
Machine Learning and Applications

Course Outline, Activities and Grading

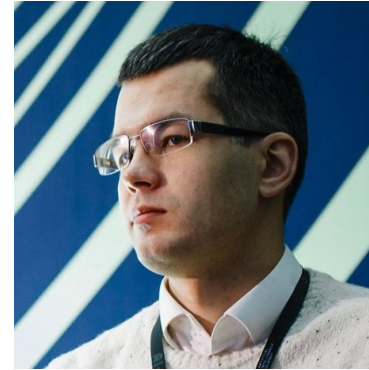
Course Organizers

Course instructor



prof. Evgeny Burnaev

Co-instructor



prof. Alexey Zaytsev

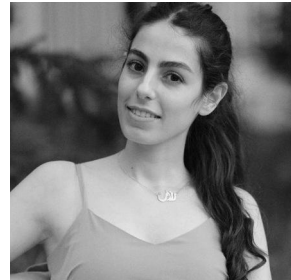
Teaching Assistants:



Artem
Gorbarenko



Daniil
Vyazhev



Razan Dibo



Damir
Akhmetov



Alexandra
.Bazarova

Course Topics

Part 1 (8 lectures & seminars):

- General Introduction (1)
- Regression, Kernel Trick (1)
- Linear Classification (1)
- Non-linear Classification (1)
- Adaboost (1)
- Gradient boosting (1)
- Gaussian process - KNN + kernel trick (1)
- Model and Feature Selection (1)

Part 2 (7 lectures & seminars):

- Unsupervised learning (1)
- Anomaly Detection (1)
- Dimensionality Reduction (1)
- Neural Networks (2)
- Transformers (1)
- Uncertainty(1)

Course Textbooks

Main

1. Hastie, T., and Tibshirani, R., and Friedman, J. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. 12 print, Springer, 2009
2. Tibshirani, R. and Hastie, T., *An Introduction to Statistical Learning*, Springer 2013
3. Bishop, C.M. *Pattern Recognition and Machine Learning*. Springer, 2007
4. Barber, D. *Bayesian Reasoning and Machine Learning*. Cambridge University Press, 2012

Additional

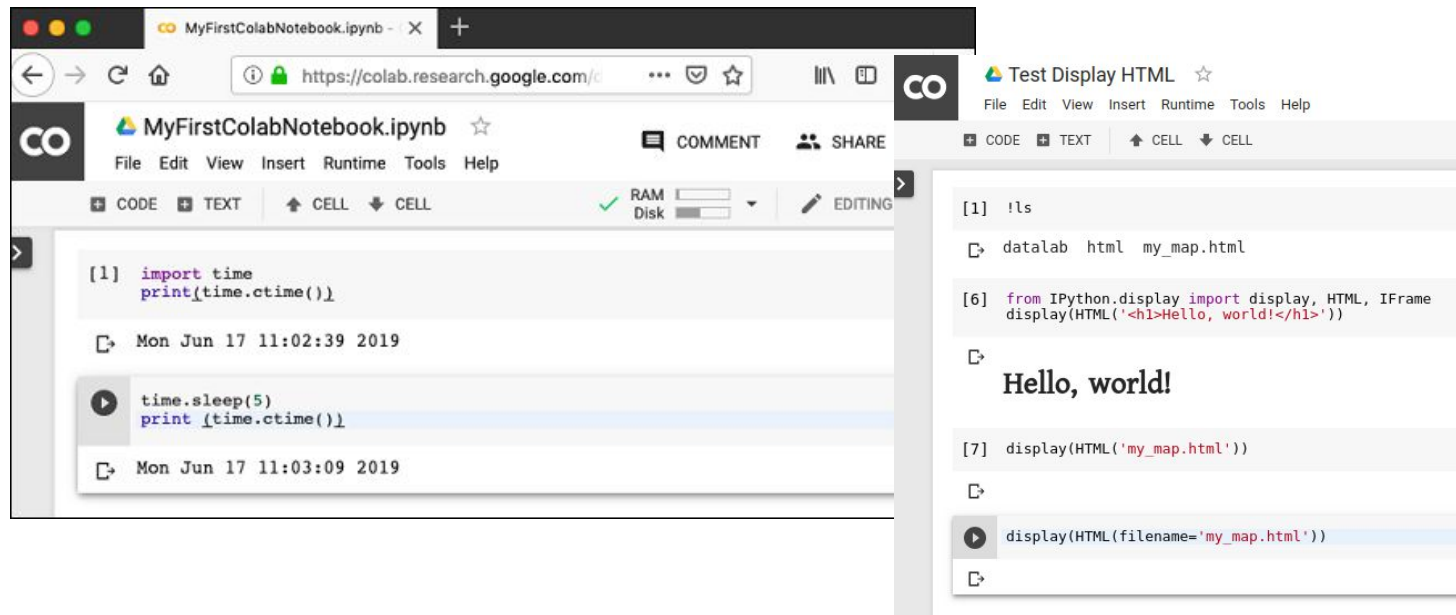
1. Rasmussen, C., and Williams, C. *Gaussian Processes for Machine Learning*. The MIT Press, 2006.
2. Mohri, M., and Rostamizadeh, A., and Talwalkar, A. *Foundations of Machine Learning*. MIT, 2012
3. Schapire, R.E., Freund, Y. *Boosting*. MIT, 2012
4. Clarke, B., and Fokoue, E., and Zhang, H.H. *Principles and Theory for Data Mining and Machine Learning*. Springer, 2009

Course Prerequisites

- Adequate understanding of **Calculus** as well as
 - **Probability Theory** and **Statistics**
 - **Linear Algebra** (applied and theoretical)
 - **Optimization Methods**
- Adequate **python programming skills**
 - basic familiarity with **numpy** and **scipy**
- Basic knowledge of **algorithms** and **complexity**

Course Software Requirements

- **Obligatory set up** [seminars + homeworks]
 - Google **colab** (colab.research.google.com)

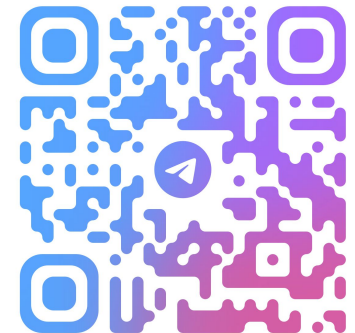


Quick start guide:

https://www.tutorialspoint.com/google_colab/your_first_colab_notebook.htm

Course Assistance and Consultation

- Should you need ...
 - **consultation** on your projects
 - **advice** on solving tough problems in the homework
- ... **we encourage you to ask** the instructor or the assistants
 - online after the end of a seminar or a lecture
 - through course group chat in Telegram:
 - through discussions in **Canvas**



communication through private messages (in *telegram, vk, etc.*) is **not welcome** unless agreed upon by both parties

Course Final Score and Grade

- The final score is computed based on activity scores thus

$$\text{Total} = \mathbf{S_hw} \times 0.25 + \mathbf{midterm} \times 0.2 + \mathbf{final\ exam} \times 0.25 + \mathbf{project} \times 0.3$$

- S_hw** is the **sum** of %score for each of the 3 homework assignments
- Each assignment is followed by a **quiz**. The quiz **does not count** toward the final grade of the course; instead, **it will be used to determine your score for the corresponding assignment**. The quiz content to validate originality and prevent plagiarism.

Final Grade	Total Score
A “Excellent”	86% and above
B “Good”	< 86% to 76%
C “Satisfactory”	< 76% to 66%
D “Poor”	< 66% to 56%
E “Very poor”	< 56% to 46%
F “Unacceptable”	< 46%

Activity	Total weight
Home assignments (3)	25%
Midterm exam	20%
Final exam	25%
Final project	30%
Total	100%

Quizzes

- Quizzes are only **available after submitting** the corresponding homework.
- Quizzes will take place during the first **10 minutes** of the first session after the assignment deadline. Your attendance is **MANDATORY**.
- Students who miss a quiz must provide a valid document for their absence to schedule a makeup quiz on an agreed date.
- Scoring Intervals of the quizzes:
 - ❑ 9-10/10: 100% of assignment grade
 - ❑ 8/10: 90%
 - ❑ 7/10 : 80%
 - ❑ 6/10: 70%
 - ❑ 5/10: 60%
 - ❑ 3-4/10: 50%
 - ❑ 1-2/10:30%
 - ❑ 0/10: 0% of assignment grade

Course Activity

- **Out-of-class preparation** is essential for success:
 - Complete homework assignments thoroughly
 - Study lecture materials and reflect on key concepts
 - Ask questions whenever unclear
- **Substantial workload:**
 - 3 assignments, 1 earlier report, 2 exam, 1 team project (final report + presentation)

Course Activity

- **Zero-Tolerance Policy on Plagiarism and Academic Dishonesty**

All assignments and exams are individual work. Any detected plagiarism or dishonesty will result in immediate course exclusion (F grade). No exceptions or excuses will be accepted.

Plagiarism includes:

- ❑ Copying solutions from current or past course participants
- ❑ Blind use of LLMs/AI tools without proper understanding
- ❑ Direct copying from any source (websites, books, papers, code repositories)
- ❑ Unauthorized collaboration or sharing of solutions
- ❑ Submitting someone else's work as your own

References to external sources will not be accepted as justification for submitted work.

Course Activity: Home Assignments

Three practical coding assignments (week 1 - week 6):

- Will be published in the middle of week 1, week 3, week 4 and will stay open for **~1-2 weeks**
- **Format:** iPython Notebook (Google Colab) with embedded LaTeX markdown explanations.
- Assignments cost **(25% of Final Grade)**

Submission Rules (Strict Compliance Required)

- Hard deadlines – **Plan your work ahead!**
- Only the most recent submission counts toward grading
- No submission = 0 points (**no exceptions or excuses accepted**)

Tip: Start early, test thoroughly, and submit incrementally to avoid last-minute issues.

Course Activity: Final Exam

- **Exams**

- **The midterm** (1 hour) and **final** exam (1.5 hours) are written exams held in Week 4 and Week 7, respectively.
- Exams consist of several theoretical questions, primarily in multiple-choice format. They include pseudocode for key algorithms from the lectures, calculation problems on important metrics, and short explanations of core machine learning methods.
- Midterm costs **20%**, Final **costs 25% of the final grade**.

- **Rules**

- Exams are **individual** assignments
- There will be **no way** to rewrite a missed exam.

Course Activity: the Final Project

- **30% of the final grade**
- **teams** of 3 - 5 students
- may be combined with **currently running parallel or already taken** courses
 - ***must be explicitly disclosed, failing to do so is plagiarism***
- A comprehensive test of
 - teamwork organization and research engineering
 - knowledge of ML, insight, validation and evaluation
 - research presentation and communication skills
- The project timeline:
 - Week 2 -- we release suggested project topics + students proposals
 - Week 3 -- Approval of project proposals (**Hard Deadline**)
 - Week 4 -- Early report ()
 - Weeks 7-8 -- Project Consultations
 - Week 8 -- Reviews of Projects
 - Week 8 – Presentation, Repo and Report Submission

The Final Project: Topics

- Final Project types
 - **Applied:** pick an interesting application and figure out how to apply machine learning algorithms to solve it
 - **Algorithmic:** propose a new learning algorithm, or a variant of some existing one to solve a general problem or group thereof
 - **Replication study:** pick a fresh preprint or an accepted conference paper, replicate its results and discuss the outcomes

The Final Project: Format, Structure and Grading

- Earlier report in **PDF report**
 - ICML 2020 template has to be used for the report
 - Early report of the project report with introduction and related work. It costs 5% out of 30% of the final grade.
- Project in a **github repo + PDF report**
 - Students must submit **a concise project report of 4-6 pages** and provide a GitHub repository with fully reproducible code **(15%)**.
- Project **in-class presentation**
 - 5-7 mins per group in-class presentation on week 8
 - Presentation costs 10% out of 30% of the final grade.e

The Final Project: Format, Structure and Grading

Concise report with **4-6 pages** (excl. appendices)

- **Introduction**, motivation and problem statement
- **Related work** and brief literature overview
- **Dataset Description**
- **ML Methods** and algorithms, proposed algorithm modifications, etc.
- **Experiments / Discussion**: details about (hyper) parameters and how you picked them, cross-validation metrics and details, discussion of failures and successes, equations, results, visualizations, tables, etc.
- **Conclusion** and directions for further research
- **References**, acknowledgements and **contributions of each team member**

The Final Project: Evaluation

- structure and clarity of the project repository
 - **reproducible** and well defined **ML pipeline**: *data acquisition, processing, modelling, validation, and report generation*
- the quality and relevance of the PDF report
 - **relevance and novelty**: *toy/real problem or common/unexplored method*
 - **technical quality**: *insightful choice of clever reasonable methods, cross-validation and general assessment of the tools/methods used*
 - literacy, quality of figures/tables and general narrative **structure**
- the project presentation (pdf + in-class presentation)
 - science **communication** skills, presentation **quality and clarity**
 - **relevant** content and summary, **knowledge** demonstrated by the team

Reminder: Student Academic Integrity

Disciplinary penalties are imposed for

- **cheating, plagiarism**, fabrication or falsification of data or results
- **copying**, rewriting, paraphrasing, or summarizing of text, discoveries, or insights without **acknowledging and / or citing the source**;
- **allowing other students to copy** one's own work, **using another student's** solutions or code

Penalties include, but are not limited to

- **getting no grade** for the project, assignment, or exam
- **redoing** an assignment or test **for a significantly reduced grade**

If you have any question, please, refer to

"Student Academic Integrity Regulations". Department of Education, Skoltech. Moscow, 2014

end of this presentation

