

Introduction to Machine Learning

Module 2A: Introduction to Convolutional Neural Networks

Instructor: Tugce Gurbuz

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Recap of yesterday

 Overparameterized ANNs are efficient universal approximators, but ANNs can memorize our data



GPT-3: Q. What do you call a droid that takes the long way around? A.R2 detour.





Recap of yesterday

- Regularization can help ANNs to better generalize
- It encourages simpler models by reducing effective number of parameters in a model.
- Some common regularization methods: L1, L2, data augmentation, dropout, early stopping, gradient descent.

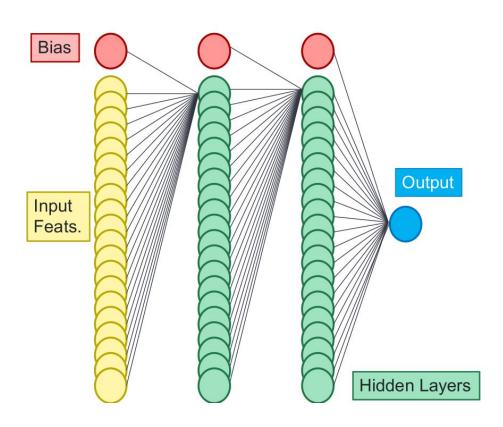
How about making smarter architectures like a human brain?





Smarter Architectures

An MLP can have MANY parameters



Data: 20 input features, single binary label

- 1 input layer with 20 nodes,
- 2 fully connected layers, 20 nodes each
- 1 final prediction node

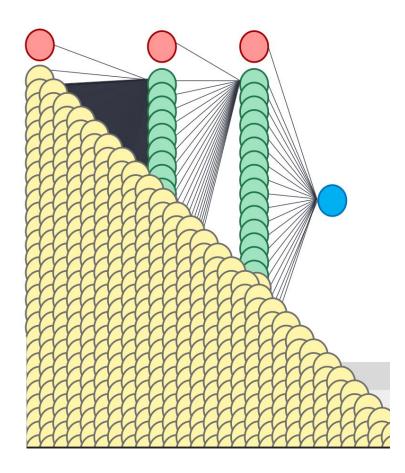
How many weights is that? (20+1)*20+(20+1)*20+(20+1)*1=861 params





Smarter Architectures

An MLP can have MANY parameters



Data: 1 input layer with 256*256 nodes,
2 fully connected layers, 20 nodes each
1 final prediction node
How many weights is that?
(256*256+1)*20+(20+1)*20+(20+1)*1
= ~1.3M params





Smarter Architectures

ConvNets <3

 Convolutional neural networks share parameters across the space -> reduces total number of parameters



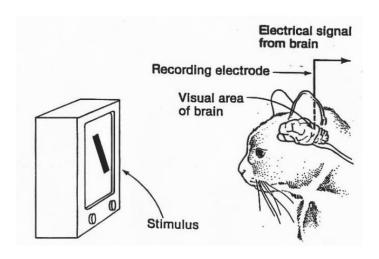


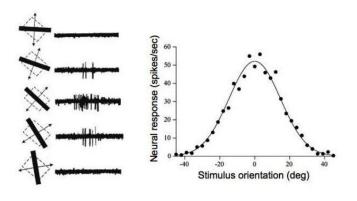
Brain is an efficient machine -> How it solves vision?





• Feature selectivity: Hubel & Wiesel, 1968



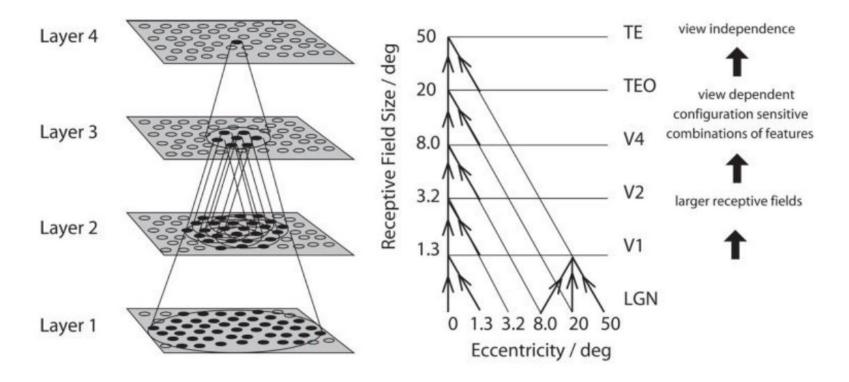


Hubel & Wiesel, 1968





Hierarchy of processing





Invariance

Translation Invariance







Rotation/Viewpoint Invariance













Size Invariance







Illumination Invariance



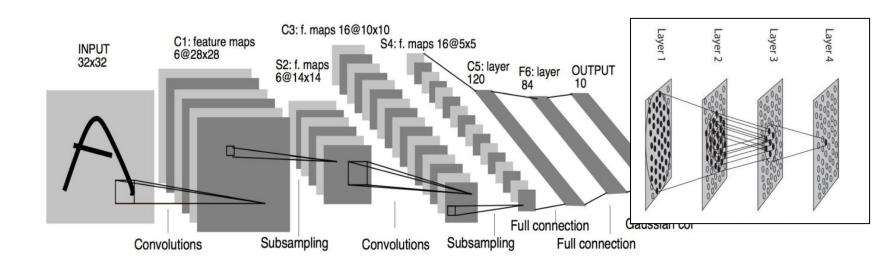








LeNet (1998) - Yann LeCun @Bell Labs







CNNs are everywhere!







CNNs are everywhere!



"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."



"two young girls are playing with lego toy."

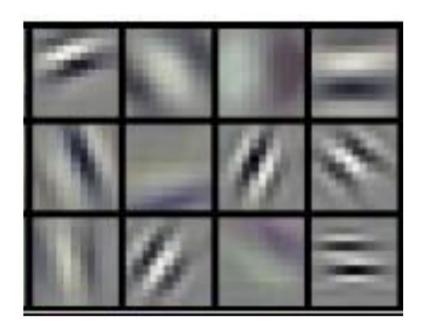


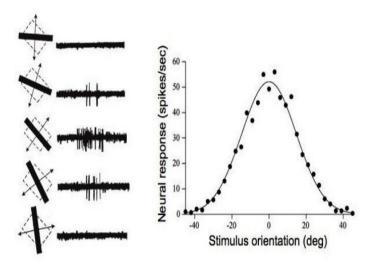
CNNs are everywhere!





Recipe: convolution + subsampling (pooling) + hierarchy





Hubel & Wiesel, 1968



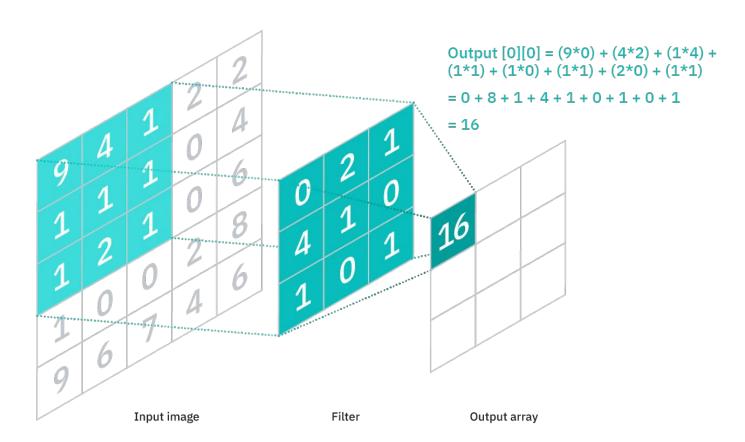








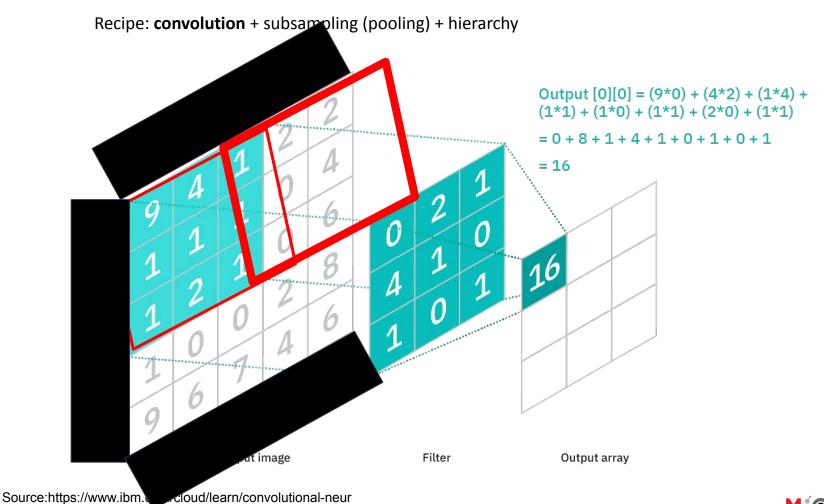








al-networks





Recipe: convolution + subsampling (pooling) + hierarchy

Definitional Note

If you have a background in signal processing or math, you may have already heard of convolution. However, the definitions in other domains and the one we use here are slightly different. The more common definition involves flipping the kernel horizontally and vertically before sliding.

For our purposes, no flipping is needed. Flipping does not affect CNN's learning performance. If you are familiar with conventions involving flipping, just assume the kernel is pre-flipped.





Recipe: convolution + subsampling (pooling) + hierarchy

Let's go to section-1 in tutorial-1 to practice it!





Recipe: convolution + subsampling (pooling) + hierarchy

Recall: filters give us global invariance

Pooling gives us local invariance







Recipe: convolution + subsampling (pooling) + hierarchy

Max-Pooling

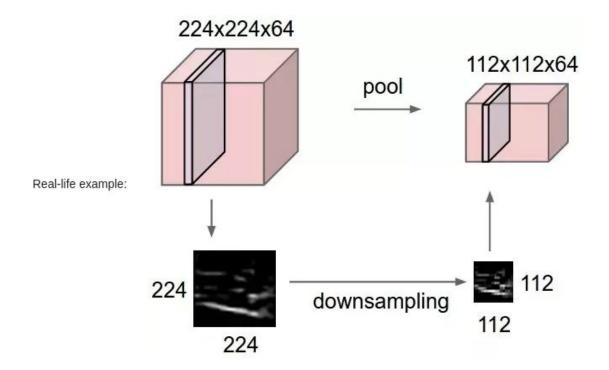
	12	20	30	0
Pictorial representation:	8	12	2	0
Pictoriai representation.	34	70	37	4
	112	100	25	12

2×2 Max-Pool	20	30
	112	37



Recipe: convolution + subsampling (pooling) + hierarchy

Max-Pooling

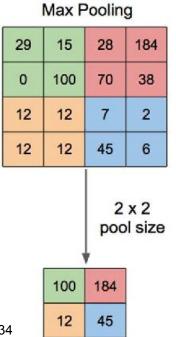






Recipe: convolution + subsampling (pooling) + hierarchy

Average-Pooling



A۷	erage	Pool	ing
31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6
	,	poo	x 2 ol size
	36	80	
	12	15	

Source:

https://www.researchgate.net/publication/3335934 51/figure/download/fig2/AS:765890261966848@1 559613876098/Illustration-of-Max-Pooling-and-Av erage-Pooling-Figure-2-above-shows-an-example -of-max.png





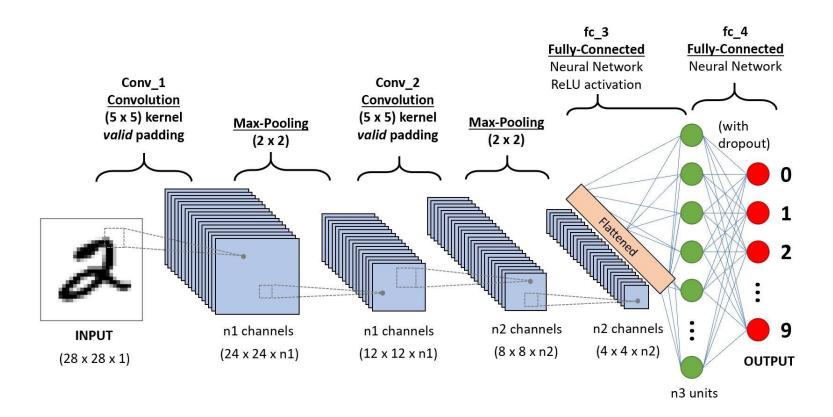
Recipe: convolution + subsampling (pooling) + hierarchy

Let's go to section-2 in tutorial-1 to practice it!

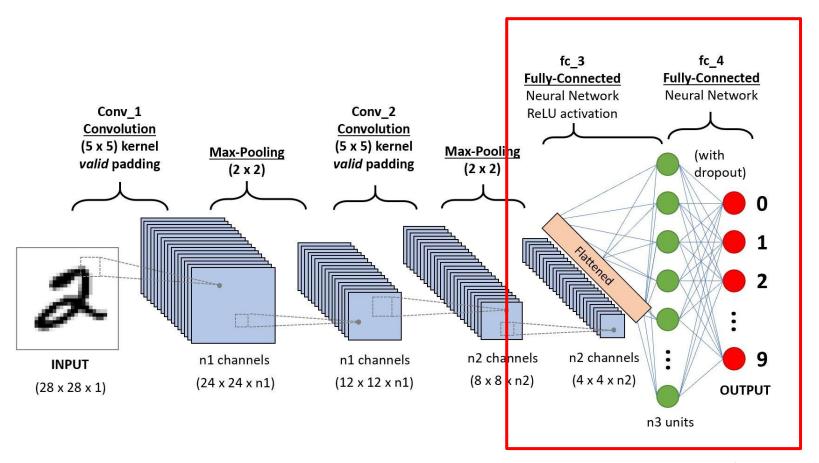
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188Z6AS6L+101CFHBAF6/4/9N
188Z6AS6L+101CFHBAF6/4/9N
188Z6AS6L+101CFHBAF6/4/9N
188WHH3524DQ319b45Vd77WCV
```













Recipe: convolution + subsampling (pooling) + hierarchy

Let's put everything together in Section 3 of tutorial 1!!

