## **Course Information**

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## Goals

- By the end of this part, you should be able to
  - Describe the goal this course
  - Summarize what you will learn
  - Understand the course evaluation
  - Know the pre-requisite for the course and prepare yourself for the difficult times ahead

### **Couse Goals**

- Define Regression and Classification, and explain the main differences between them
- Describe a few models and algorithms for them.
- Implement and apply these methods.
- Derive the theory behind ML methods taught in the course and generalize them to new problems.
- Continue to work through difficulties or initial failure to find optimal solutions.
- Assess one's own level of skill acquisition, and plan their on-going learning goals.

## (A rough) Outline of the Course

- [Apr 14] Supervised ML-I: Regression, linear regression, cost function, gradient descent, least squares.
- [Apr 21] Evaluation methods: Overfitting, regularization, bias-variance, relation to deep learning
- [Apr 28] Supervised ML-II: Classification, logistic regression, neural networks, (kernel ridge)
- [May 12] Unsupervised ML: K-means, PCA

## Structure of Each Lecture Day

- Four lecture days (with 8 lectures)
  - April 14, 21, 28 and May 12.
- From 2pm to 5:30
- Two lectures each of length 1hr 30 minutes,
   with a 30 minutes break in between.
- We will have multiple breaks in between.
   Sometimes for discussion.

### **Course Evaluation**

- A final exam (40%)
- Submit weekly reports (30%)
  - Read the lecture notes, try to do labs offline and submit a short report (at most 2-3 pages).
  - In the report, explain what you learnt and what you found difficult to understand
  - For labs, try to do as much as possible. It is not mandatory.
- Class participation (30%)
  - Participate in in-class quizes
  - Take notes and, during each break, write down a 1-minute summary of what you learnt.
  - Submit this at the end of each lecture day.

### A bit more about the final exam

- It will contain questions on what you have learned during the lectures and exercise sessions.
- You are allowed to bring one cheat sheet (A4 size paper both sides can be used) and a calculator.
- No collaborations. No cell phones. No laptops etc.

## The Teaching Team

- Toru Asahi (tasahi@waseda.jp)
- Yusuke Maruyama
   (y maruyama@aoni.waseda.jp)

### **Teaching Assistant**

- Wataru Onodera (wonodera0501@moegi.waseda.jp)
- Yuta Okamoto (yutaokamoto48@ruri.waseda.jp)

### Resources

#### Course Webpage

- https://emtiyaz.github.io/teaching/waseda18\_ml/ml.html
- The course material will also be available on the internal website of Waseda University

#### Lecture notes

- During the lectures, I will use lecture notes (with blank space for you to take note if you want).
- These will be available on the course webpage one day before the lecture. We will also provide a printed version before each lecture day.
- An annotated copy (with my annotations from the class) will be available after the lecture.

### **Books**

- Books (not required but recommended)
  - G. James, D. Witten, T. Hastie and R. Tibshirani: An introduction to statistical learning (free download from http://www-bcf.usc. edu/~gareth/ISL/).
  - T. Hastie, R. Tibshirani and J. Friedman: Elements of statistical learning (download from http://statweb.stanford.edu/~tibs/ElemStatLearn/).
  - C. Bishop: Pattern Recognition and Machine Learning.
  - K. Murphy: Machine Learning: A Probabilistic Perspective

## What not to expect!

- You will not learn ALL advanced methods.
- You will not learn ALL the details.
- This course is not about big data or largescale methods.
- This is not a course about numerical optimization, neither is it about statistics. We will use both of these and learn basic techniques only.
- We will not teach the pre-requisite for ML. You have to learn that on your own.
- This course does not teach you all that you need to know to be able to apply machine learning, but this course will get you started for sure

# Prerequisite (must know)

- Matrix calculus.
  - How to take derivative with respect to vectors and matrices.
    - https://atmos.washington.edu/~dennis/MatrixCalculus.pdf
    - https://en.wikipedia.org/wiki/Matrix\_calculus
  - You can learn more about it from wikipedia or Matrix
     Cookbook
    - http://www.imm.dtu.dk/pubdb/views/edoc\_download.php/3274/pdf/imm3274.pdf
- Basic Probability
  - Normal distribution
  - Read Chapter 2 in Bishop's book on Machine Learning

# Prerequisite (must know)

- Matrix algebra.
  - Basics: Vector and matrix multiplication,
     (https://en.wikipedia.org/wiki/Matrix\_multiplication)
  - More advance topics (see Wikipedia): Matrix inversion and determinants, rank, null and range space, eigenvalue decomposition.
  - There is also a handout posted on the course webpage.

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