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Robust Latent Feature Learning for Incomplete Big Data

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Preface

In the era of Big Data, high dimensional and incomplete (HDI) data are frequently encountered in many industrial applications, such as recommender systems, the Internet of Things, intelligent transportation, cloud computing, and so on. It is of great significance to analyze them for mining rich and valuable knowledge and patterns. Latent feature learning is one of the most popular representation learning methods tailored for HDI data due to its high accuracy, computational efficiency, and ease of scalability. The crux of analyzing HDI data lies in addressing the uncertainty problem caused by their incomplete characteristics. However, existing HDI methods do not fully consider such uncertainty.

In this book, I introduce several robust latent feature learning methods to address such uncertainty for effectively and efficiently analyzing HDI data, including robust latent feature learning based on smooth L_1 -norm, improving robustness of latent feature learning using L_1 -norm, improving robustness of latent feature learning using double-space, data-characteristic-aware latent feature learning, posterior-neighborhood-regularized latent feature learning, and generalized deep latent feature learning.

This is the first book that can help researchers and engineers fully understand how to employ robust latent feature learning to effectively and efficiently analyze HDI data. It is assumed that readers have a basic knowledge of mathematics, as well as a certain background in data mining. Readers can obtain an overview of the challenges of analyzing HDI data. In addition, this book provides several algorithms and real application cases, which can help readers quickly build their robust latent feature learning models to analyze HDI data.

Chongqing, China
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Di Wu

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Contents

| | | |
|------------|-----------------------------------------------------------------------------|----|
| 1 | Introduction | 1 |
| 1.1 | Background | 1 |
| 1.2 | Symbols and Notations | 2 |
| 1.3 | Book Organization | 3 |
| References | | 4 |
| 2 | Basis of Latent Feature Learning | 7 |
| 2.1 | Overview | 7 |
| 2.2 | Preliminaries | 8 |
| 2.3 | Latent Feature Learning | 8 |
| 2.3.1 | A Basic LFL Model | 8 |
| 2.3.2 | A Biased LFL Model | 12 |
| 2.3.3 | Algorithms Design | 13 |
| 2.4 | Performance Analysis | 13 |
| 2.4.1 | Evaluation Protocol | 13 |
| 2.4.2 | Discussion | 14 |
| 2.5 | Summary | 15 |
| References | | 17 |
| 3 | Robust Latent Feature Learning based on Smooth L_1-norm | 19 |
| 3.1 | Overview | 19 |
| 3.2 | Related Work | 20 |
| 3.3 | A Smooth L_1 -Norm Based Latent Feature Model | 21 |
| 3.3.1 | Objective Formulation | 21 |
| 3.3.2 | Model Optimization | 22 |
| 3.3.3 | Incorporating Linear Biases into SL-LF | 23 |
| 3.4 | Performance Analysis | 24 |
| 3.4.1 | General Settings | 24 |
| 3.4.2 | Performance Comparison | 25 |
| 3.4.3 | Outlier Data Sensitivity Tests | 27 |
| 3.4.4 | The Impact of Hyper-Parameter | 28 |

| | |
|------------------------------------------------------------------------------------------------|-----------|
| 3.5 Summary | 29 |
| References | 30 |
| 4 Improving Robustness of Latent Feature Learning Using L_1-Norm | 33 |
| 4.1 Overview | 33 |
| 4.2 Related Work | 34 |
| 4.3 An L_1 -and- L_2 -Norm-Oriented Latent Feature Model | 35 |
| 4.3.1 Objective Formulation | 35 |
| 4.3.2 Model Optimization | 36 |
| 4.3.3 Self-Adaptive Aggregation | 37 |
| 4.4 Performance Analysis | 39 |
| 4.4.1 General Settings | 39 |
| 4.4.2 L^3F 's Aggregation Effects | 40 |
| 4.4.3 Comparison Between L^3F and Baselines | 41 |
| 4.4.4 L^3F 's Robustness to Outlier Data | 41 |
| 4.5 Summary | 43 |
| References | 44 |
| 5 Improve Robustness of Latent Feature Learning Using Double-Space | 47 |
| 5.1 Overview | 47 |
| 5.2 Related Work | 49 |
| 5.3 A Double-Space and Double-Norm Ensembled Latent Feature Model | 49 |
| 5.3.1 Predictor Based on Inner Product Space (D^2E -LF-1) | 50 |
| 5.3.2 Predictor on Euclidean Distance Space (D^2E -LF-2) | 53 |
| 5.3.3 Ensemble of D^2E -LF-1 and D^2E -LF-2 | 56 |
| 5.3.4 Algorithm Design and Analysis | 57 |
| 5.4 Performance Analysis | 57 |
| 5.4.1 General Settings | 57 |
| 5.4.2 Performance Comparison | 59 |
| 5.5 Summary | 59 |
| References | 62 |
| 6 Data-characteristic-aware Latent Feature Learning | 67 |
| 6.1 Overview | 67 |
| 6.2 Related Work | 68 |
| 6.2.1 Related LFL-Based Models | 68 |
| 6.2.2 DPCLust Algorithm | 68 |
| 6.3 A Data-Characteristic-Aware Latent Feature Model | 70 |
| 6.3.1 Model Structure | 70 |
| 6.3.2 Step 1: Latent Feature Extraction | 71 |
| 6.3.3 Step 2: Neighborhood and Outlier Detection | 71 |
| 6.3.4 Step 3: Prediction | 73 |

| | | |
|----------|-----------------------------------------------------------------------------|------------|
| 6.4 | Performance Analysis | 76 |
| 6.4.1 | Prediction Rule Selection | 76 |
| 6.4.2 | Performance Comparison | 77 |
| 6.5 | Summary | 78 |
| | References | 81 |
| 7 | Posterior-neighborhood-regularized Latent Feature Learning | 85 |
| 7.1 | Overview | 85 |
| 7.2 | Related Work | 86 |
| 7.3 | A Posterior-Neighborhood-Regularized Latent Feature Model | 87 |
| 7.3.1 | Primal Latent Feature Extraction | 87 |
| 7.3.2 | Posterior-Neighborhood Construction | 88 |
| 7.3.3 | Posterior-Neighborhood-Regularized LFL | 89 |
| 7.4 | Performance Analysis | 91 |
| 7.4.1 | General Settings | 91 |
| 7.4.2 | Comparisons Between PLF and State-of-the-Art Models | 91 |
| 7.5 | Summary | 93 |
| | References | 93 |
| 8 | Generalized Deep Latent Feature Learning | 97 |
| 8.1 | Overview | 97 |
| 8.2 | Related Work | 98 |
| 8.3 | A Deep Latent Feature Model | 98 |
| 8.4 | Performance Analysis | 101 |
| 8.4.1 | General Settings | 101 |
| 8.4.2 | Effects of Layer Count in DLF | 101 |
| 8.4.3 | Comparison Between DLF and Related Models | 102 |
| 8.5 | Summary | 103 |
| | References | 106 |
| 9 | Conclusion and Outlook | 111 |
| 9.1 | Conclusion | 111 |
| 9.2 | Outlook | 111 |

About the Author

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