Chapter 1.4
Mining in Music Databases

Ioannis Karydis
Aristotle University of Thessaloniki, Greece

Alexandros Nanopoulos
Aristotle University of Thessaloniki, Greece

Yannis Manolopoulos
Aristotle University of Thessaloniki, Greece

ABSTRACT

This chapter provides a broad survey of music data mining, including clustering, classification and pattern discovery in music. The data studied is mainly symbolic encodings of musical scores, although digital audio (acoustic data) is also addressed. Throughout the chapter, practical applications of music data mining are presented. Music data mining addresses the discovery of knowledge from music corpora. This chapter encapsulates the theory and methods required in order to discover knowledge in the form of patterns for music analysis and retrieval, or statistical models for music classification and generation. Music data, with their temporal, highly structured and polyphonic character, introduce new challenges for data mining. Additionally, due to their complex structure and their subjectivity to inaccuracies caused by perceptual effects, music data present challenges in knowledge representation as well.

INTRODUCTION

Musical analysis is recognised as a significant part of the study of musical cognition. The analysis of music data has the objective of determining the fundamental point of contact between mind and musical sound (musical perception) (Bent, 1980). Musical analysis is the activity musicologists are engaged in and is conducted on a single piece of music, on a portion or element of a piece or on a collection of pieces. This research area embays the field of *music data mining* (henceforth called *music mining*), which deals with the theory and methods of discovering knowledge from music pieces and can be considered as a collection of (semi-) automated methods for analysing music data.

Following music-mining methodologies, music analysts extract[1] recurring structures and their organisation in music pieces, trying to understand the style and techniques of composers (Rolland & Ganascia, 2002). However, the size and peculiarities of music data may become prohibitive factors for the aforementioned task. This represents an analogy to the difficulties faced by data analysts when trying to discover patterns from databases, i.e., the huge database sizes and the large number of dimensions, which are the very reasons that paved the way for the development of *database mining,* a.k.a. *data mining* or *knowledge discovery from databases* (*KDD*). Despite the previously mentioned analogy between music mining and database mining, the nature of music data requires the development of radically different approaches. In the sequel to this section we will summarise the particular challenges that music mining presents.

Another key issue in which music mining differs from other related areas (for instance, database mining or Web mining) is the applications it finds. Discovered patterns from relational or other types of databases are usually *actionable*, in the sense that they may suggest an action to be taken. For instance, association rules from market-basket data may indicate an improvement in selling policy, or user-access patterns extracted from a Web-log file may help in redesigning the Web site. Such kinds of "actionability" are related to a form of "profit" and stem from the involved industry field (e.g., retail, insurance, telecommunications, etc.). The question, therefore, emerges: "Which is the usability of patterns extracted from music data?" In order to answer this question, one has to consider the current status of the involved industry, that is, the "music industry." The influence that music has always had on people is reflected in music commodities and services that are offered today.[2] The annual gains of the music industry are estimated to reach up to several billion dollars (Leman, 2002). Within this context, the music content is a source of economical activity. This is intensified by the ease that the Web has brought in the delivery of music content; a prominent example of this case is Napster. What is, thus, becoming of significant interest is the need for content-based searching within music collections, e.g., by using a Karaoke machine to retrieve similar songs over a Web site or by humming over a mobile phone to download a song. The corresponding research field that has been developed is called *content-based music information retrieval* (CBMIR) (Lippincott, 2002; Pfeiffer, Fischer, & Effelsberg, 1996).

It is natural, therefore, to anticipate that music mining finds applications in designing effective CBMIR systems. In fact, CBMIR has considerably biased the directions that research in music mining is now following by stating the objectives to be achieved. The contribution of music mining in CBMIR is better understood by considering that the extracted patterns describe and represent music content at different abstraction levels (e.g., by producing concept taxonomies). The description of music content with such representations helps users in posing queries using content descriptors (rational or emotional), which drastically improve the effectiveness of retrieval in CBMIR systems (Leman, 2002), compared to simplistic search using plain text descriptors like song titles or the composers' names. Additionally, searching times are decreased, since the extracted patterns constitute a more compact representation of music content. The advantages from both the aforementioned directions are evident in a broad range of commercial domains, from music libraries to consumer oriented e-commerce of music (Rolland & Ganascia, 2002).

The Challenges of Music Data Mining

Byrd and Crawford (2002) list several reasons for which it is difficult to manage music data. Since most of these issues are inherent in music data due to their nature, they also affect the process of music data mining. In particular, among the most significant problems and difficulties that arise in data mining, are: