Deep Learning (for Computer Vision)

Arjun Jain

Torch7

- Torch7 as the deep learning framework (Reason: we will discuss why in detail later)

Aim (by the end of this module)

- Understand the theory behind neural networks and its building blocks
- Be able to code using Torch7 to train models with your own data

Sources

A lot of the material has been shamelessly and gratefully collected from:

- **http://cs231n.stanford.edu/**
- https://devblogs.nvidia.com/parallelforall/deep-learning-nutshell-history-training/
- https://adeshpande3.github.io/adeshpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html
- https://research.fb.com/learning-to-segment/
- https://research.fb.com/deep-learning-tutorial-at-cvpr-2014/
- https://www.cs.ox.ac.uk/people/nando.defreitas/machinelearning/practicals/practical4.pdf
- http://torch.ch/docs/developer-docs.html
- https://github.com/torch/nn/blob/31d7d2bc86a914e2a9e6b3874c497c60517dc853/doc/module.md
- https://web.stanford.edu/group/pdplab/pdphandbook/handbookch6.html
- http://neuralnetworksanddeeplearning.com/chap2.html

A bit of history:

Hubel & Wiesel,

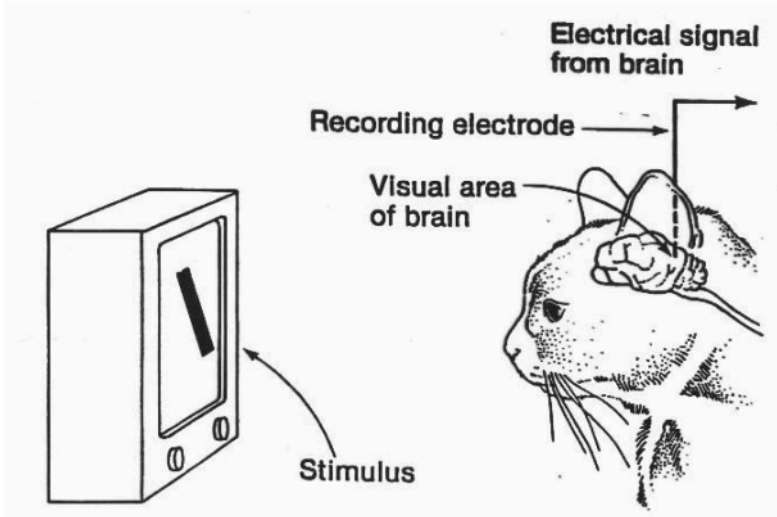
1959

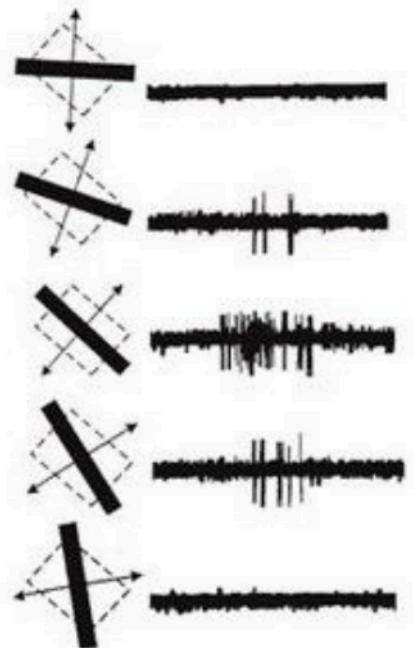
RECEPTIVE FIELDS OF SINGLE NEURONES IN
THE CAT'S STRIATE CORTEX

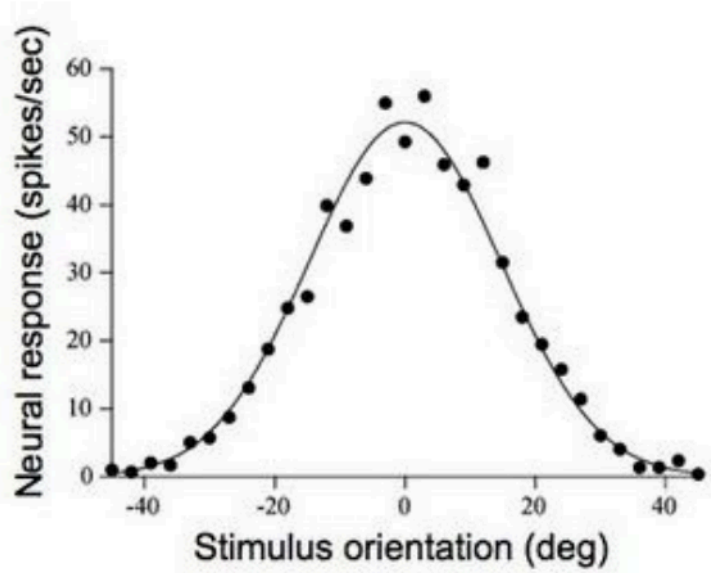
1962

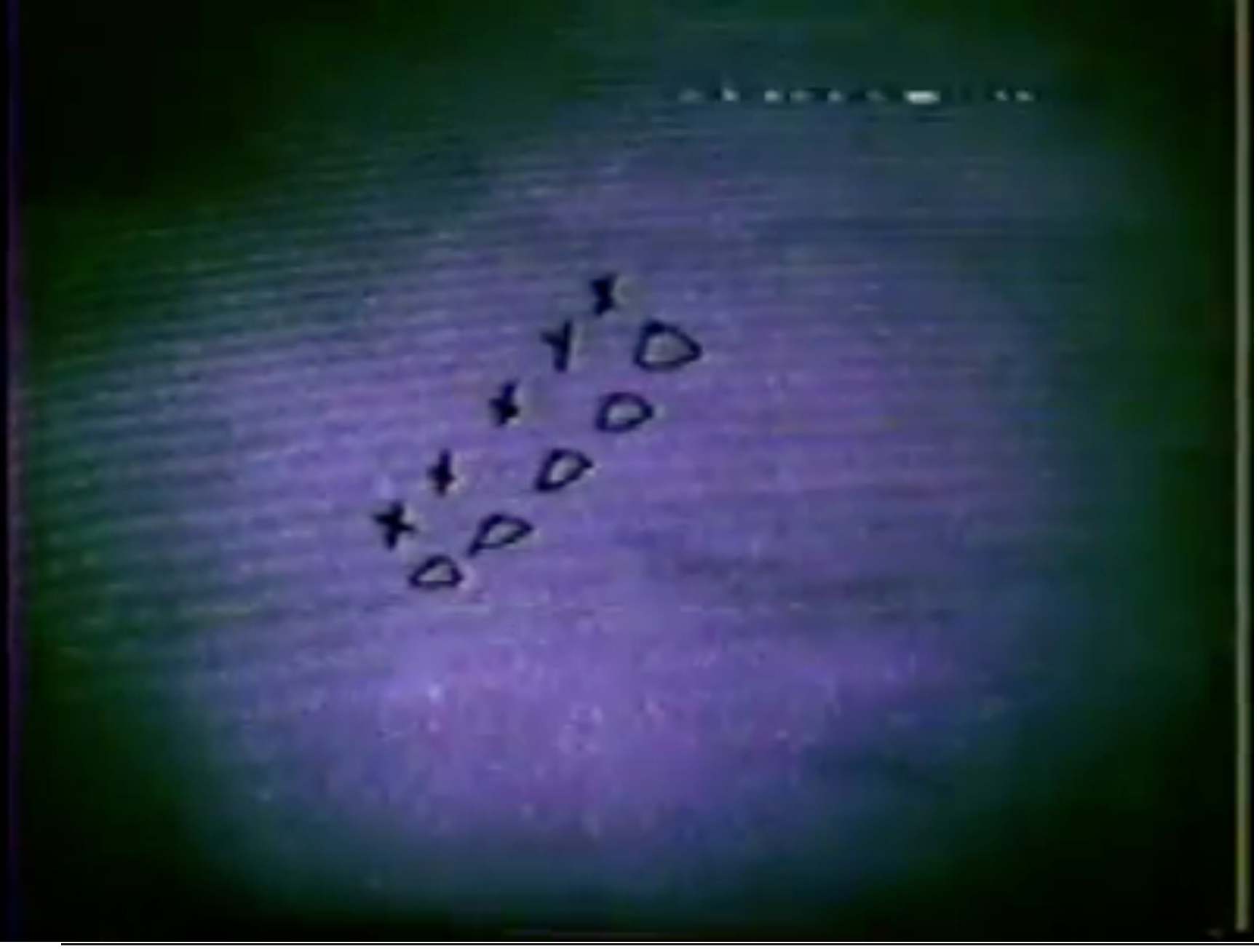
RECEPTIVE FIELDS, BINOCULAR INTERACTION
AND FUNCTIONAL ARCHITECTURE IN
THE CAT'S VISUAL CORTEX

1968...





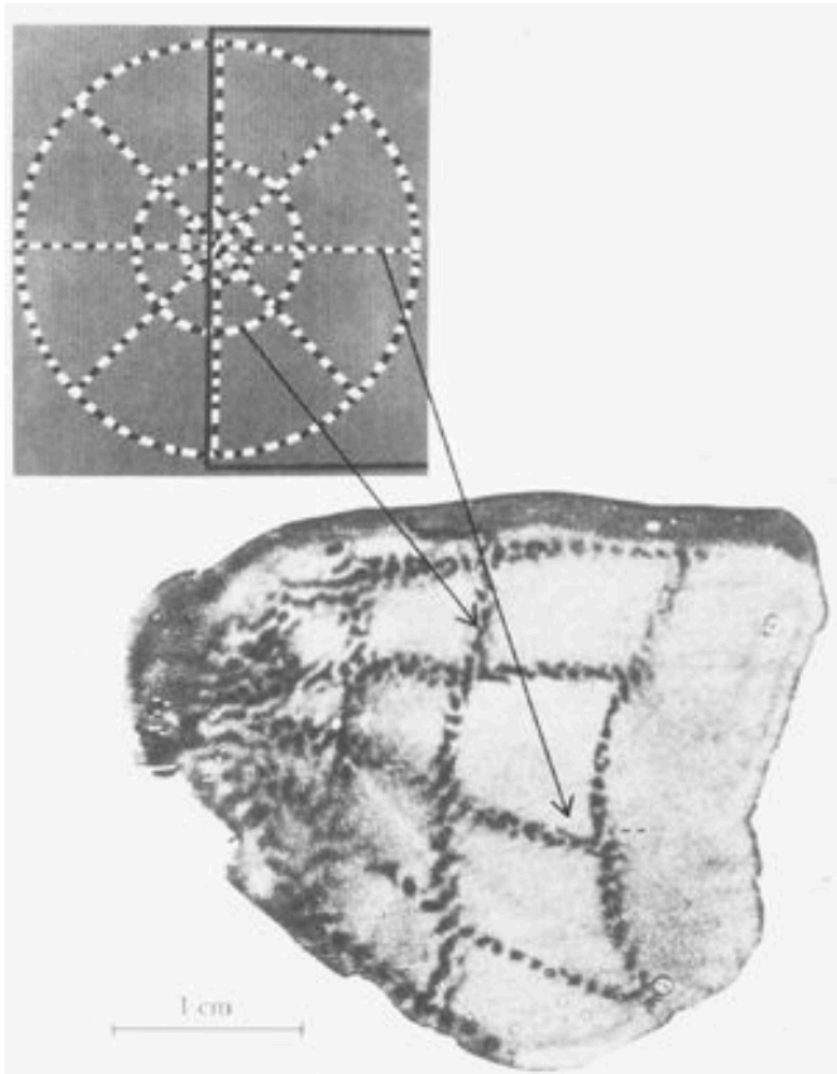




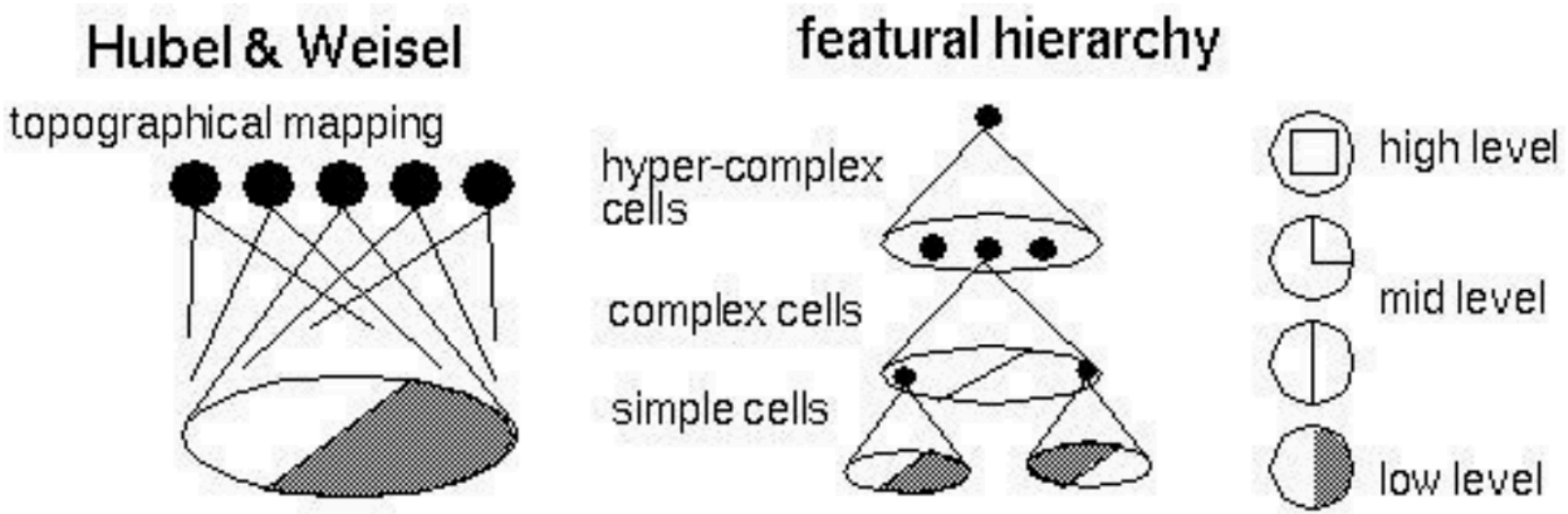
https://youtu.be/8VdFf3egwfg?t=1m10s

A bit of history

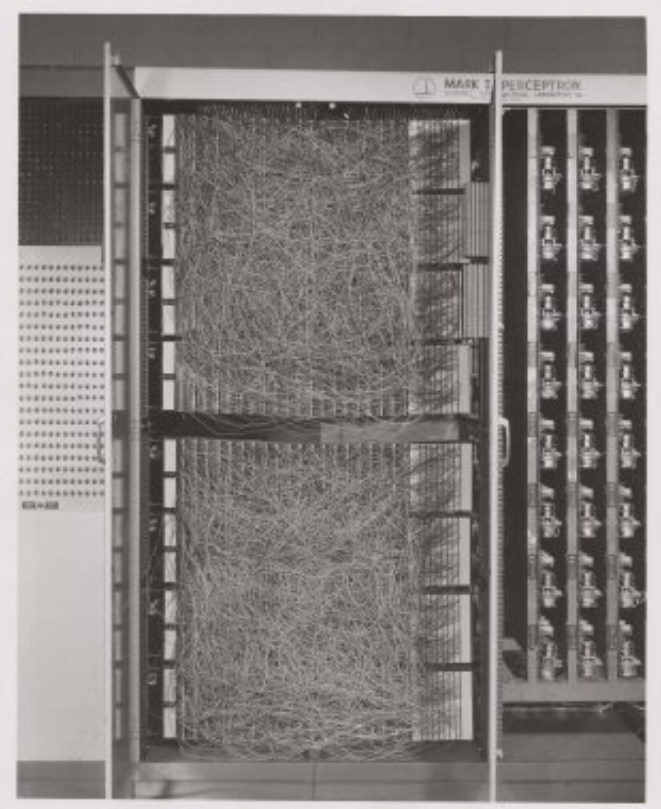
Topographical mapping in the cortex:
nearby cells in cortex represented
nearby regions in the visual field



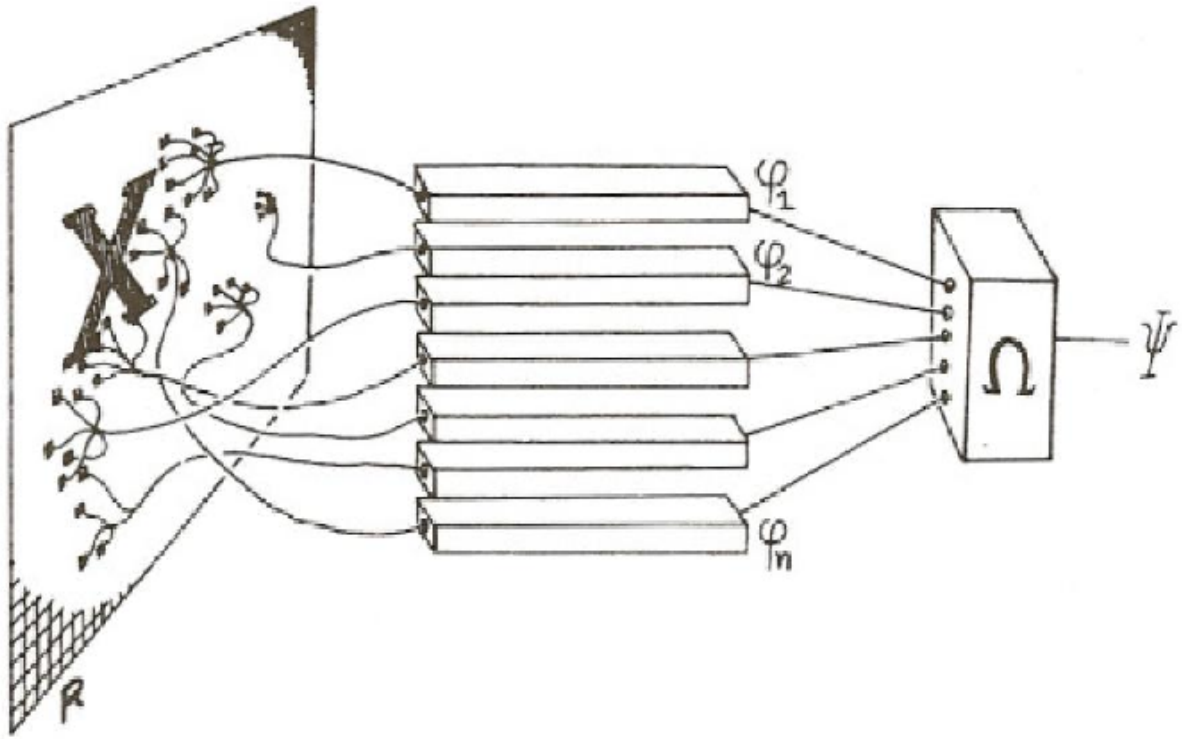
Hierarchical organization



Brief History – Mark I Perceptron – 1958



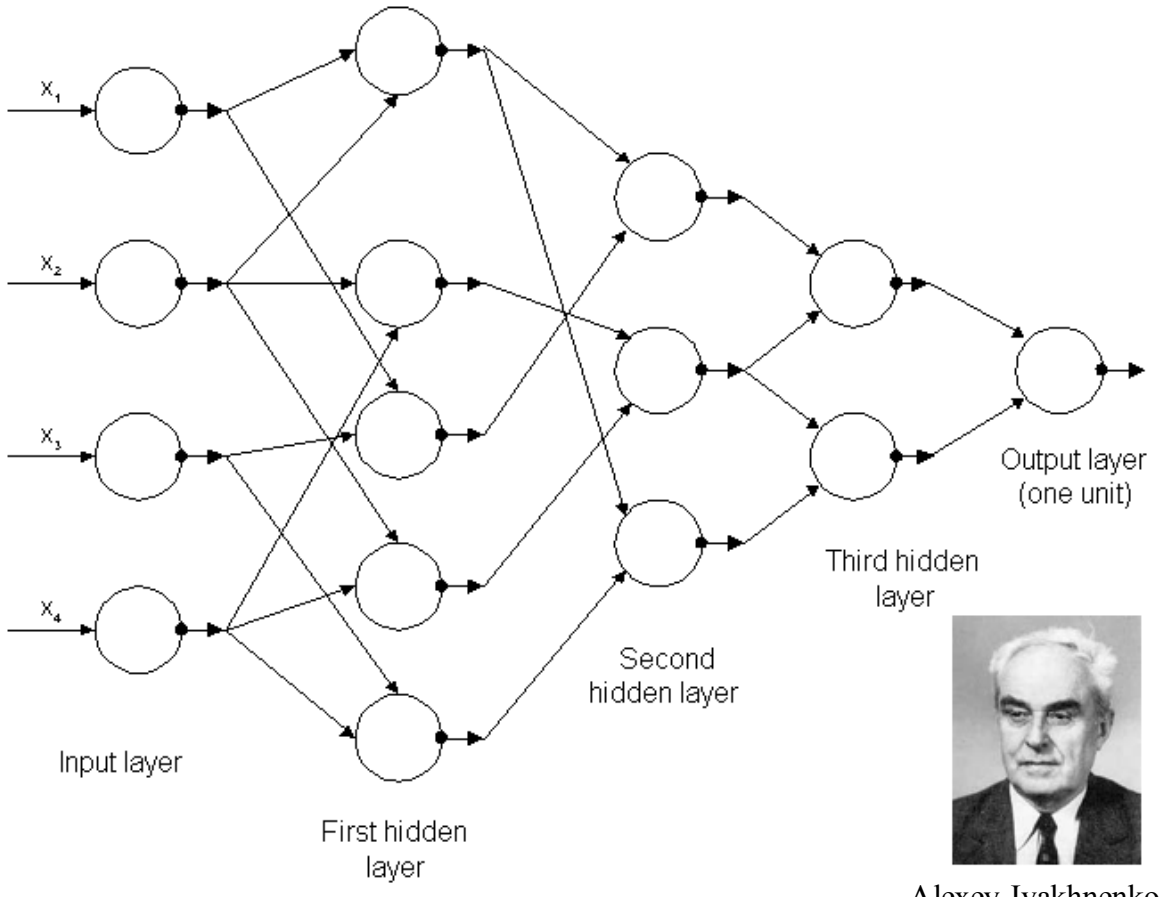
https://en.wikipedia.org/wiki/Perceptron



Perceptrons by M. L Minsky and S. Papert, 1969

Brief History – The First Deep Networks

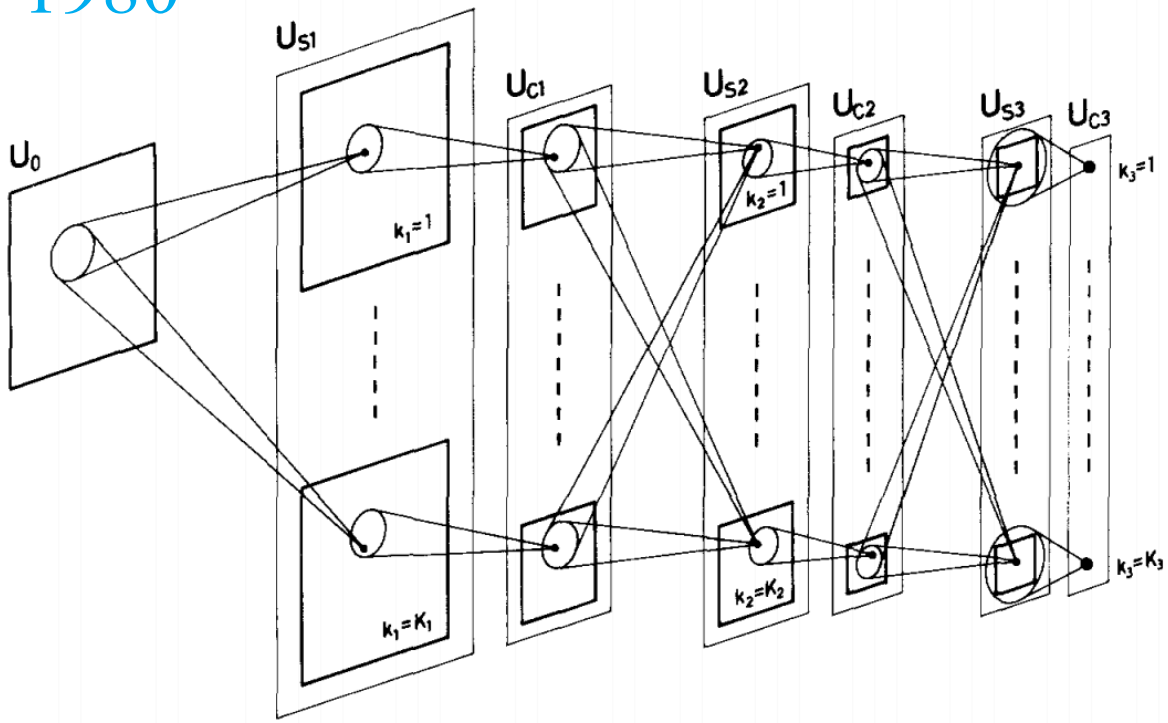
- Perceptron: single layer 1960s
- Multiple layers of non-linear features - Ivakhnenko and Lapa in 1965
- Thin but deep models with polynomial activation functions
- They did not use backpropagation

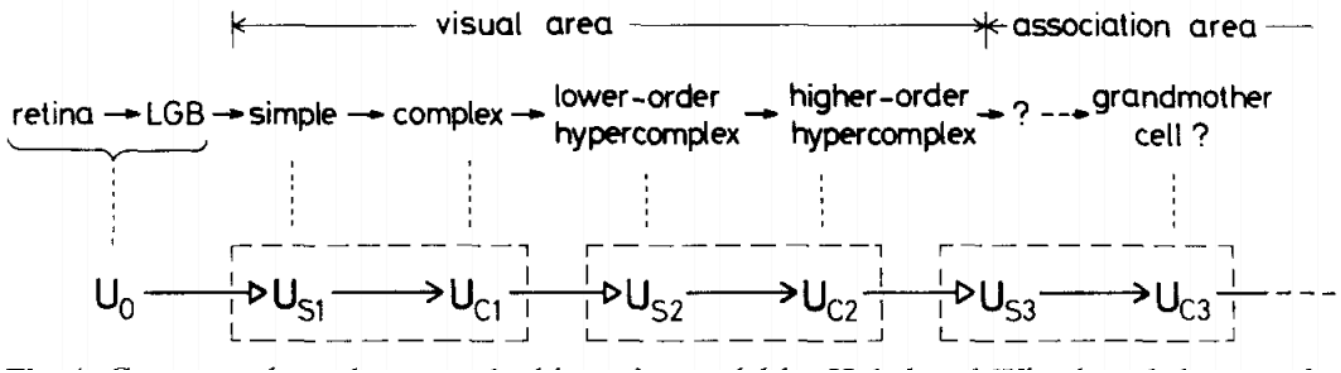


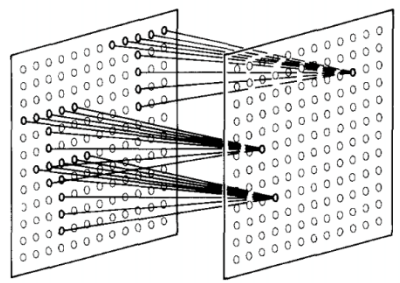
Alexey Ivakhnenko

Brief History – The First ConvNet - 1980

- Neocognitron: multiple convolutional and pooling layers similar to modern networks, but the network was trained by using a reinforcement scheme
- Did not still use backpropagation
- Translational invariant





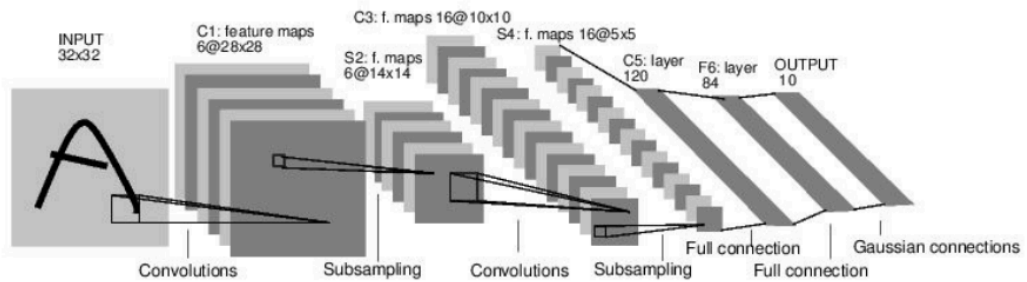


Kunihiko Fukushima

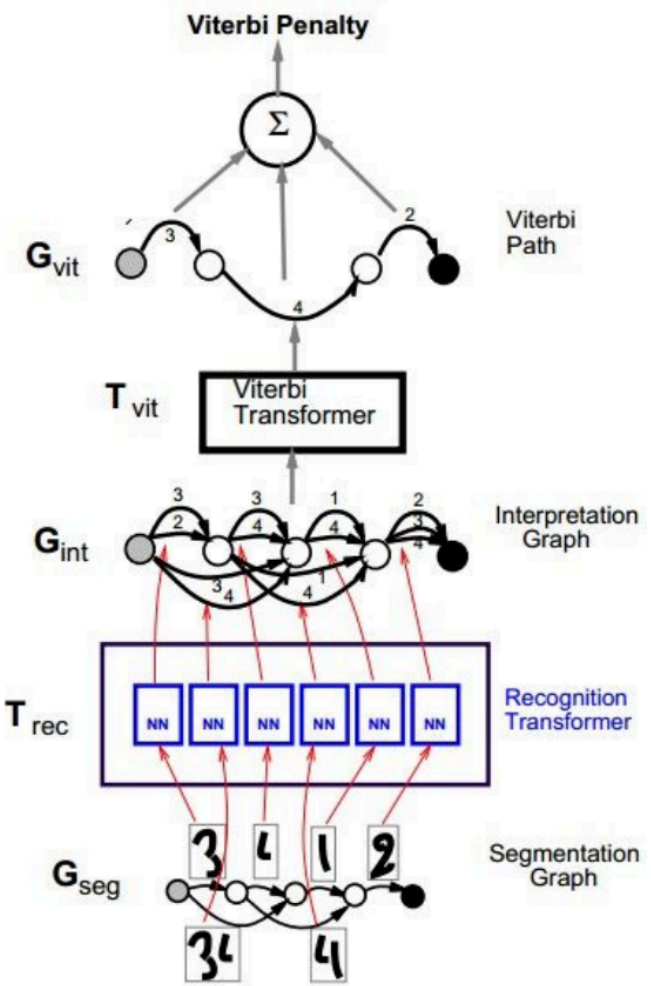
A bit of history:

Gradient-based learning applied to document recognition

[LeCun, Bottou, Bengio, Haffner 1998]

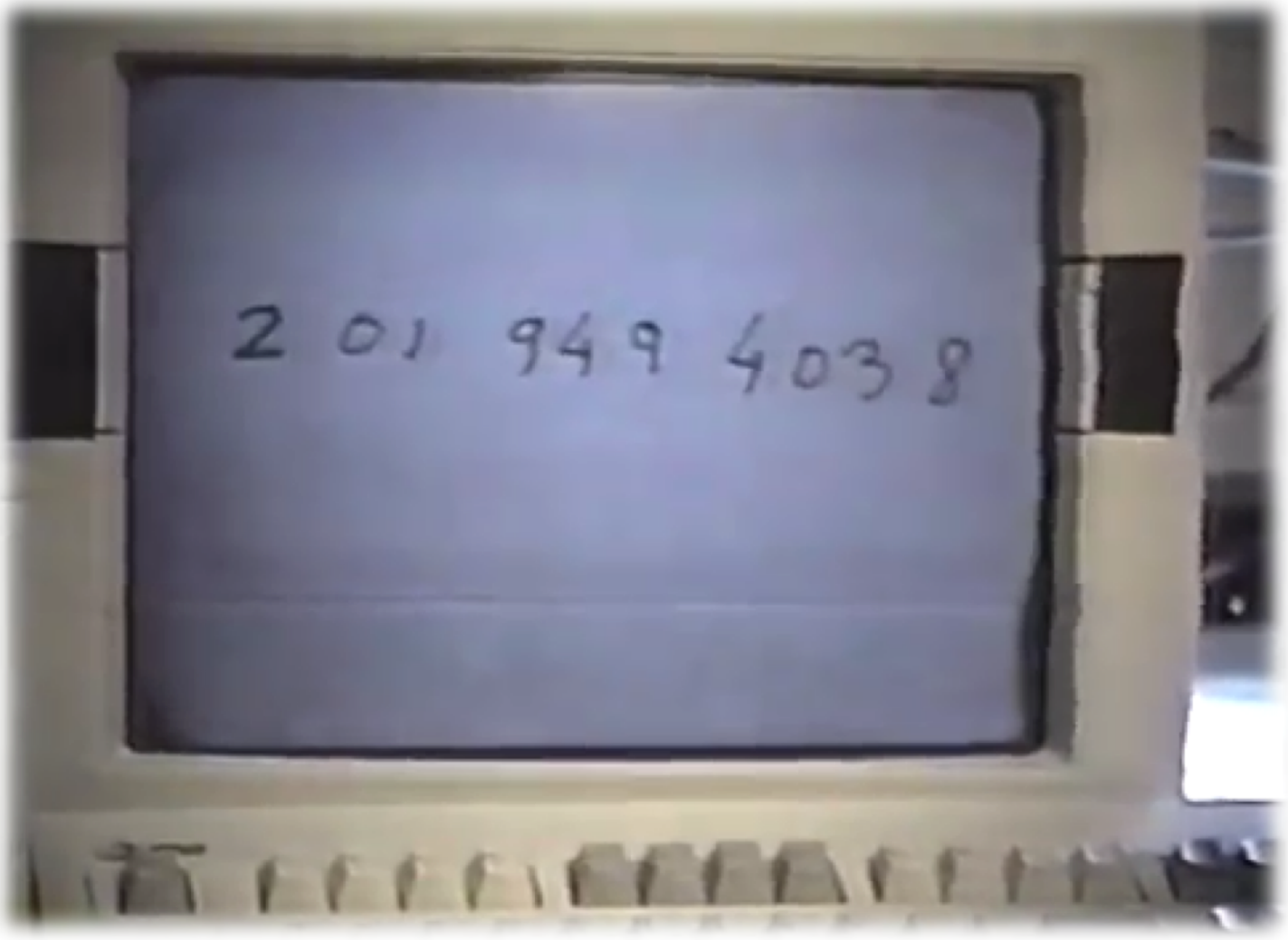


LeNet-5

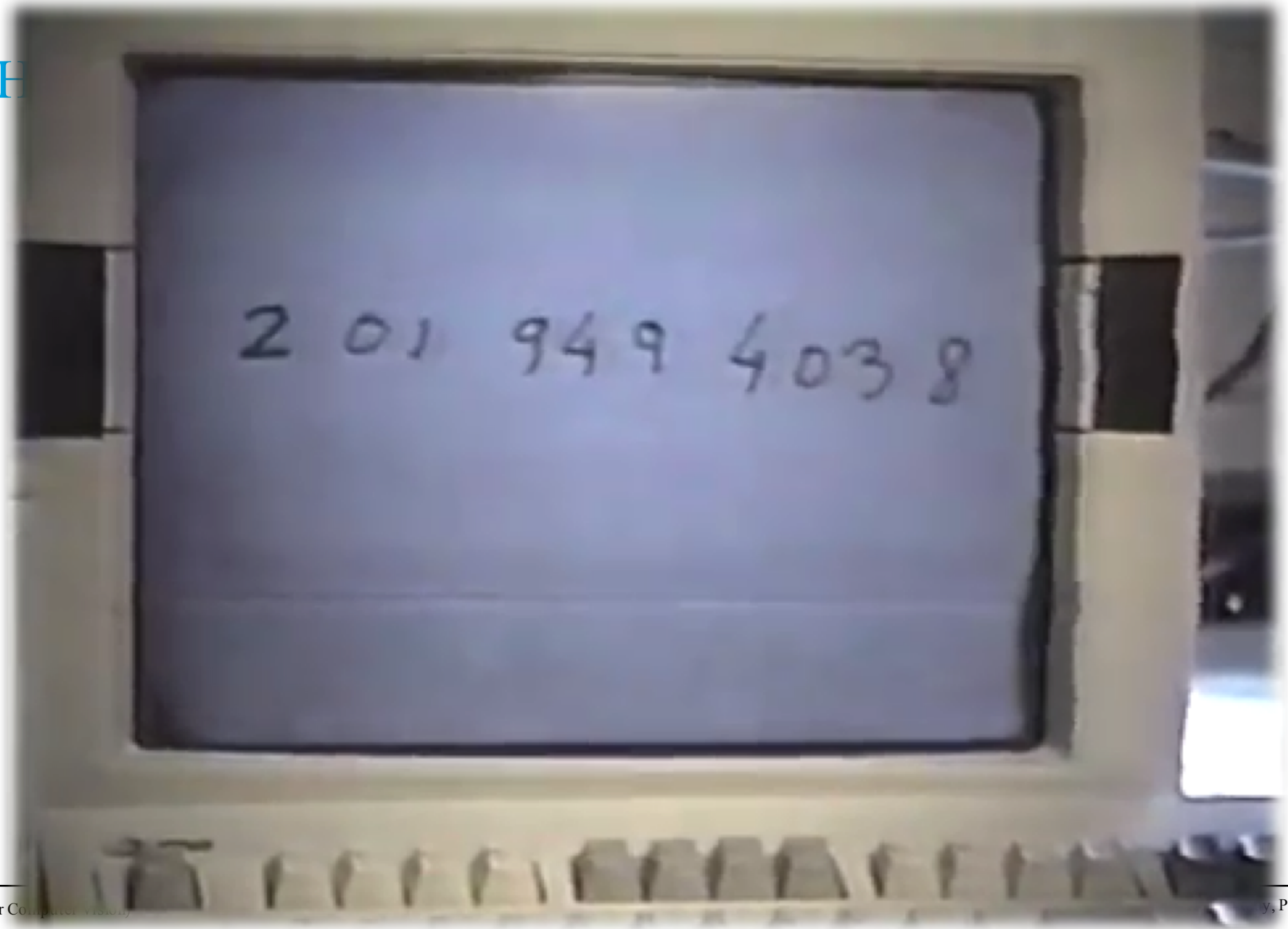


Yann LeCun

Brief History – LeNet-5 In Action



Brief H



Brief History – AI Winter

- Rapid advances led to a hype of artificial intelligence (similar to the buzz around deep learning today)
- Researchers made promises to solve AI and received lots of funding
- In the 1970s it became clear that those promises could not be kept, funding was cut dramatically
- The field of artificial intelligence dropped to near pseudo-science status
- Research became very difficult (little funding; publications almost never made it through peer review)
- Further advances such as SVMs with nice properties in terms of training, provable error bounds were preferred and took the front seat
- However, a handful of researchers continued further down this path

Brief History – AI Winter

- Those handful:

Geoffrey Hinton: University of Toronto & Google

Yann LeCun: New York University & Facebook

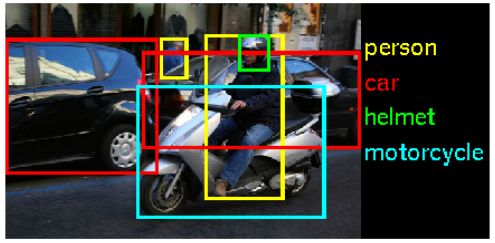
Yoshua Bengio: University of Montreal

Jürgen Schmidhuber: Swiss AI Lab & NNAISENSE

Andrew Ng: Stanford & Baidu

Brief History – The Tipping Point

- 2012 ILSVRC: ImageNet Large-Scale Visual Recognition Challenge – Annual World Cup of Computer Vision
- More than a million training images and 1000 categories



ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

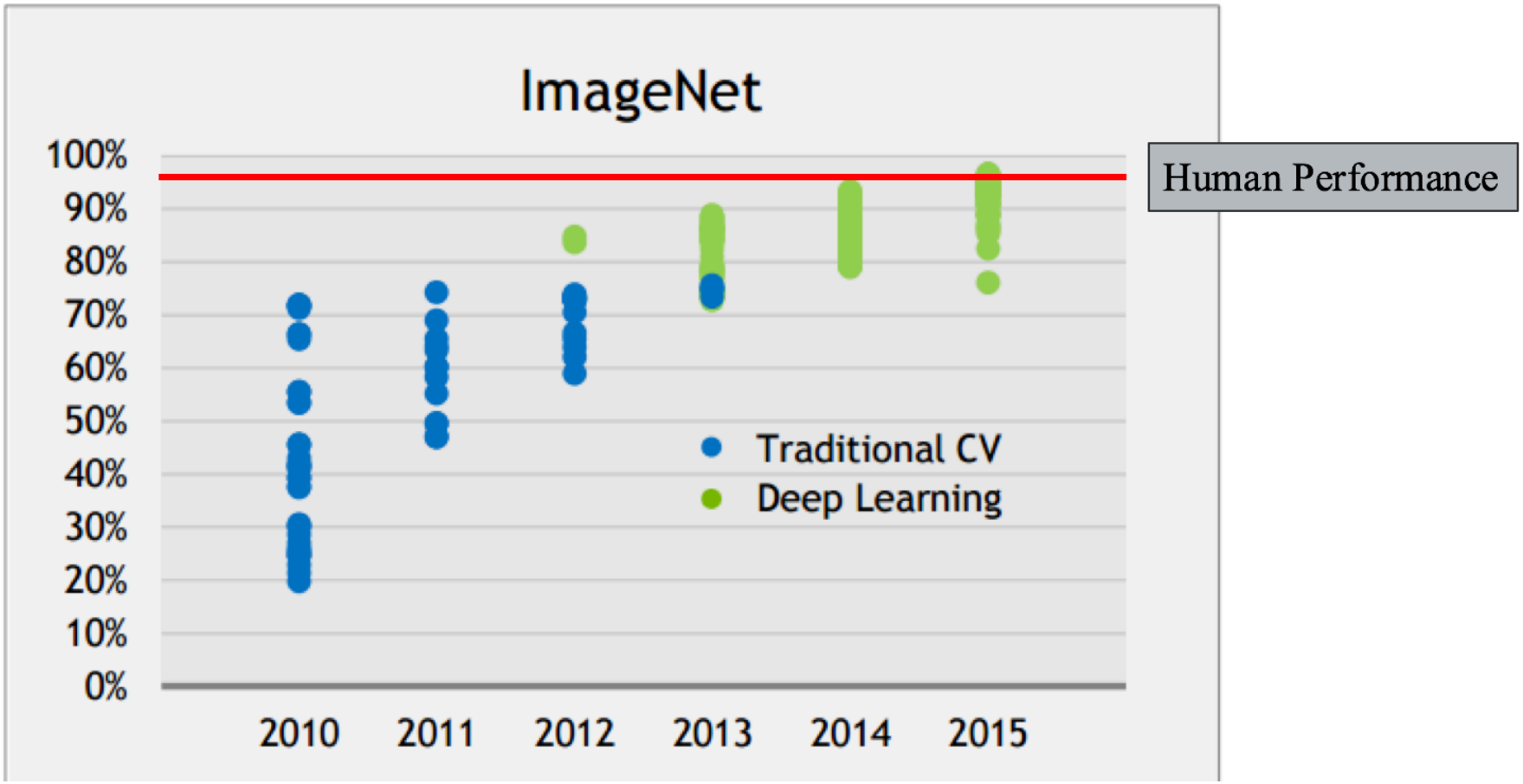
Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

Brief History – The Tipping Point

- Reported 15.4% Top 5 error rate. The next best entry achieved an error of 26.2%
- > 8000 citations (last year), by today >19000!
- The coming out party for CNNs in the computer vision community
- Shocked the computer vision community. Trained end-to-end on raw pixels, without using any feature engineering methods
- From here it was apparent that deep learning would take over computer vision and that other methods would not be able to catch up

Why ConvNets?

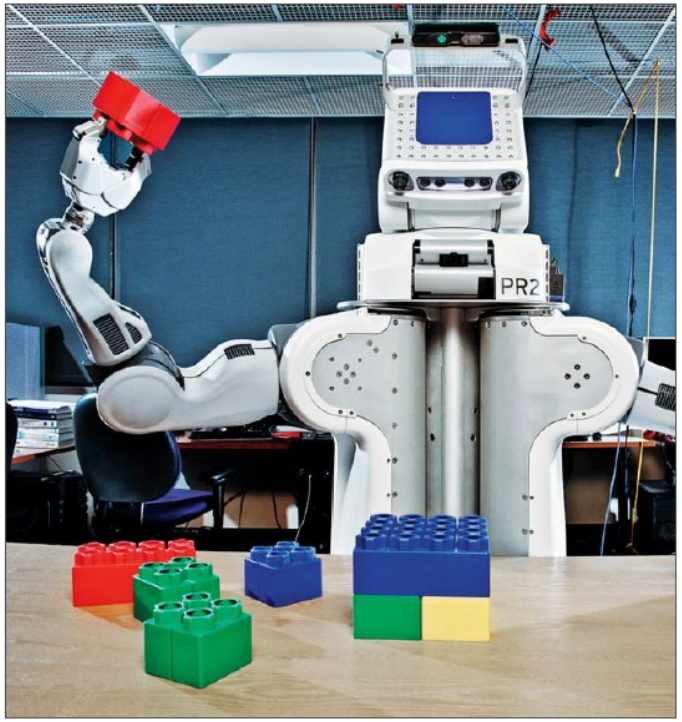


Brief History – So What Changed (since the 1970s)?

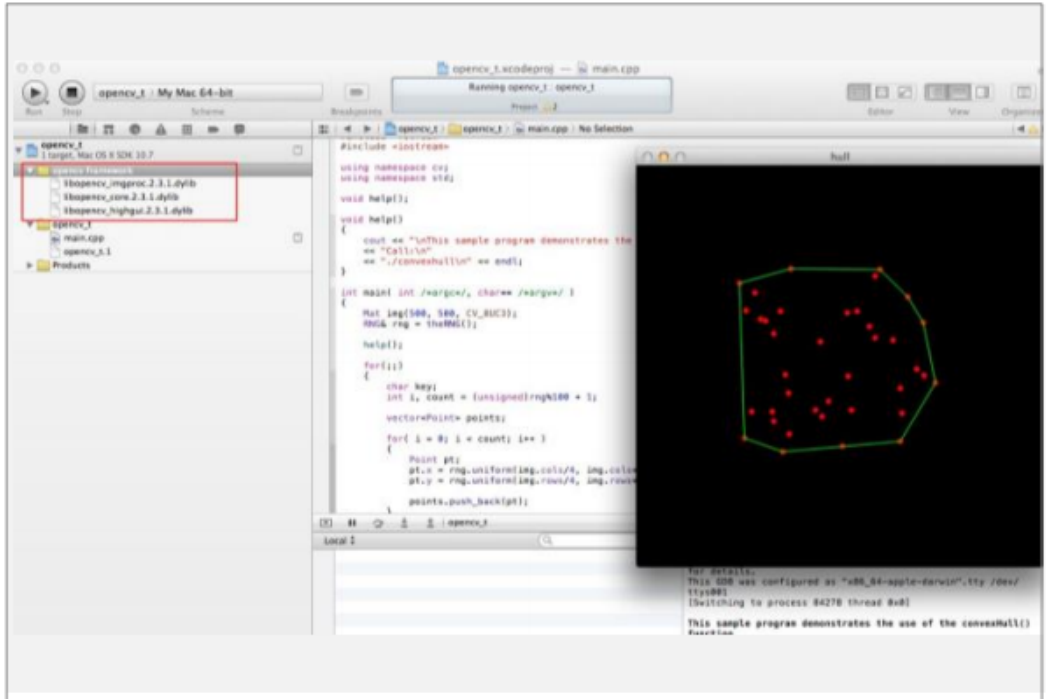
- Three things:
  - Availability of large amounts of labeled data e.g. ImageNet
  - Compute power – A single NVidia TITAN X card churns of 11 TFLOPS with ~3500 cores, **TITAN V**?
  - Algorithms:
    - ReLU - Found to decrease training time
    - Dropout – prevent overfitting to the training data

Deep Learning – Today – One Net To Rule Them All

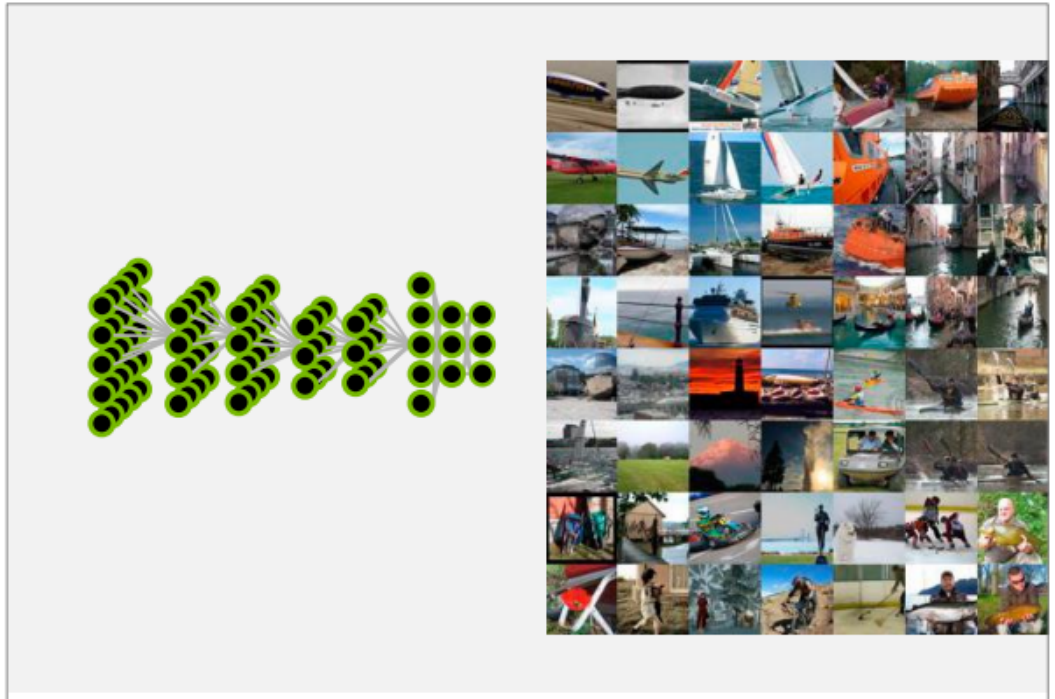
- Deep Learning == AI
- Solves problems previously unsolvable



A New Programming Model – Data Driven Paradigm



Traditional Computer Vision
Experts + Time



Deep Learning Object Detection
DNN + Data + HPC

Why Data Driven Paradigm?

- Consider Image Classification: a core task in Computer Vision

(assume given set of discrete labels)

{dog, cat, truck, plane, ...}

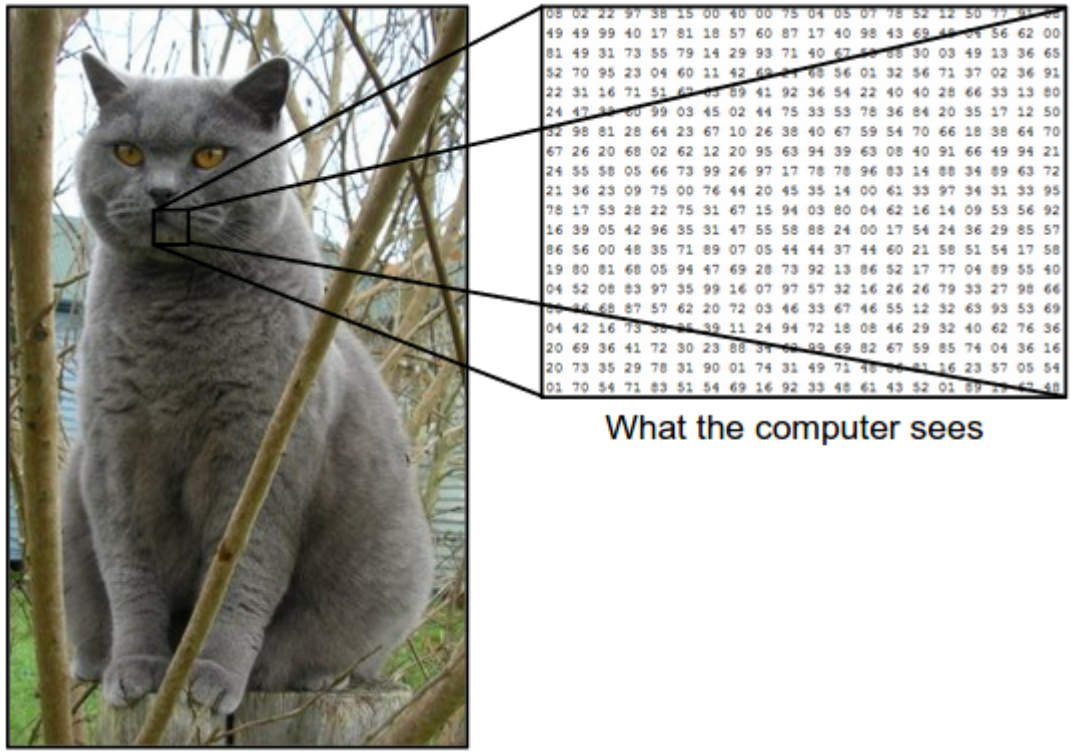
cat

Why Data Driven Paradigm?

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

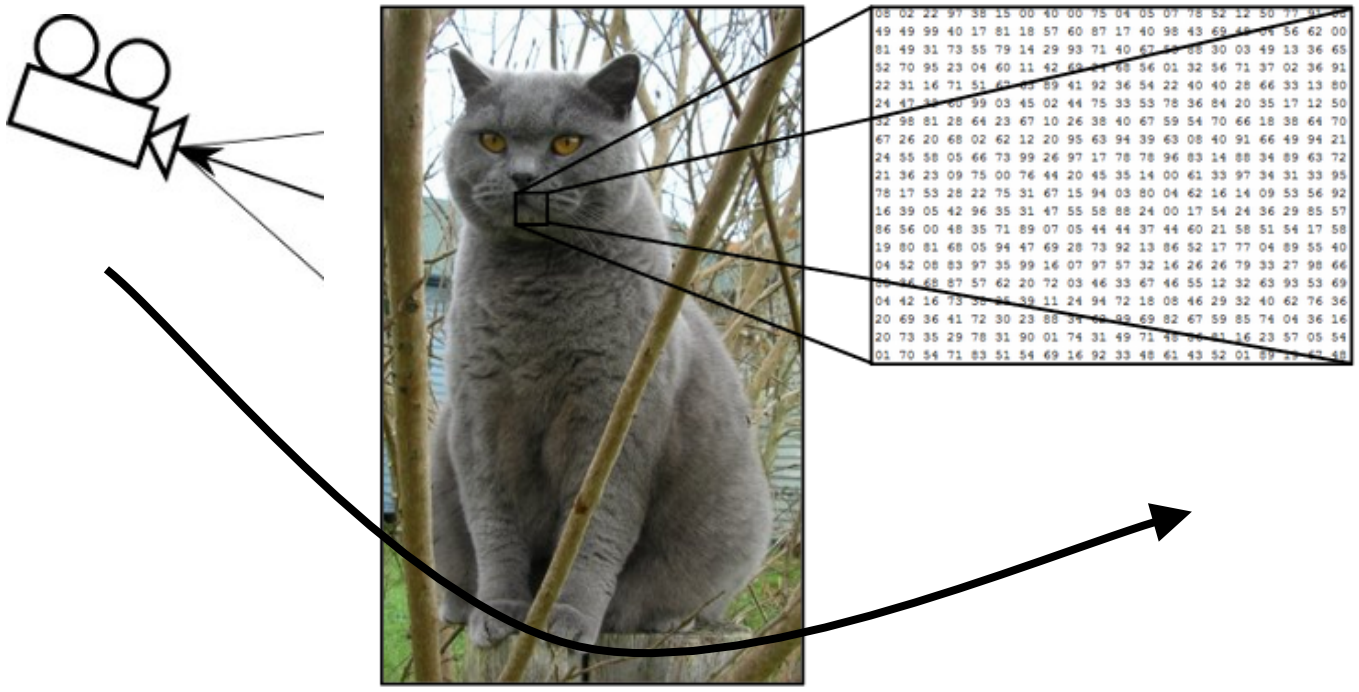
E.g.
300 x 100 x 3

(3 for 3 color channels RGB)

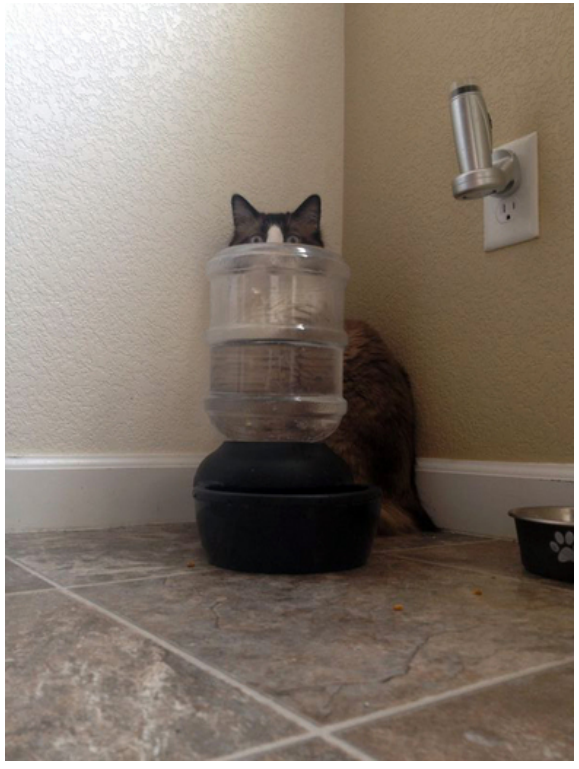


Why Data Driven Paradigm? – Invariant to Illumination

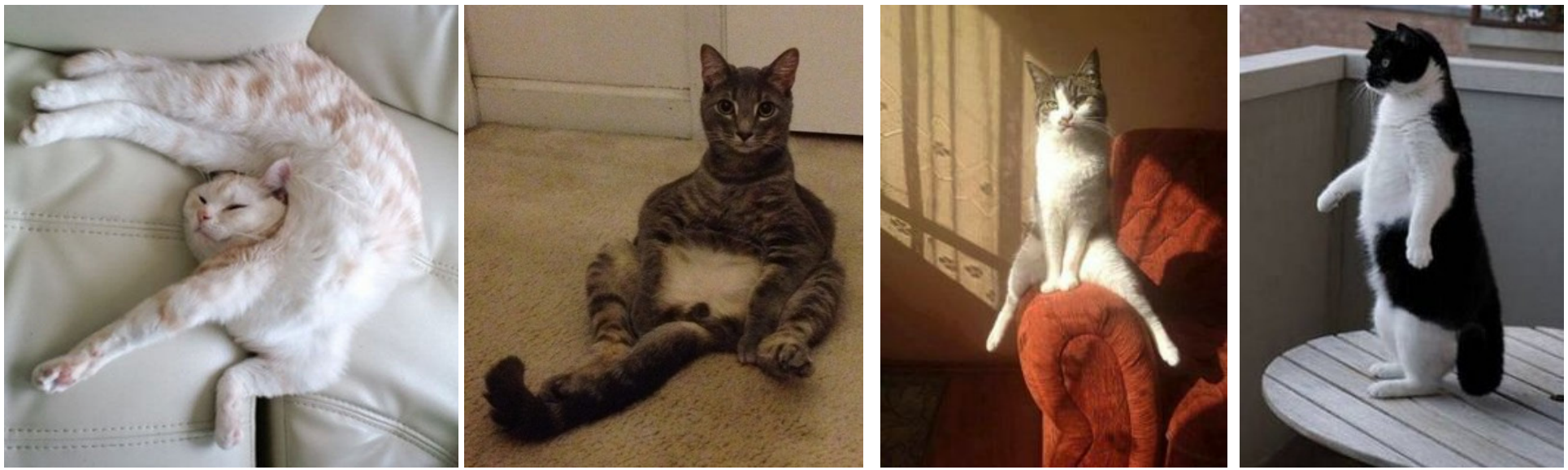
Why Data Driven Paradigm? – Invariant to Viewpoint



Why Data Driven Paradigm? – Deal with Occlusion



Why Data Driven Paradigm? – Invariant to Deformation



Why Data Driven Paradigm? – Deal with Background Clutter

Why Data Driven Paradigm? – Deal with Intra-class Variation

Why Data Driven Paradigm? – No Way To Hand Code It!

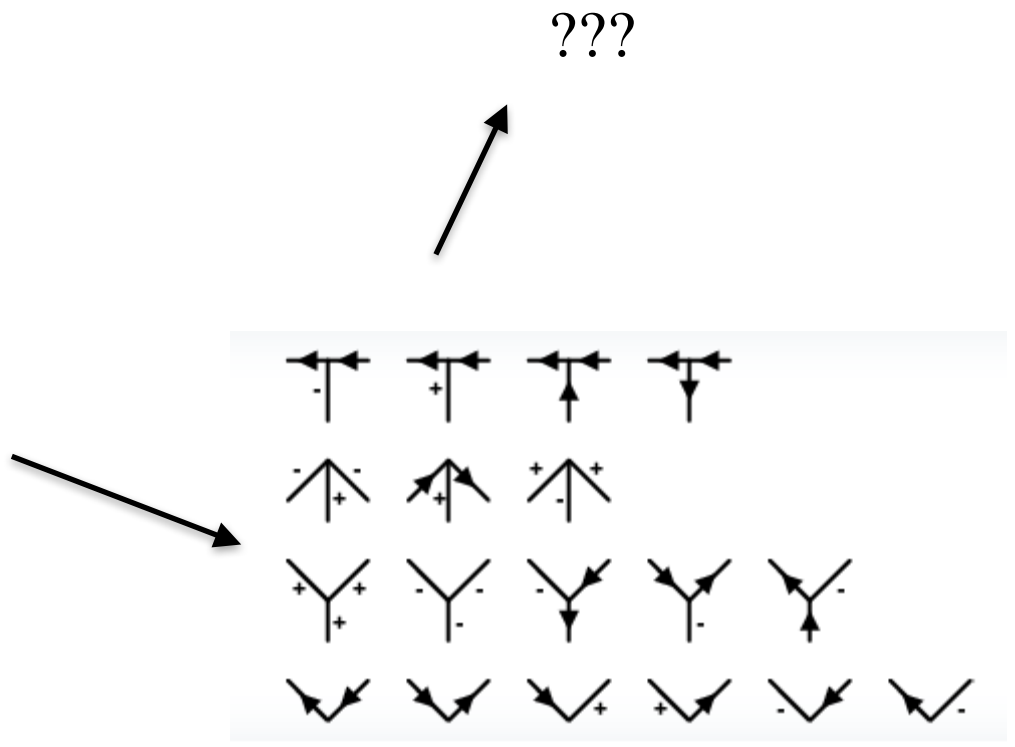
- Image classification:

```
function predict(image)
  -- ????
  return class_label
end
```

- Unlike e.g. sorting a list of numbers
- No obvious way to hard-code the algorithm for recognizing a cat, or other classes

Why Data Driven Paradigm? – People Have Attempted

- Image classification:



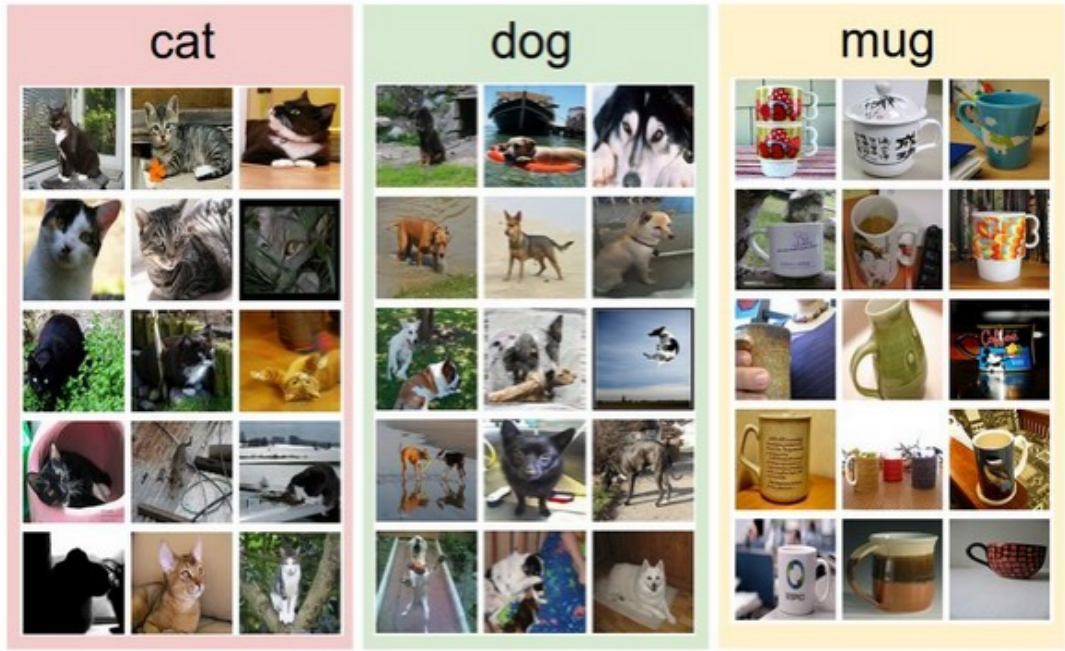
The Data Driven Paradigm

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

```
function train(train_images, train_labels)
  -- Build model: images -> labels
  return model
end


function predict(model, test_images)
  -- Predict test_labels using the model
  return test_labels
end
```

Example Training Set



Classifier 1: Nearest Neighbor Classifier

```
function train(train_images, train_labels)
  -- Build model: images -> labels
  return model
end
```

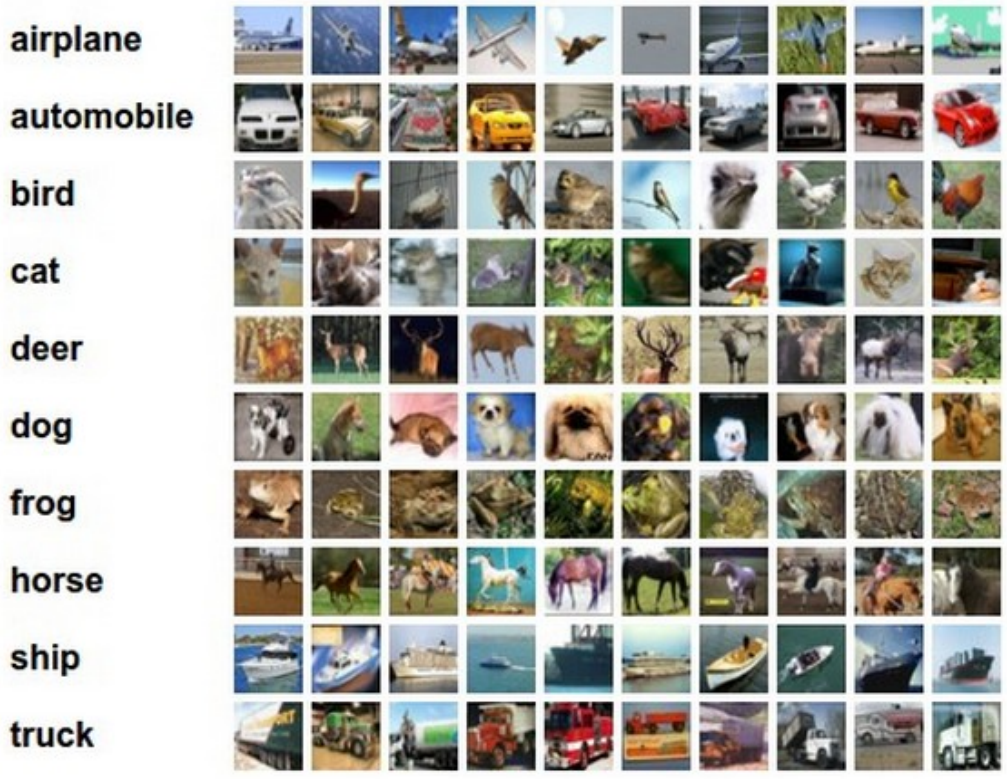
Remember all training images and their labels

```
function predict(model, test_images)
  -- Predict test_labels using the model
  return test_labels
end
```

Predict the label of the most similar training image

Example Dataset: CIFAR-10

10 labels
50,000 training images
10,000 test images.



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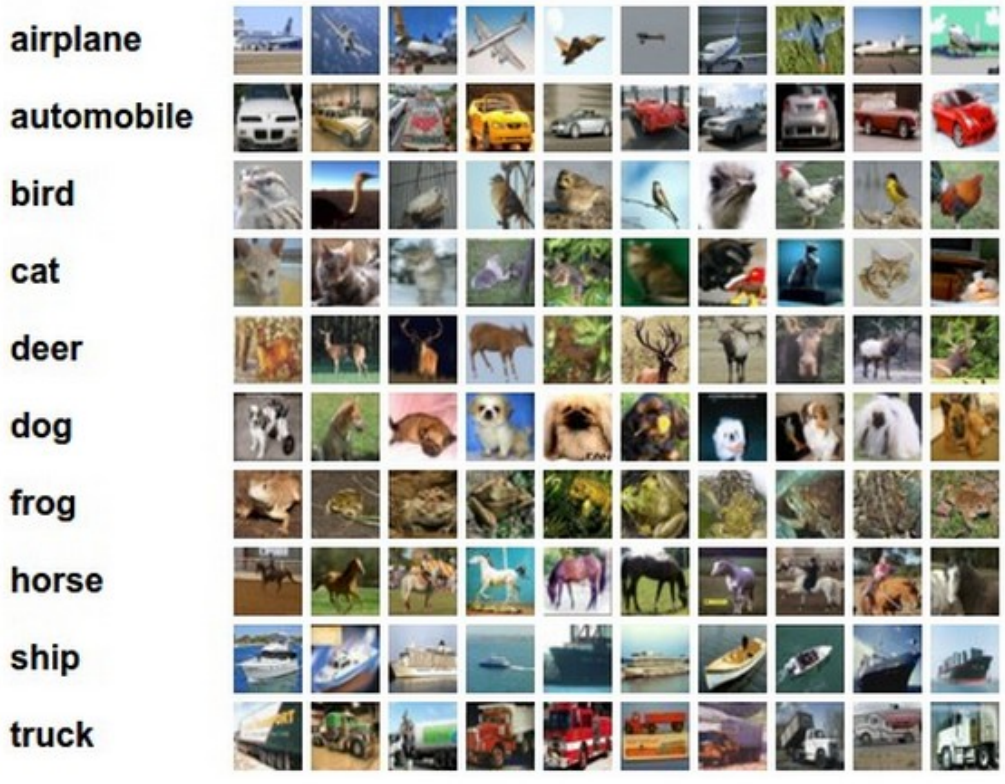
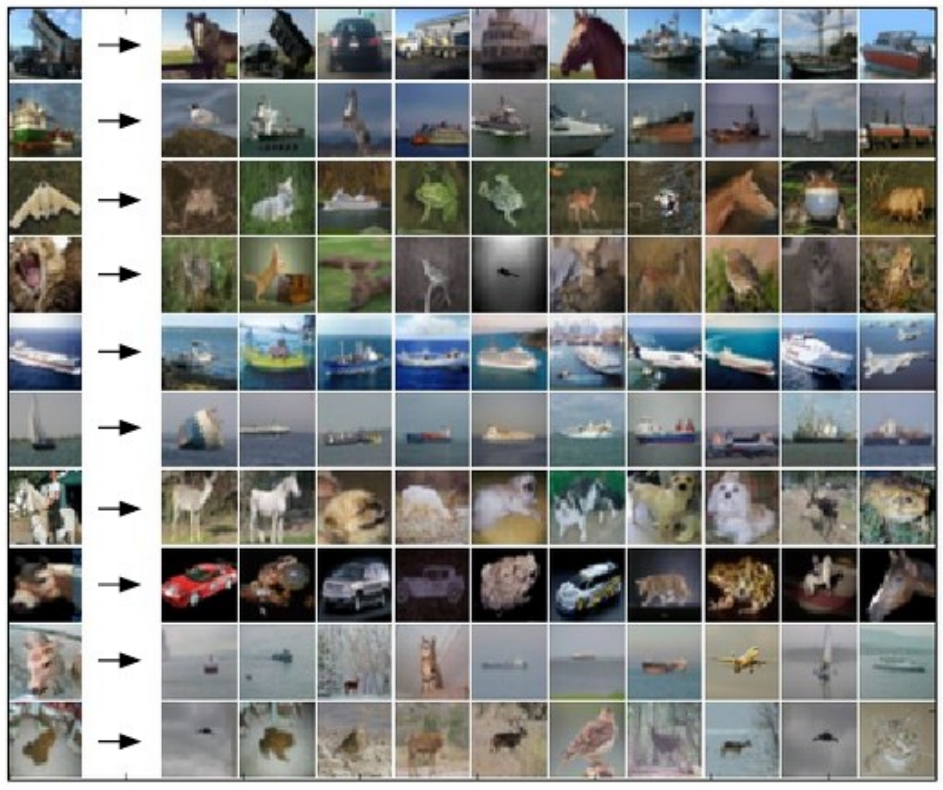
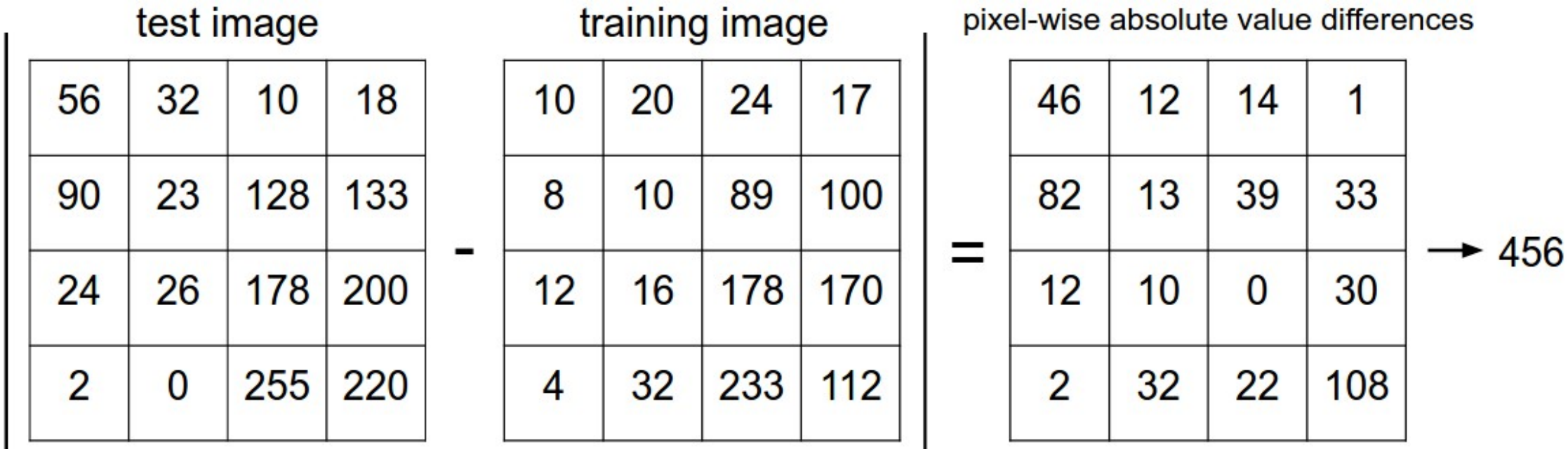


For every test image (first column), examples of nearest neighbors in rows



How Do We Compare the Images? What is the Distance Metric?

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



Nearest Neighbor Classifier

```
function predict(image)
  -- ????
  return class_label
end
```

Nearest Neighbor Classifier

In [4]:

```
local NN = torch.class("NN")

function NN:__init()
end

function NN:train(X, y)
  -- X is 2D of size N x D = 32x32x3, so each row is an example
  -- Y is 1D of size N
  self.tr_x = X
  self.tr_y = y
end

function NN:predict(x)
  -- x is of size D = 32x32x3 for which we want to predict the label
  -- returns the predicted label for the input x
  local min_idx = nil
  local min_dist = 1e10
  for i=1, self.tr_x:size(1) do
    local dist = (self.tr_x[i] - x):float():abs():sum()
    if (dist < min_dist) then
      min_dist = dist
      min_idx = i
    end
  end
  return self.tr_y[min_idx]
end
```

Nearest Neighbor Classifier

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end
```

remember the training data

Nearest Neighbor Classifier

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    end
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end
```

For the test image:

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

Nearest Neighbor Classifier

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    if (dist < min_dist) then
      min_dist = dist
      min_idx = i
    end
  end
  return self.tr_y[min_idx]
end
```

In [5]:
```
classifier = NN.new()
classifier:train(tr_x, tr_y)

itorch.image(te_x[100])
print (classifier:predict(te_x[100]))

itorch.image(te_x[110])
print (classifier:predict(te_x[110]))

itorch.image(te_x[120])
print (classifier:predict(te_x[120]))

itorch.image(te_x[130])
print (classifier:predict(te_x[130]))

itorch.image(te_x[140])
print (classifier:predict(te_x[140]))
```

Out[5]: 7

Out[5]: 7

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Nearest Neighbor Classifier

In [4]:

```
local NN = torch.class("NN")

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  -- X is 2D of size N x D = 32x32x3, so each row is an example
  -- Y is 1D of size N
  self.tr_x = X
  self.tr_y = y
end

function NN:predict(x)
  -- x is of size D = 32x32x3 for which we want to predict the label
  -- returns the predicted label for the input x
  local min_idx = nil
  local min_dist = 1e10
  for i=1, self.tr_x:size(1) do
    local dist = (self.tr_x[i] - x):float():abs():sum()
    if (dist < min_dist) then
      min_dist = dist
      min_idx = i
    end
  end
  return self.tr_y[min_idx]
end
```

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

Nearest Neighbor Classifier

In [4]:
```
local NN = torch.class("NN")

function NN:__init()
end

function NN:train(X, y)
  -- X is 2D of size N x D = 32x32x3, so each row is an example
  -- Y is 1D of size N
  self.tr_x = X
  self.tr_y = y
end

function NN:predict(x)
  -- x is of size D = 32x32x3 for which we want to predict the label
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    local dist = (self.tr_x[i] - x):float():abs():sum()
    if (dist < min_dist) then
      min_dist = dist
      min_idx = i
    end
  end
  return self.tr_y[min_idx]
end
```

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

The Choice of Distance is a **Hyperparameter**

Common choices:

L1 distance

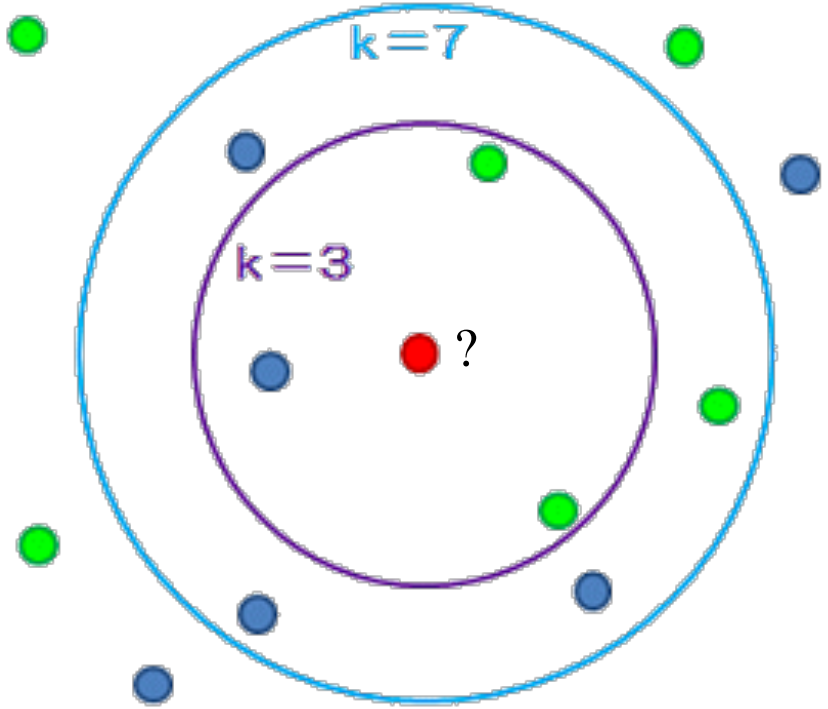
$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

L2 (Euclidean) distance

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

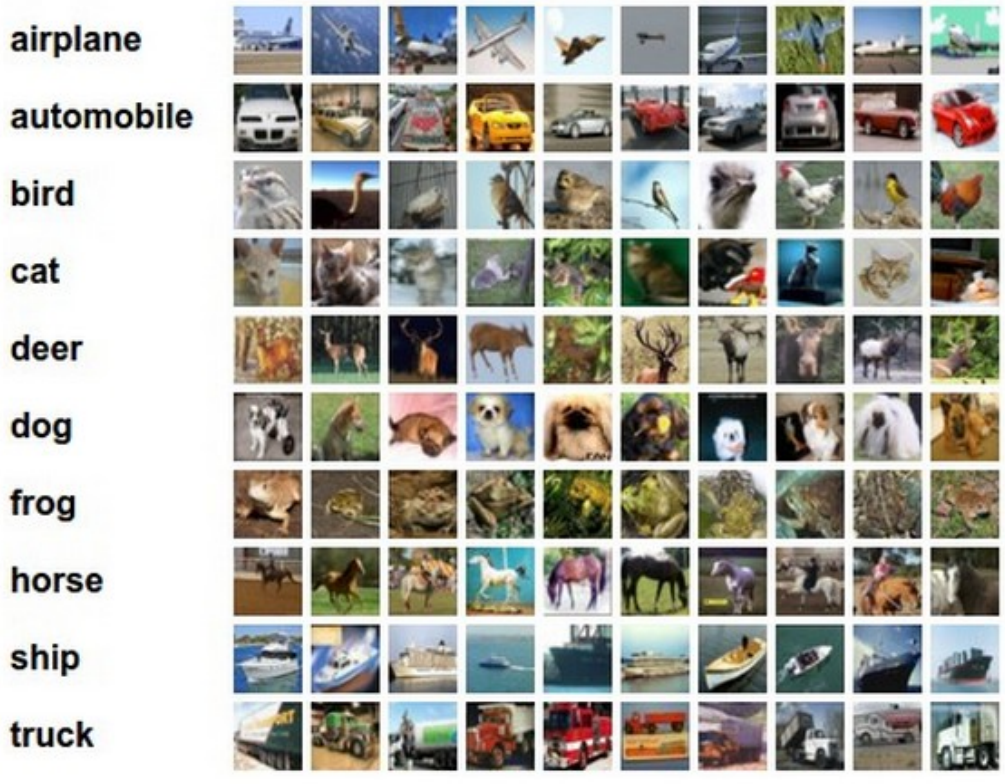
K-Nearest Neighbor Algorithm

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

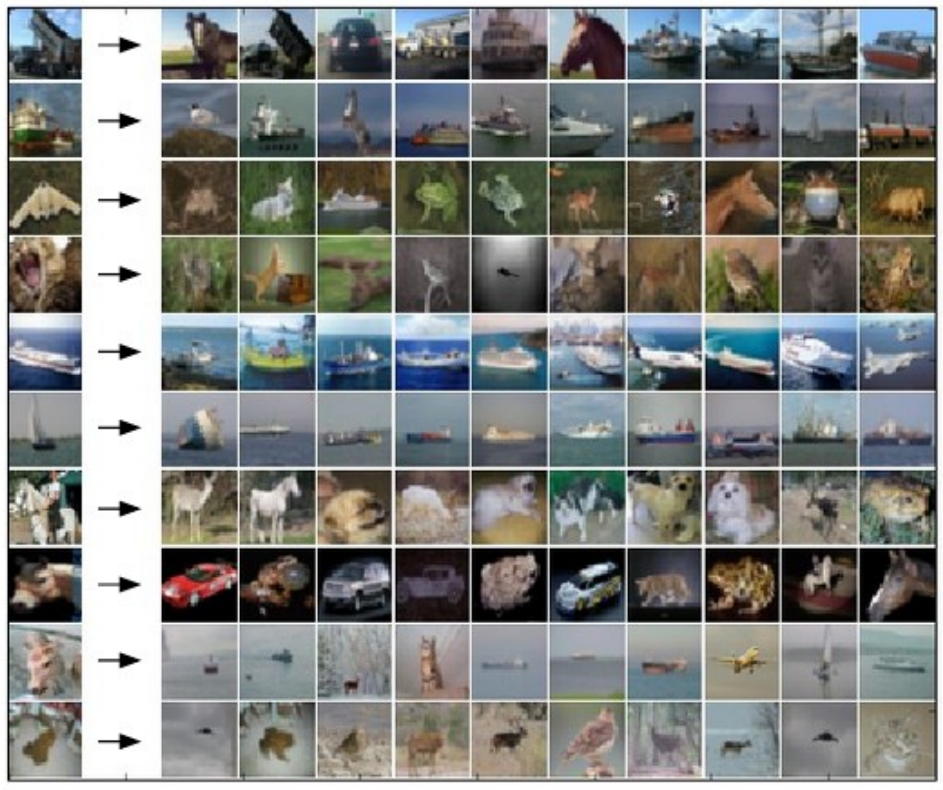


Example Dataset: CIFAR-10

10 labels
50,000 training images
10,000 test images.



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



Example Dataset: CIFAR-10

10 labels
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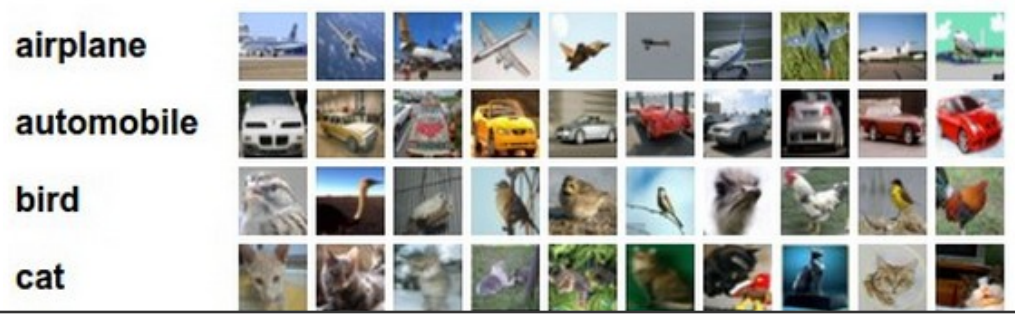
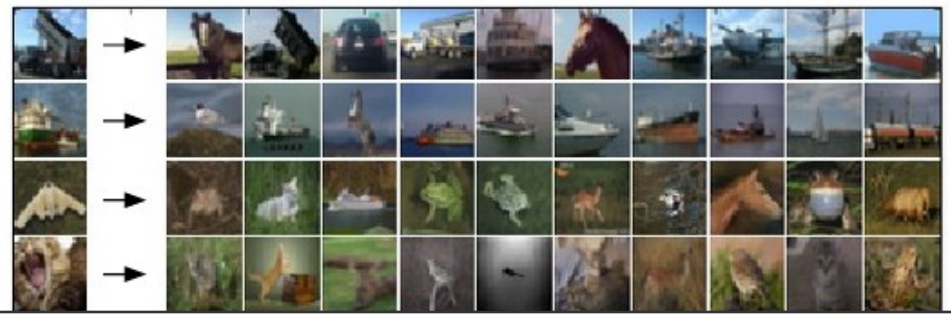


For every test image (first column),
examples of nearest neighbors in rows



Q1: What is the accuracy of the nearest neighbor classifier on the **test** data, when using the Euclidean distance? What about L1 distance?

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

Q2: What is the accuracy of the **k**-nearest neighbor classifier on the **test** data? What is the best value of **k**?

How Do We Set the **Hyperparameters**?

What is the best distance to use?

What is the best value of k to use?

How Do We Set the **Hyperparameters**?

What is the best distance to use?

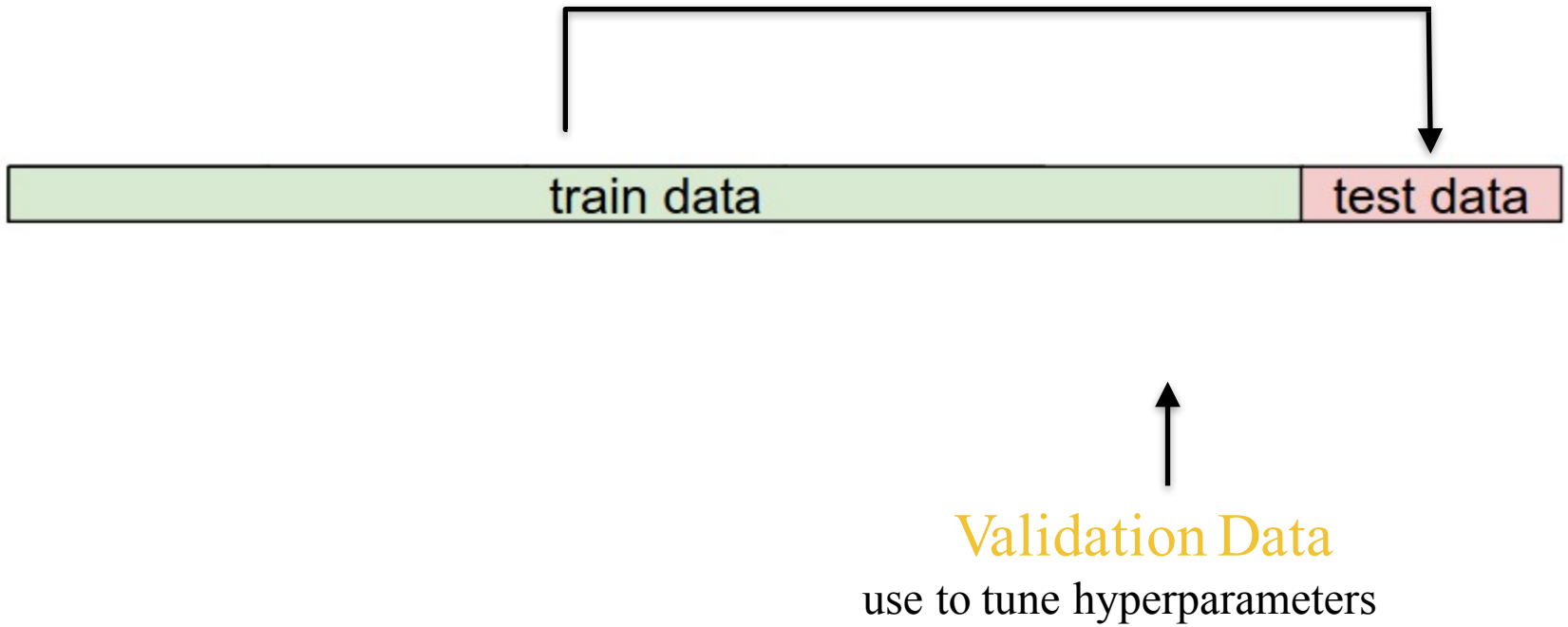
What is the best value of k to use?

Very problem-dependent.

Must try them all out and see what works best.

Try Out What Hyperparameters that Work Best on **Test Set**

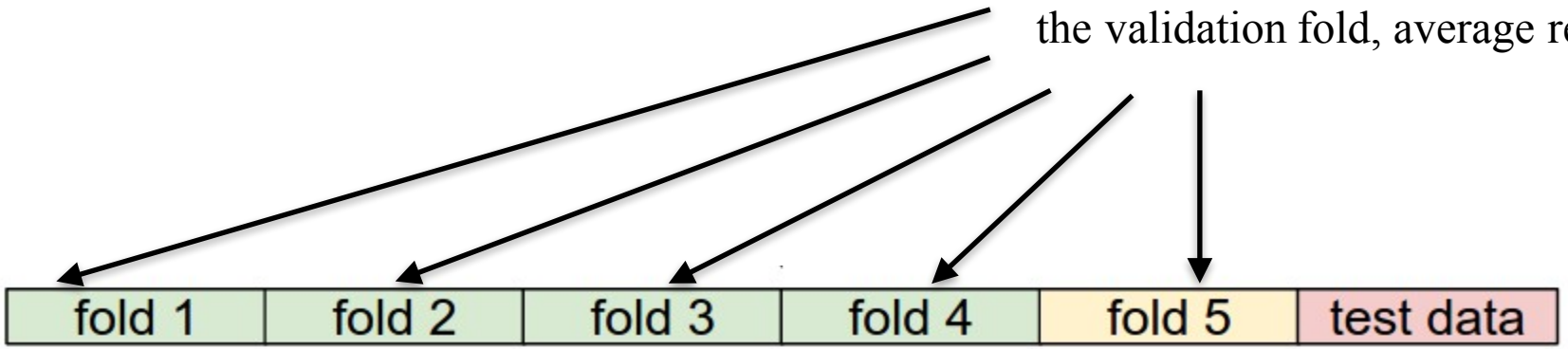
Bad idea (unless trying to win a competition where test set is given).
The test set is a proxy for the generalization performance!
Use only **VERY SPARINGLY,** at the end.



Try Out What Hyperparameters that Work Best on **Test Set**

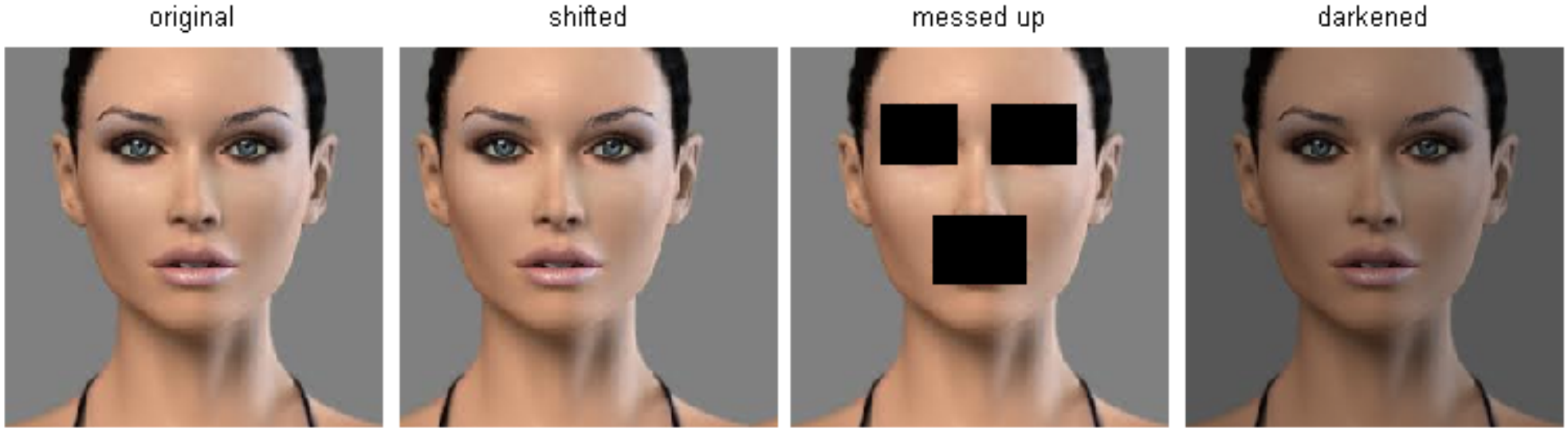
Cross-validation

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



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)

K-Nearest Neighbor on Images Never Used

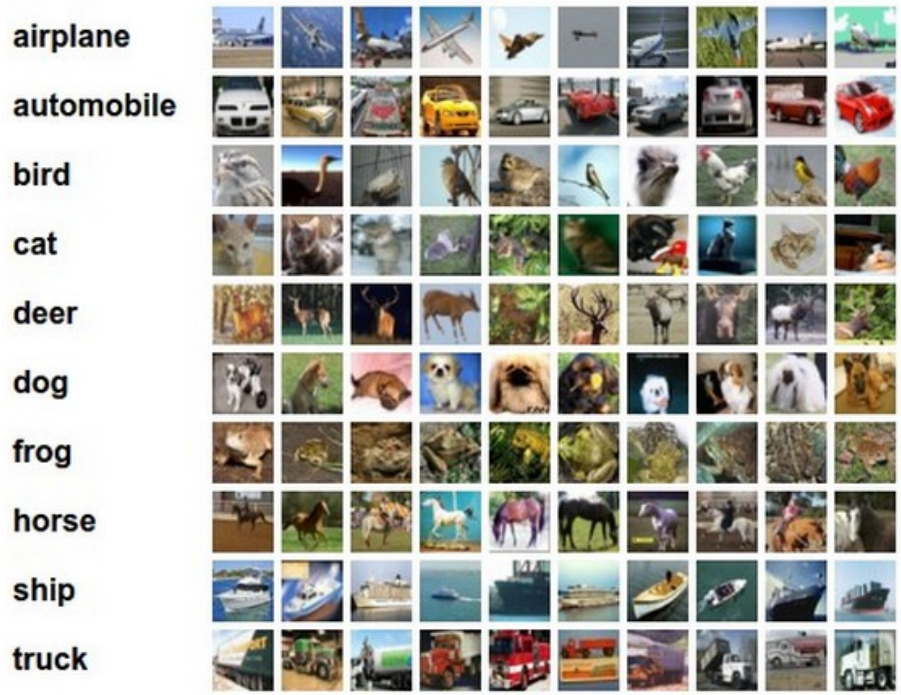
- **Image Classification:** We are given a **Training Set** of labeled images, asked to predict labels on **Test Set**. Common to report the **Accuracy** of predictions (fraction of correctly predicted images)
- We introduced the **k-Nearest Neighbor Classifier**, which predicts the labels based on nearest images in the training set
- We saw that the choice of **distance** and the value of are **hyperparameters** that are tuned using a validation set, or through **cross-validation** if the size of the dat**k**a 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.

K-Nearest Neighbor on Images Never Used

- k-NN classifier:
  - must remember all of the training data and store it for future comparisons with the test data
  - This is space inefficient because datasets may easily be gigabytes in size
  - Classifying a test image is expensive since it requires a comparison to all training images

Parametric Approach: CIFAR-10

10 labels
50,000 training images
10,000 test images
each image is an array of size **32 x 32 x 3 = 3072** numbers total



Parametric Approach

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

Image

$f(x, W)$

10 numbers, indicating class scores

parameters, or "weights"

Parametric Approach: Linear Classifier

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

10x1

3072x1

$f(x, W) = Wx$

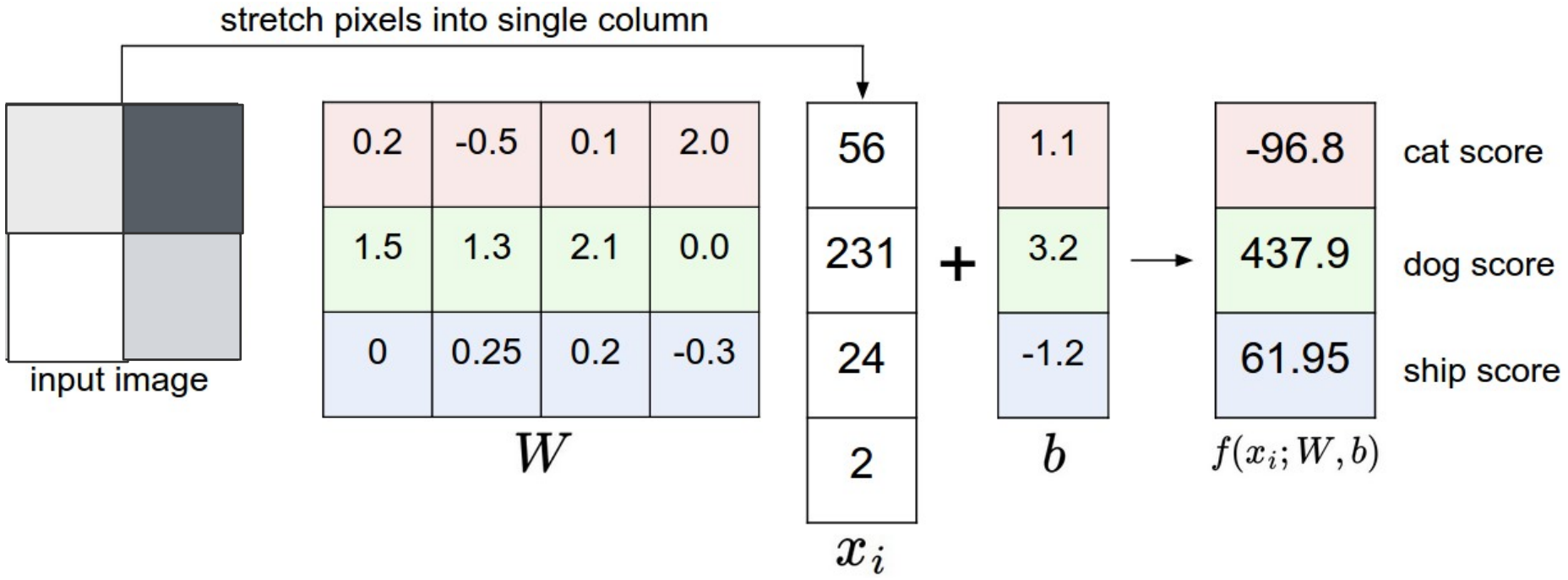
(+b) 10x1

10x3072

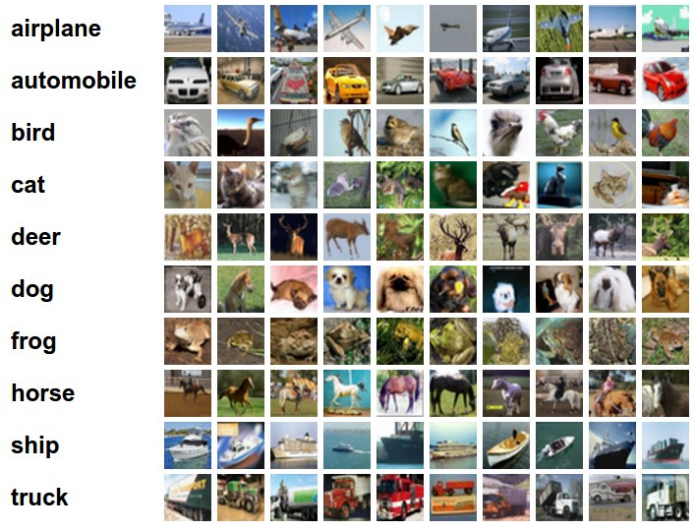
10 numbers, indicating class scores

parameters, or "weights"

Example with an Image with 4 Pixels, and 3 Classes (**cat**/**dog**/**ship**)

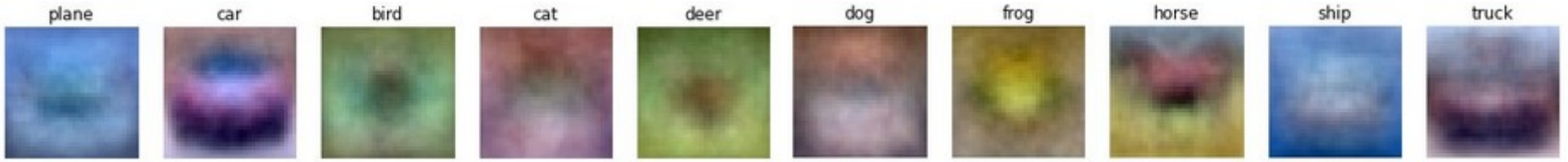


Interpreting a Linear Classifier

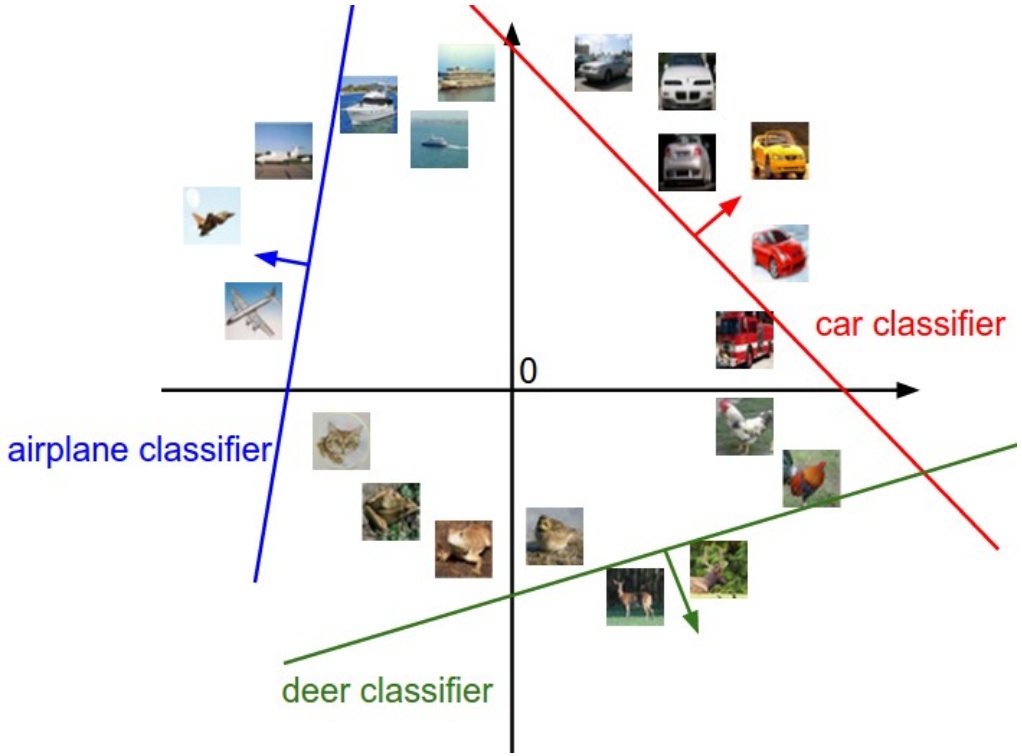


$$f(x_i, W, b) = Wx_i + b$$

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)

Thank you!