1 - Introduction

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Summary

- Course formalities
- Machine learning
- Course objectives and outline

Formalities

Formalities

Instructors

- Lectures, P1, P5, P6: Ludwig Krippahl
- P2, P3, P4: Joaquim Ferreira da Silva

Course site: aa.ssdi.di.fct.unl.pt

- Slides, notes, lecture videos

Classes

- Lectures: 2 x 1h per week, ~70% exposition, ~30% discussion
  - Streaming on YouTube, Zoom meeting afterwards
- Tutorials: 1 x 2h per week
  - Questions about exercises and assignments (Hangouts)
- Some lectures reserved for revisions and assigments

Formalities

Assessment

- Theoretical: 2 written tests or final exam.
  - Online, timed questions with long answers
  - Exam scored in two independent parts
- Practical: 2 assignments, groups of 2 students in same class.
  - Plus individual defense question during the test (so must attend test)
- Groups formed by October 18
- All submission to praticasice@gmail.com using official FCT address
  - NOTE: this address is for automated processing only
- Evaluation
  - Required: minimum of 9.5 in each component.
  - Final grade: simple average of the two components.
  - If frequency from 2016/17 - 20, do not enroll in practical classes

Formalities

Recommended Software

- Python 3.x, Spyder IDE
- Several libraries needed: NumPy, Matplotlib, Scikit-Learn, ...
- Simple instalation: Anaconda
  - https://www.anaconda.com/products/individual

Bibliography

- **Lecture notes, available on web site**
- **Bishop, Pattern Recognition and ML 2006**
- Alpaydin, Introduction to ML (2nd ed.) 2010
- Marsland, Machine Learning, 2009
- Mitchell, Machine Learning, 1997

Machine Learning

Machine Learning

- Making sense of data.

" Field of study that gives computers the ability to learn without being explicitly programmed"

(Samuel, 1959)

- More formal, operational, definition:

"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E"

(Mitchell, 1997)

Machine Learning problem

- A task that the system must perform.
- A measure of its performance
- The data used to improve its performance.

Example: automated flight ticketing

- Task: identify requests for flight information and tickets.
- Performance measure: correctly identified expressions.
- Data: Annotated voice records.

```
<book_flight> please book me on </book_flight>
<numflt> flight twenty one </numflt>

<i_want_to_go> i would like to fly </i_want_to_go>
<city_from> from philadelphia </city_from>
<city_to> to dallas </city_to>

<request1> could you please list the </request1> flights
<city_from> from boston </city_from> <city_to> to denver </city_to>
on <date> july twenty eighth </date>
```

Source: Erdogan, Using semantic analysis to improve speech recognition performance

Machine Learning problems

- Predicting prices (Regression)
- Classifying spam emails (Classification)
- Products purchased together (Association Rules)
- Grouping similar images (Clustering)
- Distributions in diagnosis (Density Estimation)

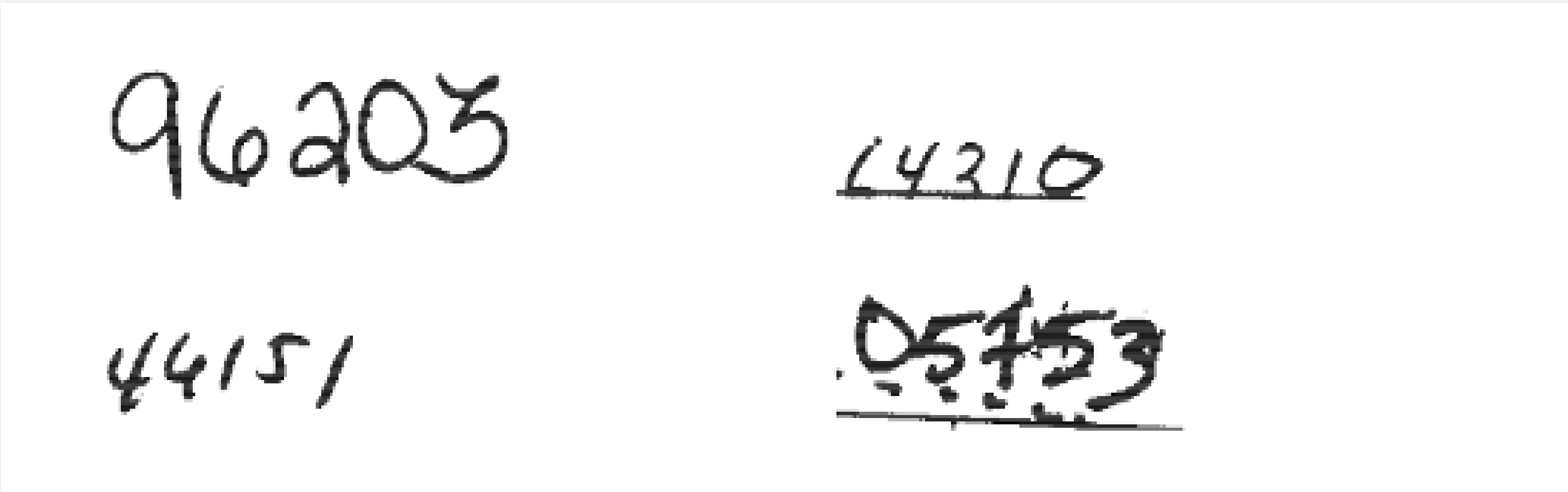
Relations to other disciplines

- Computer Science
- Statistics and Probability
- Mathematics
- Neuroscience
- Philosophy

What is Machine Learning for?

Solve problems without explicit rules

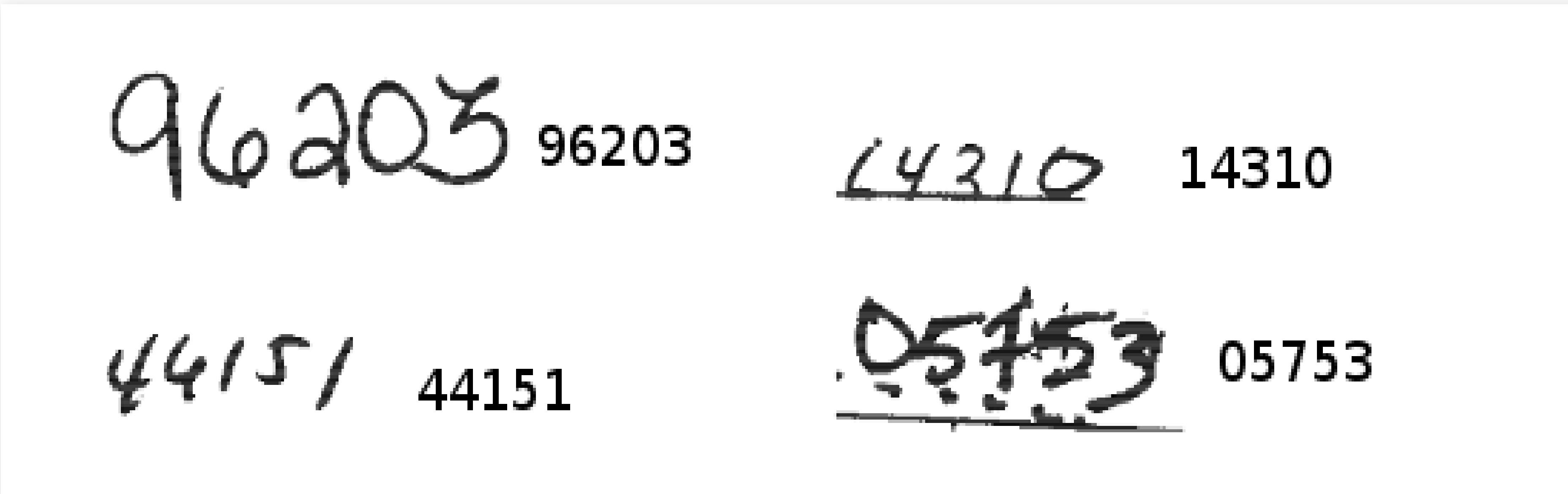
- Example: identify handwritten digits



Using ML

Solve problems without explicit rules

- Train with labelled data



- Find a function for classifying
  - Partition the input space into the 10 classes (0..9)

Using ML

Data mining

- Large volumes of data
  - Google searches
  - Facebook relations graph
  - Credit card fraud

Adaptive systems

- Need to respond to changing conditions
- Personalization (e.g. Facebook feed)
- Spam filtering (email and comments)

ML is good for tasks we do not have a recipe for...

- ... if we have the right data.

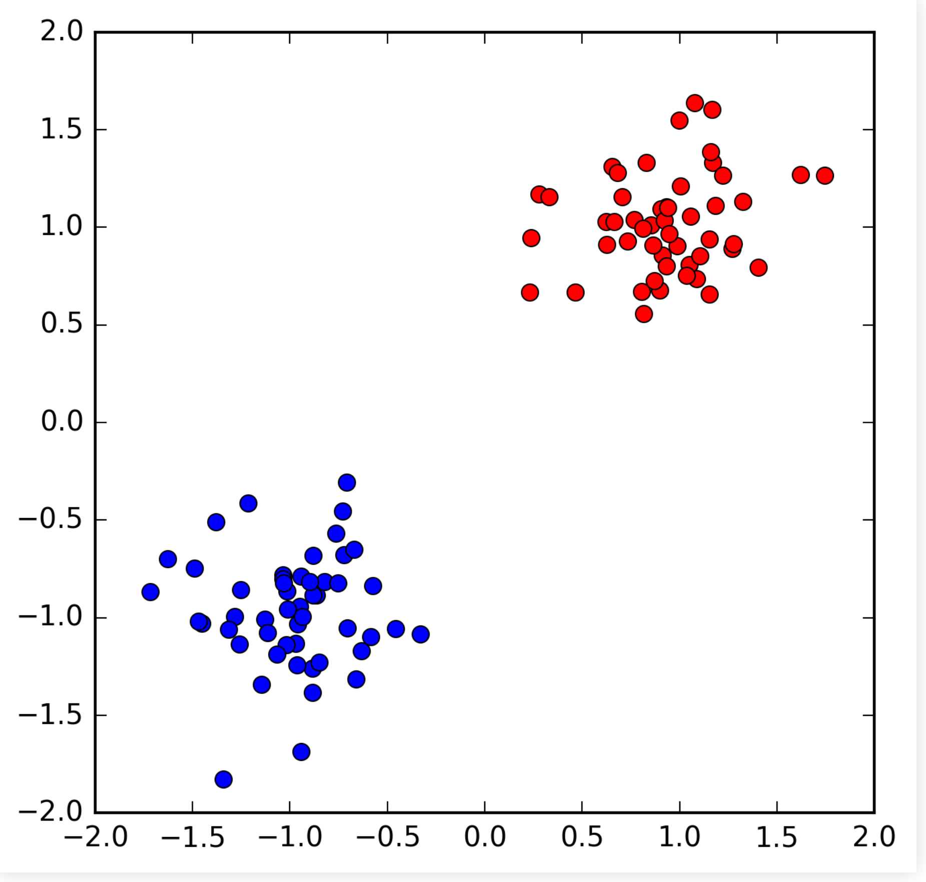
Basic Concepts

Hypothesis class

- The set of possible hypotheses
- We need to assume something about the solution

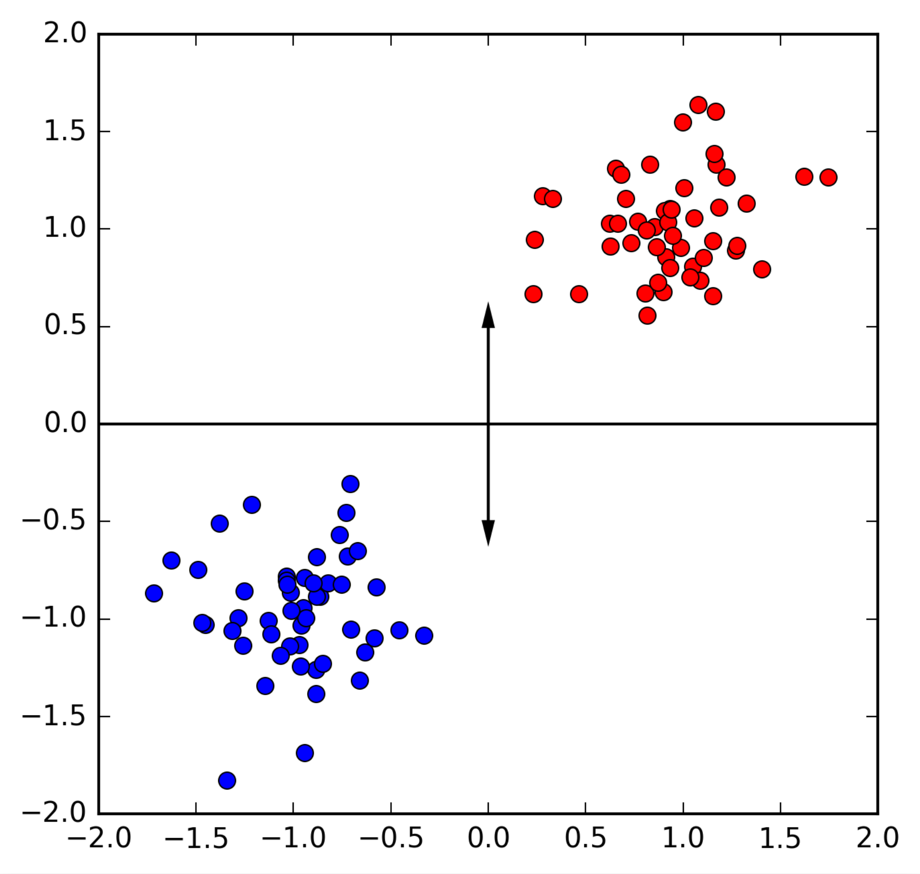
Hypothesis class

- Example: we want to separate red from blue



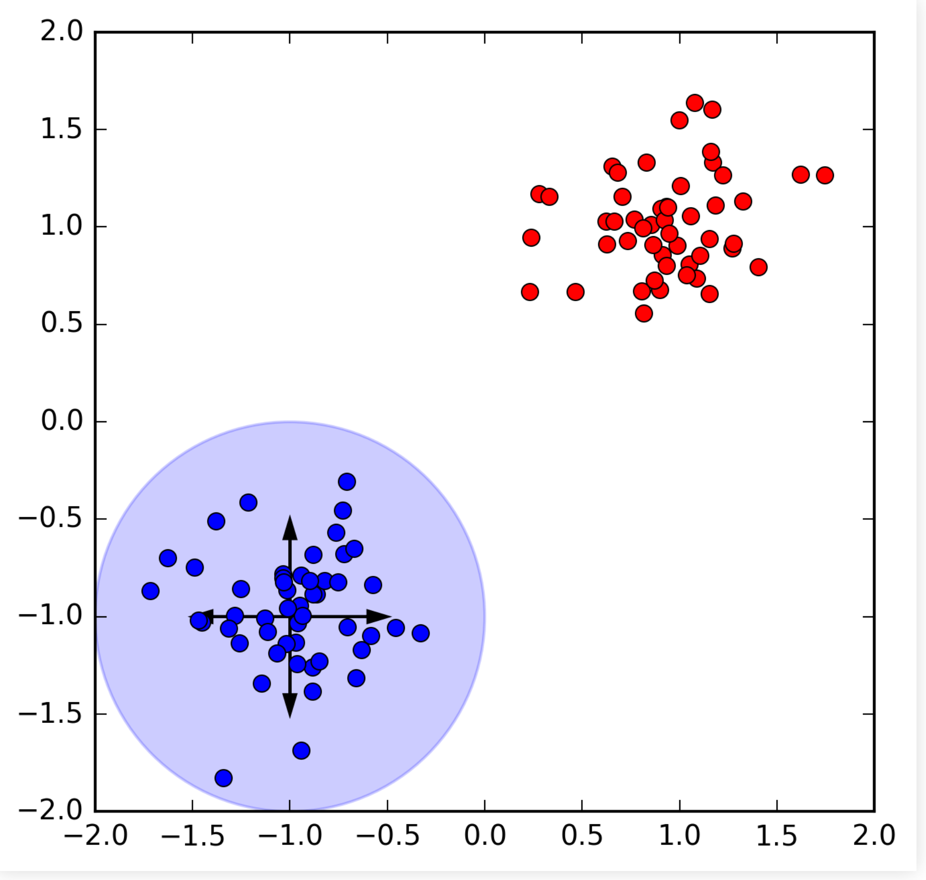
Hypothesis class: horizontal lines

- Model: $y \leq \theta_1$



Hypothesis class: circles of radius 1

- Model: $(x-\theta_1)^2 + (y-\theta_2)^2 \leq 1$



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Hypothesis class

- Set of all hypotheses

Model

- Represents the set of hypotheses (with parameters)

Hypothesis

- One element of the hypothesis class set
- One instance of the Model (e.g. instantiating parameters)
  - One line: $\theta_1 = 0 \qquad y \leq 0$
  - One circle: $\theta_1 = \theta_2 = -1 \qquad (x+1)^2 + (y+1)^2 \leq 1$

Goal: find the best hypothesis

Inductive Bias

- We are biased by what we assume from the start.
  - Hypothesis class
- But we must assume something.
  - we cannot proceed without a hypothesis class
- There is no learning without inductive bias.
  - Without inductive bias it is not possible to extrapolate from known data to unknown events (will gravity still work tomorrow?)
- Since we want to infer something outside known data we must assume some constraints

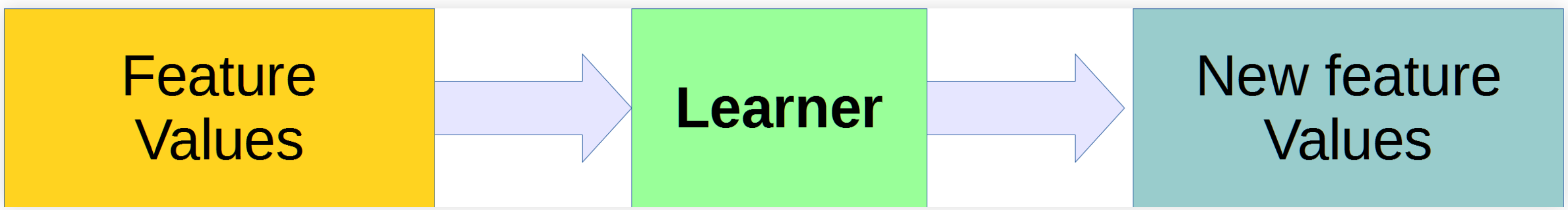
Machine learning problems

Four basic kinds of ML problems

- Unsupervised learning

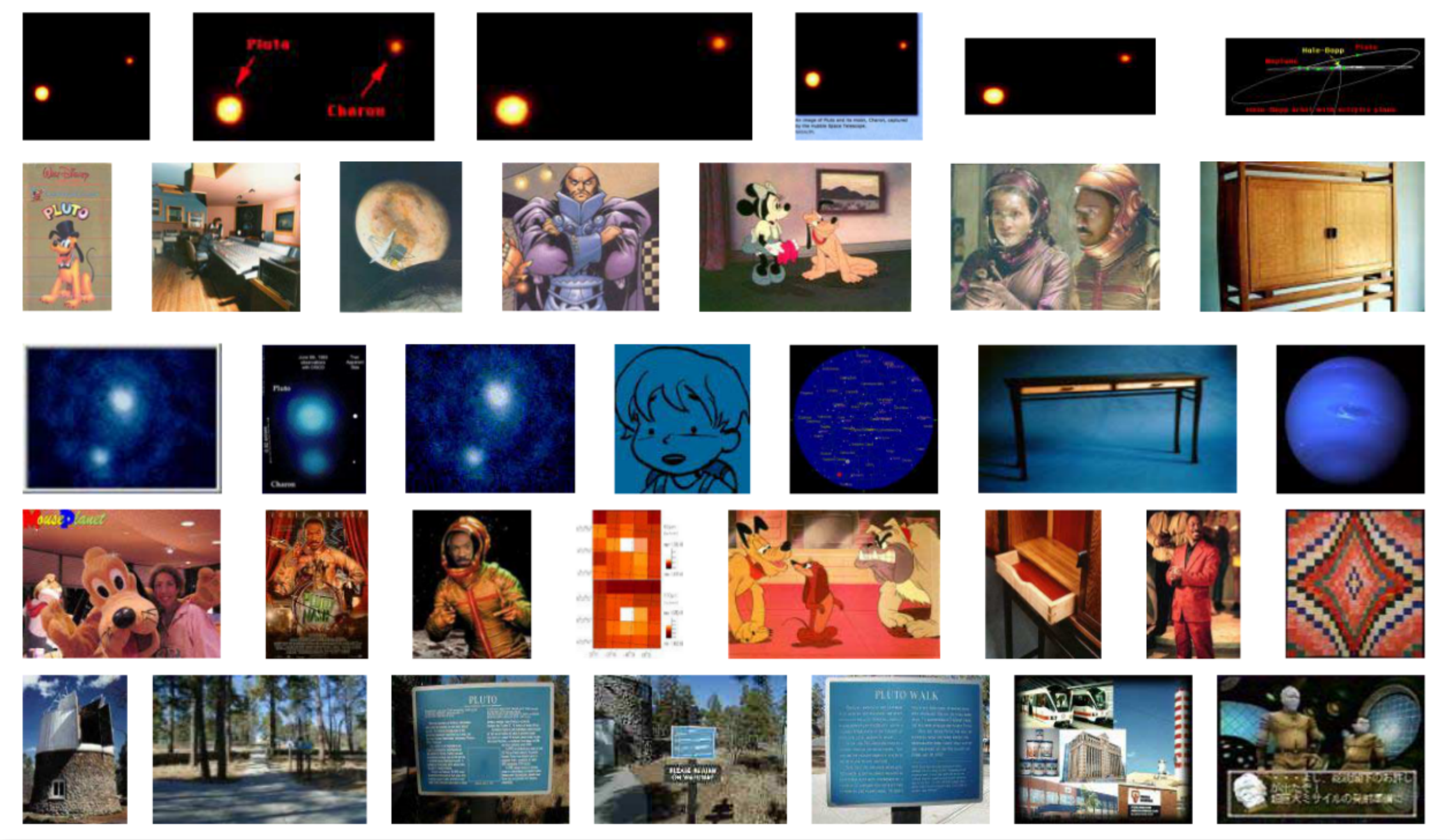
• All data is unlabelled

• Find structure in data



ML Problems

- Example: clustering images



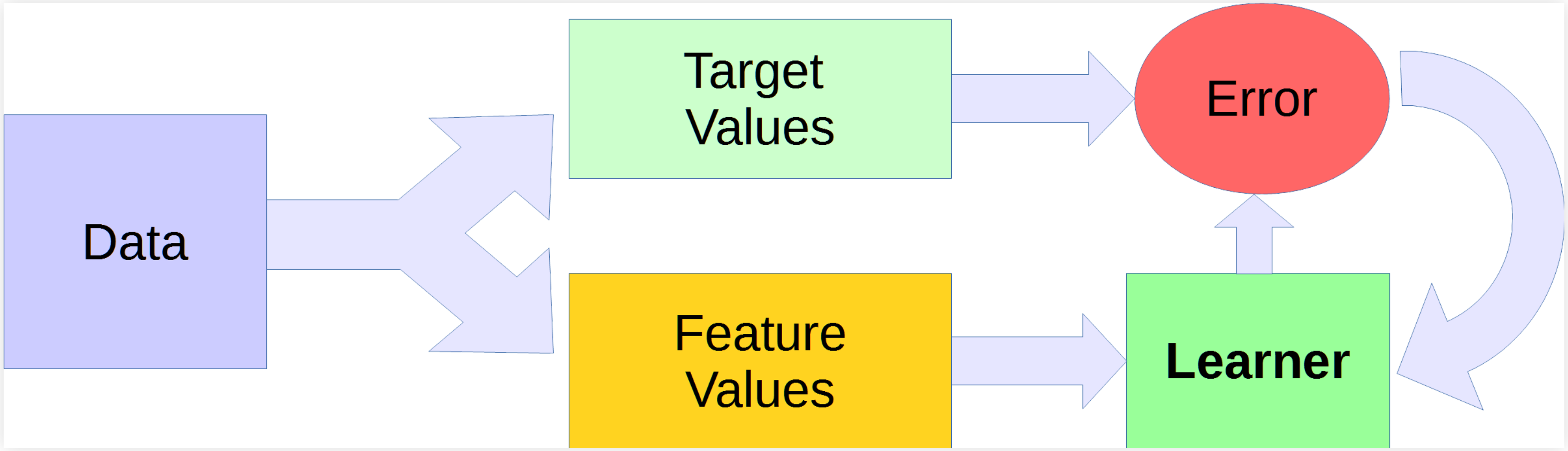
Group searches with features from image and HTML (Cai et al, Clustering of WWW Image Search Results, 2004)

Four basic kinds of ML problems

- Unsupervised learning
  - Data is unlabelled
  - Find structure in data
  - Allows us to obtain new features from the data
  - Can be used as a step in broader learning tasks
  - (preprocessing, visualization, deep learning)

Four basic kinds of ML problems

- Supervised learning
  - Training data is labelled
  - Predict value correctly



- Continuous values: Regression
- Discrete classes: Classification

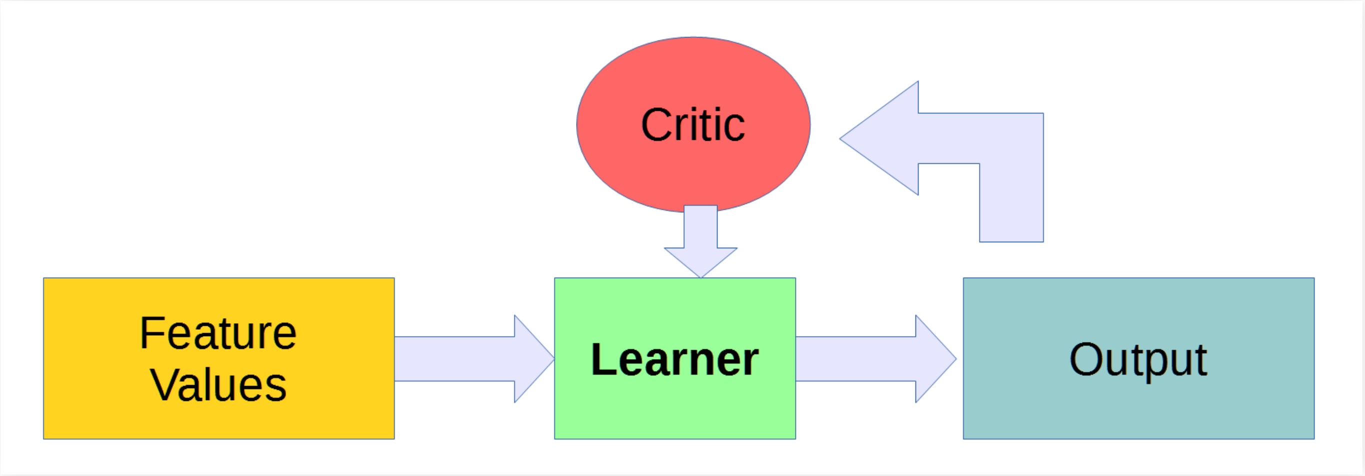
Supervised learning

- Example: face identification

Valenti et al, Machine Learning Techniques for Face Analysis, 2008

Four basic kinds of ML problems

- Unsupervised learning
- Supervised learning
- Reinforcement learning
- Optimize some output
- But no direct feedback for each case



ML Problems

Reinforcement learning

- Optimize some output
- But no direct feedback for each case

Examples

- Learn to play a game
  - Must learn to predict cost and benefit of each move.
  - But can only know final result at the end of the game.
- Robotics: locomotion, manipulation
- Control of autonomous vehicles
- Operations research: pricing, marketing, routing

Four basic kinds of ML problems

- Unsupervised learning
- Supervised learning
- Reinforcement learning
- Semi-supervised learning
  - Some data labelled, most unlabelled
  - Mixes the two approaches
  - Structure of unlabelled data helps choose hypothesis

ML Problems

Four basic kinds of ML problems

- Unsupervised learning
- Supervised learning
- Reinforcement learning
- Semi-supervised learning

Our focus in this course:

- Supervised learning
- Unsupervised learning

Course Goals

Course Goals

Objectives for this course

- Understand the foundations of ML problems and solutions
- Experience with useful ML techniques and applications
- Learn to understand the literature
- Learn to understand the mathematical formulations

Course outline

- Introduction and Supervised Learning
- Regression, Classification
- Learning Theory
- Unsupervised Learning

Summary

Summary

- Learn from data, without explicit rules
- Hypothesis class, model and hypothesis
- Inductive bias and learning
- Supervised, unsupervised, reinforcement, semi-supervised

Further reading

- Alpaydin, Chapter 1
- Mitchell, Chapter 1
- Marsland, Sections 1.1 through 1.4.