Sales Force Analytics for the Solution Selling Firm: A Predictive Model for Assessing the Impact of Sales Team Assignments

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Abstract

Many firms in several industries transform their business from selling products to selling solutions. This transformation radically changes the selling approach and, therefore, impacts the sales organization and sales management. Yet, little attention is given to this challenge in quantitative sales force modeling. Although sales force modeling, in particular sales force assignment modeling, has been the focus of research for decades, solution selling has only sparsely been investigated from a sales modeling perspective. Addressing this challenge, this work proposes a predictive model for assessing the impact of different sales team assignments. The proposed predictive model utilizes mining of operational enterprise data and serves as a sales response function for solving sales force assignment problems. Furthermore, the model can assist sales managers in estimating the impact of different sales force allocation scenarios on future sales.

Keywords
Sales Response Function, Sales Force Analytics, Sales Force Optimization, Sales Force Assignment, Sales Territory Optimization, Customer Relationship Management

Introduction

In the past decades, Business to Business (B2B) companies in several industries transformed their business from selling products to selling solutions. A solution is proposed as a set of products and services, technically and commercially integrated to address the specific needs of a customer firm (Johansson et al. 2003). Solutions selling drew attention during the last decade, yet 75 percent of the companies that attempt to offer solutions fail to return the cost of their investment (McKinsey&Company 2011). Selling solutions radically changes the selling approach. Indeed, solution selling increases the importance of long-term relationship rather than focusing on individual transactions (Tuli et al. 2007). Furthermore, successful solution selling companies sell in teams, consisting of different sales roles with specific responsibilities and skills (Johansson et al. 2003).

Sales management has proven to be a fruitful field of application for business analytics. Sales force modeling, in particular sales force assignment (assigning sales representatives to accounts), has been a subject of research for more than 40 years (Mantrala et al. 2010). However, as outlined in the related work section, little attention is given to the impact of solution selling on sales force modeling. In particular, there is no approach that tackles the challenge of assigning sales teams of a solution selling sales force.

This work addresses this gap by proposing a predictive model for assessing the sales outcome of sales team assignment options. In particular, the probability of selling a specific product or service to a customer account upon a distinct sales team assignment is predicted. The predictive model utilizes operational sales data from customer relationship management systems. This work describes how the data for the predictive model was preprocessed, how the predictive model was trained, and presents an
evaluation of the predictive model using historical sales data of an international solution selling company. The contribution of this work therefore is a predictive model which enables assessing the impact of sales team assignments on sales in a solution selling context. This predictive model can be utilized in different ways: First, the model can be used by sales managers to determine the outcome of different sales team assignment scenarios. Second, this predictive model serves as a sales response function for enabling sales force assignment optimization.

This work is structured as follows: In section Related Work the existing sales response models for sales force assignments are reviewed. Section Methodology presents the overall approach and the methodology of this work. Section Conceptualization of Metrics details the different metrics used to build the predictive model. In section Implementation of Predictive Model, implementation and performance evaluation of the predictive model are described. The paper closes with a summary and an outlook.

Related Work

To set this work in reference to contributions of other authors, this section presents a review on previous approaches to model a sales response function. The literature review follows the method proposed by Webster and Watson (2002). An extensive forward and backward search without temporal restrictions in search engine in Web of Science, Business Source Complete (EBSCO), IEEE Xplore, and Google Scholar has been performed. The keywords were: sales response function, sales force modeling, sales force analytics, sales force optimization, and sales territory optimization. Only literature that focuses on sales force management has been taken into account (e.g. no sales response function for advertising management was reviewed). A comparison along the dimensions method for determination of model, selling and buying entities that are targeted by the model, input variables, and field of application of the sales response function is depicted in Table 1.

<table>
<thead>
<tr>
<th>Method</th>
<th>Selling Entities</th>
<th>Buying Entities</th>
<th>Input Variables</th>
<th>Application</th>
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<td>Judgmental Estimation</td>
<td>Sales Reps</td>
<td>Accounts</td>
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<tr>
<td>Lodish et al. (1971)</td>
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<td>Lodish (1976)</td>
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<tr>
<td>Lodish et al. (1988)</td>
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<td>Skiera and Albers (1998)</td>
<td>Statistical (no detail provided)</td>
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Table 1. Literature overview

Several approaches have been proposed in the area of modeling a sales response function. The work of Montgomery et al. (1971), Lodish et al. (1971, 1988) and Lodish (1976) relied on judgmental estimation of parameters of a sales response function for different fields of application, such as Sales Force Allocation, Sales Call Time Allocation, Sales Force Assignment, Sales Force Sizing, Sales Force Deployment. This method is applicable for a manageable set of combinations. When assigning sales teams however, the large solution space makes judgmental estimation difficult to implement. Lucas et al. (1975) show the feasibility of applying linear regression for estimating a sales response function for the purpose of setting sales quotas and sizing the sales force. Skiera and Albers (1998, 2008) and Drexl and Haase (1999) present sales assignment models based on a sales response function model by means of statistical methods. However, these approaches have not been used for sales team assignments. Baier et al. (2012) present an approach for assigning sales reps belonging to multiple business units working in teams. However, instead of modeling sales response functions, a utility function based on judgmental criteria defined by each business unit is used. This models the perspective of each business unit rather than optimizing the sales force from a team perspective. Kawas et al (2013) present an approach for calculating headcount of different sales roles for sales opportunities. However, no individual attributes of the sales representatives were taken into account.

According to the presented literature review, no sales response functions for sales team assignments in a solution selling context have been conceptualized and implemented so far.

Methodology

The applied methodology for conducting the predictive model is in line with the Cross Industry Standard Process for Data Mining (CRISP-DM) proposed by Chapman et al. (2000). CRISP-DM is a data mining methodology providing a reference model that consists of six steps that data miners use to tackle problems. In the following, the six steps and their application for deriving a predictive model for assessing the impact of sales team assignments are described.

**Business Understanding**

The business understanding phase focuses on understanding the project objectives and requirements from a business perspective. In the context of this work, the project objective was to create a predictive model for assessing the impact of sales team assignments. For every potential sales team assignment, the implication for the probability for selling a specific product or service should be predicted.

A sales team is assigned to a specific customer and consists of at least one sales representative. The modeling assumption (based on data understanding) was that a sales representative can be assigned to more than one sales team and therefore also to multiple accounts. The sales assignment is furthermore assumed to be on a yearly basis.
Data Understanding

The data understanding phase consists of conducting the raw data needed. The predictive model relied on historical sales data, in particular sales opportunity data. Sales opportunity records were created when a sales representative or any other customer-facing employee recognized the possibility to sell a distinct product or service to a customer. In order to facilitate the implementation of the proposed metrics, historical sales opportunity data needs to contain the following information: unique ID (UID) of the assigned sales team members, UID of product or service, UID of account, UID of customer industry sector, timestamp, and the result of the historical sales opportunity (won or lost). Many tools for sales opportunity management (such as Oracle CRM, Salesforce.com, SAP CRM, Microsoft CRM) provide the functionality to store this information when creating a sales opportunity entry by default.

Data Preparation

The data preparation phase covers all activities to construct the dataset that will be fed into the model. The historical sales opportunity data needs therefore to be transformed by means of a set of metrics. The conceptualization of these metrics is detailed in section Metrics Conceptualization.

Modeling

In the modeling phase, modeling techniques are selected and applied. The resulting feature set of the data preparation phase, where metrics have been calculated using historical sales data, has been used to train a machine learning models that predict the target variable. Details on the modeling phase are provided in section Modeling.

Evaluation

At this stage in the project, the quality of the models from a data analysis perspective is evaluated. The analysis of the performance of the trained model is based on ROC analysis as suggested by Fawcett (2006).

Deployment

Although a description of deployment is not part of this work, the paper closes with several options for usage and deployment.

Conceptualization of Metrics

In the following section, the conceptualization of the metrics is formally described. Furthermore, corresponding literature that inspired the conduction of the metrics are provided.

Preliminary Definitions

The proposed metrics utilize on historical sales data, in particular historical sales opportunity data. In the following, a sales opportunity record which includes a UID of the assigned sales team members, UID of product or service, UID of account, UID of customer industry sector, timestamp, and the result of the historical sales opportunity (won or lost) is labeled as a Sales Opportunity Observation (SOO). More formally, let $O_{h,i,t,r}$ be the set of all SOOs. Furthermore, $O_{h,i,t,r} \in O$ corresponds to a SOO which represents the past opportunity of selling a distinct product or service $k \in K$ to a distinct customer account $j \in J$, assigned to a distinct sales team $l \subseteq H$ consisting of sales representatives $h \in H$. Furthermore, each SOO is created at a distinct point of time $t \in T$ and results in a specific sales result $r \in R = \{\text{won}, \text{lost}\}$. In order to reduce complexity of the following metric definitions, let $T^-$ be the set of points of time before point of time $t \in T$. Furthermore, $Q_{h,i,t,r}$ is in the following defined as the set of SOOs $O_{h,i,t,r} \forall t \in T^-$. The following metrics are related to the areas customer relationship, internal relationship, sales aptitude, and skill level.
**Customer Relationship**

Crosby et al. (1990) showed that future sales opportunities depend mostly on the relationship quality between client reps and the account. Although SOOs do not necessarily reflect relationship quality, SOO reflect interaction between the sales team and the employees of the customer account. Interaction has been proposed as a potential indicator of relationship quality (Nezlek 2003), and operational interaction data has been successfully utilized for assessing customer relationships (Kunze von Bischoffshausen et al. 2014). Therefore, the first customer relationship (CR) metric \( CR_1 \) reflects the number of SOOs the sales team \( l_0 \) has worked on at a distinct customer account \( j_0 \) prior to point of time \( t_0 \). The second metric \( CR_2 \) corresponds to metric \( CR_1 \), but only takes SOOs that were won into account. This distinction can be useful, as a won opportunity could result in more interaction, and therefore more potential to establish a relationship with the customer account, than a lost one.

\[
CR_1 = |Q_{k,l_0,j_0,t_0,r}| \quad \forall k \in K, r \in R
\]
\[
CR_2 = |Q_{k,l_0,j_0,t_0,won}| \quad \forall k \in K
\]

The metrics \( CR_3 \) and \( CR_4 \) corresponds to metric \( CR_1 \) and \( CR_2 \), however taking only one sales representative \( h_0 \in I_0 \) of the sales team \( l_0 \) into account. Creating metrics for individual team members could be relevant, as the sales team might work the first time in a distinct constellation at a customer account, but some of the sales representatives on the other hand may have already established a relationship with the customer. \( CR_3 \) and \( CR_4 \) can be computed for each team member individually.

\[
CR_3 = |Q_{k,h_0,j_0,t_0,r}| \quad \forall k \in K, r \in R
\]
\[
CR_4 = |Q_{k,h_0,j_0,t_0,won}| \quad \forall k \in K
\]

**Internal Relationship**

Apart from focusing on customer relationships, internal relationships are proposed as a crucial key driver a sales team’s selling success (Jones and Brown 2005). This suggests decomposing internal relationships into three subtypes: established relationships within the sales team, established relationships within the sales organization and established relationships within the firm. In the following, a set of metrics that are potentially related to internal relationships are proposed. The first internal relationship (IR) metric \( IR_1 \) reflects the number of SOOs sales team \( l_0 \) has worked on at any customer account prior to point of time \( t_0 \). The second metric \( IR_2 \) corresponds to metric \( IR_1 \), but only takes SOOs that resulted in sales result “won” into account. The distinction might be useful, as a won opportunity results in more interaction within the teams, and therefore a higher chance to establish a relationship with a sales team, than a lost one. Both metrics, \( IR_1 \) and \( IR_2 \), correspond to relationships within the sales team.

\[
IR_1 = |Q_{k,l_0,j_0,t_0,r}| \quad \forall k \in K, j \in J, r \in R
\]
\[
IR_2 = |Q_{k,l_0,j_0,t_0,won}| \quad \forall k \in K, j \in J
\]

Established relationships within the sales organization and established relationships within the firm on the other hand are reflected in the following. Let \( I_{h,k,j,t,r} \subseteq H \) be a set of sales representatives that has worked with sales representative \( h \in H \) in a sales team. Similarly, we can define the subset \( I_{l,k,j,t,r} \subseteq H \) of sales representatives which have worked with any member of a sales team \( l \subseteq H \). This results in metric \( IR_3 \) and \( IR_4 \). \( IR_3 \) corresponds to the number of sales representatives and other employees of the firm a sales representative \( h_0 \) has worked with. In the same way, \( IR_4 \) reflects the number of employees which have worked with any member of a sales team \( l \) before.

\[
IR_3 = |I_{l,k,l_0,j_0,t_0,r}| \quad \forall k \in K, r \in R
\]
\[
IR_4 = |Q_{k,l_0,j_0,t_0,won}| \quad \forall k \in K
\]

The metrics \( IR_5 \) and \( IR_6 \) corresponds to metrics \( IR_3 \) and \( IR_4 \), however only takes SOOs that were won into account. The underlying idea is that a won opportunity results in more interaction within the firm, and
therefore more potential to establish a relationship with employees of the firm, than a lost one. \( IR_3 \) and \( IR_5 \) can be computed for every member of a sales team individually.

\[
IR_5 = \left| \frac{Q_{k,t_0,j,t_0,\text{won}}}{Q_{k,j,t_0,\text{won}}} \right| \forall k \in K, r \in R
\]

\[
IR_6 = \left| \frac{Q_{k,t_0,j,t_0,\text{won}}}{Q_{k,t_0,\text{won}}} \right| \forall k \in K
\]

**Sales Aptitude**

One of the most examined driver of sales success is the aptitude for selling, which refers to the intrinsic personal characteristics of the sales representative (Hutt and Walker 2006). These attributes may not necessarily be directly reflected by the data, however sales performance has been proved to be correlated with aptitude (Hutt and Walker 2006). Therefore, the metrics \( SA_1 \) and \( SA_2 \) reflect the past performance of the individual sales representatives and the past performance of the sales team, by computing a ratio of won SOOs and total SOOs of a sales representative or a sales team. \( SA_1 \) represents the win ratio of all SOOs the sales team \( i_0 \) has worked on, at any customer account prior to point of time \( t_0 \). \( SA_2 \) represents the win ratio SOOs a sales representative \( h_0 \) has worked on, prior to point of time \( t_0 \).

\[
SA_1 = \left| \frac{Q_{k,j,\text{won}}}{Q_{k,j,\text{t,\text{won}}}} \right| \forall k \in K, j \in J
\]

\[
SA_2 = \left| \frac{Q_{k,h_0,\text{t,\text{won}}}}{Q_{k,h_0,\text{t,\text{won}}}} \right| \forall k \in K, j \in J
\]

In addition to the general aptitude for selling, one might consider two refinements of the aptitude: the aptitude for selling at a specific customer account \( j_0 \) and the aptitude for selling a specific product or service \( k_0 \). Hence, similarly to \( SA_1 \), \( SA_3 \) represents the win ratio of all SOOs the sales team \( i_0 \) has worked on at a distinct customer account \( j_0 \) prior to point of time \( t_0 \). Corresponding to \( SA_2 \), \( SA_4 \) represents the win ratio of SOOs a sales representative \( h_0 \) has worked on at a distinct customer account \( j_0 \) prior to point of time \( t_0 \).

\[
SA_3 = \left| \frac{Q_{k,j_0,\text{won}}}{Q_{k,j_0,\text{t,\text{won}}}} \right| \forall k \in K
\]

\[
SA_4 = \left| \frac{Q_{k,h_0,\text{t,\text{won}}}}{Q_{k,h_0,\text{t,\text{won}}}} \right| \forall k \in K
\]

For assessing the aptitude for selling a distinct product or service, similarly to \( SA_1 \), \( SA_5 \) represents the win ratio of SOOs the sales team \( i_0 \) has worked on related to a distinct product or service \( k_0 \) prior to point of time \( t_0 \). Corresponding to \( SA_2 \), \( SA_6 \) represents the win ratio of SOOs a sales representative \( h_0 \) has worked on related to a distinct product or service \( k_0 \) prior to point of time \( t_0 \).

\[
SA_5 = \left| \frac{Q_{k_0,j_0,\text{won}}}{Q_{k_0,j_0,\text{t,\text{won}}}} \right| \forall k \in K, j \in J
\]

\[
SA_6 = \left| \frac{Q_{k_0,h_0,\text{t,\text{won}}}}{Q_{k_0,h_0,\text{t,\text{won}}}} \right| \forall j \in J
\]

**Skill Level**

Skill levels, proposed as the sales representative’s learned proficiency at performing the necessary selling tasks (Hutt and Walker 2006), have been investigated as an determinant of selling success (Leong et al. 1989). Skill levels are not necessarily directly observable, but skill levels can be developed through sales experience (Hutt and Walker 2006). The following metrics reflect the skill levels along three dimensions, namely total selling skill level, product or service skill level and industry skill level.
The first metric related to skill level $SK_1$ reflects the number of SOOs the sales representative $h_o$ has worked on in total prior to point of time $t_o$.

$$SK_1 = \left| Q_{k,h_o,t_o,r} \right| \forall k \in K, j \in J, r \in R$$

The second metric $SK_2$ reflects the number of SOOs the sales representative $h_o$ has worked on that were related to a specific product or service $k_o$ prior to point of time $t_o$. The third metric $SK_3$ is the corresponding metric for a sales team $I_o$.

$$SK_2 = \left| Q_{k_o,h_o,t_o,r} \right| \forall j \in J, r \in R$$

$$SK_3 = \left| Q_{k_o,I_o,t_o,r} \right| \forall j \in J, r \in R$$

The metrics $SK_4$ and $SK_5$ reflect the specific industry experience of a sales representative or a sales team. Let $I_{B_o} \subseteq J$ be the set of customer accounts that belong to the same industry sector as customer account $j_o$.

Then, $SK_4$ represents the number of SOOs the sales representative $h_o$ has worked on that were at a customer account in the same industry as customer account $j_o$, prior to point of time $t_o$. The metric $SK_5$ is the corresponding metric for a sales team $I_o$.

$$SK_4 = \left| Q_{k,h_o,I_{B_o},r} \right| \forall j \in I_{B_o}, r \in R$$

$$SK_5 = \left| Q_{k,I_o,I_{B_o},r} \right| \forall j \in I_{B_o}, r \in R$$

$SK_6...SK_{10}$ correspond to $SK_1...SK_5$, but only takes SOOs that were won into account. These additional metrics are required, as a won opportunity might result in bigger potential to acquire selling skills.

$$SK_6 = \left| Q_{k,h_o,J_{t_o},r} \right| \forall k \in K, j \in J, r \in \mathbb{R}$$

$$SK_7 = \left| Q_{k_o,h_o,J_{t_o},r} \right| \forall j \in J, r \in \mathbb{R}$$

$$SK_8 = \left| Q_{k_o,I_o,J_{t_o},r} \right| \forall j \in J, r \in \mathbb{R}$$

$$SK_9 = \left| Q_{k,h_o,J_{t_o},r} \right| \forall j \in J_{B_o}, r \in \mathbb{R}$$

$$SK_{10} = \left| Q_{k,I_o,J_{t_o},r} \right| \forall j \in J_{B_o}, r \in \mathbb{R}$$

### Implementation of Predictive Model

This section elaborates on the preparation and evaluation of the predictive model that has been implemented using the metrics described in the previous section.

#### Data preparation

For verifying the feasibility of the proposed approach, sales data from a large global company focusing on solutions in the IT industry has been utilized. The data set consists of 59238 historical sales opportunity records that where collected during a time span of three years in a specific geographic area. Each record fulfilled the requirement of containing a UID of the assigned sales team members, UID of referred product or service, UID of customer account, UID of customer industry sector, timestamp, and the result of the historical sales opportunity (won or lost). The company implemented a very rigorous process for ensuring high quality of sales data. Therefore, there were no missing values in the data set. Furthermore, the rigorous sales process ensured that sales data reflected actual sales history (e.g. no “dummy” entries for non-existing opportunities, all sales results tracked after winning, sales team members linked accurately etc.)

In order to compute the proposed metrics, a first step in data preparation was splitting up the data set into the set of SOOs and the set that will be utilized in the modeling phase. The first two years of the three year data set was utilized as SOOs, therefore $T^-$ refers to a period of the first two years. Hence $T^+$ refers to a period of one year. This split is useful, as sales is characterized by a yearly cycle (which could be also obtained from the data), and therefore a split in full years is adequate.
As depicted in Figure 1, SOOs in $T^-$ are used to calculate the metric values of SOOs in $T^+$ which will result in a feature set utilized in the modeling phase. For example, if a sales team $i_0$ has worked on five SOOs at a distinct customer account $j_0$ in $T^-$ would result in a value of ‘5’ for metric $CR_i$ for any opportunity in period $T^+$. This resulted in a feature set of 63 features (based on the proposed metrics) and 20269 objects (corresponding to the amount of SOOs in $T^+$). The target variable is binary and represents the historical sales result of each SOO (won or lost).

**Modeling**

The resulting feature set and has been used to train a predictive model that predict the target variable (sales result). The binary target variable implicates the use of classification algorithms to train machine learning models. Multiple machine learning algorithms for solving classification problems are available. This work focuses on the application of a multilayer perceptron neural network algorithm (ANN-MLP) (Ripley 2008).

The reasons for applying this algorithm are twofold. First, the data preparation resulted in a high dimensional data set which could not be reduced by a linear feature reduction technique such as component analysis. ANN-MLP is suited to deal with a high feature set of high dimensionality. Second, the business objective of the predictive model was to calculate probabilities for realizing future sales opportunities upon a distinct assignment. In contrast to many other algorithms, ANN-MLP applied to binary classification cases can be used for probability estimation (Saerens et al. 2002).

**Evaluation**

After the ANN-MLP algorithm has been trained to resolve the binary classification task, a machine learning model is created. The model has to be evaluated to ensure its ability to classify records that do not belong to the training data. Therefore, the data was split into two subsets (Ripley 2008) for training (70% of the data set) and validation (30% of the data set) purposes. The analysis of the performance of the trained model has been conducted using ROC analysis as suggested by Fawcett (2006). The Receiver Operational Characteristic (ROC) curve of the model created with ANN-MLP is depicted in in Figure 2.

In order to compare classifiers, accuracy is furthermore measured by the area under the ROC curve (AUROC). This performance indicator AUROC was chosen due to a number of advantages in contrast to overall accuracy, such as no dependence on threshold and invariant to prior class probabilities (Bradley 1997). The size of AUROC is on an acceptable level of 0.73, as e.g. suggested by Kim (et al. 2012). The evaluation indicates that the model is approaching a level of usefulness, but there is still room for improvement.
Conclusion

This work proposed a predictive model for assessing the impact of different sales team assignments. The proposed predictive model utilizes neural network algorithms applied to a metrics-based feature set utilizing historical sales data. The suggested model is the first predictive model that is suitable for serving as a sales response function addressing the specific challenges of a team-selling and solution-oriented sales force. The predictive model can provide decision support for sales managers in two ways. First, sales managers can assess the impact of a specific allocation scenario, for example a sales manager needs support in deciding whether to assign sales team $t_1$ or $t_2$ to customer account $j_0$. Using the predictive model, a sales manager can assess the impact of different assignments on future sales opportunities at this account and, finally, on the revenue. Second, the predictive model can be utilized by an optimization model (similar to the sales force assignment models listen in Table 1) for solving the problem of assigning the sales force on an organizational level. This model could furthermore implement several constrains that are useful when doing an optimization on the organizational level (e.g. traveling time, workload).

There are several limitations related to the presented model, apart from the need of increasing the accuracy. The first one is inherently related to the application of ANN-MLP. While ANN-MLP is suited to draw hidden nonlinear correlations from high dimensional dataset, they suffer from a lack of explanatory power. This makes the underlying patterns difficult to understand. Future research will therefore dive into the interpretation using techniques such as Neural Interpretation Diagram, Garson’s algorithm, and sensitivity analysis. The second limitation relates to the fact that the model has only been implemented using the data of one firm. Although this works proves the feasibility of the suggested approach, there is a need to implement the model in several firms in order to prove generalizability. The last limitation relates to the fact that the predictive model in fact solely relies on drawing correlations from past data. Theory related to each metric provides a justification for interpreting these correlations as causations for the future, but several effects that are not part of the model can decrease its accuracy. For example assigning a sales team to a very large number of accounts and thereby a high number of future opportunities to work will definitely negatively impact future sales. This also illustrates the need of building an optimization model which utilizes the proposed sales response function in the future. This optimization model can implement certain constraints such as a reasonable workload for each sales representative or geographical aspects in order to ensure a proper use of the predictive model. Future research will furthermore integrate more data sources and metrics to increase the accuracy of the predictive model.

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