Government of Russian Federation

Federal State Autonomous Educational Institution of High Professional Education

“National Research University Higher School of Economics”

Syllabus for the course
“Advanced topics in Machine Learning”

for postgraduate program in 02.06.01 Computer and Information Science / 05.13.11 “Mathematical Theory and Software for Computing Machinery, Systems, and Networks”, 05.13.17 “Theoretical Foundations of Computer Science”

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1. Scope of Use

This program establishes the minimal requirements to postgraduate students' knowledge and skills for 02.06.01 Computer and Information Science / 05.13.11 "Mathematical Theory and Software for Computing Machinery, Systems, and Networks", 05.13.17 "Theoretical Foundations of Computer Science" and determines the content of the course and educational techniques used in teaching the course.

The present syllabus is aimed at faculty teaching the course and postgraduate students studying 02.06.01 Computer and Information Science / 05.13.11 "Mathematical Theory and Software for Computing Machinery, Systems, and Networks", 05.13.17 "Theoretical Foundations of Computer Science".

This syllabus meets the standards required by:

- Educational standards of National Research University Higher School of Economics;
- Postgraduate educational program for 02.06.01 Computer and Information Science.
- University curriculum of the postgraduate program for 02.06.01 Computer and Information Science / 05.13.11 "Mathematical Theory and Software for Computing Machinery, Systems, and Networks", 05.13.17 "Theoretical Foundations of Computer Science", approved in 2015.

2. Learning Objectives

The learning objective of the course "Advanced topics on Machine Learning" is to provide PhD students with essential theoretical and practical knowledge in modern statistical learning techniques, such as:

•Basic principles, definitions and techniques in Machine Learning
• Regularized learning.
• Classification, regression, collaborative filtering,
• Limitation of Machine Learning.
• Kernel methods and Deep Learning techniques,
• Unsupervised learning, representation learning,
• Recent developments and projects in Machine Learning

3. Main Competencies Developed after Completing the Study of This Discipline

After completing the study of the discipline the PhD student should have:
• Knowledge about regularized learning techniques.
• Knowledge about modern methods such as kernel methods and deep learning techniques.
• Knowledge about ongoing developments in Machine Learning
• Hands-on experience with large scale machine learning problems.
• Knowledge about how to design and develop machine learning programs using a programming language such as R or Python.
• Think critically with real data.

After completing the study of the discipline the PhD student should have developed the following competencies:

Competence	Code	Descriptors (indicators of achievement of the result)	Educative forms and methods aimed at generation and development of the competence
The ability to carry out research in the field of pro-	ОПК-1	PhD students obtain necessary knowledge in ma-	Assignments, additional material/reading provided

fessional activity using current research methods and information and communication technologies.		chine learning sufficient to implement and understand new methods.	
The ability to choose and apply appropriate research methods.	УК-3	The PhD student is able to choose an appropriate model for real-life problems and to calibrate the hyperparameters.	Examples covered during the lectures and tutorials. Assignments.
The ability to critically analyze and evaluate research results including those obtained in multidisciplinary areas.	УК-1	The PhD student is able to carry out comparative testing of competing models or methods.	Examples covered during the lectures and tutorials. Assignments.
The ability to do research in transformation of information into data and knowledge, models of data and knowledge representation, methods for knowledge processing, machine learning and knowledge discovery methods, principles of building and operating software for automation of these processes.	ПК-4	The PhD student is able to develop and analyze machine learning models, implement them in a programming language in large scale, and select the best model using validation techniques.	Lectures, tutorials, and assignments.

4. Place of the Discipline in the Postgraduate Program Structure

This is an elective course for 05.13.11 "Mathematical Theory and Software for Computing Machinery, Systems, and Networks", 05.13.17 "Theoretical Foundations of Computer Science".

Postgraduate students are expected to be already familiar with some statistical learning techniques, and have skills in analysis, linear algebra, optimization, computational complexity, and probability theory.

The following knowledge and competences are needed to study the discipline:

- A good command of the English language, both oral and written.
- A sound knowledge of probability theory, complexity theory, optimization, and linear algebra

5. Schedule for two semesters (4 modules)

№	Topic	Total hours	Contact hours			Self-study
			Lectures	Seminars	Practice lessons	
1.	Principles of machine learning	9	2	1		6
2.	Regularized learning	63	6	3		54
3.	Validation and error metrics	9	2	1		6

4.	Limitations machine learning	27	6	3		18
5.	Deep learning techniques	27	6	3		18
6.	Kernel methods	27	6	3		18
7.	Classic learning methods	9	2	1		6
8.	Ensemble learning	9	2	1		6
9.	Bayesian Learning	24	8	4		12
10.	Unsupervised and representation learning	63	14	7		42
11.	Clustering	18	4	2		12
12.	Speech recognition	41	4	2		35
13.	Robotics, and self-driving machines	9	2	1		6
14.	Recommender systems	9	2	1		6
15	Online Advertisement	9	2	1		6
16.	Machine Learning in Bioinformatics	9	2	1		6
17.	Machine learning in Economics	9	2	1		6
18.	Machine Learning competitions	9	2	1		6
	Total	380	74	37		269

One lecture pair (2x40 min) and one seminar (1x 40) will be held each week, evenly distributed over the Ph.D. academic year.

6. Requirements and Grading

Mid-Term Exam	2	Mid-semester test.
Homework	2	Solving 2 homework tasks. Fist homework involves implementing an optical digit recognition system. The second involves implementing an automatic speech recognition system.
Exam	1	Written exam. Preparation time – 180 min.

7. Assessment

The assessment consists of two homework and two mid-semester exams. The homework problems are based on each lecture topics and are handed out to the PhD students throughout the semester.

Final assessments are the final exam. Postgraduate students have to demonstrate knowledge of the material covered during the entire course.

8. The grade formula

The exam is worth 60% of the final mark.

Final course mark *is obtained from the following formula*: Final=0.2*(Homework)+ 0.2*(Mid-term exam)+0.6*(Exam).

The grades are rounded in favour of examiner/lecturer with respect to regularity of class and home works. All grades having a fractional part greater than 0.5 are rounded up.

Table of Grade Accordance

Ten-point Grading Scale	Five-point Grading Scale	
1 - very bad 2 – bad 3 – no pass	Unsatisfactory - 2	**FAIL**
4 – pass 5 – highly pass	Satisfactory – 3	**PASS**
6 – good 7 – very good	Good – 4	
8 – almost excellent 9 – excellent 10 – perfect	Excellent – 5	

9. Course description.

Topic 1. Principles of machine learning

Basic definitions, principles and types of machine learning.

Topic 2. Regularized learning

Regularized learning for regression, logistic classification, artificial neural networks, support vector machines and collaborative filtering

Topic 3. Validation and error metrics

Validation techniques, hyper parameter tuning, type of errors, precision, recall, F-measure, ROC

Topic 4. Limitations machine learning

Bias vs. variance trade off, generalization vs. capacity, Minimum description length principle, VC dimension, other bounds, course of dimensionality, no free lunch theorem.

Topic 5. Deep learning techniques

Shallow networks, Multilayer Neural networks, back-propagation, deep learning, convolution layers, activation units, auto-encoders, Boltzmann machines, pre-training, universal approximators.

Topic 6. Kernel methods

Construction of kernels, string-, graph-, convolution, fisher kernels, methods with kernels.

Topic 7. Classic learning methods

Decision trees, instance learning, nearest neighbor

Topic 8. Ensemble learning
Random forests, averaging, boosting, bagging,

Topic 9. Bayesian Learning
Belief networks, Naïve Bayes, Hidden Markov Models

Topic 10. Unsupervised and representation learning
Manifold learning, Spectral methods, dimensionality reduction, visualization, MDS, LLE, SOM, tSE

Topic 11. Clustering
Spectral clustering, k-means, hierarchical clustering,

Topic 12. Speech recognition
Introduction to Speech Recognition Systems,

Topic 13. Robotics, and self-driving machines
Introduction to self-driving cars, helicopters,

Topic 14. Recommender systems
Introduction to recommender systems

Topic 15. Online advertisements
Introduction to self-driving cars, helicopters,

Topic 16. Machine learning in Bioinformatics
Selected topics

Topic 17. Machine learning in Economics
Selected topics

Topic 18. Machine learning competitions,
Kaggle, Netflix price,

10. Educational technologies

The following educational technologies are used in the study process:
- discussion and analysis of the results during the tutorials;
- regular assignments to test the progress of the PhD student;
- consultation time on Monday afternoons.

11. Final exam questions

The final exam will consist of a selection of problems equally weighted. No material is allowed for the exam. Each question will focus on a particular topic presented during the lectures.

The questions consist in exercises on any topic seen during the lectures. To be prepared for the final exam, PhD students must be able to answer questions from the topics covered during the lecture.

12. Reading and Materials

Literature:

1. John Shawe-Taylor and Nello Christianini. Kernel methods for Pattern Analysis (2004). Cambridge
2. Alpaydin, E. Introduction to Machine Learning. Cambridge, MA: MIT Press, 2014

Literature for self-study:

1. C. Bishop. Neural Networks for Pattern Recognition (1995). Springer.
2. Yoshua Bengio. Learning Deep Architectures for AI (2009).
3. Articles to read, distributed in class.

13. Equipment.

The course requires a laptop and a projector.