

MULTI-CLASSIFIER-BASED RECOMMENDATION METHOD AND DEVICE, AND ELECTRONIC DEVICE

TECHNICAL FIELD

[0001] Embodiments of the present specification relate to the field of computer
5 technologies, and in particular, to multi-classifier-based recommendation methods and
devices, and electronic devices.

BACKGROUND

[0002] In recent years, with the development of e-commerce, social networks, and
mobile networks, network information data is increasing, and big data is defined as an
10 emerging data concept. In addition, the explosive growth of data has led us to an era
of massive data gaps. In a mass data environment, classifiers have developed rapidly
in terms of data recommendation to rapidly and efficiently utilize existing
information.

[0003] Most conventional classification methods assume that the data is linearly
15 separable, and a classifier is used to classify and predict all the data. With the advent
of the big data era, the requirements of data classification become higher and higher,
and the single and fuzzy data classification cannot meet the current requirements. A
new classification recommendation method is urgently needed to improve the
accuracy of data classification prediction.

SUMMARY

[0004] Embodiments of the present specification provide a multi-classifier-based
recommendation method and device, and an electronic device, to implement
diversified data classification prediction, so as to improve the accuracy of data
classification prediction.

25 **[0005]** According to the first aspect, an embodiment of the present specification
provides a multi-classifier-based recommendation method, including: performing
prediction on received feature data based on a primary classifier in a predetermined
multi-classifier to obtain first prediction data; obtaining a target sub-classifier, based

on the feature data, among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and the feature data being a highest, and $k \geq 2$; performing prediction on the feature data based on the target sub-classifier to obtain second prediction data; combining the first prediction data and the second prediction data based on a predetermined algorithm to obtain third prediction data; and recommending a to-be-recommended entity corresponding to the feature data based on the third prediction data.

[0006] Optionally, the obtaining a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier includes: if each of the k sub-classifiers has a center point of data distribution, searching for a sub-classifier whose center point is closest to a data vector of the feature data, and using the sub-classifier as the target sub-classifier.

[0007] Optionally, the obtaining a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier includes: if each of the k sub-classifiers has a Gaussian mixture model with data distribution parameters, searching for a sub-classifier whose data distribution parameters have a highest similarity with the feature data, and using the sub-classifier as the target sub-classifier.

[0008] Optionally, after the recommending the to-be-recommended entity corresponding to the feature data based on the third prediction data, the method further includes: detecting whether a user selects the recommended entity corresponding to the feature data; and updating parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on whether the user selects the recommended entity.

[0009] Optionally, the updating the parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on whether the user selects the recommended entity includes: if the user selects the recommended entity, providing positive feedback to the multi-classifier, or if the user does not select the recommended entity, providing negative feedback to the multi-classifier; and updating the parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on the positive feedback or the negative feedback.

[0010] Optionally, after the performing prediction on the feature data based on the target sub-classifier to obtain second prediction data, the method further includes: updating the center point of the target sub-classifier based on the data vector of the

feature data.

[0011] Optionally, the updating the center point of the target sub-classifier based on the data vector of the feature data includes:

$$P_{t+1} = P_t + \frac{x_t - P_t}{n_i}, n_{i+1} = n_i + 1$$

5 where P_{t+1} indicates the center point of the target sub-classifier after the updating; P_t indicates the center point of the target sub-classifier before the updating; x_t indicates the data vector; n_i indicates an amount of data allocated to the target sub-classifier before the updating; and n_{i+1} indicates an amount of data of the target sub-classifier after the updating.

10 **[0012]** According to the second aspect, an embodiment of the present specification provides a multi-classifier-based recommendation device, including: a first classification unit, configured to perform prediction on received feature data based on a primary classifier in a predetermined multi-classifier to obtain first prediction data; a search unit, configured to obtain a target sub-classifier, based on the feature data,
15 among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and the feature data being a highest, and $k \geq 2$; a second classification unit, configured to perform prediction on the feature data based on the target sub-classifier to obtain second prediction data; a combining unit, configured to combine the first prediction data and the second prediction data based
20 on a predetermined algorithm to obtain third prediction data; and a recommending unit, configured to recommend a to-be-recommended entity corresponding to the feature data based on the third prediction data.

[0013] Optionally, the search unit is configured to: if each of the k sub-classifiers has a center point of data distribution, search for a sub-classifier whose center point is
25 closest to a data vector of the feature data, and use the sub-classifier as the target sub-classifier.

[0014] Optionally, the search unit is configured to: if each of the k sub-classifiers has a Gaussian mixture model with data distribution parameters, search for a sub-classifier whose data distribution parameters have a highest similarity with the
30 feature data, and use the sub-classifier as the target sub-classifier.

[0015] Optionally, the device further includes: an updating unit, configured to: after a to-be-recommended entity corresponding is recommended, detect whether a user selects the recommended entity corresponding to the feature data; and update

parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on whether the user selects the recommended entity.

[0016] Optionally, the updating unit is configured to: if the user selects the recommended entity and performs positive feedback on the multi-classifier, or if the user does not select the recommended entity and performs negative feedback on the multi-classifier, updating the parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on the positive feedback or the negative feedback.

[0017] Optionally, the device further includes: an updating unit, configured to: after the feature data is predicted based on the target sub-classifier to obtain second prediction data, update the center point of the target sub-classifier based on the data vector of the feature data.

[0018] Optionally, the updating unit is further configured to update the center point of the target sub-classifier based on the following equation:

$$P_{t+1} = P_t + \frac{x_t - P_t}{n_i}, n_{i+1} = n_i + 1$$

where P_{t+1} indicates the center point of the target sub-classifier after the updating; P_t indicates the center point of the target sub-classifier before the updating; x_t indicates the data vector; n_i indicates an amount of data allocated to the target sub-classifier before the updating; and n_{i+1} indicates an amount of data of the target sub-classifier after the updating.

[0019] According to a third aspect, an embodiment of the present specification provides a computer readable storage medium, where the medium stores a computer program, and when the computer program is executed by a processor, the following steps are implemented: performing prediction on received feature data based on a primary classifier in a predetermined multi-classifier to obtain first prediction data; obtaining a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and the feature data being a highest, and $k \geq 2$; performing prediction on the feature data based on the target sub-classifier to obtain second prediction data; combining the first prediction data and the second prediction data based on a predetermined algorithm to obtain third prediction data; and recommending a to-be-recommended entity corresponding to the feature data based on the third prediction data.

[0020] According to a fourth aspect, an embodiment of the present specification provides an electronic device, where the electronic device includes a memory and one or more programs, and the one or more programs are stored in the memory and can be executed by one or more processors to perform the following steps: performing
5 prediction on received feature data based on a primary classifier in a predetermined multi-classifier to obtain first prediction data; obtaining a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and the feature data being a highest, and $k \geq 2$; performing prediction on the feature data based on the target
10 sub-classifier to obtain second prediction data; combining the first prediction data and the second prediction data based on a predetermined algorithm to obtain third prediction data; and recommending a to-be-recommended entity corresponding to the feature data based on the third prediction data.

[0021] One or more of the above technical solutions in the embodiments of the present specification have at least the following technical effects:

[0022] According to the multi-classifier-based recommendation method provided in the embodiment of the present specification, feature data is classified by using a primary classifier and a target sub-classifier in the multi-classifier, so that diversified data classification prediction is implemented, and the accuracy of data classification
20 prediction is improved. In addition, a sub-classifier whose data distribution has a highest similarity with the feature data is selected from the multi-classifier as the target sub-classifier, the first prediction data obtained after the primary classifier performs prediction on the feature data is obtained, the second prediction data obtained after the target sub-classifier performs prediction on the feature data is
25 obtained, and then the third prediction data is obtained by combining the first prediction data and the second prediction data, so that more accurate prediction data is obtained, thereby resolving the technical problem of low accuracy of data classification prediction in the existing technology. Further, the feature data is recommended based on the third prediction data, so that the accuracy of data
30 recommendation is improved.

BRIEF DESCRIPTION OF DRAWINGS

[0023] To describe the technical solutions in the embodiments of the present

specification more clearly, the following outlines the accompanying drawings for illustrating such technical solutions. Clearly, the accompanying drawings outlined below are some embodiments of the present specification, and a person skilled in the art can derive other drawings from such accompanying drawings without creative efforts.

[0024] FIG. 1 is a schematic flowchart illustrating a multi-classifier-based recommendation method, according to an embodiment of the present specification;

[0025] FIG. 2 is a schematic flowchart illustrating a multi-classifier-based recommendation device, according to an embodiment of the present specification; and

[0026] FIG. 3 is a schematic diagram illustrating an electronic device, according to an embodiment of the present specification.

DESCRIPTION OF EMBODIMENTS

[0027] To make the objectives, technical solutions, and advantages of the embodiments of the present specification clearer, the following description clearly and comprehensively describes the technical solutions in the embodiments of the present specification with reference to the accompanying drawings in the embodiments of the present specification. Clearly, the described embodiments are some rather than all of the embodiments of the present specification. Based on the embodiments of the present specification, a person skilled in the art can obtain other embodiments without creative efforts, which all fall within the scope of the present specification.

[0028] Embodiments of the present specification provide a multi-classifier-based recommendation method and device, and an electronic device, to implement diversified data classification prediction, so as to improve the accuracy of data classification prediction.

[0029] The main implementation principles, specific implementations, and corresponding beneficial effects of the technical solutions in the embodiments of the present specification are described below in detail with reference to the accompanying drawings.

[0030] The present specification provides a predetermined multi-classifier, including a primary classifier and k sub-classifiers, where $k \geq 2$. Based on the predetermined multi-classifier, an embodiment of the present specification further provides a multi-classifier-based recommendation method. As shown in FIG. 1, the

method includes:

[0031] S101: Perform prediction on received feature data based on a primary classifier in a predetermined multi-classifier to obtain first prediction data.

5 **[0032]** S102: Obtain, based on the feature data, a target sub-classifier among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and the feature data being a highest, and $k \geq 2$.

[0033] S103: Perform prediction on the feature data based on the target sub-classifier to obtain second prediction data.

10 **[0034]** S104: Combine the first prediction data and the second prediction data based on a predetermined algorithm to obtain third prediction data.

[0035] S105: Recommend a to-be-recommended entity corresponding to the feature data based on the third prediction data.

15 **[0036]** In a specific implementation process, the predetermined multi-classifier can perform classification prediction on the features of the to-be-recommended entity, and predict the classification of the to-be-recommended entity. The predetermined multi-classifier can also perform classification prediction on a feature that is formed by features of a user and the features of the to-be-recommended entity, predict a score of the to-be-recommended entity on the user side, and determine, based on the score, whether to recommend the entity to the user. For this purpose, the feature data
20 received by the multi-classifier can be the feature data of the to-be-recommended entity, or can be the feature data formed by combining the feature of the to-be-recommended entity and the feature of the user.

[0037] The predetermined multi-classifier performs S101 and S102 after receiving the feature data. The execution order of S101 and S102 is not limited; that is, S101
25 and S102 can be performed at the same time, or either S101 or S102 can be performed first.

[0038] In S101, the received feature data is predicted based on the primary classifier to obtain the first prediction data. Specifically, the feature data can be input to the primary classifier, and the primary classifier scores the feature data to obtain the
30 first score, that is, the first prediction data.

[0039] In S102, the target sub-classifier is determined based on the received feature data, and the sub-classifier whose data distribution has a highest similarity with the feature data is selected from the k sub-classifiers in the multi-classifier as the target

sub-classifier. The data distribution of the sub-classifier refers to the distribution of the data received and classified by the sub-classifier, or the distribution of the sample data used to form the sub-classifier through training. A higher similarity between the received feature data with the data distribution of the sub-classifier means that the sub-classifier classifies the feature data with higher accuracy.

[0040] Here, in S102, the target sub-classifier can be determined using any one of the following methods:

[0041] Method 1: If each of the k sub-classifiers in the multi-classifier has a center point of data distribution, the sub-classifier whose center point is closest to a data vector of the feature data is selected as the target sub-classifier. Each sub-classifier has a center point of data distribution. If the data vector of the feature data is closest to a center point of a sub-classifier, it indicates that the feature data has a highest similarity with the data distribution of the sub-classifier, and the sub-classifier is selected as the target sub-classifier.

[0042] In a specific implementation process, in this embodiment of the present specification, a center point of data distribution can be established and updated for any sub-classifier. First, the k sub-classifiers are initialized, and their center points of data distribution are initialized to be empty. Then, the to-be-classified feature data is received by using the multi-classifier, and when the data amount of the feature data received by the multi-classifier is less than a predetermined threshold, a sub-classifier is randomly selected as the target sub-classifier; and after the target sub-classifier performs classification prediction on the feature data, a center point of the target sub-classifier is updated based on a data vector of the feature data.

[0043] If the center point of the target sub-classifier is empty, the data vector of the feature data is used as the center point of the target sub-classifier.

[0044] If the center point of the target sub-classifier is not empty, the center point of the target sub-classifier is updated based on the following equation 1:

$$P_{t+1} = P_t + \frac{x_t - P_t}{n_i}, n_{i+1} = n_i + 1 \quad \dots \text{Equation 1,}$$

where P_{t+1} indicates the center point of the target sub-classifier after the updating; P_t indicates the center point of the target sub-classifier before the updating; x_t indicates the data vector of the feature data; n_i indicates an amount of data allocated to the target sub-classifier before the updating; and n_{i+1} indicates an amount of data of the target sub-classifier after the updating.

[0045] When the data amount of the feature data received by the multi-classifier is greater than or equal to a predetermined threshold, the distance between the data vector of the feature data and the center point of each sub-classifier is calculated. This embodiment of the present specification does not limit a specific algorithm used for calculating the distance between the data vector and the center point, and the Euclidean distance, the Manhattan distance, the Chebyshev distance, etc., can be used. A sub-classifier whose center point is closest to the data vector is selected as a target sub-classifier; and after the target sub-classifier performs classification prediction on the data vector of the feature data, the target sub-classifier is updated by using Equation 1.

[0046] Method 2: If each of the k sub-classifiers in the multi-classifier is a Gaussian mixture model with data distribution parameters, the sub-classifier whose data distribution parameters have a highest similarity with feature data is selected from the k sub-classifiers as the target sub-classifier. The similarity between the data distribution parameters and the feature data can be calculated by using a cosine similarity, a Pearson correlation coefficient, a Euclidean distance, etc.

[0047] After the target sub-classifier is obtained in S102, S103 is performed, and the second prediction data is obtained by performing prediction on the feature data based on the obtained target sub-classifier. Specifically, the feature data is input to the target sub-classifier, and the target sub-classifier scores the feature data to obtain the second score, that is, the second prediction data.

[0048] Further, after the first prediction data and the second prediction data have been obtained, S104 is performed, and the first prediction data and the second prediction data are combined based on a predetermined algorithm to obtain the third prediction data. Specifically, the predetermined algorithm can add the first prediction data and the second prediction data to obtain the third prediction data; or can multiply the first prediction data by a first weight to obtain a first product, multiply the second prediction data by a second weight to obtain a second product, and obtain the sum of the first product and the second product as the third prediction data.

[0049] After S104, S105 is performed, and the to-be-recommended entity corresponding to the feature data is recommended based on the third prediction data. Specifically, the third prediction data is sorted, and a to-be-recommended entity that corresponds to a feature data having a higher-ranked third prediction data is recommended to the user. Alternatively, it is determined whether the third prediction

data is within a predetermined range, and if the third prediction data is within the predetermined range, a to-be-recommended entity corresponding to the feature data to which the third prediction data belongs is recommended to the user.

[0050] In a specific implementation process, in this embodiment, feedback is also provided to the multi-classifier based on whether the recommended entity is selected by the user, so as to update related parameters of the multi-classifier. It is determined whether the user selects the recommended entity corresponding to the feature data; and parameters of the target sub-classifier and the primary classifier that correspond to the feature data are updated based on whether the user selects the recommended entity corresponding to the feature data. If the user selects the recommended entity, 1 is fed back to the multi-classifier, representing positive feedback, or if the user does not select the recommended entity, negative feedback is provided to the multi-classifier; and parameters of the target sub-classifier and the primary classifier that correspond to the feature data are updated based on the positive feedback or the negative feedback.

[0051] The following describes in detail a specific method for updating parameters of the target sub-classifier and the primary classifier, but the embodiment of the present specification is not limited to this updating method.

[0052] In this embodiment of the present specification, a weight vector and a relational matrix are configured for each classifier (the primary classifier and each sub-classifier). The weight vector is 0 at the time of initialization, and the relational matrix is an identity matrix at the time of initialization. Assuming that the dimension of the input sample feature is d , then the dimension of the weight vector of each classifier is $d * 1$, and the dimension of the relational matrix is $d * d$. Therefore, the weight vector of the multi-classifier and the relational matrix as a whole can be expressed as follows:

$$\tilde{\mu} = [\sqrt{\lambda}\mu^T, \mu_1^T, \dots, \mu_j^T, \dots, \mu_K^T]^T \quad \dots \text{Equation 2,}$$

$$\tilde{\Sigma} = \begin{bmatrix} \sqrt{\lambda}\Sigma & 0 & \dots & 0 \\ 0 & \Sigma_1 & \dots & 0 \\ \vdots & 0 & \ddots & 0 \\ 0 & \dots & \dots & \Sigma_k \end{bmatrix} \quad \dots \text{Equation 3,}$$

where $\tilde{\mu}$ indicates the weight vector of the multi-classifier; $\tilde{\Sigma}$ indicates the relational matrix of the multi-classifier; μ indicates the weight vector of the primary classifier; μ_1 to μ_K indicate the weight vectors of the first to the k^{th} sub-classifiers; μ_j

indicates the weight vector of the j^{th} sub-classifier; λ indicates the weight of the primary classifier, which is usually 1; Σ indicates the relational matrix of the primary classifier; and Σ_1 to Σ_k indicate the relational matrices of the first to the k^{th} sub-classifiers. To distinguish between the parameters before and after the update, the weight vector of the multi-classifier at time t can be expressed as $\tilde{\mu}_t$, and the updated weight vector can be expressed as $\tilde{\mu}_{t+1}$; similarly, the relational matrix of the multi-classifier at time t can be expressed as $\tilde{\Sigma}_t$, and the updated relational matrix can be expressed as $\tilde{\Sigma}_{t+1}$.

[0053] Assuming that the data vector of the feature data corresponding to the recommended entity is the i^{th} data vector x_t assigned to the j^{th} sub-classifier, that is, the target sub-classifier, a new data form can be constructed relative to the entire multi-classifier:

$$\tilde{x}_t = [x_t^T, 0_1^T, \dots, 0_{j-1}^T, x_t^T, 0_{j+1}^T, \dots, 0_K^T]^T \quad \dots \text{Equation 4,}$$

[0054] After the above data form is constructed, the i^{th} data vector x_t corresponds to the primary classifier and the j^{th} sub-classifier. Positive feedback or negative feedback is provided to the multi-classifier based on whether the user selects the recommended entity. For example, the user can select the recommended entity through clicking, pressing and holding, or pressing heavily. If the user selects the recommended entity, positive feedback is provided, that is, $y_t=+1$ is fed back to the multi-classifier; or if the user does not select the recommended entity, negative feedback is provided, that is, $y_t=-1$ is fed back to the multi-classifier.

[0055] The weight vectors and relational matrices of the primary classifier and the j^{th} sub-classifier are updated based on the positive feedback or the negative feedback. Specifically, the predicted loss value of the i^{th} data vector can be first calculated based on the identifier y_t that is fed back and the i^{th} data vector. If the loss value is greater than 0, the loss value is updated; otherwise the loss value is not updated. In this way, the accuracy of the update is improved.

[0056] During calculation of the loss value, the loss value of the i^{th} data vector that is predicted by the multi-classifier can be calculated by using the following equation based on y_t the i^{th} data vector, and the weight vectors and relational matrices of the primary classifier and the j^{th} sub-classifier:

$$\ell = \max \left(0, \phi \sqrt{\tilde{x}_t^T \tilde{\Sigma} \tilde{x}_t} - y_t \tilde{\mu}^T \tilde{x}_t \right) \quad \dots \text{Equation 5,}$$

where ℓ indicates the loss value; $\tilde{\phi}$ indicates a hyperparameter; $\tilde{\mathbf{x}}_t$ is constructed based on the i^{th} data vector $\mathbf{x}_t$ (see Equation 4); $\tilde{\boldsymbol{\mu}}$ and $\tilde{\boldsymbol{\Sigma}}$ respectively indicate the weight vector and relational matrix of the multi-classifier (see Equations 1 and 2). $\tilde{\phi}$ can usually be an inverse function of a normal distribution accumulation function, for example, $\tilde{\phi} = \Phi^{-1}(\eta)$.

[0057] It is determined whether the loss value ℓ is greater than 0. If the loss value ℓ is greater than 0, the weight vectors and relational matrices of the primary classifier and the j^{th} sub-classifier are updated based on $\mathbf{y}_t$ and the i^{th} data vector. On the contrary, if the loss value ℓ is not greater than 0, the weight vectors and the relationship matrices are not updated. When the weight vectors and the relational matrices are updated, other parameters of the multi-classifier can also be updated based on the i^{th} data vector, where $\tilde{\alpha}_t$ and $\tilde{\beta}_t$ can be predetermined parameters and can be updated based on the following parameters. The specific updating equations are as follows:

$$\tilde{\boldsymbol{\mu}}_{t+1} = \tilde{\boldsymbol{\mu}}_t + \tilde{\alpha}_t \mathbf{y}_t \tilde{\boldsymbol{\Sigma}}_t \tilde{\mathbf{x}}_t \quad \dots \text{Equation 6,}$$

$$\tilde{\boldsymbol{\Sigma}}_{t+1} = \tilde{\boldsymbol{\Sigma}}_t - \tilde{\beta}_t \tilde{\boldsymbol{\Sigma}}_t \tilde{\mathbf{x}}_t \tilde{\mathbf{x}}_t^T \tilde{\boldsymbol{\Sigma}}_t \quad \dots \text{Equation 7,}$$

$$\tilde{\alpha}_t = \max\{C, \max\{0, \frac{1}{\tilde{v}_t \tilde{\zeta}} (-\tilde{m}_t \tilde{\psi} + \sqrt{\tilde{m}_t^2 \frac{\tilde{\phi}^4}{4} + \tilde{v}_t \tilde{\phi}^2 \tilde{\zeta}})\}\} \quad \dots \text{Equation 8,}$$

$$\tilde{\beta}_t = \frac{\tilde{\alpha}_t \tilde{\phi}}{\sqrt{\tilde{u}_t} + \tilde{v}_t \tilde{\alpha}_t \tilde{\phi}} \quad \dots \text{Equation 9,}$$

$$\tilde{u}_t = \frac{1}{4} \left(-\tilde{\alpha}_t \tilde{v}_t \tilde{\phi} + \sqrt{\tilde{\alpha}_t^2 \tilde{v}_t^2 \tilde{\phi}^2 + 4\tilde{v}_t} \right)^2, \quad \tilde{v}_t = \tilde{\mathbf{x}}_t^T \tilde{\boldsymbol{\Sigma}}_t \tilde{\mathbf{x}}_t \quad \dots \text{Equation 10,}$$

$$\tilde{\psi} = 1 + \frac{\tilde{\phi}^2}{2} \text{ and } \tilde{\zeta} = 1 + \tilde{\phi}^2 \quad \dots \text{Equation 11,}$$

$$\tilde{m}_t = \mathbf{y}_t \tilde{\boldsymbol{\mu}}_t^T \tilde{\mathbf{x}}_t \quad \dots \text{Equation 12,}$$

where $\tilde{\boldsymbol{\mu}}_{t+1}$ indicates the updated weight vector of the multi-classifier, and $\tilde{\boldsymbol{\Sigma}}_{t+1}$ indicates the updated relational matrix of the multi-classifier. Based on Equations 1 and 2, the updated weight vectors $\boldsymbol{\mu}$ and $\boldsymbol{\mu}_j$ of the primary classifier and the j^{th} sub-classifier are obtained from $\tilde{\boldsymbol{\mu}}_{t+1}$; and the relational matrices $\boldsymbol{\Sigma}$ and $\boldsymbol{\Sigma}_j$ of the

primary classifier and the j^{th} sub-classifier are obtained from $\tilde{\Sigma}_{t+1}$. C is a hyperparameter and can be usually set to 1.

[0058] In the previously described embodiment, feature data is classified by using a primary classifier and a target sub-classifier in the multi-classifier, so that diversified data classification prediction is implemented, and the accuracy of data classification prediction is improved. In addition, a sub-classifier whose data distribution has a highest similarity with the feature data is selected from the multi-classifier as the target sub-classifier, the first prediction data obtained after the primary classifier performs prediction on the feature data is obtained, the second prediction data obtained after the target sub-classifier performs prediction on the feature data is obtained, and then the third prediction data is obtained by combining the first prediction data and the second prediction data, so that more accurate prediction data is obtained, thereby resolving the technical problem of low accuracy of data classification prediction in the existing technology. Further, the feature data is recommended based on the third prediction data, so that the accuracy of data recommendation is improved.

[0059] Further, in the previously described embodiment, feedback is provided to the multi-classifier based on whether the user selects the recommended entity, so as to implement online updating and real-time learning of the multi-classifier, so that the preferences and interests of the user can be predicted in real time based on the real-time data stream, all the received data are used only once, and no historical information needs to be stored, thereby reducing the online storage pressure and the calculation complexity. In addition, by updating the center point and the classifier parameters, the multi-classifier model can be trained online in real time, thereby reducing the operation and maintenance pressure of the model (going online and going offline).

[0060] Based on the multi-classifier-based recommendation method provided in the above embodiments, this embodiment also correspondingly provides a multi-classifier-based recommendation device. Referring to FIG. 2, the device includes: a first classification unit 21, configured to perform prediction on received feature data based on a primary classifier in a predetermined multi-classifier to obtain first prediction data; a search unit 22, configured to obtain a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and

the feature data being a highest, and $k \geq 2$; a second classification unit 23, configured to perform prediction on the feature data based on the target sub-classifier to obtain second prediction data; a combining unit 24, configured to combine the first prediction data and the second prediction data based on a predetermined algorithm to obtain third prediction data; and a recommending unit 25, configured to recommend a to-be-recommended entity corresponding to the feature data based on the third prediction data.

[0061] In an optional embodiment, the search unit 22 is configured to: if each of the k sub-classifiers has a center point of data distribution, search for a sub-classifier whose center point is closest to a data vector of the feature data, and using the sub-classifier as the target sub-classifier; or if each of the k sub-classifiers has a Gaussian mixture model with data distribution parameters, search for a sub-classifier whose data distribution parameters have a highest similarity with the feature data, and use the sub-classifier as the target sub-classifier.

[0062] In an optional embodiment, the device further includes an updating unit 26. The updating unit 26 can be configured to: after a to-be-recommended entity corresponding is recommended, detect whether a user selects the recommended entity corresponding to the feature data; and update parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on whether the user selects the recommended entity. Specifically, the updating unit 26 is configured to: if the user selects the recommended entity, provide positive feedback to the multi-classifier, or if the user does not select the recommended entity, provide negative feedback to the multi-classifier; and update the parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on the positive feedback or the negative feedback.

[0063] The updating unit 26 can be further configured to: after the feature data is predicted based on the target sub-classifier to obtain second prediction data, update the center point of the target sub-classifier based on the data vector of the feature data. Specifically, the updating unit can update the center point of the target sub-classifier based on the following equation:

$$P_{t+1} = P_t + \frac{x_t - P_t}{n_i}, \quad n_{i+1} = n_i + 1$$

where P_{t+1} indicates the center point of the target sub-classifier after the updating; P_t indicates the center point of the target sub-classifier before the updating; x_t indicates

the data vector; n_i indicates an amount of data allocated to the target sub-classifier before the updating; and n_{i+1} indicates an amount of data of the target sub-classifier after the updating.

5 **[0064]** The specific operation methods of the units of the device have been described in detail in the above in related method embodiments. Details are omitted here for simplicity.

10 **[0065]** FIG. 3 is a block diagram illustrating an electronic device 700 configured to implement a data query method, according to an example embodiment of the present specification. For example, the electronic device 700 can be a computer, a database console, a tablet device, a personal digital assistant, etc.

15 **[0066]** Referring to FIG. 3, the electronic device 700 can include one or more of the following components: a processing component 702, a memory 704, a power supply component 706, a multimedia component 708, an input/output (I/O) interface 710, and a communication component 712.

20 **[0067]** The processing component 702 generally controls the overall operation of the electronic device 700, such as operations associated with display, data communication, and recording operations. The processing component 702 can include one or more processors 720 for executing instructions to perform all or some of the steps of the method described above. In addition, the processing component 702 can include one or more modules to facilitate interaction between the processing component 702 and other components.

25 **[0068]** The memory 704 is configured to store various types of data to support operations at the electronic device 700. Examples of such data include instructions for any application or method that are performed on the electronic device 700, contact data, phone book data, messages, pictures, video, etc. The memory 704 can be implemented by any type of volatile or non-volatile storage device or a combination thereof, for example, a static random access memory (SRAM), an electrically erasable programmable read only memory (EEPROM), an erasable programmable read only memory (EPROM), a programmable read only memory (PROM), a read only memory (ROM), a magnetic memory, a flash memory, a magnetic disk, or an optical disk.

30 **[0069]** The power supply component 706 supplies power to various components of the electronic device 700. The power supply component 706 can include a power management system, one or more power supplies, and other components associated with generation, management, and distribution of electric power by the electronic

device 700.

[0070] The I/O interface 710 provides an interface between the processing component 702 and a peripheral interface module, where the peripheral interface module can be a keyboard, a click wheel, a button, etc. These buttons can include, but are not limited to, a home page button, a volume button, a start button, and a lock button.

[0071] The communication component 712 is configured to facilitate wired or wireless communication between the electronic device 700 and other devices. The electronic device 700 can access a wireless network based on a communication standard, such as Wi-Fi, 2G or 3G, or a combination thereof. In an example embodiment, the communication component 712 receives broadcast signals or broadcast-related information from an external broadcast management system through a broadcast channel. In an example embodiment, the communication component 712 further includes a near field communication (NFC) module to facilitate short-range communication. For example, the NFC module can be implemented based on the Radio Frequency Identification (RFID) technology, the Infrared Data Association (IrDA) technology, the Ultra Wideband (UWB) technology, the Bluetooth (BT) technology, and other technologies.

[0072] In an example embodiment, the electronic device 700 can be implemented by one or more application specific integrated circuits (ASICs), digital signal processors (DSPs), digital signal processing devices (DSPDs), programmable logic devices (PLDs), field programmable gate arrays (FPGAs), controllers, microcontrollers, microprocessors, or other electronic components for performing the methods described above.

[0073] In an example embodiment, a non-temporary computer-readable storage medium including instructions is provided. For example, the storage medium is the memory 704 including instructions that can be executed by the processor 720 of the electronic device 700 to perform the methods described above. For example, the non-transitory computer-readable storage medium can be a ROM, a random access memory (RAM), a CD-ROM, a magnetic tape, a floppy disk, an optical data storage device, etc.

[0074] When the instructions in the non-transitory computer-readable storage medium are executed by a processor of a mobile terminal, the electronic device is enabled to perform a multi-classifier-based recommendation method, including:

performing prediction on received feature data based on a primary classifier in a predetermined multi-classifier to obtain first prediction data; obtaining a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and the feature data being a highest, and $k \geq 2$; performing prediction on the feature data based on the target sub-classifier to obtain second prediction data; combining the first prediction data and the second prediction data based on a predetermined algorithm to obtain third prediction data; and recommending a to-be-recommended entity corresponding to the feature data based on the third prediction data.

10 **[0075]** It should be understood that the present specification is not limited to the precise structures already described above and illustrated in the accompanying drawings, and various modifications and changes can be made without departing from the scope thereof. The protection scope of the present specification should be defined by the appended claims.

15 **[0076]** The above descriptions are merely preferred embodiments of the present specification, and are not intended to limit the present specification. Any modification, equivalent replacement, improvement, etc., made without departing from the spirit and principles of the present specification shall fall within the protection scope of the present specification.

CLAIMS

What is claimed is:

1. A multi-classifier-based recommendation method, comprising:

performing prediction on a received feature data based on a primary classifier in

5 a predetermined multi-classifier to obtain a first prediction data;

obtaining a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and the feature data being highest, and $k \geq 2$;

10 performing prediction on the feature data based on the target sub-classifier to obtain a second prediction data;

combining the first prediction data and the second prediction data based on a predetermined algorithm to obtain a third prediction data; and

recommending a to-be-recommended entity corresponding to the feature data based on the third prediction data.

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2. The method according to claim 1, wherein the obtaining the target sub-classifier, based on the feature data, among the k sub-classifiers in the predetermined multi-classifier comprises:

20 if each of the k sub-classifiers has a center point of data distribution, searching for a sub-classifier whose center point is closest to a data vector of the feature data, and using the sub-classifier as the target sub-classifier.

3. The method according to claim 1, wherein the obtaining the target sub-classifier, based on the feature data, among the k sub-classifiers in the predetermined multi-classifier comprises:

25 if each of the k sub-classifiers has a Gaussian mixture model with a data distribution parameter, searching for a sub-classifier whose data distribution parameter has a highest similarity with the feature data, and using the sub-classifier as the target sub-classifier.

30

4. The method according to claim 1, wherein after the recommending the to-be-recommended entity corresponding to the feature data based on the third prediction data, the method further comprises:

detecting whether a user selects the recommended entity corresponding to the feature data; and

updating parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on whether the user selects the recommended entity.

5. The method according to claim 4, wherein the updating the parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on whether the user selects the recommended entity comprises:

if the user selects the recommended entity, providing positive feedback to the multi-classifier, or if the user does not select the recommended entity, providing negative feedback to the multi-classifier; and updating the parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on the positive feedback or the negative feedback.

6. The method according to claim 2, wherein after the performing the prediction on the feature data based on the target sub-classifier to obtain second prediction data, the method further comprises:

updating the center point of the target sub-classifier based on the data vector of the feature data.

7. The method according to claim 6, wherein the updating the center point of the target sub-classifier based on the data vector of the feature data comprises:

$$P_{t+1} = P_t + \frac{x_t - P_t}{n_i}, \quad n_{i+1} = n_i + 1,$$

wherein P_{t+1} indicates the center point of the target sub-classifier after the updating; P_t indicates the center point of the target sub-classifier before the updating; x_t indicates the data vector; n_i indicates an amount of data allocated to the target sub-classifier before the updating; and n_{i+1} indicates an amount of data of the target sub-classifier after the updating.

8. A multi-classifier-based recommendation device, comprising:

a first classification unit, configured to perform prediction on a received feature data based on a primary classifier in a predetermined multi-classifier to obtain a first

prediction data;

a search unit, configured to obtain a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and the feature data being

5 highest, and $k \geq 2$;

a second classification unit, configured to perform prediction on the feature data based on the target sub-classifier to obtain a second prediction data;

a combining unit, configured to combine the first prediction data and the second prediction data based on a predetermined algorithm to obtain a third prediction data;

10 and

a recommending unit, configured to recommend a to-be-recommended entity corresponding to the feature data based on the third prediction data.

9. The device according to claim 8, wherein the search unit is configured to:

15 if each of the k sub-classifiers has a center point of data distribution, search for a sub-classifier whose center point is closest to a data vector of the feature data, and using the sub-classifier as the target sub-classifier.

10. The device according to claim 8, wherein the search unit is configured to:

20 if each of the k sub-classifiers has a Gaussian mixture model with a data distribution parameter, search for a sub-classifier whose data distribution parameter has a highest similarity with the feature data, and use the sub-classifier as the target sub-classifier.

11. The device according to claim 8, further comprising:

25 an updating unit, configured to: after the to-be-recommended entity corresponding to the feature data is recommended, detect whether the user selects the recommended entity corresponding to the feature data; and update parameters of the target sub-classifier and the primary classifier that correspond to the feature data
30 based on whether the user selects the recommended entity.

12. The device according to claim 11, wherein the updating unit is configured to:

if the user selects the recommended entity, provide positive feedback to the

multi-classifier, or if the user does not select the recommended entity, provide negative feedback to the multi-classifier; and update the parameters of the target sub-classifier and the primary classifier that correspond to the feature data based on the positive feedback or the negative feedback.

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13. The device according to claim 9, further comprising:

an updating unit, configured to: after the feature data is predicted based on the target sub-classifier to obtain the second prediction data, update the center point of the target sub-classifier based on the data vector of the feature data.

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14. The device according to claim 13, wherein the updating unit is further configured to update the center point of the target sub-classifier based on the following equation:

$$P_{t+1} = P_t + \frac{x_t - P_t}{n_i}, n_{i+1} = n_i + 1$$

15

wherein P_{t+1} indicates the center point of the target sub-classifier after the updating; P_t indicates the center point of the target sub-classifier before the updating; x_t indicates the data vector; n_i indicates an amount of data allocated to the target sub-classifier before the updating; and n_{i+1} indicates an amount of data of the target sub-classifier after the updating.

20

15. A computer readable storage medium, wherein the medium stores a computer program, and when the computer program is executed by a processor, the following steps are implemented:

performing prediction on a received feature data based on a primary classifier in a predetermined multi-classifier to obtain a first prediction data;

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obtaining a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier, a similarity between a data distribution of the target sub-classifier and the feature data being highest, and $k \geq 2$;

performing prediction on the feature data based on the target sub-classifier to obtain a second prediction data;

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combining the first prediction data and the second prediction data based on a predetermined algorithm to obtain a third prediction data; and

recommending a to-be-recommended entity corresponding to the feature data

based on the third prediction data.

16. An electronic device, wherein the electronic device comprises a memory and one or more programs, and the one or more programs are stored in the memory and
5 can be executed by one or more processors to perform the following steps:

performing prediction on a received feature data based on a primary classifier in a predetermined multi-classifier to obtain a first prediction data;

obtaining a target sub-classifier, based on the feature data, among k sub-classifiers in the predetermined multi-classifier, a similarity between a data
10 distribution of the target sub-classifier and the feature data being highest, and $k \geq 2$;

performing prediction on the feature data based on the target sub-classifier to obtain a second prediction data;

combining the first prediction data and the second prediction data based on a predetermined algorithm to obtain a third prediction data; and

15 recommending a to-be-recommended entity corresponding to the feature data based on the third prediction data.