Vietnam National University - Ho Chi Minh

Optimization, Machine Learning and Kernel Methods.

Introduction to the course

Marco Cuturi - Princeton University

Some preliminary information

- Course is 5 days long
 - $\circ\,$ Saturday 12/06 7:30AM to 12:30AM room I.23 $\,$
 - $\circ\,$ Monday 14/06 1:30PM to 6:30 room I.23 $\,$
 - Tuesday 15/06 7:30-12:30
 - \circ Wed 16/06 7:30-12:30
 - $\circ~$ Thu 17/06 7:30-12:30
- Evaluation: currently speaking with TA's.

Some preliminary information

- email: mcuturi@princeton.edu Webpage: www.princeton.edu/~mcuturi
- Research interests: statistical learning, kernel methods, time-series, finance...
- My current job: Lecturer @ Princeton University ORFE dept.





 My next job (from 09/2010): Associate Prof. @ Kyoto University Graduate School of Informatics,



A master or PhD at Kyoto University?

- Want to go abroad for a Master or PhD in CS ? why not Kyoto University.
 - o Check http://www.g30.i.kyoto-u.ac.jp/en
 - Google KU profile
- NEW: full curriculum in english.
- Monbukagakusho grants $\approx 1.500 \text{ USD/month}$, no tuition fees.
- **Deadline** to join in October is very soon: **July 5th**.
- Another enrollment in **February 2011**, maybe easier.

• Please mention this to your friends in 3rd year, and ask me if interested.

The course

Three blocks in this course

- **Optimization** mathematical programming
- Machine Learning statistics, regression, classification
- Kernel Methods splines, reproducing kernel Hilbert spaces

Objective: cover theoretical, computational and practical aspects to build **computer programs** that can **learn** from databases

The big picture

Some intuitions on machine learning

• Imagine you have seen this movie:



• A friend comes to you and asks you:

I feel like going to the movies tonight, do you think I will like this movie?

• How would you build your answer?

Some intuitions on machine learning

Machine learning helps industries build such answers automatically

- Imagine you are a DVD rental company.
- It is **part of your business** to recommend good movies to your customers.
- **large scale task:** for 1,000's or 1,000,000's of customers every day!
- Still the same question: would you recommend *Ironman* to customer AD13242?



Some intuitions on machine learning

- A computer program also needs side information
- For instance:
 - $\circ\,$ age & background of the user $\rightarrow\,$ Check his inscription form.
 - Better! a few examples of movies AD13242 has seen, with his ratings



• Lord of the rings I (+++), Star Wars I (++), Shrek 2 (-) etc..

• How can we decide if we should recommend *Ironman* to AD13242?

A more serious problem

• Given the DNA profile of a patient...



- Can we answer (approximately) the questions:
 - What is this patient's **cancer** risk in the next years?
 - What **treatments** can be effective for this patient?

Very fast progress in last years, from theory to practice

You can do a websearch on mammaprint or 23andme





Not only biology or movies.. richly structured data is everywhere

Biology : DNA chips, complex biological pathways. Medicine : scans, 24/24 measurements of patients. Business : commercial transactions online and offline. Search engines : audio, video and textual contents. Finance : electronic markets, quotes and transactions tick by tick. Physical interactions : highway networks, mobile phones, GPS localization. Sociological and physical interactions : social networks on internet, surveillance. *etc.*

\Downarrow

Data acquisition is cheap \neq **Data** analysis is more difficult

 \downarrow

Need for data-driven algorithms to fill the gap between storing complex data and understanding it

Build decision functions

• In many situations, we want to answer a question:

Given a certain situation summarized by x, what can happen/should we do?

• In mathematical terms, we want to build a function:

$$\begin{array}{rcccc} f: & \mathcal{X} & \to & \mathcal{Y} \\ & x & \mapsto & f(x) \end{array}$$

- $\circ \mathcal{X}$ could be: images, texts, movies, *etc.*
- $\circ \mathcal{Y}$ could be: "yes/no", real numbers, sentences *etc.*

Our goal: build a **computer program** that outputs a **useful** f(x).

Build decision functions

A few examples in the industry

- Ranking answers to a problem,
- Learning jointly different related tasks,
- Learn maps between structured data, *e.g.* translation
- Build interaction maps, e.g. for proteins,

- Learn in online settings where data is provided sequentially
- Learn with very large databases: shopping.
- *etc*.







NETFLIX

What we will not do

• 100% Man-made, rule-based decision trees.



- advantages: sometimes expertise available, just need to rationalize it. etc.
- disadvantages: difficult to replicate, unadapted for large systems and new problems (DNA) where no expertise exists by definition!

What we will do:

• Use data collected in databases as the main ingredient to build f.



• Build architectures where machines can learn from these databases.

The kind of data we will handle

• Random

- Unlike deterministic systems, we assume randomness.
- Future requests are not known. Some are more likely.

• Structured, complex

 $\circ\,$ strings, texts and sequences,













Statistical Inference

Definition

Statistical inference is the process of **making conclusions** using data that is subject to random variation, for example, observational errors or sampling variation.

- **Statistical inference** = Take decisions in a random environment based on past observations.
- **statistical**: probabilistic view of the world.
- **inference**: purpose to understand and predict better.

Ingredients to pick a good f

• A set of candidates \mathcal{F} .



- A way to use the database (past observations)
 - **Data-dependent** criterion C_{data} to select f.
 - Usually given a function g, $C_{data}(g)$ big if g not accurate on the data.
- A method to find an **optimal** candidate in \mathcal{F} .

$$f = \operatorname{argmin}_{g \in \mathcal{F}} \quad C_{\mathsf{data}}(g).$$

Outline of the course

• Optimization (argmin).

- Convexity & linear programming (6 hours)
- Convex programming (4 hours)
- **Statistical Modeling** to define (C_{data}) (4 hours)
 - elementary probability,
 - \circ study of different situations and different C.
- Kernel Methods, a possible choice for \mathcal{F} (6 hours)