Lecture 10:
Training CNNs

Thursday March 2, 2017

Announcements!

- Final Project proposals due this **Today**

- I will be out of town next week. Rishit will lead class discussions.

- Next paper: **March 7** *You Only Look Once: Unified, Real-Time Object Detection.* If this paper seems too deep or confusing, look at *Fast R-CNN, Faster R-CNN*

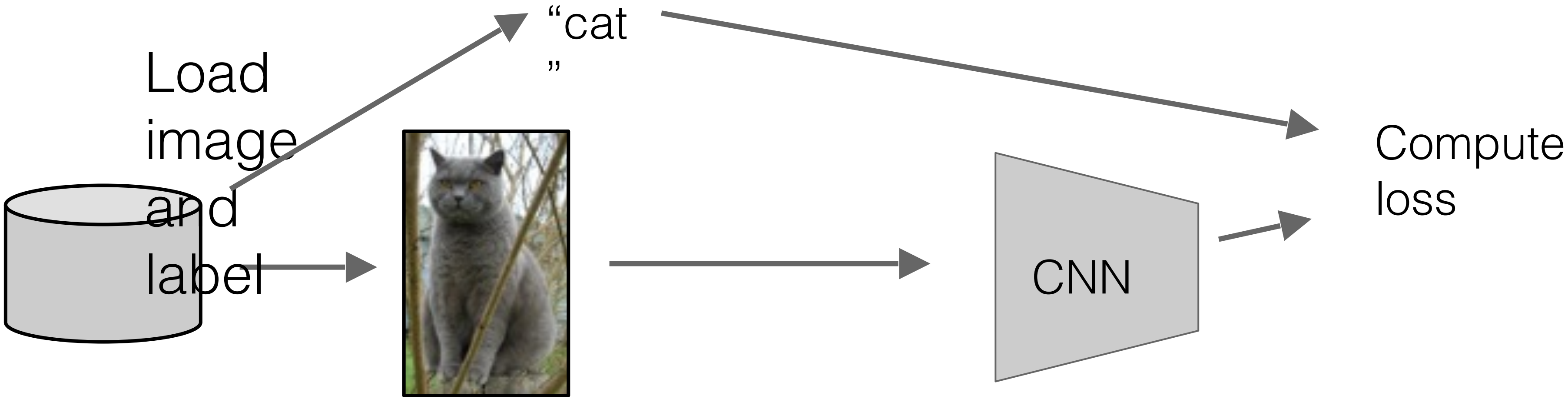
Opportunity: Google Brain Residency

What Is The Brain Residency Program?
The Google Brain Residency Program is a one-year intensive residency program focused on Deep Learning. Residents will have the opportunity to conduct cutting-edge research and work alongside some of the most distinguished deep learning scientists within the Google Brain team. To learn more about the team and what we do, visit g.co/brain

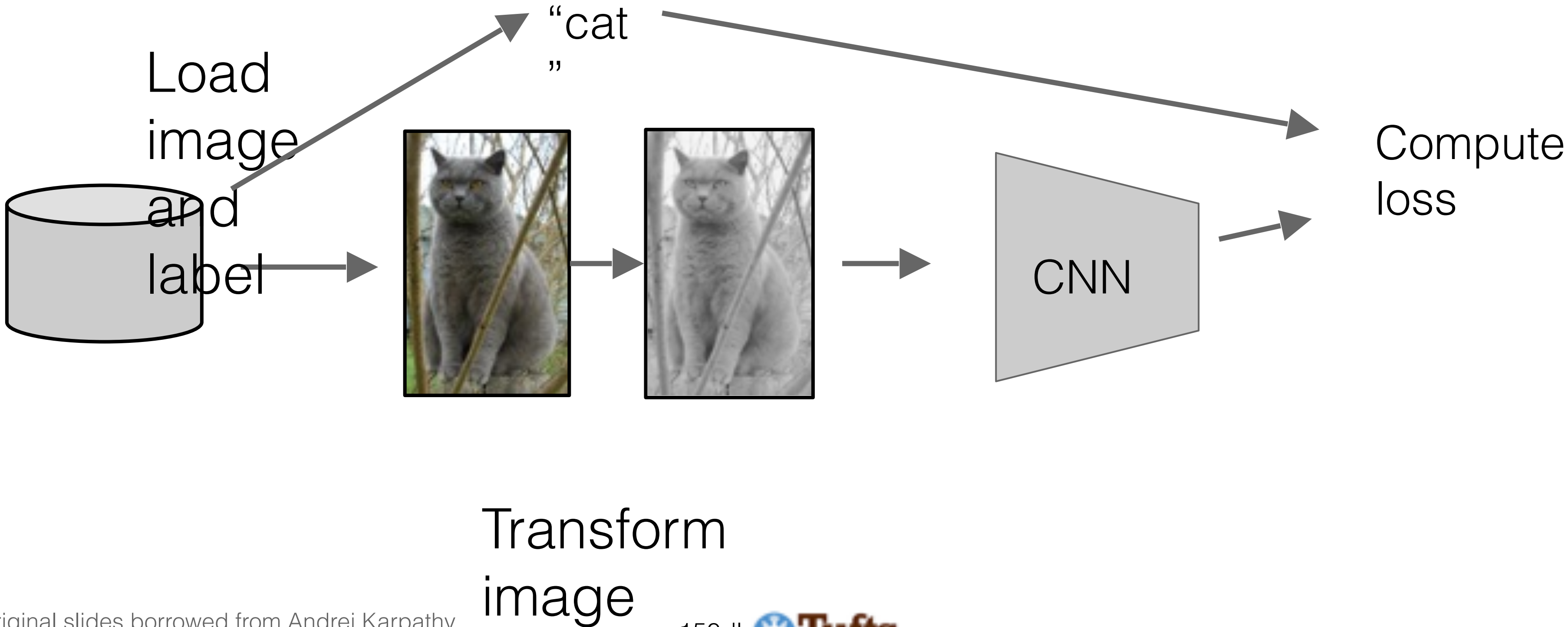
- Email contact for questions: brain-residency@google.com
- For more information on the Residency Program, check out our website at g.co/brainresidency
- More recently, we published a blog post on the Google Research Blog where we discuss updates on current Residents' progress and our program focus for 2017.

Data Augmentation

Data Augmentation



Data Augmentation

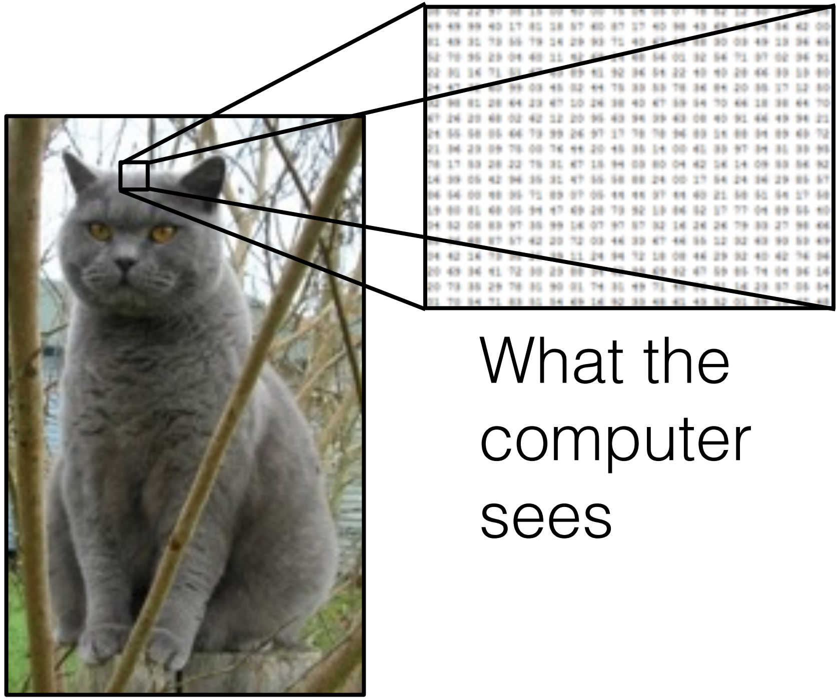


Data Augmentation

- Change the pixels without changing the label

- Train on transformed data

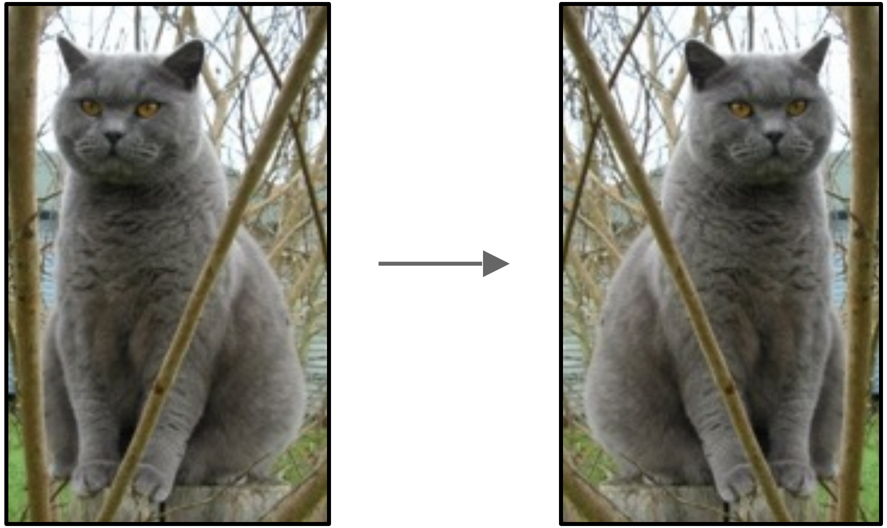
- VERY widely used



What the computer sees

Data Augmentation

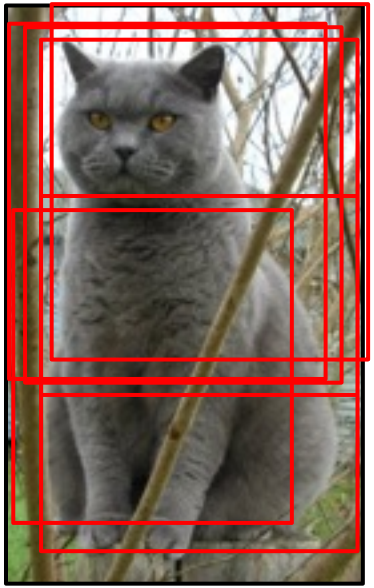
1. Horizontal flips



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

Data Augmentation
2. Random crops/scales

Training: sample random crops / scales

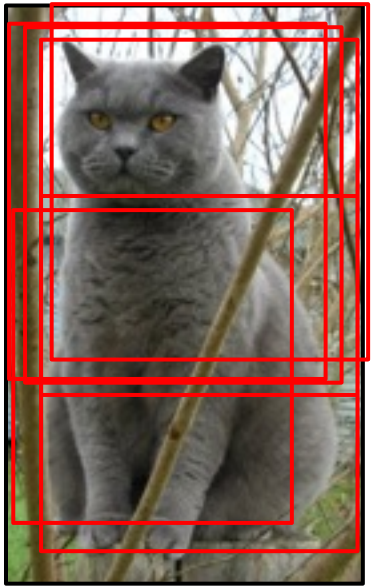


Data Augmentation
2. Random crops/scales

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



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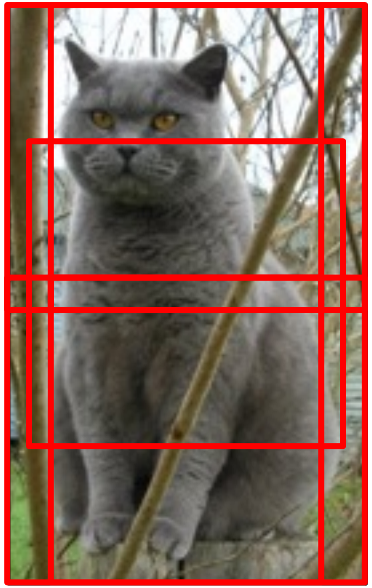
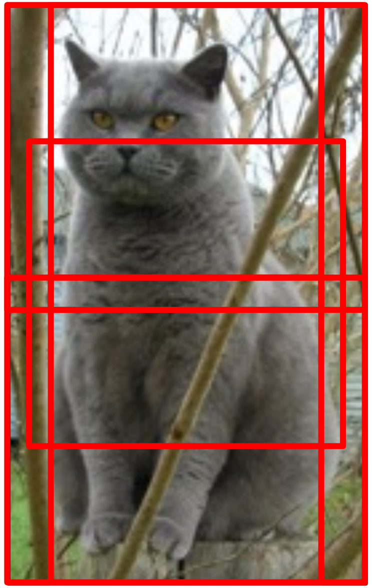
Testing: average a fixed set of crops



Data Augmentation
2. Random crops/scales



Training: sample random crops / scales

ResNet:

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

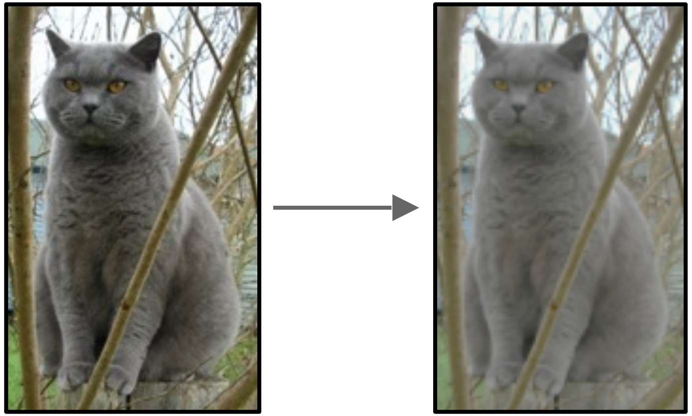
Testing: average a fixed set of crops

ResNet:

1. Resize image at 5 scales: {224, 256, 384, 480, 640}
2. For each size, use 10 224 x 224 crops: 4 corners + center, + flips

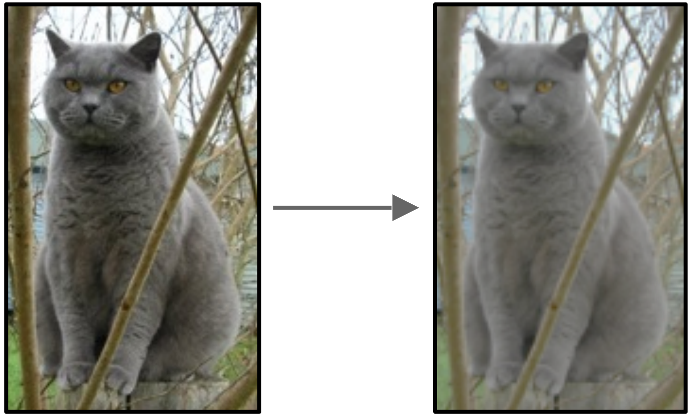
Data Augmentation
3. Color jitter

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)

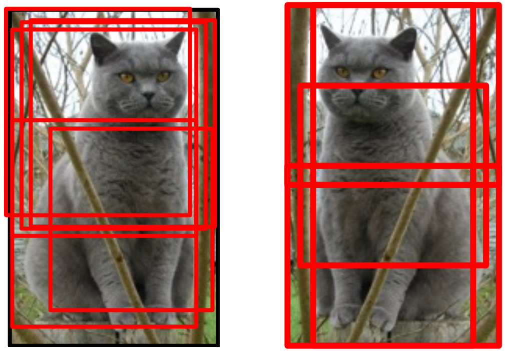
Data Augmentation
3. Color jitter

Random mix/combinations of :

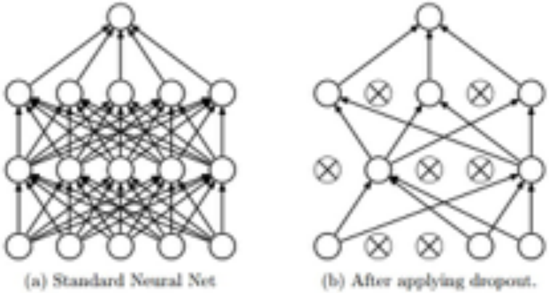
- translation
- rotation
- stretching
- shearing,
- lens distortions, … (go crazy)

A general theme:

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



Data Augmentation



Dropout

Batch normalization,
Model ensembles

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

Data Augmentation: Takeaway

- Simple to implement, use it
- Especially useful for small datasets
- Fits into framework of noise / marginalization

Transfer Learning

"You need a lot of a data if you want to train/use CNNs"

Transfer Learning

"You need a lot of a data if you want to train/use CNNs"

Not True

Transfer Learning with CNNs

1. Train on Imagenet

Transfer Learning with CNNs

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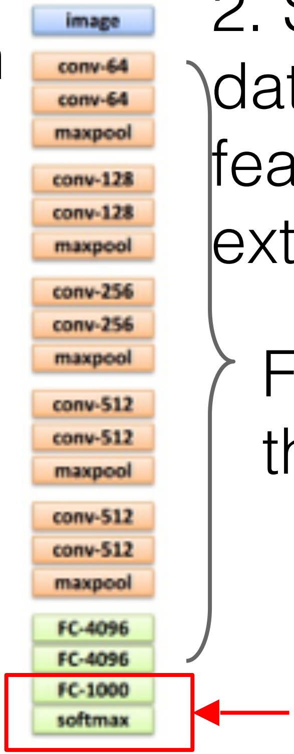


2. Small dataset: feature extractor

Freeze these

Train this

Transfer Learning with CNNs

1. Train on Imagenet

2. Small dataset: **feature extractor**

Freeze these

Train this

3. Medium dataset: **finetuning**

Freeze these

more data = retrain more of the network (or all of it)

Train this

Transfer Learning with CNNs

1. Train on Imagenet

2. Small dataset: **feature extractor**

Freeze these

Train this

3. Medium dataset: **finetuning**

Freeze these

more data = retrain more of the network (or all of it)

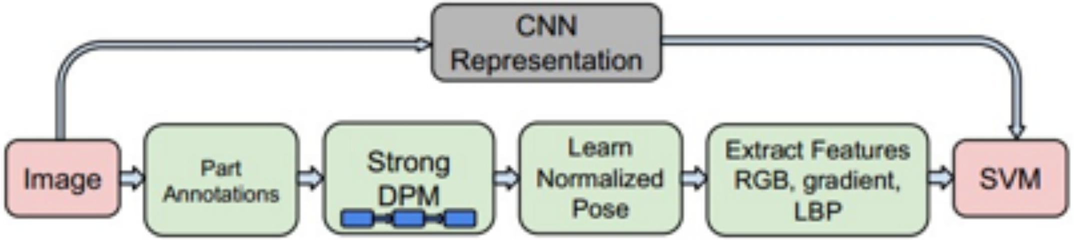
Train this

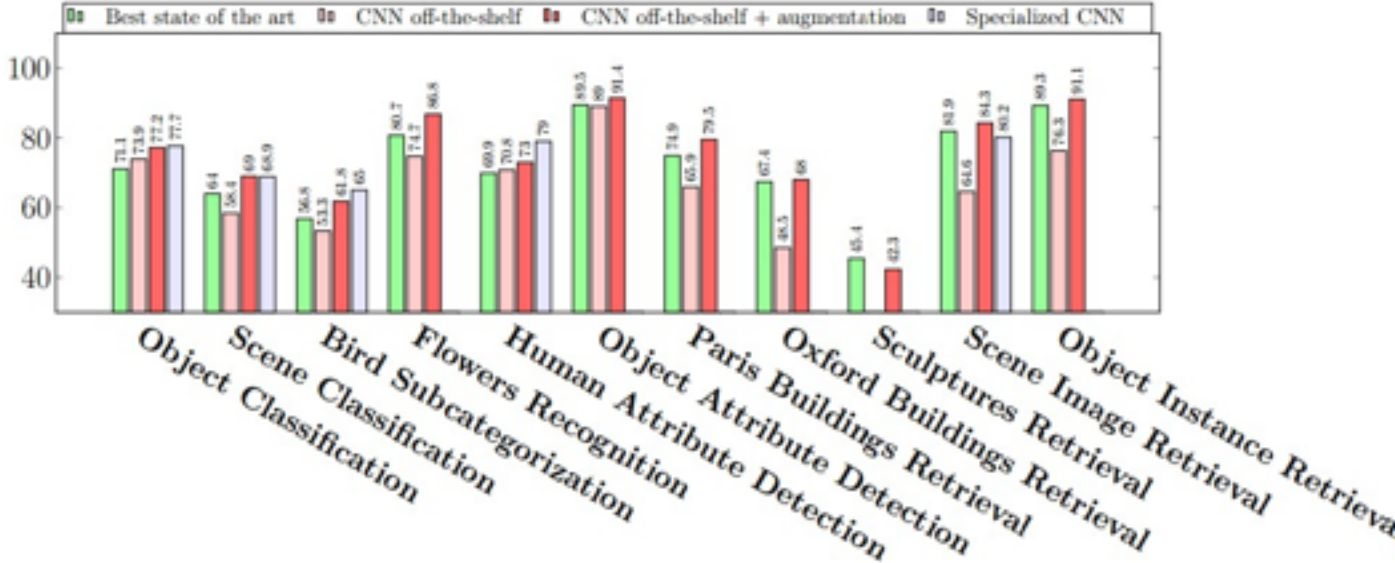
tip: use only ~1/10th of the original learning rate in finetuning top layer, and ~1/100th on intermediate layers

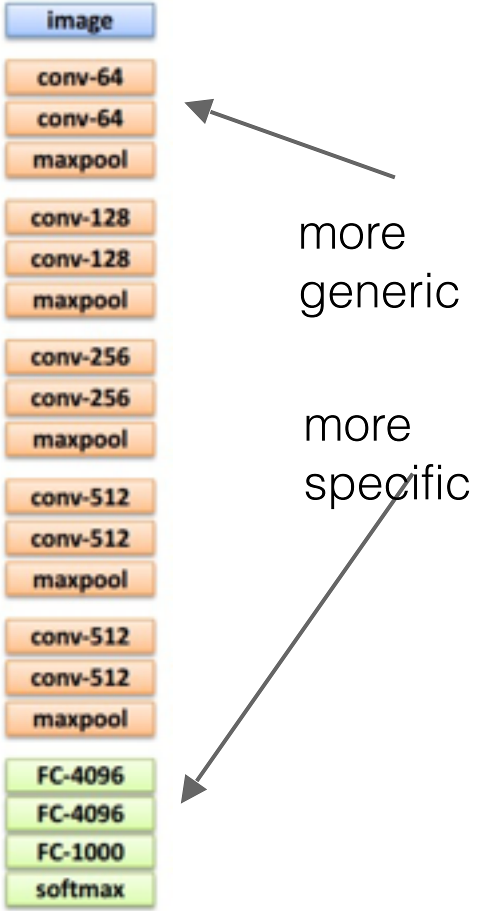
CNN Features off-the-shelf: an Astounding Baseline for Recognition
[Razavian et al, 2014]

DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition
[Donahue*, Jia*, et al., 2013]

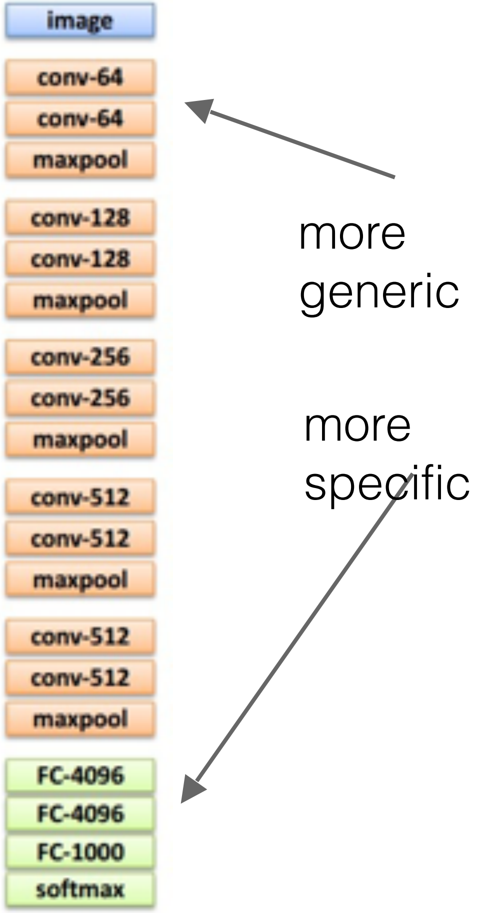
	$DeCAF_6$	$DeCAF_7$
LogReg	$\mathbf{40.94 \pm 0.3}$	40.84 ± 0.3
SVM	39.36 ± 0.3	40.66 ± 0.3
Xiao et al. (2010)	38.0	







	very similar dataset	**very different dataset**
very little data	?	?
quite a lot of data	?	?



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	?
quite a lot of data	Finetune a few layers	?

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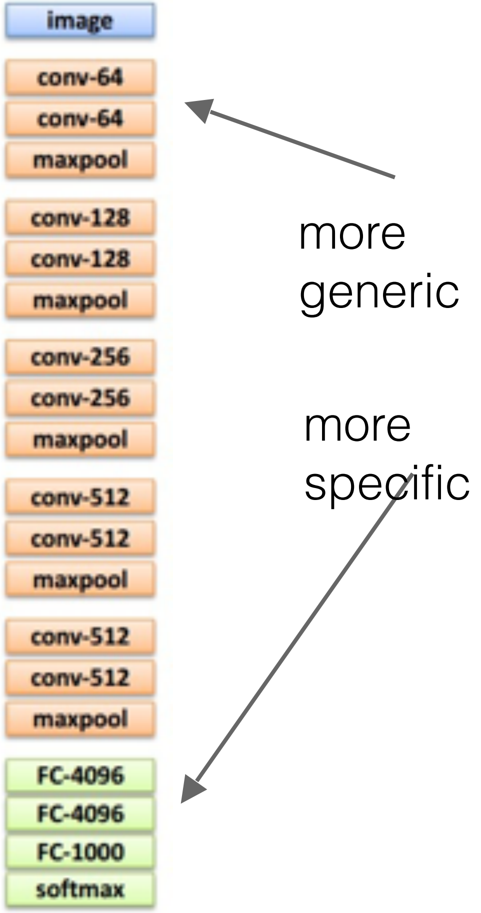
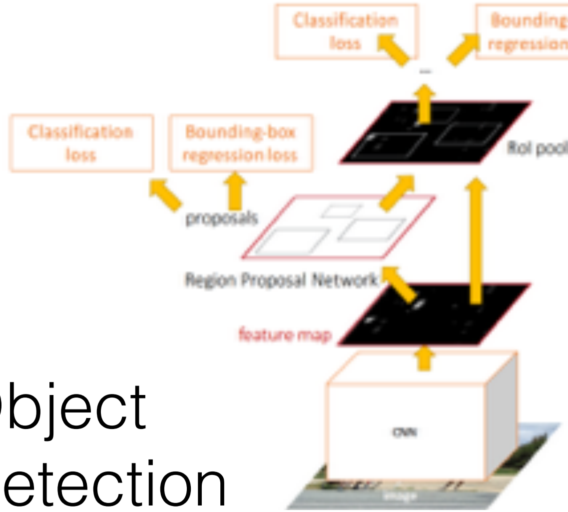


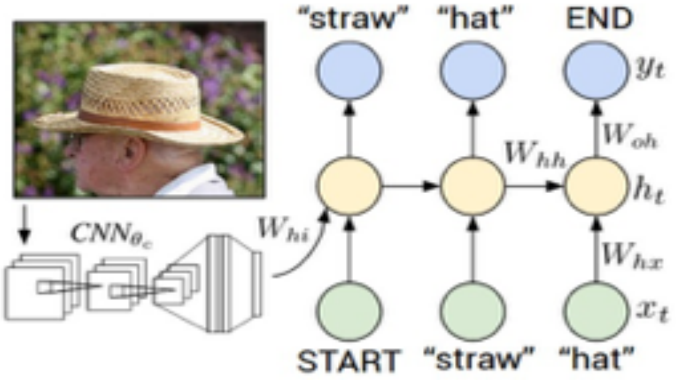
	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Transfer learning with CNNs is pervasive…
(it's the norm, not an exception)

Image Captioning:
CNN + RNN



Object Detection (Faster R-CNN)



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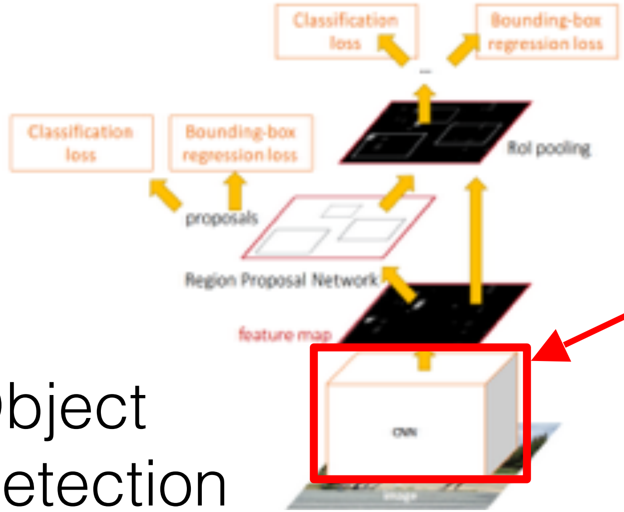
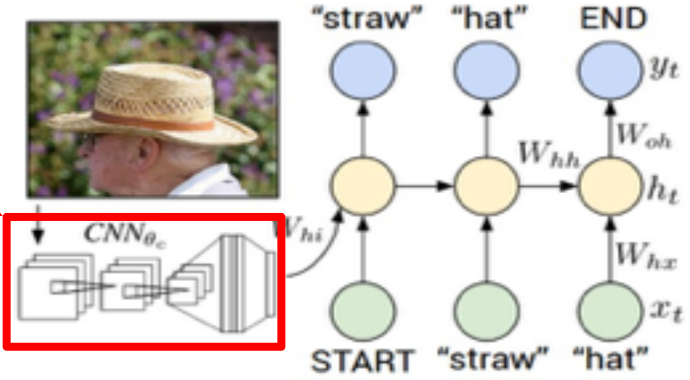


Object Detection (Faster R-CNN)

CNN pretrained on ImageNet



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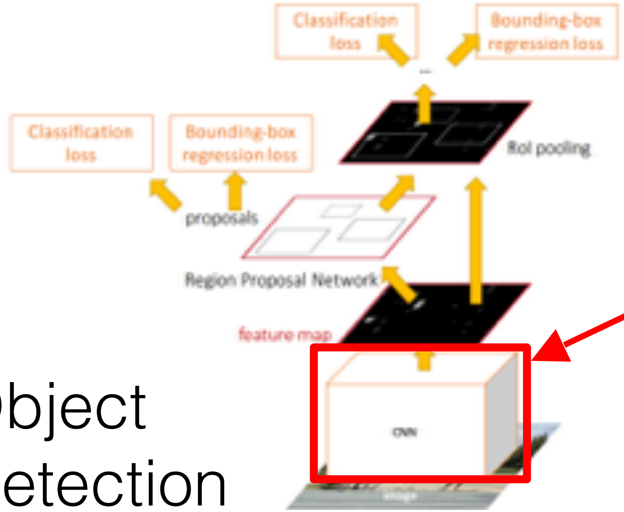

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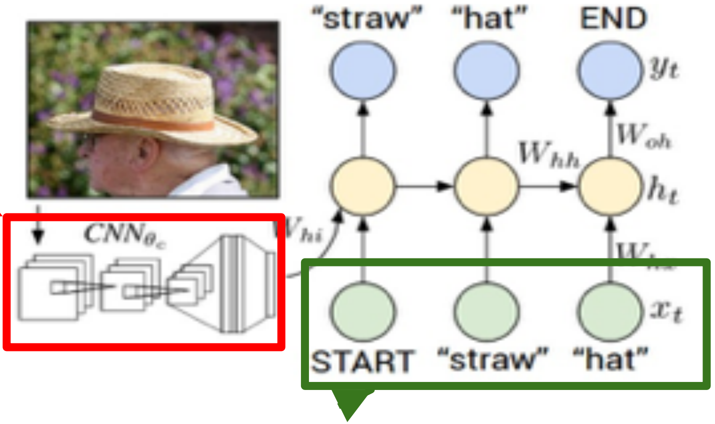
Image Captioning: CNN + RNN



Word vectors pretrained from word2vec

Takeaway for your projects/beyond:

Have some dataset of interest but it has < ~1M images?

1. Find a very large dataset that has similar data, train a big ConvNet there.
2. Transfer learn to your dataset

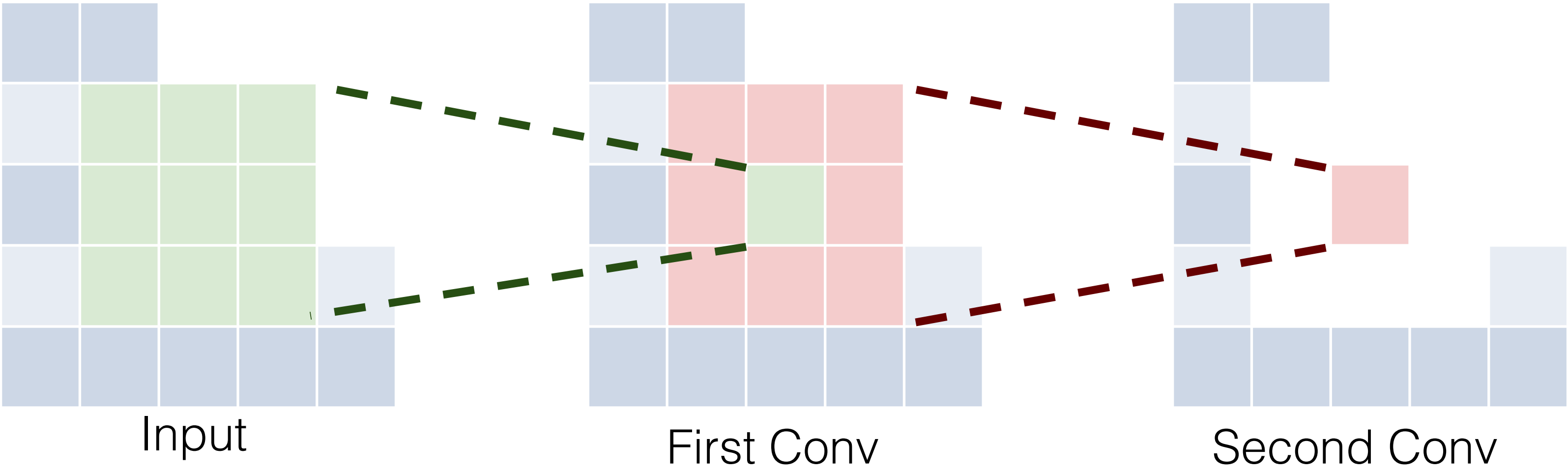
Caffe ConvNet library has a **"Model Zoo"** of pretrained models:
https://github.com/BVLC/caffe/wiki/Model-Zoo

All About Convolutions

Part I: How to stack them

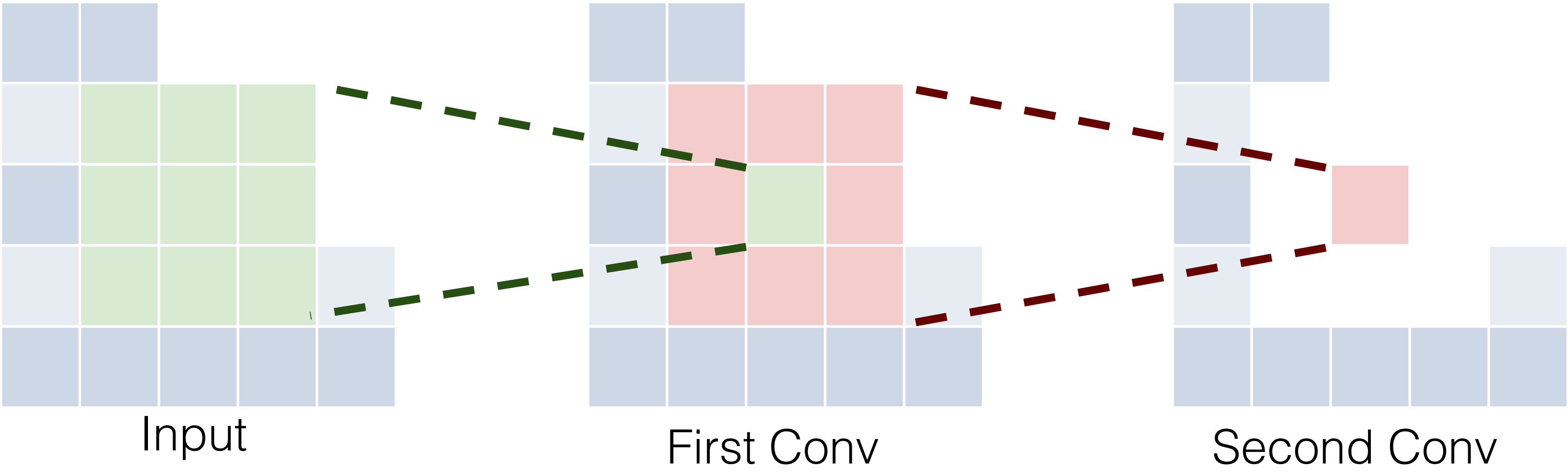
The power of small filters

Suppose we stack two 3x3 conv layers (stride 1)
Each neuron sees 3x3 region of previous activation map



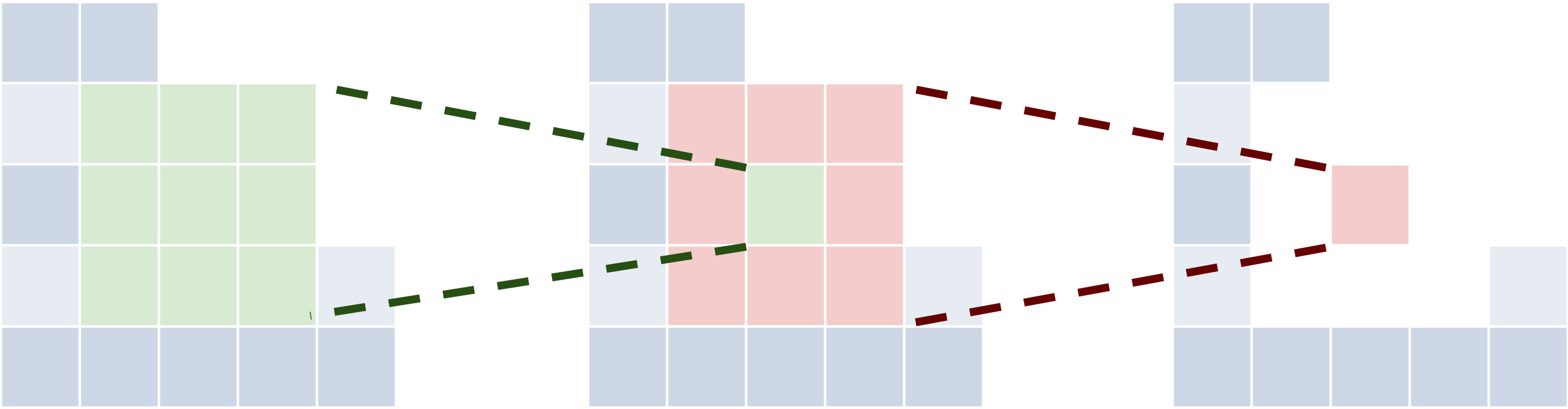
The power of small filters

Question: How big of a region in the input does a neuron on the second conv layer see?



The power of small filters

Question: How big of a region in the input does a neuron on the second conv layer see?
Answer: 5 x 5



Input First Conv Second Conv

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

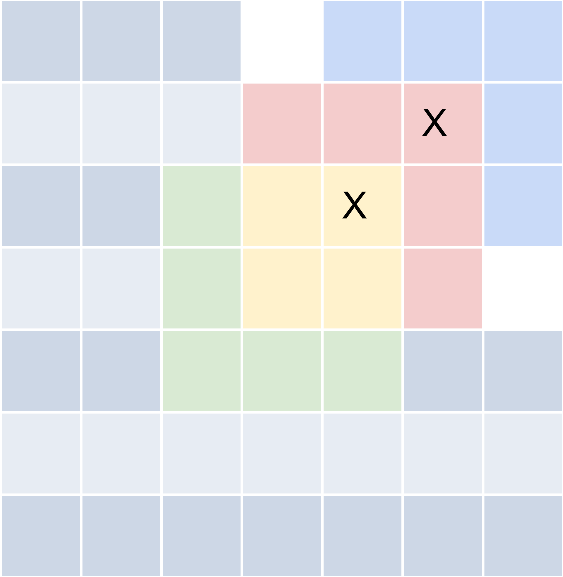
The power of small filters

Question: If we stack three 3x3 conv layers, how big of an input region does a neuron in the third layer see?

The power of small filters

Question: If we stack three 3x3 conv layers, how big of an input region does a neuron in the third layer see?

Answer: 7 x 7



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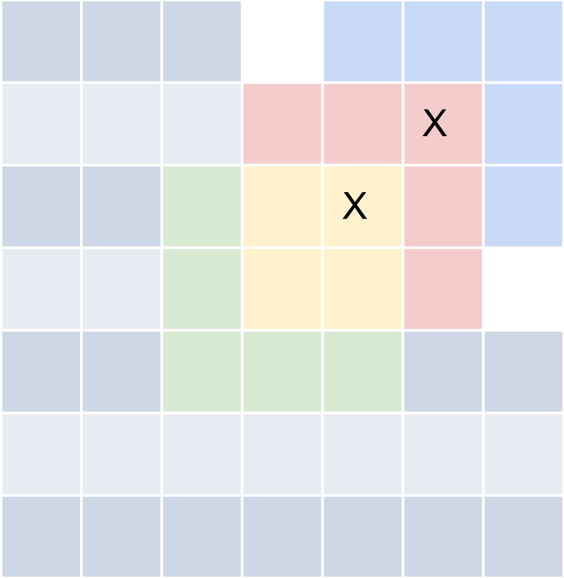

Three 3 x 3 conv gives similar representational power as a single 7 x 7 convolution

The power of small filters

Suppose input is H x W x C and we use convolutions with C filters to preserve depth (stride 1, padding to preserve H, W)

The power of small filters

Suppose input is H x W x C and we use convolutions with C filters to preserve depth (stride 1, padding to preserve H, W)

one CONV with 7 x 7 filters

Number of weights:

three CONV with 3 x 3 filters

Number of weights:

The power of small filters

Suppose input is H x W x C and we use convolutions with C filters to preserve depth (stride 1, padding to preserve H, W)

one CONV with 7 x 7 filters

Number of weights:
$= C \times (7 \times 7 \times C) = \mathbf{49\ C^2}$

three CONV with 3 x 3 filters

Number of weights:
$= 3 \times C \times (3 \times 3 \times C) = \mathbf{27\ C^2}$

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Fewer parameters, more nonlinearity = GOOD

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Number of weights:
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Number of multiply-adds:

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Number of multiply-adds:

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Suppose input is H x W x C and we use convolutions with C filters to preserve depth (stride 1, padding to preserve H, W)

one CONV with 7 x 7 filters

Number of weights:
$= C \times (7 \times 7 \times C) = 49\ C^2$

Number of multiply-adds:
$= (H \times W \times C) \times (7 \times 7 \times C)$
$=$ **$49\ HWC^2$**

three CONV with 3 x 3 filters

Number of weights:
$= 3 \times C \times (3 \times 3 \times C) = 27\ C^2$

Number of multiply-adds:
$= 3 \times (H \times W \times C) \times (3 \times 3 \times C)$
$=$ **$27\ HWC^2$**

The power of small filters

Suppose input is H x W x C and we use convolutions with C filters to preserve depth (stride 1, padding to preserve H, W)

one CONV with 7 x 7 filters

Number of weights:
$= C \times (7 \times 7 \times C) = 49\ C^2$

Number of multiply-adds:
$= \mathbf{49\ HWC^2}$

three CONV with 3 x 3 filters

Number of weights:
$= 3 \times C \times (3 \times 3 \times C) = 27\ C^2$

Number of multiply-adds:
$= \mathbf{27\ HWC^2}$

Less compute, more nonlinearity = GOOD

The power of small filters

Why stop at 3 x 3 filters? Why not try 1 x 1?

The power of small filters

Why stop at 3 x 3 filters? Why not try 1 x 1?

(note: 1x1 filters sum across all channels of the input)

H x W x C

Conv 1x1, C/2 filters ↓

H x W x (C / 2)

1. "bottleneck" 1 x 1 conv to reduce dimension

The power of small filters

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(note: 1x1 filters sum across all channels of the input)

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Conv 3x3, C/2 filters ↓

H x W x (C / 2)

1. “bottleneck” 1 x 1 conv to reduce dimension

2. 3 x 3 conv at reduced dimension

The power of small filters

Why stop at 3 x 3 filters? Why not try 1 x 1?

(note: 1x1 filters sum across all channels of the input)

H x W x C

Conv 1x1, C/2 filters ↓

H x W x (C / 2)

Conv 3x3, C/2 filters ↓

H x W x (C / 2)

Conv 1x1, C filters ↓

H x W x C

1. “bottleneck” 1 x 1 conv to reduce dimension
2. 3 x 3 conv at reduced dimension
3. Restore dimension with another 1 x 1 conv

[Seen in Lin et al, “Network in Network”, GoogLeNet, ResNet]

The power of small filters

Why stop at 3 x 3 filters? Why not try 1 x 1?

H x W x C

Conv 1x1, C/2 filters ↓

H x W x (C / 2)

Conv 3x3, C/2 filters ↓

H x W x (C / 2)

Conv 1x1, C filters ↓

H x W x C

Bottleneck sandwich

Single 3 x 3 conv

H x W x C

↓ Conv 3x3, C filters

H x W x C

The power of small filters

Why stop at 3 x 3 filters? Why not try 1 x 1?

More nonlinearity,
fewer params,
less compute!

H x W x C

Conv 1x1, C/2 filters

H x W x (C / 2)

Conv 3x3, C/2 filters

H x W x (C / 2)

Conv 1x1, C filters

H x W x C

3.25 C^2 parameters

H x W x C

Conv 3x3, C filters

H x W x C

9 C^2 parameters

The power of small filters

Still using 3 x 3 filters … can we break it up?

The power of small filters

Still using 3 x 3 filters … can we break it up?

H x W x C

Conv 1x3, C filters

H x W x C

Conv 3x1, C filters

H x W x C

The power of small filters

Still using 3 x 3 filters … can we break it up?

More nonlinearity,
fewer params,
less compute!

H x W x C

Conv 1x3, C filters

H x W x C

Conv 3x1, C filters

H x W x C

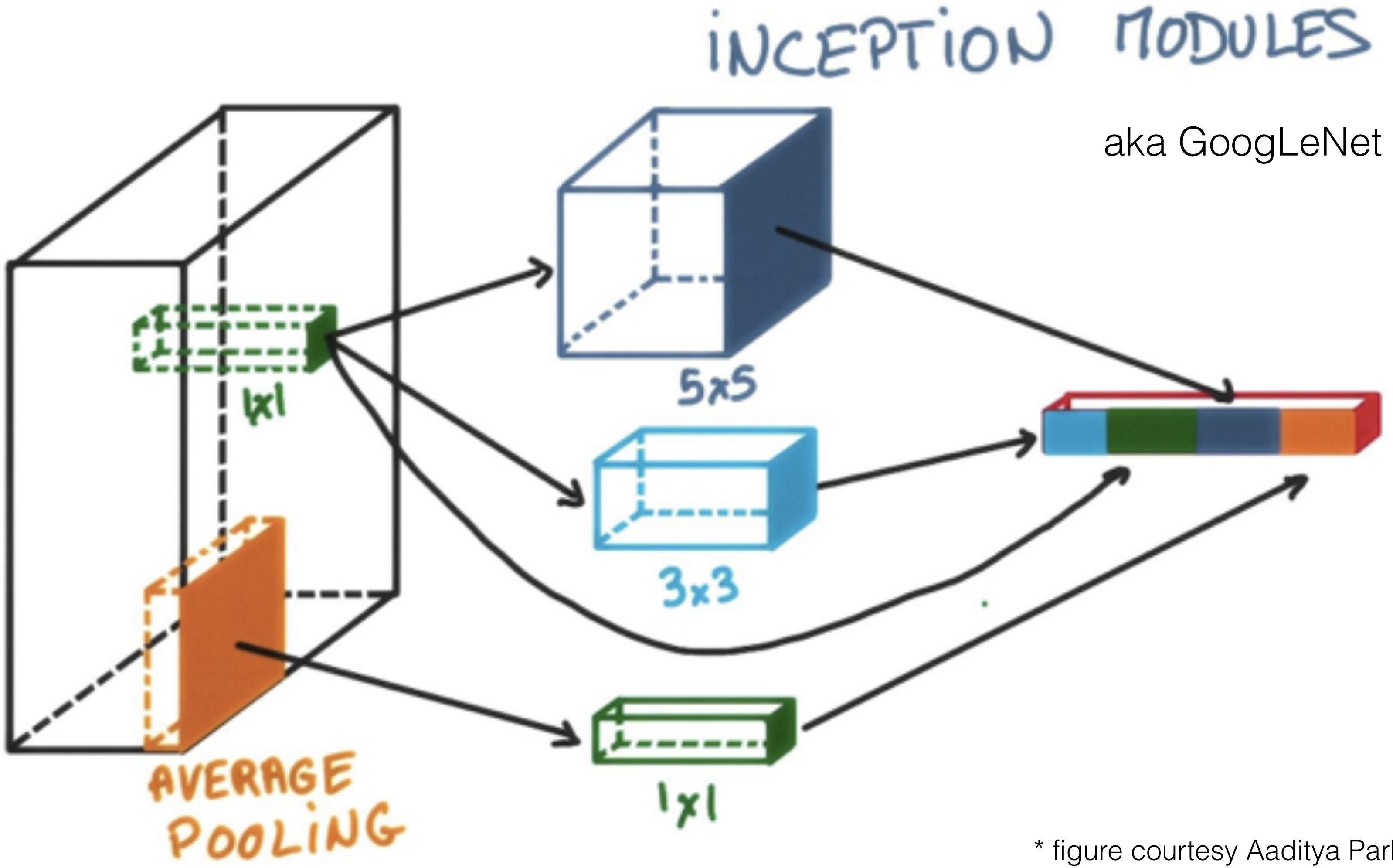
6 C^2 parameters

9 C^2 parameters

H x W x C

Conv 3x3, C filters

H x W x C

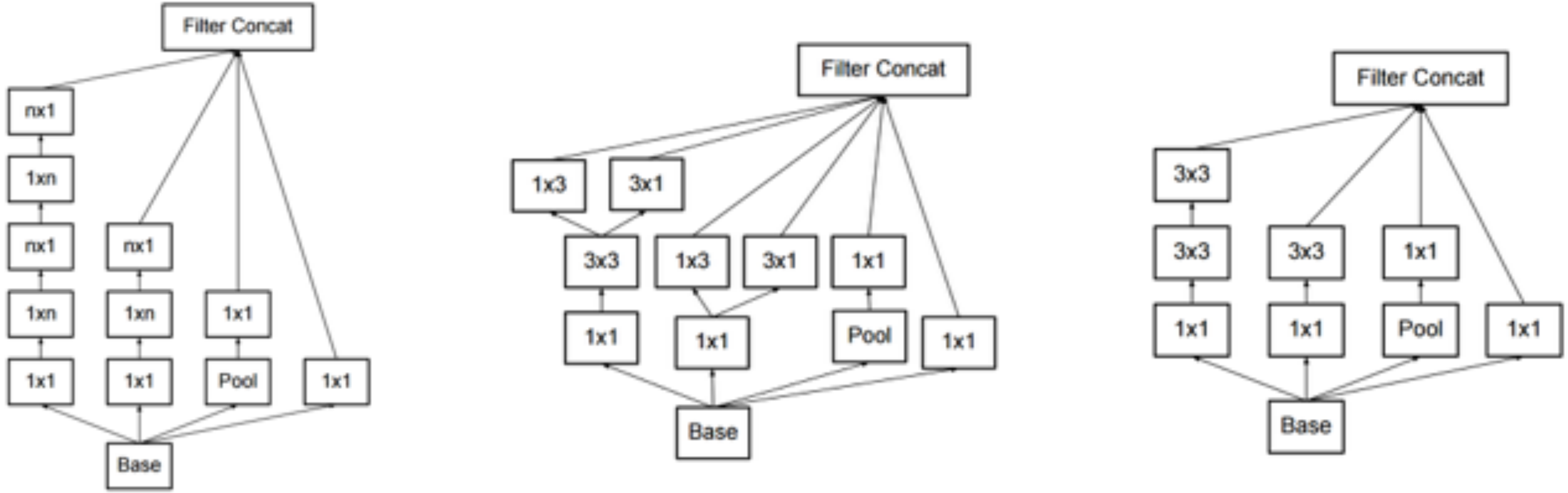


aka GoogLeNet

* figure courtesy Aaditya Parkash

The power of small filters

Latest version of GoogLeNet incorporates all these ideas



Szegedy et al, "Rethinking the Inception Architecture for Computer Vision"

How to stack convolutions: Recap

- Replace large convolutions (5 x 5, 7 x 7) with stacks of 3 x 3 convolutions
- 1 x 1 “bottleneck” convolutions are very efficient
- Can factor N x N convolutions into 1 x N and N x 1
- All of the above give fewer parameters, less compute, more nonlinearity

All About Convolutions

Part II: How to compute them

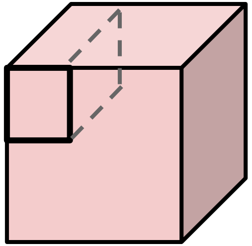
Implementing Convolutions: im2col

There are highly optimized matrix multiplication routines for just about every platform

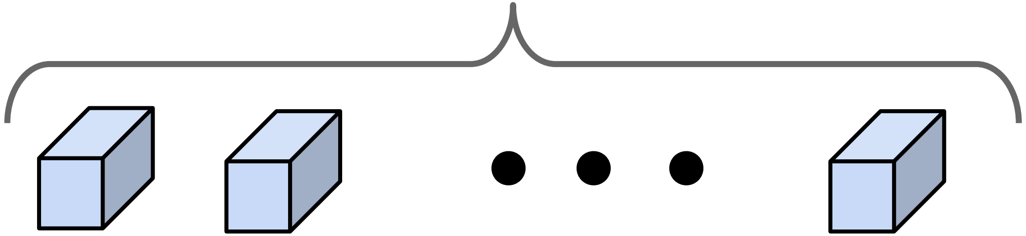
Can we turn convolution into matrix multiplication?

Implementing Convolutions: im2col

Feature map: H x W x C

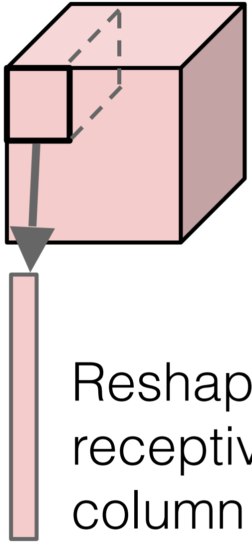


Conv weights: D filters, each K x K x C



Implementing Convolutions: im2col

Feature map: H x W x C



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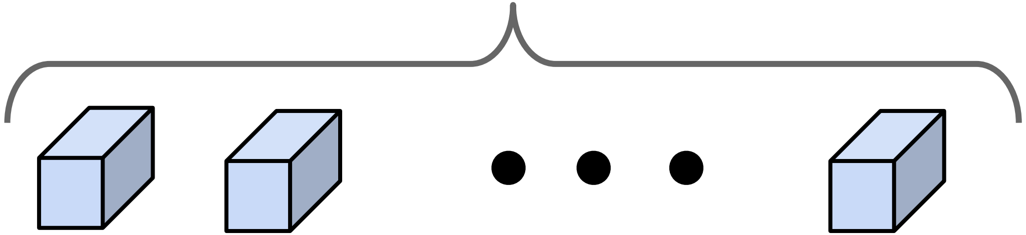
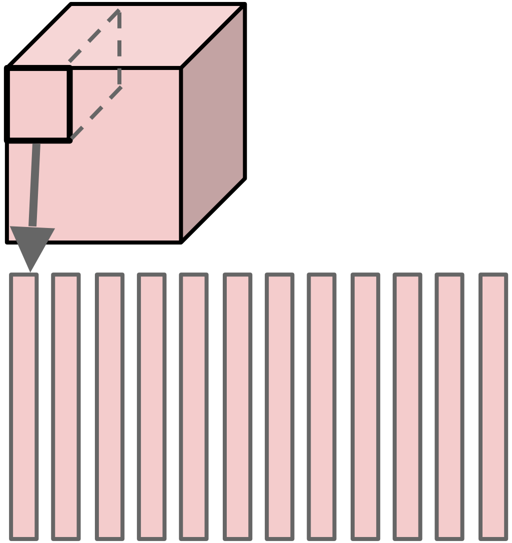


Reshape K x K x C receptive field to column with K^2C elements

Implementing Convolutions: im2col

Feature map: H x W x C



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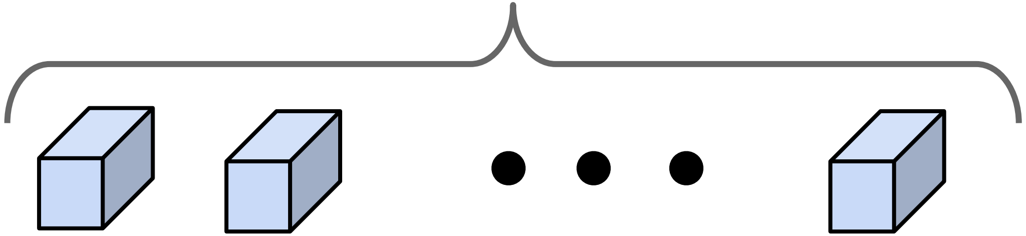
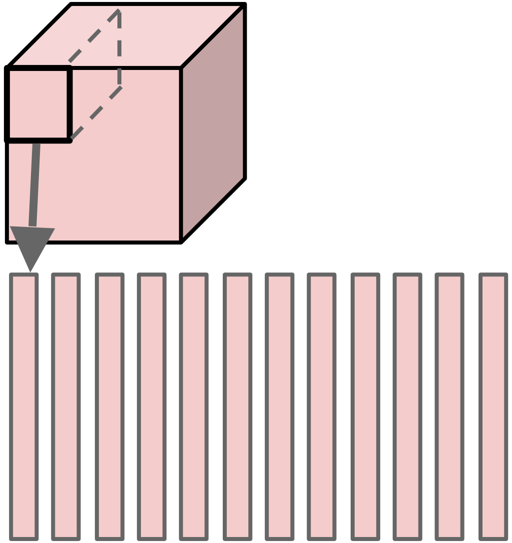


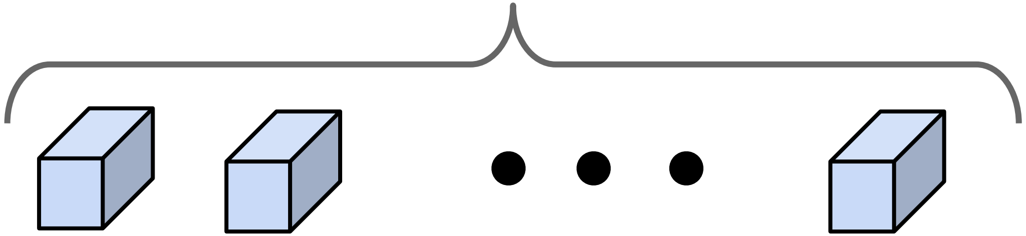
Repeat for all columns to get $(K^2C) \times N$ matrix
(N receptive field locations)

Implementing Convolutions: im2col

Feature map: H x W x C



Conv weights: D filters, each K x K x C

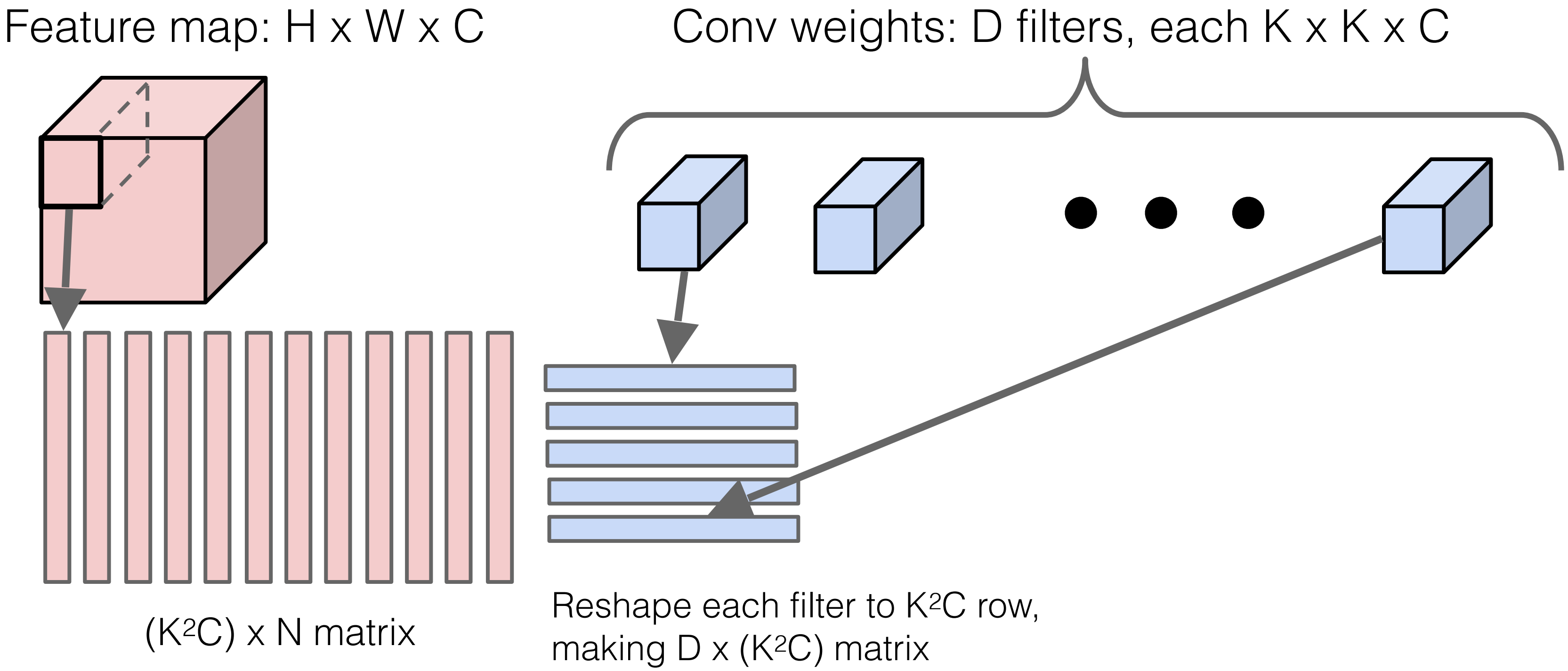


Elements appearing in multiple receptive fields are duplicated; this uses a lot of memory

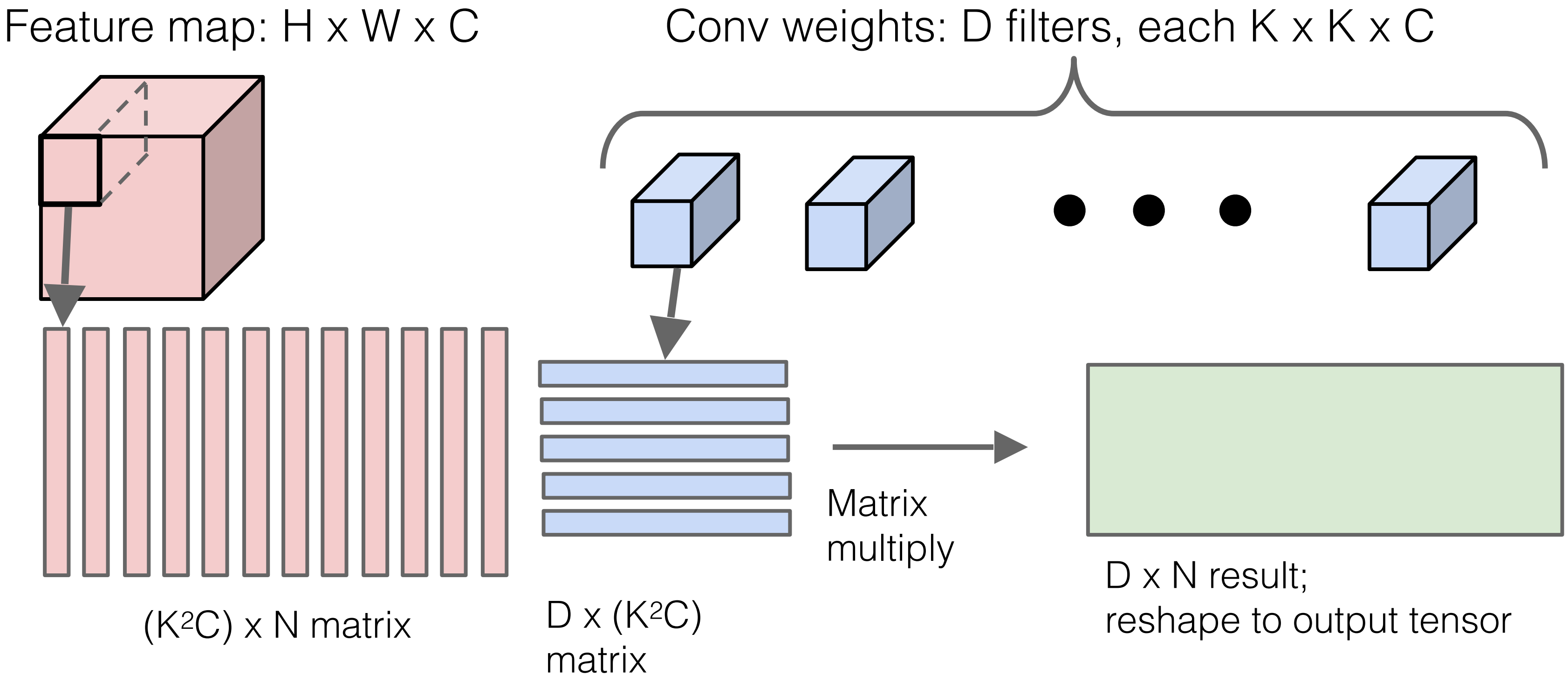
Repeat for all columns to get (K^2C) x N matrix
(N receptive field locations)

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

Implementing Convolutions: im2col



Implementing Convolutions: im2col



```
template <typename Dtype>
void ConvolutionLayer<Dtype>::Forward_gpu(const vector<Blob<Dtype>*>& bottom,
      vector<Blob<Dtype>*>* top) {
  for (int i = 0; i < bottom.size(); ++i) {
    const Dtype* bottom_data = bottom[i]->gpu_data();
    Dtype* top_data = (*top)[i]->mutable_gpu_data();
    Dtype* col_data = col_buffer_.mutable_gpu_data();
    const Dtype* weight = this->blobs_[0]->gpu_data();
    int weight_offset = M_ * K_;
    int col_offset = K_ * N_;
    int top_offset = M_ * N_;
    for (int n = 0; n < num_; ++n) {
      // im2col transformation: unroll input regions for filtering
      // into column matrix for multiplication.
      im2col_gpu(bottom_data + bottom[i]->offset(n), channels_, height_,
          width_, kernel_h_, kernel_w_, pad_h_, pad_w_, stride_h_, stride_w_,
          col_data);
      // Take inner products for groups.
      for (int g = 0; g < group_; ++g) {
        caffe_gpu_gemm<Dtype>(CblasNoTrans, CblasNoTrans, M_, N_, K_,
          (Dtype)1., weight + weight_offset * g, col_data + col_offset * g,
          (Dtype)0., top_data + (*top)[i]->offset(n) + top_offset * g);
      }
      // Add bias.
      if (bias_term_) {
        caffe_gpu_gemm<Dtype>(CblasNoTrans, CblasNoTrans, num_output_,
            N_, 1, (Dtype)1., this->blobs_[1]->gpu_data(),
            bias_multiplier_.gpu_data(),
            (Dtype)1., top_data + (*top)[i]->offset(n));
      }
    }
  }
}
```

Case study:

CONV forward in Caffe library

im2col

matrix multiply: call to cuBLAS

bias offset

```python
def conv_forward_strides(x, w, b, conv_param):
  N, C, H, W = x.shape
  F, _, HH, WW = w.shape
  stride, pad = conv_param['stride'], conv_param['pad']

  # Check dimensions
  assert (W + 2 * pad - WW) % stride == 0, 'width does not work'
  assert (H + 2 * pad - HH) % stride == 0, 'height does not work'

  # Pad the input
  p = pad
  x_padded = np.pad(x, ((0, 0), (0, 0), (p, p), (p, p)), mode='constant')

  # Figure out output dimensions
  H += 2 * pad
  W += 2 * pad
  out_h = (H - HH) / stride + 1
  out_w = (W - WW) / stride + 1

  # Perform an im2col operation by picking clever strides
  shape = (C, HH, WW, N, out_h, out_w)
  strides = (H * W, W, 1, C * H * W, stride * W, stride)
  strides = x.itemsize * np.array(strides)
  x_stride = np.lib.stride_tricks.as_strided(x_padded,
                shape=shape, strides=strides)
  x_cols = np.ascontiguousarray(x_stride)
  x_cols.shape = (C * HH * WW, N * out_h * out_w)

  # Now all our convolutions are a big matrix multiply
  res = w.reshape(F, -1).dot(x_cols) + b.reshape(-1, 1)

  # Reshape the output
  res.shape = (F, N, out_h, out_w)
  out = res.transpose(1, 0, 2, 3)

  # Be nice and return a contiguous array
  # The old version of conv_forward_fast doesn't do this, so for a fair
  # comparison we won't either
  out = np.ascontiguousarray(out)

  cache = (x, w, b, conv_param, x_cols)
  return out, cache
```

Case study:
fast_layers.py from HW

im2col

matrix multiply:
call np.dot
(which calls BLAS)

Implementing convolutions: FFT

- **Convolution Theorem:** The convolution of f and g is equal to the elementwise product of their Fourier Transforms: $$\mathcal{F}(f * g) = \mathcal{F}(f) \cdot \mathcal{F}(g)$$

- Using the **Fast Fourier Transform**, we can compute the Discrete Fourier transform of an N-dimensional vector in O(N log N) time (also extends to 2D images)

Implementing convolutions: FFT

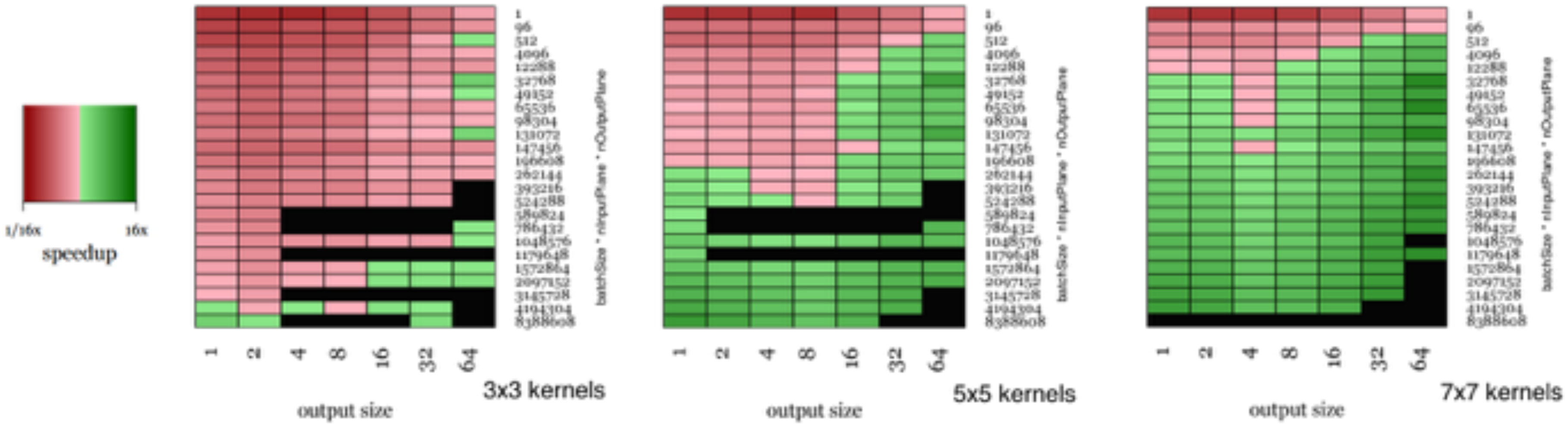
1. Compute FFT of weights: $F(W)$

2. Compute FFT of image: $F(X)$

3. Compute elementwise product: $F(W) \circ F(X)$

4. Compute inverse FFT: $Y = F^{-1}(F(W) \circ F(X))$

Implementing convolutions: FFT



FFT convolutions get a big speedup for larger filters
Not much speedup for 3x3 filters =(

Vasilache et al, Fast Convolutional Nets With fbfft: A GPU Performance Evaluation

Implementing convolution: "Fast Algorithms"

Naive matrix multiplication: Computing product of two N x N matrices takes $O(N^3)$ operations

Strassen's Algorithm: Use clever arithmetic to reduce complexity to $O(N^{\log2(7)}) \sim O(N^{2.81})$

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_{1,1} & \mathbf{A}_{1,2} \\ \mathbf{A}_{2,1} & \mathbf{A}_{2,2} \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} \mathbf{B}_{1,1} & \mathbf{B}_{1,2} \\ \mathbf{B}_{2,1} & \mathbf{B}_{2,2} \end{bmatrix}$$

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_{1,1} & \mathbf{C}_{1,2} \\ \mathbf{C}_{2,1} & \mathbf{C}_{2,2} \end{bmatrix}$$

$$\begin{aligned}
\mathbf{M}_1 &:= (\mathbf{A}_{1,1} + \mathbf{A}_{2,2})(\mathbf{B}_{1,1} + \mathbf{B}_{2,2}) \\
\mathbf{M}_2 &:= (\mathbf{A}_{2,1} + \mathbf{A}_{2,2})\mathbf{B}_{1,1} \\
\mathbf{M}_3 &:= \mathbf{A}_{1,1}(\mathbf{B}_{1,2} - \mathbf{B}_{2,2}) \\
\mathbf{M}_4 &:= \mathbf{A}_{2,2}(\mathbf{B}_{2,1} - \mathbf{B}_{1,1}) \\
\mathbf{M}_5 &:= (\mathbf{A}_{1,1} + \mathbf{A}_{1,2})\mathbf{B}_{2,2} \\
\mathbf{M}_6 &:= (\mathbf{A}_{2,1} - \mathbf{A}_{1,1})(\mathbf{B}_{1,1} + \mathbf{B}_{1,2}) \\
\mathbf{M}_7 &:= (\mathbf{A}_{1,2} - \mathbf{A}_{2,2})(\mathbf{B}_{2,1} + \mathbf{B}_{2,2})
\end{aligned}$$

$$\begin{aligned}
\mathbf{C}_{1,1} &= \mathbf{M}_1 + \mathbf{M}_4 - \mathbf{M}_5 + \mathbf{M}_7 \\
\mathbf{C}_{1,2} &= \mathbf{M}_3 + \mathbf{M}_5 \\
\mathbf{C}_{2,1} &= \mathbf{M}_2 + \mathbf{M}_4 \\
\mathbf{C}_{2,2} &= \mathbf{M}_1 - \mathbf{M}_2 + \mathbf{M}_3 + \mathbf{M}_6
\end{aligned}$$

From Wikipedia

Implementing convolution: “Fast Algorithms”

Similar cleverness can be applied to convolutions

Lavin and Gray (2015) work out special cases for 3x3 convolutions:

$$F(2,3) = \begin{bmatrix} d_0 & d_1 & d_2 \\ d_1 & d_2 & d_3 \end{bmatrix} \begin{bmatrix} g_0 \\ g_1 \\ g_2 \end{bmatrix} = \begin{bmatrix} m_1 + m_2 + m_3 \\ m_2 - m_3 - m_4 \end{bmatrix}$$

$$m_1 = (d_0 - d_2)g_0 \qquad m_2 = (d_1 + d_2)\frac{g_0 + g_1 + g_2}{2}$$

$$m_4 = (d_1 - d_3)g_2 \qquad m_3 = (d_2 - d_1)\frac{g_0 - g_1 + g_2}{2}$$

$$B^T = \begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 1 & 0 & -1 \end{bmatrix}$$

$$G = \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 1 \end{bmatrix}$$

$$A^T = \begin{bmatrix} 1 & 1 & 1 & 0 \\ 0 & 1 & -1 & -1 \end{bmatrix}$$

$$g = \begin{bmatrix} g_0 & g_1 & g_2 \end{bmatrix}^T$$

$$d = \begin{bmatrix} d_0 & d_1 & d_2 & d_3 \end{bmatrix}^T$$

Lavin and Gray, “Fast Algorithms for Convolutional Neural Networks”, 2015

Implementing convolution: “Fast Algorithms”

Huge speedups on VGG for small batches:

N	cuDNN msec	cuDNN TFLOPS	F(2x2,3x3) msec	F(2x2,3x3) TFLOPS	Speedup
1	12.52	3.12	5.55	7.03	2.26X
2	20.36	3.83	9.89	7.89	2.06X
4	104.70	1.49	17.72	8.81	5.91X
8	241.21	1.29	33.11	9.43	7.28X
16	203.09	3.07	65.79	9.49	3.09X
32	237.05	5.27	132.36	9.43	1.79X
64	394.05	6.34	266.48	9.37	1.48X

Table 5. cuDNN versus $F(2 \times 2, 3 \times 3)$ performance on VGG Network E with fp32 data. Throughput is measured in Effective TFLOPS, the ratio of direct algorithm GFLOPs to run time.

N	cuDNN msec	cuDNN TFLOPS	F(2x2,3x3) msec	F(2x2,3x3) TFLOPS	Speedup
1	14.58	2.68	5.53	7.06	2.64X
2	20.94	3.73	9.83	7.94	2.13X
4	104.19	1.50	17.50	8.92	5.95X
8	241.87	1.29	32.61	9.57	7.42X
16	204.01	3.06	62.93	9.92	3.24X
32	236.13	5.29	123.12	10.14	1.92X
64	395.93	6.31	242.98	10.28	1.63X

Table 6. cuDNN versus $F(2 \times 2, 3 \times 3)$ performance on VGG Network E with fp16 data.

Computing Convolutions: Recap

- im2col: Easy to implement, but big memory overhead
- FFT: Big speedups for small kernels
- “Fast Algorithms” seem promising, not widely used yet

Implementation Details


GEFORCE GTX
AX1200i

Spot the CPU!

Spot the CPU!

"central processing unit"

Spot the GPU!

"graphics processing unit"

Spot the GPU!

“graphics processing unit”

NVIDIA

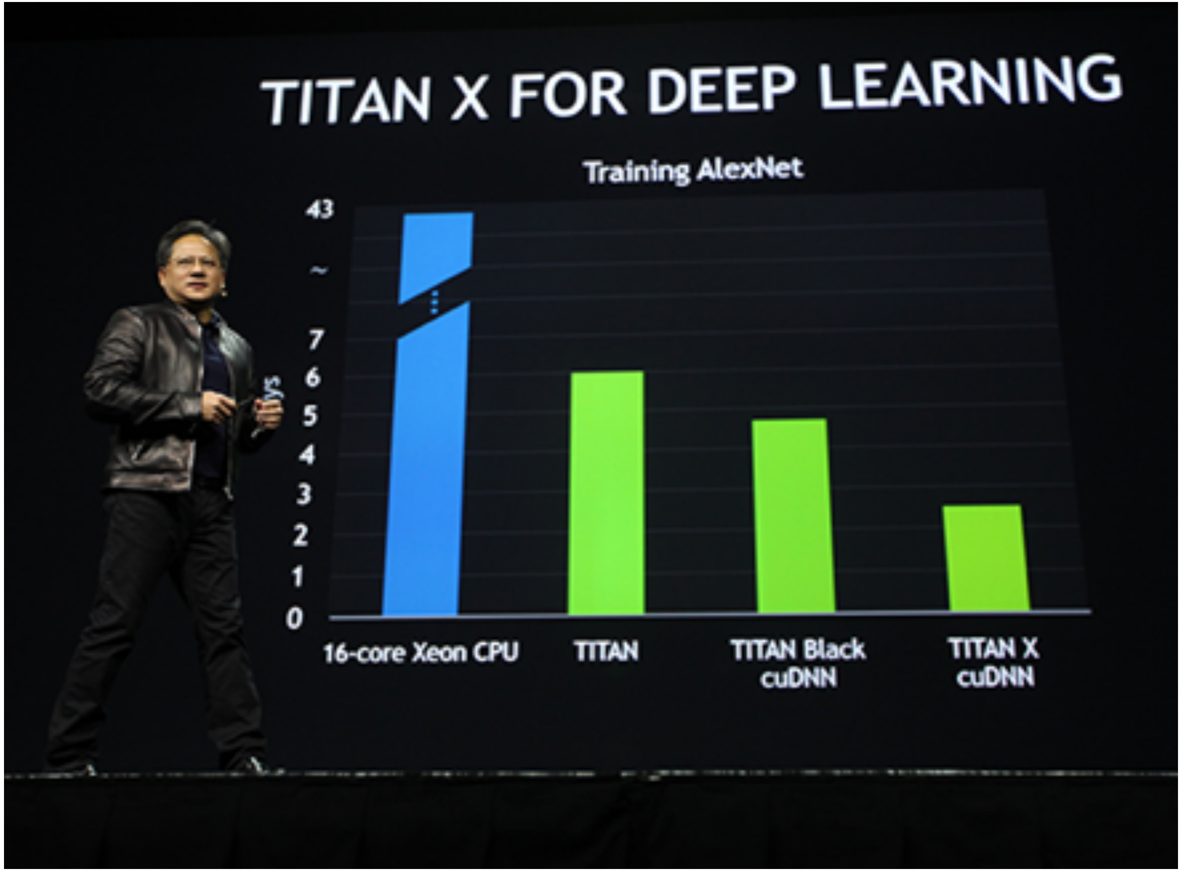
VS

AMD

VS

NVIDIA is much more common for deep learning

GTC 2015:
Introduced new Titan X GPU by bragging about AlexNet benchmarks



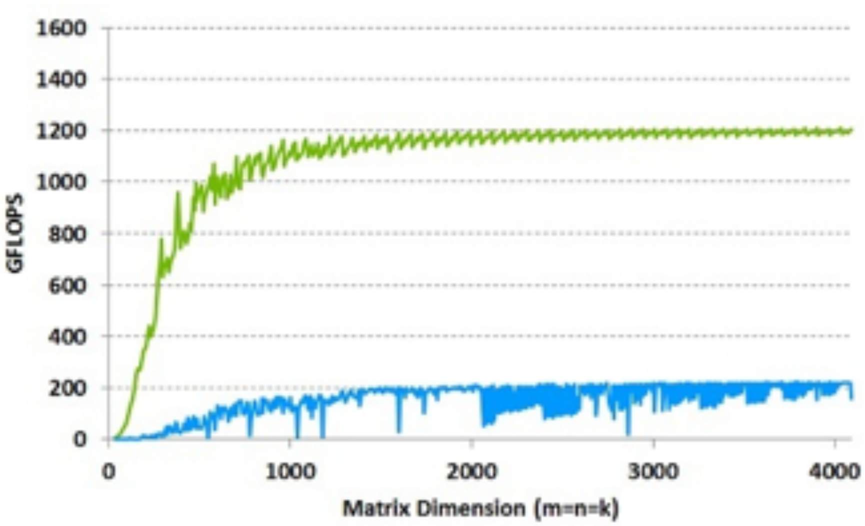
CPU
Few, fast cores (1 - 16)
Good at sequential processing

GPU
Many, slower cores (thousands)
Originally for graphics
Good at parallel computation

GPUs can be programmed

- CUDA (NVIDIA only)
  - Write C code that runs directly on the GPU
  - Higher-level APIs: cuBLAS, cuFFT, cuDNN, etc
- OpenCL
  - Similar to CUDA, but runs on anything
  - Usually slower :(
- Udacity: Intro to Parallel Programming https://www.udacity.com/course/cs344
  - For deep learning just use existing libraries

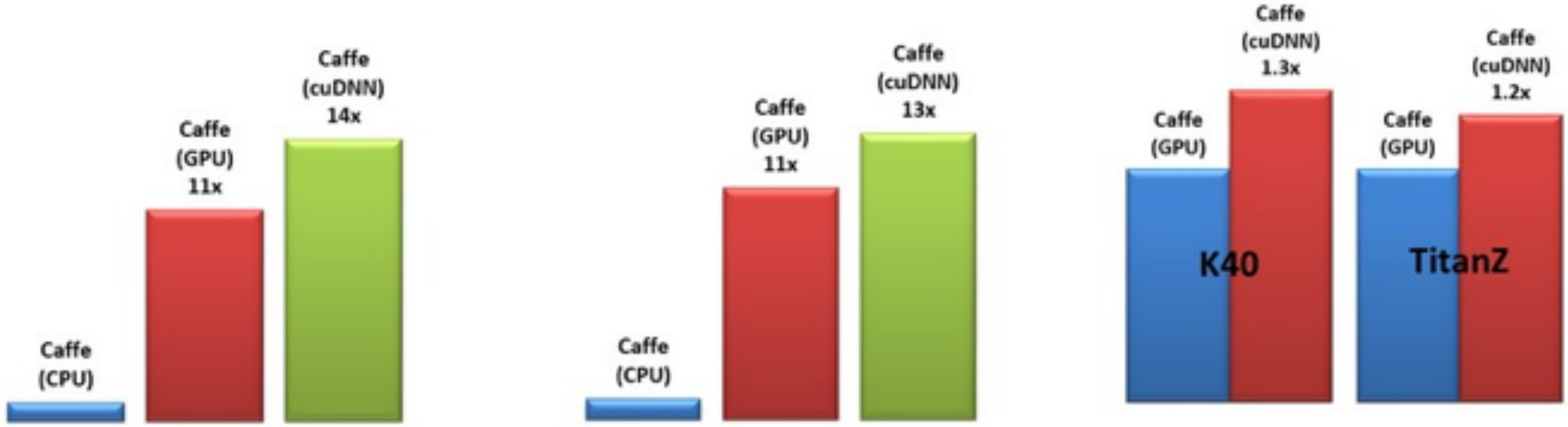
GPUs are really good at matrix multiplication:



GPU: NVIDA Tesla K40 with cuBLAS

CPU: Intel E5-2697 v2 12 core @ 2.7 Ghz with MKL

GPUs are really good at convolution (cuDNN):

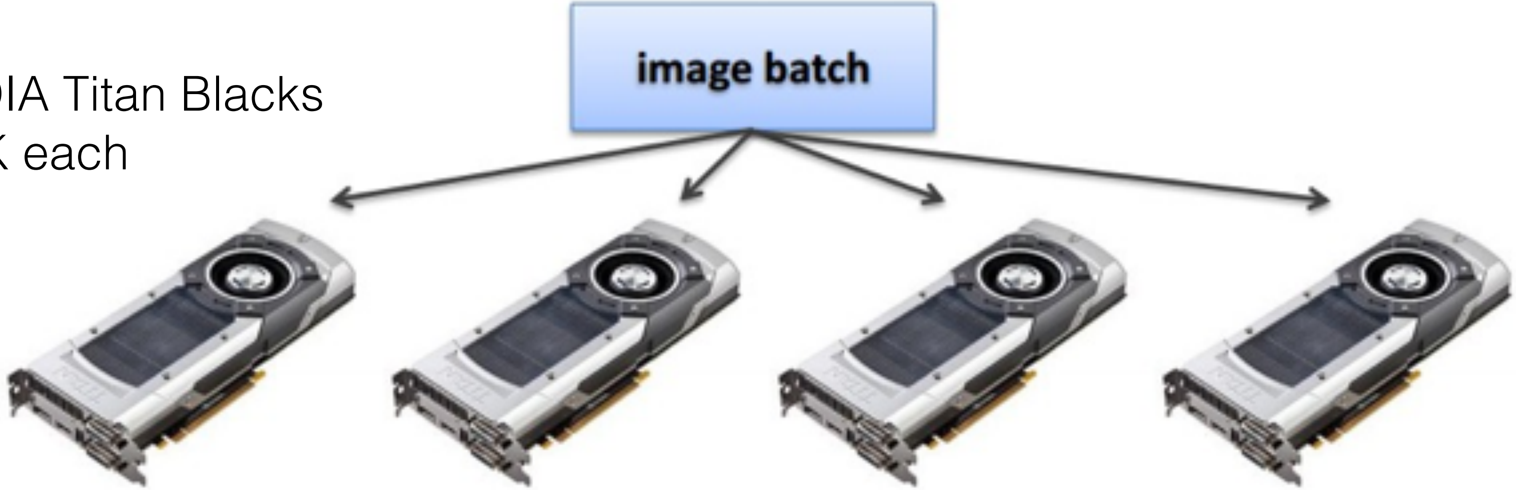


All comparisons are against a 12-core Intel E5-2679v2 CPU @ 2.4GHz running Caffe with Intel MKL 11.1.3.

Even with GPUs, training can be slow

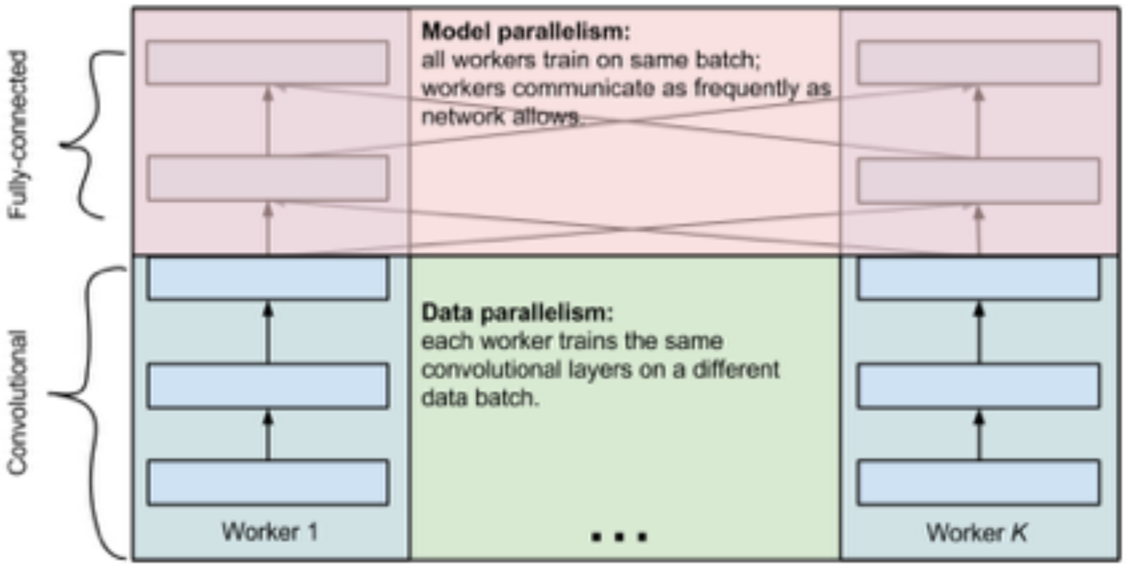
VGG: ~2-3 weeks training with 4 GPUs
ResNet 101: 2-3 weeks with 4 GPUs

NVIDIA Titan Blacks
~$1K each



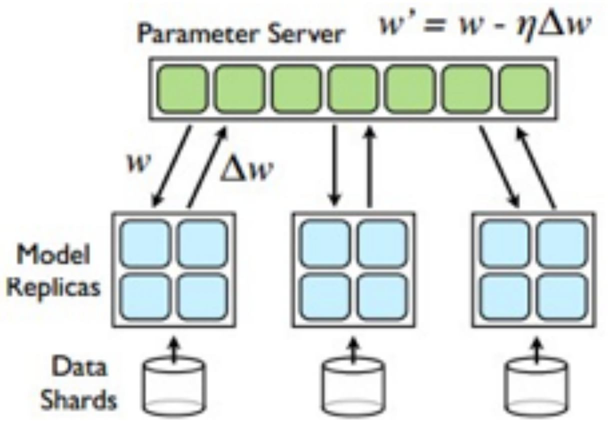
ResNet reimplemented in Torch: http://torch.ch/blog/2016/02/04/resnets.html

Multi-GPU training: More complex



Alex Krizhevsky, “One weird trick for parallelizing convolutional neural networks”

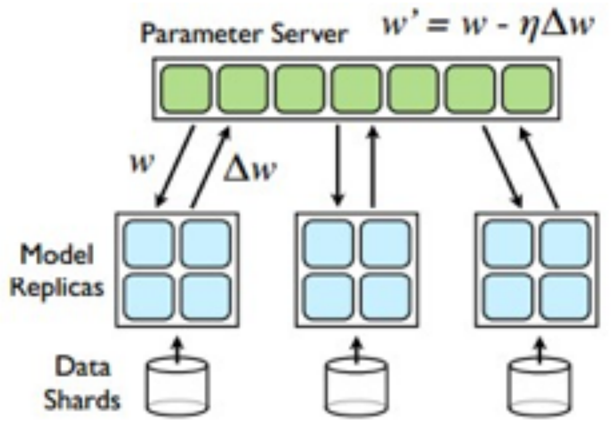
Google: Distributed CPU training



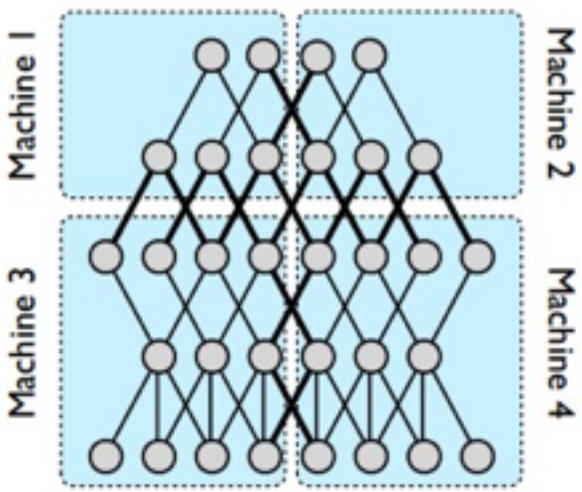
Data parallelism

[Large Scale Distributed Deep Networks, Jeff Dean et al., 2013]

Google: Distributed CPU training



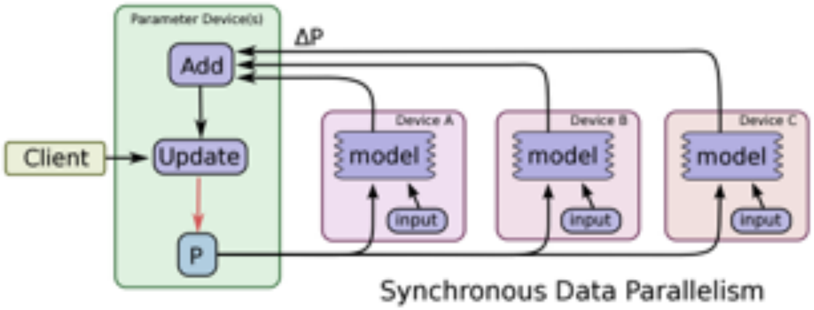
Data parallelism

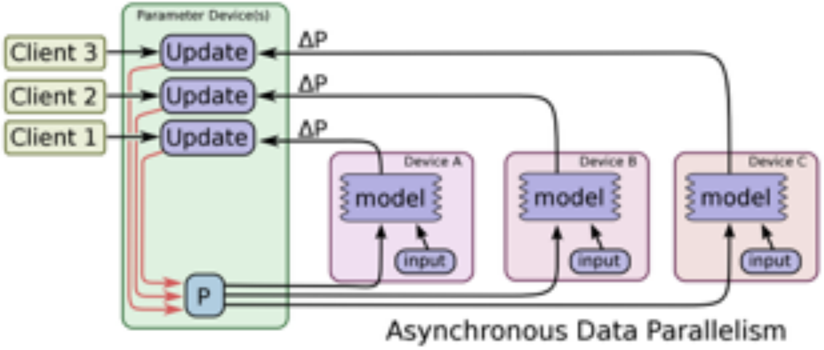


Model parallelism

[Large Scale Distributed Deep Networks, Jeff Dean et al., 2013]

Google: Synchronous vs Async





Abadi et al, "TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems"

Bottlenecks

to be aware of

GPU - CPU communication is a bottleneck.

=>

CPU data prefetch+augment thread running

while

GPU performs forward/backward pass

CPU - disk bottleneck

Moving parts lol

Hard disk is slow to read from

=> Pre-processed images
stored contiguously in files, read as
raw byte stream from SSD disk

GPU memory bottleneck

Titan X: 12 GB <- currently the max
GTX 980 Ti: 6 GB

e.g.
AlexNet: ~3GB needed with batch size 256

Floating Point Precision

Floating point precision

- 64 bit “double” precision is default in a lot of programming

- 32 bit “single” precision is typically used for CNNs for performance

Floating point precision

- 64 bit “double” precision is default in a lot of programming
- 32 bit “single” precision is typically used for CNNs for performance
  - Including in your homework!

```
class FullyConnectedNet(object):
  """
  A fully-connected neural network with an arbitrary number of hidden layers,
  ReLU nonlinearities, and a softmax loss function. This will also implement
  dropout and batch normalization as options. For a network with L layers,
  the architecture will be

  {affine - [batch norm] - relu - [dropout]} x (L - 1) - affine - softmax

  where batch normalization and dropout are optional, and the {...} block is
  repeated L - 1 times.

  Similar to the TwoLayerNet above, learnable parameters are stored in the
  self.params dictionary and will be learned using the Solver class.
  """

  def __init__(self, hidden_dims, input_dim=3*32*32, num_classes=10,
               dropout=0, use_batchnorm=False, reg=0.0,
               weight_scale=1e-2, dtype=np.float32, seed=None):
```

Floating point precision

- **Prediction**: 16 bit “half” precision will be the new standard
  - Already supported in cuDNN
  - Nervana fp16 kernels are the fastest right now
  - Hardware support in next-gen NVIDIA cards (Pascal)
  - Not yet supported in *Torch*

AlexNet (One Weird Trick paper) - Input 128x3x224x224

Library	Class	Time (ms)	forward (ms)	backward (ms)
Nervana-fp16	ConvLayer	**92**	**29**	**62**
CuDNN[R3]-fp16 (Torch)	cudnn.SpatialConvolution	96	30	66
CuDNN[R3]-fp32 (Torch)	cudnn.SpatialConvolution	96	32	64

OxfordNet [Model-A] - Input 64x3x224x224

Library	Class	Time (ms)	forward (ms)	backward (ms)
Nervana-fp16	ConvLayer	**529**	**167**	**362**
Nervana-fp32	ConvLayer	590	180	410
CuDNN[R3]-fp16 (Torch)	cudnn.SpatialConvolution	615	179	436

GoogleNet V1 - Input 128x3x224x224

Library	Class	Time (ms)	forward (ms)	backward (ms)
Nervana-fp16	ConvLayer	**283**	**85**	**197**
Nervana-fp32	ConvLayer	322	90	232
CuDNN[R3]-fp32 (Torch)	cudnn.SpatialConvolution	431	117	313

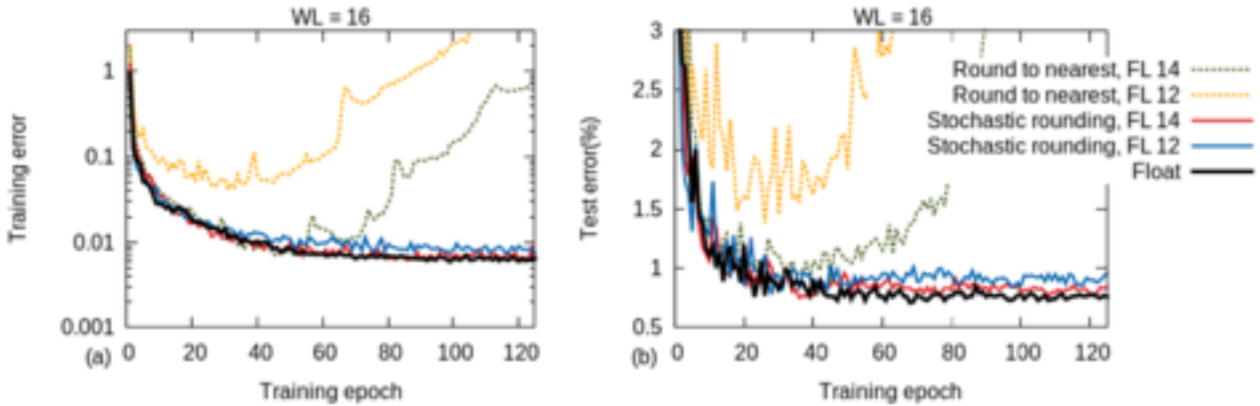
Benchmarks on Titan X, from https://github.com/soumith/convnet-benchmarks

Floating point precision

- How low can we go?

- Gupta et al, 2015:
  Train with **16-bit fixed point** with stochastic rounding

CNNs on MNIST



Gupta et al, "Deep Learning with Limited Numerical Precision", ICML 2015

Floating point precision

- How low can we go?

- Courbariaux et al, 2015:
  Train with **10-bit activations**, **12-bit parameter updates**

Courbariaux et al, “Training Deep Neural Networks with Low Precision Multiplications”, ICLR 2015

Floating point precision

- How low can we go?

- Courbariaux and Bengio, February 9 2016:
  - Train with **1-bit activations and weights**!
  - All activations and weights are +1 or -1
  - Fast multiplication with bitwise XNOR
  - (Gradients use higher precision)

Courbariaux et al, "BinaryNet: Training Deep Neural Networks with Weights and Activations Constrained to +1 or -1", arXiv 2016

Implementation details: Recap

- GPUs much faster than CPUs
- Distributed training is sometimes used
  - Not needed for small problems
- Be aware of bottlenecks: CPU / GPU, CPU / disk
- Low precison makes things faster and still works
  - 32 bit is standard now, 16 bit soon

Recap

- Data augmentation: artificially expand your data
- Transfer learning: CNNs without huge data
- All about convolutions
- Implementation details

TensorFlow

https://www.tensorflow.org

TensorFlow

- From Google
- Very similar to Theano - all about computation graphs
- Easy visualizations (TensorBoard)
- Multi-GPU and multi-node training

TensorFlow: Two-Layer Net

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
  sess.run(tf.initialize_all_variables())

  for t in xrange(100):
    _, loss_value = sess.run([train_step, loss],
                             feed_dict={x: xx, y: yy})
    print loss_value
```

TensorFlow: Two-Layer Net

Create placeholders for data and labels: These will be fed to the graph

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
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train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
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  for t in xrange(100):
    _, loss_value = sess.run([train_step, loss],
                             feed_dict={x: xx, y: yy})
    print loss_value
```

TensorFlow: Two-Layer Net

Create Variables to hold weights; similar to Theano shared variables

Initialize variables with numpy arrays

```python
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
  sess.run(tf.initialize_all_variables())

  for t in xrange(100):
    _, loss_value = sess.run([train_step, loss],
                             feed_dict={x: xx, y: yy})
    print loss_value
```

TensorFlow: Two-Layer Net

Forward: Compute scores, probs, loss (symbolically)

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
  sess.run(tf.initialize_all_variables())

  for t in xrange(100):
    _, loss_value = sess.run([train_step, loss],
                             feed_dict={x: xx, y: yy})
    print loss_value
```

TensorFlow: Two-Layer Net

Running train_step will use SGD to minimize loss

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
  sess.run(tf.initialize_all_variables())

  for t in xrange(100):
    _, loss_value = sess.run([train_step, loss],
                             feed_dict={x: xx, y: yy})
    print loss_value
```

TensorFlow: Two-Layer Net

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
  sess.run(tf.initialize_all_variables())

  for t in xrange(100):
    _, loss_value = sess.run([train_step, loss],
                             feed_dict={x: xx, y: yy})
    print loss_value
```

Create an artificial dataset;
y is one-hot like Keras

TensorFlow: Two-Layer Net

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
  sess.run(tf.initialize_all_variables())

  for t in xrange(100):
    _, loss_value = sess.run([train_step, loss],
                             feed_dict={x: xx, y: yy})
    print loss_value
```

Actually train the model

TensorFlow: Tensorboard

Tensorboard makes it easy to visualize what's happening inside your models

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

loss_summary = tf.scalar_summary('loss', loss)
w1_hist = tf.histogram_summary('w1', w1)
w2_hist = tf.histogram_summary('w2', w2)

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
  merged = tf.merge_all_summaries()
  writer = tf.train.SummaryWriter('/tmp/fc_logs', sess.graph_def)
  sess.run(tf.initialize_all_variables())

  for t in xrange(100):
    summary_str, _, loss_value = sess.run(
                                [merged, train_step, loss],
                                feed_dict={x: xx, y: yy})
    writer.add_summary(summary_str, t)
    print loss_value
```

TensorFlow: Tensorboard

Tensorboard makes it easy to visualize what's happening inside your models

Same as before, but now we create summaries for loss and weights

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

loss_summary = tf.scalar_summary('loss', loss)
w1_hist = tf.histogram_summary('w1', w1)
w2_hist = tf.histogram_summary('w2', w2)

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
  merged = tf.merge_all_summaries()
  writer = tf.train.SummaryWriter('/tmp/fc_logs', sess.graph_def)
  sess.run(tf.initialize_all_variables())

  for t in xrange(100):
    summary_str, _, loss_value = sess.run(
                                [merged, train_step, loss],
                                feed_dict={x: xx, y: yy})
    writer.add_summary(summary_str, t)
    print loss_value
```

TensorFlow: Tensorboard

Tensorboard makes it easy to visualize what's happening inside your models

Create a special "merged" variable and a SummaryWriter object

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

loss_summary = tf.scalar_summary('loss', loss)
w1_hist = tf.histogram_summary('w1', w1)
w2_hist = tf.histogram_summary('w2', w2)

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
  merged = tf.merge_all_summaries()
  writer = tf.train.SummaryWriter('/tmp/fc_logs', sess.graph_def)
  sess.run(tf.initialize_all_variables())

  for t in xrange(100):
    summary_str, _, loss_value = sess.run(
                                 [merged, train_step, loss],
                                 feed_dict={x: xx, y: yy})
    writer.add_summary(summary_str, t)
    print loss_value
```

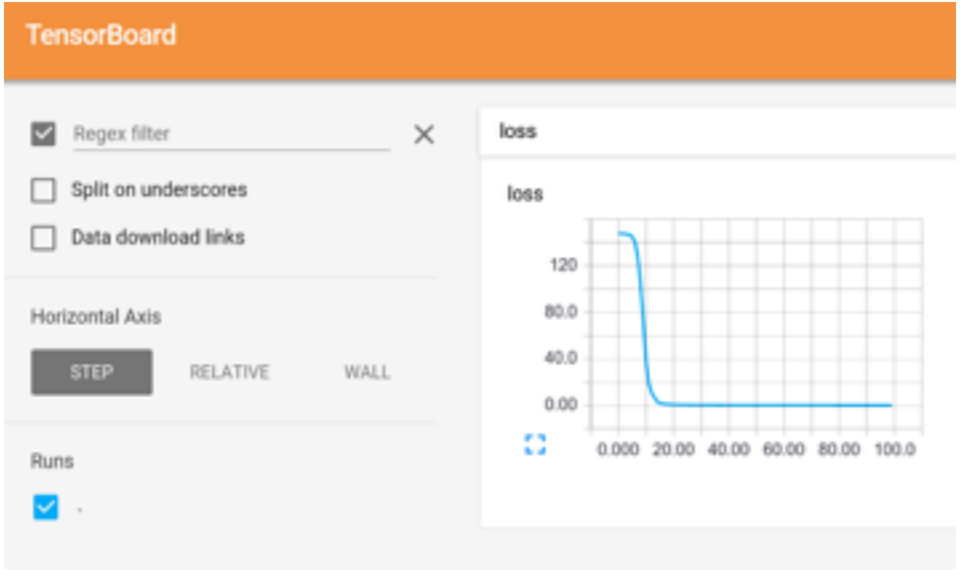
TensorFlow: Tensorboard

Tensorboard makes it easy to visualize what's happening inside your models

In the training loop, also run merged and pass its value to the writer

```python
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D])
y = tf.placeholder(tf.float32, shape=[None, C])

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32))
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32))

a = tf.matmul(x, w1)
a_relu = tf.nn.relu(a)
scores = tf.matmul(a_relu, w2)
probs = tf.nn.softmax(scores)
loss = -tf.reduce_sum(y * tf.log(probs))

loss_summary = tf.scalar_summary('loss', loss)
w1_hist = tf.histogram_summary('w1', w1)
w2_hist = tf.histogram_summary('w2', w2)

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1

with tf.Session() as sess:
    merged = tf.merge_all_summaries()
    writer = tf.train.SummaryWriter('/tmp/fc_logs', sess.graph_def)
    sess.run(tf.initialize_all_variables())

    for t in xrange(100):
        summary_str, _, loss_value = sess.run(
                                         [merged, train_step, loss],
                                         feed_dict={x: xx, y: yy})
        writer.add_summary(summary_str, t)
        print loss_value
```

TensorFlow: Tensorboard



Start Tensorboard server, and we get graphs!

TensorFlow: TensorBoard

```
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D], name='x')
y = tf.placeholder(tf.float32, shape=[None, C], name='y')

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32), name='w1')
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32), name='w2')

with tf.name_scope('scores') as scope:
  a = tf.matmul(x, w1)
  a_relu = tf.nn.relu(a)
  scores = tf.matmul(a_relu, w2)
with tf.name_scope('loss') as scope:
  probs = tf.nn.softmax(scores)
  loss = -tf.reduce_sum(y * tf.log(probs))

loss_summary = tf.scalar_summary('loss', loss)
w1_hist = tf.histogram_summary('w1', w1)
w2_hist = tf.histogram_summary('w2', w2)

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1
```

TensorFlow: TensorBoard

Add names to placeholders and variables

```python
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D], name='x')
y = tf.placeholder(tf.float32, shape=[None, C], name='y')

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32), name='w1')
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32), name='w2')

with tf.name_scope('scores') as scope:
  a = tf.matmul(x, w1)
  a_relu = tf.nn.relu(a)
  scores = tf.matmul(a_relu, w2)
with tf.name_scope('loss') as scope:
  probs = tf.nn.softmax(scores)
  loss = -tf.reduce_sum(y * tf.log(probs))

loss_summary = tf.scalar_summary('loss', loss)
w1_hist = tf.histogram_summary('w1', w1)
w2_hist = tf.histogram_summary('w2', w2)

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1
```

TensorFlow: TensorBoard

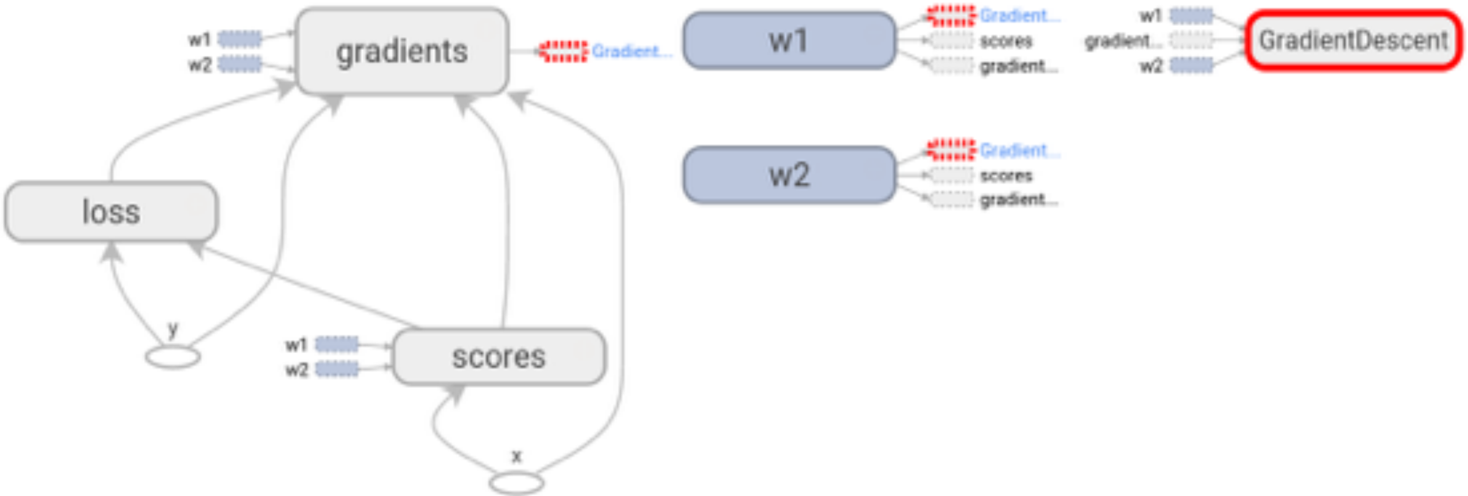
Add names to placeholders and variables

Break up the forward pass with name scoping

```python
import tensorflow as tf
import numpy as np

N, D, H, C = 64, 1000, 100, 10

x = tf.placeholder(tf.float32, shape=[None, D], name='x')
y = tf.placeholder(tf.float32, shape=[None, C], name='y')

w1 = tf.Variable(1e-3 * np.random.randn(D, H).astype(np.float32), name='w1')
w2 = tf.Variable(1e-3 * np.random.randn(H, C).astype(np.float32), name='w2')

with tf.name_scope('scores') as scope:
  a = tf.matmul(x, w1)
  a_relu = tf.nn.relu(a)
  scores = tf.matmul(a_relu, w2)
with tf.name_scope('loss') as scope:
  probs = tf.nn.softmax(scores)
  loss = -tf.reduce_sum(y * tf.log(probs))

loss_summary = tf.scalar_summary('loss', loss)
w1_hist = tf.histogram_summary('w1', w1)
w2_hist = tf.histogram_summary('w2', w2)

learning_rate = 1e-2
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

xx = np.random.randn(N, D).astype(np.float32)
yy = np.zeros((N, C)).astype(np.float32)
yy[np.arange(N), np.random.randint(C, size=N)] = 1
```

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

TensorFlow: TensorBoard

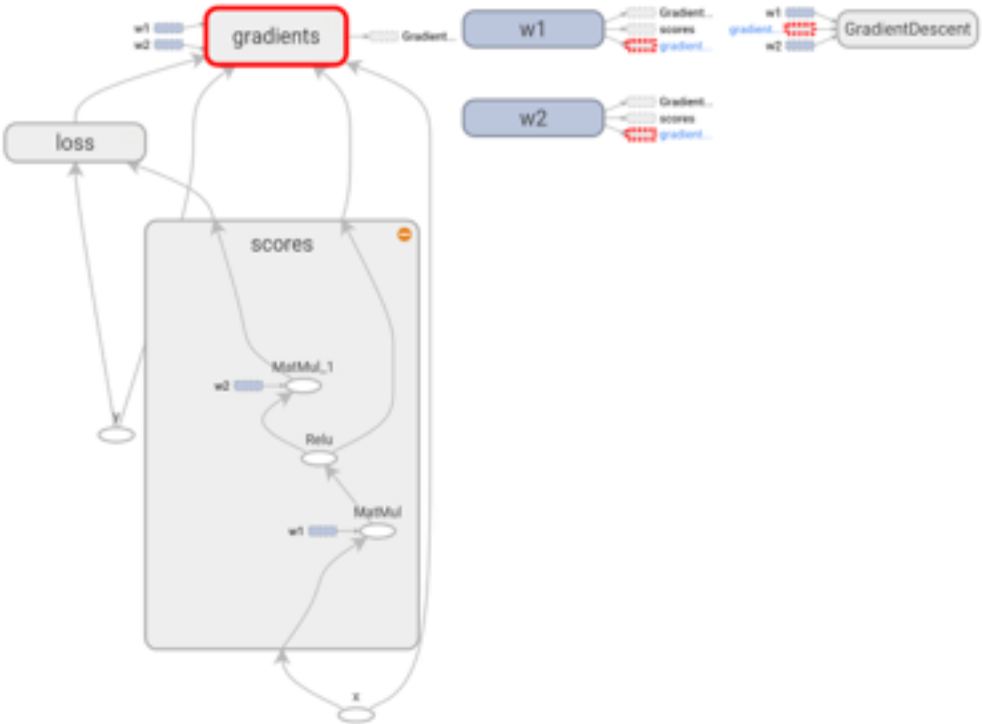


Tensorboard shows the graph!

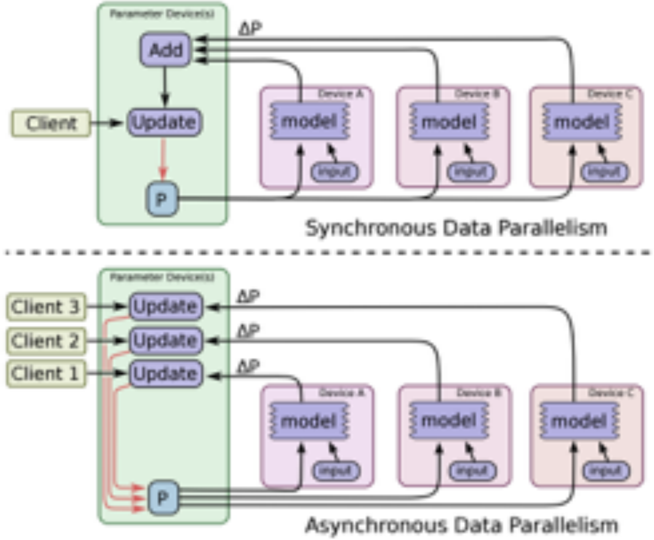
TensorFlow: TensorBoard

Tensorboard shows the graph!

Name scopes expand to show individual operations



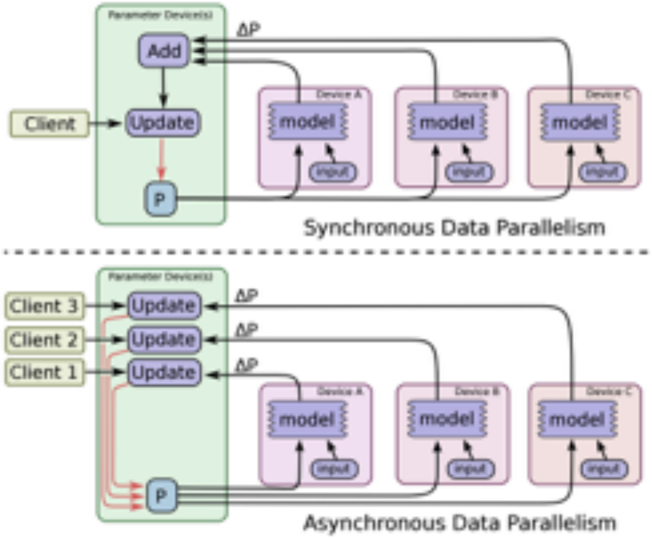
TensorFlow: Multi-GPU



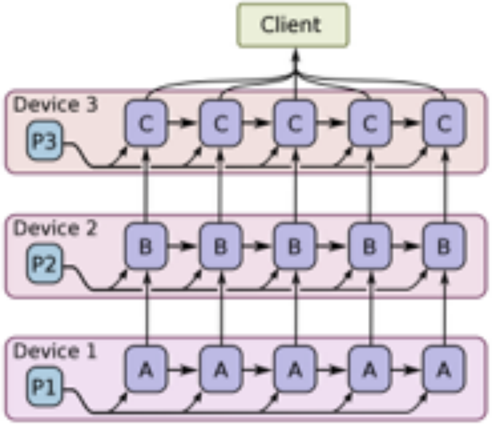
Data parallelism:
synchronous or asynchronous

TensorFlow: Multi-GPU

Data parallelism:
synchronous or asynchronous



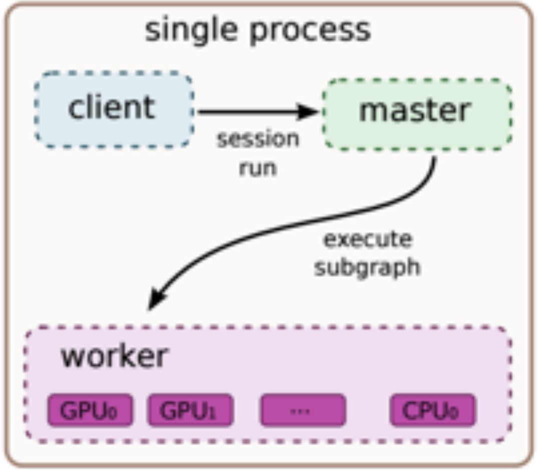
Model parallelism:
Split model across GPUs

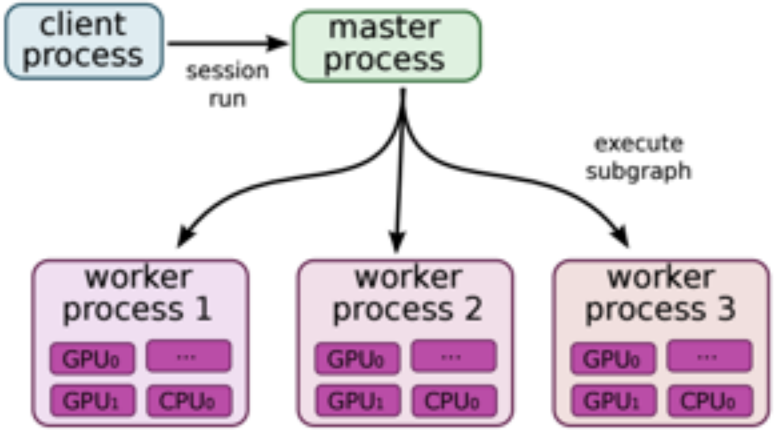


TensorFlow: Distributed

Single machine:
Like other frameworks

Many machines:
Not open source (yet) =(





TensorFlow: Pretrained Models

- You can get a pretrained models here:
- https://github.com/tensorflow/models

- Has inception, resnet, some different autoencoders

TensorFlow: Pros / Cons

(+) Python + numpy
(+) Computational graph abstraction, like Theano; great for RNNs
(+) Much faster compile times than Theano
(+) Slightly more convenient than raw Theano?
(+) TensorBoard for visualization
(+) Data AND model parallelism; best of all frameworks
(+/-) Distributed models, but not open-source yet
(-) Slower than other frameworks right now
(-) Much "fatter" than Torch; more magic
(-) Not many pretrained models

Torch

http://torch.ch/docs/getting-started.html

Torch Overview

- From NYU + IDIAP
- Written in C and Lua
- Used a lot a Facebook, DeepMind

Torch: Pretrained Models

- **loadcaffe**: Load pretrained Caffe models: AlexNet, VGG, some others
  https://github.com/szagoruyko/loadcaffe
- **GoogLeNet v1**: https://github.com/soumith/inception.torch
- **GoogLeNet v3**: https://github.com/Moodstocks/inception-v3.torch
- **ResNet**: https://github.com/facebook/fb.resnet.torch

Torch: Pros / Cons

(-) Lua
(-) Less plug-and-play than Caffe
  You usually write your own training code
(+) Lots of modular pieces that are easy to combine
(+) Easy to write your own layer types and run on GPU
(+) Most of the library code is in Lua, easy to read
(+) Lots of pretrained models!
(-) Not great for RNNs

Theano

http://deeplearning.net/software/theano/

Theano Overview

- From Yoshua Bengio's group at University of Montreal
- Embracing computation graphs, symbolic computation
- High-level wrappers: Keras, Lasagne
- Has Conditional flow (ifelse, switch)

Theano: Pretrained Models

Best choice

- **Lasagne Model Zoo** has pretrained common architectures:
- https://github.com/Lasagne/Recipes/tree/master/modelzoo
- **AlexNet with weights**: https://github.com/uoguelph-mlrg/theano_alexnet
- **sklearn-theano**: Run OverFeat and GoogLeNet forward, but no fine-tuning? http://sklearn-theano.github.io
- **caffe-theano-conversion**: CS 231n project from last year: load models and weights from caffe! Not sure if full-featured https://github.com/kitofans/caffe-theano-conversion

Theano: Pros / Cons

(+) Python + numpy
(+) Computational graph is nice abstraction
(+) RNNs fit nicely in computational graph
(-) Raw Theano is somewhat low-level
(+) High level wrappers (Keras, Lasagne) ease the pain
(-) Error messages can be unhelpful
(-) Large models can have long compile times
(-) Much “fatter” than Torch; more magic
(-) Patchy support for pretrained models

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)