

Lecture 5: Training Neural Networks, Part I

Administrative

A1 is due today (midnight)

I'm holding make up office hours on today: 5pm @ Gates 259

A2 will be released ~tomorrow. It's meaty, but educational!

Also:

- We are shuffling the course schedule around a bit
- the grading scheme is subject to few % changes

Things you should know for your Project Proposal

“ConvNets need a lot
of data to train”

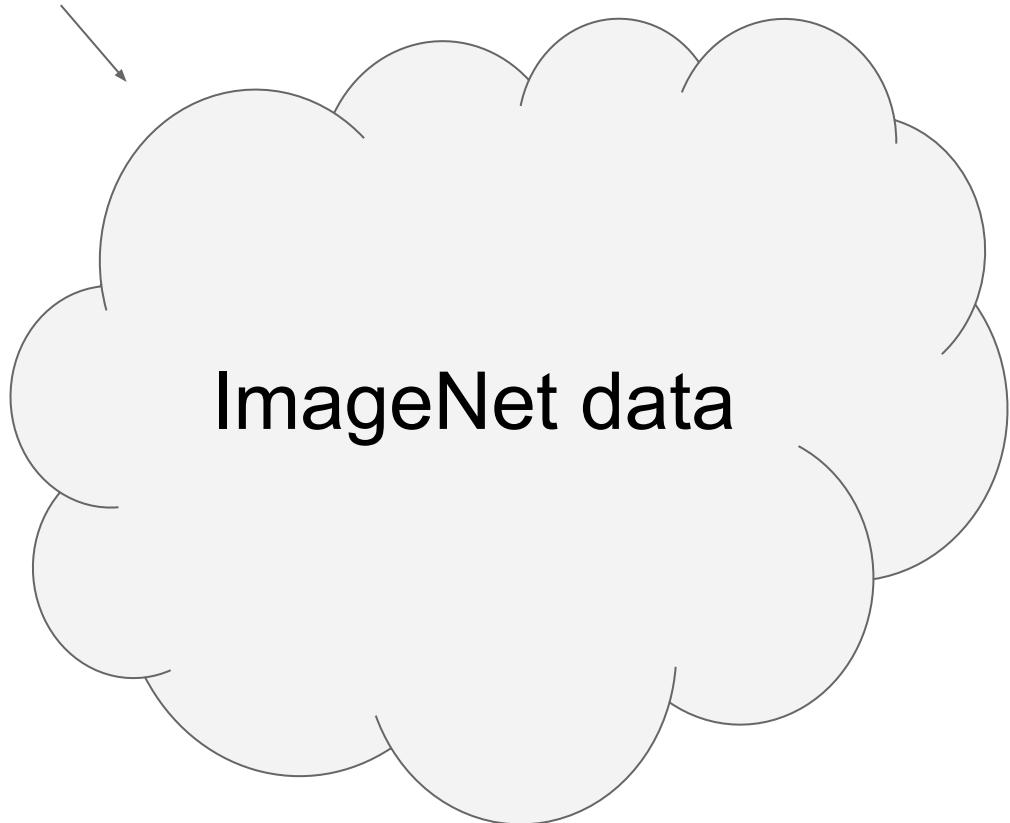
Things you should know for your Project Proposal

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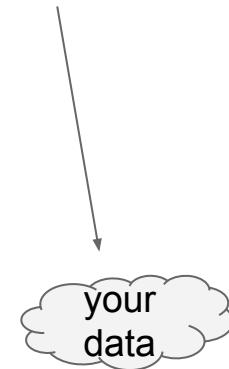


finetuning! we rarely ever
train ConvNets from scratch.

1. Train on ImageNet



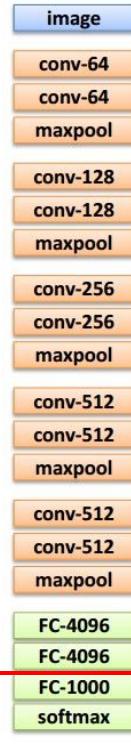
2. Finetune network on
your own data



Transfer Learning with CNNs



1. Train on ImageNet



2. If small dataset: fix all weights (treat CNN as fixed feature extractor), retrain only the classifier

i.e. swap the Softmax layer at the end



3. If you have medium sized dataset, “**finetune**” instead: use the old weights as initialization, train the full network or only some of the higher layers

retrain bigger portion of the network, or even all of it.

E.g. Caffe Model Zoo: Lots of pretrained ConvNets

<https://github.com/BVLC/caffe/wiki/Model-Zoo>

Model Zoo
Edit this page 21 days ago · 56 revisions

Check out the model zoo documentation for details.

To acquire a model:

1. download the model gist by `./scripts/download_model_from_gist.sh <gist_id>` to load the model details, architecture, solver configuration, and so on. (`<gist_id>` is optional and defaults to `caffemodels`).
2. download the model weights by `./scripts/download_model_binary.py <model_dir> where <model_dir>` is the gizt directory from the first step.

or visit the model zoo documentation for complete instructions.

Berkeley-trained models

- Flicking on Flickr Style: same as provided in `models/f/`, but listed here as a Gist for an example.
- BVLC GoogLeNet: `models/bvlc_googlenet`.

Network in Network model

The Network in Network model is described in the following ICLR-2014 paper:
<http://arxiv.org/pdf/1406.8564.pdf>

Authors: S. Ioffe, K. Lin, Q. Chen, S. Yan
International Conference on Learning Representations, 2014 (arXiv:1409.1550)

Please cite the paper if you use the models.

Models:

- NIN_imagenet_3swap_imagenet: the original, yet performs slightly better than AlexNet, and fast to train. (Note: a more compatible version with correct convolutional weights https://bitbucket.org/DONNERLUNN/nn4v1l14uspmre_wb)
- NIN_imagenet_100N: NIN model on CIFAR-10, originally published in the paper Network in Network. The error rate of this model is 10.4% on CIFAR10.

Models from the BMVC-2014 paper "Return of the Devil in the Details: Delving Deep into Convolutional Nets"

The models are trained on the ILSVRC-2012 dataset. The details can be found on the project page or in the following BMVC-2014 paper:
<http://www.robots.ox.ac.uk/~vgg/research/ILSVRC/2014/DetailsDevil.pdf>

Return of the Devil in the Details: Delving Deep into Convolutional Nets
K. Chaitfield, K. Simonyan, A. Vedaldi, A. Zisserman
British Machine Vision Conference, 2014 (arXiv ref. cs/1405.3631)

Please cite the paper if you use the models.

Models:

- VGG_CNN_S: 13.1% top-5 error on ILSVRC-2012-val
- VGG_CNN_M: 13.7% top-5 error on ILSVRC-2012-val
- VGG_CNN_M_1024: 13.5% top-5 error on ILSVRC-2012-val
- VGG_CNN_M_1024: 13.7% top-5 error on ILSVRC-2012-val
- VGG_CNN_M_128: 15.6% top-5 error on ILSVRC-2012-val
- VGG_CNN_M: 16.7% top-5 error on ILSVRC-2012-val

Models used by the VGG team in ILSVRC-2014

Places-CNN model from MIT.
Places CNN is described in the following NIPS 2014 paper:
<http://arxiv.org/pdf/1409.0575.pdf>

S. Zhao, A. Laptev, C. Xiao, A. Torralba, and A. Oliva
Learning Deep Features for Scene Recognition using Places Database.
Advances in Neural Information Processing Systems 27 (NIPS) workshop, 2014.

The project page is here

Models:

- Places205-GoogLeNet: Caffe trained on 205 scene categories of Places Database using a GPU with ~2.5 million images. The architecture is the same as the AlexNet reference network.
- Harvard-CNN: CNN trained on 193 categories (205 scene categories from Places Database and 975 object categories from the ILSVRC-2012 (ImageNet) with ~2.5 million images). The architecture is the same as the AlexNet reference network.
- Places205-DeepLab: DeepLab CNN trained on 205 scene categories of Places Database. It is trained by Google in the deep image classification.

GoogLeNet GPU Implementation from Princeton.

We implemented GoogLeNet using a single GPU. Our main contribution is an effective way to initialize the network and a trick to overcome the GPU memory constraint by accumulating gradients in memory.

- Please check <http://vision.princeton.edu/~yihui/prj/googlenet/> for more information. Pre-trained models on Imagenet and Places, and the training code are available for download.
- Model files are located in `models/`. Run `make clean` - root in the project. Otherwise, the trained model would crash on test.

Fully Convolutional Semantic Segmentation Models (FCN-Xs)

These models are described in the paper:
<http://arxiv.org/pdf/1412.7003.pdf>

Fully Convolutional Models for Semantic Segmentation
Long, J., Shelhamer, Trevor Darrell
CVPR 2015, Deepvision workshop
arXiv:1412.4705

They are available under the same license as the Caffe-built models (i.e., for unrestricted use; see the license file).

These are pre-release models. They do not run in any current version of BVLC GoogLeNet, as they require unmerged PRs. They should run in the previous branch protocol at https://bitbucket.org/DONNERLUNN/nn4v1l14uspmre_wb. The FCN-32s-PASCAL-Context model is the most complete one including various softwares, setup instructions, and Python scripts for solving and inference.

Models trained on PASCAL using extra data from Hartmann et al. and trained from the scratch (with supervision).

- FCN32-PASCAL: single stream, 32 pixel prediction stride version
- FCN16-PASCAL: three stream, 16 pixel prediction stride version
- FCN8-PASCAL: three stream, 8 pixel prediction stride version
- FCN32-PASCAL-Context: single stream, 32 pixel prediction stride version

To reproduce the validation scores, use the `val11111111` defined by the paper in protocol 7. Since SGD runs an FCN-32s-PASCAL-11111111 neural network, we only evaluate on the non-intersecting set for validation purposes.

Models trained on SIFT Flow (also known from VGG-16):

- FCN32-SIFT: single stream, 16 pixel prediction stride version
- FCN16-SIFT: three stream, 16 pixel prediction stride version
- FCN8-SIFT: three stream, 8 pixel prediction stride version
- FCN32-SIFT-Context: single stream, 32 pixel prediction stride version
- FCN16-SIFT-Context: three stream, 16 pixel prediction stride version
- FCN8-SIFT-Context: three stream, 8 pixel prediction stride version

Models trained on PASCAL-Context including training mode definition, solver configuration, and associated training data.

- FCN32-PASCAL-Context: single stream, 32 pixel prediction stride version
- FCN16-PASCAL-Context: three stream, 16 pixel prediction stride version
- FCN8-PASCAL-Context: three stream, 8 pixel prediction stride version

CaffeNet fine-tuned for Oxford Flowers dataset

http://rgf.csail.mit.edu/rgf/oxford_flowers17.html

The is the reference CaffeNet (modified Alexnet) fine-tuned for the Oxford 102 category flower dataset. The number of output in the inner product layer has been set to 102 to reflect the number of flower categories. The learning rate is 0.001. The learning rate for the inner product layer for Fine-Grained Classification is 10 times higher than the learning rate for the final fully connected. The global learning rate is reduced while the learning rate for the final fully connected is increased relative to the other layers.

After 50,000 iterations, the top-1 error is 7% on the test set of 1,020 images.

CNN Models for Salient Object Subtizing.
CNN models described in the following CVPR15 paper: "Salient Object Subtizing".

Salient Object Subtizing
J. Zhang, E. Wu, M. Saeedi, S. Sclaroff, M. Beetz, Z. Liu, X. Shen, B. Price and R. Datta
CVPR 2015

The project page is here

Models:

- AlexNet: CNN model fine-tuned on the Salient Object Subtizing dataset (~5000 images). The architecture is the same as the Caffe reference network.
- VGG16: CNN model fine-tuned on the Salient Object Subtizing dataset (~5000 images). The architecture is the same as the VGG16 network. This model gives better performance than the AlexNet model, but is slower for training and testing.

Deep Learning of Binary Hash Codes for Fast Image Retrieval

We present an effective deep learning framework to create the hash-like binary codes for fast image retrieval. The details can be found in the following CVPR15 paper:

Deep Learning of Binary Hash Codes for Fast Image Retrieval
K. Lin, H.-F. Yang, J.-H. Hsieh, C.-S. Chen
CVPR 2015, Deepvision workshop
arXiv:1412.4705

Please cite the paper if you use the model:

- cifar-10-v15: See our code release on Github, which allows you to train your own deep learning model to create binary hash codes.
- CIFAR10-48x48: Pre-trained 48x48 CNN model trained on CIFAR10.

Places_CNDS_models on Scene Recognition

Places_CNDS_models is a 10 ("Conv3d3" layer) deep Convolutional neural networks model trained on MIT Places Dataset with Deep Supervision.

The details of training this model are described in the following paper. Please cite this work if the model is useful for you.

Training Deeper Convolutional Networks with Deep Supervision
L. Liang, C. Tang, Z. Zhou, L. Leemans, arXiv:1306.0205, 2015

Models for Age and Gender Classification.

AgeGender.net are models for age and gender classification trained on the Adience-OULI dataset. See the Project page.

Age and Gender Classification using Convolutional Neural Networks
Gil Levy and Tal Hassner
IEEE Workshop on Analysis and Modeling of Faces and Gestures (AMFG),
at the Test Devt. on Computer Vision and Pattern Recognition (CVPR), Boston, June 28

If you find our models useful, please add suitable reference to our paper in your work.

GoogleNet_cars on car model classification

GoogleNet_cars is the GoogLeNet model pre-trained on Imagenet classification task and fine-tuned on the Reference Camera (modified Alexnet) for the Detroit 102 category flower dataset. The number of output in the inner product layer has been set to 102 to reflect the number of flower categories. The learning rate is 0.001. The learning rate for the inner product layer for Fine-Grained Classification is 10 times higher than the learning rate for the final fully connected. The global learning rate is reduced while the learning rate for the final fully connected is increased relative to the other layers.

A Large-Scale Car Dataset For Fine-Grained Categorization and Verification
L. Yang, F. Lu, C. C. Loy, X. Teng, arXiv:1508.08099, 2015

Holistically-Nested Edge Detection
The model and code provided are described in the ICCV 2015 paper.

Holistically-Nested Edge Detection
Seizing Xie and Zhuwen Tu
ICCV 2015

For details about training/evaluating HED, please take a look at <http://github.com/seizehx/HED>.

Model trained on BSDSD-500 Dataset (Inherited from the VGGNet):

- HED BSDSD-500

Translating Videos to Natural Language

These models are described in this NAACL-HLT 2015 paper:

Translating Videos to Natural Language Using Deep Recurrent Neural Networks
S. Venugopalan, K. Xu, J. Donahue, R. Rohrbach, R. Mooney, K. Saenko
NAACL 2015

More details can be found on this project page.

Model:
Video2Text_VGG16_inception: This model is an improved version of the mean pooled model described in the paper Lai et al., 2014. It uses video frame features from the VGG-16 layer model. This is trained on the YouTube video dataset.

Compatibility: These are pre-release models. They do not run in any current version of BVLC GoogLeNet, as they require unmerged PRs. The models are currently supported by the `current` branch of the Caffe fork provided at <https://github.com/jcjohnson/vggface2/tree/current> and <https://github.com/vishvanathanai/caffe/tree/current>.

VGG Face CNN descriptor

These models are described in this BMVC 2015 paper.

Deep Face Recognition
Dekar R., Parisi, Andrea Vedaldi, Andrew Zisserman
BMVC 2015

More details can be found on this project page.

Model: VGG Face: This is the very deep architecture based model trained from scratch using 2.6 Million images of celebrities collected from the web. The model has been imported to work with Caffe via the model format used by MacmillanNet library.

If you find our models useful, please add suitable reference to our paper in your work.

Yearbook Photo Pricing

Model from the ICCV 2015 Extreme Imaging Workshop paper:

A Century of Portraits: Exploring the Visual Historical Record of American High School Yearbooks
Gill Levy, Kate Raesly, Brian Yin, Sarah Sachs, Alyehsa Erfou
ICCV Workshop 2015

Model and predicted files: Yearbook

CNN: Constrained Convolutional Neural Networks for Weakly Supervised Segmentation

These models are described in the ICCV 2015 paper.

Constrained Convolutional Neural Networks for Weakly Supervised Segmentation
Deepa Pathak, Philipp Krahenbuhl, Trevor Darrell
ICCV 2015
arXiv:1506.03048

These are pre-release models. They do not run in any current version of BVLC GoogLeNet, as they require unmerged PRs. Full details, source code, models, protobots are available here: CNN.

Things you should know for your Project Proposal

“We have infinite
compute available
because Terminal.”

Things you should know for your Project Proposal

“We have infinite
compute available
because Terminal.”



You have finite compute.
Don't be overly ambitious.

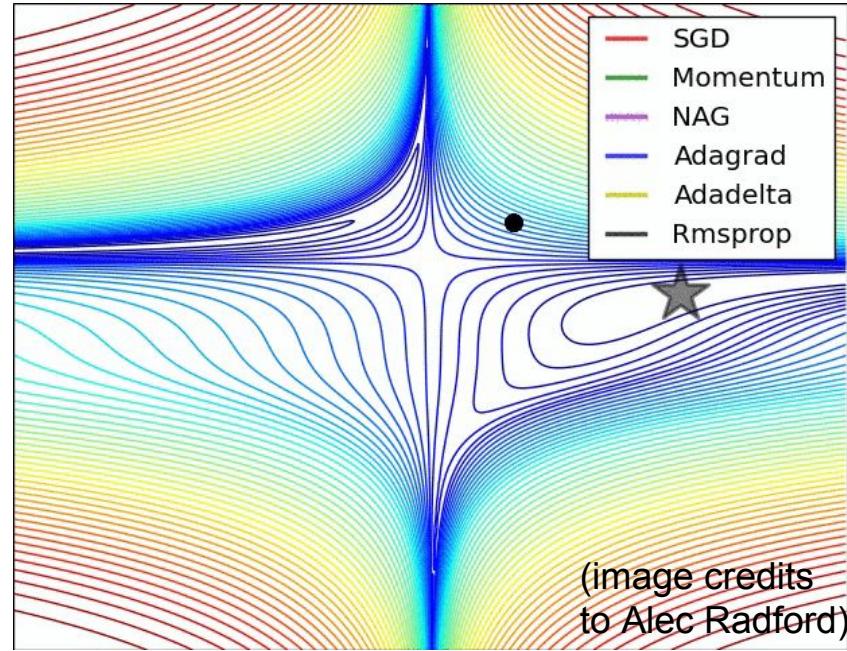
Where we are now...

Mini-batch SGD

Loop:

1. **Sample** a batch of data
2. **Forward** prop it through the graph, get loss
3. **Backprop** to calculate the gradients
4. **Update** the parameters using the gradient

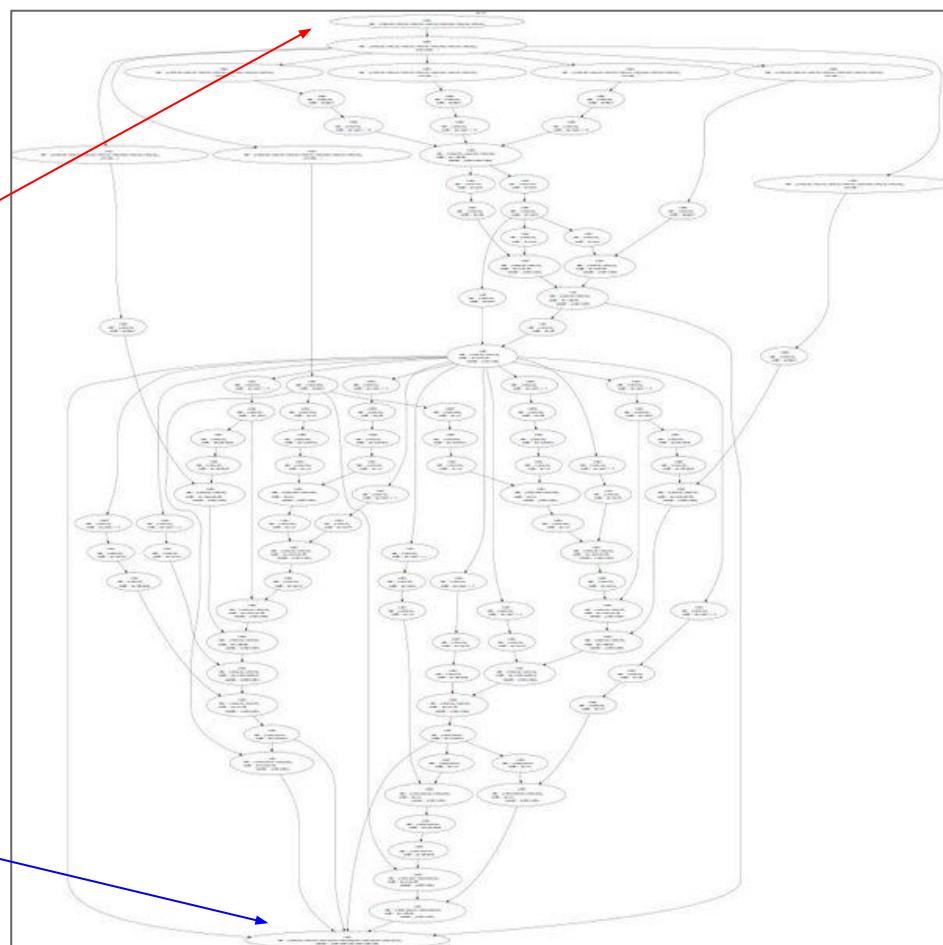
Where we are now...



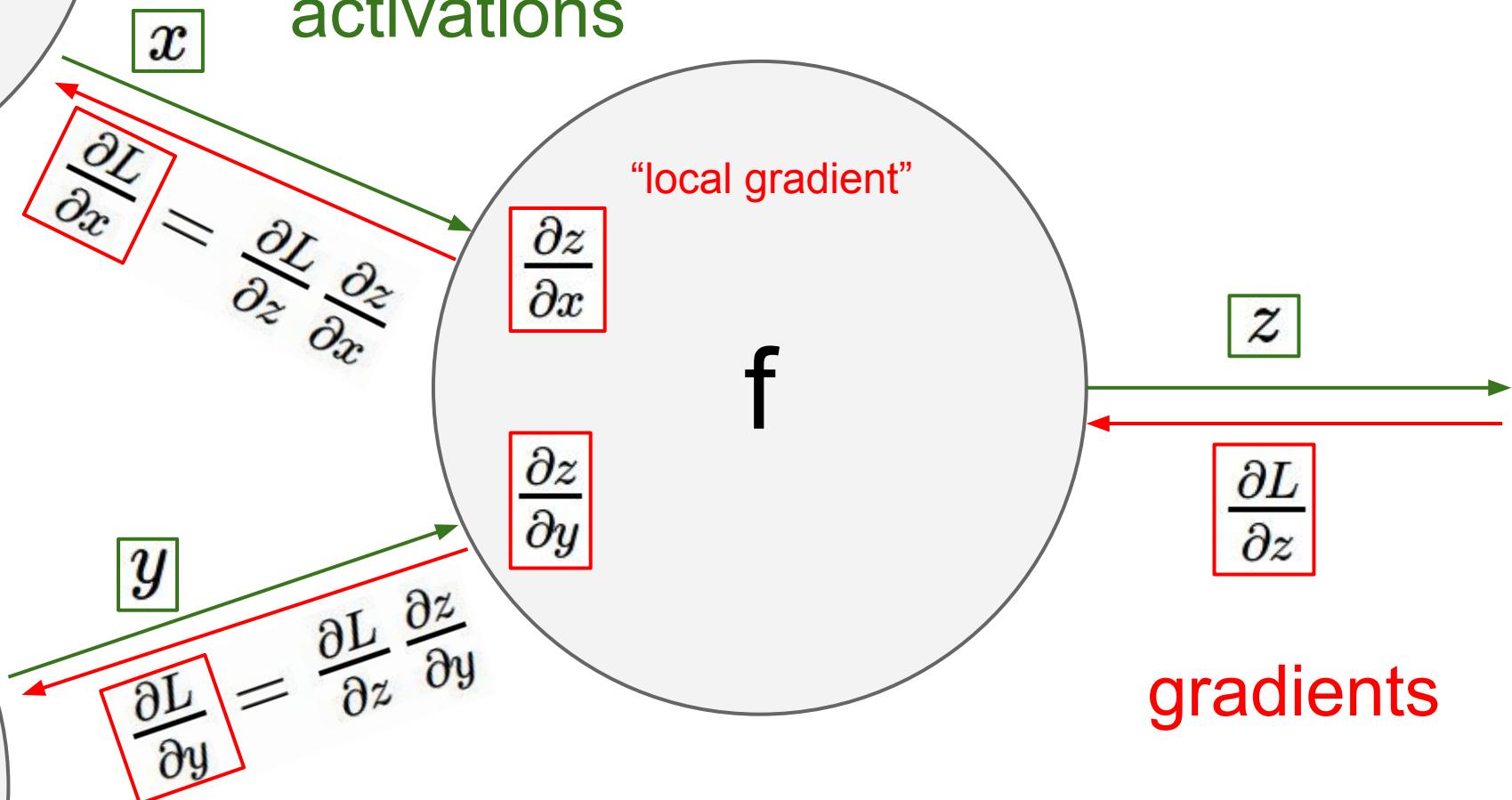
Neural Turing Machine

input tape

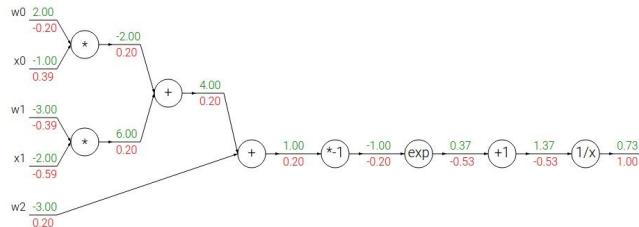
loss



activations



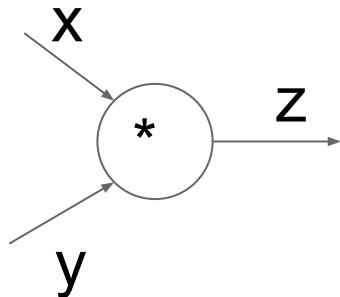
Implementation: forward/backward API



Graph (or Net) object. (Rough psuedo code)

```
class ComputationalGraph(object):  
    ...  
    def forward(inputs):  
        # 1. [pass inputs to input gates...]  
        # 2. forward the computational graph:  
        for gate in self.graph.nodes_topologically_sorted():  
            gate.forward()  
        return loss # the final gate in the graph outputs the loss  
    def backward():  
        for gate in reversed(self.graph.nodes_topologically_sorted()):  
            gate.backward() # little piece of backprop (chain rule applied)  
        return inputs_gradients
```

Implementation: forward/backward API



```
class MultiplyGate(object):  
    def forward(x,y):  
        z = x*y  
        self.x = x # must keep these around!  
        self.y = y  
        return z  
    def backward(dz):  
        dx = self.y * dz # [dz/dx * dL/dz]  
        dy = self.x * dz # [dz/dy * dL/dz]  
        return [dx, dy]
```

(x, y, z are scalars)



Example: Torch Layers



Neural Network: without the brain stuff

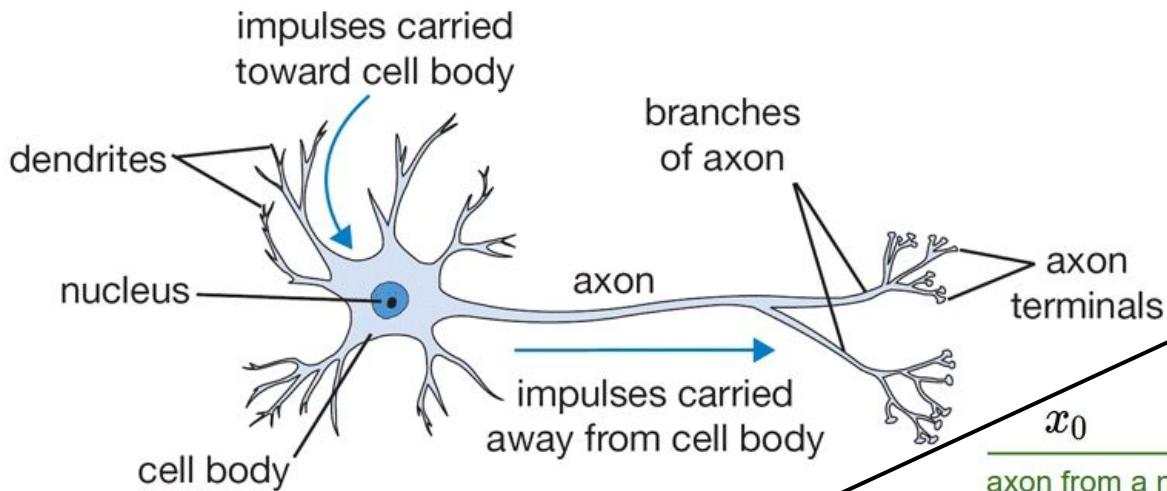
(Before) Linear score function:

$$f = Wx$$

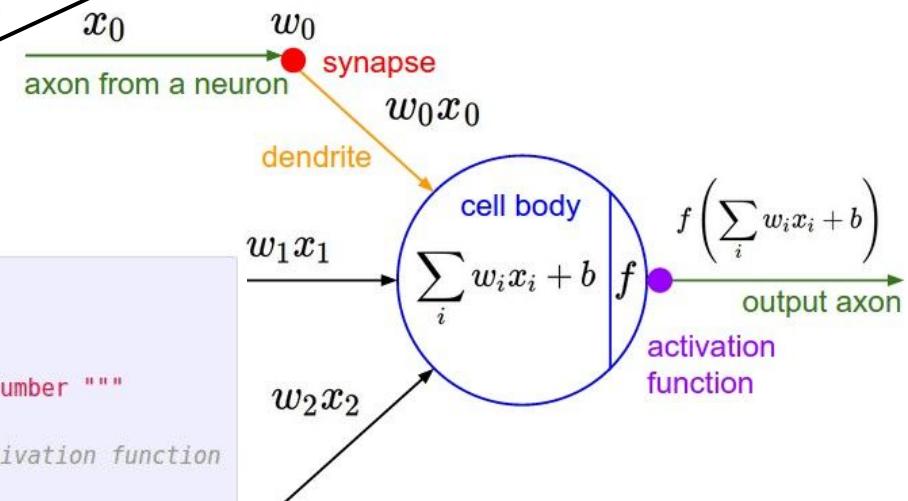
(Now) 2-layer Neural Network
or 3-layer Neural Network

$$f = W_2 \max(0, W_1 x)$$

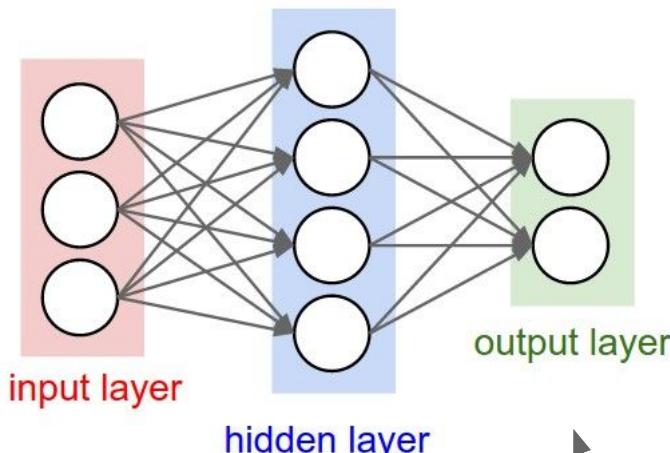
$$f = W_3 \max(0, W_2 \max(0, W_1 x))$$



```
class Neuron:
    # ...
    def neuron_tick(self, inputs):
        """ assume inputs and weights are 1-D numpy arrays and bias is a number """
        cell_body_sum = np.sum(inputs * self.weights) + self.bias
        firing_rate = 1.0 / (1.0 + math.exp(-cell_body_sum)) # sigmoid activation function
        return firing_rate
```



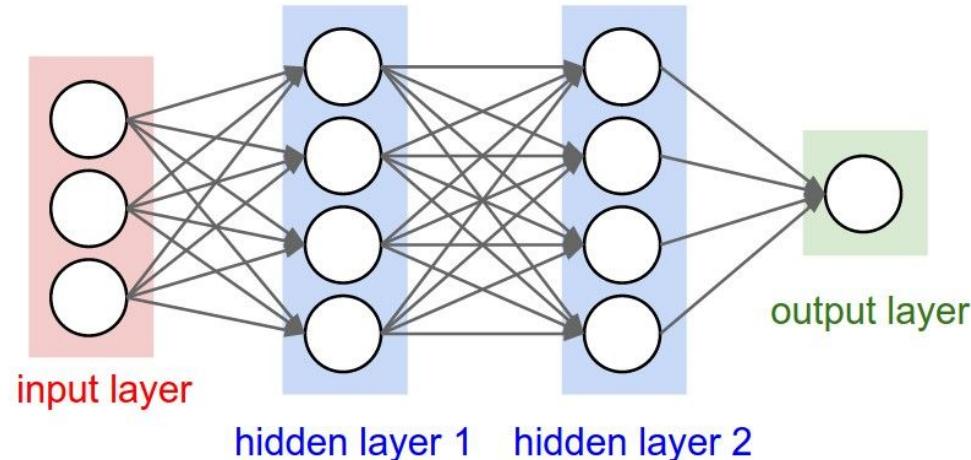
Neural Networks: Architectures



input layer

hidden layer

output layer



input layer

hidden layer 1

hidden layer 2

output layer

“2-layer Neural Net”, or
“1-hidden-layer Neural Net”

“Fully-connected” layers

“3-layer Neural Net”, or
“2-hidden-layer Neural Net”

Training Neural Networks

A bit of history...

A bit of history

The **Mark I Perceptron** machine was the first implementation of the perceptron algorithm.

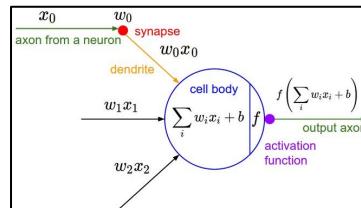
The machine was connected to a camera that used 20×20 cadmium sulfide photocells to produce a 400-pixel image.

recognized
letters of the alphabet

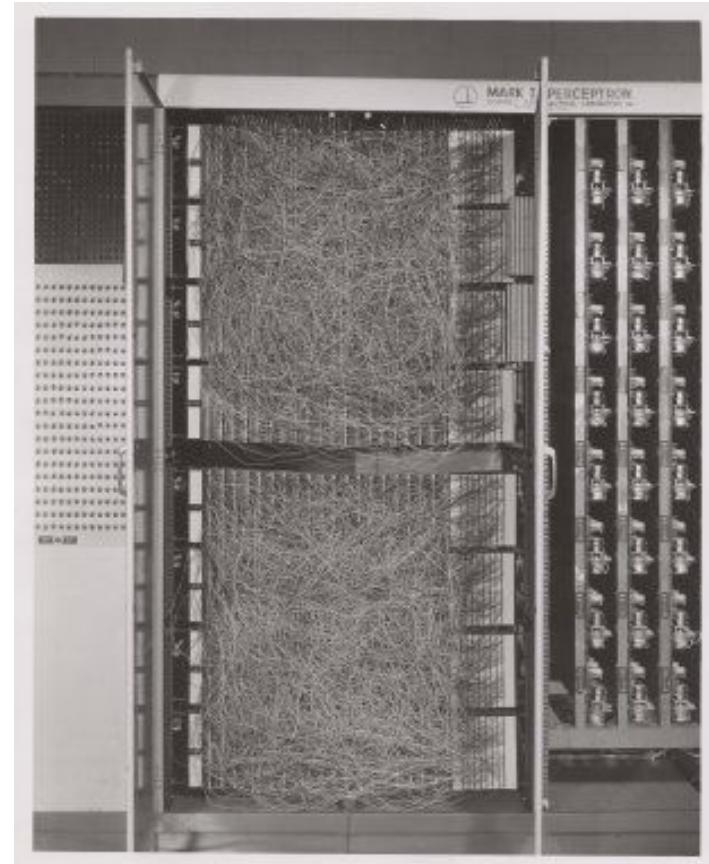
update rule:

$$w_i(t+1) = w_i(t) + \alpha(d_j - y_j(t))x_{j,i}$$

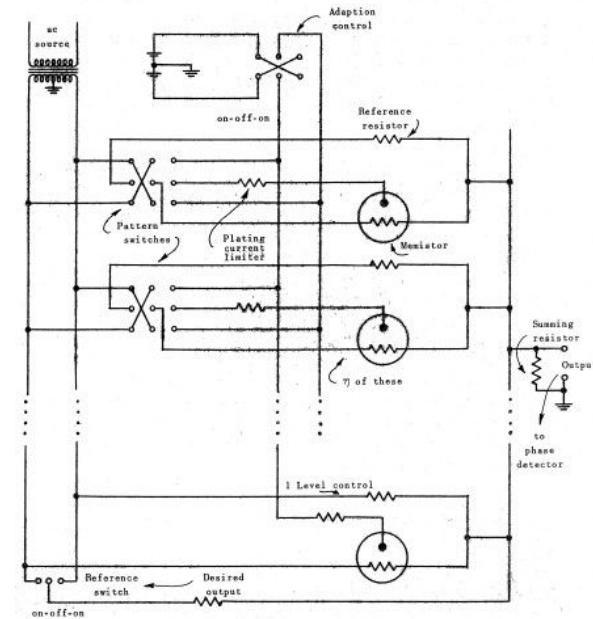
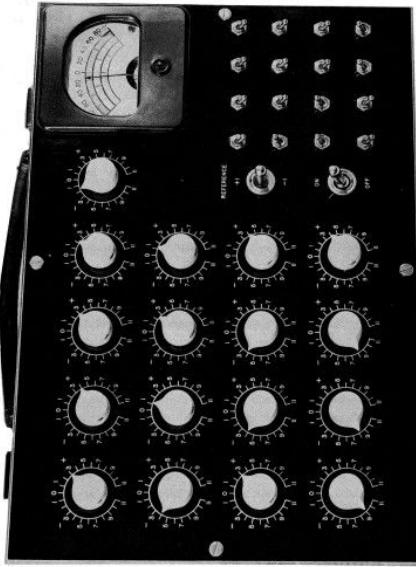
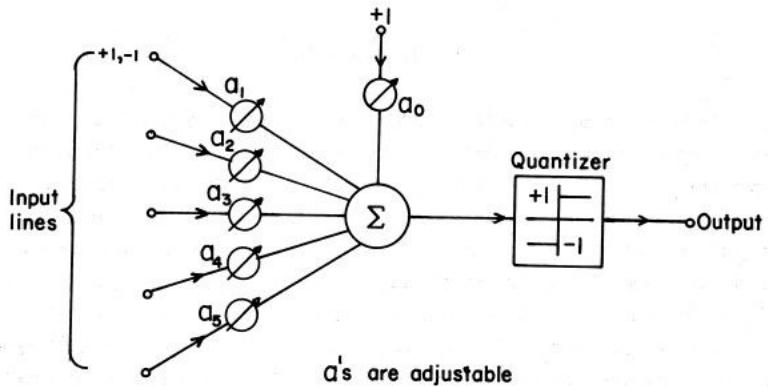
$$f(x) = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ 0 & \text{otherwise} \end{cases}$$



Frank Rosenblatt, ~1957: Perceptron

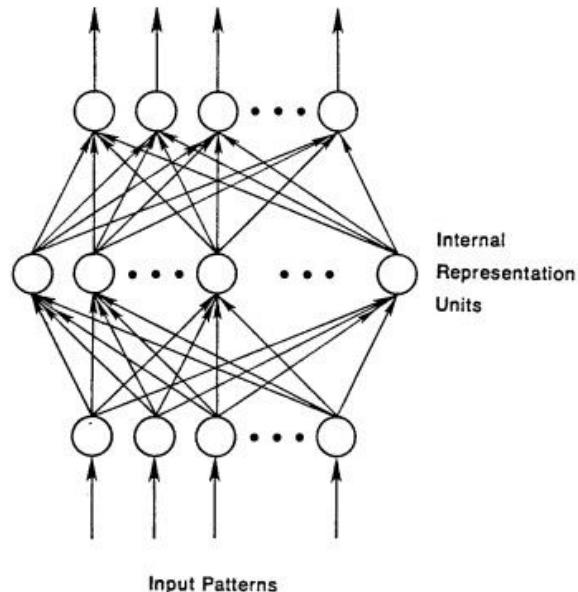


A bit of history



Widrow and Hoff, ~1960: Adaline/Madaline

A bit of history



To be more specific, then, let

$$E_p = \frac{1}{2} \sum_j (t_{pj} - o_{pj})^2 \quad (2)$$

be our measure of the error on input/output pattern p and let $E = \sum E_p$ be our overall measure of the error. We wish to show that the delta rule implements a gradient descent in E when the units are linear. We will proceed by simply showing that

$$-\frac{\partial E_p}{\partial w_{ji}} = \delta_{pj} i_{pi},$$

which is proportional to $\Delta_p w_{ji}$ as prescribed by the delta rule. When there are no hidden units it is straightforward to compute the relevant derivative. For this purpose we use the chain rule to write the derivative as the product of two parts: the derivative of the error with respect to the output of the unit times the derivative of the output with respect to the weight.

$$\frac{\partial E_p}{\partial w_{ji}} = \frac{\partial E_p}{\partial o_{pj}} \frac{\partial o_{pj}}{\partial w_{ji}}. \quad (3)$$

The first part tells how the error changes with the output of the j th unit and the second part tells how much changing w_{ji} changes that output. Now, the derivatives are easy to compute. First, from Equation 2

$$\frac{\partial E_p}{\partial o_{pj}} = -(t_{pj} - o_{pj}) = -\delta_{pj}. \quad (4)$$

Not surprisingly, the contribution of unit o_j to the error is simply proportional to δ_{pj} . Moreover, since we have linear units,

$$o_{pj} = \sum_i w_{ji} i_{pi}, \quad (5)$$

from which we conclude that

$$\frac{\partial o_{pj}}{\partial w_{ji}} = i_{pi}.$$

Thus, substituting back into Equation 3, we see that

$$-\frac{\partial E_p}{\partial w_{ji}} = \delta_{pj} i_{pi} \quad (6)$$

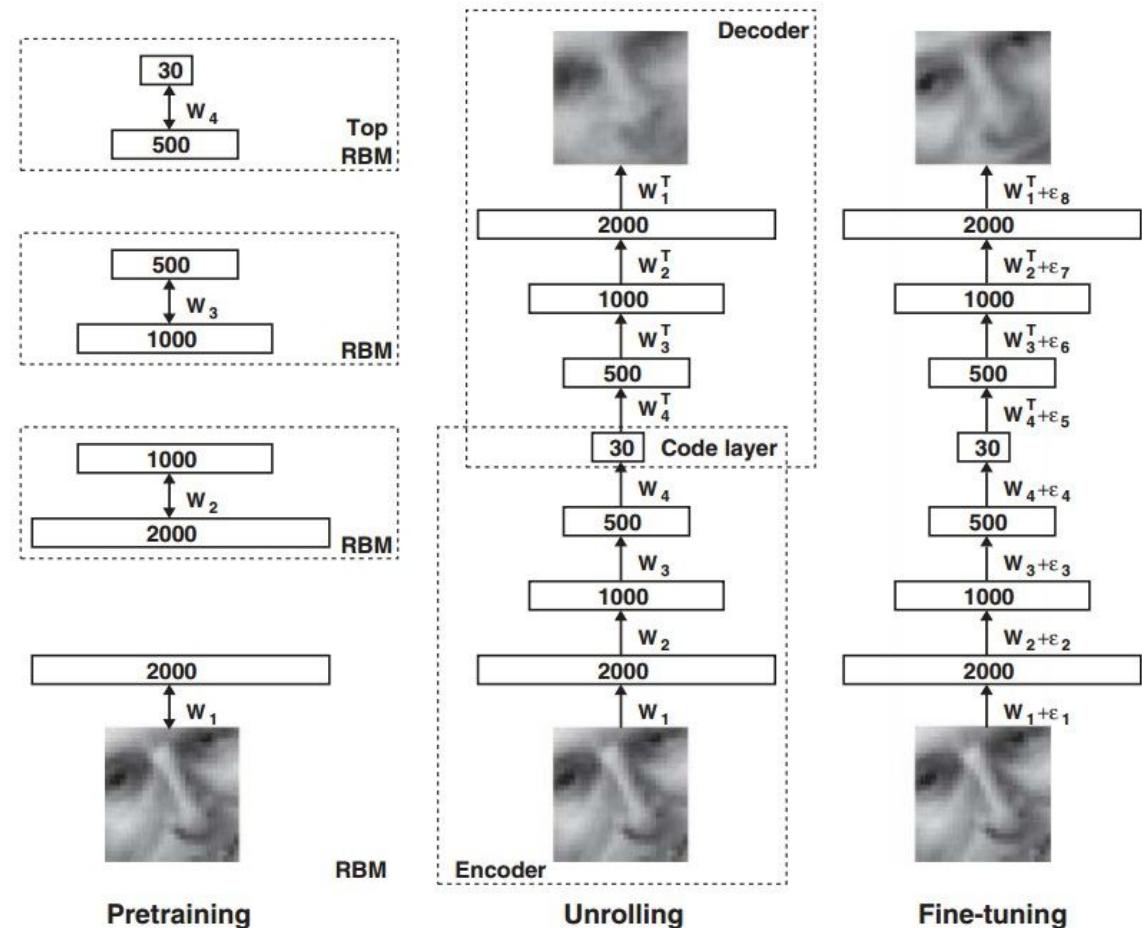
recognizable maths

Rumelhart et al. 1986: First time back-propagation became popular

A bit of history

[Hinton and Salakhutdinov 2006]

Reinvigorated research in
Deep Learning



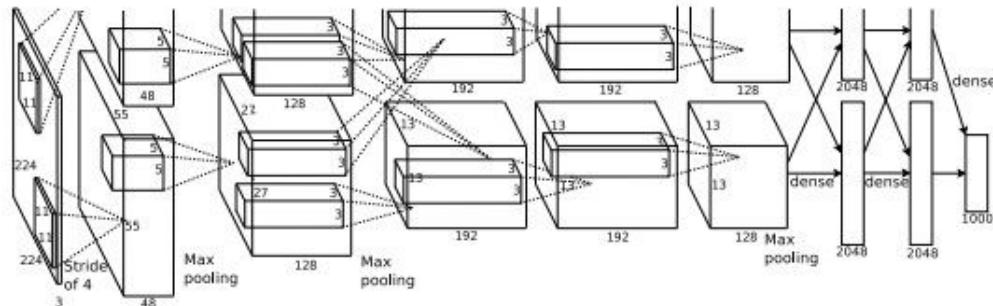
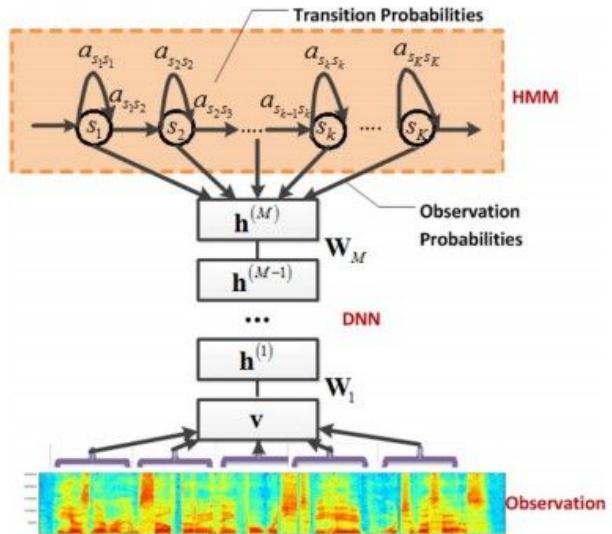
First strong results

**Context-Dependent Pre-trained Deep Neural Networks
for Large Vocabulary Speech Recognition**

George Dahl, Dong Yu, Li Deng, Alex Acero, 2010

**Imagenet classification with deep convolutional
neural networks**

Alex Krizhevsky, Ilya Sutskever, Geoffrey E Hinton, 2012



Overview

1. One time setup

activation functions, preprocessing, weight initialization, regularization, gradient checking

2. Training dynamics

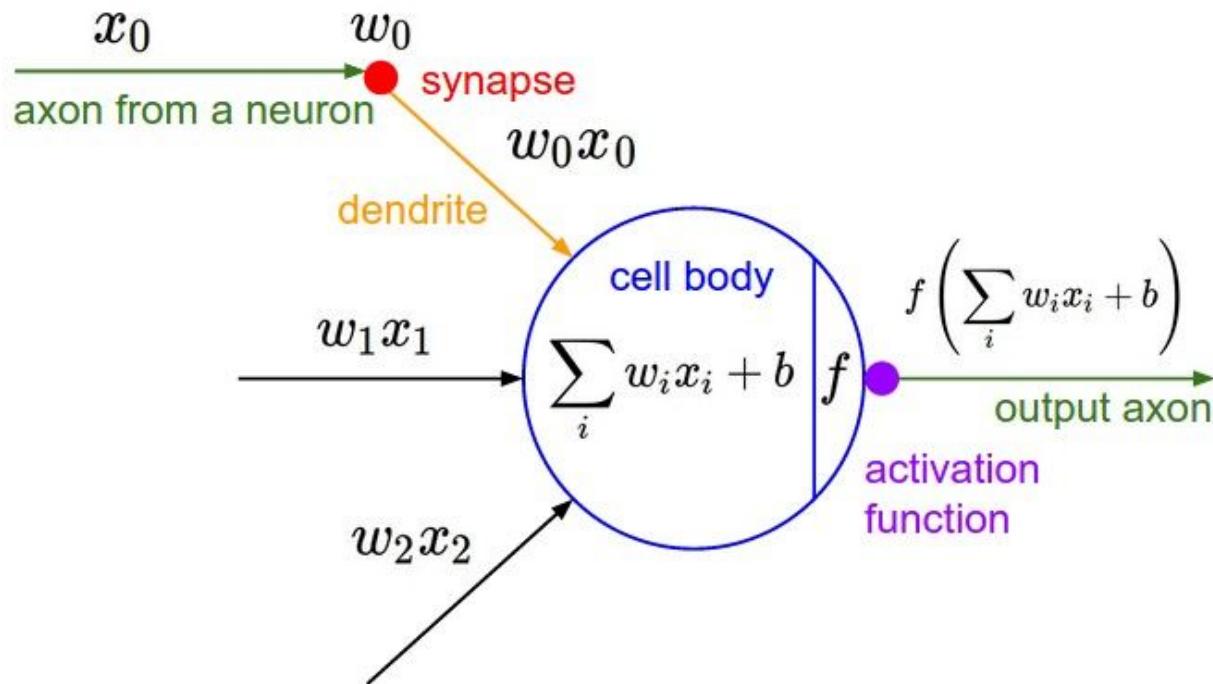
*babysitting the learning process,
parameter updates, hyperparameter optimization*

3. Evaluation

model ensembles

Activation Functions

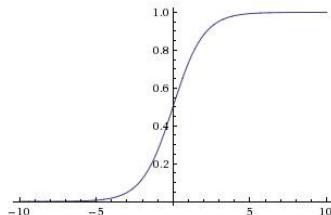
Activation Functions



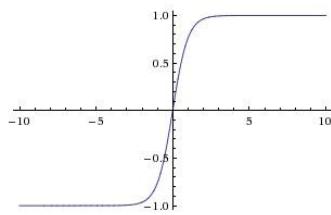
Activation Functions

Sigmoid

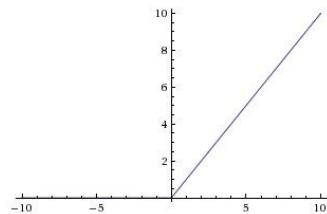
$$\sigma(x) = 1/(1 + e^{-x})$$



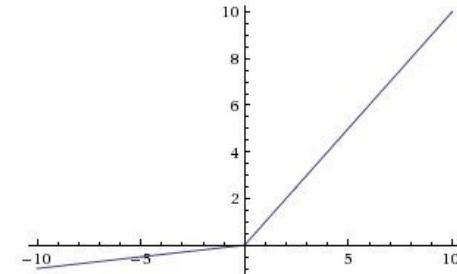
tanh tanh(x)



ReLU max(0,x)



Leaky ReLU max(0.1x, x)

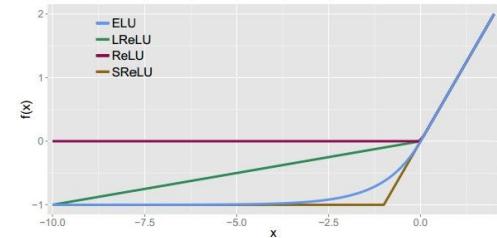


Maxout

ELU

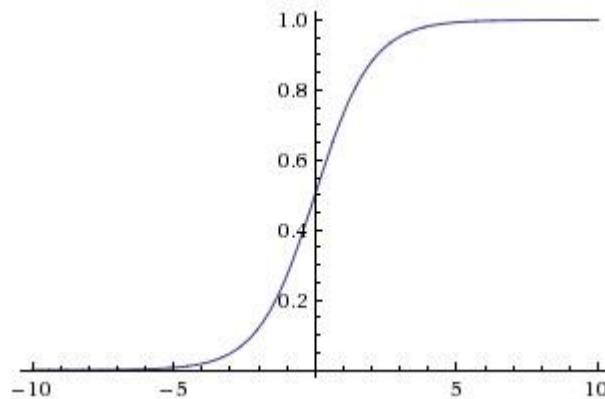
$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha (\exp(x) - 1) & \text{if } x \leq 0 \end{cases}$$



Activation Functions

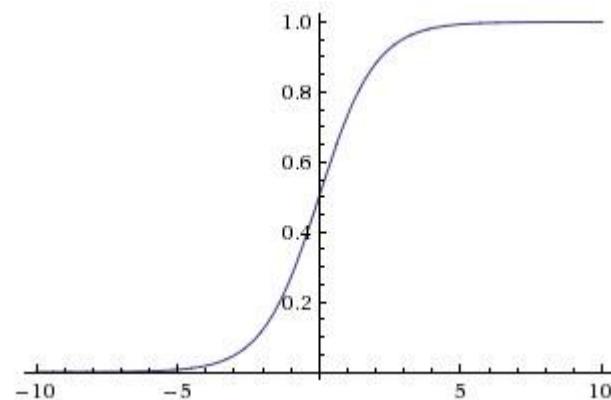
$$\sigma(x) = 1/(1 + e^{-x})$$



- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

Sigmoid

Activation Functions



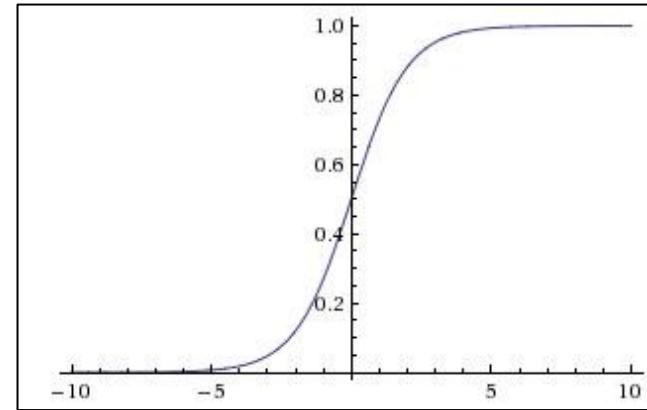
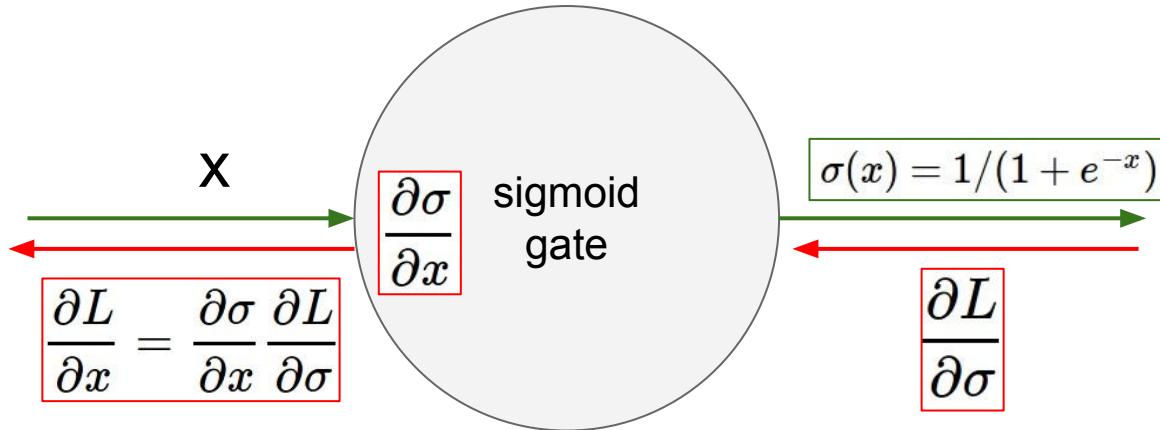
Sigmoid

$$\sigma(x) = 1/(1 + e^{-x})$$

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

3 problems:

1. Saturated neurons “kill” the gradients



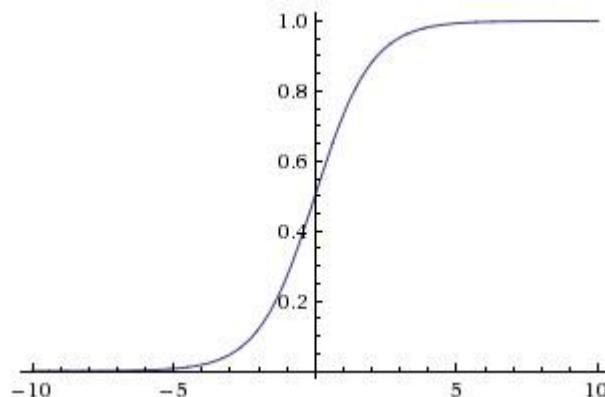
What happens when $x = -10$?

What happens when $x = 0$?

What happens when $x = 10$?

Activation Functions

$$\sigma(x) = 1/(1 + e^{-x})$$



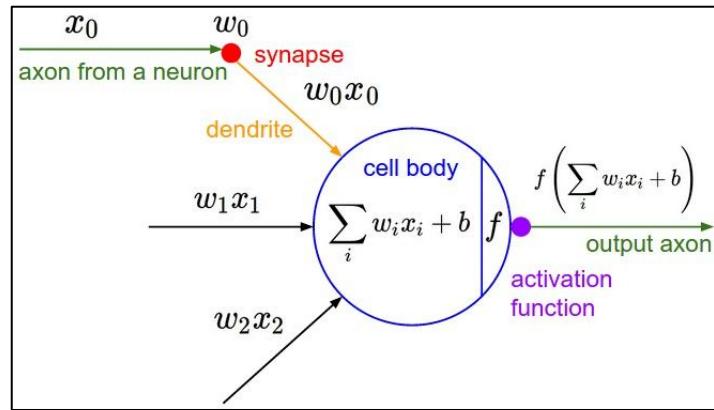
Sigmoid

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

3 problems:

1. Saturated neurons “kill” the gradients
2. Sigmoid outputs are not zero-centered

Consider what happens when the input to a neuron (x) is always positive:

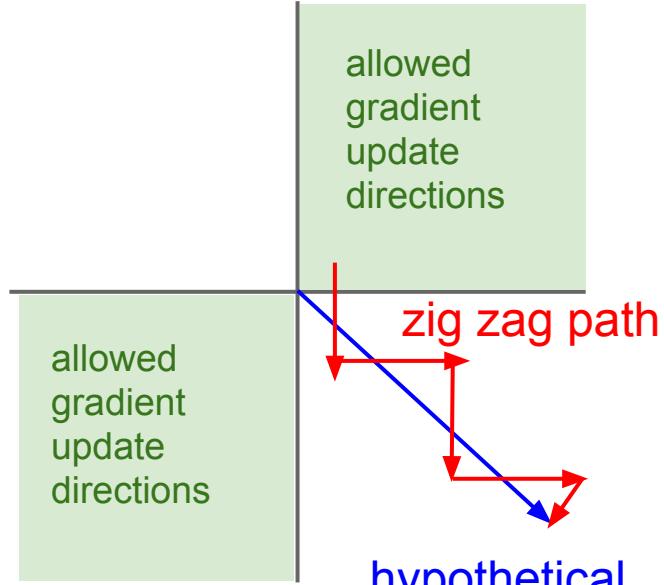


$$f \left(\sum_i w_i x_i + b \right)$$

What can we say about the gradients on w ?

Consider what happens when the input to a neuron is always positive...

$$f \left(\sum_i w_i x_i + b \right)$$



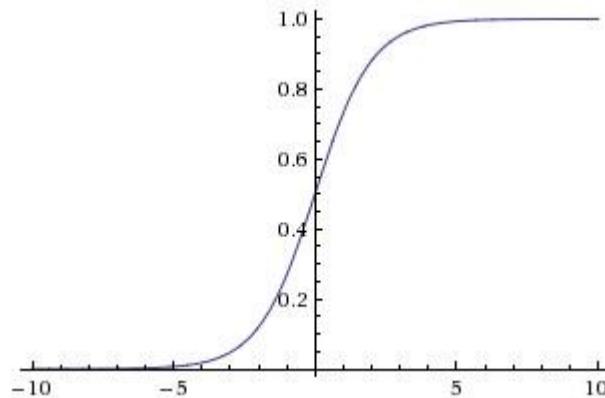
What can we say about the gradients on w ?

Always all positive or all negative :(

(this is also why you want zero-mean data!)

Activation Functions

$$\sigma(x) = 1/(1 + e^{-x})$$



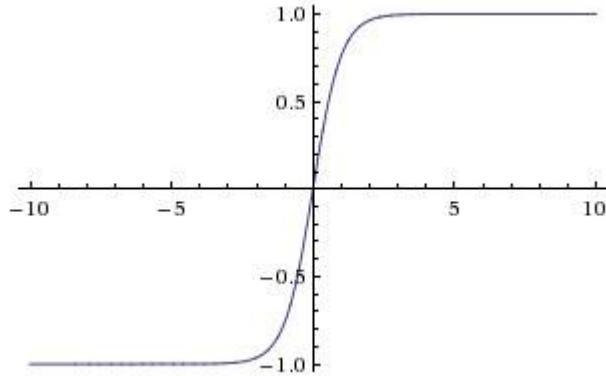
Sigmoid

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

3 problems:

1. Saturated neurons “kill” the gradients
2. Sigmoid outputs are not zero-centered
3. $\exp()$ is a bit compute expensive

Activation Functions

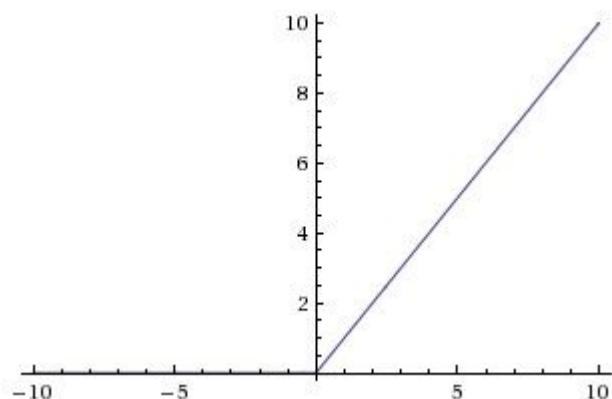


tanh(x)

- Squashes numbers to range [-1,1]
- zero centered (nice)
- still kills gradients when saturated :(

[LeCun et al., 1991]

Activation Functions

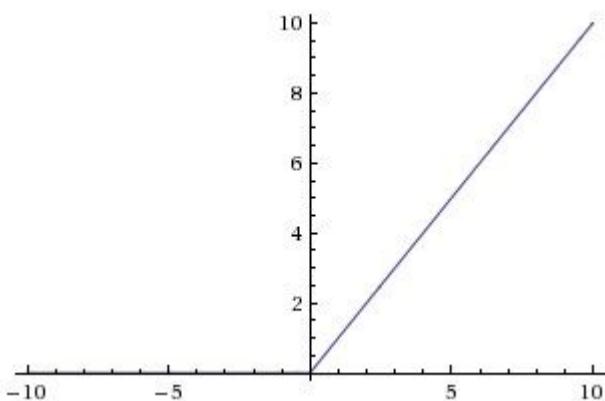


- Computes $f(x) = \max(0, x)$
- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)

ReLU
(Rectified Linear Unit)

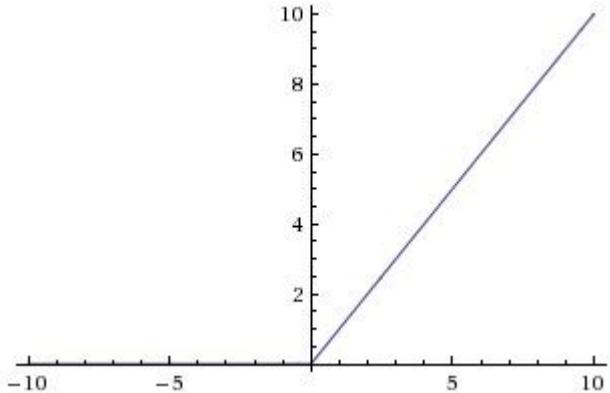
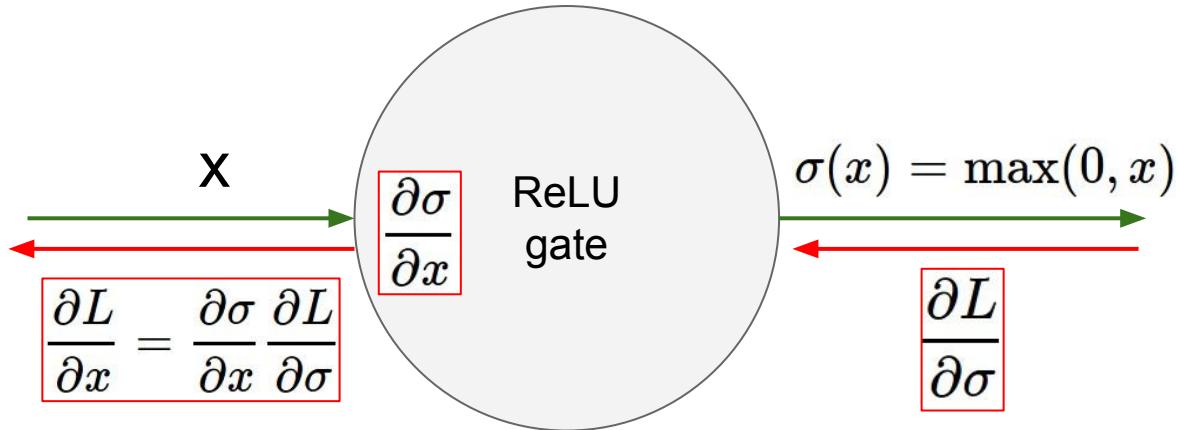
[Krizhevsky et al., 2012]

Activation Functions



ReLU
(Rectified Linear Unit)

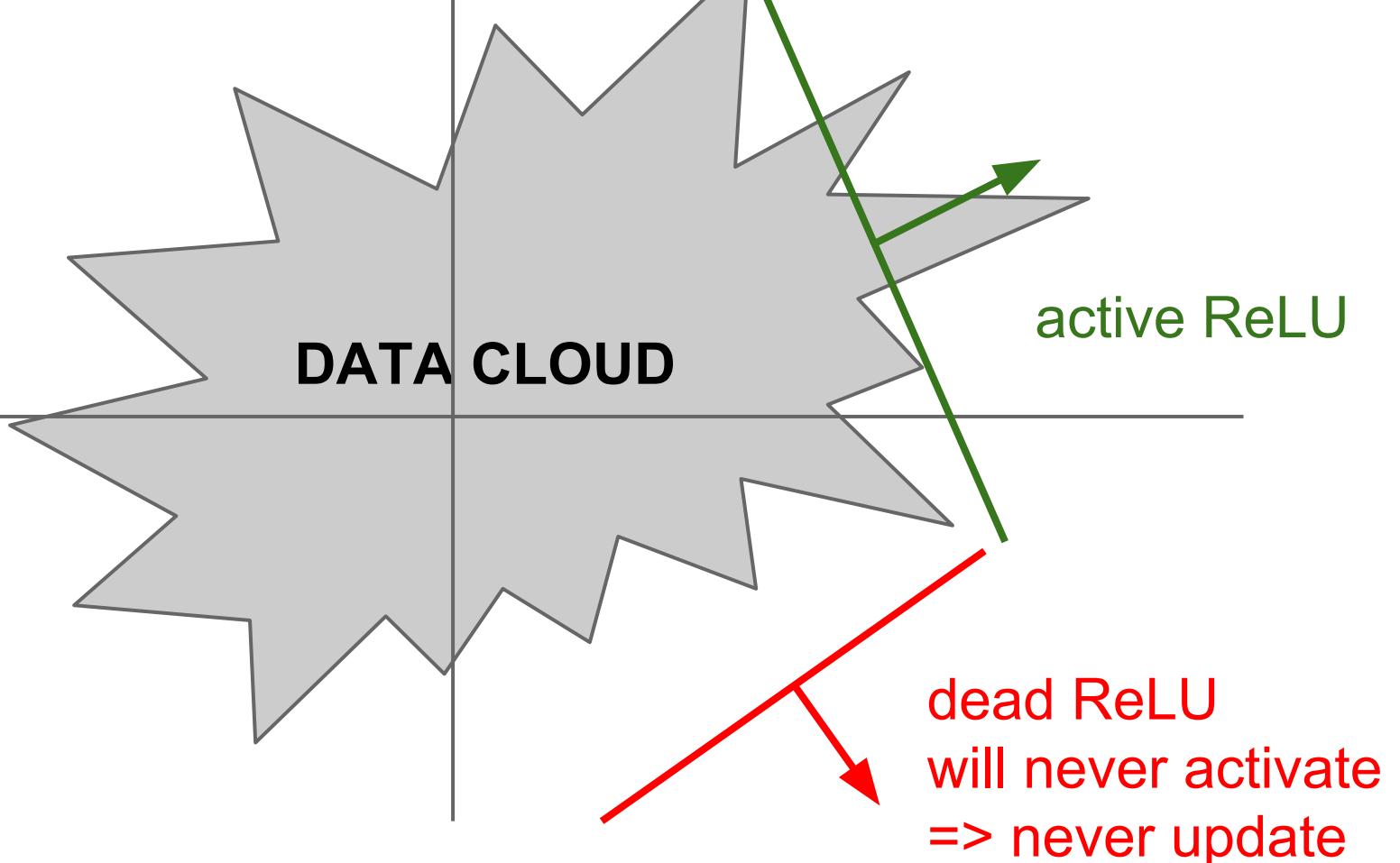
- Computes $f(x) = \max(0, x)$
- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)
- Not zero-centered output
- An annoyance:
hint: what is the gradient when $x < 0$?

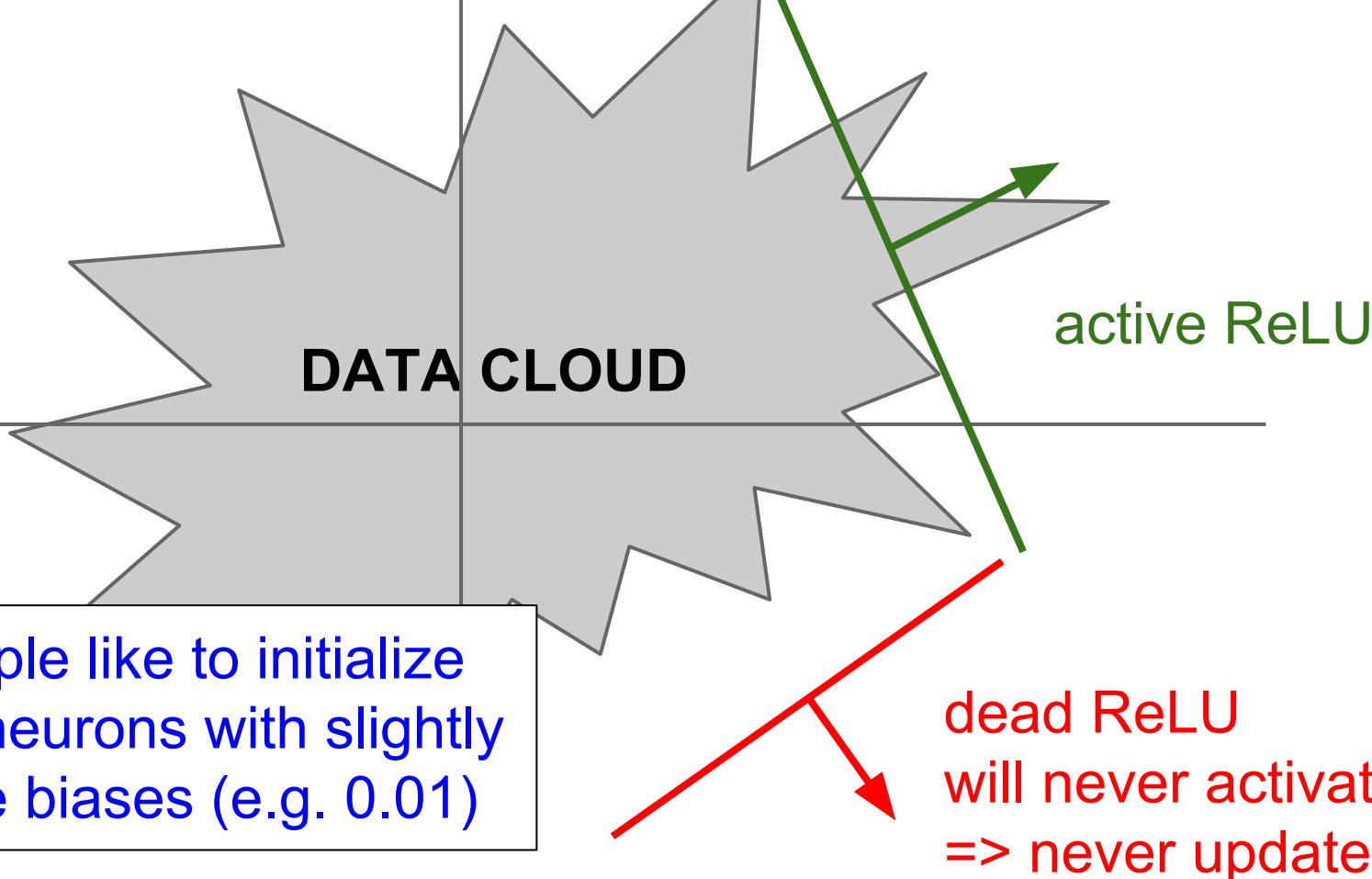


What happens when $x = -10$?

What happens when $x = 0$?

What happens when $x = 10$?

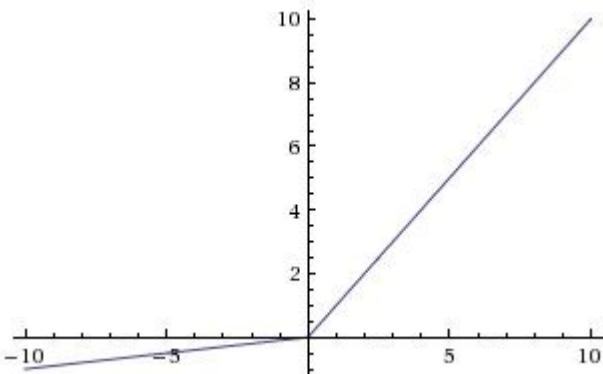




Activation Functions

[Mass et al., 2013]
[He et al., 2015]

- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- **will not “die”.**

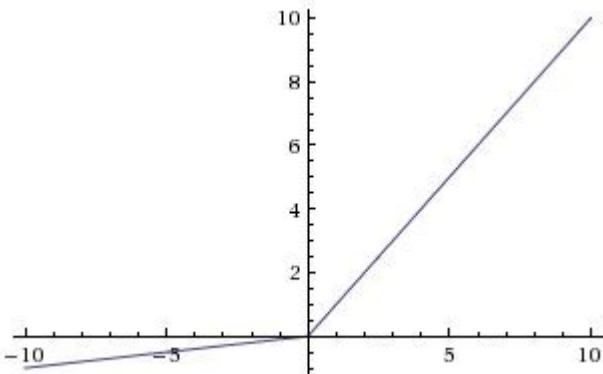


Leaky ReLU

$$f(x) = \max(0.01x, x)$$

Activation Functions

[Mass et al., 2013]
[He et al., 2015]



Leaky ReLU

$$f(x) = \max(0.01x, x)$$

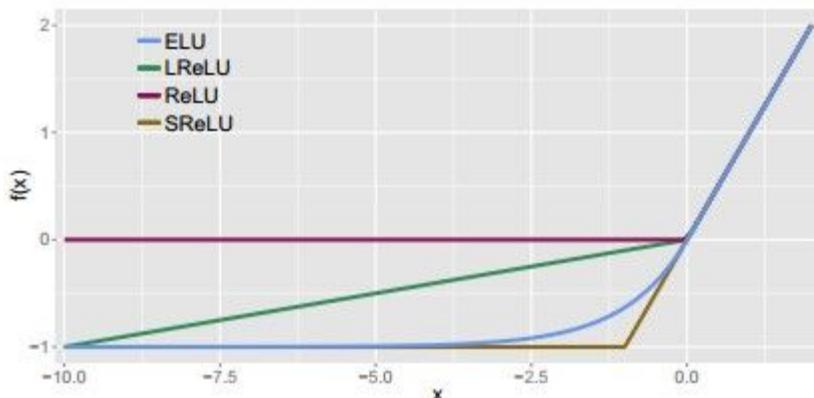
- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- **will not “die”.**

Parametric Rectifier (PReLU)

$$f(x) = \max(\alpha x, x)$$

backprop into α
(parameter)

Exponential Linear Units (ELU)



$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha (\exp(x) - 1) & \text{if } x \leq 0 \end{cases}$$

- All benefits of ReLU
- Does not die
- Closer to zero mean outputs
- Computation requires $\exp()$

Maxout “Neuron”

[Goodfellow et al., 2013]

- Does not have the basic form of dot product -> nonlinearity
- Generalizes ReLU and Leaky ReLU
- Linear Regime! Does not saturate! Does not die!

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

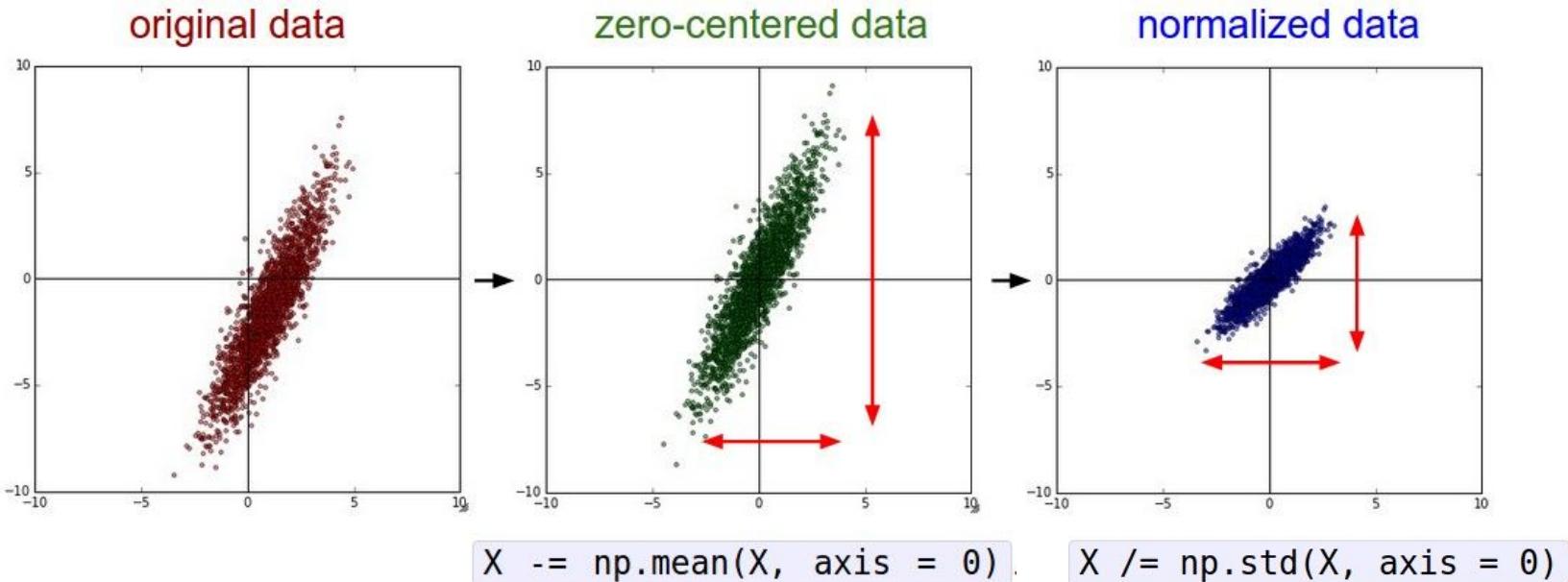
Problem: doubles the number of parameters/neuron :(

TLDR: In practice:

- Use ReLU. Be careful with your learning rates
- Try out Leaky ReLU / Maxout / ELU
- Try out tanh but don't expect much
- Don't use sigmoid

Data Preprocessing

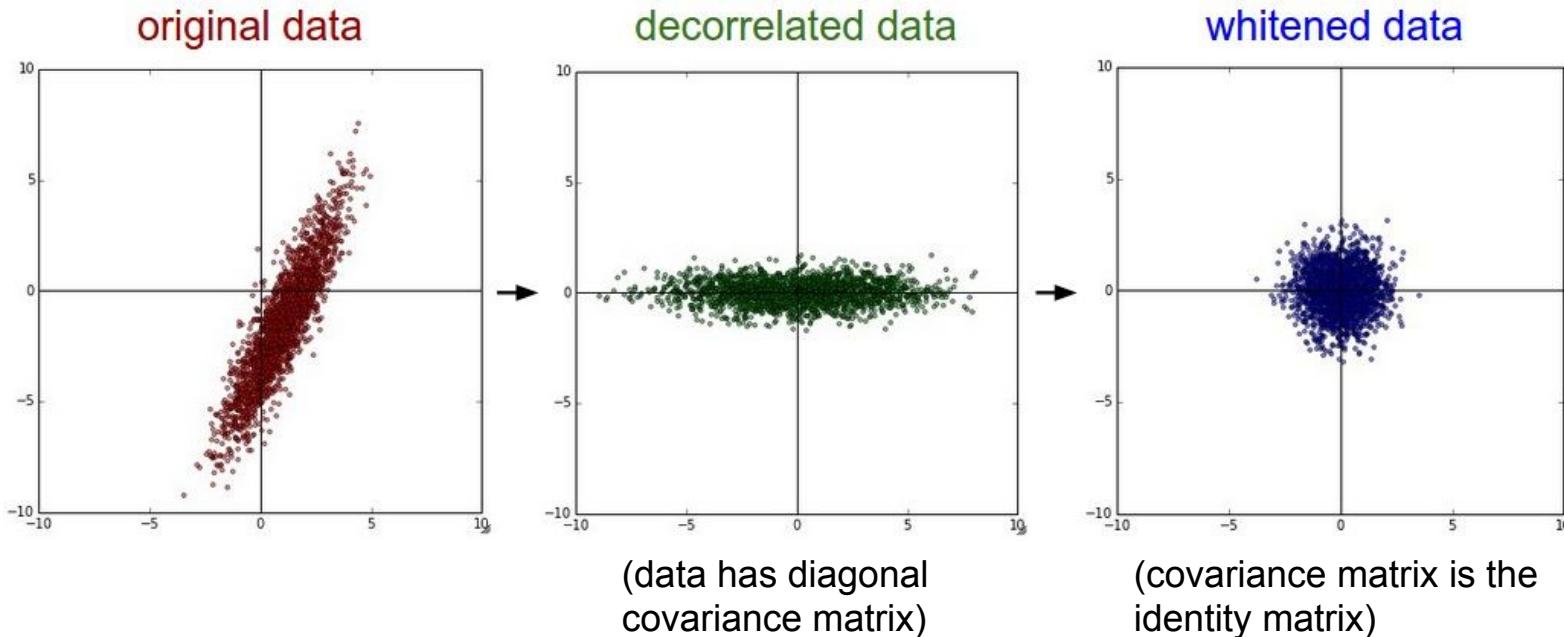
Step 1: Preprocess the data



(Assume X [NxD] is data matrix,
each example in a row)

Step 1: Preprocess the data

In practice, you may also see **PCA** and **Whitening** of the data



TLDR: In practice for Images: center only

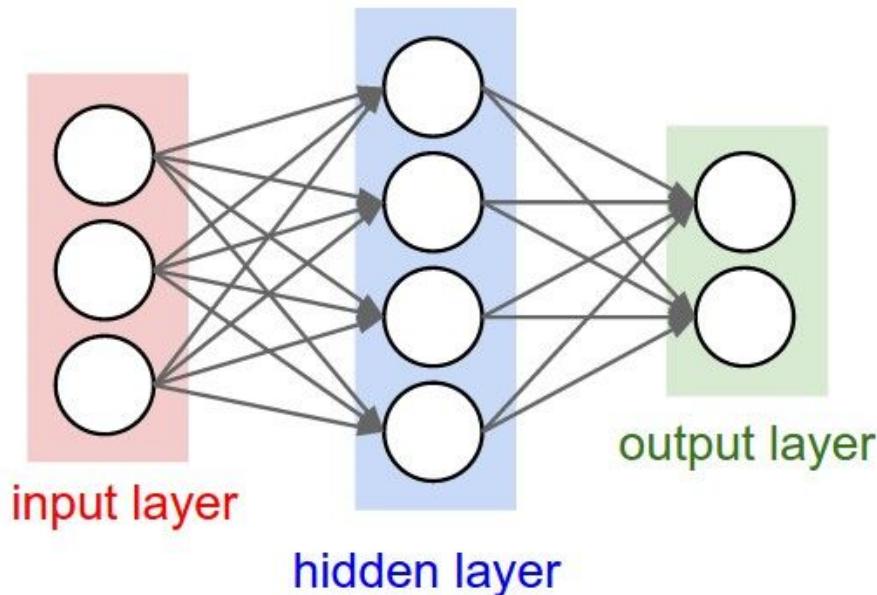
e.g. consider CIFAR-10 example with [32,32,3] images

- Subtract the mean image (e.g. AlexNet)
(mean image = [32,32,3] array)
- Subtract per-channel mean (e.g. VGGNet)
(mean along each channel = 3 numbers)

Not common to normalize variance, to do PCA or whitening

Weight Initialization

- Q: what happens when $W=0$ init is used?



- First idea: **Small random numbers**
(gaussian with zero mean and 1e-2 standard deviation)

```
W = 0.01* np.random.randn(D,H)
```

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(gaussian with zero mean and 1e-2 standard deviation)

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Works ~okay for small networks, but can lead to
non-homogeneous distributions of activations
across the layers of a network.

Lets look at some activation statistics

E.g. 10-layer net with 500 neurons on each layer, using tanh nonlinearities, and initializing as described in last slide.

```
# assume some unit gaussian 10-D input data
D = np.random.randn(1000, 500)
hidden_layer_sizes = [500]*10
nonlinearities = ['tanh']*len(hidden_layer_sizes)

act = {'relu':lambda x:np.maximum(0,x), 'tanh':lambda x:np.tanh(x)}
Hs = {}
for i in xrange(len(hidden_layer_sizes)):
    X = D if i == 0 else Hs[i-1] # input at this layer
    fan_in = X.shape[1]
    fan_out = hidden_layer_sizes[i]
    W = np.random.randn(fan_in, fan_out) * 0.01 # layer initialization

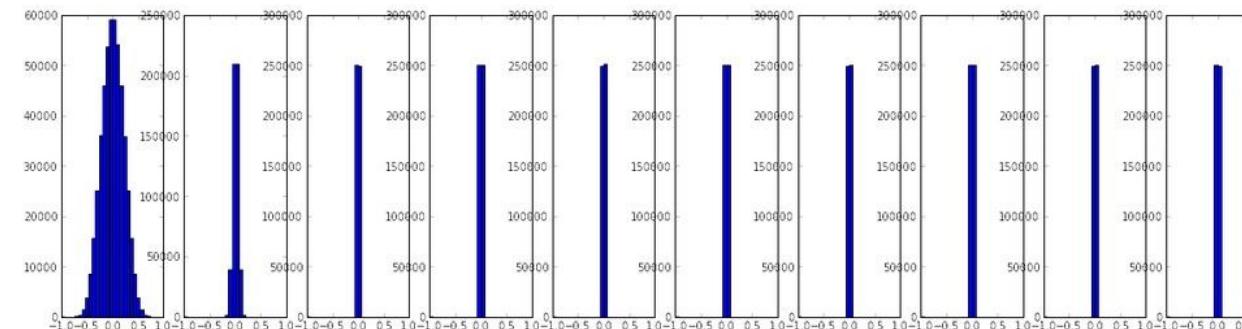
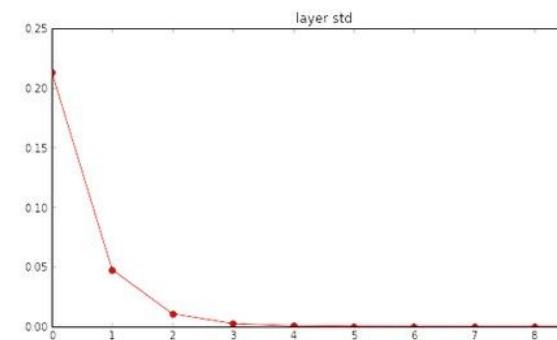
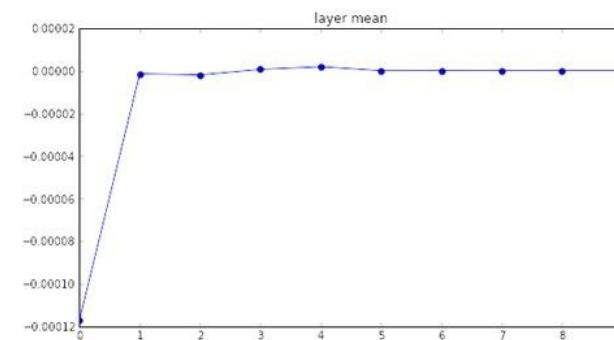
    H = np.dot(X, W) # matrix multiply
    H = act[nonlinearities[i]](H) # nonlinearity
    Hs[i] = H # cache result on this layer

# look at distributions at each layer
print 'input layer had mean %f and std %f' % (np.mean(D), np.std(D))
layer_means = [np.mean(H) for i,H in Hs.iteritems()]
layer_stds = [np.std(H) for i,H in Hs.iteritems()]
for i,H in Hs.iteritems():
    print 'hidden layer %d had mean %f and std %f' % (i+1, layer_means[i], layer_stds[i])

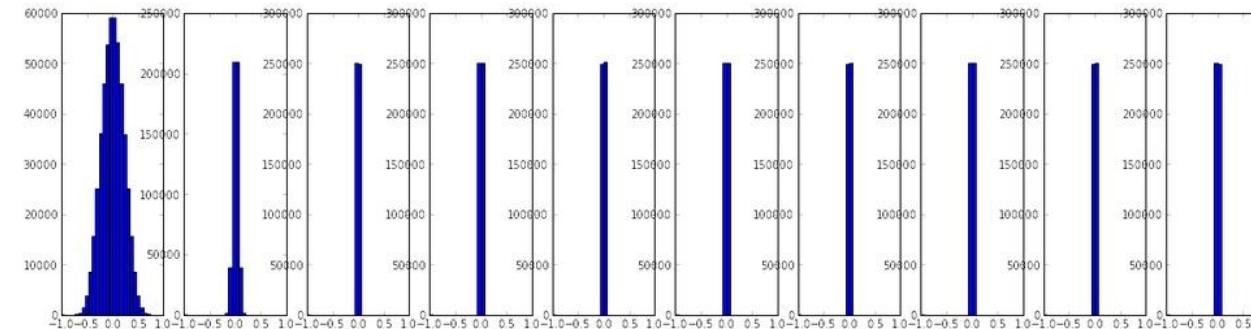
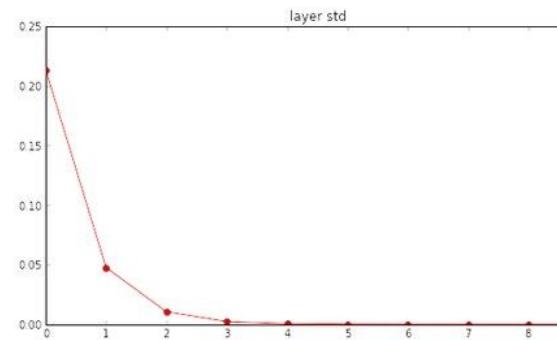
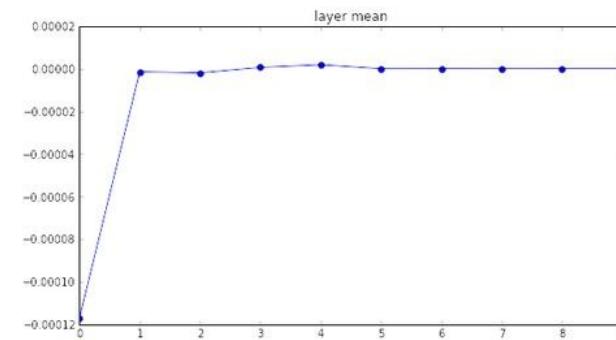
# plot the means and standard deviations
plt.figure()
plt.subplot(121)
plt.plot(Hs.keys(), layer_means, 'ob-')
plt.title('layer mean')
plt.subplot(122)
plt.plot(Hs.keys(), layer_stds, 'or-')
plt.title('layer std')

# plot the raw distributions
plt.figure()
for i,H in Hs.iteritems():
    plt.subplot(1,len(Hs),i+1)
    plt.hist(H.ravel(), 30, range=(-1,1))
```

```
input layer had mean 0.000927 and std 0.998388  
hidden layer 1 had mean -0.000117 and std 0.213081  
hidden layer 2 had mean -0.000001 and std 0.047551  
hidden layer 3 had mean -0.000002 and std 0.010630  
hidden layer 4 had mean 0.000001 and std 0.002378  
hidden layer 5 had mean 0.000002 and std 0.000532  
hidden layer 6 had mean -0.000000 and std 0.000119  
hidden layer 7 had mean 0.000000 and std 0.000026  
hidden layer 8 had mean -0.000000 and std 0.000006  
hidden layer 9 had mean 0.000000 and std 0.000001  
hidden layer 10 had mean -0.000000 and std 0.000000
```



```
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```



All activations become zero!

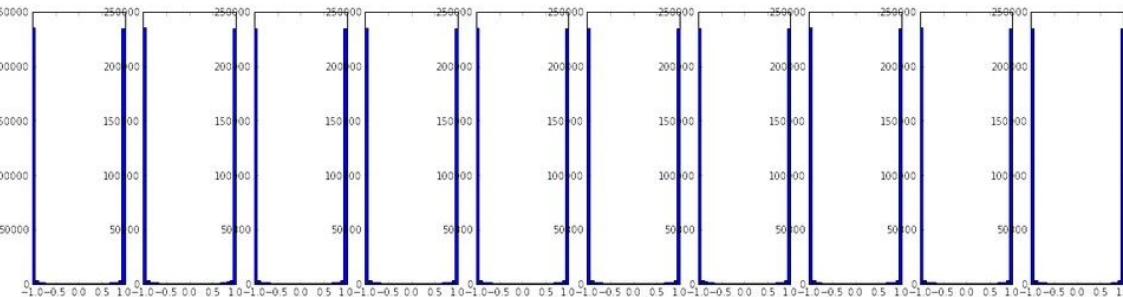
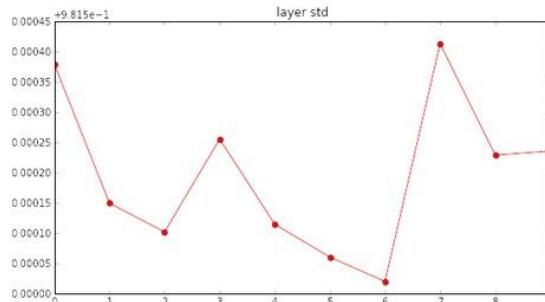
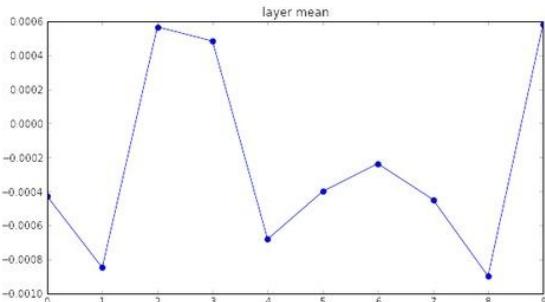
Q: think about the backward pass.
What do the gradients look like?

Hint: think about backward pass for a W^*X gate.

```
w = np.random.randn(fan_in, fan_out) * 1.0 # layer initialization
```

```
input layer had mean 0.001800 and std 1.001311  
hidden layer 1 had mean -0.000430 and std 0.981879  
hidden layer 2 had mean -0.000849 and std 0.981649  
hidden layer 3 had mean 0.000566 and std 0.981601  
hidden layer 4 had mean 0.000483 and std 0.981755  
hidden layer 5 had mean -0.000682 and std 0.981614  
hidden layer 6 had mean -0.000401 and std 0.981560  
hidden layer 7 had mean -0.000237 and std 0.981520  
hidden layer 8 had mean -0.000448 and std 0.981913  
hidden layer 9 had mean -0.000899 and std 0.981728  
hidden layer 10 had mean 0.000584 and std 0.981736
```

*1.0 instead of *0.01



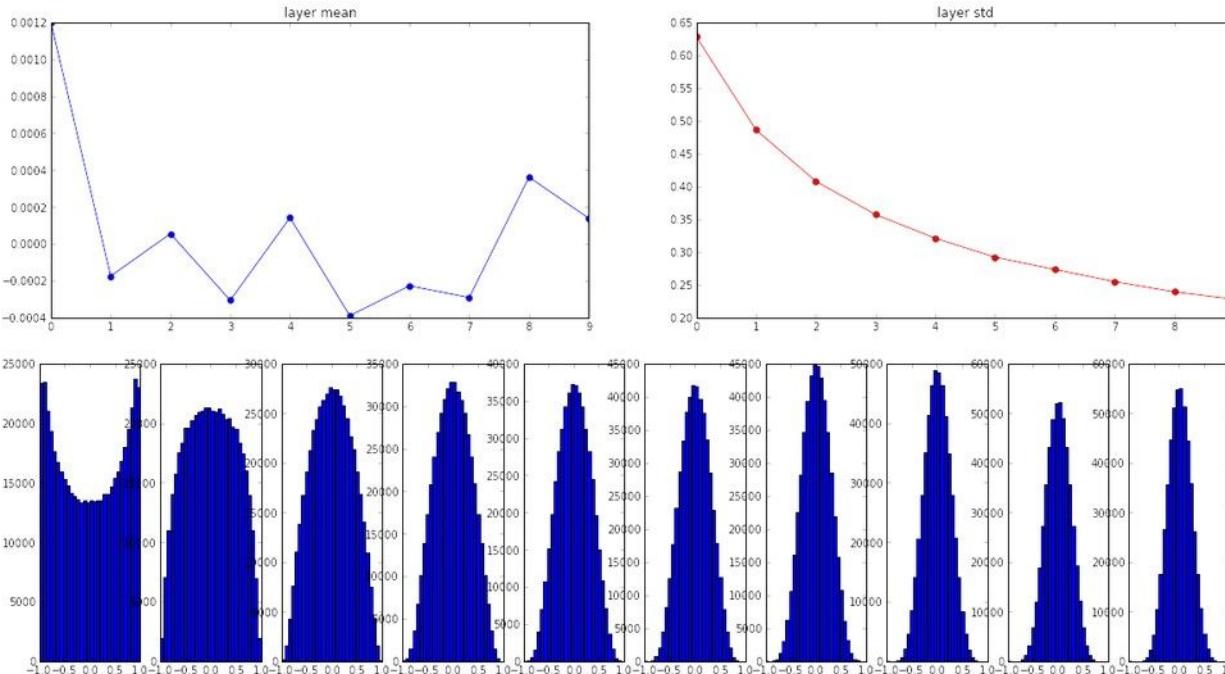
Almost all neurons completely saturated, either -1 and 1. Gradients will be all zero.

```
input layer had mean 0.001800 and std 1.001311  
hidden layer 1 had mean 0.001198 and std 0.627953  
hidden layer 2 had mean -0.000175 and std 0.486051  
hidden layer 3 had mean 0.000055 and std 0.407723  
hidden layer 4 had mean -0.000306 and std 0.357108  
hidden layer 5 had mean 0.000142 and std 0.320917  
hidden layer 6 had mean -0.000389 and std 0.292116  
hidden layer 7 had mean -0.000228 and std 0.273387  
hidden layer 8 had mean -0.000291 and std 0.254935  
hidden layer 9 had mean 0.000361 and std 0.239266  
hidden layer 10 had mean 0.000139 and std 0.228008
```

```
W = np.random.randn(fan_in, fan_out) / np.sqrt(fan_in) # layer initialization
```

“Xavier initialization”
[Glorot et al., 2010]

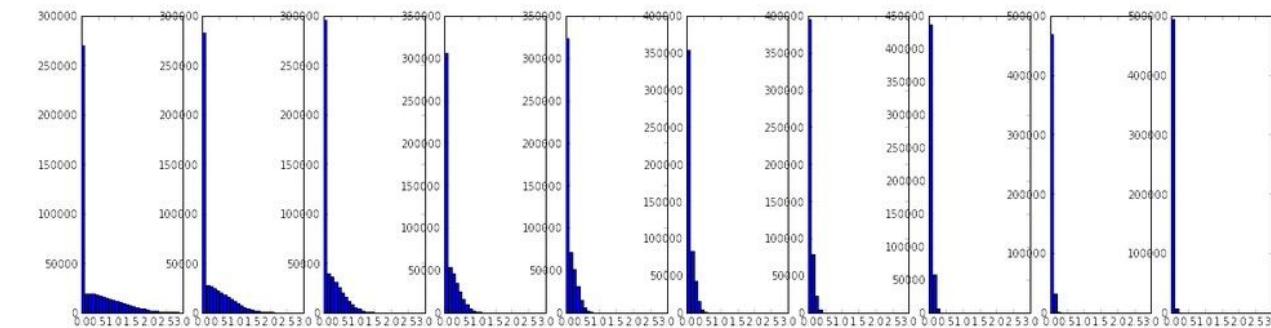
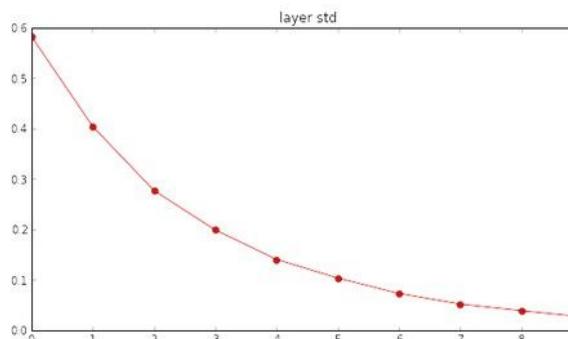
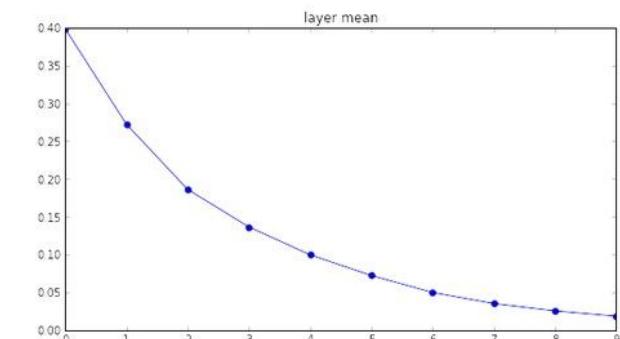
Reasonable initialization.
(Mathematical derivation
assumes linear activations)



```
input layer had mean 0.000501 and std 0.999444  
hidden layer 1 had mean 0.398623 and std 0.582273  
hidden layer 2 had mean 0.272352 and std 0.403795  
hidden layer 3 had mean 0.186076 and std 0.276912  
hidden layer 4 had mean 0.136442 and std 0.198685  
hidden layer 5 had mean 0.099568 and std 0.140299  
hidden layer 6 had mean 0.072234 and std 0.103280  
hidden layer 7 had mean 0.049775 and std 0.072748  
hidden layer 8 had mean 0.035138 and std 0.051572  
hidden layer 9 had mean 0.025404 and std 0.038583  
hidden layer 10 had mean 0.018408 and std 0.026076
```

```
W = np.random.randn(fan_in, fan_out) / np.sqrt(fan_in) # layer initialization
```

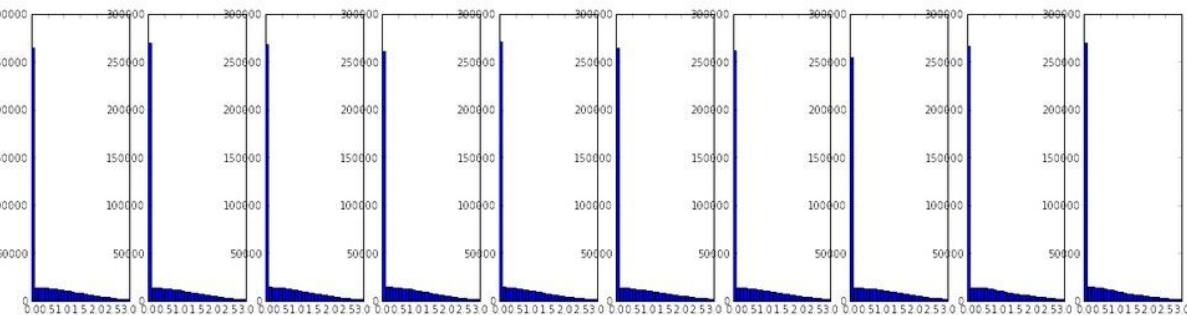
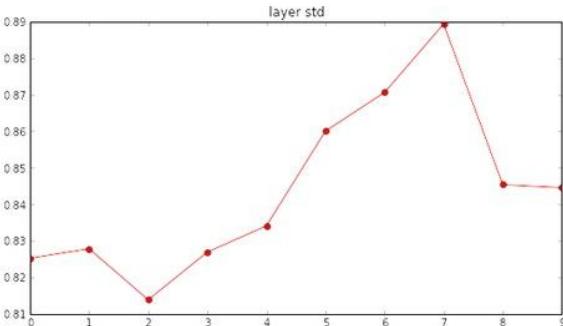
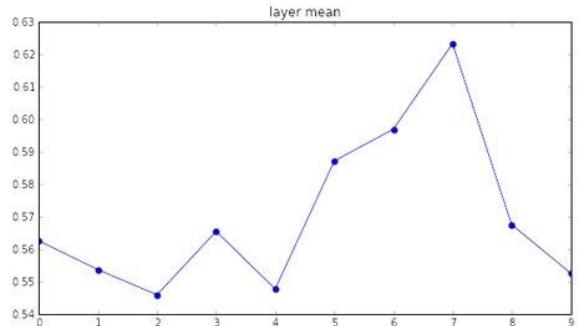
but when using the ReLU nonlinearity it breaks.



```
input layer had mean 0.000501 and std 0.999444  
hidden layer 1 had mean 0.562488 and std 0.825232  
hidden layer 2 had mean 0.553614 and std 0.827835  
hidden layer 3 had mean 0.545867 and std 0.813855  
hidden layer 4 had mean 0.565396 and std 0.826902  
hidden layer 5 had mean 0.547678 and std 0.834092  
hidden layer 6 had mean 0.587103 and std 0.860035  
hidden layer 7 had mean 0.596867 and std 0.870610  
hidden layer 8 had mean 0.623214 and std 0.889348  
hidden layer 9 had mean 0.567498 and std 0.845357  
hidden layer 10 had mean 0.552531 and std 0.844523
```

```
W = np.random.randn(fan_in, fan_out) / np.sqrt(fan_in/2) # layer initialization
```

He et al., 2015
(note additional /2)



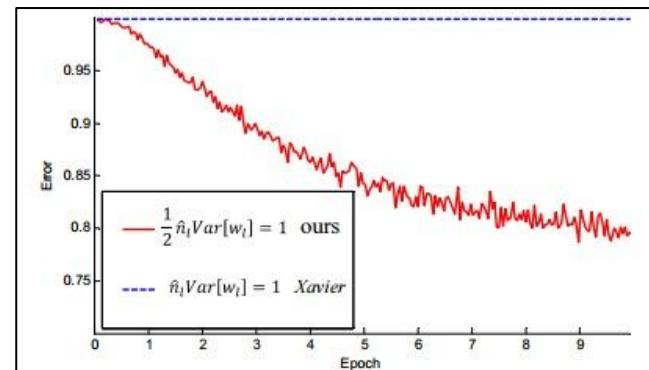
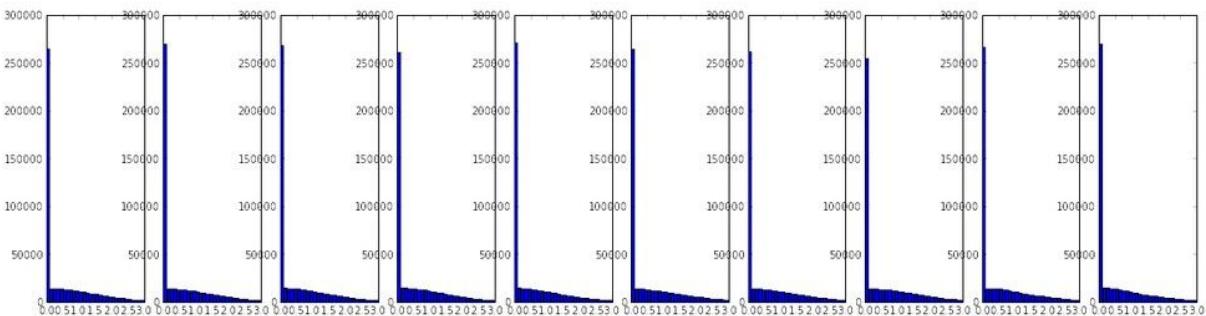
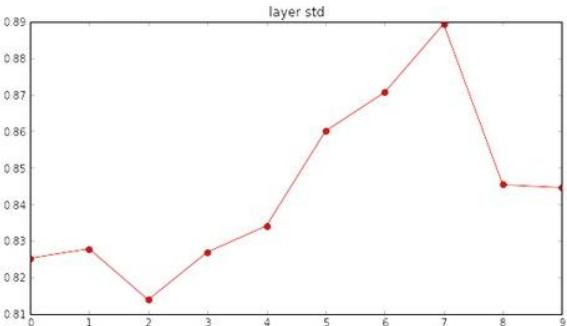
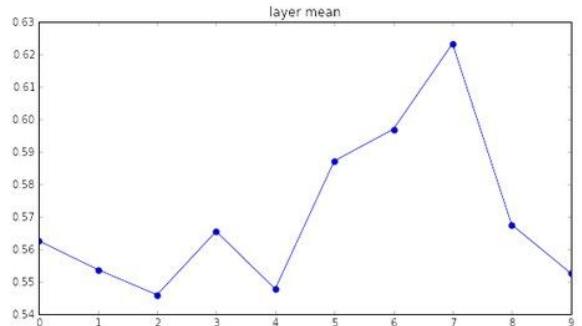
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```

```
W = np.random.randn(fan_in, fan_out) / np.sqrt(fan_in/2) # layer initialization
```

He et al., 2015
(note additional /2)



Proper initialization is an active area of research...

Understanding the difficulty of training deep feedforward neural networks

by Glorot and Bengio, 2010

Exact solutions to the nonlinear dynamics of learning in deep linear neural networks

by Saxe et al, 2013

Random walk initialization for training very deep feedforward networks

by Sussillo and Abbott, 2014

Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification

by He et al., 2015

Data-dependent Initializations of Convolutional Neural Networks

by Krähenbühl et al., 2015

All you need is a good init, Mishkin and Matas, 2015

...

Batch Normalization

[Ioffe and Szegedy, 2015]

“you want unit gaussian activations? just make them so.”

consider a batch of activations at some layer.
To make each dimension unit gaussian, apply:

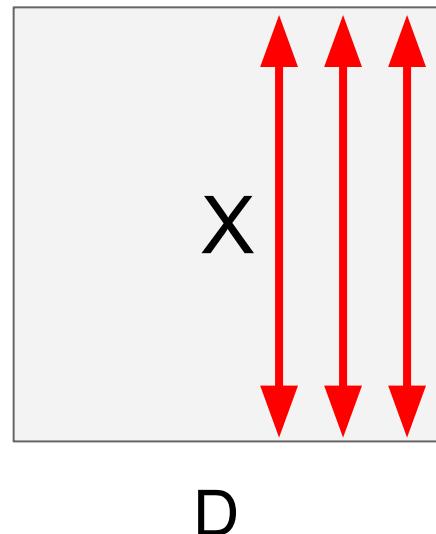
$$\hat{x}^{(k)} = \frac{x^{(k)} - \text{E}[x^{(k)}]}{\sqrt{\text{Var}[x^{(k)}]}}$$

this is a vanilla
differentiable function...

Batch Normalization

[Ioffe and Szegedy, 2015]

“you want unit gaussian activations?
just make them so.”



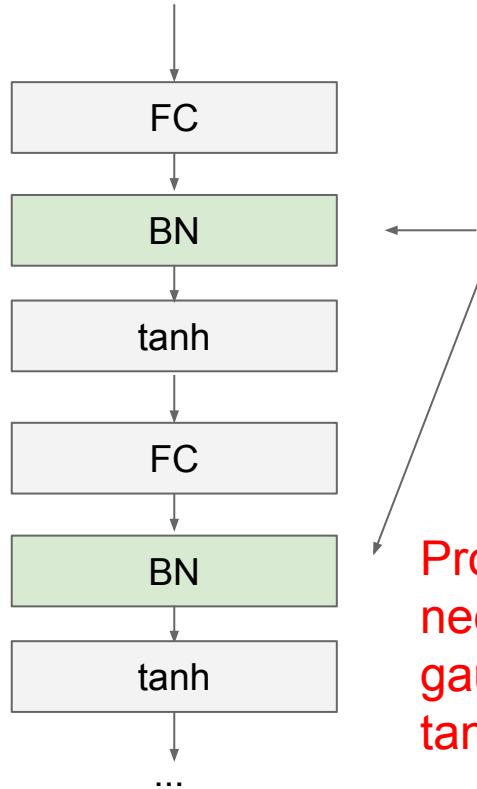
1. compute the empirical mean and variance independently for each dimension.

2. Normalize

$$\hat{x}^{(k)} = \frac{x^{(k)} - \text{E}[x^{(k)}]}{\sqrt{\text{Var}[x^{(k)}]}}$$

Batch Normalization

[Ioffe and Szegedy, 2015]



Usually inserted after Fully Connected / (or Convolutional, as we'll see soon) layers, and before nonlinearity.

Problem: do we necessarily want a unit gaussian input to a tanh layer?

$$\hat{x}^{(k)} = \frac{x^{(k)} - \text{E}[x^{(k)}]}{\sqrt{\text{Var}[x^{(k)}]}}$$

Batch Normalization

[Ioffe and Szegedy, 2015]

Normalize:

$$\hat{x}^{(k)} = \frac{x^{(k)} - \text{E}[x^{(k)}]}{\sqrt{\text{Var}[x^{(k)}]}}$$

And then allow the network to squash the range if it wants to:

$$y^{(k)} = \gamma^{(k)} \hat{x}^{(k)} + \beta^{(k)}$$

Note, the network can learn:

$$\gamma^{(k)} = \sqrt{\text{Var}[x^{(k)}]}$$

$$\beta^{(k)} = \text{E}[x^{(k)}]$$

to recover the identity mapping.

Batch Normalization

[Ioffe and Szegedy, 2015]

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_1 \dots m\}$;

Parameters to be learned: γ, β

Output: $\{y_i = \text{BN}_{\gamma, \beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i \quad // \text{mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2 \quad // \text{mini-batch variance}$$

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \quad // \text{normalize}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i) \quad // \text{scale and shift}$$

- Improves gradient flow through the network
- Allows higher learning rates
- Reduces the strong dependence on initialization
- Acts as a form of regularization in a funny way, and slightly reduces the need for dropout, maybe

Batch Normalization

[Ioffe and Szegedy, 2015]

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_1 \dots m\}$;

Parameters to be learned: γ, β

Output: $\{y_i = \text{BN}_{\gamma, \beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i \quad // \text{mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2 \quad // \text{mini-batch variance}$$

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \quad // \text{normalize}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i) \quad // \text{scale and shift}$$

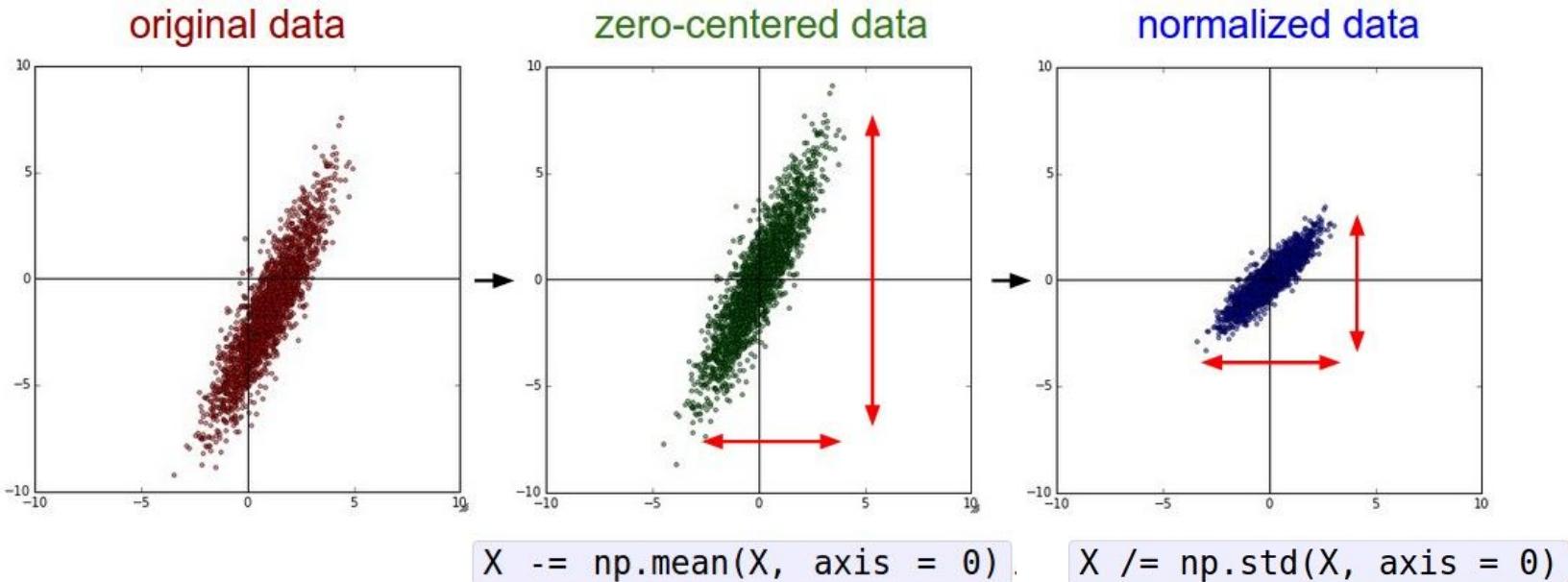
Note: at test time BatchNorm layer functions differently:

The mean/std are not computed based on the batch. Instead, a single fixed empirical mean of activations during training is used.

(e.g. can be estimated during training with running averages)

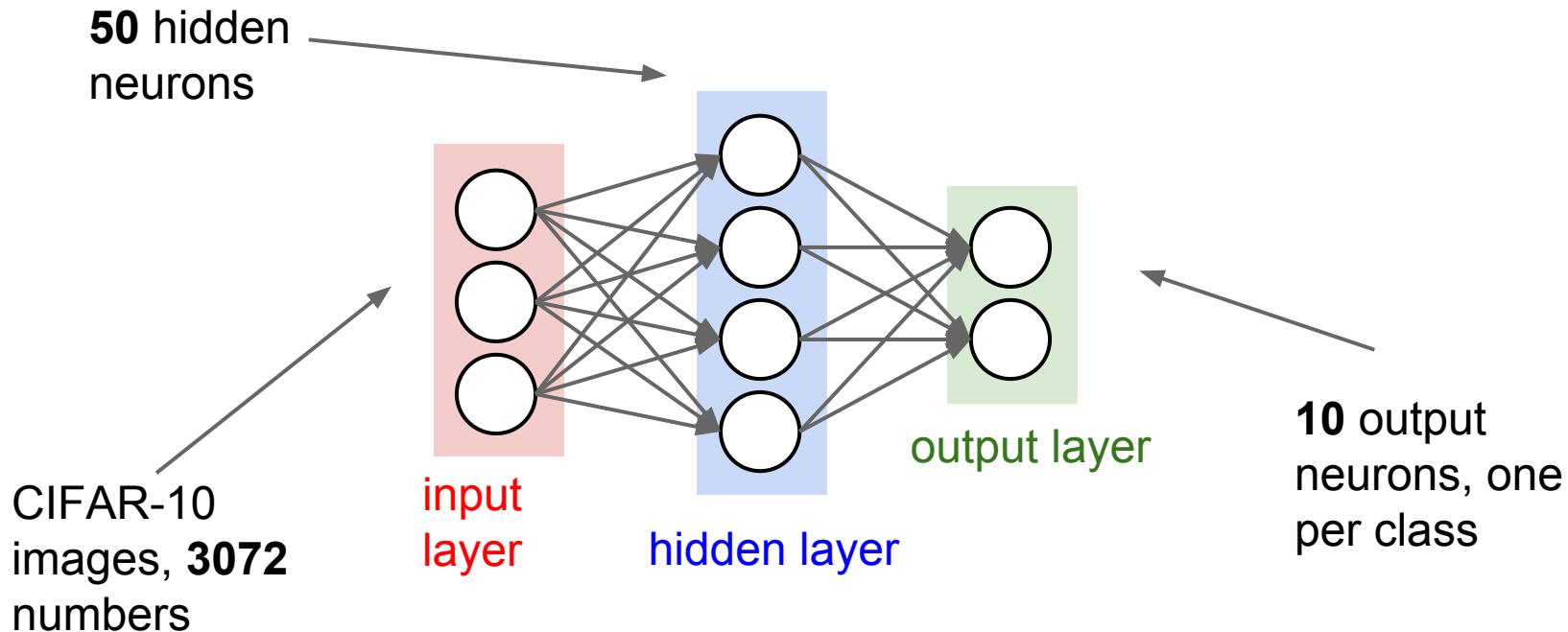
Babysitting the Learning Process

Step 1: Preprocess the data



(Assume X [NxD] is data matrix,
each example in a row)

Step 2: Choose the architecture: say we start with one hidden layer of 50 neurons:



Double check that the loss is reasonable:

```
def init_two_layer_model(input_size, hidden_size, output_size):
    # initialize a model
    model = {}
    model['W1'] = 0.0001 * np.random.randn(input_size, hidden_size)
    model['b1'] = np.zeros(hidden_size)
    model['W2'] = 0.0001 * np.random.randn(hidden_size, output_size)
    model['b2'] = np.zeros(output_size)
    return model
```

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
loss, grad = two_layer_net(X_train, model, y_train, 0.0) 0.0 disable regularization
```

2.30261216167

loss ~2.3.

“correct” for
10 classes

returns the loss and the
gradient for all parameters

Double check that the loss is reasonable:

```
def init_two_layer_model(input_size, hidden_size, output_size):
    # initialize a model
    model = {}
    model['W1'] = 0.0001 * np.random.randn(input_size, hidden_size)
    model['b1'] = np.zeros(hidden_size)
    model['W2'] = 0.0001 * np.random.randn(hidden_size, output_size)
    model['b2'] = np.zeros(output_size)
    return model
```

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
loss, grad = two_layer_net(X_train, model, y_train, 1e3)      crank up regularization
print loss
```

3.06859716482



loss went up, good. (sanity check)

Lets try to train now...

Tip: Make sure that you can overfit very small portion of the training data

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
X_tiny = X_train[:20] # take 20 examples
y_tiny = y_train[:20]
best_model, stats = trainer.train(X_tiny, y_tiny, X_tiny, y_tiny,
                                  model, two_layer_net,
                                  num_epochs=200, reg=0.0,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = False,
                                  learning_rate=1e-3, verbose=True)
```

The above code:

- take the first 20 examples from CIFAR-10
- turn off regularization ($\text{reg} = 0.0$)
- use simple vanilla ‘sgd’

Lets try to train now...

Tip: Make sure that you can overfit very small portion of the training data

Very small loss,
train accuracy 1.00,
nice!

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
X_tiny = X_train[:20] # take 20 examples
y_tiny = y_train[:20]
best_model, stats = trainer.train(X_tiny, y_tiny, X_tiny, y_tiny,
                                  model, two_layer_net,
                                  num_epochs=200, reg=0.0,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = False,
                                  learning_rate=1e-3, verbose=True)
```

```
Finished epoch 1 / 200: cost 2.302603, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 2 / 200: cost 2.302258, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 3 / 200: cost 2.301849, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 4 / 200: cost 2.301196, train: 0.650000, val 0.650000, lr 1.000000e-03
Finished epoch 5 / 200: cost 2.300044, train: 0.650000, val 0.650000, lr 1.000000e-03
Finished epoch 6 / 200: cost 2.297864, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 7 / 200: cost 2.293595, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 8 / 200: cost 2.285096, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 9 / 200: cost 2.268094, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 10 / 200: cost 2.234787, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 11 / 200: cost 2.173187, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 12 / 200: cost 2.076862, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 13 / 200: cost 1.974090, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 14 / 200: cost 1.895885, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 15 / 200: cost 1.820876, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 16 / 200: cost 1.737430, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 17 / 200: cost 1.642356, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 18 / 200: cost 1.535239, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 19 / 200: cost 1.421527, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 20 / 200: cost 1.325750, train: 0.550000, val 0.550000, lr 1.000000e-03
...
Finished epoch 195 / 200: cost 0.002694, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 196 / 200: cost 0.002674, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 197 / 200: cost 0.002655, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 198 / 200: cost 0.002635, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 199 / 200: cost 0.002617, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 200 / 200: cost 0.002597, train: 1.000000, val 1.000000, lr 1.000000e-03
finished optimization. best validation accuracy: 1.000000
```

Lets try to train now...

I like to start with small regularization and find learning rate that makes the loss go down.

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
    model, two_layer_net,
    num_epochs=10, reg=0.000001,
    update='sgd', learning_rate_decay=1,
    sample_batches = True,
    learning_rate=1e-6, verbose=True)
```

Lets try to train now...

I like to start with small regularization and find learning rate that makes the loss go down.

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
    model, two_layer_net,
    num_epochs=10, reg=0.000001,
    update='sgd', learning_rate_decay=1,
    sample_batches=True,
    learning_rate=1e-6, verbose=True)

Finished epoch 1 / 10: cost 2.302576, train: 0.080000, val 0.103000, lr 1.000000e-06
Finished epoch 2 / 10: cost 2.302582, train: 0.121000, val 0.124000, lr 1.000000e-06
Finished epoch 3 / 10: cost 2.302558, train: 0.119000, val 0.138000, lr 1.000000e-06
Finished epoch 4 / 10: cost 2.302519, train: 0.127000, val 0.151000, lr 1.000000e-06
Finished epoch 5 / 10: cost 2.302517, train: 0.158000, val 0.171000, lr 1.000000e-06
Finished epoch 6 / 10: cost 2.302518, train: 0.179000, val 0.172000, lr 1.000000e-06
Finished epoch 7 / 10: cost 2.302466, train: 0.180000, val 0.176000, lr 1.000000e-06
Finished epoch 8 / 10: cost 2.302452, train: 0.175000, val 0.185000, lr 1.000000e-06
Finished epoch 9 / 10: cost 2.302459, train: 0.206000, val 0.192000, lr 1.000000e-06
Finished epoch 10 / 10: cost 2.302420, train: 0.190000, val 0.192000, lr 1.000000e-06
finished optimization. best validation accuracy: 0.192000
```

Loss barely changing

Lets try to train now...

I like to start with small regularization and find learning rate that makes the loss go down.

loss not going down:
learning rate too low

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
    model, two_layer_net,
    num_epochs=10, reg=0.000001,
    update='sgd', learning_rate_decay=1,
    sample_batches=True,
    learning_rate=1e-6, verbose=True)

Finished epoch 1 / 10: cost 2.302576, train: 0.080000, val 0.103000, lr 1.000000e-06
Finished epoch 2 / 10: cost 2.302582, train: 0.121000, val 0.124000, lr 1.000000e-06
Finished epoch 3 / 10: cost 2.302558, train: 0.119000, val 0.138000, lr 1.000000e-06
Finished epoch 4 / 10: cost 2.302519, train: 0.127000, val 0.151000, lr 1.000000e-06
Finished epoch 5 / 10: cost 2.302517, train: 0.158000, val 0.171000, lr 1.000000e-06
Finished epoch 6 / 10: cost 2.302518, train: 0.179000, val 0.172000, lr 1.000000e-06
Finished epoch 7 / 10: cost 2.302466, train: 0.180000, val 0.176000, lr 1.000000e-06
Finished epoch 8 / 10: cost 2.302452, train: 0.175000, val 0.185000, lr 1.000000e-06
Finished epoch 9 / 10: cost 2.302459, train: 0.206000, val 0.192000, lr 1.000000e-06
Finished epoch 10 / 10: cost 2.302420, train: 0.190000, val 0.192000, lr 1.000000e-06
finished optimization. best validation accuracy: 0.192000
```

Loss barely changing: Learning rate is probably too low

Lets try to train now...

I like to start with small regularization and find learning rate that makes the loss go down.

loss not going down:
learning rate too low

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
    model, two_layer_net,
    num_epochs=10, reg=0.000001,
    update='sgd', learning_rate_decay=1,
    sample_batches=True,
    learning_rate=1e-6, verbose=True)

Finished epoch 1 / 10: cost 2.302576, train: 0.080000, val 0.103000, lr 1.000000e-06
Finished epoch 2 / 10: cost 2.302582, train: 0.121000, val 0.124000, lr 1.000000e-06
Finished epoch 3 / 10: cost 2.302558, train: 0.119000, val 0.138000, lr 1.000000e-06
Finished epoch 4 / 10: cost 2.302519, train: 0.127000, val 0.151000, lr 1.000000e-06
Finished epoch 5 / 10: cost 2.302517, train: 0.158000, val 0.171000, lr 1.000000e-06
Finished epoch 6 / 10: cost 2.302518, train: 0.179000, val 0.172000, lr 1.000000e-06
Finished epoch 7 / 10: cost 2.302466, train: 0.180000, val 0.176000, lr 1.000000e-06
Finished epoch 8 / 10: cost 2.302452, train: 0.175000, val 0.185000, lr 1.000000e-06
Finished epoch 9 / 10: cost 2.302459, train: 0.206000, val 0.192000, lr 1.000000e-06
Finished epoch 10 / 10: cost 2.302420, train: 0.190000, val 0.192000, lr 1.000000e-06
finished optimization. best validation accuracy: 0.192000
```

Loss barely changing: Learning rate is probably too low

Notice train/val accuracy goes to 20% though, what's up with that? (remember this is softmax)

Lets try to train now...

I like to start with small regularization and find learning rate that makes the loss go down.

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
    model, two_layer_net,
    num_epochs=10, reg=0.00001,
    update='sgd', learning_rate_decay=1,
    sample_batches = True,
    learning_rate=1e6, verbose=True)
```

Okay now lets try learning rate 1e6. What could possibly go wrong?

loss not going down:
learning rate too low

Lets try to train now...

I like to start with small regularization and find learning rate that makes the loss go down.

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                   model, two_layer_net,
                                   num_epochs=10, reg=0.00001,
                                   update='sgd', learning_rate_decay=1,
                                   sample_batches = True,
                                   learning_rate=1e-6, verbose=True)

/home/karpathy/cs231n/code/cs231n/classifiers/neural_net.py:50: RuntimeWarning: divide by zero en
countered in log
    data_loss = -np.sum(np.log(probs[range(N), y])) / N
/home/karpathy/cs231n/code/cs231n/classifiers/neural_net.py:48: RuntimeWarning: invalid value enc
ountered in subtract
    probs = np.exp(scores - np.max(scores, axis=1, keepdims=True))
Finished epoch 1 / 10: cost nan, train: 0.091000, val 0.087000, lr 1.000000e+06
Finished epoch 2 / 10: cost nan, train: 0.095000, val 0.087000, lr 1.000000e+06
Finished epoch 3 / 10: cost nan, train: 0.100000, val 0.087000, lr 1.000000e+06
```

loss not going down:
learning rate too low
loss exploding:
learning rate too high

cost: NaN almost
always means high
learning rate...

Lets try to train now...

I like to start with small regularization and find learning rate that makes the loss go down.

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
    model, two_layer_net,
    num_epochs=10, reg=0.000001,
    update='sgd', learning_rate_decay=1,
    sample_batches = True,
    learning_rate=3e-3, verbose=True)

Finished epoch 1 / 10: cost 2.186654, train: 0.308000, val 0.306000, lr 3.000000e-03
Finished epoch 2 / 10: cost 2.176230, train: 0.330000, val 0.350000, lr 3.000000e-03
Finished epoch 3 / 10: cost 1.942257, train: 0.376000, val 0.352000, lr 3.000000e-03
Finished epoch 4 / 10: cost 1.827868, train: 0.329000, val 0.310000, lr 3.000000e-03
Finished epoch 5 / 10: cost inf, train: 0.128000, val 0.128000, lr 3.000000e-03
Finished epoch 6 / 10: cost inf, train: 0.144000, val 0.147000, lr 3.000000e-03
```

3e-3 is still too high. Cost explodes....

loss not going down:
learning rate too low
loss exploding:
learning rate too high

=> Rough range for learning rate we should be cross-validating is somewhere [1e-3 ... 1e-5]

Hyperparameter Optimization

Cross-validation strategy

I like to do **coarse -> fine** cross-validation in stages

First stage: only a few epochs to get rough idea of what params work

Second stage: longer running time, finer search
... (repeat as necessary)

Tip for detecting explosions in the solver:

If the cost is ever $> 3 * \text{original cost}$, break out early

For example: run coarse search for 5 epochs

```
max_count = 100
for count in xrange(max_count):
    reg = 10**uniform(-5, 5) ←
    lr = 10**uniform(-3, -6)

    trainer = ClassifierTrainer()
    model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
    trainer = ClassifierTrainer()
    best_model_local, stats = trainer.train(X_train, y_train, X_val, y_val,
                                              model, two_layer_net,
                                              num_epochs=5, reg=reg,
                                              update='momentum', learning_rate_decay=0.9,
                                              sample_batches = True, batch_size = 100,
                                              learning rate=lr, verbose=False)
```

note it's best to optimize
in log space!

```
val_acc: 0.412000, lr: 1.405206e-04, reg: 4.793564e-01, (1 / 100)
val_acc: 0.214000, lr: 7.231888e-06, reg: 2.321281e-04, (2 / 100)
val_acc: 0.208000, lr: 2.119571e-06, reg: 8.011857e+01, (3 / 100)
val_acc: 0.196000, lr: 1.551131e-05, reg: 4.374936e-05, (4 / 100)
val_acc: 0.079000, lr: 1.753300e-05, reg: 1.200424e+03, (5 / 100)
val_acc: 0.223000, lr: 4.215128e-05, reg: 4.196174e+01, (6 / 100)
val_acc: 0.441000, lr: 1.750259e-04, reg: 2.110807e-04, (7 / 100)
val_acc: 0.241000, lr: 6.749231e-05, reg: 4.226413e+01, (8 / 100)
val_acc: 0.482000, lr: 4.296863e-04, reg: 6.642555e-01, (9 / 100)
val_acc: 0.079000, lr: 5.401602e-06, reg: 1.599828e+04, (10 / 100)
val_acc: 0.154000, lr: 1.618508e-06, reg: 4.925252e-01, (11 / 100)
```

→ nice

Now run finer search...

```
max_count = 100
for count in xrange(max_count):
    reg = 10**uniform(-5, 5)
    lr = 10**uniform(-3, -6)
```

adjust range

```
max_count = 100
for count in xrange(max_count):
    reg = 10**uniform(-4, 0)
    lr = 10**uniform(-3, -4)
```

```
val_acc: 0.527000, lr: 5.340517e-04, reg: 4.097824e-01, (0 / 100)
val_acc: 0.492000, lr: 2.279484e-04, reg: 9.991345e-04, (1 / 100)
val_acc: 0.512000, lr: 8.680827e-04, reg: 1.349727e-02, (2 / 100)
val_acc: 0.461000, lr: 1.028377e-04, reg: 1.220193e-02, (3 / 100)
val_acc: 0.460000, lr: 1.113730e-04, reg: 5.244309e-02, (4 / 100)
val_acc: 0.498000, lr: 9.477776e-04, reg: 2.001293e-03, (5 / 100)
val_acc: 0.469000, lr: 1.484369e-04, reg: 4.328313e-01, (6 / 100)
val_acc: 0.522000, lr: 5.586261e-04, reg: 2.312685e-04, (7 / 100)
val_acc: 0.530000, lr: 5.808183e-04, reg: 8.259964e-02, (8 / 100)
val_acc: 0.489000, lr: 1.979168e-04, reg: 1.010889e-04, (9 / 100)
val_acc: 0.490000, lr: 2.036031e-04, reg: 2.406271e-03, (10 / 100)
val_acc: 0.475000, lr: 2.021162e-04, reg: 2.287807e-01, (11 / 100)
val_acc: 0.460000, lr: 1.135527e-04, reg: 3.905040e-02, (12 / 100)
val_acc: 0.515000, lr: 6.947668e-04, reg: 1.562808e-02, (13 / 100)
val_acc: 0.531000, lr: 9.471549e-04, reg: 1.433895e-03, (14 / 100)
val_acc: 0.509000, lr: 3.140888e-04, reg: 2.857518e-01, (15 / 100)
val_acc: 0.514000, lr: 6.438349e-04, reg: 3.033781e-01, (16 / 100)
val_acc: 0.502000, lr: 3.921784e-04, reg: 2.707126e-04, (17 / 100)
val_acc: 0.509000, lr: 9.752279e-04, reg: 2.850865e-03, (18 / 100)
val_acc: 0.500000, lr: 2.412048e-04, reg: 4.997821e-04, (19 / 100)
val_acc: 0.466000, lr: 1.319314e-04, reg: 1.189915e-02, (20 / 100)
val_acc: 0.516000, lr: 8.039527e-04, reg: 1.528291e-02, (21 / 100)
```

53% - relatively good
for a 2-layer neural net
with 50 hidden neurons.

Now run finer search...

```
max_count = 100
for count in xrange(max_count):
    reg = 10**uniform(-5, 5)
    lr = 10**uniform(-3, -6)
```

adjust range

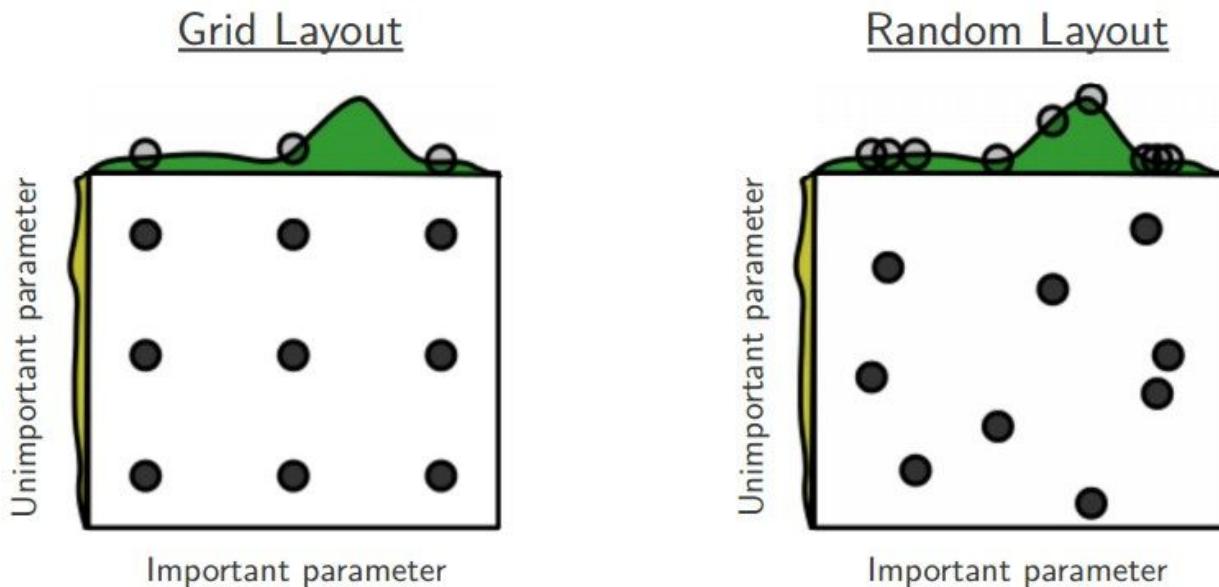
```
max_count = 100
for count in xrange(max_count):
    reg = 10**uniform(-4, 0)
    lr = 10**uniform(-3, -4)
```

```
val_acc: 0.527000, lr: 5.340517e-04, reg: 4.097824e-01, (0 / 100)
val_acc: 0.492000, lr: 2.279484e-04, reg: 9.991345e-04, (1 / 100)
val_acc: 0.512000, lr: 8.680827e-04, reg: 1.349727e-02, (2 / 100)
val_acc: 0.461000, lr: 1.028377e-04, reg: 1.220193e-02, (3 / 100)
val_acc: 0.460000, lr: 1.113730e-04, reg: 5.244309e-02, (4 / 100)
val_acc: 0.498000, lr: 9.477776e-04, reg: 2.001293e-03, (5 / 100)
val_acc: 0.469000, lr: 1.484369e-04, reg: 4.328313e-01, (6 / 100)
val_acc: 0.522000, lr: 5.586261e-04, reg: 2.312685e-04, (7 / 100)
val_acc: 0.530000, lr: 5.808183e-04, reg: 8.259964e-02, (8 / 100)
val_acc: 0.489000, lr: 1.979168e-04, reg: 1.010889e-04, (9 / 100)
val_acc: 0.490000, lr: 2.036031e-04, reg: 2.406271e-03, (10 / 100)
val_acc: 0.475000, lr: 2.0211162e-04, reg: 2.287807e-01, (11 / 100)
val_acc: 0.460000, lr: 1.135527e-04, reg: 3.905040e-02, (12 / 100)
val_acc: 0.515000, lr: 6.947668e-04, reg: 1.562808e-02, (13 / 100)
val_acc: 0.531000, lr: 9.471549e-04, reg: 1.433895e-03, (14 / 100) ←
val_acc: 0.509000, lr: 3.140888e-04, reg: 2.857518e-01, (15 / 100)
val_acc: 0.514000, lr: 6.438349e-04, reg: 3.033781e-01, (16 / 100)
val_acc: 0.502000, lr: 3.921784e-04, reg: 2.707126e-04, (17 / 100)
val_acc: 0.509000, lr: 9.752279e-04, reg: 2.850865e-03, (18 / 100)
val_acc: 0.500000, lr: 2.412048e-04, reg: 4.997821e-04, (19 / 100)
val_acc: 0.466000, lr: 1.319314e-04, reg: 1.189915e-02, (20 / 100)
val_acc: 0.516000, lr: 8.039527e-04, reg: 1.528291e-02, (21 / 100)
```

53% - relatively good
for a 2-layer neural net
with 50 hidden neurons.

But this best cross-validation result is
worrying. Why?

Random Search vs. Grid Search



Random Search for Hyper-Parameter Optimization
Bergstra and Bengio, 2012

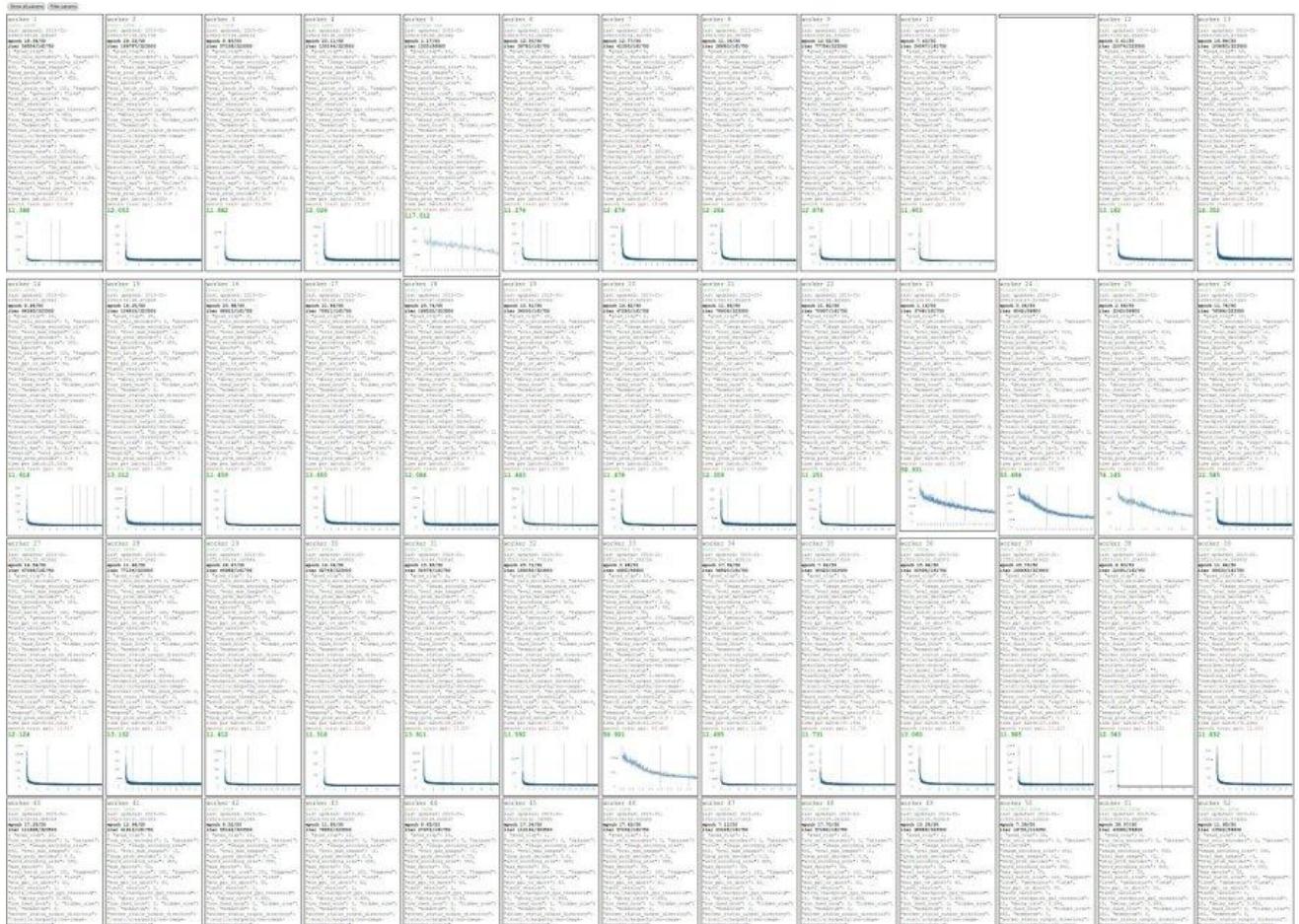
Hyperparameters to play with:

- network architecture
- learning rate, its decay schedule, update type
- regularization (L2/Dropout strength)

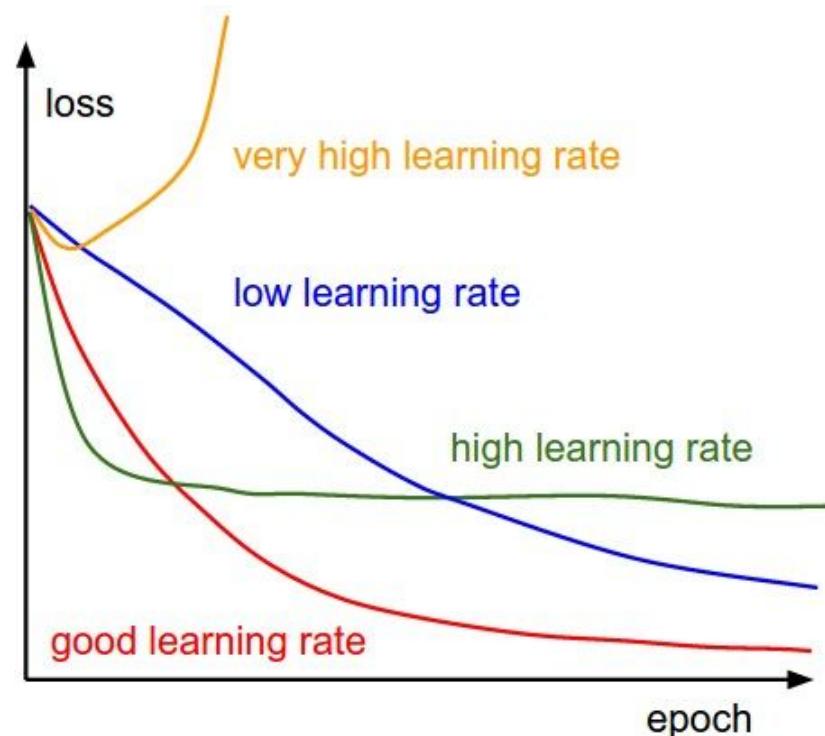
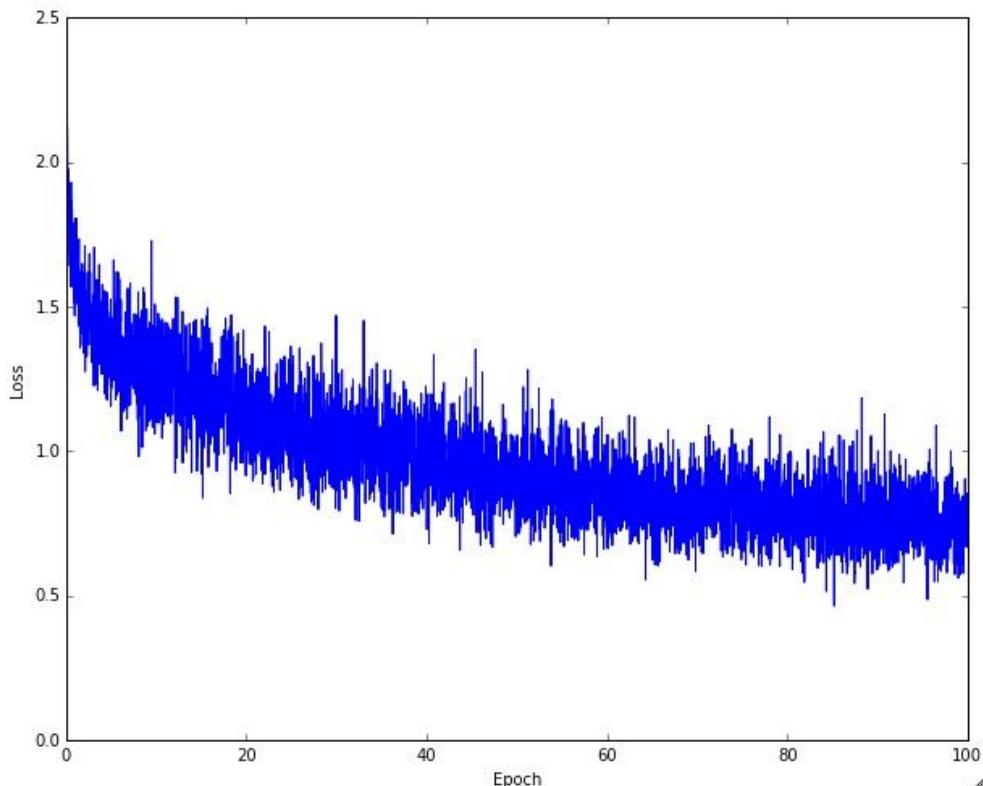
neural networks practitioner
music = loss function

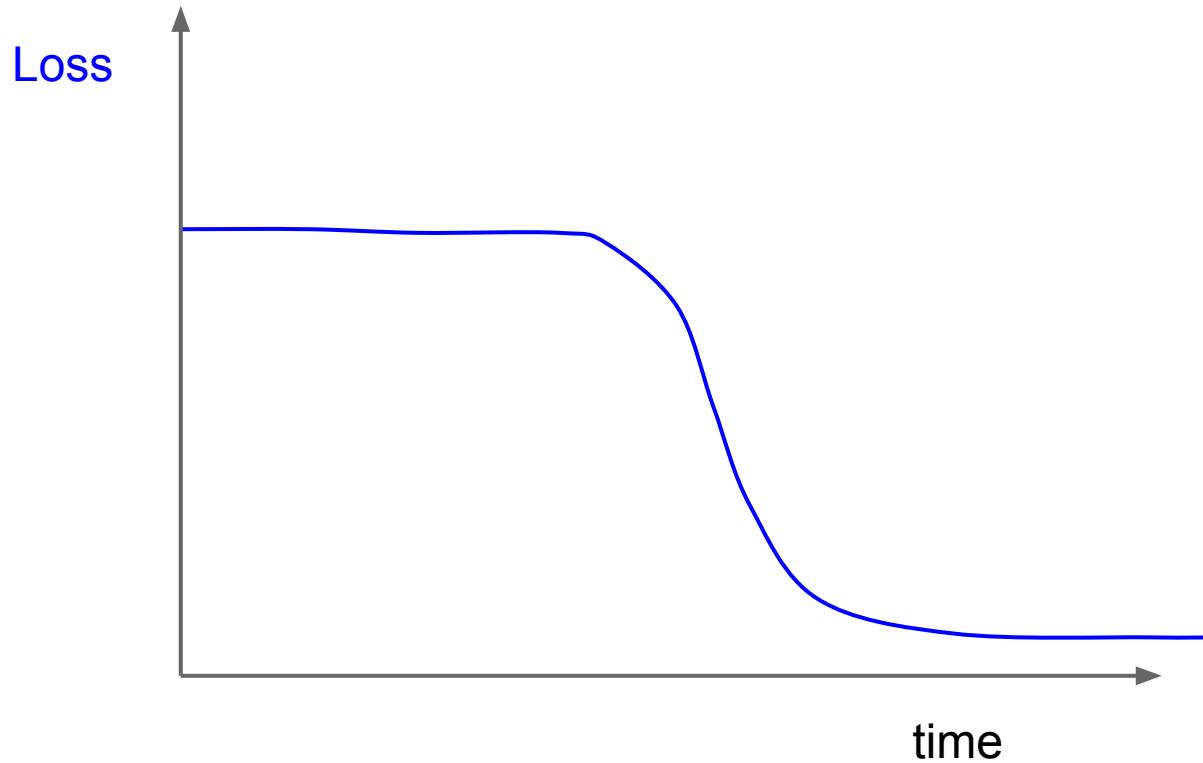


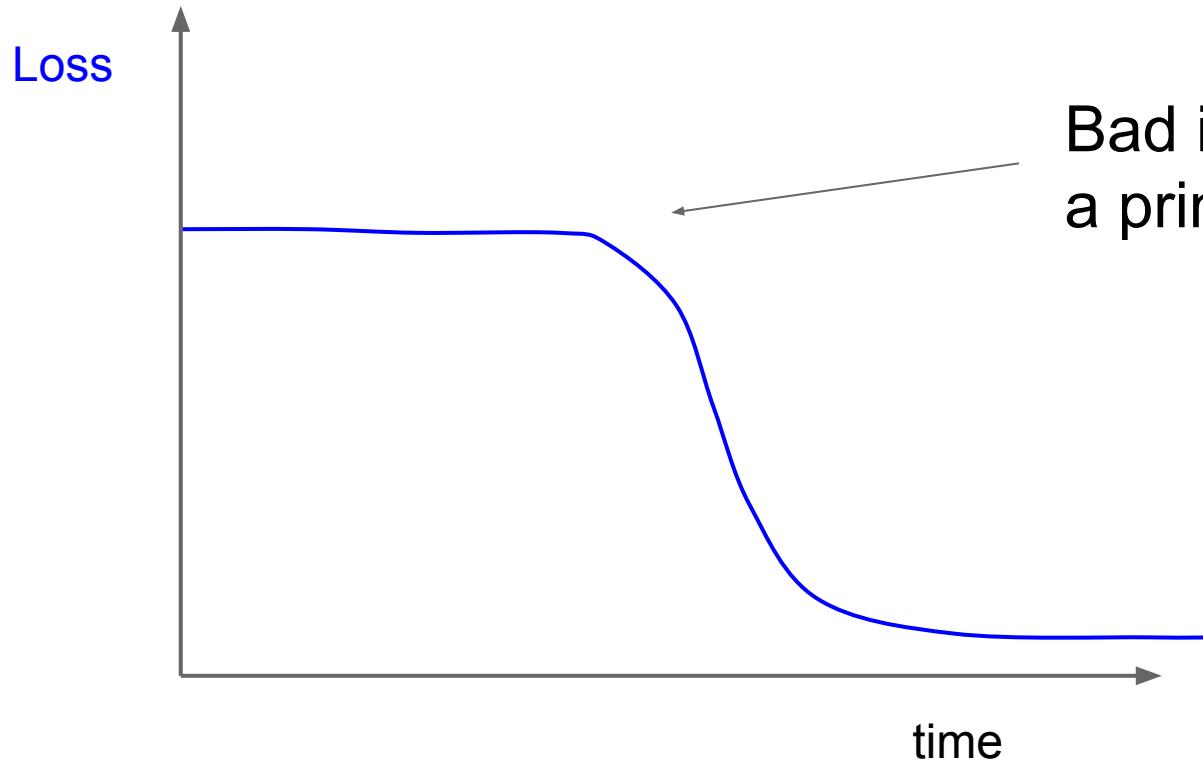
My cross-validation “command center”



Monitor and visualize the loss curve

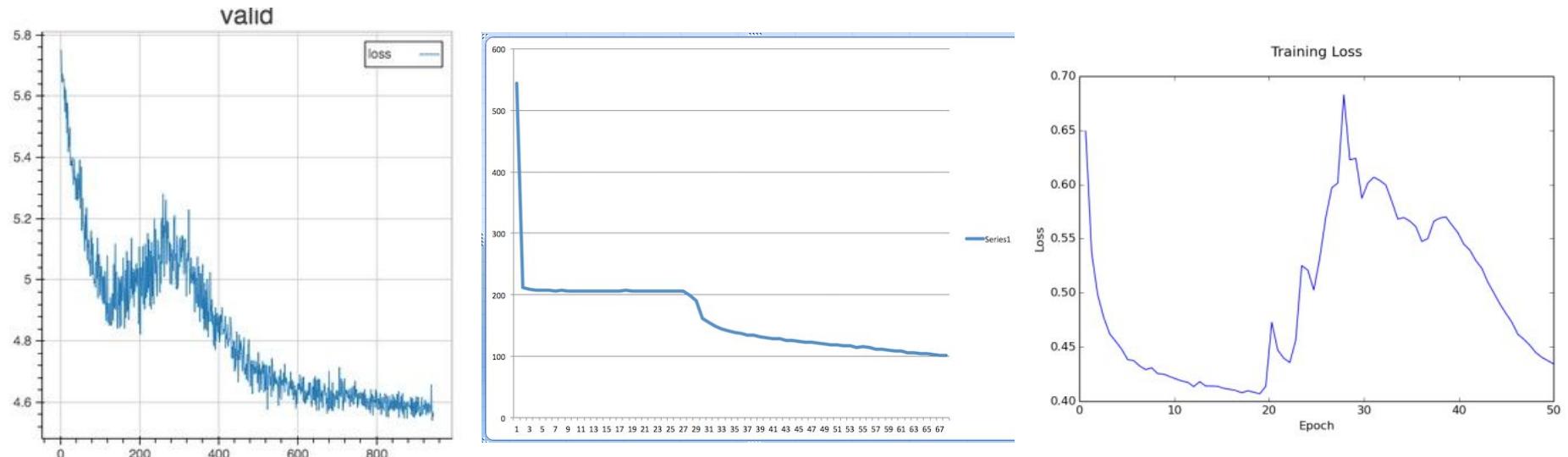


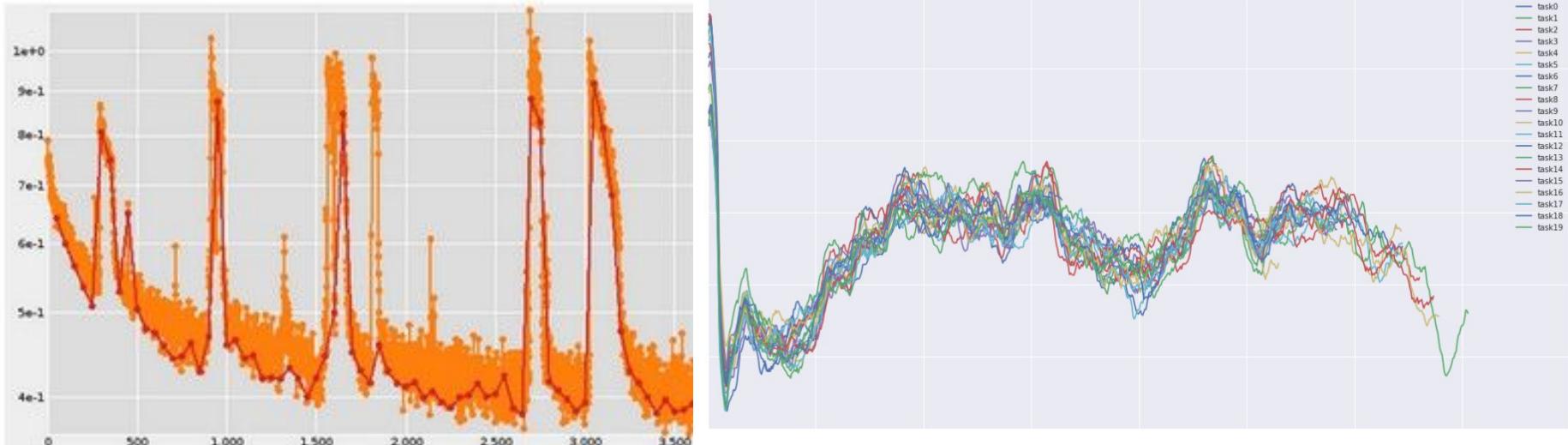


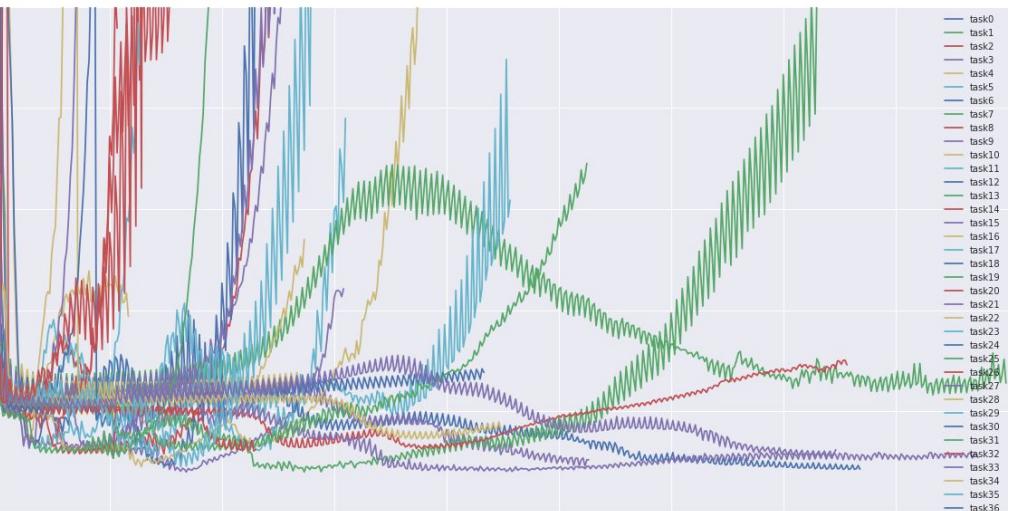
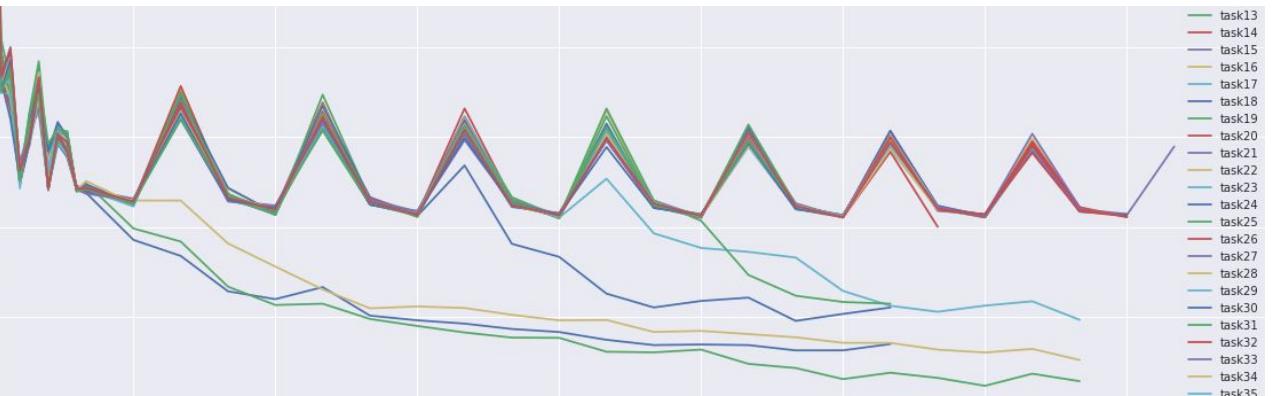


Bad initialization
a prime suspect

lossfunctions.tumblr.com Loss function specimen

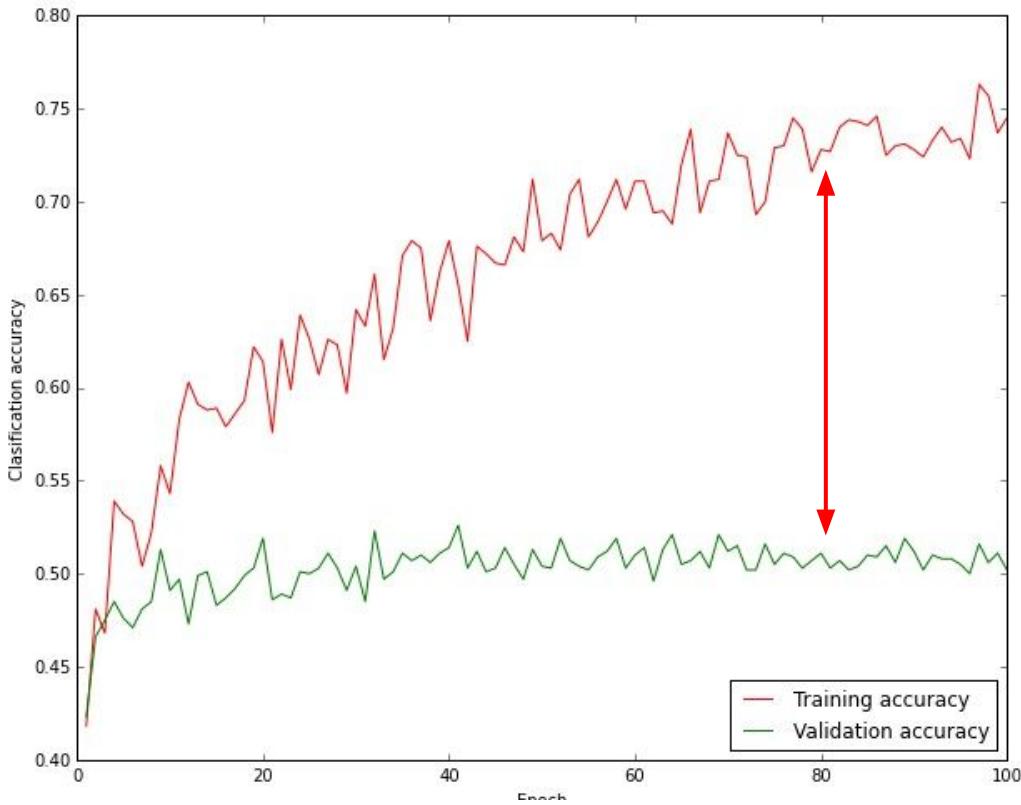






lossfunctions.tumblr.com

Monitor and visualize the accuracy:



big gap = overfitting
=> increase regularization strength?

no gap
=> increase model capacity?

Track the ratio of weight updates / weight magnitudes:

```
# assume parameter vector W and its gradient vector dW
param_scale = np.linalg.norm(W.ravel())
update = -learning_rate*dW # simple SGD update
update_scale = np.linalg.norm(update.ravel())
W += update # the actual update
print update_scale / param_scale # want ~1e-3
```

ratio between the values and updates: $\sim 0.0002 / 0.02 = 0.01$ (about okay)
want this to be somewhere around 0.001 or so

Summary

TLDRs

We looked in detail at:

- Activation Functions (use ReLU)
- Data Preprocessing (images: subtract mean)
- Weight Initialization (use Xavier init)
- Batch Normalization (use)
- Babysitting the Learning process
- Hyperparameter Optimization
(random sample hyperparams, in log space when appropriate)

TODO

Look at:

- Parameter update schemes
- Learning rate schedules
- Gradient Checking
- Regularization (Dropout etc)
- Evaluation (Ensembles etc)