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# Machine Learning and Applications

Course Outline, Activities and Grading

# Course Organizers

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## Course instructor



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## Co-instructor



prof. Alexey Zaytsev

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# Course Topics

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## Part 1 (9 lectures & seminars):

- General Introduction (1)
- Regression, Kernel Trick (1)
- Classification (1)
- Support Vector Machines (1)
- Tree-based Methods (1)
- Advanced Classification (1)
- Model and Feature Selection (1)
- Bagging & Boosting (2)

## Part 2 (7 lectures & seminars):

- Neural Networks (2)
- Bayesian ML (1)
- Gaussian Processes (1)
- Dimensionality Reduction (1)
- Anomaly Detection (1)
- Clustering (1)

# Course Textbooks

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## 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

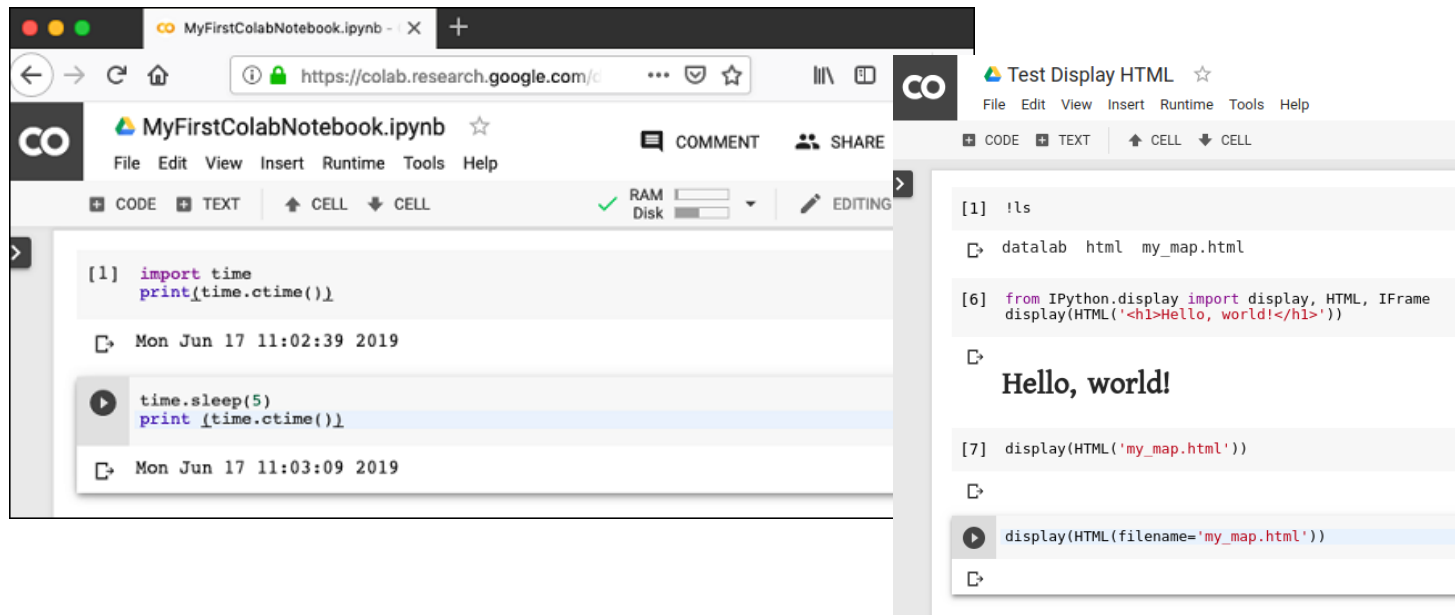
# Course Prerequisites

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- 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](https://colab.research.google.com))



**Quick start guide:**

[https://www.tutorialspoint.com/google\\_colab/your\\_first\\_colab\\_notebook.htm](https://www.tutorialspoint.com/google_colab/your_first_colab_notebook.htm)

# Course Assistance and Consultation

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- 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**: [t.me/ml2021skoltech](https://t.me/ml2021skoltech)
  - 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

$$\text{Total} = (\mathbf{S\_hw} \times 0.35) + \mathbf{S\_quiz} \times 0.3 + \mathbf{S\_proj} \times 0.27 + \mathbf{S\_rev} \times 0.08$$

- **S\_hw** is the **sum** of %score for each of the 2 homework assignments
- **S\_quiz** is the **sum** of %score for each of the 15+1 quizzes
- **S\_proj** -- the %score of the final project
- **S\_rev** is the **sum** of %score of 2 peer-reviews of projects

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

Activity	Total weight
Home assignments (2)	35%
Quizzes (15+1)	30+2%
Final Projects	27 %
Projects Reviews (2)	8%
Total	100+2%



# Course Activity

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- **Out-of-class self study** is very important
  - do homeworks, study the material and reflect on it
  - don't be afraid to ask questions
- **Workload is substantial**
  - 2 assignments, 16 quizzes, 1 project, 2 reviews
- **Zero-tolerance** policy on plagiarism and dishonesty
  - The assignments, quizzes, reviews are individual. **Any detected plagiarism in will result in an immediate exclusion of the student from the course (with an F grade). There will be no excuses accepted.** Plagiarism includes copying solutions from your peers of this year, participants of previous year classes, explicit copying of etc. Also, references to external sources as solutions (book chapters, papers, websites, etc.) will not be considered and accepted.

# Course Activity: Home Assignments

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**Two** individual assignments (week 1 - week 7):

- each assignment has practical (coding) tasks
- published in the middle of odd week and stays open for **~3 weeks**
- ipython notebook (colab) + Latex markdowns (within)

## Rules

- **hard deadline** assignments (**Plan your work ahead!!!**)
- only **the most recent submission** is graded
  - **no submission** means **zero grade** (**no excuses!**)

# Course Activity: Quizzes

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- **Quizzes**

- 10-15 mins at the beginning of each lecture **N+1** (in Canvas)
- 5 multiple choice questions based on the topic of the previous lecture **N**
- 16 lectures -> 16 quizzes
- each quiz costs 2% of the final grade ( $16 \times 2 = 32\%$  in total)

- **Rules**

- Quizzes are **individual** assignments
- There will be **no way** to rewrite a missed quiz

# Course Activity: the Final Project

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- **27% 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 3 -- we release suggested project topics
  - Week 4 -- Submission of project proposals (**Hard Deadline**)
  - Week 5 -- Feedback and approval of the projects
  - Weeks 6-7 -- Project Consultations
  - Week 7 -- Presentation, Video and Report Submission
  - Week 8 -- Peer Reviews of Projects

# The Final Project: Topics

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- 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 and Structure

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- Project in a **github repo** + **PDF report**
  - ICML 2020 [template](#) has to be used for the report
- Project **presentation** + **video**
- 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: Peer reviews and Grading

- **Peer reviews**

- **2 reviews** per student for other teams' projects
- Each review costs 4% of the final grade ( $2 \times 4 = 8\%$  in total)
- **Grade for reviews** is based on their quality and usefulness and assigned by responsible meta-reviewer (TA)

- **Meta-reviews and final projects grades**

- final grade for a project is decided by a responsible meta-reviewer
- final grades MIGHT NOT take into the account the grades of students' peer-reviews

# The Final Project: Evaluation

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- 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 + video)
  - science **communication** skills, presentation **quality and clarity**
  - **relevant** content and summary, **knowledge** demonstrated by the team



# Reminder: Student Academic Integrity

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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

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end of this presentation

