Introduction – What? Why? How?

(CIV6540 - Probabilistic Machine Learning for Civil Engineers)

Professor: James-A. Goulet

Département des génies civil, géologique et des mines
Polytechnique Montréal

Goulet (2020)
Probabilistic Machine Learning for Civil Engineers
MIT Press

Machine learning, why?

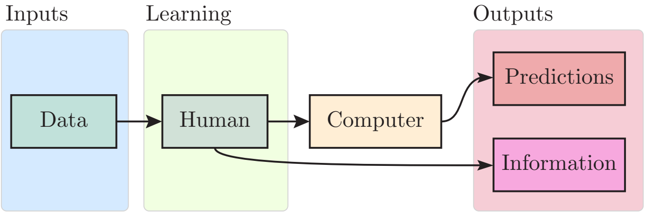
Probabilistic Reasoning →

Data →

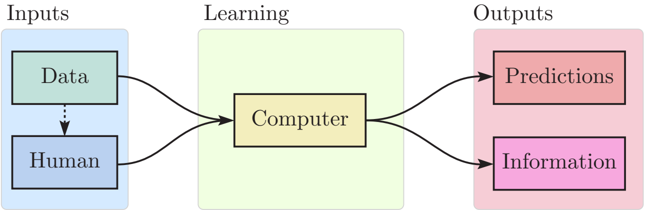
Information →

What is machine learning?

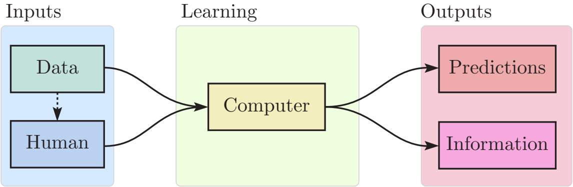
Business as usual



Machine learning



What is “Learning” in “Machine Learning”?

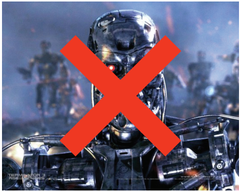


fonction(**parameters/variables**) = Predictions

Learning → Infer what **parameters/variables** explain the data

Artificial intelligence – AI

AI : reproduction of an intelligent behavior by a machine.
→ perception and dynamic interaction with its environment through the process of **taking actions** for achieving goals.



Level 1 - Limited AI
Beyond human capacity in a specific tasks

Behind limited AI:
Machine learning

Behind machine learning:
Probability theory / Decision Theory / Linear Algebra / Optimization/...

[Google images]

Section Outline

Syllabus – available on moodle

Syllabus

CIV6540E – Prob. Machine Learning for Civil Eng.
Winter 2024 | CGM Department – Polytechnique Montréal

Credits	3cr (3 - 0 - 6)
Professor	James-A. Goulet (Office B-431.4.6)
Office hours	To be announced on Moodle

1 Language

This class will be taught in English. Nevertheless, you can use either French or English when asking questions as well as when answering homeworks and exams.

2 Objectives

Learn how to

- Estimate epistemic uncertainties in models from a set of empirical observations
- Build probabilistic regression and classification models from empirical observations
- Build probabilistic models for time series of empirical data
- Estimate model parameters using sampling and optimization methods
- Propagate uncertainties through deterministic models
- Make rational decisions in uncertain contexts
- Use machine learning algorithms and apply them to civil engineering problems (structures, mining, transport and environment)

3 Classes

Classes will take place in person but you can also access the videos on YouTube. Note that you can avoid having advertisements by installing a plug-in such as Adblock or Adblock Plus. I encourage you to read the references indicated in section 4 before each class.

(Dernière mise à jour : 2024/05/24, 10:00:46) 1/3

What are the class objectives?

1- Understand the potential of machine learning for civil engineering applications

2- Create models for different problem structures: regression, classification, time-series, decision problems, etc.

3- Train models using empirical data

Understand the theory behind existing methods & algorithms

Evaluations

1. Homeworks: $5 \times 6\% = 30\%$
2. Mid-term exam: 35%
   (last week before spring break)
3. Final exam: 35%

Revision questions $\rightarrow$ moodle

Homeworks

- 5 homeworks (HW1 already on moodle)
- Teams of **1 or 2 people**.
- Collaboration between teams is encouraged
  → **One homework/code per team** (LaTeX)
- You must provide a complete solution for each problem
- Autocorrection procedure → moodle

> Online submission via dropbox
> (“TP<#TP>_<Name1>_<Name2>_CIV6540_H20XX.pdf”)
> **at the latest on the day before the class 20h00**
> Re-submission of corrected copies at the latest
> **on the following week by the end of the class**

Readings []

The "easy" way

Documentation & Algorithms

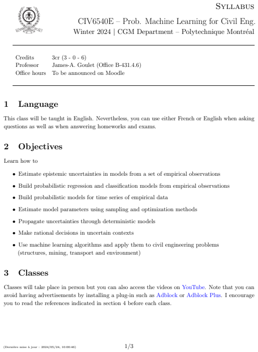
Weekly readings: referenced in the syllabus → moodle

- Goulet, J.-A.. (2020).
  Probabilistic Machine Learning for Civil Engineers. MIT Press
- Murphy, K. (2012).
  Machine learning: A probabilistic perspective. MIT Press.
- Russell, S. and Norvig, P. (1995).
  Artificial Intelligence, A modern approach. Prentice-Hall.

Handouts : On my website on before each class

Revision questions : Online on moodle

Course schedule



SYLLABUS

CIV6540E – Prob. Machine Learning for Civil Eng.
Winter 2024 | CGM Department – Polytechnique Montréal

Credits	3cr (3 - 0 - 6)
Professor	James-A. Goulet (Office B-431.4.6)
Office hours	To be announced on Moodle

1 Language

This class will be taught in English. Nevertheless, you can use either French or English when asking questions as well as when answering homeworks and exams.

2 Objectives

Learn how to

- Estimate epistemic uncertainties in models from a set of empirical observations
- Build probabilistic regression and classification models from empirical observations
- Build probabilistic models for time series of empirical data
- Estimate model parameters using sampling and optimization methods
- Propagate uncertainties through deterministic models
- Make rational decisions in uncertain contexts
- Use machine learning algorithms and apply them to civil engineering problems (structures, mining, transport and environment)

3 Classes

Classes will take place in person but you can also access the videos on YouTube. Note that you can avoid having advertisements by installing a plug-in such as Adblock or Adblock Plus. I encourage you to read the references indicated in section 4 before each class.

(Dernière mise à jour : 2024/05/24, 10:00:46) 1/3

The schedule will be adapted depending on the progression...

Questions

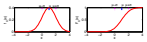
?

moodle **Forum**

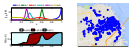
Breaks

(10 min) h+20

Subject organization

Background
- 1 Revision probability & linear algebra 
- 2 Probability distributions 

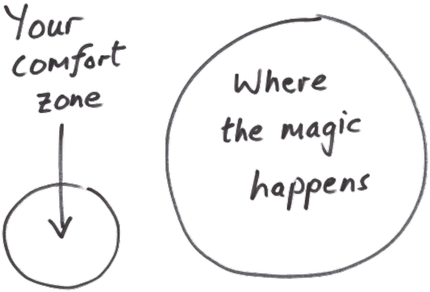
Machine Learning Basics
- 0 Introduction
- 3 Bayesian Estimation $p(A|B) = \frac{p(B|A)p(A)}{p(B)}$
- 4 MCMC sampling & Newton 

Supervised learning
- 5 Regression 
- 6 Classification 
- 7 LSTM networks for time series 

Unsupervised learning
- 7 State-space model for time-series 

Decision Making & RL
- 8 Decision Theory 
- 9 AI & Sequential decision problems

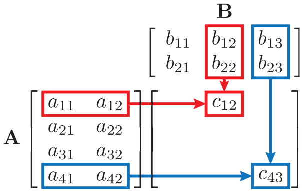
Subject organization



[intrigueme.ca]

Module 1 – Revision

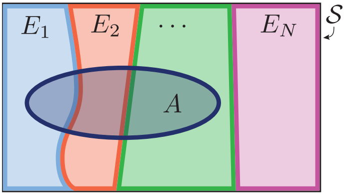
M1a – Linear Algebra [ ]



$$c_{12} = a_{11}b_{12} + a_{12}b_{22}$$

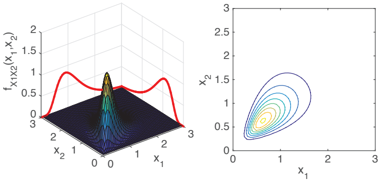
$$c_{43} = a_{41}b_{13} + a_{42}b_{23}$$

M1b – Probability theory [ ]



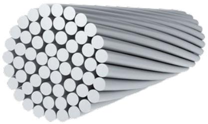
Module 2 – Probability distributions [ ]

A **probability distribution** describes the **probability density function (PDF)** of a physical phenomenon



Example: Given a cable made of 50 steel wires (ductile failure) each having a resistance $X_i \sim \mathcal{N}(x_i; 10, 3^2)$ kN.

What is $X_{\text{cable}} = \sum_{i=1}^{50} X_i$?



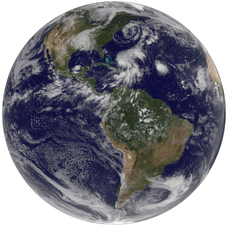
[steelwirerope.com, Der Kiureghian (2005)]

Module 3 – Bayes [ ]

Given a deadly disease so rare that **only one human on Earth has it**.

We have a screening test so that

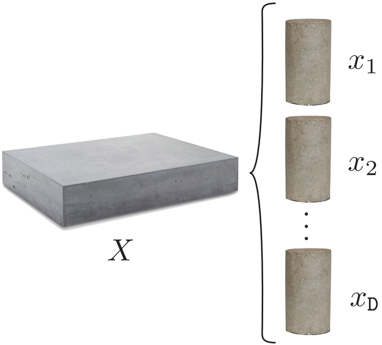
$$\text{test}+ \rightarrow \begin{cases} \Pr(\text{test} + |\text{disease}) = 0.999 \\ \Pr(\text{test} + |\neg\text{disease}) = 0.001 \end{cases}$$



[NASA]

If you test positive, should you be worried?

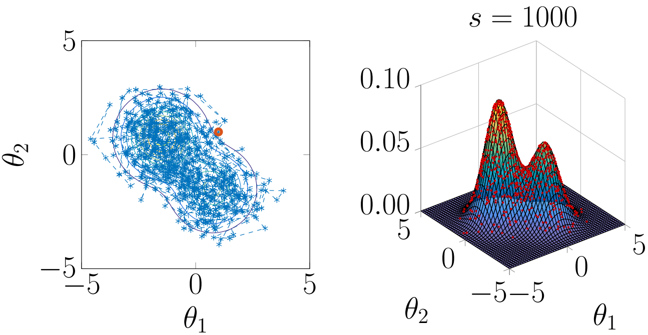
Module 3 – Bayes [ ]



Module 3 – Bayes [ ]

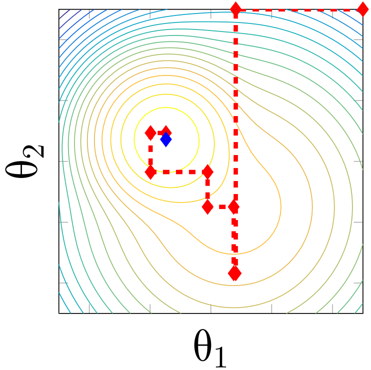
Module 4 – MCMC sampling & Newton [ ]

How do we sample form a PDF?

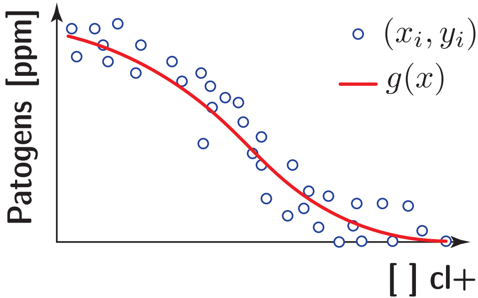


Module 4 – MCMC sampling & Newton [ ]

How do we find the maximum of a PDF?



Module 5 – Regression [ ]



Data

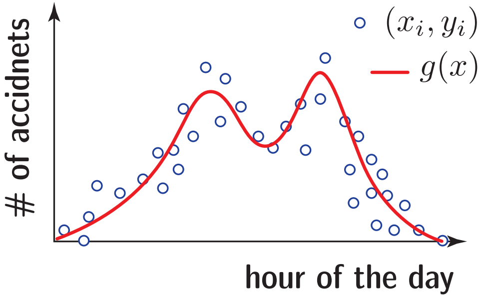
$\mathcal{D} = \{(x_i, y_i), \forall i = 1 : \mathtt{D}\}$

$x_i \in \mathbb{R}$: Covariate / Attribute / Regressor

$y_i \in \mathbb{R}$: Observation

Regression methods: mathematical models for $g(x)$

Module 5 – Regression [ ]



Data

$\mathcal{D} = \{(x_i, y_i), \forall i = 1 : \mathtt{D}\}$

$x_i \in \mathbb{R}$: Covariate / Attribute / Regressor

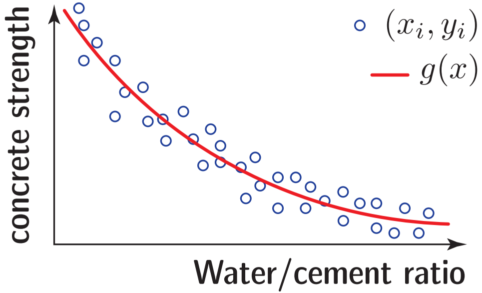
$y_i \in \mathbb{R}$: Observation

Model

$g(x) \equiv \text{fct}(x)$

Regression methods: mathematical models for $g(x)$

Module 5 – Regression [ ]



Data

$\mathcal{D} = \{(x_i, y_i), \forall i = 1 : \mathtt{D}\}$

$x_i \in \mathbb{R}$: { Covariate, Attribute, Regressor }

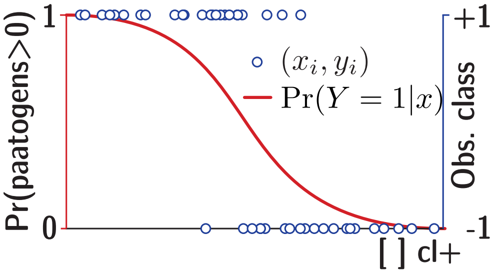
$y_i \in \mathbb{R}$: Observation

Model

$g(x) \equiv \text{fct}(x)$

Regression methods: mathematical models for $g(x)$

Module 6 – Classification [ ]



Data

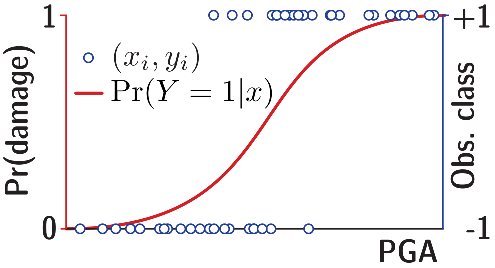
$\mathcal{D} = \{(x_i, y_i), \forall i = 1 : \mathtt{D}\}$

$x_i \in \mathbb{R}$: Covariate / Attribute / Regressor

$y_i \in \{-1, 1\}$: Observation

Classification methods: mathematical models for $\Pr(Y|x)$

Module 6 – Classification [ ]



Data

$\mathcal{D} = \{(x_i, y_i), \forall i = 1 : \mathtt{D}\}$

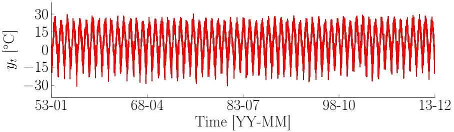
$x_i \in \mathbb{R} : \begin{cases} \text{Covariate} \\ \text{Attribute} \\ \text{Regressor} \end{cases}$

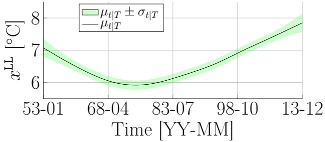
$y_i \in \{-1, 1\}$: Observation

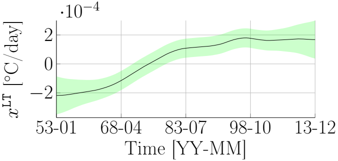
Classification methods: mathematical models for $\Pr(Y|x)$

Module 7 – Time-series [ ]

How do we interpret data when it is **time-dependent**?





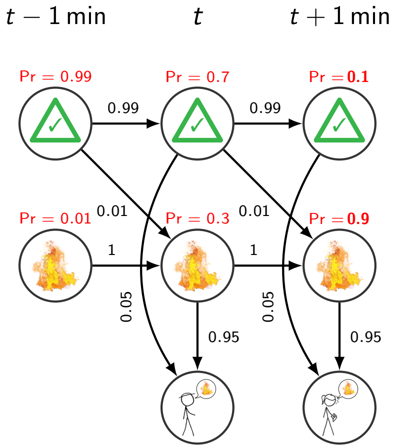


What is the annual rate of change for the average temperature?

Δ in average temperature in Montreal: $+0.06^{\circ}C/$**year**

M8 – Decision Theory

Module 8 – Decision Theory [ ]



Module 9 – AI & Sequential Decision Making []

$\mathcal{S}$ = {  }

$\mathcal{A}$ = {  }

s_t = {  }

$R(s_t)$ = {fct()}

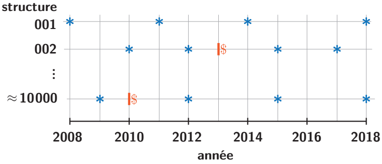
$p(s_{t+1}|s_t, a)$ = unknown... learnt by playing

Reinforcement learning $\rightarrow$ $\mathbb{Q}(s, a)$: **Long term** utility of taking an **action** a if we are in a **state** s

[https://https://youtu.be/QVyu9oVyh9Q, Google images]

What are we going to do with this in engineering?

Asset management



$$\mathcal{S} = \{\text{Infrastructure network}\}$$

$$\mathcal{A} = \{\text{wait, repair, replace}\}$$

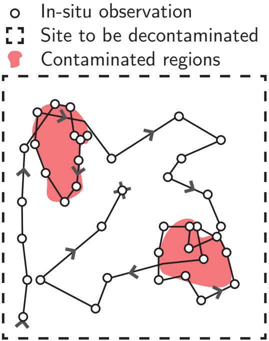
$$s_t = \{\%\text{A},\%\text{B},\%\text{C},\%\text{D}\}$$

$$R(s_t) = \{\text{fct}(s_t)\}$$

$$p(s_{t+1}|s_t, a) = \text{unknown...}$$
learnt from data

Reinforcement learning $\rightarrow$ $\mathbb{Q}(s,a)$: **Long term** utility of taking an **action** *a* if we are in a **state** *s*

Soil contamination characterization



$$\mathcal{S} = \{\text{Contaminated site}\}$$

$$\mathcal{A} = \{\text{Sampling } (\Delta x, \Delta y), \text{ stop}\}$$

$$s_t = \{[\text{Hg}]_{\mathcal{S}}\}$$

$$R(s_t) = \{\text{fct}(s_t)\}$$

$$p(s_{t+1}|s_t, a) = \text{unknown...}$$
learnt from data

Reinforcement learning $\rightarrow$ $\mathbb{Q}(s, a)$: **Long term** utility of taking an **action** a if we are in a **state** s

Emrald ash borer

$$\mathcal{S} = \{\text{Ash population}\}$$

$$\mathcal{A} = \{\text{cut, wait}\}$$

$$s_t = \{[\text{insects}]_{\mathcal{S}}\}$$

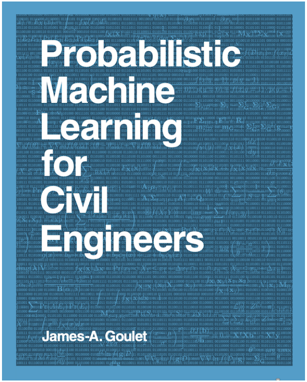
$$R(s_t) = \{\text{fct}(s_t)\}$$

$$p(s_{t+1}|s_t, a) = \text{unknown... learnt from data}$$

Reinforcement learning $\rightarrow$ $\mathbb{Q}(s, a)$: **Long term** utility of taking an **action** a if we are in a **state** s

[Google images]

Book Organization



Goulet (2020)
Probabilistic Machine Learning for Civil Engineers
MIT Press