Deep learning and Computer vision

Dmitry Yashunin
IntelliVision

Lecture 1:
Introduction
Image classification basics

Deep learning applications

Image recognition

Fun mobile app

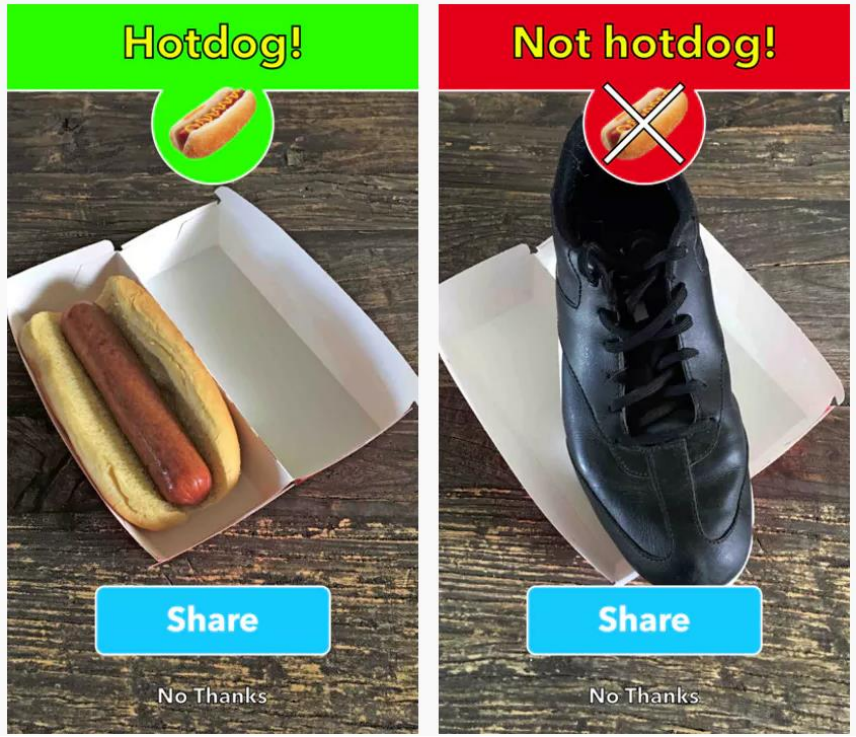
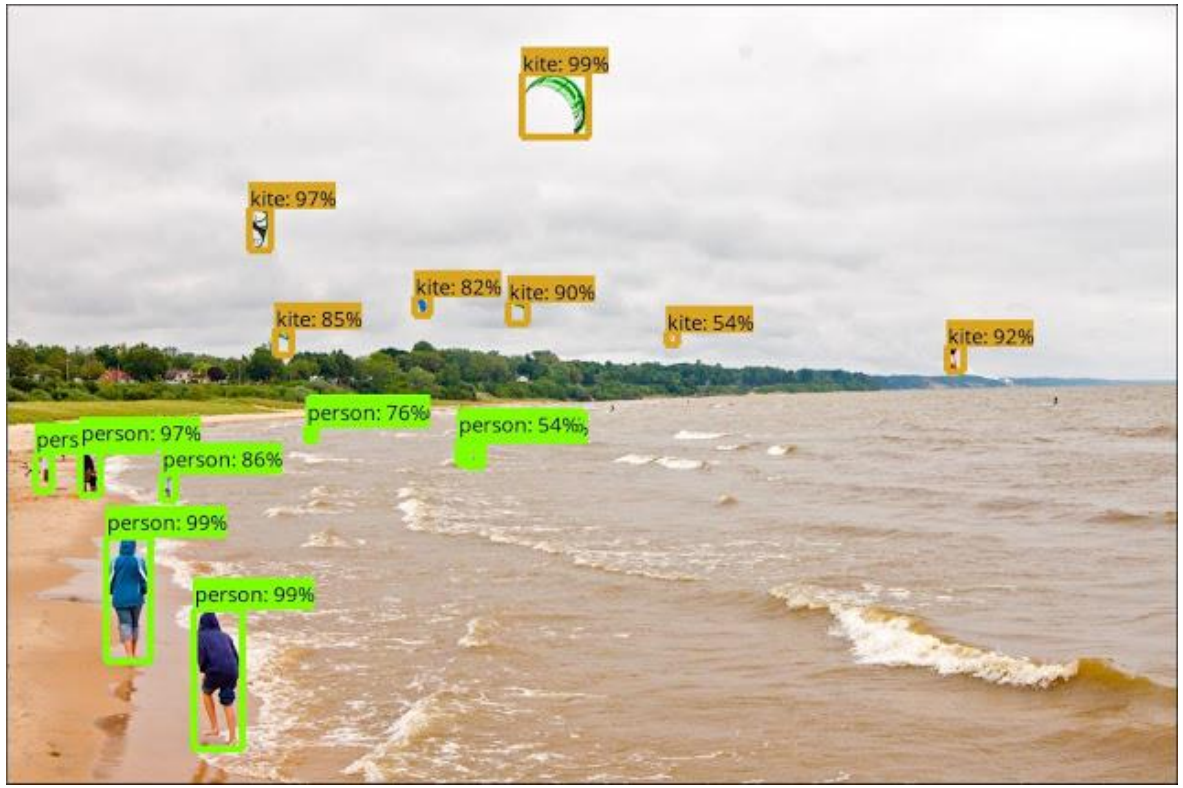
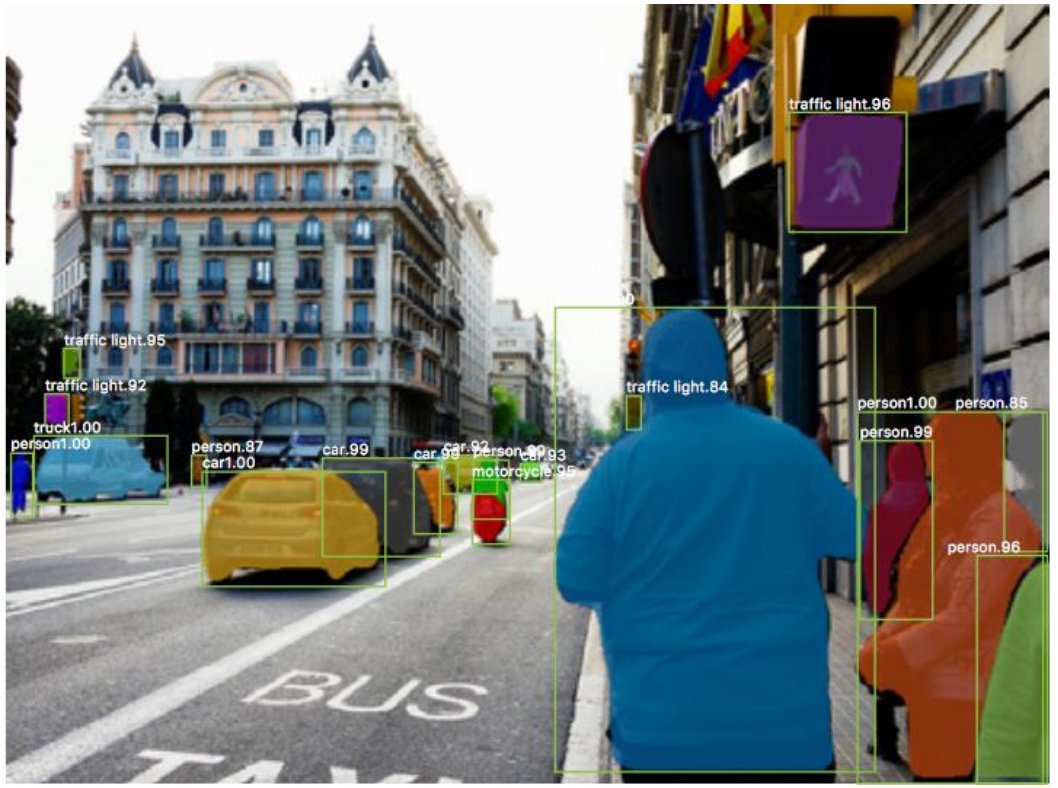


Image captioning

Describes without errors	Describes with minor errors	Somewhat related to the image
 A person riding a motorcycle on a dirt road.	 Two dogs play in the grass.	 A skateboarder does a trick on a ramp.
 A group of young people playing a game of frisbee.	 Two hockey players are fighting over the puck.	 A little girl in a pink hat is blowing bubbles.

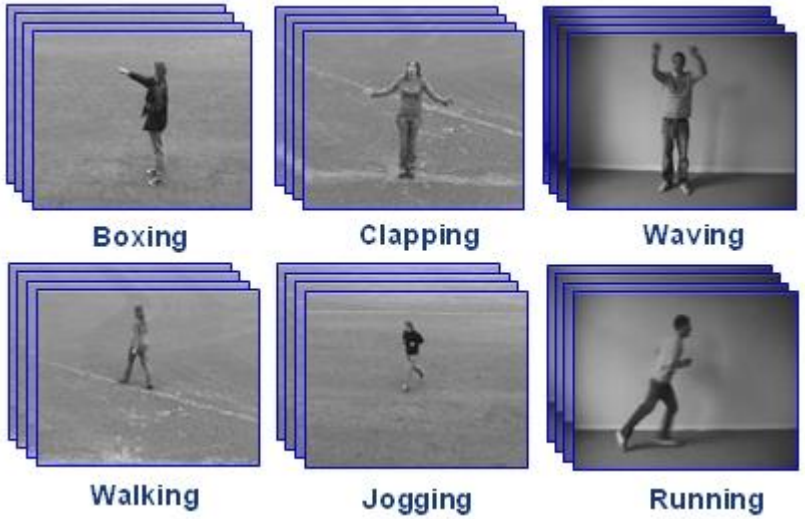
Detection and instance segmentation





Optical character recognition

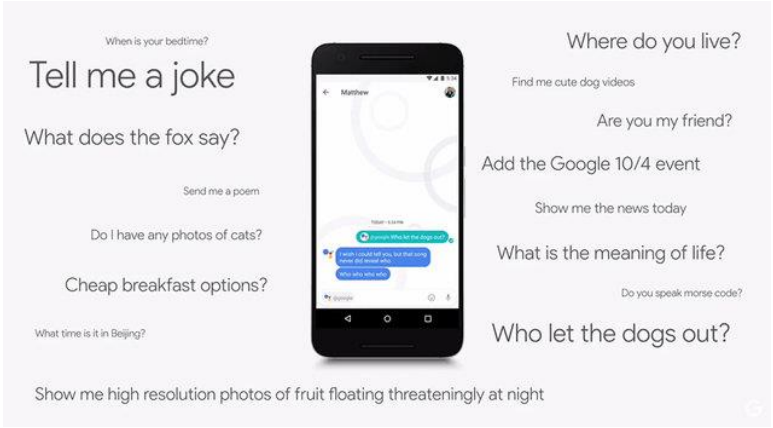
Action recognition



Speech recognition

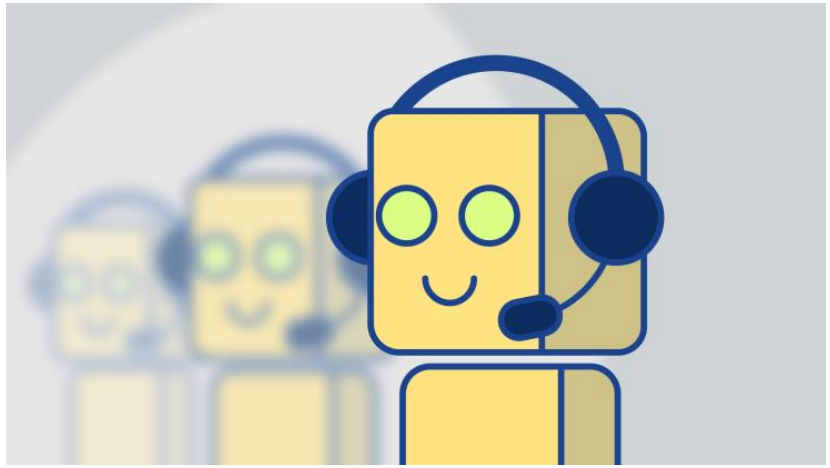
Apple Siri

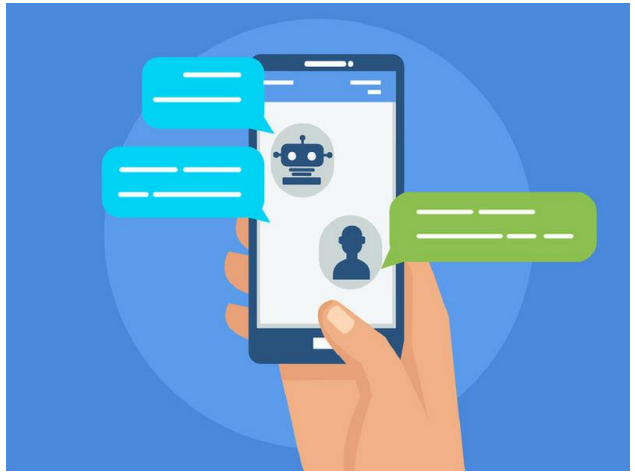
Google assistant



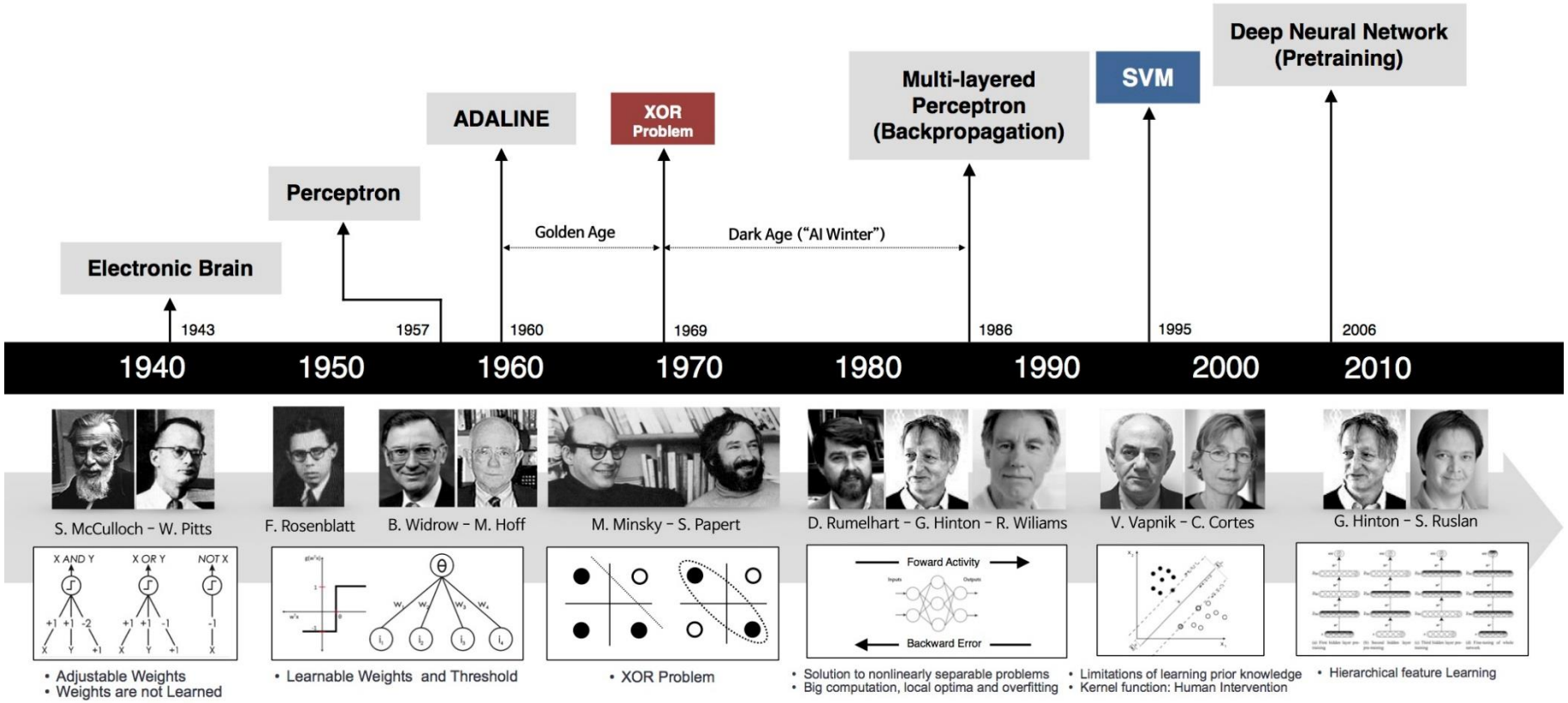
Microsoft Cortana

Chat bots



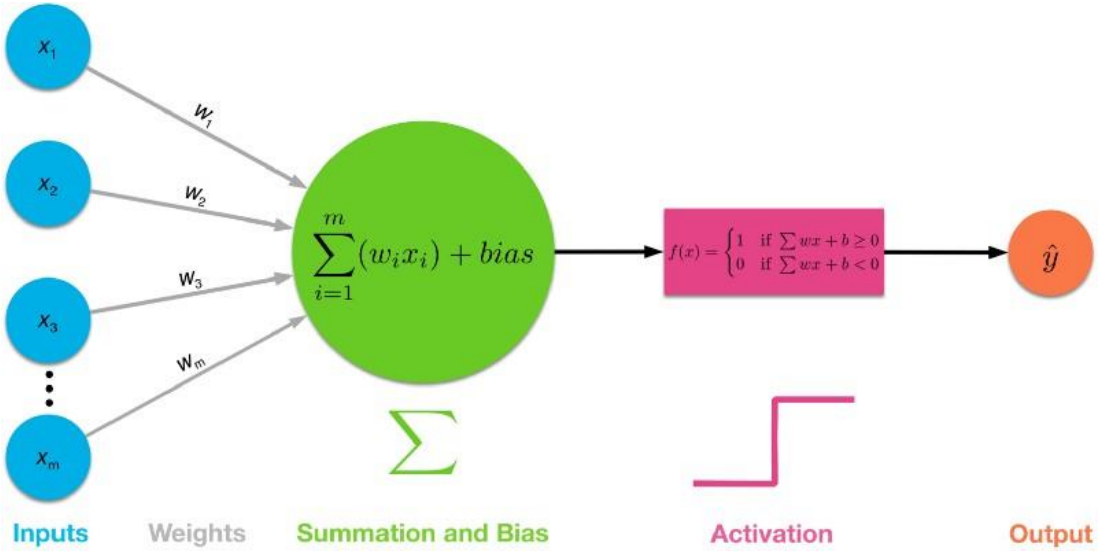


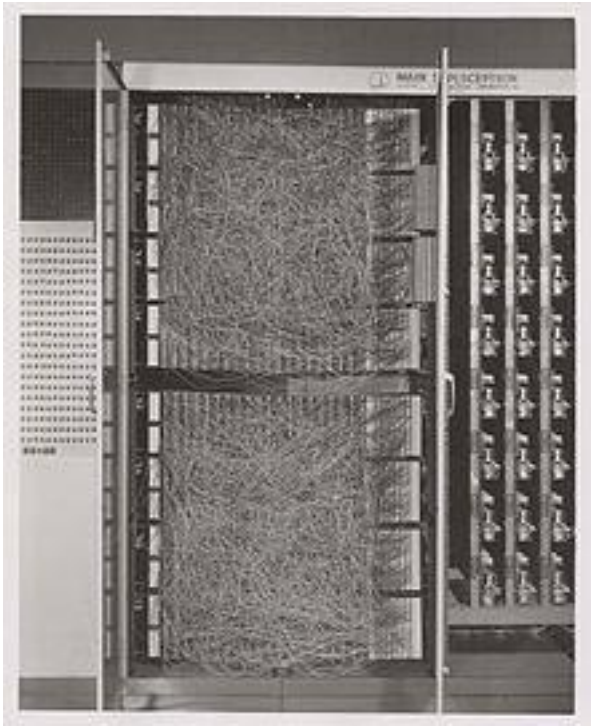
History of Deep learning

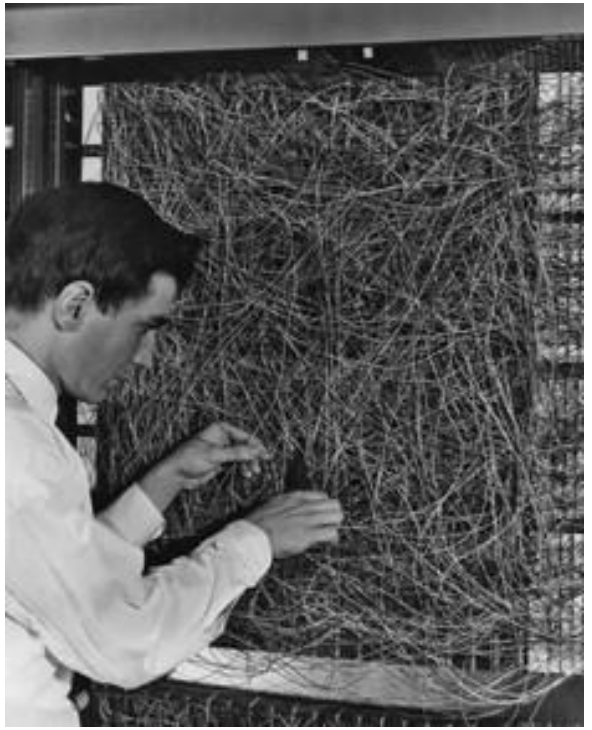


- 1943 – First artificial neuron (Threshold Logic Unit) proposed by Warren McCulloch and Walter Pitts
- 1957 – Perceptron algorithm for pattern recognition. Learning was performed using simple addition and subtraction. Developed by Frank Rosenblatt.

Single-layer perceptron





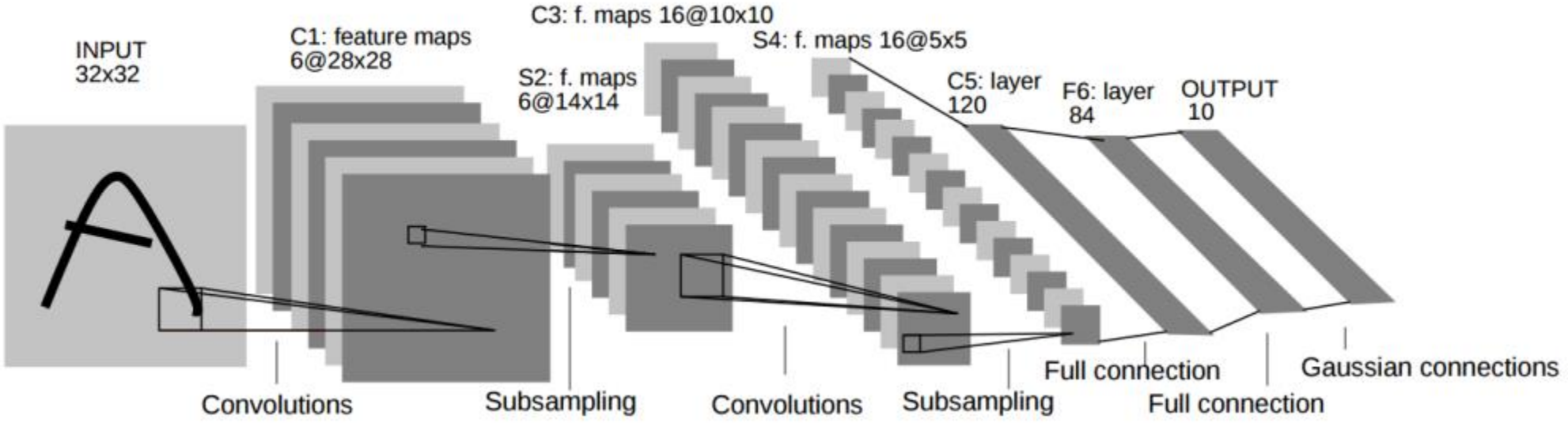


The Mark I Perceptron machine for image recognition – the first implementation of the perceptron algorithm.

The machine was connected to a camera that used 20×20 cadmium sulfide photocells to produce a 400-pixel image.

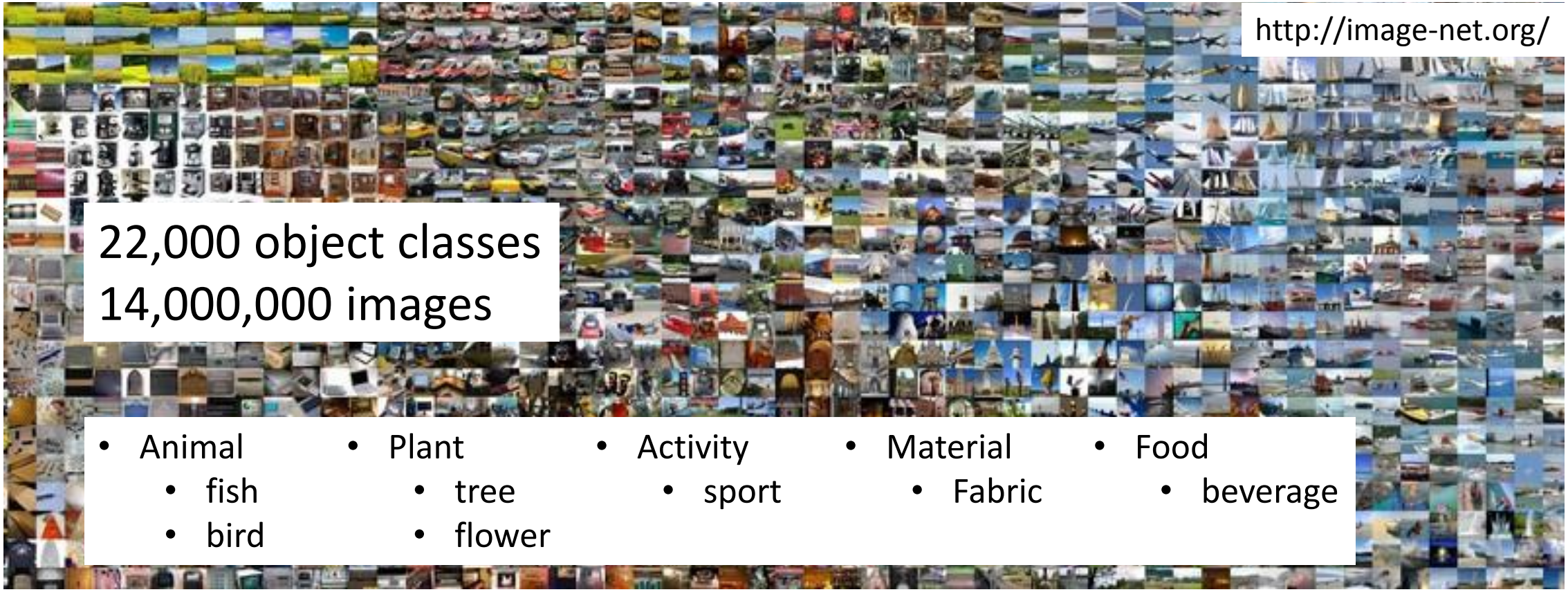
Recognized letters of the alphabet.

- 1986 – Geoffrey Hinton discovered backpropagation algorithm for training multi-layer neural nets
- 1989 – Yann LeCun combined Convolutional Neural Networks (CNN) with back propagation onto read “handwritten” digits
  Demo https://www.youtube.com/watch?v=FwFduRA_L6Q



- **2012** – Alex Krizhevsky’s CNN wins ImageNet challenge

IMAGENET Large Scale Visual Recognition Challenge (ILSVRC)



Large Scale Visual Recognition Challenge (ILSVRC)

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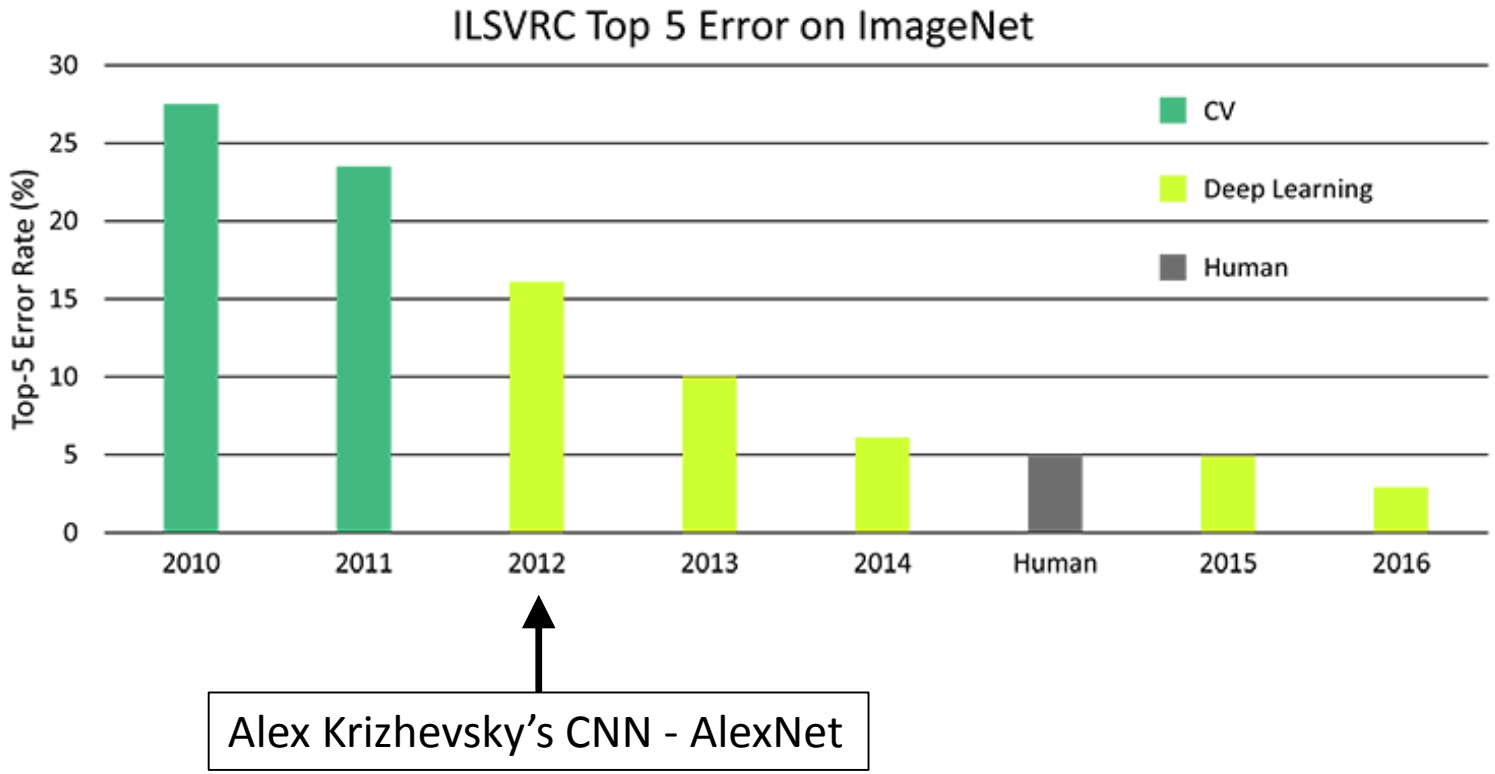


ImageNet classification challenge

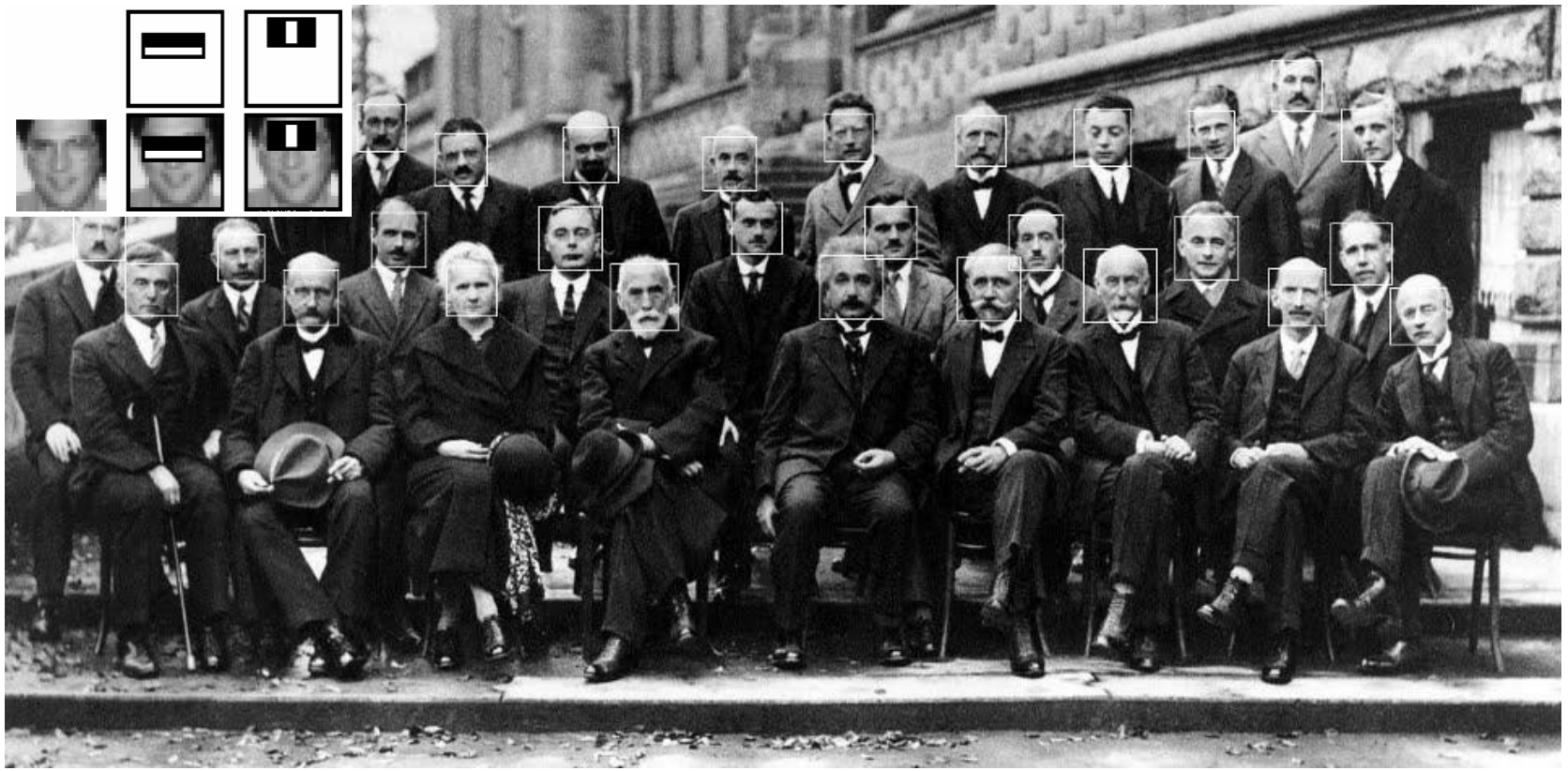
1,000 object classes

1,431,167 images

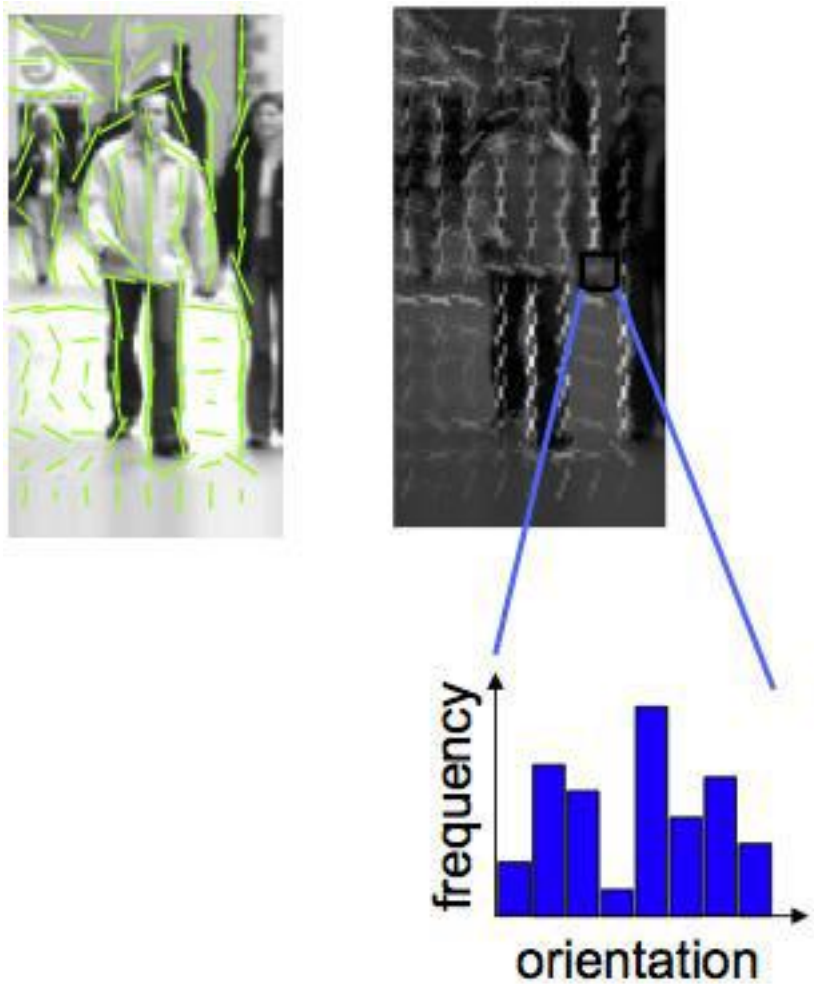
Before deep learning

Hand crafted features and heuristics:

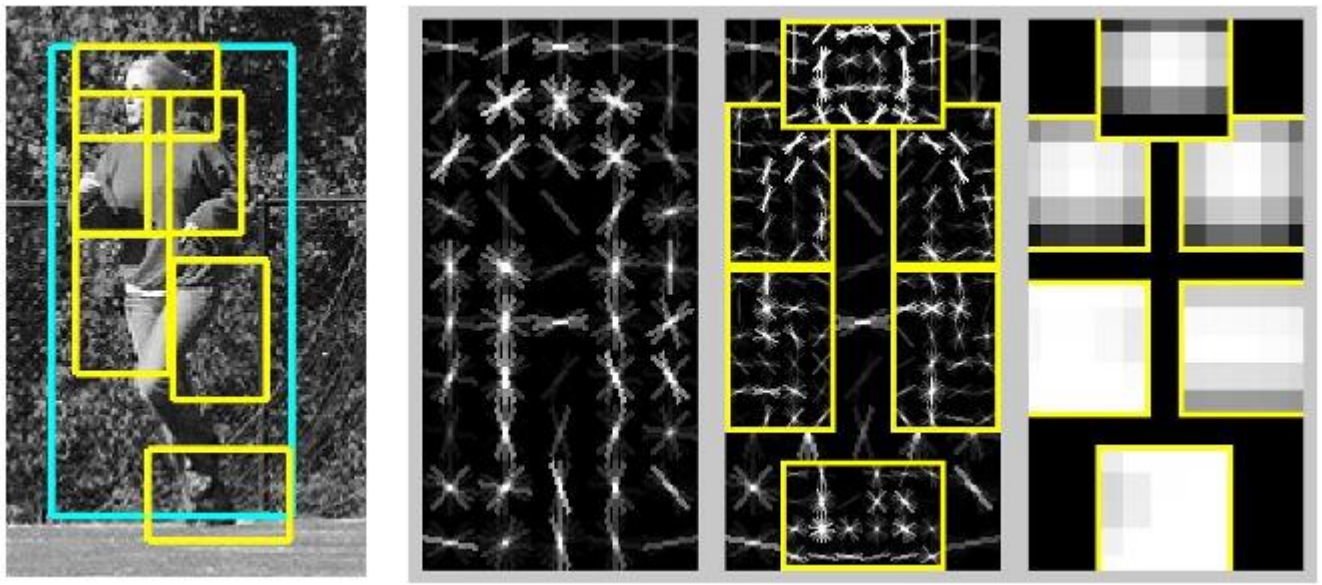
- Edges
- Blobs
- Haar like features
- LBP features
- HOG - Histogram of Oriented Gradients
- …



Face detection, Viola & Jones, 2001



HOG - Histogram of Oriented Gradients
Dalal, Triggs, 2005



Deformable Part Model (DPM)
Felzenszwalb, McAllester, Ramanan, 2008

What we will use

- Proficiency in Python
  - Numpy
    see cs231n tutorial http://cs231n.github.io/python-numpy-tutorial/
- Calculus, Linear Algebra
  - Differentiation
  - Matrix multiplication
- Machine Learning
  - Basic staff (kNN, SVM, loss functions, cross validation)

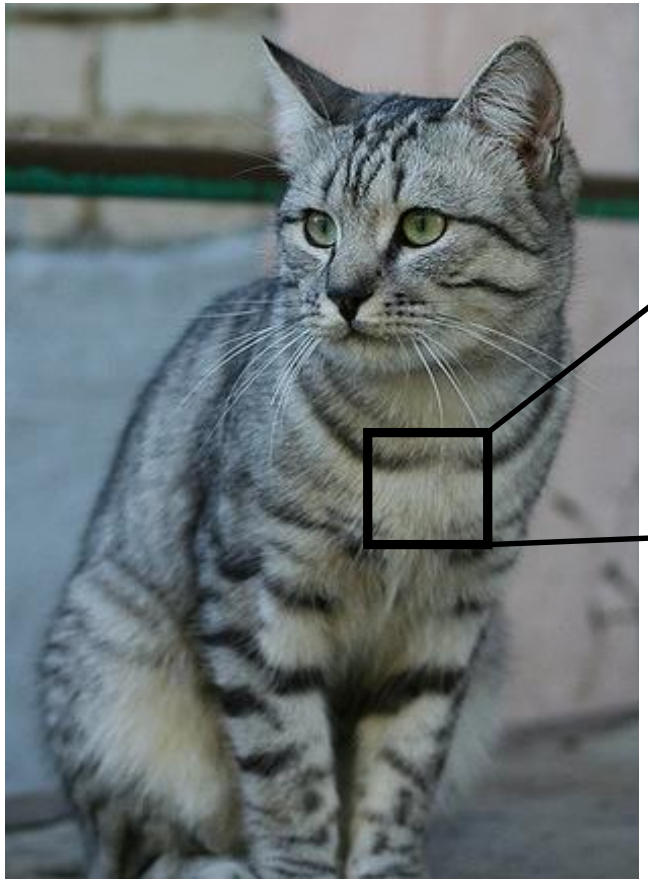
Image classification

A core task in computer vision

predict classes/labels for given images
labels: person, animal, vehicle …

cat

The problem: semantic gap

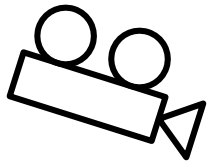


```
[[105 112 108 111 104  99 106  99  96 103 112 119 104  97  93  87]
 [ 91  98 102 106 104  79  98 103  99 105 123 136 110 105  94  85]
 [ 76  85  90 105 128 105  87  96  95  99 115 112 106 103  99  85]
 [ 99  81  81  93 120 131 127 100  95  98 102  99  96  93 101  94]
 [106  91  61  64  69  91  88  85 101 107 109  98  75  84  96  95]
 [114 108  85  55  55  69  64  54  64  87 112 129  98  74  84  91]
 [133 137 147 103  65  81  80  65  52  54  74  84 102  93  85  82]
 [128 137 144 140 109  95  86  70  62  65  63  63  60  73  86 101]
 [125 133 148 137 119 121 117  94  65  79  80  65  54  64  72  98]
 [127 125 131 147 133 127 126 131 111  96  89  75  61  64  72  84]
 [115 114 109 123 150 148 131 118 113 109 100  92  74  65  72  78]
 [ 89  93  90  97 108 147 131 118 113 114 113 109 106  95  77  80]
 [ 63  77  86  81  77  79 102 123 117 115 117 125 125 130 115  87]
 [ 62  65  82  89  78  71  80 101 124 126 119 101 107 114 131 119]
 [ 63  65  75  88  89  71  62  81 120 138 135 105  81  98 110 118]
 [ 87  65  71  87 106  95  69  45  76 130 126 107  92  94 105 112]
 [118  97  82  86 117 123 116  66  41  51  95  93  89  95 102 107]
 [164 146 112  80  82 120 124 104  76  48  45  66  88 101 102 109]
 [157 170 157 120  93  86 114 132 112  97  69  55  70  82  99  94]
 [130 128 134 161 139 100 109 118 121 134 114  87  65  53  69  86]
 [128 112  96 117 150 144 120 115 104 107 102  93  87  81  72  79]
 [123 107  96  86  83 112 153 149 122 109 104  75  80 107 112  99]
 [122 121 102  80  82  86  94 117 145 148 153 102  58  78  92 107]
 [122 164 148 103  71  56  78  83  93 103 119 139 102  61  69  84]]
```

What the computer sees

An image is just a sequence of numbers

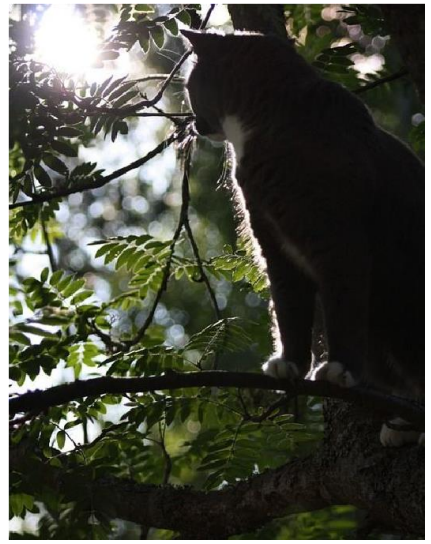
Challenges: Viewpoint variation



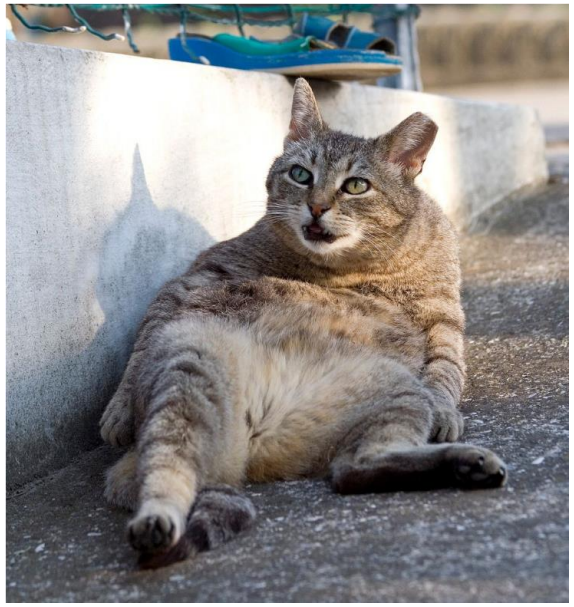
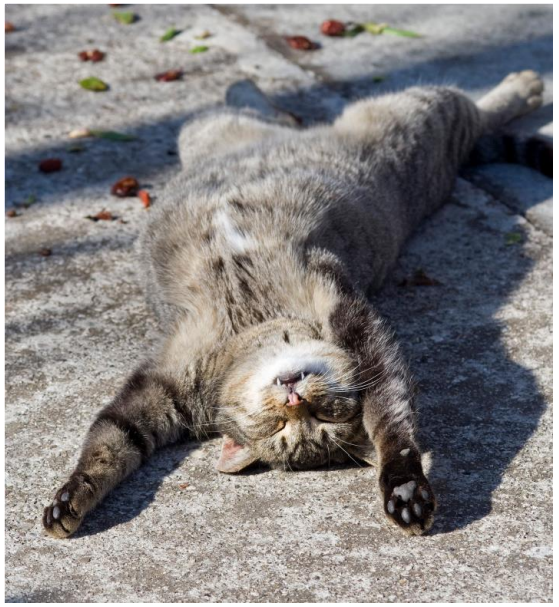
All pixels change when the camera moves!

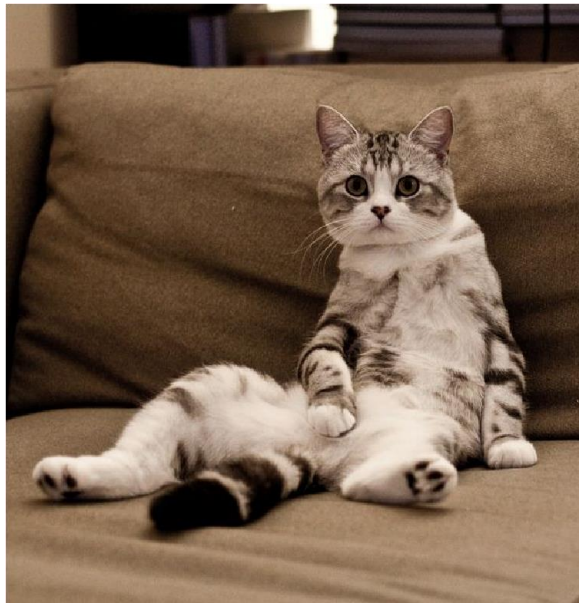
Challenges: Illumination



Challenges: Deformation



Challenges: Occlusion

Challenges: Background Clutter

Challenges: Intraclass variation

Image classifier

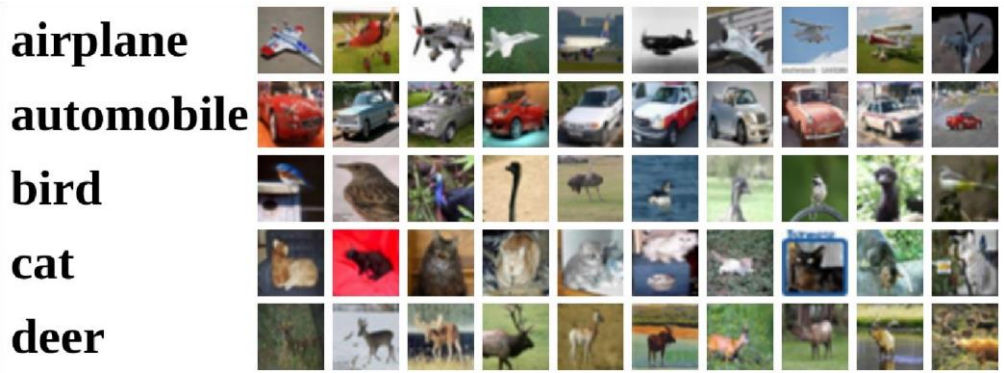
```
def classify_image(image):
  # Some magic here?
  return class_label
```

no obvious way to write the algorithm for recognizing a cat, or other classes

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

Example training dataset



First classifier: **Nearest Neighbor**

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

Memorize all data and labels

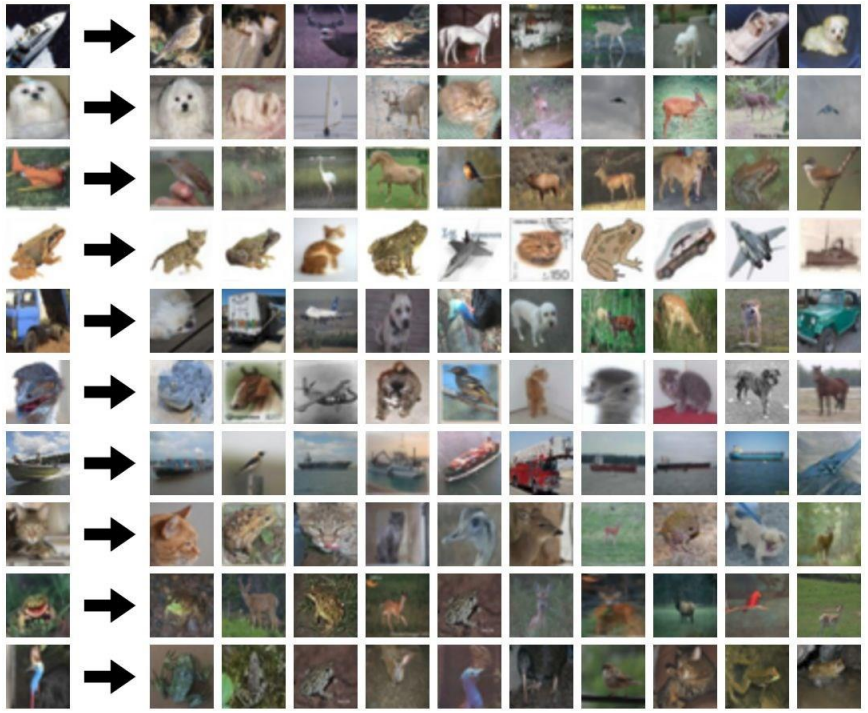
```
def predict(model, test_images):
  # Use model to predict labels
  return test_labels
```

Predict the label of the most similar training image

Example Dataset: **CIFAR10**

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

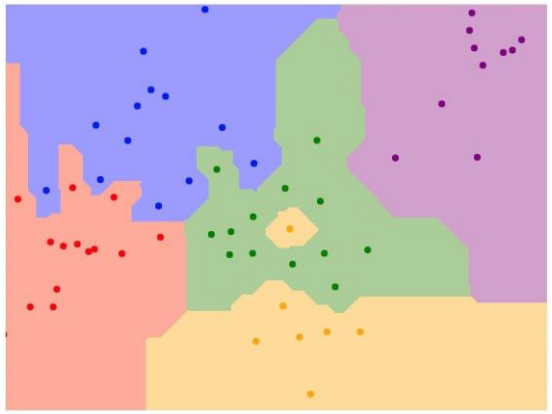
Test images and nearest neighbors



Distance Metric to compare images

L1 (Manhattan) distance

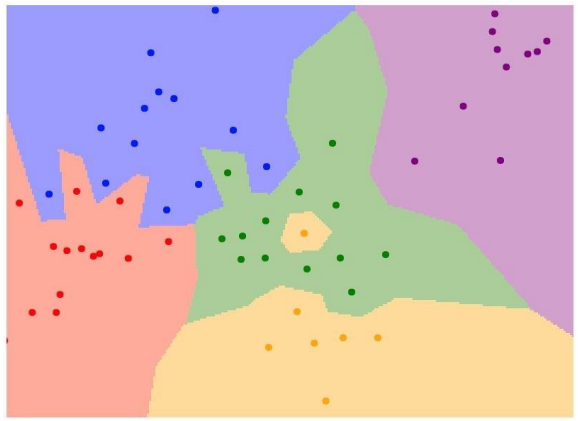
$$d_1(I_1, I_2) = \sum_{p=pixels} |I_1^p - I_2^p|$$



K=1

L2 (Euclidean) distance

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



K=1

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

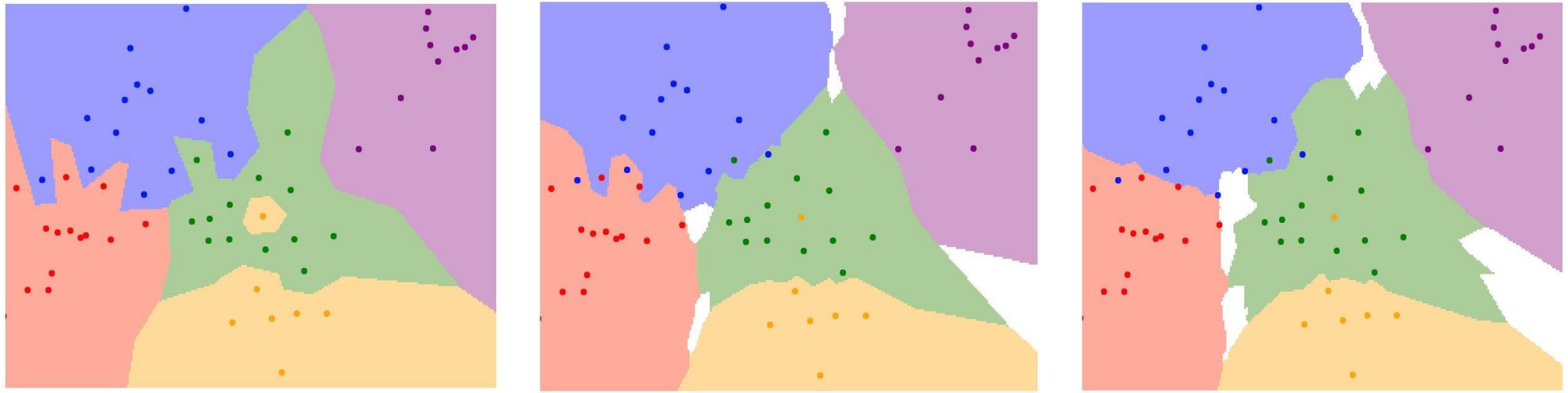
Q: With N examples, how fast are training and prediction?

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

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

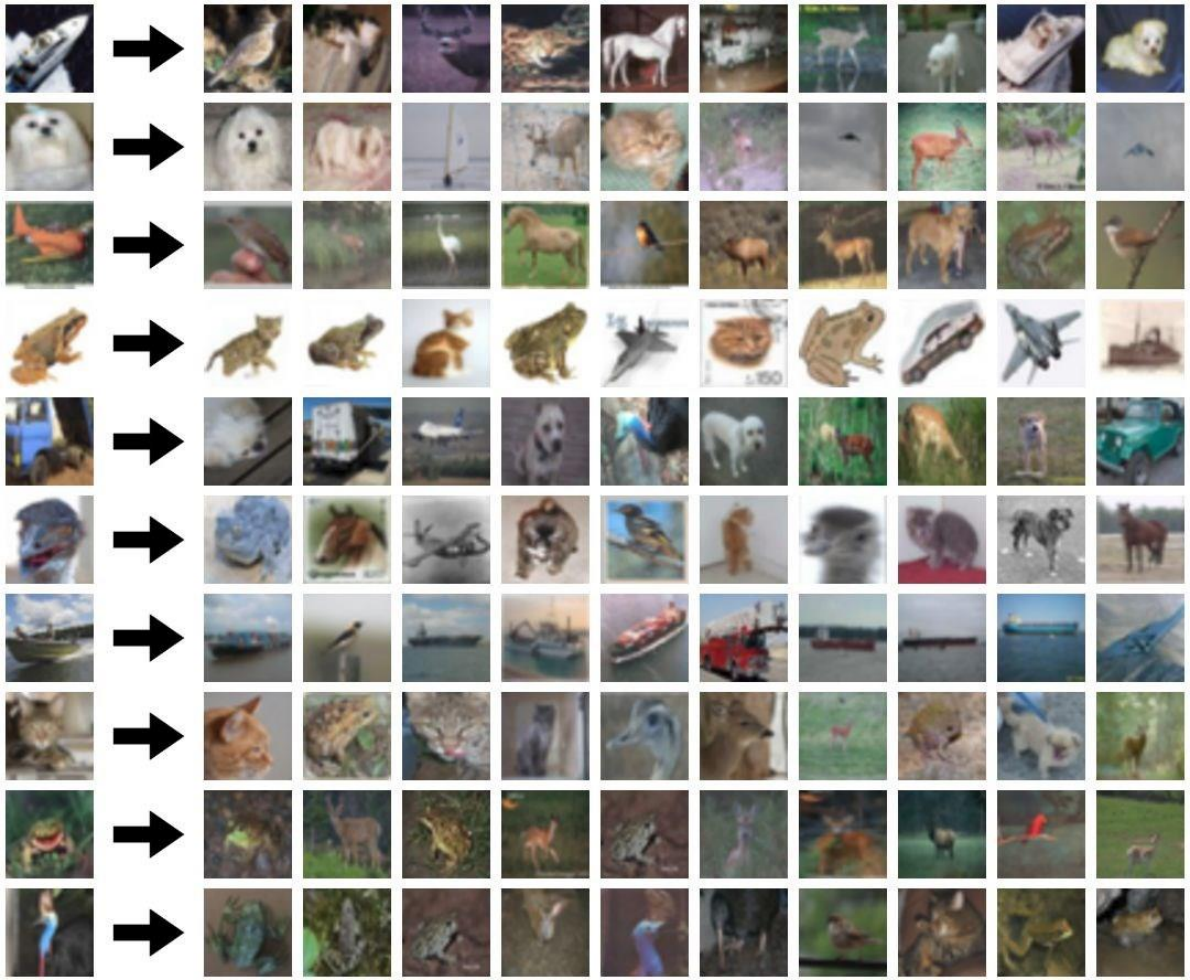
K-Nearest Neighbors

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



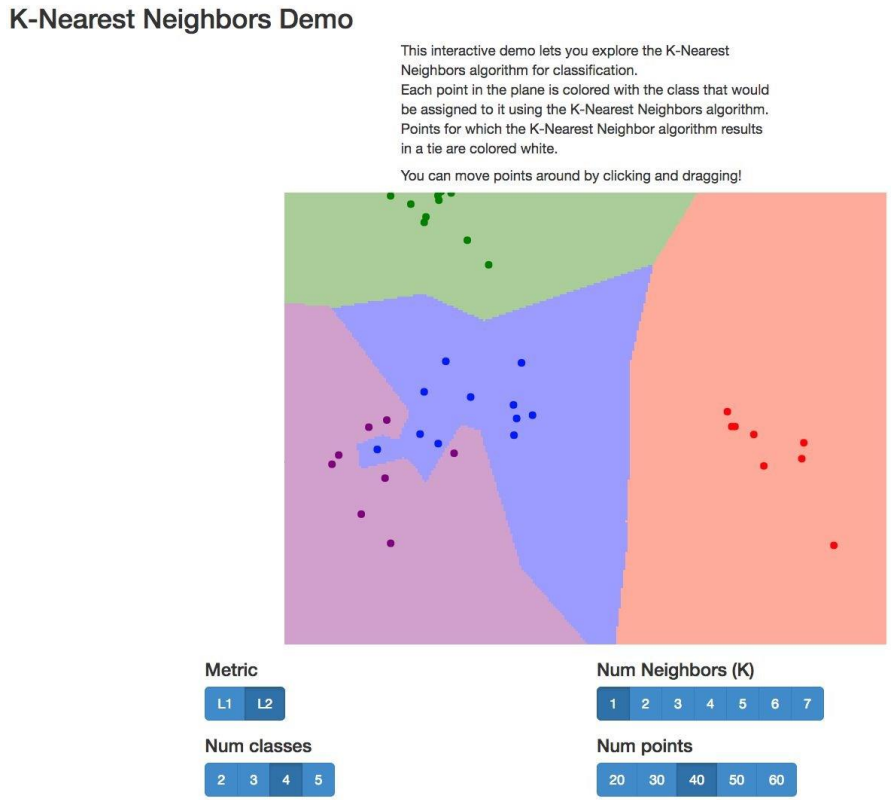
K=1 *K*=3 *K*=5

What does this look like?



What does this look like?

K-Nearest Neighbors: Demo Time



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

Hyperparameters

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

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

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

Setting Hyperparameters

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

Setting Hyperparameters

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

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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

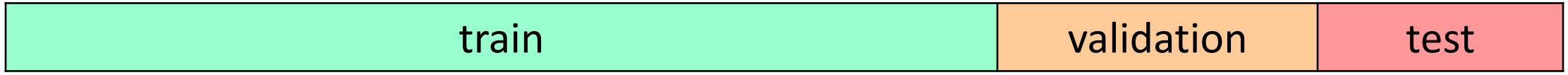
BAD: $K = 1$ always works perfectly on training data

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

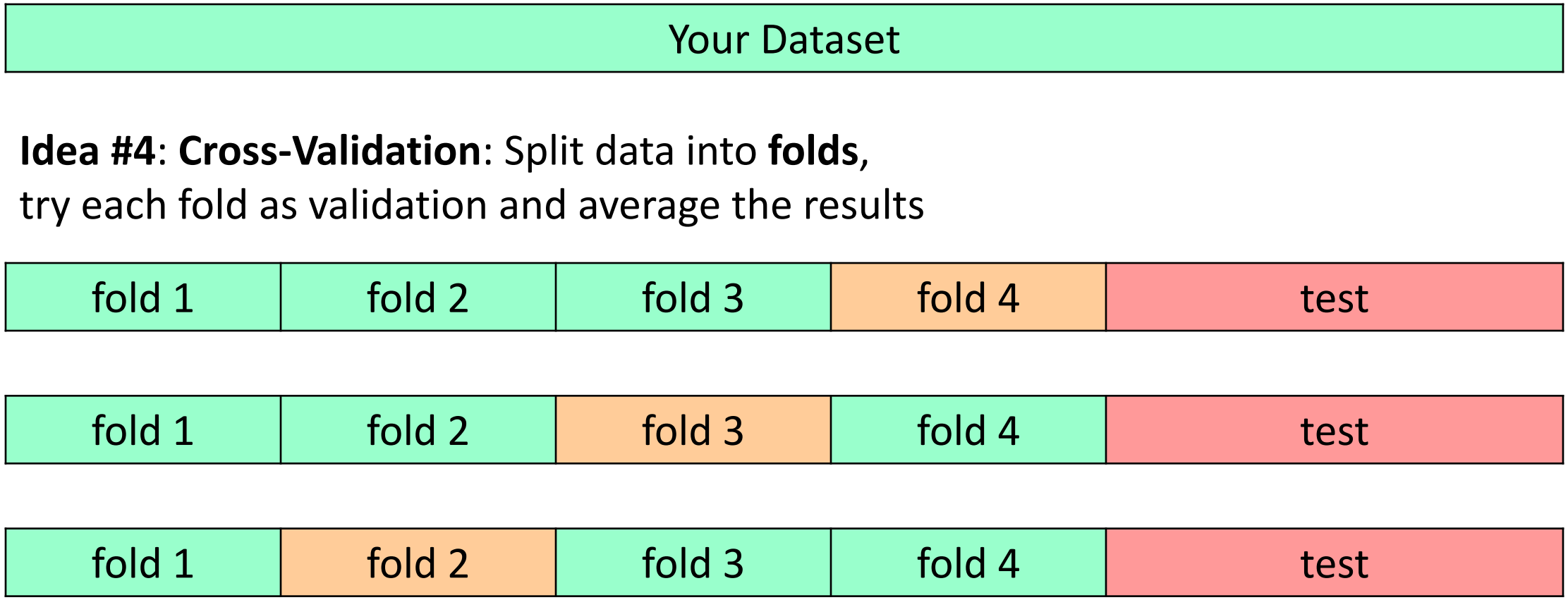
BAD: No idea how algorithm will perform on new data

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

Better!



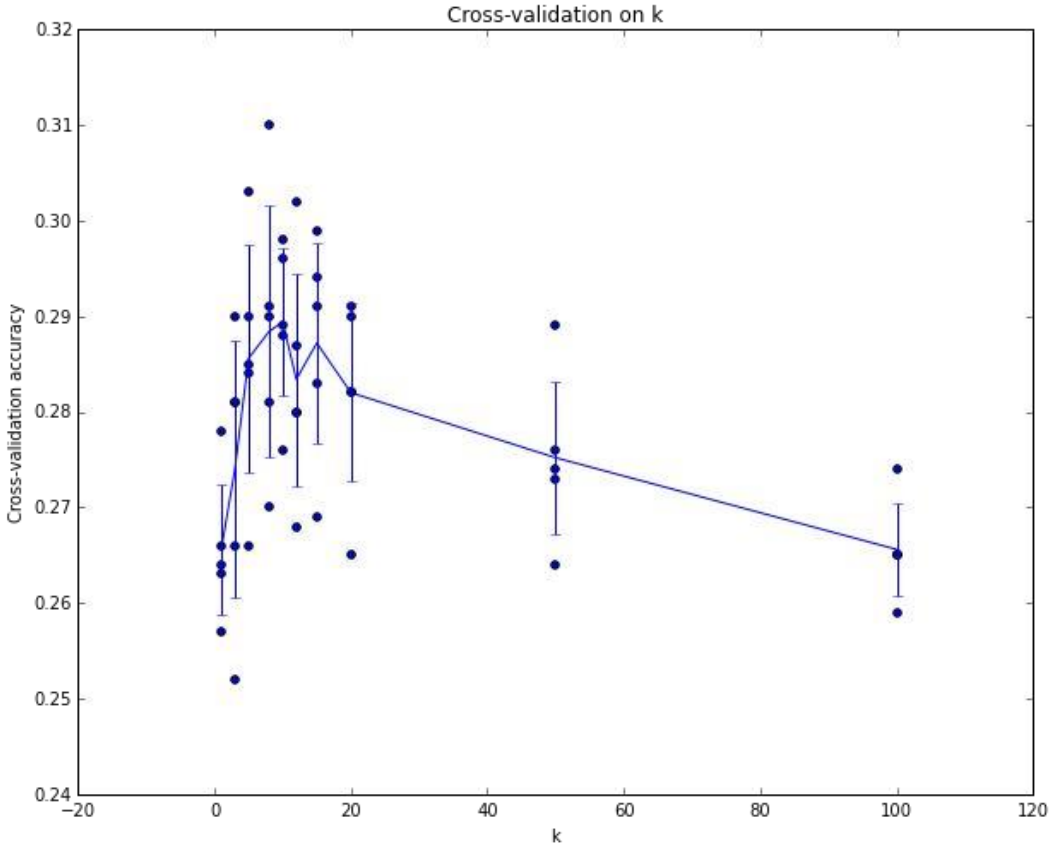
Setting Hyperparameters



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

Useful for small datasets, but not used too frequently in deep learning

Setting Hyperparameters



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

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

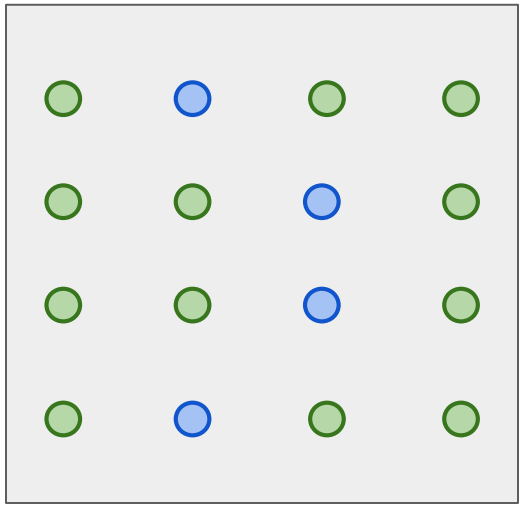
(all 3 images have same L2 distance to the one on the left)

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

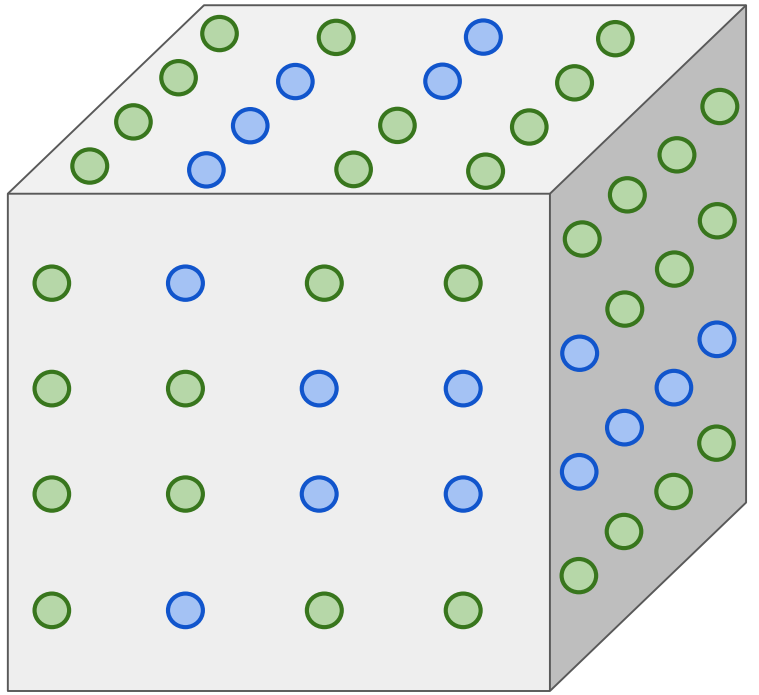
- Curse of dimensionality

Dimensions = 1
Points = 4

Dimensions = 2
Points = 4^2

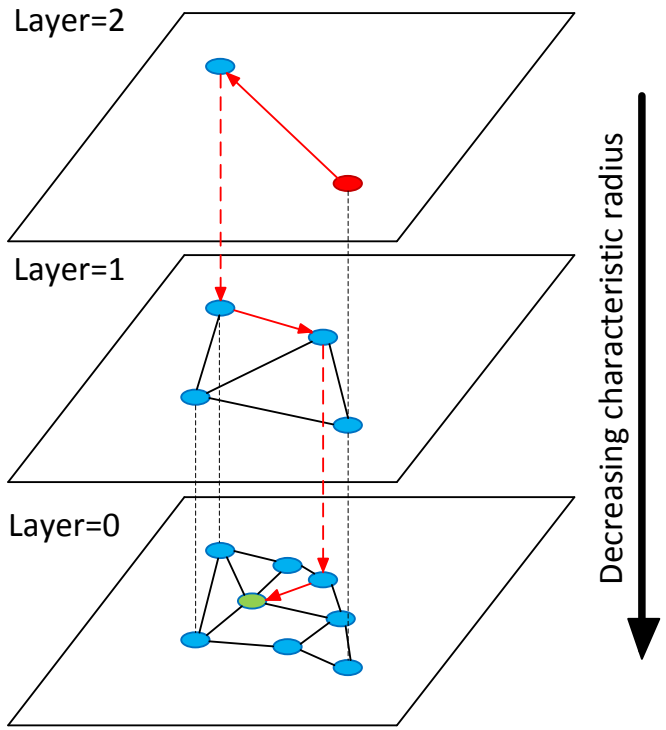


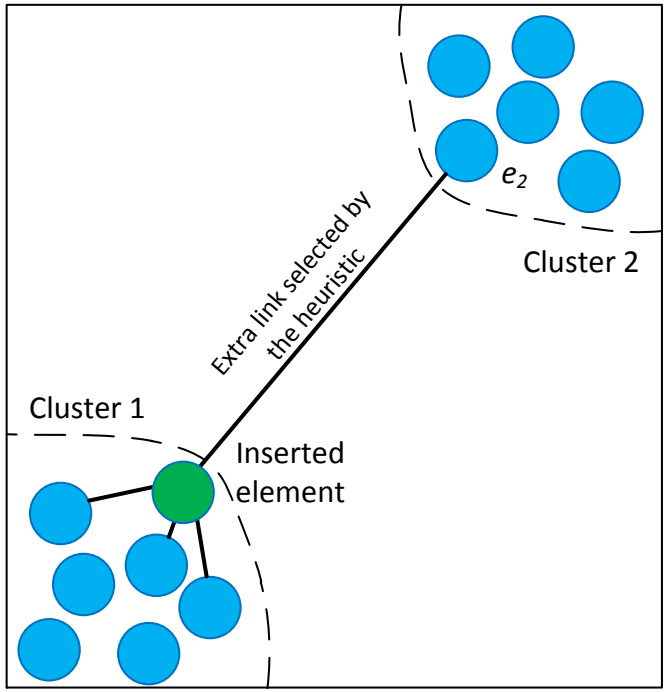
Dimensions = 3
Points = 4^3



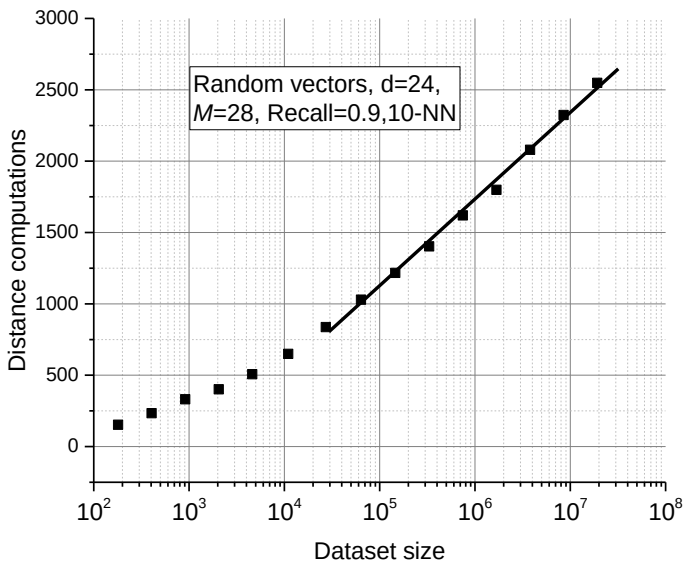
Approximate Nearest Neighbor Search (ANNS)

Hierarchical Navigable Small World (HNSW) – state of the art algorithm for ANNS

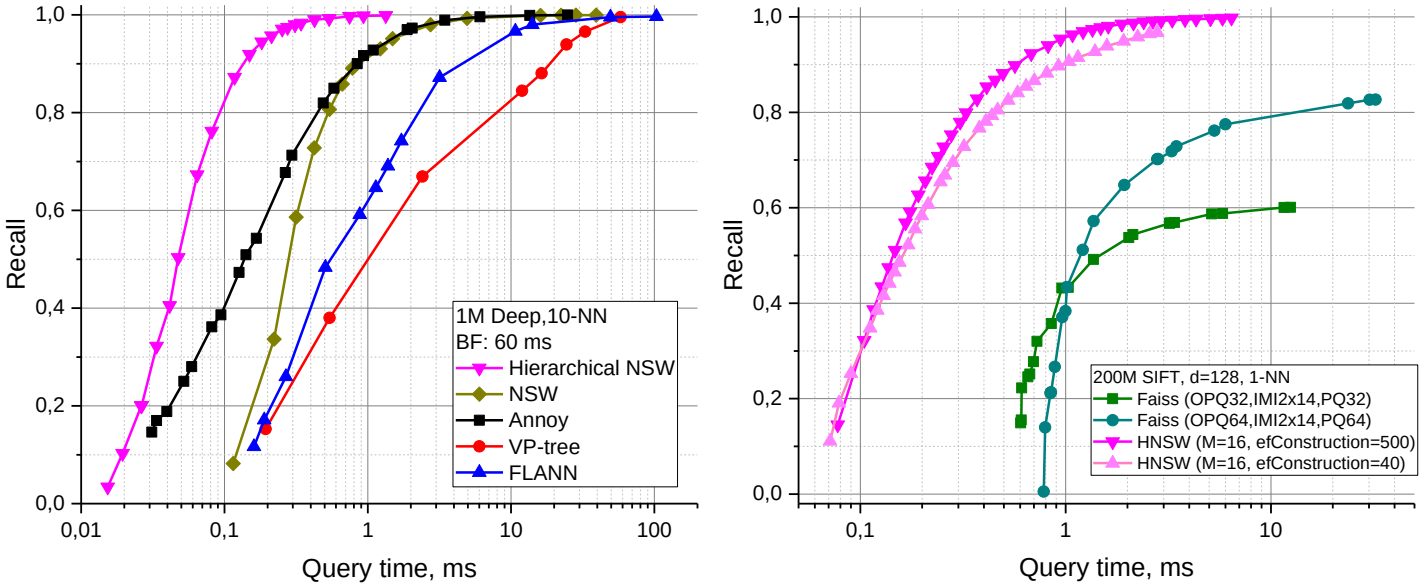




Approximate Nearest Neighbor Search (ANNS)



Scaling for the number of distance computations



Comparison of the Hierarchical NSW with open source implementations

https://arxiv.org/abs/1603.09320
https://github.com/yurymalkov/hnsw
https://github.com/erikbern/ann-benchmarks

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!

References

- **Stanford courses (in English)**
  CS231n: Convolutional Neural Networks for Visual Recognition
  http://cs231n.stanford.edu/
  Video lectures (2016)
  https://www.youtube.com/playlist?list=PLkt2uSq6rBVctENoVBg1TpCC7OQi31AlC

  CS224d: Deep Learning for Natural Language Processing
  http://cs224d.stanford.edu/
  Video lectures (2017)
  https://www.youtube.com/watch?v=OQQ-W_63UgQ&list=PL3FW7Lu3i5Jsnh1rnUwq_TcylNr7EkRe6
- **Articles and blogs**
  arxiv.org
  medium.com

Assignments

- Install Anaconda3 with python 3.5
- Install PyCharm – python IDE
- Get started with Python
- Take a look at the CS231n assignment http://cs231n.github.io/assignments2017/assignment1/
- Do k-Nearest Neighbor classifier task knn.ipynb