

# Advanced Neural Nets

---

*Welcome to the edge of data science*

# Brief review so far

---

- We studied a DENSE neural net or a multilayer perceptron
  - Very good for many general problems that can be solved by our usual bag of tricks (Regression, Forests, Bayes, Boosting)
  - Homework is a MLP (Dense) net
  - All outputs connected to all inputs
    - Use Tanh, Sigmoid, Relu etc...

# How to 'Transfer' a Model

---

- Export Weights and Bias
- Similar to a Linear regression: Instead of a column of “M” and “B” each layer has a rectangular “M” of size Inputs x Neurons (inputs of internal layers will be neurons of previous layers and a column vector of bias)
- You need activation functions used
- Typically implemented within a library

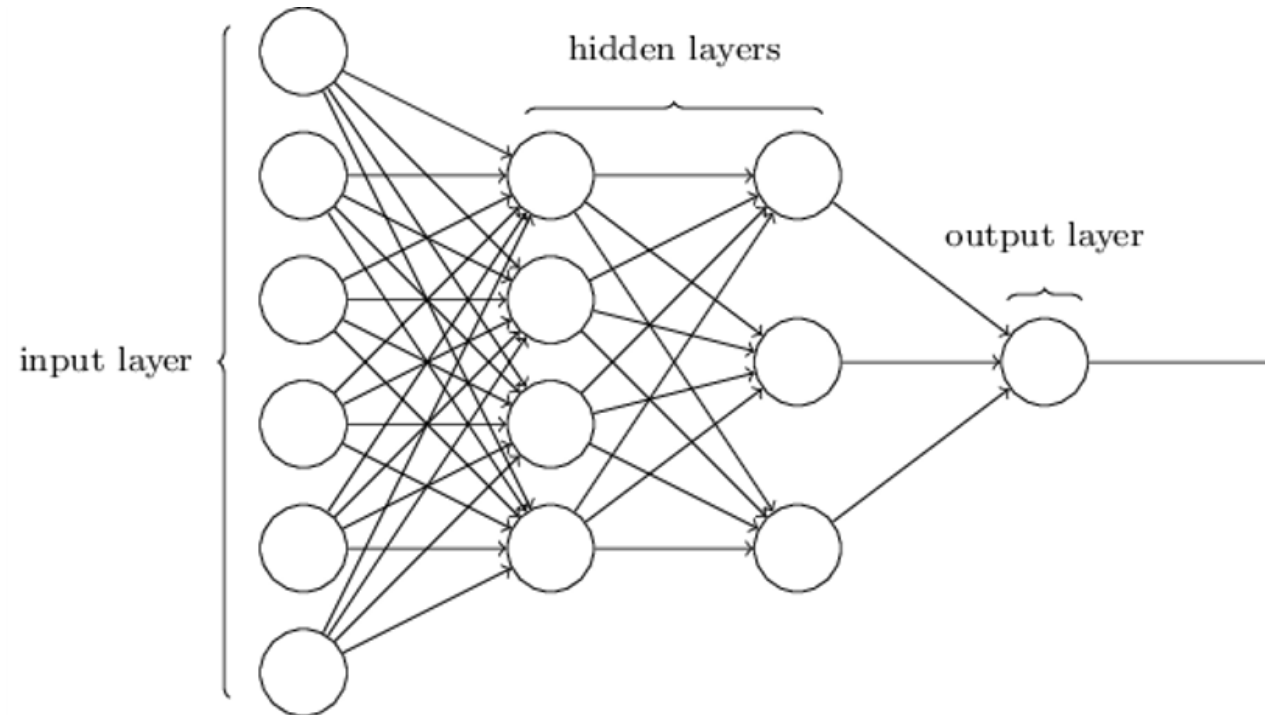
# Example

(Indices/Rows+Cols can be flipped depending on your library)

W is 4x6  
B is 4x1

W is 3x4  
B is 3x1

W is 1x3  
B is 1x1



# But wait! There's more!

---

- Recurrent Neural Net (RNN)
- The Convolution Neural Net (CNN)

# How do I model something temporal?

---

(THAT MEANS TIME-BASED)

- Language
- Videos (Movie)
- TIME SERIES MODELING

# Recurrent Neural Network

---

- Used in Natural Language Processing. (Alexa, Google, Siri)
- SOLVES THE PROBLEM: MY CURRENT OUTPUT DEPENDS ON THE PAST OUTPUT:

PREDICT THE NEXT WORD:

ROBERT WEIGHS ABOUT 200 \_\_\_\_\_ (POUNDS)

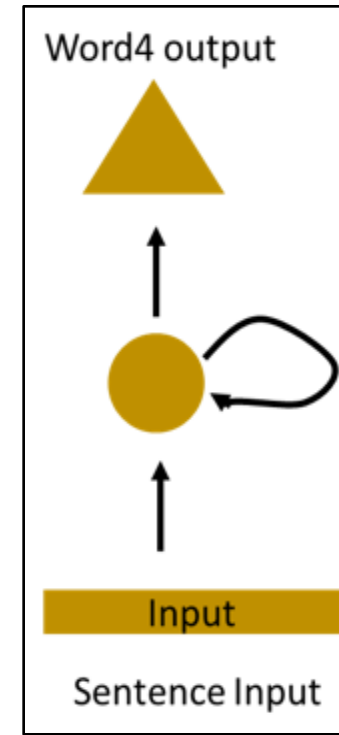
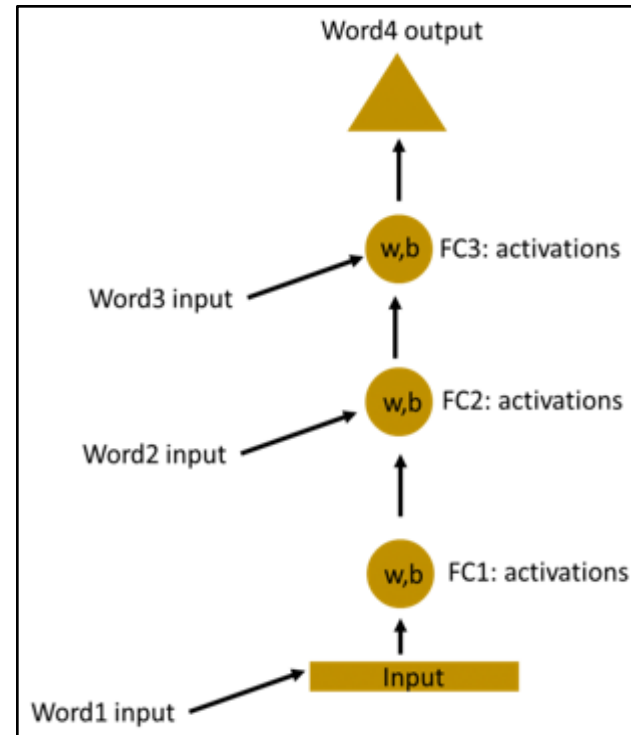
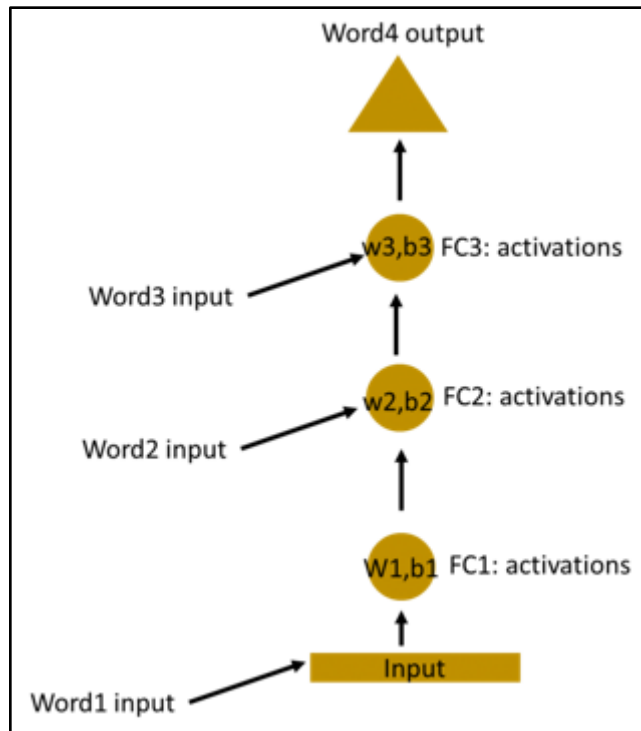
THE ANSWER DEPENDS ON THE PREVIOUS INPUTS

WHAT PART OF TEXT IS EACH WORD?

ROBERT WEIGHS ABOUT 200 POUNDS

ABOUT 200 POUNDS ROBERT WEIGHS

# How is this pulled off?





# Another view

Think of these diagrams as 'FLOW' rather than a diagram

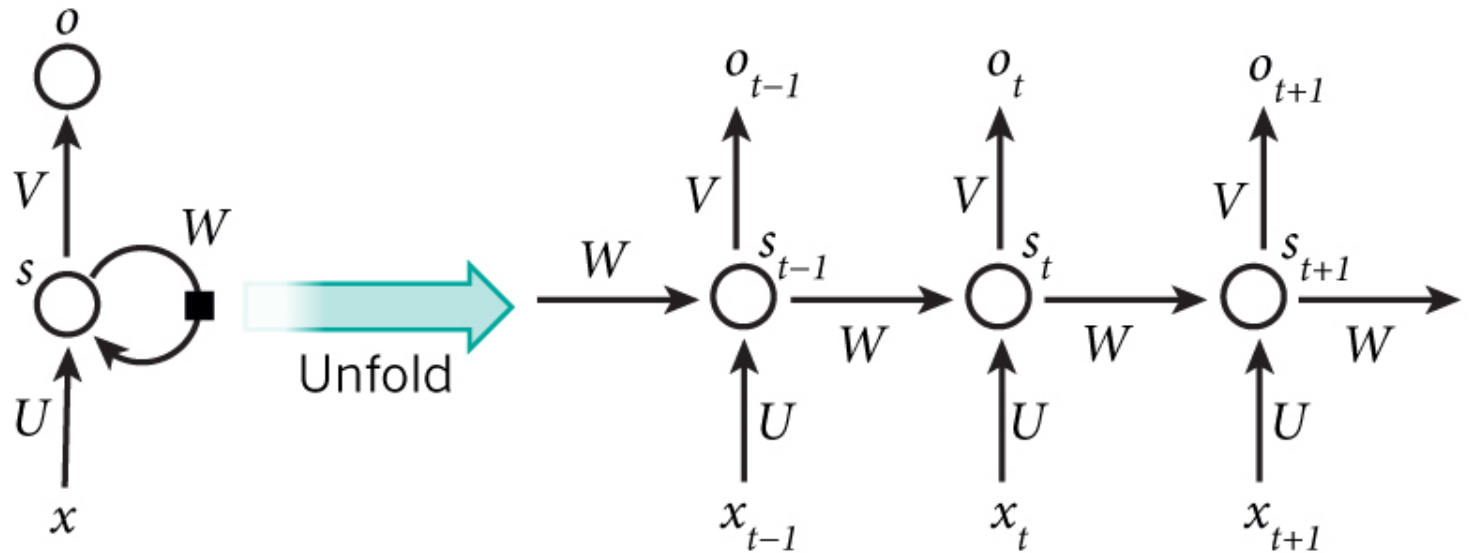
$V, U, W$ : Neuron Weights

$S$ : hidden state

$X$ : input

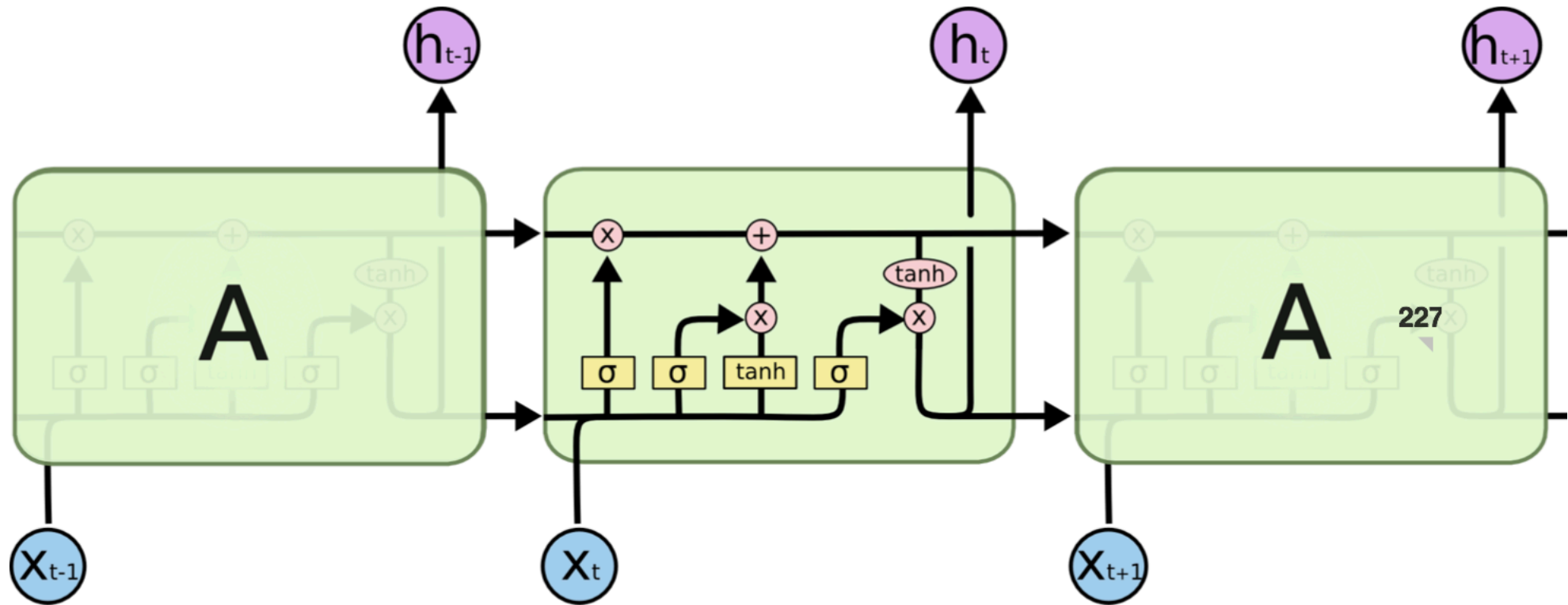
$O$ : output

Take the OUTPUT of a neural net and feed it back as new inputs for the next 'state'. The initial hidden state is typically all zeros



# What glorious Instructor does:

Long Short Term Memory (LSTM). Change 'W' to a more complex algebra



# Approve, Yoda does

---

- Bi directional RNN
  - Run the RNN Forwards AND Backwards to capture both directions of context.

# Convolutional Neural Nets (CNN)

---

- Image recognition
- Based on 'compressing' information of nearby neurons

# We need 2 new layers

---

- Convolution Layer
- Pooling Layer

# Convolution Layer

---

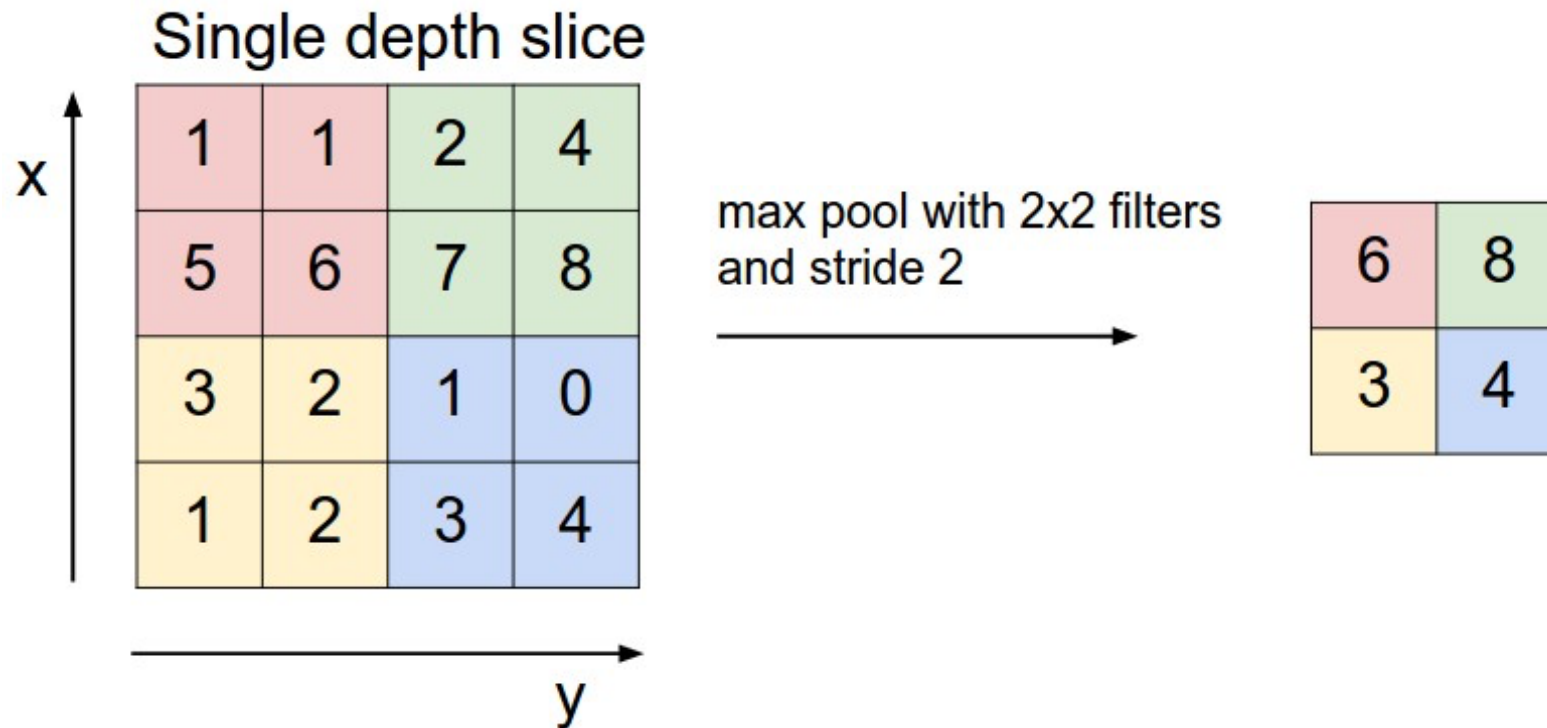
- Slide a filter across your input (typically 2-D)

$3_0$	$3_1$	$2_2$	1	0
$0_2$	$0_2$	$1_0$	3	1
$3_0$	$1_1$	$2_2$	2	3
2	0	0	2	2
2	0	0	0	1

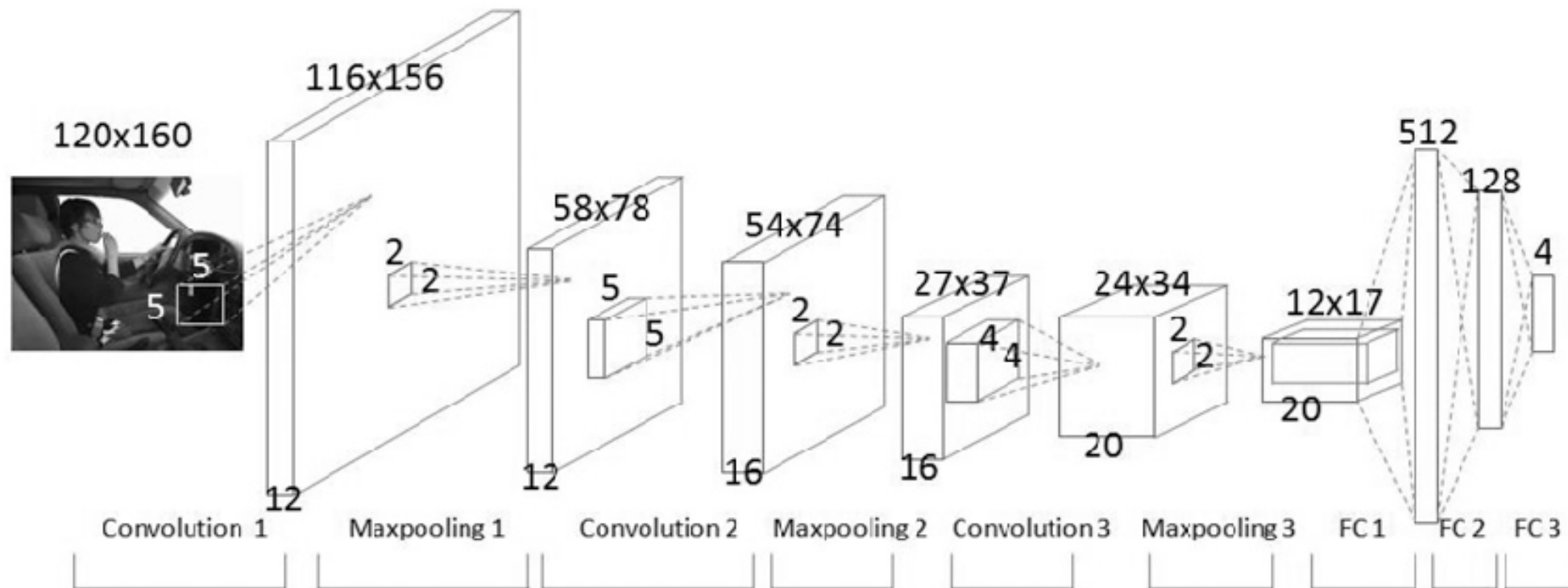
12	12	17
10	17	19
9	6	14

# Pooling layer

(Find the max value of a filter)



# Putting it together





# Transfer Learning

---

- For deep neural Nets (4+ layers), The 'Top' Layers (Closest to input) do not change much.
- After a long training cycle they are essentially fixed.
- SO when google uses 8 GPUs to Train on 10 million images they have a very solid set of 'TOP' layers
- Turns out you can 'attach' bottom layers for a related problem

# Example

---

- VGG16 (a particular CNN Architecture) is trained on IMAGENET (a public data set)
- Imagenet has 1000 classes
- Take weights, remove the final Dense portion / Create your own to train
- Achieve 99% accuracy in less than 1 epoch!

# Transfer Learning

---

- Works for all Deep nets due to diminishing gradients
- Primarily used in vision (CNN)
- Still works with other architectures

# Resources

---

- <http://cs231n.github.io/>
- <http://www.wildml.com/2015/09/recurrent-neural-networks-tutorial-part-1-introduction-to-rnns/>
- <http://karpathy.github.io/2015/05/21/rnn-effectiveness/>
- <http://scs.ryerson.ca/~aharley/vis/conv/>
- <http://runder.io/optimizing-gradient-descent/>