Deep Learning (for Computer Vision)

Arjun Jain | 1 April 2017

Agenda this Week

- Building blocks
  - Linear
  - Convolution
  - Max Pooling
  - Cross Entropy
  - Dropout
  - Batch Normalization
- Weight initializations, data preprocessing
- Choosing hyperparameters, baby sitting the learning process

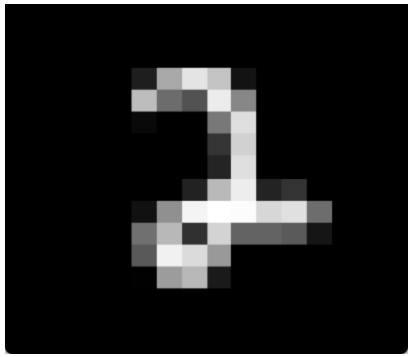
Sources

A lot of the material has been shamelessly and gratefully collected from:

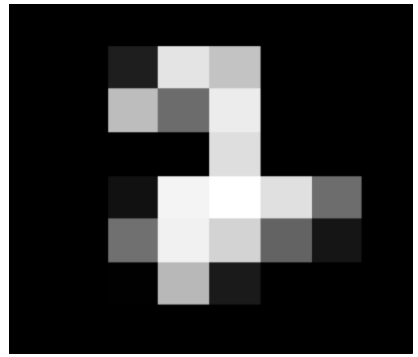
- **http://cs231n.stanford.edu/**
- https://research.fb.com/deep-learning-tutorial-at-cvpr-2014/

Building Blocks:
Max Pooling

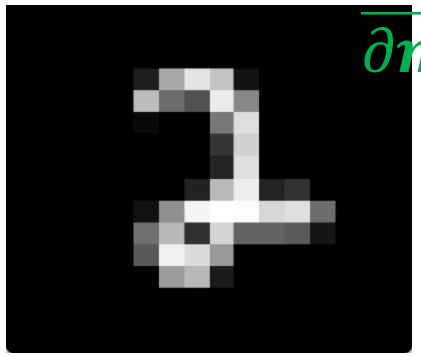
Building Blocks – Pooling (Max Pooling)



$\boldsymbol{n} \in \mathbb{R}^{4\times4}$ → Max Pooling → $\boldsymbol{m} \in \mathbb{R}^{2\times2}$

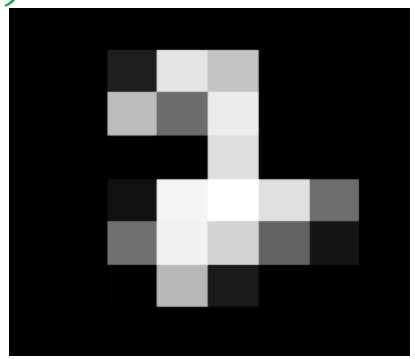


Building Blocks – Pooling (Max Pooling) – in Torch7



$\frac{\partial L}{\partial m} \cdot \frac{\partial m}{\partial n} \in \mathbb{R}^{1\times(4\times4)}$ $\quad \frac{\partial m}{\partial n} \in \mathbb{R}^{(2\times2)\times(4\times4)}$ $\quad \frac{\partial L}{\partial m} \in \mathbb{R}^{1\times(2\times2)}$

$n \in \mathbb{R}^{4\times4}$ → Max Pooling → $m \in \mathbb{R}^{2\times2}$



```
> n = torch.rand(1,4,4)
> pool = nn.SpatialMaxPooling(2, 2)
> m = pool:forward(n)
> =n
(1,.,.) =
  0.2692  0.4190  0.2095  0.9163
  0.2778  0.9199  0.5555  0.1638
  0.6936  0.2328  0.0553  0.1798
  0.3611  0.3225  0.9032  0.5106
[torch.DoubleTensor of size 1x4x4]

> =m
(1,.,.) =
  0.9199  0.9163
  0.6936  0.9032
[torch.DoubleTensor of size 1x2x2]
```

```
> nextgrad = torch.ones(1,2,2)
> pool:backward(n, nextgrad)
> =pool.gradInput
(1,.,.) =
  0  0  0  1
  0  1  0  0
  1  0  0  0
  0  0  1  0
[torch.DoubleTensor of size 1x4x4]
```

Other Pooling Layers

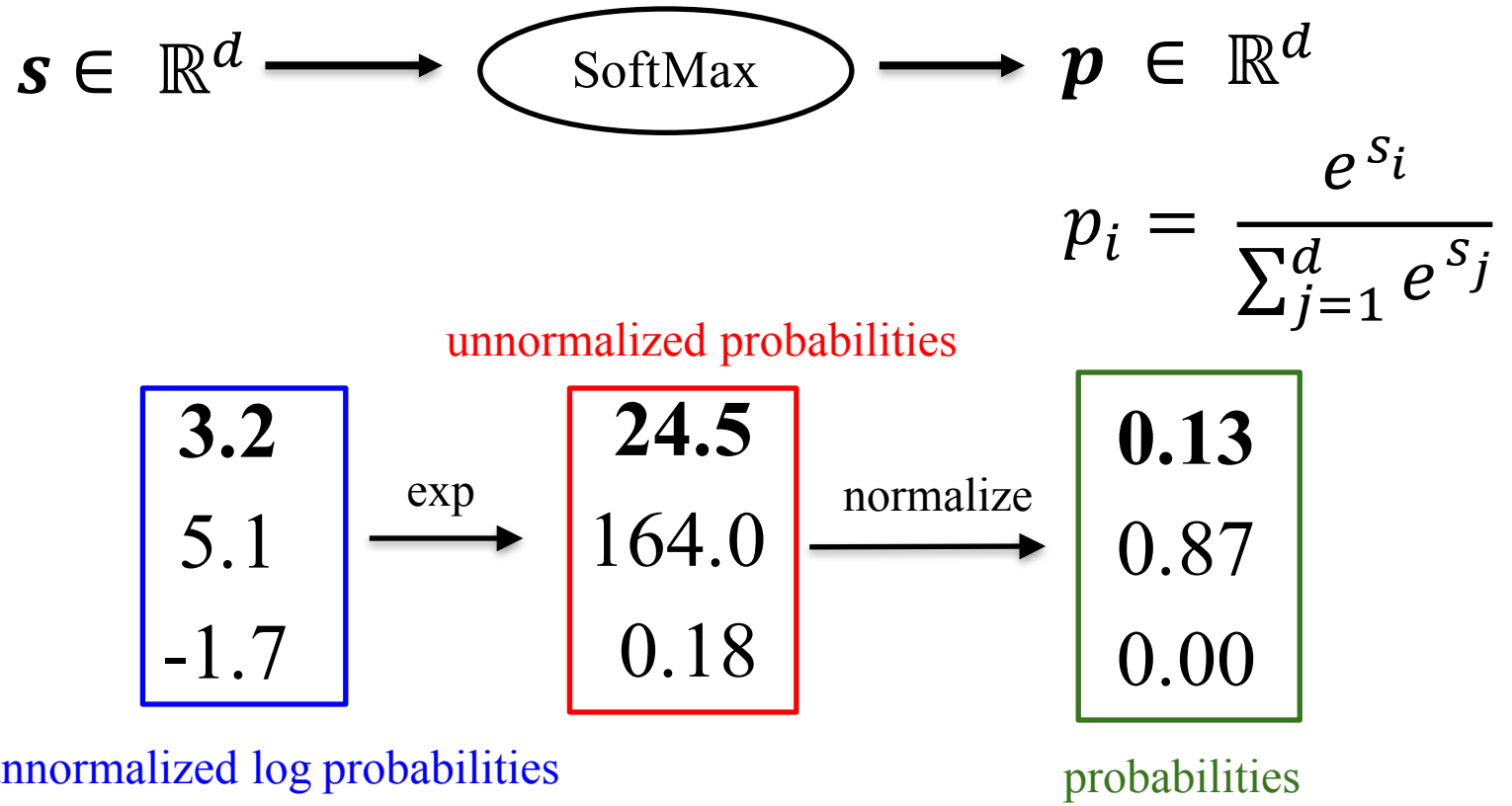
- Average Pooling
- No Pooling? **Striving for Simplicity: The All Convolutional Net**
  Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, Martin Riedmiller

Building Blocks:
SoftMax

Building Blocks – SoftMax

$$p_i = \frac{e^{s_i}}{\sum_{j=1}^{d} e^{s_j}}$$

Building Blocks – SoftMax



Building Blocks – SoftMax

$$p_i = \frac{e^{s_i}}{\sum_{j=1}^{d} e^{s_j}}$$

```
> n = torch.DoubleTensor({3.2,5.1,-1.7})
> smax = nn.SoftMax()
> m = smax:forward(n)
> m_ = nn.Exp():forward(n)
> m_ = m_ / m_:sum()
```

```
> =n
 3.2000
 5.1000
-1.7000
[torch.DoubleTensor of size 3]

> =m
 0.1300
 0.8690
 0.0010
[torch.DoubleTensor of size 3]

> =m_
 0.1300
 0.8690
 0.0010
[torch.DoubleTensor of size 3]
```

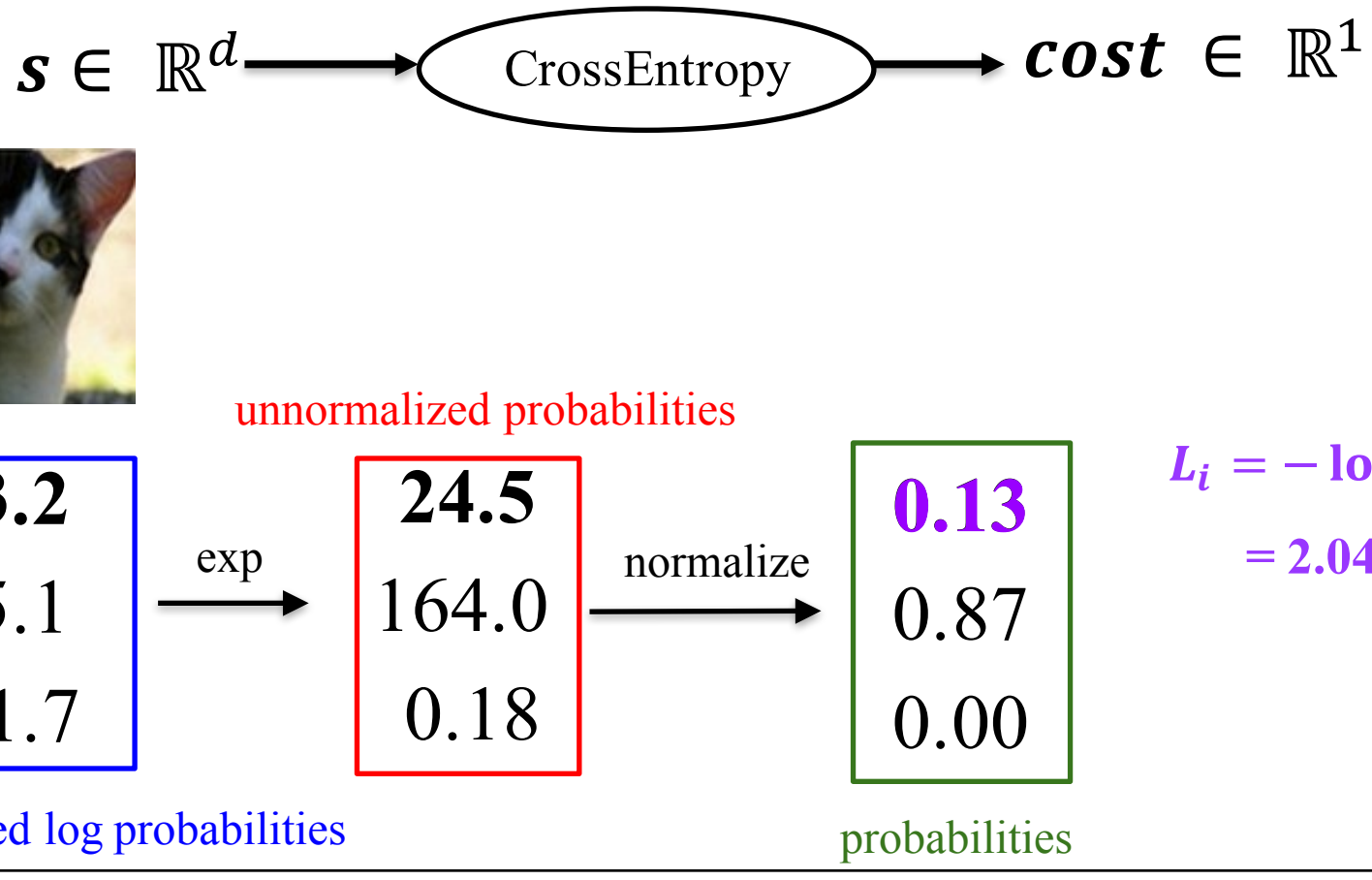
Building Blocks
Cross Entropy

Building Blocks – Cross Entropy

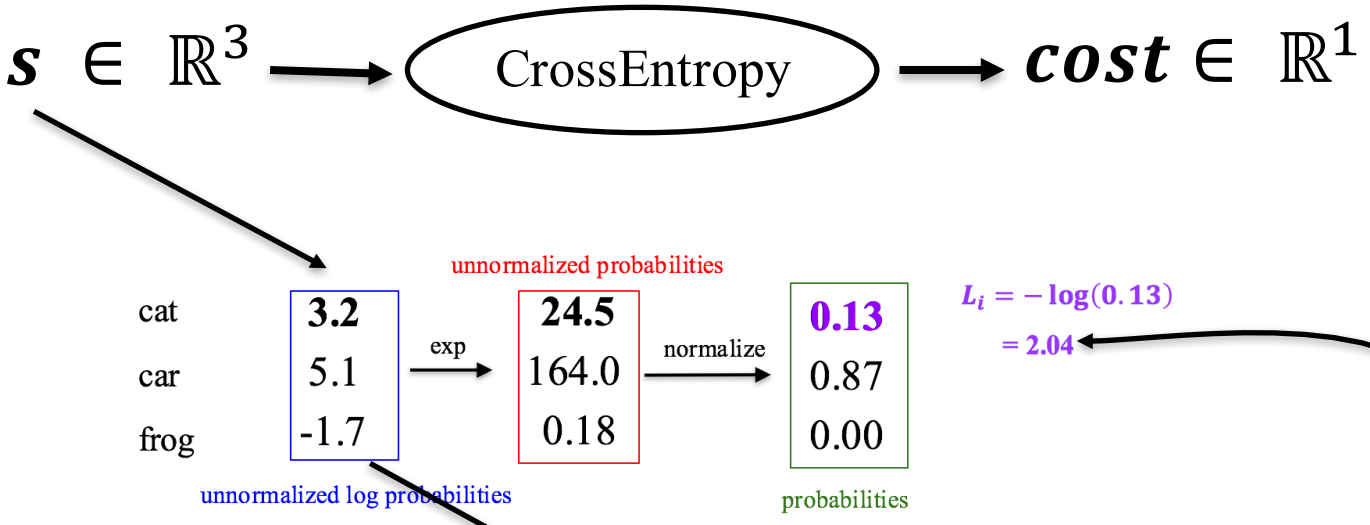
$$s = f(x_i; W) \qquad L_i = -y_i \cdot log\left(\frac{e^{s_i}}{\sum_j e^{s_j}}\right) \qquad L = \sum_i L_i$$

y_i is 1 (and 0 otherwise) if and only if sample belongs to class i

Building Blocks – Cross Entropy



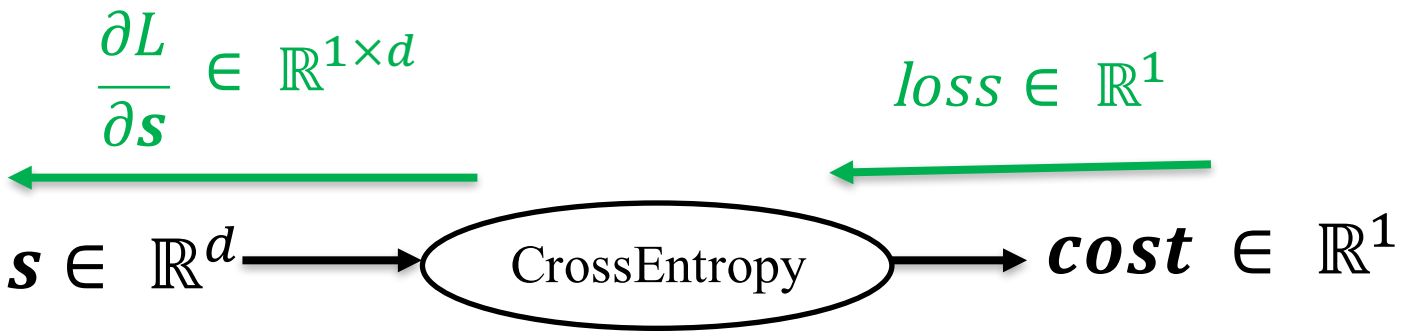
Building Blocks – Cross Entropy (in torch7)




```
o = torch.Tensor({3.2, 5.1, -1.7})
t = torch.Tensor({1})
cec = nn.CrossEntropyCriterion()
err = cec:forward(o, t)
print(err)
```

```
2.0403551528002
```

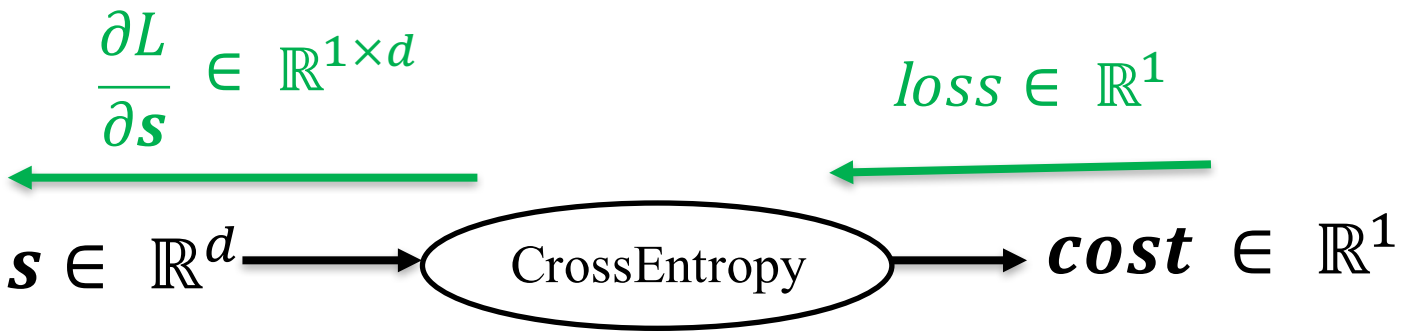
Building Blocks – Cross Entropy



$$s = f(x_i; W) \qquad L_i = -y_i \cdot log\left(\frac{e^{s_i}}{\sum_j e^{s_j}}\right) \in \mathbb{R}^{1\times d}$$

y_i is 1 (and 0 otherwise) if and only if sample belongs to class i

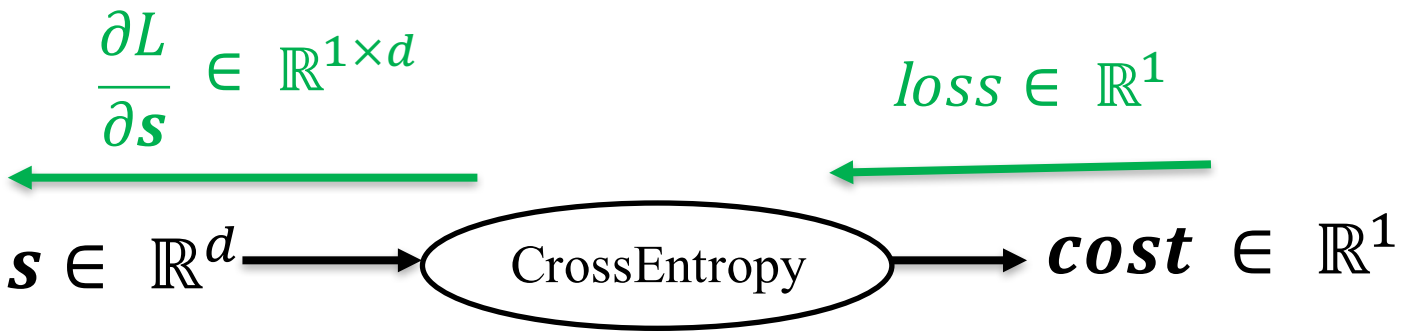
Building Blocks – Cross Entropy



$$s = f(x_i; W) \qquad p_i = \frac{e^{s_i}}{\sum_j e^{s_j}} \qquad L_i = -y_i \cdot log\left(\frac{e^{s_i}}{\sum_j e^{s_j}}\right) \qquad L = \sum_i L_i$$

y_i is 1 (and 0 otherwise) if and only if sample belongs to class i

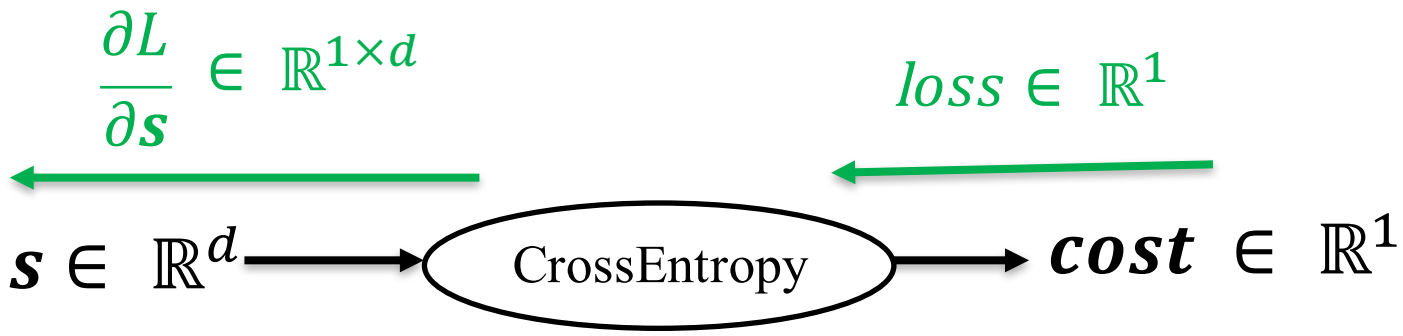
Building Blocks – Cross Entropy



$$s = f(x_i; W) \qquad p_i = \frac{e^{s_i}}{\sum_j e^{s_j}} \qquad L_i = -y_i \cdot log(p_i) \qquad L = \sum_i L_i$$

y_i is 1 (and 0 otherwise) if and only if sample belongs to class i

Building Blocks – Cross Entropy

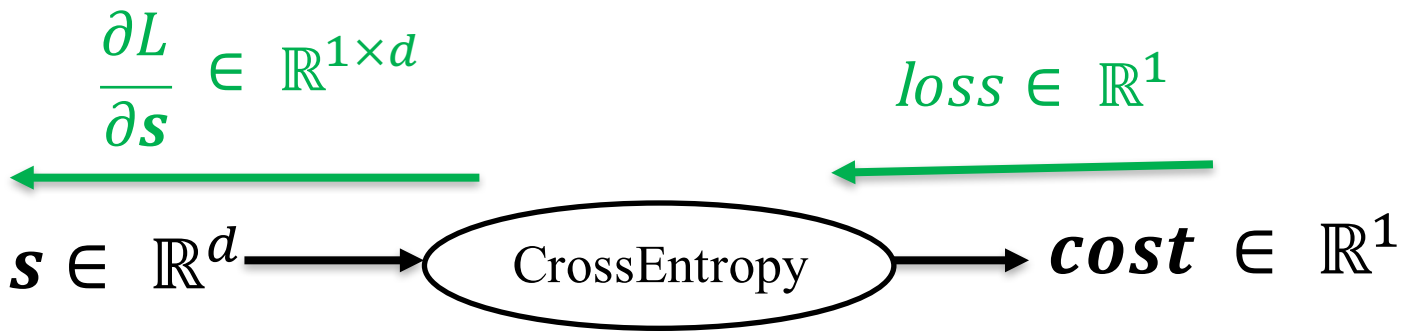


$$s = f(x_i; W) \qquad p_i = \frac{e^{s_i}}{\sum_j e^{s_j}} \qquad L_i = -y_i \cdot log(p_i) \qquad L = \sum_i L_i$$

y_i is 1 (and 0 otherwise) if and only if sample belongs to class i

What is $\frac{\partial L}{\partial s_k}$????

Building Blocks – Cross Entropy



$$s = f(x_i; W) \qquad p_i = \frac{e^{s_i}}{\sum_j e^{s_j}} \qquad L_i = -y_i \cdot log(p_i) \qquad L = \sum_i L_i$$

y_i is 1 (and 0 otherwise) if and only if sample belongs to class i

$$\frac{\partial L}{\partial s_k} = p_k - y_k$$

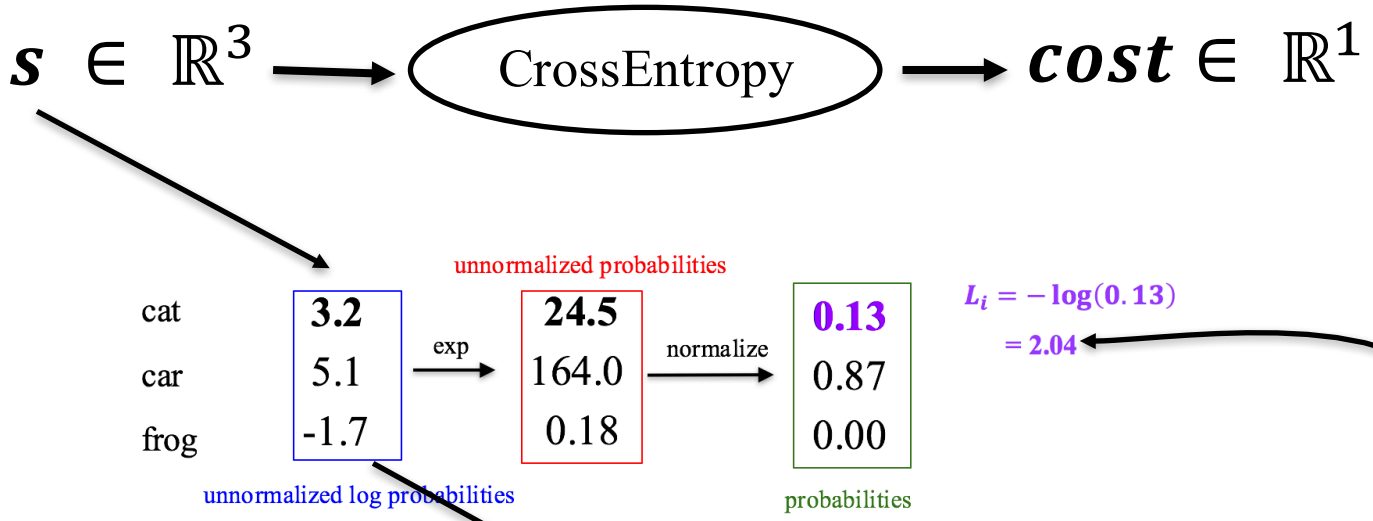
Building Blocks – Cross Entropy

$$\frac{\partial L}{\partial s_k} = p_k - y_k$$

$$\frac{\partial p_j}{\partial s_k} = \begin{cases} p_j(1-p_j) \; if \; j = k \\ -p_j p_k \quad if \; j \neq k \end{cases}$$

$$\begin{aligned}
\frac{\partial L}{\partial s_k} &= -\sum_j y_j \frac{\partial \log p_j}{\partial s_k} = -\sum_j y_j \frac{1}{p_j} \frac{\partial p_j}{\partial s_k} \\
&= -y_k(1-p_k) - \sum_{j \neq k} y_j \frac{1}{p_j}(-p_j p_k) \\
&= -y_k(1-p_k) + \sum_{j \neq k} y_j (p_k) \\
&= -y_k + y_k p_k + \sum_{j \neq k} y_j (p_k) \\
&= p_k \left(\sum_j y_j \right) - y_k = p_k - y_k
\end{aligned}$$

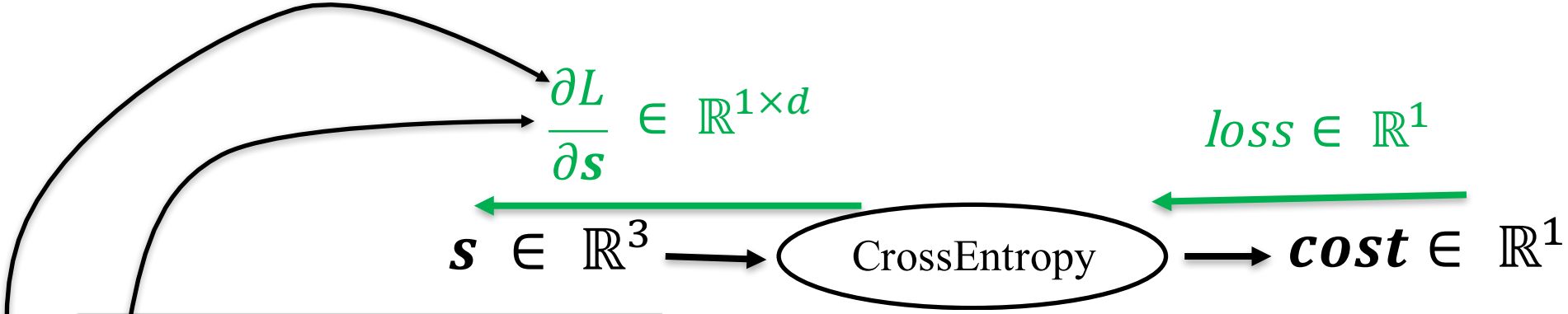
Building Blocks – Cross Entropy (in torch7)




```
o = torch.Tensor({3.2, 5.1, -1.7})
t = torch.Tensor({1})
cec = nn.CrossEntropyCriterion()
err = cec:forward(o, t)
print(err)
```

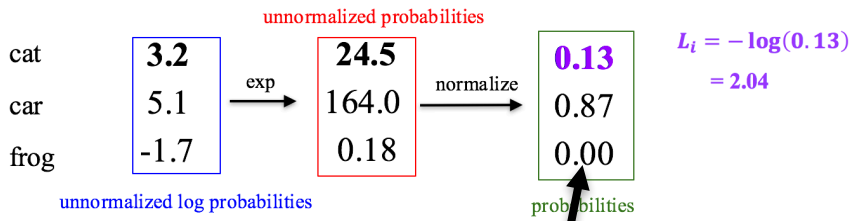
```
2.0403551528002
```

Building Blocks – Cross Entropy (in torch7)




```
dl_do = cec:backward(o, t)
print(dl_do)
```

```
-0.8700
 0.8690
 0.0010
```




```
ohat = nn.SoftMax():forward(o)
print(ohat)
```

```
0.1300
0.8690
0.0010
```

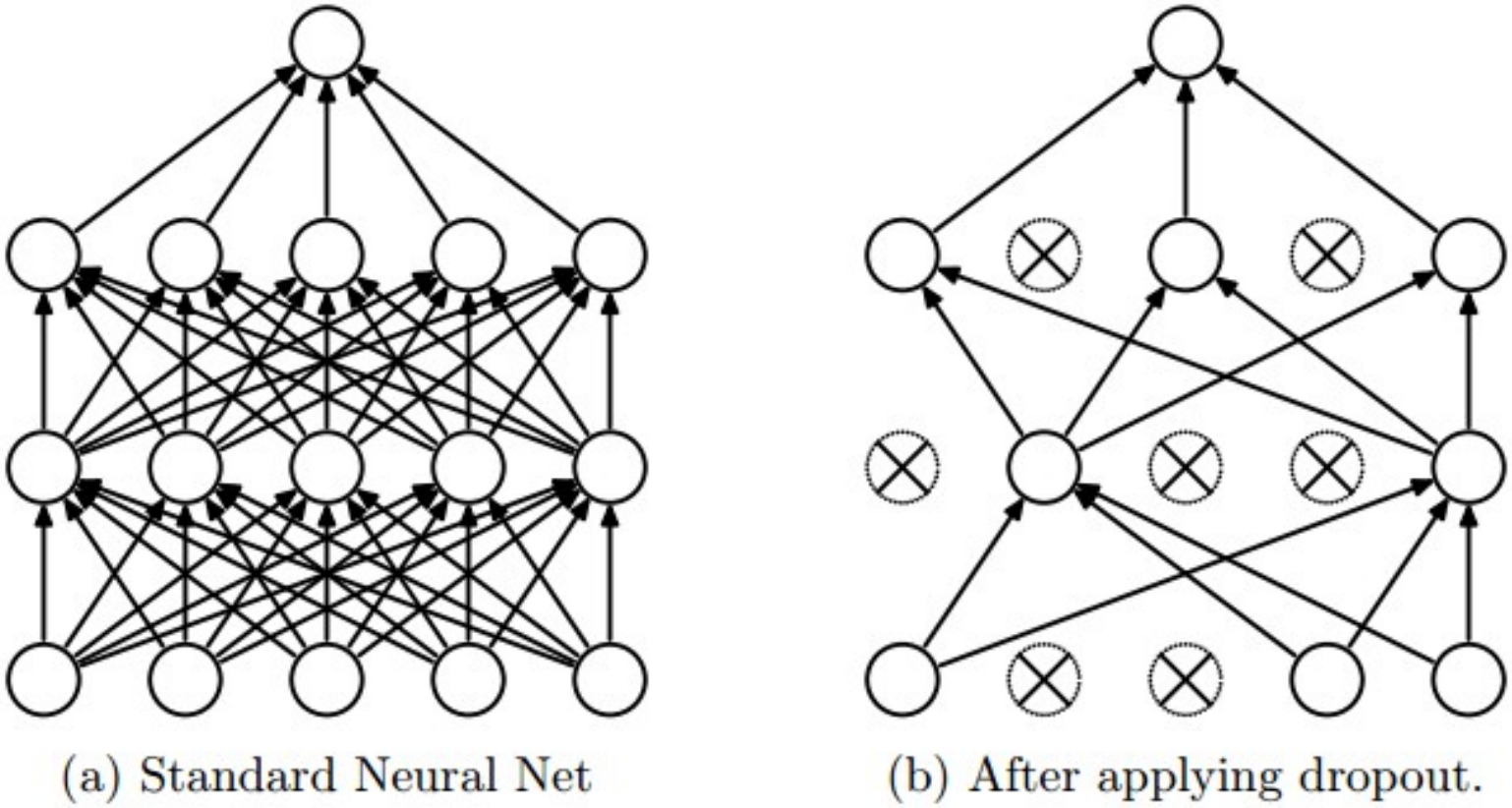
```
target = torch.Tensor({1, 0, 0})
dl_do_manual = ohat - target
print(dl_do_manual)
```

```
-0.8700
 0.8690
 0.0010
```

Building Blocks:
Dropout

Regularization: **Dropout**

"During training, randomly set some neurons to zero in the forward pass"



(a) Standard Neural Net

(b) After applying dropout.

[Srivastava et al., 2014]

```
require 'nn';
p = 0.5
x = torch.rand(5)
L1 = nn.Linear(5, 5)
L2 = nn.Linear(5, 5)
L3 = nn.Linear(5, 5)
L4 = nn.Linear(5, 1)

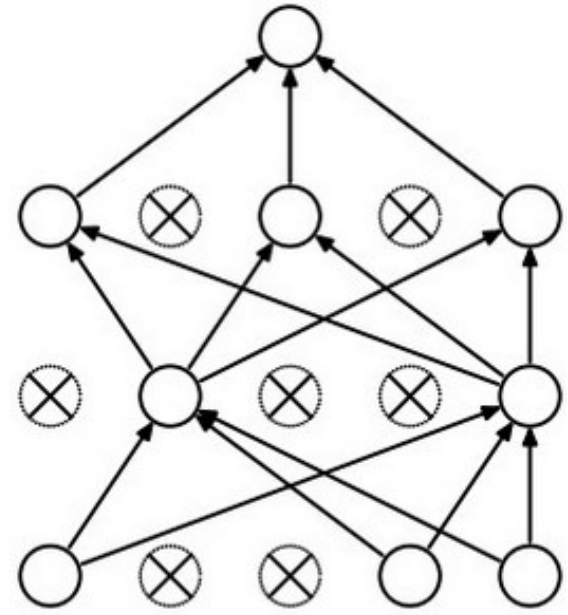

H1 = L1:forward(x)
U1 = torch.rand(H1:size(1)):gt(p):double()
H1 = H1:cmul(U1)

H2 = L2:forward(H1)
U2 = torch.rand(H2:size(1)):gt(p):double()
H2 = H2:cmul(U2)

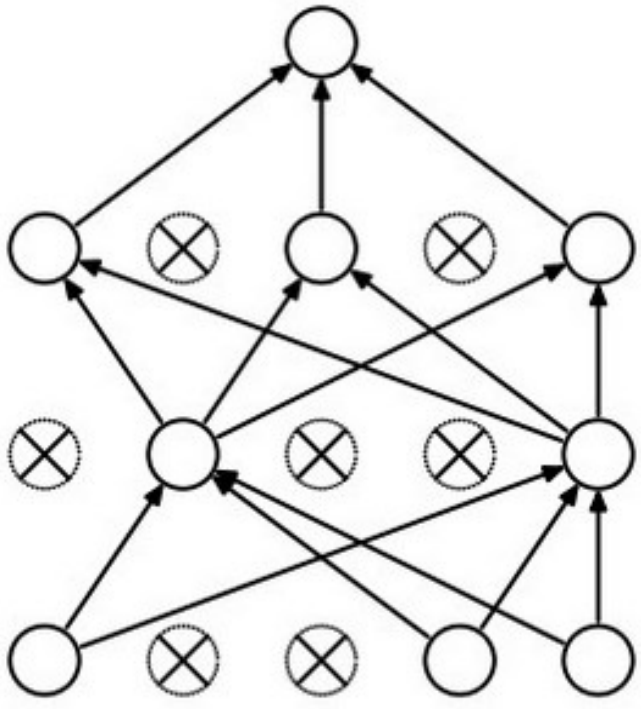
H3 = L3:forward(H2)
U3 = torch.rand(H3:size(1)):gt(p):double()
H2 = H3:cmul(U3)

out = L4:forward(H3)
```

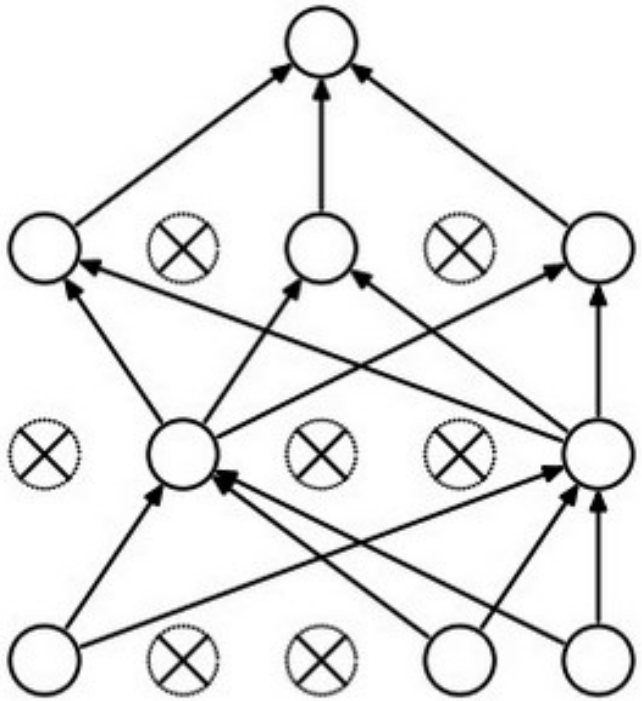
Example forward pass with a 3-layer network using dropout



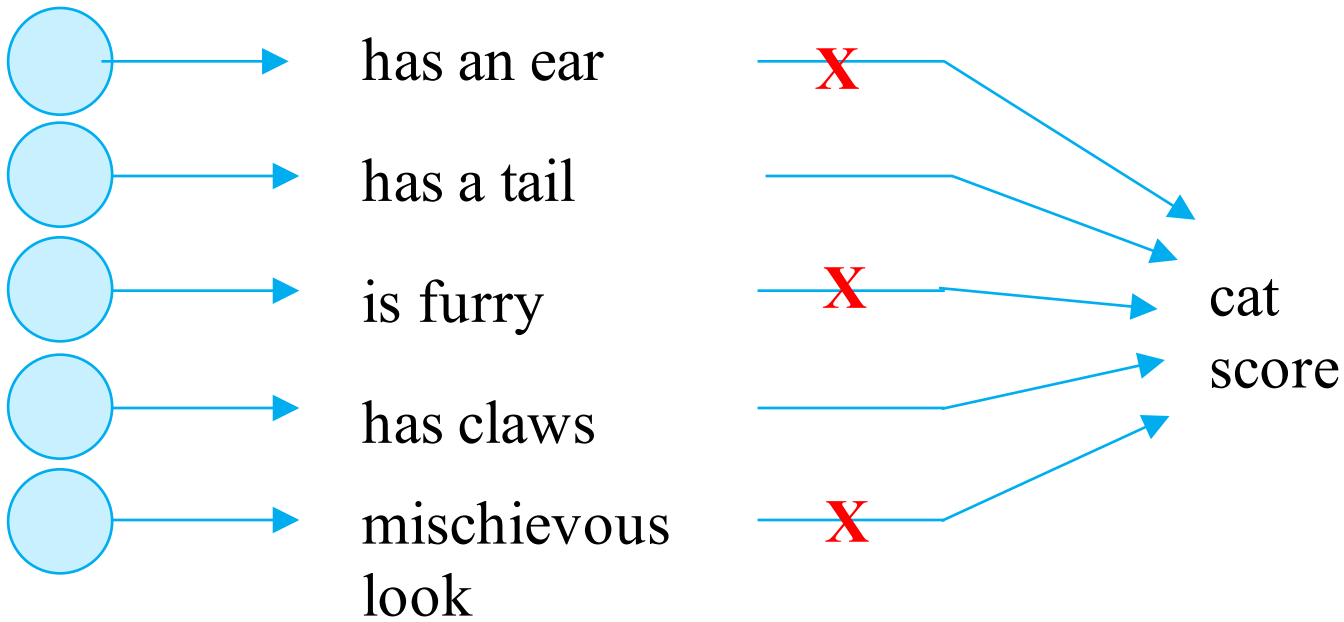
Waaaait a second…
How could this possibly be a good idea?



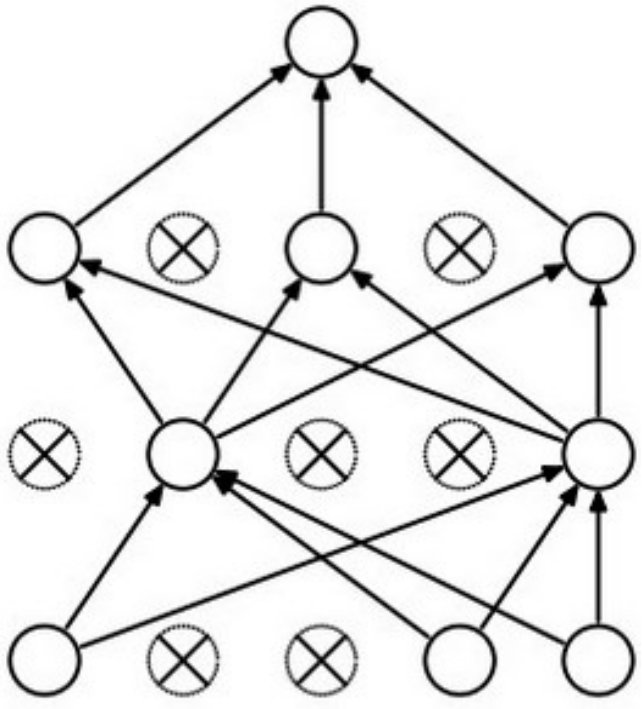
Waaaait a second…
How could this possibly be a good idea?



Forces the network to have a redundant representation.



Waaaait a second…
How could this possibly be a good idea?



Another interpretation:

Dropout is training a large ensemble of models (that share parameters).

Each binary mask is one model, gets trained on only ~one batch.

At test time….

At test time all neurons are always ON

We must scale the activations so that for each neuron:

output at test time = expected output at training time

Dropout Summary

In [21]:
```
require 'nn';
p = 0.5
x = torch.rand(5)
L1 = nn.Linear(5, 5)
L2 = nn.Linear(5, 5)
L3 = nn.Linear(5, 5)
L4 = nn.Linear(5, 1)

function forward_train(x)
    H1 = L1:forward(x)
    U1 = torch.rand(H1:size(1)):gt(p):double()
    H1 = H1:cmul(U1)

    H2 = L2:forward(H1)
    U2 = torch.rand(H2:size(1)):gt(p):double()
    H2 = H2:cmul(U2)

    H3 = L3:forward(H2)
    U3 = torch.rand(H3:size(1)):gt(p):double()
    H2 = H3:cmul(U3)

    out = L4:forward(H3)
    return out
end

function forward_test(x)
    H1 = L1:forward(x) * p
    H2 = L2:forward(H1) * p
    H3 = L3:forward(H2) * p
    out = L4:forward(H3)
    return out
end
```

Drop in forward pass

Compensate at test time

More common: "Inverted dropout"

In [ ]:

```
function forward_train(x)
    H1 = L1:forward(x)
    U1 = torch.rand(H1:size(1)):gt(p):double()
    H1 = H1:cmul(U1) / p

    H2 = L2:forward(H1)
    U2 = torch.rand(H2:size(1)):gt(p):double()
    H2 = H2:cmul(U2) / p

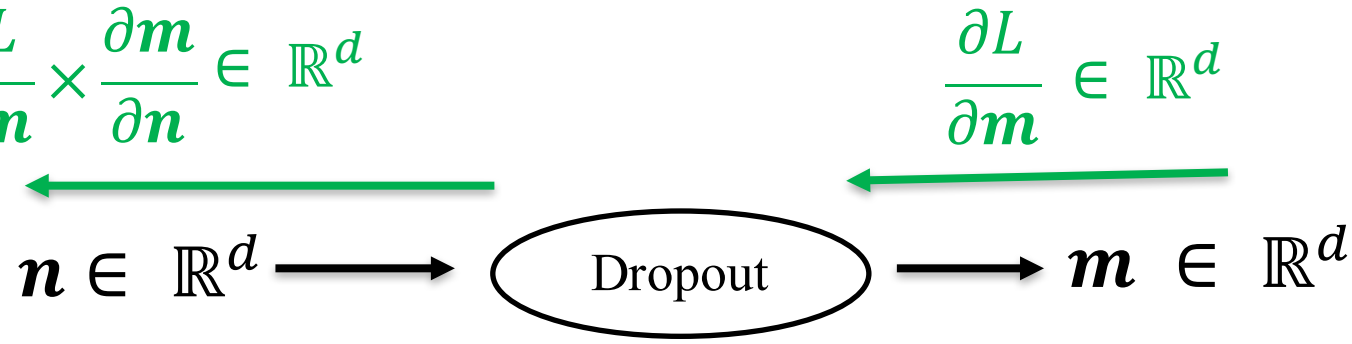
    H3 = L3:forward(H2)
    U3 = torch.rand(H3:size(1)):gt(p):double()
    H2 = H3:cmul(U3) / p

    out = L4:forward(H3)
    return out
end

function forward_test(x)
    H1 = L1:forward(x)
    H2 = L2:forward(H1)
    H3 = L3:forward(H2)
    out = L4:forward(H3)
    return out
end
```

test time is unchanged!
(as in Torch7)

Building Blocks – Dropout - Regularization




```
> n = torch.rand(5)
> drop = nn.Dropout(.5)
> drop.train = true
> =n
 0.6549
 0.2767
 0.2258
 0.5753
 0.6580
[torch.DoubleTensor of size 5]

> =drop:forward(n)
 1.3097
 0.5534
 0.4515
 1.1505
 1.3160
[torch.DoubleTensor of size 5]
```

```
> return drop:forward(n)
 1.3097
 0.5534
 0.4515
 0.0000
 0.0000
[torch.DoubleTensor of size 5]

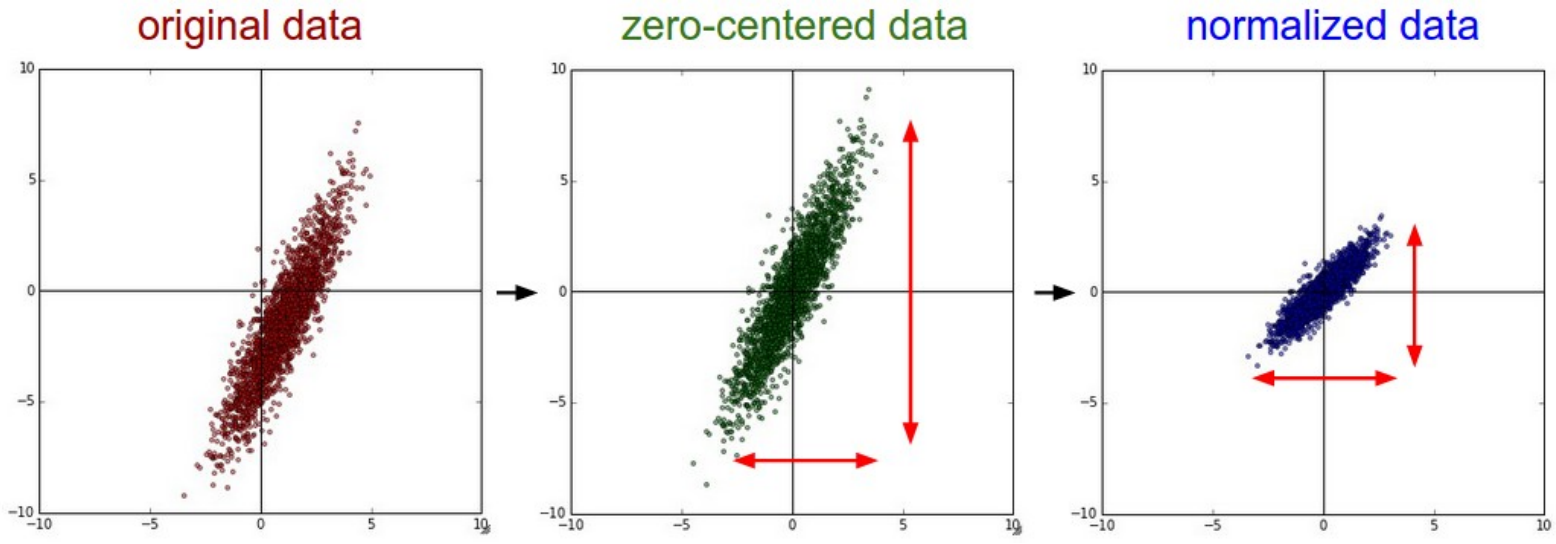
> return drop:forward(n)
 0.0000
 0.0000
 0.4515
 0.0000
 0.0000
[torch.DoubleTensor of size 5]
```

```
> drop:backward(n, torch.ones(5))
> =drop.gradInput
 0
 0
 2
 0
 0
[torch.DoubleTensor of size 5]
```

```
> drop.train = false
> m = drop:forward(n)
> =m
 0.6549
 0.2767
 0.2258
 0.5753
 0.6580
[torch.DoubleTensor of size 5]
```

Data Preprocessing

Data Preprocessing



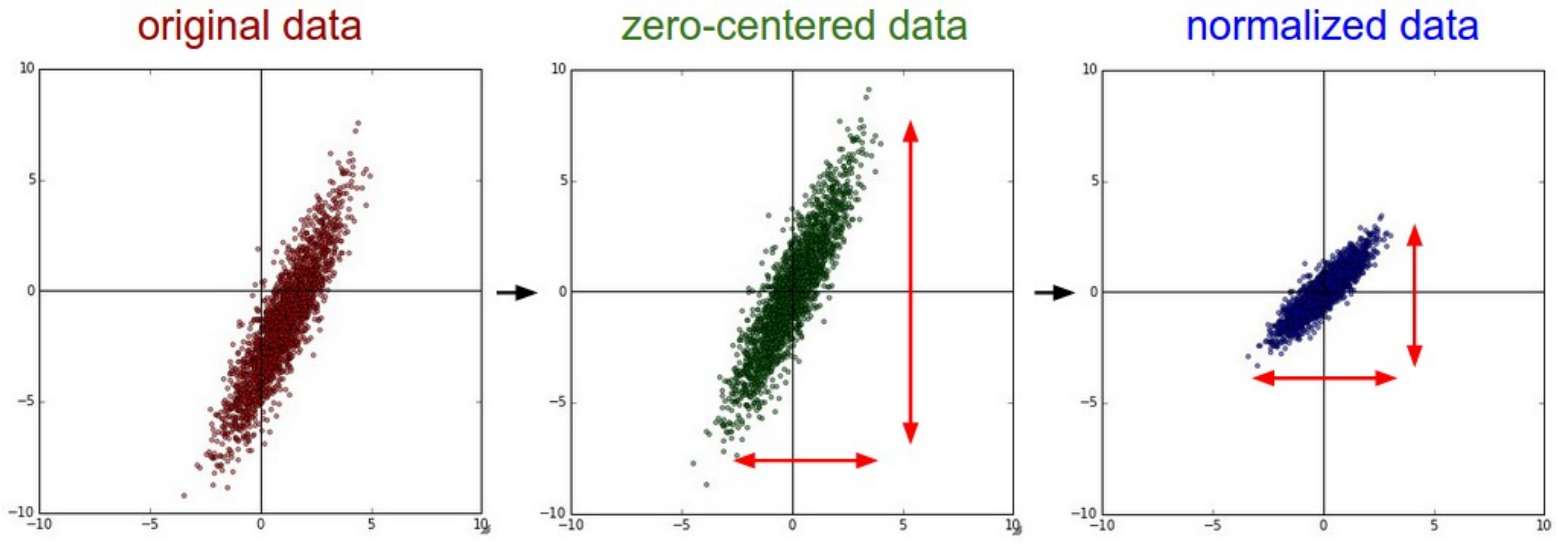
- Assume **X** [NxD] is data matrix, each example in a row
- So, in our case we have 10 examples, each 4D

```
> X = torch.rand(10,4)
> mean = X:mean(1)
> std = X:std(1)
> meanrepeated = torch.repeatTensor(mean, 10,1)
> stdrepeated = torch.repeatTensor(std, 10,1)
> =X
 0.4822  0.2837  0.6833  0.9955
 0.1640  0.0252  0.2801  0.5854
 0.7129  0.8695  0.2564  0.8241
 0.7037  0.8237  0.2027  0.1058
 0.6759  0.2490  0.0476  0.3699
 0.5486  0.4739  0.2690  0.7482
 0.4623  0.5303  0.5062  0.1874
 0.3652  0.8691  0.6733  0.3607
 0.4448  0.8708  0.8118  0.7951
 0.2013  0.6639  0.5152  0.7776
[torch.DoubleTensor of size 10x4]

> =mean
 0.4761  0.5659  0.4246  0.5750
[torch.DoubleTensor of size 1x4]

> =std
 0.1942  0.3047  0.2491  0.3013
[torch.DoubleTensor of size 1x4]
```

Data Preprocessing

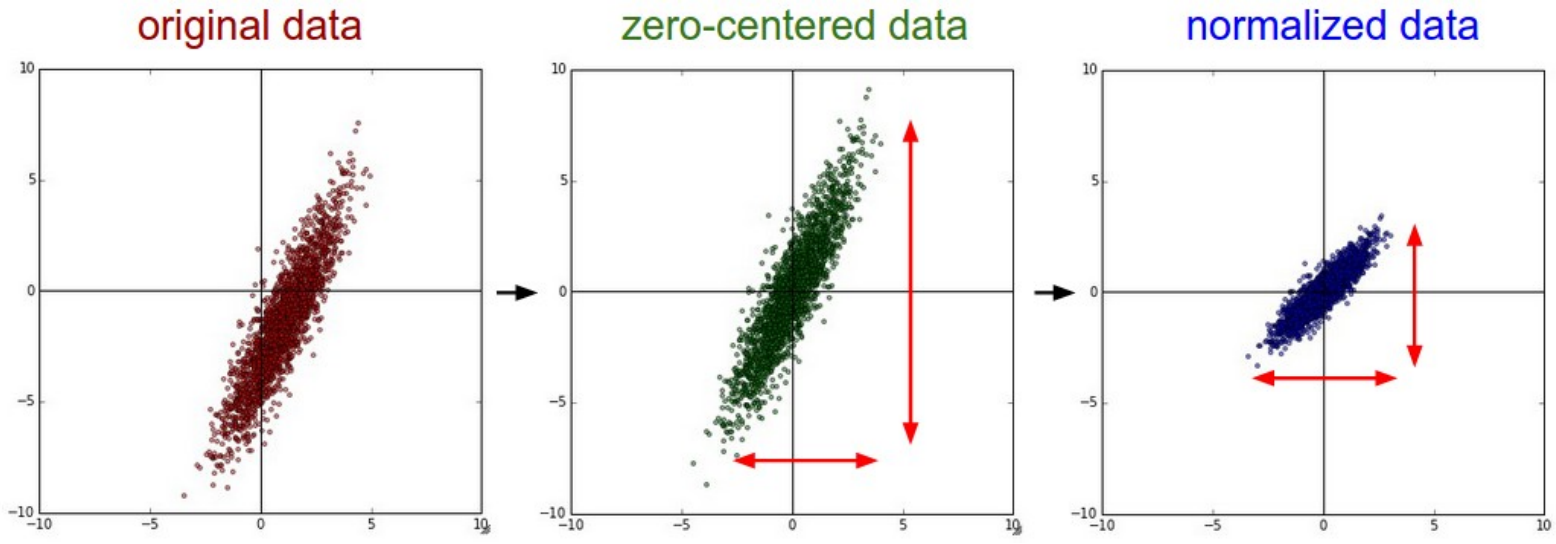



```
[> X = torch.rand(10,4)
[> mean = X:mean(1)
[> std = X:std(1)
[> meanrepeated = torch.repeatTensor(mean, 10,1)
[> stdrepeated = torch.repeatTensor(std, 10,1)
[> =meanrepeated
 0.4761  0.5659  0.4246  0.5750
 0.4761  0.5659  0.4246  0.5750
 0.4761  0.5659  0.4246  0.5750
 0.4761  0.5659  0.4246  0.5750
 0.4761  0.5659  0.4246  0.5750
 0.4761  0.5659  0.4246  0.5750
 0.4761  0.5659  0.4246  0.5750
 0.4761  0.5659  0.4246  0.5750
 0.4761  0.5659  0.4246  0.5750
 0.4761  0.5659  0.4246  0.5750
[torch.DoubleTensor of size 10x4]

[> =stdrepeated
 0.1942  0.3047  0.2491  0.3013
 0.1942  0.3047  0.2491  0.3013
 0.1942  0.3047  0.2491  0.3013
 0.1942  0.3047  0.2491  0.3013
 0.1942  0.3047  0.2491  0.3013
 0.1942  0.3047  0.2491  0.3013
 0.1942  0.3047  0.2491  0.3013
 0.1942  0.3047  0.2491  0.3013
 0.1942  0.3047  0.2491  0.3013
 0.1942  0.3047  0.2491  0.3013
[torch.DoubleTensor of size 10x4]
```

- Assume **X** [NxD] is data matrix, each example in a row
- So, in our case we have 10 examples, each 4D

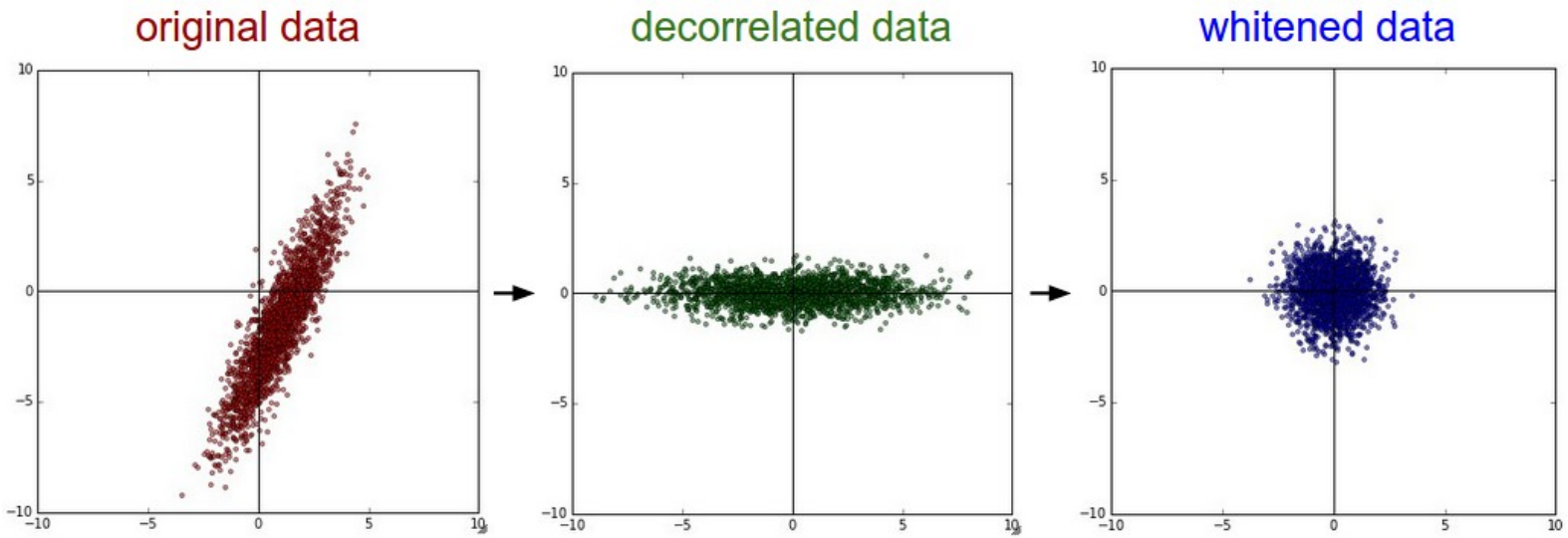
Data Preprocessing




```
[> X = torch.rand(10,4)
[> mean = X:mean(1)
[> std = X:std(1)
[> meanrepeated = torch.repeatTensor(mean, 10,1)
[> stdrepeated = torch.repeatTensor(std, 10,1)
[> X = X - meanrepeated
[> X=X:cdiv(stdrepeated)
[> =X
 0.0315 -0.9264  1.0390  1.3959
-1.6070 -1.7749 -0.5799  0.0346
 1.2192  0.9964 -0.6751  0.8270
 1.1719  0.8461 -0.8909 -1.5573
 1.0287 -1.0402 -1.5134 -0.6806
 0.3735 -0.3019 -0.6247  0.5749
-0.0709 -0.1170  0.3280 -1.2866
-0.5710  0.9953  0.9986 -0.7111
-0.1611  1.0008  1.5545  0.7308
-1.4149  0.3216  0.3639  0.6725
[torch.DoubleTensor of size 10x4]
```

- Assume **X** [NxD] is data matrix, each example in a row
- So, in our case we have 10 examples, each 4D

Data Preprocessing



data has diagonal covariance matrix

covariance matrix is the identity matrix

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

Data Preprocessing

TLDR: In practice for Images: center only

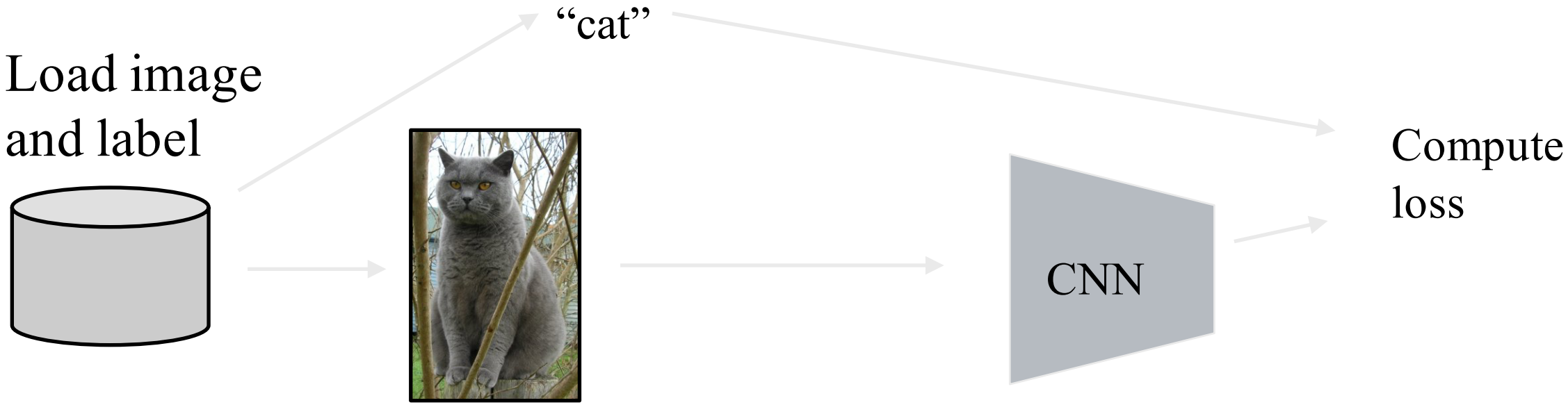
e.g. consider CIFAR-10 (**homework**!) example with [32,32,3] images

- 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)

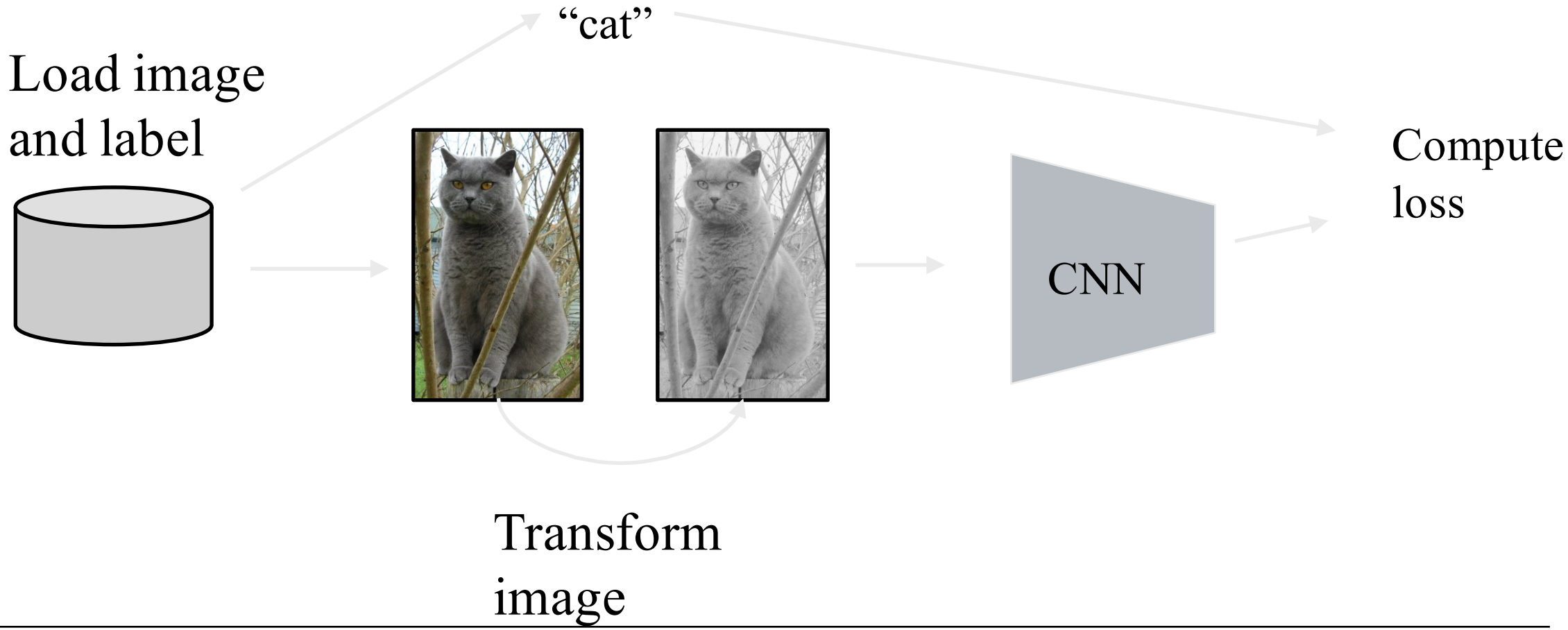
Not common to normalize variance, to do PCA or whitening

Data Augmentation

Data Augmentation

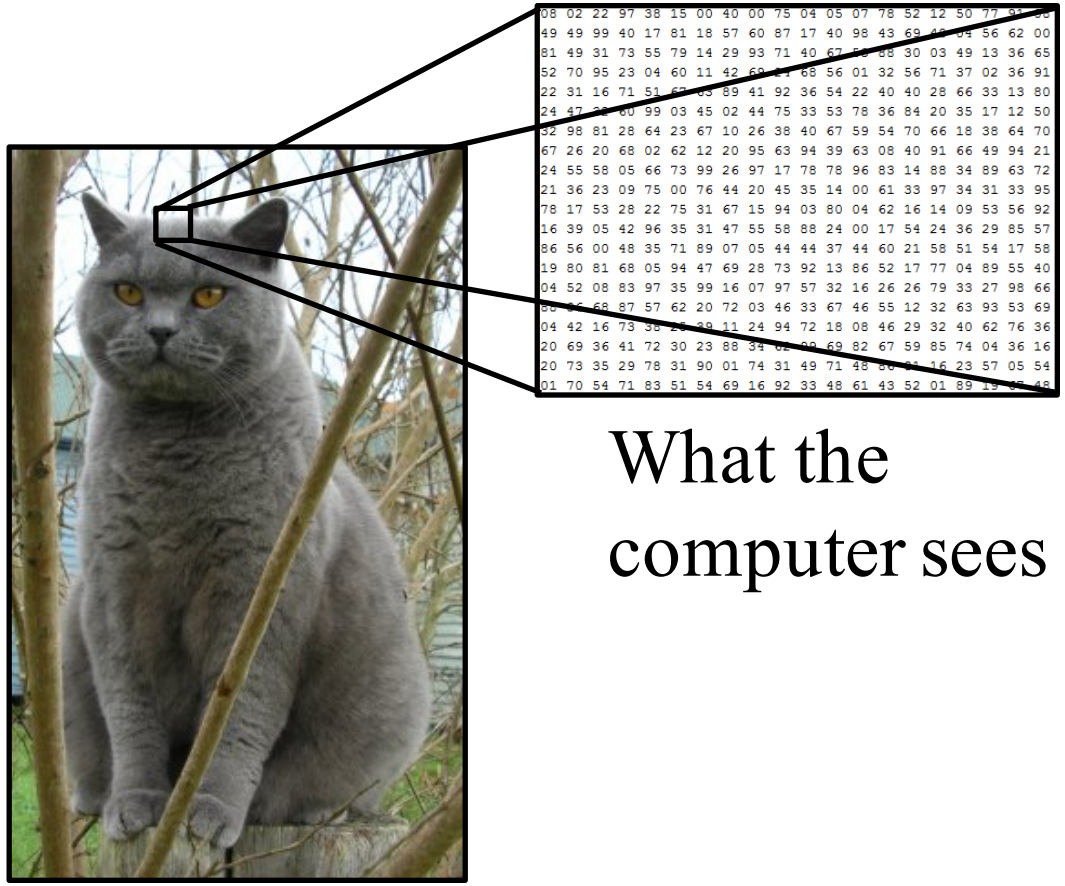


Data Augmentation



Data Augmentation

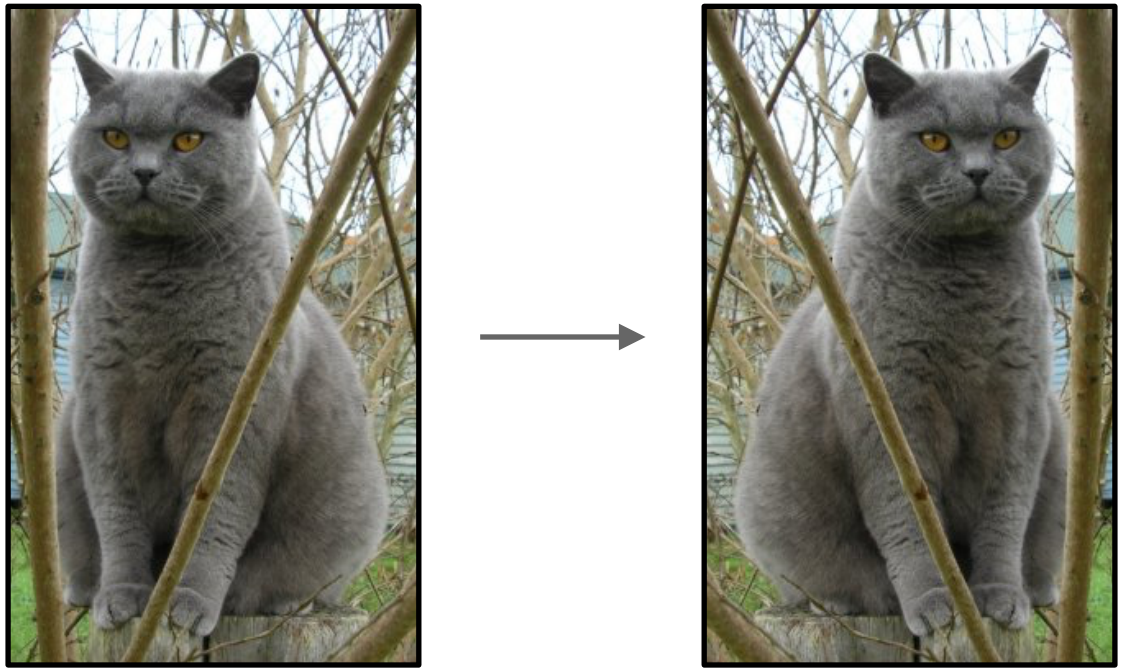
- Change the pixels without changing the label
- Train on transformed data
- VERY widely used



What the computer sees

Data Augmentation

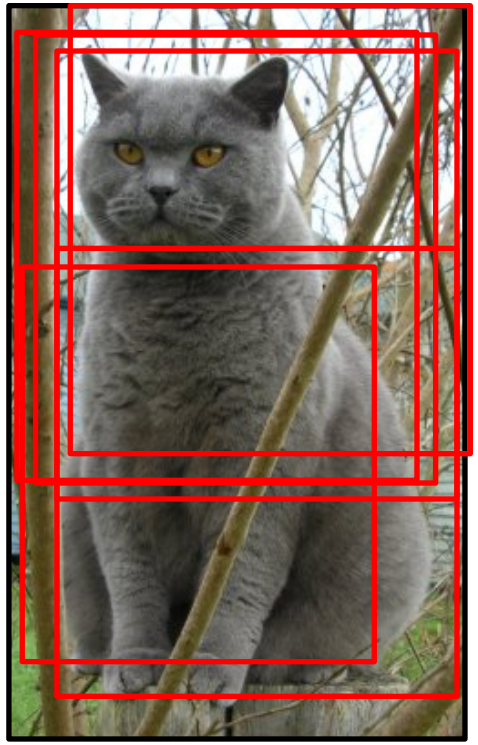
1. Horizontal flips



Data Augmentation

2. Random crops/scales

Training: sample random crops / scales



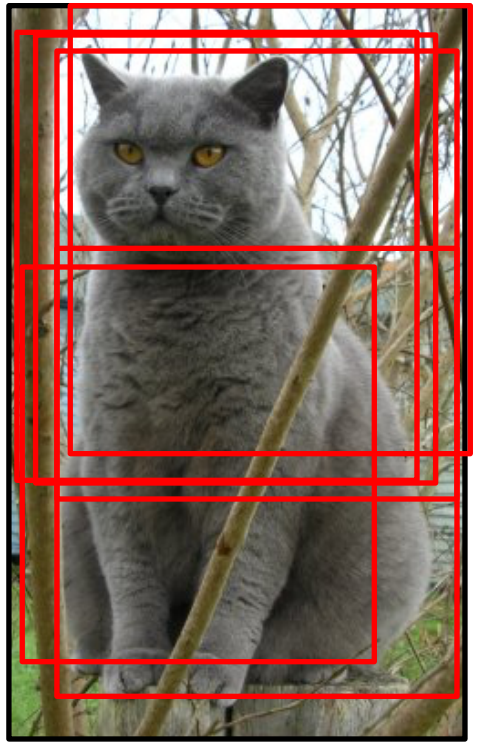
Data Augmentation

2. Random crops/scales

Training: sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 x 224 patch



Data Augmentation

2. Random crops/scales

Training: sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
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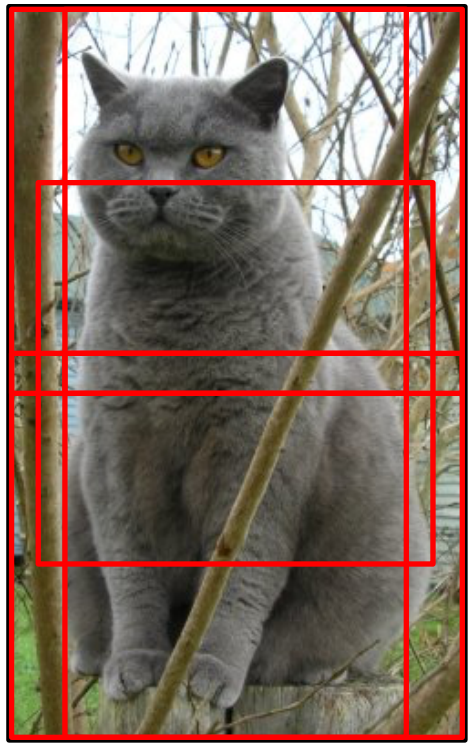
Testing: average a fixed set of crops



Data Augmentation

2. Random crops/scales

Training: sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
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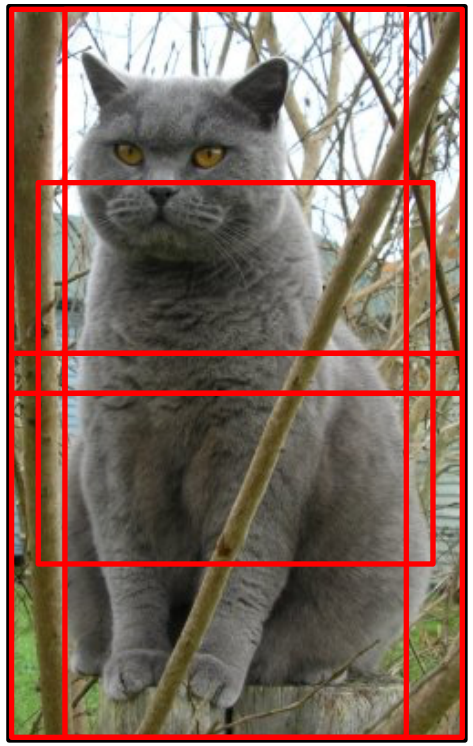
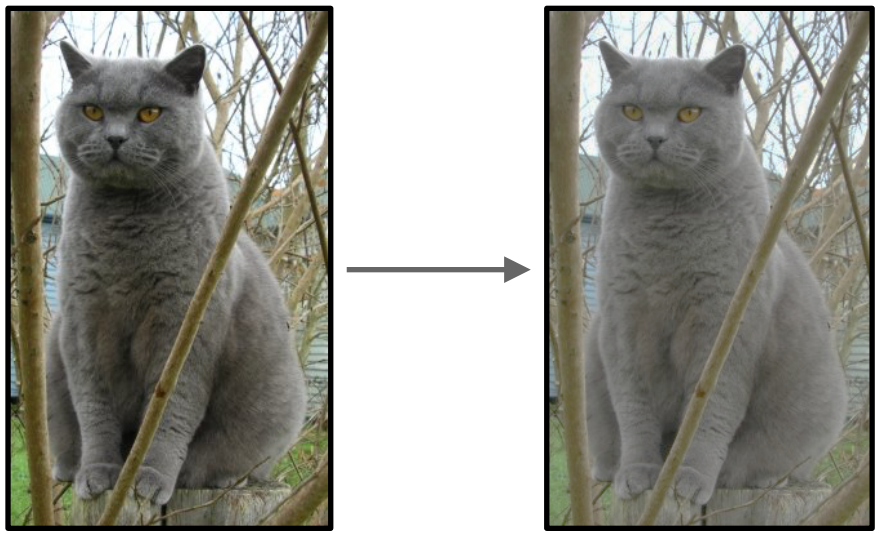


Data Augmentation

3. Color jitter

Simple:

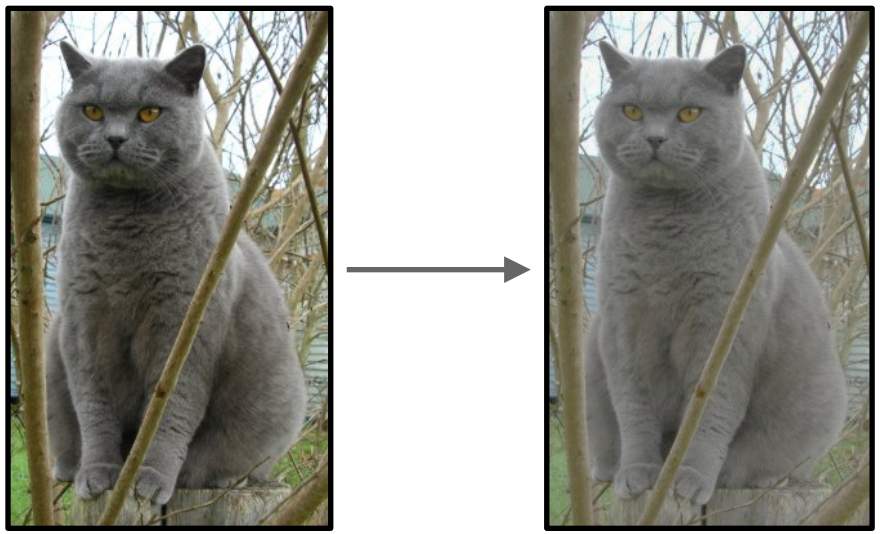
Randomly jitter contrast



Data Augmentation

3. Color jitter

Simple:
Randomly jitter contrast



Complex:

1. Apply PCA to all [R, G, B] pixels in training set

2. Sample a "color offset" along principal component directions

1. Add offset to all pixels of a training image

(As seen in [Krizhevsky et al. 2012], ResNet, etc.)

Data Augmentation

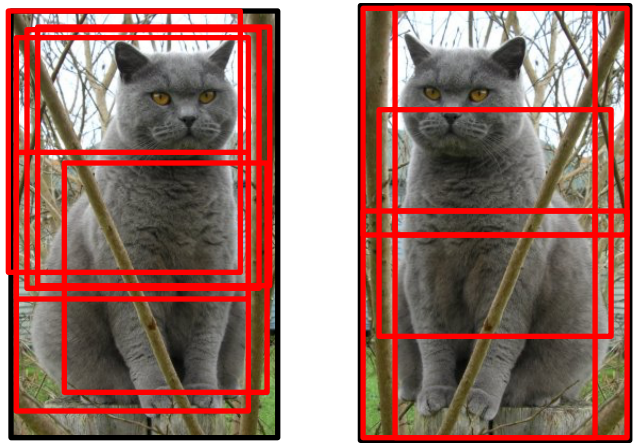
4. Get creative!

Random mix/combinations of :

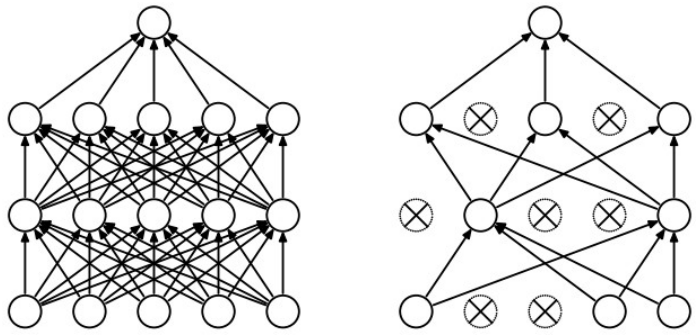
- translation (what about a pure ConvNet?)
- rotation
- stretching
- shearing,
- lens distortions, … (go crazy)

A general theme:

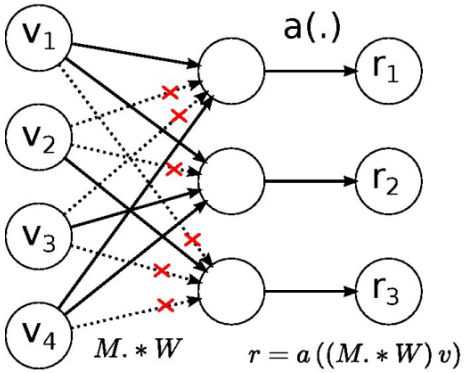
1. **Training**: Add random noise
2. **Testing**: Marginalize over the noise



Data Augmentation



Dropout



DropConnect

Batch normalization, Model ensembles

Data Augmentation: Takeaway

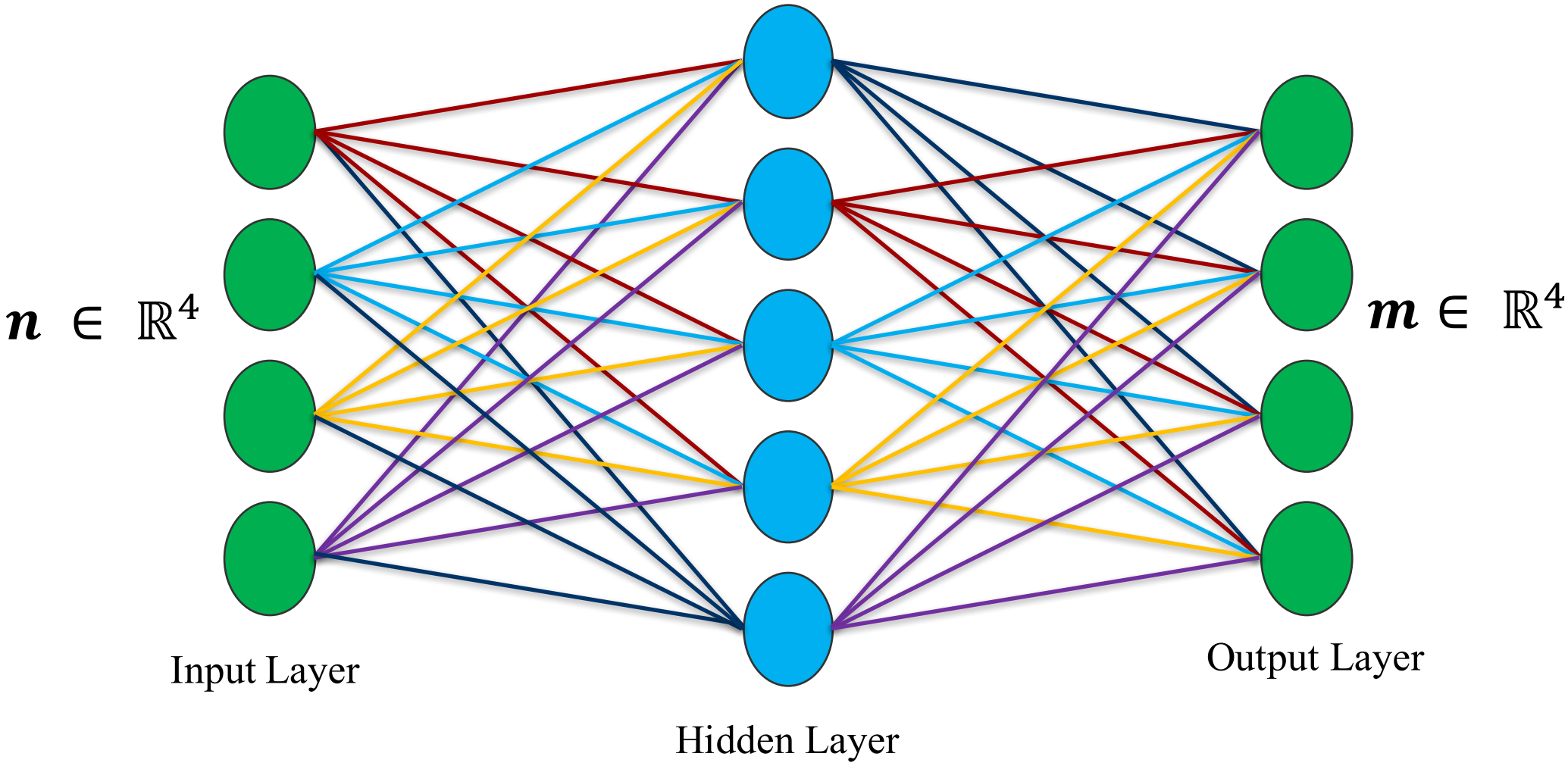
Simple to implement, use it

Especially useful for small datasets

Fits into framework of noise / marginalization

Weight Initialization

What happens when W=0 init is used?



- First idea: **Small random numbers**
  (normal distribution mean 0, sigma 1 scaled by -0.01 to 0.01)

```
self.W = torch.randn(fan_out, fan_in) * 0.01
self.b = torch.randn(fan_out)* 0.01
```

- First idea: **Small random numbers**
  (normal distribution mean 0, sigma 1 scaled by -0.01 to 0.01)

```
self.W = torch.randn(fan_out, fan_in) * 0.01
self.b = torch.randn(fan_out)* 0.01
```

Works ~okay for small networks (like our one layer cifar-10 classifier), 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 non-linearities, and initializing as described in last slide.

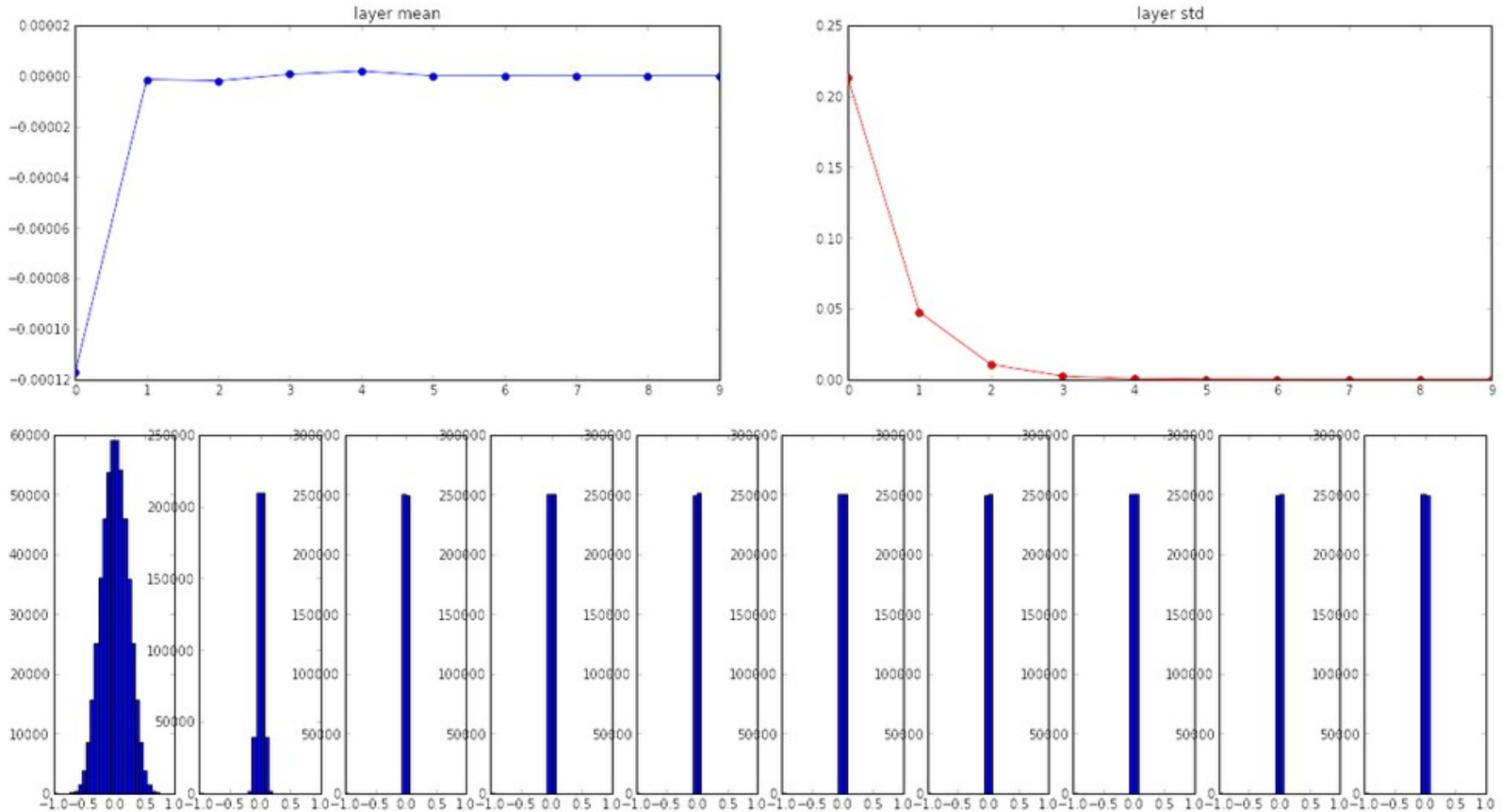
```
local Linear = torch.class("Linear")
function Linear:__init(fan_in, fan_out)
    self.output = nil
    self.W = torch.randn(fan_out, fan_in) * 0.01
    self.b = torch.randn(fan_out)* 0.01
end

-- Wx + b
function Linear:forward(xi)
    self.output = self.W * xi:reshape(x:size(1),1) + self.b
    return self.output
end

x = torch.randn(1000)
l = Linear.new(1000, 1000)
input = x
for i = 1, 10 do
    h = l:forward(input)
    h = nn.Tanh():forward(h)
    input = h
end
```

Lets look at some activation statistics

```
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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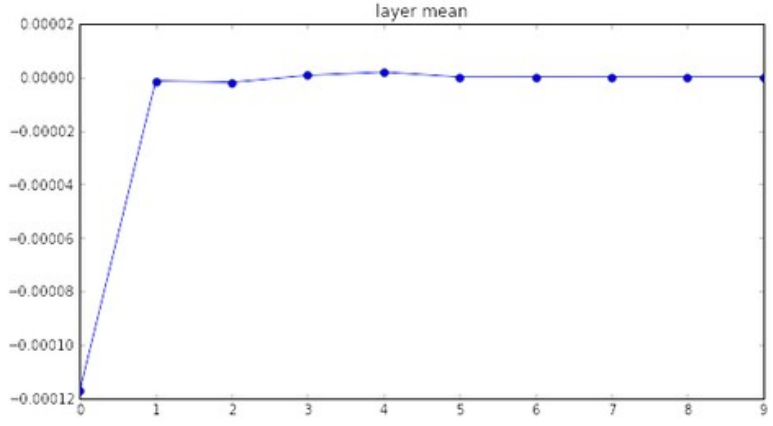
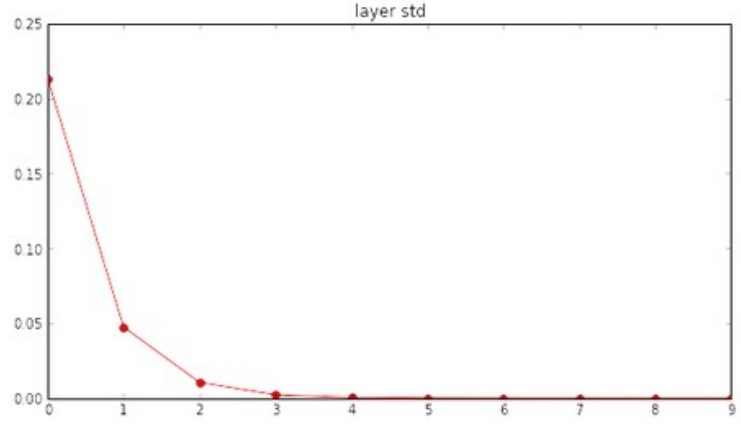
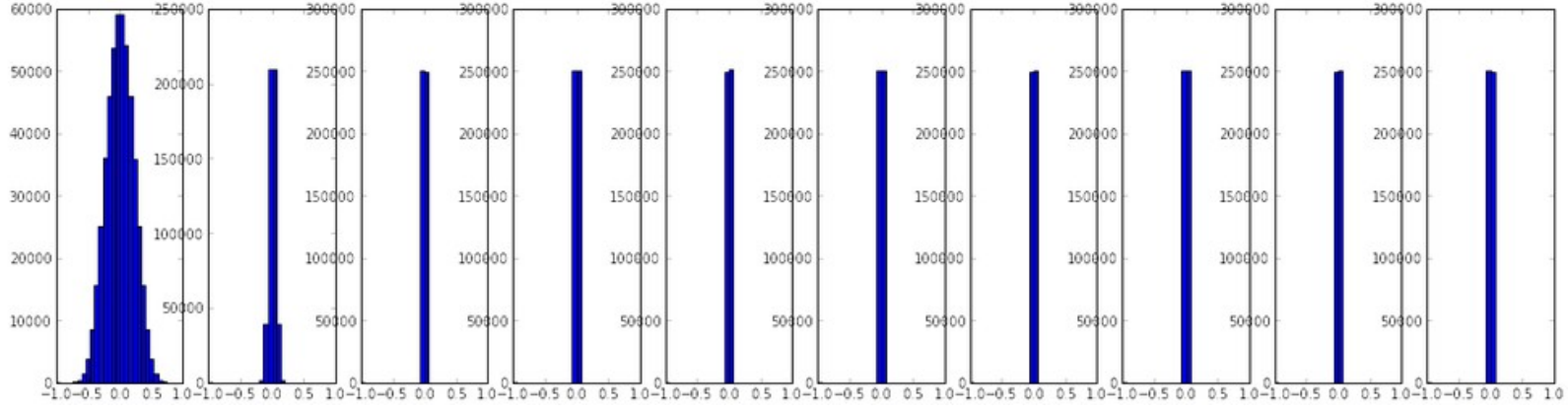
hidden layer 6 had mean -0.000000 and std 0.000119
hidden layer 7 had mean 0.000000 and std 0.000026
hidden layer 8 had mean -0.000000 and std 0.000006
hidden layer 9 had mean 0.000000 and std 0.000001
hidden layer 10 had mean -0.000000 and std 0.000000
```







All activations become zero!

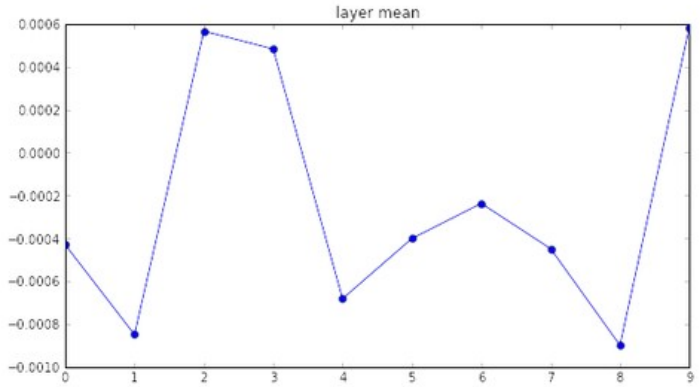
Q: think about the backward pass. What do the gradients look like?

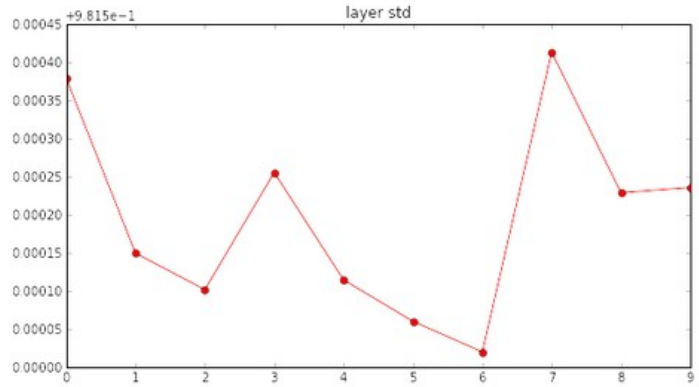
Hint: think about backward pass for a W*X gate.

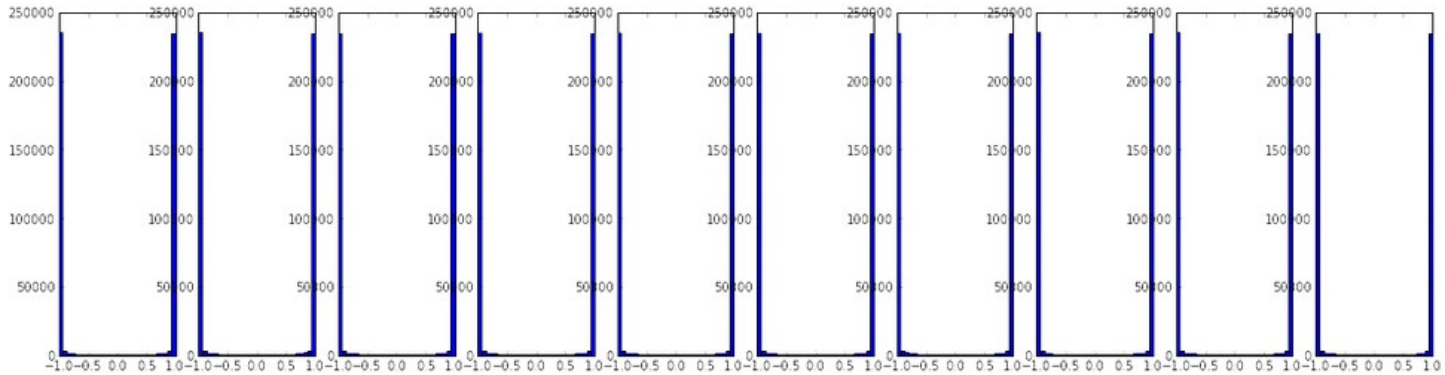
```
self.W = torch.randn(fan_out, fan_in) * 1.0
self.b = torch.randn(fan_out)* 1.0
```

*1.0 instead of *0.01

```
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
```





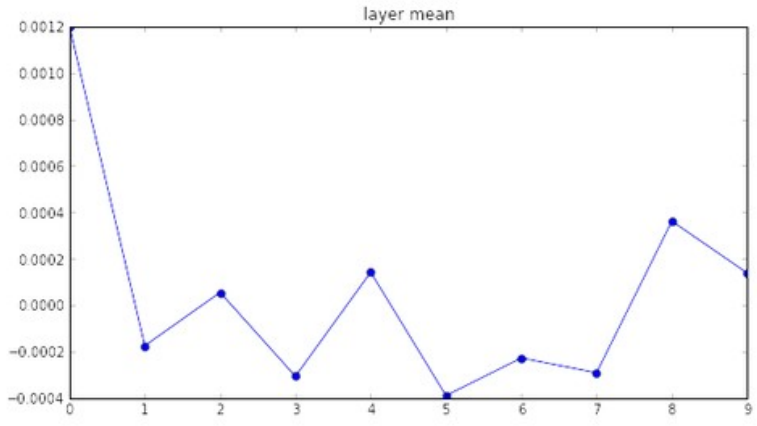


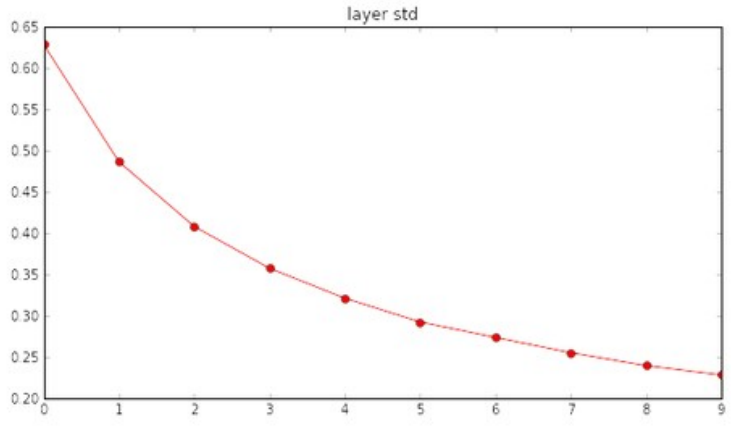
Almost all neurons completely saturated, either -1 and 1. Gradients will be all zero.

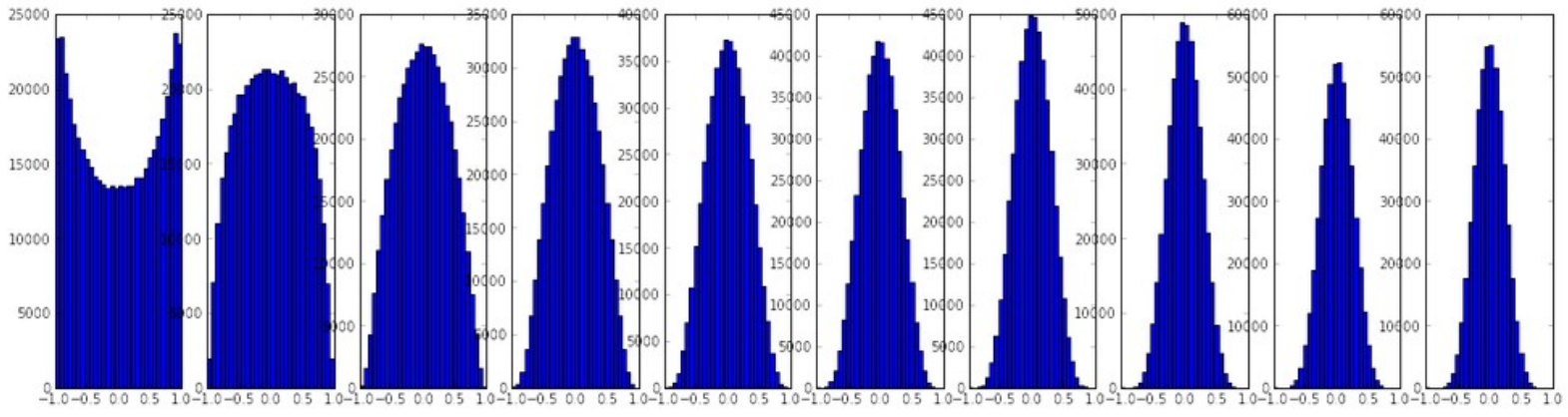
```
input layer had mean 0.001800 and std 1.001311
hidden layer 1 had mean 0.001198 and std 0.627953
hidden layer 2 had mean -0.000175 and std 0.486051
hidden layer 3 had mean 0.000055 and std 0.407723
hidden layer 4 had mean -0.000306 and std 0.357108
hidden layer 5 had mean 0.000142 and std 0.320917
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
```

```
self.W = torch.randn(fan_out, fan_in) / math.sqrt(fan_in)
self.b = torch.randn(fan_out) / math.sqrt(fan_in)
```

"Xavier initialization"
[Glorot et al., 2010]





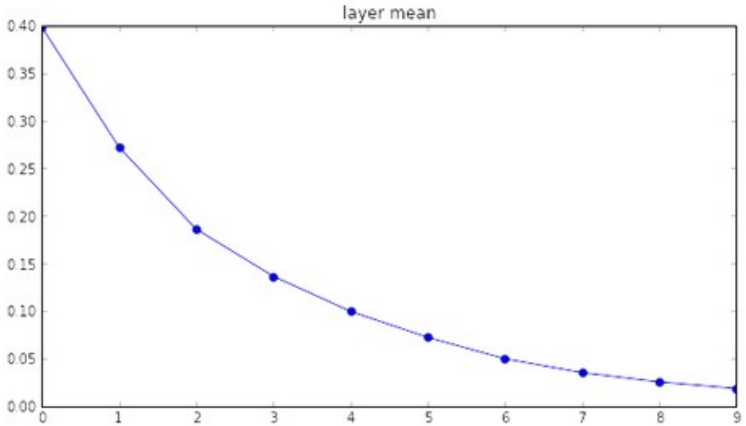


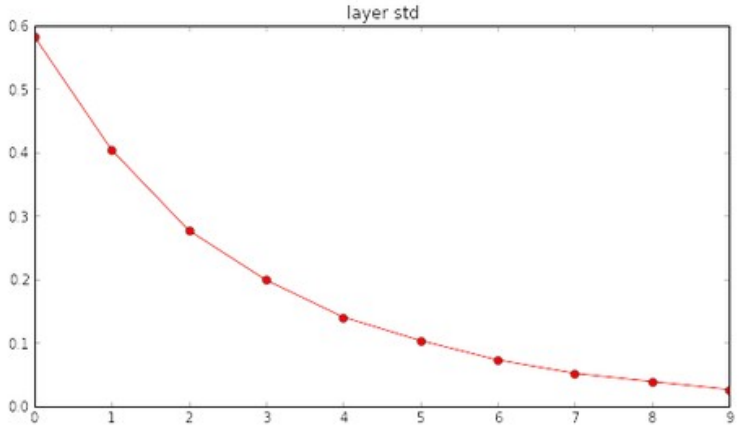
Reasonable initialization.
(Mathematical derivation assumes linear activations)

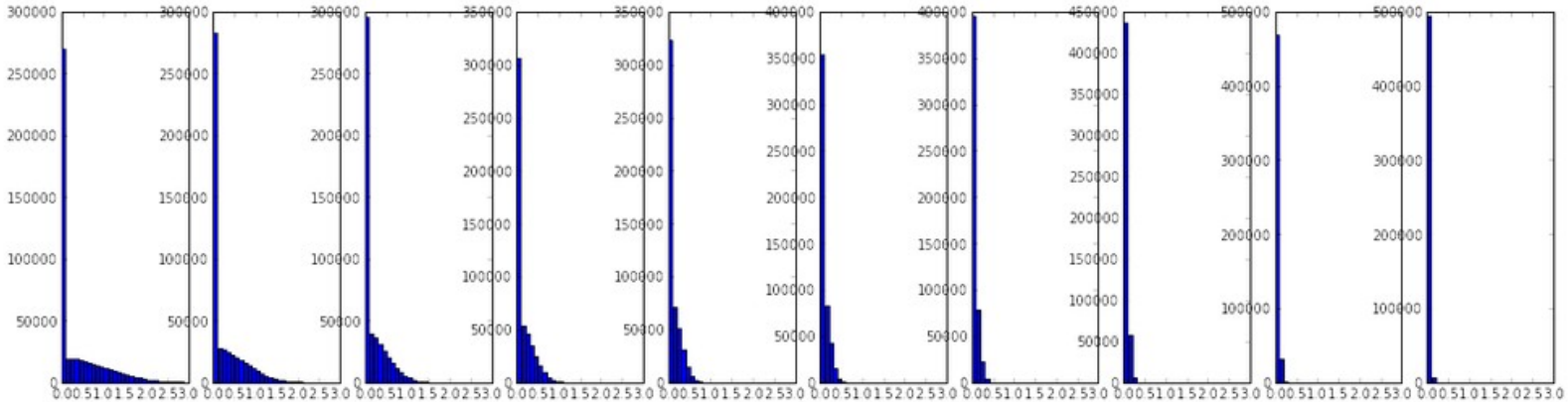
```
input layer had mean 0.000501 and std 0.999444
hidden layer 1 had mean 0.398623 and std 0.582273
hidden layer 2 had mean 0.272352 and std 0.403795
hidden layer 3 had mean 0.186076 and std 0.276912
hidden layer 4 had mean 0.136442 and std 0.198685
hidden layer 5 had mean 0.099568 and std 0.140299
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
```

```
self.W = torch.randn(fan_out, fan_in) / math.sqrt(fan_in)
self.b = torch.randn(fan_out) / math.sqrt(fan_in)
```

but when using the ReLU nonlinearity it breaks.



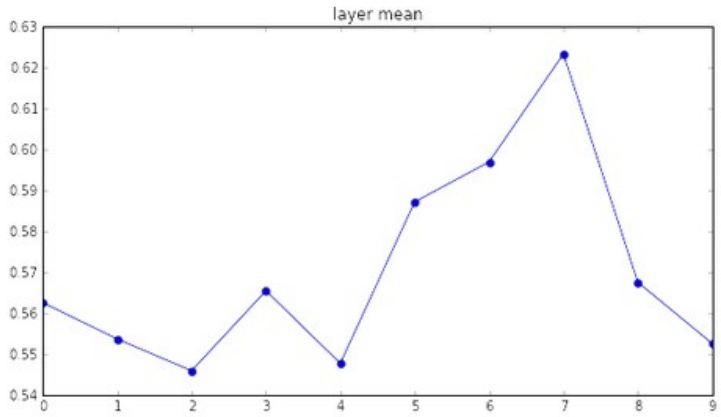


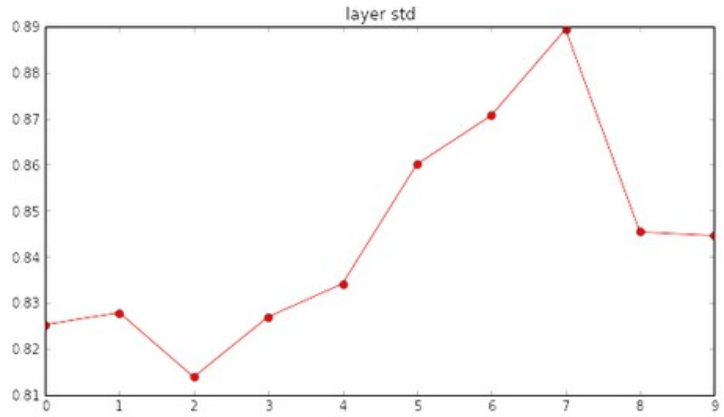


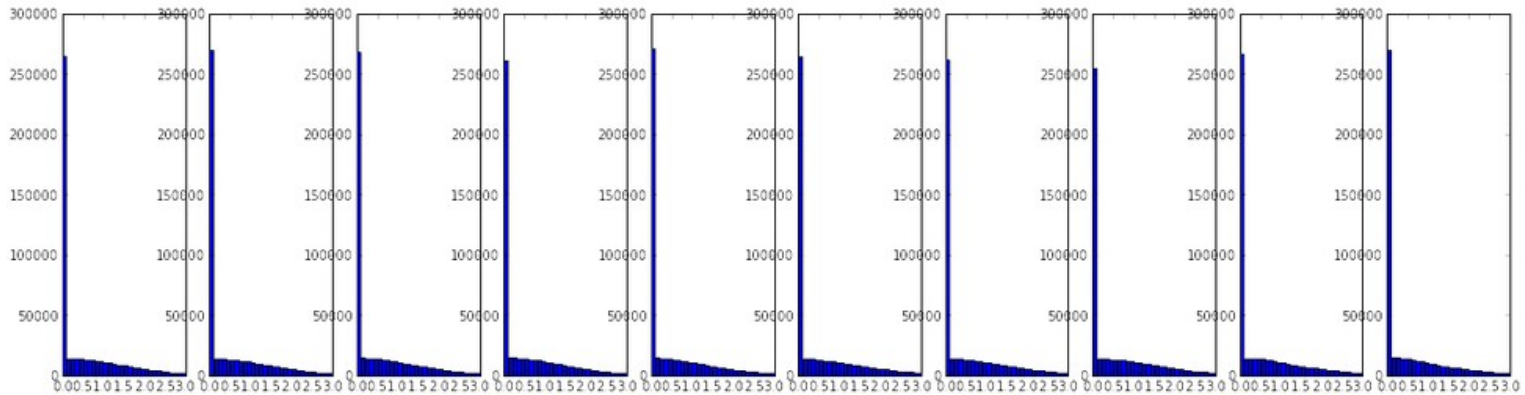
```
input layer had mean 0.000501 and std 0.999444
hidden layer 1 had mean 0.562488 and std 0.825232
hidden layer 2 had mean 0.553614 and std 0.827835
hidden layer 3 had mean 0.545867 and std 0.813855
hidden layer 4 had mean 0.565396 and std 0.826902
hidden layer 5 had mean 0.547678 and std 0.834092
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
```

```
self.W = torch.randn(fan_out, fan_in) / math.sqrt(fan_in/2)
self.b = torch.randn(fan_out) / math.sqrt(fan_in/2)
```

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



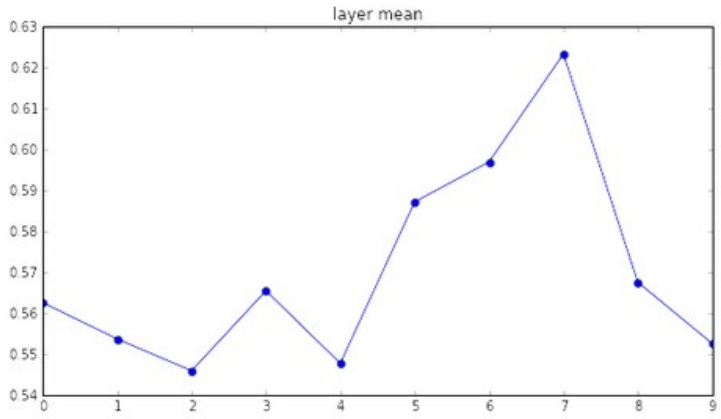


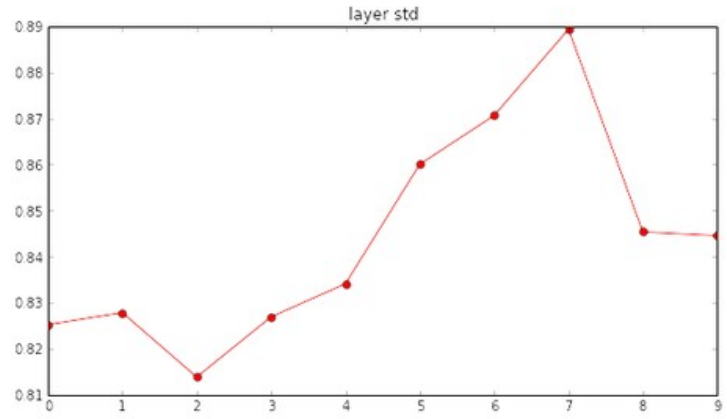


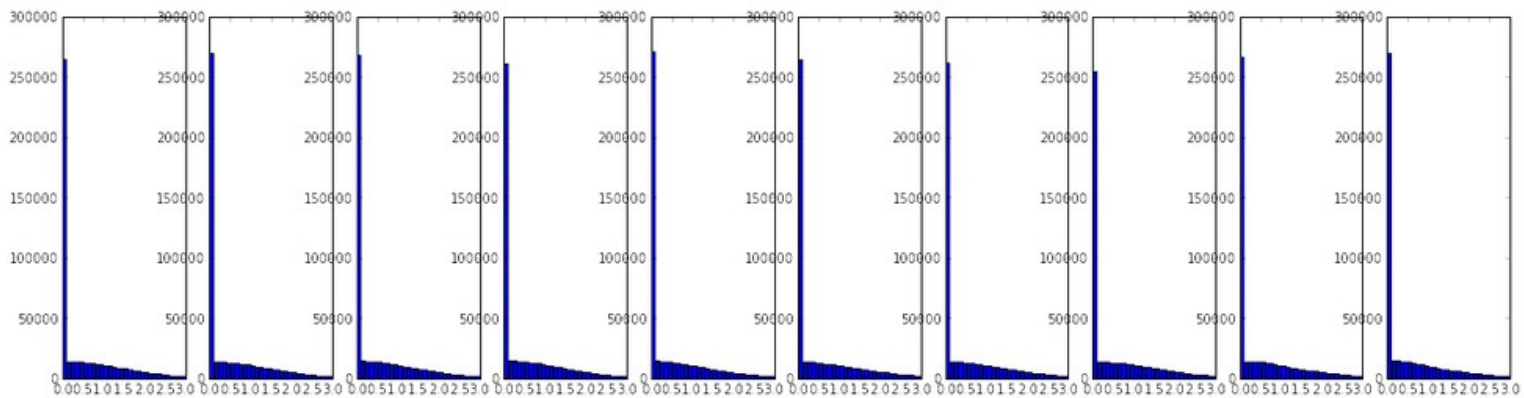
```
input layer had mean 0.000501 and std 0.999444
hidden layer 1 had mean 0.562488 and std 0.825232
hidden layer 2 had mean 0.553614 and std 0.827835
hidden layer 3 had mean 0.545867 and std 0.813855
hidden layer 4 had mean 0.565396 and std 0.826902
hidden layer 5 had mean 0.547678 and std 0.834092
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
```

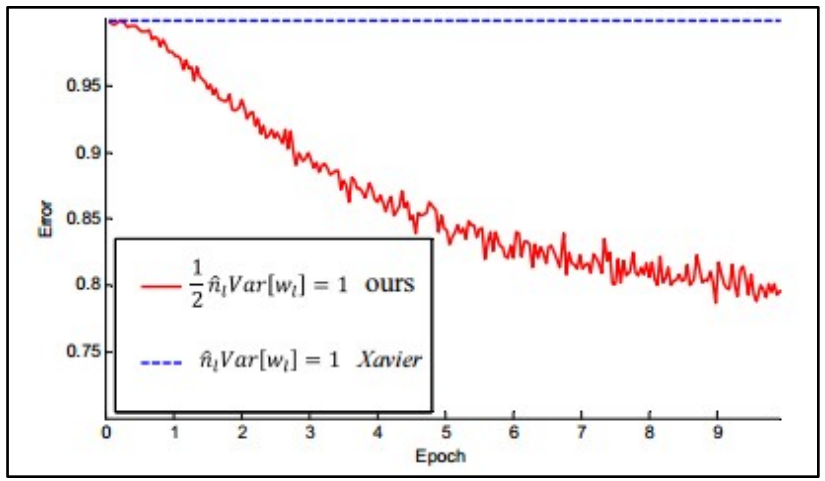
```
self.W = torch.randn(fan_out, fan_in) / math.sqrt(fan_in/2)
self.b = torch.randn(fan_out) / math.sqrt(fan_in/2)
```

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









```lua
-- "Efficient backprop"
-- Yann Lecun, 1998
local function w_init_heuristic(fan_in, fan_out)
   return math.sqrt(1/(3*fan_in))
end


-- "Understanding the difficulty of training deep feedforward neural networks"
-- Xavier Glorot, 2010
local function w_init_xavier(fan_in, fan_out)
   return math.sqrt(2/(fan_in + fan_out))
end


-- "Understanding the difficulty of training deep feedforward neural networks"
-- Xavier Glorot, 2010
local function w_init_xavier_caffe(fan_in, fan_out)
   return math.sqrt(1/fan_in)
end


-- "Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification"
-- Kaiming He, 2015
local function w_init_kaiming(fan_in, fan_out)
   return math.sqrt(4/(fan_in + fan_out))
end
```

https://github.com/e-lab/torch-toolbox/blob/master/Weight-init/weight-init.lua

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
by Mishkin and Matas, 2015

…

Batch Normalization

"you want unit gaussian activations? just make them so."

[Ioffe and Szegedy, 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 feature dimension unit gaussian, apply:

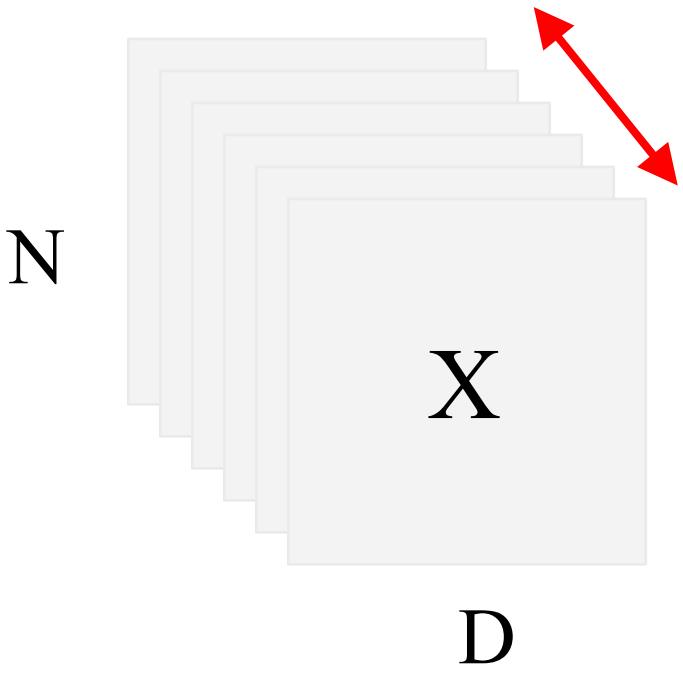
$$\widehat{x}^{(k)} = \frac{x^{(k)} - \mathrm{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}$$

this is a vanilla differentiable function...

Batch Normalization

[Ioffe and Szegedy, 2015]

"you want unit gaussian activations?
just make them so."



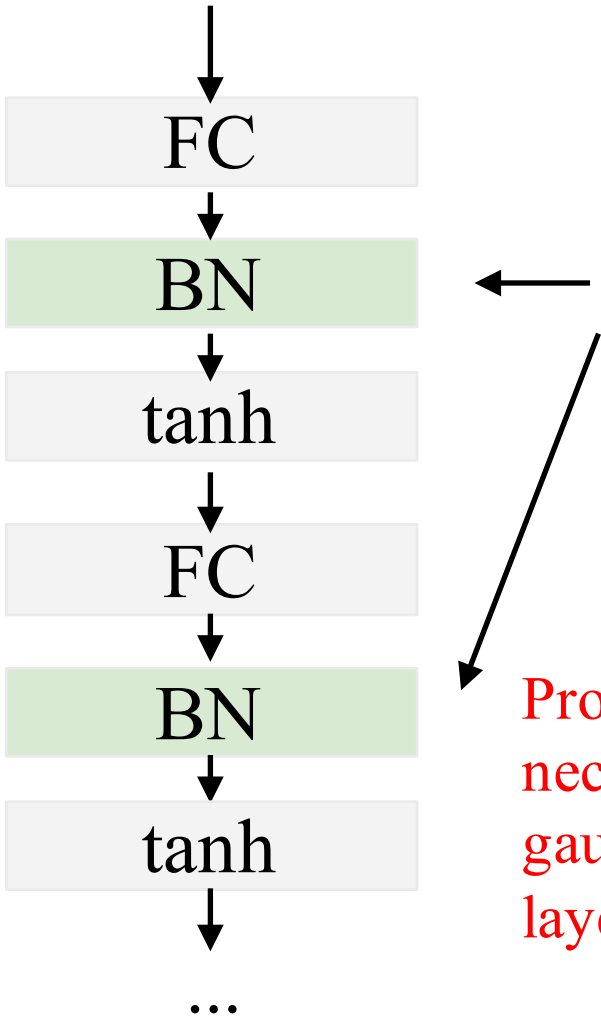
1. compute the empirical mean and variance independently for each feature dimension.

2. Normalize

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

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?

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

Batch Normalization

[Ioffe and Szegedy, 2015]

Normalize:

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

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

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

Note, the network can learn:

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

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

to recover the identity mapping.

Batch Normalization

[Ioffe and Szegedy, 2015]

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

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

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

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

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

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

- 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: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

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

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

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

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

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

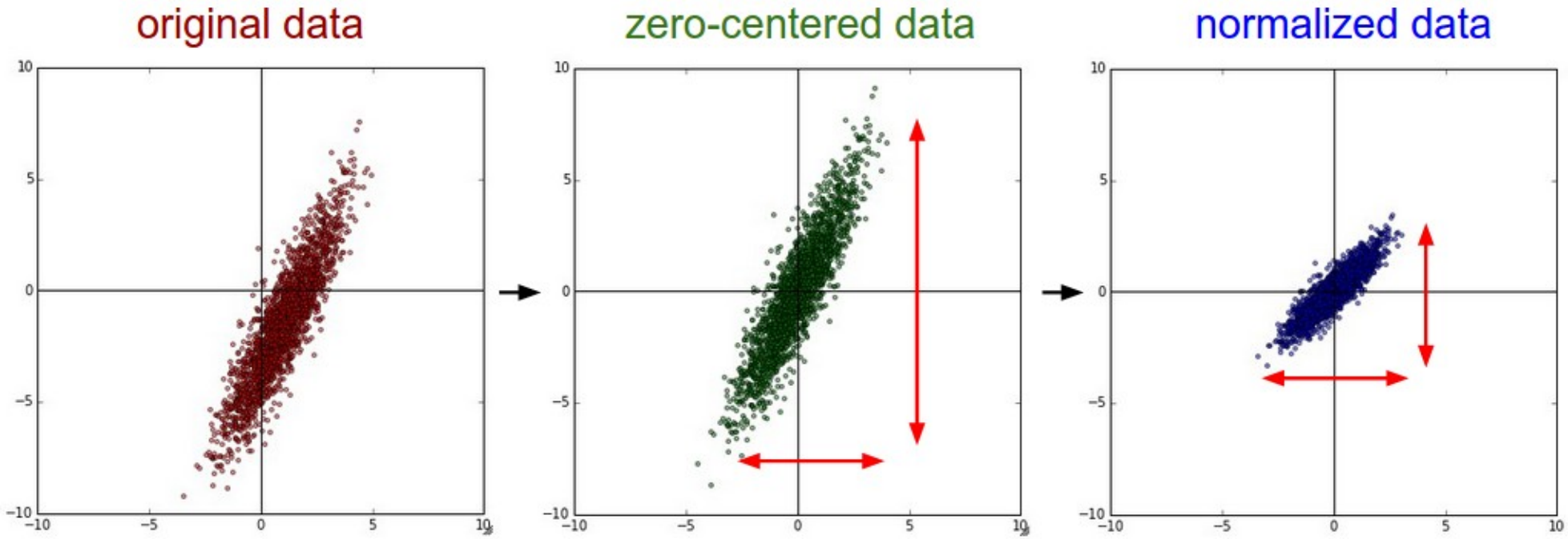
Note: at test time BatchNorm layer functions differently:

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



Mean subtract

Divide by standard deviation

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

Notebook

https://github.com/stencilman/CS763_Spring2017/blob/master/Lec3%2C4/CrossEntropy-Linear.ipynb

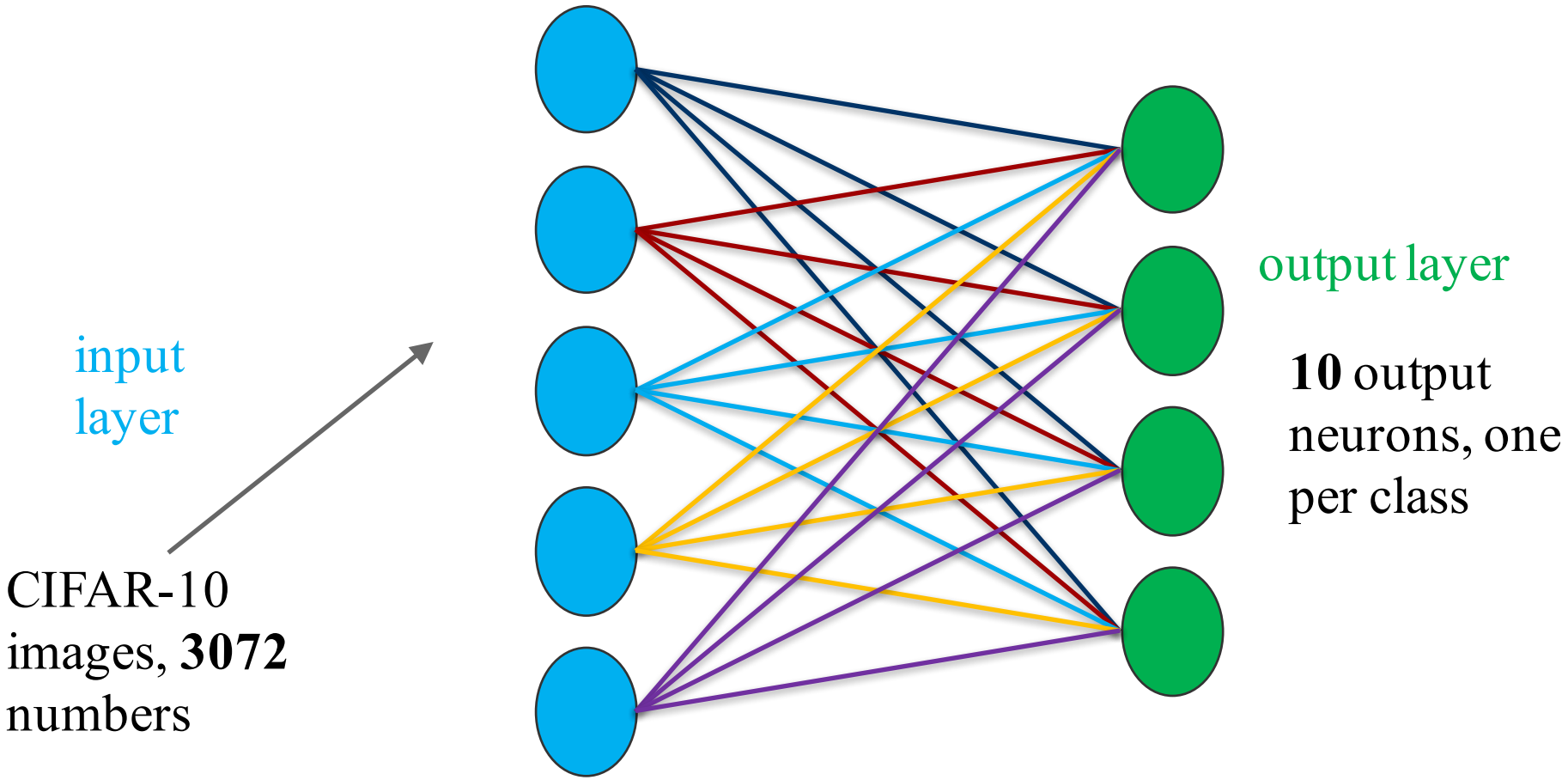
2. Data Preprocessing: We compute the mean and standard deviation 'images' and then subtract and divide by the same respectively (like AlexNet). We also visualize them.

In [3]:
```
x_mean = torch.mean(tr_x:float(), 1)
x_std = torch.std(tr_x:float(), 1)
itorch.image(x_mean)
itorch.image(x_std)
```

In [7]:
```
function get_xi(data_x, idx)
    xi = (data_x[idx]:float() - x_mean)
    xi = xi:cdiv(x_std)
    xi = xi:reshape(3*32*32)
    return xi
end
```

Step 2: Choose the architecture:

Say we start with single layer network:



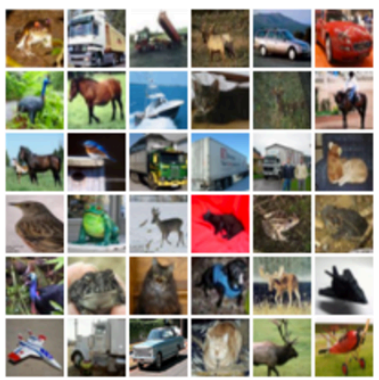
1. Data Loading: Let us load the training and the test data and check the size of the tensors. Let us also display the first few images from the training set.

In [1]:
```
-- load trainin images
tr_x = torch.load('cifar10/tr_data.bin')
-- load trainin labels
tr_y = torch.load('cifar10/tr_labels.bin'):double() + 1
-- load test images
te_x = torch.load('cifar10/te_data.bin')
-- load test labels
te_y = torch.load('cifar10/te_labels.bin'):double() + 1
print(tr_x:size())
print(tr_y:size())
```

Out[1]:
```
 50000
     3
    32
    32
[torch.LongStorage of size 4]

 50000
[torch.LongStorage of size 1]
```

In [2]:
```
-- display the first 36 training set images
require 'image';
itorch.image(tr_x[{{1,36},{},{},{}}])
```



```
function train_and_test_loop(no_iterations, lr, lambda)
    for i = 0, no_iterations do

        -- trainin input and target
        xi = get_xi(tr_x, i)
        ti = tr_y[i]

        -- Train
        op = model:forward(xi)
        loss_tr = criterion:forward(op, ti)
        dl_do = criterion:backward(op, ti)
        model:backward(xi, dl_do)

        -- Test
        idx = shuffle_te[mod(i, te_x:size(1)) + 1]
        xi = get_xi(te_x, idx)
        ti = te_y[idx]
        -- Compute loss
        op = model:forward(xi)
        loss_te = criterion:forward(op, ti, model, lambda)

        -- udapte model weights
        gradient_descent(model, lr)

        err = evaluate(model, tr_x, tr_y)
        if (err < besterr) then
            besterr = err
            bestmodel:copy(model)
        end

    end
    return (1 - besterr)*100 -- Accuracy
end
```

Double check that the loss is reasonable:

```
    op = model:forward(xi)
    loss_tr = criterion:forward(op, ti)
    print(loss_tr)
```

```
-- run it
lr = 0.00001
lambda = 0.0
train_and_test_loop(1, lr, lambda)
```

disable regularization

```
Out[11]: 2.2656910718829
```

loss ~2.3.
"correct" for
10 classes

Print Loss

Double check that the loss is reasonable:

```
    op = model:forward(xi)
    loss_tr = criterion:forward(op, ti,
    print(loss_tr)
```

```
-- run it
lr = 0.00001
lambda = 1e3
train_and_test_loop(1, lr, lambda)
```

Crank it way up regularization

```
Out[12]:  12.582525307612
```

Print Loss

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

```
tr_x = tr_x[{{1,20},{},{},{}}]
te_x = tr_x[{{1,20},{},{},{}}]
tr_y = tr_y[{{1,20}}]
print(tr_x:size())
print(tr_y:size())
```

Out[14]:
```
 20
  3
 32
 32
[torch.LongStorage of size 4]

 20
[torch.LongStorage of size 1]
```

```
-- run it
lr = 0.0001
lambda = 0
train_and_test_loop(100000, lr, lambda)
```

The above code:

- take the first 20 examples from CIFAR-10
- turn off regularization (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 100, nice!

```
-- run it
lr = 0.0001
lambda = 0
train_and_test_loop(100000, lr, lambda)
```

```
Out[54]: iter: 0, accuracy: 100%  Loss: 0.023342480719671
          -- best accuracy achieved: 20%
Out[54]: iter: 500, accuracy: 20%  Loss: 6.4891701533306
          -- best accuracy achieved: 100%
Out[54]: iter: 1000, accuracy: 100%  Loss: 3.363490690347
Out[54]: iter: 1500, accuracy: 100%  Loss: 2.3995975677242
Out[54]: iter: 2000, accuracy: 100%  Loss: 1.8909617506362
Out[54]: iter: 2500, accuracy: 100%  Loss: 1.5617572159784
Out[54]: iter: 3000, accuracy: 100%  Loss: 1.3375534142717
Out[54]: iter: 3500, accuracy: 100%  Loss: 1.1668484200641
Out[54]: iter: 4000, accuracy: 100%  Loss: 1.0398030826978
  Out[54]: iter: 98000, accuracy: 100%  Loss: 0.075056174474324
  Out[54]: iter: 98500, accuracy: 100%  Loss: 0.074695131101785
  Out[54]: iter: 99000, accuracy: 100%  Loss: 0.074675841566382
  Out[54]: iter: 99500, accuracy: 100%  Loss: 0.074908872365756
  Out[54]: iter: 100000, accuracy: 100%  Loss: 0.074439254969025
```

Lets try to train now…

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

```
-- run it
lr = 1e-7
lambda = 1e-7
train_and_test_loop(10000, lr, lambda)
```

Lets try to train now…

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

```
-- run it
lr = 1e-7
lambda = 1e-7
train_and_test_loop(10000, lr, lambda)
```

```
Out[18]: iter: 0, accuracy: 10%  Loss: 0.023248429529449
          -- best accuracy achieved: 10%

Out[18]: iter: 500, accuracy: 10%  Loss: 11.522416713458

Out[18]: iter: 1000, accuracy: 10%  Loss: 11.517536122735

Out[18]: iter: 1500, accuracy: 11%  Loss: 11.508510566527
          -- best accuracy achieved  11%

Out[18]: iter: 2000, accuracy: 13%  Loss: 11.510842908524
          -- best accuracy achieved  13%

Out[18]: iter: 2500, accuracy: 13%  Loss: 11.501224886344

Out[18]: iter: 3000, accuracy: 14%  Loss: 11.49398984774
          -- best accuracy achieved  14%

Out[18]: iter: 3500, accuracy: 16%  Loss: 11.487628759524
          -- best accuracy achieved  16%

Out[18]: iter: 4000, accuracy: 17%  Loss: 11.492140238992
          -- best accuracy achieved: 17%
```

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

```
-- run it
lr = 1e-7
lambda = 1e-7
train_and_test_loop(10000, lr, lambda)
```

```
Out[18]: iter: 0, accuracy: 10%  Loss: 0.023248429529449
          -- best accuracy achieved: 10%

Out[18]: iter: 500, accuracy: 10%  Loss: 11.522416713458

Out[18]: iter: 1000, accuracy: 10%  Loss: 11.517536122735

Out[18]: iter: 1500, accuracy: 11%  Loss: 11.508510566527
          -- best accuracy achieved  11%

Out[18]: iter: 2000, accuracy: 13%  Loss: 11.510842908524
          -- best accuracy achieved  13%

Out[18]: iter: 2500, accuracy: 13%  Loss: 11.501224886344

Out[18]: iter: 3000, accuracy: 14%  Loss: 11.49398984774
          -- best accuracy achieved  14%

Out[18]: iter: 3500, accuracy: 16%  Loss: 11.487628759524
          -- best accuracy achieved  16%

Out[18]: iter: 4000, accuracy: 17%  Loss: 11.492140238992
          -- best accuracy achieved: 17%
```

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

```
-- run it
lr = 1e-7
lambda = 1e-7
train_and_test_loop(10000, lr, lambda)
```

```
Out[18]: iter: 0, accuracy: 10%  Loss: 0.023248429529449
          -- best accuracy achieved: 10%

Out[18]: iter: 500, accuracy: 10%  Loss: 11.522416713458

Out[18]: iter: 1000, accuracy: 10%  Loss: 11.517536122735

Out[18]: iter: 1500, accuracy: 11%  Loss: 11.508510566527
          -- best accuracy achieved  11%

Out[18]: iter: 2000, accuracy: 13%  Loss: 11.510842908524
          -- best accuracy achieved  13%

Out[18]: iter: 2500, accuracy: 13%  Loss: 11.501224886344

Out[18]: iter: 3000, accuracy: 14%  Loss: 11.49398984774
          -- best accuracy achieved  14%

Out[18]: iter: 3500, accuracy: 16%  Loss: 11.487628759524
          -- best accuracy achieved  16%

Out[18]: iter: 4000, accuracy: 17%  Loss: 11.492140238992
          -- best accuracy achieved: 17%
```

Notice train/val accuracy goes to 17% though, what's up with that? (remember this is softmax)

Loss barely changing: Learning rate is probably too low

Lets try to train now…

```
-- run it
lr = 1e6
lambda = 1e-7
train_and_test_loop(10000, lr, lambda)
```

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

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.

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

```
-- run it
lr = 1e6
lambda = 1e-7
train_and_test_loop(10000, lr, lambda)
```

```
Out[19]: iter: 0, accuracy: 11%  Loss: 0.023115084740835
          -- best accuracy achieved: 11%

Out[19]: iter: 500, accuracy: 13%  Loss: nan
          -- best accuracy achieved: 13%

Out[19]: iter: 1000, accuracy: 13%  Loss: nan

Out[19]: iter: 1500, accuracy: 13%  Loss: nan

Out[19]: iter: 2000, accuracy: 13%  Loss: nan
```

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.

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

```
-- run it
lr = 1e-3
lambda = 1e-7
train_and_test_loop(3000, lr, lambda)
```

```
Out[29]: iter: 0, accuracy: 20%  Loss: 0.02357119788693
          -- best accuracy achieved: 20%
Out[29]: iter: 500, accuracy: 13%  Loss: nan
Out[29]: iter: 1000, accuracy: 13%  Loss: nan
Out[29]: iter: 1500, accuracy: 13%  Loss: nan
Out[29]: iter: 2000, accuracy: 13%  Loss: nan
Out[29]: iter: 2500, accuracy: 13%  Loss: nan
Out[29]: iter: 3000, accuracy: 13%  Loss: nan
```

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

=> Rough range for learning rate we should be cross-validating is somewhere [1e-3 … 1e-7]

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 * original cost, break out early

For example: run coarse search for 2000 iterations

```
for i = 1, 100 do
    init_model()
    lr = math.pow(10, torch.uniform(-7.0, -3.0))
    lambda = math.pow(10, torch.uniform(-5, 5))
    best_acc = train_and_test_loop(2000, lr, lambda)
    print(string.format("Try %d/%d Best val accuracy: %d, lr: %f, lambda: %f",i, 100, best_acc, lr, lambda))
end
```

note it's best to optimize in log space!

```
Out[10]: Try 1/100 Best val accuracy: 16, lr: 0.000045, lambda: 4996.489302
Out[10]: Try 2/100 Best val accuracy: 31, lr: 0.000003, lambda: 0.001315
Out[10]: Try 3/100 Best val accuracy: 25, lr: 0.000001, lambda: 0.000012
Out[10]: Try 4/100 Best val accuracy: 24, lr: 0.000002, lambda: 216.397129
Out[10]: Try 5/100 Best val accuracy: 26, lr: 0.000007, lambda: 0.000012
Out[10]: Try 6/100 Best val accuracy: 29, lr: 0.000009, lambda: 275.964597
Out[10]: Try 7/100 Best val accuracy: 30, lr: 0.000021, lambda: 0.000253
Out[10]: Try 8/100 Best val accuracy: 13, lr: 0.000809, lambda: 4.339235
Out[10]: Try 9/100 Best val accuracy: 26, lr: 0.000003, lambda: 0.000062
Out[10]: Try 10/100 Best val accuracy: 27, lr: 0.000095, lambda: 18.288190
Out[10]: Try 11/100 Best val accuracy: 14, lr: 0.000000, lambda: 1333.400659
Out[10]: Try 12/100 Best val accuracy: 8, lr: 0.000311, lambda: 0.000020
Out[10]: Try 13/100 Best val accuracy: 8, lr: 0.000617, lambda: 0.000050
Out[10]: Try 14/100 Best val accuracy: 34, lr: 0.000013, lambda: 0.124955
Out[10]: Try 15/100 Best val accuracy: 17, lr: 0.000013, lambda: 5262.631955
```

nice

Now run finer search...

```
for i = 1, 100 do
    init_model()
    lr = math.pow(10, torch.uniform(-7.0, -3.0))
    lambda = math.pow(10, torch.uniform(-5, 5))
    best_acc = train_and_test_loop(2000, lr, lambda)
    print(string.format("Try %d/%d Best val accuracy: %d, lr
end
```

adjust range

```
for i = 1, 100 do
    init_model()
    lr = math.pow(10, torch.uniform(-6.0, -4.0))
    lambda = math.pow(10, torch.uniform(-3, 1))
    best_acc = train_and_test_loop(2000, lr, lambda)
    print(string.format("Try %d/%d Best val accuracy: %d,
end
```

```
Out[11]: Try 1/100 Best val accuracy: 35, lr: 0.000055, lambda: 0.002026
Out[11]: Try 2/100 Best val accuracy: 28, lr: 0.000001, lambda: 1.994656
Out[11]: Try 3/100 Best val accuracy: 32, lr: 0.000003, lambda: 0.483409
Out[11]: Try 4/100 Best val accuracy: 37, lr: 0.000032, lambda: 1.981563
Out[11]: Try 5/100 Best val accuracy: 27, lr: 0.000003, lambda: 0.004578
Out[11]: Try 6/100 Best val accuracy: 28, lr: 0.000004, lambda: 0.082862
Out[11]: Try 7/100 Best val accuracy: 34, lr: 0.000020, lambda: 0.003083
Out[11]: Try 8/100 Best val accuracy: 28, lr: 0.000054, lambda: 0.064499
Out[11]: Try 9/100 Best val accuracy: 31, lr: 0.000003, lambda: 0.004361
Out[11]: Try 10/100 Best val accuracy: 32, lr: 0.000004, lambda: 0.001610
Out[11]: Try 11/100 Best val accuracy: 31, lr: 0.000006, lambda: 0.300821
```

37% - relatively good for a 1-layer neural net and only 2000 iterations

Now run finer search...

```
for i = 1, 100 do
    init_model()
    lr = math.pow(10, torch.uniform(-7.0, -3.0))
    lambda = math.pow(10, torch.uniform(-5, 5))
    best_acc = train_and_test_loop(2000, lr, lambda)
    print(string.format("Try %d/%d Best val accuracy: %d, lr
end
```

adjust range

```
for i = 1, 100 do
    init_model()
    lr = math.pow(10, torch.uniform(-6.0, -4.0))
    lambda = math.pow(10, torch.uniform(-3, 1))
    best_acc = train_and_test_loop(2000, lr, lambda)
    print(string.format("Try %d/%d Best val accuracy: %d,
end
```

```
Out[11]: Try 1/100 Best val accuracy: 35, lr: 0.000055, lambda: 0.002026
Out[11]: Try 2/100 Best val accuracy: 28, lr: 0.000001, lambda: 1.994656
Out[11]: Try 3/100 Best val accuracy: 32, lr: 0.000003, lambda: 0.483409
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Out[11]: Try 7/100 Best val accuracy: 34, lr: 0.000020, lambda: 0.003083
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Out[11]: Try 9/100 Best val accuracy: 31, lr: 0.000003, lambda: 0.004361
Out[11]: Try 10/100 Best val accuracy: 32, lr: 0.000004, lambda: 0.001610
Out[11]: Try 11/100 Best val accuracy: 31, lr: 0.000006, lambda: 0.300821
```
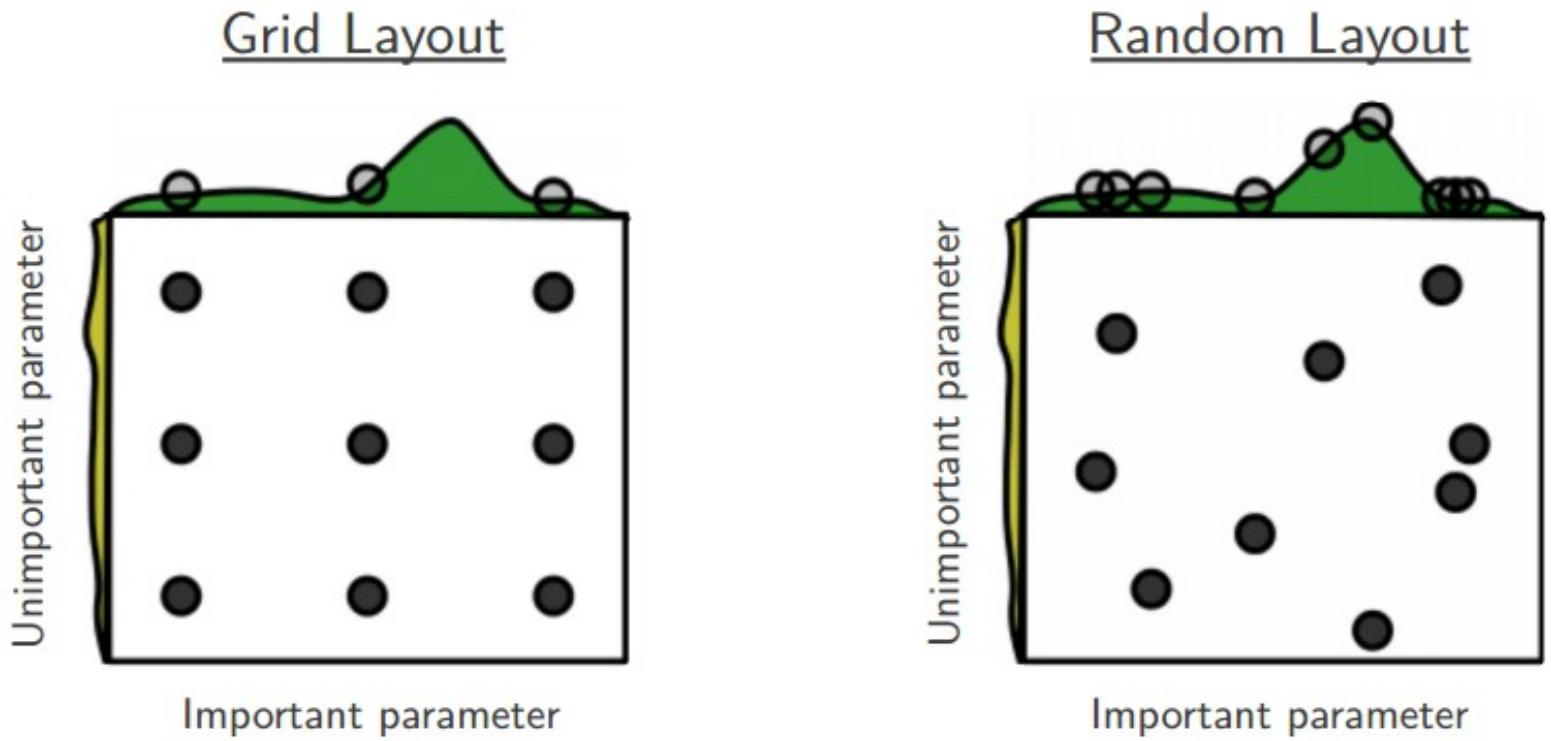

37% - relatively good for a 1-layer neural net and only 2000 iterations

Make sure the best ones are not on the boundary

Random Search vs. Grid Search



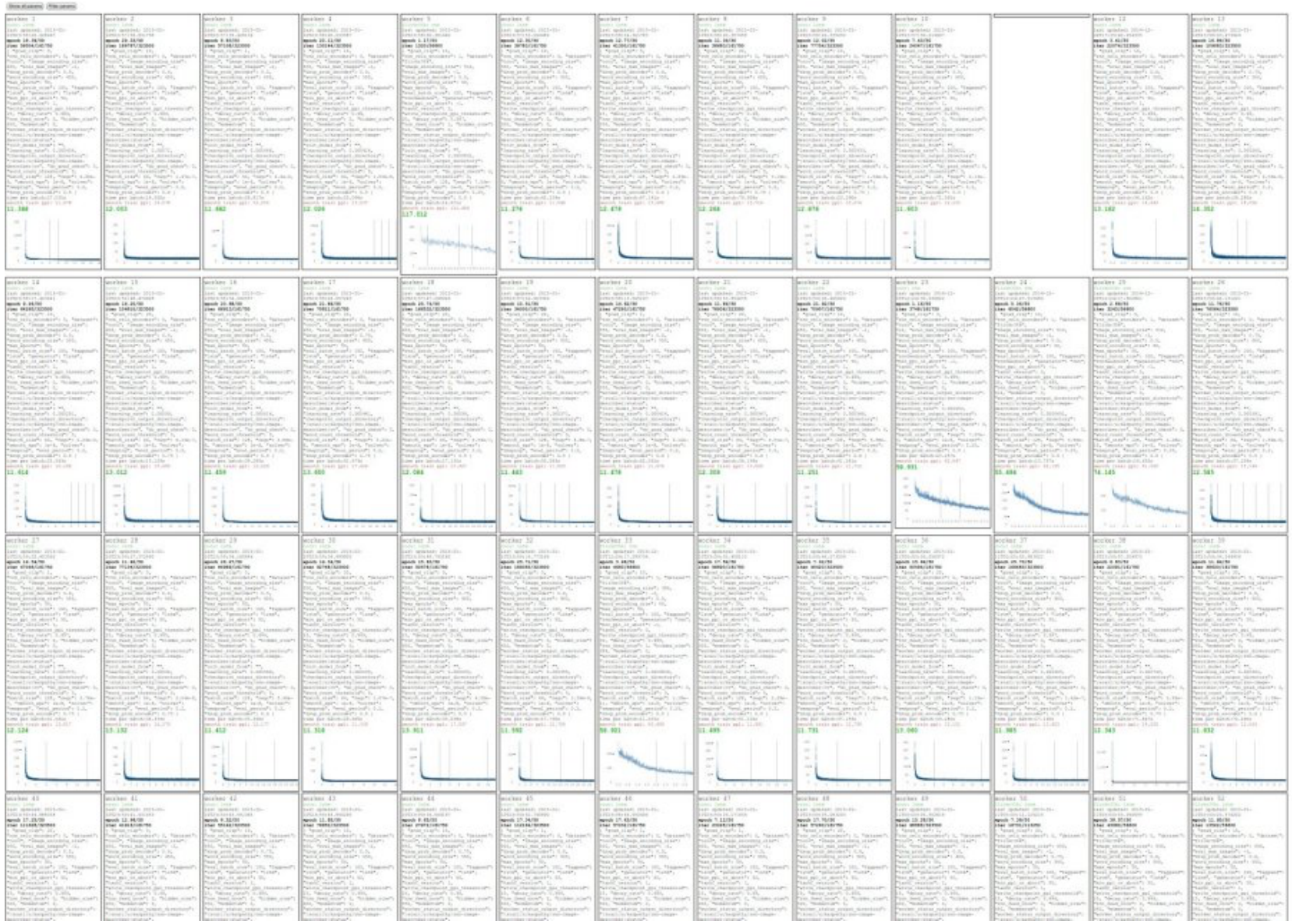
Random Search for Hyper-Parameter Optimization
Bergstra and Bengio, 2012

Hyperparameters to play with:

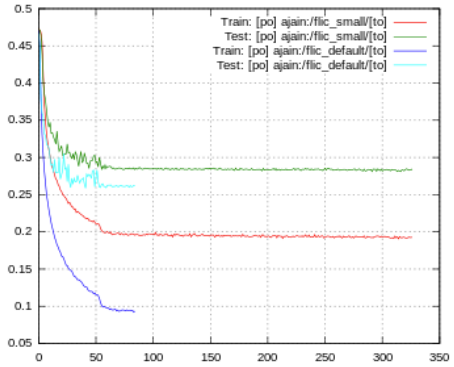
- network architecture
- learning rate, its multiplier schedule
- regularization (L2/Dropout strength)

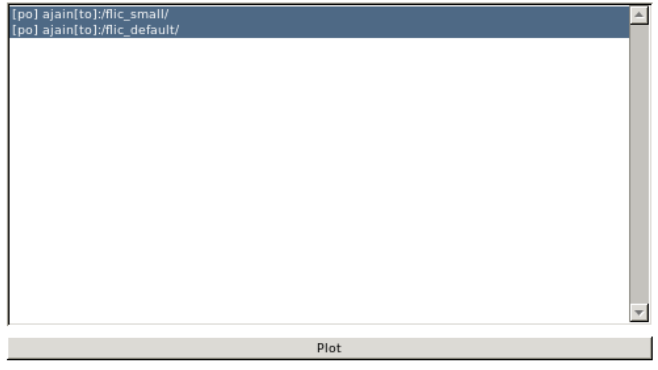
neural networks practitioner
music = loss function

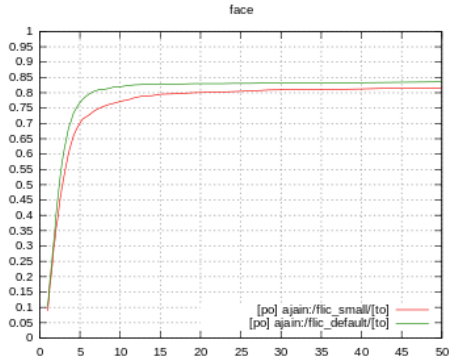
Karpathy's cross-validation "command center"

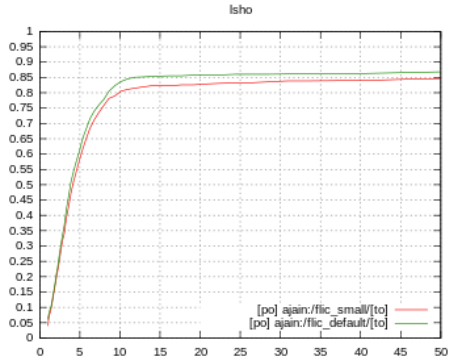


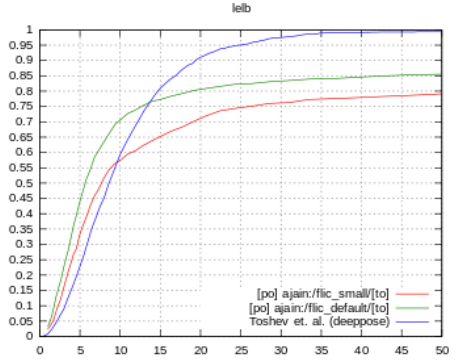
My cross-validation “command center”

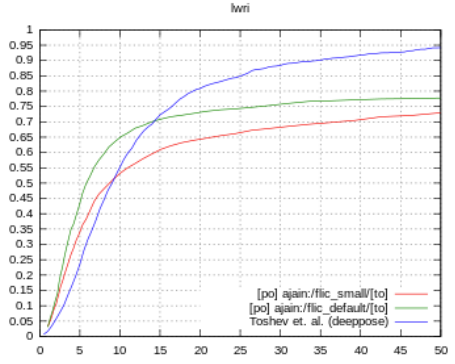












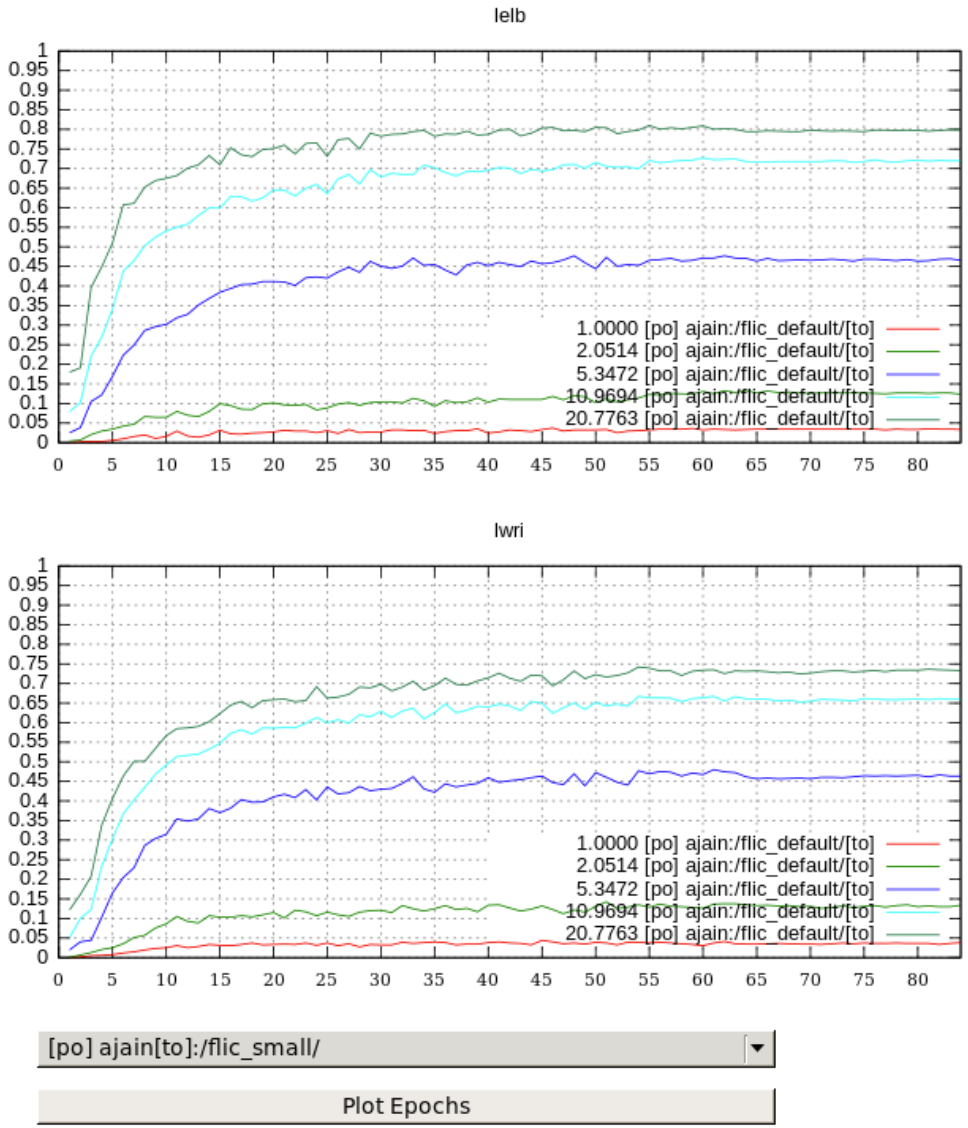
[po] ajain:/flic_small/[to]

```
2   batch_normalization = false
3   batch_size = 16
4   batch_size_per_gpu = 16
5   big_model = false
6   body_scale_range = {}
7   compress_src_model =
8   conv_1x1_size = 1
9   conv_nfeats = { 1 = { 1 = 16, 2 = 16, 3 = 16, }, 2 = { 1 = 16, 2 = 16, 3 = 16, }, 3 = { 1 = 16, 2 = 16, 3 = 16, },}
10  conv_pool = { 1 = { 1 = 2, 2 = 2, 3 = 1, }, 2 = { 1 = 2, 2 = 2, 3 = 1, }, 3 = { 1 = 2, 2 = 2, 3 = 1, },}
11  conv_size = { 1 = { 1 = 5, 2 = 5, 3 = 5, }, 2 = { 1 = 5, 2 = 5, 3 = 5, }, 3 = { 1 = 5, 2 = 5, 3 = 5, },}
12  crop_gradOutput = false
```

[po] ajain:/flic_default/[to]

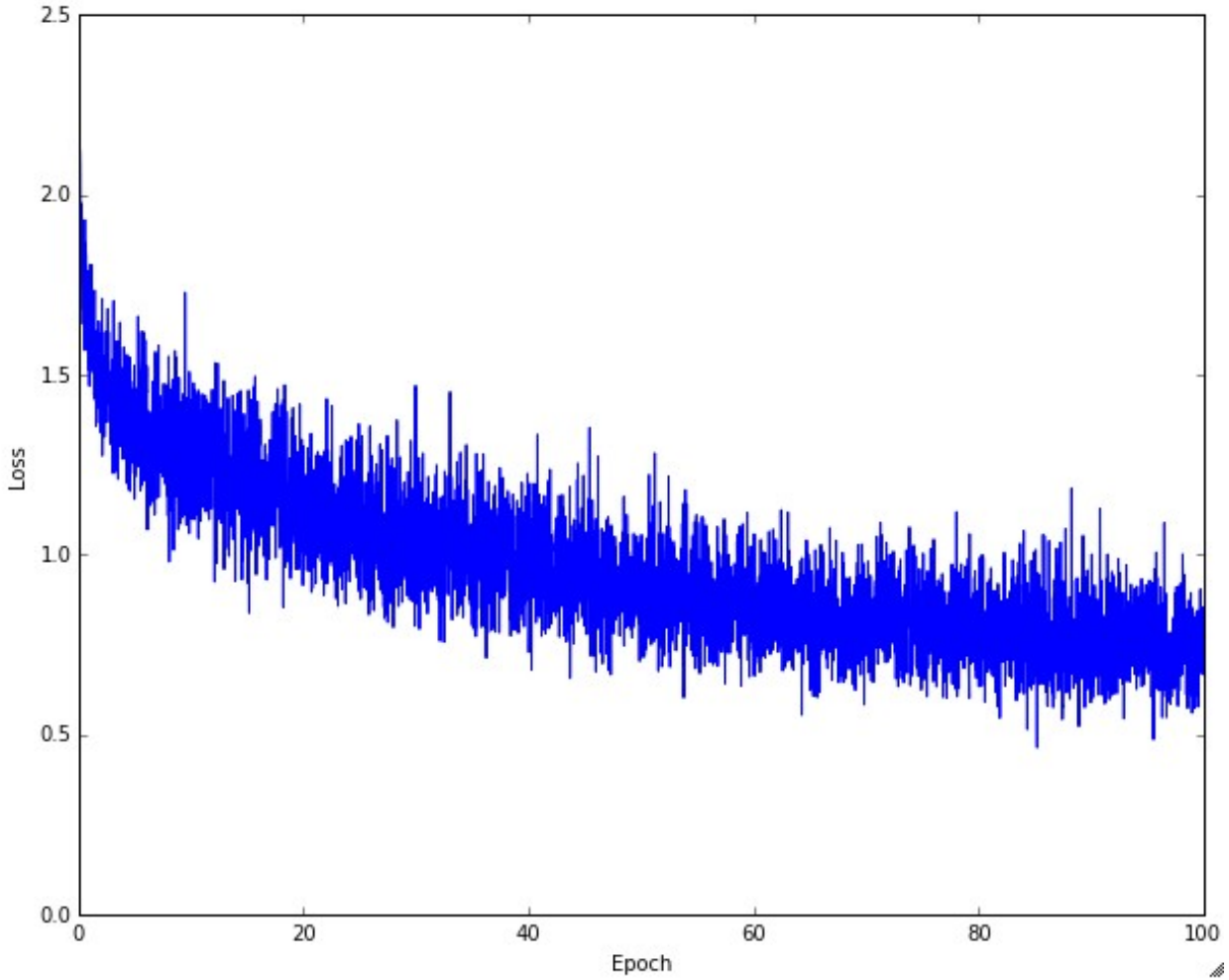
```
2   batch_normalization = false
3   batch_size = 16
4   batch_size_per_gpu = 16
5   big_model = true
6   body_scale_range = {}
7   compress_src_model =
8   conv_1x1_size = 1
9   conv_nfeats = { 1 = { 1 = 128, 2 = 128, 3 = 128, }, 2 = { 1 = 128, 2 = 128, 3 = 128, }, 3 = { 1 = 128, 2 = 128, 3 = 128, },}
10  conv_pool = { 1 = { 1 = 2, 2 = 2, 3 = 1, }, 2 = { 1 = 2, 2 = 2, 3 = 1, }, 3 = { 1 = 2, 2 = 2, 3 = 1, },}
11  conv_size = { 1 = { 1 = 5, 2 = 5, 3 = 5, }, 2 = { 1 = 5, 2 = 5, 3 = 5, }, 3 = { 1 = 5, 2 = 5, 3 = 5, },}
12  crop_gradOutput = false
```

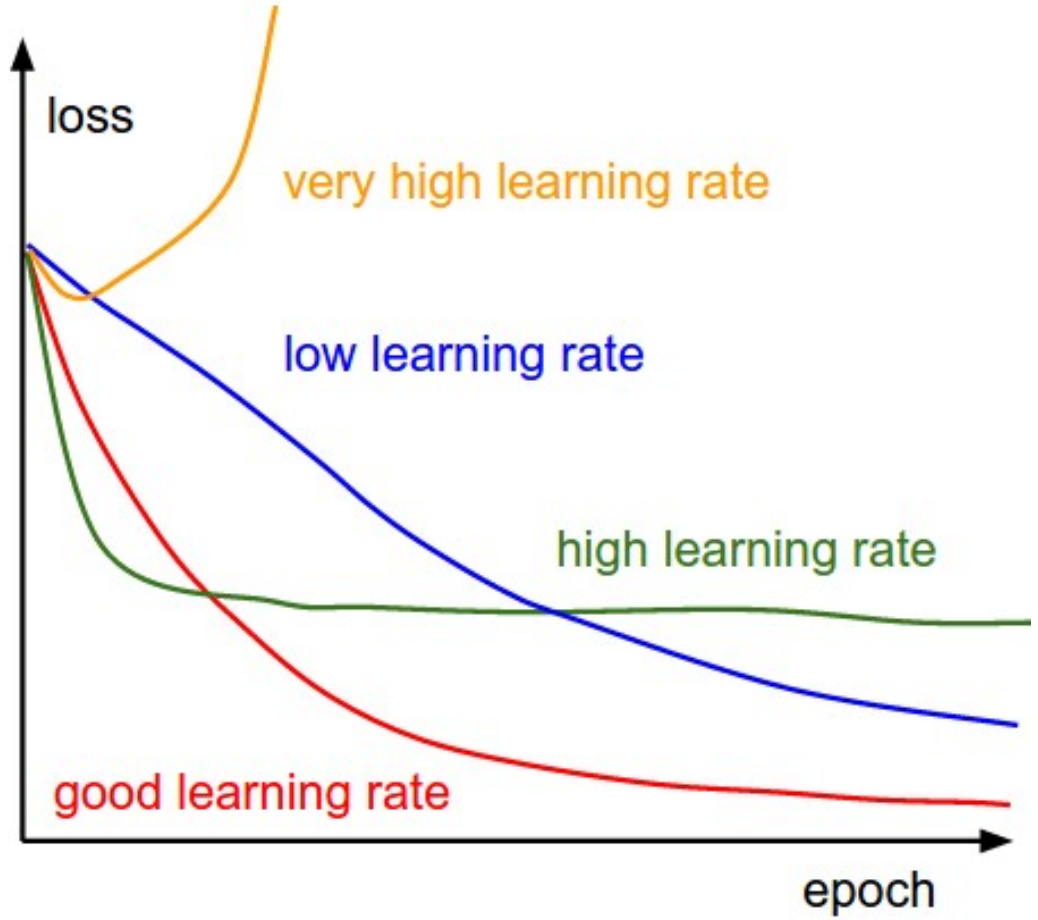
My cross-validation “command center”

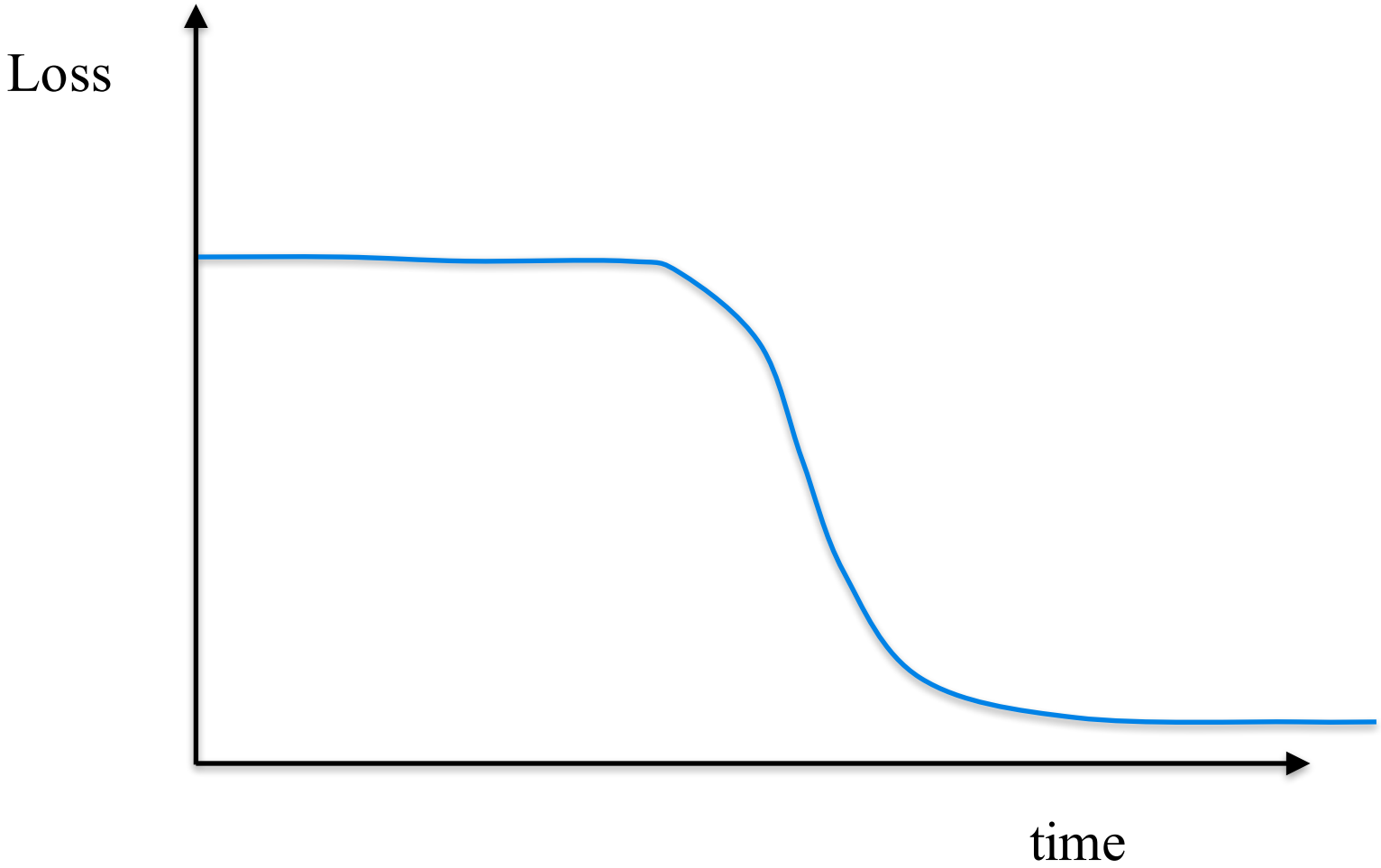


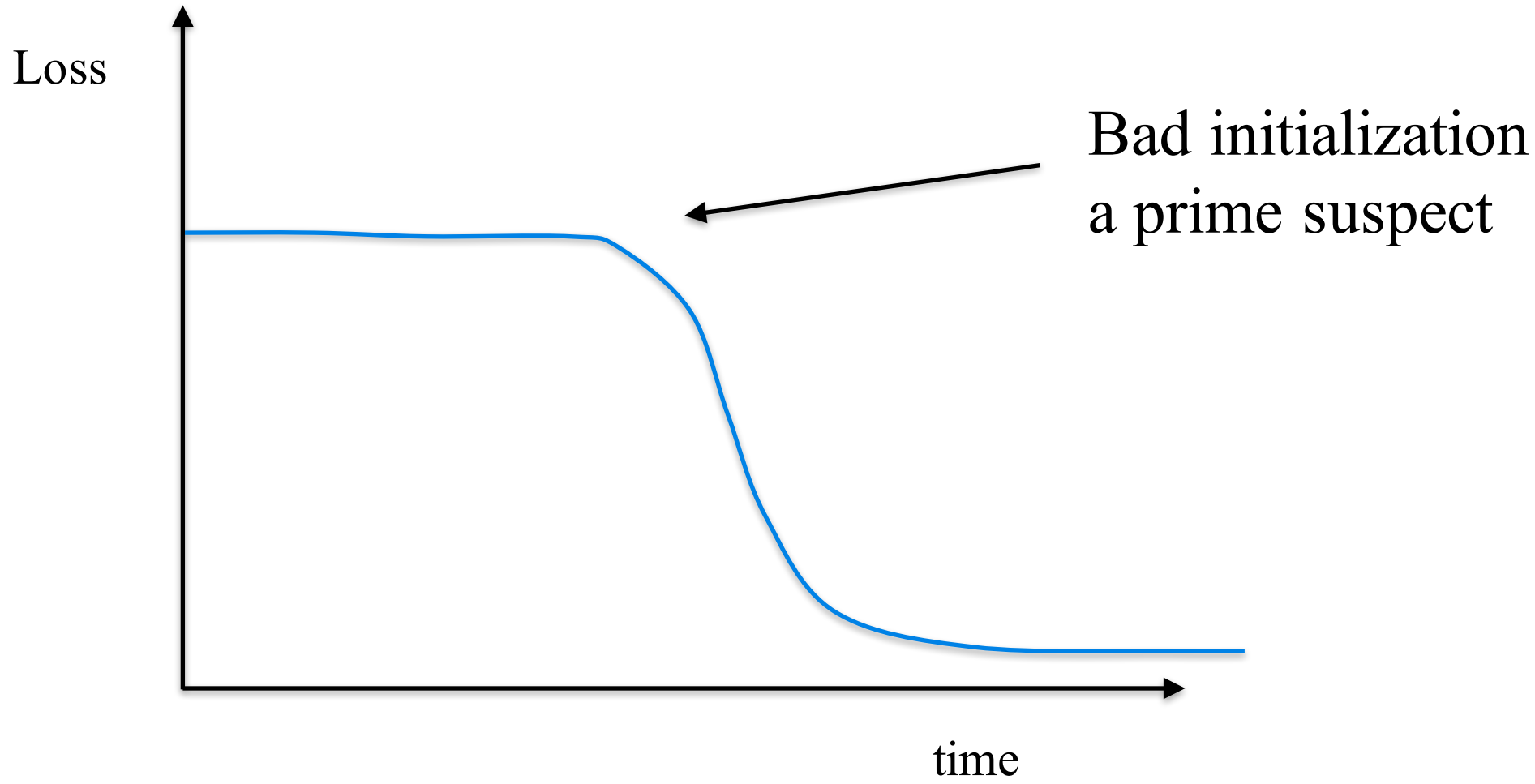
My cross-validation “command center”

Monitor and visualize the loss curve

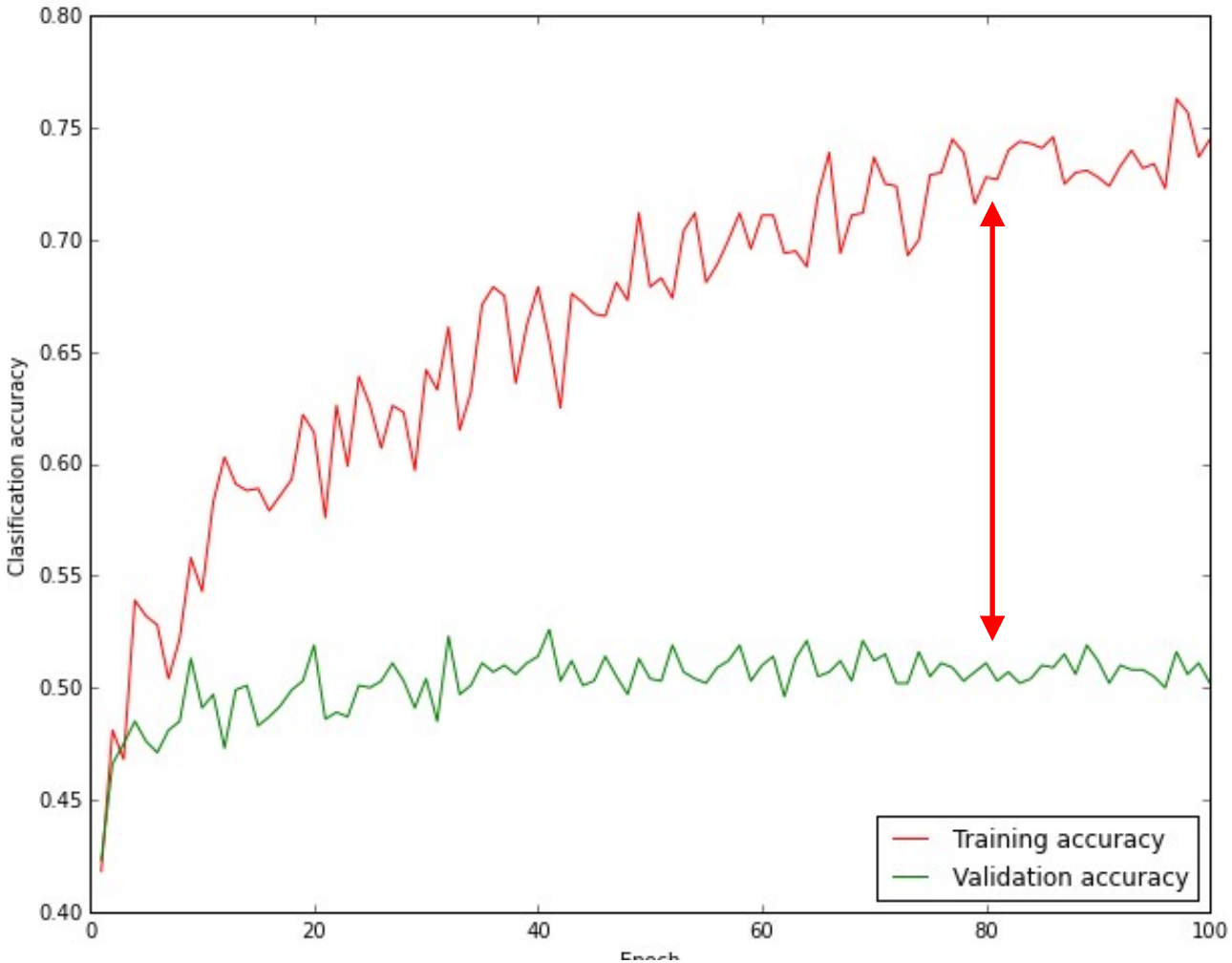





Loss
time


Loss
Bad initialization
a prime suspect
time

Monitor and visualize the accuracy:



big gap = overfitting

=> increase regularization strength?

no gap

=> increase model capacity?

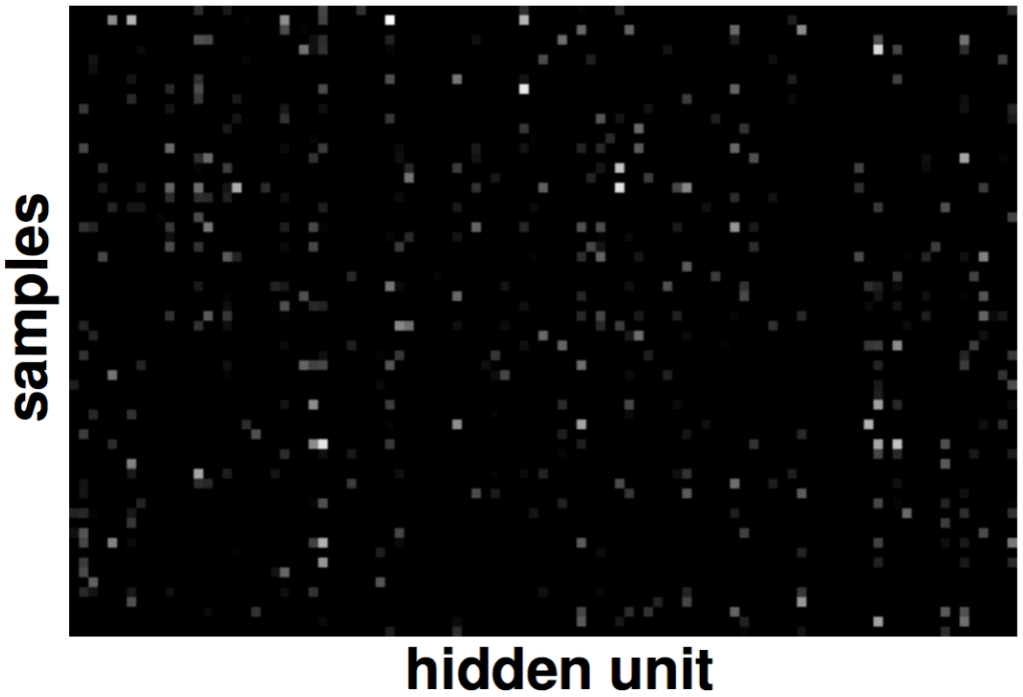
Track the ratio of weight updates / weight magnitudes:

```
function gradient_descent(model, lr)
    w_scale = torch.norm(model.W:view(model.W:nElement()), 2, 1)
    update_scale = torch.norm(lr * model.gradW:view(model.gradW:nElement()), 2, 1)
    model.W = model.W + lr * model.gradW
    model.b = model.b + lr * model.gradb
    print(update_scale/w_scale) -- Want ~1e-3
end
```

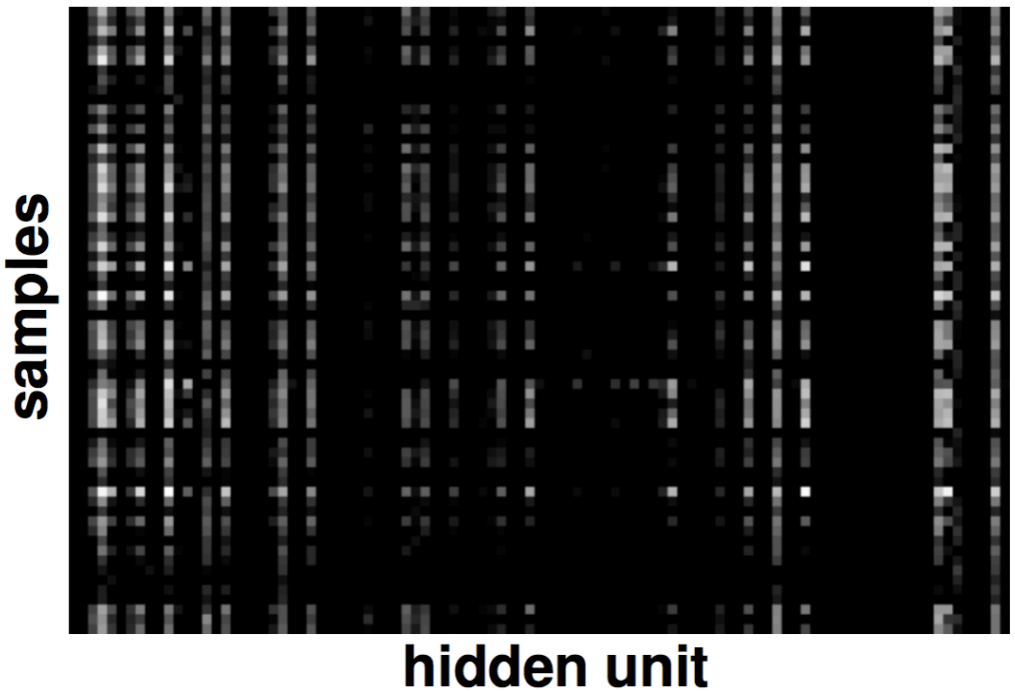
ratio between the values and updates: ~ 0.0002 / 0.02 = 0.01 (about okay)
want this to be somewhere around 0.001 or so

Visualize Activations

- Visualize features (feature maps need to be uncorrelated) and have high variance.



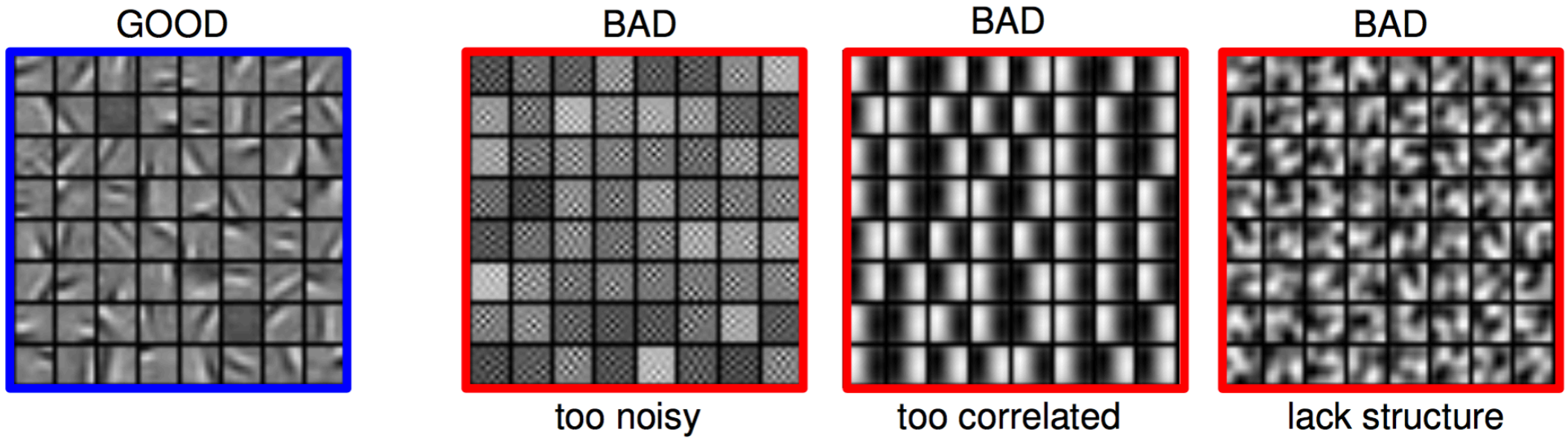
Good training: hidden units are sparse across samples and across features.



Bad training: many hidden units ignore the input and/or exhibit strong correlations.

Visualize (initial) Convolution Layer Weights

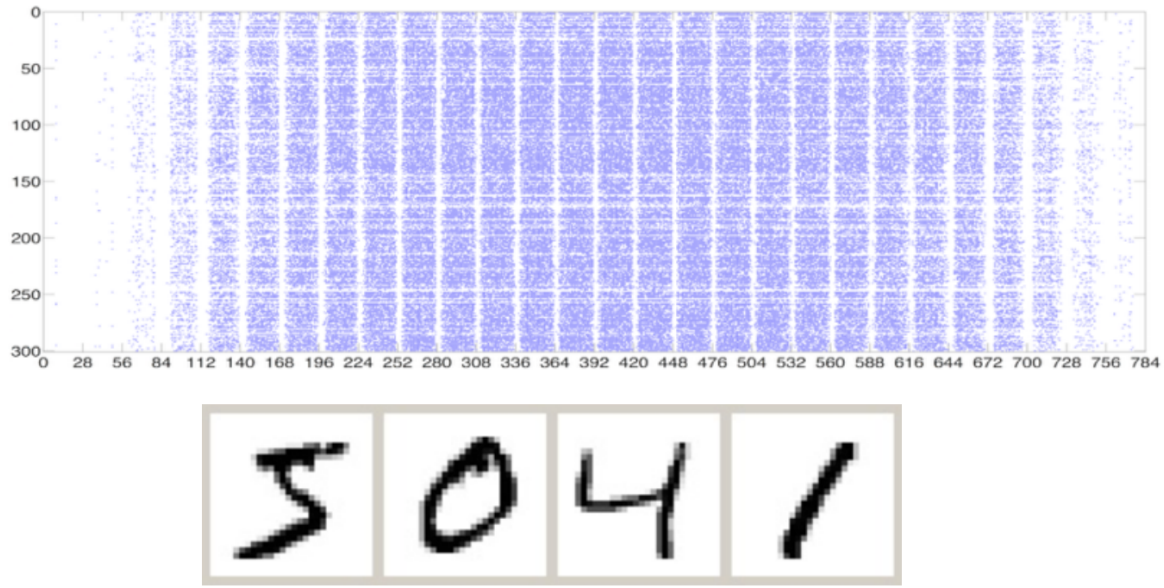
- Visualize features (feature maps need to be uncorrelated) and have high variance.



Good training: learned filters exhibit structure and are uncorrelated.

Visualize Linear Layer (Fully-Connected) Weights

- Visualization of Linear layer weights for some networks
- It has a banded structure repeated 28 times (Why?!) Hint: Images are 28x28
- Thus, looking at the weights we get some intuition



Thank you!