Deep Learning

Lecture 2

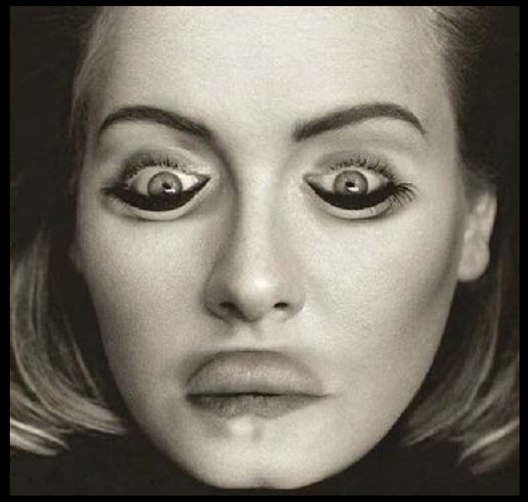
Machine Learning?

A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P*, if its performance at tasks in *T*, as measured by *P*, improves with experience *E*.

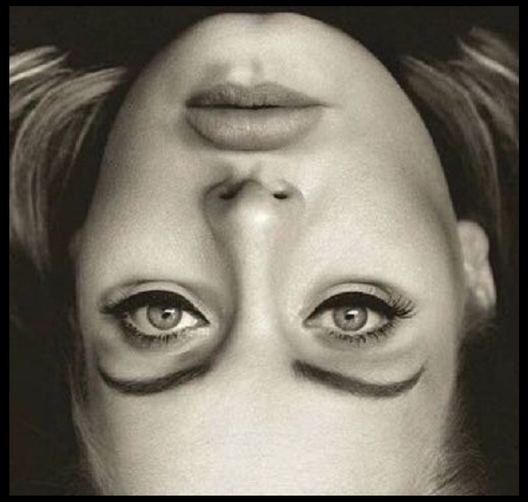
–Tom Mitchell

Learn the “structure” of the observable “world”

$p \gg 0$



$p \approx 0$



$p \approx 0$

What is the probability of observing a particular configuration of the world?

Let $\mathbb{X}$ = set of all possible configurations of the "world"

The "structure" of the world is described by a probability distribution $p_{\mathbb{X}}$

$p_{\mathbb{X}}(X) \propto$ **probability of observing configuration** X

$p_{\mathbb{X}}(Y|X) \propto$ **probability of observing features** Y **given configuration** X

Unsupervised Learning

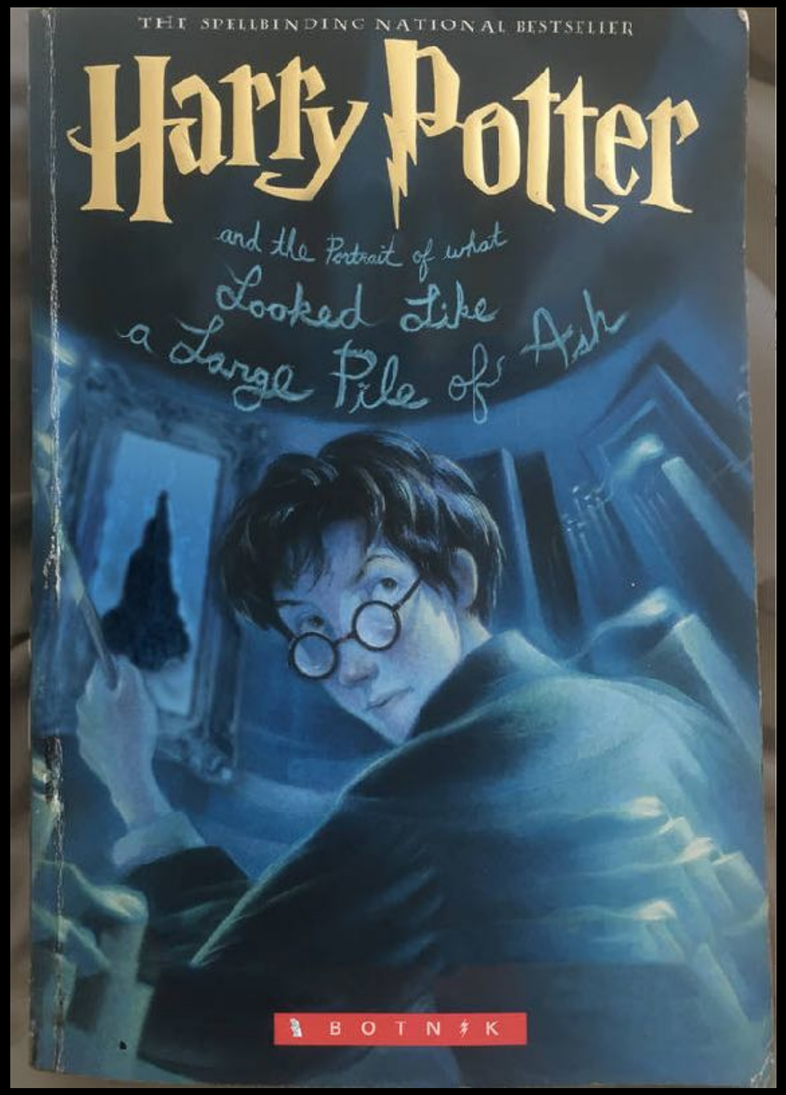
$$p_{model}(X;\theta) \approx p_{\mathbb{X}}(X)$$

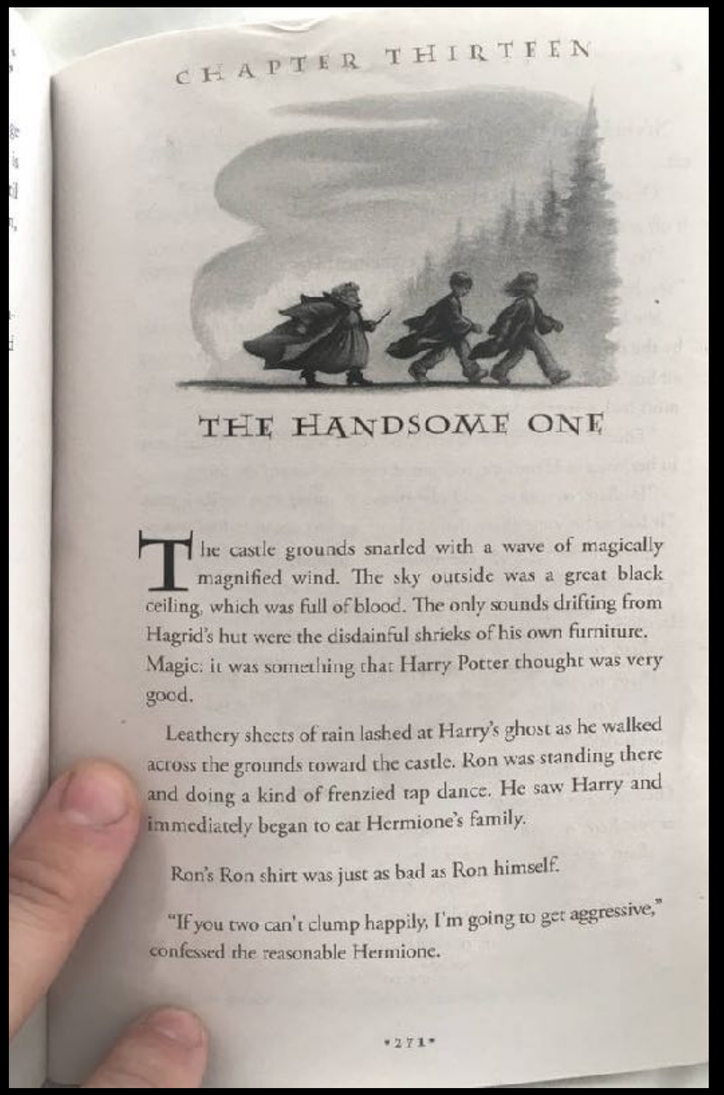
Supervised Learning

$$p_{model}(Y|X;\theta) \approx p_{\mathbb{X}}(Y|X)$$

$$x \sim p_{\text{CelebA}}(X)$$

http://research.nvidia.com/sites/default/files/pubs/2017-10_Progressive-Growing-of/karras2018iclr-paper.pdf





CHAPTER THIRTEEN

THE HANDSOME ONE

The castle grounds snarled with a wave of magically magnified wind. The sky outside was a great black ceiling, which was full of blood. The only sounds drifting from Hagrid's hut were the disdainful shrieks of his own furniture. Magic: it was something that Harry Potter thought was very good.

Leathery sheets of rain lashed at Harry's ghost as he walked across the grounds toward the castle. Ron was standing there and doing a kind of frenzied tap dance. He saw Harry and immediately began to eat Hermione's family.

Ron's Ron shirt was just as bad as Ron himself.

"If you two can't clump happily, I'm going to get aggressive," confessed the reasonable Hermione.

•271•

$$x \sim p_{\text{Harry Potter}}(X)$$

http://botnik.org/content/harry-potter.html

"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."

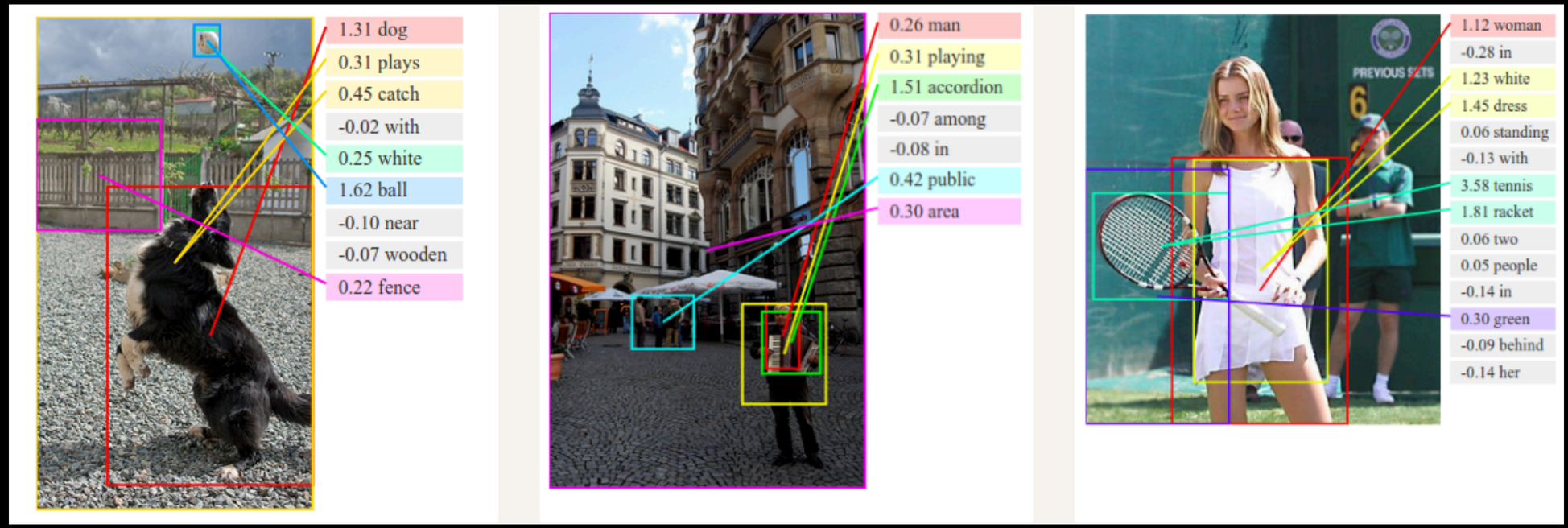
"man in blue wetsuit is surfing on wave."

$$y \sim p_{\text{coco}}(Y \mid X)$$

https://cs.stanford.edu/people/karpathy/deepimagesent/

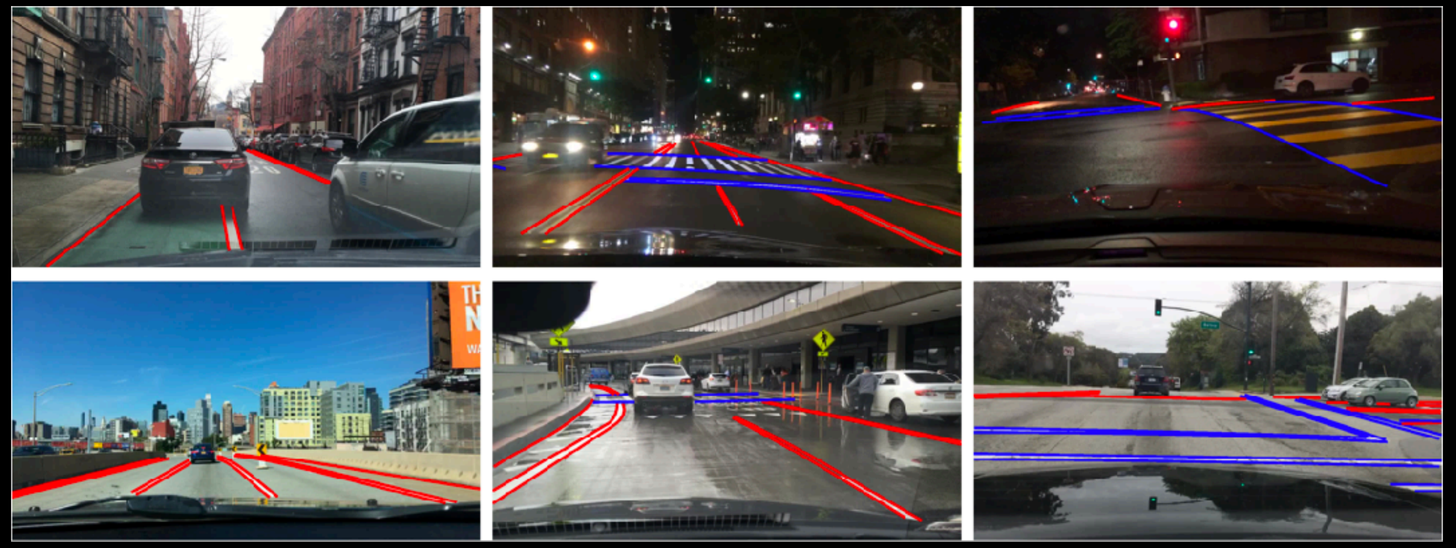
$$y \sim p_{\textbf{model}}(Y \mid X; \theta) \approx p_{\textbf{COCO}}(Y \mid X)$$

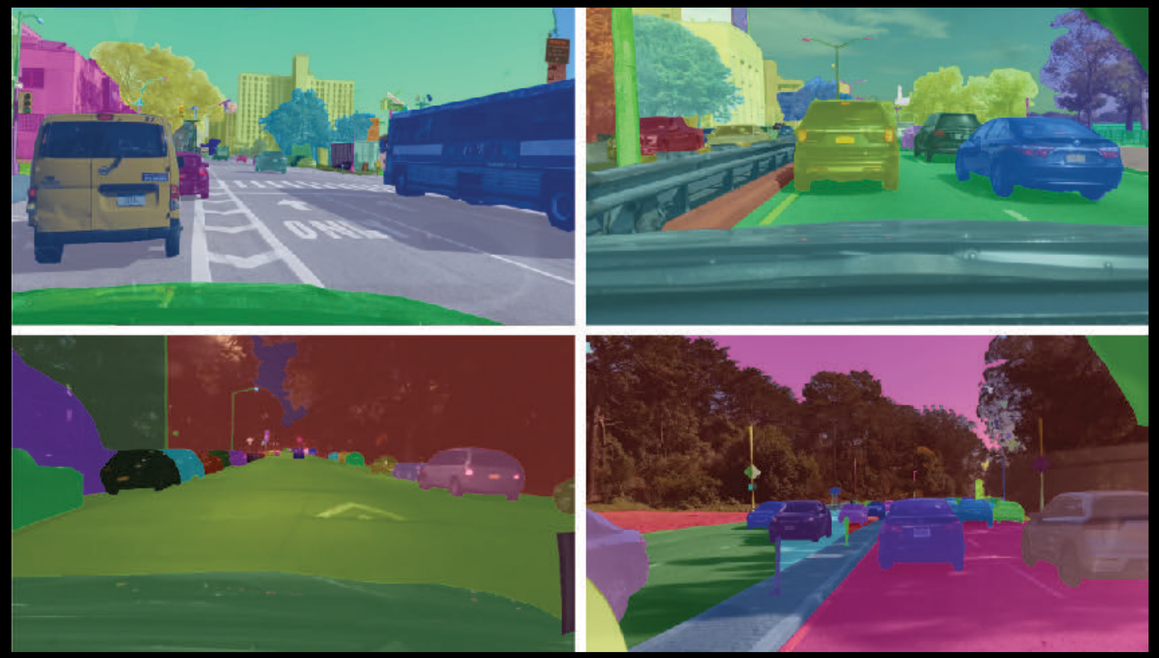
https://cs.stanford.edu/people/karpathy/deepimagesent/



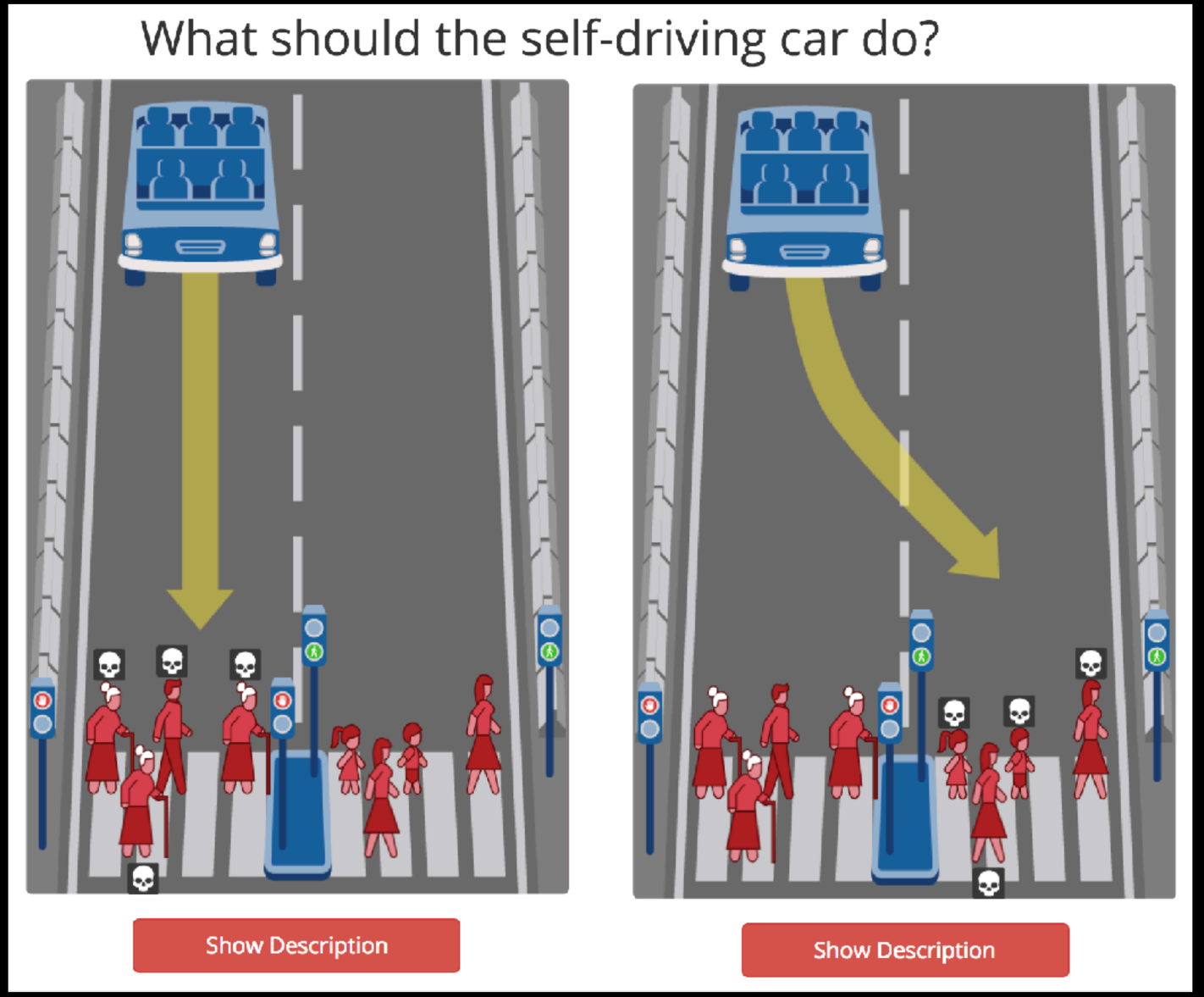
$$y \sim p_{\text{COCO+}}(Y \mid X)$$

https://cs.stanford.edu/people/karpathy/deepimagesent/





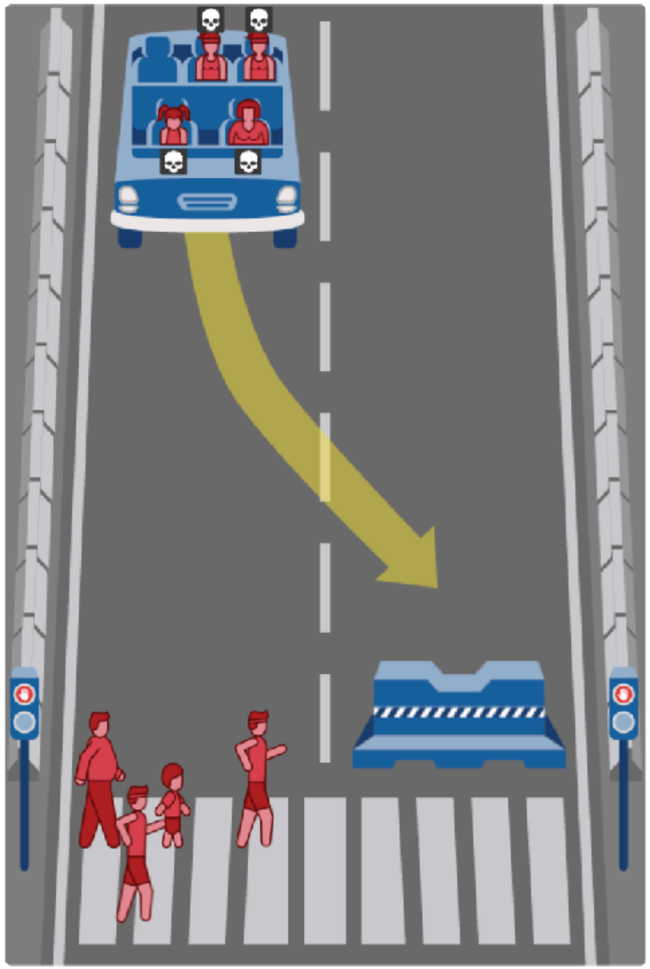
$$y_{t+1} \sim p_{\textbf{BDD100K}}(Y_t \mid X)$$



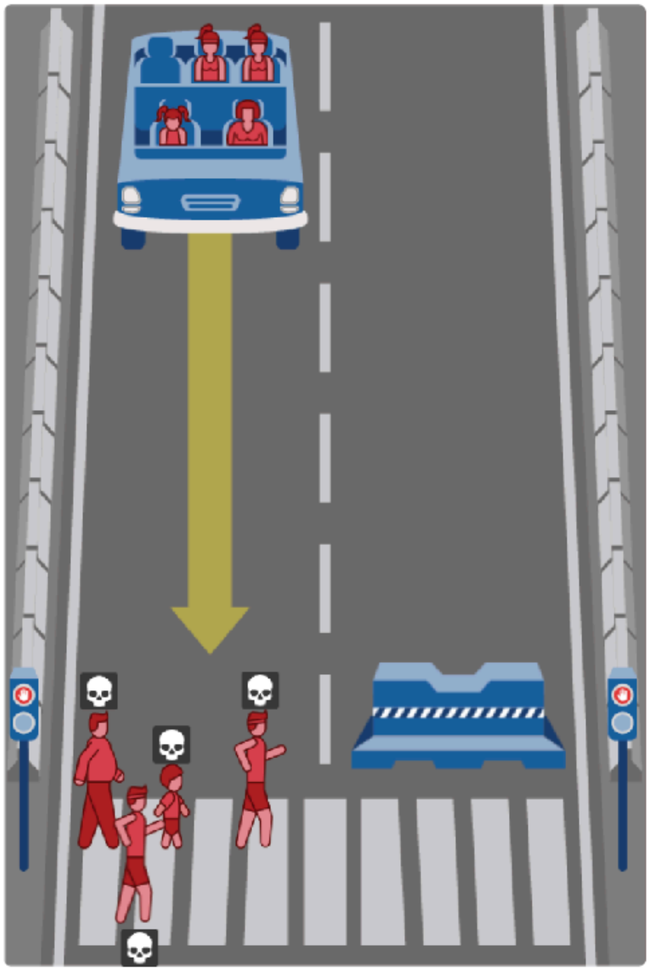
???

http://moralmachine.mit.edu/

What should the self-driving car do?



Show Description



Show Description

???!@#$%^&*???

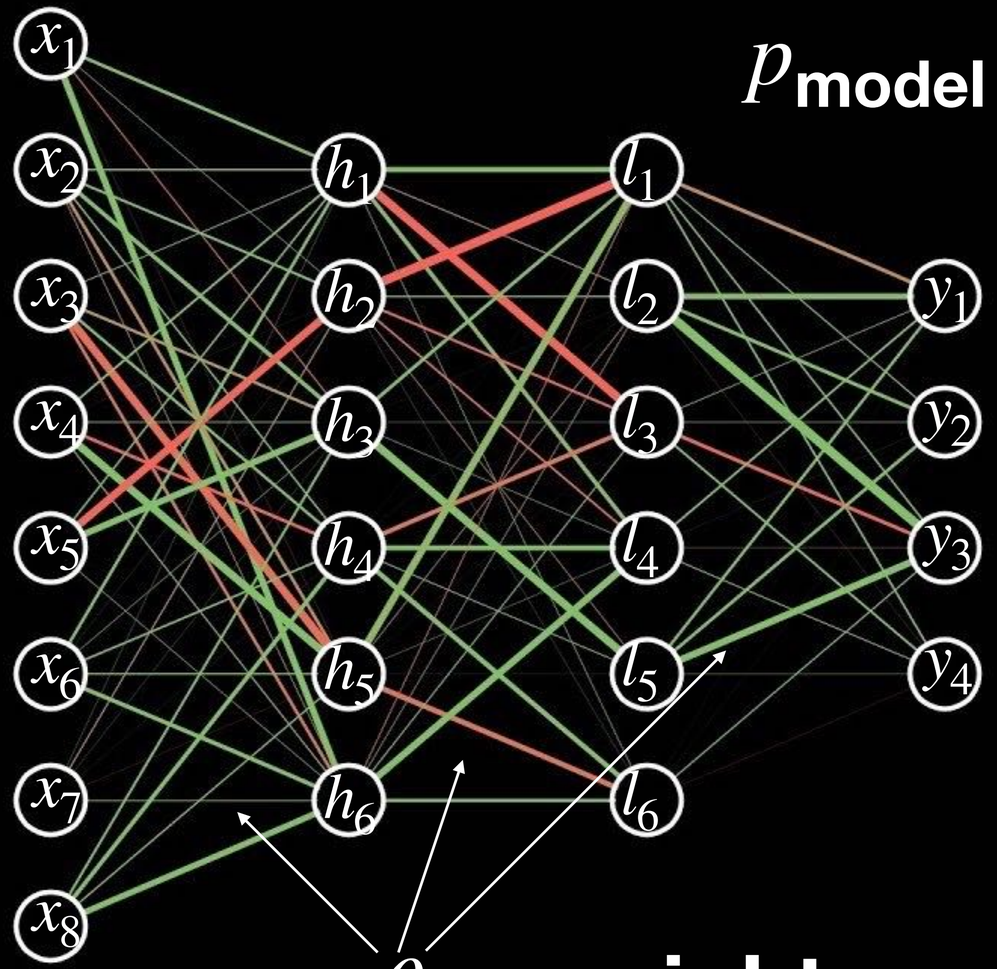
http://moralmachine.mit.edu/

How is any of this possible?

p_{model} **is "good" if** $\hat{y} \approx y$

Given sample (x, y)

x →

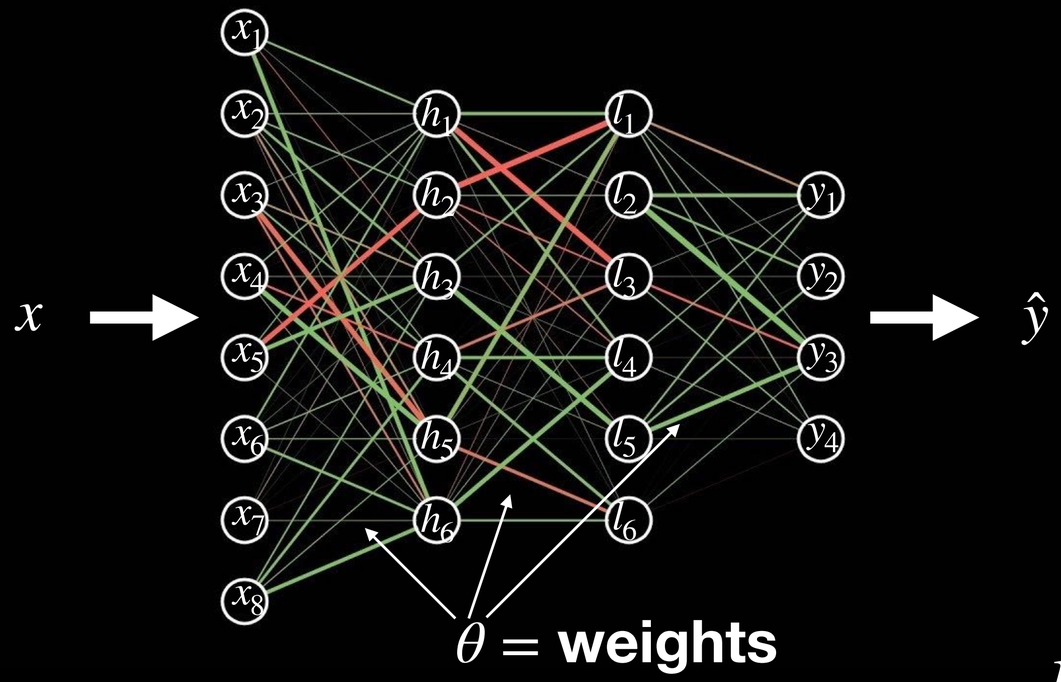


→ $\hat{y}$

True output is y

$\theta =$ **weights**

$$p_{\text{model}}(Y \mid X; \theta) \approx p_{\text{data}}(Y \mid X)$$



Classification

$$\hat{y}_1 = p(Y_1 \mid x; \theta) = 0.1$$
$$\hat{y}_2 = p(Y_2 \mid x; \theta) = 0.2$$
$$\hat{y}_3 = p(Y_3 \mid x; \theta) = 0.7$$
$$\hat{y}_4 = p(Y_4 \mid x; \theta) = 0.0$$

Regression

$$p_{\textbf{model}}(y \mid x; \theta) = \mathcal{N}(y \mid \mu = \hat{y}(x; \theta), \Sigma)$$

Maximum likelihood estimation of weights

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}}\, p_{\textbf{model}}(\mathbb{X} \mid \theta)$$

Bayes' Rule

$$p(\theta \mid \mathbb{X}) \propto p(\mathbb{X} \mid \theta) p(\theta)$$

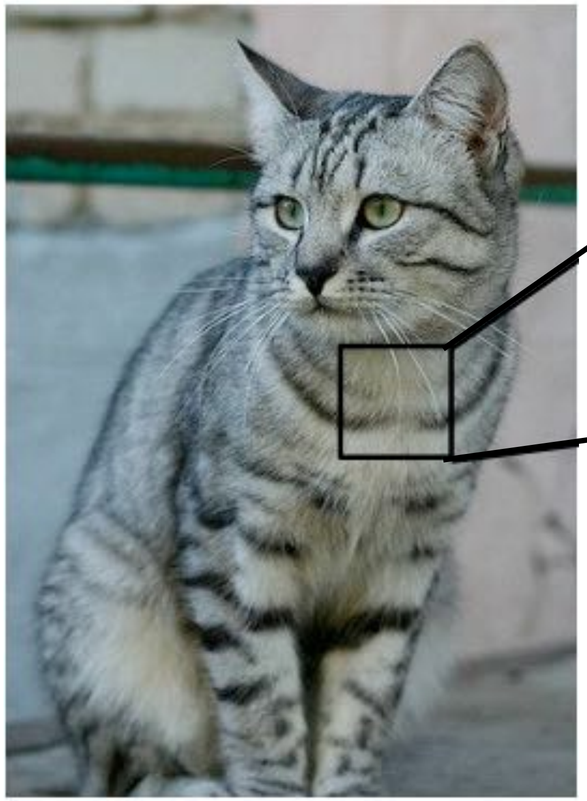
Believe it or not, this is how we train most networks!

Image Classification : A core task in Computer Vision

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

cat

The Problem : Semantic Gap




```
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 [ 91  98 102 106 104  79  98 103  99 105 123 136 110 105  94  85]
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 [ 99  81  81  93 120 131 127 100  95  98 102  99  96  93 101  94]
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 [128 112  96 117 150 144 120 115 104 107 102  93  87  81  72  79]
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 [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]]
```
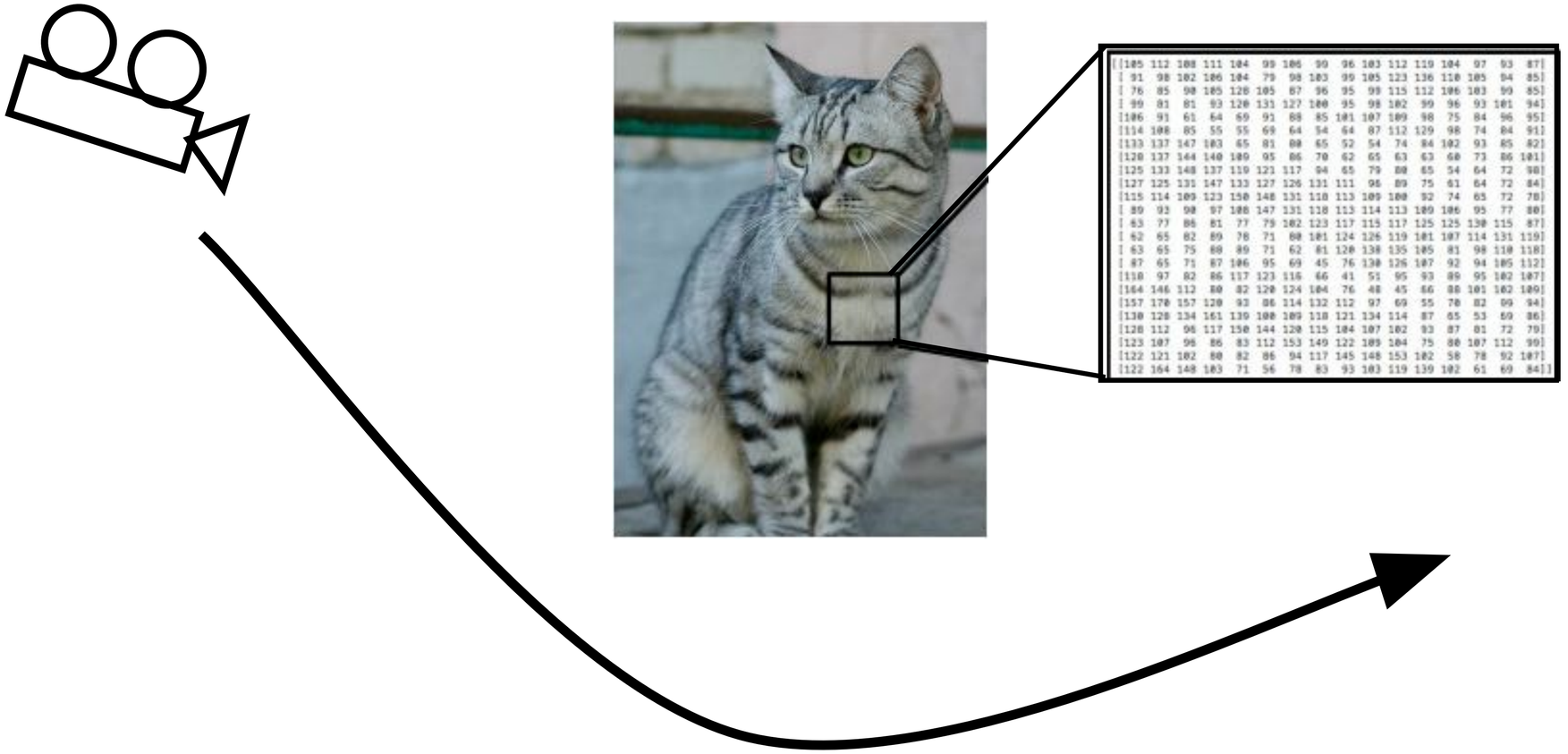

What the computer sees

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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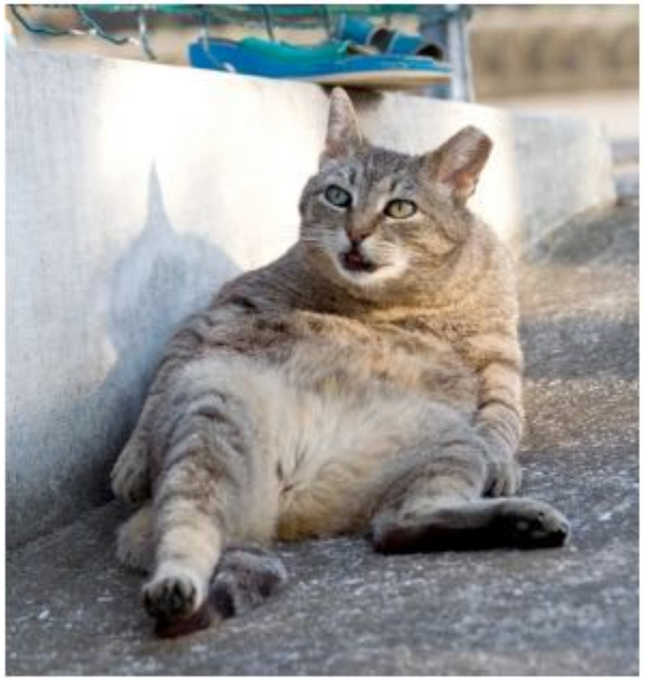
Challenges : Deformation



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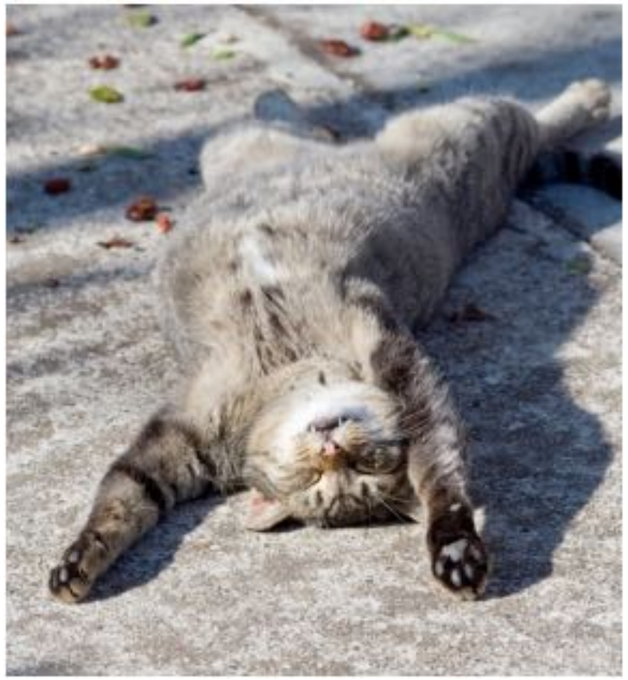

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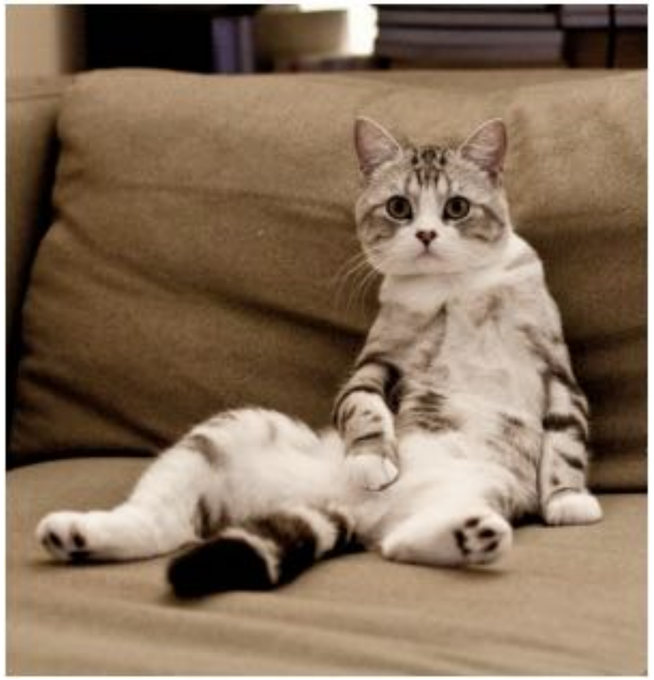

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Challenges : Occlusion

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Challenges : Background Clutter

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Challenges : Intraclass variation

An image classifier

```
def classify_image(image):
  # Some magic here?
  return class_label
```

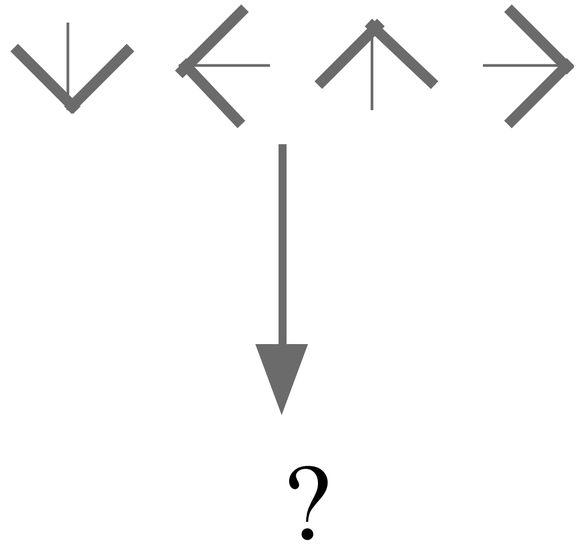
Unlike e.g. sorting a list of numbers,

no obvious way to hard-code the algorithm for recognizing a cat, or other classes.

Attempts have been made

Find edges

Find corners



?

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

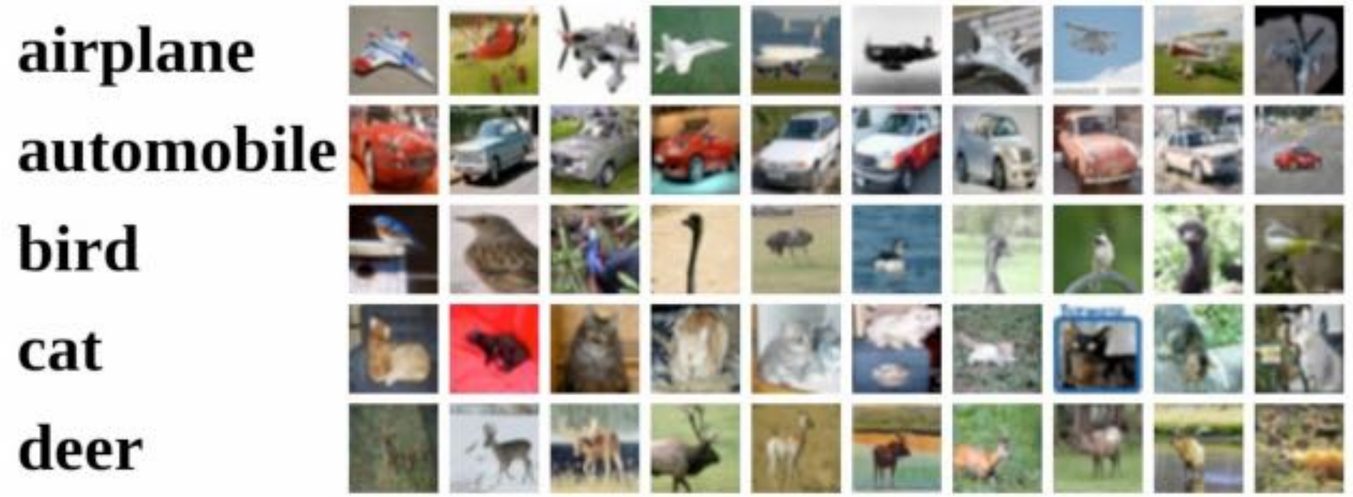
Machine Learning: Data-Driven Approach

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.

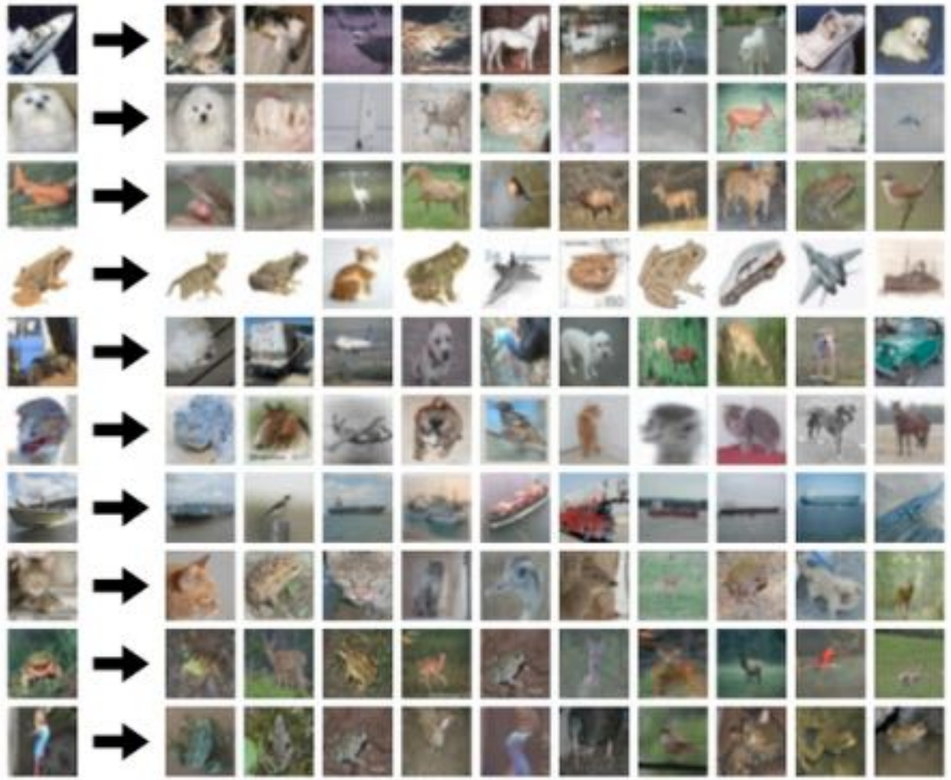
Example Dataset: **CIFAR10**

10 classes

50,000 training images

10,000 testing images

Test images and nearest neighbors

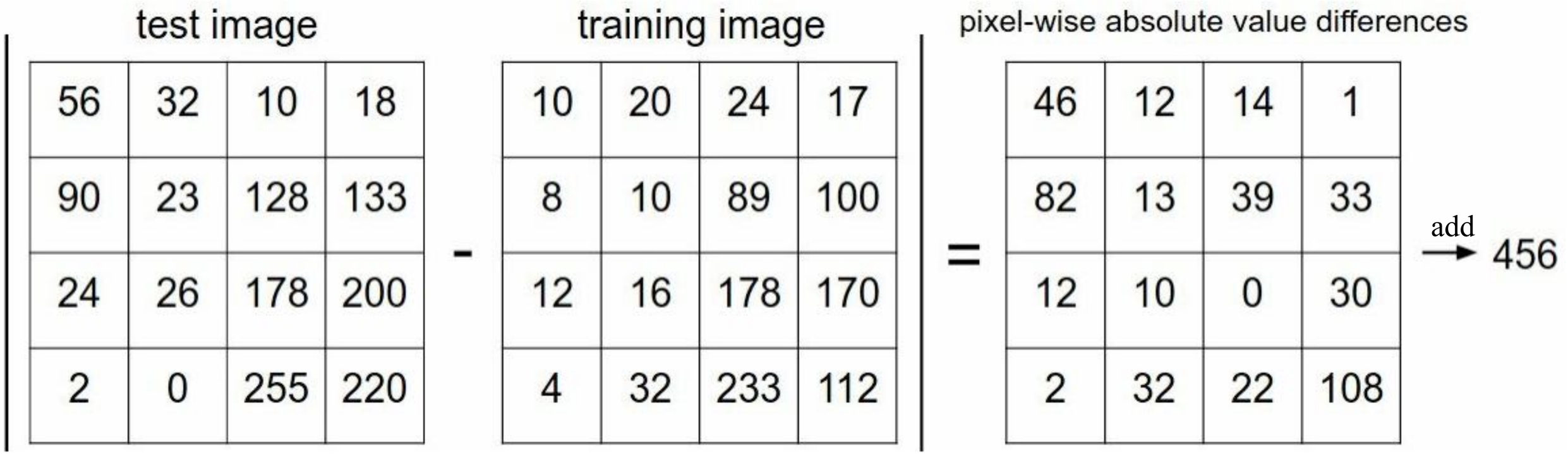


Alex Krizhevsky, “Learning Multiple Layers of Features from Tiny Images”, Technical Report, 2009.

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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Memorize training data

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```

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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```

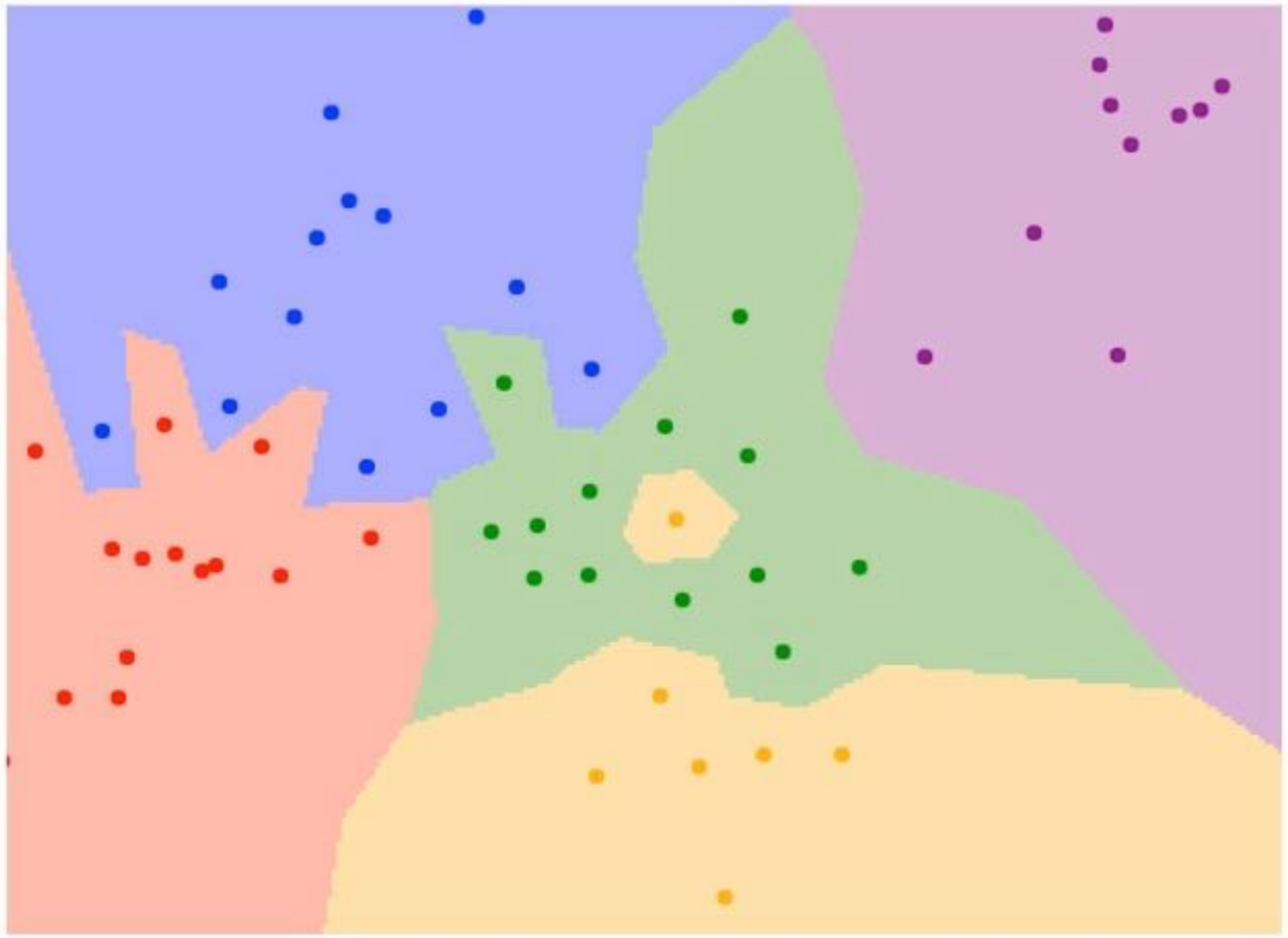
Nearest Neighbor classifier

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

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

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

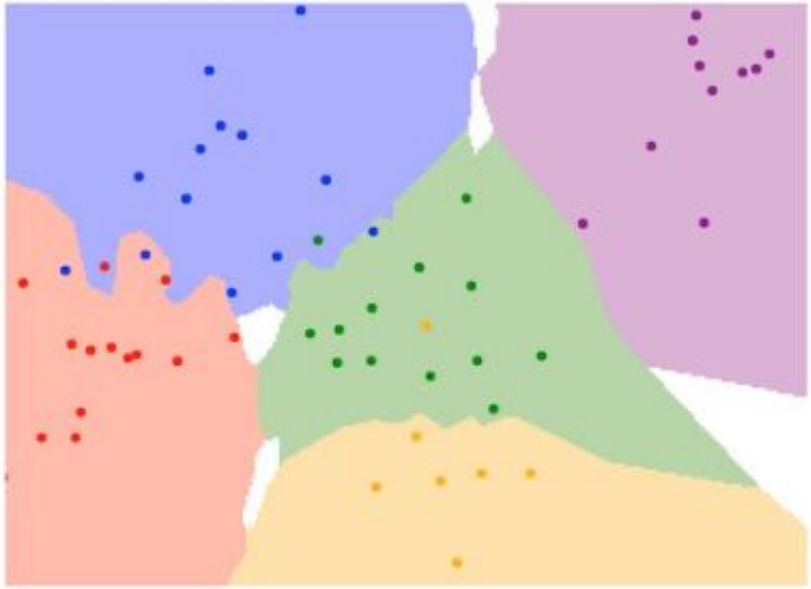
What does this look like?



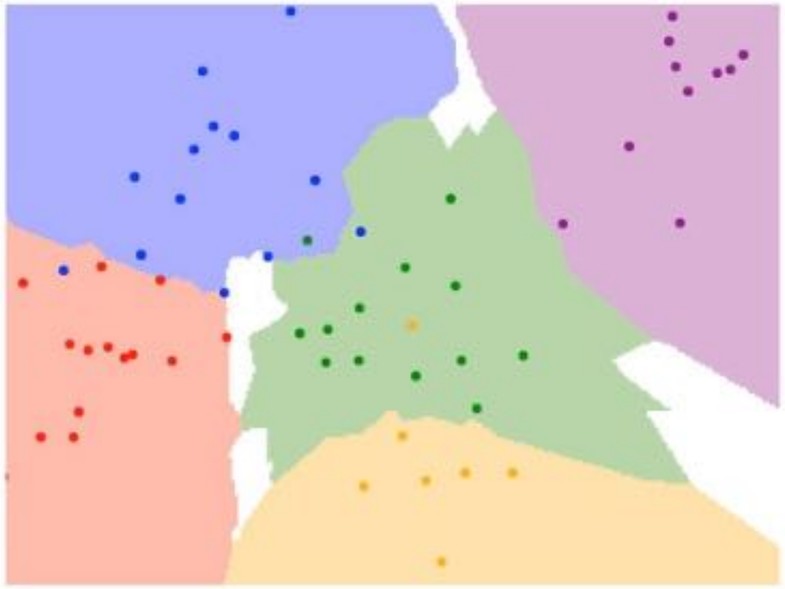
K-Nearest Neighbors

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

K = 1

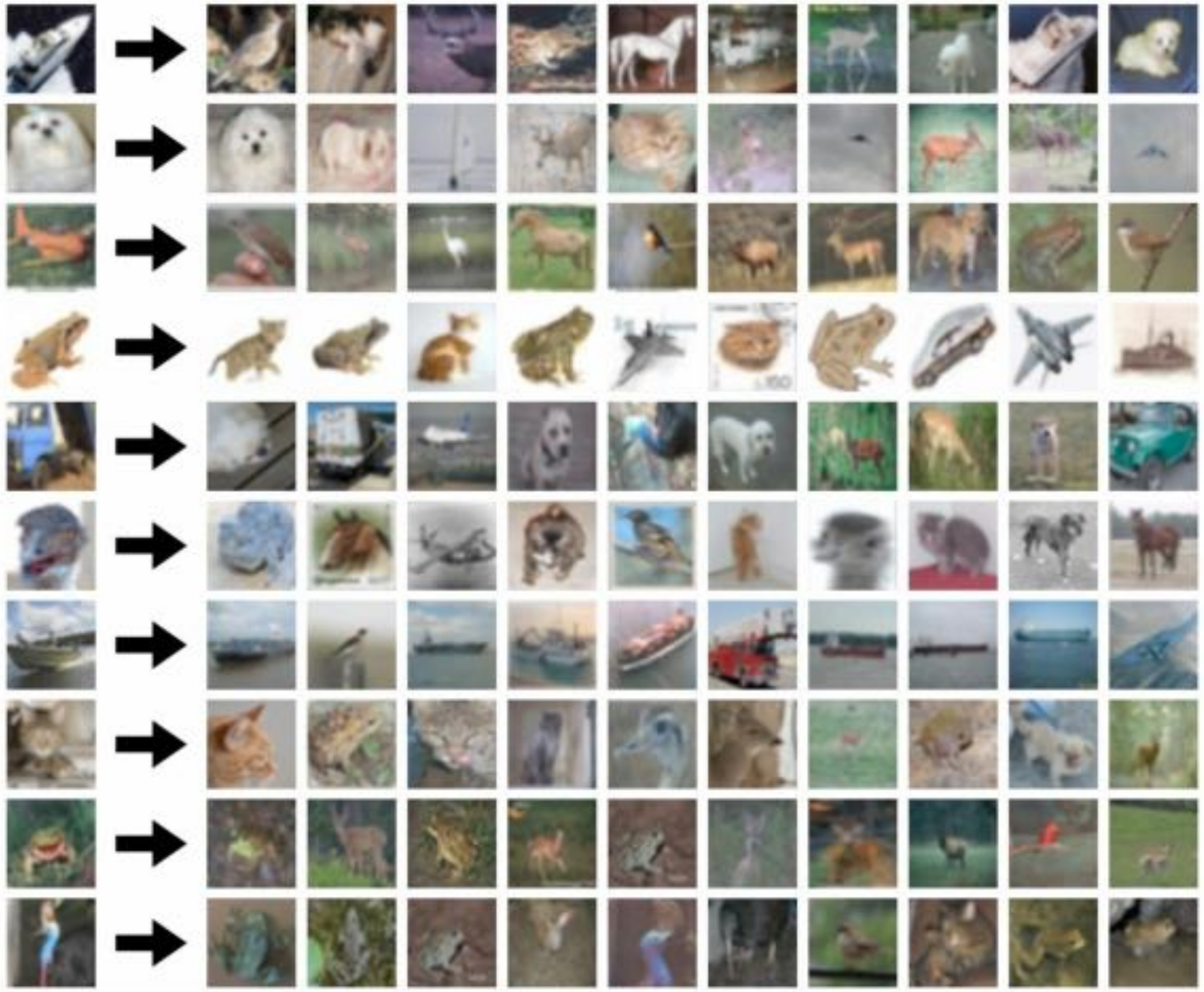


K = 3

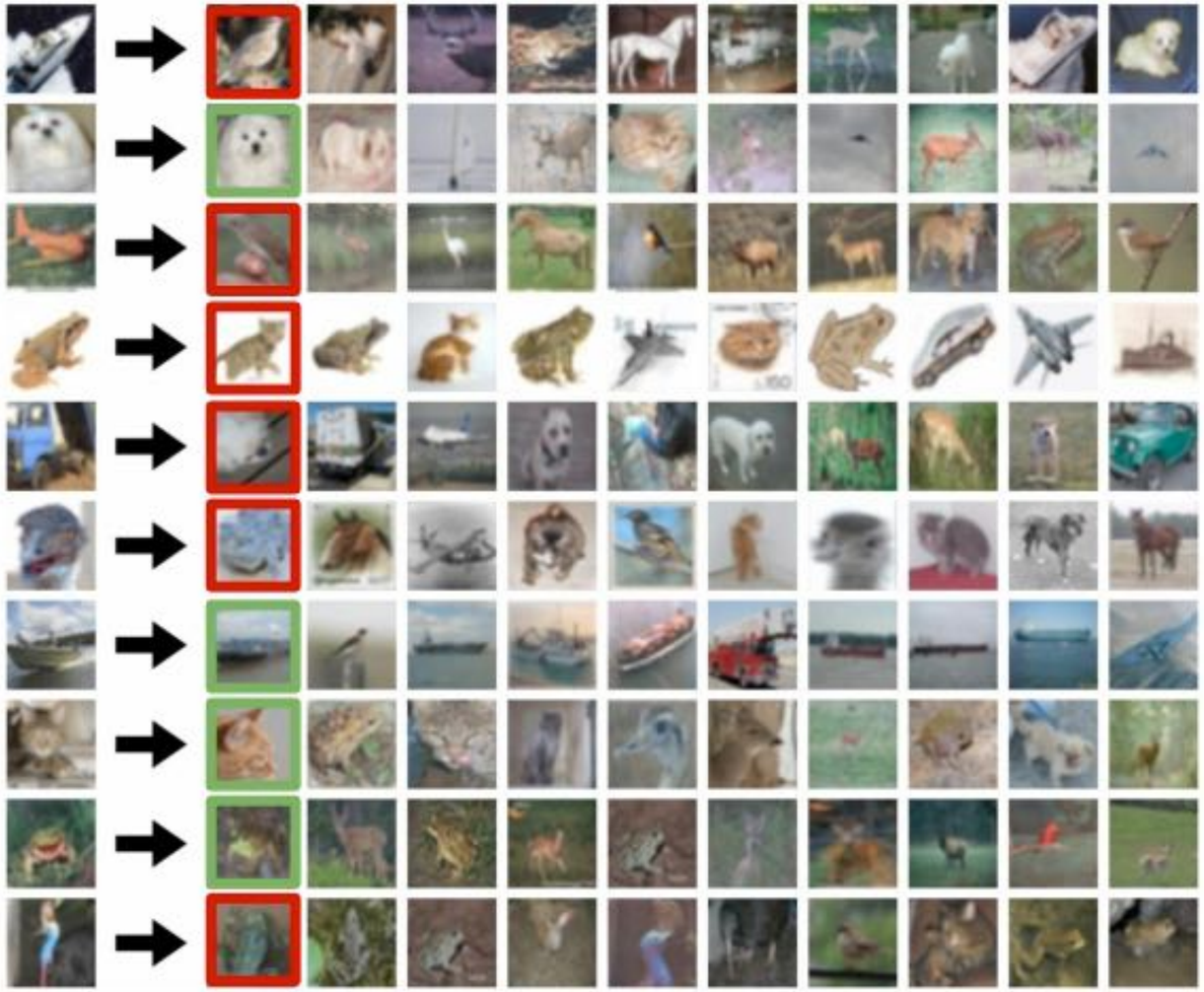


K = 5

What does this look like?



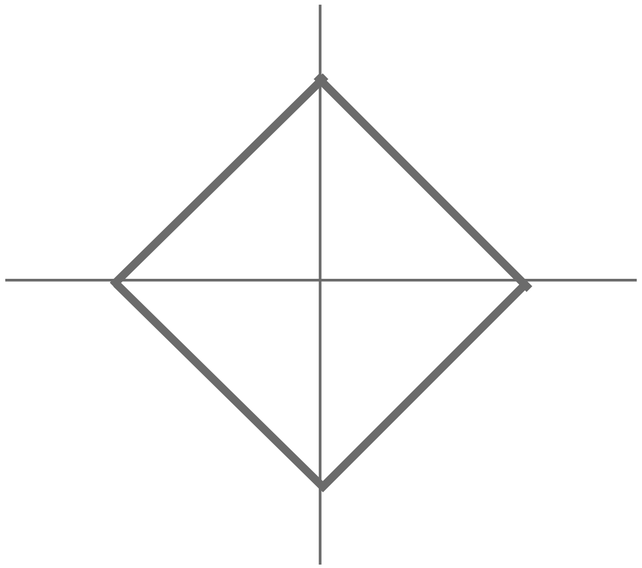
What does this look like?



K-Nearest Neighbors: Distance Metric

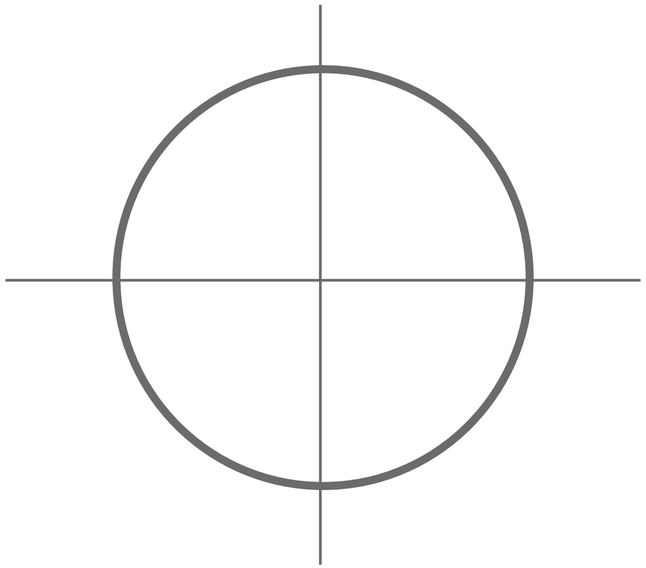
L1 (Manhattan) distance

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



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

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

K = 1

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

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BAD : K = 1 always works perfectly on training data

Your Dataset

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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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

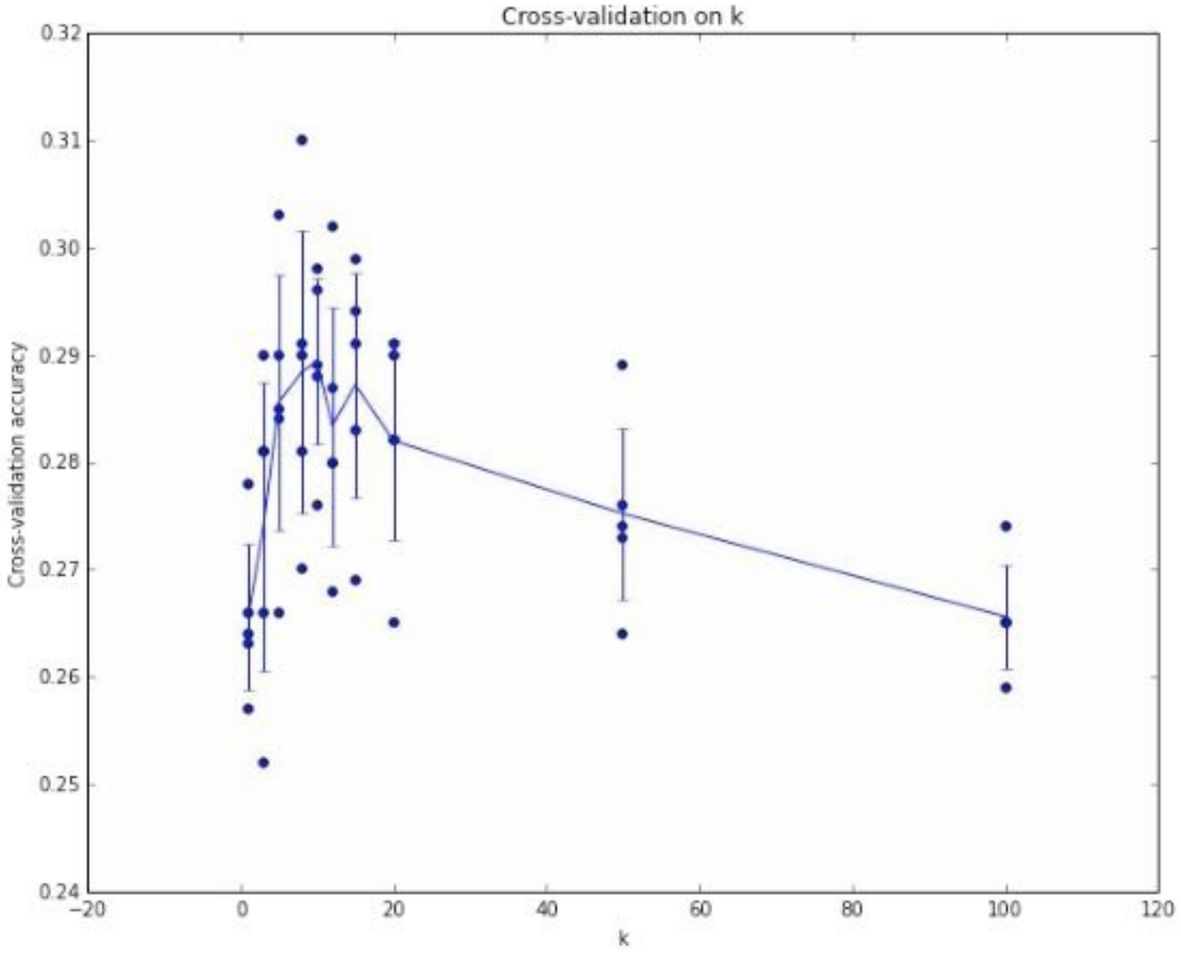
Your Dataset

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

fold 1	fold 2	fold 3	fold 4	fold 5	test
fold 1	fold 2	fold 3	fold 4	fold 5	test
fold 1	fold 2	fold 3	fold 4	fold 5	test

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

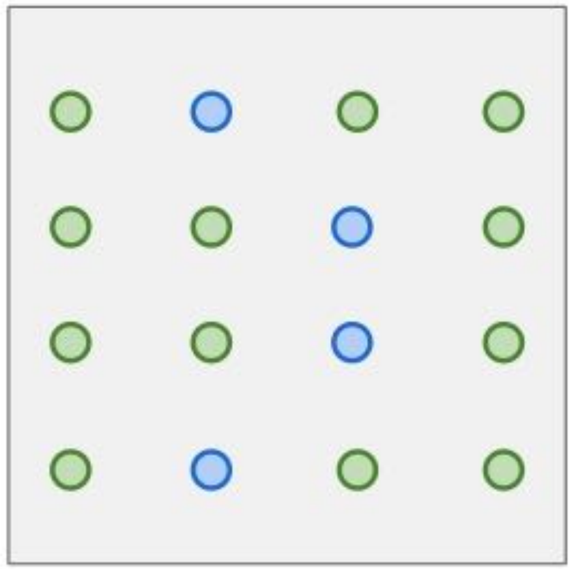
(all 3 images have same L2 distance to the one on the left)

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

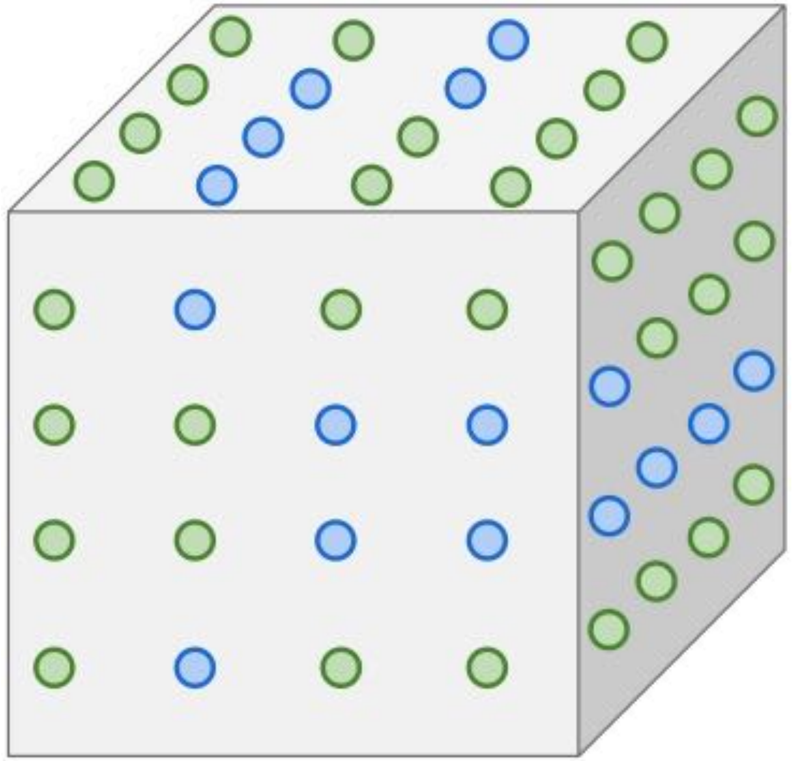
- Curse of dimensionality

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!