Lecture 6: Training Neural Networks, Part II

Tuesday February 7, 2017

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Announcements!

- Don’t worry too much if you were late on HW1
- HW2 due February 24
    - fully connected multi-layer nets, batch norm, dropout, etc.
- Email me you areas of interest for final project
    - Some ideas on class webpage
- Guidelines for paper presentations on website

Python/Numpy of the Day

- `numpy.where(<condition>, x, y)`
- Vectorized version of the ternary expression `x if condition else y`, like a vectorized list comprehension

```
In [143]: result = [(x if c else y)
   .....:           for x, y, c in zip(xarr, yarr, cond)]

In [144]: result
Out[144]: [1.1000000000000001, 2.2000000000000002, 1.3, 1.3999999999
```

- Not very fast for large arrays (because all the work is being done in pure Python)
- Will not work with multidimensional arrays.

```
In [147]: arr = randn(4, 4)

In [148]: arr
Out[148]:
array([[ 0.6372,  2.2043,  1.7904,  0.0752],
       [-1.5926, -1.1536,  0.4413,  0.3483],
       [-0.1798,  0.3299,  0.7827, -0.7585],
       [ 0.5857,  0.1619,  1.3583, -1.3865]])

In [149]: np.where(arr > 0, 2, -2)
Out[149]:
array([[ 2,  2,  2,  2],
       [-2, -2,  2,  2],
       [-2,  2,  2, -2],
       [ 2,  2,  2, -2]])

In [150]: np.where(arr > 0, 2, arr) # set only positive values to 2
Out[150]:
array([[ 2.    ,  2.    ,  2.    ,  2.    ],
       [-1.5926, -1.1536,  2.    ,  2.    ],
       [-0.1798,  2.    ,  2.    , -0.7585],
       [ 2.    ,  2.    ,  2.    , -1.3865]])
```

This is better

Pixel Recursive Super Resolution

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Google Brain

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Abstract

We present a pixel recursive super resolution model that synthesizes realistic details into images while enhancing their resolution. A low resolution image may correspond to multiple plausible high resolution images, thus modeling the super resolution process with a pixel independent conditional model often results in averaging different details–hence blurry edges. By contrast, our model is able to represent a multimodal conditional distribution by properly modeling the statistical dependencies among the high resolution image pixels, conditioned on a low resolution input. We employ a PixelCNN architecture to define a strong prior over natural images and jointly optimize this prior with a deep conditioning convolutional network. Human evaluations indicate that samples from our proposed model look more photo realistic than a strong L2 regression baseline.

1. Introduction

The problem of *super resolution* entails artificially enlarging a low resolution photograph to recover a plausible high resolution version of it. When the zoom factor is large, the input image does not contain all of the information necessary to accurately construct a high resolution image. Thus, the problem is underspecified and many plausible high resolution images exist that match the low resolution input image. This problem is significant for improving the state-of-the-art in super resolution, and more generally

Figure 1: Illustration of our probabilistic pixel recursive super resolution model trained end-to-end on a dataset of celebrity faces. The left column shows 8 × 8 low resolution inputs from the test set. The middle and last columns show 32 × 32 images as predicted by our model *vs.* the ground truth. Our model incorporates strong face priors to synthesize realistic hair and skin details.

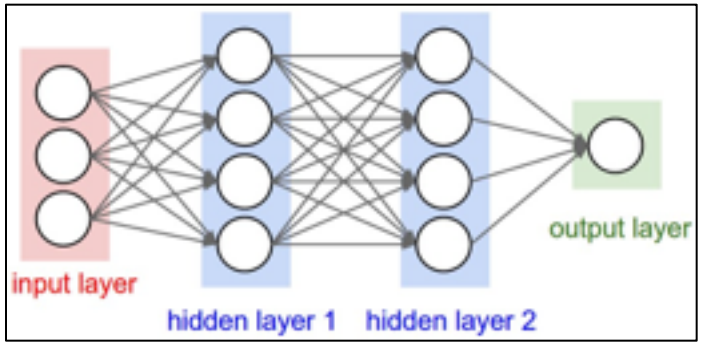
New work out on Feb 2

https://arxiv.org/pdf/1702.00783.pdf

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



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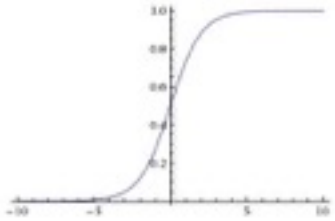
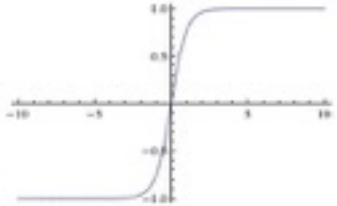
Activation Functions

Sigmoid

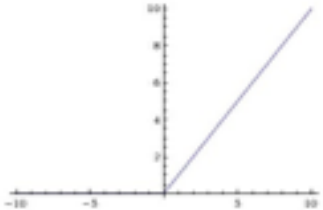
$$\sigma(x) = 1/(1+e^{-x})$$



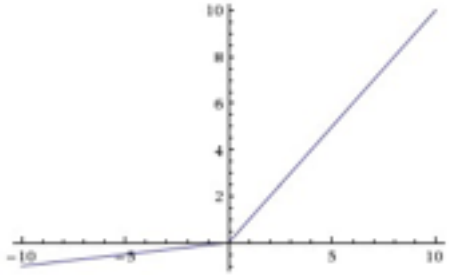
tanh tanh(x)



ReLU max(0,x)



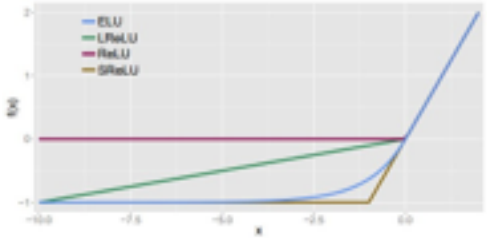
Leaky ReLU
max(0.1x, x)



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

ELU

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



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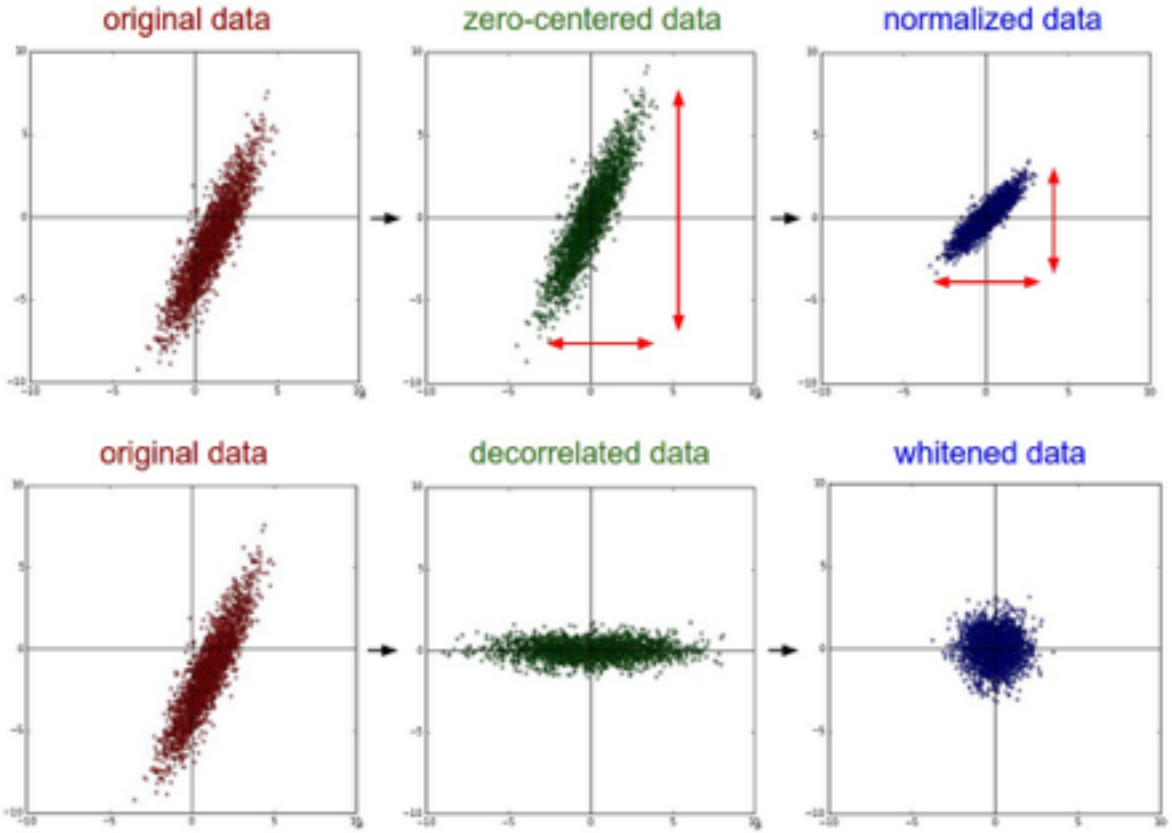
Data Preprocessing



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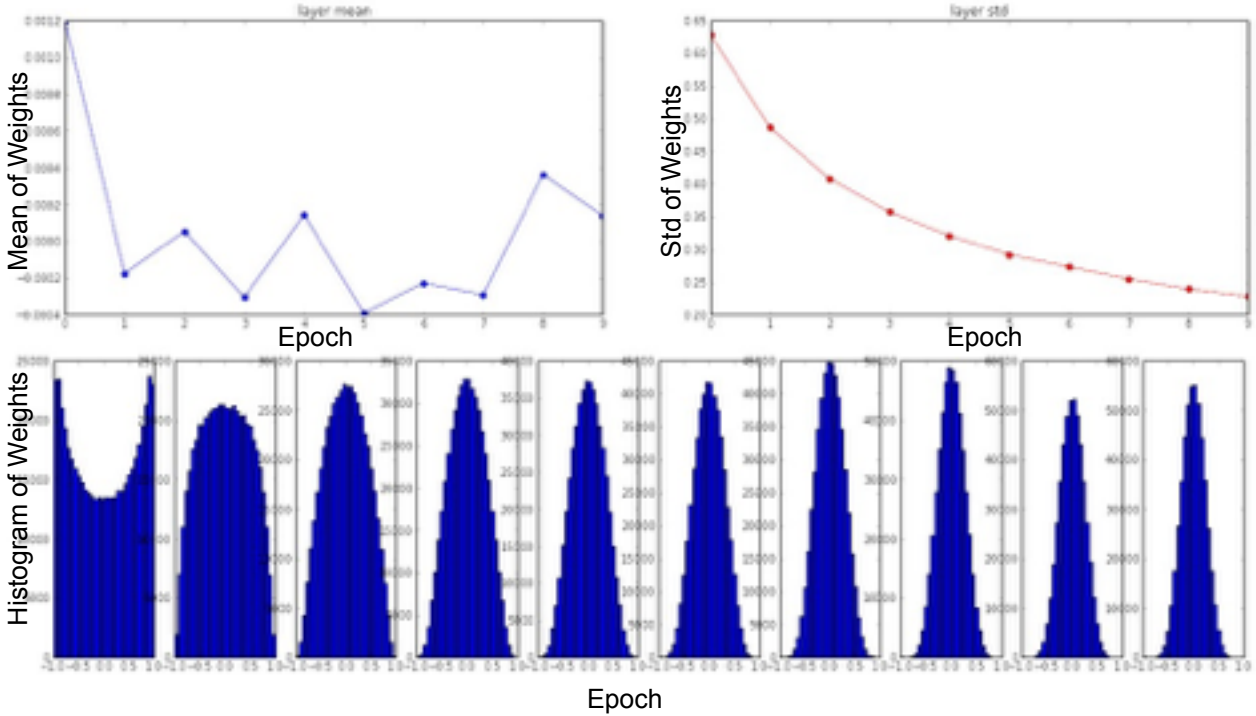
```
input layer had mean 0.001800 and std 1.001311
hidden layer 1 had mean 0.001198 and std 0.627953
hidden layer 2 had mean -0.000175 and std 0.486051
hidden layer 3 had mean 0.000055 and std 0.407723
hidden layer 4 had mean -0.000306 and std 0.357108
hidden layer 5 had mean 0.000142 and std 0.320917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

Weight Initialization

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:

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

- 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

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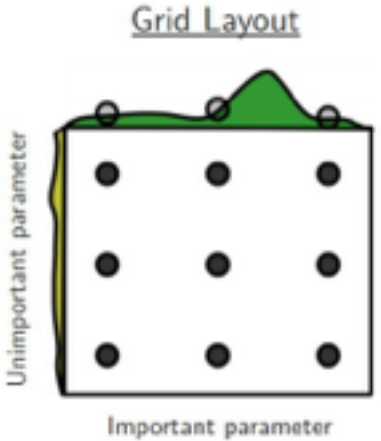
Babysitting the learning process

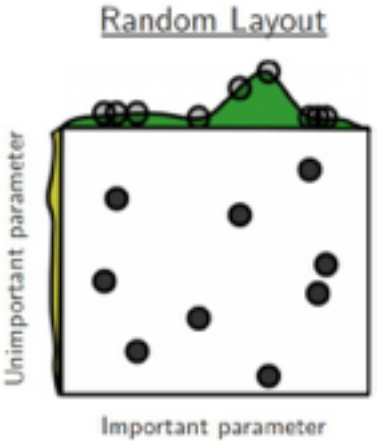
```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  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

Cross-validation





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Today:

- Parameter update schemes
- Learning rate schedules
- Dropout
- Gradient checking
- Model ensembles

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Parameter Updates

Training a neural network, main loop:

```
while True:
  data_batch = dataset.sample_data_batch()
  loss = network.forward(data_batch)
  dx = network.backward()
  x += - learning_rate * dx
```

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Training a neural network, main loop:

```
while True:
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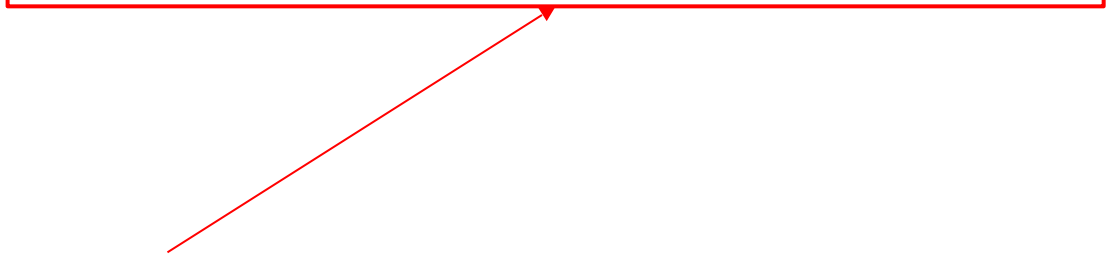

simple gradient descent update
now: complicate.

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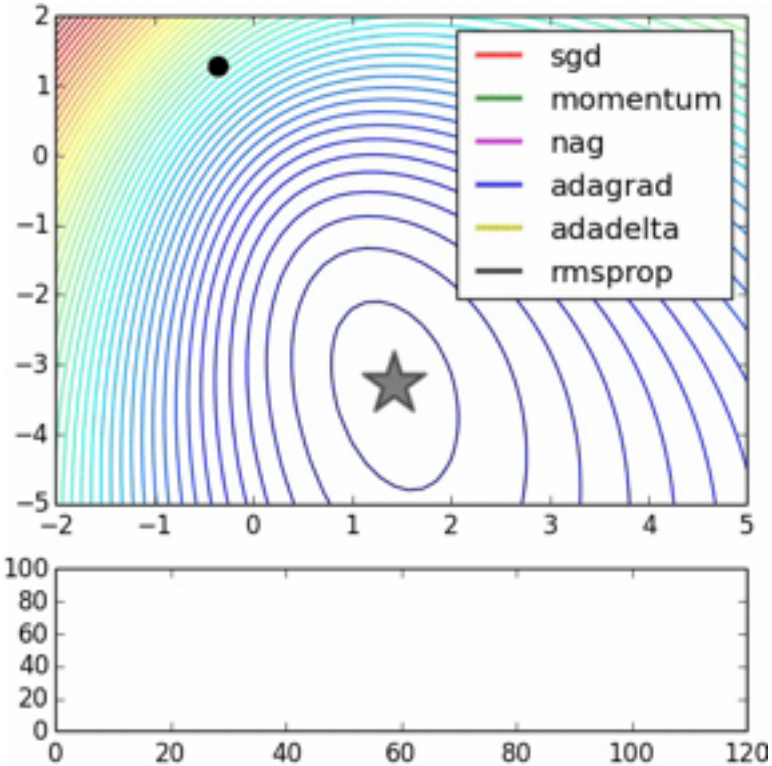

Image credits:
Alec Radford

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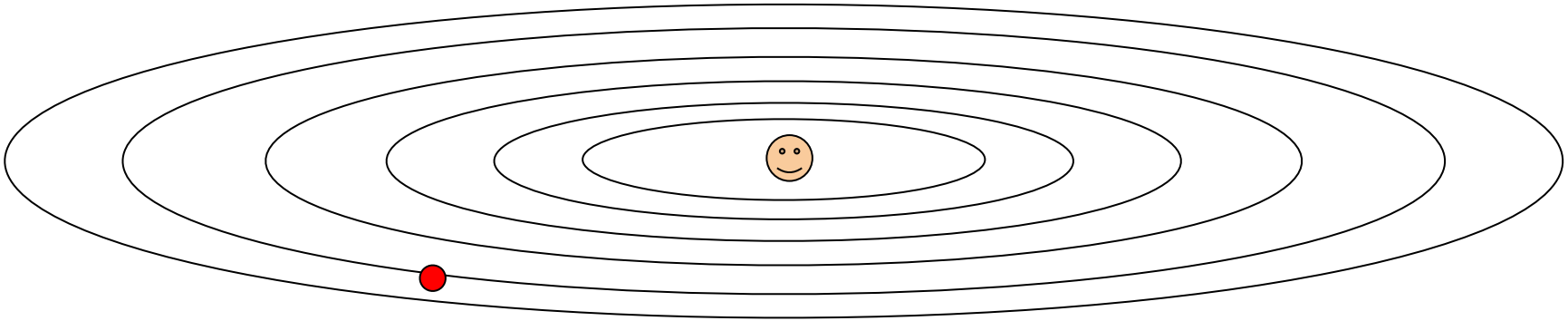
Suppose loss function is steep vertically but shallow horizontally:



Q: What is the trajectory along which we converge towards the minimum with SGD?

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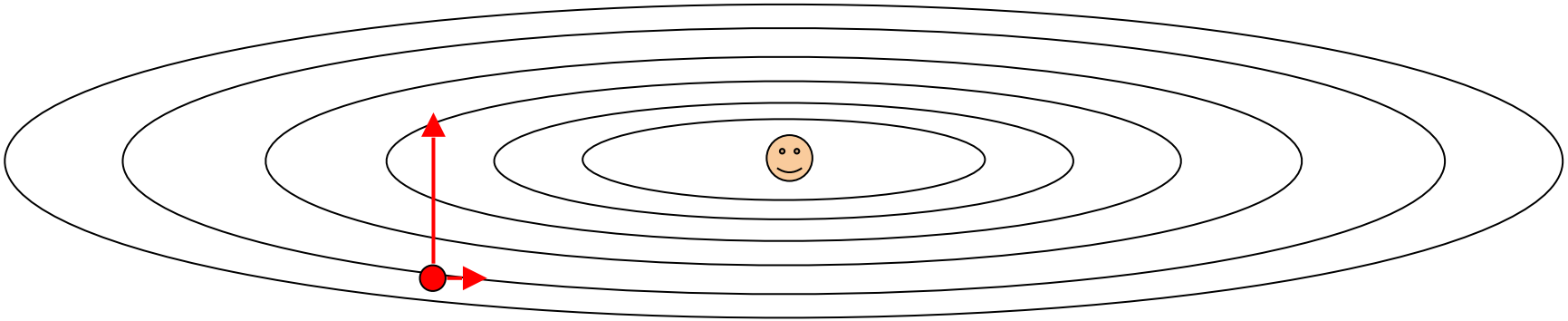
Suppose loss function is steep vertically but shallow horizontally:



Q: What is the trajectory along which we converge towards the minimum with SGD?

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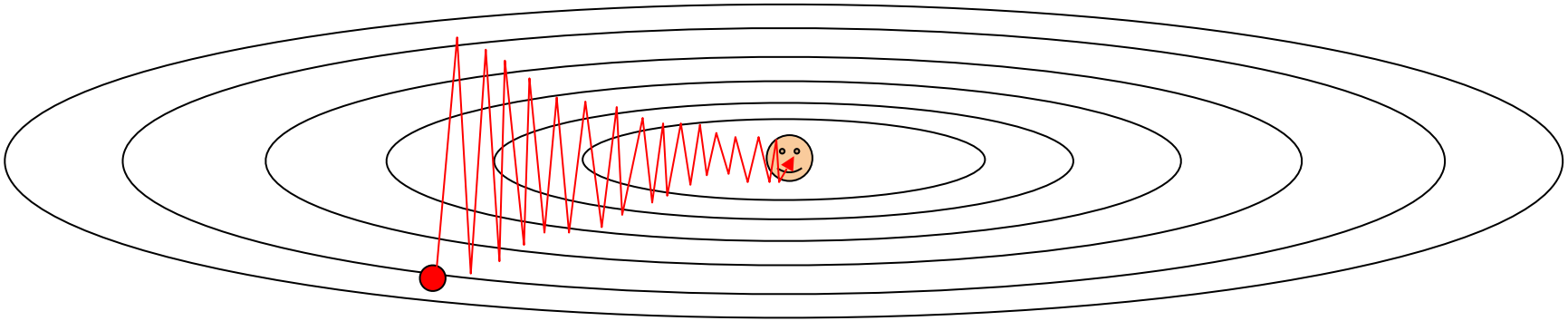
Suppose loss function is steep vertically but shallow horizontally:



Q: What is the trajectory along which we converge towards the minimum with SGD? very slow progress along flat direction, jitter along steep one

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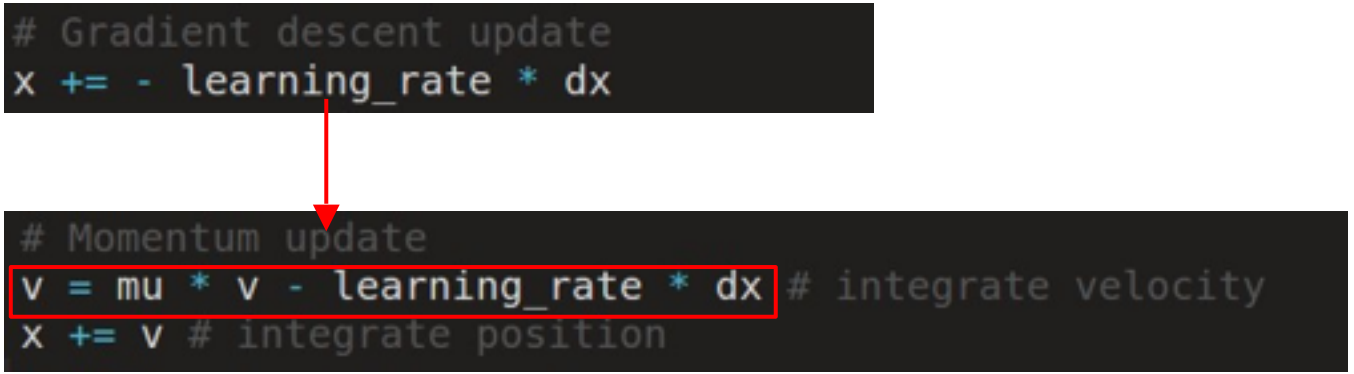
Momentum update



- Physical interpretation as ball rolling down the loss function + friction (mu coefficient).
  - mu = usually ~0.5, 0.9, or 0.99
  - (Sometimes annealed over time, e.g. from 0.5 -> 0.99)

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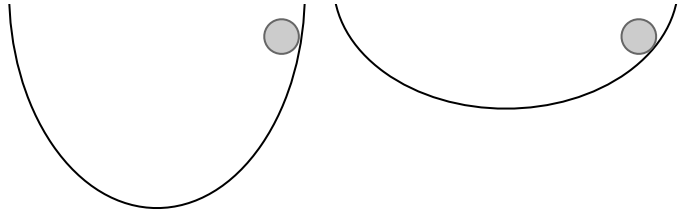
Momentum update

```
# Gradient descent update
x += - learning_rate * dx
```



```
# Momentum update
v = mu * v - learning_rate * dx # integrate velocity
x += v # integrate position
```

- Allows a velocity to “build up” along shallow directions
- Velocity becomes damped in steep direction due to quickly changing sign

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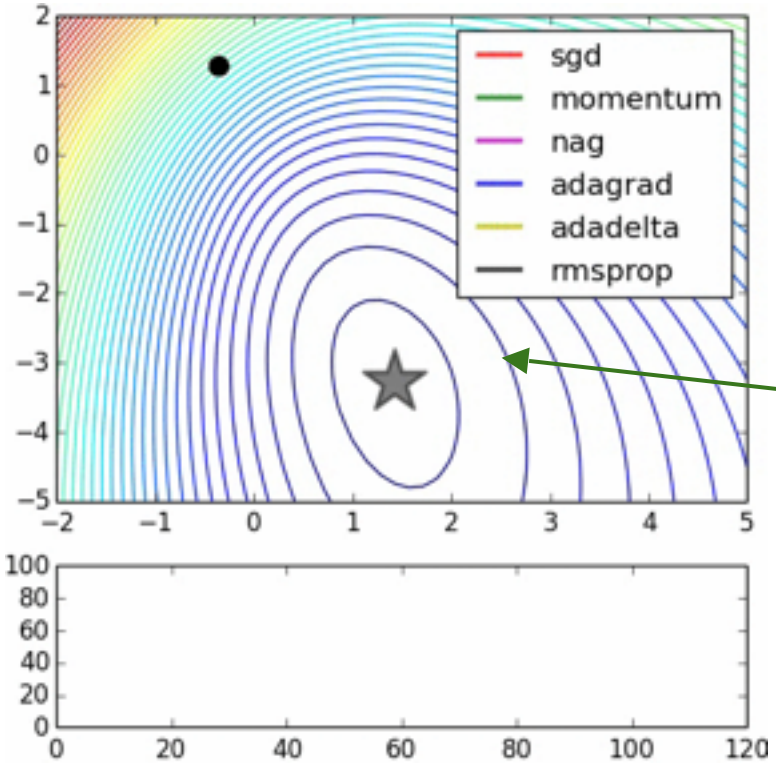
SGD

vs

Momentum



notice momentum overshooting the target, but overall getting to the minimum much faster.

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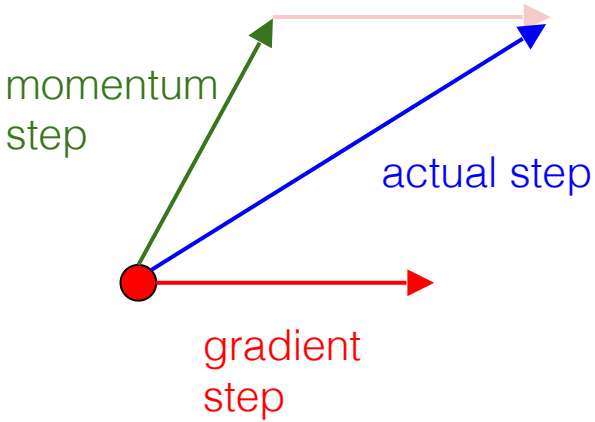
Nesterov Momentum update

```
# Momentum update
v = mu * v - learning_rate * dx # integrate velocity
x += v # integrate position
```

Ordinary momentum update:



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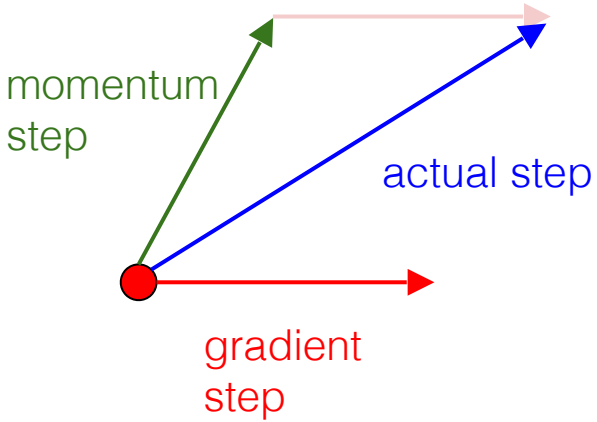
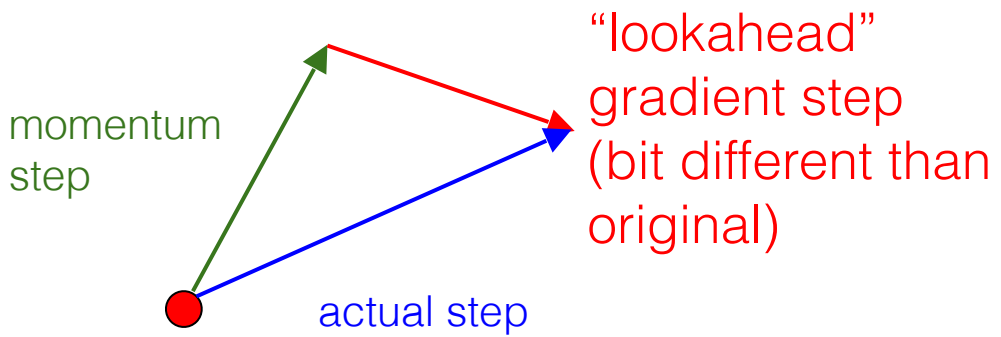
Nesterov Momentum update

Momentum update:



Nesterov momentum update



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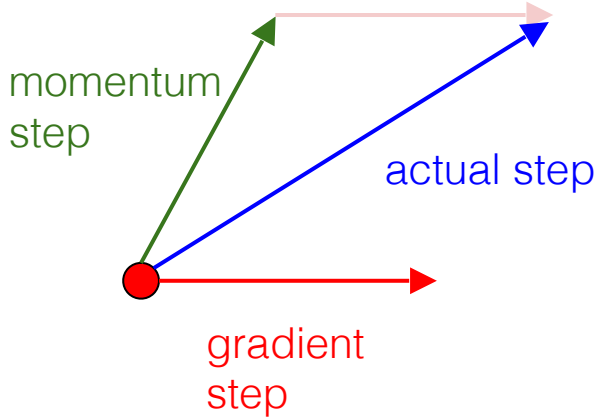
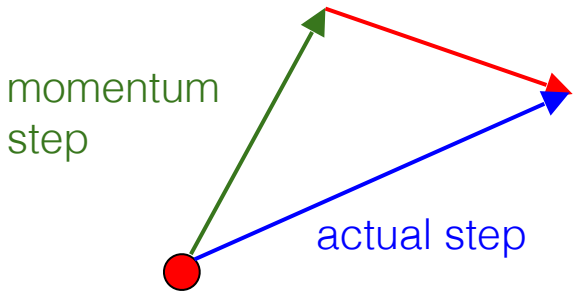
Nesterov Momentum update

Momentum update:



Nesterov momentum update



"lookahead" gradient step (bit different than original)

Nesterov: the only difference...

$$v_t = \mu v_{t-1} - \epsilon \nabla f(\theta_{t-1} + \mu v_{t-1})$$

$$\theta_t = \theta_{t-1} + v_t$$

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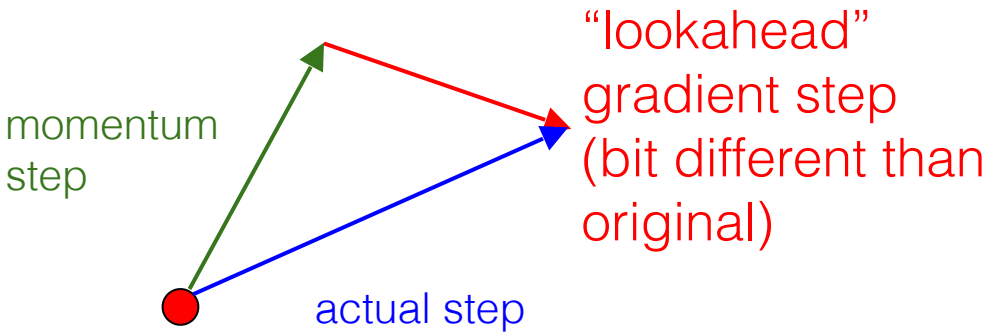
Nesterov Momentum update

```
# Nesterov momentum update rewrite
v_prev = v
v = mu * v - learning_rate * dx
x += -mu * v_prev + (1 + mu) * v
```



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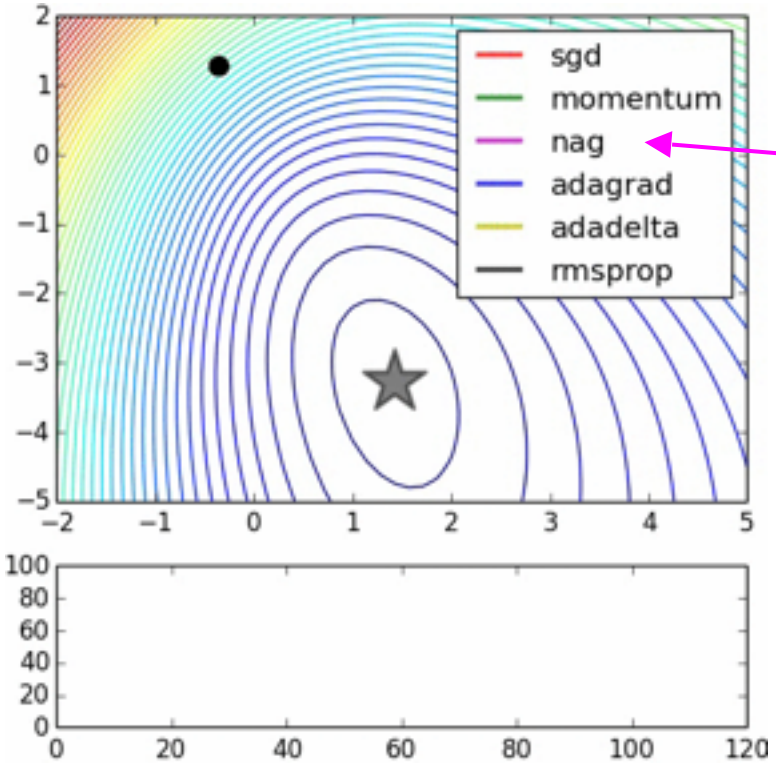
Q: What kinds of loss functions could cause problems for the momentum methods?



nag = Nesterov Accelerated Gradient

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AdaGrad update

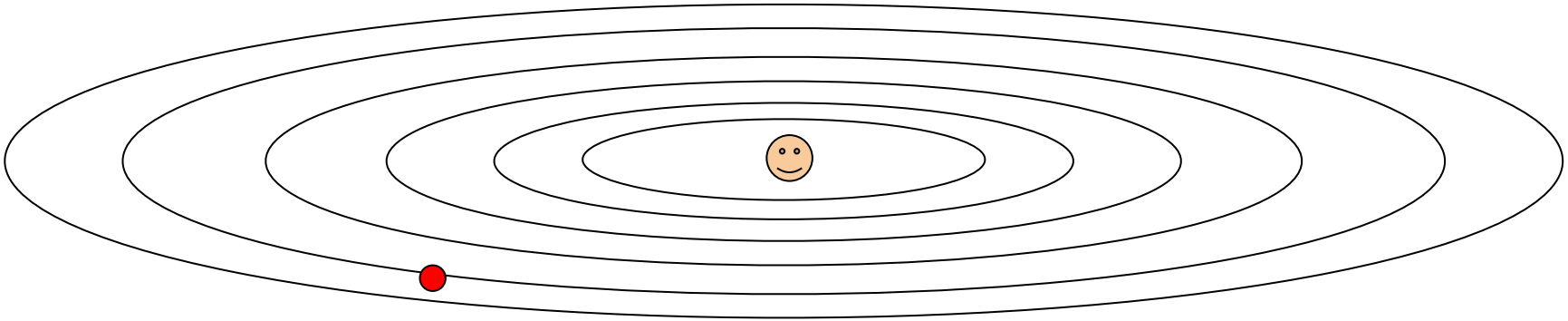
[Duchi et al., 2011]

```
# Adagrad update
cache += dx**2
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```

Added element-wise scaling of the gradient based on the historical sum of squares in each dimension

AdaGrad update

```
# Adagrad update
cache += dx**2
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```



Q: What happens with AdaGrad?

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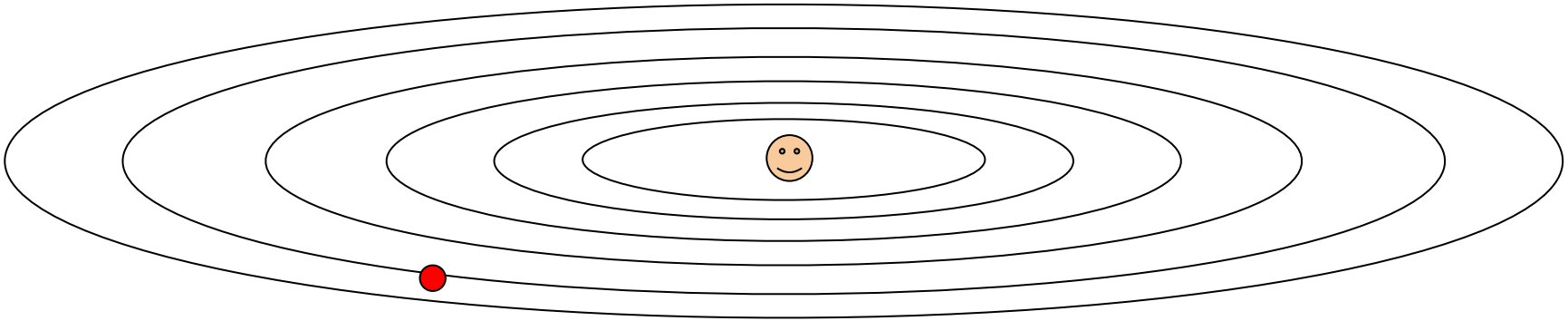
AdaGrad update

```
# Adagrad update
cache += dx**2
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```



Q2: What happens to the step size over long time?

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RMSProp update

[Tieleman and Hinton, 2012]

```
# Adagrad update
cache += dx**2
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```

```
# RMSProp
cache = decay_rate * cache + (1 - decay_rate) * dx**2
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```

rmsprop: A mini-batch version of rprop

- rprop is equivalent to using the gradient but also dividing by the size of the gradient.
  - The problem with mini-batch rprop is that we divide by a different number for each mini-batch. So why not force the number we divide by to be very similar for adjacent mini-batches?
- rmsprop: Keep a moving average of the squared gradient for each weight

$$MeanSquare(w,t) = 0.9\, MeanSquare(w,\ t-1) + 0.1\left(\partial E / \partial w(t)\right)^2$$

- Dividing the gradient by $\sqrt{MeanSquare(w,\ t)}$ makes the learning work much better (Tijmen Tieleman, unpublished).

Introduced in a slide in Geoff Hinton's Coursera class, lecture 6

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rmsprop: A mini-batch version of rprop

- rprop is equivalent to using the gradient but also dividing by the size of the gradient.
  - The problem with mini-batch rprop is that we divide by a different number for each mini-batch. So why not force the number we divide by to be very similar for adjacent mini-batches?
- rmsprop: Keep a moving average of the squared gradient for each weight

$$MeanSquare(w,t) = 0.9\, MeanSquare(w,\ t-1) + 0.1\left(\partial E / \partial w(t)\right)^2$$

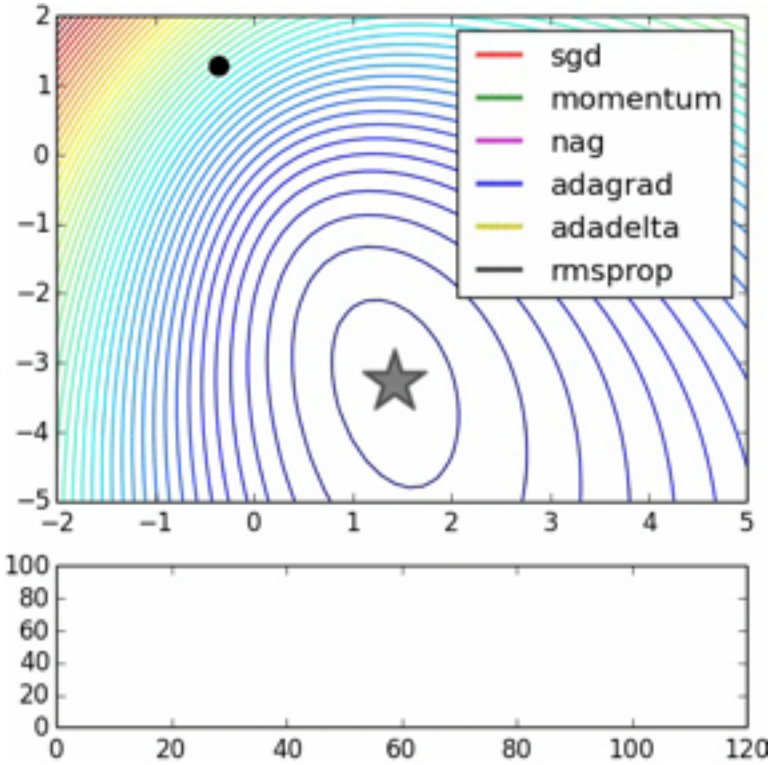
- Dividing the gradient by $\sqrt{MeanSquare(w,\ t)}$ makes the learning work much better (Tijmen Tieleman, unpublished).

Introduced in a slide in Geoff Hinton's Coursera class, lecture 6

Cited by several papers as:

[52] T. Tieleman and G. E. Hinton. Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude., 2012.

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n



adagrad
rmsprop

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Adam update

[Kingma and Ba, 2014]

(incomplete, but close)

```
# Adam
m = beta1*m + (1-beta1)*dx # update first moment
v = beta2*v + (1-beta2)*(dx**2) # update second moment
x += - learning_rate * m / (np.sqrt(v) + 1e-7)
```

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Adam update

[Kingma and Ba, 2014]

(incomplete, but close)

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```

momentum

RMSProp-like

Looks a bit like RMSProp with momentum

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Adam update

[Kingma and Ba, 2014]

(incomplete, but close)

```
# Adam
m = beta1*m + (1-beta1)*dx # update first moment
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x += - learning_rate * m / (np.sqrt(v) + 1e-7)
```

momentum

RMSProp-like

Looks a bit like RMSProp with momentum

```
# RMSProp
cache = decay_rate * cache + (1 - decay_rate) * dx**2
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Adam update

[Kingma and Ba, 2014]

```
# Adam
m,v = #... initialize caches to zeros
for t in xrange(1, big_number):
  dx = # ... evaluate gradient
  m = beta1*m + (1-beta1)*dx # update first moment
  v = beta2*v + (1-beta2)*(dx**2) # update second moment
  mb = m/(1-beta1**t) # correct bias
  vb = v/(1-beta2**t) # correct bias
  x += - learning_rate * mb / (np.sqrt(vb) + 1e-7)
```

momentum

bias correction
(only relevant in first few iterations when t is small)

RMSProp-like

The bias correction compensates for the fact that m,v are initialized at zero and need some time to “warm up”.

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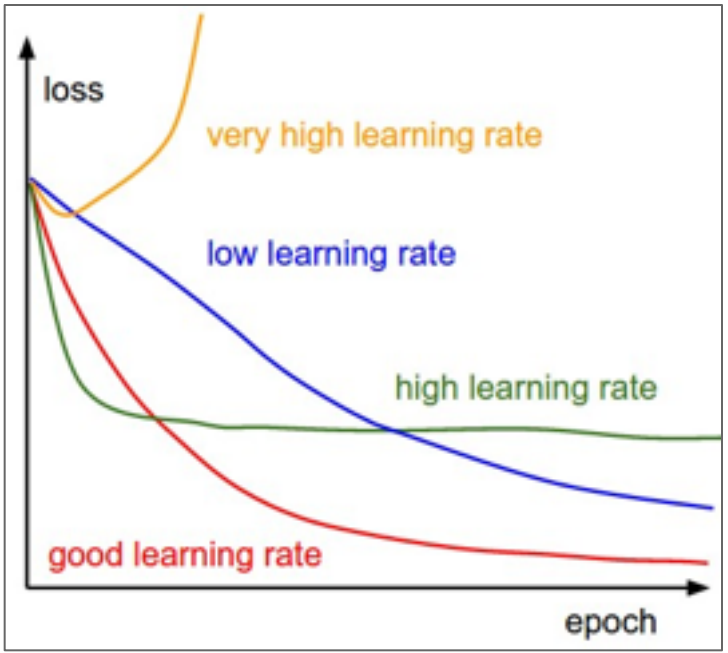
SGD, SGD+Momentum, Adagrad, RMSProp, Adam all have **learning rate** as a hyperparameter.



Q: Which one of these learning rates is best to use?

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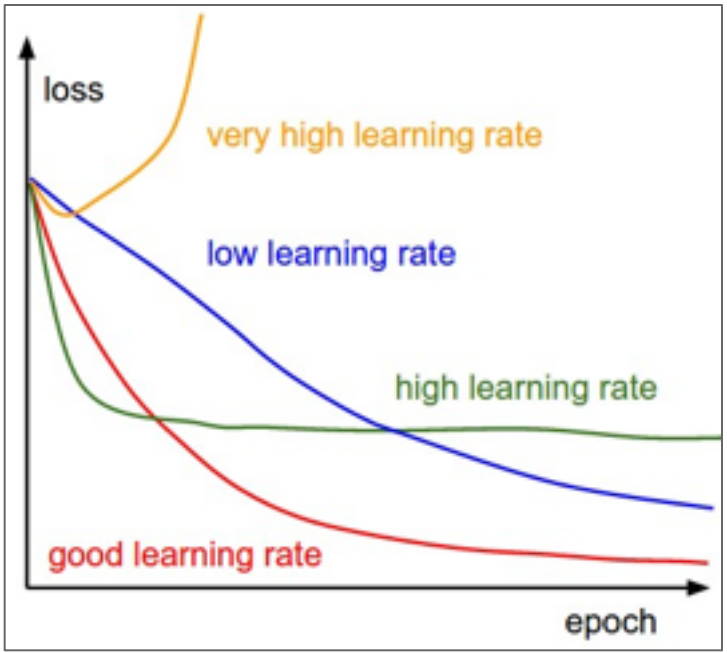
SGD, SGD+Momentum, Adagrad, RMSProp, Adam all have **learning rate** as a hyperparameter.



=> Learning rate decay over time!

step decay:
e.g. decay learning rate by half every few epochs.

exponential decay: $\alpha = \alpha_0 e^{-kt}$

1/t decay: $\alpha = \alpha_0 / (1 + kt)$

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Second order optimization methods

second-order Taylor expansion:

$$J(\boldsymbol{\theta}) \approx J(\boldsymbol{\theta}_0) + (\boldsymbol{\theta} - \boldsymbol{\theta}_0)^\top \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_0) + \frac{1}{2}(\boldsymbol{\theta} - \boldsymbol{\theta}_0)^\top \boldsymbol{H}(\boldsymbol{\theta} - \boldsymbol{\theta}_0)$$

Solving for the critical point we obtain the Newton parameter update:

$$\boldsymbol{\theta}^* = \boldsymbol{\theta}_0 - \boldsymbol{H}^{-1} \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_0)$$

notice:
no hyperparameters! (e.g. learning rate)

- Quasi-Newton methods (**BGFS** most popular):

- **L-BFGS** (Limited memory BFGS):
  Does not form/store the full inverse Hessian.

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L-BFGS

- **Usually works very well in full batch, deterministic mode** i.e. if you have a single, deterministic f(x) then L-BFGS will probably work very nicely

- **Does not transfer very well to mini-batch setting**. Gives bad results. Adapting L-BFGS to large-scale, stochastic setting is an active area of research.

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Evaluation:

Model Ensembles

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1. Train multiple independent models
2. At test time average their results

Enjoy 2% extra performance
All competition winners do this.

Fun Tips/Tricks:

- can also get a small boost from averaging multiple model checkpoints of a single model.

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Fun Tips/Tricks:

- can also get a small boost from averaging multiple model checkpoints of a single model. (different local minima)
- keep track of (and use at test time) a running average parameter vector:

```
while True:
  data_batch = dataset.sample_data_batch()
  loss = network.forward(data_batch)
  dx = network.backward()
  x += - learning_rate * dx
  x_test = 0.995*x_test + 0.005*x # use for test set
```

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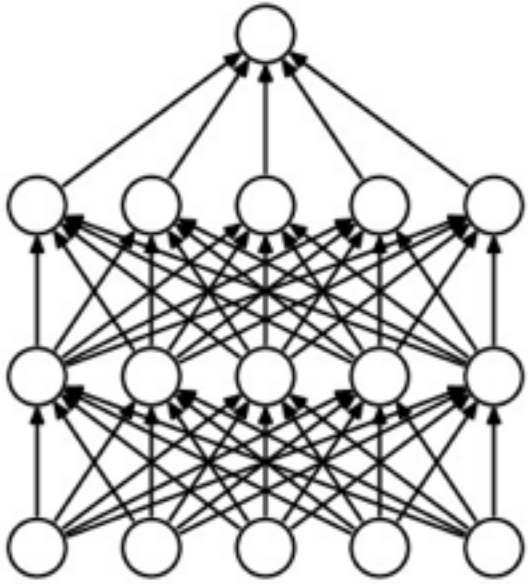
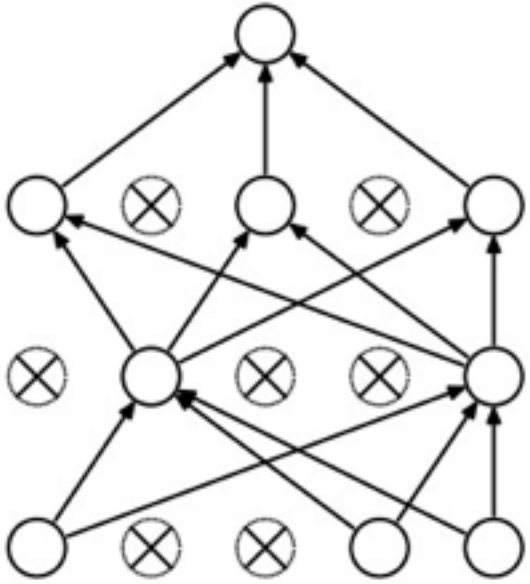
Regularization **(dropout)**

Regularization: **Dropout**

"randomly set some neurons to zero in the forward pass"



(a) Standard Neural Net



(b) After applying dropout.

[Srivastava et al., 2014]

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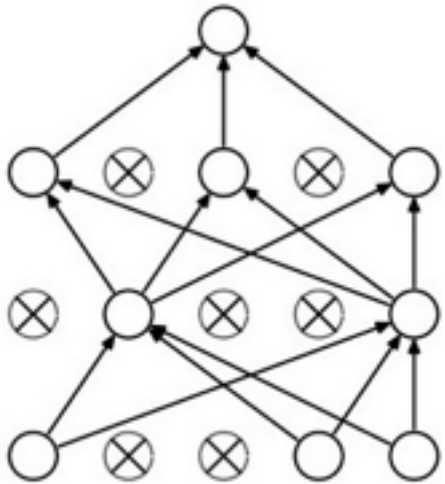
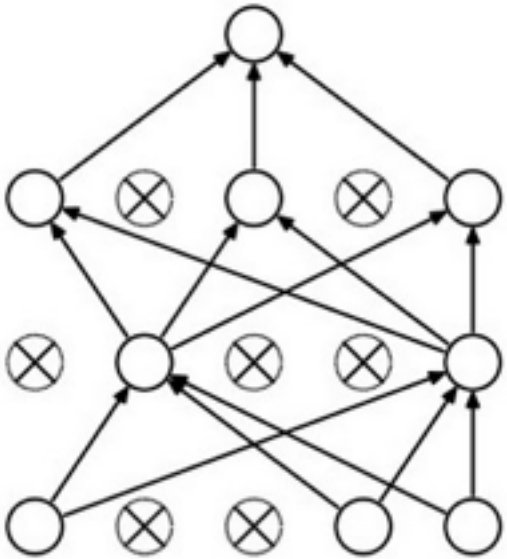
```python
p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  """ X contains the data """

  # forward pass for example 3-layer neural network
  H1 = np.maximum(0, np.dot(W1, X) + b1)
  U1 = np.random.rand(*H1.shape) < p # first dropout mask
  H1 *= U1 # drop!
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  U2 = np.random.rand(*H2.shape) < p # second dropout mask
  H2 *= U2 # drop!
  out = np.dot(W3, H2) + b3

  # backward pass: compute gradients... (not shown)
  # perform parameter update... (not shown)
```

Example forward pass with a 3-layer network using dropout



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



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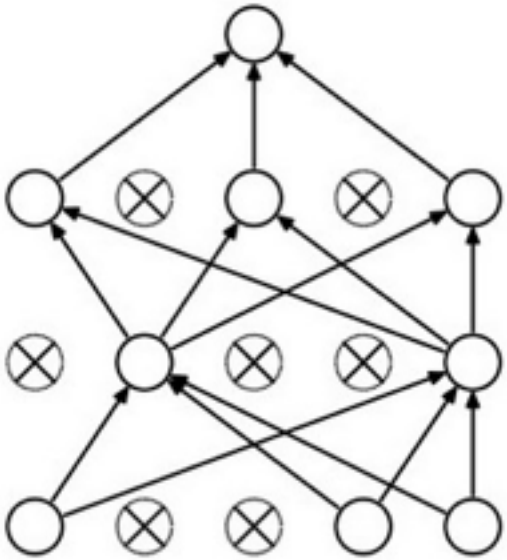

Forces the network to have a redundant representation.

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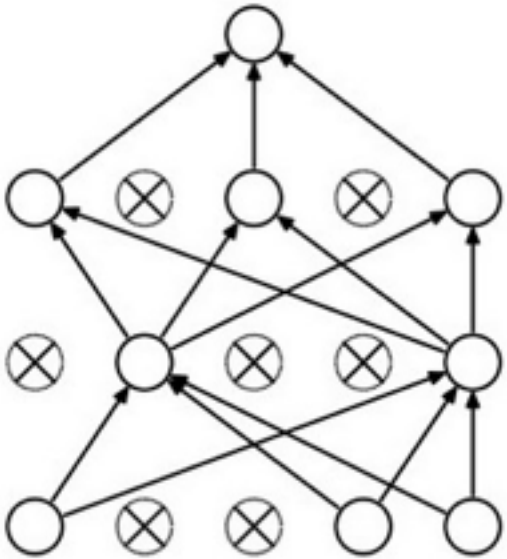
At test time….



Ideally:
want to integrate out all the noise

Monte Carlo approximation:
do many forward passes with different dropout masks, average all predictions

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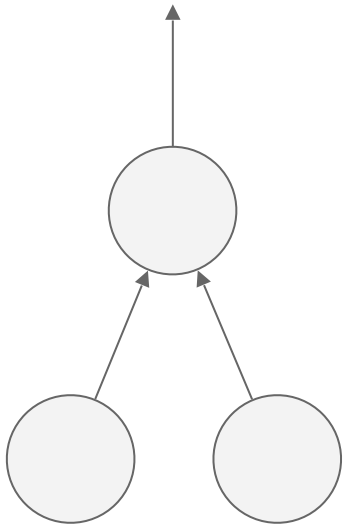
At test time….

Can in fact do this with a single forward pass! (approximately)



Leave all input neurons turned on (no dropout).

Q: Suppose that with all inputs present at test time the output of this neuron is x.

What would its output be during training time, in expectation? (e.g. if p = 0.5)

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We can do something approximate analytically

```
def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) * p # NOTE: scale the activations
  H2 = np.maximum(0, np.dot(W2, H1) + b2) * p # NOTE: scale the activations
  out = np.dot(W3, H2) + b3
```

At test time all neurons are active always
=> We must scale the activations so that for each neuron:
output at test time = expected output at training time

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Dropout Summary

```
""" Vanilla Dropout: Not recommended implementation (see notes below) """

p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  """ X contains the data """

  # forward pass for example 3-layer neural network
  H1 = np.maximum(0, np.dot(W1, X) + b1)
  U1 = np.random.rand(*H1.shape) < p # first dropout mask
  H1 *= U1 # drop!
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  U2 = np.random.rand(*H2.shape) < p # second dropout mask
  H2 *= U2 # drop!
  out = np.dot(W3, H2) + b3

  # backward pass: compute gradients... (not shown)
  # perform parameter update... (not shown)

def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) * p # NOTE: scale the activations
  H2 = np.maximum(0, np.dot(W2, H1) + b2) * p # NOTE: scale the activations
  out = np.dot(W3, H2) + b3
```

drop in forward pass

scale at test time

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More common: “Inverted dropout”

```python
p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  # forward pass for example 3-layer neural network
  H1 = np.maximum(0, np.dot(W1, X) + b1)
  U1 = (np.random.rand(*H1.shape) < p) / p # first dropout mask. Notice /p!
  H1 *= U1 # drop!
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  U2 = (np.random.rand(*H2.shape) < p) / p # second dropout mask. Notice /p!
  H2 *= U2 # drop!
  out = np.dot(W3, H2) + b3

  # backward pass: compute gradients... (not shown)
  # perform parameter update... (not shown)

def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) # no scaling necessary
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  out = np.dot(W3, H2) + b3
```

test time is unchanged!

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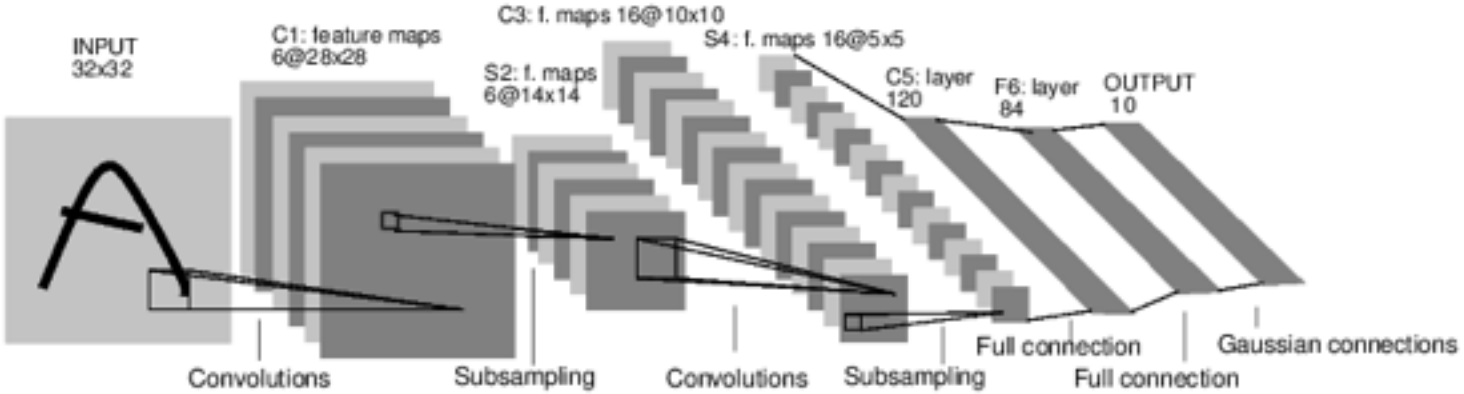
Convolutional Neural Networks



[LeNet-5, LeCun 1980]

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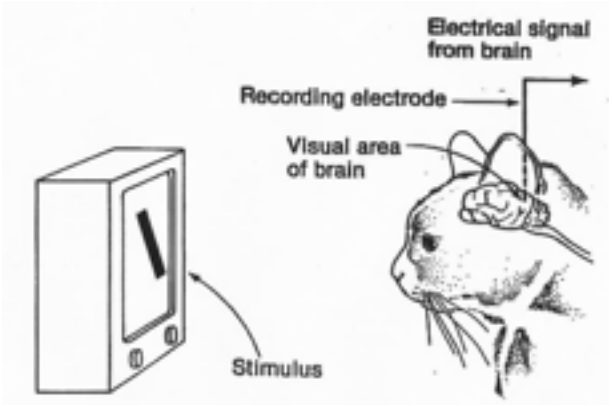
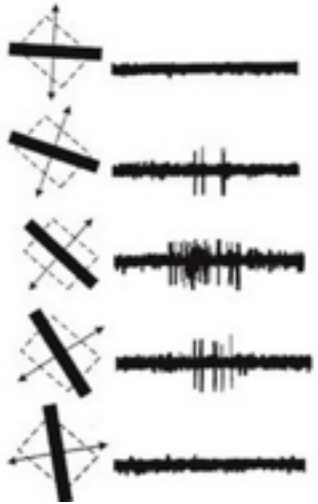
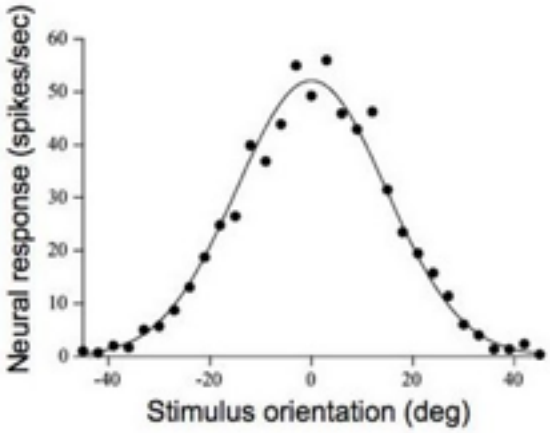
A bit of history:

Hubel & Wiesel,
1959
Receptive Fields of Single Neurons in Cat's Striate Cortex

1962
Receptive Fields, Binocular Interaction and Functional Architecture in Cat's Visual Cortex







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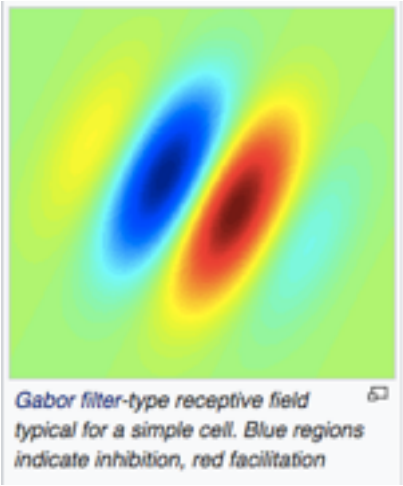
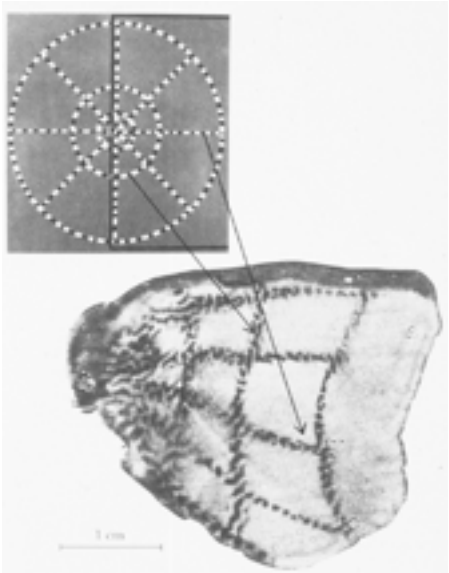
A bit of history

Simple Cell:
cell in the primary visual cortex that responds primarily to oriented edges and gratings

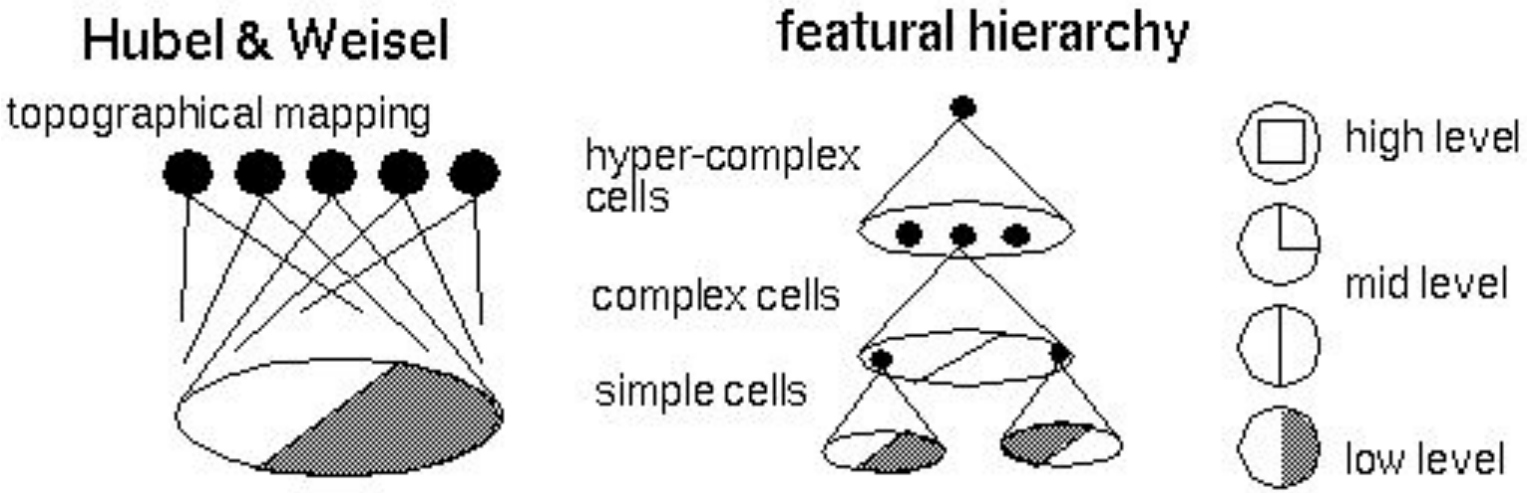


Gabor filter-type receptive field typical for a simple cell. Blue regions indicate inhibition, red facilitation

Topographical mapping in the cortex:
nearby cells in cortex represented nearby regions in the visual field



Hierarchical organization



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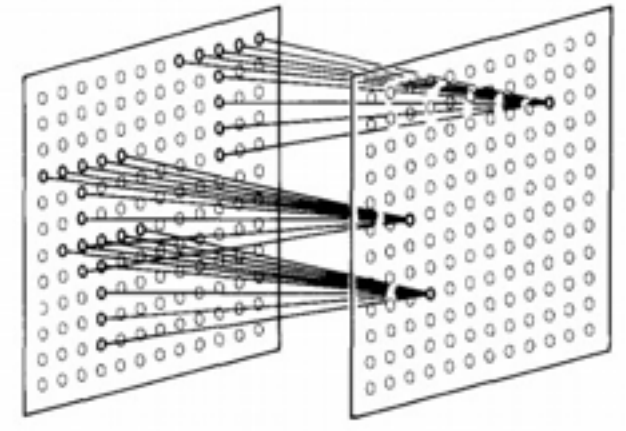
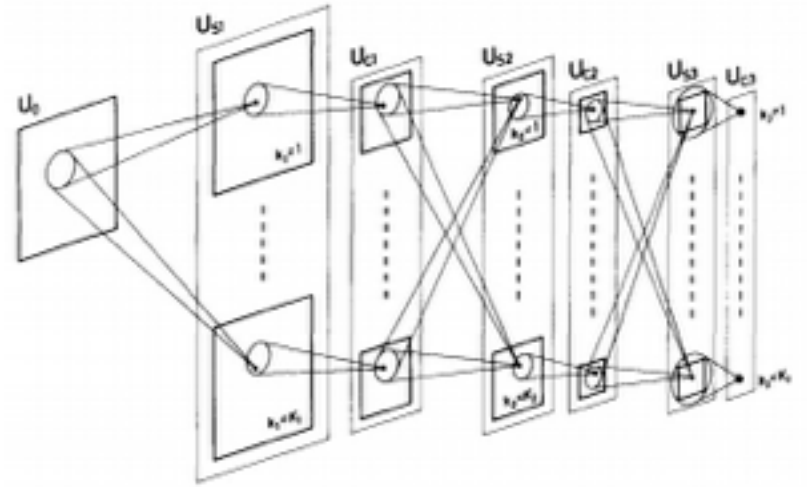
A bit of history:

Neurocognitron
[Fukushima 1980]



"sandwich" architecture (SCSCSC…)
simple cells: modifiable parameters
complex cells: perform pooling



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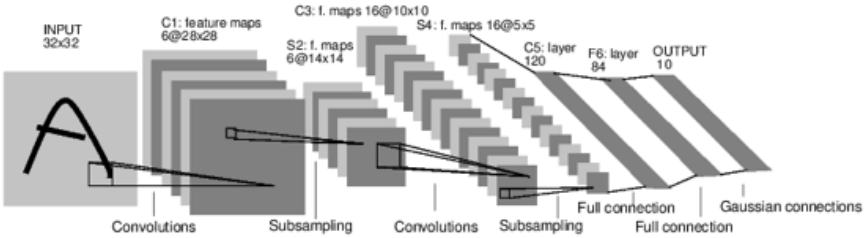
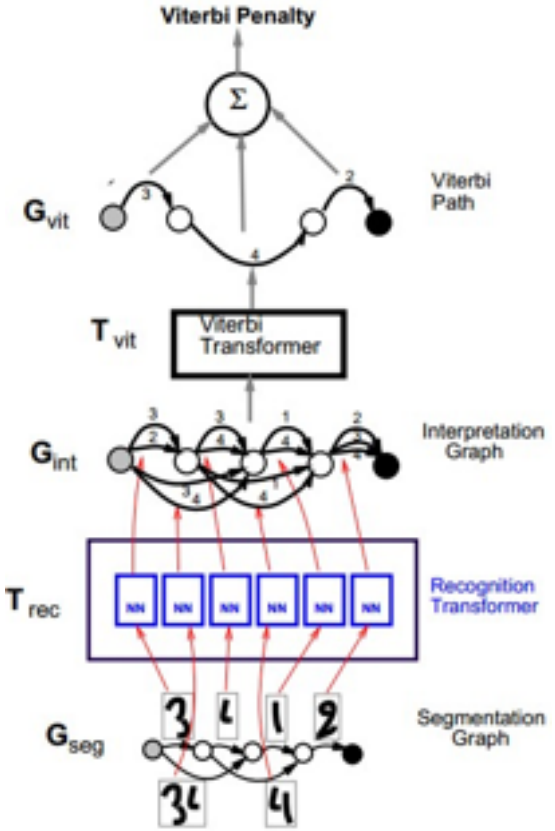
A bit of history:

Gradient-based learning applied to document recognition

[LeCun, Bottou, Bengio, Haffner 1998]



LeNet-5



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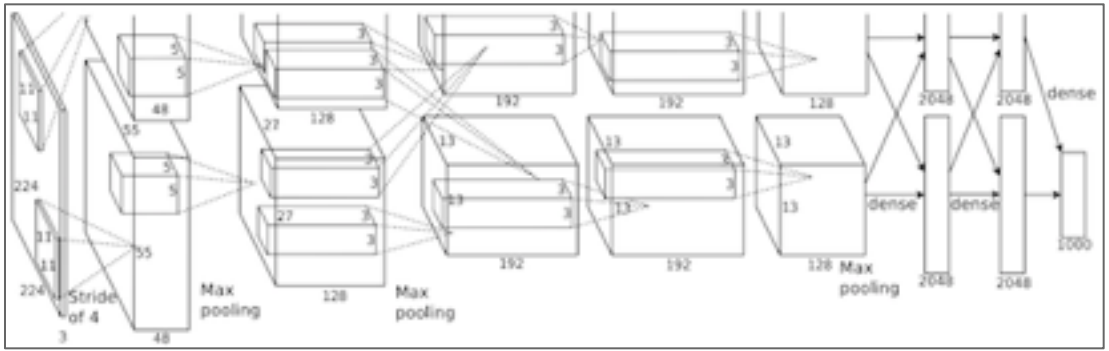
A bit of history:

ImageNet Classification with Deep Convolutional Neural Networks

[Krizhevsky, Sutskever, Hinton, 2012]

IMAGENET



"AlexNet"

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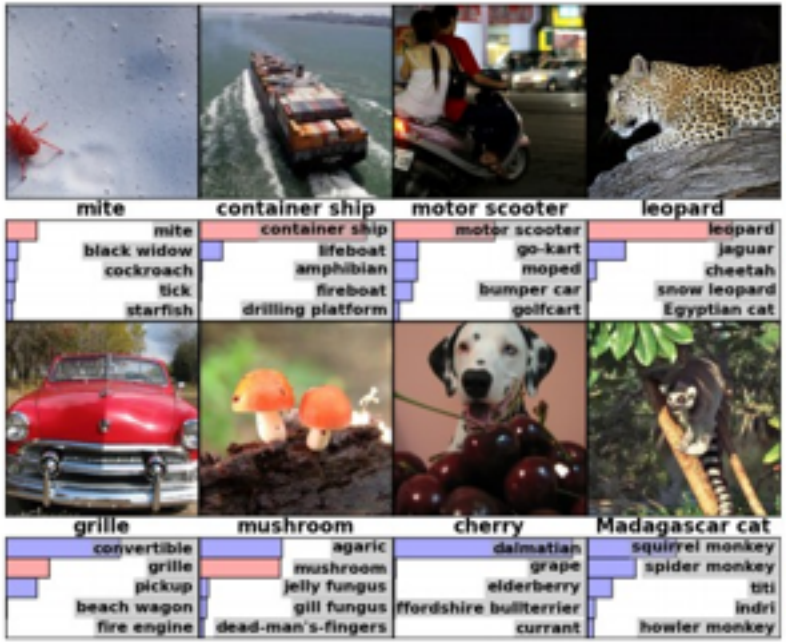
Fast-forward to today: ConvNets are everywhere

Classification



Retrieval

[Krizhevsky 2012]

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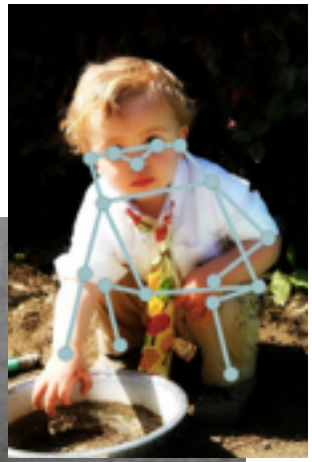
traffic light
traffic light
traffic light
traffic light
person
truck
truck
car
car
frisbee


umbrella
person
car
car
car
car
car
car
person
skateboard


BOFFARD



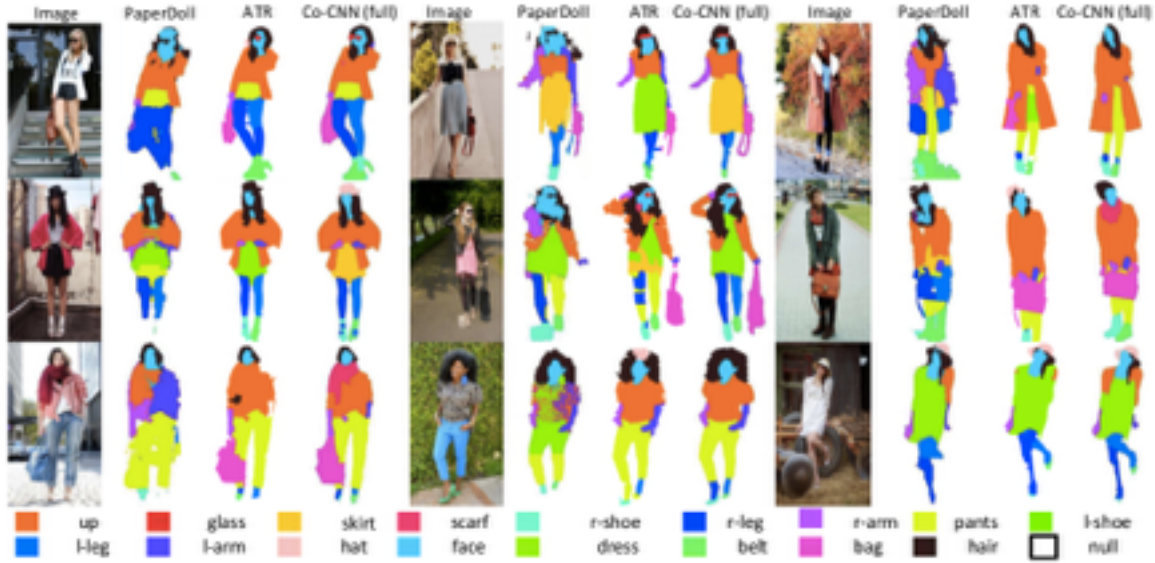


Image
PaperDoll
ATR
Co-CNN (full)
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Co-CNN (full)
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up
l-leg
glass
l-arm
skirt
hat
scarf
face
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r-leg
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bag
pants
hair
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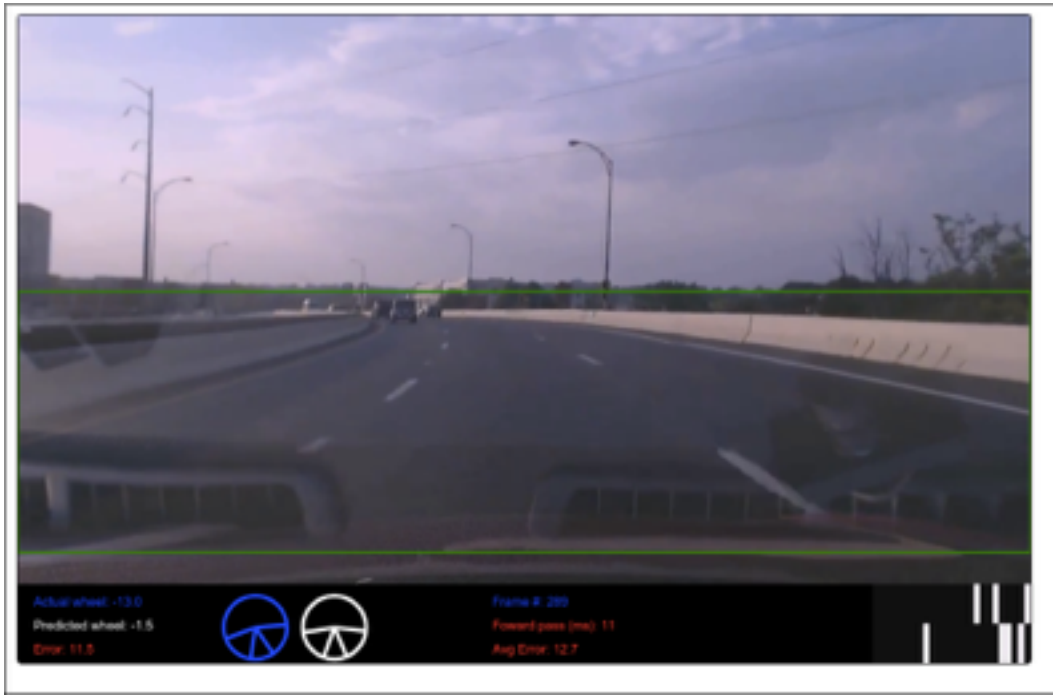
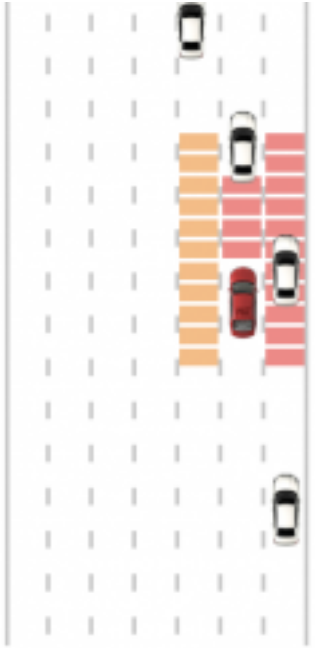
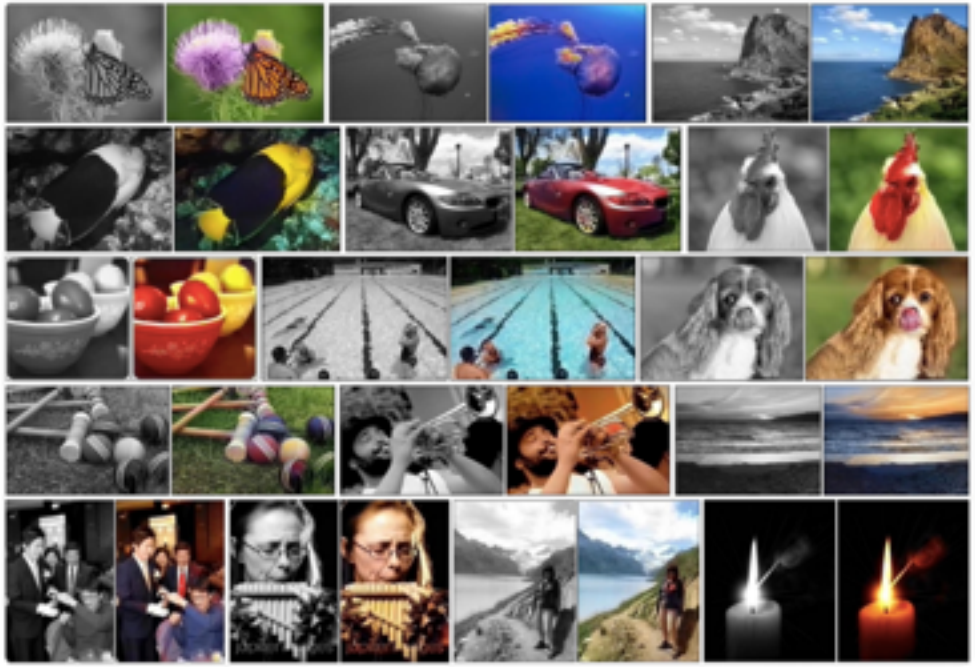
Self-Driving Cars





Art



What is the color of the coat?

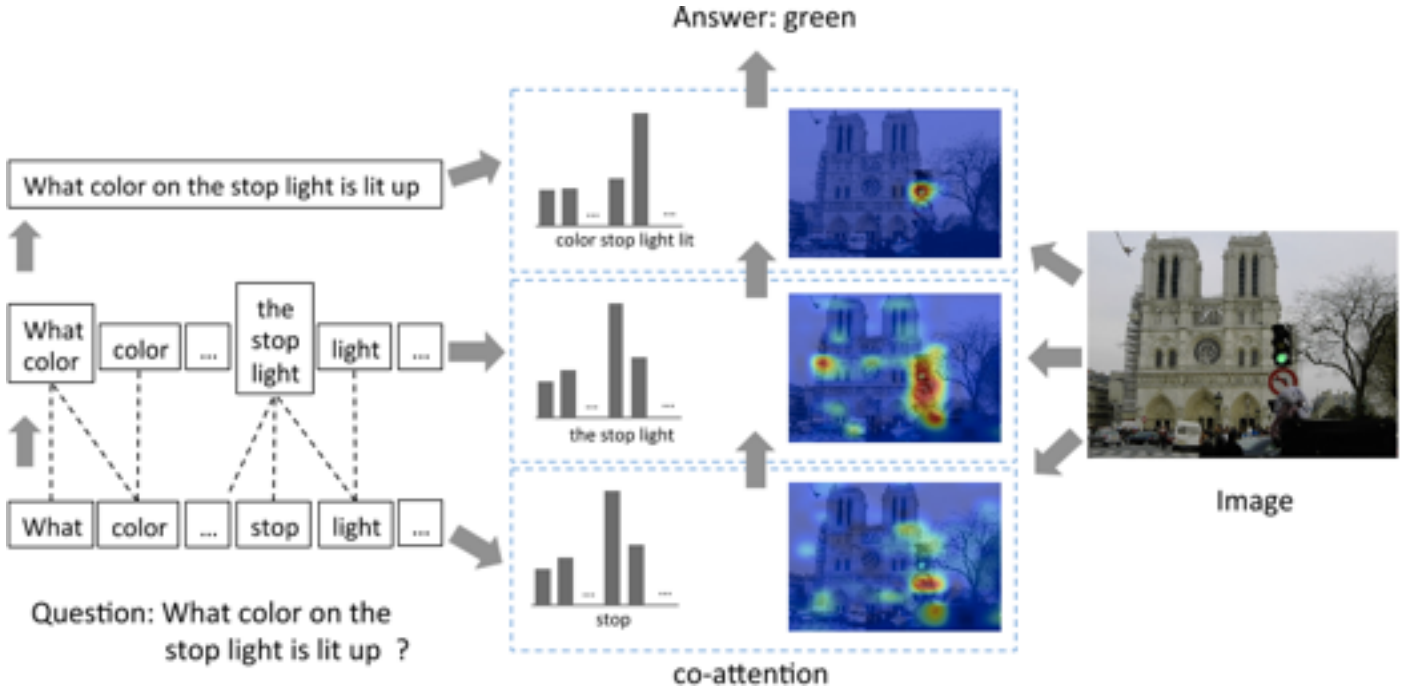
Traditional VQA: analyze the whole image -> analyze question -> give answer: brown

Attention based VQA: find coat -> judge the color of coat -> give answer: yellow

What is the color of the umbrella?

Traditional VQA: analyze the whole image -> analyze question -> give answer: green

Attention based VQA: find umbrella -> judge the color of umbrella -> give answer: red



Caffe

http://caffe.berkeleyvision.org

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Overview

- From U.C. Berkeley
- Written in C++
- Has Python and MATLAB bindings
- Good for training or finetuning feedforward models

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Most important tip...

Don’t be afraid to read the code!

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

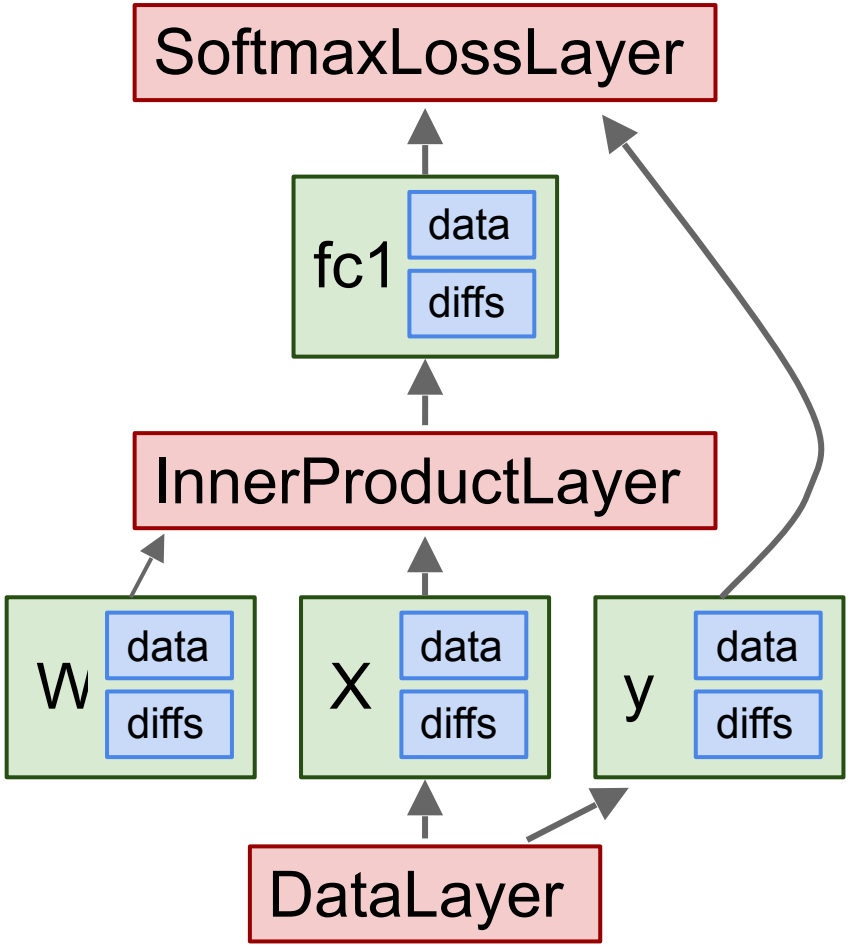
Caffe: Main classes

Blob: Stores data and derivatives (header source)

Layer: Transforms bottom blobs to top blobs (header + source)

Net: Many layers; computes gradients via forward / backward (header source)

Solver: Uses gradients to update weights (header source)



* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Protocol Buffers

"Typed JSON"
from Google

Define "message types"
in .proto files

.proto file

```
message Person {
  required string name = 1;
  required int32 id = 2;
  optional string email = 3;
}
```

https://developers.google.com/protocol-buffers/

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Protocol Buffers

"Typed JSON"
from Google

Define "message types"
in .proto files

Serialize instances to text
files (.prototxt)

.proto file

```
message Person {
  required string name = 1;
  required int32 id = 2;
  optional string email = 3;
}
```

.prototxt file

```
name: "John Doe"
id: 1234
email: "jdoe@example.com"
```

https://developers.google.com/protocol-buffers/

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Protocol Buffers

```
message NetParameter {
  optional string name = 1; // consider giving the network a name
  // The input blobs to the network.
  repeated string input = 3;
  // The shape of the input blobs.
  repeated BlobShape input_shape = 8;

  // 4D input dimensions -- deprecated.  Use "shape" instead.
  // If specified, for each input blob there should be four
  // values specifying the num, channels, height and width of the input blob.
  // Thus, there should be a total of (4 * #input) numbers.
  repeated int32 input_dim = 4;

  // Whether the network will force every layer to carry out backward operation.
  // If set False, then whether to carry out backward is determined
  // automatically according to the net structure and learning rates.
  optional bool force_backward = 5 [default = false];
  // The current "state" of the network, including the phase, level, and stage.
  // Some layers may be included/excluded depending on this state and the states
  // specified in the layers' include and exclude fields.
  optional NetState state = 6;

  // Print debugging information about results while running Net::Forward,
  // Net::Backward, and Net::Update.
  optional bool debug_info = 7 [default = false];
```

```
message SolverParameter {
  //////////////////////////////////////////////////////////////////////////////
  // Specifying the train and test networks
  //
  // Exactly one train net must be specified using one of the following fields:
  //     train_net_param, train_net, net_param, net
  // One or more test nets may be specified using any of the following fields:
  //     test_net_param, test_net, net_param, net
  // If more than one test net field is specified (e.g., both net and
  // test_net are specified), they will be evaluated in the field order given
  // above: (1) test_net_param, (2) test_net, (3) net_param/net.
  // A test_iter must be specified for each test_net.
  // A test_level and/or a test_stage may also be specified for each test_net.
  //////////////////////////////////////////////////////////////////////////////

  // Proto filename for the train net, possibly combined with one or more
  // test nets.
  optional string net = 24;
  // Inline train net param, possibly combined with one or more test nets.
  optional NetParameter net_param = 25;

  optional string train_net = 1; // Proto filename for the train net.
```

https://github.com/BVLC/caffe/blob/master/src/caffe/proto/caffe.proto

<- All Caffe proto types defined here, good documentation!

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Training / Finetuning

No need to write code!

1. Convert data (run a script)
2. Define net (edit prototxt)
3. Define solver (edit prototxt)
4. Train (with pretrained weights) (run a script)

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Step 1: Convert Data

- DataLayer reading from LMDB is the easiest
- Create LMDB using convert_imageset
- Create HDF5 file yourself using h5py
- From memory, using Python (MemoryLayer)

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Step 2: Define Net

```
name: "LogisticRegressionNet"
layers {
  top: "data"
  top: "label"
  name: "data"
  type: HDF5_DATA
  hdf5_data_param {
    source: "examples/hdf5_classification/data/train.txt"
    batch_size: 10
  }
  include {
    phase: TRAIN
  }
}
layers {
  bottom: "data"
  top: "fc1"
  name: "fc1"
  type: INNER_PRODUCT
  blobs_lr: 1
  blobs_lr: 2
  weight_decay: 1
  weight_decay: 0
  inner_product_param {
    num_output: 2
    weight_filler {
      type: "gaussian"
      std: 0.01
    }
    bias_filler {
      type: "constant"
      value: 0
    }
  }
}
layers {
  bottom: "fc1"
  bottom: "label"
  top: "loss"
  name: "loss"
  type: SOFTMAX_LOSS
}
```

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Caffe Step 2: Define Net

```
name: "LogisticRegressionNet"
layers {
  top: "data"
  top: "label"
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}
layers {
  bottom: "fc1"
  bottom: "label"
  top: "loss"
  name: "loss"
  type: SOFTMAX_LOSS
}
```

Layers and Blobs often have same name!

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Caffe Step 2: Define Net

```
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  top: "data"
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    batch_size: 10
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layers {
  bottom: "data"
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  bottom: "fc1"
  bottom: "label"
  top: "loss"
  name: "loss"
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}
```

Layers and Blobs often have same name!

Learning rates (weight + bias)

Regularization (weight + bias)

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Caffe Step 2: Define Net

```
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  top: "data"
  top: "label"
  name: "data"
  type: HDF5_DATA
  hdf5_data_param {
    source: "examples/hdf5_classification/data/train.txt"
    batch_size: 10
  }
  include {
    phase: TRAIN
  }
}
layers {
  bottom: "data"
  top: "fc1"
  name: "fc1"
  type: INNER_PRODUCT
  blobs_lr: 1
  blobs_lr: 2
  weight_decay: 1
  weight_decay: 0
  inner_product_param {
    num_output: 2
    weight_filler {
      type: "gaussian"
      std: 0.01
    }
    bias_filler {
      type: "constant"
      value: 0
    }
  }
}
layers {
  bottom: "fc1"
  bottom: "label"
  top: "loss"
  name: "loss"
  type: SOFTMAX_LOSS
}
```

Layers and Blobs often have same name!

Learning rates (weight + bias)

Regularization (weight + bias)

Number of output classes

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Caffe Step 2: Define Net

```
name: "LogisticRegressionNet"
layers {
  top: "data"
  top: "label"
  name: "data"
  type: HDF5_DATA
  hdf5_data_param {
    source: "examples/hdf5_classification/data/train.txt"
    batch_size: 10
  }
  include {
    phase: TRAIN
  }
}
layers {
  bottom: "data"
  top: "fc1"
  name: "fc1"
  type: INNER_PRODUCT
  blobs_lr: 1
  blobs_lr: 2
  weight_decay: 1
  weight_decay: 0
```

Layers and Blobs often have same name!

Set these to 0 to freeze a layer

Learning rates (weight + bias)

Regularization (weight + bias)

Number of output classes

```
  inner_product_param {
    num_output: 2
    weight_filler {
      type: "gaussian"
      std: 0.01
    }
    bias_filler {
      type: "constant"
      value: 0
    }
  }
}
layers {
  bottom: "fc1"
  bottom: "label"
  top: "loss"
  name: "loss"
  type: SOFTMAX_LOSS
}
```

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Caffe Step 2: Define Net

- .prototxt can get ugly for big models
- ResNet-152 prototxt is 6775 lines long!
- Not “compositional”; can’t easily define a residual block and reuse

```
name: "ResNet-152"
input: "data"
input_dim: 1
input_dim: 3
input_dim: 224
input_dim: 224

layer {
        bottom: "data"
        top: "conv1"
        name: "conv1"
        type: "Convolution"
        convolution_param {
                num_output: 64
                kernel_size: 7
                pad: 3
                stride: 2
                bias_term: false
        }
}

layer {
        bottom: "conv1"
        top: "conv1"
        name: "bn_conv1"
        type: "BatchNorm"
        batch_norm_param {
                use_global_stats: true
        }
}
```

```
layer {
        bottom: "res5c"
        top: "pool5"
        name: "pool5"
        type: "Pooling"
        pooling_param {
                kernel_size: 7
                stride: 1
                pool: AVE
        }
}

layer {
        bottom: "pool5"
        top: "fc1000"
        name: "fc1000"
        type: "InnerProduct"
        inner_product_param {
                num_output: 1000
        }
}

layer {
        bottom: "fc1000"
        top: "prob"
        name: "prob"
        type: "Softmax"
}
```

https://github.com/KaimingHe/deep-residual-networks/blob/master/prototxt/ResNet-152-deploy.prototxt

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Step 2: Define Net (finetuning)

Original prototxt:

```
layer {
  name: "fc7"
  type: "InnerProduct"
  inner_product_param {
    num_output: 4096
  }
}
[... ReLU, Dropout]
layer {
  name: "fc8"
  type: "InnerProduct"
  inner_product_param {
    num_output: 1000
  }
}
```

Pretrained weights:

```
"fc7.weight": [values]
"fc7.bias": [values]
"fc8.weight": [values]
"fc8.bias": [values]
```

Modified prototxt:

```
layer {
  name: "fc7"
  type: "InnerProduct"
  inner_product_param {
    num_output: 4096
  }
}
[... ReLU, Dropout]
layer {
  name: "my-fc8"
  type: "InnerProduct"
  inner_product_param {
    num_output: 10
  }
}
```

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Step 2: Define Net (finetuning)

Original prototxt:

```
layer {
  name: "fc7"
  type: "InnerProduct"
  inner_product_param {
    num_output: 4096
  }
}
[... ReLU, Dropout]
layer {
  name: "fc8"
  type: "InnerProduct"
  inner_product_param {
    num_output: 1000
  }
}
```

Same name: weights copied

Pretrained weights:

```
"fc7.weight": [values]
"fc7.bias": [values]
"fc8.weight": [values]
"fc8.bias": [values]
```

Modified prototxt:

```
layer {
  name: "fc7"
  type: "InnerProduct"
  inner_product_param {
    num_output: 4096
  }
}
[... ReLU, Dropout]
layer {
  name: "my-fc8"
  type: "InnerProduct"
  inner_product_param {
    num_output: 10
  }
}
```

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Caffe Step 2: Define Net (finetuning)

Original prototxt:

```
layer {
  name: "fc7"
  type: "InnerProduct"
  inner_product_param {
    num_output: 4096
  }
}
[... ReLU, Dropout]
layer {
  name: "fc8"
  type: "InnerProduct"
  inner_product_param {
    num_output: 1000
  }
}
```

Same name: weights copied

Pretrained weights:

```
"fc7.weight": [values]
"fc7.bias": [values]
"fc8.weight": [values]
"fc8.bias": [values]
```

Different name: weights reinitialized

Modified prototxt:

```
layer {
  name: "fc7"
  type: "InnerProduct"
  inner_product_param {
    num_output: 4096
  }
}
[... ReLU, Dropout]
layer {
  name: "my-fc8"
  type: "InnerProduct"
  inner_product_param {
    num_output: 10
  }
}
```

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Step 3: Define Solver

Write a prototxt file defining a SolverParameter

If finetuning, copy existing solver.prototxt file

- Change net to be your net
- Change snapshot_prefix to your output
- Reduce base learning rate (divide by 100)
- Maybe change max_iter and snapshot

```
net: "models/bvlc_alexnet/train_val.prototxt"
test_iter: 1000
test_interval: 1000
base_lr: 0.01
lr_policy: "step"
gamma: 0.1
stepsize: 100000
display: 20
max_iter: 450000
momentum: 0.9
weight_decay: 0.0005
snapshot: 10000
snapshot_prefix: "models/bvlc_alexnet/caffe_alexnet_train"
solver_mode: GPU
```

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Step 4: Train!

```
./build/tools/caffe train \
  -gpu 0 \
  -model path/to/trainval.prototxt \
  -solver path/to/solver.prototxt \
  -weights path/to/
pretrained_weights.caffemodel
```

https://github.com/BVLC/caffe/blob/master/tools/caffe.cpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Step 4: Train!

```
./build/tools/caffe train \
  -gpu 0 \
  -model path/to/trainval.prototxt \
  -solver path/to/solver.prototxt \
  -weights path/to/
pretrained_weights.caffemodel
```

`-gpu -1` for CPU mode

https://github.com/BVLC/caffe/blob/master/tools/caffe.cpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Step 4: Train!

```
./build/tools/caffe train \
  -gpu 0 \
  -model path/to/trainval.prototxt \
  -solver path/to/solver.prototxt \
  -weights path/to/
pretrained_weights.caffemodel
```

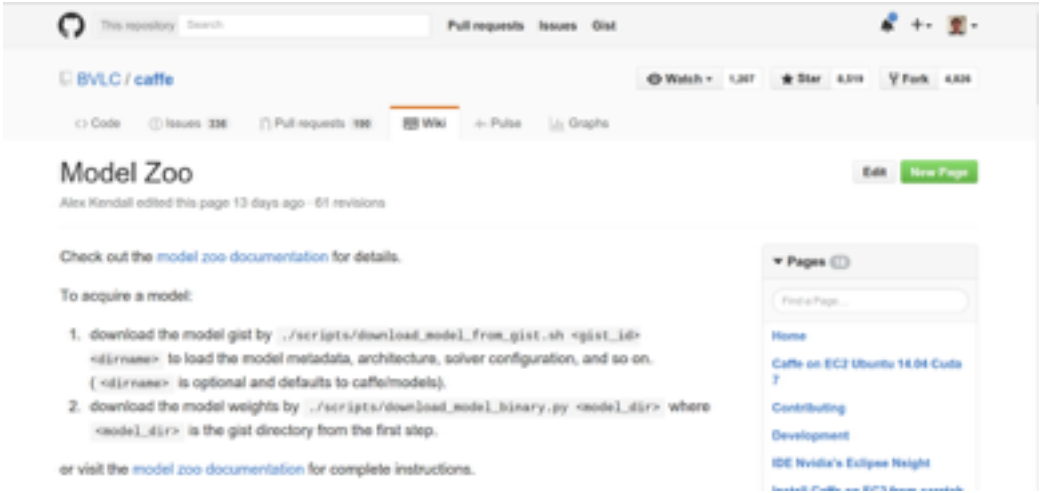
`-gpu all` for multi-GPU data parallelism

https://github.com/BVLC/caffe/blob/master/tools/caffe.cpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Model Zoo

- AlexNet, VGG, GoogLeNet, ResNet, plus others



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

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Python Interface

Not much documentation…

Look at Notebooks in `caffe/examples`

Read the code! Two most important files:

caffe/python/caffe/_caffe.cpp:

Exports Blob, Layer, Net, and Solver classes

caffe/python/caffe/pycaffe.py

Adds extra methods to Net class

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Python Interface

- Good for:
  - Interfacing with numpy
  - Extract features: Run net forward
  - Compute gradients: Run net backward (DeepDream, etc)
  - Define layers in Python with numpy (CPU only)

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe Pros / Cons

(+) Good for feedforward networks
(+) Good for finetuning existing networks
(+) Train models without writing any code!
(+) Python interface is pretty useful!
(-) Need to write C++ / CUDA for new GPU layers
(-) Not good for recurrent networks
(-) Cumbersome for big networks (GoogLeNet, ResNet)

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Blobs

```
23  template <typename Dtype>
24  class Blob {
25   public:
26    Blob()
27         : data_(), diff_(), count_(0), capacity_(0) {}
28
29    /// @brief Deprecated; use <code>Blob(const vector<int>& shape)</code>.
30    explicit Blob(const int num, const int channels, const int height,
31        const int width);
32    explicit Blob(const vector<int>& shape);
```

```
219   const Dtype* cpu_data() const;
220   void set_cpu_data(Dtype* data);
221   const int* gpu_shape() const;
222   const Dtype* gpu_data() const;
223   const Dtype* cpu_diff() const;
224   const Dtype* gpu_diff() const;
225   Dtype* mutable_cpu_data();
226   Dtype* mutable_gpu_data();
227   Dtype* mutable_cpu_diff();
228   Dtype* mutable_gpu_diff();
```

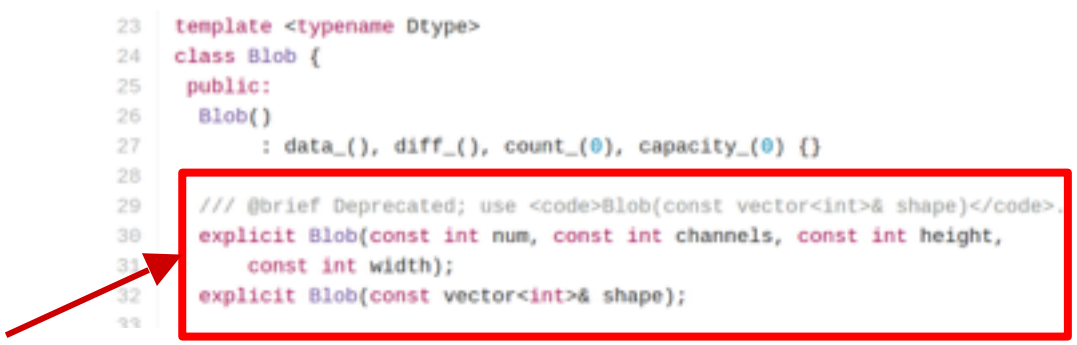
```
268  protected:
269   shared_ptr<SyncedMemory> data_;
270   shared_ptr<SyncedMemory> diff_;
271   shared_ptr<SyncedMemory> shape_data_;
272   vector<int> shape_;
273   int count_;
274   int capacity_;
```

https://github.com/BVLC/caffe/blob/master/include/caffe/blob.hpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Blobs

N-dimensional array for storing activations and weights



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268  protected:
269   shared_ptr<SyncedMemory> data_;
270   shared_ptr<SyncedMemory> diff_;
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```

https://github.com/BVLC/caffe/blob/master/include/caffe/blob.hpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Blobs

N-dimensional array for storing activations and weights

Two parallel tensors:
data: values
diffs: gradients

```
23  template <typename Dtype>
24  class Blob {
25   public:
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27         : data_(), diff_(), count_(0), capacity_(0) {}
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222   const Dtype* gpu_data() const;
223   const Dtype* cpu_diff() const;
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https://github.com/BVLC/caffe/blob/master/include/caffe/blob.hpp

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Caffe: Blobs

N-dimensional array for storing activations and weights

Two parallel tensors:
data: values
diffs: gradients

Stores CPU / GPU versions of each tensor

```
23  template <typename Dtype>
24  class Blob {
25   public:
26    Blob()
27         : data_(), diff_(), count_(0), capacity_(0) {}
28
29    /// @brief Deprecated; use <code>Blob(const vector<int>& shape)</code>.
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31        const int width);
32    explicit Blob(const vector<int>& shape);

219   const Dtype* cpu_data() const;
220   void set_cpu_data(Dtype* data);
221   const int* gpu_shape() const;
222   const Dtype* gpu_data() const;
223   const Dtype* cpu_diff() const;
224   const Dtype* gpu_diff() const;
225   Dtype* mutable_cpu_data();
226   Dtype* mutable_gpu_data();
227   Dtype* mutable_cpu_diff();
228   Dtype* mutable_gpu_diff();

268   protected:
269    shared_ptr<SyncedMemory> data_;
270    shared_ptr<SyncedMemory> diff_;
271    shared_ptr<SyncedMemory> shape_data_;
272    vector<int> shape_;
273    int count_;
274    int capacity_;
```

https://github.com/BVLC/caffe/blob/master/include/caffe/blob.hpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Layer

A small unit of computation

```
32  template <typename Dtype>
33  class Layer {
34   public:

334   /** @brief Using the CPU device, compute the layer output. */
335   virtual void Forward_cpu(const vector<Blob<Dtype>*>& bottom,
336       const vector<Blob<Dtype>*>& top) = 0;
337   /**
338    * @brief Using the GPU device, compute the layer output.
339    *        Fall back to Forward_cpu() if unavailable.
340    */
341   virtual void Forward_gpu(const vector<Blob<Dtype>*>& bottom,
342       const vector<Blob<Dtype>*>& top) {
343     // LOG(WARNING) << "Using CPU code as backup.";
344     return Forward_cpu(bottom, top);
345   }
346
347   /**
348    * @brief Using the CPU device, compute the gradients for any parameters and
349    *        for the bottom blobs if propagate_down is true.
350    */
351   virtual void Backward_cpu(const vector<Blob<Dtype>*>& top,
352       const vector<bool>& propagate_down,
353       const vector<Blob<Dtype>*>& bottom) = 0;
354   /**
355    * @brief Using the GPU device, compute the gradients for any parameters and
356    *        for the bottom blobs if propagate_down is true.
357    *        Fall back to Backward_cpu() if unavailable.
358    */
359   virtual void Backward_gpu(const vector<Blob<Dtype>*>& top,
360       const vector<bool>& propagate_down,
361       const vector<Blob<Dtype>*>& bottom) {
362     // LOG(WARNING) << "Using CPU code as backup.";
363     Backward_cpu(top, propagate_down, bottom);
364   }
```

https://github.com/BVLC/caffe/blob/master/include/caffe/layer.hpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Layer

A small unit of computation

Forward: Use “bottom” data to compute “top” data

```
32  template <typename Dtype>
33  class Layer {
34   public:
334   /** @brief Using the CPU device, compute the layer output. */
335   virtual void Forward_cpu(const vector<Blob<Dtype>*>& bottom,
336       const vector<Blob<Dtype>*>& top) = 0;
337   /**
338    * @brief Using the GPU device, compute the layer output.
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345   }
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347   /**
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349    *        for the bottom blobs if propagate_down is true.
350    */
351   virtual void Backward_cpu(const vector<Blob<Dtype>*>& top,
352       const vector<bool>& propagate_down,
353       const vector<Blob<Dtype>*>& bottom) = 0;
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355    * @brief Using the GPU device, compute the gradients for any parameters and
356    *        for the bottom blobs if propagate_down is true.
357    *        Fall back to Backward_cpu() if unavailable.
358    */
359   virtual void Backward_gpu(const vector<Blob<Dtype>*>& top,
360       const vector<bool>& propagate_down,
361       const vector<Blob<Dtype>*>& bottom) {
362     // LOG(WARNING) << "Using CPU code as backup.";
363     Backward_cpu(top, propagate_down, bottom);
364   }
```

https://github.com/BVLC/caffe/blob/master/include/caffe/layer.hpp

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Caffe: Layer

A small unit of computation

Forward: Use “bottom” data to compute “top” data

Backward: Use “top” diffs to compute “bottom” diffs

```
32  template <typename Dtype>
33  class Layer {
34   public:

334   /** @brief Using the CPU device, compute the layer output. */
335   virtual void Forward_cpu(const vector<Blob<Dtype>*>& bottom,
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352       const vector<bool>& propagate_down,
353       const vector<Blob<Dtype>*>& bottom) = 0;
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356    *        for the bottom blobs if propagate_down is true.
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359   virtual void Backward_gpu(const vector<Blob<Dtype>*>& top,
360       const vector<bool>& propagate_down,
361       const vector<Blob<Dtype>*>& bottom) {
362     // LOG(WARNING) << "Using CPU code as backup.";
363     Backward_cpu(top, propagate_down, bottom);
364   }
```

https://github.com/BVLC/caffe/blob/master/include/caffe/layer.hpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Layer

A small unit of computation

Forward: Use “bottom” data to compute “top” data

Backward: Use “top” diffs to compute “bottom” diffs

Separate **CPU** / **GPU** implementations

```
32  template <typename Dtype>
33  class Layer {
34   public:
334   /** @brief Using the CPU device, compute the layer output. */
335   virtual void Forward_cpu(const vector<Blob<Dtype>*>& bottom,
336       const vector<Blob<Dtype>*>& top) = 0;
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338    * @brief Using the GPU device, compute the layer output.
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342       const vector<Blob<Dtype>*>& top) {
343     // LOG(WARNING) << "Using CPU code as backup.";
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345   }
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348    * @brief Using the CPU device, compute the gradients for any parameters and
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352       const vector<bool>& propagate_down,
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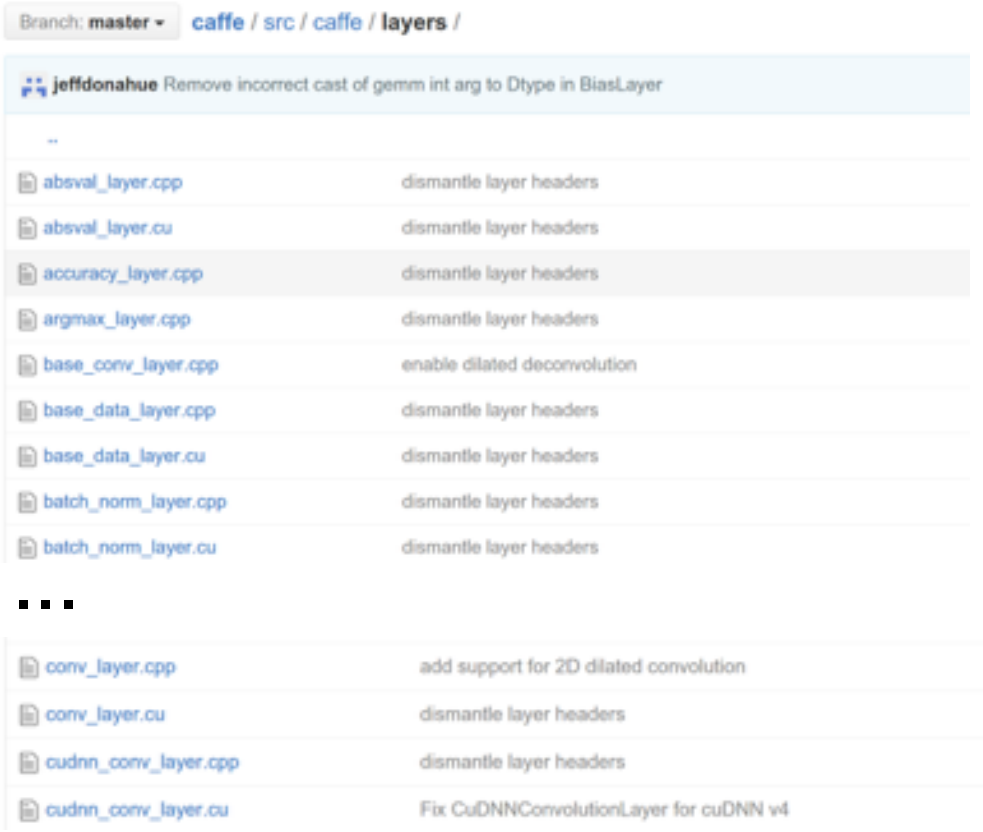
356    *        for the bottom blobs if propagate_down is true.
357    *        Fall back to Backward_cpu() if unavailable.
358    */
359   virtual void Backward_gpu(const vector<Blob<Dtype>*>& top,
360       const vector<bool>& propagate_down,
361       const vector<Blob<Dtype>*>& bottom) {
362     // LOG(WARNING) << "Using CPU code as backup.";
363     Backward_cpu(top, propagate_down, bottom);
364   }
```

https://github.com/BVLC/caffe/blob/master/include/caffe/layer.hpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Layer

Tons of different layer types:



https://github.com/BVLC/caffe/tree/master/src/caffe/layers

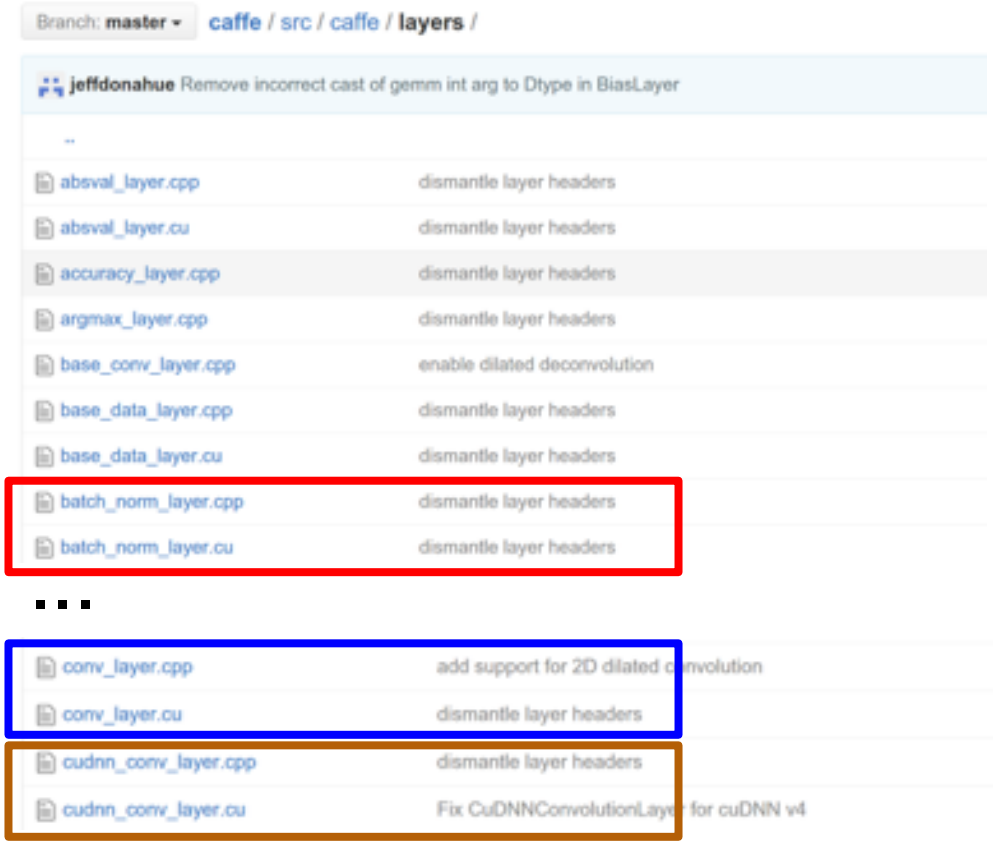
* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Layer

Tons of different layer types:

- **batch norm**
- **convolution**
- **cuDNN convolution**

.cpp: CPU implementation
.cu: GPU implementation



https://github.com/BVLC/caffe/tree/master/src/caffe/layers

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Layer

Collects layers into a DAG

Run all or part of the net
forward and **backward**

```
23  template <typename Dtype>
24  class Net {
25   public:
26    explicit Net(const NetParameter& param, const Net* root_net = NULL);
27    explicit Net(const string& param_file, Phase phase,
28        const Net* root_net = NULL);
29    virtual ~Net() {}

41    /**
42     * The From and To variants of Forward and Backward operate on the
43     * (topological) ordering by which the net is specified. For general DAG
44     * networks, note that (1) computing from one layer to another might entail
45     * extra computation on unrelated branches, and (2) computation starting in
46     * the middle may be incorrect if all of the layers of a fan-in are not
47     * included.
48     */
49    Dtype ForwardFromTo(int start, int end);
50    Dtype ForwardFrom(int start);
51    Dtype ForwardTo(int end);
52    /// @brief Run forward using a set of bottom blobs, and return the result.
53    const vector<Blob<Dtype>*>& Forward(const vector<Blob<Dtype>* > & bottom,
54        Dtype* loss = NULL);

67    /**
68     * The network backward should take no input and output, since it solely
69     * computes the gradient w.r.t the parameters, and the data has already been
70     * provided during the forward pass.
71     */
72    void Backward();
73    void BackwardFromTo(int start, int end);
74    void BackwardFrom(int start);
75    void BackwardTo(int end);
```

https://github.com/BVLC/caffe/blob/master/include/caffe/net.hpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Solver

```
40  template <typename Dtype>
41  class Solver {
42   public:
55    // The main entry of the solver function. In default, iter will be zero. Pass
56    // in a non-zero iter number to resume training for a pre-trained net.
57    virtual void Solve(const char* resume_file = NULL);
58    inline void Solve(const string resume_file) { Solve(resume_file.c_str()); }
59    void Step(int iters);
60    // The Restore method simply dispatches to one of the
61    // RestoreSolverStateFrom___ protected methods. You should implement these
62    // methods to restore the state from the appropriate snapshot type.
63    void Restore(const char* resume_file);
64    // The Solver::Snapshot function implements the basic snapshotting utility
65    // that stores the learned net. You should implement the SnapshotSolverState()
66    // function that produces a SolverState protocol buffer that needs to be
67    // written to disk together with the learned net.
68    void Snapshot();
```

https://github.com/BVLC/caffe/blob/master/include/caffe/solver.hpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Caffe: Solver

```
40  template <typename Dtype>
41  class Solver {
42   public:
55    // The main entry of the solver function. In default, iter will be zero. Pass
56    // in a non-zero iter number to resume training for a pre-trained net.
57    virtual void Solve(const char* resume_file = NULL);
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68    void Snapshot();
```

Trains a Net by running it forward / backward, updating weights

https://github.com/BVLC/caffe/blob/master/include/caffe/solver.hpp

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Caffe: Solver

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67    // written to disk together with the learned net.
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```

Trains a Net by running it forward / backward, updating weights

Handles snapshotting, restoring from snapshots

https://github.com/BVLC/caffe/blob/master/include/caffe/solver.hpp

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Caffe: Solver

Trains a Net by running it forward / backward, updating weights

Handles snapshotting, restoring from snapshots

Subclasses implement different update rules

```
40  template <typename Dtype>
41  class Solver {
42   public:
55    // The main entry of the solver function. In default, iter will be zero. Pass
56    // in a non-zero iter number to resume training for a pre-trained net.
57    virtual void Solve(const char* resume_file = NULL);
58    inline void Solve(const string resume_file) { Solve(resume_file.c_str()); }
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63    void Restore(const char* resume_file);
64    // The Solver::Snapshot function implements the basic snapshotting utility
65    // that stores the learned net. You should implement the SnapshotSolverState()
66    // function that produces a SolverState protocol buffer that needs to be
67    // written to disk together with the learned net.
68    void Snapshot();
```

```
15  template <typename Dtype>
16  class SGDSolver : public Solver<Dtype> {

83  template <typename Dtype>
84  class RMSPropSolver : public SGDSolver<Dtype> {

130 template <typename Dtype>
131 class AdamSolver : public SGDSolver<Dtype> {
```

https://github.com/BVLC/caffe/blob/master/include/caffe/sgd_solvers.hpp

* Original slides borrowed from Andrej Karpathy and Li Fei-Fei, Stanford cs231n

Overview

	Caffe	Torch	Theano	TensorFlow
Language	C++, Python	Lua	Python	Python
Pretrained	Yes ++	Yes ++	Yes (Lasagne)	Inception
Multi-GPU: Data parallel	Yes	Yes cunn.DataParallelTable	Yes platoon	Yes
Multi-GPU: Model parallel	No	Yes fbcunn.ModelParallel	Experimental	Yes (best)
Readable source code	Yes (C++)	Yes (Lua)	No	No
Good at RNN	No	Mediocre	Yes	Yes (best)

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