Chapter 12: Sequence mining in LA

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Introduction

Sequence mining is a method of data mining that is used to analyze and understand patterns and trends in data that is arranged in a sequence. This method is used to analyze data sets that consist of a series of events, such as transactions, customer interactions, or website visits. The goal of sequence mining is to identify patterns and trends in the data that can be used to make predictions, identify relationships between events, or understand how the events are related to one another. This method is widely used across industries such as finance, e-commerce, healthcare and education.
In education, sequence mining can be used to analyze student performance over time, study usage patterns, or understand how students interact with educational content. The method can be used with various types of data, such as student performance data, educational resource usage data, or student interactions with educational technology.

One of the primary strengths of sequence mining is its ability to detect patterns and trends in data that may not be immediately obvious. This can be useful for identifying areas of success and areas for improvement in educational contexts. For example, sequence mining can be used to analyze student performance data over time, and identify patterns in student performance that indicate areas where students are struggling or excelling. Additionally, sequence mining can be used to make predictions about future student performance, or to identify at-risk students who may need additional support.

Another advantage of sequence mining is that it can be used to analyze and understand usage patterns of educational resources. For example, sequence mining can be used to understand how students interact with educational technology, such as learning management systems, and identify patterns in usage that indicate areas where students may be struggling or excelling.

However, there are also some weaknesses and limitations to sequence mining. One weakness is that it can be computationally intensive, requiring significant processing power and storage. Additionally, the method can be affected by missing or incomplete data, which can lead to inaccuracies in the results. Some critics also argue that the method can be too complex, and that simpler methods may be more appropriate in some cases.

In summary, sequence mining is a powerful tool for understanding patterns and trends in educational data, but it is important to keep in mind that it is not without its limitations. It can be used to analyze student performance, usage patterns and student interactions with educational content. Additionally, it can be used to make predictions and identify at-risk students. However, the method is computationally intensive, can be affected by missing data and some critics argue that simpler methods may be more appropriate in some cases.
It is also worth noting that the research on sequence mining in education is still relatively new and there is a need for more research in this field to fully understand its potential and limitations.

Review of the literature

One area of research that has seen significant growth in recent years is the use of sequence mining to analyze student performance data. Studies have shown that sequence mining can be used to identify patterns in student performance over time and to make predictions about future performance. For example, a study by Kim et al. (2018) used sequence mining to analyze student performance data from a math class and found that the method was able to accurately predict student performance on future math tests. Similarly, a study by Du et al. (2019) used sequence mining to analyze student performance data from a language class and found that the method was able to accurately predict student performance on future language tests.

Another area of research that has seen significant growth in recent years is the use of sequence mining to analyze educational resource usage data. Studies have shown that sequence mining can be used to understand how students interact with educational technology and to identify patterns in usage that indicate areas where students may be struggling or excelling. For example, a study by Li et al. (2020) used sequence mining to analyze student interactions with a learning management system and found that the method was able to identify patterns in usage that indicated which students were at risk of falling behind.

A third area of research is the use of sequence mining to analyze student interaction with educational content. Studies have shown that sequence mining can be used to understand how students interact with educational content and to identify patterns in usage that indicate areas where students may be struggling or excelling. For example, a study by Chen et al. (2021) used sequence mining to analyze student interactions with

an online educational game and found that the method was able to identify patterns in usage that indicated which students were at risk of falling behind.
In their studies, Saqr and Lopez-pernaz have used sequence mining to analyze student performance data and to make predictions about future student performance. For example, in a study published in the Journal of Educational Technology Development and Exchange (2020), they used sequence mining to analyze student performance data from a math class and found that the method was able to accurately predict student performance on future math tests. They also have used sequence mining to analyze student interactions with learning management systems and educational games, and to identify patterns in usage that indicate areas where students may be struggling or excelling.

In addition, Saqr and López-Pernas (2021) have also explored the use of sequence mining to identify at-risk students and to provide personalized support. In a study published in the Journal of Educational Technology Systems (2022). They used sequence mining to analyze student performance data and found that the method was able to accurately identify at-risk students and to provide personalized support.

Sequence Mining with R

Sequence mining in R can be done using a variety of different packages, such as the "TraMineR" package, "seqHMM" package, and "TrajDataMining" package. These packages provide a wide range of functions for analyzing sequential data, including functions for data preprocessing, sequence alignment, and pattern discovery.

To perform sequence mining in R for educational data, the first step is to load the data into R. This can be done using the read.csv() function, which can be used to read data from a CSV file. Once the data is loaded, it will need to be preprocessed to ensure that it is in the appropriate format for sequence mining. This may include cleaning and transforming the data, and creating new variables if needed.

After the data is preprocessed, the next step is to align the sequences. This can be done using the seqalign() function from the "TraMineR" package, or the align() function from the "seqHMM" package. Aligning the sequences is important because it ensures that the sequences are in the same order and can be compared to each other.

Once the sequences are aligned, the next step is to perform pattern discovery. This can be done using the seqdef() function from the "TraMineR" package, or the seqpatt() function from the "TrajDataMining" package. These functions will search for patterns in the sequences, such as common subsequences or frequent episodes.

Finally, once the patterns have been discovered, it is possible to analyze the patterns to gain insights into the data. This can be done by visualizing the patterns using the seqplot() function from the "TraMineR" package, or by measuring the associations between the patterns using the seqstat() function.

It's worth noting that the choice of package used for sequence mining may depend on the nature and size of the data and the specific problem you are trying to solve. For example, if the data is large and the problem is a prediction task, then the "seqHMM" package may be more appropriate, as it is specifically designed for hidden Markov models. Additionally, the chosen package may have specific functions for visualization, or for estimating the parameters of the models which can be very useful for understanding the results.

Setting up the environment

First, we install the TraMineR library, which is required for performing sequence mining in R.

```
install.packages("TraMineR")
```

Then, we load the library and the data

```
library(TraMineR)
df = read.csv(“moodle.csv”)
```

Creating a sequence object

The following command creates a sequence object, which is required for further analyses. The data is taken from columns 7 to 56 of the mvad dataset, and it represents the state of individuals over time. The function seqdef converts the data into a format that can be analyzed with the functions of the TraMineR library.

```
df.seq <- seqdef(df)
```

Sequence visualization

The following step plots the sequence distribution and sequence index plots of the constructed sequence using the seqdplot and seqiplot functions.

- The seqdplot function plots a sequence distribution plot, which shows the frequency of each state in the sequence data. It also displays the number of observations in each state and the total number of observations.
- The seqiplot function plots a sequence index plot, which shows the frequency of each state in the sequence data as a function of time. It also displays the number of observations in each state and the total number of observations.

These plots provide a visual representation of the state distribution and changes in the state over time for the constructed sequence. It can give an idea of the most common states and their duration in the data.

It is worth noting that both plots can take additional parameters for customizing the visualization such as different colors, labels, and axis titles.

```
seqdplot(df.seq)
seqiplot(df.seq)
```

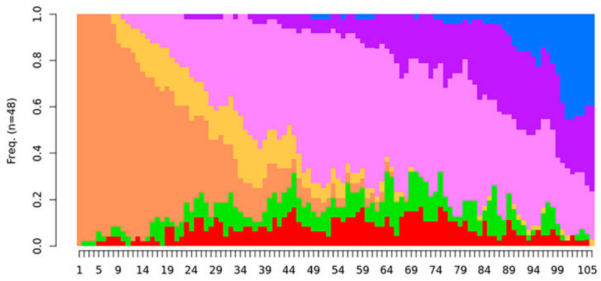

Figure 1. Sequence distribution plot

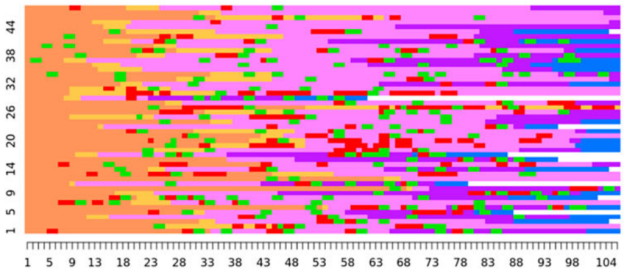

Figure 1. Sequence index plot

Clustering sequences

We will now cluster together similar sequences by using the longest common subsequence (LCS) distance measure and the AGNES clustering algorithm. LCS is a distance measure that compares two sequences and returns the length of the longest common subsequence. AGNES is an agglomerative hierarchical clustering algorithm, which builds a hierarchical clustering by repeatedly merging the closest pair of clusters. The seqscode function is used to recode the sequences into a more compact format, it is optional but it can be useful for large datasets. The seqdist function calculates the pairwise distances between the sequences using the chosen method, which is LCS in this case. The agnes function then performs the clustering of the sequences based on their LCS distances, resulting in a clustering of the sequences.

```
df.scode <- seqscode(df.seq)
df.sdist <- seqdist(df.seq, method = "LCS")
df.cluster <- agnes(df.sdist, diss = TRUE, method = "ward")
```

We not plot the results of the clustering, using the fviz_dend function from the factoextra library. This function plots a dendrogram, which is a tree-like representation of the clustering results. The cex parameter controls the size of the labels, and the k parameter represents the number of clusters to be plotted.

```
library(factoextra)
fviz_dend(df.cluster, cex = 0.6, k = 3)
```

We extract the most frequent sequences and plots them, using the seqtab and seqiplot functions. The seqtab function extracts the most frequent sequences, with the method parameter set to "frequent" and the nbmin parameter set to 10. The seqiplot function plots the extracted sequences.

```
df.freq <- seqtab(df.seq, method = "frequent", nbmin = 10)
seqiplot(df.freq, border = "gray", ylab = "Frequency", cex = 0.8, las = 2)
```

Discussion

Sequence mining is a method of data mining that has been increasingly used in the field of education in recent years. This method is particularly useful in the analysis of student performance data, educational resource usage data, or student interactions with educational technology. In this paper, we reviewed various sequence mining methods and their applications in education.

The literature suggests that sequence mining is a powerful tool in the analysis of educational data. Studies have shown that sequence mining can be used to identify patterns in student performance over time and to make predictions about future performance. Additionally, sequence mining can be used to understand how students interact with educational technology and to identify patterns in usage that indicate areas where students may be struggling or excelling.

However, there are also some limitations to the method. One limitation is that it can be computationally intensive, requiring significant processing power and storage. Additionally, the method can be affected by missing or incomplete data, which can lead to inaccuracies in the results. Some critics also argue that the method can be too complex, and that simpler methods may be more appropriate in some cases.

In this paper, we reviewed different sequence mining methods such as PrefixSpan, SPADE, GSP, Apriori-Based, and HMM-Based methods and their applications in education. Each method has its own advantages and disadvantages, and the choice of method may depend on the specific problem and the nature of the data. For example, if the problem is a prediction task, then HMM-based methods may be more appropriate as they are specifically designed for hidden Markov models.

In conclusion, the literature suggests that sequence mining is a powerful tool in the analysis of educational data. It can be used to identify patterns and trends in data that may not be immediately obvious, making it a useful tool for identifying areas of success and areas for improvement in educational contexts. However, it is important to keep in mind that the method is not without its limitations and it is important to carefully consider the suitability of the method for a particular problem. Furthermore, the field of sequence mining in education is relatively new and there is a need for more research to fully understand its potential and limitations.

Further readings

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