LECTURE 11-2

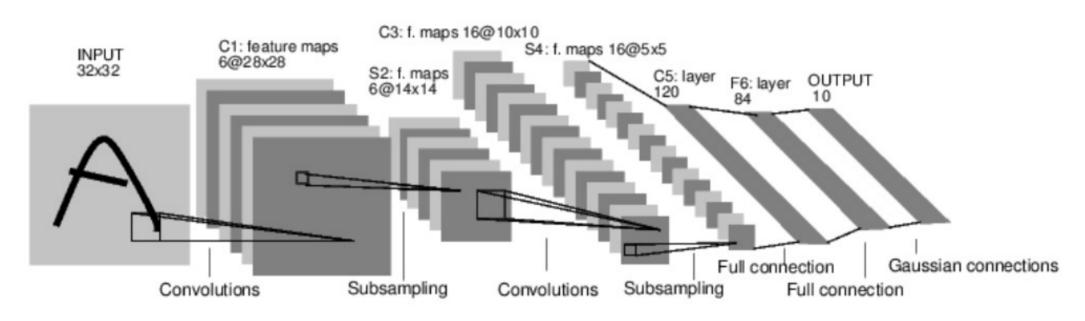
CNN CASE STUDY

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Convolutional Neural Networks

Case Study: LeNet-5

LeCun et al., 1998



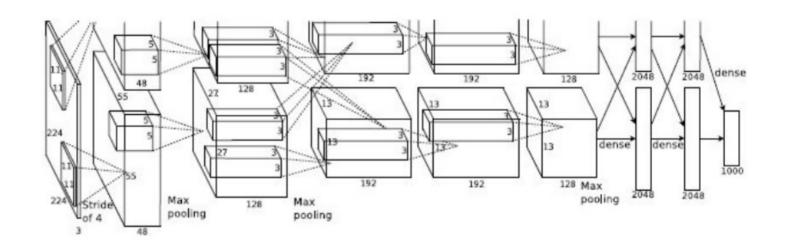
Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e architecture is [CONV-POOL-CONV-POOL-CONV-FC]

Krizhevsky et al. 2012

Input: 227 X 227 X 3 images

First Layer (CONV1):
96 11×11 filters applied at stride 4

-> Output Volume [55×55×96]



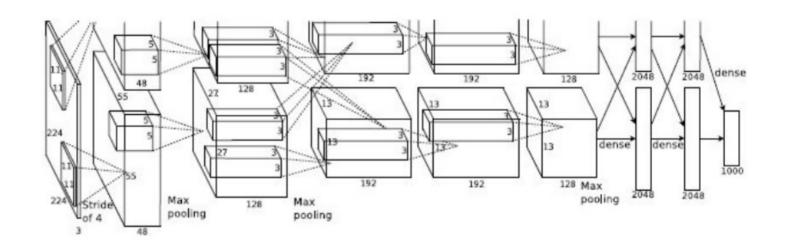
Q. What is the total number of parameters in this layer?

Krizhevsky et al. 2012

Input: 227 X 227 X 3 images

First Layer (CONV1):
96 11×11 filters applied at stride 4

->



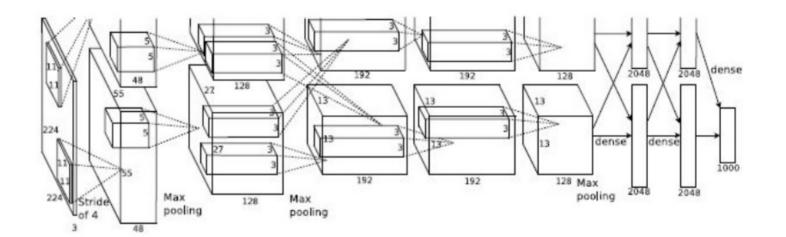
Q.
What is the output volume size?
Hint: (227-11)/4+1=55

Krizhevsky et al. 2012

Input: 227 X 227 X 3 images

First Layer (CONV1):
96 11×11 filters applied at stride 4

-> Output Volume [55×55×96]
Parameters: (11×11×3)×96=35k

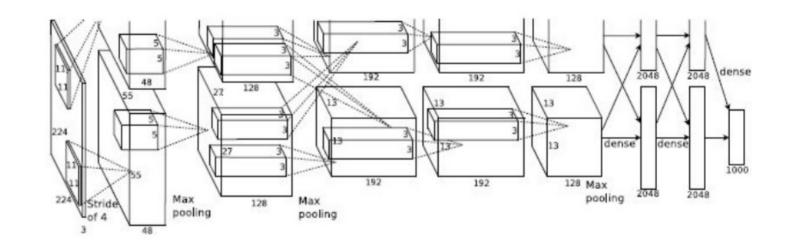


Krizhevsky et al. 2012

Input: 227 X 227 X 3 images After CONV1: 55 × 55 × 96

Second Layer (P00L1): 3×3 filters applied at stride 2

-> Output Volume: 27x27x96 Parameters: 0!

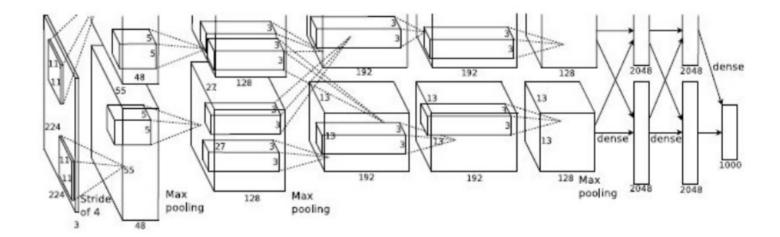


Krizhevsky et al. 2012

Input: 227 X 227 X 3 images

After CONV1: 55x55x96 After POOL1: 27x27x96

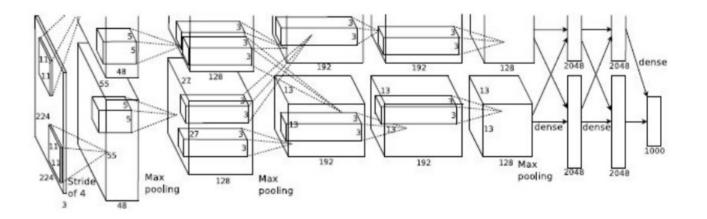
•••



Krizhevsky et al. 2012

Full (simplified) AlexNet architecture:

```
[227 × 227 × 3]
               INPUT
                CONV1: 96 11 × 11 filters at stride 4, pad 0
[27 × 27 × 96]
                MAX POOL1: 3 x 3 filters at stride 2
[27 x 27 x 96]
[27 × 27 × 96]
                NORM1: Normalization layer
[27 x 27 x 256] CONV2: 256 5x5 filters at stride 1, pad 2
[13 x 13 x 256] MAX POOL2: 3 x 3 filters at stride 2
[13 x 13 x 256] NORM2: Normalization layer
[13 x 13 x 384] CONV3: 384 3 x 3 filters at stride 1, pad 1
[13 x 13 x 384] CONV4: 384 3x3 filters at stride 1, pad 1
[13 x 13 x 256]
               CONV5: 256 3x3 filters at stride 1, pad 1
[6 x 6 x 256]
                MAX POOL3: 3x3 filters at stride 2
[4096]
                FC6: 4096 neurons
[4096]
                FC7: 4096 neurons
[1000]
                FC8: 1000 neurons (class scores)
```



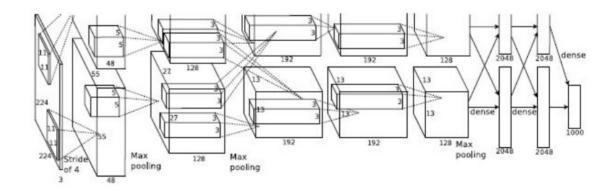
Krizhevsky et al. 2012

Full (simplified) AlexNet architecture:

```
[227 × 227 × 3]
               INPUT
[27 x 27 x 96]
               CONV1: 96 11 x 11 filters at stride 4, pad 0
[27 x 27 x 96]
               MAX POOL1:3x3 filters at stride 2
[27 × 27 × 96]
               NORM1: Normalization layer
[27 x 27 x 256] CONV2: 256 5x5 filters at stride 1, pad 2
[13 x 13 x 256] MAX POOL2: 3 x 3 filters at stride 2
[13 x 13 x 256] NORM2: Normalization layer
[13 x 13 x 384] CONV3: 384 3 x 3 filters at stride 1, pad 1
[13 x 13 x 384] CONV4: 384 3x3 filters at stride 1, pad 1
[13 x 13 x 256] CONV5: 256 3x3 filters at stride 1, pad 1
[6 x 6 x 256]
                MAX POOL3: 3x3 filters at stride 2
[4096]
               FC6: 4096 neurons
[4096]
               FC7: 4096 neurons
[1000]
               FC8: 1000 neurons (class scores)
```

Details / Retrospectives:

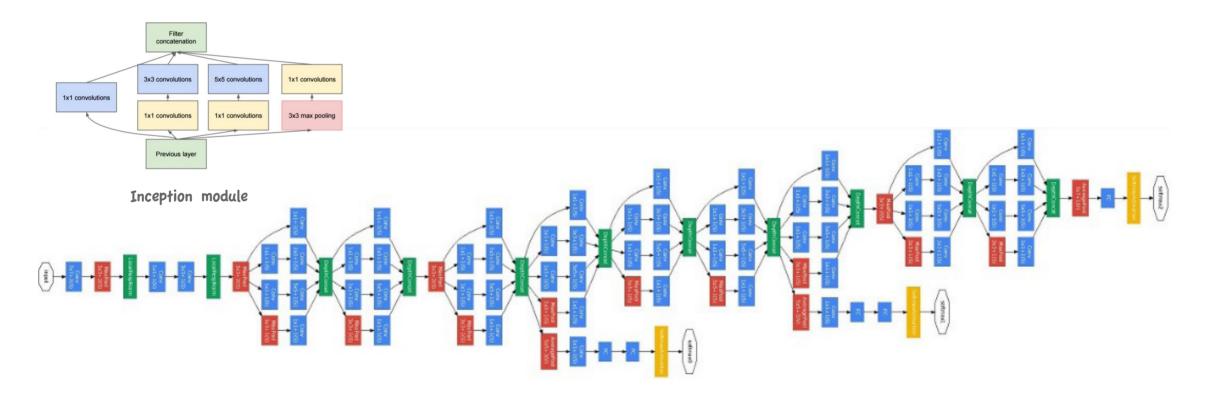
- · First use of ReLU
- · Used Norm layers (not common anymore)
- · Heavy data augmentation
- · Dropout 0.5
- · Batch size 128
- · SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- · L2 weight decay 5e-4
- · 7 CNN ensemble: 18.2% -> 15.4%



Case Study: GoogLeNet

Szegedy et al., 2014

ILSVRC 2014 winner (6.7% top 5 error)



He et al. 2015

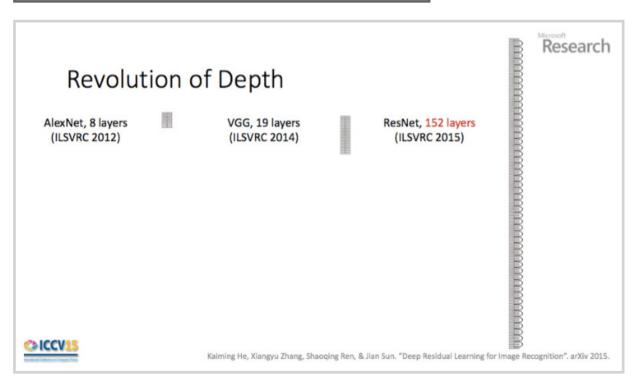
ILSVRC 2015 winner (3.6% top 5 error)

MSRA @ ILSVRC & COCO 2015 Competitoions

- · 1st places in all 5 main tracks
 - · ImageNet Classification: "Ultra-deep" (quote Yann) 152-layer nets
 - · ImageNet Detection: 16% better than 2nd
 - · ImageNet Localization: 27% better than 2nd
 - · COCO Detection: 11% better than 2nd
 - · COCO Segmentation: 12% better than 2nd

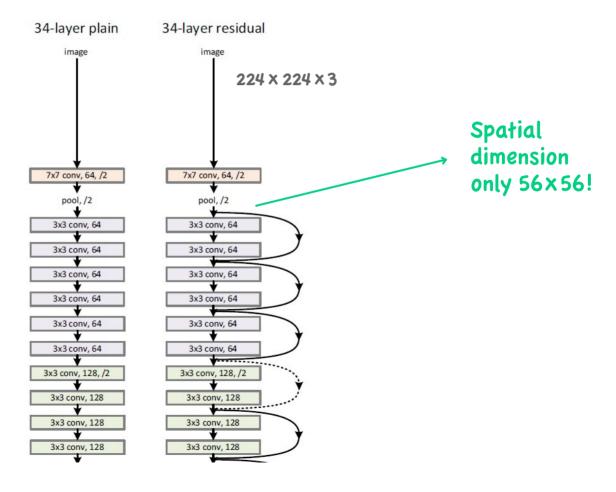
He et al. 2015

ILSVRC 2015 winner (3.6% top 5 error)

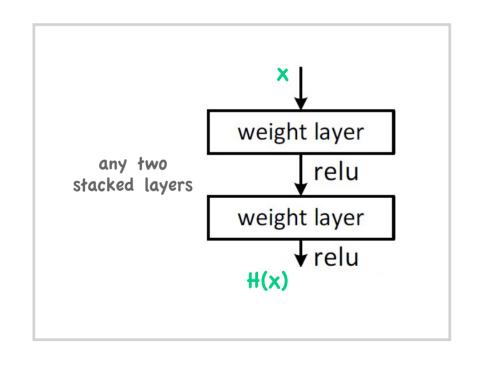


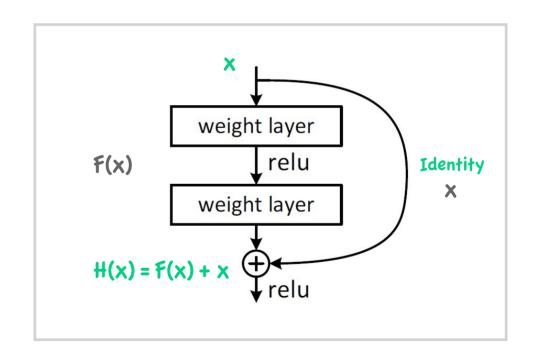
- 2-3 weeks of training on8 GPU machine
- · at runtime: faster than a VGGNet! (even though it has 8x more layers)

He et al., 2015



He et al., 2015





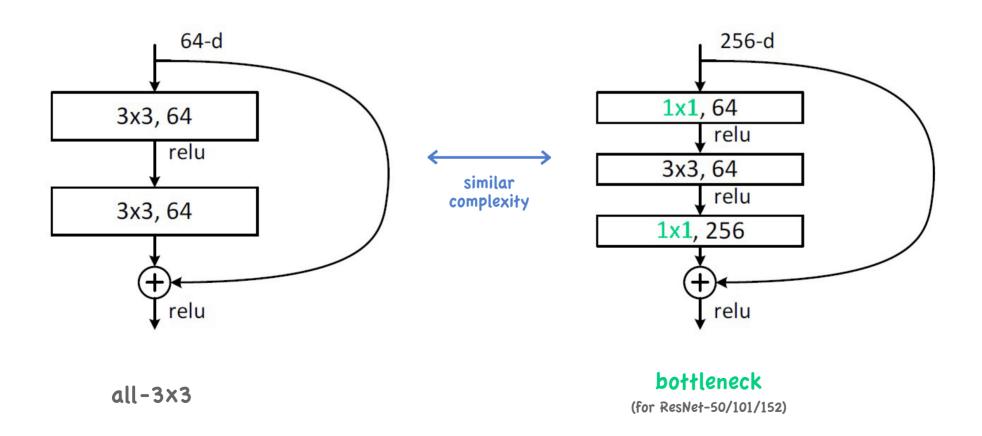
< Plaint net >

< Residual net >

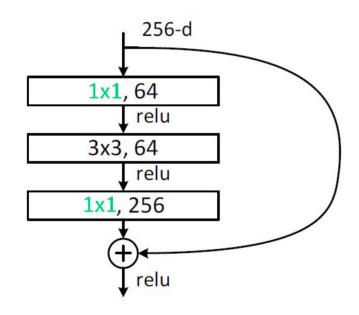
He et al. 2015

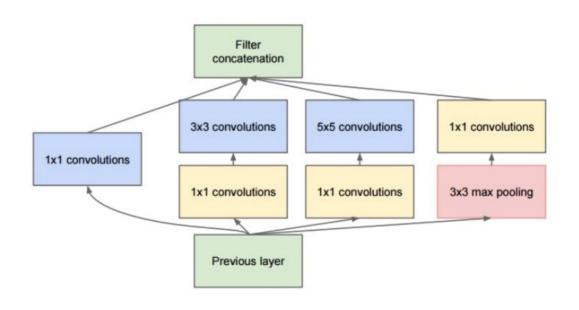
- · Batch normalization after every CONV layer
- · Xavier/2 initialization from He et al.
- · SGD + Momentum (0.9)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- · Mini-batch size 256
- · Weight decay of 1e-5
- · No dropout used

He et al., 2015



He et al., 2015



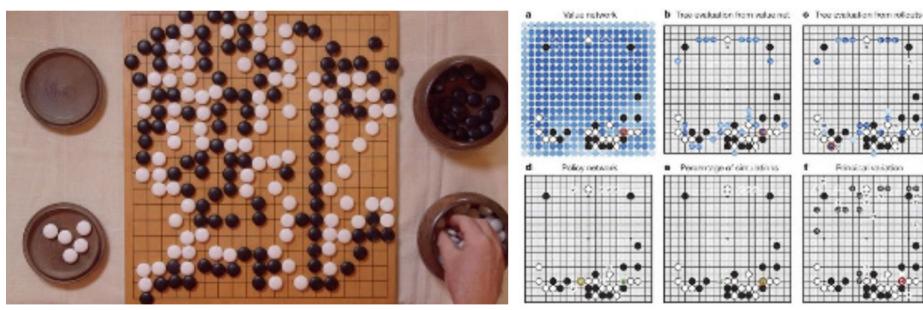


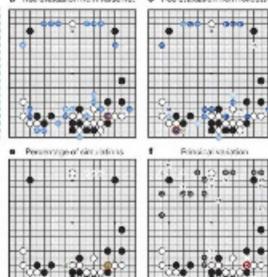
(this trick is also used in GoogLeNet)

He et al., 2015

							HE EL al., 2013
7x7 conv, 64, /2 pool, /2	layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
3x3 conv, 64 3x3 conv, 64	conv1	112×112	7×7 , 64, stride 2				
3x3 conv, 64 3x3 conv, 64	8.		3×3 max pool, stride 2				
3x3 conv, 64 3x3 conv, 120, /2 3x3 conv, 120, /2 3x3 conv, 120 3x3 conv, 126 3x3 conv, 126 3x3 conv, 126	conv2_x	56×56	$\left[\begin{array}{c} 3 \times 3, 64 \\ 3 \times 3, 64 \end{array}\right] \times 2$	$\left[\begin{array}{c} 3 \times 3, 64 \\ 3 \times 3, 64 \end{array}\right] \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$ \begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3 $	$ \begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3 $
3x3 conv, 128 3x3 conv, 256, /2 3x3 conv, 256	conv3_x	28×28	$\left[\begin{array}{c} 3 \times 3, 128 \\ 3 \times 3, 128 \end{array}\right] \times 2$	$\left[\begin{array}{c} 3 \times 3, 128 \\ 3 \times 3, 128 \end{array}\right] \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$ \begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 8 $
lad conv. 256	conv4_x	14×14	$\left[\begin{array}{c} 3 \times 3, 256 \\ 3 \times 3, 256 \end{array}\right] \times 2$	$\left[\begin{array}{c} 3 \times 3, 256 \\ 3 \times 3, 256 \end{array}\right] \times 6$	$ \begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6 $	$ \left[\begin{array}{c} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{array}\right] \times 23 $	$ \begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 36 $
33 conv, 256 33 conv, 256 33 conv, 256 33 conv, 256 33 conv, 257 34 conv, 512 34 conv, 512 34 conv, 512	conv5_x	7×7	$\left[\begin{array}{c} 3\times3,512\\ 3\times3,512 \end{array}\right]\times2$	$\left[\begin{array}{c} 3\times3,512\\ 3\times3,512 \end{array}\right]\times3$	$ \begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3 $	$ \begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3 $	$ \begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3 $
x3 conv, 512	1×1		average pool, 1000-d fc, softmax				
3x3 conv, 512 3x3 conv, 512 ave pool	FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9
avg pool fc 1000	N/7	100			8		

Case Study Bonus: DeepMind's AlphaGo







The input to the policy network is a 19x19x48 image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a 23x23 Image, then convolves k filters of kernel size 5x5 with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a 21x21 image, then convolves k filters of kernel size 3x3 with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size 1x1 with stride 1, with a different bias for each position, and applies a softmax function. The match version of AlphaGo used k=192 filters; Fig.2b and Extended Data Table 3 additionally show the results of training with k=128,256 and 384 filters.

Policy Network:

[19x19x48] Input

CONV1 : 192x5x5 filters, stride1, pad2 => [19x19x192]

CONV2...12: 192x3x3 filters, stride1, pad1 => [19x19x192]

CONV: 1x1 filter, stride1, pad0 => [19x19] (probability map of promising moves)

Convolutional Neural Networks for Sentence Classification

Yoon Kim., 2014

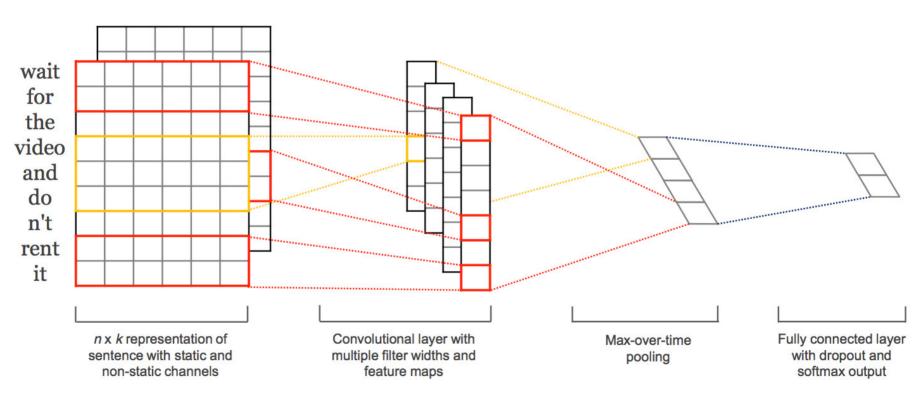


Figure 1: Model architecture with two channels for an example sentence.

NEXT LECTURE

RECURRENT NEURAL NETS (RNN)