Predicting Partner’s Digital Transformation Based on Artificial Intelligence

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Abstract: Partner’s digital transformation is one of the most important metrics for businesses, particularly for businesses in the subscription world. Hence, how to predict partner transformation is a consistent focus in the industry. In this paper, we use an AI (Artificial Intelligence) relevant algorithm to analyze partner’s digital transformation issues and propose a novel method, named the hybrid VKR (VAE, K-means, and random forest) algorithm, to predict partner transformation. We apply our algorithm to partner transformation issues. First, we show the prediction of about 5980 partners from 25689 partners, who are transformed and sorted according to important indicators. Secondly, we recap the tremendous effort that was required by the company to obtain high-quality results for economic change when a partner is transforming along with one or many of the transformation dimensions. Finally, we identify unethical behavior by looking through deal transaction data. Overall, our work sheds light on several potential problems in partner transformation and calls for improved scientific practices in this area.

Keywords: partner transformation; artificial intelligence; hybrid VKR algorithm; high-quality result

1. Introduction

Today, more and more attention has been attracted to the phenomenon of partners’ digital transformation. Many companies, such as AWS (Amazon Web Services) [1], Microsoft [2], and NetApp [3] have been launched by the partner transformation revolution, which demonstrates the importance of partner digital’s transformation. Our research industry, which is based on subscription production, is also largely influenced by partner transformation, so we are glad to take on this challenge to contribute to the strategy of our company. The company’s partners account [4] for more than 80% of the total revenue and serve as key routes to the market. As organizations are digitally evolving, there is a pressing need for a company’s partners to also transform [5,6] the way they sell to different customers. Partner’s digital transformation [6–8] is a multifaceted and fast-moving phenomenon that has significant impacts, including impacts on the business processes and models of firms. The pace of technology uptake will depend on factors such as the type of sector, market, among others. While no single indicator is able to reflect the pace of development, adoption, and diffusion, combining indicators can provide insight into the relative positioning of the different players (segmentation by industry, vertical, geo, market, sectors, size, etc.). Assessing the digital transformation of organizations (whether it be business partners, customers, or competitors) is a common question facing the industry today. What makes this evaluation intrinsically challenging is the lack of clearly defined “labels” defining the transformation level of an organization. Currently, little research exists that has been introduced to deal with a company’s digital transformation, including the data-driven method [9], the six Ts of transformation model [10], and the building blocks of successful digital transformation method [11]. However, these methods lack a useful
guide of information in the practice of advanced technology [12], such as AI (Artificial intelligence) and machine-learning technology. In this paper, we propose a VKR (VAE, K-means, and random forest) algorithm based on AI technology, which is more efficient and more easily predicts a partner’s digital transformation.

The challenge regarding a partner’s digital transformation [13–15] that exists in a company is described below:

1. How to identify partners who are transforming or are ready to transform across one or many of the transformation dimensions (such as New Buying Centers, Platform-Based Outcomes, and Customer Experience Life cycle);
2. When a partner is transforming along one or many of the transformation dimensions, how do their economics change;
3. Can we spot any unethical behavior by looking through the deal transaction data, which could put all of this at risk?

With these challenges in mind, the paper aims are to identify which partners are transferring or finishing transformation, which will help the company enlarge its business and gain much more revenue. The main contributions of this paper are described below:

1. Generalize useful data into a new database from raw data and denoise data;
2. Propose an efficient machine-learning model to predict partner transformation;
3. Analyze a transformation partner regarding their economic change;
4. Introduce a novel algorithm based on the model to identify partners with unethical behavior.

The rest of this paper is organized as follows: related works about partner transformation are described in Section 2; an introduction to our method about partner transformation is in Section 3 and shows the steps for data analysis; Section 4 provides the methodology for evaluation using the model selection process; the results and discussion are reported in Section 5; Section 6 offers a conclusion and expresses the outlook for future work.

2. Related Work

In recent years, little research has been introduced to deal with the digital transformation of a company, including the data-driven method [9], the six Ts of transformation model [10], and the building blocks of successful digital transformation method [11]. In this section, we will introduce the related work of digital transformation, including the three aforementioned methods.

2.1. Data-Driven Method

One method regarding partner transformation that utilizes a data-driven strategy for digital transformation is the data-driven method [9]. The Data-driven method is mainly used in the telecom industry, which has faced massive structural changes. Many aspects of this industry, including the customers, channels, content, and competitors, are all becoming digital, and these aspects are data-driven. The data-driven method can be characterized by three main points: (1) Grow wireless revenues, which relies on growing subscribers, growing average revenue per user, and retaining high-value subscribers; (2) grow strategic revenues, which rely on deployed software-defined platforms, rolling out new IP solutions, and having an extended footprint; (3) reduce cost structure, which relies on a streamlined organization, increased operational efficiencies, and reduced cycle time.

2.2. The Six Ts of Transformation Model

The Six Ts of Transformation model [10] is a model that could become necessary for use by educators to guide preservice school librarians in their successful transformation from teacher to school librarian leader. Using the constructs of this model in preparation programs, educators will help preservice school librarians understand their place within the school and will provide them with the tools and strategies needed to overcome barriers, such as insufficiencies in time, funding, and staffing, to enact their role as leaders.
2.3. Building Blocks of the Successful Digital Transformation Method

In general, the building blocks of a successful digital transformation method [11] is a conceptual method, which first identifies building blocks, then analyzes the technology-related factors, and, finally, analyzes the market-related factors. After analyzing all of the factors, conclusions are made to revise a firm’s business model.

Our vision is to go beyond the above three partners’ digital transformation methods (data-driven method [9], six Ts of transformation model [10], and building blocks of successful digital transformation method), as they are just provide a theoretical approach to guide firms, but they lack useful information in practice and advanced technology, such as AI (Artificial intelligence) and machine-learning technology. As such, in this paper, we propose a VKR algorithm based on AI technology to address a partner’s digital transformation, which is a more efficient and easier was to predict a partner’s digital transformation.

3. Methodology

In order to account for partner’s transformation, we have to select some useful features to measure that transformation [7,16–18]. First, we check the data set and clean the data reference description. Second, we design our machine-learning algorithm system to generate a novel model to predict partner transformation. Lastly, we give detailed implementation information about the key algorithm.

3.1. Data Preprocess and Feature Engineering

The raw datasets were provided by the company, which contains 3 databases and 14 tables. The data includes some extraneous information, which could act as noise and interfere with our determination of the issues mentioned in Section 1. As such, we need to extract the most important features before we construct a machine-learning model. We analyze key indicators of partner transformation regarding new buying centers, platform-enabled outcomes, and customer experience. These indicators are described in more detail in Figure 1. When a partner is transforming along one or many of the transformation dimensions, how do their economics change? We deeply mined the data and generated relevant indicators, which are described in Figure 1, to define transformation dimensions. The first column stands for detail indicators while the other column stands for the attributes of DB (Database) tables.

![Figure 1. Indicators of partner transformation.](image)

Based on the analysis of the confusion matrix, the highest misclassification rate observed is between the Early Majority and Late Majority. We also notice that, although the class distribution has become more uniform after using SMOTE (Synthetic Minority Over-sampling Technique).
Oversampling Technique), the misclassification rate and accuracy are still sensitive to the accuracy of ground truth labels. This may be due to the transformation scorecard that was computed being from a final select set of measures based on data availability, significance, and the business assumption that all measures are weighted on an equal footing for the overall score, the detailed information about feature importance values is described in Figure 2.

Figure 2. SHAP (Shapley Additive explanations) of feature importance values.

3.2. Machine-Learning Model Solution

In order to show our detailed work about model generation, we describe the main process of model generation. The process of our solution mainly includes data collection, data preprocessing, feature extraction [16], model training, and prediction. Figure 3 illustrates the detailed workflow of the machine-learning system solution architecture.
3.3. VKR Algorithm Analysis

Here we use VAE [5,19], K-means, and random forest algorithms as our algorithm conductor that is known as the hybrid VKR described as Algorithm 1. From there, the data is fed into the main training loop of the VAE. An encoder and decoder artificial neural network (ANN) are defined with three hidden layers and a 2D mean layer. The mean VAE layer is the feature embedding layer of a VAE and is used with representation learning to visualize the generated latent space. The VAE was trained in 80 epochs with a batch size of 128 data samples. The Adam optimizer and learning-rate scheduler have been used to train the encoder and decoder network. The VAE optimization objective (loss function) is the sum of the reconstruction loss calculated with binary cross-entropy (BCE) [20,21] and the KL (Kullback–Leibler) divergence as a measure of how the data distribution is different from a VAE latent prior distribution (Gaussian). At the end of the training process, we get a trained VAE model which is stored on a disk for easy loading and usage.

Algorithm 1: Hybrid VKR (VAE, K-means, random forest) algorithm

Input: Data matrix \( X \in \mathbb{R}^{m \times n} \), there \( m \) is total data number and \( n \) is the dimension of each data

1. Deal with missing values (Sparse coding)
2. Use normalization data to restructure the input data matrix \( X \)
   \[
   X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}
   \]
3. Build and training Model
4. Using VAE model to generate latent mean vector
5. Input latent vector to RF (Random Forest) to training model to identify partner transformation
6. Input latent vector to K-means to training model to identify an unethical issue
7. Using training VKR model to the prediction result
8. When meeting convergence condition output result

Output: Output matrix about the clustering result

4. Experiment

We conducted three experiments: (1) predict whether partner transformation will occur; (2) economic changes upon partner transformation; and (3) identifying partners with unethical behavior. Every experiment starts with a hyperparameter cluster, and once the optimal parameter values are found, they are used for the final condition to give the result.
4.1. Dataset

We have used the dataset provided from the company’s private data; this dataset contains 3 databases and 14 tables. Some of the data is presented in Table 1.

Table 1. Dataset Description.

| No. | Dataset Name   | Table Name          |
|-----|----------------|---------------------|
| 1   | reference_ss  | customers_d         |
| 2   | reference_ss  | deals_d             |
| 3   | reference_ss  | partners_d          |
| 4   | reference_ss  | products_d          |
| 5   | reference_ss  | pv_fiscal_day_to_year |
| 6   | reference_ss  | pv_sales_hierarchy  |
| 7   | sales_ss      | bookings_f          |
| 8   | sales_ss      | pipeline_f          |
| 9   | sales_ss      | pv_bookings_channel_measure |
| 10  | sales_ss      | pv_cs_deal_so_line_link |
| 11  | sales_ss      | pv_sales_order_line  |
| 12  | sales_ss      | pv_sales_order_tv   |
| 13  | sales_ss      | pv_sol_end_customer  |
| 14  | services_ss   | df_installed_product_f |

We generated our dataset from the raw dataset and trained our model from it. The attributes of the training dataset are described in Table 2.

Table 2. Training dataset description.

| Field Name                          | Type     | Description                                           |
|-------------------------------------|----------|-------------------------------------------------------|
| partner_site_party_key              | INTEGER  | PartnerId which we want to identify                   |
| annual_rcrr_rev_2017                | NUMERIC  | recurring revenue in 2017                             |
| annual_rcrr_rev_2018                | NUMERIC  | recurring revenue in 2018                             |
| nonrecurring_rev_2017               | NUMERIC  | nonrecurring revenue in 2017                          |
| nonrecurring_rev_2018               | NUMERIC  | nonrecurring revenue in 2018                          |
| order_cnt_2017                      | INTEGER  | the number of orders the partner participated in 2017 |
| order_cnt_2018                      | INTEGER  | the number of orders the partner participated in 2018 |
| multi_partner_deal_id_amt           | INTEGER  | number of multi_partner_deal each partner involved in  |
| rate_of_2017_2018                   | FLOAT    | the ratio of multipartner deals to all kinds of deals per year |
| rate_of_2018_2019                   | FLOAT    | the ratio of multipartner deals to all kinds of deals per year |
| rate_of_2019_2020                   | FLOAT    | the ratio of multipartner deals to all kinds of deals per year |
| rate_of_revenue_type_new            | FLOAT    | the percentage of new revenue                          |
| rate_of_hardware                    | FLOAT    | the percentage of hardware booking                     |

4.2. Experimental Method

The main process of the experiment is first inputting clean data into the VAE model to get a latent vector, and then for the prediction of whether a partner transformation will occur using the random forest algorithm, and finally using the K-means algorithm to identify any unethical issues.

From there, the data is fed into the main training loop of the VAE. An encoder and decoder artificial neural network (ANN) are defined with three hidden layers and a 2-D mean layer. The mean VAE layer is the feature embedding layer of a VAE and is used with representation learning to visualize the generated latent space. The VAE was trained in 80 epochs with a batch size of 128 data samples. The Adam optimizer and learning rate scheduler have been used to train the encoder and decoder network. The VAE optimization objective (loss function) is the sum of the reconstruction loss calculated with binary cross-entropy (BCE) and the KL divergence as a measure of how the data distribution is different from a VAE latent prior distribution (Gaussian). At the end of the training process, we get a trained VAE model which is stored on a disk for easy loading and usage.

Figure 4a-d show the latent space mean vector of the input data. With images as input data, it is easy to find the representation and their position in the 2-D space by mapping.
the scatter plot marks to the input images. With the given challenge datasets, a 1-D vector of color gradients is used based on the values of each of the four created transformation input features. This color gradient vector is used to isolate each of the four transformation dimensions by color strength in the scatter plot. The 256 color values are scaled to a relative percent value for each data point in the plot.

The colored areas in the latent space are mapped back to the preprocessed input data set. The corresponding x- y-coordinates of the mean vector have been determined by looking at the latent space plot. The coordinates are used with a Pandas slice operation in order to extract a subset of the data points for each transformation dimension. These subsets of the input data are then used for the analysis of the output variables (bookings, revenue, gross margin, deal size, and deal velocity) across the four transformation dimensions. Each data point represents a partner (Partner_site_party_key) or an aggregated set of such keys.
in the case of multi-partner domains such as New_Buying_Center. After finishing the VAE part, there will be an output of the latent vector; next, the latent vector will be fed into a random forest algorithm to identify partner transformation, and will also be used with a K-means algorithm to identify unethical issues.

5. Results and Discussion

After the experiment, we got the results regarding the questions stated in Section 1, which will be described in detail below.

5.1. How Do We Identify Partners Who Are Transforming or Are Ready to Transform across One or Many of the Transformation Dimensions

We used the same data as dealt with in Section 3. As previously mentioned, from the data generated dimensions including buying centers, platform-based outcomes, and customer experience lifecycle [22–24].

5.1.1. The Result of Prediction Transformation Partners

We predicted about 5980 partners who are transforming, as described in Table 3.

| partner_site_key | annual_rev_2017 | annual_rev_2018 | order_cnt_2017 | order_cnt_2018 | rate_of_revenue | rate_of_hardware | Predict |
|------------------|----------------|----------------|----------------|----------------|-----------------|-----------------|---------|
| 10018923         | 0.00E + 00     | 20442          | 24             | 43             | 0.94846009      | 0.18667505      | 1       |
| 49849595         | 0.00E + 00     | 12003.36       | 181            | 253            | 0.99975032      | 0.45579752      | 1       |
| 13451993         | 0.00E + 00     | 0.00E + 00     | 21             | 42             | 0.99720480      | 0.2295174       | 1       |
| 137250370        | 1579.72        | 0.00E + 00     | 24             | 36             | 0.96423562      | 0.19563217      | 1       |
| 12732302         | 0.00E + 00     | 28056          | 14             | 43             | 0.83266325      | 0.17856648      | 1       |
| 3488934          | 0.00E + 00     | 0.00E + 00     | 12             | 29             | 0.98468649      | 0.04304505      | 1       |
| 197212382        | 0.00E + 00     | 0.00E + 00     | 45             | 59             | 0.96037866      | 0.08788422      | 1       |
| 215969797        | 0.00E + 00     | 0.00E + 00     | 6              | 19             | 0.49645669      | 0.26122047      | 1       |
| 9823118          | 0.00E + 00     | 0.00E + 00     | 14             | 43             | 1               | 0               | 1       |
| 5639975          | 0.00E + 00     | 142830         | 0              | 21             | 1               | 0.44736842      | 1       |
| 210118079        | 18000          | 1500000        | 153            | 296            | 1               | 0.1515625       | 1       |
| 2963274          | 0.00E + 00     | 0.00E + 00     | 476            | 1283           | 1               | 0               | 1       |
| 11864141         | 0.00E + 00     | 0.00E + 00     | 10             | 34             | 0.96303497      | 0.04195804      | 1       |
| 564774           | 0.00E + 00     | 44034          | 80             | 208            | 0.96732889      | 0.06323015      | 1       |
| 222156482        | 23148.84       | 826376.4       | 384            | 665            | 0.69586588      | 0.19068726      | 1       |
| 98664892         | 2787           | 0.00E + 00     | 26             | 45             | 0.79352843      | 0.0411236       | 1       |
| 7979762          | 1671.6         | 0.00E + 00     | 29             | 83             | 0.93974556      | 0.22997344      | 1       |
| 143938004        | 0.00E + 00     | 1094.16        | 28             | 107            | 0.93018403      | 0.10434453      | 1       |
| 203076171        | 0.00E + 00     | 0.00E + 00     | 42             | 44             | 0.70866347      | 0.19794585      | 1       |
| 209649932        | 0.00E + 00     | 0.00E + 00     | 1              | 38             | 0.71361502      | 0.13849765      | 1       |
| 162572400        | 0.00E + 00     | 0.00E + 00     | 5              | 17             | 0.61871286      | 0.13646139      | 1       |
| 230369460        | 271542.12      | 1310853.96     | 28             | 76             | 1               | 0.31467964      | 1       |
| 100342751        | 6575.84        | 303184.08      | 6              | 144            | 1               | 0               | 1       |
| 121052582        | 6280.32        | 11995.68       | 13             | 28             | 1               | 0.25290698      | 1       |

5.1.2. Importance of the Transformation Dimensions Analysis

We also drew a histogram graph to describe the important dimensions of the partner transformation. The order of important dimensions is described as below (descending sort): ['rate_of_revenue_type_new', 'rate_of_hardware', 'order_cnt_2018', 'order_cnt_2017', 'multi_partner_deal_id_amt', 'annual_rccrr_rev_2018', 'rate_of_2018', 'rate_of_2019_2020', 'annual_rccrr_rev_2017', 'rate_of_2017_2018', 'nonrecurring_2018', 'nonrecurring_rev_2017'].

The three most important dimensions were further analyzed, as described in Figure 5a,b, and an anomaly was detected in the data of the 3D figure.
Figure 5. (a) Histogram of the important transformation dimensions
(Notes: [1] stands for ‘rate_of_revenue_type_new’, [2] stands for ‘rate_of_hardware’, [3] stands for ‘order_cnt_2018’, [4] stands for ‘order_cnt_2017’, [5] stands for ‘muti_partner_deal_id_amt’, [6] stands for ‘annual_rrrr_rev_2018’, [7] stands for ‘rate_of_2018’, [8] stands for ‘rate_of_2019_2020’, [9] stands for ‘annual_rrrr_rev_2017’, [10] stands for ‘rate_of_2017_2018’, [11] stands for ‘nonrecurring_2018’, [12] stands for ‘nonrecurring_rev_2017’); (b) Analysis of the three most important dimensions.

5.1.3. Discussion

From the above analysis, we predict that about 5980 partners are transforming based on the important dimensions of the partner transformation, such as buying centers, platform-based outcomes, and customer experience lifecycle. We identified that the most important indicators are the rate of revenue new type and the rate of hardware.

5.2. When a Partner Is Transforming along One or Many of the Transformation Dimensions, How Do Their Economics Change?

5.2.1. Relevant Data Collection

First, we needed to pick the useful attribute columns. According to the title, we have selected some useful attributes regarding these aspects and arranged them as Table 4.

Table 4. Partners’ transformation attributes description.

| Booking | Revenue | Gross Margin | Deal Size | Deal Velocity |
|---------|---------|--------------|-----------|---------------|
| rebate_bookings | annual_rrrr_rev_trxl_amt | sum_tss_gross_margin | list_price | shipmentConfirmed_date |
| annualized_bookings | dv_annual_rrrr_rev_usd_amt | sum_product_bookings_gross_margin | cost | booked_date |
| actual_bookings | mthly_rrrr_rev_trxl_amt | | base_price | |
| | nonrecurring_rev_trxl_amt | | | |

For most of the above attributes, we find the overall performance of each partner by finding the sum of a group of partners in these aspects. For deal velocity, the mean value of the difference between two columns is obtained to reflect the order processing speed. The result is a large table with partner_site_party_key as the primary attribute, as shown in the figure below. This table has 7316 rows and 14 attributes.

In order to have a holistic view of the data, we obtain individual statistics for each column attribute, as shown in Table 5. From Table 5, it can be observed that some points are deviating from the mean value in some columns. In order to avoid the influence of...
some abnormal conditions on the result, we have removed the partner belonging to the largest two points and the smallest two points in each column.

Table 5. Indicators of unethical behavior.

| partner_site_party_key | pre_discount_credit_sum | rebate_bookings_sum |
|------------------------|-------------------------|---------------------|
| 222124838              | 863,944.85              | −24,060             |
| 167488506              | 23,364                  | −1610               |
| 216478480              | 99,774.44               | −550                |
| 5362616                | 30,999.96               | 0                   |
| 196698880              | 800                     | 0                   |
| 3105456                | 99,000                  | 0                   |

5.2.2. Data Analysis

Next, we compare the changes and differences between partners who are transforming and those who are not. According to the classification results of Section 4.1, we divided the table into two classes and obtained the transformed tables with 2567 rows and untransformed tables with 4693 rows. We take the mean of each column to compare the two types of data, with the results being shown in Figure 6. The top is the partner that is not transforming, and the bottom is the partner that is transforming.

Figure 6. Comparison of the two types of data.

From Tables 2 and 3, we can see that the booking, revenue, and gross margin of the partners that are transforming are all larger than the mean value of the partners that are not transforming. The deal size of the partners that are not transforming is larger than the mean value of the partners that are transforming. However, there is not much difference between them in deal velocity.

5.2.3. Data Comparison Diagram

Finally, a comparison diagram is given for the two partner types for each attribute in Figure 7a–h. The blue bars represent the untransformed partner, the yellow bars represent is the transformed partner, and the vertical coordinate is the specific value of the attribute.
5.2.3. Data Comparison Diagram

Finally, a comparison diagram is given for the two partner types for each attribute in Figure 7a–h. The blue bars represent the untransformed partner, the yellow bars represent the transformed partner, and the vertical coordinate is the specific value of the attribute.

Figure 7. Comparison of the two types of data. 

(a) (b) (c) (d) (e) (f)
Figure 7. (a) Comparing rebate booking attribute with two partner types; (b) Comparing annualized booking attribute with two partner types; (c) Comparing actual booking attribute with two partner types; (d) Comparing list price booking attribute with two partner types; (e) Comparing list price booking attribute with two partner types; (f) Comparing nonrecurring revenue attribute with two partner types; (g) Comparing confirm booking attribute with two partner types; (h) Comparing monthly recurrence revenue attribute with two partner types.

5.2.4. Discussion

Recently, some research has been introduced to deal with the digital transformation of a company, including the data-driven method [9] and the six Ts of transformation model [10]. However, these methods lack the use of advanced technology, such as AI (Artificial intelligence) and machine-learning technology. In this paper, we add the use of AI technology to solve partner’s transformation issues and call for improved scientific practices in this area. In order to identify when a partner is transforming along one or many of the transformation dimensions, how do their economics change? First, we collected relevant data which impacts the partner’s transformation. Second, we analyzed the data and obtained the transformed tables with 2567 rows and untransformed tables with 4693 rows. Finally, we compared the two partner types for each attribute in Figure 7.

5.3. Can We Spot Any Unethical Behavior by Looking through Our Deal Transaction Data?

5.3.1. Anomaly Detection

Regarding the anomaly detection [8,25,26] issue, we use data mining techniques to find the main indicators of the discount, and then we use the discount relevant feature to identify any unethical behavior of the partner [27–29]. After the analysis, an important indicator of unethical behavior is the discount rate, so we chose two attributes in the table bookings_f.

Using pre_discount_credit_sum and rebate_bookings_sum as the two-dimensional data to create the horizontal and vertical coordinates, we can get a whole to scatter distribution, as shown in Figure 8. It can be seen from the figure that most of the points are concentrated together. The x-coordinate is concentrated in the range 0 to $0.1 \times 10^8$, and the y-coordinate is concentrated in the range 0 to $0.5 \times 10^9$. However, a small part of the point distribution is very discrete, which indicates that the function of anomaly detection can be realized through these two-dimensional features.
Figure 8. Whole scatter distribution of discount features (Notes: $\text{le8}$ means unit of measurement $10^8$, $\text{le9}$ means unit of measurement $10^9$).

Next, we conducted a further quantitative analysis on the data, and obtained the mean, maximum, and minimum value, as well as the median, $3/4$ value, and $1/4$ value of each column of data, as shown in Figure 9.

![Figure 9](image)

Figure 9. Quantitative analysis of the data.

As can be seen from Figure 8, the discrete points of the anomaly mainly exist in the center of the aggregation that is larger than the point. Therefore, the `partner_site_party_key` with the two-dimensional feature values greater than $75\%$ are taken as the partners of possible abnormal behaviors [30–34]. At last, we get the final result displayed in Figure 10, `partner_site_party_key` in the figure is the partner that may have unethical behavior.

![Figure 10](image)

Figure 10. Abnormal behaviors data.
5.3.2. Discussion

Recently, some research has been introduced to deal with the digital transformation of a company, including the data-driven method [9] and the six Ts of transformation model [10]. However, these methods lack the use of advanced technology, such as AI (Artificial intelligence) and machine-learning technology. In this paper, we add the use of AI technology to solve partner’s transformation issues and call for improved scientific practices in this area. From the analysis in this section, we can spot any unethical behavior by looking through our deal transaction data, which puts partner transformation at risk. First, we used data mining techniques to find the main indicators regarding discount. Second, using “pre_discount_credit_sum” and “rebate_bookings_sum” as the two-dimensional data to create the horizontal and vertical coordinates, we can get a whole to scatter distribution, which is shown in Figure 8. Finally, we identify the unethical behavior and display the detailed results in Figure 10.

6. Conclusions and Prospect

This paper analyzes the challenge of partners’ digital transformation, which includes the following issues: (1) How do we identify partners who are transforming or are ready to transform across one or many of the transformation dimensions (such as new buying centers, platform-based outcomes, and customer experience lifecycle); (2) when a partner is transforming along one or many of the transformation dimensions, how do their economics change; and (3) can we spot any unethical behavior by looking through our deal transaction data, which could put the partner transformation at risk?

To solve the above issues, we first analyzed the data, then designed the VKR algorithm, generalizing our machine-learning model to predict partner’s digital transformation, subsequent economic change, and the identification of any unethical behavior. Finally, we found the results to answer the partner’s digital transformation issues.

In order to research partner’s digital transformation more deeply in the future, there are several directions for further research. The first direction is to add more data from the company, such as combining many more features. Another interesting direction is to relax the strict positive definiteness constraint and also support compact, dense feature representations, which can be achieved with the help of fast symmetric factorization techniques.

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