tf.talk()

An Introduction to Deep Learning with TensorFlow

Peter Goldsborough

November 29, 2016

Table of Catents

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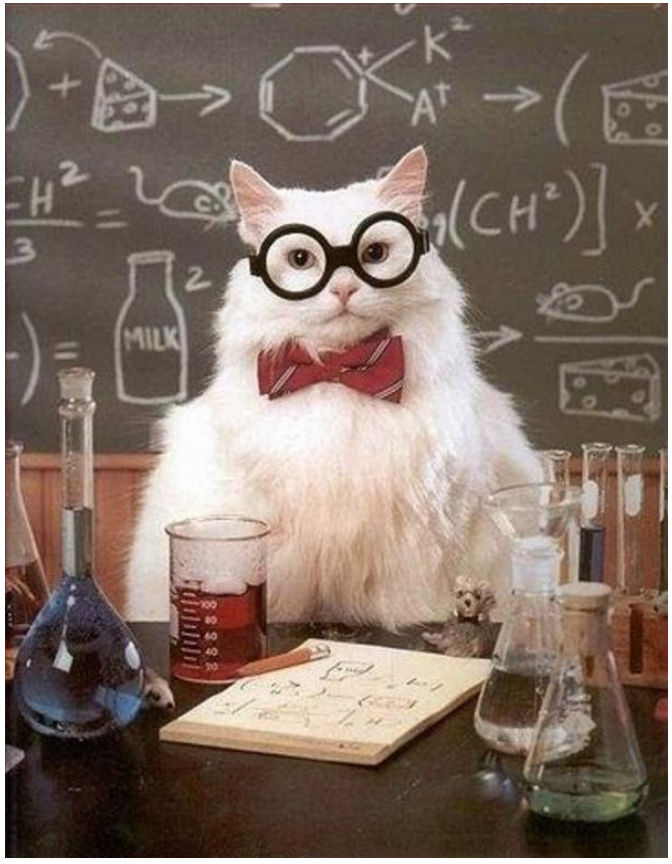

Theory

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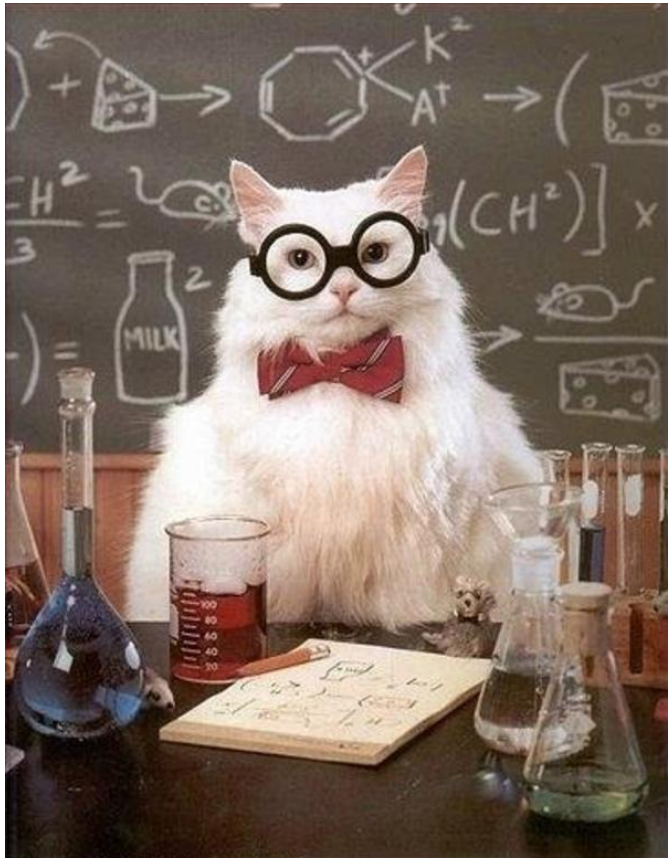
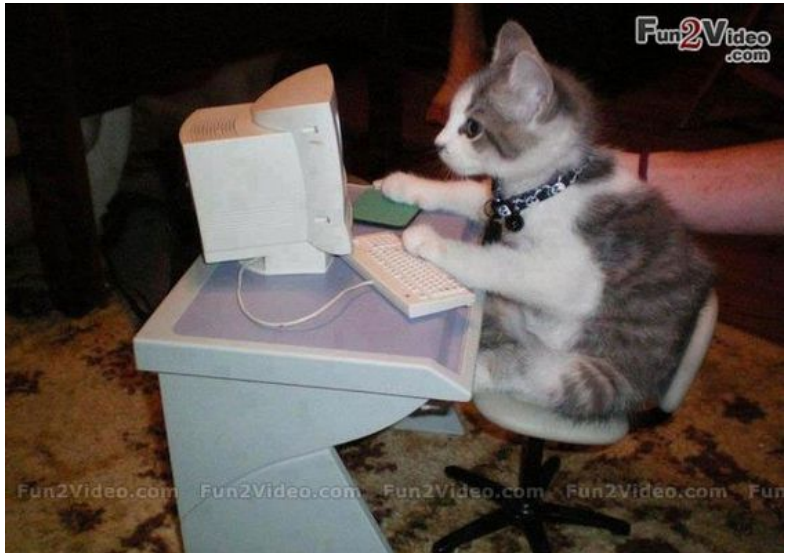


Theory



Practice

Background

Background

- CS Student @ TUM

Background

- CS Student @ TUM
- Google & Bloomberg Intern

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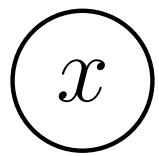
Seminar Topic: *Deep Learning With TensorFlow*

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

Neural Networks

Neural Networks



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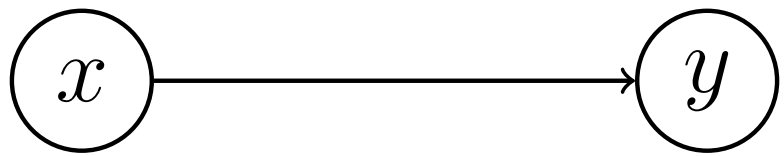

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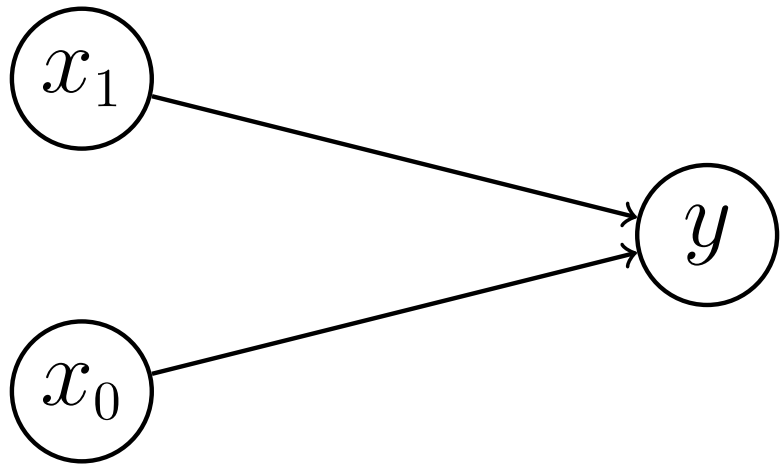

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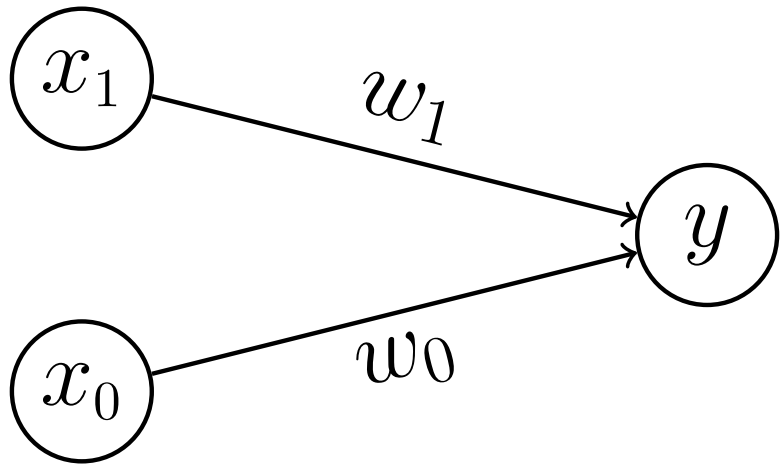

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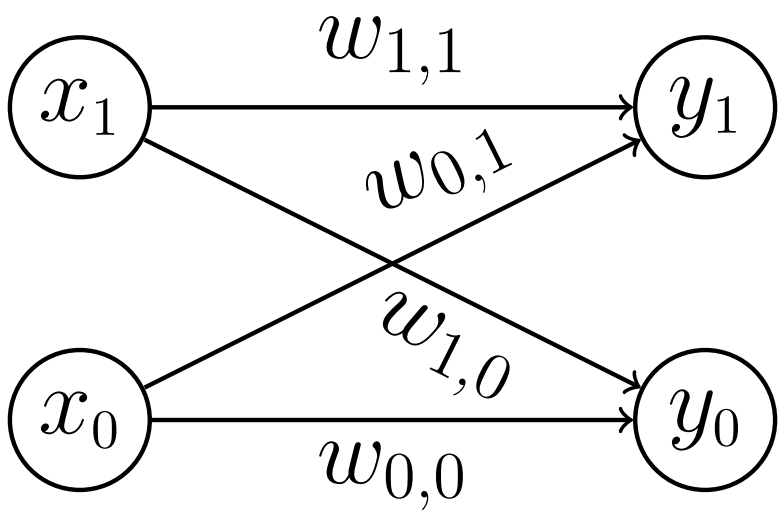

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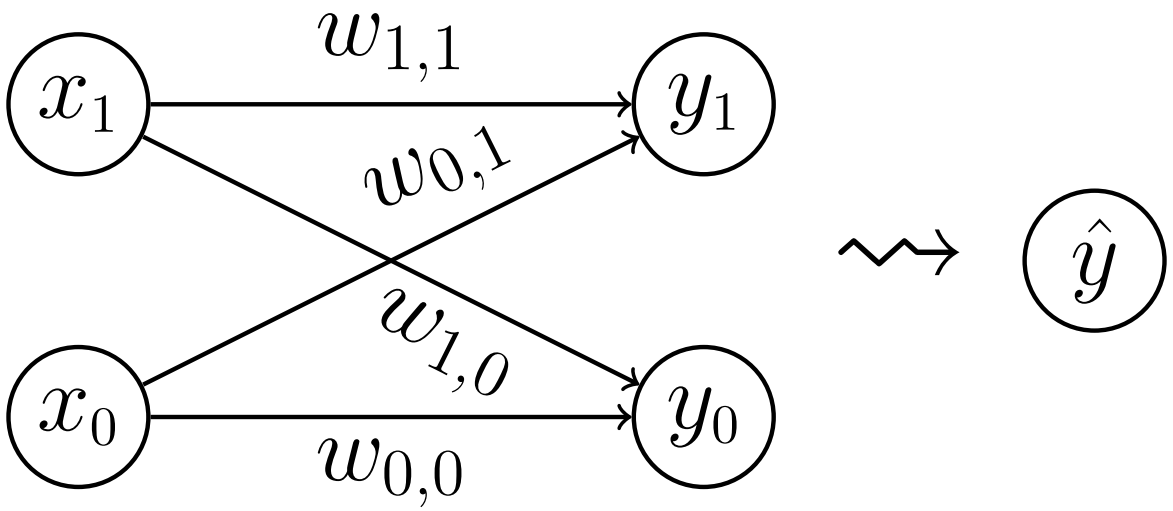

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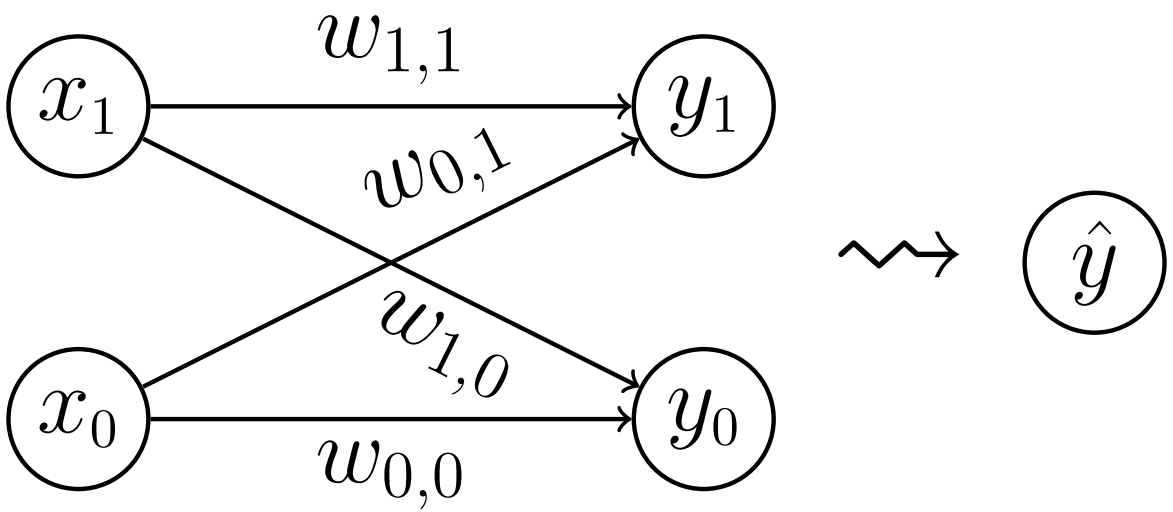
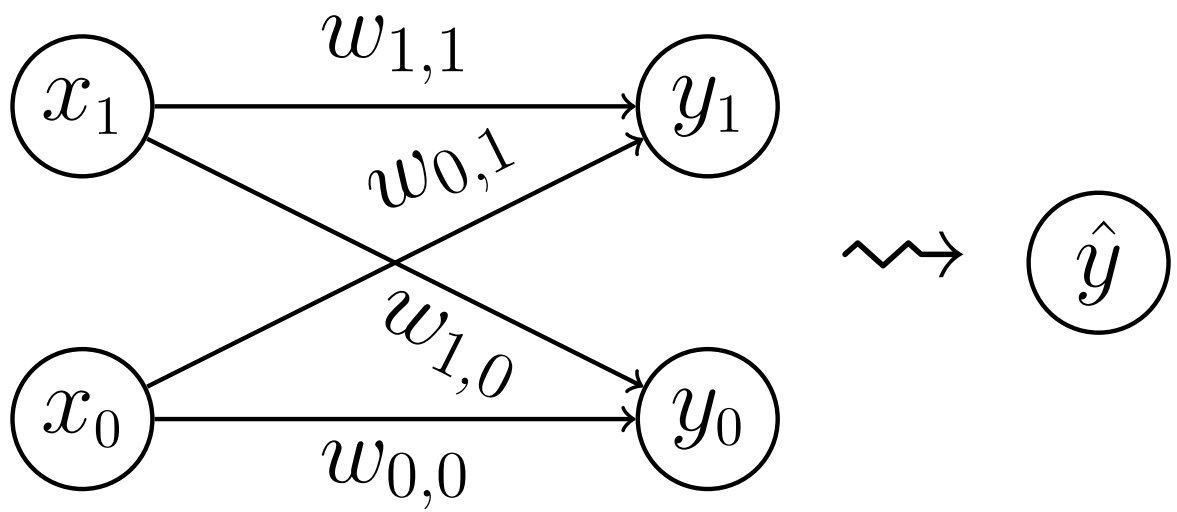


$$\underbrace{\begin{bmatrix} x_0 & x_1 \end{bmatrix}}_{\mathbf{x}} \times \underbrace{\begin{bmatrix} w_{0,0} & w_{0,1} \\ w_{1,0} & w_{1,1} \end{bmatrix}}_{\mathbf{W}} + \underbrace{\begin{bmatrix} b_0 \\ b_1 \end{bmatrix}}_{\mathbf{b}} = \underbrace{\begin{bmatrix} y_0 \\ y_1 \end{bmatrix}}_{\mathbf{y}}$$

Neural Networks



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

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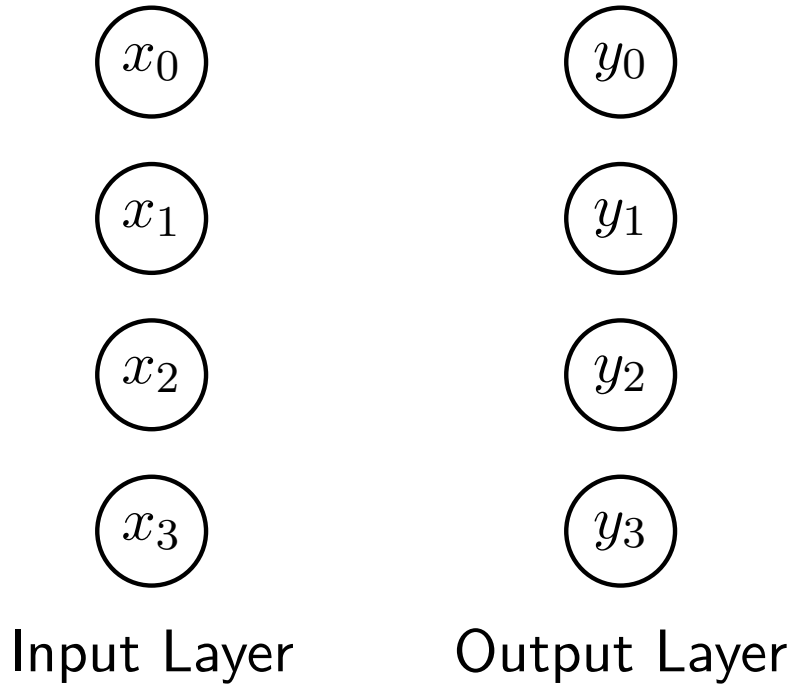

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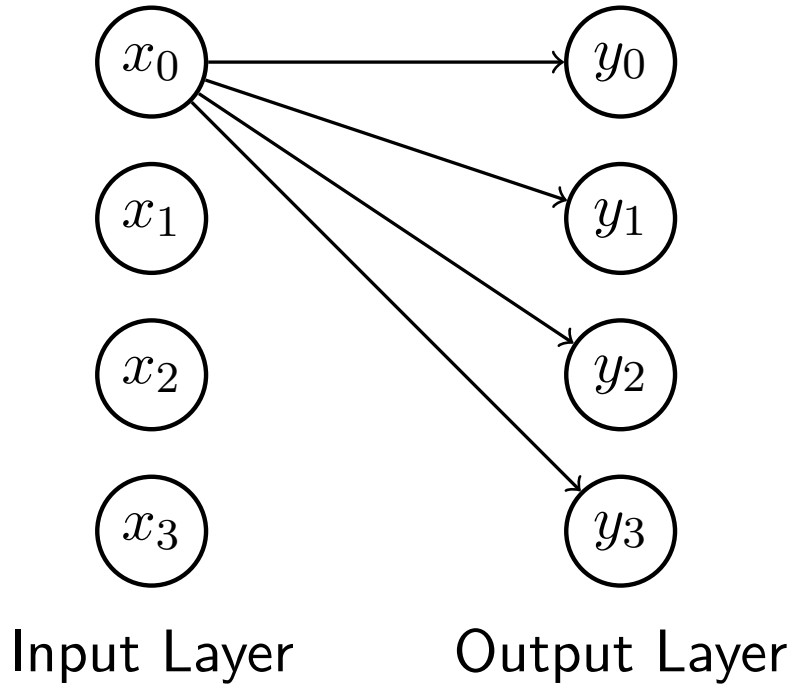

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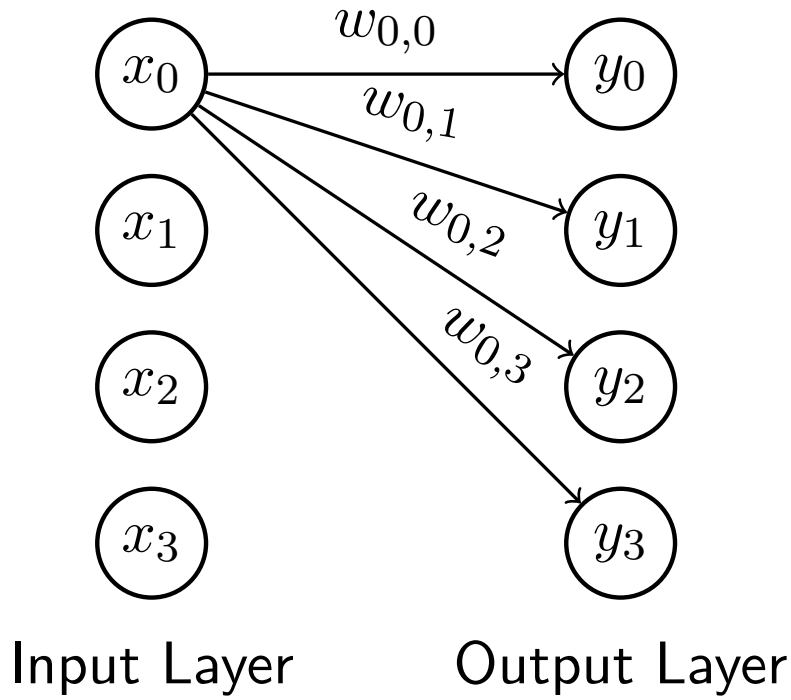

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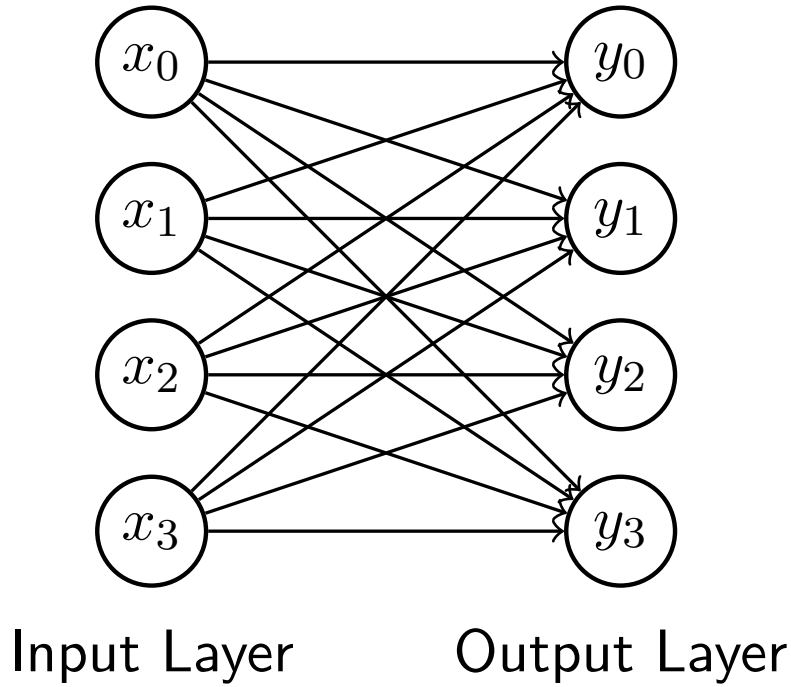
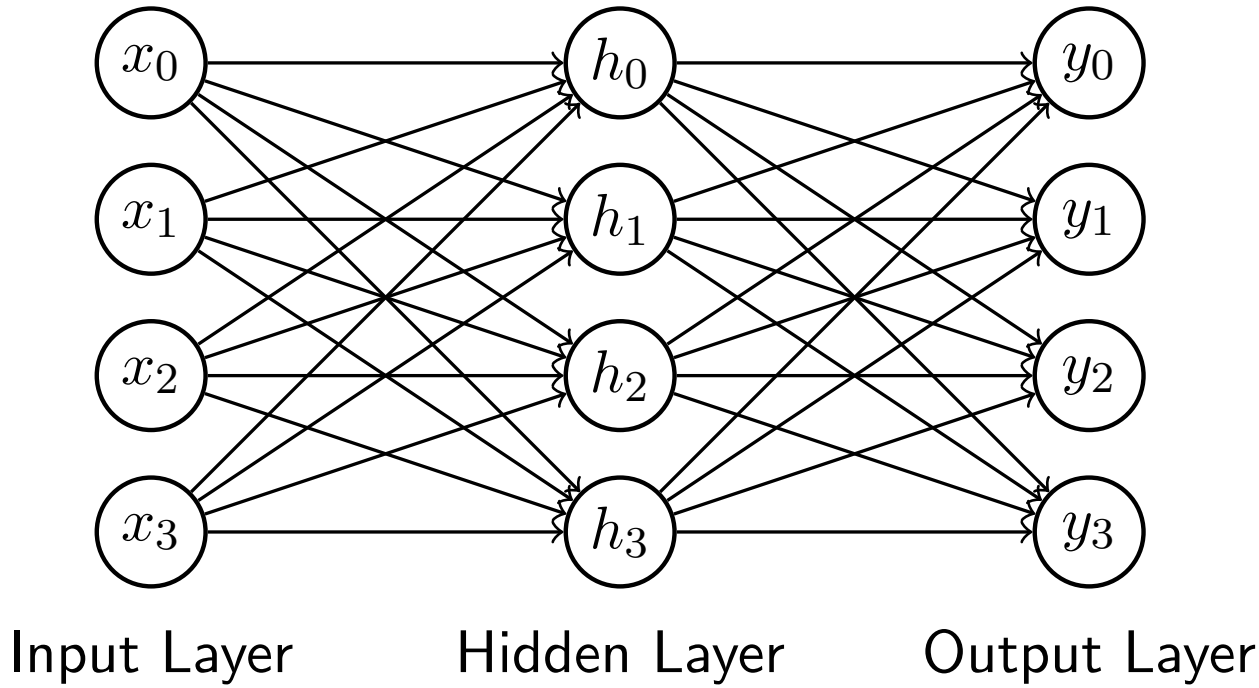


Deep Neural Networks



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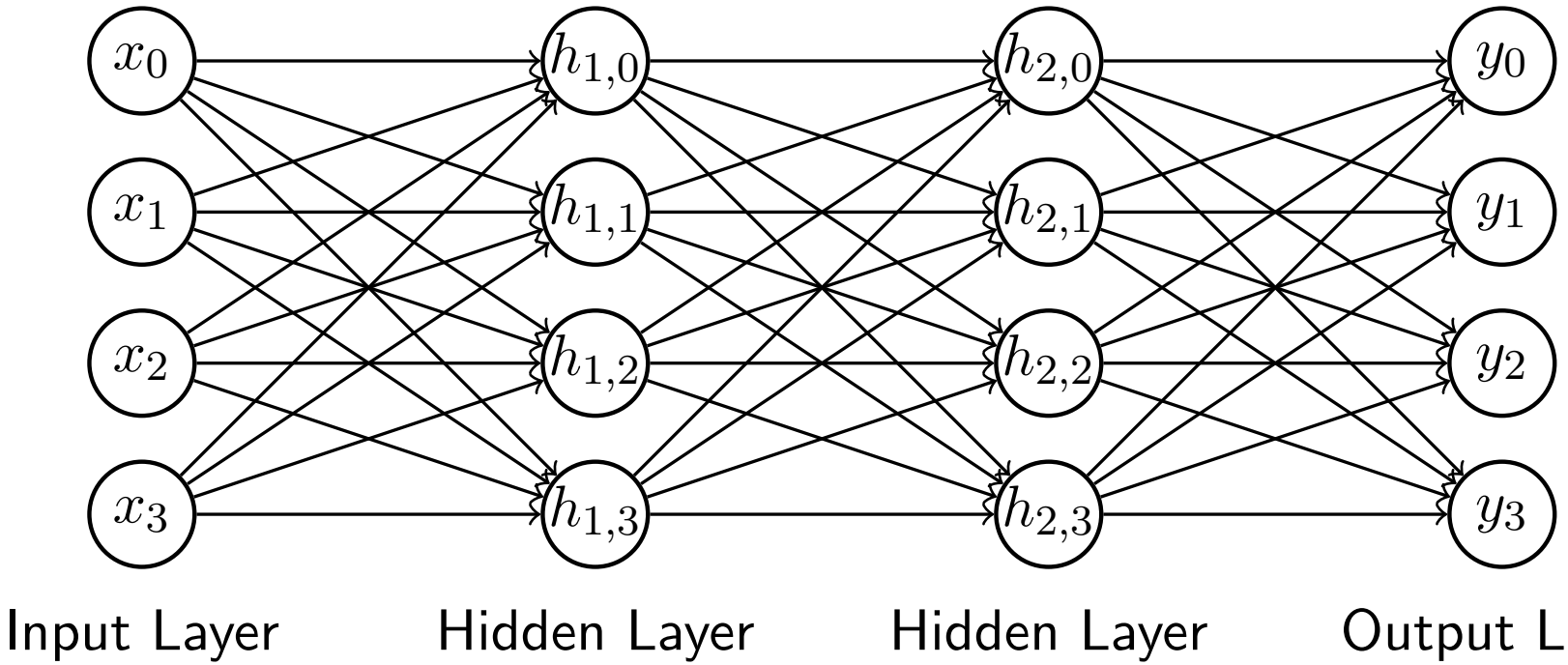


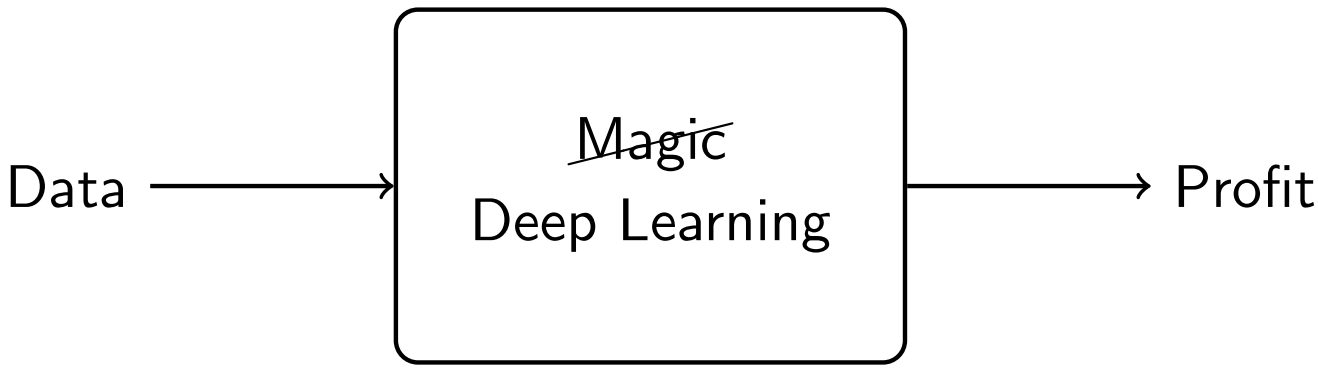
Deep Neural Networks

Deep Learning assumes that data is structured

Deep Learning assumes that data is structured

hierarchically

Deep Neural Networks



Deep Neural Networks

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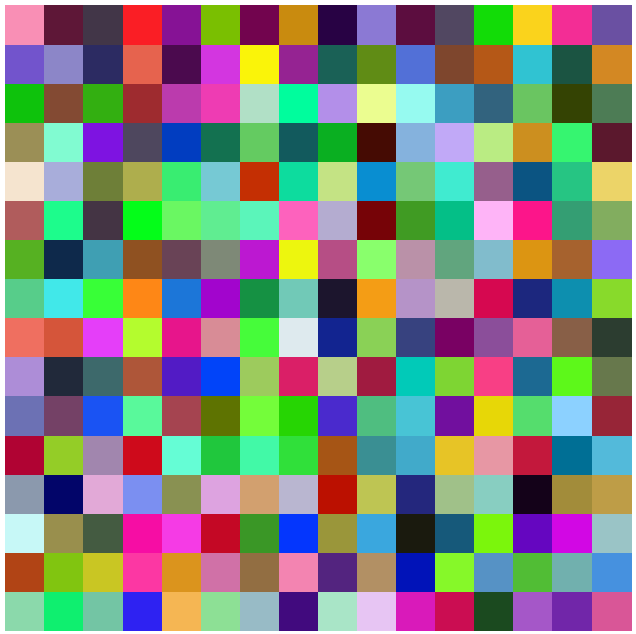

Deep Neural Networks

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68	52	41	27	27	26	9	93	61	50	29	50	22	2	90	32
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10	89	48	85	41	12	12	86	48	80	55	20	79	46	73	61
99	26	84	66	45	12	18	66	33	18	46	82	9	61	95	97
75	86	55	17	70	92	37	72	95	41	18	91	99	99	23	46
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88	6	83	49	29	53	33	11	67	60	31	32	41	47	1	50
66	44	92	72	67	61	79	43	56	35	92	1	82	17	65	29
34	23	78	56	63	86	47	68	77	22	2	69	36	27	78	65
37	84	46	41	98	49	82	32	17	77	38	66	13	57	46	4
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25	6	84	55	7	90	74	71	4	27	76	67	34	32	0	14
47	41	75	72	98	75	57	19	94	26	92	97	41	75	1	36

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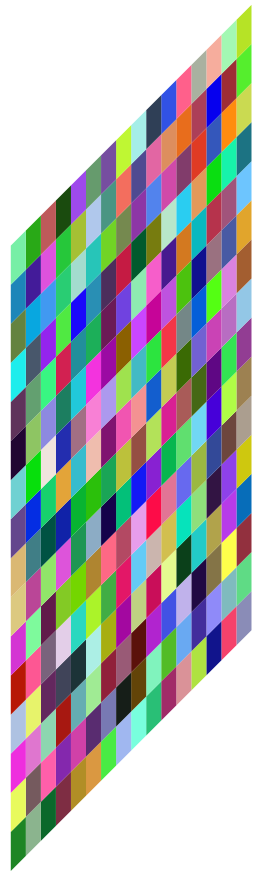

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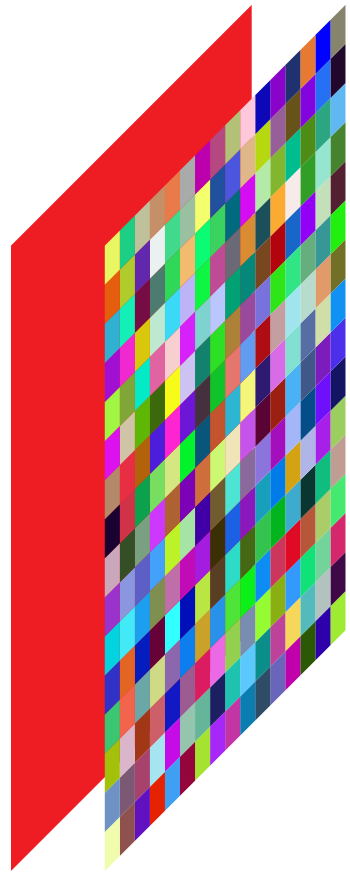

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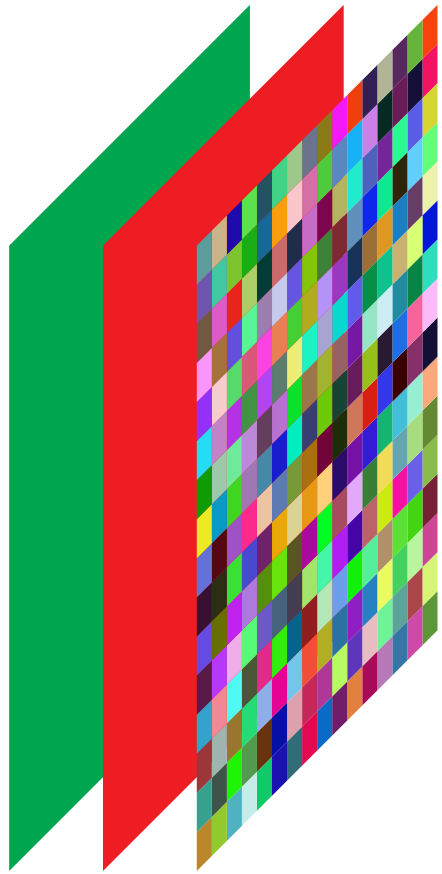

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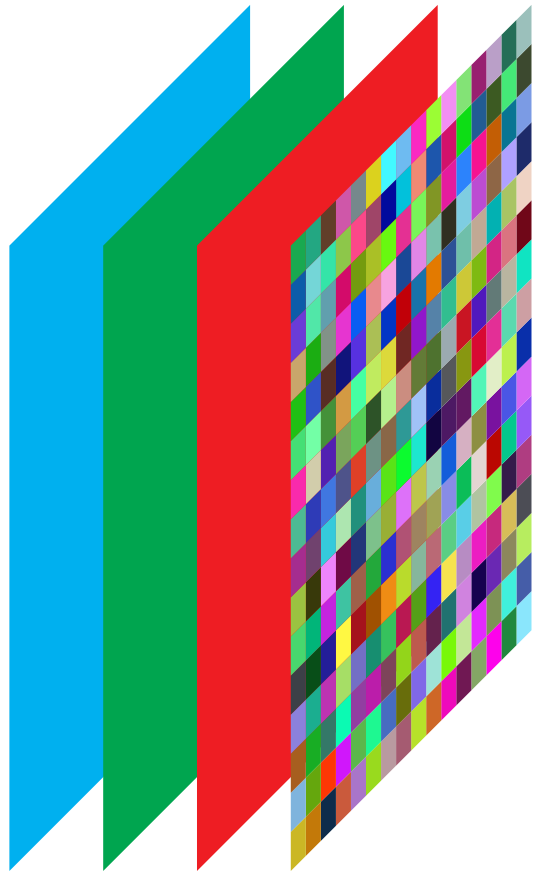

Deep Neural Networks

- 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

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Edges

Deep Neural Networks

- We want to classify images into one of k classes
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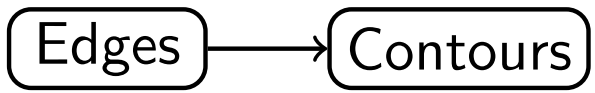

Deep Neural Networks

- We want to classify images into one of k classes
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Deep Neural Networks

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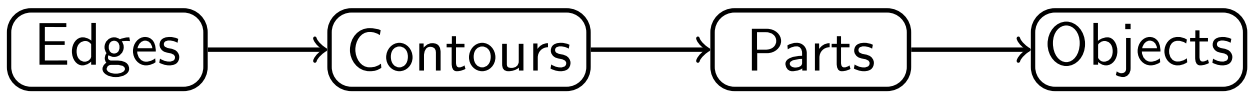


Deep Neural Networks

Why reinvent the wheel?

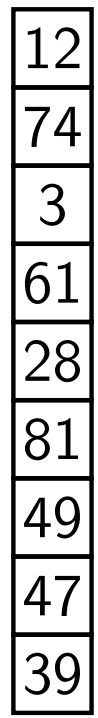
Deep Neural Networks

Why reinvent the wheel?

40	54	64
38	97	19
99	41	59

Deep Neural Networks

Why reinvent the wheel?



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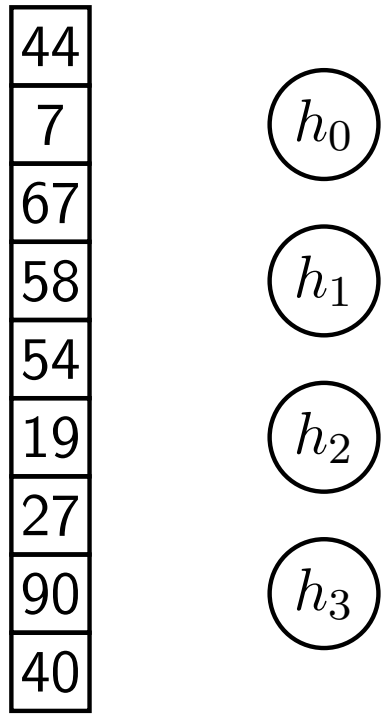

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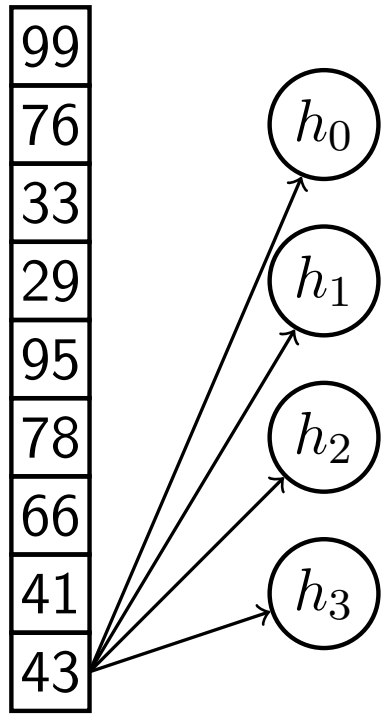

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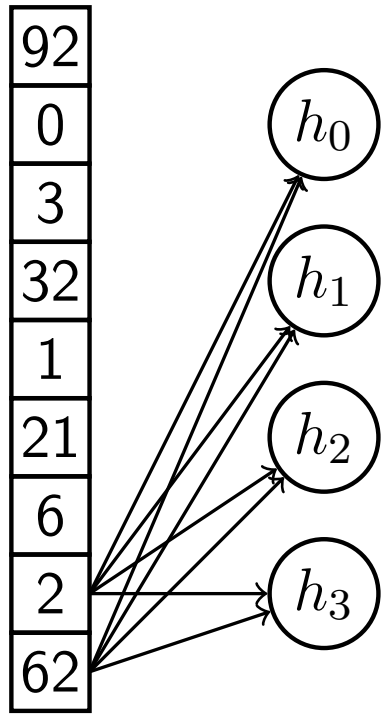

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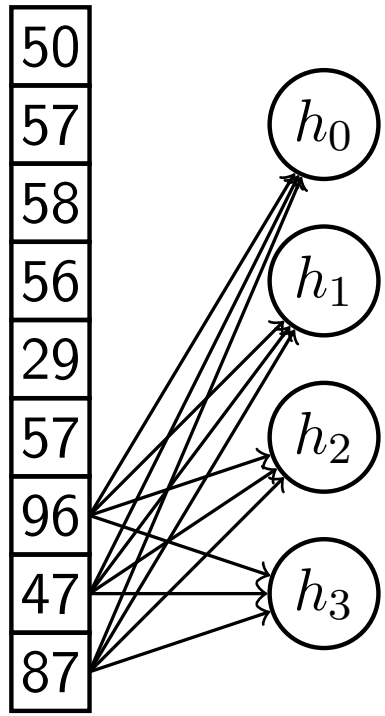

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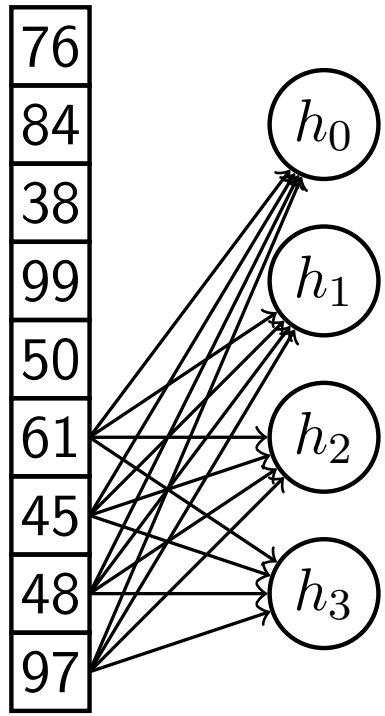

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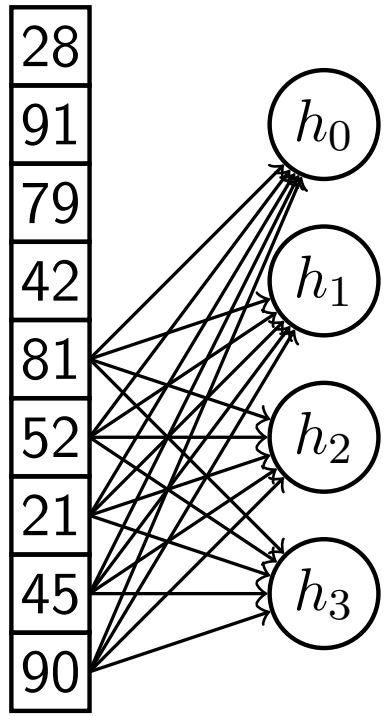

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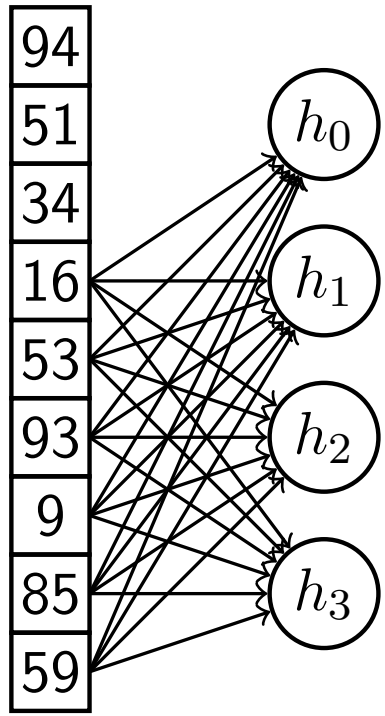

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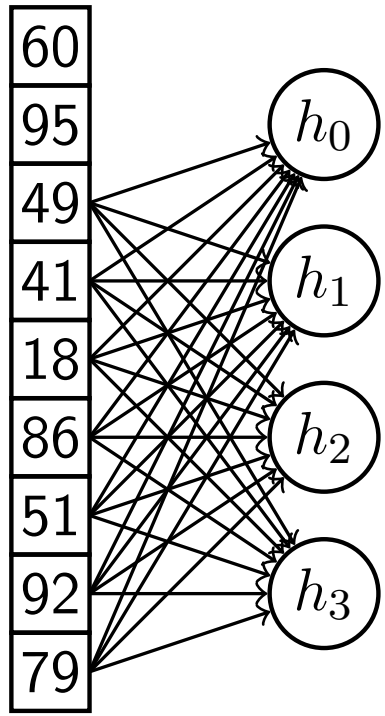

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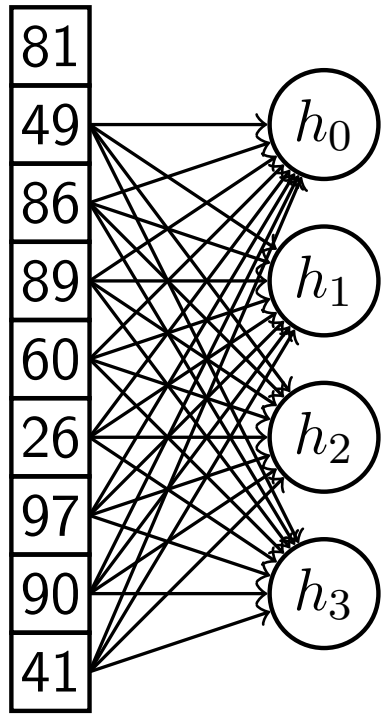

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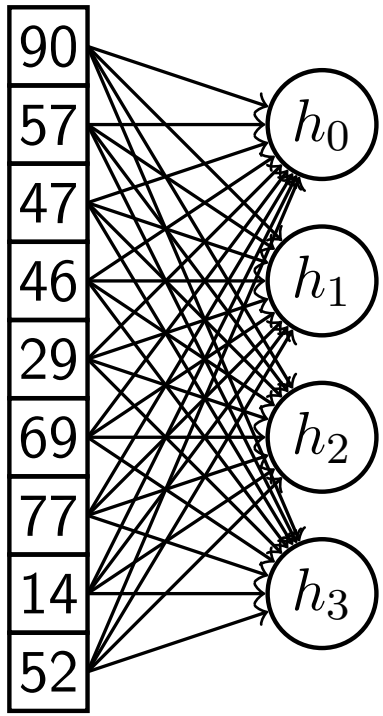

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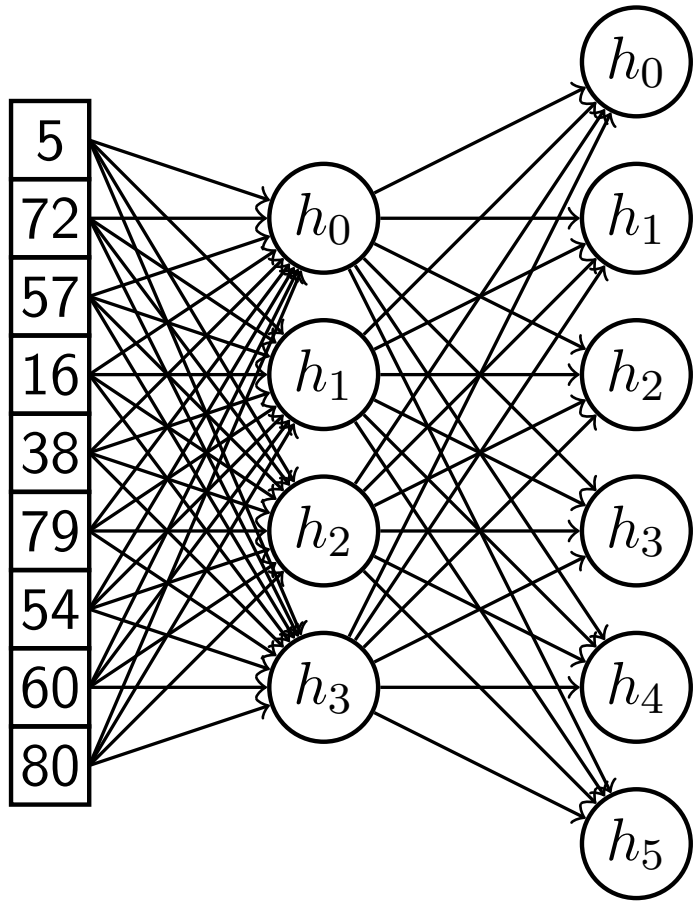

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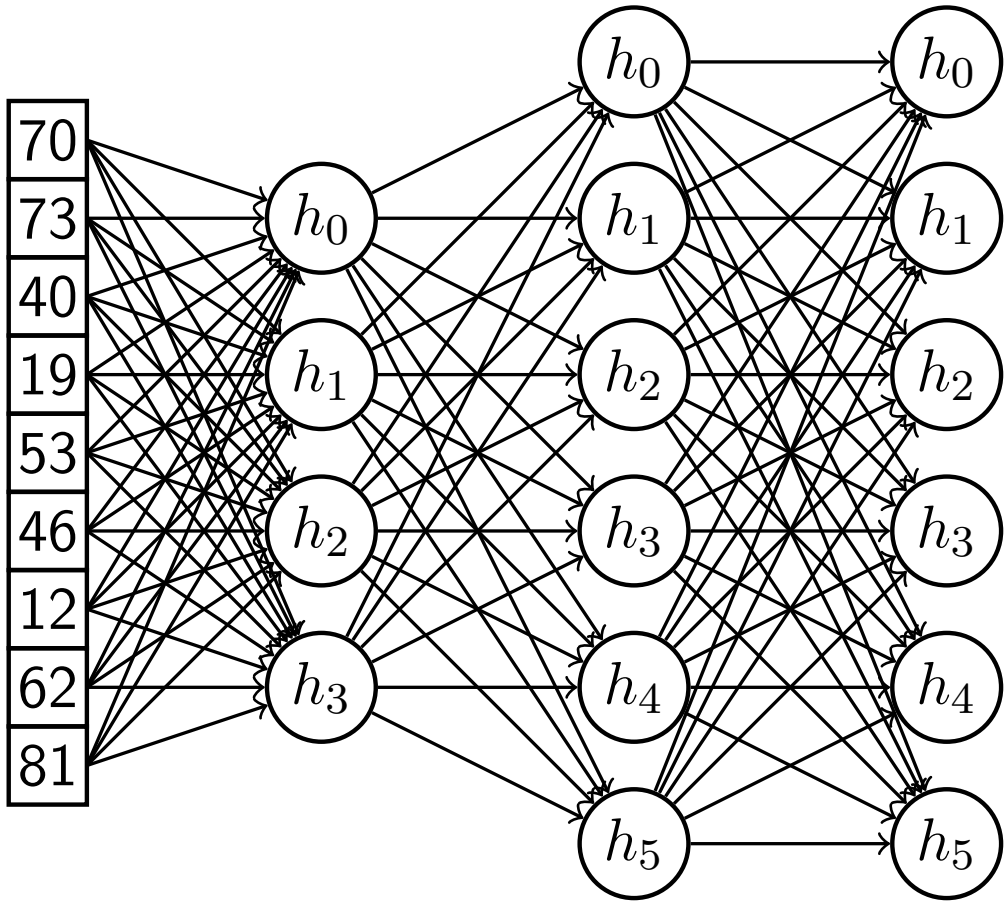

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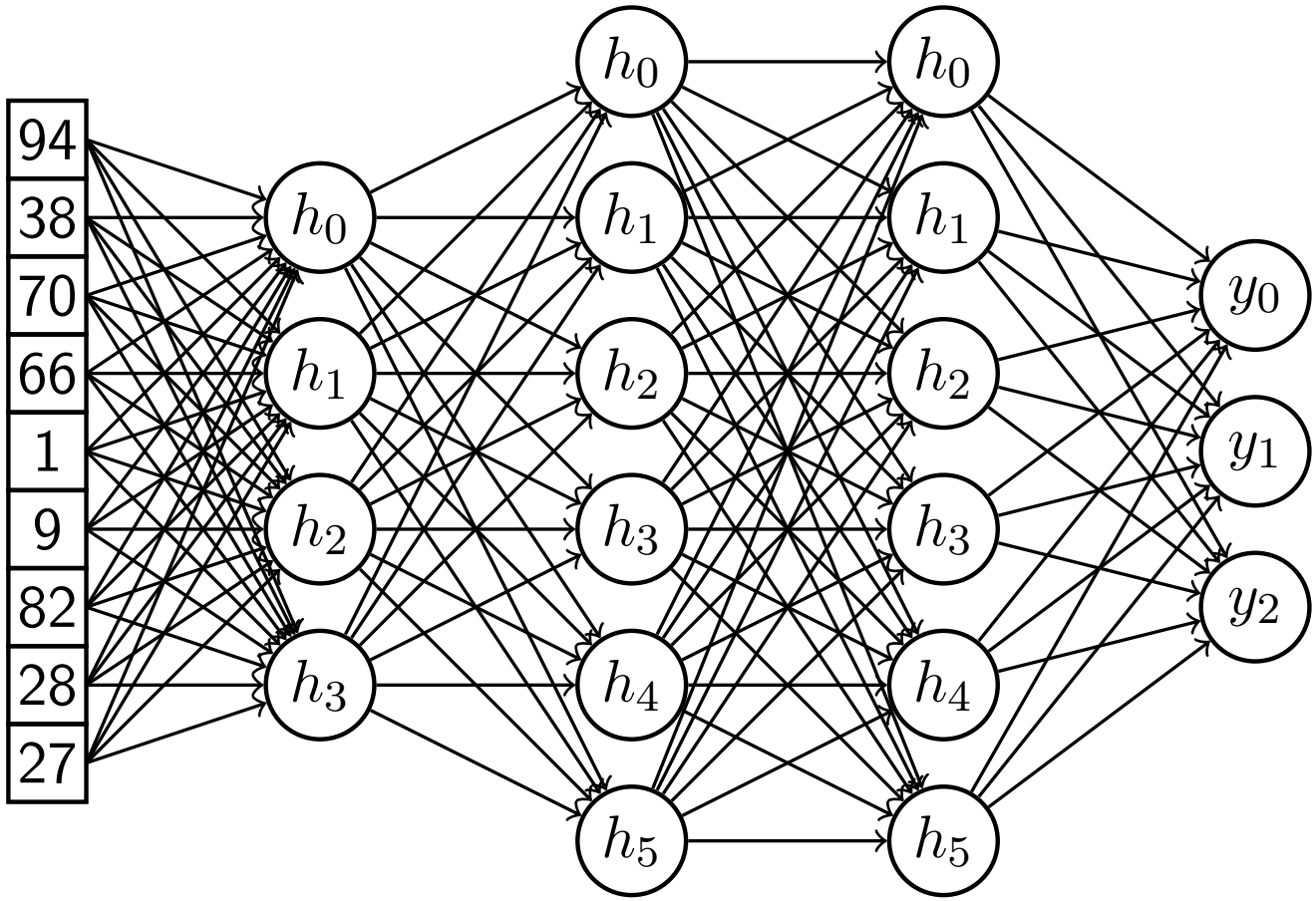

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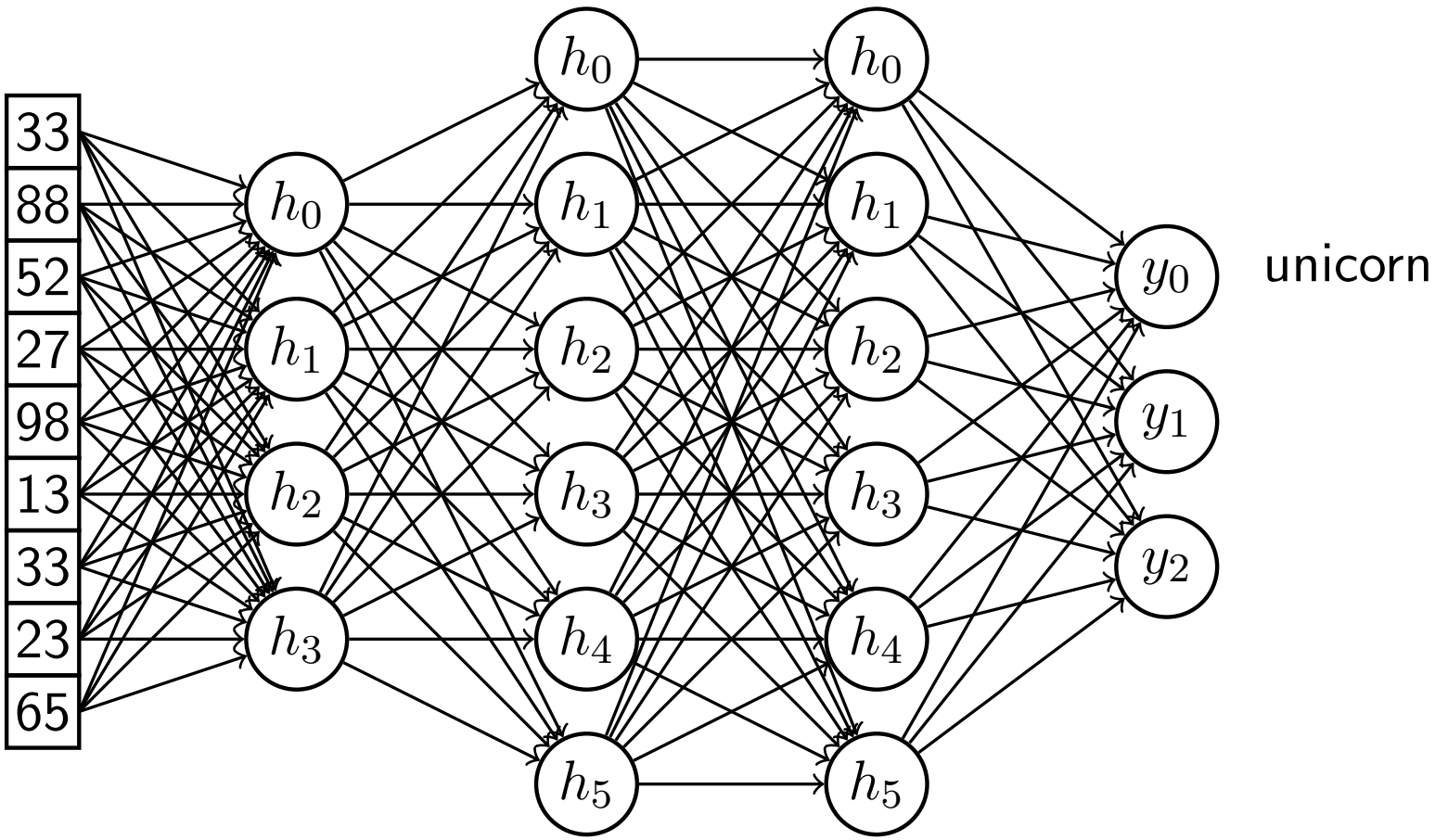

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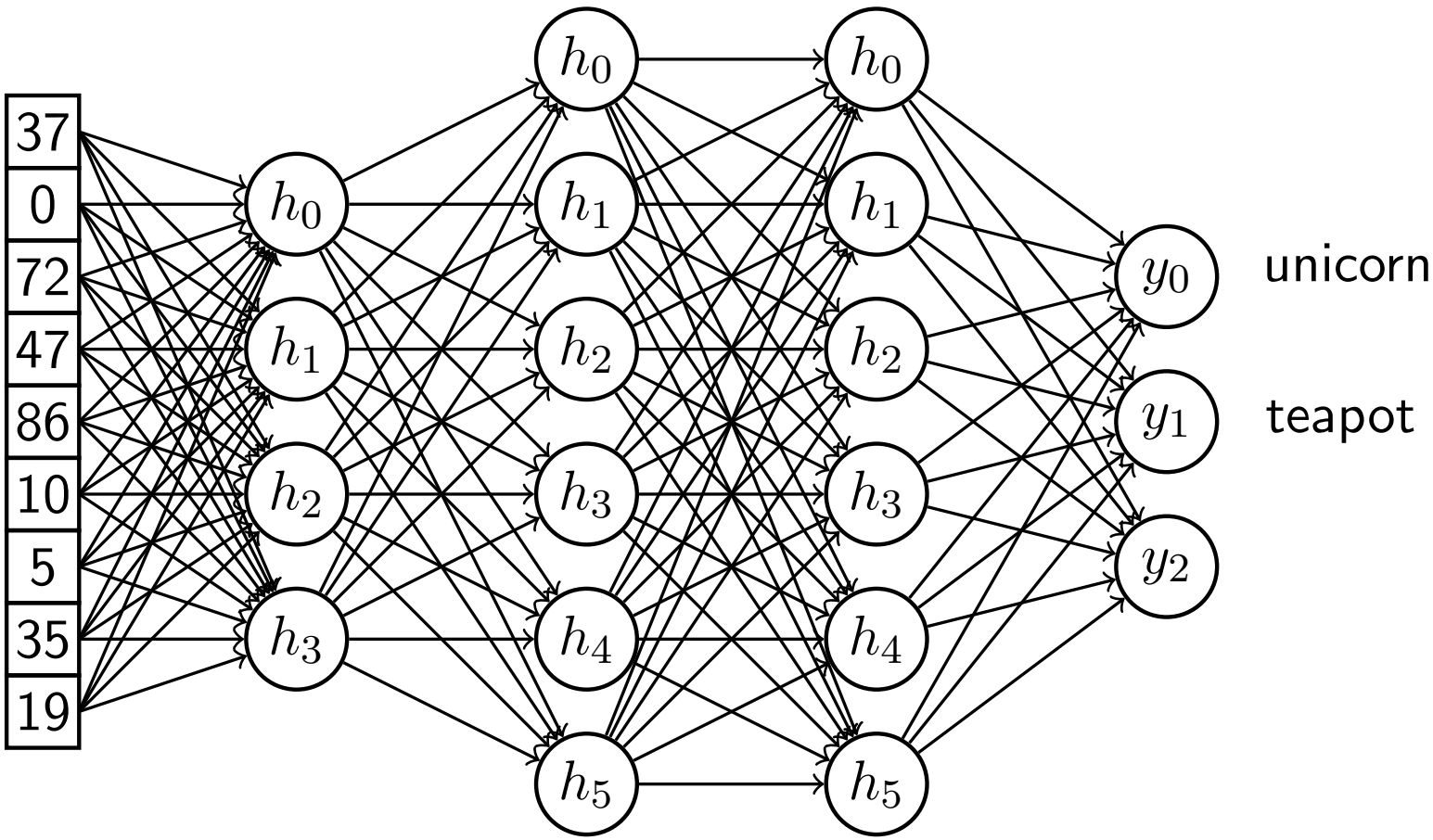
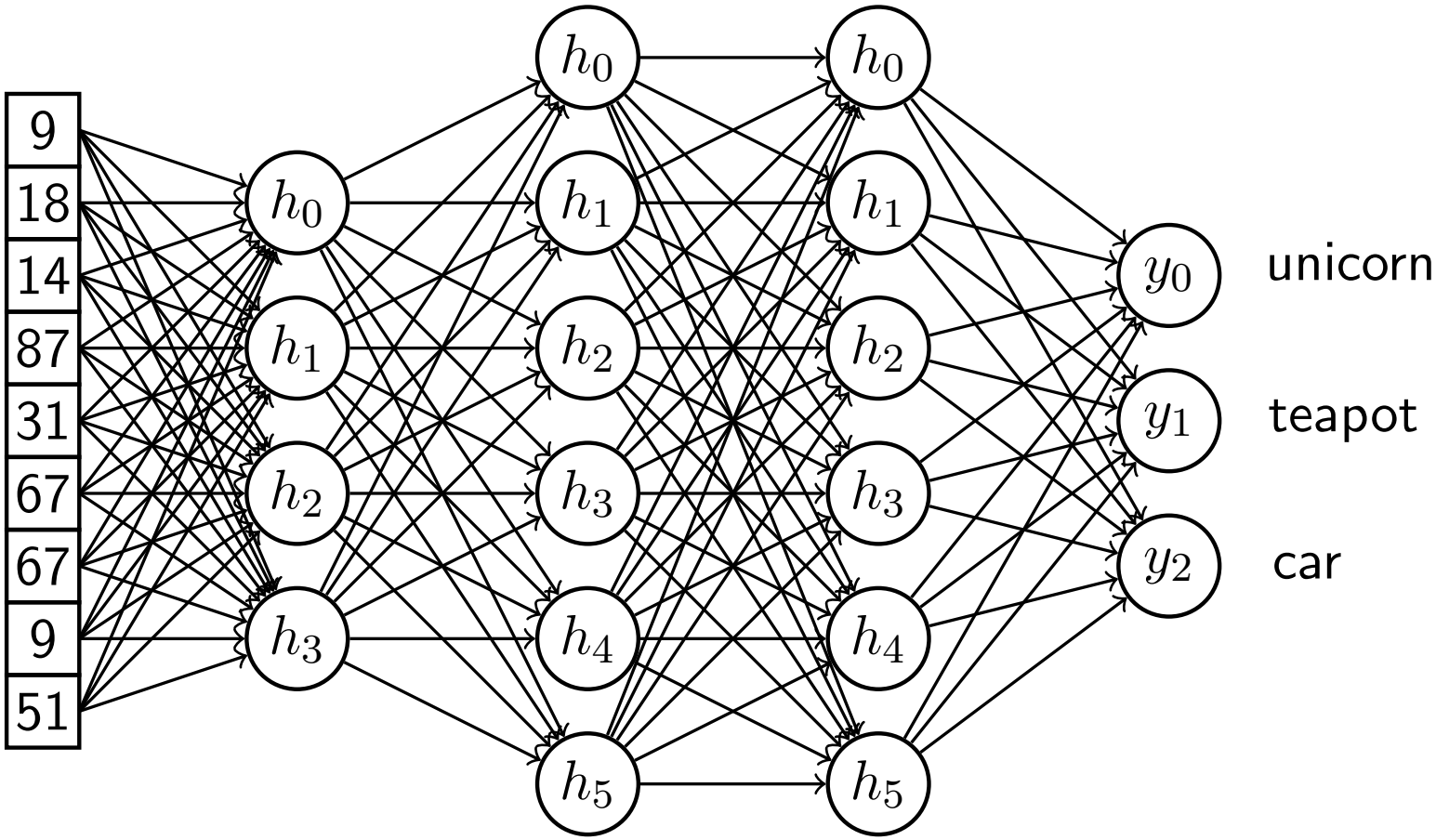


Deep Neural Networks

Why reinvent the wheel?



Time for ze kitteh

This is a cat ♥

Time for ze kitteh

Still a cat ♥♥

Time for ze kitteh

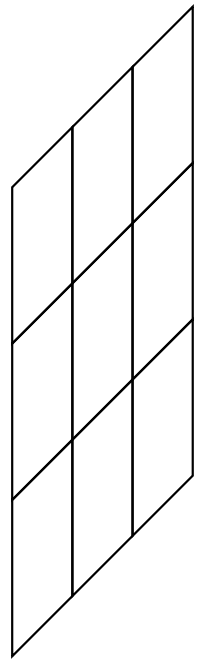
Half cat / half salad ♥♥♥

Time for ze kitteh

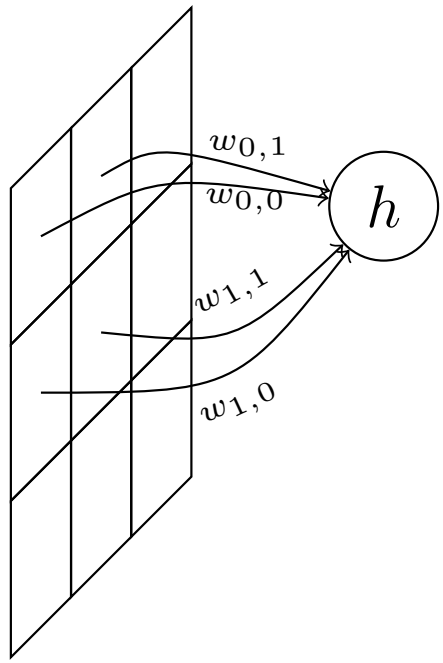
Many cats ♥♥♥♥

Weight Sharing

Weight Sharing



Weight Sharing



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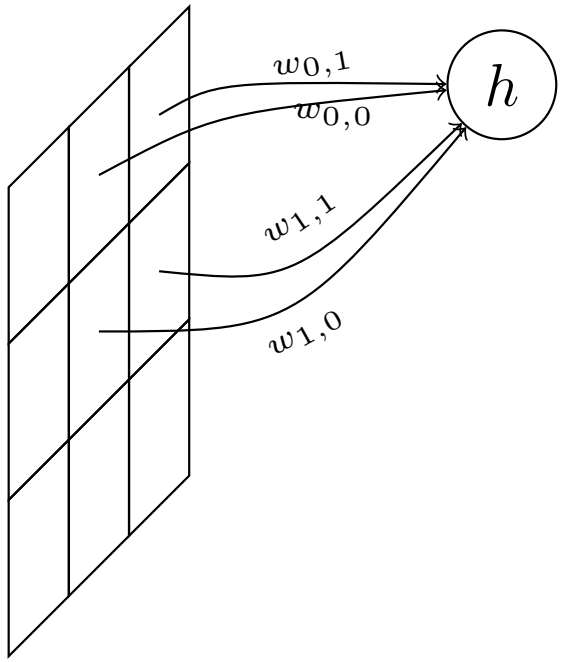

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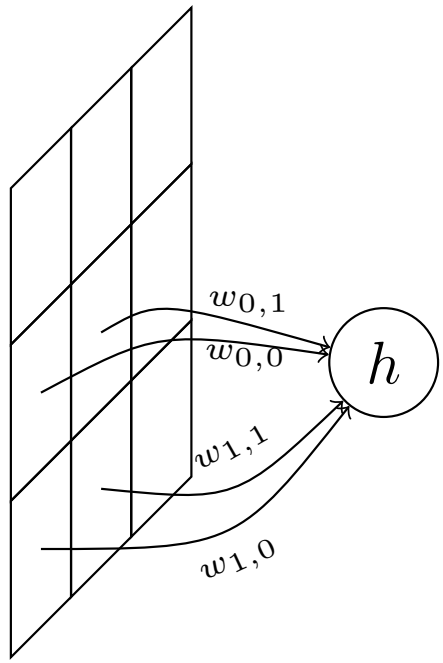
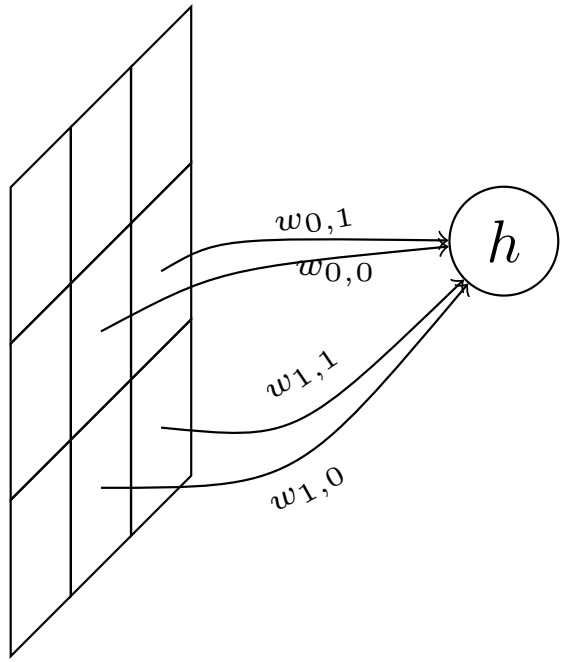
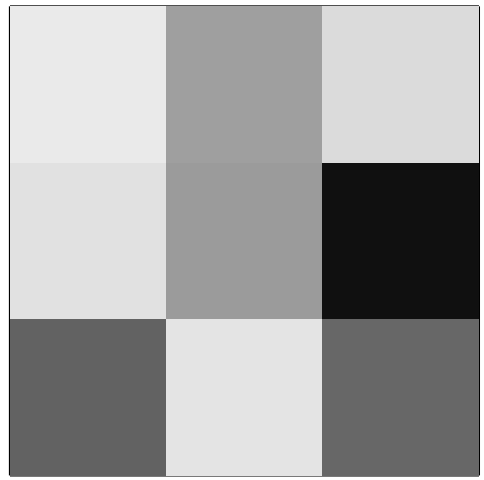


Weight Sharing



Convolutional Neural Networks: Mechanics



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

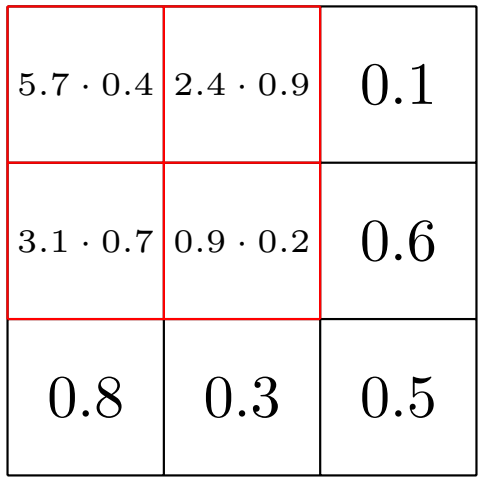
Kernel

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

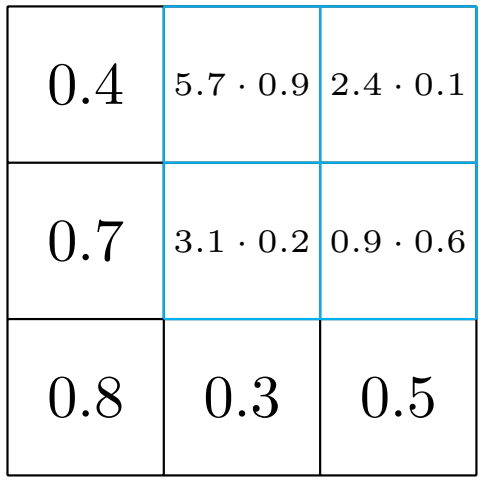
Convolutional Neural Networks: Mechanics



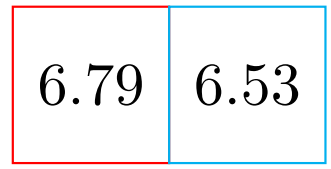
Image

Output

Convolutional Neural Networks: Mechanics

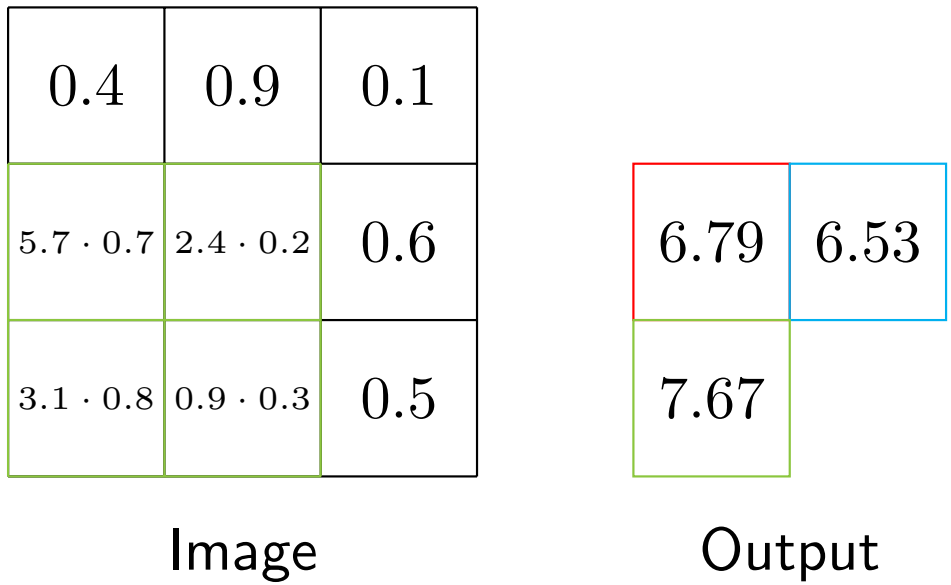


Image

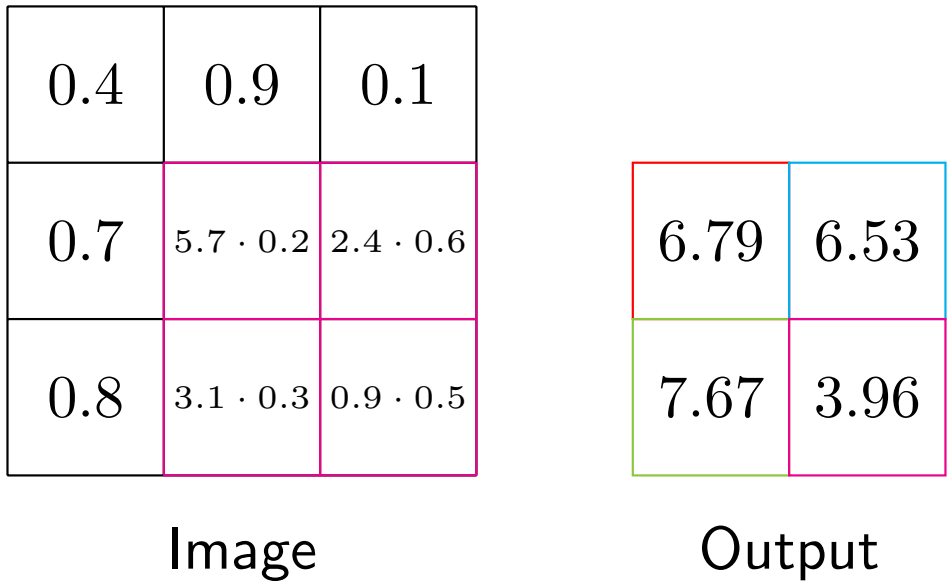


Output

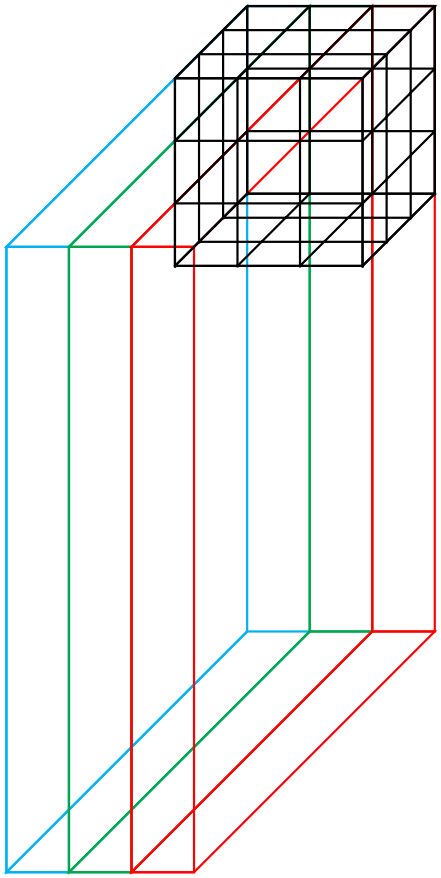
Convolutional Neural Networks: Mechanics



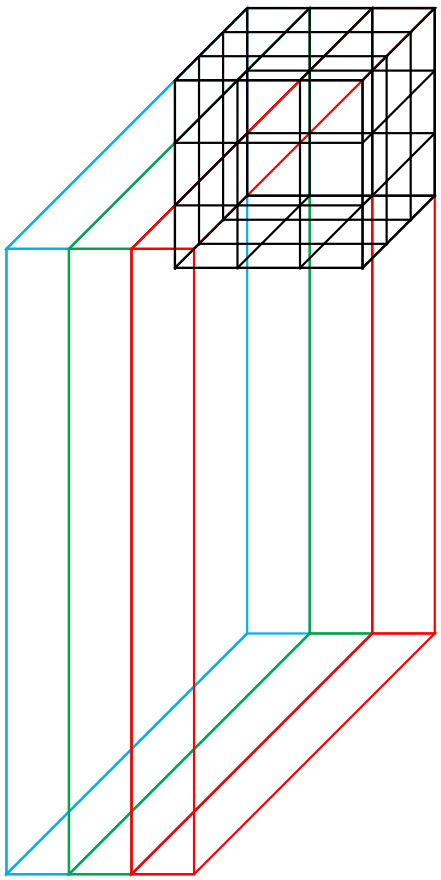
Convolutional Neural Networks: Mechanics

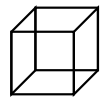


Convolutional Neural Networks: Mechanics



Convolutional Neural Networks: Mechanics





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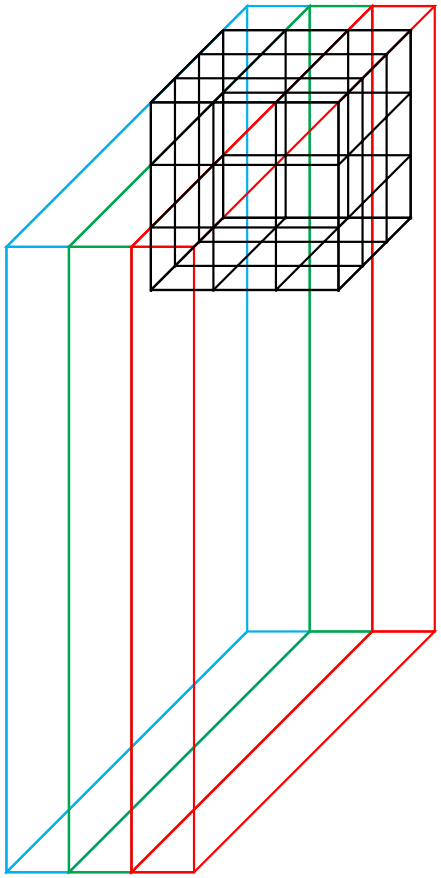
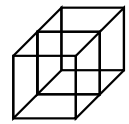
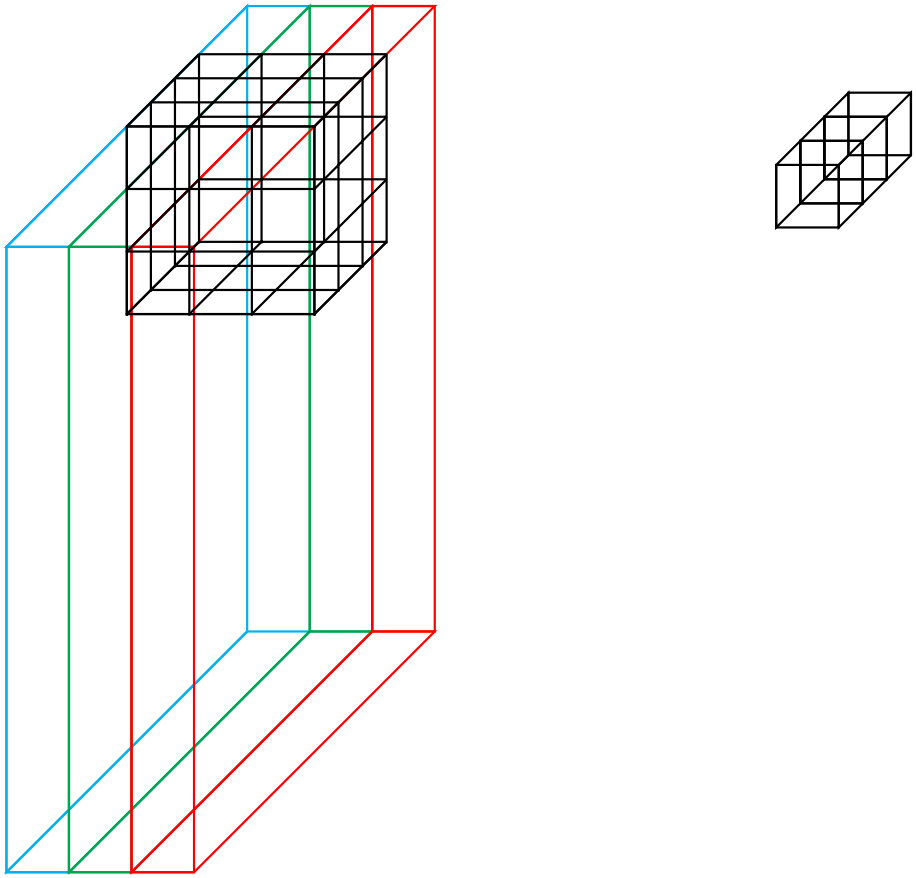
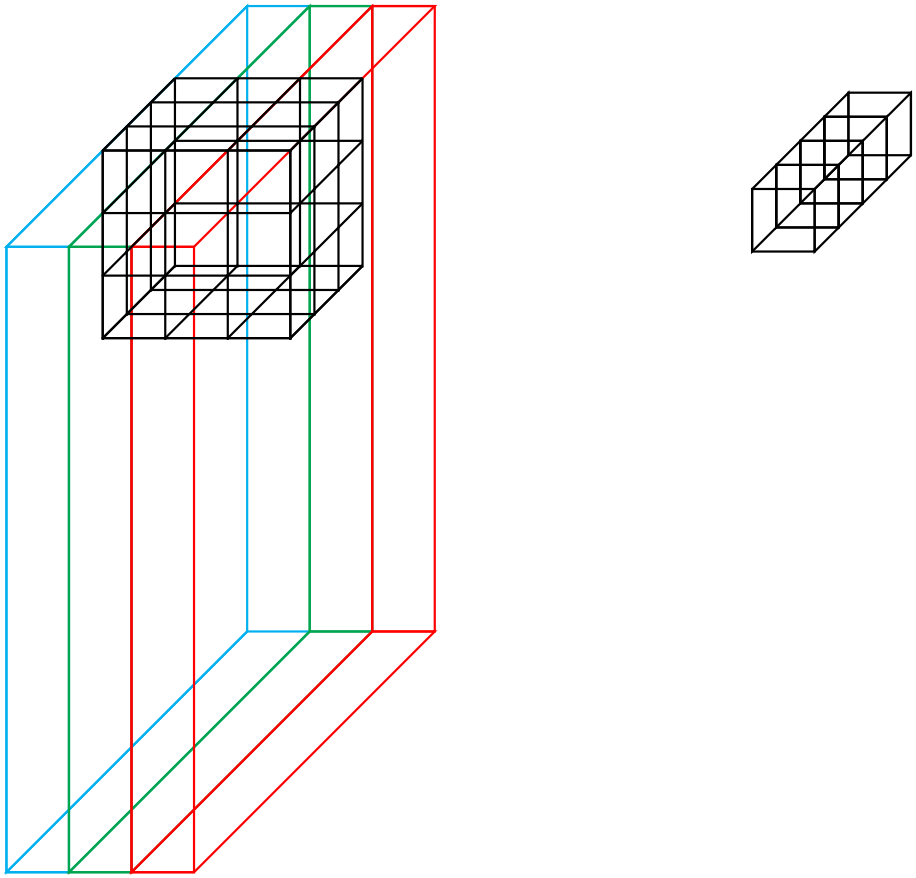




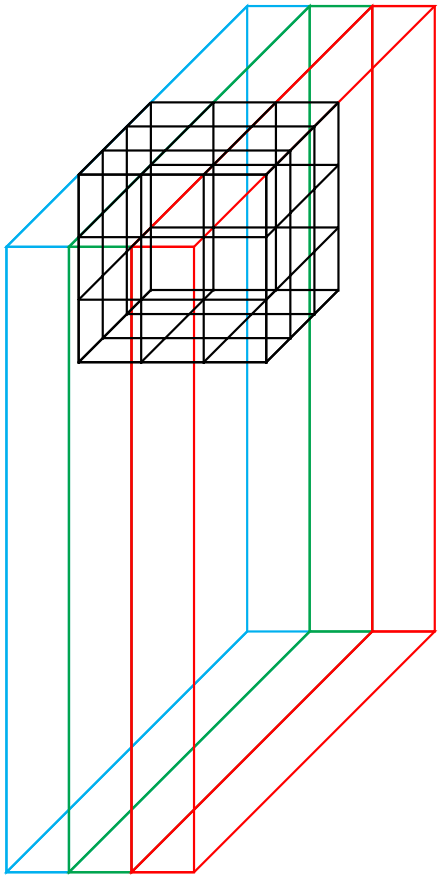
Convolutional Neural Networks: Mechanics

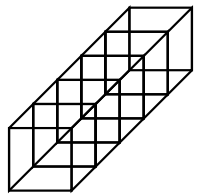


Convolutional Neural Networks: Mechanics



Convolutional Neural Networks: Mechanics





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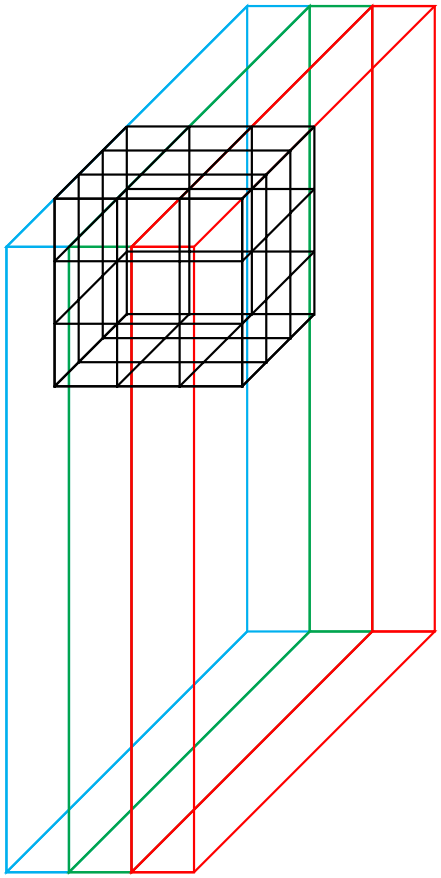

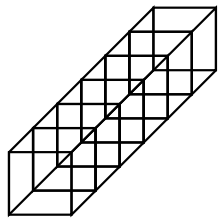

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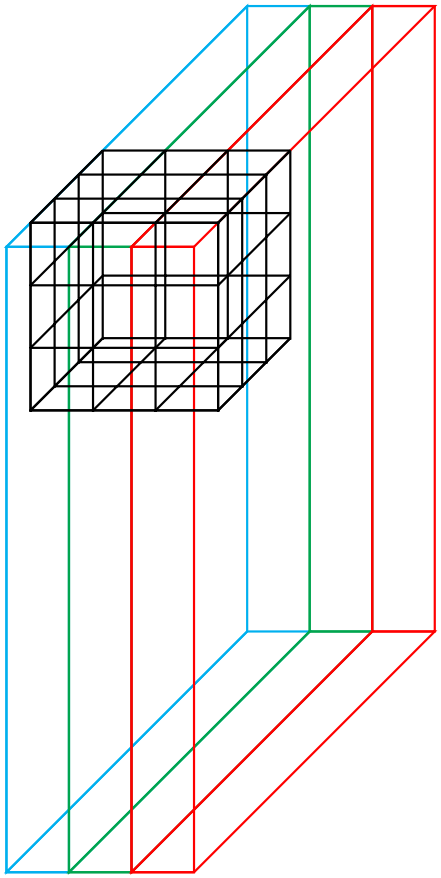

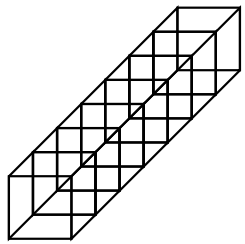

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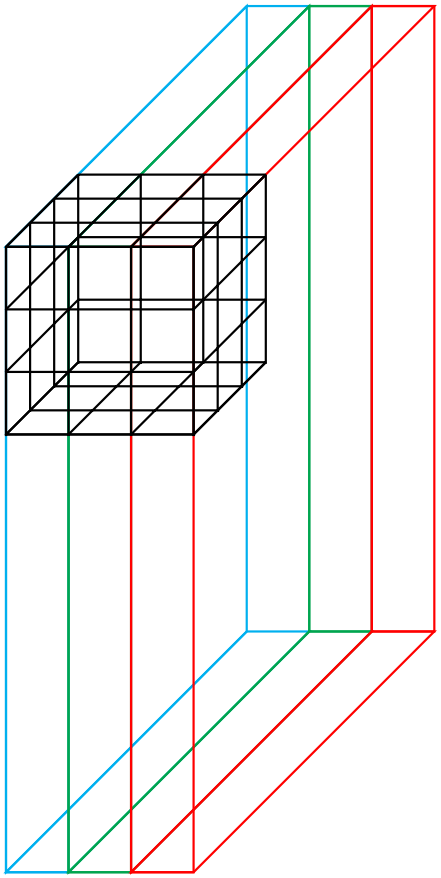

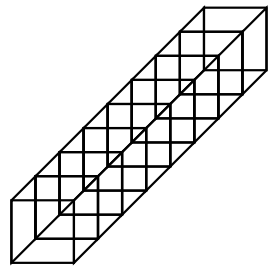

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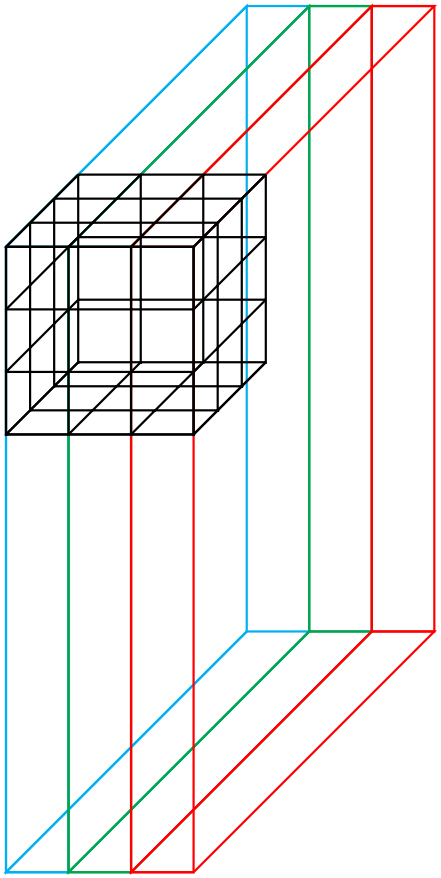

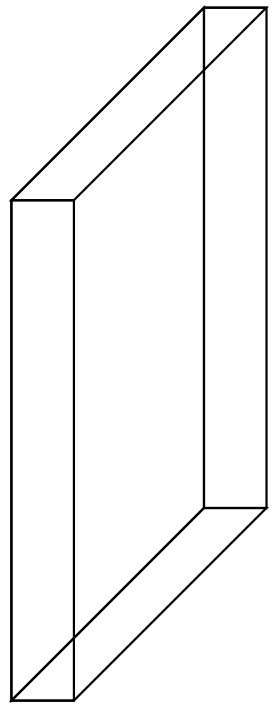

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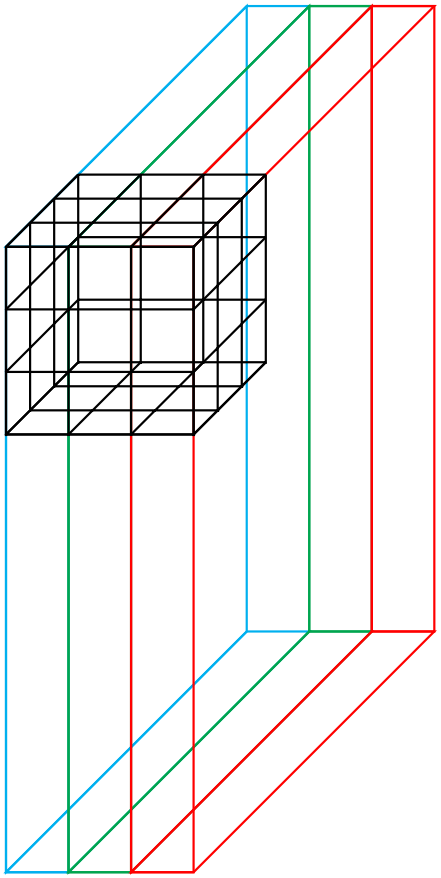

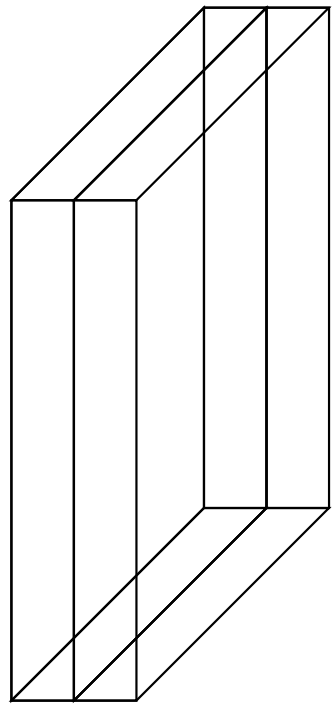

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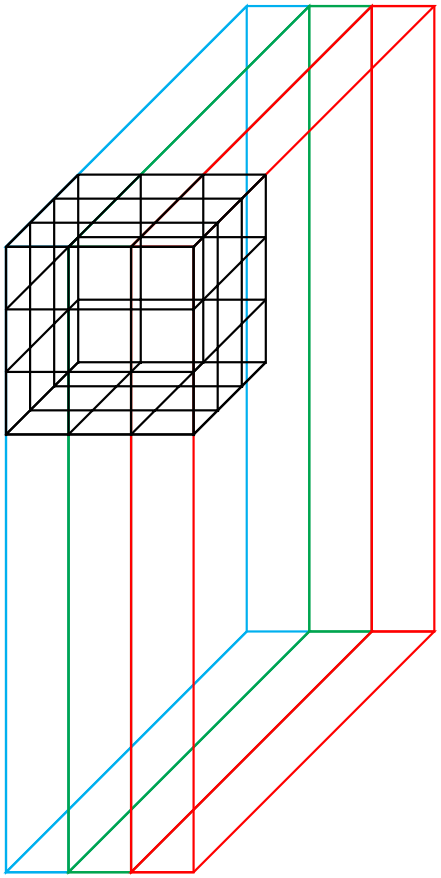
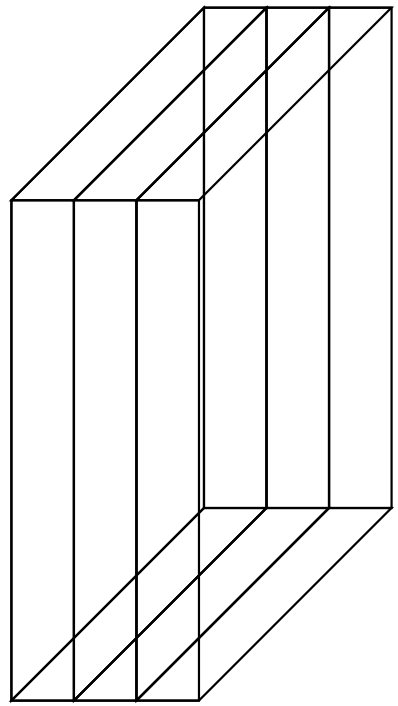
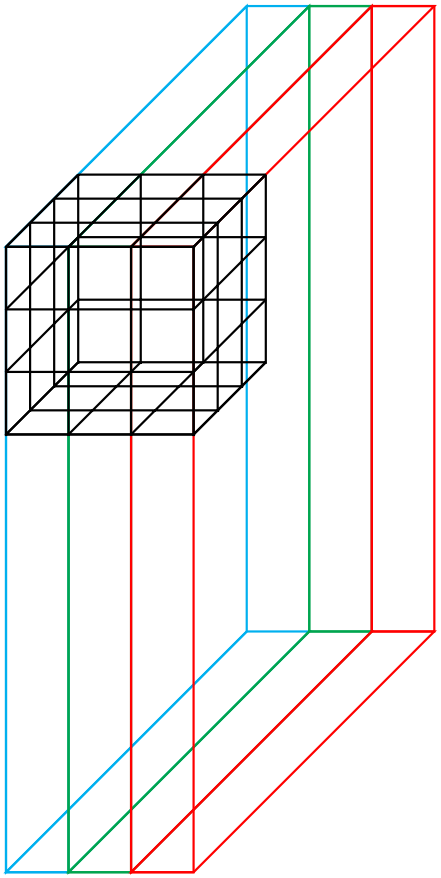
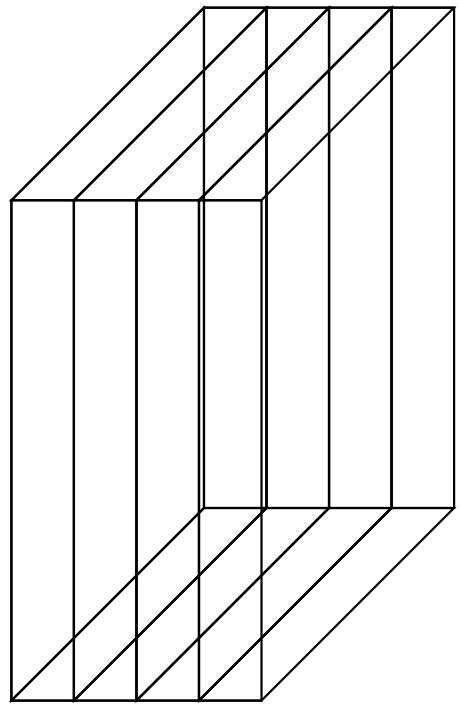




Convolutional Neural Networks: Mechanics





Recipe for a Convolutional Layer

Recipe for a Convolutional Layer

- Ingredients

Recipe for a Convolutional Layer

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

Recipe for a Convolutional Layer

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

Recipe for a Convolutional Layer

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

Recipe for a Convolutional Layer

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

- Ingredients
  1. Image I with dimensions $w \times h \times d$
  2. A kernel (filter) K of size $k \times l \times m$
- Cooking
  - Don't put the image into the oven at 150°C

Recipe for a Convolutional Layer

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

Recipe for a Convolutional Layer

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

Convolutional Neural Networks: Pooling

66	2
6	32

Convolutional Neural Networks: Pooling

66	2
6	32

Convolutional Neural Networks: Pooling

50	17
66	2

Convolutional Neural Networks: Pooling

9	50
33	66

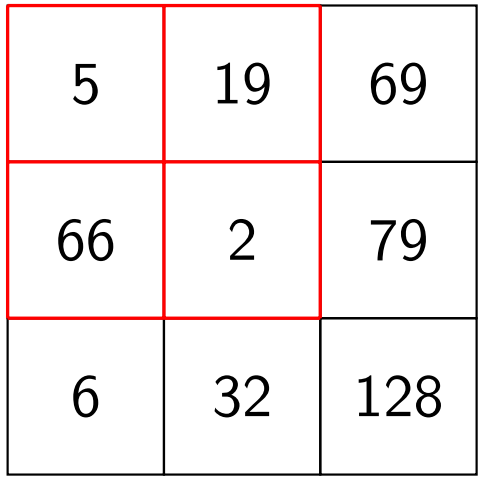
Convolutional Neural Networks: Pooling

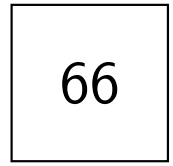
5	19	69
66	2	79
6	32	128

Convolutional Neural Networks: Pooling

5	19	69
66	2	79
6	32	128

Convolutional Neural Networks: Pooling





Convolutional Neural Networks: Pooling

5	19	69
66	2	79
6	32	128

66	79

Convolutional Neural Networks: Pooling

5	19	69
66	2	79
6	32	128

66	79
66	

Convolutional Neural Networks: Pooling

5	19	69
66	2	79
6	32	128

66	79
66	128

Convolutional Neural Networks: Pooling

5	19	69
66	2	79
6	32	128

66	79
66	128

- *Pooling* achieves translational invariance

Convolutional Neural Networks: Pooling

5	19	69
66	2	79
6	32	128

66	79
66	128

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

Convolutional Neural Networks: Pooling

5	19	69
66	2	79
6	32	128

66	79
66	128

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

Convolutional Neural Networks: Architecture

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

TensorFlow

TensorFlow

- An open source deep learning library

TensorFlow

- An open source deep learning library
- Released by Google in November 2015

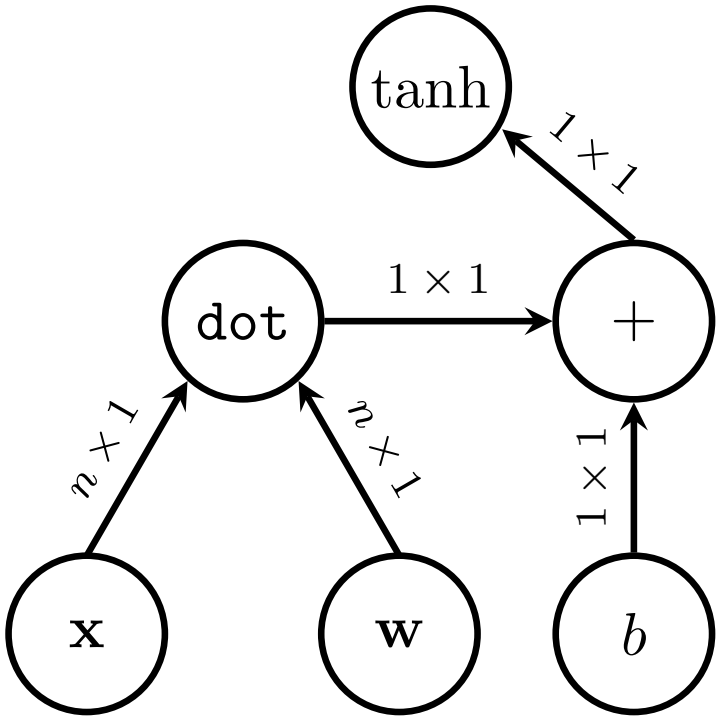
TensorFlow

- An open source deep learning library
- Released by Google in November 2015
- Especially suited to:

  "Large-scale machine learning on heterogeneous distributed systems"

Computational Paradigms

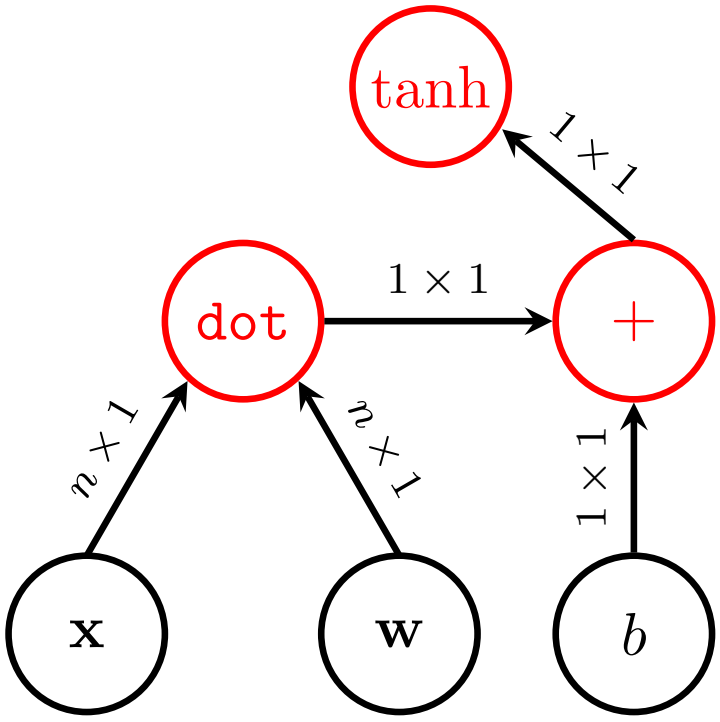
Computational Paradigms



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

Computational Graphs

Computational Paradigms

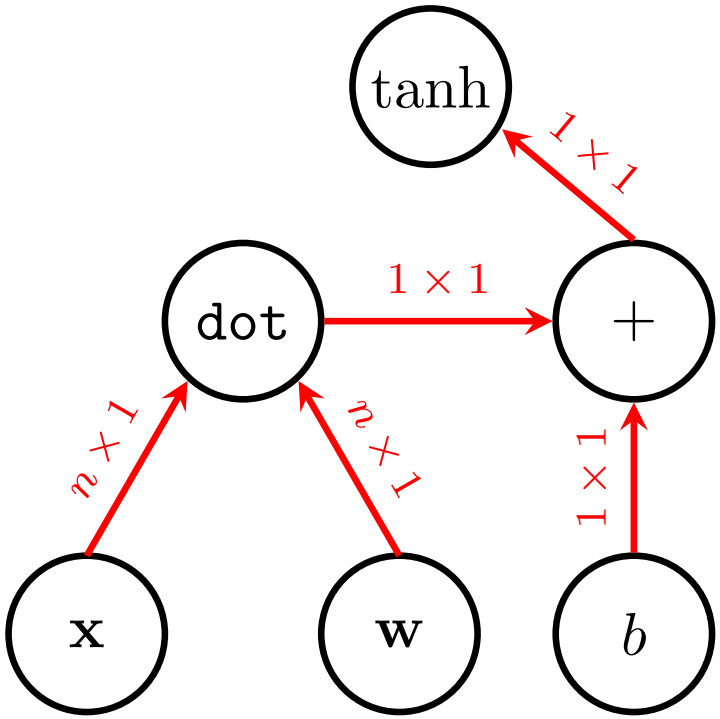


$$\hat{y} = \tanh(\mathbf{x}^\top \mathbf{w} + b)$$

Computational Graphs

1. Operations

Computational Paradigms

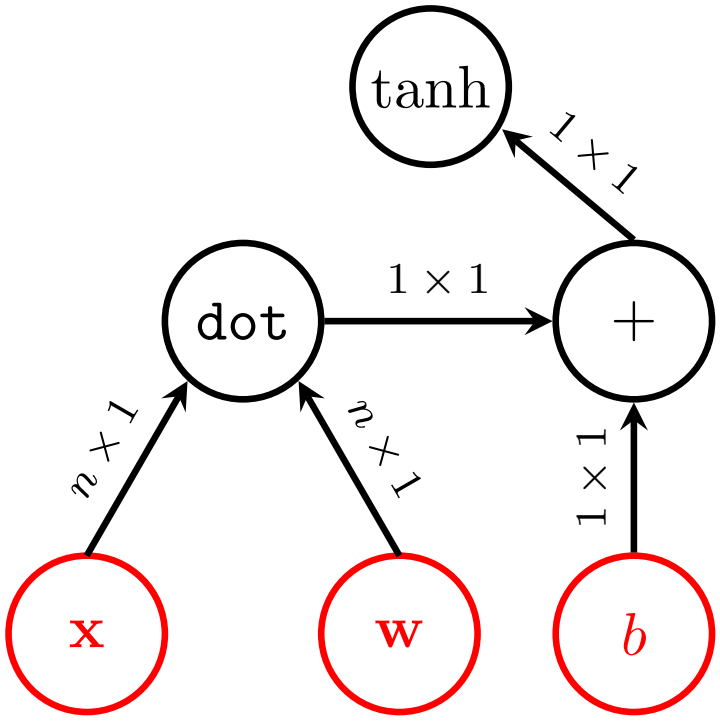


$$\hat{y} = \tanh(\mathbf{x}^\top \mathbf{w} + b)$$

Computational Graphs

1. Operations
2. Tensors

Computational Paradigms

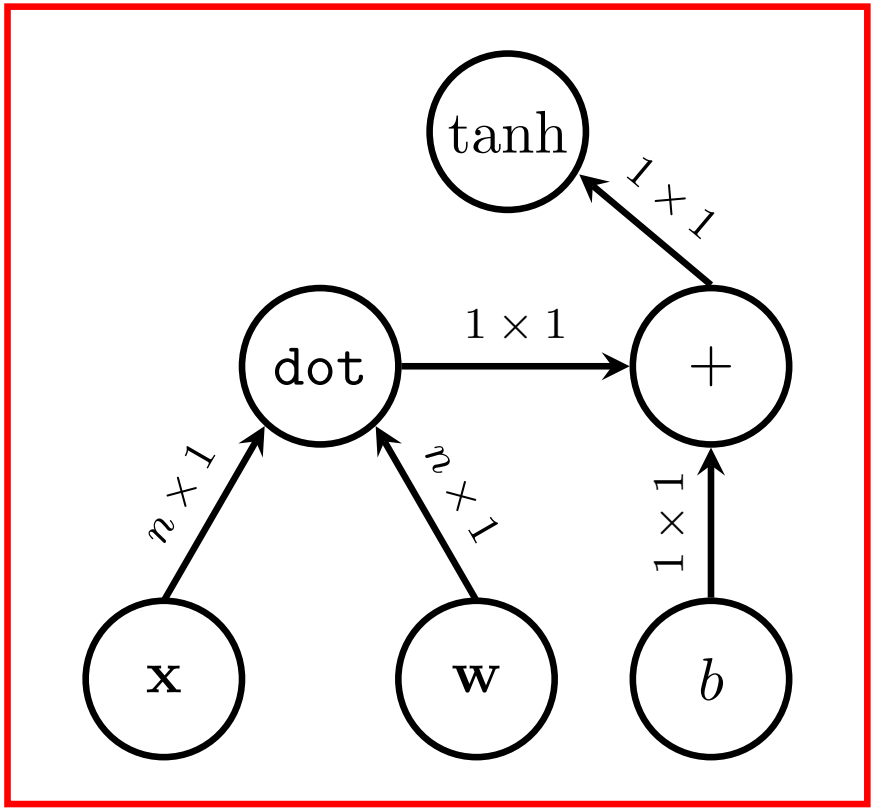


$$\hat{y} = \tanh(\mathbf{x}^\top \mathbf{w} + b)$$

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

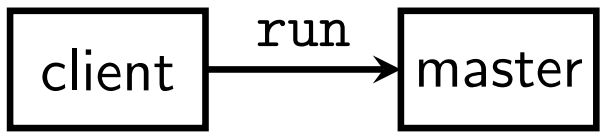
Actors

Execution Model

Actors

1. Client

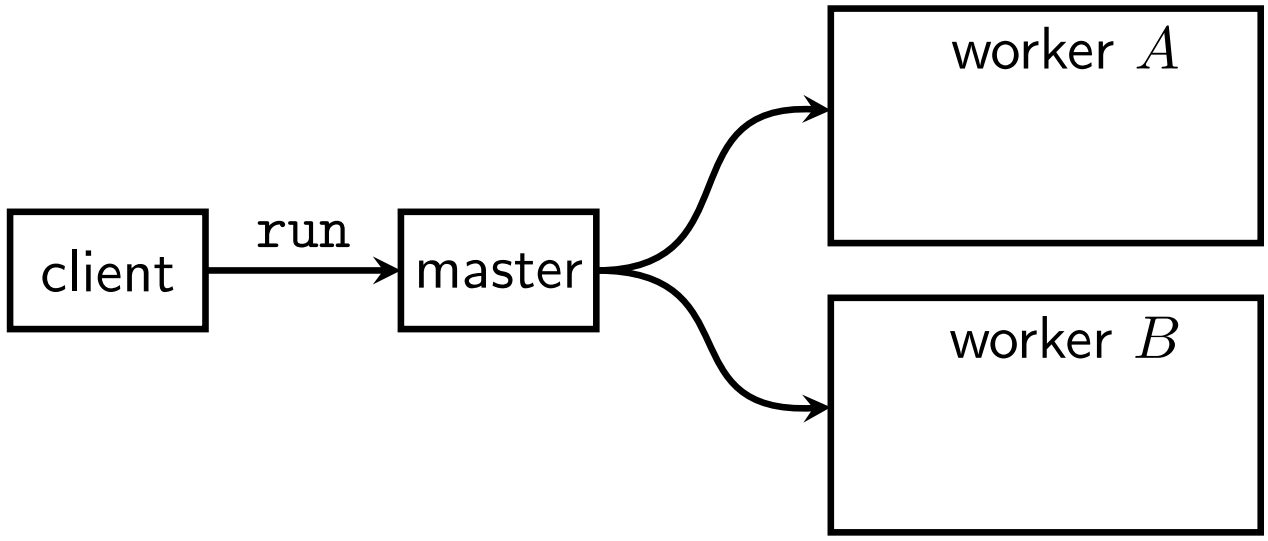
Execution Model



Actors

1. Client
2. Master

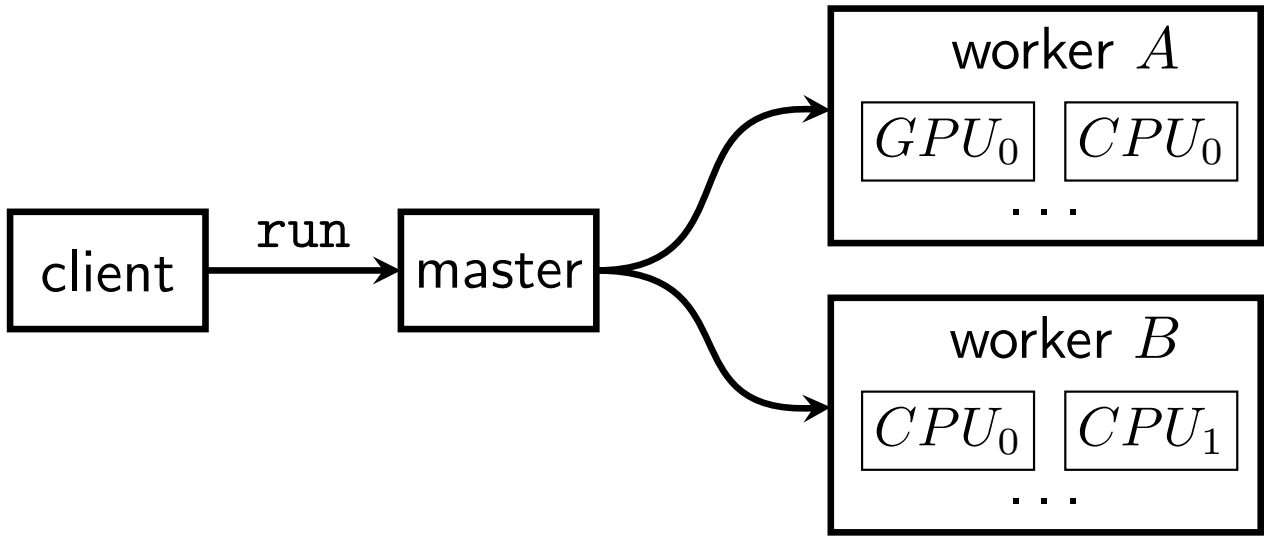
Execution Model



Actors

1. Client
2. Master
3. Workers

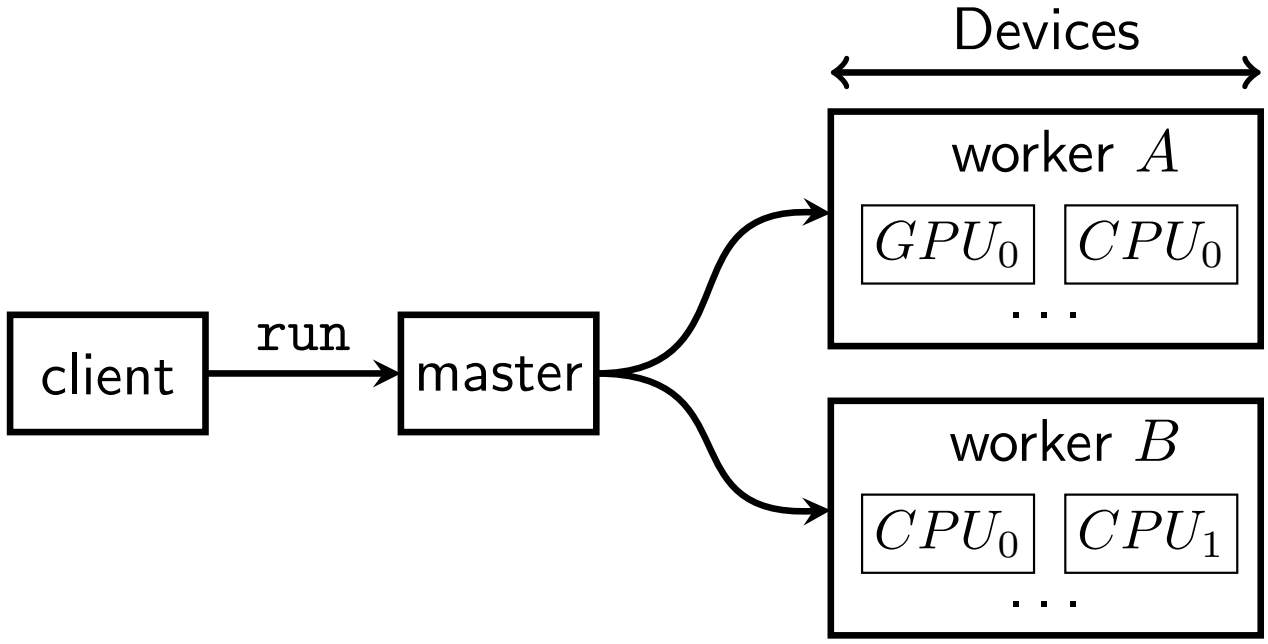
Execution Model



Actors

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

Execution Model



Actors

1. Client
2. Master
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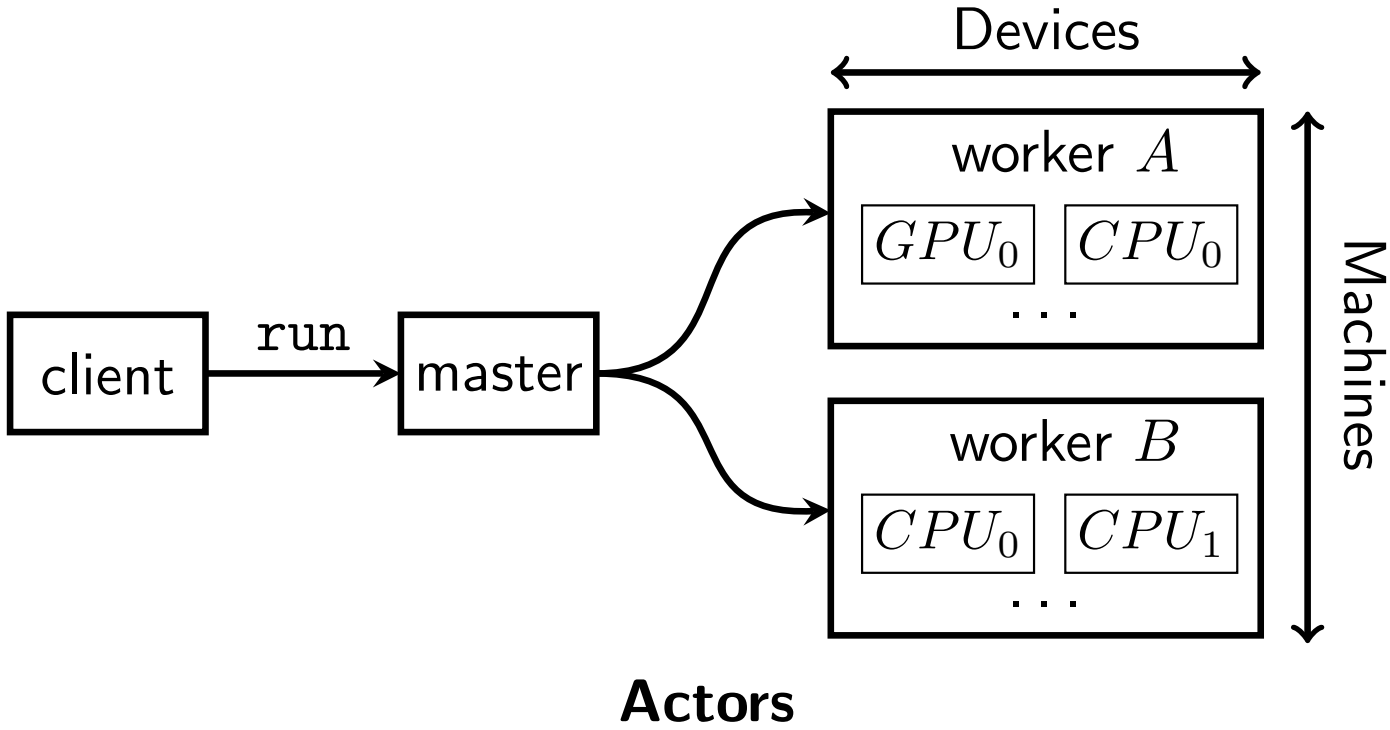
4. Devices

Execution Model



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

Visualization Tools

Visualization Tools

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

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- Easy to drown in the complexity of an architecture

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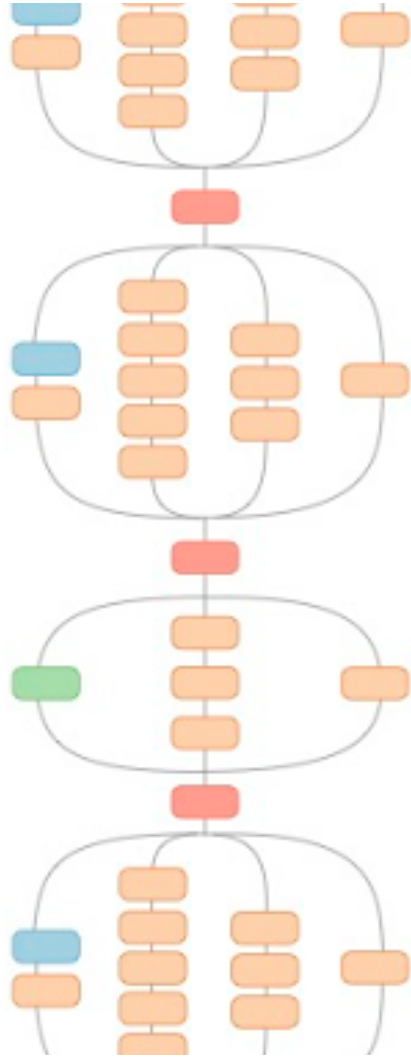
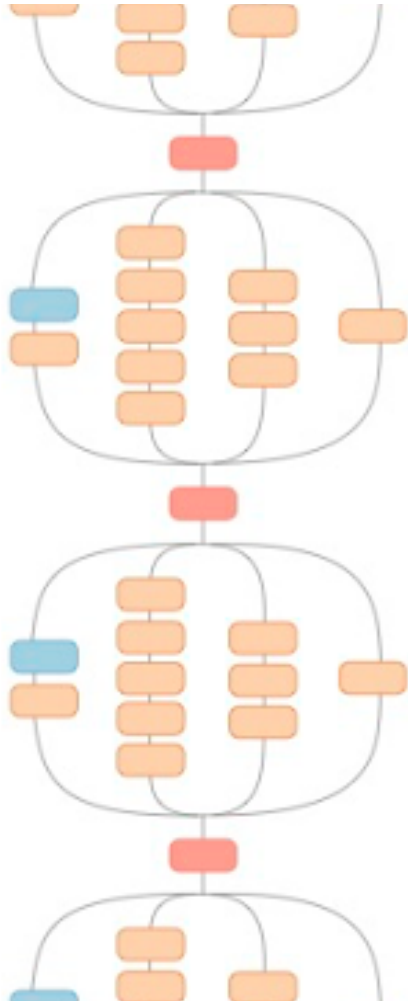
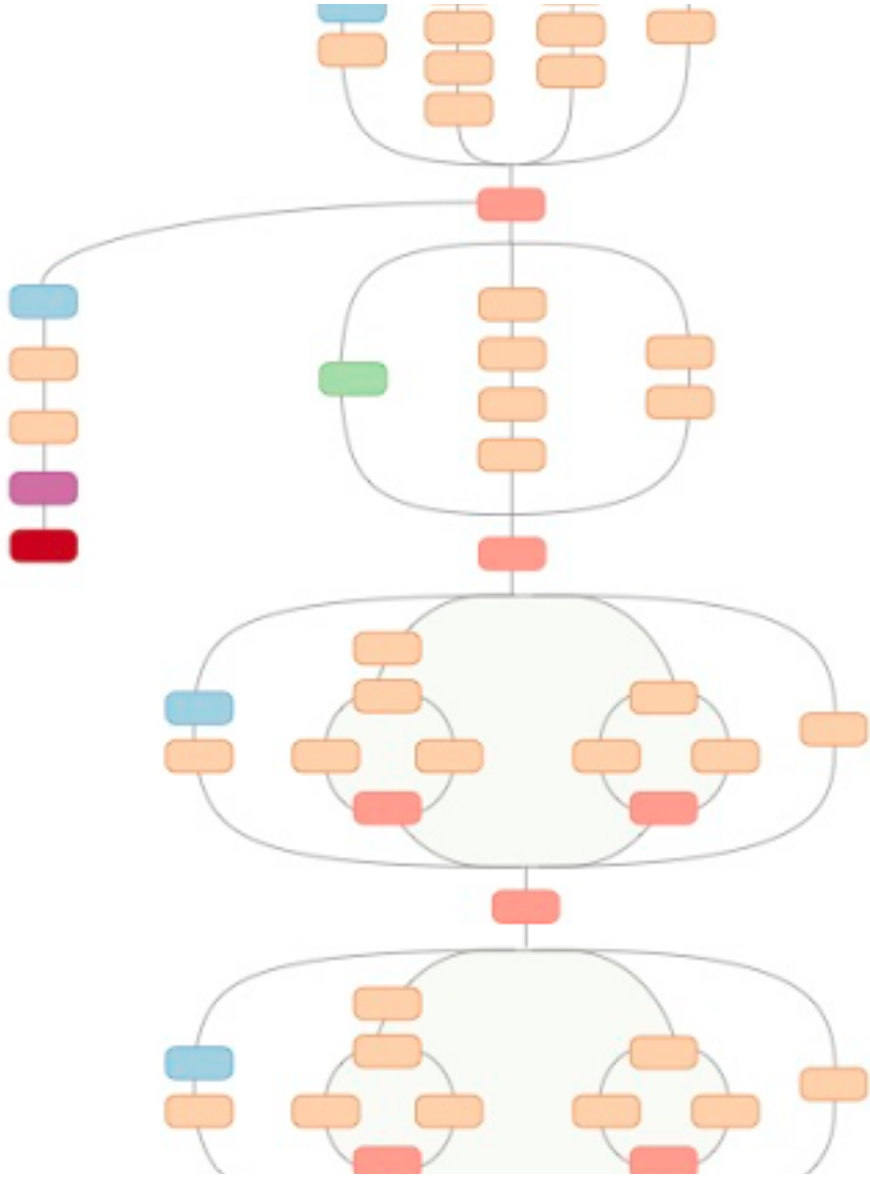
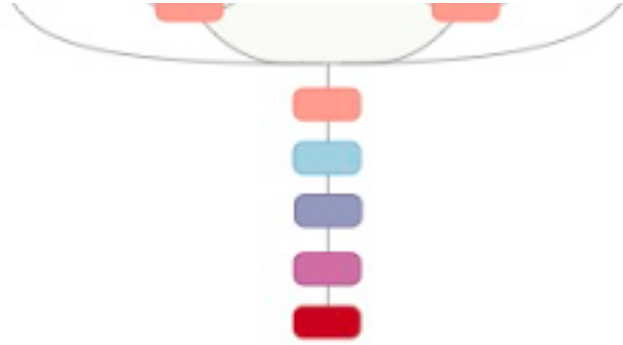
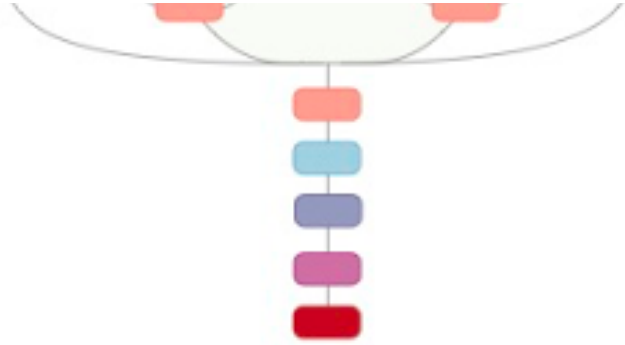










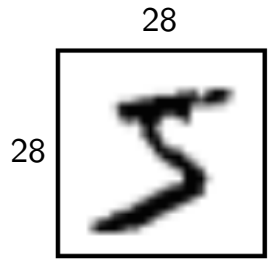
TensorBoard to the Rescue

Walkthrough

Walkthrough

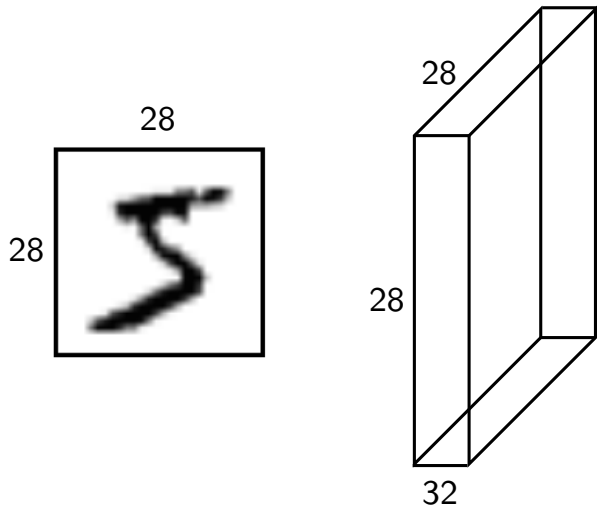
```
INPUT -> [CONV -> POOL]{2} -> FC -> OUTPUT
```

Walkthrough




```
INPUT -> [CONV -> POOL]{2} -> FC -> OUTPUT
```

Walkthrough




```
INPUT -> [CONV -> POOL]{2} -> FC -> OUTPUT
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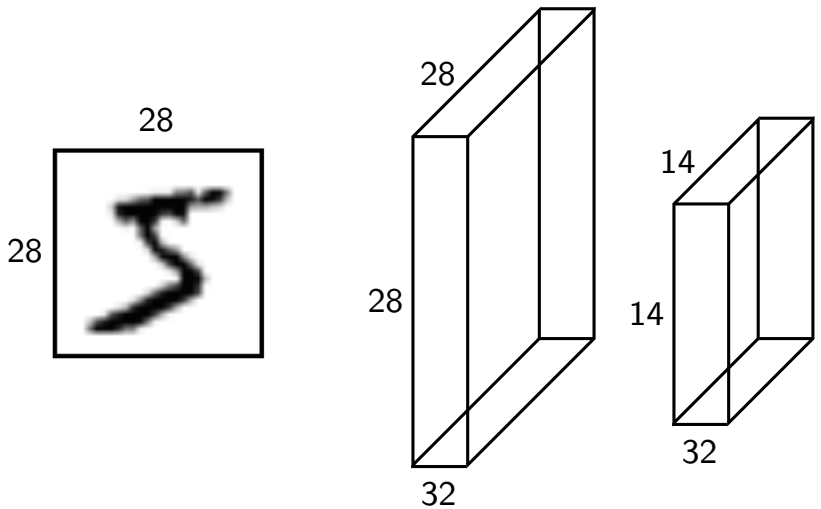
Walkthrough

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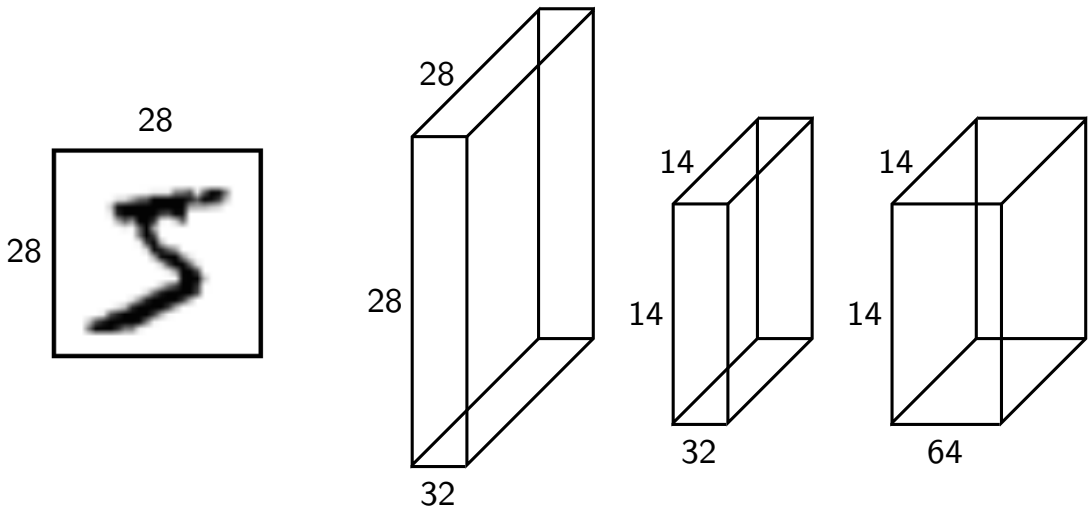
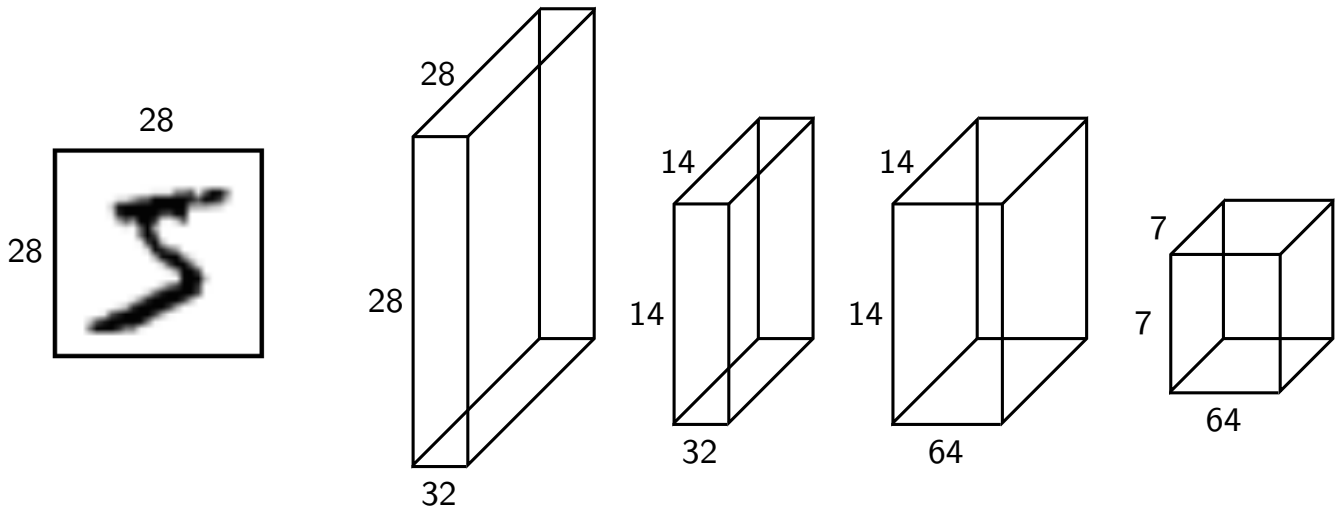
Walkthrough




```
INPUT -> [CONV -> POOL]{2} -> FC -> OUTPUT
```

Walkthrough




```
INPUT -> [CONV -> POOL]{2} -> FC -> OUTPUT
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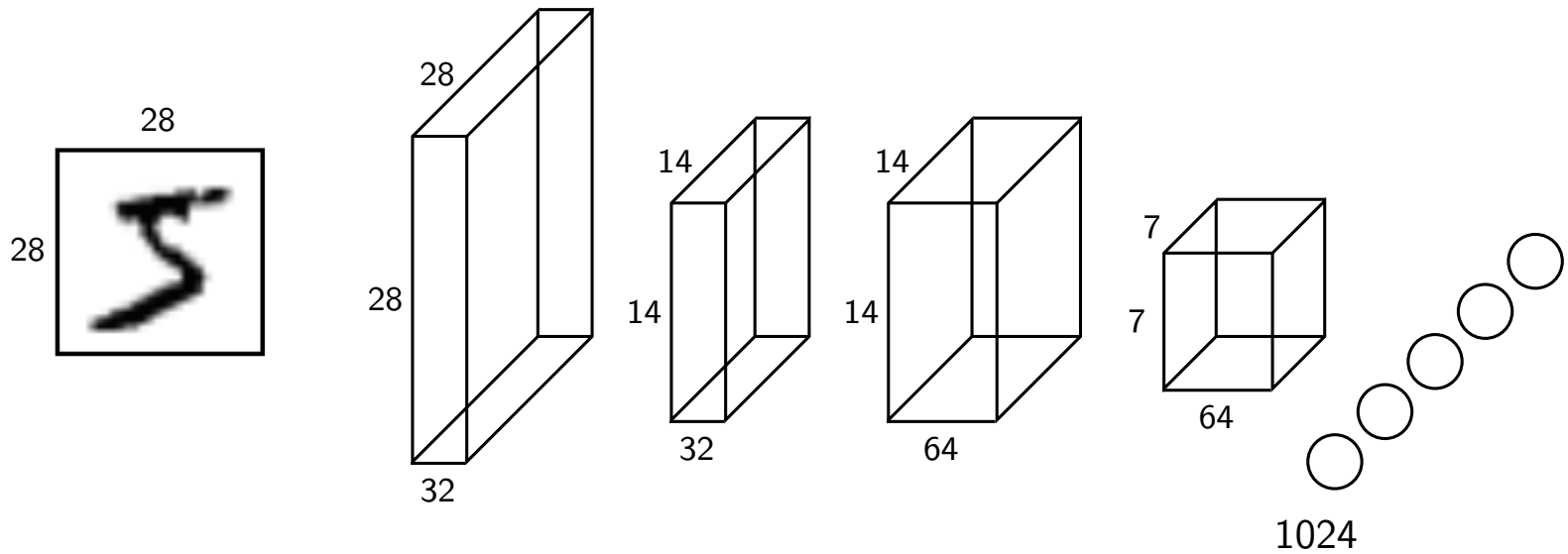
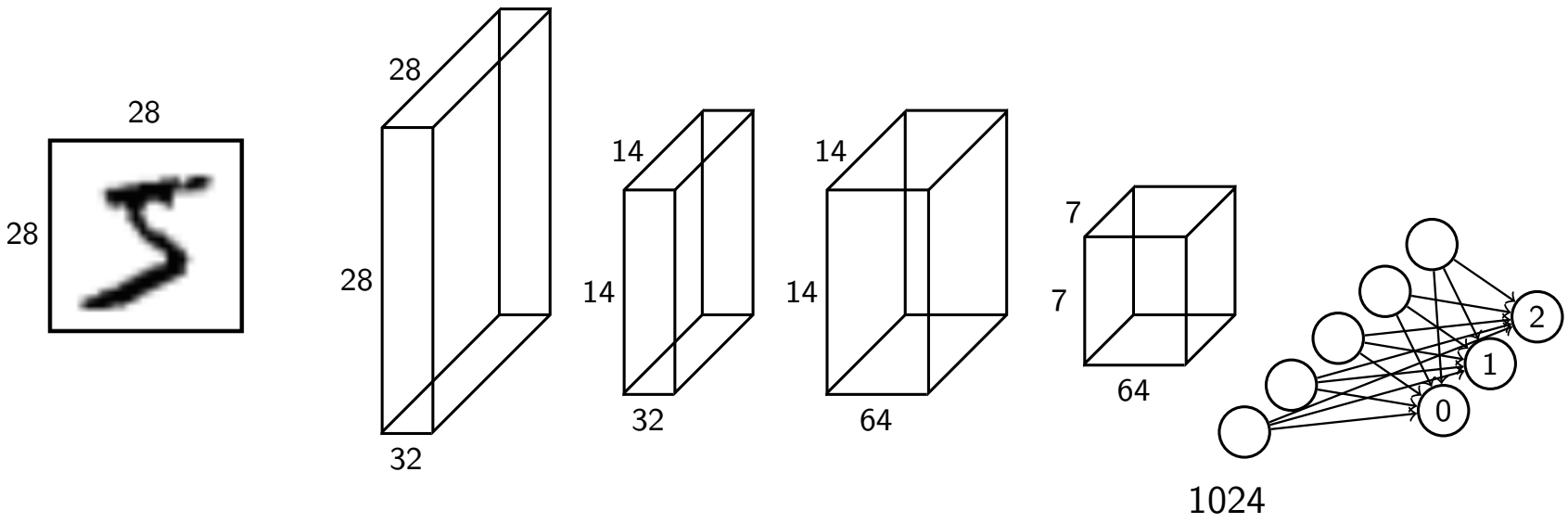
Walkthrough



`INPUT -> [CONV -> POOL]{2} -> FC -> OUTPUT`

Walkthrough



`INPUT -> [CONV -> POOL]{2} -> FC -> OUTPUT`

How do I continue?

Resources

Resources

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

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  - Deep Learning by Google @ 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

Stay in Touch!

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

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github.com/peter-can-talk/cambridge-2016

Q & A