

Convolutional Neural Networks and Natural Language Processing

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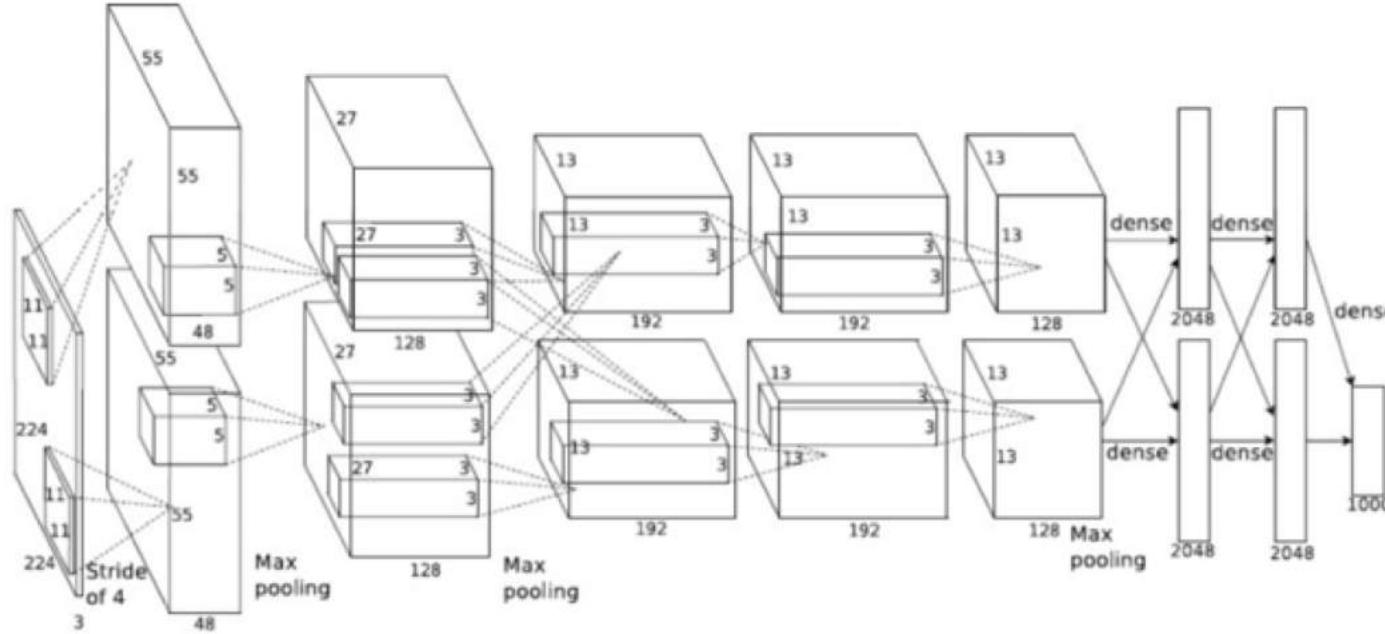
Goals

- Explain what convolutions are
- Show how to handle textual data
- Analyze a reference neural network architecture for text classification
- Demonstrate how to train and deploy a CNN for Natural Language Processing

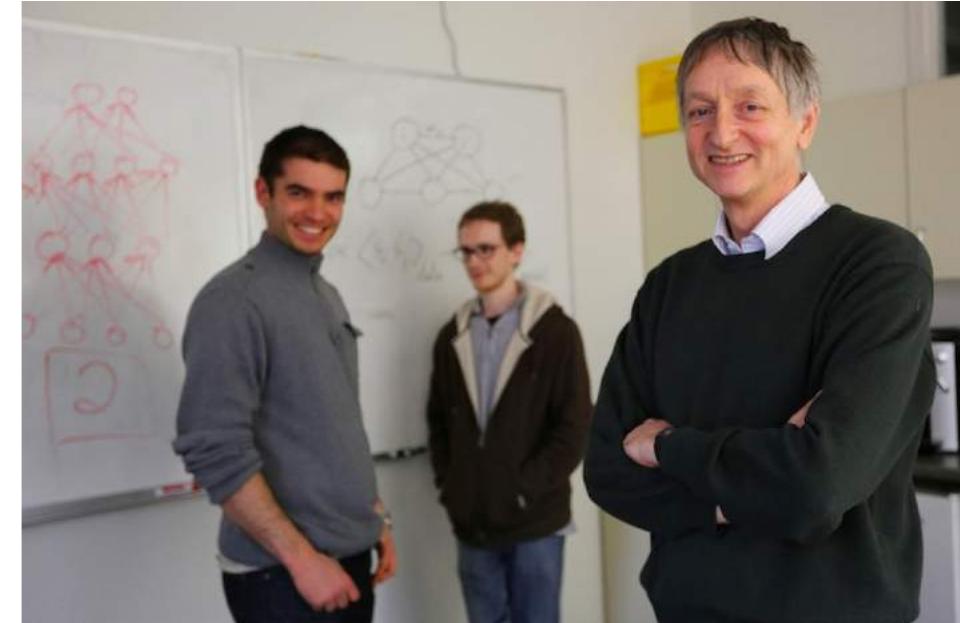
Convolutions

And where to find them

2012 - ImageNet Classification with Deep Convolutional Neural Networks



AlexNet architecture



[ImageNet classification with Deep Convolutional Neural Networks](#), Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, *Advances in neural information processing systems*, 2012

ImageNet competition



Classify images among 1000 classes:
AlexNet Top-5 error-rate, 25% => 16%!

Actual photo of the reaction from the computer vision community*



*might just be a stock photo

A photograph of a man with dark hair and glasses, wearing a grey shirt, speaking into a black microphone. A white speech bubble originates from his mouth, containing the text "I told you so!" in a bold, black, sans-serif font.

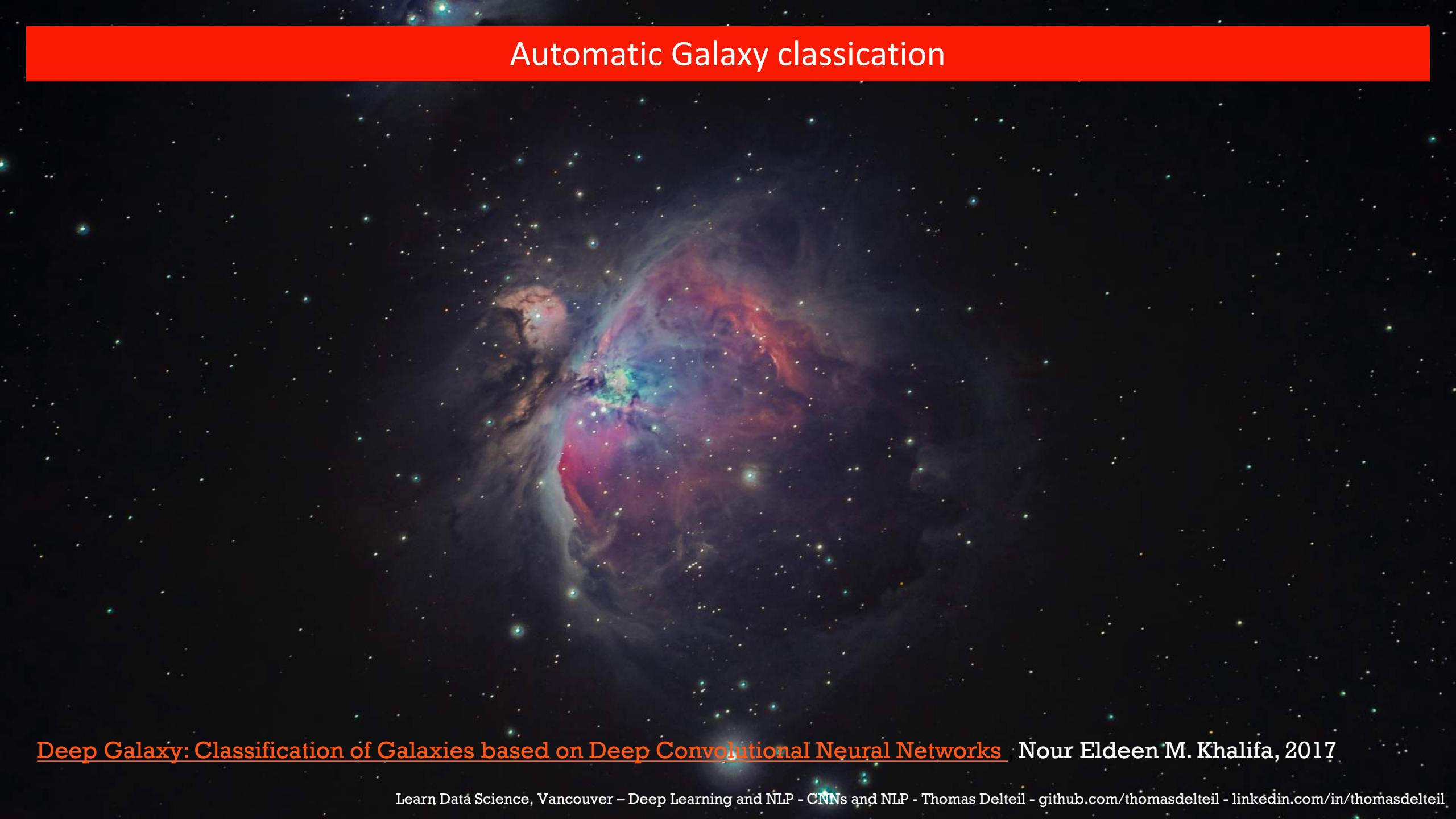
I told you
so!

Sea/Land segmentation via satellite images



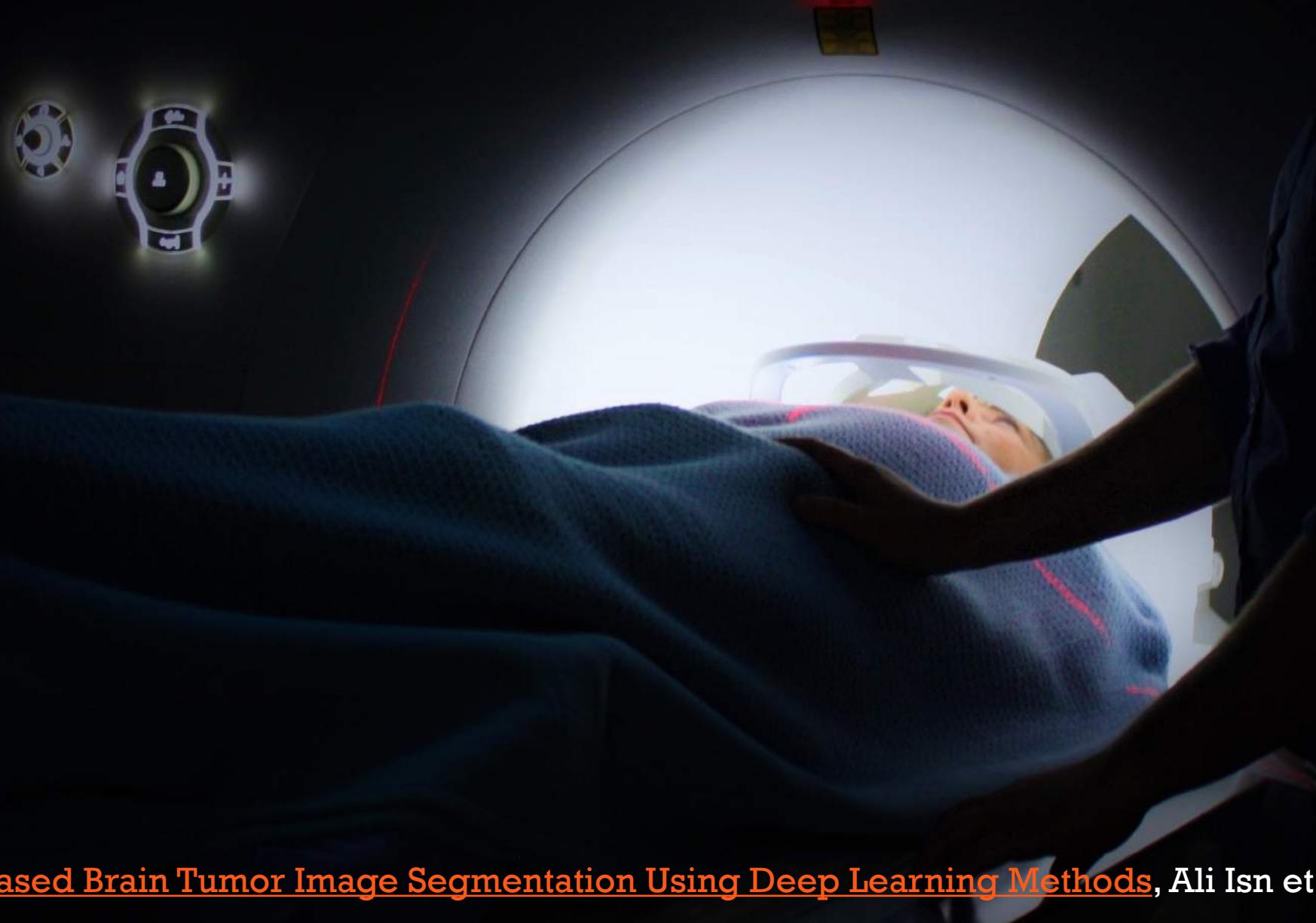
[DeepUNet: A Deep Fully Convolutional Network for Pixel-level Sea-Land Segmentation](#), Ruirui Li et al, 2017

Automatic Galaxy classification



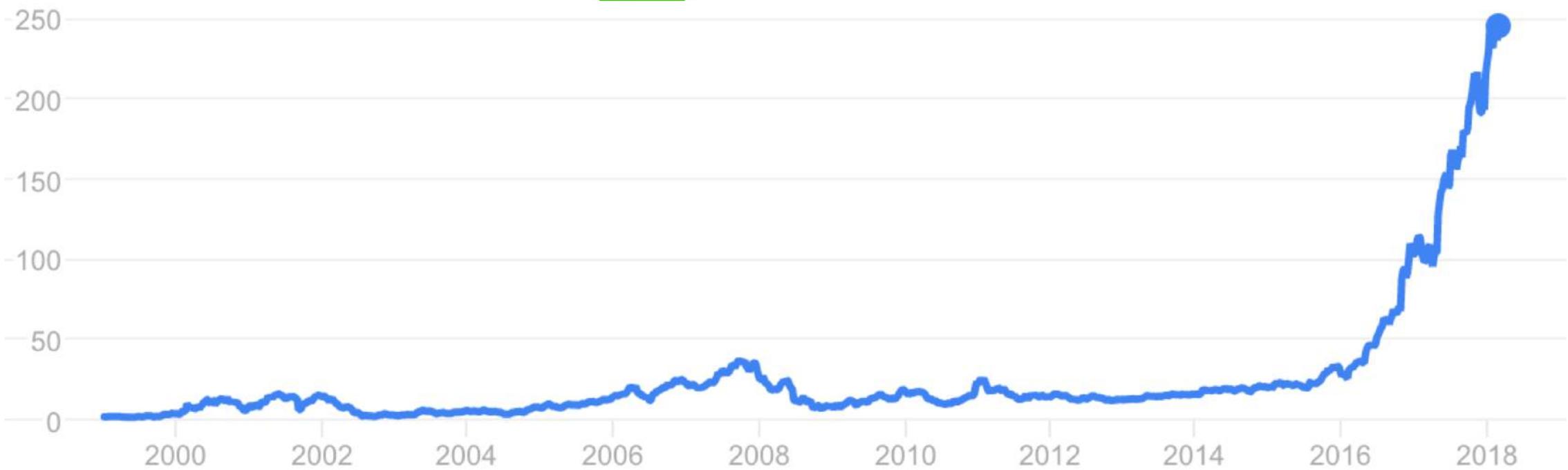
[Deep Galaxy: Classification of Galaxies based on Deep Convolutional Neural Networks](#), Nour Eldeen M. Khalifa, 2017

Medical Imaging, MRI, X-ray, surgical cameras



[Review of MRI-based Brain Tumor Image Segmentation Using Deep Learning Methods](#), Ali Isn et al. 2016

What made Convolutional Neural Networks viable?

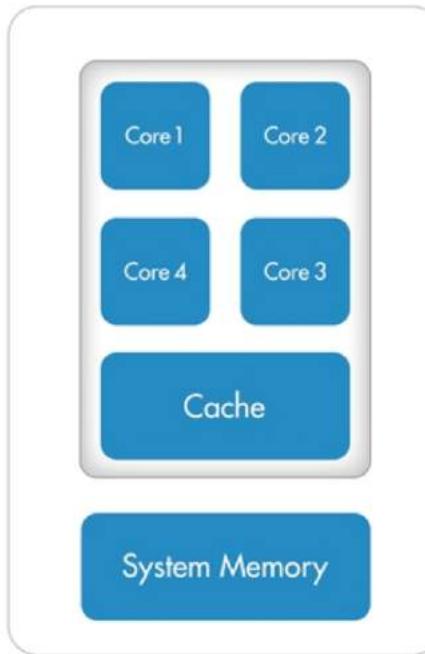


GPUs!

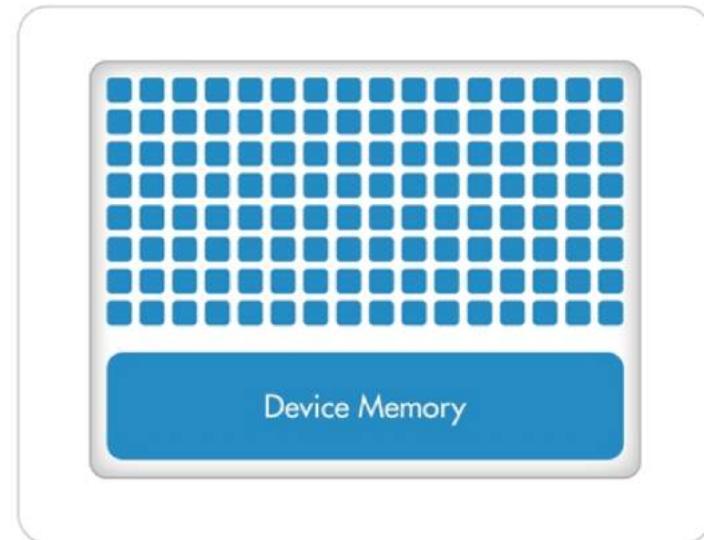


Nvidia V100, float16 Ops:
~ 120 TFLOPS, 5000+ cuda cores
(#1 Super computer 2005 135 TFLOPS)

CPU (Multiple Cores)



GPU (Hundreds of Cores)



Source: Mathworks

What is a convolution ?

It is the **cross-channel sum** of the **element-wise multiplication** of a convolutional filter (kernel/mask) computed over a sliding window on an input tensor given a certain stride and padding, **plus a bias term**. The result is called a feature map.

$$\begin{aligned} 1*2 - 1*2 - 1*3 + 0*1 + 2 &= -1 \\ 1*2 - 1*2 - 1*1 + 0*-1 + 2 &= 2 \\ 1*3 - 1*1 - 1*4 + 0*3 + 2 &= 0 \\ 1*1 - (-1)*1 - 1*3 + 0*2 + 2 &= 1 \end{aligned}$$

2	2	1
3	1	-1
4	3	2

Input matrix (3x3)
no padding
1 channel

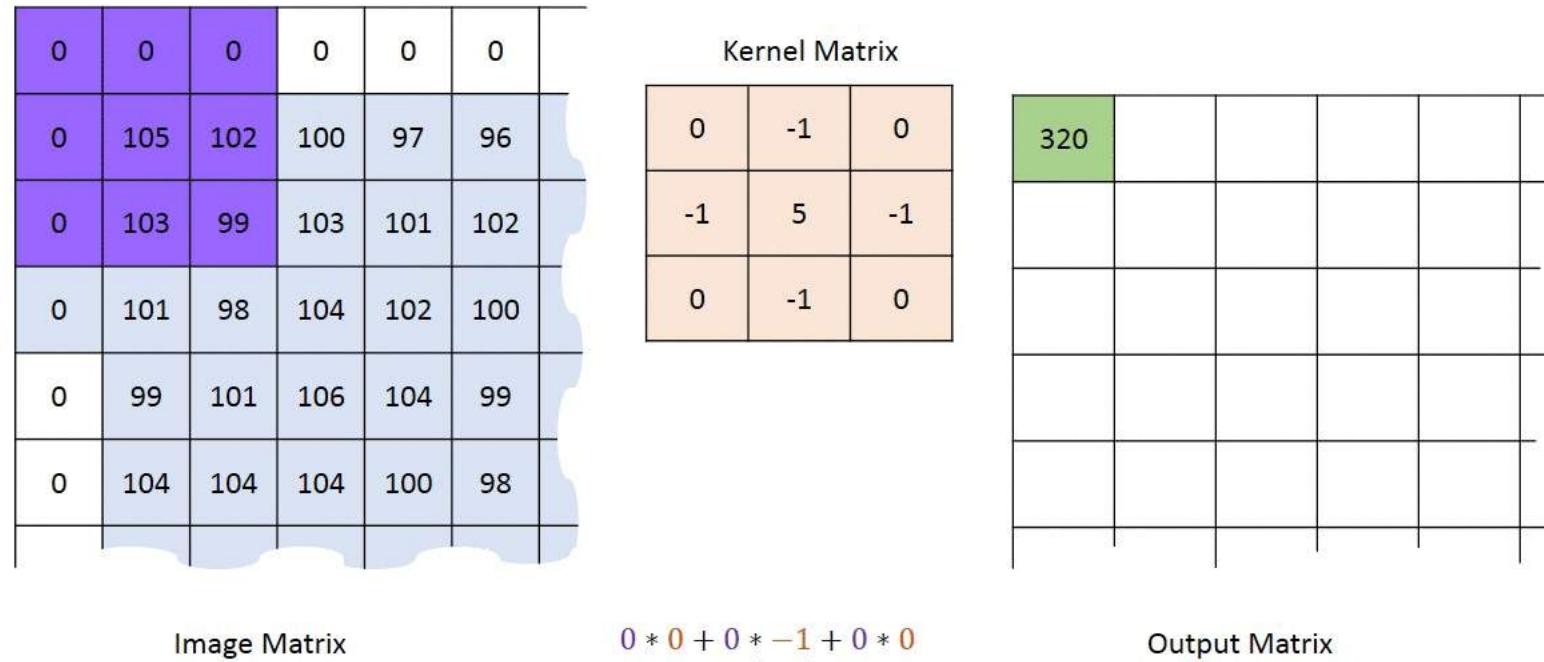
1	-1
-1	0

Kernel (2x2)
Stride 1
Bias = 2

-1	2
0	1

Feature map (2x2)

What is a convolution ? Padding



Convolution with horizontal and vertical strides = 1

Source: [Machine Learning guru - Neural Networks CNN](#)

What is a convolution ? Stride = 2

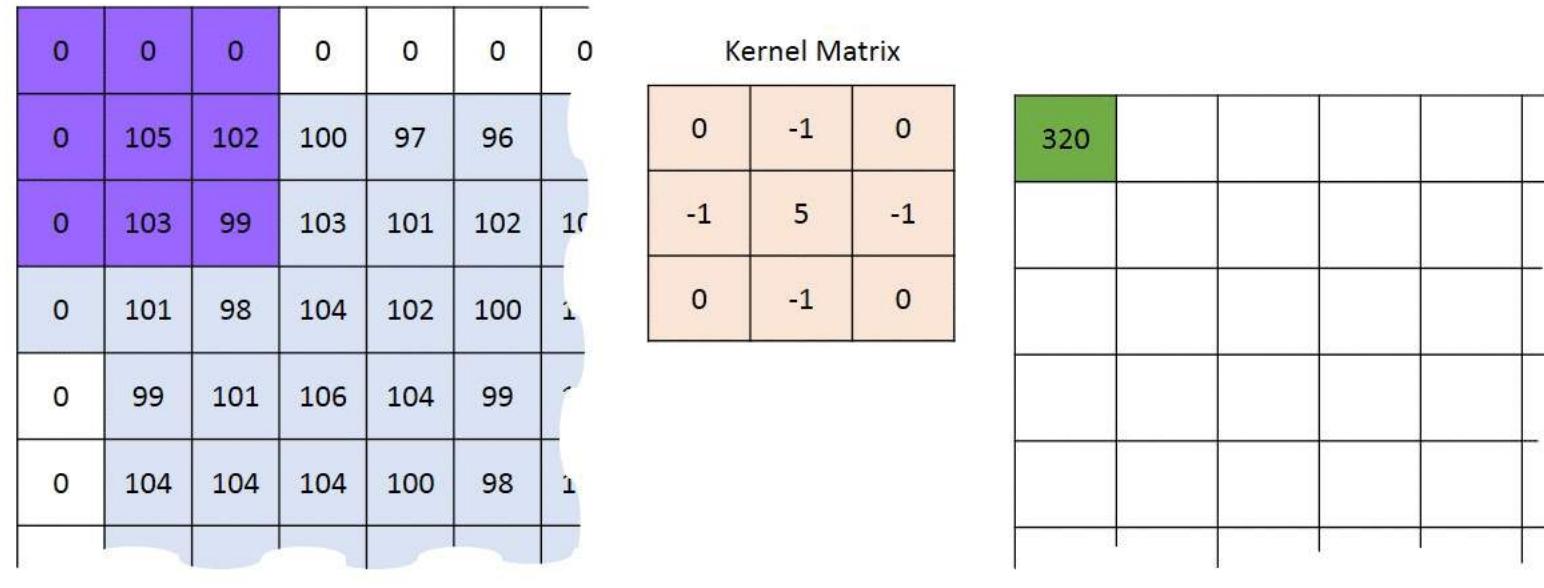


Image Matrix

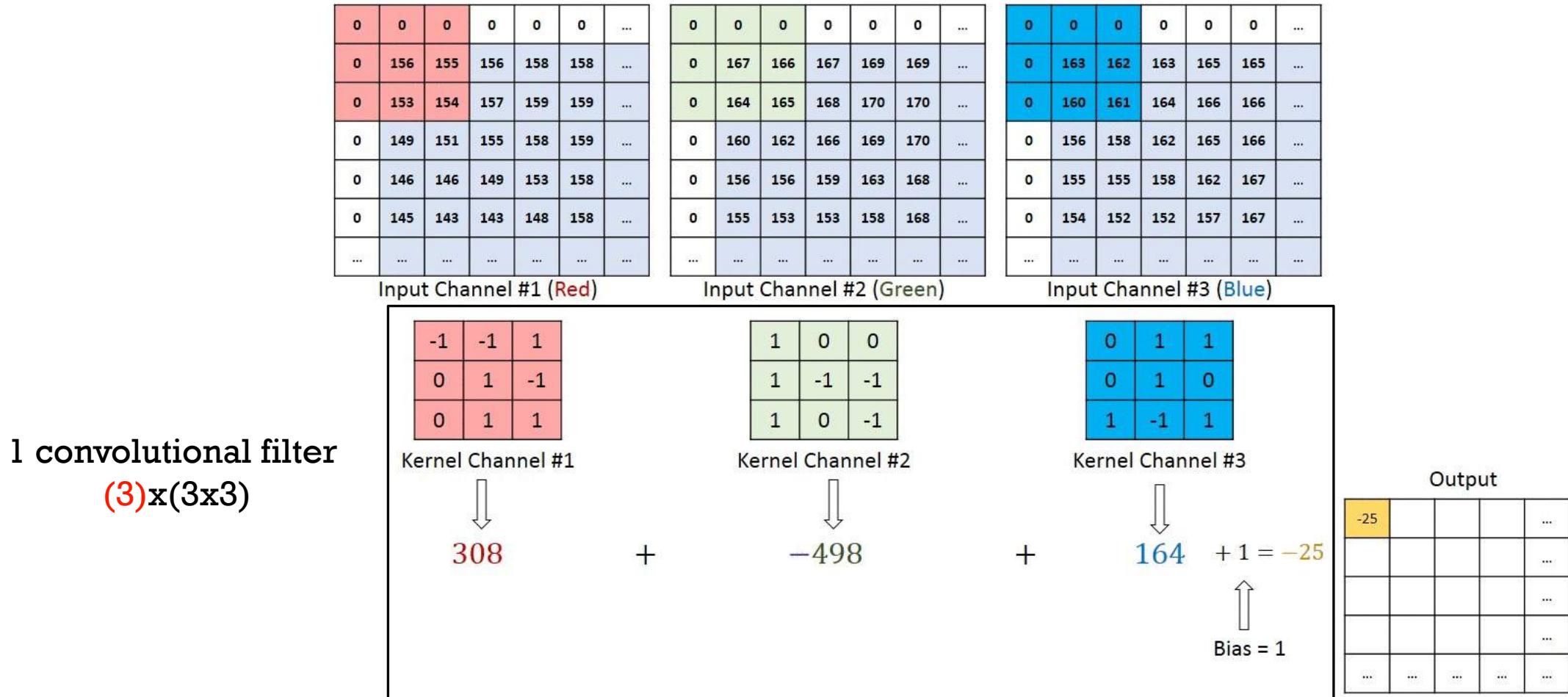
$$\begin{aligned} & 0 * 0 + 0 * -1 + 0 * 0 \\ & + 0 * -1 + 105 * 5 + 102 * -1 \\ & + 0 * 0 + 103 * -1 + 99 * 0 = 320 \end{aligned}$$

Output Matrix

Convolution with horizontal and vertical strides = 2

Source: [Machine Learning guru - Neural Networks CNN](#)

What is a convolution ? Multi Channel



Source: [Machine Learning guru - Neural Networks CNN](#)

What is a convolution ? Multi Channel

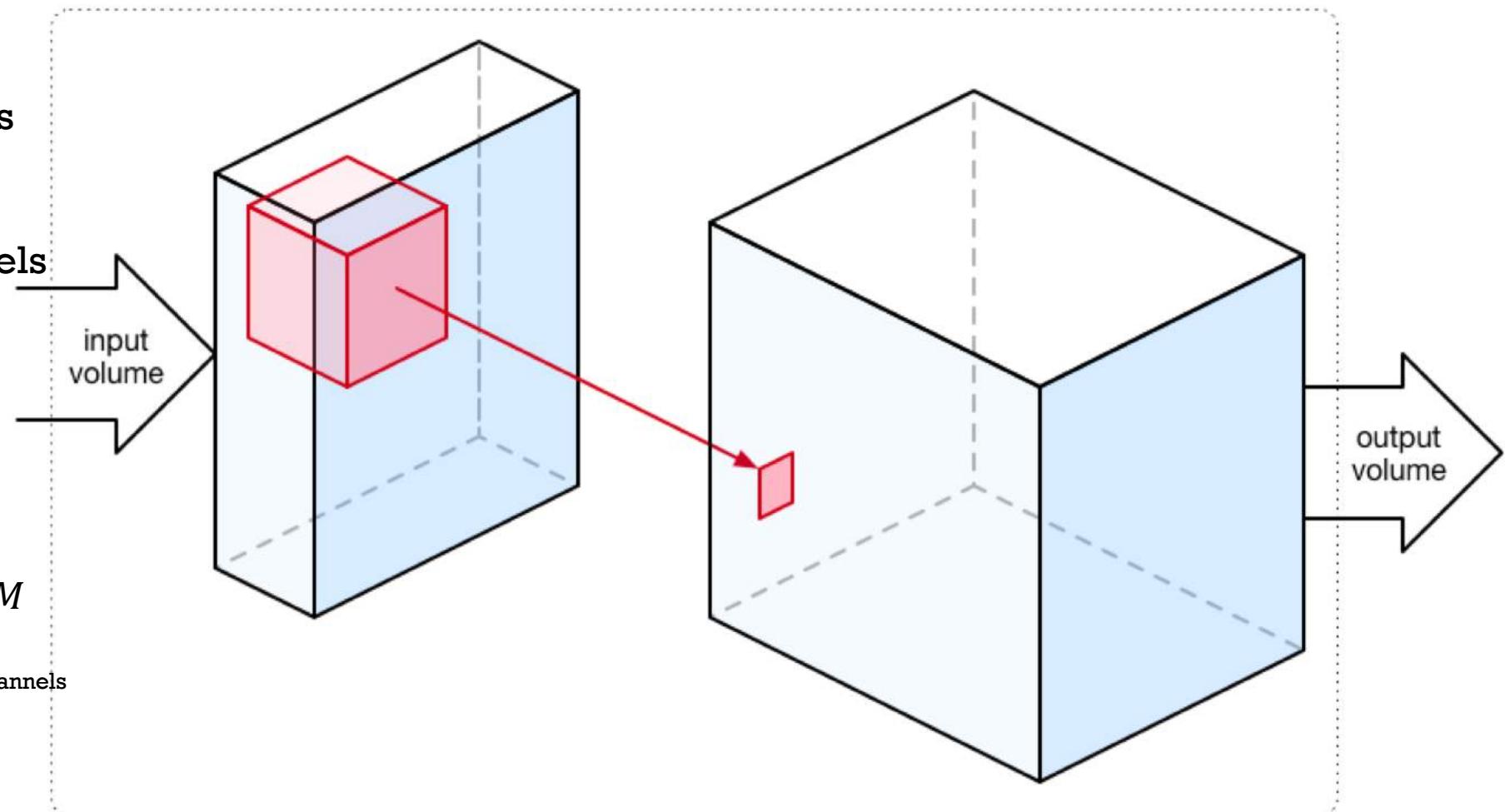
N: Number of input channels
W: Width of the kernel
H: Height of the kernel
M: Number of output channels

$$\text{Kernel size} = N * W * H$$

$$\#\text{Params} = M * N * W * H + M$$

256 convolutions of kernel (3,3) on 256 input channels

$$256 * 256 * 3 * 3 = \mathbf{\sim 0.5M}$$

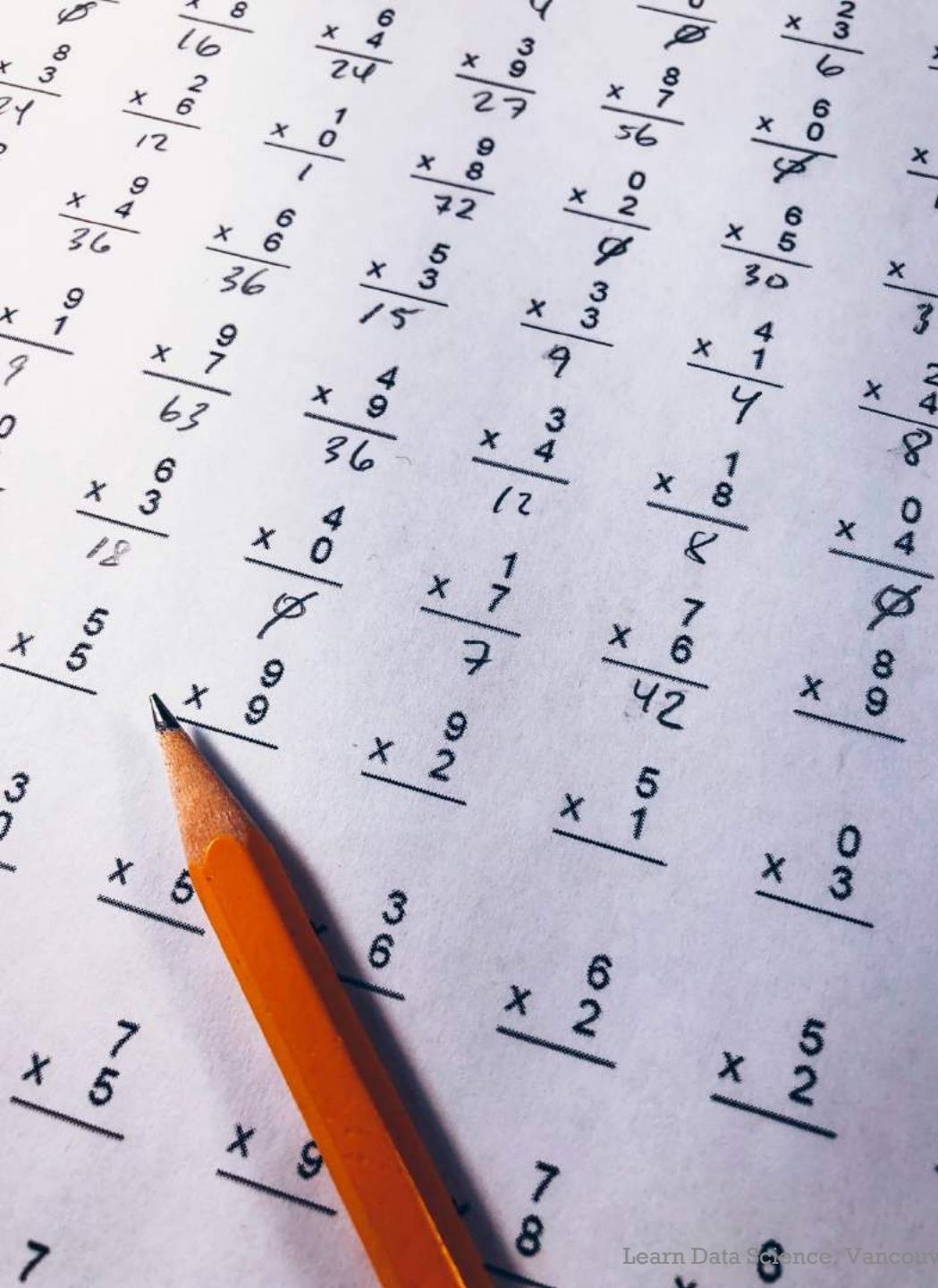


[source: Convolutional Neural Networks on the iphone with vggnet](#)

Easily parallelizable

Convolutions computations are:

- Independent (across filters and within filter)
- Simple (multiplication and sums)



Why does it work?

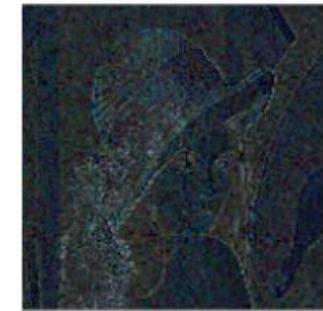
Sharpening filter

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



Laplacian filter

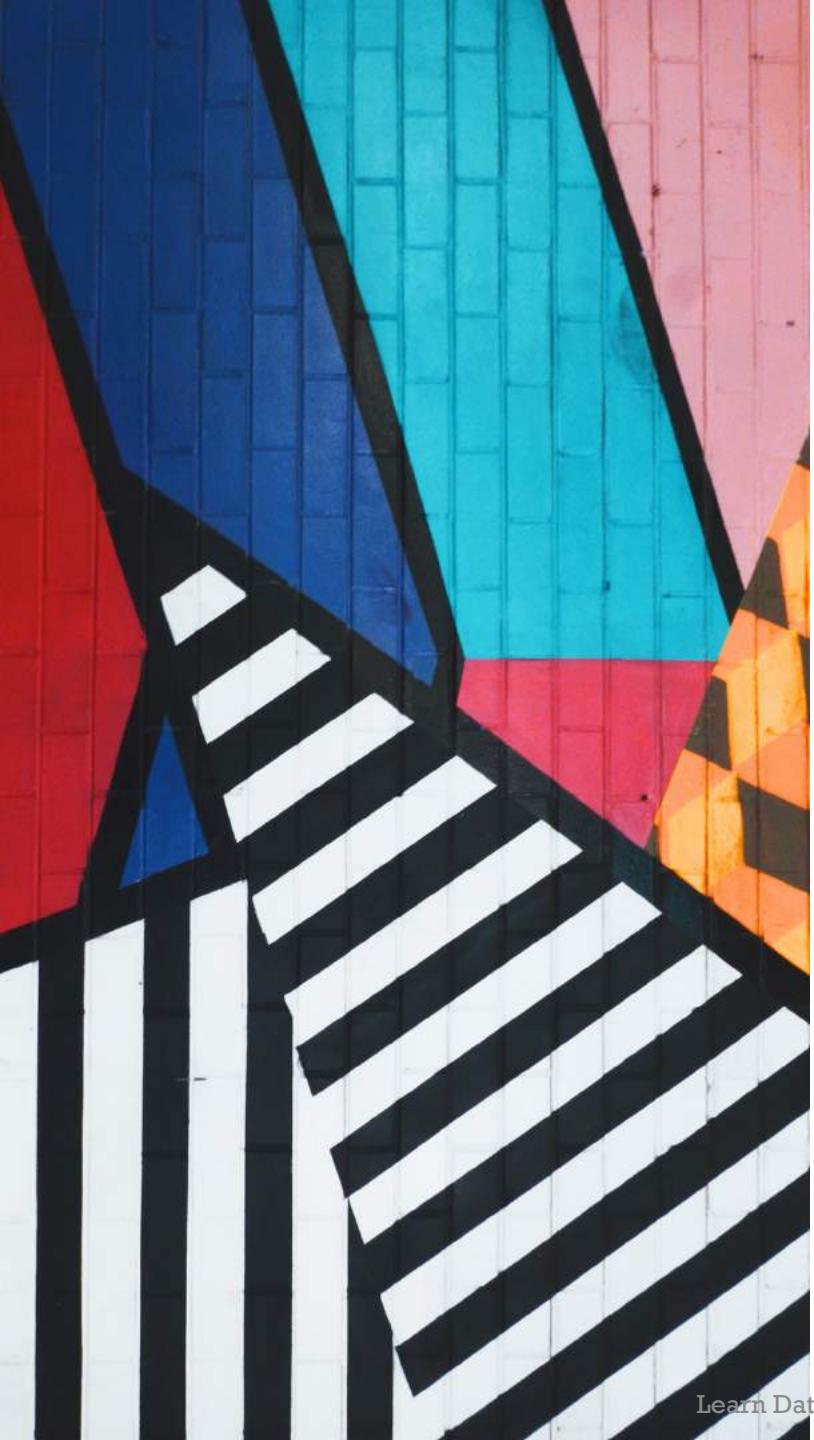
$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$



Sobel x-axis filter

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$





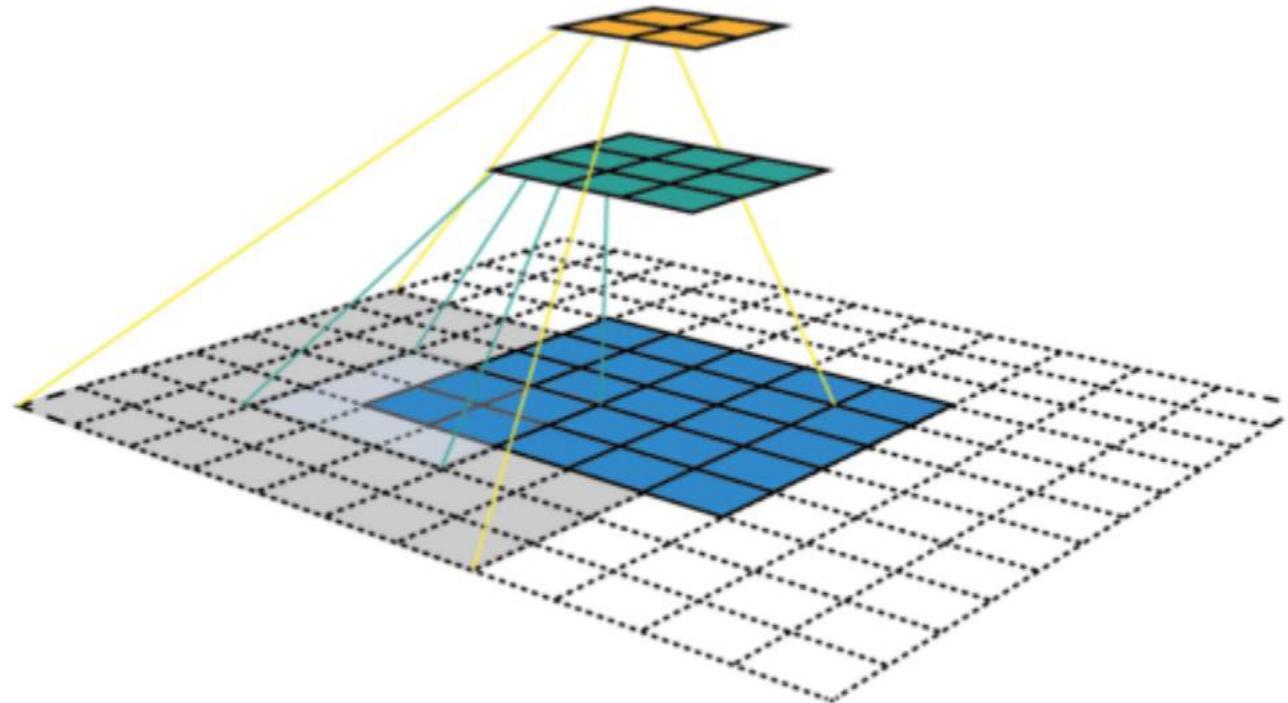
Why does it work?

- Detect patterns at larger and larger scale by stacking convolution layers on top of each others to grow the receptive field
- Applicable to spatially correlated data



Source: AlexNet first 96 filters learned represented in RGB space

Growing receptive field



[Source: ML Review, A guide to receptive field arithmetic](#)

Draw your number here

0123456789

Visualize convolutions



Downsampled drawing:

First guess:

Second guess:

Layer visibility

Input layer

Show

Convolution layer 1

Show

Downsampling layer 1

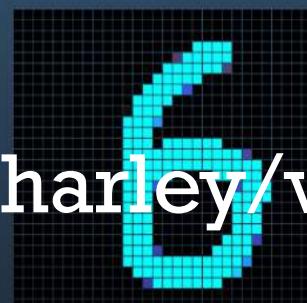
Show

Convolution layer 2

Show

Downsampling layer 2

Show



<http://scs.ryerson.ca/~aharley/vis/conv/flat.html>

Visualize convolutions

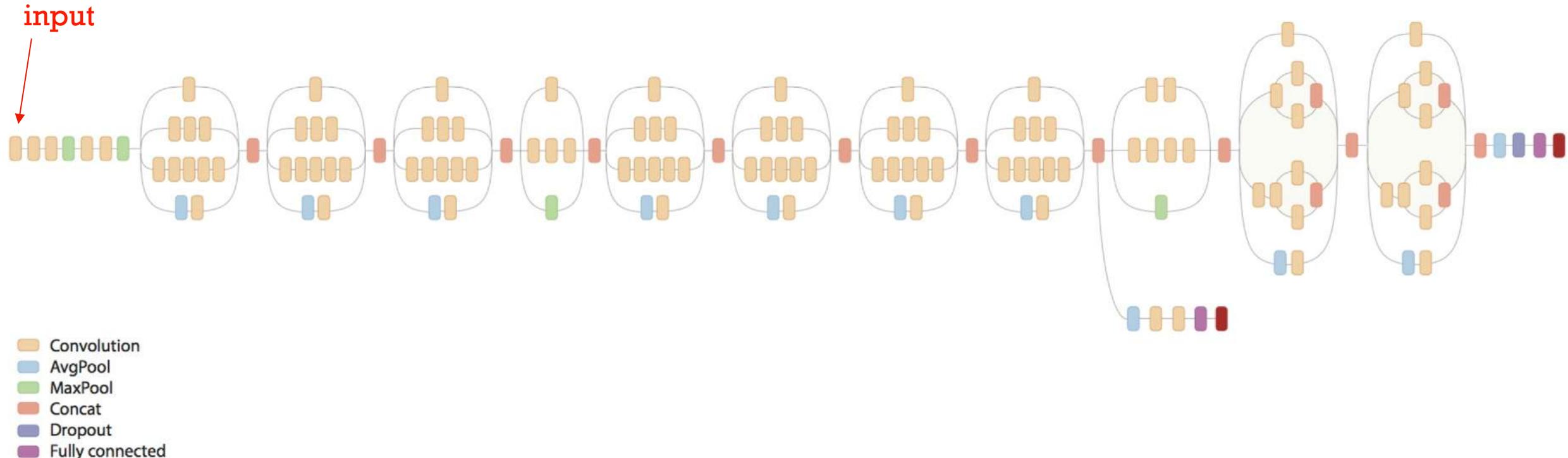
Data Set: MNIST
Hidden Neurons: 19794
Synapses: 3610000
Synapses shown: 2%
Learning: BP

Epilepsy warning



Source: Neural Network 3D Simulation

State of the art networks combines a lot of different elements

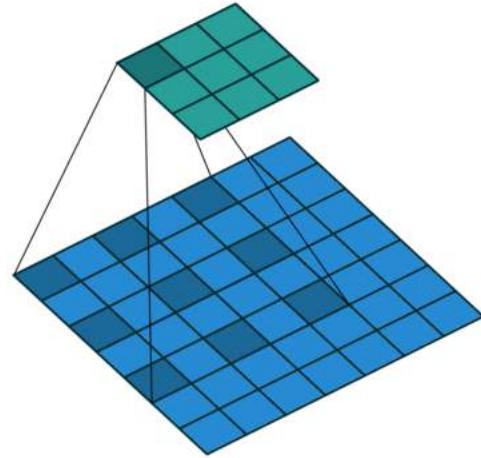


Source: Inception v3

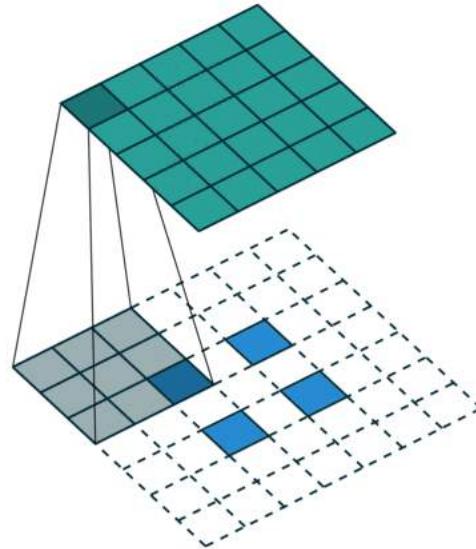
High number of parameters => Requires a lot of data to train



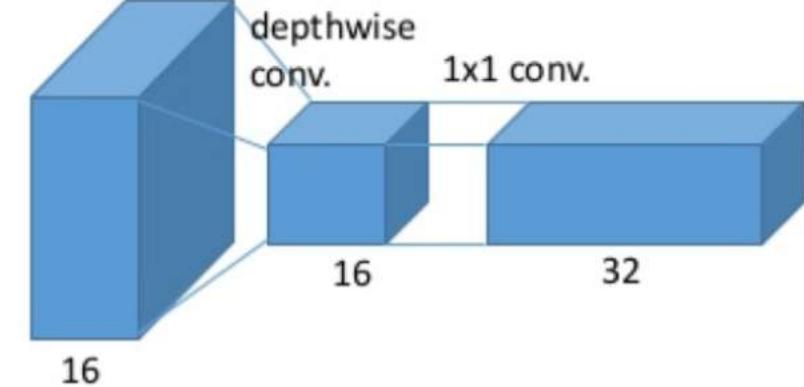
Advanced type of convolutions



Dilated Convolutions
WaveNet



**Transposed Convolutions
(deconvolution)**
EnhanceNet

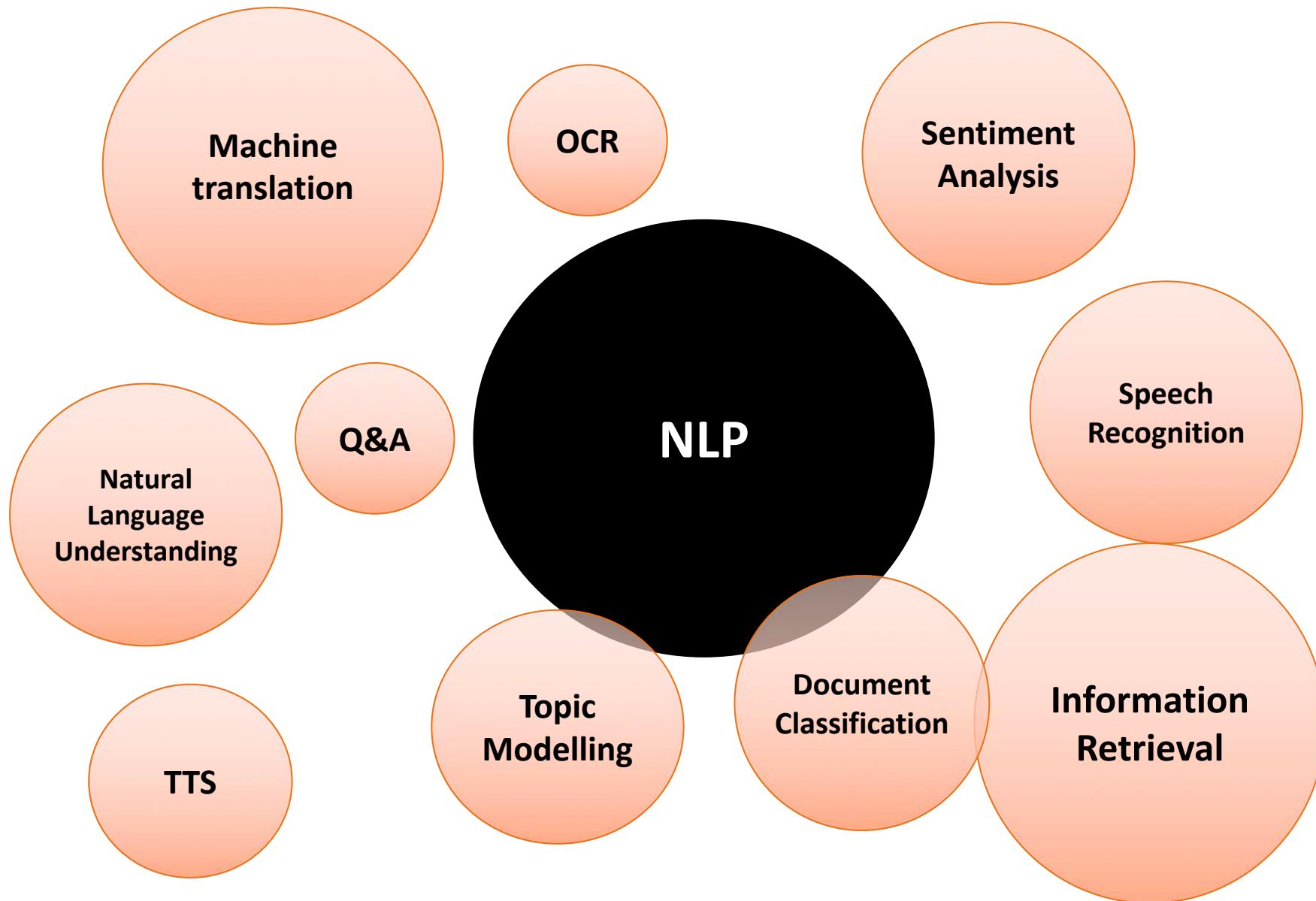


**Depth-wise separable
Convolutions**
MobileNet

[Source: An introduction to different types of convolutions](#)

On to Natural Language Processing

NLP Domains



NLP Industry Facts

£1.3T

value of company data

source: IDC, 2014

10%

of organizations expect to commercialise their data by 2020

source: Gartner, 2016



8.4 PB

of information per second as of 2020

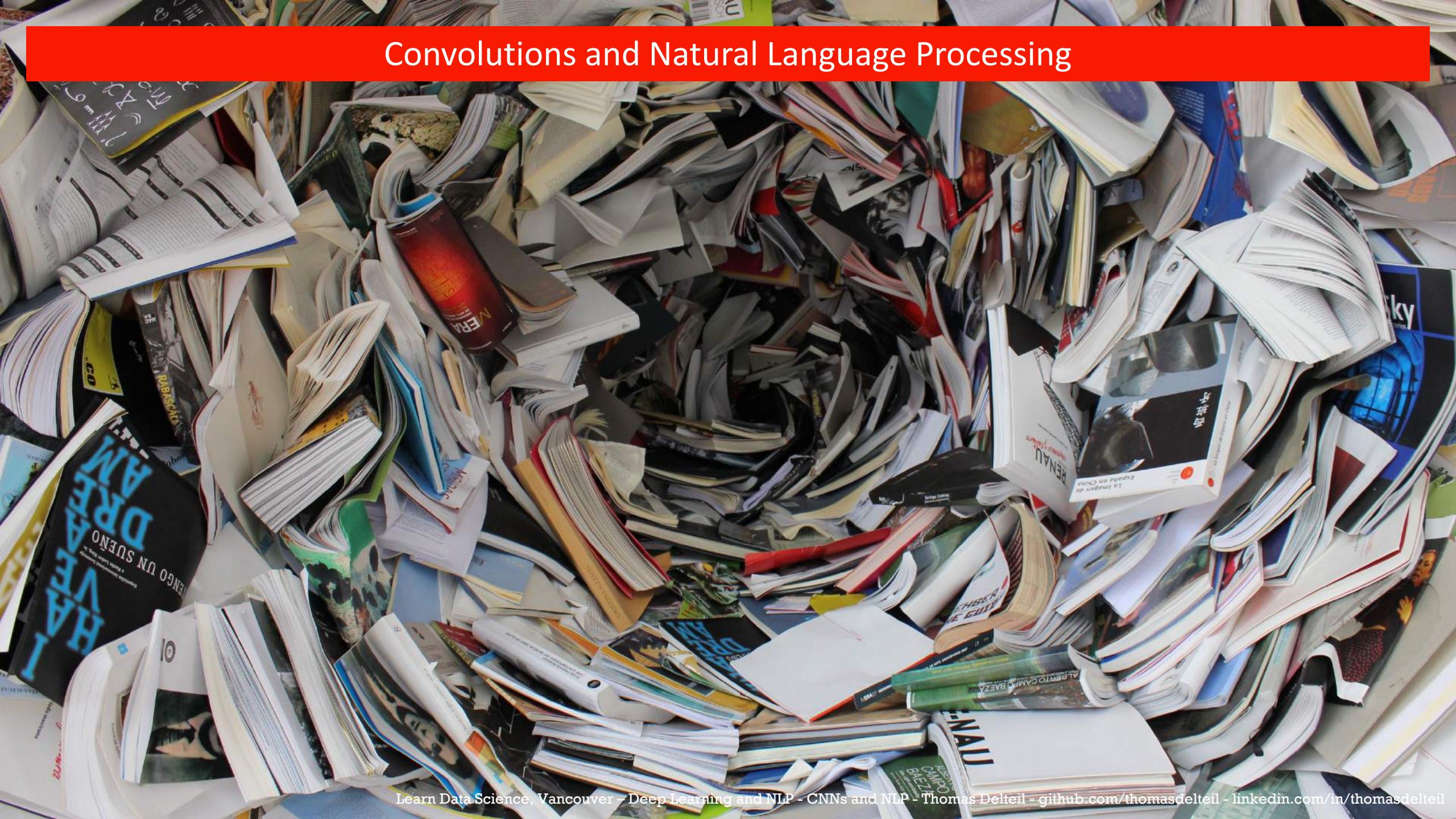
source: business2community, 2016

70%

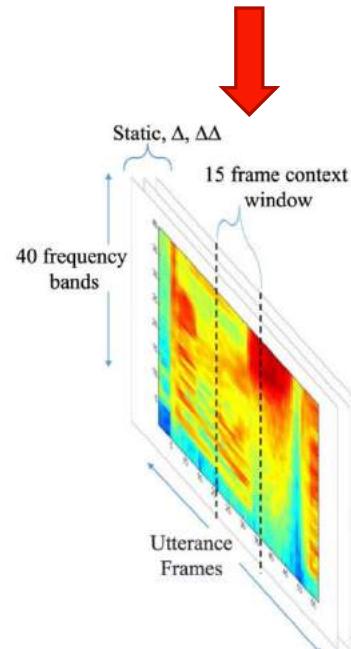
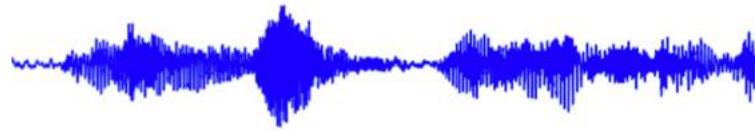
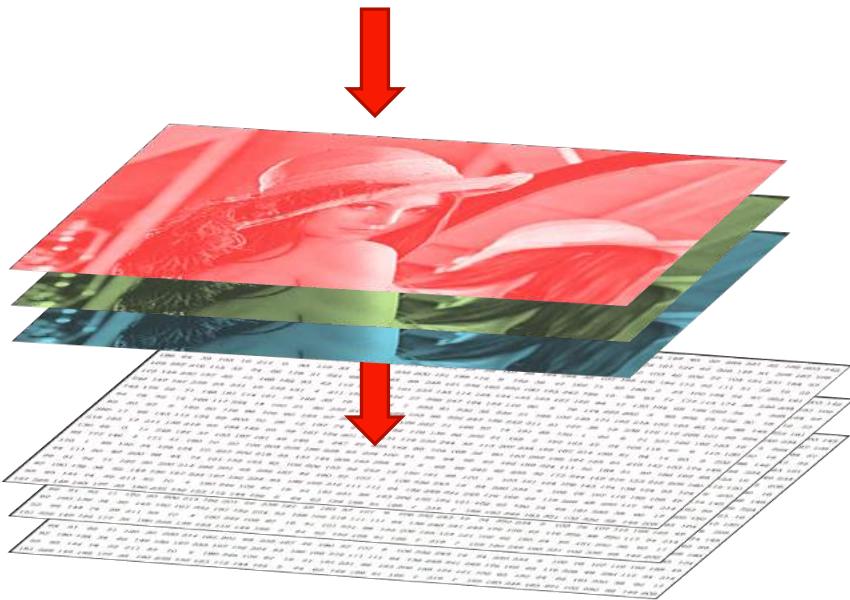
of companies use customer feedback

Source: business2community, 2016

Convolutions and Natural Language Processing



Data Representation



When I read some of the rules
for speaking the English language
correctly, I think any fool can
make a rule, and every fool will
mind it

Henry David Thoreau



source: Ossama Abdel-Hamid, Abdel-rahman Mohamed, Hui Jiang, Li Deng, Gerald Penn, and Dong Yu., Classification Convolutional Neural Networks for Speech Recognition, IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2014

Encoding Data word-level

- Word-level embedding (word2vec)

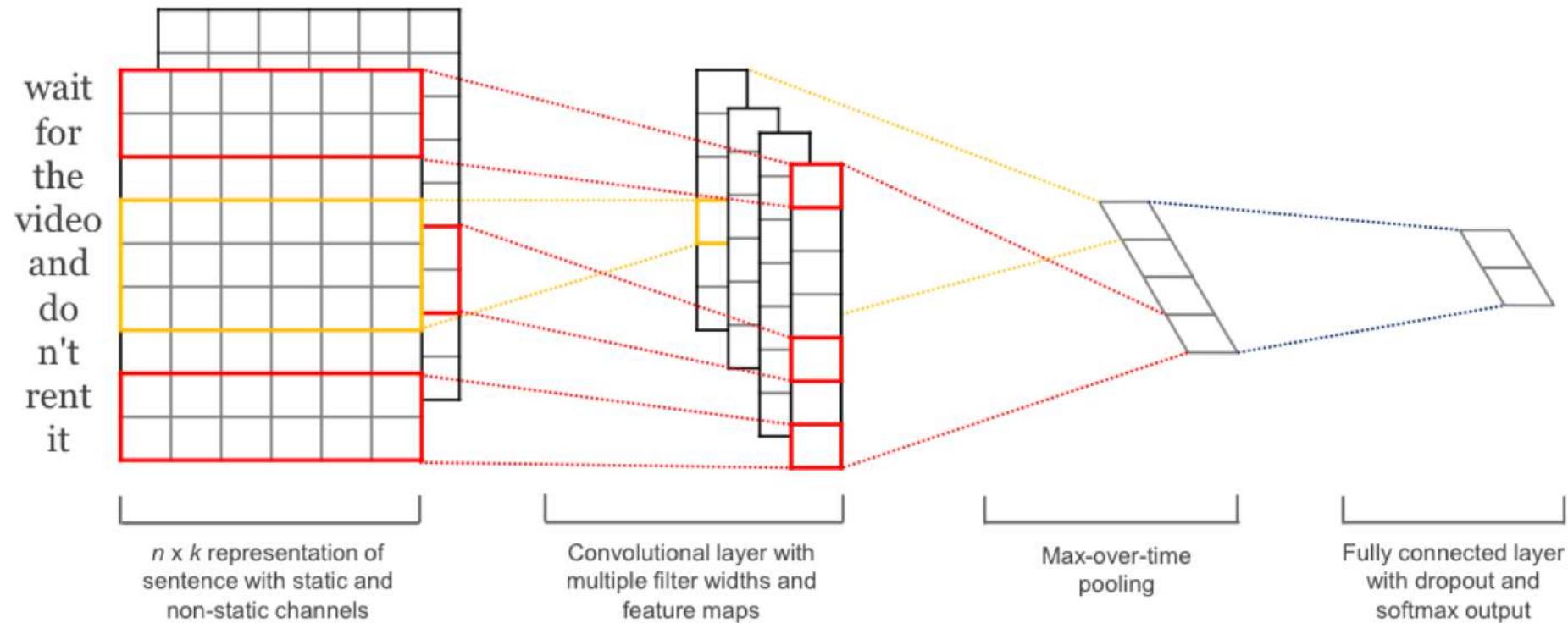
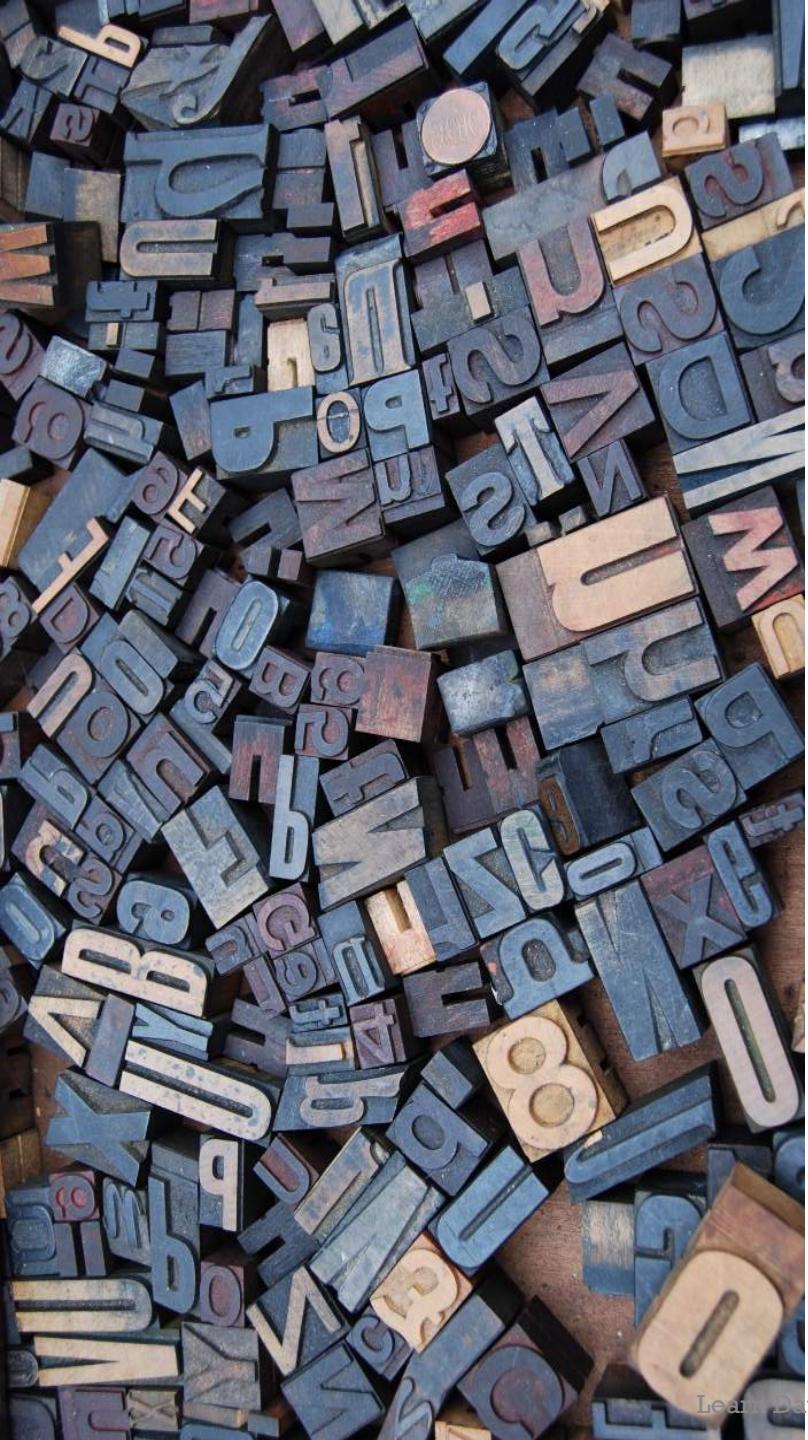


Figure 1: Model architecture with two channels for an example sentence.

Source: [Convolutional Neural Networks for Sentence Classification](#), Yoon Kim, 2014



Encoding Data – Character-level

- One-hot encoding
- Alphabet
- Sparse representation
- Character embedding

	V	A	N	C	O	U	V	E	R	N	L	P	...
-	0	0	0	0	0	0	0	0	0	1	0	0	0
.	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	1	0	0	0	0	0	0	0	0	0	0	0
B	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	0	1	0	0	0	0	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	0	0	0	1	0	0	0	0	0	0
F	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	0	0	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	0	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	1	0	0
M	0	0	0	0	0	0	0	0	0	0	0	0	0
N	0	0	1	0	0	0	0	0	0	0	1	0	0
O	0	0	0	0	1	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	0	0	0	0	0	0	1
Q	0	0	0	0	0	0	0	0	0	0	0	0	0
R	0	0	0	0	0	0	0	1	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	0	1	0	0	0	0	0	0	0
V	1	0	0	0	0	0	1	0	0	0	0	0	0
W	0	0	0	0	0	0	0	0	0	0	0	0	0
X	0	0	0	0	0	0	0	0	0	0	0	0	0
Y	0	0	0	0	0	0	0	0	0	0	0	0	0
Z	0	0	0	0	0	0	0	0	0	0	0	0	0

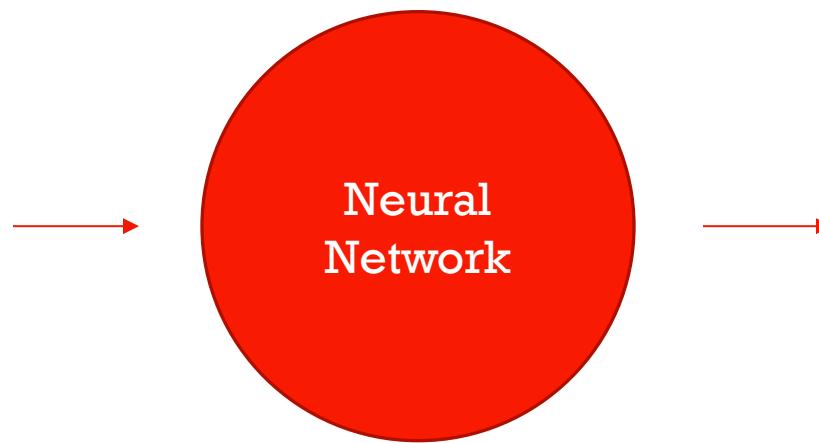
Text classification, N categories



Text classification, N categories

SCENE FROM " DAN'L DRUCE."

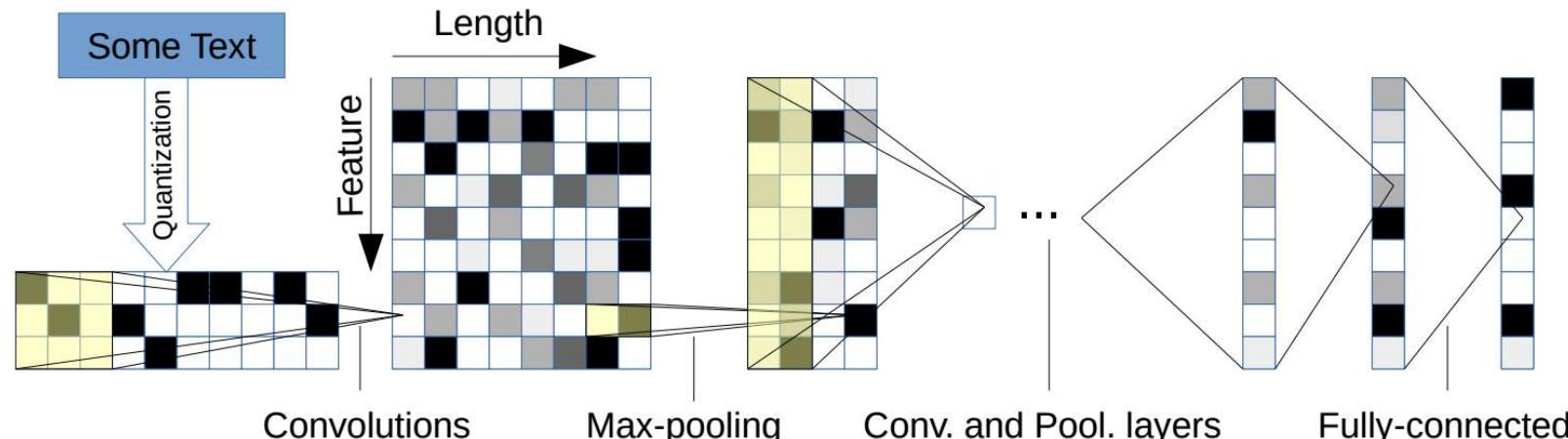
This interesting domestic drama, by Mr. W. S. Gilbert, has continued to engage the sympathies of a nightly sufficient audience at the Haymarket Theatre, where it has now been represented more than sixty times. Its subject and character were described by us, in the ordinary report of theatrical novelties, about two months ago. Our readers will probably not need to be reminded that the hero of the story, Dan'l Druce, the blacksmith, is a solitary recluse dwelling on the coast of Norfolk, where his lone cottage is visited by fugitives from party vengeance during the civil wars of the Commonwealth. His hoard of money is stolen; but a different sort of treasure, a helpless female infant, is left by some mysterious agency, and may be accepted, as in George Eliot's tale of "Silas Marner," for a Divine gift to the sad-hearted misanthrope, far better than riches. In this spirit, at least, he is content to receive the precious human charge; and so to those who would remove it from his home, Dan'l Druce here makes answer with the solemn exclamation, "Touch not the Lord's gift!" This character is well acted by Mr. Hermann Vezin.



- Fiction: 0%
- Biography: 6%
- ...
- Play: 80%**
- ...
- Documentation: 0%

Deep Neural Network: Crepe Model

Visualization with Netron



Layer	Large Feature	Small Feature	Kernel	Pool
1	1024	256	7	3
2	1024	256	7	3
3	1024	256	3	N/A
4	1024	256	3	N/A
5	1024	256	3	N/A
6	1024	256	3	3

Layer	Output Units Large	Output Units Small
7	2048	1024
8	2048	1024
9	Depends on the problem	

source: Xiang Zhang, Junbo Zhao, Yann LeCun. [Character-level Convolutional Networks for Text Classification](#). NIPS 2015

Temporal Convolution (256 69*7/1)

	V	A	N	C	O	U	V	E	R	...	1013
-	0	0	0	0	0	0	0	0	1	...	
-	0	0	0	0	0	0	0	0	0	...	
.	0	0	0	0	0	0	0	0	0	...	
A	0	1	0	0	0	0	0	0	0	...	
B	0	0	0	0	0	0	0	0	0	...	
C	0	0	0	1	0	0	0	0	0	...	
D	0	0	0	0	0	0	0	0	0	...	
E	0	0	0	0	0	0	1	0	0	...	
F	0	0	0	0	0	0	0	0	0	...	
G	0	0	0	0	0	0	0	0	0	...	
H	0	0	0	0	0	0	0	0	0	...	
I	0	0	0	0	0	0	0	0	0	...	
J	0	0	0	0	0	0	0	0	0	...	
K	0	0	0	0	0	0	0	0	0	...	
L	0	0	0	0	0	0	0	0	0	...	
M	0	0	0	0	0	0	0	0	0	...	
N	0	0	1	0	0	0	0	0	0	...	
O	0	0	0	1	0	0	0	0	0	...	
P	0	0	0	0	0	0	0	0	0	...	
Q	0	0	0	0	0	0	0	0	0	...	
R	0	0	0	0	0	0	0	1	0	...	
S	0	0	0	0	0	0	0	0	0	...	
T	0	0	0	0	0	0	0	0	0	...	
U	0	0	0	0	1	0	0	0	0	...	
V	1	0	0	0	0	1	0	0	0	...	
W	0	0	0	0	0	0	0	0	0	...	
X	0	0	0	0	0	0	0	0	0	...	
Y	0	0	0	0	0	0	0	0	0	...	
Z	0	0	0	0	0	0	0	0	0	...	

Diagram illustrating the temporal convolution operation. A 1x1008x256 input tensor is processed by 256 filters, each with a 7x1 kernel. The diagram shows the receptive field of the first filter, which covers the first 7 elements of the input sequence. Red arrows indicate the receptive fields for the first four filters.

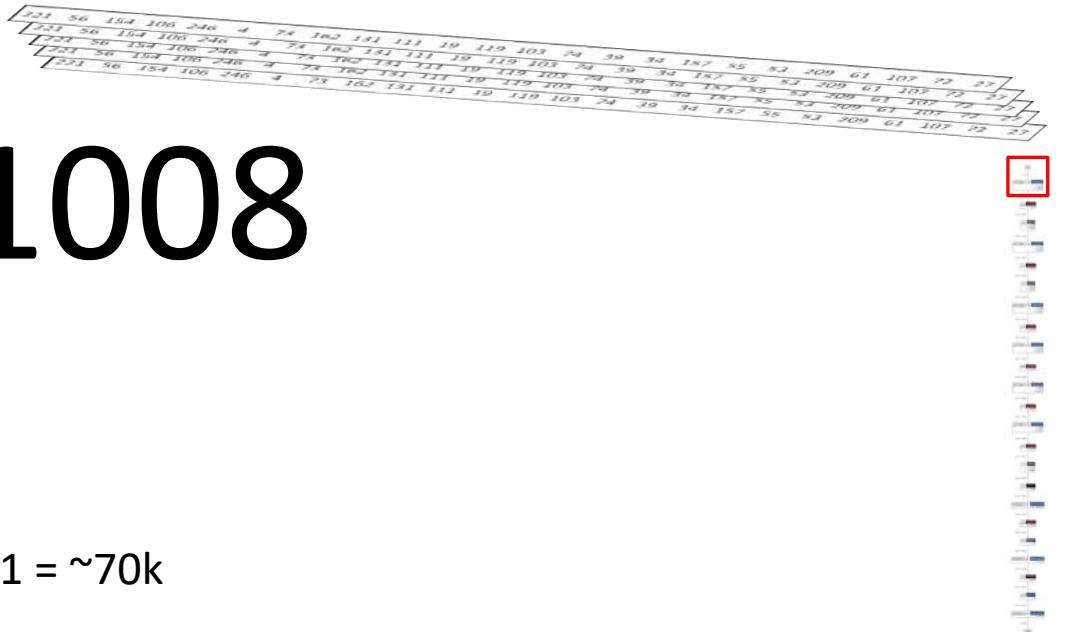
0	1	2	3	4	1007
0	6.4	1.1	3.2	0.3	-0.4	
1	-2.1	0.2	-3.4	
254	
255	1.2	3.4	-1	1.2	3.2	

x 256

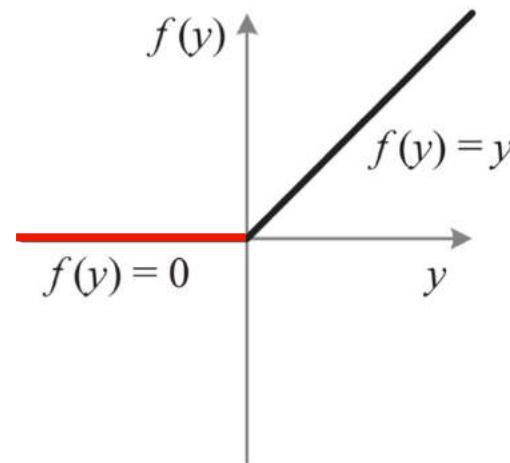
1x1008x256 = ~256k

x 1008

69x1014x1 = ~70k



Activation Function: Rectified Linear Unit (ReLU)



$$f(y) = \begin{cases} y, & y \geq 0 \\ 0, & y < 0 \end{cases}$$

	0	1	2	3	4	5	...	1007
0	6.4	1.1	3.2	0.3	-0.4	0.2
...
255	1.2	3.4	-1	1.2	3.2	2.8

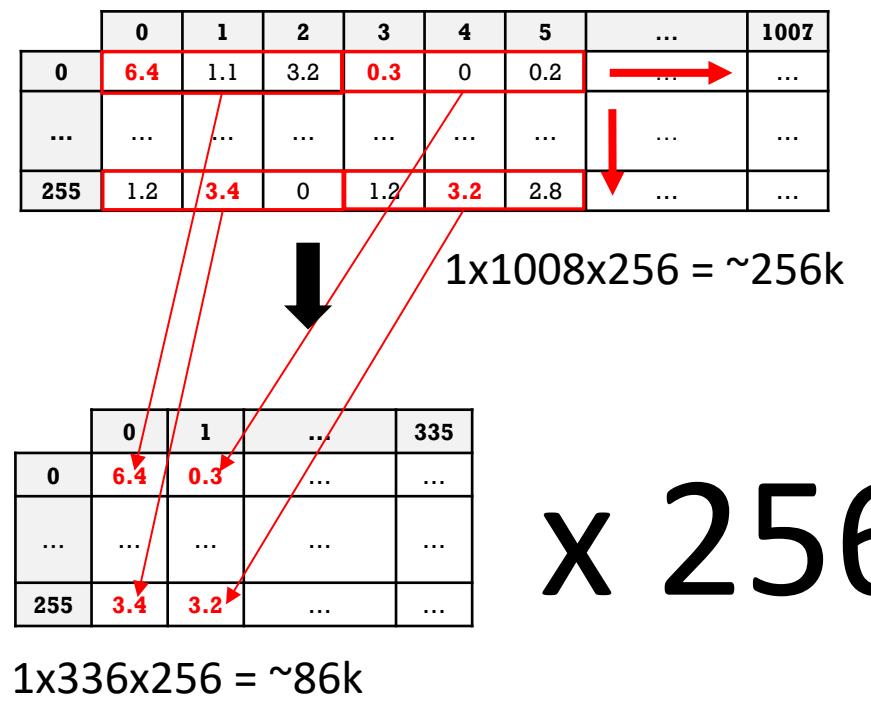
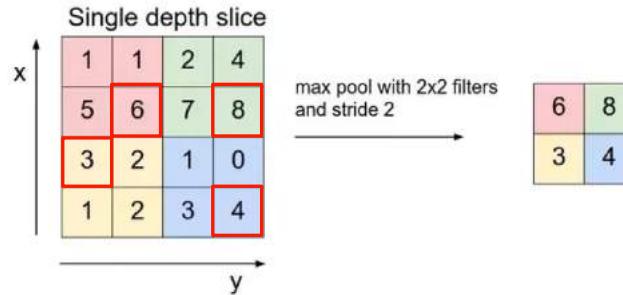
$1 \times 1008 \times 256 = \sim 256k$



	0	1	2	3	4	5	...	1007
0	6.4	1.1	3.2	0.3	0	0.2
...
255	1.2	3.4	0	1.2	3.2	2.8

$1 \times 1008 \times 256 = \sim 256k$

Down-sampling: Max-Pooling (256 1*3/3)



source : Stanford's CS231n

Fast forward...

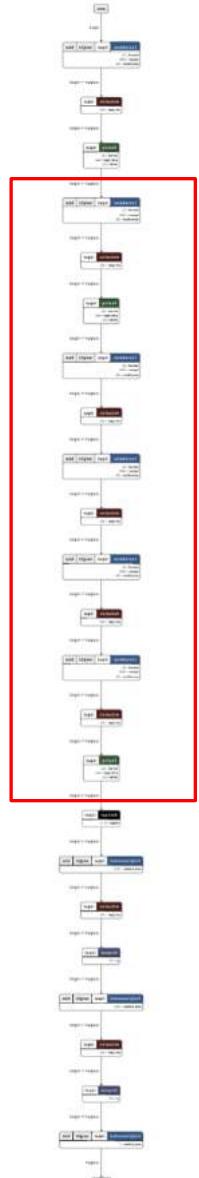
$1 \times 336 \times 256 = \text{~86k}$ <- after 1 convolution layer ($69 \times 7/1$) and 1 max pooling ($3 \times 1/3$)

$1 \times 330 \times 256 = \text{~85k}$ <- after 1 convolution layer ($1 \times 7/1$)

$1 \times 110 \times 256 = \text{~28k}$ <- 1 max-pooling ($1 \times 3/3$)

$3 \times 102 \times 256 = \text{~26k}$ <- 4 convolutions layers ($1 \times 3/1$)

$1 \times 34 \times 256 = \text{~9k}$ <- 1 max-pooling ($1 \times 3/3$)



Flattening Layer

	0	1	2	3	4	5	6	7	8	...	33
0	6.4	0.1
1	2.1	24.9
...
255	9.9

$1 \times 34 \times 256 = \sim 9k$

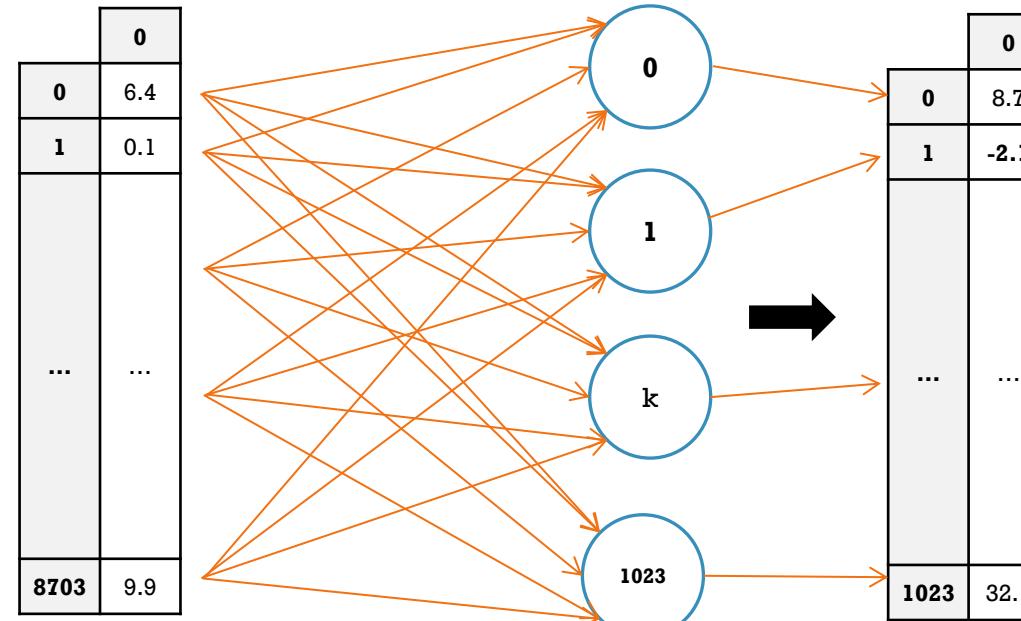
	0
0	6.4
1	0.1
...	...
34	2.1
35	24.9
...	...
...	...
...	...
8703	9.9

x 256

$8704 \times 1 \times 1 = \sim 9k$

Fully Connected / Dense layer (1024)

$$f_k(X) = \sum_{i=0}^{8703} w_{ki} * x_i + b_k$$



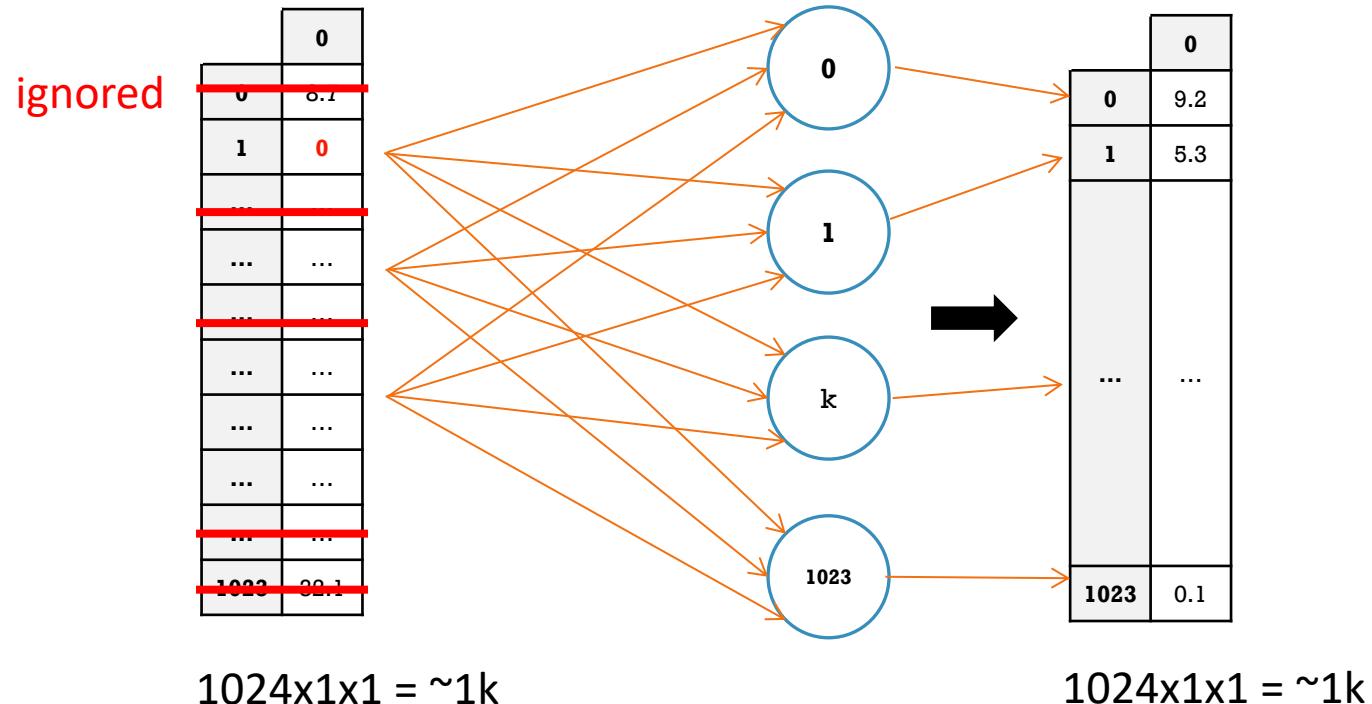
$8704 \times 1 \times 1 = \sim 9k$

$1024 \times 1 \times 1 = \sim 1k$

x 1024

Dropout ($p=0.5$) + Fully Connected Layer (1024)

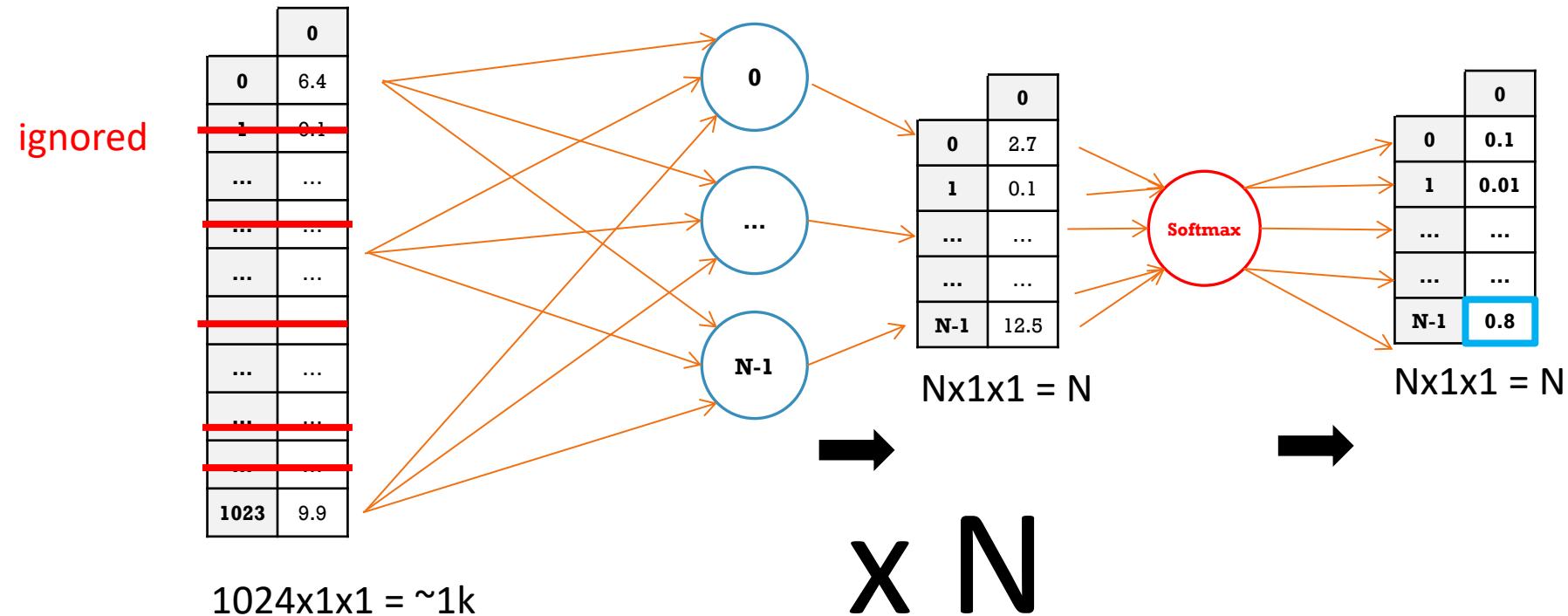
$$f_k(X) = \sum_{i=0}^{8703} w_{ki} * x_i + b_k$$



x 1024

Output: Dropout + Dense + Softmax for N categories

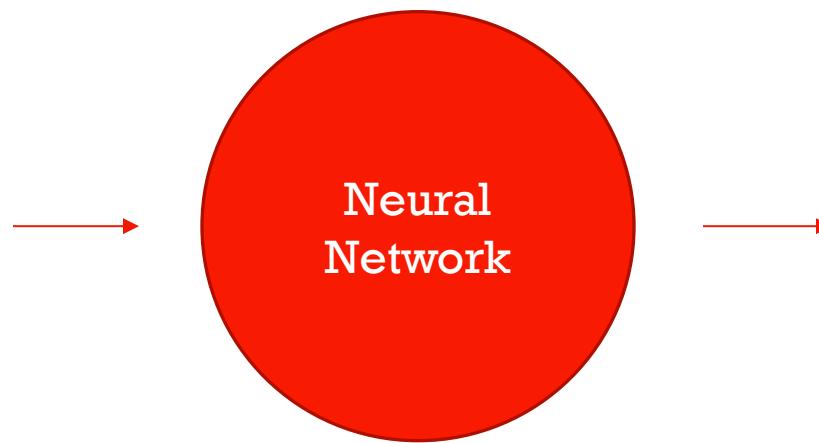
$$\text{softmax}(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=0}^{N-1} e^{z_j}}$$



Text classification, N categories

SCENE FROM " DAN'L DRUCE."

This interesting domestic drama, by Mr. W. S. Gilbert, has continued to engage the sympathies of a nightly sufficient audience at the Haymarket Theatre, where it has now been represented more than sixty times. Its subject and character were described by us, in the ordinary report of theatrical novelties, about two months ago. Our readers will probably not need to be reminded that the hero of the story, Dan'l Druce, the blacksmith, is a solitary recluse dwelling on the coast of Norfolk, where his lone cottage is visited by fugitives from party vengeance during the civil wars of the Commonwealth. His hoard of money is stolen; but a different sort of treasure, a helpless female infant, is left by some mysterious agency, and may be accepted, as in George Eliot's tale of "Silas Marner," for a Divine gift to the sad-hearted misanthrope, far better than riches. In this spirit, at least, he is content to receive the precious human charge; and so to those who would remove it from his home, Dan'l Druce here makes answer with the solemn exclamation, "Touch not the Lord's gift!" This character is well acted by Mr. Hermann Vezin.



- Fiction: 0%
- Biography: 6%
- ...
- Play: 6%
- ...
- Documentation: 80%**

How to train the network? Backward propagation!

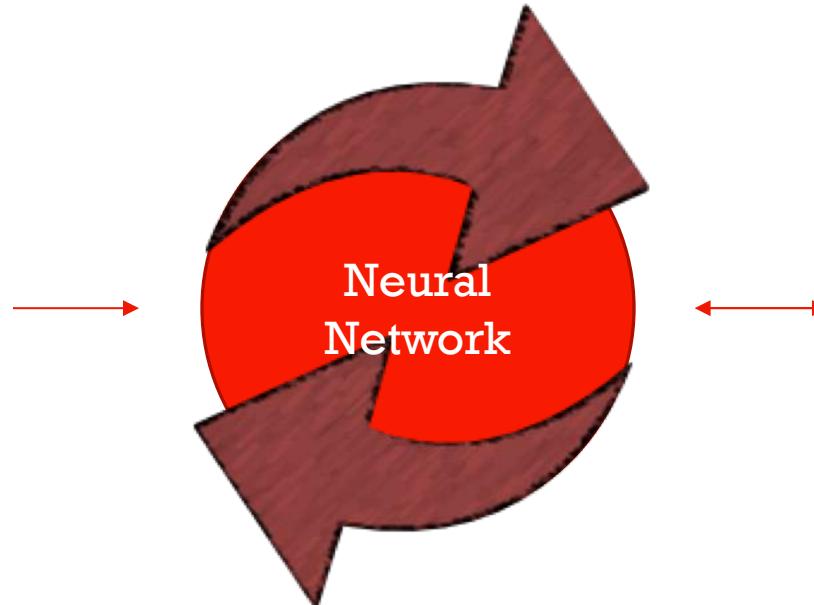


Backward propagation – Efficient Gradient Descent

$$w_{ij} = w_{ij} - \eta \cdot \frac{\partial E}{\partial w_{ij}}$$

SCENE FROM “ DAN'L DRUCE.”

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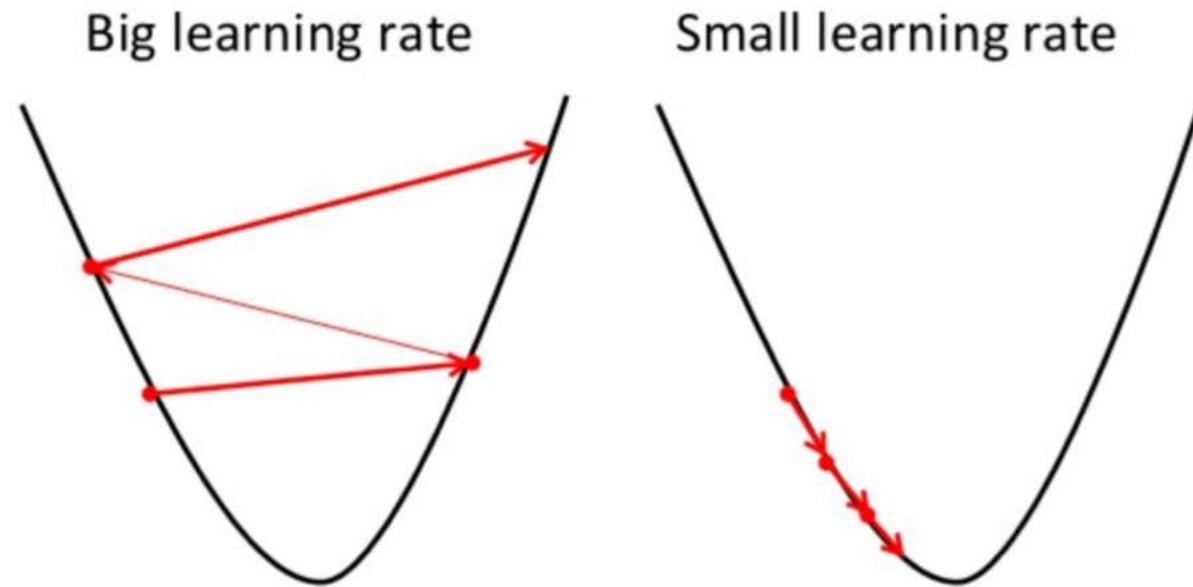


- Fiction: 0%
- Biography: 6% 0%
- ...
- Play: 6% 100%
- ...
- Documentation: 80% 0%

Update the weights of the convolutional masks and fully connected units so that the error will be minimized next time

Training Parameters: Learning Rate

Learning Rate η : How much to update the weights for every batch of documents?



[Source: Towards data Science: Gradient descent in a nutshell](#)

Training parameters: Batch Size

Batch size: How many examples to learn from in one step?

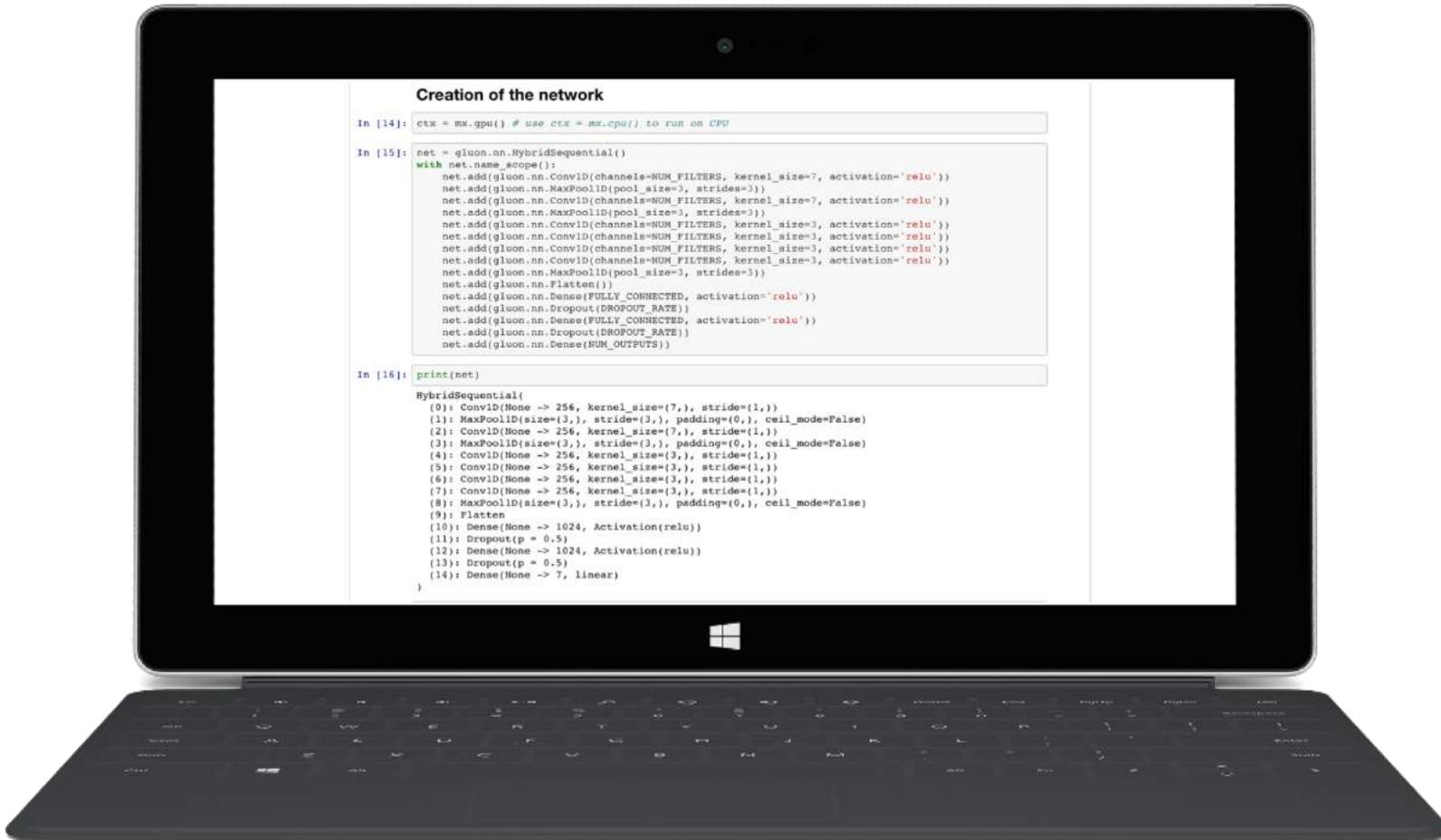


Training parameters: Number of epochs

Number of epoch: How many times should we feed the network the entire training set?



Jupyter notebook demo – Crepe in Apache MXNet/Gluon



https://github.com/ThomasDelteil/CNN_NLP_MXNet

Results

Dataset	Classes	Train Samples
AG's News	4	120,000
Sogou News	5	450,000
DBPedia	14	560,000
Yelp Review Polarity	2	560,000
Yelp Review Full	5	650,000
Yahoo! Answers	10	1,400,000
Amazon Review Full	5	3,000,000
Amazon Review Polarity	2	3,600,000

Traditional approaches

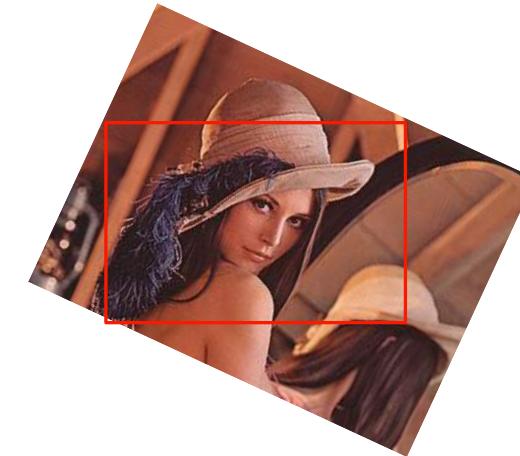
Word-based CNN

Character-level CNN

Model	AG	Sogou	DBP.	Yelp P.	Yelp F.	Yah. A.	Amz. F.	Amz. P.
BoW	11.19	7.15	3.39	7.76	42.01	31.11	45.36	9.60
BoW TFIDF	10.36	6.55	2.63	6.34	40.14	28.96	44.74	9.00
ngrams	7.96	2.92	1.37	4.36	43.74	31.53	45.73	7.98
ngrams TFIDF	7.64	2.81	1.31	4.56	45.20	31.49	47.56	8.46
Bag-of-means	16.91	10.79	9.55	12.67	47.46	39.45	55.87	18.39
LSTM	13.94	4.82	1.45	5.26	41.83	29.16	40.57	6.10
Lg. w2v Conv.	9.92	4.39	1.42	4.60	40.16	31.97	44.40	5.88
Sm. w2v Conv.	11.35	4.54	1.71	5.56	42.13	31.50	42.59	6.00
Lg. w2v Conv. Th.	9.91	-	1.37	4.63	39.58	31.23	43.75	5.80
Sm. w2v Conv. Th.	10.88	-	1.53	5.36	41.09	29.86	42.50	5.63
Lg. Lk. Conv.	8.55	4.95	1.72	4.89	40.52	29.06	45.95	5.84
Sm. Lk. Conv.	10.87	4.93	1.85	5.54	41.41	30.02	43.66	5.85
Lg. Lk. Conv. Th.	8.93	-	1.58	5.03	40.52	28.84	42.39	5.52
Sm. Lk. Conv. Th.	9.12	-	1.77	5.37	41.17	28.92	43.19	5.51
Lg. Full Conv.	9.85	8.80	1.66	5.25	38.40	29.90	40.89	5.78
Sm. Full Conv.	11.59	8.95	1.89	5.67	38.82	30.01	40.88	5.78
Lg. Full Conv. Th.	9.51	-	1.55	4.88	38.04	29.58	40.54	5.51
Sm. Full Conv. Th.	10.89	-	1.69	5.42	37.95	29.90	40.53	5.66
Lg. Conv.	12.82	4.88	1.73	5.89	39.62	29.55	41.31	5.51
Sm. Conv.	15.65	8.65	1.98	6.53	40.84	29.84	40.53	5.50
Lg. Conv. Th.	13.39	-	1.60	5.82	39.30	28.80	40.45	4.93
Sm. Conv. Th.	14.80	-	1.85	6.49	40.16	29.84	40.43	5.67

Data Augmentation

For images



For text



Humans to rephrase the examples



Synonyms
Similar semantic meaning

Data Augmentation

The quick brown fox jumps over the lazy dog



Data Augmentation

The **quick brown fox jumps over the lazy dog**

fast	hazel	leaps	idle
swift	brunette	springs	indolent
speedy	chestnut	bounds	slothful
		hops	
			hound
			pup
			mutt

Data Augmentation

The **quick brown fox jumps over the lazy dog**

fast	hazel	leaps	idle
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Data Augmentation

The **quick brown fox jumps over the lazy dog**

fast	hazel	leaps	idle
swift	brunette	springs	indolent
speedy	chestnut	bounds	slothful
		hops	
			hound
			pup
			mutt

The **swift brunette fox leaps over the slothful pup**

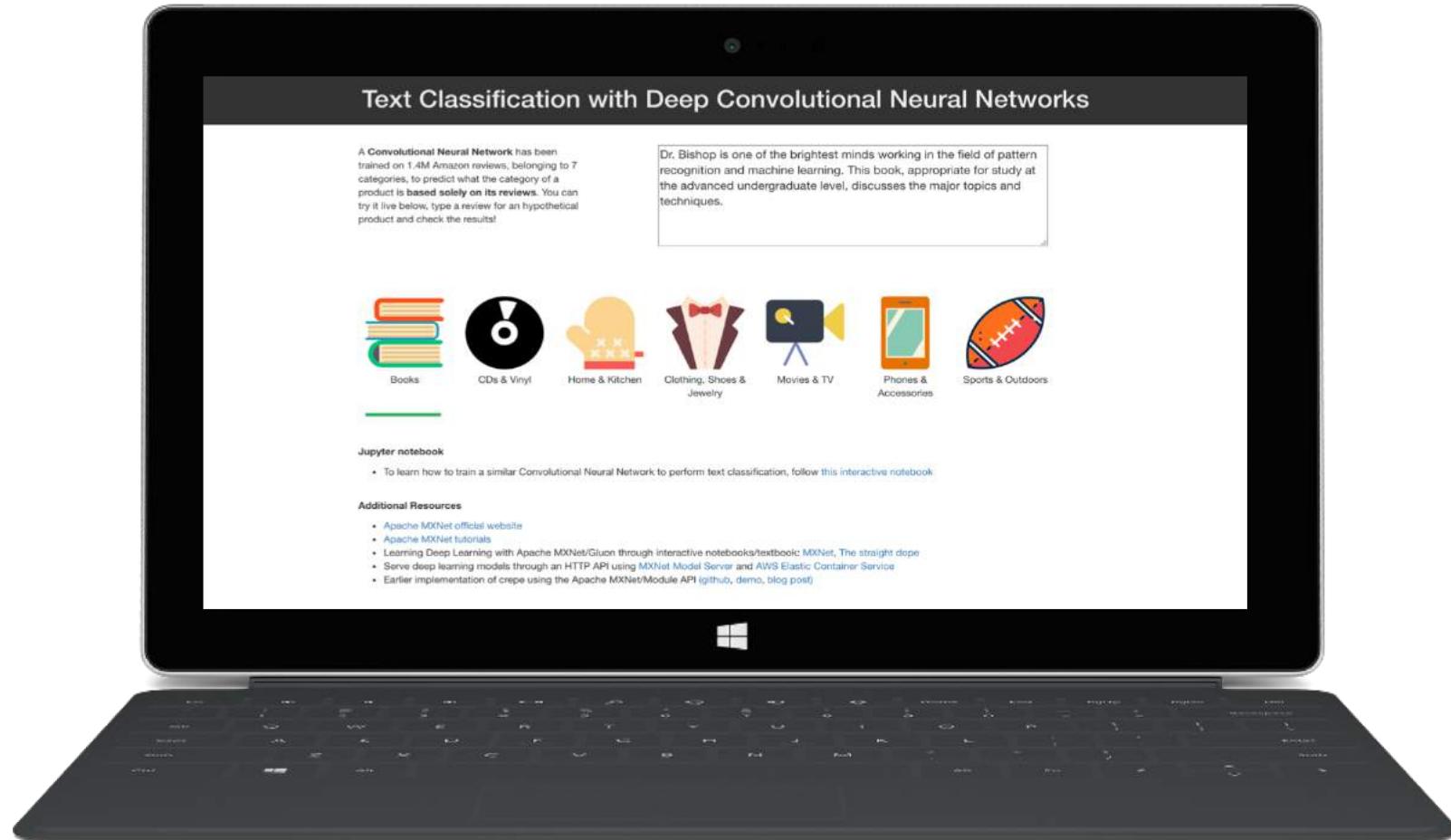
You need a large dataset



...A very large dataset!

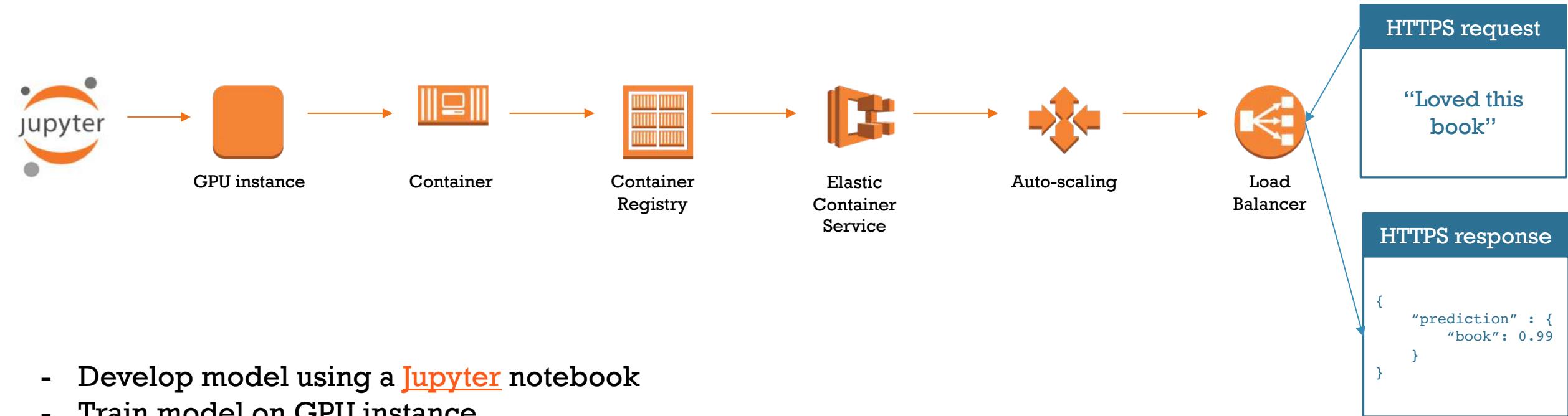


Live Demo – Classification of product category for Amazon Reviews



https://thomasdelteil.github.io/CNN_NLP_MXNet/

Workflow and Operationalization



- Develop model using a [Jupyter](#) notebook
- Train model on GPU instance
- Package model behind web API in a Docker container, e.g using [MXNet Model Server](#)
- Upload container to container registry
- Deploy container to an elastic container service
- Enjoy quick and linear scaling
- Put the API behind a load balancer with SSL termination
- Enjoy 😊

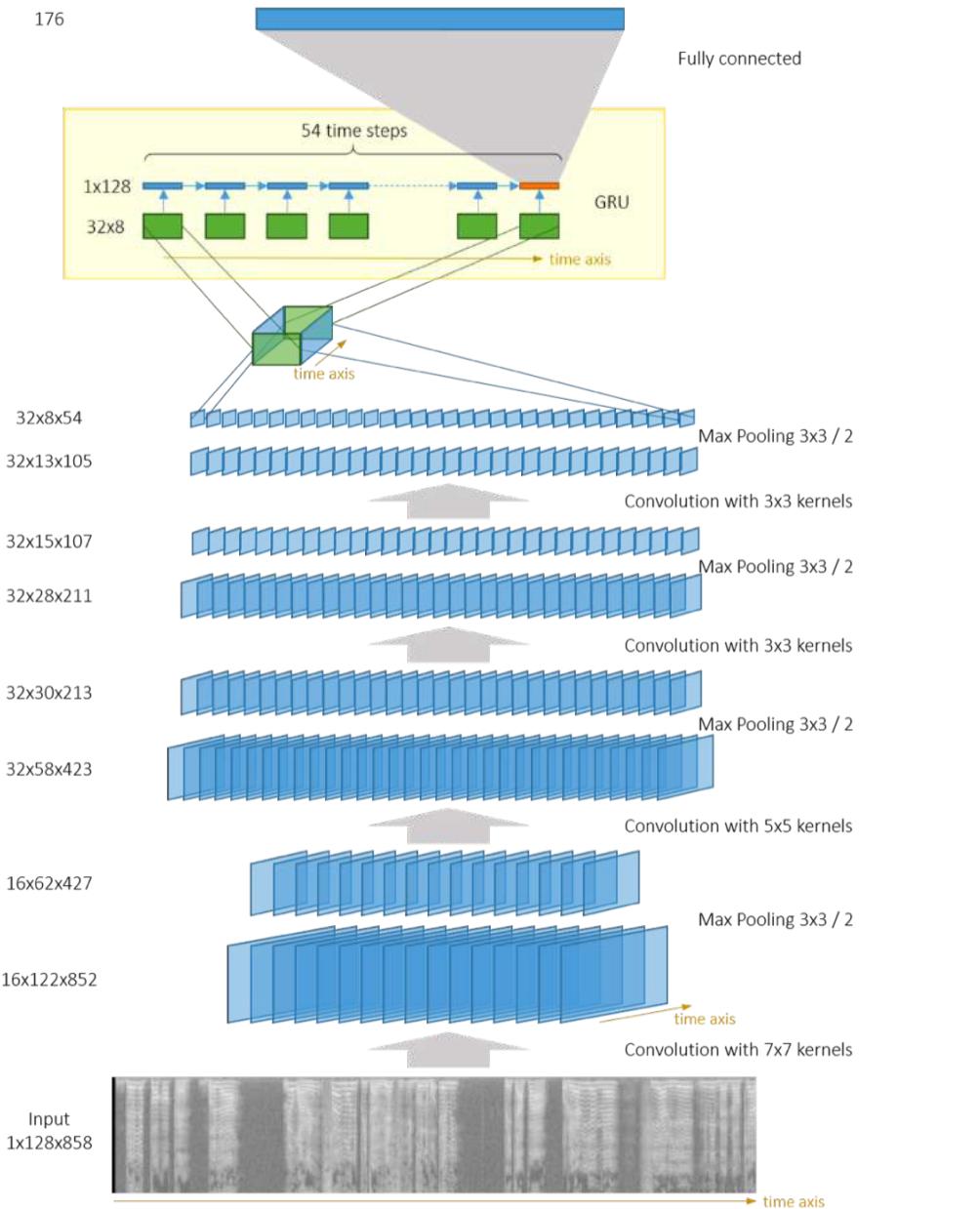
Advanced use-cases for Convolutions and NLP

CNN + LSTM: Spatially and Temporally Deep Neural Networks

- CNN for feature extraction
- LSTM for temporal representation

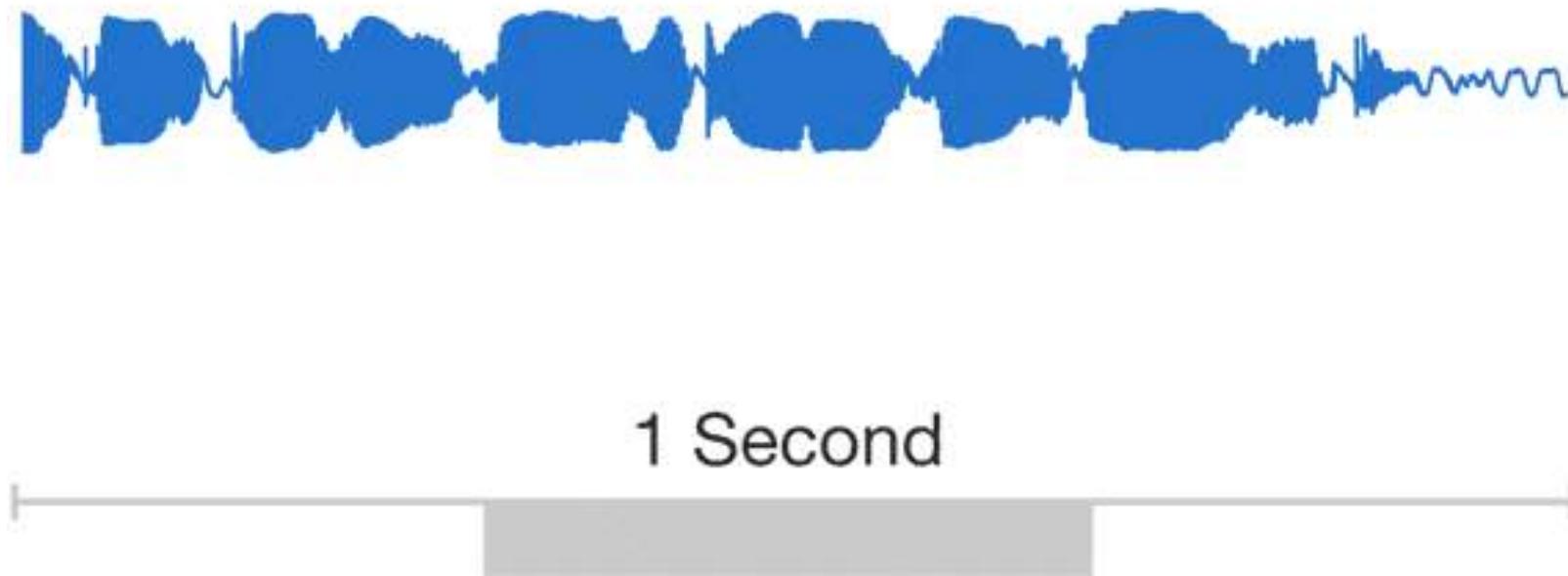
Applications:

- Video (CNN for frames, LSTM to combine them temporally)
- Text tasks
- Audio (Language detection)



Source: [Combining CNN and RNN for spoken language detection](#)

Advanced use-case: Speech Generation WaveNet



[Source: DeepMind Wavenet generative model raw audio](#)

WaveNet: Dilated Causal Convolution

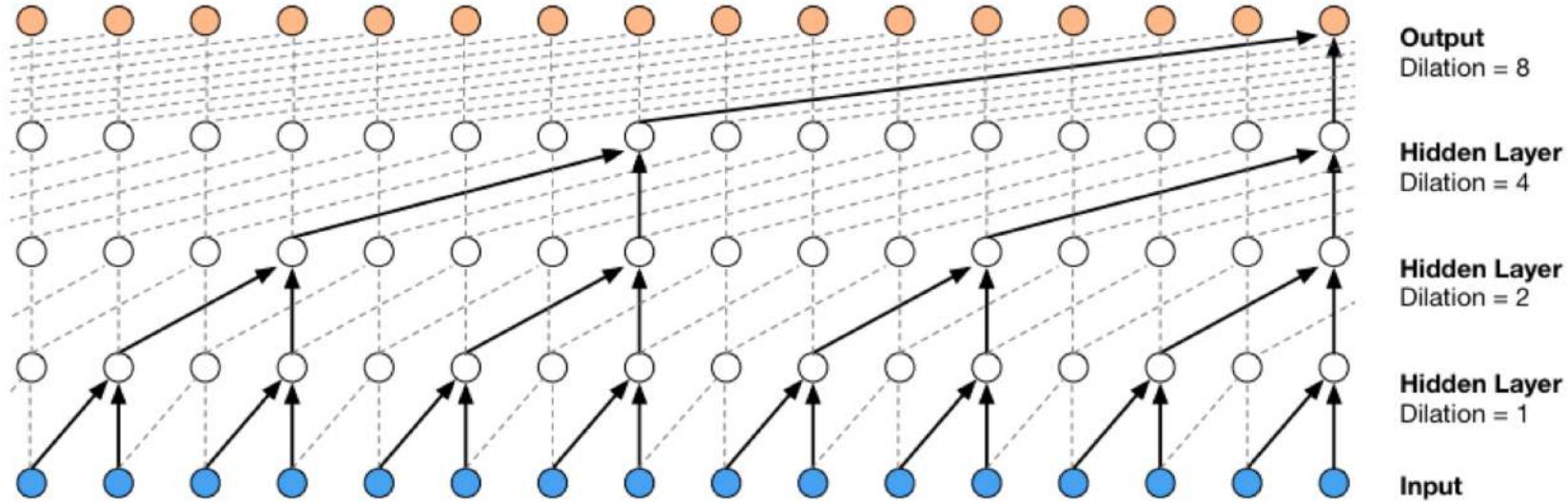
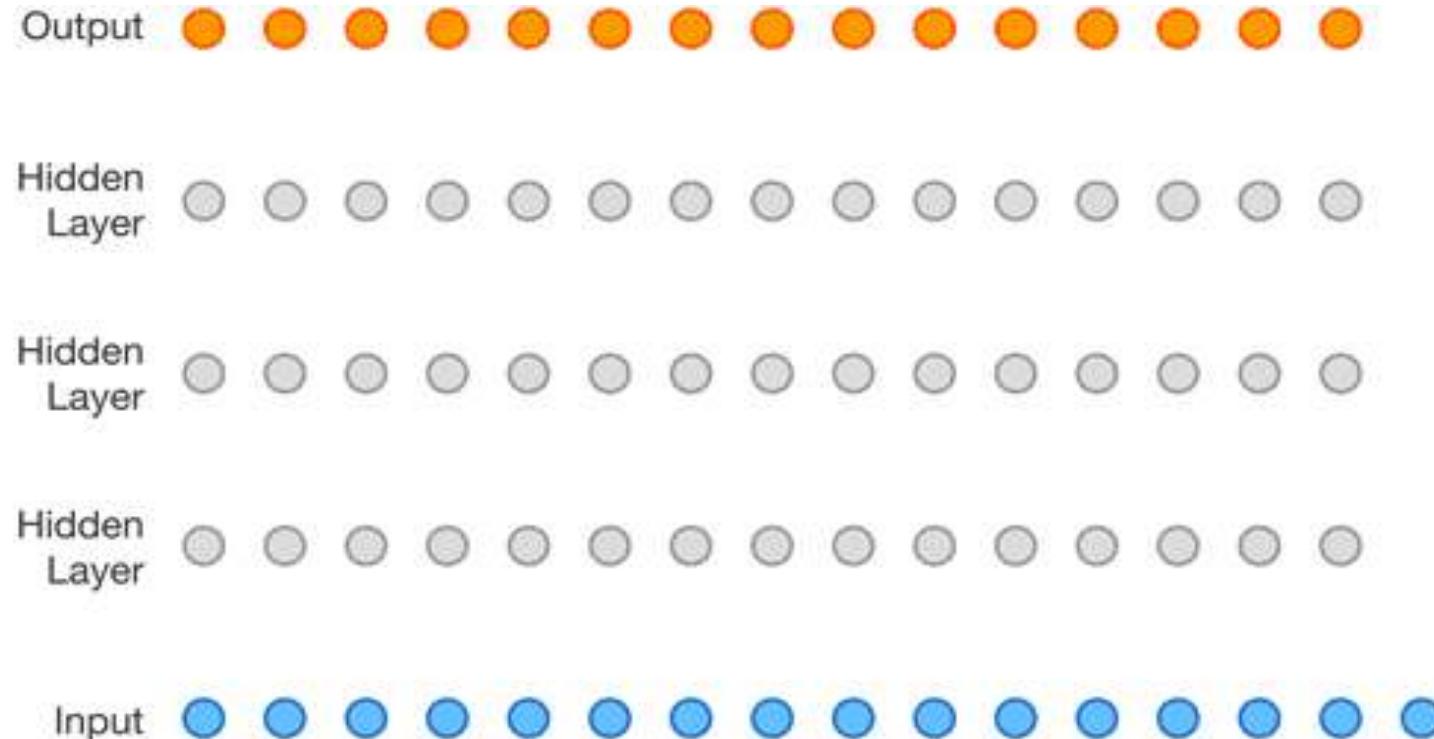


Figure 3: Visualization of a stack of *dilated* causal convolutional layers.

[Source: DeepMind Wavenet generative model raw audio](#)

WaveNet: Dilated Causal Convolution



[Source: DeepMind Wavenet generative model raw audio](#)

Summary

- Learned about convolutions
- Applied them to textual data
- Studied the crepe architecture from Zhang et al. in details
- Learned about advanced use cases and operationalization

Thank you!

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