A Causality Analysis for Nonlinear Classification Model with Self-Organizing Map and Locally Approximation to Linear Model

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Abstract: In terms of nonlinear machine learning classifier such as Deep Learning, machine-learning model is generally a black box which has issue not to be clear the causality among its output classification and input attributes. In this paper, we propose a causality analysis method with self-organizing map and locally approximation to linear model. In this method, self-organizing map generates the cluster of input data and local linear models for each node on the map provides explanation of the generated model. Applying this method to the member rank prediction model based on Deep Learning, we validated our proposed method.

1 INTRODUCTION

The effectiveness of machine learning has been re-evaluated because of the drastic improvement in accuracy of image recognition and speech recognition with Deep Learning technology. Its application to various industrial fields has greatly advanced. For example, in the field of ADAS (Advanced Driver Assistance Systems) and autonomous driving, Deep Learning is applied to the recognition of white lines, pedestrians and signs on the road and it is a technical element indispensable for automatic and safety control of cars. In addition, even in smart speakers such as Google Home and Amazon Echo, improvement of voice recognition accuracy by Deep Learning plays a large role as a background for realizing highly accurate voice conversation technology between system and human.

Meanwhile, the generated model with machine learning algorithm that performs nonlinear classification analysis such as Deep Learning, is a black box. So it is unclear which input attributes are related to the output results as the significant factor. This is the issue in the development of the system with the machine learning model. It is important to have the analysis capability to explain why the classification result is derived from the model in a form that people can understand. Understanding such classification mechanism of the model, possibility to acquire new knowledge on the model is increased. Model analysis capability is also significant to verify whether the generated model is truly valid or not. To overcome this black box issue, there are several existing methods to analyze the model. However, those do not provide the method to grasp the global tendency of relation among input attributes and output of the model. It also does not provide cluster-based causality analysis that provides analysis of the cluster including specific target object. For instance, considering the application of Deep Learning to actual data analysis such as digital marketing, we need to investigate not only on each customer but also on clusters of customers or global trend for all customers. Thus, it is essential to have object-wise, cluster-wise and global views for data analysis.

In order to correspond to these needs, we propose a new method to analyze the model in the both aspects of global and local model behavior on each target object. It actually makes clusters of the given data by the self-organizing map to visualize the data distribution and performs linear model approximation locally for each feature node on the map. Using this method, data analysts can understand the characteristics of the generated model in the aspect of global tendency in the whole feature space and local behavior for each individual feature node. In this method, each feature node on the self-organizing map is regarded as the representative point in the feature space. The linear models are calculated on each feature node to understand the relationship among input attributes and output results on the neigh-

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borhood of the specific feature node. LIME (Local Interpretable Model Agnostic Explanation) (Ribeiro, M., at al.; 2016) is used for the calculation of approximated linear model. Furthermore, the global score is obtained by calculating weighted average of the number of neighboring data for each feature node. Using the score indicating the degree of influence for each series of attributes, we can grasp the global characteristic of the analyzed model, and also carry out the influence degree analysis on each more detailed feature node and clusters.

In order to verify effectiveness of this method, we applied this method to the membership rank prediction model generated by Deep Learning from member data that has several attributes of customers in CRM such as membership rank, total price of purchased services, number of logins, and so on.

The rest of paper is organized as follows. In section 2, we explain the conventional method and issue in terms of the causality analysis of the model. Section 3 explains the proposed method and its implementation. In section 4, we apply the proposed method to a specific use case of digital marketing and validate its effectiveness, and finally conclude in section 5.

2 CONVENTIONAL METHODS AND ISSUES

2.1 Existing Methods

In terms of the analysis and explanation of output results from the machine learning model, various studies have been reported. For example, one of the methods is creating an input that maximizes the output of the deep neural network (Le, Q. et al.; 2012, Mahendran, A. and Vedaldi, A.; 2014). Classification network outputs the classification probability for each class. If you can find the input data which is the source of some class on the network, it can be regarded as the candidate of the class and helps understanding the output result from the model. Google presented the image that is recognized as the cat in the deep learning model. They generated the representative cat image with the auto encoder and this approach is categorized in this method.

There is another method which analyzes the sensitivity of the output corresponding to the amount of change of the input (Smilkov, D., et al.; 2017). If some attributes largely affects the output of the network, we can recognize that those attributes provide the important feature quantity on the model. However, this method does not provide global behavior of the model. It is simply possible to analyze effectiveness of attributes for each single input data.

Another one is the method of tracing the path of the network from output to input (Springenberg, J., et al.; 2015). This method is based on the back tracing of the network path from output to input to visualize the points that have large influence to the output. For instance, Selvaraju, R, et al. proposed visual explanations called Grad-CAM (Gradient-weighted Class Activation Mapping) (Selvaraju, R, et al.; 2017) to visualize the influencing region as the heat map on the image for the object classification with CNN. This is powerful approach for CNN model but it is also the individual object-wise analysis.

Estimation of output trend from various inputs is another method to analyze the model (Koh, P. and Liang, R.; 2017). In this approach, it generates the various input data to check out behavior of the target model. LIME is classified to this type. The detail of LIME will be described later.

A method to estimate the judgment criteria from the amount of input data change is another one (Tolomei, G. et al.; 2017). This method is based on the ensemble learning using decision tree algorithm which calculates the minimal amount of data change to change the class from A to B. For instance, this method approaches the amount of change data to transfer the class from “not well-sales” advertisement to “well-sale” one. Minimal data change caused class transfer indicates indirect explanation of classification output derived from the target model.

In this paper, we aim to construct the method of scoring the relation strength among input attributes and output results for the nonlinear classification algorithms such as Deep Learning. It should provide analysis method of global and local model behavior for structured data.

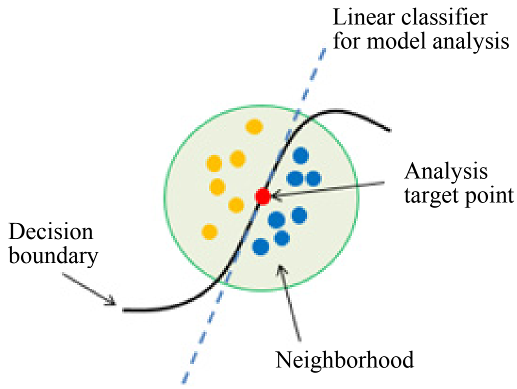


Figure 1: Locally approximation to linear model.

As a method to perform impact scoring locally on input attributes, we adopt LIME that calculates score of relationship between input and output with approximation of target model to the simple and understandable linear model. LIME is provided as OSS library and we used it to implement the proto type of our method. Figure 1 shows the outline of the local linear model approximation realized by LIME. LIME uses a machine-learning model to generate pair of input and output data randomly in the neighborhood region of each individual target object, and estimates the linear model on that. That is, the output result Y of the machine-learning model for the n-dimensional input attribute $X = (x_1, x_2, \ldots, x_n)$ is approximated by the linear model that can be described by the following equation.

$$Y = \sum_{i=1}^{n} S_i x_i + C \qquad (1)$$

In the above equation, the calculated parameter S_i is taken as the score at the input X. Here, Y, S_i and C are k-dimensional vectors in k-class classification. Each element of the coefficient S_i indicates probability increment rate for each classification class when the value of the attribute x_i is increased by 1. It can be interpreted that the influence degree on the output result is higher as the absolute value of S_i increases. In the case of multi-class classification, the sum of all the elements of the classification probability Y is always 1. For example, when each element of x_i is increased by 1 and the other input attributes are fixed, the total sum of all elements of Y is the sum of all elements of the coefficient S_i. However, since the sum of all the elements of Y is always 1, the sum of all elements of the coefficient S_i is 0. For example, utilizing these features, it can be seen that the influence score concerning the input attribute when it becomes one of a few specific classifications should be a value obtained by adding the elements of the corresponding classification of S_i. We will explain this concretely in the section of application evaluation described later on the basis of actual use case.

2.2 Issues on Existing Methods

Applying LIME to the target model, it is possible to score the degree of influence of the input attribute on the classification result with respect to each target object. However, it is impossible to score the global tendency of the influence to the output for each input attribute. It also does not provide cluster-based causality analysis which includes specific target object.

For instance, in the marketing field, when you estimate the willingness to purchase for the target customer based on the generated machine-learning model, even if LIME can provide the attribute score for each individual customer, it cannot provide what factors affect the characteristics for whole customers or the set of customers in some cluster. Therefore, it is impossible to know what kind of factors are significant for whole customers and what should be done to improve the willingness to purchase for some specific cluster.

Furthermore, when the data to be analyzed is multi-attribute/large number, it is necessary to visualize the distribution structure of data and the influence score to make data analysis more efficient. In the next section, we describe our proposed method to solve the above problem.

3 ATTRIBUTE INFLUENCE SCORING METHOD

3.1 Proposed Method

When we analyze multi-attribute data for hundreds of thousands of entities, the big data possesses a large-scale and complicated structure. Therefore, global trend cannot be grasped only by scoring input attributes locally with LIME. It is also difficult to analyze trends on similar entities' clusters. For this reason, we propose the attribute influence scoring method that uses the self-organizing map as a data structural analysis method. The following shows the processing procedure of the proposed method.

Step 1: Divide the analysing data into several target sets.

Step 2: Generate a self-organizing map to each analyzing target set to visualize the distribution structure.

Step 3: Calculate the influence scores of the attributes at each node on the self-organizing map by applying LIME for each feature node (individual object analysis).

Step 4: Calculate weighted average of distribution (overall trend analysis).

Detail of each step is described as follows.

(1) Splitting Analysis Target

In the step 1, the data is divided into multiple analysis target sets. For example, if we would like to focus on some attributes of customers as the axis of analysis, the data should be divided based on the analytical purpose such as the customer's sex, age, current affiliation, and so on.

(2) Applying self-organizing map

In the step 2, our method calculates a self-organizing map for each divided analysis target set. As a result, in the data of each target set, similar feature nodes are visualized in a form arranged close to each other, and the internal structure of each target set becomes clear. The outline of the process is illustrated in Figure 2.

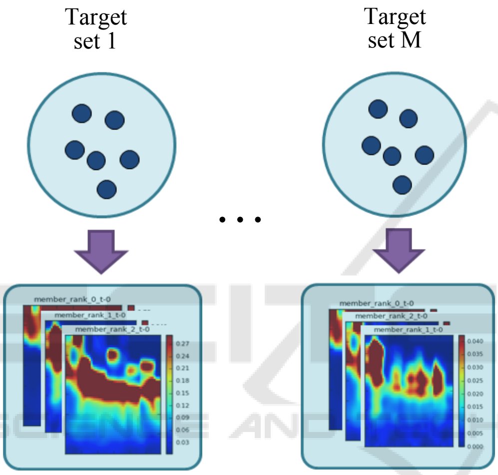


Figure 2: Generate self-organizing map for analysing target data.

Here, assume that the number of dimensions of the input attributes is D, the self-organizing map is created in which D-dimensional feature nodes are arranged on the two dimensional map for each analysing target set. Dividing the map for each attribute, we can extract D sheets of the self-organizing map that is visualized as the heat map. In the case where the number of analysis target sets is M, $D \times M$ heat maps can be extracted in total.

(3) Individual Object Analysis

In the step 3, LIME is applied to each feature node of the generated self-organizing map to calculate coefficients of linear model approximation in the neighborhood of each node. When the input attribute is D dimension, the score of LIME calculated at each node is expressed as the D dimensional vector, and each element of vector corresponds to each input attribute. Therefore, the calculation of LIME for each node also generates $D \times M$ heat maps. We call these generated maps the attribute influence score maps. Given a target analysing object, the LIME score for the feature node closest to the target object is the score value corresponding to the most similar feature node on the generated heat map. With regard to clusters that appear in self-organizing maps, we can calculate the characteristics of the clusters by taking a weighted average according to the number of hits of each feature node in the cluster.

(4) Overall Trend Analysis

In the step 4, a score indicating the overall tendency of each target set is calculated. In the step 2, a self-organizing map for each target set is calculated. At that time, a hit map is generated on which the number of hits on each feature node is recorded in the process of the self-organizing map generation. By calculating the weighted average value of the LIME scores calculated for each feature node with this hit number as a weight, a score indicating the overall tendency is output. The calculation formula of the score is as follows. Similar scores are calculated for all clusters in the designated cluster, not for the entire feature nodes, and the score for each cluster is calculated.

$$total\ score = \sum_{i=0}^{N} (h_i/H)\, s_i \tag{2}$$

Here, N is the total number of feature nodes on the self-organizing map, h_i is the hit count of feature node i, and H is the total hit count.

3.2 Implementation

LIME handles machine-learning model implemented in Python as input model. Thus, we adopted Python as the base language to implement our prototype. We used SOMPY to calculate and generate the self-organizing map. We implemented deep learning model that is input of LIME using TensorFlow and Keras. Figure 3 shows a processing pipeline of the implemented system.

Given the learning data and model, our method divides the learning data into several datasets and generates self-organizing maps for them. Using self-organizing map, learning data and model, it calculates attribute influence score maps. In addition, using attribute influence score maps and hitmaps, it outputs the total score for each attribute that indicates the global tendency of each attribute for output result. The pipeline executes the calculation of attribute score maps and total score if the divided datasets or model are changed to get other aspects of analysis.

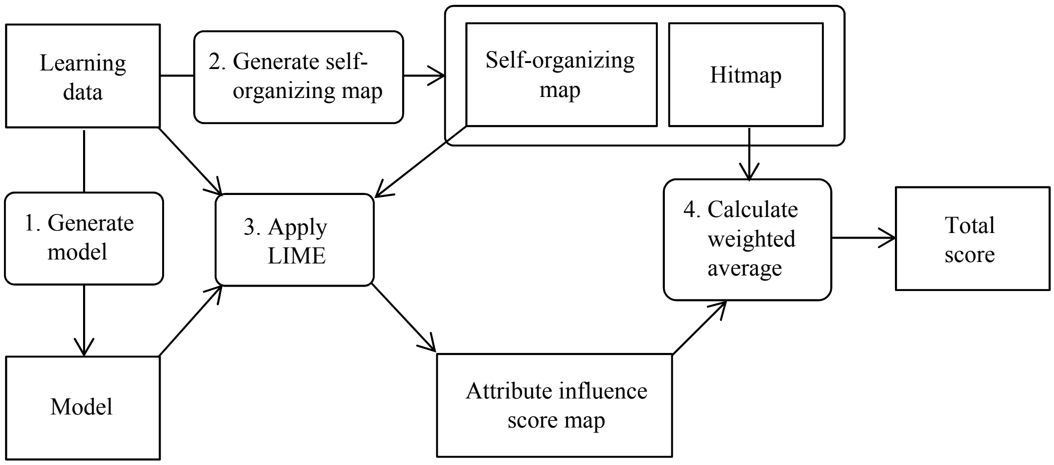


Figure 3: Process pipeline of the system.

4 EVALUATION

In this section, we describe the actual application of our attribute influence scoring method to the digital marketing use case to evaluate its validity. In this use case, it treats huge number of customer data stored in the CRM system. The attributes of customer information includes customers' service related information such as member rank, number of system login, and total price of purchased services in addition to the fundamental personal information such as address, age, sex and so on. The target model is the deep learning model to predict the member rank in the next year from the customer's information. We actually generate the model with CRM data and apply our method to analyze the model and customer data.

4.1 Global Tendency Analysis based on Target Data Segment

In the customer data used in our evaluation, there is the member rank attribute in it. Member rank has 7 grades from 0 to 6 where rank 0 is free member and other rank member is paid member. If the number of rank is bigger, the customer is higher premium member. The objective to implement measures on the marketing is to make the member's rank be higher and understand the characteristics of members in each rank.

Because objective of this analysis is considera-tion of methods for member to be higher rank, we focus on the deep learning model for rank up prediction as the analysis target. Input of this model is member's information and its output is probability to be which rank in the next year. At first, we divide customers' data. In this case, we would like to analyze rank up factor. So we divide data into 7 classes based on the current rank. In the next step, self-organizing maps are generated for all divided datasets. Then, we applied LIME to each node on the map to calculate the attribute influence score map. Because calculated score map indicates stochastic increase for each attribute and predicted rank, we can obtain rank up score for each attribute by adding score maps as for rank up of membership. Furthermore, it is also possible to calculate the global tendency score by taking weighted average using hitmap. Table 1 describes the top 3 list of influential attributes to increase the member rank in each current rank. The absolute value of the score indicates the influential degree of the attribute. Items in the table are listed descending order of the absolute value of the score. Here, the attribute name written in the form of "attribute = value" represents a category attribute. In this case, the score indicates the increment rate of the classification probability from current rank to upper rank when the category attribute value changes to the specific value. Other attributes such as total price of purchased services take continuous value. In that case, the score indicates the increase rate of classifica-tion probability to upper rank when the input attribute value increases for the size of standard deviation.

In terms of the overall tendency of the score, the absolute value of the score contributing to the rank up is smaller as the current rank is higher. Conversely, this result can also conclude that the higher the rank of member is, the lower the risk of ranking down is. From current rank 0 to 2, attributes related to automatic continuation of membership, elapsed days from last purchase, and member card application appear in the top 3, whereas as the ranking becomes

Table 1: Globally calculated influence score of input attribute.

Current Rank	Large influential attributes		
	1st	2nd	3rd
0	Automatic continuation of membership 0.387	Elapsed days from last purchase -0.124	Member card application 0.109
1	Automatic continuation of membership 0.511	Elapsed days from last purchase -0.197	Member card application 0.138
2	Automatic continuation of membership 0.365	Elapsed days from last purchase -0.179	Member card application 0.110
3	Automatic continuation of membership 0.114	Elapsed days from last purchase -0.091	Total price of purchased services 0.077
4	Total price of purchased services 0.033	Initial rank=3 -0.025	Initial rank=5 0.021
5	Total price of purchased services 0.034	Initial rank=3 -0.028	Number of purchased services -0.025
6	Total price of purchased services 0.022	Number of purchased services 0.024	Number of purchased services -0.20

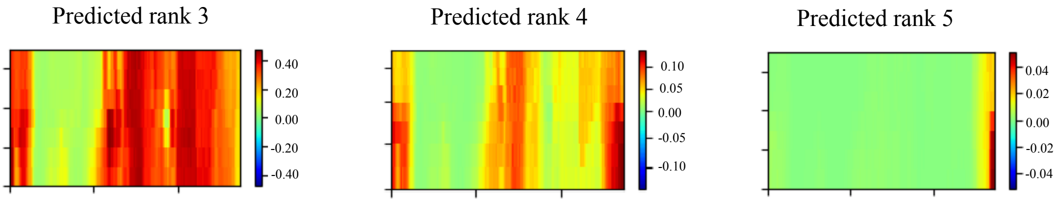
higher, attributes relating to expenditure such as total price of purchased services and initial member rank are emphasized. These calculated trends are easy to understand and make sense for humans. Furthermore, while the total price of purchased services contributes positively to the rank from 3 to 6, the sign of score for number of purchased services is negative when the current rank is 5 or higher (the score of the frequency number of service purchase at rank 5 is -0.025). From this result, it can be seen that purchase of the service with the higher unit price is more important than the number of service purchases in order for the premium members to increase the member rank further more.

At current rank 3 or less, not only the automatic continuation of membership but also the elapsed days from the last service purchase are strongly related to the rank up of membership. Since the sign of the attribute of elapsed days is negative, the possibility of rank decreases as the number of elapsed days increases. From this result, it is understood that regular following up measures for purchasing services are important, particularly for members who are in lower rank. Using the global tendency score of attribute influence degree for each target rank of customers, useful information on the direction of the rank-up measures for each layer can be obtained as described above.

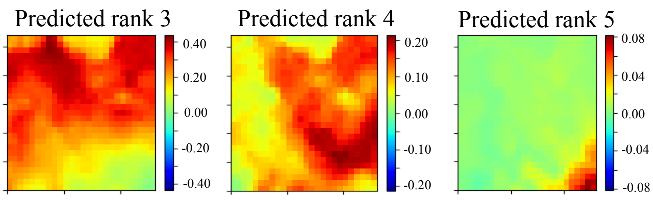
4.2 Visualization of Predicted Rank and Attribute Score

In this section, we analyze the trend of the attribute influence degree obtained from the global tendency score in more detail. From the result in the previous section, we can say that the influence degree of the automatic continuation of membership attribute is larger at lower rank from 0 to 3. Figure 4 shows an example of attribute influence score maps and component maps on automatic continuation of member attribute for current rank 0 and 3. The component map is the self-organizing map generated from the target data and score map is generated from the LIME score for each node on the component map. The global tendency score discussed in the previous section is the sum of the all scores for rank up from the current rank. Here we focus on the score maps for individual rank prediction from the target current rank to analyze our use case in more detail. Actually, looking at them, it is possible to grasp which nodes or clusters are affected strongly to predict higher rank in terms of the analyzing attribute.

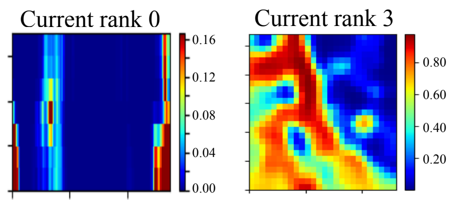
Score maps in (b) of the figure show the distributions of LIME score for current rank 3 predicted to rank 3 to 5 individually. If we consider the rank up from current rank 3, we should check out the score map of prediction rank 4 or higher. In these score maps, since the green node indicates that its score is 0, it is possible to easily search for the node with red or blue color on which the influence degree appears greatly. Also, (c) of the figure shows the component maps of the automatic continuation of membership attribute. From these maps, it can be seen that the automatic continuation of membership flag is not substantially set for any customer in the case of current rank 0, whereas customers who set automatic continuation flag in the service site are biased to the left part of the map in the case of current rank 3. Comparing this component map with the score map of predicted rank 4 in (b), we can see that the red part on the score map is similar to the relatively low blue part on the component map. From this fact, it can be confirmed that there is a possibility of low blue part on the component map. From this fact, it can be confirmed that there is a possibility of effectively working for members in the blue part who are not set to automatic continuation configuration when executing measures related to the promotion of automatic continuation of membership configuration.



(a) Score map for current rank 0 on automatic continuation attribute.

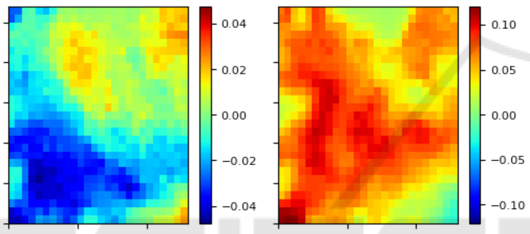


(b) Score map for current rank 3 on automatic continuation attribute.

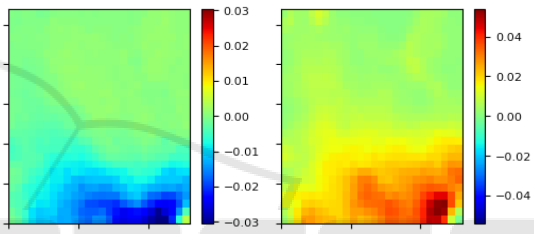


(c) Component map on the automatic continuation.

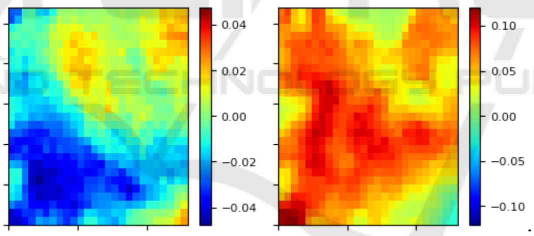
Figure 4: Score map and component map on the attribute for automatic continuation of membership.



(a) Score map for current rank 3 and predicted rank 4.



(b) Score map for current rank 3 and predicted rank 5.



(c) Component map for current rank 3.

Figure 5: Score map and component map on total price of purchased services.

Figure 5 shows score maps and component maps for attributes of the total number of purchased services and the total price of purchased services at current rank 3. In the description on the global tendency score analysis in the previous section, the score for the number of purchased services is negative in the current rank 3 or higher. As you can see on the left map in Figure 4 (a), the score is positive in the upper right, the lower right, and the middle three places. This means the negative influence is not uniform on the whole nodes even if the global tendency score is negative. On the other hand, the portion where the influence degree of both attributes is larger with respect to the prediction rank 5 in (b) is similar to the shape of larger value portion in the component map of (c). From this fact, it is considered that measures in terms of service purchase need to be individually implemented for each member's feature represented by reference vectors of these nodes on the map. However, the visualized component maps of data with multiple attributes often become complex patterns because of the complex data structure. It is necessary to consider the method of grasping customers represented by nodes.

From the above analysis, it can evaluate the detailed influence degree for each node by grasping the attribute with high influence degree at each target rank by the global tendency score and visualizing the score for each prediction class and attribute using the self-organizing map. Applying the proposed method, it is possible to provide useful information that can be utilized for planning customers' measures for membership rank up.

5 CONCLUSIONS

In this paper, we proposed the attribute influence scoring method to address the relationship among input and output data of the nonlinear classification model with self-organizing map and locally approximation to linear models. The proposed method clarifies local characteristic with LIME score on each node on the constructed self-organizing map. It also shows global attribute influence score by calculating weighted average value with LIME score and hit count on every node. Thus, our method enables analysts to have object-wise, cluster-wise and global views in terms of targeting nonlinear model. We applied our method to the actual use case of customers' membership rank-up analysis for digital marketing to evaluate the validity of our method.

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