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Leveraging BI as support tool for sales teams

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Leveraging BI as support to Sales Team in GoodData

Cíle práce

The main objective of this thesis is to define the best way to use a Business Intelligence tool to improve the performance of a sales department that works with a traditional sales funnel or sales pipeline, through the understanding of which tool and metrics are seen as the most valuable according to the stakeholders in the sales process.
The partial goals of the thesis are:
- to create set of Key Performance Indicators,
- to design data warehouse architecture,
- to design analytical dashboard.

Metodika

To achieve the objectives, there is the need to review literature for similar efforts to define a theoretical framework in which theory of sales management, performance management and monitoring, and business intelligence can be intertwined, in order to list all relevant kpi's.

The next step is the formal identification of the stakeholders in the sales process, and perform interviews with this stakeholders to quantify impact of the identified kpi's.

Thus, we can identify dimensions relevant to the kpi's, and set a logical or dimensional model, on which we can then design and prepare dashboards that include the most important (highly scored) kpi's.

During 6 months the usage of this dashboards by the salesforce will be measured, and as an evaluation of the designing process, we will conduct a comparison between actual usage and predicted usage(based on the kpi scores according to the stakeholders).

The empirical research for this thesis will be done with the sales team of GoodData Inc. and with the Good-Data platform as a BI Tool. However, the resulting framework should be applicable to any other company with a similar sales structure, regardless of company type and size or BI tool chosen.

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Klíčová slova

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Declaration

I declare that I have worked on my diploma thesis titled "Leveraging BI as support to Sales Teams" by myself and I have used only the sources mentioned at the end of the thesis. As the author of the diploma thesis, I declare that the thesis does not break copyrights of any their person.

In Prague on March 31st, 2017 ______________________________

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…To my mom, for her dedication and wisdom all my life;

… And to my father, for guiding my writing. Always.

Využitím BI jako podpůrný nástroj pro obchodní týmy

Souhrn

Zatímco údaje objev je v organizaci velmi důležitý, může prodejní týmy nemají potřebné zázemí nebo znalosti, aby odpovídajícím způsobem převést data do informací, tedy self-service BI nástroj může vést k chybnému výkladu. V tomto případě je důležité vytvořit rámec, který umožní pevné aplikace, která zobrazí popisné informace, že členové Salesforce potřeby organizace.

Takže tato práce definuje rámec, v němž se používat nástroje Business Intelligence s cílem zlepšit výkonnost prodejního oddělení, které pracuje s tradičním prodeje trychtýře nebo prodejním řetězci, a to prostřednictvím porozumění, jehož nástroje a metriky jsou považovány za nejcennější podle zúčastněných stran v procesu prodeje.

Tato práce je zaměřena na vytvoření 3 artefaktů:

- Sada doporučených klíčových ukazatelů výkonnosti (KPI)
- Datový sklad architektura v podobě logického datového modelu pro prodej.
- Design pro vizualizaci ktery ukázat prodeje souvisejících KPI.

Klíčová slova: Prodejní výkonnost, Sales Potrubní, KPI, Business Intelligence, ADR, dashboardy.

Leveraging BI as support tool for sales teams

Summary

While data discovery is very important in an organization, sales teams may not have the necessary background or knowledge to adequately convert data into information, thus a self-service BI tool may give rise to misinterpretations. In that scenario, it is important to develop a framework which gives a fixed application which displays the descriptive information that the members of the organization's salesforce need.

Thus, this thesis defines a framework in which to use a Business Intelligence tool in order to improve the performance of a sales department that works with a traditional sales funnel or sales pipeline, through the understanding of which tool and metrics are seen as the most valuable according to the stakeholders in the sales process.

This thesis focuses on the creation of 3 artifacts:

- A set of recommended Key Performance Indicators (KPI's)
- A data warehouse architecture in the form of a Logical Data Model for sales.
- A design for visualization to show sales related KPI's.

Keywords: Sales performance, Sales Pipeline, KPI's, Business Intelligence, ADR, Dashboards.

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1 Introduction

Undoubtedly what separates a business from an enterprise is the fact that businesses require sales in order to generate income, and as any part of the business, the sales process is an entity that must be properly managed. Sales management comprises all the activities, processes and decisions related to the guidance and better operation of the salesforce and the marketing operations.

Within sales management, one of the processes with highest critical importance for business is the effective conversion of potential new clients, or leads, from the pool of a predefined target market, into actual paying customers that generate revenue for a company. Unfortunately, this process has been usually neglected from academic research (Sonchen & Albers, 2010) and thus leave most sales managers to perform their tasks guided by emotions rather than empirical data, and it's not uncommon to have revenue as the one and only metric to measure success of a sales team (Miller, 2009).

Unlike B2C relationships, which are based on a high volume of transactions, most B2B sales relationships are based on customer loyalty, and incur in a higher cost of customer acquisition, and this in some cases the loss of a customer can become a very serious and potentially destructive issue for a business (Narayandas & Rangan, 2004). To counteract this possibility, some companies even choose a financial model which circles around increasing customer acquisition even when doing so lowers long-term customer retention (Ang & Buttle 2006). In order to minimize the damage caused by over-expending resources in a potential customer that will generate no revenue for the business, most B2B sales departments use a sales funnel/pipeline model. (Jordan, 2014). A sales pipeline helps managers understand the sales process and enables them to track performance both individually and collectively at any given point, allowing them to apply corrective measures on time, and forecast future revenues with higher accuracy.

The paradigm of sales management has changed significantly in the last three decades, giving rise to the boom of CRM applications which are now indispensable to the sales management process, by automating some tasks like customer loyalty assessment, lead or opportunity management, and internal sharing of customer information (Linoff & Berry 2011). But even so, within the existing research on CRM applications, there is actually little focus on B2B environments, (Gummeson, 2004) although it should be noted that there has been a recent spike in the interest for the topic. (Vershney & Singh 2013).

Although the literature suggests that there is a link between the knowledge documents a salesperson reads and their performance, (Ko & Dennis, 2004), most CRM softwares focus on supporting the operational part of the process, leaving salespeople with a huge amount of data that is difficult to interpret. Furthermore CRM systems are, more often than not, self- contained, meaning that it is difficult, if not impossible, to link CRM data with data from other systems, giving rise to information silos and multiple versions of the truth, creating distrust in the information provided by the business systems.

Business Intelligence is the latest paradigm in decision support technologies for the enterprise, with the unique goal to help its users (regardless if such user is an executive, managers, or analyst) to make better and faster decisions. The last decade has seen incredible growth both in supply and demand of BI products and services in all industries, and thus some CRM vendors have already started to include BI into the standard solutions they offer. However, the integration of BI into the CRM is still in early stages and needs time to mature before it reaches a place where users can be satisfied by it (Dinsmore, 2016). One of the biggest challenges faced by BI for sales, is that despite the huge boom of "self-service BI", the truth remains that salespeople may not have the necessary knowledge, time or disposition to correctly convert data into information, thus a BI sandbox tool, which allow all users to play with the data contained in it, may give rise to misinterpretations.(Bendoly, 2017).

In that scenario, in order to support the sales process and most importantly the sales people, it's needed to achieve an optimal visualization, or dashboard, (Lurie and Mason 2007) that helps the sales people understand their data, providing them with a complete picture that can quickly give them the information they know they need, and induce them to ask and answer new questions by highlighting unseen connections between the data.

This thesis aims to construct this optimal dashboard and evaluate its impact on a sales team.

2 Objectives and Methodology

2.1 Objectives

While data discovery is very important in an organization, sales teams may not have the necessary background or knowledge to adequately convert data into information, thus a self-service BI tool may give rise to misinterpretations. In that scenario, it is important to develop a framework which gives a fixed application which displays the descriptive information that the members of the organization's salesforce need.

Thus, the main objective of this thesis is to properly define a way to use a Business Intelligence tool in order to improve the performance of a sales department that works with a traditional sales funnel or sales pipeline, through the understanding of which tool and metrics are seen as the most valuable according to the stakeholders in the sales process.

To achieve the main objective, the development of this thesis will also tackle the creation of these 3 artifacts as partial objectives:

- A set of recommended Key Performance Indicators (KPI's)
- A data warehouse architecture in the form of a Logical Data Model for sales.
- A design for visualization (dashboard, or group of dashboards) to show sales related KPI's.

2.2 Methodology

2.2.1 Framework

A framework is needed as the base for research, as it provides support and guidance for the process of developing the thesis. This work followed the framework composition recommended by Mathiassen, Chiasson, & Germonprez, 2012, where the definition of six key factors comprises the framework within which the thesis will be formulated and developed.

These factors are summarized in Table 1.

P (Problem setting)	Salesforce in a B2B environment (Sales pipeline) requires information which is not easily available through the CRM.
A (Area of concern)	Sales force automation / CRM and lead management / Business Intelligence / B2B Sales
RQ (Research Question)	How to provide a good dashboard that helps increase sales performance?
F (Conceptual Framework)	Sales Pipeline, ADR, SaaS BI
M (Research Method)	Quantitative
CA (Contribution to A)	A: Empirical validation of the relationship between information available and sales performance metrics. P: Template of ideal dashboards for sales team

Table 1. Research Design Summary (based on Mathiassen et al., 2012)

2.2.2 Research Questions

The main objective of this thesis is to define how Business Intelligence can be used as a tool to improve the performance of a sales department which uses a sales funnel or sales pipeline model. The problem can thus be summarized in the answer to the following Research Question (RQ):

RQ: How to provide a good dashboard that helps increase sales performance?

However, the problem gives rise to two more problems that must be solved in order to correctly answer the research question.

The first problem is understanding that sales performance is not limited to increased generated revenue. While revenue may be the ultimate goal, depending on the business special emphasis may be placed in churn reduction, quick closing of deals, or increase in new customer acquisition. So in order to measure objectively any variation in sales performance, a new metric that comprises different meters of sales performance must be created and validated. This problem can be summarized in the following Support Question (SQ) :

SQ1: How do you measure sales performance?

This SQ1 is relevant in the production of the KPI's artifact.

Secondly, data that provides no insights, will by default not improve performance at all, and thus it is necessary to validate that the data is shown as a dashboard that provides the sales team with insights. Choosing the best visualization for each type of data and allowing for the most intuitive way for the users to find the information needed is a challenge. That problem can be presented as the following Support Question (SQ):

SQ2: What is a good sales dashboard?

This SQ2 is relevant in the production of both Logical Data Model and Visualization artifacts.

2.2.3 Method

Once the problem setting and area of concern are identified, extensive literature review was made in order to understand the state of the art in the related fields, while looking for similar efforts to define a theoretical framework in which theory of sales management, performance management and monitoring, and business intelligence can be intertwined, in order to list all relevant KPI's. Research gaps were also identified and analyzed. The summary of this research can be found in chapter 3 of this thesis.

The next step was the formal identification of the stakeholders in the sales process, and work with them in order to assign appropriate coefficients to each of the KPI's identified in the literature, so that their relevance and importance can be understood.

Meanwhile, dashboard prototypes were created and tested in order to achieve an ideal sales dashboard. The dashboard creation process followed the ADR method, which is an action research-based method for conducting IS design research. The process was not limited to the creation and testing of the visualization, but also included several interviews with stakeholders in order to identify all data sources and dimensions relevant to the sales process, in order to create a logical dimensional model (LDM) on top of which the dashboards were created. To populate the dashboards, an ETL process to draw the data into the DWH was also tuned.

During 6 months, the usage of this dashboards by the salesforce was measured, and general statistics analysis was made in order to better understand the actual impact of these dashboards.

Figure 1 represents the relationships and flow of knowledge during different research stages and how they help achieving the final objectives.

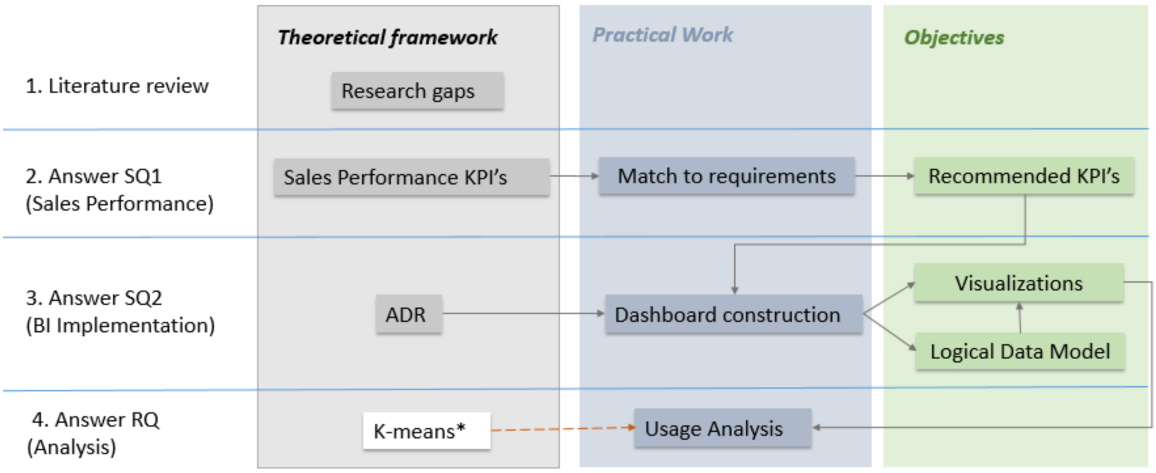


Figure 1. Research methodology in this thesis.

2.2.4 Data Sources

For this specific thesis, collaboration from Company X was achieved, upon agreement on confidentiality on its identity. Company X is a software company, based in US and in the range of 300-500 employees. All interviews and evaluations of the prototypes and sales force were done through email exchange, and this constituted the first non-structured data source for this research.

The data for the construction of the dashboard came from Salesforce, the CRM of choice for company X. Salesforce is a leader in the CRM industry, and provides programmatic access to its data by using simple, powerful, and secure application programming interfaces (APIs).

Last, the monitoring capabilities of GoodData (which constitutes their non public “BI on BI”) were used in order to obtain the usage metrics of the mentioned dashboard.

Although the empirical research for this thesis was done using GoodData platform as a BI Tool, and Salesforce as CRM, one must keep in mind that the resulting framework should be applicable to any other company with a similar sales structure, regardless of company type and size, CRM used, or BI tool chosen.

3 Literature Review

3.1 Sales in B2B

Business-to-business firms are increasingly moving from a goods-dominant logic toward a service-dominant logic (Cova & Salle, 2008) and most of the B2B transactions seem to be shifting from the sale of products into the sale of solutions, services (Oliva & Kallenberg, 2003) or systems (Davies, Brady, & Hobday, 2006). There is also an increasing complexity of buyer-seller relationships in industrial B2B markets as they are evolving from purely transactional to more relationship driven, although evidence suggests that companies that follow a B2B model seldom devote completely to one of these types (transactional vs. relational). However, there is still little empirical research studies to enlighten the field. (Narayandas & Rangan, 2004).

Obviously this changes affect the businesses in a B2B environment transversally, meaning that the sales departments are obviously affected as well. Sales in B2B is way less transactional, and has become a process that favors acquisition of new customers, and nurture the enterprise's relationships with its customers (Sheth & Sharma, 2008). In given cases, the sale of a solution to a single customer can be a process that takes up to two years. (Tuli, Kohli, & Bharadwaj, 2007). Given the long term of sales cycles in the B2B environment, the paradigm of sales has shifted from an operational management of the day to day sales process, to be an active part of the planning and executing of strategical initiatives for the company (Flaherty & Pappas, 2009).

Furthermore, the literature also shows that B2B sales are less one sided, with the salesman "pushing" the product, and more relational and multifaceted, meaning that in B2B environments both the salesperson and the customer have equal value in the negotiation, and customers emerge as co-creators of value. A B2B sales process is the encounter of two teams of individuals, each one responsible for representing, as well as possible, their company's interests, expectations and offers. (Hohenschwert & Geiger, 2015) That is the main reason why interactions in B2B sales process are difficult to categorize, as they come generally unplanned and the sales process follows a path which is clear when looking backwards, but is difficult to predict. In other words, not two B2B interactions are the same, as a B2B sale is not only a matter of purchase, but a process through which companies share with each other their knowledge, and resources. In B2B, value comes from encounters and interactions in which new ideas are created and accepted (Blocker, 2012)

3.2 Sales Funnel/Pipeline

Most industrial firms, both B2C and B2B, typically use a sales funnel or pipeline to model and manage their sales process. (Yu & Cai, 2007). The sales funnel approach, consists in dividing the sales process into various stages, in which each further stage eliminates some opportunities, while others continue through the pipeline until successful closure, securing in and increase in revenue for the firm (Söhnchen & Albers, 2010), as depicted in Figure 1. (Cooper & Budd, 2007). Some industries focus on customer retention, meaning that they value the long term of their relationship with their customers. However, companies which are new to their customer base, be it because they are startups, or businesses entering new market (as those aiming for different market segments, companies moved to new geographical location, or products facing rebranding or product re-development) find that the process of acquisition of new customers is critical. (Ang & Buttle, 2006).

The funnel does not have a standard of neither amount of stages, nor in the definition of this stages, and such the actual implementation of the funnel may differ from company to company. However, the most commonly accepted transition is as follows: suspect to prospect, prospect to lead, lead to opportunity, and opportunity to a contract with the customer, a transition that can be better depicted in Figure 2.

Although the sales funnel is a common concept, some authors agree that the ideal shape of the sales process (as shown in Figure 2) is not a funnel, but a pipe. That means that, ideally, every opportunity that goes in at the front of the pipe would ultimately turn into a customer (Patterson, 2007). The funnel shape in a business, means that there are many leaks in each stage, while a pipeline shape indicates that all opportunities that were not closed were correctly identified and ignored in the earliest stage of the process. Although that explains the difference between the concepts of pipeline and funnel in the sales process, the truth is that both concepts are usually treated as synonyms in the literature.

Pipeline management is used to measure the progress of sales efforts in relation to all potential customers, in order to forecast sales and to evaluate sales workload (Farris et al., 2010). The core idea behind pipeline management is that through the collection of data throughout the sales process a set of metrics (e.g. close rates, or sales size) can be correctly calculated and thus evaluated, giving enough time to apply corrective measures whenever they are needed. (Patterson, 2007). Additionally, pipeline management also allows for the identification of bottlenecks in the sales process. Bottlenecks in the sales process are very important, for having too many opportunities in a certain step of the process, could overload some of the sales personnel leading to a “clogging” effect (Sirias et al., 2013). If it is correctly implemented, the sales pipeline can be used not only to streamline processes and speed up sales cycles, but also as leverage to improve sales performance (Patterson, 2007) and can drive incremental sales and margin growth. (Agarwal, Shankhar, & Tiwari 2007). Usually, longer time in the pipeline corresponds to a lower probability of conversion of an opportunity into a closed deal, having 6x the average time of a deal as the threshold from which an opportunity will never recover. (Rottenberg & Baker, 2017).

In order to achieve a good implementation of the sales pipeline, companies should think of the sales process as a production process, in which the goal is to convert leads (which act as “raw materials” into closed sales, which would be the “finished goods”. (Roff-Marsh, 2004). The advantage of such approach is that companies with repetitive sales processes can optimize their sales by a division of their human resources: they can use support personnel to do initial screening, prospect qualifying, and appointment scheduling, so that the more experienced salespeople can dedicate their full attention and time on the activities that create a direct impact on the potential customers. In sales, time is the resource most difficult to find and manage, as the amount of time spent in direct customer contact is directly proportional to the productivity, and increasing the amount of time available for salespeople to interact with customers proves an excellent strategy. (Patterson, 2007).

One of the issues that sales pipeline raises, is the tracking of probability of closure or “win” ratio at each stage. (Lukes & Stanley, 2004). The win ratio should improve with time, as good project management practices are in place and salespeople gain experience and understanding of their customer base, increasing the levels of customer satisfaction and thus making it easier to obtain closed deals, so correctly measuring these “win probabilities” would give great insights on the pipeline “movements“ of next quarters.

However, these ratios are dynamic, and predicting them relies heavily on the knowledge from the sales managers, who can evaluate the current situation of the company in a holistic view. There have been many attempts to use machine learning in order to improve the win probability prediction, but such studies and their applications remain reduced to the academic sphere and little implementation of those works has achieved commercial status (Yan, et al., 2015).

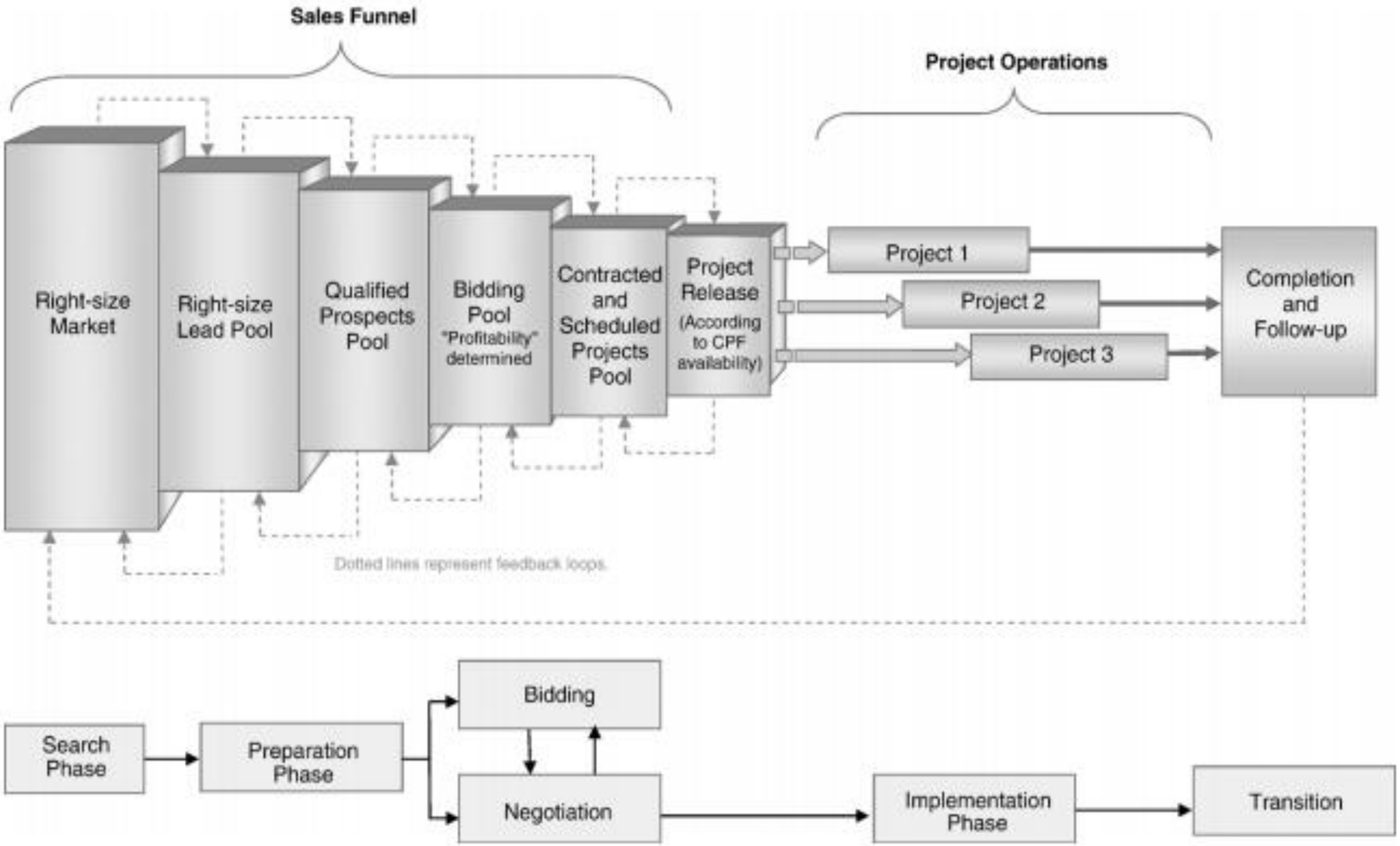


Figure 2. Sales Funnel in a B2B environment (Taken from Cooper & Budd, 2007)

3.3 Sales Force Automation and CRM

Since the sales processes have changed from transactional into models that care mainly about the relationship with the customer, information technology (IT) tools have been introduced to help with sales force automation (SFA) with the purpose of managing better the customer relationship by sharing quickly and appropriately all available customer information through the firm.

Sales technologies were developed to allow sales teams in all kind of organizations to automate repetitive tasks in order to obtain more time that could be spent looking for new customers and solving the problems of existing ones, as well as gathering market intelligence within the firm (Ahearne, et al., 2008). Salespersons who utilize IT tools into their sales tasks show improved performance, as well as efficiency and productivity gains (Rapp, Agnihotri, & Forbes, 2008). Sales force automation includes applications such as contact management, time management, and prospect or lead management and analysis (Schillewaert, et al., 2005). Technology has also been found to enhance sales performance, as measured by attainment to sales quotas (Ahearne et al., 2008), lead closure rates, and customer satisfaction (Stoddard, Clopton, & Avila, 2002).

Customer Relationship Management (CRM) refers to both a managerial philosophy and a set of technical solutions which has gained widespread diffusion in the last 20 years (Perna & Baraldi, 2014). CRM is a broad concept embracing, according to the most used definitions, three key elements: IT strategies, IT processes and IT solutions (Zablah, Bellenger, & Johnston, 2004). CRM usage has also been linked to firm performance (Krishnan, et al., 2014), and sales force automation significantly benefits sales teams by increasing customer interaction, enhanced relationship quality (Boujena, Johnston, & Merunka, 2009), and the meeting of sales objectives (Jelinek, et al., 2006).

Yet many CRM initiatives fail (King & Burgess, 2008) and the success of CRM efforts depends on the sales organizations' desire and capability to adopt and utilize IT tools, especially in B2B sales situations (Ahearne, Hughes, & Schillewaert, 2007). That may be because although CRM systems are expected to support and improve key organizational processes in certain areas, from sharing of customer information for promoting marketing orientation culture, to lead or opportunity management; there are also a series of challenges to implementing CRM ranging from organizational and cultural inertia to employee motivation and training (Perna & Baraldi, 2014). Therefore, the potential benefits of CRM constantly face a range of challenges and obstacles to implementing such technical solutions in a given organizational context.

The opportunity funnel for B2B firms is more complex and time consuming than for B2C enterprises (D'Haen & Van den Poel, 2013), and multiple researchers note the need for more empirical studies on the effects of sales force automation (Ahearne, et al., 2008). Much of what is written for sales management practitioners to improve performance is opinion based and lacks evidence based research.

3.4 Sales Force Performance Evaluation

During the last 20 or more years, management literature has been attempting to find the "right" performance measures for organizations (Neely, 2005). Sales performance is obviously critical to any business success, particularly the discovery, effective management, and efficient conversion of sales opportunities, or leads, into new revenue for the company. However, despite its importance in driving new revenue growth, new opportunity acquisition is a relatively neglected area of research (Söhnchen & Albers, 2010).

Sales performance evaluation can be seen one of the key issues for sales management in order to control and monitor its goals and objectives, and thus sales managers must utilize effective and efficient assessment processes for salespeople.

It is recommended to see sales performance evaluation as five step process: sales force objectives, determine sales strategy, set performance standards, measure and compare with standard and action taken to improve performance. Although different authors describe different models, the main idea is the same. In an evaluation, performance standards must be based on the whole company's objectives and strategy, and actual performance should be compared to it.

Thus, evaluation process begins by setting up performance standards that an employee should achieve during the measuring period. These standards must be stable and consistent, and by using them the manager must be able to recognize between outstanding, average and poor performance. This identification should drive resource allocation for bonuses or coaching time, for example. An easy and direct way many sales managers use now is evaluating their salespeople by the sales revenue they generate (Miller, 2009). Managers analyze and judge their sales force by the sales in a certain period of time. The most common measures of time used are a month, or a quarter, but yearly evaluations can be common too. The larger the revenue they generate in a given period, the better performance a salesperson has. These production numbers determine if a salesperson is satisfactory or not and often ties directly to their compensation.

Companies using more complex approaches find that simply measuring sales revenue by salesperson does not present a fair evaluation of sales activities. Steenburgh and Ahearne (2012) proposed using team performance to compensate each salesperson in the team, which is also a way that some firms evaluate their sales force. Other researchers also suggest five dimensions of sales force productivity. These five dimensions are sales force drivers, people and culture, customer results, sales force activity, and company results (Sinha, & Zoltners, 2001). Managers can allocate different importance levels to each dimension, providing a better and more reliable means of assessing sales performance across an organization.

3.5 Sales Management Metrics

A metric is a measuring system, which calculates different trends, dynamics, or characteristics. Organizations use metrics to explain phenomena, diagnose causes, share findings, and project results of future actions (Farris et al., 2010). Improvement goes hand in hand with measurement, since, what one cannot measure one cannot either improve. Data-driven decision making has been widely used in the business world over the last few years, and the most important lesson learned by both researchers and practitioners is that no single metric is likely to be adequate by itself. (Dodgson et al, 2013).

By taking advantage of a metric in the sales process, it becomes possible to determine which business cases would have the most impact on sales performance outcomes and a fully functioning analytical solution will combine critical metrics that show performance to date with metrics that indicates future performance, which organizations in the defense market could benefit from (Greenia et al., 2014).

In figure 3 is shown three kinds of evaluation criteria for estimating sales effectiveness: outcome-based measures, behavior-based measures and professional development measures. (Anderson et al. 2010)

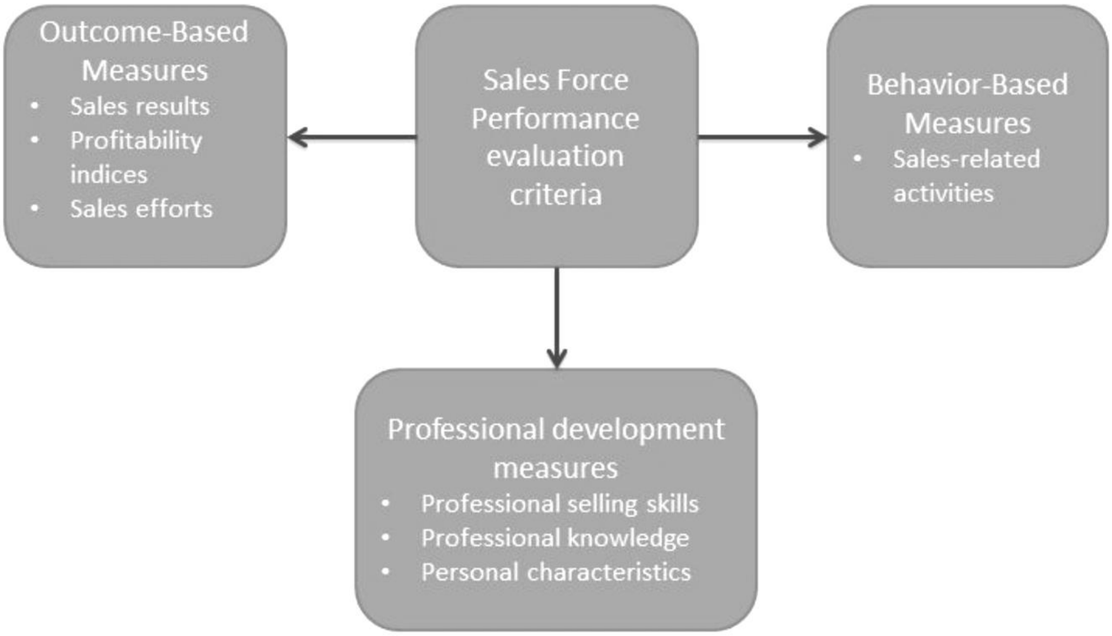


Figure 3. Salesforce Performance Evaluation. (Adapted from Anderson et al, 2010)

Specific outcome-based performance measures include: sales volume, percent of quota, market share, gross margin, contribution margin, number of orders, average order size, number of new accounts and number of lost accounts. These measures are quantitative and therefore objective. (Anderson et al. 2010)

Behavior-based measures help estimating less quantified results. For example sales preparation, new product ideas and follow up with customers. These measures should support the employee or salesperson to perform in a way that improves the company image to the customer. (Anderson et al. 2010)

Finally, Professional development measures have more indirect and long-term impact on sales so they need to be evaluated more carefully, buts often need a subjective perspective. These measures fall in to three categories: personal selling skills (listening and presentation skills), professional knowledge (awareness of organizational policies and marketing and sales strategies) and personal characteristics (enthusiasm, judgment and personal appearance). (Anderson et al. 2010)

3.5.1 KPI's found in literature

The alignment of KPIs with a company's strategy is the key to achieving its goals and objectives. Unfortunately, it is a challenge is to develop KPIs that provide a holistic and balanced view of the business. There are actually potential hundreds of candidate metrics, and selecting those that are most meaningful require understanding that a single KPI can act as more than just a singular metric when it incorporates alternative dimensions.

The evolution of data into effective ratios, aggregates and indexes is as much art as science. In most situations, the direct data elements that need to be incorporated into a particular KPI are clear, but most of the time, the real challenge is translating the data elements into meaningful metrics that have an added value to business stakeholders.

To avoid confusions, it's recommended that process-specific and function-specific metrics are eliminated and replaced with new enterprise standards that ensure enterprise-wide understanding. An effective KPI is generally never just a raw data point, but some ratio, or average. Even "raw data" kpi's are meaningful only within a context that explains their significance and imply (although not always explicitly) a comparison between the current value and previous ones.

When developing a BI solution it is important to screen the total KPI list to make sure that they are not all short-term, quantitative, and tangible indicators, which are the easiest KPI's to measure and develop. Tangible assets such as investments, real estate and inventories are a lot easier to "dollarize" than intangible assets such as employee’s skill, talent, knowledge and teamwork, but the latter are typically a much better indicator of the company's future potential.

The bottom line is that the creation of effective KPIs requires an extensive commitment in time and resources, and having a comprehensive list of available and relevant KPI’s can reduce the effort needed to deploy a solution. Tables 2 and 3 find some examples of the KPI’s found in literature for sales performance management.

	Effectiveness (selling outcomes)	**Efficiency (selling activities)**
Internally oriented (selling skill, capabilities)	Competencies: – technical knowledge (2) – presentation skills (2) – communication skills – listening skills – supervisory skills – teamwork Quota attainment (5) Sales volume (5) Sales behavior Mix change (upgrading)	Productivity Profitability of sales Gross margin Time management Cash flow and account management (2) Number of calls Number of presentations Time spent in territory
Externally oriented (marketplace metrics)	Channel feedback/satisfaction Customer feedback/satisfaction Competitive understanding New accounts introduced to product Number of customers Level of interaction with customers Performance relative to opportunities Customers’ success/goal attainment	Closing ratio – to number of calls – to number of presentations Sales penetration per account (2)

Table 2.KPI’s for salespeople (Zalloco et al, 2009)

Metric	**Definition**	**Formula**
Strike Zone (Sales Deal Size)	The Strike Zone metric measures the average value of each won business case closed	Strike Zone = (Total Order Intake Value of Won Business Cases for Selected Historical

		Period) / (Total Number of Won Business Cases for Selected Historical Period)
Close Rate	Close Rate metric measures the percentage of sales transactions closed out of the total number of potential sales pipeline transactions.	Close Rate = (Total Number of Sales Transactions Closed) / (Total Number of Pipeline Transactions To date)
Sales Leads Rated as Qualified	The sales leads rated as qualified metric measures the quality of a sales leads. A qualified sales lead is one where the key decisions maker has expressed some level of interest in what company has to sell and has the financial means to buy.	Sales Leads Rated as Qualified = (Number of Qualified Leads) / (Number of Sales Leads)
Win/Loss Ratio	Win/loss metric measures the competitive strength of a sales force by looking at the ratio of deals won to those lost.	Win/Loss Ration = (Total Number of Sales Transactions Closed) / (Total Number of Sales Transactions Lost)

Table 3: KPI’s for Sales Pipelines, Based on (Alexander & Bartels, 2017).

3.6 BI Systems in enterprises

Business Intelligence (BI) is defined by literature and academics in similar ways. Singer (2001) described BI as the set of tools, applications, technologies and processes that helps organizations get decision-making information in ways that simple reporting does not provide. Noble (2006) defines BI as the ability to provide the business an information advantage; unchanging the nature of the business but making it more efficient. Negash and

Gray (2008) defined BI as a data driven process that combines data storage and gathering with knowledge management to provide input into the business decision making process. More recently, Gartner (2017) have extended BI to be an encompassing term, which denotes not a technology or practice, but more a whole discipline which includes applications, tools, infrastructure, and practices to enable access and analysis of information to optimize performance and decision-making. The challenges In BI delivery include business and IT collaboration that results in data becoming information. Successful BI methodology should focus more on the information value chain and less on the software as is the focus of traditional information technology (IT).

Research has demonstrated that software and hardware do not provide organizations value pertaining to BI; it is the use of the information (Larson, 2009). Common stumbling blocks traditionally experienced in BI projects included: unclear requirements; lacking an understanding about how data is created and used; data quality is not measured or known; source system constraints; wrong perceptions of data meaning; results not demonstrated in a timely manner; and working with a lack of trust between IT and business stakeholders (TDWI, 2017). While these challenges still remain, the need to have information sooner has been influenced by the phenomenon of "Big Data" or data sets that are so large and complex, that cannot be handled by traditional IT methodologies and applications (Davenport, 2013).

In the BI literature, Business Intelligence Systems (BIS) are well recognized to contribute to decision-making, especially when firms operate in highly competitive environments (Popovič et al., 2012). These systems are considered a contemporary answer to the call for development of IT capabilities to use information strategically. Currently the research that focuses on strategic BI issues is still small in numbers (Alhyasat & Al-Dalahmeh, 2013) even when BIS are typically complex and have been also identified as the most important key issue for CIOs (Luftman & Ben-Zvi, 2010). BIS are most commonly identified as technological solutions holding quality information in well-designed data warehouses, connected with business-friendly tools that provide users quick access, effective analysis and insightful presentation of the information available, enabling them to make the right decisions in the quickest manner possible (Popovič et al., 2009). Studies suggest BIS enable enhancements in strategic planning, business processes, improvements of performance, and building of competitive advantage (Davenport et al., 2010) but time savings and better information for supporting decision making are still considered the main direct benefits of BIS implementation (Watson et al., 2002). Nonetheless, researchers and practitioners alike claim that obtaining those benefits depends as much on possessing the right technology, as on possessing the ability and acumen to understand and properly utilize information in the decision-making processes (Rindfleisch & Moorman, 2001).

3.7 Data visualization.

Organizations face enormous quantities of data from various sources due to the digitalization of businesses. Decision makers suffer, consequently, from an excess of irrelevant information. Furthermore, data is increasingly time-sensitive and comes in both, structured, and unstructured formats (McAfee & Brynjolfsson 2012). Information processing theory explains that the human brain can only process a fraction of all available information for making a decision and thus, having too much (or wrong) information can lead to severe problems in decision making, such as to situations in which managers routinely ignore certain information or make inaccurate decisions (Ittner & Larcker 2003). It is common problem in information processing, that individuals tend to favor information that reinforces preexisting bias instead of using all of the information available. (Clark et al., 2006)

Data visualization is a key tool to drive both end user adoption and change management activities within data initiatives and especially so in sales environments. Data is as much a part of the problem as the solution itself. There's too much of it, it's difficult to interpret and sellers hold on to tactical workload out of distrust in the data systems they are provided with. A data-driven approach to the sales engagement cycle can fundamentally improve performance. Using an analytical approach to determine client needs and sales 'signals', sales engagement can be tuned to be in sync with market needs. However, a range of technical, organizational and cultural issues need to be addressed before such a solution can truly start to deliver results.

Performance management systems should offer visual representation of the data to the users to help them digest complex information in an efficient and effective way. Instead of static visualization, performance management systems should enable interactive visualization to aid ad-hoc decision making processes (Lurie and Mason 2007).

3.8 GoodData

Unlike traditional BI vendors, GoodData is exclusively focused on delivering analytics to B2B networks, helping them monetize their data with the delivery of data and analytic products. And the 2015 Gartner’s Magical Quadrant for Business Intelligence placed GoodData in the top quartile for operations, which includes product quality, support and ease of migration.

Good Data supports a multitenant cloud and highly scalable solutions for high numbers of users. GoodData has a single code base and UI and supports strong BI-on-BI functionality to measure user engagement, a practice that also helps keep analytic applications from becoming stale. While GoodData focuses on offering benefits to businesses, in the scope of this thesis GoodData offers the great advantage of bringing data products to market quickly with the ability to immediately measure their success in engagement, as all its framework is optimized to deliver benchmarking, scorecards, and other comparative analytics to leverage the network effect. GoodData traditionally has had guided analytics, allowing for the “average” business user to consume packaged analytics and perform self-exploration to gain greater insights.

GoodData’s extensible analytical engine’s instructions are written in a human-readable analytic query language, MAQL. Which is a proprietary language with various functions that “translate” easily understandable metrics into complex SQL queries. These functions include also predictive, statistical, and mathematical and text manipulation functions. The analytical engine optimizes queries, updates shared caches and indexes, and calculates results in real-time.

3.8.1 Data Structure

GoodData projects are organized into dashboards, dashboard tabs (also called dashtabs), reports, and the metrics that are contained within those reports. At the lowest level the metrics are operations on the facts and attributes, as can be seen in Figure 4.

Figure 4. Representation of GoodData's Data Structure. (GoodData, 2015)

3.8.1.1 Fact

A fact is data of numerical nature, which may be stored in integer or decimal format. A fact is usually related to a "real life quantity" and it is thus the basic component of business intelligence. There are three types of facts: additive, non-additive, and semi-additive. Additive facts can be used in computations, such as summing them together, as is the case with revenues, users or inventory quantities. Non-additive facts cannot be added as their addition would not have a real life counterpart. For example, Unit Price or Age, make sense as facts, but cannot be added together to produce meaningful information. Semi-additive facts can be added but only within a certain context. For example, Inventory for a month is additive only within a month time period.

Most BI projects are interested in additive facts, as they are the data sources for aggregation, and eventually other techniques such as drilling in or slice-and-dice. Semi-additive facts require special context around them and must be managed carefully, as they can give rise to numbers that are misunderstood. Non-additive facts can also be obtained from other additive facts. For example, Unit Price is the result from dividing Total Price by Quantity.

In GoodData Architecture, a collection of facts related to the same business process are stored in a data unit called a fact table, which contains individual fact values and pointers to associated attributes which determine the context in which the fact data can (or at least should) be used. Usually, given this layout, Fact tables have relatively few columns and many rows.

3.8.1.2 Attribute

Contrary to Facts, which store numerical value, an attribute is a data unit that contains a set of alphanumeric values which is used to describe a fact in some way. For example, one could create an attribute called "Country" which could contain values "Colombia", "Germany", "Czech Republic", "Japan", and "Other". These attributes could be used to describe the numerical facts used to describe populations. An attribute can also be made of only numerical values. For example, for a radio station solution, an attribute called, "Dial" can be created with numerical values “90.9”, “93.4” and “102.6”, which could be used to slice the numerical facts in the solution. Keep in mind that as they are attributes, and performing mathematical operations on the „Dial“ values makes no sense analytically, the values of the previous example could be likewise stored as the character strings „ninety-nine“, „ninety three-four“ and „hundred two-six“. Thus, numerical data can be both facts and attributes. For example, Age can be tracked as a fact, but it can also be used as an attribute to enable segmentation.

3.8.1.3 Dimensions

A set of related attributes is called a dimension. For example, City, Region, and Country may be related in a dimension called, "Location." Each attribute in the dimension is a separate entity, yet they are all related to each other. A dimension is stored in a dimension table, which has (opposite to fact tables) many columns and only a few rows. Dimensions should always have consistent definitions and contents in order to create insightful reporting because of consistency between the data. For example, the Country attribute should not use two-letter abbreviations (CZ, DE, IT) along with full state names (Czech Republic, Germany, Italy). Queries looking for “CZ” will not be able to match it with the “Czech Republic” records unless they are two different attributes which are somehow linked in the dimension.

3.8.1.4 Dataset

A dataset is a related set of facts, attributes or both, which are associated with each other through connections. A connection point has a similar function to that of a database primary key: it identifies the field in the originating dataset that contains information to uniquely identify the data in other fields of another dataset.

GoodData also supports a special data model object for managing time-based data. The Date dataset manages the attributes related to time, and enables aggregation at various levels like day, week, month, quarter, and year.

3.8.2 LDM

A Logical Data Model, or LDM represents the abstract structure of a domain of information, by describing the data in as much detail as possible, without regard to how they will be physically implemented in the database. Thus, a Logical Data Model is a middle ground between a Conceptual Data Model and a Physical Data Model. The main features of a Logical Data Model are that it:

- Includes all entities and relationships among them.
- Specifies all attributes for each entity.
- Defines the primary key for each entity.
- Specifies foreign keys (keys identifying the relationship between different entities).
- Correctly implements Normalization.

In GoodData, each Logical Data Model corresponds to a GoodData project, and it provides a layer of abstraction so that users do not need to interact with the physical data model, meaning that within the GoodData Platform, the physical data model is generated from the

Logical Data Model automatically. Also, CloudConnect's LDM Modeler allows to create a simpler, more intuitive LDM. Within the GoodData Platform, the Logical Data Model is "unpacked" to build the database tables used to store data. Each attribute in a Logical Data Model becomes a different and separate database table. Each attribute label is turned into a separate column in the attribute's database table. By doing so, the physical data model is automatically normalized during the schema creation process. This method of storage is designed to achieve the best performance.

That allows for improvement of the physical data model without interfering with the user's definition of the data architecture, as well as acting as safety measure by reducing the chance of failure due to unexpected user interaction.

3.8.3 CloudConnect

One of the components GoodData offers is the CloudConnect application, a Java desktop software specifically designed for building data integrations for the GoodData platform. Through an easy-to-use graphical interface, it is possible to rapidly assemble a CloudConnect project from a large library of pre-built components. These CloudConnect projects contain the ETL graphs and LDM's for GoodData projects which are created in the CloudConnect Designer and LDM Modeler components of CloudConnect, respectively, as shown in Figure 5.

Through the logical data model, CloudConnect users can define relationships between the elements in their data. The Logical Data Model defines how the data is organized, so that when it is loaded into a project, it is used as the basis for creating the physical data model in which the data that is to be used in the project is stored. CloudConnect helps converting the visual LDM into actual MAQL Data Definition Queries which make the datamart. After the data is loaded into the datamart, almost all user operations are translated into querying the datamart, retrieving the results, and displaying them in a report.

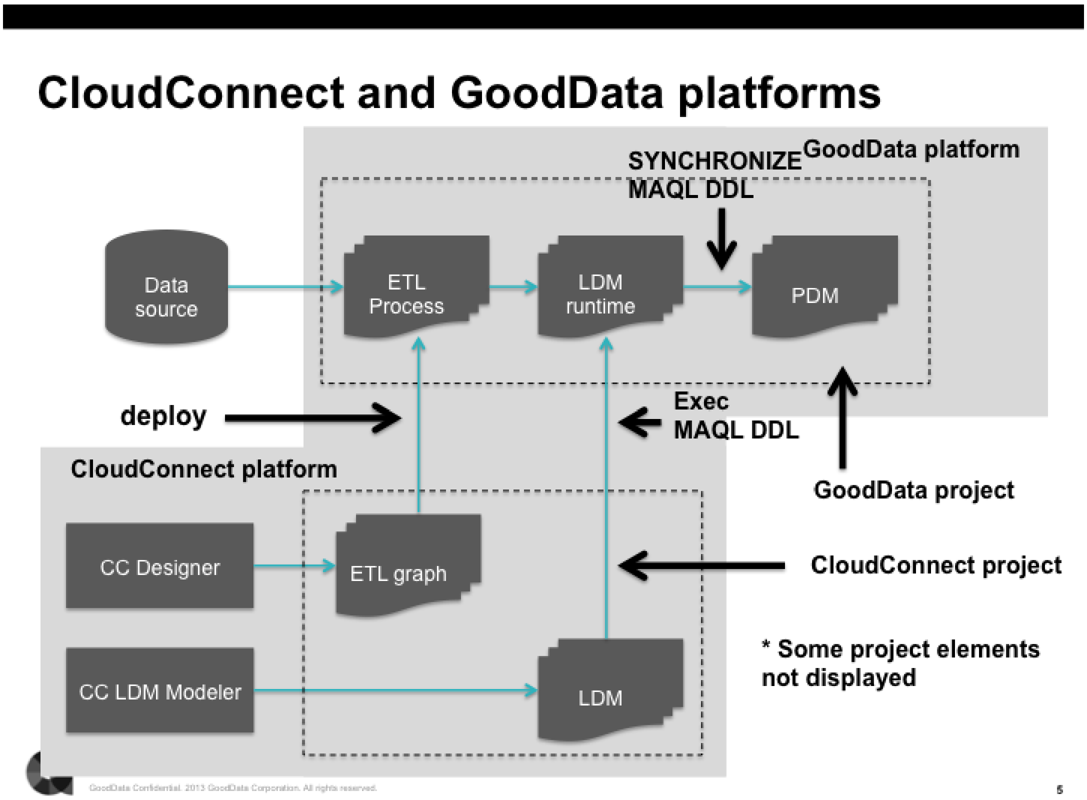


Figure 5. Relationship betwen CloudConnect and GoodData (GoodData, 2015)

As users do not need to create or manage database schemas, GoodData offers a unique advantage in order to quickly deploy prototypes, evaluate them and change them, without the hassle of manipulating (and possibly damaging) the underlying physical database.

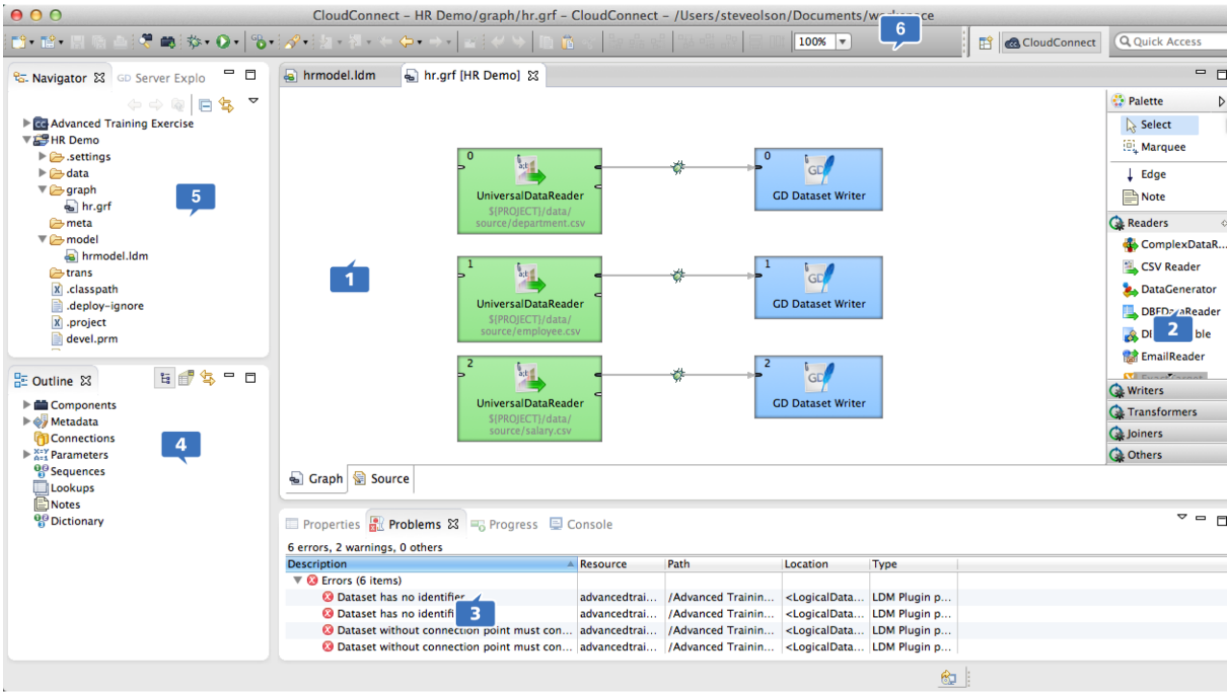


Figure 6. General View of the CloudConnect Tool (GoodData, 2015)

3.9 ADR

The method chosen to carry out this research is action design research (ADR) introduced by Sein et al. (2011). Design research seeks to develop prescriptive design knowledge, sometimes referred to as design principles, through building and evaluating innovative IT artifacts intended to solve an identified problem (Hevner et al. 2004). While traditional design research takes a technological view of the IT artifacts, makes sure that the artifact is not imposed, but birthed more organically from interaction within an organizational context. In ADR, the research problem is derived from practice and the theory that supports the artifact is increased and developed iteratively, together with stakeholders within the organization.

Four stages comprise the ADR process. The process starts from the problem formulation stage, within which tasks include determining the initial scope, deciding the roles and scope for practitioner participation, and formulating the initial research questions. In the second stage, the IT artifact is developed through several cycles of building, intervention, and evaluation (BIE) with the case organization. The main difference with other design research methods is that evaluation of the IT artifact is done at the same time than the building of the artifact, and both researcher and end user engage in continuous evaluation. The third stage requires that reflection and learning continues throughout the process, emphasizing that the prototype artifact is shaped by organizational use, perspectives and participants. Finally, all lessons learned are developed further into general solution concepts for a class of similar problems. The final stage aims at formalizing learning through design principles derived from the design research outcomes. ADR's stages and principles can be summarized as follows:

- Stage 1: Problem Formulation
    - Principle 1: Practice-Inspired Research
    - Principle 2: Theory-Ingrained Artifact
- Stage 2: Building Intervention and Evaluation
    - Principle 3: Reciprocal Shaping
    - Principle 4: Mutually Influential Roles
    - Principle 5: Authentic and Concurrent Evaluation
- Stage 3: Reflection and Learning
    - Principle 6: Guided Emergence
- Stage 4: Formalization of learning
    - Principle 7: Generalized Outcomes

3.10 Summary of Research Gaps

While sales lead management process and performance is extensively researched, a need exists for more empirical studies around CRM implementations and sales funnel activity (Ahearne, et al., 2008; Hunter & Perrault, 2006). This may be due, in part, to the difficulty of obtaining detailed sales funnel data for analysis, and particularly data that is complete, as many companies may lack the rigor and discipline of comprehensive compliance to sales funnel data entry and maintenance by field sales staff members, causing CRM initiatives to fail (King & Burgess, 2008). Much of the topical sales research is on business-to-consumer activities, and the complex industrial B2B situation is less understood (Yu & Cai, 2007). Some of the factors examined include frequency of technology usage, amount of usage of the full suite of application capabilities, level of integration of multiple technological tools, and usage of the tools for analysis; but causality could not be conclusively demonstrated due to the cross-sectional nature of these studies. (Mathieu, Ahearne & Taylor, 2007).

While CRM has been widely used in industry, it gets relatively little coverage in the academic literature (Zoltners, Sinha, & Lorimer, 2008), and the literature on the subject is highly fragmented (Zablah, Bellenger, & Johnston, 2004). Furthermore, B2B environments are usually left out as CRM studies have been focusing mostly on B2C contexts (Gummesson , 2004).

4 Practical Part

4.1 Profile of Sales Team in Company X

4.1.1 Sales Roles

The sales team can be split into a junior position, the Sales Representative (SR) and a more senior position, the Account Executive (AE), and can be defined as follows:

4.1.1.1 Sales Representative Tasks

- Researching and developing account plans along with Account Executives.
- Log all contacts and account plans into CRM.
- To assist with events, email campaigns and other activities for targeted marketing activities.
- Drive a minimum outbound calls per day
- Achieve a minimum person and/or virtual meetings per week per AE.

4.1.1.2 Account Executive Tasks

- Consistently and accurately forecast business. Quarterly commits are expected to be accurate within a given percentage.
- Log all sales activity in CRM.
- Act on leads within a given timeframe.
- Maintain a healthy pipeline (Using their revenue targets as base)
- Achieve Quarterly and Annual revenue targets.
- Understanding and qualifying in or out at any stage (not all deals are a good fit)
- Keep win rate within parameters.

- Seek support and approval from leadership to ensure the company doesn‘t over commit.

4.1.2 Sales pipeline process in Company X:

The Sales Pipeline in the company, is a specific instance of the general sales pipeline model from Cooper & Budd shown previously in Figure 2. The success of the sales pipeline is affected directly by the work of SR’s in early stages, and of AE’s through all the lifecycle of an opportunity. However, it is noticeable that because of the nature of the company, “sales success” cannot be limited to the “sales team”. Each solution is tailored particularly to the needs of a customer, and thus a technical team comprised of Sales Engineer and Business Architect accompany the whole process. Right here it is possible to see the difference between B2C and B2B environments, and it is also worth noticing that this has no relationship with the product (software). A software company that sells all the “vanilla flavor” to all its customers doesn’t worry about the implementation, delegating that task to other companies, or other divisions within the company, and such, it makes sense to isolate the sales team from other teams. However, the need to tweak and fine-tune the product for each customer, requires that a redefinition of the product is achieved, and sales teams cannot, and should not, engage the customer on their own. Furthermore, the complexity of SLA’s and legal documents in B2B far exceeds the usual “click here to accept terms” approach of companies which sell their products massively. Thus, the Financial/Legal team must also accompany the product in the last stages of the opportunity.

As not only the sales team, but also other stakeholders in the company are important in order to achieve success even if they are part of Technical or Support teams, some users thus will be granted access into the created dashboards and their use also taken into account.

The details of this specific implementation of the sales pipeline in Company X along with the roles involved can be seen in detail in Table 4.

Name in Company X	Action on Opportunity	Type	Match with Cooper&Budd's Model	Marketing	Sales Representative	Account Executive	Business Architect (Tech)	Financial & Legal Team
Stage 1	Prospect	Pre-Sales	Market	X	X	X		
Stage 2	Learn about Customer	Sales Pipeline	Lead Pool		X	X		
Stage 3	Decide on Strategy		Qualified Prospects		X	X	X	
Stage 4	Technology Validation		Bidding pool			X	X	
Stage 5	Implementation Design		Projects pool			X	X	
Stage 6	Develop and Present Business Case		Project Operations			X	X	
Stage 7	Approve		Completion			X	X	X

Table 4. Sales pipeline implementation in Company X. An X marks involvement in that stage.

4.1.3 MEDDPICC

The **MEDDIC** approach is a sales methodology based on qualification for complex (enterprise level) B2B sales environments. It was created by Dick Dunkel and Jack Napoli in the mid 90's, and it's an acronym that represents a checklist of issues that a salesperson must evaluate in order to maximize their chance of sale success.

In Company X, two extra dimensions (marked with a star) have been factored in, ending up with the MEDDPICC approach, as explained below:

METRICS: Quantifiable business benefits of the solution. Expected ROI and payback period

ECONOMIC BUYER: the person who owns the budget (or can create the budget), or the one who will cause the person in charge to make a purchase decision.

DECISION CRITERIA: Requirements that competing solutions will be evaluated against

DECISION PROCESS: Customer's process for evaluating, selecting & purchasing solution

***P**APER PROCESS: Process and timeline for gaining the necessary approvals and signatures

IDENTIFIED PAIN: Technical & business pains fueling a buying decision. What happens if it's not fixed?

CHAMPION: Person with power & influence, selling on your behalf, usually has personal motivation for wanting you to win

***C**OMPETITION: Competitive Strengths, Weaknesses & differentiators

In Company X, the importance of the MEDPICC evaluation is that it is performed on each opportunity as it goes from one stage into the next of the sales pipeline.

4.2 Definition of KPI’s for sales performance

There is a common managing mantra that claims that “You can’t improve what you don’t measure”. In that light, Key Performance Indicators play a fundamental role in any business process, and the sales performance is no exception. Although there is no “silver bullet”, no approach or unique technique that fits all enterprises, according to the ADR Team, the following guidelines are the main points to address while measuring sales performance in Company X:

Pre-Sales Process is important, meaning that some KPI’s must measure the efficacy and results of the pre-sales (Marketing) process, not in excessive detail, but it helps understanding the quality of the prospects that enter the pipeline.

Determining the pipeline (or duration) with which opportunities go from prospect to close, is paramount. The speed must be computed for every stage and opportunity, and it is defined as amount of days (including fraction of days) since the opportunity creation until the opportunity has reached the stage for the first time (<date-when-stage-has-been-reached> - <opportunity-creation-date>).The stage duration is similar to pipeline speed, but differs from it. It also must be computed for every stage and opportunity, but is defined as the amount of days (including fraction of days) that any open, or live opportunity has spent not in the pipeline, but in a specific stage. Once the opportunity closes, either won or lost, the number shouldn’t change. If the opportunity returns back to a previous stage, the duration of the stage should be accumulated.

Conversion rate between different stages give insights on the quality of the processes in each stage, and highlight possible improvements and Reference quotas are important too, as they guide the sales team to their targets and give them an easy way for benchmarking against peers and competitors.

4.3 Dashboard Creation

4.3.1 Kernel theory

Kernel theory explains that any design process must be drawn from key characteristics of organizational performance management. Together these characteristics form the foundation, or kernel, on which user requirement categories are formulated. To meet the user requirements, the design challenges are identified to prevent the key issues concerning the design of such system. Table 5 summarizes how design challenges are formulated based on the kernel theory and user requirements.

Characteristics of performance management in organizations		User requirement categories		Design challenges
C#1: Data as a crucial asset to organizations		R#1: Information scoping		DC#1: What to measure?
C#2: Information overload		R#2: Data management		DC#2: How to find data and from where?
C#3: Complexity of performance information		R#3: Functions		DC#3: How to deliver performance information to the users?
C#4: Time-sensitive, unstructured and dynamic decision making processes		R#4: User interface		
C#5: Decision makers in many organizational levels and functions				

Table 5. From requirements to design (from Lempinen, 2013)

4.3.2 List of requirements according to ADR Team

After understanding the general constraints for the cration of the dashboard are understoood, a series of interviews was performed and the general functional requirements were ellicited. The ADR team requested that the dashboard helps them to:

- Quickly understand how much has been sold against estimates, predictions, and goals
- Understand what is happening to the expected pipeline as the quarter progresses
- Identify "rock star" Sales Reps, and study what best practices are driving closed business
- Discover and manage outliers and exceptions before a deal is lost
- Understand how the pipeline stacks up against a winning sales cycle
- Identify quarterly trends and seasonality between product lines and sales regions

4.3.3 Data Sources and ETL

The main data source is the CRM that holds all sales pipeline information. Company X's CRM of choice is Salesforce which runs on Oracle Databases. All information displayed on the Salesforce.com website, are in fact records that reside in the databases. By default, salesforce offers a standard set of objects in a "sales objects" schema, whose diagram is shown in Figure 8.

Customers can create Custom Objects in Force.com, which triggers in fact the creation of an entirely new at the Database Layer. Likewise when new Custom Fields are added, new Columns are added to a Table. To access the data available in the Salesforce databases, calls can be made to some API's, namely Salesforce Object Query Language (SOQL) and Salesforce Object Search Language (SOSL). To test the queries in can be tested in the interface offered in the Force Workbench. As direct access to the databases is not available, CloudConnect's "Salesforce Query" component, which accepts SOQL statements was used in order to extract the needed data into the GoodData project with daily frequency.

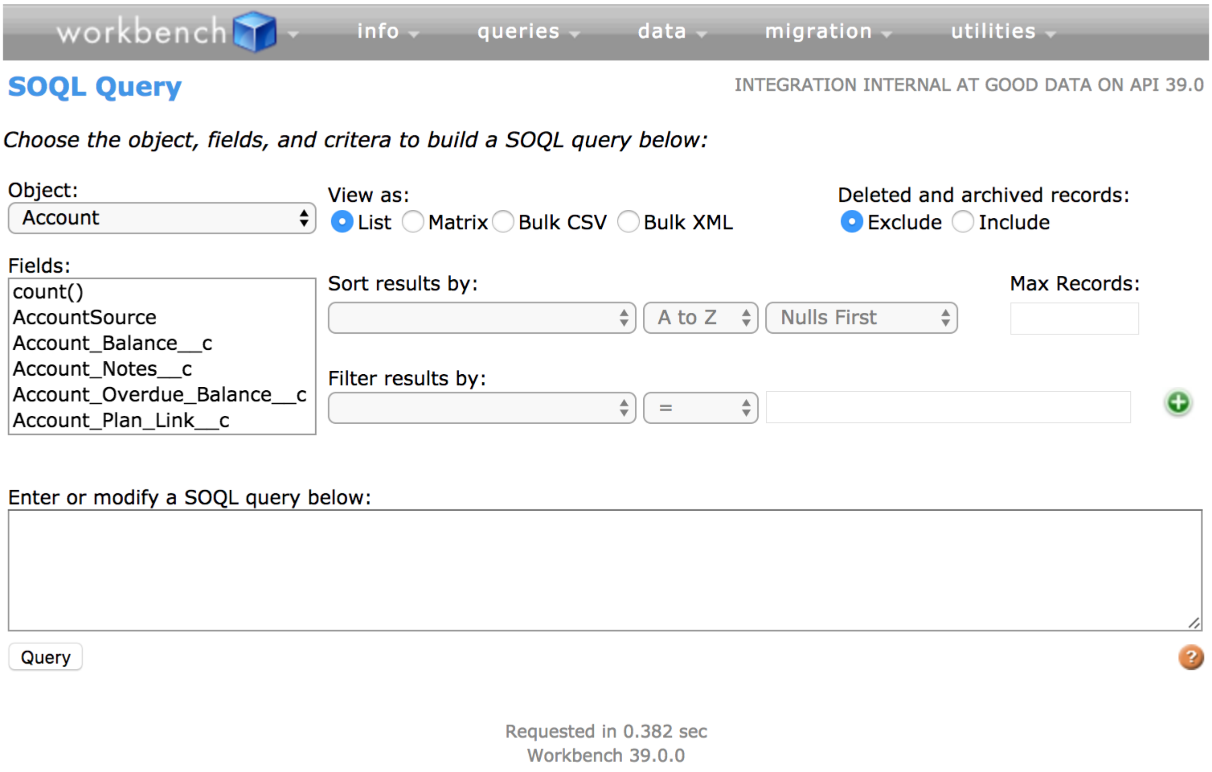


Figure 7. Salesforce's Workbench. (Salesforce, 2017)

By taking advantage of the Salesforce Data Design, which has been proved widely and has been accepted and implemented increasingly in all kind of industries, the "transformation" part of the ETL could be skipped, meaning that the data was extracted and loaded directly into the GoodData platform.

As not all objects are deemed pertinent to this study case, only the following datasets were extracted from Salesforce:

- Product
- Account
- Stage
- Activity Owner
- Opportunity Owner
- Forecast
- Opportunity
- Booking Type
- Revenue Type

- Lead
- Campaign
- Stage Speed

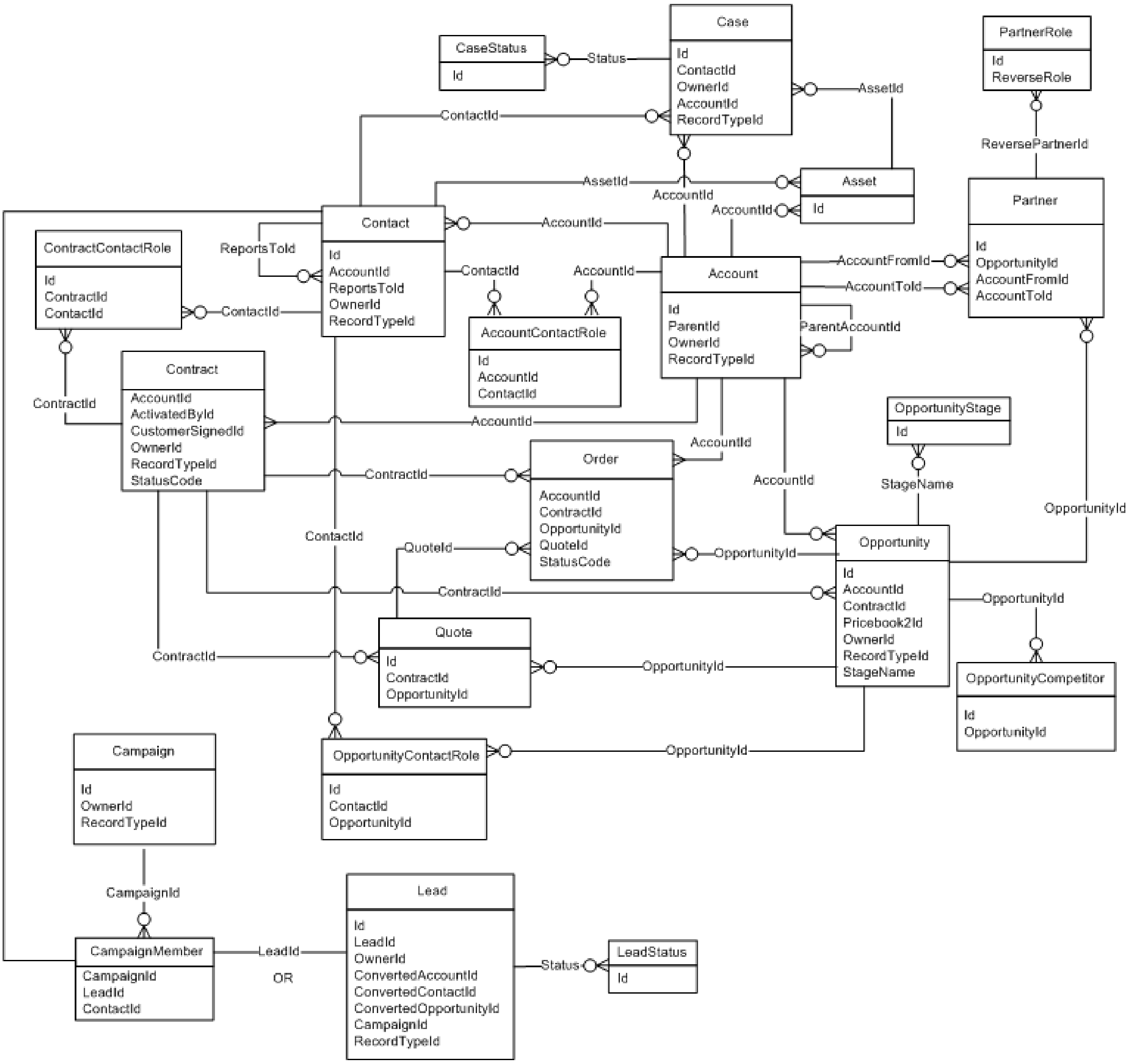


Figure 8. Salesforce “Sales object” Entity Relationship Diagram (Salesforce, 2017)

4.3.4 ADR Process

In the problem formulation stage of the ADR, it was found that while Salesforce offers their own set of graphs and dashboards, they are usually static and offer little to none chance to drill in in data. Furthermore, the layouts are usually fixed and it is difficult to navigate easily from one group of metrics to the next. The need to enrich Salesforce data came up as an issue, albeit not a critical one, for most related information is already in Salesforce thanks to the possibility to create new attributes and tables. However, for the sake of generalization, it is important to realize that other CRM's which offer limited interaction with other information systems within a company, are in even more desperate need of a centralized business intelligence solution where related KPI's can be watched and monitored.

Three stakeholders were identified: The Sales Team, the Business Architects Team and the Finance team. Together with the author, a representatives from each of these three groups formed the ADR team. Based on participant observation, and semi-structured interviews, the initial found the possibility of silos of data within the organization due to data in non-centralized databases and/or Excel spreadsheets, which make difficult the process of extracting and use of actual information the data may contain. Usual decision making requires collated information from all sources, and without an automated system to do it, it falls to staff to calculate and report their part of the KPIs, making data unreliable, and turning reporting into a tedious and time-consuming task, and reducing the use of the CRM as it is considered ineffective. Decreasing the amount of effort needed to produce reports would let sales personnel spend more time attending to clients, enabling further revenue for the Company.

The two principles which apply in this first stage of ADR are Principle 1: Practice-Inspired Research and Principle 2: Theory-Ingrained Artifact. The research activity is problem-inspired because it is solving a current issue in a real company. The projected artifact is theory-embedded, as it was built based on information withdrawn from the initial stage interactions within the ADR team and structured through industry frames of reference and implementation in a well-known BI platform.

On Stage Two, prototypes of both the LDM and the visualizations were drawn up. In order to do so, familiarization with the Salesforce underlying data structure and API's was necessary, as training with the CloudConnect tool.

The principles of ADR which apply at this stage are Principle 3: Reciprocal Shaping, Principle 4: Mutually Influential Roles, and Principle 5: Authentic and Concurrent Evaluation.

Reciprocal shaping is described as the iterative process to construct and reconstruct both the IT artifact and organizational context when solving problems. In this particular scenario, the main challenge was the need to have unified "versions of truth" that nonetheless showed different stakeholders the different numbers they wanted. While a Manager, or a financial analyst may want to see the total amount of revenue, for example, sales representatives may be interested only in the numbers that they make individually, and how they compare to other members in their team. Forcing them to see cumulative information of the company reduced for them the interest and value proposition of the solution, while holding on too much detail would be troublesome for Finance team which need information in a completely different level of grain.

Mutually influential roles happen when project participants learn from each other. As the IT based author progressively developed the BI artifact, their knowledge of sales, management, and B2B operations was increased, while the sales team and managers steadily became aware of business potential that derives from new ways of seeing and analyzing data. This realization leads to greater commitment to the project by the clients and the prospect of solution intervention by the researchers.

Regarding authentic and concurrent evaluation, it has already been identified that evaluation is a key characteristic of ADR, as it allows for the furthering and refining of the initial prototypes.

Stage 3 follows the principle 6: Guided Emergence, which allows to abstract Design principles from ADR outcomes. Sein et al (2011) argue that "the design principles capture the knowledge gained about the process of building solutions for a given domain, and encompass knowledge about creating other instances that belong to this class". A number of design principles are emerging from the case study that apply generally. Some examples include the use of cloud data warehousing to reduce the risk of data loss, the need for daily loads of data to make sure all data is current (loading processes which run more frequently than once a day turn superfluous and become an unnecessary load on the machines), the need to place data quality management techniques (even the most simple check can have huge economic impact in a B2B transaction), and the understanding that not all users can implicitly understand with ease the meaning of all numbers/metrics, but that all users can (and should) be properly trained to do understand specific metrics which are relevant to their work.

In Stage 4 the outcome of this thesis is properly formulated as an addition to the state of the art by use of the Principle 7: Generalized Outcomes which helps explain properly that although the empirical research for this thesis was done using GoodData platform as a BI Tool, and Salesforce as CRM, one must keep in mind that the resulting framework should be applicable to any other company with a similar sales structure, regardless of company type and size, CRM used, or BI tool chosen.

The summary of this ADR process can be seen in Figure 9.

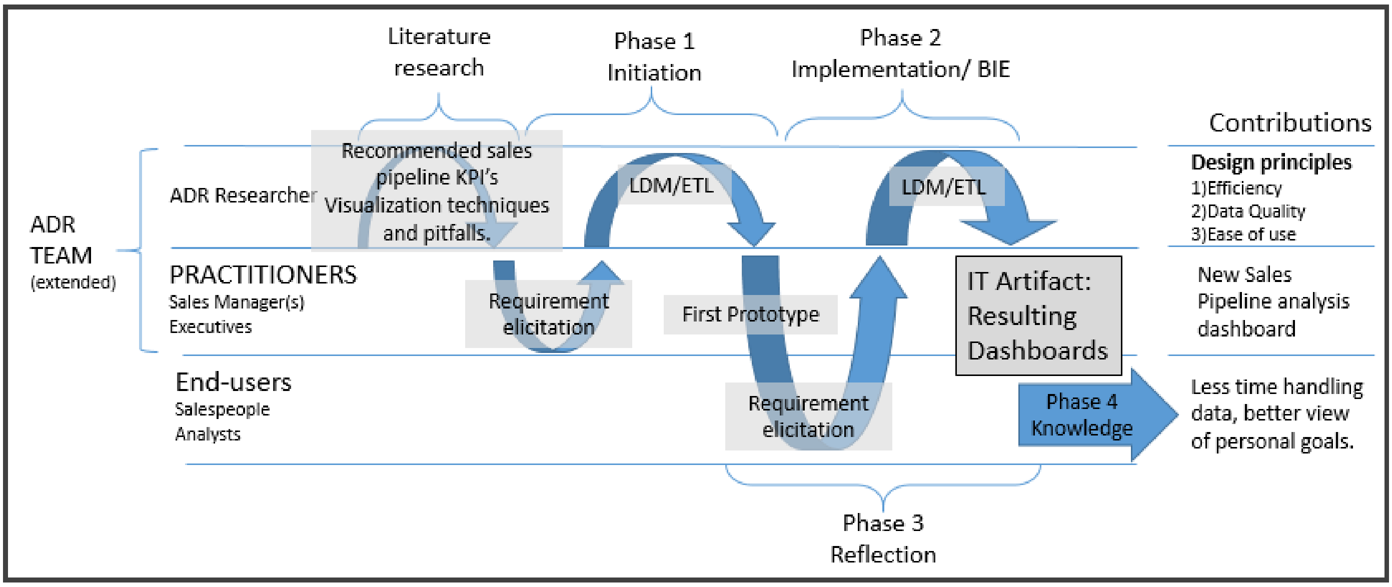


Figure 9. ADR process for Sales Pipeline Dashboard creation in Company X (Adapted from Sein et al, 2011)

4.3.4.1 Dashboard Guidelines

Based on interviews with the ADR team, the main guidelines on which to build the analysis dashboards were identified and defined. The summary of this interviews can be found on Table 6.

Topic	Stakeholder	Types of Insights
Quarter	Sales Leaders	Top Deals, Opportunity Inspection/Progress based on MEDDPICC and sales process stages
Customer	All	Pre-customer meeting briefing based on MEDDPICC
Individual	AEs & SRs	Single View of individual activity and results
Team	Managers	Team based view of activity/results
Organization	Sales Leaders	Insight into each region's key KPI's
Business		Long Range Planning & Forecasting

Table 6. Dashboard guidelines emerging from ADR process.

4.3.4.2 Recommended "tabs"

Further refining of the guidelines, gave rise to the following description of desired tabs. Each tab is meant to gather together a group of reports and metrics, which answer a specific set of questions which may be asked at a time by a given persona. This questions are formulated in a way that they create a user story, so that the flow from one tab to the other is as intuitive as possible based on the usual workflow from the sales people.

- Outlook
    - Used to give a quick summary of the quarter. For answering questions like "where do we stand?"
    - Understand how much has been sold, and where you stand in regards to your goal
    - Understand end of quarter estimates, and where you stand in regards to your goal
    - Understand how many days are left until the end of the quarter
    - Understand where you stand this quarter compared to your performance last quarter
    - Understand the above segmented by region, product, or sales rep.
- What's Changed
    - Used to keep track of weekly events. Keep in touch with the sales organization. For answering questions like "what happened over the last 7 days"
    - What happened in the last X days?
    - How much has my pipeline grown?
- Waterfall Analysis
    - Used to analyze the Sales organization's ability to close deals. For answering questions like "what happened to deals that started the quarter"
    - What happened to the deals that started the quarter?

- What happened to the new deals that were added during the quarter?

- Leaderboards
    - Used to understand the best, and worst, points of your organization. Answer questions like "who has sold the most this quarter"
    - Who had the best/worst sales?
    - Who has the best/worst win rate?
    - What deals closed fastest/slowest?
- Activities
    - Understand the activity level of your organization. Answer questions like "who is logging the most salesforce activities"
    - What is the average activity level?
    - What is the activity level for each activity type?
    - What is the activity level for each sales rep?
- Sales Cycle
    - Understand the velocity of the sales organization, and see if this is improving or worsening. Answer questions like "is my sales team getting more efficient?"
    - What is my normal sales cycle?
    - Is the sales cycle improving?
    - What deals are operating outside of normal sales cycle trends?
- Quarterly Trends

- Understand how the business is evolving over time. Are trends appearing? Are they positive or negative?. Answer questions like "Is my sales cycle getting longer or shorter?"
- Is my sales cycle improving?
- Is my sales team getting more efficient?
- Am I selling more?

Seasonality

- Understand annual sales trends. Are annual trends appearing? Are they expected?. Answer questions like "Do I sell more in spring, summer or fall?"
- What is my strongest sales quarter/month
- Should I forecast more for certain times of the year
- Do certain sales reps sell stronger at different points in the year

4.4 Performance measure

As GoodData offer a BI solution in a SaaS package, it includes in its platform the ability to track executions of its reports thanks to the underlying logs that every action, regardless if triggered by the user or by another component of the system, generates on its platform. That is the base of their Customer Success analytic app, which can be understood as their “BI on BI”, monitoring the usage by their customers and end-users for specific projects. The main use of this Customer Success app is the identification of trending projects, champion users, and early alert system of performance issues. However, we will use similar metrics in order to measure the interest of users into the created dashboard.

Access was granted to the reports that comprise dashtab and report views, with the following warning:

“When a GoodData dashtab execution happens, it also creates report executions. Furthermore, report executions are counted ONLY in the context of a dashtab execution.”

That means that:

- All the "preview" loads while creating or editing a report DO NOT count as views.
- If the user is just navigating the project, switching between dashtabs without loading new data (i.e. without changing a filter, or without pressing the reload button of your browser) DOES NOT increase view count.
- Exporting the report does not request new data, so exports as pdf or csv DO NOT count as views.
- Drill-ins are not a “properly” defined report, and thus DO NOT count as views.
- Sorting data on a report by any parameter (metric or attribute) DOES NOT increase view count.
- If one creates a new report, but doesn't imbue it into a dashboard, but leaves it to be accessed through the Reports console, or through the direct report URL, those report views DO NOT count as views.
- Executing embedded reports DO NOT count as views (As they are not linked to a dashtab)

But it also means that:

- Filters on the dashtab level, however, do trigger in most cases the request for new data, so changing a filter and clicking "Apply" IS a new view.
- If the user hits F5, or the refresh button on the browser while viewing a dashtab, it IS a new view.
- If the user just logins to GoodData and it is automatically redirected to the last dashtab they checked, it IS a new view.
- Views of embedded dashtabs COUNT as new views.
- If the user changes browser tab, and comes back, it may be a view if for some reason going back to the tab refreshes the page (if , e.g. it was left for a long time and user

has to login again to the platform) but it is the refreshing of the page which triggers the new view.

5 Results and Discussion

5.1 KPIs

Shown in table 5, the result of the analysis of the sales pipeline KPIs found in literature, their type (based on the sales process they impact), the unit in which they are measured, their direction (if the company seeks to increase or decrease that specific KPI during time) and the priority of measuring that specific KPI according to Company X's standards. For ease of reading the KPI's have been sorted from High to Low priority.

KPI Name	Type	Unit	Direction	Priority
# OF CLOSED DEALS	Pipeline Quality	Integer	Increase	High
# NEW CUSTOMERS	Revenue	Integer	Increase	High
# OF LOST DEALS	Pipeline Quality	Integer	Decrease	High
# OF NEW ENTRIES IN PIPELINE	Pipeline Quality	Integer	Increase	High
# OF S2O'S (STAGE 2 OPPORTUNITIES)	Pipeline Quality	Integer	Increase	High
AVERAGE DEAL SIZE IN SALES PIPELINE	Revenue	Currency	Increase	High
AVERAGE REVENUE PER UNIT (ARPU)	Revenue	Currency	Increase	High
AVERAGE SALES CYCLE LENGTH	Pipeline Speed	Days	Decrease	High
AVERAGE SPEND PER CUSTOMER	Revenue	Currency	Increase	High
AVERAGE TIME BETWEEN LEAD AND ACTIVITY	Pipeline Speed	Days	Decrease	High
AVERAGE TIME IN PIPELINE	Pipeline Speed	Days	Decrease	High

CLOSED WON DOLLARS	Revenue	Currency	Increase	High
CUSTOMER ACQUISITION COST	Revenue	Currency	Decrease	High
CUSTOMER LIFETIME VALUE (CLV)	Revenue	Currency	Increase	High
LEAD TO OPPORTUNITY RATIO	Pipeline Quality	Percentage	Increase	High
OPPORTUNITY-TO-WIN RATIO (PIPELINE THROUGHPUT RATE)	Pipeline Quality	Percentage	Increase	High
RATE OF CONTACT	Customer Engagement	Percentage	Increase	High
SALES REVENUE FROM NET NEW CUSTOMERS	Revenue	Currency	Increase	High
WIN TO LOST RATIO	Pipeline Quality	Percentage	Increase	High
# OF VISITS	Customer Engagement	Integer	Increase	Medium
# CHURNED CUSTOMERS	Revenue	Integer	Decrease	Medium
# OF ACTIVITIES	Customer Engagement	Integer	Increase	Medium
# OF EMAILS SENT TO CLIENTS	Customer Engagement	Integer	Increase	Medium
# OF RENEWALS	Revenue	Integer	Increase	Medium
% OF SALES LOST	Pipeline Quality	Percentage	Decrease	Medium
AVERAGE REVENUE PER PROJECT	Revenue	Currency	Increase	Medium
LEAD RESPONSE TIME	Pipeline Speed	Days	Decrease	Medium
PROBABILITY ADJUSTED PIPELINE VALUE	Revenue	Currency	Increase	Medium
SALES REVENUE LOST FROM CHURNED CUSTOMERS	Revenue	Currency	Decrease	Medium
TIME SPENT INPUTTING CLIENT INFORMATION INTO CRM.	Customer Engagement	Hours	N/A	Medium

UPSALES FROM OLD CUSTOMERS	Revenue	Currency	Increase	Medium
% OF SALES PERSONS OVER QUOTA	Sales Management	Percentage	Increase	Low
% VISITING GOAL TARGET	Customer Engagement	Percentage	Increase	Low
AVERAGE CUSTOMER SATISFACTION SCORE	Sales Management	Float Number	Increase	Low
AVERAGE NUMBER OF ACCOUNTS PER ACCOUNT MANAGER	Sales Management	Float Number	N/A	Low
AVERAGE NUMBER OF CONTACTS PER ACCOUNT	Sales Management	Float Number	N/A	Low
AVERAGE SALES REVENUE PER SALES PERSON	Revenue	Currency	Increase	Low
BUDGET ACCURACY (QUOTA ACHIEVEMENT)	Sales Management	Percentage	Increase	Low
CLICKS FROM SALES FOLLOW-UP EMAILS	Social Marketing	Clicks	Increase	Low
NUMBER OF CALLS	Customer Engagement	Integer	Increase	Low
RATE OF FOLLOW UP CONTACT	Social Marketing	Percentage	Increase	Low
SOCIAL MEDIA USAGE	Social Marketing	Clicks	Increase	Low
USAGE RATE OF MARKETING COLLATERAL	Social Marketing	Percentage	Increase	Low
YEARS OF A SALESPERSON IN COMPANY	Sales Management	Float Number	N/A	Low
YEARS OF A SALESPERSON IN SALES	Sales Management	Float Number	N/A	Low

Table 7. KPI Ranking in Company X

5.1.1 Discussion on KPI’s

Zallocco et al (2009) mentioned a disparity between the KPI’s from practitioners and researchers particularly in B2B scenarios. However, in Company X the difference between the KPI’s used and the KPI’s available in literature is minimal, what suggests that the gap between theory and practice when it comes to sales performance metrics has closed, probably due to the enhanced use of CRM automation software, especially in Company X.

Unfortunately, there is still very little interest in measuring competencies (or maybe the interest is present but there is difficulty measuring competencies in a proper and objective manner, so competences such as presentation skills, listening ability or teamwork are still taken into account on a subjective level, especially during hiring, but there are no “hard” metrics related that are periodically measured and benchmarked.

It can be noticed too, that while Anderson et al (2010) already point to this by dividing the performance metrics into three groups: outcome-based measures, behavior-based measures and professional development measures, according to those in Company X there is a relationship between the subjective and objective measures, so that by measuring all outcome-based and some of the behavior-based KPI’s, the professional development measures can be inferred. There is, however, no scientific back of this claim for now, but proving it could constitute an interesting research in the future.

In the case of Company X it can also be noted that both “Number of New Customers“ and “Revenue of New Customers“ are marked as of High importance. That shows that Company X is a mature company which is offering its products to customers in a niche, but still is aiming to obtain bigger customers. Interviewees confirmed that the company is shifting its strategy from marketing based (in which amount of new customers is more important) to account based sales (where revenue per customer is more important).

Lastly, there was no perceived need to display the forecasted probability of closing a deal. While the parameter exists in the database, and there are new machine learning approaches to predict pipeline yield, the perception is that these forecast are still not accurate, and are thus considered unreliable and not important.

5.2 Logical Data Model

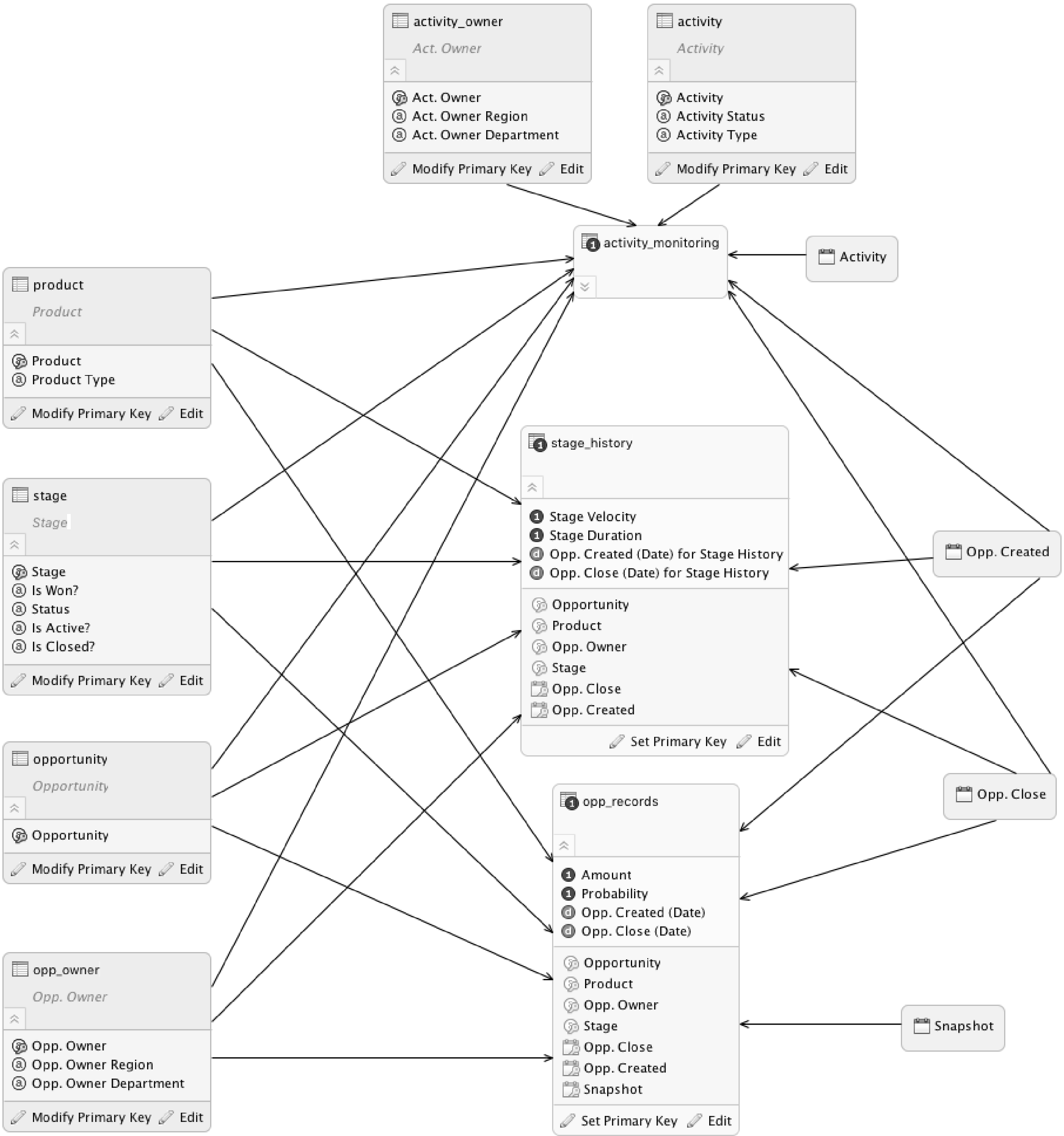


Figure 10. LDM in Cloudconnect.

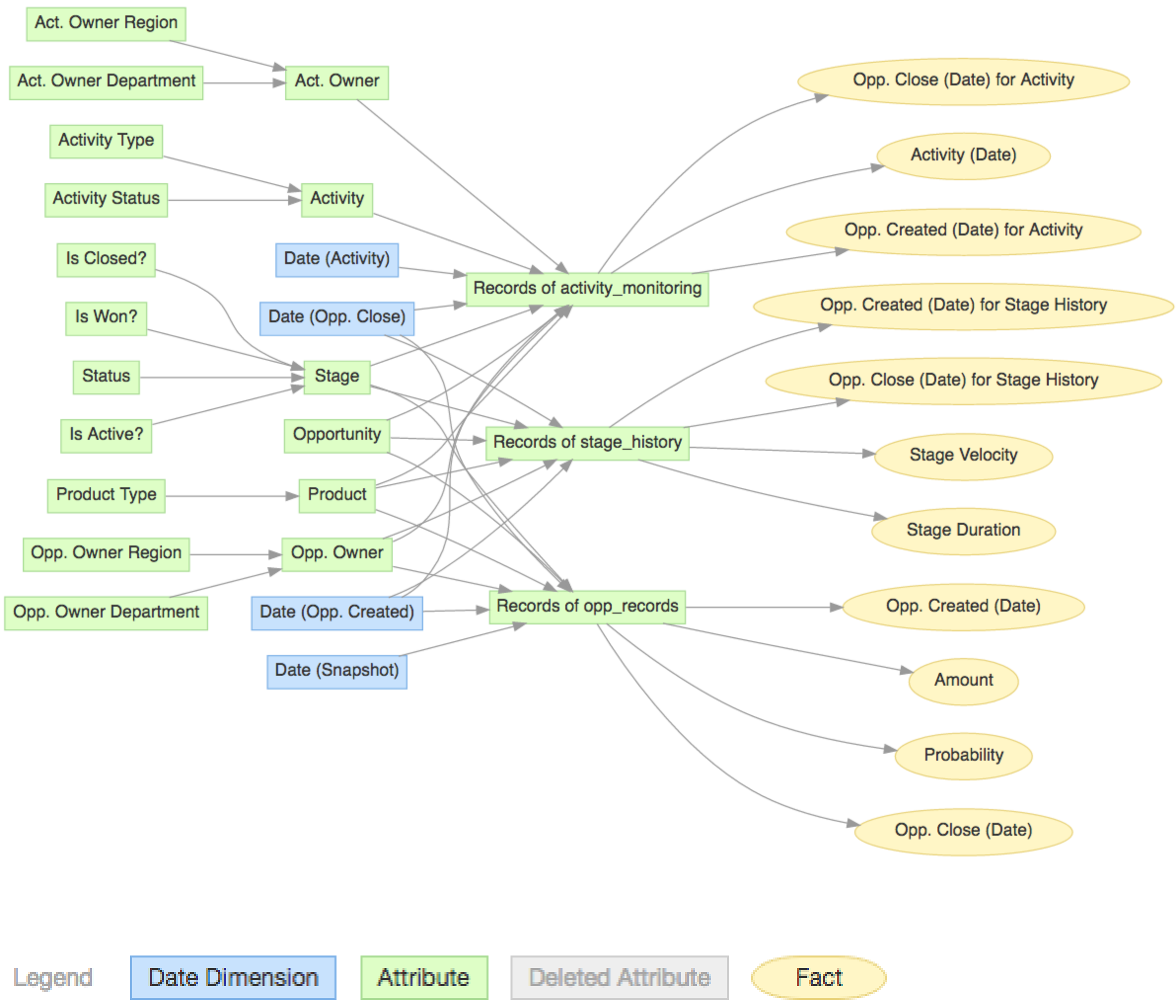


Figure 11. Final Logical Data Model (LDM) for sales pipeline analysis in Company X.

5.2.1 Discussion on Logical Data Model

One of the most important features of the LDM is the addition of date dimensions. This allows for every metric to be filtered and sliced by time attributes such as day, week, month quarter and year. All facts are snapshotted daily, as it is the minimum amount of time that holds any meaning. It is considered of little relevance the time when an activity was made, and there is a window of opportunity for a sales person to register changes in CRM. As the data capture doesn't happen in real time, loading the information in real time would be misleading.

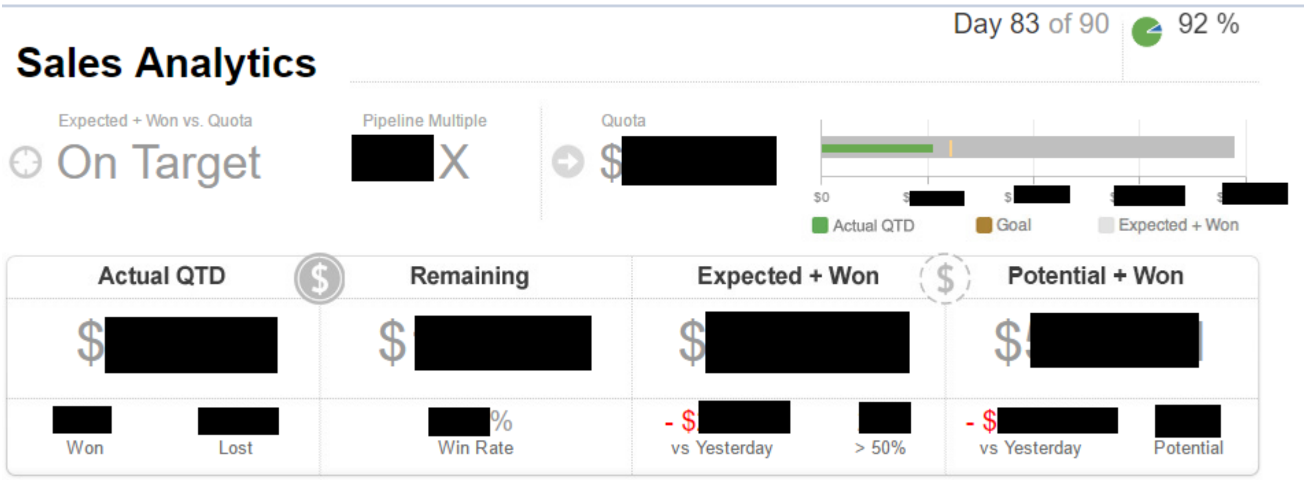
Owner represents the person that interacts with an opportunity or activity. Attributes such as role, team, seniority, years of experience, skill level, expertise in a certain topic, etc can (and eventually should) be included in the Owner dataset, but are skipped in this study. Likewise, the dataset Product can have many attributes, although there are not present in this specific implementation. Type is included as an attribute in Product but under different circumstances, specially if there are many conditions that are dependant on the type of contract, Type can be a totally independent dataset. As a matter of fact, it was considered initially apart from product, but the design was then corrected to appeal to a simpler, more understandable version. “Duration” was also considered for the “activity” dataset, but it was decided that all activities were discrete and duration of the activities escaped the scope of this particular solution.

The boolean attributes in the Stage dataset are not mandatory either, but their presence helps the definition of the stages based on status, as the names used in the company (Stage 1-7, as described in Table 7) are just a particular and specific implementation of the pipeline model, but don’t convey an implicit meaning. The booleans are not difficult to create in the ETL, and help greatly in the creation process of the visualizations when there is no familiarity with the definitions of the stages.

As the attributes of an opportunity could change from one snapshotted status to the next, the “Snapshot” dimension becomes really important, as it is by it that the joins on the opportunity dataset act like a Type 2 slowly changing dimension, which allows the tracking of historical data in an easy manner, but renders the model vulnerable to integrity issues if there are retroactive changes made to the contents of the dimension, or if new attributes are added.

5.3 Dashboard Types

5.3.1 Overview



KPI's included:

- Quota Achievement
- Quarterly Quota
- Day of Quarter
- Closed Amount
- Expected Amount in Pipeline
- Potential Amount in Pipeline
- Variation vs Yesterday (Amount and %)
- # of Opportunities Won in Quarter
- # of Opportunities Lost in Quarter

Time Dimensionality:

- Only Current information available.

Filters Available:

- Region
- Product
- Sales Representative
- Type (New, Renewal, Upsale)

5.3.2 SalesTeam Highlights

Ranked Reps by Potential Pipeline

Opp. Owner	Opp. Owner Region	# of Potential Opps.	Total Potential	Relative to Others
[redacted]	North America	81	$[redacted]	
[redacted]	EMEA	69	$[redacted]	
[redacted]	Asia-Pacific	61	$[redacted]	
[redacted]	South & Central Americ	134	$[redacted]	
[redacted]	EMEA	48	$[redacted]	

Ranked Reps by Amount Won

Opp. Owner	Opp. Owner Region	# of Won Opps.	Total Won	Relative to Others
[redacted]	EMEA	18	$[redacted]	
[redacted]	South & Central Americ	5	$[redacted]	
[redacted]	Asia-Pacific	11	$[redacted]	
[redacted]	North America	26	$[redacted]	
[redacted]	EMEA	37	$[redacted]	
[redacted]	South & Central Americ	11	$[redacted]	

KPI's included:

- Revenue from Potential Opportunities
- # of Potential Opportunities
- Sales Revenue from New Entries in Pipeline
- # of New Entries in Pipeline
- Ranking against peers

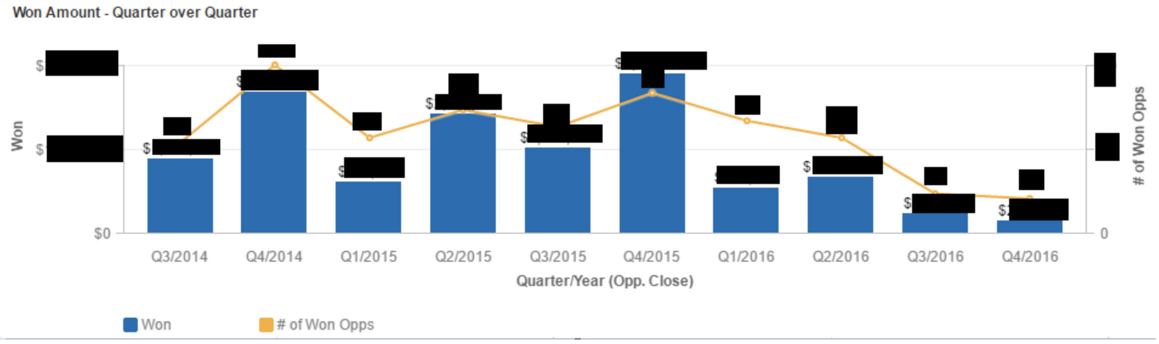
Time Dimensionality:

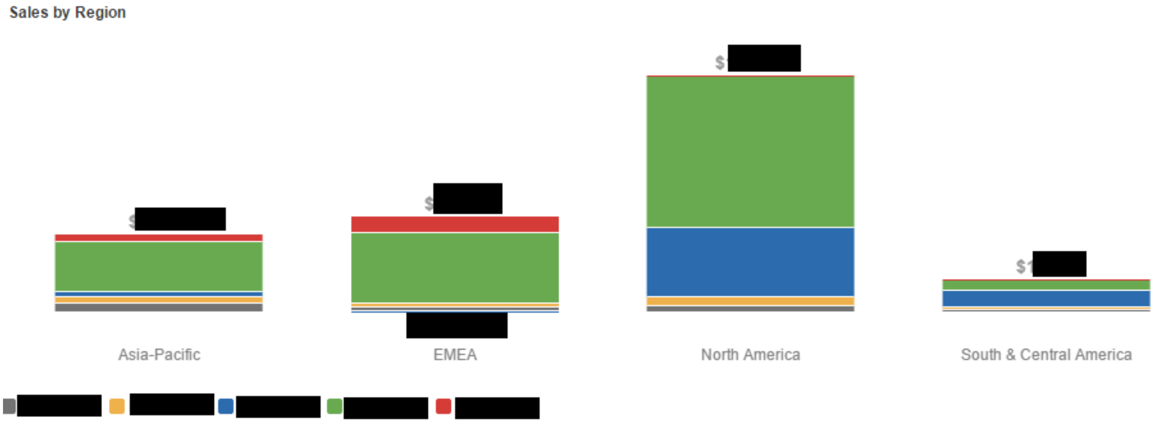
- Metrics can be filtered to a period from any day to any day. (Date Snapshot)

Filters Available:

- Region
- Product
- Sales Representative
- Type (New, Renewal, Upsale)

5.3.3 Specific Quarter





KPI's included:

- Sales Revenue from New Opportunities
- # of New Opportunities

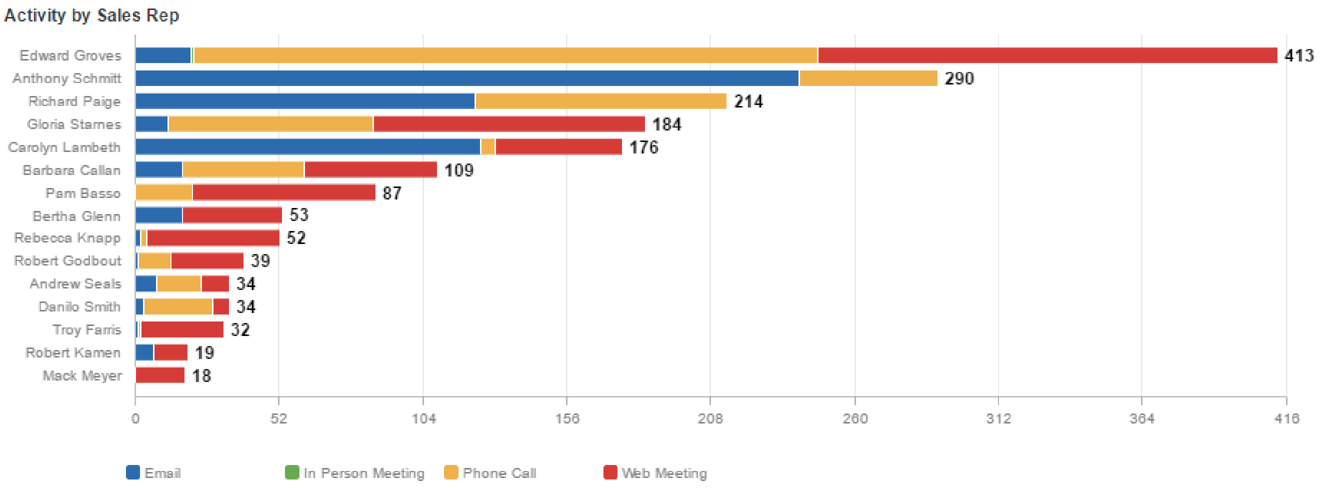
Time Dimensionality:

- All time analyzed, split in Quarter to Quarter periods.

Filters Available:

- Region in upper report (Quarterly Sales)
- Product in lower report (Regional Sales)
- Sales Representative
- Type (New, Renewal, Upsale)

5.3.4 Activities



KPI's included:

- # of Activites – Rate of Contact (By activity type)

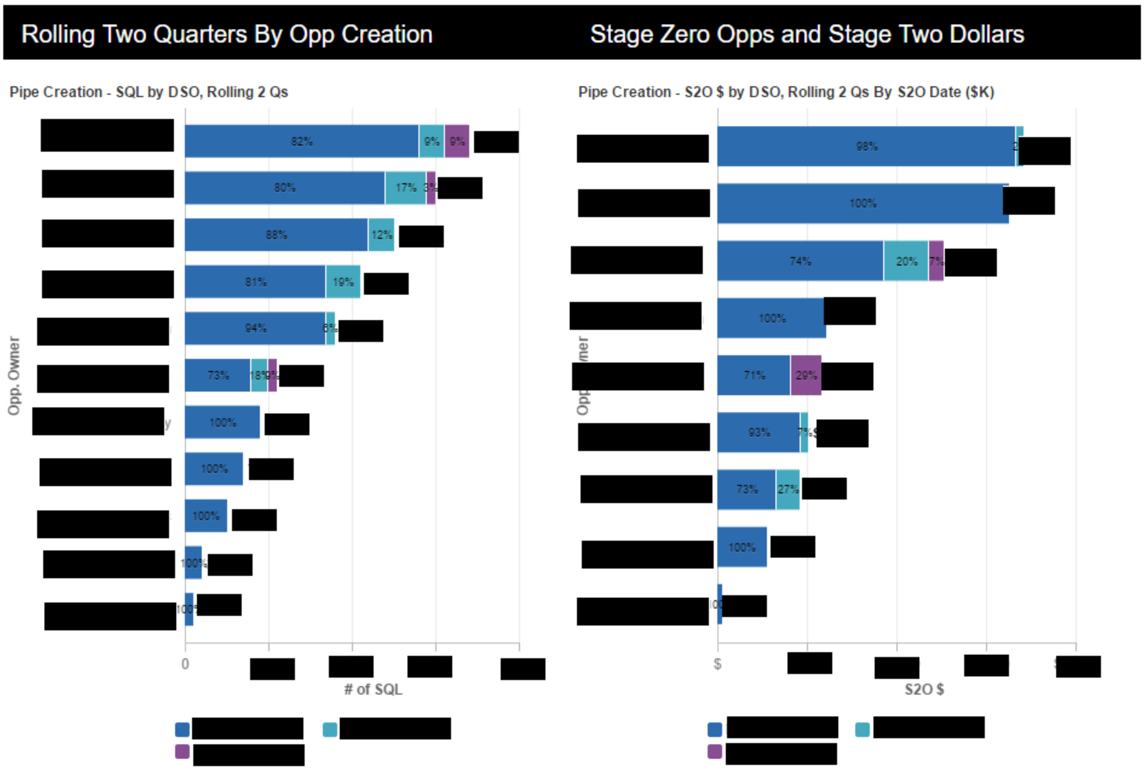
Time Dimensionality:

- Metrics can be filtered to a period from any day to any day. (Date Snapshot)

Filters Available:

- Region
- Sales Representative

5.3.5 Pipeline Creation



KPI's included:

- Sales Revenue from S2O Opportunities
- % of Revenue by Type (New, Renewal, Upsale)
- # of S2O Opportunities
- % of S2O by Product Type (New, Renewal, Upsale)

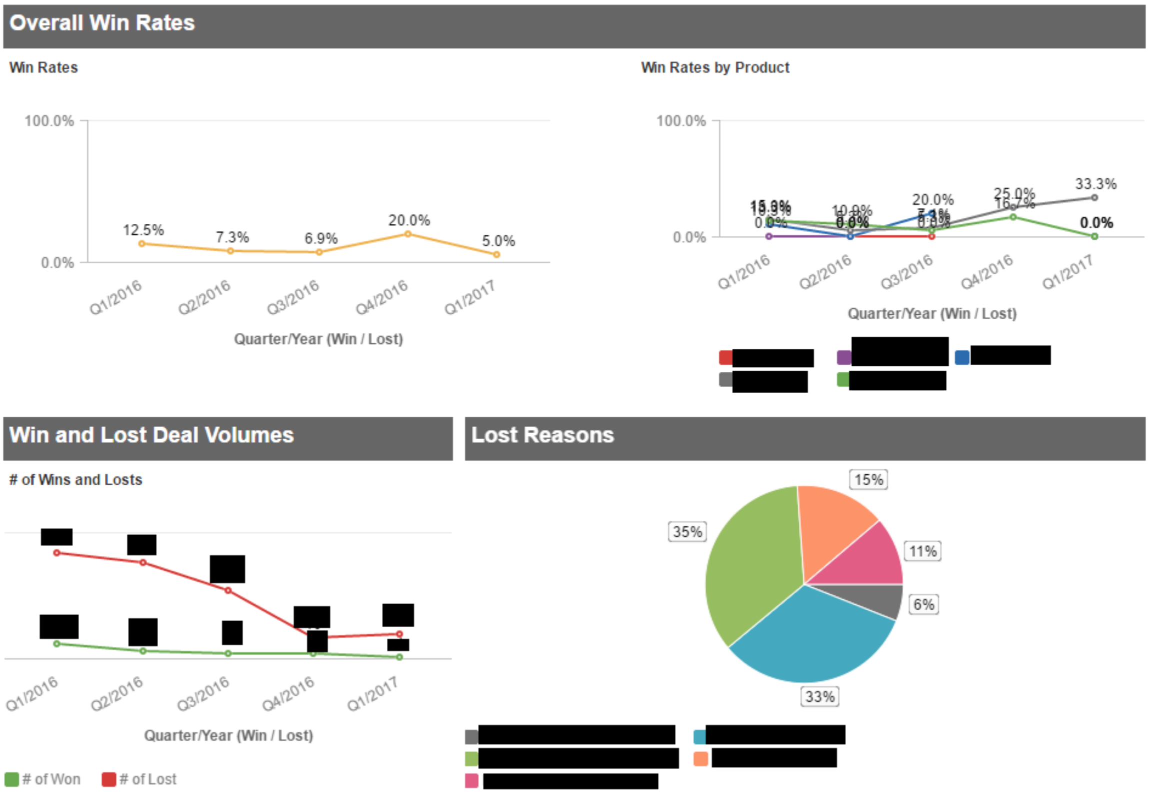
Time Dimensionality:

- Cumulative from last 2 quarters.

Filters Available:

- Region
- Product
- Sales Representative

5.3.6 Win/Loss



KPI's included:

- Win Rates
- # of Lost Deals
- Win to Lost Ratios

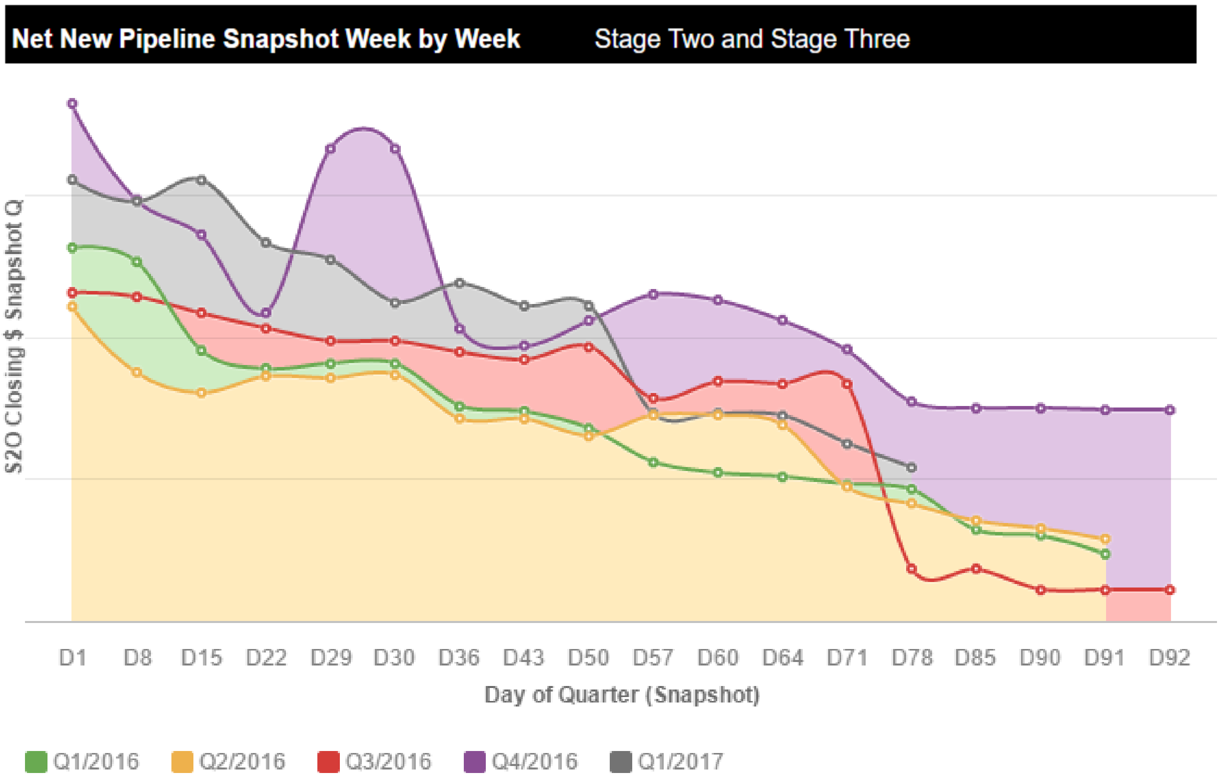
Time Dimensionality:

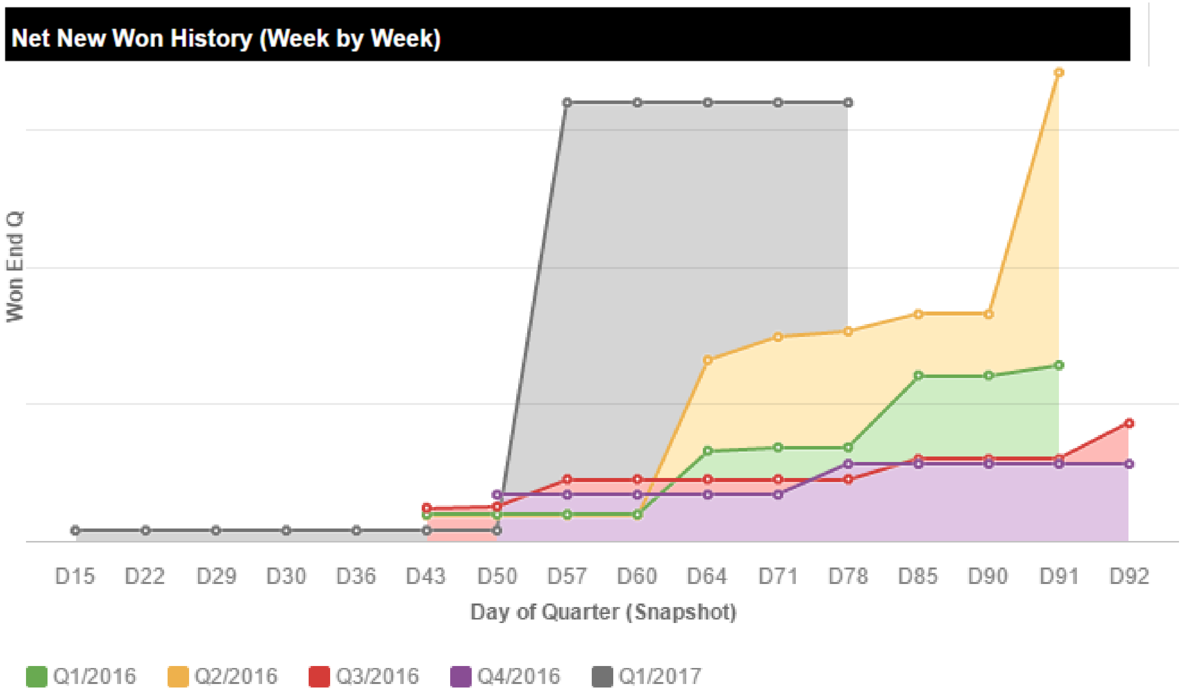
- Cumulative from last 4 quarters.

Filters Available:

- Region
- Product
- Sales Representative

5.3.7 Pipeline Coverage





KPI's included:

- # Of New Entries In Pipeline
- # Of S2O's (Stage 2 Opportunities)
- Average Deal Size In Sales Pipeline
- Average Sales Cycle Length
- Closed Won Dollars

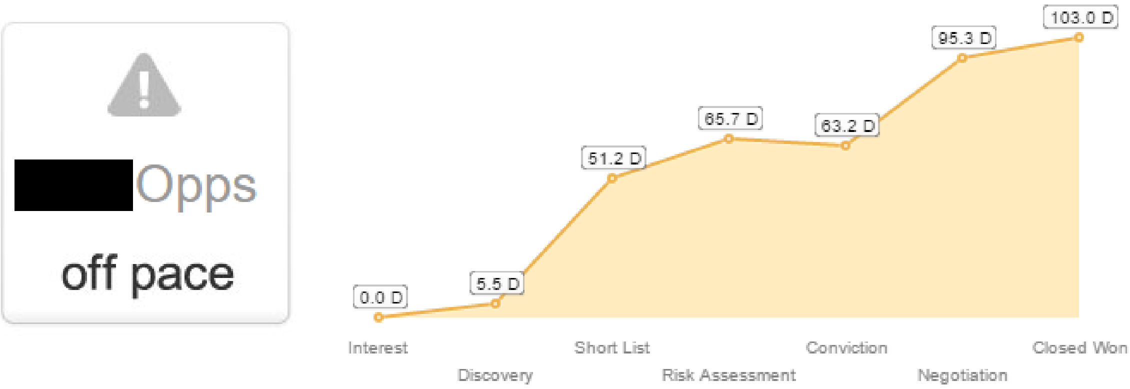
Time Dimensionality:

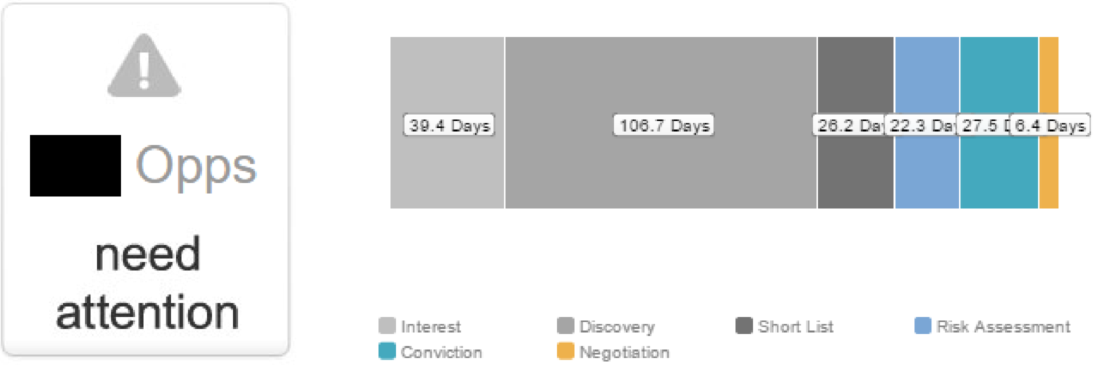
- Day to day for last 4 quarters.

Filters Available:

- Region
- Product
- Sales Representative
- Type (New, Renewal, Upsale)

5.3.8 Sales Velocity





KPI's included:

- # of Slow Opportunities
- Average Time in Pipeline
- Average Time Between Lead and Activity
- Average Sales Cycle Length

Time Dimensionality:

- Current

Filters Available:

- Region
- Product
- Sales Representative

5.4 Descriptive statistics of usage

# of Users	119
# of Sessions	1876
Average Tabs viewed per Session	2.265
Std Deviation of Tabs per Session	1.603

Table 8. Usage Statistics for the dashboards

The first thing to discuss related to the visualizations is the final acceptance they had by users. A total of 1876 sessions in 212 days, by 119 users mean that every user logged in, on average, 2.3 times per month, or once every 13.4 days. This use falls within the expected parameters, as the recommended period to self evaluate performance is once every one or two weeks. Furthermore, the average of 2.27 tabs per session (+/- 1.6) show that users usually knew exactly the content they were looking for and where to find it, and it can be suggested that the users saved time by not having to navigate all dashboards until they found the information they wanted at any given moment.

Device	**# of Sessions**	% of **Sessions**
Desktop	1868	99.6%
Mobile	8	0.4%
Grand Total	**1876**	100.0%

Table 9. Usage by device

Although the GoodData platform is completely on the cloud, and thus allows for mobile navigation, a very small amount of sessions were made through the mobile phone (8 sessions, representing 0.4%). That can be explained by the fact that the density of information in the dashboards is so high, that some details may be lost in lower resolution screens, and even though portability was not one of the principles in mind while designing the dashboards, it certainly represents a dimension in which there is a room for improvement in future versions.

Month	# of **Views**	% of **Views**
June	601	14.63%
July	803	19.55%
August	596	14.51%
September	967	23.54%
October	440	10.71%
November	373	9.08%
December	302	7.35%

Grand Total	**4108**	**100.00%**

Table 10. Usage stats by month.

The peak in number of sessions in July, probably corresponds to an increase in the demand for data, due to mid-year evaluations. Mid-year reviews are a widespread practice, that includes a summary of the tasks assigned to an employee and their progress. If a company changed strategies, like a new focus on new clients, the mid-year review is a good time to confirm changes of direction with managers. The peak in number of sessions in September may correspond with a Q3 evaluation, but there isn't certainty about the exact trigger of this peak. However, the generally declining curve of use may indicate also a certain loss of "hype" on the visualizations. Only evaluating data of usage for a longer period will show if there exists certain periodicity or stationality in the frequency of viewing the dashboards

Day of Week	# of **Views**	% of **Views**
Monday	856	20.84%
Tuesday	689	16.77%
Wednesday	730	17.77%
Thursday	880	21.42%
Friday	736	17.92%
Saturday	109	2.65%
Sunday	108	2.63%
Grand Total	**4108**	**100.00%**

Table 11. Usage by day of the week.

As for shorter term periodicity, it's seen, unsurprisingly, that Saturdays and Sundays showed a dramatic reduce in usage (as they are not usually work days). It was however curious to realize that executions in weekends amounted to almost (5%), as it was expected to be even lower. Other days are evenly represented. Further studies may yet determine if those who gather information from the dashboards outside office hours gain some additional benefit from doing so.

Dashboard	# of **Views**	% of Total
Activities	1511	36.78%
Overview	982	23.90%
Pipeline Status	706	17.19%
Specific Quarter	487	11.85%
Pipeline Coverage	173	4.21%

Win - Lost	136	3.31%
Sales Team Highlights	61	1.48%
Sales Velocity	52	1.27%
Grand Total	**4108**	**100.00%**

Table 12. Ranking of the dashboards by their total usage.

The fact that "Activities" was the most checked visualization (1511 views, i.e. 36.78% of views), shows that there has been a change of paradigm in the sales analysis in Company X, and their approach is definitely becoming more customer centric, and engagement has been playing an important lead in strategy, and possibly, in incentives to the sales force. Further detail about the impact of an activity in the opportunities down the pipeline will certainly constitute the next step in visualizations, and that is something which wasn't considered previously in the ADR artifact creation. The low count of the „"Sales Velocity" tab (52 views making only 1.27% of the total), shouldn't be linked to lack of importance. The information provided in this tab is very important but only to a very specific set of stakeholders, usually those with very high position, and such the net amount of people that use it is smaller.

Type	**# of Views**	% of **Views**
UI Execution	4108	100.0%
Automated Email	0	0.0%
Grand Total	**4108**	100.0%

Table 13. Usage by type of Execution

Lastly, the GoodData platform also offers the possibility to automatically send to the email pdf versions of the dashboards with predefined filters. However, all views of the dashboards were ad-hoc, and no email was programmed for distribution. That fact goes hand in hand with the relatively low frequency of use, and is a sign that an Early Alert System that pushes notifications on users once a KPI overcomes a threshold would be a noticeable improvement on the current dashboard sets. It should be noticed that GoodData does offer the KPI Alert system but, as many other useful features that the platform offers, it wasn't used in this study case.

6 Conclusions

6.1 Conclusions for Salespeople and Managers

The sales pipeline BI dashboard presented in this thesis was a specific solution for Company X. However, many of the issues facing the sales team of this company are faced in other organizations, so better articulation and characterization of the problem space is a valuable contribution. The findings of these thesis are applicable to a range of teams which need a similar solution that includes connection with CRM, data warehousing, business intelligence and visualization; quick recursive implementations within a general architectural strategy; and a clear alignment between different teams that aim for the same goal.

Furthermore, apart from the solution specific contributions, this thesis proves that the use of Business Intelligence and design techniques to facilitate the creation of a unique and centralized dashboard for sales pipeline has direct influence on the business in three key dimensions which are explained as follows:

The first dimension where improvement can be seen, is in the productivity gain. Time saved by salespersons, which are not anymore required to generate reports to present to their managers, have both more time to engage customers and less tasks on their to-do list, which allows them not only to engage more customers, but also engage them better so that not only the amount of opportunities at the beginning of the pipeline increase, but also the ratio of turning opportunities into successful deals increases. Furthermore, managers can also look for the information they need in a timely manner without having to wait for their underlings to give them the required data, and such, critical decisions need much less time to be taken.

The second dimension where improvement is noticed is in the quality of the information retrieved. Not only having a central repository of truth helps managers which are separated physically (some even in different continents) look at the same information by simply sharing a link, but also diminishes the chances of mishandling data, or evaluating incomplete information that does not take full consideration of all the facts relating to a client. Having a standardized set of dashboards also prevents the occurrence of undesired behavior brought by bad visualization techniques.

The third dimension is in team awareness. One of the facts that are so special of sales pipeline measuring, is that it disengages the traditional view of sales as an “activity” and forces the organization to look at sales like a whole process. Doing so allows for a holistic view where the goal is always to increase the revenue, but other factors related to the sales process such as company culture, sales behaviors, and customer satisfaction also play an important role. With that new view of the sales process, where achieving revenue quota was the only important metric, there’s room for increasing awareness of other salesforce metrics, (such those KPI’s mentioned in this thesis) and opens the door to new incentive and evaluation protocols and processes. Seeing that the only goal is not just “make money” but other factors are included as well, can motivate the salesforce into enhancing their relationship with other teams (e.g. Legal and Technical) in order to achieve their goals. This organical blooming of cross functional teams is paramount for the well being of a company, and also creates a culture that engages employees and overall drives better business in the long term.

6.2 Conclusions for Academia

This thesis provides support for two main ideas: First, the idea that sales management metric has shifted from the traditional “revenues only” metric as sales performance management, and the subsequent rise in “customer engagement” as can be seen by the lead of usage in the “Activites” tab. The second idea that this research supports, is that the gap between sales performance metrics proposed by researchers and the metrics in use by practitioners in the industry is minimal, even though a very clear distinction must be made between KPI’s depending on the team and phase of sales cycle in which they are being used (metrics differ from pre-sales & marketing, to sales, and post-sales teams) and also vary from the B2C and the B2B environments.

Also, during the development of this thesis, the synergies between a Business Intelligence implementation and ADR were abound. Designing a BI visualization, implicitly, requires a foundation by the BI analyst who understands the database principles, and has knowledge on the creation and calculation of metrics. However, a BI project won't be successful unless all the stakeholders use this foundation to build upon it, and take part in an iterative process to refine and complete the visualization. The parallels with the setting of the ADR extended Team and the Build—Evaluate process in ADR are not coincidence. However, ADR enhances BI by allowing the inference of design principles and the formalization of each constructed solution as contribution to the state of the art. Thus, ADR emerges as a methodology with special affinity to Business Intelligence related research.

Likewise, the possibility of moving around facts and attributes in the CloudConnect visualizer without need to worry about the underlying physical model, not only speeded up the iterative dashboard building process, but also allows for non-technical staff get a more "hands-on" and active approach on Business Intelligence. Although it wasn't part of this study, it is highly possible that using GoodData as educational tool, can enhance the learning curve of those with a sales, or otherwise non-technical background, who wish to follow a career path in Business Analytics, or for those academics who desire to engage in Business Intelligence research but for some reason lack the database expertise usually required to do so.

6.3 Limitations and further research

This study was conducted with a single company and, while it is expected to be representative of many similar businesses, the results, and specially the usage metrics, should be validated with those of similar solutions in other companies. Also, advanced usage tracking that allows to obtain details on which reports were drilled-in, which reports were downloaded, and the filters used everytime a report was viewed could give much better insights on the impact of the dashboards.

A comparison of similar visualizations in different tools, and comparing the times and costs of implementing similar solutions on different platforms would have been interesting, but definitely escaped the scope of this thesis.

Further evaluation of the impact of this dashboard in the performance of the sales team needed a bigger timeframe of evaluation and access to the detailed performance evaluations of the sales force. Also, the salesforce should have been split into two groups (at least): one to work as control group, and other as test group for the visualizations. However, the conditions to collaborate with Company X required that all stakeholders were granted access.

Capturing more detail on the activities in the CRM, particularly activities from early in the sales cycle, would allow for a richer understanding of what happens during the sales lead conversion cycle contributing to performance. In particular, understanding what type of meetings were held, a general idea of the topics in the phone calls made, or more details on customer's reactions can give better insights into what activities by the salesperson can truly make a change.

Development of an Early Alert System that pushes data on the users instead of waiting for data to be pulled can also have interesting results on a sales team, and the recent advances in sales pipeline predicition will surely change the way sales teams in B2B environment works, although the lack of empirical evidence that supports the use of these predictors, or awareness of such by the practitioners in Company X, was the main reason that it was left out of this thesis. However, pipeline win prediction and the use of Data Mining to establish new unforeseen patterns in the data, and thus create new KPI's and metrics, are part of the new generation BI systems which will most likely guide the decision making process in business management in the next few years.

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