(*faculty stamp*)

Z1-PU7	WYDANIE N1

COURSE DESCRIPTION

1. Course title: STATISTICS FOR DATA SCIENCE, Bayesian Data Analysis	**2. Course code SFDS_BDA**
3. Validity of course description: 2018/2019	
4. Level of studies: MSc programme	
5. Mode of studies: intramural studies	
6. Field of study: CONTROL, ELECTRONIC AND INFORMATION ENGINEERING (MACRO)	(FACULTY SYMBOL) RAU-2
7. Profile of studies: ACADEMIC	
8. Programme: DATA SCIENCE	
9. Semester: 2	
10. Faculty teaching the course: Faculty of Automatic Control, Electronics and Computer Science	
11. Course instructor: Prof. dr hab. inż. Adam Czornik	
12. Course classification: common courses	
13. Course status: compulsory ~~/elective~~	
14. Language of instruction: English	
15. Pre-requisite qualifications: Algebra and analytic geometry, Calculus and differential equations, Physics, Computer programming, Optimization methods, Numerical methods, Statistics and probability theory, Algorithms and data structures.	
16. Course objectives: The aim of the course is making students familiar with issues related to Bayesian approach to data analysis.	
17. Description of learning outcomes:	

Nr	Learning outcomes description	Method of assessment	Teaching methods	Learning outcomes reference code
1.	Student understands the Bayesian approach to data analysis. Understands the notion of prior and posterior distributions, hyperparameters and their roles.	Exam	Lecture	K2A_W01, K2A_W03
2.	Student understands the notion of conjugate pairs of distributions.	Exam	Lecture	K2A_W01, K2A_W03
3.	Student understands Bayesian approach to regression, classification, clustering and model selection problems.	Exam	Lecture	K2A_W07, K2A_W08
4.	Student is able to use procedures in R and Python environments designed to Bayesian data analyses.	Laboratory tasks	Laboratory	K2A_U01, K2A_U02, K2A_K01

5.	Student is able to perform computations and elaborate software, in the aspect of problems of computing prior and posteriori distributions, conjugate pairs, constructions of Bayesian algorithms for machine learning.	Laboratory tasks	Laboratory	K2A_U07, K2A_U08, K2A_K06
6.	Student is able to pursue analysis of the chosen dataset with the use of of Bayesian algorithms of modeling and data analysis.	Laboratory tasks	Laboratory	K2A_U07, K2A_U08, K2A_K06
7.				
8.				
9.				

18. Teaching modes and hours

Lecture 15 / ~~BA /MA Seminar / Class / Project~~ / Laboratory 15

19. Syllabus description:

Lecture:

1. Introductory issues. Bayesian data analysis versus classical statistics. Overview of the course.
2. Probability axioms. Conditional probability. Bayes rules. Prior and posterior distributions. Bayes factors. Chain rule for conditional probabilities. Examples of applications in engineering.
3. Transformation rules for probability distributions with prior distributions of parameters. Hyperparameters. Non informative priors. Informative priors. Examples of Bayesian parameter estimates versus maximum likelihood estimates.
4. Conjugate priors. Conjugate prior pairs. Beta – binomial, Dirichlet – multinomial, Gamma – Poisson. Conjugate priors for the multivariable normal distribution. Conjugate priors for exponential families. Conjugate priors as eigenfunctions.
5. Bayesian regression models. Linear regression, logistic regression, Poisson regression. Problems of setting priors to regression models parameters.
6. Bayesian classifiers. Naïve Bayes classifier. Bayesian maximum aposteriori rule. Bayesian error rate.
7. Bayesian clustering. Clustering by mixtures of probability distributions. Bayesian estimation of parameters and mixtures ranks. Bayesian k-means clustering.
8. Bayesian model selection, rank estimation and model averaging.

Laboratory:

1. Conjugate prior distributions.
2. Bayesian classification and clustering
3. Bayesian model selection and model averaging

20. Examination: semester 2

21. Primary sources:

A. Gelman, J. Carlin, H. Stern, D. Dunson, A. Vehtari, D. Rubin, (2014), Bayesian Data Analysis, CRC Press

22. Secondary sources:

J.K. Kruschke, (2010), Doing Bayesian Data Analysis, Preprint.

23. Total workload required to achieve learning outcomes

Lp.	Teaching mode :	Contact hours / Student workload hours
1	Lecture	15/30
2	Classes	/
3	Laboratory	15/30
4	Project	/
5	BA/ MA Seminar	/
6	Other	/
	Total number of hours	30/60

24. Total hours: 90

25. Number of ECTS credits: 3

26. Number of ECTS credits allocated for contact hours: 1

27. Number of ECTS credits allocated for in-practice hours (laboratory classes, projects): 2

26. Comments:

Approved:

……………………………
(date, Instructor's signature)

…………………………………………………
(*date , the Director of the Faculty Unit signature)*