CSCI 497P/597P: Computer Vision

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Image Classification and Recognition

Reading

- http://cs231n.github.io/classification/

Announcements

Goals

- Understand some of the reasons why image recognition is hard.
- Understand the standard ML pipeline for image classification problems:
  - Represent images as feature vectors
  - Learn a classifier function from labeled data
  - Classify novel images using the learned classifier
- Understand KNN classifier and why it doesn’t work so well on images.
- Understand the importance of splitting data into train/val/test sets when developing algorithms and tuning hyperparameters.

Image classification

- Given an image, produce a label
- Label can be:
  - 0/1 or yes/no: *Binary classification*
  - one-of-k: *Multiclass classification*
  - 0/1 for each of k concepts: *Multilabel classification*

Image classification - Binary classification

Is this a dog?

Yes

Image classification - Multiclass classification

Which of these is it:
dog, cat or zebra?
Dog

Image classification - Multilabel classification

Is this a dog? Yes
Is this furry? Yes
Is this sitting down? Yes

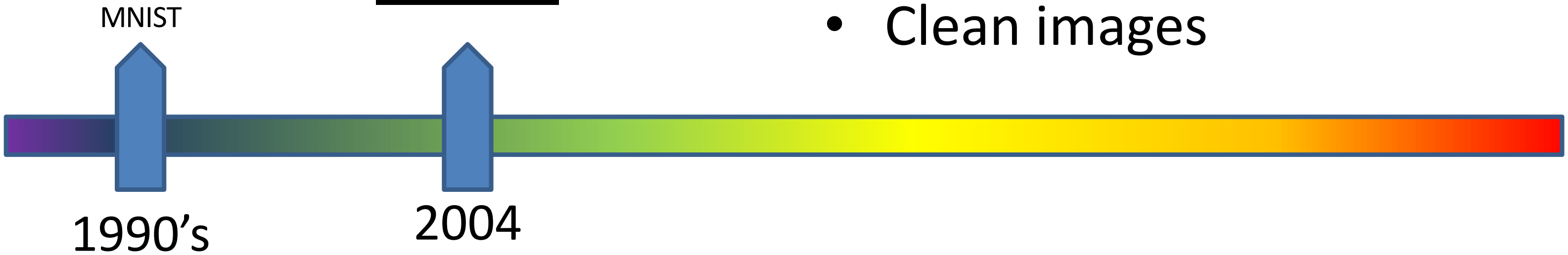
A history of classification : MNIST

- 2D
- 10 classes
- 6000 examples per class

1990’s

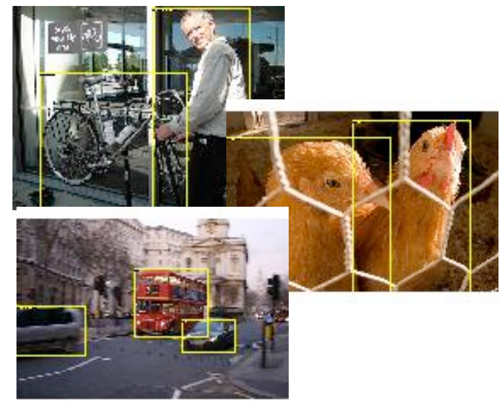
A history of classification : Caltech 101

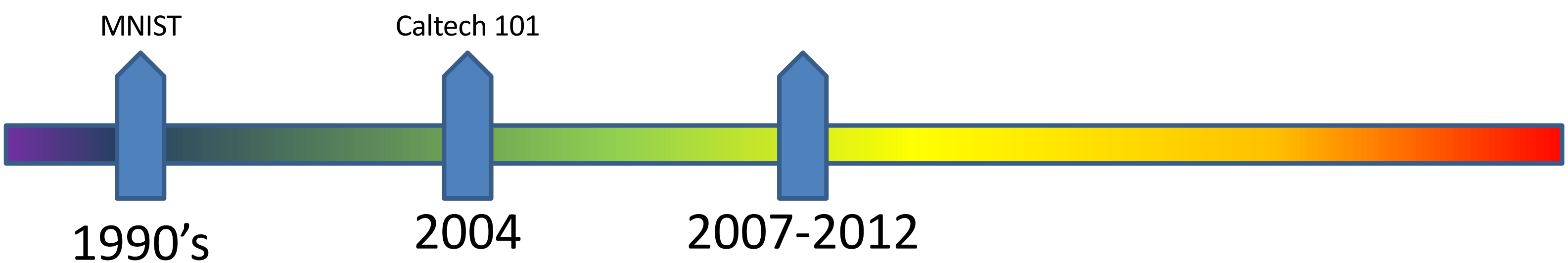
- 101 classes
- ~~10 classes~~
- 30 examples per class
- Strong category-specific biases
- Clean images



A history of classification: PASCAL VOC

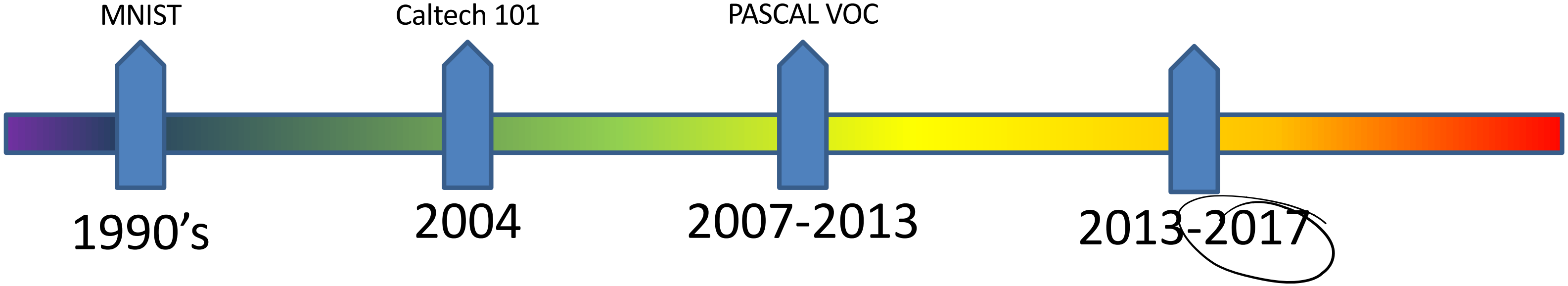
- 20 classes
- ~500 examples per class
- Clutter, occlusion, natural scenes





A history of classification: ImageNet

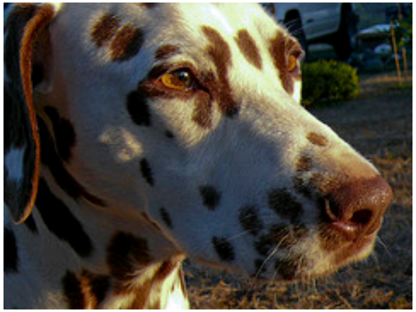
- 1000 classes
- ~1000 examples per class
- Mix of cluttered and clean images

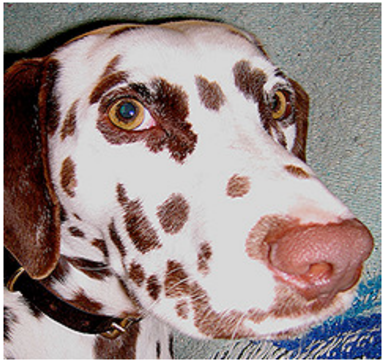


Why is recognition hard?

Pose variation

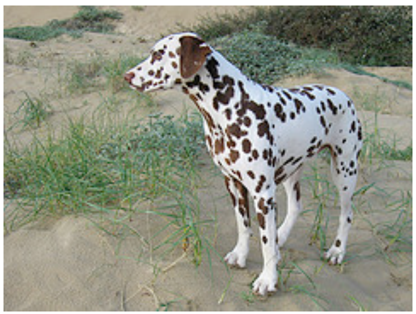
Why is recognition hard?





Lighting variation

Why is recognition hard?



Scale variation

Why is recognition hard?

Clutter and occlusion

Why is recognition hard?

Intrinsic intra-class variation

Why is recognition hard?

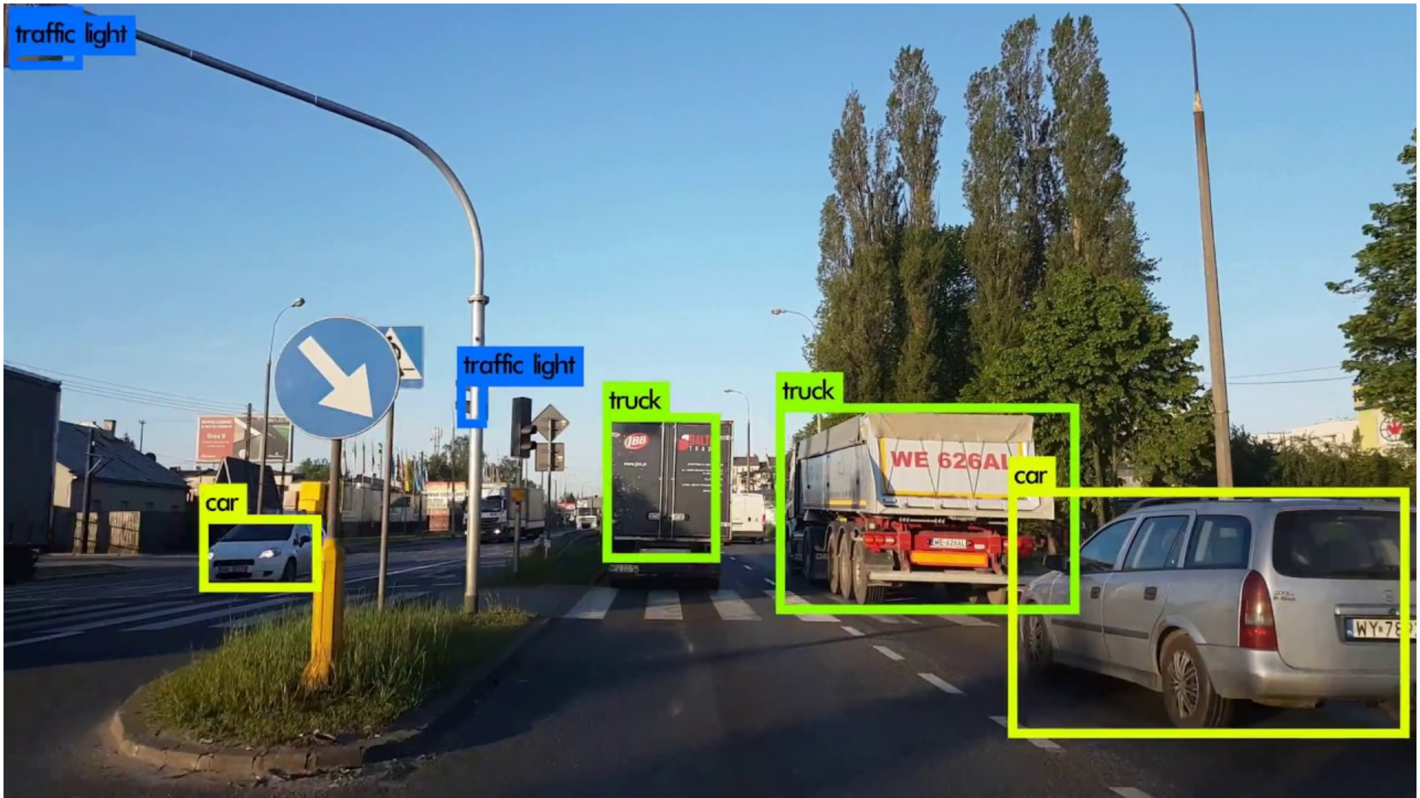
Inter-class similarity

The language of recognition

- Boundaries of classes are often fuzzy
- "A dog is an animal with four legs, a tail and a snout"
- Really?

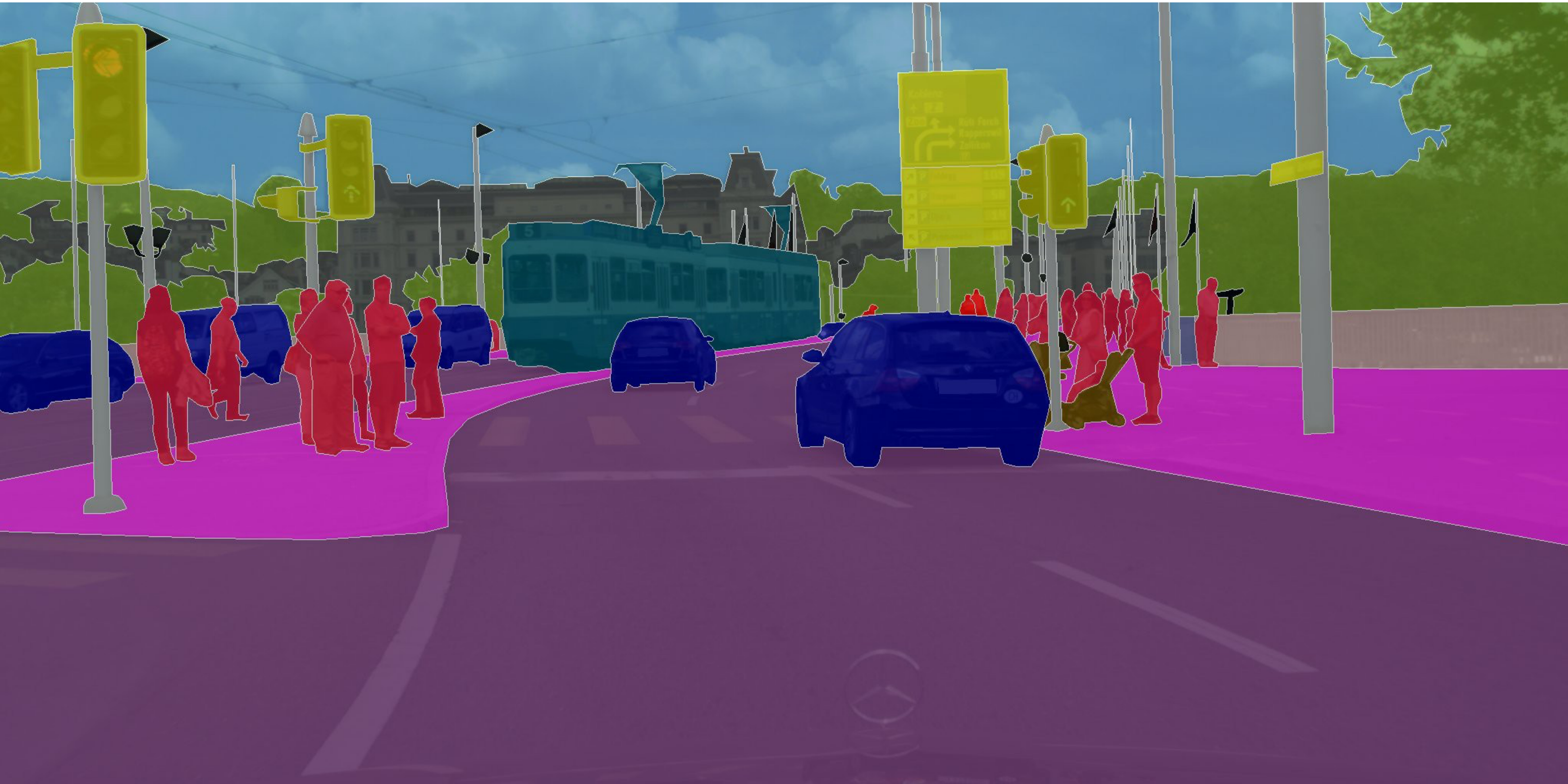
Other Recognition Problems

- Object Detection



Other Recognition Problems

- Semantic Segmentation



Other Recognition Problems

- Instance Segmentation

Semantic Segmentation

Instance Segmentation

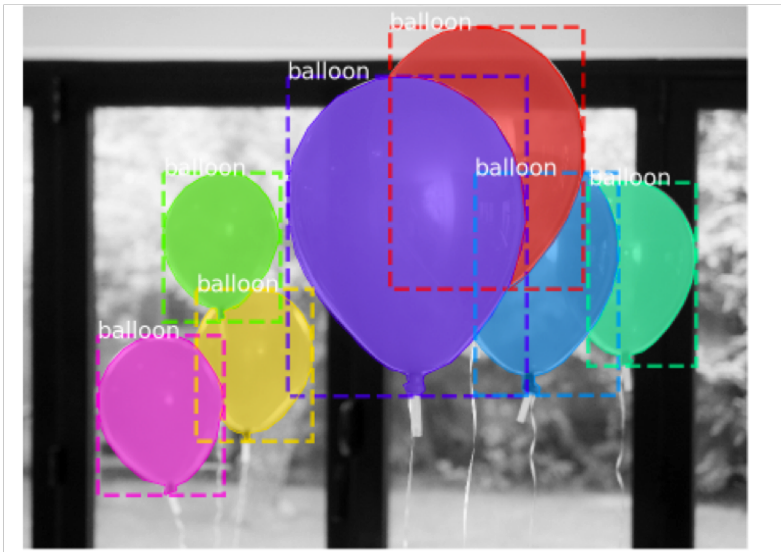


Image: https://www.jeremyjordan.me/evaluating-image-segmentation-models/

Other Recognition Problems

- Action Recognition

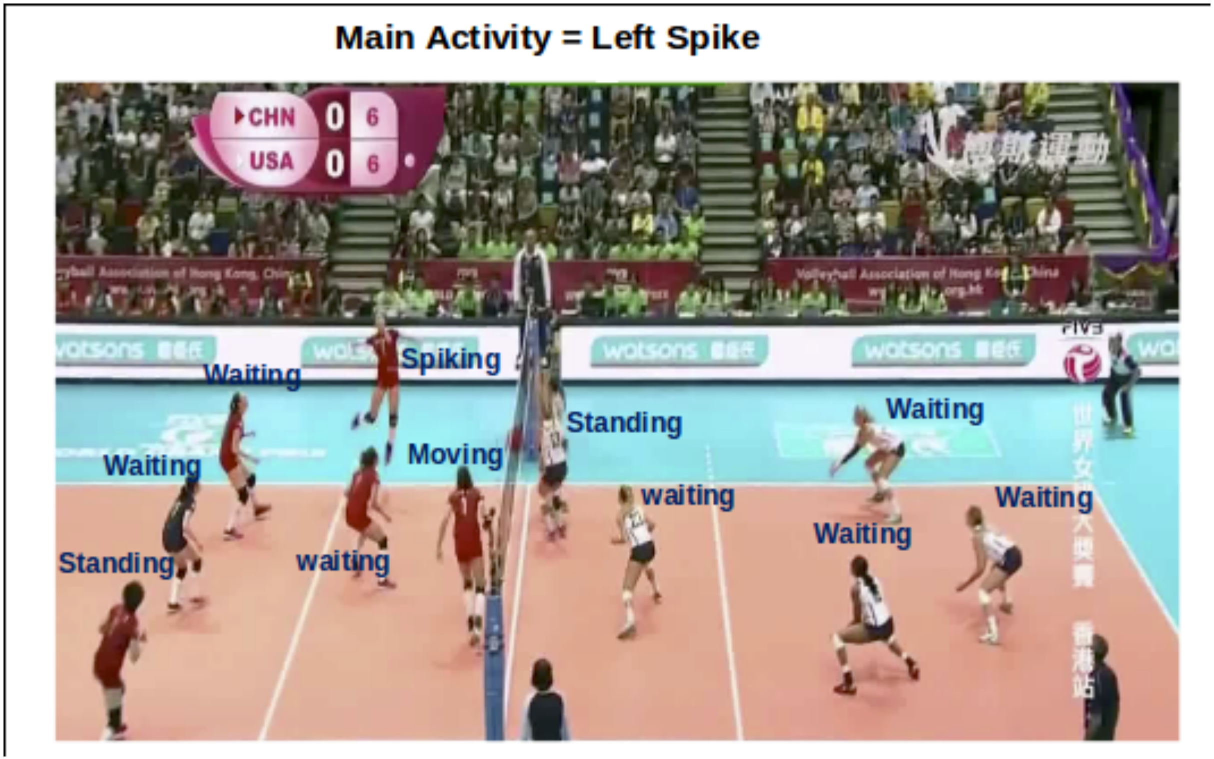


Image: http://nguyenducminhkhoi.com/project/action_recognition/

How are we going to solve this?

An image classifier

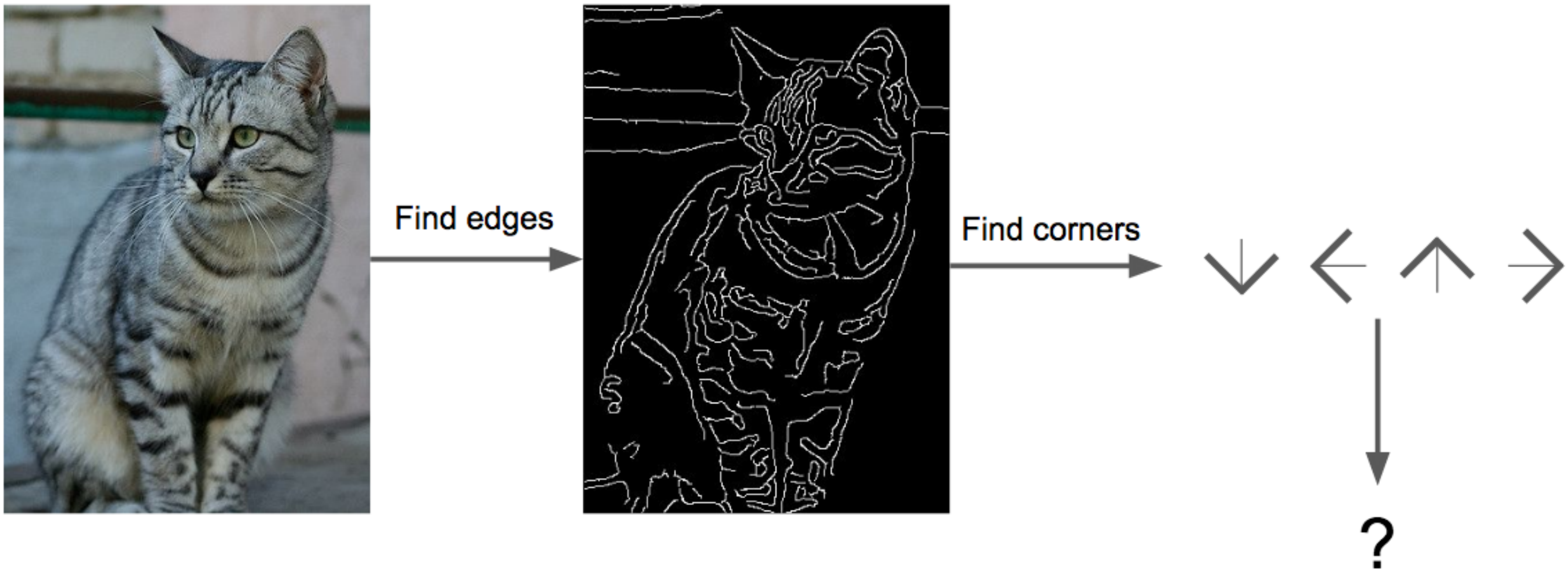
```python
def classify_image(image):
  # Some magic here?
  return class_label
```

Unlike e.g. sorting a list of numbers,

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

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Attempts have been made



Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Machine Learning: Data-Driven Approach

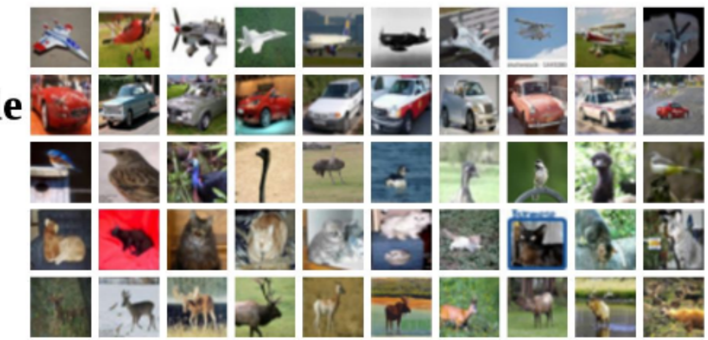
1. Collect a dataset of images and labels
2. Use Machine Learning to train a classifier
3. Evaluate the classifier on new images

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

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

Example training set

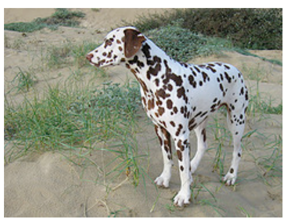
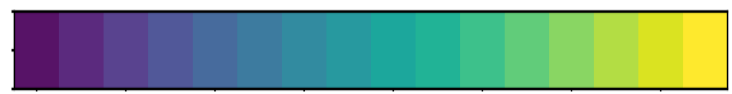
airplane
automobile
bird
cat
deer



Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Representing Images

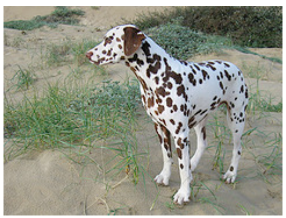
- We have images; ML works on vectors.
- To do machine learning, we need a function that takes an image and converts it into a vector.

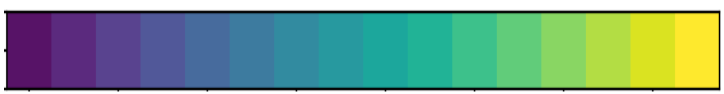
ϕ () = 

- Given an image, use ϕ to get a vector representing a point in high dimensional space

Classifying Images

- Given an image, use ϕ to get a vector and plot it as a point in high dimensional space

ϕ () = 

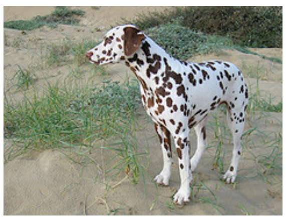
- Then, use a *classifier* function to map feature vectors to class labels:
- h() = "dog"

classifier

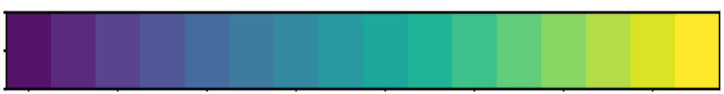
$h(\phi(img))$

Classifying Images: Pipeline

1. Represent the image in some *feature space*

ϕ () = 

2. Classify the image based on its feature representation.

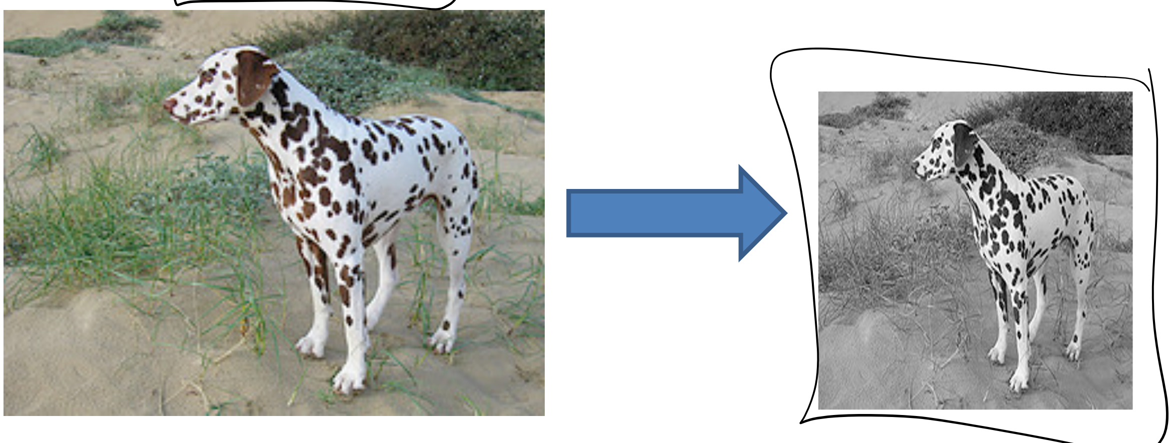
- h() = “dog”

Two important pieces

- The feature extractor (ϕ)
- The classifier (h)

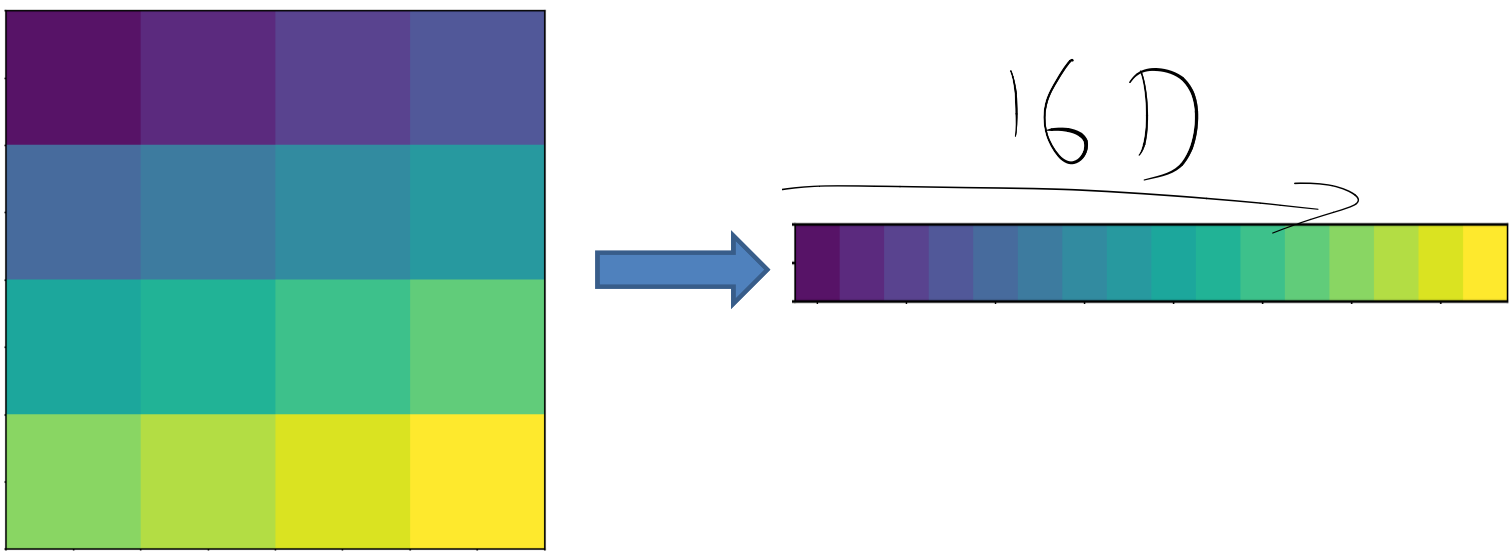
Let's make the simplest possible ϕ

- Represent an image as a vector in $\mathbb{R}^d$
- Step 1: convert image to gray-scale and resize to fixed size



Feature space: representing images as vectors

- Step 2: Flatten 2D array into 1D vector



Let’s make the simplest possible *h*

- h(x) = ”dog”
- Okay, let’s get a little less simple than that.

Let’s make a very simple *h*

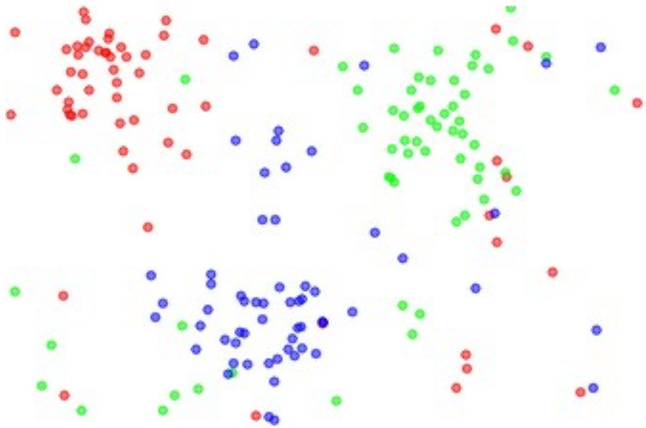
- h(x) = ”dog”
- Okay, let’s get a little less simple than that.

- I’ve never seen x before, but I’ve seen a bunch of other things.

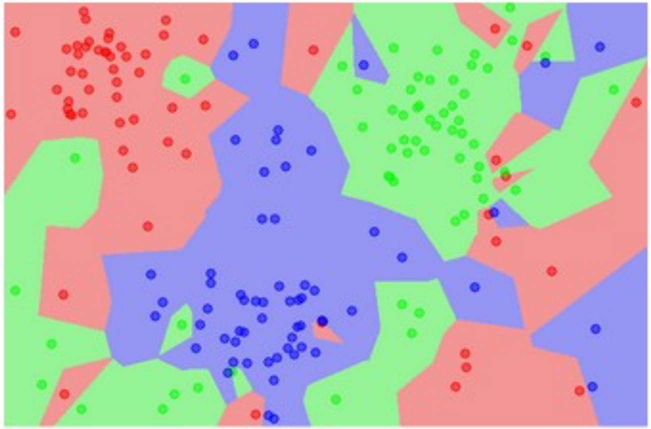
- h(x) = the label of the most similar thing to x of all the things I’ve seen.
  - assumption: **similar** data points have **similar** labels

A Simple *h*: Nearest Neighbor Classifier

the data



NN classifier



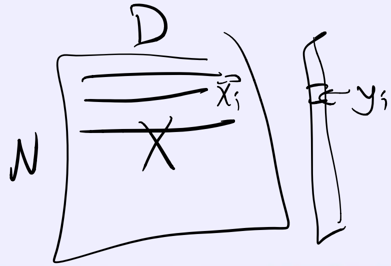
```python
def train(images, labels):
  # Machine learning!
  return model
```

→ Memorize all data and labels

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

→ Predict the label of the most similar training image

Figures: Fei-Fei Li, Justin Johnson, & Serena Yeung




```python
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
```

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

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Nearest Neighbor classifier

Memorize training data

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```

Nearest Neighbor classifier

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

Nearest Neighbor Classifier

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    # loop over all test rows
    for i in xrange(num_test):   <- 1 test example?
      # find the nearest training image to the i'th test image
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      distances = np.sum(np.abs(self.Xtr - X[i,:]), axis = 1)
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```

What's the runtime of train?

$O(1)$

What's the runtime of predict?

$O(N \cdot D)$

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Nearest Neighbor Classifier

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    return Ypred
```

What's the runtime of train?
O(1)

What's the runtime of predict?
O(N)

Ideally, it'd be the other way around:

- slow training
- fast prediction

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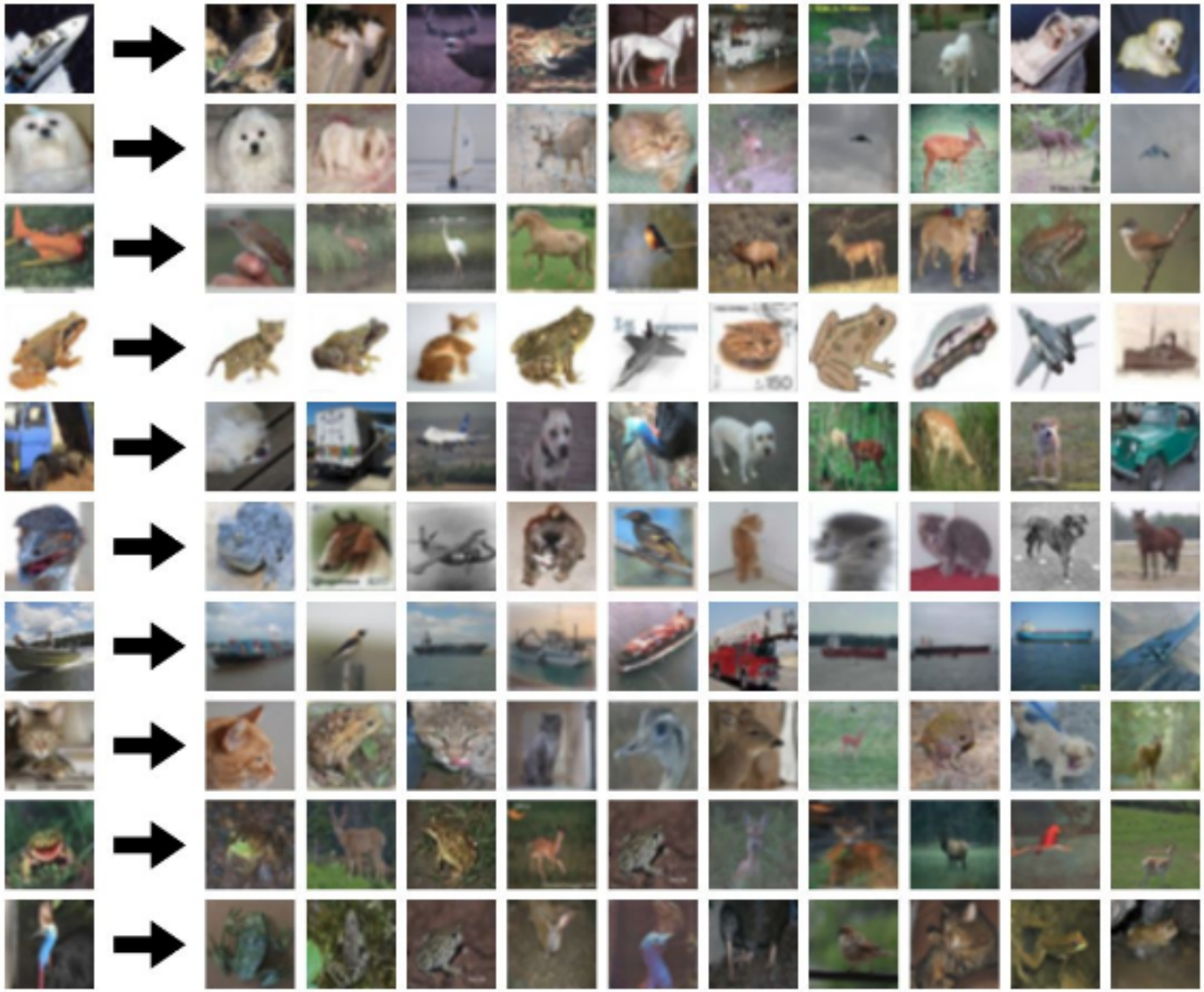
Demo:
Nearest Neighbor on MNIST



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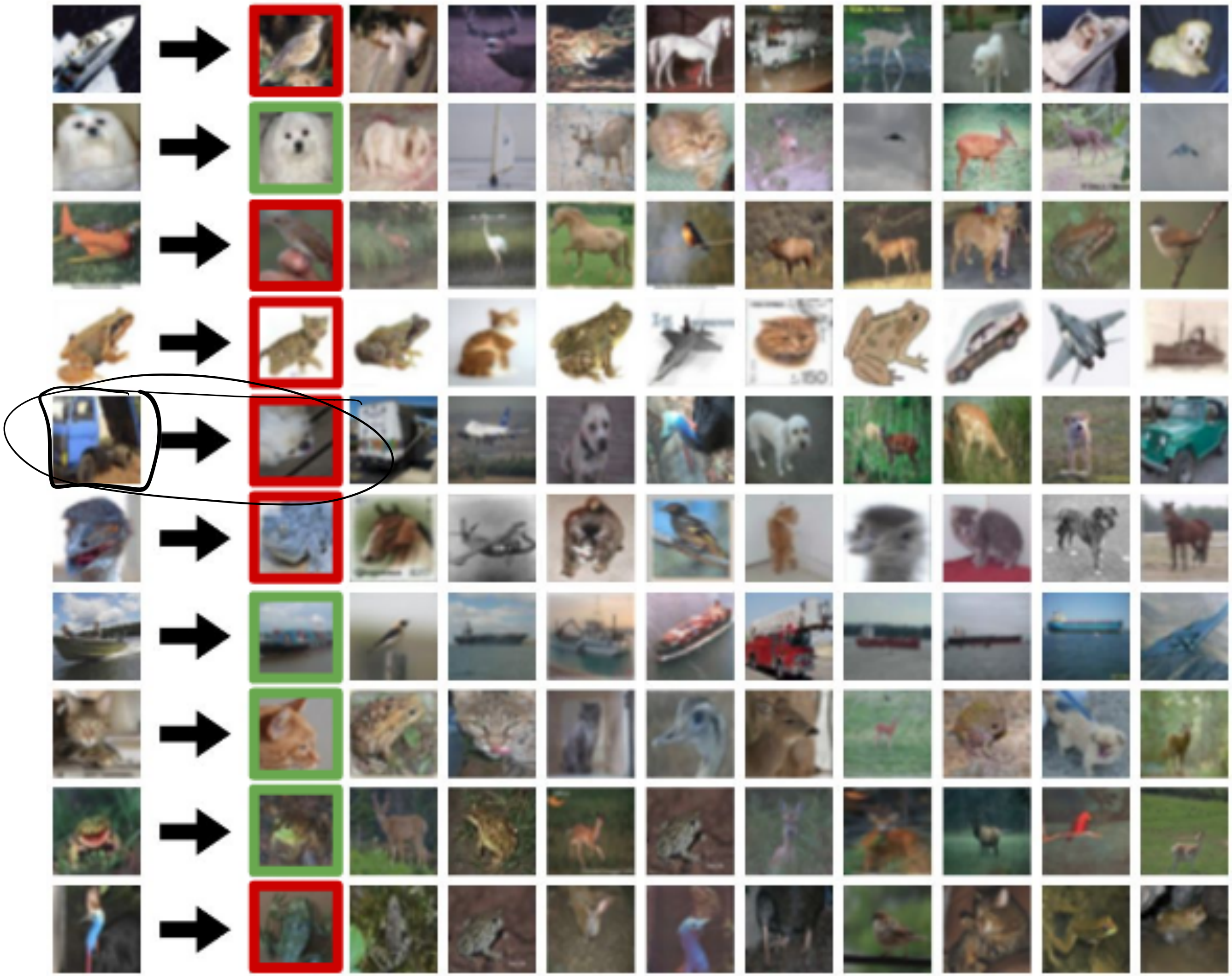

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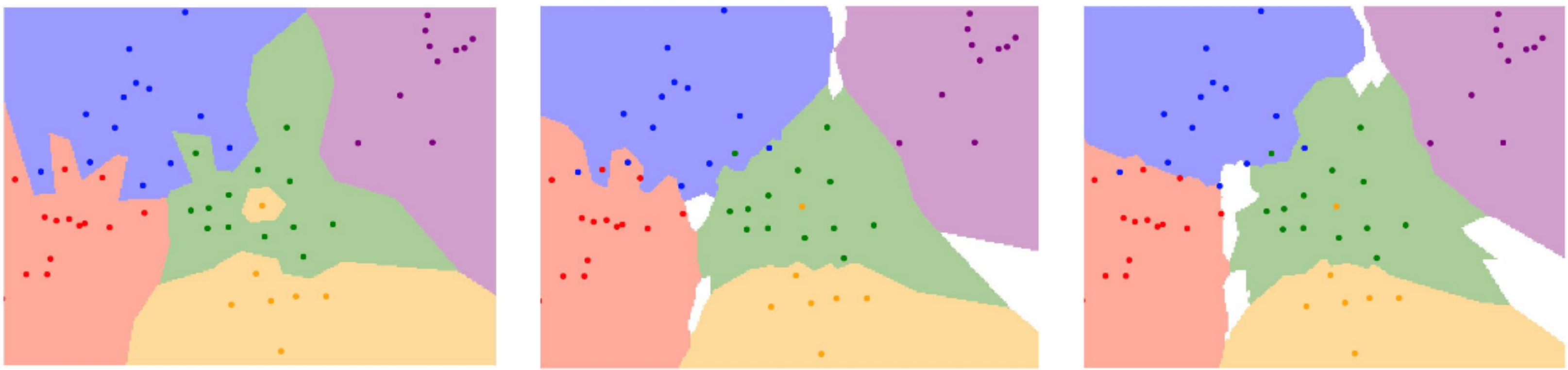
An improvement: K nearest neighbors

K-Nearest Neighbors

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

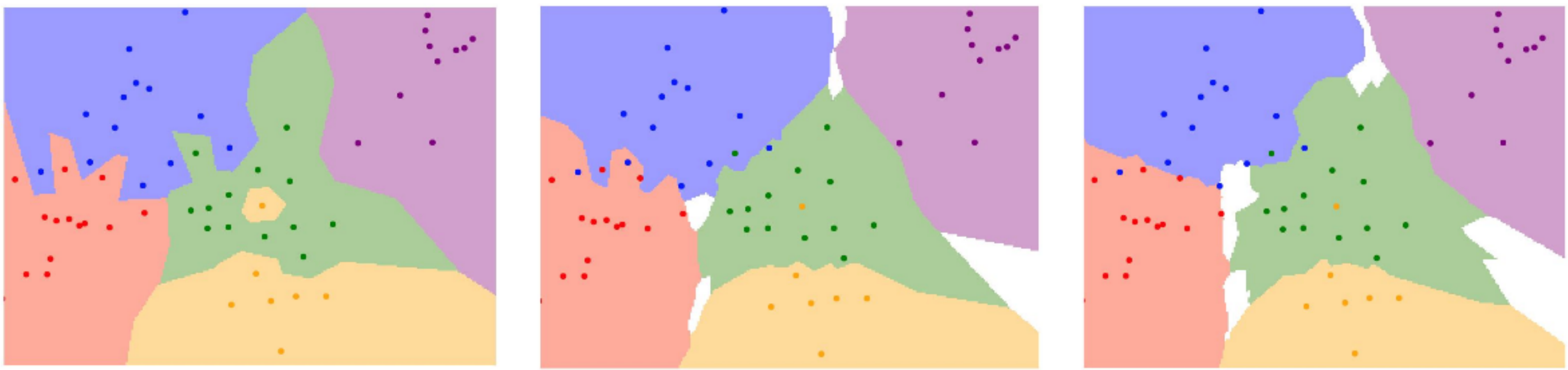


K = 1 K = 3 K = 5

An improvement: K nearest neighbors

K-Nearest Neighbors

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



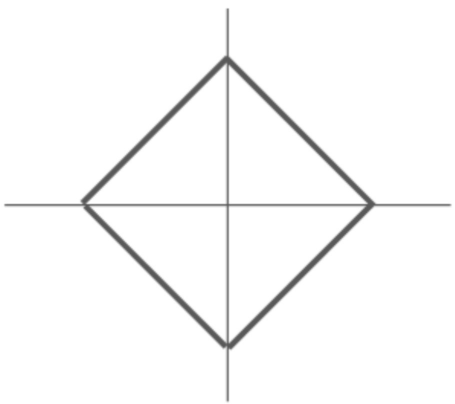
K = 1 K = 3 K = 5

- What do we mean by “nearest” anyway?

K-Nearest Neighbors: Distance Metric

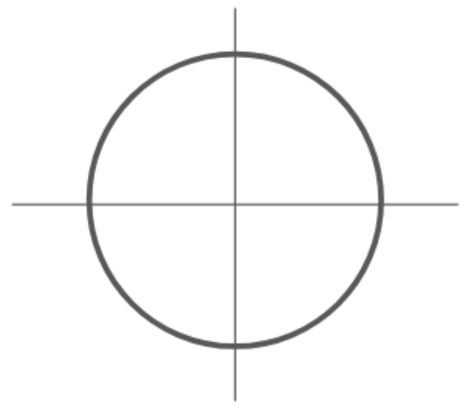
L1 (Manhattan) distance

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



L2 (Euclidean) distance

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



K-Nearest Neighbors: Distance Metric

L1 (Manhattan) distance

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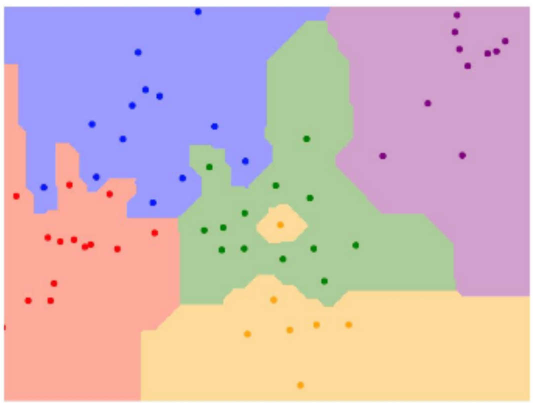

K = 1

L2 (Euclidean) distance

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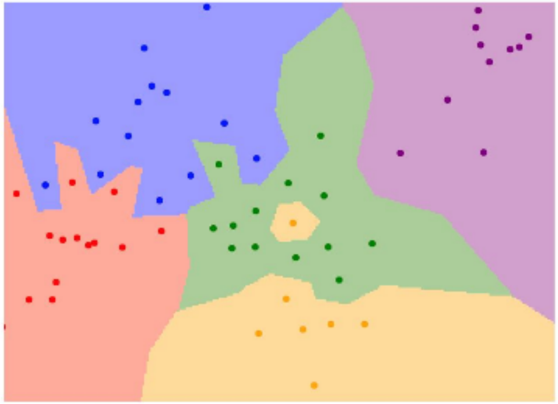

K = 1

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Demo

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