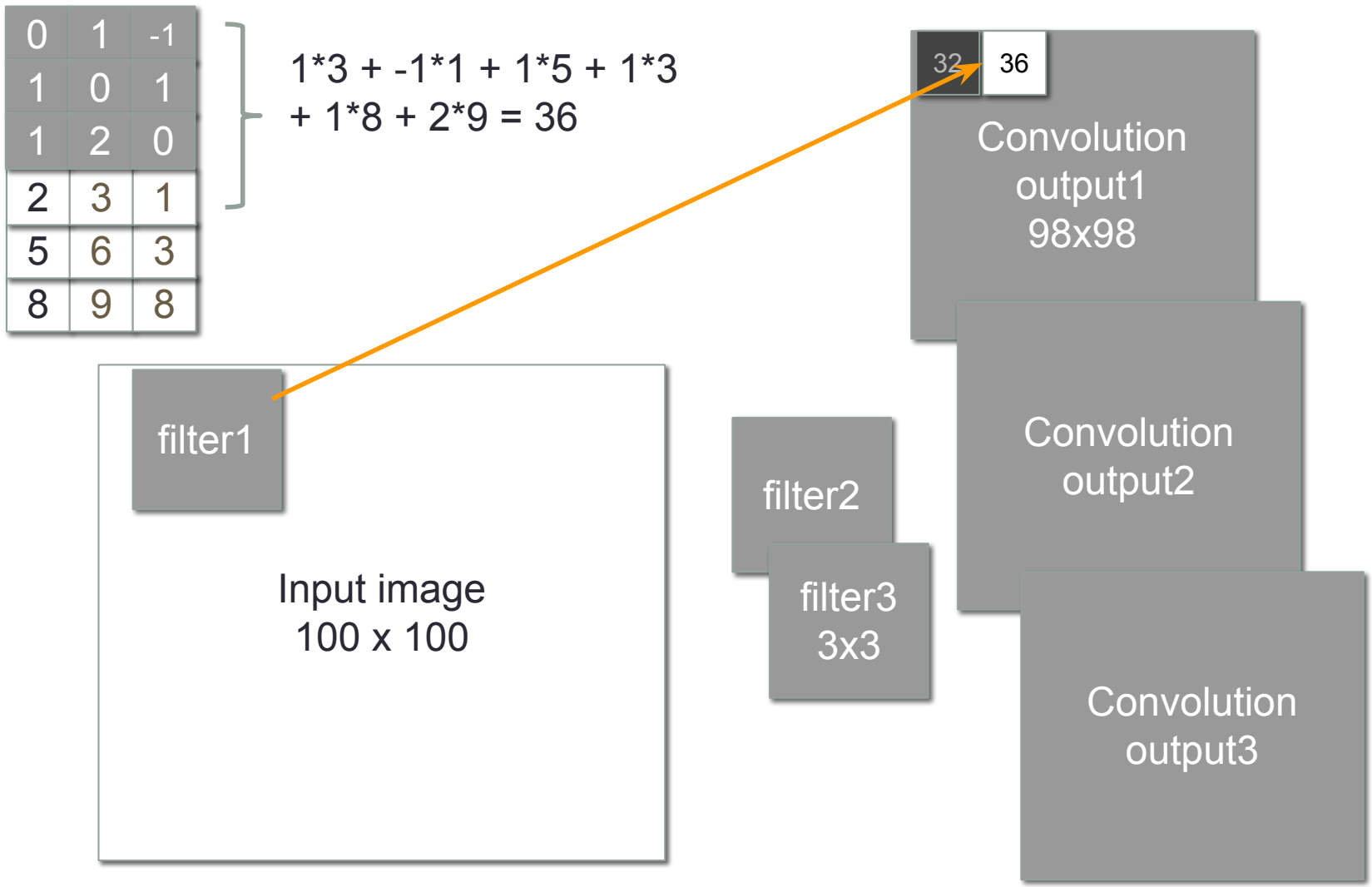


Convolutional filters

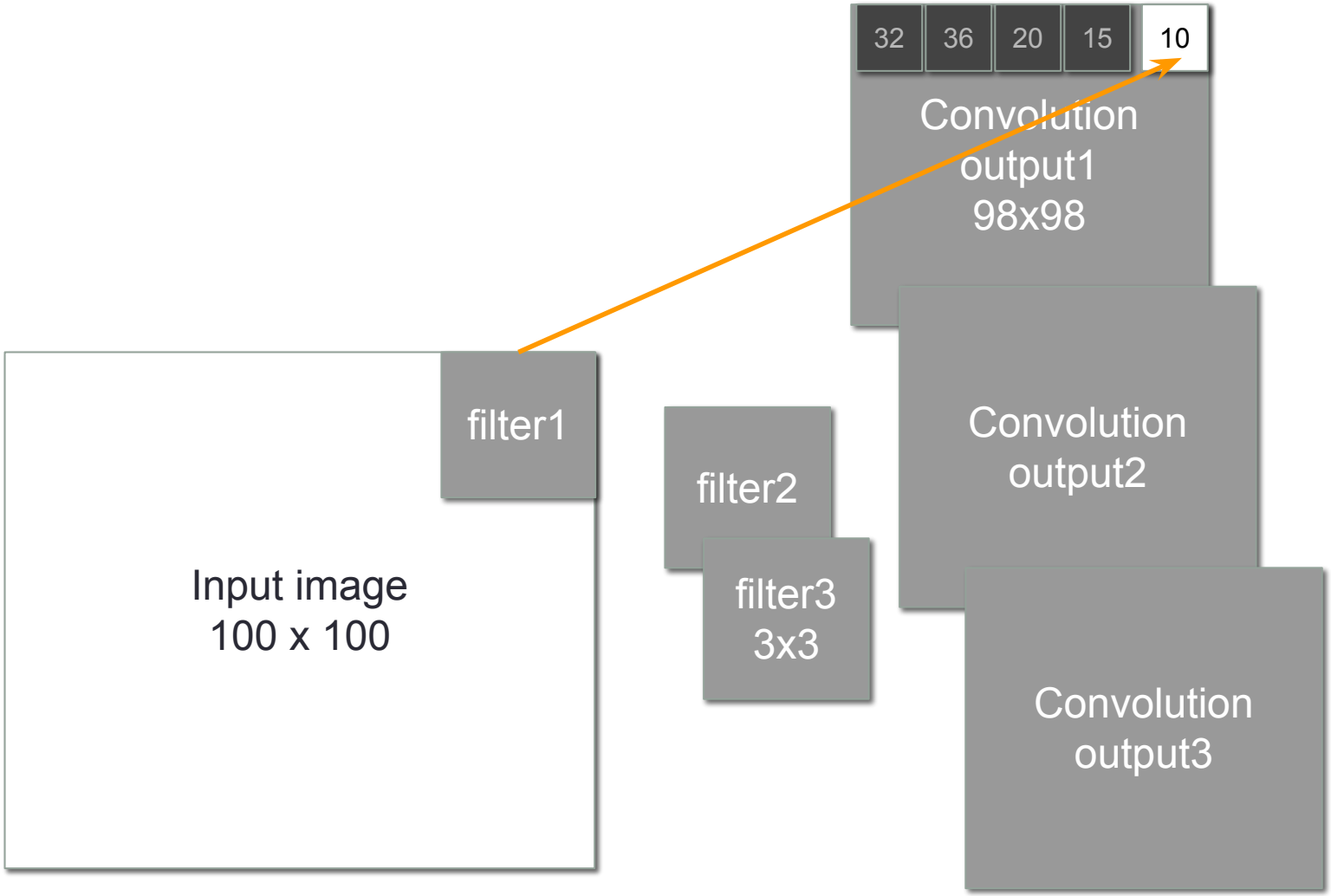


Convolutional filters

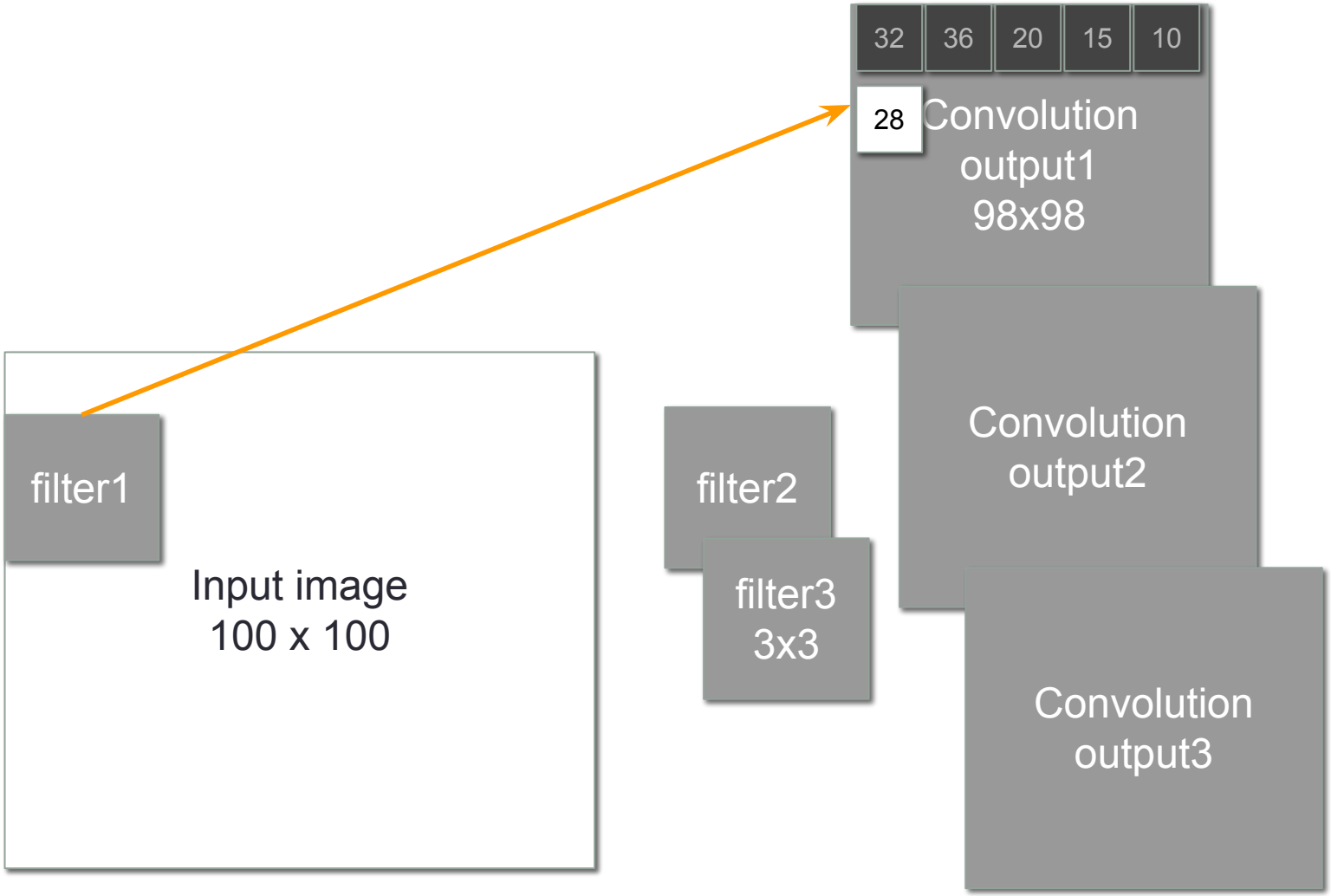
Stride of 1



Convolutional filters

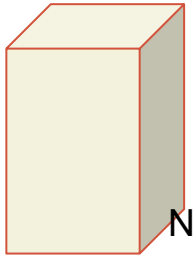


Convolutional filters



Convolutional filters

N filters means N feature maps
You get a 3 dimensional output



32	36	20	15	10
28	72	0	12	50
32	36	18	9	2
17	6	2	17	1

16

filter2

filter1

filter3
3x3

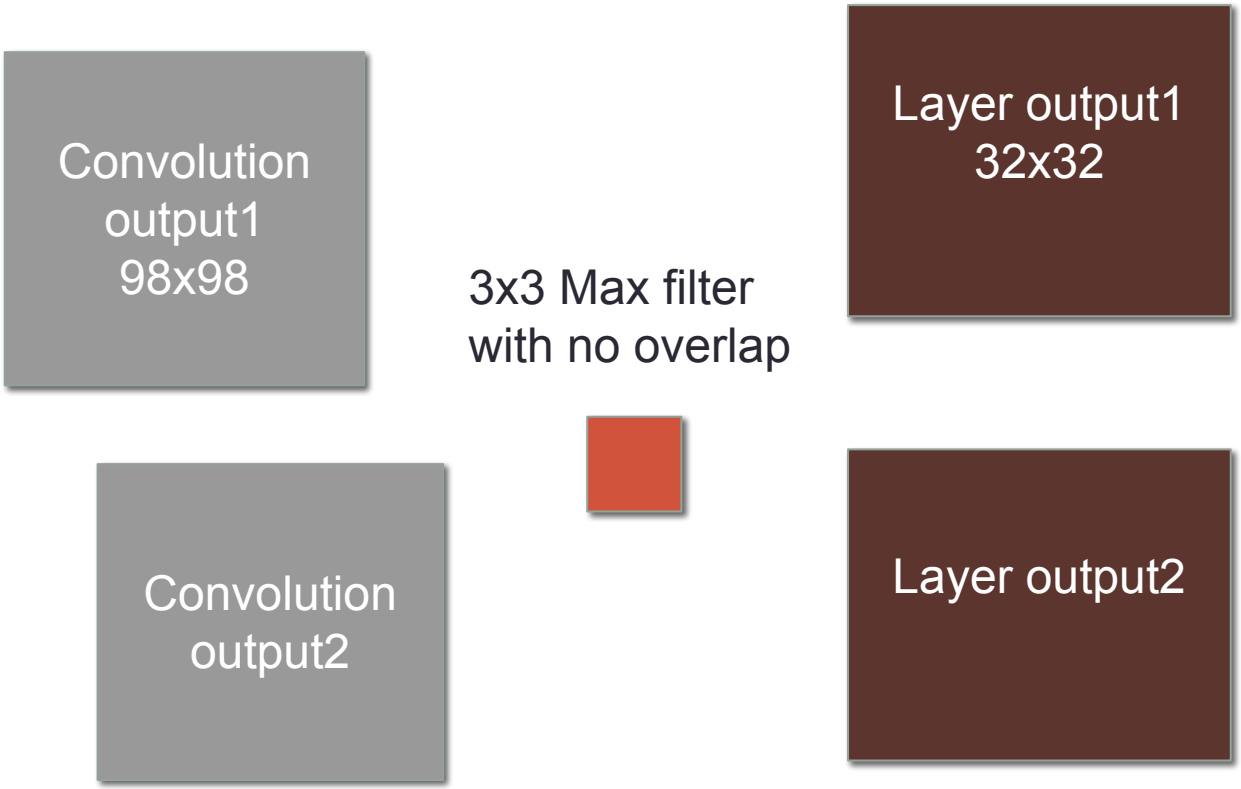
Input image
100 x 100

Convolution
output2

Convolution
output3

Pooling/subsampling

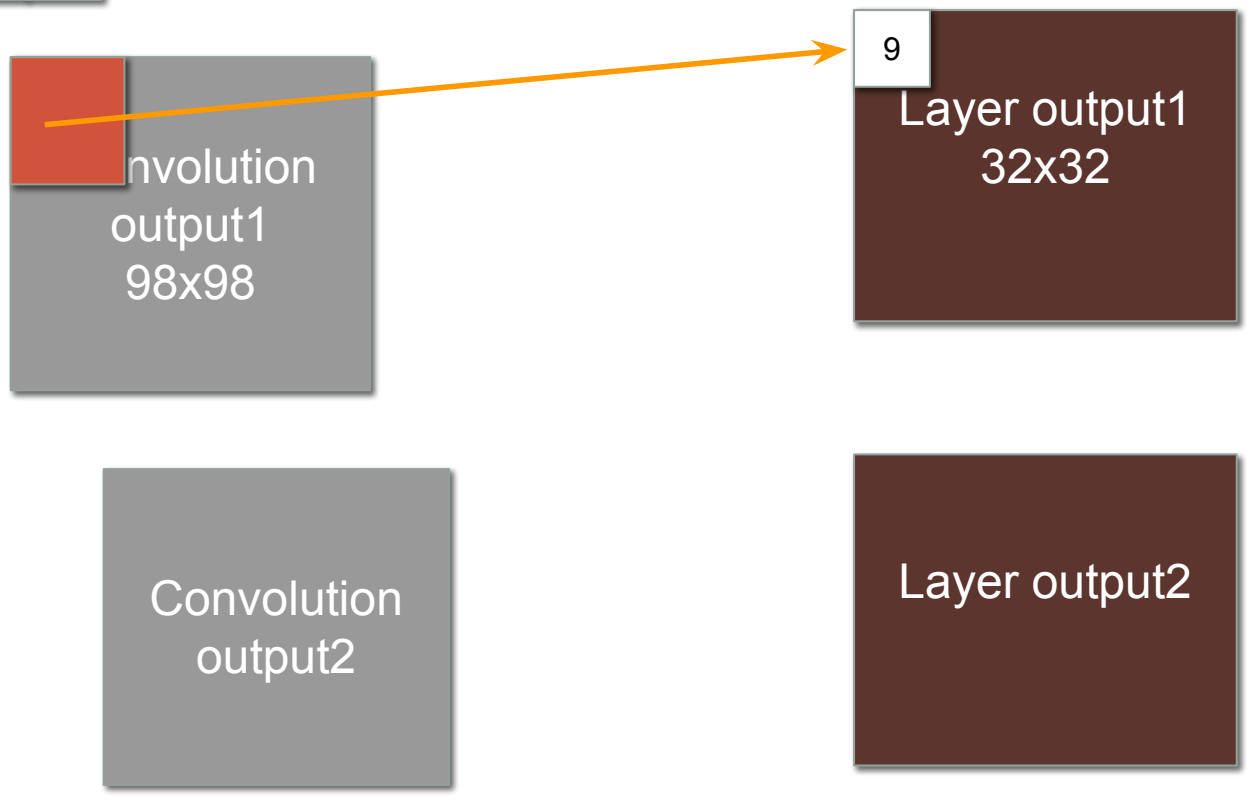
Reduce dimension of the feature maps



Pooling/subsampling

1	2	3
4	5	6
7	8	9

Max = 9

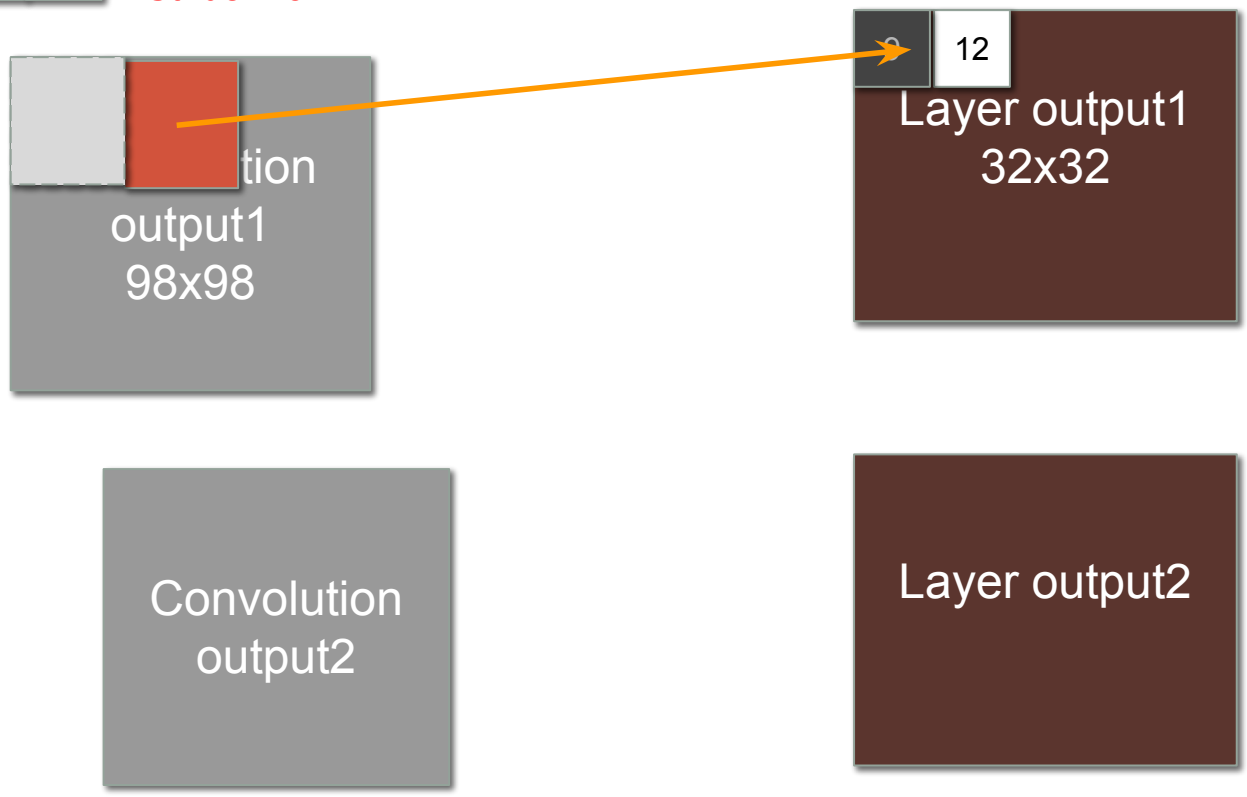


Pooling/subsampling

5	2	1
5	7	1
9	5	12

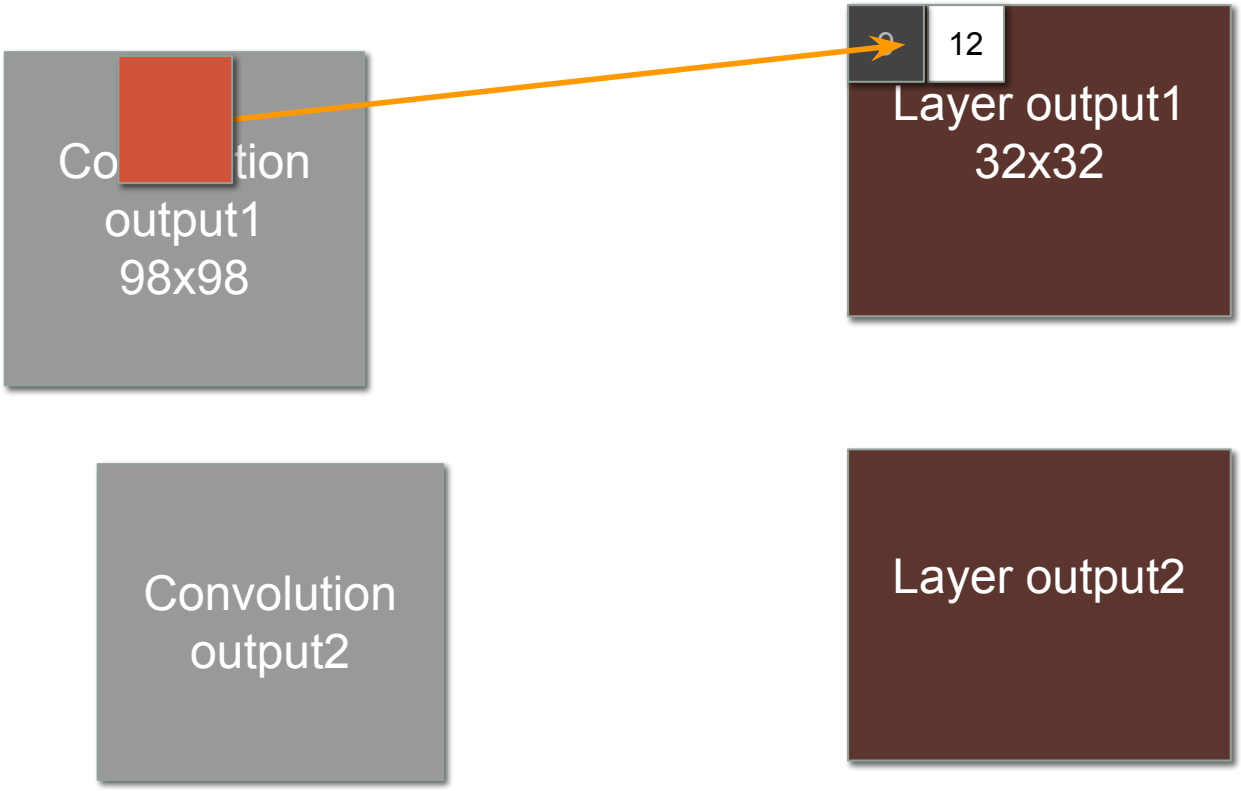
Max = 12

Stride = 3



Pooling/subsampling

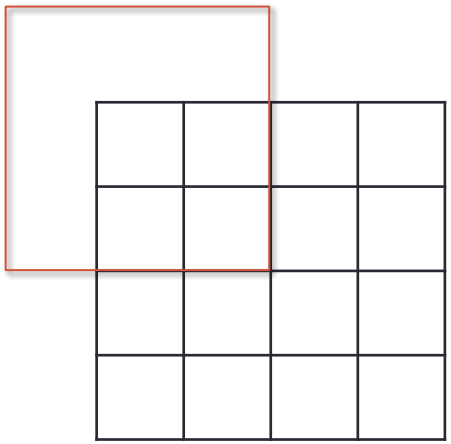
Can use other functions besides max
Example, average



Convolution puzzle

5 filters 3x3 filter pad, stride 1, pad 1

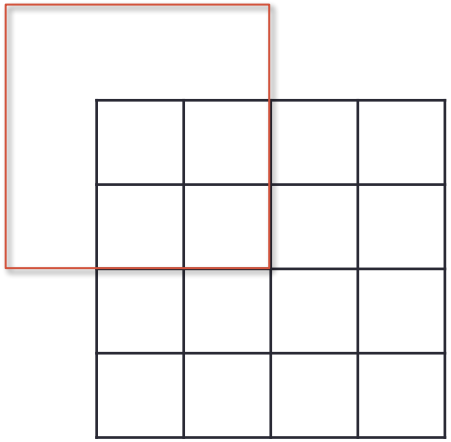
What is the output size?

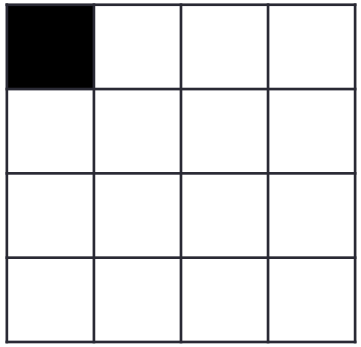


Convolution puzzle

5 filters 3x3 filter pad, stride 1, pad 1

What is the output size?

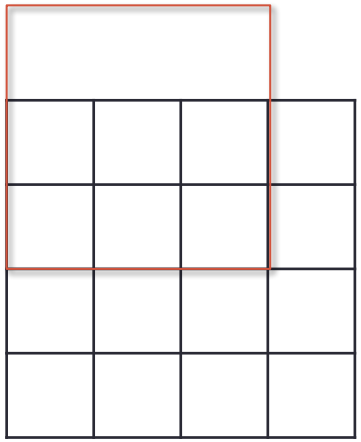


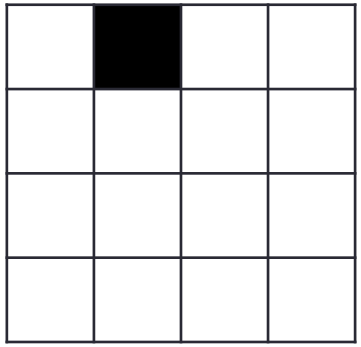


Convolution puzzle

5 filters 3x3 filter pad, stride 1, pad 1

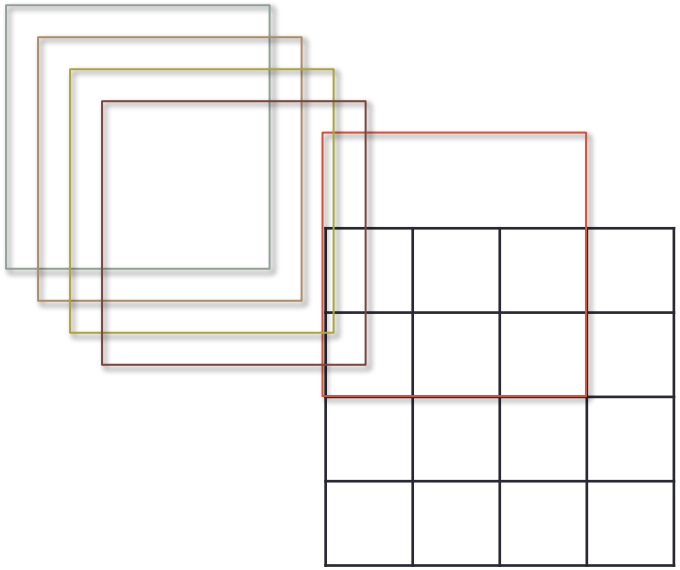
What is the output size?

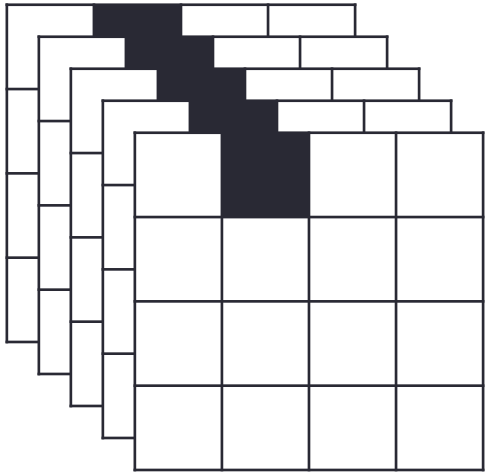




Convolution puzzle

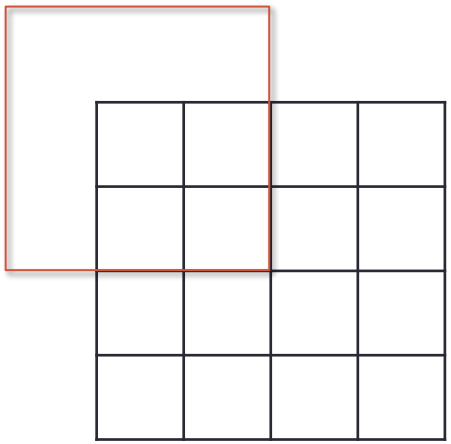
5 filters 3x3 filter pad, stride 1, pad 1





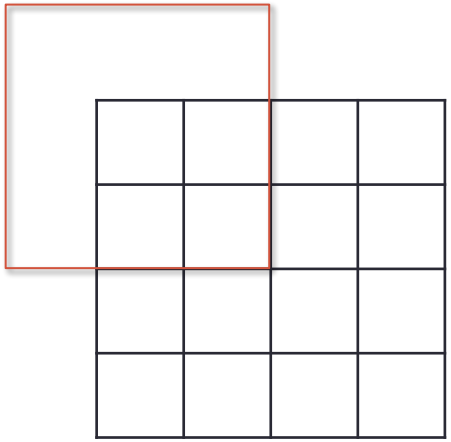
Convolution puzzle

3x3 filter pad, stride 2, pad 1



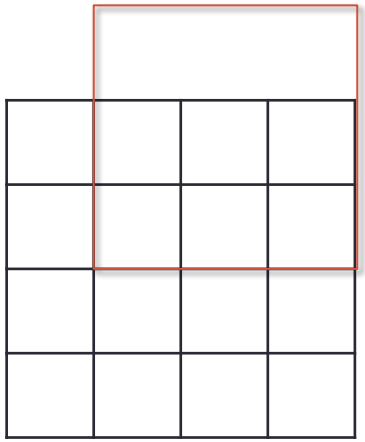
Convolution puzzle

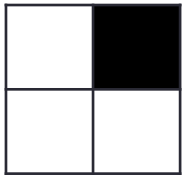
3x3 filter pad, stride 2, pad 1



Convolution puzzle

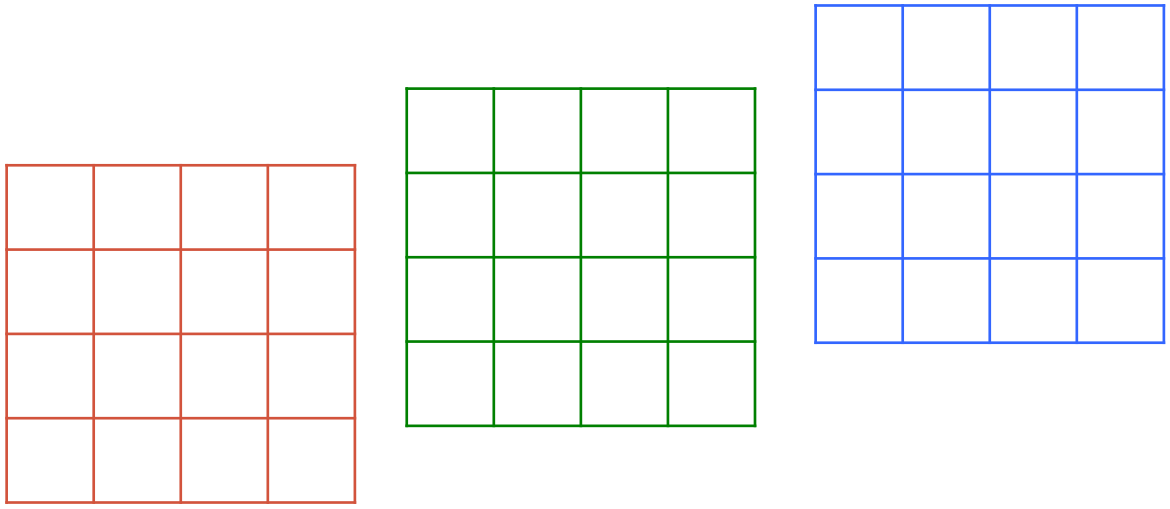
3x3 filter pad, stride 2, pad 1





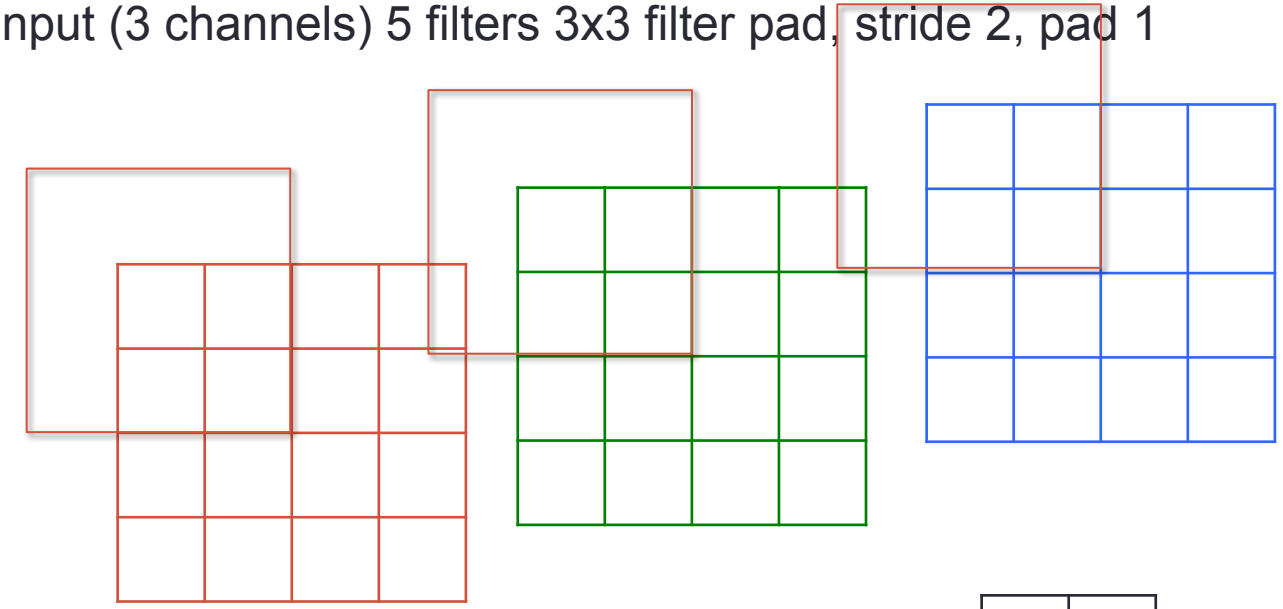
Convolution puzzle

RGB input (3 channels) 5 filters 3x3 filter pad, stride 2, pad 1

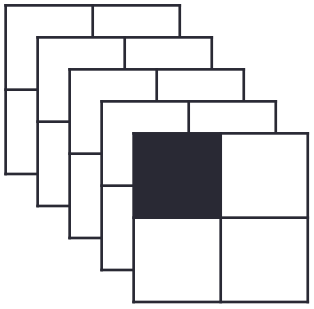


Convolution puzzle

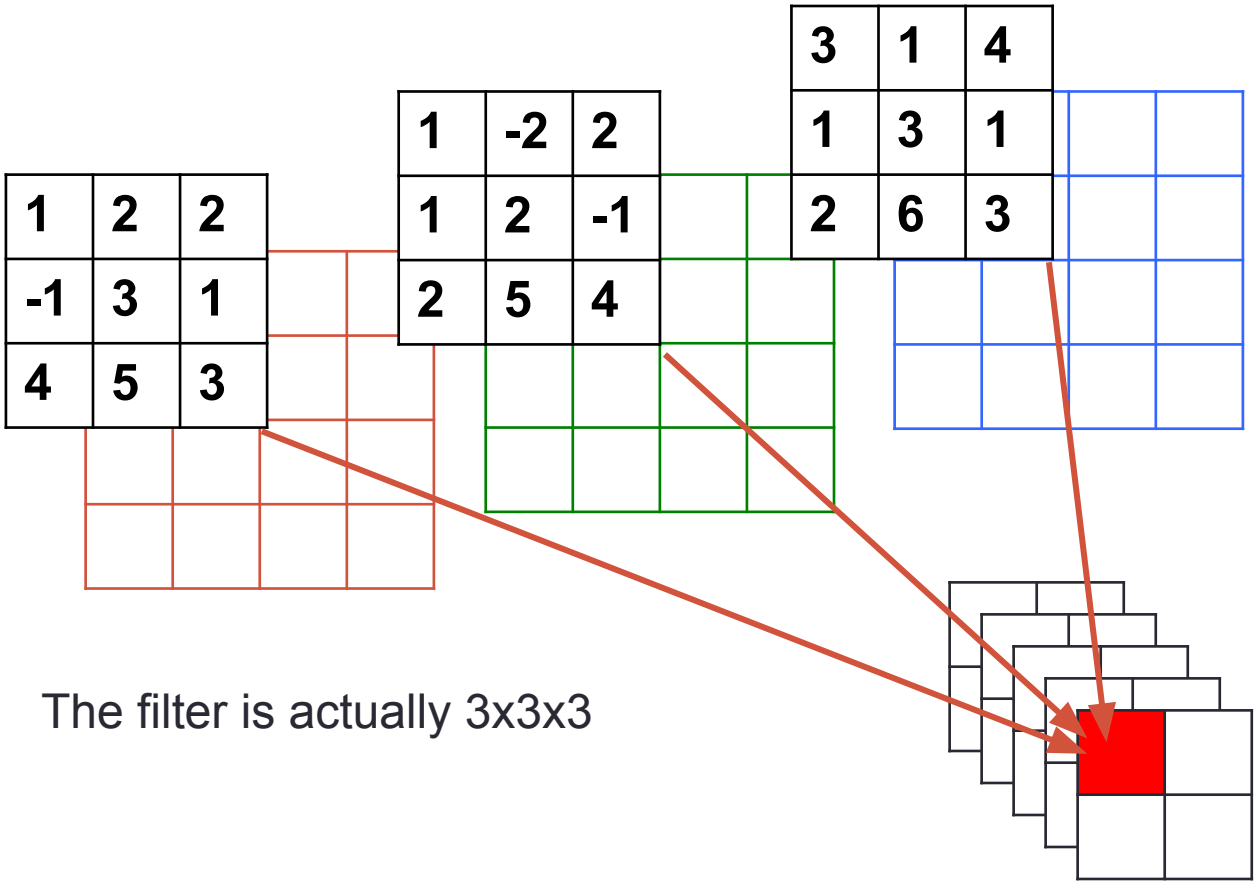
RGB input (3 channels) 5 filters 3x3 filter pad, stride 2, pad 1



The filter is actually 3x3x3



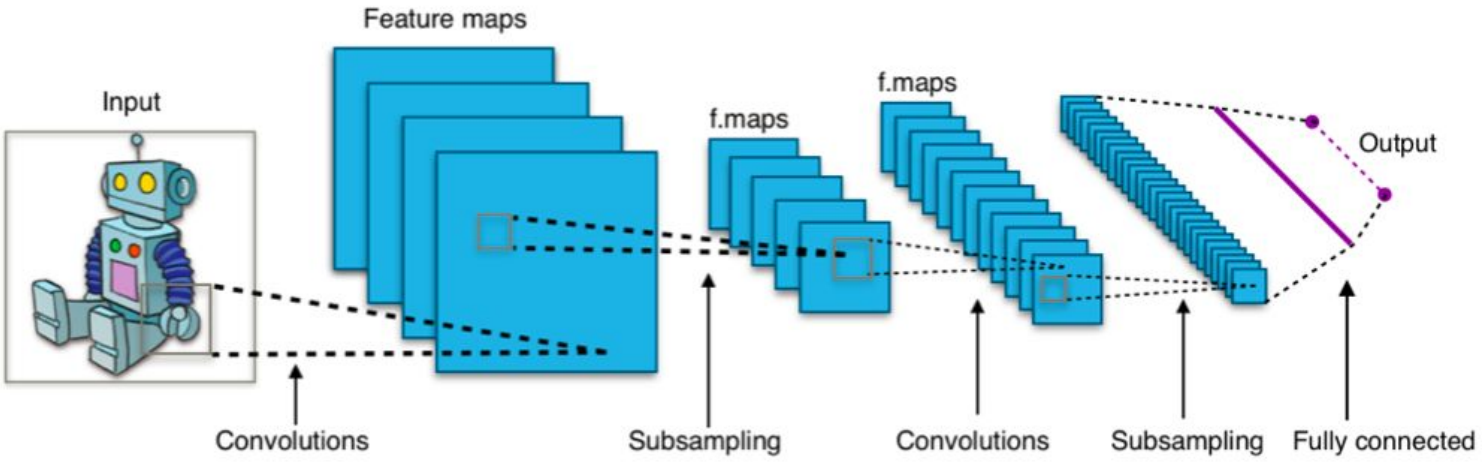
Convolution puzzle



The filter is actually 3x3x3

CNN overview

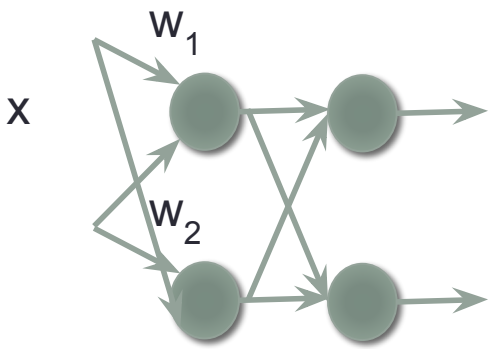
- Filter size, number of filters, filter shifts, and pooling rate are all parameters
- Usually followed by a fully connected network at the end
  - CNN is good at learning low level features
  - DNN combines the features into high level features and classify



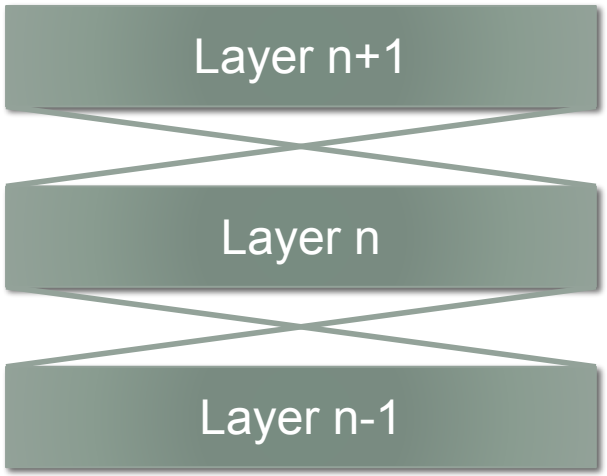
https://en.wikipedia.org/wiki/Convolutional_neural_network#/media/File:Typical_cnn.png

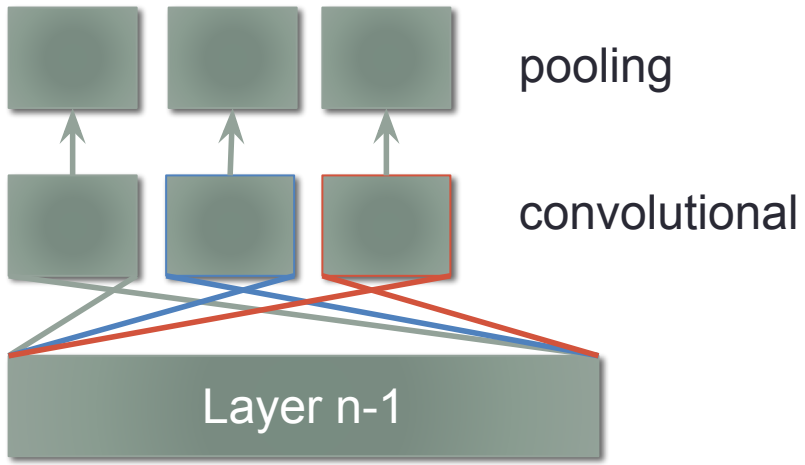
Parameter sharing in convolution neural networks

- $W^T x$



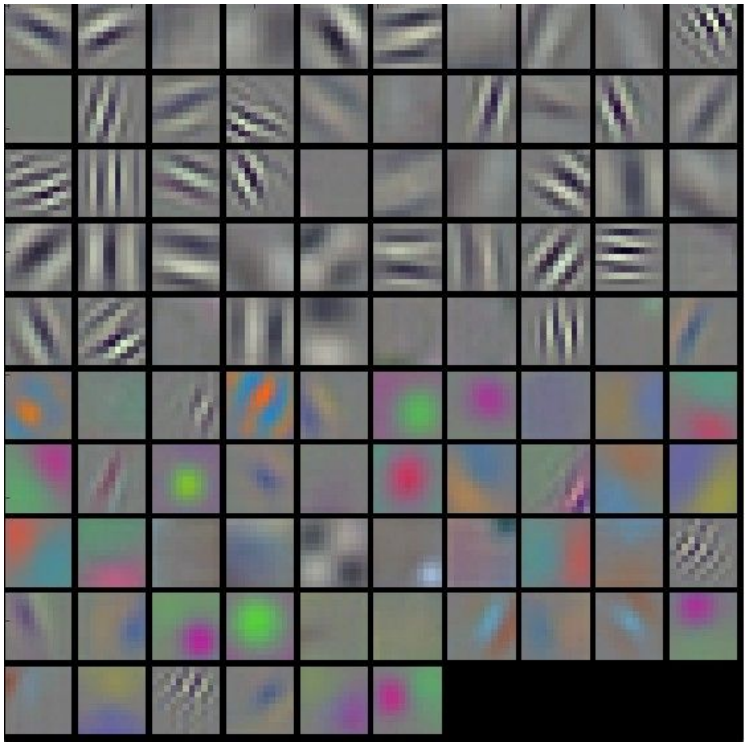
- Cats at different location might need two neurons for different locations in fully connect NNs.
- CNN shares the parameters in 1 filter
- The network is no longer fully connected





Visualizing convolutional layers

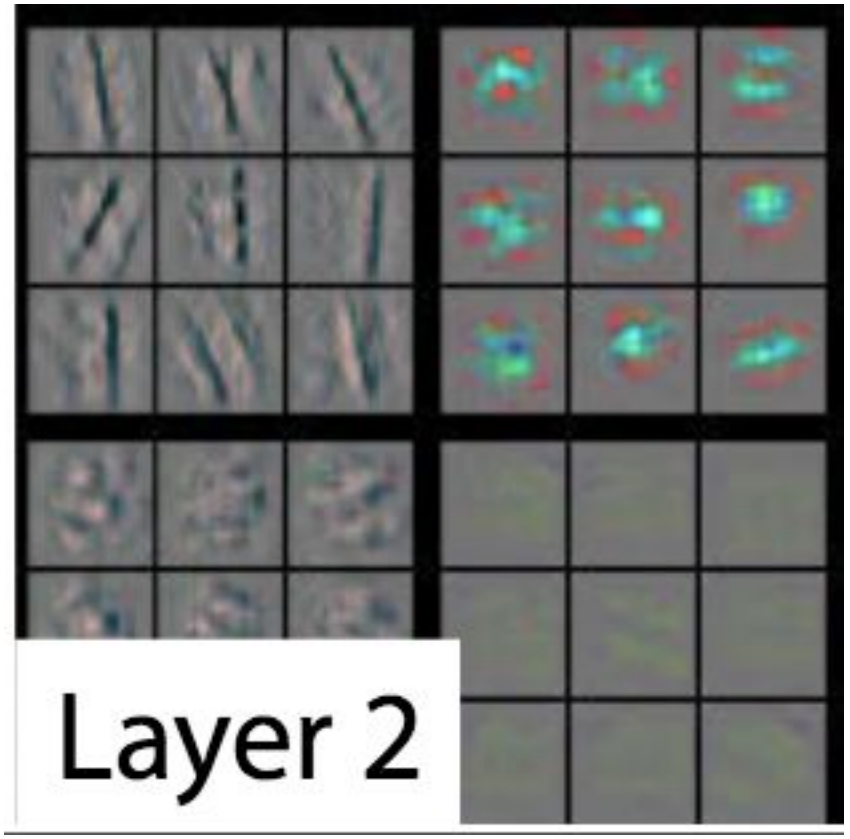
- We can visualize the weights of the filter
- “Matched filters”



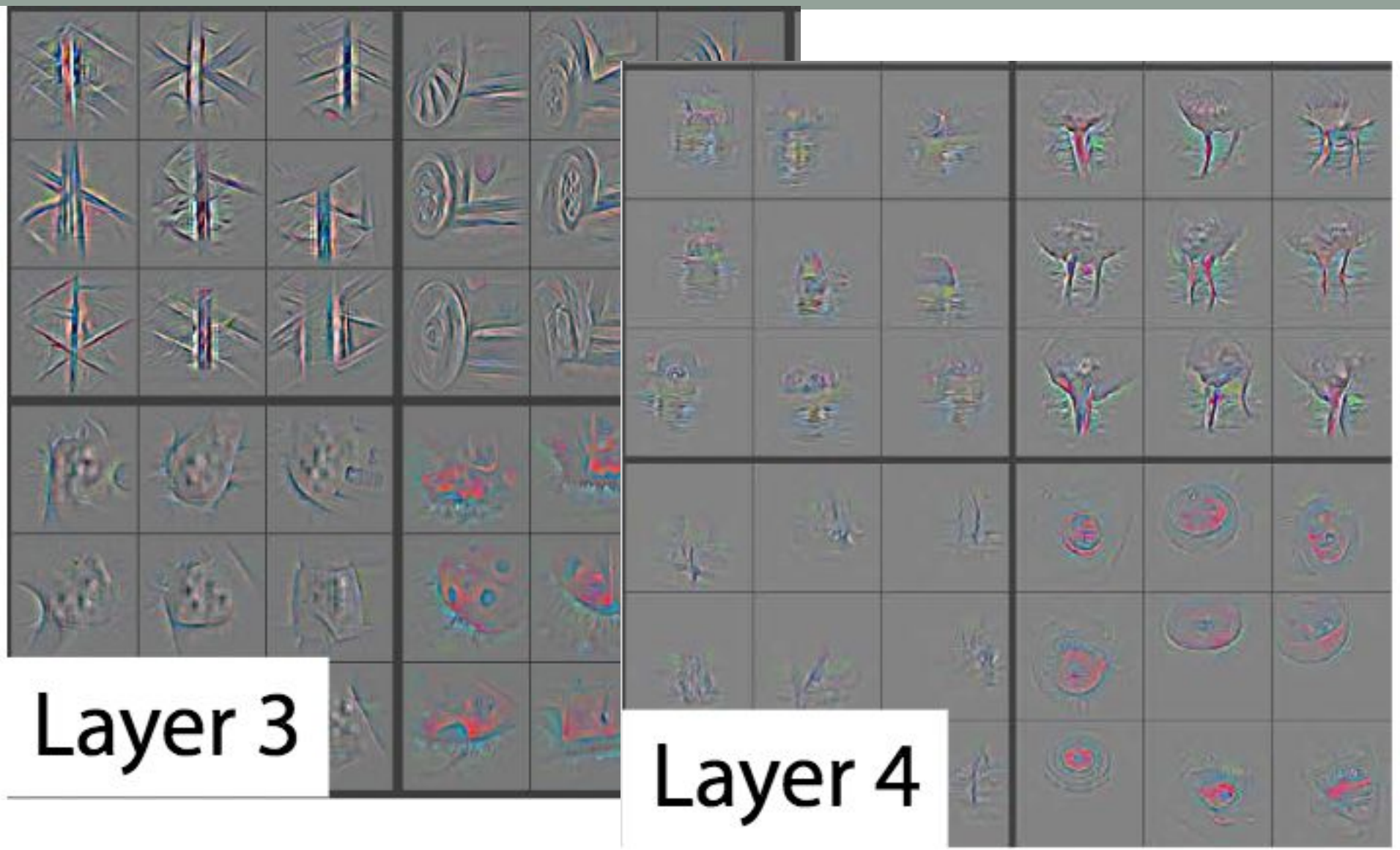
http://cs231n.github.io/understanding-cnn/

Higher layer captures higher-level concepts

Layer 1

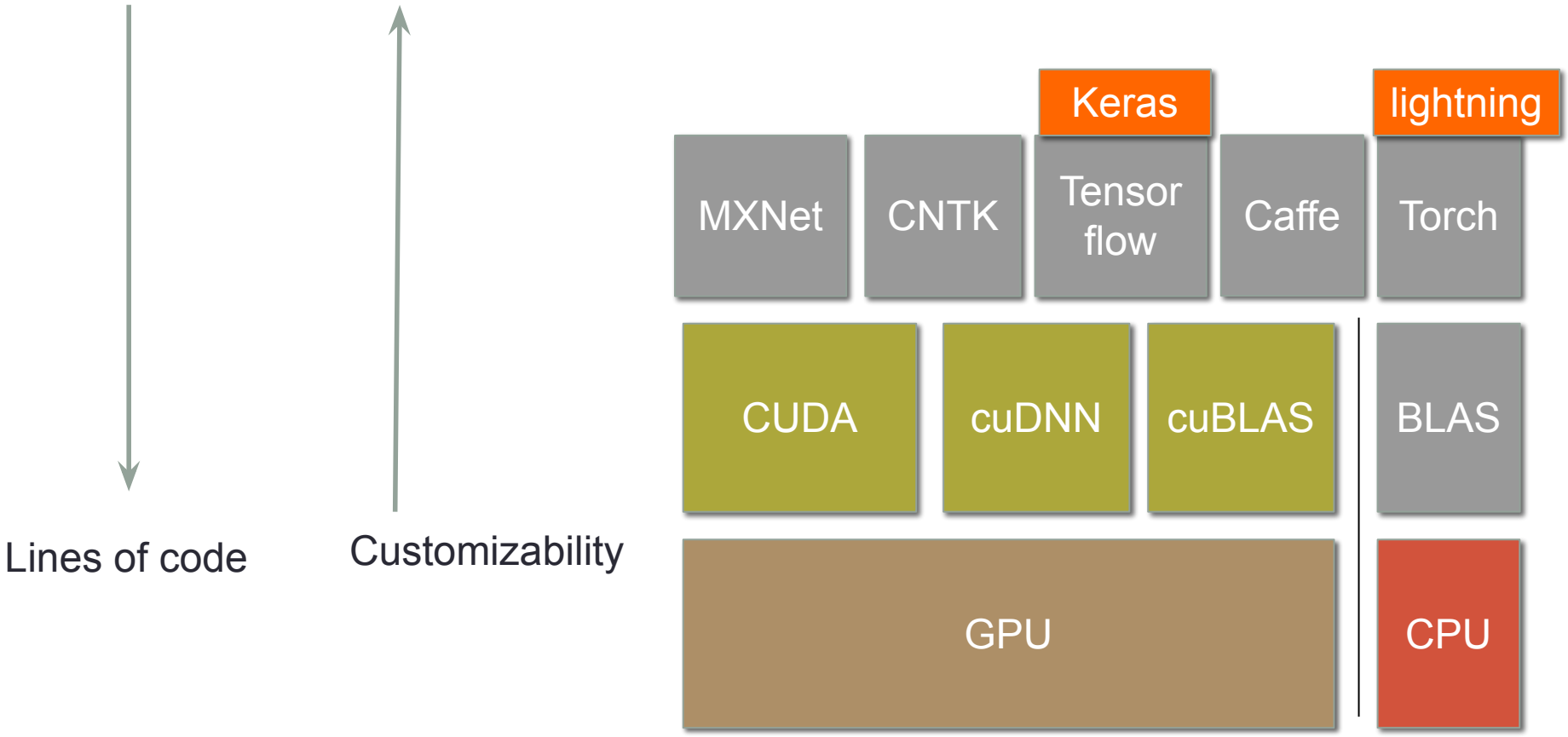


https://arxiv.org/pdf/1311.2901.pdf

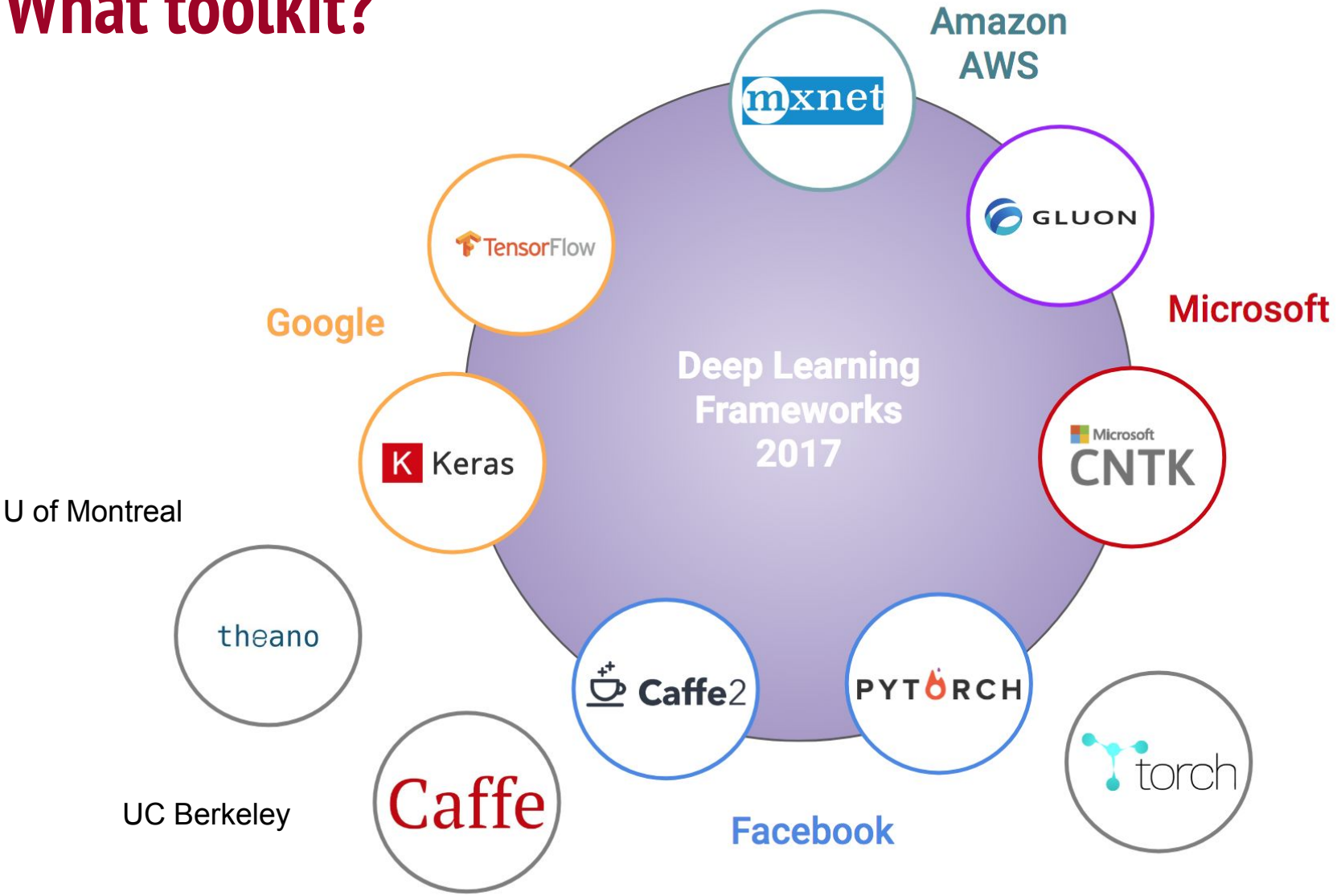

Layer 3
Layer 4

What toolkit

Tradeoff between customizability and ease of use



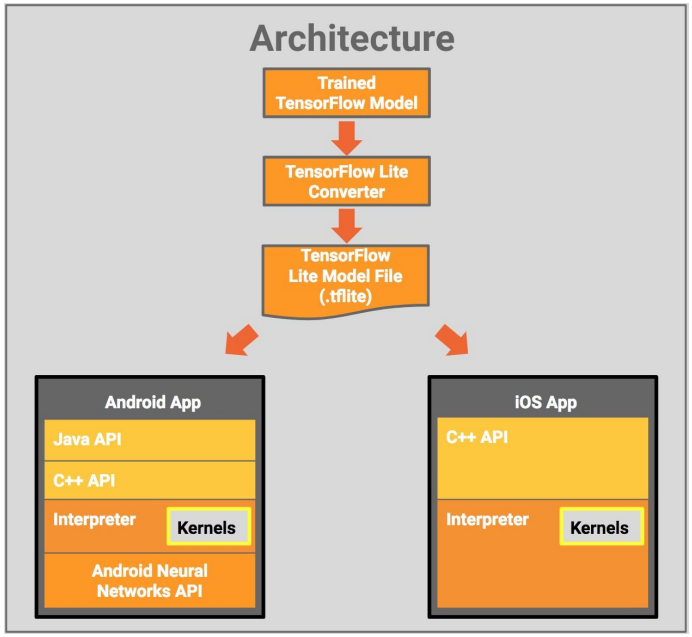
What toolkit?



https://towardsdatascience.com/battle-of-the-deep-learning-frameworks-part-i-cff0e3841750

Which?

- Easiest to use and play with deep learning: Keras
- Easiest to use and tweak: pytorch
- Easiest to deploy: tensorflow
  - Tensorflow lite for mobile
  - TensorRT support
- Best tools: TensorFlow
  - Tensorboard



Which?

- Easiest to use and play with deep learning: Keras
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  - Tensorflow lite for mobile
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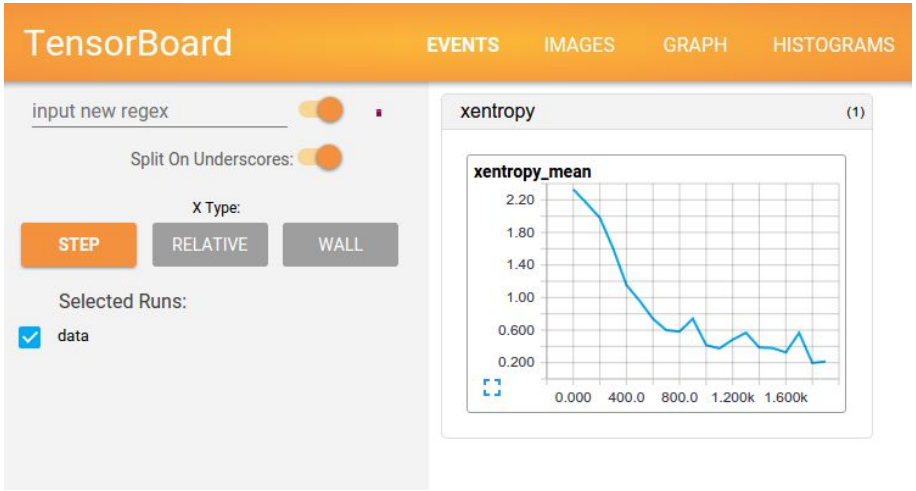
- Community: TensorFlow



Keras steps

- Define the network
- Compile the network
- Fit the network

```
def get_feedforward_nn():
  input1 = Input(shape=(21,))
  x = Dense(100, activation='relu')(input1)
  x = Dense(100, activation='relu')(x)
  x = Dense(100, activation='relu')(x)
  out = Dense(1, activation='sigmoid')(x)

  model = Model(inputs=input1, outputs=out)
  model.compile(optimizer=Adam(),
                loss='binary_crossentropy',
                metrics=['acc'])
  return model
```

```
  model_feedforward_nn.fit(x_train_char, y_train, epochs=epochs, batch_size=batch_size, verbose=ve
rbose,
                           callbacks=callbacks_list_feedforward_nn,
                           validation_data=(x_val_char, y_val))
```

Keras is easy!

Dense layer

`Dense` class

```
tf.keras.layers.Dense(
    units,
    activation=None,
    use_bias=True,
    kernel_initializer="glorot_uniform",
    bias_initializer="zeros",
    kernel_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    kernel_constraint=None,
    bias_constraint=None,
    **kwargs
)
```

Just your regular densely-connected NN layer.

`Dense` implements the operation: `output = activation(dot(input, kernel) + bias)` where `activation` is the element-wise activation function passed as the `activation` argument, `kernel` is a weights matrix created by the layer, and `bias` is a bias vector created by the layer (only applicable if `use_bias` is `True`).

Dropout layer

`Dropout` class

```
tf.keras.layers.Dropout(rate, noise_shape=None, seed=None, **kwargs)
```

Applies Dropout to the input.

The Dropout layer randomly sets input units to 0 with a frequency of `rate` at each step during training time, which helps prevent overfitting. Inputs not set to 0 are scaled up by 1/(1 - rate) such that the sum over all inputs is unchanged.

Note that the Dropout layer only applies when `training` is set to True such that no values are dropped during inference. When using `model.fit`, `training` will be appropriately set to True automatically, and in other contexts, you can set the kwarg explicitly to True when calling the layer.

(This is in contrast to setting `trainable=False` for a Dropout layer. `trainable` does not affect the layer's behavior, as Dropout does not have any variables/weights that can be frozen during training.)

Conv2D layer

`Conv2D` class

```
tf.keras.layers.Conv2D(
    filters,
    kernel_size,
    strides=(1, 1),
    padding="valid",
    data_format=None,
    dilation_rate=(1, 1),
    groups=1,
    activation=None,
    use_bias=True,
    kernel_initializer="glorot_uniform",
    bias_initializer="zeros",
    kernel_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    kernel_constraint=None,
    bias_constraint=None,
    **kwargs
)
```

2D convolution layer (e.g. spatial convolution over images).