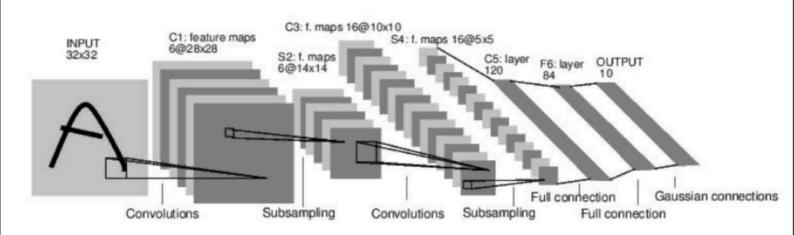
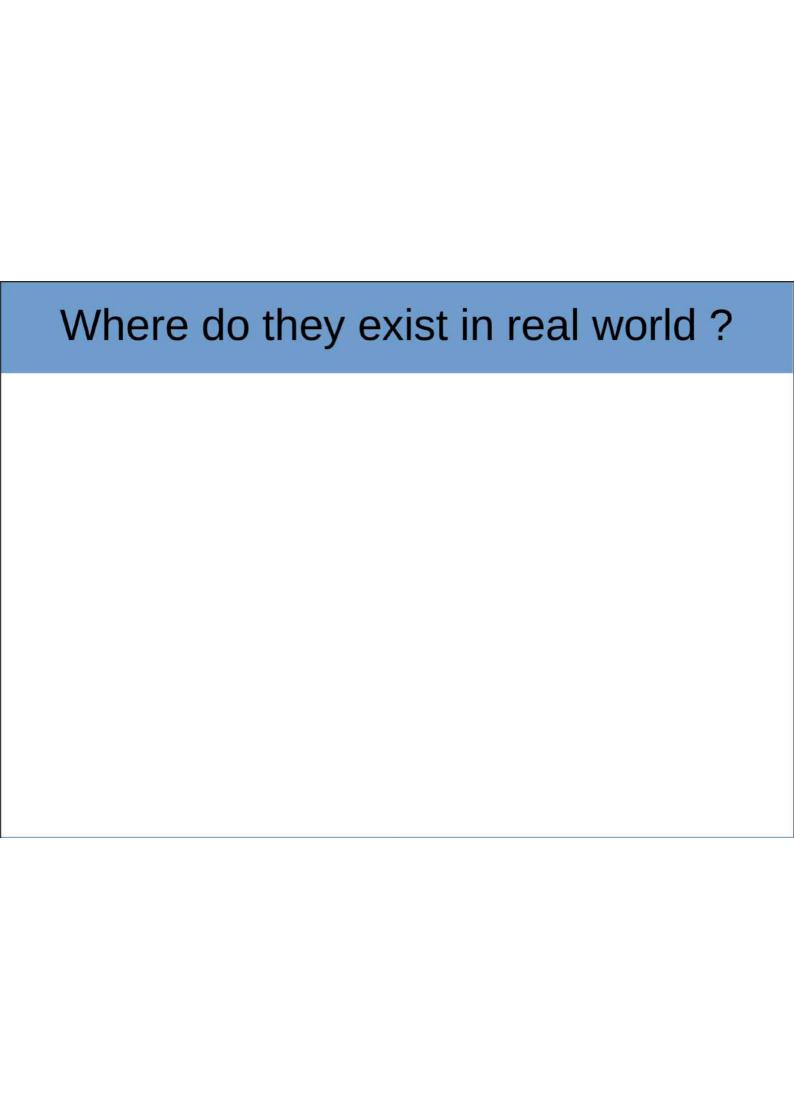
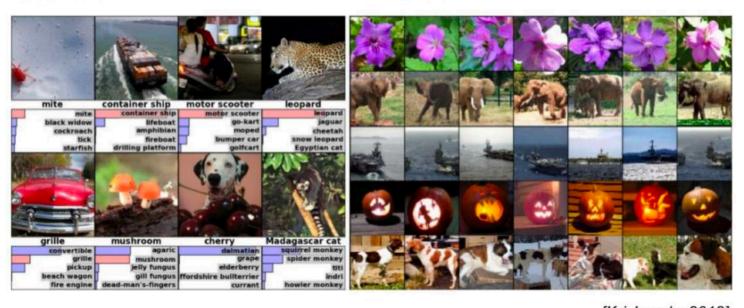


CNNs / ConvNets

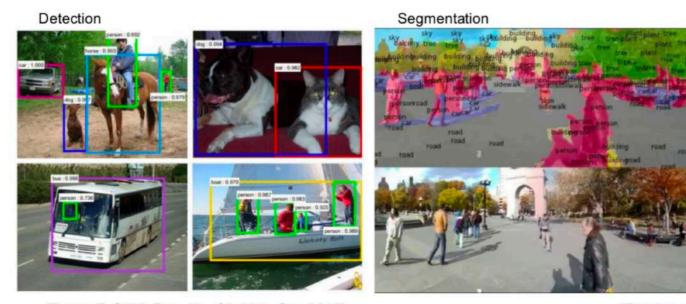




Classification Retrieval



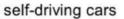
[Krizhevsky 2012]



[Faster R-CNN: Ren, He, Girshick, Sun 2015]

[Farabet et al., 2012]



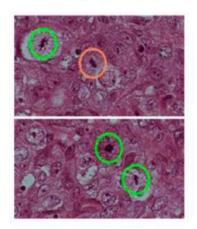




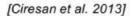
NVIDIA Tegra X1



[Toshev, Szegedy 2014]









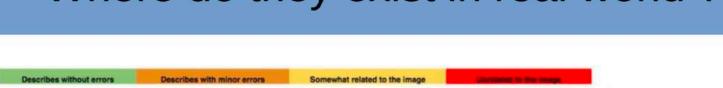
[Sermanet et al. 2011] [Ciresan et al.]



Whale recognition, Kaggle Challenge



Mnih and Hinton, 2010





A person riding a motorcycle on a dirt road.



Two dogs play in the grass.



A skateboarder does a trick



A dog is jumping to catch a





A group of young people playing a game of frisbee.



Two hockey players are fighting over the puck.



A little girl in a pink hat is



A refrigerator filled with lots of food and drinks.



A herd of elephants walking across a dry grass field.



A close up of a cat laying on a couch.



A red motorcycle parked on the side of the road.

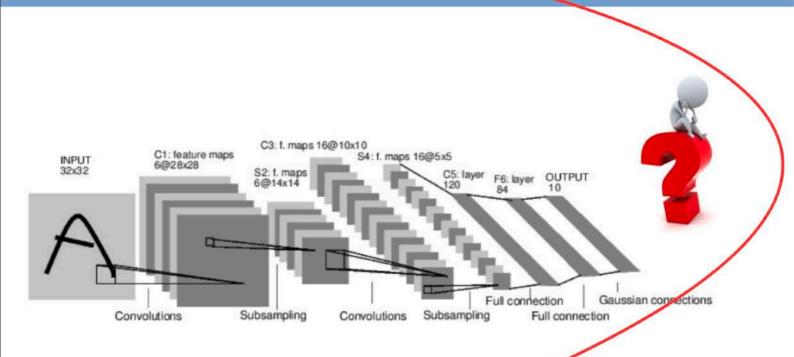


A yellow school bus parked in a parking lot.

[Vinyals et al., 2015]



So, Convolution Nets...



How do they work!

CNNs / ConvNets

· CNNs are

- Similar to Ordinary neural networks.
- Same concepts of weights and biases.
- Neurons receive inputs and preform dot product, then followed by a non linearity.

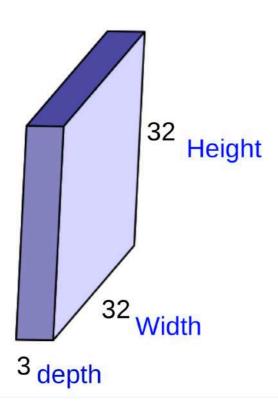
· So what does change?

- Explicit assumption that the **inputs are IMAGES**.

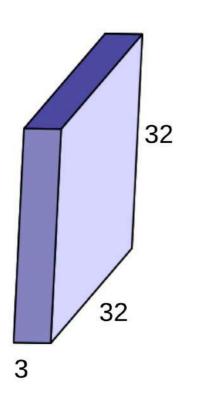
· Advantage?

- Vast reduction in the amount of parameters in the network.

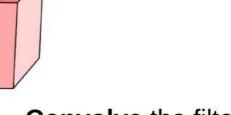
32 x 32 x 3 Image



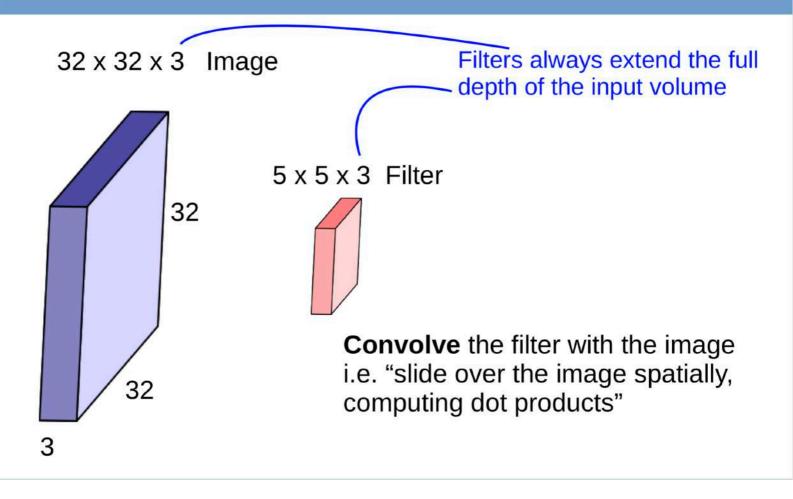
32 x 32 x 3 Image



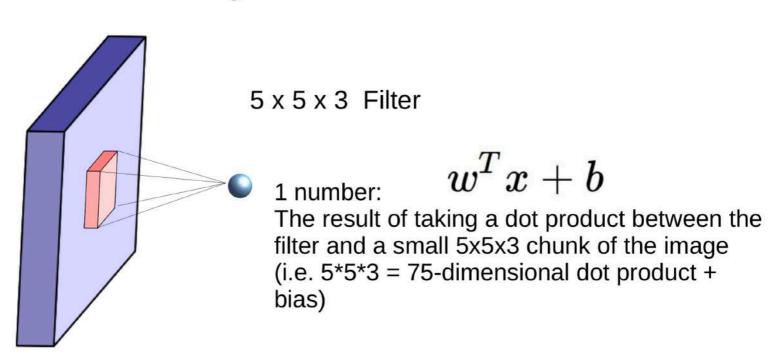
5 x 5 x 3 Filter

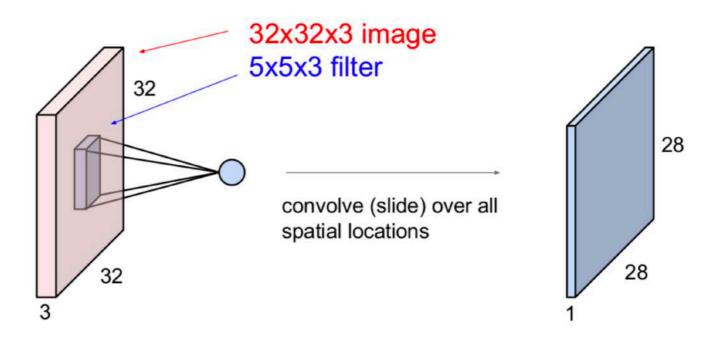


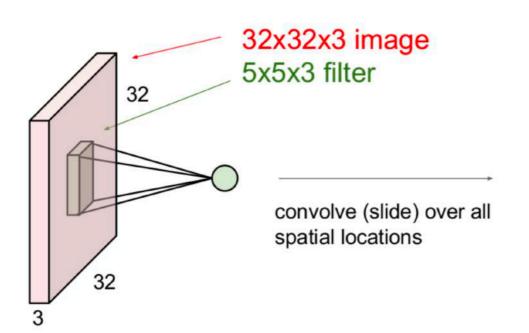
Convolve the filter with the image i.e. "slide over the image spatially, computing dot products"

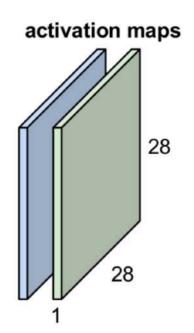


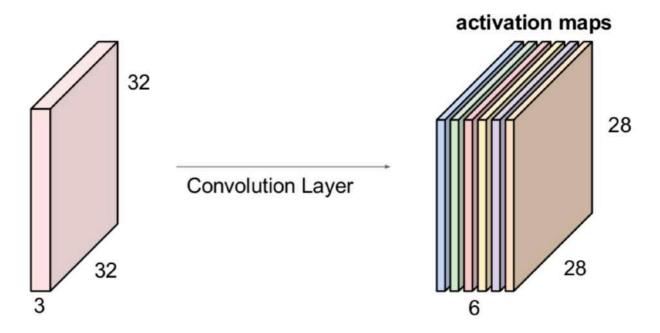
32 x 32 x 3 Image



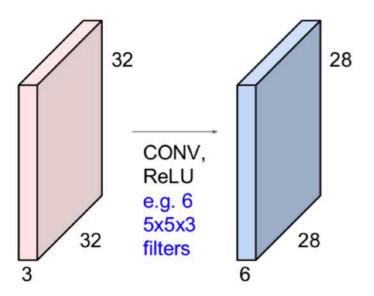


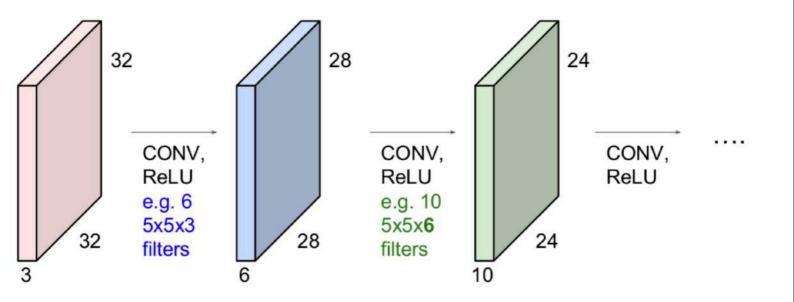




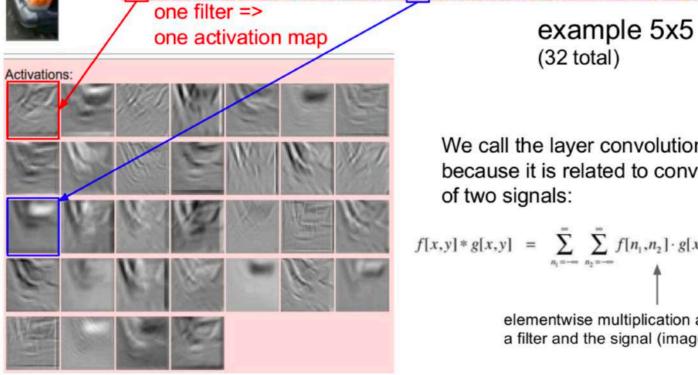


We stack these up to get a "new image" of size 28x28x6!





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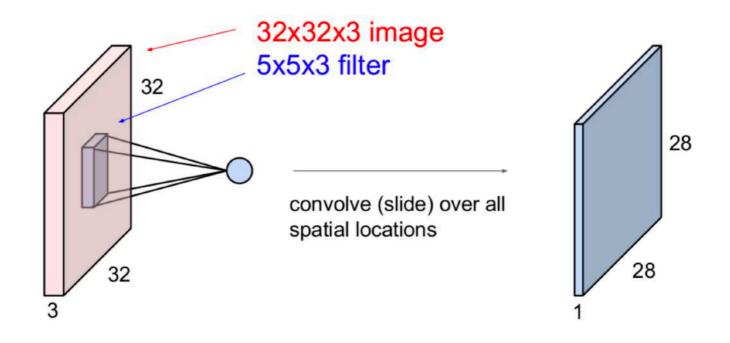


example 5x5 filters

We call the layer convolutional because it is related to convolution

$$f[x,y] * g[x,y] = \sum_{n_1 = -\infty}^{\infty} \sum_{n_2 = -\infty}^{\infty} f[n_1, n_2] \cdot g[x - n_1, y - n_2]$$

elementwise multiplication and sum of a filter and the signal (image)



7

with stride 1

7x7 input (spatially) assume 3x3 filter

7

with stride 1

7x7 input (spatially) assume 3x3 filter

7

with stride 1

7x7 input (spatially) assume 3x3 filter

7

with stride 1

7x7 input (spatially) assume 3x3 filter

7

with stride 1

7x7 input (spatially) assume 3x3 filter

7

=> 5x5 output

7

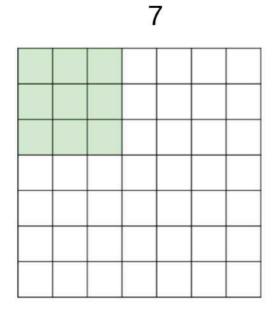
with stride 2

7x7 input (spatially) assume 3x3 filter

7

=> 3x3 output

with stride 3?

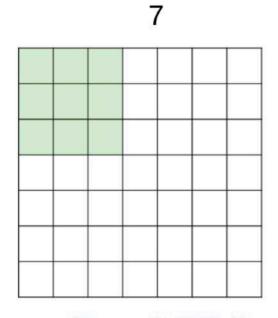


7x7 input (spatially) assume 3x3 filter

7

Output !!

with stride 3?



7x7 input (spatially) assume 3x3 filter

7

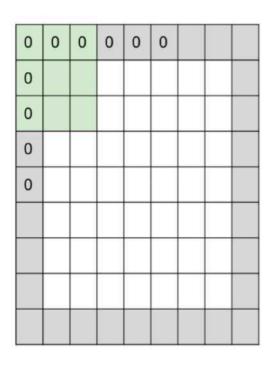
=> Doesn't FIT !!
We can not apply 3x3 filter on 7x7 input with stride 3.

In Practice: zero pad the border

| 0 | 0 | 0 | 0 | 0 | 0 | | |
|---|---|---|---|---|---|--|--|
| 0 | | | | | | | |
| 0 | | | | | | | |
| 0 | | | | | | | |
| 0 | | | | | | | |
| | | | | | | | |
| | | | | | | | |
| | | | | | | | |
| | | | | | | | |

e.g. input 7x7
3x3 filter, applied with stride 1
pad with 1 pixel border => what is the output?

In Practice: zero pad the border



e.g. input 7x7
3x3 filter, applied with stride 1
pad with 1 pixel border => what is the output?

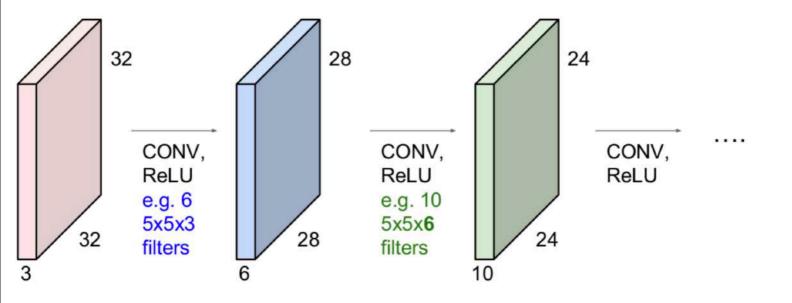
7x7 output!

in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)

```
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3
```

Remember & Notice: Shrinking Volume

32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially! (32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.



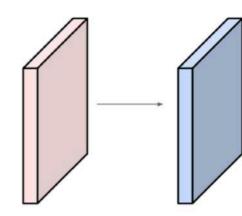
In Practice: zero pad the border

Examples time:

Input volume: 32x32x3

10 5x5 filters with stride 1, pad 2

Output volume size: ?

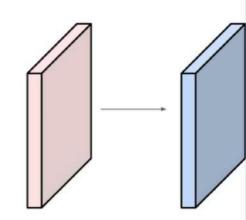


In Practice: zero pad the border

Examples time:

Input volume: 32x32x3

10 5x5 filters with stride 1, pad 2



Output volume size:

(32+2*2-5)/1+1 = 32 spatially, so

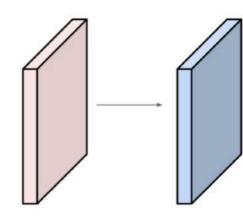
32x32x10

In Practice: zero pad the border

Examples time:

Input volume: 32x32x3

10 5x5 filters with stride 1, pad 2



Number of parameters in this layer?
each filter has
$$5*5*3 + 1 = 76$$
 params (+1 for bias)
=> $76*10 = 760$

Summary: Convolution Layer

- Accepts a volume of size $W_1*H_1*D_1$
- Require four hyperparameters:
 - Number of filters K
 - The spatial extent **F**
 - The stride **S**
 - The amount of zero padding P
- Produce a volume of size $W_2*H_2*D_2$, where

$$W_2 = (W_1 - F + 2P)/S + 1$$

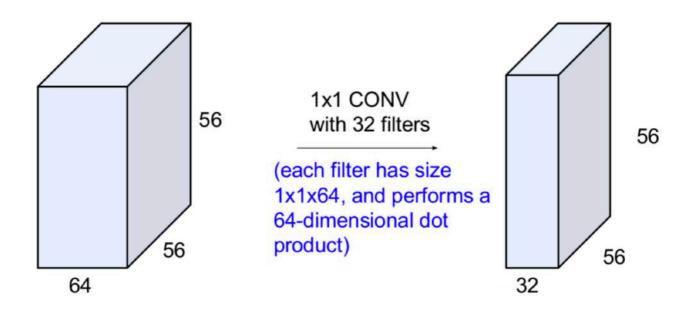
$$W_2 = (W_1 - F + 2P)/S + 1$$

$$\blacksquare$$
 $D_2 = K$

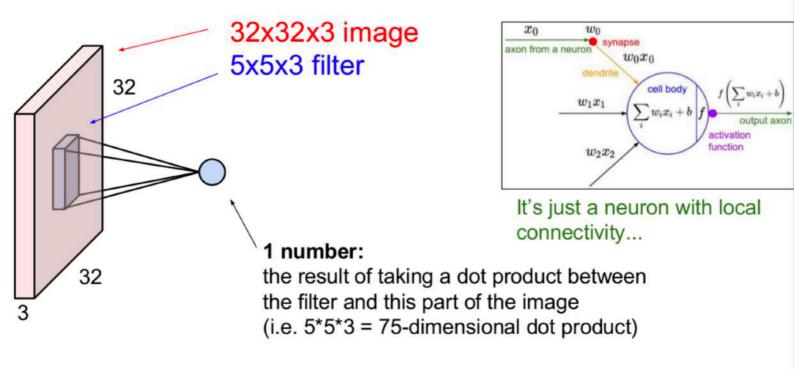
■ With parameter sharing, introduces $F^*F^*D_1$ weights per filter, for total of $(F^*F^*D_1)^*K$ weights and K biases.

An analogy

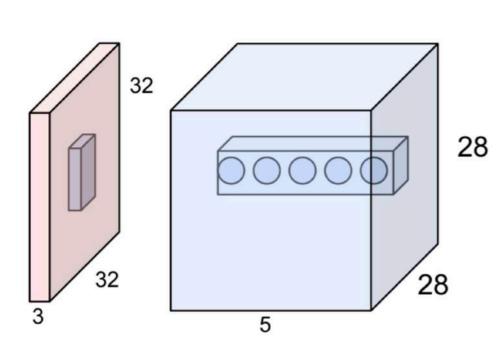
(btw, 1x1 convolution layers make perfect sense)



Brain View of CONV Layer



Brain View of CONV Layer

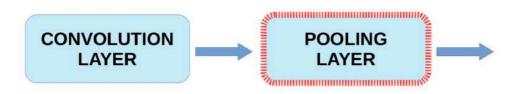


- E.g. with 5 filters, CONV layer consists of neurons arranged in a 3D grid (28x28x5)
- There will be 5 different neurons all looking at the same region in the input volume

Two more layers to go



Two more layers to go



Two more layers to go



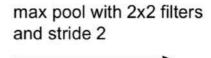
Pooling Layer

- Makes the representation smaller and more managable
- Operates over each avctivation map indiendently

Single depth slice

| 1 | 1 | 2 | 4 |
|---|---|---|---|
| 5 | 6 | 7 | 8 |
| 3 | 2 | 1 | 0 |
| 1 | 2 | 3 | 4 |

MAX POOLING



| 6 | 8 |
|---|---|
| 3 | 4 |

Summary: POOLING Layer

- Accepts a volume of size $\mathbf{W}_1 * \mathbf{H}_1 * \mathbf{D}_1$
- Requires three hyperparameter :
 - Their spetial extent **F**,
 - The stride **S**
- Produces a volume of size $W_2*H_2*D_2$

$$\blacksquare W_2 = (W_1 - F)/S + 1$$

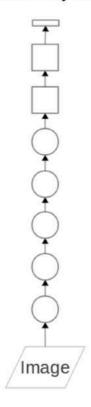
$$\blacksquare H_2 = (H_1 - F)/S + 1$$

$$\blacksquare D_2 = D_1$$

- Introduces ZERO parameters since it computes a fixed function of the input
- Note: Its not common to use zero padding for polling layer.

Case study: AlexNet

[Krizhevsky et al. 2012]



- **Deep** : 7 Hidden Layer
- Entirely Supervised Learning.
- 5 CONV LAYER + 2 FC LAYER
- 650,000 Neurons
- 60,000,000 parameters
- 630,000,000 connections
- Final feature layer: 4096-dimensional
 - Convolutional layer: convolves its input with a bank of 3D filters, then applies point-wise non-linearity
 - Fully-connected layer: applies linear filters to its input, then applies pointwise non-linearity

