

# Music Score Analysis with Process Mining

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**Abstract**—Process mining is applied to a wide variety of use cases, most typically for processes like order-to-cash and purchase-to-pay. Respective algorithms are able to discover bottlenecks, identify recurring patterns and deal with concept drifts. So far, use cases in cultural heritage scenarios are scarce. Yet, music scores provide an ideal opportunity for process mining algorithms; they are structured into notes, measures, repetitions, parts, instruments, etc. Additionally, compelling characteristics are inherent, like varying dynamics, transformations by modulations, and phase delays such as in a fugue. In this demo article, we present a tool that is able to do process-style analysis of music scores<sup>1</sup>. Most notably, it transforms scores into an event log and performs basic process discovery. We see potential not only for music theorists, but also as pedagogical tool to illustrate process mining concepts and as a means to produce event logs for advancing process mining techniques.

**Index Terms**—Process Mining, Music Analysis, Cultural Heritage

## I. INTRODUCTION

Process mining is used in a wide variety of use cases for all kinds of industrial and societal processes [1]. Event logs are at the baseline, they contain sequences of events that describe the execution of a process. Taking event logs as starting point, process mining can be used to automatically discover, monitor, and improve processes. For example, it can discover how a process is actually being executed, to find bottlenecks, or to identify opportunities for improvement. Process mining is a relatively new field, yet it is a valuable tool for any organization that wants to improve its business processes.

Use cases in the field of cultural heritage are rare so far. For instance, process mining techniques have been compared to the methodological tool *chaîne opératoire* common in archaeology [2]. We have not found any applications of process mining in music, despite the obvious parallels: Music pieces are usually denoted in a strongly formalized notation called scores. Especially orchestral pieces deal with a lot of concurrency by the instruments; in history, there were quite a few genres with similar patterns like repetitions and variations. We postulate the following research question: How can music scores be processed so that existing process mining tools can be used to analyze musical pieces?

In this demo paper, we present a proof-of-concept tool that is able to transform musical scores in the popular MusicXML notation to event logs. This enables new interpretations of musical art, for instance, by analyzing rhythm and repetitions in a process-oriented visualization. Specifically, we encode a piano piece of a recent number one hit single as event log.

The visualized results are surprisingly clear. Therefore, we are optimistic that this type of analysis can help advance not only music theory but also process mining by making the large body of music scores available as event logs. Our tool can also be used as a pedagogical instrument to vividly explain business process management concepts.

## II. PARALLELS TO PROCESS ANALYTICS

Regarding music and data mining, there not many related work applying standard data mining methods to music; a notable exception is the book Music Data Mining [3]. Baratè et al. present a musicological analysis with Petri nets as formal tools for studying concurrent, asynchronous, and parallel processes [4]. They focus on extracting groups from music scores as objects, such as episodes, themes, and rhythmic patterns, to visualize them as transition system. Musical set theory as a subdiscipline of music theory similarly organizes musical objects and describes their relationships to discover deep structures (e.g., [5]).

Besides the concurrency and repetitional characteristics, there are further features in music scores with exemplary equivalents in process analytics (in alphabetical order):

**Chord** Group of multiples notes played together; stands for activity variants.

**Dynamics** The volume of (a sequence of) notes; could represent the amount of resources consumed.

**Modulation** Refers to a key change, if a melody is replayed on a different base note; corresponds to concept drifts.

**Note** Basic unit of a score, besides pauses; can be considered the most fine-grained activity.

**Repetition** Looped parts, often explicitly denoted variations; stands for re-executions.

**Rhythm** A sequence of beats forming recognizable patterns; could represent the timing of events.

**Tempo** How fast the piece is played, corresponds to the execution speed.

Typically, these are combined in infinite possible variations. Throughout history, particular styles have formed, such as the fugue, where a musical theme is repeated in various pitches and through different instruments. It is trivial to see further parallels to process mining techniques such as frequent pattern mining and local process models.

## III. MINING APPROACH AND EXAMPLE

Our general approach is as follows. First, we parse a digital music score file. Currently, the entire piece of music is considered as one case. In a preprocessing step, we either

<sup>1</sup>The tool and a demo video are available at <https://istvank.eu/musicpm>



Fig. 1. Characteristic first and last measure from “As It Was” by Harry Styles; this measure corresponds to an activity.

select a single part (e.g., the left or right hand in a piano piece, or a specific instrument in a classic orchestra piece), or merge all notes played in parallel. We then step through the score, following repetitions, and create one activity per unique measure, c.f. Figure 1. As activity, we serialize the measure and reuse existing activities, if the same musical pattern has already been discovered. Based on the annotated tempo, we calculate a timestamp for each measure.

Our implementation is based on a Python script with the music21 library. The library is able to parse a number of digital music score formats, including the popular MusicXML, an XML-based data format. We map the input of the measures as PM4Py Event objects. PM4Py is then used to export the log as XES file and display the resulting process model.

As example piece, we chose a fairly simple piano arrangement of the worldwide number one hit “As It Was” by Harry Styles, as a MusicXML file. It is a suitable example, as the characteristic sequence shown in Figure 1 fits in one measure and is repeated several times. The resulting process model as directly-follows graph (DFG) is shown in Figure 2. It is very easy to see that the melody known from Figure 1 (when the left hand has a break) forms the first and the last measure of the song. In addition, several repetitive patterns can be recognized, including a large one, as well as the repeated succession of the characteristic sequence  $\{m5, m6, m7, m8\}$ . In the web frontend, the activities in the process model can be clicked to replay the corresponding notes as audio.

#### IV. DISCUSSION AND OUTLOOK

In this paper, we positioned process mining as technique to analyze music. This is possible, since music scores share many characteristics with business processes. As proof-of-concept, we presented a tool that transforms musical notation into event logs, so that hundreds of process mining techniques can be applied directly. In the demo, we analyzed the 2022 hit “As It Was” by Harry Styles, by transforming a piano arrangement as event log and creating a DFG.

As a next step, we plan to realize further activity notions beyond measures, such as complete melodies, and thereby validate event abstraction techniques. Similarly, we experiment with our case notion to possibly infer the process behavior of entire musical epochs. With Object-Centric Event Logs, we could model the concurrent interplay of multiple instruments and the resolution of measures to notes. We plan to discuss our tool with music theorists to evaluate its applicability. It could give a new perspective for the analysis of large music collections, e.g., the whole *Köchel catalogue*, a collection of compositions by Wolfgang Amadeus Mozart. Process models as preprocessed scores could also serve as intermediary

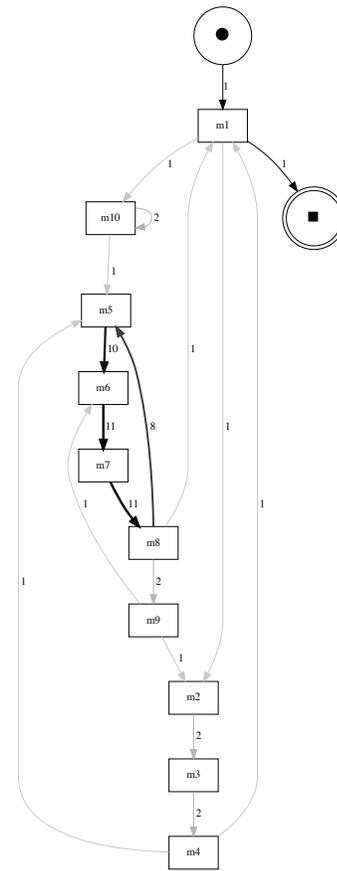


Fig. 2. Entire song “As It Was” by Harry Styles as DFG of the part played by the left hand; activities represent measures, arc labels show frequencies.

inputs to machine learning algorithms that output creative compositions or be used to explain them. Given the large body of available music scores, our tool could help advancing process mining techniques by providing countless (acoustically replayable and explainable) examples for training, or be used in teaching to illustrate BPM concepts.

Besides music scores, our approach is easily transferable to streaming settings by capturing live music. This would make the parallels to techniques such as conformance checking even clearer, as slight variations like length and hitting a wrong note are recognizable as deviations.

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