

CSCI 1470/2470
Spring 2024

Ritambhara Singh

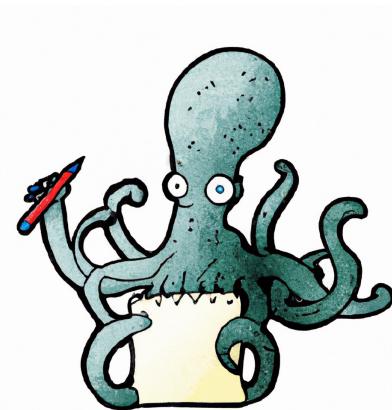
February 21, 2024
Wednesday

Multi-layer CNNs

Deep Learning

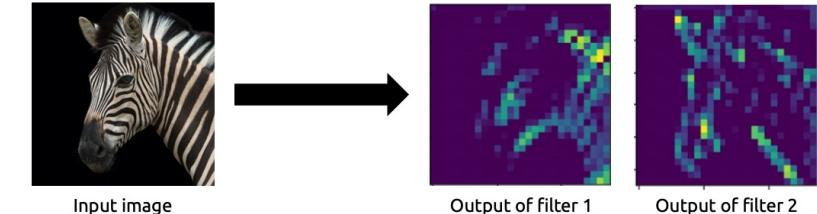


Recap



Convolution

- Filters/Kernels and Stride
- Learning filters
- CNNs are partially connected networks



Convolution in Tensorflow

- Tensorflow conv2d function
- Padding
- Application to MNIST/CIFAR

```
tf.nn.conv2d(input, filter, strides, padding)
```

Input Image (4-D Tensor) Filter/Kernel (4-D Tensor) Strides along each dimension Type of Padding (String "Valid" or "Same")

Today's goal – continue to learn about CNNs

(1) Convolutional Neural Network (CNN) architecture

(2) First successful CNN - AlexNet

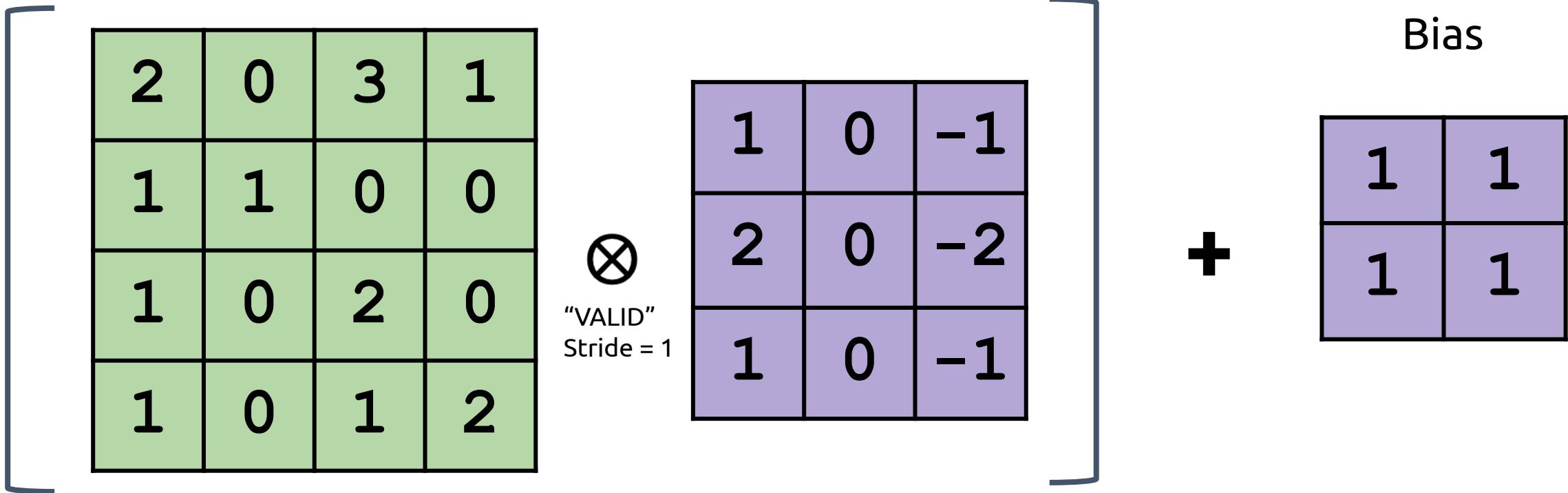
 Pooling and translational invariance

(3) Deeper CNNs!

 Residual Blocks

 Batch normalization

Bias Term in Convolution Layers



Just like a fully connected layer, we can have a learnable additive bias for convolution.

Adding a Bias in Tensorflow

If you use `tf.nn.conv2d`, bias can be added with:

`tf.nn.bias_add(value, bias)`

Conv2D output

Bias variable to add
e.g.

`tf.Variable(tf.random.normal([16]))`

for a conv2d output with 16 channels

Full documentation here:

https://www.tensorflow.org/api_docs/python/tf/nn/bias_add

Adding a Bias in Tensorflow

If you are using keras layers, bias is included by default:

```
tf.keras.layers.Conv2D(filters, kernel_sz, strides, padding, use_bias = True)
```

Number of filters

Filter Size

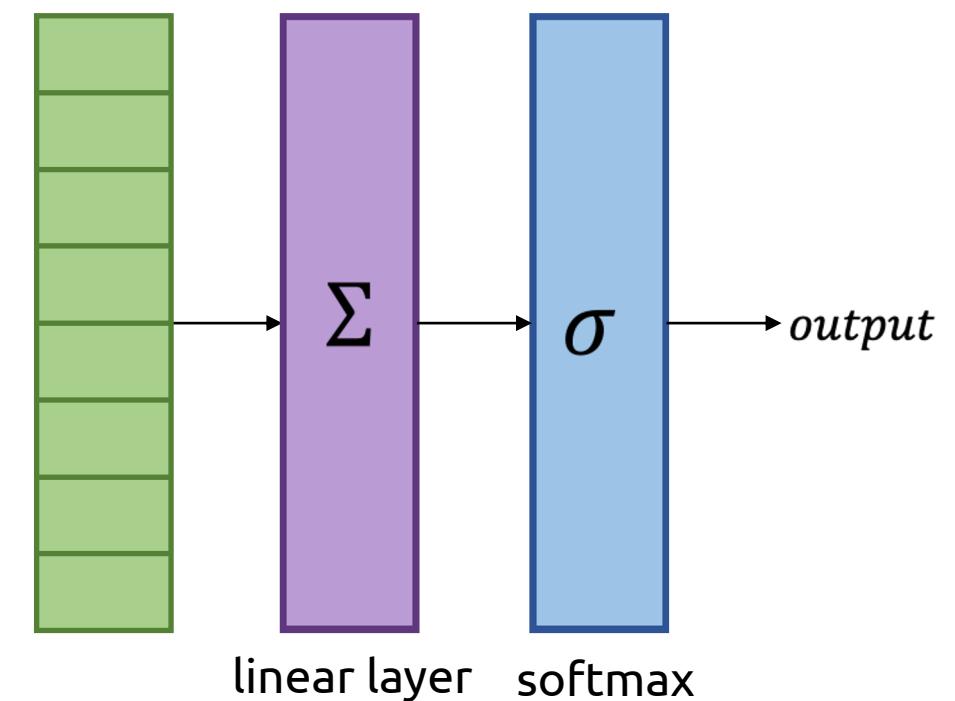
Strides along
each dimension

Type of Padding
(VALID or SAME)

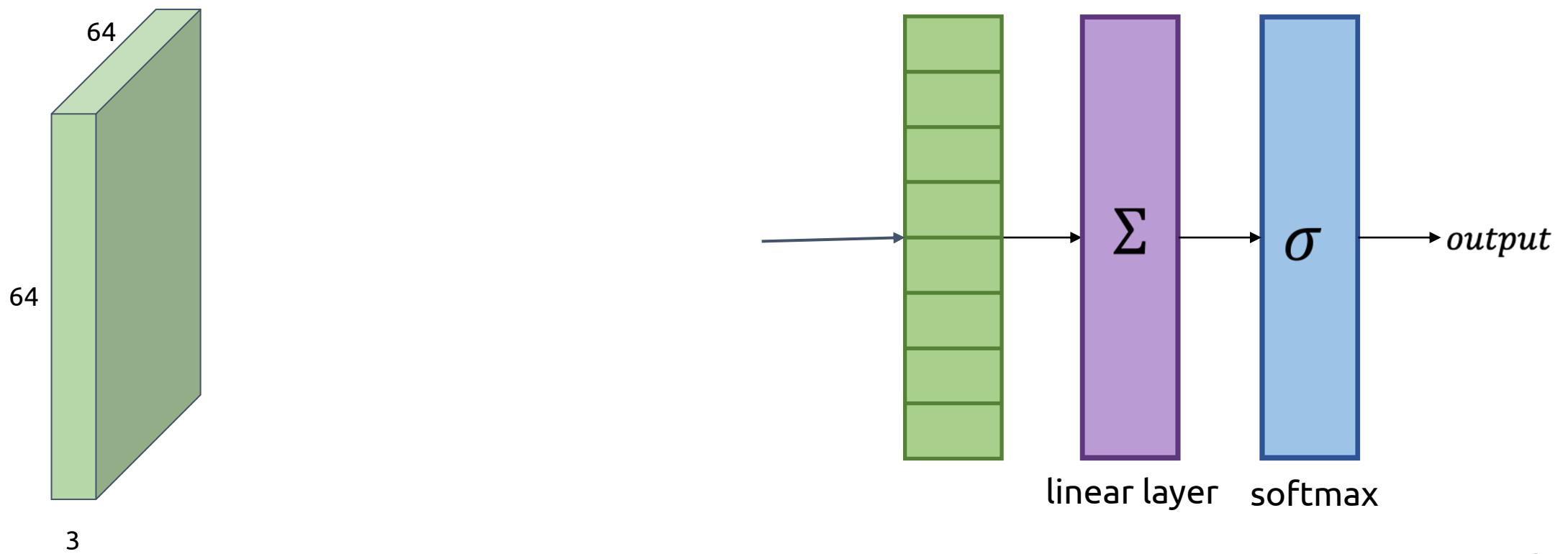
Full documentation here:

https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/Conv2D

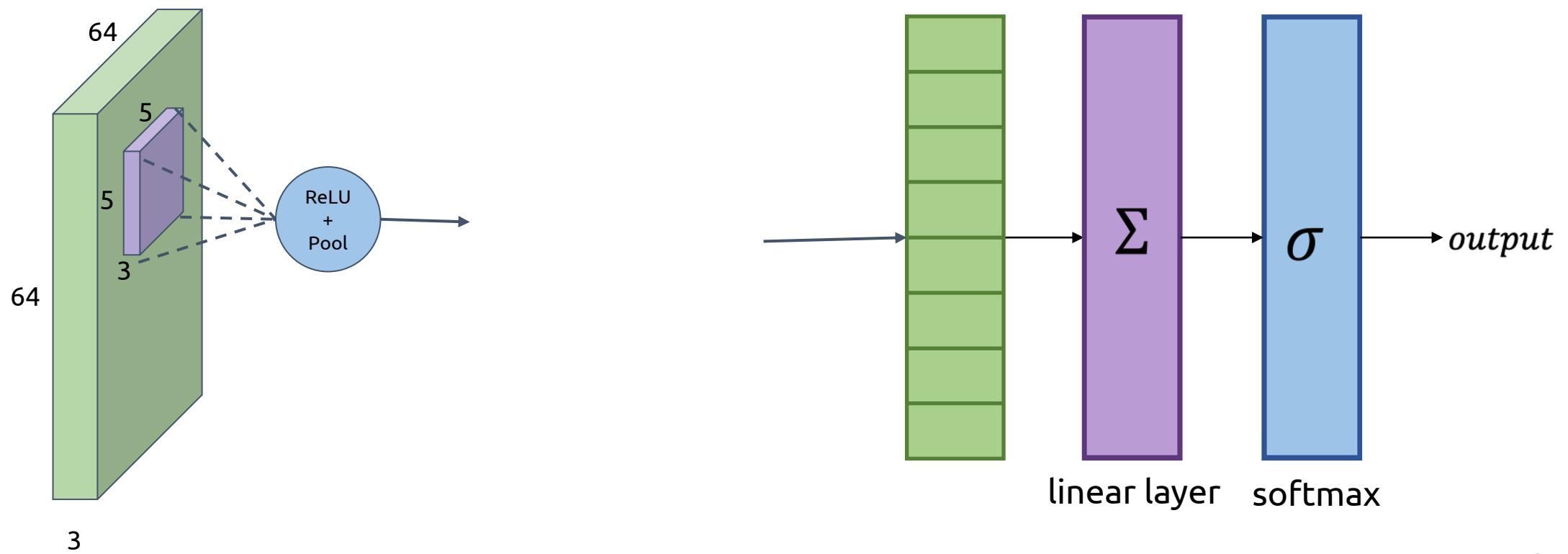
Our neural network so far



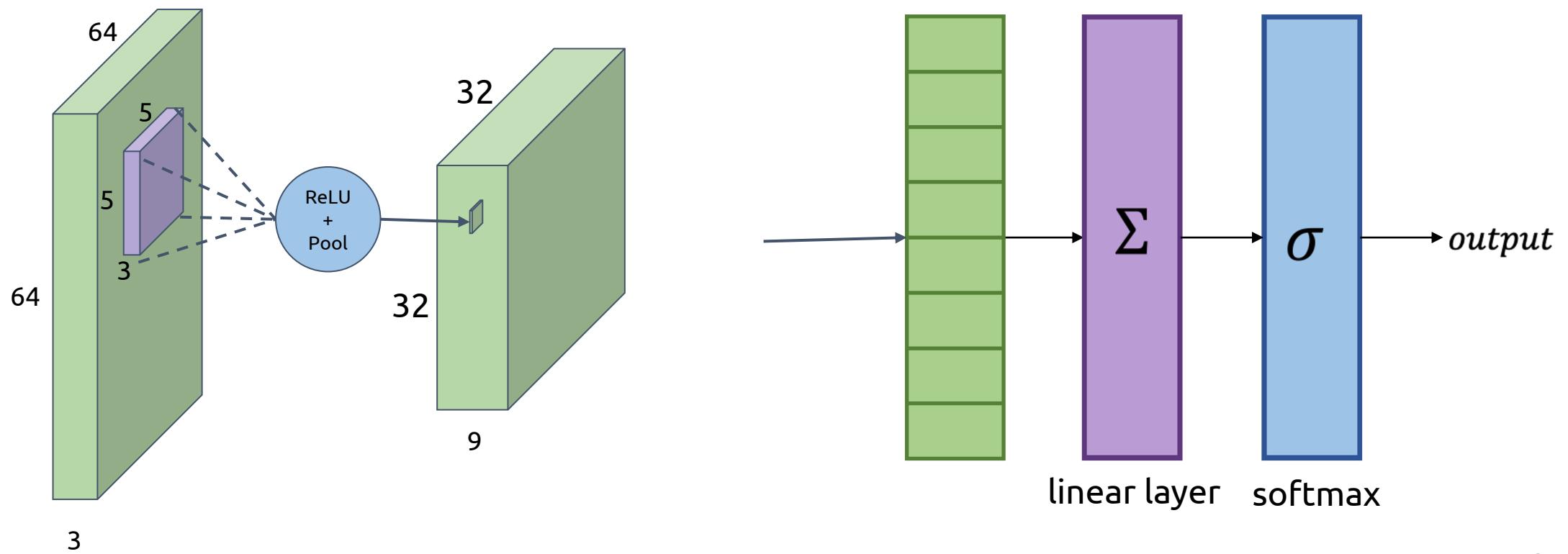
Convolutional Neural Network Architecture



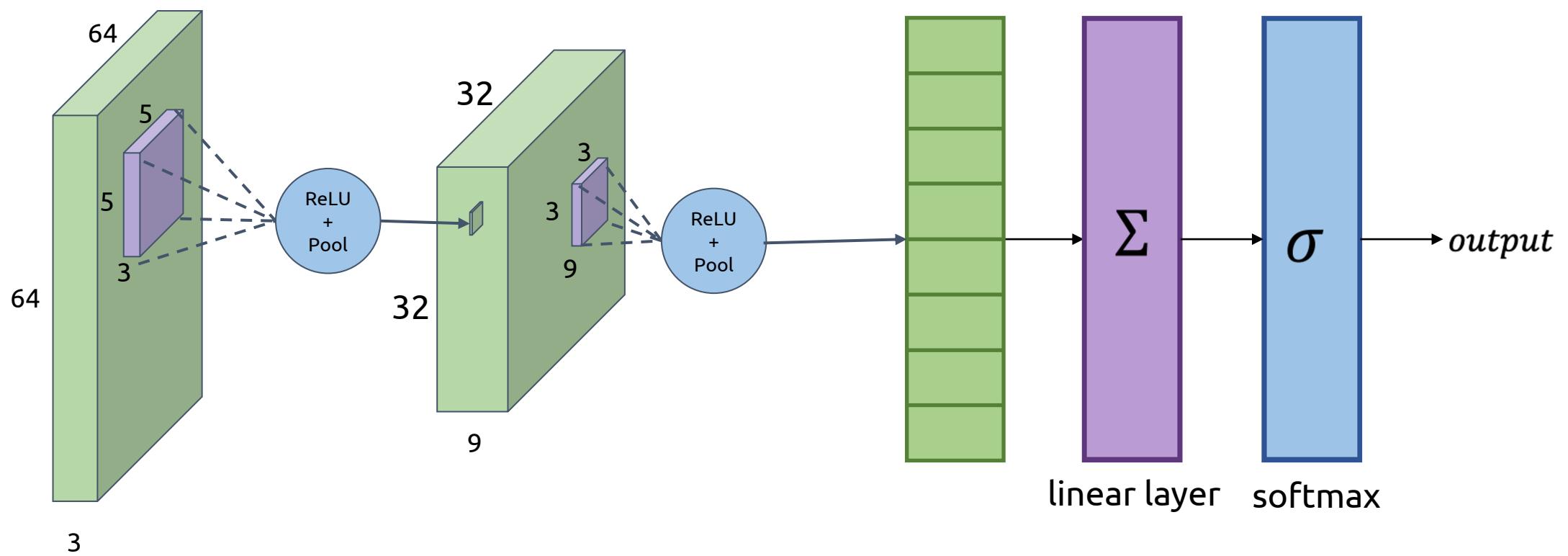
CNN Architecture



CNN Architecture

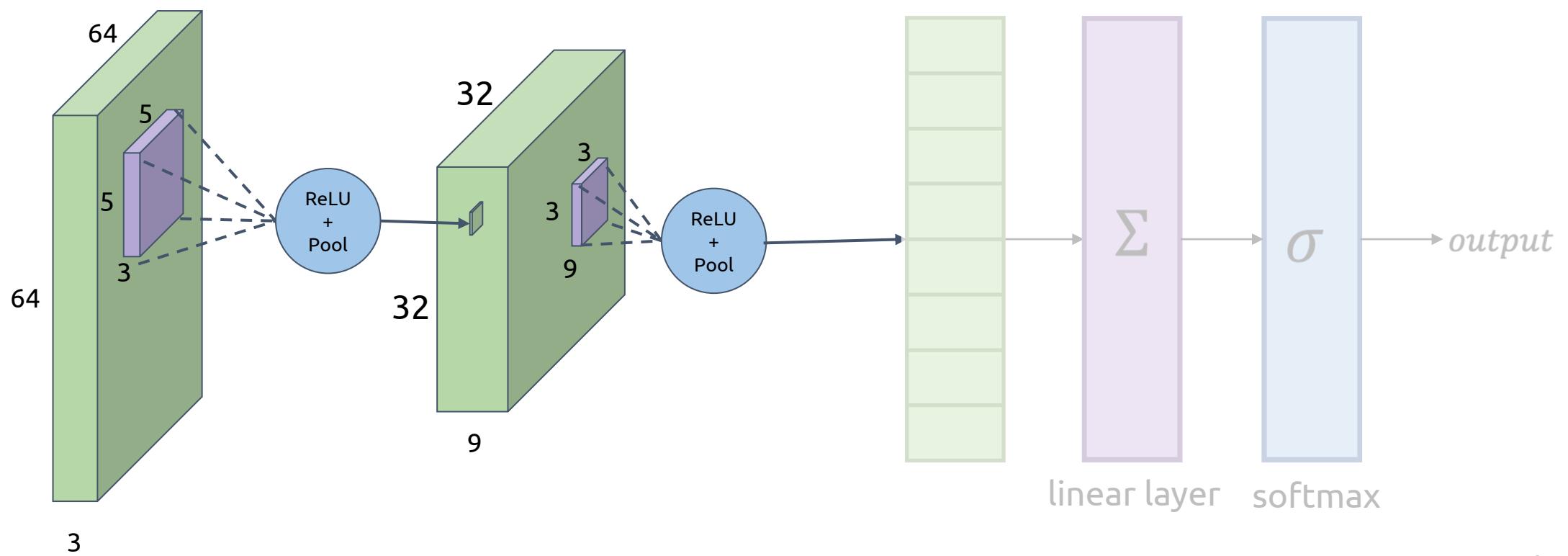


CNN Architecture

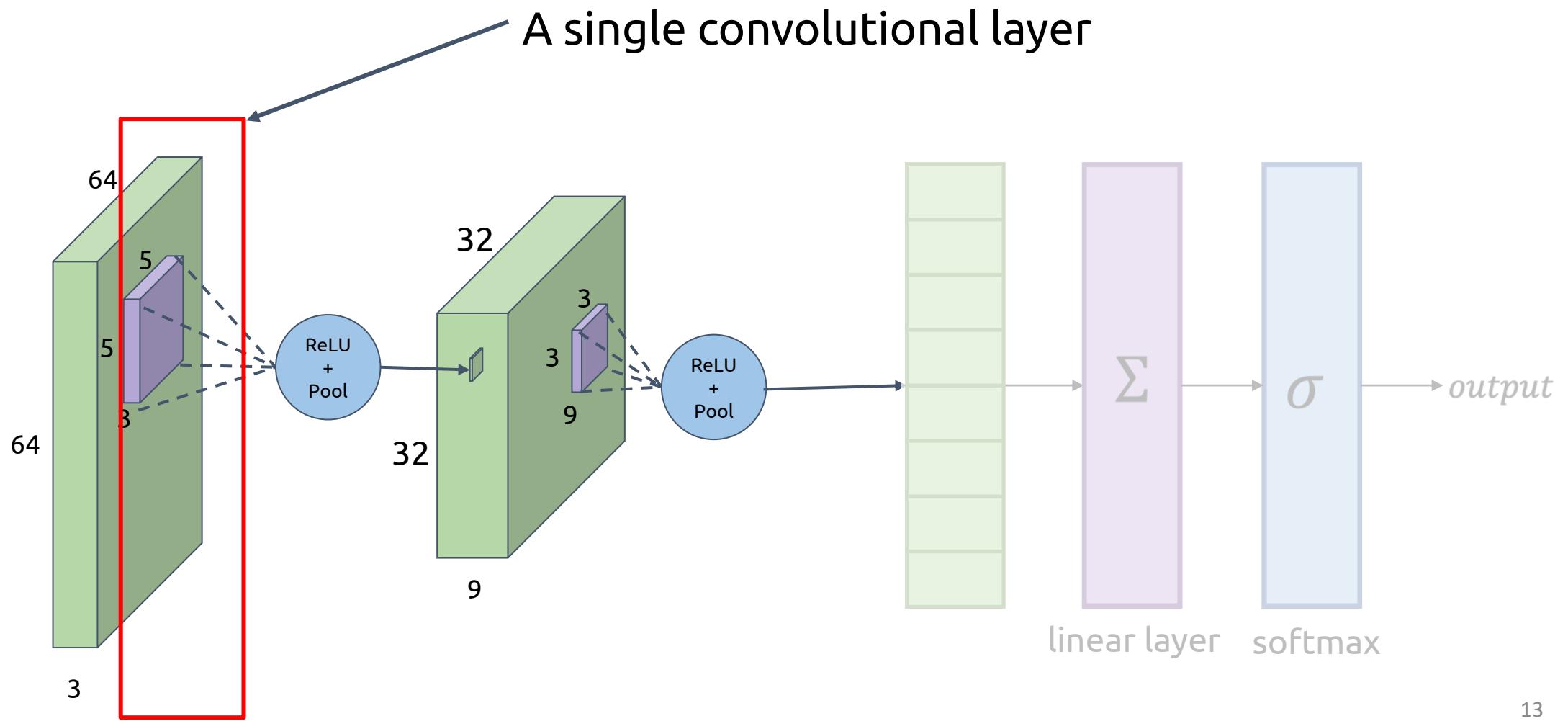


CNN Architecture

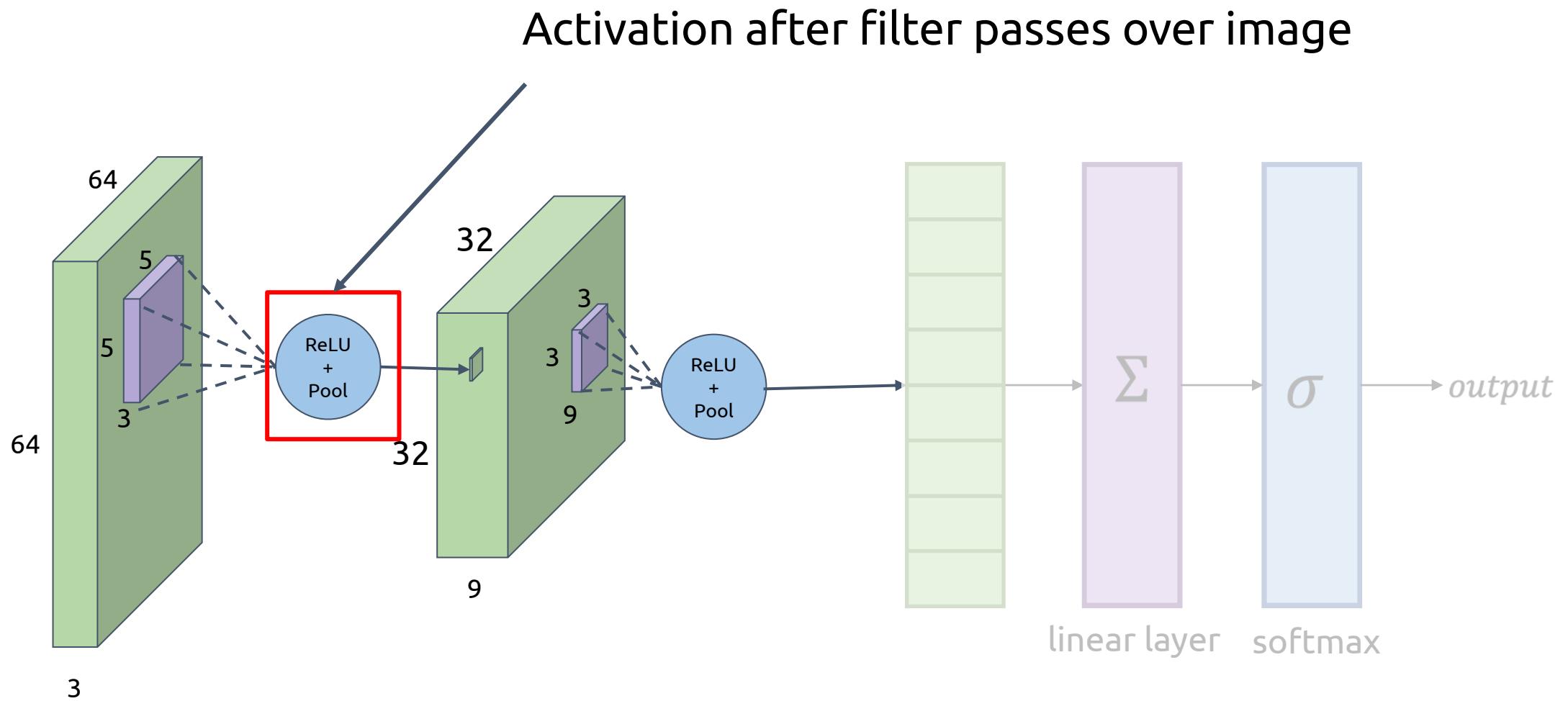
This part learns to extract ***features*** from the image



CNN Architecture

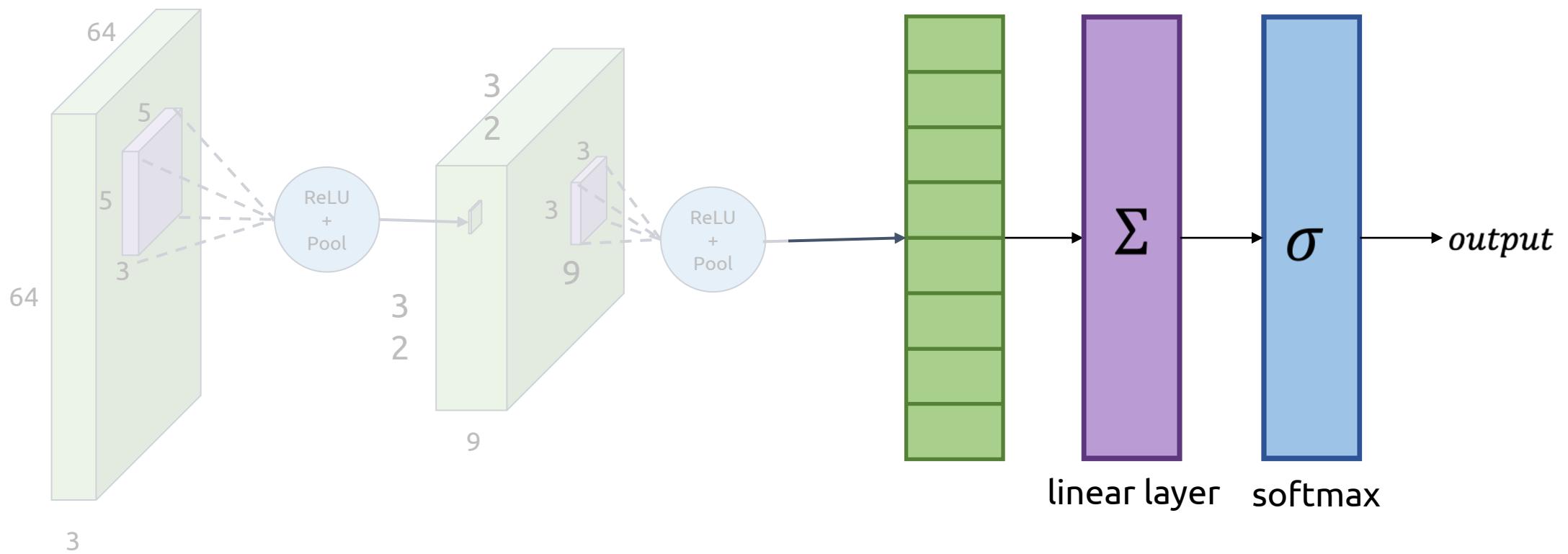


CNN Architecture

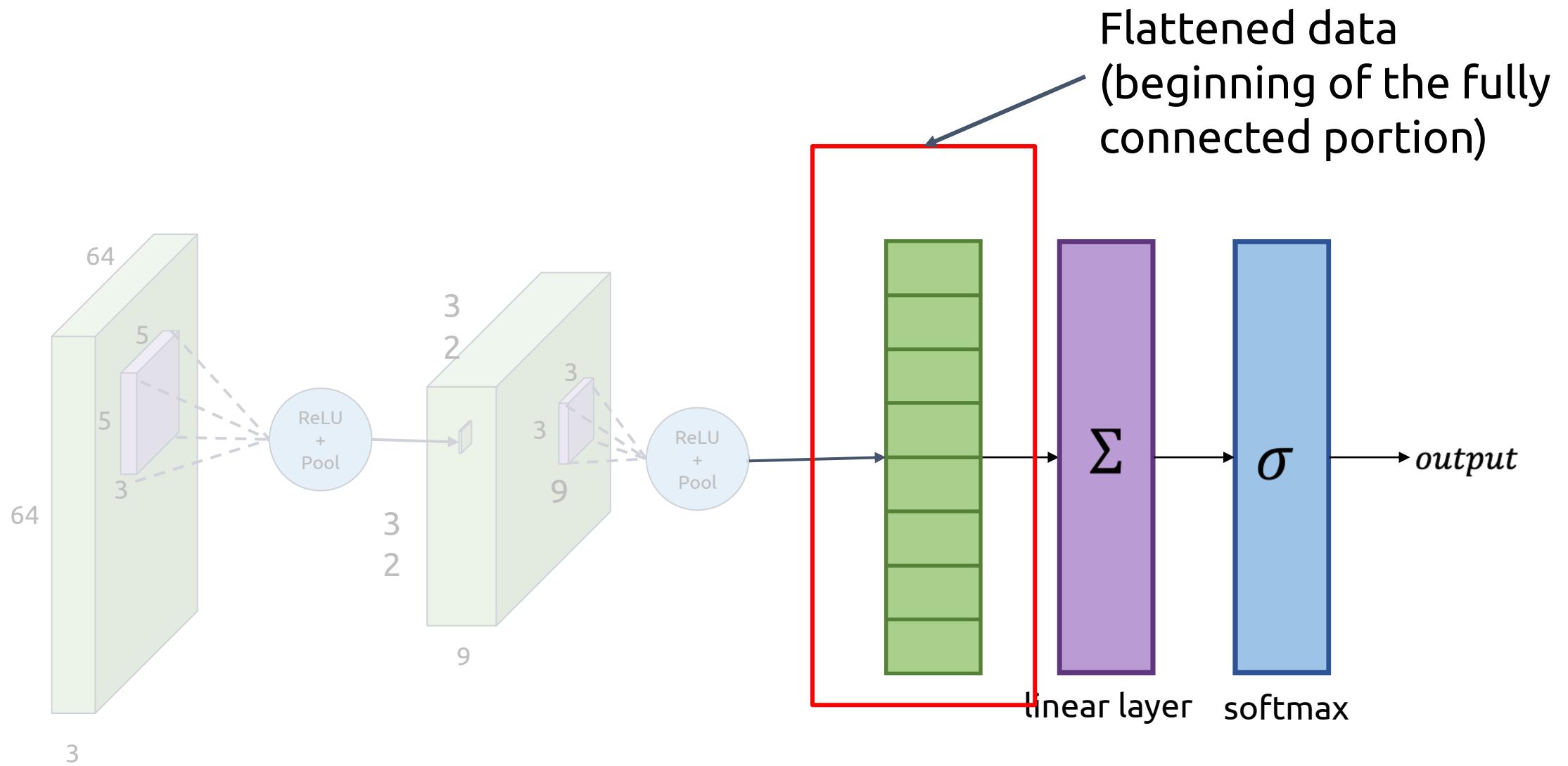


CNN Architecture

This part learns to perform a specific task
(e.g. classification) using those features

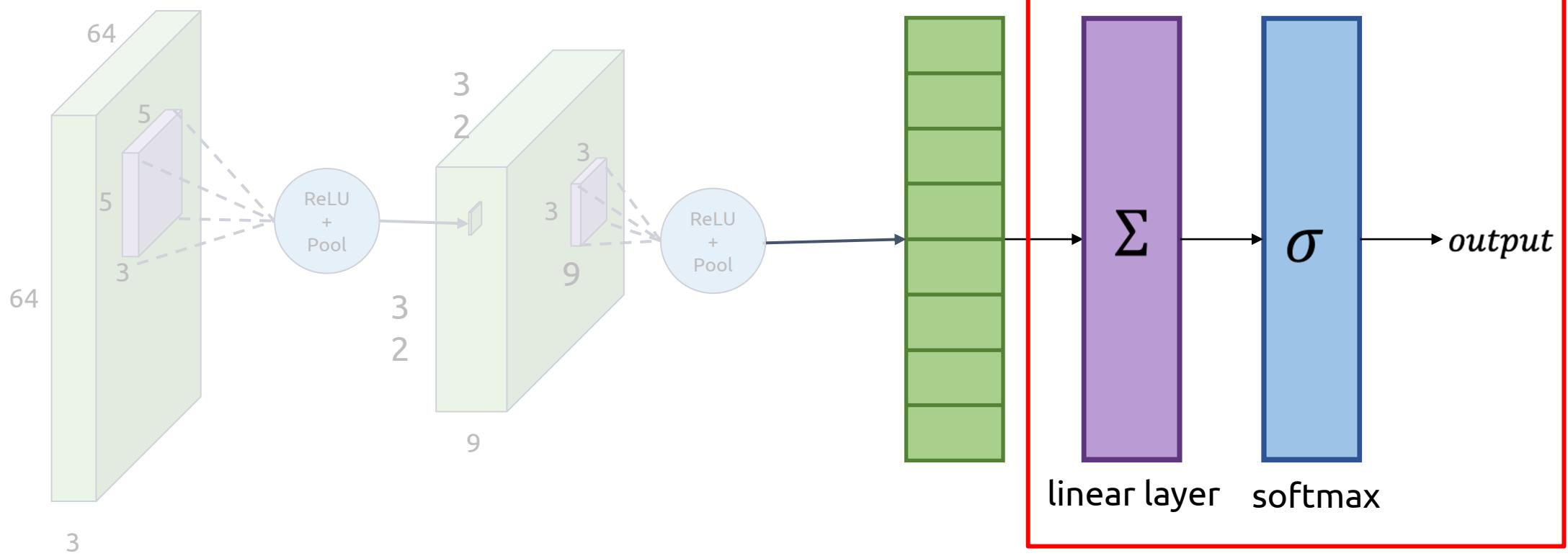


CNN Architecture



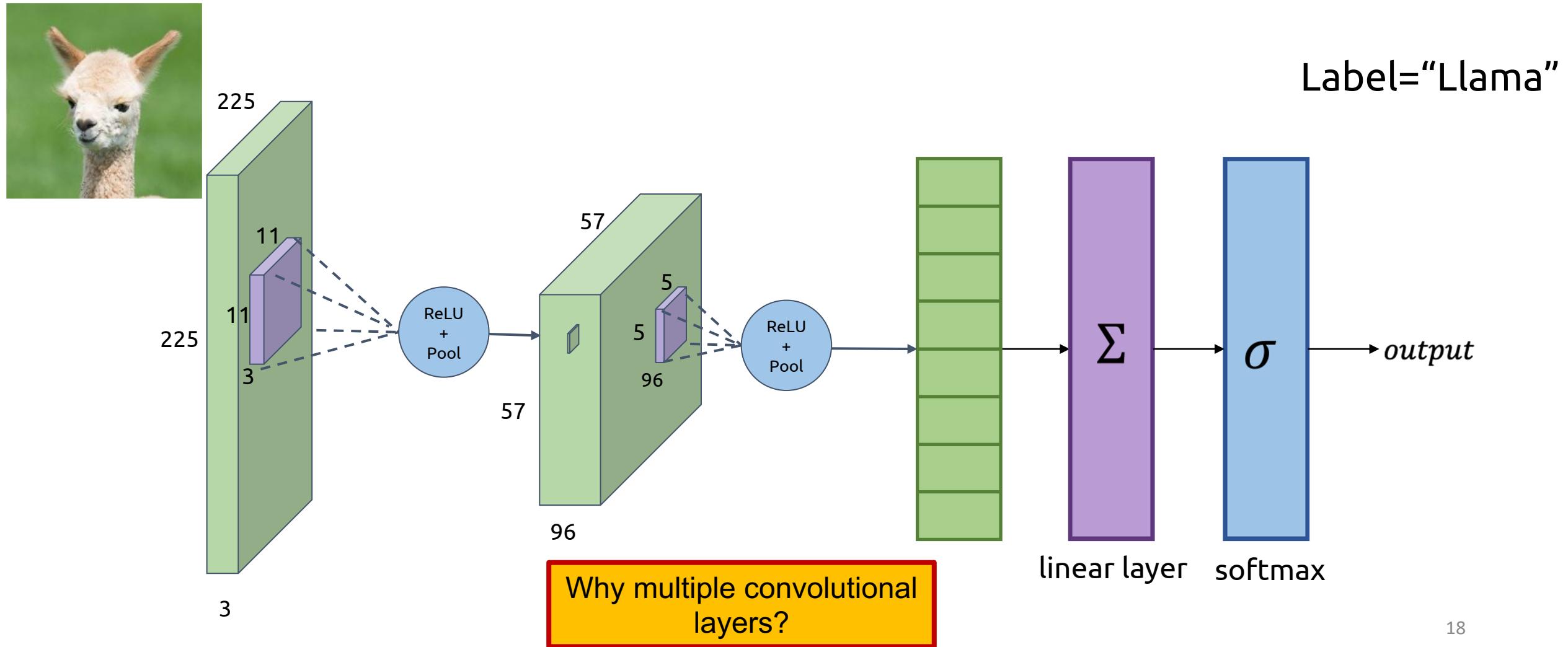
CNN Architecture

Fully connected layers
to classify input



CNN Architecture

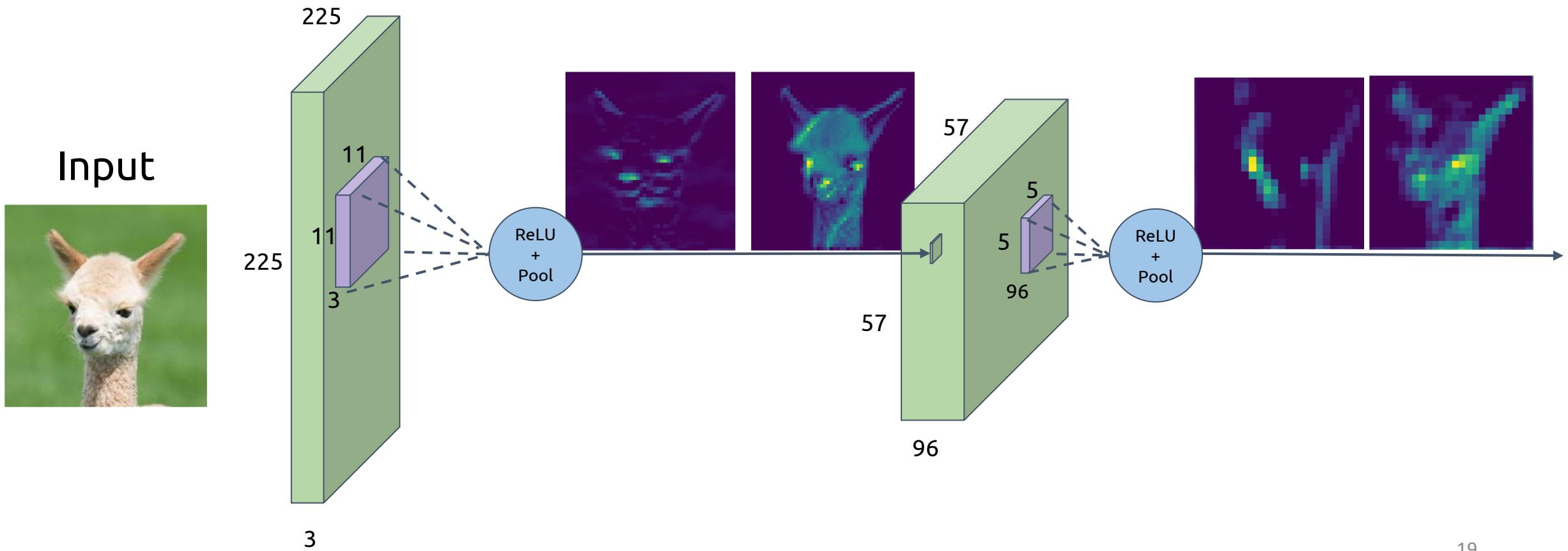
Input



Feature Extraction using multiple convolution layers

Hierarchy of features

Sequence of layers detect broader and broader features

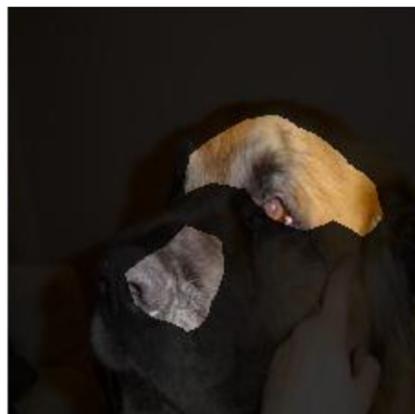




Example: Network Dissection

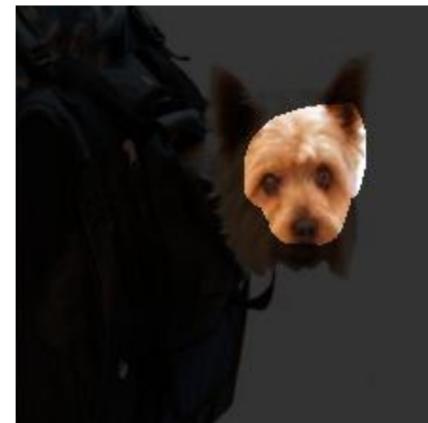
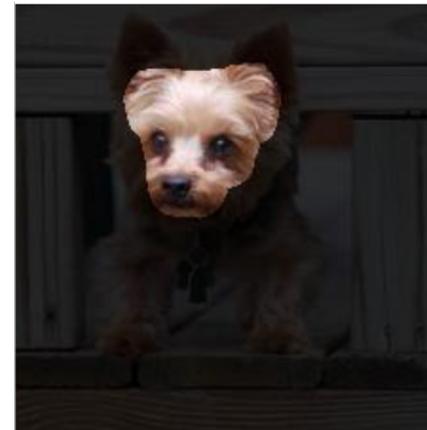
<http://netdissect.csail.mit.edu/>

Layer 3 active regions



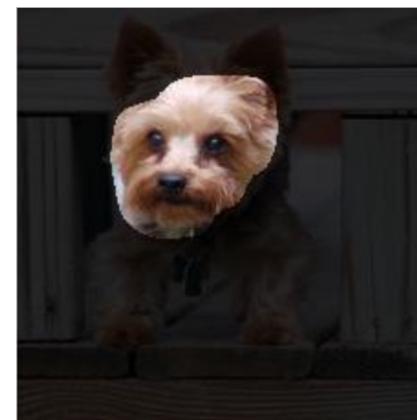
"Eye Detector"

Layer 4 active regions



"Eyes and Nose Detector"

Layer 5 active regions



ILSVRC 2012

([ImageNet](#) Large Scale Visual Recognition Challenge)

The classification task on ImageNet:

For each image, assign 5 labels in order of decreasing confidence.
one of these labels matches the ground truth

Success if



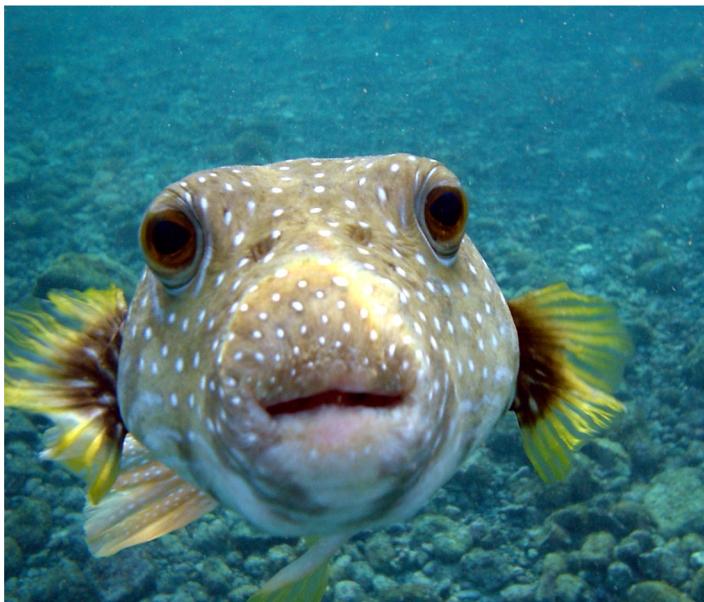
Predictions:

1. Carpet
2. Zebra
3. Llama
4. Flower
5. Horse



ILSVRC 2012

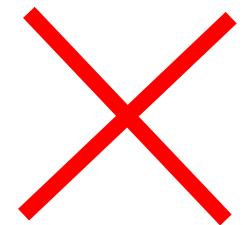
Percentage that model fails to classify is known as ***Top 5 Error Rate***



https://commons.wikimedia.org/wiki/File:Puffer_Fish_DSC01257.JPG

Predictions:

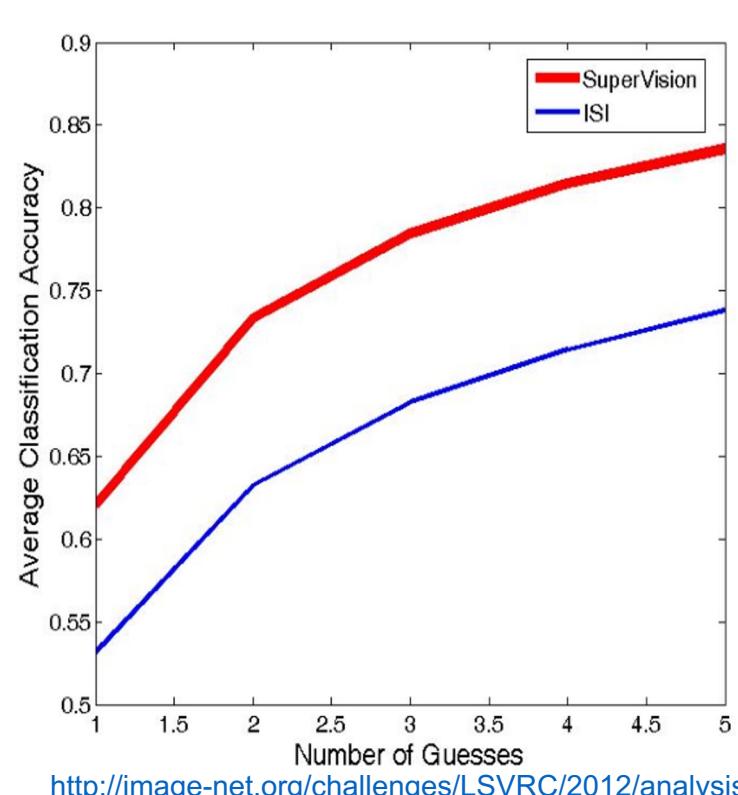
1. Sponge
2. Person
3. Llama
4. Flower
5. Boat



AlexNet: Why CNNs Are a Big Deal

Major performance boost on ImageNet at ILSVRC 2012

Top 5 error rate of 15.3% compared to 26.2% achieved by 2nd place

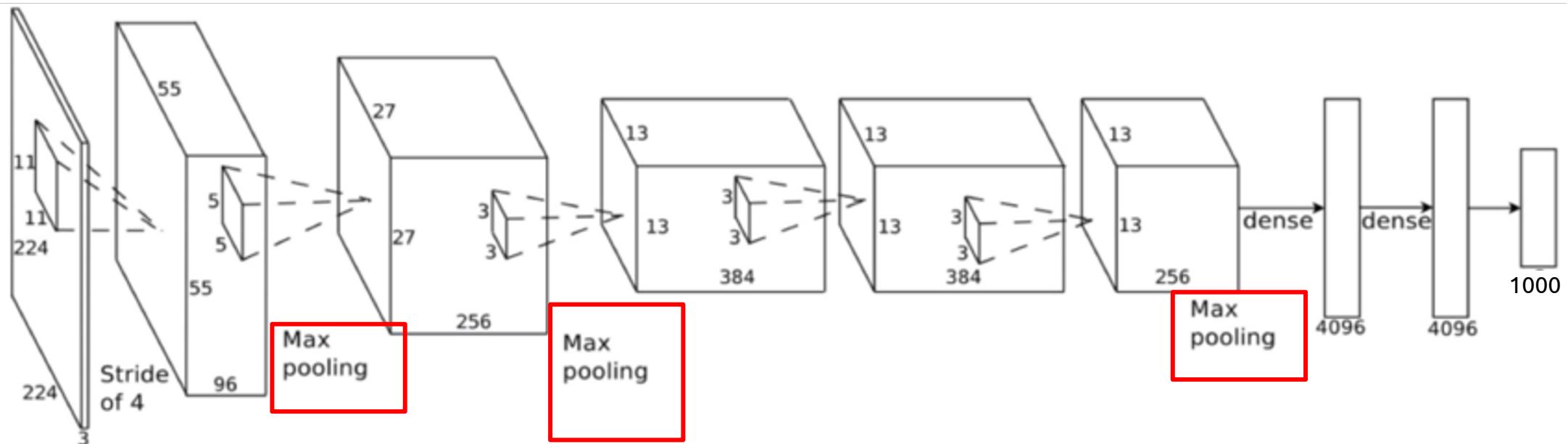


Note: SuperVision is the name of Alex's team

<http://image-net.org/challenges/LSVRC/2012/analysis/>

AlexNet

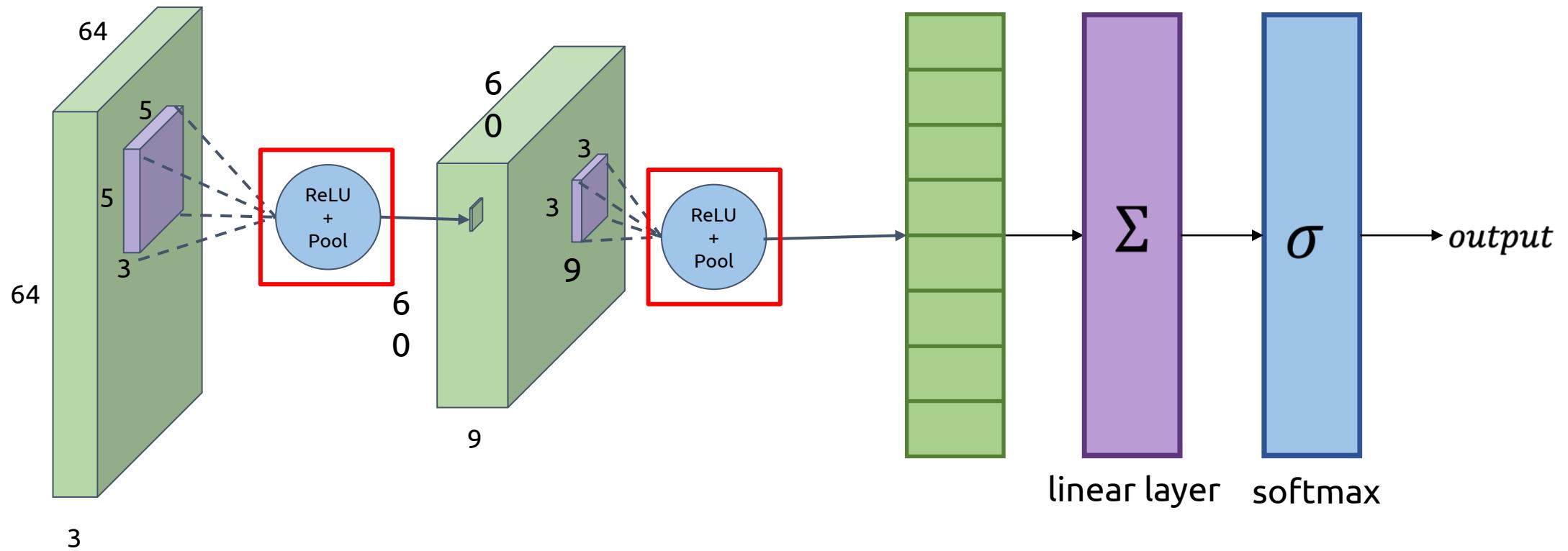
- 60 million parameters
- 5 Convolutional Layers
- 3 Fully Connected Layers



[Alex Krizhevsky et al. 2012]

<https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf>

Pooling



Max Pooling

Max pooling with stride 2 and 2x2 filters

6	3	1	-3
4	1	2	0
3	1	3	2
7	1	1	1

Max of pixels
in window



Max Pooling

Max pooling with stride 2 and 2x2 filters

6	3	1	-3
4	1	2	0
3	1	3	2
7	1	1	1

Max of pixels
in window



6	

Max Pooling

Max pooling with stride 2 and 2x2 filters

6	3	1	-3
4	1	2	0
3	1	3	2
7	1	1	1

Max of pixels
in window



6	2

Max Pooling

Max pooling with stride 2 and 2x2 filters

6	3	1	-3
4	1	2	0
3	1	3	2
7	1	1	1

Max of pixels
in window



6	2
7	

Max Pooling

Max pooling with stride 2 and 2x2 filters

6	3	1	-3
4	1	2	0
3	1	3	2
7	1	1	1

Max of pixels
in window



6	2
7	3

Max Pooling

Max pooling with stride 2 and 2x2 filters

6	3	1	-3
4	1	2	0
3	1	3	2
7	1	1	1



6	2
7	3

Why use Max Pooling?

Pooling: Motivation

Max Pooling

- Keeps track of regions with highest activations, indicating object presence
- Controllable way to lower (coarser) resolution (down sample the convolution output)



Original Image



Convolution Output



After Pooling

Other Pooling Techniques

Average pooling with stride 2 and 2x2 filters

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

Average pixel
values in each
window



4	0
3	2



Learning a Pooling Function

- The network can learn its own pooling function
- Implement via a strided convolution layer

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



1.2	0.5
0.4	1.1

Learned filter weights

13.6	0.5
8	8

So...did we achieve our goal of translational invariance?



What was Translational Invariance again?

- To make a neural net f robust in this same way, it should ideally satisfy ***translational invariance***: $f(T(x)) = f(x)$, where
 - x is the input image
 - T is a translation (i.e. a horizontal and/or vertical shift)

The diagram illustrates the concept of translational invariance. At the top, a 10x10 input image matrix is shown, followed by a large right-pointing arrow labeled T , and then a 10x10 output image matrix. The output matrix is identical to the input matrix, except for a single pixel at position (5,5) which has been shifted to position (4,4). This visualizes how a translation operation T changes the input image. Below this, two 10x10 matrices are displayed side-by-side, separated by a question mark. The left matrix is the original input image, and the right matrix is the image after the translation T . The question mark indicates that the function f should produce the same output for both inputs, demonstrating translational invariance.

$$f\left(\begin{bmatrix} 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \end{bmatrix}\right) = ? = f\left(\begin{bmatrix} 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\ \vdots & & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \end{bmatrix}\right)$$

Are CNNs Translation Invariant?

- Convolution is ***translation equivariant***
 - A translated input results in an output translated by the same amount
 - $f(T(I)) = T(f(I))$
 - $(T(I) \otimes K)(x, y) = T(I \otimes K)(x, y)$

$$f(\begin{array}{c} \text{zebra head} \\ \downarrow T \end{array}) = \begin{array}{c} \text{feature map} \\ \downarrow T \end{array}$$
$$f(\begin{array}{c} \text{zebra head} \\ \downarrow T \end{array}) = \begin{array}{c} \text{feature map} \\ \downarrow T \end{array}$$

* Here, $(I \otimes K)(x, y) = \sum_m \sum_n I(x + m, y + n)K(m, n)$

Are CNNs Translation Invariant?

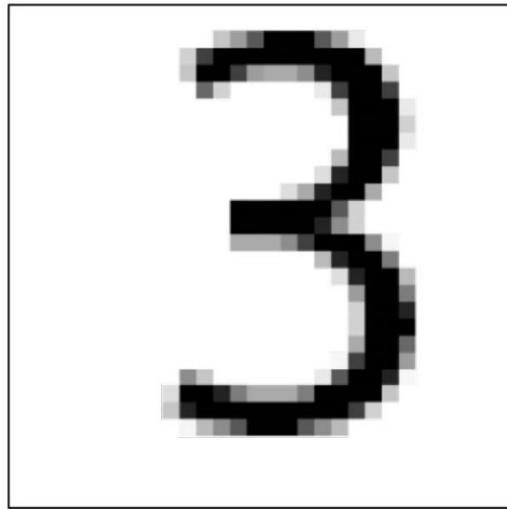
- Max pooling is intended to give invariance to small translations
 - The highest activation pixel can shift around within the pooling window, and the output does not change

$$f\left(\begin{array}{|c|c|}\hline 6 & 3 \\ \hline 4 & 1 \\ \hline\end{array}\right) = 6$$

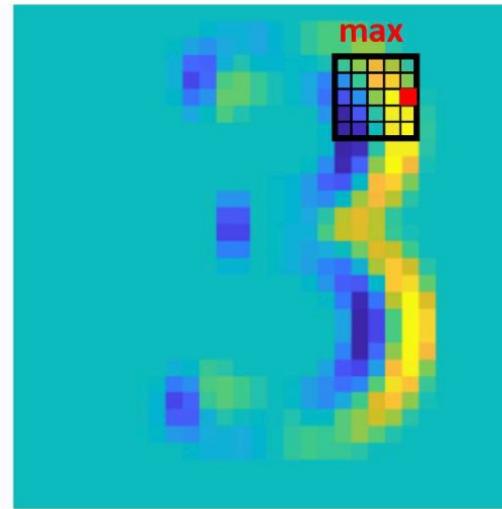
$$f\left(\begin{array}{|c|c|}\hline 1 & 5 \\ \hline 6 & 3 \\ \hline\end{array}\right) = 6$$

$$f\left(\begin{array}{|c|c|}\hline 2 & 6 \\ \hline 2 & 4 \\ \hline\end{array}\right) = 6$$

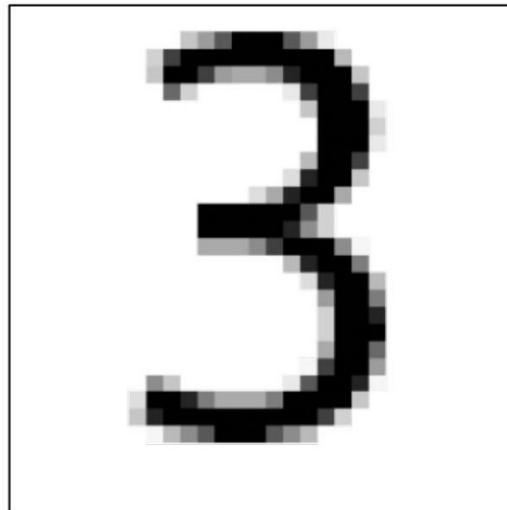
So how does it all come together?



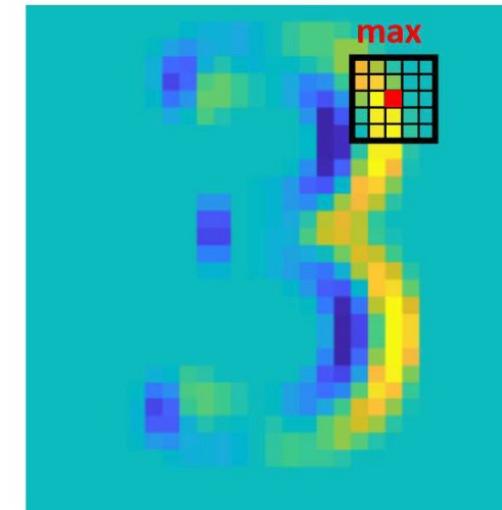
\star =



← Small shift



\star =

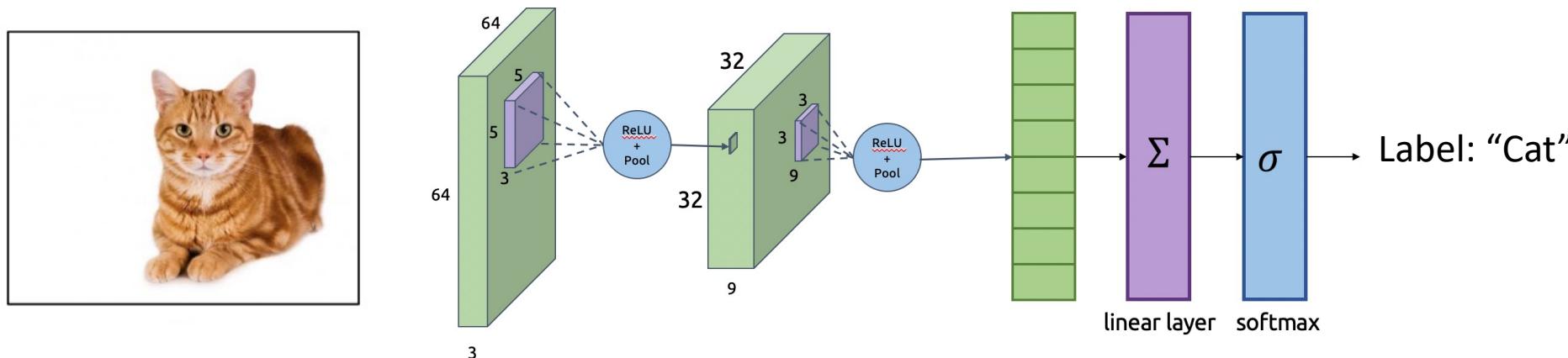


Convolution is
***translation
equivariant***

Max pooling gives
invariance to
small translations

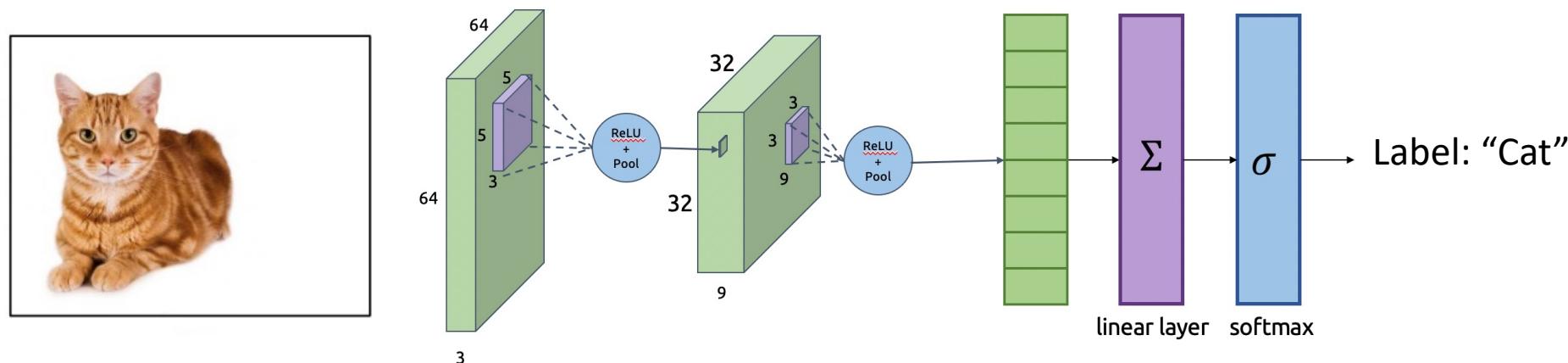
Are CNNs Translation Invariant?

- Answer: CNNs are “sort of” **translation invariant**
 - Shifting the content of the image around tends not to drastically effect the output classification probabilities...



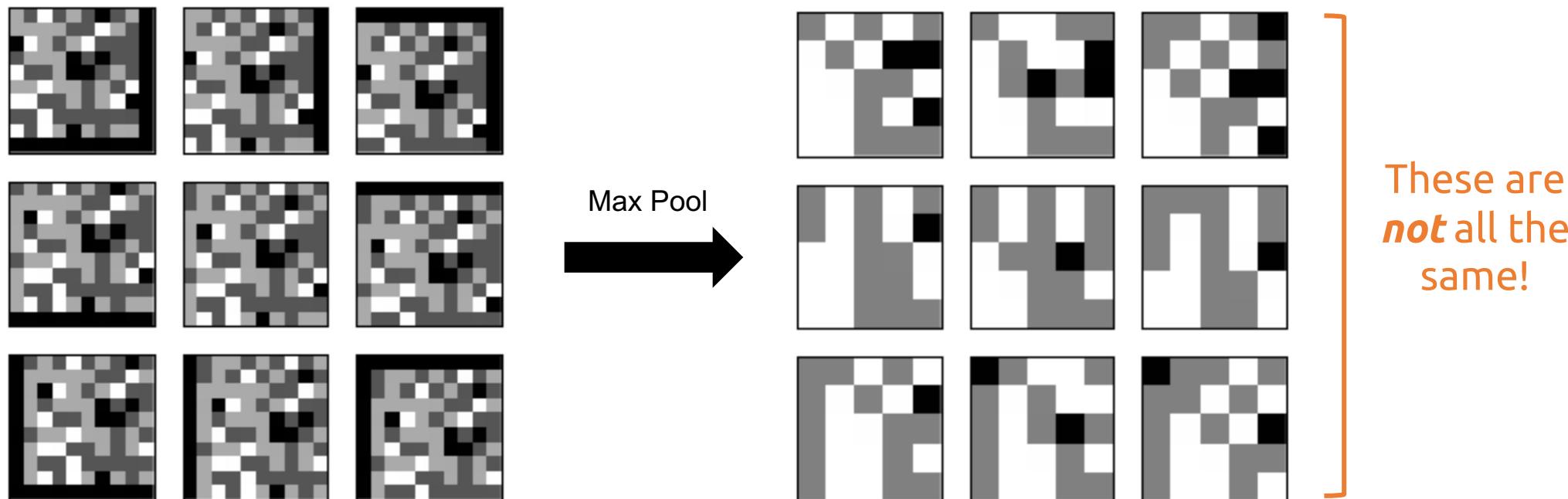
Are CNNs Translation Invariant?

- Answer: CNNs are “sort of” **translation invariant**
 - Shifting the content of the image around tends not to drastically effect the output classification probabilities...



Are CNNs Translation Invariant?

- Answer: CNNs are “sort of” translation invariant
 - Shifting the content of the image around tends not to drastically effect the output classification probabilities...
 - ...but they are *not*, strictly speaking, translation invariant



Are CNNs Translation Invariant?

- Is it possible to build a truly translation invariant CNN?
 - Yes!
 - Have to properly “pre-filter” images before pooling them
 - Comes from signal processing theory (The Sampling Theorem)
 - Take CS 1230 (Computer Graphics) if you want to learn about this!
- One effort to make a translation-invariant CNN:
<https://arxiv.org/pdf/1904.11486.pdf>

Other Invariances

Rotation/Viewpoint Invariance



Other Invariances

Rotation/Viewpoint Invariance



Size Invariance





Other Invariances

Rotation/Viewpoint Invariance



Size Invariance



Illumination Invariance

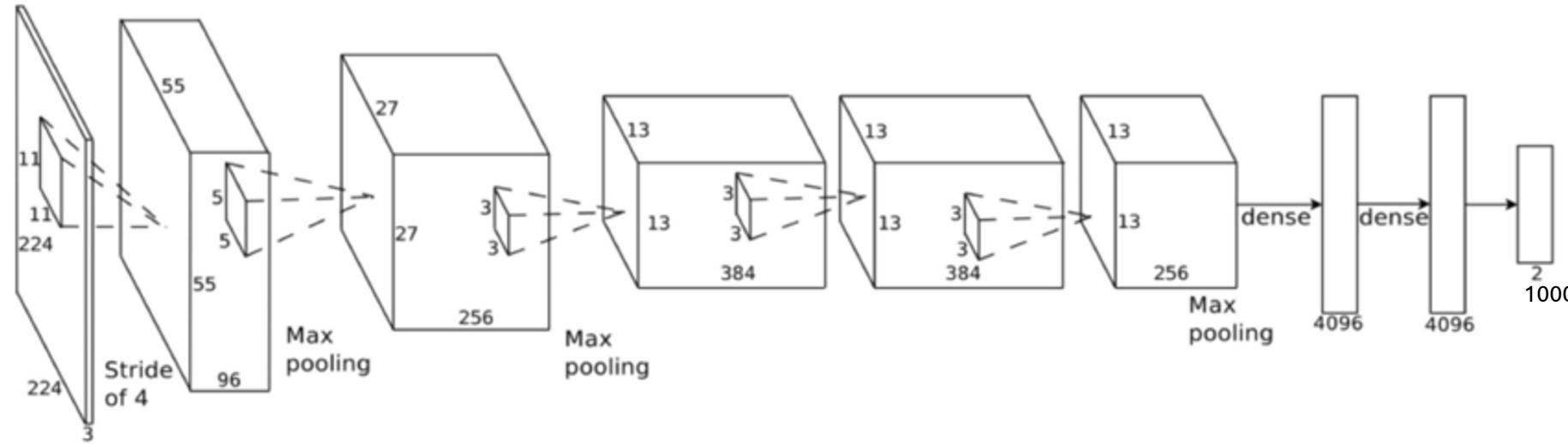


- All of these are desirable
- How do CNNs fare?
 - Max pooling gives some small amount of size invariance...
 - ...but in general, CNNs don't do well with big changes in size, pose, or lighting
- Consequence of not having these invariances?
 - Need *lots* of training data
 - Have to show the network examples of everything under different poses, lighting, etc.
 - Data Augmentation

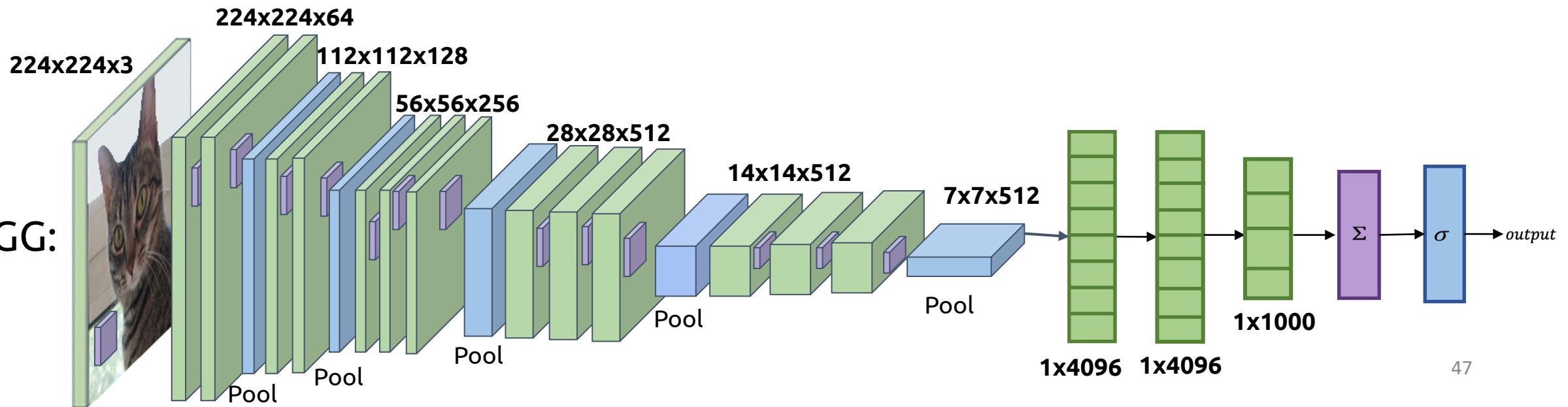
What should we do?

More Complicated Networks

AlexNet:



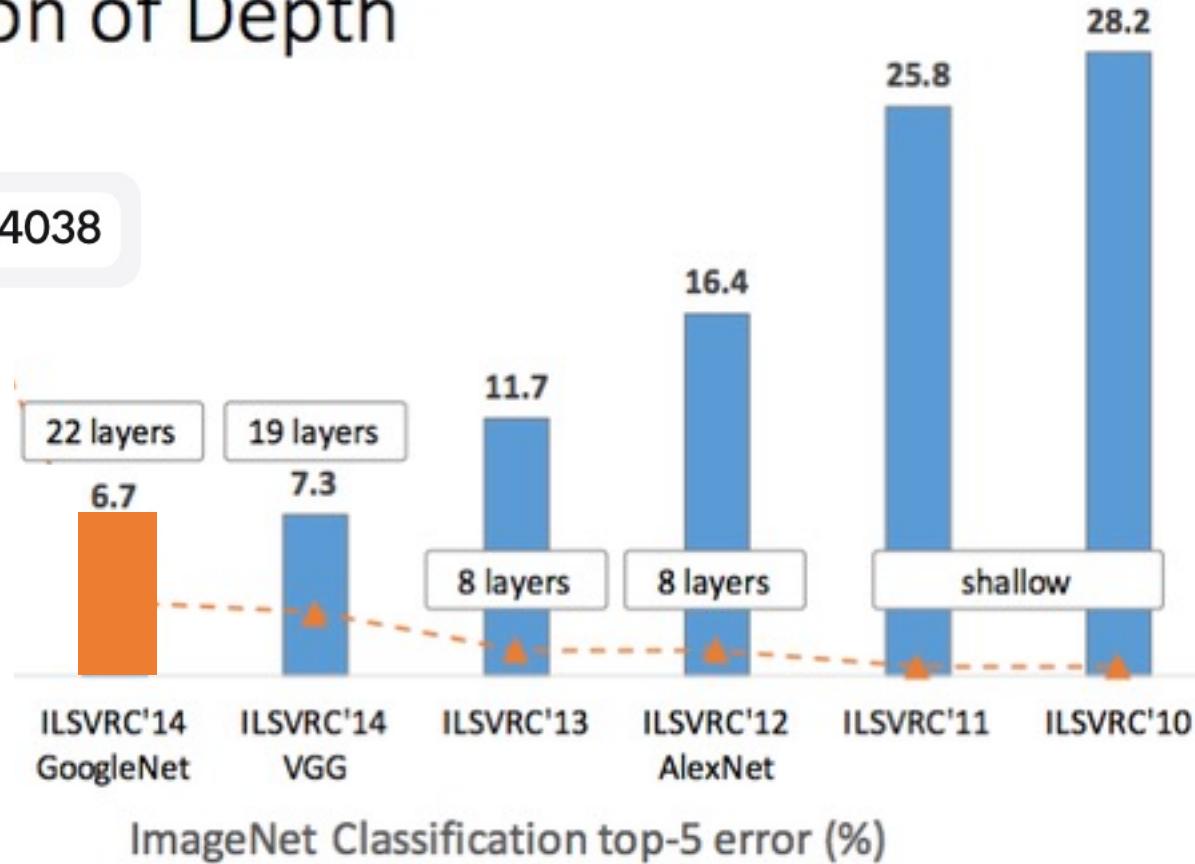
VGG:



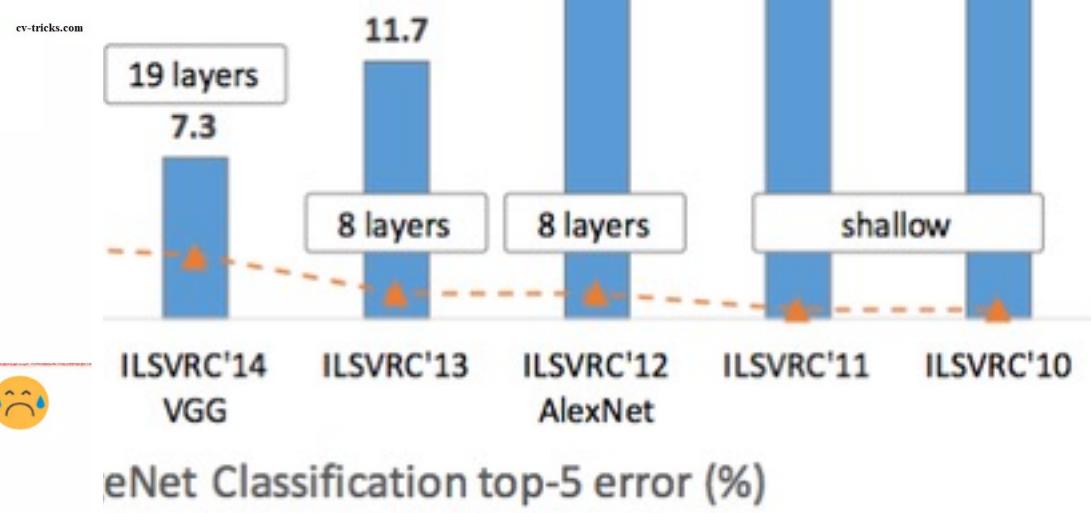
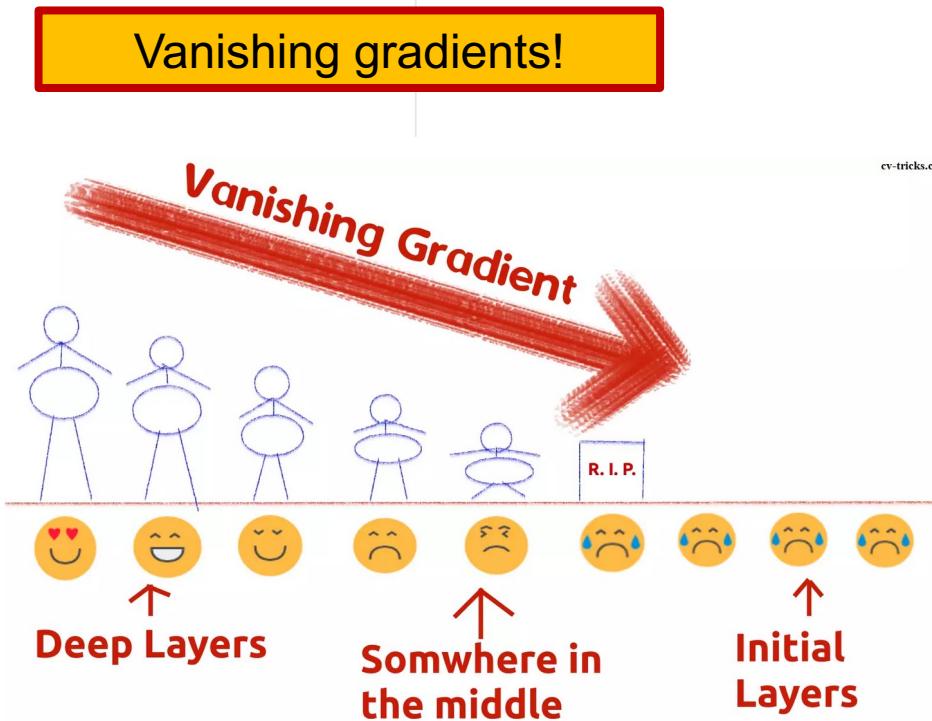
Can you guess what was
the biggest bottleneck to
adding more layers?

Revolution of Depth

Join at menti.com | use code **7447 4038**



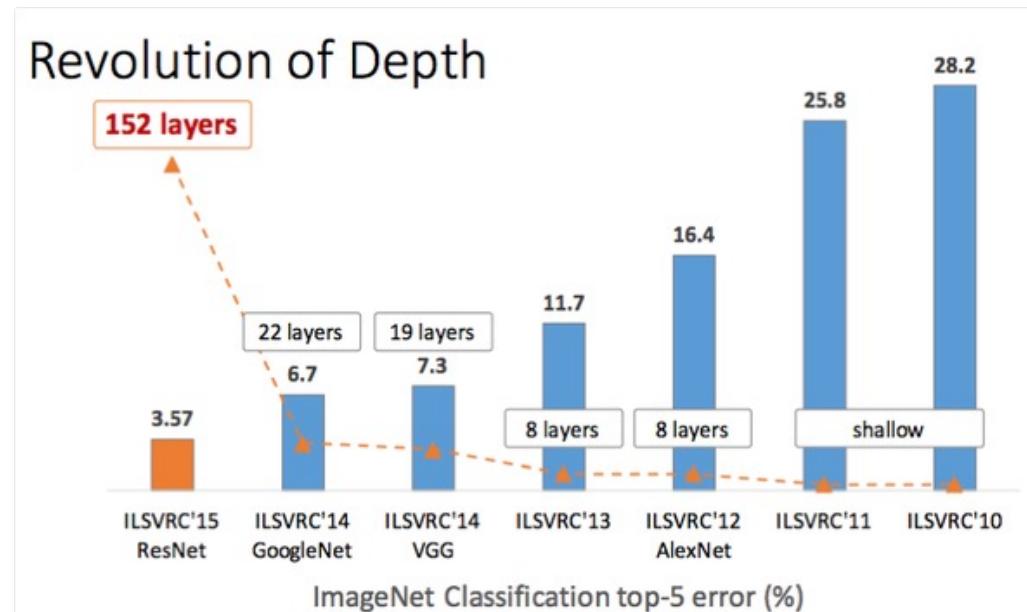
Revolution of Depth



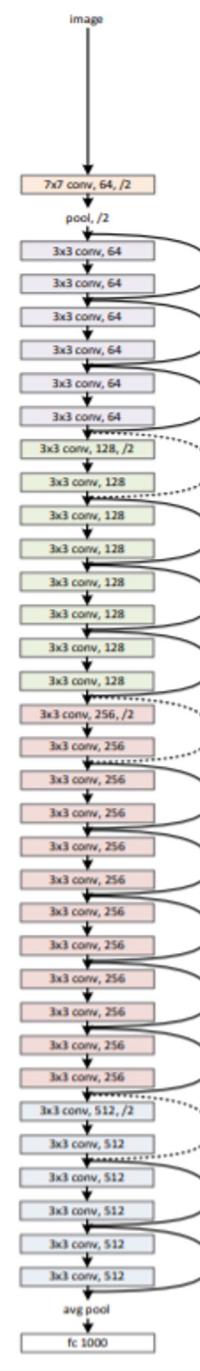
More Complicated Networks

ResNet:

Lots of layers, tons of learnable parameters
Avoids Vanishing Gradient problem
but how?



K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition.
arXiv preprint arXiv:1512.03385, 2015.

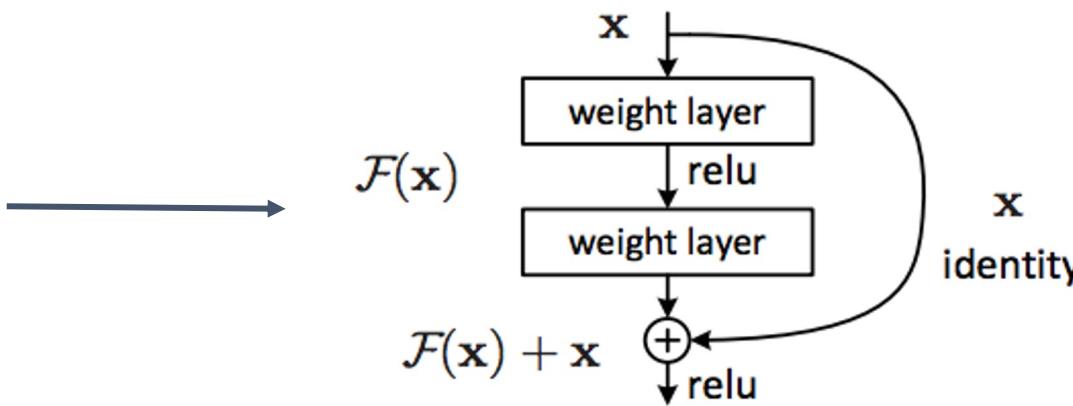


More Complicated Networks

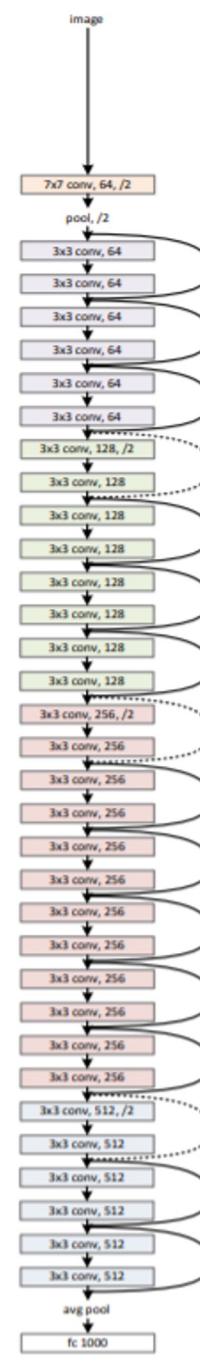
ResNet:

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Residual Block

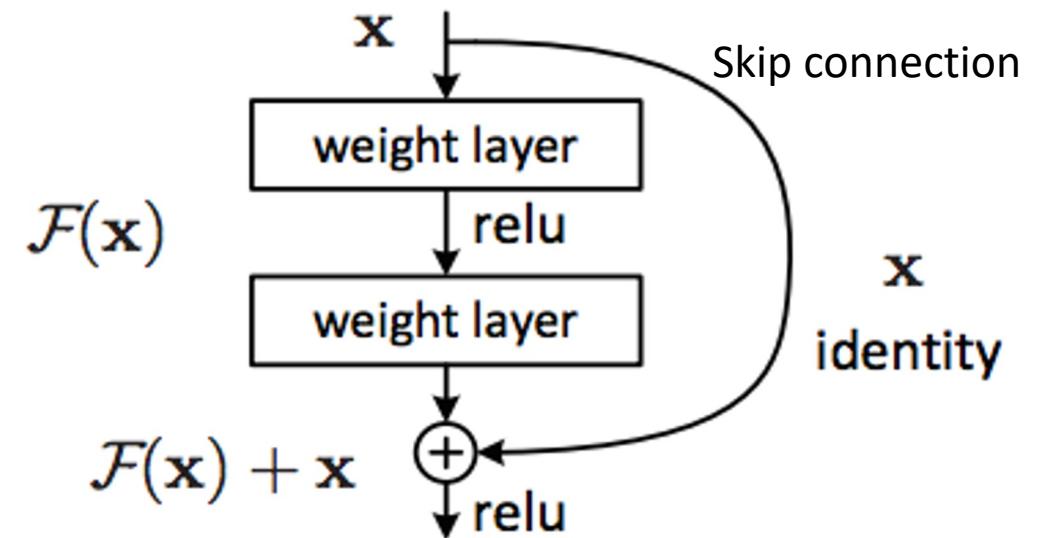


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Residual Blocks

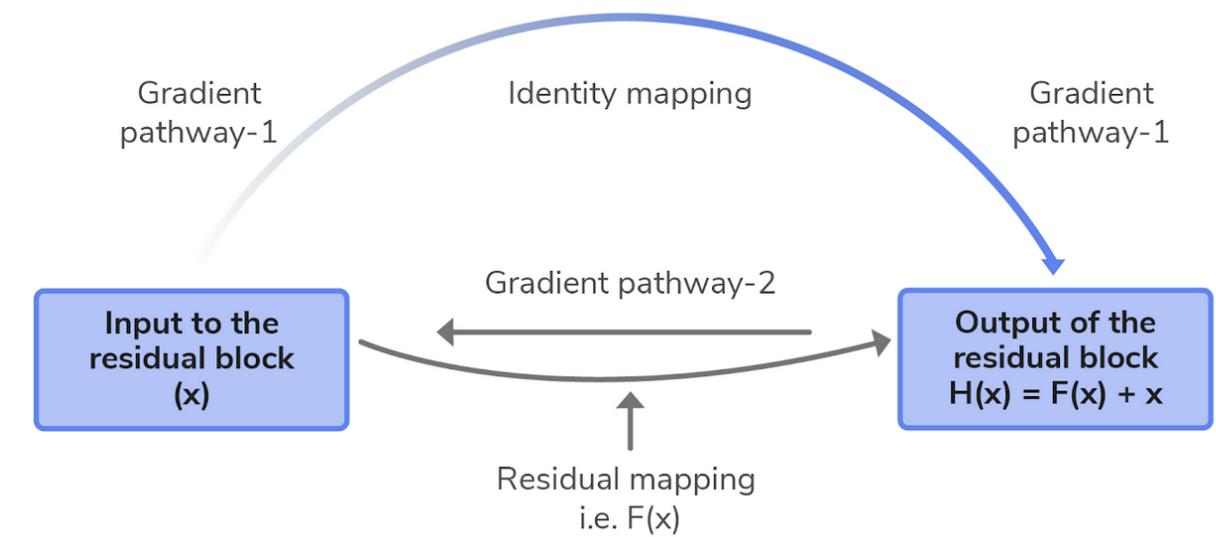
- In very deep nets, each layer often needs to learn just a small transformation of the preceding layer (identity + change)
- Idea: explicitly design the network such that the output of each layer is the identity + some deviation from it
 - Deviation is known as a residual





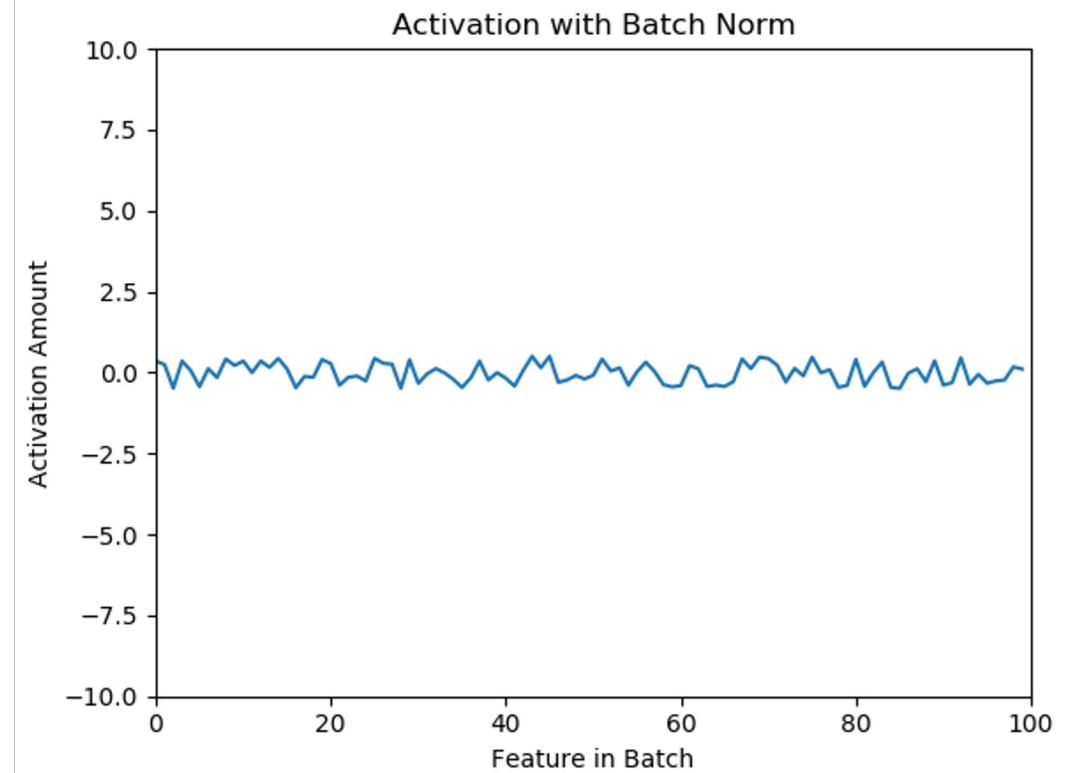
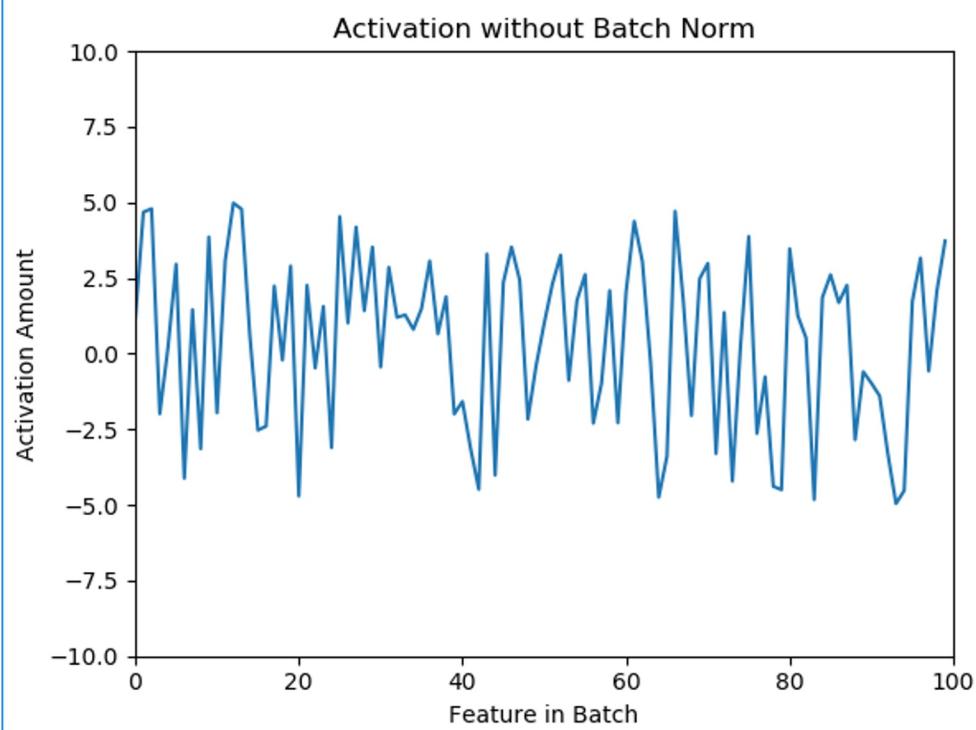
Residual Blocks

- In very deep nets, each layer often needs to learn just a small transformation of the preceding layer (identity + change)
- Idea: explicitly design the network such that the output of each layer is the identity + some deviation from it
 - Deviation is known as a residual
- Allows gradient to flow through two pathways
- **Significantly stabilizes training of very deep networks**



Batch Normalization (stabilizing training)

Idea: normalize the activations for each feature at each layer

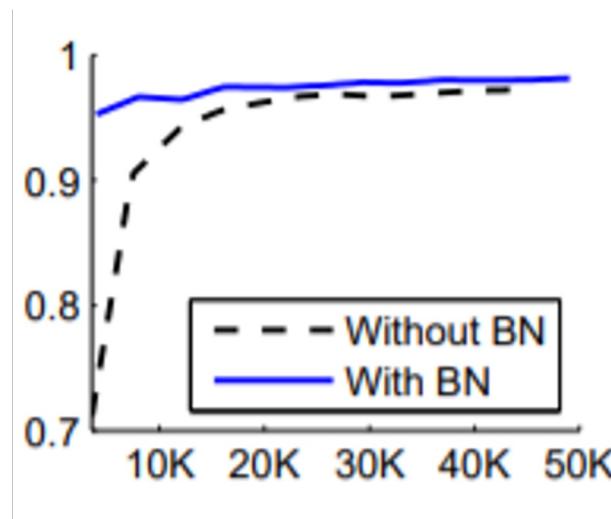


Why might we want to do this?

Batch Normalization: Motivation

More stable inputs = faster training

MNIST test accuracy vs number of training steps



<https://arxiv.org/pdf/1502.03167.pdf>

Batch Normalization: Implementation

For each feature x , Start by calculating the batch mean and standard deviation for each feature:

$$\mu_{batch} = \frac{\sum_{i=0}^{batch_size} x_i}{batch_size}$$

$$\sigma_{batch} = \sqrt{\frac{\sum_{i=0}^{batch_size} (x_i - \mu_{batch})^2}{batch_size}}$$

Batch Normalization: Implementation

Normalize by subtracting feature x's batch mean, then divide by batch standard deviation.

$$x' = \frac{x - \mu_{batch}}{\sigma_{batch}}$$

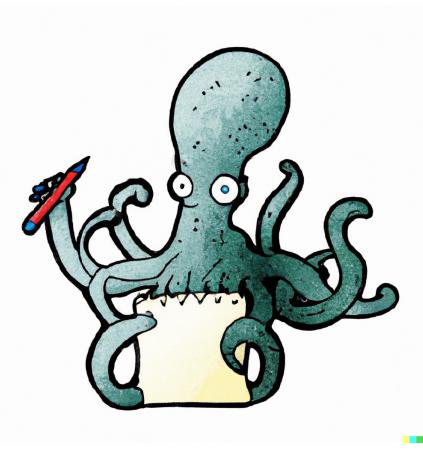
Feature x now has mean 0 and variance 1 along the batch

Batch Normalization in Tensorflow

`tf.keras.layers.BatchNormalization(input)`

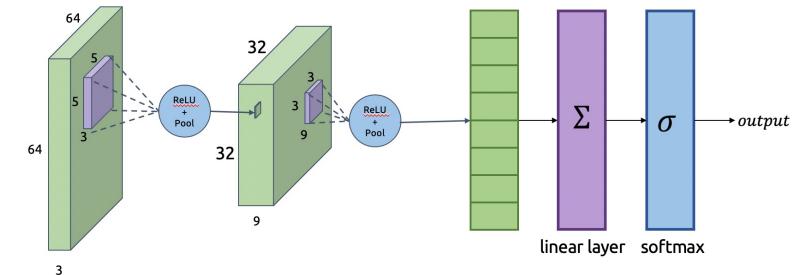
Documentation: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/BatchNormalization

Recap



CNNs

- Architecture
- AlexNet + Pooling
- CNNs are “sort of” translationally invariant



Deeper CNNs

- Many layers = vanishing gradient
- ResNet + Residual blocks
- Batch normalization

