

METHOD AND SYSTEM FOR CONSTRUCTING COMPARISON MATRIX, AND ANALYTIC HIERARCHY PROCESS METHOD AND SYSTEM

The present application claims priority to Chinese Patent Application No. 202310953347.7 filed on July 31, 2023 and entitled "METHOD AND SYSTEM FOR CONSTRUCTING COMPARISON MATRIX, AND ANALYTIC HIERARCHY PROCESS METHOD AND SYSTEM", the entire disclosure of which is incorporated herein by reference for all purposes.

Technical Field

The present application relates to the technical field of machine learning, and more specifically, to a method and system for training a matrix generator, a method and system for constructing a comparison matrix, an analytic hierarchy process method and system, and a computer-readable storage medium for implementing the above methods.

Background

An analytic hierarchy process is a comprehensive evaluation method for system analysis and decision-making, which, as a multi-factor decision-making method proposed on the basis of fully studying the human thinking process, can reasonably realize the processing process of converting qualitative problems into quantitative ones.

The analytic hierarchy process converts a complex problem processing process into a comparison of importance between several factors pairwise by constructing a hierarchical structure, thereby converting difficult-to-quantify qualitative determinations into operable importance comparisons. Specifically, the analytic hierarchy process converts a decision-making task involving multiple factors into a comparison matrix, and then obtains a priority weight of each factor at each level relative to a certain factor at the previous level by solving the eigenvector of the comparison matrix, which is a method combining qualitative and quantitative aspects. Since being proposed, the analytic hierarchy process has been widely used in various aspects of various fields, such as enterprise capability assessment, merchant value assessment, customer demand rating, supplier selection, manufacturing systems, and strategic decision-making in the financial field.

Typically, the analytic hierarchy process method includes four steps: problem modeling, construction of a comparison matrix, priority derivation, and a consistency test. Currently, the construction process of a comparison matrix needs to be implemented through manual comparison and scoring by experts. However, as the complexity of multi-factor decision-making tasks increases, the number of factors involved multiplies, resulting in a large amount of manpower and material resources required to construct the comparison matrix. In addition, the comparison matrix

constructed manually based on limited cognition has limitations and, sometimes, it is even impossible to manually construct the comparison matrix, which affects the processing efficiency of the analytic hierarchy process and constrains the application fields of the analytic hierarchy process.

Summary

To solve or at least alleviate 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 training a matrix generator comprising a factor discrimination model and a hierarchical scoring model, the method comprising the following steps: acquiring a set of factor feature combinations, as well as a factor discrimination label and a hierarchical scoring label for each of the factor feature combinations; training a first neural network model using the set of factor feature combinations and the factor discrimination label for each of the factor feature combinations as a first training set, and updating a trained first neural network model using a first loss function to obtain the factor discrimination model; and training a second neural network model using the set of factor feature combinations and the hierarchical scoring label for each of the factor feature combinations as a second training set, and updating a trained second neural network model using a second loss function to obtain the hierarchical scoring model, wherein the second loss function is constructed based at least on a factor discrimination result output by the factor discrimination model and a reciprocal of a hierarchical scoring result output by the trained second neural network model.

According to the method for training a matrix generator described in an embodiment of the present application, the matrix generator is used to generate a comparison matrix based on a plurality of input factors in an analytic hierarchy process.

According to the method for training a matrix generator described in an embodiment of the present application or any one of the above embodiments, acquiring the set of factor feature combinations comprises: acquiring a plurality of factors and a semantic vector for each of the plurality of factors; combining the semantic vector for each of the plurality of factors into a set of factor features; pairwise combining the factor features in the set of factor features to generate a plurality of factor feature pairs; and using the plurality of factor feature pairs as the set of factor feature combinations, wherein each of the factor feature combinations comprises a semantic vector of a first factor and a semantic vector of a second factor.

According to the method for training a matrix generator described in an embodiment of the present application or any one of the above embodiments, acquiring the factor discrimination label for each of the factor feature combinations comprises: acquiring the factor discrimination label for each of the factor feature combinations based on importance of the first factor relative to the second factor.

According to the method for training a matrix generator described in an embodiment of the present application or any one of the above embodiments, acquiring the factor discrimination label for each of the factor feature combinations further comprises: setting the factor discrimination label to a first value in response to determining that the first factor is more important than the second factor; and setting the factor discrimination label to a second value in response to determining that the second factor is more important than the first factor.

According to the method for training a matrix generator described in an embodiment of the present application or any one of the above embodiments, acquiring the hierarchical scoring label for each of the factor feature combinations comprises: acquiring the hierarchical scoring label for each of the factor feature combinations based on a degree of importance of the first factor relative to the second factor.

According to the method for training a matrix generator described in an embodiment of the present application or any one of the above embodiments, acquiring the hierarchical scoring label for each of the factor feature combinations further comprises: determining a score for representing the degree of importance of the first factor relative to the second factor; setting the hierarchical scoring label to the score in response to the first factor being more important than the second factor; and setting the hierarchical scoring label to a reciprocal of the score in response to the second factor being more important than the first factor.

According to the method for training a matrix generator described in an embodiment of the present application or any one of the above embodiments, the first loss function is constructed based on the factor discrimination label for each of the factor feature combinations and the factor discrimination result output by the trained first neural network model.

According to the method for training a matrix generator described in an embodiment of the present application or any one of the above embodiments, updating the trained first neural network model using the first loss function comprises: adjusting parameters of the trained first neural network model using the first loss function until the first loss function is in a convergence state, to obtain the factor discrimination model.

According to the method for training a matrix generator described in an embodiment of the present application or any one of the above embodiments, the second loss function is constructed based on the hierarchical scoring label for each of the factor feature combinations, the factor discrimination result output by the factor discrimination model, the hierarchical scoring result output by the trained second neural network model, and the reciprocal of the hierarchical scoring result output by the trained second neural network model.

According to the method for training a matrix generator described in an embodiment of the present application or any one of the above embodiments, updating the trained second neural network model using the second loss function comprises: adjusting parameters of the trained second neural network model using the second loss function

until the second loss function is in a convergence state, to obtain the hierarchical scoring model.

According to a second aspect of the present application, there is provided a system for training a matrix generator comprising a factor discrimination model and a hierarchical scoring model, the system comprising: an acquiring unit configured to acquire a set of factor feature combinations, as well as a factor discrimination label and a hierarchical scoring label for each of the factor feature combinations; a first training unit configured to train a first neural network model using the set of factor feature combinations and the factor discrimination label for each of the factor feature combinations as a first training set, and update a trained first neural network model using a first loss function to obtain the factor discrimination model; and a second training unit configured to train a second neural network model using the set of factor feature combinations and the hierarchical scoring label for each of the factor feature combinations as a second training set, and update a trained second neural network model using a second loss function to obtain the hierarchical scoring model, wherein the second loss function is constructed based at least on a factor discrimination result output by the factor discrimination model and a reciprocal of a hierarchical scoring result output by the trained second neural network model.

According to a third aspect of the present application, there is provided a computer-readable storage medium comprising instructions, wherein the instructions, when executed, perform the steps of the method for training a matrix generator according to the first aspect of the present application.

According to a fourth aspect of the present application, there is provided a method for constructing a comparison matrix, the method comprising the following steps: acquiring a set of factor features; and inputting the set of factor features into a matrix generator to obtain a comparison matrix, wherein the matrix generator is trained using the method for training a matrix generator according to the first aspect of the present application.

According to a fifth aspect of the present application, there is provided a system for constructing a comparison matrix, the system comprising: an acquiring unit configured to acquire a set of factor features; and a matrix generator configured to process the set of factor features to obtain the comparison matrix, wherein the matrix generator is trained using the method for training a matrix generator according to the first aspect of the present application.

According to a sixth aspect of the present application, there is provided a computer-readable storage medium comprising instructions, wherein the instructions, when executed, perform the steps of the method for constructing a comparison matrix according to the fourth aspect of the present application.

According to a seventh aspect of the present application, there is provided an analytic hierarchy process method, the analytic hierarchy process method comprising the following steps: acquiring a set of factor features of a plurality of factors associated

with a target task; inputting the set of factor features into a matrix generator to obtain a comparison matrix, wherein the matrix generator is trained using the method for training a matrix generator according to the first aspect of the present application; 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 weights of the plurality of factors using the comparison matrix having passed the consistency test.

According to an eighth aspect of the present application, there is provided an analytic hierarchy process system, 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 execution of the computer program causes the following operations: acquiring a set of factor features of a plurality of factors associated with a target task; inputting the set of factor features into a matrix generator to obtain a comparison matrix, wherein the matrix generator is trained using the method for training a matrix generator according to the first aspect of the present application; 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 weights of the plurality of factors using the comparison matrix having passed the consistency test.

According to a ninth aspect of the present application, there is provided a computer-readable storage medium comprising instructions, wherein the instructions, when executed, perform the steps of the analytic hierarchy process method according to the seventh aspect of the present application.

According to one or more embodiments of the present application, by utilizing a trained matrix generator to automatically construct a comparison matrix based on a set of factor features, manpower consumption in the construction process of the comparison matrix can be saved, the efficiency and accuracy of problem processing using the analytic hierarchy process can be improved, and the application fields of the analytic hierarchy process can be broadened.

Brief Description of Drawings

The above and/or other aspects and advantages of the present application will become more apparent and more readily appreciated from the following description of various aspects in conjunction with the accompanying drawings, in which the same or similar units are denoted by the same reference numerals. The drawings include:

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

FIG. 2 shows a flowchart of a method for training a matrix generator according to one or more embodiments of the present application.

FIG. 3 shows a block diagram of a system for training a matrix generator according to one or more embodiments of the present application.

FIG. 4 shows a flowchart of a method for constructing a comparison matrix according to one or more embodiments of the present application.

FIG. 5 shows a block diagram of a system for constructing a comparison matrix according to one or more embodiments of the present application.

FIG. 6 shows a flowchart of an analytic hierarchy process method according to one or more embodiments of the present application.

FIG. 7 shows a block diagram of an analytic hierarchy process system according to one or more embodiments of the present application.

Detailed Description of Embodiments

The present application is described more fully below with reference to the accompanying drawings illustrating schematic embodiments of the present application. However, the present application may be implemented in different forms and should not be interpreted as being limited to the embodiments set forth herein. The above embodiments set forth are intended to make the disclosure herein comprehensive and complete, so as to more fully convey the scope of protection of the present application to those skilled in the art.

In the present specification, terms such as "comprise" and "include" indicate that, in addition to units and steps directly and explicitly expressed in the specification and claims, the technical solutions of the present application do not exclude cases of having other units and steps not directly or explicitly expressed.

Unless specifically stated, terms such as "first" and "second" do not indicate the order of units in terms of time, space, size, etc., but 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 processes a multi-factor decision-making problem hierarchically into three layers, wherein the first layer is a problem simple description, the second layer is a factor system, and the third layer is a candidate decision.

In FIG. 1, the PSD (Problem Simple Description) of the first layer is used to describe the 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 number of factors. The candidate decision of the third layer includes 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 number of 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 a multi-objective assessment context, each candidate decision in the candidate decision set TC and its corresponding score may be output.

In the conventional analytic hierarchy process, the process of constructing a comparison matrix based on the factor system of the second layer requires experts to participate in comparison and scoring. However, when the number of factors to be compared in the decision-making problem multiplies, the manner of constructing a comparison matrix through manual comparison and scoring is not only time-consuming and labor-intensive, but also difficult to meet practical requirements, even making it impossible to construct a comparison matrix.

FIG. 2 shows a flowchart of a method for training a matrix generator according to one or more embodiments of the present application, wherein the matrix generator comprises a factor discrimination model and a hierarchical scoring model. Optionally, the matrix generator may be used to generate a comparison matrix based on a plurality of input factors in an analytic hierarchy process.

As shown in FIG. 2, in step S201, a set of factor feature combinations, as well as a factor discrimination label and a hierarchical scoring label for each of the factor feature combinations, are acquired.

Optionally, in step S201, a plurality of factors and a semantic vector for each of the plurality of factors may be acquired, the semantic vector for each of the plurality of factors may be combined into a set of factor features, the factor features in the set of factor features may be pairwise combined to generate a plurality of factor feature pairs, and the plurality of factor feature pairs may be used as the set of factor feature combinations, wherein each of the factor feature combinations may include a semantic vector of a first factor and a semantic vector of a second factor.

In an embodiment, the acquired plurality of factors involved in processing the decision-making problem to be solved 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 number of factors. Next, the plurality of factors may be represented by natural language, for example, a semantic vector for each of the plurality of factors may be acquired through a pre-trained natural language model (e.g., BERT, GPT, etc.) to constitute a set of factor features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_n\}$, wherein $em_k \in \mathbb{R}^t$ represents the semantic vector of the factor m_k , t represents the dimension of the semantic vector, and n represents the size of the set ME , i.e., the number of semantic vectors of the factors. After acquiring the set of factor features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_n\}$, the factor features

$em_1, em_2, em_3, \dots, em_k, \dots, em_n$ in the set of factor features ME may be pairwise combined to generate a plurality of factor feature pairs; for example, the factor features em_1 and em_2 may be combined to generate a factor feature pair (em_1, em_2) . Exemplarily, N factors from multiple fields may be collected and subjected to feature representation, and then a plurality of factor feature pairs are used as a set of factor feature combinations CME and represented as $(em_i, em_j) \in \text{CME}, i \neq j, i, j = \{1, 2, 3, \dots, N\}$, wherein N represents the number of factors.

In an embodiment, the factor discrimination label for a factor feature combination may be acquired based on importance of a corresponding first factor relative to a second factor in the factor feature combination. When it is determined that the first factor is more important than the second factor, the factor discrimination label of the factor feature combination composed of the first factor and the second factor may be set to a first value; and when it is determined that the second factor is more important than the first factor, the factor discrimination label of the factor feature combination composed of the first factor and the second factor may be set to a second value. Exemplarily, for a factor feature combination (em_i, em_j) , the factor discrimination label $flag_{ij}$ of the factor feature combination (em_i, em_j) may be set through the following formula (1):

$$flag_{ij} = \begin{cases} 0, & em_i < em_j \\ 1, & em_i > em_j \end{cases} \quad \text{Formula (1),}$$

wherein $em_i > em_j$ indicates that the factor m_i is more important than the factor m_j , and at this time, the factor discrimination label $flag_{ij}$ of the factor feature combination (em_i, em_j) may be set to 1; and $em_i < em_j$ indicates that the factor m_j is more important than the factor m_i , and at this time, the factor discrimination label $flag_{ij}$ of the factor feature combination (em_i, em_j) may be set to 0.

In an embodiment, the hierarchical scoring label for a factor feature combination may be acquired based on a degree of importance of a corresponding first factor relative to a second factor in the factor feature combination. Optionally, a score for representing the degree of importance of the first factor relative to the second factor may be determined, the hierarchical scoring label is set to the score when the first factor is more important than the second factor, and the hierarchical scoring label is set to a reciprocal of the score when the second factor is more important than the first factor. Exemplarily, the score of the degree of importance may include 9 levels, which are $\{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ respectively. A higher score indicates a higher degree of importance of the first factor relative to the second factor. For example, a score of 1 indicates that the first factor and the second factor have the same importance, a score of 3 indicates that the

first factor is slightly more important than the second factor, a score of 5 indicates that the first factor is obviously more important than the second factor, and a score of 9 indicates that the first factor is extremely more important than the second factor.

Exemplarily, for a factor feature combination (em_i, em_j) , the hierarchical scoring label $score_level_{ij}$ of the factor feature combination (em_i, em_j) may be set through the following formula (2) using a score $score$ of the degree of importance of the factor m_i relative to the factor m_j :

$$score_level_{ij} = \begin{cases} 1/score, & em_i < em_j \\ score, & em_i > em_j \end{cases} \quad \text{Formula (2),}$$

wherein $em_i > em_j$ indicates that the factor m_i is more important than the factor m_j , and at this time, the hierarchical scoring label $score_level_{ij}$ of the factor feature combination (em_i, em_j) may be set to the score $score$; and $em_i < em_j$ indicates that the factor m_j is more important than the factor m_i , and at this time, the hierarchical scoring label $score_level_{ij}$ of the factor feature combination (em_i, em_j) may be set to $1/score$. Exemplarily, $score \in \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$, representing the score of the degree of importance of the factor m_i relative to the factor m_j .

In step S203, the set of factor feature combinations and the factor discrimination label for each of the factor feature combinations are used as a first training set to train a first neural network model, and a trained first neural network model is updated using a first loss function to obtain the factor discrimination model.

Referring to the above example, after acquiring the factor feature combination (em_i, em_j) and the corresponding factor discrimination label $flag_{ij}$, the first training set SC may be set as:

$$SC = \{sc_1, sc_2, sc_3, \dots, sc_k, \dots, sc_{N(N-1)/2}\} \quad \text{Formula (3),}$$

wherein $sc_{N(i-1)-(i(i+1))/2+j} = ((em_i, em_j), flag_{ij})$, and N represents the number of factors.

Optionally, the first neural network model may comprise a first layer, a second layer, and an output layer, which may be respectively constructed as follows:

$$Z_1 = W_1(em_i, em_j) + b_1$$

$$Z_2 = W_2 Z_1 + b_2$$

$$\hat{y} = \text{softmax}(Z_2) \quad \text{Formula (4),}$$

wherein Z_1 is an output of the first layer, (em_i, em_j) is an input of the first layer, W_1 represents a weight of the first layer, and b_1 represents a bias of the first layer; Z_2 is an output of the second layer, Z_1 is an input of the second layer, W_2 represents a weight of the second layer, and b_2 represents a bias of the second layer; and $\hat{y}$ is an output of the output layer, and Z_2 is an input of the output layer. Exemplarily, $\text{softmax}(x) = \frac{e^x}{\sum_K e^x}$, wherein e represents the natural base, and K represents the total number of elements in the set where x is located.

Optionally, the first loss function may be constructed based on the factor discrimination label for each of the factor feature combinations and a factor discrimination result output by the trained first neural network model. Exemplarily, the first loss function $L_{sc}(y, \hat{y})$ may be constructed as follows:

$$L_{sc}(y, \hat{y}) = -\sum_{i=1}^{N(N-1)/2} y_i \ln \hat{y}_i + (1 - y_i) \ln (1 - \hat{y}_i) \quad \text{Formula (5),}$$

wherein $\ln$ represents the logarithm with e as the base, y represents the factor discrimination label, and $\hat{y}$ represents the factor discrimination result output by the trained first neural network model.

Optionally, in step S203, parameters of the trained first neural network model may be adjusted using the first loss function until the first loss function is in a convergence state, to obtain the factor discrimination model.

In step S205, the set of factor feature combinations and the hierarchical scoring label for each of the factor feature combinations are used as a second training set to train a second neural network model, and a trained second neural network model is updated using a second loss function to obtain the hierarchical scoring model. The second loss function is constructed based at least on a factor discrimination result output by the factor discrimination model and a reciprocal of a hierarchical scoring result output by the trained second neural network model.

Referring to the above example, after acquiring the factor feature combination (em_i, em_j) and the corresponding hierarchical scoring label $score_level_{ij}$, the second training set SL may be set as:

$$SL = \{sl_1, sl_2, sl_3, \dots, sl_k, \dots, sl_{N(N-1)/2}\} \quad \text{Formula (6),}$$

wherein $sl_{N(i-1)-(i(i+1))/2+j} = ((em_i, em_j), score_level_{ij})$, and N represents the number of factors.

Optionally, the second neural network model may comprise a first layer, a second layer, and an output layer, which may be respectively constructed as follows:

$$\begin{aligned} Z_1 &= W_1(em_i, em_j) + b_1 \\ Z_2 &= W_2 Z_1 + b_2 \\ \hat{y} &= softmax(Z_2) \end{aligned} \quad \text{Formula (7),}$$

wherein Z_1 is an output of the first layer, (em_i, em_j) is an input of the first layer, W_1 represents a weight of the first layer, and b_1 represents a bias of the first layer; Z_2 is an output of the second layer, Z_1 is an input of the second layer, W_2 represents a weight of the second layer, and b_2 represents a bias of the second layer; and $\hat{y}$ is an output of the output layer, and Z_2 is an input of the output layer. Exemplarily, $softmax(x) = \frac{e^x}{\sum_K e^x}$, wherein e represents the natural base, and K represents the total number of elements in the set where x is located.

Optionally, the second loss function may be constructed based on the hierarchical scoring label for each of the factor feature combinations, the factor discrimination result output by the factor discrimination model, the hierarchical scoring result output by the trained second neural network model, and the reciprocal of the hierarchical scoring result output by the trained second neural network model. Exemplarily, the second loss function $L_{sl}(y, \hat{y})$ may be constructed as follows:

$$L_{sl}(y, \hat{y}) = -\sum_{i=1}^{N(N-1)/2} flag y_i \ln \hat{y}_i + (1 - flag) \ln (1/\hat{y}_i) \quad \text{Formula (8),}$$

wherein $\ln$ represents the logarithm with e as the base, y represents the hierarchical scoring label, $\hat{y}$ represents the hierarchical scoring result output by the trained second neural network model, and $flag$ represents the factor discrimination result output by the factor discrimination model.

Alternatively, the second loss function $L_{sl}(y, \hat{y})$ may be constructed as follows:

$$L_{sl}(y, \hat{y}) = -\sum_{i=1}^{N(N-1)/2} y_i \ln \hat{y}_i + (1 - flag) \ln (1/\hat{y}_i) \quad \text{Formula (9),}$$

wherein $\ln$ represents the logarithm with e as the base, y represents the hierarchical scoring label, $\hat{y}$ represents the hierarchical scoring result output by the trained second neural network model, and $flag$ represents the factor discrimination result output by the factor discrimination model.

By introducing the factor discrimination result $flag$ output by the factor discrimination model and the reciprocal $1/\hat{y}_i$ of the hierarchical scoring result output by the trained second neural network model into the second loss function, it can adapt to the reciprocal hierarchical scoring rules in the process of constructing the comparison matrix in the analytic hierarchy process, so that the hierarchical scoring model can be better combined with the factor discrimination model, thereby improving the accuracy and rationality of matrix generation.

Optionally, in step S205, parameters of the trained second neural network model may be adjusted using the second loss function until the second loss function is in a convergence state, to obtain the hierarchical scoring model.

Optionally, after obtaining the factor discrimination model and the hierarchical scoring model, the two models may be cascaded to obtain the matrix generator, wherein a factor feature combination (em_i, em_j) may be input into the matrix generator, and the obtained output is a hierarchical scoring label $score_level_{ij}$ of the factor feature combination (em_i, em_j) . A plurality of factor feature combinations (em_i, em_j) from pairwise combinations of the set of factor features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_n\}$ are input into the matrix generator, and the hierarchical scoring label $score_level_{ij}$ for each factor feature combination (em_i, em_j) may be obtained, so as to construct the comparison matrix. The method for constructing the comparison matrix will be further described below.

FIG. 3 shows a block diagram of a system for training a matrix generator according to one or more embodiments of the present application.

As shown in FIG. 3, a system 300 for training a matrix generator may comprise an acquiring unit 310, a first training unit 320, and a second training unit 330.

The acquiring unit 310 is configured to acquire a set of factor feature combinations, as well as a factor discrimination label and a hierarchical scoring label for each of the factor feature combinations.

Optionally, the acquiring unit 310 may be configured to acquire a plurality of factors and a semantic vector for each of the plurality of factors, combine the semantic vector for each of the plurality of factors into a set of factor features, pairwise combine the factor features in the set of factor features to generate a plurality of factor feature pairs, and use the plurality of factor feature pairs as the set of factor feature combinations, wherein each of the factor feature combinations may include a semantic vector of a first factor and a semantic vector of a second factor.

Optionally, the acquiring unit 310 may be configured to acquire the factor discrimination label for a factor feature combination based on importance of a corresponding first factor relative to a second factor in the factor feature combination. When it is determined that the first factor is more important than the second factor, the factor discrimination label of the factor feature combination composed of the first factor and the second factor may be set to a first value; and when it is determined that the second factor is more important than the first factor, the factor discrimination label of the factor feature combination composed of the first factor and the second factor may be set to a second value.

Optionally, the acquiring unit 310 may be configured to acquire the hierarchical scoring label for a factor feature combination based on a degree of importance of a

corresponding first factor relative to a second factor in the factor feature combination. Optionally, a score for representing the degree of importance of the first factor relative to the second factor may be determined, the hierarchical scoring label is set to the score when the first factor is more important than the second factor, and the hierarchical scoring label is set to a reciprocal of the score when the second factor is more important than the first factor.

The first training unit 320 is configured to use the set of factor feature combinations and the factor discrimination label for each of the factor feature combinations as a first training set to train a first neural network model, and update a trained first neural network model using a first loss function to obtain a factor discrimination model. Optionally, the first loss function may be constructed based on the factor discrimination label for each of the factor feature combinations and a factor discrimination result output by the trained first neural network model.

Optionally, the first training unit 320 may be configured to adjust parameters of the trained first neural network model using the first loss function until the first loss function is in a convergence state, to obtain the factor discrimination model.

The second training unit 330 is configured to use the set of factor feature combinations and the hierarchical scoring label for each of the factor feature combinations as a second training set to train a second neural network model, and update a trained second neural network model using a second loss function to obtain a hierarchical scoring model. The second loss function is constructed based at least on a factor discrimination result output by the factor discrimination model and a reciprocal of a hierarchical scoring result output by the trained second neural network model. Optionally, the second loss function may be constructed based on the hierarchical scoring label for each of the factor feature combinations, the factor discrimination result output by the factor discrimination model, the hierarchical scoring result output by the trained second neural network model, and the reciprocal of the hierarchical scoring result output by the trained second neural network model.

By introducing the factor discrimination result output by the factor discrimination model and the reciprocal of the hierarchical scoring result output by the trained second neural network model into the second loss function, it can adapt to the reciprocal hierarchical scoring rules in the process of constructing the comparison matrix in the analytic hierarchy process, so that the hierarchical scoring model can be better combined with the factor discrimination model, thereby improving the accuracy and rationality of matrix generation.

Optionally, the second training unit 330 may be configured to adjust parameters of the trained second neural network model using the second loss function until the second loss function is in a convergence state, to obtain the hierarchical scoring model.

FIG. 4 shows a flowchart of a method for constructing a comparison matrix according to one or more embodiments of the present application.

As shown in FIG. 4, in step S401, a set of factor features is acquired.

Optionally, in step S401, a semantic vector for each of a plurality of factors associated with a target task may be acquired, and the semantic vector for each of the plurality of factors may be combined to acquire the set of factor features. Exemplarily, the acquired plurality of factors associated with the target task 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 number of factors. Next, the plurality of factors may be represented by natural language, for example, a semantic vector for each of the plurality of factors may be acquired through a pre-trained natural language model (e.g., BERT, GPT, etc.) to constitute a set of factor features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_n\}$, wherein $em_k \in \mathbb{R}^t$, represents the semantic vector of the factor m_k , t represents the dimension of the semantic vector, and n represents the size of the set ME , i.e., the number of semantic vectors of the factors.

In step S403, the set of factor features is input into a matrix generator to obtain a comparison matrix, wherein the matrix generator is trained using a method for training a matrix generator according to an aspect of the present application.

Optionally, in step S403, the set of factor features may be input into the matrix generator to generate hierarchical scoring results for a plurality of factor feature pairs from pairwise combinations of the factor features in the set of factor features, and the comparison matrix is obtained based on the hierarchical scoring results of the plurality of factor feature pairs. Exemplarily, the set of factor features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_n\}$ is input into the matrix generator, and the following comparison matrix A may be obtained:

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & \dots & a_{ij} & \dots \\ \dots & a_{ji} & \dots & \dots \\ a_{n1} & \dots & \dots & 1 \end{bmatrix} \quad \text{Formula (10),}$$

wherein i represents a row number where an element in the matrix is located, j represents a column number where an element in the matrix is located, $a_{ii} = 1, a_{ji} = 1/a_{ij}$, n represents the number of factors (which is also the dimension of the matrix), and a_{ij} comes from the value of the hierarchical scoring result $score_level_{ij}$ for each factor feature combination (em_i, em_j) output by the matrix generator.

According to one or more embodiments of the present application, by utilizing a trained matrix generator to automatically construct a comparison matrix based on a set of factor features, manpower consumption in the construction process of the comparison matrix can be saved, the efficiency and accuracy of problem processing using the analytic hierarchy process can be improved, and the application fields of the analytic hierarchy process can be broadened.

FIG. 5 shows a block diagram of a system for constructing a comparison matrix according to one or more embodiments of the present application.

As shown in FIG. 5, a system 500 for constructing a comparison matrix comprises an acquiring unit 510 and a matrix generator 520.

The acquiring unit 510 is configured to acquire a set of factor features.

Optionally, the acquiring unit 510 may be configured to acquire a semantic vector for each of a plurality of factors associated with a target task, and combine the semantic vector for each of the plurality of factors to acquire the set of factor features. Exemplarily, the acquired plurality of factors associated with the target task 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 number of factors. Next, the plurality of factors may be represented by natural language, for example, a semantic vector for each of the plurality of factors may be acquired through a pre-trained natural language model (e.g., BERT, GPT, etc.) to constitute a set of factor features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_n\}$, wherein $em_k \in \mathbb{R}^t$ represents the semantic vector of the factor m_k , t represents the dimension of the semantic vector, and n represents the size of the set ME , i.e., the number of semantic vectors of the factors.

The matrix generator 520 is configured to process the set of factor features to obtain a comparison matrix, wherein the matrix generator 520 may be trained using a method for training a matrix generator according to an aspect of the present application.

Optionally, the matrix generator 520 may be configured to process the set of factor features to generate hierarchical scoring results for a plurality of factor feature pairs from pairwise combinations of the factor features in the set of factor features, and generate the comparison matrix based on the hierarchical scoring results of the plurality of factor feature pairs. Exemplarily, the matrix generator 520 may process the set of factor features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_n\}$ to obtain the comparison matrix A as shown in the above formula (10).

FIG. 6 shows a flowchart of an analytic hierarchy process method according to one or more embodiments of the present application.

As shown in FIG. 6, in step S601, a set of factor features of a plurality of factors associated with a target task is acquired.

Optionally, in step S601, a semantic vector for each of a plurality of factors associated with a target task may be acquired, and the semantic vector for each of the plurality of factors may be combined to acquire the set of factor features. Exemplarily, the acquired plurality of factors associated with the target task 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 number of factors. Next, the plurality of factors may be represented by natural language, for example, a semantic vector for each of the plurality of factors may be acquired through a pre-trained natural language model (e.g., BERT, GPT, etc.) to constitute a set of factor

features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_n\}$, wherein $em_k \in \mathbb{R}^t$, represents the semantic vector of the factor m_k , t represents the dimension of the semantic vector, and n represents the size of the set ME , i.e., the number of semantic vectors of the factors.

In step S603, the set of factor features is input into a matrix generator to obtain a comparison matrix, wherein the matrix generator is trained using a method for training a matrix generator according to an aspect of the present application.

Optionally, in step S603, the set of factor features may be input into the matrix generator to generate hierarchical scoring results for a plurality of factor feature pairs from pairwise combinations of the factor features in the set of factor features, and the comparison matrix is obtained based on the hierarchical scoring results of the plurality of factor feature pairs. Exemplarily, the set of factor features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_n\}$ is input into the matrix generator, and the comparison matrix A as shown in the above formula (10) may be obtained.

In step S605, the comparison matrix is processed to determine priorities of the plurality of factors.

Optionally, in step S605, elements of each column in the comparison matrix may be summed to obtain a sum of elements for each column, each of the elements in the comparison matrix may be divided by the sum of elements of a corresponding column to generate a column-averaged comparison matrix, and an average value of the elements in each row of the column-averaged comparison matrix may be determined as the priorities of the plurality of factors.

As an example, after obtaining the comparison matrix A as shown in the above formula (10), elements of each column j in the comparison matrix A may be summed through the following formula (11) to obtain the sum of elements for each column j :

$$\sum_{i=1}^n a_{ij}, \forall i, j \quad \text{Formula (11),}$$

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

As an example, after obtaining the sum of elements for each column, each element in the comparison matrix may be divided by the sum of elements of the corresponding column through the following formula (12) to generate the column-averaged comparison matrix A' :

$$a_{ij}' = a_{ij} / \sum_{i=1}^n a_{ij}, \forall i, j \quad \text{Formula (12),}$$

wherein i represents a row number where an element in the matrix is located, j represents a column number where an element in the matrix is located, a_{ij}' represents

the element in the column-averaged comparison matrix A' , and n represents the number of factors (which is also the dimension of the matrix).

As an example, after obtaining the column-averaged comparison matrix A' , the average value p_i of the elements in each row of the column-averaged comparison matrix may be determined through the following formula (13) as the priorities of the plurality of factors:

$$p_i = \frac{\sum_{j=1}^n a_{ij}'}{n} \quad \text{Formula (13),}$$

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

As an example, after obtaining the average value p_i of the elements in each row, the priorities of the n factors may be represented as the following column vector P :

$$P = \begin{bmatrix} p_1, \\ p_2, \\ \dots, \\ p_n \end{bmatrix}.$$

In step S607, a consistency test is performed on the comparison matrix using the priorities of the plurality of factors, and weights of the plurality of factors are determined using the comparison matrix having passed the consistency test.

Optionally, in step S607, a maximum eigenvalue of the comparison matrix may be determined based on the priorities of the plurality of factors, a consistency index of the comparison matrix may be determined based on the maximum eigenvalue of the comparison matrix and the number of factors, a random index of the comparison matrix may be determined based on a dimension of the comparison matrix, and the consistency test is performed on the comparison matrix based on the consistency index and the random index of the comparison matrix. 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 consistency test is passed.

As an example, after obtaining the column vector 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 (14):

$$\lambda_{max} = \sum_{i=1}^n \frac{[AP]_i}{np_i} \quad \text{Formula (14),}$$

wherein i represents a row number where an element in the matrix is located, n represents the number of factors (which is also the dimension of the matrix), p_i

represents the i -th element in the column 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 of the comparison matrix A may be determined through the following formula (15):

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad \text{Formula (15),}$$

wherein n represents the number of factors (which is also the dimension of the matrix).

As an example, the random index RI of the comparison matrix A may also be determined based on the dimension n of the comparison matrix A , for example, the random index RI of the comparison matrix may be determined based on the dimension n of the comparison matrix A by way of mathematical table lookup.

As an example, after determining the consistency index CI and the random index RI of the comparison matrix A , a consistency ratio CR of the comparison matrix A may be determined through the following formula (16):

$$CR = CI/RI \quad \text{Formula (16)}$$

Exemplarily, when CR is less than 0.1, it may be determined that the comparison matrix has passed the consistency test.

Optionally, in step S607, the comparison matrix having passed the consistency test may be processed using one or more of an arithmetic mean method, a geometric mean method, and an eigenvector method to determine the weights of the plurality of factors, thereby determining an analytic hierarchy process result of the target task.

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

Referring to the analytic hierarchy process model 100 shown in FIG. 1, the PSD of the first layer may be "Which supplier has the most value?", the factor system of the second layer may include influence, reputation, execution, geographical location, etc., and the candidate decision of the third layer may include Supplier 1, Supplier 2, Supplier 3, Supplier 4, etc. Exemplarily, 235 factors such as influence, reputation, execution, and geographical location included in the factor system of the second layer may be represented as a set $M = \{m_1, m_2, m_3, \dots, m_k, \dots, m_{235}\}$, wherein $m_1, m_2, m_3, \dots, m_k, \dots, m_{235}$ represent the 235 factors respectively. Next, the plurality of factors may be represented by natural language, for example, semantic vectors of the 235 factors in the factor set $M = \{m_1, m_2, m_3, \dots, m_k, \dots, m_{235}\}$ may be acquired through a pre-trained natural language model (e.g., BERT, GPT, etc.) to constitute a set of factor features $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_{235}\}$, wherein $em_k \in \mathbb{R}^{160}$ represents a semantic vector of the factor m_k , and 160 represents the dimension of the semantic vector.

Exemplarily, the obtained set of factor features of the 235 factors $ME = \{em_1, em_2, em_3, \dots, em_k, \dots, em_{235}\}$ may be input into a matrix generator obtained by training using the method for training a matrix generator according to an aspect of the present application to generate a comparison matrix. Next, the comparison matrix may be processed with reference to respective steps of the analytic hierarchy process method shown in conjunction with FIG. 6 to determine priorities of the 235 factors, a consistency test is performed on the comparison matrix using the priorities of the factors, and weights of the 235 factors are determined using the comparison matrix having passed the consistency test. Optionally, the comparison matrix having passed the consistency test may be processed using one or more of the arithmetic mean method, the geometric mean method, and the eigenvector method to determine the weights of the above 235 factors, thereby determining the analytic hierarchy process result for the PSD of the first layer being "Which supplier has the most value?", for example, the analytic hierarchy process result is that Supplier 3 has the most value.

FIG. 7 shows a block diagram of an analytic hierarchy process system according to one or more embodiments of the present application.

As shown in FIG. 7, an analytic hierarchy process system 70 comprises a communication unit 710, a memory 720 (e.g., a non-volatile memory such as a flash memory, a ROM, a hard disk drive, a magnetic disk, an optical disc, etc.), a processor 730, and a computer program 740 stored on the memory 720 and runnable on the processor 730.

As a communication interface, the communication unit 710 is configured to establish a communication connection between the analytic hierarchy process system 70 and an external device or network (e.g., a cloud server, a mobile terminal, etc.).

The memory 720 stores the computer program 740 executable by the processor 730. In addition, the memory 720 may further store data generated when the processor 730 executes the computer program (e.g., the set of factor features, the comparison matrix, etc.) and data or commands received from the outside via the communication unit 710.

The processor 730 is configured to execute the computer program 740 to implement an 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 comprising instructions, wherein the instructions, when executed, perform a method for training a matrix generator according to an aspect of the present application. In addition, the present application may also be implemented as a computer-readable storage medium comprising instructions, wherein the instructions, when executed, perform a method for constructing a comparison matrix according to an aspect of the present application. In addition, the present application may also be implemented as a computer-readable storage medium comprising instructions, wherein the instructions, when executed, perform an analytic hierarchy process method according to an 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 divided 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 according to the present application and specific applications thereof, 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 presented 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 training a matrix generator comprising a factor discrimination model and a hierarchical scoring model, the method comprising the following steps:

acquiring a set of factor feature combinations, as well as a factor discrimination label and a hierarchical scoring label for each of the factor feature combinations;

training a first neural network model using the set of factor feature combinations and the factor discrimination label for each of the factor feature combinations as a first training set, and updating a trained first neural network model using a first loss function to obtain the factor discrimination model; and

training a second neural network model using the set of factor feature combinations and the hierarchical scoring label for each of the factor feature combinations as a second training set, and updating a trained second neural network model using a second loss function to obtain the hierarchical scoring model,

wherein the second loss function is constructed based at least on a factor discrimination result output by the factor discrimination model and a reciprocal of a hierarchical scoring result output by the trained second neural network model.

2. The method according to claim 1, wherein the matrix generator is used to generate a comparison matrix based on a plurality of input factors in an analytic hierarchy process.

3. The method according to claim 1, wherein acquiring the set of factor feature combinations comprises:

acquiring a plurality of factors and a semantic vector for each of the plurality of factors;

combining the semantic vector for each of the plurality of factors into a set of factor features;

pairwise combining the factor features in the set of factor features to generate a plurality of factor feature pairs; and

using the plurality of factor feature pairs as the set of factor feature combinations, wherein each of the factor feature combinations comprises a semantic vector of a first factor and a semantic vector of a second factor.

4. The method according to claim 3, wherein acquiring the factor discrimination label for each of the factor feature combinations comprises:

acquiring the factor discrimination label for each of the factor feature combinations based on importance of the first factor relative to the second factor.

5. The method according to claim 4, wherein acquiring the factor discrimination label for each of the factor feature combinations further comprises:

setting the factor discrimination label to a first value in response to determining that the first factor is more important than the second factor; and

setting the factor discrimination label to a second value in response to determining that the second factor is more important than the first factor.

6. The method according to claim 3, wherein acquiring the hierarchical scoring label for each of the factor feature combinations comprises:

acquiring the hierarchical scoring label for each of the factor feature combinations based on a degree of importance of the first factor relative to the second factor.

7. The method according to claim 6, wherein acquiring the hierarchical scoring label for each of the factor feature combinations further comprises:

determining a score for representing the degree of importance of the first factor relative to the second factor;

setting the hierarchical scoring label to the score in response to the first factor being more important than the second factor; and

setting the hierarchical scoring label to a reciprocal of the score in response to the second factor being more important than the first factor.

8. The method according to claim 1, wherein the first loss function is constructed based on the factor discrimination label for each of the factor feature combinations and the factor discrimination result output by the trained first neural network model.

9. The method according to claim 1, wherein updating the trained first neural network model using the first loss function comprises:

adjusting parameters of the trained first neural network model using the first loss function until the first loss function is in a convergence state, to obtain the factor discrimination model.

10. The method according to claim 1, wherein the second loss function is constructed based on the hierarchical scoring label for each of the factor feature combinations, the factor discrimination result output by the factor discrimination model, the hierarchical scoring result output by the trained second neural network model, and the reciprocal of the hierarchical scoring result output by the trained second neural network model.

11. The method according to claim 1, wherein updating the trained second neural network model using the second loss function comprises:

adjusting parameters of the trained second neural network model using the second loss function until the second loss function is in a convergence state, to obtain the hierarchical scoring model.

12. A system for training a matrix generator comprising a factor discrimination model and a hierarchical scoring model, the system comprising:

an acquiring unit configured to acquire a set of factor feature combinations, as well as a factor discrimination label and a hierarchical scoring label for each of the factor feature combinations;

a first training unit configured to train a first neural network model using the set of factor feature combinations and the factor discrimination label for each of the factor feature combinations as a first training set, and update a trained first neural network model using a first loss function to obtain the factor discrimination model; and

a second training unit configured to train a second neural network model using the set of factor feature combinations and the hierarchical scoring label for each of the

factor feature combinations as a second training set, and update a trained second neural network model using a second loss function to obtain the hierarchical scoring model,

wherein the second loss function is constructed based at least on a factor discrimination result output by the factor discrimination model and a reciprocal of a hierarchical scoring result output by the trained second neural network model.

13. The system according to claim 12, wherein the matrix generator is used to generate a comparison matrix based on a plurality of input factors in an analytic hierarchy process.

14. The system according to claim 12, wherein the acquiring unit is further configured to:

- acquire a plurality of factors and a semantic vector for each of the plurality of factors;
- combine the semantic vector for each of the plurality of factors into a set of factor features;

- pairwise combine factor features in the set of factor features to generate a plurality of factor feature pairs; and

- use the plurality of factor feature pairs as the set of factor feature combinations, wherein each of the factor feature combinations comprises a semantic vector of a first factor and a semantic vector of a second factor.

15. The system according to claim 14, wherein the acquiring unit is further configured to:

- acquire the factor discrimination label for each of the factor feature combinations based on importance of the first factor relative to the second factor.

16. The system according to claim 15, wherein the acquiring unit is further configured to:

- set the factor discrimination label to a first value in response to determining that the first factor is more important than the second factor; and

- set the factor discrimination label to a second value in response to determining that the second factor is more important than the first factor.

17. The system according to claim 14, wherein the acquiring unit is further configured to:

- acquire the hierarchical scoring label for each of the factor feature combinations based on a degree of importance of the first factor relative to the second factor.

18. The system according to claim 17, wherein the acquiring unit is further configured to:

- determine a score for representing the degree of importance of the first factor relative to the second factor;

- set the hierarchical scoring label to the score in response to the first factor being more important than the second factor; and

- set the hierarchical scoring label to a reciprocal of the score in response to the second factor being more important than the first factor.

19. The system according to claim 12, wherein the first loss function is constructed based on the factor discrimination label for each of the factor feature combinations and the factor discrimination result output by the trained first neural network model.

20. The system according to claim 12, wherein the first training unit is further configured to:

adjust parameters of the trained first neural network model using the first loss function until the first loss function is in a convergence state, to obtain the factor discrimination model.

21. The system according to claim 12, wherein the second loss function is constructed based on the hierarchical scoring label for each of the factor feature combinations, the factor discrimination result output by the factor discrimination model, the hierarchical scoring result output by the trained second neural network model, and the reciprocal of the hierarchical scoring result output by the trained second neural network model.

22. The system according to claim 12, wherein the second training unit is further configured to:

adjust parameters of the trained second neural network model using the second loss function until the second loss function is in a convergence state, to obtain the hierarchical scoring model.

23. A computer-readable storage medium, comprising instructions, wherein the instructions, when executed, perform the method for training a matrix generator according to any one of claims 1-11.

24. A method for constructing a comparison matrix, comprising the following steps:
acquiring a set of factor features; and
inputting the set of factor features into a matrix generator to obtain a comparison matrix, wherein the matrix generator is trained using the method for training a matrix generator according to any one of claims 1-11.

25. The method according to claim 24, wherein acquiring the set of factor features comprises:

acquiring a semantic vector for each of a plurality of factors associated with a target task; and

combining the semantic vector for each of the plurality of factors to acquire the set of factor features.

26. The method according to claim 24, wherein inputting the set of factor features into the matrix generator to obtain the comparison matrix comprises:

inputting the set of factor features into the matrix generator to generate hierarchical scoring results for a plurality of factor feature pairs from pairwise combinations of the factor features in the set of factor features; and

generating the comparison matrix based on the hierarchical scoring results of the plurality of factor feature pairs.

27. A system for constructing a comparison matrix, comprising:
an acquiring unit configured to acquire a set of factor features; and
a matrix generator configured to process the set of factor features to obtain the comparison matrix, wherein the matrix generator is trained using the method for training a matrix generator according to any one of claims 1-11.

28. The system according to claim 27, wherein the acquiring unit is further configured to:

acquire a semantic vector for each of a plurality of factors associated with a target task; and

combine the semantic vector for each of the plurality of factors to acquire the set of factor features.

29. The system according to claim 27, wherein the matrix generator is further configured to:

process the set of factor features to generate hierarchical scoring results for a plurality of factor feature pairs from pairwise combinations of the factor features in the set of factor features; and

generate the comparison matrix based on the hierarchical scoring results of the plurality of factor feature pairs.

30. A computer-readable storage medium, comprising instructions, wherein the instructions, when executed, perform the method for constructing a comparison matrix according to any one of claims 24-26.

31. An analytic hierarchy process method, comprising the following steps:
acquiring a set of factor features of a plurality of factors associated with a target task;
inputting the set of factor features into a matrix generator to obtain a comparison matrix, wherein the matrix generator is trained using the method for training a matrix generator according to any one of claims 1-11;

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 weights of the plurality of factors using the comparison matrix having passed the consistency test.

32. The method according to claim 31, wherein acquiring the set of factor features of the plurality of factors associated with a target task comprises:

acquiring a semantic vector for each of the plurality of factors associated with the target task; and

combining the semantic vector for each of the plurality of factors to acquire the set of factor features.

33. The method according to claim 31, wherein inputting the set of factor features into the matrix generator to obtain the comparison matrix comprises:

inputting the set of factor features into the matrix generator to generate hierarchical scoring results for a plurality of factor feature pairs from pairwise combinations of the factor features in the set of factor features; and

obtaining the comparison matrix based on the hierarchical scoring results of the plurality of factor feature pairs.

34. The method according to claim 31, 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 for each column;

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

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

35. The method according to claim 31, 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 based on the priorities of the plurality of factors;

determining a consistency index of the comparison matrix based on the maximum eigenvalue of the comparison matrix and a quantity of factors;

determining a random index of the comparison matrix based on 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.

36. The method according to claim 35, wherein the method further comprises:

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

37. An analytic hierarchy process system, comprising:

a memory;

a processor coupled to the memory; and

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

acquiring a set of factor features of a plurality of factors associated with a target task;

inputting the set of factor features into a matrix generator to obtain a comparison matrix, wherein the matrix generator is trained using the method for training a matrix generator according to any one of claims 1-11;

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 weights of the plurality of factors using the comparison matrix having passed the consistency test.

38. The system according to claim 37, wherein execution of the computer program further causes the following operations:

- acquiring a semantic vector for each of the plurality of factors associated with the target task; and

- combining the semantic vector for each of the plurality of factors to acquire the set of factor features.

39. The system according to claim 37, wherein execution of the computer program further causes the following operations:

- inputting the set of factor features into the matrix generator to generate hierarchical scoring results for a plurality of factor feature pairs from pairwise combinations of the factor features in the set of factor features; and

- obtaining the comparison matrix based on the hierarchical scoring results of the plurality of factor feature pairs.

40. The system according to claim 37, wherein execution of the computer program further causes the following operations:

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

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

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

41. The system according to claim 37, wherein execution of the computer program further causes the following operations:

- determining a maximum eigenvalue of the comparison matrix based on the priorities of the plurality of factors;

- determining a consistency index of the comparison matrix based on the maximum eigenvalue of the comparison matrix and a quantity of factors;

- determining a random index of the comparison matrix based on 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.

42. The system according to claim 41, wherein execution of the computer program further causes the following operation:

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

43. A computer-readable storage medium, comprising instructions, wherein the instructions, when executed, perform the analytic hierarchy process method according to any one of claims 31-36.