

Machine Learning Model Training Method and Device, and Electronic Device

Technical Field

The present specification relates to the computer application field, and in particular, to a machine learning model training method and device, and an electronic device.

5 Background

In the field of mobile payment, a payment platform would typically deploy, out of considerations for payment safety, a risk model constructed through supervised machine learning in a risk control system to generate risk scores on daily transactions of users, so as to promptly discover abnormal transactions of users.

10 When a risk model is being trained, those transactions having transaction abnormalities may often be marked as positive samples (e.g., account thefts that are actively reported by users, and the like), and the other transactions without transaction abnormalities are marked as negative samples. Then, supervised machine learning may be performed based on these positive samples and negative samples. When model training is completed, the model may subsequently be used
15 to generate risk scores on daily transactions of users, so that the payment platform may make risk-related decisions based on the risk scores of daily transactions of users and promptly discover abnormal transactions of users.

Summary

The present specification provides a machine learning model training method, comprising:
20 marking samples with risk labels in a training sample set as positive samples and marking samples without risk labels in the training sample set as negative samples;

training a supervised risk model based on the marked positive samples and negative samples, and assessing a risk of the negative samples respectively based on the trained model to obtain risk scores for the negative samples;

25 filtering negative samples in the training sample set that have risk scores greater than a preset threshold value; and

re-training the supervised risk model based on the positive and negative samples in the filtered training sample set.

Optionally, the filtering negative samples in the training sample set that have risk scores
30 greater than a preset threshold value comprises:

deleting the negative samples in the training sample set that have risk scores greater than the preset threshold value.

Optionally, the filtering negative samples in the training sample set that have risk scores greater than a preset threshold value comprises:

35 re-marking the negative samples in the training sample set that have risk scores greater than a

preset threshold value as positive samples.

Optionally, the re-training the supervised risk model based on the positive and negative samples in the filtered training sample set comprises:

configuring weights for loss functions corresponding to the re-marked positive samples and original positive samples in the training sample set, respectively, wherein a weight of the loss function corresponding to the re-marked positive samples is smaller than a weight of the loss function corresponding to the original positive samples; and

training the supervised risk model based on the re-marked positive samples, the original positive samples in the training sample set and the remaining negative samples in the training sample set.

Optionally, the risk scores represent probabilities at which a risk occurs; and the method further comprises:

after re-marking the negative samples that have risk scores greater than the preset threshold value as positive samples, configuring the risk scores of the positive samples as the weight of the loss function corresponding to the re-marked negative samples, and setting the weight of the loss function corresponding to original negative samples to be 1.

Optionally, the method further comprises:

constructing a prediction sample based on online data; and

assessing a risk of the prediction sample based on the re-trained model to obtain a risk score.

A machine learning model training device, comprising:

a marking module configured to mark samples with risk labels in a training sample set as positive samples and mark samples without risk labels in the training sample set as negative samples;

an assessing module configured to train a supervised risk model based on the marked positive samples and negative samples, and assess a risk of the negative samples respectively based on the trained model to obtain risk scores for the negative samples;

a filtering module configured to filter negative samples in the training sample set that have risk scores greater than a preset threshold value; and

a training module configured to re-train the supervised risk model based on the positive and negative samples in the filtered training sample set.

Optionally, the filtering module is configured to:

delete the negative samples in the training sample set that have risk scores greater than the preset threshold value.

Optionally, the filtering module is configured to:

re-mark the negative samples in the training sample set that have risk scores greater than a preset threshold value as positive samples.

Optionally, the training module is further configured to:

configure weights for loss functions corresponding to the re-marked positive samples and original positive samples in the training sample set, respectively, wherein a weight of the loss function corresponding to the re-marked positive samples is smaller a weight of the loss function corresponding to the original positive samples; and

train the supervised risk model based on the re-marked positive samples, the original positive samples in the training sample set and the remaining negative samples in the training sample set.

Optionally, the risk scores represent probabilities at which a risk occurs; and

the filtering module is further configured to:

after re-marking the negative samples that have risk scores greater than the preset threshold value as positive samples, configure the risk scores of the negative samples as the weight of the loss function corresponding to the re-marked positive samples, and set the weight of the loss function corresponding to the original positive samples to be 1.

Optionally, the assessing module is further configured to:

construct a prediction sample based on online data; and

assess a risk of the prediction sample based on the re-trained model to obtain a risk score.

The present specification further provides an electronic device, comprising:

a processor; and

a memory for storing a machine executable instruction;

wherein, by reading and executing the machine executable instruction stored in the memory and corresponding to a control logic of training of a supervised machine learning model, the processor is caused to:

mark samples with risk labels in a training sample set as positive samples and mark samples without risk labels in the training sample set as negative samples;

train a supervised risk model based on the marked positive samples and negative samples, and assess a risk of the negative samples respectively based on the trained model to obtain risk scores for the negative samples;

filter negative samples in the training sample set that have risk scores greater than a preset threshold value; and

re-train the supervised risk model based on the positive and negative samples in the filtered training sample set.

The technical solutions according to some embodiments of the present specification mark samples with risk labels in a training sample set as positive samples and mark samples without

risk labels in the training sample set as negative samples; train a supervised risk model based on the marked positive samples and negative samples, and assess a risk of the negative samples respectively based on the trained model to obtain risk scores for the negative samples; then, filter negative samples in the training sample set that have risk scores greater than a preset threshold value as suspected positive samples; and re-train the supervised risk model based on the positive and negative samples in the filtered training sample set.

On the one hand, suspected positive samples in the negative samples in the training sample set can be found and filtered out, which improves the marking accuracy of the positive and negative samples in the training sample set. On the other hand, the positive and negative samples in the filtered training sample set are used to re-train the model, which is favorable for improving the performance of the trained model.

Brief Description of the Drawings

FIG. 1 is a flow chart of a supervised machine learning model training method according to some embodiments of the present specification;

FIG. 2 is a hardware structural diagram of an electronic device that includes a supervised machine learning model device according to some embodiments of the present specification; and

FIG. 3 is a logical block diagram of a supervised machine learning model device according to some embodiments of the present specification.

Detailed Description

Exemplary embodiments will be described in detail below, and the examples of the embodiments are illustrated in the accompanying drawings. When the description below involves the accompanying drawings, identical numbers in different drawings represent identical or similar elements, unless otherwise indicated. The embodiments described in the following exemplary embodiments do not represent all embodiments that are consistent with the present specification. Conversely, they are only examples of devices and methods that are consistent with some aspects of the present specification as set forth in detail in the appended claims.

Terms used in the present application are only for the purpose of describing particular embodiments, rather than limiting the present specification. “A,” “the,” and “said” in the singular form used in the present specification and the appended claims are intended to include the plural form as well, unless clearly indicated in the context to have other meanings. It should also be understood that the term “and/or” used in the present specification refers to and includes any or all possible combinations of one or more associated listed items.

It should be understood that terms such as first, second, third, and the like may be used in the present specification to describe various information, but the information shall not be limited to these terms. These terms are only used to differentiate information of the same type from each

other. For example, without departing from the scope of the present specification, first information may also be referred to as second information, and similarly, second information may also be referred to as first information. Depending on the context, the term “if” used herein may be construed as “when...” or “at the time of...” or “in response to determination.”

5 When a supervised machine learning model is being trained, the marking accuracy of training samples typically directly determines the accuracy of the trained model. Therefore, in the model training phase, how to improve the marking accuracy of training samples to improve the accuracy of the trained model is significantly important.

For example, training a supervised risk model can be based on users’ historical transaction
10 data. When the risk model is being trained, the transactions in which risk events occurred (e.g., a user actively reports asset losses occurred in the user’s transactions) may often be marked as positive samples, and the other transactions in which no risk events occurred are marked as negative samples. However, there may typically be some transactions in which risk events occurred but not actively reported by users. This may lead to cases where some positive samples
15 are mixed in negative samples in a training sample set. If a modeler directly uses this training sample set to train a model, the accuracy of the model would inevitably be affected. Therefore, if the modeler can promptly find and filter out suspected positive samples mixed in the negative samples, the accuracy of the trained model can be significantly improved.

In view of the above, the present specification improves a conventional model training
20 process that is based on pu-learning and provides a technical solution as follows: marking unlabel samples (samples without labels) as positive samples to train a supervised machine learning model, and assessing the risk of negative samples in the training sample set using the trained supervised machine learning model to find and filter out suspected positive samples in the negative samples in the training sample set, thereby improving the marking accuracy of the
25 positive and negative samples in the training sample set.

During implementations, a training sample set comprising a plurality of samples with risk labels and a plurality of samples without risk labels may be obtained in advance. The samples with risk labels in the training sample set are marked as positive samples, the unlabel samples without labels in the training sample set are marked as negative samples, and then a supervised
30 machine learning model is trained based on the marked positive samples and negative samples.

When the model training is completed, the risk of the negative samples in the training sample set may further be assessed, respectively, based on the supervised machine learning model to obtain risk scores for the negative samples. The negative samples in the training sample set that have risk scores greater than a preset threshold value are then selected through screening. And
35 the selected negative samples are filtered out as suspected negative samples from the training

sample set.

For example, in one embodiment, the negative samples that have risk scores greater than the preset threshold value may be directly deleted from the training sample set. Alternatively, in another embodiment, the negative samples that have risk scores greater than the preset threshold value may also be classified as suspected positive samples and re-marked as positive samples. A weight may be set for the loss function corresponding to the re-marked positive samples, wherein the weight of the loss function corresponding to the re-marked positive samples is smaller than the weight of the loss function corresponding to the original positive samples.

After the suspected negative samples in the training sample set have been filtered, the supervised machine learning model may be re-trained based on the positive samples and negative samples in the filtered training sample set, to construct a risk model.

On the one hand, suspected positive samples in the negative samples in the training sample set can be found and filtered out, which improves the marking accuracy of the positive and negative samples in the training sample set.

On the other hand, the positive and negative samples in the filtered training sample set are used to re-train the model, which is favorable for improving the performance of the trained model.

The present specification will be described below with reference to exemplary embodiments and exemplary application scenarios.

Referring to FIG. 1, FIG. 1 illustrates a supervised machine learning model training method according to some embodiments of the present specification. The method comprises the following steps:

Step 102: Mark samples with risk labels in a training sample set as positive samples and mark samples without risk labels in the training sample set as negative samples.

Step 104: Train a supervised risk model based on the marked positive samples and negative samples, and assess a risk of the negative samples respectively based on the trained model to obtain risk scores for the negative samples.

Step 106: Filter negative samples in the training sample set that have risk scores greater than a preset threshold value.

Step 108: Re-train the supervised risk model based on the positive and negative samples in the filtered training sample set.

The above risk model may, for example, comprise a machine learning model trained according to a supervised machine learning method and based on training samples in a preset training sample set. The type of the above risk model is not particularly limited in the present specification, and a risk model of any type may be included in exemplary applications.

For example, in a scenario, the above risk model may be a risk model that is trained based on a training sample set constructed with users' historical transaction data and is used for assessing risks of daily transactions of the users. With this risk model, the risk of a transaction initiated by a user may be assessed to obtain a corresponding transaction risk score, and then the transaction risk score may be further used to decide if this transaction initiated by the user involves a risk.

For example, in another scenario, the above trained model may also be a credit model that is trained based on a training sample set constructed with user data, such as users' historical transaction records, default records, and repayment records, and is used for assessing risks of user credits. With this credit model, the risk of a user's credit may be assessed to obtain a corresponding credit risk score. The credit risk score may be further used to decide if this user is a user with high risks who may have risky actions, such as credit default and the like.

The technical solutions of the present specification will be described in detail below. For example, the above risk model can be a risk model for assessing the risk of a transaction initiated by a user.

It should be noted that the above risk model being used as a risk model for assessing the risk of a transaction initiated by a user is provided as an example. In exemplary applications, the above risk model may also be a supervised risk model of other types (e.g., a credit model), which is not particularly limited in the present specification.

In the present specification, a modeler may collect a lot of users' historical transaction data in advance, extract transaction characteristics in a plurality of dimensions from the collected historical transaction data as modeling characteristics, which are used to construct characteristic vectors as training samples. And based on these training samples, a characteristic matrix is constructed as a training sample set.

Here, the modeling characteristics used for constructing training samples may encompass any form of characteristics related to user transaction risks, which is not particularly limited in the present specification. For example, the modeling characteristics may comprise transaction characteristics in dimensions such as whether a user logs in at a different location, transaction time, transaction amount, and the like.

When a training sample set has been constructed, the modeler may respectively mark, based on information actively fed back by users, training samples in the training sample set, in which risk events occurred, with corresponding risk labels. At this point, the remaining training samples without risk labels are unlabel samples.

After the modeler has marked the training samples in the training sample set, in which risk events occurred, with risk labels, the training samples with the risk labels may be marked as positive samples. The remaining unlabel samples without risk labels may be marked as negative

samples. Then, the above risk model may be constructed by training a preset supervised machine learning model based on these positive samples and negative samples in the training sample set.

Here, a type of the above supervised machine learning model is not particularly limited in the present specification. For example, the above machine learning model may be a Logistic Regression (LR) model or a supervised machine learning model in other forms.

In exemplary applications, the supervised machine learning model typically uses a loss function to describe a fitting error between training samples and corresponding sample labels. In an exemplary model training process, training samples and corresponding sample labels may be input into the loss function for iterative operations, until the algorithm converges to obtain, through reverse solution, values of model parameters when the fitting error between training samples and corresponding sample labels is minimum. Namely, a process of training a supervised machine learning model through a loss function may be understood as a process of obtaining, with a loss function and reverse solution, values of optimal model parameters when the fitting error between training samples and corresponding sample labels is minimum.

After values of model parameters are obtained when the fitting error between training samples and corresponding sample labels is minimum, the model training is completed. At this point, the trained model is a risk model for assessing risks of daily transactions of users.

In the present specification, there may typically be some transactions in which risk events occurred but not actively reported by users in the historical transaction data collected by a modeler for constructing training samples in exemplary applications. This may lead to cases where some suspected positive samples may be mixed in the negative samples without risk labels in the above training sample set. Therefore, to further improve the accuracy of the marked positive samples and negative samples in the above training sample set, when the above risk model training is completed, the modeler may identify and filter out suspected positive samples in the negative samples in the training sample set by further assessing the risk of the negative samples in the above training sample set respectively using the risk model.

In implementations, when the above risk model training is completed, the modeler may use the negative samples in the original training sample set as prediction samples, input a prediction sample into the risk model for risk assessment to obtain a corresponding risk score, and then screen out negative samples in the training sample set that have risk scores greater than a preset threshold value as suspected positive samples.

Here, the value of the preset threshold value is not particularly limited in the present specification, which may be flexibly configured by one of ordinary skill in the art according to actual needs.

After the negative samples that have risk scores greater than the preset threshold value have

been screened out from the original negative samples in the training sample set, the modeler may filter these screened negative samples as suspected positive samples, so as to improve the marking accuracy of the positive and negative samples in the training sample set.

For example, two manners illustrated below may be used by the modeler to complete the
5 filtering of the negative samples that have risk scores greater than the preset threshold value.

In one illustrated embodiment, the modeler may directly delete these negative samples that have risk scores greater than the preset threshold value from the original training sample set, thereby filtering out these suspected positive samples in the above training sample set.

In the other illustrated embodiment, deletion of samples is not be used. Instead, those
10 negative samples that have risk scores greater than the preset threshold value are re-marked as suspected positive samples. A weight may be set for a loss function corresponding to the suspected positive samples, wherein this weight is less than a weight of the loss function corresponding to the original positive samples.

In exemplary applications, those negative samples may also not be re-marked as suspected
15 positive samples. Instead, these negative samples are directly re-marked as positive samples. A weight may be set for a loss function corresponding to these re-marked positive samples, wherein this weight is equal to the weight of the loss function corresponding to the original positive samples. For example, the weight of the loss function corresponding to these re-marked positive samples and the weight of the loss function corresponding to the original positive
20 samples are all set to be one.

Here, when a supervised machine learning model is being trained, two different loss functions are typically used to describe fitting errors between positive samples and corresponding sample labels and between negative samples and corresponding sample labels, respectively. Therefore, the target equation of the supervised machine learning model may
25 typically be represented by the following equation:

where, in the above equation:

$g(x_i)$ is a function expression of a machine learning model that ultimately needs to be trained, which indicates a prediction result by the trained model for a training sample x_i (i.e., the ultimately output of a risk score);

$\sum_{y_i=1} l(y_i, g(x_i))$ indicates a loss function corresponding to positive samples (samples that
30 are marked with 1), which is used for representing an error loss between the prediction result $g(x_i)$ by the model for a positive sample and a true mark $y_i = 1$; and

$\sum_{y_i=-1} l(y_i, g(x_i))$ indicates a loss function corresponding to negative samples (samples that
35 are marked with -1), which is used for representing an error loss between the prediction result $g(x_i)$ by the model for a negative sample and a true mark $y_i = -1$.

Here, the type of the above loss function $l(y_i, g(x_i))$ is not particularly limited in the present specification. For example, in an exemplary application, a common log-loss function or hinge-loss function may be selected.

Here, when the above loss function $l(y_i, g(x_i))$ is a log-loss function, it can be expressed as:

$$\text{log-loss}\{l(y_i, g(x_i)) = \log(1 + \exp(-y_i g(x_i)))\}; \text{and}$$

when the above loss function $l(y_i, g(x_i))$ is a hinge-loss function, it can be expressed as:

$$\text{hinge-loss}\{l(y_i, g(x_i)) = \max\{0, 1 - y_i g(x_i)\}\}.$$

In the present specification, since the marked suspected positive samples are still involved in the model training, it is equivalent that the training samples in the training sample set are marked into three types, i.e., “positive samples,” “negative samples,” and “suspected positive samples.” In this case, when constructing the target equation of the above model, the modeler may construct a loss function for each of the above three types of training samples, respectively. The modeler may configure a weight for the loss function corresponding to the positive samples and for the loss function corresponding to the suspected positive samples, respectively, such that the weight for the loss function corresponding to the suspected positive samples is less than the weight of the loss function corresponding to the original positive samples.

In this case, the target equation of the above supervised machine learning model may be represented by the following equation:

Here, C_+ represents a weight configured for the loss function corresponding to the suspected positive samples; and

C_- represents a weight configured for the loss function corresponding to the original positive samples, wherein the value of C_+ is less than that of C_- . For example, in an exemplary application, the value of C_+ may be set to be much smaller than that of C_- .

Here, $\sum_{y_i=1} l(y_i, g(x_i))$ represents a loss function corresponding to the original positive samples (samples that are marked with 1), $\sum_{y_i=-1} l(y_i, g(x_i))$ represents a loss function corresponding to the original negative samples (samples that are marked with -1), and $\sum_{y_i=-2} l(y_i, g(x_i))$ represents a loss function corresponding to the suspected positive samples (samples that are marked with -2).

It should be noted that the loss function corresponding to the original negative samples may be configured with a weight or may not be configured with a weight, which is not particularly limited in the present specification.

For example, in an embodiment, the loss function corresponding to the original negative samples may also be configured with a weight that is equal to the weight of the loss function corresponding to the original positive samples. In this case, the target equation of the above

supervised machine learning model may be represented by the following equation:

It should be further noted that marking positive samples as 1, marking negative samples as -1, and marking suspected positive samples as -2 as illustrated above are merely exemplary and are not used to limit the present specification. In exemplary applications, the type of the labels used for marking positive samples, negative samples, and suspected positive samples may be flexibly defined by one of ordinary skill in the art.

In the present specification, by configuring a relatively small weight for the loss function corresponding to the suspected positive samples, the contribution by the suspected positive samples to output results of the trained model may be reduced, thereby indirectly achieving the goal of filtering out the suspected positive samples in the training sample set.

In exemplary applications, the weight configured for the loss function corresponding to the suspected positive samples just needs to be smaller than the weight configured for the loss function corresponding to the original positive samples, which is not particularly limited in the present specification.

For example, in one illustrated embodiment, the risk score output by the risk model is typically used for representing a probability at which a risk occurs and is a floating-point number between 0 and 1. Therefore, a risk score of a suspected positive sample may be used as a weight of the loss function corresponding to the suspected positive sample, while the weight of the loss function corresponding to the original positive sample is set to be 1. It should be noted that, since different suspected positive samples may have different risk scores, a weight of the loss function may also be different when the loss function is used to train different suspected positive samples.

In the present specification, after the negative samples in the original training sample set that have risk scores greater than the preset threshold value have been filtered in the above-illustrated embodiments, the modeler may re-train the supervised machine learning model based on the original positive samples, the suspected positive samples, and the original negative samples in the filtered training sample set. Here, exemplary training processes will not be elaborated in the present specification.

After the above supervised machine learning model has been re-trained based on the filtered training sample set, the modeler may deploy this model in a risk control system to assess risks of daily online transactions of users based on this model and to score the daily online transactions of users to obtain risk scores. The model is then used to determine if the transactions have risks based on the obtained risk scores.

For example, in implementations, the risk control system may collect users' online transaction data, extract transaction characteristics in a plurality of dimensions from the online transaction data to construct prediction samples, input the prediction samples into the model for

risk assessment to obtain risk scores, and then compare the risk scores with a preset risk threshold value to determine whether the transactions involve risks. If the risk scores are greater than the risk threshold value, the risk control system may decide that the transactions are risky transactions and may directly terminate the transactions or to perform further verification on identities of the users. If the verification is successful, the transactions may be executed. Otherwise, the transactions may be terminated.

In the above embodiments, the training sample set comprises a large number of positive samples and unlabeled samples in the present specification. The conventional model training process is based on pu-learning to screen out reliable negative samples from the unlabeled samples, and then perform supervised machine learning based on the positive samples and reliable negative samples. Instead, in the present specification, samples with risk labels in a training sample set are marked as positive samples and samples without risk labels in the training sample set are marked as negative samples. A supervised machine learning model is trained based on the marked positive samples and negative samples. The risk of the negative samples is assessed respectively based on the trained model to obtain risk scores for the negative samples. Negative samples in the training sample set that have a risk score greater than a preset threshold value are filtered as suspected positive samples. The supervised machine learning model is re-trained based on the positive and negative samples in the filtered training sample set.

On the one hand, suspected positive samples in the negative samples in the training sample set can be found and filtered out, which improves the marking accuracy of the positive and negative samples in the training sample set.

On the other hand, the positive and negative samples in the filtered training sample set are used to re-train the model, which is favorable for improving the performance of the trained model.

Corresponding to the above method embodiments, the present specification further provides embodiments of a supervised machine learning model training device. The embodiments of the supervised machine learning model training device according to the present specification may be applied to an electronic device. The device embodiments may be implemented through software or may also be implemented through hardware or a combination of software and hardware. For example, in the software implementation, a device in the logical sense is formed by a processor of an electronic device reading corresponding computer program instructions from a non-volatile memory into a cache for execution. From a hardware perspective, FIG. 2 illustrates a hardware structural diagram of the electronic device where the supervised machine learning model training device is embodied according to the present specification. In addition to the processor, memory, network interface and non-volatile memory shown in FIG. 2, the electronic device in the

embodiments may typically comprise other hardware according to exemplary functions of the electronic device, which will not be elaborated again.

FIG. 3 is a block diagram of a supervised machine learning model training device according to an exemplary embodiment of the present specification.

5 Referring to FIG. 3, the supervised machine learning model training device 30 may be applied to the electronic device shown in FIG. 2. The supervised machine learning model training device 30 comprises: a marking module 301, an assessing module 302, a filtering module 303 and a training module 304.

10 The marking module 301 is configured to mark samples with risk labels in a training sample set as positive samples and mark samples without risk labels in the training sample set as negative samples.

The assessing module 302 is configured to train a supervised risk model based on the marked positive samples and negative samples, and assess a risk of the negative samples respectively based on the trained model to obtain risk scores.

15 The filtering module 303 is configured to filter negative samples in the training sample set that have risk scores greater than a preset threshold value.

The training module 304 is configured to re-train the supervised risk model based on the positive and negative samples in the filtered training sample set.

20 In some embodiments, the filtering module 303 is configured to:
delete the negative samples in the training sample set that have risk scores greater than a preset threshold value.

In some embodiments, the filtering module 303 is configured to:
re-mark the negative samples in the training sample set that have risk scores greater than a preset threshold value as positive samples.

25 In some embodiments, the training module 304 is further configured to:
configure weights for loss functions corresponding to the re-marked positive samples and original positive samples in the training sample set, respectively, wherein a weight of the loss function corresponding to the re-marked positive samples is smaller than a weight of the loss function corresponding to the original positive samples; and

30 train the supervised risk model based on the re-marked positive samples, the original positive samples in the training sample set and the remaining negative samples in the training sample set.

In some embodiments, the risk scores represent probabilities at which a risk occurs; and the filtering module 303 is further configured to:

35 after re-marking the negative samples that have risk scores greater than the preset threshold value as positive samples, configure the risk scores of the negative samples as the weights of the

loss function corresponding to the re-marked positive samples, and set the weight of the loss function corresponding to the original positive samples to be 1.

In some embodiments, the assessing module 302 is further configured to:

construct a prediction sample based on online data; and

5 assess a risk of the prediction sample based on the re-trained model to obtain a risk score.

The implementation processes of corresponding steps in the above-described method can be referenced for detailed description of implementation processes of functions and roles of the units of the above-described device, which will not be elaborated by the present specification.

Since the device embodiments substantially correspond to the method embodiments, the
10 description of parts of the method embodiments can be referenced for relevant parts of the device embodiments. The above-described device embodiments are merely exemplary, wherein the units described as separate parts may or may not be physically separated, and the parts illustrated as units may or may not be physical units, i.e., they can be located at one place or distributed over a plurality of network units. The objectives of the solutions of the present specification can
15 be achieved by selecting some or all of the modules as needed, which can be understood and implemented by one of ordinary skill in the art without creative effort.

The systems, devices, modules or units set forth in the foregoing embodiments may be achieved, for example, by computer chips or entities, or by products with certain functions. A typical implementation device is a computer. An exemplary form of the computer may be a
20 personal computer, a laptop computer, a cell phone, a camera phone, a smart phone, a PDA (personal digital assistant), a media player, a navigation device, an email sending and receiving device, a game console, a tablet computer, a wearable device or a combination of any of these devices.

Corresponding to the above method embodiments, the present specification further provides
25 embodiments of an electronic device, the electronic device comprising: a processor and a memory for storing a machine executable instruction, wherein the processor and the memory are typically connected to each other via an internal bus. In other possible embodiments, the device may further comprise an external interface for communications with other devices or parts.

In some embodiments, by reading and executing the machine executable instruction stored in
30 the memory and corresponding to a control logic of training of a machine learning model, the processor is caused to:

mark samples with risk labels in a training sample set as positive samples and mark samples without risk labels in the training sample set as negative samples;

train a supervised risk model based on the marked positive samples and negative samples,
35 and assess a risk of the negative samples respectively based on the trained model to obtain risk

scores for the negative samples;

filter a negative samples in the training sample set that have risk scores greater than a preset threshold value; and

re-train the supervised risk model based on the positive and negative samples in the filtered training sample set.

In some embodiments, by reading and executing the machine executable instruction stored in the memory and corresponding to a control logic of training of a supervised machine learning model, the processor is further caused to:

delete the negative samples in the training sample set that have risk scores greater than the preset threshold value.

In some embodiments, by reading and executing the machine executable instruction stored in the memory and corresponding to a control logic of training of a supervised machine learning model, the processor is further caused to:

re-mark the negative samples in the training sample set that have risk scores greater than a preset threshold value as positive samples.

In some embodiments, by reading and executing the machine executable instruction stored in the memory and corresponding to a control logic of training of a supervised machine learning model, the processor is further caused to:

configure weights for loss functions corresponding to the re-marked positive samples and original positive samples in the training sample set, respectively, wherein a weight of the loss function corresponding to the re-marked positive samples is smaller than a weight of the loss function corresponding to the original positive samples; and

train the supervised risk model based on the re-marked positive samples, the original positive samples in the training sample set and the remaining negative samples in the training sample set.

In some embodiments, by reading and executing the machine executable instruction stored in the memory and corresponding to a control logic of training of a supervised machine learning model, the processor is further caused to:

after re-marking the negative samples that have risk scores greater than the preset threshold value as positive samples, configure the risk scores of the positive samples as the weight of the loss function corresponding to the re-marked negative samples, and set the weight of the loss function corresponding to original negative samples to be 1.

In some embodiments, by reading and executing the machine executable instruction stored in the memory and corresponding to a control logic of training of a supervised machine learning model, the processor is further caused to:

construct a prediction sample based on online data; and

assess a risk of the prediction sample based on the re-trained model to obtain a risk score.

The implementation processes of corresponding steps in the above-described method can be referenced for detailed description of implementation processes of functions and roles of the units of the above-described device, which will not be elaborated by the present specification.

5 Since the device embodiments substantially correspond to the method embodiments, the description of parts of the method embodiments can be referenced for relevant parts of the device embodiments. The above-described device embodiments are merely exemplary, wherein the units described as separate parts may or may not be physically separated, and the parts illustrated as units may or may not be physical units, i.e., they can be located at one place or distributed
10 over a plurality of network units. The objectives of the solutions of the present specification can be achieved by selecting some or all of the modules as needed, which can be understood and implemented by one of ordinary skill in the art without creative effort.

 The above-described is only preferred embodiments of the present specification, which are not used to limit the present specification. Any modification, equivalent substitution, or
15 improvement made within the spirit and principle of the present specification shall be encompassed by the claims of the present specification.

What is claimed is

1. A machine learning model training method, comprising:

marking, by a computing device, samples with risk labels in a training sample set as original positive samples and marking samples without risk labels in the training sample set as negative samples;

training, by the computing device, a supervised risk model based on the original positive samples and negative samples, and assessing a risk of the negative samples respectively based on the trained model to obtain risk scores for the negative samples, wherein the risk scores represent probabilities at which a risk occurs;

filtering, by the computing device, negative samples in the training sample set that have risk scores greater than a preset threshold value;

re-marking, by the computing device, the negative samples in the training sample set that have risk scores greater than the preset threshold value as re-marked positive samples;

configuring, by the computing device, weights for loss functions corresponding to the re-marked positive samples and original positive samples in the training sample set, respectively, wherein weights of the loss functions corresponding to the re-marked positive samples is smaller than weights of the loss functions corresponding to the original positive samples;

after re-marking the negative samples that have risk scores greater than the preset threshold value as the re-marked positive samples, configuring, by the computing device, the risk scores of the negative samples that have risk scores greater than the preset threshold value as the weights of the loss function corresponding to the re-marked positive samples, and setting the weight of the loss function corresponding to the original positive samples to be one; and

re-training, by the computing device, the supervised risk model based on the original positive samples, the re-marked positive samples, and the negative samples in the filtered training sample set.

2. The method according to claim 1, further comprising:

constructing a prediction sample based on online data; and

assessing a risk of the prediction sample based on the re-trained model to obtain a risk score.

3. A machine learning model training device, comprising:

a marking module configured to mark samples with risk labels in a training sample set as original positive samples and mark samples without risk labels in the training sample set as negative samples;

an assessing module configured to train a supervised risk model based on the original positive samples and negative samples, and assess a risk of the negative samples respectively based on the trained model to obtain risk scores for the negative samples, wherein the risk scores represent probabilities at which a risk occurs;

5 a filtering module configured to

filter negative samples in the training sample set that have risk scores greater than a preset threshold value;

re-mark the negative samples in the training sample set that have risk scores greater than the preset threshold value as re-marked positive samples,

10 configure weights for loss functions corresponding to the re-marked positive samples and original positive samples in the training sample set, respectively, wherein weights of the loss functions corresponding to the re-marked positive samples is smaller than weights of the loss functions corresponding to the original positive samples; and

after re-marking the negative samples that have risk scores greater than the preset
15 threshold value as the re-marked positive samples, configure the risk scores of the negative samples that have risk scores greater than the preset threshold value as the weights of the loss function corresponding to the re-marked positive samples, and set the weight of the loss function corresponding to the original positive samples to be one; and

a training module configured to re-train the supervised risk model based on the original
20 positive samples, the re-marked positive samples, and the negative samples in the filtered training sample set.

4. The device according to claim 3, wherein the assessing module is further configured to:
construct a prediction sample based on online data; and

25 assess a risk of the prediction sample based on the re-trained model to obtain a risk score.

5. An electronic device, comprising:

a processor; and

a memory for storing a machine executable instruction;

30 wherein, by reading and executing the machine executable instruction stored in the memory and corresponding to a control logic of training of a supervised machine learning model, the processor is caused to:

mark samples with risk labels in a training sample set as original positive samples and mark samples without risk labels in the training sample set as negative samples;

35 train a supervised risk model based on the original positive samples and negative samples,

and assess a risk of the negative samples respectively based on the trained model to obtain risk scores for the negative samples, wherein the risk scores represent probabilities at which a risk occurs;

filter negative samples in the training sample set that have risk scores greater than a preset threshold value;

re-mark the negative samples in the training sample set that have risk scores greater than the preset threshold value as re-marked positive samples;

configure weights for loss functions corresponding to the re-marked positive samples and original positive samples in the training sample set, respectively, wherein weights of the loss functions corresponding to the re-marked positive samples is smaller than weights of the loss functions corresponding to the original positive samples;

after re-marking the negative samples that have risk scores greater than the preset threshold value as the re-marked positive samples, configure the risk scores of the negative samples that have risk scores greater than the preset threshold value as the weights of the loss function corresponding to the re-marked positive samples, and set the weight of the loss function corresponding to the original positive samples to be one; and

re-train the supervised risk model based on the original positive samples, the re-marked positive samples, and the negative samples in the filtered training sample set.

6. The electronic device according to claim 5, wherein the processor is further caused to: construct a prediction sample based on online data; and assess a risk of the prediction sample based on the re-trained model to obtain a risk score.

7. The method according to claim 1, further comprising:

obtaining a risk score for online transaction data based on the re-trained model;

determining whether the risk score for online transaction data is greater than a risk threshold; and

in response to determining that the risk score for the online transaction data is greater than the risk threshold, determining that an online transaction corresponding to the online transaction data is risky.

8. The method according to claim 7, further comprising:

in response to determining that the online transaction corresponding to the online transaction data is risky, terminating the online transaction.

9. The method according to claim 7, further comprising:

in response to determining that the online transaction corresponding to the online transaction data is risky, requesting verification of a user identity for the online transaction before approving the online transaction.

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10. The device according to claim 3, wherein the training module is further configured to:
obtain a risk score for online transaction data based on the re-trained model;

determine whether the risk score for the online transaction data is greater than a risk threshold; and

10 in response to determining that the risk score for online transaction data is greater than the risk threshold, determining that an online transaction corresponding to the online transaction data is risky.

11. The device according to claim 10, wherein the training module is further configured to:

15 in response to determining that the online transaction corresponding to the online transaction data is risky, terminate the online transaction.

12. The device according to claim 10, wherein the training module is further configured to:

20 in response to determining that the online transaction corresponding to the online transaction data is risky, request verification of a user identity for the online transaction before approving the online transaction.

13. The electronic device according to claim 5, wherein the processor is further caused to:

obtain a risk score for online transaction data based on the re-trained model;

25 determine whether the risk score for the online transaction data is greater than a risk threshold; and

in response to determining that the risk score for online transaction data is greater than the risk threshold, determining that an online transaction corresponding to the online transaction data is risky.

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14. The electronic device according to claim 13, wherein the processor is further caused to:

in response to determining that the online transaction corresponding to the online transaction data is risky, terminate the online transaction.

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15. The electronic device according to claim 13, wherein the processor is further caused to:
in response to determining that the online transaction corresponding to the online transaction data is risky, request verification of a user identity for the online transaction before approving the online transaction.