# ENGR 3321: Introduction to Deep Learning for Robotics

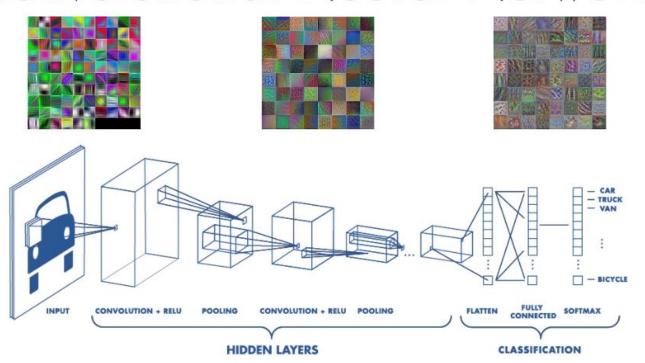
Convolutional Neural Network



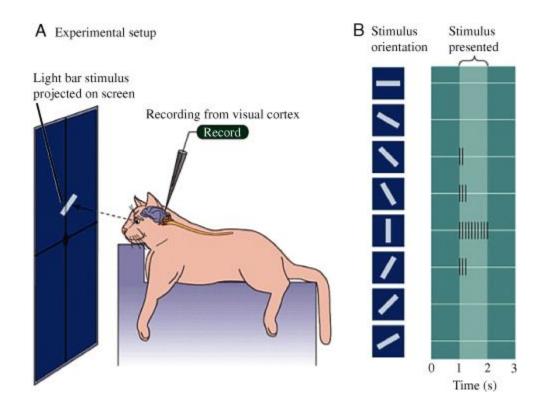
#### Outline

- Introduction
- Convolution Layer Principles
- Visualize Convolved Features
- Classical ConvNets

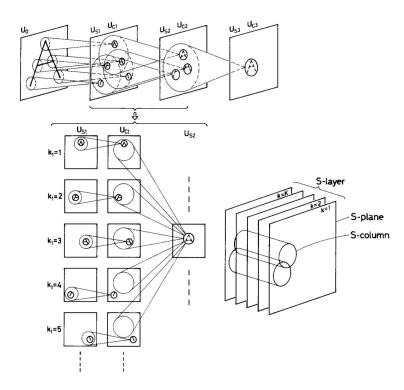
# Convolutional Neural Network



#### Hubel & Wiesel's Cat Experiment

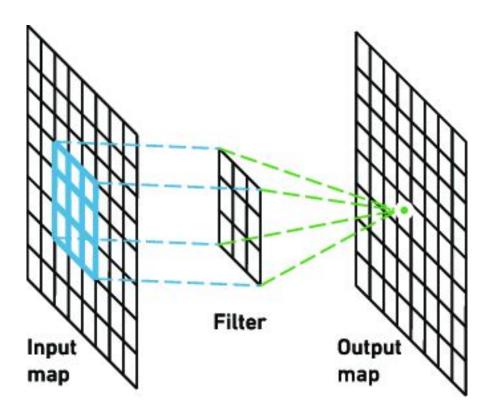


# Early ConvNet

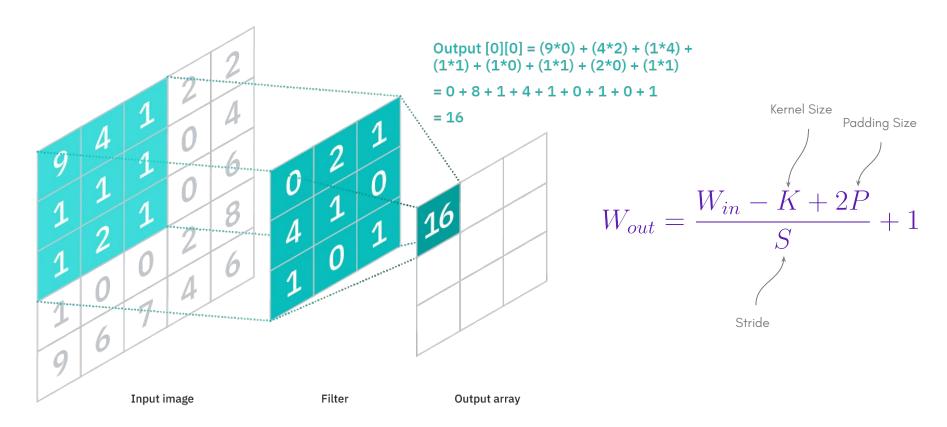


Fukushima K, Miyake S. Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition. InCompetition and cooperation in neural nets 1982 (pp. 267-285). Springer, Berlin, Heidelberg.

# Convolution Layer



# Convolution Operation



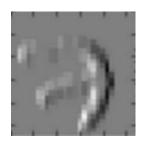
#### Pattern Detection



-1	-1	-1
1	1	1
0	0	0



-1	1	0
-1	1	0
-1	1	0

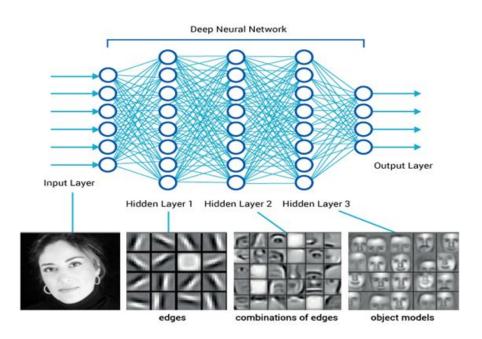


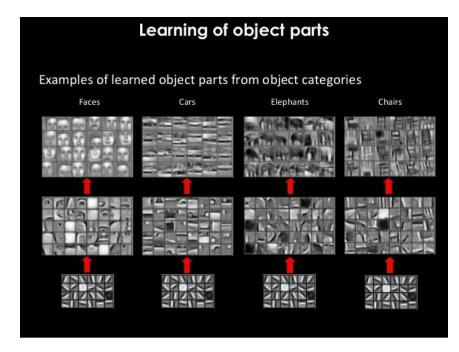


0	1	-1
0	1	-1
0	1	-1



# Patterns in Conv Layers





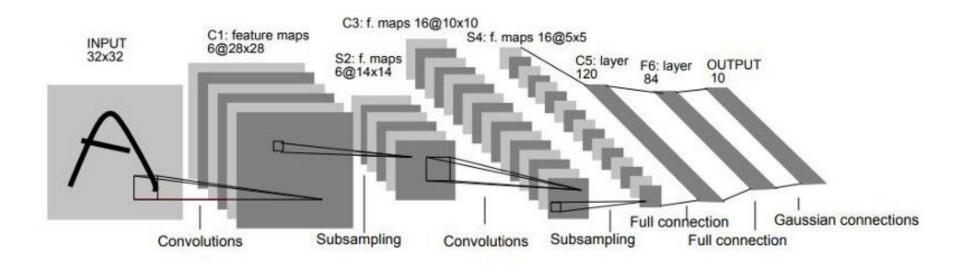
# Advantages of ConvNets (vs. MLPs)

- Spatial Hierarchies and Feature Extraction
- Parameter Efficiency
- Translation Invariance
- Classical ConvNets
- Improved Generalization with Limited Data
- Adaptability to Transfer Learning

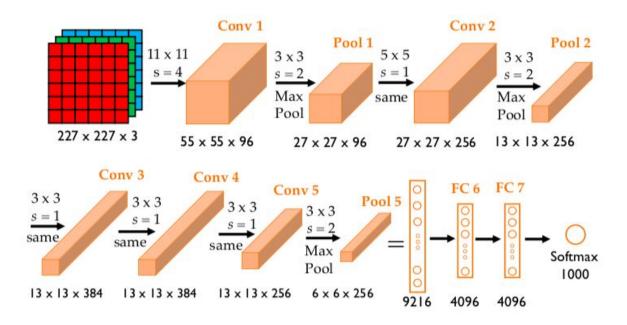
#### Online ConvNet Visualization

https://poloclub.github.io/cnn-explainer/

#### LeNet



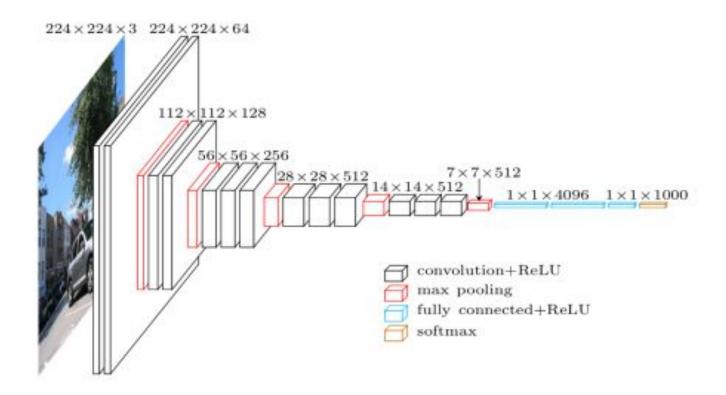
#### AlexNet



# AlexNet

	AlexNet Network - Structural Details												
Input C			utp	out	Layer	Stride	Pad	Kerne	el size	in	out	# of Param	
227	227	3	55	55	96	conv1	4	0	11	11	3	96	34944
55	55	96	27	27	96	maxpool1	2	0	3	3	96	96	0
27	27	96	27	27	256	conv2	1	2	5	5	96	256	614656
27	27	256	13	13	256	maxpool2	2	0	3	3	256	256	0
13	13	256	13	13	384	conv3	1	1	3	3	256	384	885120
13	13	384	13	13	384	conv4	1	1	3	3	384	384	1327488
13	13	384	13	13	256	conv5	1	1	3	3	384	256	884992
13	13	256	6	6	256	maxpool5	2	0	3	3	256	256	0
						fc6			1	1	9216	4096	37752832
	fc7 1 1 4096 4096											16781312	
	fc8 1 1 4096 1000											4097000	
						Total							62,378,344

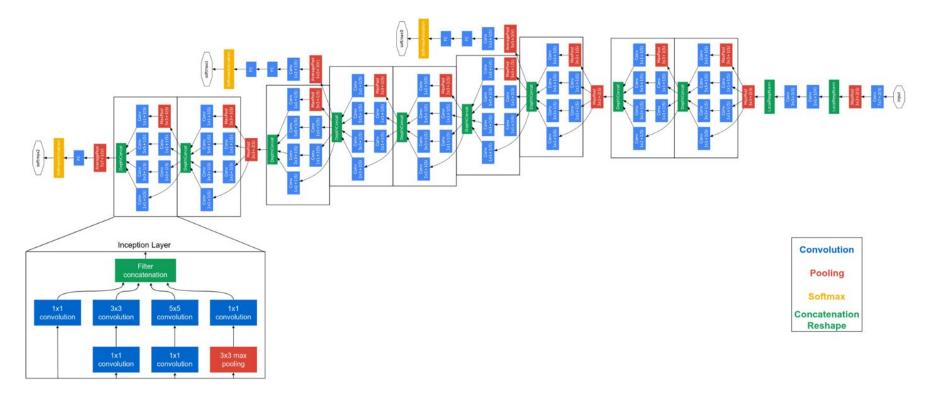
#### **VGGNet**



# **VGGNet**

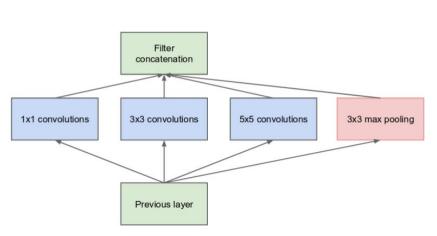
						VG	G16 - Struc	tural De	etails	3			
#	In	put L	mage		outpu	ıt	Layer	Stride	Kernel		in	out	Param
1	224	224	3	224	224	64	conv3-64	1	3	3	3	64	1792
2	224	224	64	224	224	64	conv3064	1	3	3	64	64	36928
	224	224	64	112	112	64	maxpool	2	2	2	64	64	0
3	112	112	64	112	112	128	conv3-128	1	3	3	64	128	73856
4	112	112	128	112	112	128	conv3-128	1	3	3	128	128	147584
	112	112	128	56	56	128	maxpool	2	2	2	128	128	65664
5	56	56	128	56	56	256	conv3-256	1	3	3	128	256	295168
6	56	56	256	56	56	256	conv3-256	1	3	3	256	256	590080
7	56	56	256	56	56	256	conv3-256	1	3	3	256	256	590080
	56	56	256	28	28	256	maxpool	2	2	2	256	256	0
8	28	28	256	28	28	512	conv3-512	1	3	3	256	512	1180160
9	28	28	512	28	28	512	conv3-512	1	3	3	512	512	2359808
10	28	28	512	28	28	512	conv3-512	1	3	3	512	512	2359808
	28	28	512	14	14	512	maxpool	2	2	2	512	512	0
11	14	14	512	14	14	512	conv3-512	1	3	3	512	512	2359808
12	14	14	512	14	14	512	conv3-512	1	3	3	512	512	2359808
13	14	14	512	14	14	512	conv3-512	1	3	3	512	512	2359808
	14	14	512	7	7	512	maxpool	2	2	2	512	512	0
14	1	1	25088	1	1	4096	fc		1	1	25088	4096	102764544
15	1	1	4096	1	1	4096	fc		1	1	4096	4096	16781312
16	1	1	4096	1	1	1000	fc		1	1	4096	1000	4097000
					95 - 55		Total				11-	14 tal	138,423,208

#### GoogLeNet (Inception)

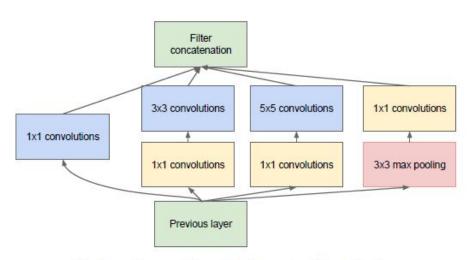


Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A. Going deeper with convolutions. InProceedings of the IEEE conference on computer vision and pattern recognition 2015 (pp. 1-9).

# GoogLeNet (Inception)



(a) Inception module, naïve version

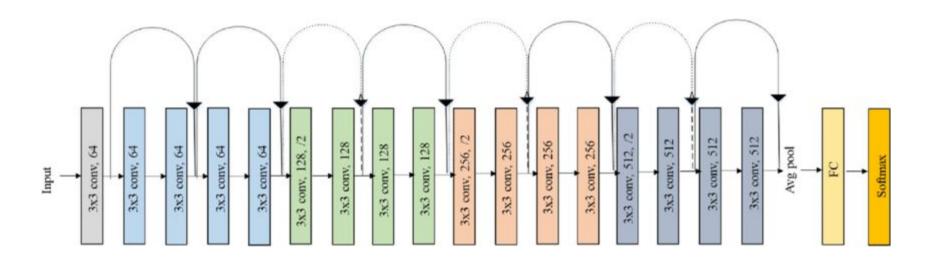


(b) Inception module with dimensionality reduction

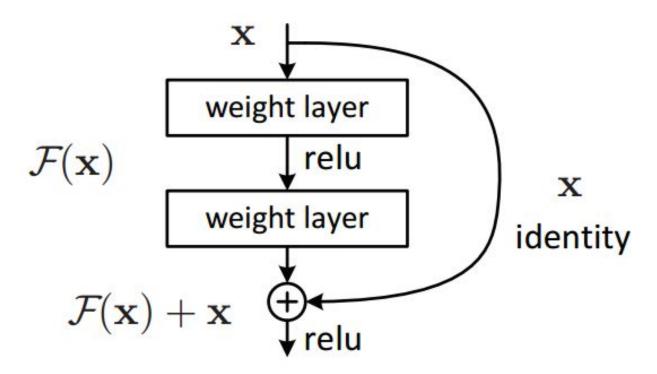
# GoogLeNet (Inception)

	Ten	out To	200		outn		GoogLe	Net - Structura	l Detai	Bad	IV.		le.	L out I	Daram
	227	227	3	112	112	64			2	1	7		3		9472
			64	56	56	64	maxpooll	convl		0.5	3	3	64	64	0
	56	56	64	56	56	64	convlxl	maxpooll	1		1	1	64	64	
				26	26										
	-	_		_							_	-			
								maxpool2							
	28	28			28		mayroola	maxpool2	1						
insention		28					convlxlc	maxpool2	î						12352
(3a)	28	28	96	28	28	128	conv3-3	convlxla	1	1	3	3	96	128	110720
		28	16			32			1	2			16	32	12832
	28	28	192					maxpool-a	1	0	1	1	192	32	6176
		_		28	28	256	depth-concat	constat, constate				$\perp$	_		
	28	28	256	28	28	128	convlxla	denth-concat	1	0	1	1	256	128	32896
	28	28	128	28	28	32	conv1x1b	depth-concat	1	0	1	1	256	32	8224
	28	28			28		maxpool-a	depth-concat	1			3	256		0
	28	28		28	28			depth-concat					256		
(39)							conv5v5	convixia							76896
	28	28		28			convlxld	maxpool-a	î	0	1	ĭ		64	16448
				28	28	480		cognitite cognitit.				П			
		=			_						-				
	28	28	480	14	14	480	maxpool3	depth-concat	2	0.5	3	3	480	480	- 0
	14			14	14	96	convlxla	maxpool3	1	0	1	1	480	96	46176
			480	14	14	16	convlxlb	maxpool3	1	0	1	1	480	16	7696
inception															179920
(40)	14	14	16	14	14	48			1	2	5	5	16	48	19248
	14	14	192	14	14	64	conv1x1d	maxpool-a	1	0	1	1	480	64	30784
		Г		14	14	512	depth-concat				Г	1			
										- 0			***		****
			512	14						0	1	1			
			512	14					1	1				64	1900
Insention	14	14	512	14	14	160	conv1x1c		î	0	1	1	64	160	10400
(4b)	14	14	96	14	14	224	conv3-3	conv1x1a	1	1	3	3	112	224	226016
															38464
	14	14	160					maxpool-a	1	-0	1	1	64	64	4160
	_	_		14	14	512	depth-concat	counted, courlist	_		-	_	_		
	14	14	512	14	14	128	conv1x1a	depth-concat	1	0	1	1	512	128	65664
	14	14	512	14	14	24	conv1x1b	depth-concat	1	0	1	1	64	24	1560
							maxpool-a								
		14		14										228	8320
(4e)		14		14									24		38464
	14	14	128	14	14	64	conv1x1d	maxpool-a	1	0	1	1	64	64	4160
				14	14	512	depth-concat	convisis, convisis,							
										_					
							convixia	depth-concat							
		14	512	14	14				1	1	3		64		0
inception	14	14	512	14	14	112			1	0	1	1	64	112	7280
(4d)									1						373536
		14				64	conv5x5	conv1x1b	1	2	5	5			
	14	14	112							U	1	·	04	04	4100
	-	-		14	14	528	depth-concat	constat, constatd	_		-	Н	_	$\vdash$	
	14	14	528	14	14	160	convlxla	depth-concat	1	0	1	1	528	160	84640
			528					depth-concat	1			1			2080
							maxpool-a	depth-concat							
	14	14		14	14	320	convixio	convlyla	1	1	3	3	160		461120
(40)	14	14	16	14	14	128	conv5x5	convlxlb	1	2	5	5	32	128	102528
	14	14	256	14	14	128	convlxld	maxpool-a	1	0	1	1	64	128	8320
	L	L		14	14	832	depth-concat	countrie, countrie, countrie, countrie			L	L	_	$\Box$	
	17	14	833	7	7	832	maynoo <sup>2,4</sup>	denth-concer	2	0.5	3	3	832	832	- 0
_	14	114			_				_		_	_			
	7	7	832	7	7		convlxla		1		1	1	832		133280
	7	7			7	32			1						26656
insent?	7	7	832	7	7	256			1	0		1	832		213248
	7	7	96	7	7	320	conv3-3		î	î				320	461120
	7	7	16	7	7	128	conv5x5	convlxlb	1		5	5	32	128	102528
	7	7	256	7	7			maxpool-a	1	0	1	1	832	128	106624
			_	7	7	832	depth-concat	convicte, convict, convicts, convicte	_			$\vdash$	_	$\sqcup$	
	7	7	832	7	7	192	conv1x1=	depth-concat	1	0	1	1	832	192	159936
	7	7	832	7	7	48	conv1x1b	depth-concat	1	-0	1	1	832	48	39984
	7	7	832	7	7	832	maxpool-a	depth-concat	1	1	3	3	832	832	0
inception			832	7	7	384							832	384	319872
(5b)	7	7	96	7	7	384					3	3		384	663936
	7				7				1	0					16512
	r.	1	364						1	,	1	1	140	And I	10010
		-	_	-	_	-			_	_	-	-	_	$\vdash$	
	7	7	1024	1	1			depth-concat	1	0	7	7	1024	1024	0
	1	1	1024	1	1	11000	fc fc	depth-concat	Tota'	0	1	1	1024	1000	1025000
	_	_	_	_	_	_			Total	_	_	_	_	_	0,414,360
1,000   1,00															

#### ResNet



#### ResNet

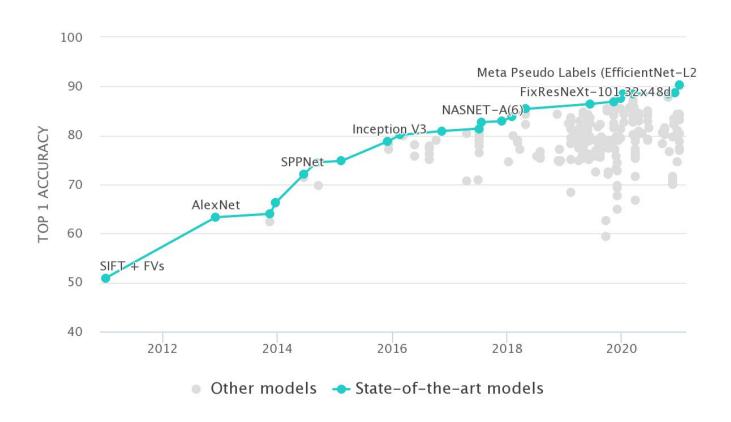


He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. InProceedings of the IEEE conference on computer vision and pattern recognition 2016 (pp. 770-778).

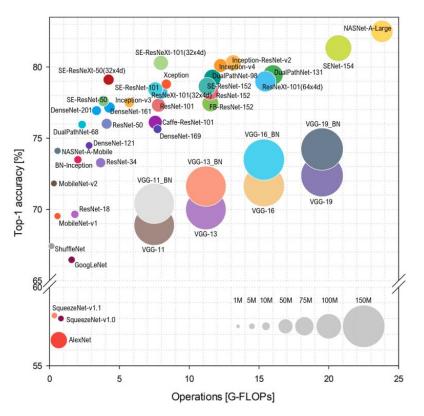
#### ResNet

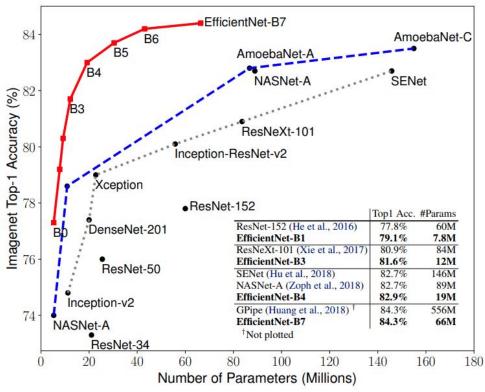
						R	esNet18 - S	Structur	al Deta	ails				
#	# Input Image				outp	ut	Layer	Stride	Pad	Kernel		in	out	Param
1			112	112	64	conv1	2	1	7	7	3	64	9472	
04	112	112	64	56	56	64	maxpool	2	0.5	3	3	64	64	0
2	56	56	64	56	56	64	conv2-1	1	1	3	3	64	64	36928
3	56	56	64	56	56	64	conv2-2	1	1	3	3	64	64	36928
4	56	56	64	56	56	64	conv2-3	1	1	3	3	64	64	36928
5	56	56	64	56	56	64	conv2-4	1	1	3	3	64	64	36928
6	56	56	64	28	28	128	conv3-1	2	0.5	3	3	64	128	73856
7	28	28	128	28	28	128	conv3-2	1	1	3	3	128	128	147584
8	28	28	128	28	28	128	conv3-3	1	1	3	3	128	128	147584
9	28	28	128	28	28	128	conv3-4	1	1	3	3	128	128	147584
10	28	28	128	14	14	256	conv4-1	2	0.5	3	3	128	256	295168
11	14	14	256	14	14	256	conv4-2	1	1	3	3	256	256	590080
12	14	14	256	14	14	256	conv4-3	1	1	3	3	256	256	590080
13	14	14	256	14	14	256	conv4-4	1	1	3	3	256	256	590080
14	14	14	256	7	7	512	conv5-1	2	0.5	3	3	256	512	1180160
15	7	7	512	7	7	512	conv5-2	1	1	3	3	512	512	2359808
16	7	7	512	7	7	512	conv5-3	1	1	3	3	512	512	2359808
17	7	7	512	7	7	512	conv5-4	1	1	3	3	512	512	2359808
	7	7	512	1	1	512	avg pool	7	0	7	7	512	512	0
18	1	1	512	1	1	1000	fc					512	1000	513000
2	3 - 1			0 0			Total		<u> </u>	5 5		-		11,511,784

#### ConvNets Benchmarks

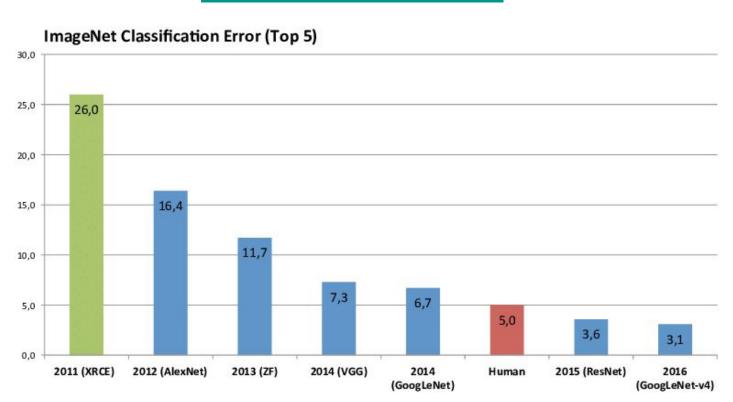


#### ConvNets Benchmarks





# ConvNets <u>Benchmarks</u>



Russakovsky O, Deng J, Su H, Krause J, Satheesh S, Ma S, Huang Z, Karpathy A, Khosla A, Bernstein M, Berg AC. Imagenet large scale visual recognition challenge. International journal of computer vision. 2015 Dec;115(3):211-52.

# ConvNets Implementation

- Models and pre-trained weights
- <u>Transfer Learning</u> Tutorial

