



Universiteit
Leiden
The Netherlands

Applying data mining in telecommunications

Radosavljevik, D.

Citation

Radosavljevik, D. (2017, December 11). *Applying data mining in telecommunications*. Retrieved from <https://hdl.handle.net/1887/57982>

Version: Not Applicable (or Unknown)

License: [Licence agreement concerning inclusion of doctoral thesis in the Institutional Repository of the University of Leiden](#)

Downloaded from: <https://hdl.handle.net/1887/57982>

Note: To cite this publication please use the final published version (if applicable).

Cover Page



Universiteit Leiden



The handle <http://hdl.handle.net/1887/57982> holds various files of this Leiden University dissertation.

Author: Radosavljevik, D.

Title: Applying data mining in telecommunications

Issue Date: 2017-12-11

Curriculum Vitae

Dejan Radosavljevik was born in 1975 in Skopje, Macedonia. After graduating from a BSc program in Computer Science at the University of Ss. Cyril and Methodius in Skopje in 2001, he has worked as a software developer for several Macedonian companies. In 2009 he completed a Master's degree in ICT in Business with cum laude distinction at Leiden University with a thesis on Prepaid Churn Modeling Using Customer Experience Management Key Performance Indicators. Since then he has worked in multiple positions related to artificial intelligence, data mining and data science at T-Mobile Netherlands B.V., in parallel to working on this PhD research at Leiden University. He currently holds the position of Lead Data Scientist within T-Mobile Netherlands.

List of Figures

- 1.1 CRISP-DM Process Model for Data Mining 9
- 2.1 Customer Experience Framework for Mobile Telecommunications . . . 22
- 2.2 Coefficient of Concordance 24
- 2.3 Coefficient of Concordance of predictors grouped in group 1 for experiment A 30
- 2.4 Gain chart of models for experiment A, B and C (training set) 32
- 3.1 Telecom call graph. 41
- 3.2 Initial energy of the simple and extended propagation technique. . . . 43
- 3.3 Spreading activation in a weighted graph. 44
- 3.4 Call Graph Details. 46
- 3.5 Implementation scenarios. 48
- 3.6 Gain and Lift chart of all models. 50
- 4.1 Gain Charts of Models Used 60
- 5.1 Actual Load vs. Linear approximation 73
- 5.2 Communication Graph of the Tools used 75
- 6.1 Overview of the Service Revenue Forecasting Process 90
- 6.2 The ETL Process in KNIME using RJDBC 92
- 6.3 Modeling Workflow in KNIME 96

List of Tables

- 1.1 Mapping of the Focus of the Thesis Chapters to the Stages of the CRISP-DM process 11
- 2.1 Sample size, churn rate and CoCs in experiments A, B1a, B1b and C . . 29
- 2.2 Grouping of variables of Model A_Incl.CEM 31
- 3.1 Social network features used in the extended tabular churn models. . . 42
- 3.2 Coefficient of Concordance of the scoring and propagation models. . . 51
- 4.1 List of contractual, demographic and CDR based features 57
- 4.2 List of network quality features per category 58
- 4.3 Model Performance 59
- 4.4 Univariate performance of predictors (CoC) 61
- 5.1 List of Input Parameters 71
- 5.2 Regression Modeling Results for Downlink Load (DL) for Country Operator 1 78
- 5.3 Regression Modeling Results for Uplink Load (UL) for Country Operator 1 78
- 5.4 Regression Modeling Results for Downlink Load (DL) for Country Operator 2 78
- 5.5 Regression Modeling Results for Uplink Load (UL) for Country Operator 2 78
- 5.6 Regression Modeling Results for Downlink Load (DL) for Country Operator 3 79
- 5.7 Regression Modeling Results for Uplink Load (UL) for Country Operator 3 79
- 5.8 Regression Modeling Results for Downlink Load (DL) for Country Operator 4 79
- 5.9 Regression Modeling Results for Uplink Load (UL) for Country Operator 4 79

6.1 Inputs used for creating service revenue models 94

6.2 Algorithm performance 100

6.3 Modeling Service Revenue Components 101