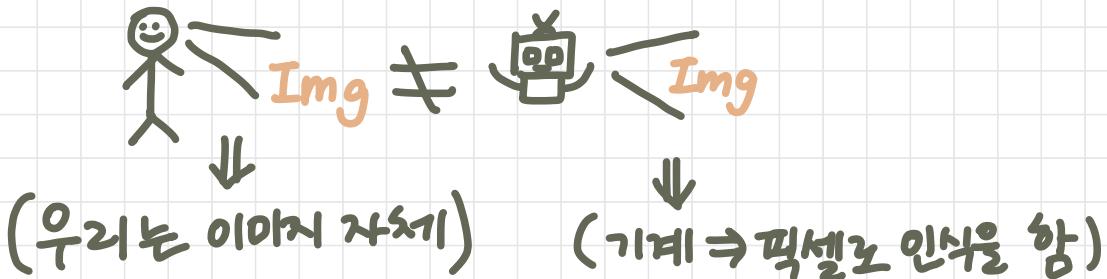


# Lecture 2: Image Classification pipeline

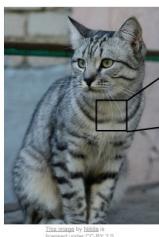
# 1/10 <CS231n 강의>

## Lec. 02 Image Classification

사람과 기계가 이미지를 인식하는게 다르다.



The Problem: Semantic Gap

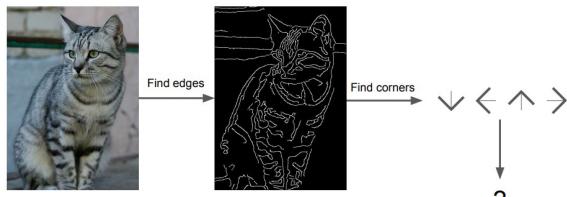


1180	112	140	111	144	89	381	90	96	283	112	119	144	97	93	87	
1181	112	140	111	144	89	381	90	96	283	112	119	144	97	93	87	
1182	95	98	94	101	146	87	96	95	99	125	112	146	180	99	85	81
1183	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1184	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1185	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1186	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1187	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1188	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1189	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1190	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1191	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1192	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1193	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1194	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1195	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1196	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1197	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1198	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1199	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1200	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1201	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1202	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1203	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1204	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1205	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
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1230	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1231	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1232	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1233	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1234	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1235	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1236	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1237	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1238	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
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1266	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1267	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1268	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1269	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1270	91	93	84	98	93	86	85	181	187	125	94	75	84	96	95	81
1271	91	93	84	98												



우리는 예상이나 이전 것  
적~당히 보고 이미지를  
인식할 수 있다!!  
~~but~~ 기계는 주어진 시점으로만  
판단 가능  $\Rightarrow$  한계

Attempts have been made



문제를 고드로 구현 Is not easy  
 $\Rightarrow$  다른 방법 사용  
 왜 not easy??  
 $\Rightarrow$  고양이의 edges 같은 걸 떼어  
 고드를 짠는데! 만약 사진이  
 뒤집히거나 그려면 기계는 인식 잘못함

### 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

Example training set

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

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



train

$\Rightarrow$  이미지를 주고 label을 주면  
 많은 데이터로 학습함

predict

$\Rightarrow$  새로운 데이터를 주고 이 사진이  
 무엇인지 인식하게 하는거.

# Example Dataset: CIFAR10

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



Distance Metric to compare images

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

test image				training image				pixel-wise absolute value differences							
56	32	10	18	10	20	24	17	46	12	14	1	82	13	39	33
90	23	128	133	8	10	89	100	12	10	0	30	12	10	0	30
24	26	178	200	12	16	178	170	2	32	22	108	4	32	233	112
2	0	255	220												

## ① Nearest Neighbor

→ 가장 가까운 이미지를 찾음

\* 근데 개구리랑 고양이가  
같다고 본다!! (사이비듯해서...)



같을 때 거리를 더해  
하나 작으면 균등하다!!

```
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
            # e.g., self.Xtr[i] is the 1'th row (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)

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

train is fast  
test is long time

!! 문제점 !!

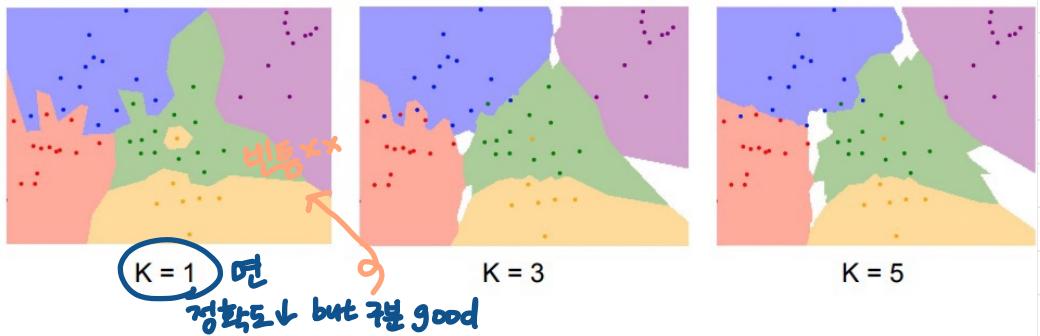
시간이 오래걸린다

⇒ 실생활 활용이 어렵다.

학습은 오래걸려도 test는 ↓

# K-Nearest Neighbors

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



## KNN (K-최근접 이웃)

$$\begin{pmatrix} k=1 \\ k=3 \\ k=5 \end{pmatrix} \rightarrow \square \rightarrow \square \square \square$$

✓ 3번 째 친구가  
평가했습니다!

아마 잘 살피기!



$K$  가 늘어날 수록  
정확도가 ↑↑

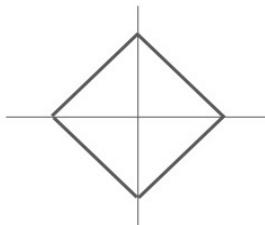
but, 성능이 뚝 떨어지거나 x x  
성능이 모호해짐.

전부 잘 단정 흐지!!

# K-Nearest Neighbors: Distance Metric

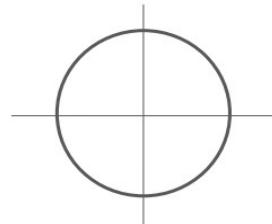
## L1 (Manhattan) distance

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



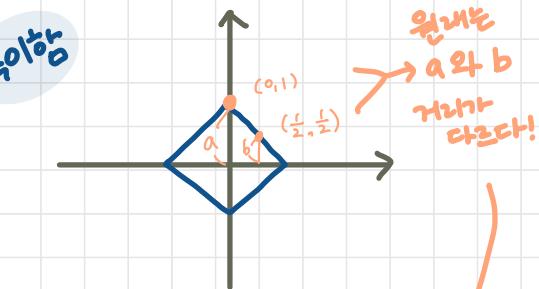
## L2 (Euclidean) distance

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



## L1 distance (Manhattan)

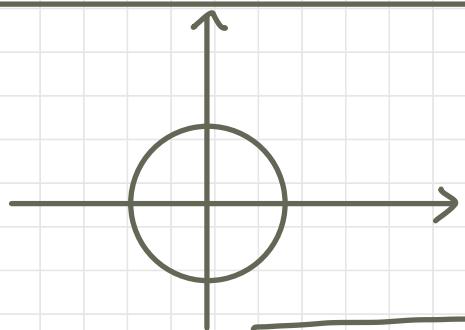
특이점



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

but!!  
Manhattan은  
직선을かない 있는  
정의 거리를 같다.

## L2 distance (Euclidean)



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

좌표평면 내의 거리계산

$(a_1, a_2), (b_1, b_2) \rightarrow$  정의

$$\sqrt{(b_1 - a_1)^2 + (b_2 - a_2)^2}$$

## K-Nearest Neighbors: Distance Metric

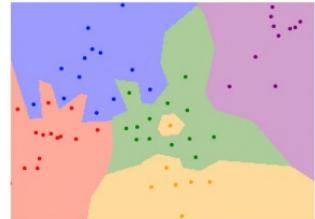
L1 (Manhattan) distance

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



L2 (Euclidean) distance

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



L1 & L2 → 예시를 보면 쉽다.

L1은 거리가 같지만!

L2는 값이 다르게 나오는걸 알 수 있다.

L1 distance는 크기를 키우거나,  
줄이는거 같은 행위가 가능...?

L2 distance는 feature 들에  
대해서 각각을 반영하겠다.

ex) 키, 몸무게는 각각 반영  $\Rightarrow$  L2 distance 사용

L1은 오밀조밀하게 분포 vs. L2는 sharpe 하게 있는지.

# Hyperparameters (KNN에서 K가 하이퍼파라미터)

What is the best value of k to use?

What is the best **distance** to use?

파라미터 → 모델안에서 모델이  
스스로 업데이트 해가는 것

하이퍼 파라미터 → 모델이  
학습할 때 이전거에 초점을  
맞추면 좋겠다 ~~ 이전느낌?  
⇒ 사용자가 지정하는 것!  
ex)  $K=1$ ,  $K=5$

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-Nearest Neighbor on images never used. KNN은 이미지 분류에 적합XX

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

① test time이 느린다.. T  
② 값, 변형, 위치이동 (픽셀이 조금만 달라도!)  
하면 다 다른 이미지를 인식함  
⇒ 성능이 좋은 알고리즘은  
아니다!!!

Original



Boxed



Shifted



Tinted



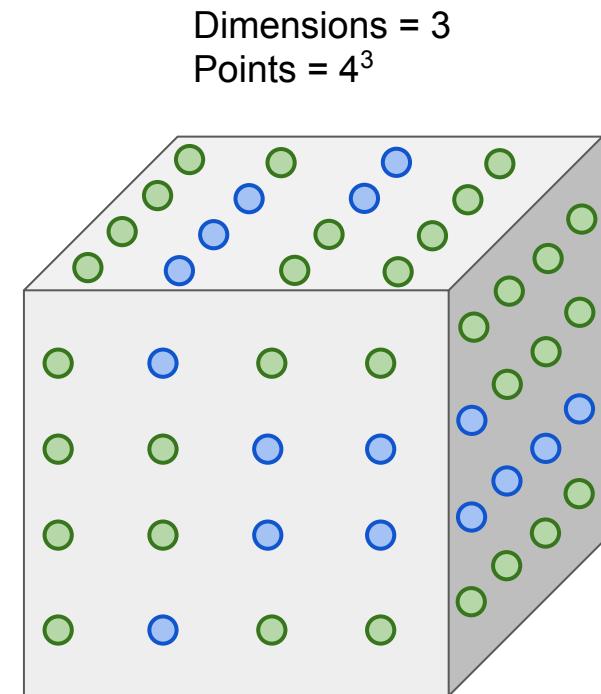
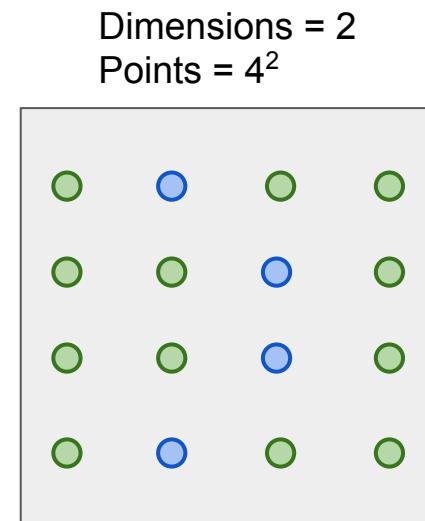
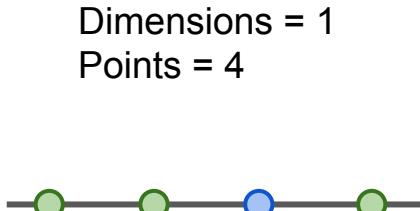
(all 3 images have same L2 distance to the one on the left)

Original image is  
CC0 public domain

< 차원의 저주... ?? > ~~ 두장에 계속 !!

## k-Nearest Neighbor on images never used.

- Curse of dimensionality



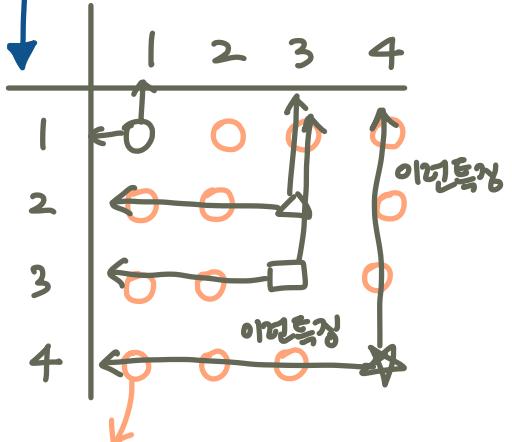
# <차원의 저주>

데이터가 가지고 있는게 ~~M~~A이지 (많아서!)  
컴퓨터가 학습을 잘 못함.  
→ 고려해야 하는 요소가 너무 많다.

data를 학습시킴  
⇒ 패턴을 찾기 위한.  
차원이 높을수록 ↑↑  
패턴을 명확하게 하기 힘들다.

## <해결방법>

- ① feature에 대한 부분을 좀 더 명확
- ② PCA (차원축소 → 의미없는 feature를 뺀다는 것)



빈 공간이 ~~M~~A으면  
모델이 학습하기 어렵다!!

## <우리가 보고싶은 data>



이런 데이터를  
찾아서 빈 공간을  
메꾼다.  
⇒ 원본한 matrix

이제  
데이터의 수를  
늘리기 위해나 (만개 → 20만 개)

# K-Nearest Neighbors: Summary < kNN Summary >

(최근접 이웃 알고리즘)

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**

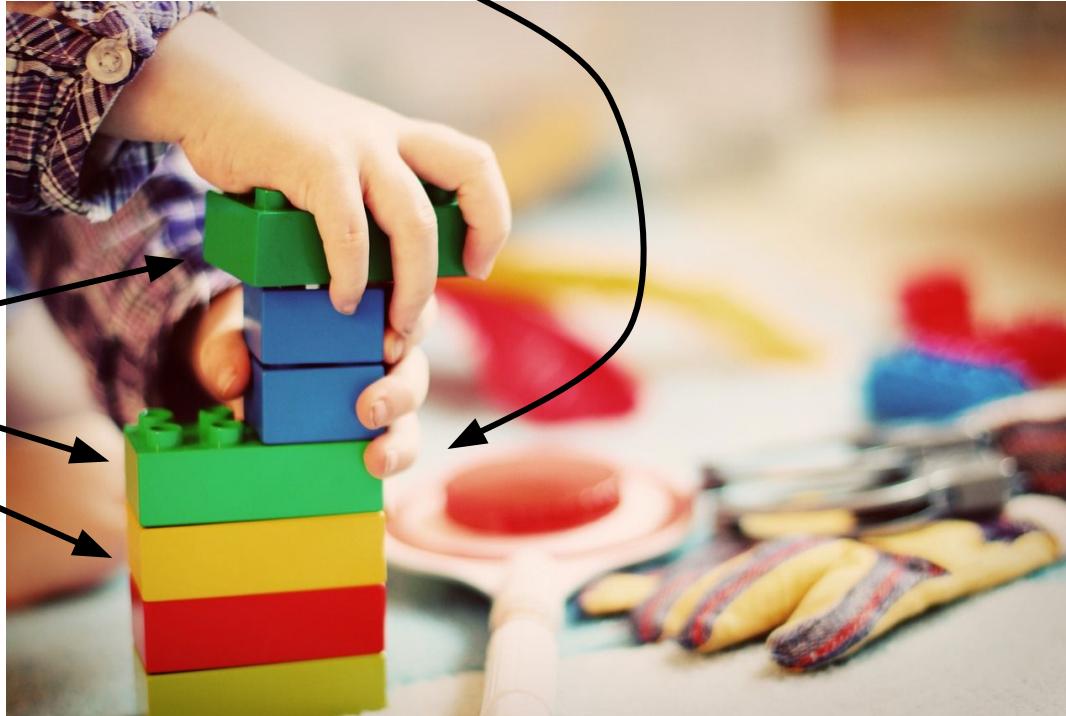
Choose hyperparameters using the **validation set**; only run on the test set once at the very end!

→ **직선**  
→ 선형적인 바탕으로 분류를 해보겠다.

# Linear Classification

# Neural Network

Linear  
classifiers



This image is CC0 1.0 public domain

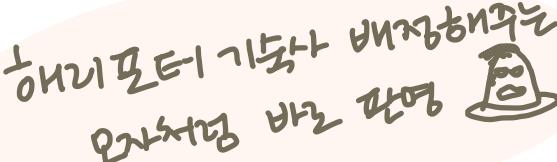
# Parametric Approach

Image



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

딥러닝 기법과 배우는 방법  
오늘처럼 바로 학습

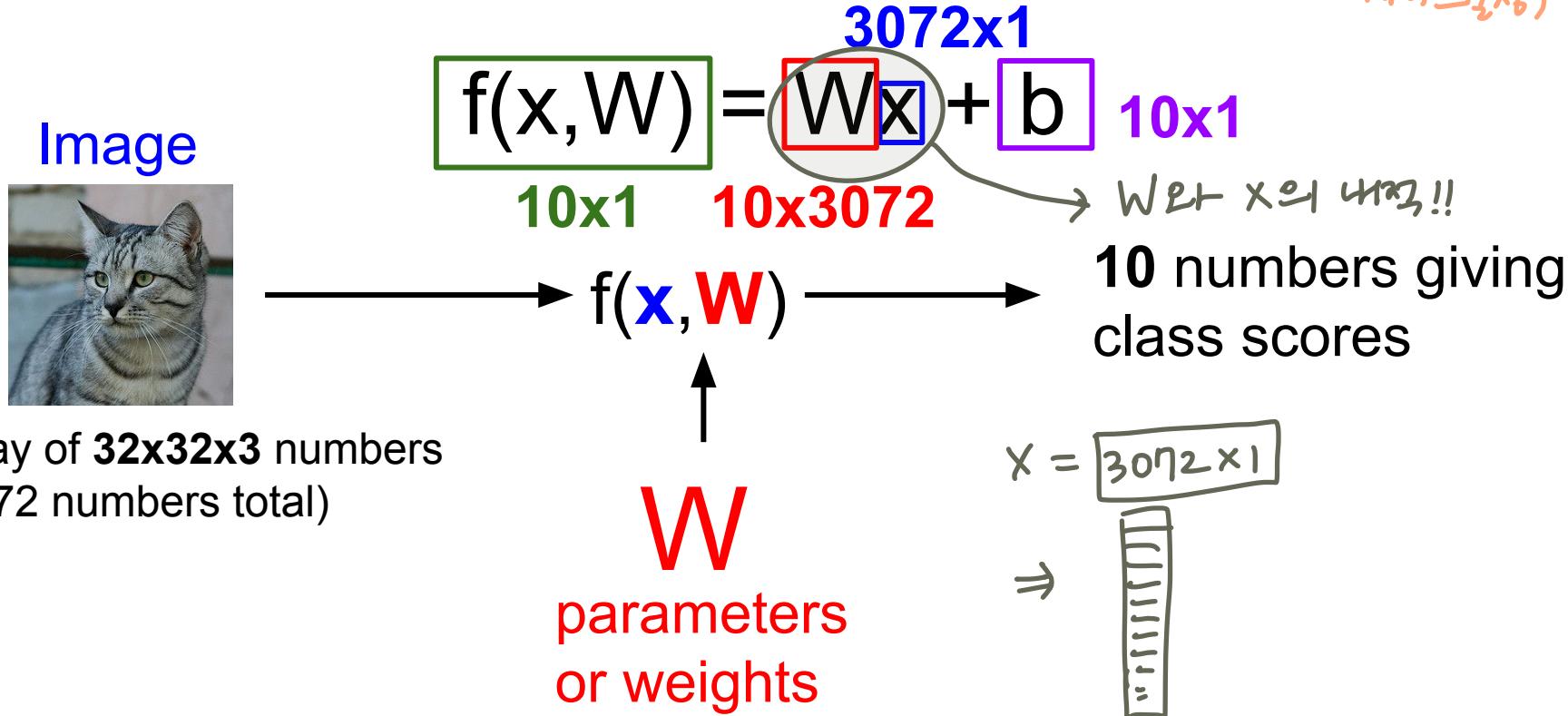


$$\text{Image} \longrightarrow f(\mathbf{x}, \mathbf{W}) \longrightarrow \begin{matrix} \text{10 numbers giving} \\ \text{class scores} \end{matrix}$$

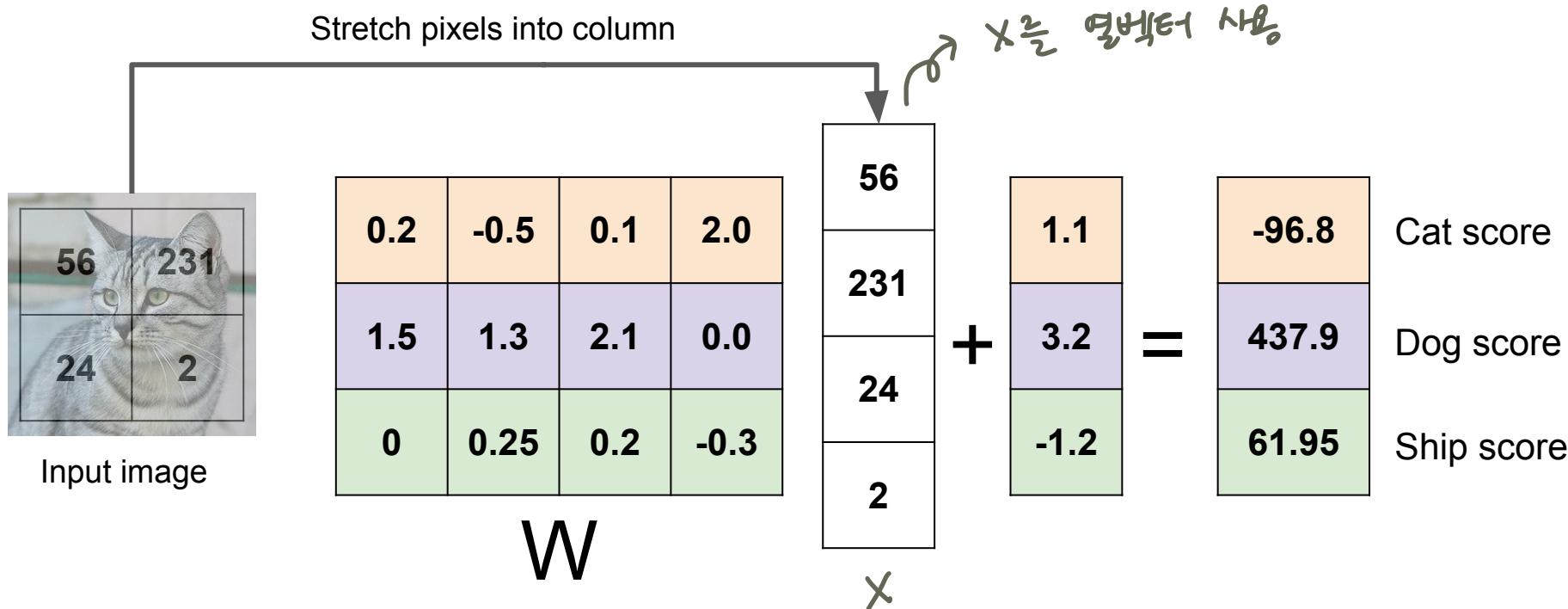
**W** *파라미터 or. 가중치*  
parameters  
or weights

# Parametric Approach: Linear Classifier

(행렬의 연산으로  
사이즈 줄임)



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



# Interpreting a Linear Classifier

airplane



automobile



bird



cat



deer



dog



frog



horse



ship



truck



하나의 품목을 더 높여주는  
부수적인 뿐만 아니라!!

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

Weight 들은  
하나의 가중치로  
만들다!  
~ 하나의 그림판에  
각각의 그림을  
놓여 놔야 하나!!

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

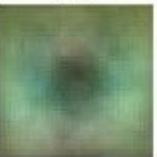
plane



car



bird



cat



deer



dog



frog



horse



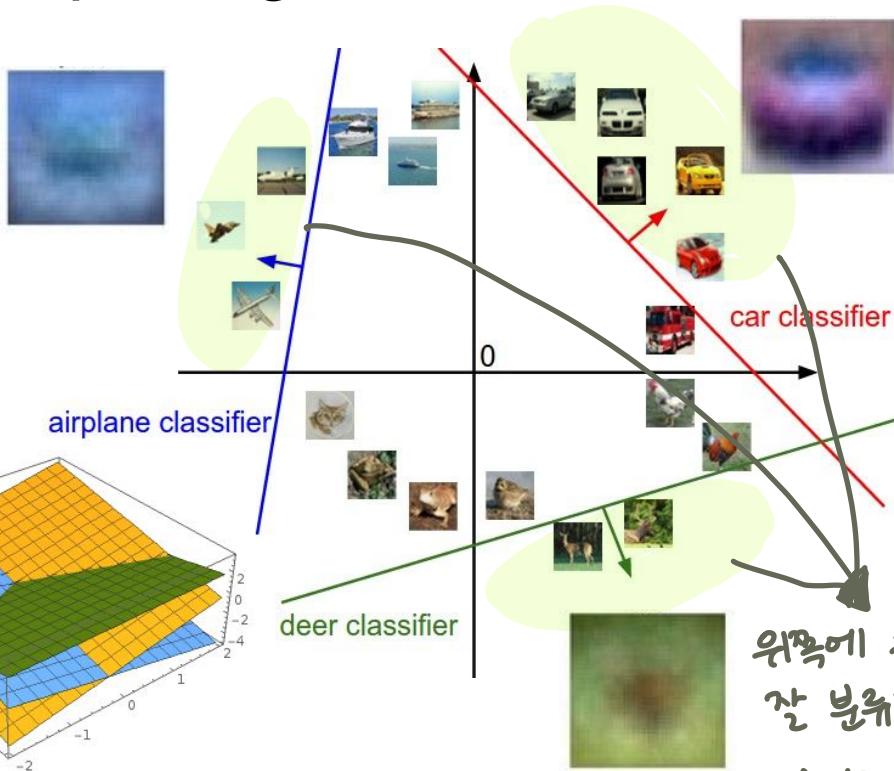
ship



truck



# Interpreting a Linear Classifier



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



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

위쪽에 위치한게  
잘 분류되었나?? (여행 사진 같은)  
⇒ Linear하게 분류가능하다!!

Cat image by Nikita is licensed under CC-BY 2.0

Plot created using [Wolfram Cloud](#)

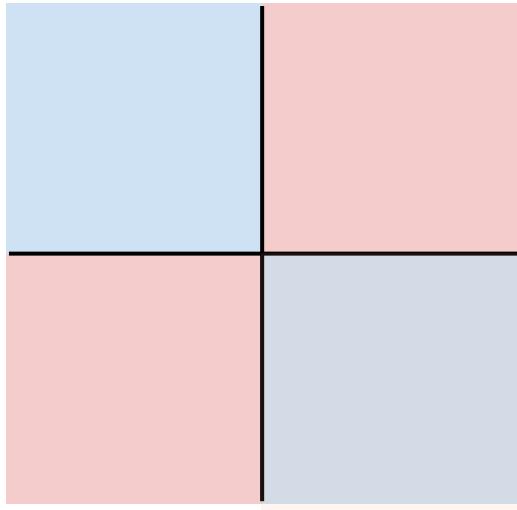
# Hard cases for a linear classifier

**Class 1:**

number of pixels > 0 odd

**Class 2:**

number of pixels > 0 even

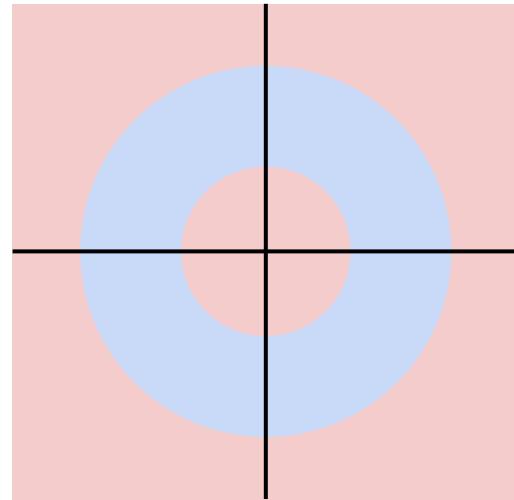


**Class 1:**

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

**Class 2:**

Everything else



**Class 1:**

Three modes

**Class 2:**

Everything else

