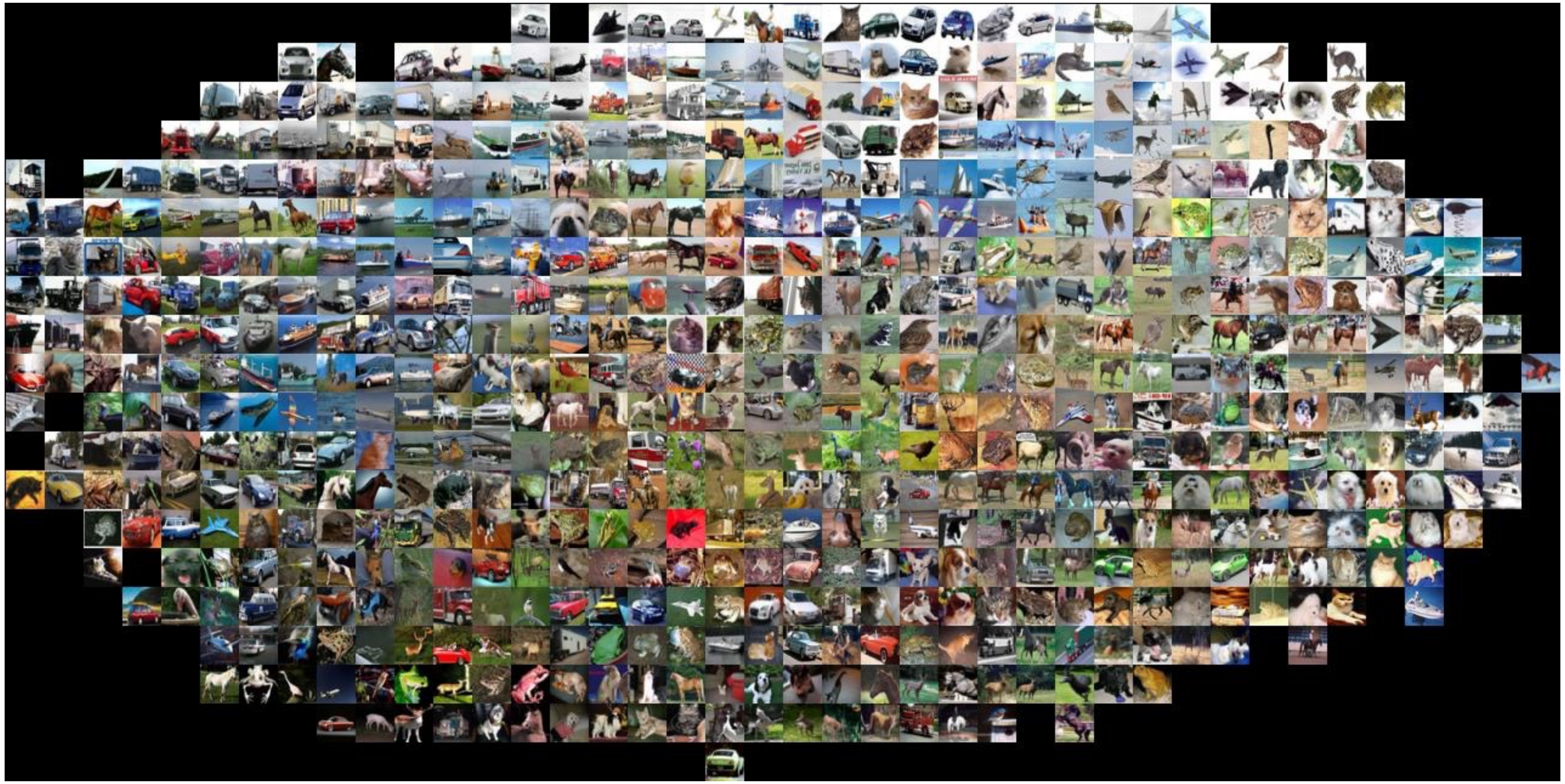
CS5670: Computer Vision

Image Classification



Some Slides from Fei-Fei Li, Justin Johnson, Serena Yeung
http://vision.stanford.edu/teaching/cs231n/

Announcements

- One more project to go – Project 5: Neural Radiance Fields
  - Tentative release date: Thursday, April 20
  - Tentative due date: Wednesday, May 3

- In-class Final Exam during the last lecture: Tuesday, May 9

Third Place

Jinzhao Kang and Xianglin Chen

Second Place

Wenqi Xiao and Zhuoyi Li

First Place

Shreyash Gupta and Srimoyee Mukhopadhyay

Last time: intro to recognition + classification

- Different problems: **image classification**, object detection

- Initial classification idea: k Nearest Neighbors

Image Classifiers in a Nutshell

- Input: an image
- Output: the class label for that image

```
def classifier(image):
      //Do some stuff
      return class_label;
```

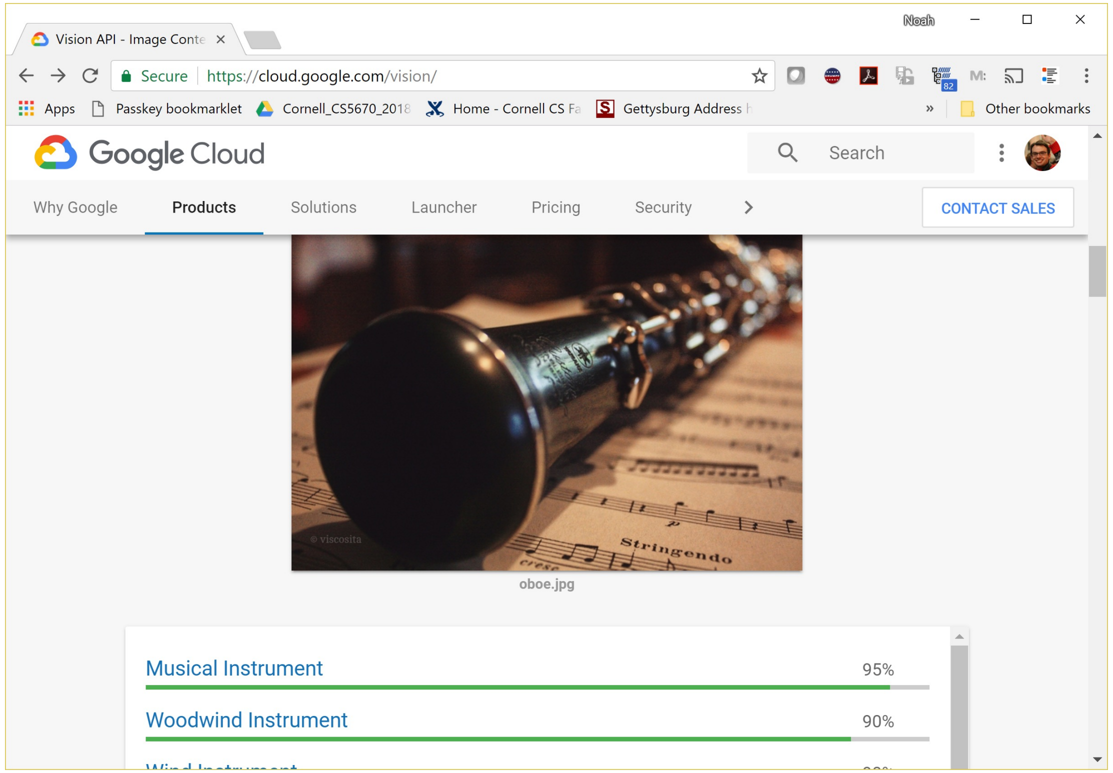
- Label is generally one or more of the discrete labels used in training
  - e.g. {cat, dog, cow, toaster, apple, tomato, truck, … }

$f($  $)$ $=$ “Cat”

$f($  $)$ $=$ “Dog”

$f($  $)$ $=$ “Toaster”

Image classification demo



https://cloud.google.com/vision/docs/drag-and-drop

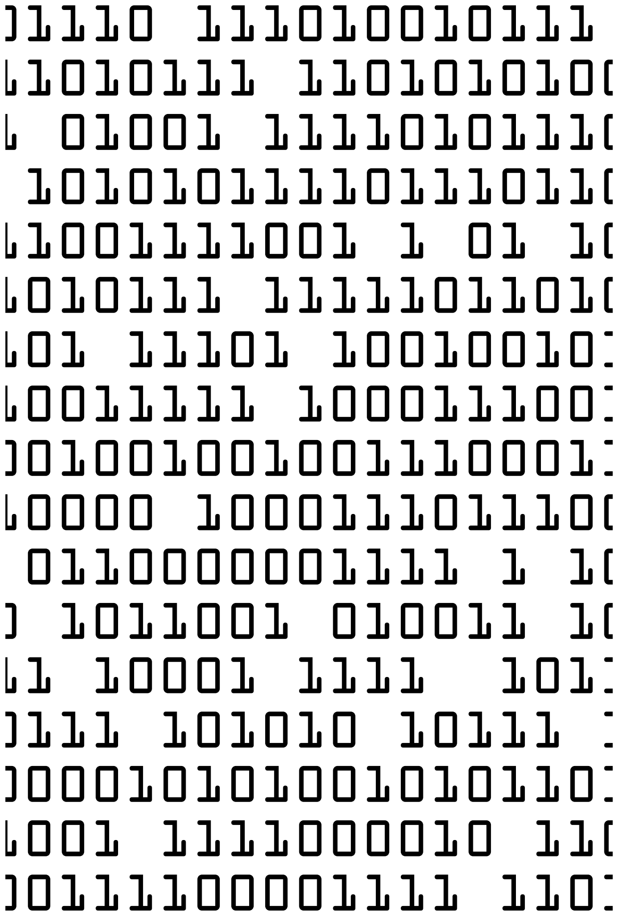
See also:

https://aws.amazon.com/rekognition/
https://www.clarifai.com/
https://azure.microsoft.com/en-us/services/cognitive-services/computer-vision/

…

The Semantic Gap

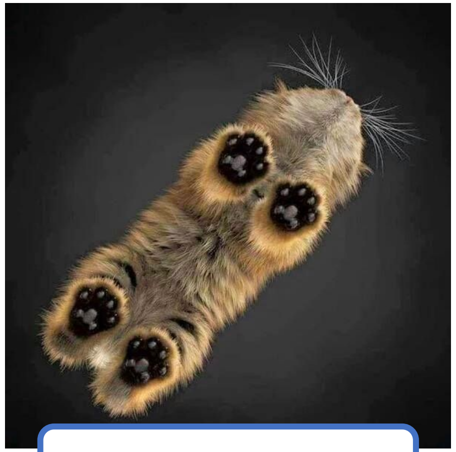
What we see



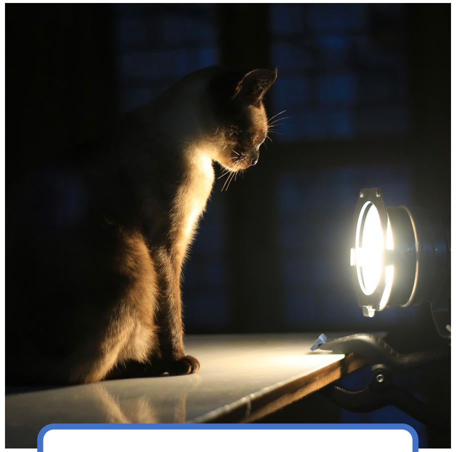
What the computer sees

Variation Makes Recognition Hard

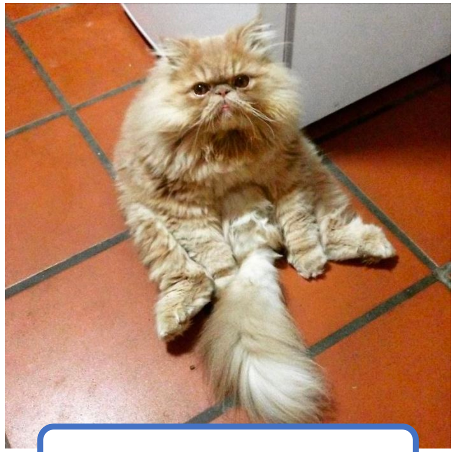
- The same class of object can appear *very* differently in different images



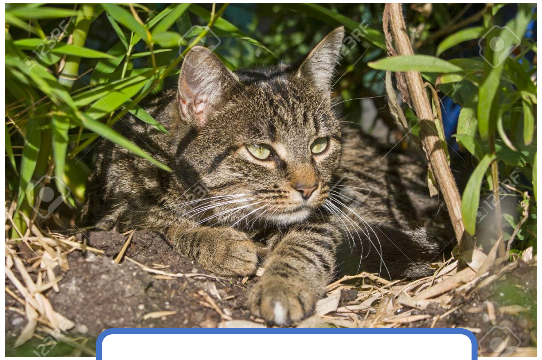
Viewpoint Variation



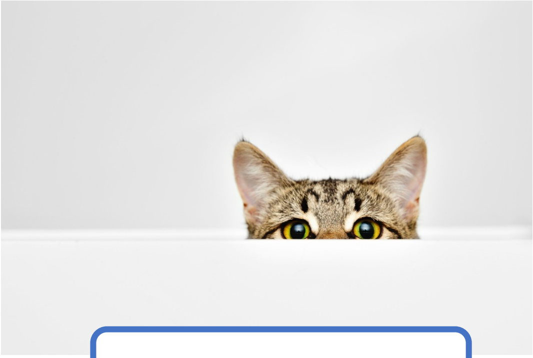
Lighting Variation



Deformation



Background Clutter



Occlusion

The Problem is Under-constrained

- Distinct realities can produce the same image…
- We generally can't compute the "right" answer, but we can compute the most likely one…
- We need some kind of prior to condition on. We can learn this prior from data:

$$f(x) = \underset{\ell_x}{argmax}\ P(\ell_x | data)$$

Images As High-Dimensional Vectors

- An image is just a bunch of numbers
- Let's stack them up into a vector
  - Our training data is just a bunch of high-dimensional points now

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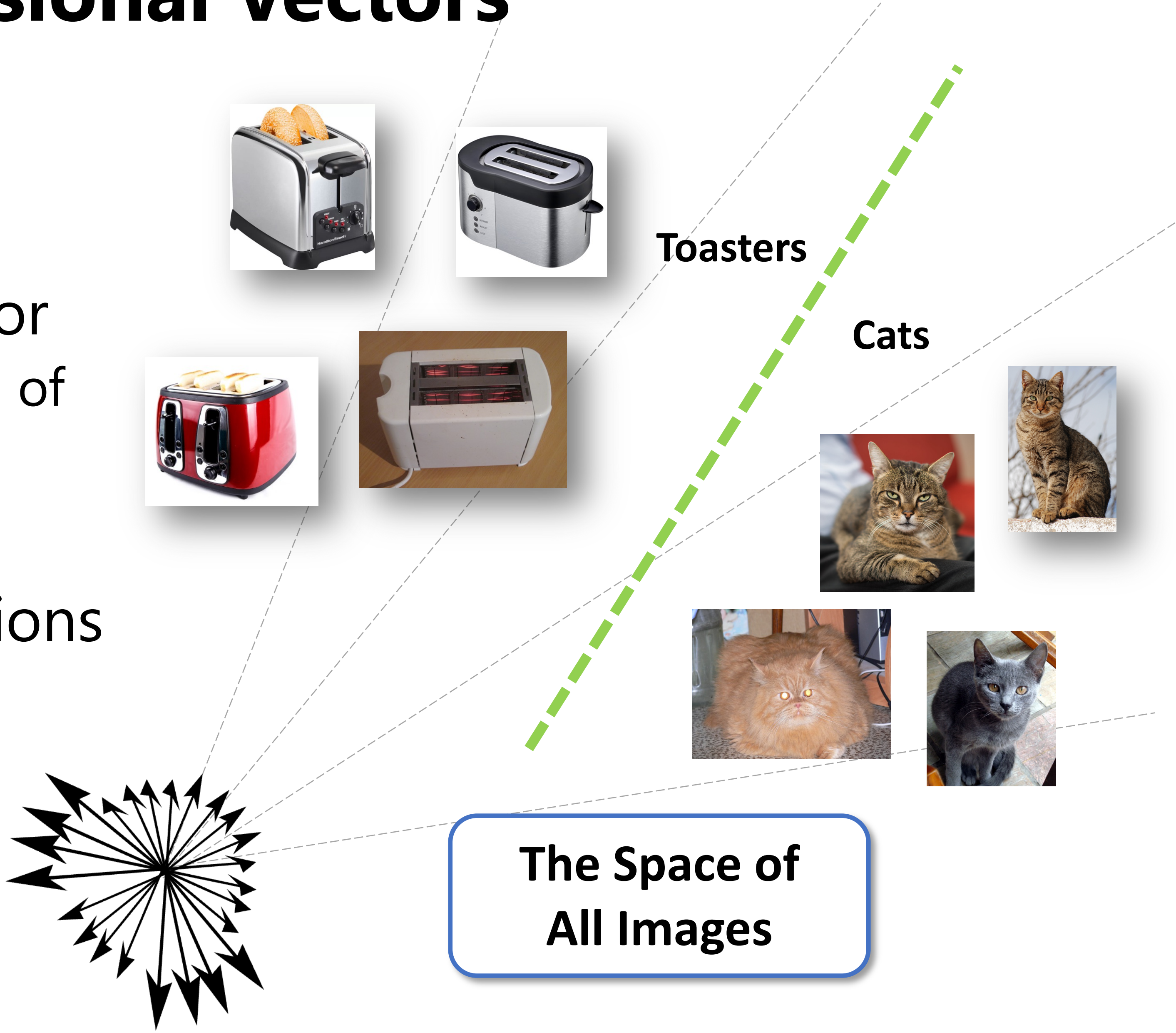

Images As High-Dimensional Vectors

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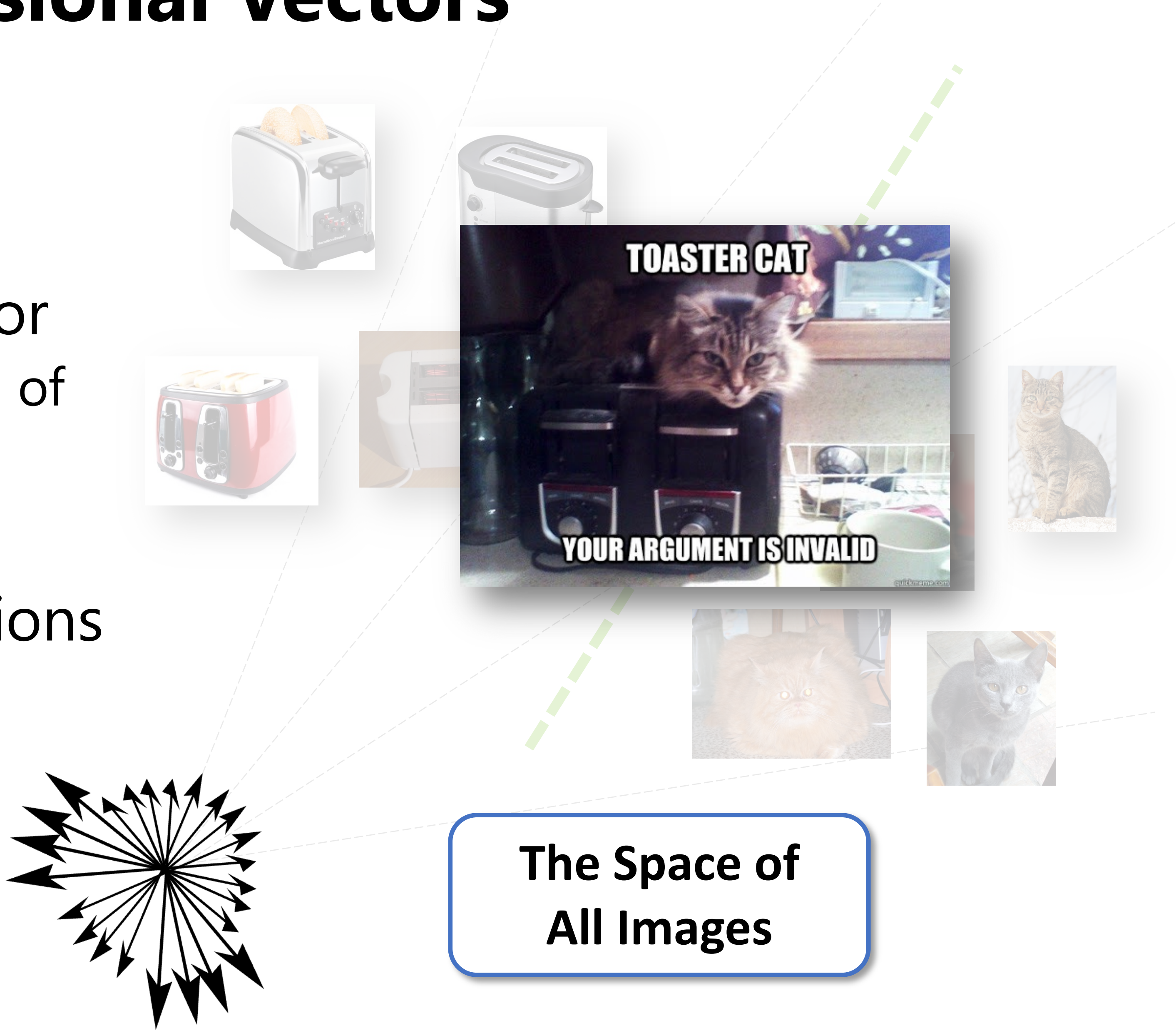


Images As High-Dimensional Vectors

- An image is just a bunch of numbers
- Let's stack them up into a vector
  - Our training data is just a bunch of high-dimensional points now
- Divide space into different regions for different classes

or

- Define a distribution over space for each class

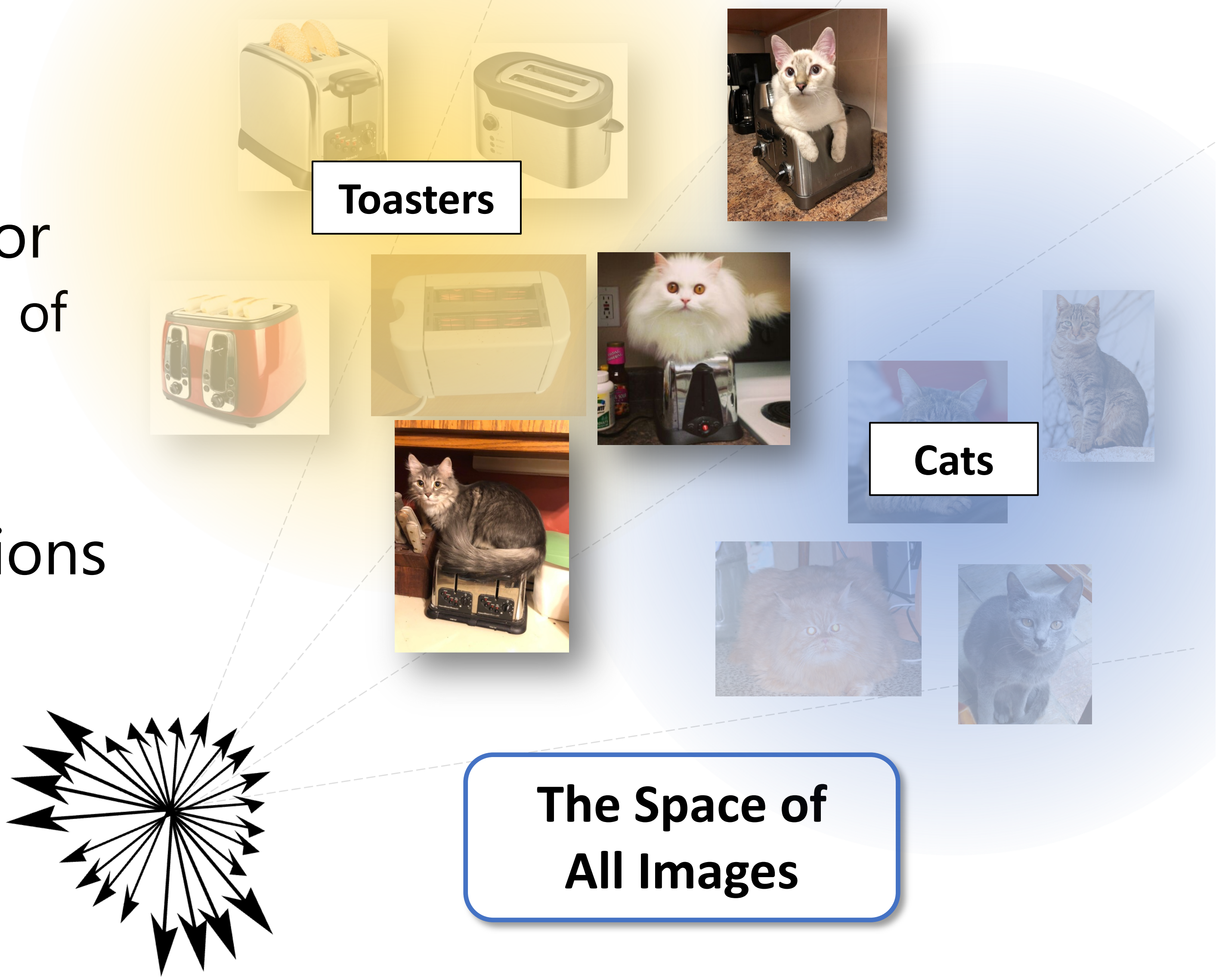
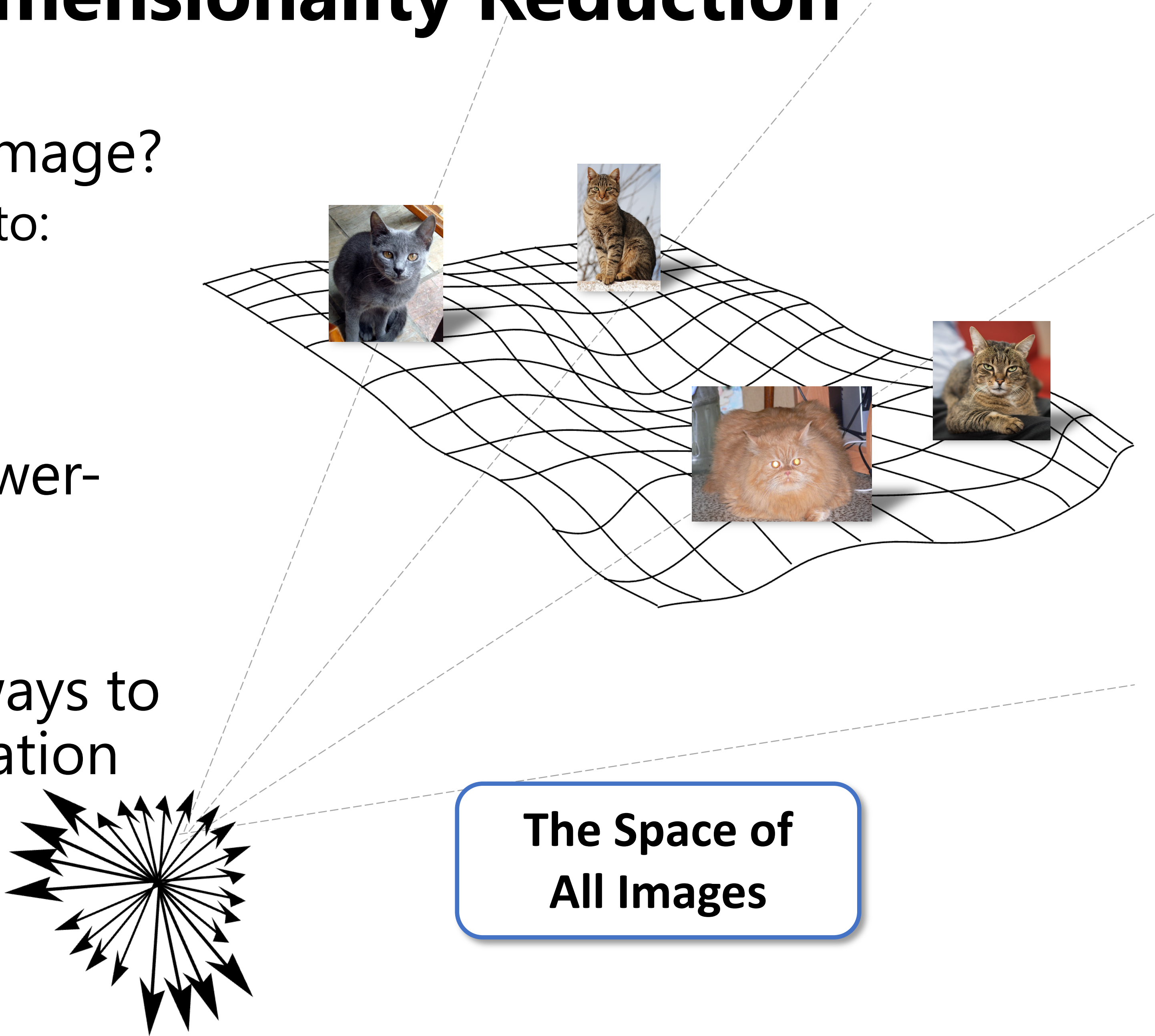


Image Features and Dimensionality Reduction

- How high-dimensional is an image?
  - Let’s consider an iPhone X photo:
    - 4032 x 3024 pixels
    - Every pixel has 3 colors
    - 36,578,304 pixels (36.5 Mega pixels)
- In practice, images sit on a lower-dimensional manifold
- Think of image features and dimensionality reduction as ways to represent images by their location on such manifolds



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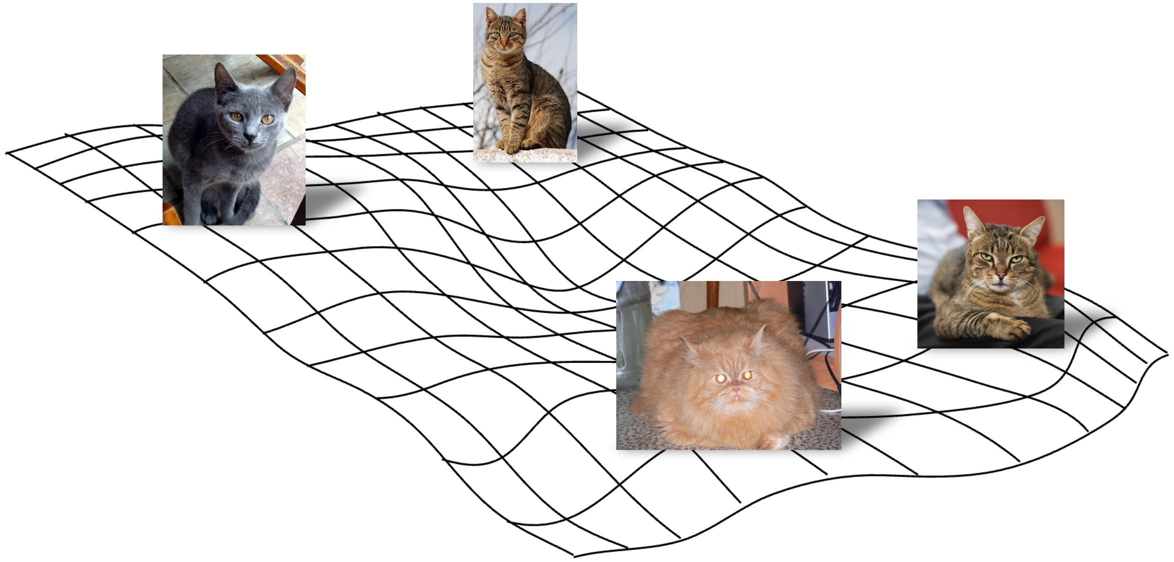


Side Note:
This also lets us deal with images of different sizes, crops, etc.

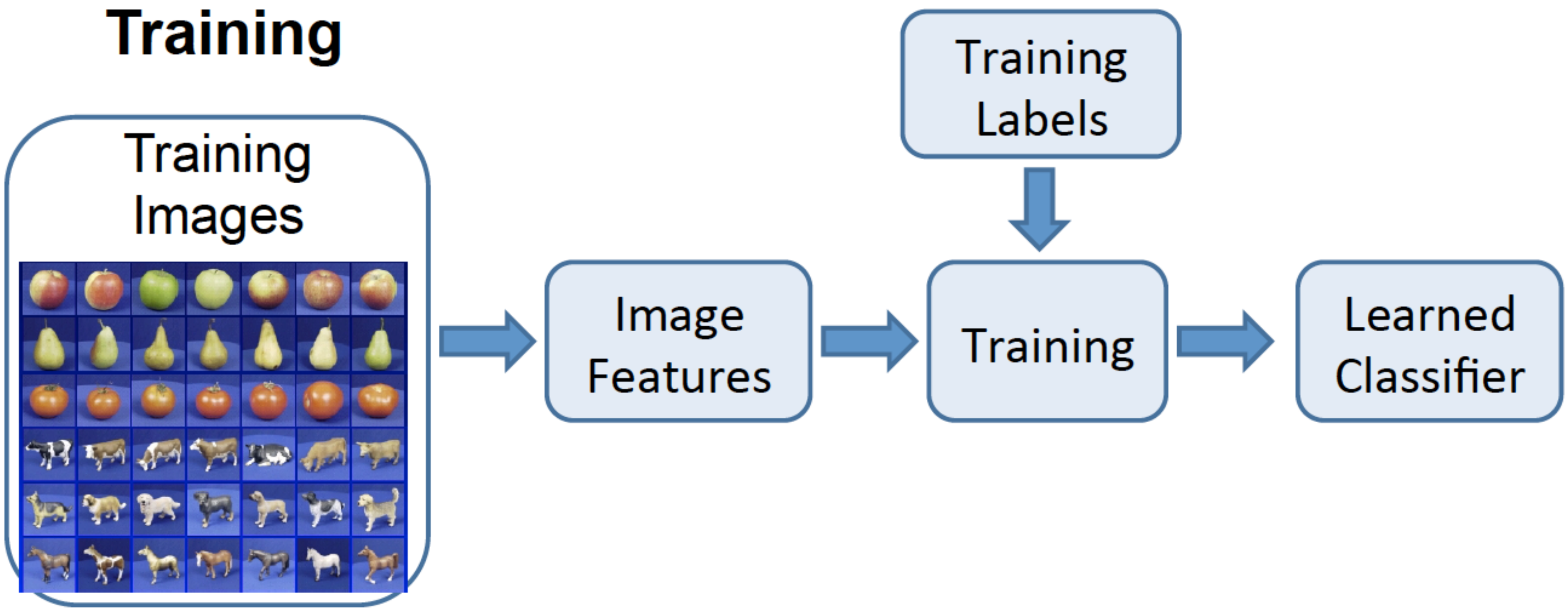
Training & Testing a Classifier

- Collect a database of images with labels
- Use ML to train an image classifier
- Evaluate the classifier on test images

Example training set

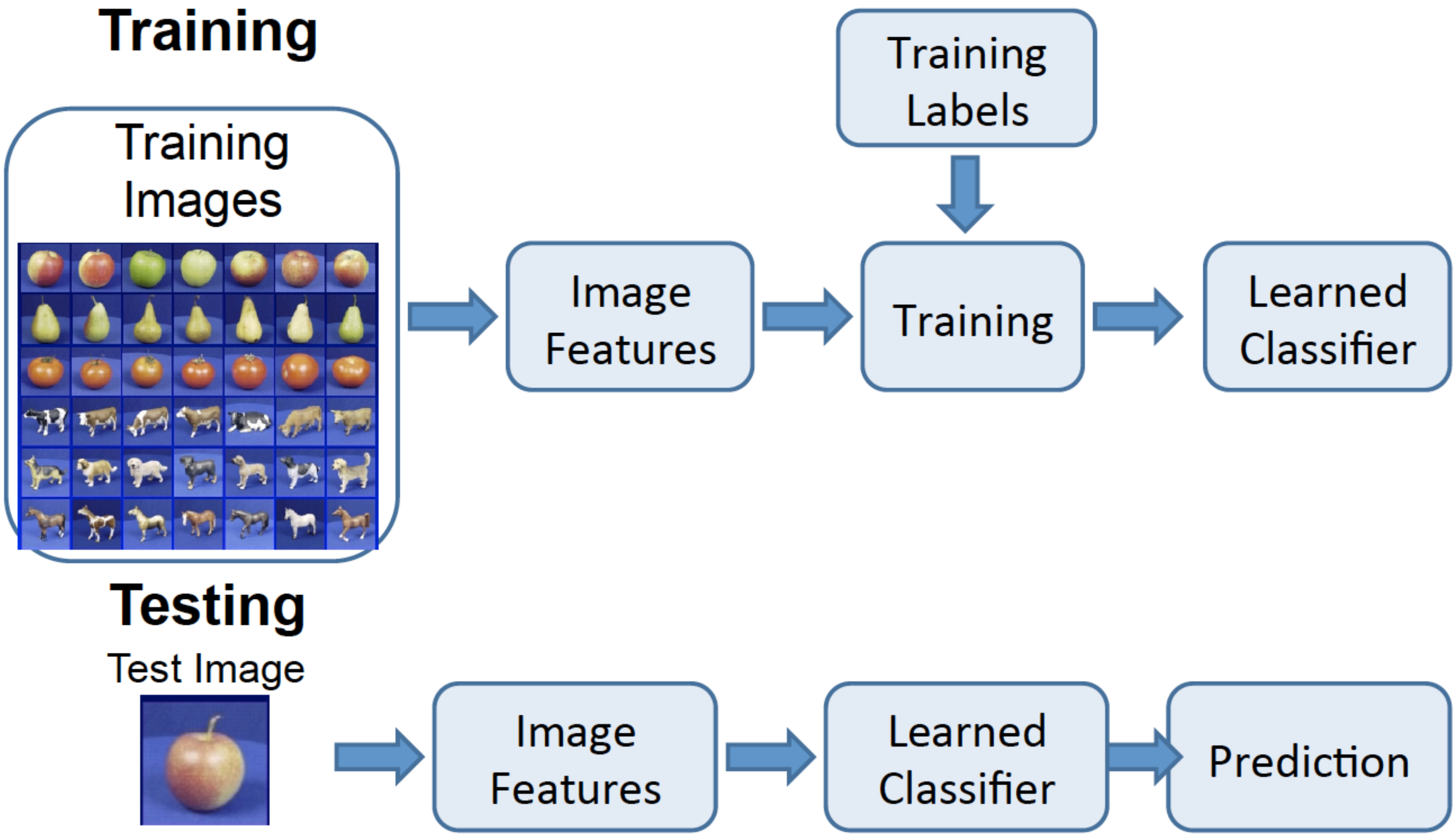
Slide from Andrej Karpathy and Fei-Fei Li   http://vision.stanford.edu/teaching/cs231n/

Training & Testing a Classifier



Dataset: ETH-80, by B. Leibe   Slide credit: D. Hoiem, L. Lazebnik

Training & Testing a Classifier



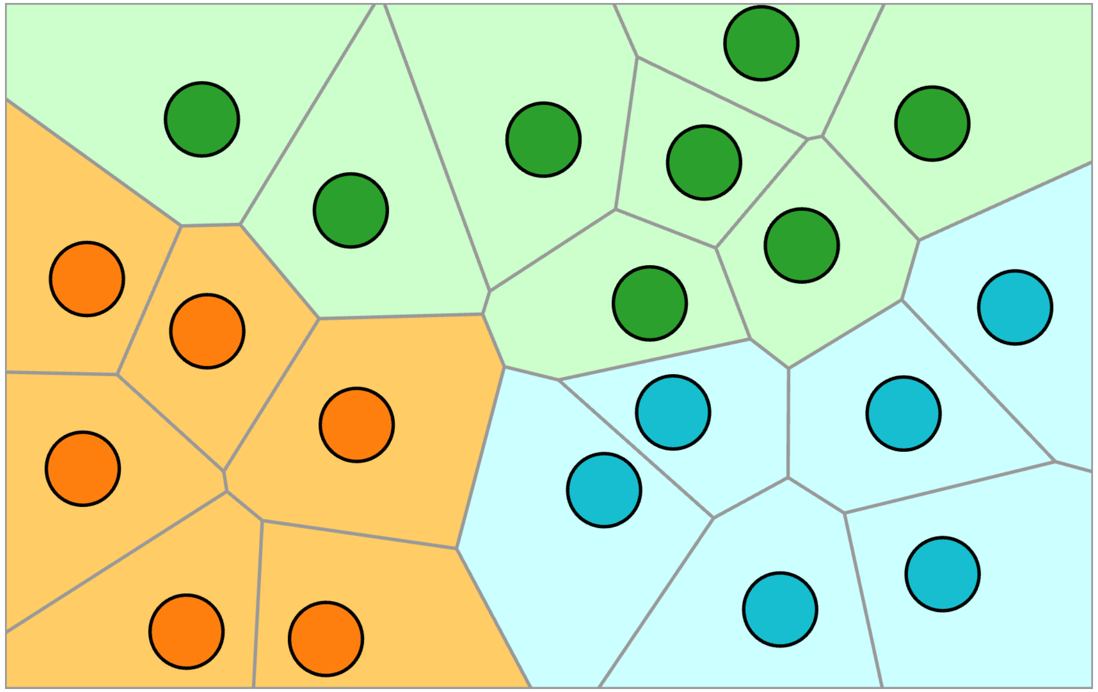
Dataset: ETH-80, by B. Leibe   Slide credit: D. Hoiem, L. Lazebnik

Classifiers

- Nearest Neighbor
- kNN (“k-Nearest Neighbors”)
- Linear Classifier
- Neural Network
- Deep Neural Network
- …

First idea: Nearest Neighbor (NN) Classifier

- Train
  - Remember all training images and their labels
- Predict
  - Find the closest (most similar) training image
  - Predict its label as the true label



CIFAR-10 and NN results

Example dataset: **CIFAR-10**
10 labels
50,000 training images
10,000 test images.

Slides from Andrej Karpathy and Fei-Fei Li
http://vision.stanford.edu/teaching/cs231n/

CIFAR-10 and NN results

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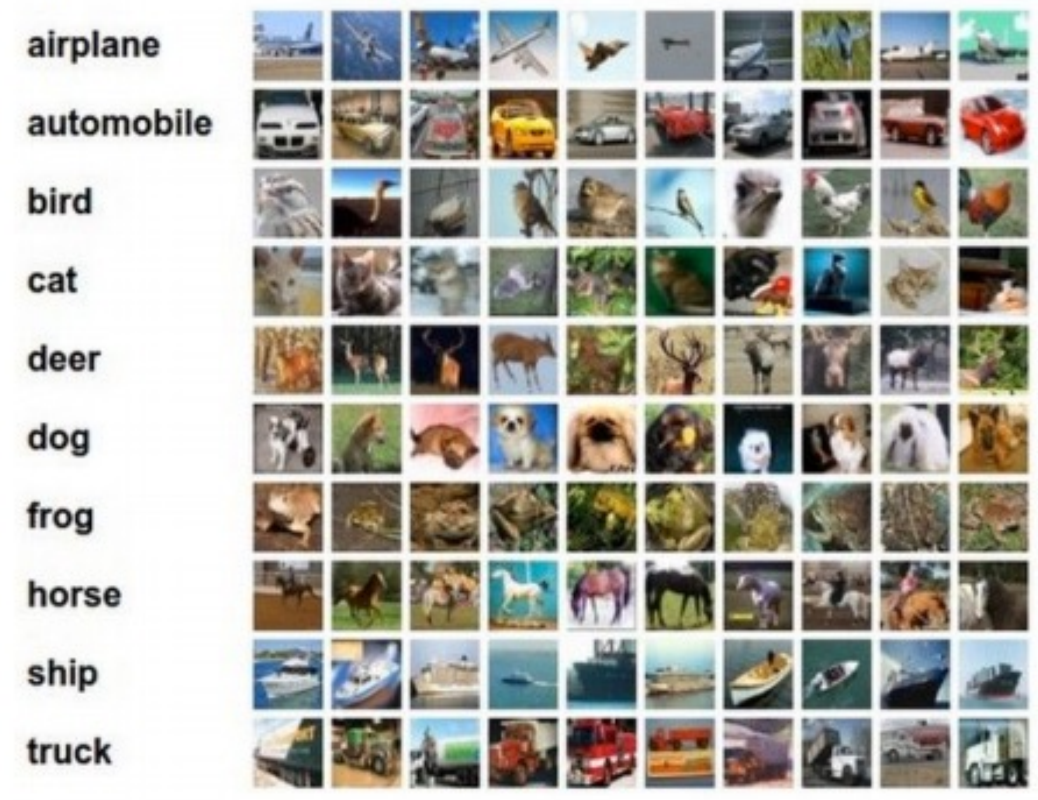
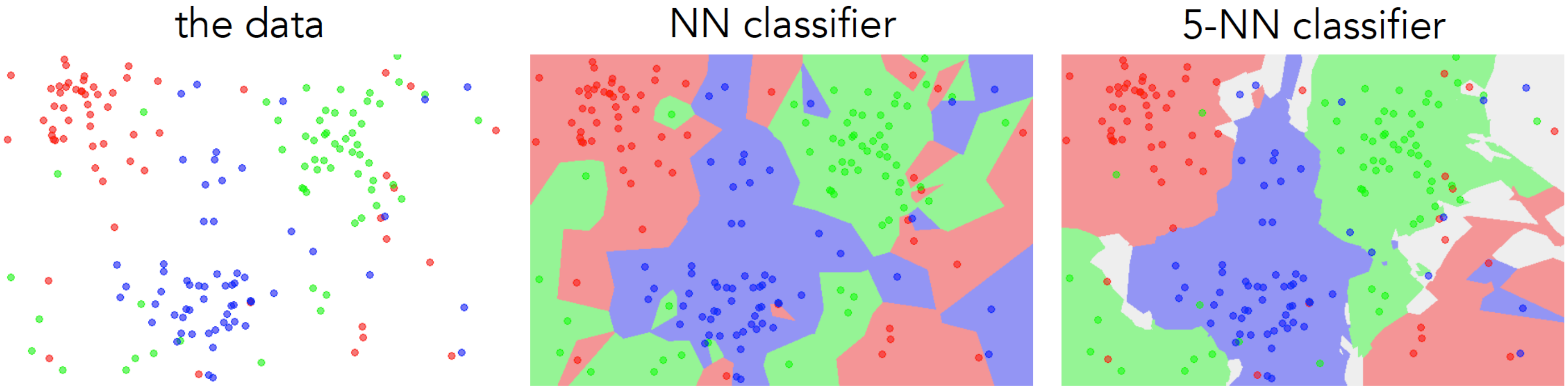


For every test image (first column), examples of nearest neighbors in rows

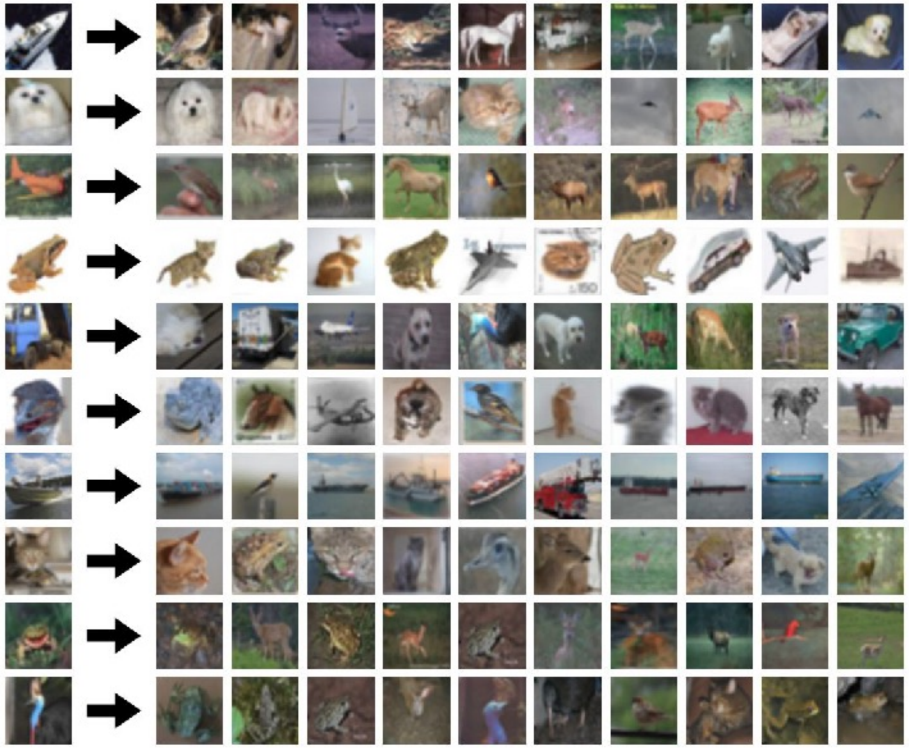
Slides from Andrej Karpathy and Fei-Fei Li
http://vision.stanford.edu/teaching/cs231n/

k-nearest neighbor

- Find the k closest points from training data
- Take **majority vote** from K closest points



What does this look like?



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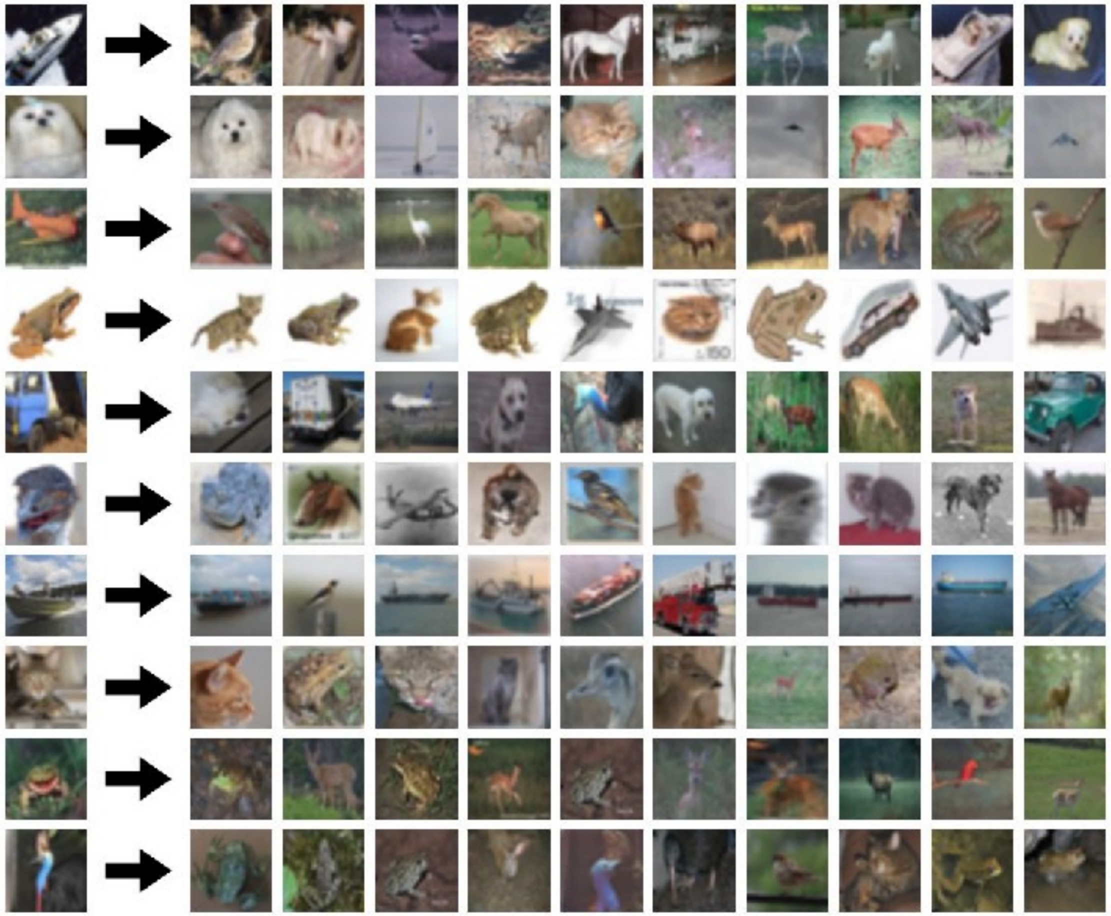


What does this look like?

How to Define Distance Between Images

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

Where I_1 denotes image 1, and p denotes each pixel

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

→ 456

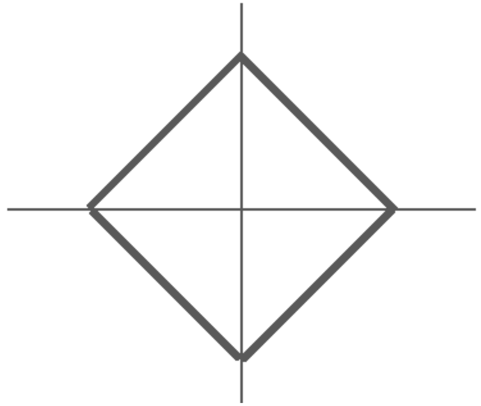
Slides from Andrej Karpathy and Fei-Fei Li http://vision.stanford.edu/teaching/cs231n/

Choice of distance metric

- Hyperparameter

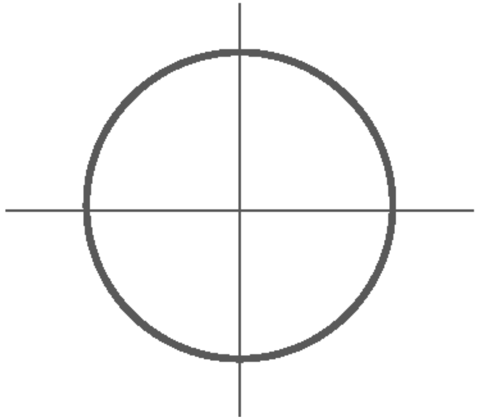
L1 (Manhattan) distance

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



L2 (Euclidean) distance

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



- Two most commonly used special cases of p-norm

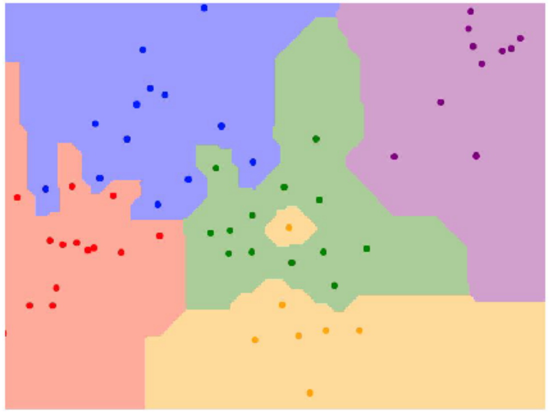
$$||x||_p = \left(|x_1|^p + \cdots + |x_n|^p\right)^{\frac{1}{p}} \qquad p \geq 1, x \in \mathbb{R}^n$$

Slide composited from Andrej Karpathy and Fei-Fei Li http://vision.stanford.edu/teaching/cs231n/

K-Nearest Neighbors: Distance Metric

L1 (Manhattan) distance

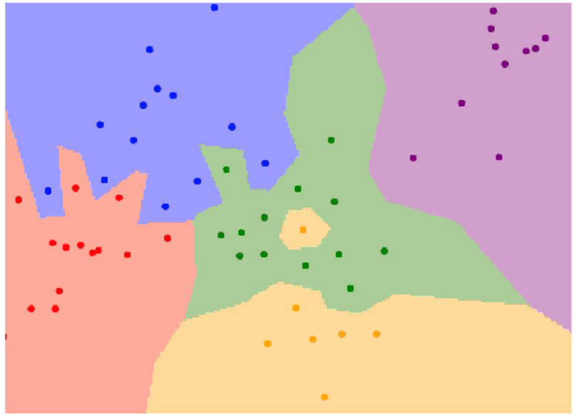
$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$



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

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

Hyperparameters

- What is the **best distance** to use?
- What is the **best value of k** to use?

- These are **hyperparameters**: choices about the algorithm that we set rather than learn

- How do we set them?
  - One option: try them all 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

Setting Hyperparameters

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

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

Setting Hyperparameters

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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

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

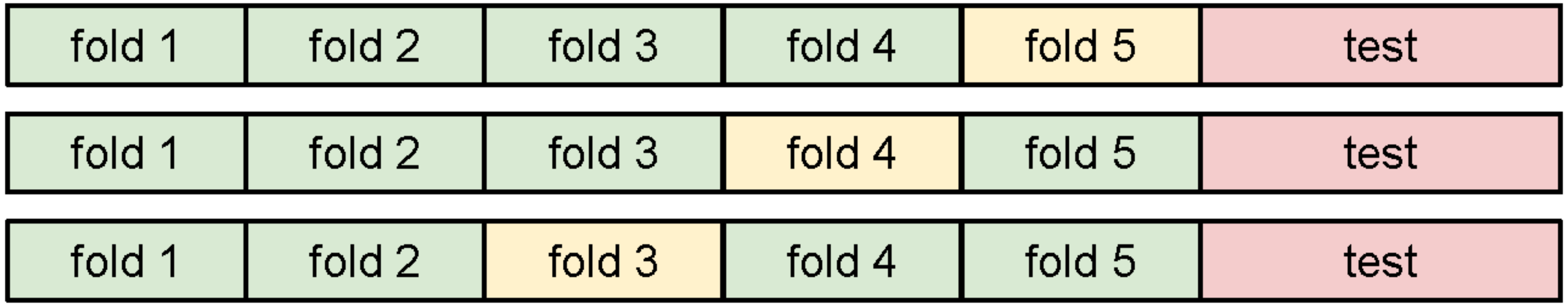
BAD: No idea how algorithm will perform on new data

Idea #3: Split data into **train**, **val**, and **test**; choose hyperparameters on val and evaluate on test

Better!

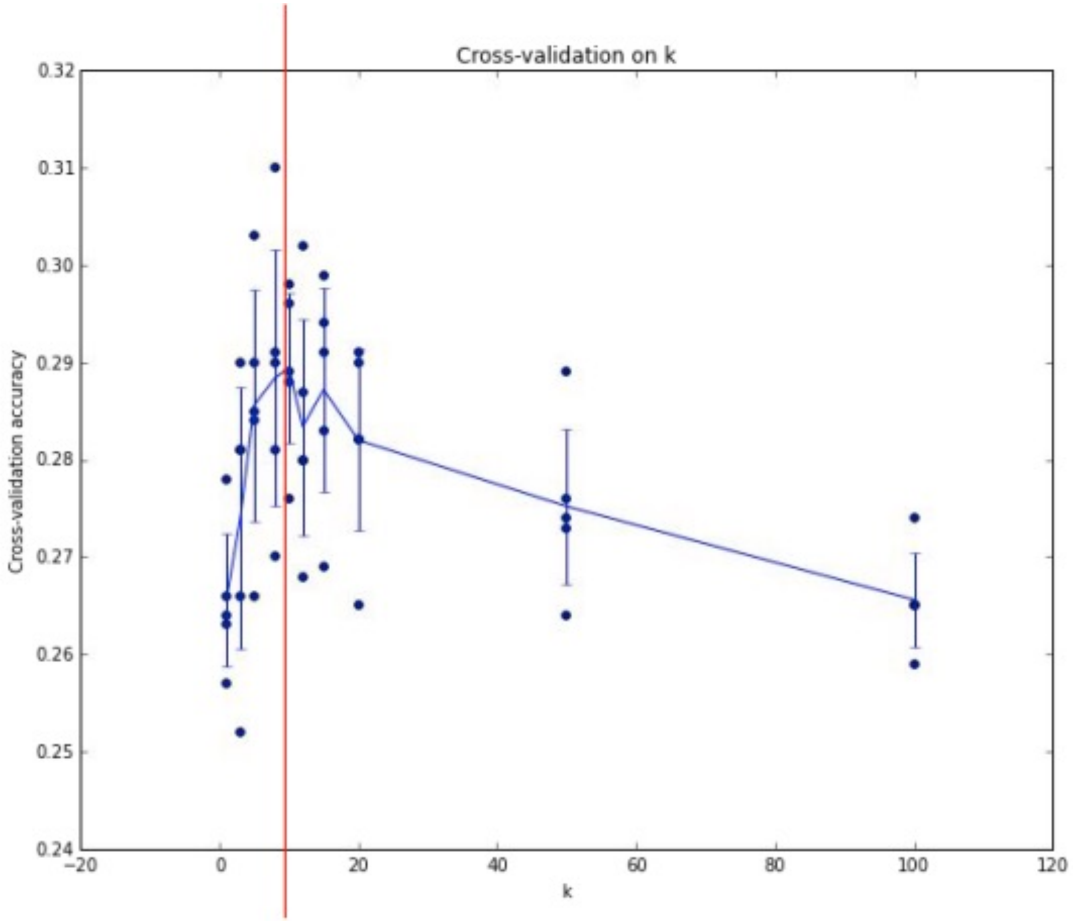
Setting Hyperparameters

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

Hyperparameter Tuning



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)

Recap: How to pick hyperparameters?

- Methodology
  - Train and test
  - Train, validate, test

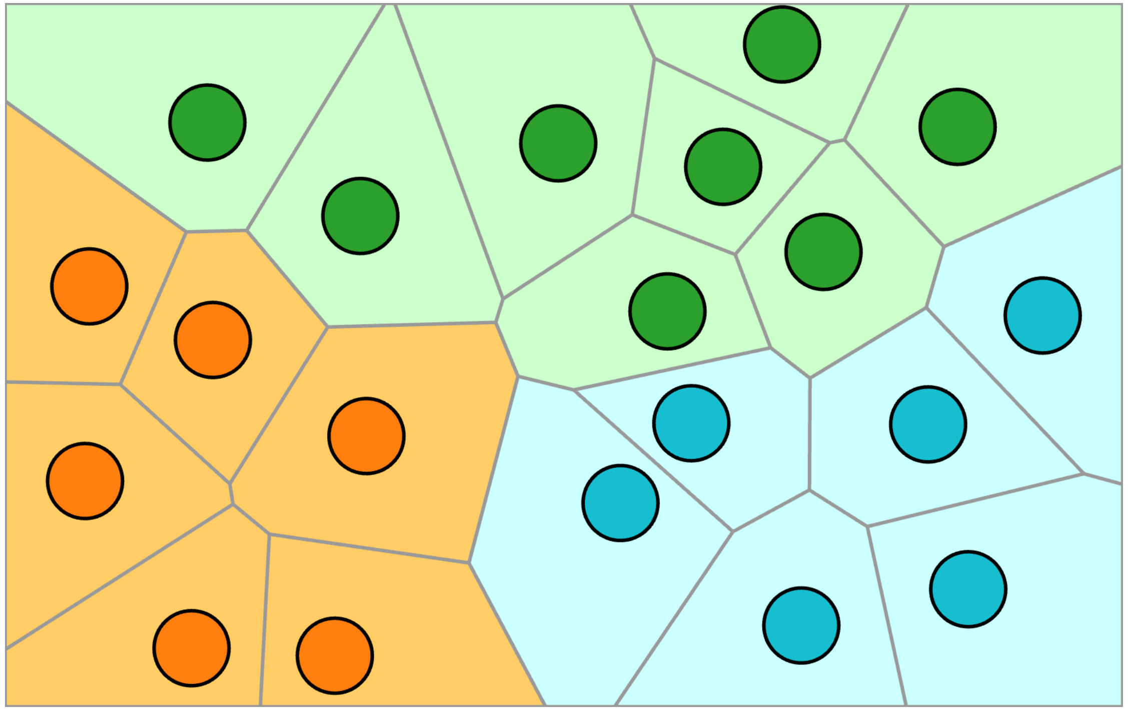
- Train an initial model
- Validate to find hyperparameters
- Test to understand generalizability

kNN – Complexity and Storage

- N training images, M test images

- Training: O(1)
- Testing: O(MN)

- We often need the opposite:
    - Slow training is ok
    - Fast testing is necessary

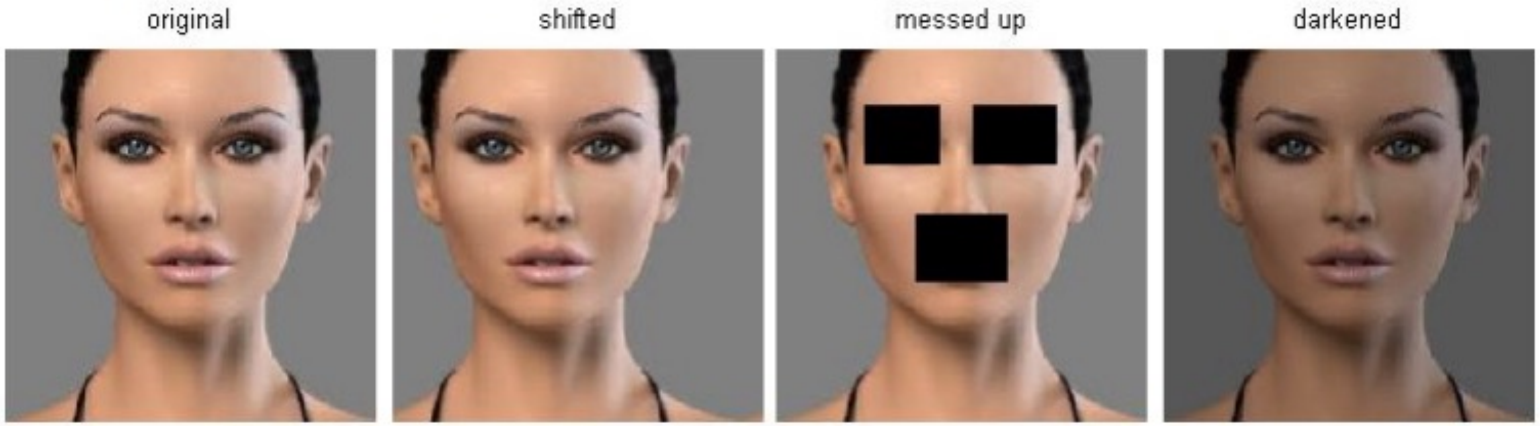


k-Nearest Neighbors: Summary

- 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!

Problems with KNN: Distance Metrics

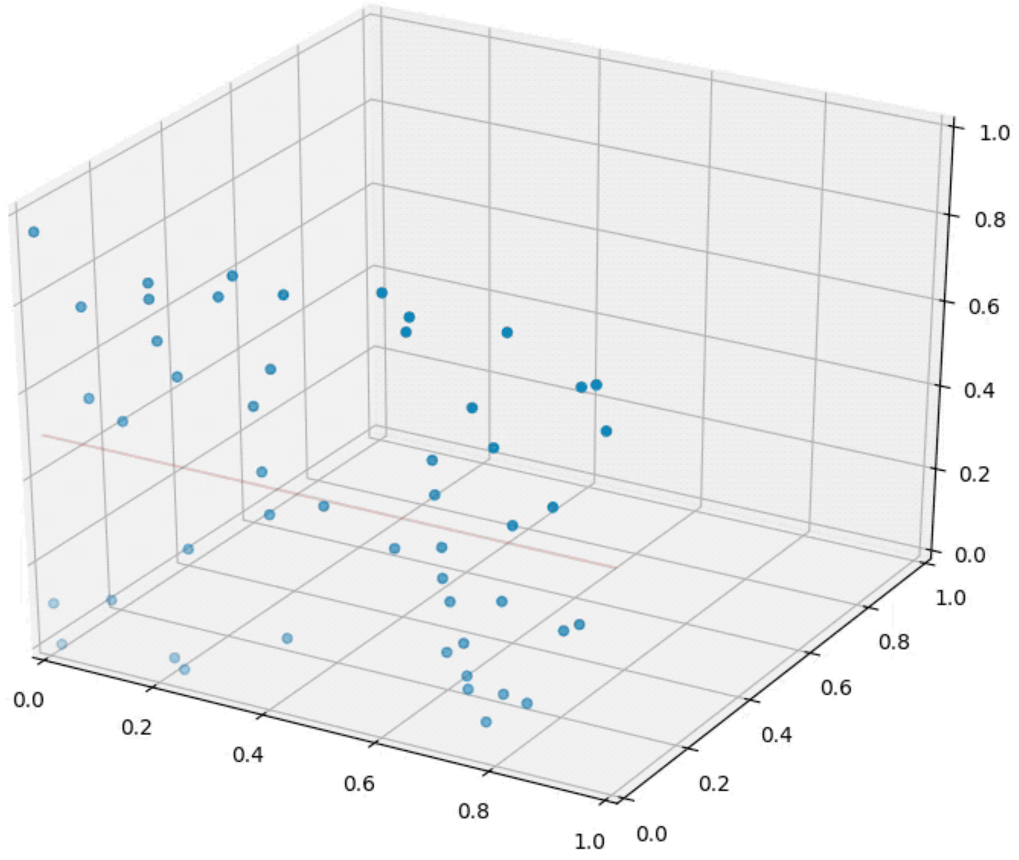
- terrible performance at test time
- distance metrics on level of whole images can be very unintuitive



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

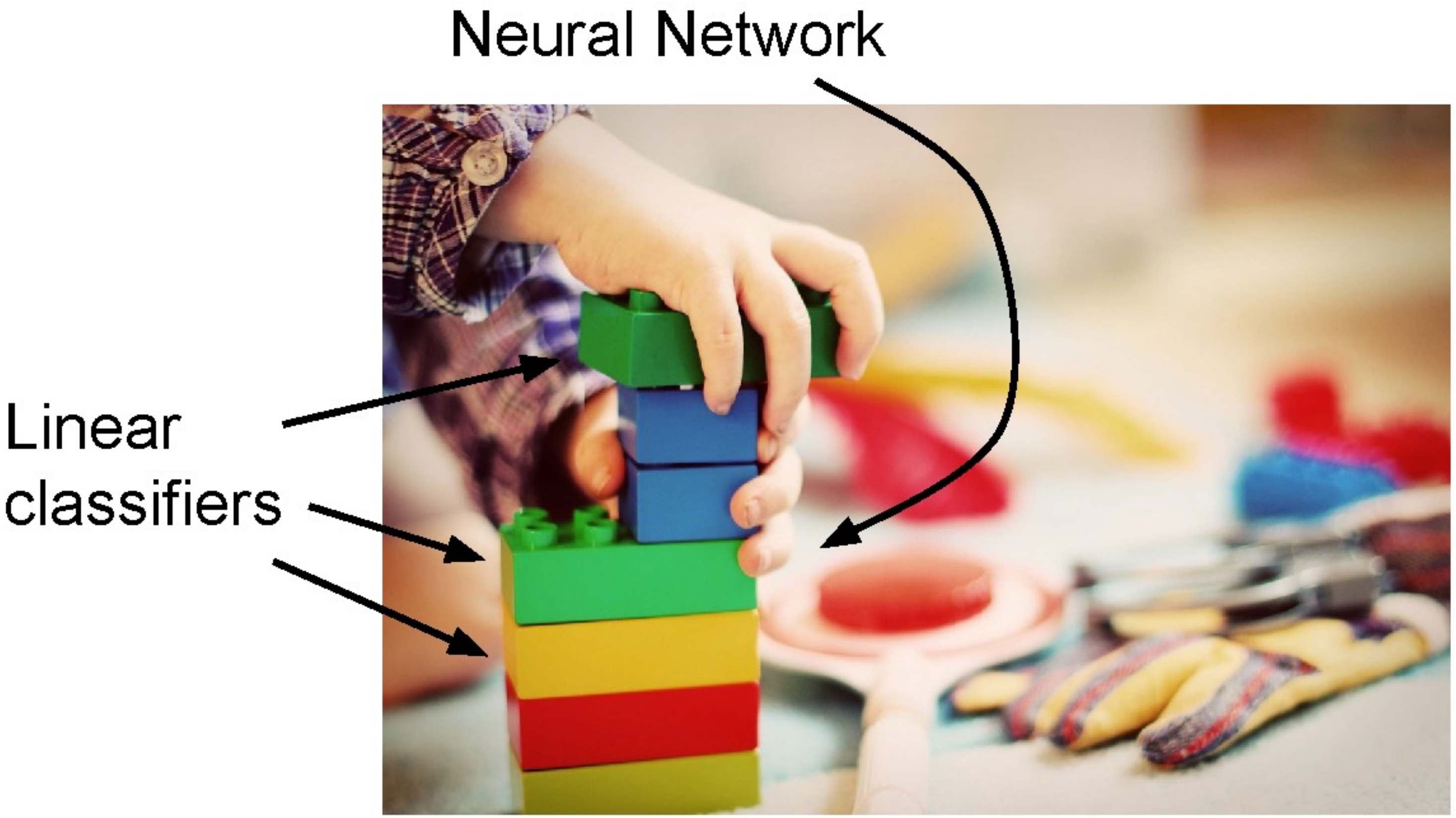
Problems with KNN: The Curse of Dimensionality

- As the number of dimensions increases, the same amount of data becomes more sparse.
- Amount of data we need ends up being exponential in the number of dimensions



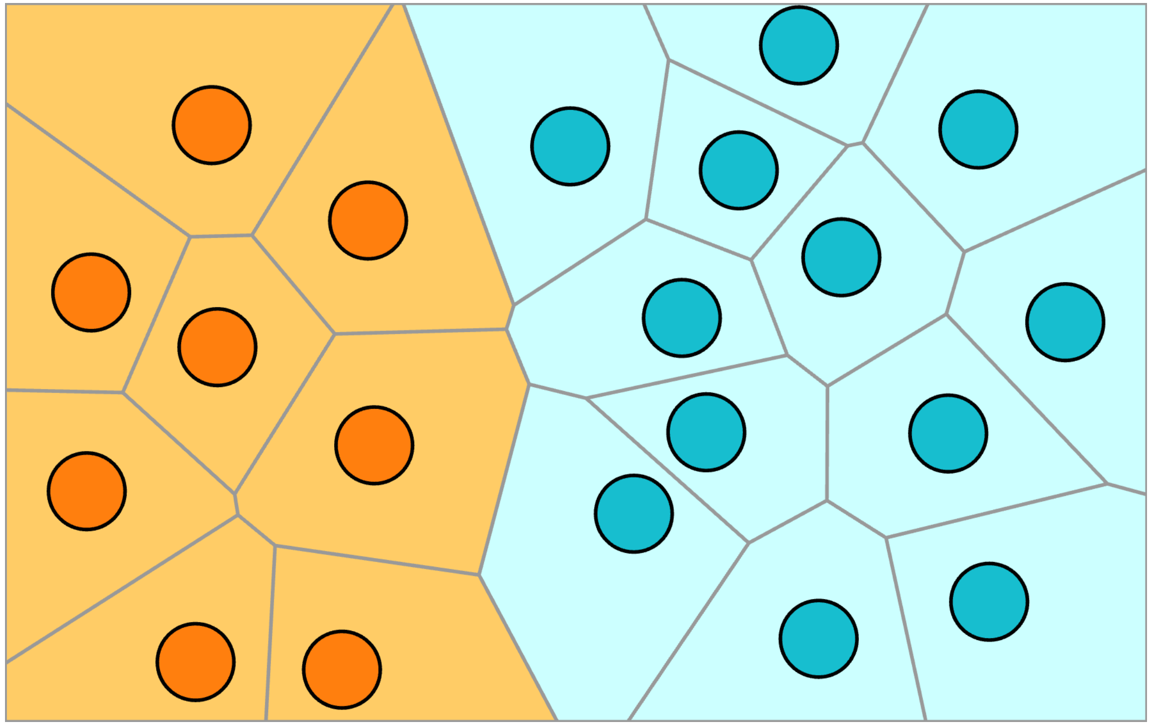
[Animation from https://www.cs.cornell.edu/courses/cs4780/2018fa/lectures/lecturenote02_kNN.html](https://www.cs.cornell.edu/courses/cs4780/2018fa/lectures/lecturenote02_kNN.html)

Linear Classifiers



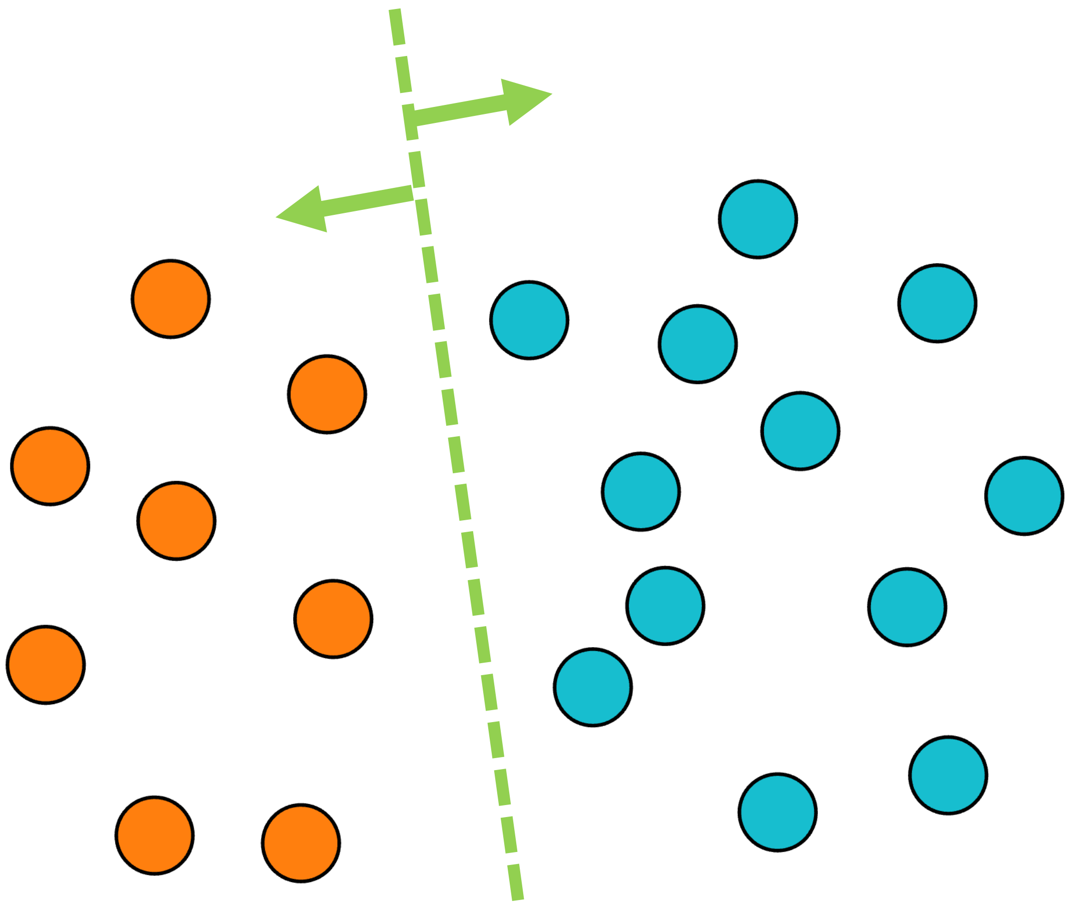
Linear Classification vs. Nearest Neighbors

- Nearest Neighbors
  - Store every image
  - Find nearest neighbors at test time, and assign same class



Linear Classification vs. Nearest Neighbors

- Nearest Neighbors
  - Store every image
  - Find nearest neighbors at test time, and assign same class
- Linear Classifier
  - Store hyperplanes that best separate different classes
  - We can compute continuous class score by calculating (signed) distance from hyperplane



We can interpret this as a linear "score function" for each class.

Score functions

class scores

Slide adapted from Andrej Karpathy and Fei-Fei Li http://vision.stanford.edu/teaching/cs231n/

Parametric Approach

image parameters

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

[32x32x3] $= 3072$
array of numbers 0...1
(3072 numbers total)

10 numbers, indicating class scores

Parametric Approach: Linear Classifier

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

3072x1

10x1 10x3072

$[32x32x3] = 3072$
array of numbers 0...1

10 numbers, indicating class scores

parameters, or “weights”

Parametric Approach: Linear Classifier

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

3072x1

(+b) 10x1

10x1

10x3072

10 numbers, indicating class scores

[32x32x3] $= 3072$
array of numbers 0...1

parameters, or “weights”

Linear Classifier

define a **score function**

data (image)

$$f(x_i, W, b) = Wx_i + b$$

class scores

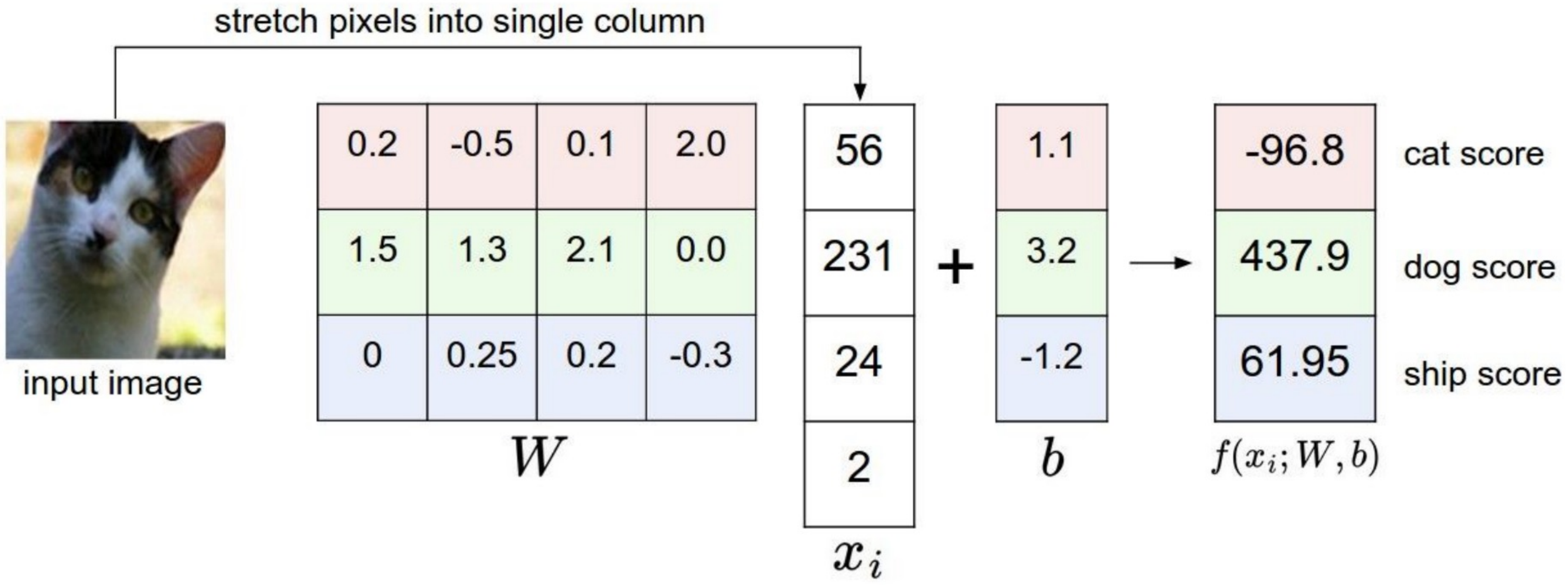
"weights"

"bias vector"

"parameters"

Interpretation: Algebraic

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



Slide adapted from Andrej Karpathy and Fei-Fei Li http://vision.stanford.edu/teaching/cs231n/

Interpretation: Geometric

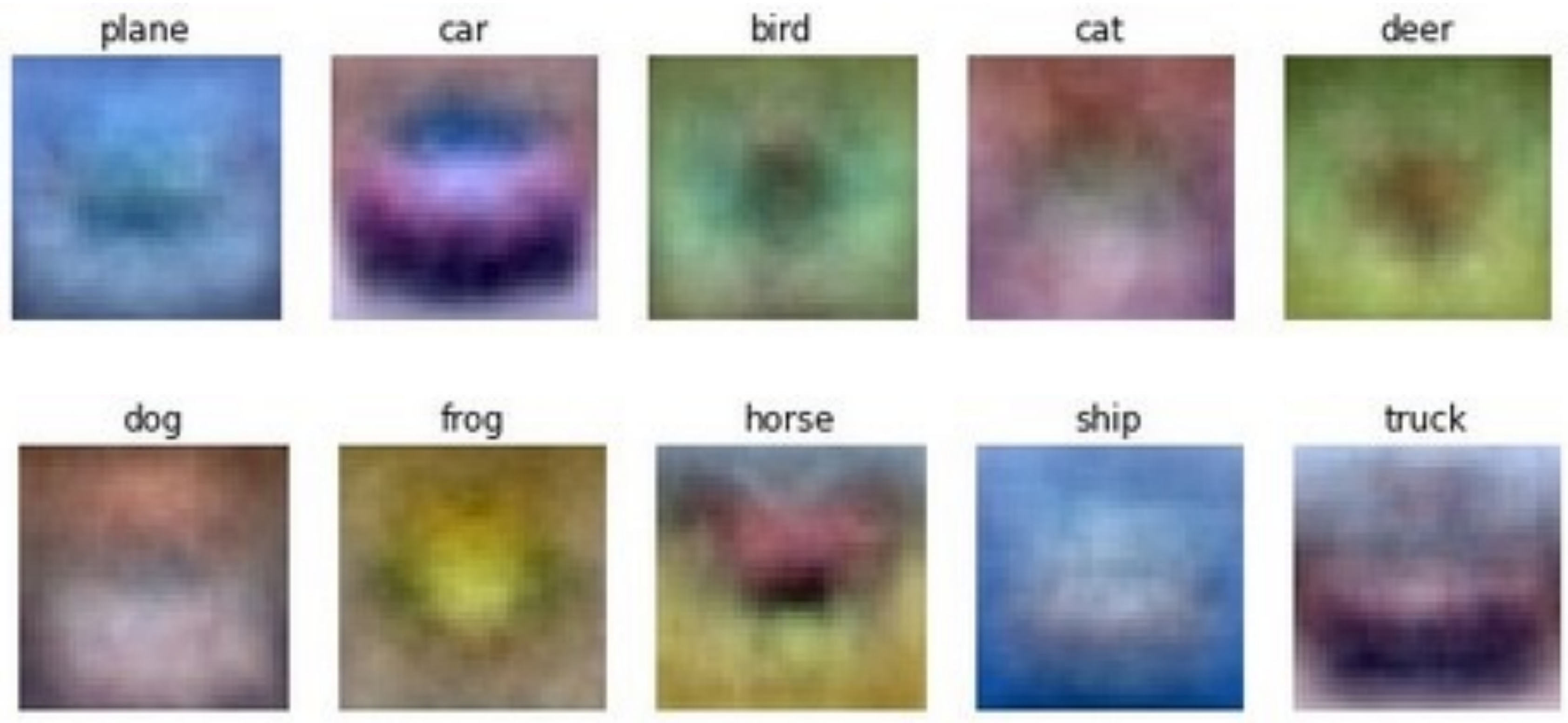
- Parameters define a hyperplane for each class:

$$f(x_i, W, b) = Wx_i + b$$

- We can think of each class score as defining a distribution that is proportional to distance from the corresponding hyperplane

Interpretation: Template matching

- We can think of the rows in W as templates for each class

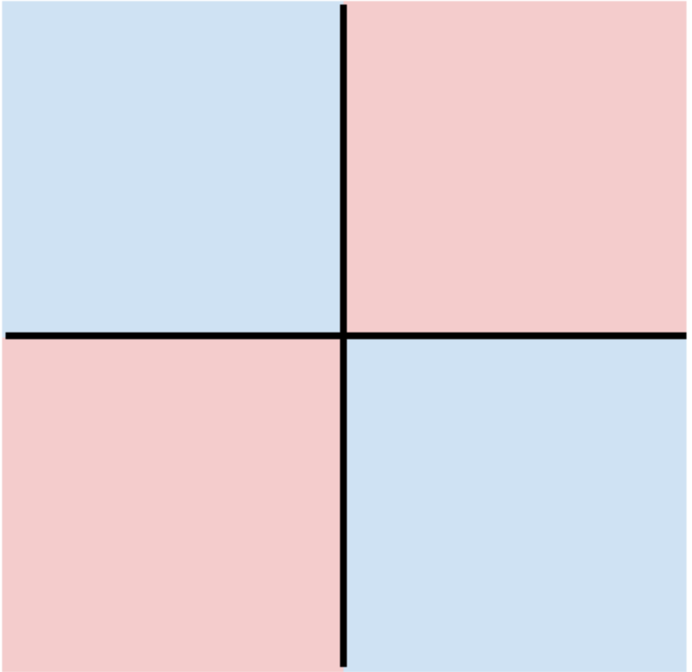


Rows of *W* in $f(x_i, W, b) = Wx_i + b$

Hard Cases for a Linear Classifier

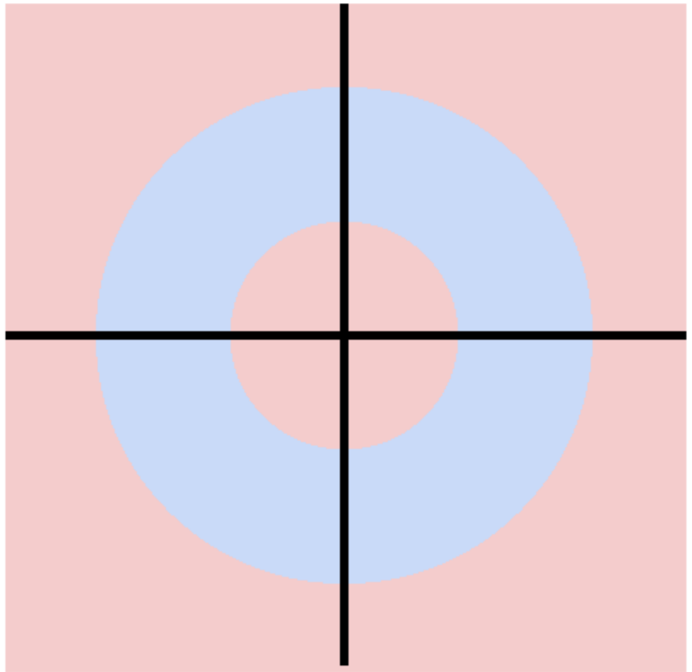
Class 1:
First and third quadrants

Class 2:
Second and fourth quadrants



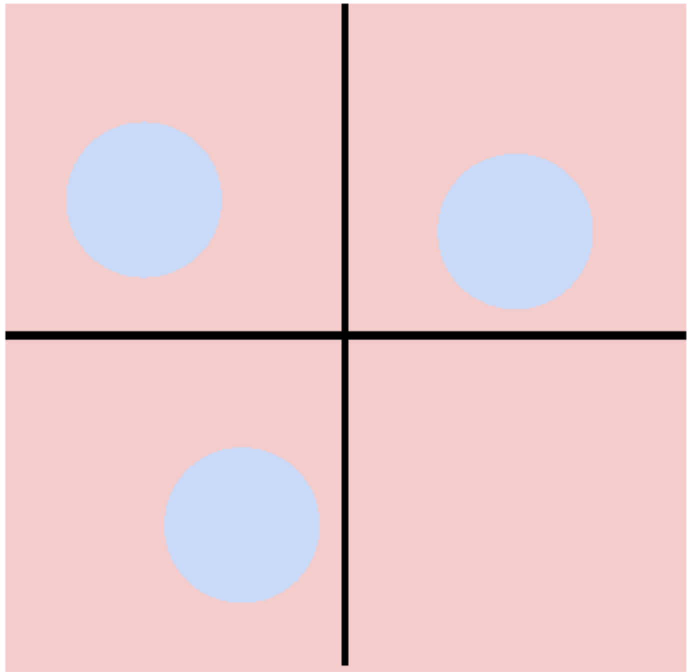
Class 1:
1 <= L2 norm <= 2

Class 2:
Everything else



Class 1:
Three modes

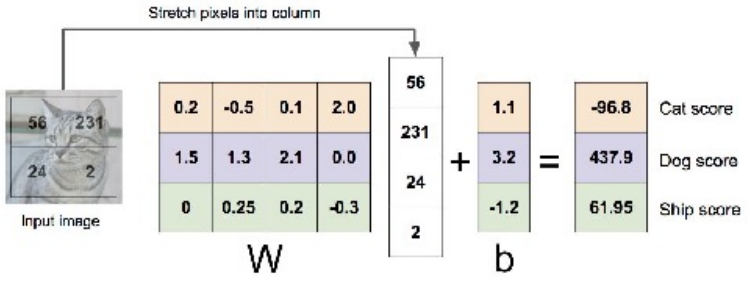
Class 2:
Everything else



Linear Classifier: Three Viewpoints

Algebraic Viewpoint

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

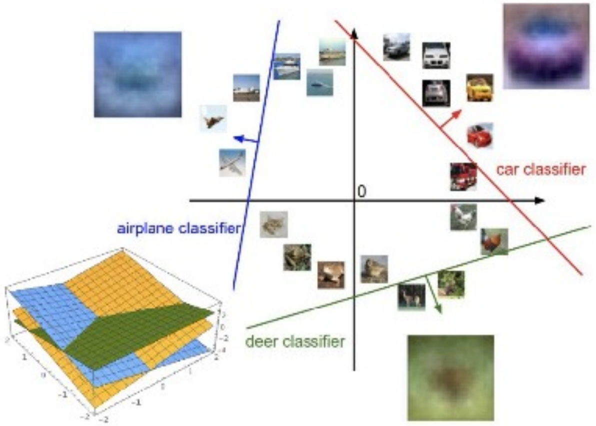


Visual Viewpoint

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

Recap

- Learning methods
  - k-Nearest Neighbors
  - **Linear classification**

- Classifier outputs a **score function** giving a score to each class
- How do we define how good a classifier is based on the training data? (Spoiler: define a *loss function*)

Linear classification

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

Output scores

TODO:

1. Define a **loss function** that quantifies our unhappiness with the scores across the training data.

2. Come up with a way of efficiently finding the parameters that minimize the loss function. **(optimization)**

Loss functions

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

A **loss function** tells how good our current classifier is

Given a dataset of examples

$$\{(x_i, y_i)\}_{i=1}^{N}$$

Where x_i is image and y_i is (integer) label

Loss over the dataset is a sum of loss over examples:

$$L = \frac{1}{N} \sum_i L_i(f(x_i, W), y_i)$$

Loss function, cost/objective function

- Given ground truth labels (y_i), scores $f(x_i, \mathbf{W})$
  - how unhappy are we with the scores?
- Loss function or objective/cost function measures unhappiness

- During training, **want to find the parameters W that minimize the loss function**

Simpler example: binary classification

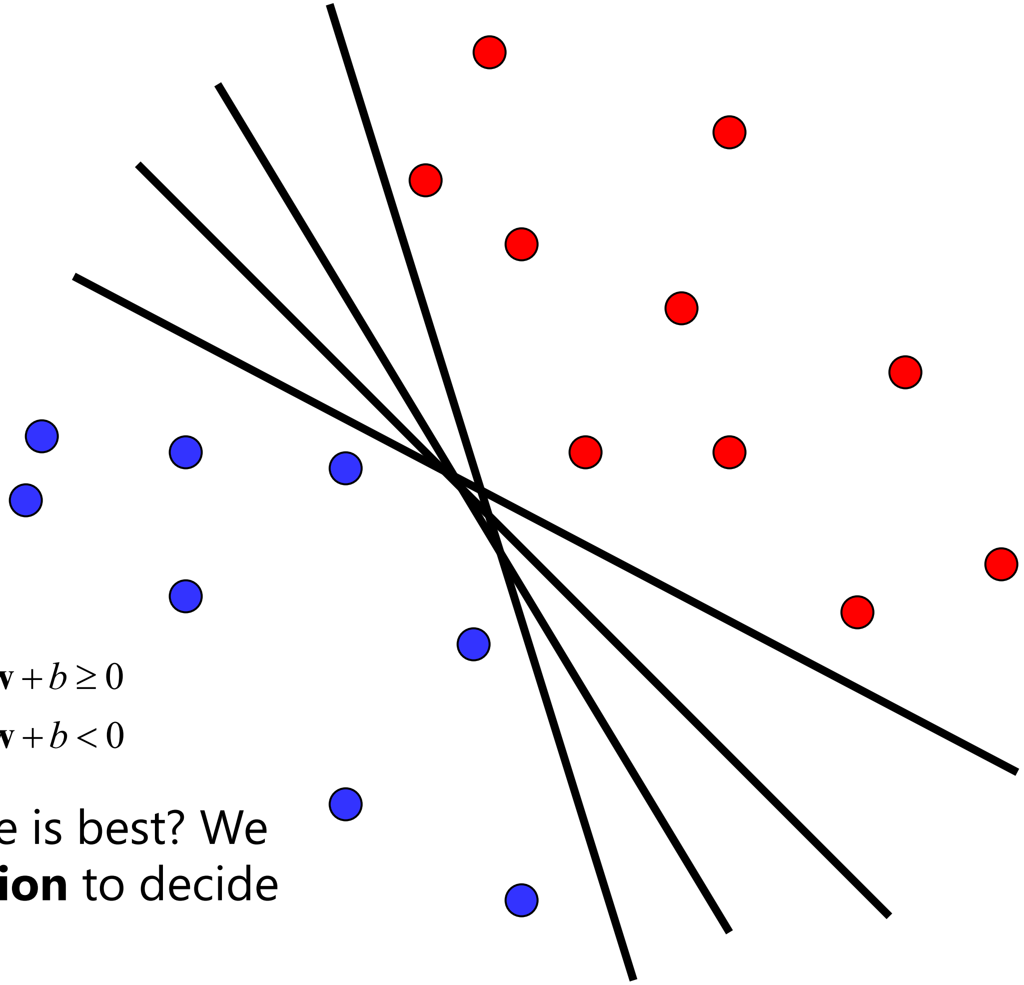
- Two classes (e.g., “cat” and “not cat”)
  - AKA “positive” and “negative” classes

cat

not cat

Linear classifiers

- Find linear function (*hyperplane*) to separate positive and negative examples



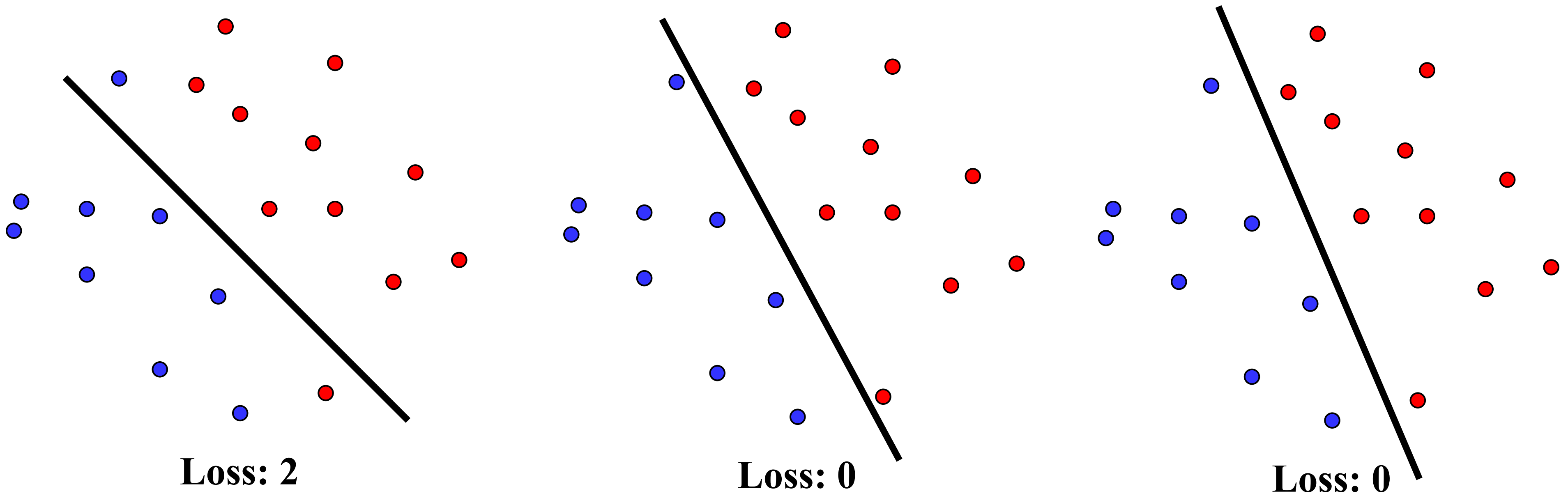
$$\mathbf{x}_i \text{ positive}: \quad \mathbf{x}_i \cdot \mathbf{w} + b \geq 0$$

$$\mathbf{x}_i \text{ negative}: \quad \mathbf{x}_i \cdot \mathbf{w} + b < 0$$

Which hyperplane is best? We need a **loss function** to decide

What is a good loss function?

- One possibility: Number of misclassified examples
  - Problems: discrete, can't break ties
  - We want the loss to lead to *good generalization*
  - We want the loss to work for more than 2 classes



Softmax classifier

- Interpret Scores as unnormalized log probabilities of classes

$f(x_i, W) = Wx_i$ (score function)

$\boxed{\dfrac{e^{f_{y_i}}}{\sum_j e^{f_j}}}$ softmax function

Squashes values into *probabilities* ranging from 0 to 1

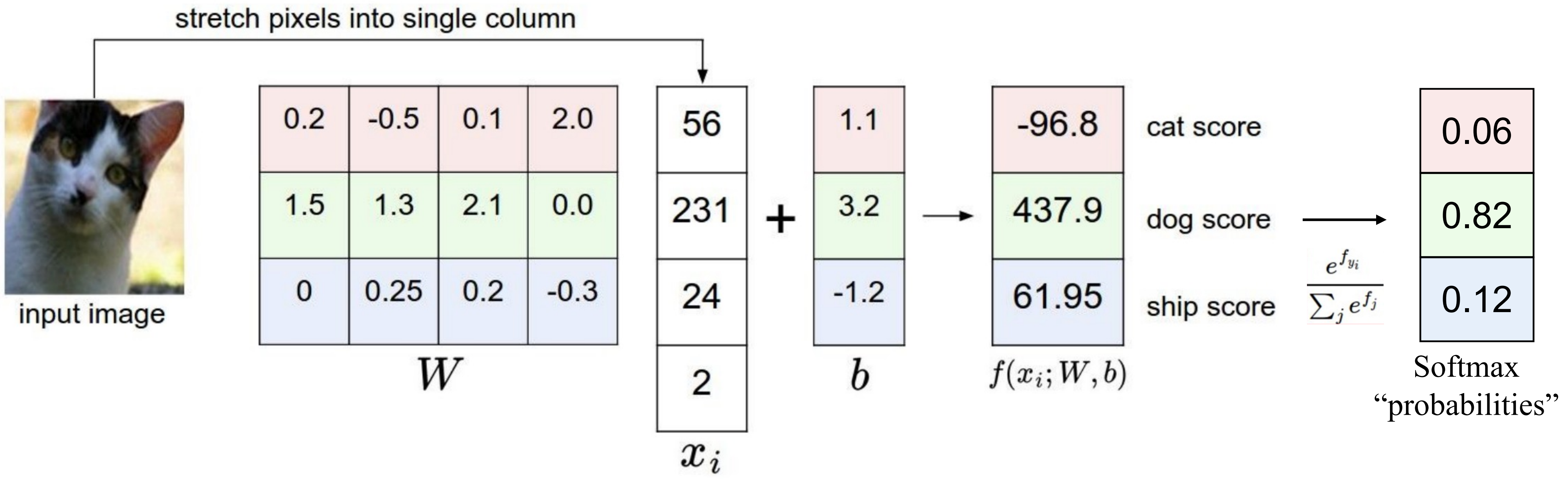
$P(y_i \mid x_i; W)$

Example with three classes:

$$[1, -2, 0] \rightarrow [e^1, e^{-2}, e^0] = [2.71, 0.14, 1] \rightarrow [0.7, 0.04, 0.26]$$

Softmax classifier

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



Cross-entropy loss

$f(x_i, W) = Wx_i$ (score function)

Cross-entropy loss

$$f(x_i, W) = Wx_i$$ (score function)

f_{y_i} : score of correct class

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}\right) \qquad L_i = -f_{y_i} + \log \sum_j e^{f_j}$$

We call L_i *cross-entropy loss*

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We call L_i *cross-entropy loss*

$$\boxed{P(y_i \mid x_i; W)}$$

i.e. we're minimizing the negative log likelihood.

Losses

- Cross-entropy loss is just one possible loss function
  - One nice property is that it reinterprets scores as probabilities, which have a natural meaning

- SVM (max-margin) loss functions also used to be popular
  - But currently, cross-entropy is the most common classification loss

Summary

- Have score function and loss function
  - Currently, score function is based on linear classifier
  - Next, will generalize to convolutional neural networks
- Find W and b to minimize loss

$$L = \underbrace{\frac{1}{N}\sum_i -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}\right)}_{\text{Average of cross-entropy loss over all training examples}} + \lambda \sum_k \sum_l W_{k,l}^2$$

Regularization term
(will talk about this later)

Questions?