

# Lecture 2: Image Classification pipeline

# Administrative: Piazza

For questions about midterm, poster session, projects,  
use Piazza instead of staff list!

SCPD students: Use your @stanford.edu address to register for Piazza; contact  
[scpd-customerservice@stanford.edu](mailto:scpd-customerservice@stanford.edu) for help.

# Administrative: Assignment 1

Out tonight, due 4/18 11:59pm

- K-Nearest Neighbor
- Linear classifiers: SVM, Softmax
- Two-layer neural network
- Image features

# Administrative: Python + Numpy

## CS231n Convolutional Neural Networks for Visual Recognition

### Python Numpy Tutorial

This tutorial was contributed by [Justin Johnson](#).

We will use the Python programming language for all assignments in this course. Python is a great general-purpose programming language on its own, but with the help of a few popular libraries (numpy, scipy, matplotlib) it becomes a powerful environment for scientific computing.

We expect that many of you will have some experience with Python and numpy; for the rest of you, this section will serve as a quick crash course both on the Python programming language and on the use of Python for scientific computing.

<http://cs231n.github.io/python-numpy-tutorial/>

# Administrative: Google Cloud

## Google Cloud Tutorial

---

For the class project and assignments, we offer an option to use Google Compute Engine for developing and testing your implementations. This tutorial lists the necessary steps of working on the assignments using Google Cloud. For each assignment, we will provide you with an image containing the starter code and all dependencies that you need to complete the assignment. This tutorial goes through how to set up your own Google Compute Engine (GCE)

<http://cs231n.github.io/gce-tutorial/>

# Image Classification: A core task in Computer Vision



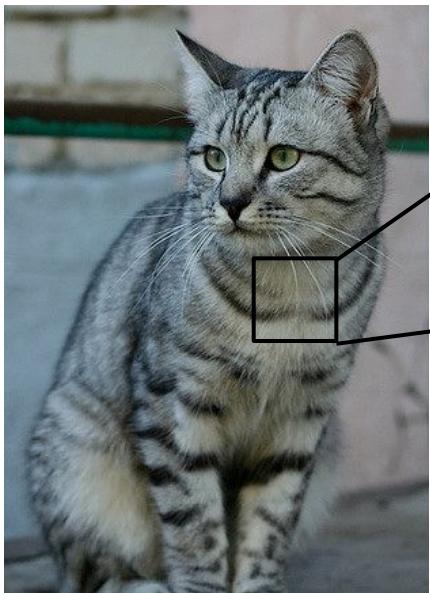
This image by [Nikita](#) is  
licensed under [CC-BY 2.0](#).

(assume given set of discrete labels)  
{dog, cat, truck, plane, ...}



cat

# The Problem: Semantic Gap



This image by Nikita is  
licensed under CC-BY 2.0

[ 105 112 108 111 104 99 106 99 96 103 112 119 104 97 93 87]
[ 91 98 102 106 104 79 98 103 99 105 123 136 110 105 94 85]
[ 76 85 90 105 128 105 87 96 95 99 115 112 106 103 99 85]
[ 99 81 93 120 131 127 100 95 98 102 99 96 93 101 94]
[106 91 61 64 69 91 88 85 101 107 109 98 75 84 96 95]
[114 108 85 55 55 69 64 54 64 87 112 129 98 74 84 91]
[133 137 147 103 65 81 80 65 52 54 74 84 102 93 85 82]
[128 137 144 140 109 95 86 70 62 65 63 63 60 73 86 101]
[125 133 148 137 119 121 117 94 65 79 80 65 54 64 72 98]
[127 125 131 147 133 127 126 131 111 96 89 75 61 64 72 84]
[115 114 109 123 150 148 131 118 113 109 100 92 74 65 72 78]
[ 89 93 90 97 108 147 131 118 113 114 113 109 106 95 77 80]
[ 63 77 86 81 77 79 102 123 117 115 117 125 125 130 115 87]
[ 62 65 82 89 78 71 80 101 124 126 119 101 107 114 131 119]
[ 63 65 75 88 89 71 62 81 128 138 135 105 81 98 110 118]
[ 87 65 71 87 106 95 69 45 76 130 126 107 92 94 105 112]
[118 97 82 86 117 123 116 66 41 51 95 93 89 95 102 107]
[164 146 112 88 82 120 124 104 76 48 45 66 88 101 102 109]
[157 170 157 128 93 86 114 132 112 97 69 55 70 82 99 94]
[130 128 134 161 139 100 109 118 121 134 114 87 65 53 69 86]
[128 112 96 117 150 144 128 115 104 107 102 93 87 81 72 79]
[123 107 96 86 83 112 153 149 122 109 104 75 80 107 112 99]
[122 121 102 88 82 86 94 117 145 148 153 102 58 78 92 107]
[122 164 148 103 71 56 78 83 93 103 119 139 102 61 69 84]]

What the computer sees

An image is just a big grid of numbers between [0, 255]:

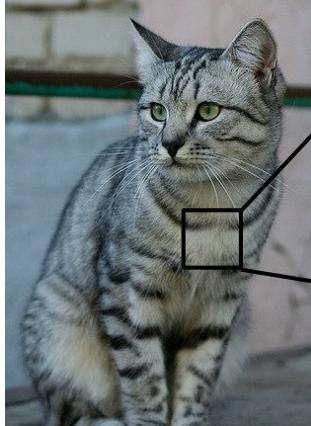
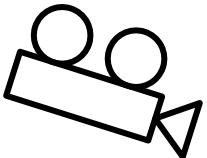
e.g. 800 x 600 x 3  
(3 channels RGB)

이미지는  
숫자로 구성된  
3D 배열로  
이뤄짐

# Challenges: Viewpoint variation

관점 포인트

여기 끝점



[1185 112 188 111 184 99 186 99 96 183 112 119 184 97 93 87] [ 91 98 182 106 104 79 98 103 99 105 123 136 118 105 94 85] [ 76 85 98 105 128 105 87 96 95 99 115 112 106 103 99 85] [ 99 80 81 85 102 103 127 98 100 98 101 108 109 98 75 84] [100 91 86 84 69 91 68 85 101 102 109 98 75 84 96 95] [114 108 85 55 55 69 64 54 64 87 112 129 98 74 84 94 91] [114 137 147 103 65 81 80 65 52 54 74 84 102 93 85 82] [128 137 144 148 105 95 86 78 62 65 63 63 68 73 86 101] [102 125 131 147 133 127 116 131 111 98 89 75 61 64 72 84] [127 125 131 147 133 127 116 131 111 98 89 75 61 64 72 84] [115 115 189 123 150 148 131 118 113 109 108 92 74 65 72 78] [ 89 93 98 97 108 147 131 118 113 114 113 108 106 95 77 80] [ 63 77 86 81 77 79 182 123 137 115 111 125 125 130 115 87] [ 62 85 88 89 73 62 81 128 138 135 105 81 98 118 118] [ 63 65 75 88 89 73 62 81 128 138 135 105 81 98 118 118] [ 87 65 71 87 100 95 69 45 76 138 126 107 92 94 105 112] [118 97 82 86 117 123 116 66 41 51 95 93 89 89 95 102 107] [164 140 112 88 80 102 126 184 78 48 66 66 66 101 102 106] [137 79 86 81 93 86 104 121 115 105 95 70 84 84 84 94] [138 128 134 161 139 180 109 118 121 134 114 87 65 53 69 86] [128 112 96 117 150 144 120 115 104 107 102 93 87 81 72 79] [123 107 96 86 83 112 153 149 122 189 184 75 88 107 112 99] [122 121 102 80 82 86 94 117 145 148 153 105 58 78 92 107] [122 164 148 103 71 56 78 83 93 103 119 139 102 61 69 84]
---

All pixels change when  
the camera moves!

This image by Nikita is  
licensed under CC-BY 2.0

# Challenges: Illumination 조명



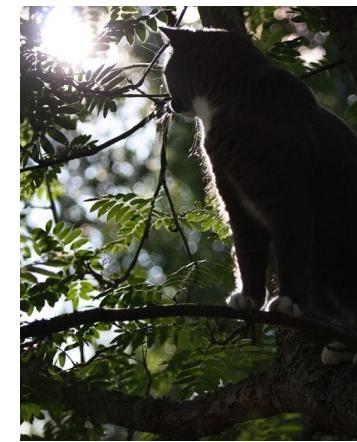
This image is CC0 1.0 public domain



This image is CC0 1.0 public domain



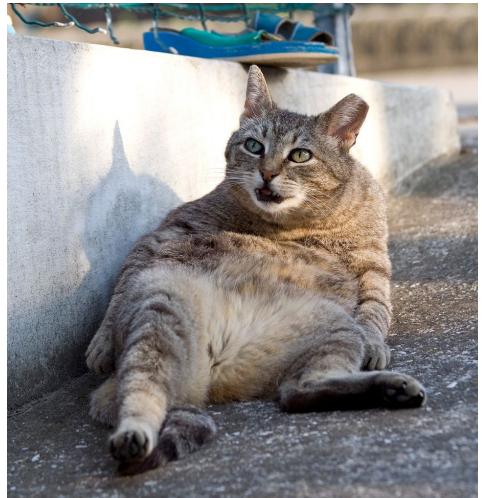
This image is CC0 1.0 public domain



This image is CC0 1.0 public domain

# Challenges: Deformation

형태 변형



[This image by Umberto Salvagnin](#)  
is licensed under CC-BY 2.0



[This image by Umberto Salvagnin](#)  
is licensed under CC-BY 2.0



[This image by sare bear is](#)  
licensed under CC-BY 2.0



[This image by Tom Thai is](#)  
licensed under CC-BY 2.0

# Challenges: Occlusion 은폐



[This image is CC0 1.0 public domain](#)



[This image is CC0 1.0 public domain](#)



[This image by jonsson is licensed under CC-BY 2.0](#)

# Challenges: Background Clutter 배경과 구분이 안됨.



[This image is CC0 1.0 public domain](#)



[This image is CC0 1.0 public domain](#)

# Challenges: Intraclass variation 고양이 내 변형



This image is CC0 1.0 public domain

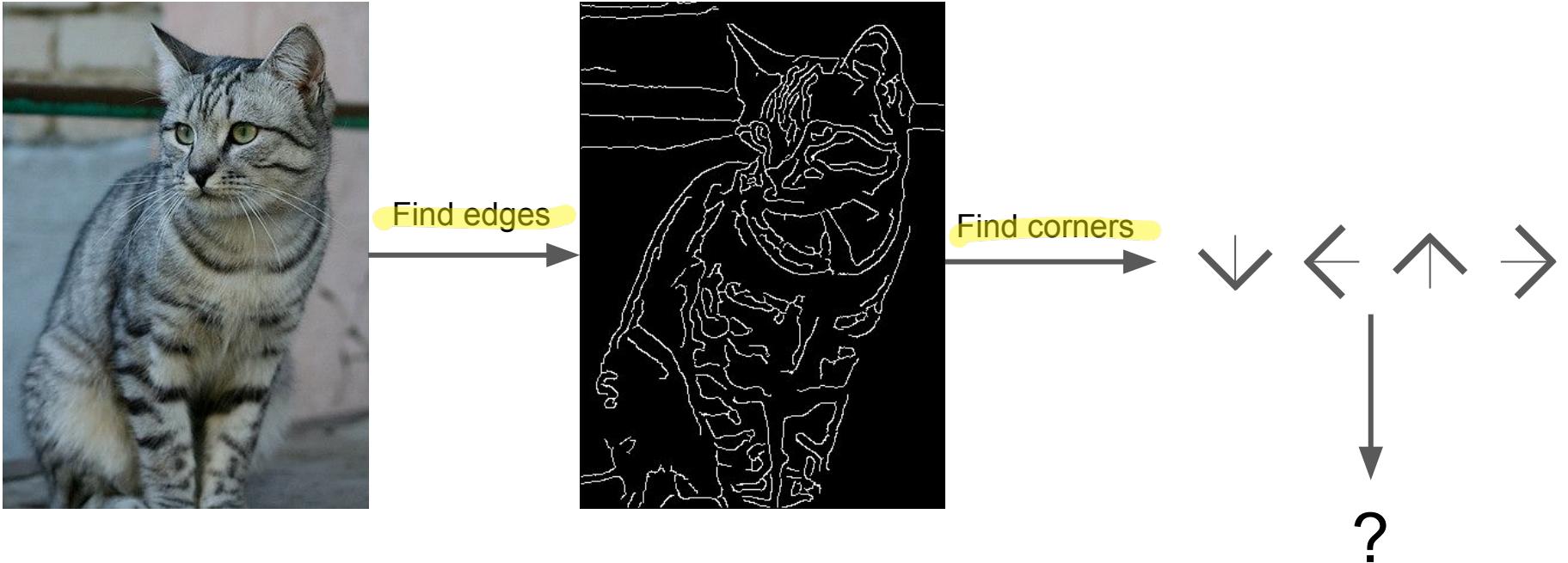
# An image classifier

```
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.

# Attempts have been made



John Canny, "A Computational Approach to Edge Detection", IEEE TPAMI 1986

# Data-Driven Approach

데이터 기반

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

Example training set

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

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

airplane



automobile



bird



cat



deer



# First classifier: Nearest Neighbor

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

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

train하기

Memorize all  
data and labels

predict하기

Predict the label  
of the most similar  
training image

가장 비슷한 training image

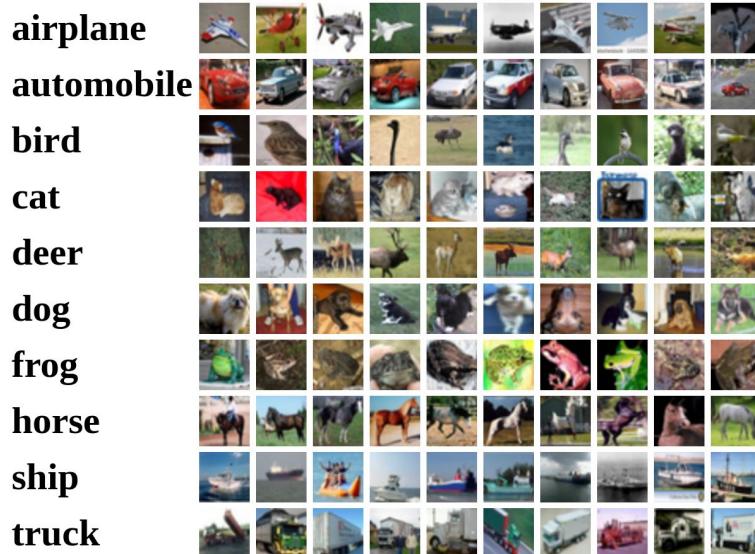
레이블을 test image로 예측

# Example Dataset: CIFAR10

10 classes

50,000 training images

10,000 testing images



Alex Krizhevsky, "Learning Multiple Layers of Features from Tiny Images", Technical Report, 2009.

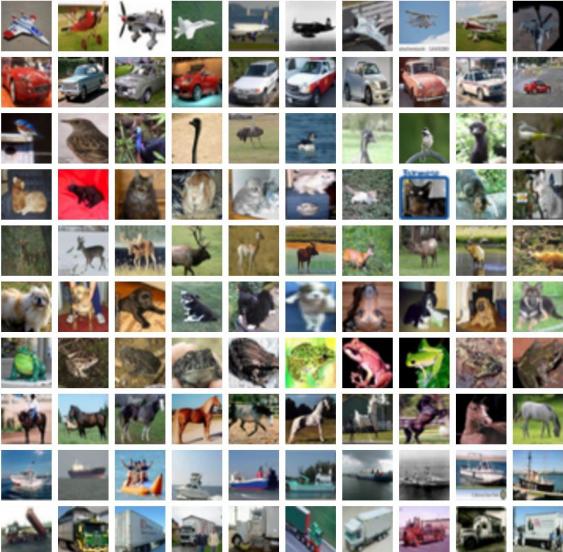
# Example Dataset: CIFAR10

10 classes

50,000 training images

10,000 testing images

airplane



automobile



bird



cat



deer



dog



frog



horse



ship



truck



Nearest Neighbor

Test images and nearest neighbors



Alex Krizhevsky, "Learning Multiple Layers of Features from Tiny Images", Technical Report, 2009.

# Distance Metric to compare images

Nearest Neighbor 이 어떻게 동작하는가?

L1 distance:  
(Manhattan)

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

test image			
56	32	10	18
90	23	128	133
24	26	178	200
2	0	255	220

training image			
10	20	24	17
8	10	89	100
12	16	178	170
4	32	233	112

-

= pixel-wise absolute value differences

46	12	14	1
82	13	39	33
12	10	0	30
2	32	22	108

add  
→ 456

hyperparameter :  
주어진 환경에서 최적의  
parameter를 찾아야 함.

ex) L1, L2 distance

```

import numpy as np

class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        """ X is N x D where each row is an example. Y is 1-dimension of size N """
        # the nearest neighbor classifier simply remembers all the training data
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        """ X is N x D where each row is an example we wish to predict label for """
        num_test = X.shape[0]
        # lets make sure that the output type matches the input type
        Ypred = np.zeros(num_test, dtype = self.ytr.dtype)

        # loop over all test rows
        for i in xrange(num_test):
            # find the nearest training image to the i'th test image
            # using the L1 distance (sum of absolute value differences)
            distances = np.sum(np.abs(self.Xtr - X[i,:]), axis = 1)
            min_index = np.argmin(distances) # get the index with smallest distance
            Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

        return Ypred

```

## Nearest Neighbor classifier

```

import numpy as np

class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        """ X is N x D where each row is an example. Y is 1-dimension of size N """
        # the nearest neighbor classifier simply remembers all the training data
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        """ X is N x D where each row is an example we wish to predict label for """
        num_test = X.shape[0]
        # lets make sure that the output type matches the input type
        Ypred = np.zeros(num_test, dtype = self.ytr.dtype)

        # loop over all test rows
        for i in xrange(num_test):
            # find the nearest training image to the i'th test image
            # using the L1 distance (sum of absolute value differences)
            distances = np.sum(np.abs(self.Xtr - X[i,:]), axis = 1)
            min_index = np.argmin(distances) # get the index with smallest distance
            Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

        return Ypred

```

## Nearest Neighbor classifier

Memorize training data

```

import numpy as np

class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        """ X is N x D where each row is an example. Y is 1-dimension of size N """
        # the nearest neighbor classifier simply remembers all the training data
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        """ X is N x D where each row is an example we wish to predict label for """
        num_test = X.shape[0]
        # lets make sure that the output type matches the input type
        Ypred = np.zeros(num_test, dtype = self.ytr.dtype)

        # loop over all test rows
        for i in xrange(num_test):
            # find the nearest training image to the i'th test image
            # using the L1 distance (sum of absolute value differences)
            distances = np.sum(np.abs(self.Xtr - X[i,:]), axis = 1)
            min_index = np.argmin(distances) # get the index with smallest distance
            Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

        return Ypred

```

## Nearest Neighbor classifier

For each test image:  
 Find closest train image  
 Predict label of nearest image

```

import numpy as np

class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        """ X is N x D where each row is an example. Y is 1-dimension of size N """
        # the nearest neighbor classifier simply remembers all the training data
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        """ X is N x D where each row is an example we wish to predict label for """
        num_test = X.shape[0]
        # lets make sure that the output type matches the input type
        Ypred = np.zeros(num_test, dtype = self.ytr.dtype)

        # loop over all test rows
        for i in xrange(num_test):
            # find the nearest training image to the i'th test image
            # using the L1 distance (sum of absolute value differences)
            distances = np.sum(np.abs(self.Xtr - X[i,:]), axis = 1)
            min_index = np.argmin(distances) # get the index with smallest distance
            Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

        return Ypred

```

## Nearest Neighbor classifier

**Q:** With N examples,  
how fast are training  
and prediction?

```

import numpy as np

class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        """ X is N x D where each row is an example. Y is 1-dimension of size N """
        # the nearest neighbor classifier simply remembers all the training data
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        """ X is N x D where each row is an example we wish to predict label for """
        num_test = X.shape[0]
        # lets make sure that the output type matches the input type
        Ypred = np.zeros(num_test, dtype = self.ytr.dtype)

        # loop over all test rows
        for i in xrange(num_test):
            # find the nearest training image to the i'th test image
            # using the L1 distance (sum of absolute value differences)
            distances = np.sum(np.abs(self.Xtr - X[i,:]), axis = 1)
            min_index = np.argmin(distances) # get the index with smallest distance
            Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

        return Ypred

```

## Nearest Neighbor classifier

**Q:** With N examples,  
how fast are training  
and prediction?

**A:** Train O(1),  
predict O(N)

```

import numpy as np

class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        """ X is N x D where each row is an example. Y is 1-dimension of size N """
        # the nearest neighbor classifier simply remembers all the training data
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        """ X is N x D where each row is an example we wish to predict label for """
        num_test = X.shape[0]
        # lets make sure that the output type matches the input type
        Ypred = np.zeros(num_test, dtype = self.ytr.dtype)

        # loop over all test rows
        for i in xrange(num_test):
            # find the nearest training image to the i'th test image
            # using the L1 distance (sum of absolute value differences)
            distances = np.sum(np.abs(self.Xtr - X[i,:]), axis = 1)
            min_index = np.argmin(distances) # get the index with smallest distance
            Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

        return Ypred

```

⊕ 속도를 개선한 ANN, Flann 이 있다.

## Nearest Neighbor classifier

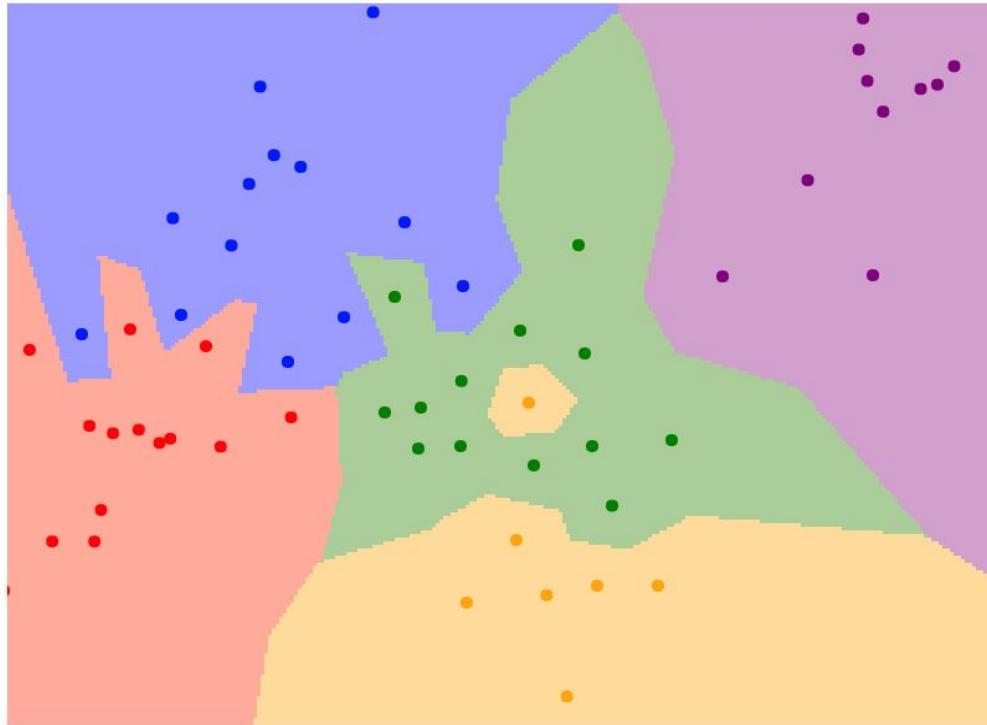
~~Q: With N examples, how fast are training and prediction?~~

**A:** Train O(1),  
predict O(N)

This is bad: we want classifiers that are **fast** at prediction; **slow** for training is ok

**prediction O(1) 중요!**

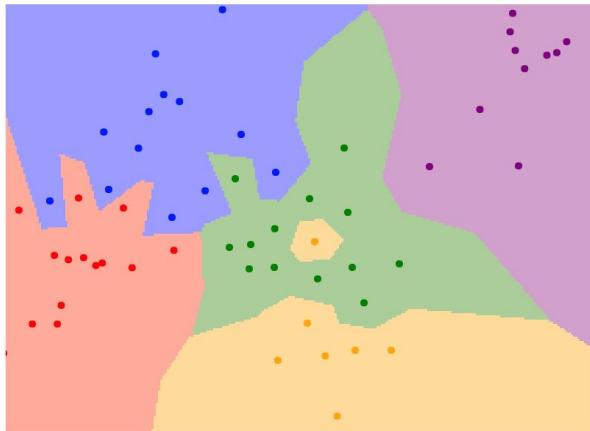
# What does this look like?



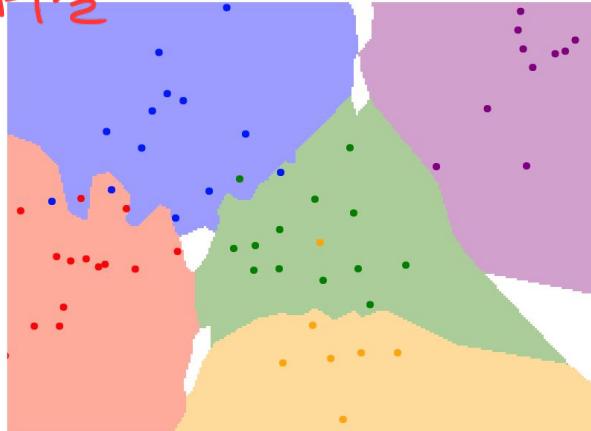
# K-Nearest Neighbors

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

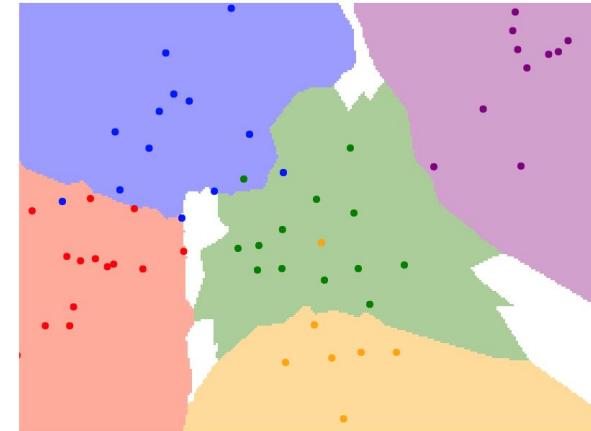
다수결



$K = 1$



$K = 3$



$K = 5$

# What does this look like?



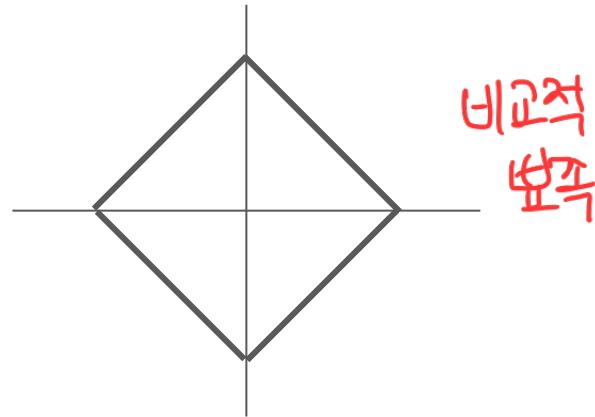
# What does this look like?



# K-Nearest Neighbors: Distance Metric

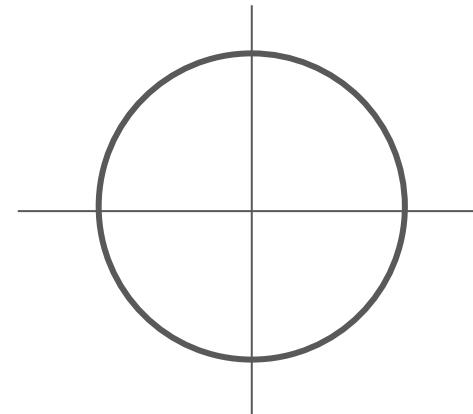
L1 (Manhattan) distance

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



L2 (Euclidean) distance

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

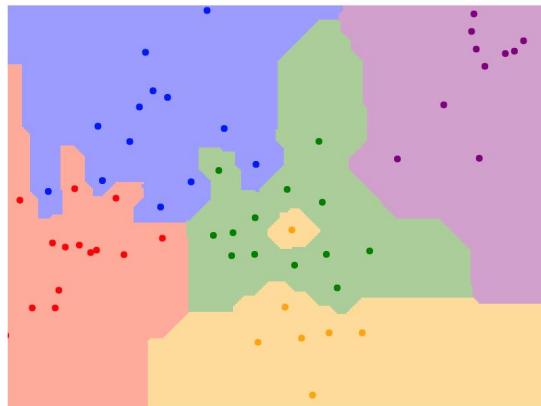


# K-Nearest Neighbors: Distance Metric

*hyperparameter* .

L1 (Manhattan) distance

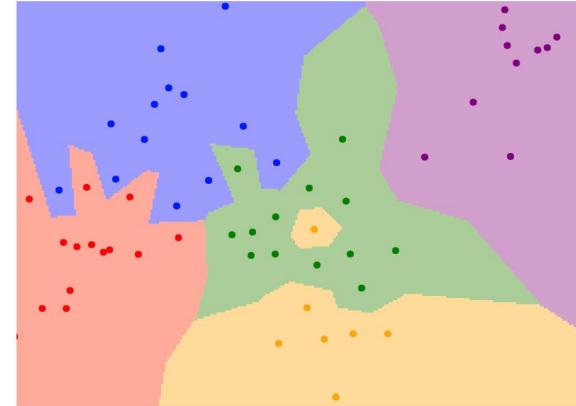
$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$



$K = 1$

L2 (Euclidean) distance

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



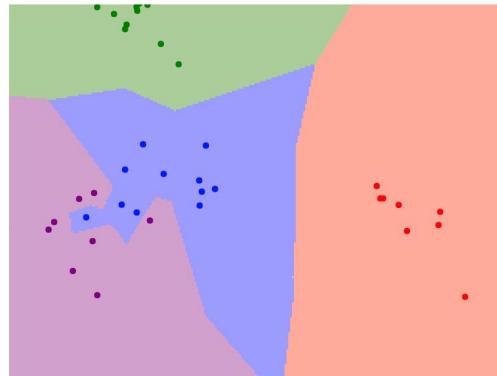
$K = 1$

# K-Nearest Neighbors: Demo Time

## K-Nearest Neighbors Demo

This interactive demo lets you explore the K-Nearest Neighbors algorithm for classification. Each point in the plane is colored with the class that would be assigned to it using the K-Nearest Neighbors algorithm. Points for which the K-Nearest Neighbor algorithm results in a tie are colored white.

You can move points around by clicking and dragging!



Metric

L1 L2

Num classes

2 3 4 5

Num Neighbors (K)

1 2 3 4 5 6 7

Num points

20 30 40 50 60

<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

문제에 따라 각각의 parameter를 실험하고

최적의 것을 적용한다.

# 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.

# Setting Hyperparameters

**Idea #1:** Choose hyperparameters  
that work best on the data

Your Dataset

# Setting Hyperparameters

Idea #1: Choose hyperparameters  
that work best on the data

BAD: K = 1 always works  
perfectly on training data

Your Dataset

# Setting Hyperparameters

**Idea #1:** Choose hyperparameters that work best on the data

**BAD:** K = 1 always works perfectly on training data

Your Dataset

**Idea #2:** Split data into **train** and **test**, choose hyperparameters that work best on test data

train

test

# Setting Hyperparameters

**Idea #1:** Choose hyperparameters that work best on the data

**BAD:**  $K = 1$  always works perfectly on training data

Your Dataset

**Idea #2:** Split data into **train** and **test**, choose hyperparameters that work best on test data

**BAD:** No idea how algorithm will perform on new data

train

test

# Setting Hyperparameters

**Idea #1:** Choose hyperparameters that work best on the data

**BAD:**  $K = 1$  always works perfectly on training data

Your Dataset

**Idea #2:** Split data into **train** and **test**, choose hyperparameters that work best on test data

**BAD:** No idea how algorithm will perform on new data

train

test

**Idea #3:** Split data into **train**, **val**, and **test**; choose hyperparameters on val and evaluate on test

**Better!**

train

validation

test

# Setting Hyperparameters

Your Dataset

~~Idea #4:~~ Idea #4: **Cross-Validation:** Split data into **folds**,  
try each fold as validation and average the results

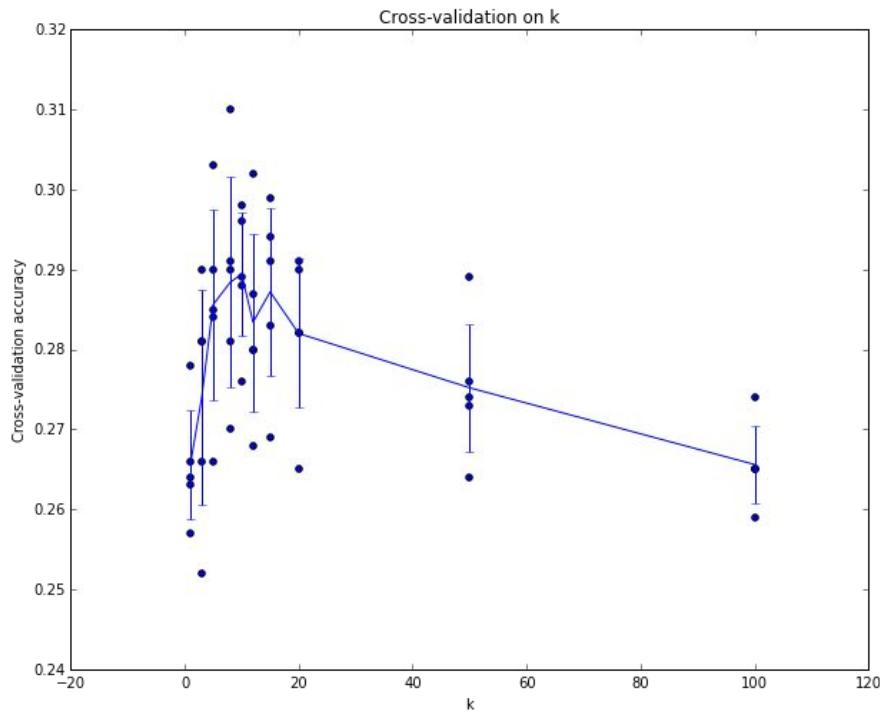
fold 1	fold 2	fold 3	fold 4	fold 5	test
--------	--------	--------	--------	--------	------

fold 1	fold 2	fold 3	fold 4	fold 5	test
--------	--------	--------	--------	--------	------

fold 1	fold 2	fold 3	fold 4	fold 5	test
--------	--------	--------	--------	--------	------

Useful for small datasets, but not used too frequently in deep learning

# 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  $k \approx 7$  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)

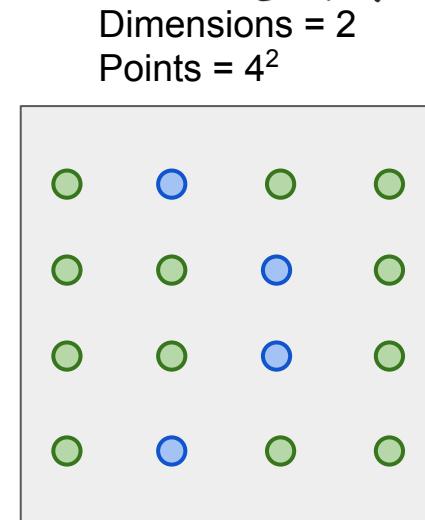
Original image is  
CC0 public domain

# k-Nearest Neighbor on images **never used**.

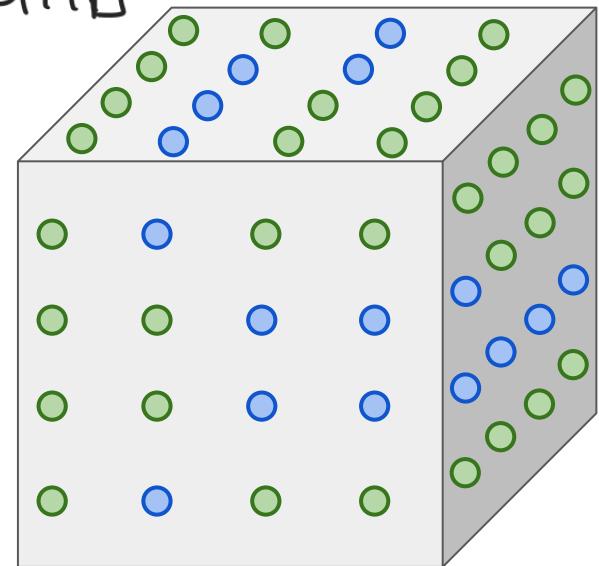
- Curse of dimensionality

차원이 늘어날수록 point 개수가 많아지고 분류하기 어려워짐

Dimensions = 1  
Points = 4



Dimensions = 3  
Points =  $4^3$



# K-Nearest Neighbors: Summary

In **Image classification** we start with a **training set** of images and labels, and must predict labels on the **test set**

The **K-Nearest Neighbors** classifier predicts labels based on nearest training examples

Distance metric and K are **hyperparameters**

Choose **hyperparameters** using the **validation set**; only run on the test set once at the very end!

test set은 마지막에 한 번

# Linear Classification

선형 분류

# Neural Network

Linear  
classifiers



This image is CC0 1.0 public domain

*Two young girls are playing with lego toy.* *Boy is doing backflip on wakeboard*



*Man in black shirt is playing guitar.*

*Construction worker in orange safety vest is working on road.*

*Image capturing*

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015  
Figures copyright IEEE, 2015. Reproduced for educational purposes.

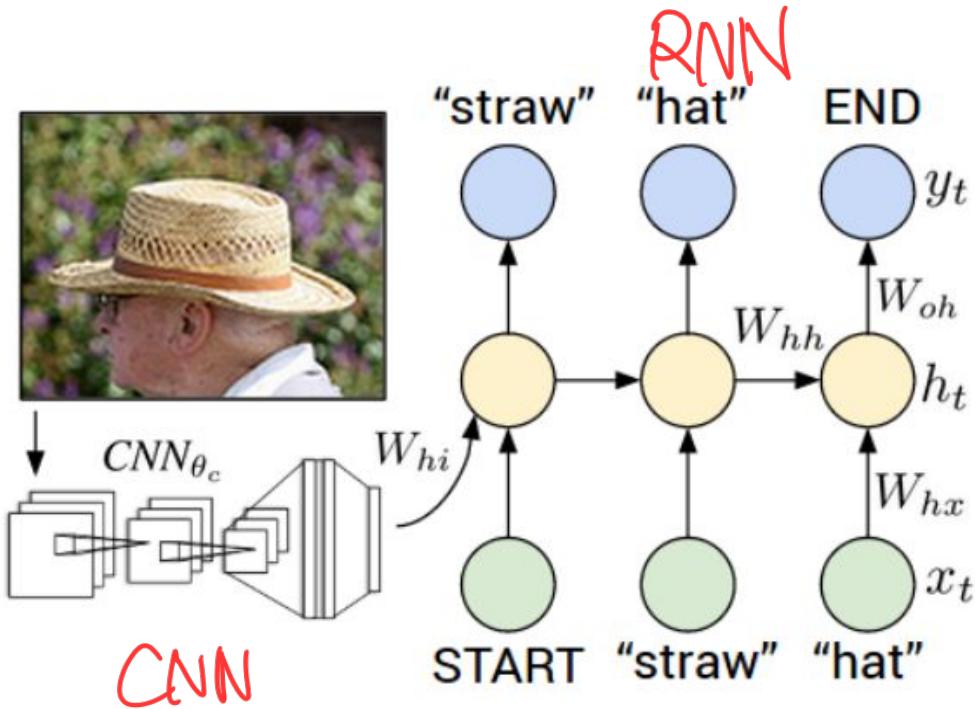
*Two young girls are playing with lego toy.*   *Boy is doing backflip on wakeboard*



*Man in black shirt is playing guitar.*



*Construction worker in orange safety vest is working on road.*



Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015  
Figures copyright IEEE, 2015. Reproduced for educational purposes.

# Recall CIFAR10

airplane



automobile



bird



cat



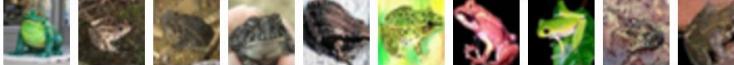
deer



dog



frog



horse



ship



truck



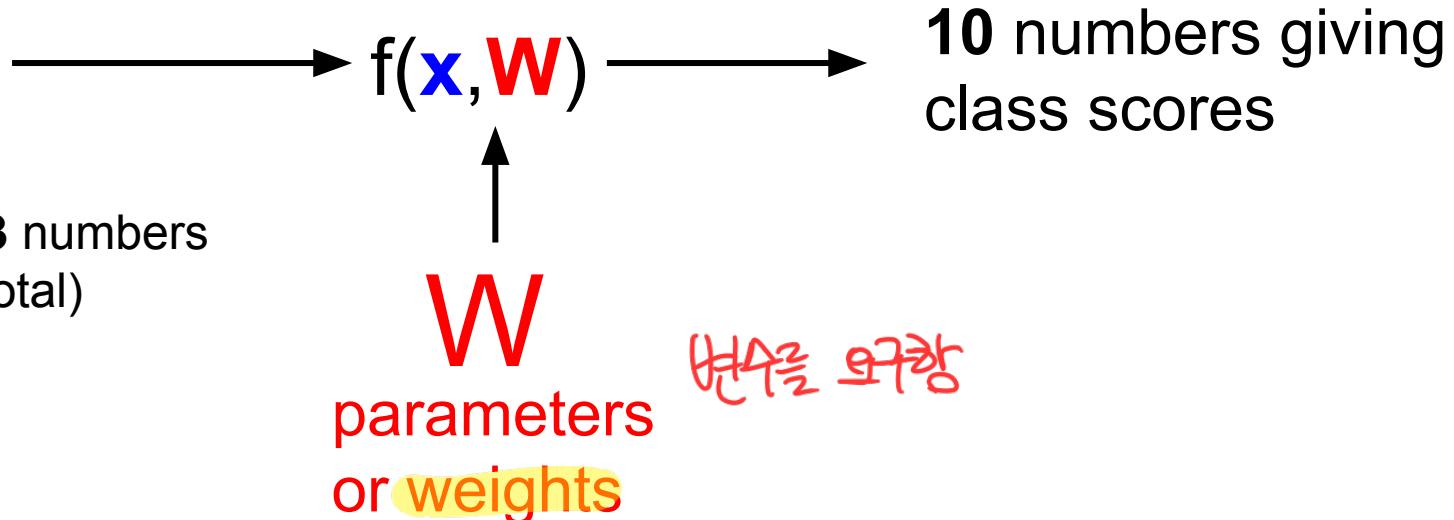
**50,000** training images  
each image is **32x32x3**

**10,000** test images.

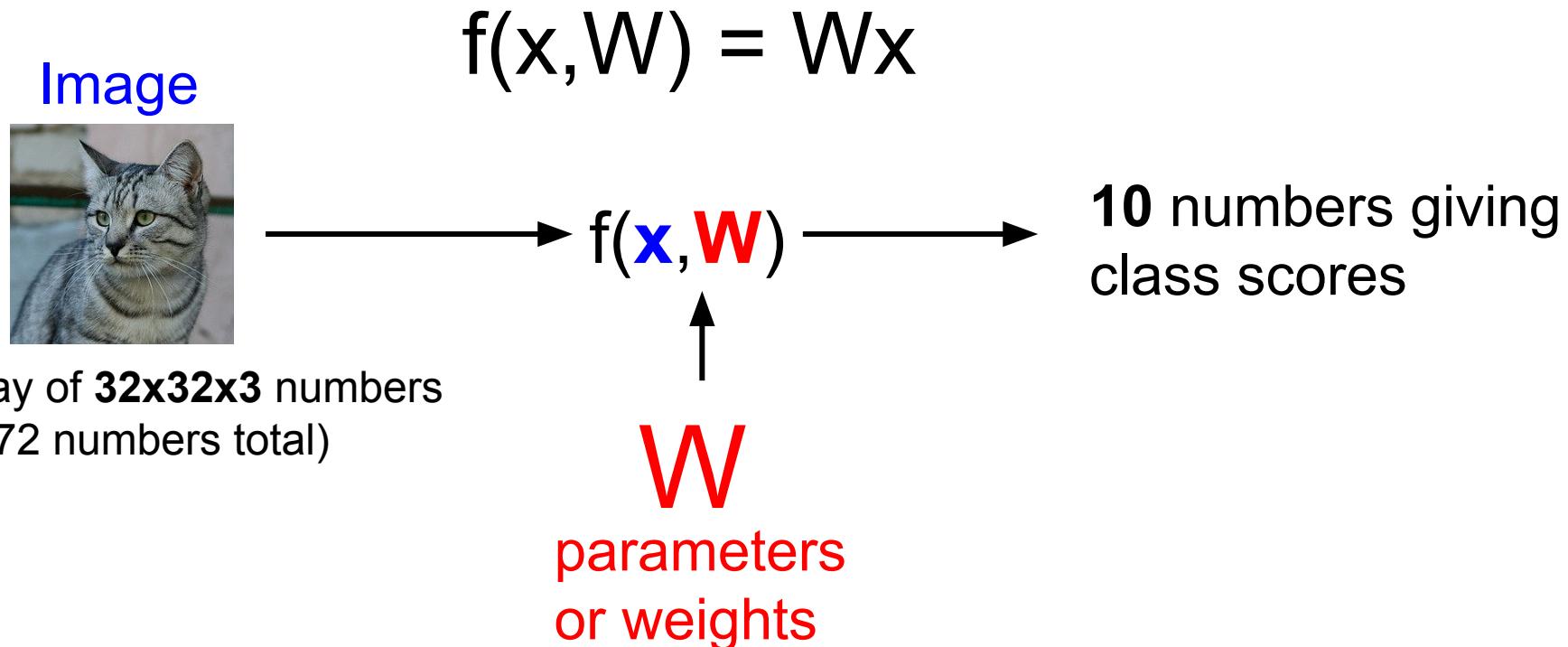
# Parametric Approach

파라미터 접근방식 (Nearest neighbor는 Non-parameter였음)

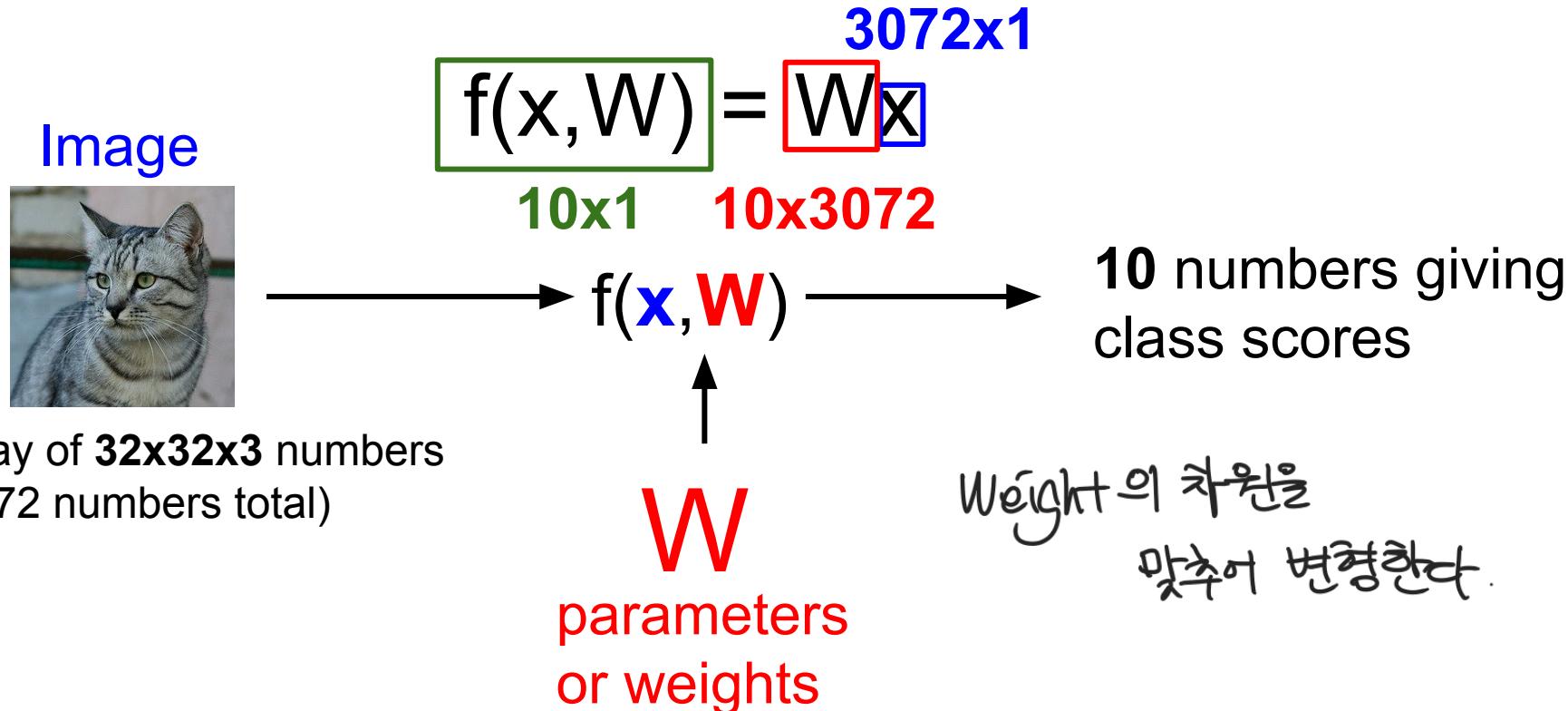
## Image



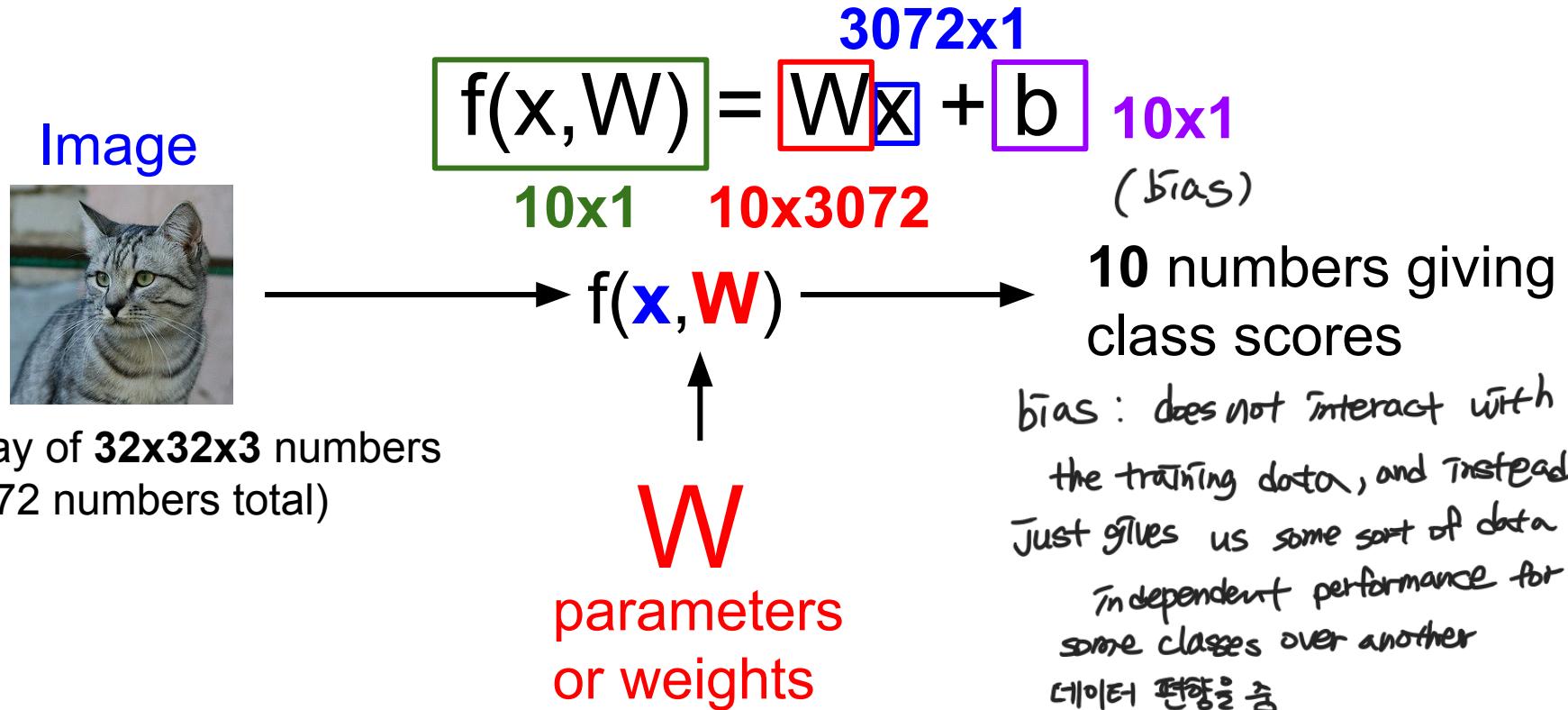
# Parametric Approach: Linear Classifier



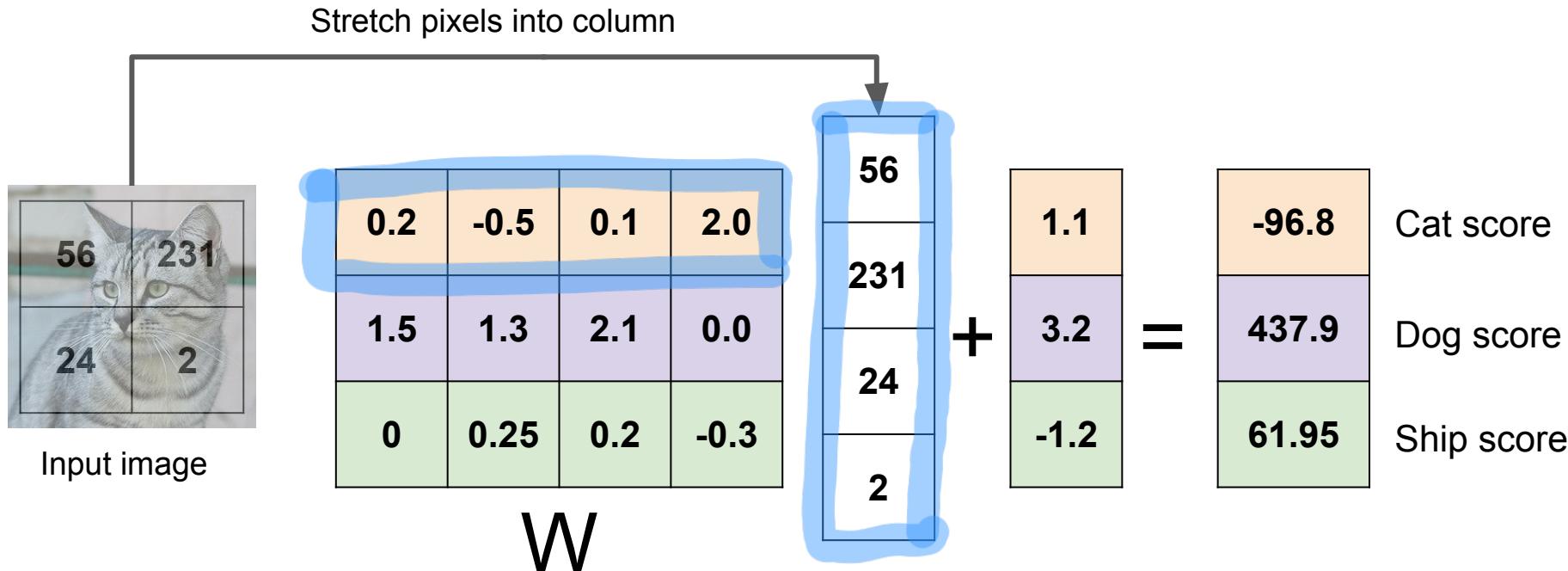
# Parametric Approach: Linear Classifier



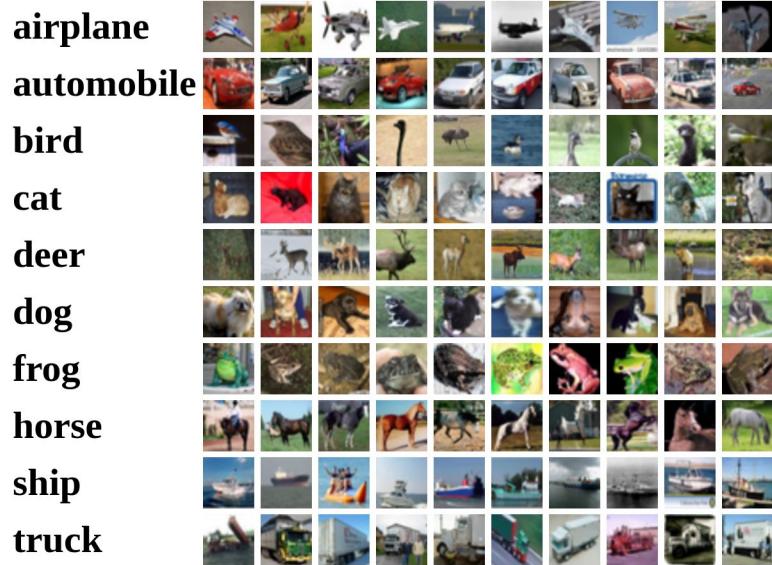
# Parametric Approach: Linear Classifier



# Example with an image with 4 pixels, and 3 classes (cat/dog/ship)



# Interpreting a Linear Classifier

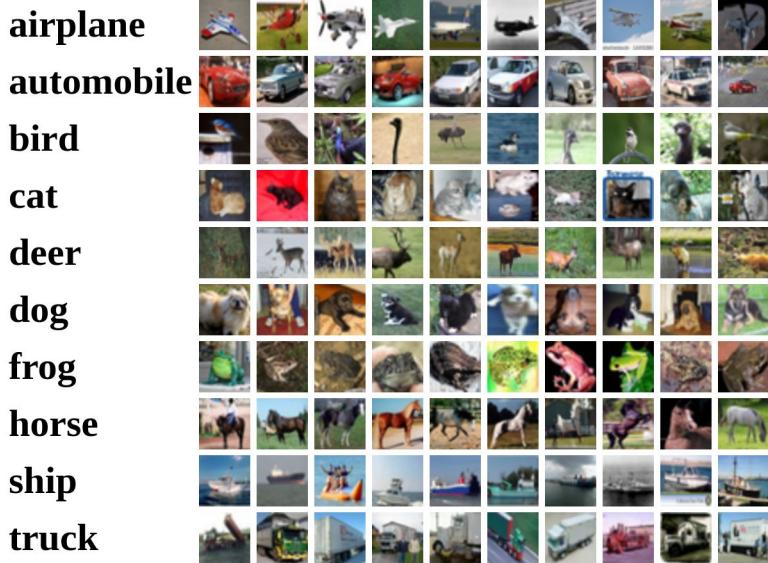


$$f(x, W) = Wx + b$$

What is this thing doing?

이미지 내의 모든 픽셀의 값에 대하여  
가중치를 곱하여 처리한 것의 합

# Interpreting a Linear Classifier

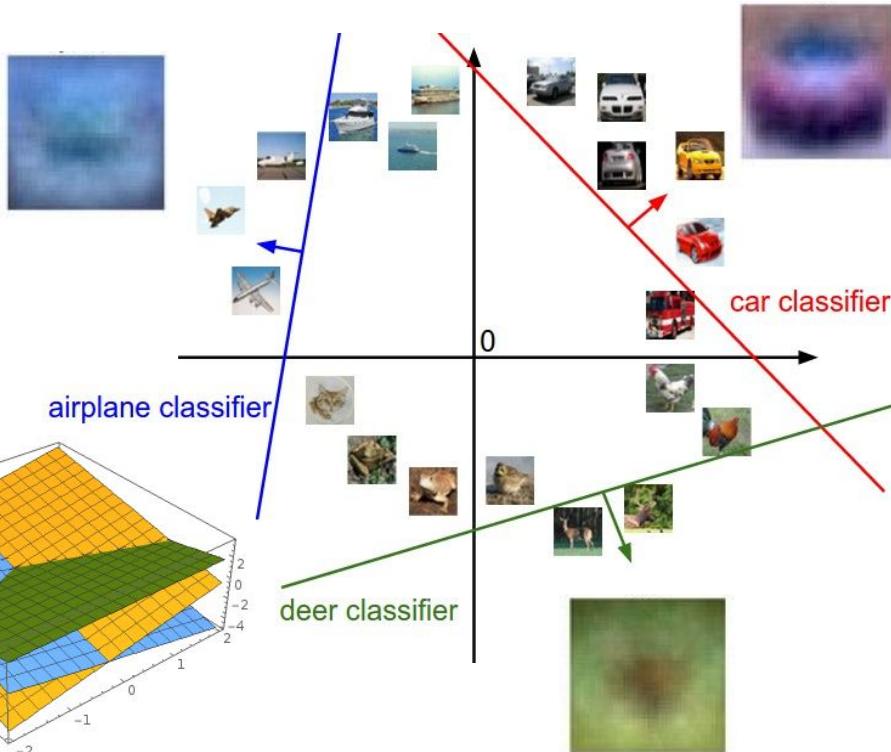


$$f(x, W) = Wx + b$$

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)

Plot created using [Wolfram Cloud](#)

[Cat image](#) by [Nikita](#) is licensed under [CC-BY 2.0](#)

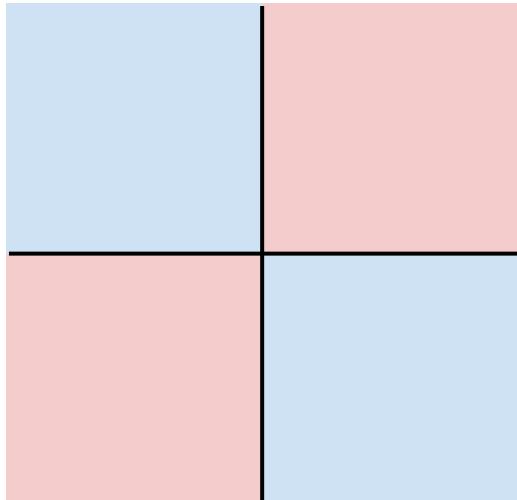
# Hard cases for a linear classifier

**Class 1:**

number of pixels > 0 odd

**Class 2:**

number of pixels > 0 even

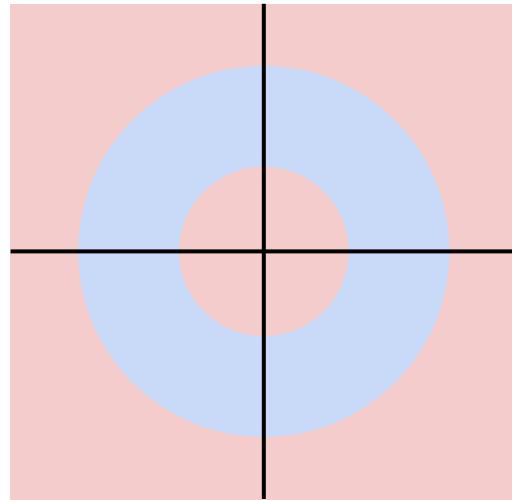


**Class 1:**

$1 \leq L_2 \text{ norm} \leq 2$

**Class 2:**

Everything else

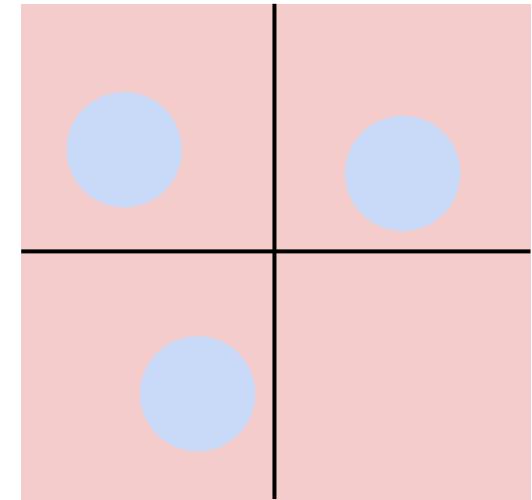


**Class 1:**

Three modes

**Class 2:**

Everything else



# So far: Defined a (linear) score function $f(x, W) = Wx + b$

Example class scores for 3 images for some  $W$ :

How can we tell whether this  $W$  is good or bad?



airplane	-3.45	-0.51	3.42
automobile	-8.87	<b>6.04</b> <i>good</i>	4.64
bird	0.09	5.31	2.65
cat	<b>2.9</b> <i>bad</i>	-4.22	5.1
deer	4.48	-4.19	2.64
dog	8.02	3.58	5.55
frog	3.78	4.49	<b>-4.34</b> <i>bad</i>
horse	1.06	-4.37	-1.5
ship	-0.36	-2.09	-4.79
truck	-0.72	-2.93	6.14

Cat image by [Nikita](#) is licensed under [CC-BY 2.0](#)

Car image is [CC0 1.0](#) public domain

Frog image is in the public domain

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

# Coming up:

- Loss function
- Optimization
- ConvNets!

정량화는

(quantifying what it means to have a “good”  $W$ )

(start with random  $W$  and find a  $W$  that minimizes the loss)

(tweak the functional form of  $f$ )

비틀다. 수정하다.