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A study of the impact of corporate market forecasting capability on the accuracy of strategic decision-making based on computational analysis of business data

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ABSTRACT

This study focuses on the computational analysis of business data, constructs a market prediction framework that integrates K-means clustering, feature standardization and improved N-BEATS model, and verifies its effect on the accuracy of enterprise strategic decision-making based on multi-source data. The study selects real-time transaction data and weather data from 800 merchants under Alibaba, extracts key features through standardization and correlation analysis, and improves the model by introducing topological features and multi-attention mechanism, which significantly optimizes the time series prediction accuracy and reduces the RMSE by 18.6%. The empirical analysis for tissue paper category shows that the forecast error rate of the time series decomposition method is only 0.58%, which is better than the traditional trend method and seasonal index method. Through the regression analysis of 328 business managers' questionnaires, data-driven analysis $\beta=0.617$, $p<0.001$ and innovative forecasting $\beta=0.594$, $p<0.001$ have a significant positive effect on strategic decision-making accuracy and consensus.

Keywords: market forecasting, strategic decision making, N-BEATS model, time series decomposition, data-driven

1. Introduction

Market forecasting is a crucial part of enterprise management, which can help enterprises to identify potential risks early, take effective preventive measures, reduce business risks, and safeguard the stable development of the enterprise through the analysis and prediction of market trends, consumer demand, competitors and other factors [1-2]. At the same time, market forecasting can also help enterprises find and grasp market opportunities in a timely manner, better formulate business

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strategies and sales plans, and improve operational efficiency and customer satisfaction [3-4]. In addition, market forecasting can help enterprises make more accurate production plans, optimize resource allocation and production efficiency, and improve market competitiveness and enterprise efficiency [5-6]. The ultimate purpose of market forecasting is to assist the scientific decision-making of enterprises, but it is not clear how the precision of enterprise strategic decision-making responds to market forecasting capabilities.

With the rapid development of information technology, data analysis plays an increasingly important role in enterprise market forecasting and decision-making. And the ultimate purpose of data analysis is to provide support for enterprise decision-making. Using data analysis can, enterprises can obtain rich information and knowledge to help them better understand and predict market demand, optimize operation management, and improve decision-making efficiency and accuracy [7-9]. In the process of prediction and decision-making, enterprises can use data visualization technology to display the analysis results in the form of charts, reports, etc., to help decision makers understand the data and analysis results more intuitively [10-11]. In addition, enterprises can also use prediction models and decision-making models to optimize and simulate decision-making and improve the efficiency and accuracy of decision-making, so that analytical behavior can not only help enterprises to make strategic decisions, but also assist the management to make daily decisions [12-13]. The key to data-oriented decision-making lies in transforming the analysis results into practical actions, and only by applying the analysis results to practical decision-making can the efficiency and precision of decision-making be truly improved. Therefore, starting from data, we explore the mechanism of the role of the level of enterprise market forecasting ability on the accuracy of strategic decision-making, and provide theoretical and scientific support for enterprise decision-making in a fuzzy environment.

This study takes historical sales data as the core, and constructs a complete market prediction framework through a systematic data acquisition and preprocessing process, combined with feature analysis and improved deep learning models. The specific methodological ideas are as follows, K-means clustering algorithm is used to clean and classify the heterogeneous data from multiple sources to eliminate noise interference. And key features are extracted through standardization methods and correlation analysis, and min-max standardization and z-score standardization are used to eliminate the difference in scale to ensure the comparability of continuous data such as GDP and CPI. Clarify the degree of influence of variables such as activity strength and commodity price on sales volume. On the basis of the traditional N-BEATS model, topological features extracted by the persistent homology method and the multi-head self-attention mechanism are introduced to optimize the model's ability to capture the trend and seasonality of the time series, so as to achieve high-precision sales forecasts. The enhancement of market forecasting capability directly contributes to the accuracy of corporate strategic decision-making. On the one hand, highly accurate forecast results can provide management with reliable demand trend analysis and optimize supply chain efficiency. On the other hand, the data-driven forecasting framework enhances the transparency and interpretability of the decision-making basis by quantifying the impact of key factors such as activity intensity and commodity prices, thus improving the team's consensus on strategic goals.

2. Data processing and characterization and predictive modeling

This study takes historical sales data as the core, and builds a high-precision market forecasting framework through a systematic data acquisition and preprocessing process combined with an improved deep learning model.

2.1. Data source acquisition and pre-processing

In the process of data source collection, it is necessary to obtain the historical sales data information of different kinds of products according to the different time periods, and analyze the sales of products in the consecutive time, and then according to the order situation of the products in this time, so that we can accurately get the sales tendency of the current products in the market, in order to make the enterprise to the market demand information of the products can be more accurate and reliable. At the same time, the enterprise can also be provided through the Excel system of all different models of the enterprise's historical sales data and orders of data, data source for the pre-processing operation. While processing the data source will need to use the method of K-means clustering to establish a model, K-means clustering belongs to a clustering algorithm, and clustering is based on a certain criterion, the existence of a similar part of the object under study for the division of the formation of a number of classes of a process, as far as possible, to maintain in a larger degree. For any matrix M of features, the clustering algorithm can partition it into K clusters, and there is no intersection between each cluster. Sample data in the same cluster can be grouped into one category, while different clusters are the result of categorizing different categories. The value of K is set and then the distance between the data points in the cluster is estimated and iterated in the cluster analysis method to arrive at the optimal center of clustering, which has an internal number of K, where the distance is defined in terms of the Euclidean distance.

According to the Euclidean distance definition graph in three-dimensional space, it can be understood that the length between a line in space is, the two endpoints in three-dimensional space about the Euclidean distance defined value, which is calculated by the formula: $|ED| = \sqrt{x^2 + y^2 + z^2}$. Therefore, the number of samples in each of the samples distributed in the cluster and the sum of the squares of the maximum lengths of the clustering area, is shown in Equation (1):

$$CSS = \sum_{b}^{p} \sum_{a}^{q} \left(x_a - \gamma_a \right)^2 \tag{1}$$

Where p indicates the number of samples present in the cluster; q indicates the number of features present in each sample; x indicates the data points of all the samples in the cluster; γ indicates the center of clustering within the cluster; a indicates the features that make up the data points; and b indicates the sign of each data sample. The overall sum of squares is the sum of all intra-cluster sums of squares in each data, and the smaller the value of the overall sum of squares, the smaller the difference that exists between the samples in each cluster is expressed on behalf of the clustering process as an indication of a better effect of the clustering process.

2.2. Characterization

After completing the acquisition and preprocessing of the data source, further in-depth analysis of the data features is required to extract the key influencing factors and provide reliable input features for subsequent model construction.

2.2.1. Continuous data processing. For continuous characteristic data, that is, numerical data, its data processing is very common. And there are a variety of methods for data processing, each of which is set by the outline standard is different, for example, in this paper, GDP, CPI and PPI data units can be set to ten million or one million, at this time, due to the unit problem caused by the size of the number of problems, the use of the original data at this time may have a very high impact on the prediction accuracy of the model. Therefore, standardization is needed. Standardization can be prescribed mathematical formula to convert the original data into a standard normal distribution, so that the converted data mean is 0, standard deviation is 1. Commonly used processing methods are min-max standardization and z-score standardization of the two methods, which are described below.

1) The method of min-max standardization. min-max standardization is a common data standardization method, mainly used to convert the data to the range of $[0,1]$, if there is a minimum and maximum data, after the conversion of the value of 0 or 1, in order to minimize the impact of the value of the original data interval, the formula is shown in (2):

$$x_{inout} = \frac{x_i - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

Where, $X_{\min}$ denotes the minimum value taken by the new retailer in the historical sales and $X_{\max}$ denotes the maximum value taken by the new retailer in the historical sales.
2) z-score normalization method. Z-score normalization is a common way of data processing. It subtracts the mean from the original data and divides it by the standard deviation, and while processing the data it also obtains a standard normal-tai distribution with a mean of 0 and a standard deviation of 1. This method is mainly used in cases where the maximum as well as minimum values are not available and the conversion formula is shown in (3):

$$y_i = \frac{x_i - \overline{x}}{s} \tag{3}$$

Through the analysis of the two numerical standardization processing methods, combined with the sample data, this paper chooses max-min standardization for numerical processing, which can effectively improve the model prediction accuracy.

2.2.2. Activity data correlation analysis. In this paper, in order to extract features related to sales volume from the sample data and use them as inputs to the prediction model for the existence of promotional activities, Spearman's rank correlation coefficient was used for the correlation analysis between the variables, which is calculated as shown in Equation (4).

$$\rho = \frac{\sum_{i=1}^{N}(x_i - \overline{x})(y_i - \overline{y})}{\left[\sum_{i=1}^{N}(x_i - \overline{x})^2 \sum_{i=1}^{N}(y_i - \overline{y})^2\right]^{\frac{1}{2}}} \tag{4}$$

A total of 16 features, including the number of sales, were analyzed for correlation in the sample data. It is obtained that the number of sales is related to activity strength, number of activities, activity time, store type, commodity price, evaluation index and GDP, CPI and PPI, of which the Spearman rank correlation coefficients of activity strength, number of activities, and activity time are 0.76, 0.89, and 0.63 respectively, which is a strong correlation; The Spearman rank correlation coefficients of commodity price and evaluation indexes are 0.54 and 0.52 respectively, which are medium correlation; the Spearman rank correlation coefficients of store type, GDP, CPI and PPI are 0.36, 0.23, 0.31 and 0.3 respectively, which are weak correlation. The above feature vectors are used as input vectors of the model, and the number of sales is used as the output vector to construct a sales prediction model for the presence of promotional activities in new retail enterprises.

2.3. Construction of an improved N-BEATS model

Based on the characterization results, this study further constructs an improved N-BEATS forecasting model, which enhances the accuracy and interpretability of time series forecasting by fusing topological features with multiple attention mechanisms.

In this paper, we propose to use the topological features extracted from the time series historical sales data using the persistent homology method as the supplementary information of the sales forecasting model. In the above work, we have completed the extraction of the topological structure from the sales data and transformed it into the form of vectors, and we have introduced the multi-head self-attention mechanism so that the forecasting model can pay attention to this part of the topological features in the training process, which is expected to achieve the result of improving the performance of forecasting. Results. This section describes how to construct the improved fused multi-head attention and N-BEATS model.

The N-BEATS model is divided into three panels, the first of which has the length of the input history lookback window. We set the length of the input window (the window length of the backtracking window) to be a multiple of the length of the prediction future window H. In the experiments of this paper the window length of the backtracking window is between 2H-7H. The outputs of the current plate are the prediction result for the current window time point and the prediction result for the future prediction window time point.

The second plate consists of two parts, the first part is a fully connected network that generates forward and backward prediction coefficients and contains the relu activation function.

The other part of the second panel consists of forward g_e^f and backward g_e^b. This part accepts forward θ_e^f and backward θ_e^b predictions to generate forward prediction results and backward prediction results. The task of this part of the architecture is to continuously optimize the accuracy of the partial backward prediction results by appropriately mixing the basis vectors provided by g_e^f. Additionally, the module predicts the backward expansion coefficients θ_e^b used by g_c in order to generate the estimates for x_e, which helps the downstream blocks by removing the input components that do not contribute to the prediction.

The third panel of this model is a hierarchical two-residual topology.This architecture has two residual branches, one running on the inverse prediction at each level, and the other running on the prediction branch at each level.In the special case of the first block, its input is the model-level input x. For all the other blocks, the inverse residual branch x can be thought of as performing a sequential analysis of the input signals. The previous block removes the approximated part of the signal $\hat{x}_{e-1}$, making the prediction of the downstream blocks easier. This structure also facilitates more fluid gradient backpropagation. More importantly, each block outputs a partial prediction $\hat{y}_e$ that is aggregated first at the stack level and then at the whole network level, providing a hierarchical decomposition. The final prediction is the sum of all partial predictions. This makes the network more transparent to the gradient flow when the stack is allowed to have arbitrary g_e^f and g_e^b for each layer. In the special case where g_e^f and g_e^b are shared on the heap, this is crucial to achieve interpretability by aggregating meaningful partial predictions.An improved example of the N-BEATS model is shown in Figure 1.

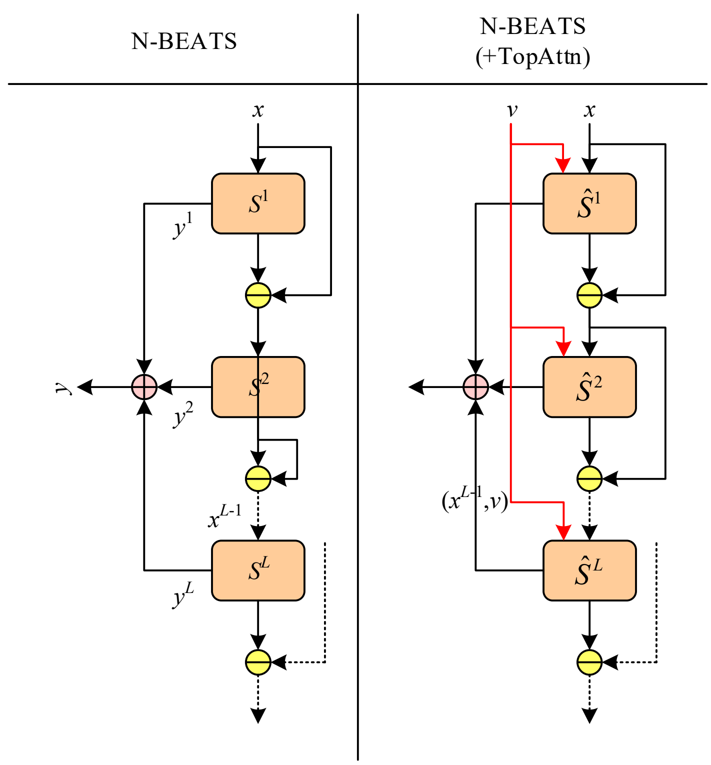

Fig. 1. Model improvement comparison diagram

Based on the choice of g_e^f and g_e^b, N-BEATS has two architectural configurations, one for generalized deep learning, and the other for adding inductive bias to make it interpretable, designing trending and seasonal decompositions into the model to make the stack outputs easier to interpret.

A typical feature of a trending model is that most of the time it is a monotonic function or at least a slowly varying one, and to simulate this behavior Constraints $g_{s,\ell}^b$ and $g_{s,\ell}^f$, as a polynomial of p, a function that varies slowly over the prediction window:

$$\hat{y}_{s,\ell} = \sum_{i=0}^{p} \theta_{s,\ell,i}^f t^i \tag{5}$$

Here the time vector $T = [0,1,2,\ldots,H-2,H-1]^T / H$ is defined on a discrete grid from 0 to $(H-1)/H$, predicting H steps. Alternatively, the trend prediction in matrix form is:

$$\hat{y}_{s,\ell}^r = T\theta_{s,\ell}^f \tag{6}$$

where $\theta_{s,\ell}^f$ is the polynomial coefficients predicted by the ℓ-layer FC network of the stack s; and $T = \left[1,t,\ldots,t^p\right]$ is the power matrix of t. If p is low, it will model the trend by $\hat{y}_{s,\ell}^r$.

The other is a seasonal model, which is typically characterized by a regular, periodic fluctuation. Therefore, to model seasonality, constraints $g_{s,\ell}^b$ and $g_{s,\ell}^f$ are made to belong to the class of periodic functions, i.e., $y_t = y_t - \Delta$, where Δ is a seasonal cycle.

$$g_{s,\ell}^b = \sum_{i=0}^{p} \theta_{s,\ell,i}^b y_t \tag{7}$$

$$g_{s,\ell}^f = \sum_{i=0}^{p} \theta_{s,\ell,i}^f y_t \tag{8}$$

The overall interpretable architecture consists of two stacks: the trend stack followed by the seasonality stack. The result of combining the dual residual stacks of the prediction and backpropagation principles is firstly removed from input window x before the seasonality stack is entered in input window x, and secondly the partial predictions of the trend and seasonality are available as separate interpretable outputs. Structurally, each stack consists of and connects several blocks, each sharing their respective unlearnable $g_{s,\ell}^b$ and $g_{s,\ell}^f$. The number of blocks for both trend and seasonality is three. We find that sharing all weights between blocks in a stack in addition to sharing $g_{s,\ell}^b$ and $g_{s,\ell}^f$ yields better verification performance.

The general N-BEATS model is assembled from L double residual blocks. When $1 \le l \le L$, each block consists of a nonlinear mapping.

$$S^t : H^T \to H^h \tag{9}$$

where h denotes the number of internal dimensions and the subsequent two mappings produce the dual output of the l st block as $x^I = x^{l-1} - U^t\left(S^I\left(x^{I-1}\right)\right), y^I = V^t\left(S^t\left(x^{I-1}\right)\right)$, where $U^t \in H^{T\times h}$, $V' \in H^{p\times h}$, and $x^0 = x$. When x' generates the following connections of computational blocks, y' the final model predictions are computed by componentwise summation $y \in H^p$, $y = y^1 + \cdots + y^L$.

Importantly, x serves as an interface for integrating additional information in this formulation. In this paper, the input signals to each block are enriched by the output of the topological attention mechanism, so that $\hat{S}^t : H^{2T} \to H^h$.

$$x_{TopAttn}^t = \left(x^t, v\right), v = TopAttn\left(B_1,\ldots,B_W\right) \tag{10}$$

In this paper, we propose the model in which the time series signal x is fed into N-BEATS in its original form, and its topological attention representation v is provided as a complementary signal to each block.

3. Empirical characterization

After completing data preprocessing and model construction, this chapter will focus on the integration and feature engineering of multi-source data to provide basic support for subsequent empirical analysis.

3.1. Data overview

This study centers on the transaction data of 800 merchants provided by Alibaba's Ant Gold Service from July 25, 2024 to October 17, 2024, covering key business indicators such as online and offline transaction records, user consumption behaviors, sales trends, etc., and combines it with the weather data of 122 provinces and cities in China obtained by Python crawler during the same period (including temperature, precipitation, wind speed, and other At the same time, we combine the weather data (including temperature, precipitation, wind speed and other meteorological indicators) obtained from 122 provinces and cities in China through Python crawler during the same period of time to build a multi-dimensional data set. The “customer traffic” in the transaction data is defined as “the number of users using Alipay to complete consumption per unit of time”, while the weather data is used to analyze the potential impact of environmental factors on consumption behavior.

By integrating commercial data and external environmental data, the study builds a market forecasting model based on time series analysis and machine learning, aiming to explore the effect of enterprise data-driven forecasting capabilities on the accuracy of strategic decisions (e.g. inventory management, marketing resource allocation, service optimization, etc.). The spatial and temporal breadth and diversity of data coverage provide an empirical basis for verifying the robustness and practical application value of the prediction model, and also provide a key support for quantifying the contribution of data computational analysis in strategic decision optimization.

3.2. Feature engineering

3.2.1. Feature extraction. Feature extraction is an important step after data cleaning, which provides a large enough feature set for machine learning for subsequent feature selection and model training. For the collected data source basic information is not enough to provide a large enough feature set to reflect the regularity of the traffic, so the main work of this subsection lies in discovering the hidden feature information in the traffic data, constructing the derived features, and improving the feature set. Figure 2 shows the time series graphs of mall restaurant merchants and snack street fast food merchants.

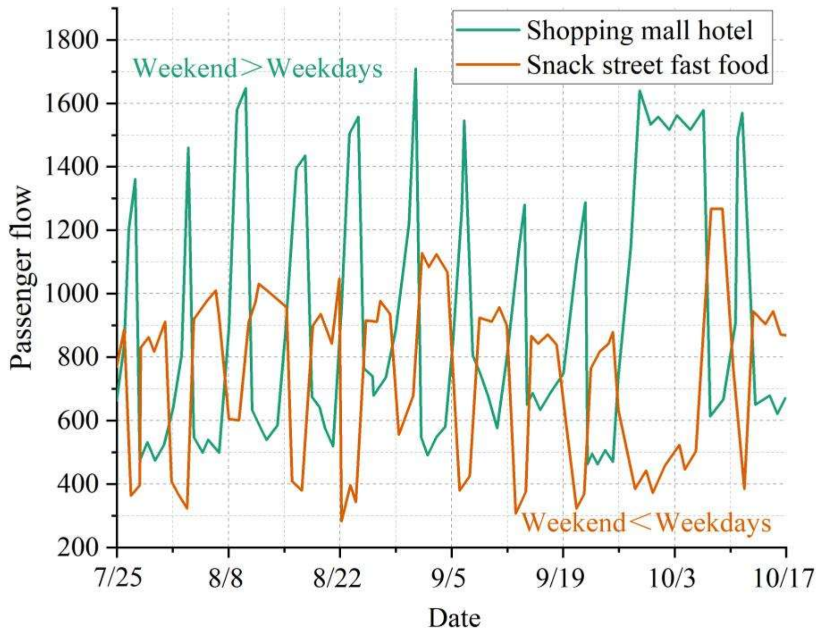

Fig. 2. Different merchant time series

Figure 2 demonstrates the time-series comparison of the patronage of shopping mall restaurant merchants and snack street fast food merchants in a specific time period. The following characteristics can be observed through the time-series curves. The holiday effect is significant: both types of merchants show significant fluctuations in customer traffic during holidays (e.g., weekends and National Day holidays). This effect may be positive or negative. The holiday traffic of shopping malls and restaurants is significantly higher than that of weekdays, and the peak value can be up to 1.5 times of that of weekdays. The traffic flow of fast food in Snack Street increased on holidays, but the increase was more moderate (about 20%), presumably because fast food consumption is more dependent on daily commuting demand, and the holiday dispersion effect is weaker.

According to the guess of Figure 2, the average value of the traffic rate of "Week X" of each week in the historical period of the training set is calculated, and the few extreme values of the average flow rate of less than 200 are removed, and the historical "Week X Average" of 200-2000 customer flow of 800 stores is represented by using a scatter plot, and the average value of Week X is shown in Figure 3.

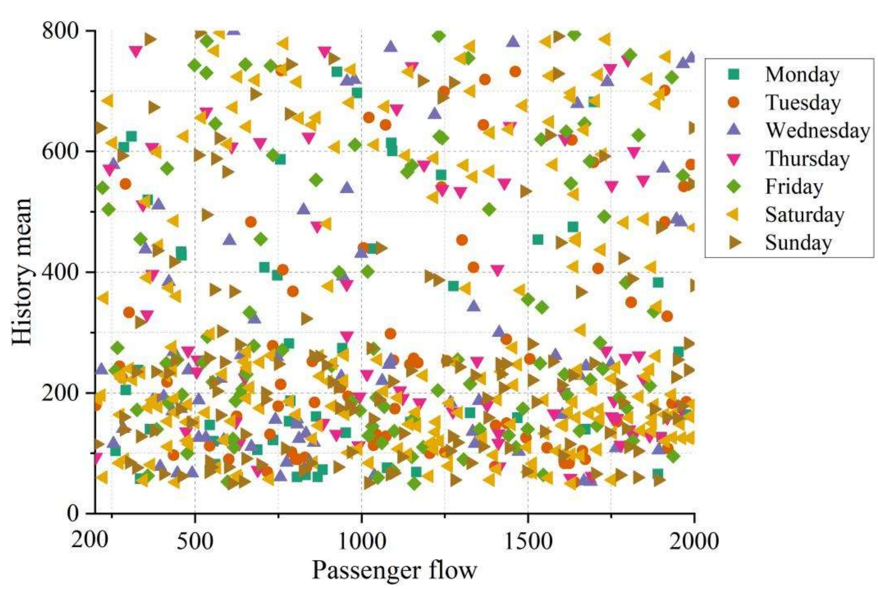

Fig. 3. Weekly X mean

Figure 3 shows the historical average traffic distribution of the 800 stores by day of the week (week X) through a scatterplot, with the following main features, the highest average value of traffic (about 1,500-2,000 visits) on weekends (Saturdays and Sundays), especially on Sundays, which can reach the peak in some stores. Weekdays: Traffic flow is relatively stable from Monday to Thursday (average value of 800-1200 person-times), and shows an upward trend on Friday (average value of 1300-1600 person-times), which may be related to the pre-consumption warm-up before the weekend. Some stores saw traffic far exceeding the average value on Saturday (the upper limit of the dispersion reached 2,500 visits). Tuesday has the smallest dispersion (standard deviation of about 150), suggesting relatively stable consumer demand during weekdays.

3.2.2. Feature selection. After completing data preprocessing it is necessary to select meaningful features to input into the model for learning and training. And feature selection means selecting the subset of features that makes a certain evaluation criterion optimal, so that the classification or regression model constructed on that subset achieves an accuracy that is similar to or even better than the prediction results obtained using the original feature set.

In the previous feature extraction, we introduced many new variables and obtained a feature set about the enterprise market, but in the real task, we often encounter the problem of dimensionality disaster due to too many attributes, which also increases the difficulty of the learning task. If we can select the optimal features from the original feature set, so that the subsequent training only needs to construct the model on a portion of the features, the problem of dimensionality disaster can be mitigated. For the introduction of new features other than the original feature set, feature engineering needs to verify that its addition to the feature set really improves the accuracy of prediction, rather than useless features that only increase the computational complexity.

In order to avoid the redundancy of features caused by the strong linear correlation between variables, the correlation between the two features was calculated by using the Pearson correlation coefficient test, and the characteristics were analyzed according to the correlation of the activity data in Chapter 2, including "week X", "whether it is a weekend", "maximum temperature", "minimum temperature", "number of activities", "activity intensity", "effective time", "sales volume", "commodity price", "evaluation index", "gross domestic product", "consumer price index", "store type", "customer flow" and other related characteristicsto obtain a correlation coefficient plot as shown in Figure 4.

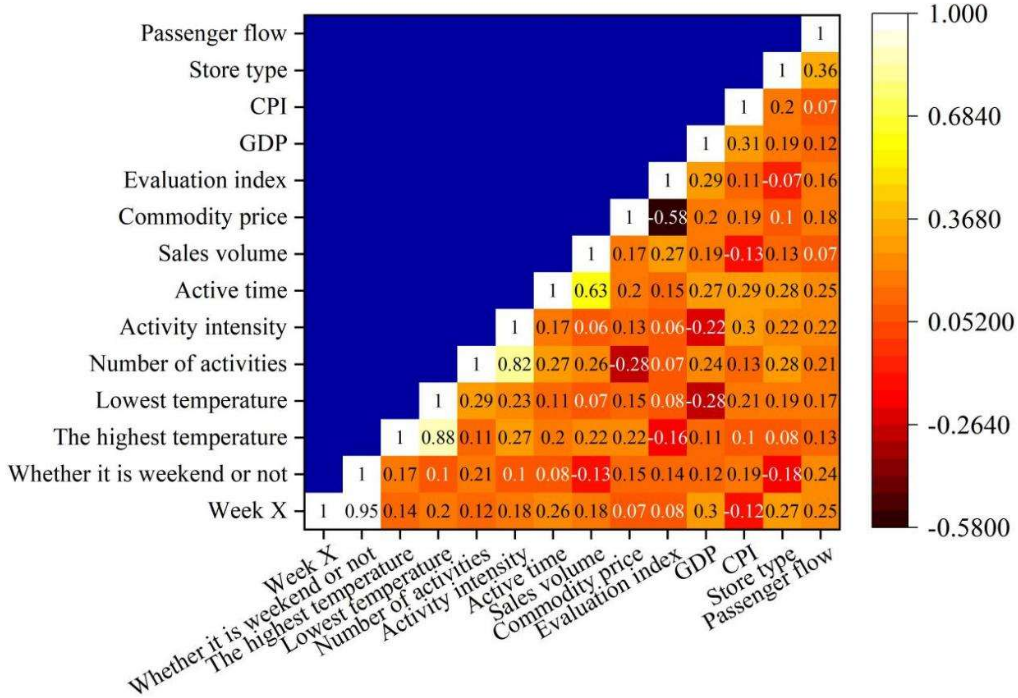

Fig. 4. Variable correlation

From the correlation of the variables in the enterprise market forecasting model in Figure 4, it can be seen that the correlation between "week X" and "whether it is a weekend" is 0.95, showing a strong positive correlation, the correlation coefficient between "maximum temperature" and "minimum temperature" is 0.88, and the correlation coefficient between "number of activities" and "activity intensity" is 0.82, also showing a strong positive correlation. The correlation coefficients of "activity time" and "sales volume", "commodity price" and "evaluation index" were 0.63 and -0.58, respectively, showing a moderate positive correlation and a medium negative correlation. The correlation between "GDP" and "CPI", as well as between "store type" and "customer flow" was 0.31 and 0.36, respectively, showing a weak positive correlation. There was no obvious relationship between the other variables.

4. Research and establishment of demand forecasting model for tissue paper

To further validate the practical application value of the forecasting model, this chapter selects the tissue paper category for a case study of demand forecasting to explore the advantages of the decomposition method in specific scenarios.

4.1. Determination of factors in the model

Taking a key well-known tissue brand as an example, its sales data for the calendar year from January 2022 to December 2024 is shown in Table 1, based on which the sales data can be calculated to obtain the required long-term trend T and seasonal index S. Table 1 shows the tissue brand's sales data for the calendar year and the decomposition of the relevant factors.

Table 1. The annual sales data and related factors of a paper towel brand

Period	Sales volume (10,000cases)	Moving average	Seasonal index S	Long-term trend T
2022.1	127.39	-	-	140.143
2022.2	127.68	-	-	140.388
2022.3	128.38	-	-	140.503

2022.4	128.86	-	-	140.579
2022.5	129.27	-	-	140.775
2022.6	129.38	-	-	140.996
2022.7	133.44	-	-	141.202
2022.8	135.55	-	-	141.207
2022.9	139.58	-	-	141.359
2022.10	129.62	-	-	141.406
2022.11	130.34	-	-	141.436
2022.12	130.54	-	-	141.475
2023.1	131.04	130.84	100.15%	141.475
2023.2	131.51	131.14	100.28%	141.718
2023.3	132.52	131.46	100.81%	141.905
2023.4	131.97	131.80	100.13%	141.998
2023.5	132.35	132.06	100.22%	142.059
2023.6	133.66	132.32	101.01%	142.346
2023.7	139.12	132.68	104.85%	142.683
2023.8	143.66	133.15	107.89%	142.713
2023.9	144.90	133.83	108.27%	142.821
2023.10	132.14	134.27	98.41%	142.902
2023.11	133.66	134.48	99.39%	143.158
2023.12	134.08	134.76	99.50%	143.557
2024.1	135.49	135.05	100.33%	143.632
2024.2	137.33	135.42	101.41%	143.692
2024.3	137.83	135.91	101.41%	143.716
2024.4	137.90	136.35	101.14%	144.056
2024.5	137.91	136.84	100.78%	144.168
2024.6	138.16	137.31	100.62%	144.194
2024.7	144.44	137.68	104.91%	144.429
2024.8	146.49	138.13	106.05%	144.439
2024.9	147.53	138.36	106.63%	144.48
2024.10	142.74	138.58	103.00%	144.581
2024.11	143.51	139.46	102.90%	144.742
2024.12	143.39	140.28	102.22%	144.979

4.2. Time series decomposition and model certification

4.2.1. Moving averages. The sales volume of tissue paper fluctuates and changes in a yearly cycle (12 periods of data), and the moving average of each period is calculated, and the results of the calculation are shown in the table.

$$M_i(12)=\frac{X_i+X_{i-1}+\ldots+X_{i-11}}{12}=\frac{\sum_{i=0}^{11}X_{i-1}}{12}(t>12) \tag{11}$$

The calculated results are not seasonal, and the stochastic factor has been offset to a certain extent by the positive and negative fluctuations after averaging the data over 12 periods, i.e., it can be assumed that the stochastic fluctuations have no effect on the model. The moving average here reflects a long-term trend.

4.2.2. Seasonal analysis. Here the seasonal index S is a ratio, so we divide the observed value by the moving average to get the seasonal index, and the calculation results are shown in Table 2.We need to adjust the index after we get the average seasonal index of each month, and the corrected seasonal index is shown in Table 2.By asking the monthly average seasonal index of the calendar year, the prediction model also abates the random fluctuation to a certain extent, and finally corrects the value of the seasonal index makes the data more effective and accurate.

Table 2. Seasonal index of tissue sales

Month	2022	2023	2024	Mean seasonal index	Revised seasonal index
1	-	100.15%	100.33%	100.24%	98.17%
2	-	100.28%	101.41%	100.85%	98.35%
3	-	100.81%	101.41%	101.11%	99.43%
4	-	100.13%	101.14%	100.64%	98.20%
5	-	100.22%	100.78%	100.50%	98.18%
6	-	101.01%	100.62%	100.82%	98.33%
7	-	104.85%	104.91%	104.88%	102.34%
8	-	107.89%	106.05%	106.97%	104.63%
9	-	108.27%	106.63%	107.45%	105.08%
10	-	98.41%	103.00%	100.71%	98.31%
11	-	99.39%	102.90%	101.15%	99.24%
12	-	99.50%	102.22%	100.86%	98.37%

4.2.3. Long-term trends. Observing the time series of tissue paper sales, it can be seen that the model not only has seasonal fluctuations, but in the long term, there is also a trend of increasing over the years, which is related to the increase in the level of economic development and the growth of population, which must be taken into account when the forecasting model is built. This long-term linear growth trend can be used to find the best fitting parameters by the least squares method. Set $y_i = a + bx_i, i = 1, 2, \ldots 36$ (here a total of 36 issues of paper towel sales data), here we use the method of least squares to find the parameters of the linear trend formula, the core idea of the method of least squares is to use a straight line to approximate the past period of historical data, expressed in mathematical language is: so that the object model of the time series of the actual observed value of the time series of y_i and the linear trend model of the predicted value of each of the $\overline{y_i}$ minimum sum of the squares of the deviations, that is, the value of $\sum\left(y_i, \overline{y_i}\right)^2$ is the smallest.

The least squares method is used to determine the values of the parameters, the specific derivation process is omitted here, and the formulas for parameters a and b are:

$$\begin{aligned} \hat{b} &= \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \\ \hat{a} &= \bar{y} - \hat{b}\bar{x} \end{aligned} \tag{12}$$

Find $\hat{a} = 143.283, \hat{b} = 0.026$, so the long-term trend $T_i = 143.283 + 0.026t$ (t is the period value).

4.3. *Comparative analysis of forecast results*

According to the 36-period data of the sales of a key well-known paper towel brand in Table 1, we predicted the value obtained by the long-term trend method established according to formula (11), and the value obtained by the seasonal index in Table 2 using the latest data in the 36th period of the data prediction, respectively, we predicted to obtain the predicted data for the future periods, and finally we compared these data with the actual results of the sales of the paper towel market, paper towel sales volume prediction and actual results Comparative analysis is shown in Table 3.

Table 3. A comparative analysis of tissue sales forecast and actual results

	2025.1	2025.2	2025.3	Average error rate
Actual value	146.37	145.26	146.39	-
Trend forecasting	143.74	146.52	144.62	-
Absolute error	2.63	1.26	1.77	-
Error rate	1.80%	0.87%	1.21%	1.29%
Forecast by seasonal index method	144.38	144.81	145.10	-
Absolute error	1.99	0.45	1.29	-
Error rate	1.36%	0.31%	0.88%	0.85%
Decomposition prediction	145.382	144.293	145.837	-
Absolute error	0.988	0.967	0.553	-
Error rate	0.68%	0.67%	0.38%	0.58%

From Table 3, we can see that the error analysis of the forecast value and actual sales volume of the three forecasting models of trend method, seasonal index method and decomposition method, we can see that the time series decomposition method model established by the multiplication model performs the best with an average error rate of about 0.58% and less fluctuation, followed by the seasonal index method, and the trend method performs the worst with about 1.29% and more fluctuation. For the tissue industry, the decomposition method forecasting model can fully meet its forecasting needs, so as to guide industrial companies to produce tissue and commercial companies to sell tissue according to the forecast value.

5. An empirical study of the effect of firms' market forecasting capabilities on strategic decision-making

Based on the results of the model validation, this chapter quantifies the mechanism of the direct influence of the firm's market forecasting ability on the effectiveness of strategic decision-making through questionnaire and regression analysis.

5.1. Sample Selection and Data Collection

This study adopts mixed sampling method to obtain samples, focusing on middle and senior managers of enterprises nationwide, with emphasis on covering industries that rely on market forecasts, such as manufacturing, finance and information technology. Data were collected through on-site distribution, such as MBA training courses and corporate internship channels, combined with online questionnaires, and a total of 328 valid questionnaires were recovered, which meets the sample size requirements for SEM analysis of structural equation modeling. In order to control the homoscedastic bias CMV, the time-administration method was used to fill out the questionnaire module and anonymization at 1-week intervals.

The questionnaire was designed using a Likert 5-level scale, covering the three core variables of enterprise market forecasting ability, decision-making process support, and strategic decision-making effect, and setting up inverse questions and logical check items to identify invalid data. In the data cleaning stage, questionnaires with missing values >20%, logical contradictions and mechanical completion were excluded, and 295 valid samples were finally retained. The reliability test shows that the Cronbach's α coefficients of each variable are higher than 0.7, indicating that the data have high internal consistency and structural validity.

5.2. *Reliability analysis*

5.2.1. Variable Definition and Pretest Analysis. This paper includes three main variables: enterprise market forecasting capability, decision-making process support, and strategic decision-making effectiveness. Enterprise market forecasting ability includes data-driven analyzing ability and innovative forecasting ability; decision-making process support includes data input quality and decision execution efficiency; and strategic decision-making effect includes decision precision and decision consensus. In order to make the formal scale have good reliability, this paper firstly conducted a pre-test. The internal consistency reliability of the scales was examined by manipulating Cronbach's coefficients based on the pre-study data. The results show that the reliabilities of these indicators are above, which shows that there is a good internal consistency. The pretest scale reliability analysis is shown in Table 4.

Table 4. Reliability analysis of pretest scale

Variable		All dimensions Cronbach's α	Variable Cronbach's α
Enterprise market forecasting ability	Data-driven analytics	0.861	0.857
	Innovative forecasting ability	0.858	
Decision process support	Data entry quality	0.922	0.925
	Decision execution efficiency	0.825	
Effect of strategic decision	Decision accuracy	0.811	0.824
	Decision consensus degree	0.916	

5.2.2. Confidence analysis of the effectiveness of strategic decision-making. The article measures the effect of strategic decision-making through two dimensions, decision precision ACC and decision consensus CNS, and describes the measurement results of the decision precision ACC dimension in terms of the following five question items, ACC1: The market data on which the decisions are based have been rigorously verified; ACC2: The decision results are highly matched with the actual market demand; ACC3: The decision's prediction of the future trend is reliable; ACC4: No major deviation occurs during decision implementation; ACC5: Decision adjustments can respond to changes in the external environment in a timely manner. The items of the CNS of decision consensus are: CNS1: team members have a high degree of understanding of the decision goal; CNS2: different opinions are fully discussed and integrated in the decision-making process; CNS3: the final decision is broadly supported by team members; CNS4: the team collaborates smoothly and without conflict in the process of decision implementation; and CNS5: changes in the existing environment will not weaken the team's agreement on the decision. The final results of the confidence analysis of the effectiveness of strategic decision-making are shown in Table 5.

Table 5. Reliability analysis results of strategic decision effectiveness

Dimensionality	Item	CITC coefficient	Effect of strategic decision Cronbach's α	Strategic decision effect total table Cronbach's α
Decision accuracy ACC	ACC1: The market data on which the decision is based is rigorously verified	0.737	0.873	0.916
	ACC2: The result of the decision is highly matched to the	0.788		

	actual market demand			
	ACC3: Decisions have reliability in predicting future trends	0.665		
	ACC4: There was no major deviation in the implementation of the decision	0.749		
	ACC5: Decision adjustment can respond to changes in external environment in time	0.664		
Decision consensus degree CNS	CNS1: Team members have a high degree of agreement on the decision goals	0.730	0.901	
	CNS2: Different opinions are fully discussed and integrated in the decision-making process	0.714		
	CNS3: The final decision was widely supported by the team members	0.657		
	CNS4: Smooth and conflict-free teamwork during decision execution	0.715		
	CNS5: Changes in the existing environment do not weaken the team's agreement with the decision	0.704		

From the above table, it can be seen that the CITC coefficients of all the items of strategic decision-making effect are greater than 0.35 and the Cronbach's α coefficient of the total scale is 0.916, and the Cronbach's α coefficients of the two factors of decision-making accuracy ACC and decision-making consensus CNS are 0.873 and 0.901 respectively, which are both greater than 0.7. Therefore, it can be considered that the scale of the enterprise's market forecasting and strategic decision-making effect constructed by this paper has good reliability. The scale of strategic decision-making effect has good reliability.

5.3. *Regression analysis of the effect of firms' market forecasts on the effectiveness of strategic decision-making*

In order to better test the impact of corporate market forecasting on the effectiveness of strategic decision-making, this paper conducted a multiple regression analysis of the relationship between data-driven analysis and innovative forecasting and the dimensions of strategic decision-making effectiveness, respectively. The specific analysis results are shown in Table 6.

Table 6. Regression analysis results of market forecast and strategic decision

		ACC	CNS	R2	Adjusted R2	Sig.	F
Data-driven analysis	β	0.617	0.663	0.582	0.580	0.000	283.94
	Sig.	0.000	0.000				
	R2	0.437	0.418				
	Adjusted	0.435	0.415				

	R2						
	F	137.28	109.21				
Innovative forecasting	β	0.594	0.567	0.497	0.494	0.000	217.29
	Sig.	0.000	0.000				
	R2	0.408	0.392				
	Adjusted R2	0.406	0.391				
	F	97.26	83.09				

As can be seen from Table 6, data-driven analysis has a significant positive effect on both decision precision and decision consensus, with regression coefficients of 0.617 and 0.663, respectively, corresponding to a probability of significance of 0.000, which is significant at the level of significance. Meanwhile, innovativeness prediction also has a significant positive effect on both decision precision and decision consensus, with regression coefficients of 0.594 and 0.567, respectively, corresponding to a probability of significance of 0.000, which is significant at the 0.01 level. The above effects.

6. Conclusion

This study systematically verifies the role of corporate market forecasting capability in enhancing the accuracy of strategic decision-making by constructing a forecasting framework that integrates multi-source data with improved N-BEATS model.

1) Characteristic correlation analysis shows that variables such as activity intensity Spearman coefficient 0.89 and commodity price 0.54 have a significant effect on sales volume.

2) Long-term trend analysis shows that the average annual growth rate of sales volume is 1.5%, and the seasonal index correction indicates that July-September is the peak sales season, with a seasonal index of 104.88% to 107.45%. Compared with the trend method (average error rate of 1.29%) and the seasonal index method of 0.85%, the forecast error rate of the decomposition method is only 0.58%, and the volatility is significantly reduced, which proves the superiority of this method in demand forecasting.

3) Regression analysis showed that data-driven analysis $\beta=0.617$, $p<0.001$ and innovative prediction $\beta=0.594$, $p<0.001$ had a significant positive effect on both strategic decision precision ACC and consensus CNS. Among them, the CITC=0.737 of "strict data verification" and the CITC=0.664 of "response speed of decision adjustment" were the highest in the dimension of decision-making accuracy, and the consensus dimension was reflected in the CITC=0.715 of "smooth team collaboration" and CITC=0.730 of "goal consistency". The explanatory power of the model $R^2=0.582\sim0.497$ further verifies the core role of prediction ability in strategic decision-making optimization.

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