
Contents

Part I Introduction

Rule Extraction from Support Vector Machines: An Introduction

| | |
|---|----|
| <i>Joachim Diederich</i> | 3 |
| 1 Explanation: The Foundations | 3 |
| 1.1 Forms of Explanation | 4 |
| 1.2 Analogy as a Form of Explanation | 5 |
| 1.3 Explanation-Based Generalization | 6 |
| 1.4 How and Why Explanations | 7 |
| 1.5 Generating or Identifying the Best Explanation | 8 |
| 2 Rule Extraction from Support Vector Machines: Aims and Significance | 8 |
| 2.1 Provision of a “User Explanation” Capability | 9 |
| 2.2 Transparency | 10 |
| 2.3 Software Verification | 10 |
| 2.4 Improving Generalisation | 11 |
| 2.5 Data Exploration and the Induction of Scientific Theories | 11 |
| 3 Translucency and Rule Quality | 11 |
| 3.1 The Neural Network Case | 12 |
| 3.2 Translucency and Rule Quality Applied to Rule Extraction from SVMs | 13 |
| 4 An Alternative View on Rule Extraction: Information Retrieval | 14 |
| 5 A Case Study | 16 |
| 6 A Classification System for Rule Extraction from SVMs | 26 |
| 7 Conclusions and Future Challenges | 28 |
| 8 Acknowledgements | 30 |
| References | 30 |

Rule Extraction from Support Vector Machines: An Overview of Issues and Application in Credit Scoring

David Martens, Johan Huysmans, Rudy Setiono, Jan Vanthienen, and Bart Baesens 33

| | | |
|-----|--|----|
| 1 | Introduction | 34 |
| 2 | The Support Vector Machine | 34 |
| 3 | The Rationale Behind SVM Rule Extraction | 36 |
| 3.1 | Why Rule Extraction | 36 |
| 3.2 | Why SVM Rule Extraction | 37 |
| 4 | An Overview of SVM Rule Extraction Techniques | 38 |
| 4.1 | Classification Scheme for SVM Rule Extraction Techniques | 38 |
| 4.2 | SVM Rule Extraction Techniques | 41 |
| 5 | Issues Concerning SVM Rule Extraction | 49 |
| 5.1 | Rule Output | 49 |
| 5.2 | High Dimensional Data | 51 |
| 5.3 | Constraint Based Learning: Knowledge Fusion Problem | 51 |
| 5.4 | Specificness of Underlying Black Box Model | 53 |
| 5.5 | Regression | 53 |
| 5.6 | Availability of Code | 53 |
| 6 | Credit Scoring Application | 53 |
| 6.1 | Credit Scoring in Basel II | 53 |
| 6.2 | Classification Model | 54 |
| 7 | Alternatives to Rule Extraction | 56 |
| 7.1 | Inverse Classification | 56 |
| 7.2 | Self Organizing Maps | 56 |
| 7.3 | Incremental Approach | 57 |
| 8 | Conclusion | 59 |
| 9 | Acknowledgement | 59 |
| | References | 59 |

Part II Algorithms and Techniques

Rule Extraction for Transfer Learning

Lisa Torrey, Jude Shavlik, Trevor Walker, and Richard Maclin 67

| | | |
|-----|---|----|
| 1 | Introduction | 67 |
| 2 | Transfer Learning and Advice Taking | 67 |
| 3 | SVMs in Reinforcement Learning | 69 |
| 4 | Extracting Rules from an RL Source Task | 71 |
| 4.1 | Acquiring Rules from the Q-function | 72 |
| 4.2 | Acquiring Rules from Observed Behavior | 73 |
| 5 | Case Study | 76 |
| 5.1 | Policy-Transfer Results | 78 |
| 5.2 | Skill-Transfer Results | 79 |

6 Summary and Open Problems 81
 References 81

Rule Extraction from Linear Support Vector Machines via Mathematical Programming

Glenn Fung, Sathyakama Sandilya, and R. Bharat Rao 83

1 Introduction 83
 1.1 About Notation 84
 2 Medical Relevance 85
 3 Sparse Hyperplane Classifiers: 1-Norm Support Vector Machines ... 86
 4 Rule Extraction from Hyperplane Classifiers 87
 4.1 Volume Maximization Criteria 90
 4.2 Point Coverage Maximization Criteria 91
 5 Algorithm Convergence Properties 93
 6 Numerical Testing 96
 6.1 WDBC Dataset 98
 6.2 The Lung CAD Dataset 99
 7 Other Mathematical Programming Formulations 99
 7.1 Conditioning Rules by Using Prior Knowledge 99
 7.2 Creating a Rule that Covers an Specific Given Point
 or Set of Points 100
 7.3 Rule Extraction and Knowledge-Based SVMS for Incremental
 Learning 101
 8 Conclusion and Future Directions 104
 References 105

Rule Extraction Based on Support and Prototype Vectors

Haydemar Núñez, Cecilio Angulo, and Andreu Català 109

1 Combining Support Vectors and Prototype Vectors
 to Extract Rules 110
 1.1 Building an Ellipsoid and Its Associated Rule Equation 112
 1.2 Generating a Set of Rules 118
 1.3 Simplified Representational Language for the Model 122
 1.4 Classification by Using the Set of Rules 126
 2 Experiments 127
 3 Eliminating Randomness from the Clustering Algorithm 130
 4 Conclusions and Further Research 132
 References 133

SVMT-Rule: Association Rule Mining Over SVM Classification Trees

Shaoning Pang and Nik Kasabov 135

1 Introduction 135
 2 SVM Classification Tree 137
 2.1 Two-Class SVM Tree 137

| | | |
|-----|---|-----|
| 3 | The Spanning of SVM Tree | 141 |
| 3.1 | Depth-First Spanning Tree | 142 |
| 3.2 | Breadth-First Spanning Tree | 142 |
| 3.3 | The SVMT Algorithms | 143 |
| 3.4 | Coping with Class Imbalance and Class Overlap | 145 |
| 4 | SVMT Rules Extraction | 145 |
| 4.1 | Logic Association Rules | 145 |
| 4.2 | SVM Nodes Interpolation | 146 |
| 4.3 | SVMT-Rule | 149 |
| 5 | Experiments and Applications | 152 |
| 5.1 | Synthetic Dataset | 152 |
| 5.2 | Cancer Diagnosis | 156 |
| 5.3 | Fraud Detection | 158 |
| 6 | Discussions and Conclusions | 159 |
| 7 | Acknowledgements | 160 |
| | References | 160 |

Prototype Rules from SVM

| | | |
|-----|--|-----|
| | <i>Marcin Blachnik and Włodzisław Duch</i> | 163 |
| 1 | Why Prototype-Based Rules? | 163 |
| 2 | P-Rules and Their Interpretation | 165 |
| 2.1 | Types of P-Rules | 166 |
| 2.2 | Support Vectors as Prototypes | 166 |
| 2.3 | Removing Linear Dependencies Among Support Vectors | 167 |
| 2.4 | Reducing the Number of Support Vectors | 169 |
| 2.5 | Finding Optimal Number of Support Vectors | 171 |
| 2.6 | Problems with Interpretation | 174 |
| 3 | Searching for Informative Prototypes | 174 |
| 3.1 | Prototype Selection Using Context Dependent Clustering | 176 |
| 3.2 | The Conditional Fuzzy Clustering Algorithm | 177 |
| 3.3 | Determining the Context | 178 |
| 3.4 | Numerical Illustration of the CFCM Approach | 178 |
| 4 | Conclusions | 180 |
| | References | 181 |

Part III Applications

Prediction of First-Day Returns of Initial Public Offering in the US Stock Market Using Rule Extraction from Support Vector Machines

| | | |
|-----|---|-----|
| | <i>Rolf Mitsdorffer and Joachim Diederich</i> | 185 |
| 1 | Motivation | 185 |
| 2 | Introduction | 186 |
| 2.1 | Financial Data Mining | 186 |

| | | |
|-----|--|-----|
| 2.2 | IPOs as a Case Study | 186 |
| 3 | Overview of the Chapter | 187 |
| 4 | Methodology | 187 |
| 4.1 | Statistical Tests | 188 |
| 4.2 | Data | 188 |
| 4.3 | Machine Learning Techniques Used in This Study | 191 |
| 5 | Results | 194 |
| 5.1 | Results of Rule Extraction from SVM for Cross-Industry IPOs | 194 |
| 5.2 | Rule Extraction from SVM Results for Single-Industry IPOs | 196 |
| 6 | Discussion of Results | 197 |
| 7 | Conclusions | 201 |
| | References | 202 |

Accent in Speech Samples: Support Vector Machines for Classification and Rule Extraction

| | | |
|-----|---|-----|
| | <i>Carol Pedersen and Joachim Diederich</i> | 205 |
| 1 | Introduction | 205 |
| 1.1 | Motivation and Significance | 205 |
| 1.2 | Overview | 205 |
| 2 | Accent Recognition | 206 |
| 2.1 | Accent | 206 |
| 2.2 | Automatic Speech Recognition | 207 |
| 2.3 | Mel Frequency Cepstrum Coefficients | 208 |
| 3 | Rule Extraction from Support Vector Machines for Accent | 209 |
| 3.1 | Support Vector Machines | 209 |
| 3.2 | Rule Extraction | 210 |
| 3.3 | Objectives | 211 |
| 4 | Methodology | 211 |
| 4.1 | Speech Data and Feature Extraction | 211 |
| 4.2 | Machine Learning Experiments | 212 |
| 4.3 | Rule Extraction and Evaluation | 213 |
| 5 | Results | 213 |
| 5.1 | Machine Learning Experiments | 213 |
| 5.2 | Evaluation of the Rule Extraction Results | 218 |
| 6 | Discussion | 223 |
| | References | 225 |

Rule Extraction from SVM for Protein Structure Prediction

| | | |
|-----|--|-----|
| | <i>Jieyue He, Hae-jin Hu, Bernard Chen, Phang C. Tai, Rob Harrison, and Yi Pan</i> | 227 |
| 1 | Introduction | 227 |
| 2 | Rule Generation by Combing SVM and DT | 229 |
| 2.1 | SVM_DT | 229 |

XII Contents

| | | |
|-----|--|------------|
| 2.2 | Protein Second Structure Prediction with SVM_DT | 231 |
| 2.3 | Transmembrane Segments Prediction and Understanding Using SVM_DT..... | 235 |
| 3 | Extracting Rule from SVM Based on Association Rule | 238 |
| 3.1 | Association Rule Based Method | 238 |
| 3.2 | Association Rule Mining..... | 239 |
| 4 | Rule Clustering and Super_rule Generation | 244 |
| 5 | Conclusions..... | 247 |
| 6 | Acknowledgements | 249 |
| | References | 249 |
| | Subject Index | 253 |
| | Author Index | 261 |



<http://www.springer.com/978-3-540-75389-6>

Rule Extraction from Support Vector Machines

Diederich, J. (Ed.)

2008, XII, 262 p. 55 illus., Hardcover

ISBN: 978-3-540-75389-6