COURSE SPECIFICATION FORM,
approved by the Academic Council 17.06.2015 (#39)

SECTION A: DEFINITIVE

Items in this section may be reviewed and developed within Schools as part of the Annual Program Monitoring Process and in line with the Guidelines to Modifications to Programs and Courses.

1.	**General course information**		
1.1	School: SSH	1.6	Credits (ECTS): 6
1.2	Course Title: Statistical Learning	1.7	Course Code: MATH 540
1.3	Pre-requisites:	1.8	Effective from: *(year)*
1.4	Co-requisites:		
1.5	Programs: *(in which the course is offered)* ☒ Core ☐ Elective		

2. Course description (max.150 words)

The course covers theoretical foundations and applications of machine learning models. Topics include supervised methods for regression and classification (linear models, trees, neural networks, ensemble methods, instance-based methods), Bayesian parametric learning, density estimation and clustering, sequential models. Programming projects covering a variety of real-world applications are assigned.

Remark: For students who took this course previously as special topics in math during their undergraduate studies at NU, there will be a separate set of assignments and they will undergo a separate evaluation. For such students the focus will be on statistical learning theory including but not limited to probably approximately correct (PAC) learnability, learning via uniform convergence, bias-complexity tradeoff, the VC dimension, Rademacher complexities, covering numbers, proof of the fundamental theorem of learning theory.

3.	**Summative assessment methods** (tick if applicable)**:**				
3.1	Examination	☒	3.5	Presentation	☐
3.2	Term paper	☐	3.6	Peer-assessment	☐
3.3	Project	☒	3.7	Essay	☐
3.4	Laboratory Practicum	☐	3.8	Other *(specify)*	Homework

4. Course aims

Students will:
1) Use real-world data to draw conclusions about the real-world phenomena using unsupervised and supervised learning methods,
2) Build machine learning models and validate their quality,
3) Use modern programming languages for building and training machine learning models.

5. Course learning outcomes (CLOs)

5.1 By the end of the course the student will be expected to be able to:
1) Derive mathematical expressions for a few simple algorithms like ordinary least squares regression, ridge regression, k-means and PCA
2) Implement clustering, regression and classification algorithms using modern programming languages.
3) Apply gradient descent to solve simple convex optimization problems, and stochastic gradient descent to solve nonconvex optimization problems.
4) Assess whether the solution to a real-world machine learning problem might involve one or more of clustering, regression or classification.

	5) Prepare reports and presentations with reproducible code.
5.2	

CLO ref #	Program Learning Outcome(s) to which CLO is linked	Graduate Attribute(s) to which CLO is linked
1	1, 2, 3	1, 2, 3
2	4	1, 2, 4
3	1b, 1c, 3	1, 2, 3
4	3	1, 2, 3
5	6	5

SECTION B: NON-DEFINITIVE

Course Syllabus Template

Details of teaching, learning and assessment

Items in this Section should be considered annually (or each time a course is delivered) and amended as appropriate, in conjunction with the Annual Program Monitoring Process. The template can be adapted by Schools to meet the necessary accreditation requirements.

6.	**Detailed course information**		
6.1	Academic Year: 2021-2022	6.3	Schedule (class days, time):
6.2	Semester: Fall	6.4	Location (building, room):

7. Course leader and teaching staff

Position	Name	Office #	Contact information	Office hours/or by appointment
Course Leader				
Course Instructor(s)	Zhenisbek Assylbekov		Zhassylbekov@ nu.edu.kz	
Teaching Assistant(s)				

8. Course Outline

Session	**Date** tentative	**Topics and Assignments**	**Course Aims** (ref. # only, see item 4)	**CLOs**
1	Week 1	Introduction. Statistical Learning Framework. Empirical Risk Minimzation. PAC Learning.	1, 2, 3	1-4
2	Week 2	Ordinary least squares. Ridge regression.	1, 2, 3	1-4
3	Week 3	Features. Hyperparameters and validation. MLE and MAP for regression.	1, 2, 3	1-4
4	Week 4	Bias-variance tradeoff. Kernel methods.	1, 2, 3	1-4
5	Week 5	Sparse least squares. LASSO.	1, 2, 3	1-4
6	Week 6	Nonlinear least squares. Optimization, Gradient descent.	1, 2, 3	1-4
7	Week 7	**Midterm-1**	1, 2, 3	1-4
8	Week 8	Neural networks. Training neural networks.	1, 2, 3	1-4
9	Week 9	Classification. Logistic regression.	1, 2, 3	1-4
10	Week 10	Multivariate Gaussians. Gaussian discriminant analysis. Support vector machines.	1, 2, 3	1-4
11	Week 11	Nearest neighbor classification. K-means clustering.	1, 2, 3	1-4
12	Week 12	Mixture of Gaussians. Expectation-Maximization algorithm.	1, 2, 3	1-4
13	Week 13	Decision trees. Random Forests. Boosting.	1, 2, 3	1-4

14	Week 14	**Midterm-2**		5

9.	**Learning and Teaching Methods** (briefly describe the approaches to teaching and learning to be employed in the course)
0	**Attendance/Participation**: During the lectures I will randomly sample students and ask them questions. A student gets 2 points if he/she is present, regardless whether his/her answers are correct or wrong. Absent students receive 0 points.
1	**Homework:** Homework will be assigned on a regular basis. Some problems from HW will require programming. Homework will not be collected; it will serve as preparation for the exams.
2	**Examination**: These are oral examinations. I will allocate ~30 minutes for each student during the midterm week. In the exam, I will ask questions or assign problems or ask you to show the solutions of HW assignments. Expect ~5 topics per exam.
3	**Project**: An individual project will be assigned. Details will be provided later, but it will involve reproducing an existing (baseline) model, attempting to improve it, evaluating against the baseline, and writing a report.

10.	**Summative Assessments**			
#	**Activity**	**Date** (tentative)	**Weighting (%)**	**CLOs**
	Attendance	Weeks 1-14	10	1-4
	Midterm-1	Week 7	30	1-4
	Midterm-2	Week 14	30	1-5
	Project	Exam period	30	1-4

11. Grading

Letter Grade	**Percent range**	**Grade description** (where applicable)
A	[95, 100]	
A-	[90, 94]	
B+	[85, 89]	
B	[80, 84]	
B-	[75, 79]	
C+	[70, 74]	
C	[65, 69]	
C-	[60, 64]	
D+	[55, 59]	
D	[50, 54]	
F	[0, 49]	

12. Learning resources (use a full citation and where the texts/materials can be accessed)

E-resources, including, but not limited to: databases, animations, simulations, professional blogs, websites, other e-reference materials (e.g. video, audio, digests)	
E-textbooks	
Laboratory physical resources	

Special software programs	Python.
Journals (inc. e-journals)	
Text books	There is no textbook for this class. Instead, there is a set of comprehensive lecture notes from Berkeley's CS189 class: http://www.eecs189.org/

13. Course expectations

Students are expected to actively and positively participate in this class, including (but not limited to):

- Attendance: students must report all absences for health reasons to the Department of Student Affairs.
    - It is the student's responsibility to understand material covered when there is an absence.
    - Students are expected to arrive to class on time.
- Learning: Students are expected to learn all the material in the course. Not all information will be presented in class; therefore, students are expected to study outside of class.
    - Students should allocate at least nine hours a week outside of class for study and improvement.
- Language: English is the official language of instruction for this university; therefore, all work is expected to be done neatly and accurately in English.
- Electronic Devices: All pagers, cell phones or other related electronic personal communication devices must be turned off during a class session.
- Calculators: Students will need a calculator during instruction time, when working on homework, and tests. It is your responsibility to have a calculator with you.

14. Academic Integrity Statement

Students are required to abide by the Student Code of Conduct and Disciplinary Procedures (approved by the AC on 05.02.2014), specifically, paragraphs 13-16 (plagiarism and cheating). Cheating will not be tolerated. Working in groups on homework problems is encouraged. Talking or looking at your classmate's paper during a quiz/exam is not allowed under any circumstances. All forms of cheating are grounds for a failing grade in the course for all parties involved.

15. E-Learning

16. Approval and review

Date of Approval:	**Minutes #:**	**Committee:**
Date(s) of Approved Change:	**Minutes #:**	**Committee:**