Lecture 2:
Image Classification pipeline

Administrative

First assignment will come out tonight (or tomorrow at worst)
It is due **January 20** (i.e. in two weeks). Handed in through CourseWork
It includes:

- Write/train/evaluate a kNN classifier
- Write/train/evaluate a Linear Classifier (SVM and Softmax)
- Write/train/evaluate a 2-layer Neural Network (backpropagation!)
- Requires writing numpy/Python code

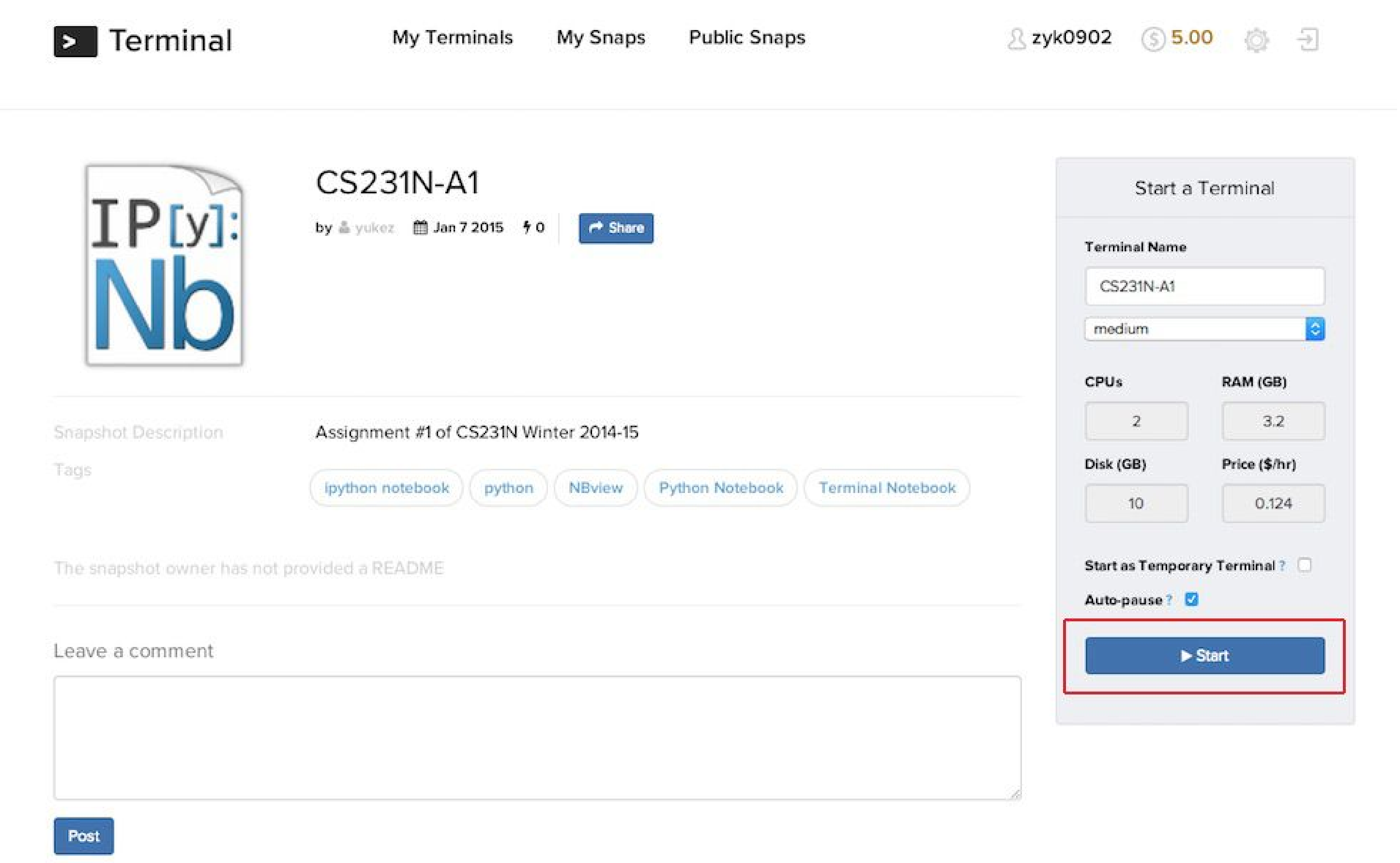
Warning: don’t work on assignments from last year!

Compute: Can use your own laptops, or Terminal.com http://cs231n.github.io/python-numpy-tutorial/

CS231n Convolutional Neural Networks for Visual Recognition

Python Numpy Tutorial

```
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
```


Terminal
My Terminals
My Snaps
Public Snaps
zyk0902
5.00
IP[y]:
Nb
CS231N-A1
by yukez
Jan 7 2015
0
Share
Snapshot Description
Assignment #1 of CS231N Winter 2014-15
Tags
ipython notebook
python
NBview
Python Notebook
Terminal Notebook
The snapshot owner has not provided a README
Leave a comment
Post
Start a Terminal
Terminal Name
CS231N-A1
medium
CPUs
2
RAM (GB)
3.2
Disk (GB)
10
Price ($/hr)
0.124
Start as Temporary Terminal ?
Auto-pause ?
Start

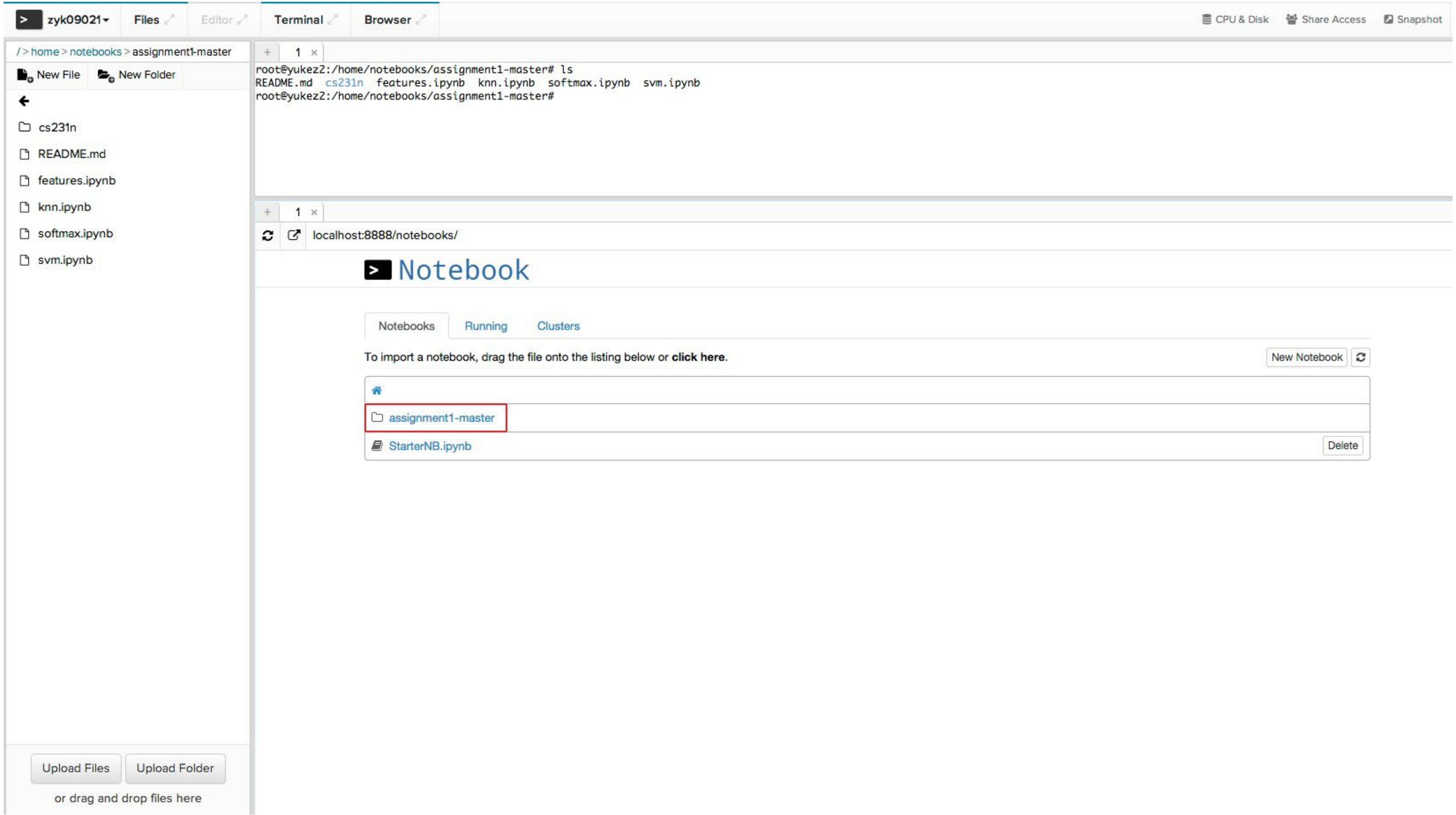

zyk09021
Files
Editor
Terminal
Browser
CPU & Disk
Share Access
Snapshot
/ > home > notebooks > assignment1-master
New File
New Folder
cs231n
README.md
features.ipynb
knn.ipynb
softmax.ipynb
svm.ipynb
Upload Files
Upload Folder
or drag and drop files here
root@yukez2:/home/notebooks/assignment1-master# ls
README.md cs231n features.ipynb knn.ipynb softmax.ipynb svm.ipynb
root@yukez2:/home/notebooks/assignment1-master#
localhost:8888/notebooks/
Notebook
Notebooks
Running
Clusters
To import a notebook, drag the file onto the listing below or click here.
New Notebook
assignment1-master
StarterNB.ipynb
Delete

Image Classification: a core task in Computer Vision

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

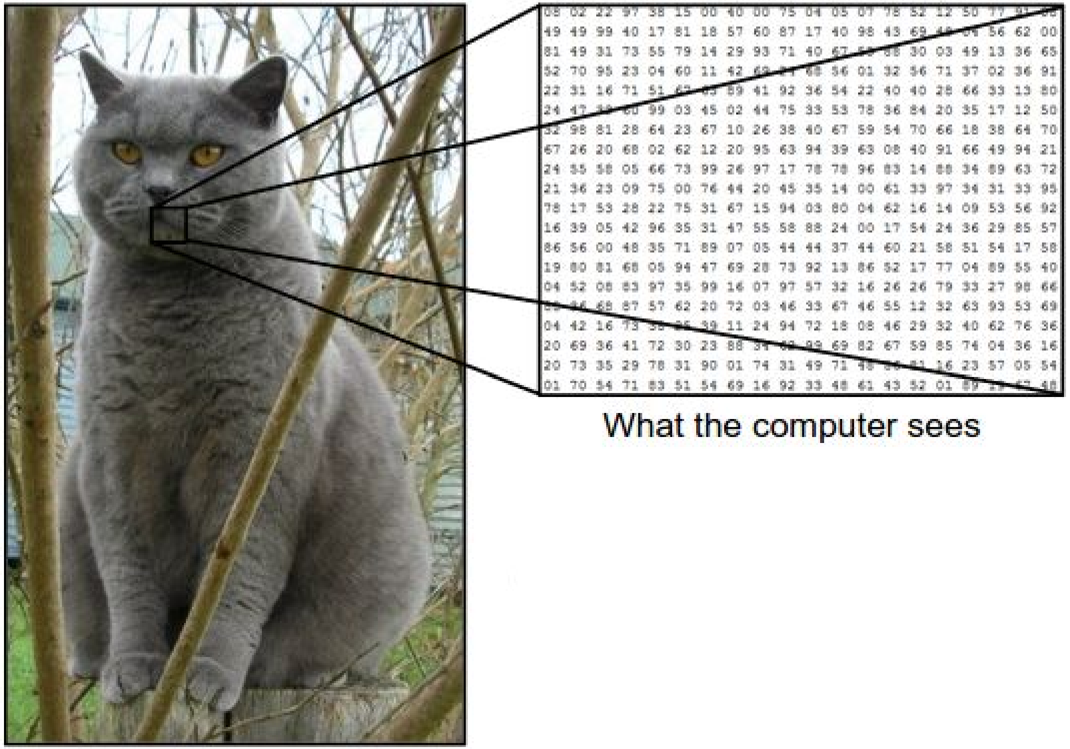
→ cat

The problem:
semantic gap

Images are represented as 3D arrays of numbers, with integers between [0, 255].

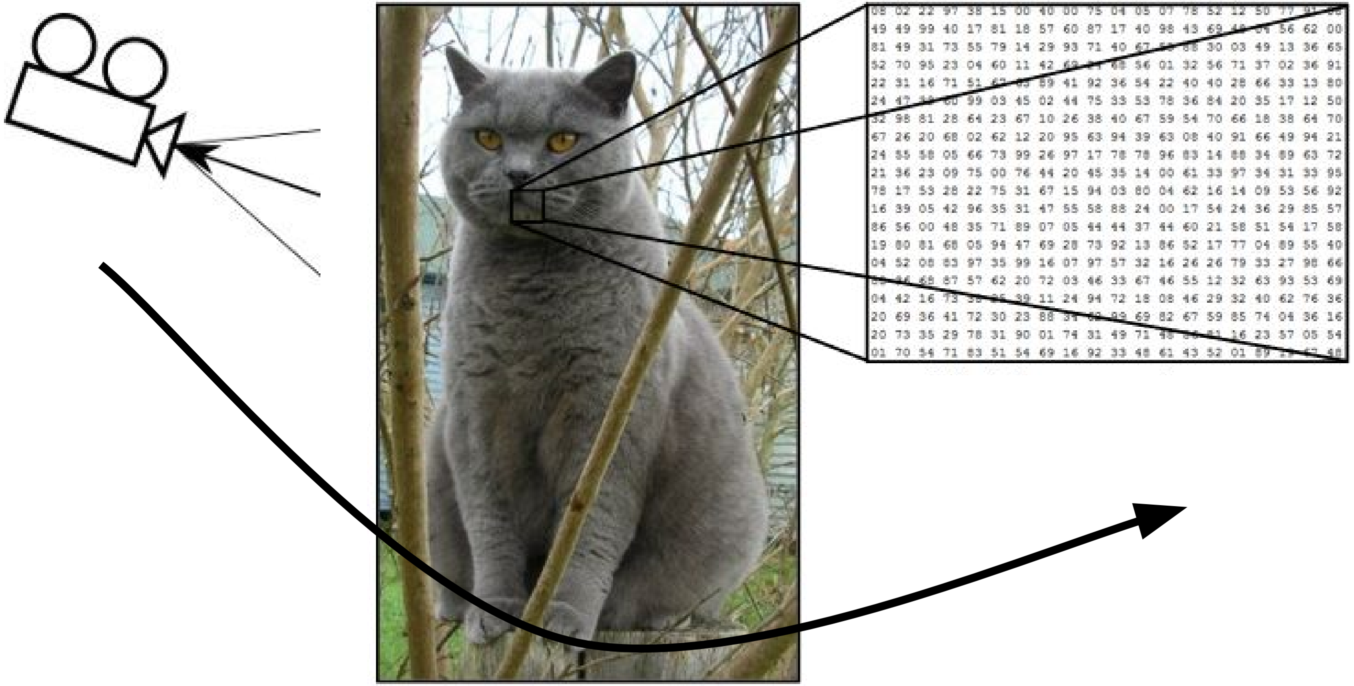
E.g.
300 x 100 x 3

(3 for 3 color channels RGB)



What the computer sees

Challenges: Viewpoint Variation

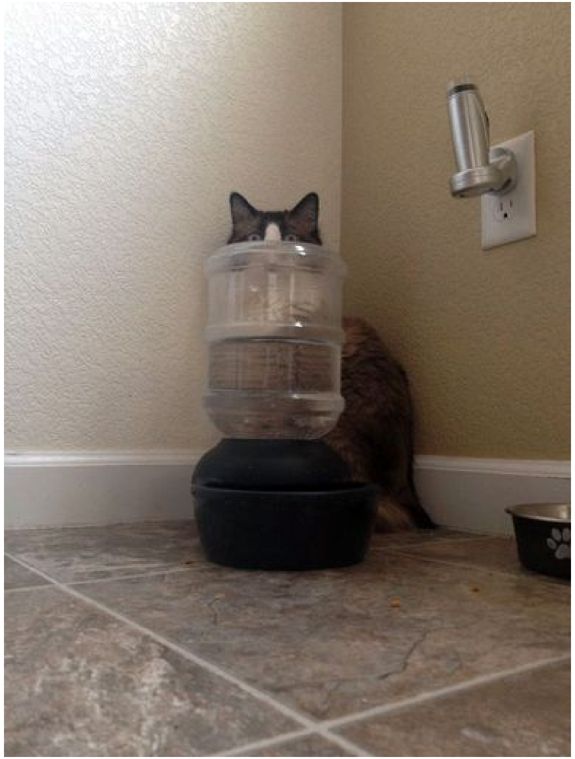


Challenges: Illumination

Challenges: Deformation




Challenges: Occlusion



Challenges: Background clutter

Challenges: Intraclass variation

An image classifier

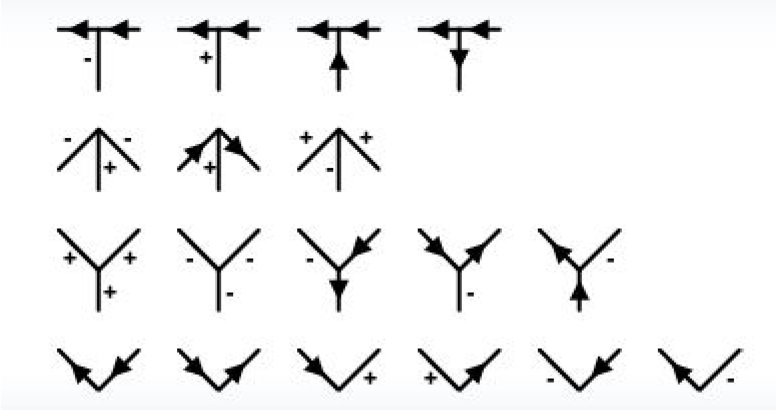
```python
def predict(image):
    # ????
    return class_label
```

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

???



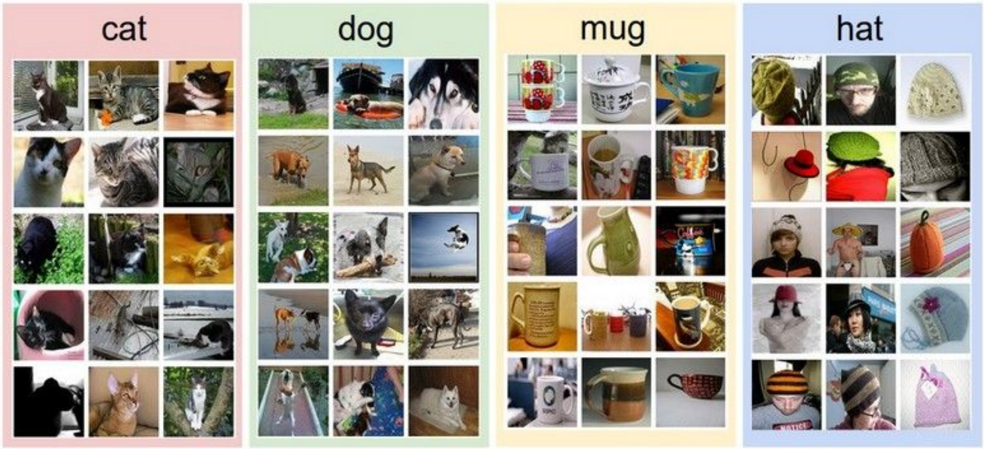
Data-driven approach:

1. Collect a dataset of images and labels
2. Use Machine Learning to train an image classifier
3. Evaluate the classifier on a withheld set of test images

```
def train(train_images, train_labels):
  # build a model for images -> labels...
  return model

def predict(model, test_images):
  # predict test_labels using the model...
  return test_labels
```

Example training set



First classifier: **Nearest Neighbor Classifier**

```
def train(train_images, train_labels):
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  return test_labels
```
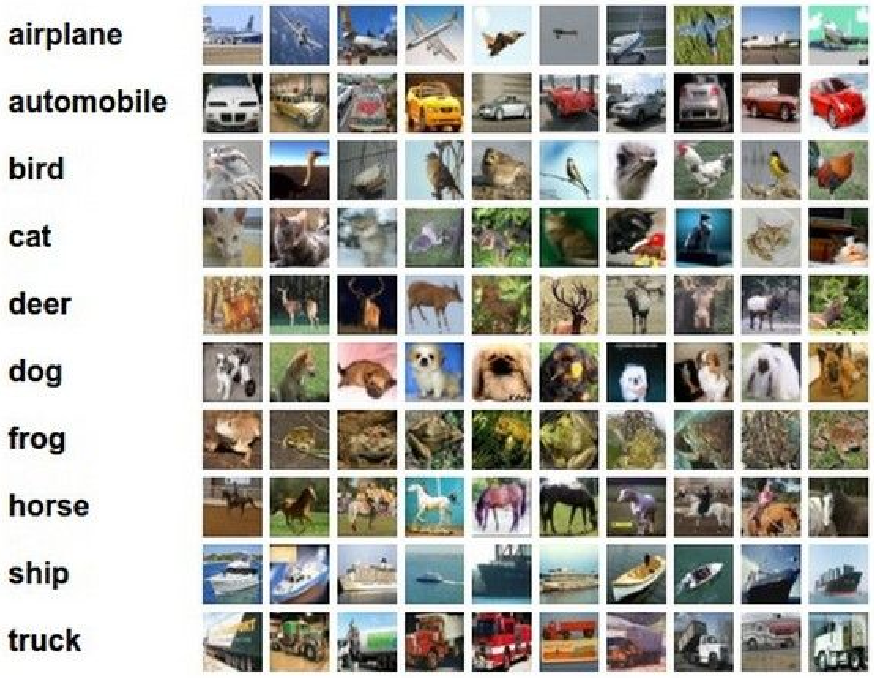

Remember all training images and their labels

Predict the label of the most similar training image

Example dataset: **CIFAR-10**
10 labels
50,000 training images, each image is tiny: 32x32
10,000 test images.



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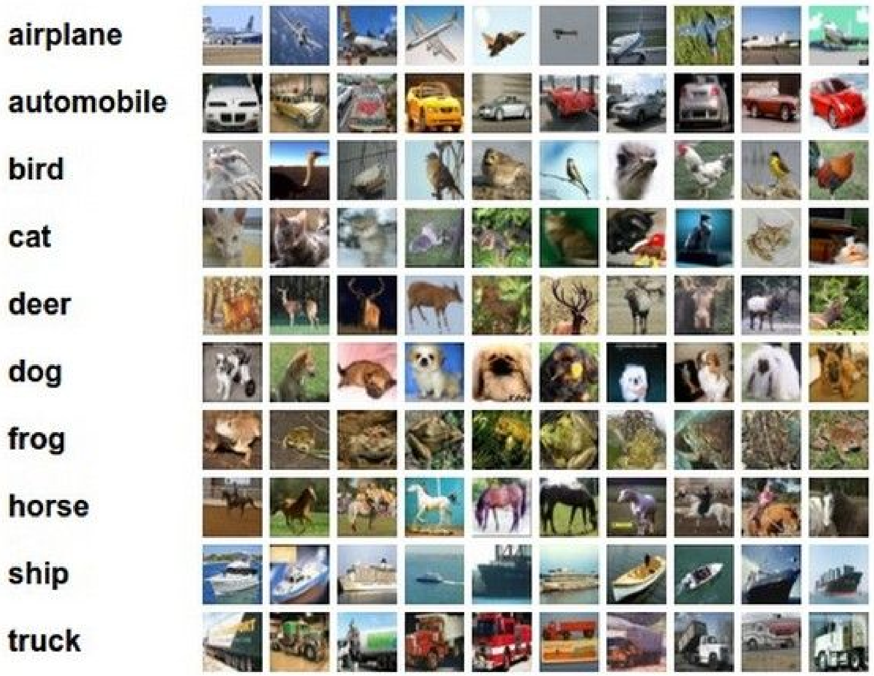

For every test image (first column), examples of nearest neighbors in rows

How do we compare the images? What is the **distance metric**?

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
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Nearest Neighbor classifier

remember the training data

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      Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

    return Ypred
```

Nearest Neighbor classifier

for every test image:

- find nearest train image with L1 distance
- predict the label of nearest training image

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Nearest Neighbor classifier

Q: how does the classification speed depend on the size of the training data?

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Nearest Neighbor classifier

Q: how does the classification speed depend on the size of the training data?
linearly :(

This is **backwards**:
- test time performance is usually much more important in practice.
- CNNs flip this: expensive training, cheap test evaluation

Aside: Approximate Nearest Neighbor

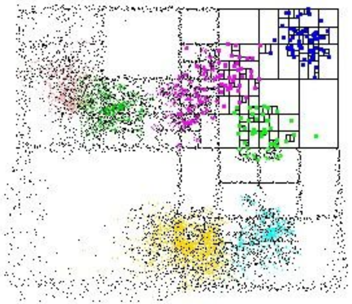
find approximate nearest neighbors quickly

ANN: A Library for Approximate Nearest Neighbor Searching

David M. Mount and Sunil Arya

Version 1.1.2

Release Date: Jan 27, 2010



What is ANN?

ANN is a library written in C++, which supports data structures and algorithms for both exact and approximate nearest neighbor searching in arbitrarily high dimensions.

In the nearest neighbor problem a set of data points in d-dimensional space is given. These points are preprocessed into a data structure, so that given any query point q, the nearest or generally k nearest points of P to q can be reported efficiently. The distance between two points can be defined in many ways. ANN assumes that distances are measured using any class of distance functions called Minkowski metrics. These include the well known Euclidean distance, Manhattan distance, and max distance.

Based on our own experience, ANN performs quite efficiently for point sets ranging in size from thousands to hundreds of thousands, and in dimensions as high as 20. (For applications in significantly higher dimensions, the results are rather spotty, but you might try it anyway.)

The library implements a number of different data structures, based on kd-trees and box-decomposition trees, and employs a couple of different search strategies.

The library also comes with test programs for measuring the quality of performance of ANN on any particular data sets, as well as programs for visualizing the structure of the geometric data structures.

FLANN - Fast Library for Approximate Nearest Neighbors

- Home
- News
- Publications
- Download
- Changelog
- Repository

What is FLANN?

FLANN is a library for performing fast approximate nearest neighbor searches in high dimensional spaces. It contains a collection of algorithms we found to work best for nearest neighbor search and a system for automatically choosing the best algorithm and optimum parameters depending on the dataset.

FLANN is written in C++ and contains bindings for the following languages: C, MATLAB and Python.

News

- (14 December 2012) Version 1.8.0 is out bringing incremental addition/removal of points to/from indexes
- (20 December 2011) Version 1.7.0 is out bringing two new index types and several other improvements.
- You can find binary installers for FLANN on the Point Cloud Library project page. Thanks to the PCL developers!
- Mac OS X users can install flann though MacPorts (thanks to Mark Moll for maintaining the Portfile)
- New release introducing an easier way to use custom distances, kd-tree implementation optimized for low dimensionality search and experimental MPI support
- New release introducing new C++ templated API, thread-safe search, save/load of indexes and more.
- The FLANN license was changed from LGPL to BSD.

How fast is it?

In our experiments we have found FLANN to be about one order of magnitude faster on many datasets (in query time), than previously available approximate nearest neighbor search software.

Publications

More information and experimental results can be found in the following papers:

- Marius Muja and David G. Lowe: **"Scalable Nearest Neighbor Algorithms for High Dimensional Data"**. Pattern Analysis and Machine Intelligence (PAMI), Vol. 36, 2014. [PDF] [BibTeX]
- Marius Muja and David G. Lowe: **"Fast Matching of Binary Features"**. Conference on Computer and Robot Vision (CRV) 2012. [PDF] [BibTeX]
- Marius Muja and David G. Lowe, **"Fast Approximate Nearest Neighbors with Automatic Algorithm Configuration"**, in International Conference on Computer Vision Theory and Applications (VISAPP'09), 2009 [PDF] [BibTeX]

The choice of distance is a **hyperparameter**
common choices:

L1 (Manhattan) distance

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

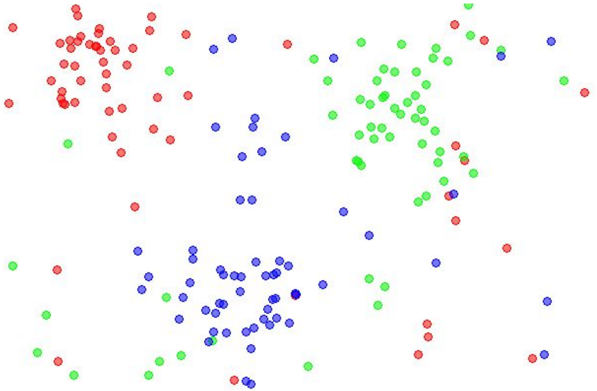
L2 (Euclidean) distance

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

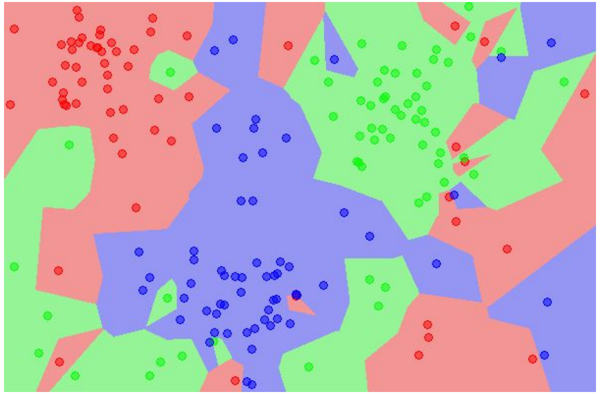
k-Nearest Neighbor

find the k nearest images, have them vote on the label

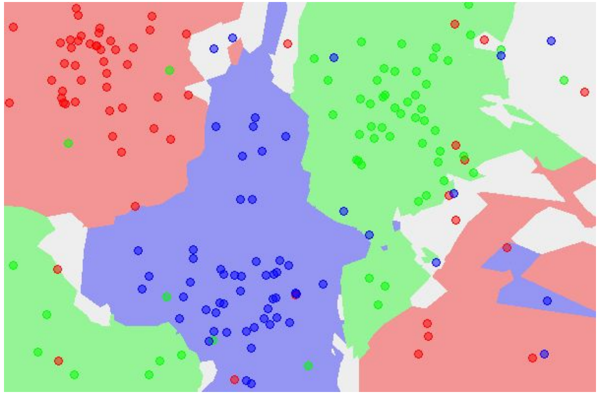
the data



NN classifier

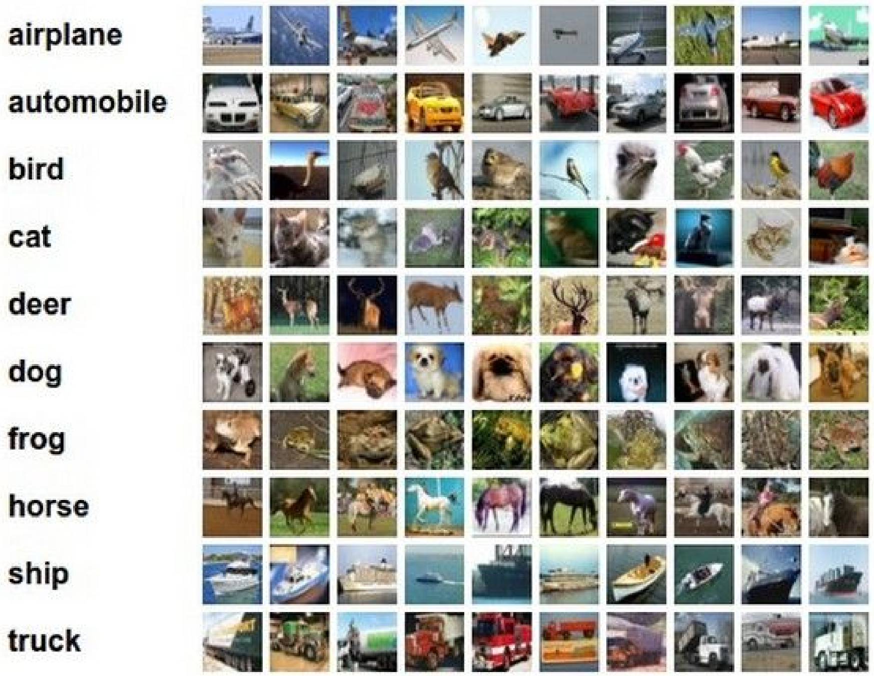


5-NN classifier



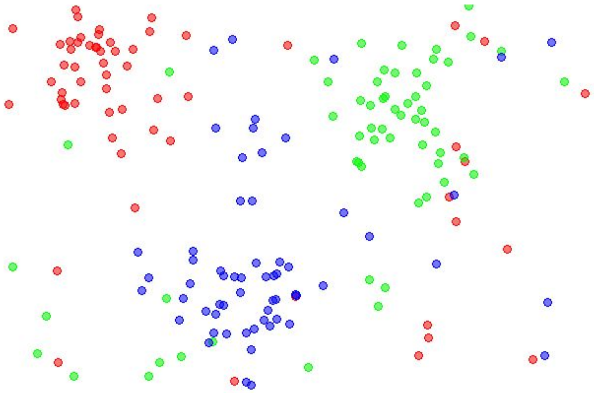
http://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

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

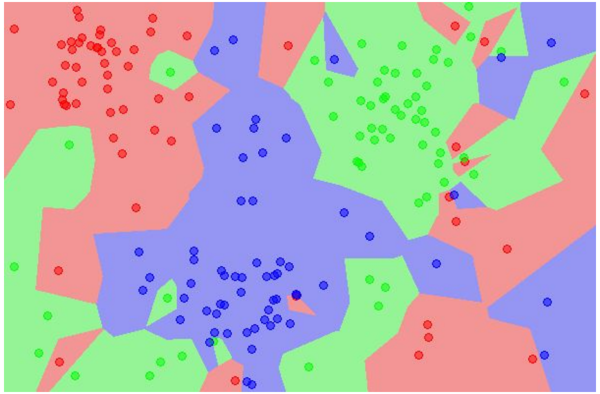


For every test image (first column), examples of nearest neighbors in rows

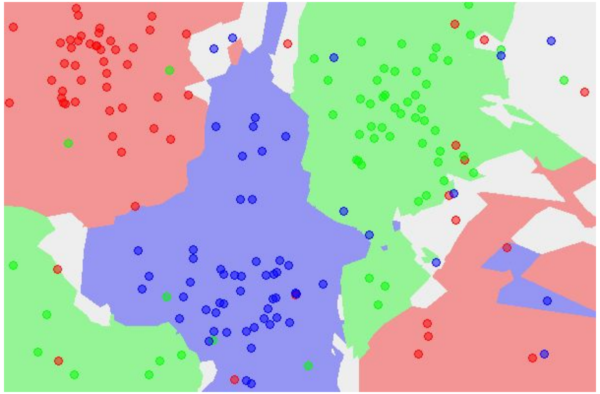
the data



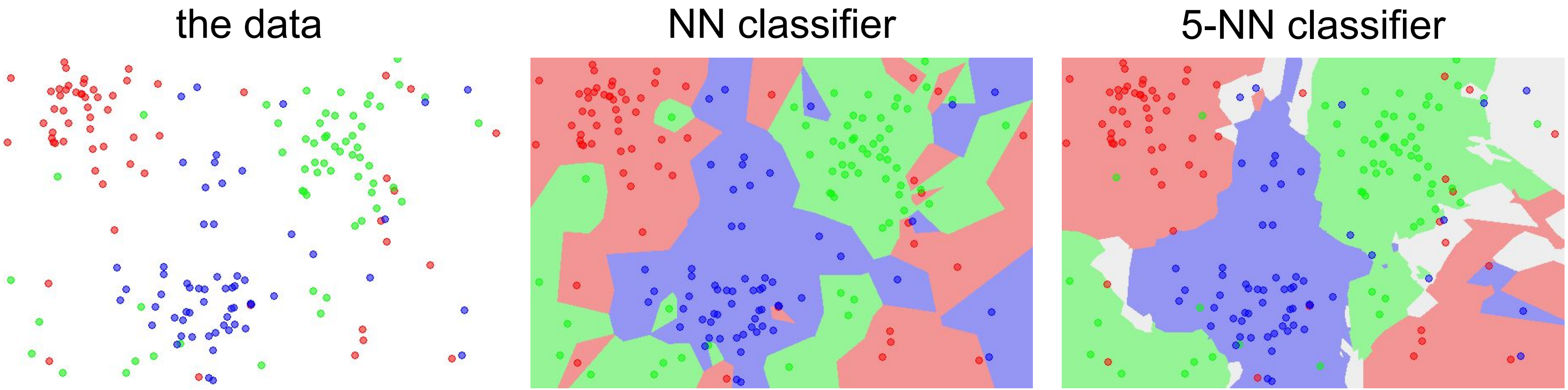
NN classifier



5-NN classifier



Q: what is the accuracy of the nearest neighbor classifier on the training data, when using the Euclidean distance?



Q2: what is the accuracy of the **k-**nearest neighbor classifier on the training data?

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

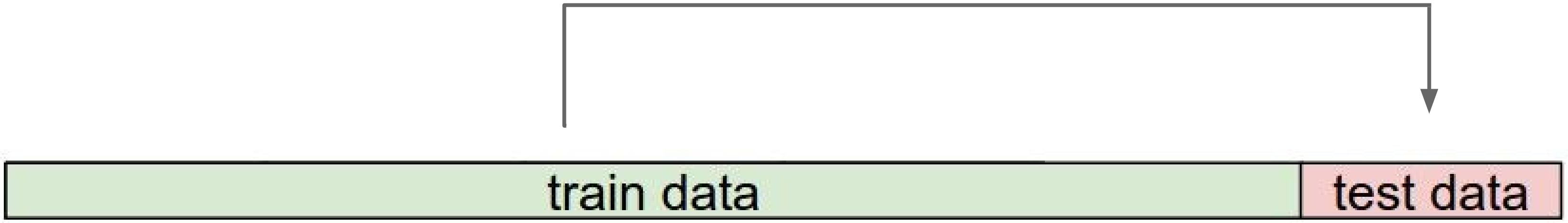
i.e. how do we set the **hyperparameters**?

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

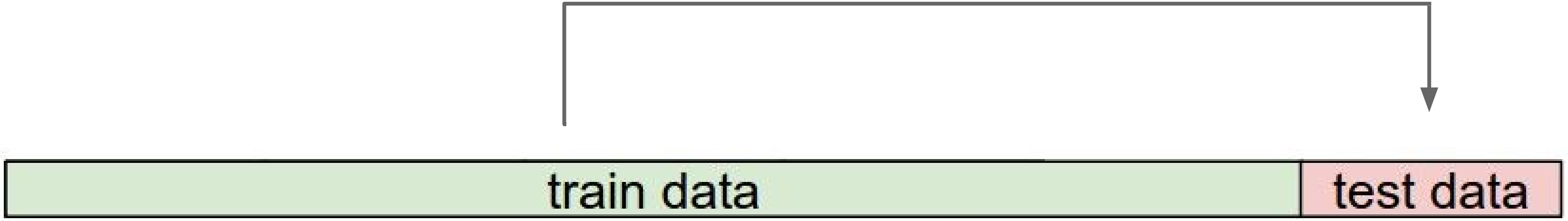
i.e. how do we set the **hyperparameters**?

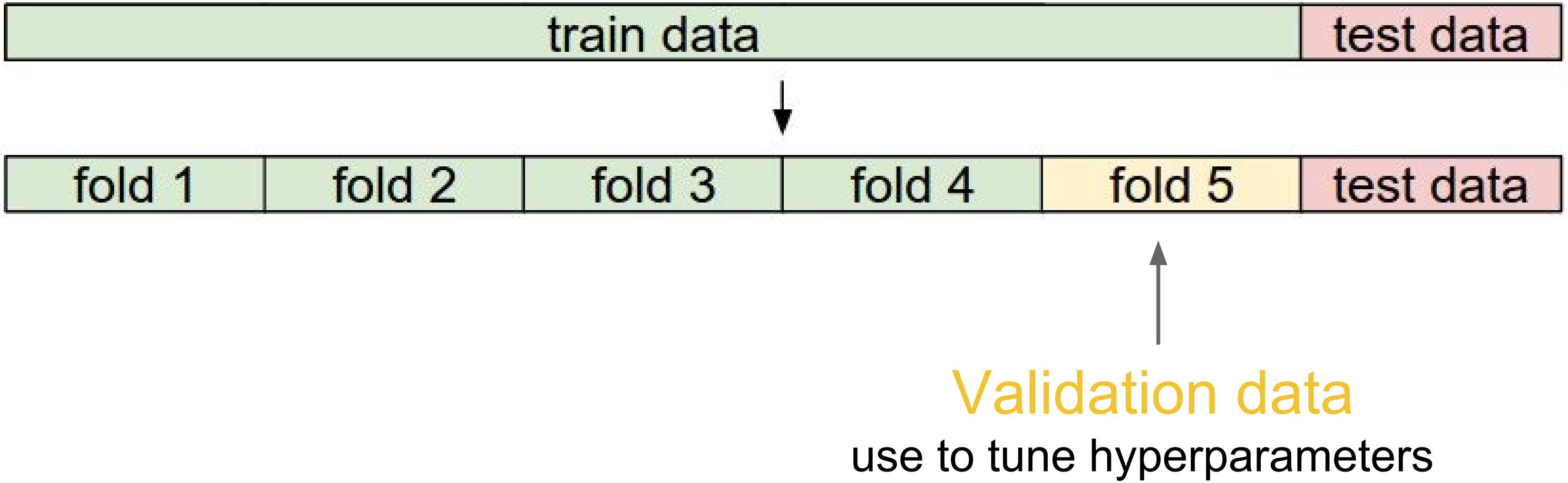
Very problem-dependent.
Must try them all out and see what works best.

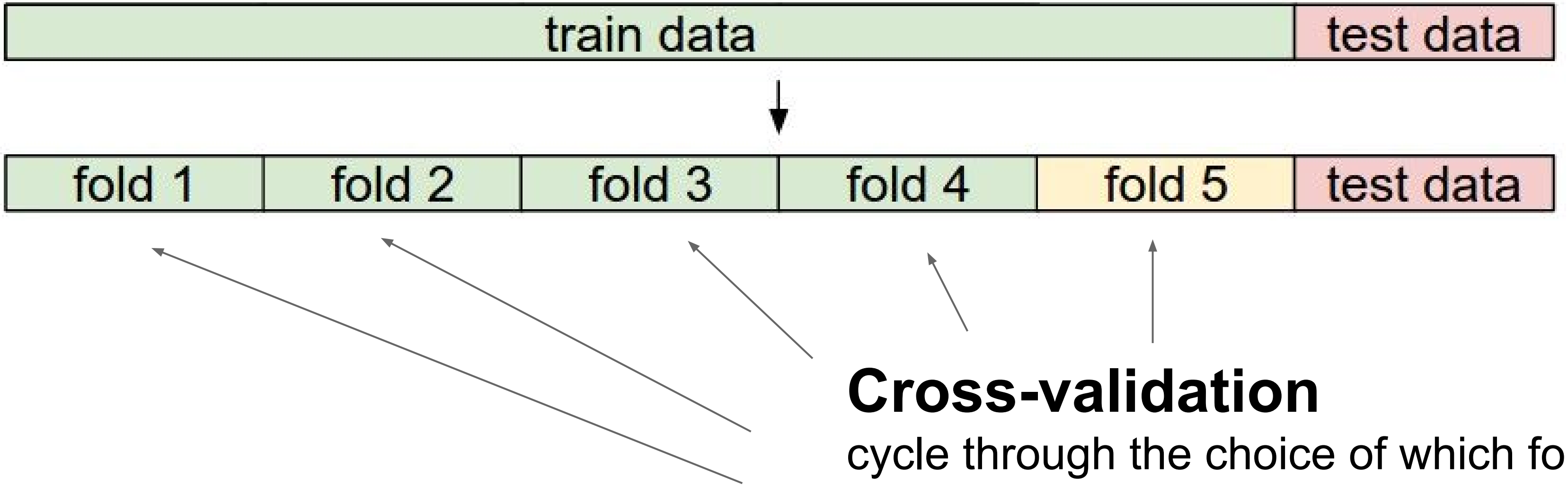
Try out what hyperparameters work best on test set.



Trying out what hyperparameters work best on test set:
Very bad idea. The test set is a proxy for the generalization performance!
Use only **VERY SPARINGLY,** at the end.

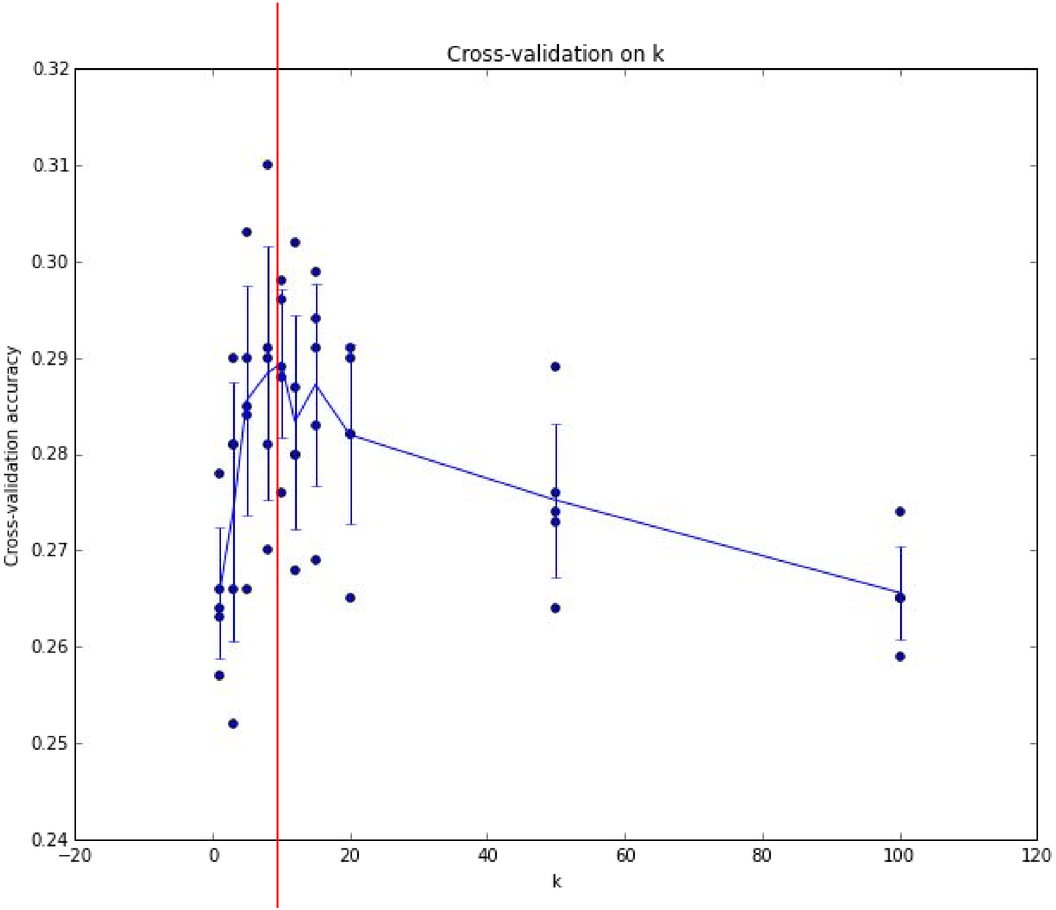



train data
test data
fold 1
fold 2
fold 3
fold 4
fold 5
test data
Validation data
use to tune hyperparameters



Cross-validation

cycle through the choice of which fold is the validation fold, average results.



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

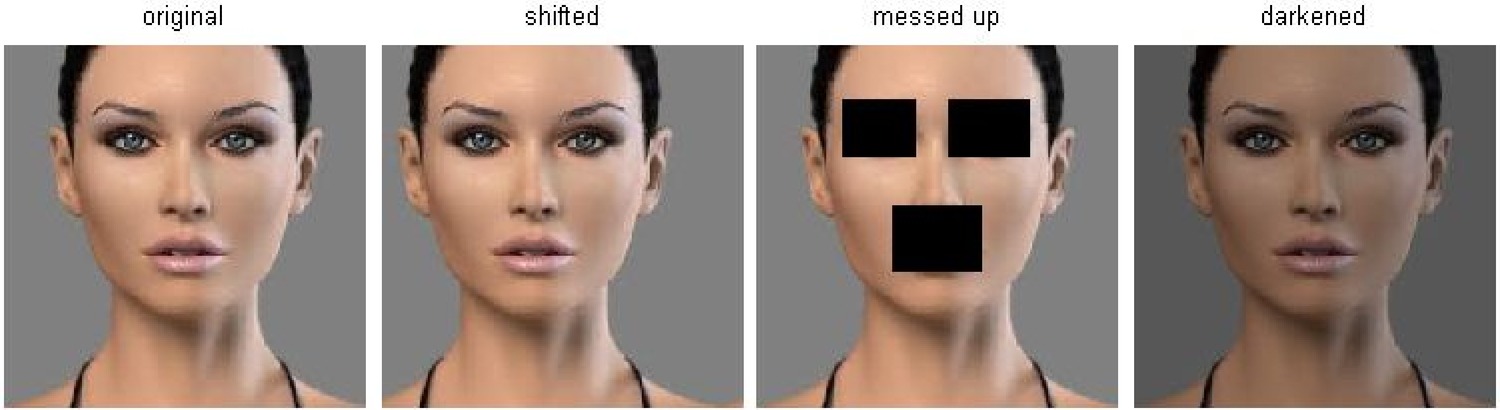
Each point: single
outcome.

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.**

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

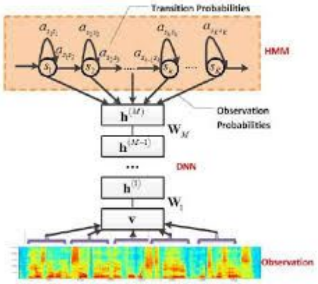


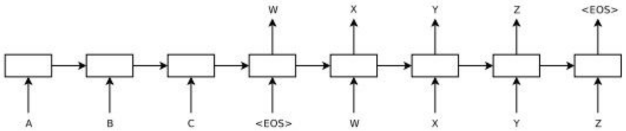
(all 3 images have same L2 distance to the one on the left)

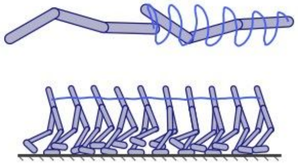
Summary

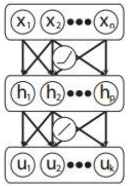
- **Image Classification:** We are given a **Training Set** of labeled images, asked to predict labels on **Test Set**. Common to report the **Accuracy** of predictions (fraction of correctly predicted images)
- We introduced the **k-Nearest Neighbor Classifier**, which predicts the labels based on nearest images in the training set
- We saw that the choice of distance and the value of k are **hyperparameters** that are tuned using a **validation set**, or through **cross-validation** if the size of the data is small.
- Once the best set of hyperparameters is chosen, the classifier is evaluated once on the test set, and reported as the performance of kNN on that data.

Linear Classification

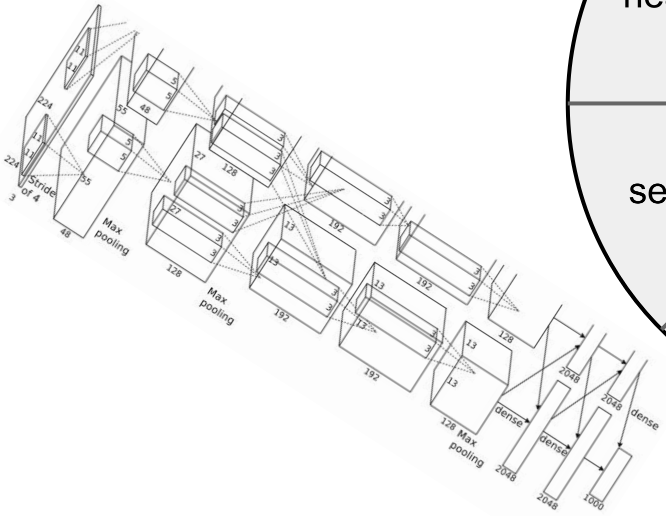

Transition Probabilities
HMM
Observation Probabilities
DNN
Observation

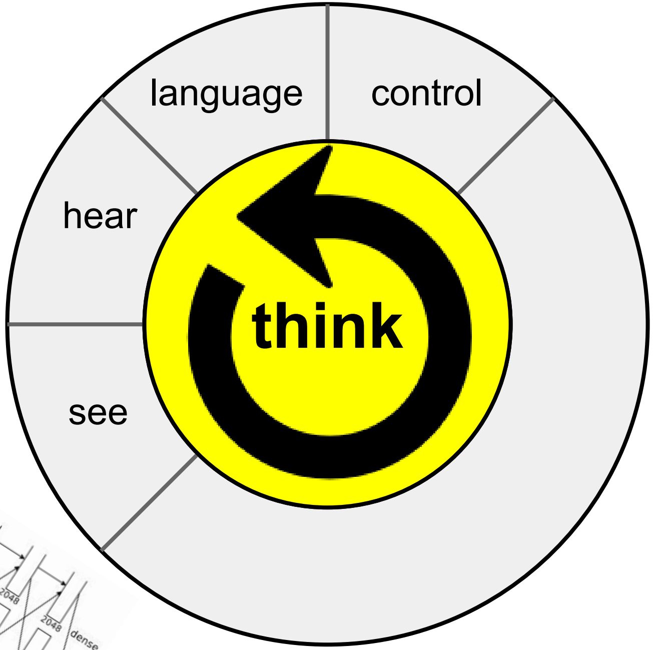

W X Y Z <EOS>
A B C <EOS> W X Y Z






OXYGEN


Stride of 4
Max pooling
Max pooling
Max pooling
dense
dense
dense


language
control
hear
see
think

Neural Networks practitioner

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

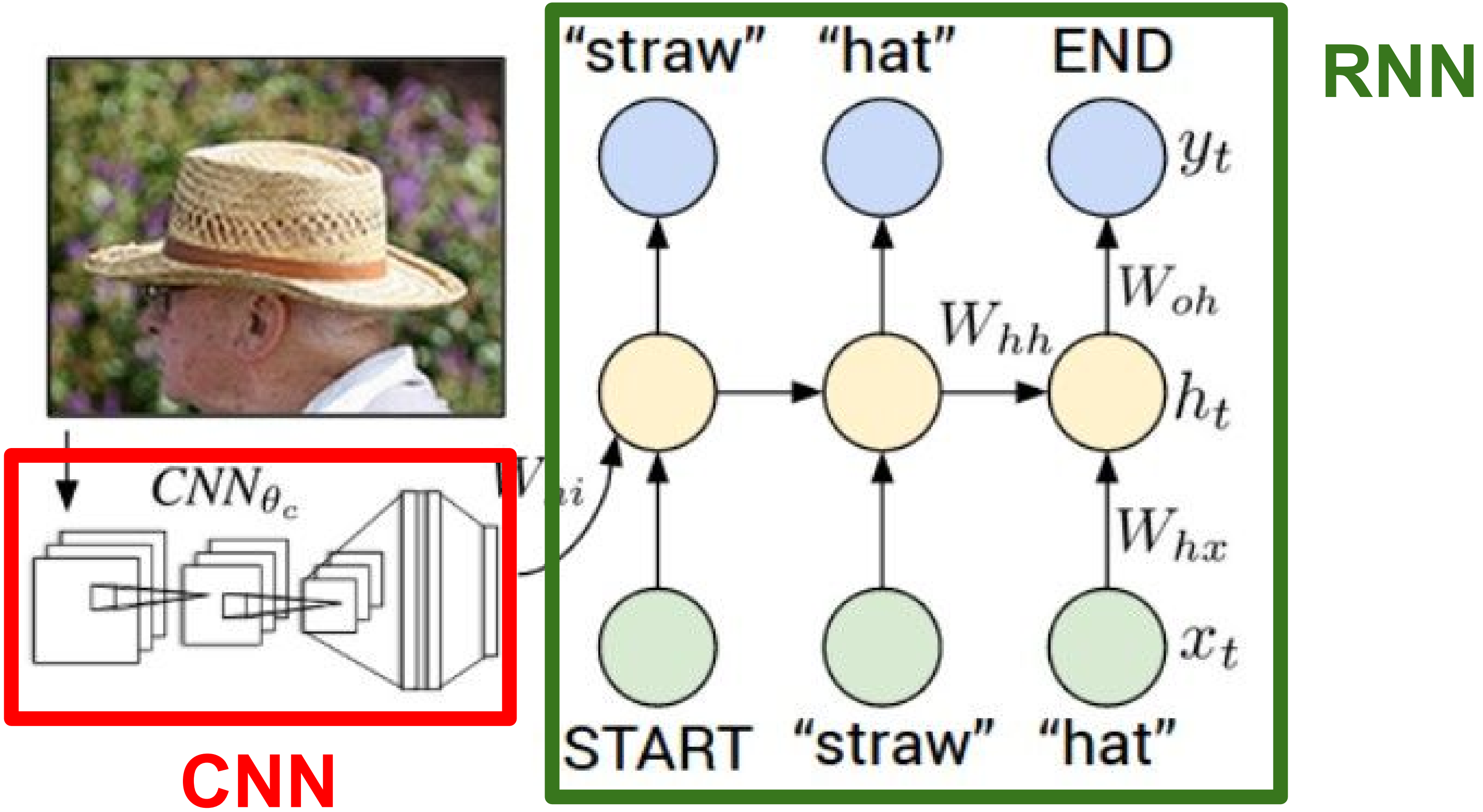
"boy is doing backflip on wakeboard."

"girl in pink dress is jumping in air."

"black and white dog jumps over bar."

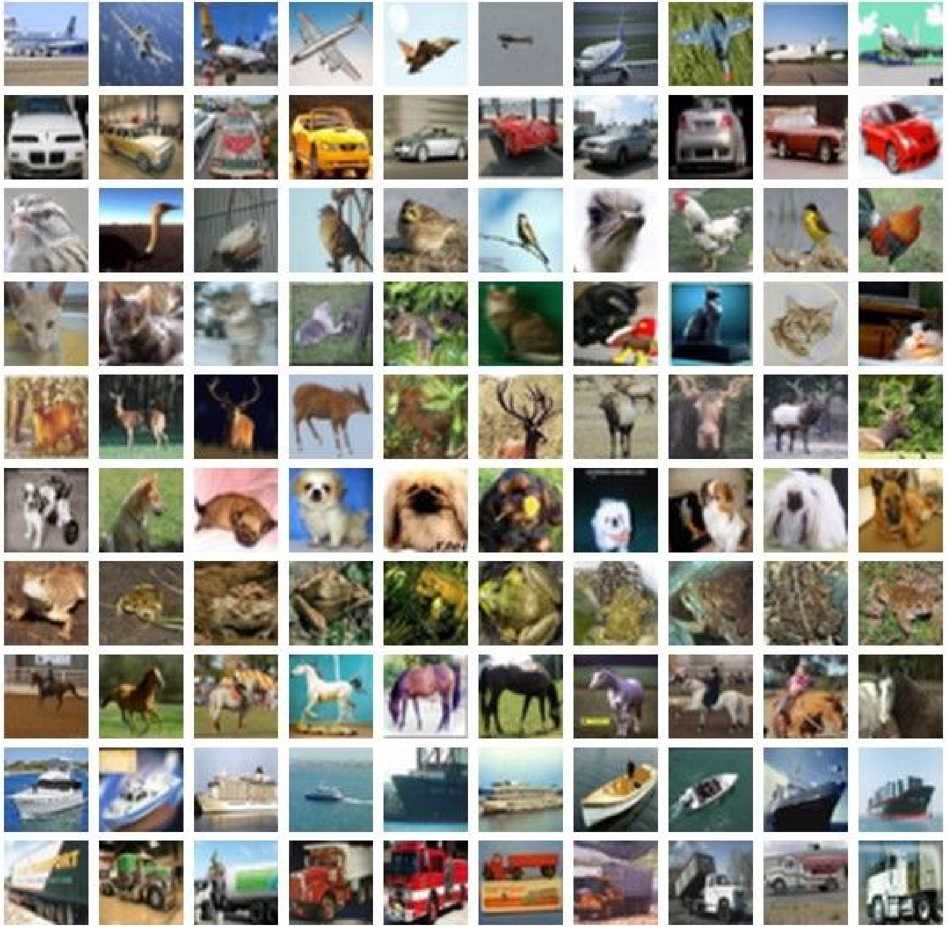
"young girl in pink shirt is swinging on swing."

"man in blue wetsuit is surfing on wave."



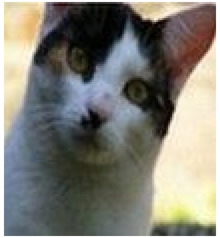
"straw"
"hat"
END
RNN
y_t
W_{oh}
W_{hh}
h_t
CNN_{θ_c}
W_{hi}
W_{hx}
x_t
START
"straw"
"hat"
CNN

airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck



Example dataset: **CIFAR-10**
10 labels
50,000 training images
each image is **32x32x3**
10,000 test images.

Parametric approach



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

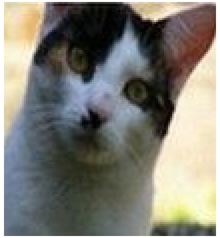
image parameters

$f(\mathbf{x},\mathbf{W})$ →

10 numbers, indicating class scores

Parametric approach: **Linear classifier**

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



[32x32x3]
array of numbers 0...1

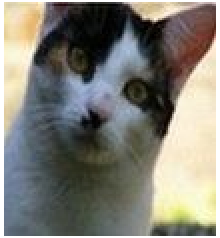
10 numbers,
indicating class
scores

Parametric approach: **Linear classifier**

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

3072x1

10x1 **10x3072**



[32x32x3]
array of numbers 0...1

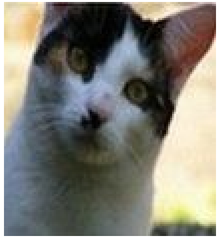
10 numbers, indicating class scores

parameters, or "weights"

Parametric approach: **Linear classifier**

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

10x1 **10x3072** **3072x1** **10x1**



[32x32x3]
array of numbers 0...1

10 numbers, indicating class scores

parameters, or "weights"

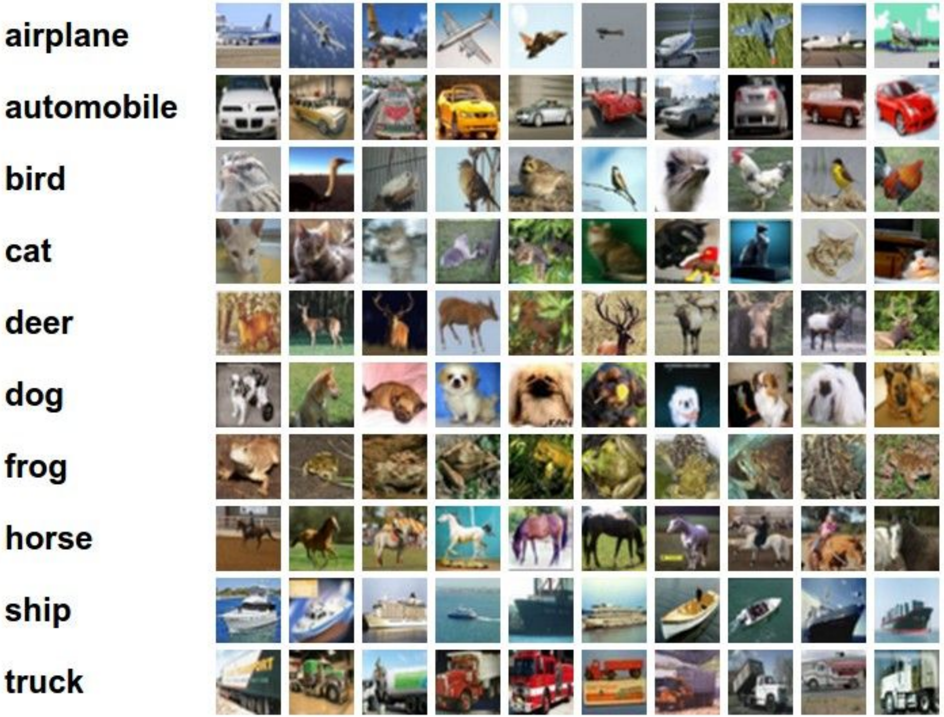
Example with an image with 4 pixels, and 3 classes (cat/dog/ship)

stretch pixels into single column

input image

$$\underbrace{\begin{bmatrix} 0.2 & -0.5 & 0.1 & 2.0 \\ 1.5 & 1.3 & 2.1 & 0.0 \\ 0 & 0.25 & 0.2 & -0.3 \end{bmatrix}}_{W} \underbrace{\begin{bmatrix} 56 \\ 231 \\ 24 \\ 2 \end{bmatrix}}_{x_i} + \underbrace{\begin{bmatrix} 1.1 \\ 3.2 \\ -1.2 \end{bmatrix}}_{b} \rightarrow \underbrace{\begin{bmatrix} -96.8 \\ 437.9 \\ 61.95 \end{bmatrix}}_{f(x_i; W, b)} \begin{matrix} \text{cat score} \\ \text{dog score} \\ \text{ship score} \end{matrix}$$

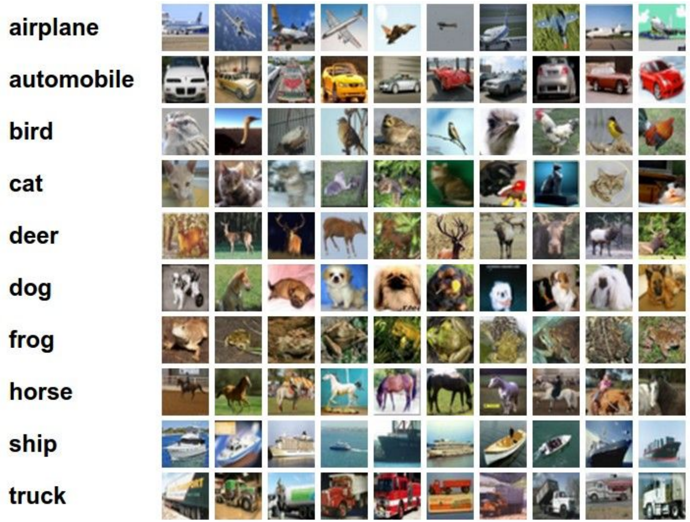
Interpreting a Linear Classifier



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

Q: what does the linear classifier do, in English?

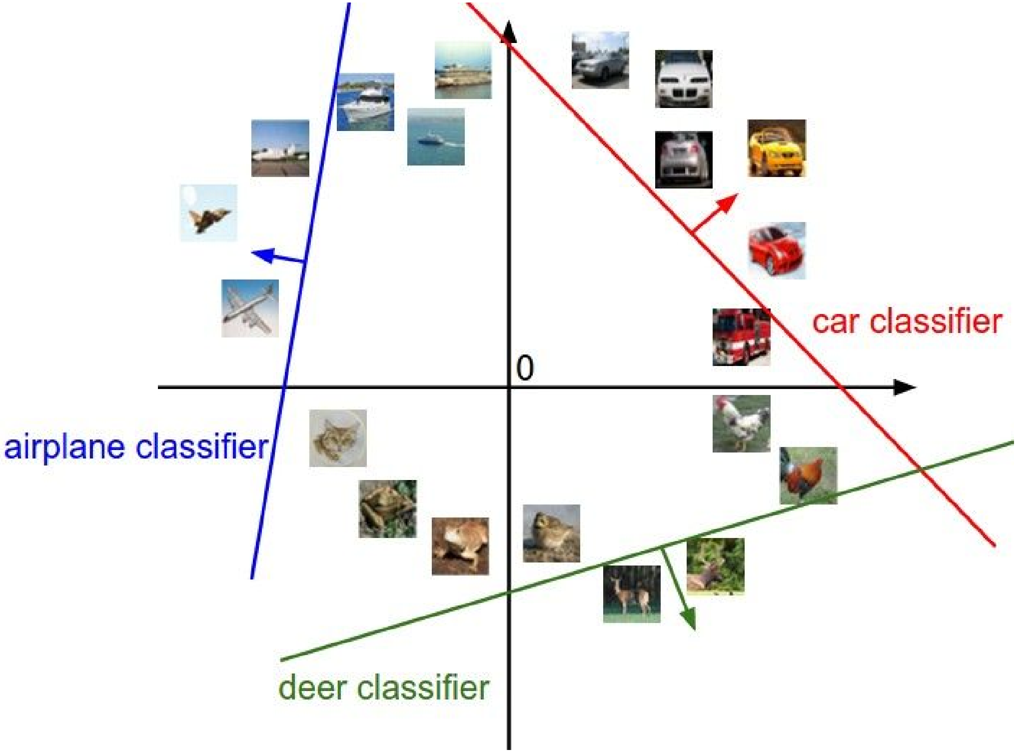
Interpreting a Linear Classifier



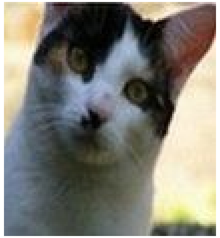
$$f(x_i, W, b) = Wx_i + b$$

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

Interpreting a Linear Classifier

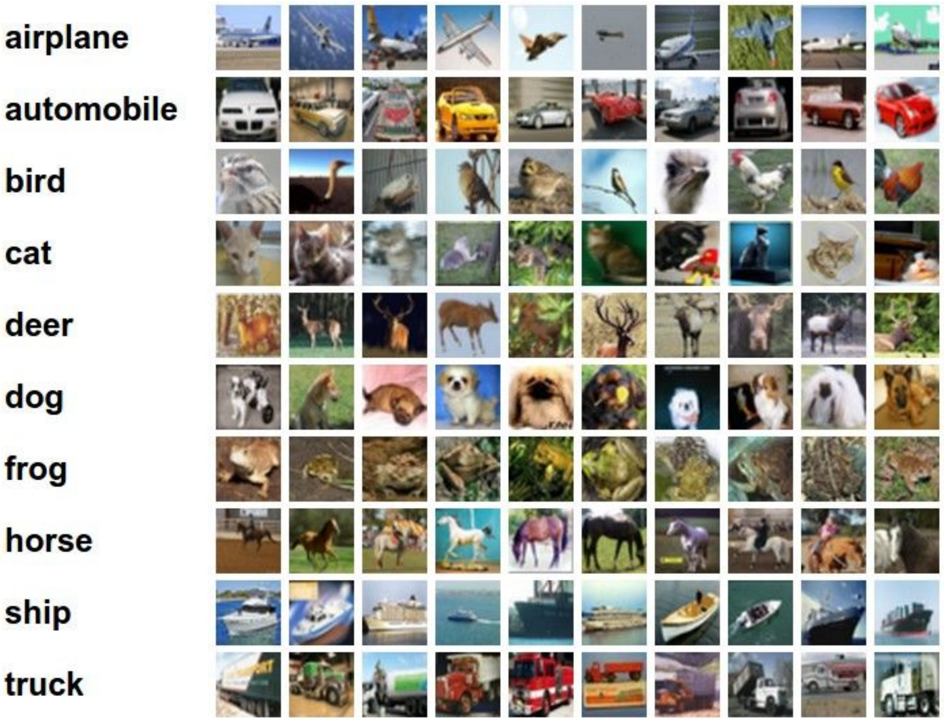


$$f(x_i, W, b) = Wx_i + b$$



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

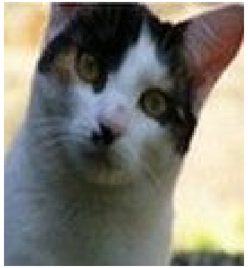
Interpreting a Linear Classifier



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

Q2: what would be a very hard set of classes for a linear classifier to distinguish?

So far: We defined a (linear) **score function**: $f(x_i, W, b) = Wx_i + b$



Example class scores for 3 images, with a random W:

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

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

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)