Machine Learning
Lecture 1: introduction

Jan Chorowski
Instytut Informatyki
Wydział Matematyki i Informatyki Uniwersytet Wrocławski

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Slides taken from presentations by: A. Ng, P. Vincent, Y. LeCun, W. Zaremba, R. Salakhutdinov, L. Fei-Fei, A. Karpathy, argmax.ai ML course

Practical Information

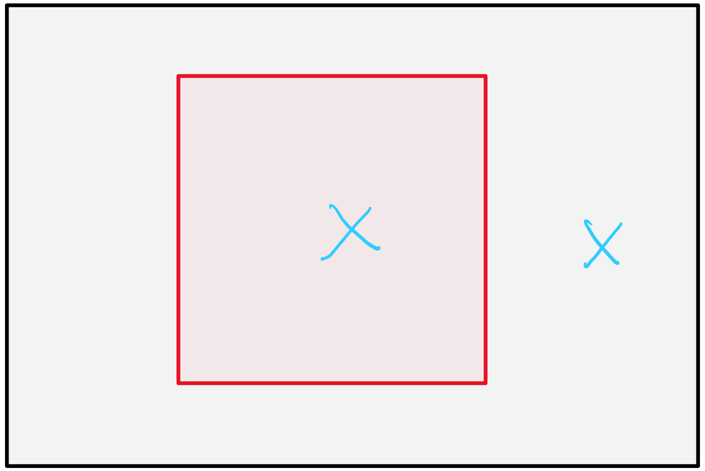
- Course Materials:
  - SKOS (announcements, course rules etc.): https://skos.ii.uni.wroc.pl/course/view.php?id=331
  - Teams: announcements, lecture recordings, communication
    Important: **Prefer Teams over email.** Don't be shy and reply to your colleagues!
  - Github (lecture notes, assignment notebooks): https://github.com/janchorowski/ml_uwr
  - USOS: grades
- On-line Resources:
  - http://cs229.stanford.edu/
  - https://argmax.ai/ml-course/
- Textbooks
  - Bishop, Pattern Recognition and Machine Learning (PRML)
  - Kevin Murphy "Machine Learning"

ML INTUITIONS

What is Machine Learning?

Compare these two tasks:

1. In-Out: determine if a point is inside, or outside of a rectangle

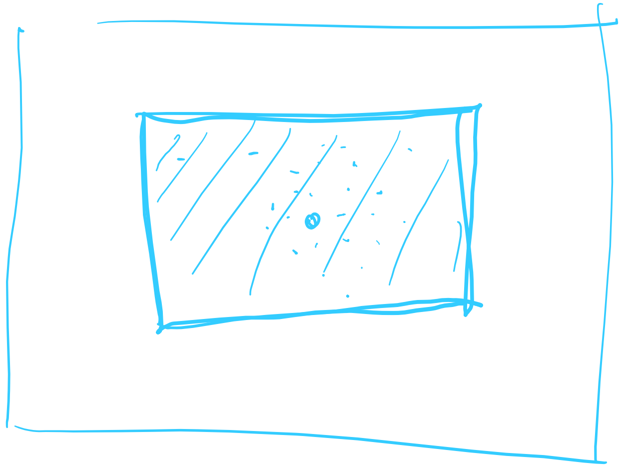


2. Bird-Spotting: given a photograph, tell if it contains a bird

In-Out task

It is an algorithmic task:

- Can define formal invariants
- Can design an algorithm, e.g.:
  1. Flood-fill from the query point
  2. If image border reached -> out
     Else -> In



Bird Spotting

It’s a Machine Learning task!

Can’t formulate any invariants.

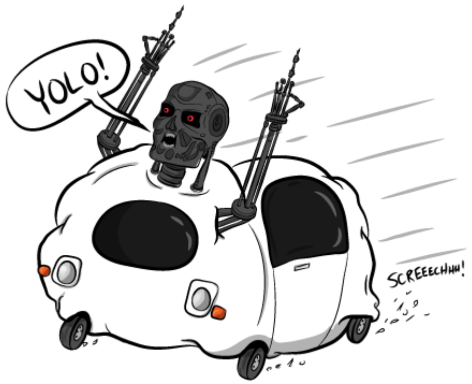
Can’t design an algorithm.

Can produce a **dataset of examples**

Then let a computer search for a function which matches the data!

Where is machine learning?

- Everywhere!
- web search ☺
- and ads ☹
- recommendations
- Self-driving cars



http://theoatmeal.com/blog/google_self_driving_car

Supervised Learning

$$Input \rightarrow Output$$

- Classification: assign data to classes
- Regression: compute numerical outcomes
- Structure prediction (e.g. parse tree from text)

ML Example: classification

- Assign small images to one of ten categories

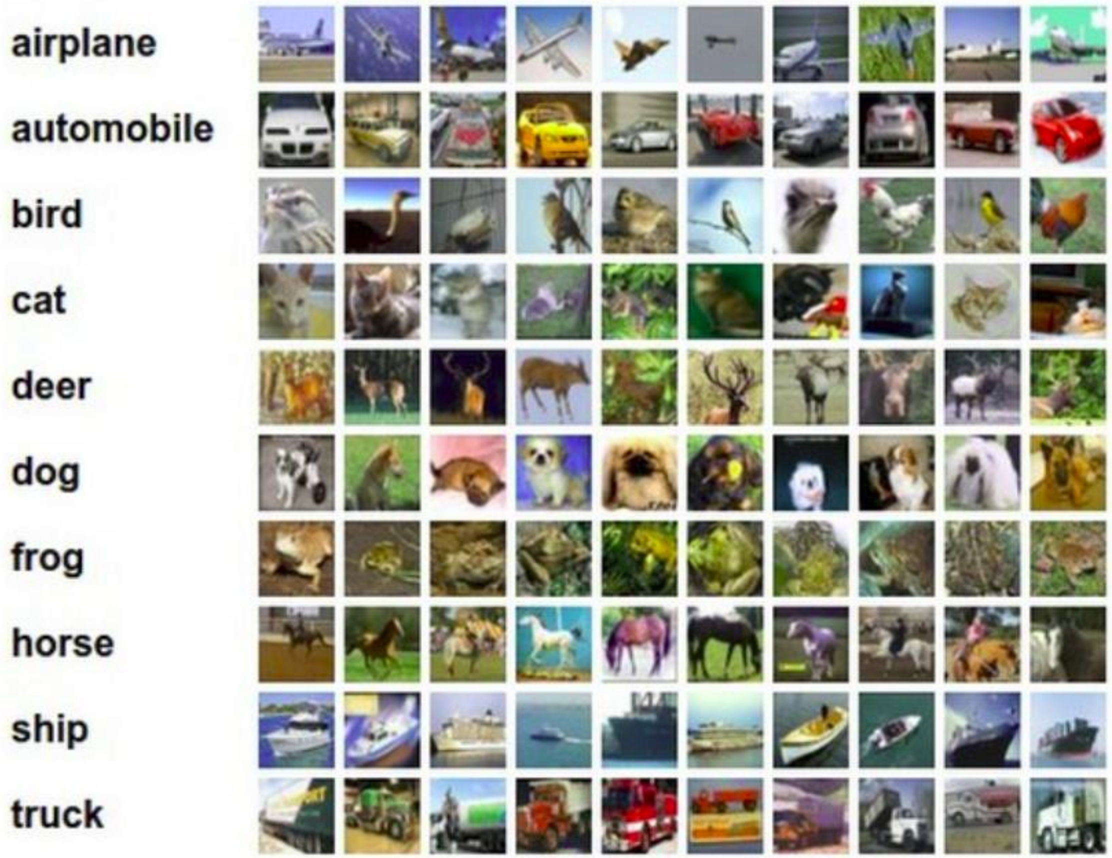
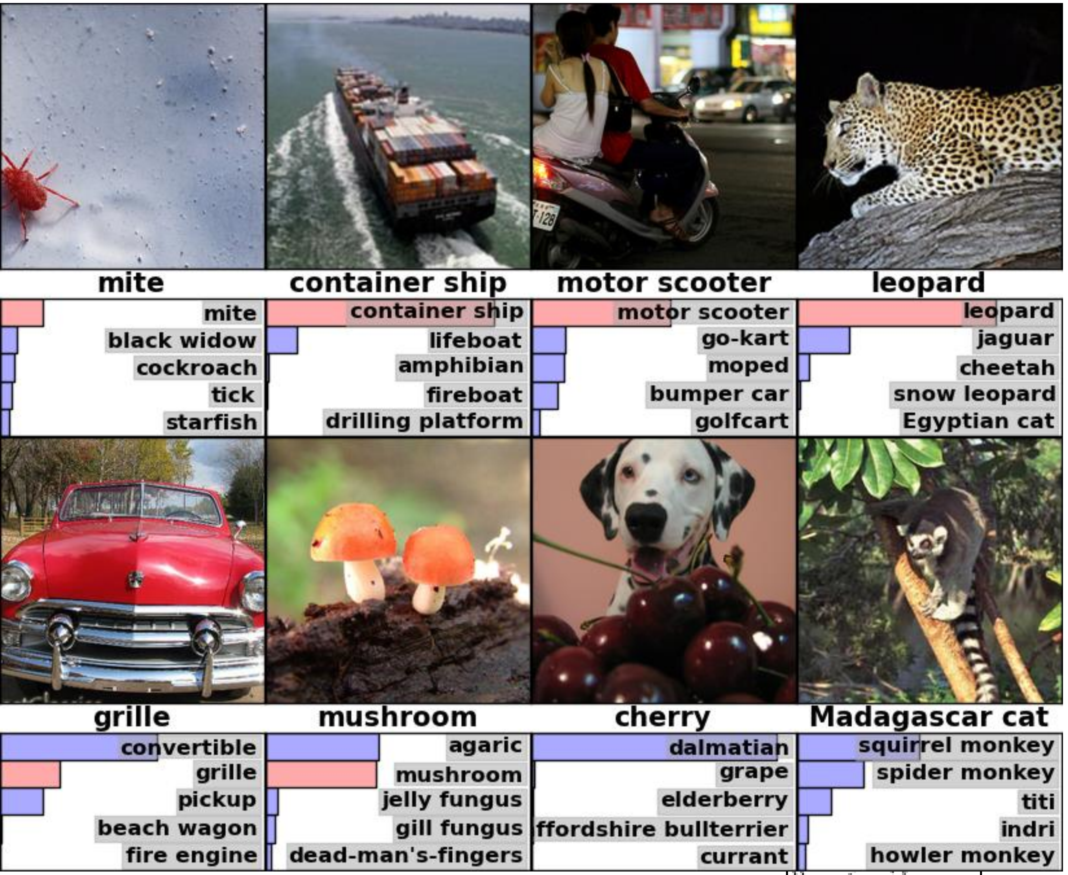
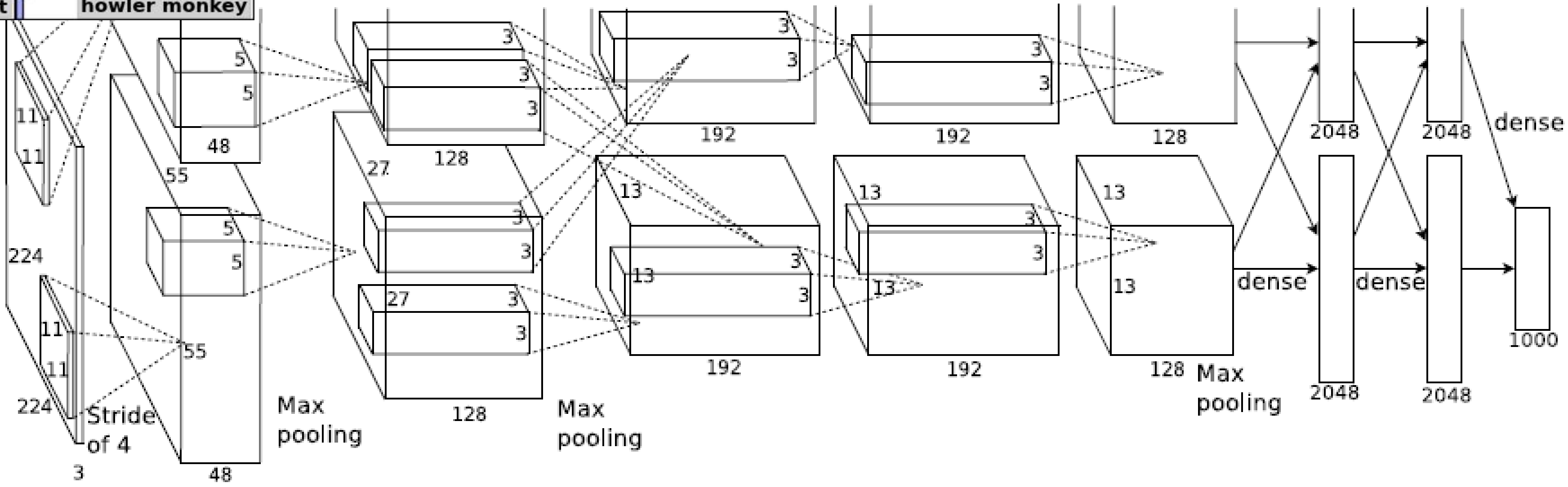
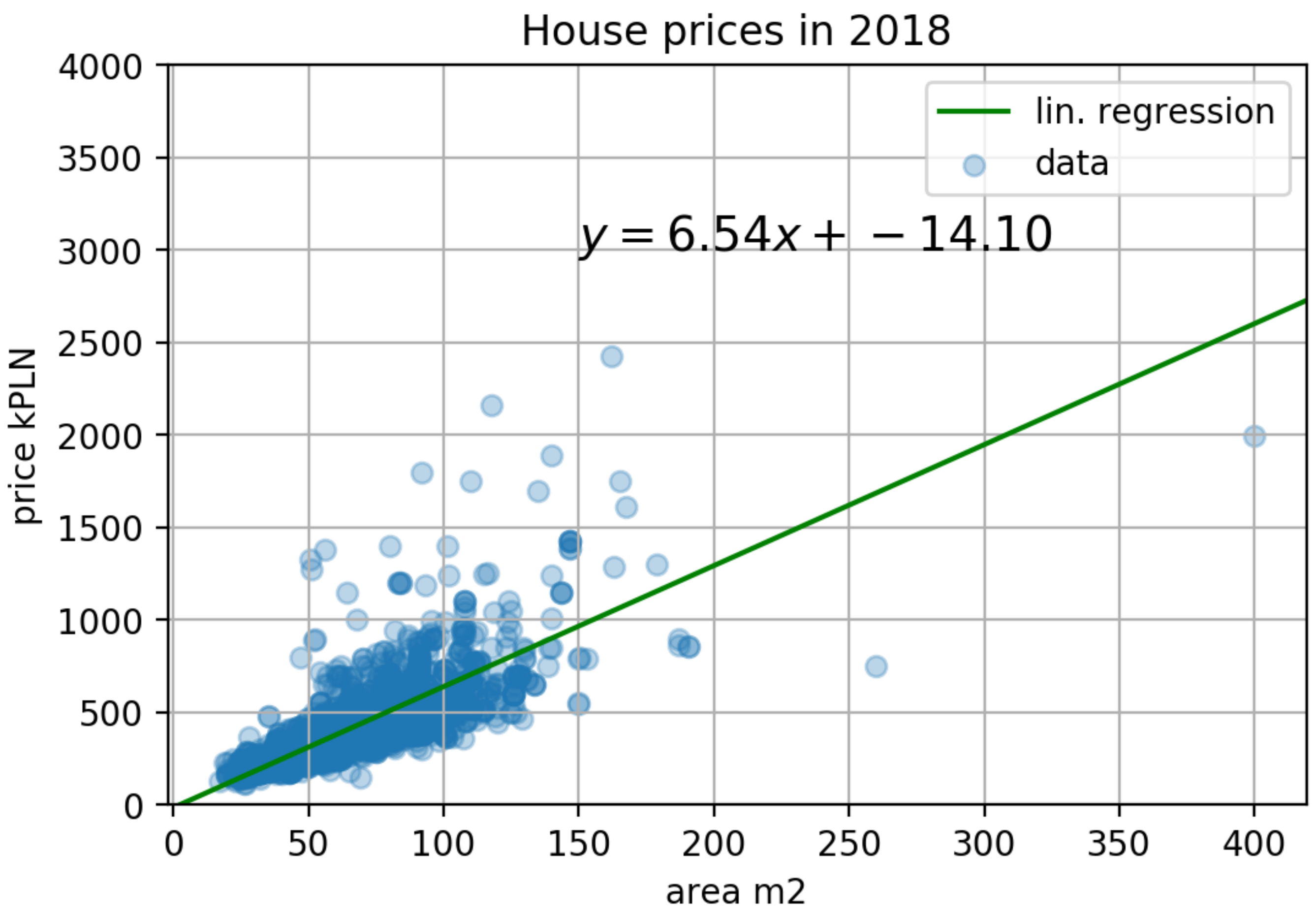


Image recognition





ML Example: Regression



„Real-Life” Example: Sorting Cucumbers


Google Cloud Platform

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How a Japanese cucumber farm... deep learning and TensorFlow

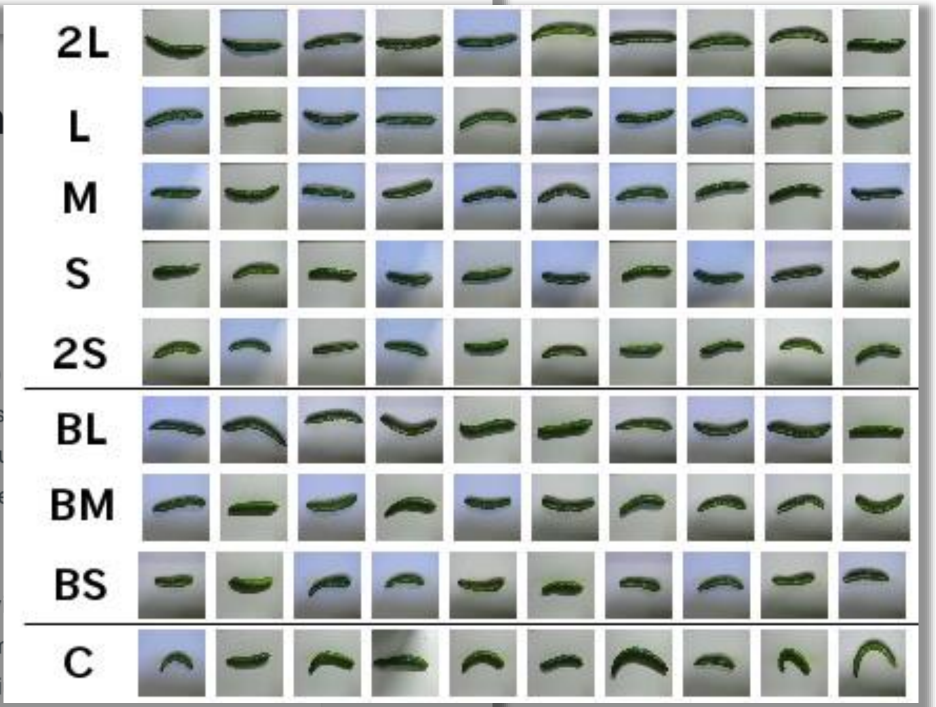
Wednesday, August 31, 2016

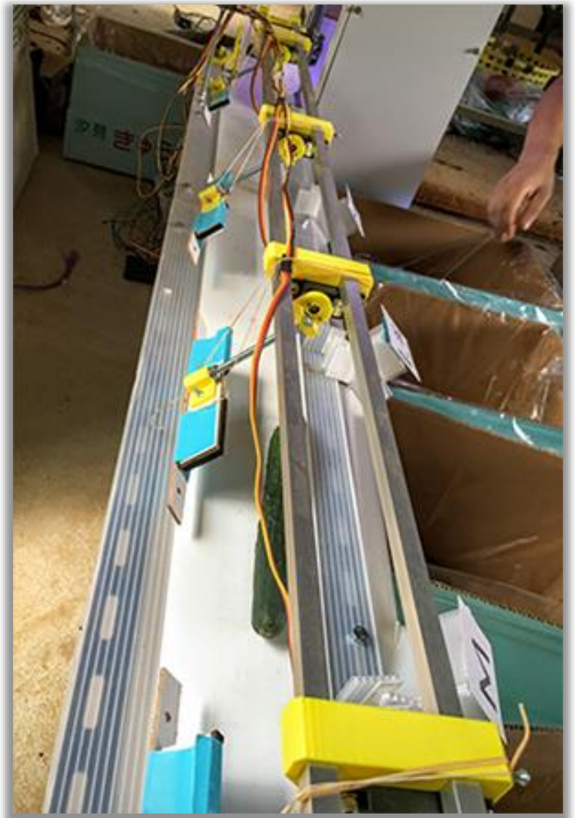
Posted by Kaz Sato, Developer Advocate, Google Cloud Platform

It's not hyperbole to say that use cases for machine learning and deep ... by our imaginations. About one year ago, a former embedded systems ... Japanese automobile industry named Makoto Koike started helping o... farm, and was amazed by the amount of work it takes to sort cucumbe... and other attributes.

Makoto's father is very proud of his thorny cucumber, for instance, hav... delivering fresh and crispy cucumbers, with many prickles still on them... cucumbers with a vivid color and lots of prickles are considered premi... much higher prices on the market.

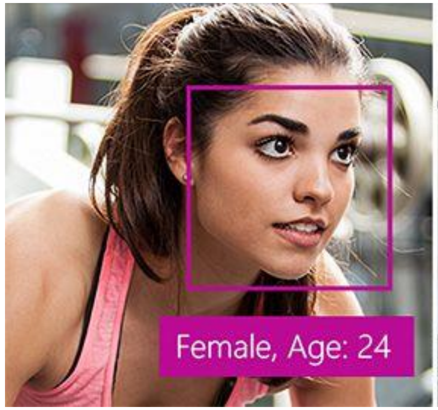
But Makoto learned very quickly that sorting cucumbers is as hard and tricky as actually growing them. "Each cucumber has different color, shape, quality and freshness," Makoto says.

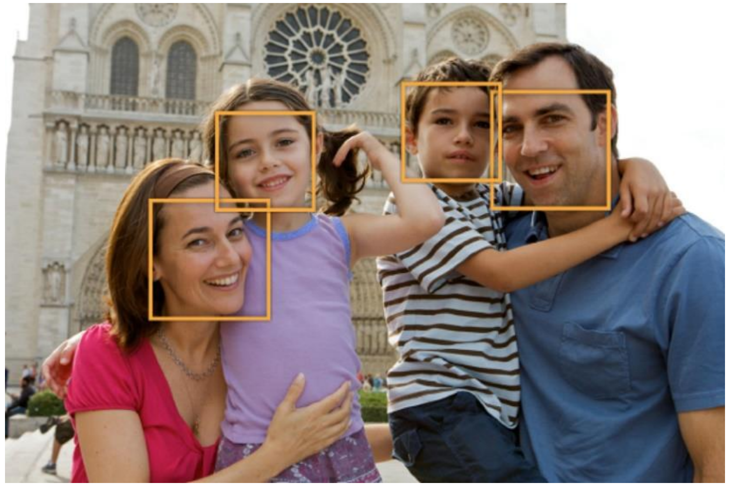




Source: https://cloud.google.com/blog/big-data/2016/08/how-a-japanese-cucumber-farmer-is-using-deep-learning-and-tensorflow

ML example: face detection
classify each image patch as face/non-face

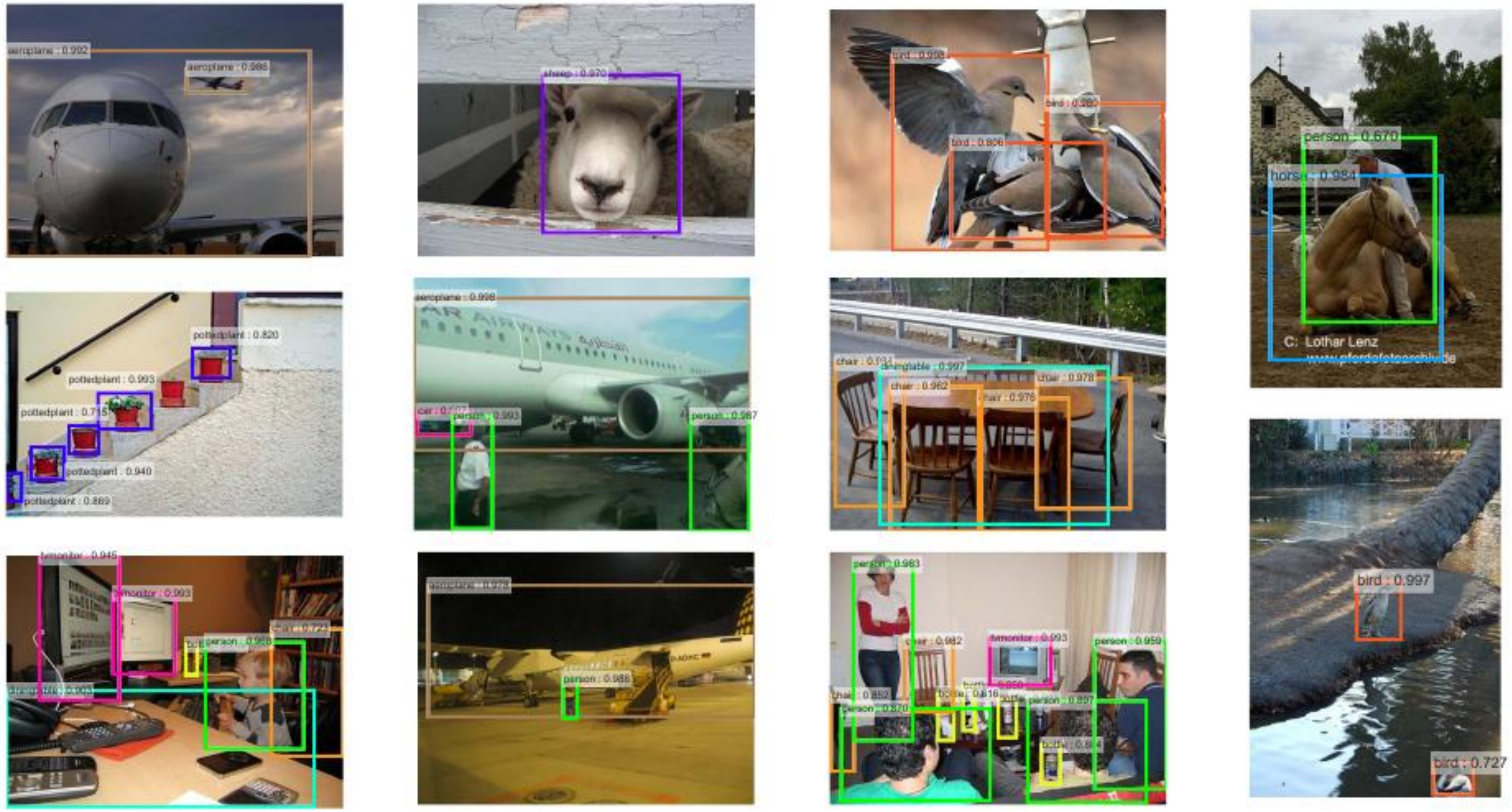




Source: Microsoft and Apple face detection API documentations, wykop.pl

Object Detection

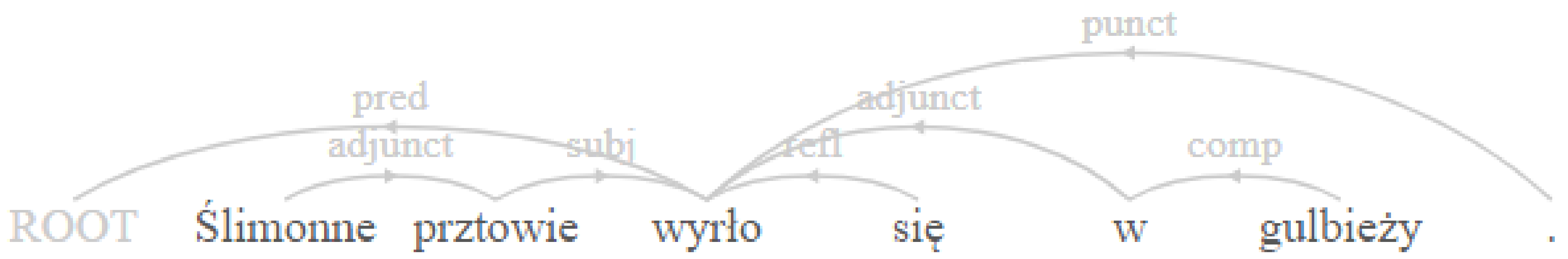
- https://www.youtube.com/watch?v=WZmSMkK9VuA



(Ren, He, Girshick and Sun, „Faster R-CNN", 2015)

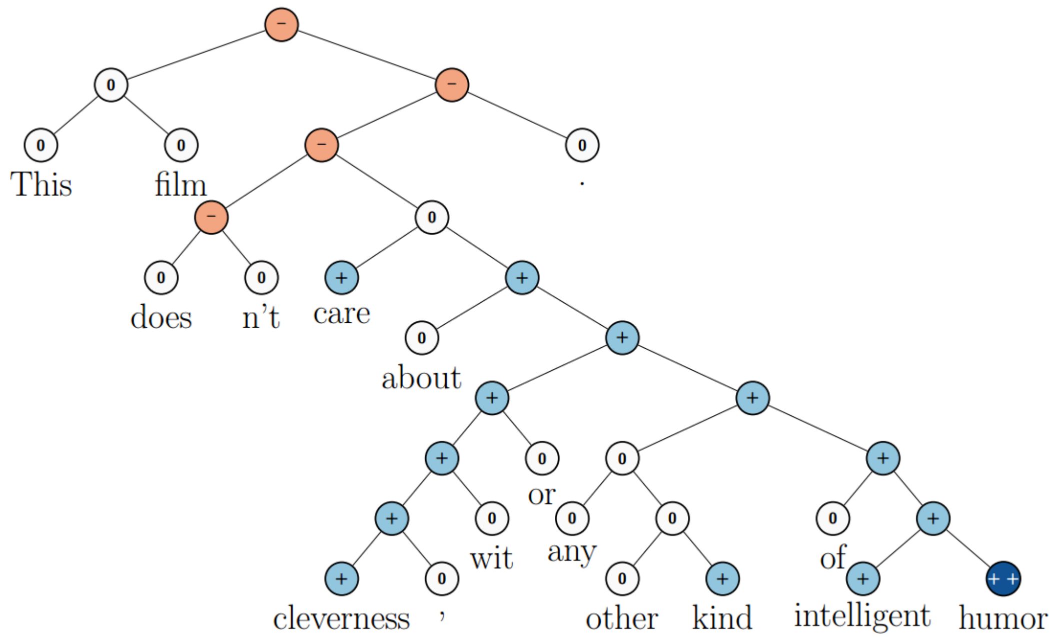
Natural Language Processing

- http://zapotoczny.pl/parser/

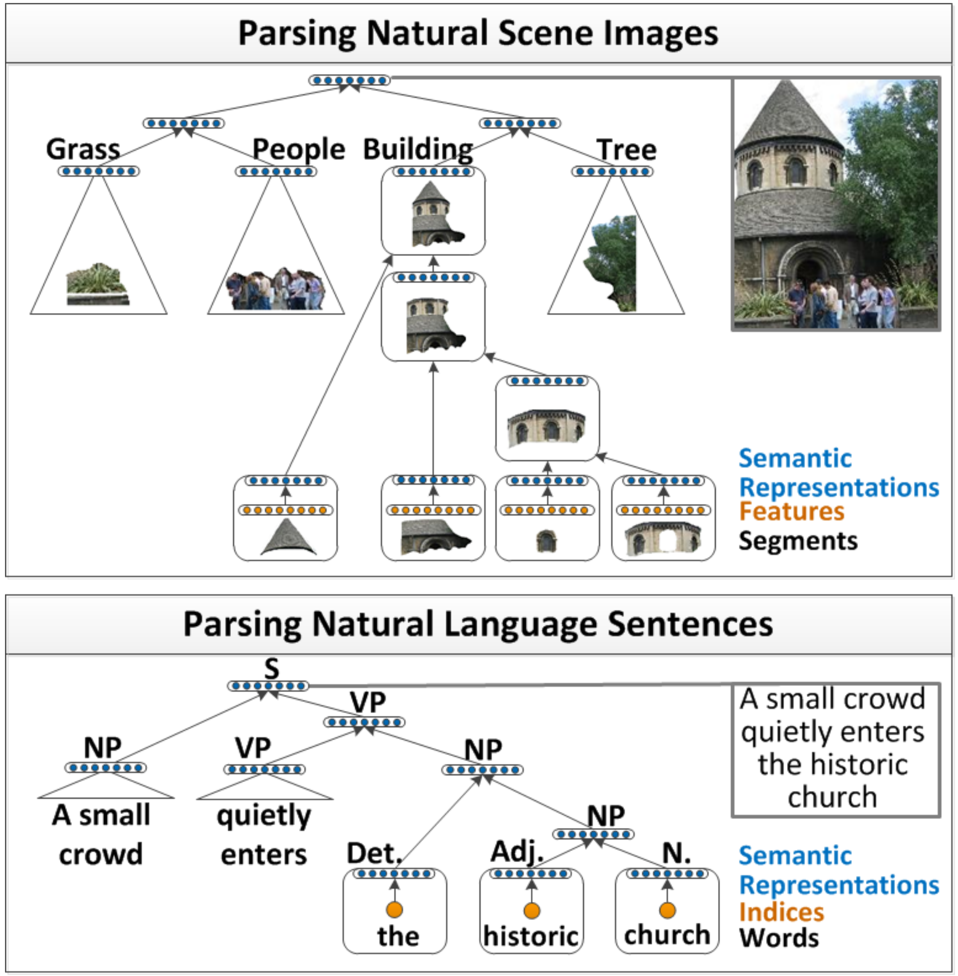


Parsing

Sentiment recognition



Scene understanding



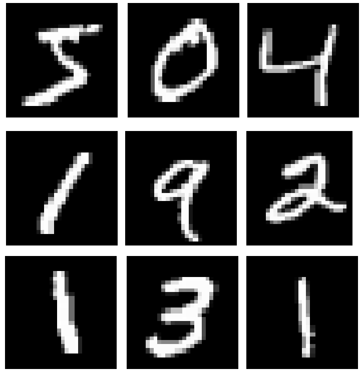
Unsupervised learning

$$I \rightarrow ?$$

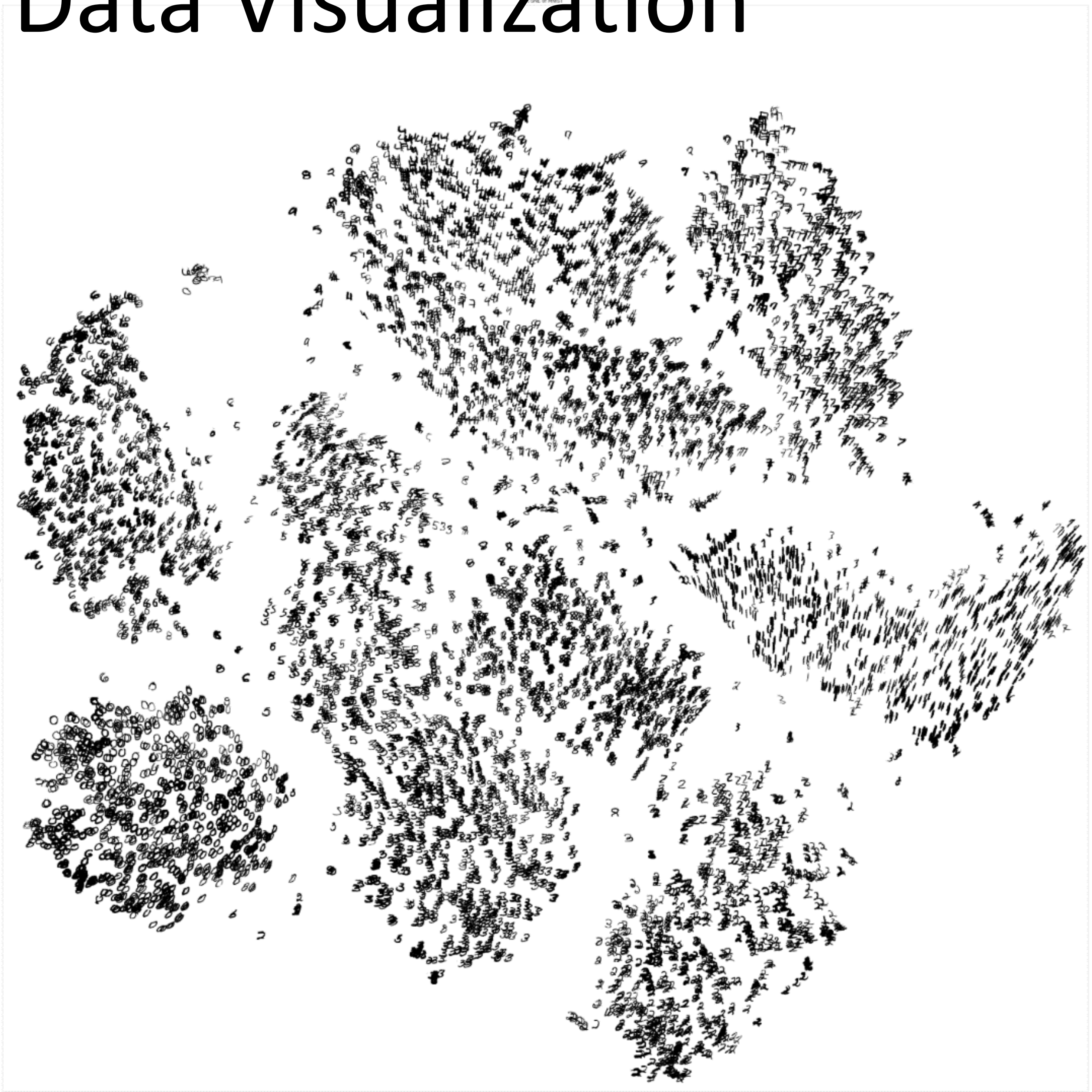
- Visualization: present the data in 2D
- Clustering: discover groups in data
- Generation: learn to generate fake data

ML Example: t-SNE Data Visualization

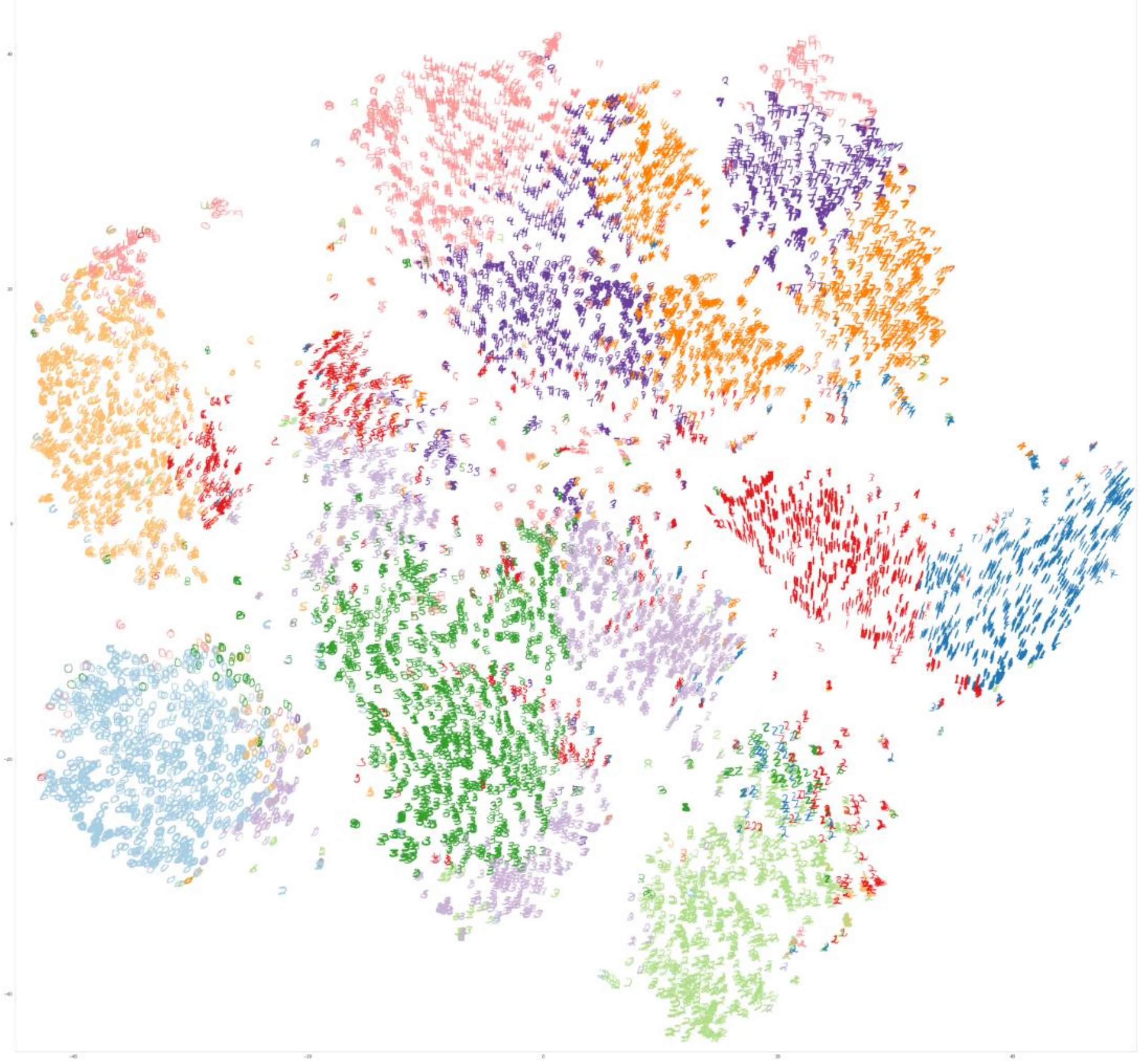
Data: small images of digits



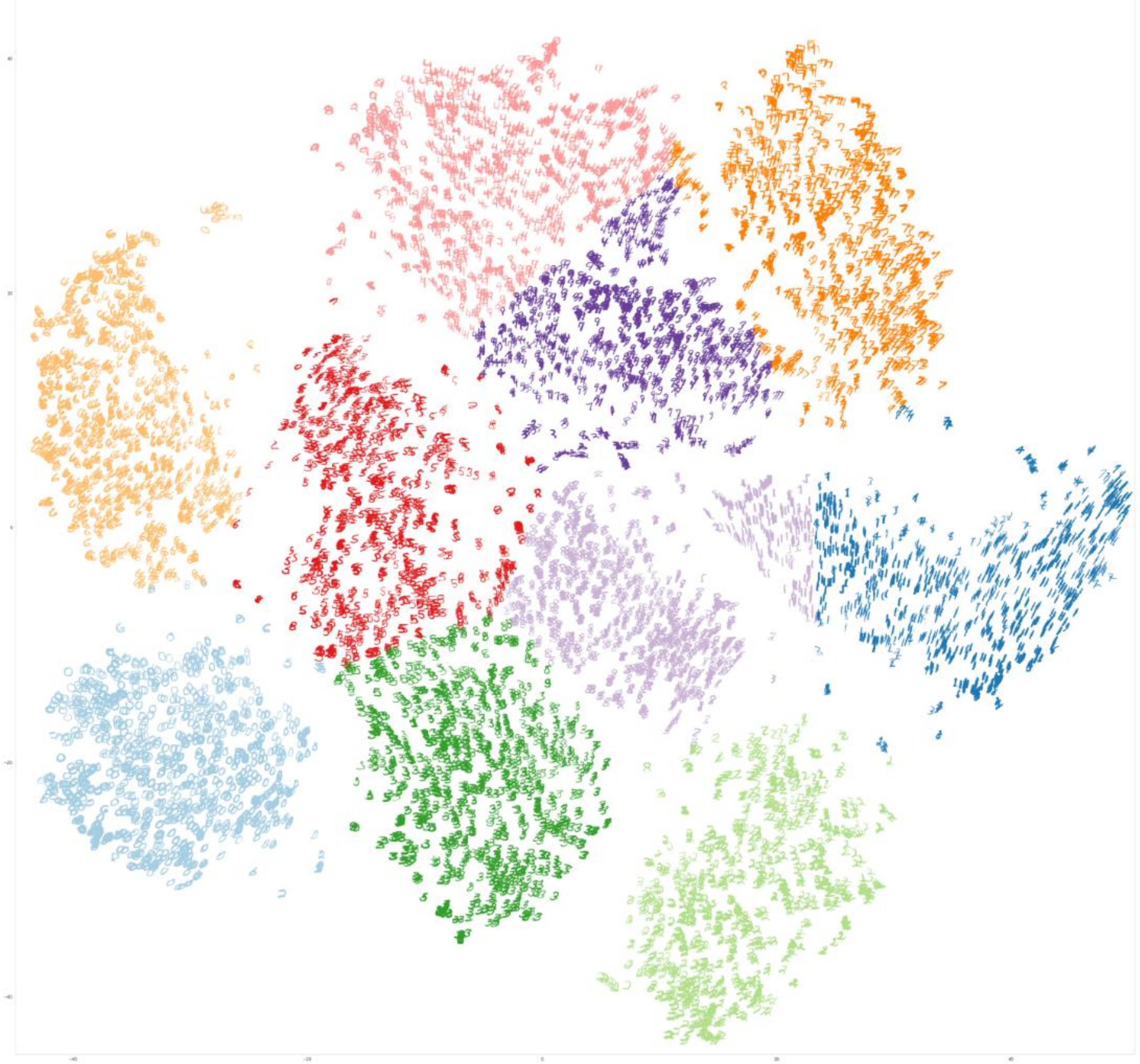
Task: place each image on the 2D plane, such that similar images are close



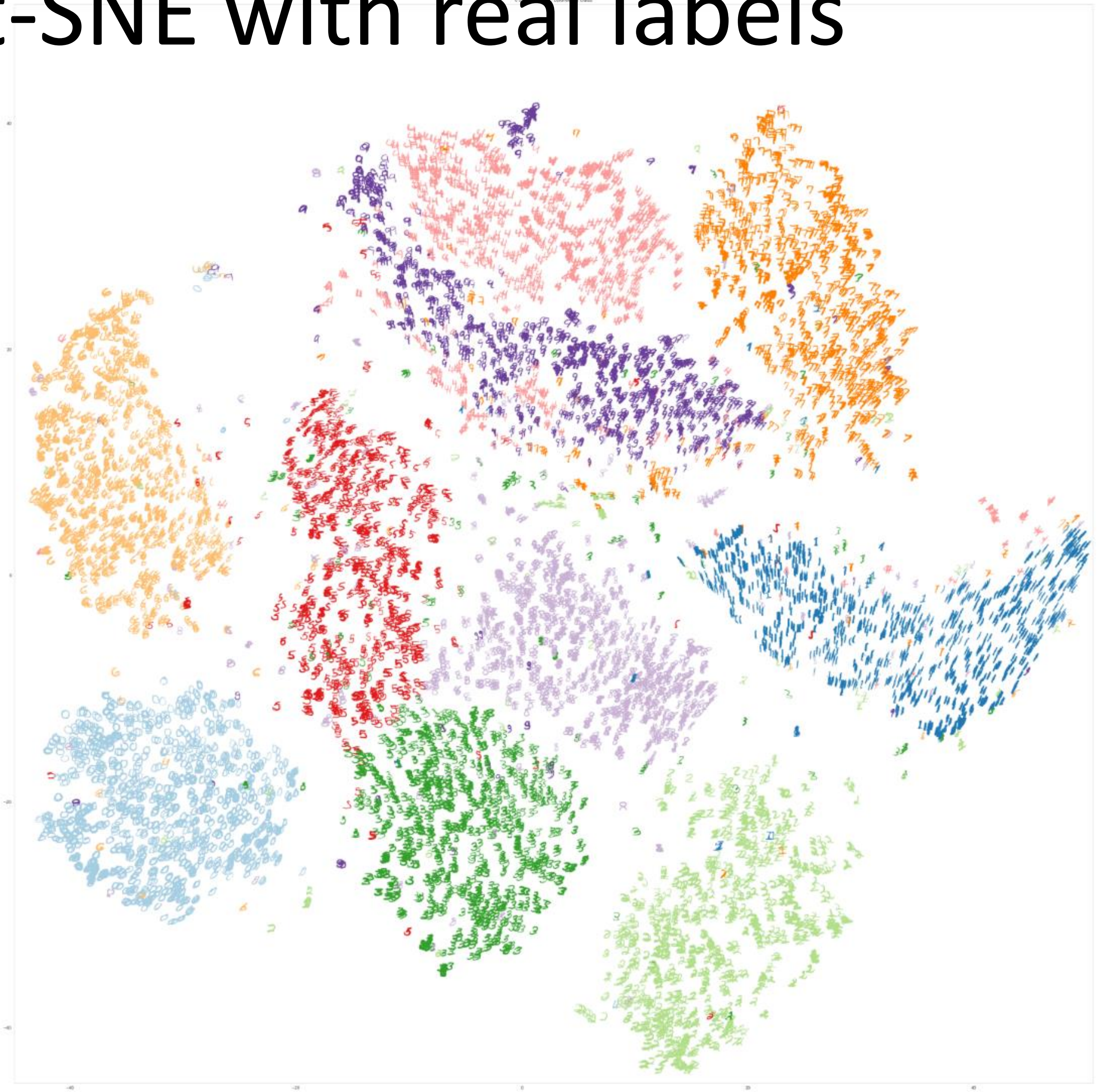
t-SNE colored by clustering in data space



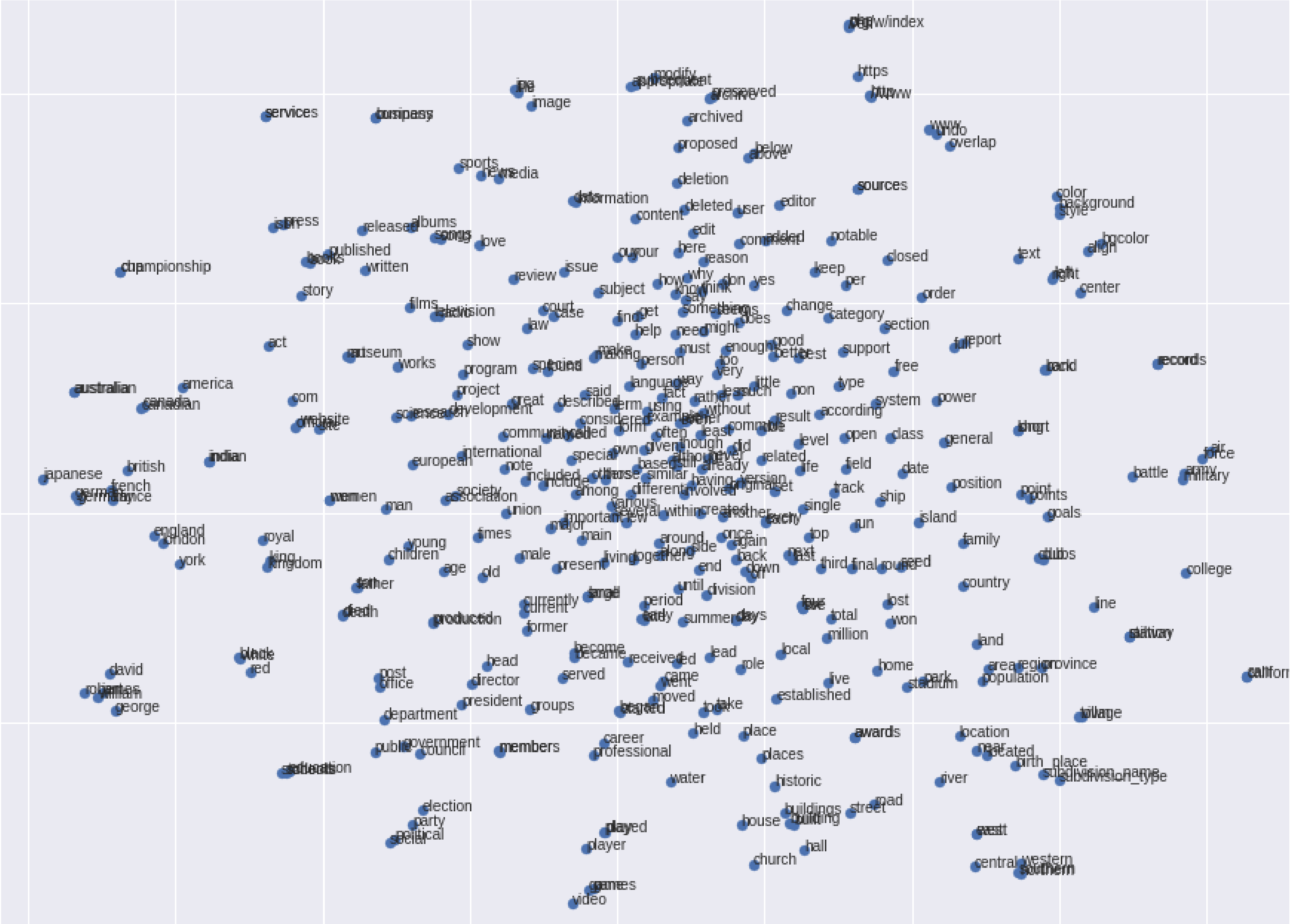
t-SNE colored by clustering in t-SNE space



t-SNE with real labels



Putting words into a vector space



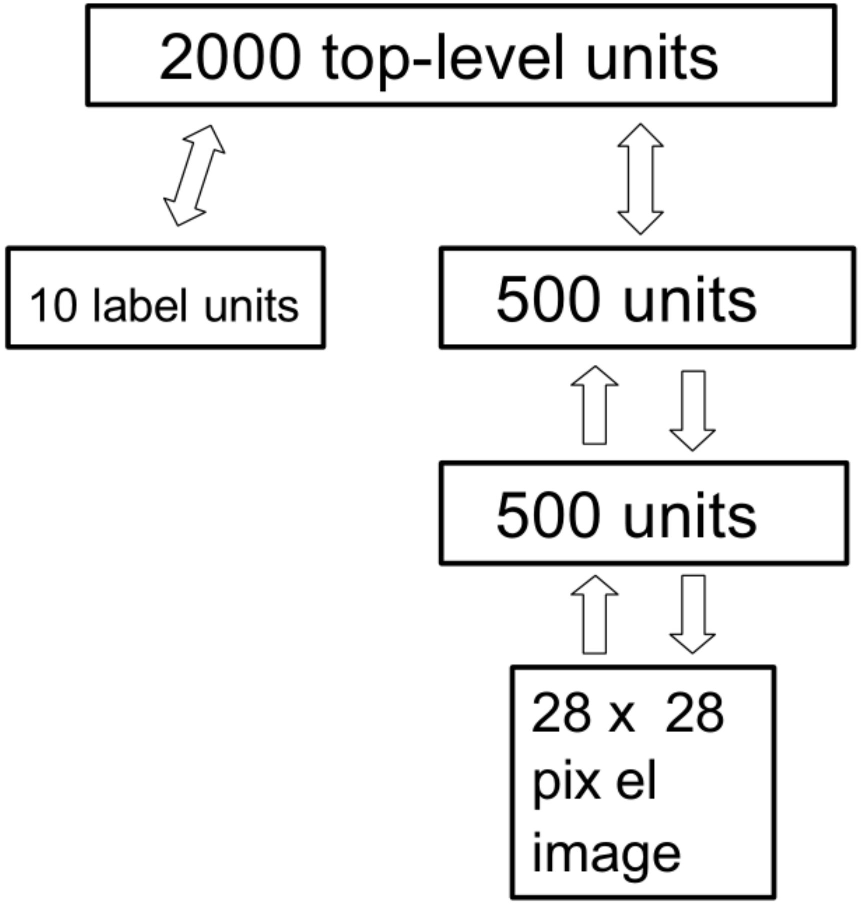
ML Example: Album cover generation

Image by Alec Radford

Other Examples

Combine aspects of supervised and unsupervised learning

Conditional Digit Generation

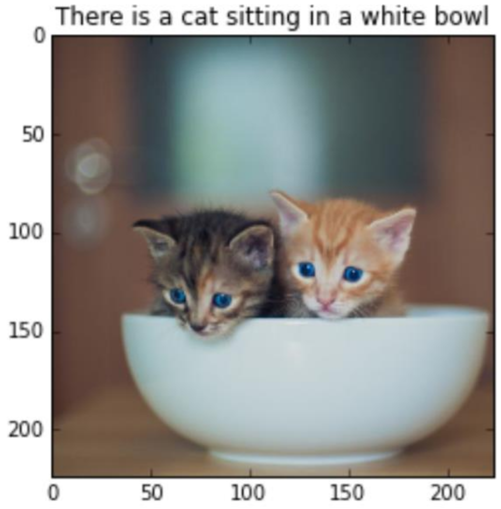


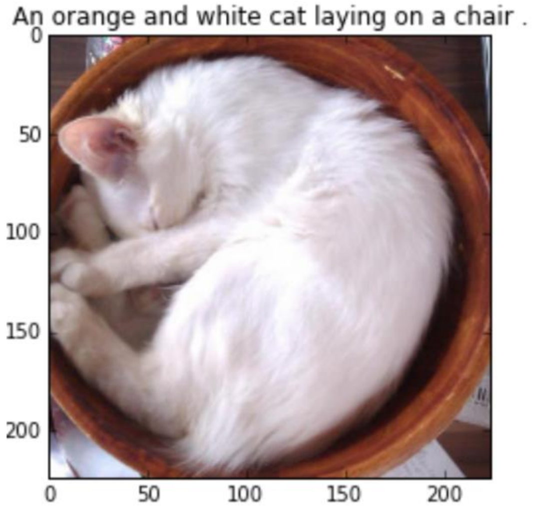
Demo: http://www.cs.toronto.edu/~hinton/adi/index.htm

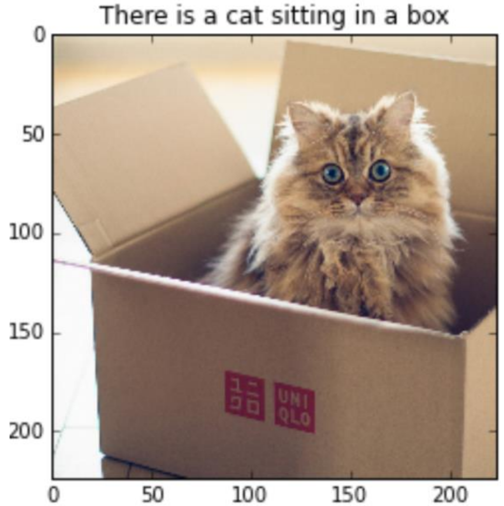
Putting text and images into vector space

(Kiros, Salakhutdinov, Zemel, TACL 2015)

Caption generation (Xu et al ICML 2015)

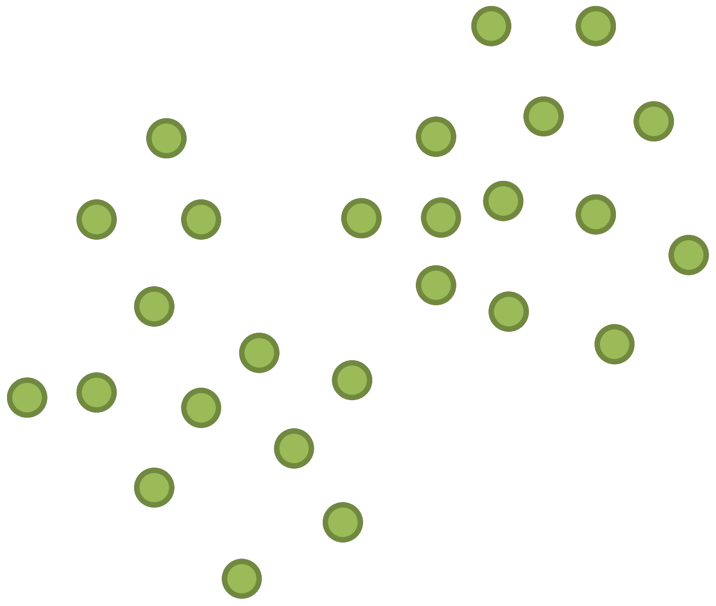






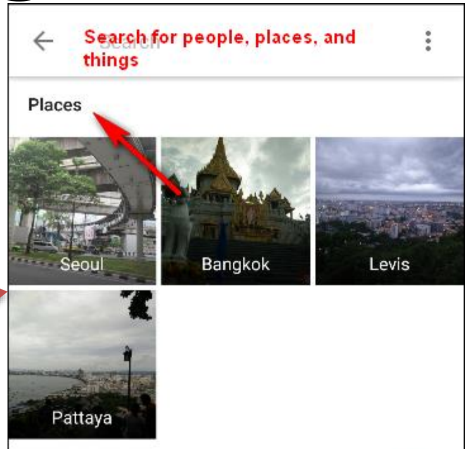
Summary: learning tasks taxonomy

- Supervised:
  - Learn an input-output relation, instant feedback
- Unsupervised:
  - Learn the density of data
  - Learn how to generate data
  - Group data into clusters
- Reinforcement:
  - Reward information given after a series of actions
  - Think of learning strategy in games



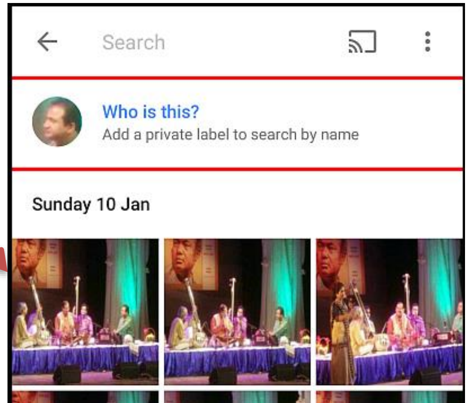
ML Example: Google Photos app

Algos and Data



Sup. learning

Unsup. learning



ML Intuitions Summary

In Machine Learning behavior is specified with data!

Algorithms discover patterns in the data and produces a models

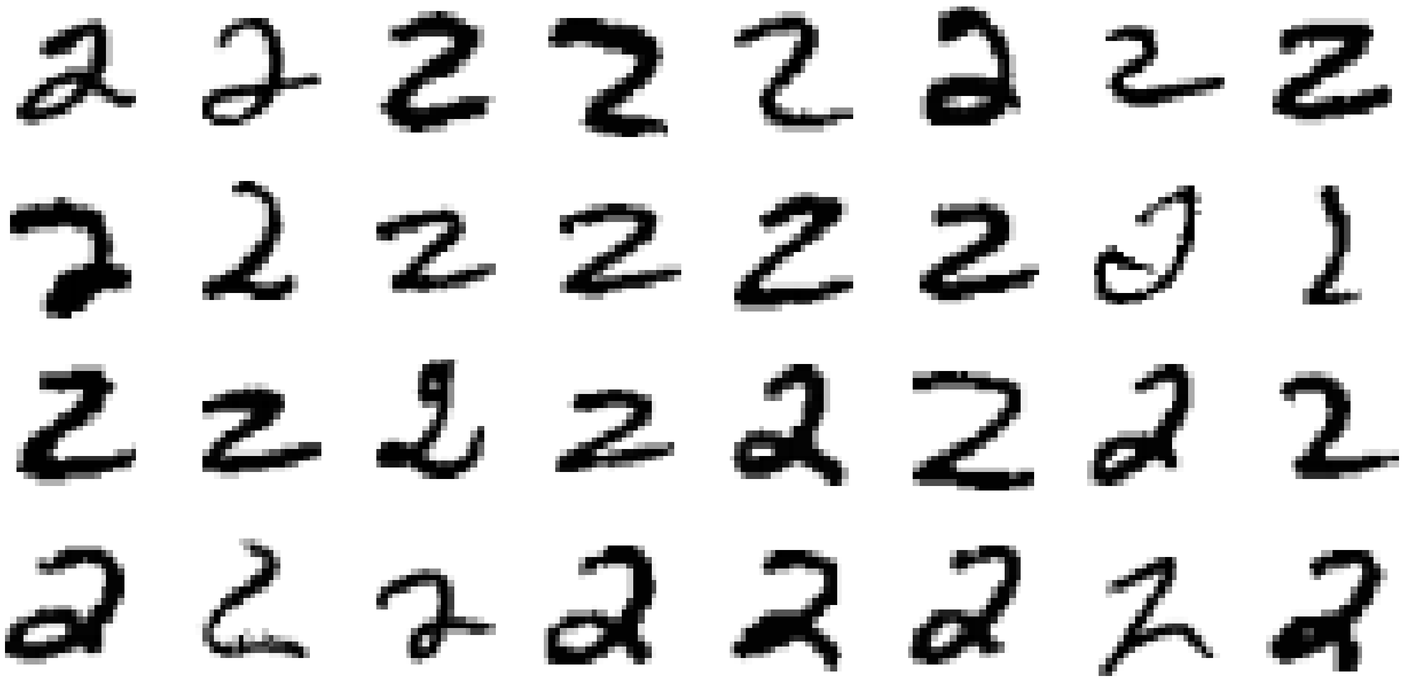
Model can ask questions about new data

- „Is there any face in the image?”
- “Is this review favorable?”
- „What is the object in the image?”
- “What caption is most likely given this image?”

SIMPLEST ML ALGORITHM:
K-NEAREST NEIGHBORS

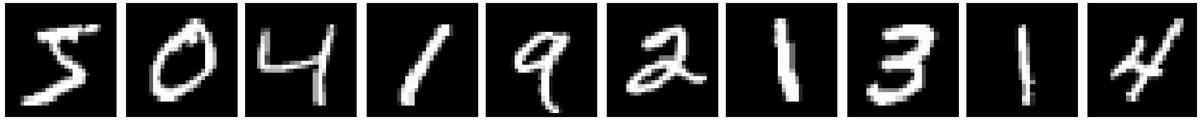
Example: Digit Classification

- Task: recognize handwritten digits
- Input: images 28 x 28 pixel values ($[0,1]^{784}$)
- Output: {0,1,…,9}

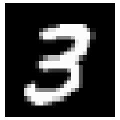


The 1-NN algorithm

- Collect examples – pairs of (input, output):

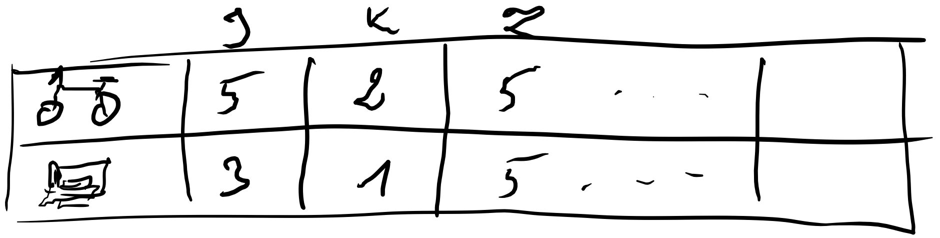


5 0 4 1 9 2 1 3 1 4

- To classify a new instance  :
  - Find the most similar element of the train set 
  - Return its label

K-NN use: recommendations

- Items are similar if users rate them similarly
- Training (offline):
  - Represent each item by its scores
  - Compute the distance between scores



- Recommendation generation (online):
  - Find nearest neighbors for each item recently browsed/put into the cart

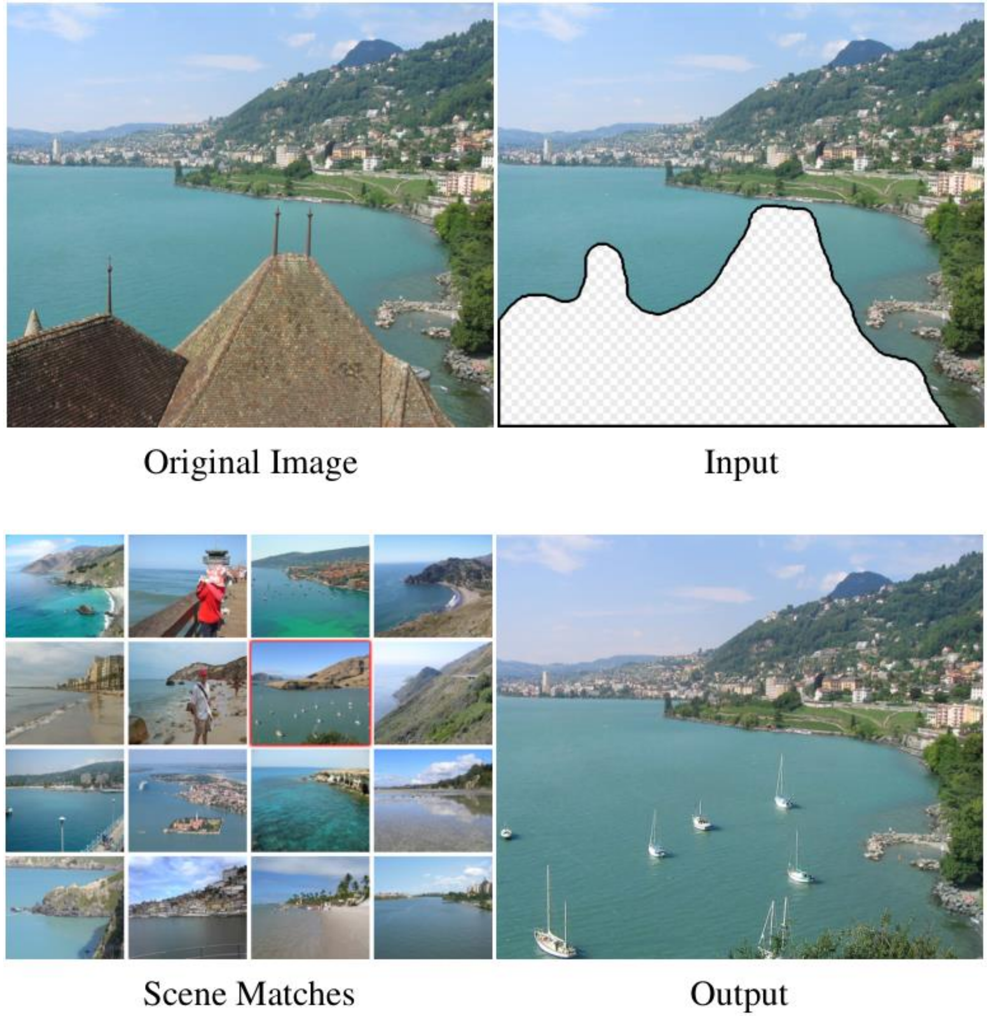
Amazon patented this:

US007113917B2

(12) **United States Patent**
Jacobi et al.

(10) **Patent No.:** **US 7,113,917 B2**
(45) **Date of Patent:** ***Sep. 26, 2006**

K-NN use: inpainting



- Find similar photos
  - Use Gist descriptors
- Match and copy

- Works poorly with 1000 images…
- But is good with >1000000

Hays, Efros „Scene Completion Using Millions of Photographs”

Alternative realities

Input

Alternative inpainting results

K-NN use: dialog system

A system Adrian Łańcucki coded based on Reddit.
Real (cherry-picked) conversation from Festiwal nauki:

- User: hi
- Bot: Hi.
- User: i like you
- Bot: Your in if u want.
- User: lmao
- Bot: Ayy lmao.
- User: ayyy
- Bot: Who are you?
- User: im a nurse
- Bot: Gott im Himmel. You have become the host.
- User: and what are you ?
- Bot: I am just a talking robot. But I like my job.
- User: thats great

K-NN DETAILS

K-NN task

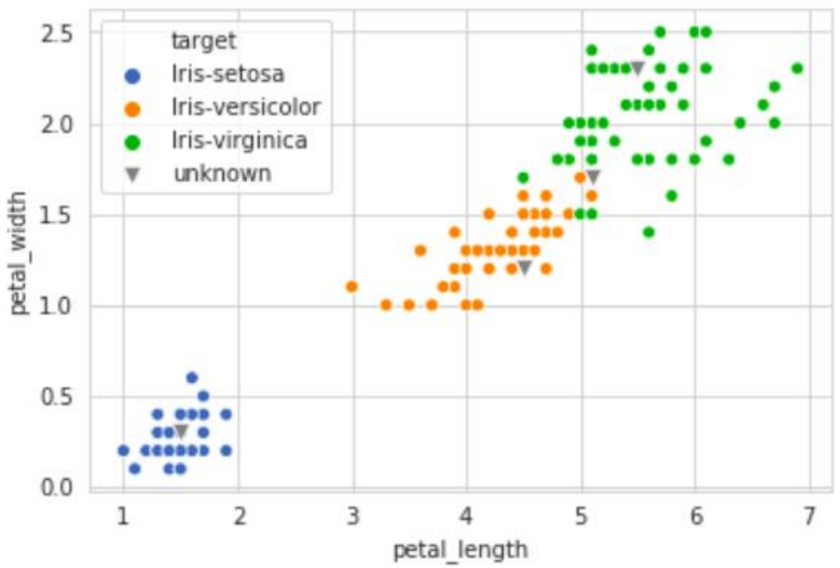
K-NN is a ML method that takes

a set of pairs $\mathcal{D} = \{(x_i\ y_i)\}$

and produces

predictions for new data $y \approx f(x, \mathcal{D})$

petal_length	petal_width	target
1.4	0.2	Iris-setosa
1.4	0.2	Iris-setosa
1.3	0.2	Iris-setosa
1.5	0.2	Iris-setosa
1.4	0.2	Iris-setosa
1.7	0.4	Iris-setosa



K-NN for classification

Let $\mathcal{N}_K(x, \mathcal{D})$ be the K nearest neighbors of a vector x.

Then:

$$p(y = c|x, \mathcal{D}, K) = \frac{1}{K} \sum_{i \in \mathcal{N}_K(x,\mathcal{D})} \mathbb{I}(y_i = c)$$

Decision rule is

$$y = \arg\max_c p(y = c|x, \mathcal{D}, K)$$

Where $\mathbb{I}(\cdot)$ is the indicator function

$$\mathbb{I}(e) = \begin{cases} 1 \text{ if } e \text{ is true} \\ 0 \text{ if } e \text{ is false} \end{cases}$$

K-NN for regression

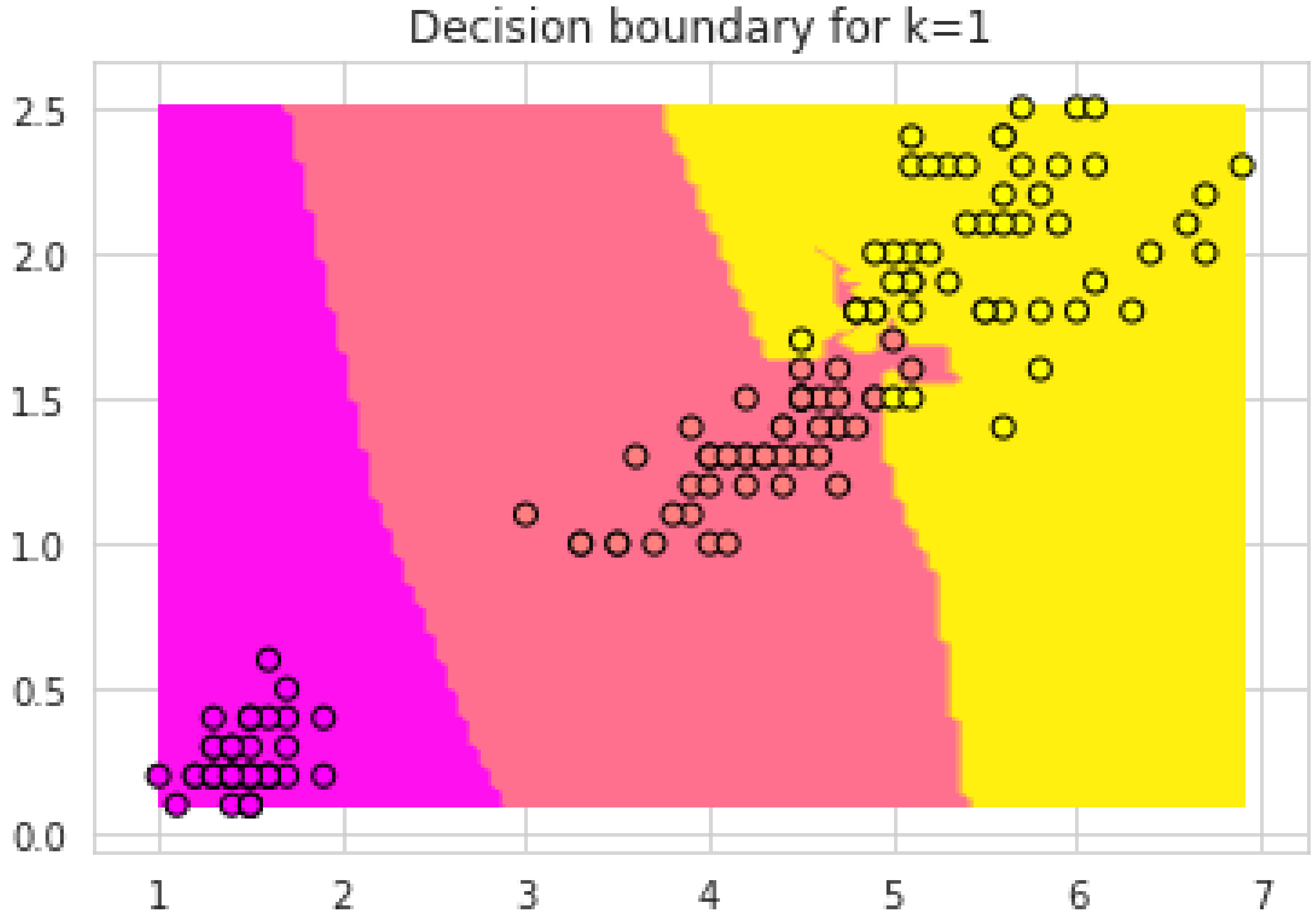
Let $\mathcal{N}_K(x, \mathcal{D})$ be the K nearest neighbors of a vector x.

Then:

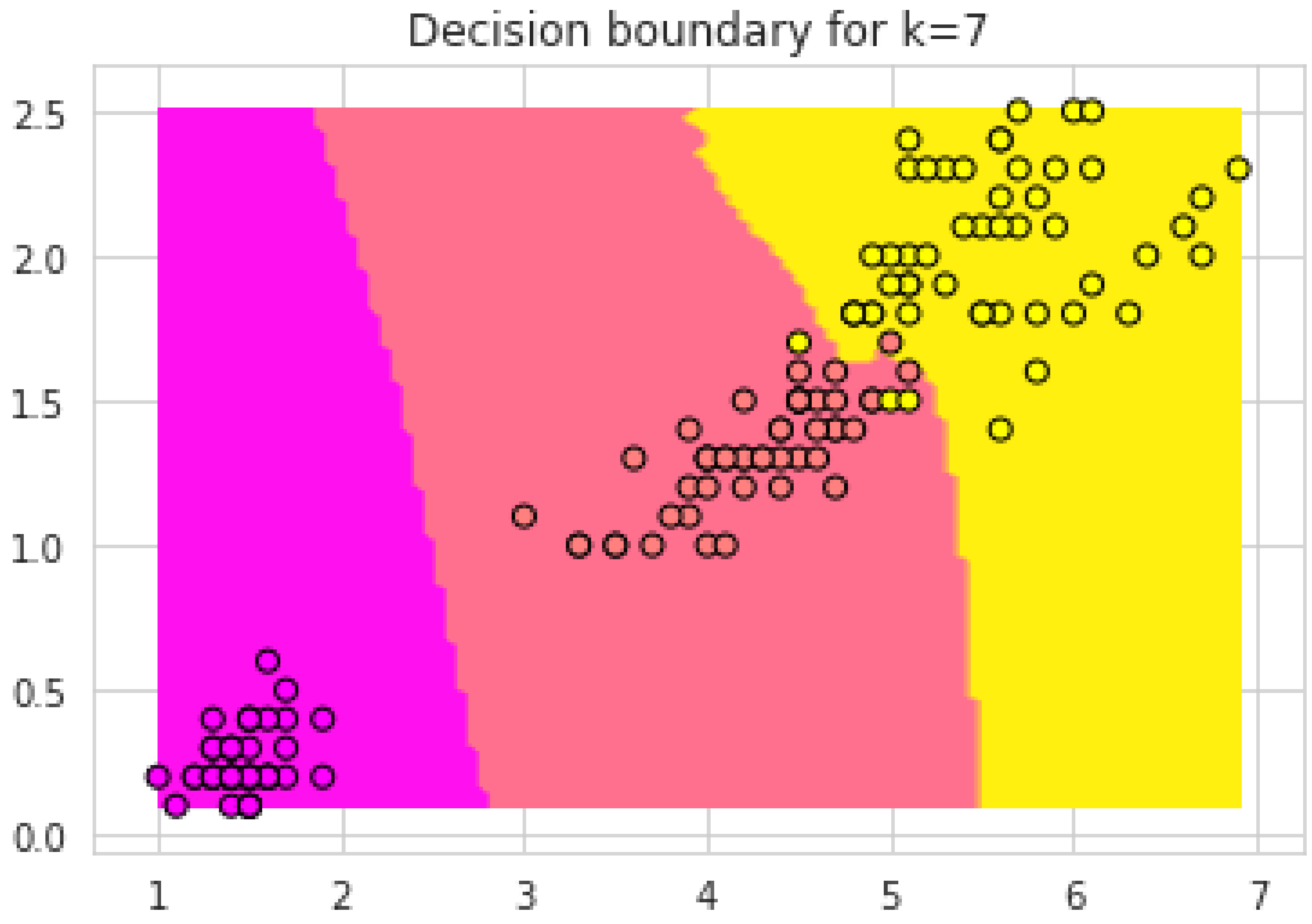
$$y = \frac{1}{C} \sum_{i \in \mathcal{N}_K(x,\mathcal{D})} \frac{1}{d(x_i, x)} y_i$$

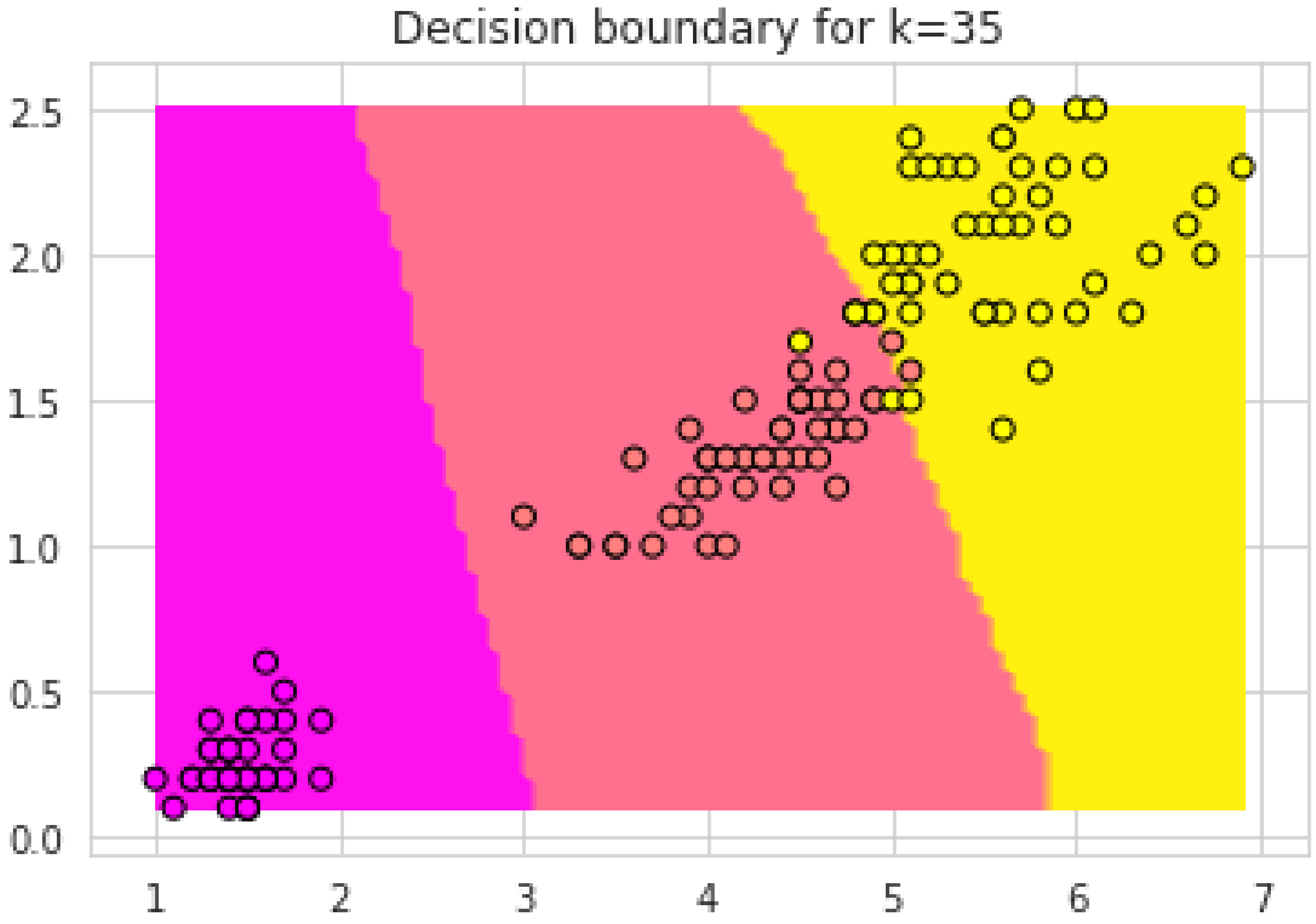
where $C = \sum_{i \in \mathcal{N}_K(x,\mathcal{D})} \frac{1}{d(x_i,x)}$

K-NN: choosing K



Decision boundary for k=1
2.5
2.0
1.5
1.0
0.5
0.0
1
2
3
4
5
6
7


Decision boundary for k=7
2.5
2.0
1.5
1.0
0.5
0.0
1
2
3
4
5
6
7


Decision boundary for k=35
2.5
2.0
1.5
1.0
0.5
0.0
1
2
3
4
5
6
7

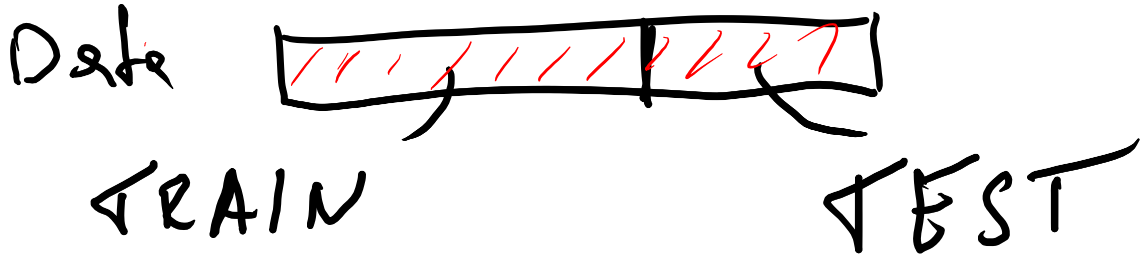
K-NN: choosing K

- How many neighbors to use?

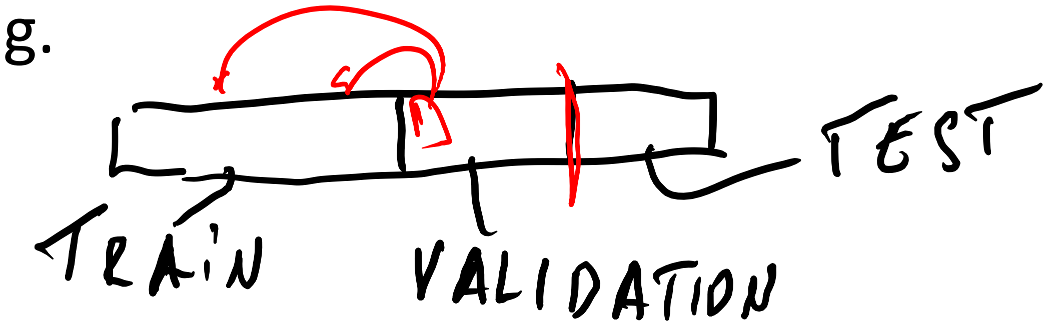
- KNN solves a task
- Pick K to maximize performance o it!

Measuring performance: Hold-out set

- Large data case!!!
- Split the training data into two parts:



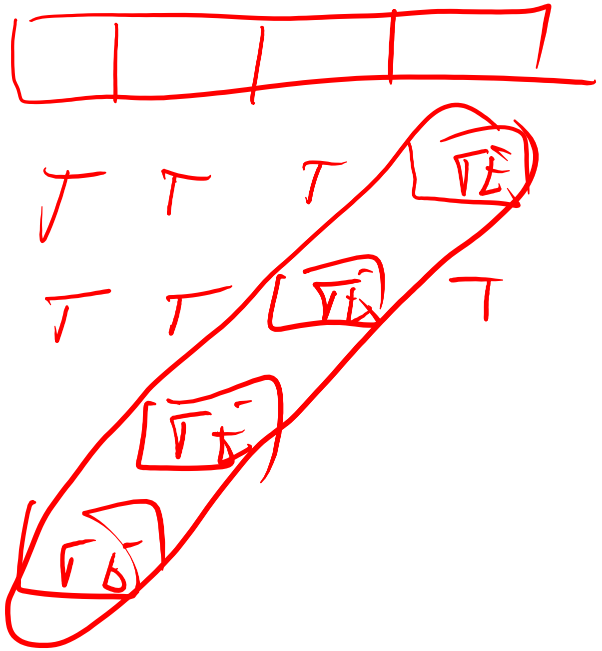
- Train only on training, then test on testing.
- Often we do a three-way split:



- Then:
  - Train many models on training (different algos, parameters)
  - Use validation to choose best model
  - Test on testing

Cross-validation

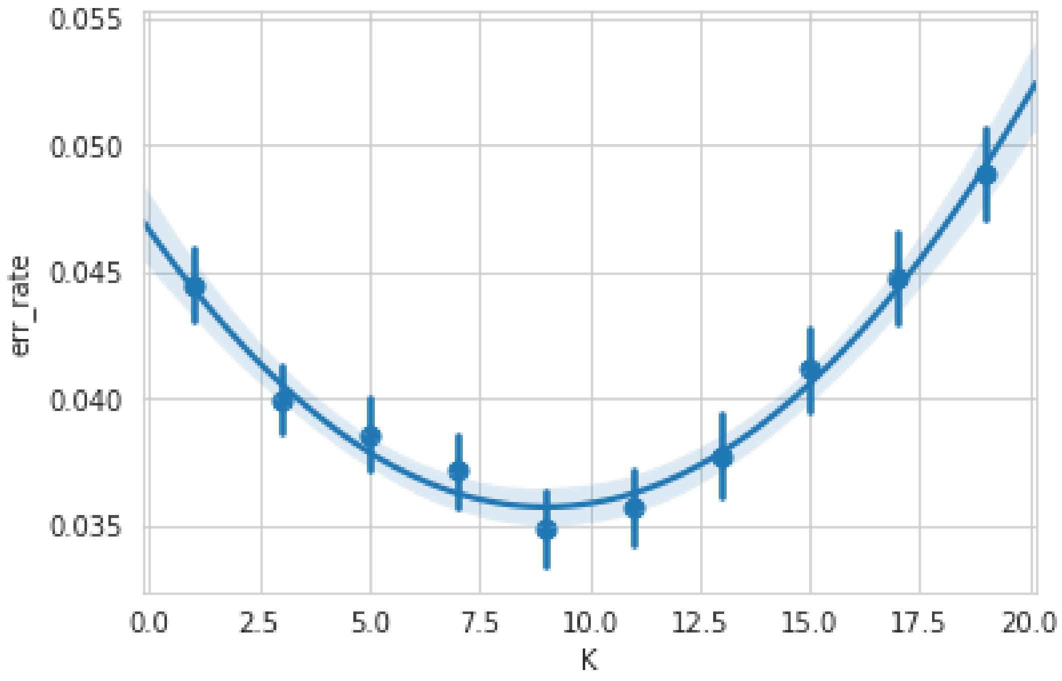
- Small data case!!
- Hold-out set makes inefficient data use
- Idea:
  - Divide the data into k sets (~5,10)
  - For i=1..k
    - Train on all but the i-th set
    - may further split to choose the model…
    - Test on the i-th set
  - Finally:
  - take the answers on the testing sets and use them to compute the performance measures
- Extreme case: leave-one-out (jackknife) – always use all but one sample to train!



Bootstrap

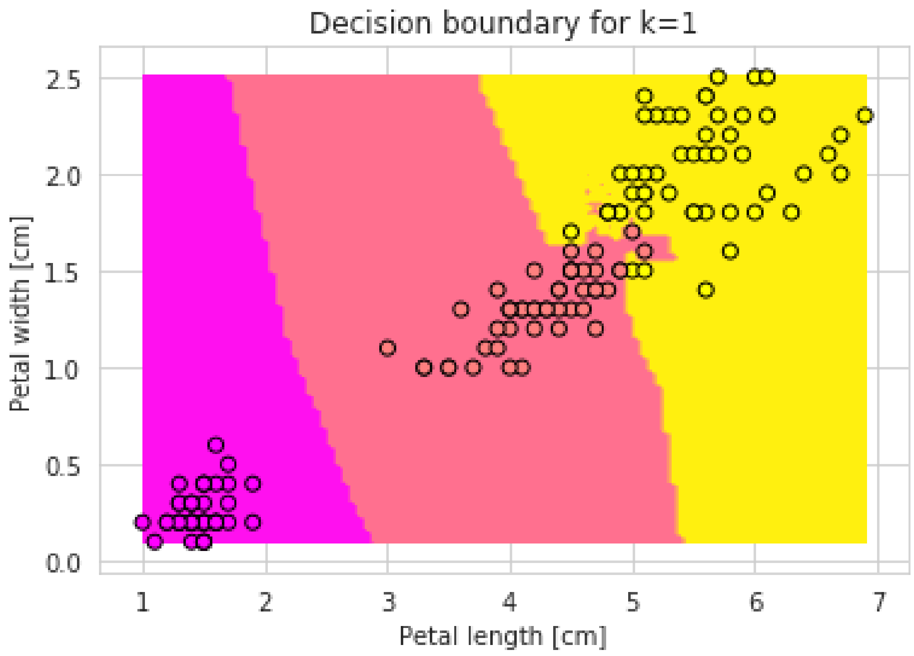
- Small data case!!
- Sample with replacement m samples
  - About 37% will not be selected
- Train on the selected samples
- Test on the remaining ones
- Optionally repeat.

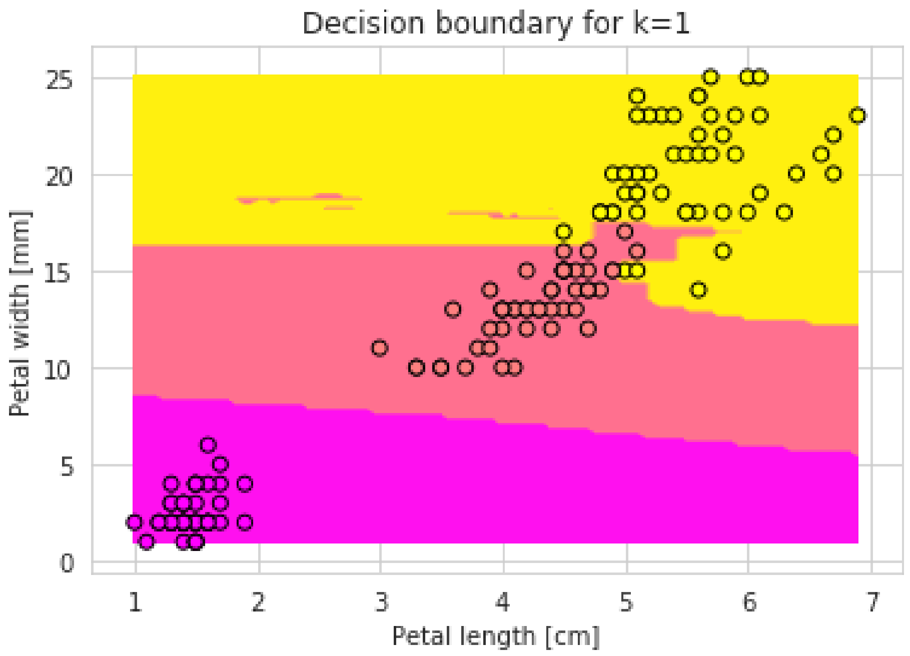
Bootstrap for choosing K



K-NN: data scaling issues

- What has changed?





Data Normalization

Map each input to $[-1,1]$ range

Or scale each input to have mean 0, variance 1

$$x_{new} = \frac{x - \mu}{\sigma}$$

Nota Bene:

This corresponds to a Mahalanobis distance

$$\sqrt{(u - v)^T \Sigma^{-1} (u - v)}$$

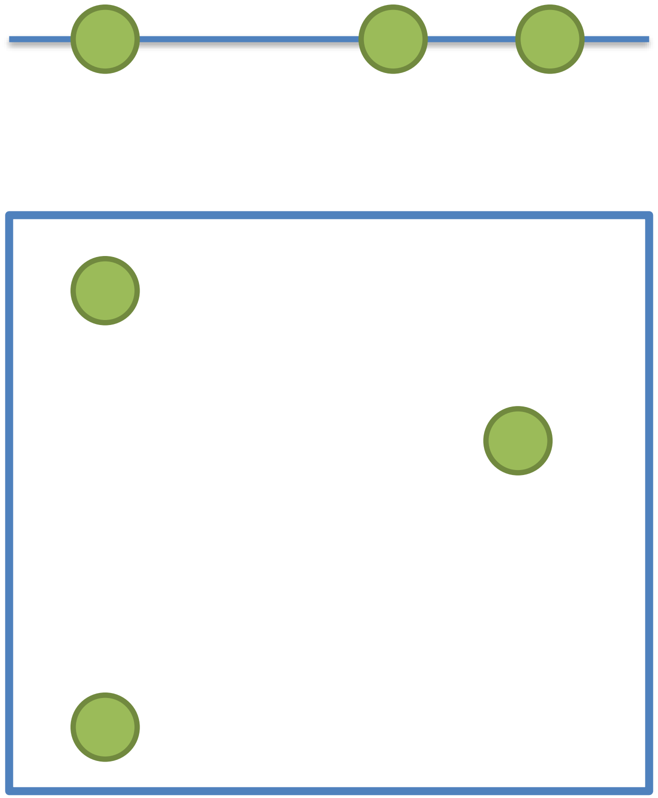
with $\Sigma = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_D^2 \end{bmatrix}$

KNN requires lots of data

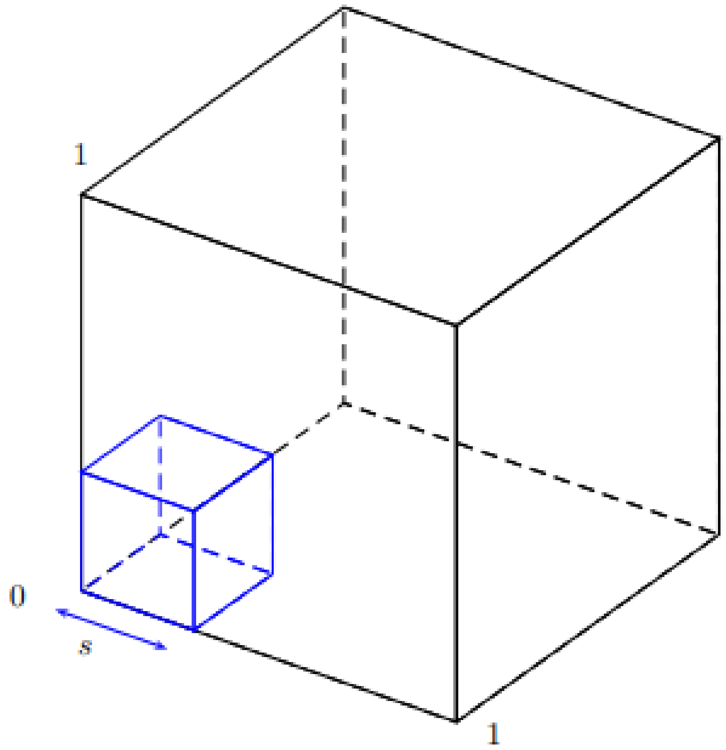
- Consider recognizing postal codes (5 digits)
- Will this work if we treat each postal code as a single image (10^5 combinations)?
- If we treat each digit separately, how to accommodate for:
  - Uniform style (slant, thickness) of digits in one code.
  - Segmentation, joins, overlaps of digits.

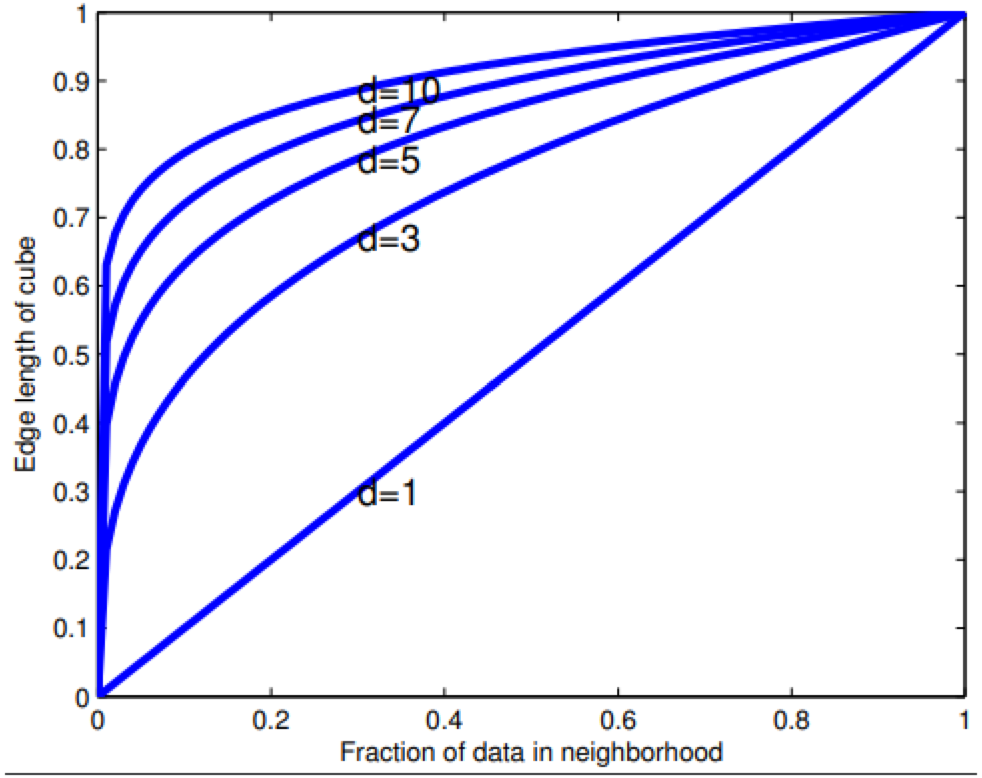
Curse of dimensionality

- In highly dimensional spaces, things are dissimilar (far away from each other):
- Let N be the number of points.
- The average distance between points grows with data dimensionality.
- In other words, there are fewer neighbors within a radius from each point.



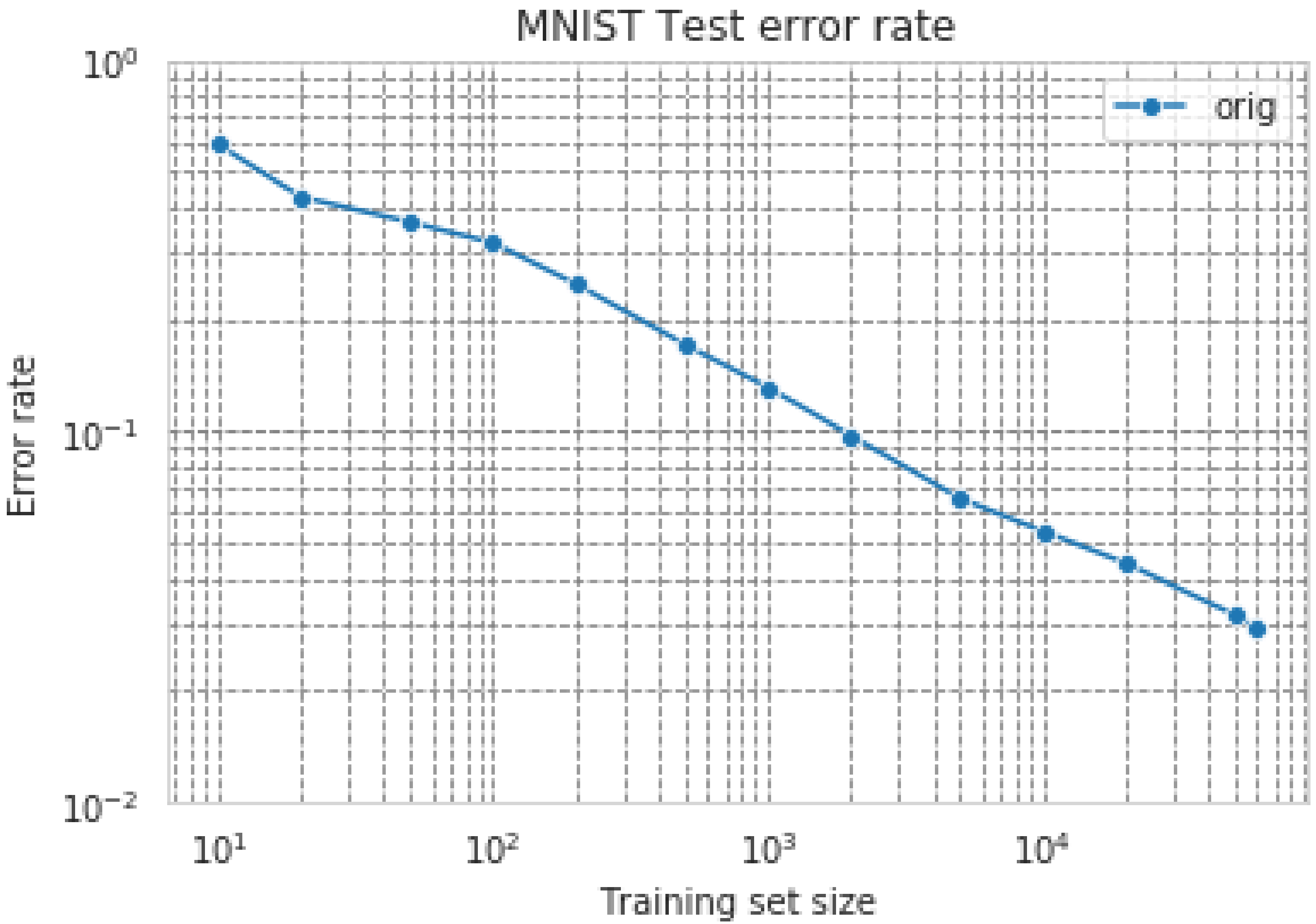
Curse of dimensionality





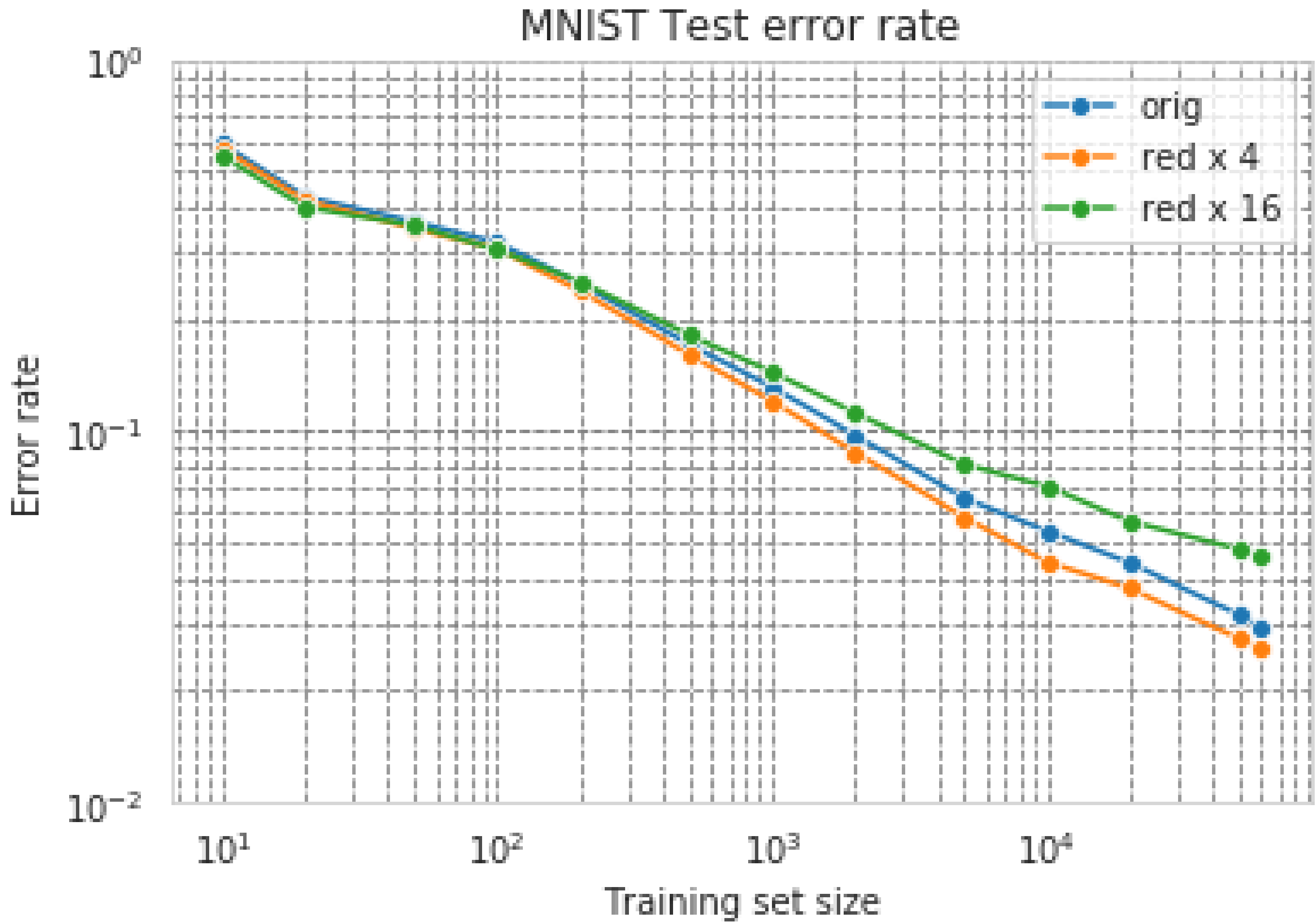
Img source: K. Murphy, Machine Learning fig. 1.16

K-NN, scaling with amount of data



K-NN, scaling with amount & dimensionality of data

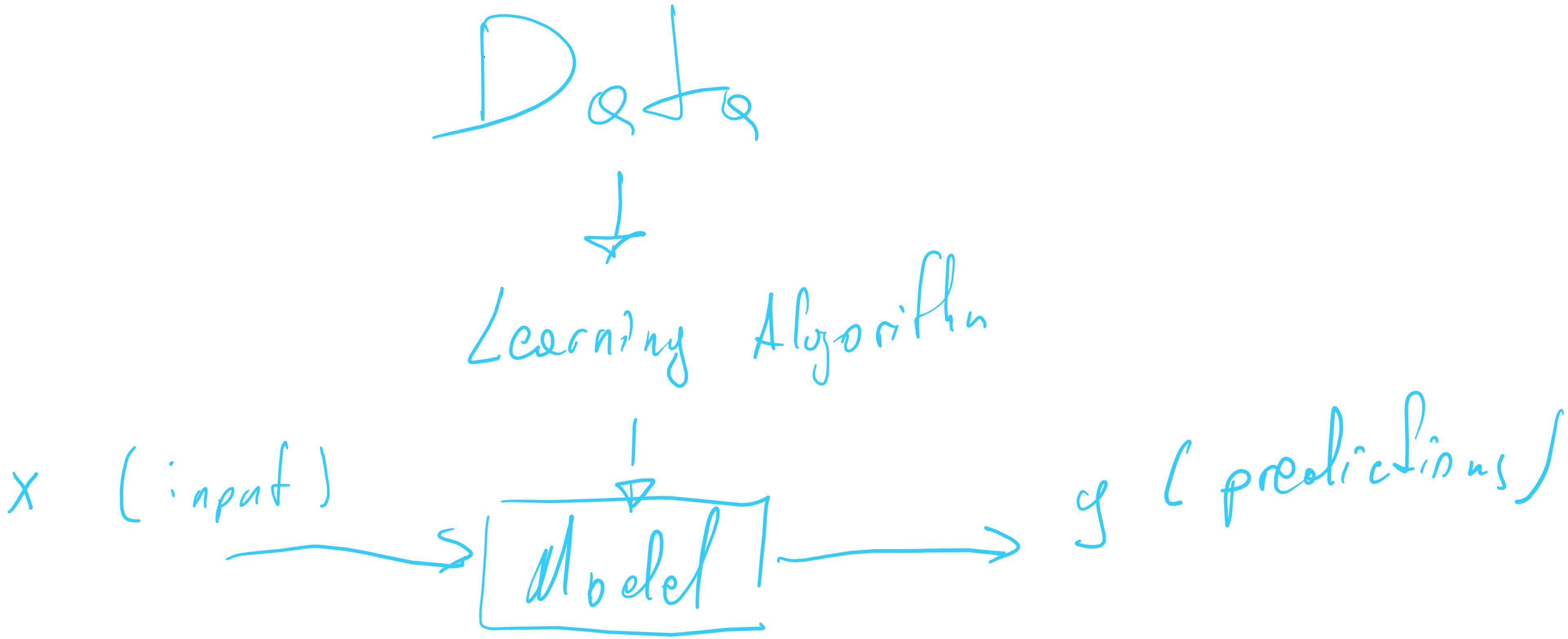
K-NN, scaling with amount & dimensionality of data



LECTURE SUMMARY

Quick summary

- ML algorithms distill data into models.
- We will call this learning from examples.



When to use machine learning

- Easy to get examples, hard to devise an exact algorithm
- Don’t know how to program a solution
  (e.g. speech recognition, language processing, translation rely heavily on data)
- We need to automatically tune or adapt the solution to the user
- The solution changes over time
- Question: when shouldn’t we use learning?

Programming vs. learning

- Requires thorough problem understanding
- Formally define pre- and post-conditions
- Implement the solution
- Prove the correctness

- Can have only a partial understanding of the problem – intuitions and a-priori assumptions
- Collect many examples of input-output
- Crucial aspect – generalization – will the learned solution work on new data?

Quick Summary

- ML is about problem solving
- Tasks (and desired behaviors) are defined with data
- Success is measured on the task,
  models are good if they work well, bad otherwise