Introduction to Machine Learning

Pascal Fua
(Mathieu Salzmann for 2-3 weeks)
IC-CVLab

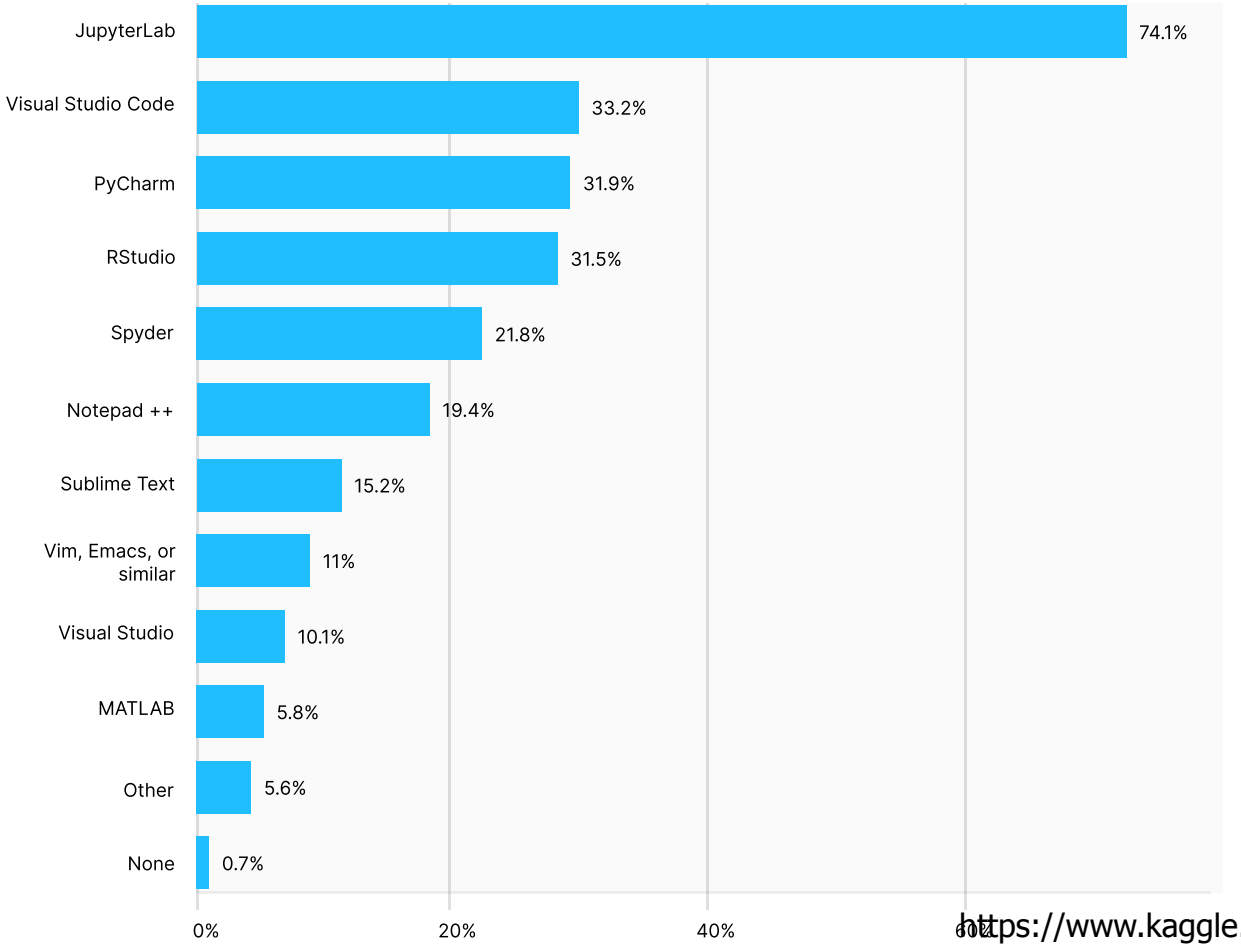
General Organization

- Lectures: Tuesdays 8:15-10 in CM3
- Exercises: Tuesdays 10:15-12 in CE1100, 1101, and 1103.
- Mini-project with two milestones (10% of grade, each).
- Written exam (80% of grade).

- Slides: https://moodle.epfl.ch/course/view.php?id=16159
- Main references:
  - C.M. Bishop, Pattern Recognition and Machine Learning, Springer, 2006

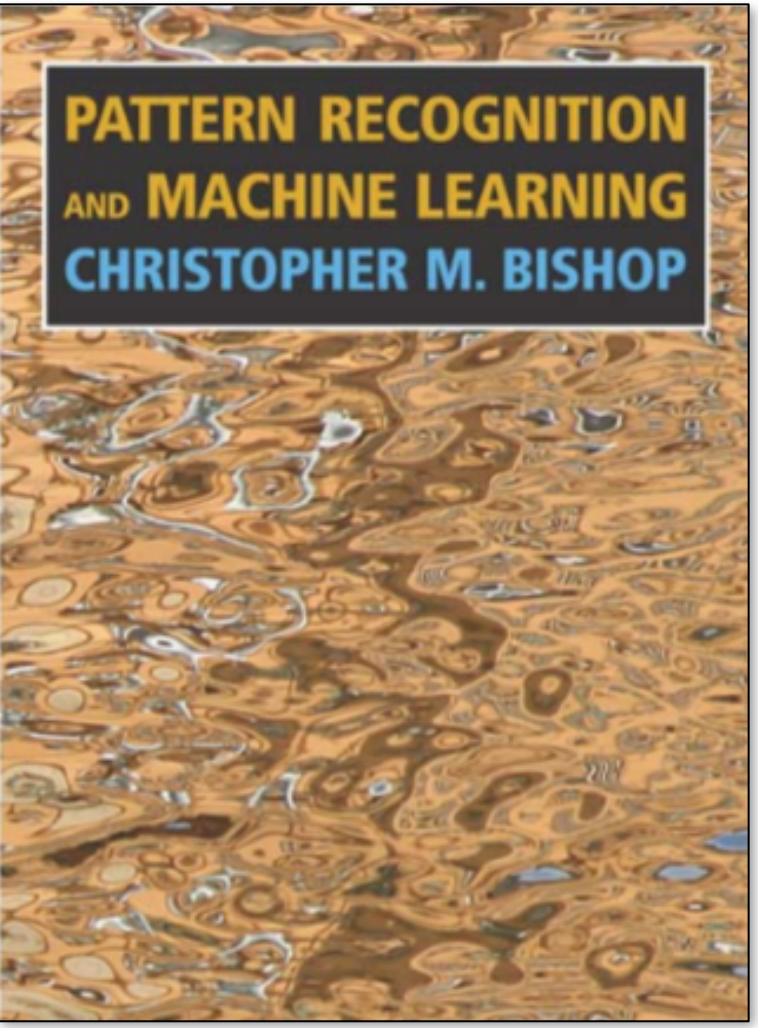
General organization: Exercises

- The practical exercises will be done in Python
  - According to a 2020 survey among data scientists regarding the most commonly used coding environments:



https://www.kaggle.com/kaggle-survey-2020

Recommended Book

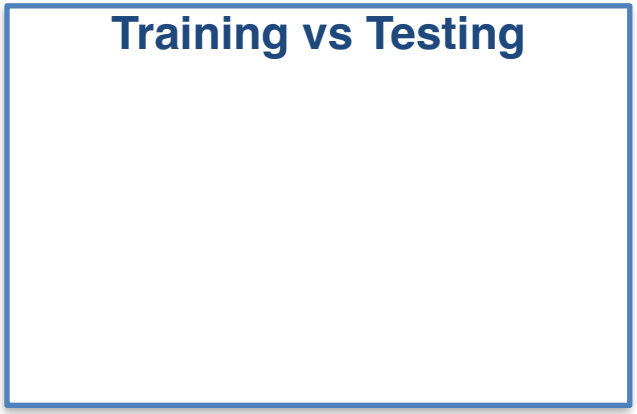


Pattern Recognition and Machine Learning.
Christopher Bishop, Springer, 2006.

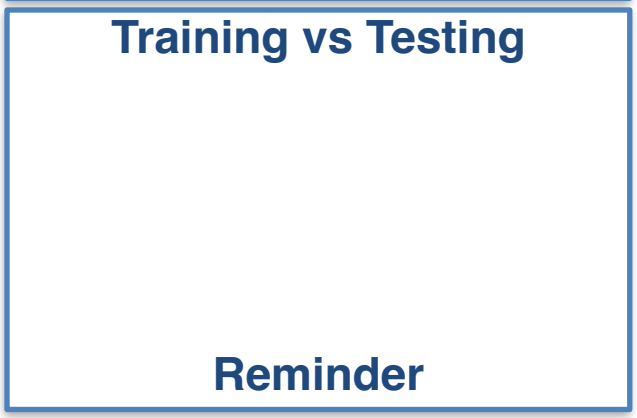
- Available for free on the web.
- We will use the same notations.

https://www.microsoft.com/en-us/research/uploads/prod/2006/01/Bishop-Pattern-Recognition-and-Machine-Learning-2006.pdf

Slide Codes



Normal slide: It is part of the course and I may ask exam questions about it.

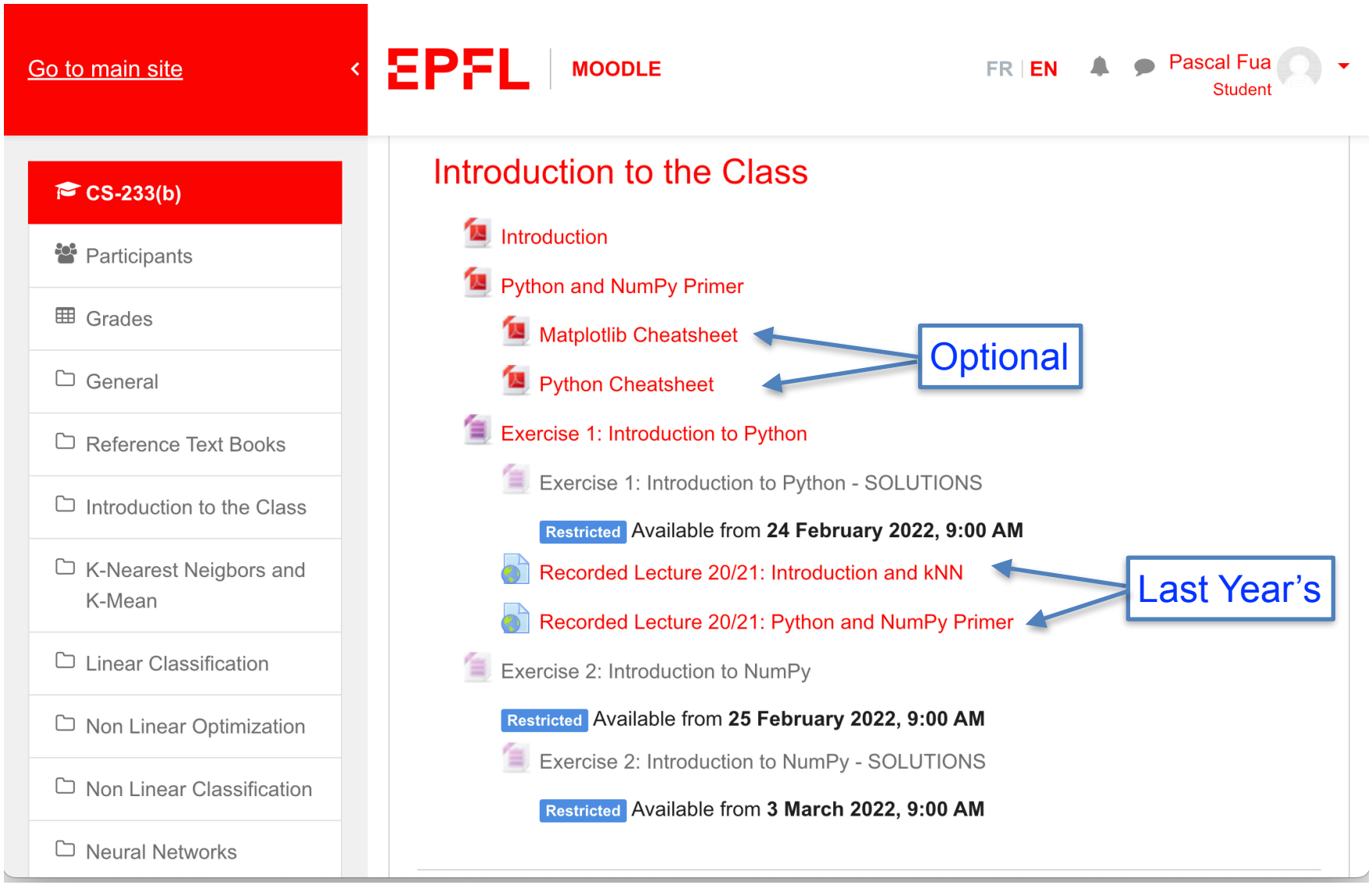


Reminder slide: We have already covered this earlier in the class. Go back to the appropriate lecture if you do not remember.

Optional slide: This is additional material for people interested in more details. I will not ask direct exam questions on this.

Reference to book or paper for even more details.

Moodle Page


Go to main site
EPFL
MOODLE
FR | EN
Pascal Fua
Student
CS-233(b)
Participants
Grades
General
Reference Text Books
Introduction to the Class
K-Nearest Neigbors and K-Mean
Linear Classification
Non Linear Optimization
Non Linear Classification
Neural Networks
Introduction to the Class
Introduction
Python and NumPy Primer
Matplotlib Cheatsheet
Python Cheatsheet
Optional
Exercise 1: Introduction to Python
Exercise 1: Introduction to Python - SOLUTIONS
Restricted Available from 24 February 2022, 9:00 AM
Recorded Lecture 20/21: Introduction and kNN
Recorded Lecture 20/21: Python and NumPy Primer
Last Year's
Exercise 2: Introduction to NumPy
Restricted Available from 25 February 2022, 9:00 AM
Exercise 2: Introduction to NumPy - SOLUTIONS
Restricted Available from 3 March 2022, 9:00 AM

Forewords

- Machine Learning is great!
- But even if you excel at it, it won't be enough to pass an interview in a big US tech company (Google, Meta, Nvidia, Microsoft,…)
  - This was a clear message from our visits at Nvidia and Google with the bachelor students
- You need to be prepared for coding interviews!
  - I cannot do this in the context of this course, but the next slides provides links to resources that could help you to prepare (the links were provided by José Alvarez at Nvidia)
  - Of course, you won't be evaluated on this in the context of this course

Optional

Coding Interviews: Resources

- Main book
  - https://github.com/Avinash987/Coding/blob/master/Cracking-the-Coding-Interview-6th-Edition-189-Programming-Questions-and-Solutions.pdf

- Algorithms books
  - https://github.com/Mcdonoughd/CS2223/blob/master/Books/Algorithhms%204th%20Edition%20by%20Robert%20Sedgewick%2C%20Kevin%20Wayne.pdf
  - https://sd.blackball.lv/library/Introduction_to_Algorithms_Third_Edition_(2009).pdf

Optional

Coding Interviews: Resources

- Coding environments
  - https://coderpad.io
  - https://codesignal.com
  - https://www.hackerrank.com
  - https://coderbyte.com

- Other resources
  - http://elementsofprograminginterviews.com/sample/epilight_python_new.pdf
  - https://github.com/Olshansk/interview#coding-practice
  - https://blog.pramp.com/top-8-mistakes-in-technical-interviews-according-to-data-27d2572bda1f
  - https://github.com/jwasham/coding-interview-university#coding-question-practice

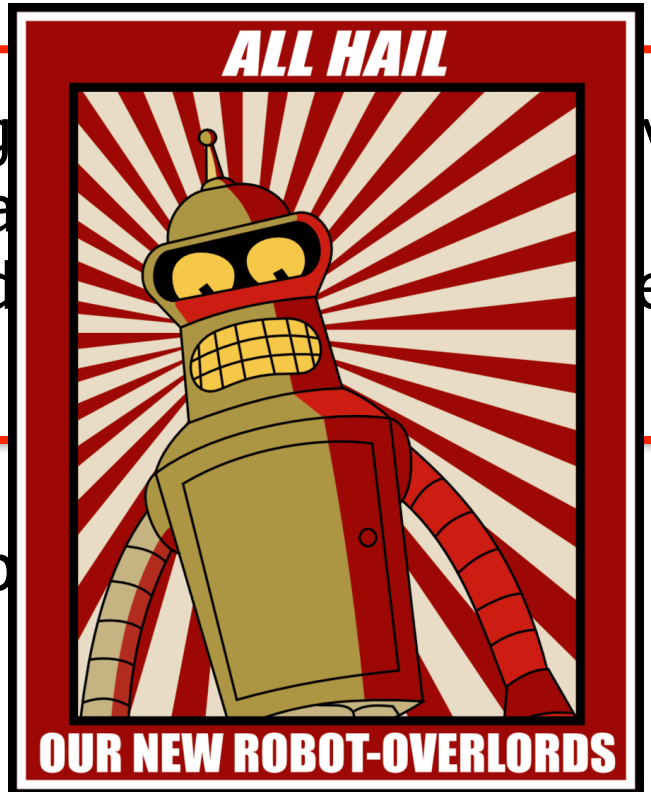
Optional

Human vs Machine Learning

What is Machine Learning?

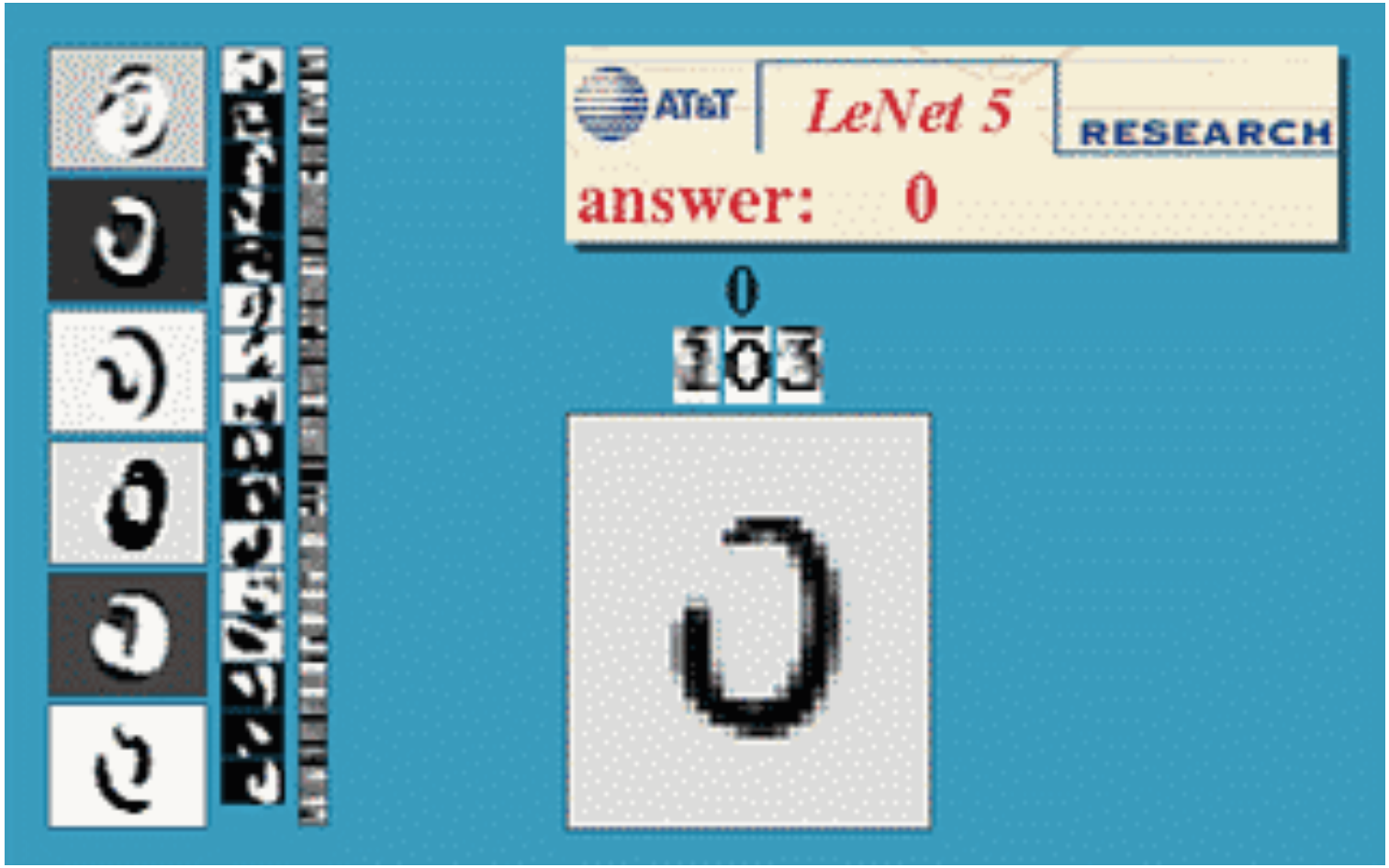
- Machine Learning is the science of getting computers to learn and act like humans do, and improve their learning over time in autonomous fashion, by feeding them data and information in the form of observations and real-world interactions.

- Machine learning alg vide knowledge to computers through da interaction with the world. It is then used edictions given new observations.



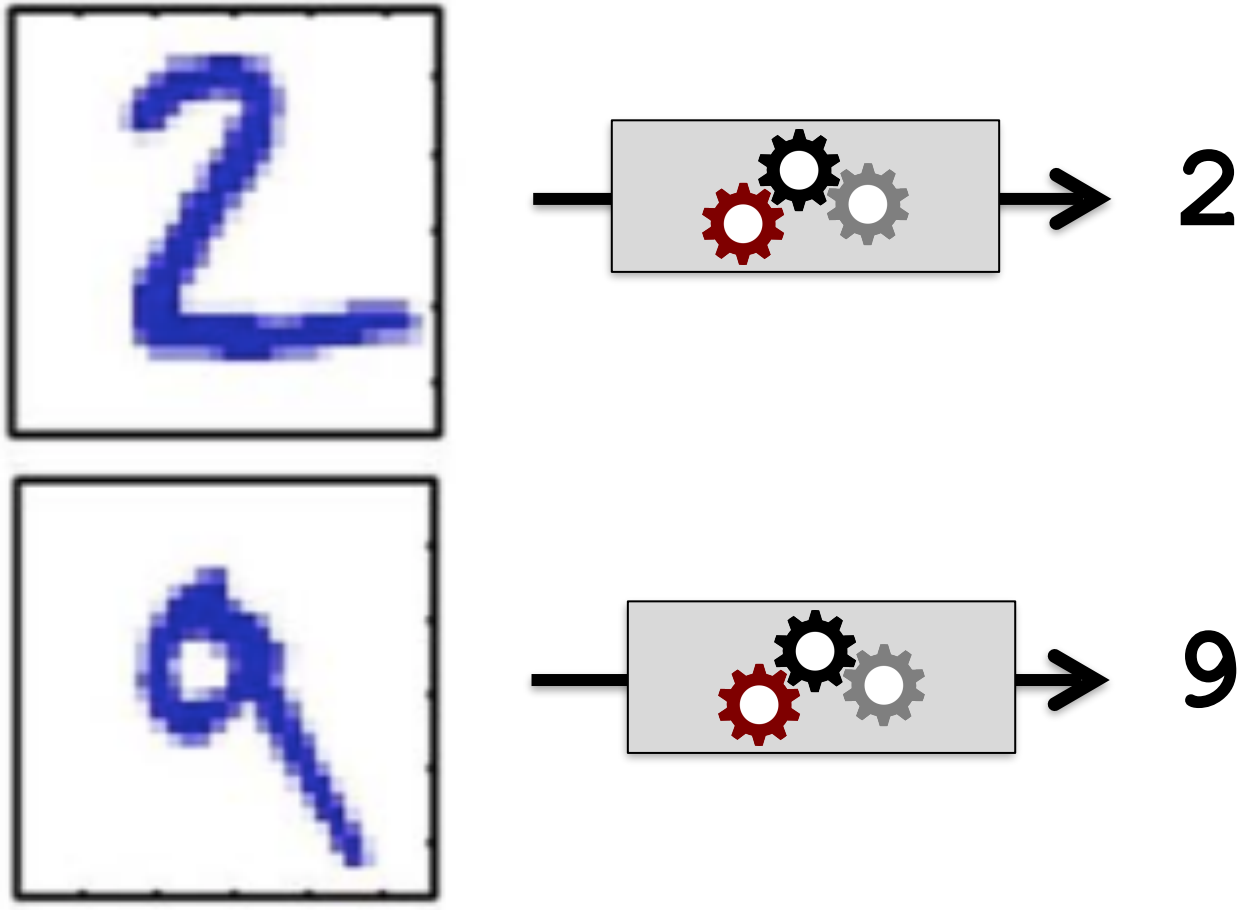
- Machine learning is ap

Recognizing Hand-Written Digits

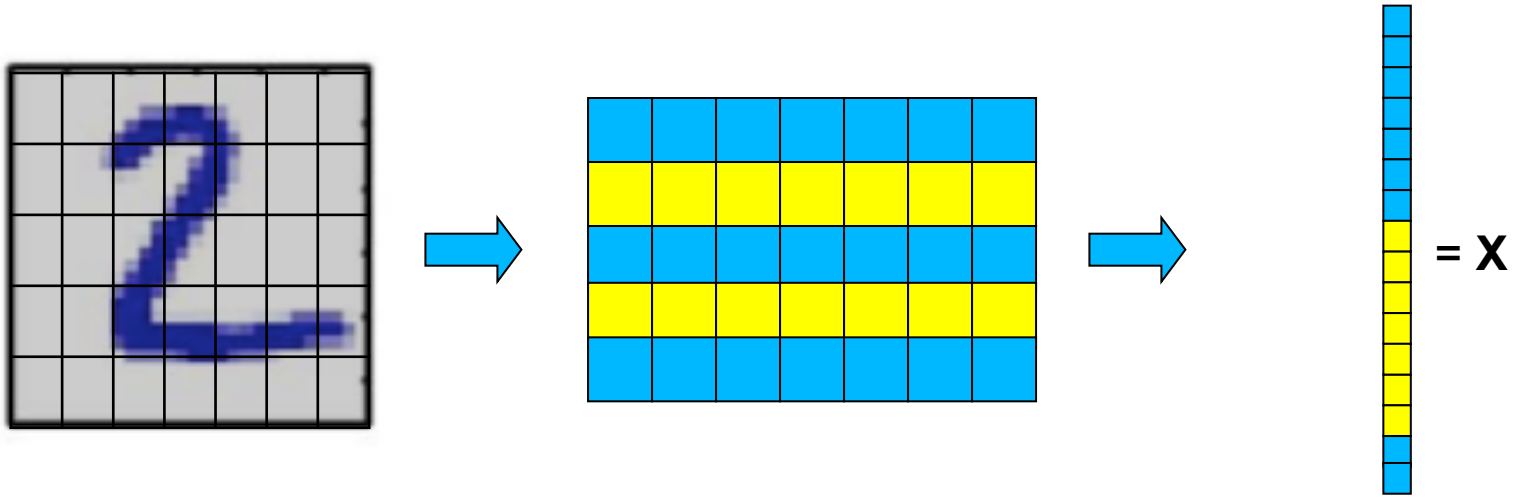


LeNet (1989-1999)

Recognizing Hand-Written Digits



Predictor and Labels



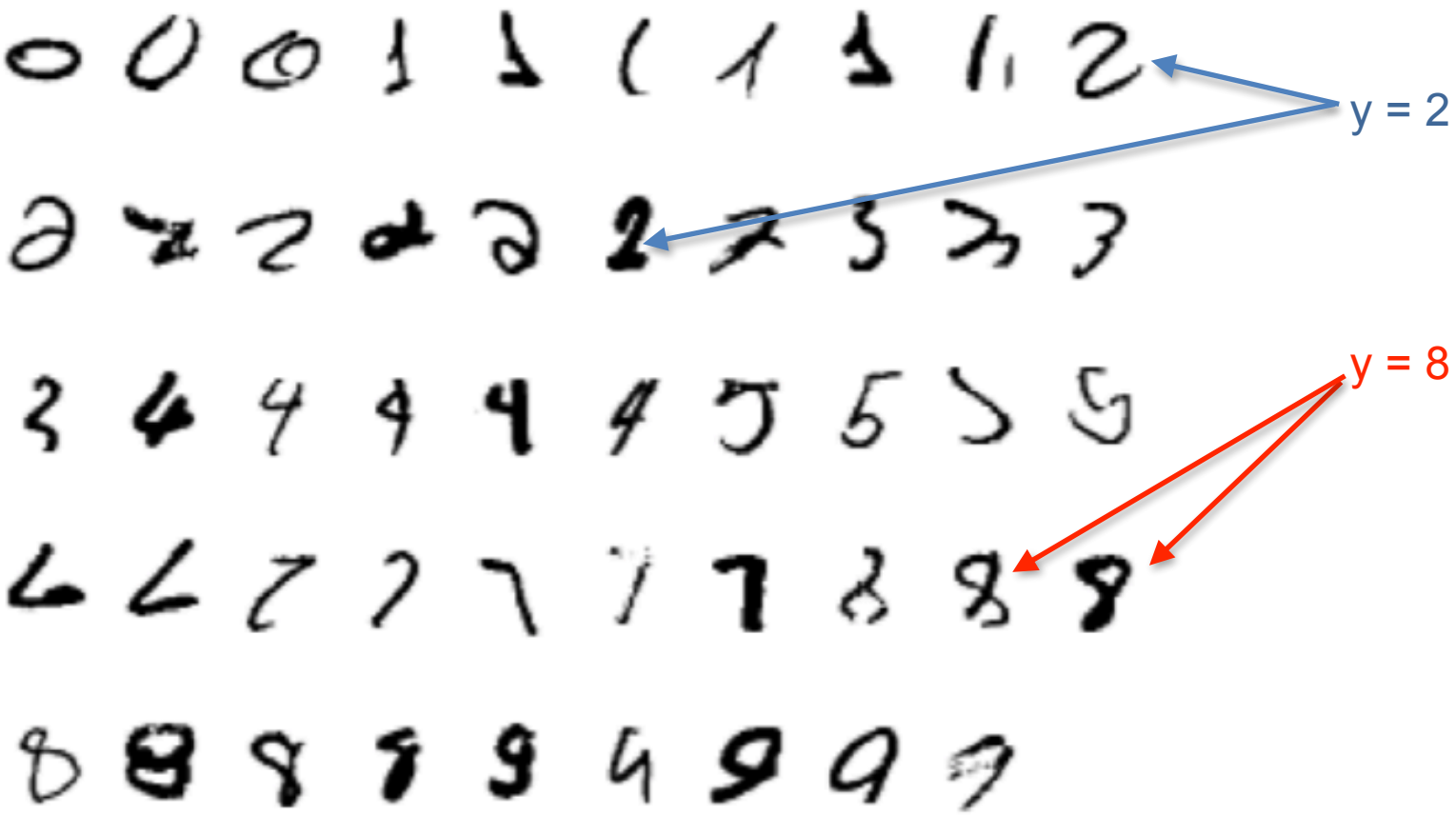
28x28 pixels

x is a 784-D Vector

$$\boxed{y} : \mathbf{x} \in \mathbb{R}^{784} \rightarrow \boxed{\{0, 1, 2, \cdots, 9\}} \quad ?$$

Predictor **Labels**

Labeled Training Set



$$T = \{(\mathbf{x}_n, t_n) \quad \text{for} \quad 1 \leq n \leq N\}$$

Supervised Classification

Minimize:

Predicted label for sample n

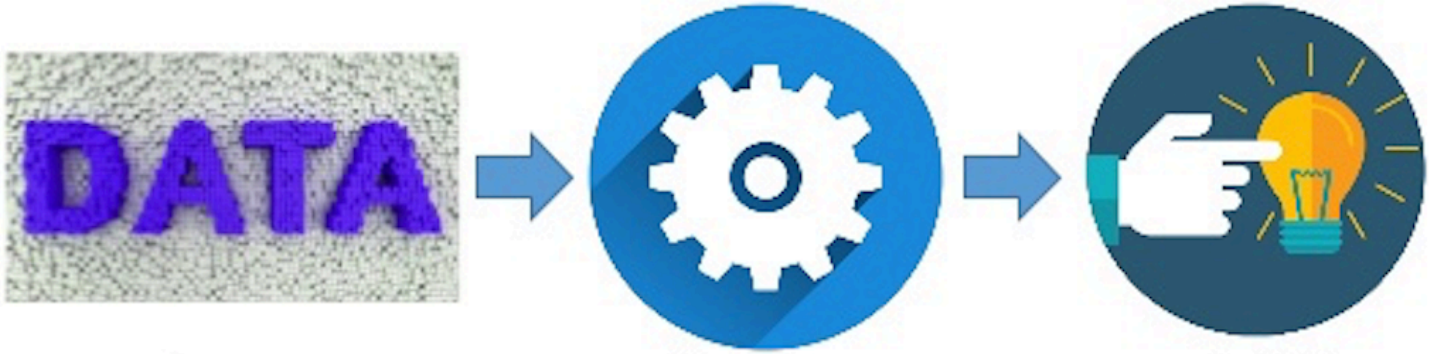
$$E(\mathbf{w}) = \sum_{n=1}^{N} L(y(\mathbf{x}_n; \mathbf{w}), t_n)$$

True label for sample n

- **x:** Feature vector
- **w:**Model parameters
- t: Label
- y: Predictor
- L: Loss Function
- E: Error Function

—> ML is an optimization problem

Generic Scheme



Medical Research

Data: Feature vectors that characterize mothers.

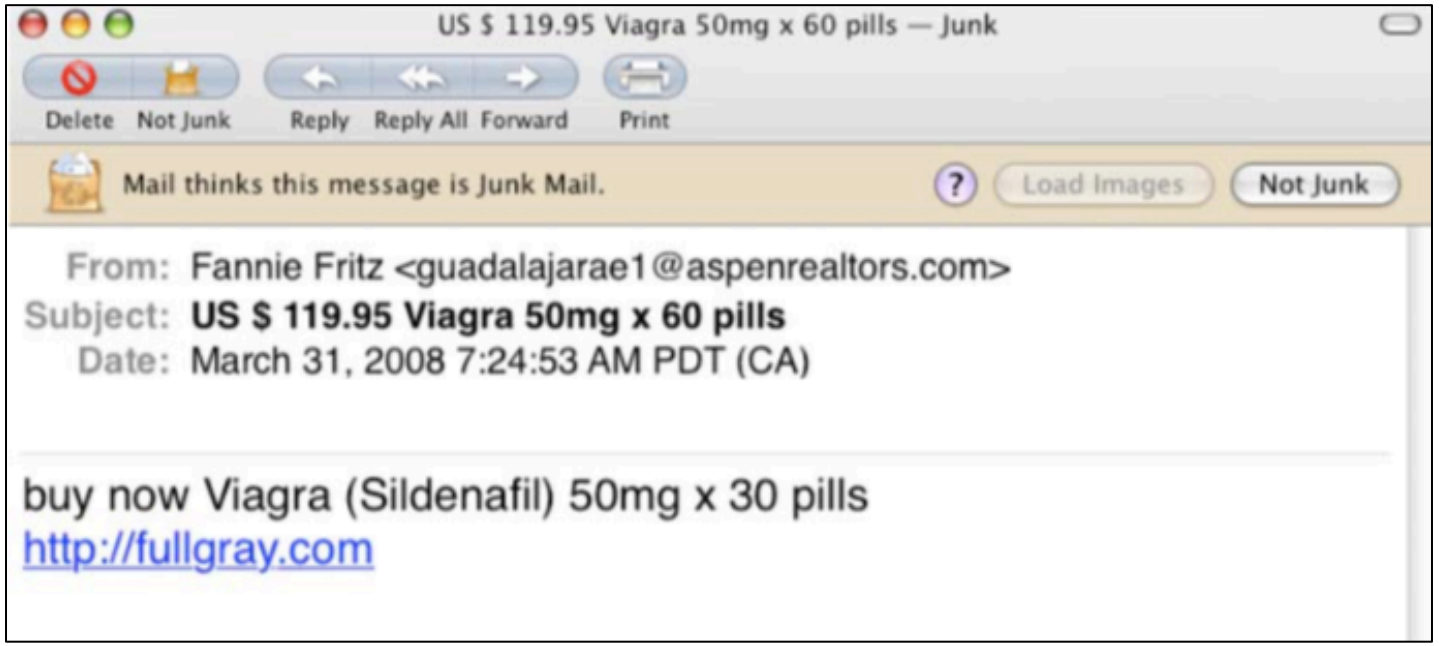
	Age at delivery	Weight prior to pregnancy (pounds)	Smoker	Doctor visits during 1st trimester	Race	Birth Weight (grams)
Patient 1	29	140	Yes	2	Caucasian	2977
Patient 2	32	132	No	4	Caucasian	3080
Patient 3	36	175	No	0	African-Am	3600
*	*	*	*	*	*	*
*	*	*	*	*	*	*
Patient 189	30	95	Yes	2	Asian	3147

Feature vector

Image from Lumen Learning

Insight: What characteristics of a mother contribute most to low birth weight.

Spam Detection



Feature vector:

$$\mathbf{x} = \begin{pmatrix} \#\text{viagra} \\ \#\text{pills} \\ \vdots \end{pmatrix}$$

Labels:

Spam, Not Spam

Model parameters:

$\mathbf{w}$

Predictor: $y(\mathbf{x},\mathbf{w})=\{\text{Spam, Not Spam}\}$

Recommender Systems

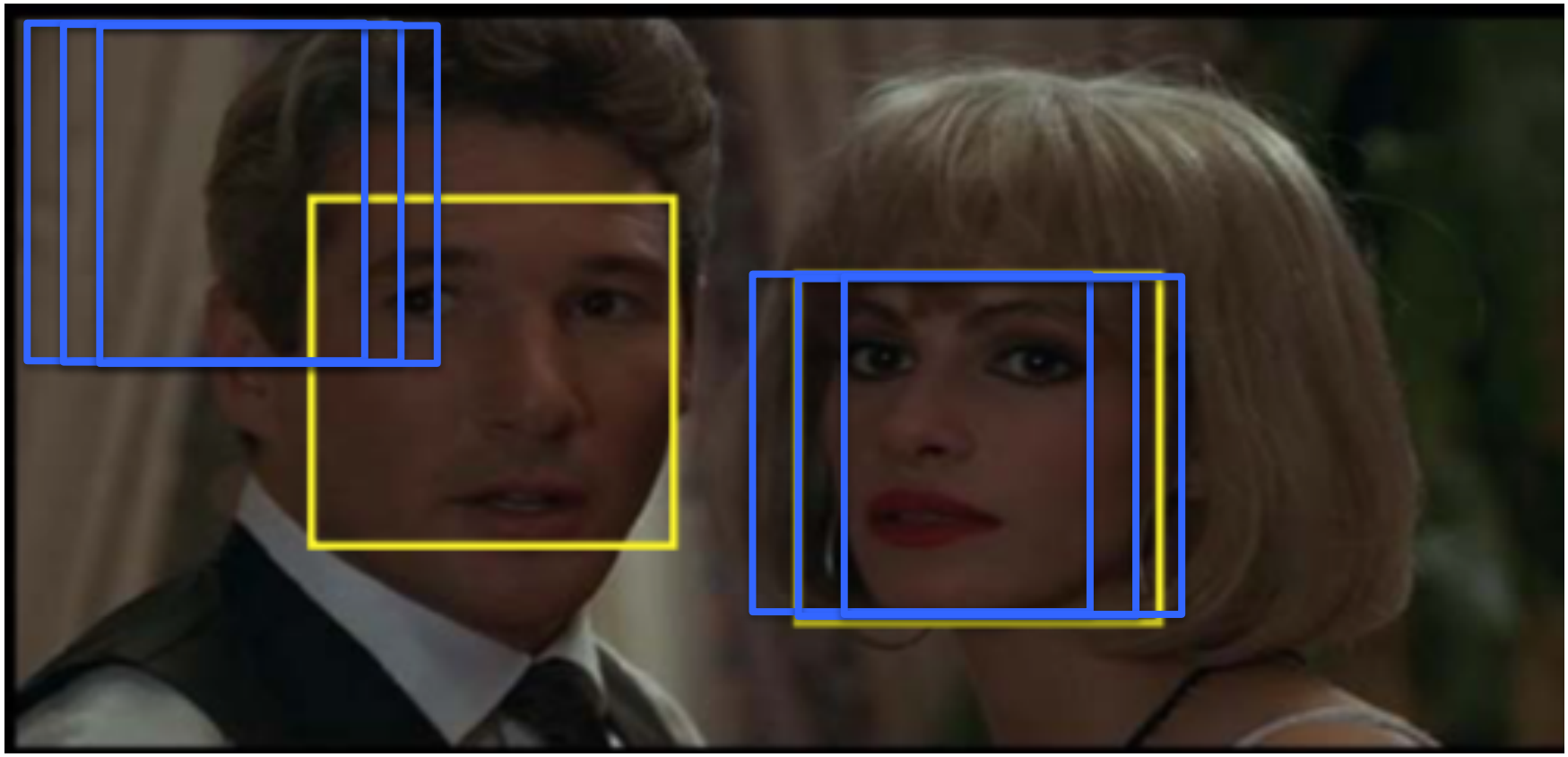
Feature vector:

- What films have you watched?
- Did you like them?

Predictor:

- List of films to propose.

Face Detection



$$y : \mathbf{x} \in \mathbb{R}^{W \times H} \rightarrow v \in \{\text{face}, \text{not face}\}$$

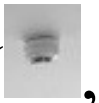
Labeled Training Set

Faces: Near frontal with varying ages, ethnicity, gender, lighting, …

Non-faces: Images containing anything else.

Supervised Learning

Train using an annotated training set:

{( , face), ( , face), ( , face), … , ( , not-face), ( , not-face), ( , not-face), …..}

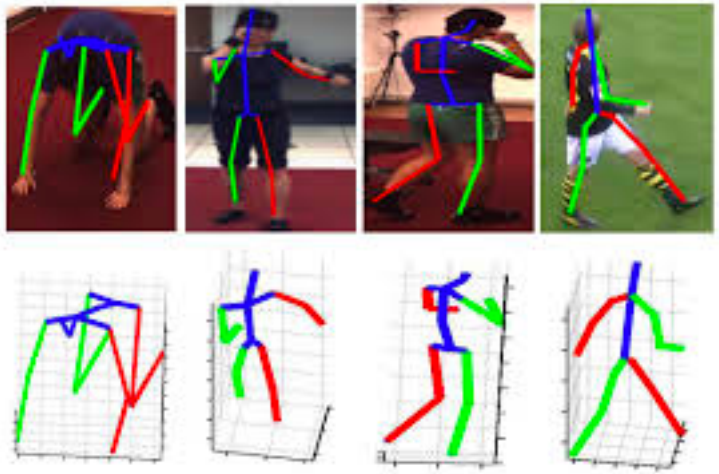
Run on images that do not belong to the test set:

 → Face or not?

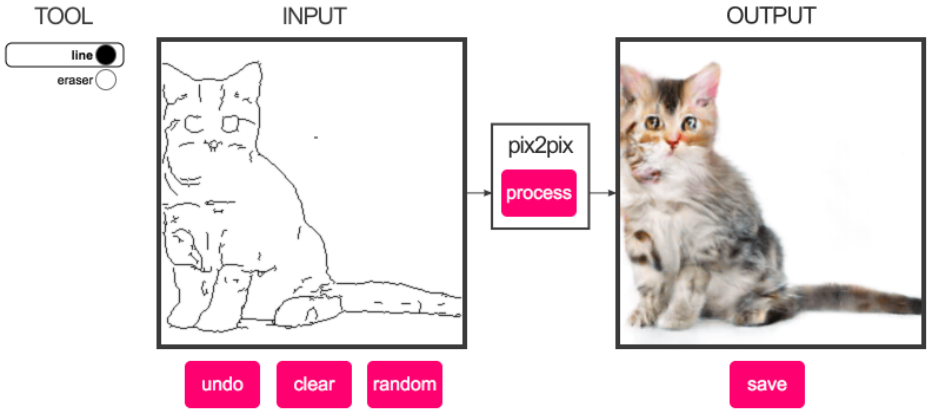
Demo

- Image recognition:
  - https://adamharley.com/nn_vis/mlp/2d.html

Demos



[Pose Estimation](https://vitademo.epfl.ch)



[Image Synthesis]

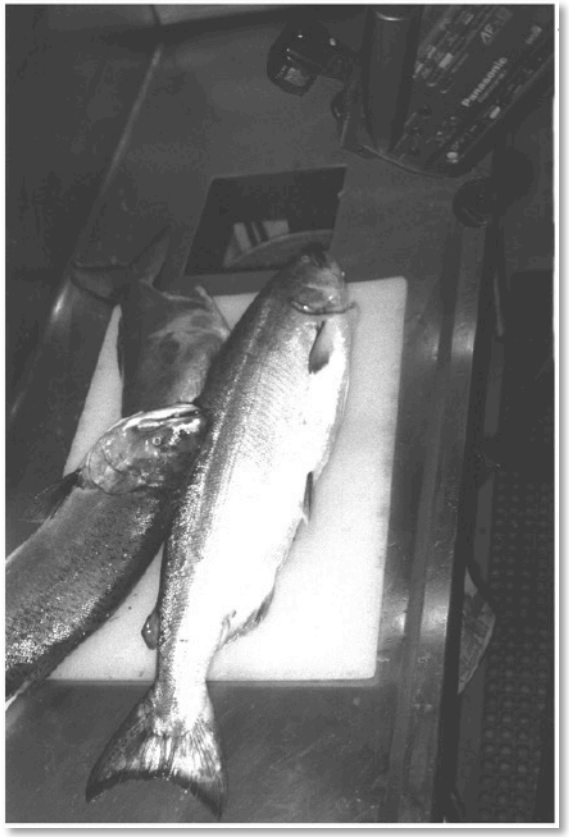
Under the IBM Board Corporate Governance Guidelines, the Directors and Corporate Governance Committee and the full Board annually review the financial and other relationships between the independent director s and IBM as part of the assessment of director independence. The Directors and Corporate Governance Committee makes recommendations to the Board about the independence of non-management directors, and the Board determines whether those directors are independent. In addition to this annual assessment of director independence, independence is monitored by the Directors and Corporate Governance Committee and the full Board on an ongoing basis.

[Text Analysis]

More Demos

- Image generation from text:
  - https://openai.com/dall-e-2/
- Data visualization (and more…):
  - https://experiments.withgoogle.com/ai/drum-machine/view/

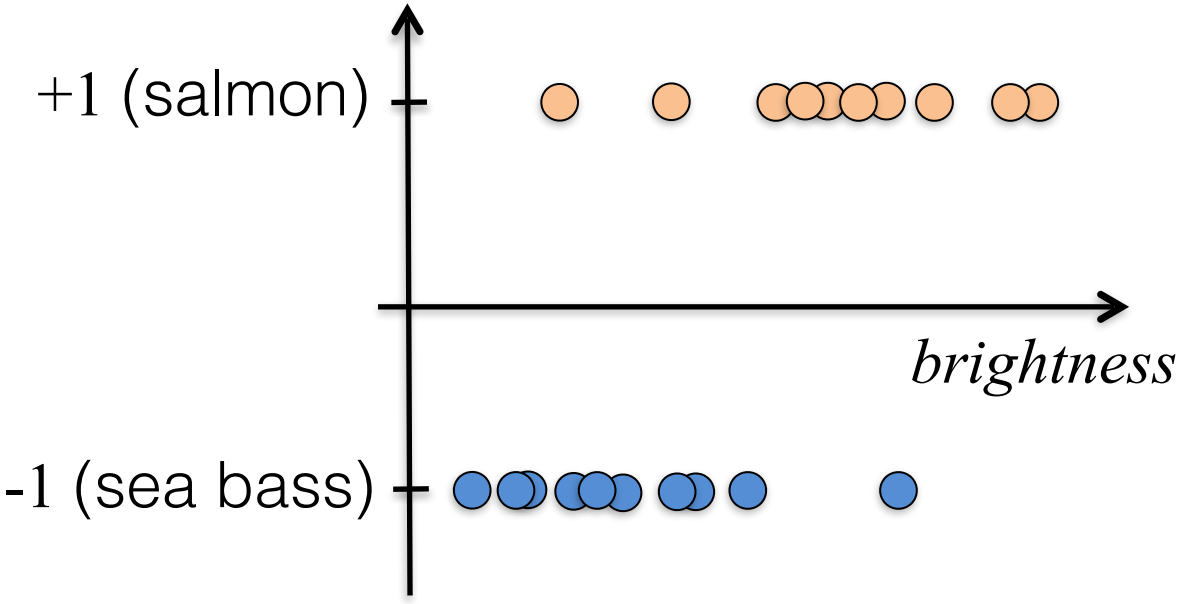
Binary Classification



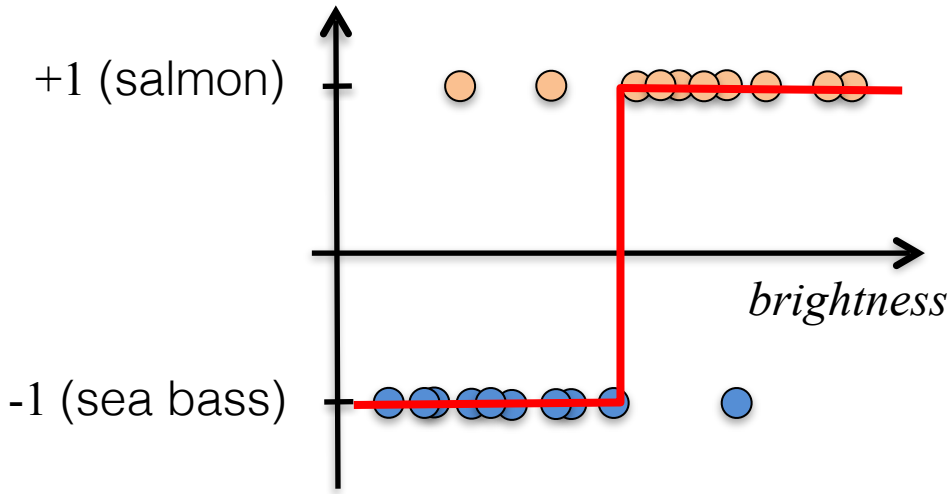
Salmon or sea bass?

Brightness as a Feature

Some algorithm → *brightness*



1D Model



Model:

$$\begin{cases} -1 & \text{if brightness } < \text{T} \\ 1 & \text{otherwise} \end{cases}$$

Model parameters:

$$\mathbf{w} = \{T\}$$

Error function:

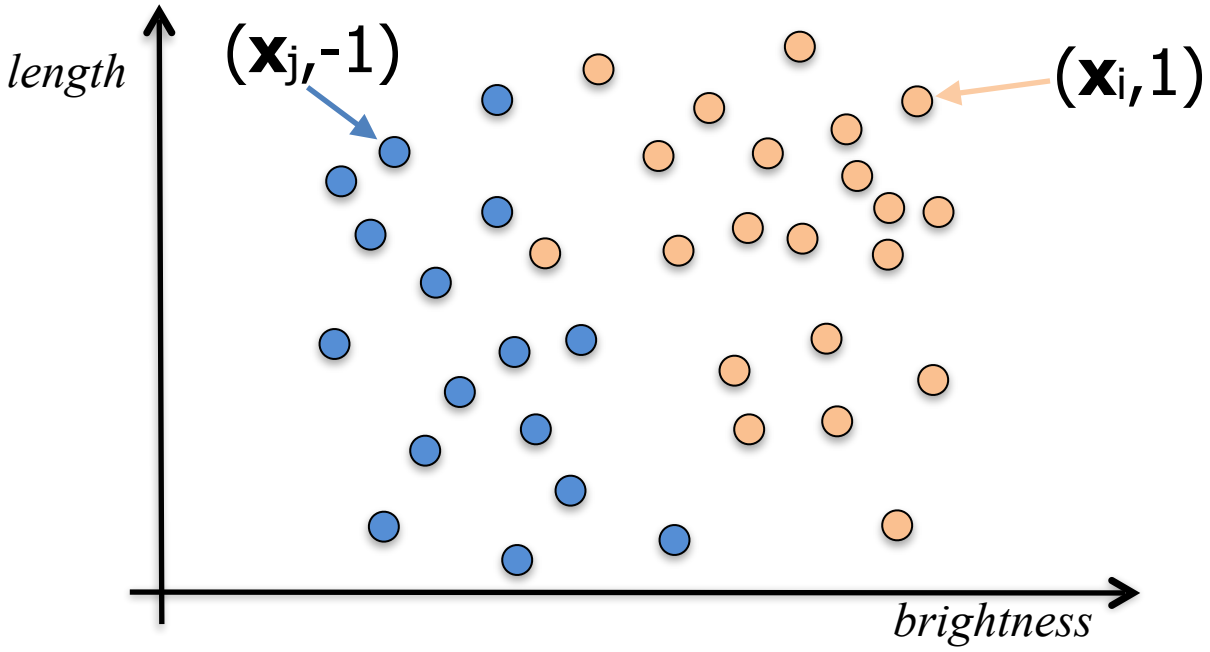
$$E(\mathbf{w}) = \#\text{salmons with brightness } < T + \#\text{seabasses with brightness } \geq T$$

Learning: Minimizing E(**w**) w.r.t. to **w**

2D Model

Some algorithm

$$\begin{pmatrix} brightness \\ length \end{pmatrix}$$



→ +1(Salmon)

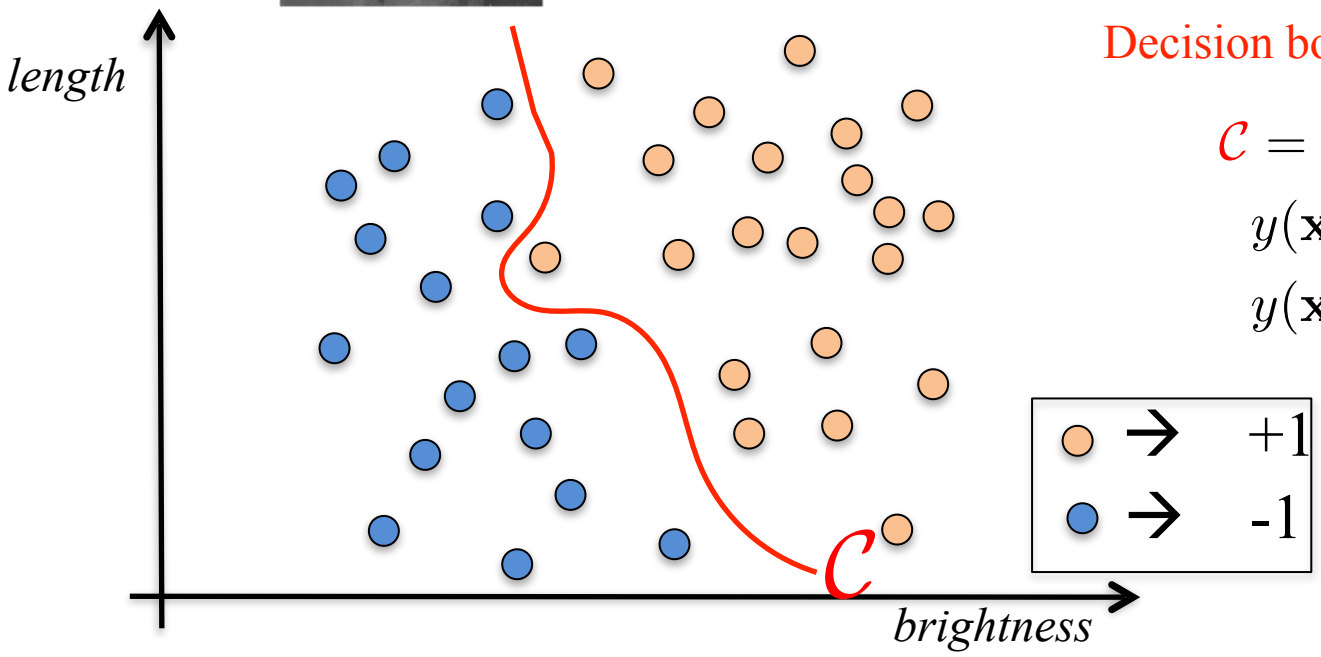
→ -1 (Sea Bass)

Each circle denotes a 2-dimensional sample $\mathbf{x}_i$ of dimension 2, which is assigned a label $t_i \in \{-1, 1\}$.

Decision Boundary

Some algorithm

$$\begin{pmatrix} brightness \\ length \end{pmatrix}$$



Decision boundary:

$$\mathcal{C} = \{\mathbf{x} \in R^2, y(\mathbf{x}, \mathbf{w}) = 0\}$$

$$y(\mathbf{x}, \mathbf{w}) > 0 : Salmon$$

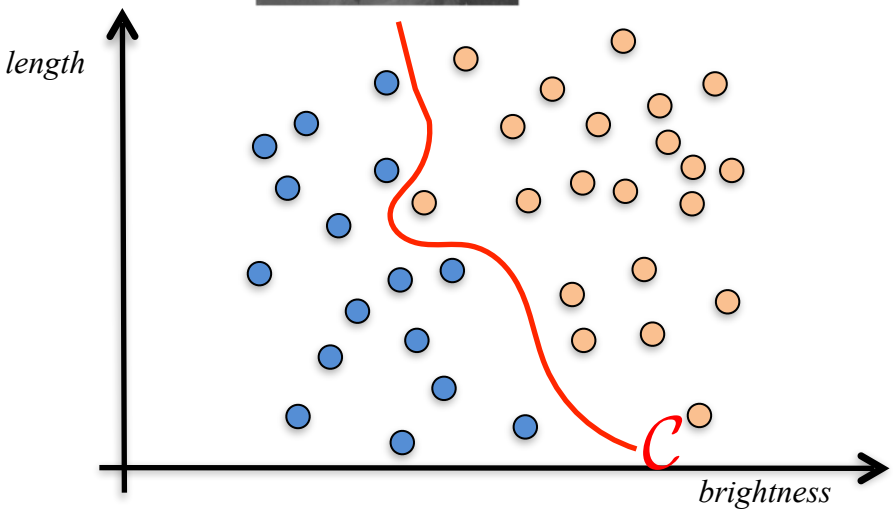
$$y(\mathbf{x}, \mathbf{w}) < 0 : Bass$$

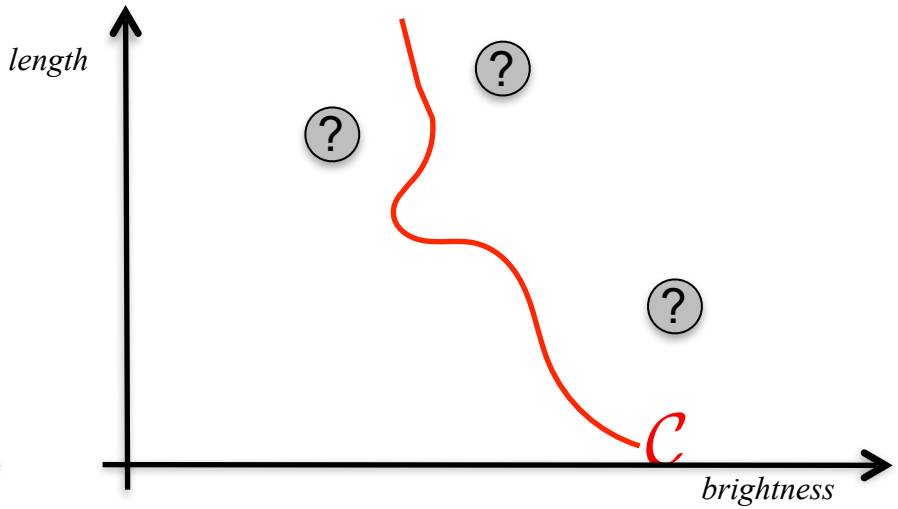
In this class, we will discuss:
- How to define y.
- How to choose **w**.

Training vs Testing

Some algorithm

$$\begin{pmatrix} brightness \\ length \end{pmatrix}$$





Training set = {●,●}

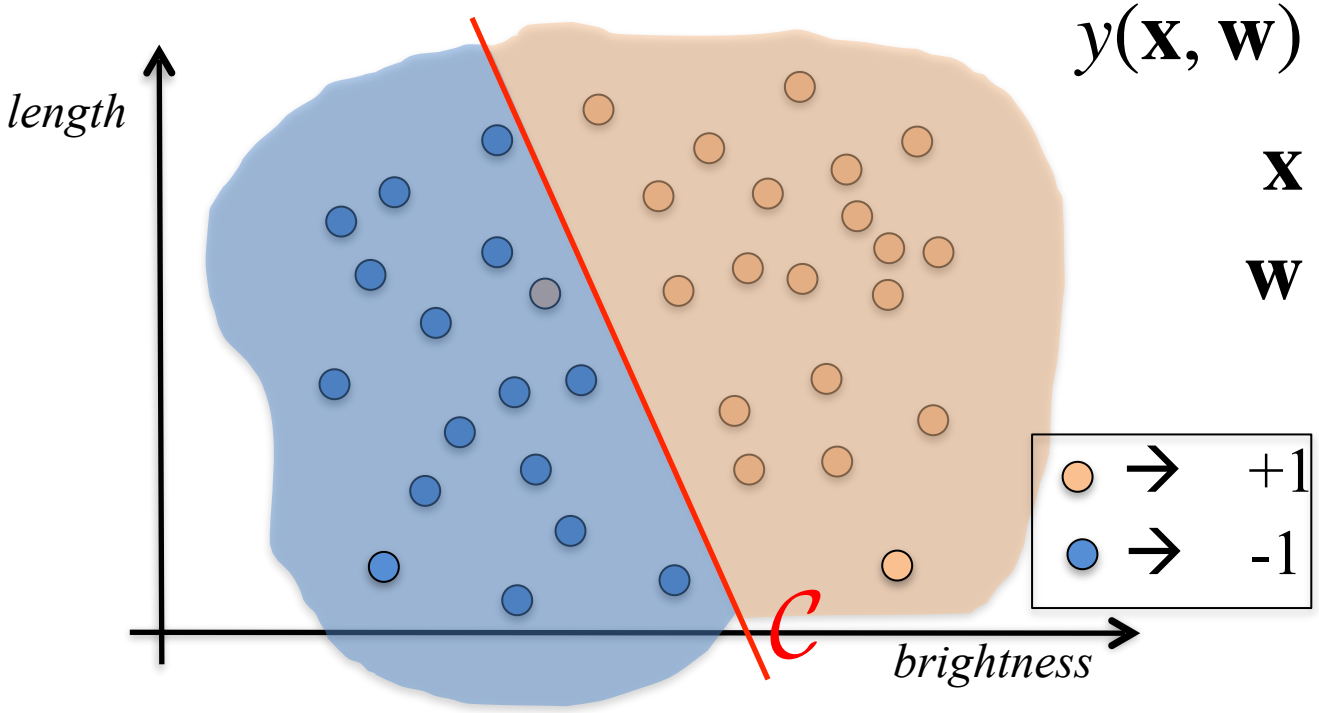
Test set = {?,?,?, ...}

1. Use the training set to learn the model.
2. Measure performance on the test set.
   —> Makes sense only if both have the same statistical distribution.

Linear 2D Model

Some algorithm →

$$\begin{pmatrix} brightness \\ length \end{pmatrix}$$



$$y(\mathbf{x}, \mathbf{w}) = w_0 + w_x b + w_y l$$

$$\mathbf{x} = [b, l]$$

$$\mathbf{w} = [w_0, w_x, w_y]$$

—> Important special case.

Course Outline

Introduction

- ML Basics
- K Nearest Neighbors
- K Means

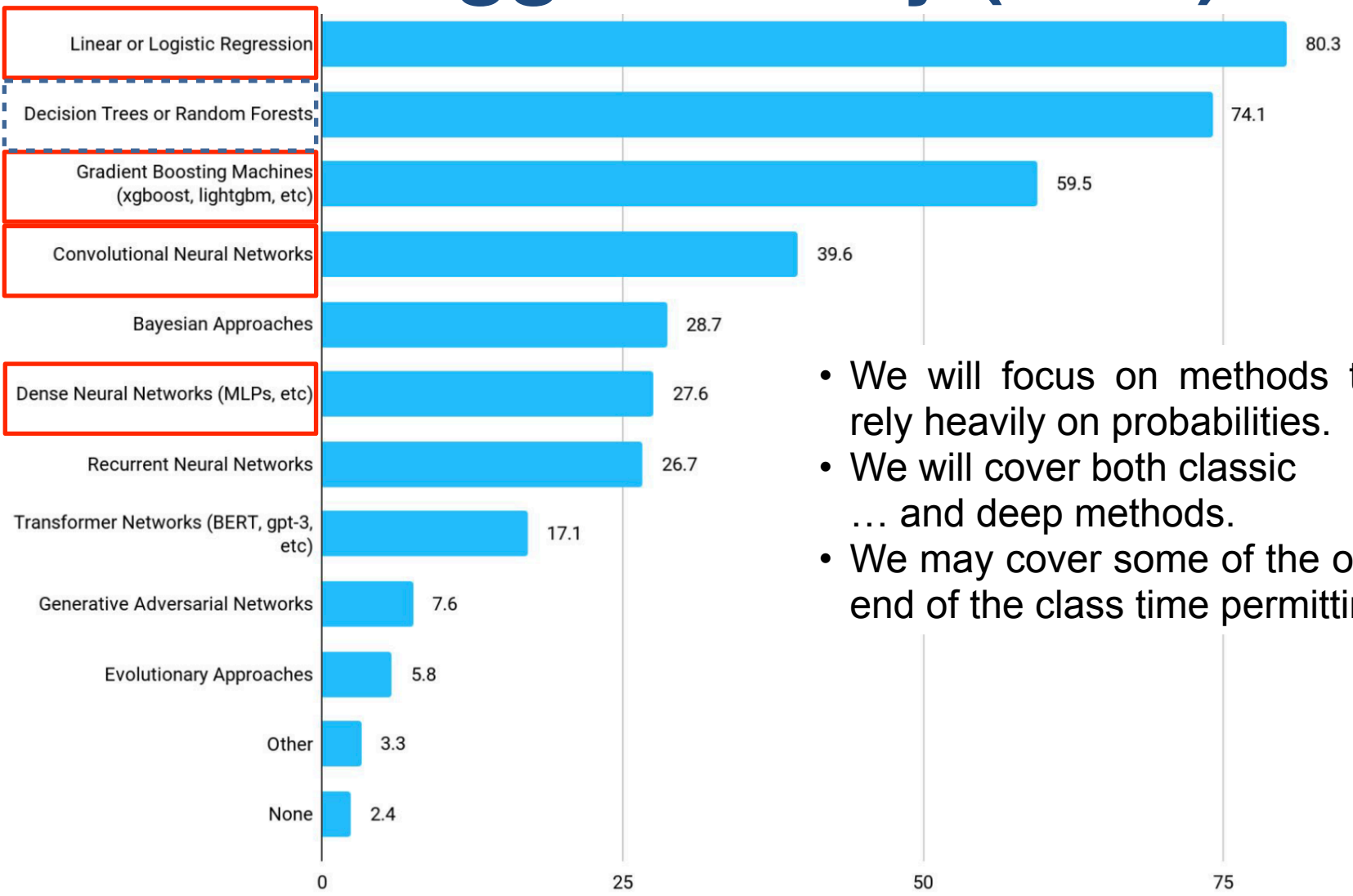
Linear ML

- Linear Regression
- Logistic Regression
- Max Margin Classifiers

Nonlinear ML

- AdaBoost
- Polynomial Support Vector Machines
- Kernel Methods
- Artificial Neural Networks

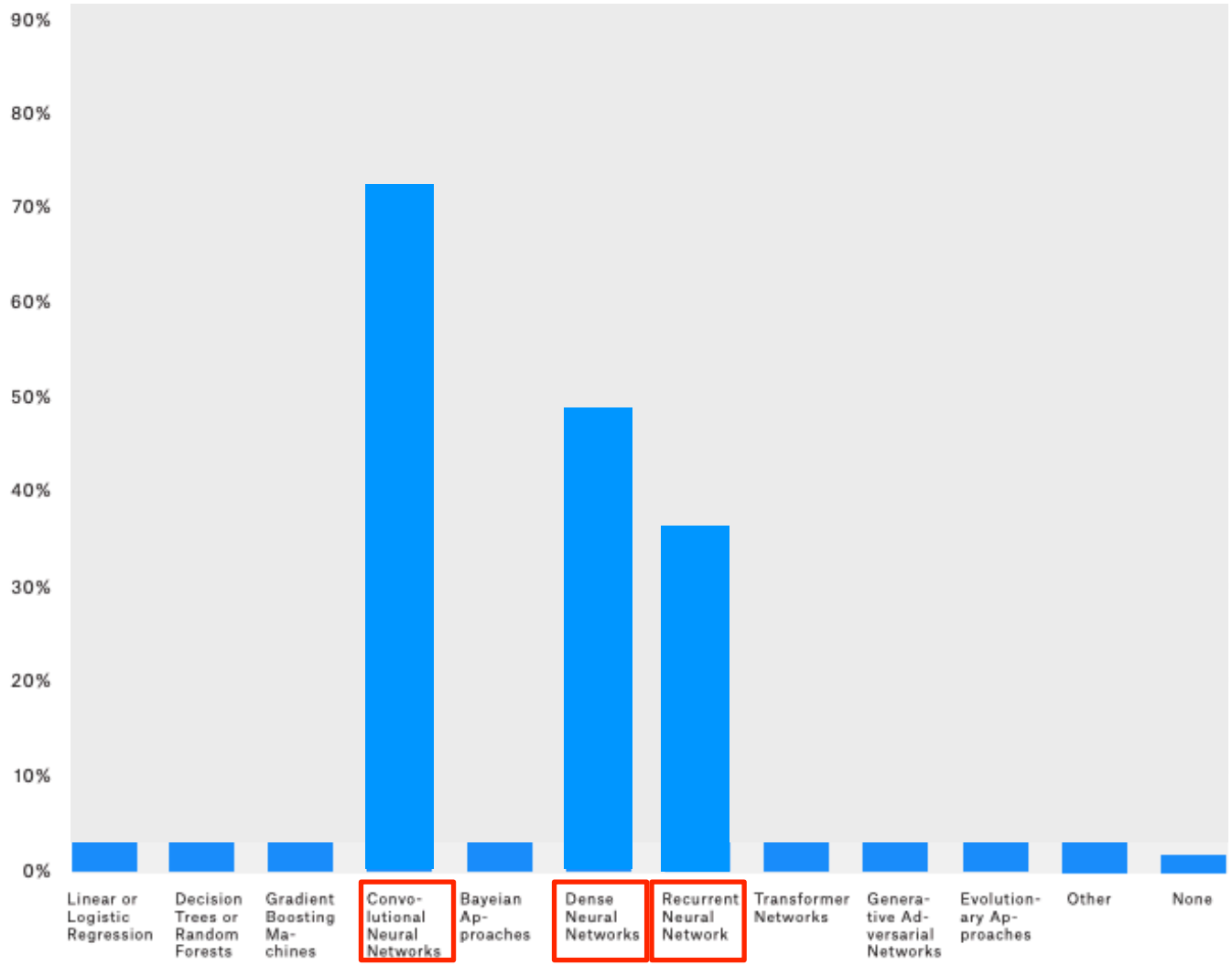
Kaggle Survey (2021)



- We will focus on methods that do not rely heavily on probabilities.
- We will cover both classic … and deep methods.
- We may cover some of the others at the end of the class time permitting.

What data science methods do you use at work?

My Erroneous Perception



- Will it evolve in that direction?
- Time will tell.