Bridging Constraint-based Sequential Pattern Mining and Machine Learning

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Abstract

In this tutorial, we focus on constraint-based sequential pattern mining and present a hands-on introduction to the open-source Seq2Pat: Sequence-to-Pattern generation library. Seq2Pat is designed to search for frequent patterns in large-scale sequence databases with a declarative modeling frontend to specify constraints on the desired properties of patterns. Beyond traditional pattern mining, the particular focus of this tutorial is to bridge pattern mining and machine learning to utilize patterns found in training predictive models. We show how Seq2Pat can serve as an integrator technology between raw sequential data and learning tasks. This is demonstrated on real-world applications from digital behavior analysis for intent prediction and intruder detection.

1 Introduction

Sequential Pattern Mining (SPM) is highly relevant in various practical applications including the analysis of medical treatment history (Bou Rjeily et al. 2019), user purchases (Requena et al. 2020), call patterns, and digital clickstream (Agrawal and Srikant 1995; Srikant and Agrawal 1996). A recent survey can be found in (Gan et al. 2019).

In SPM, we are given a set of sequences that is referred to as sequence database. As shown in the example in Table 1, each sequence is an ordered set of items. Each item might be associated with a set of attributes to capture item properties, e.g., price, timestamp. A pattern is a subsequence that occurs in at least one sequence in the database maintaining the original ordering of items. The number of sequences that contain a pattern defines the frequency. Given a sequence database, SPM is aimed at finding patterns that occur more than a certain frequency threshold.

In practice, finding the entire set of frequent patterns in a sequence database is not the ultimate goal. The number of patterns is typically too large and may not provide significant insights. It is thus important to search for patterns that are not only frequent but also capture specific properties of the application at hand. This has motivated research in Constraint-based SPM (CSPM) (Pei, Han, and Wang 2007; Chen et al. 2008). The goal of CSPM is to incorporate constraint reasoning into sequential pattern mining to find smaller subsets of interesting patterns.

As an example, let us consider online retail clickstream analysis. We might not be interested in all frequent browsing patterns. For instance, the pattern ⟨login, logout⟩ is likely to be frequent but offers little value. Instead, we seek recurring clickstream patterns with unique properties, e.g., frequent patterns from sessions where users spend at least a minimum amount of time on a particular set of items with a specific price range. Such constraints help reduce the search space for the mining task and help discover patterns that are more effective in knowledge discovery than arbitrarily frequent clickstreams.

Regarding pattern mining tools to utilize in practice, the Python tech stack lacks readily available libraries. Although a few Python libraries exist for SPM, see, e.g., (Gao 2019; Dagenais 2016), Seq2Pat is the first CSPM library in Python that supports several anti-monotone and non-monotone constraint types. Unfortunately, other CSPM implementations are either not available in Python, hence missing the opportunity to integrate with ML applications, or limited to a few constraint types, most commonly, gap, maximum span, and regular expressions (Yu and Hayato 2006; Bermingham 2018; Aoga, Guns, and Schaus 2016; Fournier-Viger et al. 2016).

In our recent AAAI-IAAI 2022 paper (Wang et al. 2022), we introduced the Seq2Pat library¹ to fill this gap. Building on this approach, we then proposed the Dichotomic Pattern Mining (DPM) framework in subsequent papers (Wang and Kadioglu 2022; Ghosh et al. 2022). DPM supports the end-to-end solution framework for CSPM applications and their deployment in real-world scenarios. This tutorial is based on these recent papers by the presenters, in collaboration with other researchers from academia and practitioners from industry.

Table 1: Example sequence database with three sequences.

<table>
<thead>
<tr>
<th>SEQUENCE DATABASE ⟨(item, price, timestamp)⟩</th>
</tr>
</thead>
<tbody>
<tr>
<td>⟨(A, 5, 1), (A, 5, 1), (B, 3, 2), (A, 8, 3), (D, 2, 3)⟩</td>
</tr>
<tr>
<td>⟨(C, 1, 3), (B, 3, 8), (A, 3, 9)⟩</td>
</tr>
<tr>
<td>⟨(C, 4, 2), (A, 5, 5), (C, 2, 5), (D, 1, 7)⟩</td>
</tr>
</tbody>
</table>

¹https://github.com/fidelity/seq2pat
2 Tutorial Outline

This tutorial is designed to cover the following sections blending presentation with live demos using publicly available notebooks\(^1\). The main learning objective is to enable participants with a practical knowledge of the field ready to uptake Seq2Pat in their applications.

2.1 Background

We start with an introduction to sequence databases and the problem definition for SPM and CSPM with illustrative examples. We also briefly touch base on Multi-valued Decision Diagrams (MDD) (Bergman et al. 2016; Hosseininasab, van Hoeve, and Ciré 2019) as the underlying technology behind Seq2Pat.

2.2 Sequence-to-Pattern Generation

The tutorial continues with the presentation of Seq2Pat (Wang et al. 2022), the supported types of constraints, and a demo of usage examples. In the running demo, we show how Seq2Pat supports traditional SPM, and then, how constraints are added in a declarative way to evolve from SPM to CSPM.

2.3 Dichotomic Pattern Mining

Next, we move beyond pattern mining and consider the case where sequence databases are associated with positive and negative outcomes. This is often the case in practice where a subset of sequences lead to desired outcomes while the rest ends in the opposite. For these scenarios, we introduce our Dichotomic Pattern Mining (DPM) framework (Wang and Kadioglu 2022) which embeds Seq2Pat to find the frequent sequences that uniquely distinguish positive sequences from negative sequences.

2.4 Bridging Mining and Learning

The tutorial so far covers the constraint-based pattern mining and its extension to the dichotomic setting. Nevertheless, this is still in the realm of traditional pattern mining where the goal is limited to knowledge extraction for post-analysis.

The main contribution of this tutorial is to bridge the mining approach with machine learning. To that end, we present the idea of enhancing sequence-to-pattern generation with pattern-to-feature generation. The goal of pattern-to-feature generation is to transform the extracted patterns into feature vectors that can be used in machine learning models as input for downstream prediction tasks.

For pattern-to-feature generation, we present two possible approaches. The first approach is based on a search algorithm with rolling windows, and the second approach is based on formulating the problem as a constraint-satisfaction. The constraint-satisfaction problem is then modeled and solved via Constraint Programming (CP). We discuss the trade-offs between solving the feature generation problem locally versus globally, and pose a challenge to the CP/SAT community to increase the efficiency of constraint models for faster resolution as needed in large-scale problems relevant to industry applications.

2.5 Applications in Digital Behavior Analysis

Finally, to highlight the practical relevance of the tutorial and inspire other applications, we cover two real-world scenarios based on digital behavior analysis.

As shown in our recent work (Ghosh et al. 2022), DPM serves an integration technology between raw sequential data to machine learning models in downstream applications. We present the case for Intent Prediction Problem based on clickstream sequences of shoppers from a fashion retailer in e-commerce. The positive and negative outcomes are exhibited in purchasing behavior, which can be distinguished via extracted patterns from Seq2Pat. Next, pattern-to-feature generation leads to features for machine learning models to predict shopper intent.

The main take-aways from the intent prediction application are as follows:

- Our framework enables classical machine learning algorithms (e.g., Logistic Regression), which inherently cannot deal with sequence data, to operate on features extracted from sequences. This is an indirect approach for sequence modeling as opposed to direct approaches such as Recurrent Neural Networks and its extensions.
- We compare the performance of the indirect approach with sophisticated machine learning algorithms (e.g., Long Short-Term Memory (LSTM)) that operates on sequences directly.
- We highlight promising results with the added benefit of retaining the interpretable nature of linear models as opposed to latent embeddings used in deep neural networks.
- Moreover, our approach allows data augmentation, in which we combine LSTM models with Seq2Pat features for the best prediction performance.

The same findings are also shown for Intruder Detection Problem emerging in sequential log analysis.

2.6 Tutorial Presenters

The tutorial is presented by Xin Wang and Serdar Kadioğlu. Their short biography is highlighted below.

**Xin Wang** is a Principal Data Scientist in the AI Center of Excellence at Fidelity Investments. Previously, he was a Research Scientist at Philips Research North America. Dr. Wang obtained his doctorate from the Dept. of Computer Science at University of Connecticut. His applied research expertise covers Machine Learning, Data Mining, Optimization, and Recommender Systems.

**Serdar Kadioğlu** is the Group Vice President of Artificial Intelligence in the AI Center of Excellence at Fidelity Investments and an Adjunct Associate Professor in the Dept. of Computer Science at Brown University. Previously, he led the Advanced Constraint Technology Research and Development team at Oracle and worked at Adobe. Dr. Kadioğlu’s algorithmic research is at the intersection of Artificial Intelligence and Discrete Optimization with practical interests in building robust and scalable products while contributing to the open-source ecosystem.

\(^1\)https://github.com/fidelity/seq2pat/tree/master/notebooks
References


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