Course Syllabus

Title of the course	Business Analytics		
Title of the Academic Program	Sociology and Social Informatics		
Type of the course	Elective		
Prerequisites	Data Analysis in Sociology or Introduction to Programming in R Information Systems Methods of Social Research		
ECTS workload	6		
Total indicative study hours	Directed Study	Self-directed study	Total
	48	180	228
Course Overview	This elective course aims to stimulate students to apply the methods and concepts they learned in courses on data analysis and research methods to solving practical tasks in business and marketing analytics. The seminar part is blended with MOOCs that introduce specific data analysis techniques as tools for solving typical problems in business analytics. The lecture part provides a gentle introduction to several fundamental concepts in business analytics (lifetime value, churn, segmentation, what-if analysis, business processes) and analytical techniques (choice models, complexity reduction), while guiding students through tailored cases relevant for data economy. We will discuss the business context of each case, leverage analytical techniques that solve the tasks at hand, and discuss the effective delivery of results. The course is targeted at undergraduate social science students aiming at careers in business-oriented jobs in marketing, sales and service analytics. This is a rather intense course that requires motivation and genuine interest in business analytics, team work, and a large amount of independent study. To success in the course, participants are expected to be familiar with the linear regression fundamentals and data management techniques in R. Familiarity with machine learning techniques is not required but will be an asset.		
Intended Learning Outcomes (ILO)	After completing this course, students will be able to create simple analytical pipelines for solving typical business analytical tasks and leverage various analytical techniques in R for estimating customer lifetime value, time to reorder, for predicting churn, consumer preferences and customer satisfaction. In addition, students will learn how to choose the right data analysis technique for the task at hand, select features for segmentation, design scenarios describing customers' behavior using what-if analysis, and how to deliver the results to the audience.		
Teaching and Learning Methods	The course includes lectures and seminars with hands-on analysis practice. The lectures will work through cases where business analytical tasks can be solved with research instruments and techniques of linear and choice models, survival analysis, and dimension reduction techniques. Mandatory part of the course involves completing MOOCs on marketing analytics and business processes which will be tightly		

	integrated with the course: we will discuss the MOOC videos and cases along with home readings and build on typical tasks from the MOOC during seminars. In addition, the course involves a substantial project-work component where students first work individually and then organize in teams to produce a complete business analytical report, from task setup to recommendations.

Content and Structure of the Course

№	Topic / Course Chapter	Total	Directed Study		Self-directed Study
			Lectures	Tutorials	
1	Introduction to Data Analysis for Consumer Behavior and Client Analytics. Customer Lifetime Value	24	2	2	20
2	Customer Segmentation and Unit Economics	26	2	4	20
3	Customer Churn. Churn Prevention	26	2	4	20
4	Predicting Customer's Time to Churn	22		2	20
5	What-If Analysis	36	4	2	30
6	Consumer Preferences and Choice Modeling	30	4	6	20
7	Customer Satisfaction	38	4	4	30
8	Introduction to Business Process Analytics	26	4	2	20
Total study hours		228	22	26	180

Indicative Assessment Methods and Strategy	The grade for the course is calculated by the following formula: *Final grade* = 0.15*project 1 + 0.15*project 2 (ind) + 0.20*project 2(team) + 0.25 * MOOC + 0.25 * in-class activity MOOC results (25% of the final grade) "Marketing Analytics in R: Statistical Modeling" (all chapters), "Marketing Analytics in R: Choice Modeling" (all chapters) and "Business Process Analytics in R" (chapter 1) at DataCamp. In-class engagement (25% of the final grade) which includes in-class individual and pair tasks, participation in the discussion of business cases and home reading, and the presentation of extra techniques and materials relevant for the topic. Two case-based projects. Project 1 (15%) is an individual task on reworking the given code and interpreting the results with regard to

	customer lifetime value. Project 2 consists of an individual (15%) and team work (20%) where each student undertakes part of the analytical report and works on a personal task while the team composes and submits an executive report summarizing the findings. Each project task is graded by the correctness of using data analysis techniques, interpretation of results, embeddedness in the business task at hand and the quality of delivery. There is no exam in this course.
Readings / Indicative Learning Resources	<u>Mandatory</u> Blattberg, Robert C., Byung-Do Kim, and Scott A. Neslin. Database Marketing. Vol. 18. International Series in Quantitative Marketing. New York, NY: Springer New York, 2008. URL: https://proxylibrary.hse.ru:2084/book/10.1007/978-0-387-72579-6 Chapman, Christopher N., and Elea McDonnell Feit. R for Marketing Research and Analytics. Use R! Springer International Publishing, 2015. URL: https://proxylibrary.hse.ru:2084/book/10.1007/978-3-319-14436-8 McDonnell Feit, Elea. "Marketing Analytics in R: Choice Modeling." (online course) DataCamp. URL: https://www.datacamp.com/courses/marketing-analytics-in-r-choice-modeling Pflieger, Verena. "Marketing Analytics in R: Statistical Modeling." (online course) DataCamp. URL: https://www.datacamp.com/courses/marketing-analytics-in-r-statistical-modeling Struhl, Steven M. Artificial intelligence marketing and predicting consumer choice: an overview of tools and techniques. London: Kogan Page, 2017. URL: https://proxylibrary.hse.ru:2137/toc.aspx?bookid=128167 <u>Optional</u> Gorenshteyn, Dmitriy. "Cluster Analysis in R" (online course) DataCamp. URL: https://www.datacamp.com/courses/cluster-analysis-in-r Janssenswillen, Gert. "Business Process Analytics in R" (online course) DataCamp. URL: https://www.datacamp.com/courses/business-process-analytics-in-r

Indicative Self- Study Strategies	**Type**	**+/–**	**Hours**

	Reading for seminars / tutorials (lecture materials, mandatory and optional resources)	+	30
	Assignments for seminars / tutorials / labs	+	20
	E-learning / distance learning (MOOC / LMS)	+	40
	Fieldwork	-	-
	Project work	+	90
	Other (please specify)	-	-
	Preparation for the exam	-	-
Academic Support for the Course	Academic support for the course is provided via LMS, where students can find: guidelines and recommendations for doing the course; guidelines and recommendations for self-study; samples of assessment materials. MOOCs are provided by DataCamp For the Classroom < https://www.datacamp.com/groups/education>.		
Facilities, Equipment and Software	R and RStudio for your OS. A room with a projector is required.		
Course Instructors	Ilya Musabirov, MSc, MA (imusabirov@hse.ru, https://www.hse.ru/en/staff/ilya.musabirov) Anna Shirokanova, PhD (a.shirokanova@hse.ru, https://www.hse.ru/en/staff/shirokanova)		

Intended Learning Outcomes (ILO) Delivering

Programme ILO(s)	Course ILO(s)	Teaching and Learning Methods for delivering ILO(s)	Indicative Assessment Methods of Delivered ILO(s)
UC-3 Ability to solve problems in professional practice based on analysis and synthesis	Students solve analytical problems using data analysis techniques suitable for the task; develop policies and scenarios using several methods of analysis	Seminar discussion, in-class individual and group tasks, MOOCs	MOOCs, in-class engagement, project 1, project 2
PC-9 Ability to compose and present research and analytical development projects in accordance with regulatory documents	Students select data features to be used in segmentation procedures; as a team, students develop analytical pipelines covering necessary tasks and combining individual results into a summary report	Case analysis at lectures, seminar discussion	Project 1, project 2
PC-10 Ability to process and analyze data to prepare analytical decisions, expert	Students perform various statistical analyses, use them appropriately, and develop suggestions	Case analysis at lectures, seminar discussion	Project 1, project 2

advice, and recommendations	(recommendations, policies, scenarios) for the task (churn prevention, segmentation, etc.)		
PC-11 Ability to plan and carry out project works in the fields of public opinion research and organization of work of marketing services providers	Students can plan the analytical data cycle, from formulating requests for data collection, to data cleaning and dimension reduction, to data analysis and reporting the recommendations	Case analysis at lectures, seminar discussion	In-class engagement, project 2
PC-12 Ability to participate in analytical and consulting activities	Students work individually and in teams to interpret the results and develop policies and scenarios for the company	Case analysis at lectures, MOOCs	MOOCs, in-class engagement, project 1, project 2
PC-13 Ability to use the methods of collecting, processing, and interpreting comprehensive social information to solve organizational and managerial tasks, including those outside the immediate scope of activities	Students collect information on the business context of a given case and evaluate possible solutions to a given task	MOOCs, seminar discussion	MOOCs, in-class engagement, project 1, project 2

Course Content

1. Introduction to Data Analysis for Consumer Behavior and Client Analytics. Customer Lifetime Value

Basic concepts of consumer behavior and client analytics. Differences and similarities between typical academic research and business analytics pipelines. Customer acquisition, conversion, churn, segmentation, consumer behavior. Market basket analysis. Association rules. Classification of consumer behavior models. Generic marketing strategies. Types of business models. Statistical methods for client analytics. Life-time value (CLV, LTV). Net profit. Predicting future margin with current sales data.

Predicting customer lifetime value with linear regression in R. Omitted variable problem. Multicollinearity. Model validation. Risk of overfitting: use of statistics (AIC), automatic model selection, out-of-sample validation. Adjusted R-squared.

Core reading: Blattberg, Robert C., Byung-Do Kim, and Scott A. Neslin. Database Marketing. Vol. 18. International Series in Quantitative Marketing. New York, NY: Springer New York, 2008, pp. 105-131.
Further reading: Customer Lifetime Value Tutorial (online). URL: https://www.datacamp.com/community/tutorials/customer-life-time-value
Practice tasks: Pflieger, Verena. "Marketing Analytics in R: Statistical Modeling." (online course), Chapter 1.
Project work: project 1.

2. Customer Segmentation and Unit Economics

Factors of customer segmentation: demographics, technology, geography, lifestyles, behavior, new/returning contract, time from last purchase, frequency and value of spending, etc. Reducing the complexity of extensive correlated data. Differences between the goals of LTV models and segmentation techniques. Business-related criteria for segmentation: RFM (recency, frequency, monetary) analysis.

Analytical techniques for customer segmentation: PCA, cluster analysis (k-means, DBSCAN, agglomerative algorithms). Applications of PCA for exploration in customer analytics. Reducing multicollinearity, building an index, visualizing multidimensional data. Visualizing correlations. Standardizing variances (scaling). Loadings of principal components. Interpretation of principal components. PCA model specification. Kaiser-Guttman criterion. Scree plot. Biplot of variables and components. Further analysis: fitting loadings to linear regression. Clustering algorithms. Distances between data points. Linkage criteria. Dendrogram plot. Applications of cluster analysis for customer analytics in R.

Core reading: Chapman, Christopher N., and Elea McDonnell Feit. R for Marketing Research and Analytics. Use R! Springer International Publishing, 2015, pp. 299-338.
Further reading: RFM Analysis in R (online). URL: https://blog.rsquaredacademy.com/introducing-rfm/; DBSCAN: density-based clustering for discovering clusters in large datasets with noise - Unsupervised Machine Learning (online). URL: http://www.sthda.com/english/wiki/wiki.php?id_contents=7940
Practice tasks: Gorenshteyn, Dmitriy. "Cluster Analysis in R" (online course) DataCamp, Chapter 2, 3.
Project work: project 1, project 2.

3. Customer Churn. Churn Prevention

How to predict customer churn? How to detect and prevent customer churn? Factors of churn: expectations, performance, disconfirmation (disappointment based on perceived quality), satisfaction, churn intention/switching decisions.

Push-pull-mooring paradigm for churn and service switching. Measurement of latent variables: satisfaction and expectation disconfirmation. Models of satisfaction, expectation disconfirmation, performance. Sources of data: Experts, logs, surveys. Case: Yandex Music vs. Spotify.

Predicting client's churn with logistic regression in R. The meaning of p-value. Interpretation of logistic regression coefficients. Model selection based on significance vs. theory. Inspecting the results of automatic model selection. In-sample model fit for logistic regression: Pseudo-R-squared (interpretation of reasonable, good, and very good fit); accuracy calculation. The rule of "garbage in, garbage out". Accuracy. Confusion matrix. Finding the optimal threshold: a table of potential payoffs. Composing a payoff matrix. Dealing with overfitting: out-of-sample validation and cross-validation. Splitting the sample in R. Specifying on train and predicting on test subsamples. K-fold methods of cross-validation. Accuracy for out-of-sample vs. cross validation. Addressing churn using segmentation and advertisement. Naive Bayes in predicting churn. Description of task and data for the project.

Core reading: Blattberg, Robert C., Byung-Do Kim, and Scott A. Neslin. Database Marketing. Vol. 18. International Series in Quantitative Marketing. New York, NY: Springer New York, 2008, pp. 607-633.
Further reading: Struhl, Steven M. Artificial intelligence marketing and predicting consumer choice: an overview of tools and techniques. London: Kogan Page, 2017, Chapter 07.
Practice tasks: Pflieger, Verena. "Marketing Analytics in R: Statistical Modeling." (online course) DataCamp, Chapter 2.
Project work: project 1, project 2.

4. Predicting Customer's Time to Churn

Predicting time till next purchase with survival analysis. Addressing churn using segmentation and advertisement.

Survival function. Censored data problem. Survival analysis models: pros and cons. Applications of survival models in customer analytics. Types of data censoring (left, interval, right, type I, type II, random). Assumptions of survival

analysis. Survival curve analysis by Kaplan-Meier. Survival function and cumulative hazard function. Cumulative risk. Hazard rate. Kaplan-Meier estimation with a categorical covariate.

Cox proportional hazards (CPH) model for multiple covariates. Assumptions of CPH. Interpretation of coefficients for categorical and continuous predictors. Survival plot. Visualization of CPH estimates. When assumptions are violated: stratified Cox model, model time-dependent coefficients. Prediction of survival curve for new customers. CPH model interpretation, calculation of customer lifetime value.

Core reading: Blattberg, Robert C., Byung-Do Kim, and Scott A. Neslin. Database Marketing. Vol. 18. International Series in Quantitative Marketing. New York, NY: Springer New York, 2008, pp. 607-633.
Further reading: Survival Analysis: Intuition & Implementation (online). URL: https://towardsdatascience.com/survival-analysis-intuition-implementation-in-python-504fde4fcf8e
Practice tasks: Pflieger, Verena. "Marketing Analytics in R: Statistical Modeling." (online course) DataCamp, Chapter 3.
Project work: project 2 (optional).

5. What-If Analysis

The analytical pipeline: database, model, dashboard, what-if analysis. Use of simulations in business for decision making. Scenarios as ways to construct prediction on data. From scenario, to simulation model, to prediction. What-if analysis vs. Extraction, Transformation and Loading (ETL) approach.
Source variables and scenario parameters. Seven stages of what-if analysis: goal analysis, business modeling, data source analysis, multidimensional modeling, simulation modeling, data design and implementation, and validation (if failed, repeat 4-7). Activity diagram (scenario diagram). Case: productivity of branches.

Stating the assumptions required to perform what-if analysis of models. Grouping assumptions into scenarios describing different ways of customers' reaction to the policies. Building what-if models for each policy for each scenario. Compare and reflect on the results of scenario models. Reactive programming. Functions in R.

Core reading: Rizzi S. What-If Analysis. In: Liu L., Özsu M.T. (eds) Encyclopedia of Database Systems. Springer, New York, 2018. URL: https://proxylibrary.hse.ru:2084/referenceworkentry/10.1007/978-1-4614-8265-9_466

Further reading: Struhl, Steven M. Artificial intelligence marketing and predicting consumer choice: an overview of tools and techniques. London: Kogan Page, 2017, Chapter 04; What-if Analysis and the Sensitivity Report (online). URL: https://coursera.org/lecture/business-analytics-decision-making/4-what-if-analysis-and-the-sensitivity-report-L9bG9
Practice tasks: replicate the example from "Slides and sample code from "What If In Excel & R"" (online). URL: http://zomalex.co.uk/slides-and-sample-code-from-what-if-in-excel-r-presentation/; McDonnell Feit, Elea. "Marketing Analytics in R: Choice Modeling." (online course) DataCamp, Chapter 1.
Project work: project 2 (optional).

6. Consumer Preferences and Choice Modeling

Introduction to consumer preference theory. Utility analysis. Cardinal utility, ordinal utility. Indifference curves show combinations that give equal utility. Marginal rate of substitution (MRS). Constraints: income, price, time.

Uses of choice models in marketing and business analytics. Modeling customers' choice by product features. Multinomial logit models for choice vs. Conjoint analysis: when and where. Choice-based and metric conjoint. Sample size for a conjoint survey.

Preparing the data for choice modeling. Managing and summarizing choice data. Selecting the features for modeling. Building Choice Models. Modeling different preferences for different groups of customers with hierarchical models (mixed logit models).

Reporting choice models: choice share predictions, willingness-to-pay metric. Preference share vs. market share forecast. The "red bus/blue bus problem" in multinomial logistic models.

Core reading: Chapman, Christopher N., and Elea McDonnell Feit. R for Marketing Research and Analytics. Use R! Springer International Publishing, 2015, pp. 363-400.
Further reading: Struhl, Steven M. Artificial intelligence marketing and predicting consumer choice: an overview of tools and techniques. London: Kogan Page, 2017, Chapter 05.
Practice tasks: McDonnell Feit, Elea. "Marketing Analytics in R: Choice Modeling." (online course) DataCamp, Chapters 2-4.
Project work: project 2.

7. Customer Satisfaction

Customer feedback surveys. Net promoter score (NPS) for measuring loyalty. Promoters, passives and detractors. Customer satisfaction survey (CSAT) for meeting expectations. Post-purchase surveys, product/service development survey, usability surveys. Expectation disconfirmation theory of post-purchase satisfaction. Key constructs: expectations, perceived performance, disconfirmation of beliefs and satisfaction. Inputs to expectations of value. Measuring the perceived performance: overall quality, interaction, service experience, value for money, social status. Problems of customer satisfaction surveys. Self-selection, overdelivering, expectation adjustment.

Combining survey and behavior data. Discovering patterns with Bayesian networks (Bayes nets). Trimming groups of variables, defining the importance of predictors.

Core reading: Chapman, Christopher N., and Elea McDonnell Feit. R for Marketing Research and Analytics. Use R! Springer International Publishing, 2015, pp. 339-361.
Further reading: Struhl, Steven M. Artificial intelligence marketing and predicting consumer choice: an overview of tools and techniques. London: Kogan Page, 2017, Chapter 07.
"bnlearn: Practical Bayesian Networks in R" (online). URL: http://www.bnlearn.com/examples/useR19-tutorial/
Practice tasks: Pflieger, Verena. "Marketing Analytics in R: Statistical Modeling." (online course) DataCamp, Chapter 4.
Project work: in-class group tasks.

8. Introduction to Business Process Analytics

Process mining. Business process data: extraction, processing and analysis. Process as a control flow, process as performance, process as the organizational background. Association rule mining. Markov chain models and sequential association rules.

Identifying the process and process stakeholders. Collecting process information.
Event data processing: event log objects, exploratory and descriptive analysis, conditional process analysis, process visualizations and process dashboards.
Case study: order-to-cash process.

Core reading: Chapman, Christopher N., and Elea McDonnell Feit. R for Marketing Research and Analytics. Use R! Springer International Publishing, 2015, pp. 339-361.

Further reading: Business Process Analysis with bupaR package (online). URL: https://www.bupar.net/materials/20170904%20poster%20bupaR.pdf

Struhl, Steven M. Artificial intelligence marketing and predicting consumer choice: an overview of tools and techniques. London: Kogan Page, 2017, Chapter 08.

Practice tasks: Janssenswillen, Gert. "Business Process Analytics in R" (online course) DataCamp, Chapter 1.

Project work: in-class group tasks, project 2 (optional).

Assessment Methods and Criteria

Assessment Methods

Types of Assessment	Forms of Assessment	Modules			
		1	2	3	4
	Project	*	*		
	In-class Engagement	*	*		
	MOOC	*	*		
Summative Assessment	Exam				

Assessment Criteria

In-class Engagement

In-class engagement includes students' performance at seminar discussions where they work through home reading, complete individual and pair tasks, or present extra techniques and materials relevant to this course.

Grades	Assessment Criteria
«Excellent» (8-10)	A critical analysis which demonstrates original thinking and shows strong evidence of preparatory learning and research and broad background knowledge of the subject
«Good» (6-7)	The student shows certain evidence of preparatory learning and background knowledge, occasionally fails to maintain the discussion on home reading or in-class tasks.
«Satisfactory» (4-5)	Satisfactory overall, showing a fair knowledge of the topic and analytical techniques but frequently failing to perform them appropriately. The student expresses considerable hesitation in

	answering follow-up questions on home reading/ in-class tasks or provides incomplete or partly irrelevant answers to the questions.
«Fail» (0-2)	The student demonstrates extremely limited and scarce evidence of relevant knowledge and practical skills in addressing the topic. Refusal to offer relevant information or an informed opinion in answering follow-up questions.

Project Work

In module 1, students submit an individual home project. The project focuses on reworking/adapting the programming code in R in order to calculate customer life-time value, given parts of similar code. This tasks develops data wrangling skills of students, while they also apply the newly learned techniques and write a client-oriented memo based on the results.

In module 2, students organize into teams of 2-3 people and work together on the project. The second project is due towards the end of the course, and it reproduces the whole cycle of customer analytics, from data screening, to the analytical pipeline, to creating an executive report targeted at the company's management. The second project consists of two parts, each graded separately, i.e., individual scripts of team members where individual contribution is transparent, and the final presentation and accompanying script developed for the client. Further details are available in LMS.

Grades	Assessment Criteria
«Excellent» (8-10)	A well-structured, analytical presentation of the project. Student shows strong evidence and broad background knowledge. In a group presentation, all members contribute solidly, and each contribution builds on the previous one. Answers to follow-up questions reveal a good range and depth of knowledge beyond that covered in the presentation and show confidence in discussion. The code is reproducible, well-organized and commented, engaging analytical techniques relevant for the task.
«Good» (6-7)	Clearly organized analysis, showing evidence of good overall knowledge of the topic. The presenter of the project work highlights key points and responds to follow-up questions appropriately, with occasional minor mistakes. In group presentations, there is evidence that the group has met together to discuss the task and is presenting the results of that discussion, in an order previously agreed upon but lacks some knowledge to address the necessary points. The code is reproducible, has some logic in its structure and occasional explanatory comments. Some assumptions are not checked, some results

	might be lacking all the sufficient interpretation.
«Satisfactory» (4-5)	The analysis takes a very basic approach to the topic, using broadly appropriate but suboptimal material and a limited understanding of the terms used, lacking focus or structure. The presentation of project work is largely unstructured, and some points are irrelevant to the topic. Knowledge of the topic is limited, and there may be evidence of basic misunderstanding. In a group presentation, most of the work is done by one student and the individual contributions do not add up. The code is only partly reproducible and lacks student's comments; some of the applied techniques are not relevant for the task; some results are interpreted incorrectly.
«Fail» (0-2)	Fails to submit the project or to demonstrate enough knowledge to meet the project's requirements.

Detailed Assessment Criteria for Project 2

Part of the Report	**Assessment Criteria** (basic and *advanced**)
1 Exploratory Data Analysis	Analyst… • uses appropriate graphs and tables in accordance to analytical graphic principles; • connects data to business logic (segmentation types, KPIs, etc.); • tells a well-structured story about current situation; • proposes some hypotheses based on business logic and EDA results; • sets a baseline to refer to from the further steps; • *appropriately uses theories about domain area*;* • *appropriately uses advanced graphics to convey complex relationships in data**.
2 Predictive Model	Analyst… • builds basic (logistic regression, survival analysis, etc.) models; • evaluates the models, focusing not only on accuracy, but also on false positives and false negatives, and suggests a business-level evaluation of models (e.g. monetary gain/losses, opportunity cost due to unpredicted or early churn, etc.); • compares the models analyzing where they disagree with each other and proposing an explanation why; • explains modeling results for the customer, both referring to EDA results and using classification models evaluation tools; • *uses appropriately the advanced machine learning (ML) models, compares them with the simpler models and reflects on improvements*;* • *uses appropriately model analysis/variable importance evaluation techniques (e.g. LIME package) to involve advanced modelling*

	results into the story.*
3 Churn Prevention Policy	Analyst… • designs two competing churn prevention policies (one can be based on EDA and heuristics, PCA, or clustering results and should define a target segment or segments, the other one can be based on logistic regression or survival analysis model, or both can be based on different ML models); • explains the reasoning behind the segments/target groups for both policies; • suggests measures to prevent/reduce churn for each policy; • describes both policies using customer lifetime value model and appropriate terminology; • *leverages scientific research on customer lifecycle and churn in telecom companies in order to motivate the suggested policy*;* • *describes a marketing campaign or business actions based on developed policy*.*
4 What-If analysis	Analyst… • makes and states plausible assumptions required to perform what-if analysis of models; • groups these assumptions into scenarios describing different ways of customers' reaction to the policies; • builds what-if models for each policy for each scenario; • compares and reflects on the results of scenario models; • suggests and motivates the choice of a policy based on the modelling results; • *builds an interactive app for what-if analysis*.*
5 Executive Report	Analyst… • describes existing situation; • summarizes the segmentation-based/ML based analysis of churn; • lays out proposed policies; • describes the results of scenario analysis and the estimated results of policy implementation. The report should be client-oriented. Do not put code or other technical details in it, use plain language/ business terms, do not try to put everything you have done in the executive report (there are individual scripts for that), and build a coherent story for your client with a take-home message.

MOOC

The *MOOC* grade evaluates successful and timely completion of the nine chapters of online courses assigned by instructors (exercises and theory videos from all the chapters should be completed within the time assigned). Late completion is penalized (see the table below).

There are two online MOOCs to cover, four chapters each, where each chapter can bring up to 3 points, and another stand-alone introductory chapter that can earn 1 extra point. The maximum sum of points for MOOCs is 25, which translates into 25 per cent of the grade. You can monitor your own progress by looking at the progress bars while doing the online course.

Points per MOOC Chapter	Assessment Criteria
3	The student has watched all the videos in the chapter and completed all the exercises in time (100 % progress in due time).
2	The student has watched most or all of the videos in the chapter and completed all the exercises after the deadline or has missed one or two exercises by deadline (at least 61 % progress in due time or 100 % progress after the deadline).
1	The student has watched some of the videos in the chapter and completed some exercises (30-60 % progress in due time or after deadline).
0	The student has barely started this MOOC chapter in due time (0-29 % progress).

Samples of Assessment Material: Tasks for Project 1 and Project 2

Project 1. You are to re-work the Python code in R, step by step. You will be working with a data set similar to the one described in the case ("history.csv", in the same folder). Some steps have been done for you; now, complete the rest of the case.

Project 2. As a freelance analyst you are hired to develop client retention measures (recommendations) for a company. You have a dataset with socio-demographics and behavior data for the customers and the outcome (churn). Your aim is to use heuristics and exploratory and predictive tools in order to not only (1) analyze customer churn, but also (2) suggest some measures to prevent it and (3) estimate their efficiency. For each task you are provided with recommendations "what an analyst would do?" which should guide you through the task and serve as a foundation for your work assessment.

Your workflow, ideally, would consist of the following tasks:

- perform exploratory data analysis targeted to explain to your customer the current situation with churn and its structure;
- build a predictive model, analyze and explain its results;
- use the prediction model of churn or tenure and/or
    - a segmentation based on exploratory data analysis (EDA) and/or
    - PCA/clustering or heuristics to suggest churn prevention policies;
- analyze your policies via what-if modelling; and
- produce the final report for your customer.

For each task you are provided with recommendations "What Would an Analyst Do?" which should guide you through the task and serve as a foundation for your work assessment.

Recommendations to Students on Strategies of Completing the Course Successfully

We recommend completing the MOOC chapters in advance (a few days before the seminar) and discussing their contents, both in theory and in the methods part, in class. If you complete the MOOC in advance, you can arrange a meeting with instructor to discuss the questions before the seminar discussion. It is easier to complete all the online course tasks when they are given, not afterwards; not only will you lose points for late submission, but you will also gain more from regular practice in R.

Since many topics are new and the format of the tasks may appear unfamiliar, take note of the concepts introduced in the online cases and look them up in reference books and online materials after you complete the practical task of the MOOC. In addition, it will be useful to organize a vocabulary both for the new terms in this course and a coding 'cheat sheet' for all the new functions and packages you study in online tasks which you may later re-use for solving some typical tasks. As another option, join forces with fellow students to organize shared notes for this course where you can collect, under separate bookmarks, the new techniques, key terms, and R functions.

A tip for making teams for project 2 groups: seek out for students with skills that are complementary to yours and allocate responsibilities in advance. Your group will need someone to organize the tasks among others, to be in charge of writing the slides/ text of the executive report, preparing the clean and reproducible code out of individual contributions, and someone in charge of the oral presentation. Distribute your time and effort accordingly. Remember that the audience for this group project is meant in the business people; therefore, adapt the report's narrative so as to make it closer to the business milieu than to the academy. Have a Plan B. If some of your team members fail to perform their part, the overall team work can still be a success; plan in advance and solve any arising conflicts together.

Recommendations to Students on Organization of Self-Study

This course can appear challenging in three ways: new concepts, new data analysis techniques, and new working formats (executive report, individual vs. team code scripts).

To help you understand and use business analytical terms, read and watch as much about the topic as possible, to gain the language of business analytics. Make full use of the electronic resources of the library and business cases available in it, such as World Bank reports, OECD resources, and business periodicals (see https://library.hse.ru/e-resources). Since this is an elective course, we expect you to follow your passion in choosing and studying business analytics. You are most heartily encouraged to read and share any extra academic or business materials and cases dealing with the topics covered in the course.

To enhance your learning new data analysis techniques, especially in MOOCs, we thoroughly recommend that you take note and store (e.g. in a separate script) all the new functions you learn online, and make comments on their use. It will usually take you a few times before you can apply them independently and accurately.

You can also organize a study group to go through home tasks and reading together and discuss them immediately as it often helps gain a deeper and more versatile understanding of the subject. Make use of the library or the students' co-working room if you need some extra help in reading concentration.

Recommendations to Instructors for Teaching This Course

Teaching business analytics to advanced undergraduate students requires them to change the focus of their work from academic research to business processes, which requires numerous examples of good practice on the part of instructors.

We embrace the pedagogical framework of end-to-end analytical pipeline (see Jeyaraj, 2019 for details) where students themselves know the basics of collecting the data (including scrapping), maintaining them in a database, performing statistical analyses and delivering the results in a report. This course rests on a good knowledge of previous courses that students had covered before, which included working with databases, tools for web data scrapping, introduction to data visualization, and courses on data analysis in R.

All these skills empower students for conducting their own analyses and research, thus helping the success of the technical part of the course. In a similar manner, instructors should better make use of the existing ecosystem of courses already available to students before they take this elective course, and combine that.

Jeyaraj, A. (2019). Teaching Tip Pedagogy for Business Analytics Courses. Journal of Information Systems Education, 30(2), 67–83. Retrieved from https://proxylibrary.hse.ru:2072/login.aspx?direct=true&db=bth&AN=136851145&site=eds-live

Special Conditions for Organization of Learning Process for Students with Special Needs

The following types of comprehension of learning information (including e-learning and distance learning) can be offered to students with disabilities (by their written request) in accordance with their individual psychophysical characteristics:

1. *for persons with vision disorders:* a printed text in enlarged font; an electronic document; audios (transferring of learning materials into the audio); an individual advising with an assistance of a sign language interpreter; individual assignments and advising.
2. *for persons with hearing disorders: a* printed text; an electronic document; video materials with subtitles; an individual advising with an assistance of a sign language interpreter; individual assignments and advising.
3. *for persons with muscle-skeleton disorders: a* printed text; an electronic document; audios; individual assignments and advising.