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Data Mining For Business Process Reengineering

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INTRODUCTION

Data mining in organizational environments is conducted in human social contexts. This environment is vastly more complex and subtle than the mechanistic, engineered world of the miner. This difference is significant, in that many of the signs encountered in the human world of data mining activities are often equivocal, and the decision rules are more heuristic. “Mining” for patterns in organizational databases is thus more like mineralogical—or, better yet, archeological research in which the relationships between data are fuzzy, messy, equivocal, or unknown. The purpose of this paper is to examine more fully the implications of that shift. The use of data mining technology was part of our cycle time study of the Poplar County Criminal Justice System (a fictitious name). In this paper we will report on the use of data mining in the Poplar County Criminal Justice System (PCCJS) study.

THE POPLAR COUNTY CRIMINAL JUSTICE SYSTEM STUDY

Located in the southeastern United States, Poplar County (fictitious) contains a large metropolitan area of roughly one million people. Recent growth patterns have created problems with the county’s infrastructure. One of—if not *the* most problematic infrastructure has been the County Jail. The jail is constantly overcrowded. Originally built for a population of about 1500 inmates, the jail now regularly houses about 2300-2500 inmates. This overcrowding has created a number of problems, some of which have prompted lawsuits from inmates as well as from the Federal Courts.

The Poplar County Commissioners have taken steps to increase the Jail’s capacity; however, it has also determined that some of the overcrowding was associated with the length of time required to bring cases to trial and adjudicate them. Consequently, the Commissioners asked the researchers for their help in resolving some of these issues. The study began with interviews of County Jail personnel. Those interviews revealed many problems with which the Jail had responsibility but little control. For example, they had no control over who came into the Jail and who went out. They could not tell law enforcement officers that they could not take in prisoners, nor could they force the Courts to release more prisoners to make room. The interviews revealed the systematic interrelationships between the Jail and other agencies within the Poplar County Criminal Justice System (PCCJS).

To gain a better understanding of the PCCJS and the determinants of jail overcrowding, three intelligence strategies were employed. The first two strategies involved interviewing important PCCJS personnel, including but not limited to the County Sheriff’s Office, General Sessions Court Clerk’s Office, Pretrial Services, District Attorney’s Office, local police departments, and so on. The first strategy involved objective questioning aimed at better understanding the effects of formal PCCJS workflows on jail overcrowding. This line of questioning led to the development of a PCCJS workflow process chart. That diagram provided a map to explain how the actions of one group impacted jail overcrowding. The second strategy involved subjective questioning aimed at eliciting beliefs as to how effectively and efficiently the formal workflow process worked. This second line of questioning was intended to “breathe life” into the workflow diagram by ascertaining trouble spots and bottlenecks as well as pinpointing possible solutions. Because of limited space, only the general process diagram for PCCJS is presented in Appendix I.

The third strategy was to analyze PCCJS transaction data to ascertain the system’s overall performance. This data, which was drawn from almost all agencies within the PCCJS, was stored in Poplar County’s Information Systems Services database. Unfortunately, the database was designed for tracking but not performance evaluation; that is, the database could report where and when a case was supposed to go next, but not how long it took to process an incoming jail inmate.

However, the researchers faced a dilemma in integrating the three types of data. On the one hand, the objective and subjective data gleaned from the interviews was used to construct a *graph-theoretic* workflow process diagram. On the other hand, the relational structure of the County’s PCCJS relational database was set-theoretic. At issue was how to analyze set-theoretic data to support graph-theoretic BPR in a cost and time effective manner.

DATA MINING

A major difficulty with the dataset was its internal relational structure. Like all relational databases, the PCCJS database was build upon a set theory foundation. That foundation gives relational database management systems wide applicability to those problems that can be conceived in and resolved through sets. For example, large numbers of customer-based transactions have long been successfully stored and analyzed through set-theoretic relational database systems.

However, many of the problems faced in BPR in general—and in the PCCJS study in particular—are often better understood in a graph-theoretic framework. (e.g., path analysis). Under these circumstances, traditional set-theoretic relational database capabilities have limited usefulness. Newer capabilities, particularly those based on data mining technologies, have built upon traditional relational database systems by incorporating graph-theoretic tools. The power of data mining technologies has been widely applied and investigated in the marketing and financial domains.

The problems facing BPR are different in many ways from those faced by marketing and financial organizations. One of the most evident is that marketing and finance researchers are more involved with “simple” (i.e., direct) relationships, whereas BPR researchers are more concerned with long chains of interacting processes (i.e., “hidden information”). This difference appears in the tools these researchers use: marketing and finance researchers are more interested in set-theoretic problems; BPR researchers, in graph-theoretic problems. Yet data mining technologies incorporate graph-theoretic algorithms. Consequently, they should at first glance be able to support hypothesis generation in BPR activities. The purpose of this paper is to investigate the extent to which graph-theoretic data mining algorithms can generate BPR hypotheses.

We started with the following two questions:

- Whether the presence of a type of reset reason is associated with another type of reset reason. — Association Rules analysis
- Whether the presence of a type of reset reason is followed by another type of reset reason over a period of time; showing a sequential pattern — Sequential Pattern Analysis

The layout of the study’s data set is provided in Appendix II. For example, whenever there is a status change in the case (#9749904),

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the change is recorded into the PCCJS system with a specific reason. The sequence of the reset reasons in the order of time is AR =>AT =>AT =>FA =>AT =>FF =>BW =>AT. If a case goes well as scheduled, there will be a smaller number of reset reasons for the case in that sequence. By using the technique of sequential pattern analysis, it is hoped that we could identify potentially problematic and/or meaningful sequential patterns of reset reasons in the cases under consideration.

Analysis of Association Rules Using Clementine

The data set used for our analysis is randomly select from 1997 to 2000: 09/28/97-10/04/97, 11/23/97-11/29/97, 02/22/98-02/28/98, 06/14/98-06/20/98, 07/26/98-08/01/98, 10/04/98-10/10/98, 02/28/99-03/06/99, 04/18/99-04/24/99, 07/11/99-07/17/99, 10/17/99-10/23/99, 02/06/00-02/12/00, and 04/16/00-04/22/00. The SPSS, a statistical software package, is used to detect missing value, invalid data, and outliers. The data cleaning process should be conducted at first before performing further analysis, because the problem of missing data, incorrect or invalid data, and outliers could have a significantly destructive impact on final results. Fortunately, there are no missing values, incorrect data, and outliers in this data set; as a result, all observations are used for data mining analysis.

To conduct an analysis for association rules, the interested items, which are the reset reasons for our study, need to be recorded in a binary format (yes or no; 1 or 0). Since our original data set is in a different format (refer to Appendix 1), data conversion process is required. SAS is used for this data conversion. There are 28 possible reset reasons resulting in 28 fields in the converted version. An example of data conversion can be shown as below.

After the conversion, there are a total of 10,319 records to be used to perform data mining analysis. Clementine version 5.01, one of several commercial data mining tools, is selected to discover any association rules for reset reasons. The result of this analysis appears in Appendix III. Unfortunately, we were not able to find out any relevant or meaningful association rules among reset reasons.

Analysis of Sequential Patterns of Reset Reasons Using IntelligentMiner

The sequential pattern technique is used to search for any meaningful sequential patterns of the reset reasons. The potential findings would hopefully contribute to any reduction in cycle time of the jailing processes. For the sequential pattern analysis type, we had to use IntelligentMiner version 6.1 by IBM because Clementine version 5.01did not support this type of analysis which we overlooked at the outset of this project. So, we ended up doing data preparation again for this new data mining tool. Prior to conducting data mining analysis with the IntelligentMiner, data preparation, such as data cleaning and combining files into a single file, was performed with SAS and a new data file based on our original data set was produced as a flat file. The IntelligentMiner accepts input data in the form of either flat file format or database table/view. The data file produced from SAS is inputted into the IntelligentMiner under Data Wizard in the IntelligentMiner. Before performing mining or any analysis, a data object must be created and specified as input data through Data Wizard. Then, sequential pattern analysis for reset reason can be conducted. There are three input fields specified for the analysis:

- Transaction group field: Booking Number
- Transaction field: Create Date (Date the record was created or date the reset occurred)
- Item field: Reset Reason

The result of this analysis appears in Appendix IV. The result is somewhat interesting in the sense that there are many sequential patterns with consecutive AT reset reasons in the data set:

AT=>AT (38%), AT=>AT=>AR (27%), RP=>AT=>AT(25%), RP=>AT=>AT=>AR (19%), and AT=>AT=>AT (16%). Especially, existence of the last sequential pattern with three consecutive AT reset reasons calls for further analysis. This result gives a clue as to which area the PCCJS Commissioners look into to speed up the handling of the cases on their system.

Discussion

The result of association rules analysis does not help us answer the first question we had at the beginning. After careful evaluation on the all identified association rules, it is conclude that there is no relevant or meaningful association rule among the reset reasons in cases. This interpretation might make sense because most algorithms implementing association rules analysis are based on a simple counting algorithm. However, the result of sequential pattern analysis help us generate several BPR hypotheses, i.e., which areas we should look into to possibly reduce the number of reset reasons in cases, and, in turn, speed up the overall jail processing time for cases in the PCCJS system. As pointed out earlier, there are five significant sequential patterns in the reset reasons:

1. AT=>AT (38%)
2. AT=>AT=>AR (27%)
3. RP=>AT=>AT(25%)
4. RP=>AT=>AT=>AR (19%)
5. AT=>AT=>AT (16%)

The first identified sequential pattern tells that 38 % of the total cases under consideration involves two reset reasons of AT that is either reassignment of a defending attorney or request for determent of case by defending attorney. The next three sequential patterns are more specialized ones that are already factored into the first pattern. One of the most interesting and significant is the last sequential pattern: 16% of the total cases under consideration involves three reset reasons of AT. The next phase of this study will be to further investigate such cases that have these identified sequential patterns.

As in any IS project, selection of a right data software tool is important especially when a given project needs to meet a tight deadline. We started with Clementine 5.01 by SPSS for association rules analysis because of easy access to this data mining tool. Since the sequential pattern analysis is one of the most typical data mining techniques discussed in the literature, we inadvertently assumed that this feature would be supported in Clementine. Even if there were some features available in Clementine to identify possible sequence patterns, we could not find a feature that specifically implements sequential pattern analysis. After switching to IntelligentMiner for sequential pattern analysis, we also ran the same data set for association rules analysis in IntelligentMiner for performance comparison. The result of association rules analysis from Intelligent Miner was same as that from Clementine, but there was a significant difference in processing time (20-30 min in Clementine vs. 5-10 min in IntelligentMiner). The Intelligent Miner provides both descriptive result and visualized result, unlike Clementine that provides only the descriptive result. With the Intelligent Miner, the conversion of data to be represented in a binary format is not required (refer to the subsection of "analysis of association rules using Clementine"). Hence,

Table 1: Original format

Booking No.	. . . .	Reset Reasons	. . . .
97049600	. . . .	AR	. . . .
97049600	. . . .	AT	. . . .
97049600	. . . .	VR	. . . .
97049700	. . . .	AT	. . . .
97049700	. . . .	VP	. . . .

Table 2: Converted format

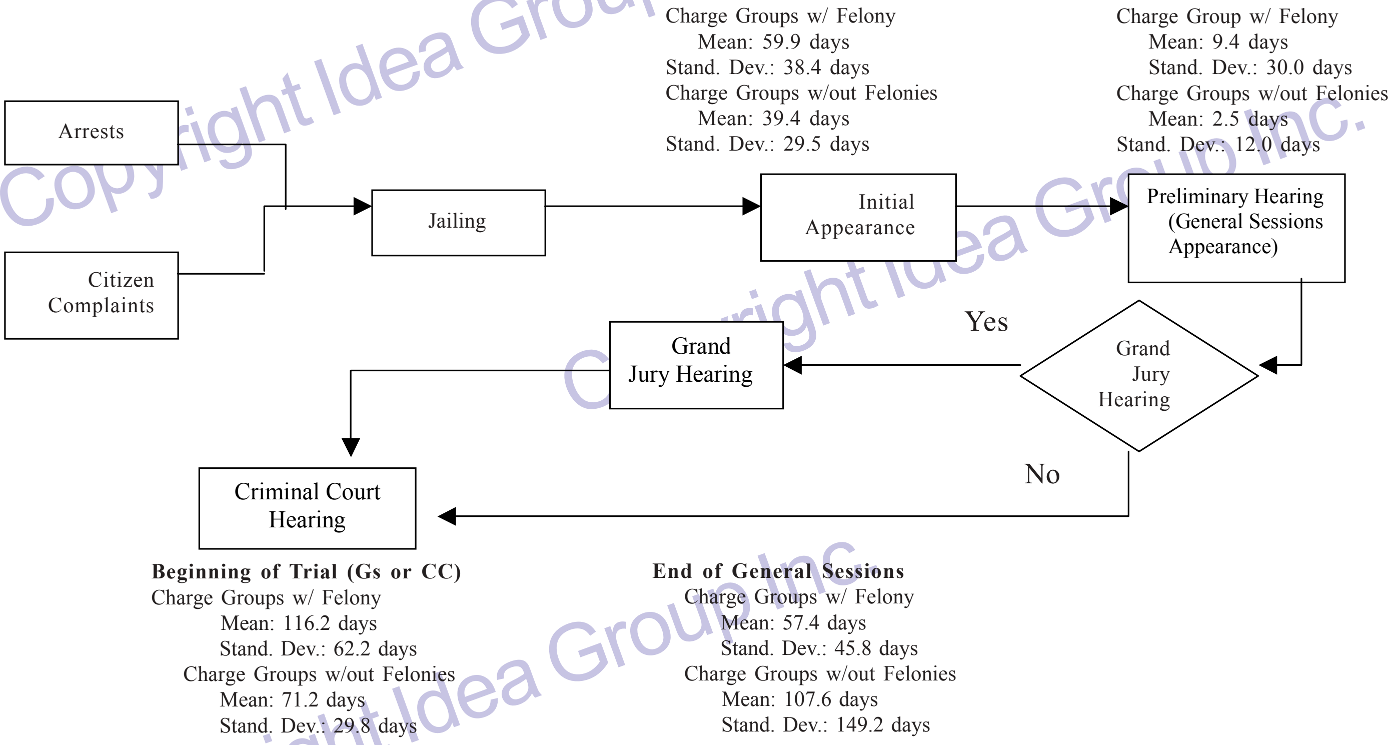
Booking No.	. . . .	AR	AT	. . .	VP	VR	. . . . .
97049600	. . . .	1	1	. . .	0	1	. . . . .
97049700	. . . .	1	0	. . .	1	0	. . . . .

the same data format can be used to perform both association rule analysis and sequential pattern analysis. Based on our observation, IntelligentMiner is a more comprehensive data mining tool and can handle more complicated analysis than Clementine. However, it seems that Clementine is easier to understand and use than IntelligentMiner.

CONCLUSION

So far, we demonstrate how data mining technology can provide a support for analyzing business processes in the PCCJS system. The power of data mining technologies has been widely applied and investigated in the marketing and financial domains. One of the most evident is that marketing and finance researchers are more involved with simple relationships, whereas BPR researchers are more concerned with long chains of interacting processes. However, an appropriate application of data mining technology to BPR effort can be beneficial. We were able to come up with relevant and meaningful hypotheses for BPR in the PCCJS system by using data mining technology, specifically sequential pattern analysis: which areas we should look into in order to speed up the case handling process. This valuable outcome would have not been possible without data mining technology considering the large volume of data on hand. We hope that this study will contribute to broadening the scope of applicability of data miming technology in business process reengineering.

APPENDIX 1



Charge Groups w/ Felony
Mean: 59.9 days
Stand. Dev.: 38.4 days
Charge Groups w/out Felonies
Mean: 39.4 days
Stand. Dev.: 29.5 days

Charge Group w/ Felony
Mean: 9.4 days
Stand. Dev.: 30.0 days
Charge Groups w/out Felonies
Mean: 2.5 days
Stand. Dev.: 12.0 days

Beginning of Trial (Gs or CC)
Charge Groups w/ Felony
Mean: 116.2 days
Stand. Dev.: 62.2 days
Charge Groups w/out Felonies
Mean: 71.2 days
Stand. Dev.: 29.8 days

End of General Sessions
Charge Groups w/ Felony
Mean: 57.4 days
Stand. Dev.: 45.8 days
Charge Groups w/out Felonies
Mean: 107.6 days
Stand. Dev.: 149.2 days

APPENDIX II

RNI#	Booking number	Charge Code	Court Code	Arrest Agency	Officer ID	Arrest Date & Time	Charge Time	Charge Group Disposed Date	Charge Group Disposed Indicator	Probation Start Date	Court Divisi on	Court Date	Court Sessi on	Reset Reaso n	Creat dat
162905	97049904	1	GS	SO	S2529	9/30/97 09:27	9/6/00 8:45	8/6/1998	Y	8/6/1998	7	8/6/98	1	AR	09/30 4:3
162905	97049904	1	GS	SO	S2529	9/30/97 09:27	9/6/00 8:45	8/6/1998	Y	8/6/1998	7	8/6/98	1	AT	10/01 14:(
162905	97049904	1	GS	SO	S2529	9/30/97 09:27	9/6/00 8:45	8/6/1998	Y	8/6/1998	7	8/6/98	1	AT	10/29 14:5
162905	97049904	1	GS	SO	S2529	9/30/97 09:27	9/6/00 8:45	8/6/1998	Y	8/6/1998	7	8/6/98	1	FA	11/12 11:4
162905	97049904	1	GS	SO	S2529	9/30/97 09:27	9/6/00 8:45	8/6/1998	Y	8/6/1998	7	8/6/98	1	AT	12/03 13:5
162905	97049904	1	GS	SO	S2529	9/30/97 09:27	9/6/00 8:45	8/6/1998	Y	8/6/1998	7	8/6/98	1	FF	01/07 17:4
162905	97049904	1	GS	SO	S2529	9/30/97 09:27	9/6/00 8:45	8/6/1998	Y	8/6/1998	7	8/6/98	1	BW	07/26 12:5
162905	97049904	1	GS	SO	S2529	9/30/97 09:27	9/6/00 8:45	8/6/1998	Y	8/6/1998	7	8/6/98	1	AT	07/27 10:5

1. RNI #: Number assigned to a criminal by Sheriff's department for identification.
2. Booking #: Number assign by courts system for grouping all charges against a defendant.
3. Charge Code: Code identifying the crime.
4. Court Code: GS for General Sessions.
5. Arrest Agency: Code of arresting agency. MP = Local Police, SO = Sheriff's Department.
6. Officer ID: Officer's assign number.
7. Arrest Date and Time: Date and Time of the arrest.
8. Charge Time: Date and time the inmate was entered into the system in the sally port.
9. Charge Group Disposed Date: Self explanatory.
10. Charge Group Disposed Indicator: Y = all charges disposed. N = All charges not disposed. D = Case on Diversion.
11. Probation Start Date: Self explanatory.
12. Court Division: Self explanatory.
13. Court Date: Date assign for defendant to be in court.
14. Court Session: - 1 = 9AM, 2 = 1PM, 3 = 10:30AM, 4 = 4PM
15. Reset Reason:
    AR: Arraignment; AT: Attorney; BW: Bench Warrant; D1: Application for Diversion;
    D2: End of Diversion; DP: Disposition; FA: Final Settings for Attorney;
    FF: Final Forfeiture; PH: Preliminary Hearing; RP: Report to Court; TR: Trial;
    VR: Video Arraignment; TT: Total Time.
16. Create Date: Date the record was created.

APPENDIX III

Support(%)	Confidence(%)	Rule Body	Rule Head
16.2225	92.0300	[AR]+[AT]+[DP]	==> [RP]
18.6452	91.6600	[AR]+[DP]	==> [RP]
20.2539	89.2400	[DP]	==> [RP]
17.5308	89.1100	[AT]+[DP]	==> [RP]
18.7809	90.5600	[VR]	==> [AT]
11.4740	88.5600	[PH]	==> [AT]
11.7841	88.0500	[VR]+[RP]	==> [AT]
16.2225	87.0100	[RP]+[AR]+[DP]	==> [AT]
10.3111	87.0000	[FF]	==> [AT]
19.6724	86.6800	[DP]	==> [AT]
17.6277	86.6600	[AR]+[DP]	==> [AT]
17.5308	86.5600	[RP]+[DP]	==> [AT]
11.4740	96.8100	[FF]	==> [AR]
10.1173	96.4000	[BW]	==> [AR]
48.7063	82.9100	[RP]	==> [AT]
37.7847	81.8600	[RP]+[AR]	==> [AT]
16.2225	92.5400	[RP]+[AT]+[DP]	==> [AR]
18.6452	92.0600	[RP]+[DP]	==> [AR]
20.3411	89.6200	[DP]	==> [AR]
17.6277	89.6100	[AT]+[DP]	==> [AR]

APPENDIX IV

Sequence Support	Item sets	Sequence Support	Item sets	Sequence Support	Item sets	Sequence Support	Item sets
51.72	AT	20.002	DP	14.042	AT	11.668	RP
	AR		RP		RP		AT
							VR
40.406	RP	19.76	RP	13.577	RP		
	AT		AT		RP	11.474	PH
			AT		AT		AT
46.138	RP		AR		AT		
	AR					11.455	FF
		19.508	DP	13.364	RP		AR
38.085	AT		AT		RP		
	AT				RP	11.154	RP
		18.762	AT		AR		AT
37.475	RP		VR				AT
	AT			13.306	RP		AT
	AR	18.413	DP		VR		
			RP			11.086	RP
32.804	RP		AR	13.218	AT		AR
	RP				RP		AR
		17.463	DP		AT		
27.406	AT		AT			10.96	AT
	AT		AR	13.005	RP		AT
	AR				RP		VR
		17.153	DP		RP		
26.514	RP		RP		AT	10.922	RP
	RP		AT				RP
	AT			12.899	RP		AT
		16.223	RP		AT		AT
26.156	RP		RP		RP		AR
	RP		RP				
	AR			12.501	AT	10.902	AR
		16.038	AT		AT		AT
25.254	RP		AT		AT		
	AT		AT		AR	10.747	AR
	AT						AT
		15.99	AR	12.249	RP		AR
20.709	RP		AR		AT		
	RP				RP	10.534	AT
	AT	15.874	DP		AT		AR
	AR		RP				AT
			AT	12.23	AT		
20.341	DP		AR		AR		
	AR				AR		