



Image Classification: A core task in Computer Vision



This imposity NMA is in served under CC-BY 2.0 (assume given set of discrete labels) {dog, cat, truck, plane, ...}

— cat



Data-Driven Approach

- Collect a dataset of images and labels
- 2. Use Machine Learning to train a classifier
- 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







First classifier: Nearest Neighbor

```
def train(images, labels):
    # Machine learning!
    return model
Memorize all
data and 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



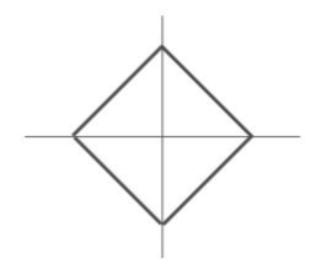




Distance Metric

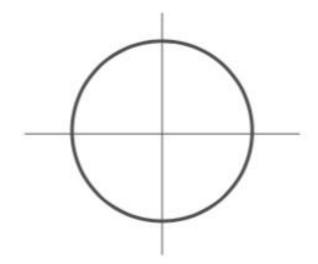
L1 (Manhattan) distance

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



L2 (Euclidean) distance

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





Distance Metric

Distance Metric to compare images

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

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	add → 456
=	12	10	0	30	→ 456
	2	32	22	108	

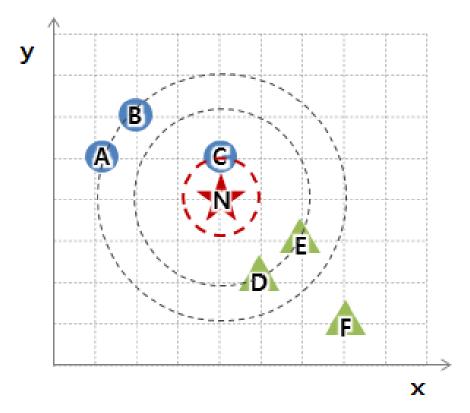






K-Nearest Neighbor은 가까이 있는 k개 데이터로 데이터를 분류하는 알고리즘.

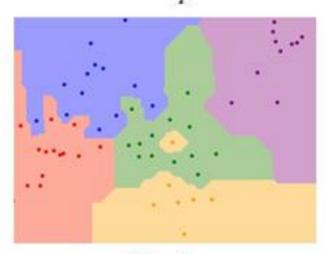
Q. 그림에서 K=1, K=3, K=5일 때, N은 어떤 데이터로 분류되는가?





L1 (Manhattan) distance

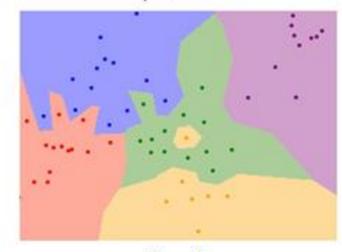
$$d_1(I_1,I_2) = \sum_p |I_1^p - I_2^p|$$



K = 1

L2 (Euclidean) distance

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



K = 1

Distance를 구하는 방법에 따라 K-NN의 결과가 달라질 수 있음.

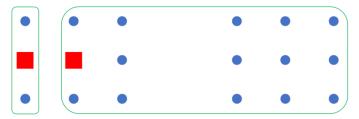




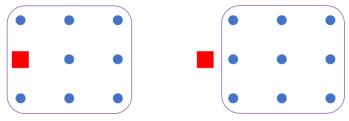


(추가) K-Means Clustering

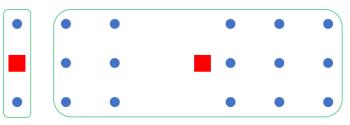
EM 알고리즘 기반으로 작동 (Expectation 스텝 & Maximization 스텝) – K는 중심의 개수



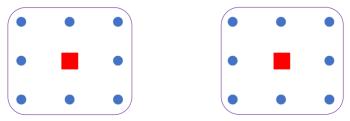
[1] 모든 파란 점을 가까운 중심에 Clustering (Expectation 스텝)



[3] 모든 파란 점을 가까운 중심에 Clustering (Expectation 스텝)



[2] 중심을 Cluster(군집)에 맞게 업데이트 (Maximization 스텝)



[4] 이 과정을 중심의 위치가 수렴할 때까지 반복









유사하게 보이는 사진끼리 Distance가 가까움!! Image Classification은 제대로 되지 않고 있는 모습!!!





Hyperparameter

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.

Hyperparameter란 학습을 할 때에 더 효과가 좋도록 하는 주 변수가 아닌 자동 설정되는 변수를 의미한다. (학습자가 직접 설정해주는 변수!!!)
(Ex. Learning rate, batch size, epoch, hidden layer의 개수 등)





Hyperparameter

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

Train / Test 비율은 일반적으로 70/30 데이터가 많은 경우에는 90/10으로 사용

새로운 방법 참고 : <u>https://www.youtube.com/watch?v=AK60jzjDvlg&t=42</u>



Hyperparameter

Setting Hyperparameters

Your Dataset

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





KNN이 사용되지 않는 이유

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)







KNN이 사용되지 않는 이유

k-Nearest Neighbor on images never used.

- Curse of dimensionality

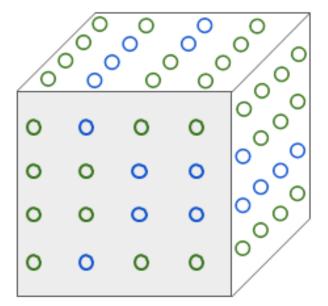


Points = 4

Dimensions = 2Points = 4^2

0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

Dimensions = 3Points = 4^3







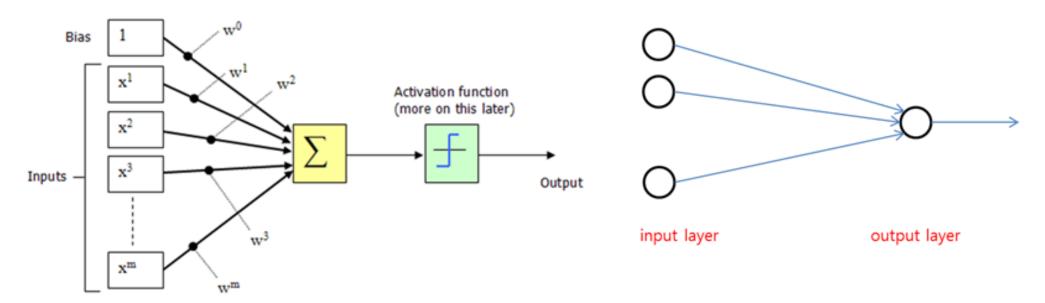
Linear Classifier의 쉬운 예시

$$d(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b > 0$$
 이면 $\rightarrow \mathbf{x} \in \omega_1$
 $d(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b < 0$ 이면 $\rightarrow \mathbf{x} \in \omega_2$

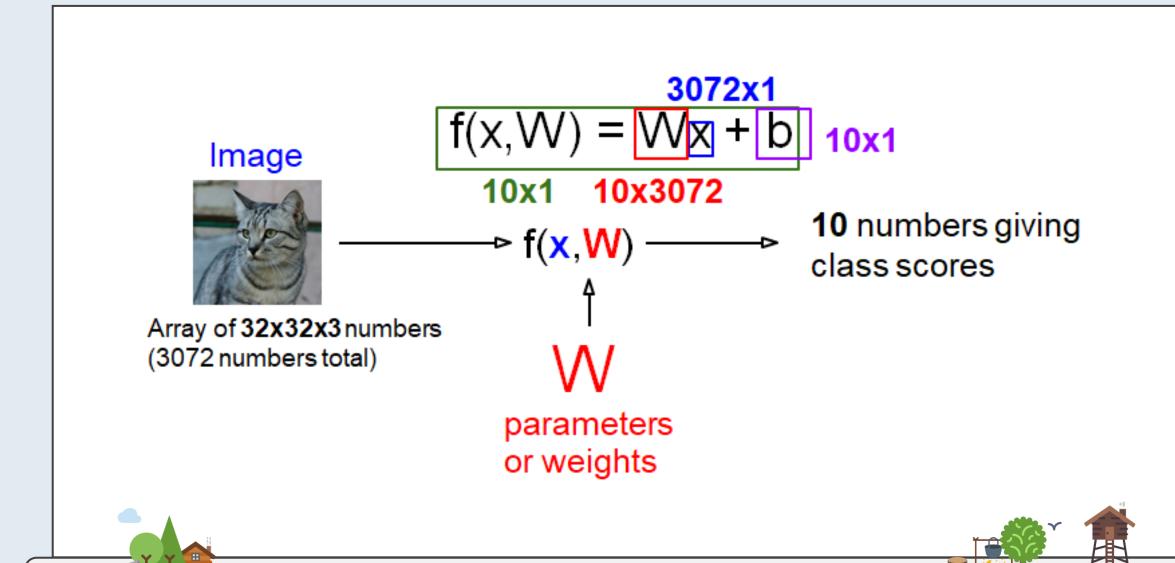
$$d(\mathbf{x}) = x_1 + x_2 - 0.5 \stackrel{>}{<} 0$$



Linear Classification은 Neural Network에 사용된다. (Activation Function에 대해서는 이후 강의에 나오지만, Logistic Regression은 먼저 공부해보는 것을 추천)



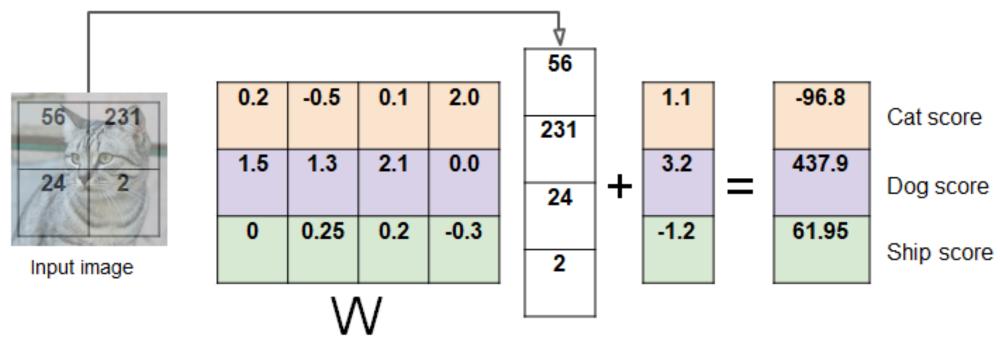




BOAZ

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

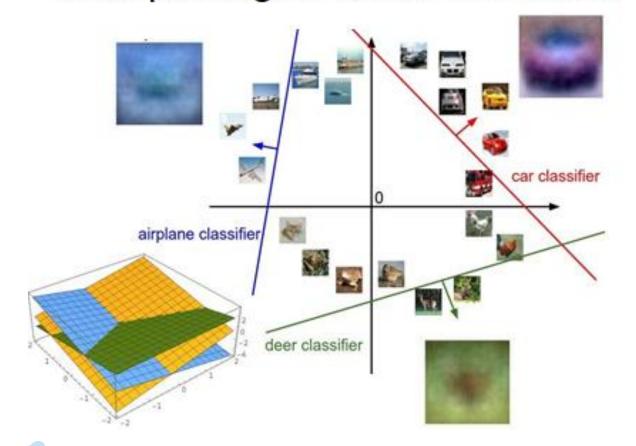








Interpreting a Linear Classifier



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



Array of 32x32x3 numbers (3072 numbers total)





Hard cases for a linear classifier

Class 1:

number of pixels > 0 odd

Class 2:

number of pixels > 0 even

Class 1:

1 <= L2 norm <= 2

Class 2: Every

thing else

Class 1: Thr ee modes

Class 2: Every thing 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	6.04	4.64
bird	0.09	5.31	2.65
cat	2.9	-4.22	5.1
deer	4.48	-4.19	2.64
dog	8.02	3.58	5.55
frog	3.78	4.49	-4.34
horse	1.06	-4.37	-1.5
ship	-0.36	-2.09	-4.79
truck	-0.72	-2.93	6.14





CS231n: http://cs231n.stanford.edu/syllabus.html

K-NN 참고: http://kkokkilkon.tistory.com/14

Ratsgo's Blog: https://ratsgo.github.io/machine%20learning/2017/04/19/KC/

Linear Classifier 참고: http://www.whydsp.org/237



