Image Classification

- K-Nearest Neighbor
- Linear classifiers

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Image Classification: A core task in Computer Vision

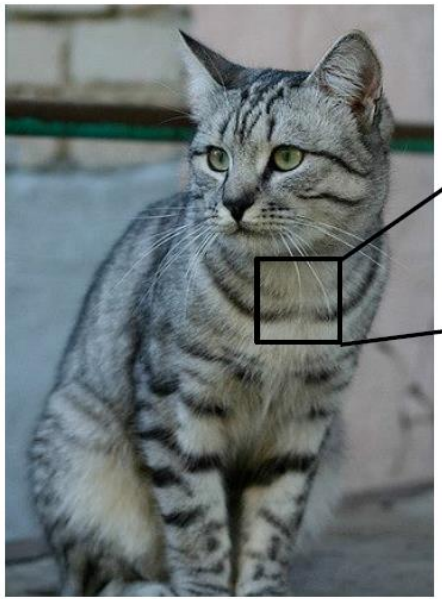
(assume given set of discrete labels)
{dog, cat, truck, plane, ...}

cat

The Problem: Semantic Gap

600

800

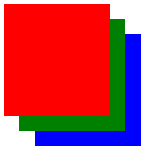



```
[[105 112 108 111 104  99 106  99  96 103 112 119 104  97  93  87]
 [ 91  98 102 106 104  79  98 103  99 105 123 136 110 105  94  85]
 [ 76  85  90 105 120 105  87  96  95  99 115 112 106 103  99  85]
 [ 99  81  81  93 120 131 127 100  95  98 102  99  96  93 101  94]
 [106  91  61  64  69  91  88  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]
 [ 63  65  75  88  89  71  62  81 120 138 135 105  81  98 110 118]
 [ 87  65  71  87 106  95  69  45  76 130 126 107  92  94 105 112]
 [118  97  82  86 117 123 116  66  41  51  95  93  89  95 102 107]
 [164 146 112  80  82 120 124 104  76  48  45  66  88 101 102 109]
 [157 170 157 120  93  86 114 132 112  97  69  55  70  82  99  94]
 [130 128 134 161 139 100 109 118 121 134 114  87  65  53  69  86]
 [128 112  96 117 150 144 120 115 104 107 102  93  87  81  72  79]
 [123 107  96  86  83 112 153 149 122 109 104  75  80 107 112  99]
 [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]]
```

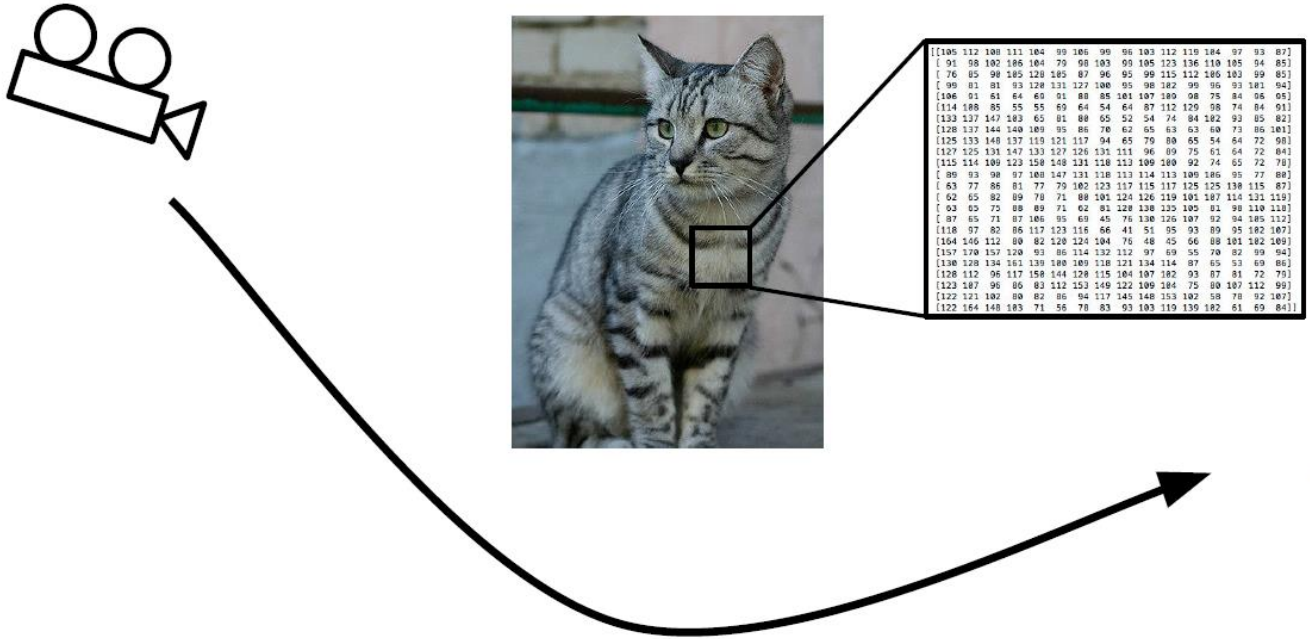
What the computer sees

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

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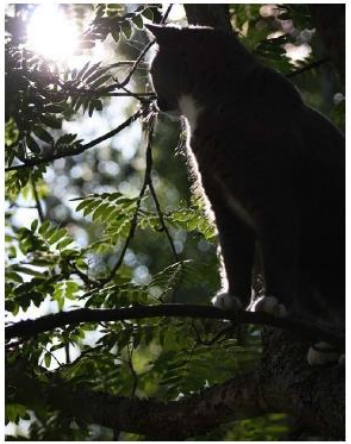

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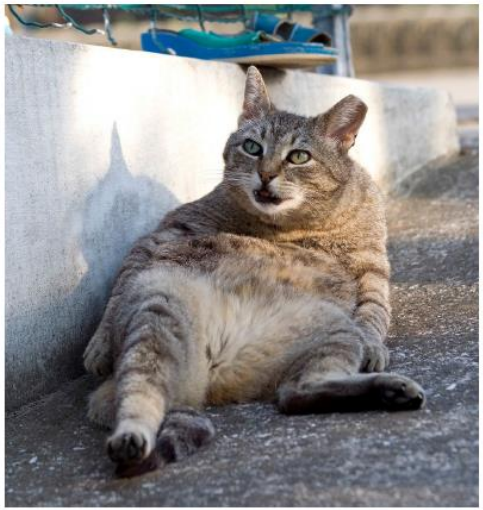
Challenges: Deformation



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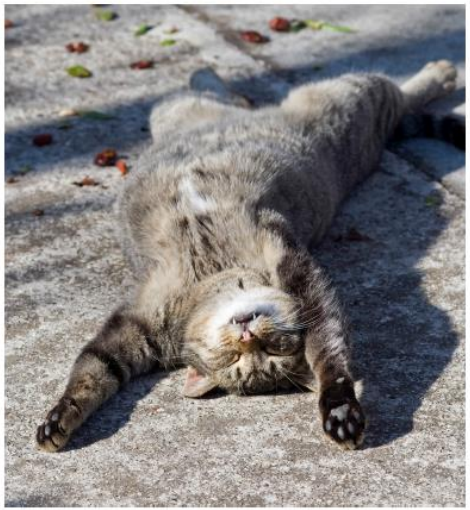

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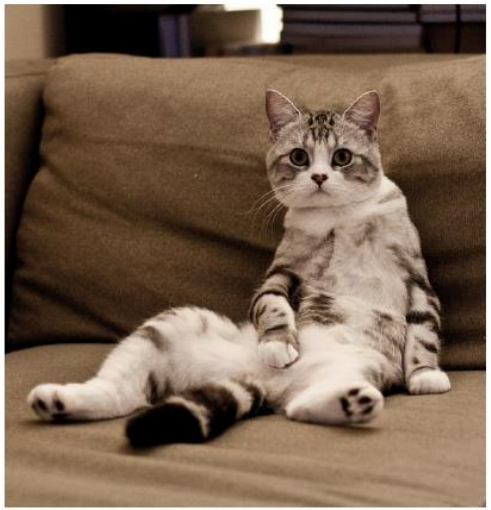
This image by sare bear is licensed under CC-BY 2.0



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Challenges: Occlusion

This image is CC0 1.0 public domain

This image is CC0 1.0 public domain

This image by jonsson is licensed under CC-BY 2.0

Challenges: Background Clutter

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Challenges: Intraclass variation

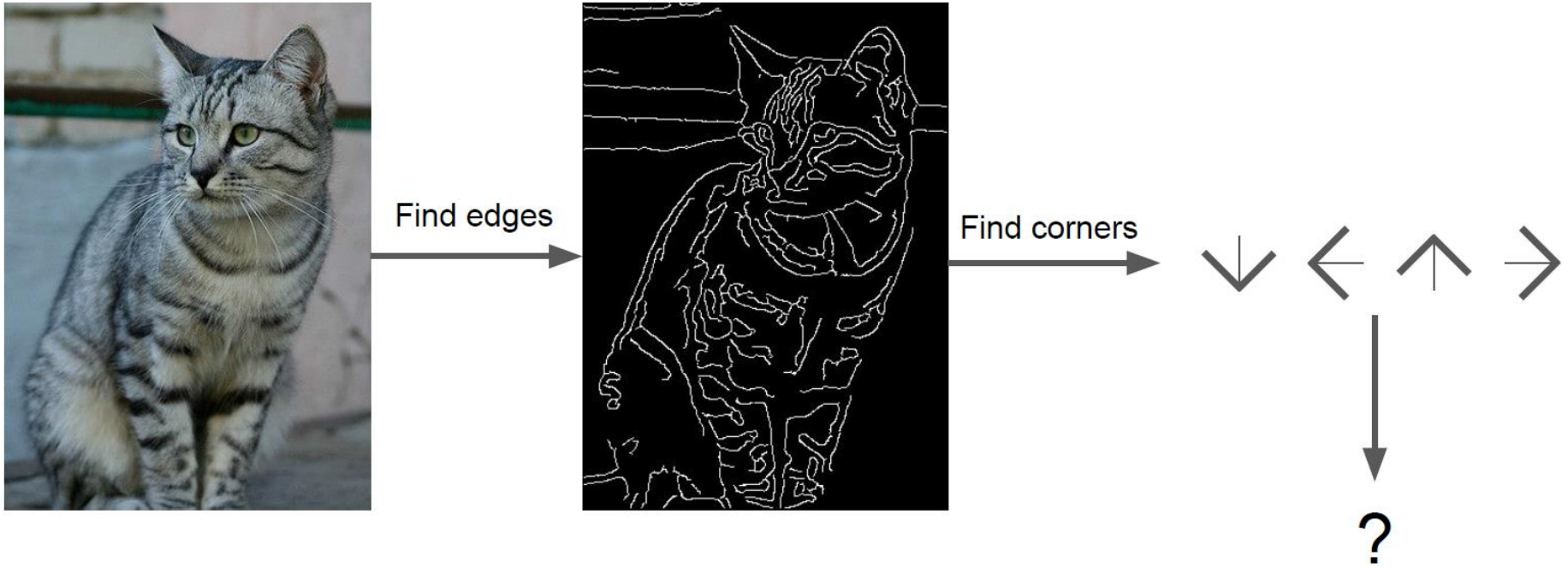
An image classifier

```
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

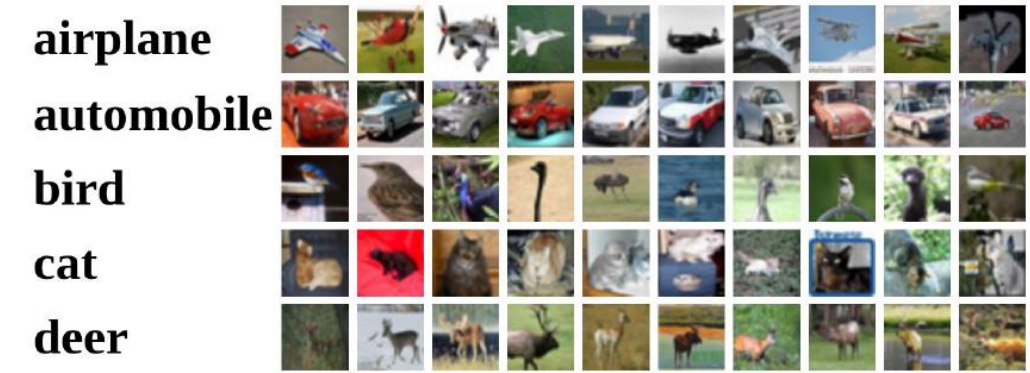
Machine Learning: Data-Driven Approach

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
```

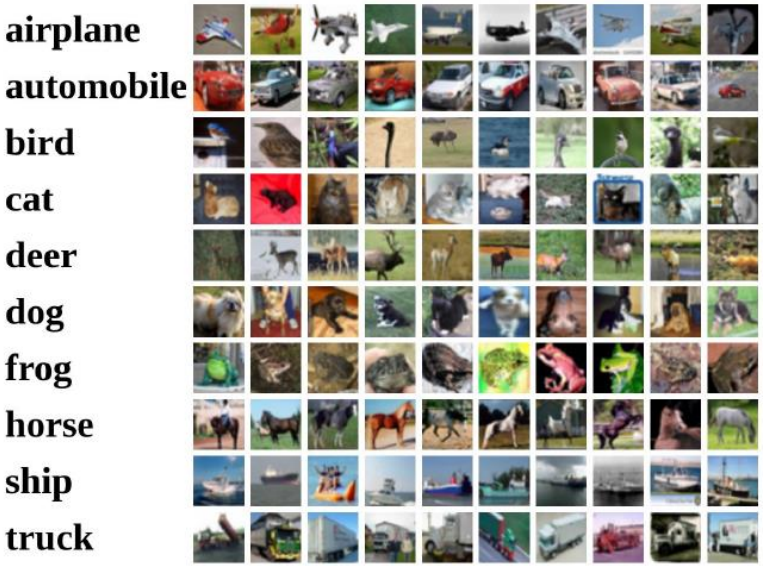
Memorize all data and labels

```
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.

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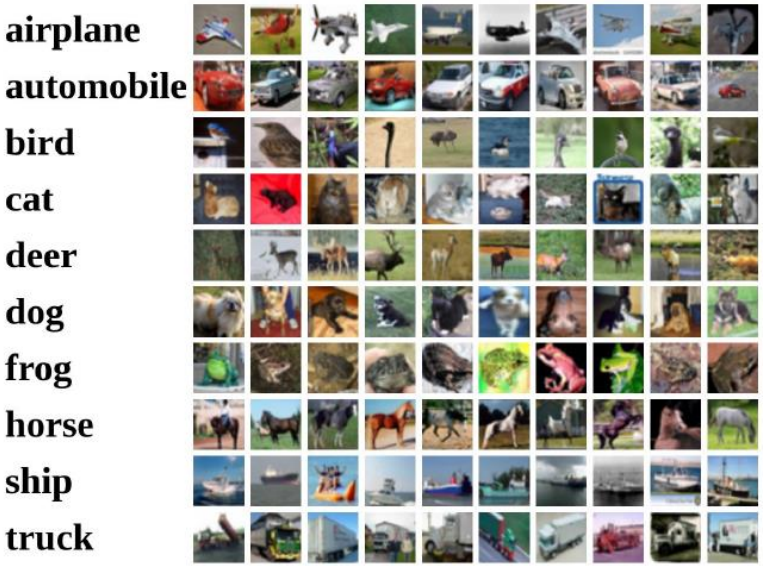
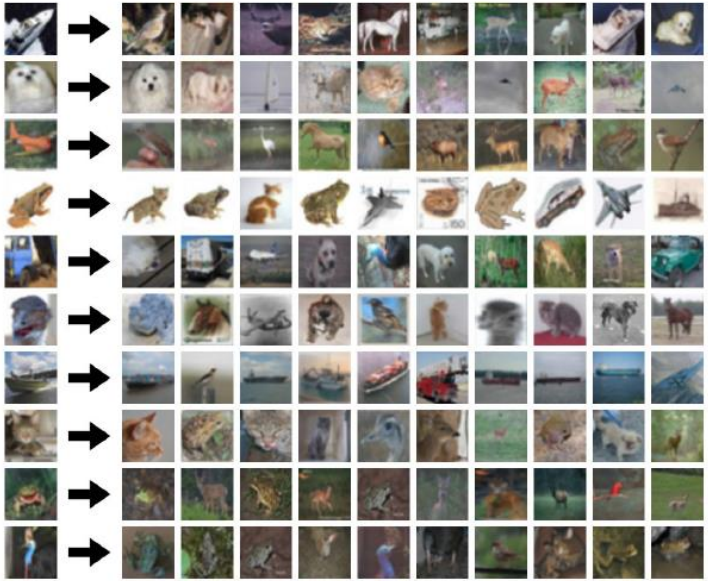


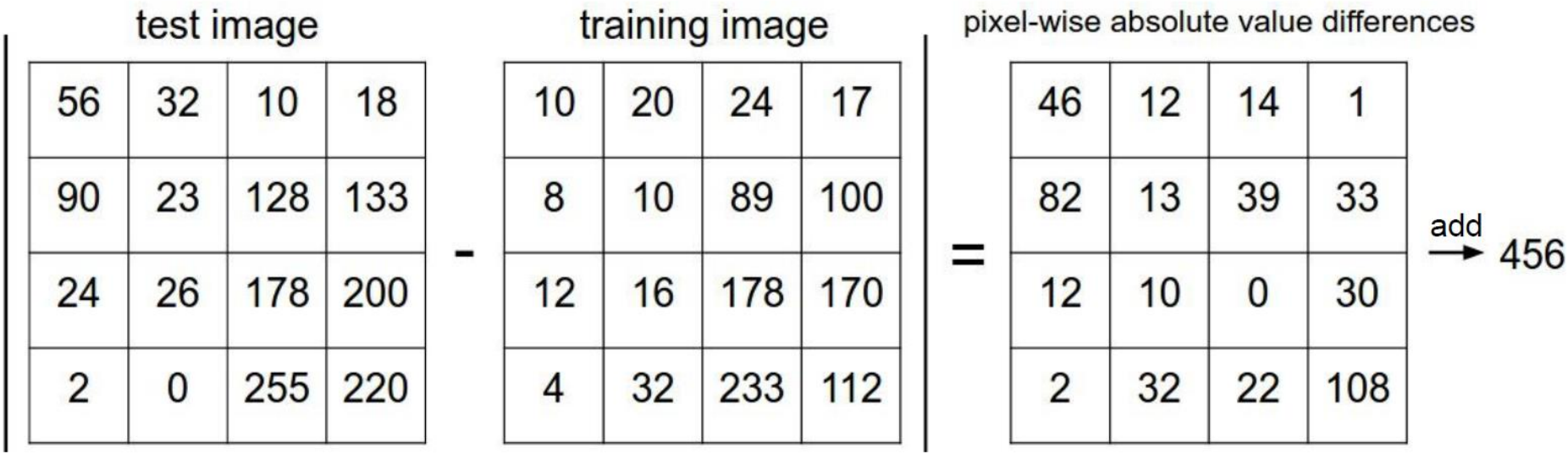
Test images and nearest neighbors



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

Distance Metric to compare images

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



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
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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

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Nearest Neighbor classifier

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

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Nearest Neighbor classifier

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

A: Train O(1),
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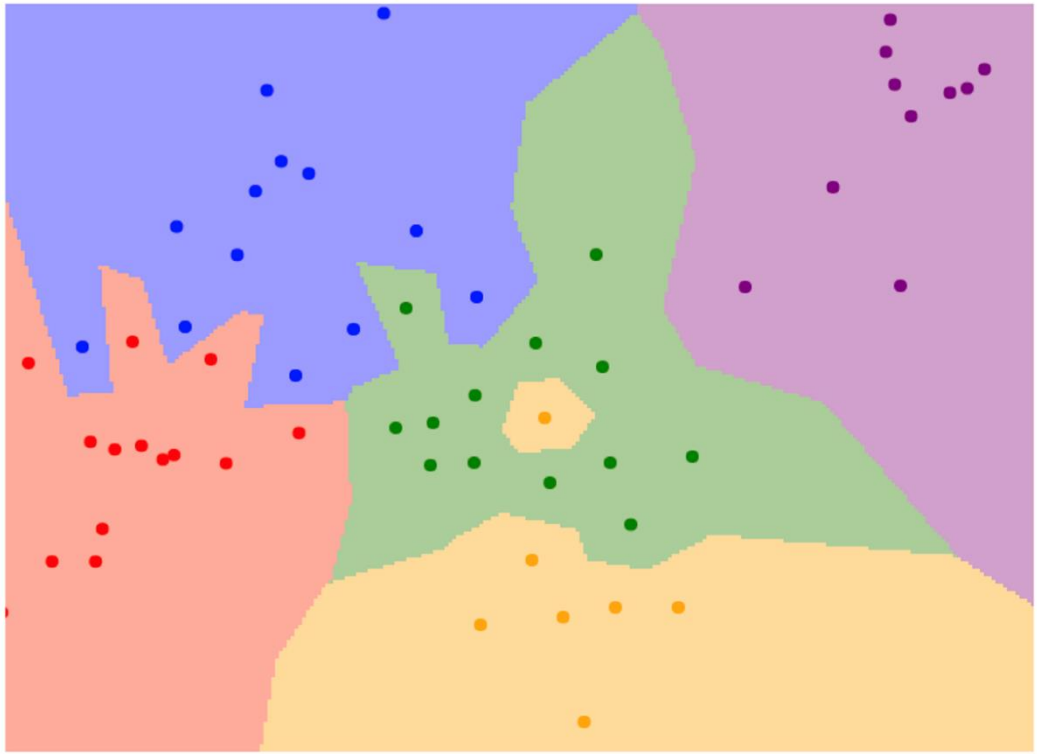
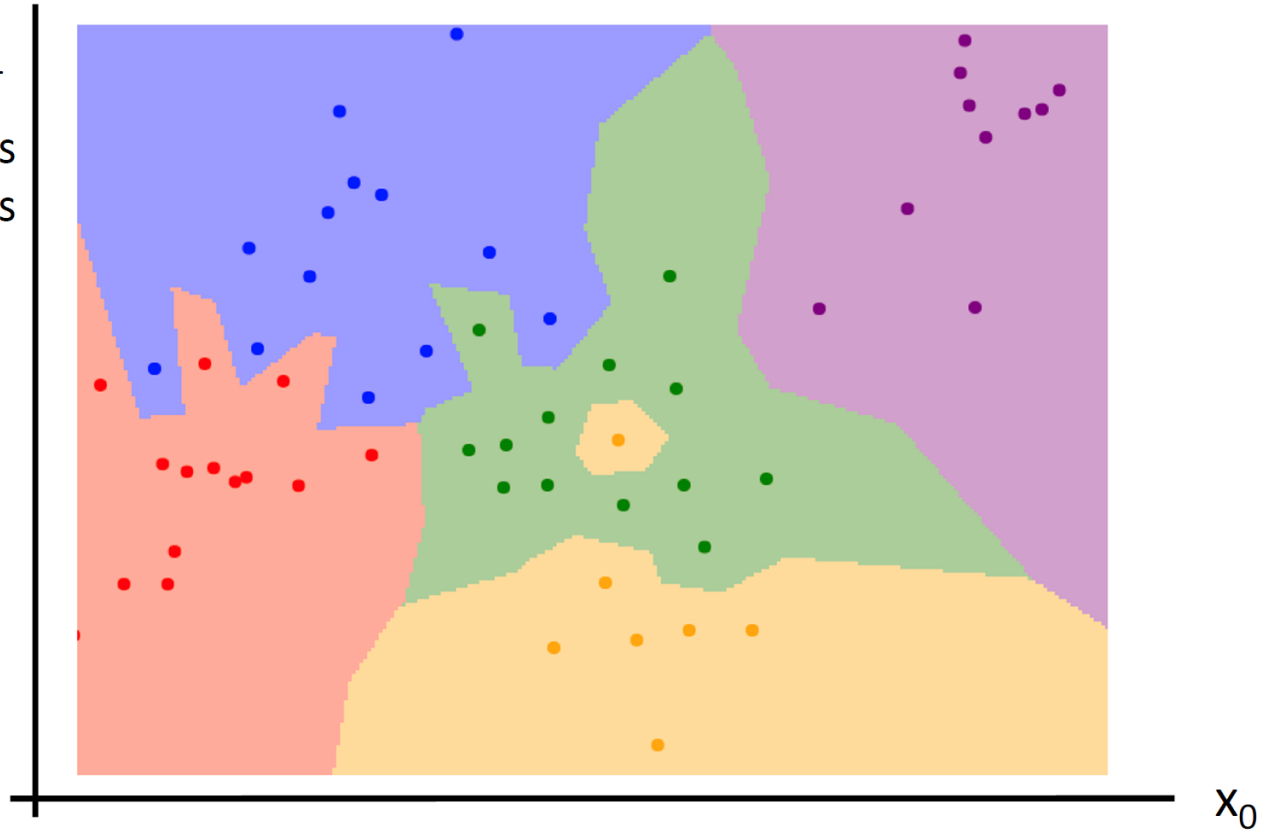
This is bad: we want classifiers that are **fast** at prediction; **slow** for training is ok

What does this look like?



Nearest Neighbor **Decision Boundaries**

Nearest neighbors in two dimensions



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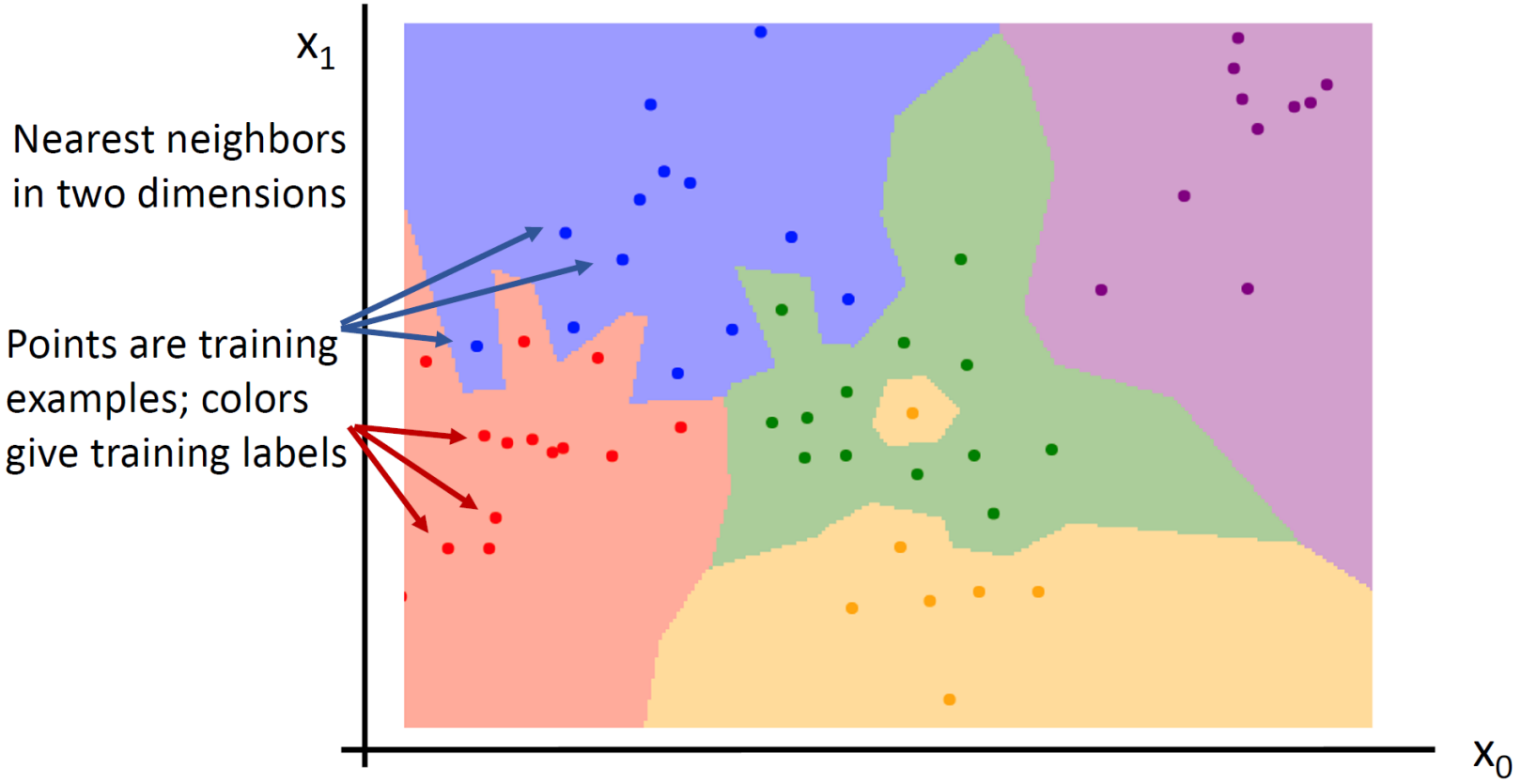

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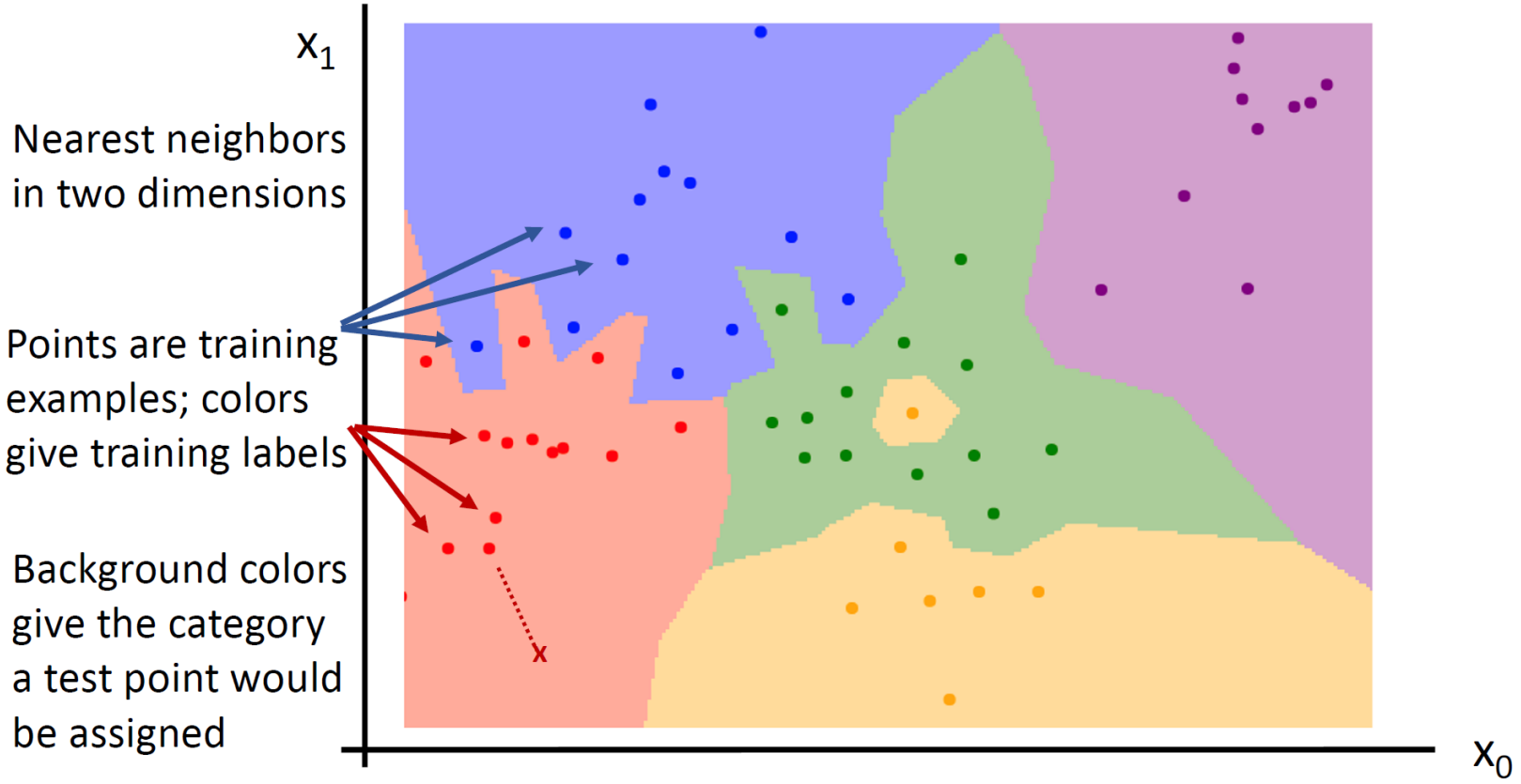

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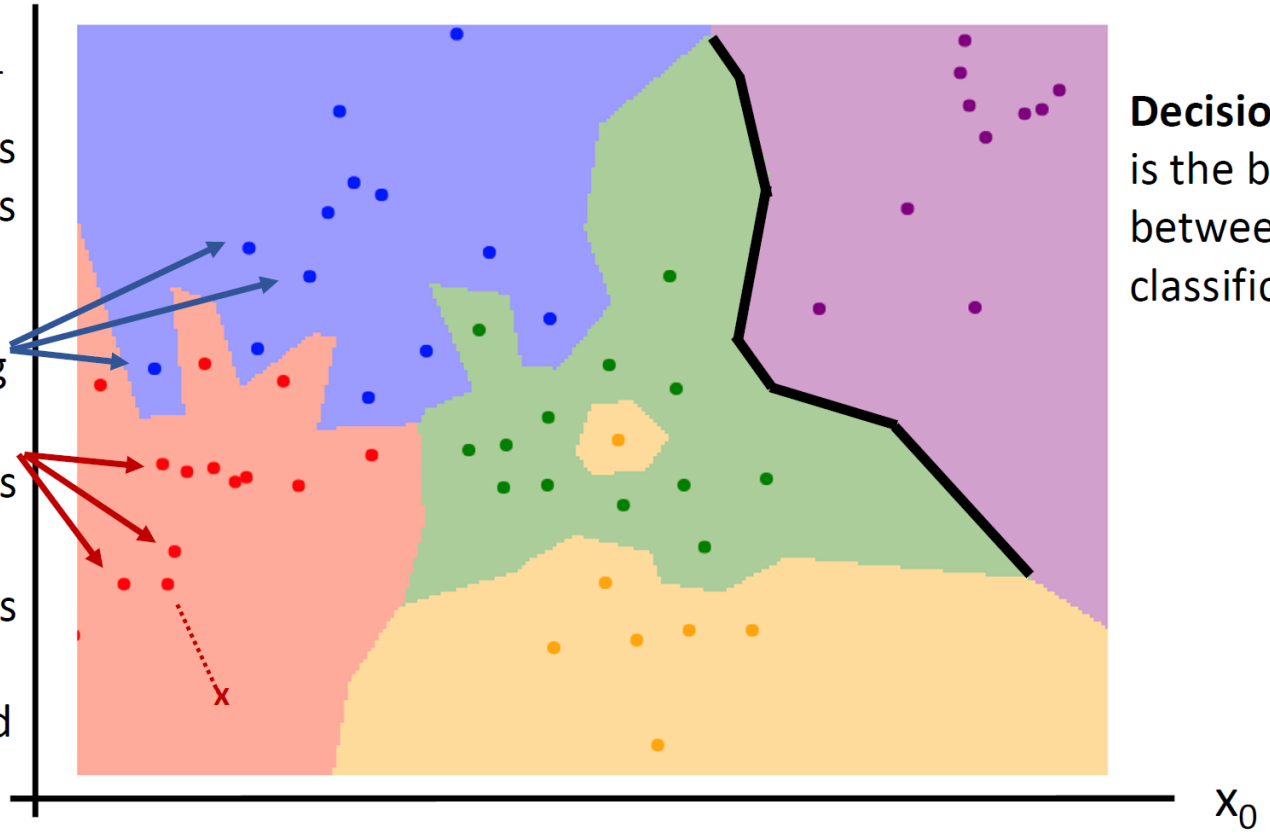


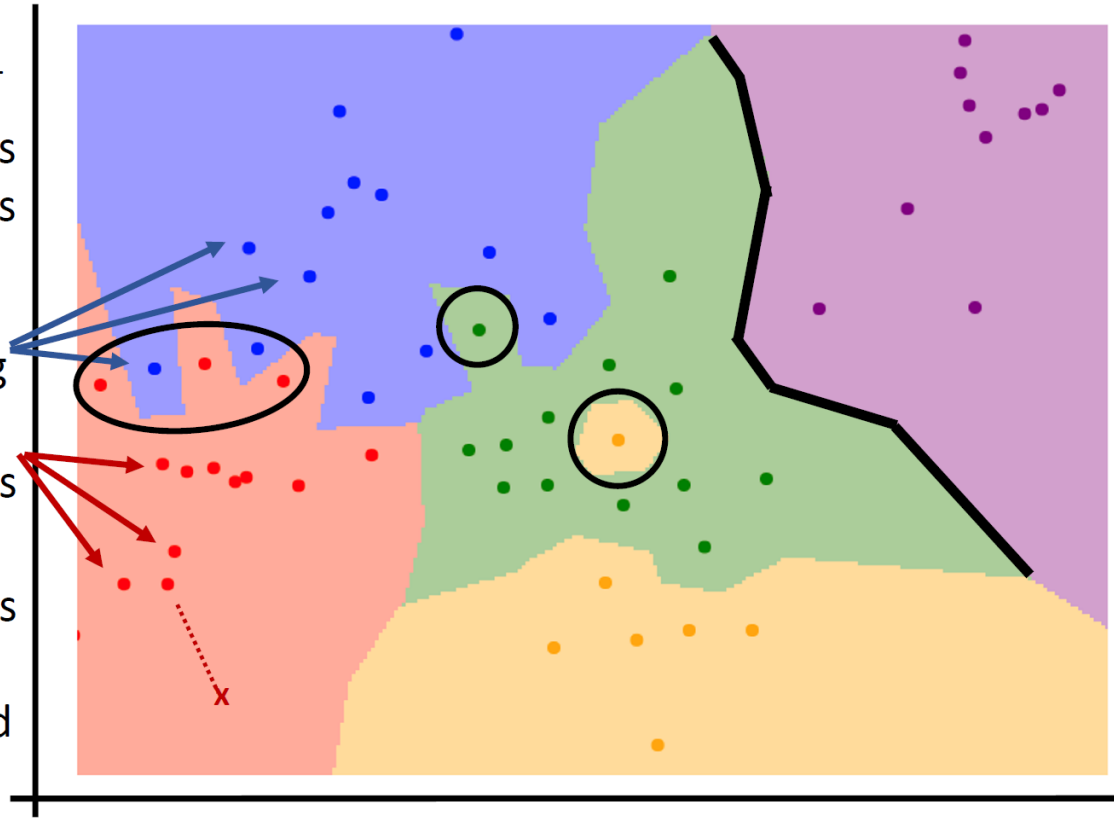
Nearest neighbors in two dimensions

Points are training examples; colors give training labels

Background colors give the category a test point would be assigned

Decision boundary is the boundary between two classification regions

Nearest Neighbor **Decision Boundaries**



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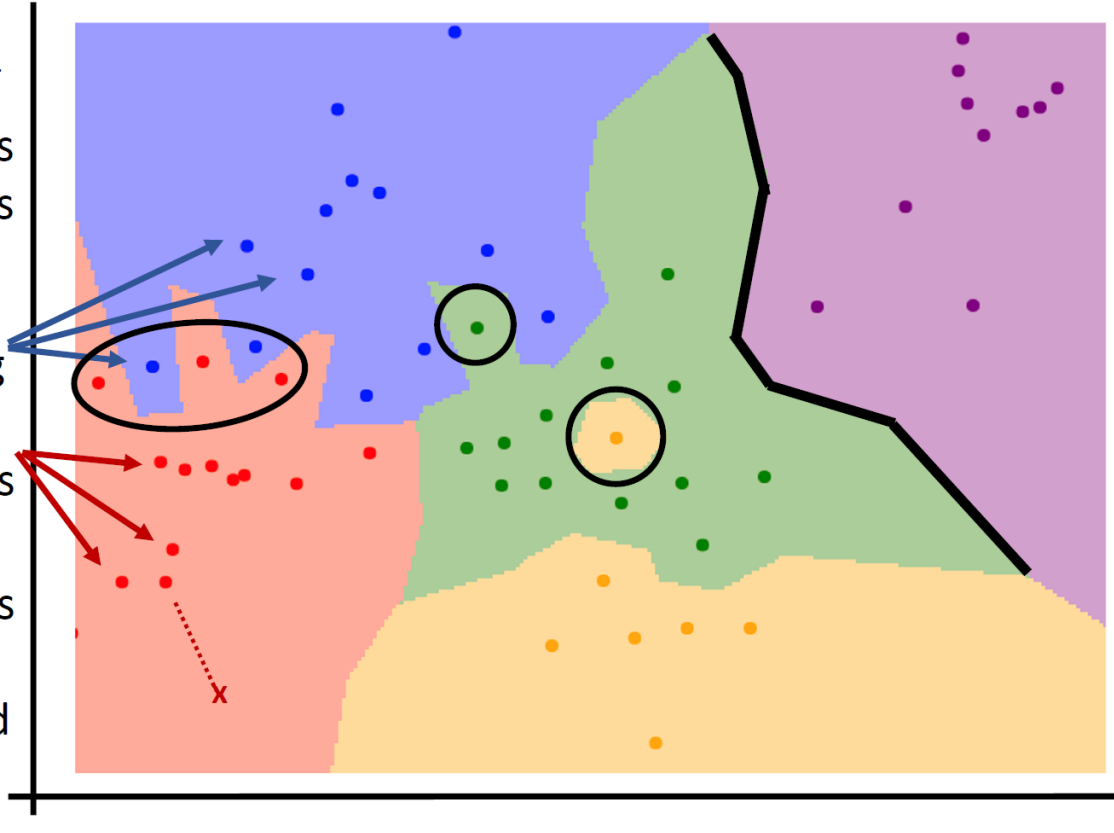
Decision boundaries can be noisy; affected by outliers

Nearest Neighbor **Decision Boundaries**



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Decision boundary is the boundary between two classification regions

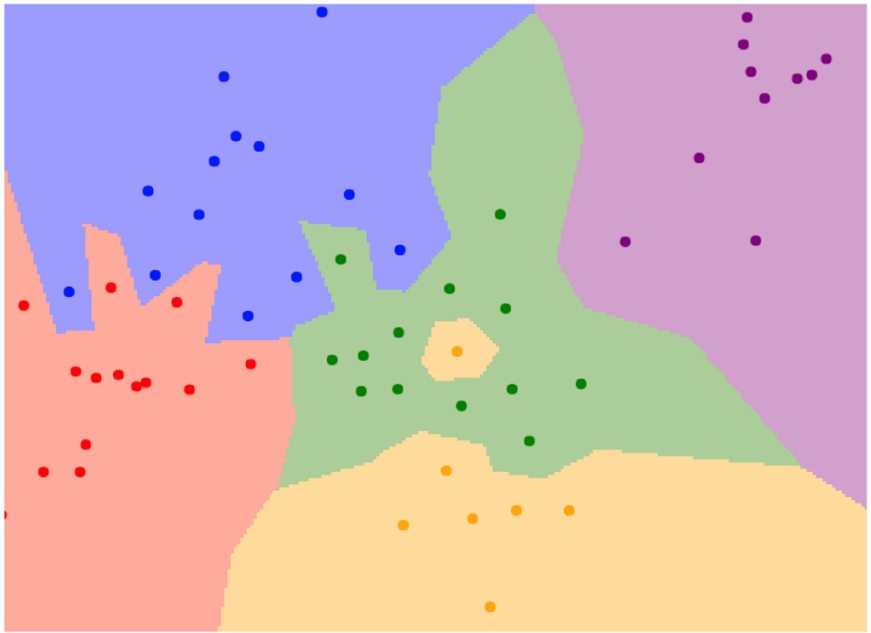
Decision boundaries can be noisy; affected by outliers

How to smooth out decision boundaries? Use more neighbors!

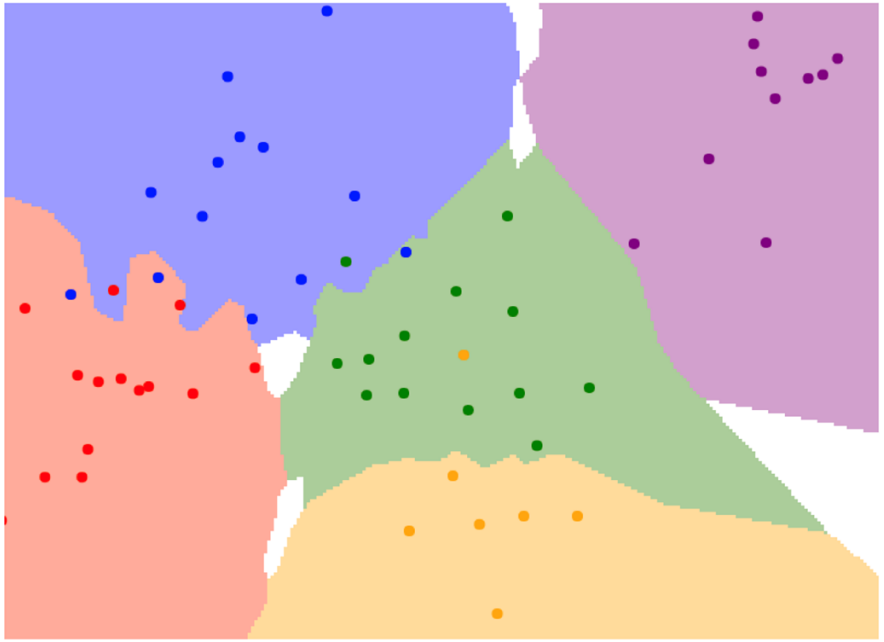
K-Nearest Neighbors

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

K = 1



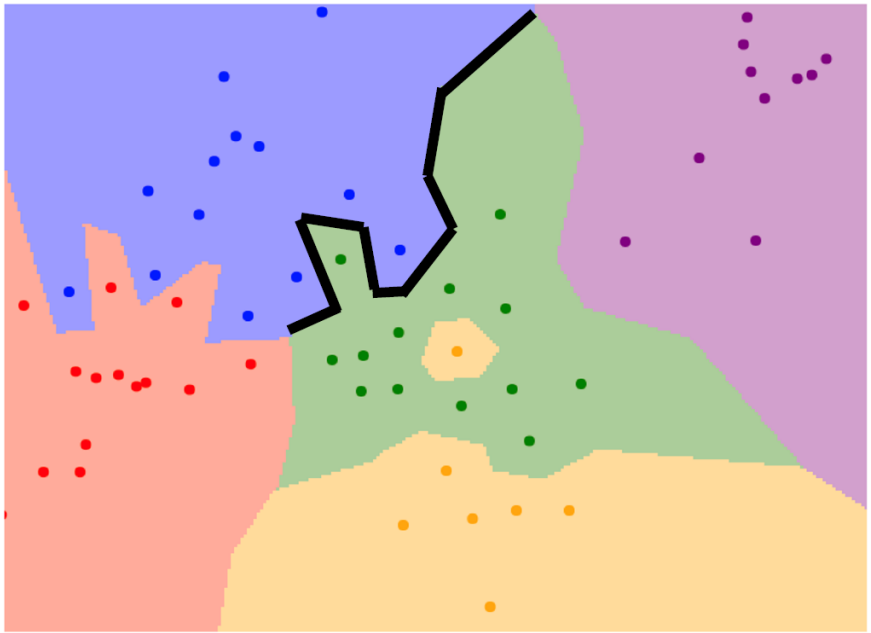
K = 3



K-Nearest Neighbors

Using more neighbors helps smooth out rough decision boundaries

K = 1



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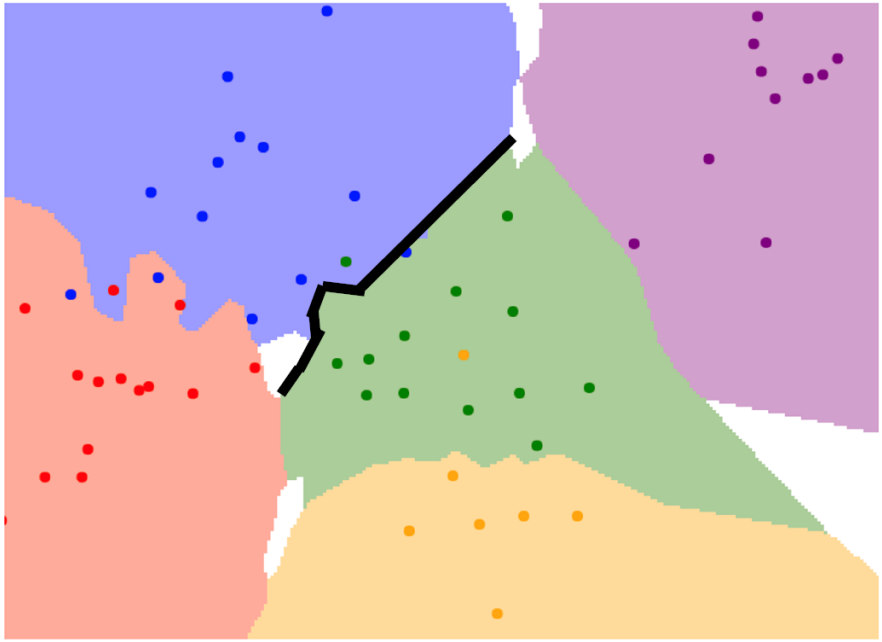
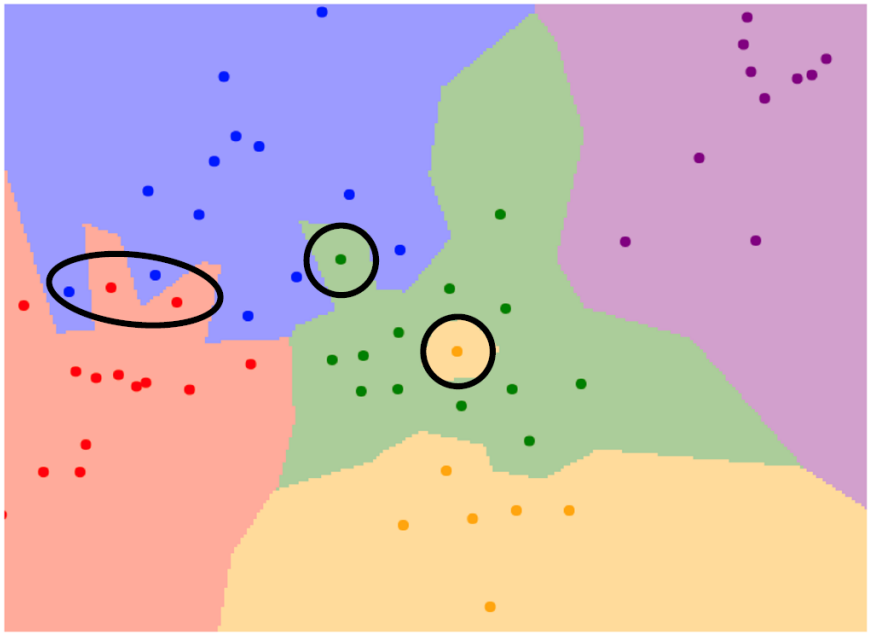


K-Nearest Neighbors

Using more neighbors helps reduce the effect of outliers

K = 1



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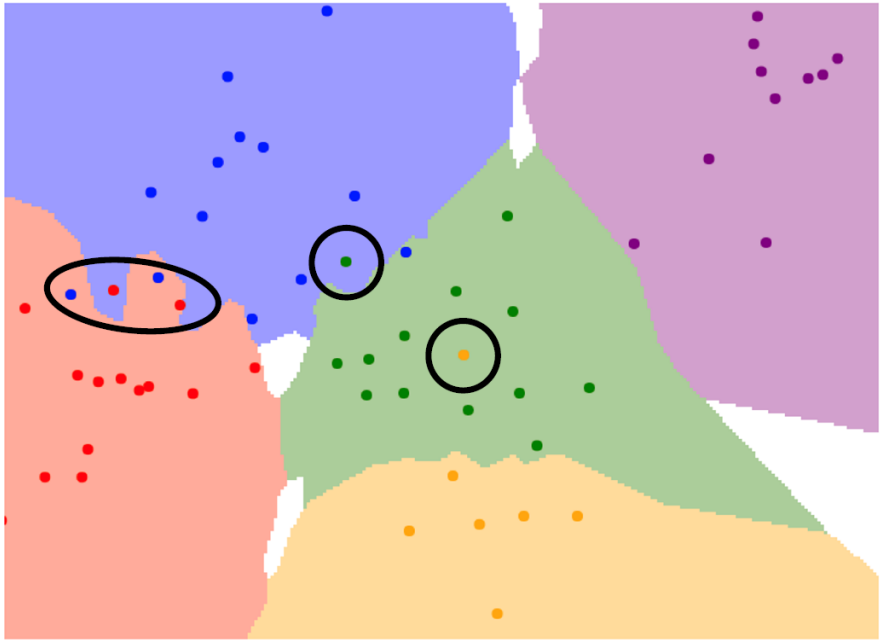
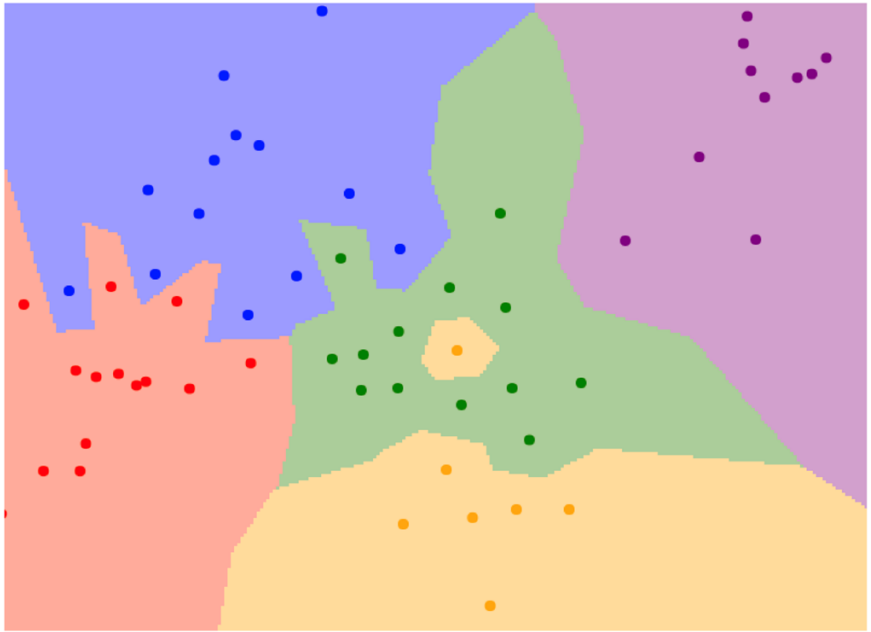


K-Nearest Neighbors

When K > 1 there can be ties between classes.
Need to break somehow!

K = 1



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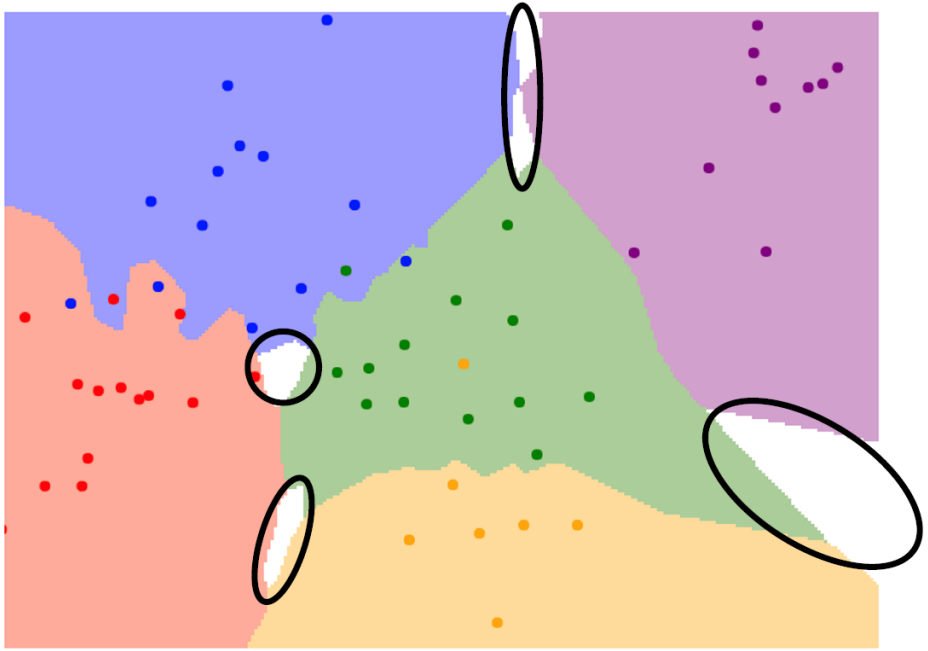
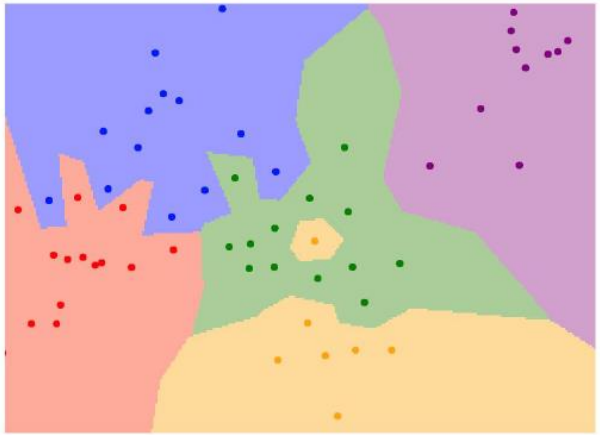
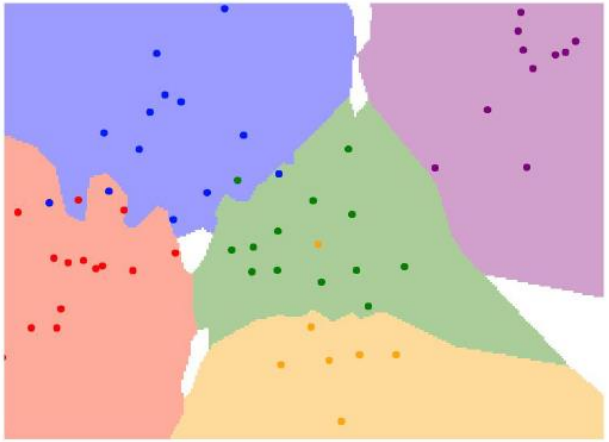


K-Nearest Neighbors

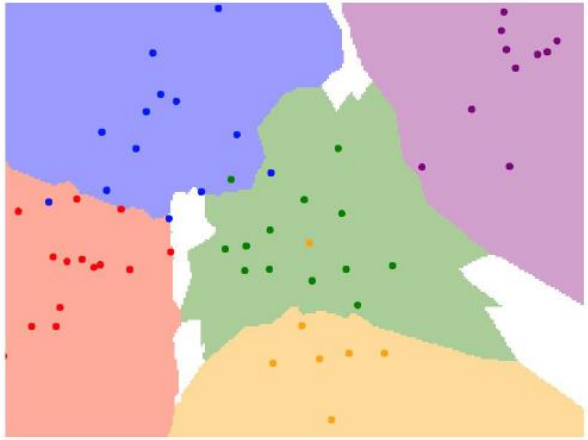
Instead of copying label from nearest neighbor,
take **majority vote** from K closest points



K = 1

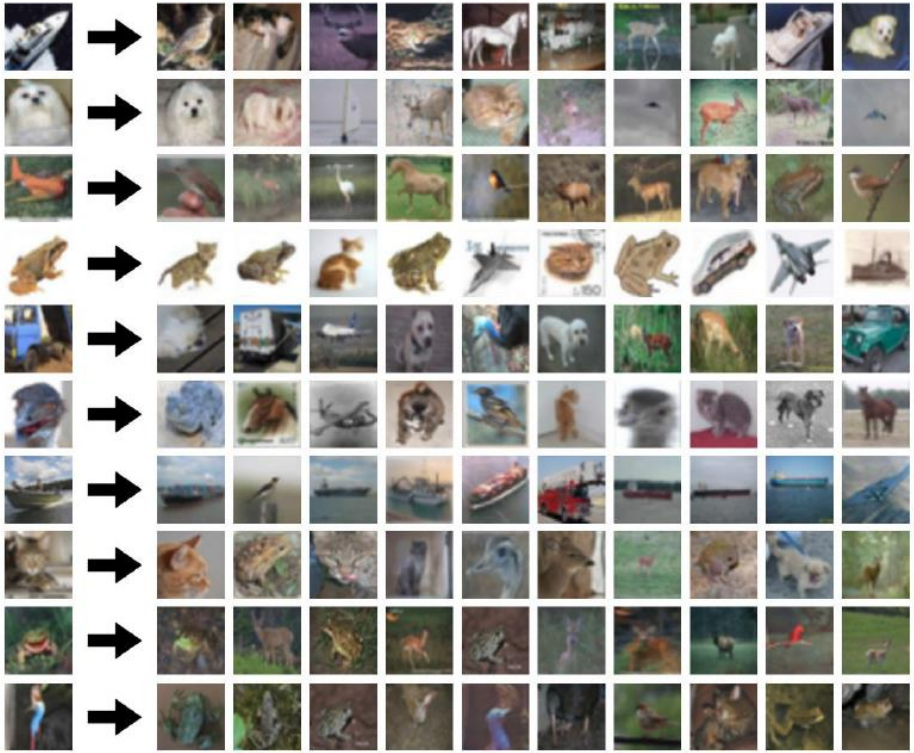


K = 3



K = 5

What does this look like?



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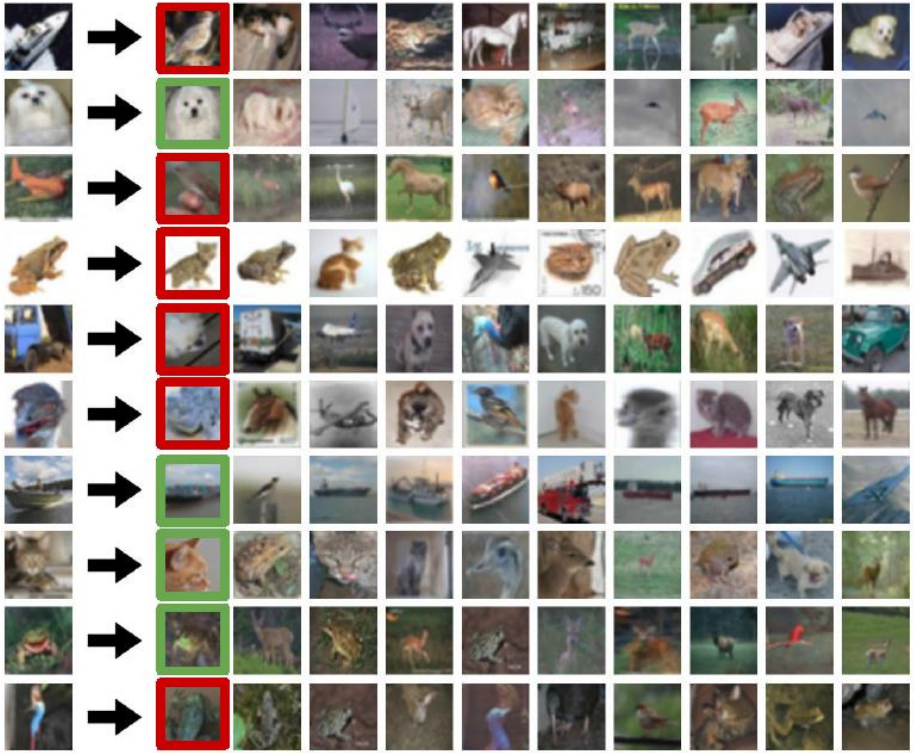
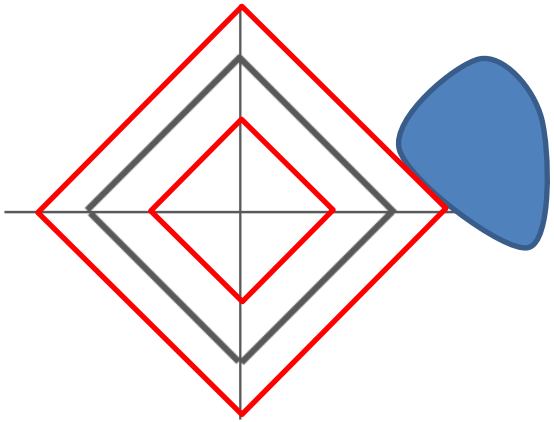


K-Nearest Neighbors: Distance Metric

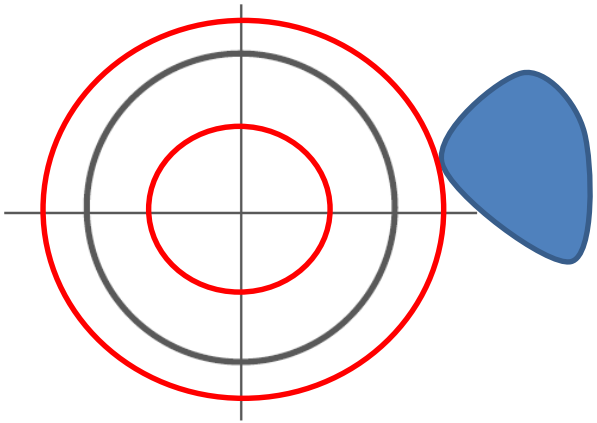
L1 (Manhattan) distance

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



L2 (Euclidean) distance

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



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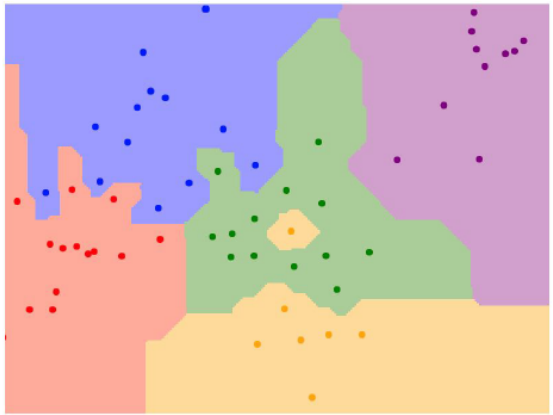

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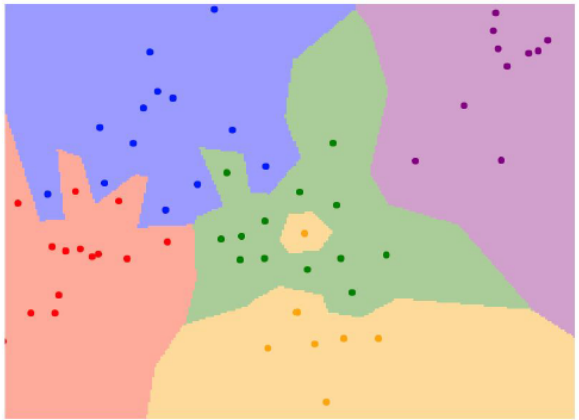

K = 1

K-Nearest Neighbors: Distance Metric

With the right choice of distance metric, we can apply K-Nearest Neighbor to any type of data!

K-Nearest Neighbors: **Distance Metric**

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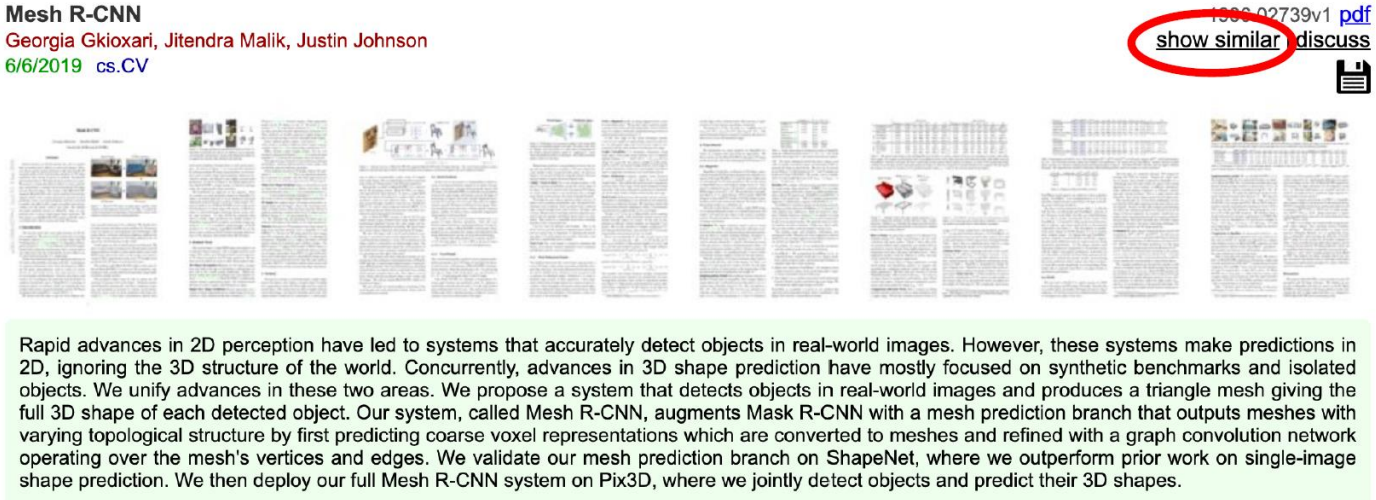
Example: Compare research papers using tf-idf similarity



Mesh R-CNN
Georgia Gkioxari, Jitendra Malik, Justin Johnson
6/6/2019 cs.CV

1906.02739v1 pdf
show similar discuss

Rapid advances in 2D perception have led to systems that accurately detect objects in real-world images. However, these systems make predictions in 2D, ignoring the 3D structure of the world. Concurrently, advances in 3D shape prediction have mostly focused on synthetic benchmarks and isolated objects. We unify advances in these two areas. We propose a system that detects objects in real-world images and produces a triangle mesh giving the full 3D shape of each detected object. Our system, called Mesh R-CNN, augments Mask R-CNN with a mesh prediction branch that outputs meshes with varying topological structure by first predicting coarse voxel representations which are converted to meshes and refined with a graph convolution network operating over the mesh's vertices and edges. We validate our mesh prediction branch on ShapeNet, where we outperform prior work on single-image shape prediction. We then deploy our full Mesh R-CNN system on Pix3D, where we jointly detect objects and predict their 3D shapes.

http://www.arxiv-sanity.com/search?q=mesh+r-cnn

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

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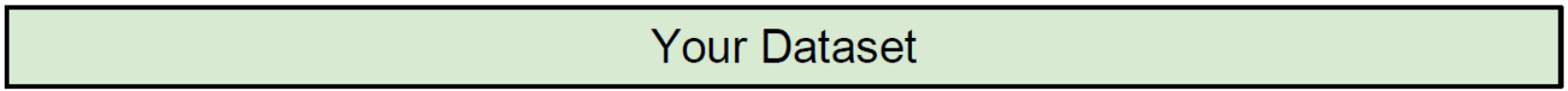
These are **hyperparameters**: choices about the algorithm that we set rather than learn

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



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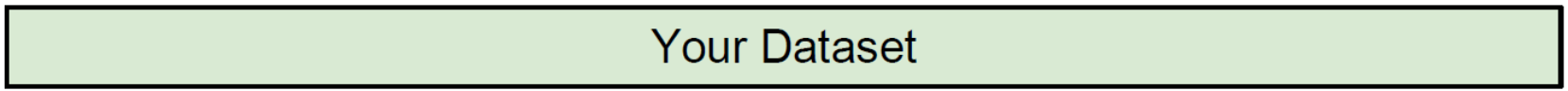
BAD: K = 1 always works perfectly on training data



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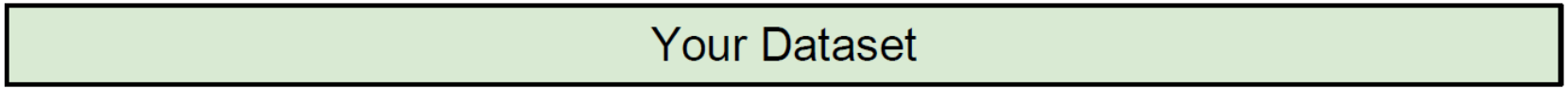

Idea #2: Split data into **train** and **test**, choose hyperparameters that work best on test data

Setting Hyperparameters

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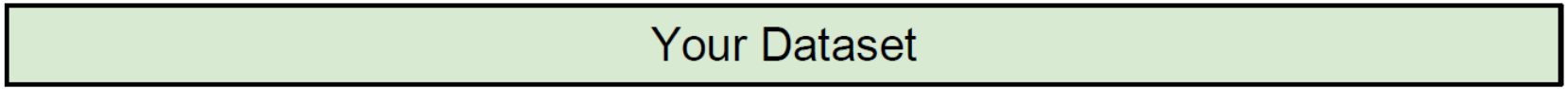

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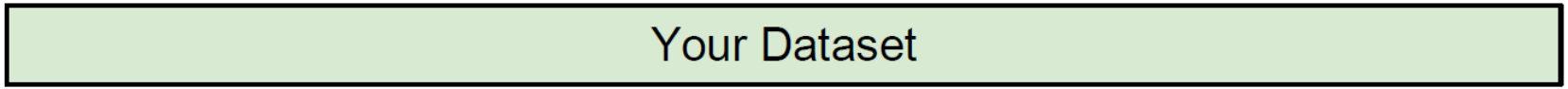


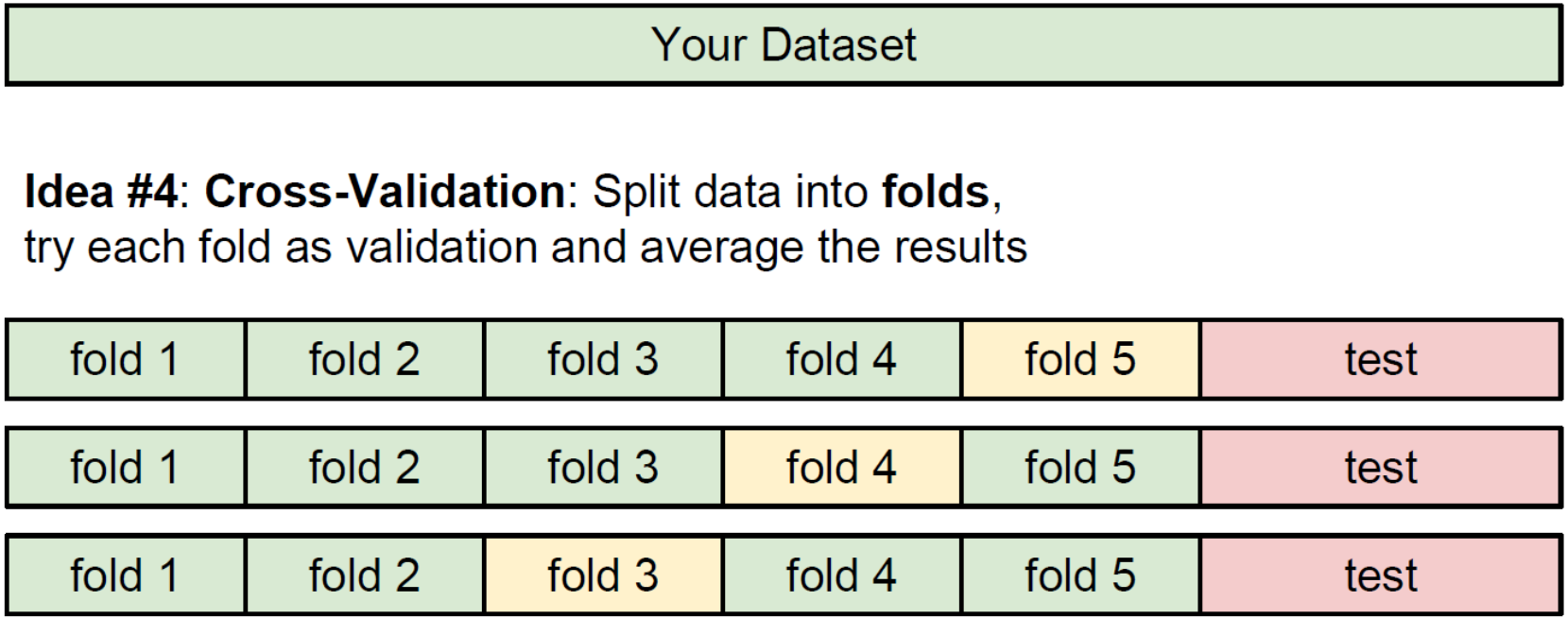
Idea #2: Split data into **train** and **test**, choose hyperparameters that work best on test data

BAD: No idea how algorithm will perform on new data

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

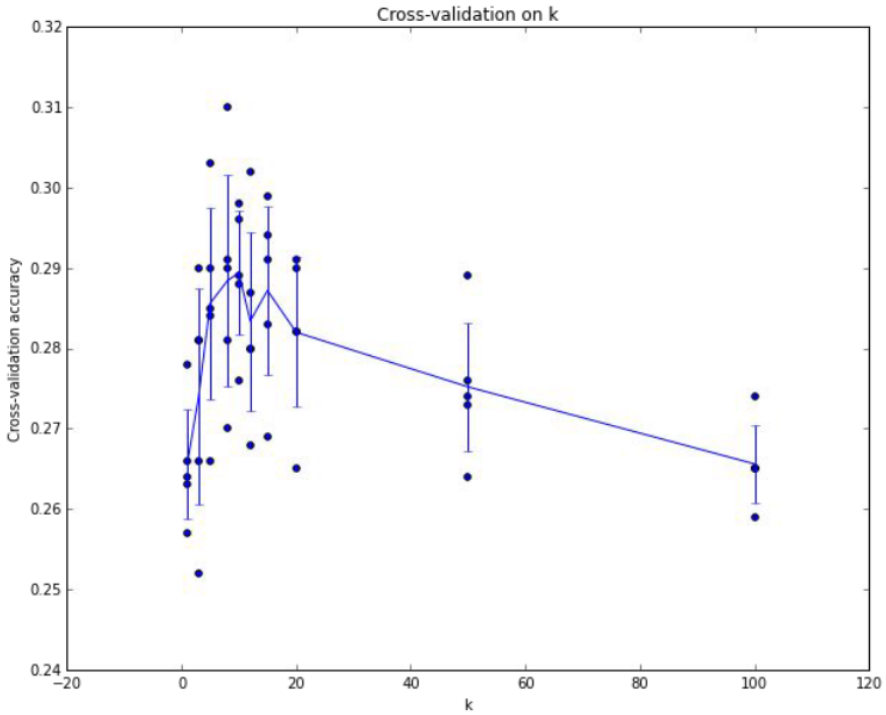
Better!

Setting Hyperparameters



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: Universal Approximation

As the number of training samples goes to infinity, nearest neighbor can represent any(*) function!

(*) Subject to many technical conditions. Only continuous functions on a compact domain; need to make assumptions about spacing of training points; etc.

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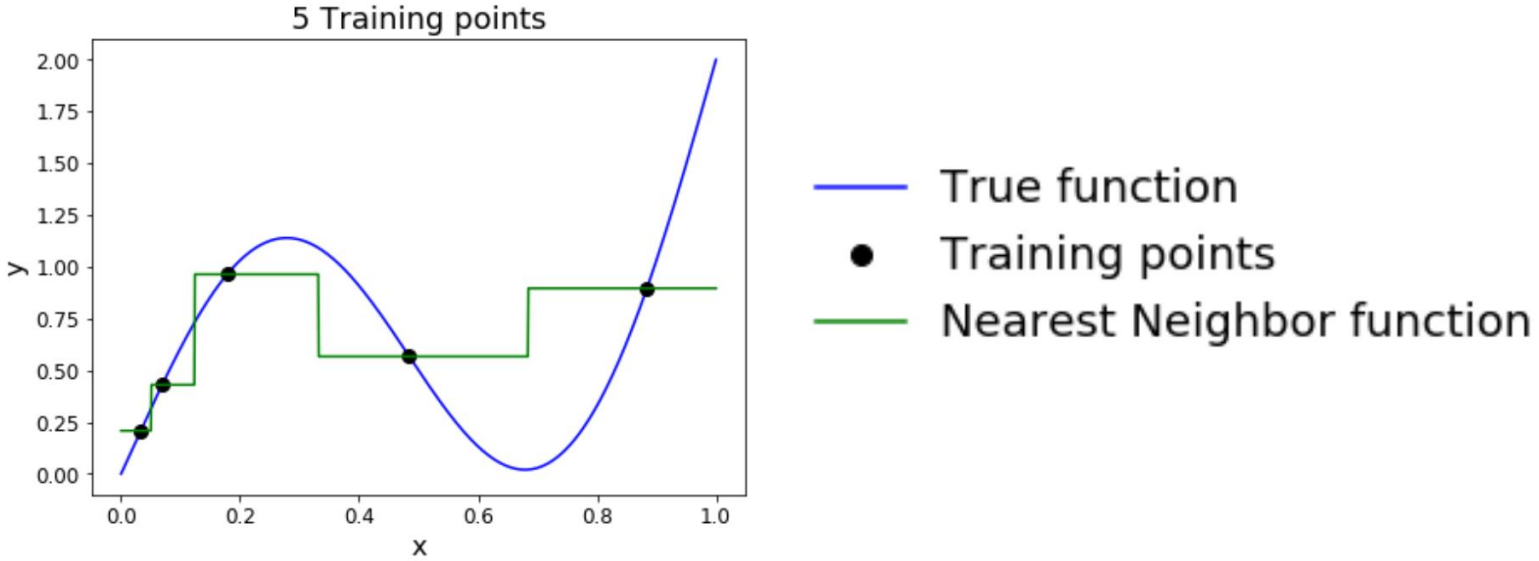

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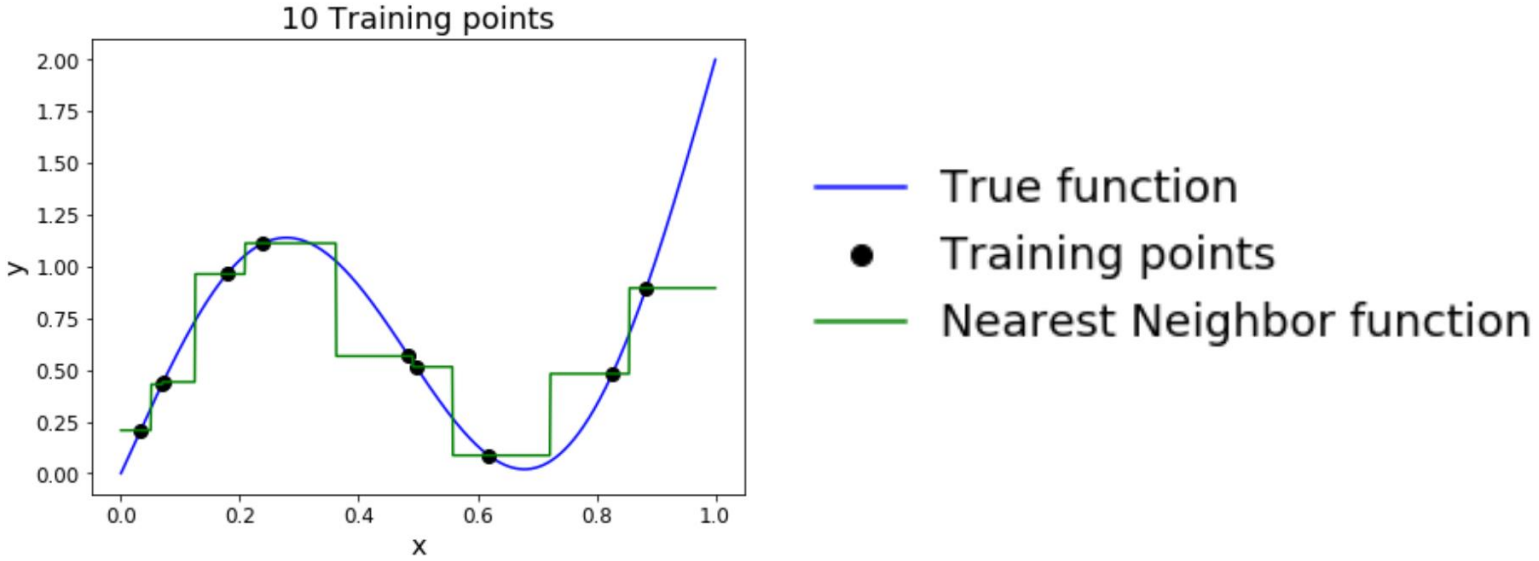

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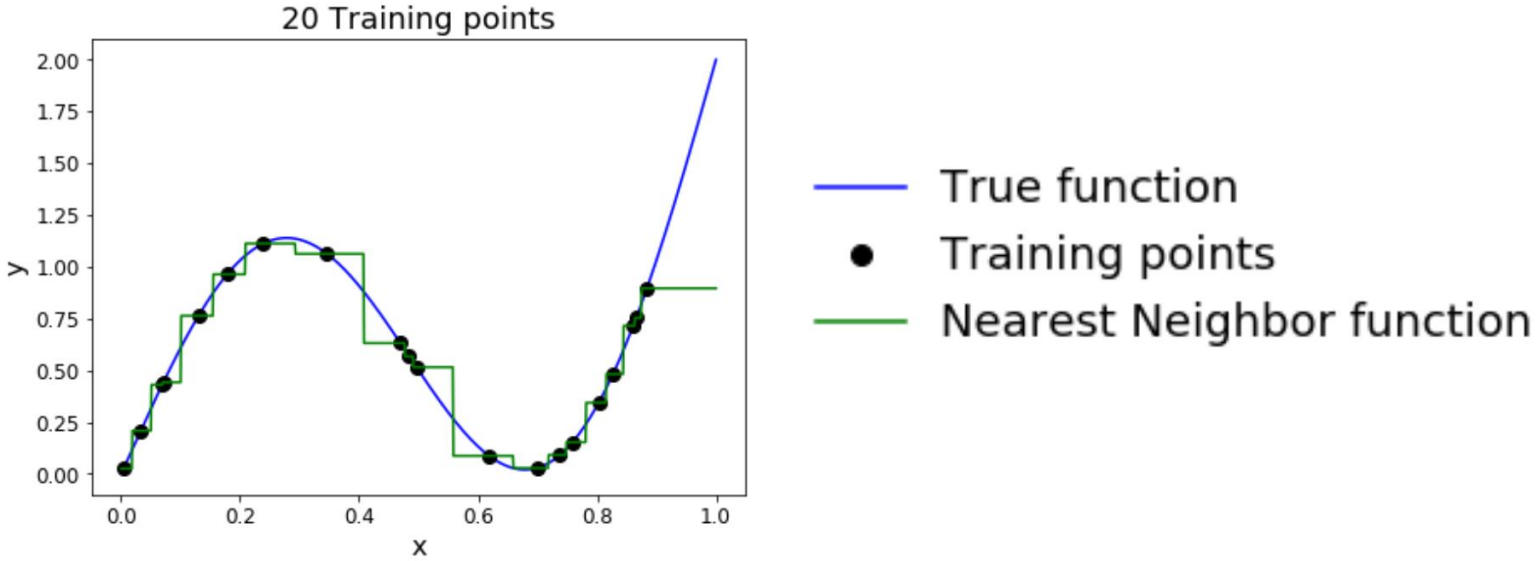

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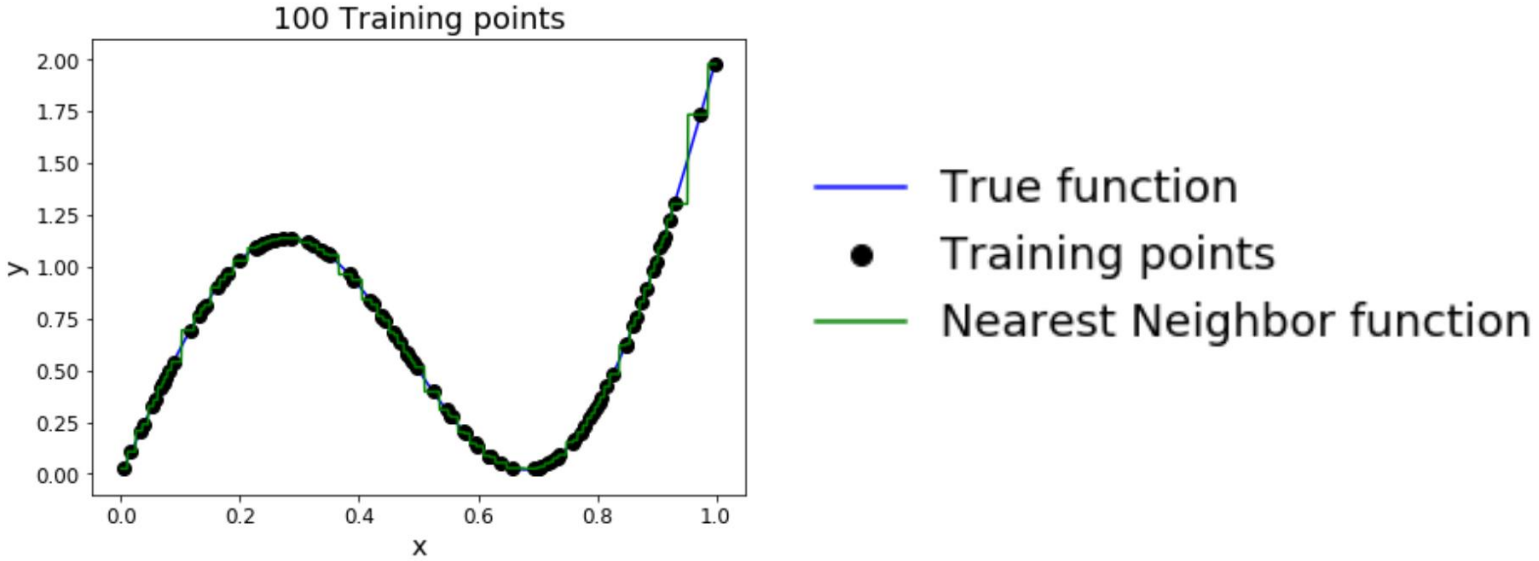

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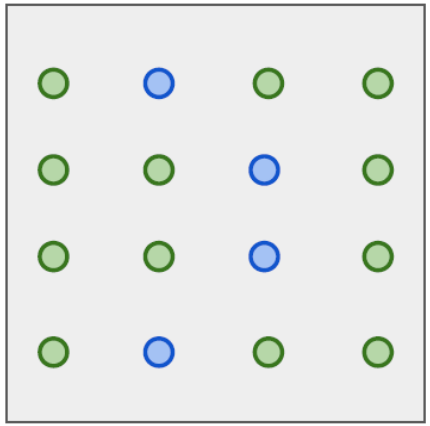
k-Nearest Neighbor on images **never used.**

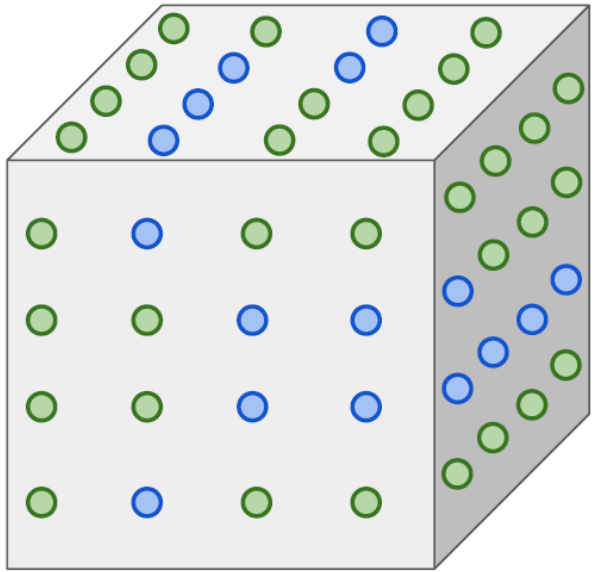
- Curse of dimensionality

Dimensions = 1
Points = 4

Dimensions = 2
Points = 4^2



Dimensions = 3
Points = 4^3



Problem: Curse of Dimensionality

Curse of dimensionality: For uniform coverage of space, number of training points needed grows exponentially with dimension

Number of possible 32x32 binary images:

$2^{32x32} \approx 10^{308}$

Number of elementary particles in the visible universe: (source)

$\approx 10^{97}$

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)

Nearest Neighbor with ConvNet features works well!

Devlin et al, “Exploring Nearest Neighbor Approaches for Image Captioning”, 2015

Nearest Neighbor with ConvNet features works well!

Example: Image Captioning with Nearest Neighbor

A bedroom with a bed and a couch.

A cat sitting in a bathroom sink.

A train is stopped at a train station.

A wooden bench in front of a building.

Devlin et al, "Exploring Nearest Neighbor Approaches for Image Captioning", 2015

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**

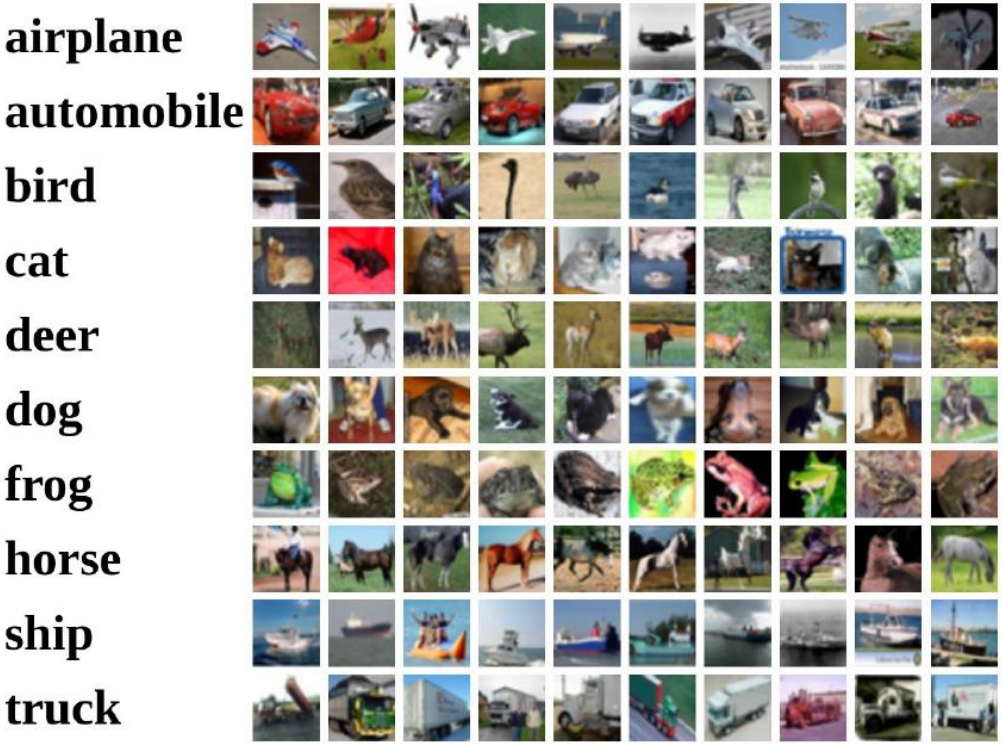
Choose hyperparameters using the **validation set**; only run on the test set once at the very end!

Linear Classification

Neural Network

Linear classifiers

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

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

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Array of **32x32x3** numbers
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parameters
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Parametric Approach: Linear Classifier

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

3072x1

10x1

10x3072

Image

Array of **32x32x3** numbers
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f(**x**, **W**)

10 numbers giving class scores

W

parameters or weights

Parametric Approach: Linear Classifier

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

3072x1

10x1

10x3072

10x1

Image

Array of **32x32x3** numbers
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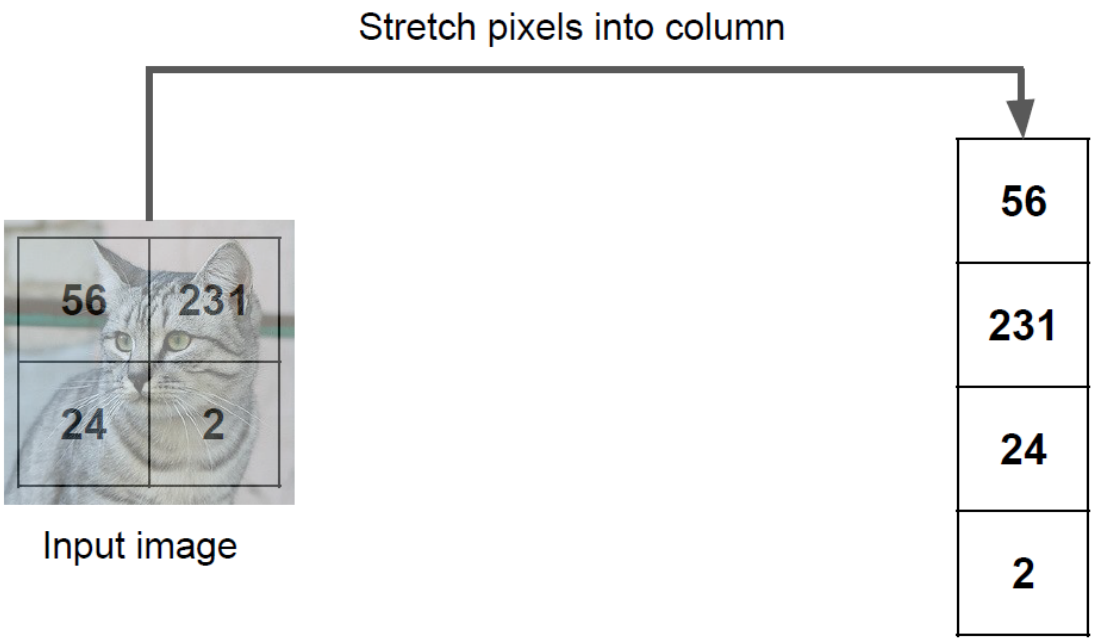
f(**x**, **W**)

10 numbers giving class scores

W

parameters or weights

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



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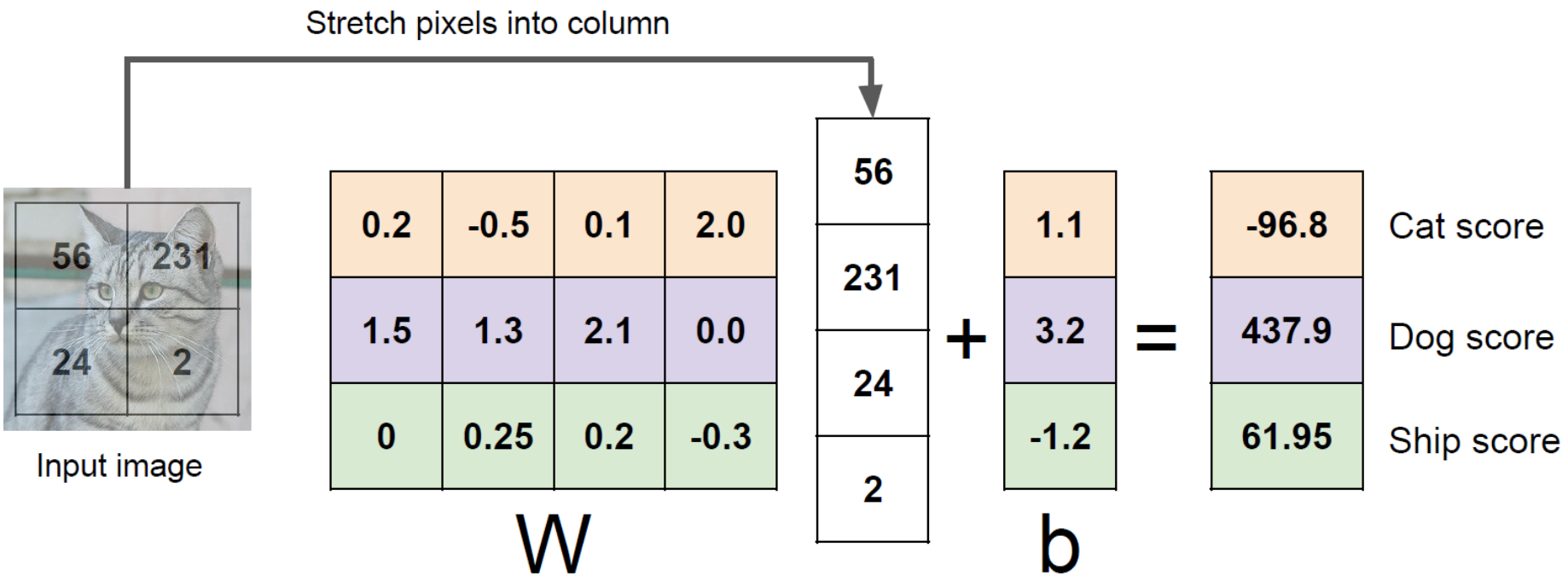

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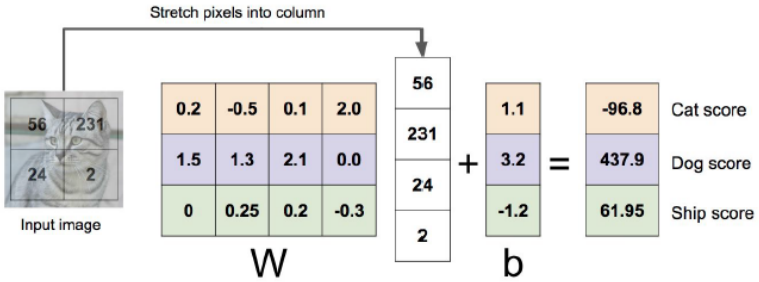
Algebraic Viewpoint

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



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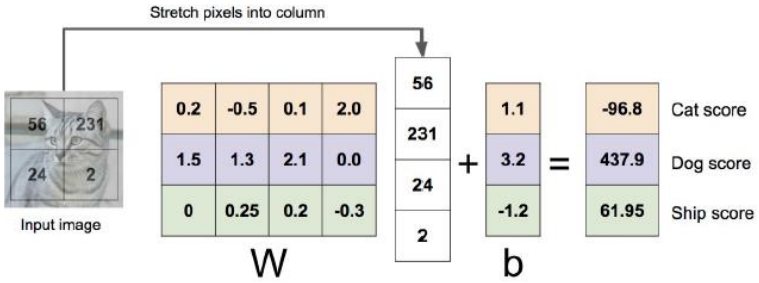
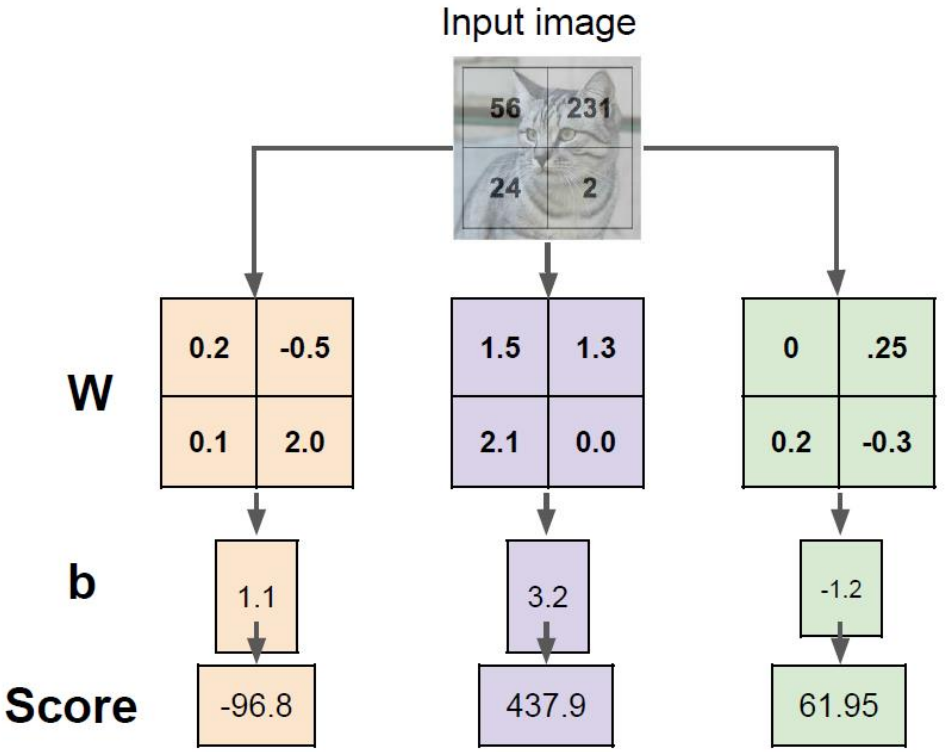
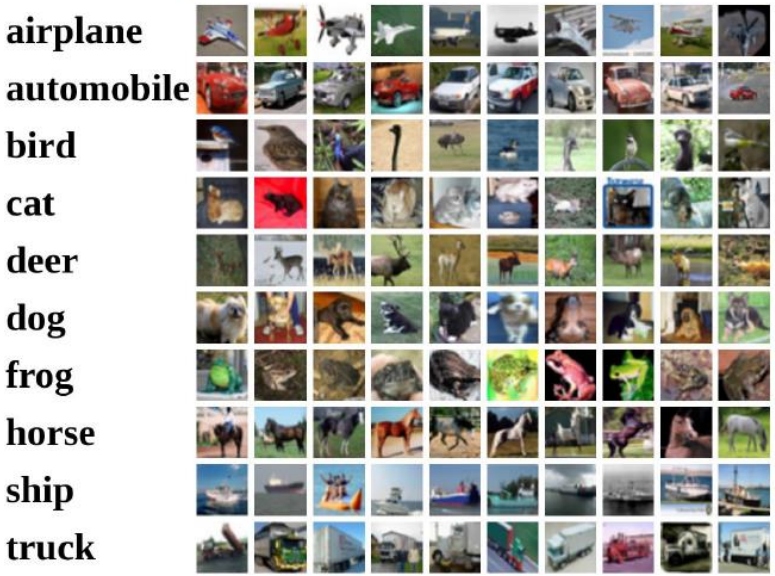
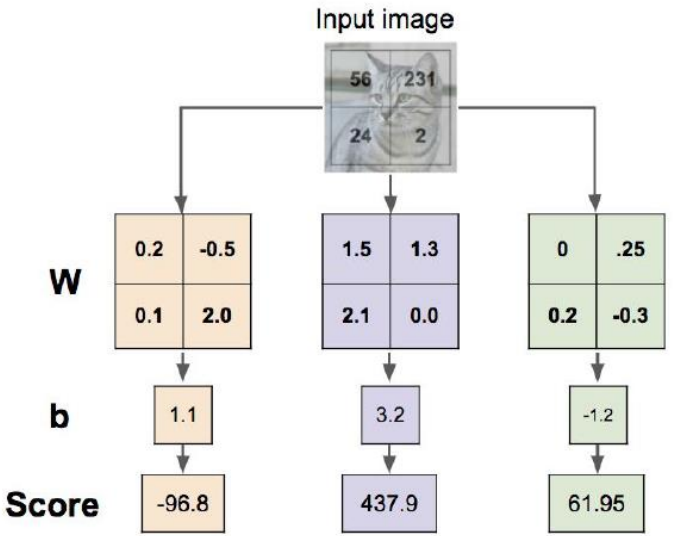


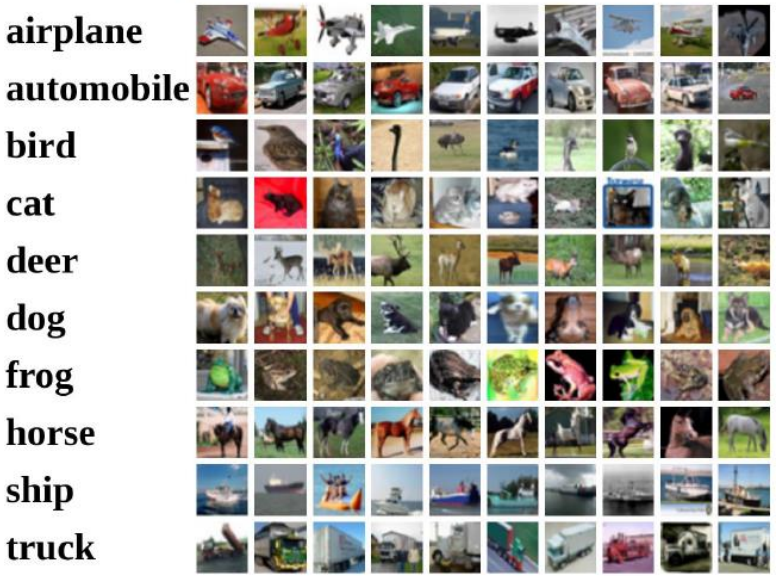


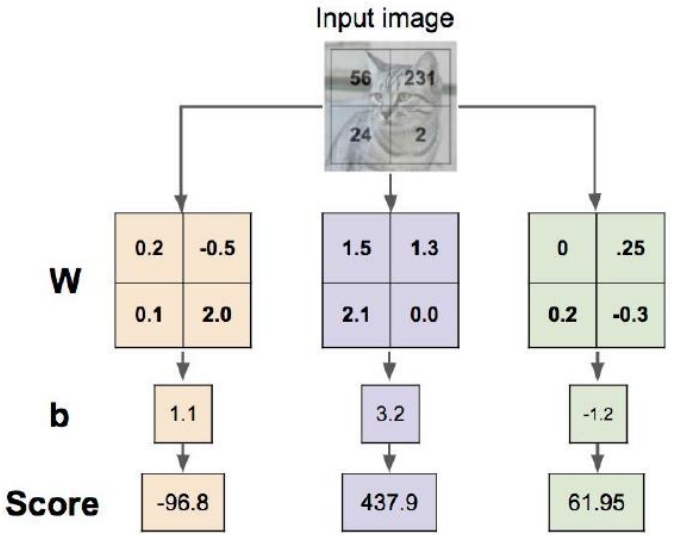
Interpreting a Linear Classifier





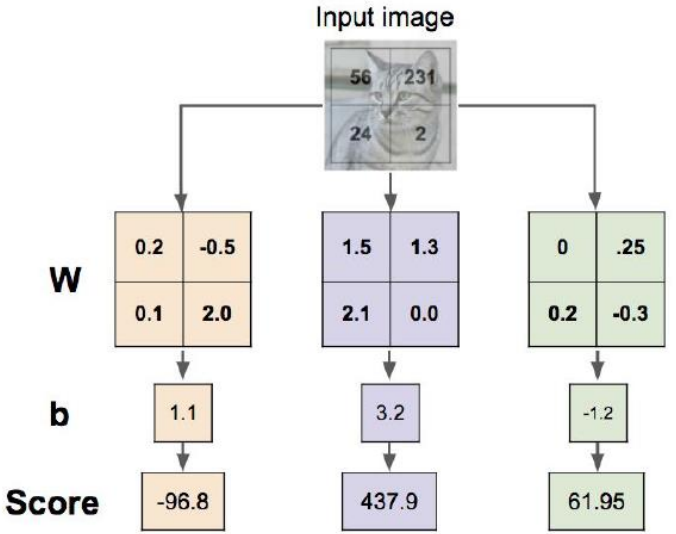
Interpreting a Linear Classifier: Visual Viewpoint





Interpreting a Linear Classifier: Visual Viewpoint

Linear classifier has one "template" per category

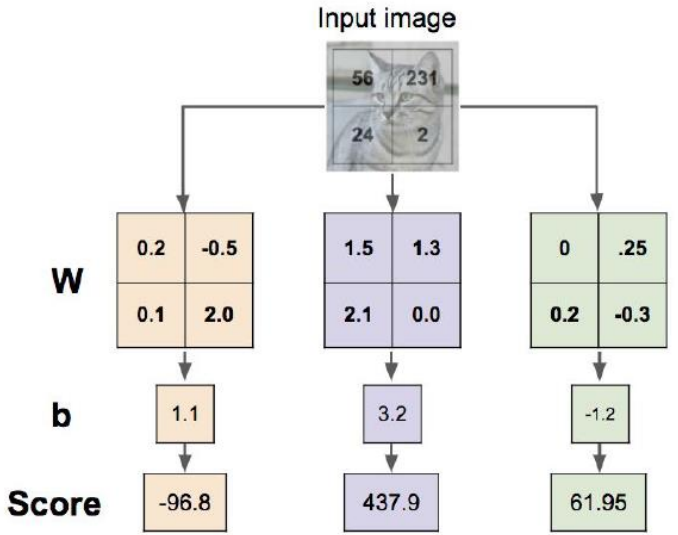


Interpreting a Linear Classifier: Visual Viewpoint

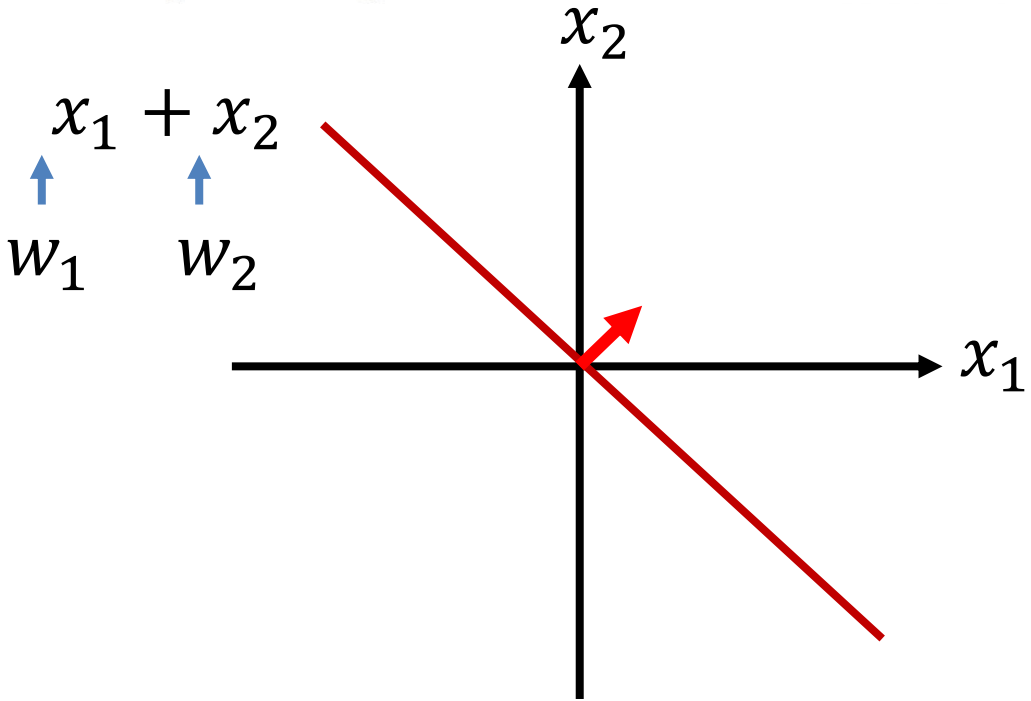
Linear classifier has one "template" per category

A single template cannot capture multiple modes of the data

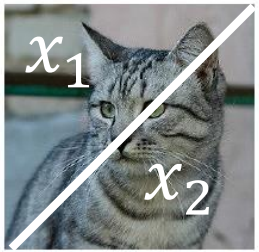
e.g. horse template has 2 heads!



Interpreting a Linear Classifier: Geometric Viewpoint



$$f(x,W) = Wx + b \qquad \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$



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

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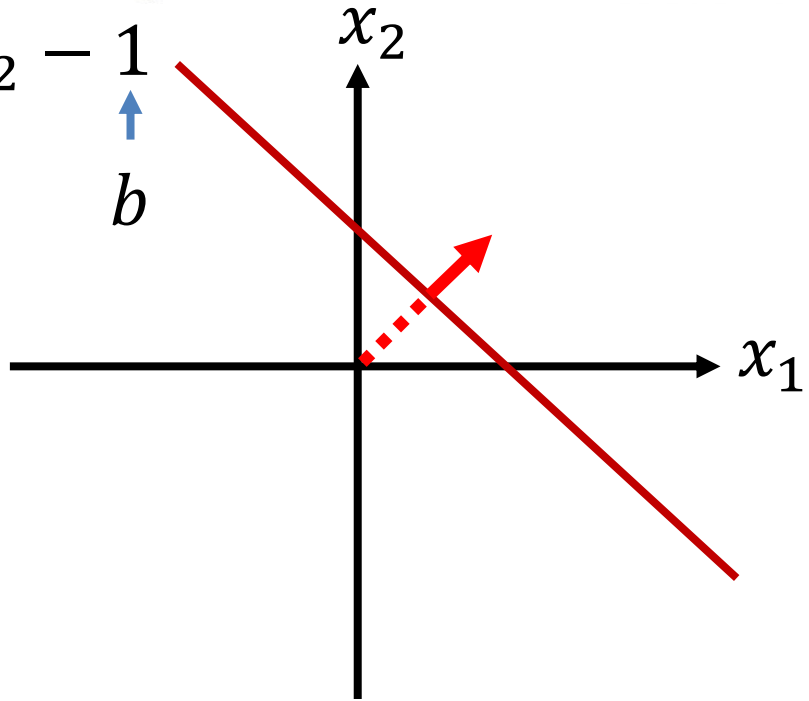
$x_1 + x_2 - 1$

w_1 w_2 b



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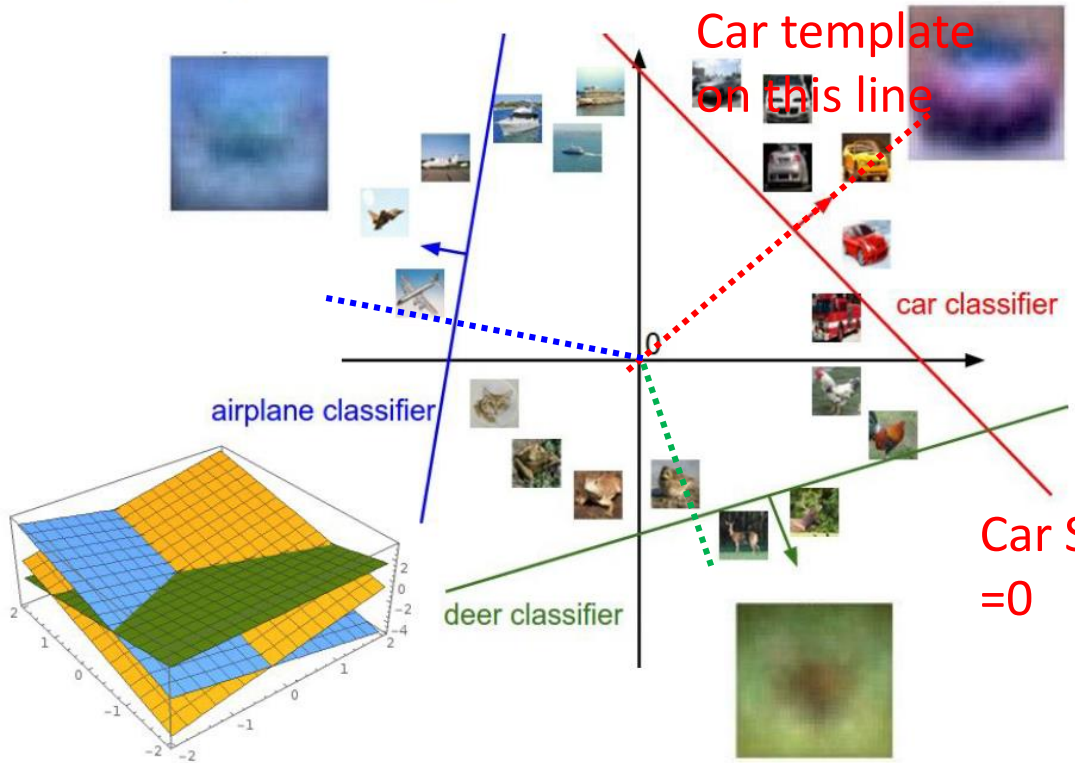


$$f(x,W) = Wx + b$$

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Car score increases this way

Car Score =0

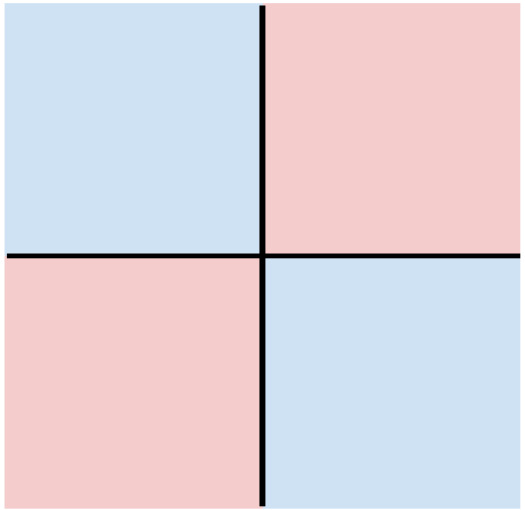
Array of **32x32x3** numbers (3072 numbers total)

Plot created using Wolfram Cloud

Hard cases for a linear classifier

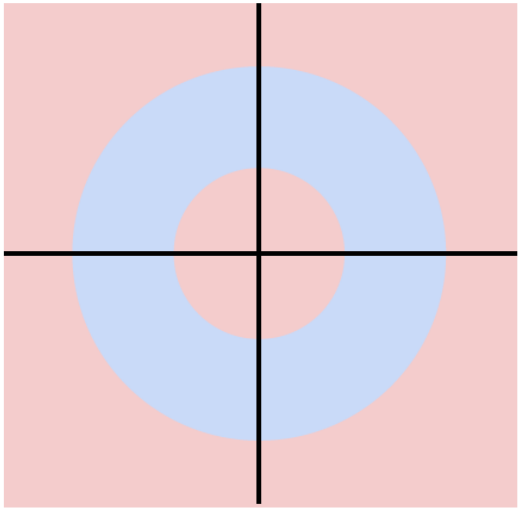
Class 1:
First and third quadrants

Class 2:
Second and fourth quadrants



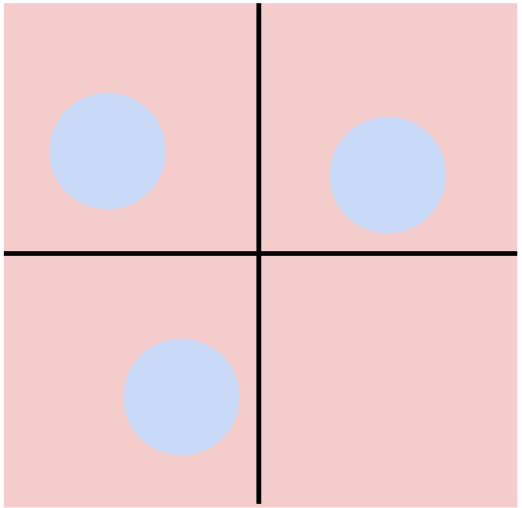
Class 1:
1 <= L2 norm <= 2

Class 2:
Everything else



Class 1:
Three modes

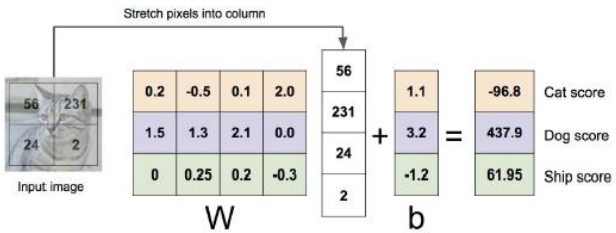
Class 2:
Everything else



Linear Classifier: Three Viewpoints

Algebraic Viewpoint

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

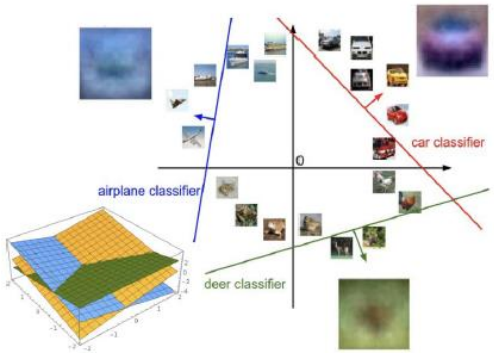


Visual Viewpoint

One template per class

Geometric Viewpoint

Hyperplanes cutting up space



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

Given a W, we can compute class scores for an image x.

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)