When Sales Meet Process Mining:
A Scientific Approach to Sales Process and Performance Management

Research-in-Progress

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Abstract

Selling has long been considered as an "art" driven by personal intuition and native sales talent. However, significant changes have occurred over the past 30 years, as a result of technological advances and changing customer expectations. As one answer to these changes, practitioners and scholars have promoted the idea of "sales as a science", relying on documented, repeatable ways of selling that reflect scientific methods. We argue that process mining is a relevant candidate for empowering "sales as a science" via its capacity to analyze, discover, and enhance end-to-end processes. Through a design science approach, we propose a framework for applying process mining to sales, comprising a refined notation and seven process mining analysis scenarios. Our study represents a first step towards gaining a better understanding of real-world sales processes based on digital traces from operational systems e.g., customer relationship management (CRM) systems, or emerging technologies e.g., smart watches.

Keywords: Sales as a Science, Process Mining, Scientific Workflow, Sales Performance, Sales Force Automation, Customer Relationship Management

Introduction

Selling has long been considered as an art – the art of convincing customers of a product or service's usefulness, which started long time before the use of money, when a pig was bartered for a day of labour. The first bestsellers on sales, such as *How to Win Friends and Influence People* (Carnegie, 1936) and *How to Master the Art of Selling* (Hopkins et al., 1982), propagated the idea of sales as an art. They helped sales representatives to develop their innate talents and interpersonal skills, for instance, by playing with emotions in order to close deals faster. However, significant changes have marked the sales profession in the past 30 years (Dixon and Tanner Jr, 2012; Marshall et al., 1999; Moncrief et al., 2006): Increased competitive pressure, technological advances such as sales force automation and online sales

channels, a globalization of sales activities and their increasing complexity, involving more people (e.g., marketing, production, technical experts) and eventually more interactions. Furthermore, owing to "new" sources of information, customers have more specific needs and higher expectations (Thull, 2010).

As a result, being successful in selling has become more difficult, and relying only on an "artistic" approach does not provide sufficient results (Costell, 2004; Homburg et al., 2012). As a consequence, scholars and practitioners seek to bring scientific rigor to sales in order to increase sales productivity and reduce risks (Churchill Jr et al., 1985; Rentz et al., 2002; Verbeke et al., 2011). SPIN selling was one of the first scientific sales approaches developed from the observations of 35,000 sales calls by experienced sales professionals in more than 20 countries towards the end of 1980s (Rackham et al., 1988). More recently, the concept of "sales as a science" was coined and is being adopted in many companies (Costell, 2004; HBR, 2014; Ledingham et al., 2006). It implies systemization and quantification of selling activities and is often associated with three components: 1) a structured sales process, 2) the use of key indicators, and 3) support by means of sales tools. Companies thereby establish a documented, repeatable way of selling that reflects scientific methods and allows them to generally get the same results within the laws of large numbers. While some analysts predict that "in the near future, sales operations will monitor sales activity with the same detail that occurs in manufacturing processes" (Wurster et al., 2013), however, to date, sales processes have been barely studied in academic research. Interestingly, and despite the increasing penetration of CRM and other sales tools, companies make little use of data maintained in these systems or other digital traces to support quantification and systemization of selling activities. We argue that process mining is a relevant candidate for promoting "sales as a science" through its capacity to analyze, discover and enhance end-to-end processes (van der Aalst, 2011). This motivates our research, which aims at contributing to the development of a scientific approach in sales and addresses two research questions: 1) What are the challenges in managing sales processes? 2) How can process mining be used to address these challenges? In view of our research objectives, we opted for a design science research approach to develop a process mining framework for sales and demonstrate its capacity to address current challenges in managing sales processes. This research-in-progress paper presents a preliminary version of the framework and early evaluation results.

The remainder of this paper is structured as follows. First, we introduce the concept of process mining and review current challenges in managing sales processes. We then present our research methodology. Next, we present our framework applied to selected challenges in sales. Finally, we summarize the contributions of our paper, and describe the next steps toward completing this research.

Literature Review

Process Mining

Process mining provides a set of tools that support multiple ways to discover, monitor, and improve processes based on event logs (van der Aalst, 2011). It thereby enables a link to be established between process models and "reality" (see Figure 1). Process mining relies on the following set of basic components (van der Aalst, 2011; 2012). To begin with, *information systems* capture activities happening in the "real world". To perform process mining on that data, the digital traces captured in the information systems must be extracted and transformed into *event logs*. There are three minimum requirements: First, it must be possible to define an activity name for well-defined steps. Second, it should be possible to identify distinct cases. The case provides the means to group together instances of the same process, while the activity describes well-defined steps. Finally, the activities must be available in an ordered manner. Furthermore, the analysis can be extended by enriching the events with *additional information* such as an indication of the resource performing the activity, or any other relevant data related to the case. The literature distinguishes two event data types: *historic data* refers to complete event logs from the past, while *current data* represents ongoing processes typically used to perform operational support. Finally, a *process model* is primarily used to express the ordering of activities, but it can also express other properties embedded in event logs. It is also worth mentioning that one can distinguish a "de jure" model from a "de facto" process model; the former is normative since it intends to steer or control the reality, while the latter derives from event logs, which means that the model seeks to describe a reality.

Process mining techniques applied on a combination of current data, historic data, "de jure" models, and "de facto" models lead to a large spectrum of actions. First, observations made on historic data can lead to

a "de facto" model that can trigger a *redesign* of the "de jure" model. For example, if we observed a repeated deviant pattern to execute the process with a better performance, then it makes sense to replace the current "de jure" model with this new pattern. Second, one can harness the power of process mining to make necessary *adjustments*. For the sake of the example one can mention a delegation trigger for overloaded employees. Third, if a particular characteristic of the case always shows a deviant behavior that is undesirable, then it is probably necessary to *intervene*. For example, if an employee often wrongly executes the process then specific training could be the output of the process mining analysis. Fourth, the power of process mining could be used to provide *operational support*. In this case, process mining could leverage historic data to provide recommendations for the next best step to perform during runtime execution (Schonenberg et al., 2008).
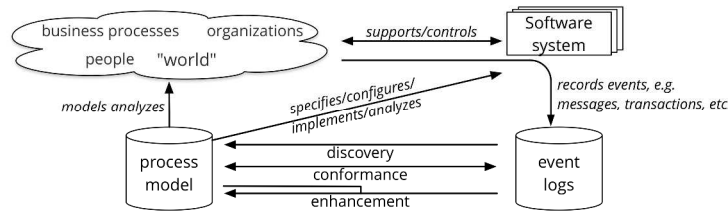
Figure 1. Overview of process mining (van der Aalst, 2011)

When analyzing the various domains and purposes in which process mining could be applied, processes fall within a continuum ranging from *structured* to highly *unstructured* processes. On the one hand, a model that can match most of the event data set (e.g. 80%) without being too complex to comprehend can be defined as structured (van der Aalst, 2011). This type of model can typically be seen in production or logistics processes in which activities are usually executed in a controlled manner and with very predictable outcomes (Mans et al., 2013). On the other hand, applying process discovery techniques on highly unstructured processes will lead to models that are too complex to be insightful. Nonetheless, similar events can be grouped into subsets through data clustering techniques, thus offering the opportunity to analyze them independently (Song et al., 2009). The intrinsic complexity of highly unstructured processes makes data analysis tasks challenging. However, the room for improvement is bigger here compared to the analyses of structured processes (Mans et al., 2015; van der Aalst, 2011).

Returning to sales, selling involves both structured and unstructured processes. On the one hand, owing to the standardized nature of mass-market products or services, transactional and automatic selling will most likely result in processes considered as structured. On the other hand, selling complex solutions implies adaptations to customer expectations and buying processes, resulting in intense interactions that tend to be unstructured. In the end, sales may shift between *structured* and *unstructured* processes.

Challenges in Sales Process and Performance Management

In their attempt to overcome the artistic approaches in sales, Rackham et al., (1988) were among the first to suggest treating sales based on facts. Their idea seeks to bring scientific rigor to a field that has been traditionally driven by a sales representative's selling skills (Churchill Jr et al., 1985; Rentz et al., 2002; Verbeke et al., 2011). The so-called, "sales as a science" relies on a structured approach mainly based on three components (Costell, 2004; HBR, 2014; Ledingham et al., 2006): 1) a *structured sales process* that defines stages and milestones of a sale, 2) the use of *performance measurements* that measure what happens along the sales process, and 3) *sales tools* that support and automate the sales process and the performance measurements. On this basis, data from the field is used to support decision-making.

Among these three components, empirical studies find that a defined sales process has significant impact on sales results, but only half of a company's sales force relies on it when it is implemented (Cummings, 2006; Jordan and Kelly, 2015). Sales processes have specific characteristics that set them apart from other business processes, where variation is reduced to its maximum in order to save time and maintain the same quality standard (Mans et al., 2013). In personal and consultative selling, the beginning of sale can be triggered by a large variety of events and by both, sales organizations or customers (Moncrief and Marshall, 2005). Therefore, process inputs can take different forms, from a request for proposal by a prospect to a phone call by a sales representative, and can occur on different distribution channels: A sale can start online via an e-shop and continues along a traditional sales presentation (Homburg et al., 2012).

Compared to other operational business processes e.g. in production and logistics, sales encounter many variations. Though they share similar milestones (e.g., product demonstration, presentation, quota, contract), what happens between these can vary significantly based on a customer needs, competitors, product and service types (Viio, 2011). Therefore, sales processes do not always follow a similar sequence of activities, but rather adapt their activities to the context. In addition, sales processes can stop at any time: Customers can switch to competitors if they find or receive a better offer (Buell et al., 2010), and this type of churn may be hard to detect in a non-contractual settings as the end of the relation is not clearly defined (Hopmann and Thede, 2005). If taken apart some on the sales processes' characteristics can be found in other less structured processes (e.g., healthcare), but once together they make sales processes unique.

Based on an extensive literature review, we identified seven challenges related to implementing and using sales processes that are repeatedly mentioned in studies on sales: *1) (Re)Define the level of sales processes' structure and 2) guide sales representative*: While a very structured sales process provides clear guidance, it nevertheless runs the risks of being too rigid and of preventing sales representatives from adapting to customer behaviors (Canning and Brennan, 2004; Viio and Grönroos, 2014). Companies must then design sales processes that define key sales activities, while maintaining enough flexibility to adapt to various situations, including different customers and buying processes (Homburg et al., 2012; Viio and Grönroos, 2014). *3) Understand factors influencing sales process variability*: Though variability per se is not negative, companies must identify the sources of variations in order to eliminate what decreases quality, safety or increases costs (Hall and Johnson, 2009; Johnston and Marshall, 2016). On the one hand, these can be caused by internal factors (e.g., experience and age of sales representatives (Gohmann et al., 2005), knowledge, goal clarity, skills (Avila et al., 1988; Minna Rollins et al., 2015), sales approach (Marshall et al., 1999; Moncrief et al., 2006), while on the other, variability can also have external origins, for instance, customers with very sophisticated needs and expectations (Homburg et al., 2012; Thull, 2010). The latter would require sales representatives to adapt their techniques. *4) Assess the sales processes' conformity to their process model:* The definition and implementation of sales processes are aligned with a strategy to have more standardized sales, e.g., increasing sales productivity (Hall and Johnson, 2009). Consequently, companies must assess to what extent their sales force follows the defined sales processes. *5) Analyze the efficiency of sales activities and identify bottlenecks:* Sales have become more complex, involving more people and eventually more interactions (Dixon and Tanner Jr, 2012; Minna Rollins et al., 2015). It is often unclear what activities are pending, and who is responsible to make the progress happens in a sale (Bächli-Bolvako, 2011; Dwyer et al., 2000; Jaramillo and Marshall, 2004). *6) Identify factors influencing sales performance*: Many factors drive sales performance, from selling skills to the degree of adaptiveness (Verbeke et al., 2011). As a result, sales managers are unable to provide actionable advice to their sales representatives when they are asked to increase growth by for instance 8% (Ledingham et al., 2006). *7) Provide disqualification criteria to avoid spending time on dead sales:* Spending time on activities that will never lead to contracts is one of the sales representatives' primary concerns (Krogue, 2015). Sales process must therefore prevent this to happen.

Research Objectives and Methodology

Despite the increasing interest in scientific approaches to sales, little research has been conducted on sales processes. We argue that process mining has the capacity to address current challenges in managing sales processes (van der Aalst, 2011): a) It provides a comprehensive understanding of end-to-end processes and allows one to establish links between processes and "reality", b) it can then assess individual activities and measure their impacts on sales results, and c) it can connect multiple data sources and can therefore leverage data from the new generation of sales tools, which facilitates the documentation of sales activities via mobile and smartwatch applications (Salesforce research, 2015).

Our research objective is to design a process mining framework as a scientific approach to address current challenges in managing sales processes. As our main research result is an artifact that intends to solve identified organizational problems, we opted for a design science approach (Hevner et al., 2004). In order to guide the development of this artifact, we relied on the design science research methodology (DSRM) as suggested by Peffers et al., (2007). It fosters rigorous and systematic design science research by means of a six-step framework:

1) Identify and motivate problem: The research problem arose from a two-year industry-funded research project investigating sales performance management. During this project, we conducted interviews with 16 companies and analyzed their current sales processes and performance management approach. We observed that most of the companies were unsatisfied with either the definition, the effectiveness or the adoption of their sales processes and did rarely monitor their existing processes. In parallel, we reviewed academic and professional literature to identify current challenges in managing sales processes. We benefited from two recent literature reviews collecting more than 200 papers in the area of sales activities, sales and sales management, sales process, buying process, relationship initiation and marketing, and buying, purchasing, and supply chain management (Bächli-Bolvako, 2011; Viio, 2011). Due to the applied character of sales and in order to reflect the latest trends, we included books (i.e., Homburg et al., 2012; Johnston and Marshall, 2016), analyst reports (i.e., *Gartner*, *Forbes*, *Salesforce research*) and professional magazines (i.e., *Harvard Business Review, MIT Sloan Management Review*). From the literature, we identified 25 challenges that we classified and grouped in order to remove redundancy. We evaluated these challenges in the interviews with the 16 companies (see Table 1). The results are seven distinct and validated challenges.

2) Define objective of a solution: Based on the previous step, we aim at providing a framework to systematically apply process mining to address the aforementioned challenges. This framework should serve as a communication vehicle between sales managers and directors who need to express their sales challenges, and data scientists who must clearly identify the users' requirements for implementation. By defining a common ground to address current challenges in sales with process mining, our solution also aims to benchmark the results from multiple organizations.

3) Design and development: In designing our framework, we build on the process mining workflow notation (Bolt et al., 2015) to express how process mining could be applied to sales-related challenges. To refine this notation for sales process mining, we used the insights from the interviews with the 16 companies (see step 1) that we then generalized (Table 2). Second, we use and adapt the notation to elaborate how process mining can solve the seven challenges.

4) Demonstration: We successfully instantiated our framework for the seven identified challenges. Due to space restriction, we describe only the most relevant challenge (i.e., N° 6) from the interviews.

5) Evaluation: Our current research activities focus on the evaluation of the framework with real company data, but is out of scope of this research-in-progress publication.

6) Communication: This research-in-progress paper is part of our communication activities and will be complemented by a journal paper that includes the evaluation of our framework.

A Framework for Applying Process Mining to Sales

Scope

Our research results in a framework that guides professionals in applying process mining to improve sales processes and performance. By providing domain-specific challenges, a notation and solutions, we aim to provide a common ground that facilitates not only the application of process mining to effectively manage sales processes, but also allows to enable the discussions within distinct organizations. We also seek to enhance the communication between stakeholders with various backgrounds such as sales managers, technical engineers, and data scientists. When developing the framework, we set the scope to personal consultative selling, i.e. selling complex solutions that require adaptation based on customer needs (Rackham and DeVincentis, 1998). This context is characterized by rather unstructured processes and is at the origin of most challenges in sales organizations (Dixon and Tanner Jr, 2012). It differs from automatic transaction selling, e.g. using online channels, which usually does not vary significantly from one customer to another.

Process Mining Framework

The framework comprises 1) a refinement of the scientific workflow notation defined by Bolt et al., (2015) to incorporate sales-specific characteristics, and 2) an answer to the seven challenges identified, documented by means of the scientific workflow. The framework is abstract as it is not linked to any specific algorithm or tool. Its purpose is to represent domain-specific process mining scenarios that are repeatable and help to answer sales-specific challenges that can be implemented with process mining

tools such as ProM or RapidProM. Figure 2 depicts the refined notation (on the left) and illustrates an example (on the right). The origin of the notation (e.g. "S", "E$_H$") and its refinement for sales are further detailed in the table Table 1.
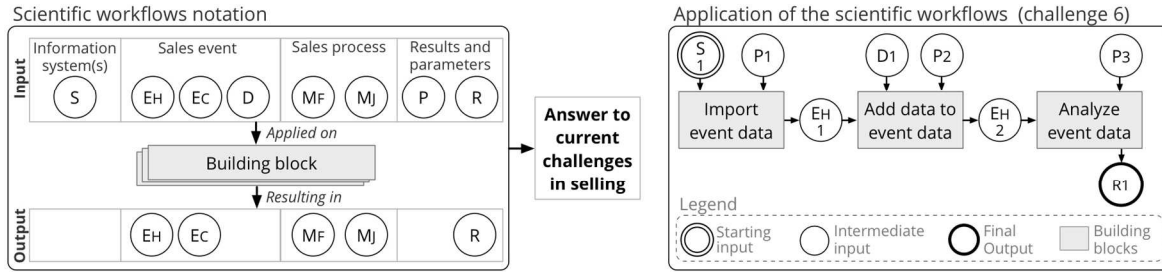
Figure 2. Domain-specific notation for scientific workflows in "sales process mining"

The scientific workflow notation is composed of the following elements: *Inputs* and *outputs* (represented by circles) and *building blocks* (represented by rectangles). The building blocks (represented by rectangles) are "logical units of work" that take one or several inputs to produce a specific output. They are not linked to any specific algorithm and "cannot be conceptually split while maintaining their generality" (Bolt et al., 2015). For instance, the building block *import event data* takes *information system* as input to produce *event logs* on the output. In the case of sales, the relevant information systems that capture sales activities are typically customer relationship management (for customer interactions and sales proposals), enterprise planning systems (for sales orders), but also spreadsheets. In this building block, data from different source systems may be combined to produce event logs (i.e. left-hand side on Figure 2: E_C for current event, E_H for historic event). This output can then become an input for additional building blocks that focus on filtering or splitting the event logs, on discovering the "de facto" model (M_F) from the historic and current sales process instances or on comparing them to "de jure" models (M_J). Thus, it is possible to define a sequence of actions that will result in a final output, which provides answers or insights to tackle the business challenge at hand (i.e. *R* for result). Altogether, Bolt et al. define 19 building blocks for process mining activities. The eight different input/output elements are explained in Table 1, along with their refinement for the sales context.

Original scientific workflows (Bolt et al., 2015)	Refined scientific workflows for sales process mining	Concrete examples
(S) *Information system (S):* Support the process execution	(S) *Information system (S):* -Customer relationship management system -Enterprise resource planning system -Individual spreadsheet -E-shop / Website / Customer portal	Salesforce, Microsoft Dynamics CRM, Google Analytics, Excel.
(E) *Event data set (E):* Record the execution of the process	(EH) *Historic sales event data set (E_H):* Record terminated sales activities.	1) Prospecting (e.g., phone call, email), 2) presentation to customer, 3) closing the sale.
	(EC) *Current sales event data set (E_C):* Record ongoing sales activities.	Same as E_H except the sale is still ongoing and therefore further actions are expected.
(D) *Additional data set (D):* contextual information	(D) *Additional data set (D):* Contextual information gained from external sources.	Customer satisfaction / feedback, demographic data.
(M) *Process model (M):* Represent the behavior of a process	(MJ) *"De jure" sales process model (M_J):* Expected behavior of a sales process.	BPMN modeled at hand by a sales manager to represent how the sales should be executed.
	(MF) *"De facto" sales process model (M_F):* Actual behavior of a sales process.	BPMN discovered by a process discovery algorithm showing how sales are actually executed.

ⓟ *Set of parameters (P):* Configure the building blocks	ⓟ*Set of parameters (P):* Parameters to be discussed between sales managers and data analysts.	The minimum Likert score that should be obtained on a customer satisfaction feedback to consider the sales as a success.
ⓡ*Result (R):* Output of a building block, except process models and event data sets	ⓡ*Result (R):* information supporting the analysis of sales	Binary value indicating if a historic sales event fits a "de jure" process model (i.e. replay fitness)

Table 1. Domain-specific refinement for scientific workflow notation: Inputs and outputs

Table 2 provides an overview of the most important challenges that we identified from sales literature and classified along the four steps of the performance management cycle, widely used in sales performance initiatives (Armstrong and Baron, 2005). For each challenge a process mining scenario has been developed using the scientific workflow notation. Due to space limitations, the table only outlines the relevant building blocks for these scenarios. It is important to note that for each challenges described in Table 2, the case is defined as the set of all activities that occur in a sale between the stakeholders (e.g., customer, sales representative, expert) and the products or services proposed by or to the customer.

Sales PMC	Challenges from literature	Improve-ment actions	Process mining scenario (relevant building blocks)	Importance (n=16)
Plan	*1. (Re)Define the level of sales processes' structure*	- Redesign	- Filter event data - Split event data - Discover process model from event data - Compare process model - Evaluate process model using event data - Generate report	Mean: 3.68 Median: 4
	3. Understand factors influencing sales process variability	- Adjust - Intervene	- Split event data - Discover process model from event data - Enrich process model using event data	Mean: 3.43 Median: 4
Act	*4. Assess the sales processes' conformity to their process model*	- Intervene	- Evaluate process model using event data	Mean: 3.69 Median: 4
	2. Provide guidance to sales representatives during sales	- Support	- Filter event data - Split event data - Discover process model from event data - Analyze event data - Generate report	Mean: 3.88 Median: 4
Monitor	*5. Analyze the efficiency of sales activities and identify bottlenecks*	- Adjust - Intervene - Redesign	- Filter event data - Enrich process model using event data	Mean: 4.07 Median: 4
Review	*6. Identify factors influencing performance*	- Intervene - Support	- Analyze event data	Mean: **4.56** Median: **5**
	7. Identify disqualification criteria to avoid sales representatives spending their time on dead sales	- Adjust	- Analyze event data	Mean: 4.00 Median: 4

Table 2. Overview of the framework, with process mining scenarios and evaluation results

Demonstration of the framework

In the following, we will demonstrate how the framework can be applied to the challenge that was considered the most relevant by the 16 sales managers interviewed (i.e. challenge 6: "Identify factors influencing performance"). By applying the process mining framework to this challenge, the goal is to increase the understanding of how different factors – for example customer or product characteristics – impact sales performance, in order to intervene into these factors or to provide recommendations to sales managers and representatives. The scientific workflow is depicted as part of Figure 2 (previous page): As input, historical event data E_{H1} is imported from an information system $S1$ (e.g., CRM). Relevant events may be a first customer contact, the demonstration of the product/service to the customer, the preparation of an offer and its confirmation by the customer. Although this may look straightforward, this task is an integral part of the process mining effort and may be challenging (van der Aalst, 2011). The complexity will indeed depend on the variety of the systems used and their capacity to extract data at a process level. Using more channels to reach the customer will also make the tasks harder (Blattberg et al., 2008). In a recent study, Khodakarami and Chan (2014) reveal that some companies that use CRM systems continue to use spreadsheets to document customer-related activities. In this case, the spreadsheet should also be used as an input. To analyze the impact of customer-related factors, one may desire to enrich the event with external data such as demographic information or customer feedback. If this data is not in $S1$, it may be added through the building block "Add data to event data", resulting in an enriched event data E_{H2}.

Finally, by applying the building block "Analyze event data" on E_{H2}, one can analyze the data or visualize it (Bolt et al., 2015); the result is the final output $R1$. Visualization of the data itself is important as it can serve to confirm a hypothesis or reject it, and it can help to find implicit but potentially useful information in the data (Keim et al., 2006). For instance, one typical process mining visualization graph is the dotted chart in Figure 3. Like a Gantt chart, a dotted chart shows the spread of events over time (Song and van der Aalst, 2007). On this visual representation, one can group the sales-related events on the vertical axis by trace, event type (e.g., phone calls, email, or presentation), or originator (i.e., sales representatives, customers). Moreover, one can color the data and use symbols based on an attribute of the events (e.g., time, customer satisfaction, or price). By offering many ways to navigate and visualize event data, users can obtain useful insights from a dotted chart. For instance, it is possible to check if activities performed at a certain time leads to better sales outcomes. As another example, a dotted chart can also help to find whether the duration of sales tends to be longer over time for a certain type of customer. These two examples are only two of the many possible observations that can be made with a dotted chart and they can ultimately lead to take concrete improvement actions. For instance, some factors may be improved by offering specific training or coaching activities for sales representatives. Nonetheless, the application of a dotted chart is not an end in itself, as further analysis may be needed to investigate the observations. However, it supports sales managers in quantification of sales activities and understanding the factors influencing performance.
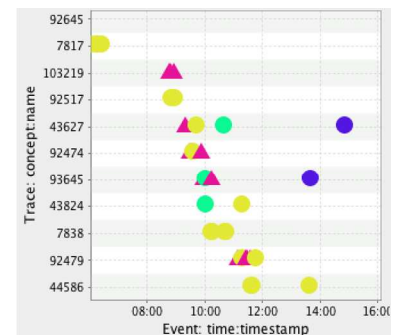
Figure 3: Illustration of a dotted chart

Outlook

To complete our full research, the natural progression is to apply the framework with "real" data from organizations. In this endeavor, we encounter a recurrent problem with process mining applicability: find, merge, and clean data from disparate sources are error-prone tasks (van der Aalst et al., 2012, C1). This is work in progress, but we are already confronted with different settings: some fully integrated CRM, ERP, as well as some disparate spreadsheets. Therefore, we have to reconcile the data from multiple sources and some cleaning is necessary to ensure that cases (i.e. sales processes) are coherent – particularly when multiple sources were involved. Having to clean the data is not surprising as practical experiences reveal that "real" event logs are often far from ideal (Bose et al., 2013). We anticipate from our first round of interviews that some companies involved in our research may not be able to tackle some challenges because of data-quality issues. We deliberately choose to perform this task in an iterative and interactive

way as suggested by Suriadi et al., (2013) and van Eck et al., (2015). It allows us to rationalize the understanding of data and avoid misinterpretation, which globally improve the project's effectiveness.

In light of a lesson learned from Suriadi et al. (2013), we also established that teams, with which we collaborate for the data extraction, are composed of complementary profiles (i.e., process improvement experts), while we take on the role of process mining experts. Note that we also choose to drive the data extraction from questions we derived from our challenges, as suggested by Suriadi et al., (2013) and van der Aalst et al., (2011; 2012). Once the data is extracted, we plan to implement the scenarios via our framework. The final step is to formalize our results and communicate the companies' specific findings to the participants and submit the scientific findings as a full research paper.

Summary and Discussion

To date, existing studies have applied process mining to both structured processes (such as manufacturing and logistics) and unstructured processes (such as healthcare). However, researchers have paid little attention to the sales domain, which contains both process types and which are at the origin of many problems in sales organizations. This motivates our research, which investigates the *current challenges in managing sales processes* and how *process mining could be leveraged to address these.* We start by identifying challenges in selling outlined in the sales literature, refine them, and submit them to 16 practitioners for evaluation. For the resulting seven challenges, we propose a framework for applying process mining. The framework comprises a refined domain-specific notation based Bolt et al. (2015) as well as detailed scientific workflows for the seven challenges. In this research-in-progress paper, we outline the framework and demonstrate it for the challenge that was considered to be the most relevant by 16 experts.

The scientific workflow notation provides an abstract description, but is not linked to a particular implementation, software, or algorithm. Therefore, it is an alternative to existing notations that rely on a limited number of elements of higher abstraction (Mans et al., 2015). Our framework is intended to serve as communication vehicle between sales managers and data scientists. It supports practitioners by defining how process mining can be used to find the right level of formalism of companies' sales processes, with the aim to ease the transition of sales from "art" to "science". By providing domain-specific solutions that are repeatable, our framework supports the implementation of process mining in the sales profession. By doing so, we aim to contribute to the knowledge of applying process mining among sales organizations that share common challenges in sales. By guiding domain-specific process mining analysis, we expect to facilitate not only the application of process mining, but also the sharing of information and thus attempt to address the "cross-organizational mining" challenge from the manifesto (van der Aalst et al., 2012, C7). Indeed, many companies sell their products using multi-level distribution channels (with retailers, wholesalers and the manufacturer) and increasing number of online channels. With the trend towards cross-channel strategies in sales, different organizations, may be involved in the sales processes and may be interested to share their experiences and the findings produced by process mining analysis—without necessarily having to share their raw data nor a common infrastructure. We expect that our framework will facilitate these cross-organizational discussions and contribute also to process improvements. Moreover, we also seek to facilitate the exchange of experience and knowledge of using process mining for sales amongst practitioners and researchers.

From an academic perspective, our study represents a first step towards gaining a better understanding of real-world sales processes based on digital traces from CRM systems and emerging technologies used in sales, such as smart watches. The dilemma of process structure, the growing complexity of sales, and the expanding amount of data produced generated by emerging technologies used in sales, e.g., by smartwatches (Salesforce research, 2015) open a promising perspective for further research and the development of specific process mining techniques for "sales as a science". For instance, comparing factors that influence sales performance and the variability levels required by industry with process mining techniques could lead to interesting insights towards understanding modern sales. Furthermore, developing ways to integrate process mining into the managerial sales practices are important, because "the future of business is to do things by design, not by chance" (Ledingham et al., 2006).

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