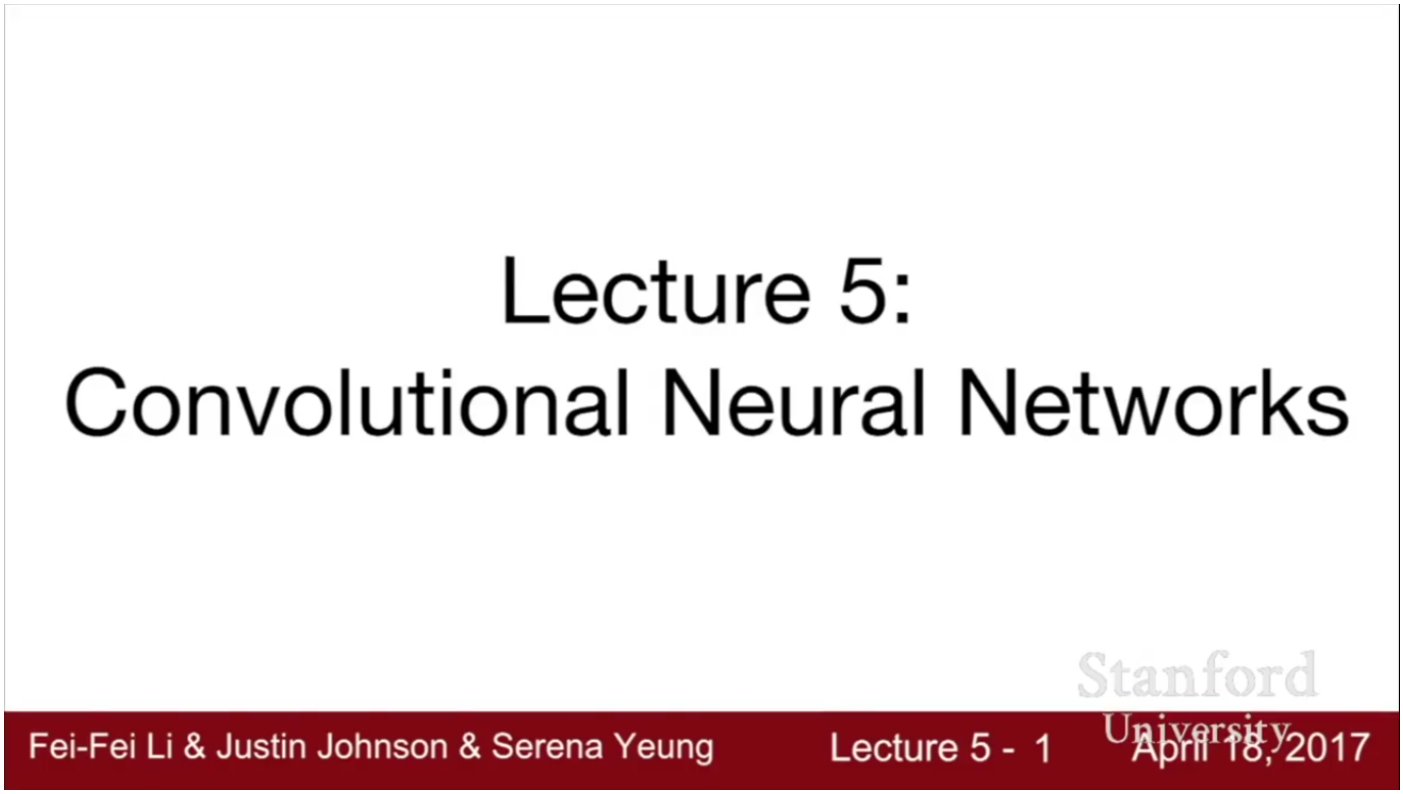
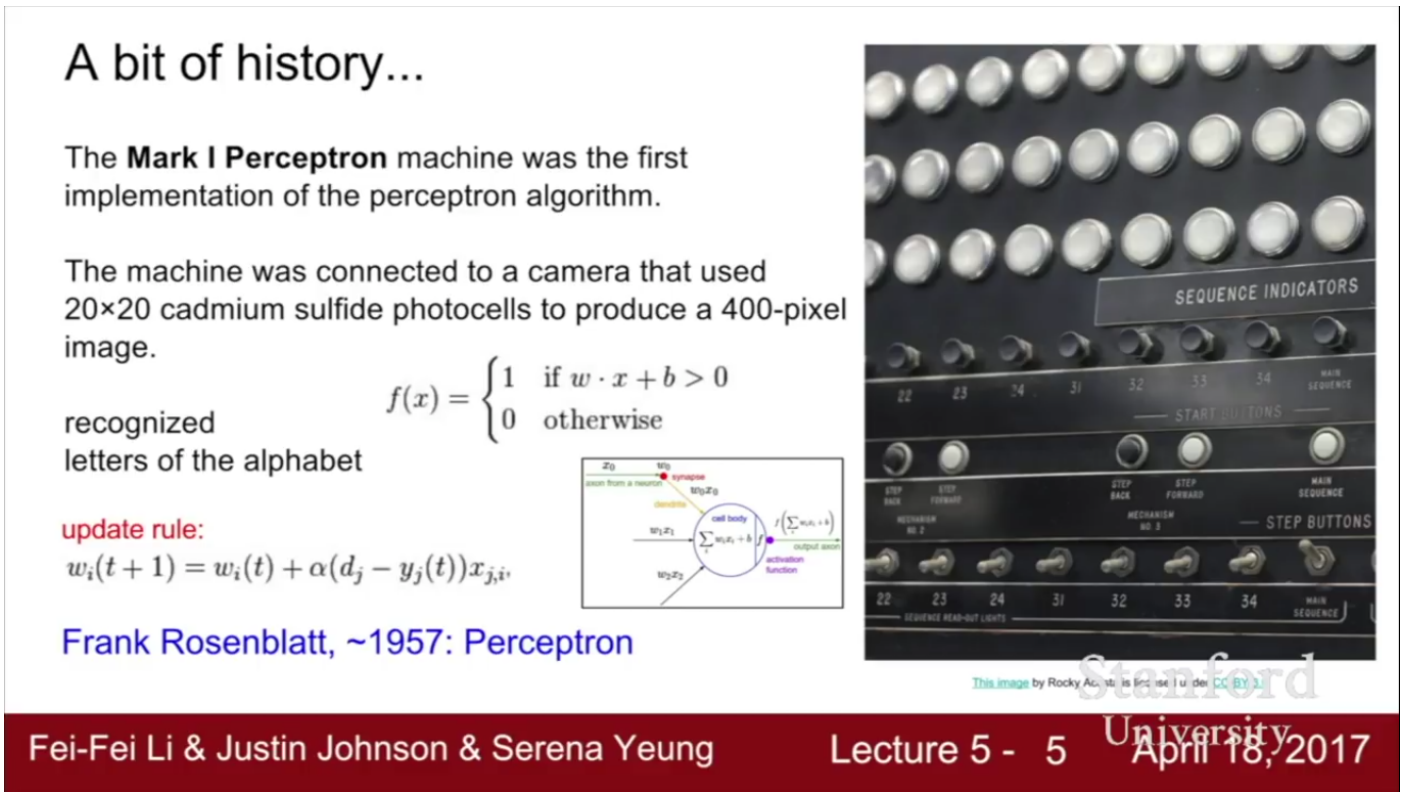
lec5

Creation Date: 04/01/2020 21:18
Last Updated: 09/01/2020 13:33

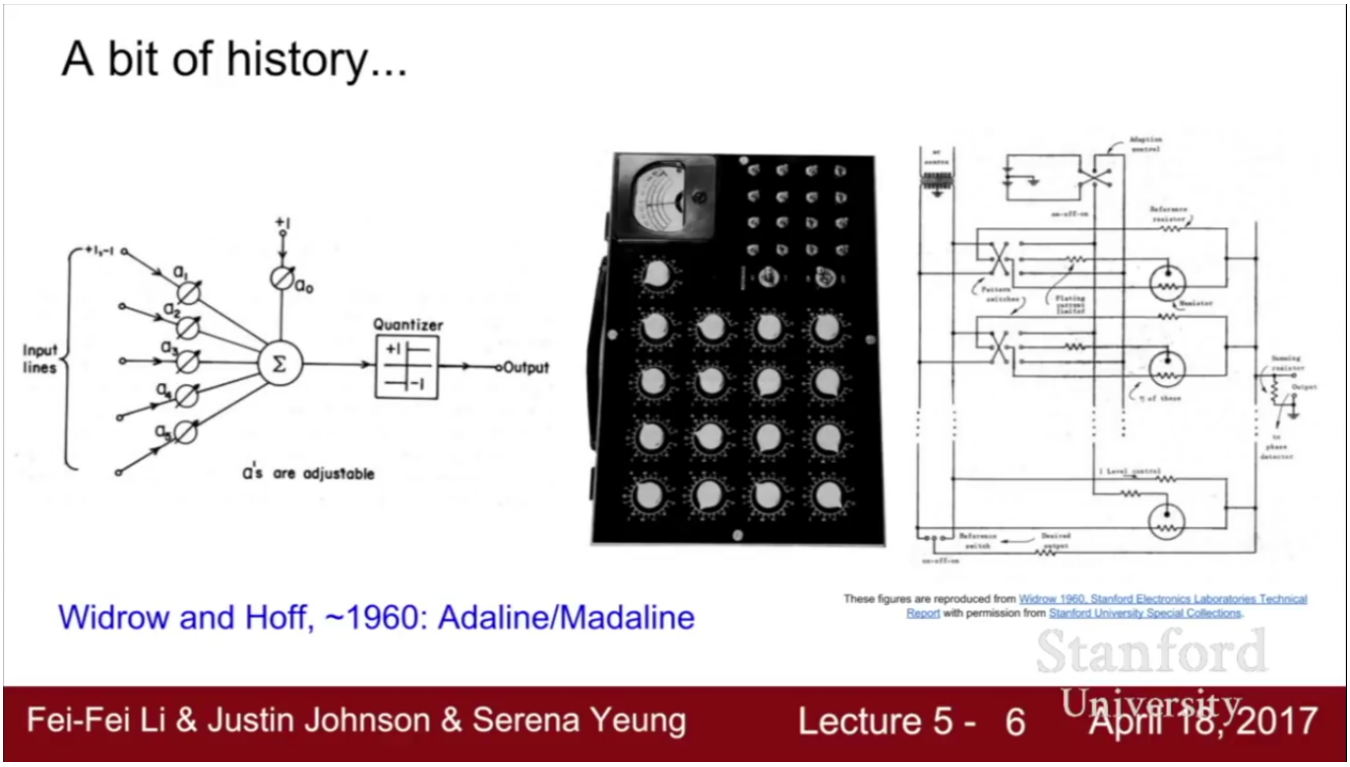
Lec 5: Convolutional Neural Networks



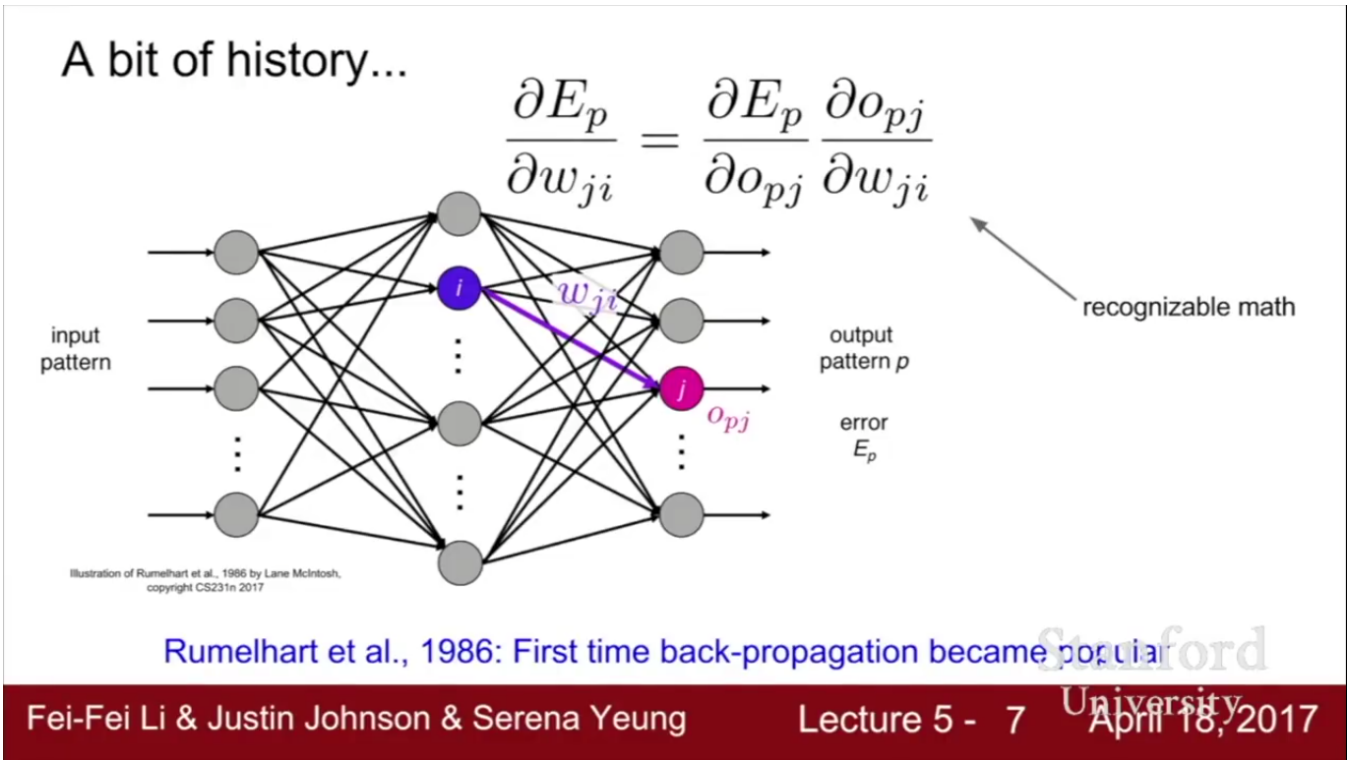
- In CNN we **maintain spatial structure.**



- During this time backprop technique was not yet created.
- We took the weights and adjusted them to work for the machine.

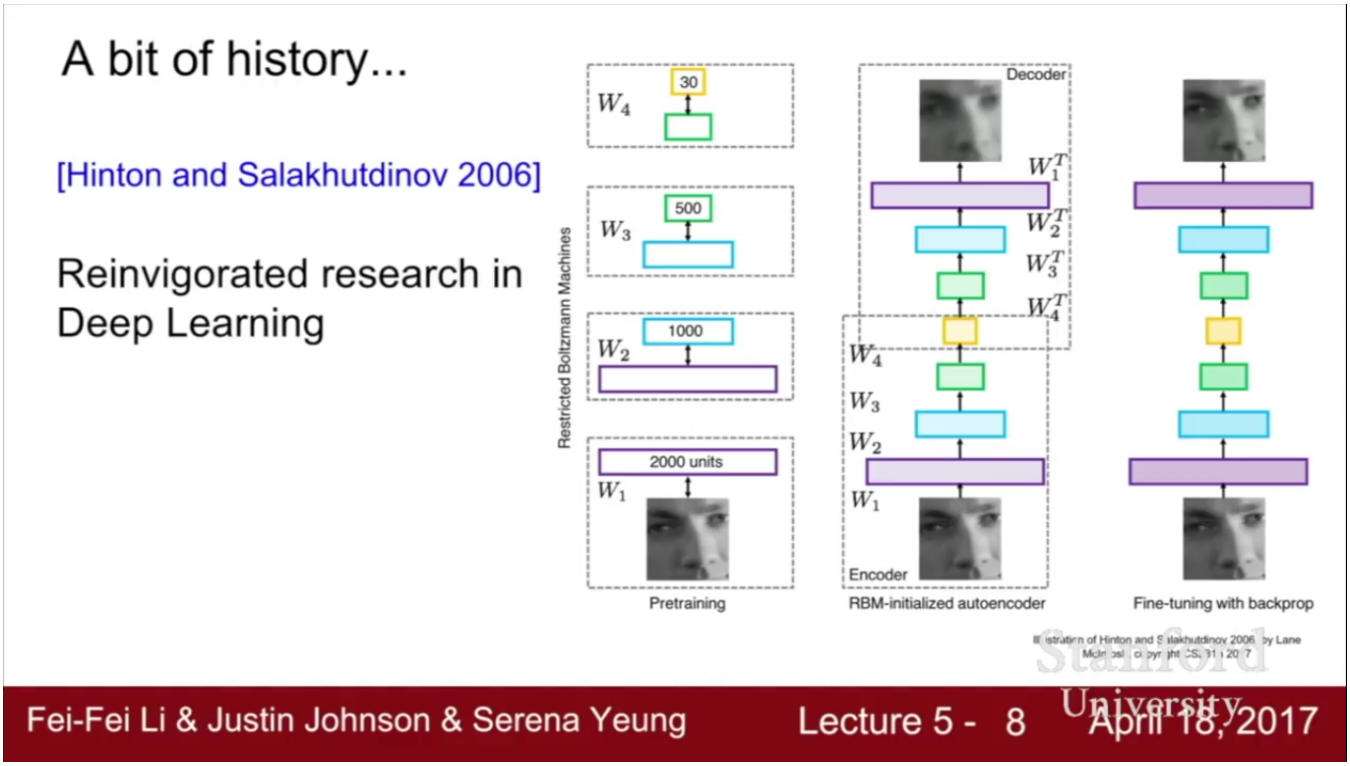


- In Adaline/Madaline they formed multi-layer perceptrons.
- **Backpropagation was introduced for the first time in 1986 by *Rumelhart***

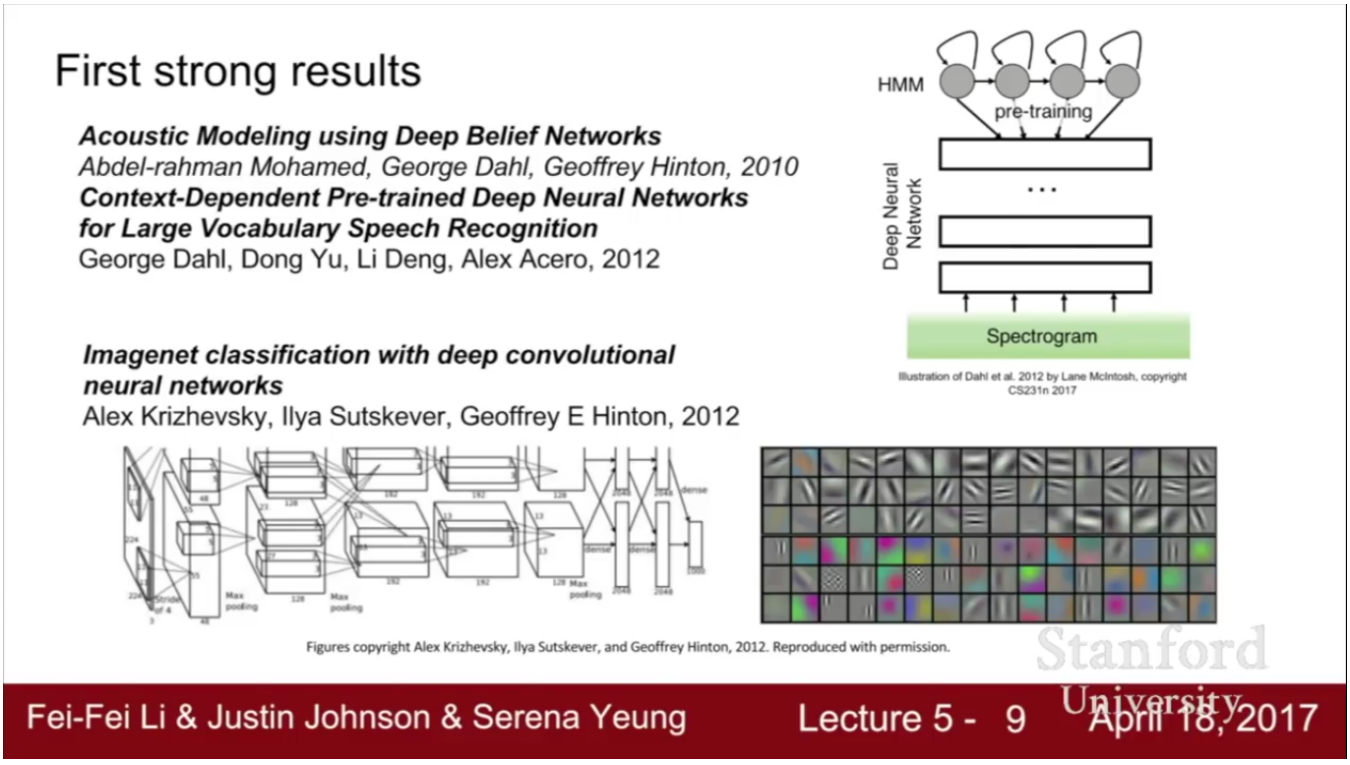


- **AI winter sets in.**

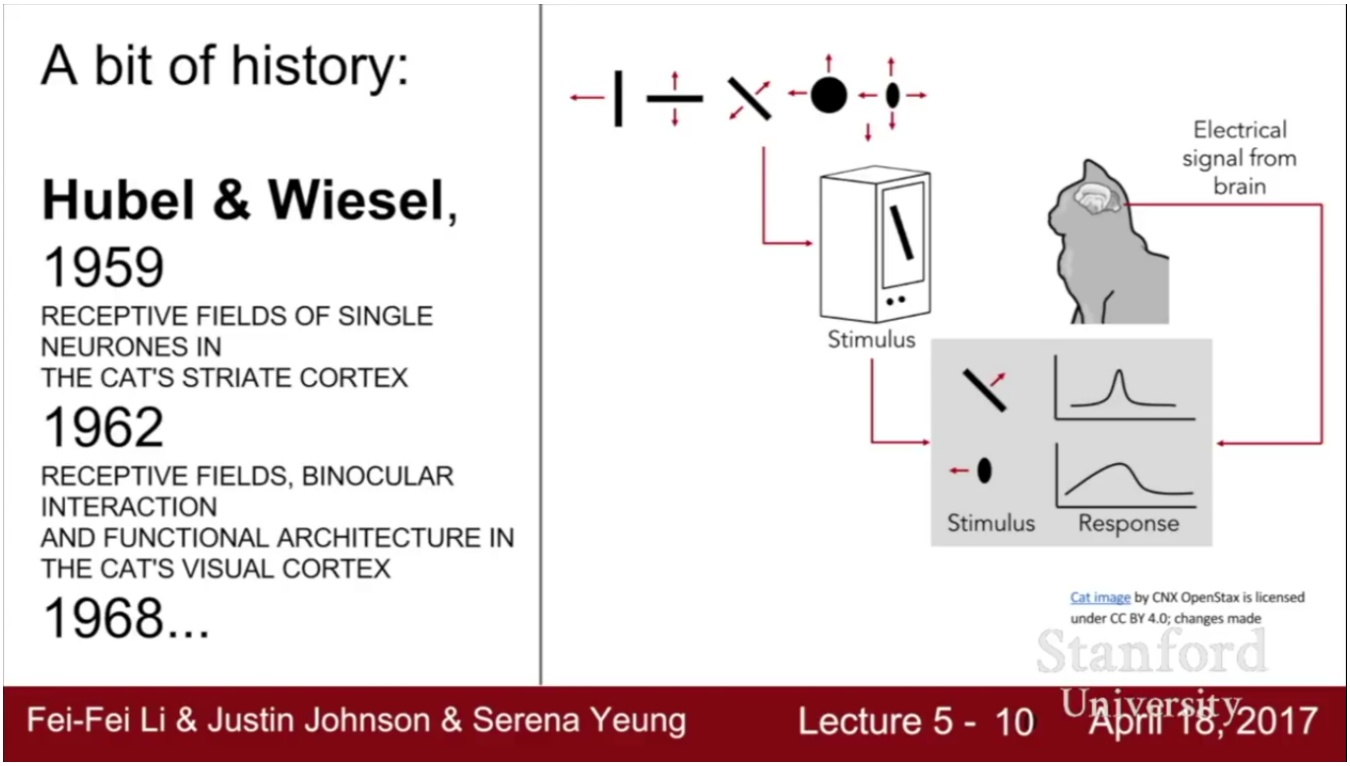
- But during those time the NN was not able to scale up to deeper and larger networks.



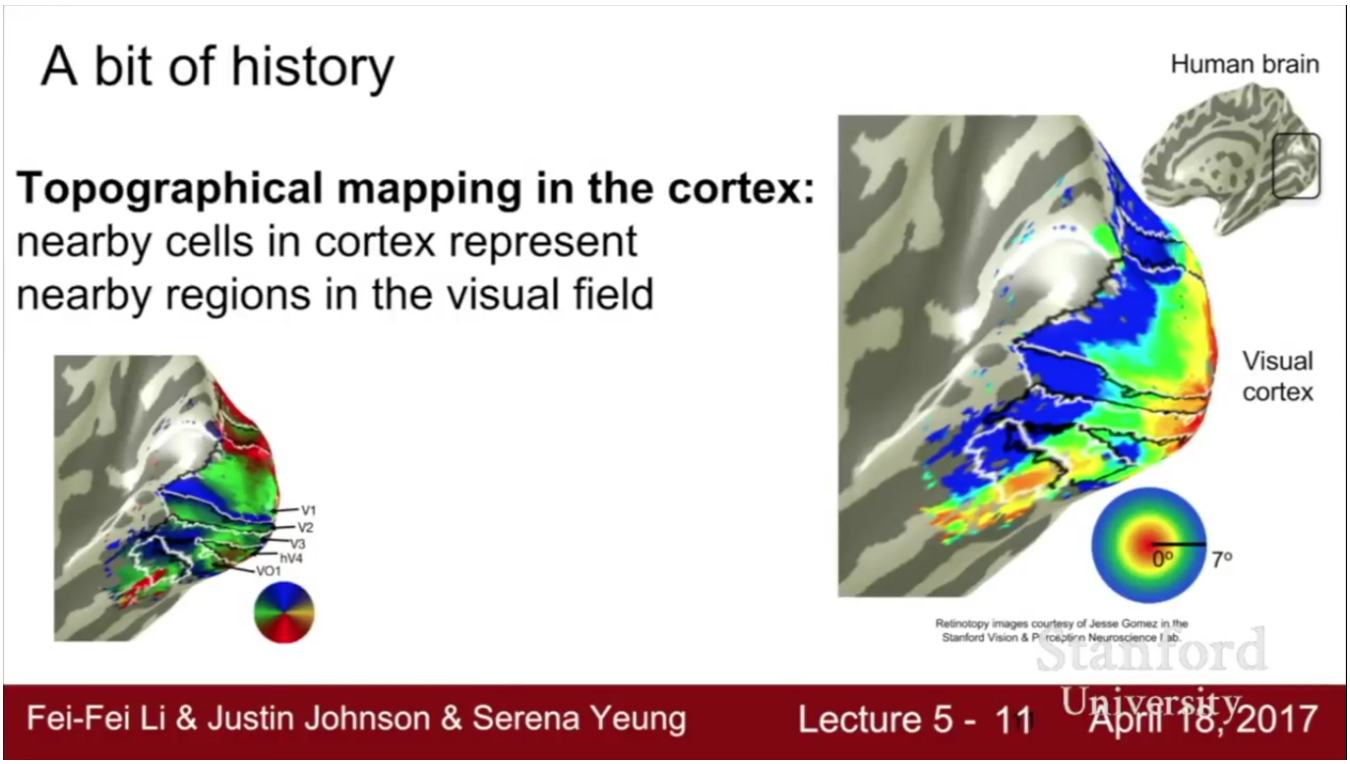
- Here, each of the hidden layers are restricted boltzmann machines.
- After getting the result from the hidden layers, they were fed into the NN



- It took almost 6 years to have a breakthrough result in NN (AlexNet)



- Electrodes were put inside the cat's brain and various visual stimulus were given to check the response.



Hierarchical organization

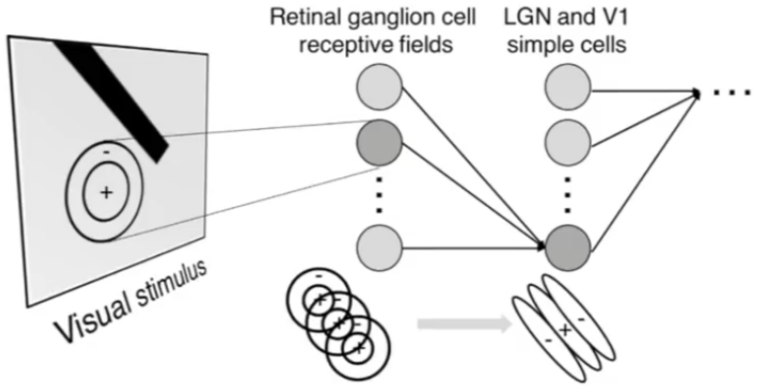


Illustration of hierarchical organization in early visual pathways by Lane McIntosh, copyright CS231n 2017

Simple cells:
Response to light orientation

Complex cells:
Response to light orientation and movement

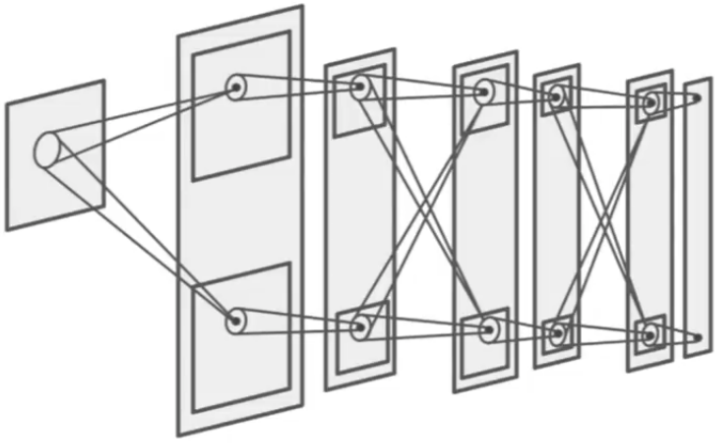
Hypercomplex cells:
response to movement with an end point

No response

Response (end point)

A bit of history:

Neurocognitron
[Fukushima 1980]

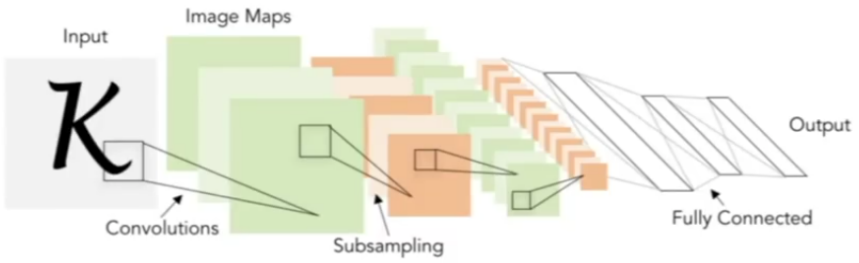


"sandwich" architecture (SCSCSC…)
simple cells: modifiable parameters
complex cells: perform pooling

A bit of history:

Gradient-based learning applied to document recognition

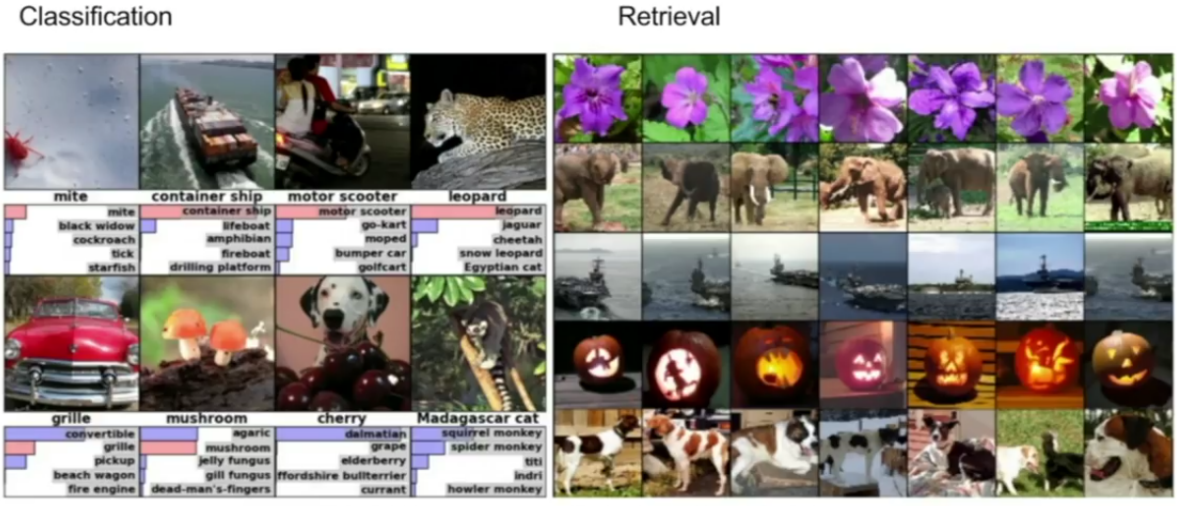
[LeCun, Bottou, Bengio, Haffner 1998]



LeNet-5

- This was used in postal services to read the pincode.

Fast-forward to today: ConvNets are everywhere



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Fast-forward to today: ConvNets are everywhere

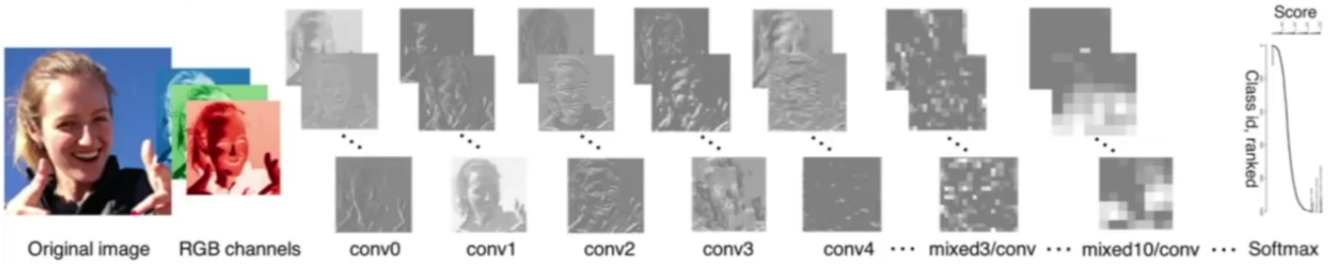
Photo by Lane McIntosh. Copyright CS231n 2017.

self-driving cars

NVIDIA Tesla line
(these are the GPUs on rye01.stanford.edu)

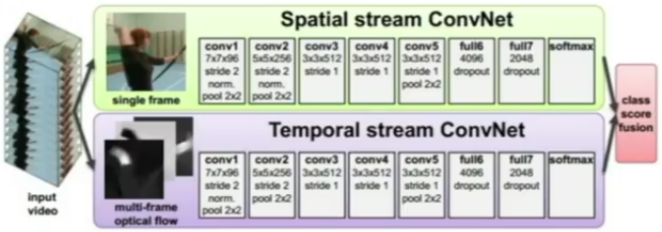
Note that for embedded systems a typical setup would involve NVIDIA Tegras, with integrated GPU and ARM-based CPU cores.

Fast-forward to today: ConvNets are everywhere



[Taigman et al. 2014]

Activations of inception-v3 architecture [Szegedy et al. 2015] to image of Emma McIntosh, used with permission. Figure and architecture not from Taigman et al. 2014.



[Simonyan et al. 2014]

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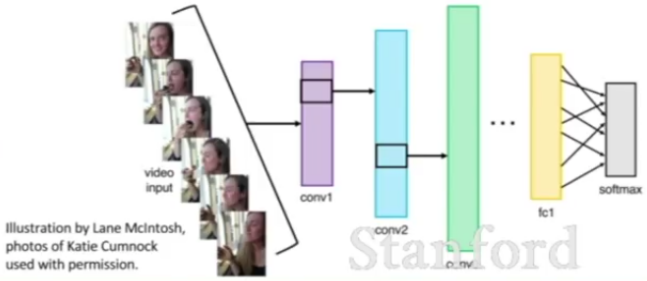
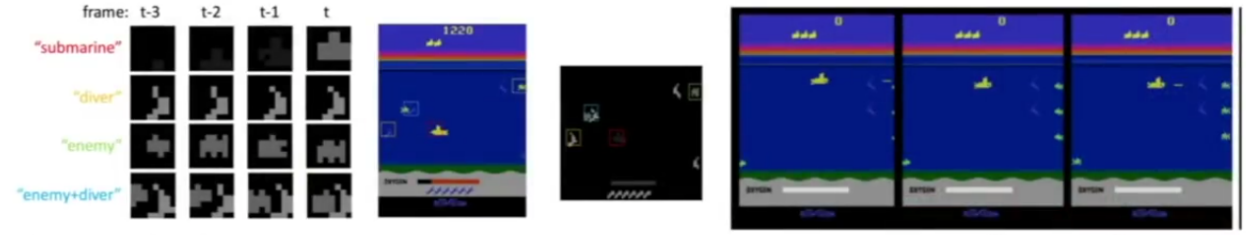


Illustration by Lane McIntosh, photos of Katie Cumnock used with permission.

Fast-forward to today: ConvNets are everywhere

Images are examples of pose estimation, not actually from Toshev & Szegedy 2014. Copyright Lane McIntosh.

[Toshev, Szegedy 2014]



[Guo et al. 2014]

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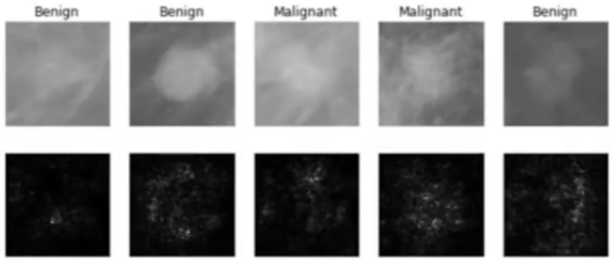
Fast-forward to today: ConvNets are everywhere



[Levy et al. 2016]

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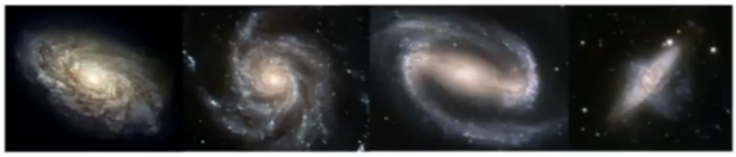

[Dieleman et al. 2014]

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

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Whale recognition, Kaggle Challenge

Photo and figure by Lane McIntosh; not actual example from Mnih and Hinton, 2010 paper.

Mnih and Hinton, 2010

No errors

A white teddy bear sitting in the grass

Minor errors

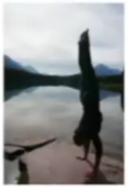
A man in a baseball uniform throwing a ball

Somewhat related

A woman is holding a cat in her hand

A man riding a wave on top of a surfboard

A cat sitting on a suitcase on the floor



A woman standing on a beach holding a surfboard

Image Captioning

[Vinyals et al., 2015]
[Karpathy and Fei-Fei, 2015]

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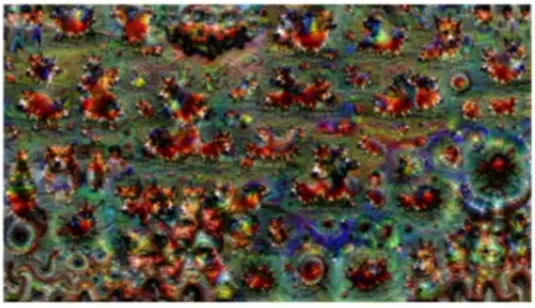
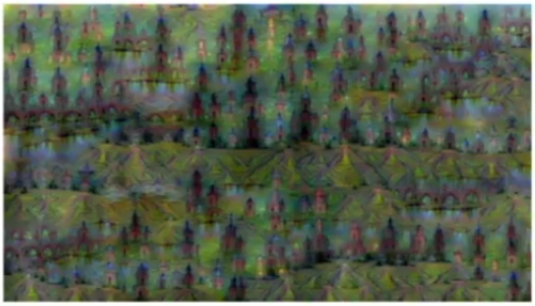
Captions generated by Justin Johnson using Neuraltalk2





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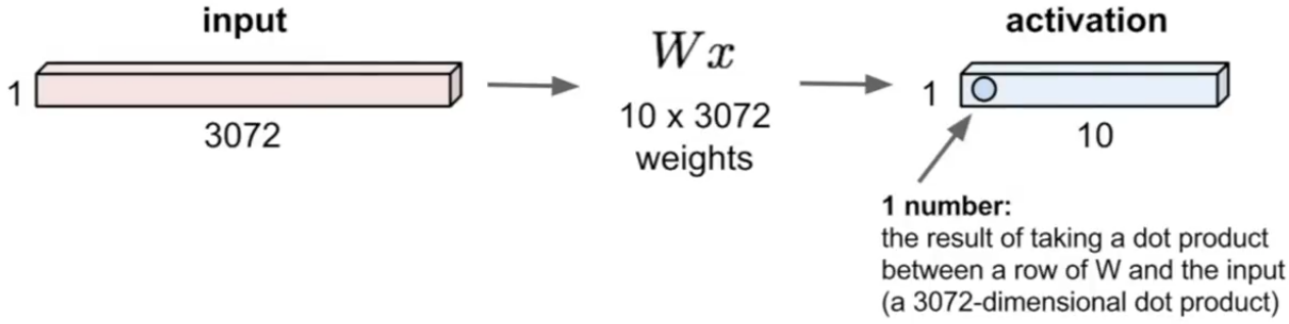
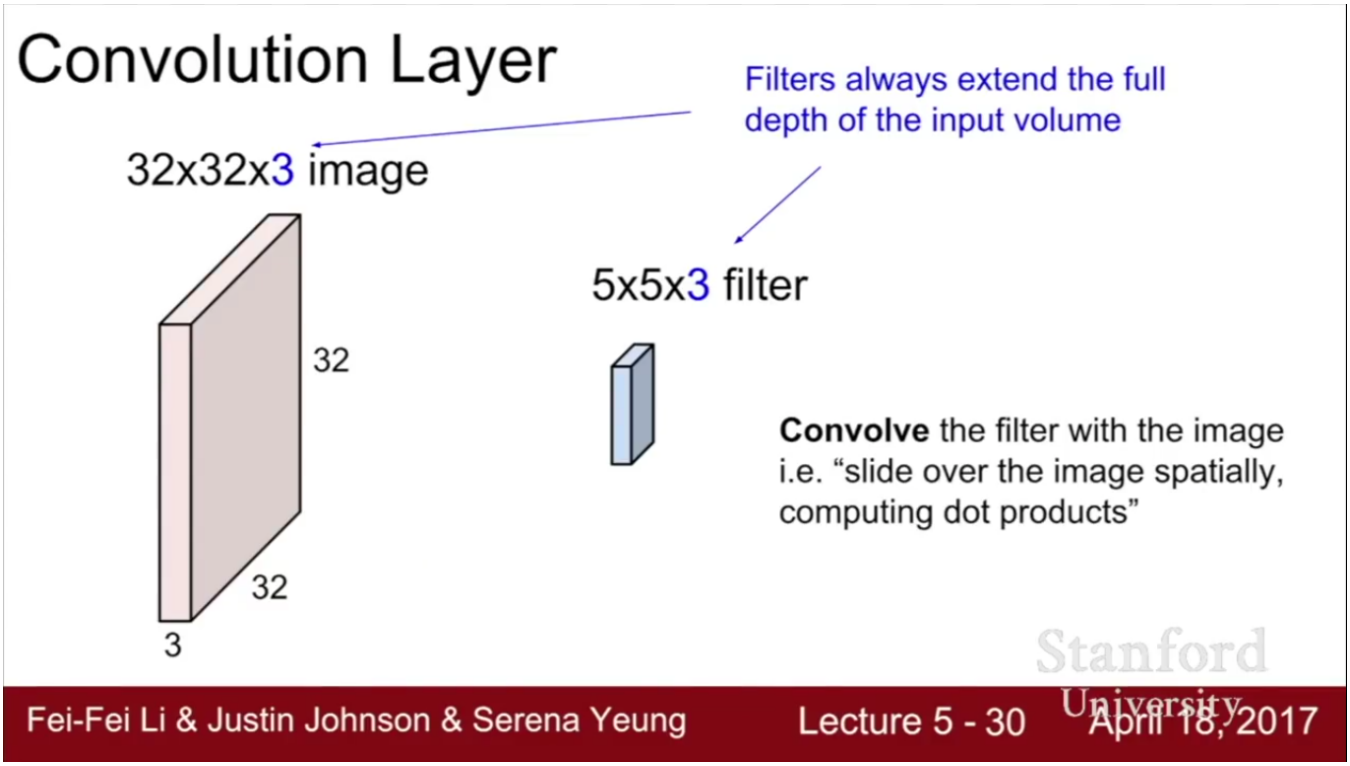
Gatys et al, "Image Sty... Tran... using Convoluti... Neural Networks", CVPR 2016
Gatys et al, "Controlling Pe... tual Fa... to ... Neural Style Transfer", CVPR 2017

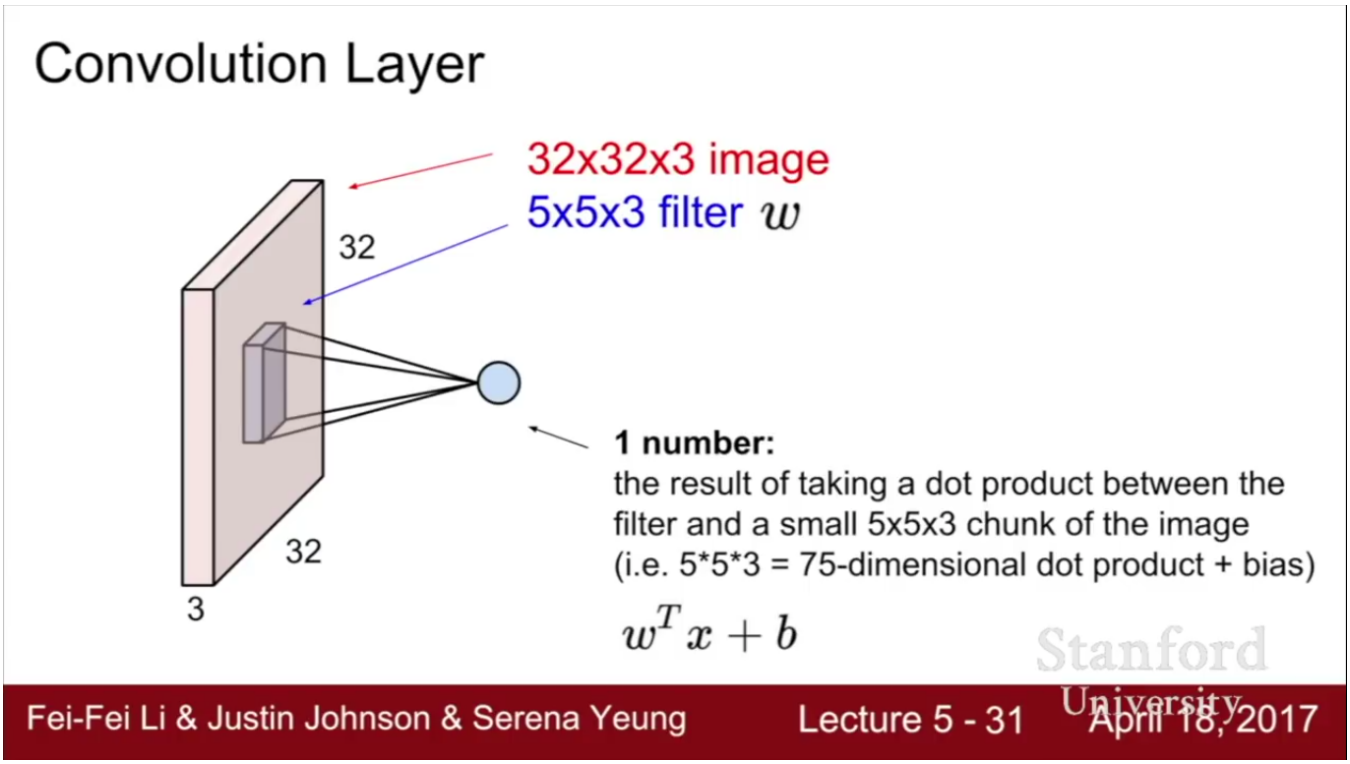
Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1

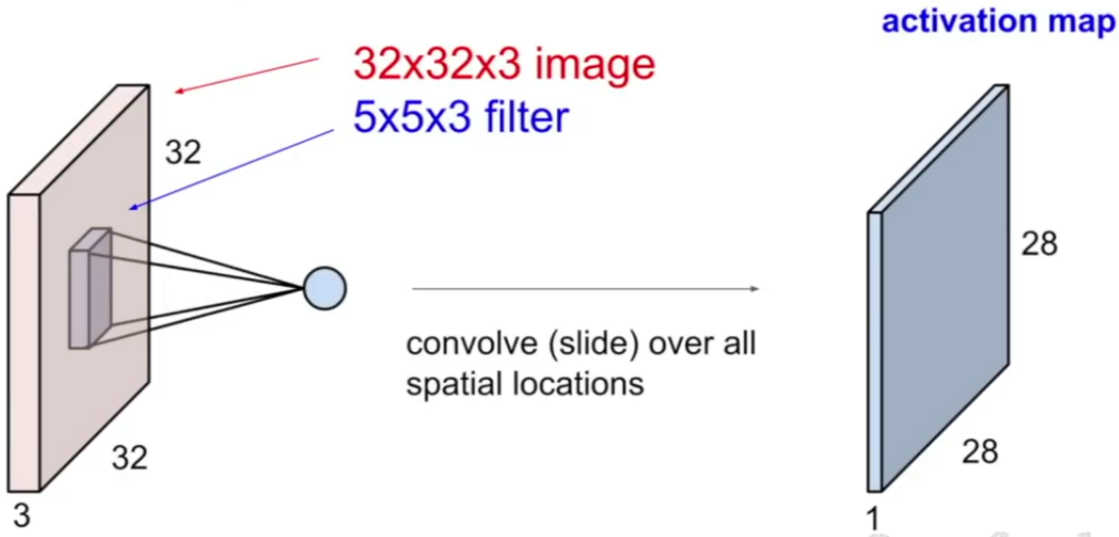


- Fully Connected layer doesn't preserve spatial structure since we just flatten the image into a vector.

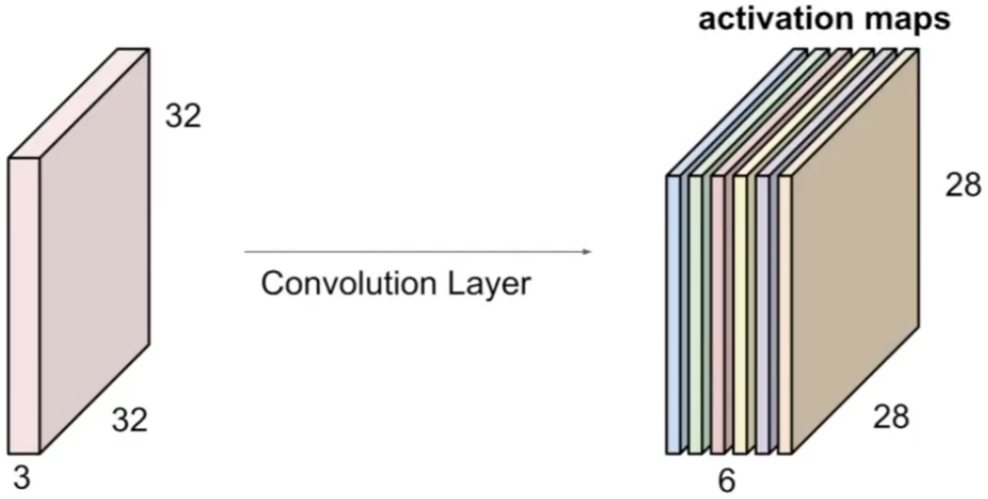




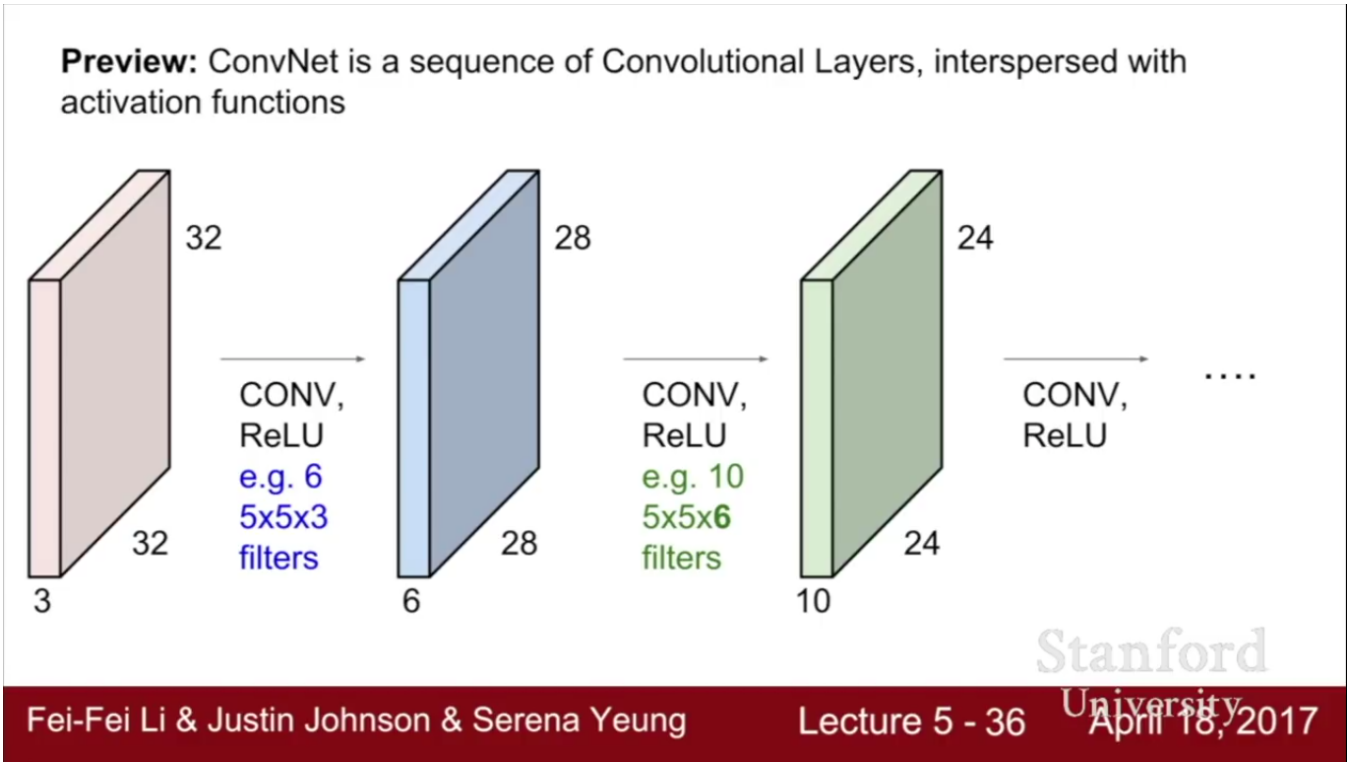
Convolution Layer

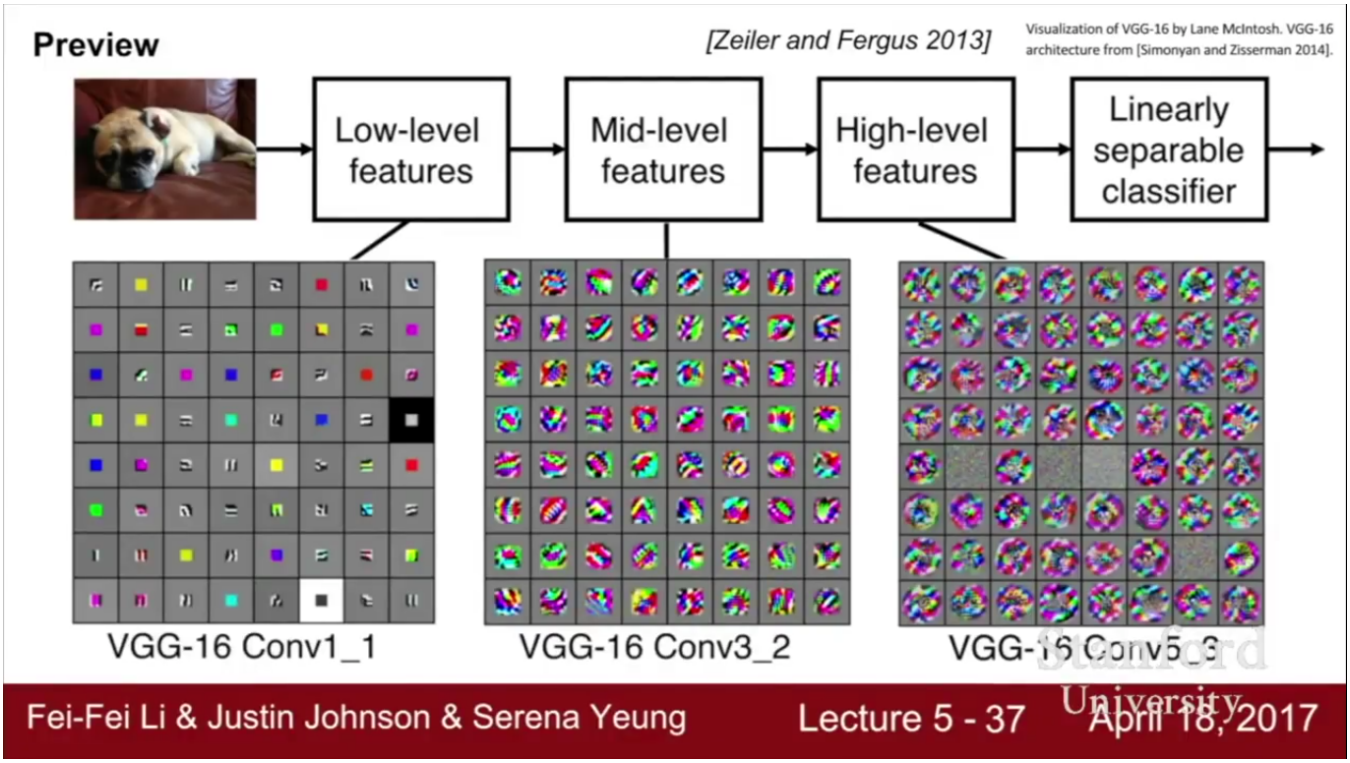


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

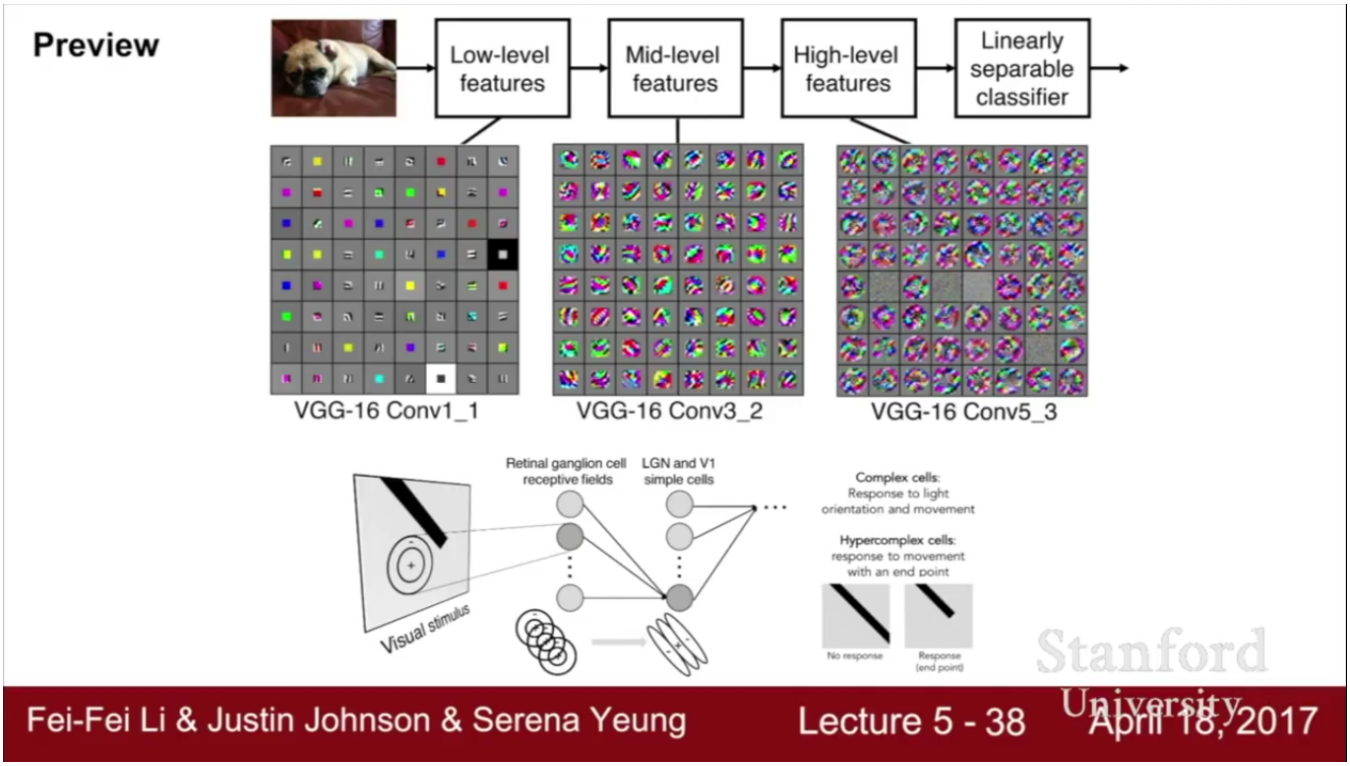


We stack these up to get a "new image" of size 28x28x6!

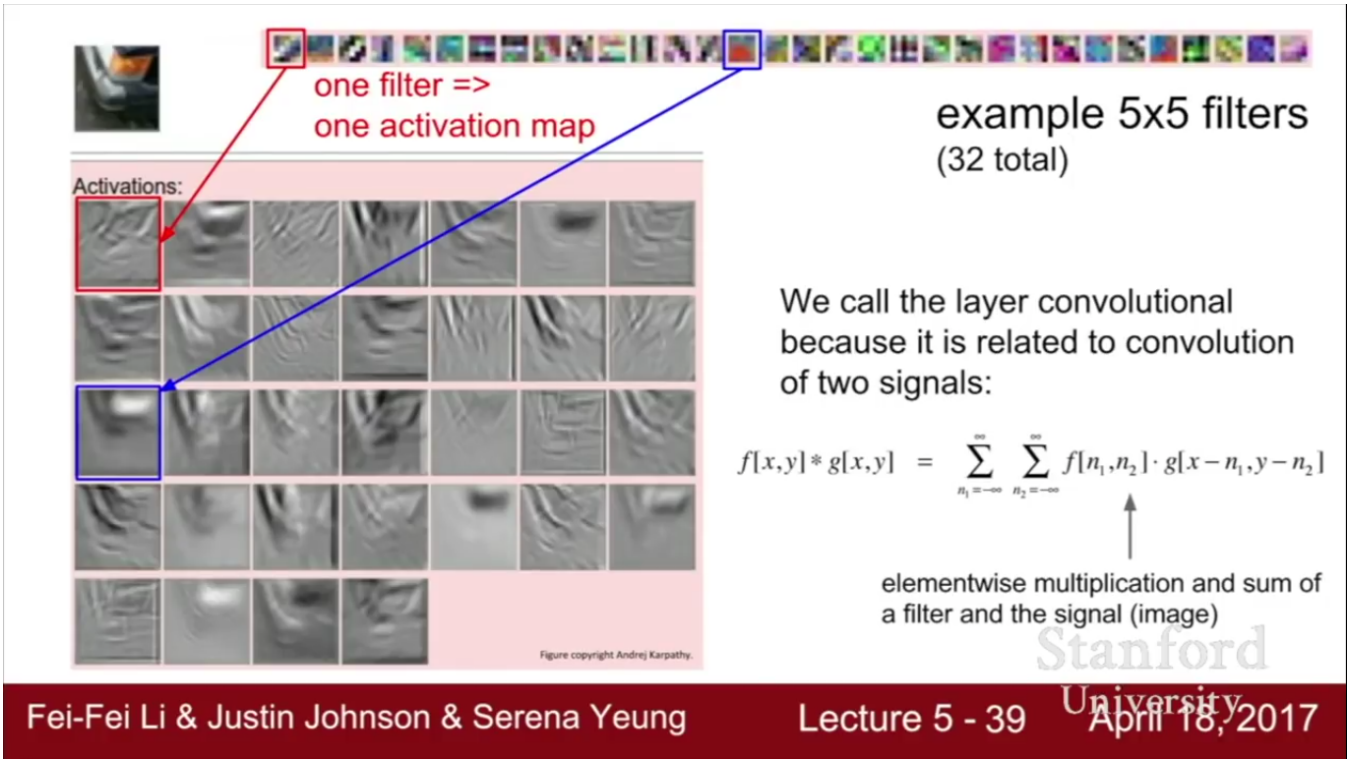




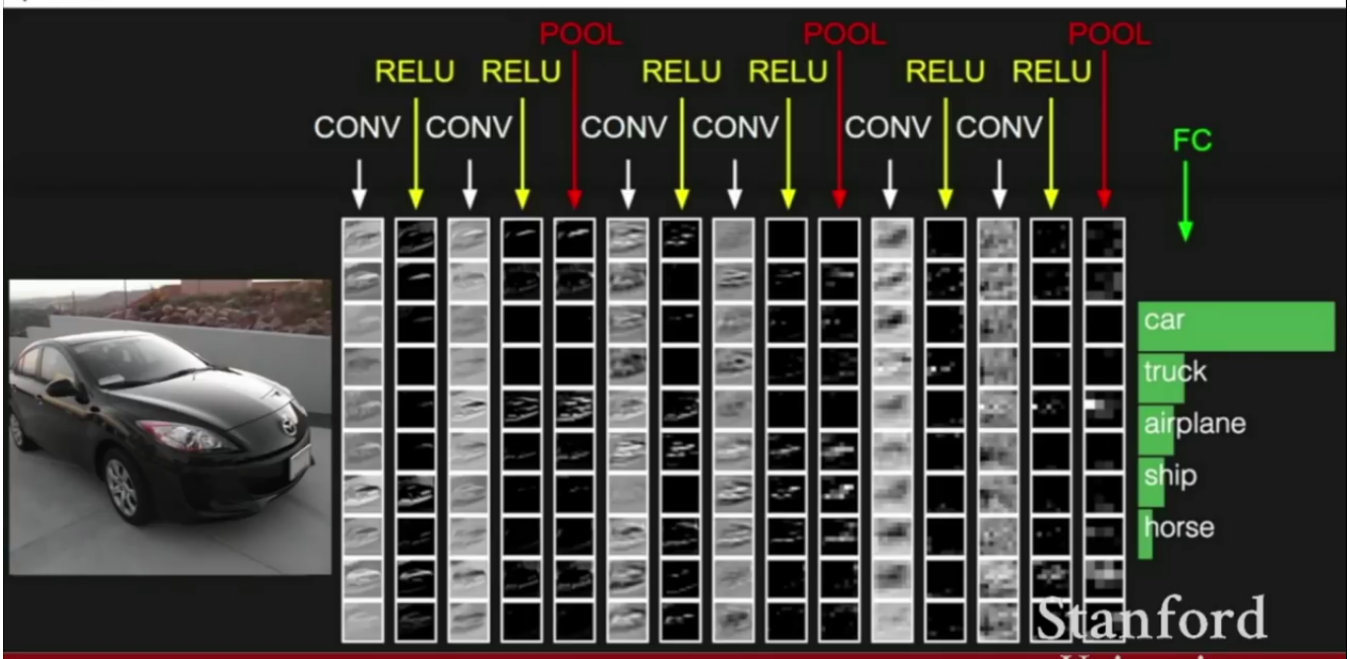
- So the activation maps when stacked form layers, and the layer at the beginning learn simple, low-level features where as deeper layers learn more complex features.

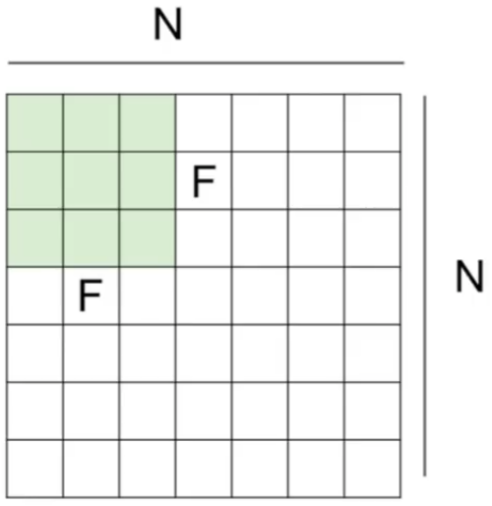


- We can notice that the NN mimics the earlier experiment.



preview:

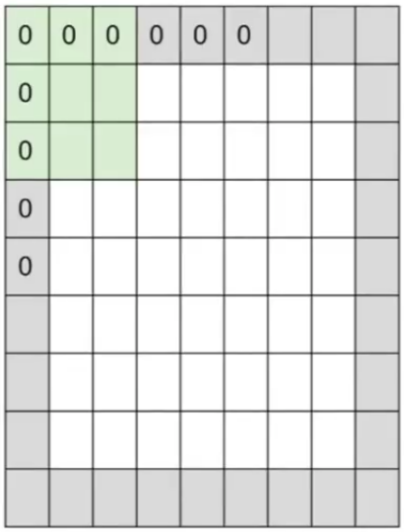




Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

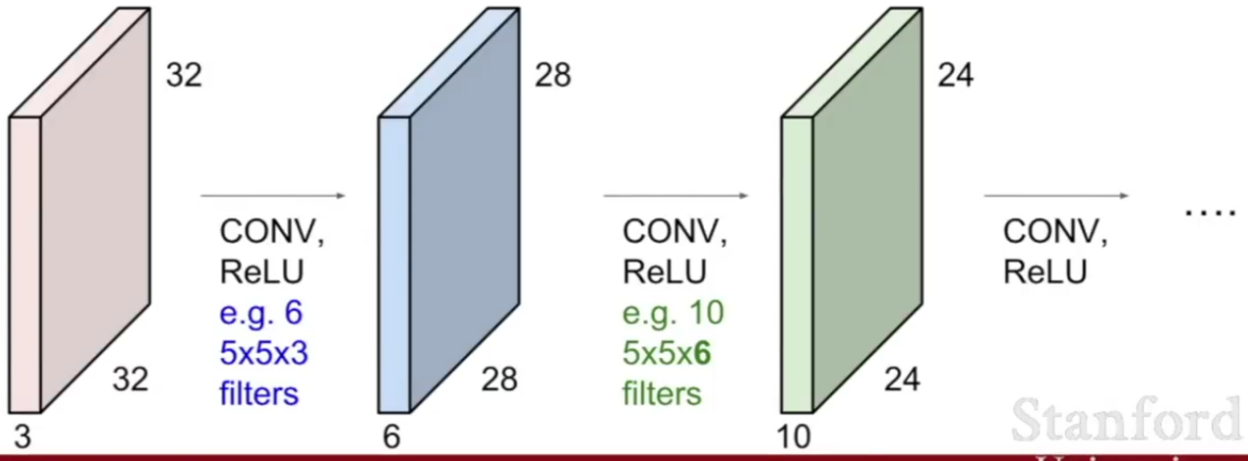
In practice: Common to zero pad the border



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

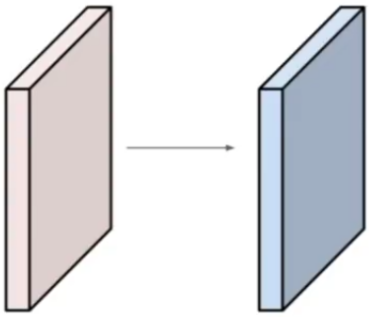
Remember back to…
E.g. 32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially!
(32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.



- **Shrinking too fast is not good, doesn't work well.**
- Hence padding is used, and max-pool is done after some depths.

- **IMPORTANT**

Examples time:



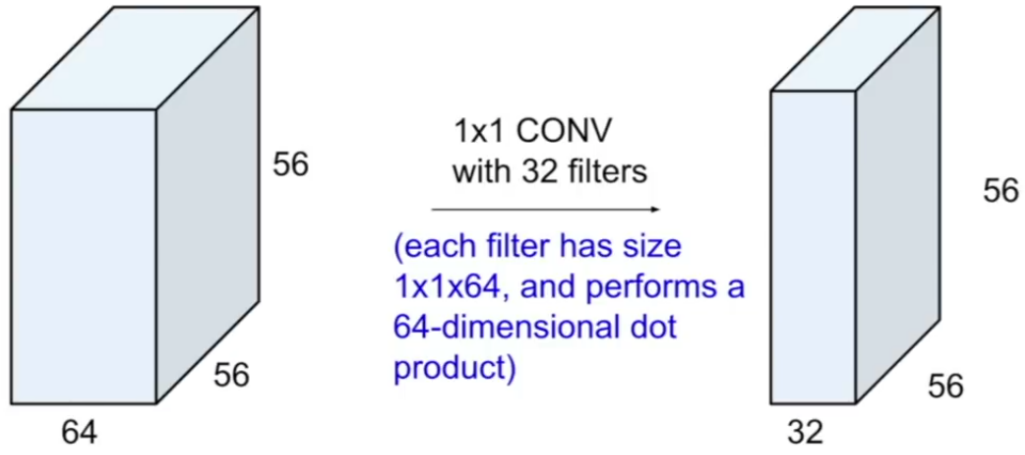
Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

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

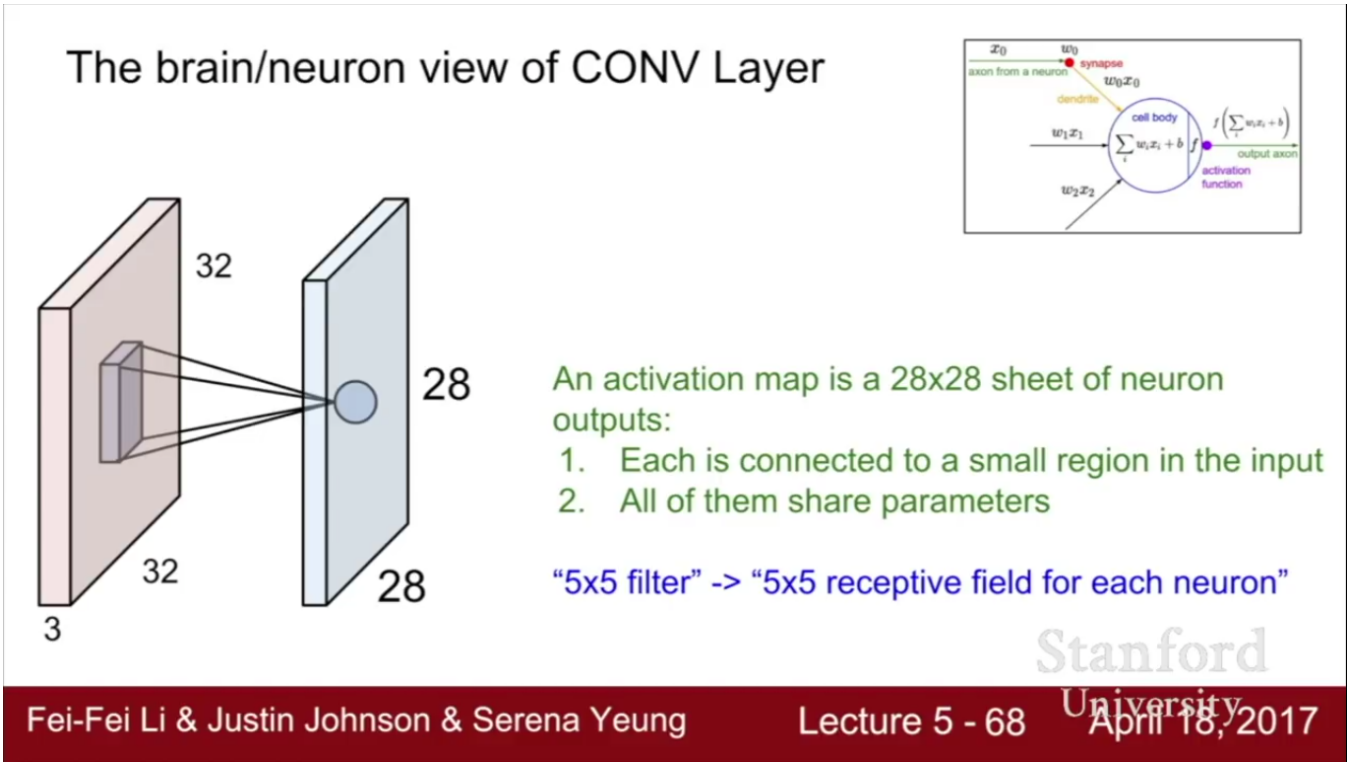
Summary. To summarize, the Conv Layer:

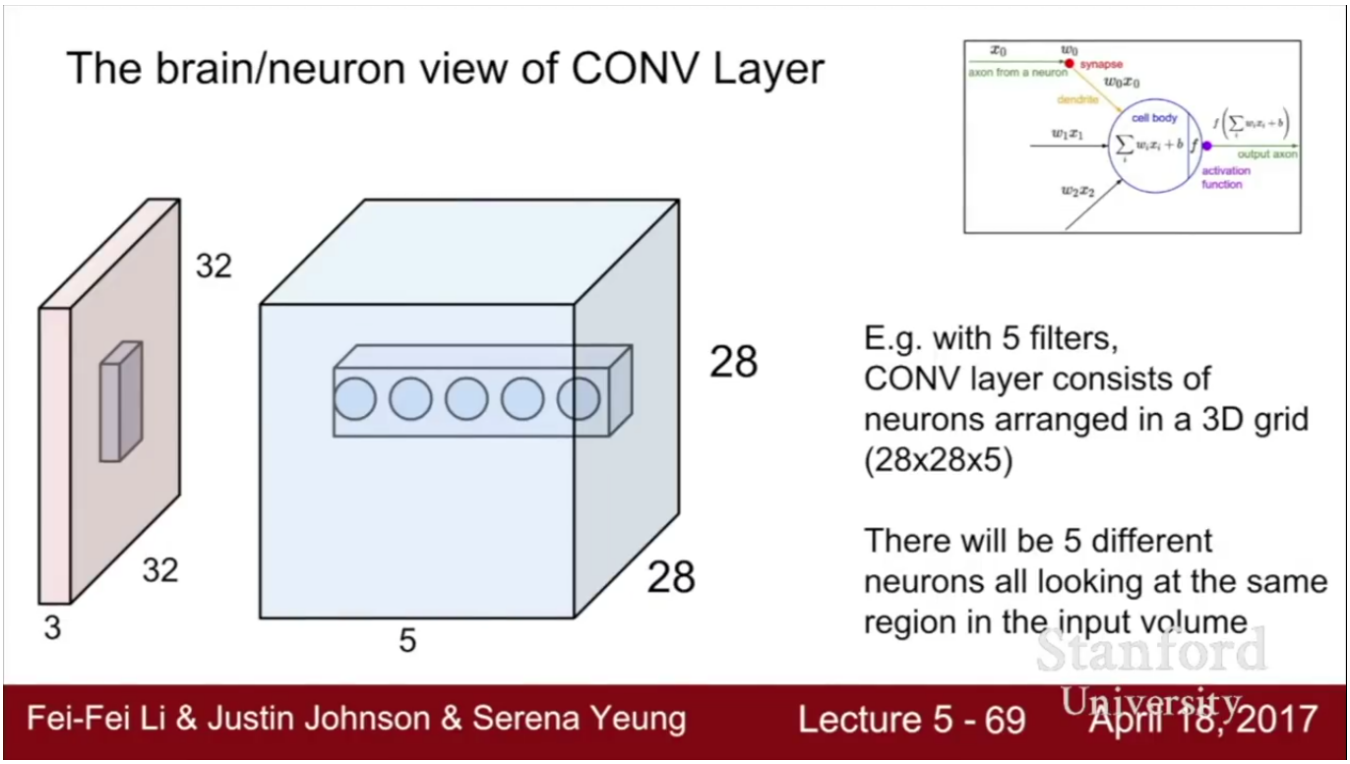
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
  - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

(btw, 1x1 convolution layers make perfect sense)



- Receptive Field:



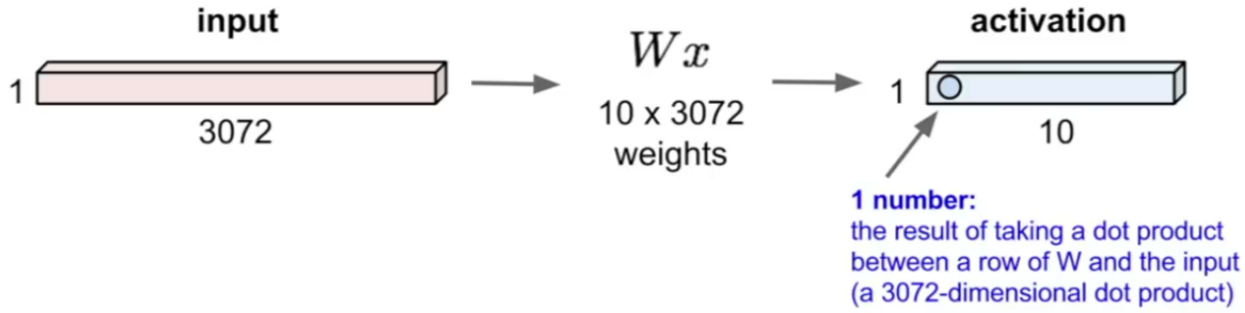


- Here we can notice that in the activation map,different filters were applied to the same spatial location.

Reminder: Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1

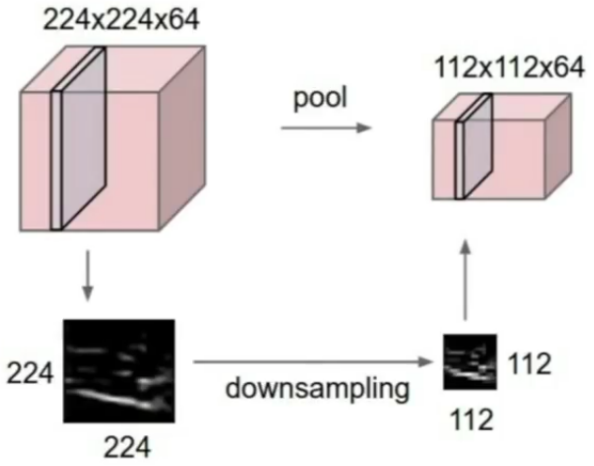
Each neuron looks at the full input volume



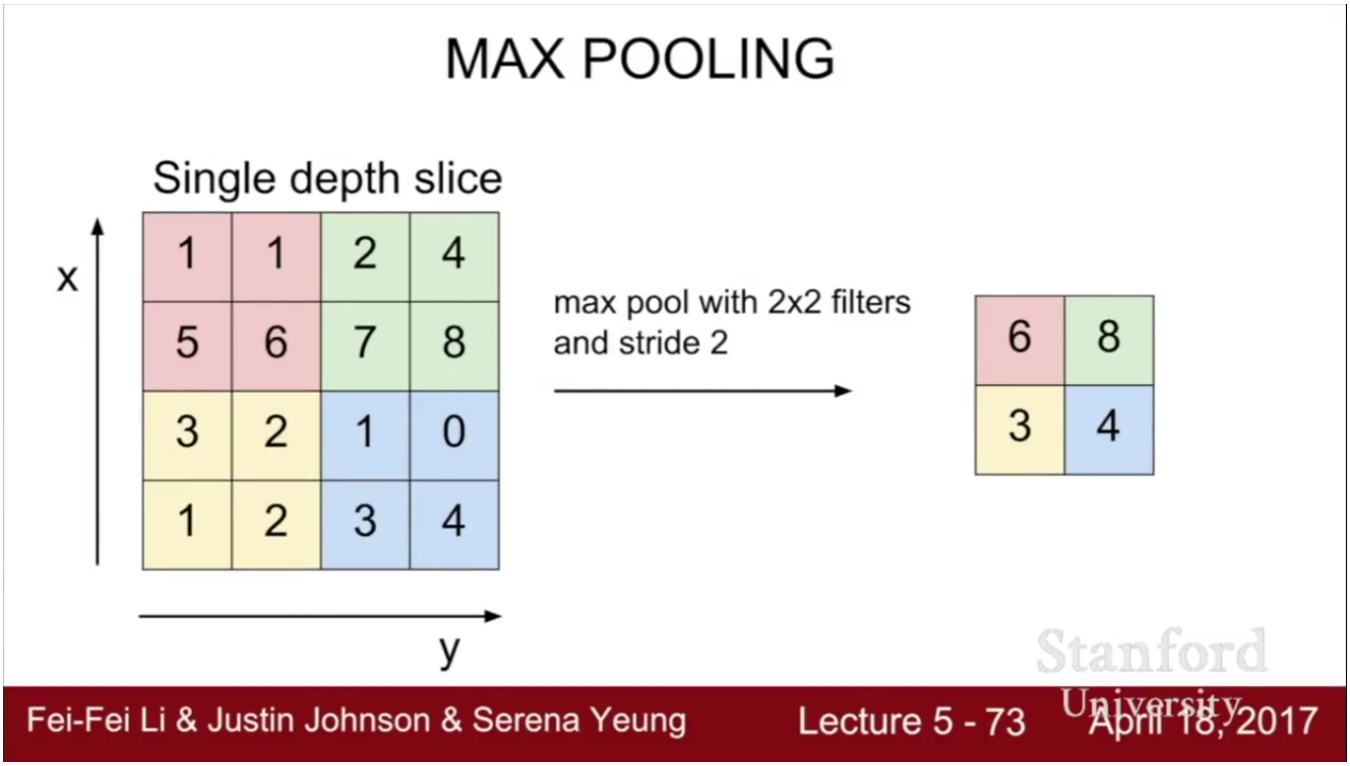
1 number:
the result of taking a dot product between a row of W and the input (a 3072-dimensional dot product)

Pooling layer

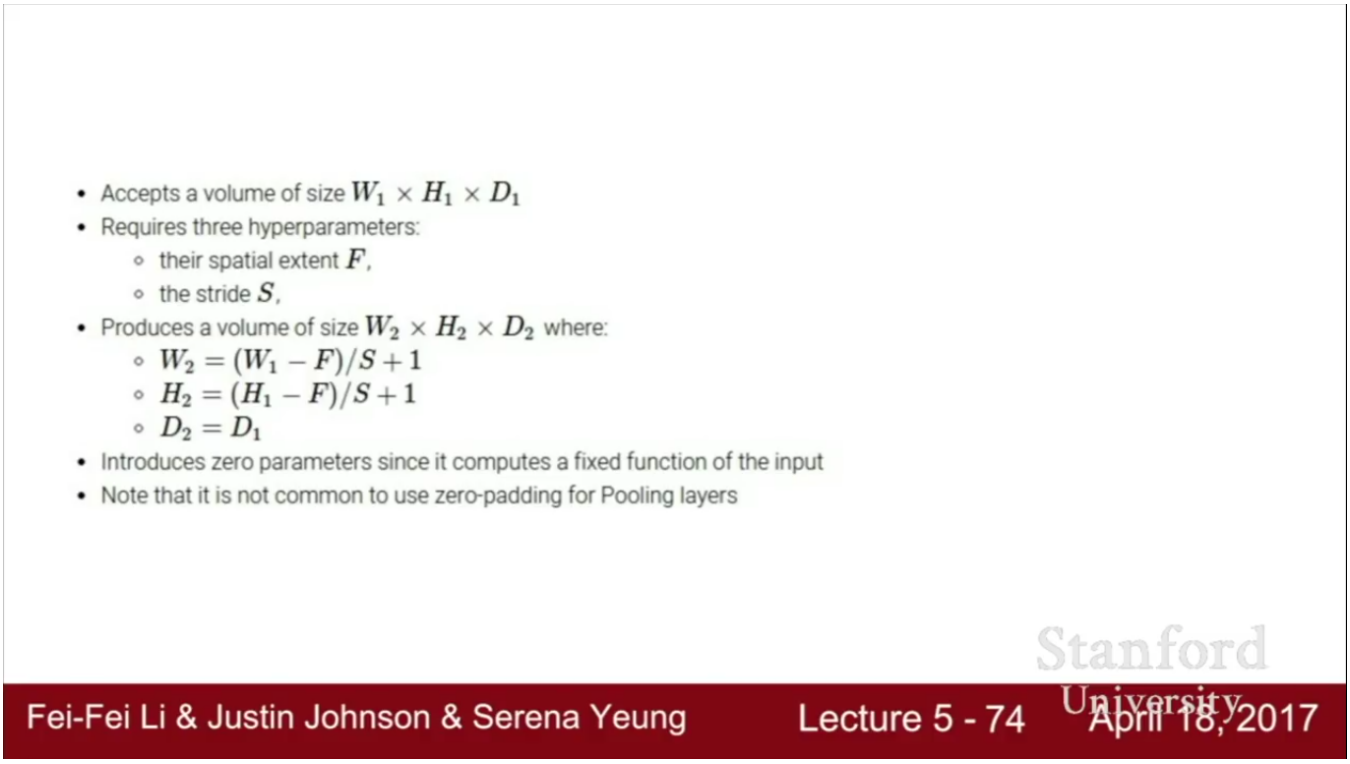
- makes the representations smaller and more manageable
- operates over each activation map independently:



- Pooling doesn't change the depth, it only changes the spatial dimensions.

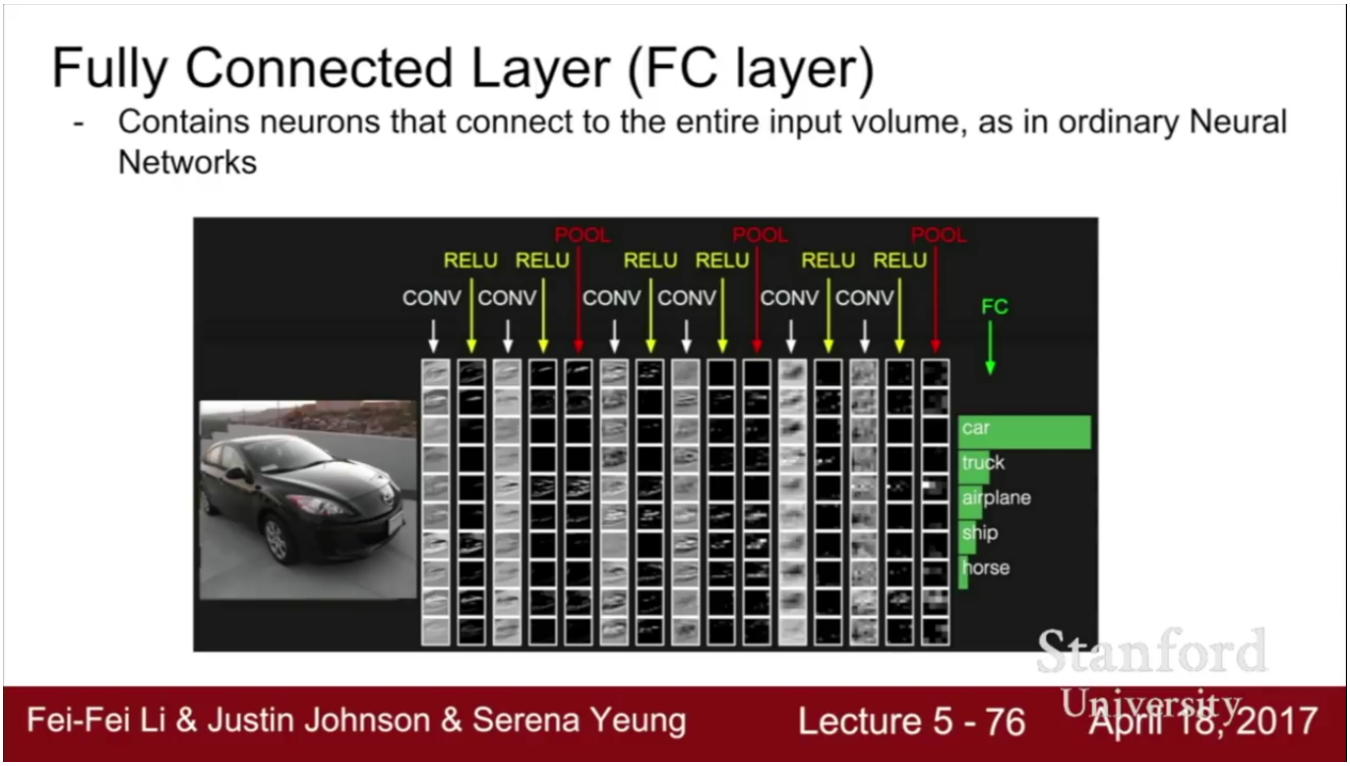


- While pooling, we usually avoid overlapping with enough large stride.
- **Max Pooling is done because it mimics the notion whether any neuron fired in the considered region.**



- Pooling layers have 0 parameters.

- The depth remains same after pooling since the pooling is done on each layer separately.



- **For FULLY CONNECTED LAYERS, we flatten the convolutional output of size (w,h,d) into a vector of size (wxhxd) X 1 vector and then connect each of the neurons to the FC layer.**
- ***Even though the final layers will have less number of neurons the information present in them will be the accumulated information passed through the entire network.***