



Giovanni Ponti

# Advances in Mining Complex Data: Modeling and Clustering



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**Giovanni Ponti**

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to Mari





# Preface

In the last years, there has been a great production of data that come from different application contexts. However, although technological progress provides several facilities to digitally encode any type of event, it is important to define a suitable representation model which underlies the main characteristics of the data. This aspect is particularly relevant in fields and contexts where data to be archived can not be represented in a fix structured scheme, or that can not be described by simple numerical values. We hereinafter refer to these data with the term *complex data*.

Although it is important define ad-hoc representation models for complex data, it is also crucial to have analysis systems and data exploration techniques. Analysts and system users need new instruments that support them in the extraction of patterns and relations hidden in the data. The entire process that aims to extract useful information and knowledge starting from raw data takes the name of *Knowledge Discovery in Databases* (KDD). It starts from raw data and consists in a set of specific phases that are able to transform and manage data to produce models and knowledge. There have been many knowledge extraction techniques for traditional structured data, but they are not suitable to handle complex data.

Investigating and solving representation problems for complex data and defining proper algorithms and techniques to extract models, patterns and new information from such data in an effective and efficient way are the main challenges which this thesis aims to face. In particular, two main aspects related to complex data management have been investigated, that are the way in which complex data can be modeled (i.e., *data modeling*), and the way in which homogeneous groups within complex data can be identified (i.e., *data clustering*). The application contexts that have been objective of such studies are *time series data*, *uncertain data*, *text data*, and *biomedical data*.

It is possible to illustrate research contributions of this thesis by dividing them into four main parts, each of which concerns with one specific area and data type:

**Time Series** — A time series representation model has been developed, which is conceived to support accurate and fast similarity detection. This model is called *Derivative time series Segment Approximation (DSA)*, as it achieves a concise yet feature-rich time series representation by combining the notions of *derivative estimation*, *segmentation* and *segment approximation*.

**Uncertain Data** — Research in uncertain data mining went into two directions. In a first phase, a new proposal for partitional clustering has been defined by introducing the *Uncertain K-medoids (UK-medoids)* algorithm. This approach provides a more accurate way to handle uncertain objects in a clustering task, since a cluster representative is an uncertain object itself (and not a deterministic one). In addition, efficiency issue has been addressed by defining a distance function between uncertain objects that can be calculated offline once per dataset.

In a second phase, research activities aimed to investigate issues related to hierarchical clustering of uncertain data. Therefore, an agglomerative centroid-based linkage hierarchical clustering framework for uncertain data (*U-AHC*) has been proposed. The key point lies in equipping such scheme with a more accurate distance measure for uncertain objects. Indeed, it has been resorted to *information theory* field to find a measure able to compare probability distributions of uncertain objects used to model uncertainty.

**Text Data** — Research results on *text data* can be summarized in two main contributions. The first one regards clustering of *multi-topic documents*, and a framework for hard clustering of documents according to their mixtures of topics has been proposed. Documents are assumed to be modeled by a generative process, which provides a mixture of probability mass functions (pmfs) to model the topics that are discussed within any specific document. The framework combines the expressiveness of generative models for document representation with a properly chosen information-theoretic distance measure to group the documents.

The second proposal concerns *distributional clustering of XML documents*, focusing on the development of a distributed framework for efficiently clustering XML documents. The distributed environment consists of a peer-to-peer network where each node in the network has access to a portion of the whole document collection and communicates with all the other nodes to perform a

clustering task in a collaborative fashion. The proposed framework is based on modeling and clustering XML documents by structure and content. Indeed, XML documents are transformed into *transactional data* based on the notion of *tree tuple*. The framework is based on the well-known paradigm of *centroid-based partitional clustering* to conceive the distributed, transactional clustering algorithm.

**Biomedical Data** — Research results on time series and uncertain data have been involved to support effective and efficient biomedical data management. The focus regarded both proteomics and genomics, investigating Mass Spectrometry (MS) data and microarray data. In the specific, a *Mass Spectrometry Data Analysis (MaSDA)* system has been defined. The key idea consists in exploiting temporal information implicitly contained in MS data and model such data as time series. The major advantages of this solution are the dimensionality and the noise reduction. As regards micrarray data, U-AHC has been employed to perform clustering of microarray data with probe-level uncertainty. A strategy to model probe-level uncertainty has been defined, together with a hierarchical clustering scheme for analyzing such data. This approach performs a gene-based clustering to discover clustering solutions that are well-suited to capture the underlying gene-based patterns of microarray data.

The effectiveness and the efficiency of the proposed techniques in clustering complex data are demonstrated by performing intense and exhaustive experiments, in which such proposals are extensively compared with the main state-of-the-art competitors.

*Giovanni Ponti*



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