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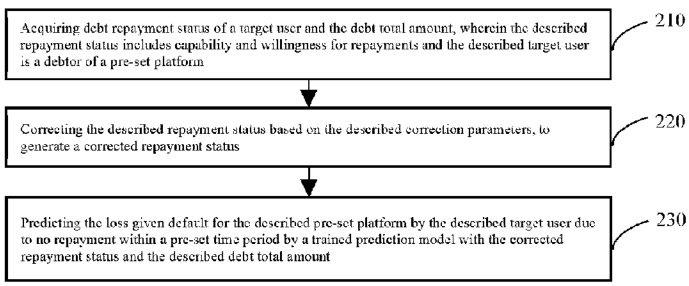
(54) Title: DEFAULT LOSS RATE PREDICTION METHOD AND DEVICE



(57) Abrégé/Abstract:
Disclosed in the present invention are loss given default prediction method and device. The described method comprises: acquiring debt repayment status of a target user and the debt total amount, wherein the repayment status includes capability and willingness for repayments and the target user is a debtor of a pre-set platform; based on macro-environment features, generating corresponding correction parameters; correcting the repayment status based on the correction parameters, to generate a corrected repayment status; and predicting the loss given default for the pre-set platform by the target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the debt total amount. The process of predicting loss given default considers macro environment changes, permitting compatibility of the predicted loss given default with long-term macroscopic changes, to ensure accuracy of loss given default prediction and improve risk management for financial institutions.

ABSTRACT

Disclosed in the present invention are loss given default prediction method and device. The described method comprises: acquiring debt repayment status of a target user and the debt total amount, wherein the repayment status includes capability and willingness for repayments and the target user is a debtor of a pre-set platform; based on macro-environment features, generating corresponding correction parameters; correcting the repayment status based on the correction parameters, to generate a corrected repayment status; and predicting the loss given default for the pre-set platform by the target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the debt total amount. The process of predicting loss given default considers macro environment changes, permitting compatibility of the predicted loss given default with long-term macroscopic changes, to ensure accuracy of loss given default prediction and improve risk management for financial institutions.

Date reçue / Date received 2021-11-30

DEFAULT LOSS RATE PREDICTION METHOD AND DEVICE

Technical Field

[0001] The present invention relates to the field of finance, in particular, to a method and a device for loss given default prediction.

Background

[0002] In Jun. 2014, the second of the Basel Accords (Basel II) is issued by the Basel Committee on Banking Supervision. Compared with the previous Basel I, the main feature of the Basel II is the "Internal Rating-Based Approach" as credit risk measurement techniques for banks, to enhance risk management sensitivity. The Internal Rating-Based Approach implies the estimation, measurement, and management for risk levels of investment portfolios based on internal risk features, further used as principals for risk decisions. With satisfying the Basel II, banks can adopt the Internal Rating-Based Approach to assess probability of default (PD), loss given default (LGD), exposure at default (EAD), and maturity (M), and further determine the capitals required. The Basel II suggests international banks to provide internal data and management standards, for constructing a 2-dimentional rating system with customer ratings and debt ratings. The risk management accuracy, sensitivity, and standardization are improved, where PD and LGD are used as quantitative basis for customer ratings and debt ratings, as the main core for the Internal Rating-Based Approach. With the inclusion of the LGD and the PD into the risk management schemes, the significance of the LGD is more and more highlighted, and emphasized by the regulatory community, the industry, and the theoretical circles. Constructions of LGD assessment mode become a major problem for national banks and financial business to settle the Basel II, and improve risk assessment skills, comprehensive market competitiveness and profits.

Summary

[0003] To solve the limitations of the current technologies, the present invention aims to provide a loss given default prediction method and device.

[0004] To achieve the forementioned aims, from the first perspective, a loss given default prediction method is provided, comprising:

acquiring debt repayment status of a target user and the debt total amount, wherein the described repayment status includes capability and willingness for repayments and the described target user is a debtor of a pre-set platform;

correcting the described repayment status based on the described correction parameters, to generate a corrected repayment status; and

Date reçue / Date received 2021-11-30

predicting the loss given default for the described pre-set platform by the described target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the described debt total amount.

[0005] In some embodiments, the described pre-set module training processing consist of:

acquiring training data sets, including historical user samples with default on the described pre-set platform, wherein each described historical user sample includes corresponding repayment status, debt total amount, and the resulted loss given default to the described pre-set platform;

training each pre-set weak classifier with the described training data sets, until the loss functions of each described weak classifier satisfying pre-set conditions; and

combining the described weak classifier to generate corresponding boosting learners, wherein the described pre-set model consists of the described boosting learner.

[0006] In some embodiments, the described debt total amount includes the total costs to regain the debt from the target user by the pre-set platform, and the debt balance of the target user within a pre-set time period.

[0007] In some embodiments, the described user feature further includes the education background of the described target user.

[0008] In some embodiments, wherein the described correction of the described repayment status based on macro environment features, the generated corrected repayment status includes:

correcting the described repayment status based on macro environment features and user features of the described target user, to generate the corrected repayment status, wherein the described user feature includes occupation of the described target user.

[0009] In some embodiments, the described capability of repayment includes income and loans of the described target user.

[0010] From the second perspective, a loss given default prediction device is provided in the present invention, comprising:

an acquisition module, configured to acquire debt repayment status of a target user and the debt total amount, wherein the described repayment status includes capability and willingness for repayments;

a correction module, configured to correct the described repayment status based on the described correction parameters, to generate a corrected repayment status; and

a prediction module, configured to predict the loss given default for the described pre-set platform by the described target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the described debt total amount.

[0011] In some embodiments, the described device further comprises a training module. the described training module is further configured to acquire training data sets, including historical user samples with

Date reçue / Date received 2021-11-30

default on the described pre-set platform, wherein each described historical user sample includes corresponding repayment status, debt total amount, and the resulted loss given default to the described pre-set platform; train each pre-set weak classifier with the described training data sets, until the loss functions of each described weak classifier satisfying pre-set conditions; and combine the described weak classifier to generate corresponding boosting learners, wherein the described pre-set model consists of the described boosting learner.

[0012] From the third perspective, a readable computer storage medium with computer programs stored, wherein any of the procedures in the forementioned method are performed when the described computer programs are executed on the described processor.

[0013] From the fourth perspective, a computer system is provided in the present invention, comprises:

one or more processors; and

a storage medium related to the described one or more processors, configured for storing the program commands, wherein the described program commands are executed by the described one or more processors for performing the following procedures:

acquiring debt repayment status of a target user and the debt total amount, wherein the described repayment status includes capability and willingness for repayments and the described target user is a debtor of a pre-set platform;

correcting the described repayment status based on the described correction parameters, to generate a corrected repayment status; and

predicting the loss given default for the described pre-set platform by the described target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the described debt total amount.

[0014] The present invention provides the following benefits that:

a loss given default is provided in the present invention, comprising: acquiring debt repayment status of a target user and the debt total amount, wherein the repayment status includes capability and willingness for repayments and the target user is a debtor of a pre-set platform; based on macro-environment features, generating corresponding correction parameters; correcting the repayment status based on the correction parameters, to generate a corrected repayment status; and predicting the loss given default for the pre-set platform by the target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the debt total amount. The process of predicting loss given default considers macro environment changes, permitting compatibility of the predicted loss given default with long-term macroscopic changes, to ensure accuracy of loss given default prediction and improve risk management for financial institutions.

Date reçue / Date received 2021-11-30

furthermore, the present invention further proposes the correction of the described repayment status based on macro environment features, wherein the generated corrected repayment status includes: correcting the described repayment status based on macro environment features and user features of the described target user, to generate the corrected repayment status, to further ensure a better representation of user real repayment status after correction, and guaranteed the accuracy of the prediction.

[0015] All applications of the present invention are not necessary to include all the described features.

Detailed descriptions of the drawings

[0016] For better explanation of the technical proposal of embodiments in the present invention, the accompanying drawings are briefly introduced in the following. Obviously, the following drawings represent only a portion of embodiments of the present invention. Those skilled in the art are able to create other drawings according to the accompanying drawings without making creative efforts.

[0017] Fig. 1 is a procedure schematic diagram of the prediction model generation provided in the present invention;

Fig. 2 is a process flow diagram of the method provided in the present invention;

Fig. 3 is a structure diagram of the device provided in the present invention; and

Fig. 4 is a structure diagram of the system provided in the present invention.

Detailed descriptions

[0018] In order to make the objective, the technical scheme, and the advantages of the present invention clearer, the present invention will be explained further in detail precisely below with references to the accompanying drawings. Obviously, the embodiments described below are only a portion of embodiments of the present invention and cannot represent all possible embodiments. Based on the embodiments in the present invention, the other applications by those skilled in the art without any creative works are falling within the scope of the present invention.

[0019] The loss given default is the proportion of overall risk exposure occupied by loss of asset to the creditor if a borrower defaults. In the present invention, based on the Basel II, the definitions of defaults, and practical needs, the following conditions may apply for user defaults, including principal overdue more than 1 day; interest overdue more than 1 day; and the user debt being classified as other debt types other than the normal debt according to the five-tier loan classification. The loss includes debt principals, interests, and direct or indirect costs during the debt collection. In detail, the loss can be calculated based on the following equation: financial loss = EAD – NPV (collected) + NPV (principal), wherein EAD is risk exposure, NPV(collected) is the net present value of the collected portion during the debt collection, and NPV(principal) the net present value of the principal during the debt collection. NPV(collected) =

Date reçue / Date received 2021-11-30

$\sum_1^T \mathrm{R_{it}}(1+\mathrm{r_t})^{-1}$, wherein $\mathrm{R_{it}}$ is the i^{th} amount due for the t^{th} installment of debt collection; $\mathrm{r_t}$ is the discount rate for i^{th} amount due for the t^{th} installment of debt collection discount; and T is the time period from the default to debt discharge. $\mathrm{NPV(principal)} = \sum_1^T C_{in}(1+r_n)^{-1}$, wherein C_{in} is the debt collection cost of i^{th} amount due for the n^{th} installment; and r_n is the discount rate for the i^{th} amount due for the t^{th} installment of debt collection cost discount.

[0020] In detail, the collected portion can include direct cash collection and non-cash collection; the cost portion can include the direct cost and indirect cost, wherein the direct cost includes courts costs, processing costs, legal bills, and other related costs for debt collection, and the indirect cost can include labor and office expenses.

[0021] In order to solve the technical problems in the background, a loss given default prediction method is provided in the present invention, to prevent the probability of user defaults in a pre-set time interval, to improve the risk management of financial institutions.

[0022] Embodiment 1

In detail, the described process includes:

Step 1, training loss given default prediction models.

As shown in Fig. 1, the described prediction models are boosting trainers, constructed by combining multiple weak classifiers based on strategies. With multiple-iteration trainings, each iterative training can generate a weak classifier, wherein each weak classifier takes the value of the loss function gradient descent of the last training in the present model as an estimate of residuals, in order to train based on the estimated value. The loss function is represented as L(y, f(x)), wherein x is an iv variable generated by Information Value calculation based on the repayment status, and y is the real loss determined by the training samples, and f(x) is the predicted loss in the training process.

[0023] In detail, the loss function includes macroscopic variables determined by the macro environment. Preferably, the related data can be acquired from relative industry research websites, and the described macroscopic variables can be determined by the acquired data.

[0024] The models can be re-trained with corrected macroscopic variables to improve the prediction accuracy.

[0025] The described residuals can be represented as $r_{mi} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]$.

[0026] Based on the generated weak classifier, the following calculation can be performed: $C_{mj} = argmin \sum_{x_i \in R_{mj}} L((y_i, f_{m-1}(x_i) + C)$, wherein C_{mj} is the minimum accumulated residual sum, c is a constant term, m is the vector value of the m^{th} column, and R_{mj} is the related parameter of the m^{th} column and the j^{th} column in the associated matrix.

Date reçue / Date received 2021-11-30

[0027] Based on linear searching algorithm, the value of the leaf node regions to minimize the loss function can be estimated, to generate $f_m(x) = f_{m-1}(x) + \sum_{j=1}^{j} C_{mj} I\left(x \in R_{mj}\right)$, wherein $f_m(x)$ is the m$^{\text{th}}$ weak classifier function for loss function minimizing, j is the number of weak classifiers, and $I\left(x \in R_{mj}\right)$ is the inertia momentum constant representing optimization direction for the weak classifier to avoid the local optimization problems.

[0028] Based on f(x) corresponding to all weak classifiers, the final model can be obtained:

$$\tilde{f}(x) = f_M(x) = \sum_{m=1}^{m} \sum_{j=1}^{j} c_{mj} I\left(x \in R_{mj}\right)$$

The described weak classifier training data sets include historical user samples collected from internal pre-set platforms, wherein each historical user sample includes corresponding repayment status, debt total, and the resulting loss given default. In particular, the described loss given default can be obtained by debt total of historical user samples and the actual resulting financial loss by the described historical user samples on the pre-set platform.

[0029] The prediction process of using the described prediction model for loss given default prediction includes:

S1, acquiring debt repayment status of a target user and the debt total amount;

wherein the described target users are users taking loans from the pre-set platforms.

[0030] The repayment status includes capability and willingness for repayments, determined by user account using status, occupation changes in a pre-set period, and credit reports verified by the user.

[0031] The debt total amount includes the debt balance of the target user and the total costs to regain the debt from the target user by the pre-set platform.

[0032] S2, based on correcting the described repayment status based on macro environment features and user features,

wherein the macro environment features can be calculated by unemployment rate in the target user active region, income-to-debt ratio, banking amounts, expenses amount, and other macroscopic data. Preferably, the corresponding correction parameters can be generated by corresponding environment features, and the repayment status can be corrected based on the correction parameters.

[0033] The described user features include education, occupation, working experiences, and other features of the target user. The user features can further include a pre-set risk estimation corresponding to the user.

[0034] As shown in Table 1, the corresponding correction parameters can be determined by user features, and the repayment status is corrected based on the correction parameters.

[0035] Table 1

Occupation		Correction parameters

Date reçue / Date received 2021-11-30

	Risk assessment scale	Graduate degree	Undergraduate degree	Post-secondary degree and lower
Civil servant	A	1.2	1.15	1.1
	B	1.1	1	0.9
Real estates	A	1.1	1.05	1
	B	1	0.9	0.8
Communications	A	1.1	1.05	1
	B	1	0.9	0.8

S3, with the trained prediction models, the loss given default to the pre-set platform when the target user defaults within a pre-set time interval based on the corrected repayment status and the debt total amount.

[0036] Based on the predicted loss given default, the collection rate of debt total to the pre-set platform when the target user defaults can be generated. The collection rate calculation formula is: collection rate = 1 – loss given default.

[0037] With corresponding tests to predict using the described model, the model regression R^2 is 96%, MSE is 0.005, and MAE is 0.02. Therefore, the described model can be used to well predict loss given defaults to the platform offering loans due to user defaults.

[0038] Embodiment 2

corresponding to the forementioned embodiment, a loss given default prediction method is provided in the present invention as shown in Fig.2, comprising

210, acquiring debt repayment status of a target user and the debt total amount, wherein the described repayment status includes capability and willingness for repayments and the described target user is a debtor of a pre-set platform;

220, correcting the described repayment status based on the described correction parameters, to generate a corrected repayment status; and

230, predicting the loss given default for the described pre-set platform by the described target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the described debt total amount.

[0039] Preferably, the described training process of the pre-set model comprises

240, acquiring training data sets,

including historical user samples with default on the described pre-set platform, wherein each described historical user sample includes corresponding repayment status, debt total amount, and the resulted loss given default to the described pre-set platform

Date reçue / Date received 2021-11-30

[0040] 241, training each pre-set weak classifier with the described training data sets, until the loss functions of each described weak classifier satisfying pre-set conditions; and

242, combining the described weak classifier to generate corresponding boosting learners, wherein the described pre-set model consists of the described boosting learner.

[0041] Preferably, the described debt total amount includes the total costs to regain the debt from the target user by the pre-set platform, and the debt balance of the target user within a pre-set time period.

[0042] Preferably, the described user feature further includes the education background of the described target user.

[0043] Preferably, the described user feature further includes the education background of the described target user.

[0044] Preferably, the described capability of repayment includes income and loans of the described target user.

[0045] Embodiment 3

corresponding to the forementioned method, a loss given default prediction device is predicted, comprising:

an acquisition module 310, configured to acquire debt repayment status of a target user and the debt total amount, wherein the described repayment status includes capability and willingness for repayments;

a correction module 320, configured to correct the described repayment status based on the described correction parameters, to generate a corrected repayment status; and

a prediction module 330, configured to predict the loss given default for the described pre-set platform by the described target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the described debt total amount.

[0046] Preferably, the described device further comprises a training module, wherein the described training module is further configured to acquire training data sets, including historical user samples with default on the described pre-set platform, wherein each described historical user sample includes corresponding repayment status, debt total amount, and the resulted loss given default to the described pre-set platform; train each pre-set weak classifier with the described training data sets, until the loss functions of each described weak classifier satisfying pre-set conditions; and combine the described weak classifier to generate corresponding boosting learners, wherein the described pre-set model consists of the described boosting learner.

[0047] The described correction module 320 is further configured to correct the described repayment status based on macro environment features and user features of the described target user, for generating the

Date reçue / Date received 2021-11-30

corrected repayment status, wherein the described user feature includes occupation of the described target user.

[0048] Embodiment 4

corresponding to the forementioned method, device, and system, a computer system is provided in the embodiment 4 of the present invention, comprising: one or more processors; and a storage medium related to the described one or more processors, configured for storing the program commands, wherein the described program commands are executed by the described one or more processors for performing the following procedures:

acquiring debt repayment status of a target user and the debt total amount, wherein the described repayment status includes capability and willingness for repayments and the described target user is a debtor of a pre-set platform;

correcting the described repayment status based on the described correction parameters, to generate a corrected repayment status; and

predicting the loss given default for the described pre-set platform by the described target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the described debt total amount.

[0049] In particular, a schematic of the computer system structure, shown in Fig. 4, comprises a processor 1510, a video display adaptor 1511, a disk driver 1512, an input/output connection port 1513, an internet connection port 1514, and a memory 1520. The forementioned processor 1510, video display adaptor 1511, disk driver 1512, input/output connection port 1513, and internet connection port 1514 are connected and communicated via the system bus control 1530.

[0050] In particular, the processor 1510 can adopt a universal CPU (central processing unit), a microprocessor, an ASIC (application specific integrated circuit) or the use of one or more integrated circuits. The processor is used for executing associated programmes to achieve the technical strategies provided in the present invention.

[0051] The memory 1520 can adopt a read-only memory (ROM), a random access memory (RAM), a static memory, a dynamic memory, etc. The memory 1520 is used to store the operating system 1521 for controlling the electronic apparatus 1500, and the basic input output system (BIOS) 422 for controlling the low-level operations of the electronic apparatus 1500. In the meanwhile, the memory can also store the internet browser 1524, data storage management system 1524, the device label information processing system 1525, etc. The described device label information processing system 1525 can be a program to achieve the forementioned methods and procedures in the present invention. In summary, when the technical strategies are performed via software or hardware, the codes for associated programs are stored

Date reçue / Date received 2021-11-30

in the memory 1520, then called and executed by the processor 1510.The input/output connection port 1513 is used to connect with the input/output modules for information input and output. The input/output modules can be used as components that are installed in the devices (not included in the drawings), or can be externally connected to the devices to provide the described functionalities. In particular, the input devices may include keyboards, mouse, touch screens, microphones, various types of sensors, etc. The output devices may include monitors, speakers, vibrators, signal lights, etc.

[0052] The internet connection port 1514 is used to connect with a communication module (not included in the drawings), to achieve the communication and interaction between the described device and other equipment. In particular, the communication module may be connected by wire connection (such as USB cables or internet cables), or wireless connection (such as mobile data, WIFI, Bluetooth, etc.)

[0053] The system bus control 1530 include a path to transfer data across each component of the device (such as the processor 1510, the video display adaptor 1511, the disk driver 1512, the input/output connection port 1513, the internet connection port 1514 and the memory 1520).

[0054] Besides, the described electronic device 1500 can access the collection condition information from the collection condition information database 1541 via a virtual resource object, so as for conditional statements and other purposes.

[0055] To clarify, although the schematic of the forementioned device only includes the processor 1510, the video display adaptor 1511, the disk driver 1512, the input/output connection port 1513, the internet connection port 1514, the memory 1520 and the system bus control 1530, the practical applications may include the other necessary components to achieve successful operations. It is comprehensible for those skilled in the art that the structure of the device may comprise of less components than that in the drawings, to achieve successful operations.

[0056] By the forementioned descriptions of the applications and embodiments, those skilled in the art can understand that the present invention can be achieved by combination of software and necessary hardware platforms. Based on this concept, the present invention is considered as providing the technical benefits in the means of software products. The mentioned computer software products are stored in the storage media such as ROM/RAM, magnetic disks, compact disks, etc. The mentioned computer software products also include using several commands to have a computer device (such as a personal computer, a server, or a network device) to perform portions of the methods described in each or some of the embodiments in the present invention.

[0057] The embodiments in the description of the present invention are explained step-by-step. The similar contents can be referred amongst the embodiments, while the differences amongst the embodiments are emphasized. In particular, the system and the corresponding embodiments have similar contents to the method embodiments. Hence, the system and the corresponding embodiments are described concisely, and

Date reçue / Date received 2021-11-30

the related contents can be referred to the method embodiments. The described system and system embodiments are for demonstration only, where the components that are described separately can be physically separated or not. The components shown in individual units can be physical units or not. In other words, the mentioned components can be at a single location or distributed onto multiple network units. All or portions of the modules can be used to achieve the purposes of embodiments of the present invention based on the practical scenarios. Those skilled in the art can understand and apply the associated strategies without creative works.

[0058] The forementioned contents of preferred embodiments of the present invention shall not limit the applications of the present invention. Therefore, all alterations, modifications, equivalence, improvements of the present invention fall within the scope of the present invention.

Date reçue / Date received 2021-11-30

Claims:

1. A device comprising:

    an acquisition module, configured to acquire debt repayment status of a target user and the debt total amount, wherein a repayment status includes capability and willingness for repayments;

    a correction module, configured to:

        correct the repayment status based on a correction parameters,

        generate a corrected repayment status; and

    a prediction module, configured to predict the loss given default for a pre-set platform by a target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and a debt total amount.

2. The device of claim 1, further comprises a training module configured to:

    acquire training data sets, including historical user samples with default on the pre-set platform, wherein each historical user sample includes any one or more of corresponding repayment status, debt total amount, and the resulted loss given default to the pre-set platform;

    train each pre-set weak classifier with training data sets, until the loss functions of each weak classifier satisfying pre-set conditions; and

    combine the weak classifier to generate corresponding boosting learners, wherein a pre-set model consists of a boosting learner.

3. The device of claim 1, the correction module is further configured to correct the repayment status based on macro environment features and user features of the target user, for generating the corrected repayment status, wherein a user feature includes occupation of the target user.

Date Reçue/Date Received 2022-02-07

4. The device of claim 1, wherein the debt total amount includes total costs to regain debt from the target user by the pre-set platform, and the debt balance of the target user within a pre-set time period.

5. The device of claim 3, wherein the user feature further includes an education background of the target user.

6. The device of claim 1, wherein the capability of repayment includes income and loans of the target user.

7. The device of any one of claims 1 to 6, wherein the loss given default is the proportion of overall risk exposure occupied by loss of asset to the creditor if a borrower defaults.

8. The device of any one of claims 1 to 7, wherein the Basel II, the definitions of defaults, and practical needs, the following conditions may apply for user defaults, including principal overdue more than 1 day, interest overdue more than 1 day, and the user debt being classified as other debt types other than the normal debt according to the five-tier loan classification.

9. The device of any one of claims 1 to 8, wherein the loss includes debt principals, interests, and direct or indirect costs during the debt collection. In detail, the loss can be calculated based on the following equation: financial loss = EAD – NPV (collected) + NPV (principal), wherein EAD is risk exposure, NPV(collected) is the net present value of the collected portion during the debt collection, and NPV(principal) the net present value of the principal during the debt collection wherein $\mathrm{NPV(collected)} = \sum_1^T \mathrm{R_{it}}(1+\mathrm{r_t})^{-1}$, wherein $\mathrm{R_{it}}$ is $\mathrm{i^{th}}$ amount due for $\mathrm{t^{th}}$ installment of debt collection; $\mathrm{r_t}$ is a discount rate for the $\mathrm{i^{th}}$ amount due for the $\mathrm{t^{th}}$ installment of debt collection discount; and T is a time period from the default to debt discharge, wherein $\mathrm{NPV(principal)} = \sum_1^T C_{in}(1+r_n)^{-1}$, wherein C_{in} is a debt collection cost of $\mathrm{i^{th}}$ amount due for $\mathrm{n^{th}}$ installment, and r_n is a discount rate for the $\mathrm{i^{th}}$ amount due for the $\mathrm{t^{th}}$ installment of debt collection cost discount.

Date Reçue/Date Received 2022-02-07

10. The device of any one of claims 1 to 9, wherein the collected portion can include direct cash collection and non-cash collection, wherein the cost portion can include the direct cost and indirect cost, wherein the direct cost includes any one or more of courts costs, processing costs, legal bills, and costs for debt collection, and the indirect cost can include any one or more of labor and office expenses.

11. The device of any one of claims 1 to 10, wherein the prediction models are boosting trainers, constructed by combining multiple weak classifiers based on strategies, wherein with multiple-iteration trainings, each iterative training can generate a weak classifier, wherein each weak classifier takes a value of a loss function gradient descent of the last training in the present model as an estimate of residuals, in order to train based on an estimated value wherein the loss function is represented as L(y, f(x)), wherein x is an iv variable generated by information value calculation based on the repayment status, and y is real loss determined by training samples, and f(x) is a predicted loss in the training process.

12. The device of any one of claims 1 to 11, wherein the loss function includes macroscopic variables determined by a macro environment, wherein related data can be acquired from relative industry research websites, and macroscopic variables can be determined by acquired data.

13. The device of any one of claims 1 to 12, wherein the prediction model can be re-trained with corrected macroscopic variables to improve prediction accuracy.

14. The device of any one of claims 1 to 13, wherein the estimate of residuals can be represented as $r_{mi} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]$.

15. The device of any one of claims 1 to 14, wherein based on a generated weak classifier, the following calculation can be performed: $C_{mj} = argmin \sum_{x_i \in R_{mj}} L((y_i, f_{m-1}(x_i) + C)$, wherein C_{mj} is a minimum accumulated residual sum, c is a constant term, m is a vector value of a mth column, and R_{mj} is related parameter of the mth column and a jth column in a associated matrix.

Date Reçue/Date Received 2022-02-07

16. The device of any one of claims 1 to 15, wherein based on linear searching algorithm, a value of leaf node regions to minimize the loss function can be estimated, to generate $f_m(x) = f_{m-1}(x) + \sum_{j=1}^{j} C_{mj} I\left(x \in R_{mj}\right)$, wherein $f_m(x)$ is a m[th] weak classifier function for loss function minimizing, j is a number of weak classifiers, and $I\left(x \in R_{mj}\right)$ is inertia momentum constant representing optimization direction for the weak classifier to avoid local optimization problems.

17. The device of any one of claims 1 to 16, wherein based on f(x) corresponding to all weak classifiers, a final model can be obtained:

$$\tilde{f}(x) = f_M(x) = \sum_{m=1}^{m} \sum_{j=1}^{j} c_{mj} I\left(x \in R_{mj}\right)$$

18. The device of any one of claims 1 to 17, wherein weak classifier training data sets include historical user samples collected from internal pre-set platforms, wherein the loss given default can be obtained by debt total of historical user samples and the actual resulting financial loss by the historical user samples on the pre-set platform.

19. The device of any one of claims 1 to 18, wherein the target users are users taking loans from the pre-set platforms.

20. The device of any one of claims 1 to 19, wherein the repayment status includes the capability and the willingness for repayments, determined by user account using status, occupation changes in a pre-set period, and credit reports verified by the user.

21. The device of any one of claims 1 to 20, wherein based on correcting the repayment status based on macro environment features and user features, wherein the macro environment features can be calculated by unemployment rate in the target user active region, income-to-debt ratio, banking amounts, expenses amount, and other macroscopic data, wherein, the corresponding correction parameters can be generated by corresponding environment features, and the repayment status can be corrected based on the correction parameters.

Date Reçue/Date Received 2022-02-07

22. The device of any one of claims 1 to 21, wherein the user features include any one or more of education, occupation, and working experiences of the target user wherein the user features can further include a pre-set risk estimation corresponding to the user.

23. The device of any one of claims 1 to 22, with the trained prediction models, the loss given default to the pre-set platform when the target user defaults within a pre-set time interval based on the corrected repayment status and the debt total amount.

24. The device of any one of claims 1 to 23, wherein the predicted loss given default, the collection rate of debt total to the pre-set platform when the target user defaults can be generated, wherein the collection rate calculation formula is: collection rate = 1 – loss given default.

25. The device of any one of claims 1 to 24, wherein corresponding tests to predict using the model, the model regression R^2 is 96%, MSE is 0.005, and MAE is 0.02, wherein the model can be used to well predict loss given defaults to the platform offering loans due to user defaults.

26. A computer system comprising:

one or more processors; and

a storage medium related to the one or more processors, configured for storing program commands, wherein the program commands are executed by the one or more processors configured to:

acquire debt repayment status of a target user and a debt total amount, wherein a repayment status includes capability and willingness for repayments and the target user is a debtor of a pre-set platform;

correct the repayment status based on correction parameters, to generate a corrected repayment status; and

Date Reçue/Date Received 2022-02-07

predict a loss given default for the pre-set platform by the target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the debt total amount.

27. The system of claim 26, further comprises a training module configured to:

acquire training data sets, including historical user samples with default on the pre-set platform, wherein each historical user sample includes any one or more of corresponding repayment status, debt total amount, and the resulted loss given default to the pre-set platform;

train each pre-set weak classifier with training data sets, until the loss functions of each weak classifier satisfying pre-set conditions; and

combine the weak classifier to generate corresponding boosting learners, wherein a pre-set model consists of a boosting learner.

28. The system of claim 26, the correction module is further configured to correct the repayment status based on macro environment features and user features of the target user, for generating the corrected repayment status, wherein a user feature includes occupation of the target user.

29. The system of claim 26, wherein the debt total amount includes total costs to regain debt from the target user by the pre-set platform, and the debt balance of the target user within a pre-set time period.

30. The system of claim 28, wherein the user feature further includes an education background of the target user.

31. The system of claim 26, wherein the capability of repayment includes income and loans of the target user.

32. The system of any one of claims 26 to 31, wherein the loss given default is the proportion of overall risk exposure occupied by loss of asset to the creditor if a borrower defaults.

Date Reçue/Date Received 2022-02-07

33. The system of any one of claims 26 to 32, wherein the Basel II, the definitions of defaults, and practical needs, the following conditions may apply for user defaults, including principal overdue more than 1 day, interest overdue more than 1 day, and the user debt being classified as other debt types other than the normal debt according to the five-tier loan classification.

34. The system of any one of claims 26 to 33, wherein The loss includes debt principals, interests, and direct or indirect costs during the debt collection. In detail, the loss can be calculated based on the following equation: financial loss = EAD – NPV (collected) + NPV (principal), wherein EAD is risk exposure, NPV(collected) is the net present value of the collected portion during the debt collection, and NPV(principal) the net present value of the principal during the debt collection wherein $\mathrm{NPV(collected)} = \sum_1^T \mathrm{R_{it}}(1 + \mathrm{r_t})^{-1}$, wherein $\mathrm{R_{it}}$ is $\mathrm{i^{th}}$ amount due for $\mathrm{t^{th}}$ installment of debt collection; $\mathrm{r_t}$ is a discount rate for the $\mathrm{i^{th}}$ amount due for the $\mathrm{t^{th}}$ installment of debt collection discount; and T is a time period from the default to debt discharge, wherein $\mathrm{NPV(principal)} = \sum_1^T C_{in}(1 + r_n)^{-1}$, wherein C_{in} is a debt collection cost of $\mathrm{i^{th}}$ amount due for $\mathrm{n^{th}}$ installment, and r_n is a discount rate for the $\mathrm{i^{th}}$ amount due for the $\mathrm{t^{th}}$ installment of debt collection cost discount.

35. The system of any one of claims 26 to 34, wherein the collected portion can include direct cash collection and non-cash collection, wherein the cost portion can include the direct cost and indirect cost, wherein the direct cost includes any one or more of courts costs, processing costs, legal bills, and costs for debt collection, and the indirect cost can include any one or more of labor and office expenses.

36. The system of any one of claims 26 to 35, wherein the prediction models are boosting trainers, constructed by combining multiple weak classifiers based on strategies, wherein with multiple-iteration trainings, each iterative training can generate a weak classifier, wherein each weak classifier takes a value of a loss function gradient descent of the last training in the present model as an estimate of residuals, in order to train based on an estimated value wherein the loss function is represented as L(y, f(x)), wherein x is an iv variable generated by information value calculation based on the repayment status, and y is real loss determined by training samples, and f(x) is a predicted loss in the training process.

Date Reçue/Date Received 2022-02-07

37. The system of any one of claims 26 to 36, wherein the loss function includes macroscopic variables determined by a macro environment, wherein related data can be acquired from relative industry research websites, and macroscopic variables can be determined by acquired data.

38. The system of any one of claims 26 to 3137, wherein the prediction model can be re-trained with corrected macroscopic variables to improve prediction accuracy.

39. The system of any one of claims 26 to 38, wherein the estimate of residuals can be represented as $r_{mi} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]$.

40. The system of any one of claims 26 to 39, wherein based on a generated weak classifier, the following calculation can be performed: $C_{mj} = argmin \sum_{x_i \in R_{mj}} L((y_i, f_{m-1}(x_i) + C)$, wherein C_{mj} is a minimum accumulated residual sum, c is a constant term, m is a vector value of a m^{th} column, and R_{mj} is related parameter of the m^{th} column and a j^{th} column in a associated matrix.

41. The system of any one of claims 26 to 40, wherein based on linear searching algorithm, a value of leaf node regions to minimize the loss function can be estimated, to generate $f_m(x) = f_{m-1}(x) + \sum_{j=1}^{j} C_{mj} I\left(x \in R_{mj}\right)$, wherein $f_m(x)$ is a m^{th} weak classifier function for loss function minimizing, j is a number of weak classifiers, and $I\left(x \in R_{mj}\right)$ is inertia momentum constant representing optimization direction for the weak classifier to avoid local optimization problems.

42. The system of any one of claims 26 to 41, wherein based on f(x) corresponding to all weak classifiers, a final model can be obtained:

$$\tilde{f}(x) = f_M(x) = \sum_{m=1}^{m} \sum_{j=1}^{j} c_{mj} I\left(x \in R_{mj}\right)$$

Date Reçue/Date Received 2022-02-07

43. The system of any one of claims 26 to 42, wherein weak classifier training data sets include historical user samples collected from internal pre-set platforms, wherein the loss given default can be obtained by debt total of historical user samples and the actual resulting financial loss by the historical user samples on the pre-set platform.

44. The system of any one of claims 26 to 43, wherein the target users are users taking loans from the pre-set platforms.

45. The system of any one of claims 26 to 44, wherein the repayment status includes the capability and the willingness for repayments, determined by user account using status, occupation changes in a pre-set period, and credit reports verified by the user.

46. The system of any one of claims 26 to 45, wherein based on correcting the repayment status based on macro environment features and user features, wherein the macro environment features can be calculated by unemployment rate in the target user active region, income-to-debt ratio, banking amounts, expenses amount, and other macroscopic data, wherein, the corresponding correction parameters can be generated by corresponding environment features, and the repayment status can be corrected based on the correction parameters.

47. The system of any one of claims 26 to 46, wherein the user features include any one or more of education, occupation, and working experiences of the target user wherein the user features can further include a pre-set risk estimation corresponding to the user.

48. The system of any one of claims 26 to 47, with the trained prediction models, the loss given default to the pre-set platform when the target user defaults within a pre-set time interval based on the corrected repayment status and the debt total amount.

49. The system of any one of claims 26 to 48, wherein the predicted loss given default, the collection rate of debt total to the pre-set platform when the target user defaults can be generated, wherein the collection rate calculation formula is: collection rate = 1 – loss given default.

Date Reçue/Date Received 2022-02-07

50. The system of any one of claims 26 to 49, wherein corresponding tests to predict using the model, the model regression R^2 is 96%, MSE is 0.005, and MAE is 0.02, wherein the model can be used to well predict loss given defaults to the platform offering loans due to user defaults.

51. A method comprising:

acquiring debt repayment status of a target user and a debt total amount, wherein a repayment status includes capability and willingness for repayments and a target user is a debtor of a pre-set platform;

correcting the repayment status based on correction parameters, to generate a corrected repayment status; and

predicting a loss given default for the pre-set platform by the target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the debt total amount.

52. The method of claim 51, is characterized in that, the training process of the pre-set model comprises:

acquiring training data sets, including historical user samples with default on the pre-set platform, wherein each historical user sample includes corresponding repayment status, debt total amount, and the resulted loss given default to the pre-set platform;

training each pre-set weak classifier with the training data sets, until the loss functions of each weak classifier satisfying pre-set conditions; and

combining the weak classifier to generate corresponding boosting learners, wherein the pre-set model consists of the boosting learner.

53. The method of claim 51 and 52, wherein the correction of the repayment status based on macro environment features, is characterized in that, the generated corrected repayment status includes:

Date Reçue/Date Received 2022-02-07

correcting the repayment status based on macro environment features and user features of the target user, to generate the corrected repayment status, wherein the user feature includes occupation of the target user.

54. The method of claim 51 and 52, wherein the debt total amount includes total costs to regain debt from the target user by the pre-set platform, and the debt balance of the target user within a pre-set time period.

55. The method of claim 53, wherein the user feature further includes an education background of the target user.

56. The method of claim 51 and 52, wherein the capability of repayment includes income and loans of the target user.

57. The method of any one of claims 51 to 56, wherein the loss given default is the proportion of overall risk exposure occupied by loss of asset to the creditor if a borrower defaults.

58. The method of any one of claims 51 to 57, wherein the Basel II, the definitions of defaults, and practical needs, the following conditions may apply for user defaults, including principal overdue more than 1 day, interest overdue more than 1 day, and the user debt being classified as other debt types other than the normal debt according to the five-tier loan classification.

59. The method of any one of claims 51 to 58, wherein The loss includes debt principals, interests, and direct or indirect costs during the debt collection. In detail, the loss can be calculated based on the following equation: financial loss = EAD – NPV (collected) + NPV (principal), wherein EAD is risk exposure, NPV(collected) is the net present value of the collected portion during the debt collection, and NPV(principal) the net present value of the principal during the debt collection wherein $\mathrm{NPV(collected)} = \sum_1^T \mathrm{R_{it}}(1+\mathrm{r_t})^{-1}$, wherein $\mathrm{R_{it}}$ is $\mathrm{i^{th}}$ amount due for $\mathrm{t^{th}}$ installment of debt collection; $\mathrm{r_t}$ is a discount rate for the $\mathrm{i^{th}}$ amount due for the $\mathrm{t^{th}}$ installment of debt collection discount; and T is a time period from the default to debt discharge, wherein $\mathrm{NPV(principal)} = \sum_1^T C_{in}(1+r_n)^{-1}$, wherein C_{in} is a debt collection cost of $\mathrm{i^{th}}$ amount due for $\mathrm{n^{th}}$ installment, and r_n is a discount rate for the $\mathrm{i^{th}}$ amount due for the $\mathrm{t^{th}}$ installment of debt collection cost discount.

Date Reçue/Date Received 2022-02-07

60. The method of any one of claims 51 to 59, wherein the collected portion can include direct cash collection and non-cash collection, wherein the cost portion can include the direct cost and indirect cost, wherein the direct cost includes any one or more of courts costs, processing costs, legal bills, and costs for debt collection, and the indirect cost can include any one or more of labor and office expenses.

61. The method of any one of claims 51 to 60, wherein the prediction models are boosting trainers, constructed by combining multiple weak classifiers based on strategies, wherein with multiple-iteration trainings, each iterative training can generate a weak classifier, wherein each weak classifier takes a value of a loss function gradient descent of the last training in the present model as an estimate of residuals, in order to train based on an estimated value wherein the loss function is represented as L(y, f(x)), wherein x is an iv variable generated by information value calculation based on the repayment status, and y is real loss determined by training samples, and f(x) is a predicted loss in the training process.

62. The method of any one of claims 51 to 61, wherein the loss function includes macroscopic variables determined by a macro environment, wherein related data can be acquired from relative industry research websites, and macroscopic variables can be determined by acquired data.

63. The method of any one of claims 51 to 62, wherein the prediction model can be re-trained with corrected macroscopic variables to improve prediction accuracy.

64. The method of any one of claims 51 to 63, wherein the estimate of residuals can be represented as $r_{mi} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]$.

65. The method of any one of claims 51 to 64, wherein based on a generated weak classifier, the following calculation can be performed: $C_{mj} = argmin \sum_{x_i \in R_{mj}} L((y_i, f_{m-1}(x_i) + C)$, wherein C_{mj} is a minimum accumulated residual sum, c is a constant term, m is a vector value of a mth column, and R_{mj} is related parameter of the mth column and a jth column in a associated matrix.

Date Reçue/Date Received 2022-02-07

66. The method of any one of claims 51 to 65, wherein based on linear searching algorithm, a value of leaf node regions to minimize the loss function can be estimated, to generate $f_m(x) = f_{m-1}(x) + \sum_{j=1}^{j} C_{mj} I\left(x \in R_{mj}\right)$, wherein $f_m(x)$ is a mth weak classifier function for loss function minimizing, j is a number of weak classifiers, and $I\left(x \in R_{mj}\right)$ is inertia momentum constant representing optimization direction for the weak classifier to avoid local optimization problems.

67. The method of any one of claims 51 to 66, wherein based on f(x) corresponding to all weak classifiers, a final model can be obtained:

$$\tilde{f}(x) = f_M(x) = \sum_{m=1}^{m} \sum_{j=1}^{j} c_{mj} I\left(x \in R_{mj}\right)$$

68. The method of any one of claims 51 to 67, wherein weak classifier training data sets include historical user samples collected from internal pre-set platforms, wherein the loss given default can be obtained by debt total of historical user samples and the actual resulting financial loss by the historical user samples on the pre-set platform.

69. The method of any one of claims 51 to 68, wherein the target users are users taking loans from the pre-set platforms.

70. The method of any one of claims 51 to 69, wherein the repayment status includes the capability and the willingness for repayments, determined by user account using status, occupation changes in a pre-set period, and credit reports verified by the user.

71. The method of any one of claims 51 to 70, wherein based on correcting the repayment status based on macro environment features and user features, wherein the macro environment features can be calculated by unemployment rate in the target user active region, income-to-debt ratio, banking amounts, expenses amount, and other macroscopic data, wherein, the corresponding correction parameters can be generated by corresponding environment features, and the repayment status can be corrected based on the correction parameters.

Date Reçue/Date Received 2022-02-07

72. The method of any one of claims 51 to 71, wherein the user features include any one or more of education, occupation, and working experiences of the target user wherein the user features can further include a pre-set risk estimation corresponding to the user.

73. The method of any one of claims 51 to 72, with the trained prediction models, the loss given default to the pre-set platform when the target user defaults within a pre-set time interval based on the corrected repayment status and the debt total amount.

74. The method of any one of claims 51 to 73, wherein the predicted loss given default, the collection rate of debt total to the pre-set platform when the target user defaults can be generated, wherein the collection rate calculation formula is: collection rate = 1 – loss given default.

75. The method of any one of claims 51 to 74, wherein corresponding tests to predict using the model, the model regression R^2 is 96%, MSE is 0.005, and MAE is 0.02, wherein the model can be used to well predict loss given defaults to the platform offering loans due to user defaults.

76. A readable computer storage medium with computer programs stored thereon configured to:

acquire debt repayment status of a target user and a debt total amount, wherein a repayment status includes capability and willingness for repayments and the target user is a debtor of a pre-set platform;

correct the repayment status based on correction parameters, to generate a corrected repayment status; and

predict a loss given default for a pre-set platform by the target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the debt total amount.

77. The method of claim 76, wherein the training process of the pre-set model comprises:

Date Reçue/Date Received 2022-02-07

acquiring training data sets, including historical user samples with default on the pre-set platform, wherein each historical user sample includes corresponding repayment status, debt total amount, and the resulted loss given default to the pre-set platform;

training each pre-set weak classifier with the training data sets, until the loss functions of each weak classifier satisfying pre-set conditions; and

combining the weak classifier to generate corresponding boosting learners, wherein the pre-set model consists of the boosting learner.

78. The method of claim 76 and 77, wherein the correction of the repayment status based on macro environment features, is characterized in that, the generated corrected repayment status includes:

    correcting the repayment status based on macro environment features and user features of the target user, to generate the corrected repayment status, wherein the user feature includes occupation of the target user.

79. The method of claim 76 and 77, wherein the debt total amount includes total costs to regain debt from the target user by the pre-set platform, and the debt balance of the target user within a pre-set time period.

80. The method of claim 78, wherein the user feature further includes an education background of the target user.

81. The method of claim 76 and 77, wherein the capability of repayment includes income and loans of the target user.

82. The device of any one of claims 76 to 81, wherein the loss given default is the proportion of overall risk exposure occupied by loss of asset to the creditor if a borrower defaults.

Date Reçue/Date Received 2022-02-07

83. The device of any one of claims 76 to 82, wherein the Basel II, the definitions of defaults, and practical needs, the following conditions may apply for user defaults, including principal overdue more than 1 day, interest overdue more than 1 day, and the user debt being classified as other debt types other than the normal debt according to the five-tier loan classification.

84. The device of any one of claims 76 to 83, wherein The loss includes debt principals, interests, and direct or indirect costs during the debt collection. In detail, the loss can be calculated based on the following equation: financial loss = EAD – NPV (collected) + NPV (principal), wherein EAD is risk exposure, NPV(collected) is the net present value of the collected portion during the debt collection, and NPV(principal) the net present value of the principal during the debt collection wherein $\mathrm{NPV(collected)} = \sum_1^T \mathrm{R_{it}}(1+\mathrm{r_t})^{-1}$, wherein $\mathrm{R_{it}}$ is i^{th} amount due for t^{th} installment of debt collection; $\mathrm{r_t}$ is a discount rate for the i^{th} amount due for the t^{th} installment of debt collection discount; and T is a time period from the default to debt discharge, wherein $\mathrm{NPV(principal)} = \sum_1^T C_{in}(1+r_n)^{-1}$, wherein C_{in} is a debt collection cost of i^{th} amount due for n^{th} installment, and r_n is a discount rate for the i^{th} amount due for the t^{th} installment of debt collection cost discount.

85. The device of any one of claims 76 to 84, wherein the collected portion can include direct cash collection and non-cash collection, wherein the cost portion can include the direct cost and indirect cost, wherein the direct cost includes any one or more of courts costs, processing costs, legal bills, and costs for debt collection, and the indirect cost can include any one or more of labor and office expenses.

86. The device of any one of claims 76 to 85, wherein the prediction models are boosting trainers, constructed by combining multiple weak classifiers based on strategies, wherein with multiple-iteration trainings, each iterative training can generate a weak classifier, wherein each weak classifier takes a value of a loss function gradient descent of the last training in the present model as an estimate of residuals, in order to train based on an estimated value wherein the loss function is represented as L(y, f(x)), wherein x is an iv variable generated by information value calculation based on the repayment status, and y is real loss determined by training samples, and f(x) is a predicted loss in the training process.

Date Reçue/Date Received 2022-02-07

87. The device of any one of claims 76 to 86, wherein the loss function includes macroscopic variables determined by a macro environment, wherein related data can be acquired from relative industry research websites, and macroscopic variables can be determined by acquired data.

88. The device of any one of claims 76 to 87, wherein the prediction model can be re-trained with corrected macroscopic variables to improve prediction accuracy.

89. The device of any one of claims 76 to 88, wherein the estimate of residuals can be represented as $r_{mi} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]$.

90. The device of any one of claims 76 to 89, wherein based on a generated weak classifier, the following calculation can be performed: $C_{mj} = argmin \sum_{x_i \in R_{mj}} L((y_i, f_{m-1}(x_i) + C)$, wherein C_{mj} is a minimum accumulated residual sum, c is a constant term, m is a vector value of a mth column, and R_{mj} is related parameter of the mth column and a jth column in a associated matrix.

91. The device of any one of claims 76 to 90, wherein based on linear searching algorithm, a value of leaf node regions to minimize the loss function can be estimated, to generate $f_m(x) = f_{m-1}(x) + \sum_{j=1}^{j} C_{mj} I\left(x \in R_{mj}\right)$, wherein $f_m(x)$ is a mth weak classifier function for loss function minimizing, j is a number of weak classifiers, and $I\left(x \in R_{mj}\right)$ is inertia momentum constant representing optimization direction for the weak classifier to avoid local optimization problems.

92. The device of any one of claims 76 to 91, wherein based on f(x) corresponding to all weak classifiers, a final model can be obtained:

$$\tilde{f}(x) = f_M(x) = \sum_{m=1}^{m} \sum_{j=1}^{j} c_{mj} I\left(x \in R_{mj}\right)$$

Date Reçue/Date Received 2022-02-07

93. The device of any one of claims 76 to 92, wherein weak classifier training data sets include historical user samples collected from internal pre-set platforms, wherein the loss given default can be obtained by debt total of historical user samples and the actual resulting financial loss by the historical user samples on the pre-set platform.

94. The device of any one of claims 76 to 93, wherein the target users are users taking loans from the pre-set platforms.

95. The device of any one of claims 76 to 94, wherein the repayment status includes the capability and the willingness for repayments, determined by user account using status, occupation changes in a pre-set period, and credit reports verified by the user.

96. The device of any one of claims 76 to 95, wherein based on correcting the repayment status based on macro environment features and user features, wherein the macro environment features can be calculated by unemployment rate in the target user active region, income-to-debt ratio, banking amounts, expenses amount, and other macroscopic data, wherein, the corresponding correction parameters can be generated by corresponding environment features, and the repayment status can be corrected based on the correction parameters.

97. The device of any one of claims 76 to 96, wherein the user features include any one or more of education, occupation, and working experiences of the target user wherein the user features can further include a pre-set risk estimation corresponding to the user.

98. The device of any one of claims 76 to 97, with the trained prediction models, the loss given default to the pre-set platform when the target user defaults within a pre-set time interval based on the corrected repayment status and the debt total amount.

99. The device of any one of claims 76 to 98, wherein the predicted loss given default, the collection rate of debt total to the pre-set platform when the target user defaults can be generated, wherein the collection rate calculation formula is: collection rate = 1 – loss given default.

Date Reçue/Date Received 2022-02-07

100.The device of any one of claims 76 to 99, wherein corresponding tests to predict using the model, the model regression R^2 is 96%, MSE is 0.005, and MAE is 0.02, wherein the model can be used to well predict loss given defaults to the platform offering loans due to user defaults.

Date Reçue/Date Received 2022-02-07

Drawings

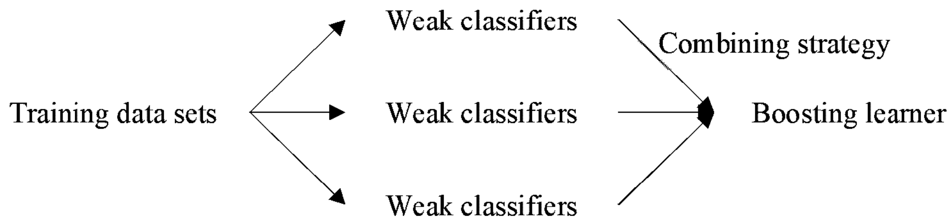


Fig. 1

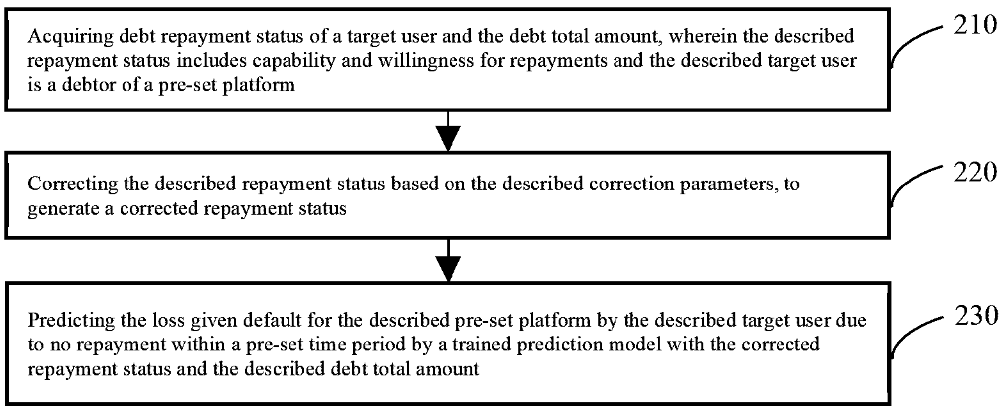


Fig. 2

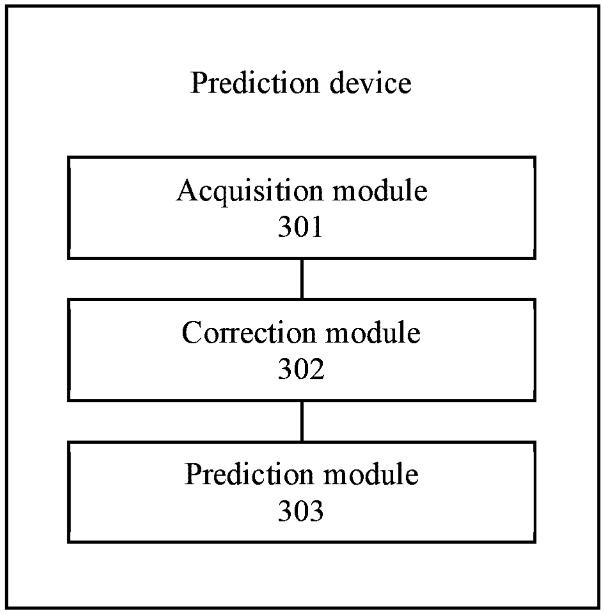


Fig. 3

Date reçue / Date received 2021-11-30

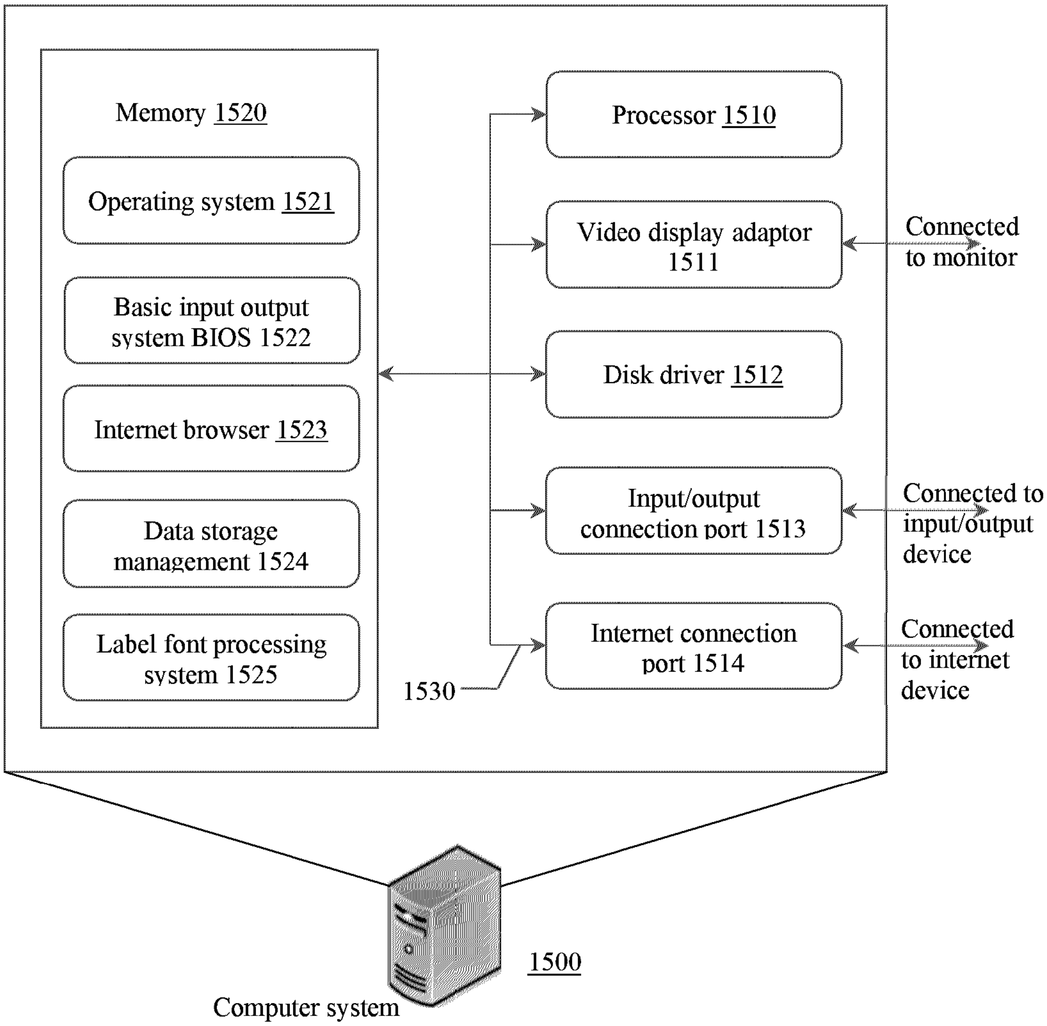
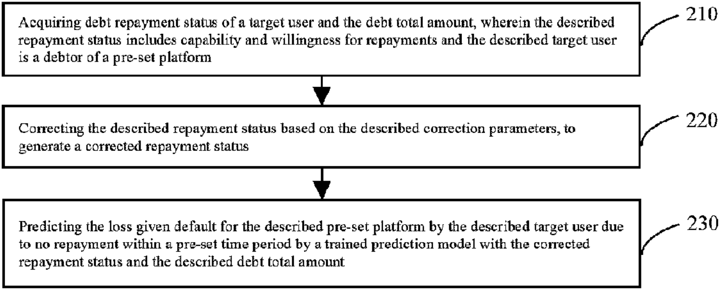

Memory 1520
Operating system 1521
Basic input output system BIOS 1522
Internet browser 1523
Data storage management 1524
Label font processing system 1525
Processor 1510
Video display adaptor 1511
Connected to monitor
Disk driver 1512
Input/output connection port 1513
Connected to input/output device
Internet connection port 1514
Connected to internet device
1530
1500
Computer system

Fig. 4


Acquiring debt repayment status of a target user and the debt total amount, wherein the described repayment status includes capability and willingness for repayments and the described target user is a debtor of a pre-set platform
210
Correcting the described repayment status based on the described correction parameters, to generate a corrected repayment status
220
Predicting the loss given default for the described pre-set platform by the described target user due to no repayment within a pre-set time period by a trained prediction model with the corrected repayment status and the described debt total amount
230