

METHODS AND APPARATUSES FOR TRAINING USER CLASSIFICATION MODEL AND USER CLASSIFICATION PROCESSING METHODS AND APPARATUSES

TECHNICAL FIELD

[0001] The present specification relates to the field of data processing technologies, and in particular, to methods and apparatuses for training a user classification model and user classification processing methods and apparatuses.

BACKGROUND

[0002] Currently, to promote user activity on a platform, service platforms such as an e-commerce platform and a financial platform generally formulate some incentive policies and incentive behaviors, so as to improve response enthusiasm of the platform user for a target service, and further improve user activity on the platform. Therefore, how to determine a user who has a high degree of recognition with the incentive policies and the incentive behaviors and customize a service for the user is critical. Correspondingly, how to provide a method for training a user classification model becomes an urgent problem to be alleviated.

SUMMARY

[0003] One or more embodiments of the present specification provide methods and apparatuses for training a user classification model and user classification processing methods and apparatuses, so as to train a user classification model that has an accurate user classification result.

[0004] According to a first aspect, a method for training a user classification model is provided, where the user classification model includes a graph neural network, a first classification network, and a second classification network, and the method includes: obtaining a sample user, where the sample user has tag data that is used to represent a response behavior of the sample user for a predetermined incentive behavior; in a pre-

constructed user relationship network graph, using the sample user as a target node, and performing node representation aggregation on the target node by using the graph neural network, to obtain a user representation; separately inputting the user representation into the first classification network and the second classification network to obtain a first predicted value and a second predicted value, where the first predicted value represents a probability that the sample user belongs to a first user group formed by a first-type user and a second-type user, the second predicted value represents a probability that the sample user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has the response behavior, the second-type user has the response behavior only under the predetermined incentive behavior, and the third-type user always does not have the response behavior; determining a current loss value based on the first predicted value and/or the second predicted value, and the tag data; and adjusting a parameter of the user classification model with a goal of minimizing the current loss value.

[0005] According to a second aspect, a user classification processing method is provided, including: obtaining a user classification model obtained by training based on the method in the first aspect, where the user classification model includes a graph neural network, a first classification network, and a second classification network; inputting each to-be-processed user into the user classification model, so as to determine, by using the graph neural network, the first classification network, and the second classification network, a first estimated value and a second estimated value that are corresponding to each to-be-processed user, where the first estimated value represents a probability that a corresponding to-be-processed user belongs to a first user group formed by a first-type user and a second-type user, the second estimated value represents a probability that a corresponding to-be-processed user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has a response behavior for a predetermined incentive behavior, the second-type user has a response behavior only under the predetermined incentive behavior, and the third-type user always does not have a response behavior; and for each to-be-processed user, determining, based on the first estimated value and the second estimated value that are corresponding to the to-be-processed user, whether to perform the predetermined incentive behavior for the to-be-processed user.

[0006] According to a third aspect, an apparatus for training a user classification model is provided, where the user classification model includes a graph neural network,

a first classification network, and a second classification network, and the apparatus includes: a first acquisition module, configured to obtain a sample user, where the sample user has tag data that is used to represent a response behavior of the sample user for a predetermined incentive behavior; an aggregation module, configured to: in a pre-constructed user relationship network graph, use the sample user as a target node, and perform node representation aggregation on the target node by using the graph neural network, to obtain a user representation; an input acquisition module, configured to separately input the user representation into the first classification network and the second classification network to obtain a first predicted value and a second predicted value, where the first predicted value represents a probability that the sample user belongs to a first user group formed by a first-type user and a second-type user, the second predicted value represents a probability that the sample user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has the response behavior, the second-type user has the response behavior only under the predetermined incentive behavior, and the third-type user always does not have the response behavior; a first determining module configured to determine a current loss value based on the first predicted value and/or the second predicted value, and the tag data; and an adjustment module, configured to adjust a parameter of the user classification model with a goal of minimizing the current loss value.

[0007] According to a fourth aspect, a user classification processing apparatus is provided, including: a second acquisition module, configured to obtain a user classification model obtained by training based on the apparatus in the third aspect, where the user classification model includes a graph neural network, a first classification network, and a second classification network; a second determining module, configured to input each to-be-processed user into the user classification model, so as to determine, by using the graph neural network, the first classification network, and the second classification network, a first estimated value and a second estimated value that are corresponding to each to-be-processed user, where the first estimated value represents a probability that a corresponding to-be-processed user belongs to a first user group formed by a first-type user and a second-type user, the second estimated value represents a probability that a corresponding to-be-processed user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has a response behavior for a predetermined incentive behavior, the second-type user has a response behavior only under the predetermined incentive behavior, and

the third-type user always does not have a response behavior; and a third determining module, configured to: for each to-be-processed user, determine, based on the first estimated value and the second estimated value that are corresponding to the to-be-processed user, a processing method related to the predetermined incentive behavior.

[0008] According to a fifth aspect, a computer readable storage medium that stores a computer program is provided, and when the computer program is executed on a computer, the computer is caused to perform the method of the first aspect.

[0009] According to a sixth aspect, a computing device is provided and includes a memory and a processor. Executable code is stored in the memory, and when executing the executable code, the processor implements the method of the first aspect.

[0010] According to a seventh aspect, a computer readable storage medium that stores a computer program is provided, and when the computer program is executed on a computer, the computer is caused to perform the method of the second aspect.

[0011] According to an eighth aspect, a computing device is provided and includes a memory and a processor. Executable code is stored in the memory, and when executing the executable code, the processor implements the method of the second aspect.

[0012] According to the method and the apparatus provided in the embodiments of the present specification, first, in a user relationship network graph, a sample user is used as a target node, and node representation aggregation is performed on the target node by using a graph neural network of a user classification model, to obtain a user representation aggregated with attribute features of the target node and a neighbor. The user representation can more comprehensively and accurately represent a characteristic of the sample user, and provide a basis for accurate user classification. Then, the user representation is separately input into a first classification network and a second classification network of the user classification model, so as to obtain a first predicted value that represents a probability that the sample user belongs to a first user group formed by a first-type user (which always has a response behavior) and a second-type user (which has a response behavior only under a predetermined incentive behavior), and a second predicted value that represents a probability that the sample user belongs to a second user group formed by the second-type user and a third-type user (which always does not have a response behavior). Then, a current loss value is determined based on the first predicted value and/or the second predicted value and tag data that is used to represent a response behavior of the sample user for the predetermined incentive behavior. A parameter of the user classification model is adjusted with a goal of

minimizing the current loss value, so as to train the user classification model. In addition, the graph neural network can obtain, through aggregation, a more comprehensive and accurate user representation that can represent the characteristic of the sample user. The first classification network and the second classification network can jointly learn a capability of determining a user (a user with a high requirement) that has a response behavior only under the predetermined incentive behavior, so a classification result of the user classification model obtained through training is more accurate.

BRIEF DESCRIPTION OF DRAWINGS

[0013] To describe the technical solutions in the embodiments of the present disclosure more clearly, the following briefly describes the accompanying drawings needed for describing the embodiments. Clearly, the accompanying drawings in the following description show merely some embodiments of the present disclosure, and a person of ordinary skill in the art can still derive other drawings from these accompanying drawings without creative efforts.

[0014] FIG. 1 is a schematic diagram illustrating an implementation framework of an embodiment disclosed in the present specification;

[0015] FIG. 2 is a schematic flowchart of a method for training a user classification model according to an embodiment;

[0016] FIG. 3 is a schematic diagram of a tag data setting scenario according to an embodiment;

[0017] FIG. 4 is a schematic flowchart of a user classification processing method according to an embodiment;

[0018] FIG. 5 is a schematic block diagram of an apparatus for training a user classification model according to an embodiment; and

[0019] FIG. 6 is a schematic block diagram of a user classification processing apparatus according to an embodiment.

DESCRIPTION OF EMBODIMENTS

[0020] The following describes in detail the technical solutions in the embodiments of the present specification with reference to the accompanying drawings.

[0021] Embodiments of the present specification disclose methods and apparatuses for training a user classification model and user classification processing methods and apparatuses. The following first describes an application scenario and a technical idea of the method for training a user classification model, which are specifically as follows:

[0022] As described above, to promote user activity on a platform and provide a better customized service for users, service platforms such as an e-commerce platform and a financial platform need to classify users, determine users with a relatively high degree of recognition on an incentive policy and an incentive behavior, and push some incentive policies and incentive behaviors to the users, so as to improve response enthusiasm of the platform user for a target service and improve user activity on the platform. Therefore, how to provide a method for training a user classification model is crucial.

[0023] In view of this, the inventor proposes a method for training a user classification model. FIG. 1 is a schematic diagram illustrating an implementation framework of an embodiment disclosed in the present specification. The user classification model includes a graph neural network, a first classification network, and a second classification network. In a training process, a user sample set can be first constructed, where the user sample set includes each sample user and tag data of each sample user, the tag data can represent a response behavior of the sample user for a predetermined incentive behavior, and the predetermined incentive behavior is a behavior used to motivate a user to respond to a target service.

[0024] Then, a user relationship network graph is obtained. In a case, the user relationship network graph can be constructed based on a social relationship (and a transaction relationship, a transfer relationship, etc.) of each sample user in the user sample set. In another case, the user relationship network graph constructed for each sample user in the user sample set can be directly obtained from a target data source. Each node in the user relationship network graph is corresponding to each user. The users include a sample user and a user that has a buddy relationship (or has a transaction relationship, a transfer relationship, etc.) with the sample user. Each edge represents a buddy relationship (or a transaction relationship, a transfer relationship, etc.) between users corresponding to nodes. As shown in FIG. 1, a local diagram of the user relationship network graph is shown.

[0025] In a training process, a sample user is selected from a user sample set. In a user relationship network graph, the sample user is used as a target node, and node

representation aggregation is performed on the target node by using a graph neural network, to obtain a user representation. The user representation is aggregated with attribute features of the sample user and a neighboring user of the sample user. The user representation can comprehensively and accurately represent a user characteristic in a diversified method. Then, the user representation is separately input into the first classification network and the second classification network to obtain a first predicted value and a second predicted value, that is, a probability (the first predicted value) that the sample user belongs to a first user group formed by a first-type user and a second-type user that is obtained by means of prediction by using the first classification network, and a probability (the second predicted value) that the sample user belongs to a second user group formed by the second-type user and a third-type user that is obtained by means of prediction by using the second classification network.

[0026] The first-type user always has a response behavior, that is, the first-type user always has a response behavior with or without a predetermined incentive behavior. The second-type user has a response behavior only under the predetermined incentive behavior. The third-type user always does not have a response behavior, that is, the third-type user does not have a response behavior with or without the predetermined incentive behavior.

[0027] It can be understood that, to provide a higher-quality service for users of different types, and optimize an asset structure and balance profitability, it is required to accurately determine a user that has a high requirement for the predetermined incentive behavior (that is, has a response behavior only under the predetermined incentive behavior). Correspondingly, in this embodiment of the present specification, it is set that the probability that the sample user belongs to the first user group formed by the first-type user and the second-type user is obtained by means of prediction by the first classification network, and the probability that the sample user belongs to the second user group formed by the second-type user and the third-type user is obtained by means of prediction by the second classification network.

[0028] The user classification model can provide a user classification service for each type of platform, for example, classify users of an e-commerce platform, or classify users of a financial platform. It can be understood that the predetermined incentive behavior has a relationship with a target service of a platform to which the user classification model is applied. In an example scenario, the user classification model is applied to an e-commerce platform, and a user classification service is provided for a

product sales service provided by the e-commerce platform. The predetermined incentive behavior can include implementing one of the following for the target service (product sales service): issuing a user benefit (for example, issuing a product coupon), pushing an additional service (for example, giving a gift, giving a bonus point, or giving ant energy), providing a discount, etc. Correspondingly, having a response behavior means purchasing a product, and not having a response behavior means not purchasing a product.

[0029] In another example scenario, the user classification model is applied to a financial platform, and a user classification service is provided for a credit service provided by the financial platform. The predetermined incentive behavior can include implementing one of the following for the target service (credit service): pushing an additional service (for example, giving a gift), providing a discount (for example, reducing a rate of interest), etc. Correspondingly, having a response behavior means subscribing to the credit service, and not having a response behavior means not subscribing to the credit service.

[0030] In still another example scenario, the user classification model is applied to a content platform, and a user classification service is provided for a content push service provided by the content platform. Correspondingly, the scheduled incentive behavior can include implementing one of the following for the target service (content push service): pushing an additional service (for example, giving a gift, giving a bonus point, or giving a quantity of times of playing a specified mini-game or a currency value), etc. Correspondingly, having a response behavior means accepting content pushing, and not having a response behavior means not accepting content pushing.

[0031] In still another example scenario, the user classification model is applied to a social platform, and a user classification service is provided for an online activity push service provided by the social platform. Correspondingly, the predetermined incentive behavior can include implementing one of the following for the target service (online activity push service): pushing an additional service (for example, giving a gift, giving a bonus point, or giving a quantity of times of playing a specified mini-game or a currency value), etc. Correspondingly, having a response behavior means participating in an online activity, and not having a response behavior means not participating in an online activity.

[0032] Then, after the first predicted value and the second predicted value are obtained, a current loss value can continue to be determined based on the first predicted value

and/or the second predicted value and the tag data. A larger current loss value indicates a larger difference between the tag data and the first predicted value and/or the second predicted value, that is, lower accuracy of the first classification network and/or a prediction result of the first classification network. Correspondingly, a parameter of the user classification model is adjusted with a goal of minimizing the current loss value, that is, with a goal of improving accuracy of the prediction result of the user classification model.

[0033] In the previous process, a user representation aggregated with attribute features of the sample user and a neighbor of the sample user, that is, aggregated with diversified information, is obtained by using the graph neural network, which more comprehensively and accurately represents the user characteristic, and provides a basis for subsequent user classification. In addition, the first predicted value represents a probability that the sample user belongs to a first user group formed by a first-type user and a second-type user, where a larger first predicted value indicates a higher probability that the sample user belongs to the first user group. The second predicted value represents a probability that the sample user belongs to a second user group formed by the second-type user and a third-type user, and a larger second predicted value indicates a higher probability that the sample user belongs to the second user group. Correspondingly, when both the first predicted value and the second predicted value are large, this can represent that the sample user is more likely to belong to the second-type user (a user that has a response behavior only under the predetermined incentive behavior). The parameter of the user classification model is adjusted with a goal of minimizing the current loss value, so the first classification network and the second classification network can jointly learn a capability of determining a user (a user with a high requirement) that has a response behavior only under the predetermined incentive behavior, and the user classification model can more accurately determine the user with a high requirement for the predetermined incentive behavior, thereby improving accuracy of a user classification result.

[0034] With reference to specific embodiments, the following describes in detail a method for training a user classification model and a user classification processing method provided in the present specification.

[0035] FIG. 2 is a flowchart of a method for training a user classification model according to an embodiment of the present specification. The method is performed by an electronic device, and the electronic device can be implemented by using any

apparatus, device, platform, device cluster, etc. that has a calculation and processing capability. The user classification model includes a graph neural network, a first classification network, and a second classification network. As shown in FIG. 2, the method includes the following steps S210–S250:

[0036] In step S210, obtain a sample user, where the sample user has tag data that is used to represent a response behavior of the sample user for a predetermined incentive behavior.

[0037] In an implementation, before the user classification model is trained, a user sample set used for training the user classification model can be first constructed, and the sample user in step S210 can be taken from the user sample set. The user sample set can include a plurality of sample users (that is, a user identifier and an attribute feature of the sample user) and tag data corresponding to each user. The sample user included in the user sample set is related to an application scenario of the user classification model. For example, if the user classification model is applied to an e-commerce platform, and a user classification service is provided for a product sales service of the e-commerce platform, each sample user in the user sample set is a user of the e-commerce platform. If the user classification model is applied to a financial platform, and a user classification service is provided for a credit service of the financial platform, each sample user in the user sample set is a user of the financial platform. If the user classification model is applied to a content platform or a social platform, each sample user in the user sample set is a user of the content platform or the social platform.

[0038] In addition, in a case, sample users in the user sample set can further include both a user of a platform to which the user classification model is applied and a user of another platform bound to the platform.

[0039] The previous platforms are merely examples for description, and the user classification model can be further applied to another platform on which users need to be classified.

[0040] Subsequently, the electronic device can obtain a sample user from the user sample set. In an embodiment, the present specification further provides a specific obtaining method of the user sample set. The user sample set can be obtained in the following method:

[0041] In step 11, divide user groups into a control group in which the predetermined incentive behavior is not applied and a test group in which the predetermined incentive behavior is applied. In this step, users in the user groups are randomly divided into a

control group and a test group, and each group includes a plurality of users. The predetermined incentive behavior is not applied to a user of the control group, and the predetermined incentive behavior is applied to a user of the test group.

[0042] Then, in step 12, determine, based on a group to which any first user in the user groups belongs and whether the response behavior is performed, first tag data of the first user.

[0043] Specifically, in a case, the first user belongs to the test group. Step 12 specifically includes: If the first user has a response behavior, setting the first tag data to include a first tag belonging to the first-type user and a second tag belonging to the second-type user; and if the first user does not have the response behavior, setting the first tag data to include only a third tag belonging to the third-type user.

[0044] It can be understood that the first user belongs to the test group to which the predetermined incentive behavior is applied. If the first user has the response behavior, it can represent that the first user has the response behavior (which can belong to the second-type user) in a case in which the predetermined incentive behavior is applied. In addition, the first user can also have the response behavior (which can belong to the first-type user) in a case in which the predetermined incentive behavior is not applied. Correspondingly, the first tag data can be set to include the first tag belonging to the first-type user and the second tag belonging to the second-type user. On the contrary, if the first user does not have the response behavior, that is, the first user does not respond when the predetermined incentive behavior is applied, it can be considered that the first user does not have the response behavior when the predetermined incentive behavior is not applied, that is, the first user belongs to the third-type user. Correspondingly, the first tag data can be set to include only the third tag belonging to the third-type user.

[0045] The first tag, the second tag, and the third tag can be a same tag, for example, a first value (for example, 1), or can be different tags. In a case in which the first tag, the second tag, and the third tag are a same tag, as shown in FIG. 3, in a case in which the first user belongs to the test group, and the first user has the response behavior, the first tag data of the first user can be represented as [1, 1, 0]. In a case in which the first user belongs to the test group and the first user does not have the response behavior, the first tag data of the first user can be represented as [0, 0, 1]. A value at the first position of the first tag data indicates whether the first user belongs to the first-type user, a value at the second position indicates whether the first user belongs to the second-type user,

and a value at the third position indicates whether the first user belongs to the third-type user, where "1" indicates yes, and "0" indicates no.

[0046] In another case, the first user belongs to the control group. Step 12 specifically includes: if the first user has the response behavior, setting the first tag data to include only a first tag belonging to the first-type user; and if the first user does not have the response behavior, setting the first tag data to include a second tag belonging to the second-type user and a third tag belonging to the third-type user.

[0047] In this implementation, the first user belongs to the control group to which the predetermined incentive behavior is not applied. If the first user has the response behavior, it is considered that the first user belongs to the first-type user. Correspondingly, the first tag data is set to include only the first tag belonging to the first-type user. On the contrary, if the first user does not have the response behavior, it is considered that the first user can belong to the third-type user. In addition, it is considered that the first user can have the response behavior in a case in which the predetermined incentive behavior is applied. Correspondingly, it is determined that the first user can also belong to the second-type user, and correspondingly, the first tag data is set to include the second tag belonging to the second-type user and the third tag belonging to the third-type user.

[0048] Correspondingly, if the first tag, the second tag, and the third tag are a same tag and are first values (for example, one), as shown in FIG. 3, in a case in which the first user belongs to the control group, and the first user has the response behavior, the first tag data of the first user can be represented as [1, 0, 0]. In a case in which the first user belongs to the control group and the first user does not have the response behavior, the first tag data of the first user can be represented as [0, 1, 1].

[0049] Based on the previous method of determining the tag data, the electronic device can calibrate the tag data of each user in the user group based on the group to which the user belongs and whether the user performs the response behavior, to obtain the user sample set.

[0050] The predetermined incentive behavior is related to a service provided by a platform to which the user classification model is applied. The predetermined incentive behavior can be different when services are different. In an embodiment, the predetermined incentive behavior includes implementing one of issuing a user benefit, pushing an additional service, or providing a discount for a target service.

[0051] It can be understood that the electronic device can perform, for each sample user in the user sample set, the user classification model training procedure provided in the embodiments of the present specification, so as to train the user classification model. In this embodiment of the present specification, one sample user is used as an example to describe a process of training the user classification model by using each sample user in the user sample set. That is, similar processing can be performed for each sample user in the user sample set.

[0052] Then, after obtaining the sample user, in a pre-constructed user relationship network graph, the electronic device uses the sample user as a target node, and performs node representation aggregation on the target node by using the graph neural network, to obtain a user representation in step S220.

[0053] Each node in the user relationship network graph is corresponding to each user, where the user corresponding to each node can be a sample user or a user that has a buddy relationship (or a specified relationship such as a transaction relationship or a transfer relationship) with the sample user, and an edge in the user relationship network graph represents a buddy relationship (or a specified relationship such as a transaction relationship or a transfer relationship) between users corresponding to nodes. Generally, users that have a specified relationship such as a buddy relationship are more likely to have similar behavior habits. Correspondingly, the user relationship network graph can represent behavior similarity and risk conductivity information between users to some extent.

[0054] In this step, node representation aggregation is performed on the target node (the sample user) by using the graph neural network in the user relationship network graph, so a user representation that can represent a user characteristic more comprehensively and accurately can be obtained, and a basis is provided for improving a user classification result.

[0055] In an embodiment, the graph neural network includes k aggregation layers. A specific configuration of step S220 is: sequentially performing, at the k aggregation layers, k levels of vector aggregation on the target node, where each level of vector aggregation includes: determining a current-level aggregation vector of the target node based on at least an upper-level aggregation vector of each neighboring node of the target node, where an initial-level aggregation vector of each node is determined based on an attribute feature of a corresponding user.

[0056] To sequentially perform k levels of vector aggregation on the target node v at the k aggregation layers, an initial-level aggregation vector h_v^0 of the target node v is first determined based on the attribute feature of the target node v , and an initial-level aggregation vector h_u^0 of each neighboring node u is determined based on the attribute feature of each neighboring node u of the target node v . Then, k levels of vector aggregation are performed on the target node v based on at least the initial-level aggregation vector h_u^0 , to obtain an aggregation vector h_v^k of the k th aggregation layer as a user representation of a user corresponding to the target node v . In an implementation, k levels of vector aggregation can be jointly performed for the target node v based on the initial-level aggregation vector h_v^0 and the initial-level aggregation vector h_u^0 , to obtain an aggregation vector h_v^k of the k th aggregation layer as the user representation of the user corresponding to the target node v . Subsequently, an example in which k levels of vector aggregation are performed for the target node v based on the initial-level aggregation vector h_v^0 and the initial-level aggregation vector h_u^0 is used for description.

[0057] Specifically, in a vector aggregation process at each level, each of the previous neighboring nodes u is a node connected to the target node v . It can be understood that, at each aggregation layer, in addition to performing vector aggregation for the target node v , vector aggregation further needs to be performed for each neighboring node, to obtain a current-level aggregation vector of each neighboring node. When vector aggregation is performed for each neighboring node u , an upper-level aggregation vector of the neighboring node u and an upper-level aggregation vector of its neighboring node need to be used. By analogy, the current-level aggregation vector that is of the target node v and that is obtained by means of aggregation at an i th aggregation layer includes an attribute feature of an i -order neighboring node of the target node v . As such, after aggregation at the k aggregation layers, attribute features of the target node v and a k -order neighboring node of the target node v are aggregated in the aggregation vector h_v^k of the target node v .

[0058] In an embodiment, the previous process of determining the initial-level aggregation vector h_v^0 can be: encoding each attribute feature of the target node v , and using a vector obtained by means of encoding as the initial-level aggregation vector h_v^0 . Or linear or non-linear transformation can be performed on the vector obtained by

means of encoding, and the transformed vector is used as the initial-level aggregation vector h_v^0 .

[0059] In an embodiment, a process of determining an i th-level vector aggregation (that is, vector aggregation at the i th aggregation layer) of the target node v can include: first obtaining a neighboring aggregation vector $h_{N(v)}^{i-1}$, that is, a neighboring aggregation result, by using an aggregation function AGG_i of the i th aggregation layer and based on an upper-level (that is, an $(i-1)$ th level) aggregation vector h_u^{i-1} of the neighboring node u of the target node v , where $N(v)$ represents a neighboring node set of the target node v , that is:

$$h_{N(v)}^{i-1} = AGG_i\{h_u^{i-1}, u \in N(v)\} \quad (1)$$

[0060] Then, a current-level (i th level) aggregation vector h_v^i of the target node v is determined based on the neighboring aggregation vector $h_{N(v)}^{i-1}$ and an upper-level (that is, the $(i-1)$ th level) aggregation vector h_v^{i-1} of the target node v , that is:

$$h_v^i = W^i \cdot f(h_{N(v)}^{i-1}, h_v^{i-1}) \quad (2)$$

where f represents a comprehensive function applied to the neighboring aggregation vector $h_{N(v)}^{i-1}$ and the upper-level vector h_v^{i-1} of the target node v , and W^i is a parameter of i th level aggregation. In different embodiments, comprehensive operations in the function f can include splicing, or summing, or averaging, $h_{N(v)}^{i-1}$ and h_v^{i-1} .

[0061] The aggregation function AGG_i for neighboring aggregation can use different forms and algorithms. For example, the aggregation function AGG_i can be but is not limited to a pooling operation and a summation operation.

[0062] Considering that importance of each neighboring node u of the target node v relative to the target node v is different, a proportion of each neighboring node during aggregation can be determined based on importance of each neighboring node u relative to the target node v . Correspondingly, in an embodiment, the determining a current-level aggregation vector of the target node based on at least an upper-level aggregation vector of each neighboring node of the target node includes: determining a weight value of each neighboring node relative to the target node based on an upper-level aggregation vector of the target node and the upper-level aggregation vector of each neighboring node; and determining the current-level aggregation vector of the target node based on the upper-level aggregation vector of the target node, the upper-level aggregation vector

of each neighboring node, and the weight value of each neighboring node relative to the target node.

[0063] Each weight value represents importance of a corresponding neighboring node relative to the target node, and a larger weight value represents higher importance of the corresponding neighboring node relative to the target node. In a case, the weight value can be a weight value calculated based on an attention mechanism. In an implementation, the weight value of each neighboring node u relative to the target node v can be determined by using the following equation:

$$\alpha(h_v^{i-1}, h_u^{i-1}) = \frac{\exp(s^i \tanh_1(W_1^i h_v^{i-1} + W_2^i h_u^{i-1}))}{\sum_{j \in N(v) \cup \{v\}} \exp(s^i \tanh_1(W_3^i h_v^{i-1} + W_4^i h_j^{i-1}))}, \quad (3)$$

where $\alpha(h_v^{i-1}, h_u^{i-1})$ represents the weight value of the neighboring node u relative to the target node v at the i th aggregation layer, s^i , W_1^i , W_2^i , W_3^i , and W_4^i are to-be-trained parameters at the i th aggregation layer, and $\tanh_1()$ represents a first activation function predetermined at the i th aggregation layer.

[0064] Then, after the weight value of each neighboring node u relative to the target node v is determined, a current-level (i th level) aggregation vector of the target node is determined based on an upper-level ($(i-1)$ th level) aggregation vector of the target node v , an upper-level ($(i-1)$ th level) aggregation vector of each neighboring node u , and a weight value of each neighboring node relative to the target node. Specifically, it can be expressed by using the following equation:

$$h_v^i = \tanh_2(\sum_{j \in N(v) \cup \{v\}} \alpha(h_v^{i-1}, h_j^{i-1}) h_j^{i-1} W_5^i); \quad (4)$$

where W_5^i represents a to-be-trained parameter at the i th aggregation layer, and $\alpha(h_v^{i-1}, h_j^{i-1})$ represents a weight value of a node j relative to the target node v . h_j^{i-1} represents an upper-level ($(i-1)$ th level) aggregation vector of a node j , and the node j can be each neighboring node u or the target node v . $\tanh_2()$ represents a second activation function predetermined at the i th aggregation layer.

[0065] It can be understood that the initial-level aggregation vector of the target node v can be used as a zero-level aggregation vector. Based on this, in the first to the k th aggregation layers, aggregation is performed on the target node v level by level, and an output vector h_v^k of the k th aggregation layer of the target node v can be obtained. The user representation of the sample user can be separately obtained by using the sample user as the target node.

[0066] Then, in step S230, separately input the user representation into the first classification network and the second classification network, to obtain a first predicted value and a second predicted value. The first predicted value represents a probability that the sample user belongs to a first user group formed by a first-type user and a second-type user, and the second predicted value represents a probability that the sample user belongs to a second user group formed by the second-type user and a third-type user. The first-type user always has a response behavior, that is, the first-type user always has a response behavior with or without a predetermined incentive behavior. The second-type user has a response behavior only under the predetermined incentive behavior. The third-type user always does not have a response behavior, that is, the third-type user does not have a response behavior with or without the predetermined incentive behavior.

[0067] In this step, the user representation is separately input into the first classification network and the second classification network, so as to separately predict, by using the first classification network and the second classification network, a user category to which the sample user belongs, so as to obtain the first predicted value corresponding to the first classification network and the second predicted value corresponding to the second classification network, so as to separately obtain the probability that the sample user belongs to the first user group formed by the first-type user and the second-type user, and the probability that the sample user belongs to the second user group formed by the second-type user and the third-type user.

[0068] A larger first predicted value indicates a higher possibility that the sample user belongs to the first user group. A larger second predicted value indicates a higher possibility that the sample user belongs to the second user group. When both the first predicted value and the second predicted value are relatively large, it can represent that the sample user is highly likely to be a second-type user (a user that has a response behavior only under a predetermined incentive behavior).

[0069] In an implementation, the first classification network and the second classification network can each include a plurality of non-linear mapping layers, and an activation function used by the first classification network and the second classification network can be a Leaky-Relu function.

[0070] Then, in step S240 after obtaining the first predicted value and the second predicted value, the electronic device determines a current loss value based on the first predicted value and/or the second predicted value, and the tag data. In an

implementation, the current loss value can be determined based on a predetermined loss function, and based on the first predicted value and/or the second predicted value, and the tag data. The predetermined loss function can be a cross-entropy function. Then, in step S250, adjust a parameter of the user classification model with a goal of minimizing the current loss value.

[0071] It can be understood that a larger current loss value indicates a larger difference between the tag data and the first predicted value and/or the second predicted value, that is, lower accuracy of the first classification network and/or a prediction result of the first classification network. Correspondingly, a parameter of the user classification model is adjusted with a goal of minimizing the current loss value, that is, with a goal of improving accuracy of the prediction result of the user classification model. Specifically, after the current loss value is determined, a parameter gradient of the user classification model is determined based on the current loss value by using a backpropagation algorithm. An updated parameter of the user classification model is determined by using the determined model parameter gradient and the parameter of the user classification model. Further, the parameter of the user classification model is adjusted based on the updated parameter. The parameter gradient of the user classification model is obtained with a goal of minimizing the current loss value. Minimizing the current loss value can implement monitoring of the classification result of the user classification model and maintain its accuracy.

[0072] It can be understood that, with reference to the previous method of obtaining the user sample set, it can be learned that there can be four types of tag data of sample users in the user sample set, and the four types of tag data can be respectively represented as [1, 0, 0], [0, 1, 1], [1, 1, 0], and [0, 0, 1].

[0073] The first classification network needs to predict a probability that a user belongs to the first user group formed by the first-type user and the second-type user. In a training process, the first classification network uses the first-type user and the second-type user as positive samples, and uses the third-type user as a negative sample for training. The second classification network needs to predict a probability that a user belongs to the second user group formed by the second-type user and the third-type user. In a training process, the second classification network uses the second-type user and the third-type user as positive samples, and uses the first-type user as a negative sample for training.

[0074] In view of this, with reference to the four types of tag data that sample users in the user sample set have, for a sample user that has tag data that includes only the first tag belonging to the first-type user, the sample user is used only to train the first classification network. For a sample user that has tag data that includes only the third tag belonging to the third-type user, the sample user is only used to train the second classification network. Any sample user that has tag data of the second tag of the second-type user can be used to train both the first classification network and the second classification network.

[0075] Correspondingly, in an embodiment, in step S240, it is specifically set that if the tag data includes only the first tag belonging to the first-type user, a first loss value is determined based on the first predicted value and the tag data. Correspondingly, in step S250, it is specifically set that parameters of the graph neural network and the first classification network are adjusted with a goal of minimizing the first loss value. In this implementation, the first predicted value represents the probability that the user belongs to the first-type user and the second-type user. The first loss value determined based on the first predicted value and the tag data can represent a difference between a prediction result of the first classification network and an actual result. A larger first loss value indicates a larger difference between the prediction result of the first classification network and the actual result. Correspondingly, parameters of the graph neural network and the first classification network are adjusted with a goal of minimizing the first loss value, so the first classification network learns a feature of the first-type user, and can further better learn a capability of distinguishing a user belonging to the first-type user, and further learn a capability of predicting whether a user belongs to the first user group (that is, the first-type user or the second-type user).

[0076] In another embodiment, in step S240, it is specifically set that if the tag data includes only a third tag belonging to the third-type user, a second loss value is determined based on the second predicted value and the tag data. Correspondingly, in step S250, it is specifically set that parameters of the graph neural network and the second classification network are adjusted with a goal of minimizing the second loss value. In this implementation, the second predicted value represents the probability that the user belongs to the second-type user and the third-type user. The second loss value determined based on the second predicted value and the tag data can represent a difference between a prediction result of the second classification network and an actual result. A larger second loss value indicates a larger difference between the prediction

result of the second classification network and the actual result. Correspondingly, parameters of the graph neural network and the second classification network are adjusted with a goal of minimizing the second loss value, so the second classification network learns a feature of the third-type user, and can further better learn a capability of distinguishing a user belonging to the third-type user, and further learn a capability of predicting whether a user belongs to the second user group (that is, the second-type user or the third-type user).

[0077] In another embodiment, in step S240, it is specifically set that if the tag data includes the second tag belonging to the second-type user, a third loss value is determined based on the first predicted value, the second predicted value, and the tag data. Correspondingly, in step S250, it is specifically set that parameters of the graph neural network, the first classification network, and the second classification network are adjusted with a goal of minimizing the third loss value.

[0078] In this implementation, the first predicted value and the tag data can be used to determine a first sub-loss value in the third loss value, and the second predicted value and the tag data can be used to determine a second sub-loss value of the third loss value. Further, the parameters of the graph neural network and the first classification network are adjusted with a goal of minimizing the first sub-loss value, and the parameters of the graph neural network and the second classification network are adjusted with a goal of minimizing the second sub-loss value, so the first classification network learns a capability of predicting whether a user belongs to the first user group (that is, the first-type user or the second-type user), and the second classification network learns a capability of predicting whether a user belongs to the second user group (that is, the second-type user or the third-type user). Further, the first classification network and the second classification network can jointly learn a capability of determining a user (a user with a high requirement) that has a response behavior only under the predetermined incentive behavior, so the user classification model can more accurately determine a user with a high requirement for the predetermined incentive behavior, and improve accuracy of the user classification result.

[0079] In the previous embodiment, the user classification model can be trained in a partial tag learning method by using the specified four types of tag data (that is, the tag data that includes the second tag belonging to the second-type user can be used to train both the first classification network and the second classification network), thereby greatly improving sample utilization, and reducing sample tagging costs to some extent.

[0080] The previous steps S210 to S250 is an iterative model training process. To train a better user classification model, the previous process can be iteratively performed for a plurality of times. That is, after step S250, step S210 is performed again based on the updated parameter of the user classification model. A stop condition of the iterative model training process can include: A quantity of iterative training times reaches a predetermined times threshold, duration of iterative training reaches predetermined duration, a current loss value is less than a specified loss threshold, etc.

[0081] An execution process of steps S210 to S250 is reviewed. The previous embodiment is described by using one sample user as an example. In another embodiment, the previous step S210 to step S230 can alternatively be performed for a batch of sample users (that is, a plurality of sample users), so as to separately obtain the first predicted value and the second predicted value that are corresponding to each sample user. Then, the current loss value is determined based on the first predicted value and the second predicted value that are corresponding to each sample user, and the tag data of each sample user, and the user classification model is trained with a goal of minimizing the current loss value. In this embodiment, the current loss value is determined for a batch of sample users, and then a model parameter of the user classification model is adjusted. As such, a quantity of times of adjusting the parameter of the user classification model can be reduced, and it is easier to implement the training process.

[0082] In this embodiment, a user representation aggregated with attribute features of the sample user and a neighbor of the sample user, that is, aggregated with diversified information, is obtained by using the graph neural network, which more comprehensively and accurately represents the user characteristic, and provides a basis for subsequent user classification. In addition, the parameter of the user classification model is adjusted with a goal of minimizing the current loss value, so the first classification network and the second classification network can jointly learn a capability of determining a user (a user with a high requirement) that has a response behavior only under the predetermined incentive behavior, and the user classification model can more accurately determine the user with a high requirement, thereby improving accuracy of a user classification result.

[0083] Corresponding to the previous method embodiments, an embodiment of the present specification further provides a user classification processing method. The method is performed by an electronic device, and the electronic device can be

implemented by using any apparatus, device, platform, device cluster, etc. that has a calculation and processing capability. FIG. 4 is a schematic flowchart of a user classification processing method. The method includes S410 to S430.

[0084] In step S410, obtain a user classification model, including a graph neural network, a first classification network, and a second classification network. The user classification model is a model obtained by training based on the previous method for training a user classification model. For a specific training procedure of the user classification model, reference can be made to the previous method embodiment, and details are omitted here for simplicity.

[0085] In step S420, input each to-be-processed user into the user classification model, so as to determine, by using the graph neural network, the first classification network, and the second classification network, a first estimated value and a second estimated value that are corresponding to each to-be-processed user, where the first estimated value represents a probability that a corresponding to-be-processed user belongs to a first user group formed by a first-type user and a second-type user, the second estimated value represents a probability that a corresponding to-be-processed user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has a response behavior for a predetermined incentive behavior, the second-type user has a response behavior only under the predetermined incentive behavior, and the third-type user always does not have a response behavior. In an implementation, each to-be-processed user and the previous sample user can belong to a same platform user.

[0086] In this step, a user identifier of a to-be-processed user can be input into the user classification model, and the to-be-processed user corresponding to the user identifier can be used as a target node. In a pre-constructed user relationship network graph, node representation aggregation is performed on the to-be-processed node by using the graph neural network of the user classification model, to obtain a user representation of each to-be-processed user. Then, the user representation of each to-be-processed user is separately input into the first classification network and the second classification network, so as to obtain the first estimated value and the second estimated value that are corresponding to each to-be-processed user.

[0087] For a process of determining, by using the graph neural network, the first classification network, and the second classification network, the first estimated value and the second estimated value that are corresponding to each to-be-processed user,

refer to the previous process of determining the first predicted value and the second predicted value that are corresponding to the sample user, and details are omitted here for simplicity.

[0088] Then, in step S430, for each to-be-processed user, determine, based on the first estimated value and the second estimated value that are corresponding to the to-be-processed user, a processing method related to the predetermined incentive behavior. The first estimated value and the second estimated value that are corresponding to each to-be-processed user can represent a user category to which the to-be-processed user belongs. For a to-be-processed user that belongs to the second-type user, there is a higher possibility that the to-be-processed user has a response behavior for the predetermined incentive behavior. Correspondingly, whether a to-be-processed user belongs to the second-type user can be determined based on the first estimated value and the second estimated value that are corresponding to each to-be-processed user, and then a processing method related to the predetermined incentive behavior is determined based on a result of whether the to-be-processed user belongs to the second-type user. The processing method related to the predetermined incentive behavior includes but is not limited to: whether a predetermined incentive degree is implemented, an incentive degree of implementing the predetermined incentive behavior (for example, the predetermined incentive behavior is to issue a coupon, the incentive degree is a specific amount of the coupon, the predetermined incentive behavior is to provide a discount, and the incentive degree is a discount degree), an occasion for implementing the predetermined incentive behavior, etc.

[0089] It can be understood that a higher first estimated value represents a higher possibility that a corresponding to-be-processed user belongs to the first user group, and a higher second estimated value represents a higher possibility that a corresponding to-be-processed user belongs to the second user group. Correspondingly, when the first estimated value is relatively high (that is, higher than a predetermined first threshold) and the second estimated value is relatively high (that is, a predetermined second threshold), it can represent that a corresponding to-be-processed user belongs to the second-type user. The second-type user is a user that has a response behavior only under the predetermined incentive behavior. This type of user has a higher requirement for the predetermined incentive behavior. Correspondingly, this type of user is a user to which the predetermined incentive behavior is more suitable for implementing. In an embodiment, step S430 can be specifically set as follows: In step 31, if a first estimated

value corresponding to a to-be-processed user is higher than a first threshold, and a corresponding second estimated value is higher than a second threshold, determine the to-be-processed user as a candidate target user for whom the predetermined incentive behavior is to be implemented. In step 32, if a first estimated value corresponding to the to-be-processed user is not greater than the first threshold, and/or a corresponding second estimated value is not greater than the second threshold, determine not to implement the predetermined incentive behavior for the to-be-processed user.

[0090] To better provide a higher-quality service for a user and promote user activity on a platform, after target users are determined, such target users can be further ranked, so as to determine a priority of implementing the predetermined incentive behavior for each target user. In an embodiment, after determining all candidate target users for whom the predetermined incentive behavior is to be implemented, the electronic device can further determine, based on a sum value of a first estimated value and a second estimated value that are corresponding to each target user, a priority of implementing the predetermined incentive behavior for each target user.

[0091] In an implementation, the electronic device can directly determine, based on the sum value of the first estimated value and the second estimated value that are corresponding to each target user, the priority of implementing the predetermined incentive behavior for each target user. A larger sum value of a first estimated value and a second estimated value that are corresponding to a target user indicates a higher priority corresponding to the target user.

[0092] In another implementation, for each target user, the electronic device can determine an incentive behavior gain value of the target user based on a sum value of a first estimated value and a second estimated value that are corresponding to the target user, and further determine a priority corresponding to each target user based on ranking of incentive behavior gain values of the target users.

[0093] Specifically, the electronic device can pre-store a static response value corresponding to each target user, and the static response value represents a probability that a corresponding target user performs a response behavior when the predetermined incentive behavior is not applied. In this implementation, for each target user, the electronic device can calculate the sum value of the first estimated value and the second estimated value that are corresponding to the target user, further calculate a ratio of the sum value to the static response value corresponding to the target user, and use the ratio as the incentive behavior gain value of the target user. Then, the priority of

implementing the predetermined incentive behavior for each target user is determined based on the ranking of the incentive behavior gain values of the target users. A larger incentive behavior gain value of each target user indicates that the target user has more enthusiasm in performing a response behavior when the predetermined incentive behavior is applied to the target user, and correspondingly, a corresponding priority of implementing the predetermined incentive behavior for the target user is higher. In an implementation, a sequence of implementing the predetermined incentive behavior for each target user is determined and/or an incentive degree corresponding to implementing the predetermined incentive behavior for each target user is determined based on the priority corresponding to the target user. A higher priority indicates a higher sequence of implementing the predetermined incentive behavior, and a higher priority indicates a higher incentive degree corresponding to implementing the predetermined incentive behavior for the target user.

[0094] In the previous method of determining the priority corresponding to the target user, a consumption (expenditure) level of the target user does not need to be considered, and the priority corresponding to the target user is determined only based on enthusiasm of the target user in performing a response behavior to the predetermined incentive behavior. The predetermined incentive behavior is preferentially implemented for a target user with high enthusiasm, so as to implement a more high-quality and accurate service for the user, and better improve user experience.

[0095] In an example scenario, when the user classification model is applied to a financial platform, and a user classification service is provided for a credit service provided by the financial platform, the user representation can represent whether the user is a risk user (for example, whether the user repays on time) or determine a risk level of the user. For this scenario, the user classification model can be used to determine a user with a low risk and a high requirement (that is, a user who is active in repayment and has high enthusiasm in performing a response behavior to the predetermined incentive behavior).

[0096] The previous content describes specific embodiments of the present specification, and other embodiments are within the scope of the appended claims. In some situations, the actions or steps described in the claims can be performed in an order different from the order in the embodiments and the desired results can still be achieved. In addition, the process depicted in the accompanying drawings does not necessarily need an illustrated particular execution order to achieve the desired results.

In some implementations, multi-tasking and concurrent processing is feasible or can be advantageous.

[0097] Corresponding to the previous method embodiments, an embodiment of the present specification provides an apparatus 500 for training a user classification model. The user classification model includes a graph neural network, a first classification network, and a second classification network. A schematic block diagram of the apparatus is shown in FIG. 5, including:

- a first acquisition module 510, configured to obtain a sample user, where the sample user has tag data that is used to represent a response behavior of the sample user for a predetermined incentive behavior;

- an aggregation module 520, configured to: in a pre-constructed user relationship network graph, use the sample user as a target node, and perform node representation aggregation on the target node by using the graph neural network, to obtain a user representation;

- an input acquisition module 530, configured to separately input the user representation into the first classification network and the second classification network to obtain a first predicted value and a second predicted value, where the first predicted value represents a probability that the sample user belongs to a first user group formed by a first-type user and a second-type user, the second predicted value represents a probability that the sample user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has the response behavior, the second-type user has the response behavior only under the predetermined incentive behavior, and the third-type user always does not have the response behavior;

- a first determining module 540, configured to determine a current loss value based on the first predicted value and/or the second predicted value, and the tag data; and

- an adjustment module 550, configured to adjust a parameter of the user classification model with a goal of minimizing the current loss value.

[0098] In an optional implementation, the graph neural network includes k aggregation layers; and

- the aggregation module 520 is specifically configured to sequentially perform, at the k aggregation layers, k levels of vector aggregation on the target node, where each level of vector aggregation includes: determining a current-level aggregation vector of the target node based on at least an upper-level aggregation vector of each

neighboring node of the target node, where an initial-level aggregation vector of each node is determined based on an attribute feature of a corresponding user.

[0099] In an optional implementation, the aggregation module 520 is specifically configured to determine a weight value of each neighboring node relative to the target node based on an upper-level aggregation vector of the target node and the upper-level aggregation vector of each neighboring node; and

determine the current-level aggregation vector of the target node based on the upper-level aggregation vector of the target node, the upper-level aggregation vector of each neighboring node, and the weight value of each neighboring node relative to the target node.

[0100] In an optional implementation, the sample user is selected from a user sample set, and the apparatus further includes a sample set acquisition module (not shown in the figure). The sample set acquisition module is configured to obtain the user sample set, specifically including:

a division unit (not shown in the figure), configured to divide user groups into a control group in which the predetermined incentive behavior is not applied and a test group in which the predetermined incentive behavior is applied; and

a first determining unit (not shown in the figure), configured to determine, based on a group to which any first user in the user groups belongs and whether the response behavior is performed, first tag data of the first user.

[0101] In an optional implementation, the first user belongs to the test group; and the first determining unit is specifically configured to: if the first user has the response behavior, set the first tag data to include a first tag belonging to the first-type user and a second tag belonging to the second-type user; and

if the first user does not have the response behavior, set the first tag data to include only a third tag belonging to the third-type user.

[0102] In an optional implementation, the first user belongs to the control group; and the first determining unit is specifically configured to: if the first user has the response behavior, set the first tag data to include only a first tag belonging to the first-type user; and

if the first user does not have the response behavior, set the first tag data to include a second tag belonging to the second-type user and a third tag belonging to the third-type user.

[0103] In an optional implementation, the first determining module 540 is specifically configured to: if the tag data includes only a first tag belonging to the first-type user, determine a first loss value based on the first predicted value and the tag data; and

the adjustment module 550 is specifically configured to adjust parameters of the graph neural network and the first classification network with a goal of minimizing the first loss value.

[0104] In an optional implementation, the first determining module 540 is specifically configured to: if the tag data includes only a third tag belonging to the third-type user, determine a second loss value based on the second predicted value and the tag data; and

the adjustment module 550 is specifically configured to adjust parameters of the graph neural network and the second classification network with a goal of minimizing the second loss value.

[0105] In an optional implementation, the first determining module 540 is specifically configured to: if the tag data includes a second tag belonging to the second-type user, determine a third loss value based on the first predicted value, the second predicted value, and the tag data; and

the adjustment module 550 is specifically configured to adjust parameters of the graph neural network, the first classification network, and the second classification network with a goal of minimizing the third loss value.

[0106] In an optional implementation, the predetermined incentive behavior includes implementing one of issuing a user benefit, pushing an additional service, or providing a discount for a target service.

[0107] Corresponding to the previous method embodiments, an embodiment of the present specification provides a user classification processing apparatus 600. A schematic block diagram of the apparatus is shown in FIG. 6, including:

a second acquisition module 610, configured to obtain a user classification model, where the user classification model includes a graph neural network, a first classification network, and a second classification network; and the user classification model is a model trained based on the previous apparatus for training a user classification model;

a second determining module 620, configured to input each to-be-processed user into the user classification model, so as to determine, by using the graph neural network, the first classification network, and the second classification network, a first estimated value and a second estimated value that are corresponding to each to-be-

processed user, where the first estimated value represents a probability that a corresponding to-be-processed user belongs to a first user group formed by a first-type user and a second-type user, the second estimated value represents a probability that a corresponding to-be-processed user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has a response behavior for a predetermined incentive behavior, the second-type user has a response behavior only under the predetermined incentive behavior, and the third-type user always does not have a response behavior; and

a third determining module 630, configured to: for each to-be-processed user, determine, based on the first estimated value and the second estimated value that are corresponding to the to-be-processed user, a processing method related to the predetermined incentive behavior.

[0108] In an optional implementation, the third determining module 630 includes:

a second determining unit (not shown in the figure), configured to: if a first estimated value corresponding to a to-be-processed user is higher than a first threshold, and a corresponding second estimated value is higher than a second threshold, determine the to-be-processed user as a candidate target user for whom the predetermined incentive behavior is to be implemented; and

a third determining unit (not shown in the figure), configured to: if a first estimated value corresponding to the to-be-processed user is not greater than the first threshold, and/or a corresponding second estimated value is not greater than the second threshold, determine not to implement the predetermined incentive behavior for the to-be-processed user.

[0109] In an optional implementation, the third determining module 630 further includes:

a fourth determining unit (not shown in the figure), configured to determine, based on a sum value of a first estimated value and a second estimated value that are corresponding to each target user, a priority of implementing the predetermined incentive behavior for each target user.

[0110] In an optional implementation, the fourth determining module is configured to: for each target user, determine an incentive behavior gain value of the target user based on a sum value of a first estimated value and a second estimated value that are corresponding to the target user; and

determine a priority corresponding to each target user based on ranking of a gain value of an incentive behavior of the target user.

[0111] In an optional implementation, the second determining module 620 is specifically configured to: in a pre-constructed user relationship network graph, separately use each to-be-processed user as a to-be-processed node, and perform node representation aggregation on the to-be-processed node by using the graph neural network, to obtain a user representation of each to-be-processed user; and

separately input the user representation of each to-be-processed user into the first classification network and the second classification network, so as to obtain the first estimated value and the second estimated value that are corresponding to each to-be-processed user.

[0112] The previous apparatus embodiment corresponds to the method embodiment. For specific descriptions, refer to some descriptions of the method embodiment. Details are omitted here for simplicity. The apparatus embodiment is obtained based on a corresponding method embodiment, and has a same technical effect as the corresponding method embodiment. For specific descriptions, refer to the corresponding method embodiment.

[0113] An embodiment of the present specification further provides a computer readable storage medium, where the computer readable storage medium stores a computer program, and when the computer program is executed in a computer, the computer performs the method for training a user classification model provided in the present specification.

[0114] An embodiment of the present specification further provides a computing device, including a memory and a processor, where the memory stores executable code, and when the processor executes the executable code, the method for training a user classification model provided in the present specification is implemented.

[0115] An embodiment of the present specification further provides a computer readable storage medium, where the computer readable storage medium stores a computer program, and when the computer program is executed in a computer, the computer performs the user classification processing method provided in the present specification.

[0116] An embodiment of the present specification further provides a computing device, including a memory and a processor. The memory stores executable code, and

when executing the executable code, the processor implements the user classification processing method provided in the present specification.

[0117] The embodiments in the present specification are described in a progressive way. For same or similar parts of the embodiments, references can be made to the embodiments. Each embodiment focuses on a difference from other embodiments. Particularly, storage medium and computing device embodiments are similar to a method embodiment, and therefore are described briefly. For related parts, references can be made to related descriptions in the method embodiment.

[0118] A person skilled in the art should be aware that in the previous one or more examples, functions described in the embodiments of present disclosure can be implemented by hardware, software, firmware, or any combination thereof. When the present disclosure is implemented by software, the functions can be stored in a computer readable medium or transmitted as one or more instructions or code in the computer readable medium.

[0119] The objectives, technical solutions, and beneficial effects of the embodiments of the present disclosure are further described in detail in the previous specific implementations. It should be understood that the earlier-described descriptions are merely specific implementations of the embodiments of the present disclosure, but are not intended to limit the protection scope of the present disclosure. Any modification, equivalent replacement, or improvement made based on the technical solutions of the present disclosure shall fall within the protection scope of the present disclosure.

CLAIMS

What is claimed is:

1. A method for training a user classification model, wherein the user classification model comprises a graph neural network, a first classification network, and a second classification network, and the method comprises:

obtaining a sample user, wherein the sample user has tag data that is used to represent a response behavior of the sample user for a predetermined incentive behavior;

in a pre-constructed user relationship network graph, using the sample user as a target node, and performing node representation aggregation on the target node by using the graph neural network, to obtain a user representation;

separately inputting the user representation into the first classification network and the second classification network to obtain a first predicted value and a second predicted value, wherein the first predicted value represents a probability that the sample user belongs to a first user group formed by a first-type user and a second-type user, the second predicted value represents a probability that the sample user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has the response behavior, the second-type user has the response behavior only under the predetermined incentive behavior, and the third-type user always does not have the response behavior;

determining a current loss value based on the first predicted value and/or the second predicted value, and the tag data; and

adjusting a parameter of the user classification model with a goal of minimizing the current loss value.

2. The method according to claim 1, wherein the graph neural network comprises k aggregation layers; and

the performing node representation aggregation on the target node by using the graph neural network comprises:

sequentially performing, at the k aggregation layers, k levels of vector aggregation on the target node, wherein each level of vector aggregation comprises: determining a current-level aggregation vector of the target node based on at least an upper-level aggregation vector of each neighboring node of the target node, wherein an initial-level aggregation vector of each node is determined based on an attribute feature of a corresponding user.

3. The method according to claim 2, wherein the determining a current-level aggregation vector of the target node based on at least an upper-level aggregation vector of each neighboring node of the target node comprises:

determining a weight value of each neighboring node relative to the target node based on an upper-level aggregation vector of the target node and the upper-level aggregation vector of each neighboring node; and

determining the current-level aggregation vector of the target node based on the upper-level aggregation vector of the target node, the upper-level aggregation vector of each neighboring node, and the weight value of each neighboring node relative to the target node.

4. The method according to claim 1, wherein the sample user is selected from a user sample set, and the user sample set is obtained by:

dividing user groups into a control group in which the predetermined incentive behavior is not applied and a test group in which the predetermined incentive behavior is applied; and

determining, based on a group to which any first user in the user groups belongs and whether the response behavior is performed, first tag data of the first user.

5. The method according to claim 4, wherein the first user belongs to the test group; and the determining first tag data of the first user comprises:

if the first user has the response behavior, setting the first tag data to comprise a first tag belonging to the first-type user and a second tag belonging to the second-type user; and

if the first user does not have the response behavior, setting the first tag data to comprise only a third tag belonging to the third-type user.

6. The method according to claim 4, wherein the first user belongs to the control group; and the determining first tag data of the first user comprises:

if the first user has the response behavior, setting the first tag data to comprise only a first tag belonging to the first-type user; and

if the first user does not have the response behavior, setting the first tag data to comprise a second tag belonging to the second-type user and a third tag belonging to the third-type user.

7. The method according to claim 1, wherein the determining a current loss value comprises:

if the tag data comprises only a first tag belonging to the first-type user, determining a first loss value based on the first predicted value and the tag data; and

the adjusting a parameter of the user classification model comprises:

adjusting parameters of the graph neural network and the first classification network with a goal of minimizing the first loss value.

8. The method according to claim 1, wherein the determining a current loss value comprises:

if the tag data comprises only a third tag belonging to the third-type user, determining a second loss value based on the second predicted value and the tag data; and

the adjusting a parameter of the user classification model comprises:

adjusting parameters of the graph neural network and the second classification network with a goal of minimizing the second loss value.

9. The method according to claim 1, wherein the determining a current loss value comprises:

if the tag data comprises a second tag belonging to the second-type user, determining a third loss value based on the first predicted value, the second predicted value, and the tag data; and

the adjusting a parameter of the user classification model comprises:

adjusting parameters of the graph neural network, the first classification network, and the second classification network with a goal of minimizing the third loss value.

10. The method according to any one of claims 1-9, wherein the predetermined incentive behavior comprises implementing one of issuing a user benefit, pushing an additional service, or providing a discount for a target service.

11. A user classification processing method, comprising:

obtaining a user classification model obtained by training based on the method according to claim 1, wherein the user classification model comprises a graph neural network, a first classification network, and a second classification network;

inputting each to-be-processed user into the user classification model, so as to determine, by using the graph neural network, the first classification network, and the second classification network, a first estimated value and a second estimated value that are corresponding to each to-be-processed user, wherein the first estimated value represents a probability that a corresponding to-be-processed user belongs to a first user group formed by a first-type user and a second-type user, the second estimated value

represents a probability that a corresponding to-be-processed user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has a response behavior for a predetermined incentive behavior, the second-type user has a response behavior only under the predetermined incentive behavior, and the third-type user always does not have a response behavior; and

for each to-be-processed user, determining, based on the first estimated value and the second estimated value that are corresponding to the to-be-processed user, a processing method related to the predetermined incentive behavior.

12. The method according to claim 11, wherein the determining a processing method related to the predetermined incentive behavior comprises:

if a first estimated value corresponding to a to-be-processed user is higher than a first threshold, and a corresponding second estimated value is higher than a second threshold, determining the to-be-processed user as a candidate target user for whom the predetermined incentive behavior is to be implemented; and

if a first estimated value corresponding to the to-be-processed user is not greater than the first threshold, and/or a corresponding second estimated value is not greater than the second threshold, determining not to implement the predetermined incentive behavior for the to-be-processed user.

13. The method according to claim 12, wherein the determining a processing method related to the predetermined incentive behavior further comprises:

determining, based on a sum value of a first estimated value and a second estimated value that are corresponding to each target user, a priority of implementing the predetermined incentive behavior for each target user.

14. The method according to claim 13, wherein the determining a priority of implementing the predetermined incentive behavior for each target user comprises:

for each target user, determining an incentive behavior gain value of the target user based on a sum value of a first estimated value and a second estimated value that are corresponding to the target user; and

determining a priority corresponding to each target user based on ranking of a gain value of an incentive behavior of the target user.

15. The method according to any one of claims 11-14, wherein the inputting each to-be-processed user into the user classification model, and determining a first estimated value and a second estimated value that are corresponding to each to-be-processed user comprises:

in a pre-constructed user relationship network graph, separately using each to-be-processed user as a to-be-processed node, and performing node representation aggregation on the to-be-processed node by using the graph neural network, to obtain a user representation of each to-be-processed user; and

separately inputting the user representation of each to-be-processed user into the first classification network and the second classification network, so as to obtain the first estimated value and the second estimated value that are corresponding to each to-be-processed user.

16. An apparatus for training a user classification model, wherein the user classification model comprises a graph neural network, a first classification network, and a second classification network, and the apparatus comprises:

a first acquisition module, configured to obtain a sample user, wherein the sample user has tag data that is used to represent a response behavior of the sample user for a predetermined incentive behavior;

an aggregation module, configured to: in a pre-constructed user relationship network graph, use the sample user as a target node, and perform node representation aggregation on the target node by using the graph neural network, to obtain a user representation;

an input acquisition module, configured to separately input the user representation into the first classification network and the second classification network to obtain a first predicted value and a second predicted value, wherein the first predicted value represents a probability that the sample user belongs to a first user group formed by a first-type user and a second-type user, the second predicted value represents a probability that the sample user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has the response behavior, the second-type user has the response behavior only under the predetermined incentive behavior, and the third-type user always does not have the response behavior;

a first determining module configured to determine a current loss value based on the first predicted value and/or the second predicted value, and the tag data; and

an adjustment module, configured to adjust a parameter of the user classification model with a goal of minimizing the current loss value.

17. A user classification processing apparatus, comprising:

a second acquisition module, configured to obtain a user classification model obtained by training based on the apparatus according to claim 16, wherein the user

classification model comprises a graph neural network, a first classification network, and a second classification network;

a second determining module, configured to input each to-be-processed user into the user classification model, so as to determine, by using the graph neural network, the first classification network, and the second classification network, a first estimated value and a second estimated value that are corresponding to each to-be-processed user, wherein the first estimated value represents a probability that a corresponding to-be-processed user belongs to a first user group formed by a first-type user and a second-type user, the second estimated value represents a probability that a corresponding to-be-processed user belongs to a second user group formed by the second-type user and a third-type user, the first-type user always has a response behavior for a predetermined incentive behavior, the second-type user has a response behavior only under the predetermined incentive behavior, and the third-type user always does not have a response behavior; and

a third determining module, configured to: for each to-be-processed user, determine, based on the first estimated value and the second estimated value that are corresponding to the to-be-processed user, a processing method related to the predetermined incentive behavior.

18. A computing device, comprising a memory and a processor, wherein the memory stores executable code, and when executing the executable code, the processor implements the method according to any one of claims 1 to 10 and 11 to 15.