# Lecture 2:
# Image Classification pipeline

# Administrative: Piazza

For questions about midterm, poster session, projects,
use Piazza instead of staff list!

SCPD students: Use your @stanford.edu address to register for Piazza; contact scpd-customerservice@stanford.edu for help.

# Administrative: Assignment 1

Out tonight, due 4/18 11:59pm

- K-Nearest Neighbor
- Linear classifiers: SVM, Softmax
- Two-layer neural network
- Image features

# Administrative: Python + Numpy

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/

# Administrative: Google Cloud

## Google Cloud Tutorial

For the class project and assignments, we offer an option to use Google Compute Engine for developing and testing your implementations. This tutorial lists the necessary steps of working on the assignments using Google Cloud. For each assignment, we will provide you with an image containing the starter code and all dependencies that you need to complete the assignment. This tutorial goes through how to set up your own Google Compute Engine (GCE)

http://cs231n.github.io/gce-tutorial/

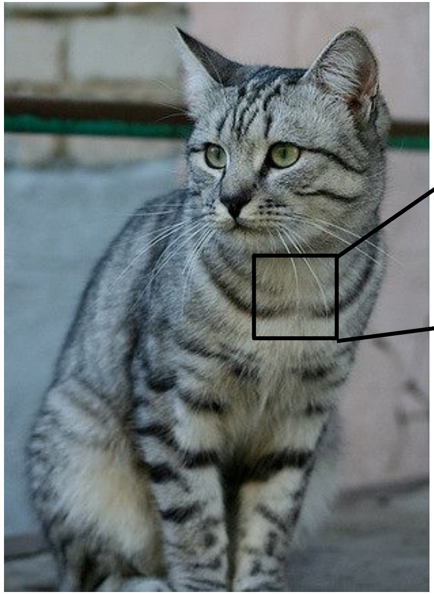
# **Image Classification**: A core task in Computer Vision



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

→ cat

# **The Problem**: Semantic Gap





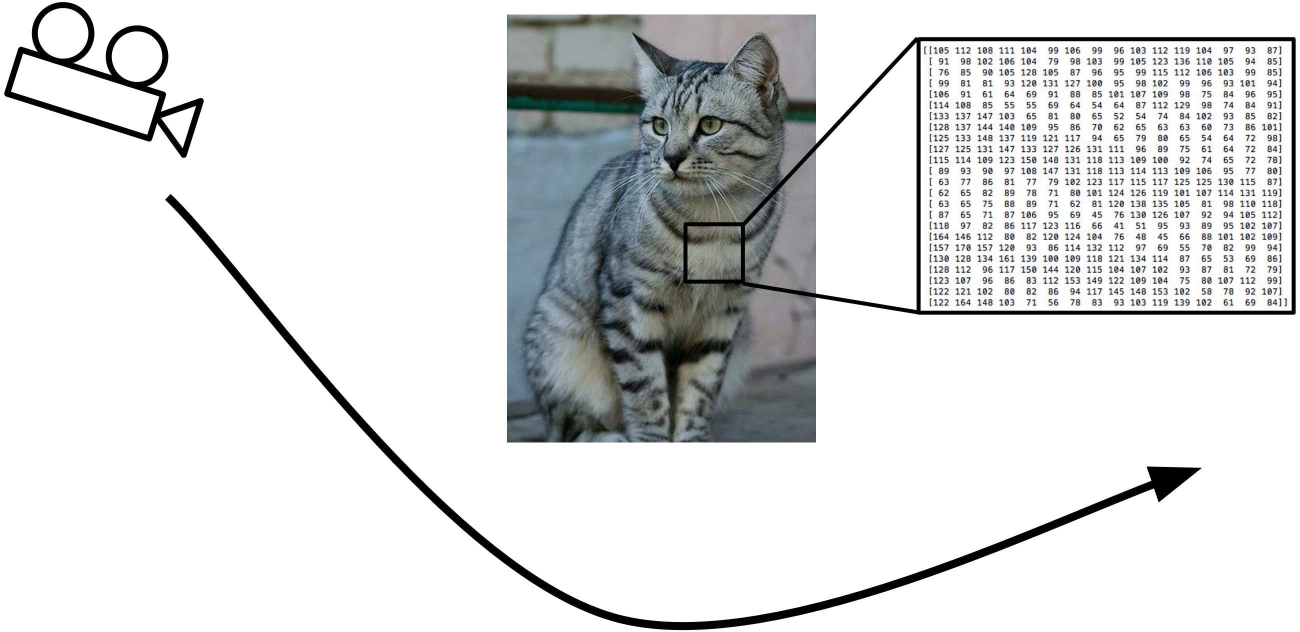
```
[[105 112 108 111 104  99 106  99  96 103 112 119 104  97  93  87]
 [ 91  98 102 106 104  79  98 103  99 105 123 136 110 105  94  85]
 [ 76  85  90 105 128 105  87  96  95  99 115 112 106 103  99  85]
 [ 99  81  81  93 120 131 127 100  95  98 102  99  96  93 101  94]
 [106  91  61  64  69  91  88  85 101 107 109  98  75  84  96  95]
 [114 108  85  55  55  69  64  54  64  87 112 129  98  74  84  91]
 [133 137 147 103  65  81  80  65  52  54  74  84 102  93  85  82]
 [128 137 144 140 109  95  86  70  62  65  63  63  60  73  86 101]
 [125 133 148 137 119 121 117  94  65  79  80  65  54  64  72  98]
 [127 125 131 147 133 127 126 131 111  96  89  75  61  64  72  84]
 [115 114 109 123 150 148 131 118 113 109 100  92  74  65  72  78]
 [ 89  93  90  97 108 147 131 118 113 114 113 109 106  95  77  80]
 [ 63  77  86  81  77  79 102 123 117 115 117 125 125 130 115  87]
 [ 62  65  82  89  78  71  80 101 124 126 119 101 107 114 131 119]
 [ 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



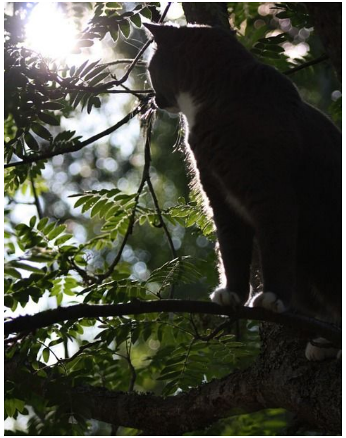

All pixels change when
the camera moves!

# **Challenges**: Illumination

This image is CC0 1.0 public domain

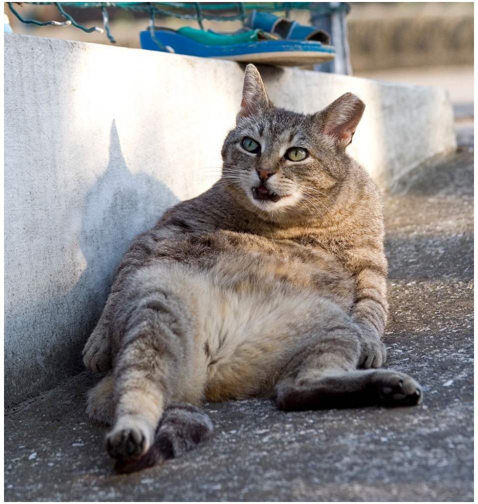
This image is CC0 1.0 public domain

This image is CC0 1.0 public domain

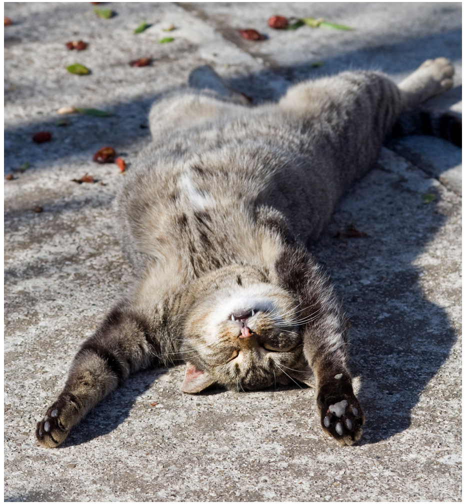


This image is CC0 1.0 public domain

# **Challenges**: Deformation

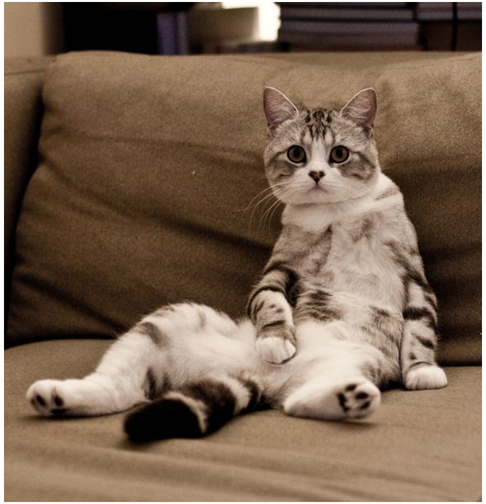












# **Challenges**: Occlusion

This image is CC0 1.0 public domain

This image is CC0 1.0 public domain

This image by jonsson is licensed under CC-BY 2.0

# **Challenges**: Background Clutter

This image is CC0 1.0 public domain

This image is CC0 1.0 public domain

# **Challenges**: Intraclass variation

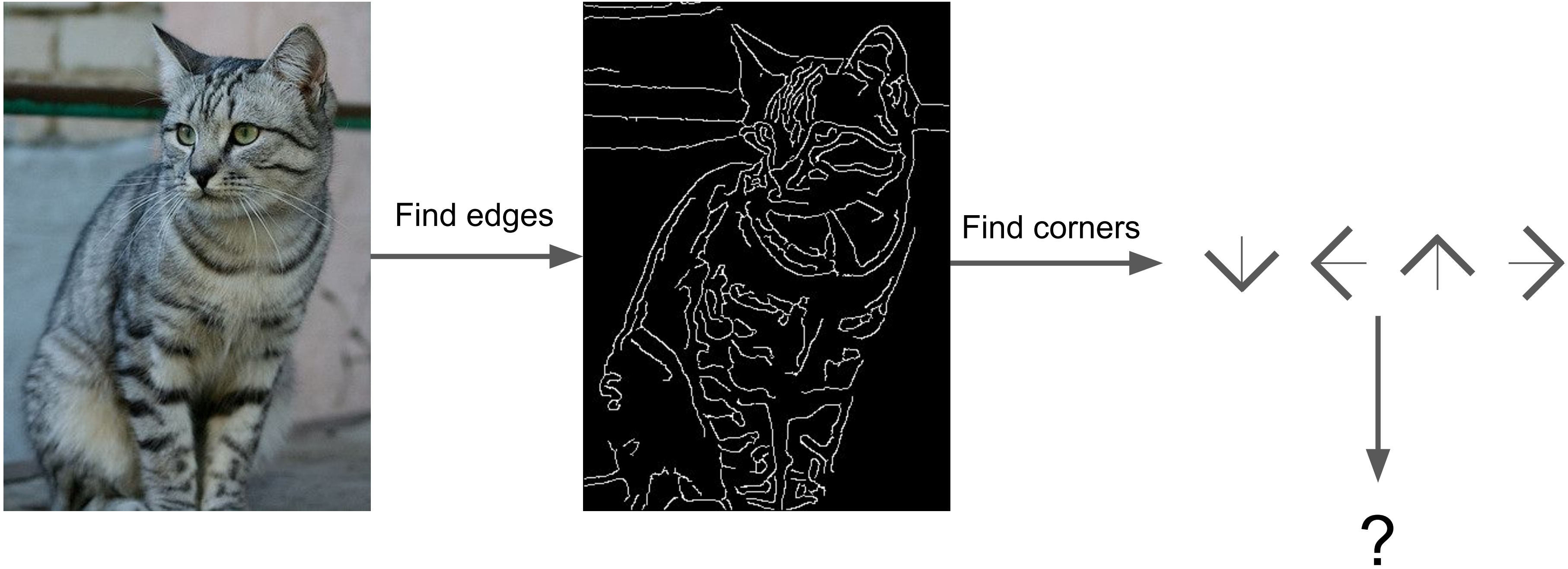
# An image classifier

```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.

# Attempts have been made




John Canny, “A Computational Approach to Edge Detection”, IEEE TPAMI 1986

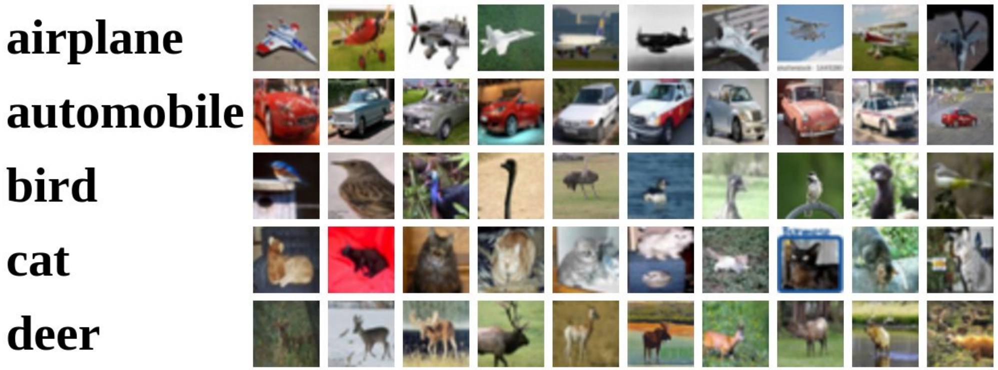
# Data-Driven Approach

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**



# First classifier: **Nearest Neighbor**

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

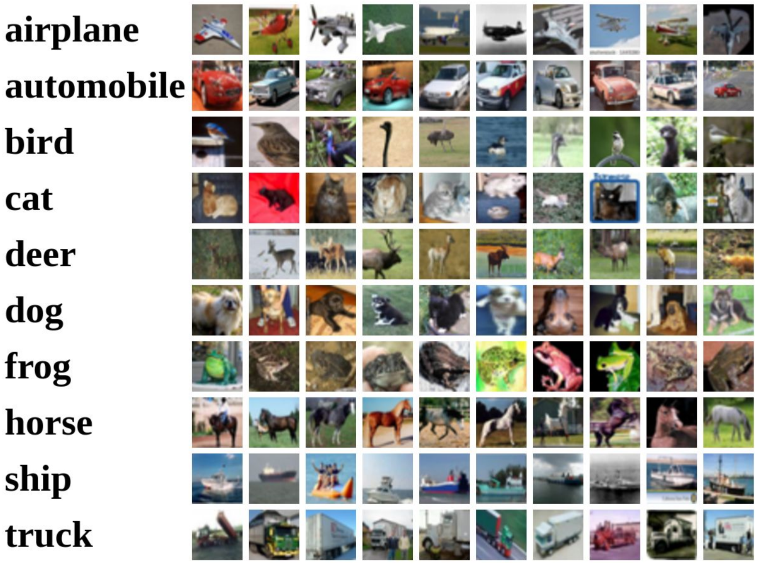
Memorize all data and labels

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

Predict the label of the most similar training image

# Example Dataset: **CIFAR10**

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



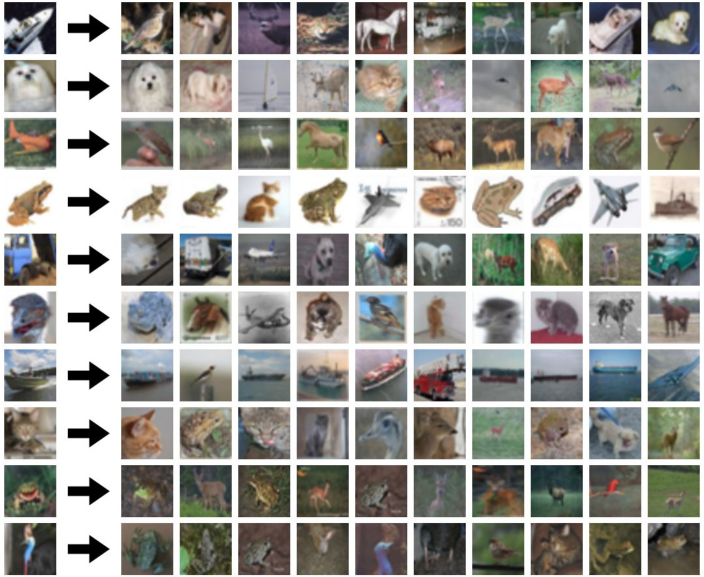

Alex Krizhevsky, “Learning Multiple Layers of Features from Tiny Images”, Technical Report, 2009.

# Example Dataset: **CIFAR10**

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

airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck

Test images and nearest neighbors



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

# **Distance Metric** to compare images

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

test image

| | | | |
|---|---|---|---|
| 56 | 32 | 10 | 18 |
| 90 | 23 | 128 | 133 |
| 24 | 26 | 178 | 200 |
| 2 | 0 | 255 | 220 |

-

training image

| | | | |
|---|---|---|---|
| 10 | 20 | 24 | 17 |
| 8 | 10 | 89 | 100 |
| 12 | 16 | 178 | 170 |
| 4 | 32 | 233 | 112 |

=

pixel-wise absolute value differences

| | | | |
|---|---|---|---|
| 46 | 12 | 14 | 1 |
| 82 | 13 | 39 | 33 |
| 12 | 10 | 0 | 30 |
| 2 | 32 | 22 | 108 |

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

## 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

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```

## Nearest Neighbor classifier

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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

```python
import numpy as np

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# Nearest Neighbor classifier

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

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import numpy as np

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# Nearest Neighbor classifier

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**A**: Train O(1),
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```

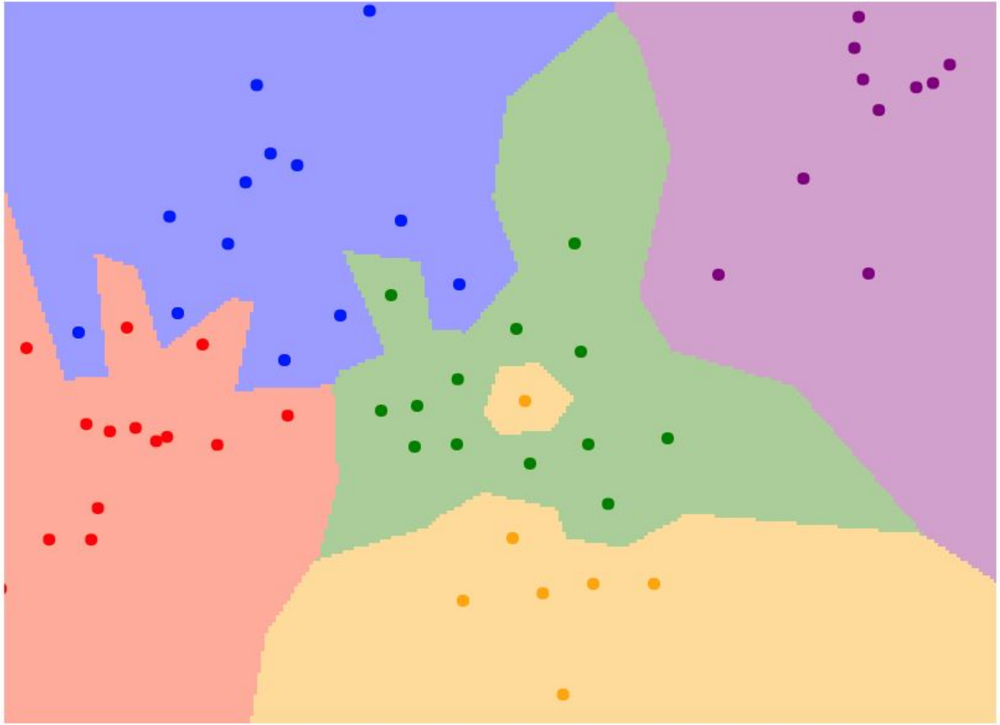
# Nearest Neighbor classifier

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

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

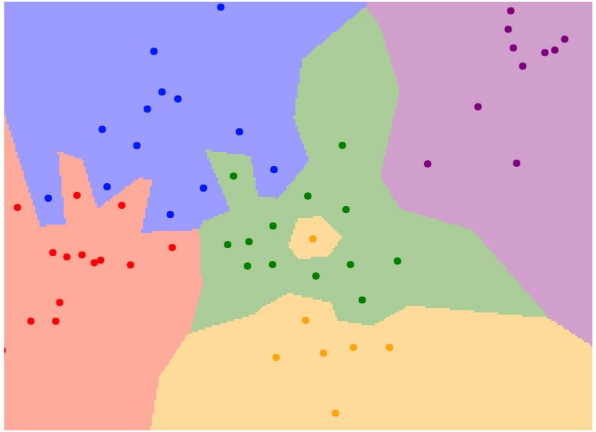
This is bad: we want classifiers that are **fast** at prediction; **slow** for training is ok

# What does this look like?

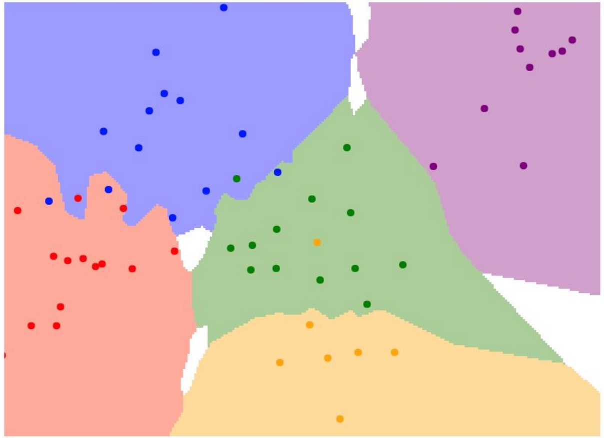


# K-Nearest Neighbors

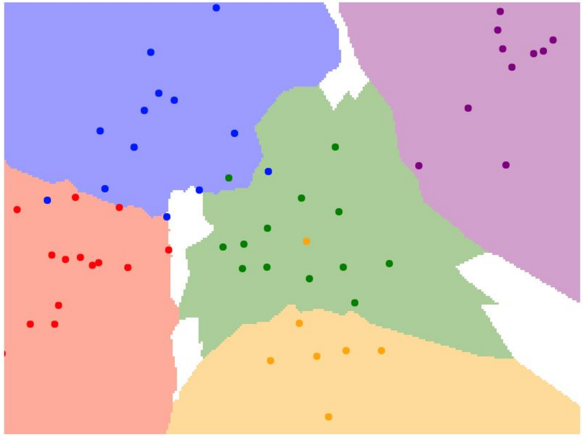
Instead of copying label from nearest neighbor, take **majority vote** from K closest points



K = 1

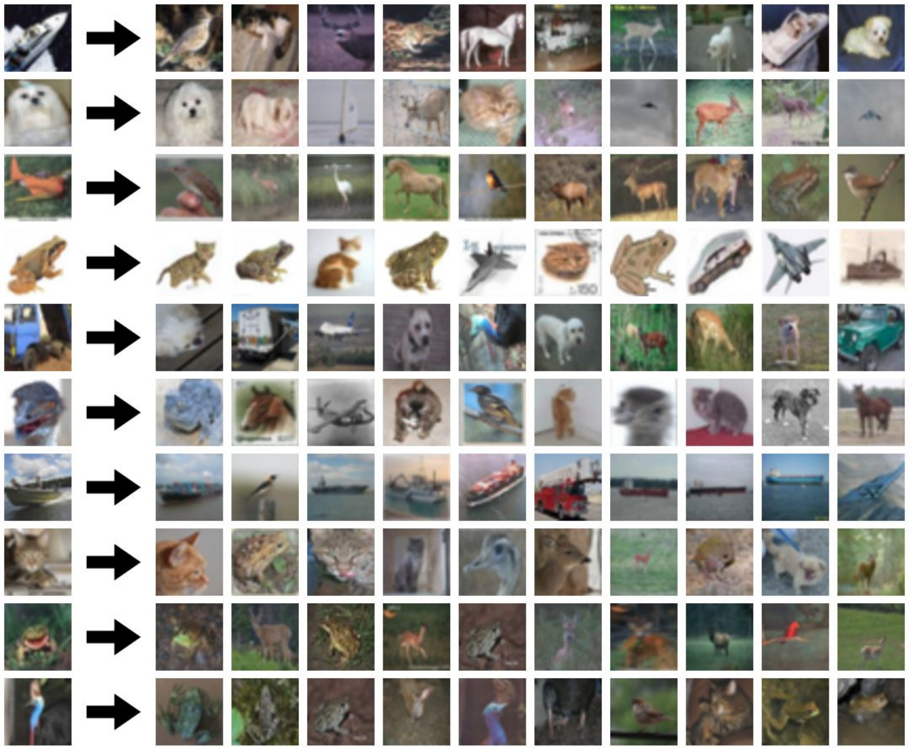


K = 3



K = 5

# What does this look like?

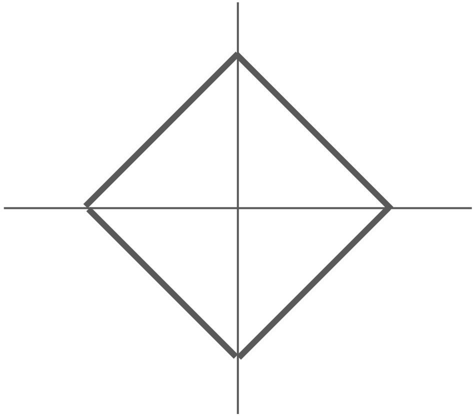


# What does this look like?

# K-Nearest Neighbors: Distance Metric

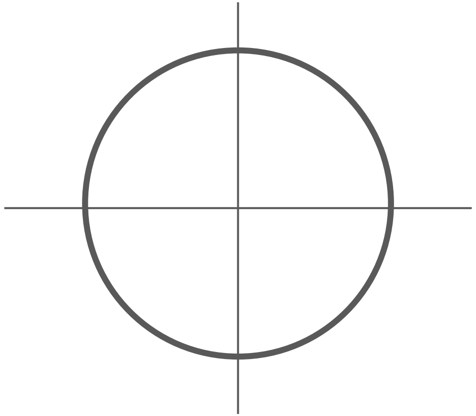
## L1 (Manhattan) distance

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



## L2 (Euclidean) distance

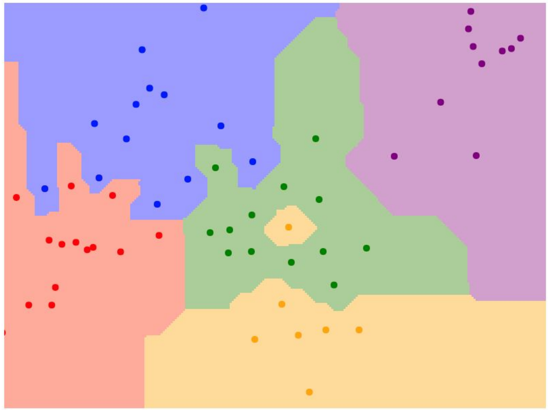
$$d_2(I_1, I_2) = \sqrt{\sum_p \left(I_1^p - I_2^p\right)^2}$$



# K-Nearest Neighbors: Distance Metric

L1 (Manhattan) distance

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



K = 1

L2 (Euclidean) distance

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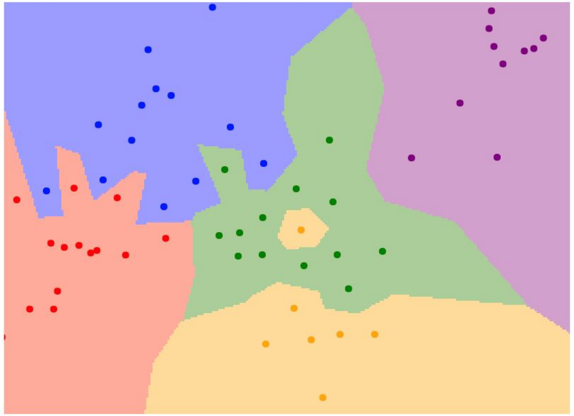
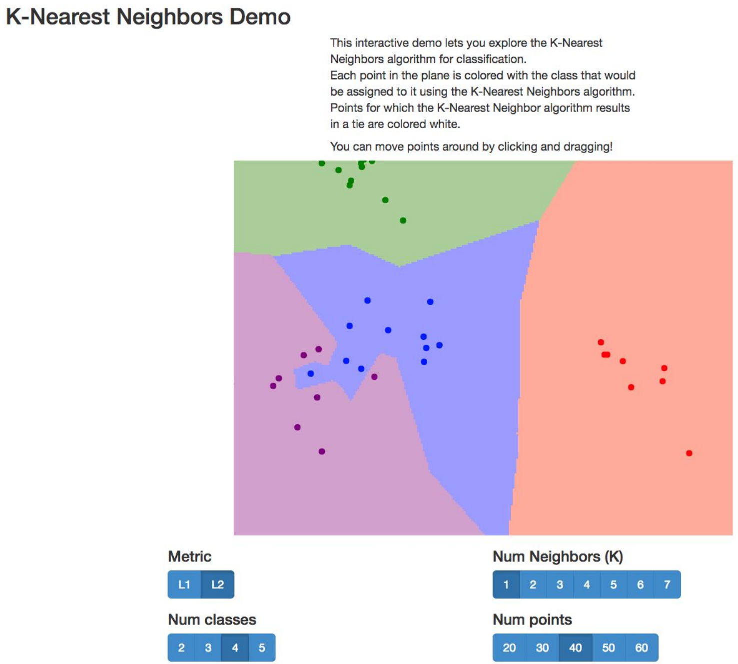


K = 1

# K-Nearest Neighbors: Demo Time




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

# Hyperparameters

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

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

# Hyperparameters

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

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

Very problem-dependent.
Must try them all out and see what works best.

# Setting Hyperparameters

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

Your Dataset

# Setting Hyperparameters

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

**BAD**: K = 1 always works perfectly on training data

| Your Dataset |
|---|

# Setting Hyperparameters

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

**BAD**: K = 1 always works perfectly on training data


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

# Setting Hyperparameters

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

**BAD**: K = 1 always works perfectly on training data

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 |
|---|---|

# Setting Hyperparameters

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

**BAD**: K = 1 always works perfectly on training data

Your Dataset

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

**BAD**: No idea how algorithm will perform on new data

| train | test |
|---|---|

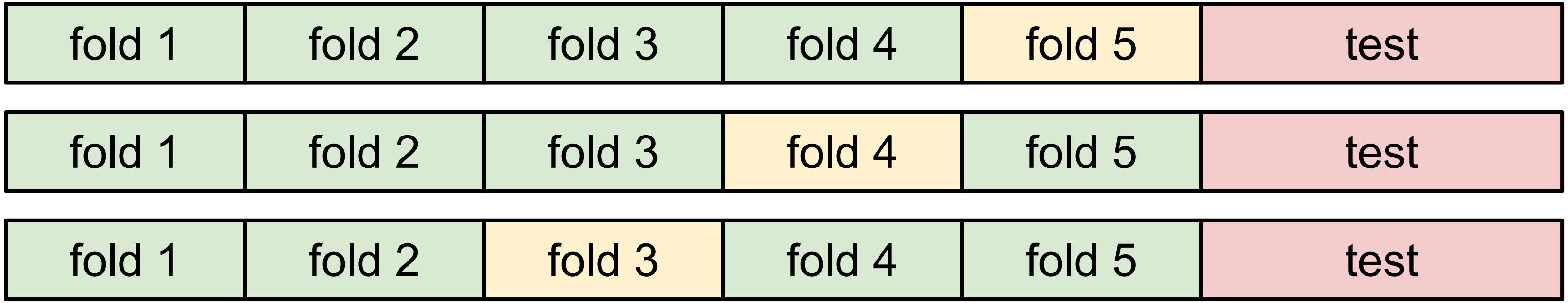
**Idea #3**: Split data into **train**, **val**, and **test**; choose hyperparameters on val and evaluate on test

**Better!**

| train | validation | test |
|---|---|---|

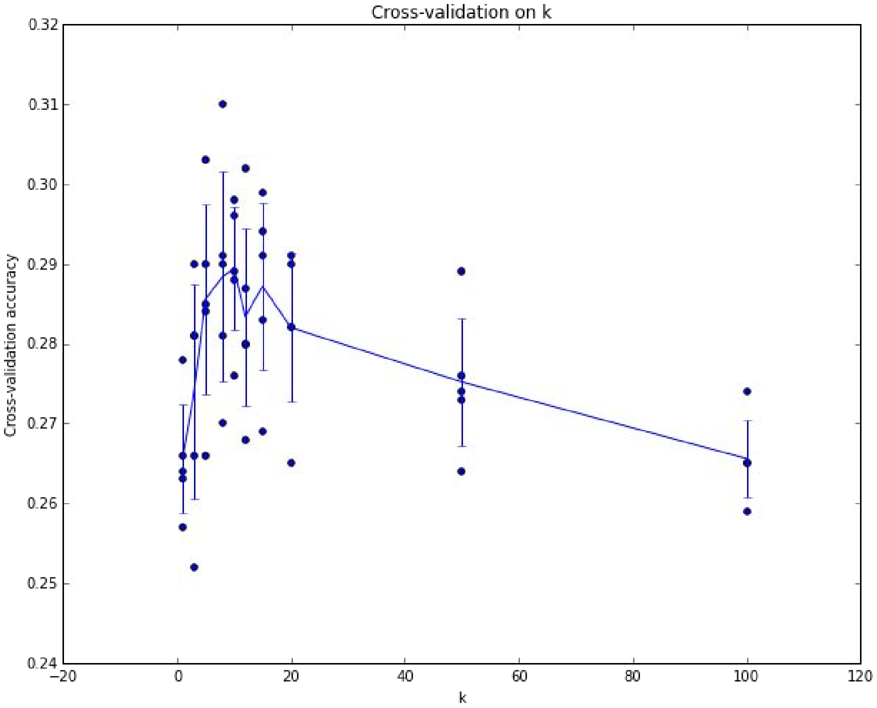
# Setting Hyperparameters


**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)

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

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

Original

Boxed

Shifted

Tinted



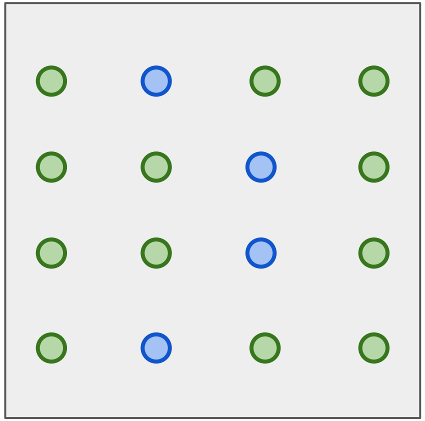
(all 3 images have same L2 distance to the one on the left)

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

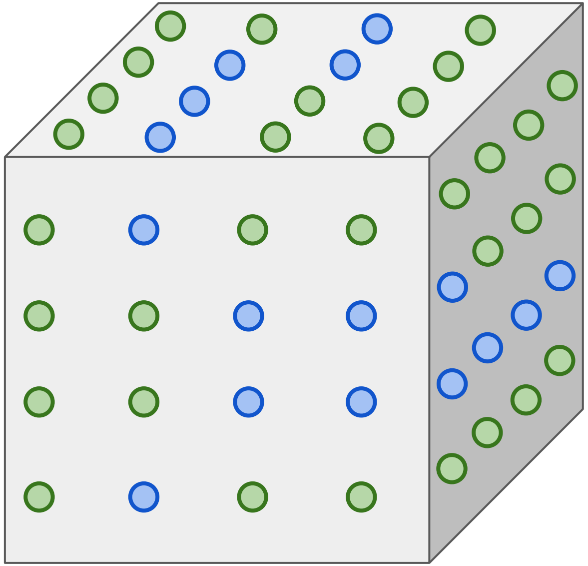
- Curse of dimensionality

Dimensions = 1
Points = 4

Dimensions = 2
Points = $4^2$



Dimensions = 3
Points = $4^3$



# 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

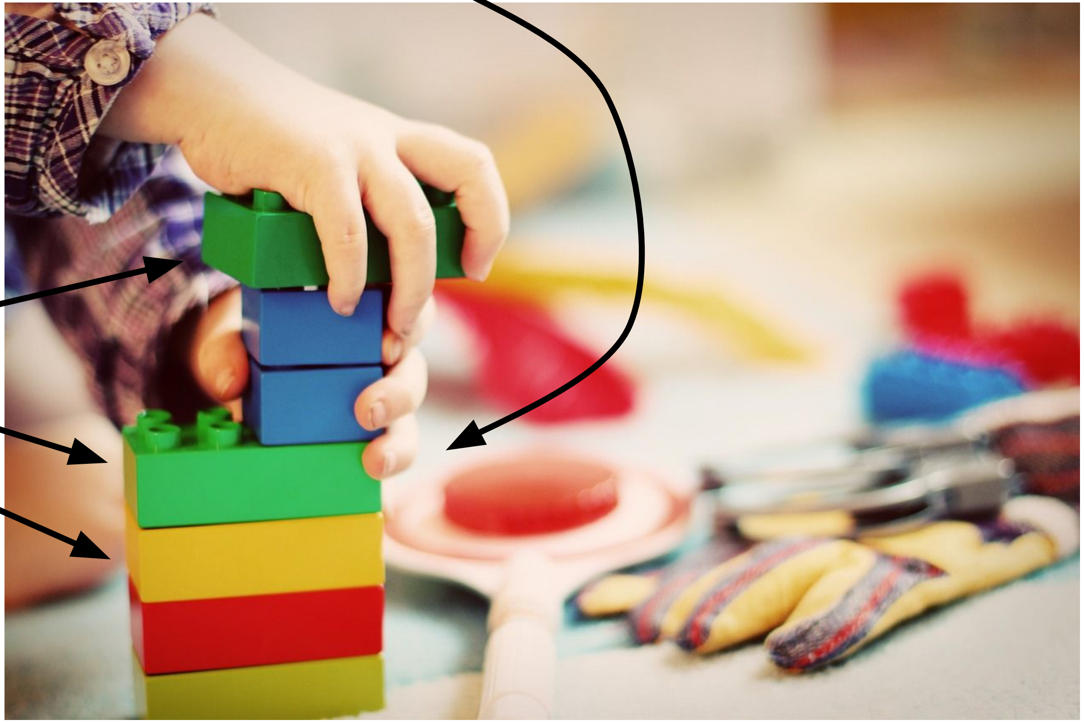
Distance metric and K are **hyperparameters**

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

# Linear Classification

Neural Network

Linear
classifiers



This image is CC0 1.0 public domain

*Two young girls are playing with lego toy.*

*Boy is doing backflip on wakeboard*

*Man in black shirt is playing guitar.*

*Construction worker in orange safety vest is working on road.*

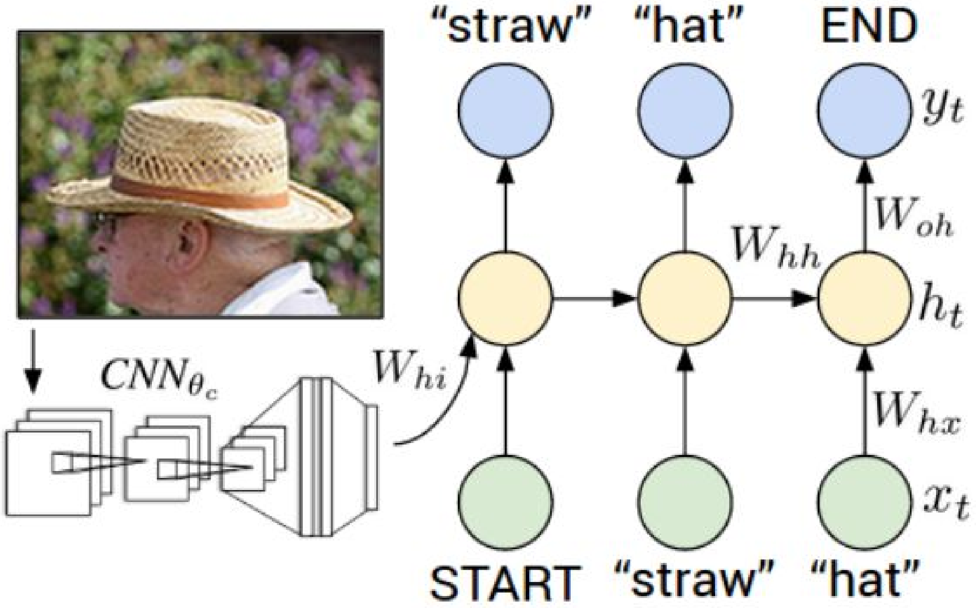
Karpathy and Fei-Fei, “Deep Visual-Semantic Alignments for Generating Image Descriptions”, CVPR 2015

*Two young girls are playing with lego toy.*

*Boy is doing backflip on wakeboard*

*Man in black shirt is playing guitar.*

*Construction worker in orange safety vest is working on road.*




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

# Recall CIFAR10

airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck

**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**)

**10** numbers giving
class scores

W

parameters
or weights

# Parametric Approach: Linear Classifier

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

Image

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

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

**10** numbers giving
class scores

W
parameters
or weights

# Parametric Approach: Linear Classifier

3072x1

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

10x1 10x3072

Image

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

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

**10** numbers giving class scores

W

parameters
or weights

# Parametric Approach: Linear Classifier

3072x1

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

10x1

10x1 10x3072

Image

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

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

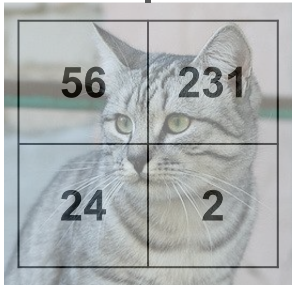
**10** numbers giving
class scores

W

parameters
or weights

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

Stretch pixels into column




Input image

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

# Interpreting a Linear Classifier


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

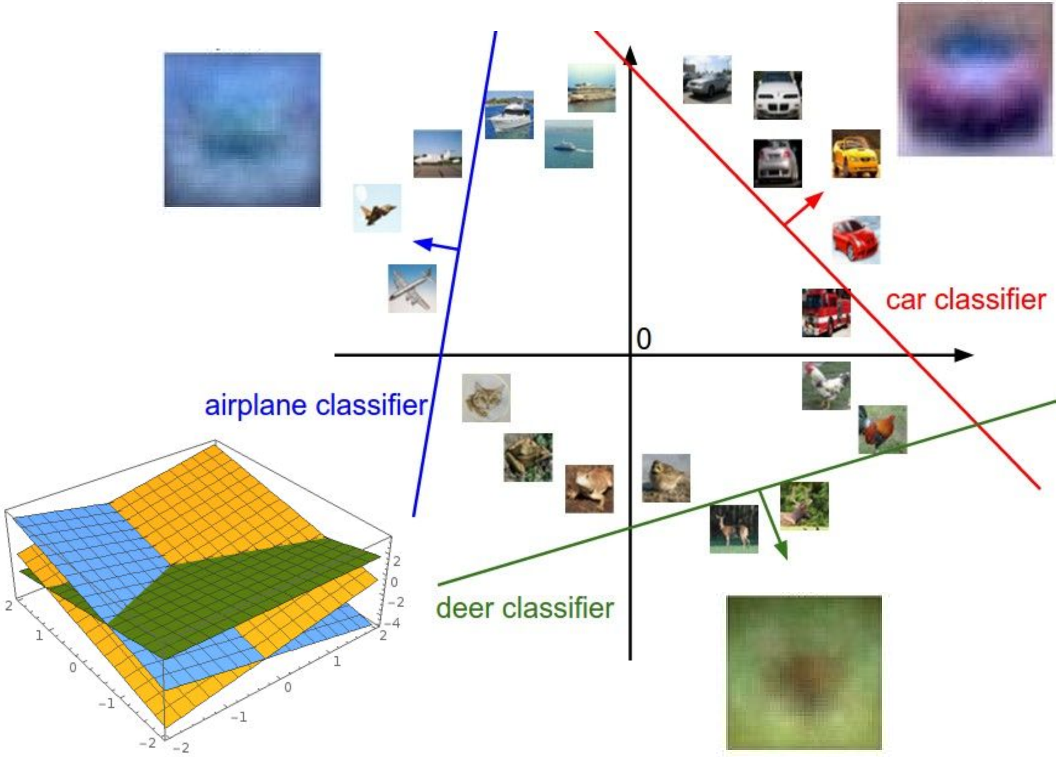
What is this thing doing?

# Interpreting a Linear Classifier


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

Example trained weights of a linear classifier trained on CIFAR-10:

# Interpreting a Linear Classifier




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

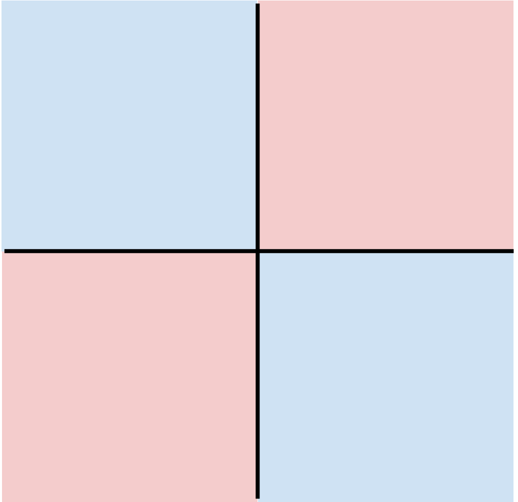
Array of **32x32x3** numbers
(3072 numbers total)

Plot created using Wolfram Cloud

# Hard cases for a linear classifier

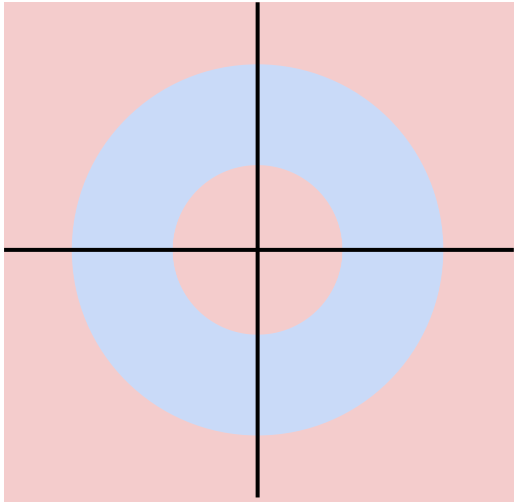
**Class 1**:
number of pixels > 0 odd

**Class 2**:
number of pixels > 0 even



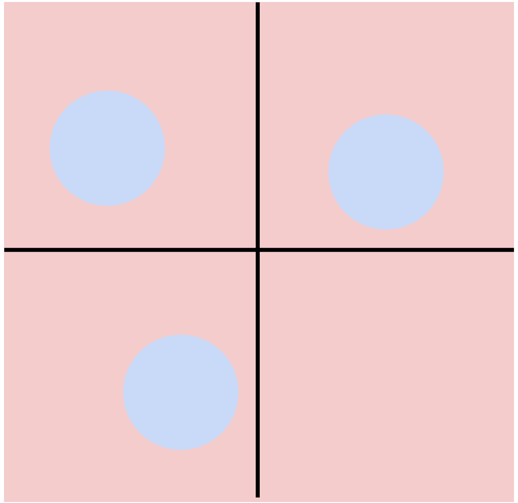
**Class 1**:
1 <= L2 norm <= 2

**Class 2**:
Everything else



**Class 1**:
Three modes

**Class 2**:
Everything else



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

Example class scores for 3 images for some W:

How can we tell whether this W is good or bad?



| | | | |
|---|---|---|---|
| **airplane** | -3.45 | -0.51 | 3.42 |
| **automobile** | -8.87 | **6.04** | 4.64 |
| **bird** | 0.09 | 5.31 | 2.65 |
| **cat** | **2.9** | -4.22 | 5.1 |
| **deer** | 4.48 | -4.19 | 2.64 |
| **dog** | 8.02 | 3.58 | 5.55 |
| **frog** | 3.78 | 4.49 | **-4.34** |
| **horse** | 1.06 | -4.37 | -1.5 |
| **ship** | -0.36 | -2.09 | -4.79 |
| **truck** | -0.72 | -2.93 | 6.14 |

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

# Coming up:

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