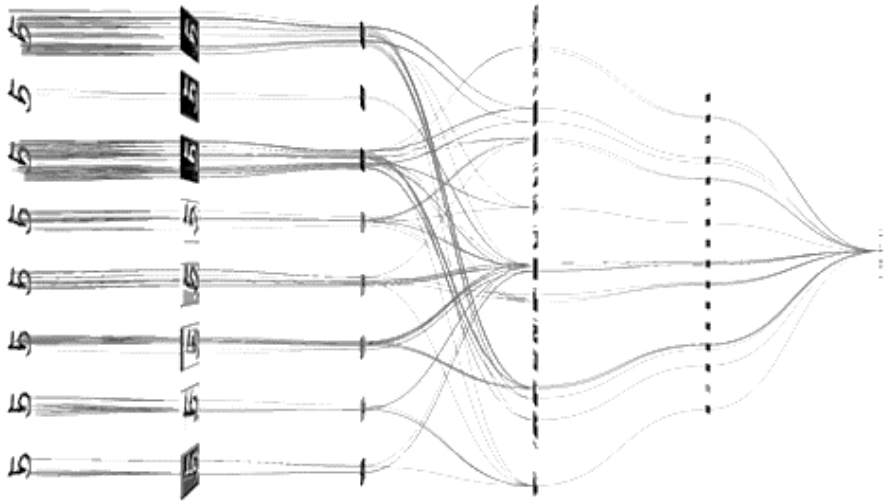
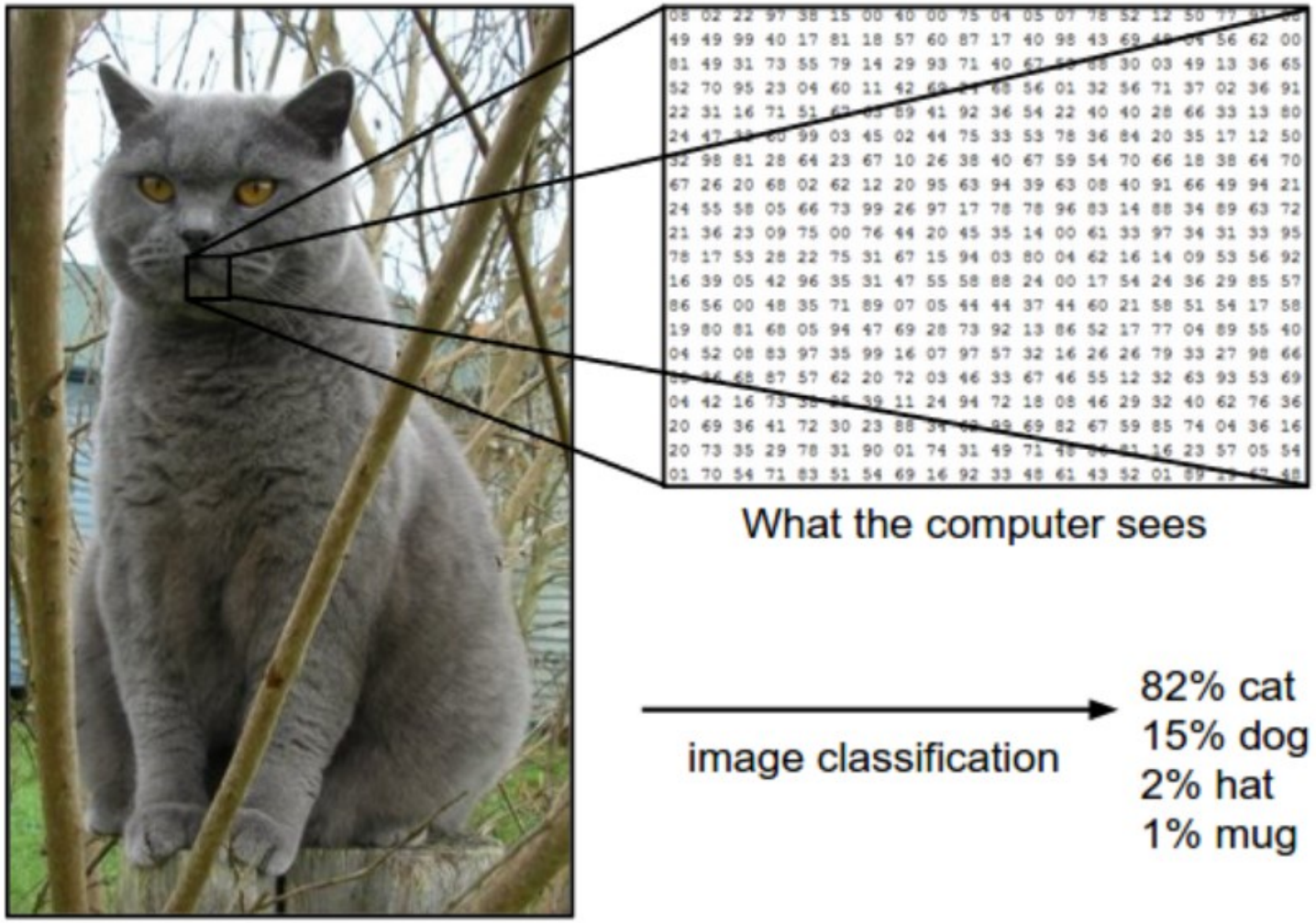
Convolutional Neural Network



Fast Campus
Start Deep Learning with TensorFlow

Image Classification

- A core task in Computer Vision



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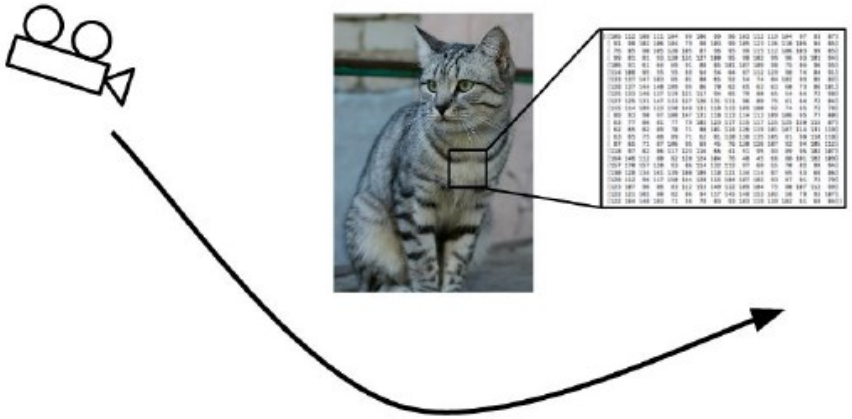
Challenges of Recognition

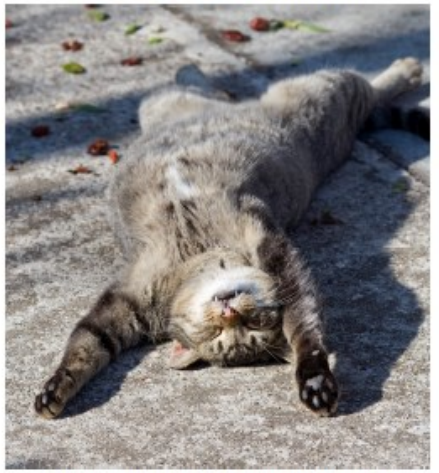
Viewpoint



Illumination

This image is CC0 1.0 public domain

Deformation



This image by Umberto Salvagnin is licensed under CC-BY 2.0

Occlusion

This image by jonsson is licensed under CC-BY 2.0

Clutter

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Intraclass Variation

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An Image Classifier

```
def classify_image(image):
  # Some magic here?
  return class_label
```

Unlike e.g. sorting a list of numbers,

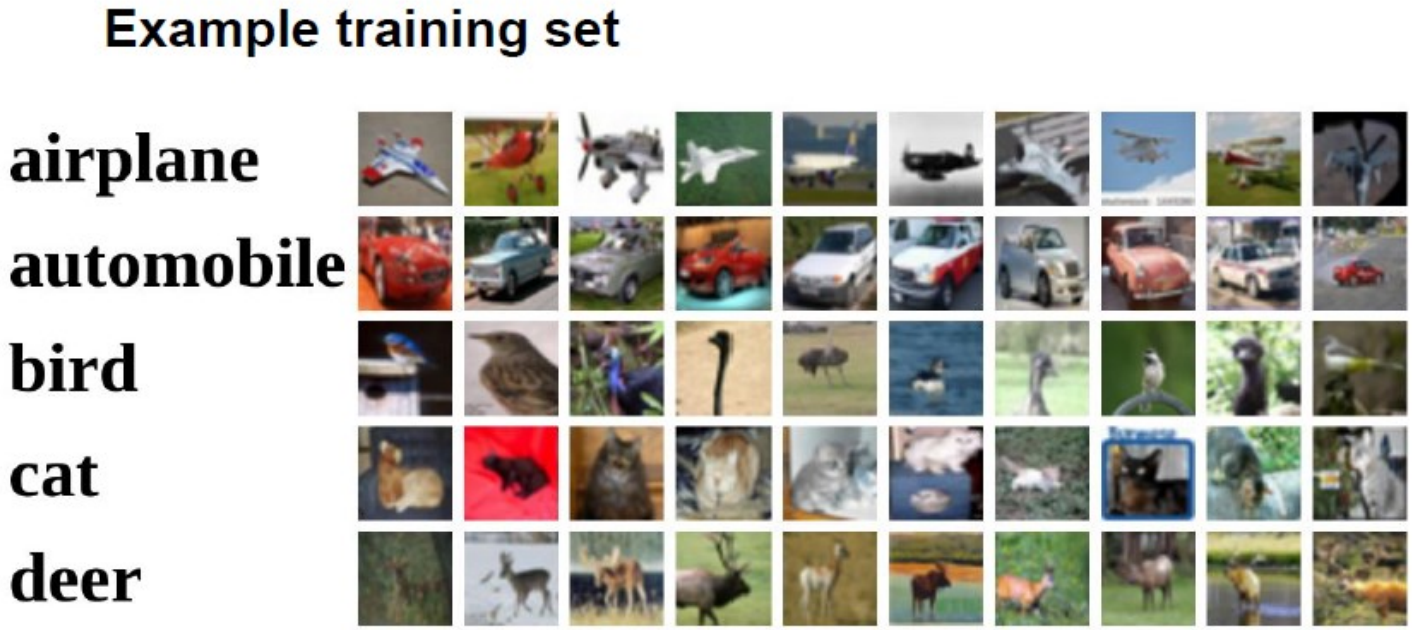
no obvious way to hard-code the algorithm for recognizing a cat, or other classes.

Data-Driven Approach

1. Collect a dataset of images and labels
2. Use Machine Learning to train a classifier
3. Evaluate the classifier on new images

```
def train(images, labels):
  # Machine learning!
  return model
```

```
def predict(model, test_images):
  # Use model to predict labels
  return test_labels
```



First Classifier – Nearest Neighbor

```
def train(images, labels):
  # Machine learning!
  return model
```

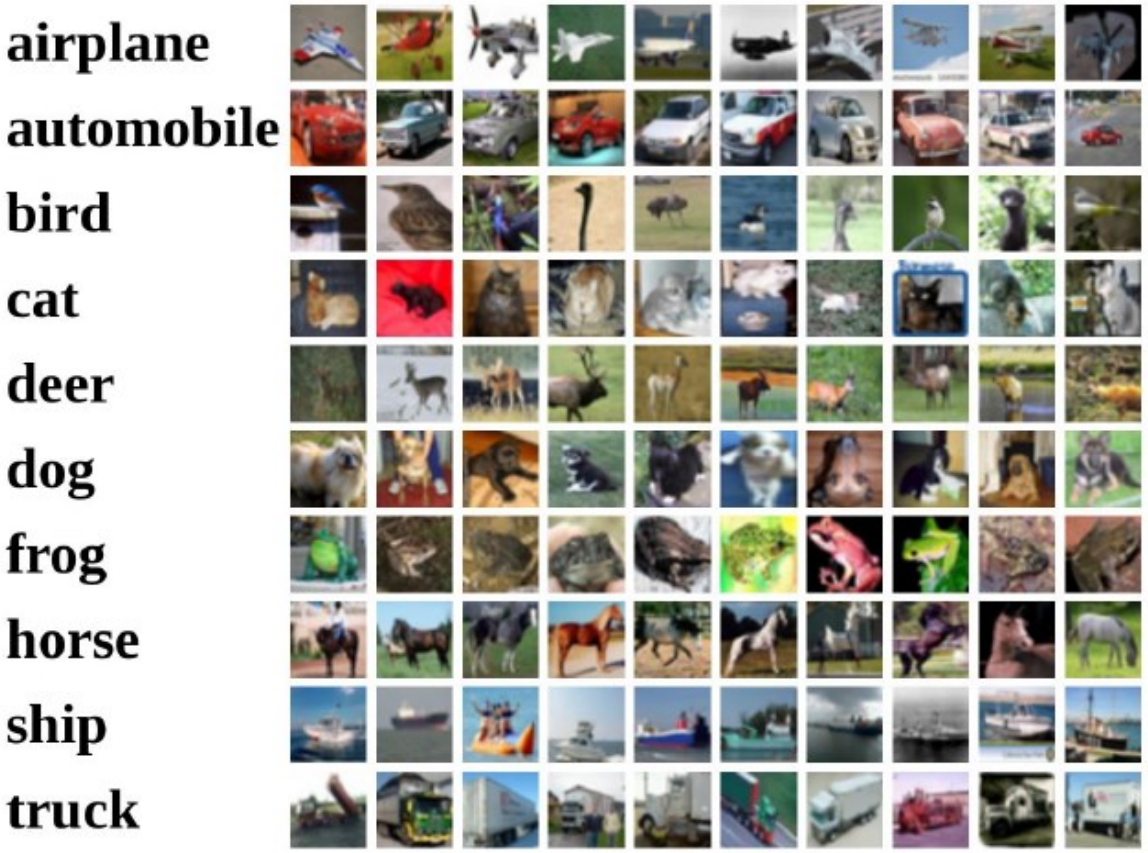
Memorize all data and labels

```
def predict(model, test_images):
  # Use model to predict labels
  return test_labels
```

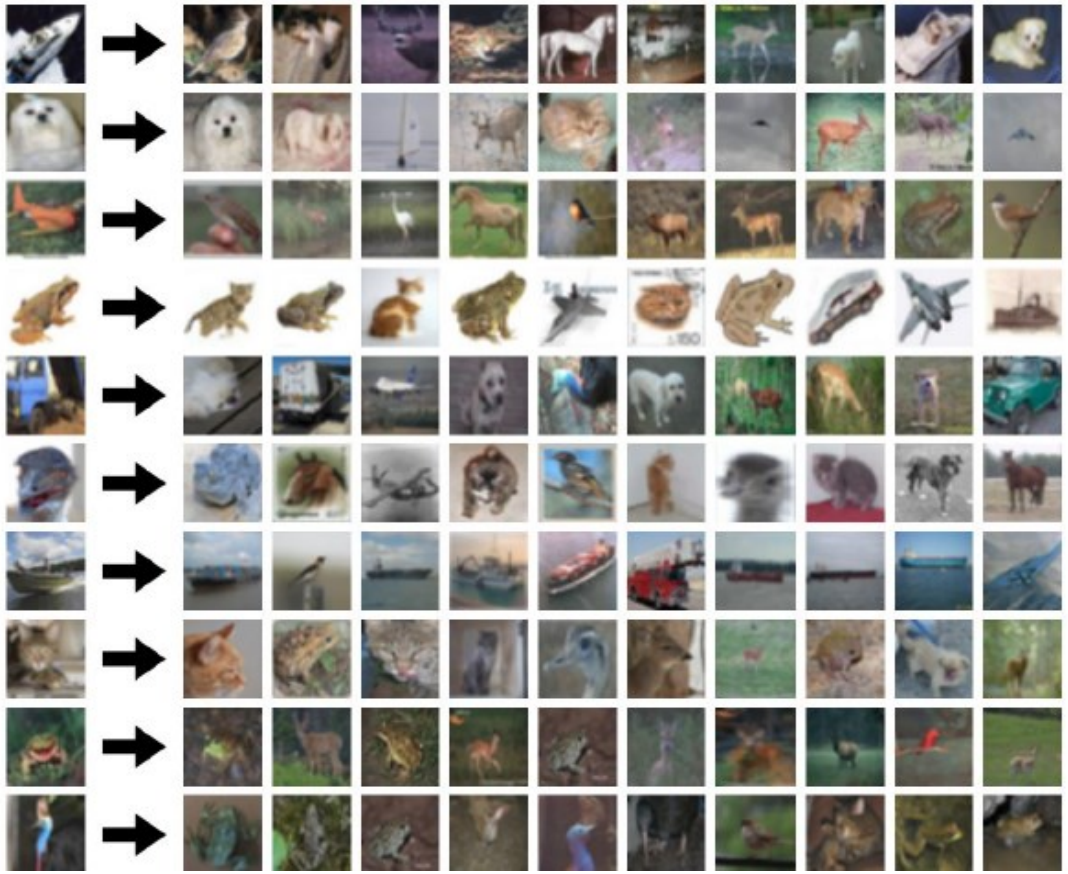
Predict the label of the most similar training image

Example Dataset: CIFAR10

10 classes
50,000 training images
10,000 testing images

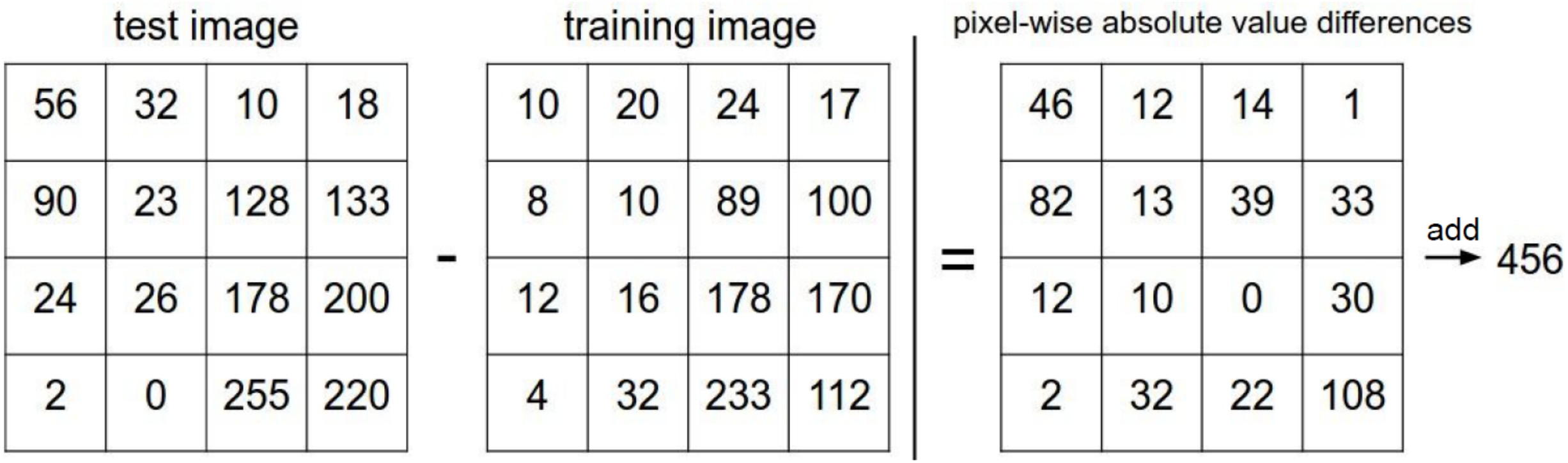


Test images and nearest neighbors



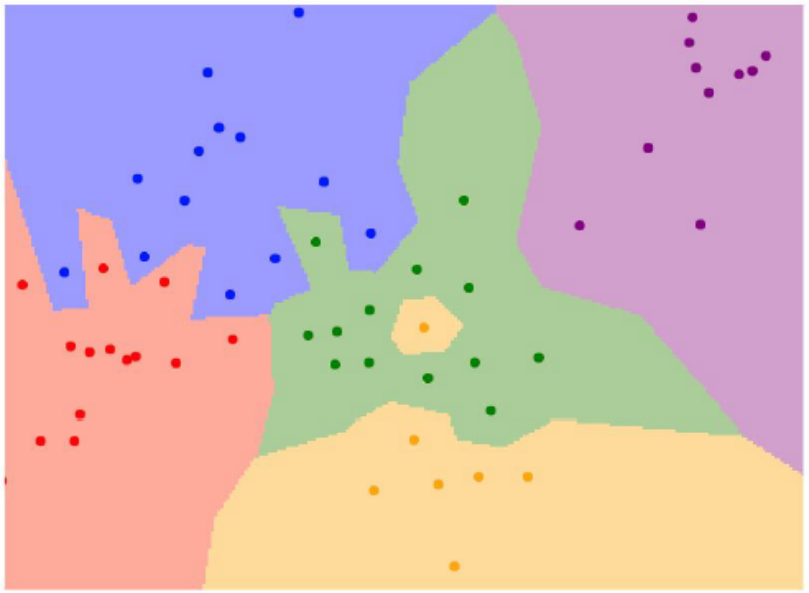
Distance Metric

L1 distance: $$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

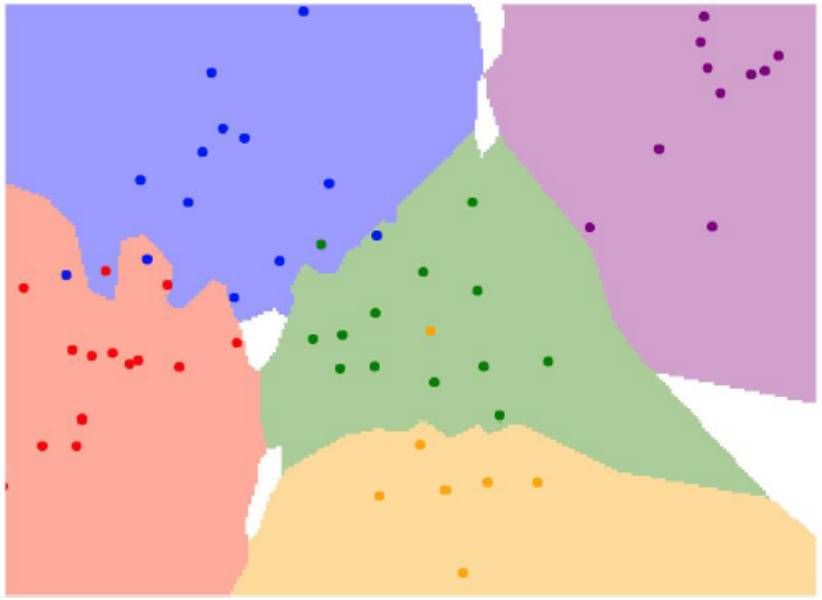


K-Nearest Neighbors

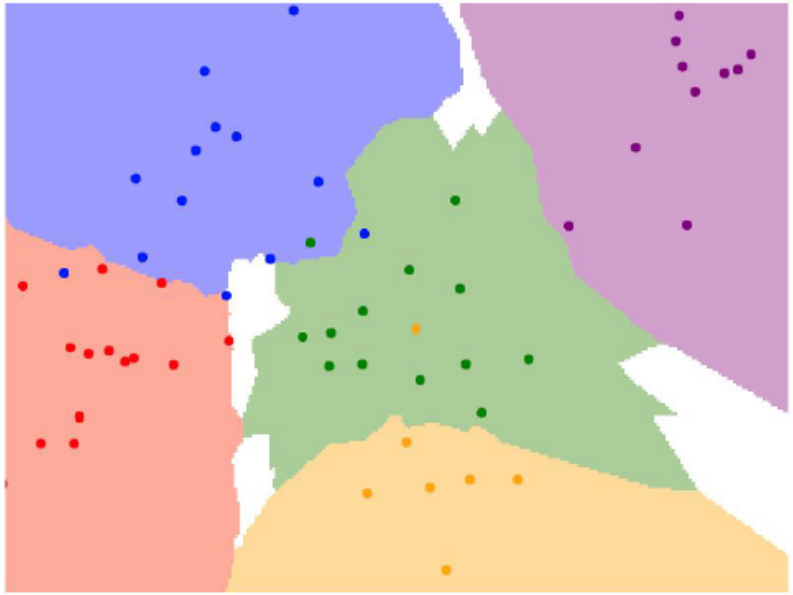
Instead of copying label from nearest neighbor,
take **majority vote** from K closest points



K = 1



K = 3

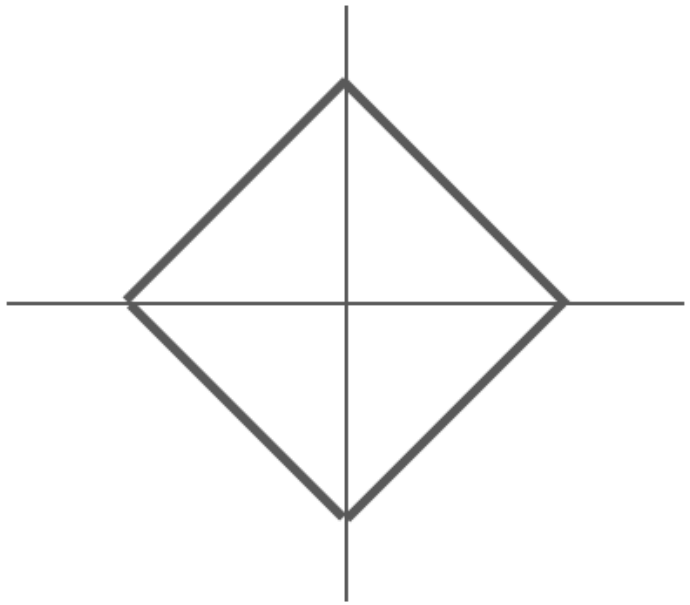


K = 5

K-Nearest Neighbors: Distance Metric

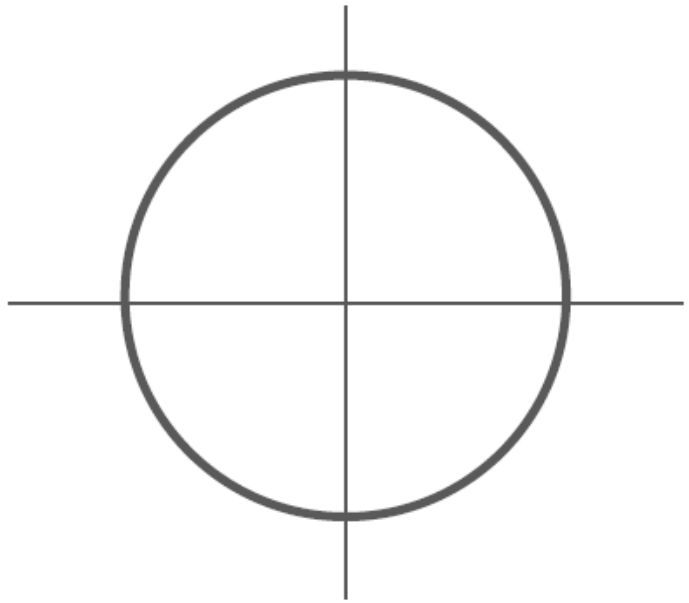
L1 (Manhattan) distance

$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$



L2 (Euclidean) distance

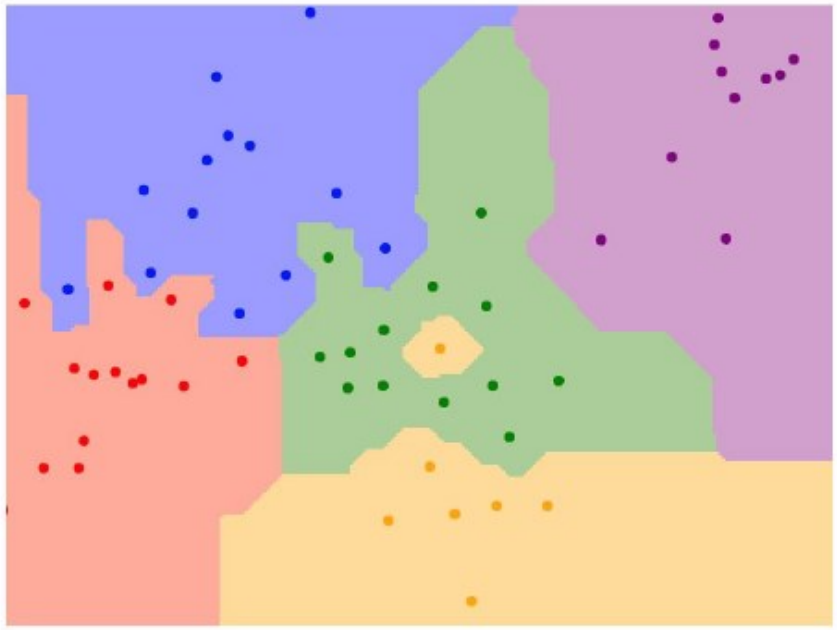
$$d_2(I_1, I_2) = \sqrt{\sum_p (I_1^p - I_2^p)^2}$$



K-Nearest Neighbors: Distance Metric

L1 (Manhattan) distance

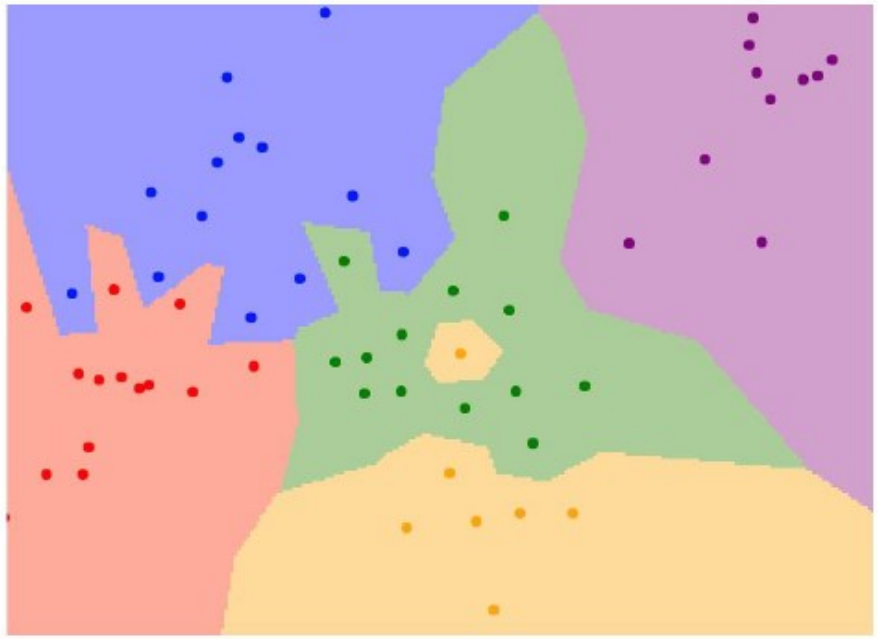
$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$



K = 1

L2 (Euclidean) distance

$$d_2(I_1, I_2) = \sqrt{\sum_p (I_1^p - I_2^p)^2}$$



K = 1

http://vision.stanford.edu/teaching/cs231n-demos/knn/

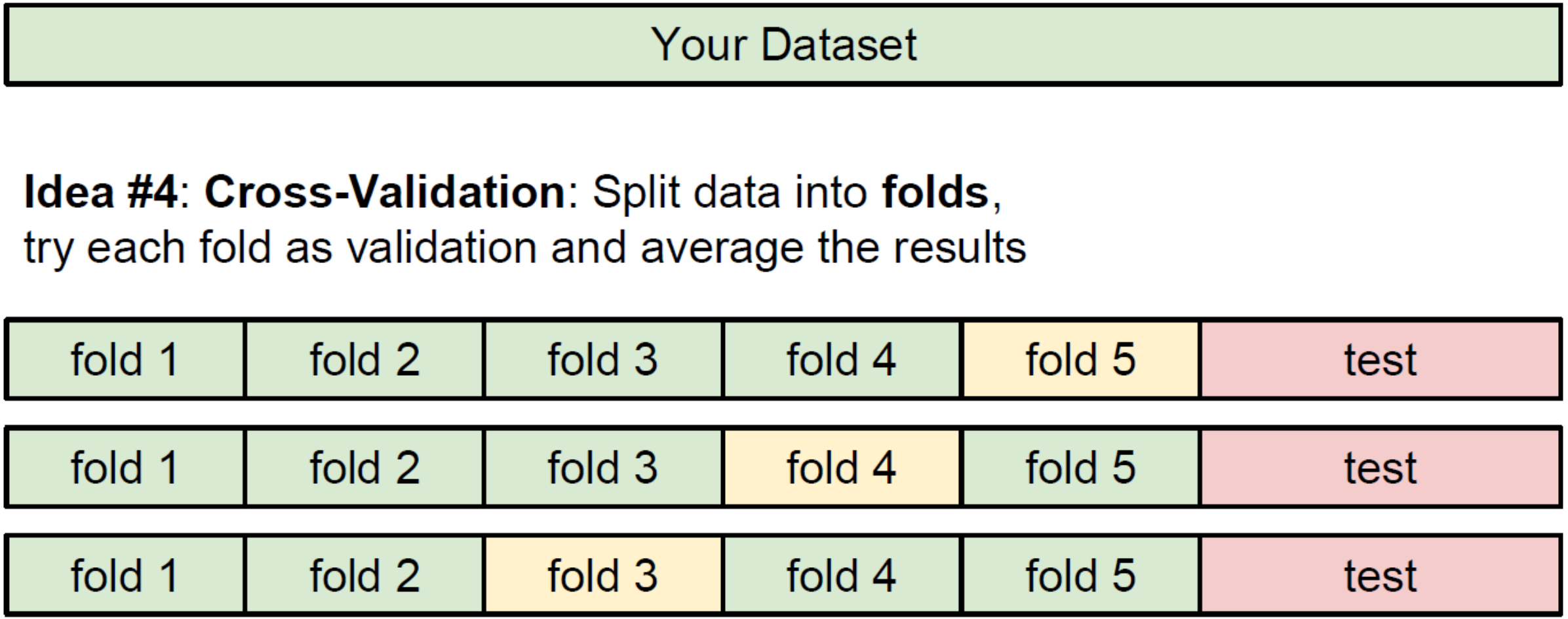
Hyperparameters

What is the best value of **k** to use?
What is the best **distance** to use?

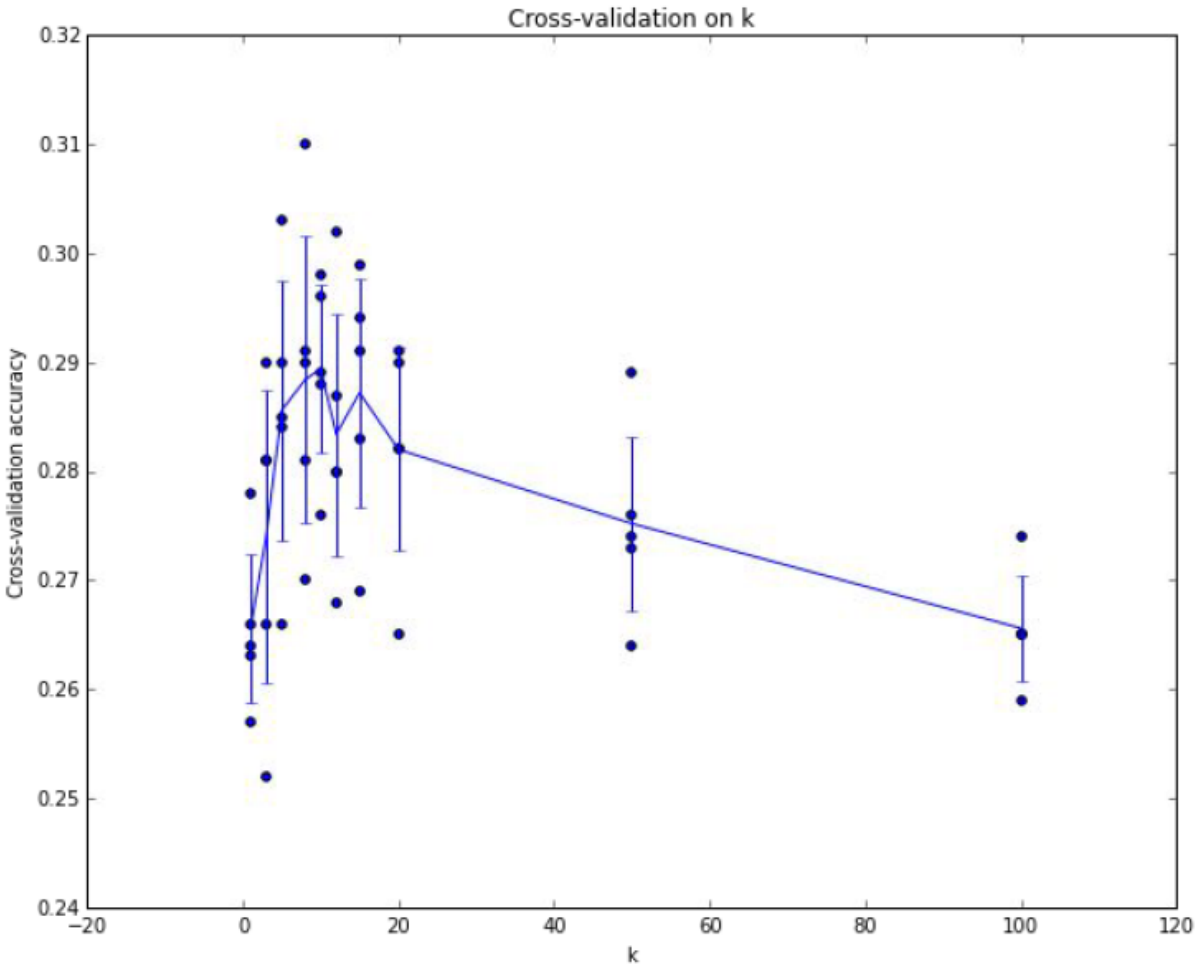
These are **hyperparameters**: choices about the algorithm that we set rather than learn

Very problem-dependent.
Must try them all out and see what works best.

K-fold Cross-Validation



Setting Hyperparameters



Example of
5-fold cross-validation
for the value of **k.**

Each point: single
outcome.

The line goes
through the mean, bars
indicated standard
deviation

(Seems that k ~= 7 works best
for this data)

K-Nearest Neighbor on Images NEVER Used

- Very slow at test time
- Distance metrics on pixels are not informative

Original

Boxed

Shifted

Tinted

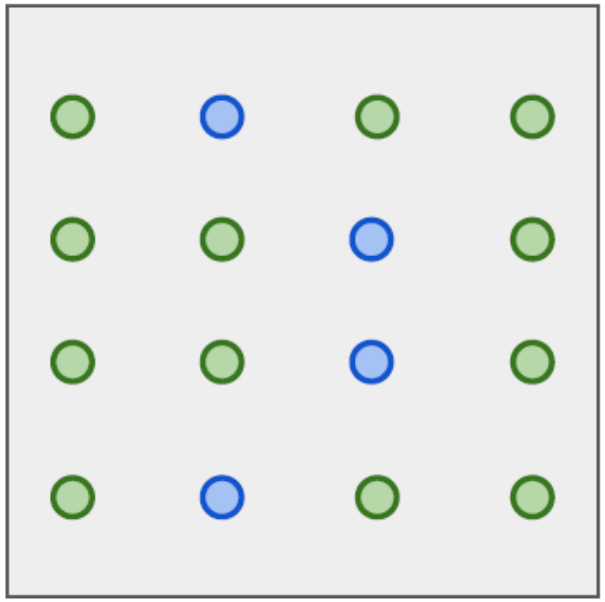
(all 3 images have same L2 distance to the one on the left)

Curse of Dimensionality

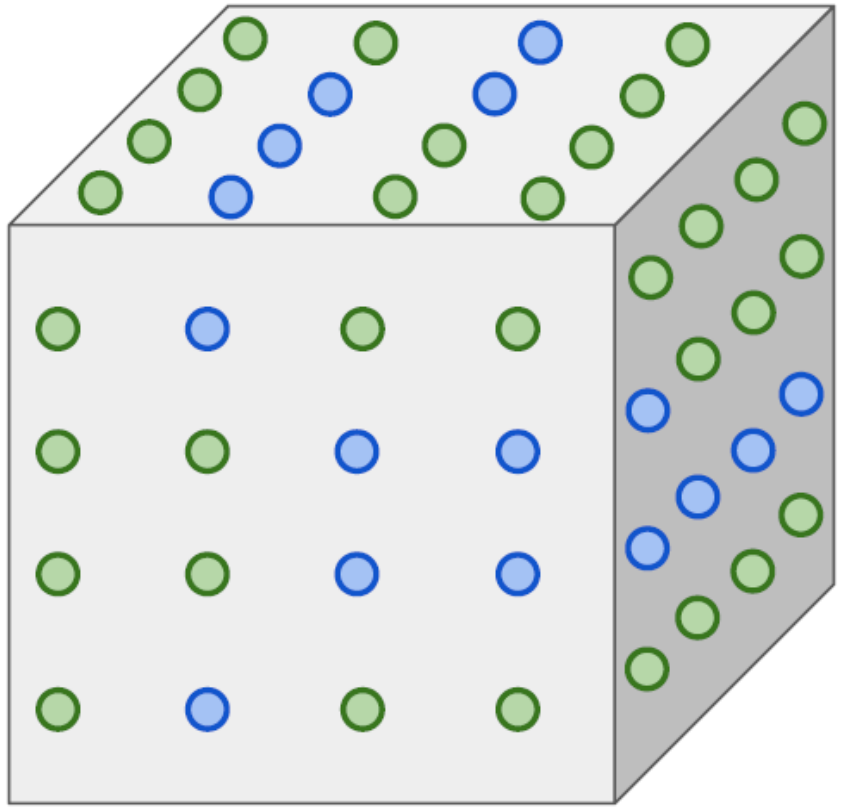
- Curse of dimensionality

Dimensions = 1
Points = 4

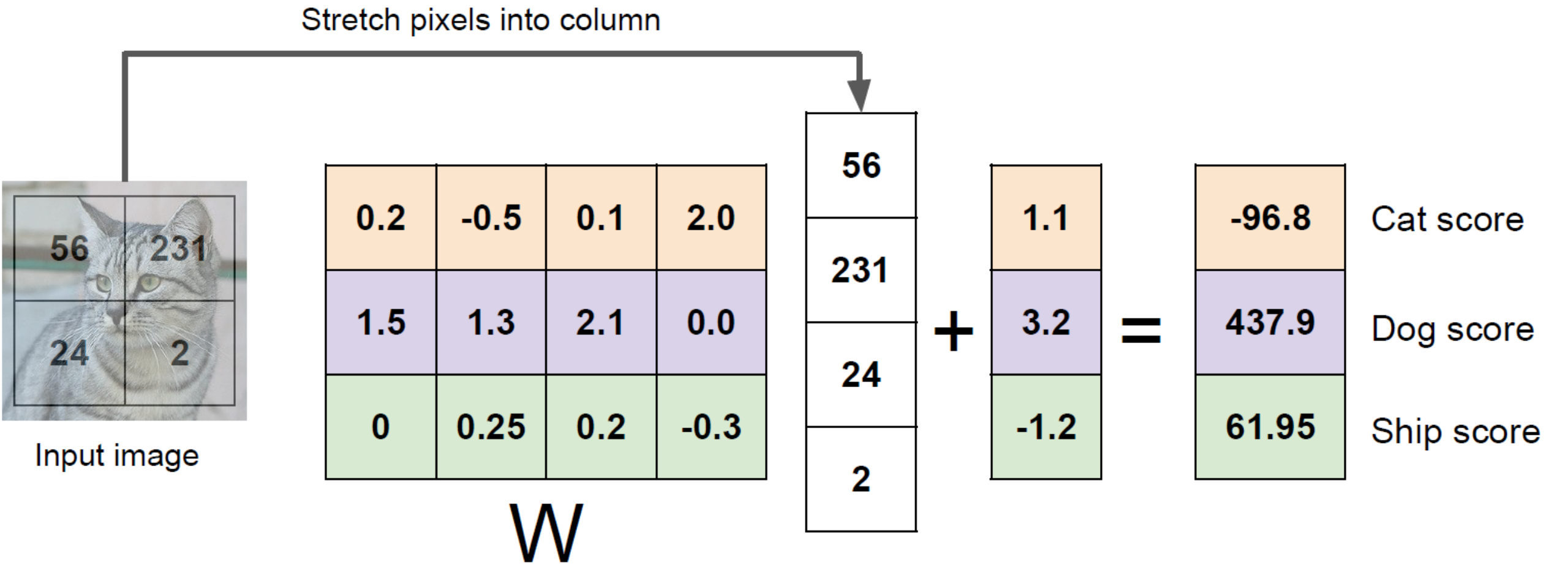
Dimensions = 2
Points = 4^2



Dimensions = 3
Points = 4^3



Linear Classifier

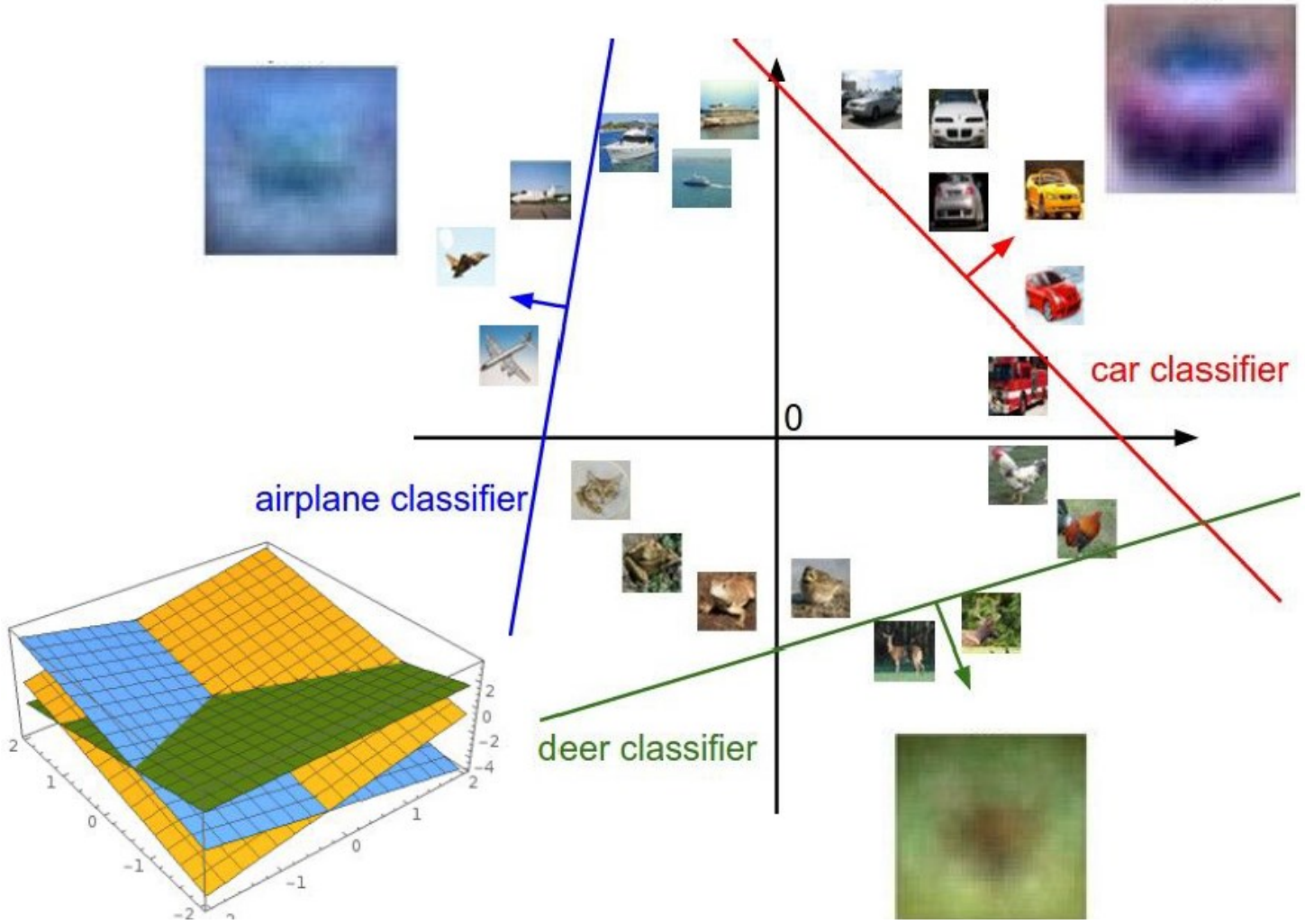


Interpreting a Linear Classifier

$$f(x,W) = Wx + b$$

Example trained weights of a linear classifier trained on CIFAR-10:

Interpreting a Linear Classifier



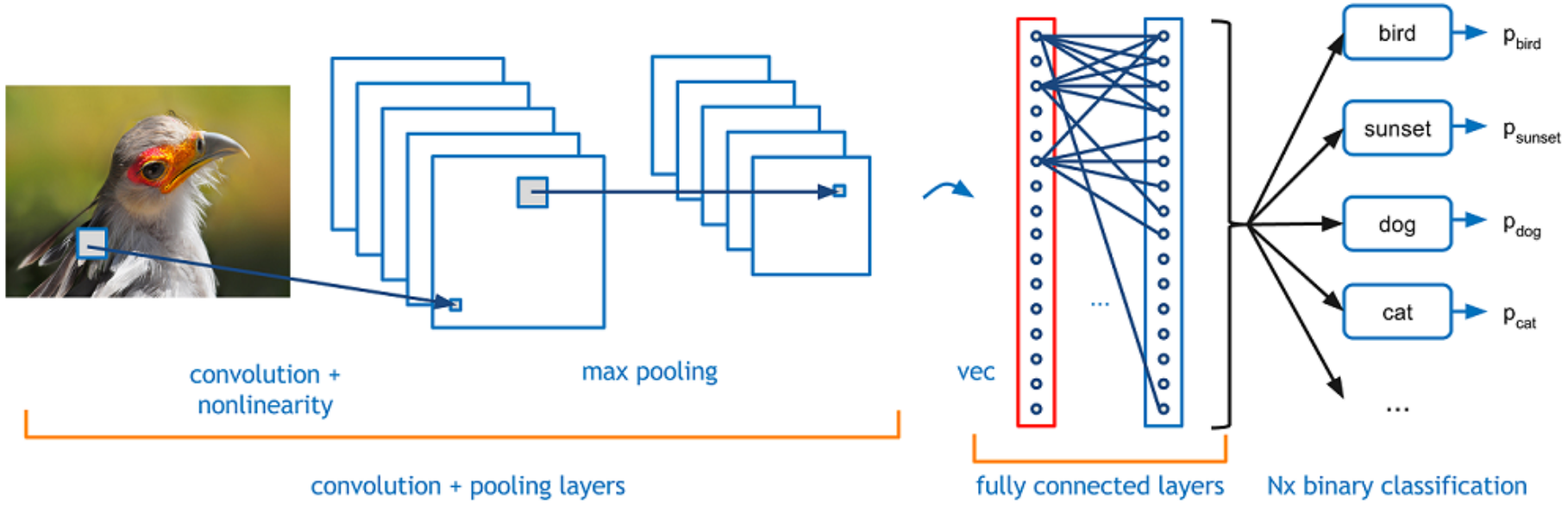
$$f(x,W) = Wx + b$$

Array of **32x32x3** numbers
(3072 numbers total)

Convolutional Neural Network

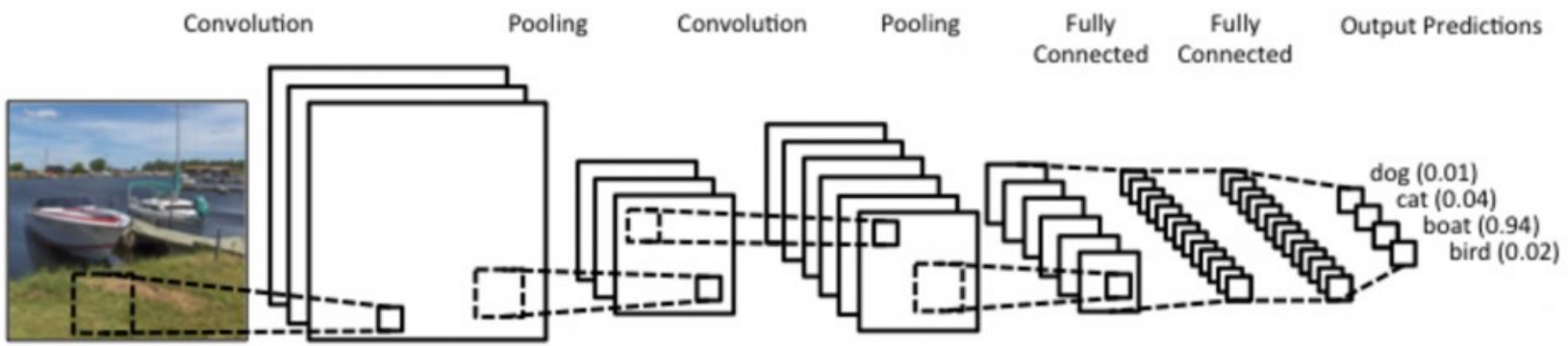
What We See

What Computers See



Convolutional Neural Network

- 이미지 인식에 가장 널리 사용됨
- 일반적으로 convolution layer, pooling layer, fully-connected layer로 구성
- Parameter(weight) sharing
- Convolution과 pooling layer는 feature를 추출하고 fully-connected layer는 어떤 class에 속하는지 판단하는 역할을 수행



Convolution Filters(Hand Crafted)

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

	0	1	0	
	1	-4	1	
	0	1	0	

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

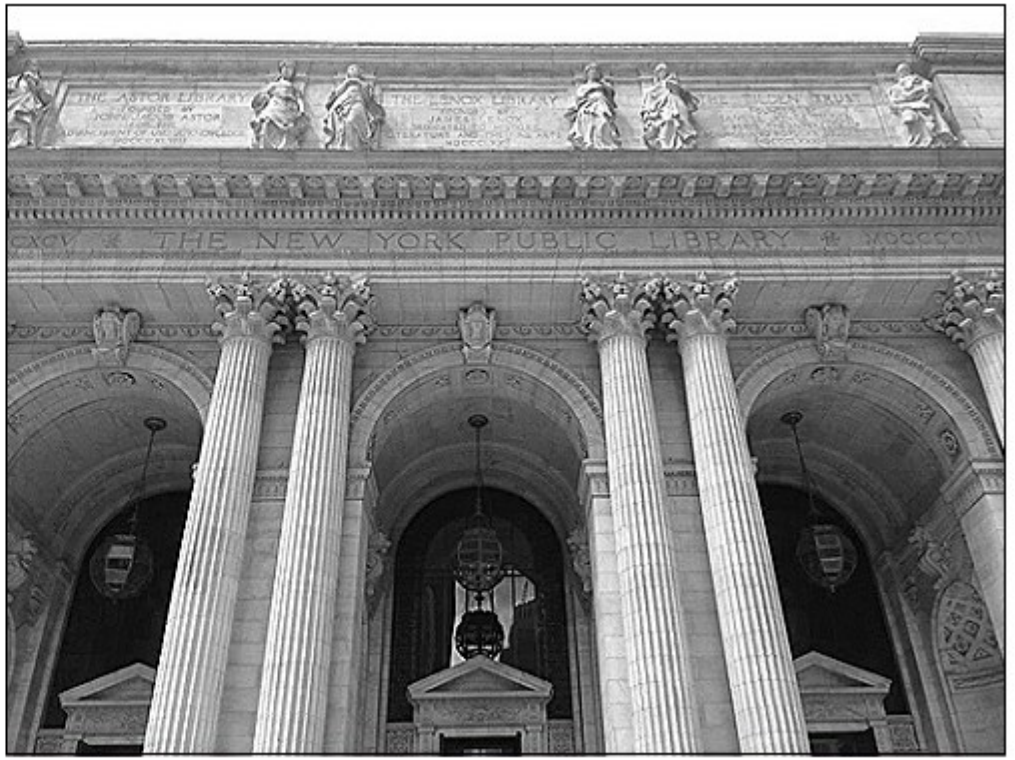
	-2	-1	0	
	-1	1	1	
	0	1	2	

Let's Try!

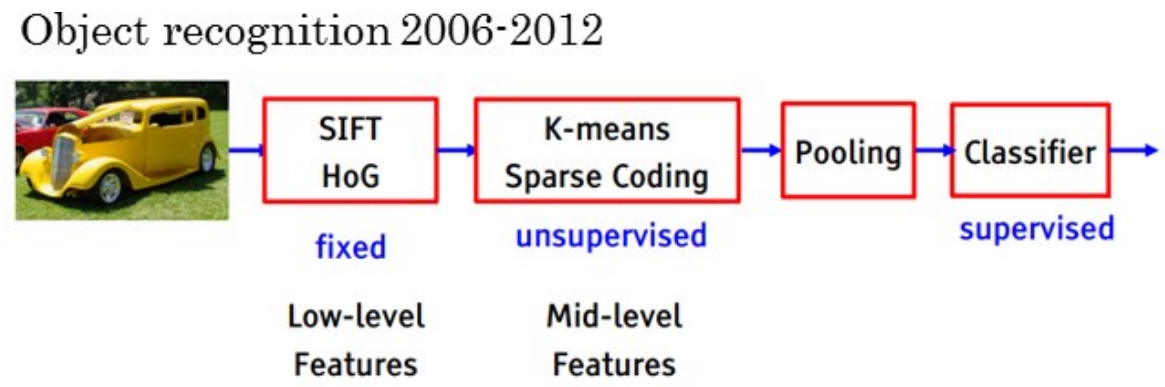
- http://setosa.io/ev/image-kernels/

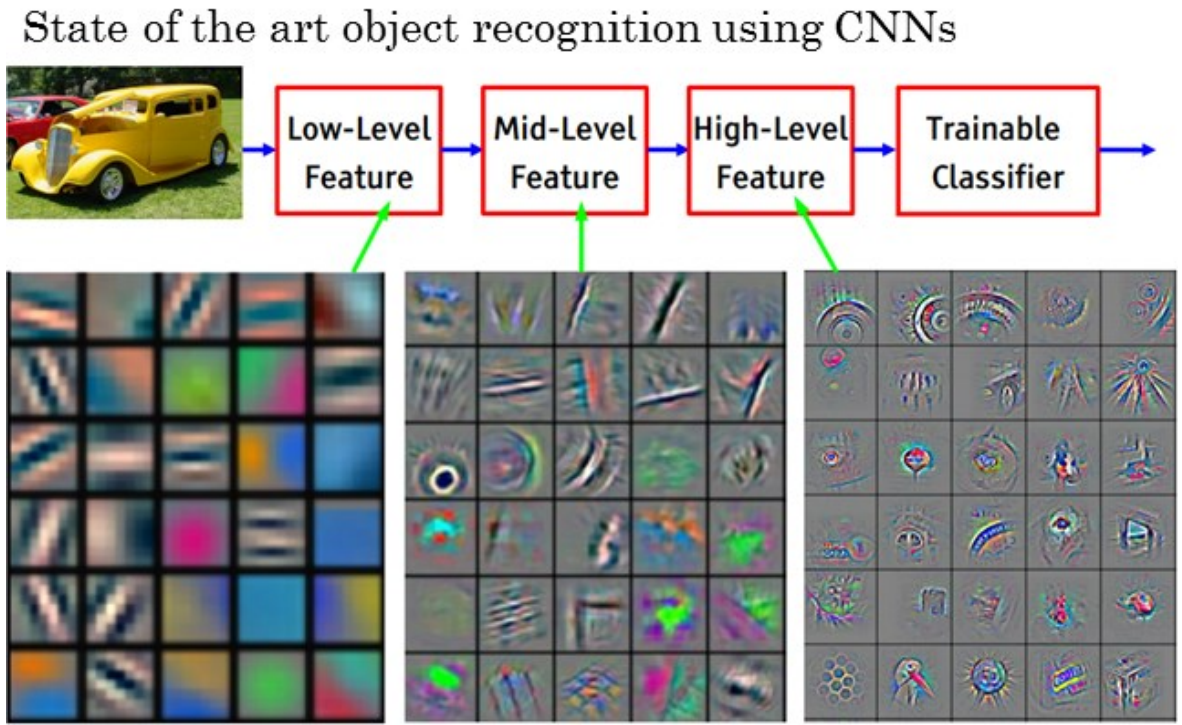
0	-1	0
-1	5	-1
0	-1	0

sharpen



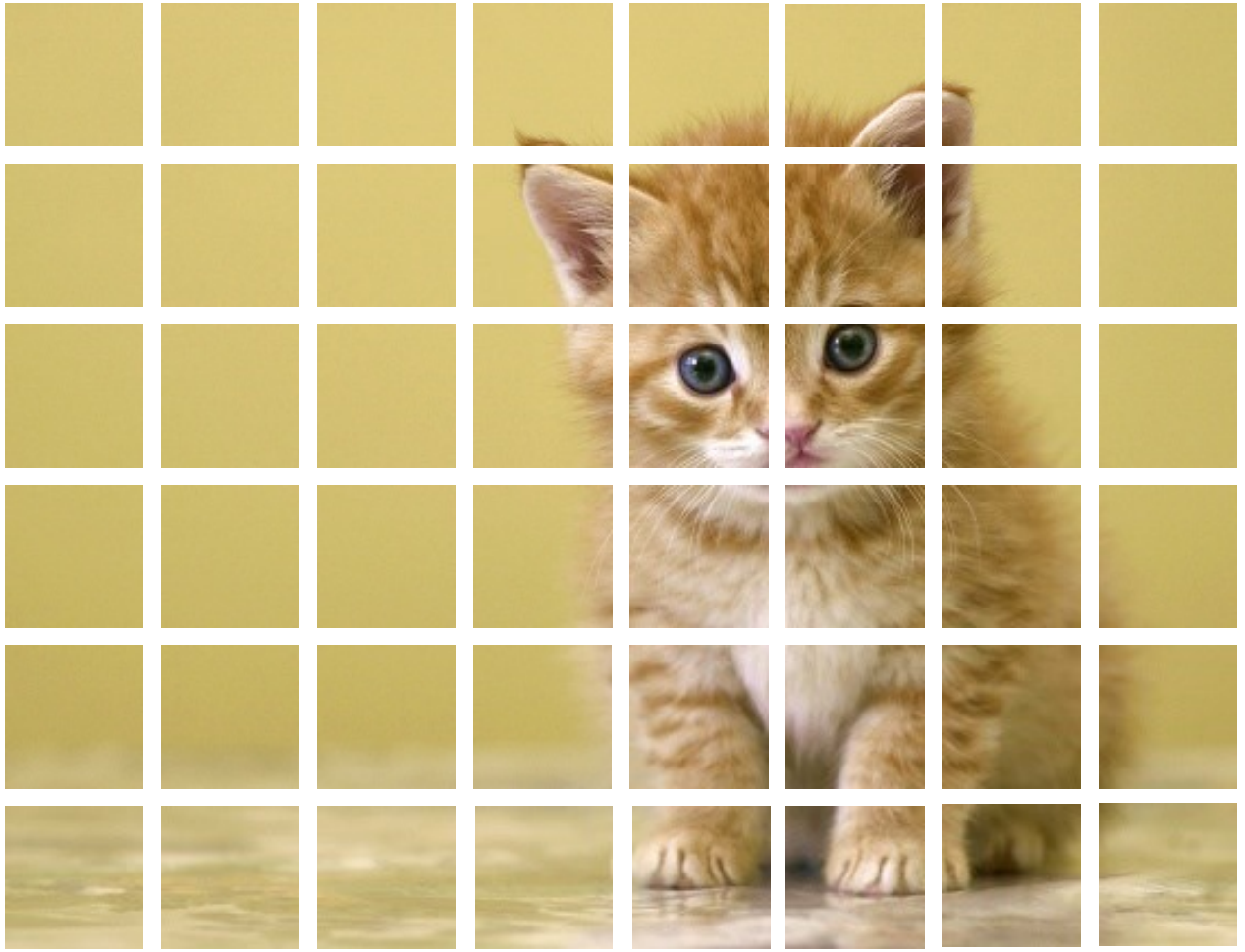
Before and After



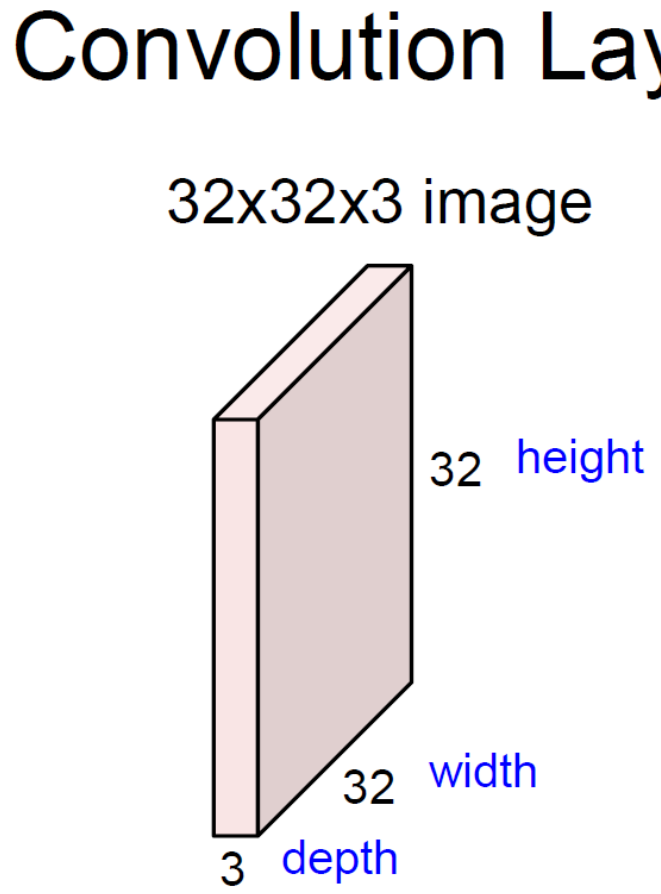


CNN 동작원리

- 이미지를 작은 tile로 나누고, 작은 network를 통해 tile에서 특정 feature를 추출(예: 귀)
- Newtork가 다음 tile로 이동하면서 같은 방법으로feature를 추출(동일한 weight 사용)
- 다른 feature(예: 눈)를 추출하는 network를 추가로 만들고 위와 같은 방법으로 tile을 하나씩 network에 적용
- 추출된 모든 feature들을 잘 조합하여 최종적으로 이미지를 판단



Convolution Layer
- From Stanford CS231n

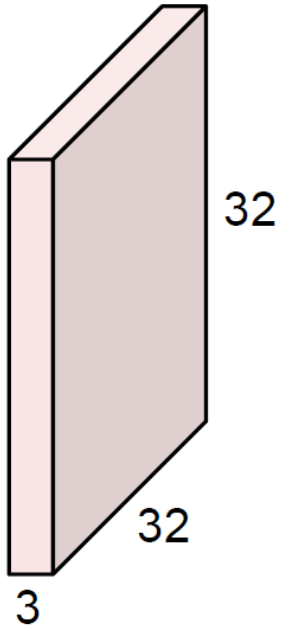


Slide Credit : Stanford CS231n

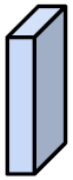
Convolution Layer
- From Stanford CS231n

Convolution Layer

32x32x3 image



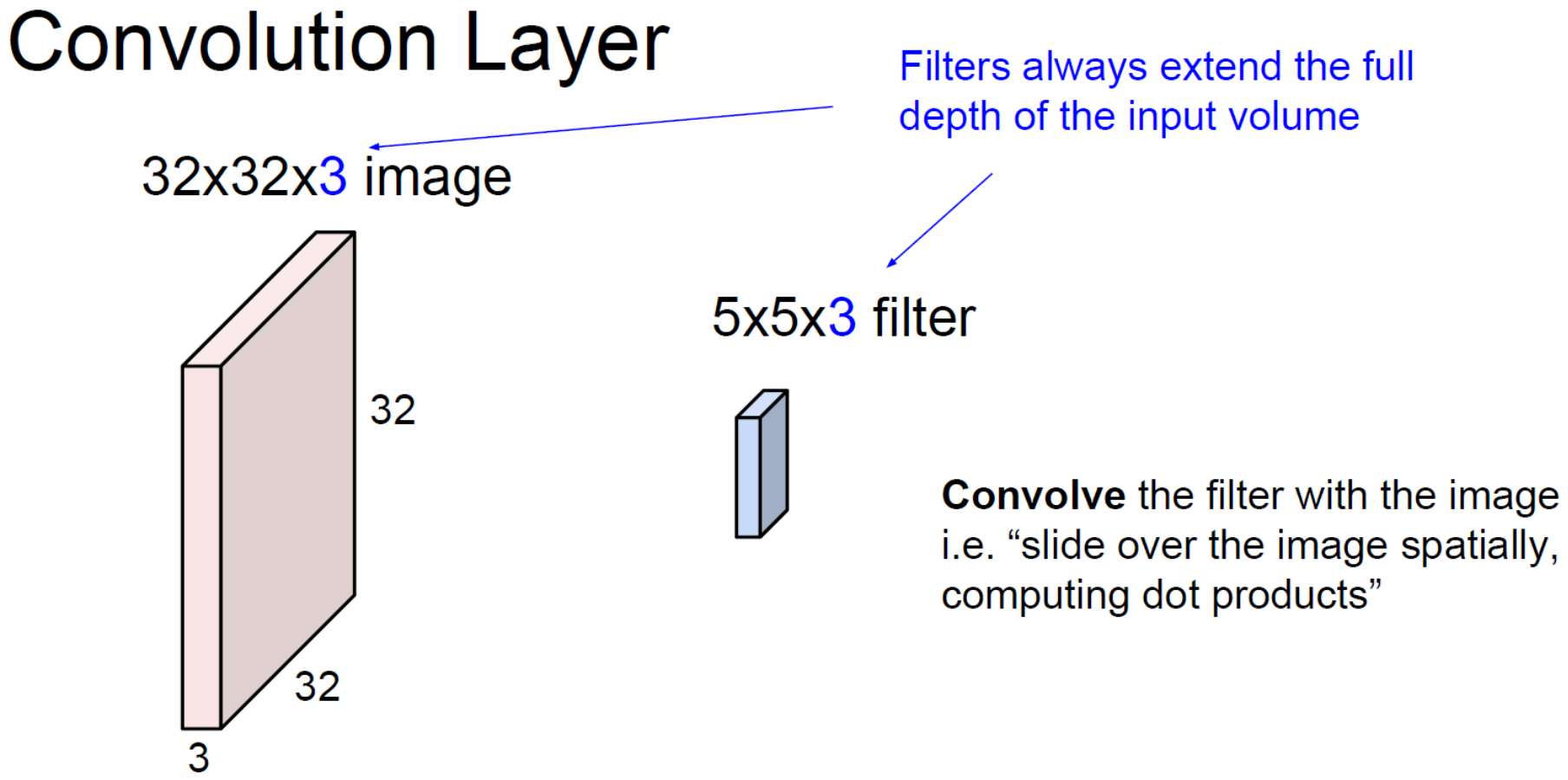
5x5x3 filter



Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Slide Credit : Stanford CS231n

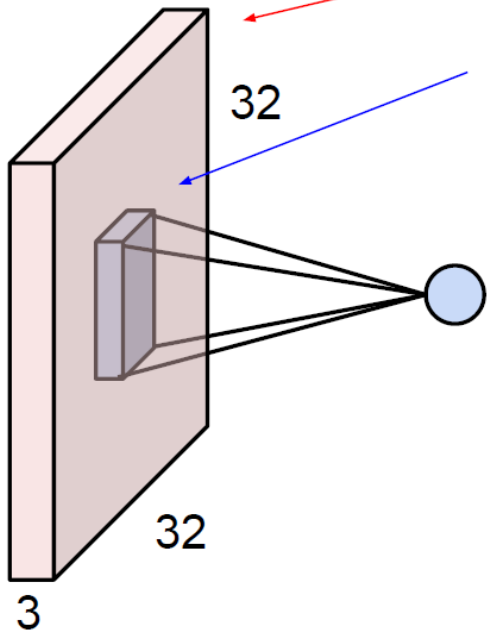
Convolution Layer
- From Stanford CS231n



Slide Credit : Stanford CS231n

Convolution Layer
- From Stanford CS231n

Convolution Layer



32x32x3 image

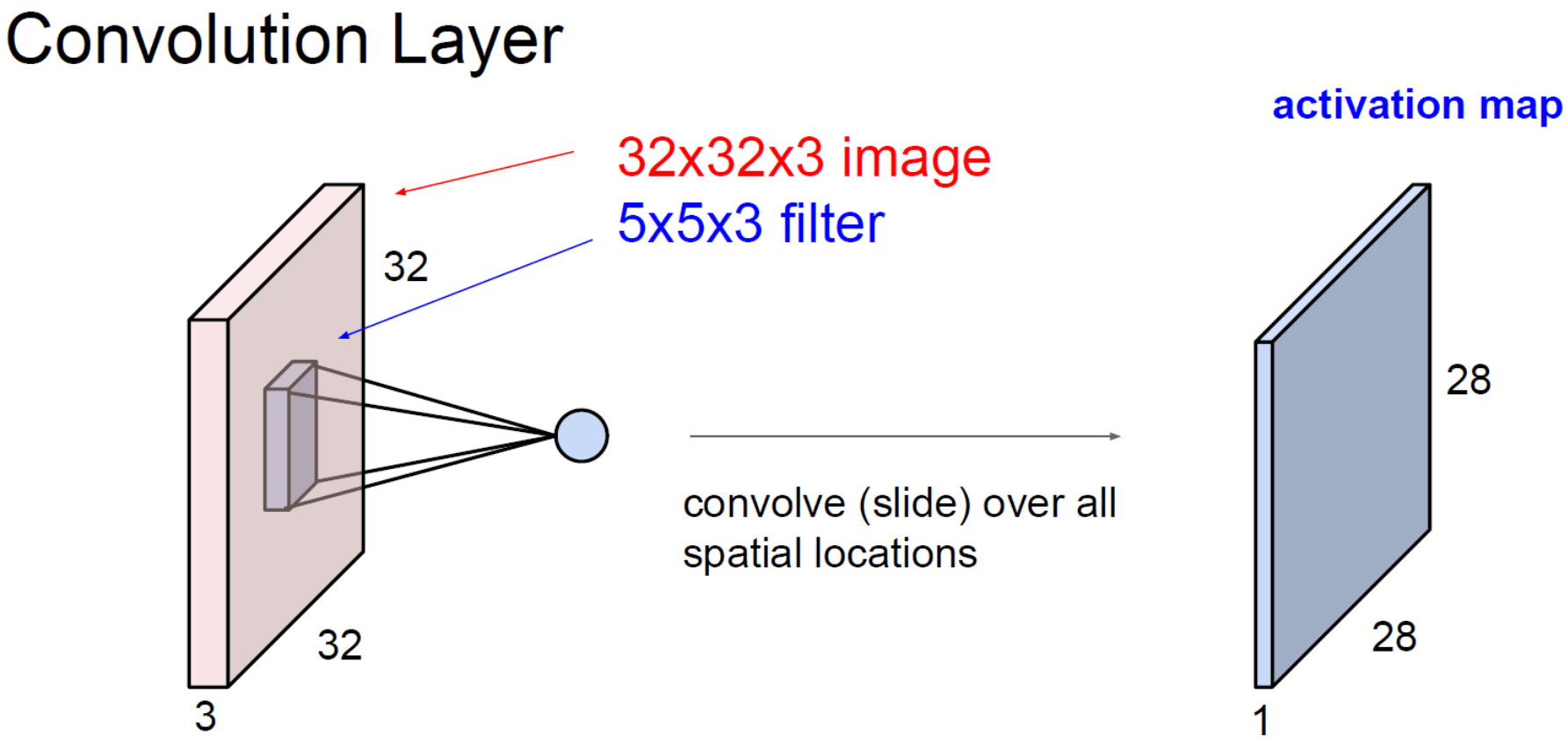
5x5x3 filter w

1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

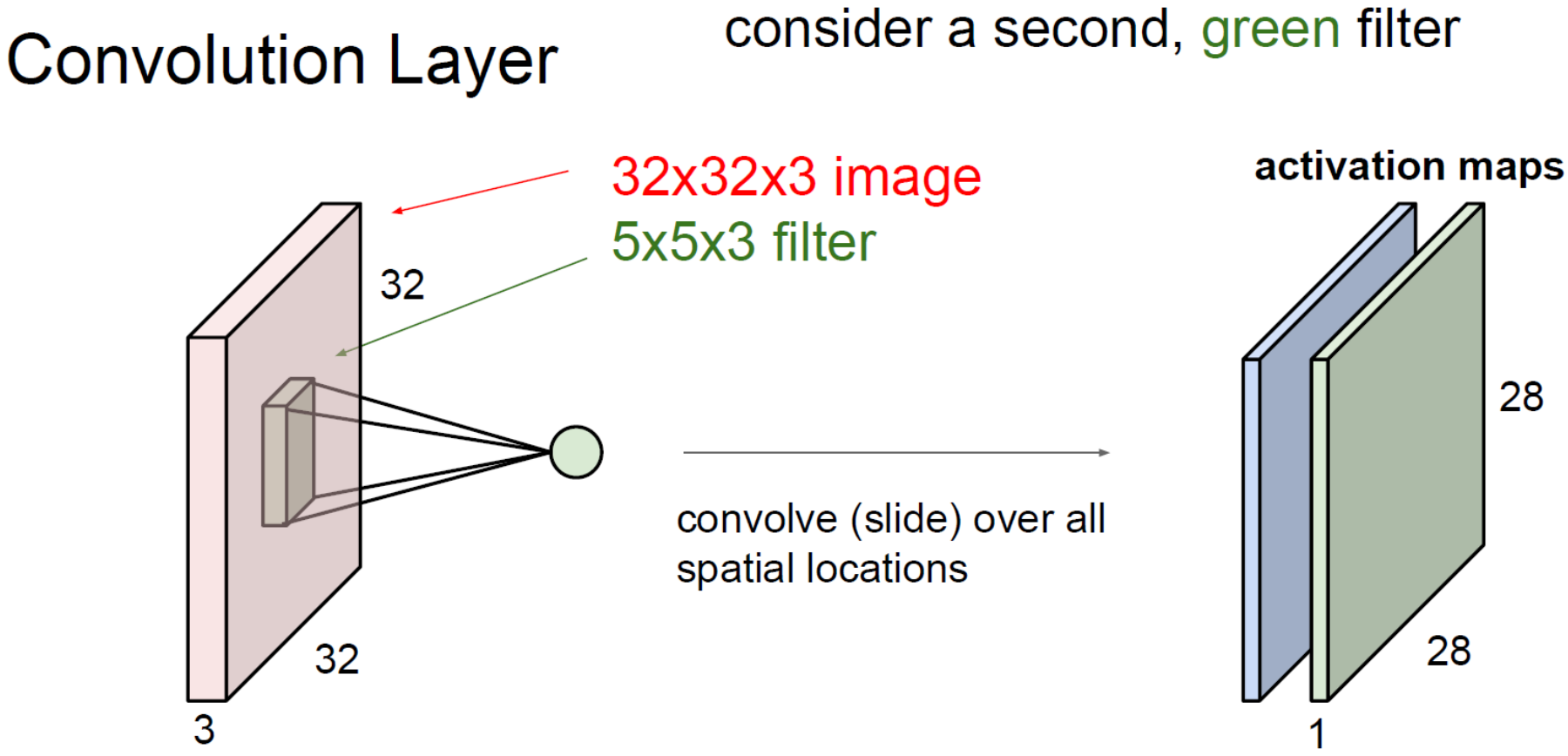
Slide Credit : Stanford CS231n

Convolution Layer
- From Stanford CS231n



Slide Credit : Stanford CS231n

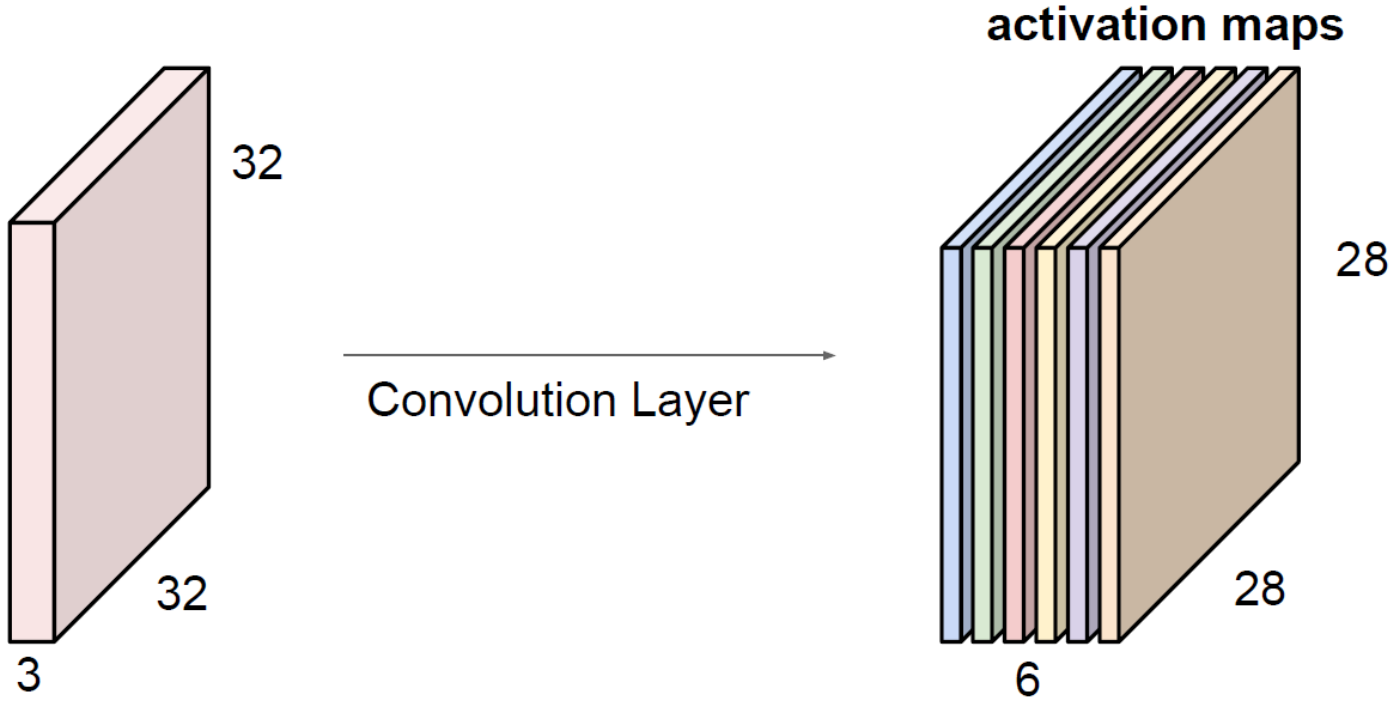
Convolution Layer
- From Stanford CS231n



Slide Credit : Stanford CS231n

Convolution Layer
- From Stanford CS231n

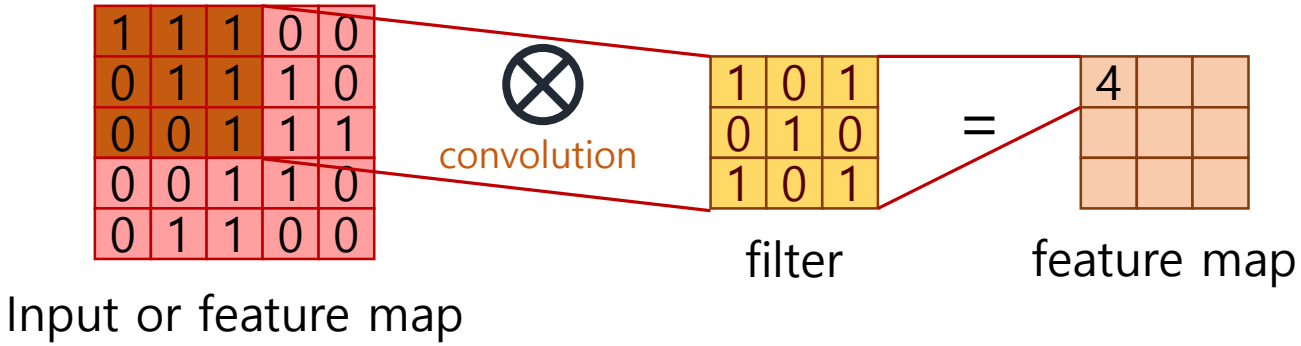
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



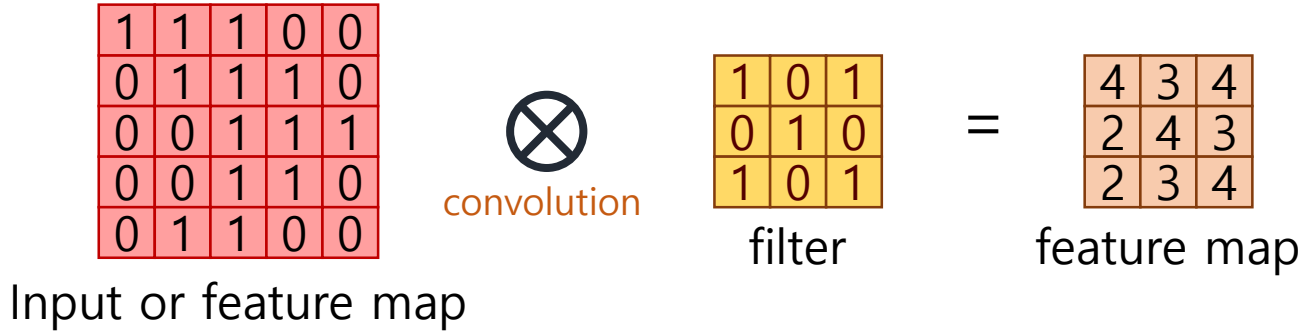
We stack these up to get a "new image" of size 28x28x6!

Slide Credit : Stanford CS231n

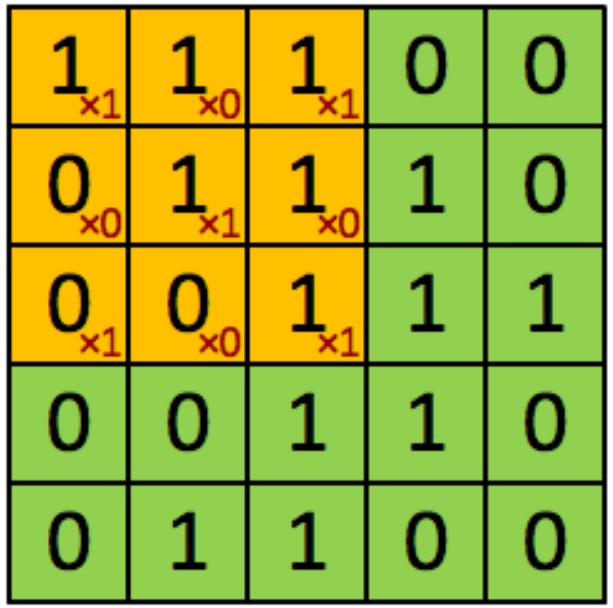
Convolution

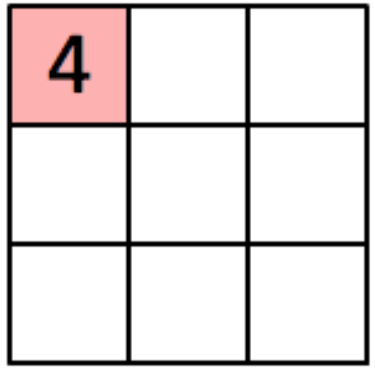


- Convolution 연산 : 같은 위치에 있는 숫자끼리 곱한 후 모두 더함
  - 1X1 + 1X0 + 1X1 + 0X0 + 1X1 + 1X0 + 0X1 + 0X0 + 1X1 = 4
- Filter가 옆으로 이동 후 같은 연산 수행
- 옆으로 모두 이동한 이후에는 아래로 이동 후 같은 연산 수행



Convolution



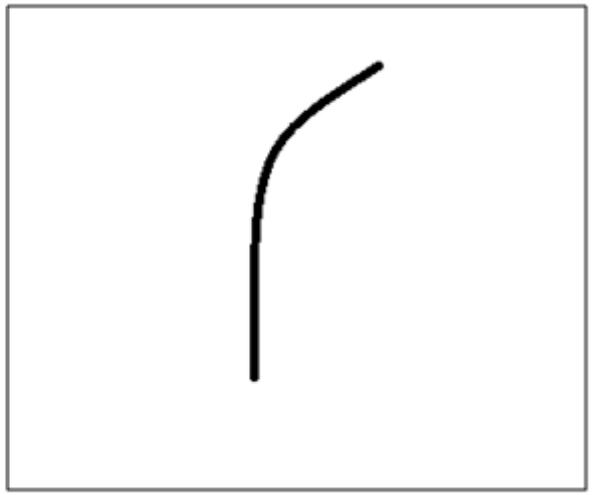


Credit : Leonardo's gitbook

Feature Extractor

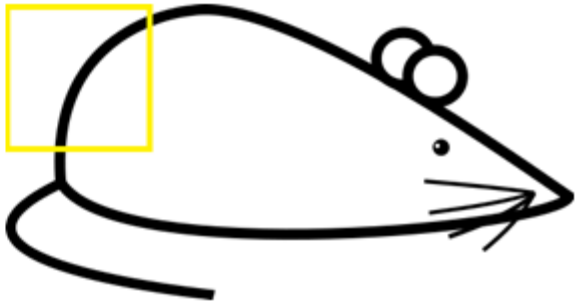
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter



Visualization of a curve detector filter

Original image



Visualization of the filter on the image

Credit : Adit Deshpande's blog

Feature Extractor

Visualization of the receptive field

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

*

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = (50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600 (A large number!)

Visualization of the filter on the image

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

Pixel representation of receptive field

*

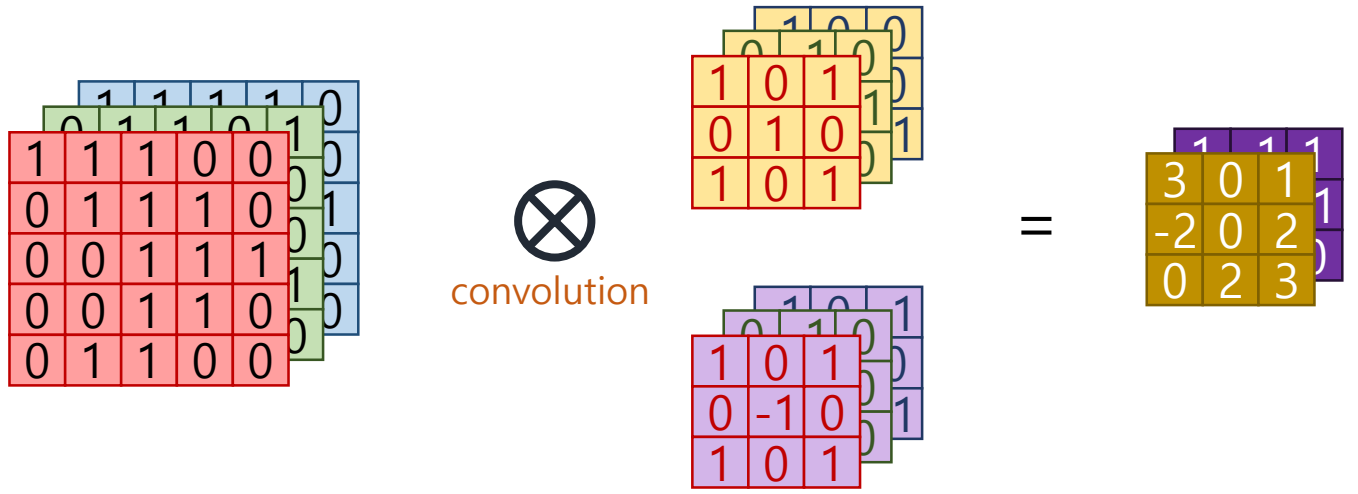
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = 0

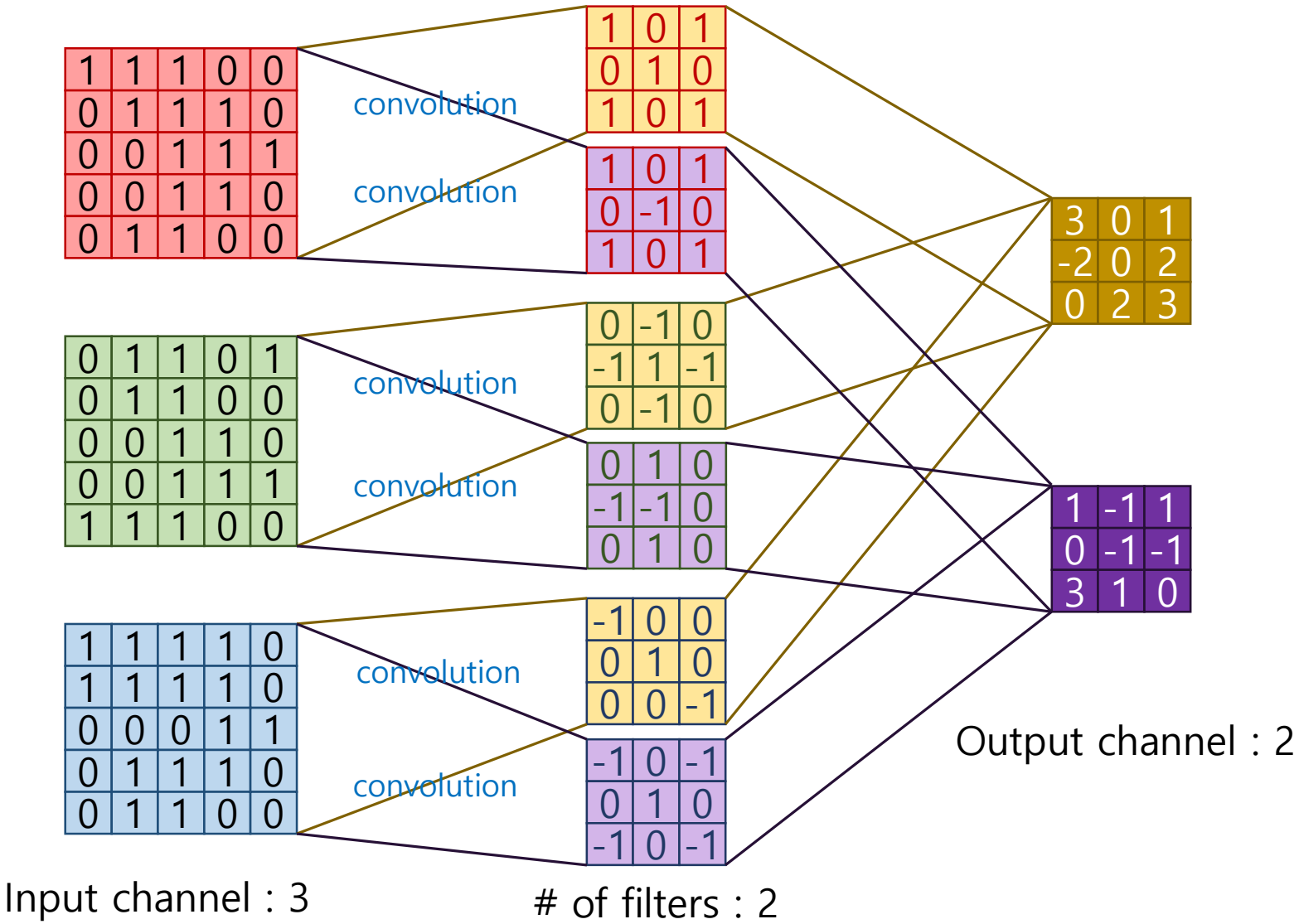
Credit : Adit Deshpande's blog

Convolution
(Multi Channel, Many Filters)

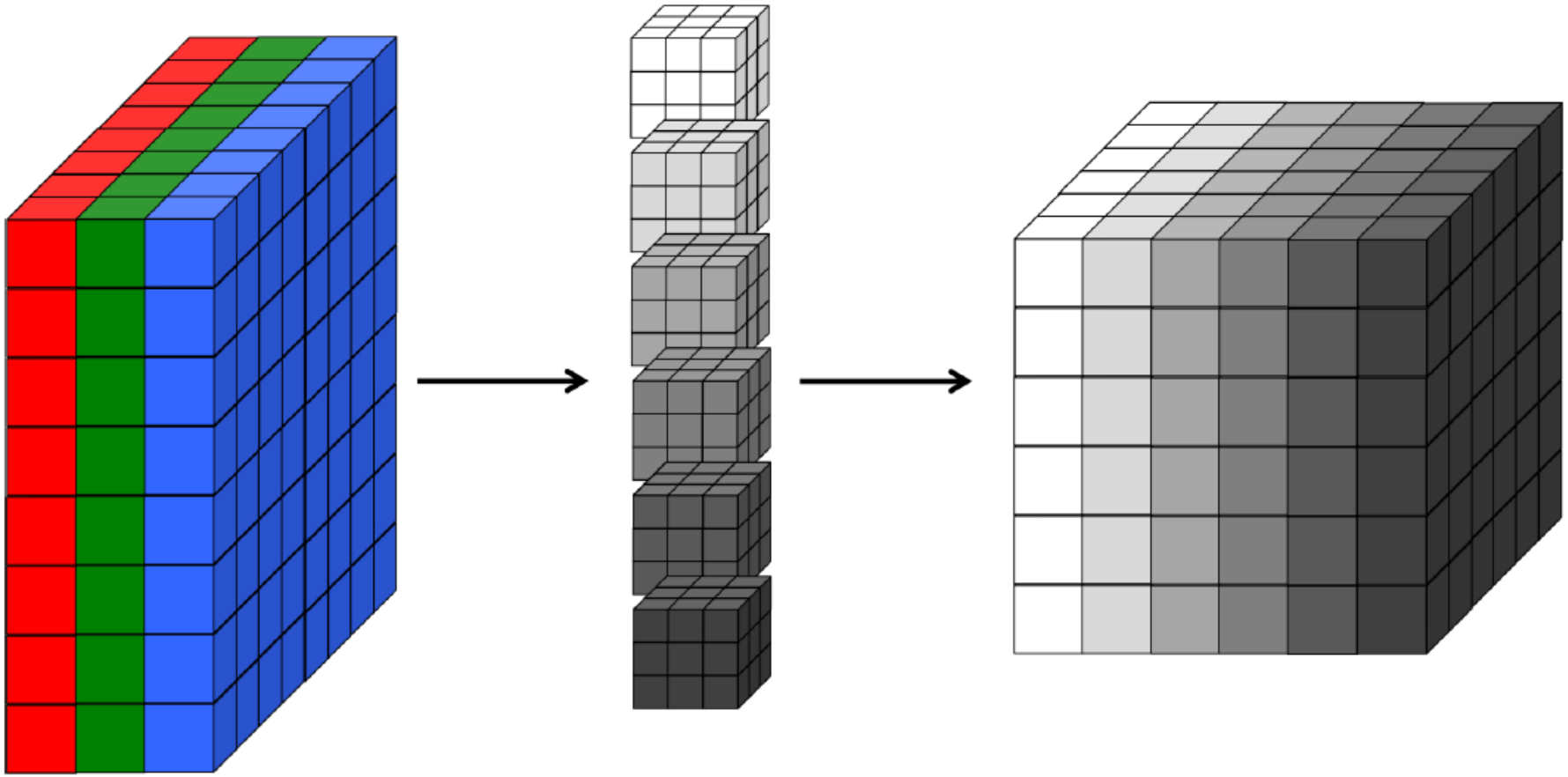


Input channel : 3 # of filters : 2 Output channel : 2

Convolution
(Multi Channel, Many Filters)



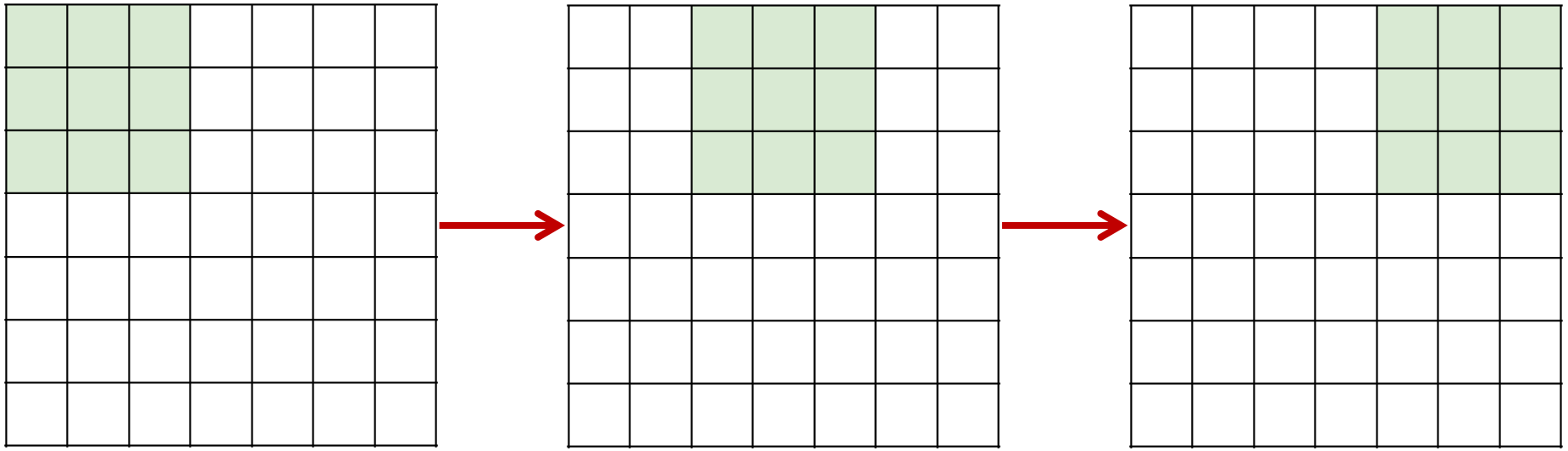
Visualization of a Convolution Layer



Picture Credit : fundamentals of deep learning by Nikhil

Options of Convolution

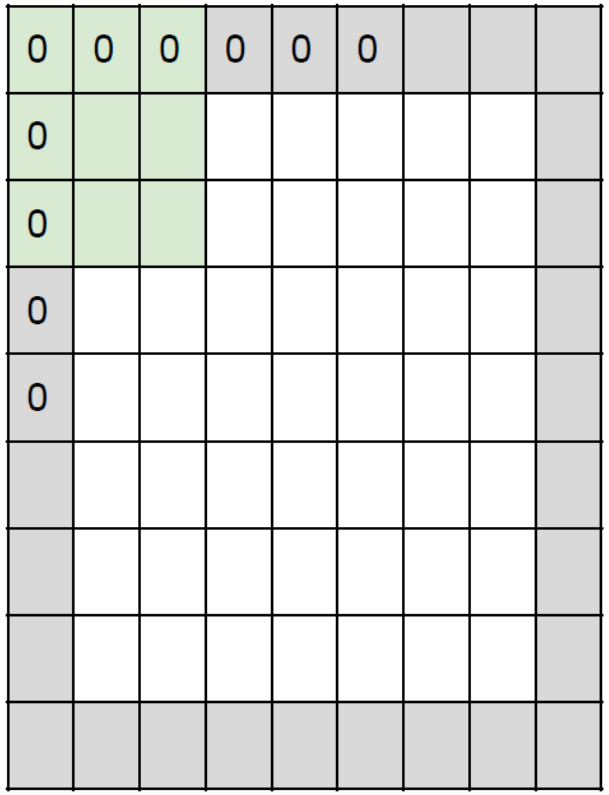
- Stride : filter가 한 번 convolution을 수행 한 후 옆으로(혹은 아래로) 얼마나 이동할 것인가
  - 예) 7x7 input, 3x3 convolution filter with stride 2 → 3x3 output!



Slide Credit : Stanford CS231n

Options of Convolution

- Zero Padding



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Slide Credit : Stanford CS231n

Quiz

- 다음의 각 경우에 convolution layer의 output size는?
  1. 32x32x3 input, 10 5x5 filters with stride 1, pad 0
  2. 32x32x3 input, 10 5x5 filters with stride 1, pad 2
  3. 32x32x3 input, 10 3x3 filters with stride 2, pad 1

- Answer
  1. 28x28x10
  2. 32x32x10
  3. 16x16x10

Input이 $W_i \times H_i \times C_i$ 이고,
$F \times F$ filter를 K개 사용하고,
stride는 S,
zero padding은 P 만큼 했을 경우,
output feature map size($W_o \times H_o \times C_o$)는,

$$W_o = \frac{(W_i - F + 2P)}{S} + 1$$

$$H_o = \frac{(H_i - F + 2P)}{S} + 1$$

$$C_o = K$$

tf.nn.conv2d

- Signature:

```
tf.nn.conv2d(input, filter, strides, padding,
use_cudnn_on_gpu=None, data_format=None, name=None)
```

- Docstring:

Computes a 2-D convolution given 4-D `input` and `filter` tensors.

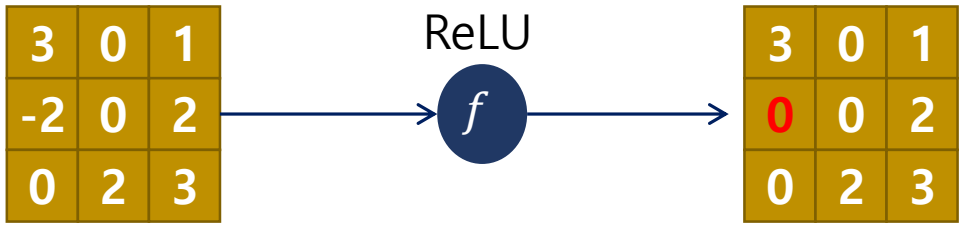
Given an input tensor of shape

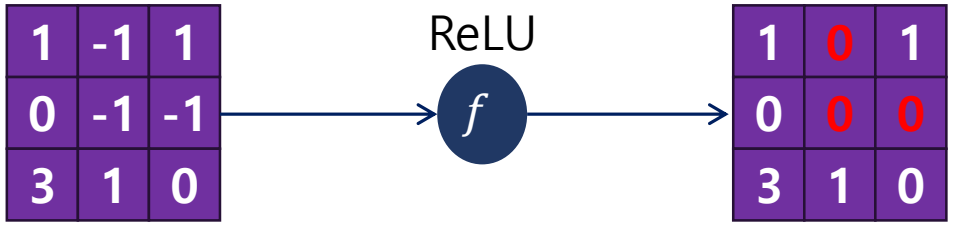
`[batch, in_height, in_width, in_channels]`

and a filter / kernel tensor of shape

`[filter_height, filter_width, in_channels, out_channels]'

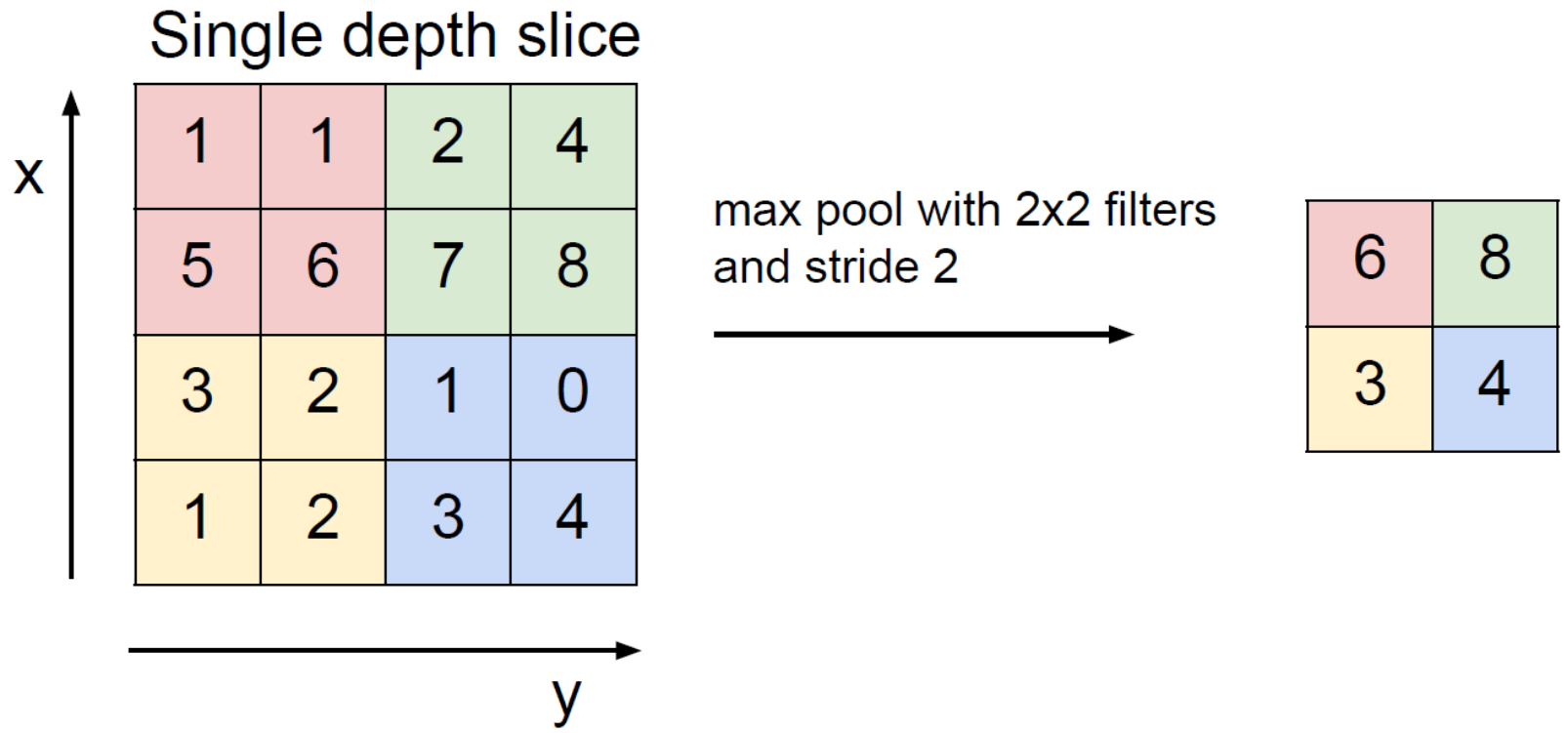
ReLU





Pooling Layer

- Max pooling을 많이 사용함



2x2 Max Pooling with Stride=1

tf.nn.max_pool

- Signature:

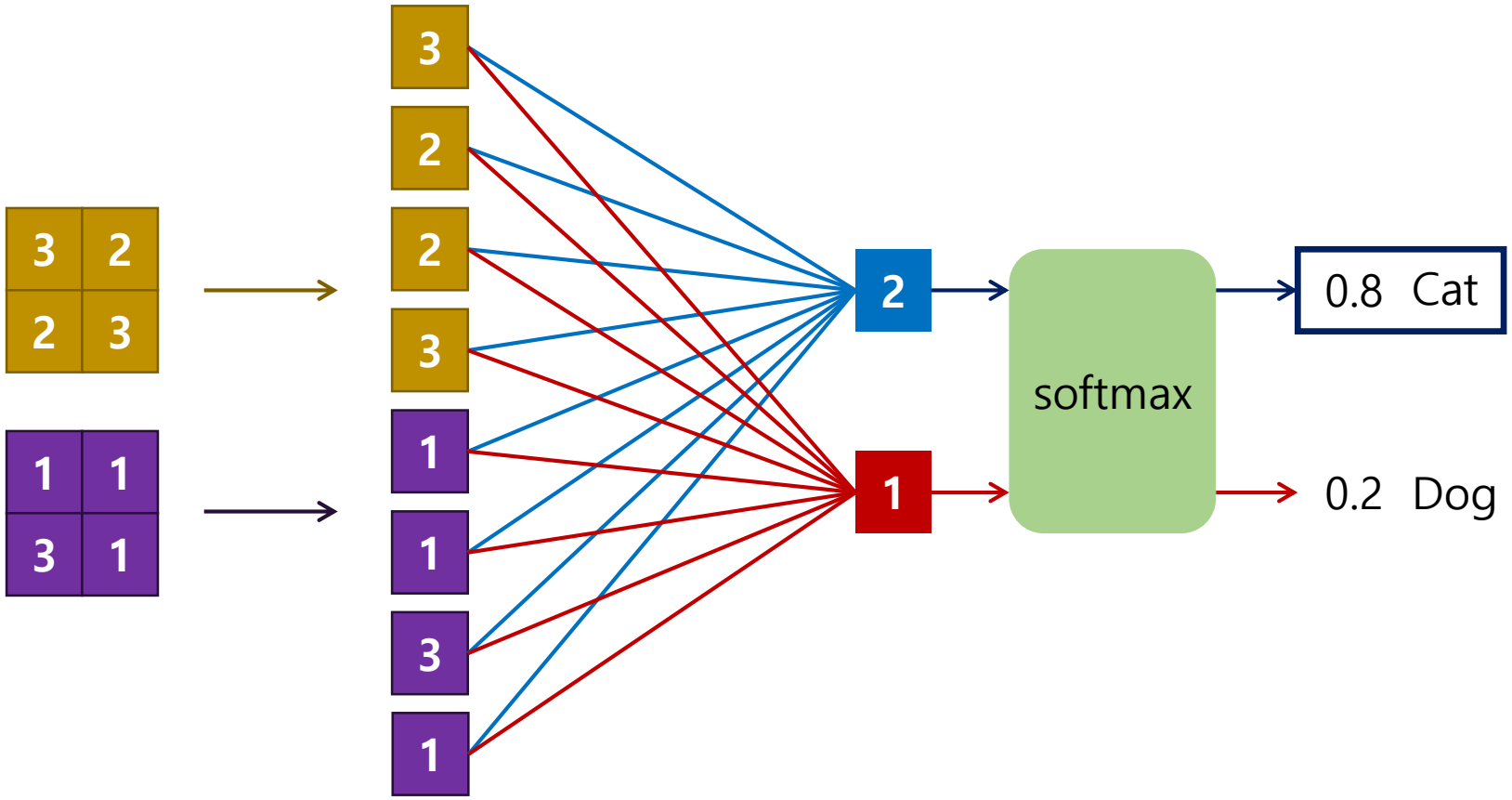
```
tf.nn.max_pool(value, ksize, strides, padding, data_format='NHWC', name=None)
```

- Docstring:

Performs the max pooling on the input.

- Args:
  - value: A 4-D `Tensor` with shape `[batch, height, width, channels]` and type `tf.float32`.
  - ksize: A list of ints that has length >= 4. The size of the window for each dimension of the input tensor.
  - strides: A list of ints that has length >= 4. The stride of the sliding window for each dimension of the input tensor.
  - padding: A string, either `'VALID'` or `'SAME'`. The padding algorithm.
  - data_format: A string. 'NHWC' and 'NCHW' are supported.
  - name: Optional name for the operation.

Fully-Connected Layer



CNN의 특징

- Convolution Layer – parameter(weight) sharing
- Good for local invariance – pooling
- 연산량은 Convolution layer가 대부분을 차지
- Parameter 수는 FC layer가 대부분을 차지

Model	Params (M)	Conv (%)	FC (%)	Ops (M)	Conv (%)	FC (%)
AlexNet	61	3.8	96.2	725	91.9	8.1
VGG-F	99	2.2	97.8	762	87.4	12.6
VGG-M	103	6.3	93.7	1678	94.3	5.7
VGG-S	103	6.3	93.7	2640	96.3	3.7
VGG-16	138	10.6	89.4	15484	99.2	0.8
VGG-19	144	13.9	86.1	19647	99.4	0.6
NIN	7.6	100	0	1168	100.0	0.0
GoogLeNet	6.9	85.1	14.9	1566	99.9	0.1

CNN 사용을 위해 결정할 것들

- Input image size
- Layer 수 (convolution, fully connected 각각)
- Layer별 filter size
- Layer별 filter 수
- Batch size
- Optimizer
- Learning rate
- Regularization method 등등…