Introduction to Deep Learning

Dr. Arjun Jain

Agenda

- History and Evolution of Neural Networks
- Tipping Point for Deep Learning
- Why Deep Learning and the Data Driven Paradigm
- Training a classifier (without any trainable parameters) – KNN
- Training a classifier (with trainable parameters) – Linear Classifier

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Brief History

Hubel & Wiesel,

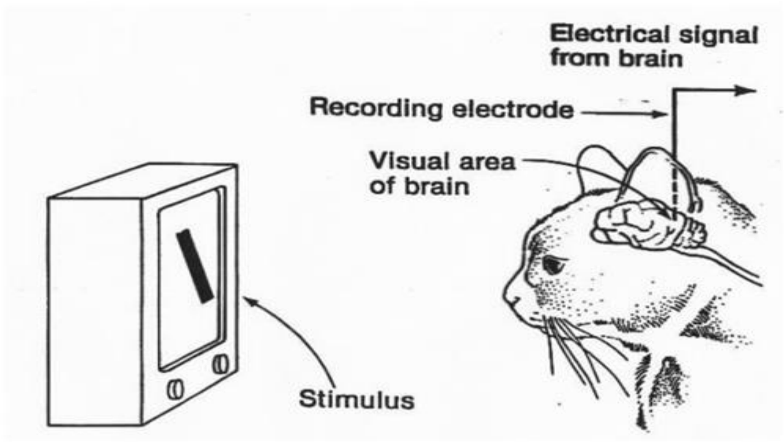
1959

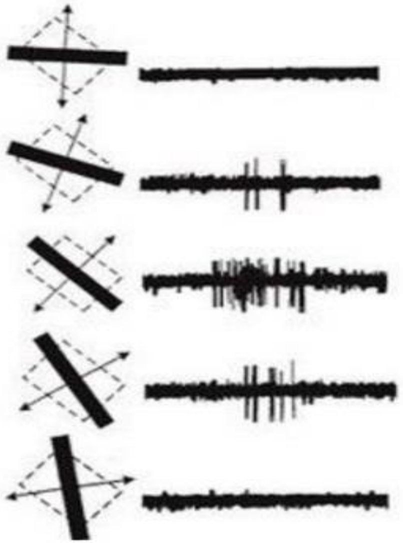
RECEPTIVE FIELDS OF SINGLE NEURONES IN
THE CAT'S STRIATE CORTEX

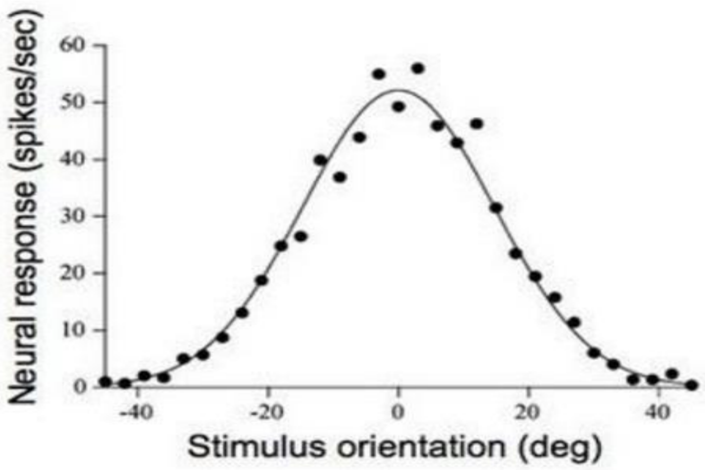
1962

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

1968...







Sourced from: Receptive fields of single Neurons in the Cat's Striate Cortex by D.H.Hubel and T.N.Wiesel

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Video Source: Cortical Neuron, Hubel & Wiesel, Youtube (https://youtu.be/8VdFf3egwfg)

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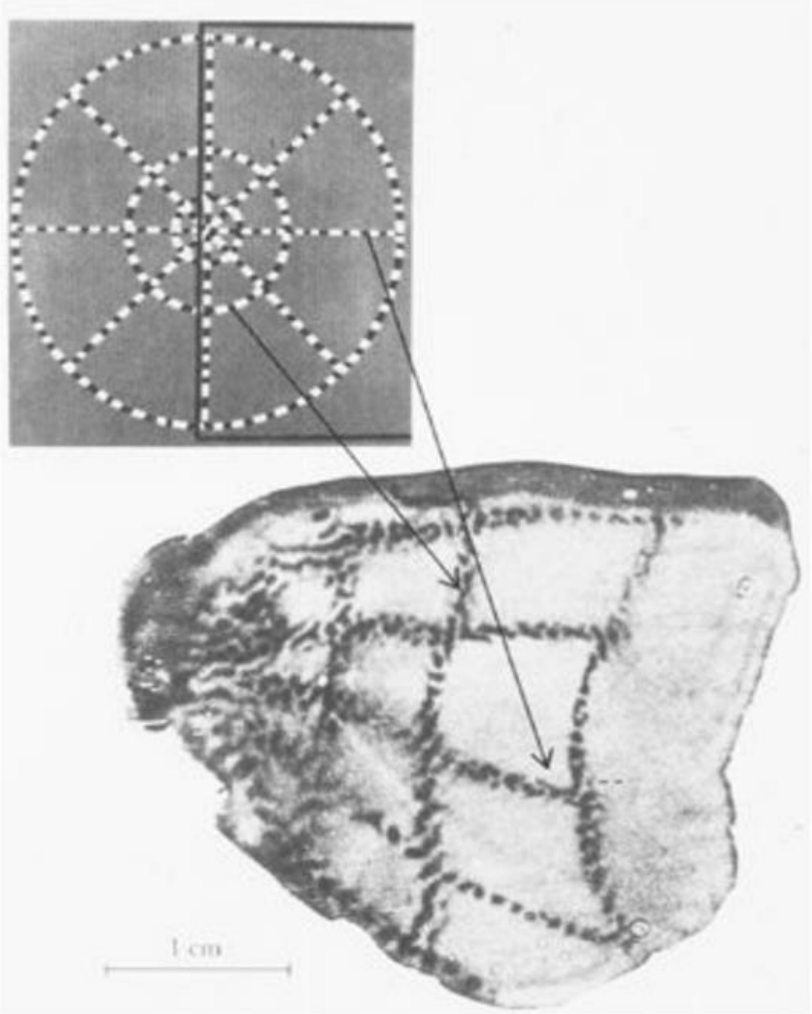
Brief History

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



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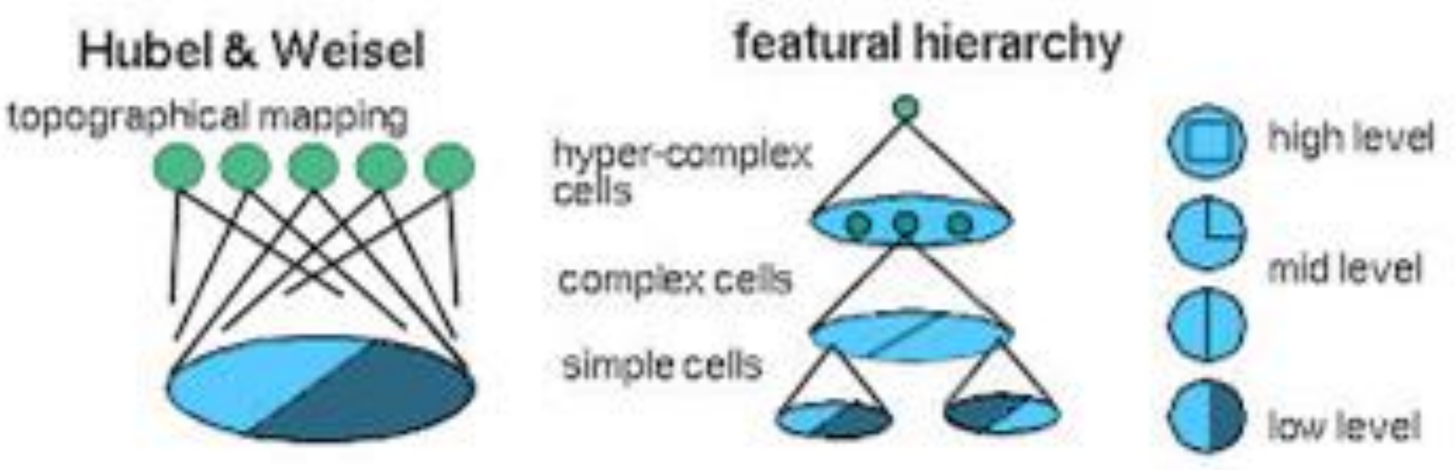
Hierarchical Organization



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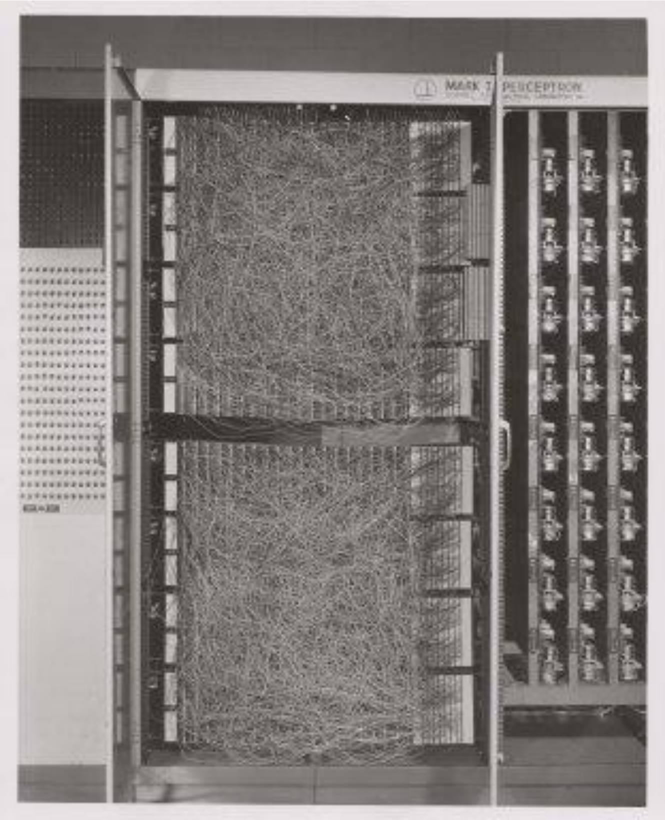
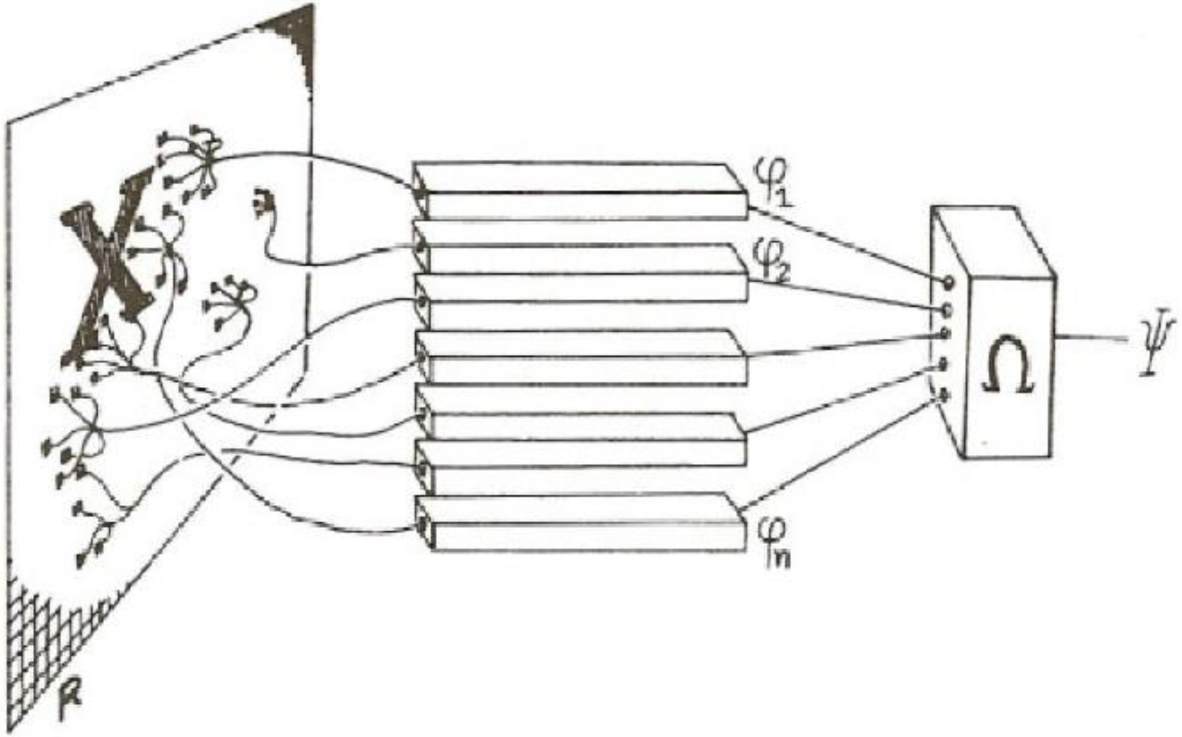
Brief History – Mark I Perceptron – 1958





Source: Perceptrons, Wikipedia

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

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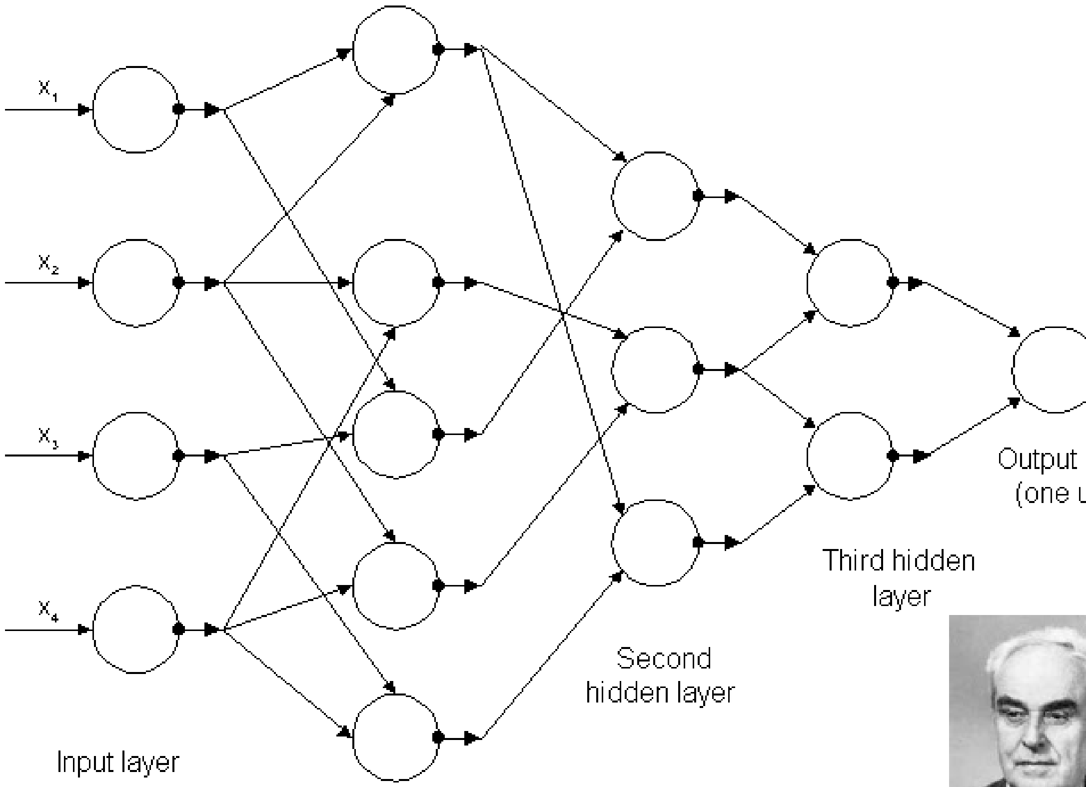
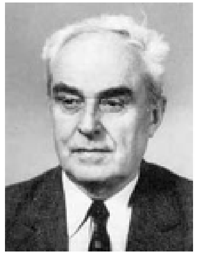
Brief History – The First Deep Networks

- 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

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Brief History – The First ConvNet - 1980

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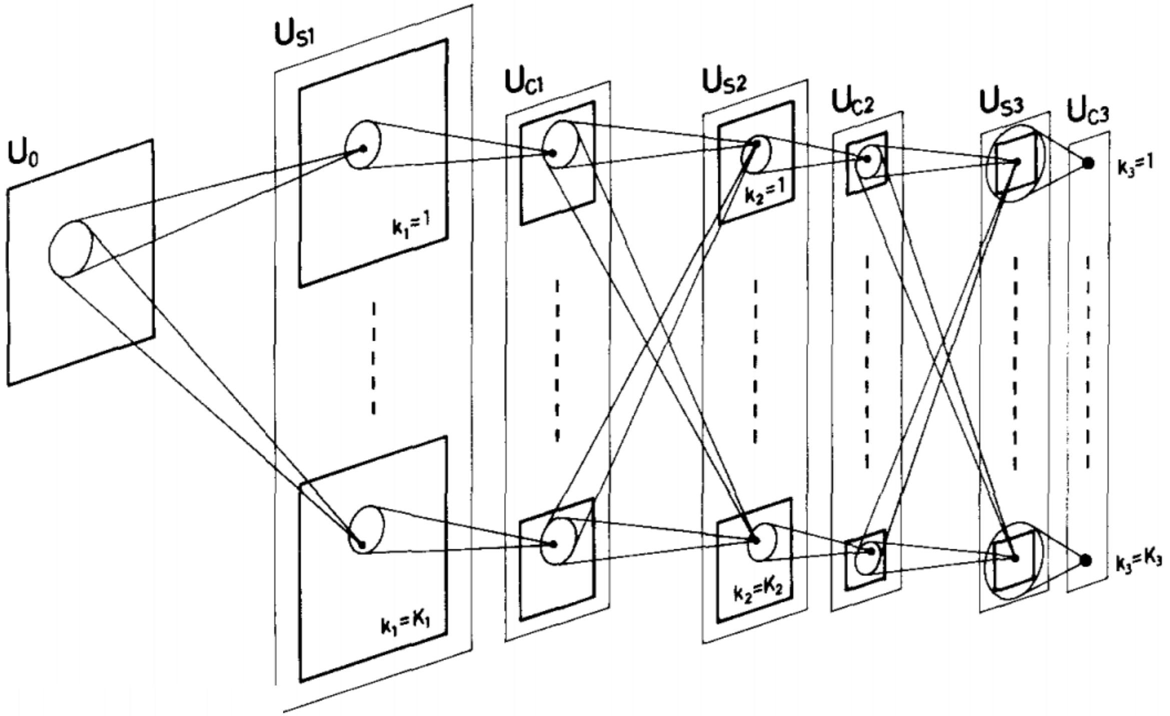
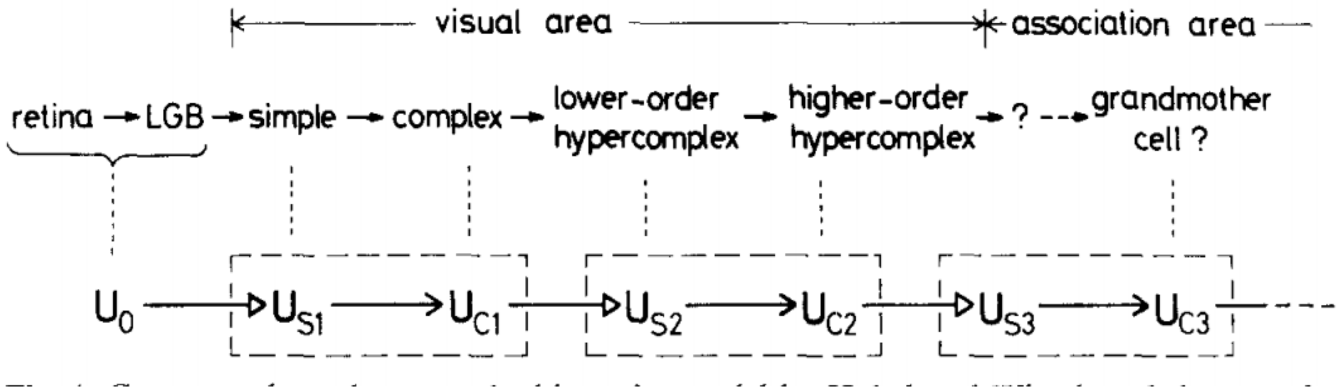
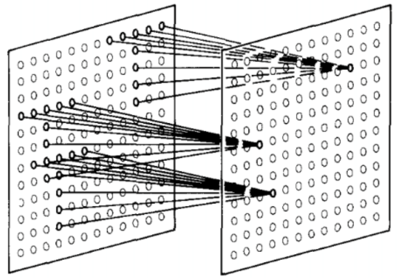
Learning for Life



- 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

Image Credits : Google

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Brief History

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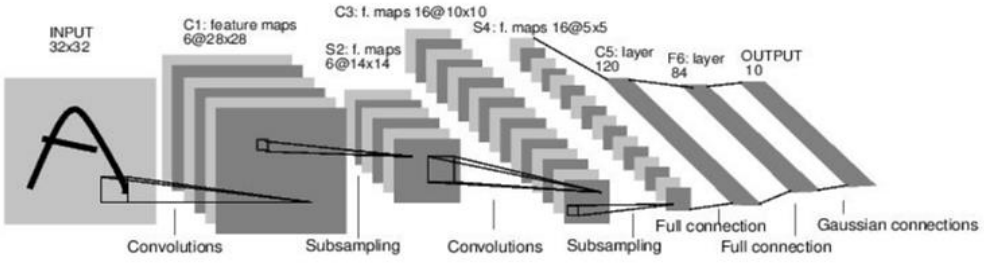
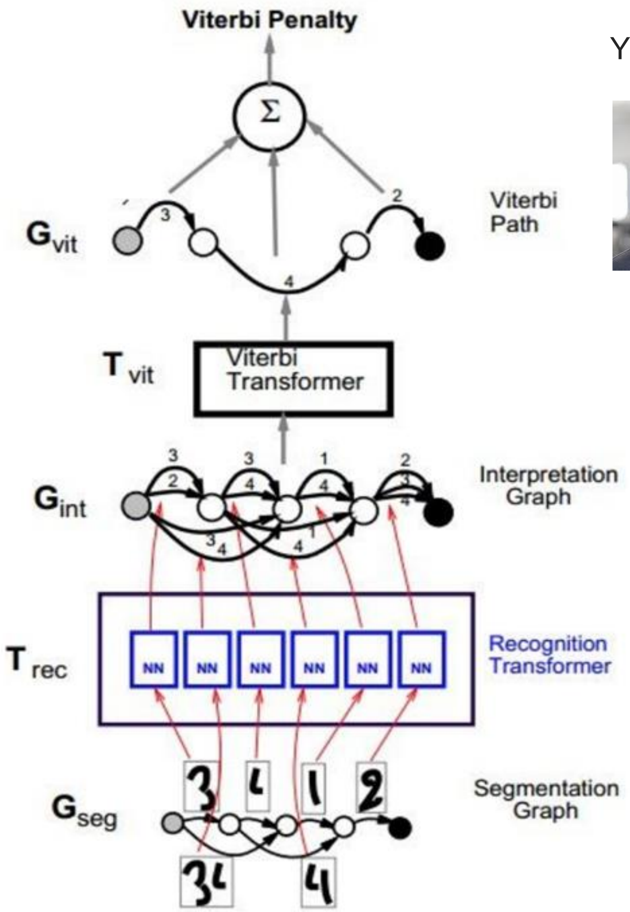
A bit of history:

Gradient-based learning applied to document recognition

[LeCun, Bottou, Bengio, Haffner 1998]



LeNet-5



Yann LeCun

Sourced from: GradientBased Learning Applied to Document Recognition, LeCun et al. (1998)

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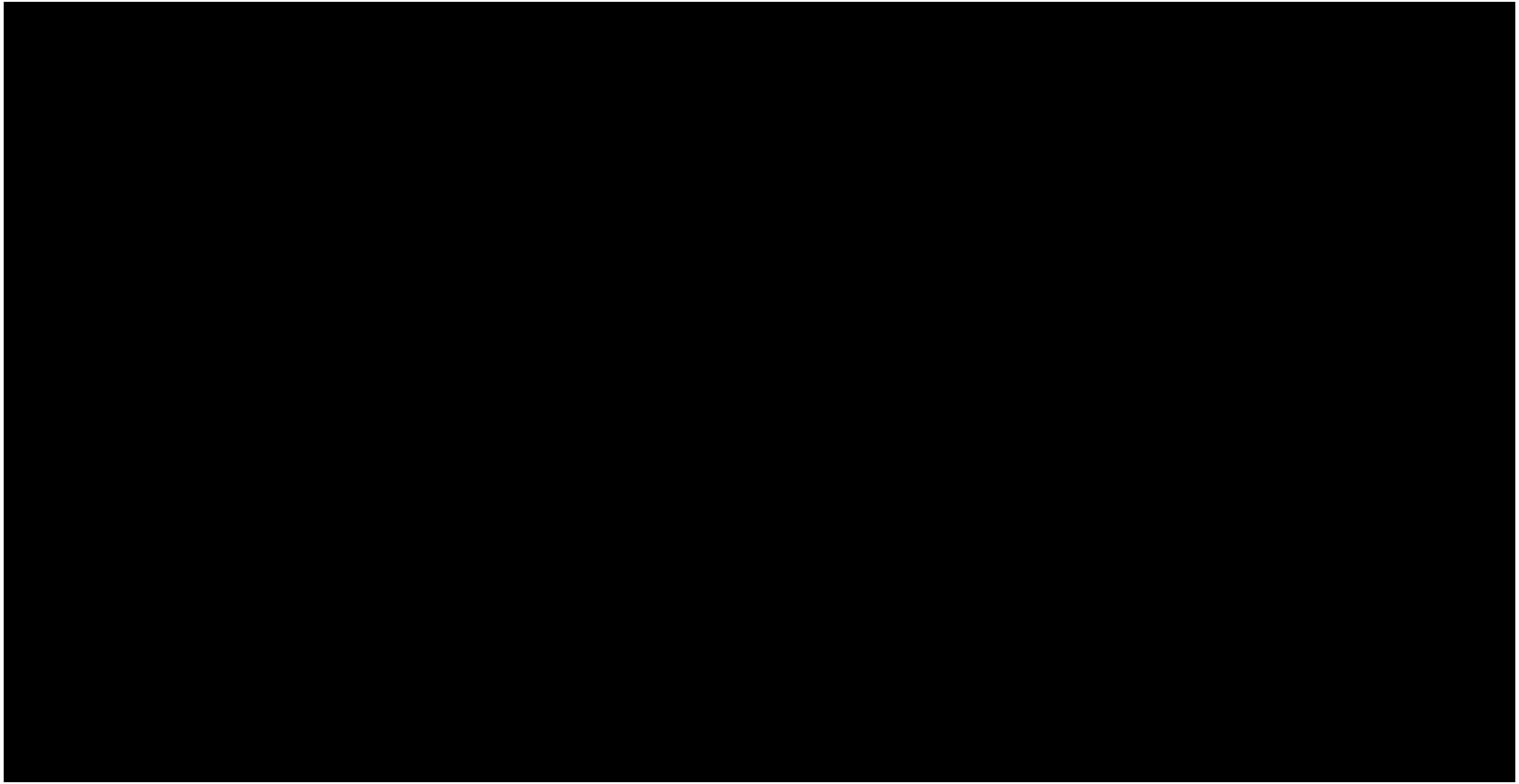
Brief History – LeNet-5 in Action



Video Source: Convolutional Network Demo from 1993, Youtube (https://youtu.be/FwFduRA_L6Q?t=6s)

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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

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Brief History – AI Winter

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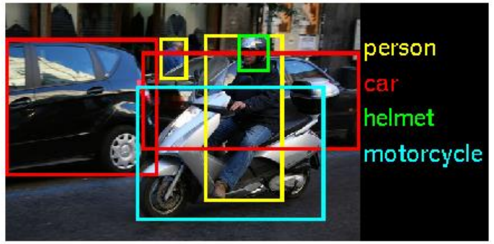
Brief History – The Tipping Point

- 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
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Ilya Sutskever
University of Toronto
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University of Toronto
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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

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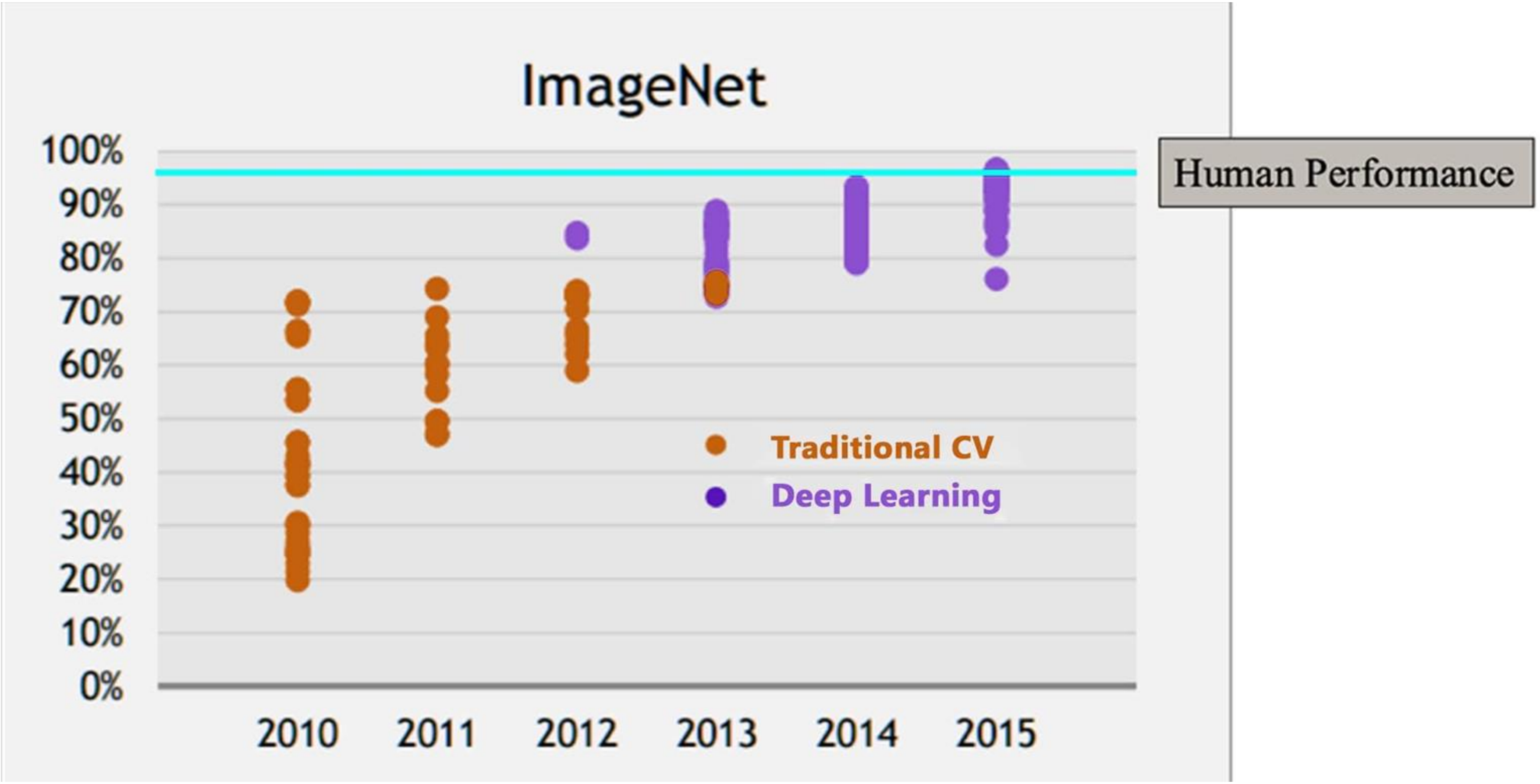
Why ConvNets?



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Brief History – So What Changed (since the ‘70s)?

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

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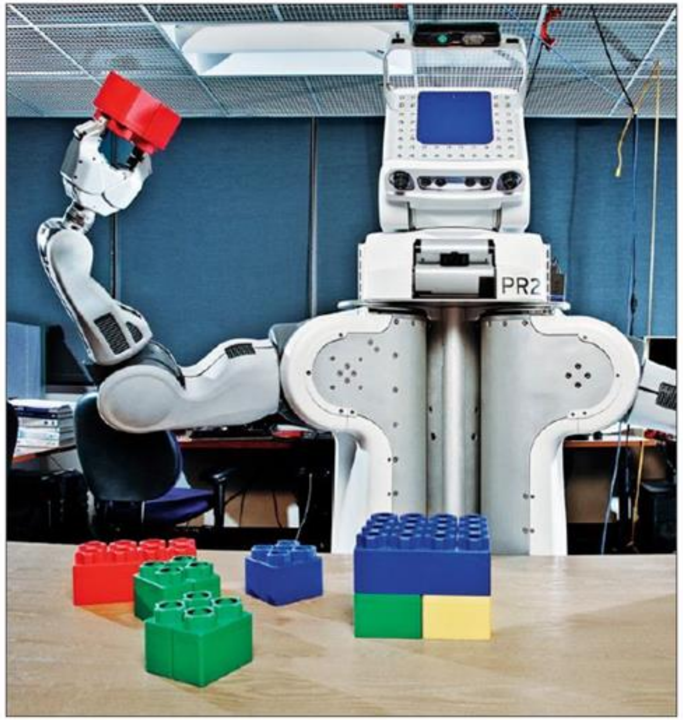
Deep Learning – Today – One Net To Rule Them All

- Deep Learning == AI
- Solves problems previously unsolvable



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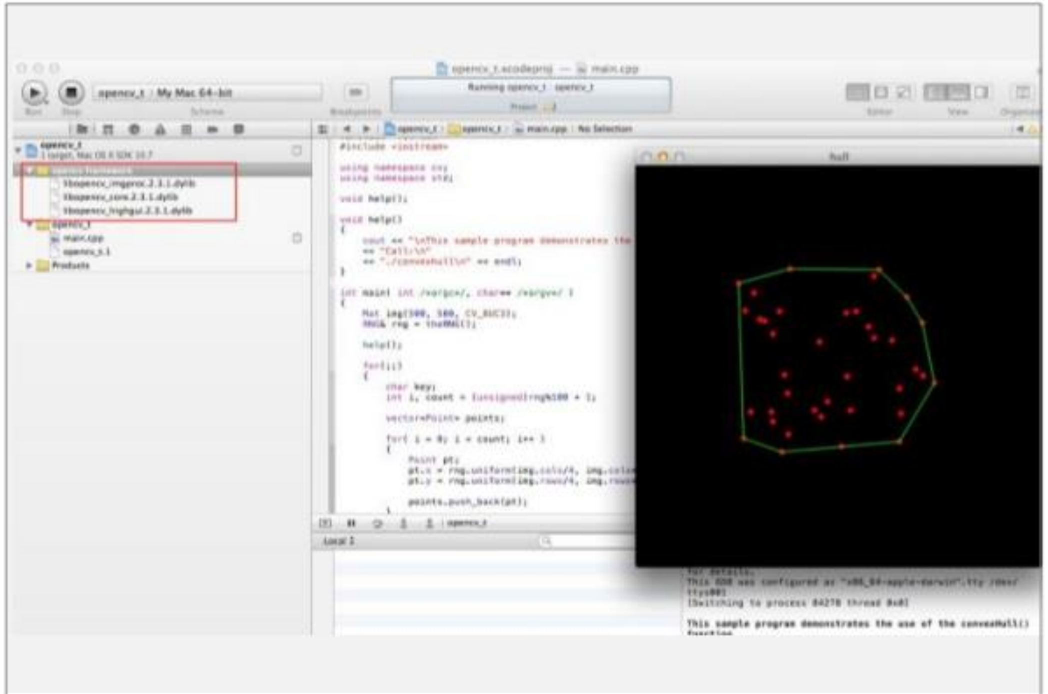
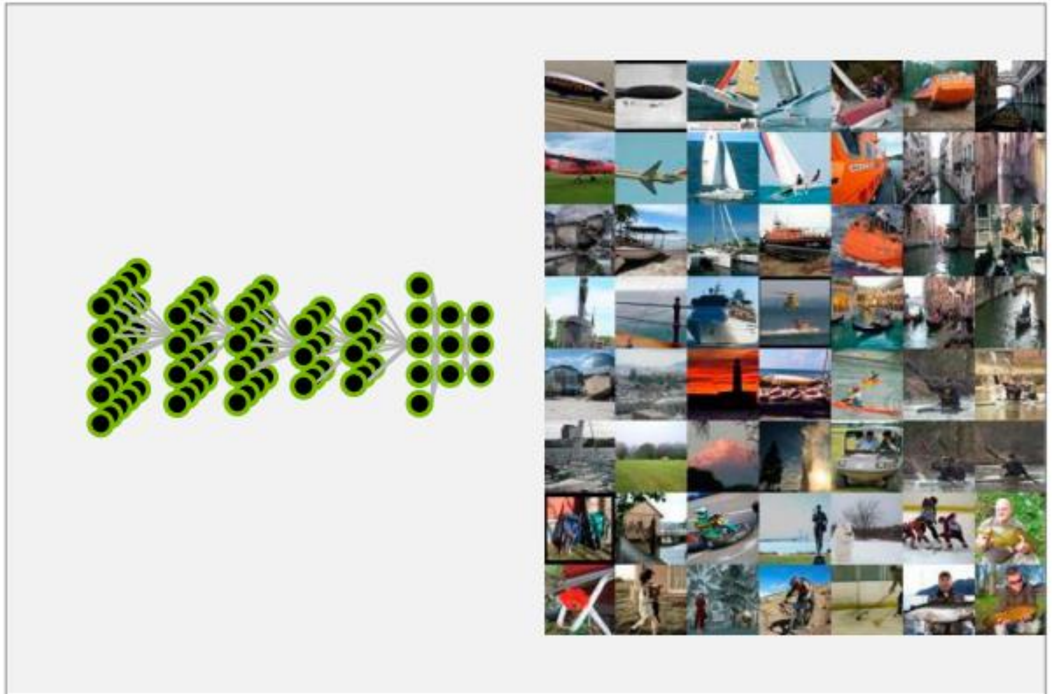
A New Programming Model – Data Driven Paradigm



Traditional Computer Vision
Experts + Time



Deep Learning Object Detection
DNN + Data + HPC

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Why Data Driven Paradigm?

- Consider Image Classification: a core task in Computer Vision

(assume given set of discrete labels)

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

Dog

Image Source: Google

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What is Classification?

Input (Image, text, audio, etc.)

Classifier

(choose one from N labels)

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

Dog

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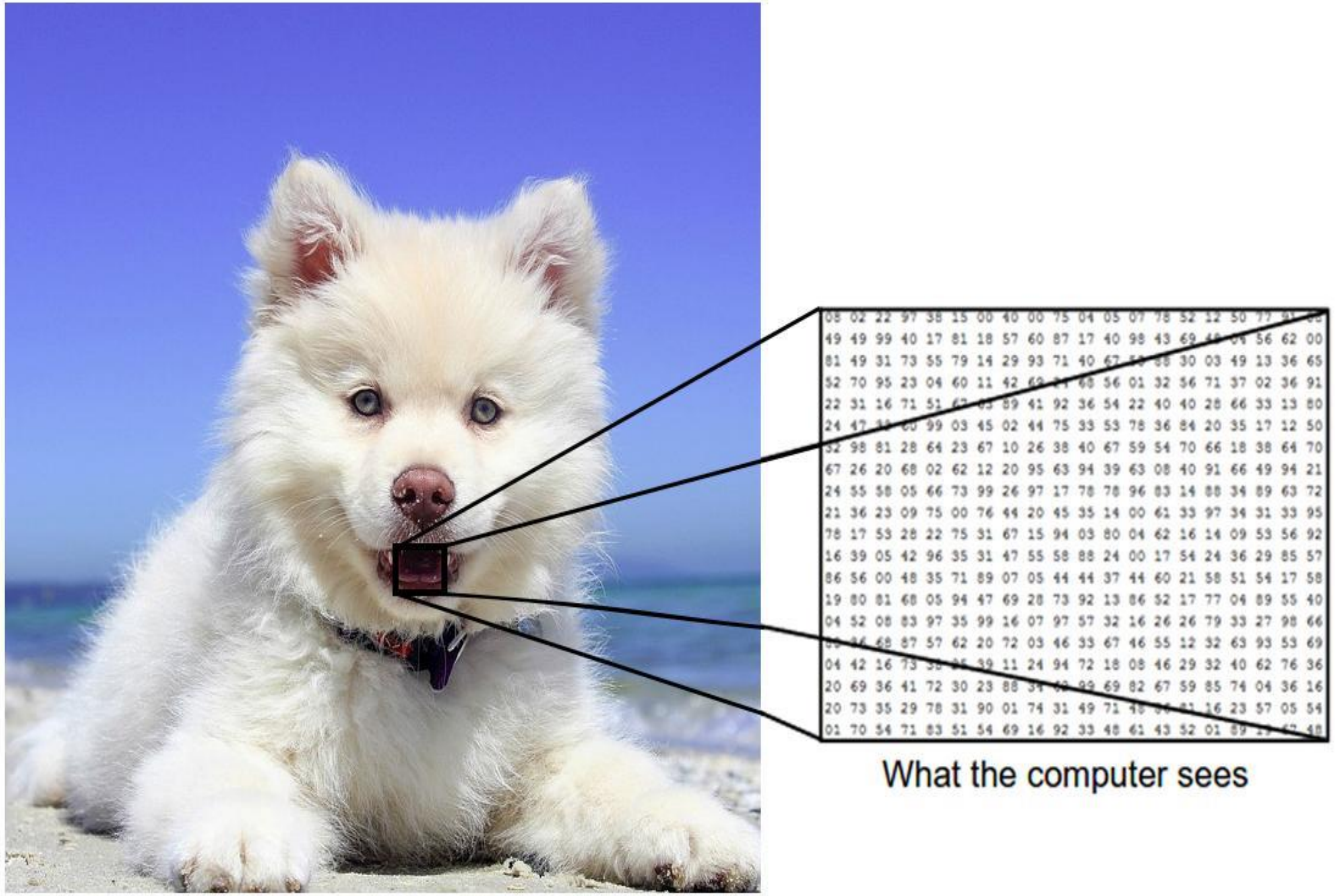
Why Data Driven Paradigm?

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)



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Why Data Driven Paradigm? – Invariant to Illumination

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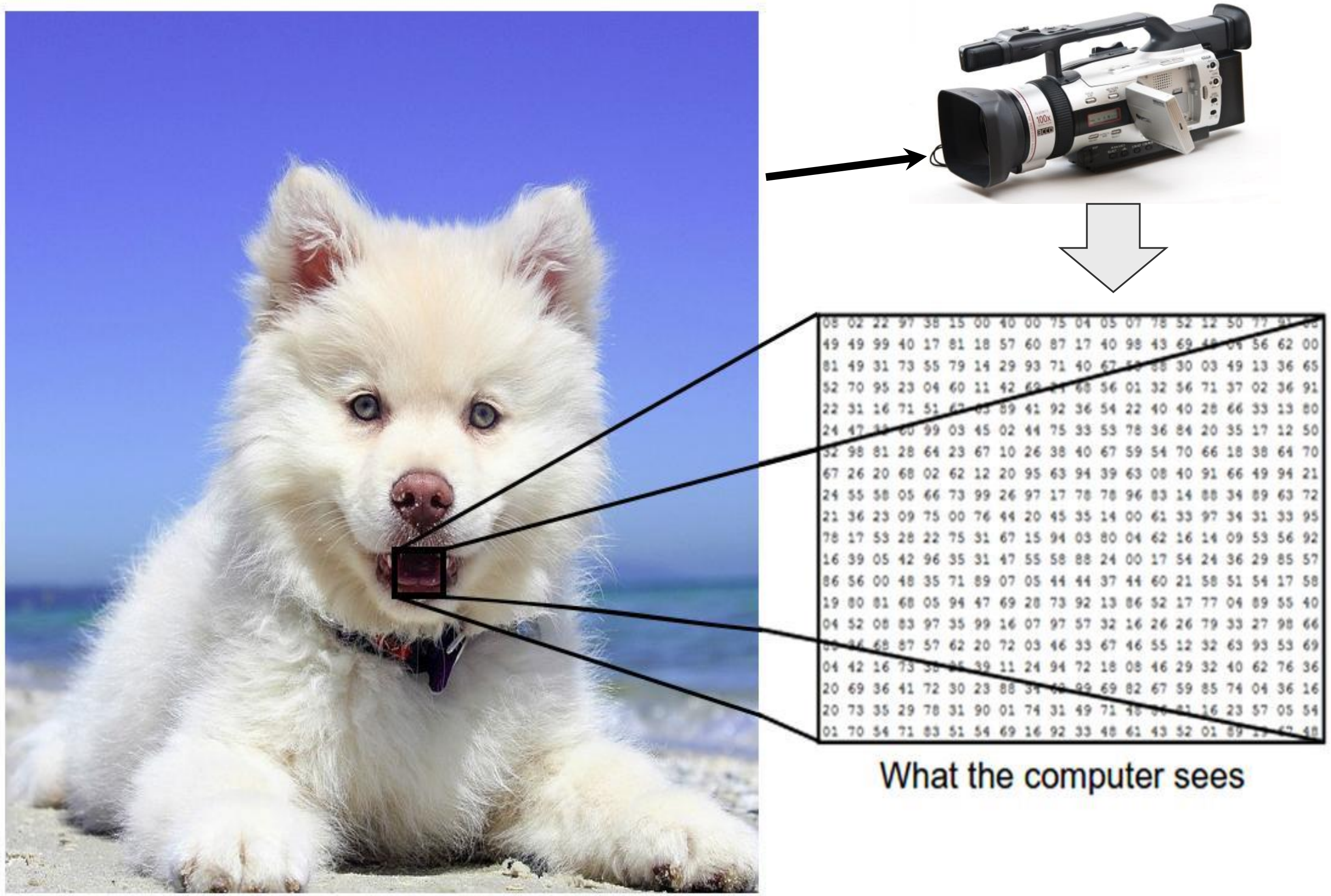
Why Data Driven Paradigm? – Invariant to Viewpoint



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Why Data Driven Paradigm? – Deal with Occlusion

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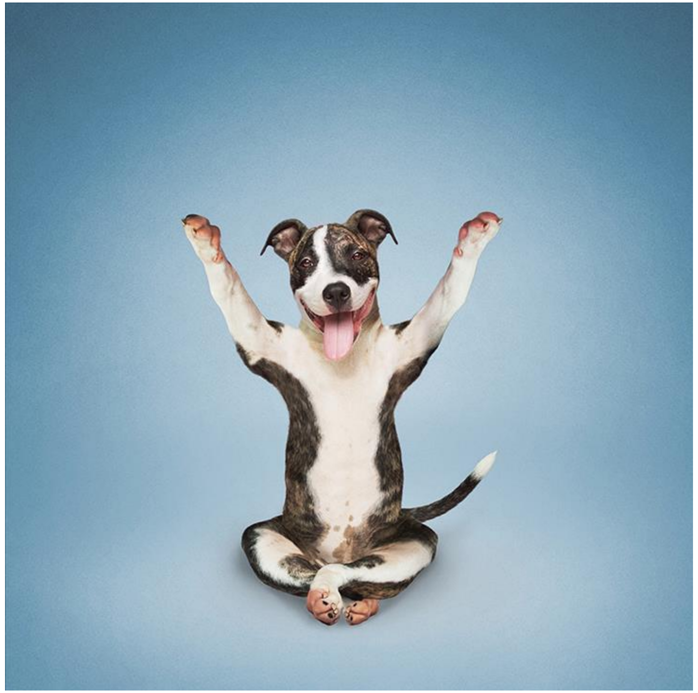
Why Data Driven Paradigm? – Invariant to Deformation



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Why Data Driven Paradigm? Deal with Background Clutter

Image Source: Google

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Why Data Driven Paradigm? Deal with Intra-class Variation

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

- Image classification:

```
Def 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

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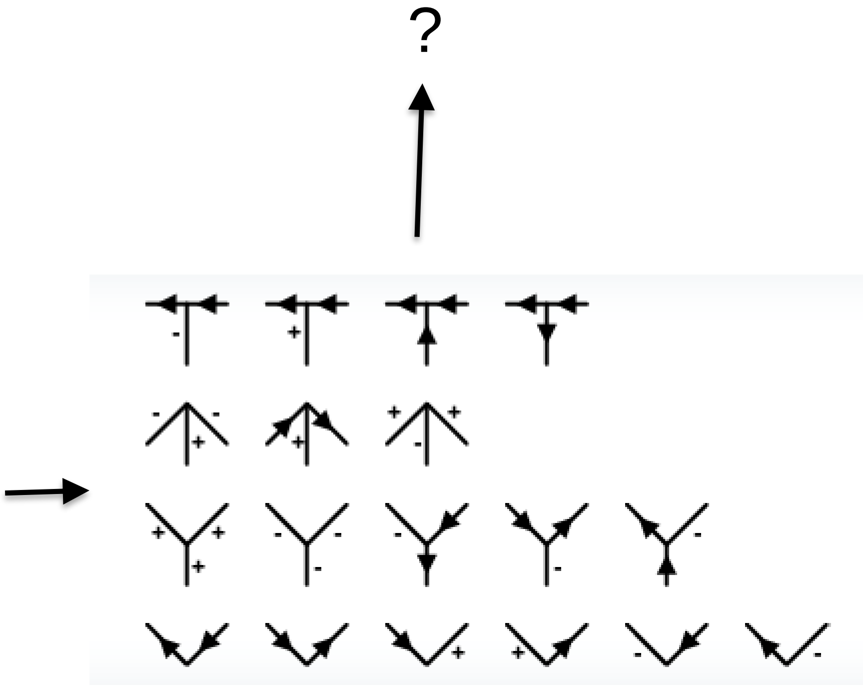
Why Data Driven Paradigm?

- Image classification:



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The Data Driven Paradigm

1. Prepare a dataset of labelled images
2. Use Machine Learning to train an image classifier
3. Then evaluate the performance of classifier using a withheld set of test images(these images shouldn't be used to train the classifier).

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


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

Example Training Set

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Agenda

- History and Evolution of Neural Networks
- The AI Winter and then the Tipping Point for Deep Learning
- Why Deep Learning
- The Data Driven Paradigm
- **Training a classifier (without any trainable parameters) – KNN**
- Training a classifier (with trainable parameters) – Linear Classifier
- How to split our data into training, validation and test sets

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Classifier 1: Nearest Neighbor Classifier

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

Train the model with labelled training data and remember all training images with their labels

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

Predict the label of the most similar training image

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Train vs. Test

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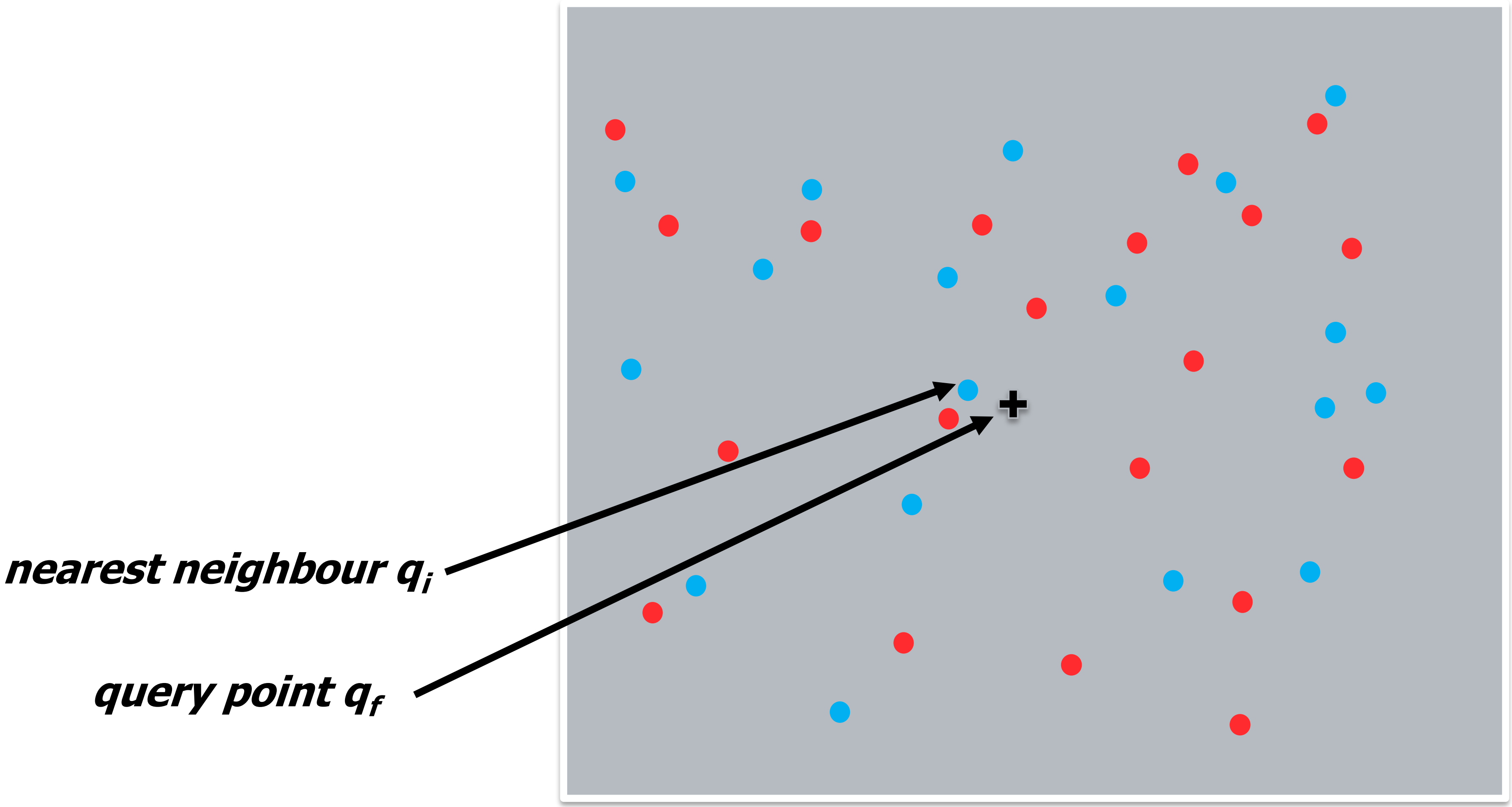
1-Nearest Neighbour



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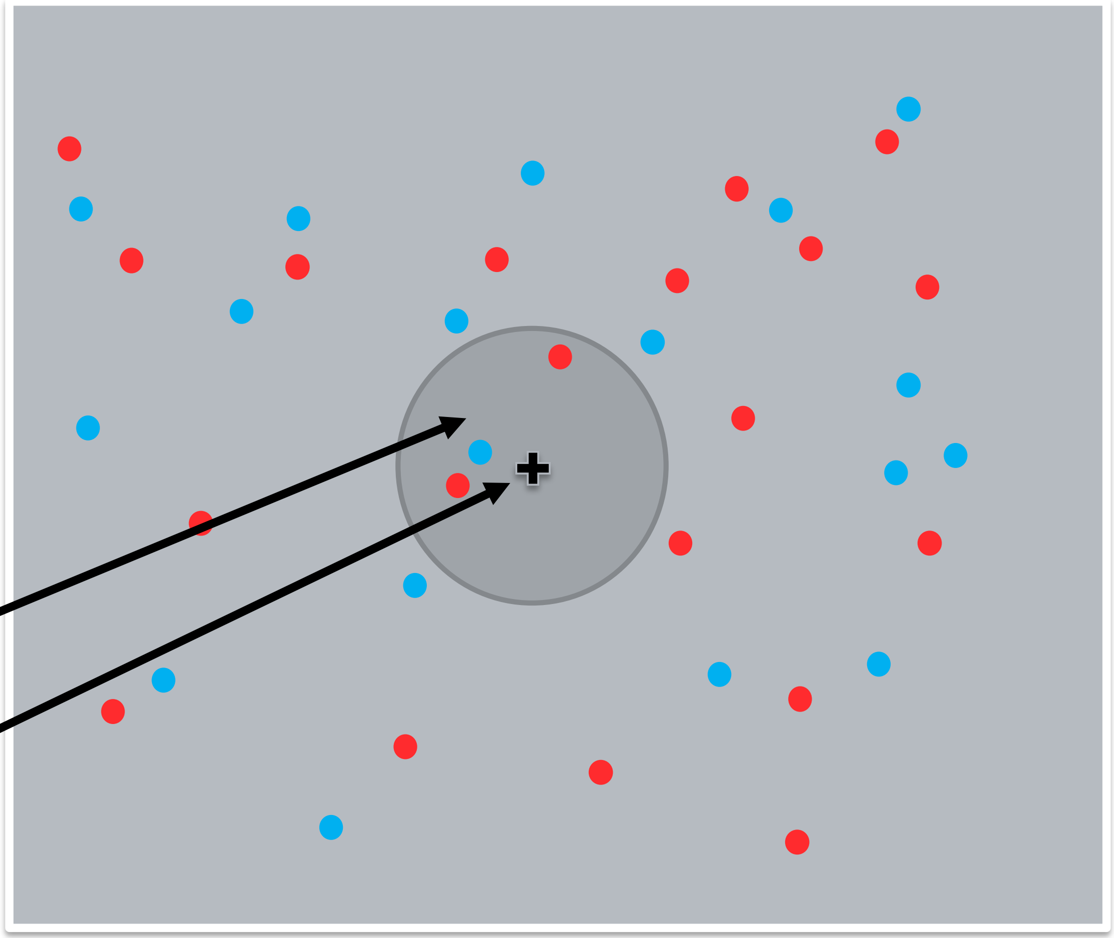

3 nearest neighbors,
2 red, 1 blue

query point q_f

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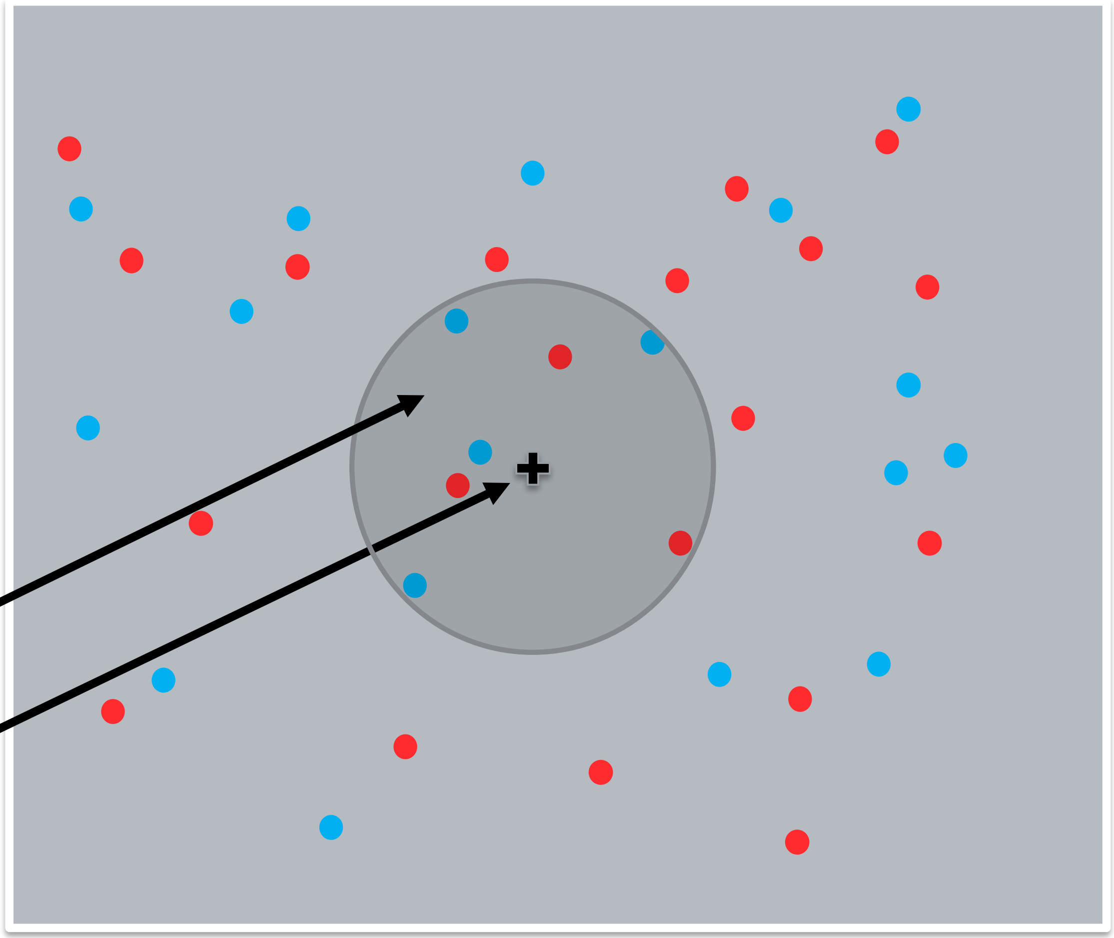
1-Nearest Neighbour



3 nearest neighbors,
3 red, 4 blue

query point q_f

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Example Dataset: MNIST

0
1
2
3
4
5
6
7
8
9

10 labels
60,000 training images
10,000 test images.

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

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

→ 456

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Nearest Neighbor Classifier

```python
class NN:
    def __init__(self):
        pass

    def train(self, X, y):
        # X is 2D if size N x D = 23x23x3, so each row is an example
        # y is 1D of size N
        self.tr_x = X
        self.tr_y = y

    def predict(self, x):
        # x is of size D = 32x32x3 for which we want to predict the label
        # returns the predicted label for the input x
        min_idx = None
        min_dist = 100000000
        for test_sample in range(len(self.tr_x)):
            dist = 0
            for each_value in range(len(self.tr_x[0])):
                dist += abs(float((self.tr_x[test_sample][each_value] - x[each_value])))
            if dist < min_dist:
                min_dist = dist
                min_idx = test_sample
        return self.tr_y[min_idx]
```

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Nearest Neighbor Classifier

remember the training data

```
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            if dist < min_dist:
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        return self.tr_y[min_idx]
```

For the test image:

- find nearest train image with minimum distance from the test image
- predict the label of nearest training image

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Nearest Neighbor Classifier

```
In [ ]: # Changing dimensions to N x D = 28x28x3
        # Number of samples you want in training data. 60,000 is max.
        N = 5000
        x_tr = []
        for i in range(N):
            x_tr.append(x_train[i,:].flatten())
        x_te = []
        for i in range(10000):
            x_te.append(x_test[i,:].flatten())
        print(len(x_tr),len(x_tr[0]))
        print(len(x_te),len(x_te[0]))


        class NN:
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                pass

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```

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

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Nearest Neighbor Classifier

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```

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

A: Linearly!

This is **backwards**:

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

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The Choice of Distance is a **Hyperparameter**

L1 distance

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

L2 (Euclidean) distance

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

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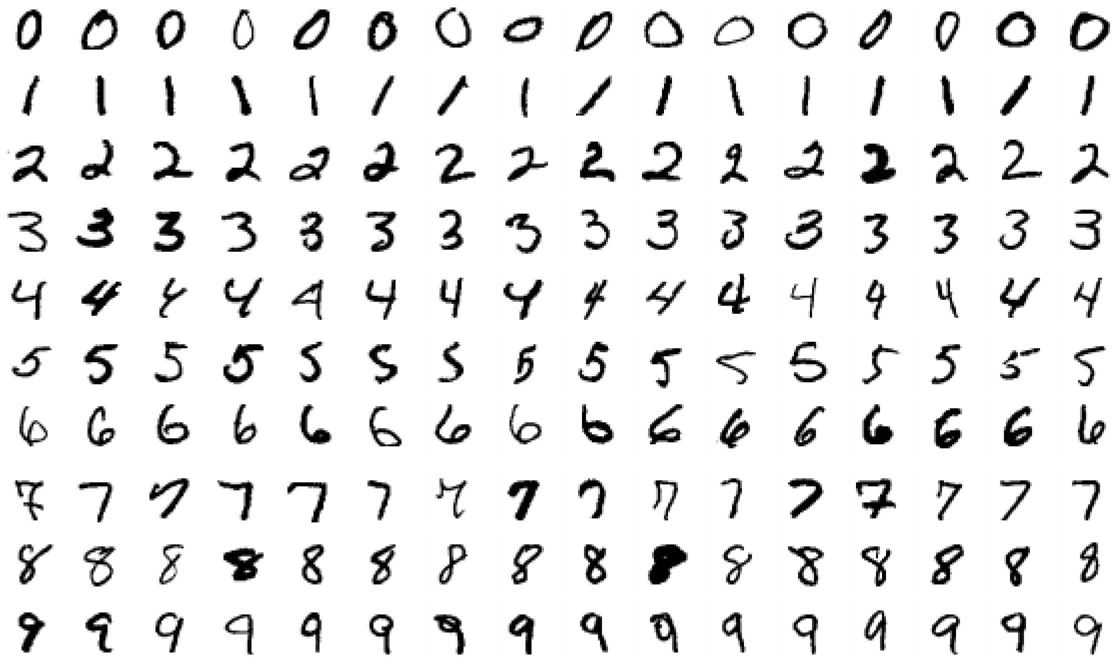
Example Dataset: MNIST

0
1
2
3
4
5
6
7
8
9



10 labels
60,000 training images
10,000 test images.

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

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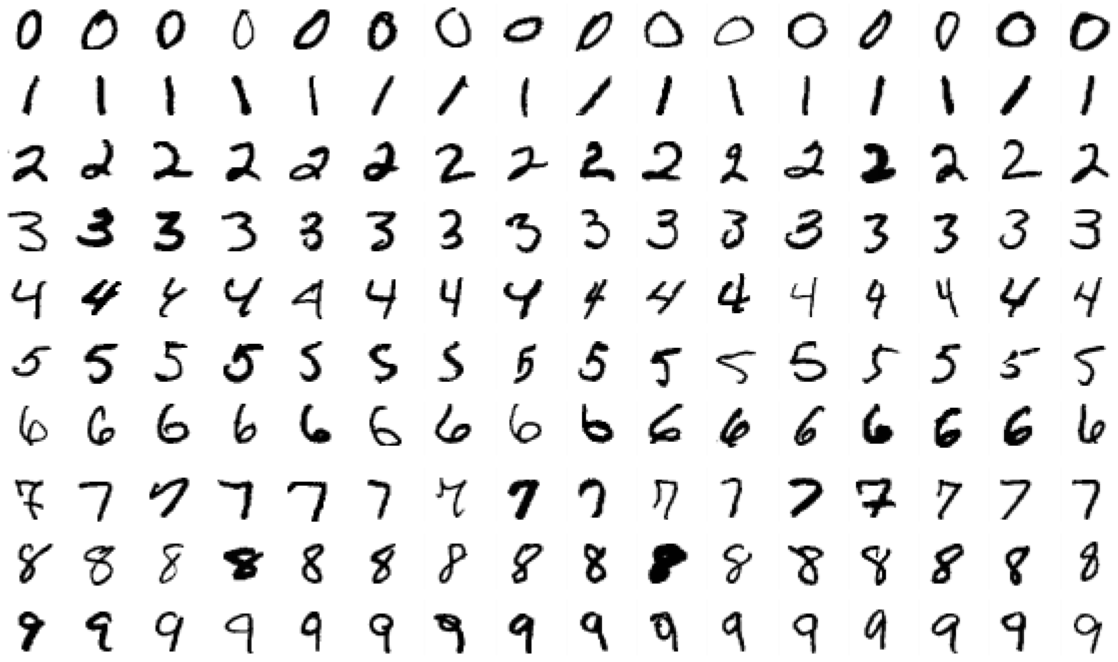
Example Dataset: MNIST

0
1
2
3
4
5
6
7
8
9



10 labels
60,000 training images
10,000 test images.

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

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How Do We Set the **Hyperparameters**?

Best Distance to use?

What should be the best value of k to use? Is it random?

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How Do We Set the **Hyperparameters**?

Best Distance to use?

What should be the best value of k to use? Is it random?

This is a very problem dependent.

One should try various K and see what works best with the problem.

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

Validation Data
(used to tune hyperparameters)

Bad idea to use test data to tune hyperparameters

- *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.

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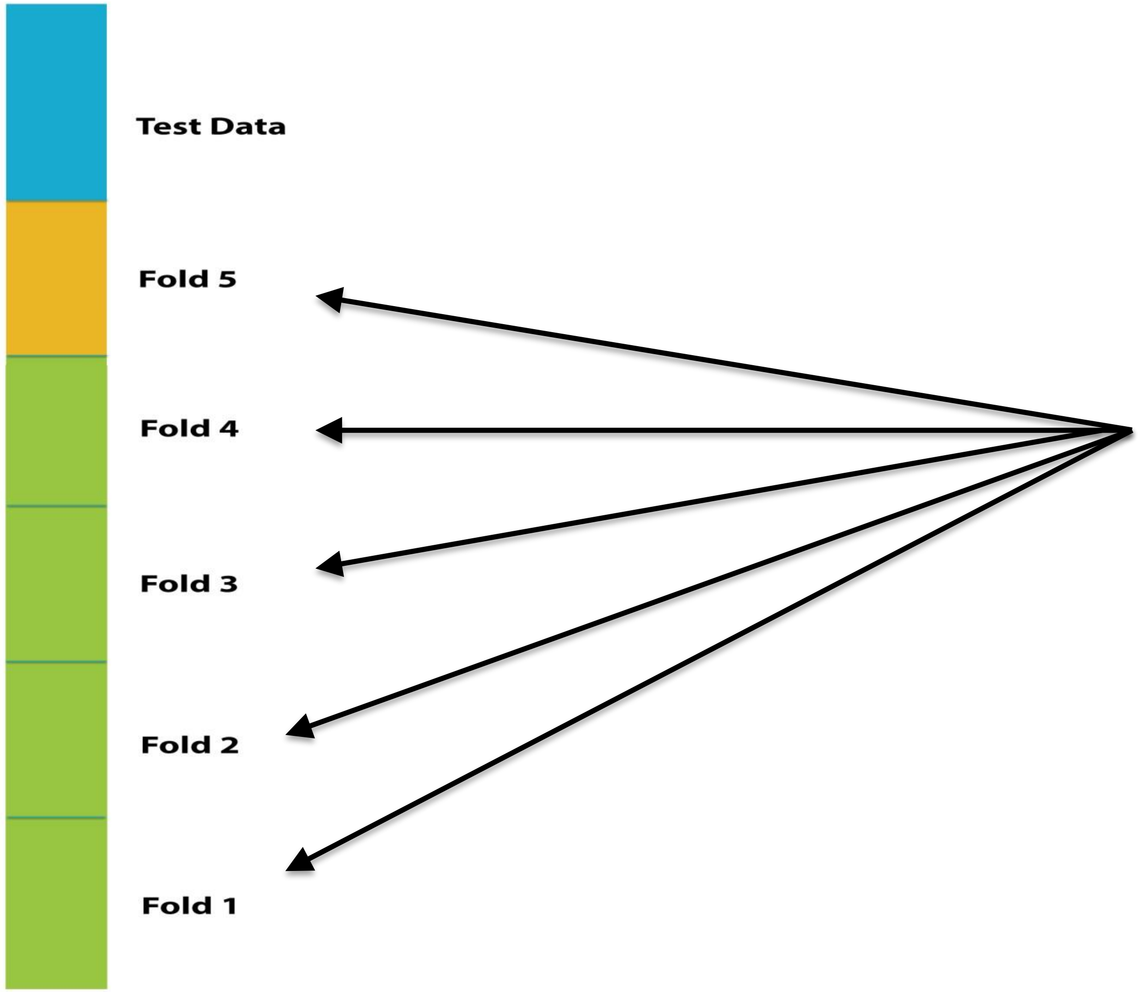
Try Out What Hyperparameters Work Best on **Test Set?**



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

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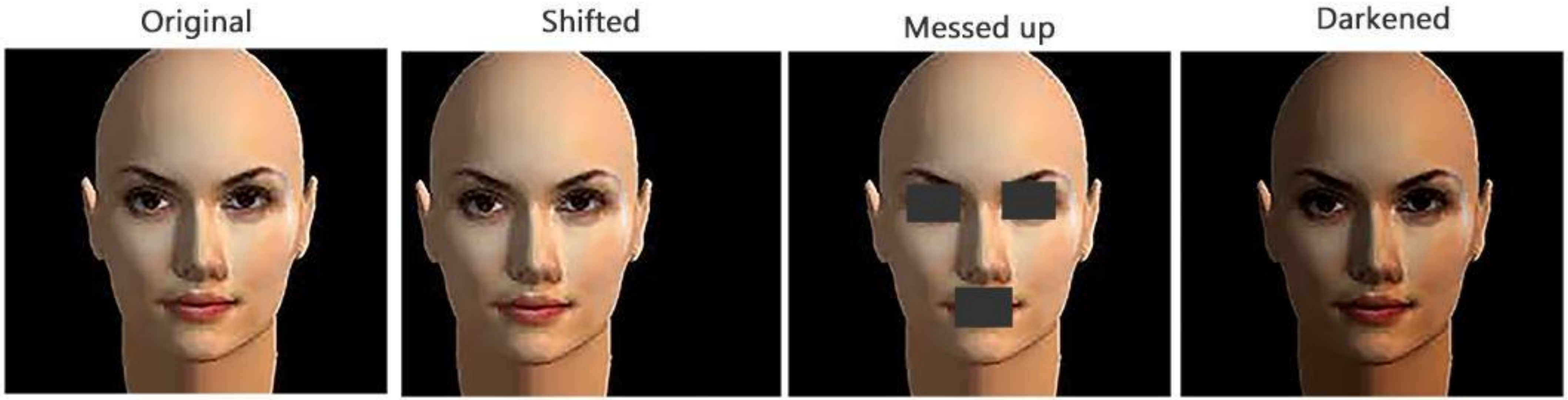
K-Nearest Neighbor on Images Never Used

- 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)

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K-Nearest Neighbor Summary

- **Image Classification:** We are provided with given **Training Data set** and labeled images, and we are asked to predict labels on **Test Data Set**. Common to report the **Accuracy** of predictions (fraction of correctly predicted images)
- We introduced the **k-Nearest Neighbor Classifier**, whose prediction is based on the labels of the nearest images in the **Training Data Set**
- If the size of data set is small the choice of distance and value of hyper parameters are tuned using a Validation Data Set or cross validation method.
- Once we choose the best set of hyper parameters, the classifier model is evaluated using **Test Data Set** and its performance on this data set is reported as the KNN classifier performance on that data.

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K-Nearest Neighbor

- k-NN classifier:
  - Need to remember all of the training data and store it for future comparisons with the test data or unseen data
  - This can be very Space consuming since datasets may easily be Gigabytes in size
  - Image classification using k-NN can be very expensive as it needs to compare test image with all the training images

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K-Nearest Neighbor Algorithm

When to consider

- Data a vector $\in \mathbb{R}^d$
- Lots of Training Data

Advantages

- Training is very fast
- Learn complex target functions
- Do not lose information

Disadvantages

- Slow at query time
  - Presorting and indexing training samples into search trees can reduce query time
- Easily fooled by irrelevant attributes

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Agenda

- History and Evolution of Neural Networks
- The AI Winter and then the Tipping Point for Deep Learning
- Why Deep Learning
- The Data Driven Paradigm
- Training a classifier (without any trainable parameters) – KNN
- **Training a classifier (with trainable parameters) – Linear Classifier**
- How to split our data into training, validation and test sets

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Parametric Approach: MNIST

10 labels
60,000 training images
10,000 test images
each image is an array of size **28 x 28 = 784** numbers total

0
1
2
3
4
5
6
7
8
9

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Parametric Approach: Linear Classifier

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Learning for Life

Image

[28x28]
array of numbers
0...255
(784 numbers total)

10x1 **10x784** **784x1**

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

10x1

10 numbers, indicating class scores

Input image

weights or parameters

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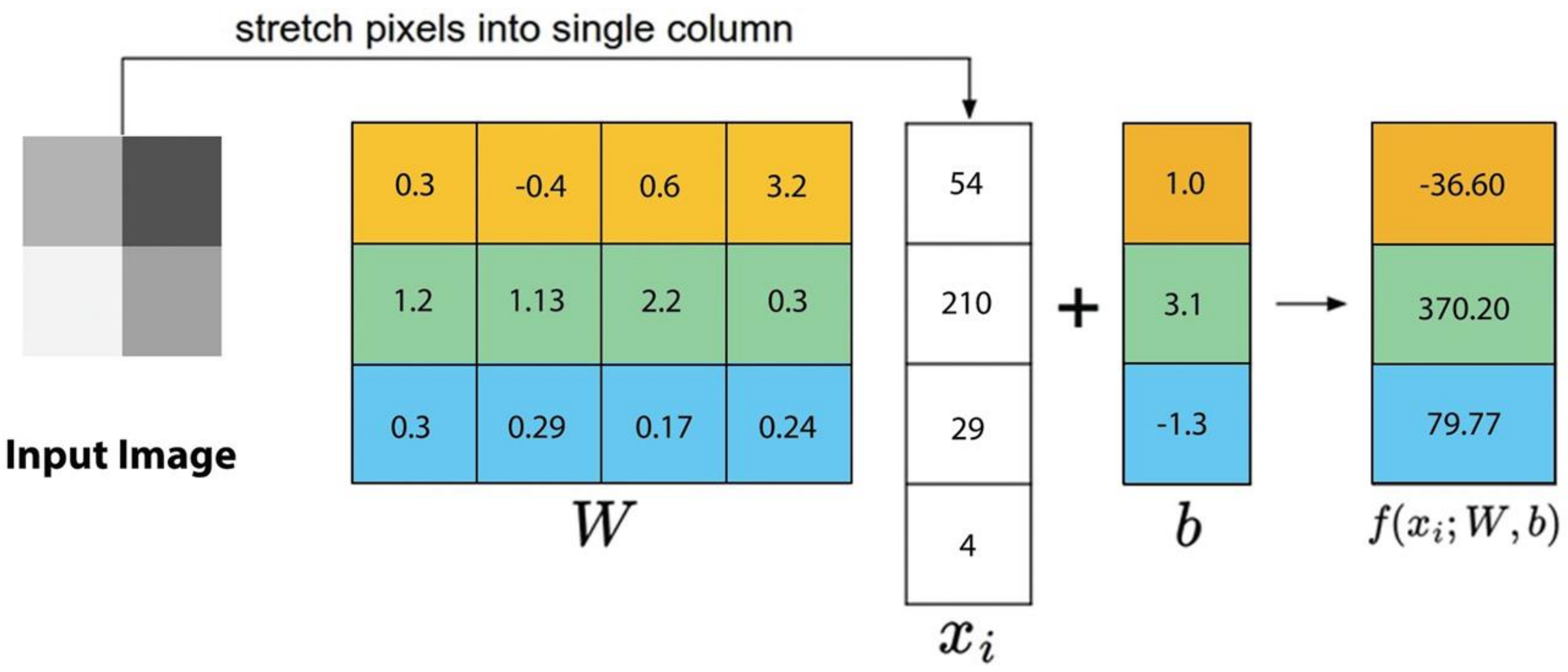
Example with an Image with 4 Pixels, and 3 Classes (1/2/3)



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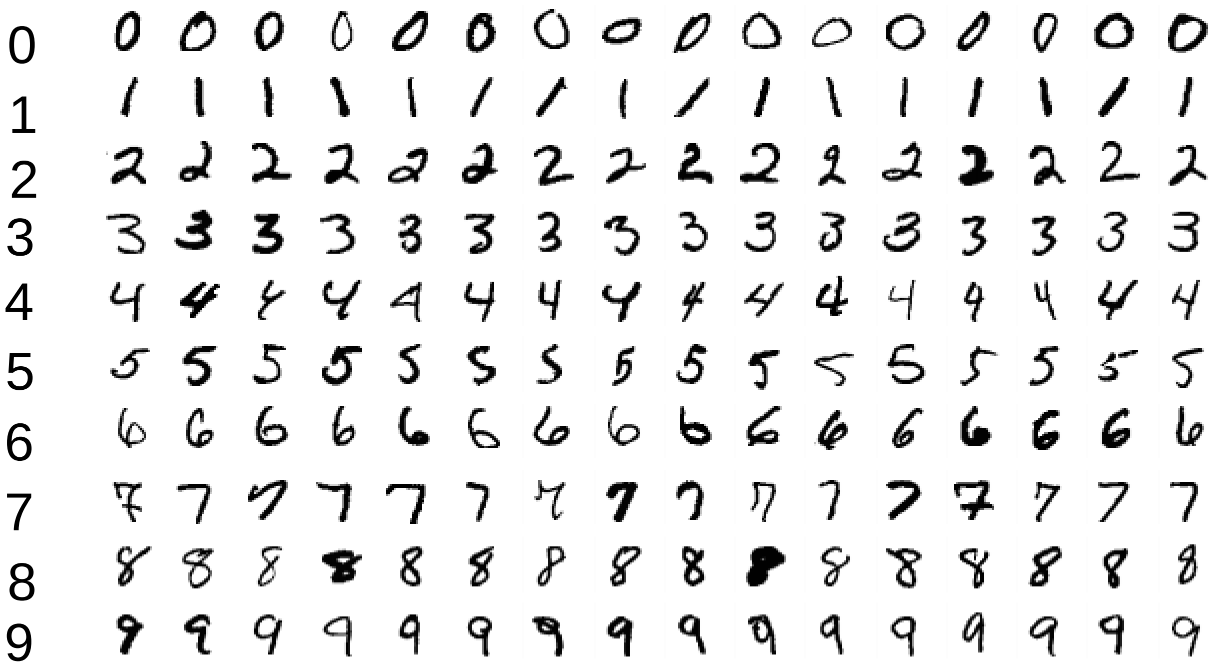
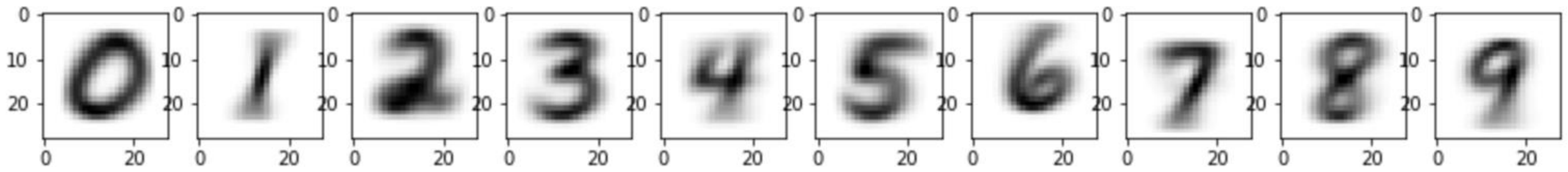
Interpreting a Linear Classifier



10x784

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

Example trained weights of a linear classifier trained on MNIST:



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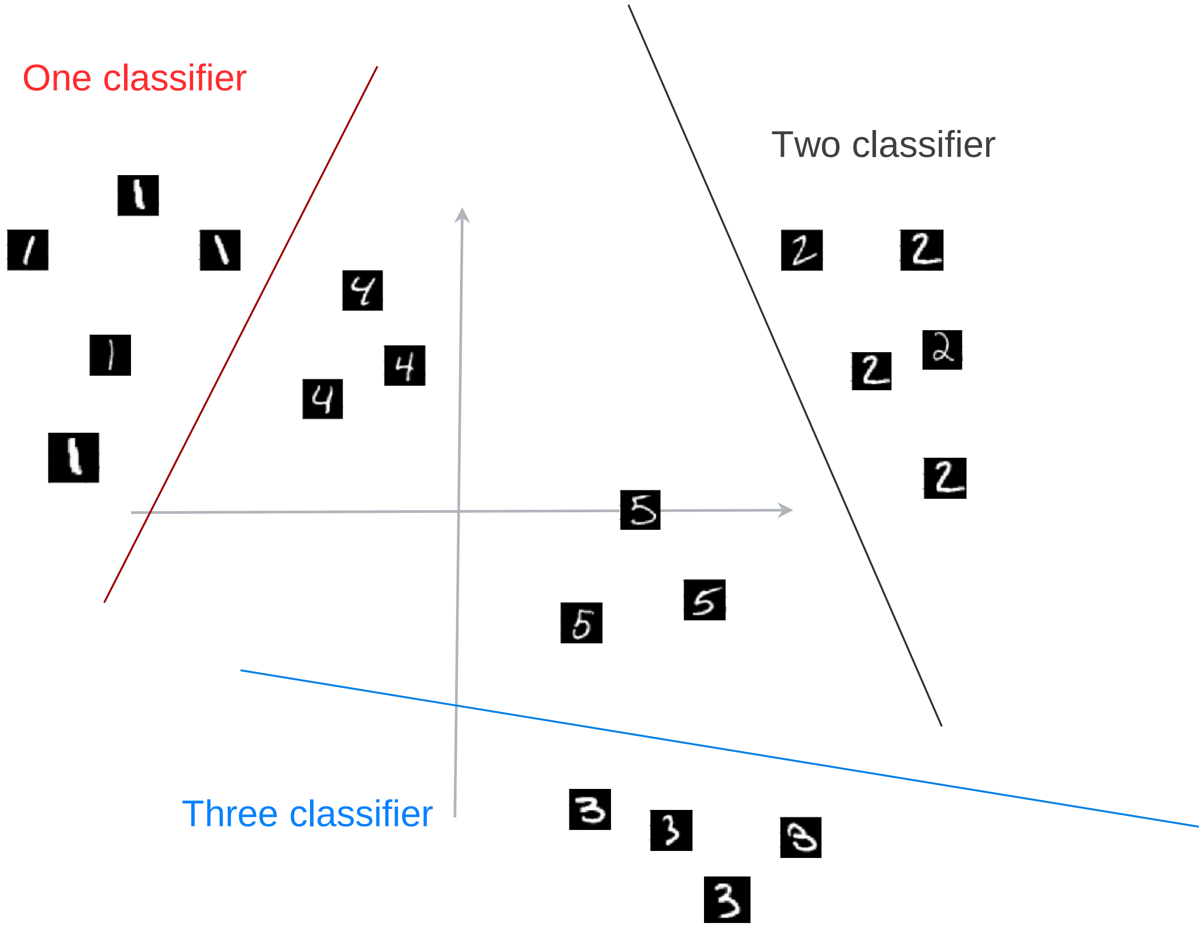
Interpreting a Linear Classifier



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

[28x28]
array of numbers 0…255
(784 numbers total)

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Summary

- Evolution of NN
- Why data-driven
- Simple classifier like k-NN and its limitations
- Parametric approach and its benefits
- What next - what does a parametric approach lead us to?

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Thank you!