**PROCESS MINING: RESEARCH OPPORTUNITIES IN AIS**

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September 12, 2010

**Abstract** Process mining is the systematic analysis of the information contained in an event log, which is a data set constructed from the information recorded in modern IT systems. That data consists of both information entered by users, and meta-information about that transaction, such as data stamps and user identity. Critically, meta-information is automatically recorded by the system, beyond the control of the user to manipulate or prevent recording, which makes event logs valuable control tools. Moreover, event log data is so rich that numerous modes of analysis can be conducted on it, yielding many different insights into underlying business processes. Process mining has been widely researched in computer science and management science, as well as adopted in industry with the support of leading high tech companies. This paper provides AIS researchers with an introduction to process mining, a primer on how it is undertaken, and a discussion on why it can add value to both accounting research and practice.

**Keywords** Event logs, process mining, AIS research methods.

1. **Introduction**

Process Mining is the systematic analysis of the information contained in the “event logs” that can be constructed from the data collected and stored by modern IT systems.[[1]](#footnote-1) An event log is defined as *“a chronological record of computer system activities which are saved to a file on the system. The file can later be reviewed by the system administrator to identify users’ actions on the system or processes which occurred on the system.”[[2]](#footnote-2)* Importantly, the information recorded in the event log consists not only of the data entered by a user, but contextual information about that transaction, which includes at a minimum, its location in a sequence of related transactions, perhaps accompanied by a timestamp, and the authorized identity of the individual making the entry. It is this contextual meta-information that makes the event log potentially more insightful about the business processes of the company than the transactional data alone, but obtaining those insights requires both that the event log be systematically structured to facilitate analysis, and that an appropriate methodology is applied to mine the data contained in the event log.

There is a very large literature on process mining in computer science, engineering and management (Schimm, 2003; Rozinat et al, 2007; Lijie et al 2009; van der Aalst, 2010; van der Aalst and Weijters, 2004).[[3]](#footnote-3) The process mining literature in accounting is more limited. Jans et al (2010) examines the use of process mining techniques in internal auditing, emphasizing how the meta-information contained in an event log extends the domain of auditing from its reliance on information largely entered by the auditee. Gehrke and Mueller-Wickop (2010) develop an algorithm for creating and analyzing event logs in the SAP™ enterprise resource planning system.

A business process is a *“defined set of business activities that represent the steps required to achieve a business objective”*.[[4]](#footnote-4) In addition to process mining, the identification and analysis of processes is also central to such modern business practices as Business Process Analysis (BPA), Business Activity Monitoring (BAM), and Business Intelligence (BI), all of which aim to give management with a holistic understanding of how businesses operate.

BPA is concerned with examining operational processes to eliminate inefficiencies and bottlenecks. Thus, BPA has a wider domain that process mining, since it concerns all processes taking place in an organization, or between organizations, and not just what is recorded in the firm’s ERP system, and is more closely related to business process reengineering (Hammer, 1990). Business Intelligence, like process mining, focuses on the analysis of process related data, but while the latter uses the event log, the former restricts itself to data mining of transactional data and the presentation of information about key performance indicators on a dashboard. Business Activity Monitoring is essentially business intelligence on a more real time basis. Process mining thus both complements and differs from these other process analysis methodologies by focusing on the meta-information about transactions contained in the event log. That restricts its scope relative to other operationally oriented methodologies, but it also allows insights not otherwise possible about why transactions take place and who is involved with doing them (Ko, et al, 2009).

In this paper we provide an overview of process mining and the two basic steps involved in undertaking it: the construction of an event log from the raw data stored in an IT system, and the choice of the methodologies to analyze the event log. We begin my making the case for why process mining is likely to add value in accounting practice and research.

1. **Why Do Process Mining in Accounting?**

Van der Aalst (2009) makes the case for process mining using the analogy of GPS navigation systems used in cars.[[5]](#footnote-5) He argues that the capability of those systems to not just display a map, but to make it interactive—by displaying points of interest along the route, distance and time to destination, real time traffic information and so forth—is far superior to what most existing information systems offer their users. Process mining, in his view, is a way of enhancing the value added of IT systems by adding context to data in the same way that the GPS unit does to maps, and hence providing users with a better understanding of how business processes actually operate and how they can be improved.

Another loose analogy that might be more familiar to AIS researchers is that of XBRL. XBRL tags are often described as providing meta-information, or information about the information that is being tagged. For example, a sales figure drawn from the face of a company’s income statement can be tagged with information about the accounting period that it refers to, the accounting standard used, the monetary unit and data format it is measured in, even whether it has been audited, all of which greatly increases the insights that the user obtains relative to just seeing the sales number alone. Moreover, once accounting statements are tagged, researchers can then analyze those tags to better understand the information they convey, for example, what the implications are of the company choosing to use an extension tag rather than a standard one (Debreceny et al 2010).

Modern IT systems, particularly enterprise resource planning (ERP) systems, can be thought of as doing the equivalent of “tagging” the data that is entered into it, by independently recording such information as the time the data entry was made, which authorized user made it and whether any corrections were subsequently made to that initial entry. ERPs tend to use relational databases and along these systems logs, data dictionaries, and information fields to track information about information (meta information). It is similar to meta-information about the data in the ERP system, along with the transaction entry itself, which is extracted into an event log in a systematic fashion that facilitates its analysis. Process mining is the methodology for analyzing that meta-information now contained in the event log, the equivalent of the accounting researcher analyzing not just the data on the face of the accounting statement, but also the data within its XBRL tags.

There is, however, a fundamental difference between process mining and XBRL tagging. In the case of XBRL, it is the individual in the company or the corporate publisher preparing the accounting statements for submittal to the SEC, who is responsible for tagging the data. By contrast, IT systems record meta-information about data entries automatically and without the ability of the user to prevent or alter the recording of that information.[[6]](#footnote-6) It is this feature that Jans et al (2010) emphasize when pointing out the value of process mining as an audit tool: *“what makes an event log such a unique and potentially invaluable resource for auditing is not only that it provides the auditor with more data to analyze, but also because that additional data is recorded automatically and independently of the person whose behavior is the subject of the audit.”*

The power of process mining of event logs comes not just from gaining meta-information about individual transaction data entries, but the ability that provides to detect patterns across transactions and the users entering that data. In particular, process mining is used to make an normative as opposed to descriptive assessments about how business processes Such a comparison is the essence of auditing, but it can also be used in management monitoring and process improvement by management accountants.

To illustrate we can raise the issue that if a large company of the problems faces when it lays off a large number of managers whose responsibilities included authorization of transactions. To satisfy segregation of duty controls, these responsibilities were spread amongst numerous managers, but after the layoffs the absence of designated signees meant that those who remained instituted ad-hoc work-around arrangements without adequate documentation. The company faced great difficulty in reestablishing adequate controls as a result. In this situation , process mining can be used not only determine what the new arrangements were after the layoffs, but could also have been used before the event to determine how the layoffs would have affected the segregation of duty controls in order that remedies could have been devised upfront.

We discuss other potential applications of process mining to accounting later in this paper. But first, we discuss the steps involved in process mining, beginning most critically, with the creation of the event logs.

1. **Event Log Creation**

While ERP systems record meta-information automatically about data entries, that information is not stored in any systematic or easily accessible fashion. Moreover, most IT systems can record more meta-information than they actually do in practice, with the data capture feature not fully turned on in the absence of any demand for that information. In addition, the more information that is recorded in the IT system in addition to the actual data being entered, the slower the system tends to get (or at least, that is what many IT administrators believe, which results in the same outcome). In short, those seeking to do process mining have to first construct the event log, ideally determining in advance which information is to be recorded, but if that not possible, then making use of the information that already exists within the ERP system.

The starting point of event log creation is taking advantage of the fact that at the very minimum virtually all ERP systems will at least independently date stamp transactions (i.e. rather than rely only on the date entered by the user) and require users entering data to enter their login information. This date and originator information is by itself sufficient for a large amount of process mining analysis to be undertaken, but obviously more can be done if other meta-information is gathered, such as initial and corrected data entries, fingerprint or other biometric information to preclude use of stolen login passwords, or even all keystrokes.

The meta-information that is captured by the ERP system is located across numerous tables, whose logic schema depends on the characteristics of each ERP system as well as individual company settings, facts which increase the hurdles facing the researcher. The scope and power of process mining is dependent on how comprehensive the event log is in including data on all activities relevant to the process being analyzed. Thus, when creating the event log it is essential to first develop a holistic understanding of the activities that constitute the process of interest to the researcher. Jans (2009) and Gehrke and Mueller-Wickop (2010) both develop methodologies for extracting data from ERP systems and organizing it systematically into an event log, but each is forced to do this step from first principles and adopt somewhat different procedures in each case. The challenge facing process mining researchers is that there is as yet to no established or best practices in event log creation.

For example, when the log data is authorizations of transactions, the underlying activities can be ‘sign purchase order’, ‘release purchase order’, ‘pay invoice’ ‘alter purchase order’, ‘return goods to supplier’, and so forth. Activity identification is a matter of judgment by the researcher, trading off the comprehensiveness of the process understanding versus the desire to reduce the size of the resulting event log and the difficulty in its process mining.

Jans et al (2010) provide the following example of a sequence of data entry events into an ERP system and the meta-information that the system automatically records concerning that transaction and the users entering it:

1. on Feb 12, 8:23 AM: Mike entered invoice No. 3 in system, filling out the supplier (AT&T), posting date (02-10-2010), invoice value (100 USD) and description (internet services Jan 2010)
2. on Feb 12, 8:43 AM: John changed ‘Value’ from ‘100USD’ to ‘120USD’
3. on Feb 12, 8:44 AM: John signed invoice No. 3

The transactional data would only show the final entry with a value of $120 with a posting date of Feb 10, and that is what the accountant or researcher would see too if this was a paper based ledger system. However, in this case the ERP system also records as meta-information the identities of all those users who “touch” the transaction, the actual time and date they did so and all entered data points, even those subsequently overwritten. This makes it clear that two separate individuals were involved with entering data on this transaction and that the dates they did so do not coincide with the entered date, and, of course, not only was the entry amount changed, but that change was only authorized by the same person making the change. While there may well be a perfectly acceptable reason for this sequence of events, this is information which would clearly make an auditor want to question further what is happening with this transaction.

Two points should be kept in mind, however, with this example. First, as discussed above, whether all this meta-information is actually recorded and stored depends on whether a choice had been made earlier by the IT administrators to keep track of this data. Secondly, the history of this transaction is apparent from the event log because all relevant data had already been extracted and arranged into an easy to read narrative format. In reality, those various pieces of information would be stored at various locations in the IT system, and the researcher seeking to construct an event log would have to aggregate and assemble it before being able to obtain such insights so readily. Another factor that facilitated determining what had really happened with this transaction was that the event log extract consists only of those entries relevant to it alone. In practice, even the best constructed event log would consist of a few anomalous transactions amongst a mass of routine ones and it requires the systematic procedures of process mining to extract the former from the latter.

1. **The Methodologies of Process Mining**

Given the wealth of information potentially contained in an event log, methodologies continue to be developed to mine them. In this section we briefly discuss the range of different ways of analyzing the information in event logs. Event log data is so rich that there are numerous lenses through which the information can be viewed, yielding many different types of insights into how underlying business processes operate. To return to the GPS analogy, all maps tell you how to get from A to B, but the better the unit, the more points of interest you are going to see on the way.

At the most generic level, there are three fundamental process mining *perspectives*: the process perspective, the organizational perspective and the case perspective, which correspond to analyzing the event log to determine “How the process was undertaken?”, “Who was involved in the process?” and “What happened with this particular transaction?” respectively.

The *process perspective* can be used by researchers to compare the process as it is meant to be performed against how it actually is and thus identify control failures and weaknesses. Adopting the *organizational perspective* enables underlying relations between those entering data or between those individuals and specific tasks to be made visible. The obvious use of this perspective is in checking segregation of duty controls. The *case perspective* focuses on a single process instance, tracing back its history and relationships of users that are involved in that history. This will be useful when analyzing, for example the size of an order or the related supplier.

The methodologies of process mining can be further classified by the approach followed to search for answers to these three perspectives. There are at least five different such approaches in process mining: 1. process discovery, 2. conformance check, 3. performance analysis, 4. social networks analysis, 5. decision mining and verification. Fully exploring the potential to AIS researchers of these different techniques of process mining is beyond the scope of this introductory paper. Jans et al (2010) provides more details as to what each of these entails, and we only provide an outline here to demonstrate the wide scope of process mining and the many different kinds of process insights that it can offer the researcher or accounting practitioner:

1. **Process Discovery:** In process discovery the event log is mined to reveal paths with no a-priori process to guide the discovery process. In other words, the aim here is simply explore the business process to see if there are any anomalies or unusual transactions.
2. **Conformance Check:** A conformance check does, as its name suggests, a confirmation as to whether the process reality matches the expectation or a standard. The expectation model can be either descriptive or prescriptive, in much the same way that standards in costing can be attainable or ideal. The point of comparing against a prescriptive model is often to see how employees have had to deviate from established procedures because of an unexpected constraint, such as the lack of key personnel or the need to expedite an order to please an important customer.
3. **Performance Analysis:** Performance analysis techniques focus on the measurement of business process’ performances. Typically, performance analysis creates reports on Key Performance Indicators (KPI), such as throughput time of a process.
4. **Social Network Analysis:** Social network analysis utilizes the information contained in the event log about which authorized user entered each transaction. Not only does this allow the behavior of that individual employee to be tracked, but also the social networks that they are part of in the workplace and beyond to be ascertained. The ability of this technique to detect collusion is obvious and a capability perhaps never before available to auditors.
5. **Decision Mining and Verification:** Decision mining focuses on decision points in a discovered process model is used to test assertions on a case by case basis. For example, this technique can examine whether after a user changes an invoice, whether that person’s next step is to seek a new authorization, or instead, to input receipt of the good. Acceptable variations from standard practice can be built into the analysis to detect material deviations.

In this section we have discussed three different perspectives when doing process mining and five different approaches, which yields a possible fifteen different combinations of possible analytic paradigms. Some of these possibilities will presumably prove to be more useful for AIS research than others, but it will take a sustained investigative effort before it can be determined which is which.

The actual tools used in implementing these methodologies consist of various software that systematically analyzes the data contained in event logs. Gehrke and Mueller-Wickop (2010) develop their own algorithm using Java and the SAP™ proprietary Remote Function Call, since their focus is entirely on that ERP system. By contrast, the open source site [www.processmining.org](http://www.processmining.org) which is a collaboration between academics and such leading IT firms as Phillips and IBM, is devoted to developing generic tools for process mining. Their products include ProM, a generic open-source software for implementing process mining tools in a standard environment and ProMimport, a framework for the extraction of MXML-formatted logs from various information systems.[[7]](#footnote-7) The full discussion of these and other tools of process analysis, such as YAWL (“Yet Another Workflow Language”) and the role played in process mining by Petri Nets and other workflow analysis and visualization tools, is beyond the scope of this paper(see ter Hofstede et al, 2010).

1. **Conclusion**

If process mining is the equivalent of a GPS system, then this paper is only the most rudimentary map for AIS researchers into a methodology whose promise has prompted a very large scale research initiative in computer management sciences, as well as in industry. For process mining to become as widely adopted in AIS as it is in other disciplines, accounting academics have to acknowledge that the proven value of process mining in those research areas indicates that it surely would be anomalous if it is not equally impactful in our own. What is clearly needed is integrative AIS research that reviews the existing process mining literature and discusses its application to specific accounting problems.

What are the kinds of problems in accounting that process mining can provide fresh insights into? While processes are important in several areas of accounting, particularly in management accounting, the focus of the extant process mining literature in accounting by Jans et al (2010) and Gehrke and Mueller-Wickop (2010) has been on auditing. That is not surprising because an essential aspect of auditing is the identification and examination of anomalous transactions. As Statement of Auditing Standards Number 56 states *“A basic premise underlying the application*

*of analytical procedures is that plausible relationships among data may reasonably be expected to exist and continue in the absence of known conditions to the contrary. Particular conditions that can cause variations in these relationships include, for example, specific unusual transactions or events, accounting changes, business changes, random fluctuations, or misstatements.”* (AICPA, 1988).

Process mining offers auditors a new and powerful tool to perform analytic procedures. Researchers have explored many different analytic procedure tools, ranging from simple ratio analysis to continuity equations and cluster analysis (Hirst and Koonce, 1996; Kogan et al 2010; Thiprungsri, 2010). Process mining does not replace these techniques, but rather, provides way of refining their results. One of the major problems with any analytic procedures technique is the number of false positives, caused not by material anomalous transactions, but rather, as SAS 56 states, by routine business changes or random fluctuations. One possible way of separating the audit relevant from the immaterial is to examine the circumstances which gave rise to transactions flagged as potentially suspicious.

Thus, Kogan et al 2010 use continuity equations as a means of modeling business processes to use as a benchmark in audit tests. With access to the universe of data provided by a continuous auditing system, they have the ability to provide modeling of complex business processes to an unprecedented level of detail. However, continuity equations are based only on transactional data, which means that while Kogan et al (2010) can detect anomalies, they cannot be sure if the cause is an unusual but acceptable business event—such as a need to expedite an order for a valued customer—or caused by fraud. It is at this point that process mining can be used to explore in depth the circumstances which gave rise to that anomaly and to either deal with a control failure, or alternatively to refine the continuity equation benchmark to reduce future instances of false positives.

This procedure uses process mining as a follow up to a first step in which transactional data is analyzed and filtered to a set of potentially suspicious events which require further examination. Of course process mining can itself be used as the primary or even only analytic procedure, and it is an open research question whether a combination of data and process mining yields more efficient results, similar insights or different ones, meaning that the two techniques are either complements or substitutes. But given the greater research effort in auditing into transaction based analytic procedures, there is some advantage in using process costing as a validation check and follow up to those more familiar methodologies, rather than trying to convince auditors to abandon those established procedures altogether in favor of process mining.

Hence, consider the tests that are used in a large Latin American Bank to examine anomalous transitory accounts. A transitory account is a holding account used to store funds until a more appropriate destination account for them can be determined. Not all of these accounts can be examine in detail without prohibitive cost, hence Kim et al (2009) used continuous auditing techniques to identify transitory accounts that are particularly anomalous. The problem is that any transitory account is anomalous to some extent, which makes it more difficult to identify ones that are particularly suspicious. Process mining offers promise here to better understand the process by which a transitory account is created and to detect patterns in such behavior across branches or individual tellers or customers. For example, if incorrect entry of account numbers is a source of transitory accounts, process mining can inform the bank when such errors are more likely to occur, for instance, late in the day, or with newer tellers.

Another application of process mining to help refine the results of transactional analytic procedures arises in the work undertaken by Thiprungsri (2010) to apply the statistical technique of cluster analysis to auditing. Again, the intention with that work is to follow the spirit of SAS 56 by developing new methods of identifying outliers in transactional data, but as with all such techniques the issue is separating suspicious outliers from merely unusual ones. Applying process mining to the entirety of a firm’s data warehouse may be prohibitively costly and difficult to do in a timely fashion, but once a cluster is identified, which by definition is small and anomalous, then process mining can be applied to the event logs of just those transactions to see what the commonalities are that made them cluster together

Process mining can also be used by itself to better understand and set benchmarks for processes and when linked to a continuous monitoring system, to intervene in the system when ongoing processes deviate materially from those benchmarks. Such conformance testing is the most fundamental use of process mining, and it will take much research to develop it to the extent that it can be used in real time, which is where it can have the most impact on process efficiency. Such uses of process mining blurs the distinction between it and business process management, which also suggests that its main user might be internal auditors or managements as opposed to external auditors, who for independence reasons, would not want to intervene in business processes that they subsequently have to audit.

However, it needs to be kept in mind that these suggested applications of process mining to accounting are highly preliminary, since it is only by a sustained research effort that the full potential of process mining can be established. And when considering the potential of process mining in AIS research, the argument put forward by Jans et al (2010) for the applicability of process mining to auditing can also be applied more generally: *“Audit practice as we know it has evolved in a world where the auditor only had access to input data. Those of us who grew up in that world can only imagine how different auditing would have been if the starting point was the meta-data in the event log and auditors were as familiar with the tools of process mining to exploit that data, as they are with such data mining techniques as regression analysis used with input data. Technology moves on, and so, we hope, will auditing*.*”*

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1. An event log is also known in IT as an “audit log”.. [↑](#footnote-ref-1)
2. <http://www.fas.org/irp/congress/1996_hr/s960605a.htm>. [↑](#footnote-ref-2)
3. A collection of over one hundred process mining papers is maintained at the website of the Business Process Mining Center: <http://is.tm.tue.nl/staff/wvdaalst/BPMcenter/reports.htm>. [↑](#footnote-ref-3)
4. [www.modernanalyst.com/Resources/Articles/tabid/115/articleType/ArticleView/articleId/936/More-Confusing-SOA-Terms.aspx](http://www.modernanalyst.com/Resources/Articles/tabid/115/articleType/ArticleView/articleId/936/More-Confusing-SOA-Terms.aspx) [↑](#footnote-ref-4)
5. <http://prom.win.tue.nl/research/wiki/blogs/pre2009/process_mining_tutorial_esscass_2009>. [↑](#footnote-ref-5)
6. All of process mining analysis has to assume that the typical user entering data into a company’s IT systems lacks the super-user privileges that would enable them to subvert these controls. [↑](#footnote-ref-6)
7. <http://prom.win.tue.nl/research/wiki/tools/start>. [↑](#footnote-ref-7)