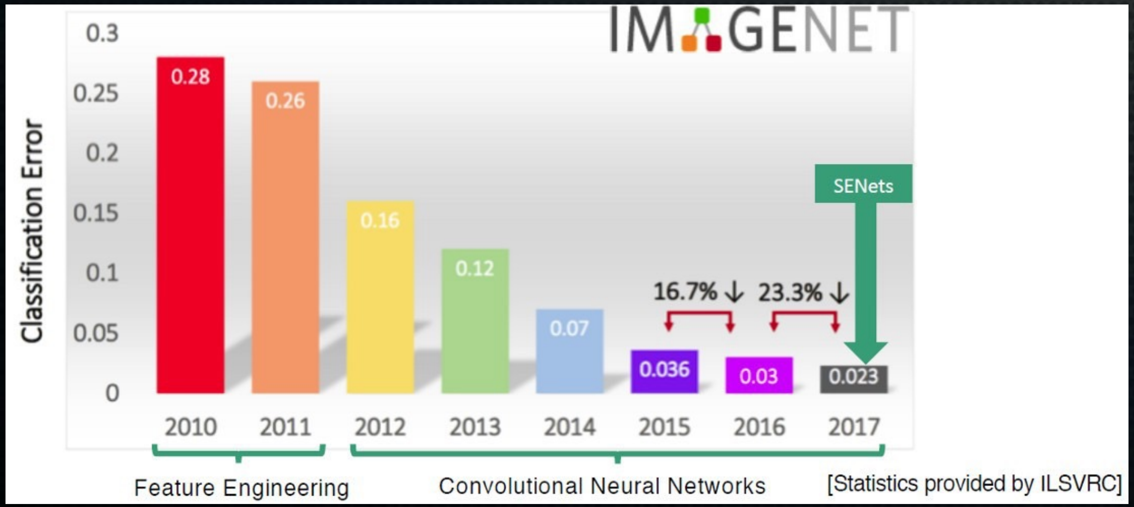
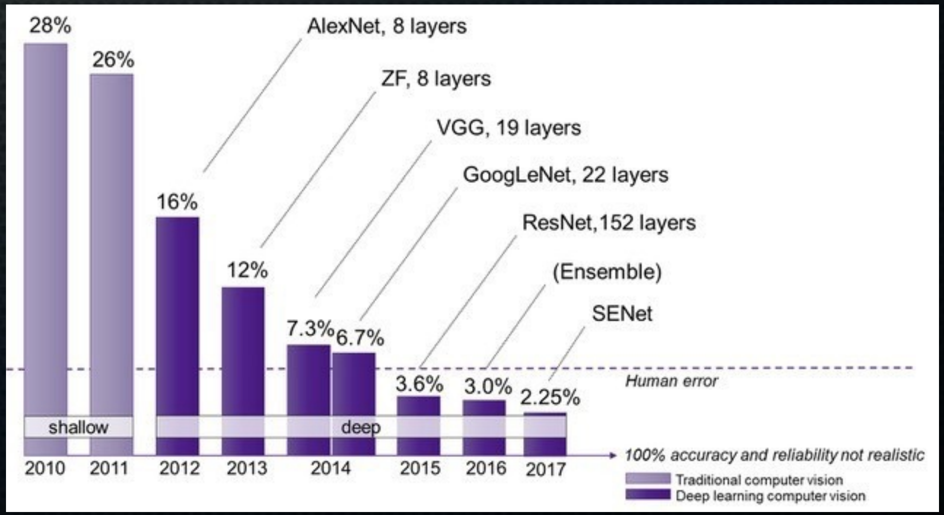
Convolutional neural networks

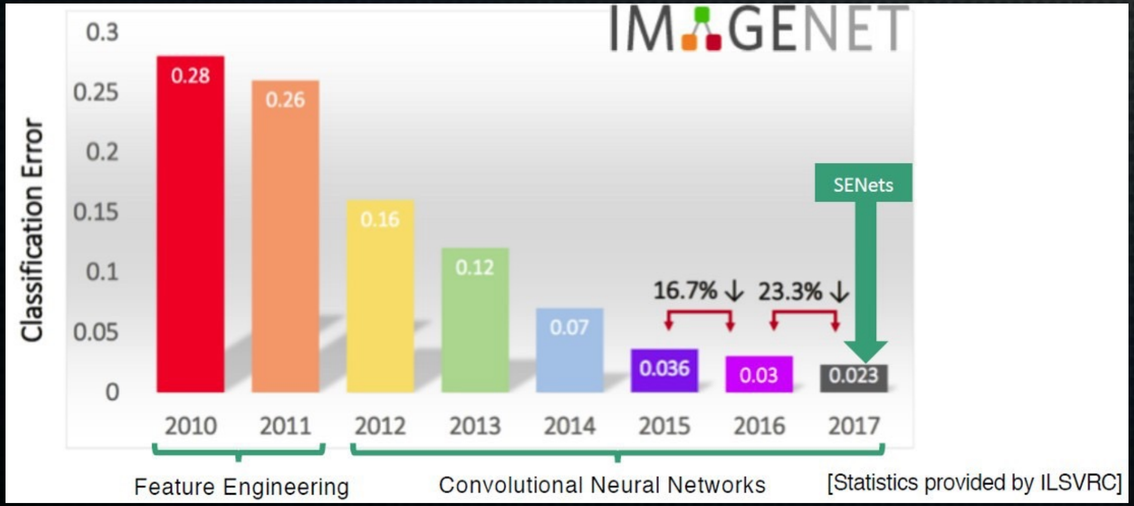
- These dense neural networks are not what made the huge strides in deep learning over the last few years.

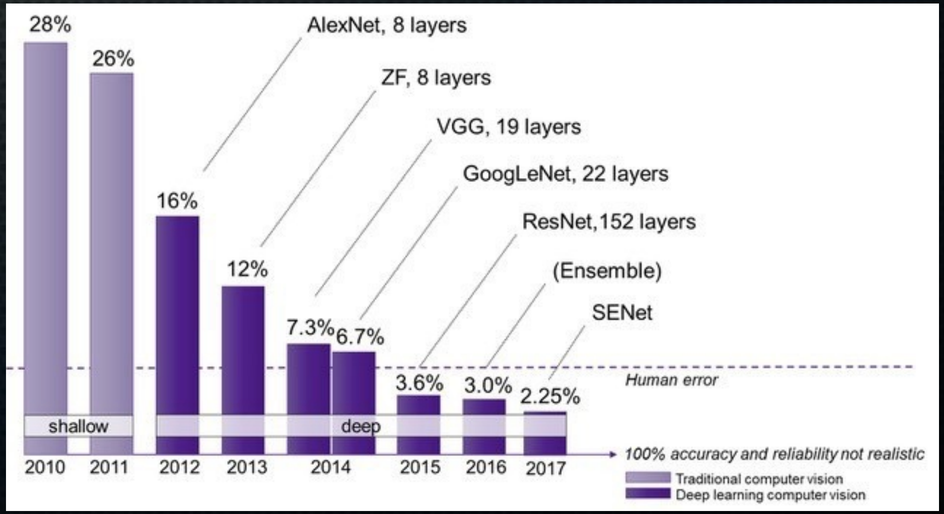




Convolutional neural networks

- These dense neural networks are not what made the huge strides in deep learning over the last few years.
- Instead, those are deep convolutional neural networks



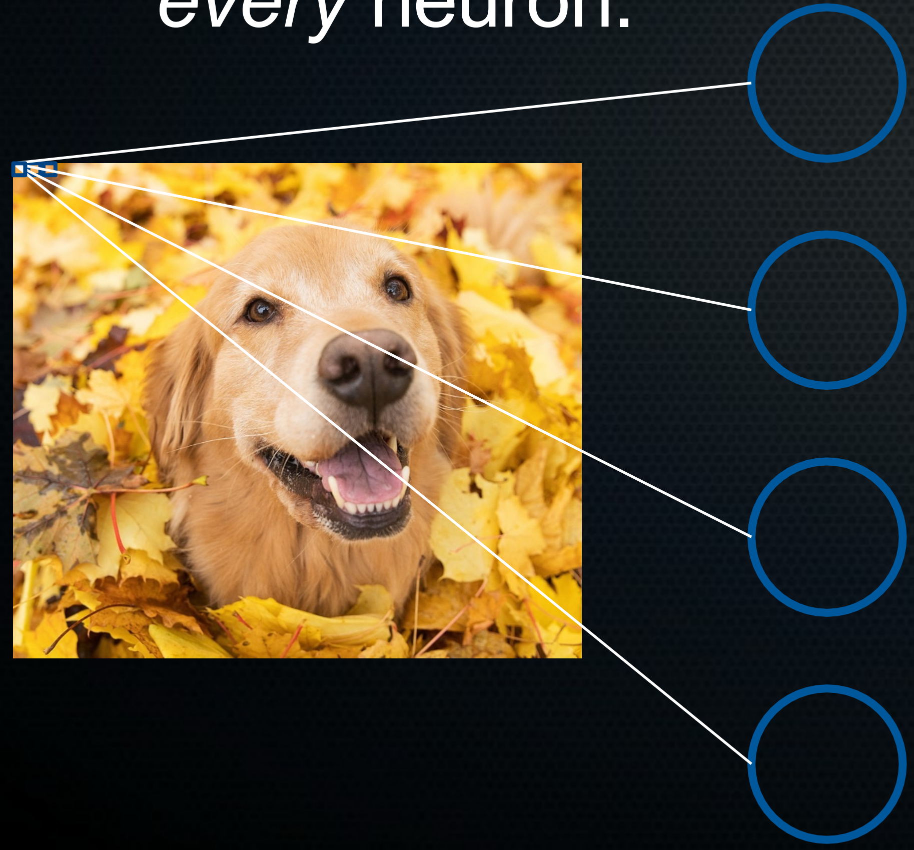


Convo-what now?

- Let’s look at an image

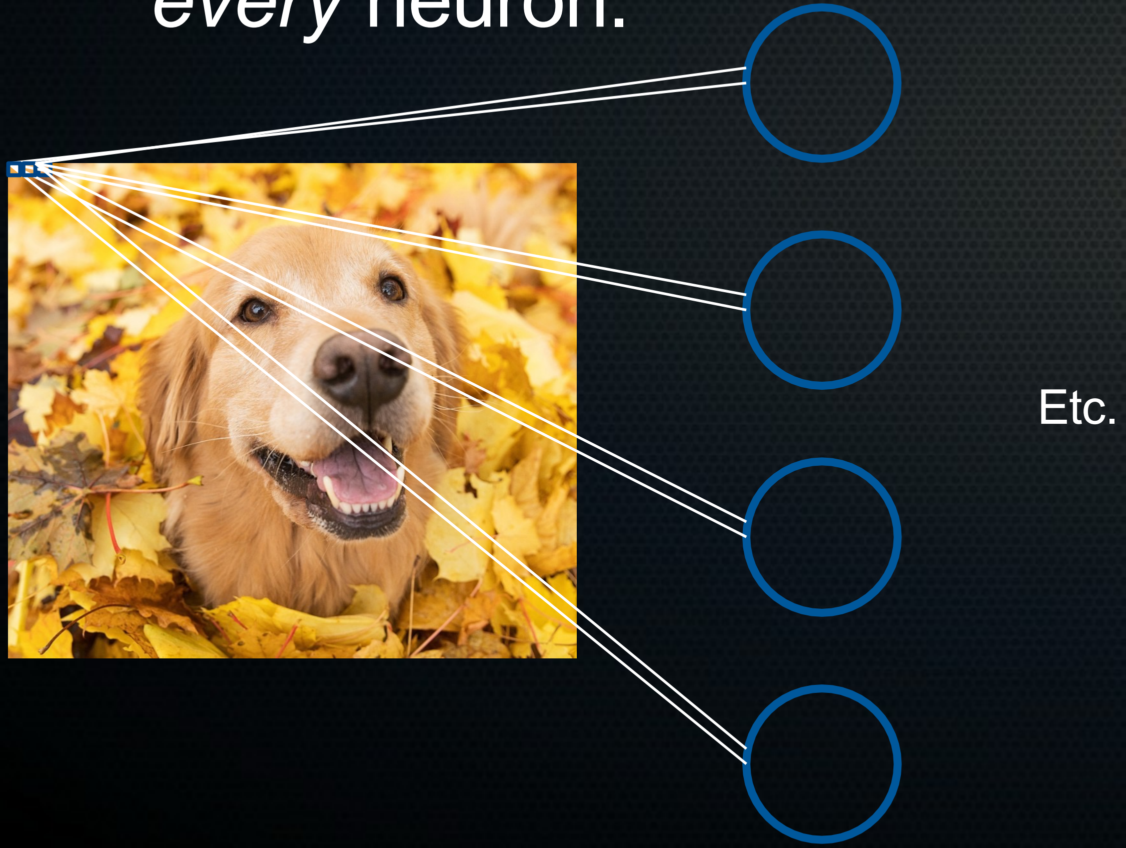
Convo-what now?

- Let’s look at an image
- In a dense architecture, every pixel value is connected to *every* neuron.



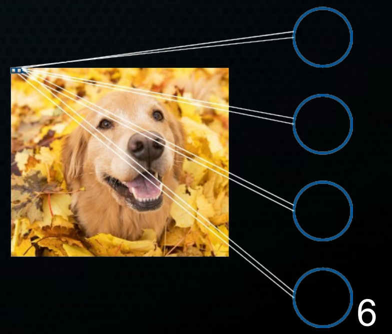
Convo-what now?

- Let's look at an image
- In a dense architecture, every pixel value is connected to *every* neuron.



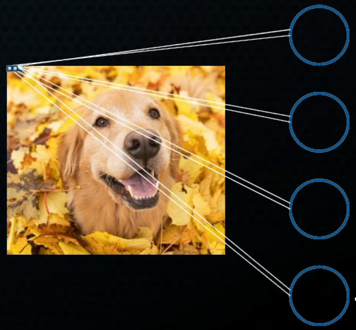
Convo-what now?

- Let’s look at an image
- In a dense architecture, every pixel value is connected to *every* neuron.
- This gives problems:
  - You get an *insane* amount of parameters to optimise. 250*250 pixels * 20 HL 1 neurons = 1,250,020 weights and biases. You can forget about any sort of findable or achievable (global) optimum.
  - There is no locality: if you want your network to know whether or not there is a dog in an image, all these parameters must be optimised so that you can recognise the dog anywhere.



Convo-what now?

This is madness!



Convo-what now?

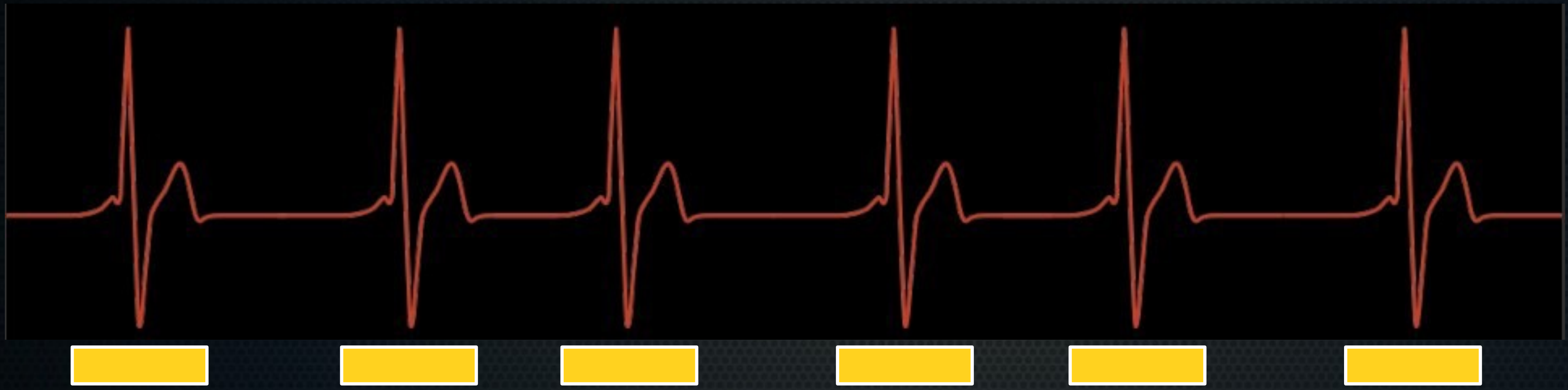
- The answer: convolution. Let’s look at a 1D example!

- When is the heart beating?

These slides were gladly ~~stolen~~ borrowed (with permission) from Marc Pages Gallego

Convo-what now?

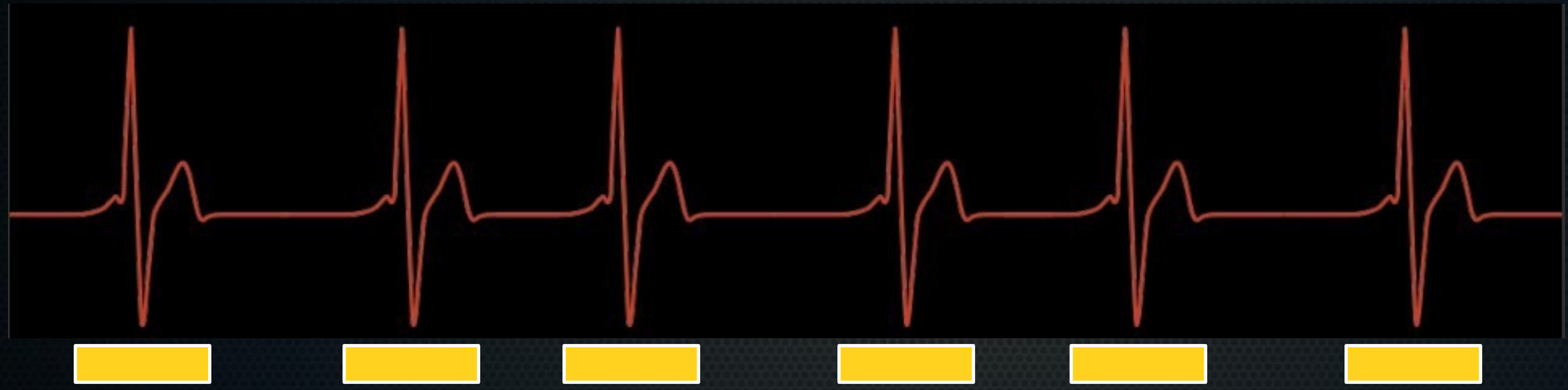
- The answer: convolution. Let's look at a 1D example!



- When is the heart beating?

Convo-what now?

- The answer: convolution. Let's look at a 1D example!

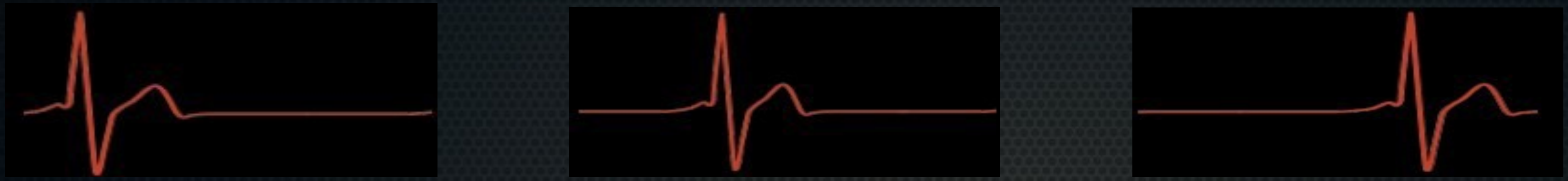


$$\text{signal} = x = \begin{bmatrix} 0 & 0 & 0 & 1 & -1 & 0.5 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\text{label} = y = \begin{bmatrix} 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Convo-what now?

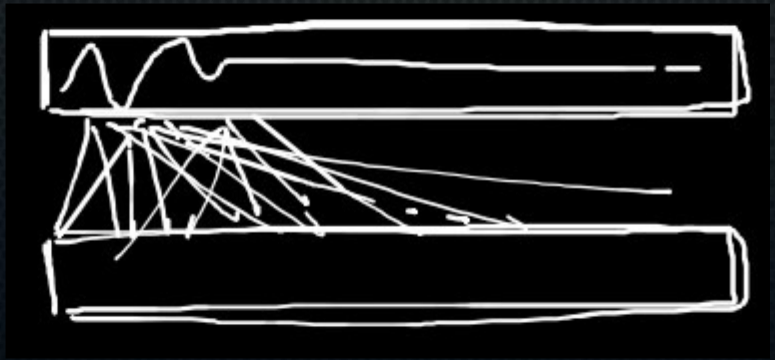
- Signal can be at different positions in the sequence:



Convo-what now?

- Signal can be at different positions in the sequence:

- Dense network needs to optimise such that different weights somehow cause the network to output 1 for different positions of the signal:

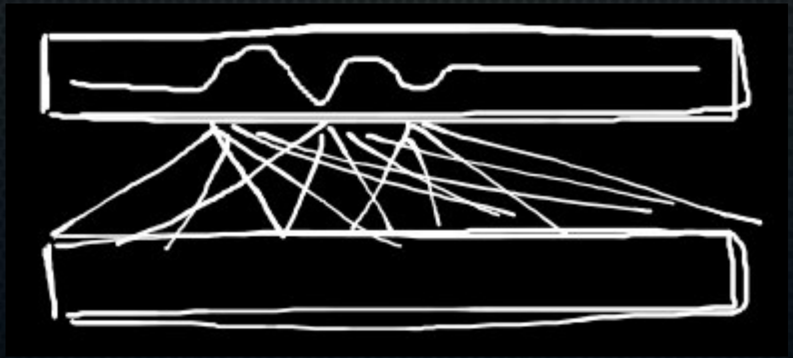


$$\text{label} = y = [1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$$

Convo-what now?

- Signal can be at different positions in the sequence:

- Dense network needs to optimise such that different weights somehow cause the network to output 1 for different positions of the signal:

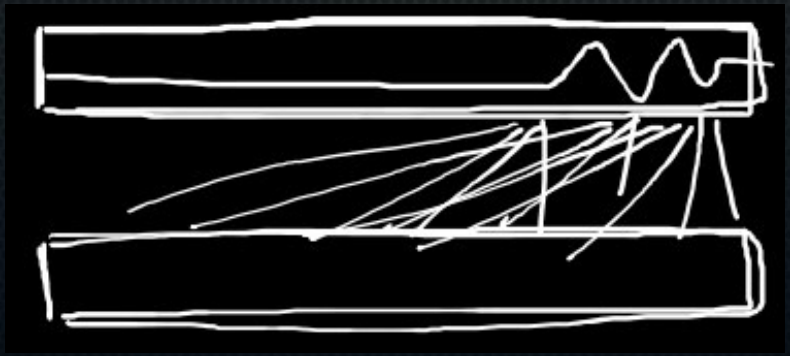


$$\text{label} = y = [1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$$

Convo-what now?

- Signal can be at different positions in the sequence:

- Dense network needs to optimise such that different weights somehow cause the network to output 1 for different positions of the signal:



$$\text{label} = y = [0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 1 \quad 1]$$

Convo-what now?

- Convolution:

Input

0	0	0	1	-1	0.5	0	0	0	0

Kernel

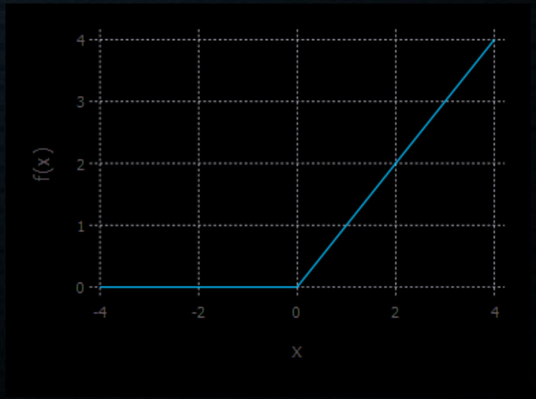
2

Kernel output

0									

ReLu output

0	0	0	1	-1	0.5	0	0	0	0



Convo-what now?

- Convolution:

Input	0	0	0	1	-1	0.5	0	0	0	0

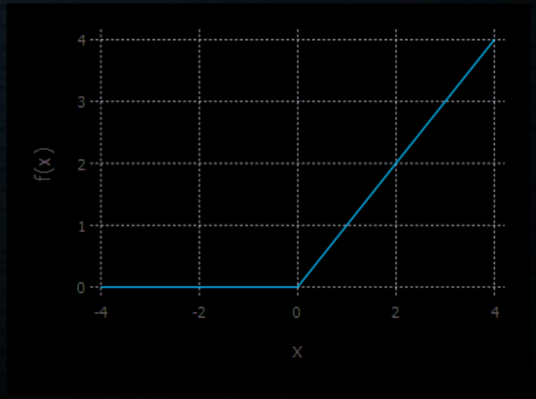
*

Kernel	2

→ Convolve (move) the kernel over the sequence

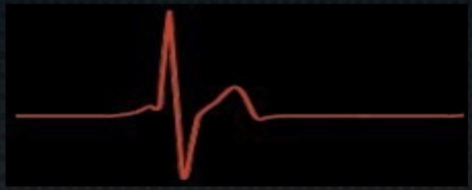
Kernel output	0									

ReLu output	0									



Convo-what now?

- Convolution:



Input

0	0	0	1	-1	0.5	0	0	0	0

*

Kernel

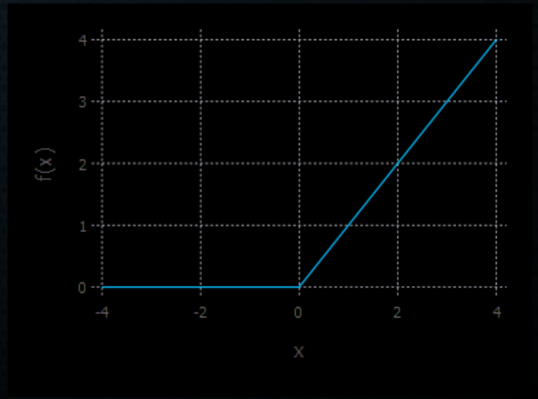
2

Kernel output

0	0								

ReLu output

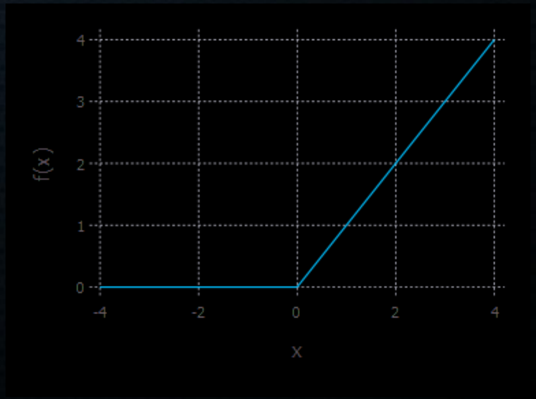
0	0								



Convo-what now?

- Convolution:

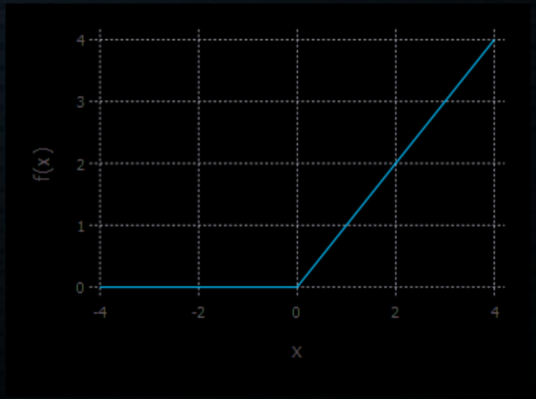
Input	0	0	0	1	-1	0.5	0	0	0	0
			*							
Kernel			2							
Kernel output	0	0	0							
ReLu output	0	0	0							



Convo-what now?

- Convolution:

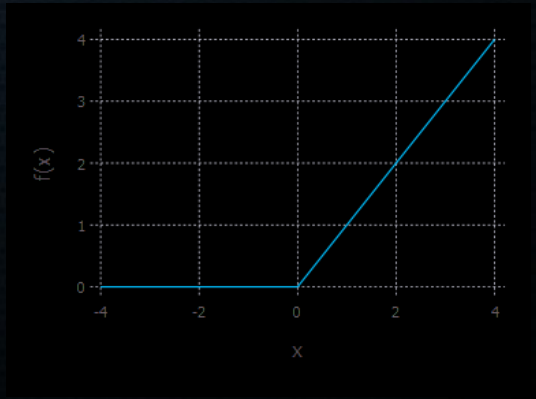
Input	0	0	0	1	-1	0.5	0	0	0	0
				*						
Kernel				2						
Kernel output	0	0	0	2						
ReLu output	0	0	0	1						



Convo-what now?

- Convolution:

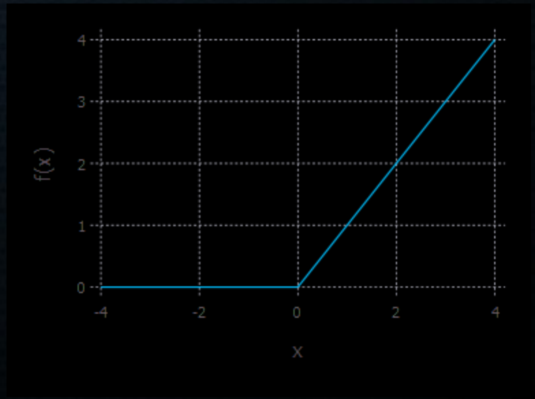
Input	0	0	0	1	-1	0.5	0	0	0	0
										*
Kernel										2
Kernel output	0	0	0	2	-2	1	0	0	0	0
ReLu output	0	0	0	2	0	1	0	0	0	0



Convo-what now?

- Convolution:

Input	0	0	0	1	-1	0.5	0	0	0	0
										*
Kernel										2
Kernel output	0	0	0	2	-2	1	0	0	0	0
ReLu output	0	0	0	2	0	1	0	0	0	0



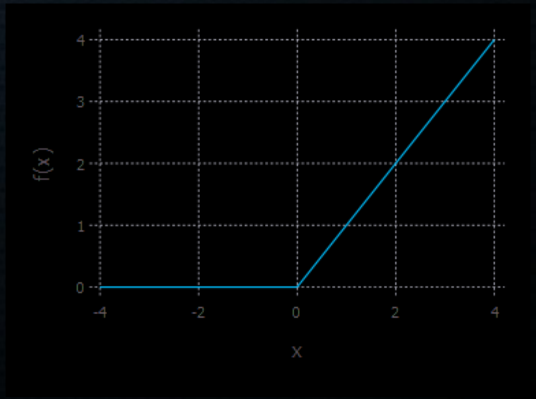
This is a kernel that detects positive numbers

Convo-what now?

- Convolution:

Input	0	0	0	1	-1	0.5	0	0	0	0
										*
Kernel										2
Kernel output	0	0	0	2	-2	1	0	0	0	0
ReLu output	0	0	0	2	0	1	0	0	0	0

Just like a neuron has weights, this kernel has a trainable weight (2)



This is a kernel that detects positive numbers

Convo-what now?

- Convolution:

Input

0	0	0	1	-1	0.5	0	0	0	0

* * *

Kernel

0	2	1

→ A kernel can have a size >1

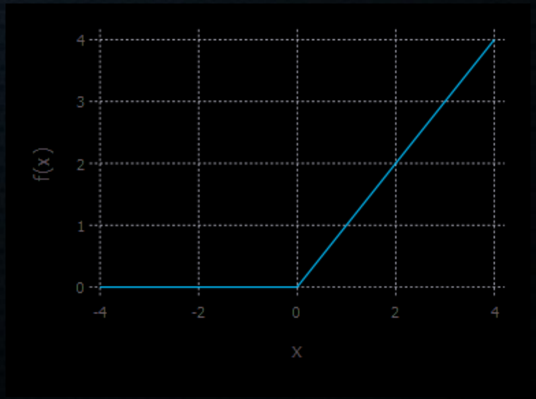
+

Kernel output

-	0								-

ReLu output

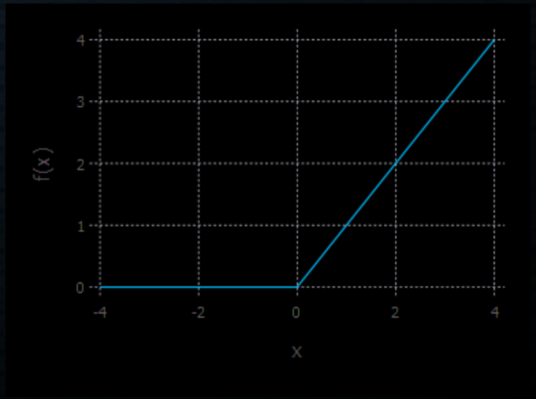
-	0								-



Convo-what now?

- Convolution:

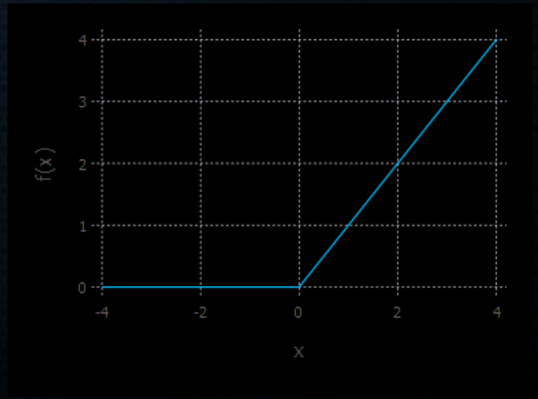
Input	0	0	0	1	-1	0.5	0	0	0	0
		*	*	*						
Kernel		0	2	1						
			+							
Kernel output	-	0	1							-
ReLu output	-	0	1							-



Convo-what now?

- Convolution:

Input	0	0	0	1	-1	0.5	0	0	0	0
			*	*	*					
Kernel			0	2	1					
				+						
Kernel output	-	0	1	1						-
ReLu output	-	0	1	1						-



Convo-what now?

- Convolution:

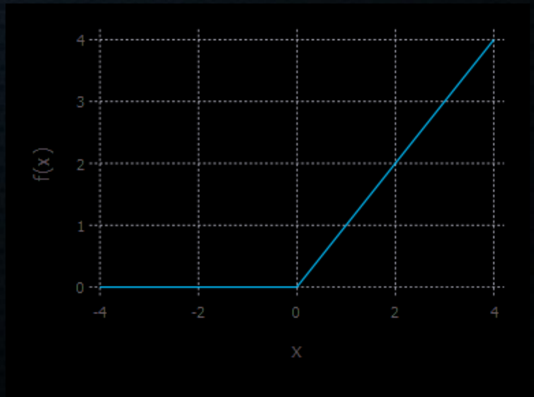
Input	0	0	0	1	-1	0.5	0	0	0	0

* * *

Kernel	0	2	1

+

Kernel output	-	0	1	1	-1.5					-
ReLu output	-	0	1	1						-

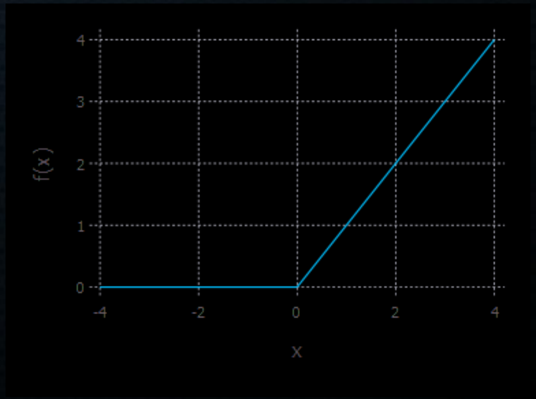


Convo-what now?

- Convolution:

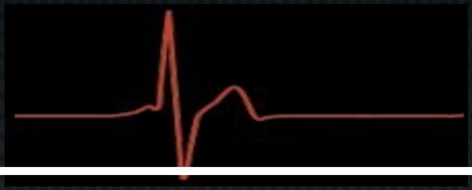
Input	0	0	0	1	-1	0.5	0	0	0	0
								*	*	*
Kernel								0	2	1
									+	
Kernel output	-	0	1	1	-1.5	1	0	0	0	-
ReLu output	-	0	1	1	0	1	0	0	0	-

Note shrinkage due to edge effects



Convo-what now?

- Convolution:



Input	0	0	0	0	1	-1	0.5	0	0	0	0	0

* * *

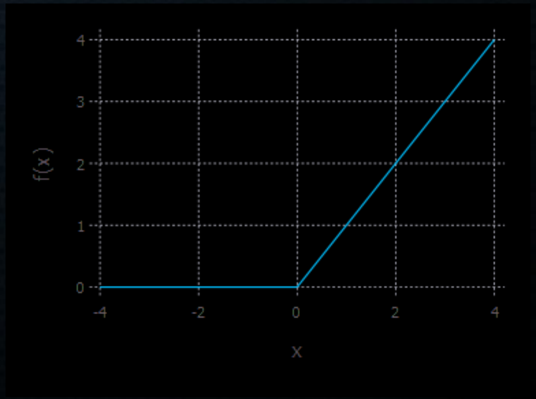
Kernel	0	2	1

\+

Kernel output	0	0	1	1	-1.5	1	0	0	0	0

Could fix by *padding* the input

ReLu output	0	0	1	1	0	1	0	0	0	0

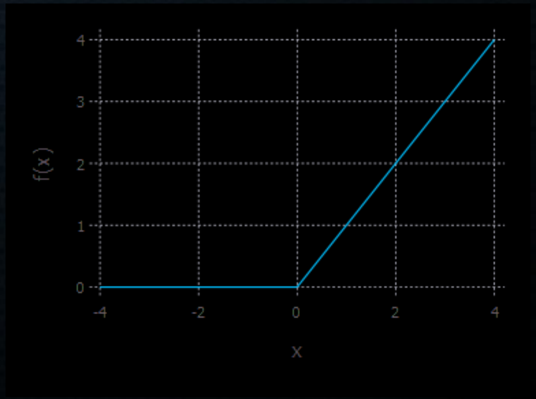


Convo-what now?

- Convolution:

Input	0	0	0	1	-1	0.5	0	0	0	0
	*	*	*							
Kernel	0	2	1							
	$\underbrace{\quad\quad}_{+}$									
Kernel output	-	0								-
ReLu output	-	0								-

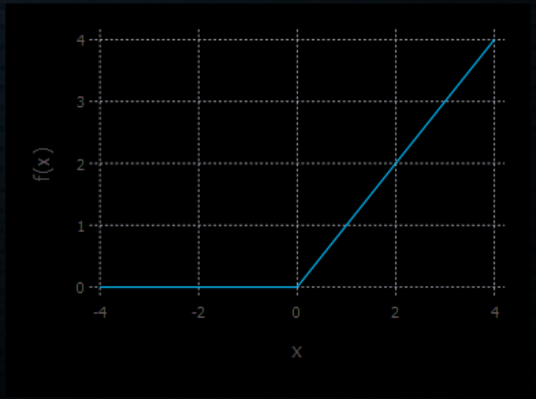
→ Or could compress output size further by changing *stride* (step size). Stride = 3 now.



Convo-what now?

- Convolution:

Input	0	0	0	1	-1	0.5	0	0	0	0
				*	*	*				
Kernel				0	2	1				
					+					
Kernel output	-	0	-	-	-1.5					-
ReLu output	-	0	-	-	0					-



Convo-what now?

- Convolution:

Size = 3
Stride = 3

Input

0	0	0	1	-1	0.5	0	0	0	0

* * *

Kernel

0	2	1

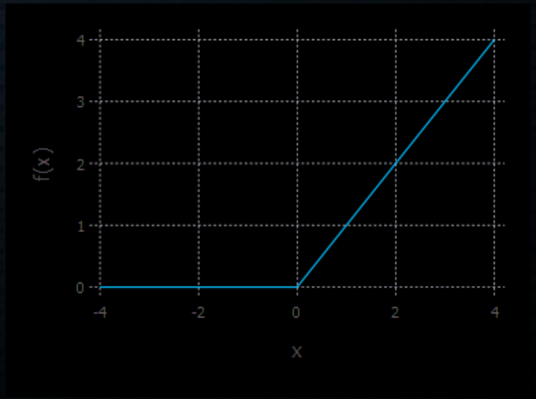
+

Kernel output

-	0	-	-	-1.5	-	-	0	-	-

ReLu output

-	0	-	-	0	-	-	0	-	-



Convo-what now?

- Convolution:

Size = 3
Stride = 3

Input

0	0	0	1	-1	0.5	0	0	0	0

Kernel

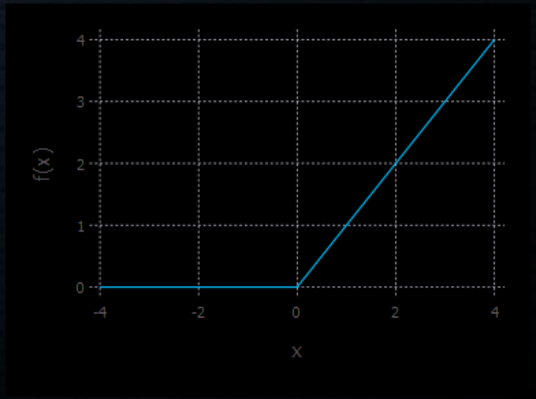
0	2	1

Kernel output

0	-1.5	0

ReLu output

0	0	0



This example is not useful because I randomly picked some weights for the kernel. But normally you can train these weights by backpropagation such that the network works well!

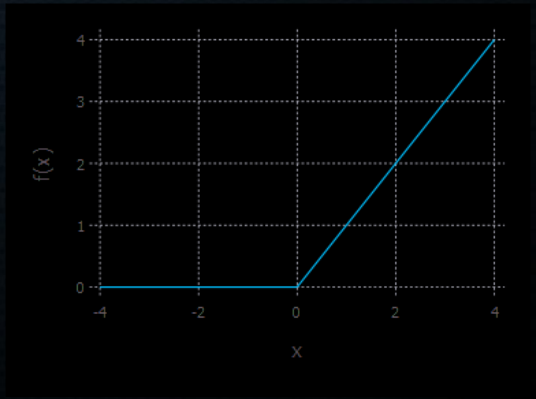
Convo-what now?

- Convolution:

Size = 3
Stride = 1

Input	0	0	0	1	-1	0.5	0	0	0	0
								*	*	*
Kernel								0	2	1
									+	
Kernel output	-	0	1	1	-1.5	1	0	0	0	-
ReLu output	-	0	1	1	0	1	0	0	0	-

Note shrinkage due to edge effects

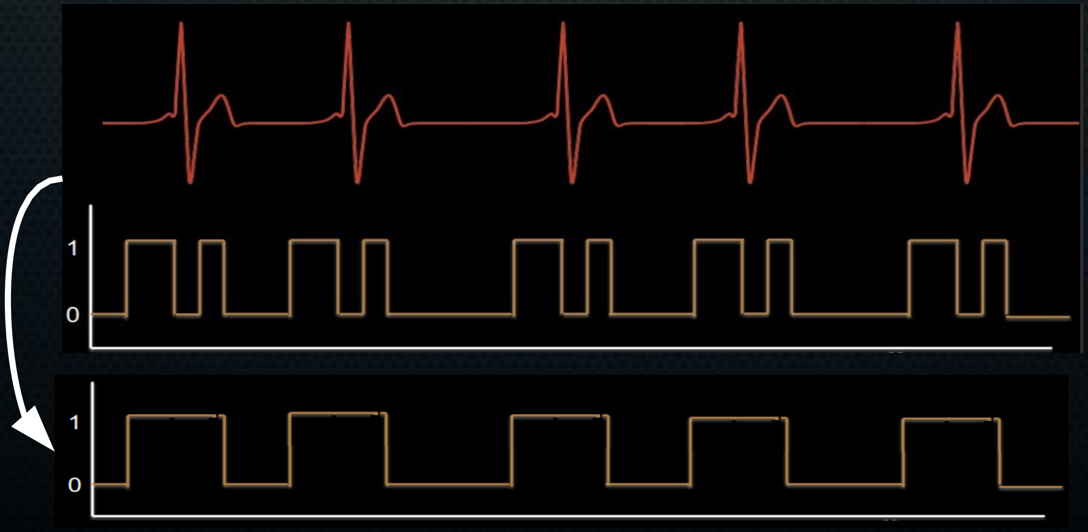


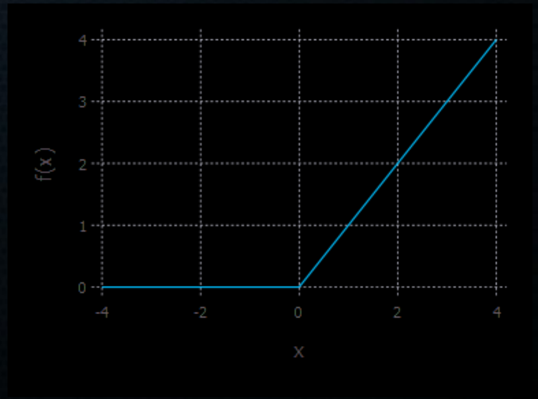
Convo-what now?

Input	0	0	0	1	-1	0.5	0	0	0	0
								*	*	*
Kernel								0	2	1
									+	
Kernel output	-	0	1	1	-1.5	1	0	0	0	-
ReLu output	-	0	1	1	0	1	0	0	0	-

Size = 3
Stride = 1

Not optimal, but by adding another convolution layer, you might get to something like:





2D convolution

- Size = 2*2; stride = 1

0	22	0	1
12	2	3	23
3	34	26	2
0	22	86	3
4	3	1	4

0	2
2	0

68		

2D convolution

- Size = 2*2; stride = 1

0	22	0	1
12	2	3	23
3	34	26	2
0	22	86	3
4	3	1	4

0	2
2	0

68	4	

2D convolution

- Size = 2*2; stride = 1

0	22	0	1
12	2	3	23
3	34	26	2
0	22	86	3
4	3	1	4

0	2
2	0

68	4	8

2D convolution

- Size = 2*2; stride = 1

0	22	0	1
12	2	3	23
3	34	26	2
0	22	86	3
4	3	1	4

0	2
2	0

68	4	8
10		

Etc.

Another type of convolution: max pooling

- Size = 2*2; stride = 1; just take the maximum value in the kernel area

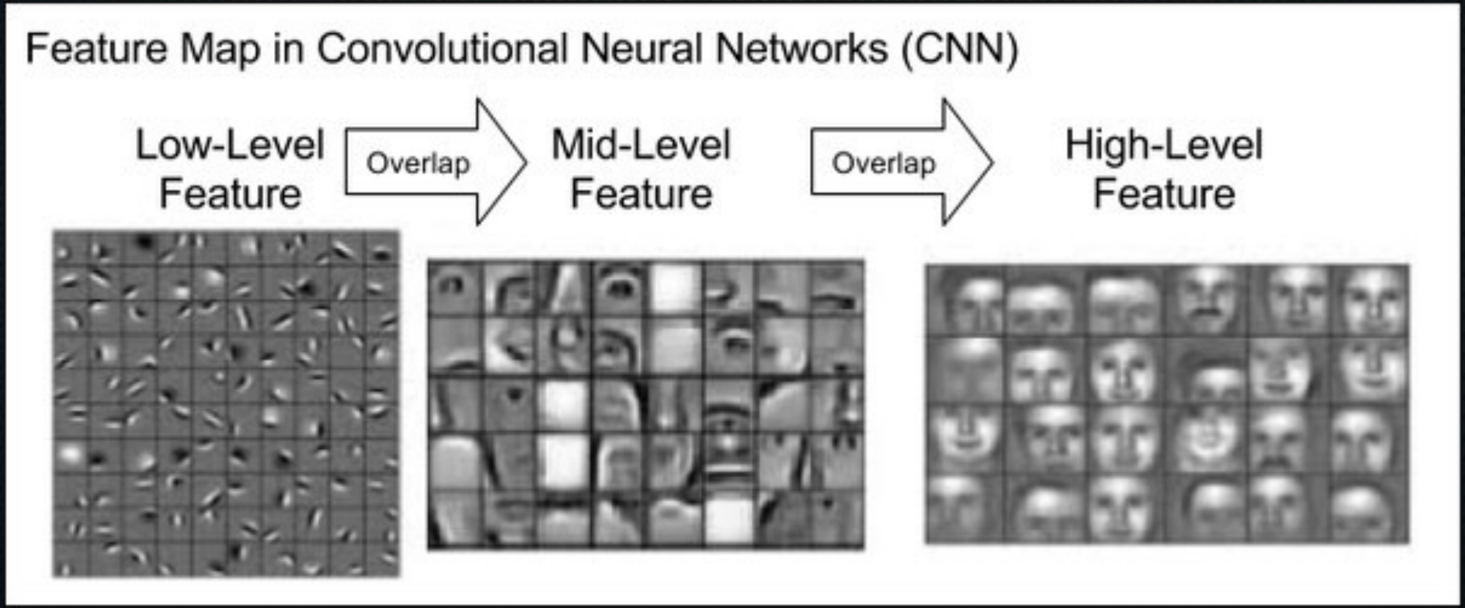
0	22	0	1
12	2	3	23
3	34	26	2
0	22	86	3
4	3	1	4

22	22	23
34	26	26
34	86	86
22	86	86

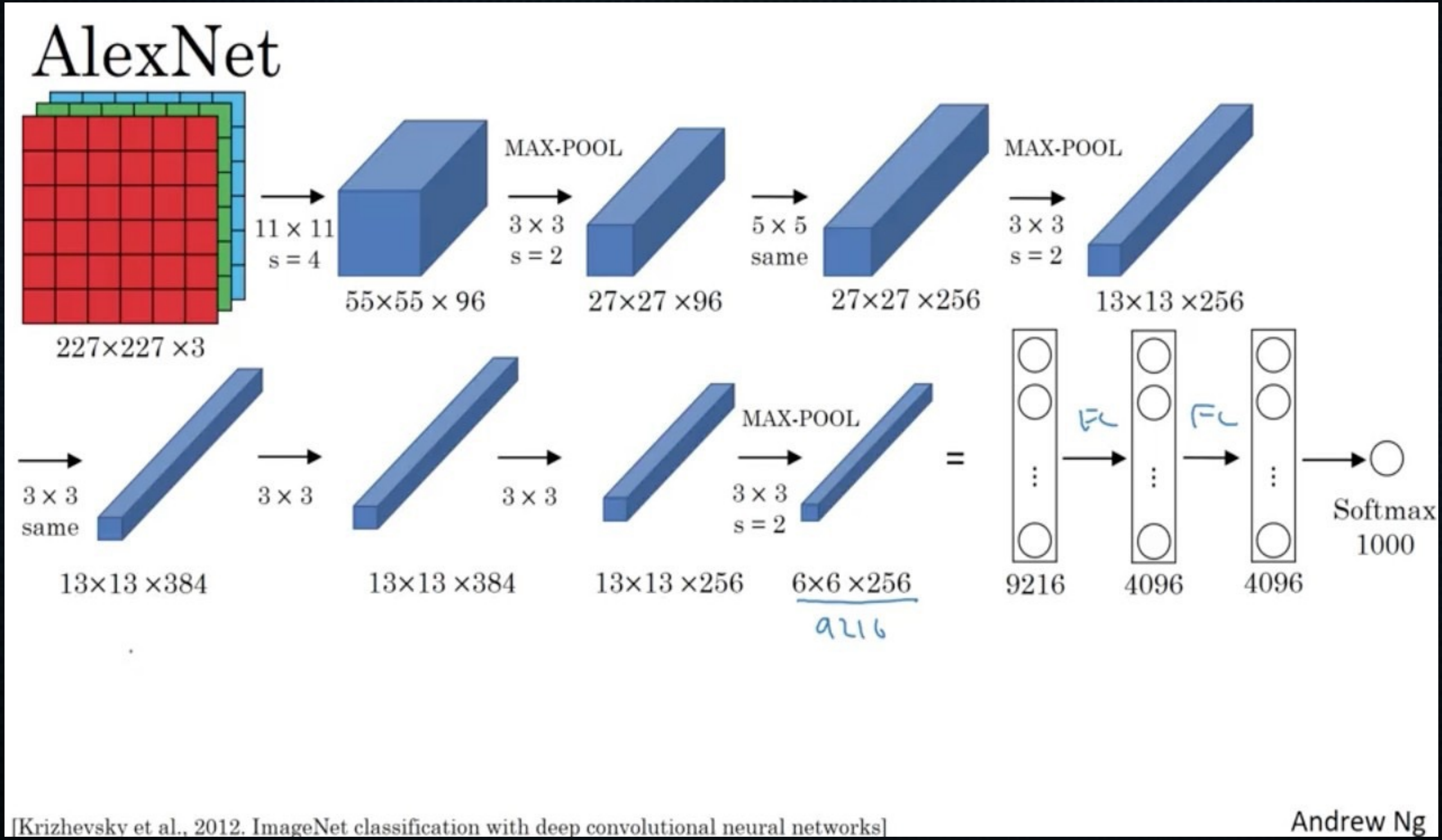
Another type of convolution: pooling/averaging

Use in face detection

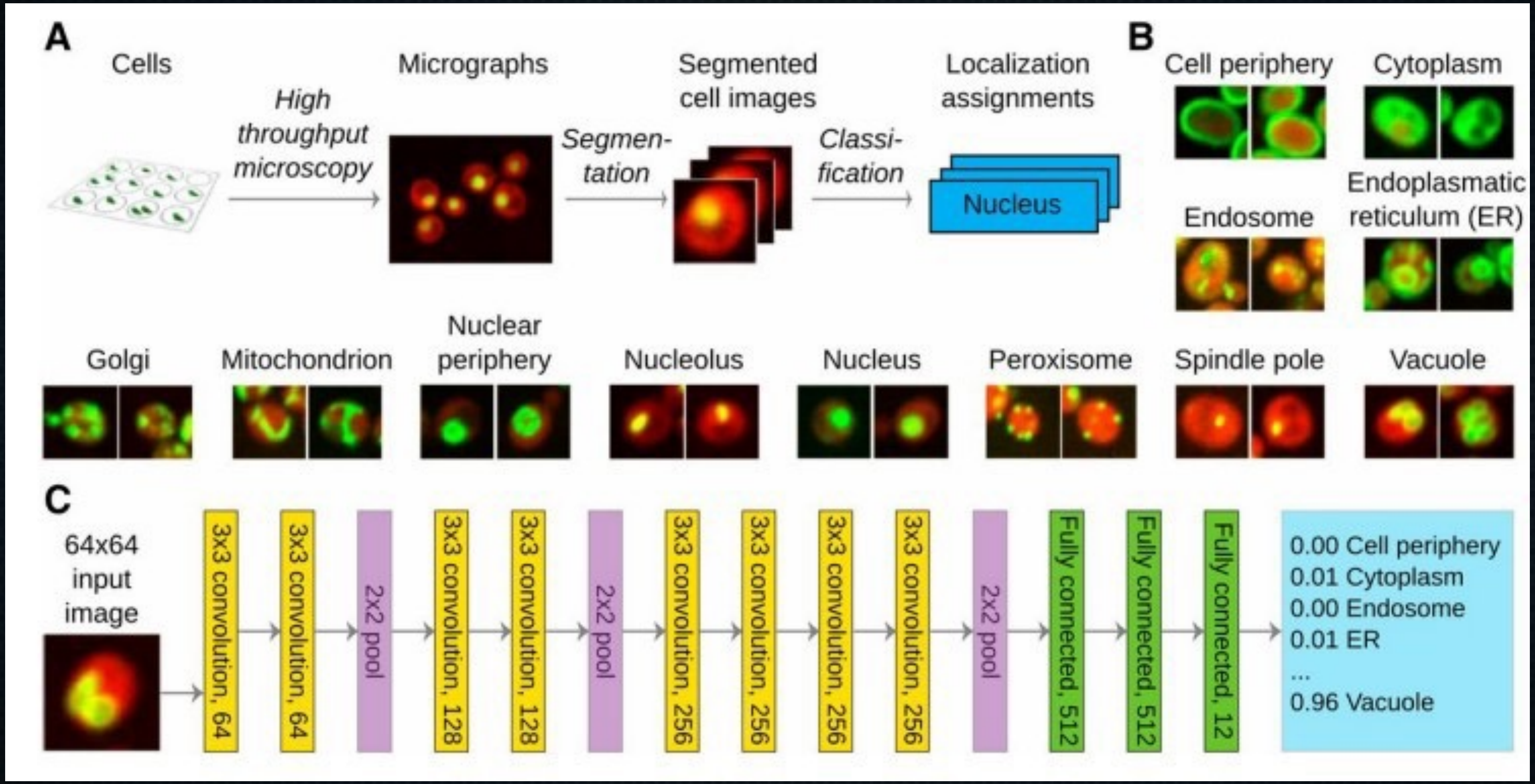
- Since kernels so few parameters: can use *many* of them per layer → each becomes sensitive to different image features



Example AlexNet (2012)



Biological use



Pärnamaa, T., & Parts, L. (2017). Accurate classification of protein subcellular localization from high-throughput microscopy images using deep learning. G3: Genes, Genomes, Genetics, 7(5), 1385-1392.

Biological use

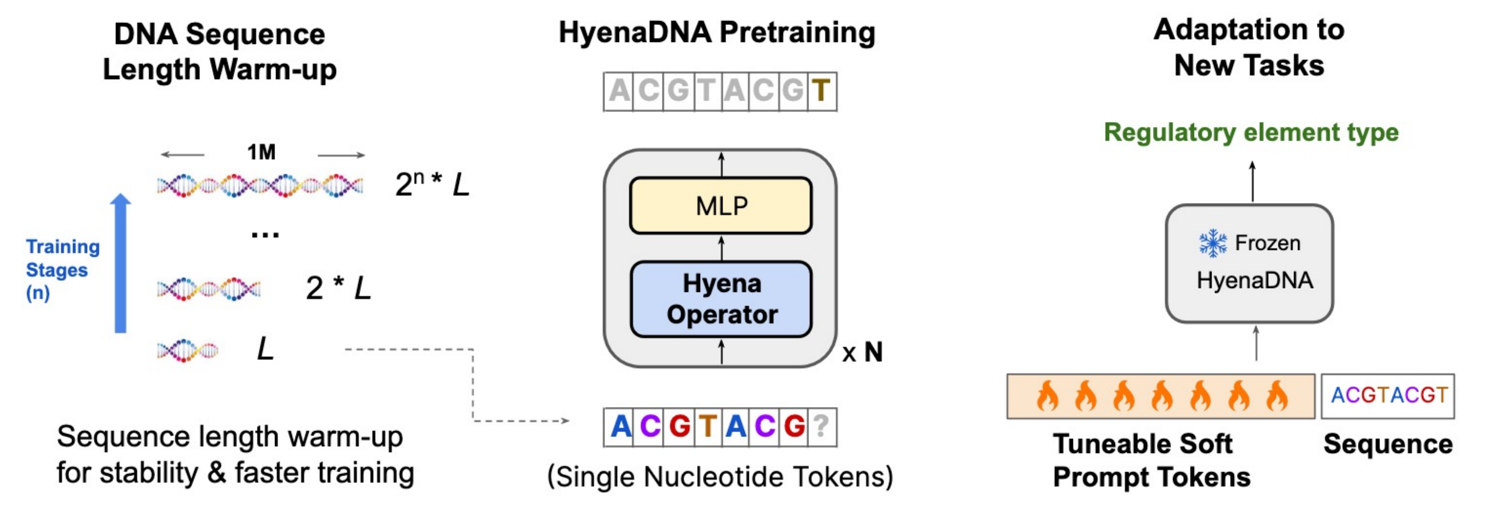
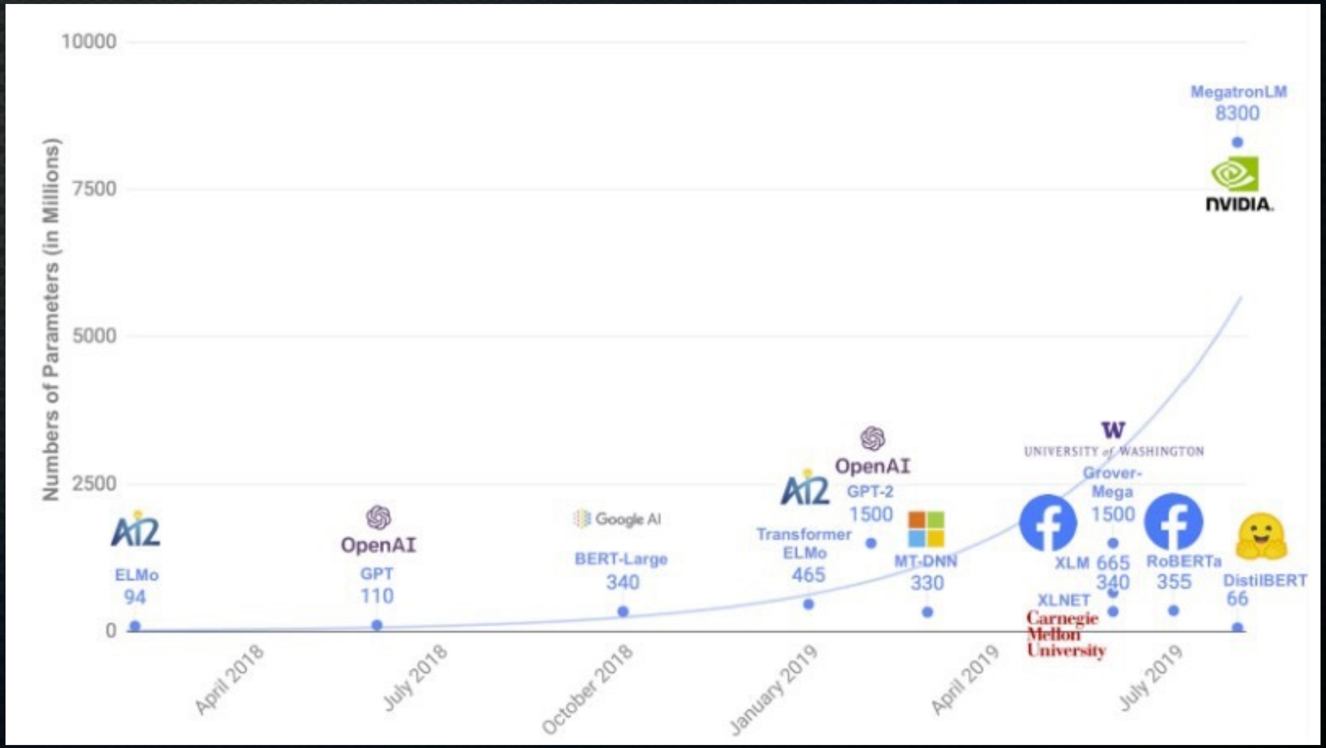


Figure 1.1: HyenaDNA recipe for long-range foundation models in genomics. The HyenaDNA architecture is a simple stack of Hyena operators (Poli et al., 2023) trained using next token prediction. (See Fig. 1.3 for block diagram of architecture). We introduce a new sequence length scheduling technique to stabilize training, and provide a method to leverage the longer context length to adapt to novel tasks without standard fine-tuning by filling the context window with learnable soft prompt tokens.

There’s a lot more

- Batch normalisation
- Vanishing gradient problem
- Dropout
- Recurrent neural nets



Implementation

- We are not going to implement convolutional neural networks ourselves: implementing backpropagation properly on a simple dense network is already taxing enough.
- Still, doing that should give you a solid basis for understanding convolutional neural networks, and we'll introduce the Keras library for building (convolutional) neural networks next Monday.

Afternoon practical

- Implement backpropagation yourself
- Train a dense neural network on the MNIST dataset