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The Linkage to Business Goals in Data Science Projects

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Abstract

Modern data analytics equips businesses to make data-driven decisions by revealing patterns and insights that enhance strategic planning, operational efficiency, and process optimization. Its applications encompass personalized marketing through customer segmentation, predictive modelling for fraud detection, and enhancing security. A significant methodology in this realm is the Cross-Industry Standard Process for Data Mining (CRISP-DM), where the Business Understanding phase aims to ensure data science projects align with overarching business goals. However, challenges arise when these business objectives are ambiguous, ill-defined, or evolving. The complexity of data analytics projects underscores the need for domain expertise and robust collaboration between data scientists, business stakeholders, and domain experts. The imperative is to bridge the technical and business perspectives, manage expectations, and define project scopes. The short paper at hand addresses the question how data analytic goals can systematically align with business objectives in data science projects. By incorporating methods from Enterprise Architecture Management, we propose a structured approach for goal determination in data science projects, ensuring business and data mining objectives are seamlessly integrated.

Keywords Data science projects, Business understanding, Business goals, Enterprise Architecture Management, Business performance indicators.

1 Introduction

The current trends of data analytics empower enterprises to make informed and data-driven decisions. Organizations can uncover insights and patterns that can guide strategic planning, operational improvements, and optimize processes across various departments. Application cases range from customer segmentation to personalize marketing campaigns and offer targeted products and services, resulting in improved customer satisfaction and loyalty an, up to the development of predictive models and algorithms to detect anomalies, potential fraud, and security breaches. In general, an effective allocation of resources may lead to a reduction of costs and an improvement of productivity.

The Cross-Industry Standard Process for Data Mining (CRISP-DM) is a widely used methodology for data mining and data science projects (Shearer 2000). The Business Understanding phase as the first stage of the CRISP-DM cycle focuses on establishing a clear understanding of the project objectives, requirements, and constraints from a business perspective. The primary goal is to align the data science project with the organization's overall goals and to define specific objectives that can be addressed through data analysis. Once a clear understanding of the business objectives is established, one can translate them into specific, measurable data science goals. These goals serve as the foundation for the project and guide the subsequent analysis and modelling work. However, the business objectives may be vague, ill-defined, or subject to change (Haertel et al. 2022; Martinez et al. 2021). Thus, it is difficult to align the data analytics project with the overarching goals of the organization and may require iterative discussions as well as clarifications with stakeholders. Further, data analytics projects often involve complex domains, and the absence of domain expertise can impede the understanding of business processes, relevant metrics, and underlying contextual factors. Collaboration with domain experts is crucial to gaining a deep understanding of the business context and formulating meaningful data science questions. Effective communication and collaboration between data scientists, business stakeholders, and domain experts are essential for successful Business Understanding. Bridging the gap between technical and business perspectives, understanding business requirements, and managing expectations can be challenging, particularly when stakeholders have varying levels of data literacy. Defining the scope of the data analytics project is crucial, as it helps prioritize objectives, allocate resources, and set realistic expectations. However, balancing ambitious goals with time and resource constraints can be challenging. Stakeholder involvement and clear scoping guidelines can aid in managing project scope effectively. Therefore, in the short paper at hand we pursue the following scientific questions:

***RQ**: How can data analytic goals be related to business goals in a structured manner for data science projects?*

In order to address the challenges in the identification of business goals in data science projects and the associated derivation of data mining goals, the paper at hand aims at providing a method for the structured determination of goals in data analytics projects. For this purpose, methods from Enterprise Architecture Management will be used and linked to the structure of data analytics models. The linkage allows to define business goals and to derive data mining goals in data science projects.

2 Related Work

First, the current state in the research field is to be presented with a literature review. For this purpose, a structured literature analysis was conducted following the guidelines of vom Brocke et al. (2009) as well as Webster and Watson (2002). A literature search was carried out in several literature databases (Web of Science, IEEE, ACM Digital Library and Scopus) using the search terms (("Business goal identification" OR "Business understanding phase" OR "Business objectives") AND ("Data mining" OR "Data science" OR "Data analytics")). After cleaning duplicates and screening for included papers, 14 papers were collected as a result.

The research papers collectively underscore the necessity of aligning data mining and big data analytics techniques with business objectives. Ali & Wallace (1997) and Peral et al. (2017) both focus on using data mining techniques for business objectives, with the former mapping business objectives to data mining algorithm parameters and the latter identifying relevant Key Performance Indicators (KPIs). Charest et al. (2008) and Park et al. (2017) propose frameworks for integrating data mining into decision support technology and aligning big data analytics with business objectives. Nino (2015) offers a practical case study on Big Data Analytics application in a servitization context, while Nouman Zafar (2017) conducts a systematic review of model-driven engineering techniques in Big Data Analytics. Sharma and Osei-Bryson suggest tools and methodologies for the often overlooked "Business Understanding" phase of data mining projects. They propose an organization-ontology based framework, a formal framework for task implementation and dependencies, a method for formulating well-defined business objectives, and an improved knowledge discovery and data mining process model (Sharma and Osei-Bryson 2008, 2009, 2015). Next to these, Sundararaman et al. (2011) build a connection between data quality and business objectives in decision support systems, and Tardio and Peral (2015) present a novel approach for automatically deriving KPIs from data mining techniques. Finally, Zemmouri et al. (2014) address the issue of coordination and knowledge sharing in a multi-view Knowledge Discovery in Databases process through a goal-driven modelling approach. Despite their specific focal points, all works concur on the need to bridge the gap between business goals and data analytics methods.

While none of these works explicitly link KPIs from the enterprise architecture field to data mining goals, they all propose methodologies for connecting business objectives and KPIs to data mining techniques, which could serve as a foundation for our approach. Peral et al. (2017) propose an approach combining data mining techniques with the identification of KPIs for business objectives. They demonstrate the applicability of the approach in the fields of Massive Open Online Courses (MOOCs) and Open Data from the University of Alicante. Sharma and Osei-Bryson (2015) describe a novel method that incorporates value-focused thinking, goal question metric method, and SMART criteria to aid in the development of well-formed business objectives. They provide a step-by-step approach with an illustrative example to demonstrate the implementation of each step. The framework by Sundararaman et al. (2011) establishes a relationship between data quality measurements and the quality of business outcomes. Although not explicitly focused on KPIs, the framework could be seen as a starting point for linking business objectives to KPIs.

3 Prerequisites

This section explores three critical pillars in contemporary business planning. Enterprise Architecture Modelling provides a holistic view of the organization's structure, operations, and technology (Ahlemann 2012). The comprehensive perspective is invaluable when setting business goals in data analytics projects, as it helps to understand the organization's current state, its strategic direction, and how data analytics can support this strategy. By defining what constitutes success in the form of Key Performance Indicators (KPI), Business Performance Measurement ensures that the goals set in data analytics projects are measurable and achievable (Murphy et al. 1996). Moreover, it facilitates the tracking and evaluation of progress towards goals, which allows for adjustments and optimizations along the way.

3.1 Enterprise Architecture Modelling

Enterprise Architecture (EA) is a strategic planning discipline that is used by organizations to map out their information systems and technological assets in a way that aligns with their operational goals and strategies (Ahlemann 2012). EA provides a comprehensive view of the interrelationships between an organization's information systems, infrastructure, and business processes. Several models and methodologies are used in Enterprise Architecture to describe various aspects of an organization. A common Enterprise Architecture Framework is The Open Group Architecture Framework (TOGAF)(Desfray and Raymond 2014). TOGAF is a set detailed methods and supporting tools for developing an enterprise architecture. It provides a standard way to organize and govern the EA process, including defining an organization's structure, its IT systems as well as services, and how it operates. Archimate is a modelling language for EA, which is closely aligned to TOGAF. It provides a coherent and holistic view of an organization's architecture and allows for the creation of integrated models of an organization's business processes, organizational structures, information flows, software applications, and technical infrastructure. Further, the Zachman Framework is one of the earliest and most influential EA frameworks. It presents a matrix, cross-referencing different stakeholder perspectives with various architectural focus areas, like data, function, and network.

In terms of modelling Key Performance Indicators (KPIs) within EA, the Balanced Scorecard (BSC) is often used. The BSC is a strategic planning and management system that organizations use to align business activities with the vision and strategy of the organization, improve internal and external communications, and monitor organization performance against strategic goals. It is divided into four categories: Financial, Customer, Internal Process, and Learning & Growth, and each of these categories includes relevant KPIs. TOGAF does not explicitly define a way to model Key Performance Indicators (KPIs), but it does provide a structure where KPIs can be identified and aligned with the organization's business objectives. The “Event Diagram” artifact of TOGAF is a business event-driven process model that can be leveraged during the Vision Phase (Phase A) to define the business goals of an enterprise, identify the business events that trigger business processes, and model how these processes interact and inter-relate. This helps in better understanding the business context and allows for the establishment of a solid foundation for subsequent architecture work. KPIs play an essential role in this phase as they provide quantifiable metrics to measure the achievement of these business goals. Specifically, for each business process identified and catalogued in the Event Diagram, relevant KPIs can be defined to measure its performance and effectiveness. For example, suppose the Event Diagram models a sales order process. In that case, potential KPIs could include metrics like "Order Processing Time," "Percentage of Orders Processed Correctly," or "Customer Satisfaction Rate." By linking KPIs to the business processes outlined in the Event Diagram, enterprise architects can ensure alignment between the organization's business goals and the architecture being developed. This, in turn, allows the organization to better track, measure, and optimize its business performance against its strategic objectives.

3.2 Business Performance Measurement

Business performance measurement involves the use of a system of metrics to assess the efficiency, effectiveness, and overall performance of an organization. The criteria for determining a company's success are not universally agreed upon (Barnes and Ho 2012). While some believe success is reflected by financial ratios and positive or increasing values in metrics like profitability, sales turnover, sales growth, or ROI (Ahmad and Seet 2009; Murphy et al. 1996; Venkatraman and Ramanujam 1986), these aren't always the paramount focus, particularly for rapidly expanding businesses like start-ups. As they are seen as risk investments with strategic value (Anderson et al. 2002), these businesses primarily concentrate on non-financial performance indicators, such as operational ones. Therefore, measures like product quality, market share, company reputation, customer satisfaction, as well as employee satisfaction and work-life balance, become significant (Ahmad et al. 2011; Ahmad and Seet 2009; Murphy et al. 1996).

3.3 Data Analytical Modelling

Data analytical modelling is a cornerstone in the realm of data science (Shearer 2000). It offers a structured methodology to extract meaningful insights from datasets. At the heart of this discipline lies the quest to decipher relationships between variables, employing techniques that range from neural network architectures to advanced statistical methods. The fundamental concept of mapping inputs to outputs is essential, reflected by the simple formulation y=f(x). The richness of these methodologies is reflected in machine learning, statistical learning or other approaches and underpins their diverse applications across various domains (Goodfellow et al. 2016; Hastie et al. 2008).

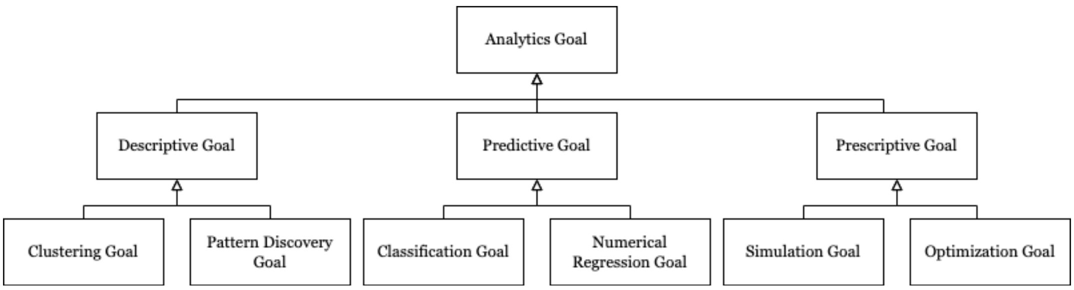

Figure 1: Overview of Data Analytics Goals according to Nalchigar and Yu (2018)

The data science field encompasses various types based on the nature and purpose of the analysis. Descriptive analytics focuses on understanding past events and identifying patterns or trends within data. This form provides a retrospective view of what has happened, often visualized through graphs, charts, and dashboards but also clustering and patten discovery techniques. Predictive analytics, on the other hand, employs statistical models and machine learning algorithms to forecast future events based on historical data, helping organizations anticipate potential outcomes. Lastly, prescriptive analytics goes a step further by not only predicting future scenarios but also offering recommendations on how to handle or optimize these forthcoming situations. Predictive and prescriptive analytics both aim to model a target variable but serve distinct purposes. Essentially, while predictive provides insights into likely future events, prescriptive advises on how to shape those events.

The objectives in data analytic problems can also be classified depending on the application. Nalchigar and Yu (2018) publishes a model to illustrate the structure of data analytic problems. In this model, the differentiation of the objectives is analysed and classified as well (see Figure 1).

Furthermore, it should be noted that the terms data analytics, data mining and data science are often used synonymously. In the present context, the term data analytics is used when a concrete analytical problem is to be addressed. The term data science as well as data science project is oriented to the holistic formation of data processing, data management and data analysis.

4 The Linkage to Business Goals in Data Science Projects

In the following, we will explain the approach that enables a link between business goals and data analytics goals and thus, the development of suitable business goals in data science projects.

The foundation is formed by modeling from Enterprise Architecture Management. Various frameworks are available in EAM, including the TOGAF framework. In this framework, the event diagram is suitable (see Figure 2) to realize a goal-oriented design of business processes and business functions. In particular, it provides for the modeling of business goals. Empirical studies have already shown that a detailed and distinctive EAM can positively influence the success of data analytic applications in a company (Stecher et al. 2020). Based on an EAM model with declared business goals, a performance indicator, in most cases described as a Key Performance Indicator (KPI), can be assigned to the business goal. This assignment is already included in the EAM framework, e.g., TOGAF. The KPI or individual factors of this KPI can now be taken as a target variable for a data analytic problem and consequently be linked. Thus, the direct influence of a data analytics goal on a KPI and therefore on a business goal can be shown. The type of data analytics goal (Nalchigar and Yu 2018) can be determined depending on the data type and the characteristics of the linked KPI factor or KPI.

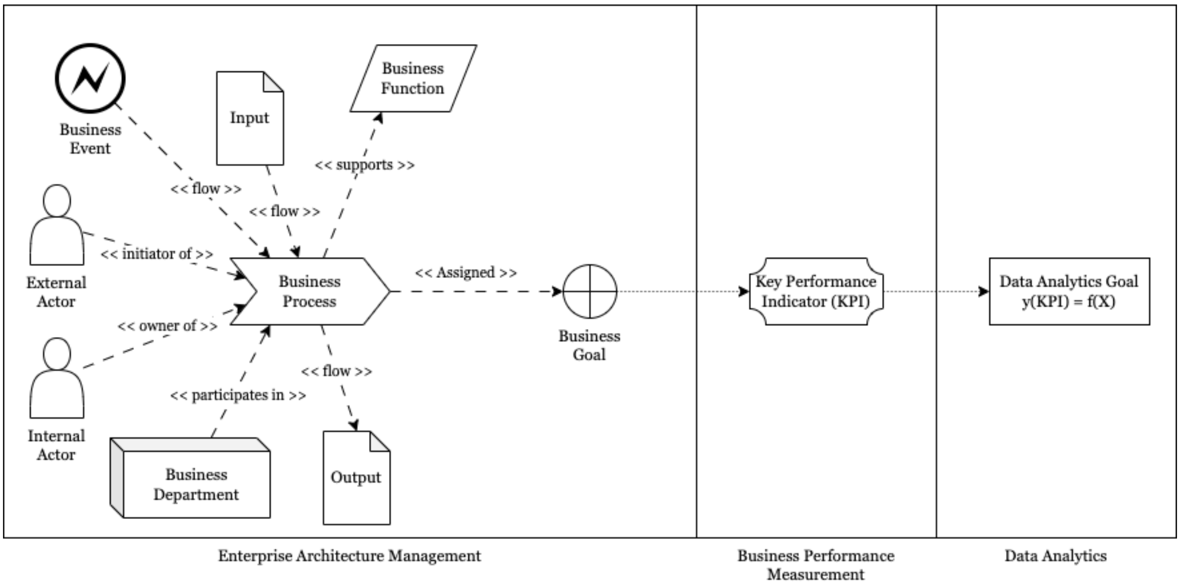

Figure 2: Linkage between Enterprise Architecture Management, Business Performance Measurement und Data Analytics

It can be stated that the following three steps must be fulfilled for the procedure:

i. EAM model with a definition of busines goals.
ii. An assignment of KPI to the EAM business goal
iii. An assignment of KPI or part of KPI as a target variable for a data analytic problem.

The TOGAF framework does not have to be assumed as the chosen EAM framework. Alternative EAM frameworks that include modeling of business goals can be utilized (e.g. Archimate)(Takeuchi and Yamamoto 2019). The definition of accompanying KPIs should be provided in an EAM framework. For the appropriate definition of KPIs for the business objectives, KPI libraries from service management can be accessed (ServiceNow 2023). A framework such as in Figure 1 (Nalchigar and Yu 2018) can be applied to link data analytic problems and data analytic goals but is not limited to this.

5 Demonstration

The following example demonstrates the linkage between the objectives of the EA and the data analysis goals (see Figure 3). The example is based on a business process of a travel agency (Desfray and Raymond 2014). The business process ("Reserve Trip") implements the process of arranging a reservation ("Trip") to a customer ("Client") by placing an "Order". The "Sales Department", which is responsible for the corporate function "Sales", organizes the business process.

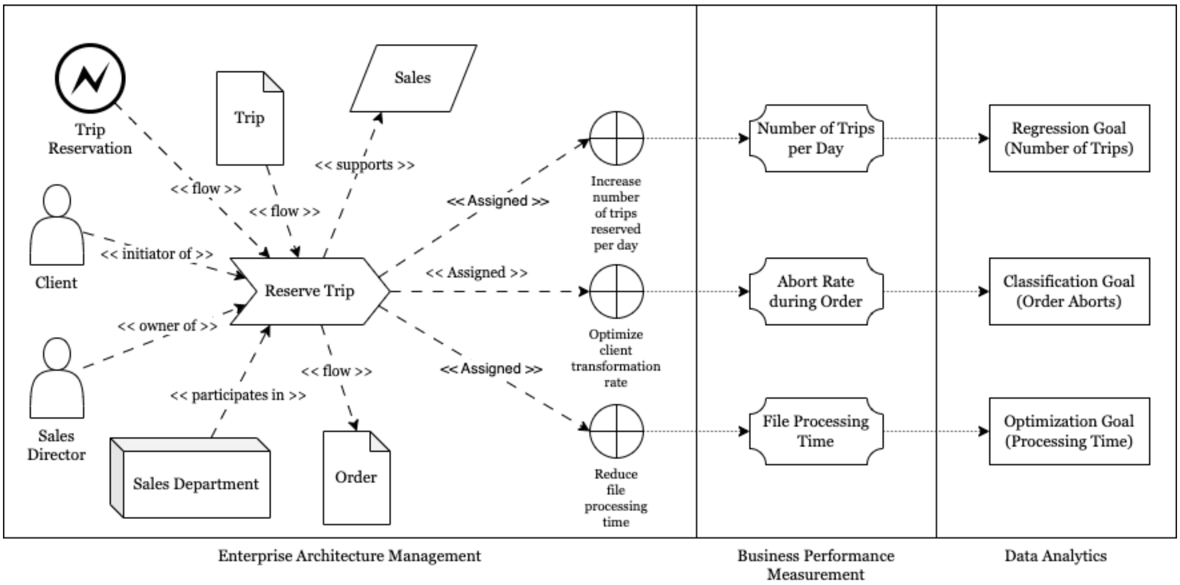

Figure 3: Demonstration of the Linkage on a Sales use case

The modelled event diagram from the TOGAF framework results in three different business objectives for the "Reserve Trip" business process. On the one hand, the processing time of the order data is to be reduced, which is directed at the technical infrastructure as well as the design of the process. On the other hand, the improvement of the rate of contract completions and the number of trips booked per day are strongly oriented towards the customer. Performance indicators can be directly linked to these business goals. These are the "File Processing Time", the "Abort Rate during Order", which indicates how many customers end the order process without completing a contract, and naturally the "Number of Trips per day".

The whole or parts of these performance indicators may be defined as a target variable of a data science project. With the definition of the target variable, a corresponding analysis goal can be derived and thus the link between the business goal and the data analysis goal can be determined. In the example, the "Number of Trips" as part of a KPI is a suitable target variable and a corresponding numerical regression objective can be declared. With the "File Processing Time" an optimization problem could be implemented and with the "Order Aborts" as part of the abort rate a classification target could be identified. These mappings are not limited and may certainly be extended. With respect to the "File Processing Time" a regression problem can be constructed alternatively. The assignment is accordingly not unique and can also depend on the available data.

6 Conclusion

In this short paper, it was demonstrated that EAM methods and performance indicators can be used to establish a link of business goals to data-analytical target values. To complete the scientific contribution, the result shall be embedded in the Design Science Research (Hevner et al. 2004) and the methodology will be further detailed. Furthermore, it is intended to show that in more complex as well as in real world practical business examples, the link between business goals and data analytic goals can be established. A case study is planned for the future research to show that the approach can be used in general, as the short paper at hand only includes an exemplary case.

Finally, it should be noted that the development of appropriate business goals for data analysis requires a well-defined EAM. Furthermore, it has to be investigated to what extent the challenges from the data science project management and the failure of projects due to poorly declared goals can be overcome and an improvement can be generated (Martinez et al. 2021).

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