Data Technology Apply in Business Decision Making: How to Use Data Information to Make Business Decisions in the Digital Age

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Abstract: Data are an important asset of an enterprise, changing the way information is connected and reshaping the future of the enterprise. To make business decisions quickly and without mistakes, business managers must rely on data and information. The construction of enterprise data information will follow the DIKW model, the seven-step process rule, the four-layer technical framework and the underlying powerful algorithm foundation. Data capature, data cleaning and standardization, and data modeling are the basis for making business decisions based on data information. This academic paper will talk about the basic methods of data standardization and data modeling. It comes from working practice.

1 INTRODUCTION

Business decision is a process in which enterprises or organizations make decisions on future actions after analyzing, calculating and judging the factors affecting the realization of goals based on objective possibilities and certain tools, skills and methods with the help of certain information and experience. For business managers, management is decision-making. "Decision-making occupies the core position in management activities and runs through the entire process of management activities." (Li, 2020)

Efficient and high-quality decision-making drives the enterprise to continuously provide high-quality products (or services), making the enterprise stand out and win in the fierce market competition. In today's digital era, the speed and amplitude of change are far beyond the past, which puts forward higher requirements on the decision-making ability of enterprises, and the decision-making must be both good and fast. However, in the real business world, the decisions made by enterprise managers fail to reach the expected goals due to the lack of systematic methods. "According to Microsoft, more than 74 percent of business decisions are behind schedule or fail......" jean-Paul Sartre wrote in his book The Difficulty of Making Decisions. The actual situation is so bad, what kind of decision-making mechanism can provide enterprise managers with ways and means to get out of the decision-making dilemma? Based on years of enterprise management experience and systematic learning summary, the article author has been studying the management advantages of advanced enterprises in recent years, and comes to the conclusion that only by relying on digital technology can we make high-quality decisions and avoid decision-making mistakes. The digital technology mentioned here is not only the summary of the past data information and experience, but also the simulation and prediction of the future trend. For example, Amazon's personalized recommendation based on big data derives more than one third of its revenue from recommendation functions. McKinsey defines "Industry 4.0" as the digitization of manufacturing, with sensors embedded in almost all components and equipment, and the widespread introduction of cyber-physical systems that analyze all available data. Relying on digital technology, senior managers, middle managers and first line managers respectively focus on strategic decisions, management decisions and daily rountine operation decisions, and they play their own role to ensure the continuous and efficient operation of the enterprise and its survival in the ever-changing business world.

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2 DATA-DRIVEN BUSINESS DECISIONS ARE AN INEVITABLE CHOICE FOR ENTERPRISES

2.1 Definition of Business Decisions

Talking about business decision, let's take a look at its definition first: Business decision is made by the relevant organization of the enterprise to enhance the strength of the enterprise, improve the profitability of the production and operation of the decision. Business decision-making mechanism is a mechanism by which enterprise managers make decisions on production, management and other business activities under the condition of having sufficient legal person property rights. The business decision mechanism is in the main position in the operation mechanism. It is not only the basis of designing other mechanisms, but also runs through the operation of other mechanisms. A sound decision-making mechanism is a necessary condition for effective decision-making.

2.2 The Main Points of Decision Theory

Since the second World War, many operational researchers, statisticians, computer scientists and behavioral scientists have been trying to find a scientific way of making decisions in the field of management in order to make clear and rational choices on complex multi-scheme problems. With the study of this aspect, decision theory has been developed rapidly. Decision Theory School is an emerging management School based on statistics and behavioral science and using computer technology and research methods. The main representatives of traditional theories are Herbert Simon, A. Simon and James G. March. The core theory is the decision theory proposed by Herbert Simon, and the main viewpoints are as follows:

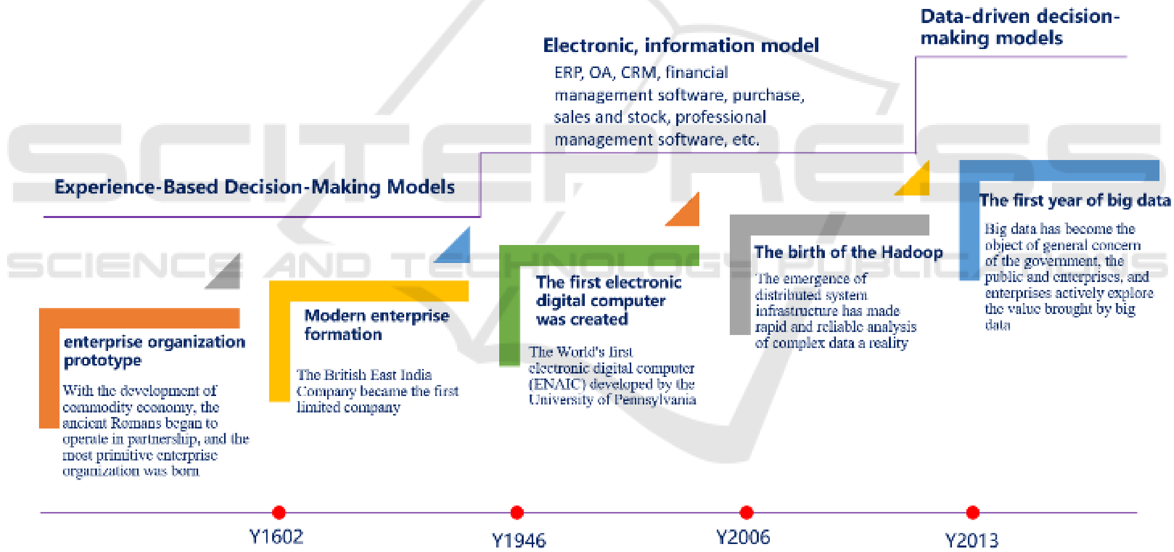

Figure 1: Three stages of business decisions rely on.

- Management is decision-making: Simon et al. believe that the whole process of management activities is decision-making process. Determining objectives, making plans and selecting plans are business plans and planning decisions; Mechanism design, production unit organization and authority allocation are organizational decisions; Inspection of plan execution, wIP control and selection of control means are control decisions. Decision-making runs through the whole management process, so management is decision-making.
- Decision making is divided into procedural decision making and non-procedural decision making: procedural decision making refers to the decision made in accordance with established procedures; Special treatment is required when the problem is widespread, new, unstructured, or so important and complex that there is no routine procedure to follow. Decisions on such questions are called non-procedural decisions.
- Satisfactory code of conduct: Simon thinks, because the organization under the changing external environment influence, to collect all the data which are

difficult, and some action plans are more difficult to list the sites, and the person's knowledge and ability is limited, so when making decision, it is difficult to obtain the best solution, in practice, even able to find out the best solution, in economic terms have to consider, People also tend not to pursue it, but to make decisions based on satisfying principles.

With the development of digital technology, modern decision-making theory has gradually come into being, represented by Venkat Venkatraman. In his book The Digital Matrix: New Rules for Business Transformation through Technology, he provided three decision-making methods conducive to success: first, how to avoid getting lost in the dynamic ecosystem: carefully build and participate in various ecosystems; The second is how to work with different companies to build new capabilities and create new business value: to connect with competitors and potential Allies; Finally, how to design the organizational structure to reflect the new and powerful model of human-computer interaction: using powerful machines to amplify the enterprise's potential.

2.3 The Three Stages of Development of Business Decisions

With the application of new advanced informatization and digital technologies such as artificial intelligence, cloud computing, big data, blockchain, Internet of Things, and the Internet, the degree of digitization of society continues to increase, and data have become an important element in building a modern society. From 2020, data have become the fifth largest factor of production after land, labor, capital and technology. It is an important asset of enterprises and, of course, an important asset of individuals, organizations and even countries. "In the digital age, companies need to have a new understanding of data, because data has become the new core asset." (Ram, 2020) Business decisions based on data information will not affect the quality of decision-making due to the subjective factors of managers, and avoid decision-making mistakes or major decision-making mistakes. "Information and value form the 'foundation' of decision-making: what we can do, what we know, and what we want." (Carl, 2017) The evolution process of the basis for supporting decision-making is shown in Figure 1: The three stages of the business decision-making model are the empirical decision-making model, the electronic information decision-making model and the data-driven decision-making model. Since 2013, enterprises have entered the data-driven decision-making model. The data-driven decision-making model reflects that the entire business chain of the enterprise's R&D, planning, organization, production, coordination, sales, service and innovation uses digital decision-making, and supports the strategic decision-making and planning of the entire enterprise, enabling the enterprise to achieve overall Decision intelligence, and ultimately lead the transformation of enterprises and even the industry through data-driven. The Fraunhofer Institute in Germany put forward the concept of Industry 4.0. The institute believes that the logical starting point of Industry 4.0 is to adapt to the rapid changes in the competitive environment. How does an enterprise adapt to the rapid changes in the market + users + products + technology, it can be seen that the traditional low-frequency decision-making mechanism cannot adapt to the high-frequency decision-making needs in emergencies, and data-driven fast and high-quality decision-making is an inevitable choice for modern enterprises.

3 THE FORMATION PROCESS OF BUSINESS DECISION DRIVEN BY DATA INFORMATION FROM DIKW MODEL

Just like the accumulation of knowledge, the formation of data-driven decision mechanism is essentially a process of enterprise capacity building. Enterprise-related data are collected, processed, identified, processed and presented, and finally become the knowledge and wisdom to guide enterprise operation and management. This process is presented by DIKW model as shown in Figure 2, which is to understand this process from the cognitive level.

3.1 The Relationship Between DIKW Model and Enterprise to Make Intelligent Business Decision

DIKW shows the universal process of evolution from data, information, knowledge to wisdom. This model will also be followed by intelligent decision-making based on data information from the enterprise.

- D-Data: Data can be numbers, words, images, symbols, etc. It comes directly from facts and can be obtained through original observation or measurement.

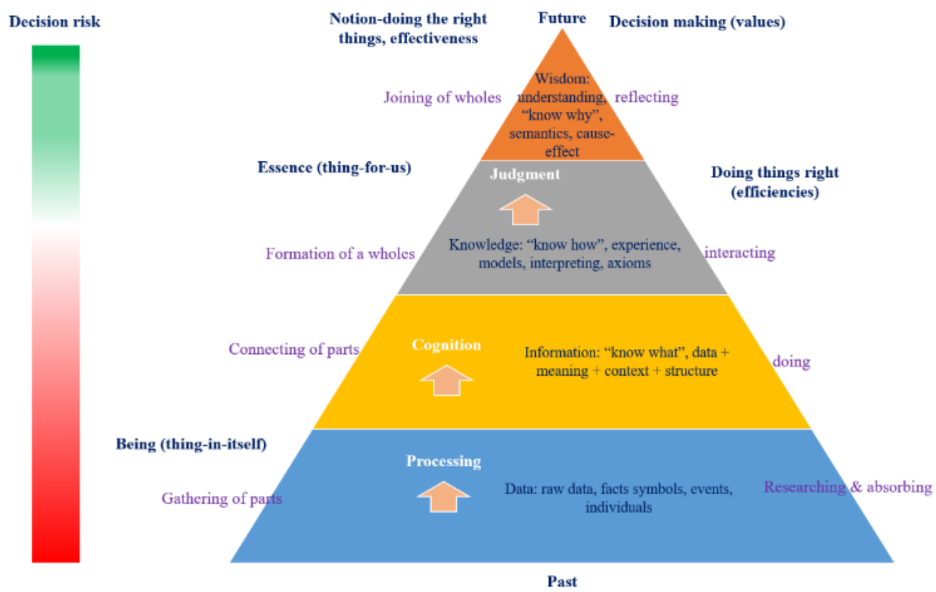

Figure 2: DIKW model and business Intelligence decision process.

- I-Information: by organizing and processing data in a certain way and analyzing the relationship between data, data become meaningful, which are Information. Information can answer simple questions such as: Who? What? Where to? What time? So information can also be thought of as data that is understood.
- K-knowledge: Knowledge is useful information filtered, refined and processed from relevant information. It is a collection of information that makes information useful. It is a process of judging and confirming information, which combines experience, context, interpretation and reflection. Knowledge establishes meaningful connections between data and information, and between information and the application of information in action. It embodies the essence, principles and experience of information. Knowledge answered, "Well?" Problems to help enterprise modeling and simulation.
- W-Wisdom: Wisdom is an extrapolated, nondeterministic, nonjudgmental process. Unlike previous stages, wisdom focuses on the future, trying to understand what was not understood or done in the past. Wisdom can be summarized as the ability to make sound judgments and decisions, including the best use of knowledge. Wisdom answers the question "Why?"

3.2 Smart Business Decisions Take Time to Build

It takes time, maybe a year or even a few of years, from data capature to the extraction of information then to intelligent decisions of enterprises. First of all, data capature is complicated, because data sources are online, offline, inside and outside the company, including historical data and model-based forecast data. Secondly, after the data are obtained, how to organize the data to make it information, involves data cleaning, sorting, association and other technical problems; Thirdly, the information obtained from data capatureis massive and needs to be processed, extracted and abstracted. This process involves the use of various analytical methods, and it is a process that is gradually deepened with business insight. Only when enterprise managers' cognitive level reaches a certain level, and with the assistance of IT technology, can they be data-driven. Digital decision making focuses on the automation and optimization of specific business decisions. (Venkat, 2018)

4 HOW IS THE DATA-DRIVEN DECISION PROCESS IMPLEMENTED FROM THE PERSPECTIVE OF PROCESS CONSTRUCTION

The process of implementing data-driven decision-making is divided into 7 levels, as shown in Figure 3 below:

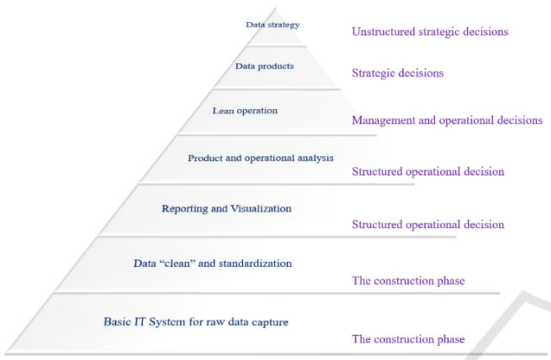

Figure 3: The 7 stages of data-driven enterprise business decision making.

1) Basic IT system: The first level is the "basic IT system", which is a data-driven foundation, and its function is to complete data capature. It mainly refers to the software system and its supporting hardware equipment used by the enterprise in the actual operation process, such as various business systems of the enterprise, financial management software, CRM system; hardware equipment such as sensors, detectors, etc., these systems complete "data capature" task. "It can be said that the best, latest and most flexible ideas come from the end." (Tencent, 2020) The raw data obtained after data capature are non-standard and unusable. They must be processed before they are meaningful, thus entering the next stage of "data cleaning and standardization".

2) Data cleaning and standardization: At the "data cleaning and standardization" level, what we are trying to achieve is to break down data barriers so that data can flow normally within the enterprise. (Wang, 2020) The work of this stage covers: a) data cleaning; b) Data integration; c) Data distribution and transformation; d) Data reduction and other pre-processing work.

3) Data reporting and Visualization: The question in this step is: How do you make the data visible? The simplest and most straightforward method is "data reporting." It is to construct various forms according to daily business usage and fill in a large amount of data in the forms. Some enterprises make reports manually, some enterprises use report engine to make reports, and some enterprises enter the stage of data analysis and visualization. Through BI and other analysis tools, they delegate the right of data analysis to the user end, helping the business to quickly get data and quickly make reports, and even do some analysis independently. From "basic IT systems" to "data reporting and visualization," the first three levels are, in some ways, the foundation for data analysis and application. For an enterprise, complete the three levels, some companies are done manually, some companies are localized deployment of IT systems, some companies is done by the cloud IT systems, only the three levels of ability, can be said that the enterprise has the use of data to guide the operation, the decision-making, management and so on the basis of data applications.

4) Product and operation analysis: the first target is the monitoring of daily operation; Second, when the daily analysis has become a routine part of the job, the enterprise products and business people will find simple daily analysis cannot solve the problem of complex management and strategic decision, unable to bring a surprise to customers, which requires the user, product, channel, market, demand, and so on aspects of deep analysis and research. In this process, many business-specific analysis topics and data models have emerged to help enterprises better understand the market, and capture customers and potential business opportunities. The most representative example of this is "user portraits".

5) Lean operation: At the level of "lean operation", all analyses are no longer isolated from each other, but more based on an actual business scenario to realize the overall management of all processes in this scenario. If multiple applications or systems can be built in each field of the enterprise, then these aggregations can basically support the main enterprise operation and management.

6) Data product: Data mining is an evolutionary product generated by enterprise data, and it is one of the many ways for enterprises to realize the value of internal data. Data products in the physical industry are often due to the fact that the internal data capabilities of the enterprise have grown to a certain stage, and some internal data and analysis methods of the enterprise have already met the conditions for independent realization, so they are taken out by the enterprise as a type of product and provided to the market. Data products are formed, and the data products of entity enterprises serve more within the organization.

7) Data Strategy: Companies use data strategically to accelerate decision-making through

business insights and ultimately achieve their strategic goals. After long-term scientific governance, data have become a strategic resource for enterprises, and data information are used to gain competitive advantages and achieve business goals.

5 SEE HOW DATA-DRIVEN DECISION-MAKING GOALS ARE ACHIEVED WITH THE TECHNICAL FRAMEWORK OF IT

In order to achieve data-driven decision-making goal, the technical architecture of the enterprise system is divided into four levels: data capture → data standardization → mining data value → making intelligent decisions, as shown in Figure 4:

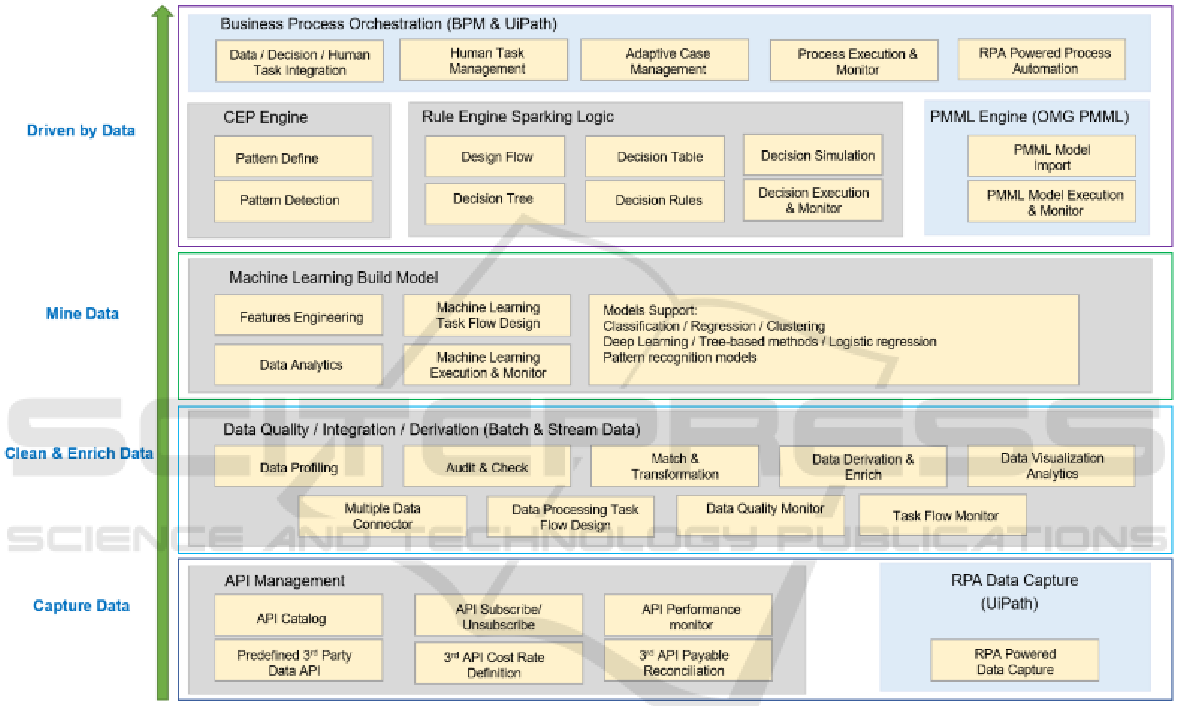

Figure 4: A 4-tier technical framework for data-driven business decisions

Data capture: The data API management platform uses RPA technology for data aggregation, integrates the data scattered in various information islands, and displays the data source and data call records at the same time to ensure the stability of data calls.

Real-time data processing (cleaning, standardization, etc.), data quality management: CEP stream computing software, powerful stream data computing capability, can handle complex events; massive data throughput, millisecond-level response.

Data mining: Machine learning platform, with powerful integration capabilities of data and tools, can be easily expanded; general technology can preset more than 2,000 modules of Hull's advanced algorithms, auxiliary modeling, etc.

Intelligent business decision: decision engine platform; timely early warning and rapid response operation monitoring system; data visualization system. FICO, IBM, Experian and other technologies achieve easy-to-use, agile, and intelligent effects.

6 EXAMPLE: DATA CLEANING, STANDARDIZATION METHODS

The previous part succinctly shows the IT technical architecture that data support business decision-making. Data collection can rely on various software systems, hardware equipment established by the enterprise in the past, or even collect data manually, and complete the aggregation through RPA robots. The aggregated data are waiting for cleaning and standardization. This process cannot be done manually and must rely on technology. “Data by themselves do not express any meaning, they are only when data are combined with logic that we can discover and express insights.” (Zhou, 2021) Therefore, this chapter will introduce data cleaning and standardization methods, which are part of big data processing and come from work practice. The methods are as follows:

6.1 Data Normalization

1) Data normalization: Data normalization is to map the dimensional features of the data into a specified range, [0, 1] or [-1, 1], and a compression dimension. Normalization types can be divided into:

$$\begin{cases} \mathbf{X} = \dfrac{\mathbf{X}_{old} - \min(\mathbf{X}_{old})}{\max(\mathbf{X}_{old}) - \min(\mathbf{X}_{old})}, \quad [0,1] \\ \mathbf{X} = \dfrac{2(\mathbf{X}_{old} - \min(\mathbf{X}_{old}))}{\max(\mathbf{X}_{old}) - \min(\mathbf{X}_{old})} - 1, \quad [-1,1] \end{cases} \tag{1}$$

- Max-min normalization, the equation is as (1), where X_{old} is the original data set with m samples and n features. $\min(X_{old})$ and $\max(X_{old})$ represent the extreme values for each feature of the original data set.
- Mean normalization, the equation for mean normalization is as (2), where $mean(X_{old})$ represents the mean value of each feature of the original data set.

$$\mathbf{X} = \frac{\mathbf{X}_{old} - mean(\mathbf{X}_{old})}{\max(\mathbf{X}_{old}) - \min(\mathbf{X}_{old})} \tag{2}$$

- Non-linear normalization: Take the logarithm of the original data. Non-linear normalization does not scale the dimensional features of the original data to a certain range, but reduces the scale (dimension) of the dimensional features. Usually in some data processing, the logarithm of the original data is often taken before further processing. The reason for this is that the logarithmic function is a monotonically increasing function in its definition domain. After taking the logarithm, it will not change the nature and correlation of the data, and it can also compress the scale (dimension) of the feature.

2) Additional notes on data normalization methods:

Features: Normalization will change the data distribution of the original data, and the original information is not preserved. The purpose of scaling different features is to make the influence weights of each feature dimension on the objective function to be the same. At the same time, due to the different degrees of scaling and transformation for different features, the projected contour lines of those flat distribution objective functions tend to be circular, which also changes the distribution type of the original data.

Functions: a) Speed up the training: such as the convergence speed of the objective function in the iterative algorithm; b) Balance the weights of the features in each dimension to avoid the interference of the features with too large or too small a numerical scale on the model

Disadvantage: After normalizing the data, although the weight of each dimension is balanced, it also changes the data distribution of the original data, that is, destroys the data structure.

6.2 z-score

Scale the data to a data distribution centered at 0 and a standard deviation of 1 (Note: a data distribution with a mean of 0 and a standard deviation of 1 is not necessarily a normal distribution, it may also be a t distribution or other distribution), in addition, z-score retains the original data information and does not change the original data distribution type. The purpose of the z-score is also to make different features of the raw data comparable. The z-score equation is shown in (3)

$$\mathbf{X} = \mathbf{X}_{old} - mean(\mathbf{X}_{old}) \tag{3}$$

In the equation, μ is the vector of the mean of each column feature of the original data set, μ=mean (Xold), σ is the vector of the standard deviation of each feature of the original data set.

Comparison of data normalization and z-score:

The same aspect of normalization and z-score: both perform linear transformation on the original data, that is, both translate the sample points and then shorten the distance, so that the different features of the original data are comparable

The difference between normalization and z-score: a) the impact of normalization on the objective function is reflected in the value, while the impact of z-score on the objective function is reflected in the geometric distribution of the data; b) normalization changes the amount of data level and also change the distribution of the data, Z-score only changes the magnitude of the data but does not change the distribution type of the data; c) z-score normalizes the data, does not change the contour projection of the objective function, and will Continue to maintain the flatness of the original objective function, and normalize the data to make the contour projection of the objective function appear circular; d) In the gradient descent algorithm, normalizing the data helps to speed up the convergence of the algorithm.

Data normalization and z-score usage scenarios:

- Using gradient descent parameter estimation model: using normalized data can improve the convergence speed of the algorithm
- PCA dimensionality reduction algorithm needs to be decentralized, so Z-Score processing can be used
- For specific requirements on value range, data should be normalized, such as image processing, where pixel intensity must be normalized to fit a certain range (RGB color range 0 to 255).
- Probabilistic models are insensitive to feature dimensional differences and can be standardized without using measurement indicators (such as decision trees).

In general, z-Score processing is used when it is uncertain which data processing method to use, because it does not change the data distribution type, that is, does not break the data structure.

6.4 Centralization/Zero Meanization

After centralizing the data, the mean value of the data is a 0 vector, which is to translate the original data to the vicinity of the origin. The centralized processing of data is a process of translation one by one, and does not change the type of data distribution. Suitable for PCA dimensionality reduction algorithm. The centralized preprocessing expression is as (4)

$$\mathbf{X} = \frac{\mathbf{X}_{old} - \boldsymbol{\mu}}{\boldsymbol{\sigma}} \tag{4}$$

The function is to facilitate the calculation of the covariance matrix, remove the influence of the intercept term (bias term), and increase the orthogonality of the basis vector.

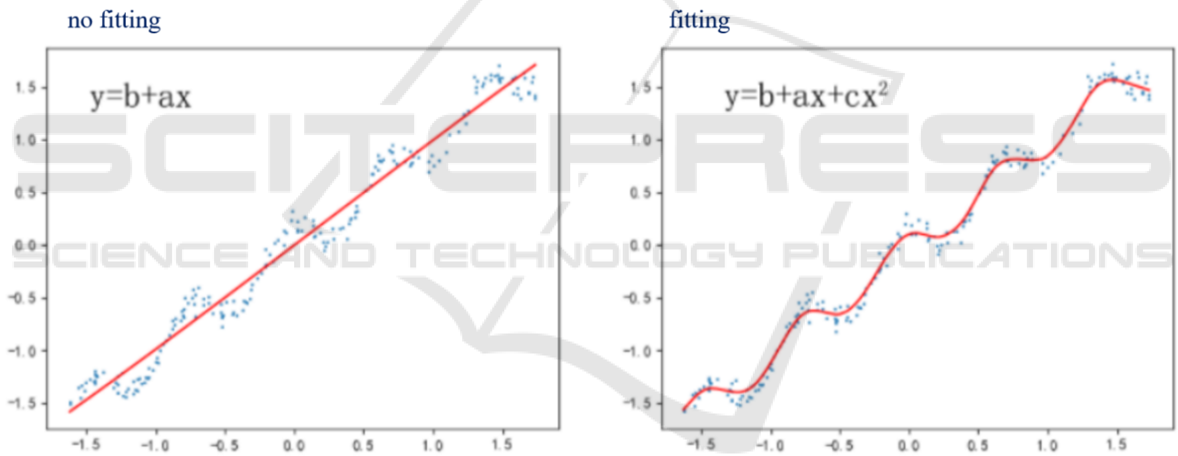

Figure5Fitting of Linear Regression.

6.3 Regularization

Regularize the data to scale a certain norm (L1 norm, L2 norm) of each sample to 1, that is, calculate its p-norm for each sample, and then for each element in the sample Divide by this norm such that the p-norm of each sample of the processed data is equal to 1. The equation is as (5)

$$\mathbf{X} = \frac{\mathbf{X}_{old}}{\|\mathbf{X}_{old}\|_p} \Rightarrow \|\mathbf{X}\|_p = 1 \tag{5}$$

Regularization processing data is mainly used in text classification and clustering, and has a great effect on the need to calculate the similarity between samples, such as (6) calculating the cosine similarity of sample X_1 and sample X_2

$$\cos(\underbrace{\mathbf{x}_1}_{old}, \underbrace{\mathbf{x}_2}_{old}) = \frac{\underbrace{\mathbf{x}_1}_{old} \cdot \underbrace{\mathbf{x}_2}_{old}}{\underbrace{\|\mathbf{x}_1\|_2^2}_{old} \underbrace{\|\mathbf{x}_2\|_2^2}_{old}} \xrightarrow{\text{L2 regularization processing}} \cos(\mathbf{x}_1, \mathbf{x}_2) = \mathbf{x}_1 \cdot \mathbf{x}_2 \tag{6}$$

7 EXAMPLES: DATA MODELING, MACHINE LEARNING METHODS

Machine learning is for modeling, so as to predict the future under the built model and guide decision-making. Here are some basic methods of machine learning:

7.1 Polynomial Features

Polynomial feature is a way to increase the dimension of data. In linear regression, when using simple X_1 and X_2 features to fit the curve, it cannot be completed - underfitting, but we can create new features such as X^2 to fit the data, a better model may be obtained, so we sometimes do a polynomial process on the features, that is, change the features X_1, X_2 into X_1^2, X_2^2, as shown in the following figure

7.2 Data Conversion

According to the central limit theorem in probability theory, when the sample size is infinite, the limit of many distributions is the normal distribution. Many random variables in reality are formed by the combined influence of a large number of independent random factors, and each of these factors plays a small role in the overall impact. Such random variables tend to approximate a normal distribution. (Objective background to the Central Limit Theorem).

From the point of view of entropy (used to measure the degree of confusion of information), the entropy of the normal distribution is the largest among all other distributions when the mean and variance of the data are known (the original data distribution type is unknown). According to the entropy standard, "maximum entropy" is approximately equivalent to "the closest uniform distribution under the same constraints", that is, it is more practical. It can be understood in this way that "entropy maximization" is to make the ideal closer to reality, let the special approach the general, and thus make the model more general. Note that the entropy of the normal distribution is actually determined by the variance, and the "maximum entropy of normal variables" is a conclusion in the context of a fixed variance. Different variances obviously lead to different normal distributions, and a normal distribution with higher entropy has more variance - and is also closer to "uniform" on the real axis.

Many machine learning models use normal distributions, such as linear regression machine learning models that require data features to be normally distributed. If the data features are not normally distributed, sometimes it is necessary to find a mathematical transformation to transform the features according to the normal distribution. Methods as below:

1) Logarithmic transformation: For data distributions that are highly skewed (eg, Skewness is more than 3 times its standard error), we can take logarithmic processing. Among them, it can be divided into natural logarithm and logarithm with base 10. Among them, logarithm with base 10 has the strongest correction force, but sometimes it is overcorrected and converts positive skewness into negative skewness. The equation is as (7)

$$X = \log(Xold) \tag{7}$$

2) Square root transformation: The square root transformation normalizes the samples that obey the Poisson distribution or the samples with mild skewness, or when the variance of each sample is positively correlated with the mean, the square root transformation can be used to make the variance homogeneous sex. The expression is as (8)

$$\Xi=\sqrt{X_{old}} \tag{8}$$

3) Reciprocal transformation: It is often used for data with large fluctuations at both ends of the distribution. The reciprocal transformation can reduce the influence of extreme values. The expression is as (9)

$$\Xi=1/\Xi_{o\lambda\delta} \tag{9}$$

4) Square root inverse rotation transformation: commonly used for data subject to binomial distribution or percentage. It is generally believed that the equal overall rate is small (such as <30%) or large (such as >70%), and the deviation from normality is more obvious. Through the inverse transformation of the square root of the sample rate, the data can be close to the normal distribution, and the variance can be achieved. homogeneity requirements. The expression is as (10)

$$\Xi=\alpha\sigma\iota\nu(\sqrt{X_{old}}\,) \tag{10}$$

5) BOX-COX transformation: usually used when the continuous response variable does not meet the normal distribution. In some cases (P value of characteristic distribution < 0.003) the above methods (square transformation, etc.) are difficult to achieve normalization, so Box-Cox transformation can be considered, but when P value > 0.003, using both methods Yes, the ordinary square transformation is preferred. (About the technical example, write it here first, and we will discuss it together when we have the opportunity)

8 CONCLUSIONS

Standardized data information is the basis for business decisions. Data information is first and foremost a perceptron of the environment. With the help of technologies such as artificial intelligence, they work side by side with corporate decision makers to make up for human shortcomings and help the entire organization run efficiently.

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