Discovering Exclusive Patterns in Frequent Sequences

International Journal of Data Mining, Modelling and Management
2010 2(3), pp.252-267

Weiru Chen, Jing Lu, Malcolm Keech

http://inderscience.metapress.com/content/82h2g74424746278/

Discovering exclusive patterns in frequent sequences

Weiru Chen

Faculty of Computer Science and Technology,
Shenyang Institute of Chemical Technology, Shenyang China
E-mail: WillC@china.com

Jing Lu*

School of Computing and Communications,
Southampton Solent University, East Park Terrace, Southampton UK
E-mail: Jing.Lu@solent.ac.uk
*Corresponding Author

Malcolm Keech

Faculty of Creative Arts Technologies and Science,
University of Bedfordshire, Park Square, Luton UK
E-mail: Malcolm.Keech@beds.ac.uk

Abstract: This paper presents a new concept for pattern discovery in frequent sequences with potentially interesting applications. Based on data mining, the approach aims to discover exclusive sequential patterns (ESP) by checking the relative exclusion of patterns across data sequences. ESP mining pursues the post-processing of sequential patterns and augments existing work on structural relations patterns mining. A three phase ESP mining method is proposed together with component algorithms, where a running worked example explains the process. Experiments are performed on real-world and synthetic datasets which showcase the results of ESP mining and demonstrate its effectiveness, illuminating the theories developed. An outline case study in workflow modelling gives some insight into future applicability.

Keywords: frequent sequences; sequential patterns post-processing; exclusive sequential patterns (ESP); ESP mining; workflow modelling.

Biographical notes: Professor Weiru Chen is the Dean of the Faculty of Computer Science and Technology at the Shenyang Institute of Chemical Technology (SYICT), China. He received his BSc in Computer Application (1985) from Dalian University of Technology, China, and MSc in Computer Science and Application (1988) from Northeastern University, China. His research interests include software architecture, software reliability engineering, data mining and grid computing, and he is also a Director of the Liaoning Computer Federation in China.

Dr Jing Lu is a Research Fellow in Computer Science at Southampton Solent University, UK. Her research focus lies in data mining and sequential patterns post-processing, with particular application to web access patterns mining and modelling. Jing Lu has been engaged in curriculum design, research and consultancy in knowledge management and intelligent systems at the University since the start of 2007. Jing was awarded her PhD in late

2006 from the University of Bedfordshire in the area of knowledge discovery and data mining.

Dr Malcolm Keech is Associate Dean, Creative Arts Technologies & Science at the University of Bedfordshire. He has worked extensively in computing and IT development and management, both in the academic and industrial sectors. While Malcolm's original subject background lies in mathematics (BA Oxford, MSc/PhD Manchester), his professional experience includes periods at the London School of Economics, the Universities of London and Manchester, Florida State University, British Telecom and British Aerospace.

1 Introduction

Discovering sequential patterns from very large databases is an important data mining application. The conceptual approach and original mining method were first introduced by Agrawal & Srikant (1995) using a sequence database as input, where each data sequence consists of a list of items, and given a user-specified minimum support threshold. Sequential patterns mining aims therefore to find all of the frequent sub-sequences in the sequence database, i.e. those sub-sequences whose ratios of occurrence exceed the minimum support threshold.

Sequential patterns mining has featured in many application domains, e.g. the analysis of customer behaviour to discover frequent buying patterns; analysis of web access to discover user navigation patterns; prediction of natural disasters; and analyses of DNA and patients' medical records. Driven by the applications, several techniques for sequential patterns mining have been proposed in the literature (Pei et al., 2001; Zaki, 2001; Lin and Lee, 2005).

With the successful implementation of efficient and scalable algorithms for mining sequential patterns, related research areas have emerged. For example, frequent episodes in event sequences (Mannila et al., 1997; Atallah et al., 2004); path traversal patterns in web logs (Chen et al., 1998; Li et al., 2005); periodic patterns in time-stamped databases (Yang et al., 2001; Sheng et al., 2006); and structural relation patterns in sequence databases (Lu, Chen et al., 2008) all take the mining of sequential patterns to novel structured forms.

Structural relation patterns have been introduced to extend the search for complex patterns often hidden behind large sequences of data (Lu, Chen et al., 2008). Discovering these patterns is based on the post-processing of sequential patterns mining results: some sequential patterns may be supported by the same data sequence, and these have been called concurrent patterns; while some others may not possibly occur together in the same data sequence, and these have been called exclusive patterns. Furthermore, some sequential patterns may occur more than once in a data sequence, such that an iterative relationship can be expressed, and this was called an iterative pattern. Structural relation patterns is the general designation of patterns that consists of sequential patterns, concurrent patterns, exclusive patterns, iterative patterns and their composition.

Structural relation patterns mining has motivated the graph-based modelling of concurrent sequential patterns (Lu, Chen et al., 2010) and has also been applied in the web mining context for the identification of concurrency across web access patterns (Lu, Keech et al., 2009). This paper will focus on exclusive patterns, proposing specifically exclusive sequential patterns, and a corresponding mining method is described and explained through a running worked example. The relevance of the exclusive methodology is highlighted within the context of workflow modelling.

The remainder of the paper is structured as follows: the idea of exclusion in frequent sequences is introduced in section 2 and exclusive sequential patterns (ESP) are defined formally. In section 3, an ESP mining method is presented, which is specified along with its component algorithms. An experimental evaluation using real and synthetic datasets is given in section 4 which showcases the results of ESP mining. In section 5, we describe potential applications as well as indicate future research directions by suggesting a model to represent ESPs graphically.

2 Exclusion and Exclusive Sequential Patterns

This section first reviews the basic concepts in sequential patterns mining and then introduces formally the definition of exclusive sequential patterns and the problem of mining ESPs.

2.1 Preliminaries

We adopt the notation used in Prefixspan (Pei et al., 2001) for sequential patterns mining. Let $I=\{i_1,\ldots, i_t\}$ be a set of t items. A data sequence $S=\langle s_1,\ldots, s_l\rangle$ is an ordered list of items, where $s_i \in I$, $1 \leq i \leq l$, and s_i is also called an element of the sequence. The number of items in a sequence is called the length of the sequence. A data sequence of length l is called an l-sequence.

A sequence $S_1=\langle X_1, X_2,\ldots, X_u\rangle$ is contained in another sequence $S_2=\langle Y_1, Y_2,\ldots, Y_v\rangle$ if $u \leq v$ and there exist integers $1 \leq i_1 < i_2 < \ldots < i_u \leq v$ such that $X_j = Y_{i_j}$ $(1 \leq j \leq u)$, and it is denoted by $S_1 \angle S_2$. If sequence S_1 is contained in sequence S_2, then S_1 is called a sub-sequence of S_2 and S_2 a super-sequence of S_1.

A sequence database (SDB) is a set $\{S_1, S_2, \ldots, S_n\}$, where each S_i $(1 \leq i \leq n)$ is a data sequence. The support in SDB of any given data sequence S is defined as $Sup(S)=|\{S_i : S \subseteq S_i\}|/n$, where $|\ldots|$ denotes the number of sequences. Given a fraction minsup $(0 < minsup \leq 1)$ as the minimum support threshold, S is called a sequential pattern in SDB if $Sup(S) \geq minsup$. A sequential pattern is called a maximal sequence if it is not contained in any other sequential patterns.

Example 1 (Running example). Table 1 shows a sequence database SDB={<abdac>, <eaebcac>, <babfaec>, <afbacfc>} and the set of sequential patterns mined (SP) with a minsup of 50%. This will be used as a running worked example in the paper.

Table 1 A sample sequence database and its supported sequential patterns

Seq ID	Sequence	Sequential Patterns with minsup=50%
S_1	<abdac>	a, b, c, aa, **ab**, ac, ba, bc, aac, aba, abc, bac, abac
S_2	<eaebcac>	a, b, c, e, aa, **ab**, ac, **ae**, ba, bc, cc, ec, aac, aba, abc, acc, aec, bac, bcc, abac, abcc
S_3	<babfaec>	a, b, c, e, f, aa, **ab**, ac, **ae**, **af**, ba, bc, bf, ec, fa, fc, aac, aba, abc, abf, aec, afa, afc, bac, baf, bfc, fac, abac, abfc, afac, bafc
S_4	<afbacfc>	a, b, c, f, aa, **ab**, ac, **af**, ba, bc, bf, cc, fa, fc, aac, aba, abc, abf, acc, afa, afc, bac, baf, bcc, bfc, fac, abac, abcc, abfc, afac, bafc

2.2 Problem Definition

Given a sequence database SDB=$\{S_1, S_2,\ldots, S_n\}$; let α, β be two of the sequential patterns mined from SDB with minimum support threshold minsup and assume that α, β are not contained in each other.

With regard to a particular data sequence S∈SDB, sequential patterns α and β have an exclusive relationship if and only if one of them has occurred in S but not both, i.e. $((\alpha\angle S)\wedge\neg(\beta\angle S))\vee(\neg(\alpha\angle S)\wedge(\beta\angle S))$. This is represented by $[\alpha\text{–}\beta]_S$, where the notation '–' represents the exclusive relationship.

It may be interesting to detect exclusive relationships within the whole sequence database SDB or within a particular sub-set of SDB, i.e. those data sequences where either α or β or both appear. The exclusive degree can thus be absolute or relative as defined respectively below.

Definition 1. The absolute exclusion of sequential patterns α and β is defined by

$$\text{exclusion}(\alpha,\beta)=|\{S_k:[\alpha\text{–}\beta]_{S_k}\}|/n \quad (1)$$

where S_k∈SDB and $1\le k\le n$, while the relative exclusion of sequential patterns α and β is defined by

$$\text{exclusion}(\alpha,\beta)=|\{S_k:[\alpha\text{–}\beta]_{S_k}\}|/|\{S_k:(\alpha\angle S_k)\vee(\beta\angle S_k)|\quad (2)$$

It can be seen from formula (1) that absolute exclusion is defined as the fraction of data sequences that contains either α or β (not both); while the denominator of formula (2) is the number of relevant data sequences from SDB, i.e. the sub-set which contains either α or β (or both), and forms part of a relative measure.

Example 2 For the sequential patterns pair ab and ae shown in bold in Table 1, according to Definition 1, both its absolute exclusion and relative exclusion are the same, i.e. exclusion(ab,ae)=2/4=50%.

For another pair of sequential patterns ae and af, also shown in bold, the absolute exclusion can be calculated as

exclusion(ae,af)=2/4=50%;

while its relative exclusion is

exclusion(ae,af)=2/3≈67%.

The user-specified minimum support threshold (i.e. minsup) has been used as the frequency measurement for mining frequent itemsets and sequential patterns.

Another percentage value, the minimum exclusion threshold ($0<minexc\leq 1$), is introduced below to check the exclusive relationship of sequential patterns. The absolute exclusion of a pair of sequential patterns (e.g. α and β) is related to the total number of data sequences, while the focus of relative exclusion is on those data sequences which support either (or both) of α or β. We will use relative exclusion throughout the rest of the paper as the standard.

Definition 2. Let minexc be the user-specified minimum exclusion. If

$$exclusion(\alpha,\beta)\geq minexc$$

is satisfied, then α and β are called Exclusive Sequential Patterns (ESP). This is represented by ESP=[α–β] where there is no particular order, i.e. [α–β]=[β–α].

Therefore, further to Example 2, if minexc=65%, then only ae and af constitute an exclusive sequential pattern given by ESP=[ae–af]; if minexc=50%, there are two exclusive patterns, i.e. ESP={[ae–af], [ab–ae]}.

Problem statement: given a sequence database SDB={S_1, S_2,…, S_n} and sequential patterns mining results {sp_1,sp_2,…,sp_m} (i.e. sequential patterns which satisfy a minimum support threshold minsup), exclusive sequential patterns mining aims to discover the set of all exclusive patterns beyond a given user-specified minimum exclusion minexc.

Definition 3. An exclusive sequential pattern $ESP_1=[a_1–a_2]$ is contained in another exclusive pattern $ESP_2=[b_1–b_2]$ if $(a_1\angle b_1)\wedge(a_2\angle b_2)\vee(a_1\angle b_2)\wedge(a_2\angle b_1)$. This is denoted by $ESP_1\angle ESP_2$. Exclusive sequential patterns are called maximal if they are not contained in any other exclusive patterns.

For example, among exclusive sequential patterns [e–f], [e–af], [e–abf], [e–abfc] and [aec–abfc], because [e–f]∠[e–af]∠[e–abf]∠[e–abfc]∠[aec–abfc], the maximal exclusive pattern is [aec–abfc].

Extending the exclusive relationship to three sequential patterns α, β and γ results in $[\alpha–\beta–\gamma]_S$, that is $((\alpha\angle S)\wedge\neg(\beta\angle S)\wedge\neg(\gamma\angle S))\vee(\neg(\alpha\angle S)\wedge(\beta\angle S)\wedge\neg(\gamma\angle S))\vee(\neg(\alpha\angle S)\wedge\neg(\beta\angle S)\wedge(\gamma\angle S))$. And, more generally, let {sp_1,sp_2,…,sp_r} be a set of r sequential patterns mined under minimum support minsup. If they are not contained in each other, then $[sp_1–sp_2–\ldots–sp_r]_S$ represents r sequential patterns which are exclusive with respect to data sequence S.

Definition 4. The absolute exclusion of sequential patterns sp_1,sp_2,…,sp_r is defined as

$$exclusion(sp_1,sp_2,\ldots,sp_r)=|\{S_k:[sp_1–sp_2–\ldots–sp_r]_{S_k}\}|/n$$

where $S_k\in SDB$ and $1\leq k\leq n$, while the relative exclusion of sequential patterns sp_1,sp_2,…,sp_r is defined as

$$exclusion(sp_1,sp_2,\ldots,sp_r)=|\{S_k:[sp_1–sp_2–\ldots–sp_r]_{S_k}\}|/|S_k:(\exists i=1,...,r), sp_i\angle S_k|.$$

If $exclusion(sp_1,sp_2,\ldots,sp_r)\geq minexc$ is satisfied, then sp_1,sp_2,… and sp_r are called Exclusive Sequential Patterns.

3 ESP Mining Method and Algorithms

The exclusive relationship of any pair of sequential patterns can be checked following the problem definition above. It can be determined whether or not a pair constitutes an exclusive sequential pattern using Definitions 1 and 2 under a given minimum exclusion threshold. How to find all the possible exclusive combinations from a sequential patterns set is a challenging issue. This section will discuss the mining method for ESPs with a focus in particular on the search for pairs of exclusive patterns.

3.1 Support Data Structure

Before proposing the ESP mining method and component algorithms, a compact data structure called **support vector**, $Supp(sp_i)$, is defined for every sequential pattern sp_i $(1 \le i \le m)$ as:

$$Supp(sp_i)=\begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix},$$

where $v_k=1$ $(1 \le k \le n)$ if sequential pattern sp_i $(1 \le i \le m)$ is contained in data sequence S_k $(1 \le k \le n)$, i.e. $sp_i \angle S_k$; otherwise $v_k=0$.

For example, for the SDB in Table 1 and sequential patterns ae and af from the set SP,

$$Supp(ae)=\begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} \text{ and } Supp(af)=\begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}.$$

Putting all the support vectors together forms a **support matrix**, Supp[SDB,SP], with data sequences S_k $(1 \le k \le n)$ as rows and sequential patterns sp_i $(1 \le i \le m)$ as columns:

	sp_1	…	sp_i	…	sp_m
S_1	v_{11}	…	v_{1i}	…	v_{1m}
…	…	…	…	…	…
S_k	v_{k1}	…	v_{ki}	…	v_{km}
…	…	…	…	…	…
S_n	v_{n1}	…	v_{ni}	…	v_{nm}

$Supp[S_k,sp_i]=v_{ki}=1$ if $sp_i \angle S_k$ $(1 \le k \le n,\ 1 \le i \le m)$, i.e. sequential pattern sp_i $(1 \le i \le m)$ is contained in data sequence S_k $(1 \le k \le n)$; otherwise $Supp[S_k,sp_i]=v_{ki}=0$.

3.2 Pairwise Exclusion Method

Now we split the problem of mining exclusive sequential patterns into three phases and explain the approach based on the exclusion of pairs of patterns with the running example. Consider the sequence database SDB={<abdac>, <eaebcac>, <babfaec>, <afbacfc>} and sequential patterns SP={a, b, c, e, f, aa, ab, ac, ae, af, ba, bc, bf, cc, ec, fa, fc, aac, aba, abc, abf, acc, aec, afa, afc, bac, baf, bcc, bfc, fac, abac, abcc, abfc, afac, bafc} from Table 1 with minexc=65%.

The three main phases in the method are described below:

Phase 1. Initialisation. Construct the support matrix Supp[SDB,SP] – delete columns sp_d ($1 \le d \le m$) from Supp[SDB,SP] where $Supp[S_k,sp_d]=1$ ($\forall k$, $1 \le k \le n$). All 1s means these sequential patterns are supported by all the data sequences and they are not able to constitute an ESP with any other sequential pattern.

Construct the support matrix Supp[SDB,SP], which has four data sequences as rows and 35 sequential patterns as columns. By eliminating the columns with all 1s, this results in Table 2.

Table 2 A support matrix example

	e	f	ae	af	bf	ec	fa	fc	abf	...	afa	afc	bfc	fac	abfc	afac	bafc
S_1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
S_2	1	0	1	0	0	1	0	0	0	...	0	0	0	0	0	0	0
S_3	1	1	1	1	1	1	1	1	1	...	1	1	1	1	1	1	1
S_4	0	1	0	1	1	0	1	1	1	...	1	1	1	1	1	1	1

Phase 2. Exclusion Checking. We need to repeatedly check the exclusion of a given pair of sequential patterns and determine whether or not they constitute an exclusive pattern. First of all, generate all the possible pairs of sequential patterns (sp_i,sp_j), where $1 \le i \le m$, $1 \le j \le m$, $i<j$ and they are not contained in each other. Then, for each pair of sequential patterns (sp_i,sp_j), repeat the following:

a) Sum their support vectors as

$$Supp[S_k,sp_i]+Supp[S_k,sp_j];$$

b) Count the total number of entries in the resulting vector above which have value 1 and 2, denoted by w_1 and w_2 respectively;

c) Calculate the exclusion from

$$exclusion(sp_i,sp_j)= w_1/(w_1+ w_2)$$

d) If $exclusion(sp_i,sp_j) \ge minexc$, then sp_i and sp_j constitute an exclusive sequential pattern $[sp_i–sp_j]$.

For example, some of the possible combinations of the sequential patterns from Table 2 are: (e,f), (e,af), (e,bf), (e,fa), (e,fc), (e,abf), (e,afa), (e,afc), (e,bfc), (e,fac), (e,abfc), (e,afac),…, (ae,af),…, (afa,bfc), (afa,fac), (afa,abfc), (afc,bfc), (afc,fac), (bfc,fac), (bfc,afac), (fac,abfc), (abfc,afac).

Combinations such as (e,ae), (ec,aec) or (fc,abfc) are not taken further because one of their patterns is contained by the other in the pair.

Consider the shaded pair (ae,af) in Table 2 for example and sum the support vectors as follows:

$$Supp[S_k,ae]+Supp[S_k,af]=\begin{bmatrix}0\\1\\1\\2\end{bmatrix}.$$

Counting the total number of entries in the vector, i.e. $w_1=2$ and $w_2=1$, leads to an exclusion(ae,af) of $2/(2+1) \approx 67\% > 65\%$; therefore ae and af constitute an exclusive sequential pattern given by ESP=[ae–af].

Repeat the steps as above and, by the end, the complete set of 128 ESPs can be expressed as {[e–f], [e–af], [e–bf], [e–fa], [e–fc], [e–abf], [e–afa], [e–afc], [e–bfc], [e–fac], [e–abfc], [e–afac], [f–ae], [f–ec], [f–aec], [ae–af], [ae–bf], [ae–ec], [ae–fa], [ae–fc], [ae–abf], [ae–afa], [ae–afc], [ae–bfc], [ae–fac], [ae–abfc], [ae–

afac], [af–aec], [bf–ec], [bf–aec], [ec–fa], [ec–fc], [ec–abf], [ec–afc], [ec–bfc], [ec–fac], [ec–abfc], [ec–afac], [fa–aec], [fc–aec], [abf–aec], [aec–afa], [aec–afc], [aec–bfc], [aec–fac], [aec–abfc], [aec–afac],..., [aec–abcc], [aec–bafc], [abcc–abfc], [abcc–afac]}.

Phase 3. Optimisation. Find the maximal exclusive sequential patterns according to Definition 3 and delete all non-maximal patterns from ESP.

For example, [e–f]∠[e–af]∠[e–abf]∠[e–abfc]∠[aec–abfc], [f–ae]∠[f–aec], [ae–af]∠[ae–abf]∠[aec–afac],…,[ae–bf]∠[ae–bfc]∠[aec–abfc]. Deleting the exclusive patterns which are contained in other exclusive patterns results in the set of six maximal exclusive sequential patterns:

[ae–abcc], [aec–abfc], [aec–afac], [aec–bafc], [abcc–abfc], [abcc–afac].

The three phases described above for pairwise exclusion can be extended to multi-ESP mining, where the mutual exclusion of sequential patterns is sought more generally. The initialisation phase remains the same while checking the exclusion of sequential patterns $sp_1,sp_2,\ldots,sp_r$ in phase 2 is performed according to Definition 4. An extension of Definition 3 would embrace the optimisation phase reducing the exclusive sequential patterns found to the maximal set.

3.3 Algorithm Development

Following the pairwise exclusion method, we develop algorithms corresponding to each phase above. Notation is used to simplify the algorithms proposed in pseudo code below:

SubSeq(sp_i) – represents a set of sub-sequences of sequential patterns sp_i.

esp – represents a particular exclusive sequential pattern; esp[1] is the first sequential pattern and esp[2] is the second of the pair.

Algorithm 1 Initialisation
Input: Sequence database SDB={S_1, S_2, …, S_n} and sequential patterns SP={$sp_1,sp_2,\ldots,sp_m$}.
Output: Support matrix Supp[n,m].
Method:

```
(1) Define an empty support matrix Supp[n,m] with n rows and m columns
(2) for each sequential pattern sp_i∈SP do
(3)     {for each data sequence S_k∈SDB do
(4)         {if sp_i∠S_k                         //sp_i is occurred in S_k
(5)               Supp[k,i]=1;
(6)           else
(7)               Supp[k,i]=0;}
(8)       delete sp_i from Supp if Supp(k,i)=1, ∀k=1,…,n}
```

Algorithm 2 Exclusion checking and ESP output
Input: Support matrix Supp[n,m], sub-sequence sets SubSeq(sp_i) and user-specified minimum exclusion minexc.
Output: Exclusive sequential patterns ESP.
Method:

```
(1) q=0; ESP=∅;
```

```
(2) for (i=1; i<m; i++) do                //get the first of the pair of sequential patterns
(3)     {for (j=i+1; j<m; j++) do                       //get the second of the pair
(4)         {w1=0; w2=0;
(5)             if ¬(spi∈SubSeq(spj))∧¬(spj∈SubSeq(spi))
                                            //i.e. spi and spi are not contained in each other
(6)                 {for (k =1; k<n; k++) do
(7)                     {w=Supp[k,i]+Supp[k,j];
(8)                       Case w=1                  //only one of spi or spj occurred in Sk
(9)                            w1=w1+1;
(10)                      Case w=2                       //both spi and spj occurred in Sk
(11)                           w2=w2+1;
(12)                      excl= w1/(w1+w2);                          //exclusion(spi,spi)
(13)                      if excl≥minexc
(14)                        {espq=[spi–spj];          //a new exclusive sequential pattern
(15)                          ESP=ESP∪espq; q=q+1;}}
(16)    }}}
```

Algorithm 3 Optimisation
Input: Exclusive sequential patterns ESP={esp_1,esp_2,…,esp_q}.
Output: Maximal exclusive sequential patterns.
Method:

```
(1) for (r=1;  r<q; r++) do                                  // while ESP is not empty
(2)   {for (s=r+1; s≤q; s++) do
(3)       {if (espr[1]∈SubSeq(esps[1])∧espr[1]∈SubSeq(esps[2]))∨
              (espr[2]∈SubSeq(esps[1])∧espr[2]∈SubSeq(esps[1]))
                         //espr is contained in another exclusive sequential pattern esps
(4)        ESP=ESP - espr;}}                                   // delete espr from ESP
```

These algorithms complete the pairwise exclusion method for the discovery of exclusive sequential patterns. While it is non-trivial to extend the approach to the general case, this will be the subject of future work.

4 Experiments

The empirical analysis of the proposed ESP mining method was performed on a real dataset as well as a synthetic dataset that was especially created to test the exclusive sequential patterns mining algorithms.

4.1 Customers Orders Dataset

Sample real datasets can be obtained from Blue Martini's Customer Interaction System in the public domain at http://cobweb.ecn.purdue.edu/KDDCUP/, last accessed: 7 August 2009. Three categories of data, i.e. Customer information, Orders information and Click-stream information are collected by the Blue Martini application server and further details about the data are provided in Kohavi et al. (2000).

The Orders dataset corresponds to customer purchase data made up of Customer IDs, Order IDs and Product IDs. It contains data collected from 1,821 customers' behaviour between 28 January 2000 and 31 March 2000, and it includes 3,420 records (i.e. 3,420 purchases), 1,917 orders and 999 different kinds of product. Table 3 illustrates the format and contents of the Orders data.

Table 3 Format/content of the Orders dataset

Customer ID	Order ID	Product ID
…	…	…
62	3550	19155
62	30018	40393
96	100	13147
132	136	13147
184	4124	40353
184	4124	44477
184	4124	45371
184	23126	35289
224	228	13143
224	228	14087
…	…	…

Sequential Patterns Mining

The method and algorithms for ESP mining described in section 3 have been implemented using Microsoft Visual C++, where sequential patterns mining within certain minimum support thresholds (minsup) will be performed first. We use the PrefixSpan algorithm available from the IlliMine system package, a partially open-source data mining package at http://illimine.cs.uiuc.edu/, last accessed 7 August 2009. Table 4 illustrates the sequential patterns mining results under different minsup for the Orders dataset.

Table 4 Sequential patterns mining results on the Orders dataset

minsup (%)	Number of k-sequences	
	1-sequence	2-sequence
3	1	-
2.5	2	-
2	4	-
1.5	11	-
1	23	-
0.5	64	1

Table 4 shows that, (e.g.) when minsup=0.5%, there are 64 sequential patterns with a unique item and there is one sequential pattern with two items. Note that a sequence of length k is known as a k-sequence; the 2-sequence in Table 4 is (35277 35273), which shows that only 0.5% of customers who purchased product 35277 also bought product 35273.

Exclusive Sequential Patterns Mining

Based on the sequential patterns discovered above, user-specified exclusion thresholds (minexc) are set to mine pairs of exclusive patterns. Table 5 highlights the number of exclusive sequential patterns mined under different minsup and minexc combinations.

Table 5 ESP mining results on the Orders dataset

minsup	Pairwise Combinations	ESP numbers under different minexc						
		100%	99%	…	91%	…	70%	…
2.5%	1	1	1	…	1	1	1	1
2%	6	5	6	…	6	6	6	6
1.5%	55	50	51	…	55	55	55	55
1%	253	228	229	…	249	…	253	253

Table 5 shows that, under a specific minsup, the number of ESPs increases to the asymptote of pairwise combinations as minexc decreases – as shown in the shadow part of the table. We are more interested in the exclusive patterns discovered as minsup increases (i.e. those sequential patterns supported by more data sequences) and with larger minexc (i.e. the probability of these sequential patterns being exclusive is higher). In this example, there is one ESP=[39961–40341] when minsup=2.5% and minexc=100%. This exclusive pattern not only corresponds to products 39961 and 40341 having been purchased by at least 2.5% customers (i.e. 46 out of 1,821), but also these products are 100% exclusive, i.e. any customers who bought one of them did not buy the other one.

Relationship Between minexc and minsup

Table 5 demonstrates that the minimum exclusion thresholds minexc can be quite large compared with the small minsup values in this case. There could be some relationship between these two thresholds and it is worth considering this further to indicate guidelines for future parameter setting.

The minimum support implies that, for any single sequential pattern α, the probability of it occurring in data sequences is P, where minsup$\leq$P$\leq$1; and the probability of it not occurring in data sequences is (1-P). For any two sequential patterns α and β, the probability of them both occurring together in a data sequence is $P*P=P^2$; the probability of neither of them occurring in a data sequence is $(1-P)^2$; the probability of either of them occurring in a data sequence is $1-(1-P)^2$; and the probability of one and only one of them occurring in a data sequence is $(1-(1-P)^2)-P^2$.

Applying this elementary analysis to the definition of (relative) exclusion in formula (2), the probability of sequential patterns α and β being (relatively) exclusive will be:

$$\mathrm{Pexc}(P) = \frac{1-(1-P)^2 - P^2}{1-(1-P)^2} = 1 - \frac{P}{2-P} \qquad (3)$$

The upper bound for this probability occurs when P=minsup, so it is natural to apply this in formula (3) for an initial 'best estimate' of exclusive probability

Pexc(P). For example, when P=minsup=2.5~1% (from Table 5), the probability of any pair of sequential patterns being exclusive is calculated as between 98.7% and 99.5%. That is, the most interesting ESPs should be found when minexc is set around 98-100%.

4.2 Synthetic Dataset

In this section, we performed ESP mining experiments on a large-scale synthetic dataset which was drawn from the IBM Almaden data generator – http://www.almaden.ibm.com/cs/projects/iis/hdb/Projects/data_mining/datasets/syndata.html, last accessed 7 August 2009 – which has been used in sequential patterns mining studies (Agrawal and Srikant, 1995; Pei et al., 2001).

This synthetic dataset generator produces a database of sequences whose characteristics can easily be controlled by the user. It requires the specification of the average number of transactions in a sequence |C|, the average number of items in a transaction |T|, the average length of maximal potentially large sequences |S|, the number of different items |N| and the number of data sequences |D|. For example, C50-T1-S4-N50-D10K means that the dataset contains 10,000 data sequences and 50 different items, where the average number of items in a transaction (i.e. event) is set to 1 and the average number of transactions per data sequence is set to 50.

Sequential Patterns Mining

Table 6 illustrates the relationship between minsup and the number of sequential patterns found in the C50-T1-S4-N50-D10K synthetic dataset as a result of sequential patterns mining.

Table 6 Sequential patterns mining results on the synthetic dataset

minsup (%)	Number of k-sequences		
	1-sequence	2-sequence	3-sequence
70	16	14	-
60	22	80	-
50	26	184	-
40	31	346	221

The table shows that, (e.g.) when minsup=60%, there are 22 sequential patterns with a unique item and 80 sequential patterns with two items.

Exclusive Sequential Patterns Mining

Before performing ESP mining, formula (3) has been used to predict the probability of exclusion for the four minsup values (70~40%) in Table 6 and the results are:

Pexc(minsup=70%)≈46%; Pexc(minsup=60%)≈57%;
Pexc(minsup=50%)≈67%; Pexc(minsup=40%)=75%;

Using these Pexc values as a guideline, a corresponding series of minexc has been used for the synthetic dataset and Table 7 shows the ESP mining results.

Table 7 ESP mining results on the synthetic dataset

(minsup=70%)

minexc	≥45.5%	45%	44.5%	44%	43.5%	43%
No. of ESPs	0	4	10	18	35	53

(minsup=60%)

minexc	≥58%	57.5%	57%	56.5%	56%	55.5%
No. of ESPs	0	1	6	15	50	109

(minsup=50%)

minexc	≥67%	66.5%	66%	65.5%	65%	64.5%
No. of ESPs	0	8	37	112	257	508

(minsup=40%)

minexc	≥76.5%	76%	75.5%	75%	74.5%	74%
No. of ESPs	0	3	24	241	1092	3241

It can be seen from the range of shaded minexc values in Table 7 that Pexc is close to the point beyond which no ESPs are discovered. Therefore, formula (3) can potentially be used to guide how to set up the minimum exclusion threshold to obtain a limited number of the most useful exclusive patterns.

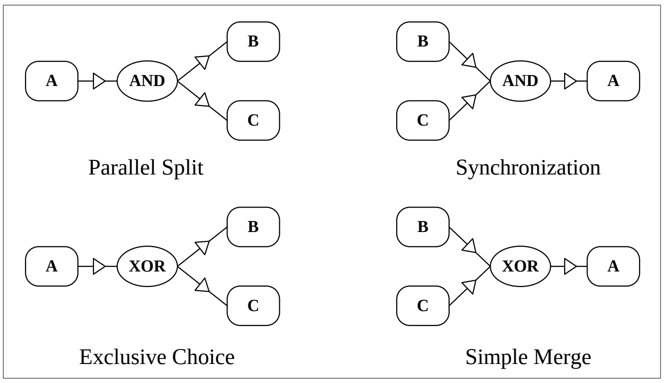
5 Applications of ESP

Exclusive Sequential Patterns mining is a new technique based on traditional sequential patterns mining and, as such, it can be applied to the corresponding range of domains. For example, when using a database with transactions performed by customers at any instant, it is possible to predict what would be the customers' regular buying or non-buying behaviour, based on their past transactions; or one could analyse medical records of patients for temporal patterns between symptoms, diagnosis, treatment and examination results. Other applications include web access patterns mining and process analysis of scientific experiments.

A promising application area for ESP mining is in workflow modelling. The research work of van der Aalst et al. (2003) has resulted in the identification of twenty patterns describing the control-flow perspective of workflow systems. White (2004) demonstrated that most of the patterns can be modelled with a Business Process Diagram and a UML Activity Diagram to describe the behaviour of business processes. Russel et al. (2006) presented a systematic review of these workflow patterns and provided a formal description of each of them in the form of a Coloured Petri-Net (CPN) model.

Among the original control-flow patterns there are five basic types: sequence, parallel split, synchronization, exclusive choice and simple merge. Figure 1 shows the latter four constructs graphically.

Figure 1 Graphical representation of workflow control patterns



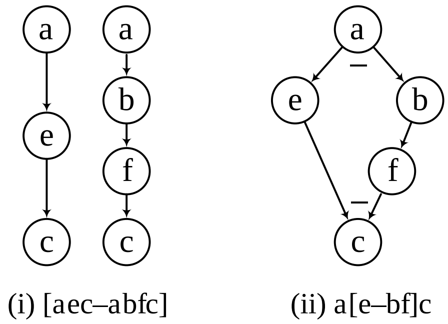
The parallel split pattern allows a single thread of execution to be split into two (or more) branches which can execute tasks concurrently. Synchronization comes into play once the control node receives input on one of its incoming branches, at a point in the workflow process where multiple parallel activities converge into one single thread of execution. The concurrent sequential patterns mining and modelling proposed by Lu, Chen et al. (2008, 2010) can discover and represent parallel split and synchronization patterns, i.e. it is applicable to this first aspect of workflow model design.

The exclusive choice pattern is defined as being a location in a process where the flow can be split into two or more alternative branches. The pattern is exclusive in that only one of the alternatives may be chosen for the process to continue. Simple merge is defined similarly as being a location in a process where a set of alternative incoming branches forms a single exclusive path. It is natural to consider how exclusive sequential patterns can be applied to these two workflow control patterns as an extension of current research.

The use of graph-based modelling in data mining has led to the development of a novel model called Sequential Patterns Graph (SPG) that explores the inherent relationship among sequential patterns (Lu et al., 2004). In this model, nodes of SPG correspond to items in a sequential pattern and directed edges are used to denote the sequence relation between two elements. The idea has been adapted for modelling concurrent sequential patterns (and called ConSP-Graph) with two special nodes, called fork nodes and synchronizer nodes respectively, to represent the concurrent relationship (Lu, Chen et al., 2010).

The SPG and ConSP-Graph idea could further be applied to the modelling of exclusive sequential patterns. For example, one of the maximal ESPs discovered in section 3.2 – [aec–abfc] – can be represented graphically by Figure 2(i). It is clear that <aec> and <abfc> share a common prefix a and a common postfix c. Taking out the common prefix and/or postfix leads to another graph in Figure 2(ii), where the corresponding algebraic representation is a[e–bf]c.

Figure 2 Graphical representation of ESP



Two special nodes can be characterised to represent the exclusive relationships in Figure 2(ii): the start node a here can be seen as a type of exclusive fork node, allowing independent execution of its alternative branches to nodes e and b, where only one of them is chosen; the final node c can be seen similarly as an exclusive synchronizer node, with alternative branches from nodes e and f allowing no more than one outgoing sequential relation (and none in this case).

The expression and construction method of ConSP-Graph can be adapted to a potential ESP-Graph representation, where the notation '–' is used in the model for connecting exclusive paths. The formal definition and approach for this is another research direction to be pursued.

References

Aalst, W.M.P. van der, Hofstede, A.H.M. ter, Kiepuszewski, B. and Barros, A.P. (2003) 'Workflow patterns', Distributed and Parallel Databases, Vol. 14, No. 3, pp.5-51.

Agrawal, R. and Srikant, R. (1995) 'Mining sequential patterns', Proceedings of 11th International Conference on Data Engineering, Taipei, Taiwan, IEEE Computer Society Press, pp.3-14.

Atallah, M.J., Gwadera, R. and Szpankowski, W. (2004) 'Detection of Significant Sets of Episodes in Event Sequences', Proceedings of the 4th International Conference on Data Mining, pp.3-10.

Chen, M.S., Park, J.S. and Yu, P.S. (1998) 'Efficient data mining for path traversal patterns', IEEE Transactions on Knowledge and Data Engineering, Vol. 10, No.2, pp.209-221.

Kohavi, R., Brodley, C., Frasca, B., Mason, L. and Zheng, Z.J. (2000). 'KDD-Cup 2000 Organizers' Report: Peeling the onion', SIGKDD Explorations, Vol. 2, No. 2, pp.86-98.

Li, H.F., Lee, S.Y. and Shan, M.K. (2005) 'DSM-TKP: Mining top-k path traversal patterns over web click-streams', Proceedings of IEEE/WIC/ACM International Conference, pp.326-329.

Lin, M.Y. and Lee, S.Y. (2005) 'Fast discovery of sequential patterns through memory indexing and database partitioning', Journal of Information Science and Engineering, Vol. 21, No. 1, pp.109-128.

Lu, J., Wang, X.F., Adjei, O. and Hussain, F. (2004) 'Sequential patterns graph and its construction algorithm,' Chinese Journal of Computers, 27(6), pp.782-788.

Lu, J., Chen, W. R., Adjei, O. and Keech, M. (2008) 'Sequential patterns post-processing for structural relation patterns mining," International Journal of Data Warehousing & Mining, 4(3), pp.71-89.

Lu, J., Keech, M. and Chen, W. R. (2009) 'Concurrency in web access patterns mining', International Conference on Data Mining, World Academy of Science, Engineering and Technology, Vol. 58, pp.600-609, ISSN 2070-3724.

Lu, J., Chen, W. R. and Keech, M. (2010) 'Graph-based modelling of concurrent sequential patterns', International Journal of Data Warehousing & Mining, 6(2), to appear.

Mannila, H., Toivonen, H. and Verkamo, A.I. (1997) 'Discovery of frequent episodes in event sequence', Data Mining and Knowledge Discovery, Vol. 1, No. 3, pp.259-289.

Pei, J., Han, J.W., Mortazavi-Asl, B. and Pinto, H. (2001) 'PrefixSpan: Mining sequential patterns efficiently by prefix-projected pattern growth', Proceedings of the 7th International Conference on Data Engineering, Heidelberg, Germany, pp.215-224.

Russel, N., ter Hofstede, A., Aalst, W.M.P. van der. and Mulyar, N. (2006) 'Workflow Control-flow Patterns. A revised View', BPM Centre Report, BMP-06-22, http://is.tm.tue.nl/staff/wvdaalst/BPMcenter/

Sheng, C., Hsu, W. and Lee, M.L. (2006) 'Mining Dense Periodic Patterns in Time Series Data', Proceedings of the 22nd International Conference on Data Engineering, pp.115.

White, S. (2004) 'Process Modeling Notations and Workflow Patterns', The Workflow Handbook 2004, Future Strategies Inc., Lighthouse Point, pp. 265-294.

Yang, J., Wang, W. and Yu, P.S. (2001) 'Infominer: Mining Surprising Periodic Patterns', Proceedings of the 7th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 395-400.

Zaki, M.J. (2001) 'SPADE: an efficient algorithm for mining frequent sequences', Machine Learning, 42(1/2), pp.31-60.