CS 4803 / 7643: Deep Learning

Topics:

- Image Classification
- Supervised Learning view
- K-NN

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Georgia Tech

Administrativia

- Waitlist
  - MS-ML or ML-PhD not yet in? Come talk to me.
- Canvas
  - Anybody not have access?
- Piazza
  - 70 people signed up. Please use that for questions.

HW0

- Class Webpage
  - https://www.cc.gatech.edu/classes/AY2019/cs7643_fall/
- Theory
  - https://www.cc.gatech.edu/classes/AY2019/cs7643_fall/assets/hw0.pdf
- Implementation:
  - https://www.cc.gatech.edu/classes/AY2019/cs7643_fall/hw0-q8/

Python+Numpy Tutorial

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/

Plan for Today

- Image Classification
- Supervised Learning view
- K-NN
- Linear Classifiers

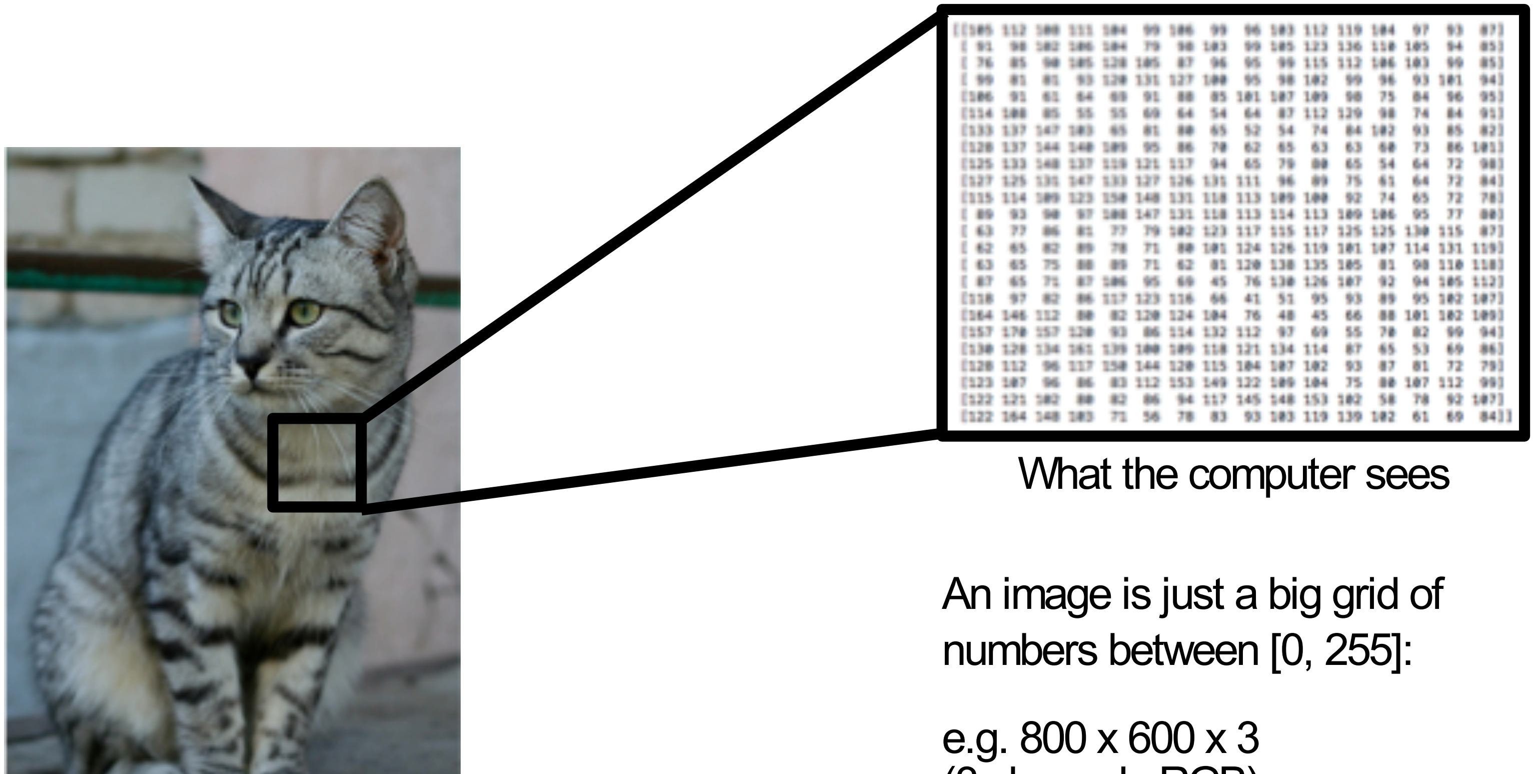
Image Classification

Image Classification: A core task in Computer Vision

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

cat

The Problem: Semantic Gap

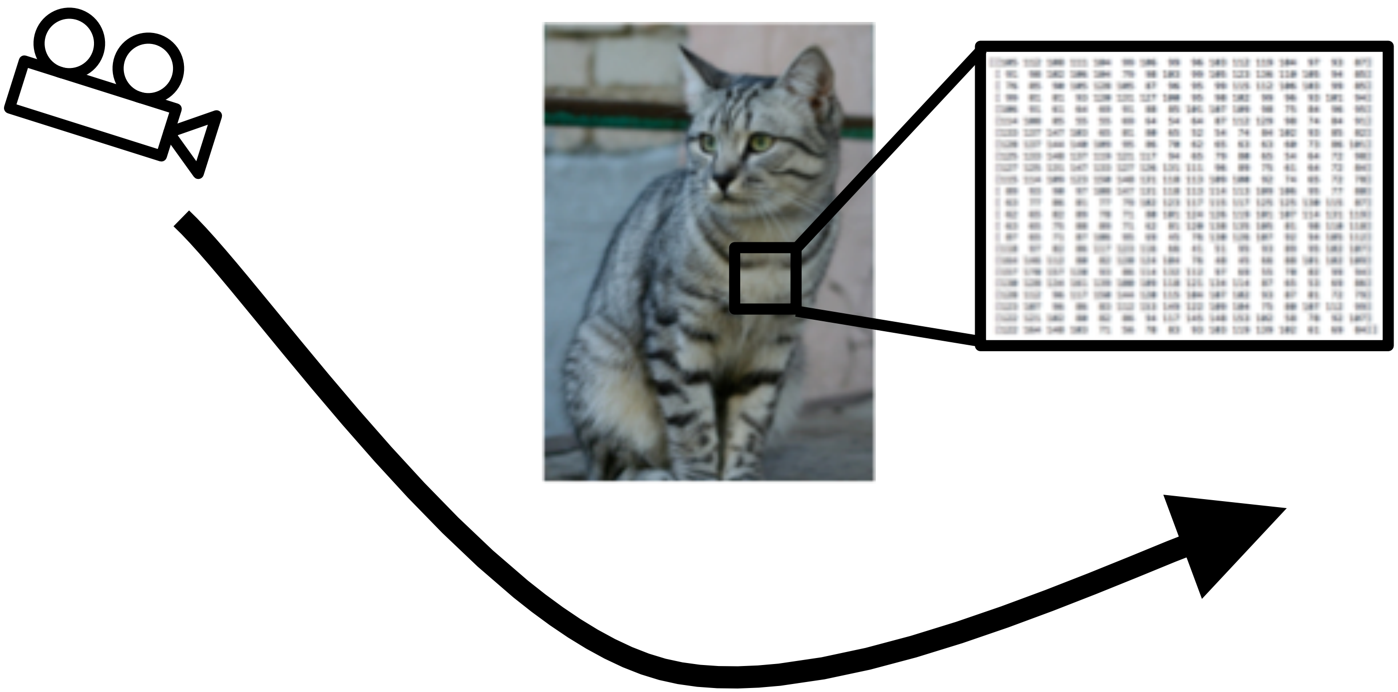


What the computer sees

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

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Challenges: Deformation

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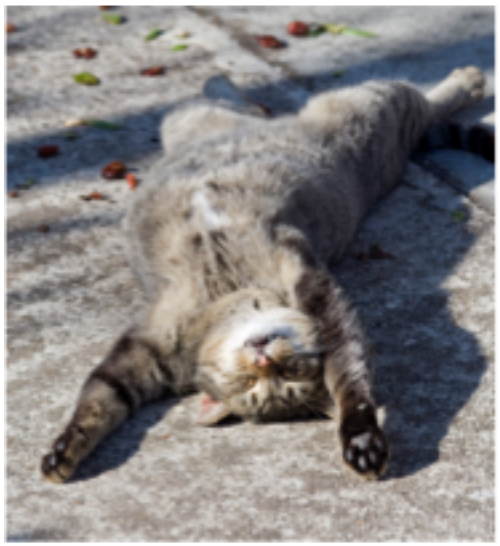
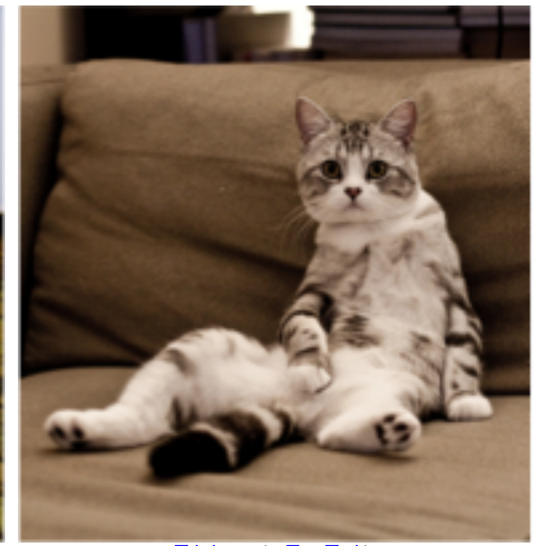


[redacted] by [redacted] is licensed under [redacted]

[redacted] by [redacted] is licensed under [redacted]



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Challenges: Occlusion

Challenges: Background Clutter

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

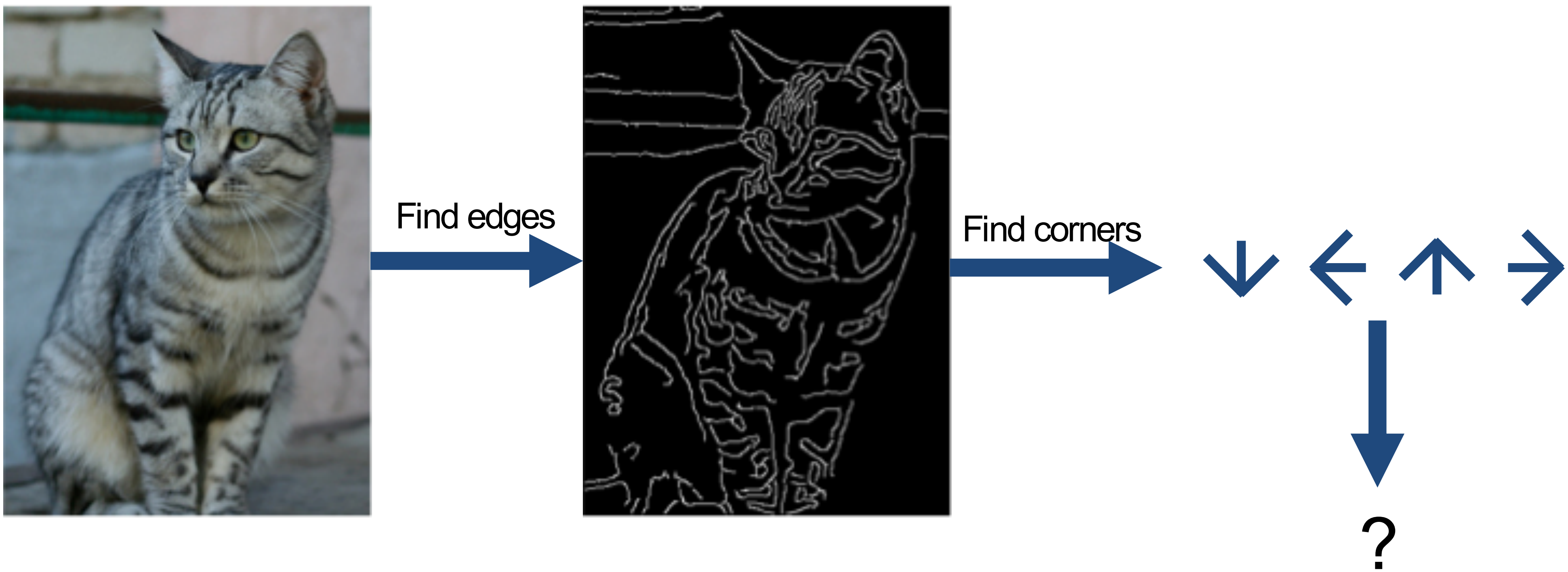
An image classifier

```
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

ML: A 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

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

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

Example training set

Supervised Learning

Supervised Learning

- Input: x (images, text, emails…)
- Output: y (spam or non-spam…)
- (Unknown) Target Function
  - f: X → Y (the "true" mapping / reality)
- Data
  - $(x_1,y_1), (x_2,y_2), \ldots, (x_N,y_N)$
- Model / Hypothesis Class
  - h: X → Y
  - $y = h(x) = \text{sign}(w^T x)$
- Learning = Search in hypothesis space
  - Find best h in model class.

Procedural View

- Training Stage:
  - Training Data { (x,y) } $\rightarrow$ f (Learning)

- Testing Stage
  - Test Data x $\rightarrow$ f(x) (Apply function, Evaluate error)

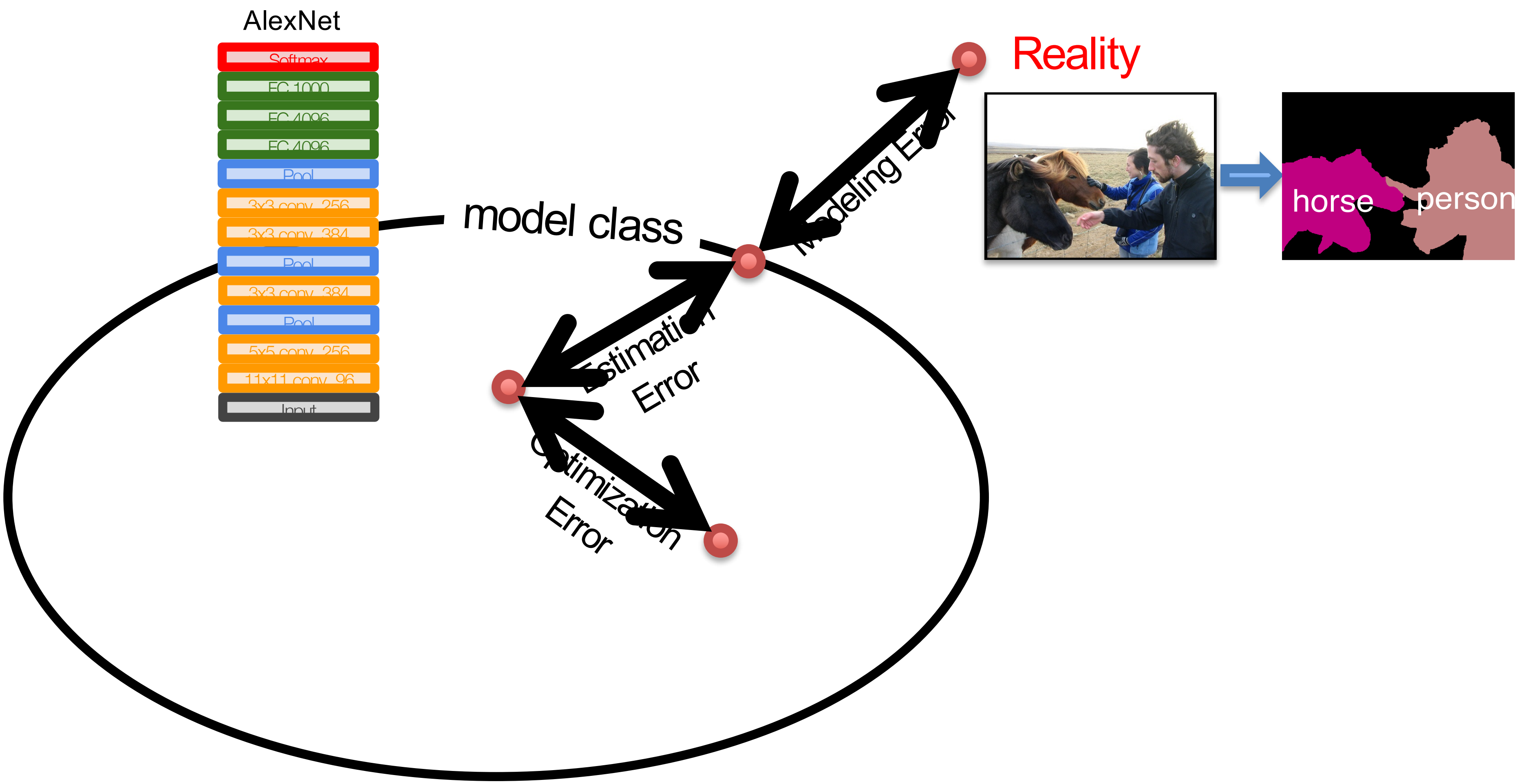
Statistical Estimation View

- Probabilities to rescue:
  - X and Y are *random variables*
  - $D = (x_1,y_1), (x_2,y_2), \ldots, (x_N,y_N) \quad \sim P(X,Y)$
- IID: Independent Identically Distributed
  - Both training & testing data sampled IID from P(X,Y)
  - Learn on training set
  - Have some hope of *generalizing* to test set

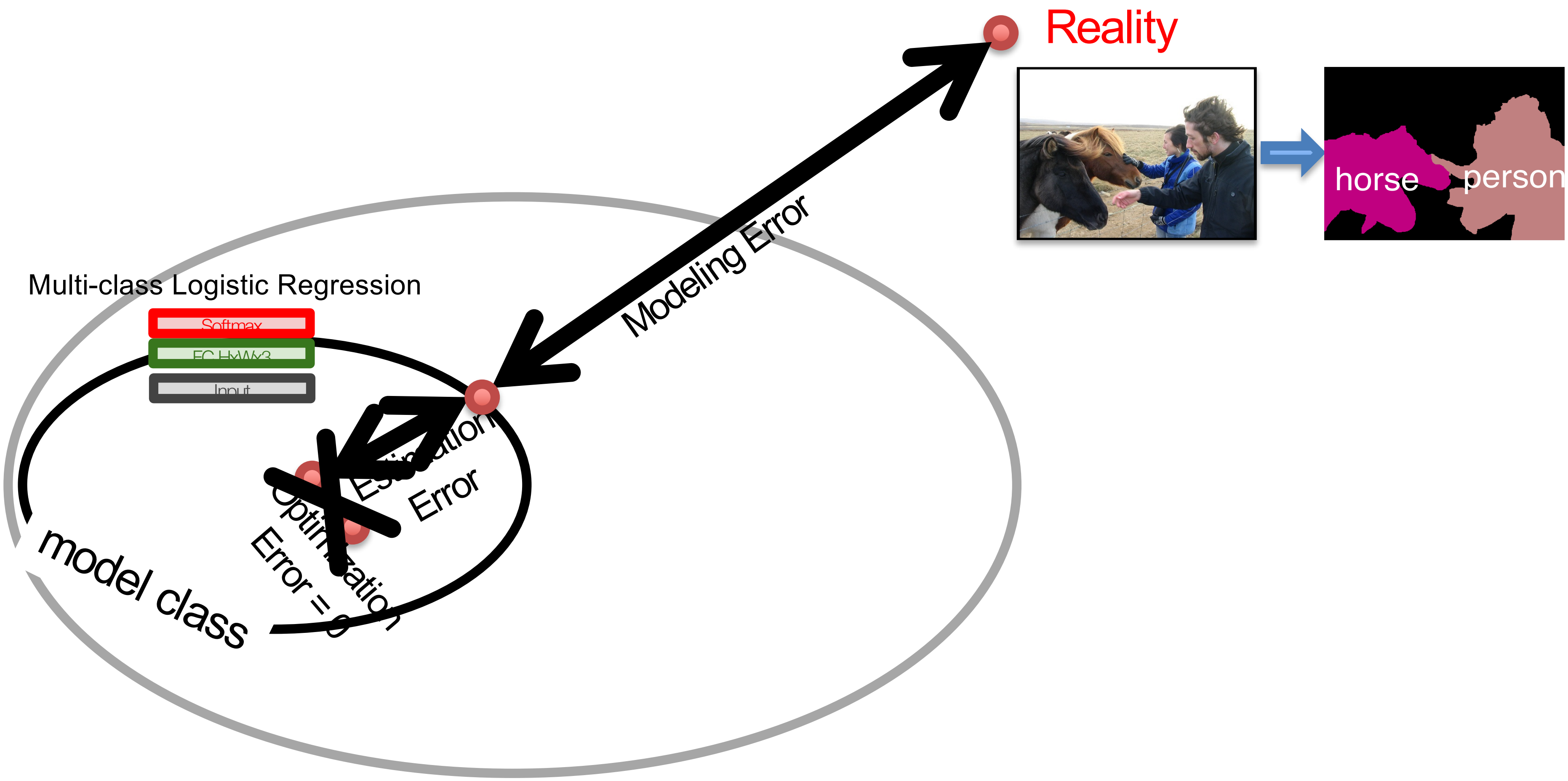
Error Decomposition

- Reality

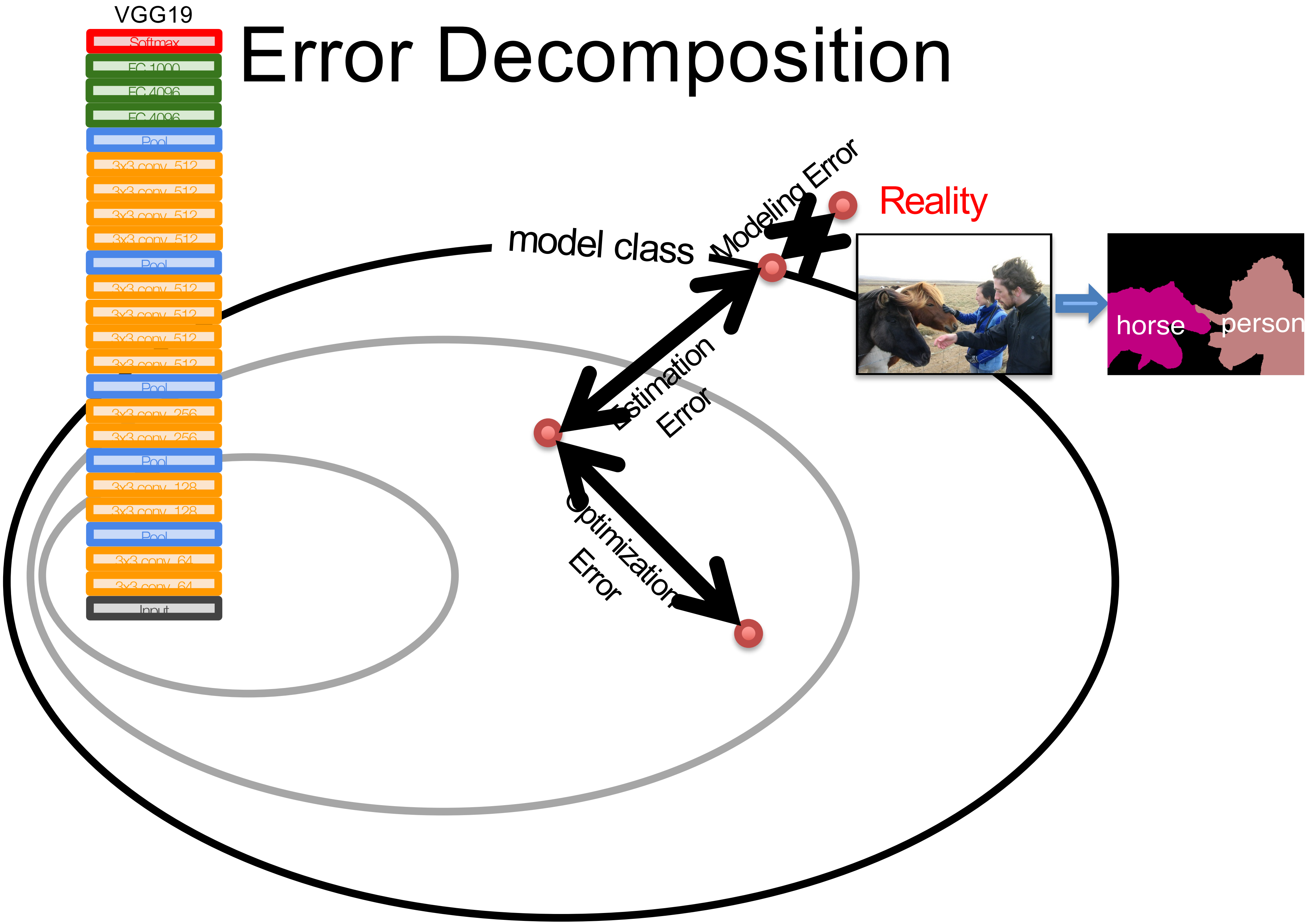
Error Decomposition



Error Decomposition



Error Decomposition



Error Decomposition

- Approximation/Modeling Error
  - You approximated reality with model
- Estimation Error
  - You tried to learn model with finite data
- Optimization Error
  - You were lazy and couldn't/didn't optimize to completion
- Bayes Error
  - Reality just sucks

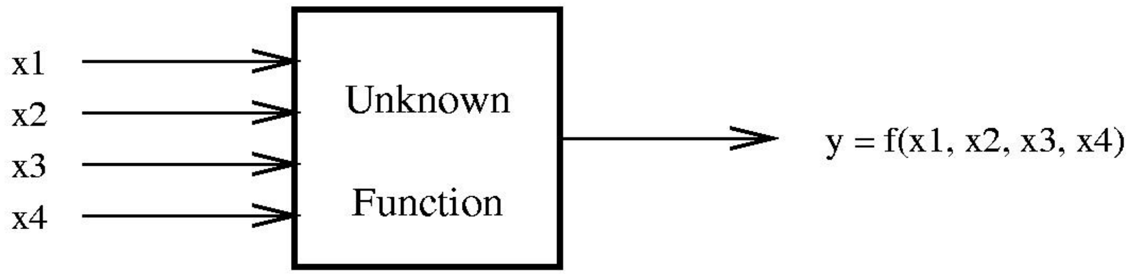
Guarantees

- 20 years of research in Learning Theory oversimplified:

- If you have:
  - Enough training data D
  - and H is not too complex
  - then *probably* we can generalize to unseen test data

Learning is hard!

A Learning Problem

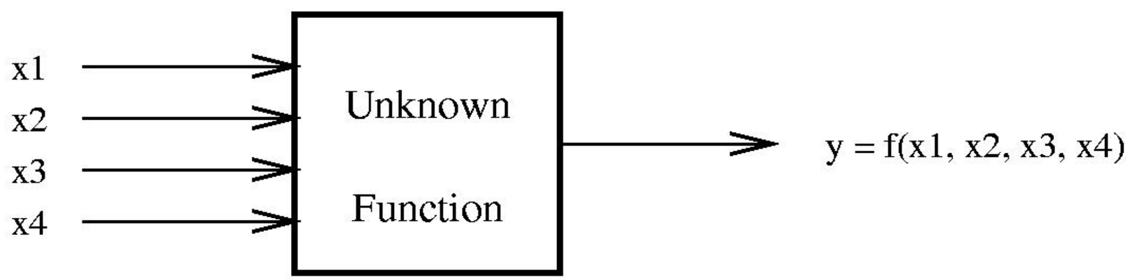


Example	x_1	x_2	x_3	x_4	y
1	0	0	1	0	0
2	0	1	0	0	0
3	0	0	1	1	1
4	1	0	0	1	1
5	0	1	1	0	0
6	1	1	0	0	0
7	0	1	0	1	0

Learning is hard!

- No assumptions = No learning

A Learning Problem



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5	0	1	1	0	0
6	1	1	0	0	0
7	0	1	0	1	0

First classifier: **Nearest Neighbor**

```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

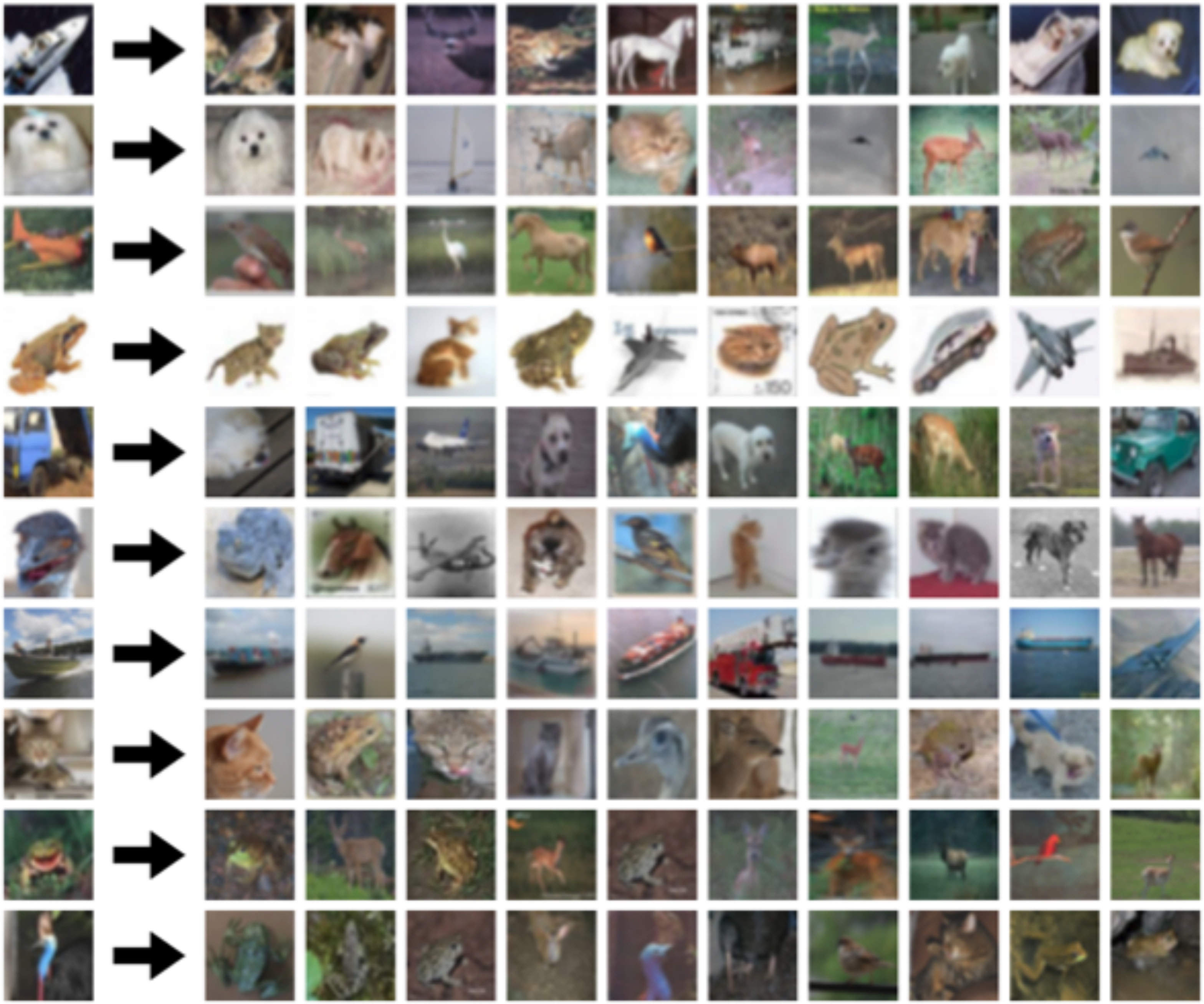
Example Dataset: **CIFAR10**

10 classes

50,000 training images
10,000 testing images

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

Nearest Neighbours



Nearest Neighbours

Instance/Memory-based Learning

Four things make a memory based learner:

- *A distance metric*

- *How many nearby neighbors to look at?*

- *A weighting function (optional)*

- *How to fit with the local points?*

1-Nearest Neighbour

Four things make a memory based learner:

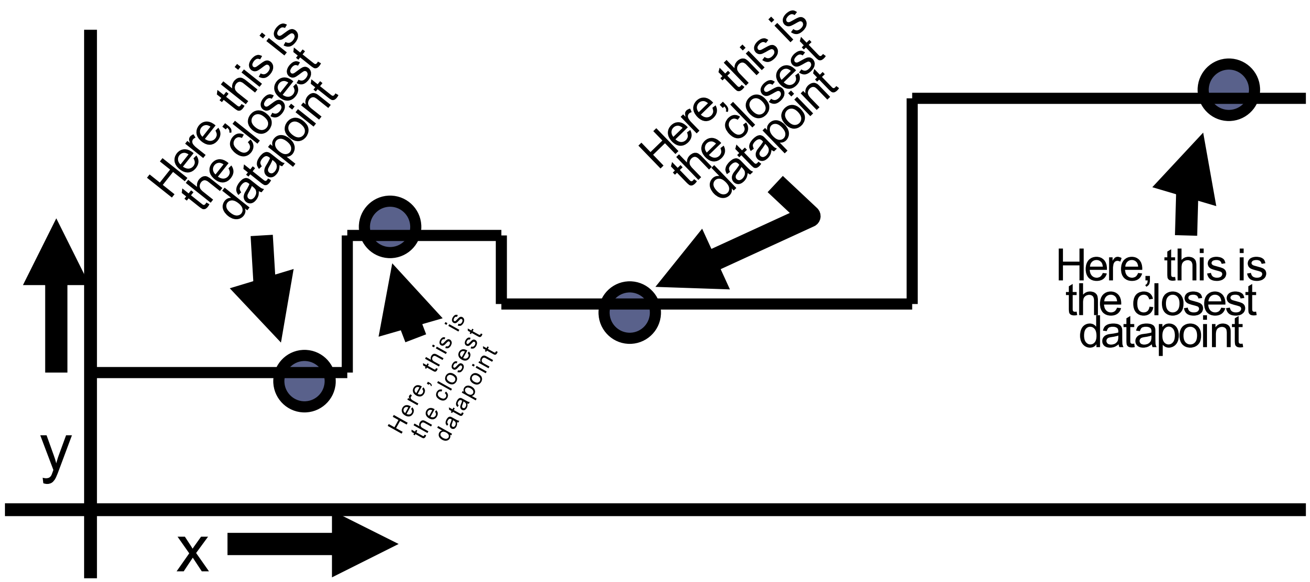
- *A distance metric*
  - **Euclidean (and others)**
- *How many nearby neighbors to look at?*
  - **1**
- *A weighting function (optional)*
  - **unused**
- *How to fit with the local points?*
  - **Just predict the same output as the nearest neighbour.**

k-Nearest Neighbour

Four things make a memory based learner:

- *A distance metric*
  - **Euclidean (and others)**
- *How many nearby neighbors to look at?*
  - **k**
- *A weighting function (optional)*
  - **unused**
- *How to fit with the local points?*
  - **Just predict the average output among the nearest neighbours.**

1-NN for Regression



Distance Metric to compare images

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

$$\left| \overset{\text{test image}}{\begin{bmatrix} 56 & 32 & 10 & 18 \\ 90 & 23 & 128 & 133 \\ 24 & 26 & 178 & 200 \\ 2 & 0 & 255 & 220 \end{bmatrix}} - \overset{\text{training image}}{\begin{bmatrix} 10 & 20 & 24 & 17 \\ 8 & 10 & 89 & 100 \\ 12 & 16 & 178 & 170 \\ 4 & 32 & 233 & 112 \end{bmatrix}} \right| = \overset{\text{pixel-wise absolute value differences}}{\begin{bmatrix} 46 & 12 & 14 & 1 \\ 82 & 13 & 39 & 33 \\ 12 & 10 & 0 & 30 \\ 2 & 32 & 22 & 108 \end{bmatrix}} \xrightarrow{\text{add}} 456$$

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Nearest Neighbor classifier

```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
```

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Nearest Neighbor classifier

Memorize training data

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    return Ypred
```

Nearest Neighbor classifier

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

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Nearest Neighbor classifier

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

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Nearest Neighbor classifier

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

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```

Nearest Neighbor classifier

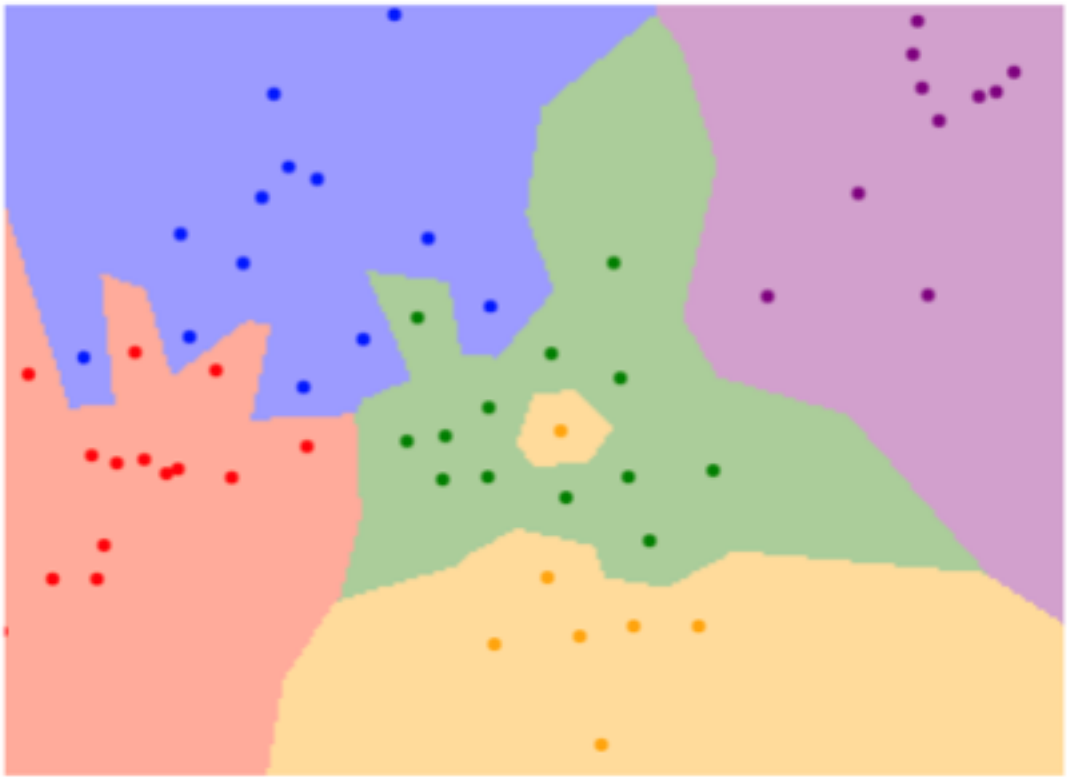
Q: With N examples, how fast are training and prediction?

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

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

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

What does this look like?



Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Nearest Neighbour

- Demo 1
  - http://vision.stanford.edu/teaching/cs231n-demos/knn/
- Demo 2
  - http://www.cs.technion.ac.il/~rani/LocBoost/

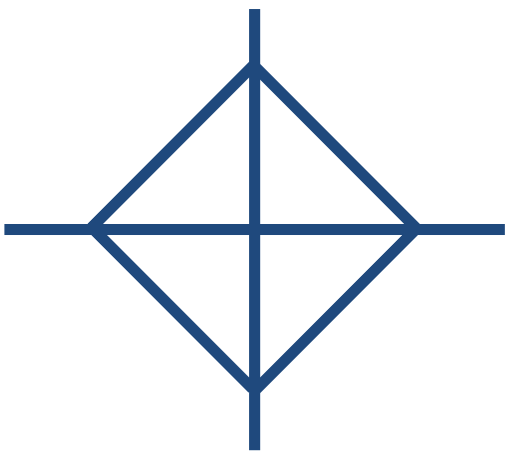
Parametric vs Non-Parametric Models

- Does the capacity (size of hypothesis class) grow with size of training data?
  - Yes = Non-Parametric Models
  - No = Parametric Models

K-Nearest Neighbors: Distance Metric

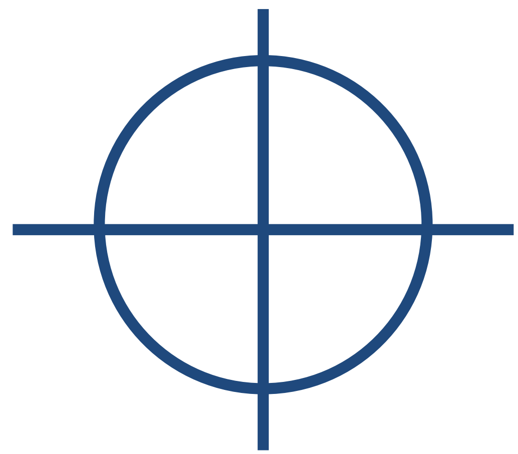
L1 (Manhattan) distance

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



L2 (Euclidean) distance

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



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

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.

Hyperparameters

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

Your Dataset

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Hyperparameters

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

BAD: K = 1 always works perfectly on training data

Your Dataset

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

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

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

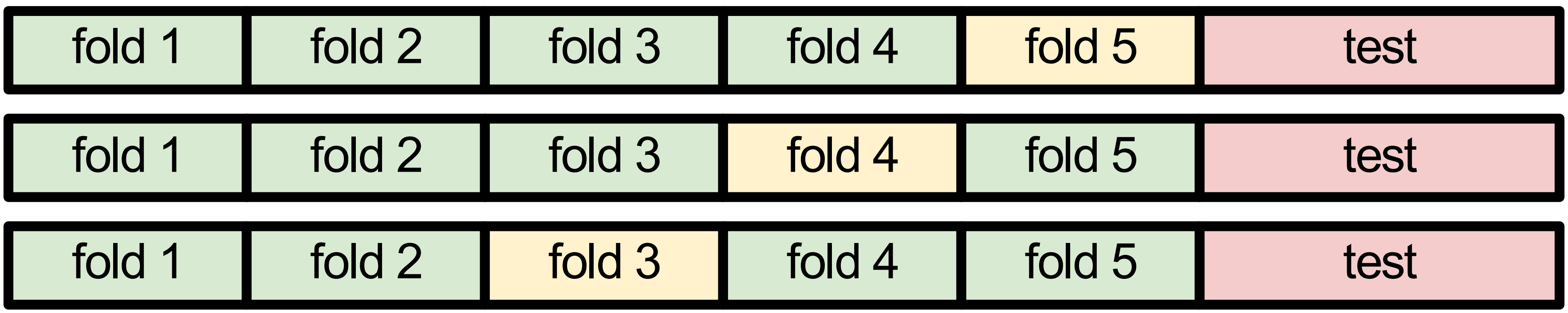
Better!

train	validation	test

Hyperparameters

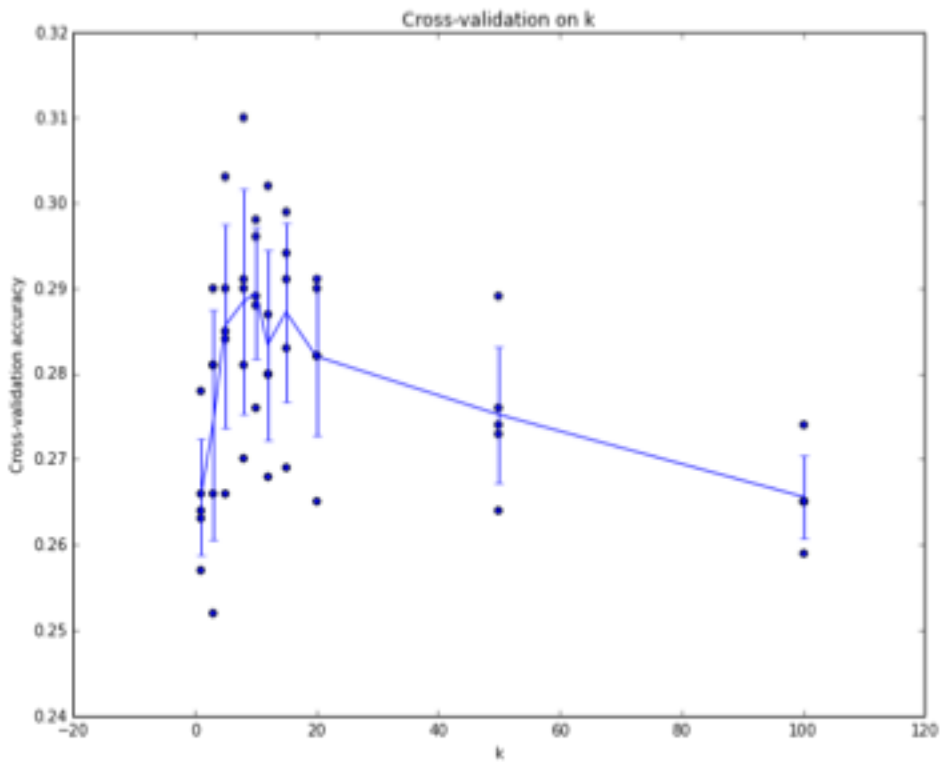
Your Dataset

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



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

Setting Hyperparameters



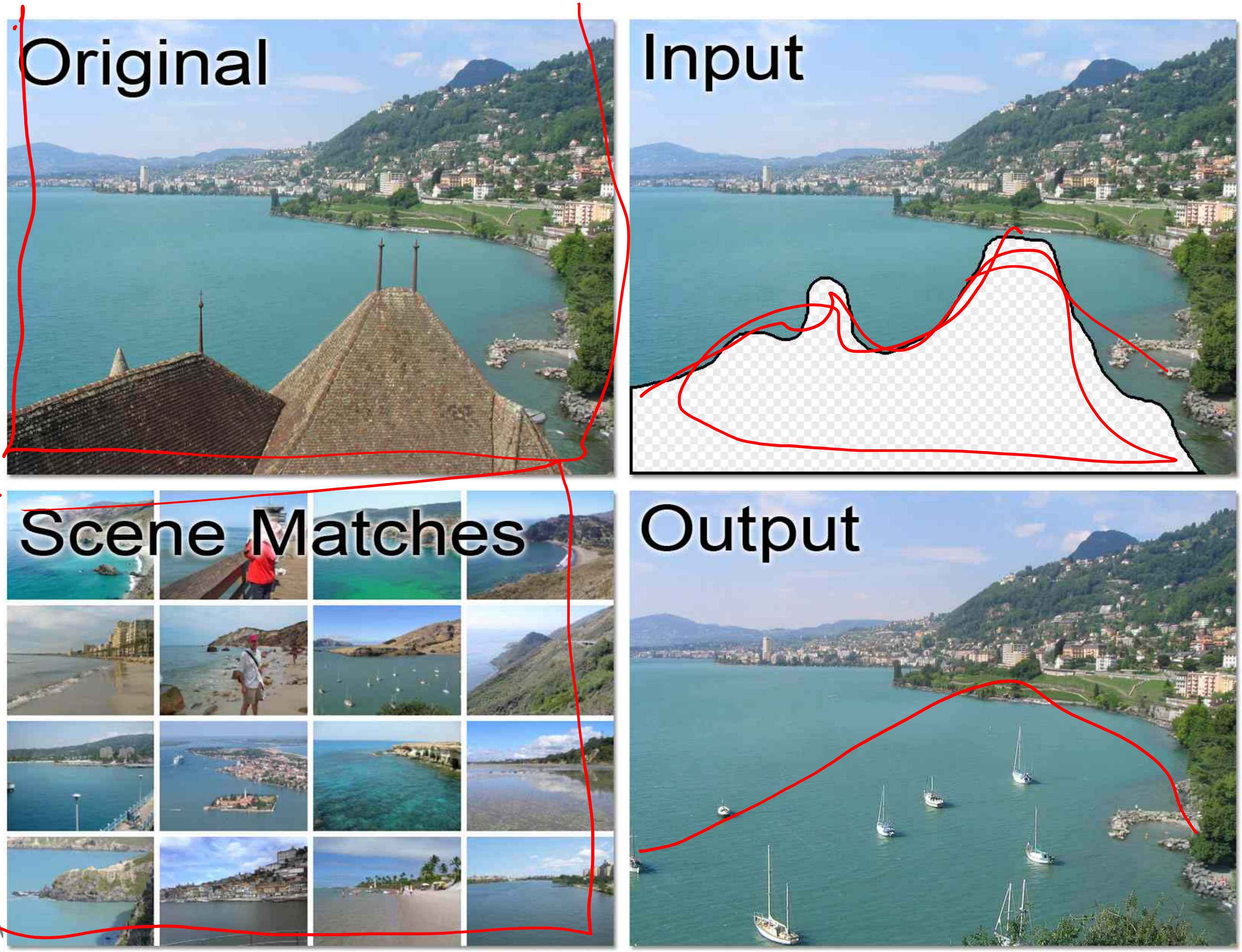
Example of
5-fold cross-validation for the value of **k.**

Each point: single outcome.

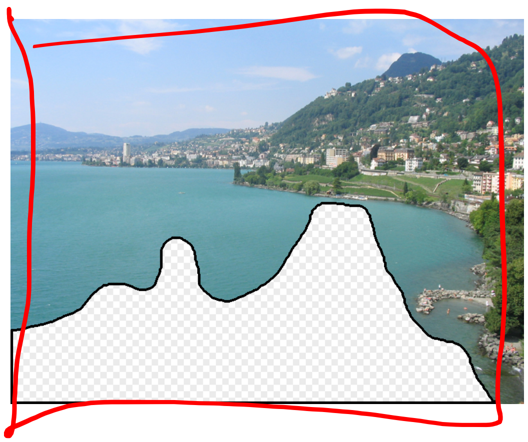
The line goes through the mean, bars indicated standard deviation

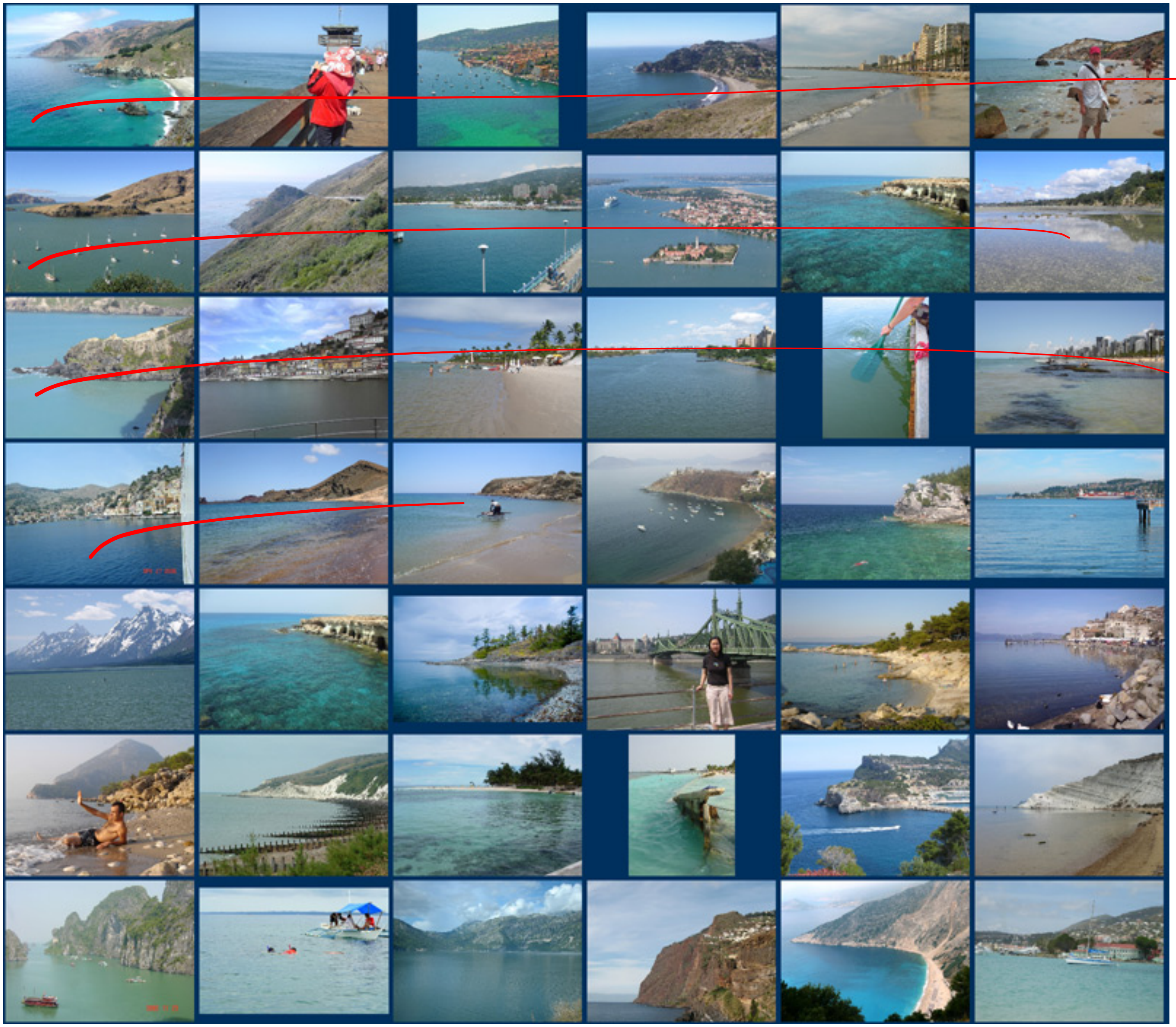
(Seems that k ~= 7 works best for this data)

Scene Completion [Hayes & Efros, SIGGRAPH07]




Hays and Efros, SIGGRAPH 2007

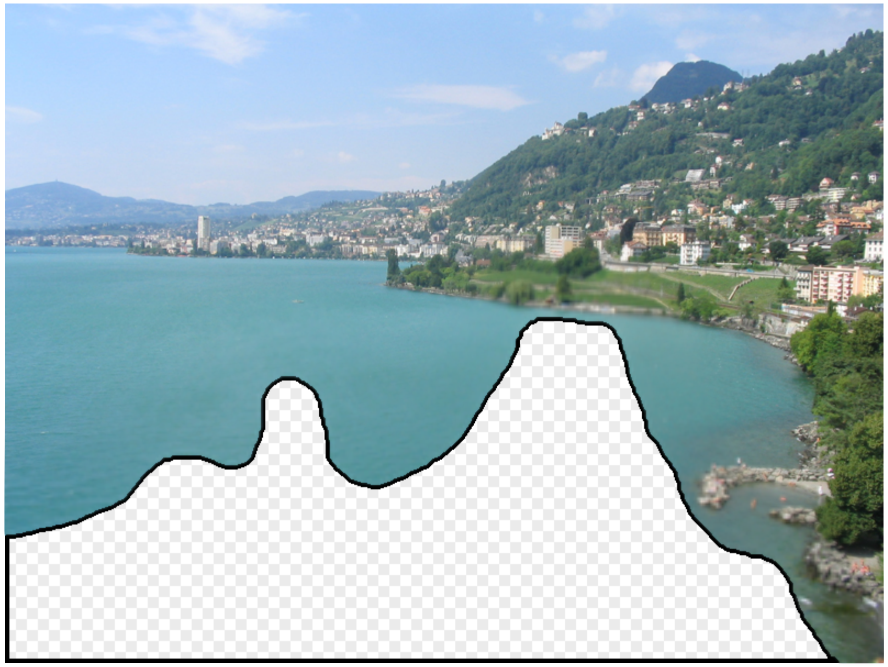




… 200 total

Hays and Efros, SIGGRAPH 2007

Context Matching



Hays and Efros, SIGGRAPH 2007

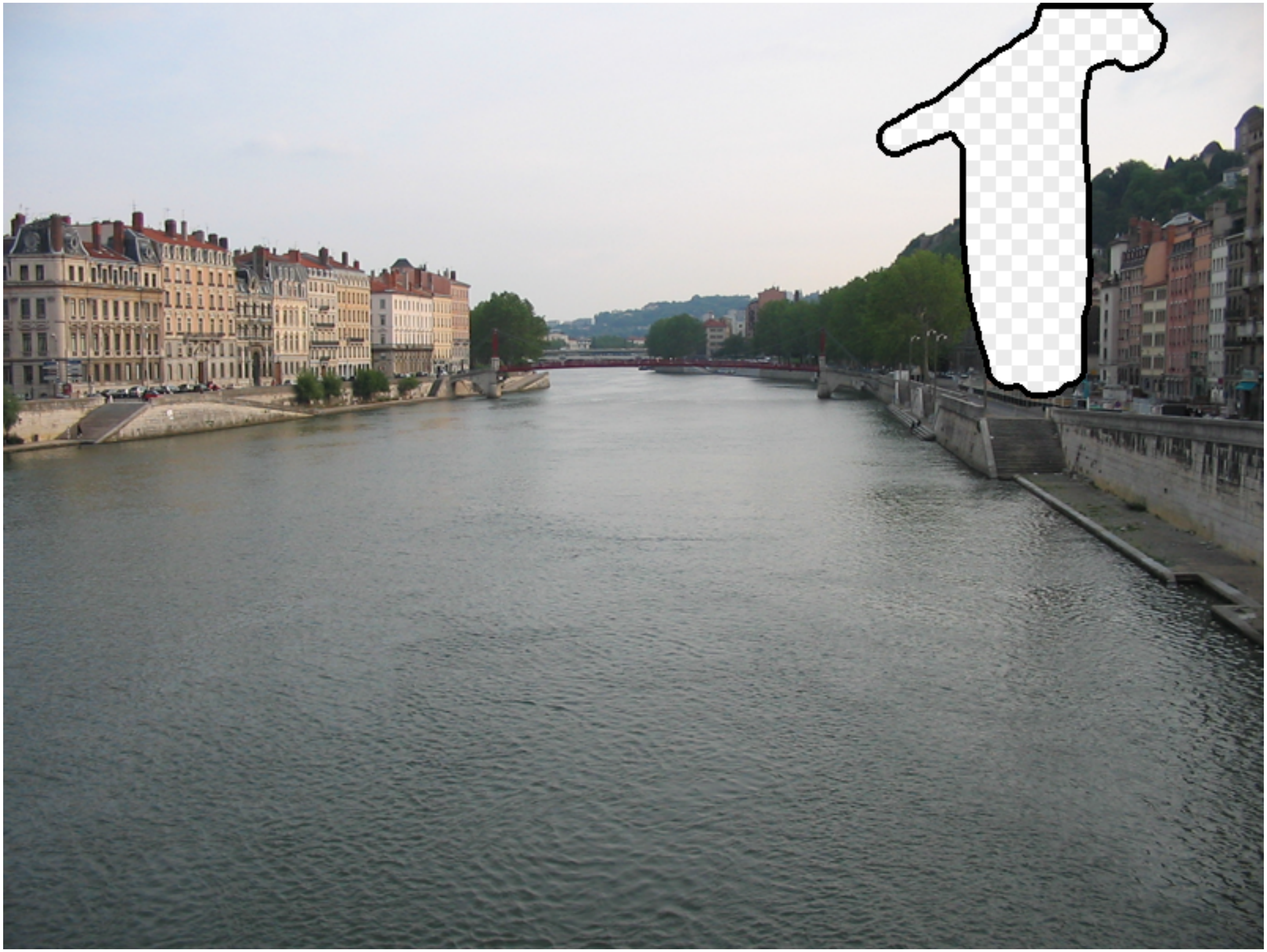
Graph cut + Poisson blending

Hays and Efros, SIGGRAPH 2007

Hays and Efros, SIGGRAPH 2007

Hays and Efros, SIGGRAPH 2007

Hays and Efros, SIGGRAPH 2007



Hays and Efros, SIGGRAPH 2007

Hays and Efros, SIGGRAPH 2007

Problems with Instance-Based Learning

- Expensive
  - No Learning: most real work done during testing
  - For every test sample, must search through all dataset – very slow!
  - Must use tricks like approximate nearest neighbour search
- Doesn't work well when large number of irrelevant features
  - Distances overwhelmed by noisy features
- Curse of Dimensionality
  - Distances become meaningless in high dimensions
  - (See proof in next lecture)

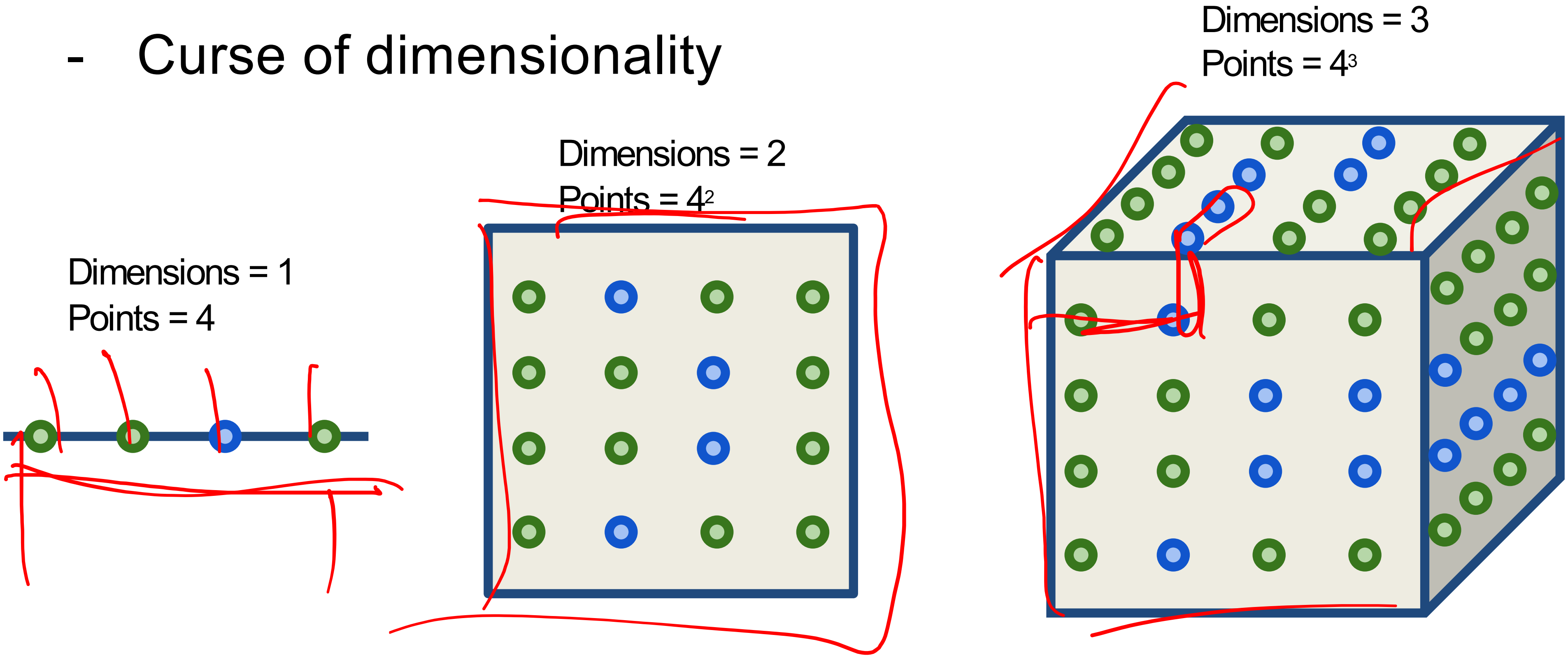
k-Nearest Neighbor on images **never used.**

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

- Curse of dimensionality



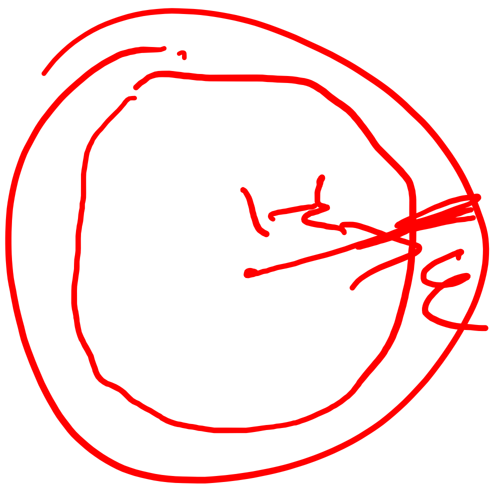
Curse of Dimensionality

- Consider: Sphere of radius 1 in d-dims
- Consider: an outer ε-shell in this sphere
- What is $\dfrac{\textit{shell volume}}{\textit{sphere volume}}$?

$r=1$ $\quad 2R$

πR^2

$\frac{4}{3}\pi R^3$

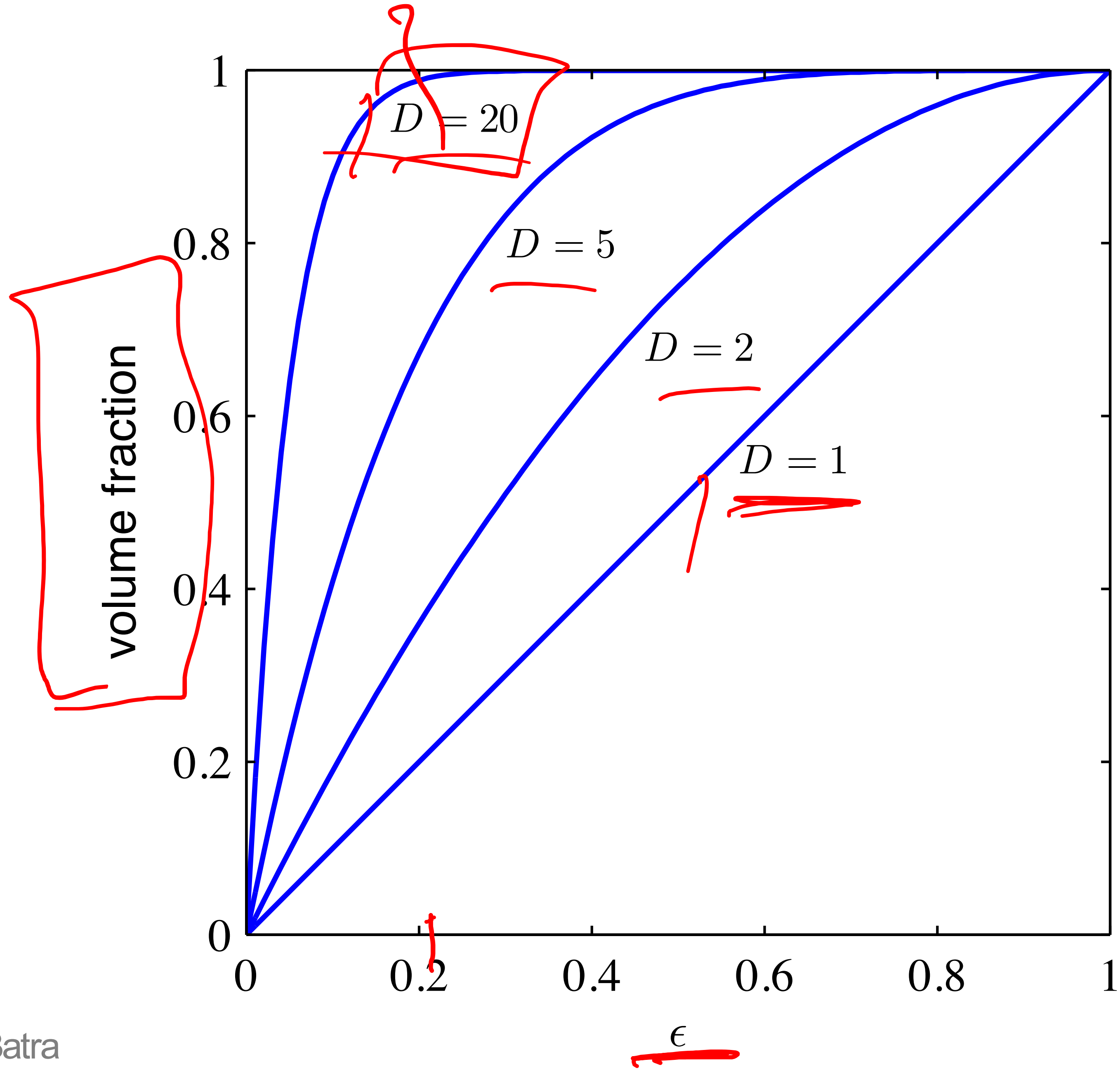


$$\frac{1^d - (1-\epsilon)^d}{1^d}$$

$$1 - (1-\epsilon)^d$$

R^d

Curse of Dimensionality



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!