

METHOD AND SYSTEM FOR CONSTRUCTING ANOMALY DETECTION MODEL, AND ANALYTIC HIERARCHY PROCESS METHOD AND SYSTEM

The present application claims priority to Chinese Patent Application No. 202311212872.X, filed on September 19, 2023, and entitled "METHOD AND SYSTEM FOR CONSTRUCTING ANOMALY DETECTION MODEL, AND ANALYTIC HIERARCHY PROCESS METHOD AND SYSTEM", the entire disclosure of which is incorporated herein by reference.

Technical Field

The present application relates to a method and system for constructing a time series anomaly detection model, an analytic hierarchy process method and system, and a computer-readable storage medium for implementing the above methods.

Background

The analytic hierarchy process method, as a comprehensive evaluation method for system analysis and decision-making, is a multi-factor decision-making method proposed on the basis of fully studying the human thinking process, capable of reasonably realizing quantitative processing of qualitative problems.

The analytic hierarchy process method transforms a complex decision-making process into comparisons of the importance between several factors in pairs by constructing a hierarchical structure, thereby converting qualitative judgments that are difficult to quantify into operable comparisons of importance. Specifically, the analytic hierarchy process method first obtains weights of a plurality of factors by solving a matrix, and then multiplies the weights of the plurality of factors by corresponding factor values, thereby using the product of the plurality of weights and the factor values as a basis for decision-making. For example, the analytic hierarchy process method may be applied to aspects, such as enterprise capability assessment, merchant value assessment, customer demand rating, supplier selection, manufacturing systems, and strategic decision-making in the financial field. However, in the current analytic hierarchy process method, the process of solving the weights of factors relies only on comparisons of importance between several factors, while ignoring that the factor value itself may present an anomaly with time variation. This results in allocating a larger weight to an anomalous factor during the analytic hierarchy process, thereby causing a relatively large error in an analysis result of the analytic hierarchy process method. For example, when using the analytic hierarchy process method to perform merchant value assessment, turnover, as one of several factors, may have time series anomalous values over time. In this case, if only the comparisons of importance between several factors

are relied on to allocate a larger weight to the turnover as one of the factors, a relatively large error would be introduced into an analysis result of the analytic hierarchy process method, thereby causing an output analytic hierarchy result, i.e., the merchant value, to lose its reference value.

Summary

To solve or at least mitigate one or more of the above problems, the following technical solutions are provided.

According to a first aspect of the present application, there is provided a method for constructing a time series anomaly detection model, the method comprising the following steps: acquiring a time series data set comprising time series data of one or more factors; generating a training data set based on the time series data set; and training a neural network model using at least the training data set to construct the time series anomaly detection model, wherein a layer bias parameter in the neural network model is modulated based on entropy information determined by the training data set.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application, acquiring the time series data set comprises: taking data generated by each factor within each time period of a plurality of continuous time periods as the time series data of the factor; and acquiring the time series data set based on the time series data of each of the one or more factors.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application or any one of the above embodiments, generating the training data set based on the time series data set comprises: converting the time series data set into a matrix form to generate the training data set.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application or any one of the above embodiments, converting the time series data set into a matrix form to generate the training data set comprises: taking the time series data of each factor in the time series data set as a row of elements or a column of elements in a matrix to generate the training data set, wherein each element in the row of elements or the column of elements corresponds to the data generated by the factor within each time period.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application or any one of the above embodiments, the method further comprises: determining whether an anomaly exists in the time series data based on a continuous change trend of the time series data of each factor; determining a time series anomaly label corresponding to the time series data of each factor according to a determination result to obtain a time series anomaly label set corresponding to the time series data set; and updating the trained neural network model

using a loss function based on the time series anomaly label set and an output of the trained neural network model, to construct the time series anomaly detection model.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application or any one of the above embodiments, the neural network model comprises: a first layer constructed using a first activation function and a first layer bias parameter modulated based on the entropy information determined by the training data set; a second layer constructed using a second activation function and a second layer bias parameter modulated based on the entropy information determined by the training data set; and an output layer constructed using a softmax function.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application or any one of the above embodiments, the neural network model is further constructed by: determining an input of the first activation function based on a first layer weight and the training data set; determining an input of the second activation function based on a second layer weight and an output of the first layer; and determining an input of the softmax function based on an output of the second layer.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application or any one of the above embodiments, the layer bias parameter in the neural network model is modulated by: modulating the layer bias parameter through multiplying the entropy information determined by the training data set by the layer bias parameter in the neural network model.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application or any one of the above embodiments, the entropy information is determined by the following steps: for each row of elements or each column of elements in the training data set, determining a probability factor of each element in the row of elements or the column of elements relative to the elements in the row of elements or the column of elements; determining an information amount of the elements in the row or the column using the probability factor; and taking the information amount of the elements in the row or the column as the entropy information of the time series data of the factor corresponding to the elements in the row or the column.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application or any one of the above embodiments, the probability factor is determined by the following step: taking a ratio of each element in the row or the column to a sum of the elements in the row or the column as the probability factor.

According to the method for constructing a time series anomaly detection model described in an embodiment of the present application or any one of the above embodiments, the time series anomaly detection model is used at least for correcting a

weight of the one or more factors according to the time series data of the one or more factors in an analytic hierarchy process method.

According to a second aspect of the present application, there is provided a system for constructing a time series anomaly detection model, the system comprising: a memory; a processor coupled to the memory; and a computer program stored on the memory and running on the processor, wherein running of the computer program causes the following operations: acquiring a time series data set comprising time series data of one or more factors; generating a training data set based on the time series data set; and training a neural network model using at least the training data set to construct the time series anomaly detection model, wherein a layer bias parameter in the neural network model is modulated based on entropy information determined by the training data set.

According to a third aspect of the present application, there is provided a computer-readable storage medium, comprising instructions, wherein the instructions, when run, execute the steps of the method for constructing a time series anomaly detection model according to the first aspect of the present application.

According to a fourth aspect of the present application, there is provided an analytic hierarchy process method, the analytic hierarchy process method comprising the following steps: acquiring a first weight of each of a plurality of factors associated with a target task; acquiring time series data of each factor, and acquiring a second weight of each of the plurality of factors at least based on the time series data of each factor using the time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to the first aspect of the present application; and determining a target weight corresponding to each of the plurality of factors based on the first weight and the second weight.

According to a fifth aspect of the present application, there is provided an analytic hierarchy system, the analytic hierarchy system comprising: a memory; a processor coupled to the memory; and a computer program stored on the memory and running on the processor, wherein running of the computer program causes the following operations: acquiring a first weight of each of a plurality of factors associated with a target task; acquiring time series data of each factor, and acquiring a second weight of each of the plurality of factors at least based on the time series data of each factor using the time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to the first aspect of the present application; and determining a target weight corresponding to each of the plurality of factors based on the first weight and the second weight.

According to a sixth aspect of the present application, there is provided a computer-readable storage medium, comprising instructions, wherein the instructions, when run, execute the steps of the analytic hierarchy process method according to the fourth aspect of the present application.

The analytic hierarchy solution proposed according to one or more embodiments of the present application, in a process of determining a target weight of each of a plurality

of factors associated with a target task, in addition to determining a first weight of each factor, further determines a second weight of each factor based on time series data of each factor through a constructed time series anomaly detection model, thereby fully considering possible anomalies of a factor value itself with time variation in the process of determining the target weight of the factor, avoiding allocating a larger weight to an anomalous factor during the analytic hierarchy process, and significantly improving the analytic hierarchy result. The solution for constructing a time series anomaly detection model according to one or more embodiments of the present application innovatively proposes a neural network model modulated by an entropy coefficient, which is capable of modulating a layer bias parameter in the neural network model based on entropy information determined by a training data set, thereby improving the training efficiency of the time series anomaly detection model and the accuracy of identifying time series anomalies of data using the time series anomaly detection model.

Brief Description of Drawings

The above and/or other aspects and advantages of the present application will become clearer and easier to understand through the following description of various aspects in conjunction with the accompanying drawings, in which the same or similar elements are denoted by the same reference numerals. The accompanying drawings include:

FIG. 1 shows a schematic diagram of a typical analytic hierarchy process model.

FIG. 2 shows a flowchart of a method for constructing a time series anomaly detection model according to one or more embodiments of the present application.

FIG. 3 shows a block diagram of a system for constructing a time series anomaly detection model according to one or more embodiments of the present application.

FIG. 4 shows a flowchart of an analytic hierarchy process method according to one or more embodiments of the present application.

FIG. 5 shows a block diagram of an analytic hierarchy system according to one or more embodiments of the present application.

Detailed Description of Embodiments

The present application is described more comprehensively below with reference to the accompanying drawings, in which illustrative embodiments of the present application are shown. However, the present application may be implemented in different forms and should not be construed as limited to the embodiments set forth herein. The embodiments provided above are intended to make the disclosure herein complete and comprehensive, thereby conveying the scope of protection of the present application more fully to those skilled in the art.

In this specification, terms such as "comprise" and "include" indicate that, apart from the units and steps that are directly and explicitly expressed in the specification and

claims, the technical solution of the present application does not exclude the presence of other units and steps that are not directly or explicitly expressed.

Unless otherwise specified, terms such as "first" and "second" do not indicate the order of units in terms of time, space, size, etc., which, instead, are merely used to distinguish between units.

Hereinafter, various exemplary embodiments according to the present application will be described in detail with reference to the accompanying drawings.

FIG. 1 shows a schematic diagram of a typical analytic hierarchy process model.

As shown in FIG. 1, an analytic hierarchy process model 100 hierarchically processes a multi-factor decision-making problem into three layers, wherein the first layer is a problem simple description (PSD), the second layer is a factor system, and the third layer is a candidate decision.

In FIG. 1, the problem simple description (PSD) of the first layer is used to describe a decision-making problem to be solved. The factor system of the second layer includes a plurality of factors involved in processing the decision-making problem to be solved, and the plurality of factors may be represented as a set $M = \{m_1, m_2, m_3, \dots, m_k, \dots, m_n\}$, wherein $m_1, m_2, m_3, \dots, m_k, \dots, m_n$ represent the plurality of factors, and n represents the size of the set M , i.e., the quantity of the factors. The candidate decisions of the third layer include a plurality of candidate decisions involved in processing the decision-making problem to be solved, and the plurality of candidate decisions may be represented as a set $TC = \{tc_1, tc_2, tc_3, \dots, tc_k, \dots, tc_o\}$, wherein $tc_1, tc_2, tc_3, \dots, tc_k, \dots, tc_o$ represent the plurality of candidate decisions, and o represents the size of the set TC , i.e., the quantity of the candidate decisions. It should be noted that the processing manner of the candidate decision layer varies with different decision-making problems. For example, in a single-choice decision-making problem, a certain candidate decision in the candidate decision set TC is output; in the context of multi-objective evaluation, each candidate decision in the candidate decision set TC and its corresponding score may be output.

As an example, referring to FIG. 1, the decision-making problem to be solved described by the Problem Simple Description (PSD) of the first layer may include enterprise capability assessment, merchant value assessment, customer demand rating, supplier selection, manufacturing systems, strategic decision-making, etc. Exemplarily, when the decision-making problem to be solved described by the problem simple description of the first layer is merchant value assessment, the factor system of the second layer may be implemented as $M = \{m_1, m_2, m_3, m_4, m_5\} = \{\text{turnover, profit, marketshare, customer volume, number of transactions}\}$, and the candidate decision of the third layer may be implemented as a value score for the merchant.

In the conventional analytic hierarchy process method, the process of solving for the weights assigned to the plurality of factors relies only on a comparison of importance

between the plurality of factors, ignoring that the factor value itself may have an anomaly with time variation, which leads to assigning larger weights to anomalous factors during the analytic hierarchy process method and, thereby, results in large errors in the analysis results of the analytic hierarchy process method, such as finally output candidate decisions and their corresponding scores being inaccurate. For example, when using the analytic hierarchy process method to perform merchant value assessment, turnover, as one of several factors, may show time series anomalies over time. At this time, in the event that a larger weight is assigned to the turnover that has statistical errors relying only on the comparison of importance between several factors, it will cause large errors in the analysis results of the analytic hierarchy process method, i.e., an assessed merchant value will lose reference value.

Accordingly, it is desirable to consider time series variation of factor values while considering importance of the factors themselves during execution of the analytic hierarchy process method. That is, it is expected to propose an analytic hierarchy process method capable of integrating time series variation information of factors, so as to avoid assigning larger weights to anomalous factors in the analytic hierarchy process method.

FIG. 2 shows a flowchart of a method for constructing a time series anomaly detection model according to one or more embodiments of the present application.

As shown in FIG. 2, in step S201, a time series data set is acquired, the time series data set comprising time series data of one or more factors.

Optionally, in step S201, data generated by each factor within each time period of a plurality of continuous time periods may be taken as the time series data of the factor, and the time series data set may be acquired based on the time series data of each of the one or more factors.

In an embodiment, when using an analytic hierarchy process method to assess merchant value, factors associated with merchant value assessment may include, for example, turnover, profit, market share, customer volume, and number of transactions. Exemplarily, for the turnover as one of the factors, an accumulated turnover in each month of 36 consecutive months may be acquired as time series data of the factor; for the profit as one of the factors, an accumulated profit in each month of 36 consecutive months may be acquired as time series data of the factor. By analogy, for the factors of turnover, profit, market share, customer volume, and number of transactions, data generated in each month of 36 consecutive months may be respectively acquired as time series data of the corresponding factors, thereby acquiring a time series data set comprising the time series data of the plurality of factors of turnover, profit, market share, customer volume, and number of transactions.

In step S203, a training data set is generated based on the time series data set.

Optionally, in step S203, the time series data set may be converted into a matrix form to generate the training data set.

In an embodiment, the time series data of each factor in the time series data set may be taken as a row of elements in a matrix to generate the training data set, wherein each element in the row of elements corresponds to the data generated by the factor within each time period. Exemplarily, for the factors of turnover, profit, market share, customer volume, and number of transactions, after acquiring the time series data set comprising the time series data of the plurality of factors of turnover, profit, market share, customer volume, and number of transactions, the time series data set may be converted into a training data set in a matrix form with 5 rows (i.e., the quantity of factors) and 36 columns (i.e., the quantity of time periods), wherein a row of elements in the matrix corresponds to the time series data of one factor, and each element in the row of elements corresponds to the data generated by the factor within each time period. In an embodiment, the time series data of each factor in the time series data set may be taken as a column of elements in a matrix to generate the training data set, wherein each element in the column of elements corresponds to the data generated by the factor within each time period.

As an example, for N factors, an acquired time series data set C may be represented as $C = \{C_1, C_2, \dots, C_N\}$, wherein $C_1, C_2, \dots, C_N$ respectively represent time series data of each factor. As an example, the time series data set C may be converted into a matrix form through the following formula (1) to generate the training data set:

$$C = \{C_1, C_2, \dots, C_N\} = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1t} \\ c_{21} & \dots & c_{ij} & \dots \\ \dots & c_{ji} & \dots & \dots \\ c_{N1} & \dots & \dots & c_{Nt} \end{bmatrix} \quad \text{Formula (1)}$$

wherein t represents the quantity of the plurality of continuous time periods, N represents the quantity of factors, and each element in the matrix corresponds to the data generated by a factor within each time period. For example, element c_{11} represents the data generated by the first factor within the first time period among the t continuous time periods, and element c_{ij} represents the data generated by the i -th factor within the j -th time period among the t continuous time periods. Exemplarily, the time series data C_1 of the first factor may be converted into the first row of elements in the matrix, the time series data C_2 of the second factor may be converted into the second row of elements in the matrix, and the time series data C_N of the N -th factor may be converted into the N -th row of elements in the matrix.

In step S205, a neural network model is trained using at least the training data set to construct the time series anomaly detection model, wherein a layer bias parameter in the neural network model is modulated based on entropy information determined by the training data set.

Optionally, the neural network model may be implemented as an entropy regression model, which may include a first layer, a second layer, and an output layer, wherein: the first layer is constructed using a first activation function and a first layer bias parameter modulated based on the entropy information determined by the training data

set; the second layer is constructed using a second activation function and a second layer bias parameter modulated based on the entropy information determined by the training data set; and the output layer is constructed using a softmax function. Optionally, an input of the first activation function may be determined based on a first layer weight and the training data set; an input of the second activation function may be determined based on a second layer weight and an output of the first layer; and an input of the softmax function may be determined based on an output of the second layer. Optionally, the layer bias parameter may be modulated by multiplying the entropy information determined by the training data set by the layer bias parameter in the neural network model.

In an embodiment, the neural network model may be implemented through the following formula (2):

$$\begin{aligned} Z_1 &= \sigma(W_1 C_i) + H_i b_1 \\ Z_2 &= \sigma(W_2 Z_1) + H_i b_2 \quad \text{Formula (2)} \\ \hat{y} &= \text{softmax}(Z_2) \end{aligned}$$

wherein the above three equations respectively represent the first layer, the second layer, and the output layer of the neural network model, Z_1 represents the output of the first layer, Z_2 represents the output of the second layer, $\hat{y}$ represents the output of the neural network model, σ represents the activation function $\sigma(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$, e represents the natural logarithm, W_1 represents the weight of the first layer, C_i represents the training data set (for example, it may be acquired with reference to formula (1) above, where i represents the quantity of factors), H_i represents the entropy information determined by the training data set C_i , b_1 represents the bias of the first layer, W_2 represents the weight of the second layer, b_2 represents the bias of the second layer, and $\text{softmax}(x) = \frac{e^x}{\sum_{Z_2} e^x}$ may act on each element of Z_2 , $x \in Z_2$.

Optionally, the entropy information H_i may be determined by the following steps: for each row of elements or each column of elements in the training data set C_i , determining a probability factor of each element in the row or the column relative to the elements in the row or the column; using the probability factor to determine an information amount of the elements in the row or the column; and taking the information amount of the elements in the row or the column as the entropy information of the time series data of the factor corresponding to the elements in the row or the column. Optionally, a ratio of each element in the row or the column to a sum of the elements in the row or the column may be taken as the probability factor.

In an embodiment, the probability factor of each element relative to the elements in its row may be calculated through the following formula (3):

$$p_{c_{ij}} = \frac{c_{ij}}{\sum_{j=1}^t c_{ij}} \quad \text{Formula (3)}$$

wherein $p_{c_{ij}}$ represents the probability factor of the element c_{ij} relative to the elements in the row where the element c_{ij} is located, and $\sum_{j=1}^t c_{ij}$ represents the sum of the elements in the row where the element c_{ij} is located.

In an embodiment, the entropy information of the time series data of the factor may be calculated through the following formula (4):

$$H_i = -\sum_{j=1}^t p_{c_{ij}} \log(2, p_{c_{ij}}) \quad \text{Formula (4)}$$

wherein H_i represents the entropy information of the time series data C_i of the factor, $p_{c_{ij}}$ represents the probability factor of the element c_{ij} relative to the elements in the row where the element c_{ij} is located, which may be calculated with reference to formula (3) above, and $\log(2, p_{c_{ij}})$ represents the logarithm of $p_{c_{ij}}$ to the base 2. It is understandable that the entropy information of each row of elements in the training data set in the matrix form as shown in formula (1) above may be determined using formula (4). For example, for the first row of elements $c_{11}, c_{12}, \dots, c_{1t}$ corresponding to the time series data of the first factor in the training data set in the matrix form as shown in formula (1) above, formula (3) above may be used to calculate the probability factor of each element in the first row of elements $c_{11}, c_{12}, \dots, c_{1t}$ relative to the elements $c_{11}, c_{12}, \dots, c_{1t}$ in its row. For instance, the ratio of element c_{11} to the sum of the first row of elements $c_{11}, c_{12}, \dots, c_{1t}$ is taken as the probability factor p_{11} of element c_{11} , the ratio of element c_{12} to the sum of the first row of elements $c_{11}, c_{12}, \dots, c_{1t}$ is taken as the probability factor p_{12} of element c_{12} , and so on. After calculating the probability factors $p_{11}, p_{12}, \dots, p_{1t}$ of each element in the first row of elements $c_{11}, c_{12}, \dots, c_{1t}$ relative to the elements $c_{11}, c_{12}, \dots, c_{1t}$ in its row, formula (4) may be used to determine the entropy information of the first row of elements $c_{11}, c_{12}, \dots, c_{1t}$, i.e., calculating $-p_{c_{ij}} \log(2, p_{c_{ij}})$ for each probability factor $p_{c_{ij}}$ and summing each calculated $-p_{c_{ij}} \log(2, p_{c_{ij}})$ to obtain the entropy information H_1 of the first row of elements $c_{11}, c_{12}, \dots, c_{1t}$. Similarly, the entropy information H_i of the i -th row of elements in the training data set in the matrix form as shown in formula (1) above may be calculated through the above process.

By modulating the layer bias parameters in the neural network model (e.g., the layer biases b_1 and b_2 in formula (2) above) based on the entropy information determined by the training data set, there is no need to collect a large number of time series anomaly samples, thereby being capable of improving the training efficiency of the time series anomaly detection model and the accuracy of identifying data time series anomalies using the time series anomaly detection model.

Optionally, the method for constructing a time series anomaly detection model according to one or more embodiments of the present application may further include: determining whether an anomaly exists in the time series data based on a continuous change trend of the time series data of each factor; determining a time series anomaly label corresponding to the time series data of each factor according to a determination result to obtain a time series anomaly label set corresponding to the time series data set; and updating the trained neural network model using a loss function based on the time series anomaly label set and an output of the trained neural network model, to construct the time series anomaly detection model. Optionally, parameters of the trained neural network model may be adjusted using the loss function until the loss function is in a convergence state, to obtain the time series anomaly detection model.

In an embodiment, for N factors, the acquired time series data set C may be represented as $C = \{C_1, C_2, \dots, C_N\}$, wherein $C_1, C_2, \dots, C_N$ respectively represent the time series data of each factor. As an example, the time series anomaly label of the time series data of a factor without anomaly may be set to 0, and the time series anomaly label of the time series data of a factor with anomaly may be set to 1, thereby obtaining a time series anomaly label set $Y = \{y_1, y_2, \dots, y_N\}$ corresponding to the time series data set C , wherein $y_1, y_2, \dots, y_N$ respectively represent the time series anomaly labels of $C_1, C_2, \dots, C_N$.

In an embodiment, the loss function $L_{sc}(y, \hat{y})$ may be constructed through the following formula (5):

$$L_{sc}(y, \hat{y}) = -\sum_{i=1}^N y^{(i)} \ln \hat{y}^{(i)} + (1 - y^{(i)}) \ln (1 - \hat{y}^{(i)}) \quad \text{Formula (5)}$$

wherein N represents the quantity of factors, $y^{(i)}$ represents the time series anomaly label of the time series data of the i -th factor, $\hat{y}^{(i)}$ represents the output of the trained neural network model for the i -th factor, and $\ln$ represents the logarithm to the base e .

The time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to one or more embodiments of the present application may be used to detect anomalies existing in the time series data. Optionally, the time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to one or more embodiments of the present application may be used in an analytic hierarchy process method to correct a weight of one or more factors according to the time series data of the one or more factors, and the correction process will be described in detail hereinafter.

The method for constructing a time series anomaly detection model according to one or more embodiments of the present application innovatively proposes a neural network model modulated by an entropy coefficient, which is capable of modulating a layer bias parameter in the neural network model based on entropy information determined by a training data set, thereby improving the training efficiency of the time series anomaly detection model and the accuracy of identifying time series anomalies of data using the time series anomaly detection model.

FIG. 3 shows a block diagram of a system for constructing a time series anomaly detection model according to one or more embodiments of the present application.

As shown in FIG. 3, a system 30 for constructing a time series anomaly detection model includes a communication unit 310, a memory 320 (e.g., non-volatile memory such as flash memory, ROM, hard disk drive, magnetic disk, optical disk), a processor 330, and a computer program 340 stored on the memory 320 and runnable on the processor 330.

The communication unit 310 serves as a communication interface and is configured to establish a communication connection between the system 30 for constructing the time series anomaly detection model and an external device or network (e.g., a cloud server, a mobile terminal, etc.).

The memory 320 stores the computer program 340 executable by the processor 330. In addition, the memory 320 may also store data (e.g., time series data set, training data set, etc.) generated when the processor 330 executes the computer program, as well as data or commands received from the outside via the communication unit 310.

The processor 330 is configured to execute the computer program 340 to implement the method for constructing a time series anomaly detection model according to one or more embodiments of the present application.

FIG. 4 shows a flowchart of an analytic hierarchy process method according to one or more embodiments of the present application.

As shown in FIG. 4, in step S401, a first weight of each of a plurality of factors associated with a target task is acquired.

Optionally, in step S401, a comparison matrix may be constructed based on a pairwise comparison of importance degrees between the plurality of factors. The comparison matrix is processed to determine priorities of the plurality of factors; a consistency test may be performed on the comparison matrix using the priorities of the plurality of factors; and the first weight of each of the plurality of factors may be determined using the comparison matrix having passed the consistency test.

In an embodiment, elements of each column in the comparison matrix may be summed to obtain a sum of the elements of each column; each element in the comparison matrix may be divided by the sum of the elements of the corresponding column to generate a column-averaged comparison matrix; and an average value of elements of each row in the column-averaged comparison matrix may be determined as the priorities of the plurality of factors.

As an example, a comparison matrix A as shown in the following formula (6) may be obtained based on the plurality of factors $m_1, m_2, m_3, \dots, m_k, \dots, m_n$ associated with the target task through automated construction:

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & \dots & a_{ij} & \dots \\ \dots & a_{ji} & \dots & \dots \\ a_{n1} & \dots & \dots & 1 \end{bmatrix} \quad \text{Formula (6)}$$

wherein i represents the row number where the element is located in the matrix, j represents the column number where the element is located in the matrix, $a_{ii} = 1$, $a_{ji} = 1/a_{ij}$, n represents the quantity of factors (also the dimension of the matrix), and a_{ij} may be determined based on the importance degree of factor m_i relative to factor m_j .

As an example, after obtaining the comparison matrix A as shown in formula (6) above, the elements of each column j in the comparison matrix A may be summed through the following formula (7) to obtain the sum of the elements of each column j :

$$\sum_{i=1}^n a_{ij}, \forall i, j \quad \text{Formula (7)}$$

wherein i represents the row number where the element is located in the matrix, j represents the column number where the element is located in the matrix, a_{ij} represents the element in the comparison matrix A , and n represents the quantity of factors (also the dimension of the matrix).

As an example, after obtaining the sum of the elements of each column, each element in the comparison matrix A may be divided by the sum of the elements of the corresponding column through the following formula (8) to generate a column-averaged comparison matrix A' :

$$a_{ij}' = a_{ij} / \sum_{i=1}^n a_{ij}, \forall i, j \quad \text{Formula (8)}$$

wherein i represents the row number where the element is located in the matrix, j represents the column number where the element is located in the matrix, a_{ij}' represents the element in the comparison matrix A' subjected to column average, and n represents the quantity of factors (also the dimension of the matrix).

As an example, after obtaining the comparison matrix A' subjected to column average, the average value p_i of elements of each row in the comparison matrix A' subjected to column average may be determined through the following formula (9) as the priorities of the plurality of factors:

$$p_i = \sum_{j=1}^n a_{ij}' / n \quad \text{Formula (9)}$$

wherein i represents the row number where the element is located in the matrix, j represents the column number where the element is located in the matrix, a_{ij}' represents the element in the comparison matrix A' subjected to column average, and n represents the quantity of factors (also the dimension of the matrix). After obtaining

the average value p_i of the elements of each row, the priorities of the n factors may be represented as $P = [p_1, p_2, \dots, p_n]$.

In an embodiment, a maximum eigenvalue of the comparison matrix may be determined according to the priorities of the plurality of factors; a consistency index of the comparison matrix may be determined according to the maximum eigenvalue of the comparison matrix and the quantity of the factors; a random index of the comparison matrix may be determined according to a dimension of the comparison matrix; and the consistency test may be performed on the comparison matrix based on the consistency index and the random index of the comparison matrix. In an embodiment, when a ratio of the consistency index to the random index of the comparison matrix is less than a predetermined threshold, it may be determined that the comparison matrix passes the consistency test; subsequently, the comparison matrix having passed the consistency test may be processed to determine the priorities of the plurality of factors, and the priorities of the plurality of factors may be taken as the first weight of the corresponding elements.

As an example, after obtaining P representing the priorities of the plurality of factors, the maximum eigenvalue λ_{max} of the comparison matrix A may be determined through the following formula (10):

$$\lambda_{max} = \sum_{i=1}^n \frac{[AP]_i}{np_i} \quad \text{Formula (10)}$$

wherein i represents the row number where the element is located in the matrix, n represents the quantity of factors (also the dimension of the matrix), p_i represents the i -th element in vector P , and $[AP]_i$ represents the i -th element in $[AP]$.

As an example, after determining the maximum eigenvalue λ_{max} of the comparison matrix A , the consistency index CI the comparison matrix A may be determined through the following formula (11):

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad \text{Formula (11)}$$

wherein n represents the quantity of factors (also the dimension of the matrix), and λ_{max} represents the maximum eigenvalue of the comparison matrix A .

As an example, the random index RI of the comparison matrix A may also be determined according to the dimension n of the comparison matrix A , for example, by means of mathematical table lookup. As an example, after determining the consistency index CI and the random index RI of the comparison matrix A , the consistency ratio CR of the comparison matrix A may be determined through the following formula (12):

$$CR = CI/RI \quad \text{Formula (12)}$$

Exemplarily, when the consistency ratio CR is less than 0.1, it may be determined that the comparison matrix passes the consistency test. Subsequently, the comparison

matrix having passed the consistency test may be processed to determine the priorities of the plurality of factors (for example, by formula (7) to formula (9) described above), and the priorities of the plurality of factors may be taken as the first weight of the corresponding elements. Exemplarily, the determined priorities of the n factors may be represented as a priority weight matrix $\check{P} = [\check{p}_1, \check{p}_2, \dots, \check{p}_n]$, which may respectively serve as the first weight of the n factors.

In step S403, time series data of each factor is acquired, and a second weight of each of the plurality of factors is acquired at least based on the time series data of each factor using the time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to one aspect of the present application.

Optionally, in step S403, data generated by each factor within each time period of a plurality of continuous time periods may be taken as the time series data of the factor; the time series data of each factor may be taken as a row of elements or a column of elements in a time series matrix to generate the time series matrix in a matrix form, wherein each element in the row of elements or the column of elements corresponds to the data generated by the factor within each time period; and the time series matrix may be input into the time series anomaly detection model to obtain the second weight of each of the plurality of factors.

As an example, for the i -th factor, the acquired time series data B_i may be represented as $B_i = \{b_{11}, b_{12}, b_{13}, \dots, b_{1k}, \dots, b_{1t}\}$, wherein t represents the quantity of the plurality of continuous time periods, and $b_{11}, b_{12}, b_{13}, \dots, b_{1k}, \dots, b_{1t}$ represent the data generated within each time period. As an example, for n factors, the acquired time series matrix B may be represented as:

$$B = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1t} \\ b_{21} & \dots & b_{ij} & \dots \\ \dots & b_{ji} & \dots & \dots \\ b_{n1} & \dots & \dots & b_{nt} \end{bmatrix} \quad \text{Formula (13)}$$

wherein t represents the quantity of the plurality of continuous time periods, n represents the quantity of factors, and each element in the matrix corresponds to the data generated by a factor within each time period. For example, element b_{11} represents the data generated by the first factor within the first time period among the t continuous time periods, and element b_{ij} represents the data generated by the i -th factor within the j -th time period among the t continuous time periods. Exemplarily, the first row of elements in the time series matrix B represents the time series data B_1 of the first factor, the second row of elements in the time series matrix B represents the time series data B_2 of the second factor, and so on.

As an example, the time series matrix B as shown in formula (13) above may be input into the time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to one aspect of the present application to obtain the second weight of each of the plurality of factors, which

may be represented, for example, as a time series anomaly weight matrix $\hat{P}=[\hat{p}_1, \hat{p}_2, \dots, \hat{p}_n]$.

In step S405, a target weight corresponding to each of the plurality of factors is determined based on the first weight and the second weight.

Optionally, in step S405, a product of the first weight and the second weight may be determined as the target weight corresponding to each of the plurality of factors. As an example, the target weight $\bar{P} = [\bar{p}_1, \bar{p}_2, \dots, \bar{p}_n]$ may be determined through the following formula (14) and formula (15):

$$\bar{P} = \check{P} \cdot \hat{P} \quad \text{Formula (14)}$$

$$\bar{p}_i = \check{p}_i * \hat{p}_i, i = \{1, 2, \dots, n\} \quad \text{Formula (15)}$$

wherein $\check{P}$ represents the first weight of the factors, $\hat{P}$ represents the second weight of the factors, n represents the quantity of factors, $\check{p}_i$ represents the first weight of the i -th factor, $\hat{p}_i$ represents the second weight of the i -th factor, and $\bar{p}_i$ represents the target weight of the i -th factor.

Optionally, the analytic hierarchy process method according to one or more embodiments of the present application may further include acquiring a score corresponding to each of the plurality of factors, and determining an analytic hierarchy result based on the score of each factor and the target weight corresponding to the factor. Optionally, the analytic hierarchy result may be determined based on a sum of products of the score of each factor and the target weight corresponding to the factor. As an example, a decision value S obtained using the analytic hierarchy process method as the analytic hierarchy result may be determined through the following formula (16):

$$S = \bar{P} \times \bar{V} = \sum_{i=1}^n \bar{p}_i \bar{v}_i \quad \text{Formula (16)}$$

wherein, $\bar{P}$ represents the target weights of the factors, $\bar{V} = [\bar{v}_1, \bar{v}_2, \dots, \bar{v}_n]$ represents the scores of the factors that have undergone normalization processing, n represents the quantity of factors, $\bar{p}_i$ represents the target weight of the i -th factor, and $\bar{v}_i$ represents the score of the i -th factor.

Specific implementation of the analytic hierarchy process method according to one or more embodiments of the present application will be further described below by taking supplier value assessment as an example.

As described above in conjunction with FIG. 1, when the decision-making problem to be solved described by the problem simple description of the first layer is merchant value assessment, the factor system of the second layer may include 5 factors, i.e., $M = \{m_1, m_2, m_3, m_4, m_5\} = \{\text{turnover, profit, marketshare, customer volume, number of transactions}\}$, and the candidate decision of the third layer may be implemented as a value score for the merchant.

As an example, a comparison matrix A as shown in the following formula (17) may be obtained based on m_1, m_2, m_3, m_4, m_5 through automated construction:

$$A = \begin{bmatrix} 1 & 1/2 & 4 & 3 & 3 \\ 2 & 1 & 7 & 5 & 5 \\ 1/4 & 1/7 & 1 & 1/2 & 1/3 \\ 1/3 & 1/5 & 2 & 1 & 1 \\ 1/3 & 1/5 & 3 & 1 & 1 \end{bmatrix} \quad \text{Formula (17)}$$

As an example, the comparison matrix A may be processed with reference to formula (7) to formula (12) and relevant descriptions above to determine the priorities of the five factors, and a consistency test may be performed on the comparison matrix A using the priorities of the five factors, and a first weight of each of the five factors may be determined using the comparison matrix having passed the consistency test. Exemplarily, the determined priorities of the five factors may be represented as a priority weight matrix $\tilde{P} = [0.262, 0.474, 0.054, 0.099, 0.110]$, which may respectively serve as the first weight of the five factors.

Then, time series data of the five factors may be acquired, and a second weight of each of the five factors may be obtained at least based on the time series data of each factor using the time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to one aspect of the present application. Exemplarily, for turnover as one of the factors, an accumulated turnover in each month of 36 consecutive months may be acquired as time series data of the factor; for profit as one of the factors, an accumulated profit in each month of 36 consecutive months may be acquired as time series data of the factor. By analogy, for the five factors of turnover, profit, market share, customer volume, and number of transactions, data generated in each month of 36 consecutive months may be respectively acquired as the time series data of the corresponding factors, thereby acquiring time series data of the five factors of turnover, profit, market share, customer volume, and number of transactions.

As an example, referring to the description of step S403 above, the time series data of the above five factors in 36 months may be converted into a matrix form to construct a time series matrix B with 5 rows and 36 columns as shown in the following formula (18):

$$B = \begin{bmatrix} 342213 & 451131 & \dots & \dots & 419872 \\ 243287 & 312764 & \dots & \dots & 298745 \\ 0.15 & 0.14 & \dots & \dots & 0.99 \\ 2341 & 99999 & \dots & \dots & 1987 \\ 5435 & 4892 & \dots & \dots & 4329 \end{bmatrix} \quad \text{Formula (18)}$$

As an example, the time series matrix B as shown in formula (18) above may be input into the time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to one aspect of the present application to obtain the second weight of each of the five factors, which may be represented, for example, as a time series anomaly weight matrix $\hat{P} = [0.83, 0.78, 0.02, 0.03, 0.92]$.

Then, a target weight corresponding to each of the five factors may be determined based on the first weights and the second weights of the above five factors. Optionally, a product of the first weight and the second weight of the five factors may be determined as the target weight corresponding to each of the five factors. As an example, the target weights $\bar{P} = [\bar{p}_1, \bar{p}_2, \dots, \bar{p}_5]$ may be determined as $\bar{P}=[0.217, 0.370, 0.001, 0.003, 0.01]$ with reference to formula (14) and formula (15) above.

After determining the target weight of each of the five factors, a score corresponding to each of the five factors may be acquired, and an analytic hierarchy result may be determined based on the scores of the five factors and the target weights corresponding to the factors. Optionally, the analytic hierarchy result may be determined based on a sum of products of the score of each factor and the target weight corresponding to the factor. As an example, a decision value S obtained using the analytic hierarchy process method as the analytic hierarchy result may be determined using the following formula (19):

$$S = \bar{P} \times \bar{V} = \sum_{i=1}^n \bar{p}_i \bar{v}_i = 0.217 \times 0.36 + 0.370 \times 0.27 + 0.001 \times 0.16 + 0.003 \times 0.23 + 0.01 \times 0.52 = 0.184 \quad \text{Formula (19)}$$

wherein $\bar{V} = [0.36, 0.27, 0.16, 0.23, 0.52]$ represents the scores of the five factors that have undergone normalization processing, $\bar{P} = [0.217, 0.370, 0.001, 0.003, 0.01]$ represents the target weights of the five factors, and the decision value 0.184 may serve as a valuation result for assessing the supplier value.

FIG. 5 shows a block diagram of an analytic hierarchy system according to one or more embodiments of the present application.

As shown in FIG. 5, an analytic hierarchy system 50 includes a communication unit 510, a memory 520 (e.g., non-volatile memory such as flash memory, ROM, hard disk drive, magnetic disk, optical disk), a processor 530, and a computer program 540 stored on the memory 520 and runnable on the processor 530.

The communication unit 510 serves as a communication interface and is configured to establish a communication connection between the analytic hierarchy system 50 and an external device or network (e.g., a cloud server, a mobile terminal, etc.).

The memory 520 stores the computer program 540 executable by the processor 530. In addition, the memory 520 may also store data (e.g., first weight of factors, second weight of factors, target weight of factors, etc.) generated when the processor 530 executes the computer program and data or commands received from the outside via the communication unit 510.

The processor 530 is configured to execute the computer program 540 to implement the analytic hierarchy process method according to one or more embodiments of the present application.

The present application may also be implemented as a computer-readable storage medium, wherein the computer storage medium includes instructions that, when run, execute the method for constructing a time series anomaly detection model according

to one aspect of the present application. In addition, the present application may also be implemented as a computer-readable storage medium, wherein the computer storage medium includes instructions that, when run, execute the analytic hierarchy process method according to one aspect of the present application.

Where applicable, various embodiments provided by the present application may be implemented using hardware, software, or a combination of hardware and software. Moreover, where applicable, various hardware components and/or software components set forth herein may be combined into composite components comprising software, hardware, and/or both without departing from the scope of the present application. Where applicable, various hardware components and/or software components set forth herein may be separated into sub-components comprising software, hardware, or both without departing from the scope of the present application. In addition, where applicable, it is contemplated that software components may be implemented as hardware components, and vice versa.

Software (such as program codes and/or data) according to the present application may be stored on one or more computer storage media. It is also contemplated that the software identified herein may be implemented using one or more general-purpose or special-purpose computers and/or systems that are networked and/or otherwise. Where applicable, the order of various steps described herein may be changed, combined into composite steps, and/or divided into sub-steps to provide the features described herein.

The embodiments and examples presented herein are provided to best illustrate embodiments in accordance with the present application and its specific applications, and thereby enable those skilled in the art to implement and use the present application. However, those skilled in the art will know that the above description and examples are provided only for the convenience of illustration and example. The proposed description is not intended to cover every aspect of the present application or to limit the present application to the precise form disclosed.

CLAIMS

1. A method for constructing a time series anomaly detection model, the method comprising the following steps:

acquiring a time series data set comprising time series data of one or more factors;

generating a training data set based on the time series data set; and

training a neural network model using at least the training data set to construct the time series anomaly detection model, wherein a layer bias parameter in the neural network model is modulated based on entropy information determined by the training data set.

2. The method according to claim 1, wherein acquiring the time series data set comprises:

taking data generated by each factor within each time period of a plurality of continuous time periods as the time series data of the factor; and

acquiring the time series data set based on the time series data of each of the one or more factors.

3. The method according to claim 1, wherein generating the training data set based on the time series data set comprises:

converting the time series data set into a matrix form to generate the training data set.

4. The method according to claim 2 or 3, wherein converting the time series data set into a matrix form to generate the training data set comprises:

taking the time series data of each factor in the time series data set as a row of elements or a column of elements in a matrix to generate the training data set, wherein each element in the row of elements or the column of elements corresponds to the data generated by the factor within each time period.

5. The method according to claim 1, the method further comprising:

determining whether an anomaly exists in the time series data based on a continuous change trend of the time series data of each factor;

determining a time series anomaly label corresponding to the time series data of each factor according to a determination result to obtain a time series anomaly label set corresponding to the time series data set; and

updating the trained neural network model using a loss function based on the time series anomaly label set and an output of the trained neural network model, to construct the time series anomaly detection model.

6. The method according to claim 1, wherein the neural network model comprises:

a first layer constructed using a first activation function and a first layer bias parameter modulated based on the entropy information determined by the training data set;

a second layer constructed using a second activation function and a second layer bias parameter modulated based on the entropy information determined by the training data set; and

an output layer constructed using a softmax function.

7. The method according to claim 6, wherein the neural network model is further constructed by:

determining an input of the first activation function based on a first layer weight and the training data set;

determining an input of the second activation function based on a second layer weight and an output of the first layer; and

determining an input of the softmax function based on an output of the second layer.

8. The method according to claim 1, wherein the layer bias parameter in the neural network model is modulated by:

modulating the layer bias parameter through multiplying the entropy information determined by the training data set by the layer bias parameter in the neural network model.

9. The method according to claim 4, wherein the entropy information is determined by the following steps:

for each row of elements or each column of elements in the training data set, determining a probability factor of each element in the row of elements or the column of elements relative to the elements in the row of elements or the column of elements;

determining an information amount of the elements in the row or the column using the probability factor; and

taking the information amount of the elements in the row or the column as the entropy information of the time series data of the factor corresponding to the elements in the row or the column.

10. The method according to claim 9, wherein the probability factor is determined by the following step:

taking a ratio of each element in the row or the column to a sum of the elements in the row or the column as the probability factor.

11. The method according to claim 1, wherein the time series anomaly detection model is used at least for correcting a weight of the one or more factors according to the time series data of the one or more factors in an analytic hierarchy process method.

12. A system for constructing a time series anomaly detection model, wherein the system comprises:

a memory;

a processor coupled to the memory; and

a computer program stored on the memory and running on the processor, wherein running of the computer program causes the following operations:

- acquiring a time series data set comprising time series data of one or more factors;
- generating a training data set based on the time series data set; and
- training a neural network model using at least the training data set to construct the time series anomaly detection model, wherein a layer bias parameter in the neural network model is modulated based on entropy information determined by the training data set.

13. The system according to claim 12, wherein the running of the computer program causes acquiring the time series data set to comprise:

- taking data generated by each factor within each time period of a plurality of continuous time periods as the time series data of the factor; and
- acquiring the time series data set based on the time series data of each of the one or more factors.

14. The system according to claim 12, wherein the running of the computer program causes generating the training data set based on the time series data set to comprise:

- converting the time series data set into a matrix form to generate the training data set.

15. The system according to claim 13 or 14, wherein the running of the computer program causes converting the time series data set into a matrix form to generate the training data set to comprise:

- taking the time series data of each factor in the time series data set as a row of elements or a column of elements in a matrix to generate the training data set, wherein each element in the row of elements or the column of elements corresponds to the data generated by the factor within each time period.

16. The system according to claim 12, wherein the running of the computer program further causes the following operations:

- determining whether an anomaly exists in the time series data based on a continuous change trend of the time series data of each factor;
- determining a time series anomaly label corresponding to the time series data of each factor according to a determination result to obtain a time series anomaly label set corresponding to the time series data set; and
- updating the trained neural network model using a loss function based on the time series anomaly label set and an output of the trained neural network model, to construct the time series anomaly detection model.

17. The system according to claim 12, wherein the neural network model comprises:
a first layer constructed using a first activation function and a first layer bias parameter modulated based on the entropy information determined by the training data set;

a second layer constructed using a second activation function and a second layer bias parameter modulated based on the entropy information determined by the training data set; and

an output layer constructed using a softmax function.

18. The system according to claim 17, wherein the running of the computer program further causes the neural network model to be constructed by:

determining an input of the first activation function based on a first layer weight and the training data set;

determining an input of the second activation function based on a second layer weight and an output of the first layer; and

determining an input of the softmax function based on an output of the second layer.

19. The system according to claim 12, wherein the running of the computer program further causes the layer bias parameter in the neural network model to be modulated by:

modulating the layer bias parameter through multiplying the entropy information determined by the training data set by the layer bias parameter in the neural network model.

20. The system according to claim 15, wherein the running of the computer program further causes the entropy information to be determined by the following steps:

for each row of elements or each column of elements in the training data set, determining a probability factor of each element in the row or the column relative to the elements in the row or the column;

determining an information amount of the elements in the row or the column using the probability factor; and

taking the information amount of the elements in the row or the column as the entropy information of the time series data of the factor corresponding to the elements in the row or the column.

21. The system according to claim 20, wherein the running of the computer program further causes the probability factor to be determined by the following step:

taking a ratio of each element in the row or the column to a sum of the elements in the row or the column as the probability factor.

22. The system according to claim 12, wherein the time series anomaly detection model is used at least for correcting a weight of the one or more factors according to the time series data of the one or more factors in an analytic hierarchy process method.

23. A computer-readable storage medium, comprising instructions, wherein the instructions, when run, execute the method for constructing a time series anomaly detection model according to any one of claims 1-11.

24. An analytic hierarchy process method, comprising the following steps:

acquiring a first weight of each of a plurality of factors associated with a target task;
acquiring time series data of each factor, and acquiring a second weight of each of the plurality of factors at least based on the time series data of each factor using the time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to any one of claims 1-11; and

determining a target weight corresponding to each of the plurality of factors based on the first weight and the second weight.

25. The method according to claim 24, wherein acquiring the first weight of each of the plurality of factors associated with the target task comprises:

constructing a comparison matrix based on a pairwise comparison of importance degrees between the plurality of factors;

processing the comparison matrix to determine priorities of the plurality of factors;
and

performing a consistency test on the comparison matrix using the priorities of the plurality of factors, and determining the first weight of each of the plurality of factors using the comparison matrix having passed the consistency test.

26. The method according to claim 25, wherein processing the comparison matrix to determine the priorities of the plurality of factors comprises:

summing elements of each column in the comparison matrix to obtain a sum of the elements of each column;

dividing each element in the comparison matrix by the sum of the elements of the corresponding column to generate a column-averaged comparison matrix; and

determining an average value of elements of each row in the column-averaged comparison matrix as the priorities of the plurality of factors.

27. The method according to claim 25, wherein performing the consistency test on the comparison matrix using the priorities of the plurality of factors comprises:

determining a maximum eigenvalue of the comparison matrix according to the priorities of the plurality of factors;

determining a consistency index of the comparison matrix according to the maximum eigenvalue of the comparison matrix and a quantity of the factors;

determining a random index of the comparison matrix according to a dimension of the comparison matrix; and

performing the consistency test on the comparison matrix based on the consistency index and the random index of the comparison matrix.

28. The method according to claim 27, wherein the method further comprises:

determining that the comparison matrix passes the consistency test in response to a ratio of the consistency index to the random index of the comparison matrix being less than a predetermined threshold;

processing the comparison matrix having passed the consistency test to determine the priorities of the plurality of factors; and

taking the priorities of the plurality of factors as the first weight of the corresponding element.

29. The method according to claim 24, wherein the second weight of each of the plurality of factors is further obtained by:

taking data generated by each factor within each time period of a plurality of continuous time periods as the time series data of the factor;

generating a time series matrix in a matrix form by taking the time series data of each factor as a row of elements or a column of elements in the time series matrix, wherein each element in the row of elements or the column of elements corresponds to the data generated by the factor within each time period; and

inputting the time series matrix into the time series anomaly detection model to obtain the second weight of each of the plurality of factors.

30. The method according to claim 24, wherein determining the target weight corresponding to each of the plurality of factors based on the first weight and the second weight comprises:

determining a product of the first weight and the second weight as the target weight corresponding to each of the plurality of factors.

31. The method according to claim 24, wherein the method further comprises:

acquiring a score corresponding to each of the plurality of factors; and

determining an analytic hierarchy result based on the score of each factor and the target weight corresponding to the factor.

32. The method according to claim 31, wherein determining the analytic hierarchy result based on the score of each factor and the target weight corresponding to the factor comprises:

determining the analytic hierarchy result based on a sum of products of the score of each factor and the target weight corresponding to the factor.

33. An analytic hierarchy system, comprising:

a memory;

a processor coupled to the memory; and

a computer program stored on the memory and running on the processor, wherein running of the computer program causes the following operations:

acquiring a first weight of each of a plurality of factors associated with a target task;

acquiring time series data of each factor, and acquiring a second weight of each of the plurality of factors at least based on the time series data of each factor using the time series anomaly detection model constructed by the method for constructing a time series anomaly detection model according to any one of claims 1-11; and

determining a target weight corresponding to each of the plurality of factors based on the first weight and the second weight.

34. The system according to claim 33, wherein the running of the computer program causes acquiring the first weight of each of the plurality of factors associated with the target task to comprise:

- constructing a comparison matrix based on a pairwise comparison of importance degrees between the plurality of factors;

- processing the comparison matrix to determine priorities of the plurality of factors;
- and

- performing a consistency test on the comparison matrix using the priorities of the plurality of factors, and determining the first weight of each of the plurality of factors using the comparison matrix having passed the consistency test.

35. The system according to claim 34, wherein the running of the computer program causes processing the comparison matrix to determine the priorities of the plurality of factors to comprise:

- summing elements of each column in the comparison matrix to obtain a sum of the elements of each column;

- dividing each element in the comparison matrix by the sum of the elements of the corresponding column to generate a column-averaged comparison matrix; and

- determining an average value of elements of each row in the column-averaged comparison matrix as the priorities of the plurality of factors.

36. The system according to claim 34, wherein the running of the computer program causes performing the consistency test on the comparison matrix using the priorities of the plurality of factors to comprise:

- determining a maximum eigenvalue of the comparison matrix according to the priorities of the plurality of factors;

- determining a consistency index of the comparison matrix according to the maximum eigenvalue of the comparison matrix and a quantity of the factors;

- determining a random index of the comparison matrix according to a dimension of the comparison matrix; and

- performing the consistency test on the comparison matrix based on the consistency index and the random index of the comparison matrix.

37. The system according to claim 36, wherein the running of the computer program further causes:

- determining that the comparison matrix passes the consistency test in response to a ratio of the consistency index to the random index of the comparison matrix being less than a predetermined threshold;

- processing the comparison matrix having passed the consistency test to determine the priorities of the plurality of factors; and

- taking the priorities of the plurality of factors as the first weight of the corresponding element.

38. The system according to claim 33, wherein the running of the computer program causes the second weight of each of the plurality of factors to be further obtained by:

taking data generated by each factor within each time period of a plurality of continuous time periods as the time series data of the factor;

generating a time series matrix in a matrix form by taking the time series data of each factor as a row of elements or a column of elements in the time series matrix, wherein each element in the row of elements or the column of elements corresponds to the data generated by the factor within each time period; and

inputting the time series matrix into the time series anomaly detection model to obtain the second weight of each of the plurality of factors.

39. The system according to claim 33, wherein the running of the computer program causes determining the target weight corresponding to each of the plurality of factors based on the first weight and the second weight to comprise:

determining a product of the first weight and the second weight as the target weight corresponding to each of the plurality of factors.

40. The system according to claim 33, wherein the running of the computer program further causes:

acquiring a score corresponding to each of the plurality of factors; and

determining an analytic hierarchy result based on the score of each factor and the target weight corresponding to the factor.

41. The system according to claim 40, wherein the running of the computer program causes determining the analytic hierarchy result based on the score of each factor and the target weight corresponding to the factor to comprise:

determining the analytic hierarchy result based on a sum of products of the score of each factor and the target weight corresponding to the factor.

42. A computer-readable storage medium, comprising instructions, wherein the instructions, when run, execute the analytic hierarchy process method according to any one of claims 24-32.