

Convolution Neural Network

- A convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery.

Convolution Neural Network

- Facebook uses neural nets for their automatic tagging algorithms
- Google for their photo search
- Amazon for their product recommendations
- Pinterest for their home feed personalization
- Instagram for their search infrastructure.



Image classification

- Most popular, use case of these networks is for image processing.

How Humans identify images??

- For humans, this task of recognition is one of the first skills we learn from the moment we are born and is one that comes naturally and effortlessly as adults.
- Most of the time we are able to immediately characterize the scene and give each object a label, all without even consciously noticing.

**What's
that?**

A Train



**What's
this?**

A Train

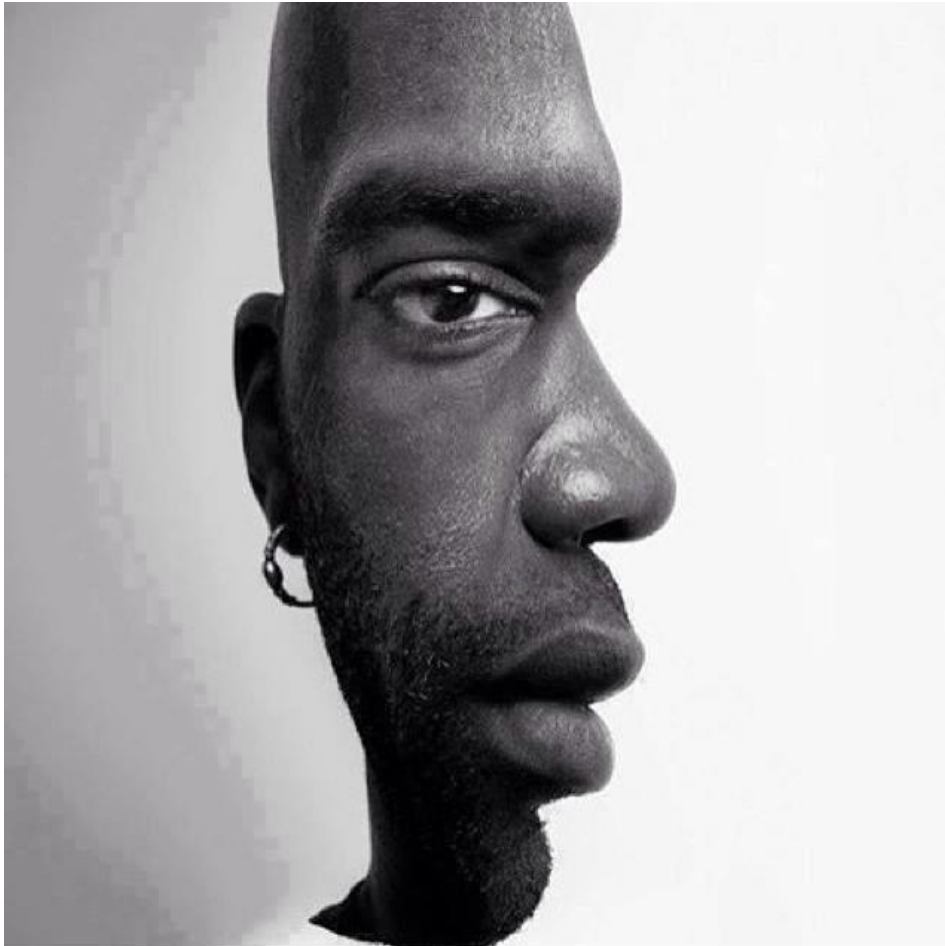


Teach Machine

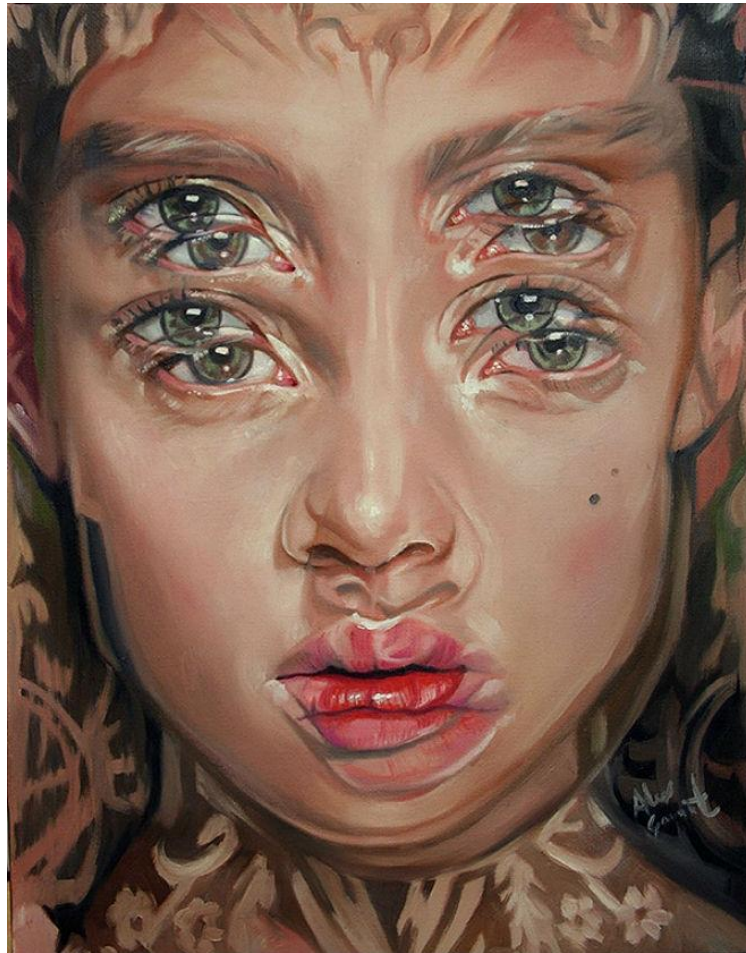
Human skills of being able to :

- Quickly recognize patterns
- Generalize from prior knowledge

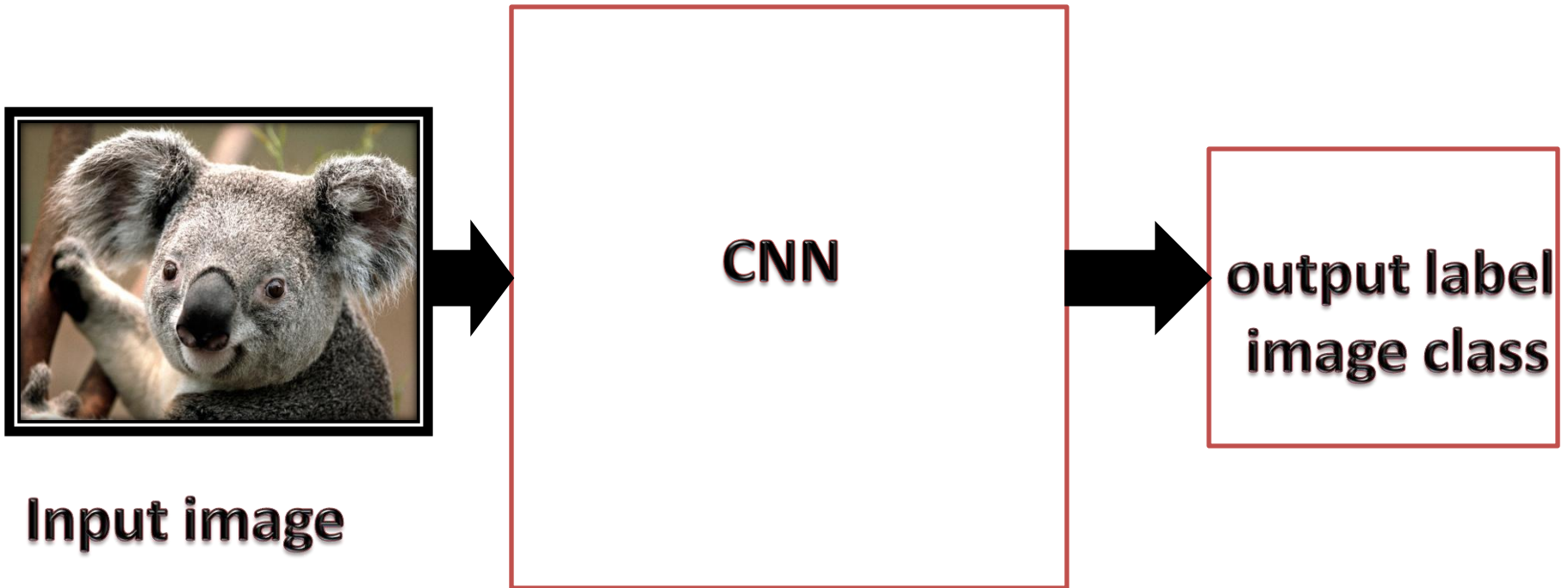
illusions



illusions

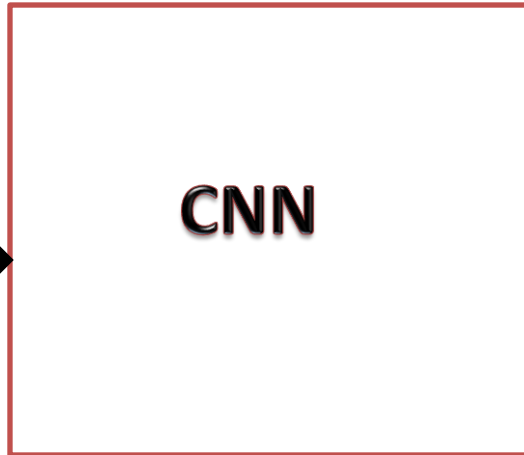
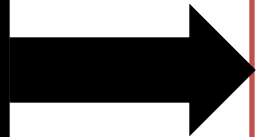


Convolution Neural Network



Convolution Neural Network

Input image



output image



Input image



output image



How Does Computer See an image??

When a computer sees an image ,it will see an array of pixel values. Depending on the resolution and size of the image, it will see a 32 x 32 x 3 array of numbers (The 3 refers to RGB values).



What we see

08	02	22	97	38	15	00	40	00	75	04	05	07	78	52	12	50	77	91	08
49	49	99	40	17	81	18	57	60	87	17	40	98	43	69	48	04	56	62	00
81	49	31	73	55	79	14	29	93	71	40	67	53	88	30	05	49	13	36	65
52	70	95	23	04	60	11	42	69	24	68	56	01	32	56	71	37	02	36	91
22	31	16	71	51	67	63	89	41	92	36	54	22	40	40	28	66	33	13	80
24	47	32	60	99	03	45	02	44	75	33	53	78	36	84	20	35	17	12	50
32	98	81	28	64	23	67	10	26	38	40	67	59	54	70	66	18	38	64	70
67	26	20	68	02	62	12	20	95	63	94	39	63	08	40	91	66	49	94	21
24	55	58	05	66	73	99	26	97	17	78	78	96	83	14	88	34	89	63	72
21	36	23	09	75	00	76	44	20	45	35	14	00	61	33	97	34	31	33	95
78	17	53	28	22	75	31	67	15	94	03	80	04	62	16	14	09	53	56	92
16	39	05	42	96	35	31	47	55	58	88	24	00	17	54	24	36	29	85	57
86	56	00	48	35	71	89	07	05	44	44	37	44	60	21	58	51	54	17	58
19	80	81	68	05	94	47	69	28	73	92	13	86	52	17	77	04	89	55	40
04	52	08	83	97	35	99	16	07	97	57	32	16	26	26	79	33	27	95	66
88	36	68	87	57	62	20	72	03	46	33	67	46	55	12	32	63	93	53	69
04	42	16	73	38	25	39	11	24	94	72	18	08	46	29	32	40	62	76	36
20	69	36	41	72	30	23	88	34	62	99	69	82	67	59	85	74	04	36	16
20	73	35	29	78	31	90	01	74	31	49	71	48	86	81	16	23	57	05	54
01	70	54	71	83	51	54	69	16	92	33	48	61	43	52	01	89	19	67	48

What computers see

How Does Computer See an image??



What we see

```
08 02 22 97 38 15 00 40 00 75 04 05 07 78 52 12 50 77 91 08
49 49 99 40 17 81 18 37 60 87 17 40 98 43 69 48 04 36 62 00
81 49 31 73 55 79 14 29 93 71 40 87 53 88 30 03 49 13 36 65
52 70 95 23 04 60 11 42 69 24 68 56 01 32 56 71 37 02 36 91
22 31 16 71 51 67 63 89 41 92 36 54 22 40 40 28 66 33 13 80
24 47 32 60 99 03 45 02 44 75 33 53 78 36 84 20 35 17 12 50
32 98 81 28 64 23 67 10 26 38 40 87 59 54 70 66 18 38 64 70
67 26 20 68 02 62 12 20 95 63 94 39 63 08 40 91 66 49 94 21
24 55 58 05 66 73 99 26 97 17 78 78 96 83 14 88 34 89 63 72
21 36 23 09 75 00 76 44 20 45 35 14 00 61 33 97 34 31 33 95
78 17 53 28 22 75 31 67 15 94 03 80 04 62 16 14 09 53 56 92
16 39 05 42 96 35 31 47 55 58 88 24 00 17 54 24 36 29 85 57
86 56 00 48 35 71 89 07 05 44 44 37 44 60 21 58 51 54 17 58
19 80 81 68 05 94 47 69 28 73 92 13 86 52 17 77 04 89 55 40
04 52 08 83 97 35 99 16 07 97 57 32 16 26 26 79 33 27 98 66
88 36 68 87 57 62 20 72 03 46 33 67 46 55 12 32 63 93 53 69
04 42 16 73 38 25 39 11 24 94 72 18 08 46 29 32 40 62 76 36
20 69 36 41 72 30 23 88 34 62 99 69 82 67 59 85 74 04 36 16
20 73 35 29 78 31 90 01 74 31 49 71 48 86 81 16 23 57 05 54
01 70 54 71 83 51 54 69 16 92 33 48 61 43 52 01 89 19 67 48
```

What computers see

These numbers, when we perform image classification, are the only inputs available to the computer.

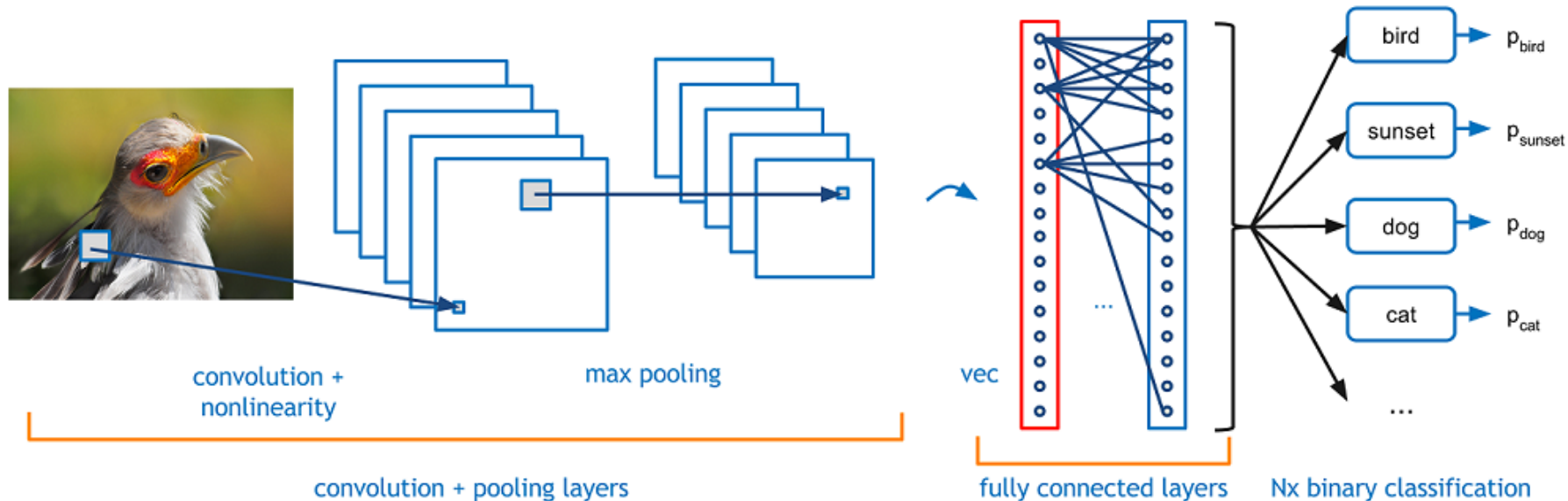
The idea is that you give the computer this array of numbers and it will output numbers that describe the probability of the image being a certain class (80% for flower, 15% for sky etc).

What We Want the Computer to Do

- we want the computer to do is to be able to differentiate between all the images it's given and figure out the **unique features** that make a dog a dog , that make a cat a cat or that make a flower a flower .
- The computer is able to perform image classification by looking for low level features such as edges and curves, and then building up to more abstract concepts through a series of **convolutional layers**.

Convolution Neural Network

CNNs take the image, pass it through a series of convolutional, nonlinear, pooling (downsampling), and fully connected layers, and get an output.



How computer sees an image



Humans see this

-1	-1	-1	-1	-1	-1	-1	-1	-1	0.9	-0	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	0.3	1	0.3	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-0	1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	0.8	1	0.6	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	0.5	1	0.8	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	0.1	1	0.9	-0	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-0	1	1	-0	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	0.9	1	0.3	-1	-1	-1	-1	0.5	1	0.9	0.1	-1	-1
-1	-1	0.3	1	0.9	-1	-1	-1	0.1	1	1	1	1	1	-1	-1
-1	-1	0.8	1	0.3	-1	-1	0.4	1	0.7	-0	-0	1	1	-1	-1
-1	-1	1	1	0.1	-1	0.1	1	0.3	-1	-1	-0	1	0.6	-1	-1
-1	-1	1	1	0.8	0.3	1	0.7	-1	-1	-1	0.5	1	0	-1	-1
-1	-1	0.8	1	1	1	1	0.5	0.2	0.8	0.8	1	0.9	-1	-1	-1
-1	-1	-0	0.8	1	1	1	1	1	1	1	1	0.1	-1	-1	-1
-1	-1	-1	-0	0.8	1	1	1	1	1	1	0.2	-1	-1	-1	-1
-1	-1	-1	-1	-1	-0	0.3	0.8	1	0.5	-0	-1	-1	-1	-1	-1

Computer sees this

How computer sees an image

-1	-1	-1	-1	-1	-1	-1	-1	0.9	-0	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	0.3	1	0.3	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-0	1	1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	0.8	1	0.6	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	0.5	1	0.8	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	0.1	1	0.9	-0	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-0	1	1	-0	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	0.9	1	0.3	-1	-1	-1	-1	0.5	1	0.9	0.1	-1	-1
-1	-1	0.3	1	0.9	-1	-1	-1	0.1	1	1	1	1	1	-1	-1
-1	-1	0.8	1	0.3	-1	-1	0.4	1	0.7	-0	-0	1	1	-1	-1
-1	-1	1	1	0.1	-1	0.1	1	0.3	-1	-1	-0	1	0.6	-1	-1
-1	-1	1	1	0.8	0.3	1	0.7	-1	-1	-1	0.5	1	0	-1	-1
-1	-1	0.8	1	1	1	1	0.5	0.2	0.8	0.8	1	0.9	-1	-1	-1
-1	-1	-0	0.8	1	1	1	1	1	1	1	0.1	-1	-1	-1	-1
-1	-1	-1	-0	0.8	1	1	1	1	1	0.2	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-0	0.3	0.8	1	0.5	-0	-1	-1	-1	-1	-1

Computer sees this

-1	-1	-1	-1	-1	-1	-1	-1	-1	0.9	-0	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	0.3		0.3	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-0				-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	0.8		0.6	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	0.5		0.8		-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	0.1					-0	-1	-1	-1	-1	-1	-1
-1	-1	-1	-0					-0	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1							-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	0.9				0.3	-1	-1	-1	-1	0.5		0.1	-1
-1	-1	0.3						-1	-1	0.1					-1
-1	-1	0.8					0.3	-1	-1	0.4		0.7	-0	-0	-1
-1	-1						0.1	-1	0.1		0.3	-1	-1	-0	0.6
-1	-1						0.8	0.3		0.7	-1	-1	-1	0.5	0
-1	-1	0.8							0.5	0.2	0.8	0.8		0.9	-1
-1	-1	-0	0.8											0.1	-1
-1	-1	-1	-0	0.8										0.2	-1
-1	-1	-1	-1	-1	-1	-1	-0	0.3	0.8		0.5	-0	-1	-1	-1

Same matrix, highlight the cells based on cell value

How computer sees an image



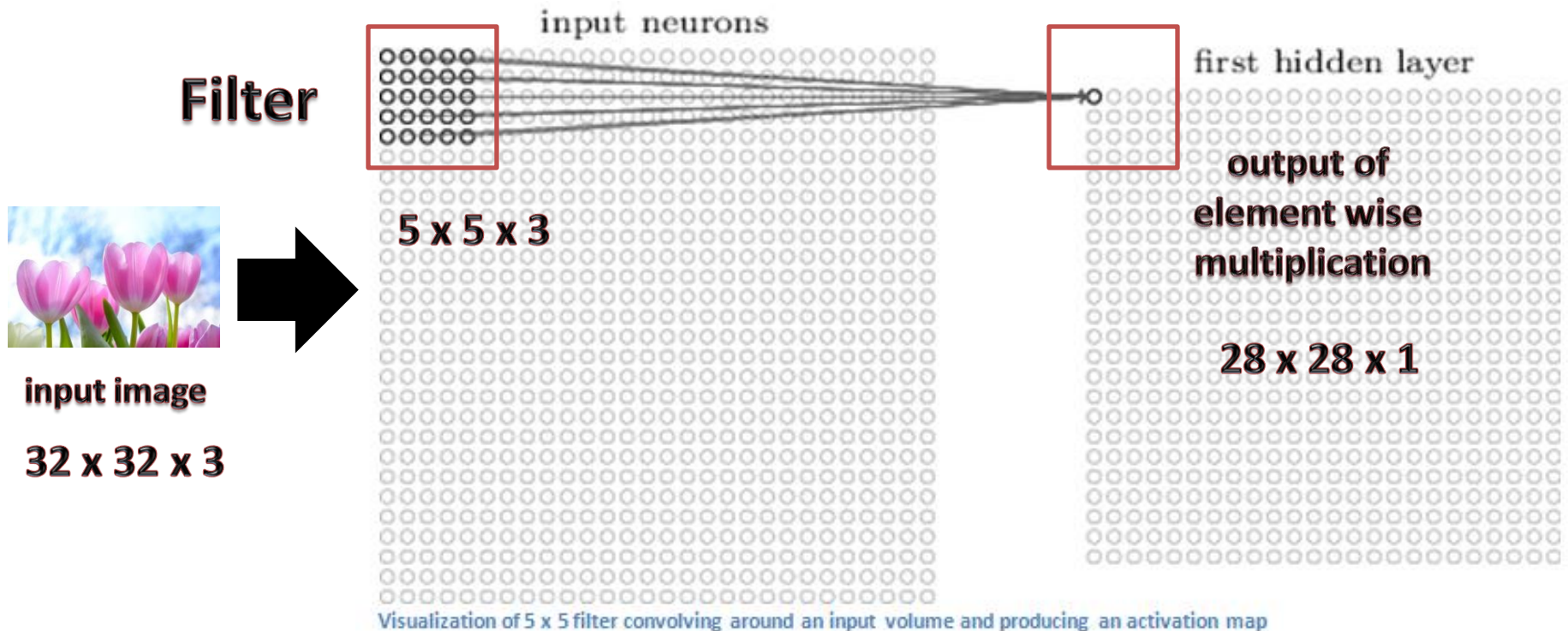
Human Vision



Computer Vision

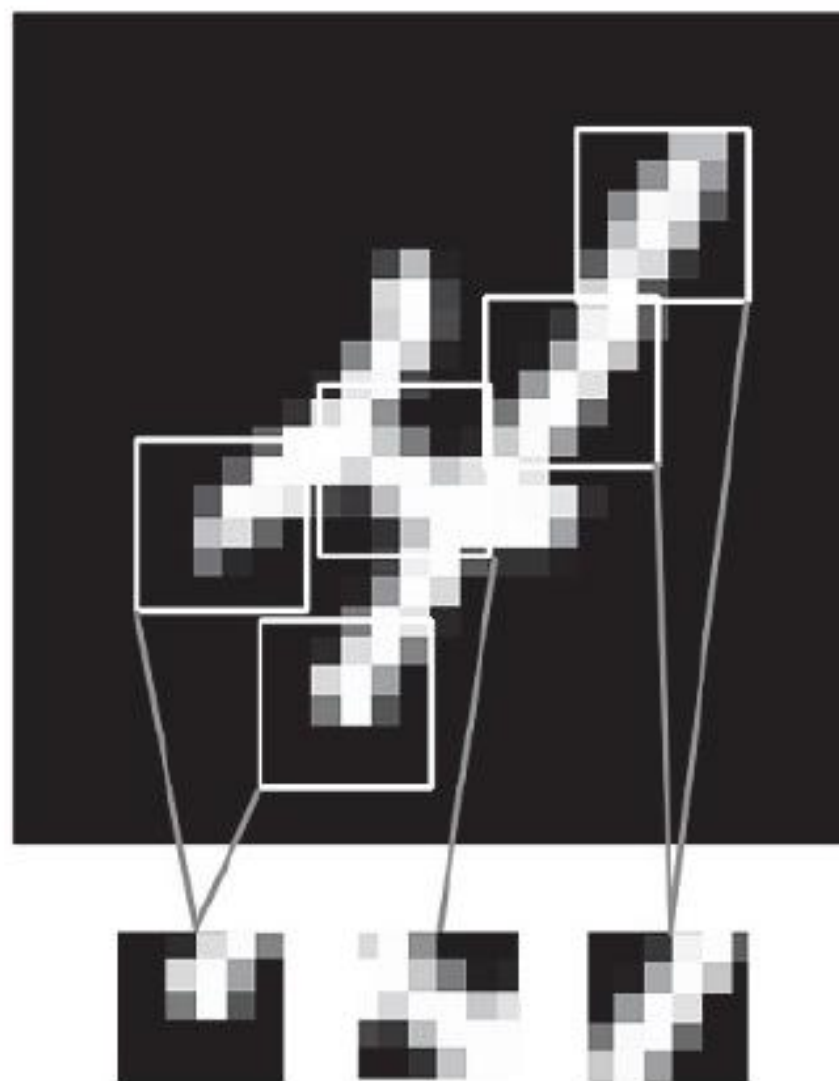
Convolution Neural Network

- **First Layer – Math Part**
 - The first layer in a CNN is always a **Convolutional Layer**.



Convolutional Layer

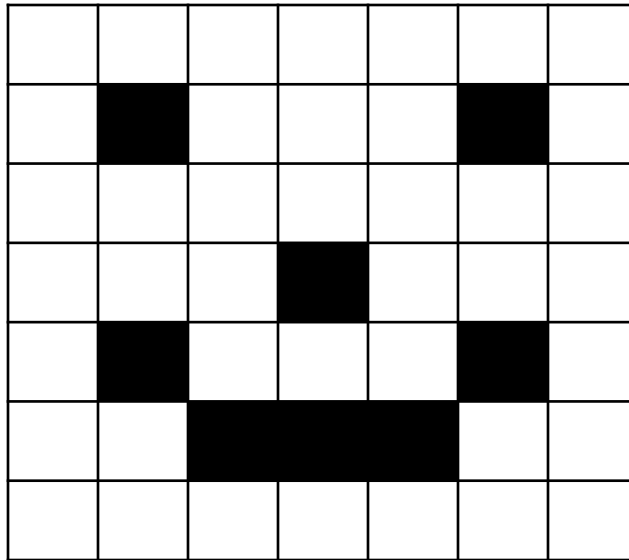
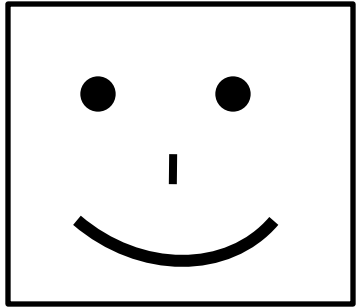
- The fundamental difference between a **densely-connected layer** and a **convolution layer** :
 - Dense layers learn global patterns in their input feature space
 - Convolution layers learn local patterns i.e. in the case of images, patterns found in small 2D windows of the inputs.



Convolutional Layer

- The patterns they learn are *translation-invariant* :
 - *after learning a certain pattern in the bottom right corner of a picture, a convnet is able to recognize it anywhere, e.g. in the top left corner.*
 - *A densely-connected network would have to learn the pattern anew if it appeared at a new location*
- This makes convnets very data-efficient when processing images : they need less training samples to learn representations that have generalization power

CNN



0	0	0	0	0	0	0
0	1	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	1	0	0	0	1	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0

Step1-Convolution

0	0	0	0	0	0	0
0	1	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	1	0	0	0	1	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0

Input image



0	0	1
1	0	0
0	1	1

**Feature
Detector**



0	1	0	0	0
0	1	1	1	0
1	0	1	2	1
1	4	2	1	0
0	0	1	2	1

Feature Map1

Kernel Matrix examples

1	1	1
1	1	1
1	1	1

Unweighted 3x3 smoothing kernel

0	1	0
1	4	1
0	1	0

Weighted 3x3 smoothing kernel with Gaussian blur

0	-1	0
-1	5	-1
0	-1	0

Kernel to make image sharper

-1	-1	-1
-1	9	-1
-1	-1	-1

Intensified sharper image



Gaussian Blur

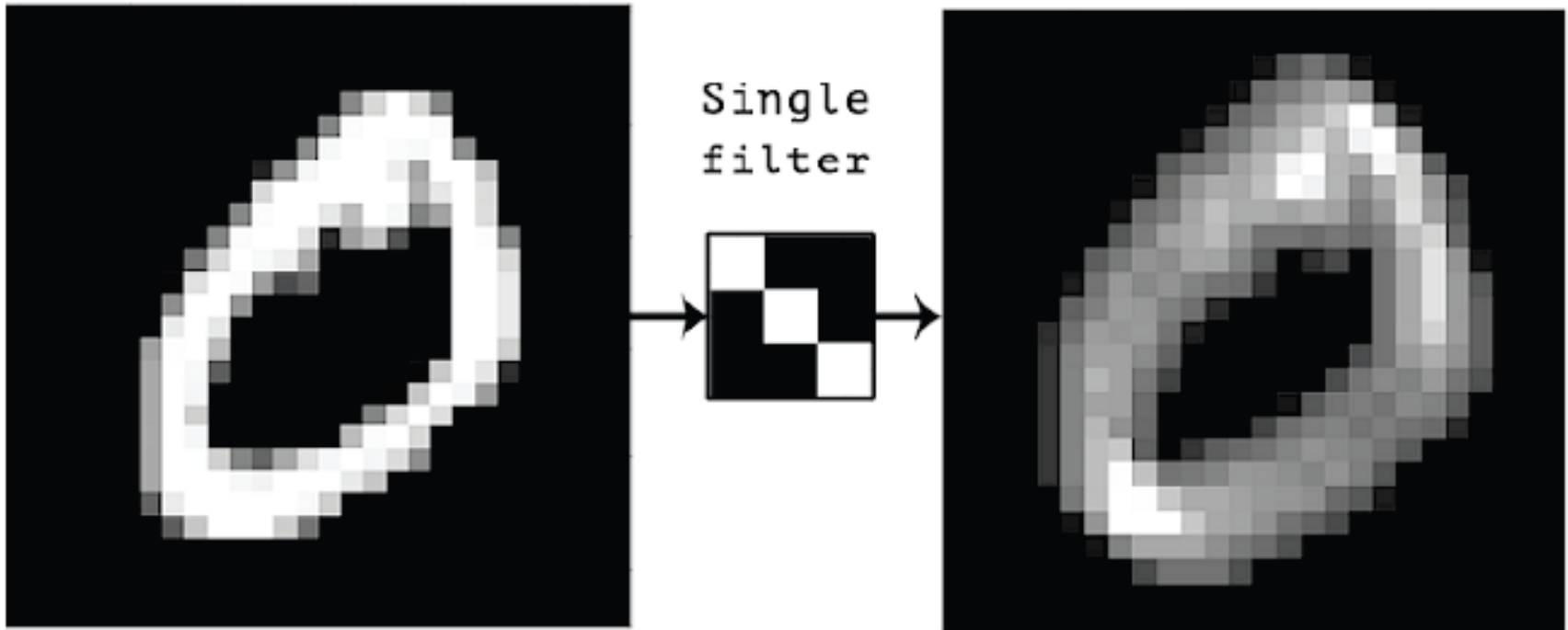


Sharpened image

Many Filters in Convolution Layer

- Each Kernel matrix captures a specific type of pattern in input data
- Apply different filters by changing the kernel function
- There are many kernel functions/filters
 - Filter for detecting the curves
 - Filter for detecting the circles
 - Filter for detecting the sharp edges
 - Filter for detecting the straight lines

Feature Map / Response Map



- convolution is most typically done with 3x3 windows and no stride (stride 1).

Step1-Convolution

0	0	0	0	0	0	0
0	1	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	1	0	0	0	1	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0

Input image



0	1	0
0	0	0
1	1	1

**Feature
Detector**



0	0	0	0	0
1	1	1	1	1
1	1	0	1	1
1	2	4	2	1
1	0	0	0	1

Feature Map2

Step1-Convolution

0	0	0	0	0	0	0
0	1	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	1	0	0	0	1	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0

Input image



0	0	1
1	0	0
0	1	1

**Feature
Detector**

0	1	0	0	0
0	1	0	0	0
1	0	0	0	0
1	1	0	0	0
0	1	0	0	0

0	1	0	0	0
0	1	0	0	0
1	1	0	0	0
0	1	1	1	0
1	0	1	1	0

0	1	0	0	0
0	1	1	1	0
1	0	1	2	1
1	4	2	1	0
0	0	1	2	1

Feature Map

Effective Convolution with Kernel Matrix

1	1	1	0	0	1	1
1	1	0	1	0	1	1
1	0	0	1	1	1	0
0	0	0	0	0	1	1
1	1	0	0	0	0	1
1	0	0	1	1	1	0
1	1	1	0	0	1	1

kernel matrix

1	1	1
1	1	1
1	1	1

- Use Kernel
 - To enhance intensity
 - or to make the image smooth
 - or to make it sharp

6	5			

Effective Convolution with Kernel Matrix

1	1	1	0	0	1	1
1	1	0	1	0	1	1
1	0	0	1	1	1	0
0	0	0	0	0	1	1
1	1	0	0	0	0	1
1	0	0	1	1	1	0
1	1	1	0	0	1	1

kernel matrix

0	1	0
1	1	1
0	1	0

- There are different versions of kernels

3				

Many Filters in Convolution Layer

1	1	1	0	0	1	1
1	1	0	1	0	1	1
1	0	0	1	1	1	0
0	0	0	0	0	1	1
1	1	0	0	0	0	1
1	0	0	1	1	1	0
1	1	1	0	0	1	1

0	0	1
0	1	1
1	1	1

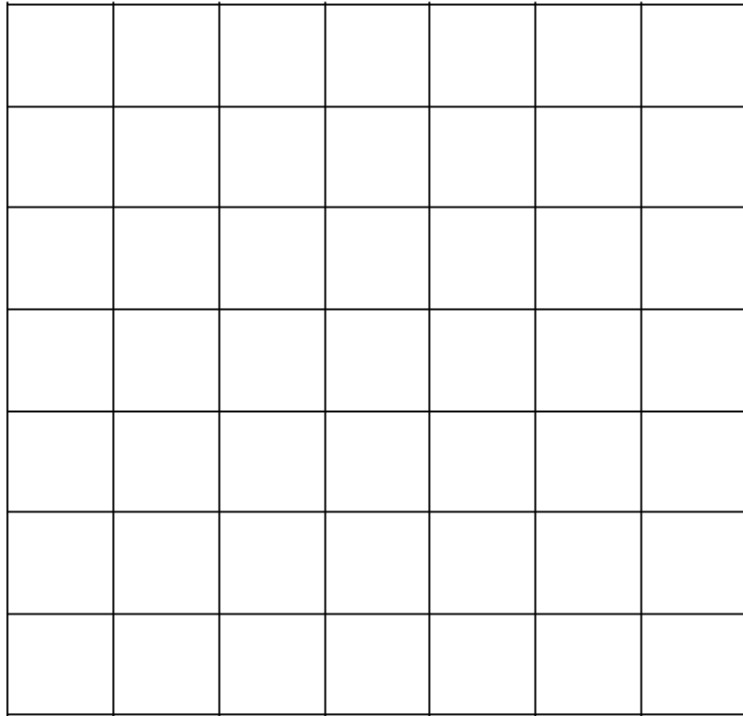
1	1	1
1	1	0
1	0	0

0	0	15
0	15	0
15	0	0

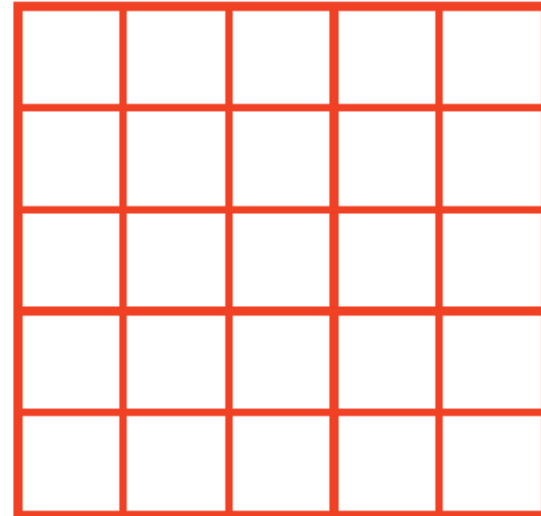
0	10	0
10	10	10
0	10	0

Different kernel matrices

First Hidden Layer in CNN is Convolution Layer



- By Applying filters and kernel we are creating new convoluted features
- The hidden layer in ANN is now the convoluted layer
- Convoluted features keep the input data integrity intact with lesser data points

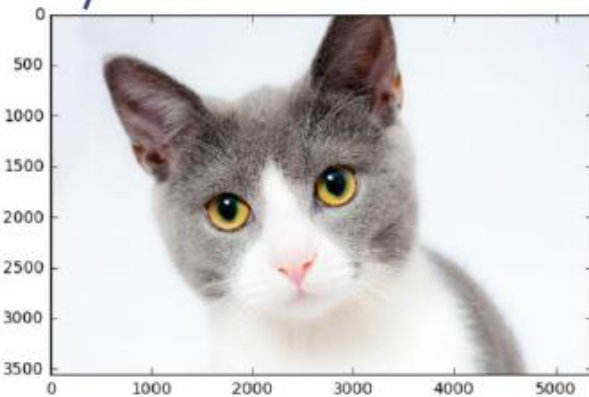
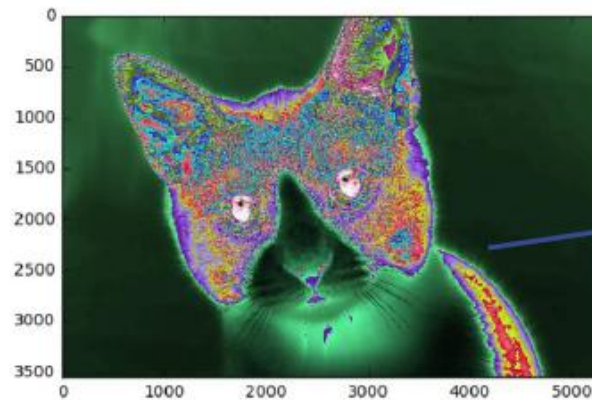
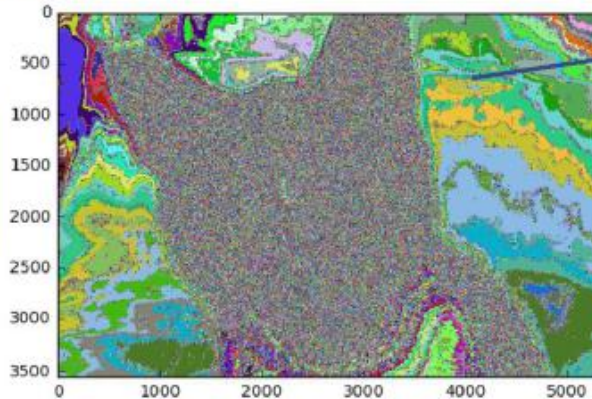


Convolved features

Different filters capture different features

A filter to capture overall shape and edges

A filter to ignore white spaces on image



The depth in convolution layer

- Every filter gives us a resultant matrix (activation map)

0	0	0	0	0	0	0	0	0
0	1	1	1	0	0	1	1	0
0	1	1	0	1	0	1	1	0
0	1	0	0	1	1	1	0	0
0	0	0	0	0	0	1	1	0
0	1	1	0	0	0	0	1	0
0	1	0	0	1	1	1	0	0
0	1	1	1	0	0	1	1	0
0	0	0	0	0	0	0	0	0

1	1	1
1	1	1
1	1	1

4	5	4	2	3	4	4
5	6	5	4	6	6	5
3	3	3	3	6	6	5
3	3	2	2	4	5	4
3	3	2	2	4	5	4
5	6	4	3	4	5	4
3	4	3	3	4	4	3

The depth in convolution layer

- With two filters we will get two activation maps i.e depth=2

0	0	0	0	0	0	0	0	0
0	1	1	1	0	0	1	1	0
0	1	1	0	1	0	1	1	0
0	1	0	0	1	1	1	0	0
0	0	0	0	0	0	1	1	0
0	1	1	0	0	0	0	1	0
0	1	0	0	1	1	1	0	0
0	1	1	1	0	0	1	1	0
0	0	0	0	0	0	0	0	0

1	1	1
1	1	1
1	1	1

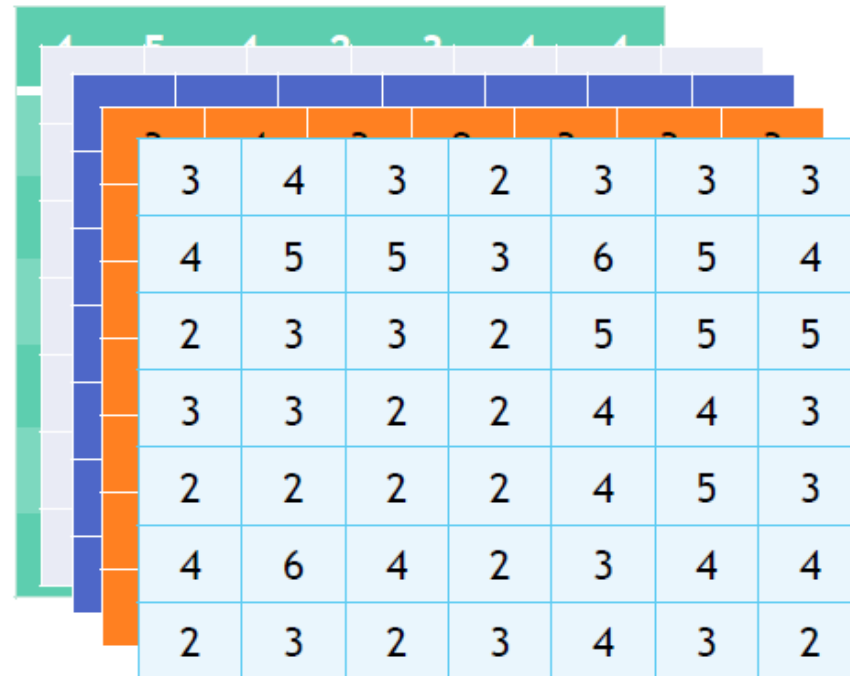
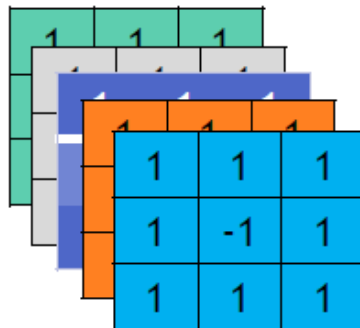
1	1	1
1	-1	1
1	1	1

4	5	4	2	3	4	4	
5	3	4	3	2	3	3	3
5	4	5	5	3	6	5	4
5	2	3	3	2	5	5	5
5	3	3	2	2	4	4	3
5	2	2	2	2	4	5	3
5	4	6	4	2	3	4	4
5	2	3	2	3	4	3	2

The depth in convolution layer

- If we apply 10 different filters then we will get 10 resultant matrices. The depth is 10

0	0	0	0	0	0	0	0	0
0	1	1	1	0	0	1	1	0
0	1	1	0	1	0	1	1	0
0	1	0	0	1	1	1	0	0
0	0	0	0	0	0	1	1	0
0	1	1	0	0	0	0	1	0
0	1	0	0	1	1	1	0	0
0	1	1	1	0	0	1	1	0
0	0	0	0	0	0	0	0	0



Max Pooling

Pooling layer

- Pooling helps in further downsizing the data
- Pooling is used to avoid overfitting and increase the robustness
- Reduces lot of computation time

What happens in pooling layer

- Down sampling of the data.
- Since we preserved lot of information in each convolution layer, we can comfortably down sample it, in this pooling layer
- Yes, we do loose some information, but we will not loose the overall integrity of the data
- It is still good enough for a classification model
- Generally we try max pooling with 2X2 filter with stride 2

How many parameters in pooling layer

- No parameters
- We just perform down sampling, that's it. No further activation and no further parameters
- Number of parameters in pooling layer=0

Max Pooling

0	1	0	0	0
0	1	1	1	0
1	0	1	2	1
1	4	2	1	0
0	0	1	2	1

Feature Map

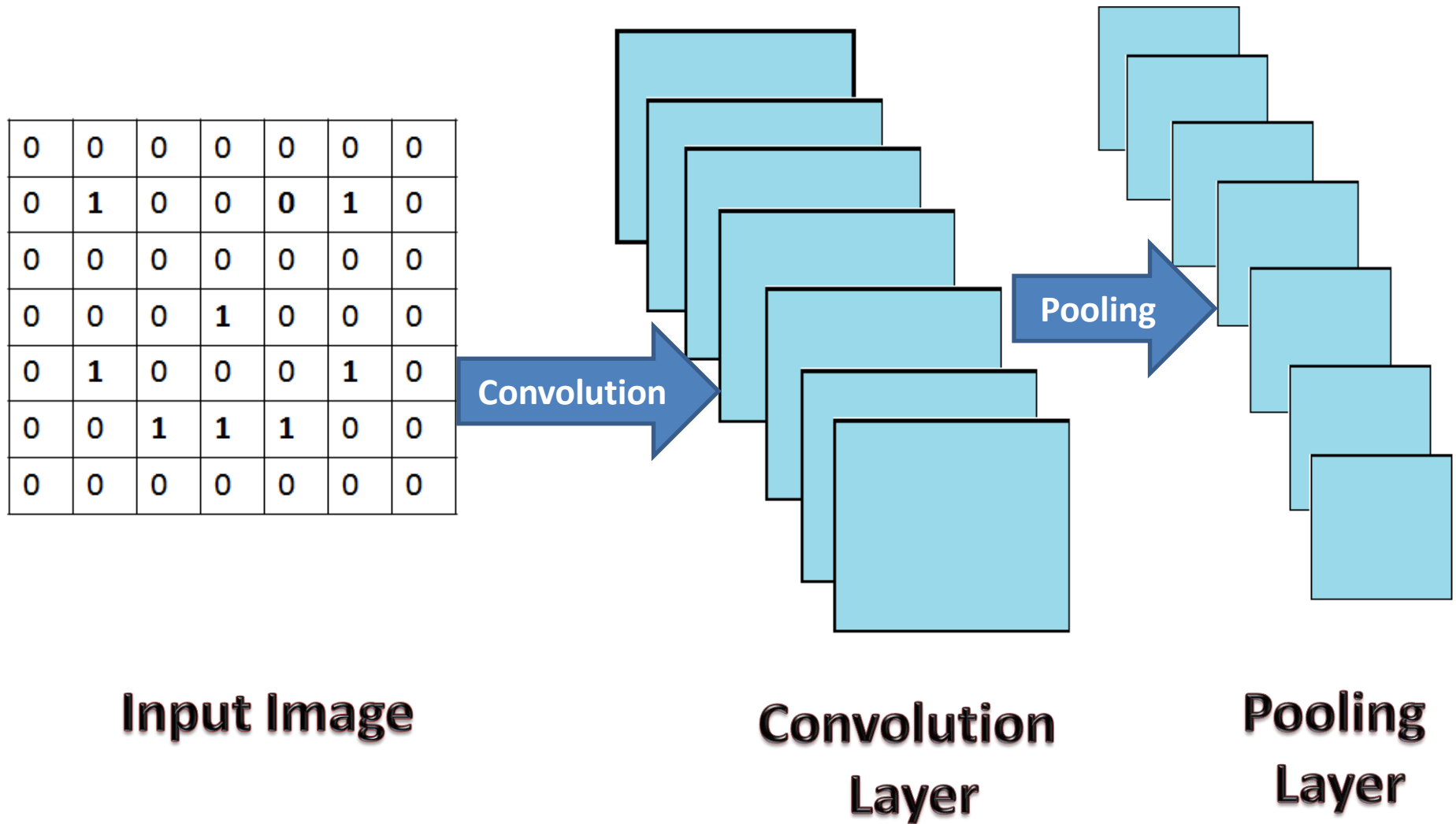


1	1	0
4	2	1
0	2	1

**Pool
Feature Map**

Max pooling is usually done with 2x2 windows and stride 2, so as to downsample the feature maps

Max Pooling



Flattening

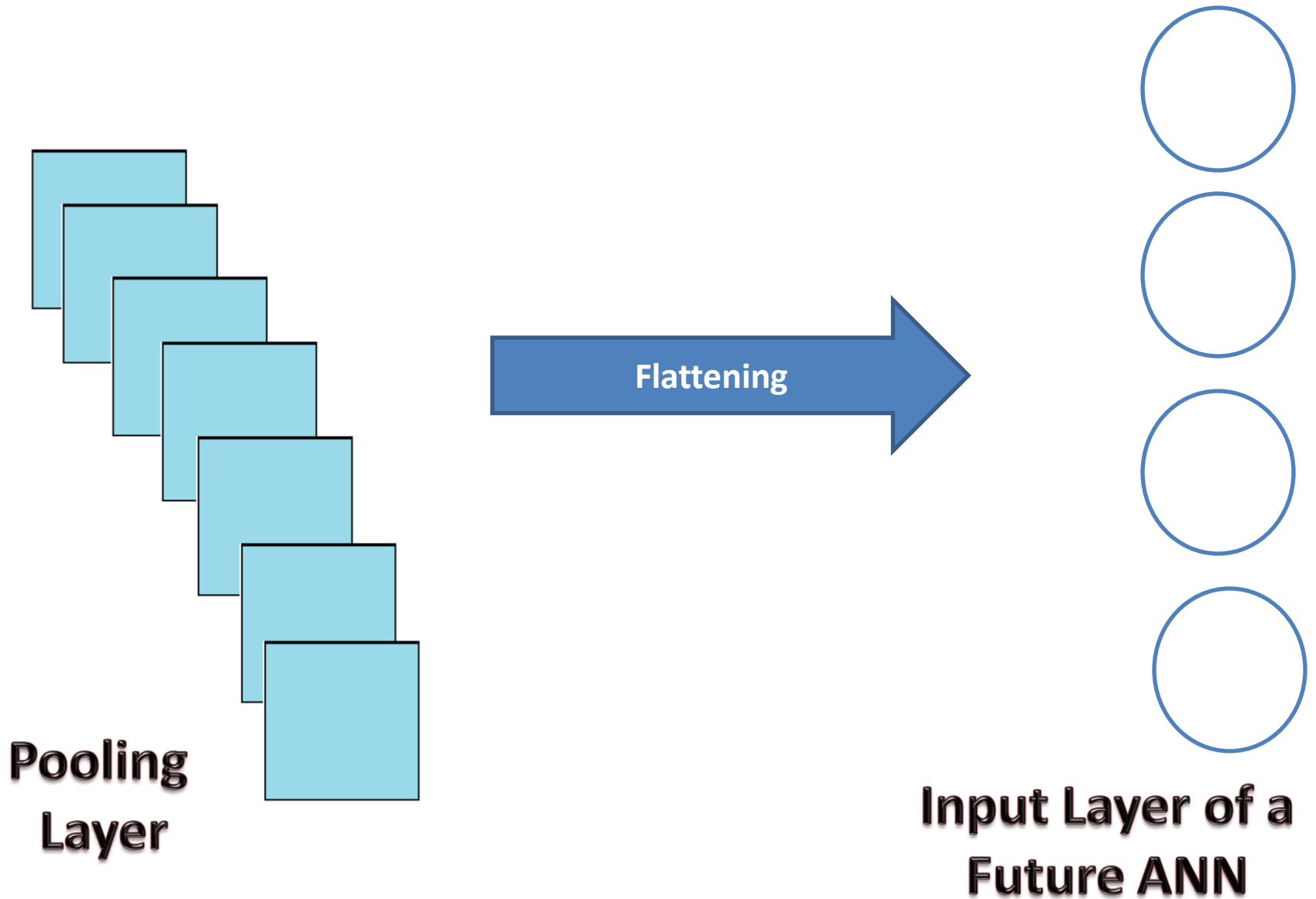
1	1	0
4	2	1
0	2	1

**Pool
Feature Map**

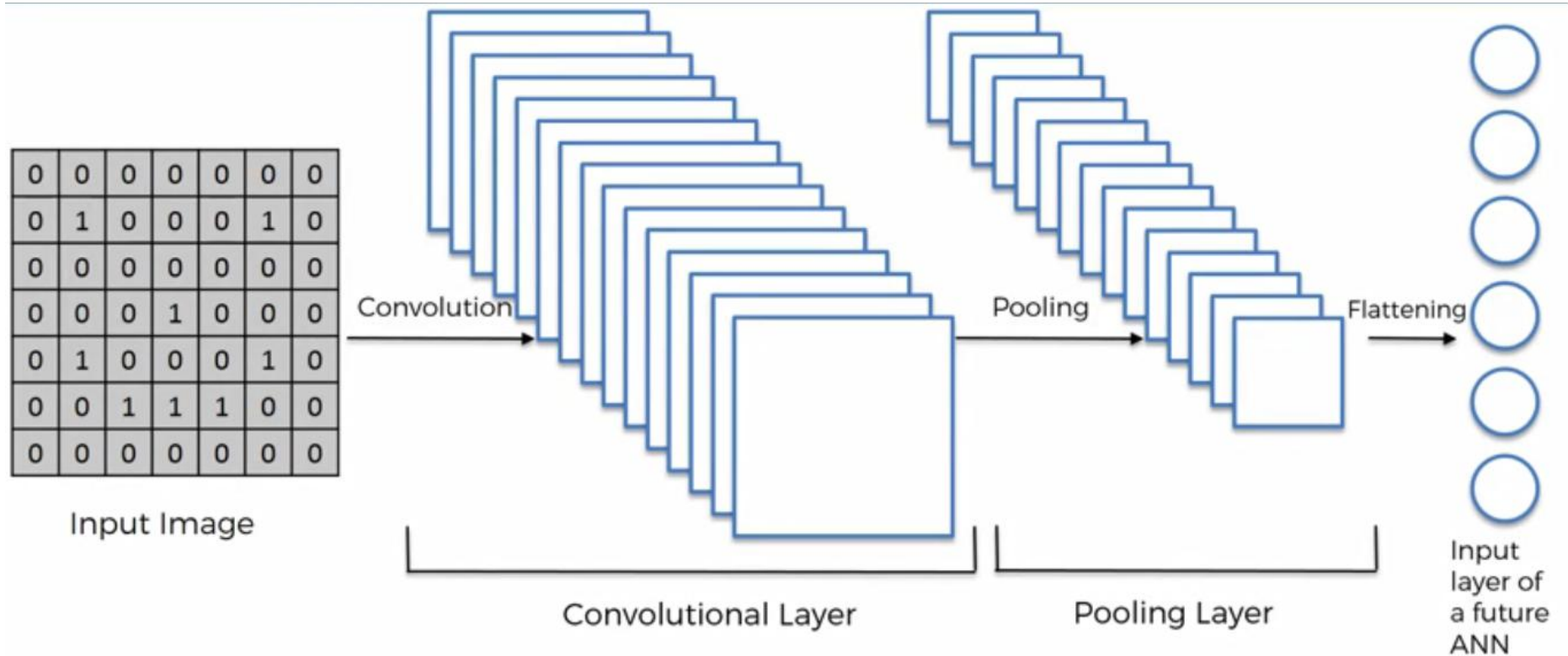


1
1
0
4
2
1
0
2
1

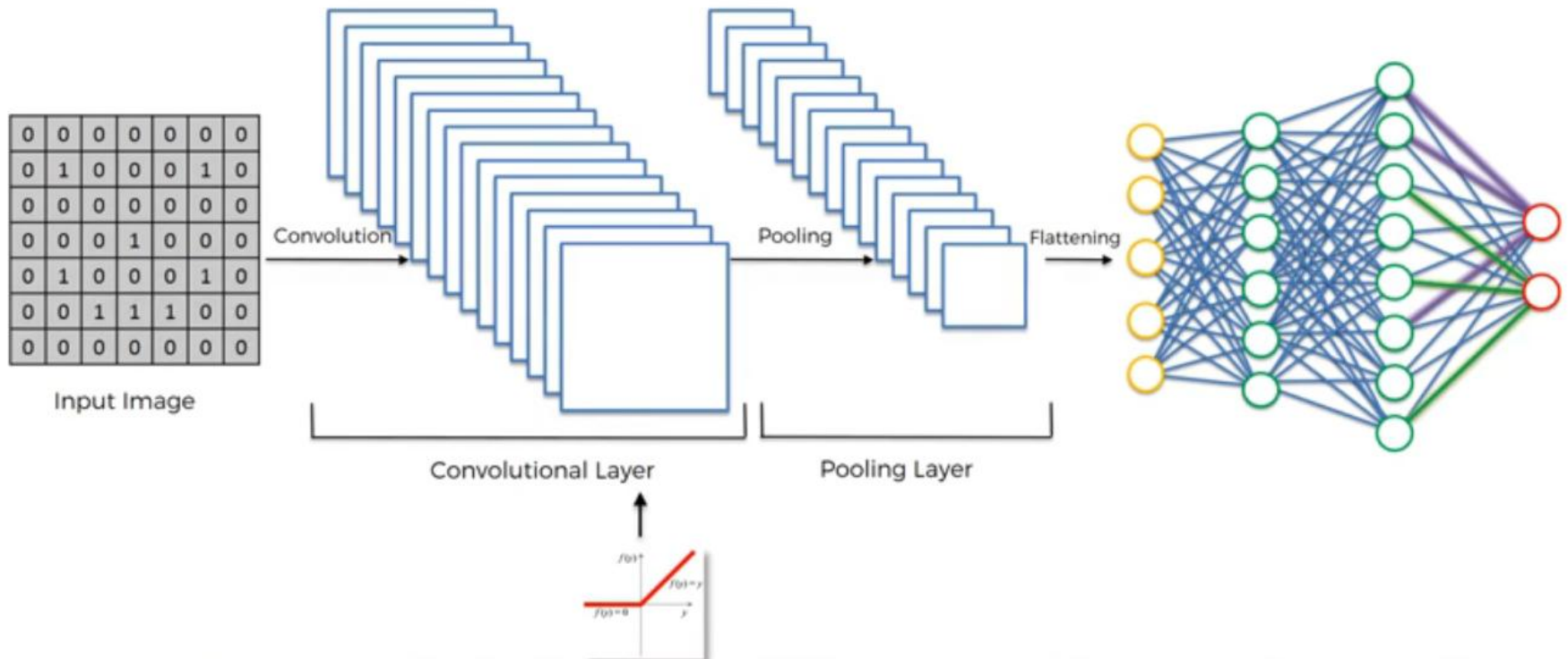
Flattening



Flattening



Full Connection



Data Augmentation

- *Having too few samples to learn from, rendering us unable to train a model able to generalize to new data.*
- *Given infinite data, our model would be exposed to every possible aspect of the data distribution at hand.*
- *Data augmentation takes the approach of generating more training data from existing training samples, by "augmenting" the samples via a number of random transformations that yield believable-looking images.*
- *The goal is that at training time, our model would never see the exact same picture twice. This helps the model get exposed to more aspects of the data and generalize better.*

Generation of cat pictures via random data augmentation



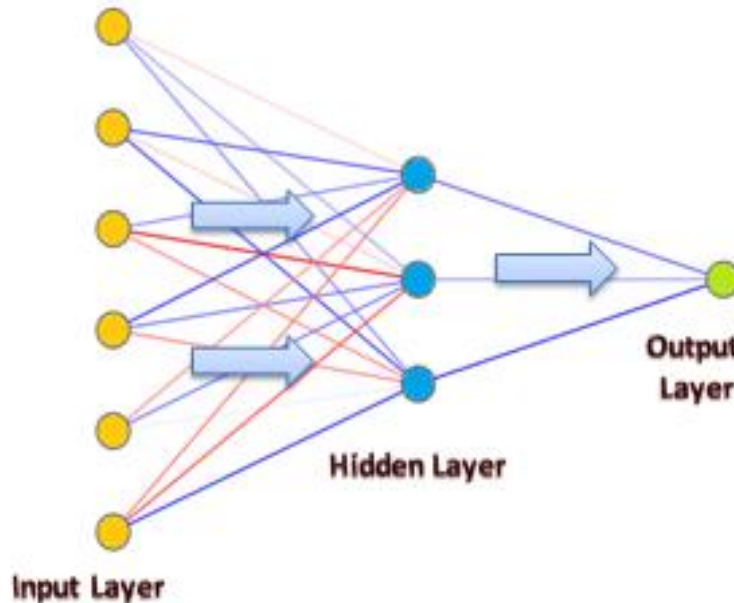
Feedforward networks

- A major characteristic of all neural networks , such as densely-connected networks and convolutional networks, is that they are feedforward.

- Each input is independent of the other inputs



- With sequential inputs, we have to



used between

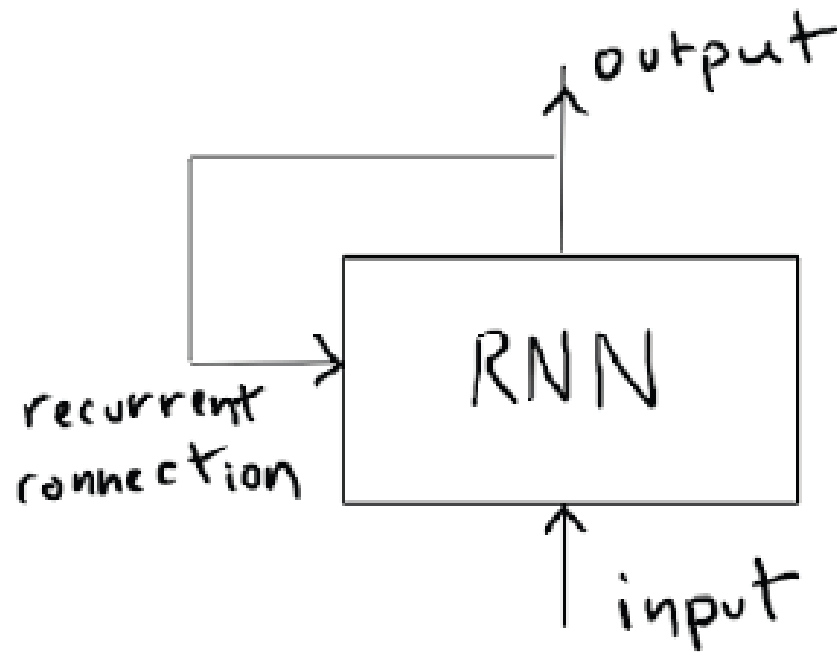
is a points, we re network

at once, i.e. turn it into a single datapoint.

RNN

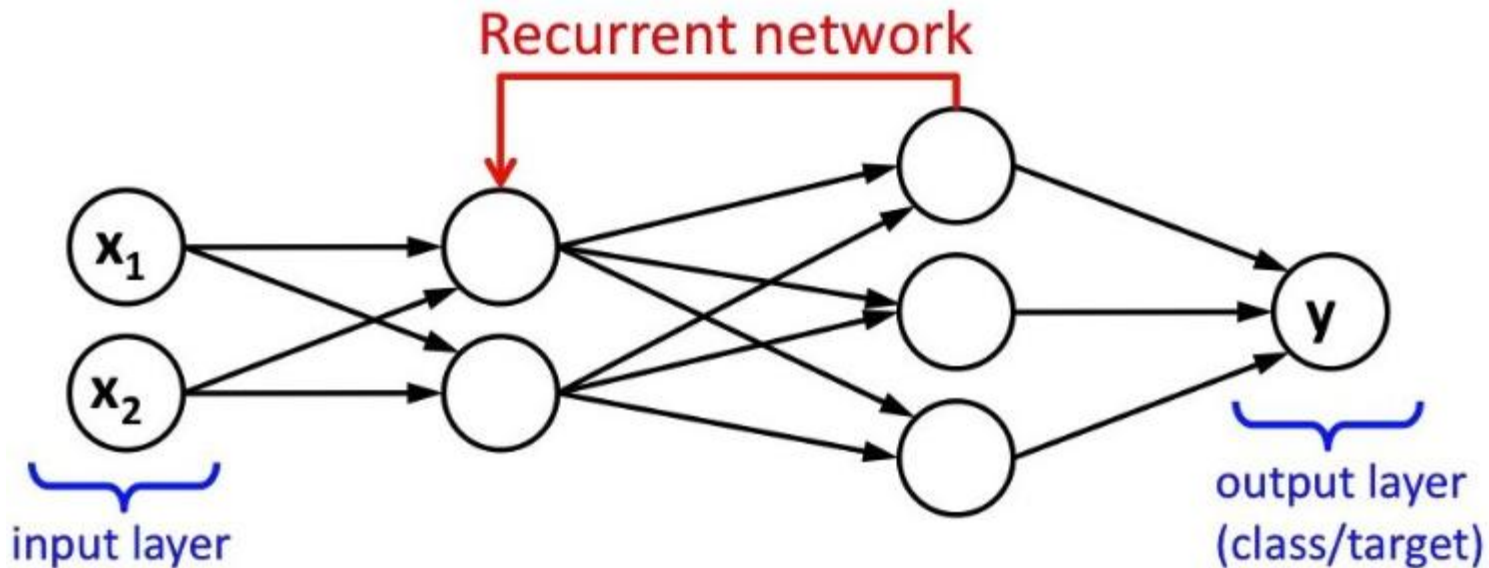
- Biological intelligence processes information incrementally while maintaining an internal model of what it is processing, built from past information and constantly getting updated as new information comes in.
- **Recurrent Neural Networks (RNNs) adopt the same principle**
- They process sequences by iterating through the sequence elements and maintaining a "state" containing information relative to what they have seen so far.

- RNNs are a type of neural network that has an internal loop



Recurrent Neural Network

On recurrent neural networks(RNN), the previous network state also influences the output, so recurrent neural networks also have a **"notion of time"**.



Recurrent Neural Network

Multiple ways that you could use a recurrent neural network compared to the forward networks.

one to one

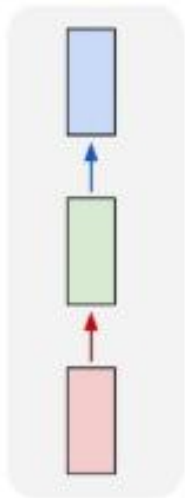


Image in
Label out

one to many

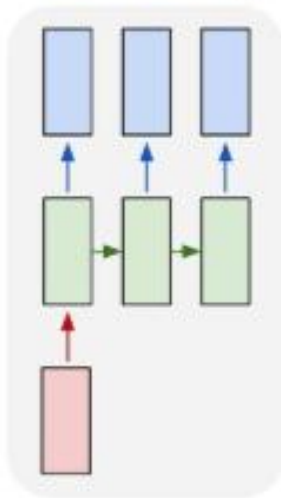
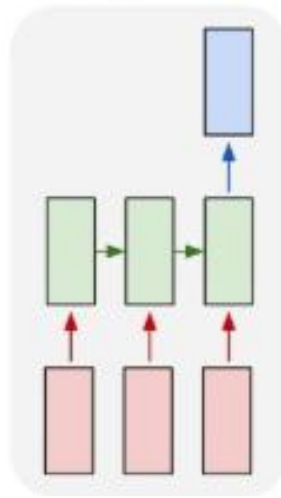


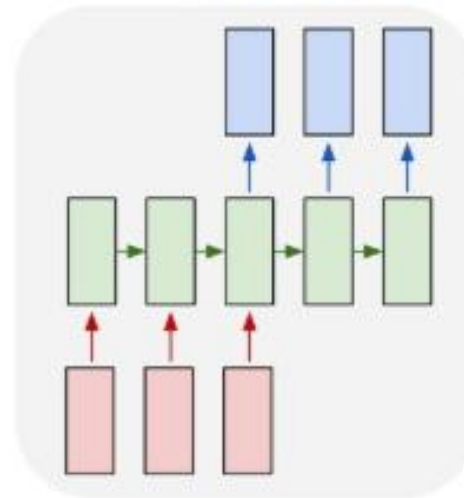
Image in
Words out

many to one



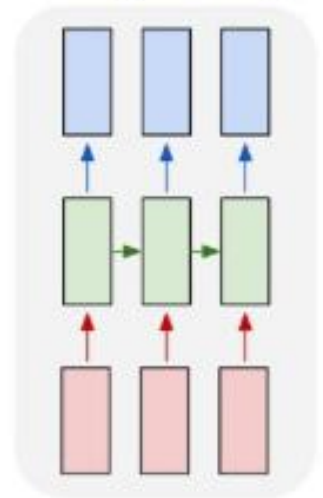
Words In
sentiment out

many to many



English In
French out

many to many

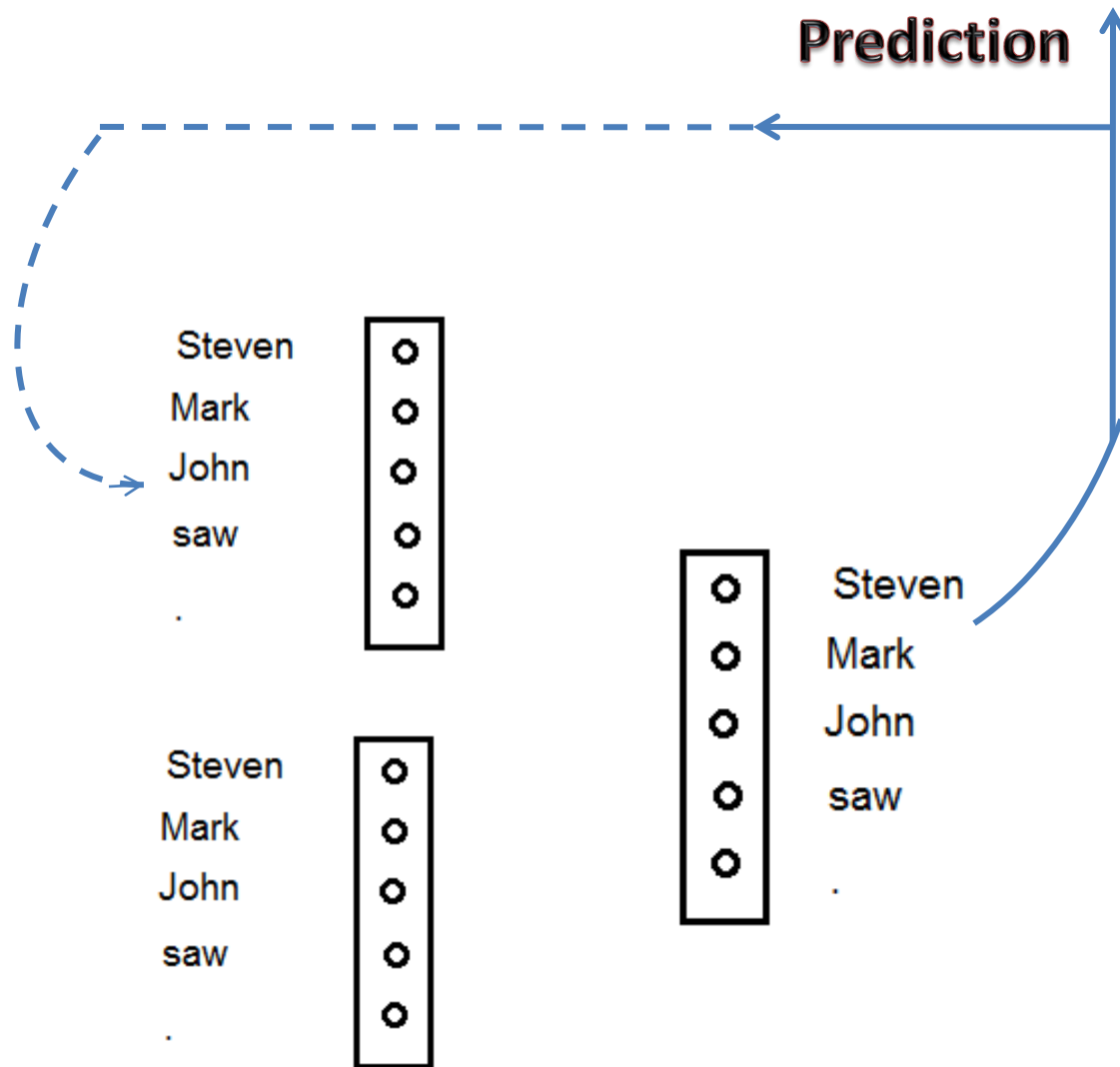


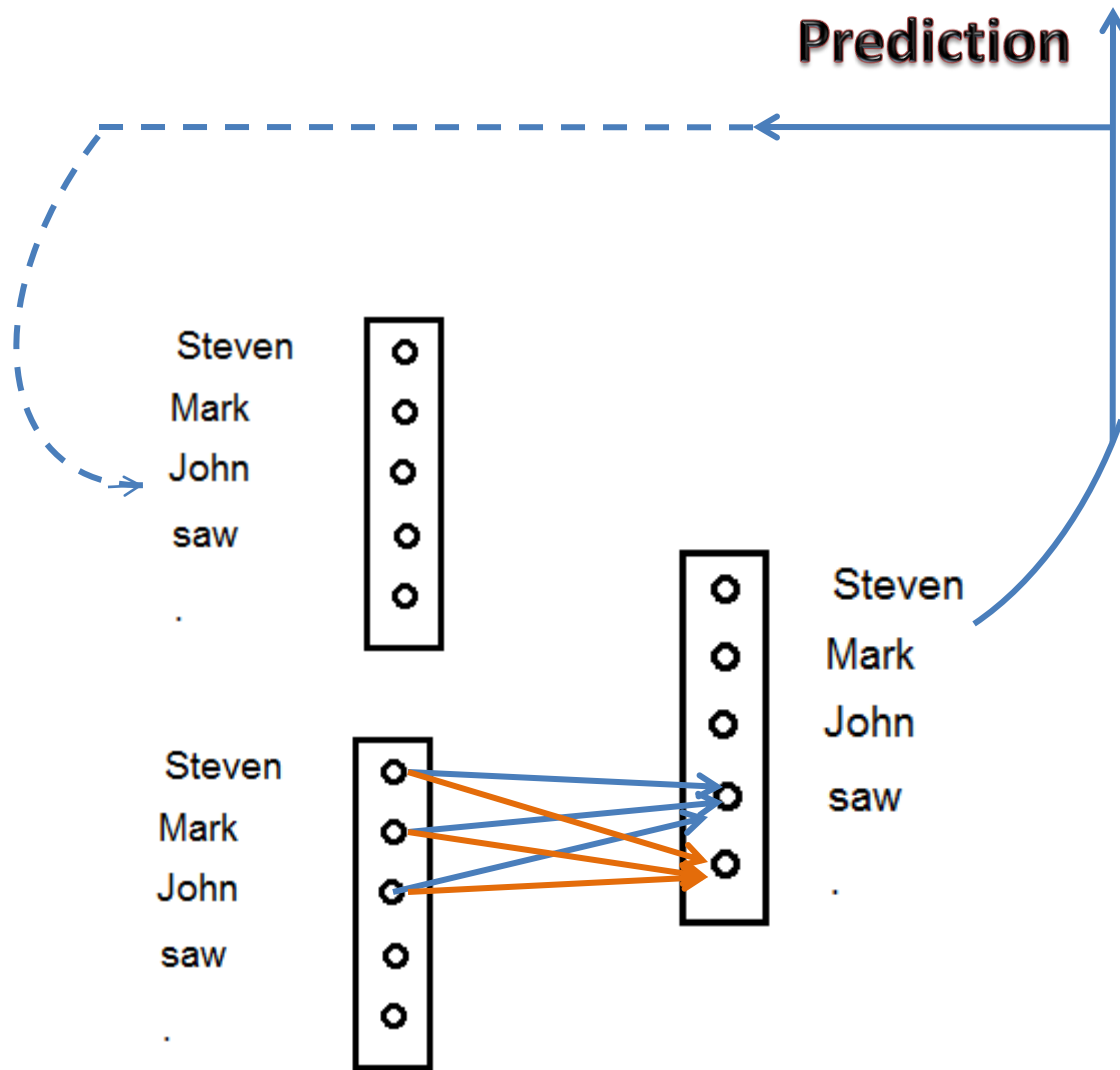
Video In
Label out

Recurrent Neural Network

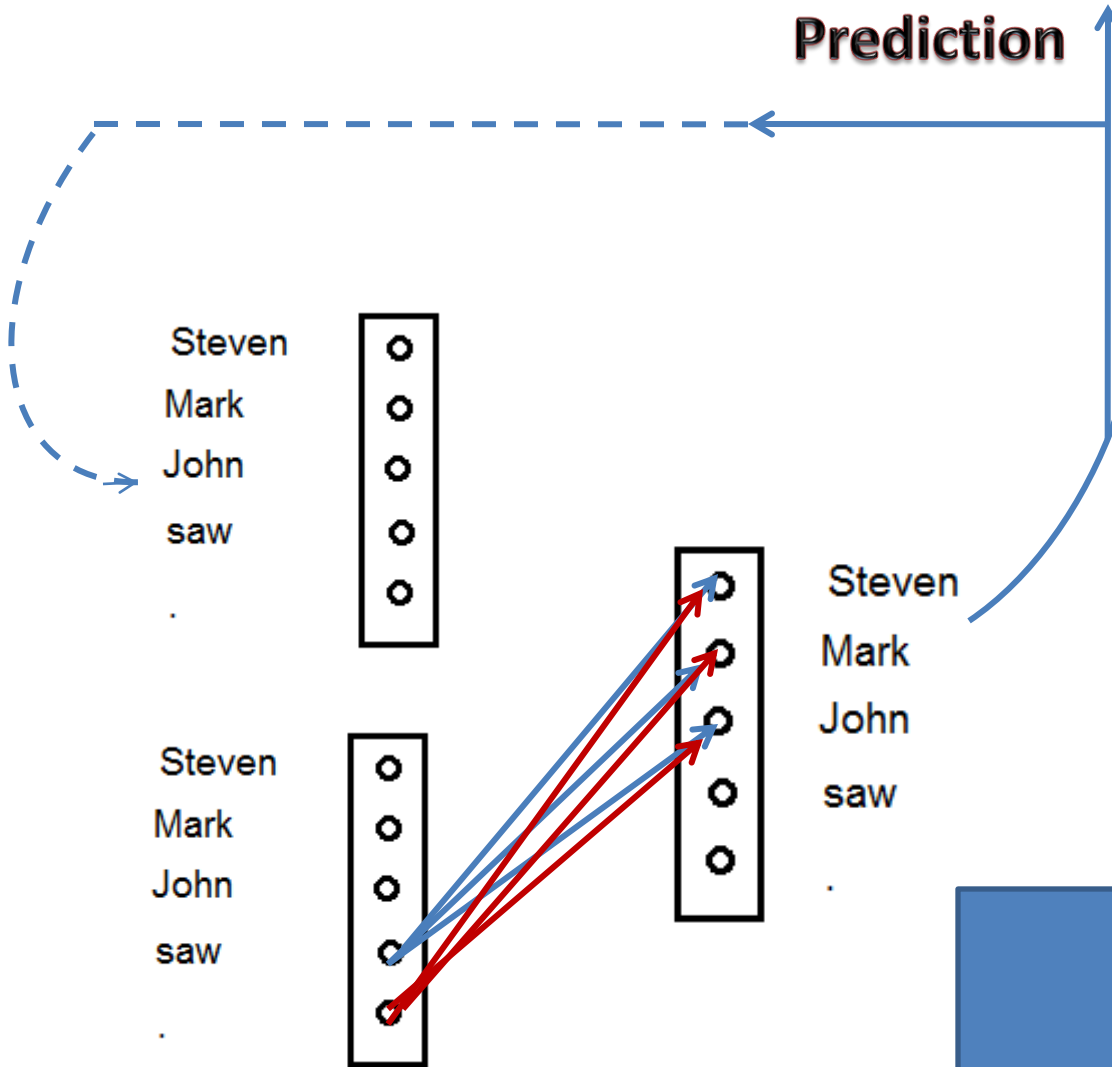
- Steven saw Mark.
- Mark saw John.
- John saw Steven.
- Small Dictionary of words ::
{Steven, Mark, John, saw, .}

Steven saw Mark.
Mark saw John.
John saw Steven.





Prediction



Steven saw Mark.

Steven saw Mark saw John saw ...

Steven.Mark.John.