Extracting knowledge patterns in a data lake for management effectiveness

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Abstract—With the correlation collision between different types of data becomes more and more intense, a meaningful and far-reaching data revolution has arrived. Enterprises urgently require a hybrid data platform that can effectively break data silos, and unify data aggregation and sharing. Once the data lake was born, it has been a promising method for enterprises to profoundly improve their Business Intelligence. In this paper, we combine principle component analysis (PCA) with a network-based approach to extract a visual knowledge pattern from data sources in data lake, so as to improve management effectiveness.

1 Introduction

Big data, once it appeared, has the power to show amazing methods instead of traditional ways of doing business, as well as the management of organizational knowledge [1]. Due to the advent of big data, managers today understand their enterprise, their surroundings, their customers and their competitors better. Therefore, they tend to be able to achieve a faster decision making, accurately develop new products according to customer needs, increase customer loyalty, explore a series of new markets, improve operating income, and ultimately reinforce management effectiveness. [2]. In other words, big data analytics can be a great investment for companies to improve organization performance and stay competitive with their business competitors. [3].

Nevertheless, traditional data warehouses extract data and integrate data after converting it to a common static pattern. Thus, they are called centralized data stores [4]. Now that this way of data integration ultimately leads to severe information silos, companies require finding an effective method to link and structure the various flows from the information silos that help address specific issues flexibility [5].

Data Lake is the most promising and relevant solution for this emergency [6], and is used as a multifunctional data repository to store largescale of raw data, offering extraction, exploration and monitoring capabilities [7]. Although data lake breaks the data silos, if there is no proper method of data integration in a heterogeneous environment, the data lake will fall into an awkward situation and eventually become a useless swamp.

Network analysis is always regarded as a flexible and intuitive analysis method. In the paper, we propose an approach based on the method of network analysis to extract an inner relationship involving constructs coming from heterogeneous source of a data lake, trying to help companies build a pattern that makes it more intuitive to understand the relationship between various kinds of performance and capabilities.

It is universally acknowledged that, big data has 4 main characteristics (4V): volume, velocity, variety, and value. In a big data scenario, it is significant to reduce dimensions of the data in order to increase the velocity, meanwhile, cut back data volume and type. Principle component analysis (PCA) allows considering all the elements and finally achieving dimensional reduction. Hence, we combine PCA with the network-based approach to extract a visual knowledge pattern to improve management effectiveness. The main contribution of this article includes:

- This paper uses a network-based model to extract visual knowledge patterns.
- Introduce the PCA algorithm and achieve dimension reduction by this method.

We used the following structure in this paper: In section 2, we review related works. In section 3, we narrate and propose the network model based on PCA. Section 4 shows steps to extract visual knowledge patterns. In section 5, we summarize the paper, and draw conclusions.

2 Related Literature

2.1 Data lake

First proposed by James Dixon, data lake is described as a tool that works across a variety of data sources [8]. Although there is no generally accepted concept or
definition here, the relevant definitions of different scholars or institutions are highly correlated.

For instance, Tyagi and Demirkan claim that in the data lake, any type of data can be used and analyzed directly without being predefined [9]. Analogously, Alserafi A., Abelló A., Romero O., and Calders T. introduce data lake as “Data lakes save the crude data format without conversion or pre-order and can be accessible using read mode.” [10]. Miloslavskaya and Tolstoy define data lake as “A data lake holds structured, unstructured and semi-structured data in its native format and can capture data without damaging the data structure” and “This can be considered as a huge data set that has access to almost all historical and new information in real time. In this case, once the data is queried, the schema will be defined” [11]. Endris K.M., Rohde P.D., Vidal M.E., and Auer S. say that “To solve the problem of data integration, especially the heterogeneous data, a number of data lake systems are appeared, focusing more on data input and on metadata management.” [4]. Llave [12] defines a data lake from a business perspective as “an ability to improve business effectiveness where you can get raw, unaltered data from various source systems.” or “the place where you can find all the data in your company.”

Obviously, there is a strong agreement in the concept of data lake. However, there are various management approaches, paradigms and frameworks to solve the problems due to limitations caused by the characteristics of data lake.

2.2 Approaches and techniques in the big data context

Compared with traditional data warehouses, data lakes have many clear advantages, but they do have some limitations as well [13]. While data lake aims at getting rid of human effort before using the data, the dilemma is just postponed because there were still difficulties in preparing and cleaning the database. Introducing Kayak, a framework, Maccioni and Tortone [14] tackle this problem and help scientists to define and optimize data pipelines. Using Kayak, users can tailor their needs according to the precise requirements and create an output that meets those requirements. To integrate data silos and machine learning technologies into a data lake, Wibowo M., Sulaiman S., and Shamsuddin S.M. present Rough Set as a predicting method, because the calculation results, transformations, for the purpose of obtaining the best calculation results, $\mu_i$ in the above-mentioned formula is solved according to the following principles:

$$\mu_i = \mu_{i1} \cdot x_1 + \mu_{i2} \cdot x_2 + \mu_{i3} \cdot x_3 + \ldots + \mu_{ip} \cdot x_p$$

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$\ldots$

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a) \( y_i \) and \( y_j \) (\( i \neq j, j = 1, 2, 3..., p \)) should be independent of each other;

b) \( y_1 \) refers to be one of the linear combinations of \( x_1, x_2, x_3..., x_p \) with the largest variance; \( y_2 \) (not related to \( y_1 \)) is one of the linear combinations of \( x_1, x_2, x_3, ..., x_p \) with the second largest variance. Analogously, \( y_p \) (not related to \( y_1, y_2, y_3, ..., y_{p-1} \)) has the smallest variance among all linear combinations of \( x_1, x_2, x_3, ..., x_p \).

The variables \( y_i \) defined according to the above principles are sequentially called the first, second, third, ... principal components of the original variables \( x_i \). Among them, \( y_1 \) holds the largest proportion in the total variance, and it has the strongest ability to integrate the original variables \( x_1, x_2, x_3, ..., x_p \), and the remaining principal components \( y_2, y_3, ..., y_p \) gradually decrease in proportion to the total variance. That is, their ability to integrate the original variables \( x_1, x_2, x_3, ..., x_p \) weakens in turn.

In the practical application of principal component analysis, generally only the previous few principal components with larger variances are selected. We determine the number of principal components based on the cumulative variance contribution rate and the eigenvalues of principal components, combined with actual needs. Thus, we implement the reduction of dimension by keeping the components with higher variance and a larger amount of information, and removing components with little differences and inadequate information [18].

3.2 Build a network

Consider a situation where \( z \) can be explained by three principal components, and each principal component can be explained by two or three factors from different data sources, as shown in Fig. 1.

In this section, we show how to extract the visual knowledge patterns, using the previously stated network model. Because the factors from different data sources and the target constructs are in the same network, extracting the pattern simply needs to calculate the shortest path between the two of the target constructs. Since in this model, the principal component \( y_i \) is the concept that we build, rather than the real data we extract from a data lake, it is ignored when calculating the shortest path. We discussed paths from \( z_1 \) to \( z_2 \), \( z_2 \) to \( z_3 \), and \( z_3 \) to \( z_1 \), in the network model proposed in the previous section, as is shown in Fig. 3, Fig. 4, and Fig. 5.
Figure 5. The knowledge pattern from z3 to z1

As we can see in the three visual knowledge patterns, it can be found that from one construct, through related factors, to another construct, at least one path can be drawn (there are two paths connecting z1 with z3). In real-world situations, it might be more complicated and not limited to studying the relationship among only a few constructs. More parameters will be considered in order to better and more accurately model the real situation.

As we mentioned in the introduction, the patterns extracted from the network model flexibly and intuitively show the relevance of the constructs. In the business context, it reflects the internal relationship between the various capabilities, development potentials and performances that companies are concerned about. Enterprise managers can use this method to effectively use the data in their databases plus external data and extract patterns to help them gain an in-depth understanding of their companies, surroundings and then make decisions effectively. Also, the approach can be broadened to more common areas to extract patterns from a certain network or complex networks [23], including social network, electrical transmission network, railway network, mobile signal network, and many other kinds of networks.

5 Conclusion

Nowadays, data lakes have been applied more and more widely, and some companies have started building their own data lakes. Compared with traditional data warehouses, data lakes have many clear advantages, but they do have some limitations as well. Helping organizations to enhance their management skills and effectiveness, in this paper, we put forward a network-based approach combined with PCA algorithm to extract visual knowledge patterns in a data lake scenario. As a result, the approach makes it more intuitive to appreciate the relationship between various kinds of performance and capabilities from heterogeneous business data. Thus, this method can enable enterprises to improve their competitiveness comprehensively.

The method we used in this paper can easily deal with traditional structured and semi-structured data, while it is difficult to handle the various types of unstructured data at the same time. Therefore, future work will continue to attach importance to novel and flexible approaches that can deal with all three types of data simultaneously from heterogeneous sources in data lakes.

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