CS688: Web-Scale Image Retrieval

Linear Classification

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(윤성의)

Course URL:
http://sglab.kaist.ac.kr/~sungeui/IR

KAIST

Class Objectives

- Introduction to image classification
  - Nearest neighbor search
  - Representation (features)
  - Linear classifier
- Recently performed within deep neural net with an end-to-end optimization

Image Classification: A core task in Computer Vision

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

cat

Detection:

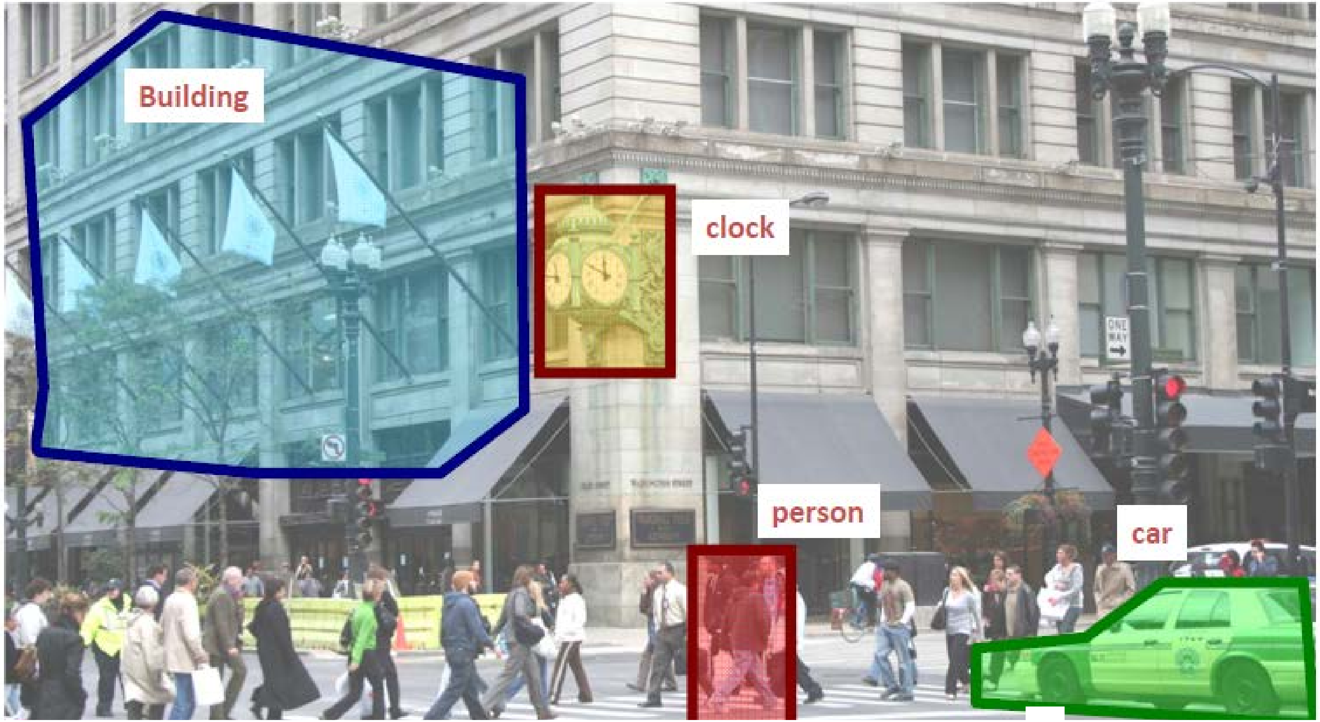
Does this image contain a car? [where?]

Detection:

Does this image contain a car? [where?]

Detection:

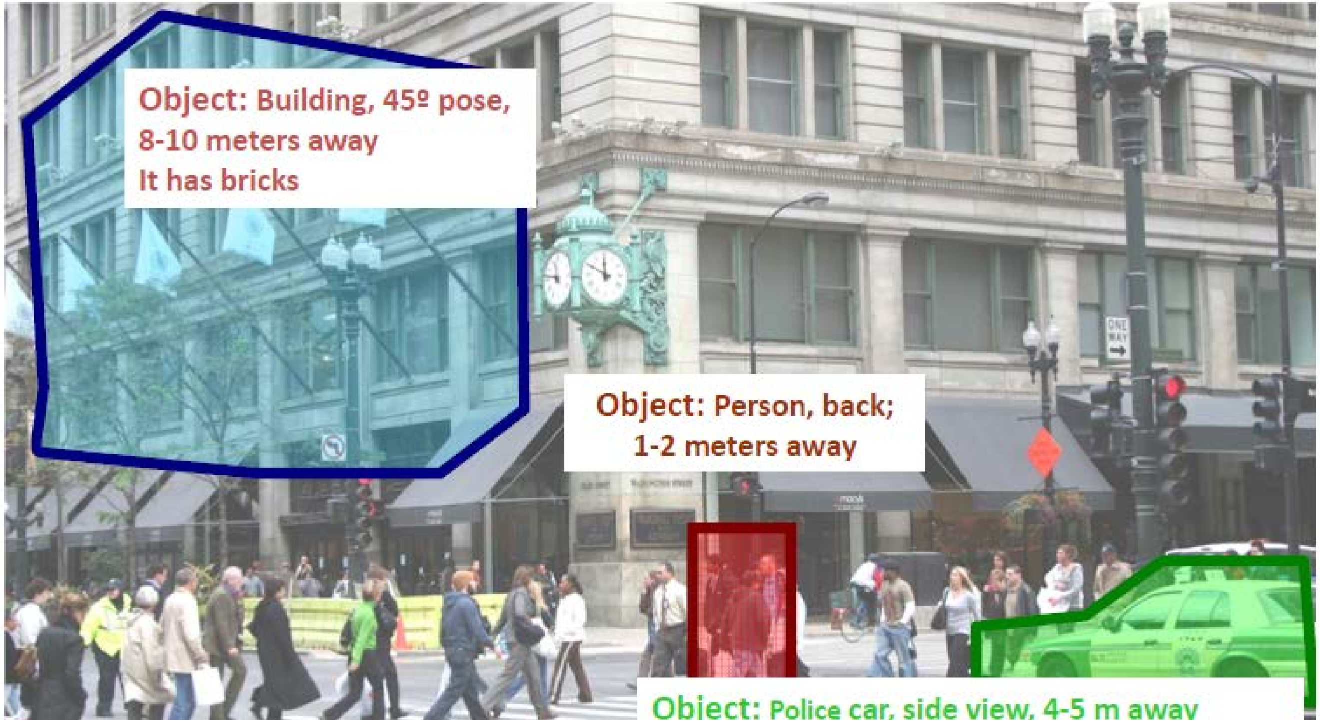
Which object does this image contain? [where?]



Detection:

Accurate localization (segmentation)

Detection: Estimating object semantic & geometric attributes



Categorization vs Single instance recognition

Does this image contain the Chicago Macy building's?

Categorization vs Single instance recognition

Where is the crunchy nut?

Activity or Event recognition

What are these people doing?

Applications of Object Recognitions and Image Retrieval

Computational photography

Assistive technologies

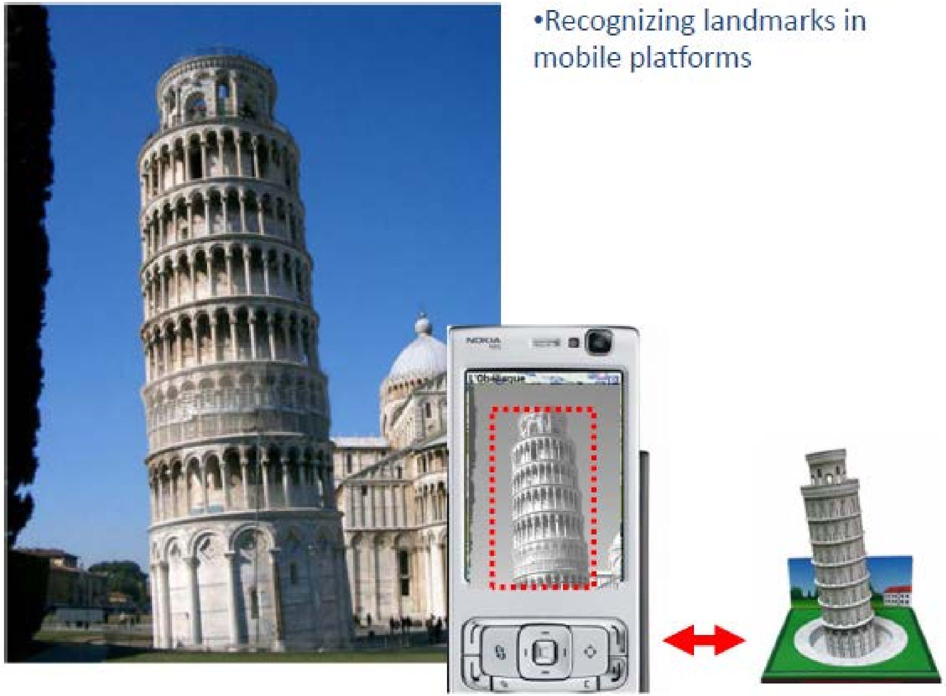
Surveillance

Security

Assistive driving

Applications of Object Recognitions and Image Retrieval

•Recognizing landmarks in mobile platforms



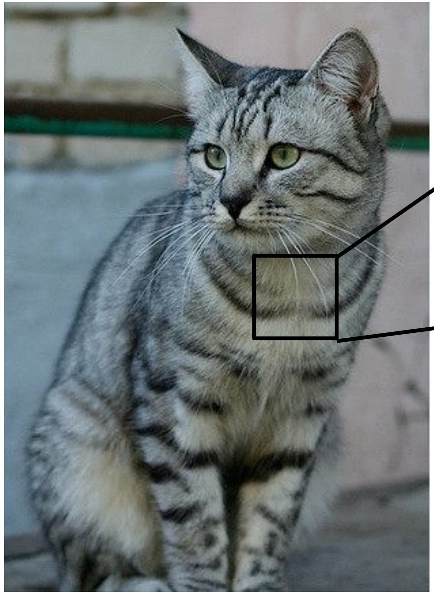
+ GPS

Visual Recognition

- Design algorithms that are capable to
  - Classify images or videos
  - Detect and localize objects
  - Estimate semantic and geometrical attributes
  - Classify human activities and events

Why is this challenging?

The Problem: Semantic Gap




```
[[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  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]
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 [122 121 102  80  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]]
```
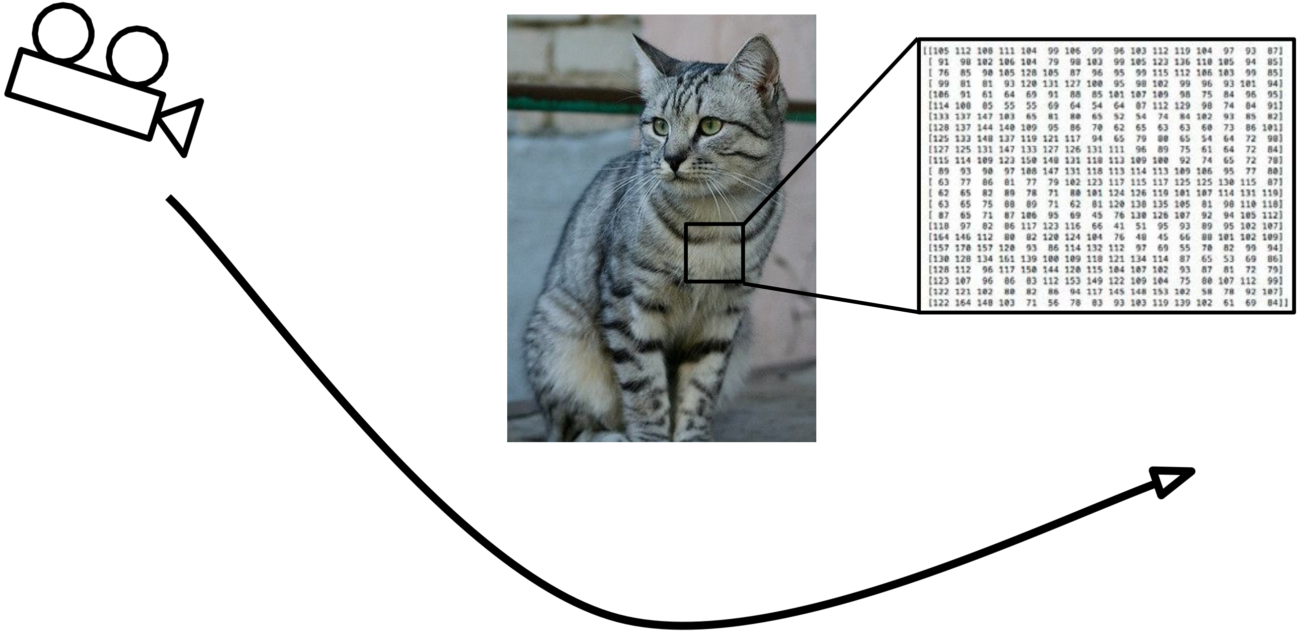

What the computer sees

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

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

Challenges: Viewpoint variation



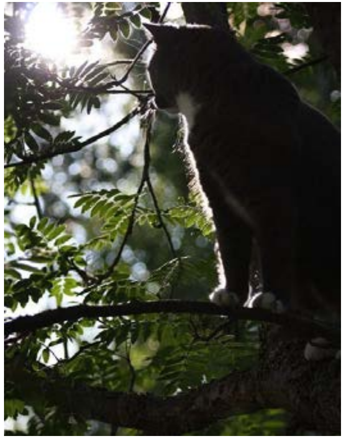
All pixels change when
the camera moves!

Challenges: Illumination

This image is CC0 1.0 public domain

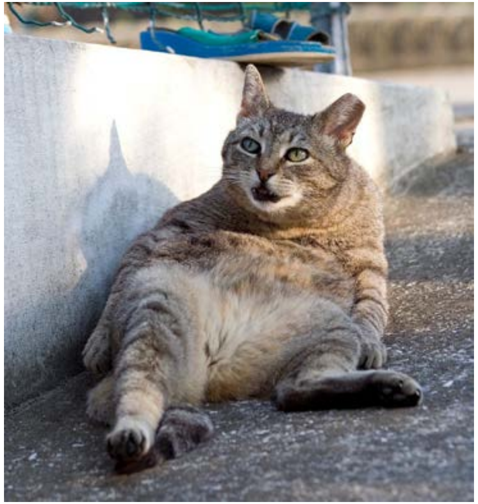
This image is CC0 1.0 public domain

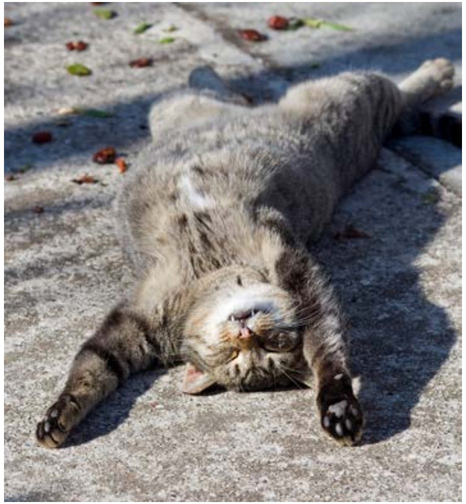
This image is CC0 1.0 public domain

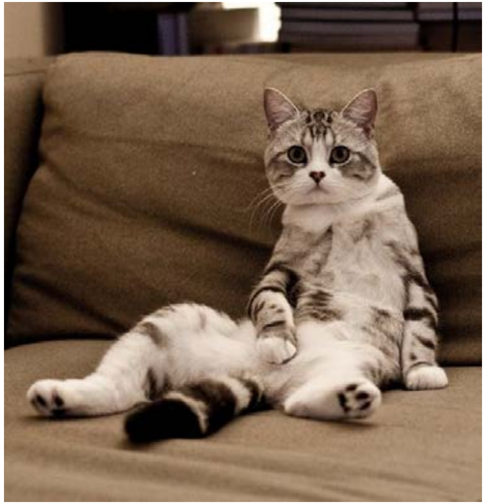


This image is CC0 1.0 public domain

Challenges: Deformation







Challenges: Occlusion

This image is CC0 1.0 public domain

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Challenges: Background Clutter

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

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

Challenges: Intraclass variation

This image is CC0 1.0 public domain

Many Object Types

ImageNet Large Scale Visual Recognition Challenge [IJCV 15]

- **Contains 14 M images as 2014**
- **Based on Wordnet**
  - **21k synonym set, synset**
  - **Each synset is populated about 650 images**

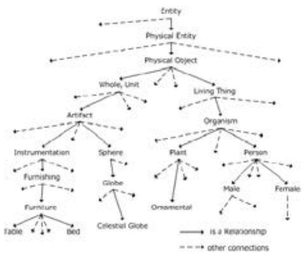
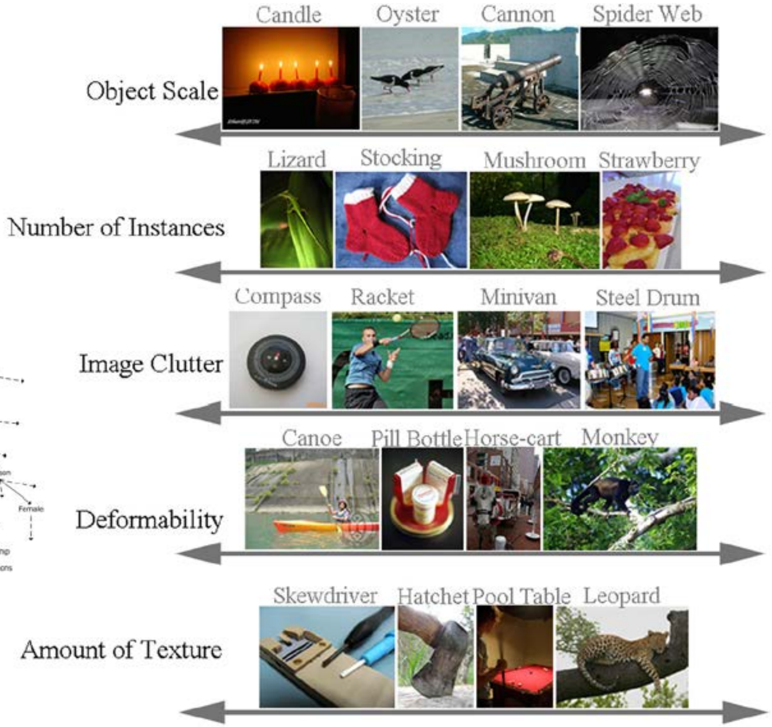


Fig. 2. An example of WordNet nouns taxonomy

- **Annotations**
  - **Image-level: its class**
  - **Object-level: bounding box w/ label**



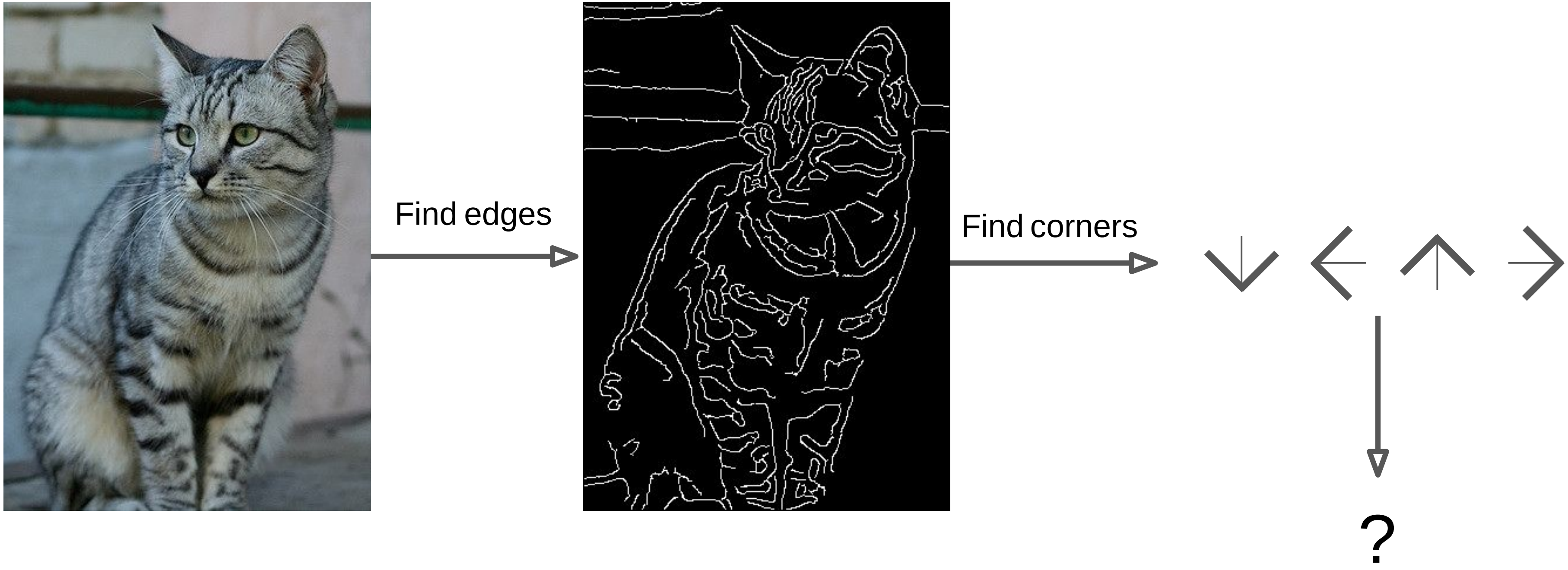
An image classifier

```
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

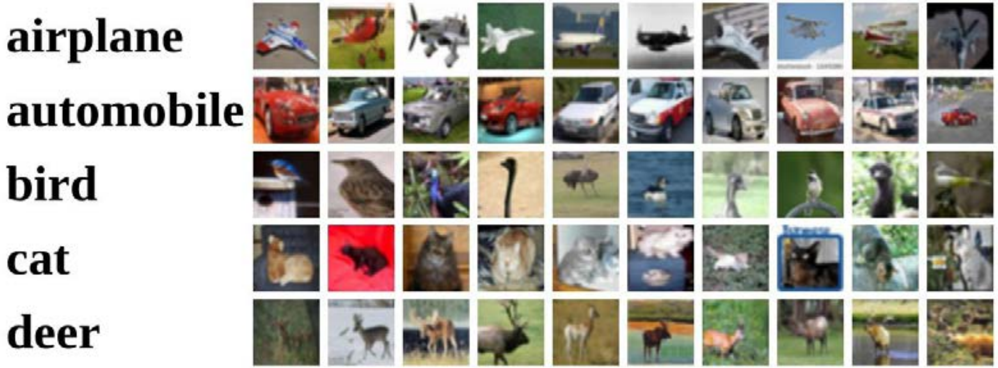
Machine Learning: Data-Driven Approach

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
```

Example training set



First classifier: **Nearest Neighbor**

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

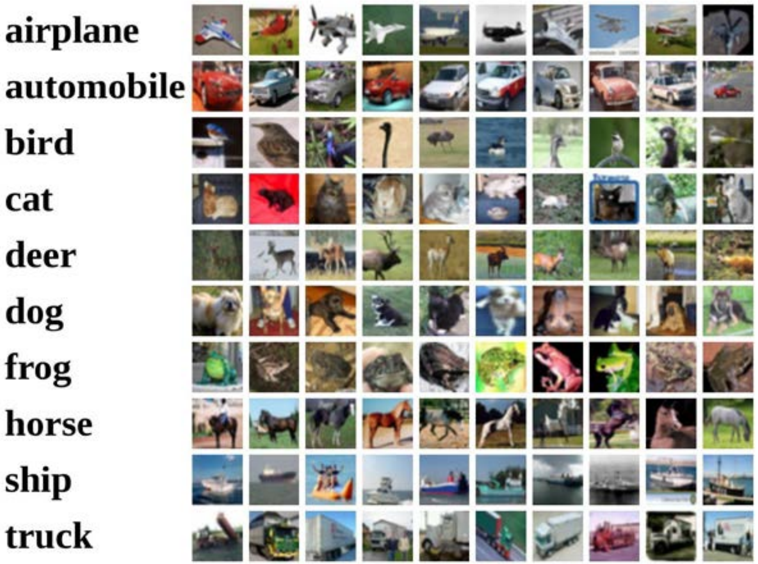
Memorize all data and labels

```
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

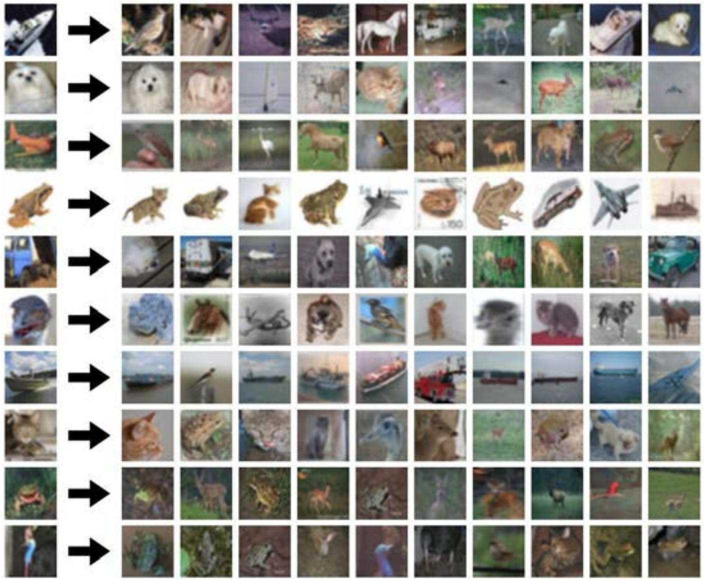


Alex Krizhevsky, "Learning Multiple Layers of Features from Tiny Images", Technical Report, 2009.

Example Dataset: **CIFAR10**

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

Test images and nearest neighbors



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

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
12	10	0	30
2	32	22	108

$\xrightarrow{\text{add}}$ 456

K-Nearest Neighbors Classifier

For each test image:

Find closest train image

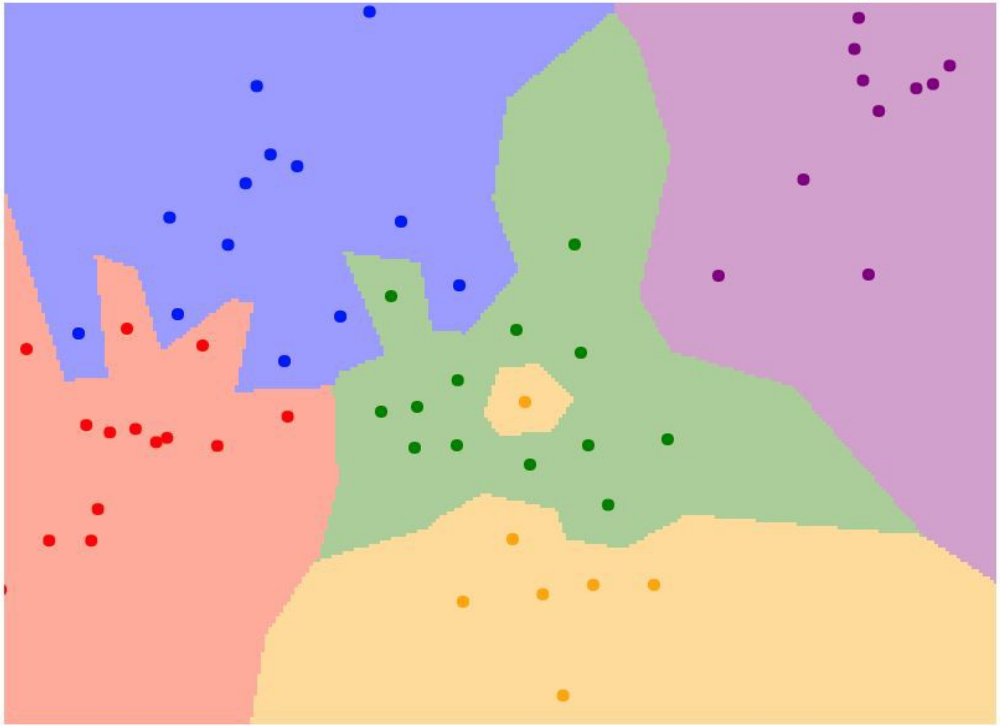
Predict label of nearest image

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

A: Naïve approach: Train O(1), predict O(N)

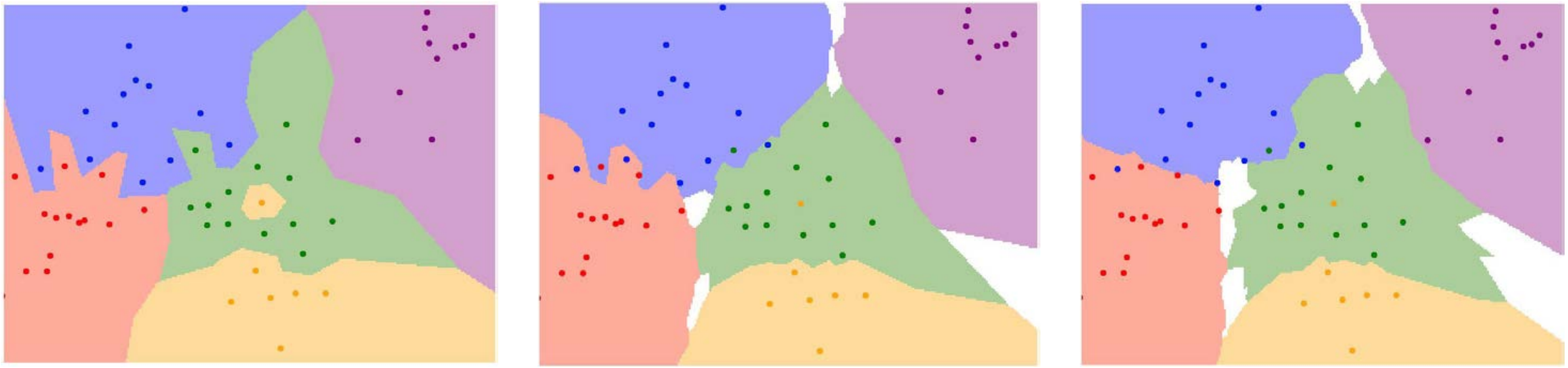
This is bad: we want classifiers that are fast at prediction; slow for training is ok

What does this look like?



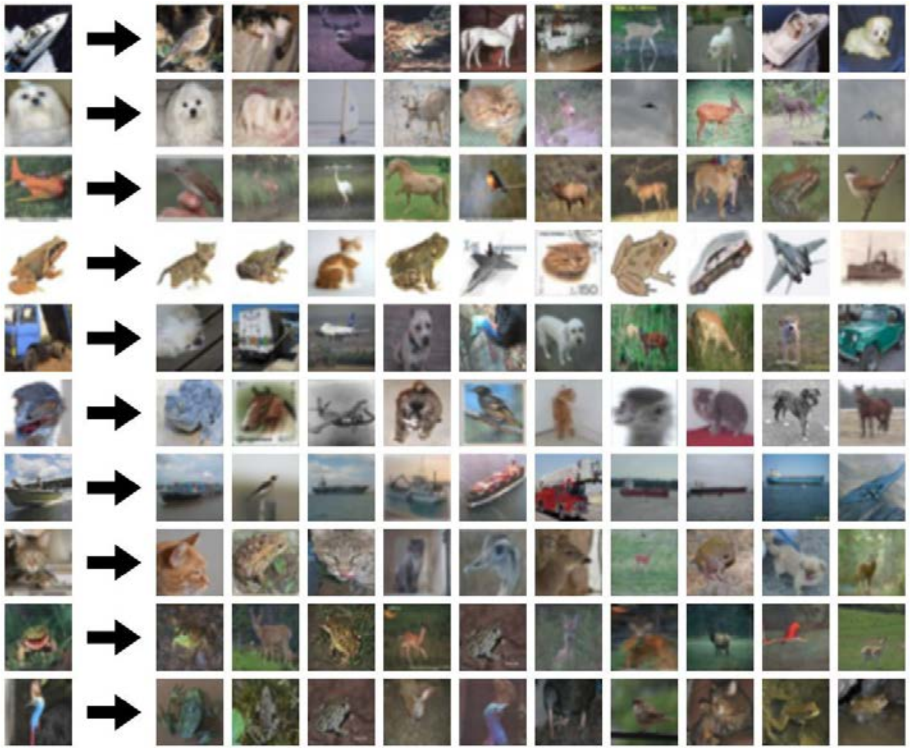
K-Nearest Neighbors

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



K = 1　　　K = 3　　　K = 5

What does this look like?

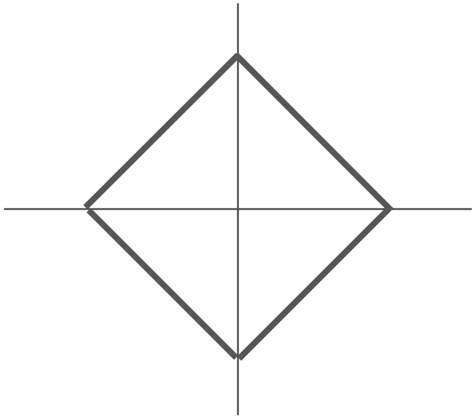


What does this look like?

K-Nearest Neighbors: Distance Metric

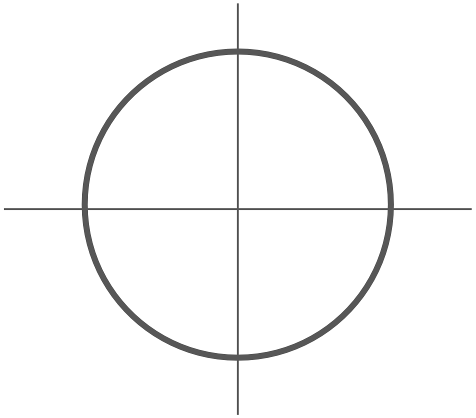
L1 (Manhattan) distance

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



L2 (Euclidean) distance

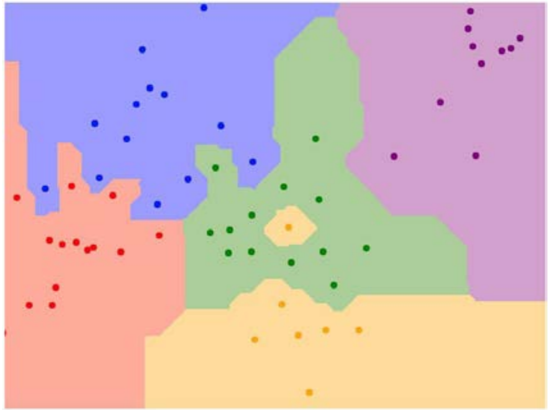
$$d_2(I_1, I_2) = \sqrt{\sum_p \left(I_1^p - I_2^p \right)^2}$$



K-Nearest Neighbors: Distance Metric

L1 (Manhattan) distance

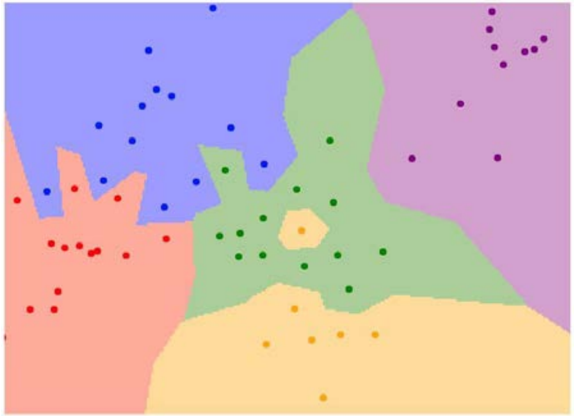
$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$



K = 1

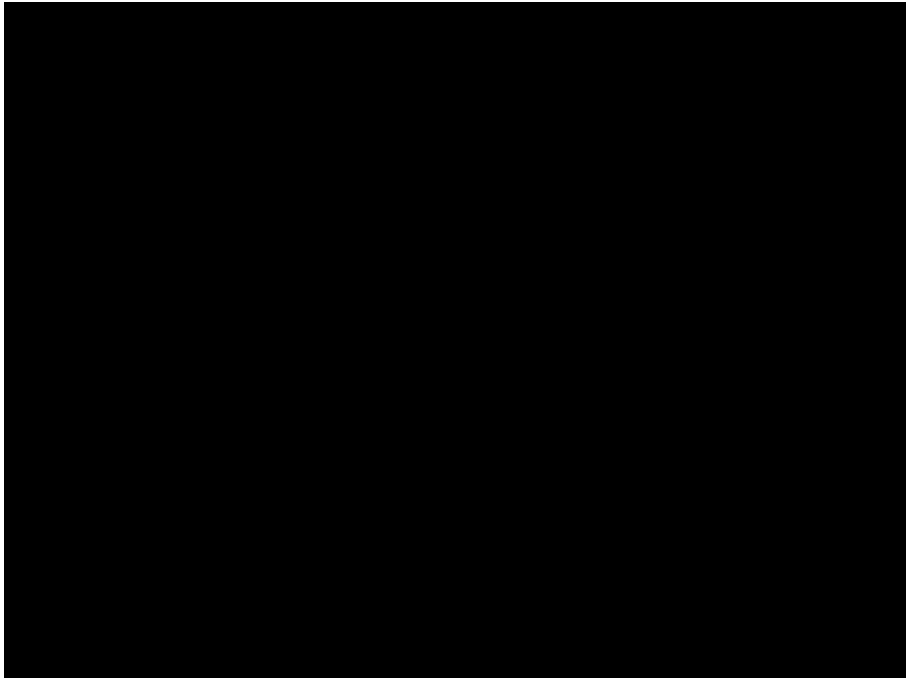
L2 (Euclidean) distance

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



K = 1

K-Nearest Neighbors: Demo Time



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.

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

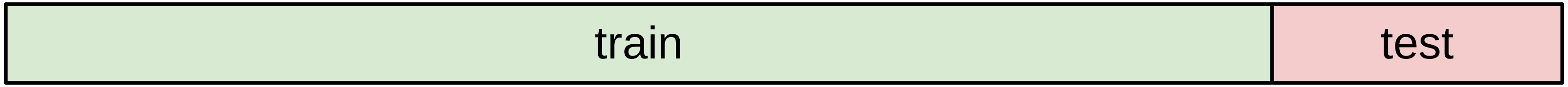
Your Dataset

Setting Hyperparameters

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

BAD: K = 1 always works perfectly on training data

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



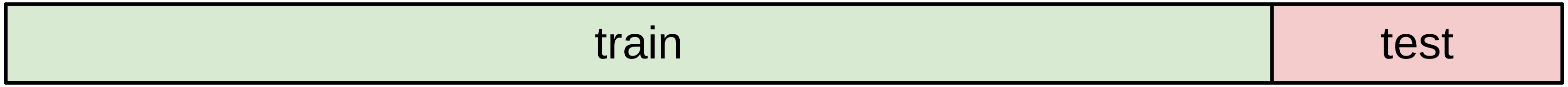
Setting Hyperparameters

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

BAD: K = 1 always works perfectly on training data

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



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

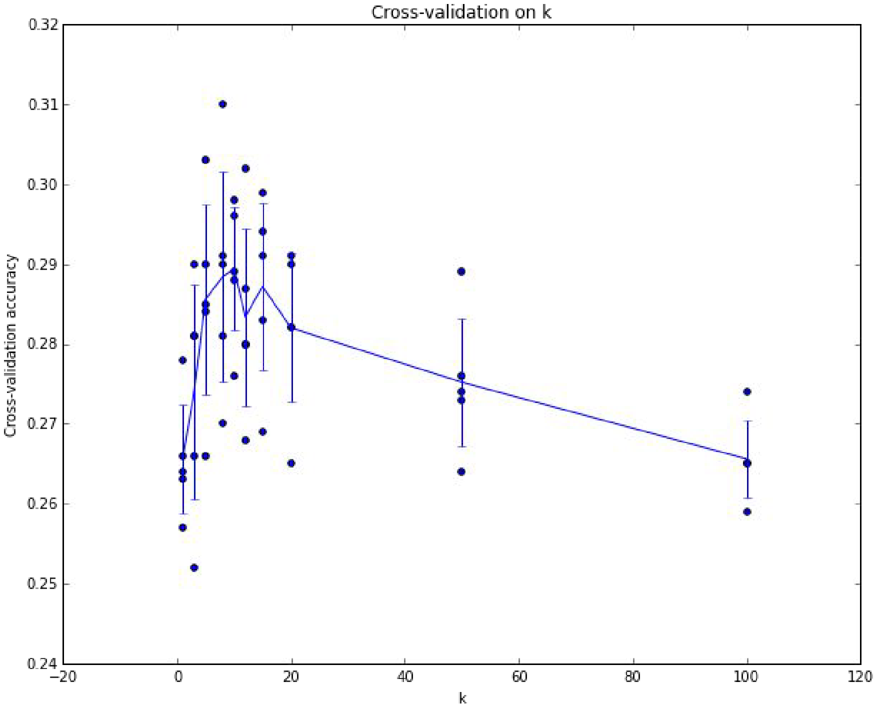
Your Dataset

Idea #4: **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 ~= 7 works best
for this data)

k-Nearest Neighbor on images **are not frequently used.**

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

Original

Boxed

Shifted

Tinted

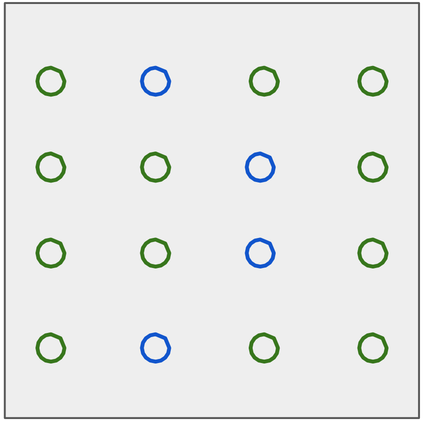
(all 3 images have same L2 distance to the one on the left)

k-Nearest Neighbor on images **are not frequently used.**

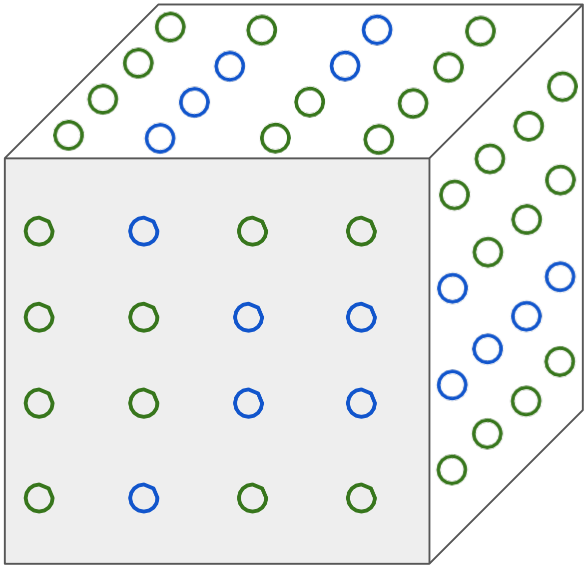
- Curse of dimensionality

Dimensions = 1
Points = 4

Dimensions = 2
Points = 4^2



Dimensions = 3
Points = 4^3

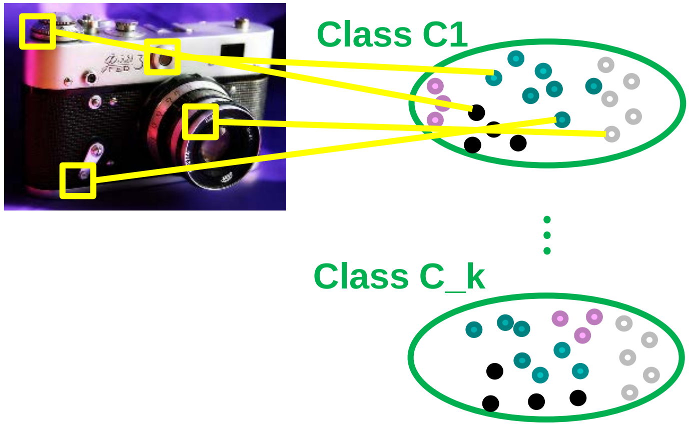


Classification through Image Search

- Image search
  - Find images that have smaller distances to the query
  - Handle lots of data even without any labels
- Classification
  - Fine classes that have smaller distances to the query
  - Utilize labels
- Classification using image search
  - Naïve Bayes Nearest Neighbor (NBNN)
  - Image classification and Retrieval are ONE

Naïve Bayes Nearest Neighbor (NBNN) Classifier [CVPR 08]

- **Extract and collect features for each category**

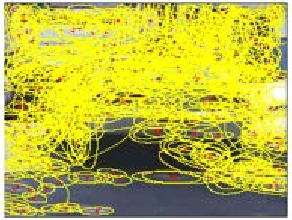


At runt time:

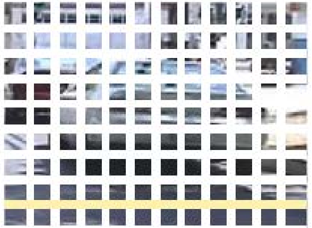
- **Extract features for a query image**
- **Measure their distances from all the categories**
- **Pick the category w/ the lowest distance**

Representation

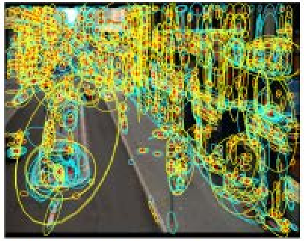
- **Building blocks: sampling strategy**



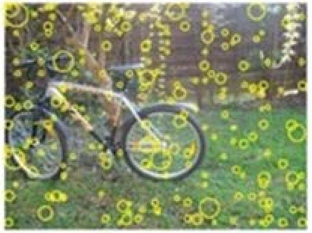
Interest operators



Dense, uniformly



Multiple interest operators



Randomly

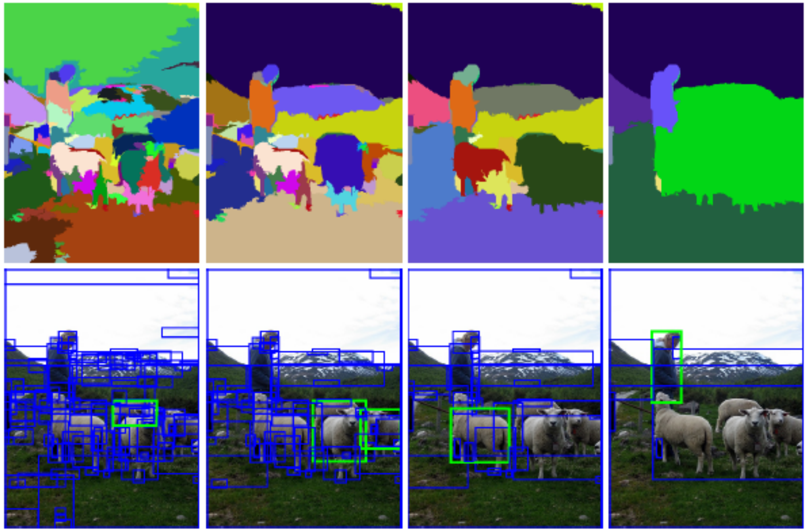
Image credits: L. Fei-Fei, E. Nowak, J. Sivic

- **Recently, features from convolution neural nets**

KAIST

Region Proposals

- Adopted commonly by many recognition approaches

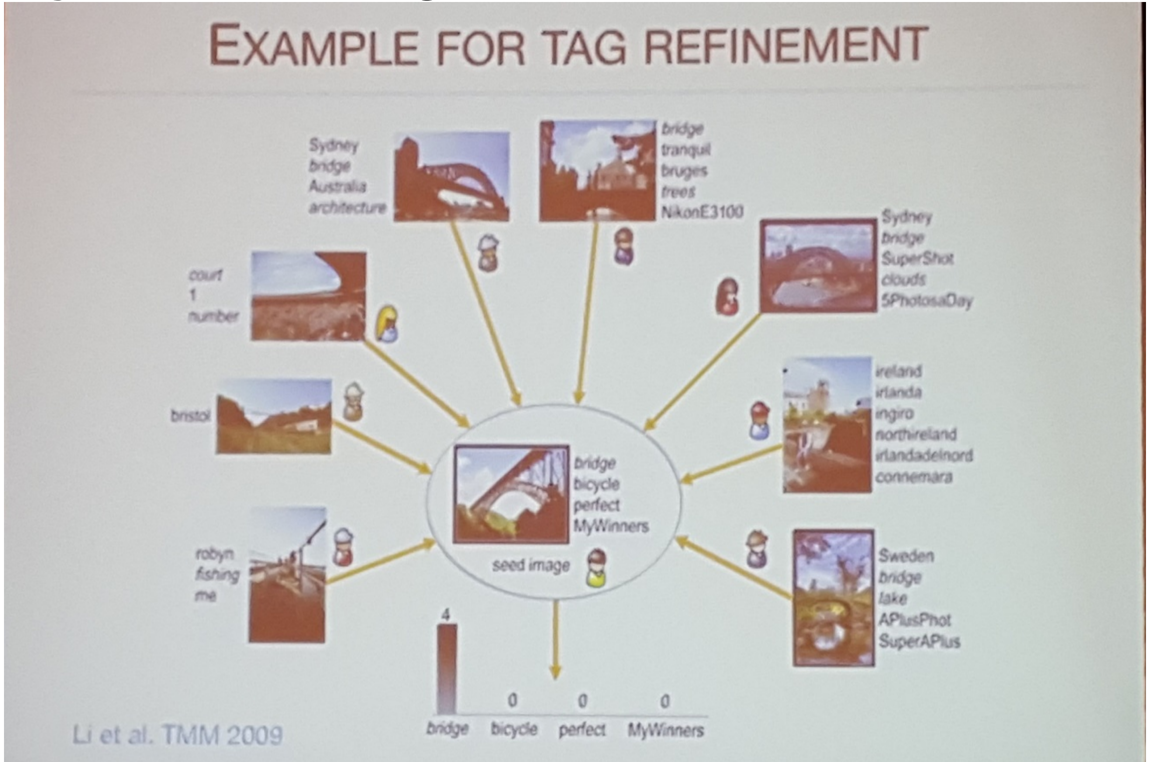


Identify different regions as candidates of objects

Selective Search, Uijlings et al.

KNN for Tag Transfer

- **Identify similar images and transfer their tags**



Captured at CVPR 16

Hashing techniques

- Fast in high-dimensional problems
  - E.g., Locality sensitive hashing
- Used for binary code embedding to compute compact representation
  - Will be discussed later

Semantic-Aware Retrieval

- **Many image search methods are unsupervised**
  - **Caused by large diversity and quantity of visual data**
- **(Weakly or semi-)supervised learning have to be adopted widely**
  - **Under rapid progress mainly on supervised learning thanks to recent deep learning**
  - **Spherical hashing is unsupervised, but there are also many supervised techniques**

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!

Linear Classification

Neural Network

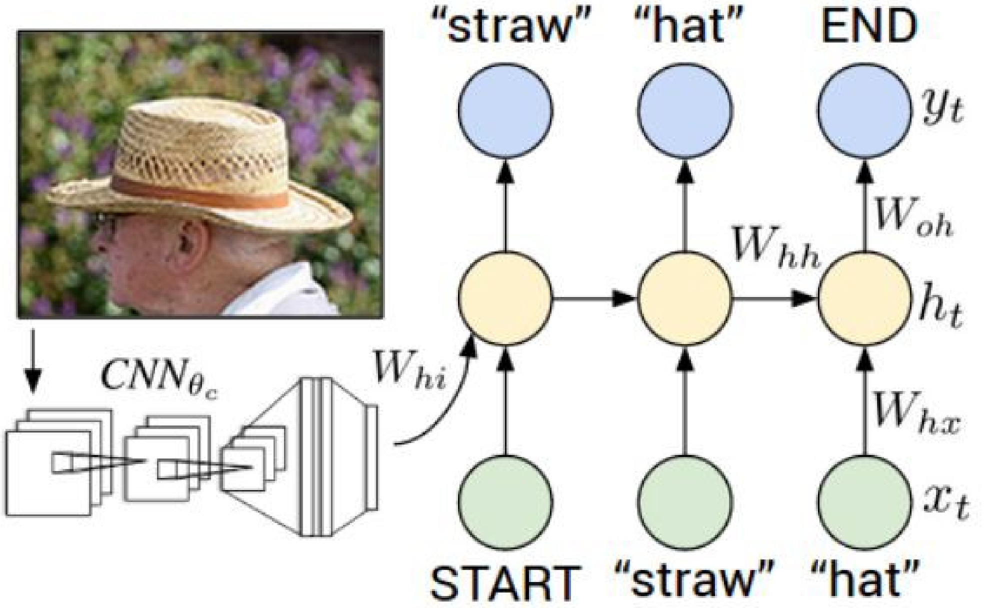
Linear classifiers

Two young girls are playing with lego toy.

Boy is doing backflip on wakeboard

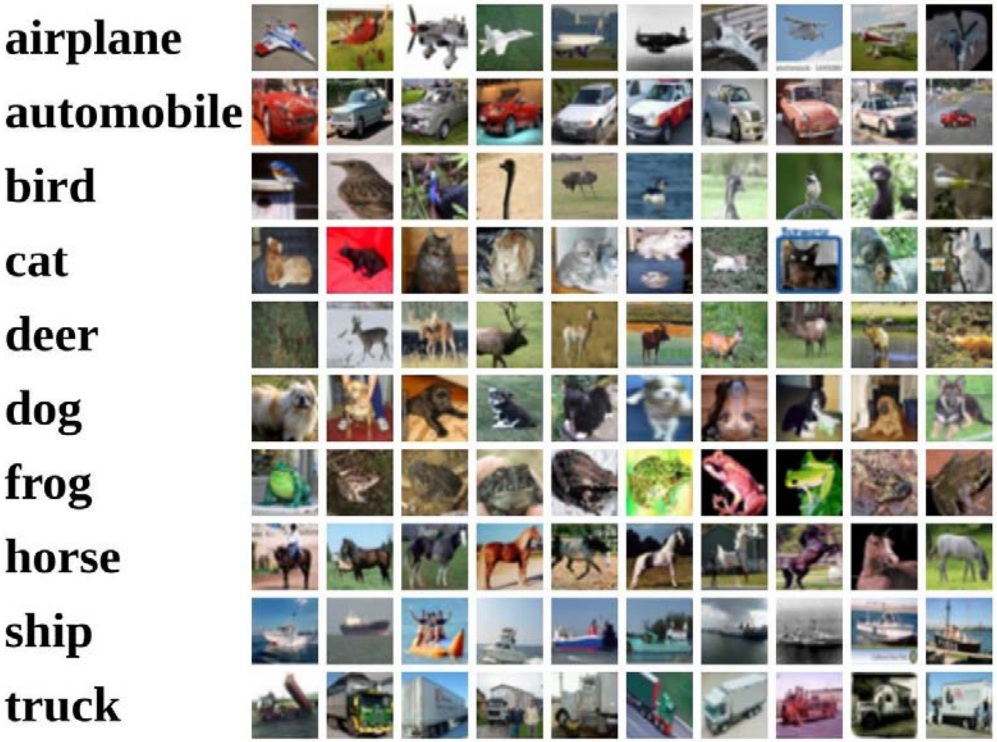
Man in black shirt is playing guitar.

Construction worker in orange safety vest is working on road.



Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

Recall CIFAR10



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

10,000 test images.

Parametric Approach

Image

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

f(**x**,**W**)

W

parameters
or weights

10 numbers giving
class scores

Parametric Approach: Linear Classifier

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

Image

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

$f(\mathbf{x},\mathbf{W})$

10 numbers giving
class scores

W

parameters
or weights

Parametric Approach: Linear Classifier

3072x1

$$f(x,W) = \boxed{W}\boxed{x}$$

10x1 10x3072

Image

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

$f(\mathbf{x},\mathbf{W})$

10 numbers giving
class scores

W

parameters
or weights

Parametric Approach: Linear Classifier

3072x1

$$\underbrace{f(x,W) = \underbrace{\boxed{W}}_{10\text{x}3072}\,\overbrace{\boxed{x}}^{3072\text{x}1} + \underbrace{\boxed{b}}_{10\text{x}1}}_{10\text{x}1}$$

10x1

10x1 10x3072

Image

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

$\longrightarrow f(\mathbf{x},\mathbf{W}) \longrightarrow$ **10** numbers giving class scores

W

parameters
or weights

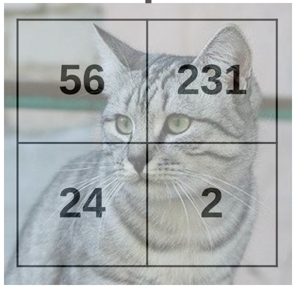
Example with an image with 4 pixels, and 3 classes (cat/dog/ship)

Stretch pixels into column

Input image

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

Stretch pixels into column



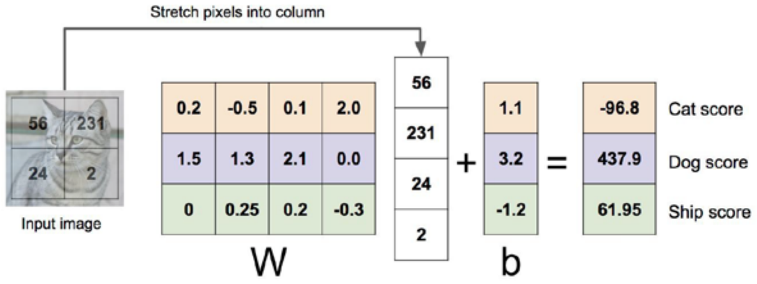
Input image

$$\underbrace{\begin{bmatrix} 0.2 & -0.5 & 0.1 & 2.0 \\ 1.5 & 1.3 & 2.1 & 0.0 \\ 0 & 0.25 & 0.2 & -0.3 \end{bmatrix}}_{W} \begin{bmatrix} 56 \\ 231 \\ 24 \\ 2 \end{bmatrix} + \underbrace{\begin{bmatrix} 1.1 \\ 3.2 \\ -1.2 \end{bmatrix}}_{b} = \begin{bmatrix} -96.8 \\ 437.9 \\ 61.95 \end{bmatrix} \begin{array}{l} \text{Cat score} \\ \text{Dog score} \\ \text{Ship score} \end{array}$$

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

Algebraic Viewpoint

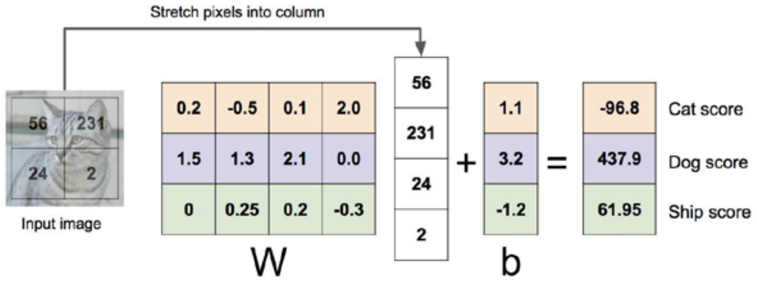
$$f(x,W) = Wx$$

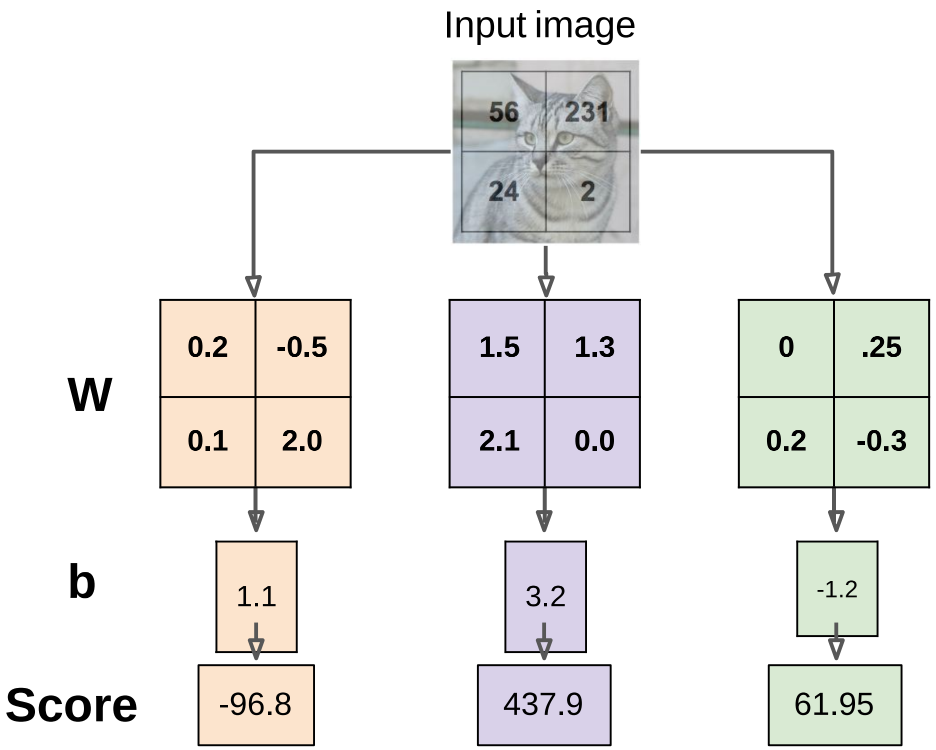


Example with an image with 4 pixels, and 3 classes (cat/dog/ship)

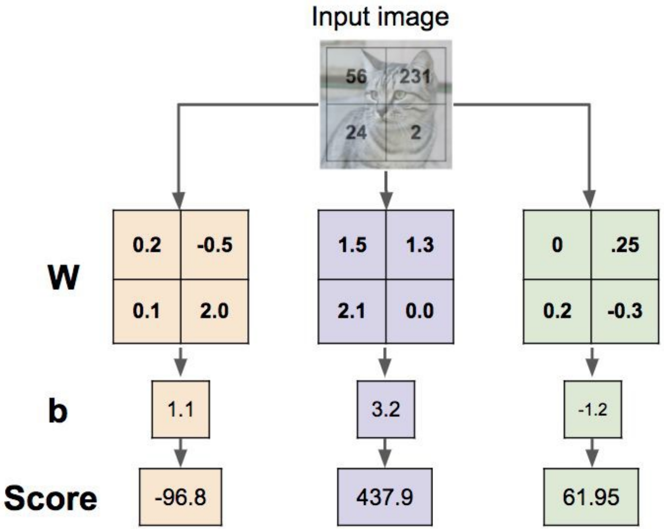
Algebraic Viewpoint

f(x,W) = Wx

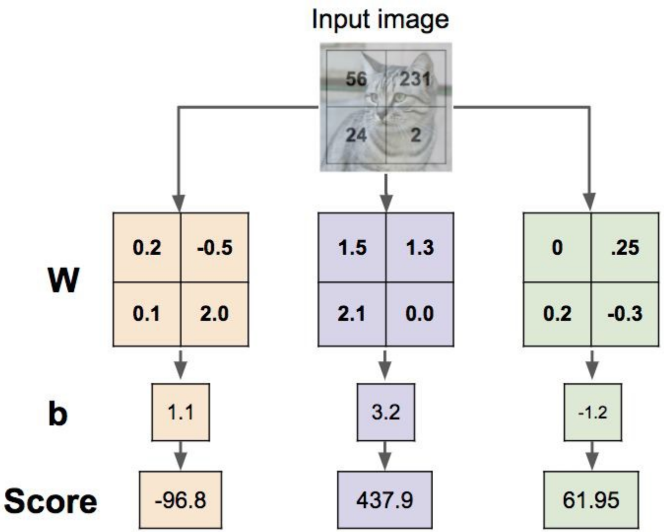




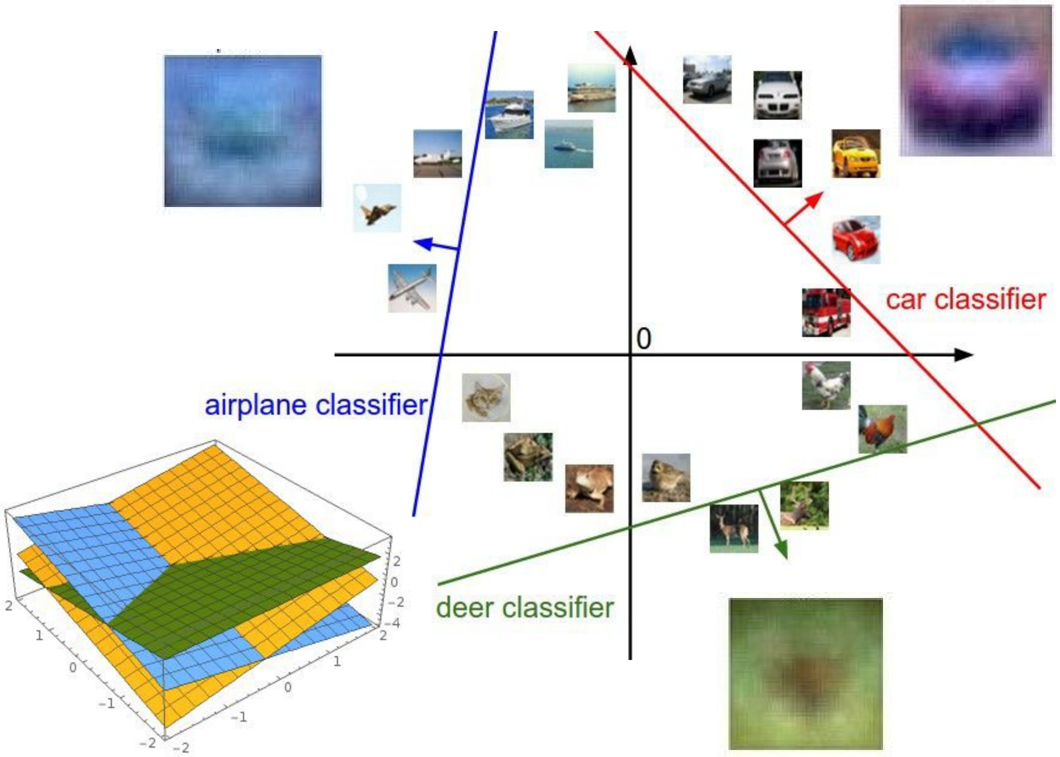
Interpreting a Linear Classifier



Interpreting a Linear Classifier: Visual Viewpoint



Interpreting a Linear Classifier: Geometric Viewpoint



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

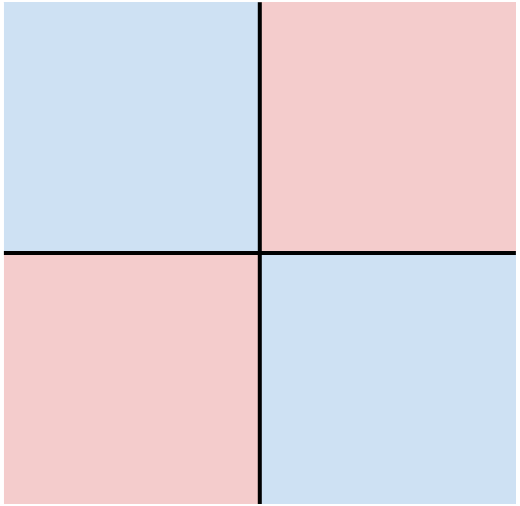
Array of **32x32x3** numbers
(3072 numbers total)

Plot created using Wolfram Cloud

Hard cases for a linear classifier

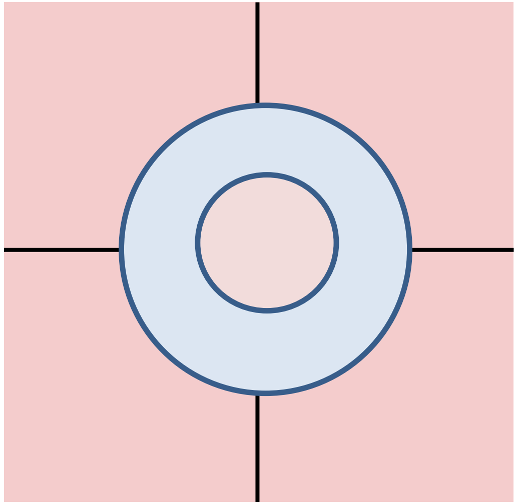
Class 1:
First and third quadrants

Class 2:
Second and fourth quadrants



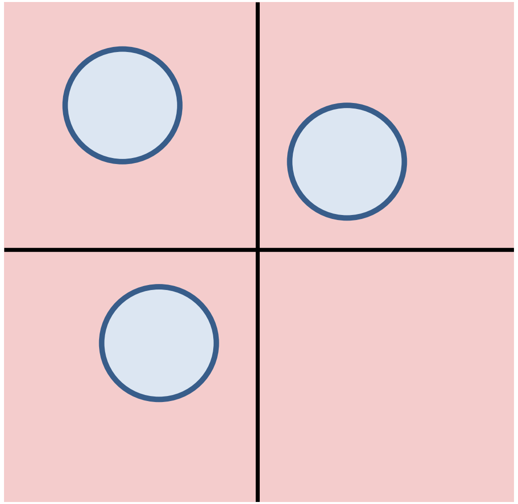
Class 1:
1 <= L2 norm <= 2

Class 2:
Everything else



Class 1:
Three modes

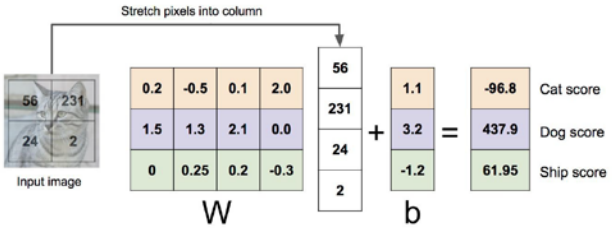
Class 2:
Everything else



Linear Classifier: Three Viewpoints

Algebraic Viewpoint

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

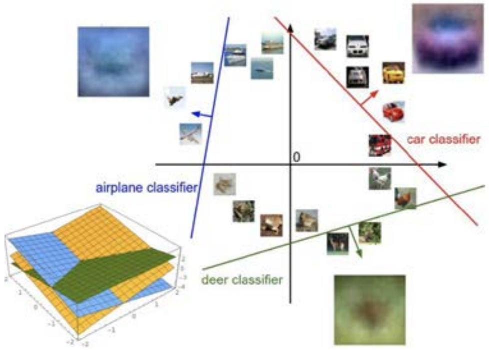


Visual Viewpoint

One template
per class

Geometric Viewpoint

Hyperplanes
cutting up space



So far: Defined a (linear) <u>score function</u> $f(x,W) = Wx + b$

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

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

Coming up:

- Loss function (quantifying what it means to have a “good” W)
- Optimization (start with random W and find a W that minimizes the loss)
- ConvNets! (tweak the functional form of f)

Next Time and Homework

- Bag of visual words approach

- Go over the next lecture slides
- Come up with one question on what we have discussed today
  - 1 for typical questions (that were answered in the class)
  - 2 for questions with thoughts or that surprised me

- Write questions at least 4 times