Introduction to Machine Learning feat. TensorFlow

Peter Goldsborough

July 10, 2016

July 10, 2016

Table of Catents

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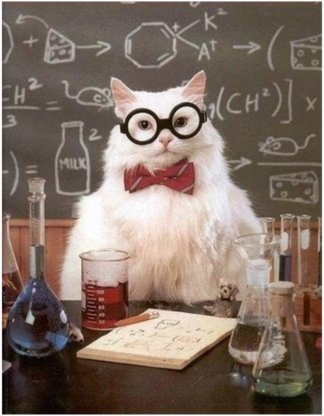

Theory

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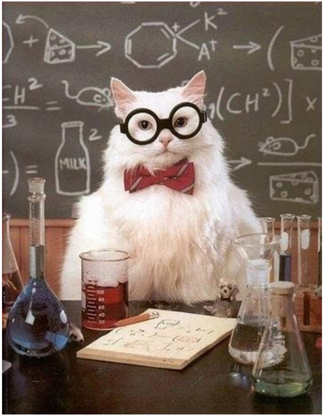

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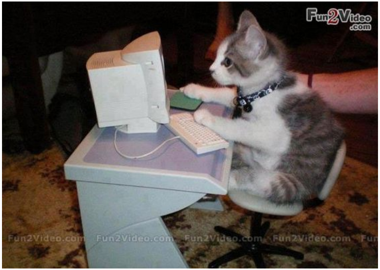

Practice

Background

Background

- CS Student @ TUM

Background

- CS Student @ TUM
- Google & Bloomberg Intern

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- I like cats

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Seminar Topic: *Deep Learning With TensorFlow*

`github.com/peter-can-write/tensorflow-paper` github.com/peter-can-talk/python-meetup-munich-2016

Time to go Deeper

What if the meaning of life is to spend your time thinking about the meaning of life?

Deep Learning

Deep Learning

The why

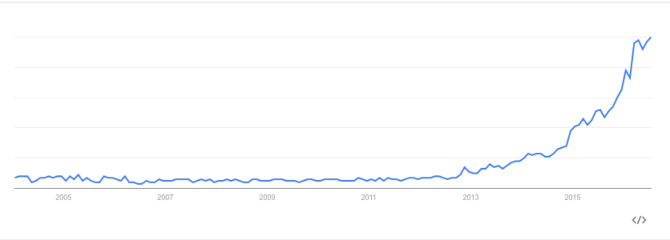
Deep Learning

The why, the what

Deep Learning

The why, the what and the ugly

Deep Learning



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- Then we call neural network *deep*, if
  1. It is trained at more than 10,000m below sea level, or
  2. $\mathcal{L} > 1$
- To really understand why many layers are a good idea, we must understand why few layers might be a bad idea

Universal Approximation Theorem

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- Theoretically, a single layer is just enough
- However, we would need exponentially many units for discrete functions
- And infinitely many for continuous functions
- Just use an infinitely sized hash table

The Curse of Dimensionality

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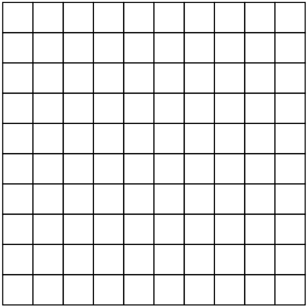

2 features $= 100$ outputs

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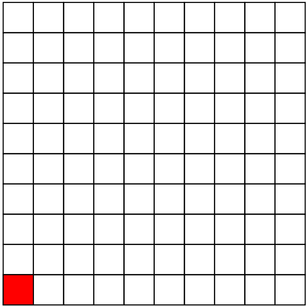

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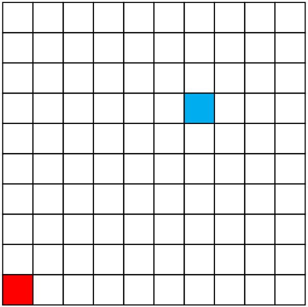

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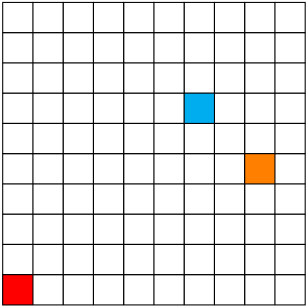

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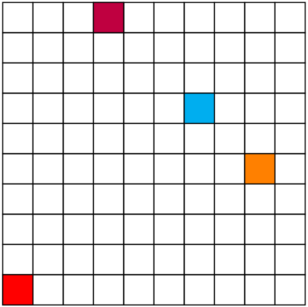

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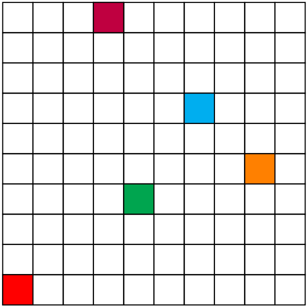

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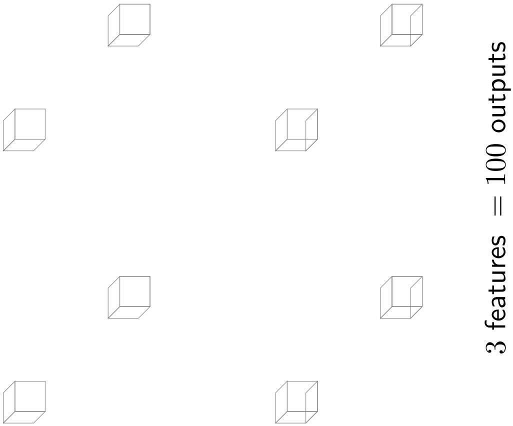

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We make assumptions about our data

The Curse of Dimensionality

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- Don't need as much data any more!

The Curse of Dimensionality

Deep Learning assumes that data is structured

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hierarchically

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Note:
According to the *No Free Lunch Theorem* it is just as bad as flipping a coin.

Convolutional Neural Networks

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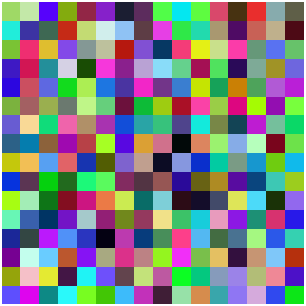

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71	76	55	37	72	15	90	69	62	79	50	99	15	14	18	97
24	4	35	87	87	58	34	92	97	63	55	95	79	95	24	6
92	93	68	61	57	66	2	93	79	57	33	14	46	49	62	34
5	60	69	40	79	16	59	79	87	51	83	66	81	54	56	12
75	14	65	56	63	99	23	21	33	87	71	48	70	85	64	85
81	92	77	85	91	39	57	47	92	2	69	84	80	95	21	84
49	0	82	22	89	8	37	52	62	54	23	82	52	53	32	91
76	33	64	43	98	83	69	50	9	67	93	30	21	32	13	71
29	85	34	67	42	39	61	4	52	29	14	8	0	10	34	79
63	22	95	87	13	41	98	40	8	50	95	90	49	57	44	19
74	23	79	80	58	2	64	8	30	21	62	47	7	95	21	46
93	41	73	46	76	34	44	74	6	79	15	12	25	64	21	10
41	51	32	98	6	37	77	7	92	54	1	8	3	58	99	49
77	92	49	88	36	56	60	63	62	59	45	41	38	8	87	1
74	99	60	61	73	55	3	23	37	84	94	95	40	80	78	84
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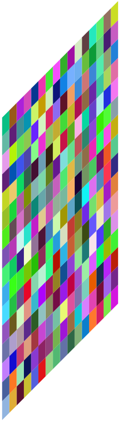

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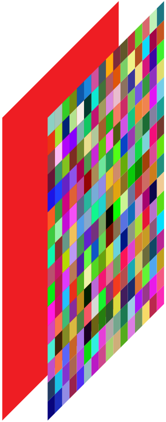

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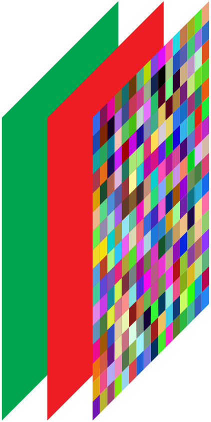

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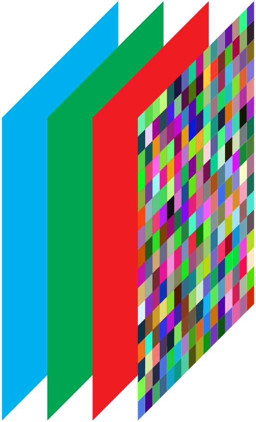

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- First idea: just feed the pixels into a neural network

$$\underset{R}{\begin{bmatrix} 116 & 80 \\ 170 & 194 \end{bmatrix}} \quad \underset{G}{\begin{bmatrix} 82 & 78 \\ 5 & 236 \end{bmatrix}} \quad \underset{B}{\begin{bmatrix} 76 & 139 \\ 245 & 236 \end{bmatrix}}$$

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$$\texttt{concatenate(}R\texttt{.flatten, }G\texttt{.flatten, }B\texttt{.flatten)}$$

Convolutional Neural Network

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$$\mathbf{x} = \left[116, 80, 170, 194, 82, 78, 5, 236, 76, 139, 245, 236\right]$$

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  2. It assumes every pixel has entirely new information

Convolutional Neural Networks

This is a cat ♥

Convolutional Neural Networks

Still a cat ♥♥

Convolutional Neural Networks

Half cat / half salad ♥♥♥

Convolutional Neural Networks

Minecraft cat ♥♥♥♥

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- Wouldn't it make sense to reuse that information?
- Yes!

Weight Sharing

Convolutional Neural Network: Mechanics

Recipe for a Convolutional Neural Network

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- Ingredients

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  - Put the image into the oven at 150°C

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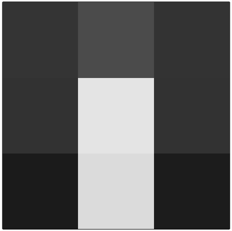
  - Compute the "dot product" for each configuration
  - (This is a convolution $I * K$)

Convolutional Neural Network: Mechanics



Image

Convolutional Neural Network: Mechanics

0.4	0.9	0.1
0.7	0.2	0.6
0.8	0.3	0.5

Image

Convolutional Neural Network: Mechanics

0.4	0.9	0.1
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Image

5.7	2.4
3.1	0.9

Kernel

Convolutional Neural Network: Mechanics

$5.7 \cdot 0.4$	$2.4 \cdot 0.9$	0.1
$3.1 \cdot 0.7$	$0.9 \cdot 0.2$	0.6
0.8	0.3	0.5

Image

Convolutional Neural Network: Mechanics

$5.7 \cdot 0.4$	$2.4 \cdot 0.9$	0.1
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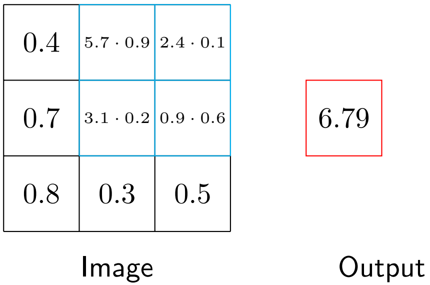
Image

6.79

Output

Convolutional Neural Network: Mechanics



Convolutional Neural Network: Mechanics

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0.7	$3.1 \cdot 0.2$	$0.9 \cdot 0.6$
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6.79	6.53

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Convolutional Neural Network: Mechanics

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Convolutional Neural Network: Mechanics

0.4	0.9	0.1
0.7	$5.7 \cdot 0.2$	$2.4 \cdot 0.6$
0.8	$3.1 \cdot 0.3$	$0.9 \cdot 0.5$

Image

6.79	6.53
7.67	3.96

Output

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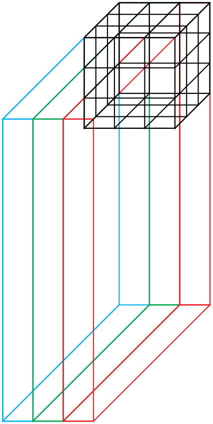
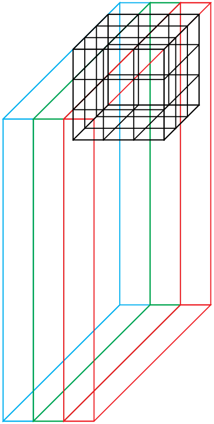
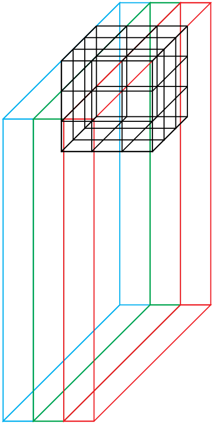


Convolutional Neural Networks: Mechanics



Convolutional Neural Networks: Mechanics



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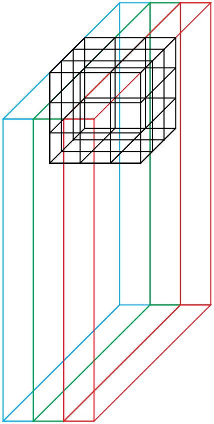

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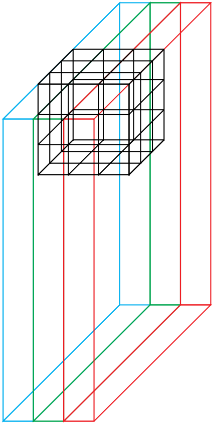

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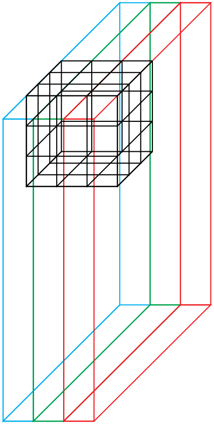

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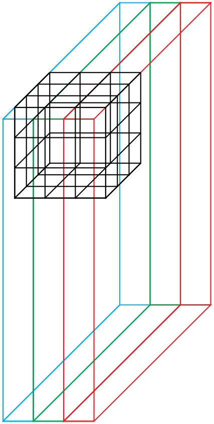

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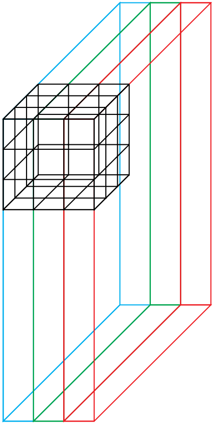

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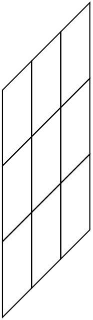

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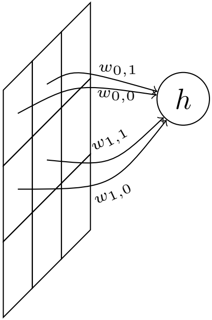

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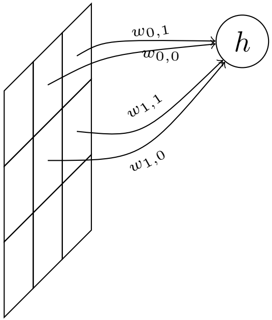

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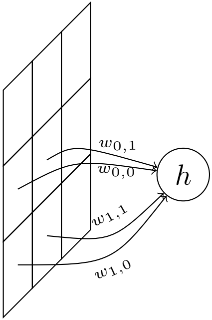

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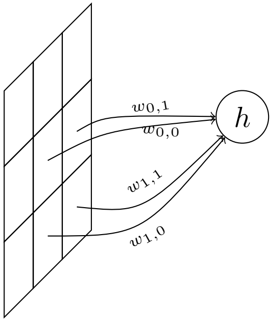

Convolutional Neural Network: Hyperparameters

- Convolutional Neural Networks have three hyperparameters

Convolutional Neural Network: Hyperparameters

- Convolutional Neural Networks have three hyperparameters
  1. Kernel size

Convolutional Neural Network: Hyperparameters

- Convolutional Neural Networks have three hyperparameters
  1. Kernel size
  2. Kernel stride

Convolutional Neural Network: Hyperparameters

- Convolutional Neural Networks have three hyperparameters
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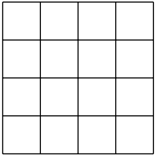
  3. Padding (valid or same)



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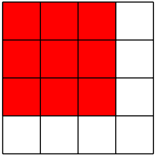

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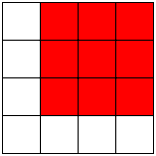

Convolutional Neural Network: Hyperparameters

- Convolutional Neural Networks have three hyperparameters
  1. Kernel size
  2. Kernel stride
  3. Padding (valid or same)

0	0	0	0	0	0
0					0
0					0
0					0
0					0
0	0	0	0	0	0

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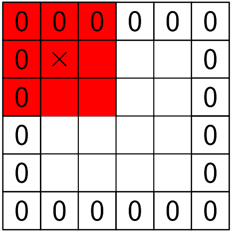

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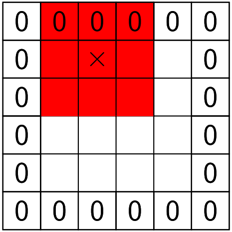

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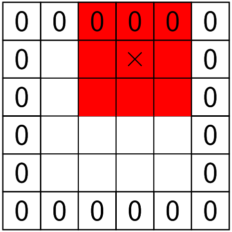

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0	0	0	0	0	0
0				×	0
0					0
0					0
0					0
0	0	0	0	0	0

Convolutional Neural Networks: Pooling

- *Pooling* achieves translational invariance

Convolutional Neural Networks: Pooling

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- A form of downsampling

Convolutional Neural Networks: Pooling

- *Pooling* achieves translational invariance
- A form of downsampling
- The maximum stays the maximum

66	2
6	32

Convolutional Neural Networks: Pooling

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6	2
66	32

Convolutional Neural Networks: Pooling

- *Pooling* achieves translational invariance
- A form of downsampling
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2	66
6	32

Convolutional Neural Networks: Pooling

- *Pooling* achieves translational invariance
- A form of downsampling
- The maximum stays the maximum

32	6
2	66

Convolutional Neural Network: Architecture

```
INPUT ->
[[CONV -> RELU]*N -> POOL?]*M ->
[FC -> RELU]*K -> FC
```

[?]

Convolutional Neural Networks: Intuition

Convolutional Neural Networks: Intuition

- Each layer of a ConvNet learns to detect features

Convolutional Neural Networks: Intuition

- Each layer of a ConvNet learns to detect features
- Later layers combine features of earlier layers

Convolutional Neural Networks: Intuition

- Each layer of a ConvNet learns to detect features
- Later layers combine features of earlier layers
- For early layers, we can still gain an intuition of what they do

What's in a kernel?

0	1	0
0	1	0
0	1	0

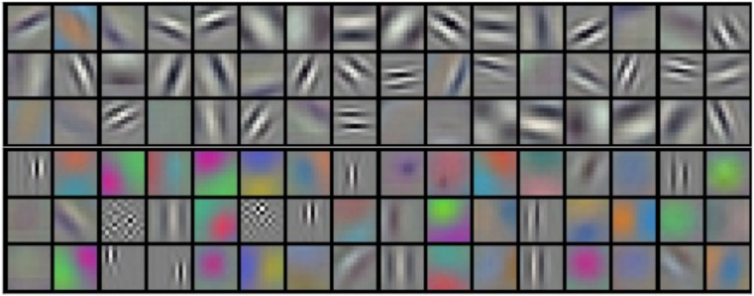
Patterns

What's in a kernel?

0	0	0
-1	1	0
0	0	0

Features

Convolutional Neural Networks: Intuition



Recurrent Neural Networks

LSTMs

Deep Learning

- Why the recent success of deep learning?

Deep Learning

- Why the recent success of deep learning?
- Three reasons

Deep Learning

- Why the recent success of deep learning?
- Three reasons
    1. Better hardware

Deep Learning

- Why the recent success of deep learning?
- Three reasons
  1. Better hardware
  2. More data

Deep Learning

- Why the recent success of deep learning?
- Three reasons
  1. Better hardware
  2. More data
  3. Better methods

The Ugly

References