Preface

Graph embedding is a computational methodology aiming at representing data as a graph, along with the attributes attached to its nodes and edges. Derived from topological graph theory and algebra, the subject of graph embedding has become important and prominent worldwide with a wide spectrum of applications in pattern analysis, representation, visualization, and classification.

This book is composed of coherent chapters contributed by experts and researchers from both academia and industry in the fields of machine learning, applied statistics, artificial intelligence, computer vision, and pattern classification. Fundamental theories are presented in each chapter to help readers quickly gain the knowledge or review the essential topics. Case studies, experiments, and applications are also provided to further inspire the readers for insightful understanding.

This book may be used as an excellent reference book for researchers or major textbook for graduate student courses requiring minimal undergraduate prerequisites at academic institutions. Existing courses related or focused on graph embedding include the CSE 704 manifold and subspace learning of SUNY-Buffalo, EE364a convex optimization of Stanford University, and graph embedding for pattern recognition hosted by the ICPR 2010 conference in Istanbul.

Chapter "Multilevel Analysis of Attributed Graphs for Explicit Graph Embedding in Vector Spaces" provides the introduction of the graph embedding and describes the multilevel analysis of attributed graphs for explicit graph embedding. Chapter "Feature Grouping and Selection Over an Undirected Graph" presents a method for simultaneous feature grouping and sparseness structures over a given undirected graph and provides a convex and non-convex penalty function. Chapter "Median Graph Computation by Means of Graph Embedding into Vector Spaces" introduces the graph embedding from its solution on the graph representation for the computational complexity and in particular presents one graph embedding method: the median graph. Chapter "Patch Alignment for Graph Embedding" describes the patch alignment framework, which unifies the existing manifold learning-based dimension reduction algorithm and provides a general platform for specific algorithm design. Chapter "Feature Subspace Transformations for Enhancing K-Means Clustering" presents a feature subspace transformation method to transform the database and use the k-means clustering method after that. Motivated by the sparse representation for high-dimensional data analysis, chapter "Learning with ℓ^1-Graph for High Dimensional Data Analysis" presents a method to construct a robust $\ell 1$ graph and uses the $\ell 1$ graph for various machine learning tasks. Chapter "Graph-Embedding Discriminant Analysis on Riemannian Manifolds for Visual Recognition" presents a graph embedding method to embed Riemannian manifolds into reproducing kernel Hilbert spaces and employs many kernel-based learning algorithms. After introducing several linearization methods for subspace learning, chapter "A Flexible and Effective Linearization Method for Subspace Learning" presents a flexible manifold embedding method for semi-supervised and unsupervised subspace learning. Among many applications for horizontal anomaly detection, chapter "A Multi-graph Spectral Framework for Mining Multi-source Anomalies" presents a method to detect objects with inconsistent behavior using multiple information sources. Chapter "Graph Embedding for Speaker Recognition" presents the application of graph embedding to the speaker recognition.

We would like to sincerely thank all the contributors of this book for presenting their research in an easily accessible manner and for putting such discussion into a historical context. We would like to thank Brett Kurzman from Springer for support to this book project.

Boston, MA Yun Fu
Golden Valley, MN Yunqian Ma