`tf.talk()`

An Introduction to Deep Learning with TensorFlow

Peter Goldsborough

September 16, 2016

Table of Catents

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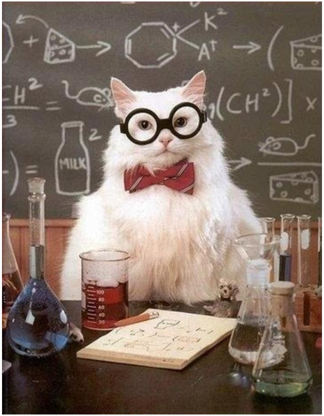

Theory

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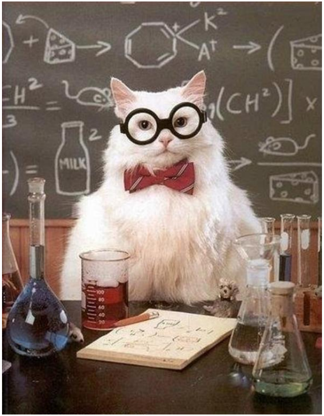
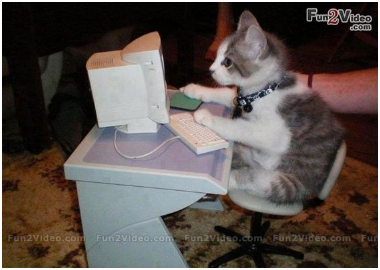


Theory



Practice

Background

Background

- CS Student @ TUM

Background

- CS Student @ TUM
- Google & Bloomberg Intern

Background

- CS Student @ TUM
- Google & Bloomberg Intern

Seminar Topic: *Deep Learning With TensorFlow*

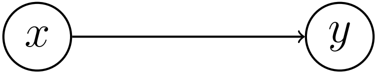
`github.com/peter-can-write/tensorflow-paper`

Neural Networks

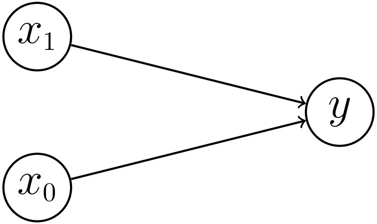
Neural Networks

x

Neural Networks



Neural Networks



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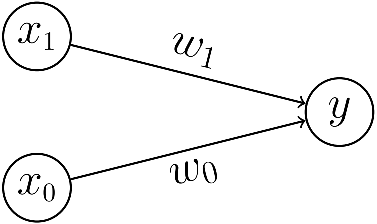

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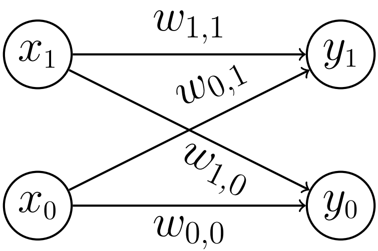

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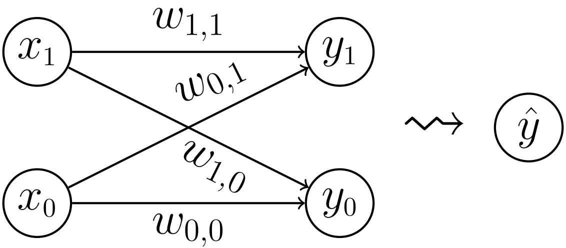

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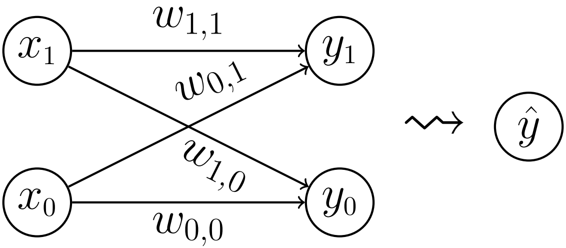
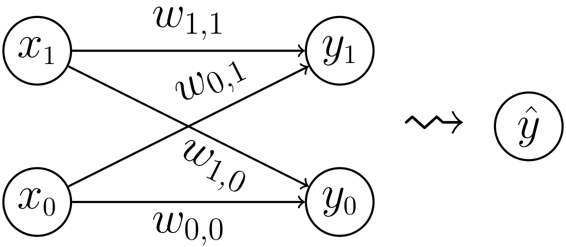


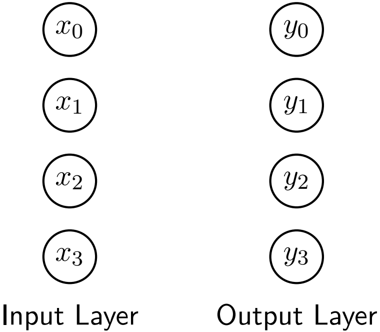
$$\underbrace{\begin{bmatrix} x_0 & x_1 \end{bmatrix}}_{\mathbf{x}} \times \underbrace{\begin{bmatrix} w_{0,0} & w_{0,1} \\ w_{1,0} & w_{1,1} \end{bmatrix}}_{\mathbf{W}} + \underbrace{\begin{bmatrix} b_0 \\ b_1 \end{bmatrix}}_{\mathbf{b}} = \underbrace{\begin{bmatrix} y_0 \\ y_1 \end{bmatrix}}_{\mathbf{y}}$$

Neural Networks



$$\underbrace{\begin{bmatrix} x_0 & x_1 \end{bmatrix}}_{\mathbf{x}} \times \underbrace{\begin{bmatrix} w_{0,0} & w_{0,1} \\ w_{1,0} & w_{1,1} \end{bmatrix}}_{\mathbf{W}} + \underbrace{\begin{bmatrix} b_0 \\ b_1 \end{bmatrix}}_{\mathbf{b}} = \underbrace{\begin{bmatrix} y_0 \\ y_1 \end{bmatrix}}_{\mathbf{y}} \rightsquigarrow \hat{\mathbf{y}}$$

Neural Networks



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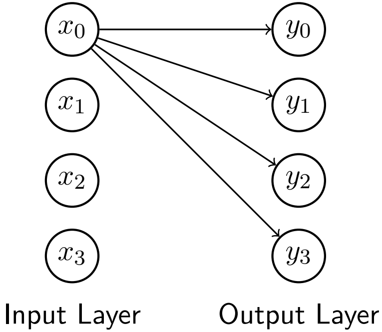

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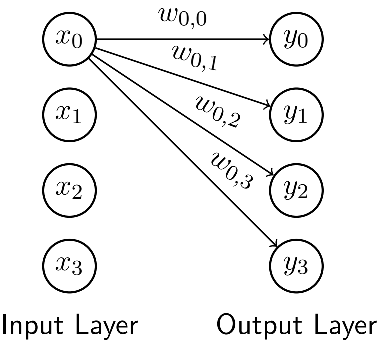

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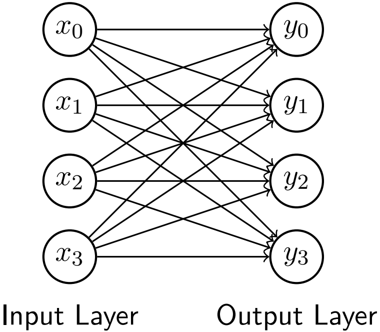
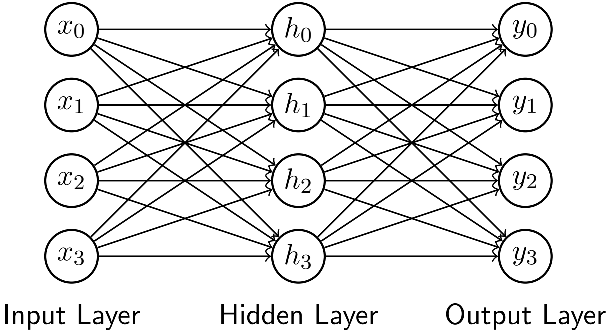


Deep Neural Networks



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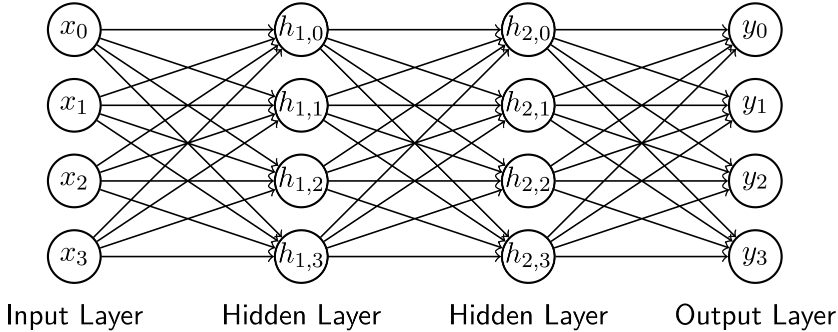

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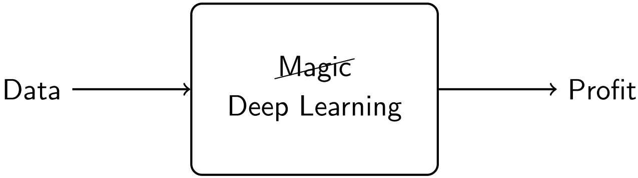


Deep Neural Networks

Deep Learning assumes that data is structured

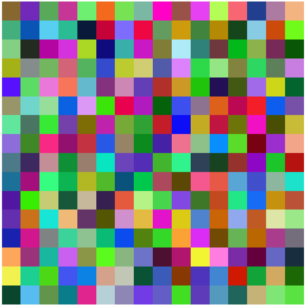
Deep Learning assumes that data is structured

hierarchically

Deep Neural Networks

Deep Neural Networks

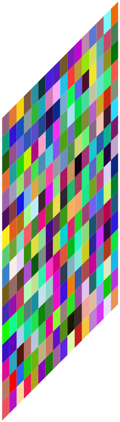
Deep Neural Networks



Deep Neural Networks

47	6	89	83	19	73	78	39	62	96	53	47	96	45	91	92
21	88	79	48	24	74	26	81	47	22	33	57	52	30	77	47
26	10	70	63	61	68	75	82	73	22	66	14	21	42	87	8
28	28	40	32	34	8	4	33	62	59	12	62	56	10	72	49
35	60	75	72	36	37	60	73	63	96	87	26	45	48	36	66
37	50	77	54	37	65	69	86	43	96	45	76	44	40	56	28
2	15	29	82	29	29	53	76	57	56	73	16	36	87	71	10
3	63	75	73	23	45	24	32	82	72	32	11	65	93	59	46
29	43	77	89	97	21	45	95	96	84	54	61	79	34	20	87
75	93	97	18	73	80	19	35	97	16	21	87	61	39	5	24
38	83	83	97	53	13	32	75	3	91	7	60	70	83	26	79
40	50	74	42	18	6	49	1	3	20	51	26	63	41	17	17
44	85	5	20	91	68	14	68	39	45	43	89	14	77	46	80
79	71	74	38	70	91	47	29	40	5	25	29	24	62	59	76
64	14	24	95	8	97	42	96	81	93	33	50	56	23	35	3
11	70	85	59	57	91	92	1	57	76	16	12	64	70	27	22

Deep Neural Networks



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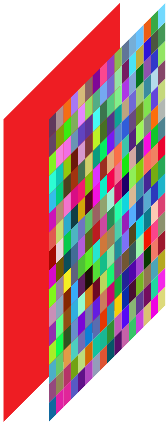

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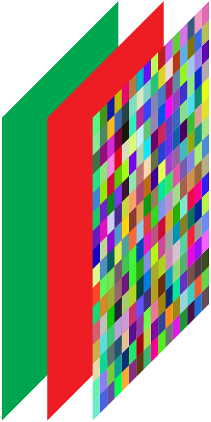

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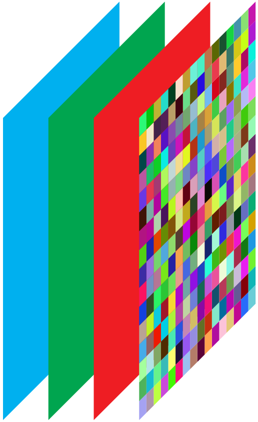


Deep Neural Networks

- We want to classify images into one of k classes

Deep Neural Networks

- We want to classify images into one of k classes
- Extract hierarchical features

Deep Neural Networks

- We want to classify images into one of k classes
- Extract hierarchical features

Edges

Deep Neural Networks

- We want to classify images into one of k classes
- Extract hierarchical features

$\boxed{\text{Edges}} \longrightarrow \boxed{\text{Contours}}$

Deep Neural Networks

- We want to classify images into one of k classes
- Extract hierarchical features

Edges $\longrightarrow$ Contours $\longrightarrow$ Parts

Deep Neural Networks

- We want to classify images into one of k classes
- Extract hierarchical features

Edges $\longrightarrow$ Contours $\longrightarrow$ Parts $\longrightarrow$ Objects

Why reinvent the wheel?

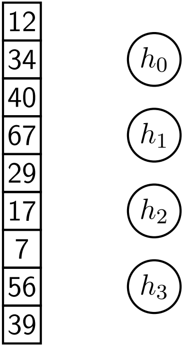
Why reinvent the wheel?

78	87	55
60	53	46
88	63	91

Why reinvent the wheel?

42
3
32
23
39
39
73
16
5

Why reinvent the wheel?



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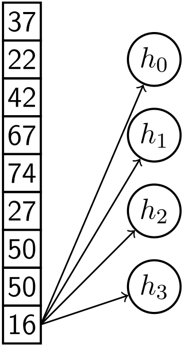

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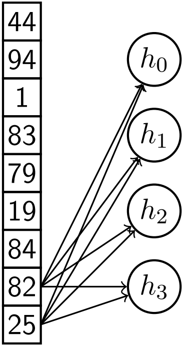

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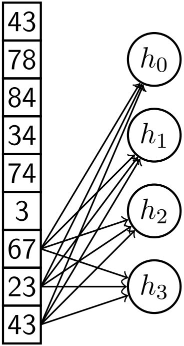

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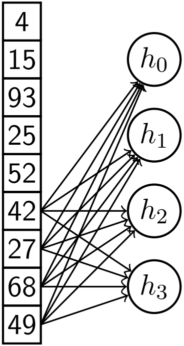

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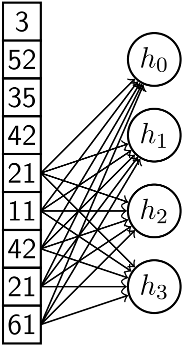

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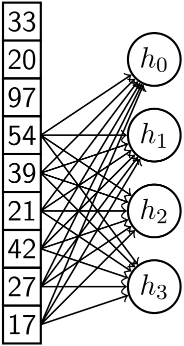

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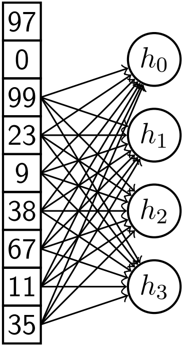

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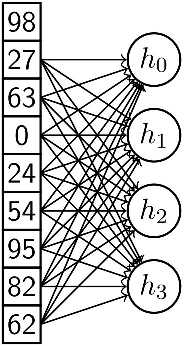

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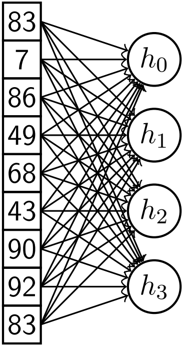

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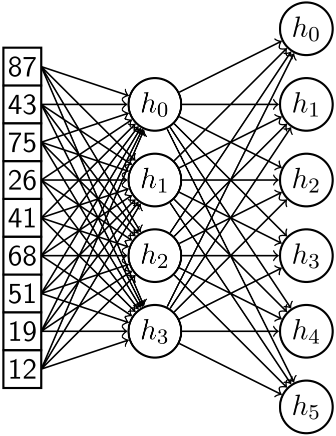

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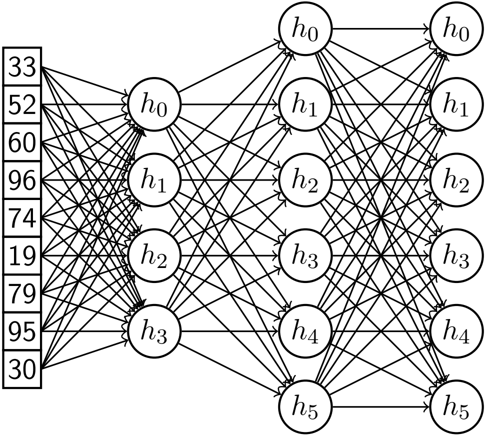

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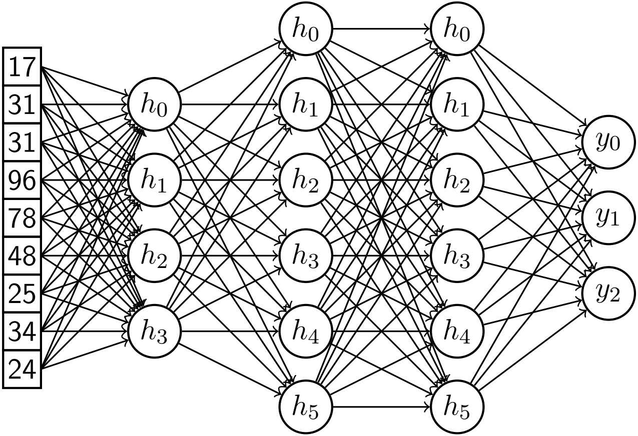

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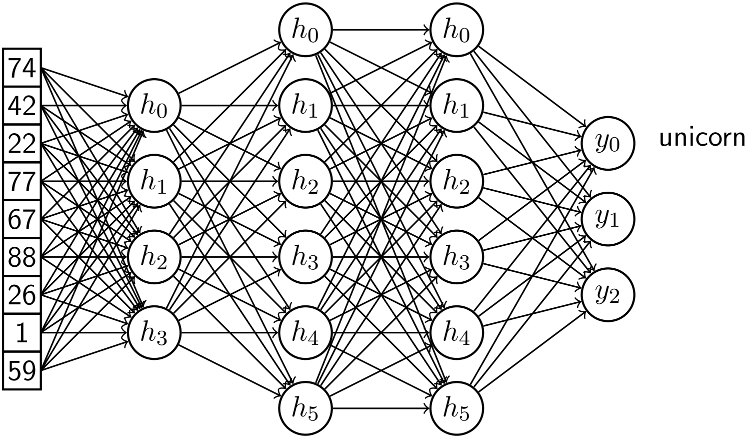

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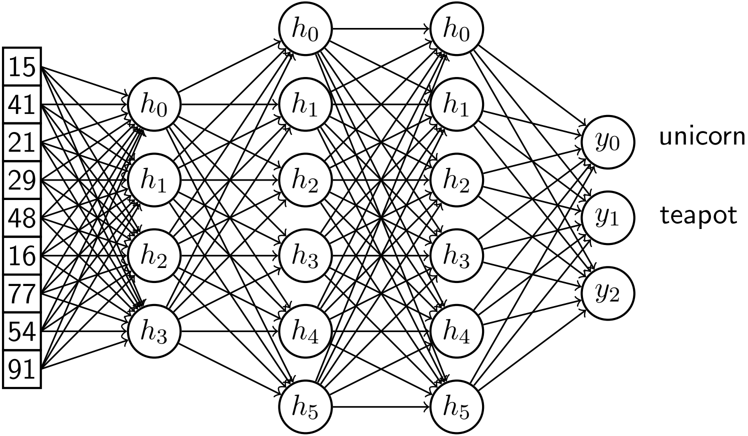

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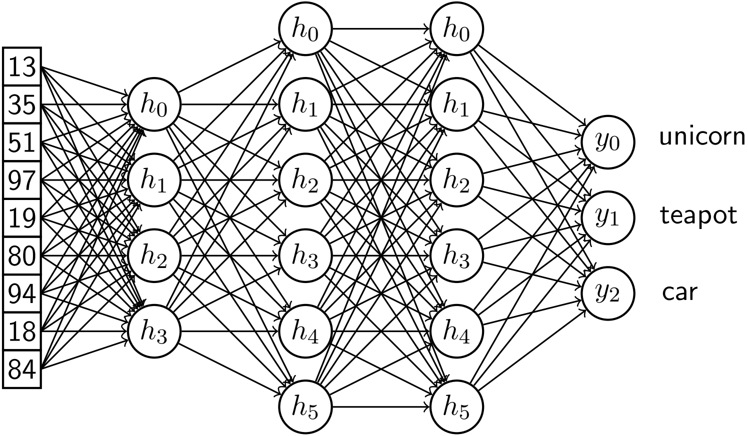


Time for ze kitteh

This is a cat ♥

Time for ze kitteh

Still a cat ♥♥

Time for ze kitteh

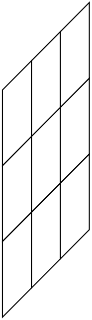
Half cat / half salad ♥♥♥

Time for ze kitteh

Many cats ♥♥♥♥

Weight Sharing

Weight Sharing



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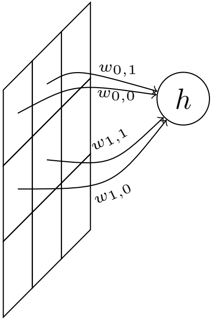

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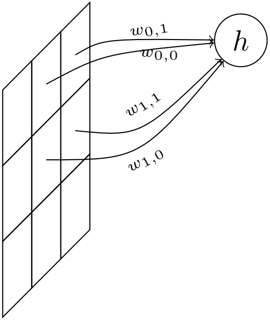
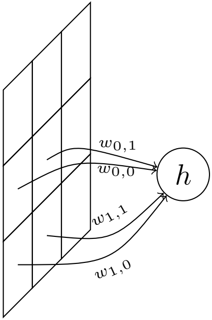


Convolutional Neural Networks: Mechanics

Weight Sharing



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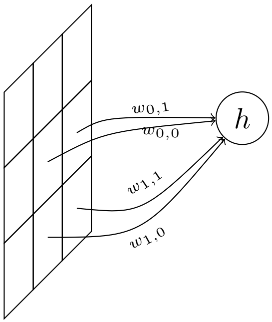

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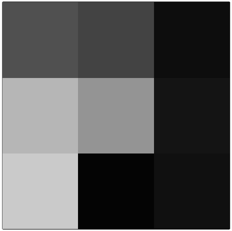


Image

Convolutional Neural Networks: Mechanics

0.4	0.9	0.1
0.7	0.2	0.6
0.8	0.3	0.5

Image

Convolutional Neural Networks: Mechanics

0.4	0.9	0.1
0.7	0.2	0.6
0.8	0.3	0.5

Image

5.7	2.4
3.1	0.9

Kernel

Convolutional Neural Networks: 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

6.79

Output

Convolutional Neural Networks: Mechanics

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

Image

6.79	6.53

Output

Convolutional Neural Networks: Mechanics

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

Image

6.79	6.53
7.67	

Output

Convolutional Neural Networks: Mechanics

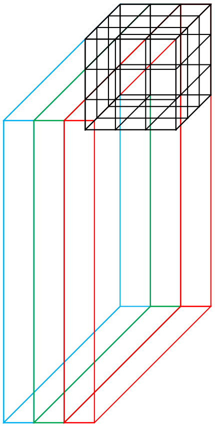
0.4	0.9	0.1
0.7	$5.7 \cdot 0.2$	$2.4 \cdot 0.6$
0.8	$3.1 \cdot 0.3$	$0.9 \cdot 0.5$

Image

6.79	6.53
7.67	3.96

Output

Convolutional Neural Networks: Mechanics



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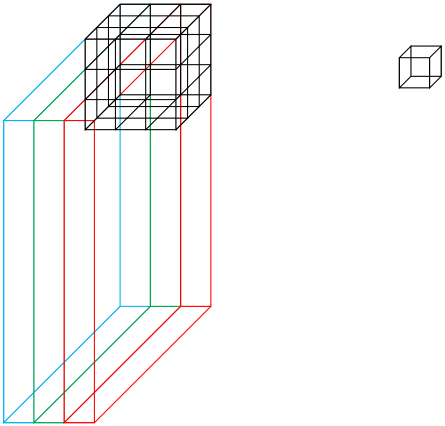

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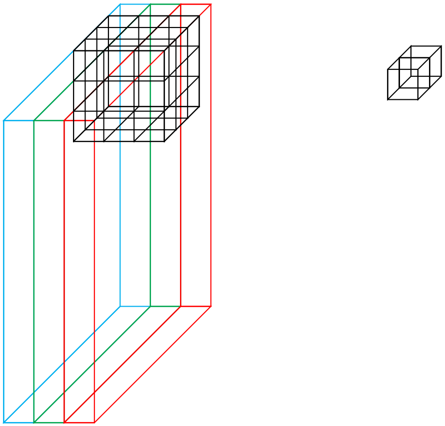

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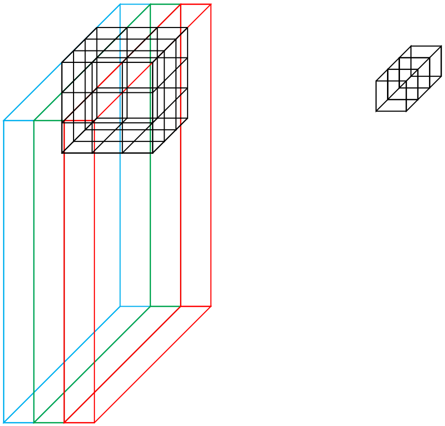

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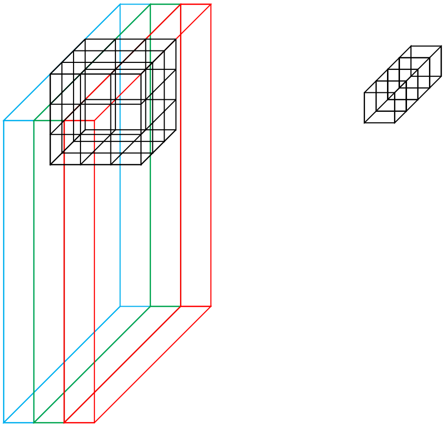

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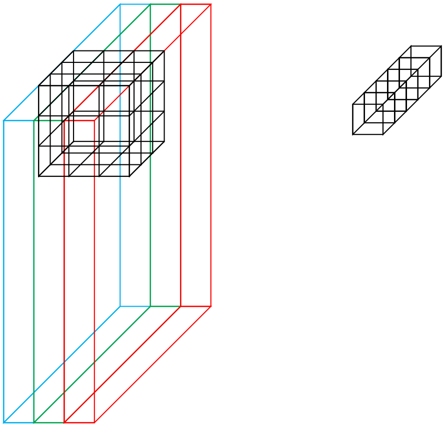

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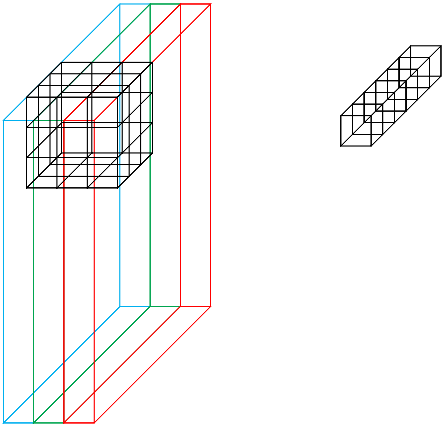

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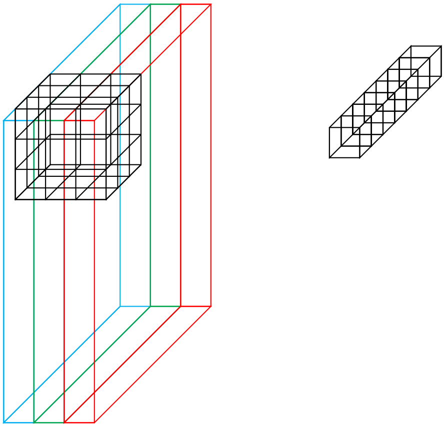

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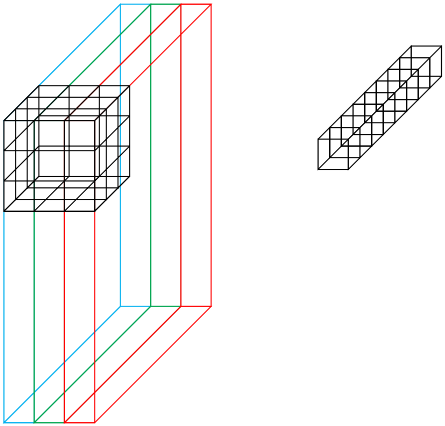

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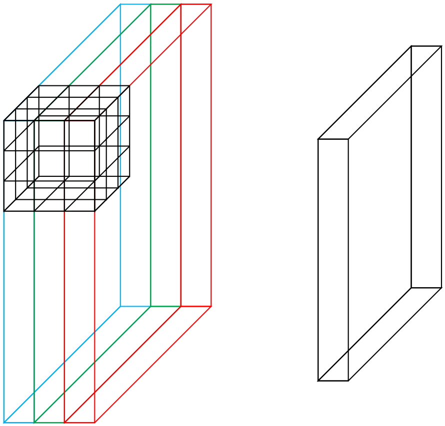

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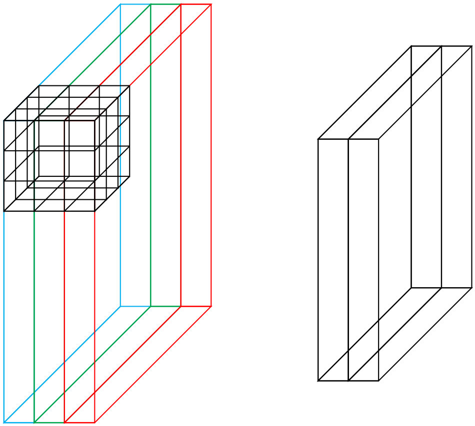

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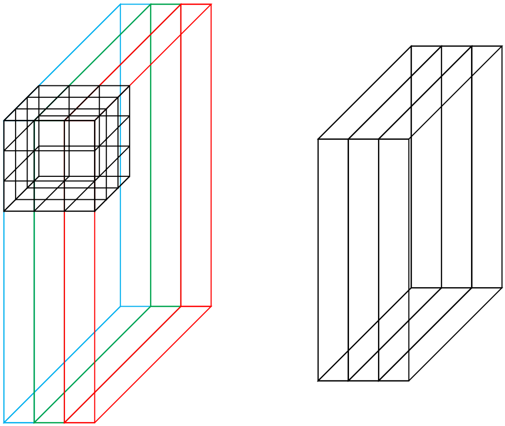

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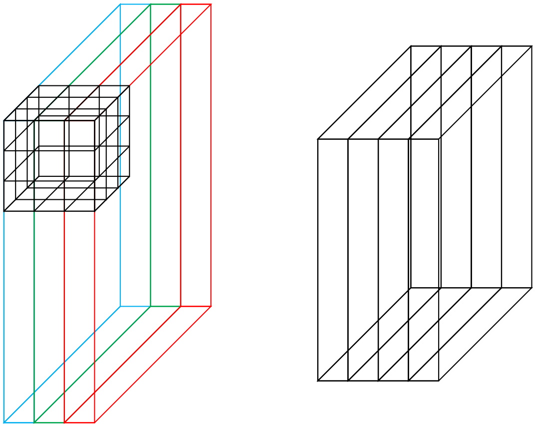
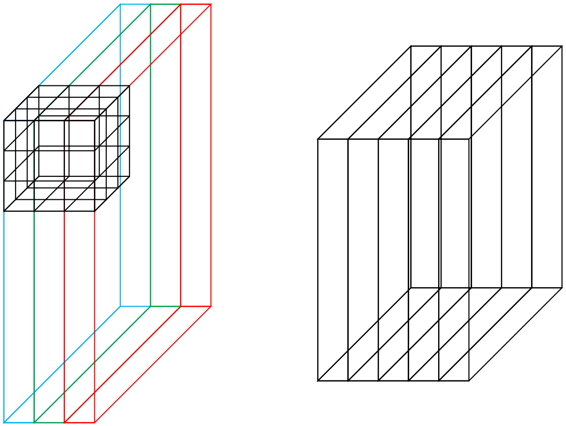


Convolutional Neural Networks: Mechanics



Recipe for a Convolutional Neural Network Layer

Recipe for a Convolutional Neural Network Layer

- Ingredients

Recipe for a Convolutional Neural Network Layer

- Ingredients
  1. Image I with dimension $w \times h \times d$

Recipe for a Convolutional Neural Network Layer

- Ingredients
  1. Image I with dimension $w \times h \times d$
  2. A kernel (filter) K of size $k \times l \times m$

Recipe for a Convolutional Neural Network Layer

- Ingredients
  1. Image I with dimension $w \times h \times d$
  2. A kernel (filter) K of size $k \times l \times m$
- Cooking

Recipe for a Convolutional Neural Network Layer

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  1. Image I with dimension $w \times h \times d$
  2. A kernel (filter) K of size $k \times l \times m$
- Cooking
  - Put the image into the oven at 150°C

Recipe for a Convolutional Neural Network Layer

- Ingredients
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  1. Image I with dimension $w \times h \times d$
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  - Don't put the image into the oven at 150°C
  - Slide the kernel across the image

Recipe for a Convolutional Neural Network Layer

- Ingredients
  1. Image I with dimension $w \times h \times d$
  2. A kernel (filter) K of size $k \times l \times m$
- Cooking
  - Don't put the image into the oven at 150°C
  - Slide the kernel across the image
  - Compute the "dot product" for each configuration

Convolutional Neural Networks: Pooling

66	2
6	32

Convolutional Neural Networks: Pooling

66	2
6	32

Convolutional Neural Networks: Pooling

6	2
66	32

Convolutional Neural Networks: Pooling

2	66
6	32

Convolutional Neural Networks: Pooling

32	6
2	66

Convolutional Neural Networks: Pooling

5	19	69
66	2	79
6	32	128

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- *Pooling* achieves translational invariance

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- *Pooling* achieves translational invariance
- A form of downsampling

Convolutional Neural Networks: Pooling

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66	128

- *Pooling* achieves translational invariance
- A form of downsampling
- Other pooling functions possible

Convolutional Neural Networks: Architecture

```
INPUT -> [CONV+ -> POOL?]+ -> FC+ -> OUTPUT
```

Convolutional Neural Networks: Intuition

What's in a kernel?

Convolutional Neural Networks: Intuition

0	1	0
0	1	0
0	1	0

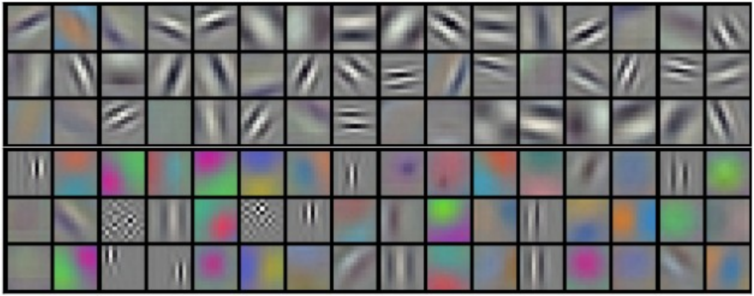
Patterns

Convolutional Neural Networks: Intuition

0	0	0
-1	1	0
0	0	0

Features

Convolutional Neural Networks: Intuition



TensorFlow

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- An open source deep learning library

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- Released by Google in November 2015

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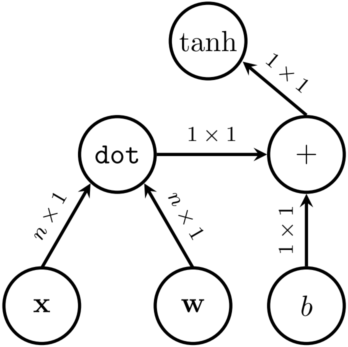
- Especially suited to:
  - "Large-scale machine learning on
  - heterogeneous distributed systems"

Computational Paradigms

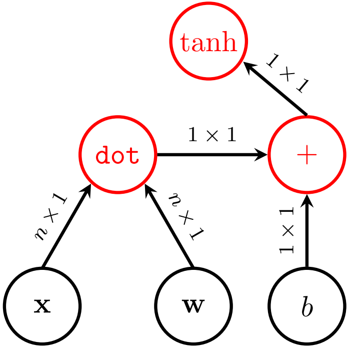
Computational Paradigms



$$\hat{y} = \tanh(\mathbf{x}^\top \mathbf{w} + b)$$

Computational Graphs

Computational Paradigms

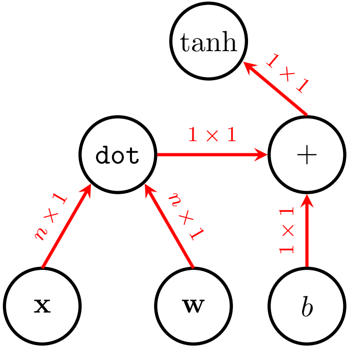


$$\hat{y} = \tanh(\mathbf{x}^\top \mathbf{w} + b)$$

Computational Graphs

1. Operations

Computational Paradigms

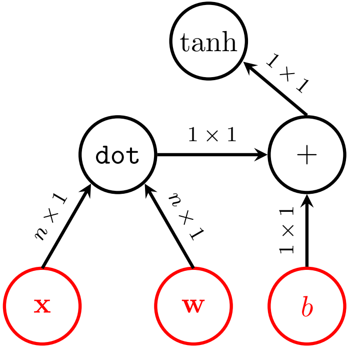


$$\hat{y} = \tanh(\mathbf{x}^\top \mathbf{w} + b)$$

Computational Graphs

1. Operations
2. Tensors

Computational Paradigms



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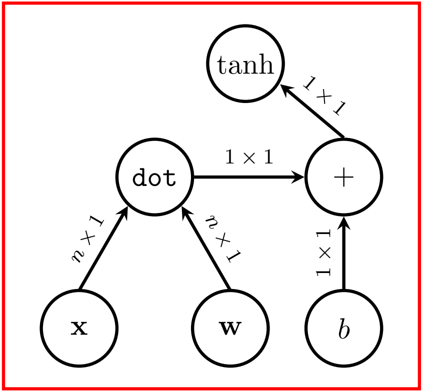
Computational Graphs

1. Operations
2. Tensors
3. Variables

Computational Paradigms



$$\hat{y} = \texttt{session.run}(\tanh(\mathbf{x}^\top \mathbf{w} + b))$$

Computational Graphs

1. Operations
2. Tensors
3. Variables
4. Sessions

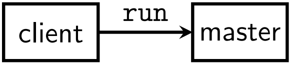
Execution Model

Execution Model

client

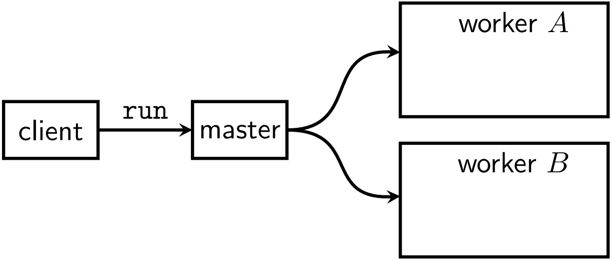
1. Client

Execution Model



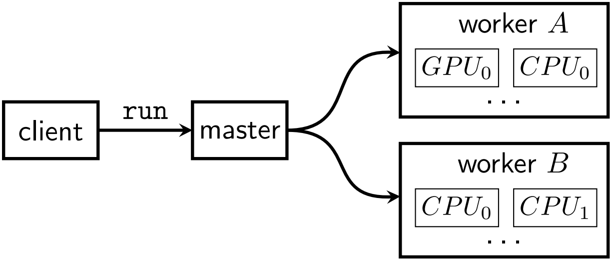
1. Client
2. Master

Execution Model



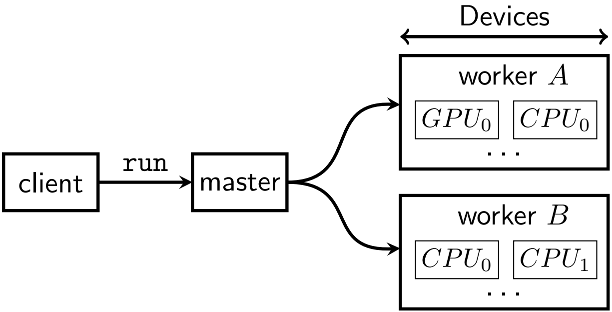
1. Client
2. Master
3. Workers

Execution Model



1. Client
2. Master
3. Workers
4. Devices

Execution Model



1. Client
2. Master
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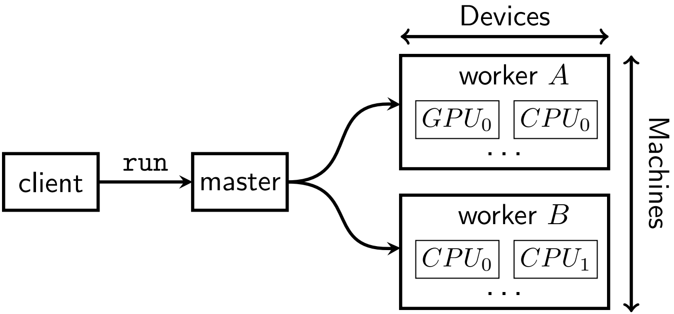
4. Devices

Execution Model



1. Client
2. Master
3. Workers
4. Devices

Visualization Tools

Visualization Tools

- Deep Neural Networks have the tendency of being . . . deep

Visualization Tools

- Deep Neural Networks have the tendency of being ... deep
- Easy to drown in the complexity of an architecture

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Visualization Tools

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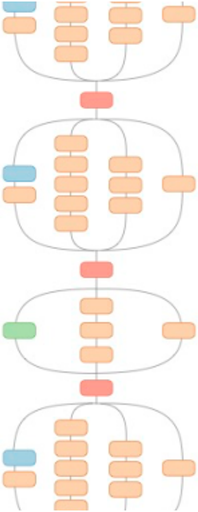

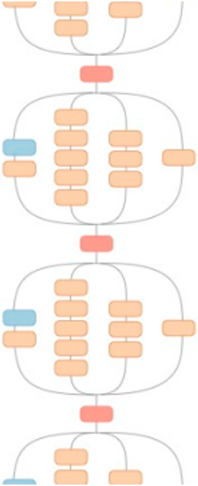

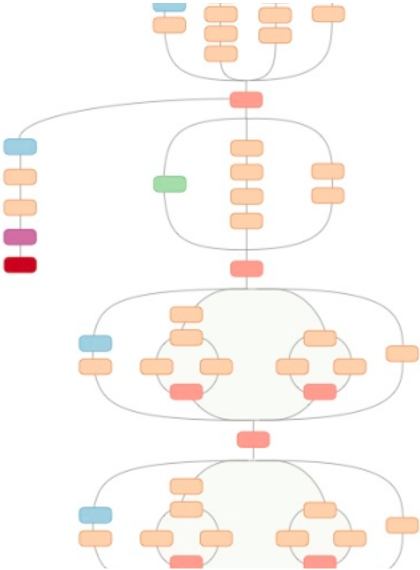

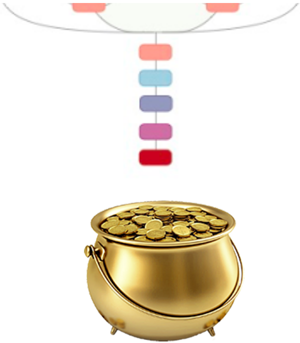

TensorBoard to the Rescue

Walkthrough

How do I continue?

Resources

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- MOOCs
  - Machine Learning by Andrew Ng @ Coursera
  - Deep Learning by Google @ Udacity
  - Machine Learning Nanodegree @ Udacity

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- Websites
  - http://colah.github.io
  - http://cs231n.github.io
  - http://karpathy.github.io
  - http://www.deeplearningbook.org
  - https://www.kaggle.com
  - https://www.tensorflow.org

PyCon Germany

- 29-30 October in Munich
- Talks on machine learning, deep learning and data science
- 15% off: VISITMUC16

Stay in Touch!

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- linkedin.com/in/petergoldsborough
- github.com/goldsborough

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- linkedin.com/in/petergoldsborough
- github.com/goldsborough

github.com/peter-can-talk/pycon-uk-2016

Q & A