SERVER APPARATUS, SYSTEM, AND METHOD FOR DETERMINING ONE OR MORE PARAMETERS OF DATA ANALYSIS MODELS

TECHNICAL FIELD

[0001] Various aspects of this disclosure relate to a server apparatus, system, and method for determining one or more parameters of data analysis models, such as, but not limited to, a recovery or backup data analysis models.

BACKGROUND

[0002] The following discussion of the background is intended to facilitate an understanding of the present disclosure only. It should be appreciated that the discussion is not an acknowledgment or admission that any of the material referred to was published, known, or is part of the common general knowledge of the person skilled in the art in any jurisdiction as of the priority date of the disclosure.

[0003] The field of financial technology has seen significant growth in recent years, and data analysis models, such as, but not limited to, scoring models, have become service products that provide critical insights to users. The stability and quality of these services are important, given their widespread adoption by organizations such as banks, insurance institutions, credit institutions, and other financial entities.

[0004] In this context, risk data or security data from relevant individuals or organizations are often utilized to construct data analysis models. The risk data or security data may encompass operational risk parameters, security parameters, compliance parameters, credit stability parameters, and other related metrics. These models are typically delivered through an analysis model platform or system, as a software as a service (SaaS), enabling users to initiate requests for data analysis results.

[0005] Upon receiving requests for data analysis, the data analysis model retrieves corresponding data from its database to generate analysis outcomes. However, issues can arise due to factors like missing data or abnormalities in the model itself, resulting in abnormal analysis results, such as failed retrieval of analysis results or degraded (e.g., inaccurate) analysis outputs.

[0006] To mitigate these challenges and ensure service stability and quality, current data analysis models employ disaster recovery mechanisms designed to address failures of both the analysis models themselves and their underlying data sources.

[0007] In one existing solution, the existing disaster recovery mechanisms for data analysis models may be targeted at service failures of the data analysis models. When a data source fails, disaster recovery is often handled in a relatively simple and crude manner by automatically returning a standby analysis result, such as a standby score, and using it as the final analysis result.

[0008] In another existing solution, dual data analysis models may be deployed to address the issue of data source failures, with an auxiliary model (sometimes referred to as a standby model) using a different data source from the primary model. However, due to differences between the auxiliary model and the primary model, it may lead to stability issues in the analysis results, resulting in significant differences between the analysis results generated by the auxiliary model and those generated by the primary model.

[0009] Existing disaster recovery mechanisms for data analysis models are often coupled with the data analysis model's own logic, and lacks flexibility. When it is necessary to modify the disaster recovery logic, the model has to be reconfigured and redeployed with the reconfigured logic. Additionally, existing disaster recovery solutions typically only support single disaster recovery, making it difficult to adapt to different business scenarios and customers' varying requirements for the stability of analysis results.

[0010] There exists a need for improved disaster recovery models that can enhance the reliability and resilience of data analysis models and services.

SUMMARY

[0011] The disclosure seeks to provide a system, server apparatus, and method for determining one or more parameters of data analysis models, in particular recovery or backup data analysis models that replaces one or more main models in the event of failure of the main models.

[0012] In some embodiments, the provided parameter determination solution may be capable of acquiring an initial data set, with data in the initial data set suitable for input into a main model, which may also be a primary data analysis model, to obtain a first analysis result. When the initial data set and/or the first analysis result meet preset conditions, a disaster recovery data set is acquired, and data extracted from the disaster recovery data set is input into a disaster recovery model. The disaster recovery model is used to obtain a second analysis result, and the disaster recovery data set is at least partially different from the initial data set.

The second analysis result is scaled according to a scaling strategy to obtain a third analysis result corresponding to the primary model and used to replace the first analysis result. The scaling strategy represents the scaling ratio between the range of the first analysis result of the primary model and the range of the second analysis result of the disaster recovery model. Through the technical solution provided, when there are specific issues with the primary model or the data set it uses, such as when the data set used for the primary model has missing data or the first analysis result output by the primary model is abnormal due to missing data or other reasons, the disaster recovery model can be utilized along with its corresponding data set to obtain a second analysis result. Furthermore, a scaling (stretching and/or shrinking) strategy is applied to scale the second analysis model to obtain a third analysis result, which replaces the first analysis result that should have been output by the primary model. Thus, the disaster recovery data parameter determination solution through an effective scaling (stretching and/or shrinking) strategy can fully meet the requirements for analysis result stability and can effectively overcome the issue of distribution differences between disaster recovery analysis results and primary analysis results. Moreover, compared to some known solutions that improve analysis results based on quantiles of historical analysis results generated by auxiliary models, the solution still exhibits higher stability in analysis results. Additionally, the scaling strategy-based solution can dynamically adjust the disaster recovery logic by adjusting the degree of scaling, thereby ensuring continuous stability of analysis results for different clients over a longer period of time. Furthermore, compared to quantile-based solutions known to the inventor, the scaling strategy-based solution allows for flexible configuration of the scaling strategy, such as based on model correspondence, model data density, and customer group diversification. Besides, compared to quantile-based solutions known to the inventor, the scaling strategy-based solution has fewer constraints on the disaster recovery model, enabling the selection of a suitable model from among many disaster recovery models by appropriately configuring the scaling strategy without sacrificing the input integrity of the disaster recovery model. The present disclosure expands the range of options for disaster recovery models and also facilitates support for various types of disaster recovery. Furthermore, compared to quantile-based solutions known to the inventor, the scaling strategy-based solution allows for the full use of third-party standby sources to replace faulty third-party sources in the disaster recovery model, solving the problem of missing input data for the model. According to an aspect of the present disclosure there is provided a server apparatus, the server apparatus comprising a processor, the processor configured to: obtain a first dataset for input into a first

data analysis model; determine, based on at least one of the first dataset and/or a first analysis result of the first data analysis model, whether the first data analysis model is in a first condition; wherein in a positive determination that an output of the first data analysis model meets the first condition; obtain a second dataset for input into a second data analysis model to obtain a second analysis result; process the second analysis result based on a scaling strategy to obtain a third analysis result; and replace the first analysis result with the third analysis result.

[0013] In some embodiments, the scaling strategy comprises a ratio between a first possible range of the first analysis result and a second possible range of the second analysis result.

[0014] In some embodiments, the second possible range is smaller than the first possible range.

[0015] In some embodiments, the scaling strategy comprises at least one scaling function, and wherein the at least one scaling function is a univariate polynomial function or a linear function.

[0016] In some embodiments, the first condition is an abnormal condition.

[0017] In some embodiments, the processor is further configured to determine whether the first dataset contains missing data.

[0018] In some embodiments, the at least one scaling function comprises a first scaling function associated with a first range of the second analysis result, and a second scaling function associated with a second range of the second analysis result.

[0019] In some embodiments, the processor is further configured to monitor one or more changes to the second scaling function.

[0020] In some embodiments, the processor is configured to obtain a plurality of first dataset and a plurality of second data analysis models, each of the plurality of first dataset corresponding to one of the plurality of second data analysis models.

[0021] In some embodiments, the processor is configured to perform scaling test processing using a historical dataset of the second data analysis model based on an updated scaling strategy to obtain a third test analysis result.

[0022] In some embodiments, the second data analysis model is a data disaster recovery model.

[0023] In some embodiments, the first data analysis model is a scoring model.

[0024] According to another aspect of the present disclosure there is provided a method, the method comprises: obtaining a first dataset for input into a first data analysis model; determining, based on at least one of the first dataset and a first analysis result of the first data

analysis model, whether the first data analysis model is in a first condition; wherein in a positive determination that an output of the first data analysis model meets the first condition; obtaining a second dataset for input into a second data analysis model to obtain a second analysis result; processing the second analysis result based on a scaling strategy to obtain a third analysis result; and replacing the first analysis result with the third analysis result.

[0025] In some embodiments, processing the second analysis result based on the scaling strategy further comprises defining at least one scaling function, wherein the at least one scaling function is a univariate polynomial function or a linear function.

[0026] In some embodiments, the method further comprises defining a first scaling function associated with a first range of the second analysis result, and defining a second scaling function associated with a second range of the second analysis result.

[0027] In some embodiments, the method further comprises monitoring one or more changes to the second scaling function.

[0028] In some embodiments, the method the first condition is an abnormal condition.

[0029] According to another aspect of the present disclosure there is provided a disaster recovery system, the disaster recovery system arranged in data or signal communication with a main data analysis model, the disaster recovery system comprising a processor configured to: detect a first dataset for input into the main data analysis model; determine, based on at least one of the first dataset and/or a first analysis result of the main data analysis model, whether the main data analysis model is in an abnormal condition; wherein in a positive determination that the main data analysis model is in the abnormal condition; obtain a second dataset for input into a disaster recovery model to obtain a second analysis result; process the second analysis result based on a scaling strategy to obtain a third analysis result; and replace the first analysis result with the third analysis result.

[0030] In some embodiments, the processor is configured to monitor, on a real-time basis, whether main data analysis model is in the abnormal condition.

[0031] According to another aspect of the present disclosure there is provided a non-transitory computer-readable medium storing computer executable code comprising instructions for processing data according to any one of the described methods.

BRIEF DESCRIPTION OF THE DRAWINGS

[0032] The disclosure will be better understood with reference to the detailed description when considered in conjunction with the non-limiting examples and the accompanying drawings, in which:

- FIG. 1A is a schematic block diagram of a server apparatus for determining one or more parameters of data analysis models, such as one or more parameters associated with the input dataset and/or output dataset of a score model.
- FIG. 1B is a schematic block diagram comprising the server apparatus of FIG. 1A, implemented as a system for determining one or more parameters of data analysis models.
- FIG. 2 is a flow chart depicting a method for determining data parameters according to an embodiment.
- FIG. 3 is a flow chart of a method for customizing scaling strategy according to users' preference according to an embodiment.
- FIG. 4 is a flow chart illustrating an embodiment of acquiring of initial dataset according to an embodiment.
- FIG. 5 is a flow chart illustrating the determination of whether an initial data set and/or a first analysis result meet the first condition, according to an embodiment.
- FIG. 6 is a flow chart illustrating a method for performing scaling processing on a second analysis result according to a scaling strategy, according to an embodiment.
- FIG. 7 is a flow chart illustrating a method for determining whether multiple initial datasets and/or the first analysis results meet pre-set conditions based on obtaining multiple sets of different disaster recovery data sets.
- FIG. 8 is a flow chart of a method for detecting a change or update to the scaling strategy according to an embodiment.
- FIG. 9 is a general flow chart of a method for determining one or more parameters of data analysis models.

DETAILED DESCRIPTION

[0033] The following detailed description refers to the accompanying drawings that show, by way of illustration, specific details and embodiments in which the disclosure may be practiced. These embodiments are described in sufficient detail to enable those skilled in the

art to practice the disclosure. Other embodiments may be utilized and structural, and logical changes may be made without departing from the scope of the disclosure. The various embodiments are not necessarily mutually exclusive, as some embodiments can be combined with one or more other embodiments to form new embodiments.

[0034] Embodiments, which are non-limiting examples, described in the context of one of the enclosure systems, server devices, or methods are analogously valid for the other systems, devices, or methods. Similarly, embodiments described in the context of a system are analogously valid for a device or a method, and vice-versa.

[0035] Features that are described in the context of an embodiment may correspondingly be applicable to the same or similar features in the other embodiments. Features that are described in the context of an embodiment may correspondingly be applicable to the other embodiments, even if not explicitly described in these other embodiments. Furthermore, additions and/or combinations and/or alternatives as described for a feature in the context of an embodiment may correspondingly be applicable to the same or similar feature in the other embodiments.

[0036] In the context of various embodiments, the articles “a”, “an” and “the” as used with regard to a feature or element include a reference to one or more of the features or elements. Furthermore, as used in the present disclosure and the appended claims, the term “by” may also mean “from”, depending on the context. Furthermore, as used in the present disclosure and the appended claims, the term “if” may also mean “when” or “upon”, depending on the context. Furthermore, as used in the present disclosure and the appended claims, the words “and/or” may refer to and encompass any and all possible combinations of one or more of the associated listed items.

[0037] As used herein, the term “data” may be understood to include information in any suitable analogue or digital form, for example, provided as a file, a portion of a file, a set of files, a signal or stream, a portion of a signal or stream, a set of signals or streams, waveforms, and the like. The term data, however, is not limited to the aforementioned examples and may take various forms and represent any information as understood in the art.

[0038] As used herein, the term “first”, “second”, “third”, “fourth”, “fifth”, etc. are used to distinguish one element/feature from another, and, unless otherwise stated, may not denote order, priority or sequence.

[0039] As used herein, the term “module” refers to, forms part of, or includes an application Specific Integrated Circuit (ASIC); an electronic circuit; a combinational logic circuit; a field programmable gate array (FPGA); a processor (shared, dedicated, or group) that executes code;

other suitable hardware components that provide the described functionality; or a combination of some or all of the above, such as in a system-on-chip. The term module may include memory (shared, dedicated, or group) that stores code executed by the processor. A single module or a combination of modules may be regarded as a device. A processor may include one or more modules. For example, multiple modules described in the present disclosure may form a processor.

[0040] As used herein, the term “associate”, “associated”, and “associating” indicate a defined relationship (or cross-reference) between two items.

[0041] As used herein, the term “obtain”, in the context of obtaining data, broadly include pull technology used any time a transfer of data is initiated by a request sent from a client to a server. Push technology, on the other hand, is implemented any time a transfer of information is initiated by a server without waiting on a request from a client. In some embodiments, the term obtain may include receive.

[0042] As used herein, “memory” may be understood as a non-transitory computer-readable medium in which data or information can be stored. References to “memory” included herein may thus be understood as referring to volatile or non-volatile memory, including random access memory (“RAM”), read-only memory (“ROM”), flash memory, solid-state storage, magnetic tape, hard disk drive, optical drive, etc., or any combination thereof. Furthermore, it is appreciated that registers, shift registers, processor registers, data buffers, etc., are also embraced herein by the term memory. It is appreciated that a single component referred to as “memory” or “a memory” may be composed of more than one different type of memory, and thus may refer to a collective component including one or more types of memory. It is readily understood that any single memory component may be separated into multiple collectively equivalent memory components, and vice versa. Furthermore, while memory may be depicted as separate from one or more other components (such as in the drawings), it is understood that memory may be integrated within another component, such as on a common integrated chip.

[0043] As used herein, the term “scoring model” is a data analysis model which may include statistical tool(s) used to evaluate and predict the likelihood of a particular outcome based on various input variables. In the context of data analysis and predictive modelling, scoring models may include an analysis of historical data to identify patterns and relationships between input variables and desired outcomes, generate scores or predictions for new data to assess future outcomes or behaviours, utilize techniques such as regression analysis, decision trees, or machine learning algorithms to process inputs and produce scores. The scoring models may

include three key components, (i.) input variables (features) or dataset, which comprise data points analysed by the scoring model; (ii.) scoring algorithm, which comprise a mathematical formula or method used to process inputs, and (iii.) scoring output, which comprises analysis result of the model that can be a numerical score or categorical classification. In some embodiments, these models are widely employed in fields such as finance, marketing, and healthcare to assess risks, predict customer behaviour, or evaluate treatment effectiveness. The effectiveness of a scoring model is often evaluated using metrics such as accuracy, precision, and recall.

[0044] As used herein, the term "configured to" broadly refers to an arrangement, a design, and/or a program to perform a specific function. It implies a purposeful arrangement or adaptation for achieving the stated functionality. For example, a processor configured to process data may include hardware (e.g. electronic circuitry, chips), and/or software working in tandem to process the data.

[0045] According to an aspect of the disclosure and with reference to FIG. 1A and FIG. 1B, there is provided a server apparatus for processing data. The server apparatus may be part of a distributed system, server apparatus arranged or operable to process data or dataset to determine whether a first data analysis model, which may be a primary data analysis model, is in a first condition, such as an abnormal condition. In a positive determination that the first data analysis model is in the first condition, the server apparatus may activate a second data analysis model, which may be a recovery model, to determine one or more data parameters associated with the first data analysis model.

[0046] The server apparatus may comprise a processor and a memory, the processor is capable of being configured to execute instructions stored in the memory to receive a data packet associated with a data analysis module/model. In the embodiment illustrated in FIG. 1A and FIG. 1B, the server apparatus may be a communications server apparatus. The communications server apparatus may be in the form of a server computer 100, the server computer 100 may be a single server as illustrated schematically in FIG. 1A, or have the functionality performed distributed across multiple server components.

[0047] In some embodiments, the server computer 100 may include a data analysis module configured to receive data for analysis. In other embodiments, the server computer 100 may be arranged in data communication with a data analysis model and/or configured to receive output analysis results, which may be in the form of a quantitative score, from the data analysis model.

[0048] In some embodiments, the server computer 100 includes a communication interface 102. The communication interface 102 may be configured to send and receive data, which may include an initial dataset, the initial dataset may further include audio data packets and/or text (converted from audio) data packets. The communication interface 102 may include a transmitter module and/or a receiver module allowing the server apparatus to communicate over a communications network. The communication interface 102 may include one or more user-interfaces configured to provide users for user control and may include, for example, one or more computing peripheral devices such as display monitors, computer keyboards and the like.

[0049] The server computer 100 may further include a processor in the form of processing unit 104 and a memory 106. The memory 106 may be used by the processing unit 104 to store, for example, the data packets for analysis, historical data associated with one or more data analysis models, and/or other parameters such as output scores, to be processed.

[0050] As shown in FIG. 1B, the processing unit 104 may be configured to receive, from a terminal device 110, a request for data analysis 111, for processing. The request for data analysis 111 may be parsed to obtain information or data relating to one or more primary data analysis (scoring) models to be used, dataset information, type of request (e.g. financial, credit, etc.).

[0051] The server computer 100 and one or more terminal devices 110 may be connected via a network 120 to form a system 150 for processing the data. The network 120 may be an Internet or Intranet network, and may include an interface gateway. In some embodiments, the system 150 may comprise one or more data analysis model management module 130, the data analysis model management module 130 configured to obtain the parsed request 111 and determine whether a primary data analysis model 131 or a secondary data analysis model 132 is to be used. The primary data analysis model 131 or a secondary data analysis model 132 may output a first analysis result 112, or a third analysis result 113, respectively.

[0052] In some embodiments, the data analysis model management module 130 may form part of the server computer 100 or may be arranged in data or signal communication with the server computer 100.

[0053] In some embodiments, the data analysis model management module 130 may obtain a first dataset (e.g. the parsed request 111) for input into a first data analysis model. The first data analysis model may be a main model or a primary model. The data analysis model management module 130 may then be configured to, determine, based on at least one of the

first dataset and a first analysis result of the first data analysis model, whether the first data analysis model is in a first condition. If the first data analysis model is deemed not to be in the first condition, the first analysis result is returned to the terminal device 110 in response to a user request sent from the terminal device 110.

[0054] However, in a positive determination that the output of the first data analysis model meets the first condition, the data analysis model management module 130 may be configured to, obtain a second dataset for input into a second data analysis model, to obtain a second analysis result, process the second analysis result based on a scaling strategy to obtain a third analysis result; and then replace the first analysis result with the third analysis result. In other words, the third analysis result will be returned to the terminal device 110 in response to the user request sent from the terminal device 110.

[0055] In some embodiments, the scaling strategy may comprise a ratio between a first possible range of the first analysis result and a second possible range of the second analysis result. The second possible range may be smaller than the first possible range.

[0056] In some embodiments, the scaling strategy comprises at least one scaling function, and wherein the at least one scaling function may be a univariate polynomial function or a linear function.

[0057] In some embodiments, the first condition may be an abnormal condition.

[0058] In some embodiments, in order to determine whether the first data analysis model is at the first condition, the processor is further configured to determine whether the first dataset contains missing data.

[0059] In some embodiments, the at least one scaling function comprises a first scaling function associated with a first range of the second analysis result, and a second scaling function associated with a second range of the second analysis result.

[0060] In some embodiments, the data analysis model management module 130 is further configured to monitor one or more changes to the second scaling function. Such monitoring may be done periodically, and/or on a real time basis.

[0061] In some embodiments, the data analysis model management module 130 is configured to obtain a plurality of first dataset and a plurality of second data analysis models, each of the plurality of first dataset corresponding to one of the plurality of second data analysis models.

[0062] In some embodiments, the data analysis model management module 130 is configured to perform scaling test processing using a historical dataset of the second data

analysis model based on the updated scaling strategy to obtain a third test analysis result. The second data analysis model may be a data disaster recovery model. The first data analysis model may be a scoring model.

[0063] In some embodiments, there may be multiple primary (first) data analysis model 131 and multiple secondary data analysis model 132, each of the multiple secondary (second) data analysis model 132 corresponding to each primary data analysis model 131.

[0064] FIG. 2 is a flow chart depicting a method 200 for determining data parameters. The method comprises the following steps.

[0065] Step S210: Acquiring an initial data set, where the data in the initial data set is suitable for being input into a primary model to obtain a first analysis result. The primary model may be an example of the first data analysis model, which may be a scoring model.

[0066] The initial dataset may be an example of the first dataset, the initial dataset corresponding to the primary model and for input into the primary model, and the data in the initial dataset is suitable for input into the primary model to obtain the first analysis result. The primary model can provide analysis results based on a specific operational process and/or logical algorithm according to the input data, which is referred to as the first analysis result.

[0067] It is appreciable that datasets, including the initial dataset and the second dataset, can have different dataset fields. For example, dataset Ai can have fields ai_field1 to ai_fieldn; dataset Bi can have fields bi_field1 to bi_fieldn; dataset Ci can have fields ci_field1 to ci_fieldn, where i refers to an integer from 0 to n, with $0 \leq i \leq n$.

[0068] Correspondingly, the data in the datasets, including the initial dataset and disaster recovery datasets, can be sample data with different field values, meaning that the sample data in the dataset can have corresponding values for each field. The field values of the sample data in the dataset can be input into the first data analysis model, and the corresponding fields constitute the feature variables (also known as input parameters) used by the first data analysis model. In this embodiment, the data in the initial dataset can include sample data with different field (feature variable/input parameter) values, which can be input into the primary model, and the primary model can output the first analysis result accordingly based on the input data. Dataset fields (feature variables/input parameters) involve information about a certain dimension of the sample data (sample type), such as but not limited to characteristics like age, education level, income status, default situation, etc.

[0069] The initial dataset can be obtained in response to the request for data analysis by a user, such as a customer. It may be appreciable that the information, data, and signals may be

secured, authorized, and encrypted. Users or customers of the system 150 and model management module 130 can be interchangeably used, such as but not limited to banks, insurance companies, credit institutions, etc., which can request analysis results as users but typically cannot access or understand the configured disaster recovery strategies. Hence, users may be distinguished from operators who can modify (add, change, and delete) disaster recovery strategies, such as analysts.

[0070] In an non-limiting example, when a user request is received through an interface gateway, the user request can be parsed to obtain the data information required for the user request (such as a scoring analysis request). In a specific example, the feature variable, in the form of input parameter information required for data analysis can be determined, and the dataset that needs to be obtained can be determined based on the determined feature variable or input parameter information.

[0071] For example, for the first part of input parameters (such as a0_field1 and a0_field2), if it is determined that dataset A0 in a database DB1 needs to be obtained; for the second part of input parameters (such as b0_field2), it is determined that dataset B0 in another database DB2 needs to be obtained; for the third part of input parameters (such as c0_field1, c0_field2, and c0_field3), it is determined that dataset C0 in database 140 needs to be obtained. Alternatively, the dataset information requested by the user can be directly obtained, thereby determining and obtaining the corresponding initial dataset.

[0072] In another implementation example, the primary model for analysis can be determined based on the user's data analysis request, and then the dataset required by the primary model can be determined based on the determined primary model. For example, it can be determined based on the user's request that the primary model corresponding to the data analysis is model 1, and based on the determined primary model, such as model 1, the associated initial dataset (such as A0 stored in the DB1, B0 stored in DB2, and C0 stored in 140) can be determined and obtained according to the feature variables (input parameters) required by the primary model.

[0073] The obtained initial dataset can be one or more, and can come from a single database or multiple databases or data sources.

[0074] Step S220: Determining whether the initial data set and/or the first analysis result meet the first condition, which may include pre-set conditions. It may be determined whether the first analysis result meets the pre-set conditions.

[0075] Step S230: When the initial data set and/or the first analysis result meet pre-set conditions, the method 200 comprises acquiring a second dataset, an example of which may be a disaster recovery data set, and inputting data extracted from the disaster recovery data set into a second data analysis model, which may be a disaster recovery model. The disaster recovery model may be used to obtain a second analysis result, and the disaster recovery data set is at least partially different from the initial data set.

[0076] The data in the disaster recovery data set can include sample data with different field, e.g. feature variable/input parameter values, which can be input into the disaster recovery model, and the disaster recovery model can output a second analysis result accordingly based on the input second dataset. Similarly, the disaster recovery data set can be stored in a database, such as database 140.

[0077] The disaster recovery data set is at least partially different from the initial data set. For example, the initial data set can be A0, B0, and C0 as described earlier, and the disaster recovery data set can be data set C1 stored in database 140. The obtained disaster recovery data set can be one or more, and can come from a single database or multiple databases (data sources). In some embodiments, one or more databases may be arranged in a decentralized configuration, such as a distributed ledger technology.

[0078] In some embodiments, the disaster recovery model associated with the main model can be determined based on the main model, and then the disaster recovery data set can be determined and obtained accordingly based on the feature variables (input parameters) required by the disaster recovery model. For example, based on the determined main model being model 1, the disaster recovery model configured for model 1 can be determined as model 3, and the required disaster recovery data set C1 can be determined based on the feature variables required by model 3 (such as c1_field1, c1_field2).

[0079] Furthermore, the data, such as sample data corresponding to the feature variables required by the disaster recovery model, such as c1_field1, c1_field2, of the disaster recovery dataset, can be input into the disaster recovery model, and the disaster recovery model will provide an analysis result based on the input data, which is the second analysis result here.

[0080] Step S240: Performing scaling processing on the second analysis result according to a scaling strategy to obtain a third analysis result corresponding to the primary model and used to replace the first analysis result, where the scaling strategy characterizes the stretching or shrinking ratio between the range of the first analysis result of the primary model and the range of the second analysis result of the disaster recovery model.

[0081] The scaling strategy may include a characterization of a ratio, such as a stretching or shrinking ratio between the first analysis result range of the main model and the second analysis result range of the disaster recovery model. Whether to stretch or shrink and the corresponding stretching or shrinking ratio can be determined based on the correspondence between the analysis result range of the main model and the analysis result range of the disaster recovery model. The scaling strategy is a stretching strategy, i.e., the size of the analysis result range of the disaster recovery model is always smaller than the size of the analysis result range of the main model.

[0082] In some embodiments, the scaling strategy may include a scaling factor. In some embodiments, the scaling strategy may be adjustable, for example, the scaling function structure and/or scaling factor are adjustable. For example, the scaling factor can be adjusted by means of a scaling configuration module of the model management module 130. With disaster recovery processing based on the scaling relationship, issues such as data loss from a data source and abnormalities of the main model caused by other reasons can be handled in a relatively simple and flexible manner, and have generally less constraints and higher flexibility for the models and data used for disaster recovery.

[0083] In some embodiments, the scaling strategy may be configured according to the characteristics of the main model and the disaster recovery model and/or the characteristics of the data and/or customer characteristics of the main model and/or disaster recovery model, providing disaster recovery data analysis results with relatively small differentiation and high stability.

[0084] In some embodiments, the scaling strategy may include a scaling function, which includes a univariate polynomial function. The coefficients of the univariate polynomial function are the scaling factors of the scaling function relationship. The scaling function relationship includes a univariate quadratic function.

[0085] For example, a univariate quadratic scaling function can be represented as:

$$y = ax^2 + bx + c$$

wherein a, b, c are scaling factors, y is the third analysis result, and x is the second analysis result.

[0086] Table 1

Model	**Model Fields**	**Dependent dataset**	**Dataset Fields**		**Scaling function relationship**
Model 1	Score3（Score1）	A0	a0_field1 a0_field2	Model 3	a*Score2^2+b*Score2+c=Score3 （Rounding） User api=0001
		B0	b0_field2		
		C0	c0_field1 c0_field2 c0_field3		
Model 3	Score2	C1	c1_field1 c1_field2	*	

[0087] Table 1 exemplarily shows an exemplary model data dependency and stretching strategy relationship table.

[0088] In the example shown in the Table 1, the main model is Model 1, and the corresponding disaster recovery model is Model 3. The initial datasets that the main model depends on are A0, B0, and C0. More specifically, the feature variables (fields) that the main model depends on are a0_field1, a0_field2 (from A0), b0_field2 (from B0), c0_field1, c0_field2, c0_field3 (from C0). The disaster recovery dataset, i.e. third dataset, that the disaster recovery model depends on is C1. More specifically, the feature variables or fields that the disaster recovery model depend on are c1_field1, c1_field2 from C1. Under normal circumstances, in response to a customer's request, the main model, which is Model 1, will be used to obtain the first analysis result, labelled as score1, using the dependent datasets or sample data corresponding to the dependent feature variables. However, if it is necessary to obtain disaster recovery analysis results due to reasons such as data sources or models, the disaster recovery model, labelled Model 3, will be used to obtain the second analysis result Score2. Then, according to the given scaling function relationship, which is the univariate quadratic scaling function relationship in this case, the disaster recovery analysis result is determined, i.e., the third analysis result Score3 used to replace the first analysis result, i.e. Score1, in parentheses in Table 1.

[0089] In some embodiments, the correspondence between the range of the disaster recovery analysis result (Score3) of Model 3 and the range of the analysis result (Score1) of Model 1 determines whether the scaling strategy is stretching or shrinking, i.e. adjustment of

the ratio. Preferably, the range of the disaster recovery analysis result (Score3) of Model 3 is smaller than the range of the analysis result (Score1).

[0090] Table 1 also indicates a possible configuration of a user API, which can be used to configure different scaling strategies based on different users. Different scaling strategies may refer to the same function structure (such as both being univariate quadratic functions) but with different scaling factors; or, different scaling strategies may refer to different function structures (such as both being univariate quadratic functions but with different forms); or, different scaling strategies comprising a combination of both.

[0091] In some embodiments, the step S240 may include the following method 300 for customizing scaling strategy according to users' preference, as depicted in FIG. 3. The method 300 include the following steps.

[0092] Step S301: determining the scaling strategy corresponding to the user based on the user's request, and

[0093] Step S302: performing scaling processing on the second analysis result according to the scaling strategy corresponding to the user.

[0094] As an example, when the scaling strategy includes a univariate polynomial function with adjustable scaling coefficients, the univariate polynomial scaling function can be compatible with lower-degree scaling functions by adjusting the scaling coefficients. For example, when the scaling strategy includes a univariate quadratic scaling function with adjustable coefficients, the scaling coefficient a (see Table 1) can be set to a non-zero value, at which point the scaling function will represent the quadratic relationship between the analysis result range of the main model and the analysis result range of the disaster recovery model. The scaling coefficient a can also be set to zero, and the scaling coefficient b (see Table 1) can be set to a non-zero value, at which point the scaling function will represent the linear relationship between the analysis result range of the main model and the analysis result range of the disaster recovery model. In some specific cases, both scaling coefficients a and b can be set to zero, and the scaling coefficient c can be set to a non-zero value, at which point the corresponding third analysis result within the analysis result range of the disaster recovery model will be a constant. Further features may be achieved through disaster recovery processing based on a univariate polynomial scaling function. Without limitation, the analysis data of the main model and the analysis data of the disaster recovery model are usually not linearly corresponding, and there may also be differences in distribution density. Scaling processing based on a univariate polynomial scaling function may be adept in solving the

problem. Disaster recovery processing based on a univariate polynomial scaling function combined with adjustable scaling relationships may achieve technical effect(s) greater than simple superposition. For example, disaster recovery processing based on a univariate polynomial scaling function combined with adjustable scaling relationships can allow operators, such as analysts, to handle dynamic changes in the correspondence between the main model and the disaster recovery model caused by various dynamic factors (such as time changes or different distribution demands of customer groups for analysis results or disaster recovery analysis results) through the model management module 130 (scaling configuration module), especially in cases of nonlinear correspondence and differences in distribution density.

[0095] In some embodiments, the acquiring the initial dataset of step S210 may include the method 400, depicted as a flow chart in FIG. 4, as follows.

[0096] Step S401: inputting the data extracted from the initial data set into the main or primary data analysis model to obtain the first analysis result; and/or

[0097] Step S402: calculating or inferring, based on the relevant data of the initial data set, such as a sample dataset corresponding to the input parameters involved in the main model, to obtain the first analysis result. In step S402, if there are issues with the data in the initial data set and/or issues with the main model itself, the output results of the main model may be abnormal, including but not limited to no output value or errors, or output values not meeting the specifications. Further, the operation of obtaining a disaster recovery data set described below can be performed.

[0098] It may be contemplated that although the data of the acquired initial data set may be suitable for being input into the main model to obtain the first analysis result, it does not mean that the data of the initial data set have to be input into the main model. In some embodiments, the data of the initial dataset may be verified without inputting the data of the initial data set into the main model to attempt to obtain the first analysis result.

[0099] In some embodiments, the determination of whether the initial data set and/or the first analysis result meet the first condition may include the following steps, in the form of a method 500, depicted as a flow chart in FIG. 5, as follows:

[00100] Step S501: verifying whether the first analysis result is abnormal, where the preset conditions include the first analysis result being abnormal; and/or

[00101] Step S502: verifying whether any data in the initial data set is missing, where the preset conditions include data missing from the initial data set.

[00102] In a positive determination that the data in the initial data set is missing, the operation of obtaining a disaster recovery data set may be performed. The data missing from the initial data set can include substantive missing data. For example, the missing data refers to the lack of sample data corresponding to the fields (feature variables/input parameters) required to determine the analysis result based on the user's request. In another example, the missing data can include the proportion of missing sample data corresponding to the fields (feature variables/input parameters) being greater than a predetermined threshold.

[00103] A status flag for indicating whether to execute disaster recovery logic can be set, and for example, through the aforementioned determination/verification, when the first condition, which may include preset conditions, are met, the status flag is set to active. Thus, it can be determined whether to execute disaster recovery logic based on the status of the status flag.

[00104] In some embodiments, performing scaling processing on the second analysis result according to a scaling strategy may include the following steps, in the form of a method 600 of configuring multiple scaling functions for multiple second analysis result ranges of a single disaster recovery model. Each scaling function may correspond to one second analysis result range, and the multiple second analysis result ranges do not overlap with each other. Correspondingly, scaling the second analysis results according to the scaling strategy may include the following steps, as depicted as a flow chart in FIG. 6.

[00105] Step S601: Determining the second analysis result range in which the second analysis result is located to determine the corresponding scaling function, and

[00106] Step S602: Scaling the second analysis result using the corresponding scaling function.

[00107] After performing scaling operations on the second analysis results based on steps S601 and S602, the result may be directly obtaining a third analysis result for substitution or replacement. In some embodiments, the third analysis result may be further processed or parsed.

[00108] It is contemplated that defining or configuring multiple scaling functions for multiple analysis result ranges of a single disaster recovery model may lead to further advantages. In some embodiments, a single disaster recovery model configured with multiple analysis result ranges does not imply that the main model is equipped with only one disaster recovery model, but may be understood to refer to the possibility of configuring multiple analysis result ranges for one of the disaster recovery models itself. In some embodiments, the analysis results of the main model and the disaster recovery model may comprise corresponding differences in different ranges, such as differences in distribution density, slope,

power, and/or customer demand. Configuring different scaling functions for different ranges may increase the robustness of the disaster recovery model.

[00109] In a non-limiting example, three scaling functions can be configured for three ranges of a disaster recovery model (such as Model 3), wherein

a. the scaling function for the range [n0, n1] is $y=a0x^2+b0x+c0$;

b. the scaling function for the range (n1, n2] is $y=a1x^2+b1x+c1$; and

c. the scaling function for the range (n2, n3] is $y=a2x^2+b2x+c2$.

[00110] It may be conceivable to have more or fewer ranges. Additionally, it is also conceivable that the scaling strategy in this embodiment, such as the structure and/or scaling coefficients of the scaling functions, can be adjustable, and the starting points, endpoints, and openness/closedness of the ranges are also adjustable. Multiple scaling functions are all presented as univariate quadratic functions and can be configured to be compatible or incompatible with lower powers as needed. For instance, in an example, the scaling coefficient a for multiple ranges can all be 0; in another specific example, the scaling coefficient a for multiple ranges can be at least partially non-zero; in yet another specific example, within certain specific ranges, such as the range [n0, n1] or another specific range, or additionally set lower limit range [0,n0) or upper limit range (n3, $+\infty$), both scaling coefficients a and b can be set to 0, so that for second analysis results falling within these ranges, a constant substituted analysis result (third analysis result) will be correspondingly provided.

[00111] As an optional step, the method for determining data parameters may further include returning or displaying the first analysis result or the third analysis result to the client. For example, the client can initiate a request to the interface gateway through a client terminal, and correspondingly, the final analysis result, which is the first analysis result or the third analysis result depending on whether disaster recovery is performed, can be returned to the client. The generation of disaster recovery analysis results can be imperceptible to the client, meaning that the client does not know that the returned result is a disaster recovery analysis result (third analysis result), and always treats the returned analysis result as a normal analysis result; however, also cover providing the client with the status indicating whether the result is a disaster recovery analysis result, allowing the client to selectively perform further processing based on this status.

[00112] The above-mentioned data parameter determination solution has the advantages of high stability of analysis results, high flexibility of disaster recovery logic, and low constraints on disaster recovery models and data.

[00113] In some embodiments, the initial dataset may be obtained or acquired, and the data in the initial dataset determined if suitable for input into the primary model to obtain a first analysis result. The initial dataset and/or the first analysis result may be determined to meet preset conditions. When the preset conditions are met, the method can further include acquiring or loading the disaster recovery dataset, input the data extracted from the disaster recovery dataset into the disaster recovery model to obtain a second analysis result. In a positive determination the initial dataset and/or the first analysis result meet the preset conditions, multiple sets of different disaster recovery datasets corresponding to multiple different disaster recovery models may be acquired, each set of disaster recovery datasets includes at least one disaster recovery dataset. Multiple disaster recovery models can be correspondingly equipped.

[00114] In some embodiments, each of the multiple disaster recovery models may correspond to a set of disaster recovery datasets, and the dataset includes at least one disaster recovery dataset; meanwhile, any disaster recovery dataset can correspond to one disaster recovery model, or can also correspond to multiple disaster recovery models. In a specific example, disaster recovery model A corresponds to a set of disaster recovery datasets {a, b, c}, while disaster recovery model B corresponds to another set of disaster recovery datasets {c, d}.

[00115] In some embodiments, the primary model can be directly equipped with a plurality of or multiple disaster recovery models. The directly equipped disaster recovery models may include disaster recovery models whose disaster recovery analysis results, according to the scaling strategy, can be used as alternative analysis results to replace the analysis results of the primary model. In an non-limiting example, primary model 1 may be directly equipped with two disaster recovery models: model 2 and model 3. The primary model can be indirectly equipped with multiple sets of disaster recovery models, such as the nested disaster recovery models described above. Indirectly equipped disaster recovery models mean that the alternative analysis results determined by the scaling strategy for the disaster recovery analysis results of the indirectly equipped disaster recovery models cannot be directly used to replace the analysis results of the primary model, but are used to replace the analysis results of another disaster recovery model; and the analysis results of this other disaster recovery model, according to another scaling strategy, can be used as alternative analysis results for the analysis results of the primary model, or can be used to replace the analysis results of another nested disaster recovery model, which can sequentially generate alternative analysis results according to their respective scaling strategies until an alternative analysis result for replacing the analysis result of the primary model is obtained. In a specific example, primary model 1 is directly equipped

with one disaster recovery model: model 2, and this model 2 itself is also directly equipped with one disaster recovery model: model 3, so primary model 1 is indirectly equipped with disaster recovery model 3. At this point, these disaster recovery models can be acquired as needed, such as based on a given nesting depth (e.g., two layers) or other given conditions (e.g., until a termination condition for acquiring alternative disaster recovery analysis results is satisfied, as described below). In some other embodiments, it can be a combination of these two.

[00116] In the various embodiments comprising multiple disaster recovery models, multiple corresponding data analysis results may be obtained as output from each of the multiple disaster recovery models, by inputting the multiple sets of data extracted from the multiple sets of disaster recovery datasets into multiple different disaster recovery models to obtain multiple alternative second analysis results.

[00117] The multiple datasets can be input into their corresponding disaster recovery models, respectively, to obtain multiple alternative second analysis results corresponding to the multiple different disaster recovery models. For example: including disaster recovery dataset a, disaster recovery dataset b, disaster recovery dataset c, extracting data a1 from disaster recovery dataset a, extracting data b1, b2 from disaster recovery dataset b, and extracting data c3 from disaster recovery dataset c. Disaster recovery model A corresponds to a set of disaster recovery datasets {a, b, c}, while disaster recovery model B corresponds to another set of disaster recovery datasets {b, c}, and disaster recovery model C corresponds to yet another set of disaster recovery datasets {a, c}. At this point, a set of data [a1, b1, b2, c3] from the dataset group corresponding to disaster recovery model A is input into a disaster recovery model A, similarly, data [b1, b2, c3] is input into a disaster recovery model B, and data [a1, c3] is input into a disaster recovery model C, to obtain analysis result A1 output by disaster recovery model A, analysis result B1 output by disaster recovery model B, and analysis result C1 output by disaster recovery model C, respectively, thereby obtaining three alternative second analysis results A1, B1, and C1.

[00118] In some embodiments, the scaling processing on the second analysis results according to a scaling strategy to obtain a third analysis result, which is used to replace the first analysis result, may include screening the multiple alternative second analysis results to determine the eligible target second analysis result and its corresponding target disaster recovery model.

[00119] Various different screening conditions and/or screening methods and/or screening rules can be used to determine the eligible target second analysis result. For example, where there are multiple candidate second analysis results, the second analysis result closest to the average or at the median can be taken as the target second analysis result. As another example, an additional screening module, such as a historical data screening module, can be set up to screen and obtain the target second analysis result. For example, the fastest returned qualified second analysis result can be taken as the target second analysis result. A given second analysis result threshold or range can be set, so that second analysis results greater than, greater than or equal to, less than, less than or equal to, or falling within or not falling within the range are considered qualified (or unqualified) analysis results. The above-mentioned second analysis result threshold or range can be determined based on experience or historical data.

[00120] In some embodiments, nested disaster recovery models may be included. In such cases where nested disaster recovery models are included, the second analysis results can be obtained sequentially according to the nesting order, where the screening rules include, but are not limited to, the analysis result closest to the mean of historical data, and this screening can be performed together with the meeting of preset conditions, obtaining of multiple sets of disaster recovery datasets, and/or obtaining of multiple second analysis results.

[00121] In an example, for the same request, the second analysis result of a (sub) disaster recovery model 2 directly configured by the primary model 1 may be obtained, and then the second analysis result, for example, a score of 85, of the disaster recovery model 3 directly configured by the sub-disaster recovery model 2 (i.e., the disaster recovery model 3 indirectly configured by the primary model 1) is obtained, while the mean of the analysis results in the historical data of the primary model is 88, so 85 is selected as the target second analysis result.

[00122] In some situations where a quick response is required, the second analysis result with the fastest response can be taken as the target second analysis result and the acquisition of second analysis results can be stopped.

[00123] In particular, one or more of the various described methods may be explicitly combined with a one-variable polynomial scaling function and/or an adjustable scaling coefficient and/or multiple scaling functions corresponding to multiple ranges. In the equipped multiple disaster recovery models, one or more of the disaster recovery models can be equipped with multiple analysis result ranges. As mentioned, the configuration of multiple analysis result ranges for a single disaster recovery model may not mean that the primary model is only

equipped with one disaster recovery model, but refers to the configuration of multiple analysis result ranges for one of the disaster recovery models itself.

[00124] After the screening process, the target second analysis result may be converted into a third analysis result according to the scaling strategy corresponding to the target disaster recovery model.

[00125] The target second analysis result can be obtained by screening multiple alternative second analysis results that have not been scaled, and then scaling processing is performed to obtain a third analysis result used to replace the first analysis result (primary analysis result). This screening process can eliminate abnormal and unstable second analysis results, thereby selecting the most reliable and stable result for subsequent processing, which further improves the stability of disaster recovery analysis results.

[00126] It may be appreciable that one primary model can be equipped with multiple disaster recovery models, and multiple disaster recovery analysis results modified/stretched from the multiple second analysis results can be obtained, and mean processing is performed on the multiple disaster recovery second analysis results to obtain a third analysis result for replacing the first analysis result (primary analysis result). The risk that may be brought by the analysis result of a single disaster recovery model may be dispersed, so that the overall analysis result does not rely on the output of a single disaster recovery model, reducing the impact of fluctuations in the analysis results of a single disaster recovery model on the final result, and also improving the stability of the disaster recovery analysis results.

[00127] In some embodiments, there is provided a method 700, depicted as a flow chart in FIG. 7, as follows:

[00128] Step S701: Obtaining an initial data set. The data in the initial data set may be suitable for being input into the primary model to obtain the first analysis result.

[00129] Step S702: Determining whether the initial data set and/or the first analysis result meet preset conditions.

[00130] When the preset conditions are met, the data parameter determination method may further include step S703, i.e. obtaining a disaster recovery data set, input data extracted from the disaster recovery data set into the disaster recovery model to obtain a second analysis result, and specifically include:

[00131] Step S704: In a positive determination that the initial data set and/or the first analysis result meet the preset conditions, obtain multiple sets of different disaster recovery data sets

(i.e. second dataset) corresponding to multiple different disaster recovery models, each set of disaster recovery data sets including at least one disaster recovery data set, and

[00132] Step S705: Input multiple sets of second dataset extracted from multiple sets of disaster recovery datasets into multiple different disaster recovery models to obtain multiple second analysis results.

[00133] In some embodiments, if the obtained multiple second analysis results will not be screened (optimized), and then the multiple second analysis results will be scaled.

[00134] In some embodiments, the method may include Step S706: Performing scaling processing on the second analysis results according to a scaling strategy to obtain a third analysis result corresponding to the primary model and used to replace the first analysis result, and specifically include:

[00135] Step S707: Converting multiple second analysis results into multiple fourth analysis results respectively according to the scaling strategies corresponding to multiple different disaster recovery models, and

[00136] Step S708: Performing mean processing on multiple fourth analysis results to obtain a third analysis result.

[00137] In some embodiments, the scaling processing can be performed on multiple second analysis results to obtain multiple scaled intermediate analysis results, i.e., fourth analysis results, and then mean processing, such as averaging or median calculation, is performed on the multiple fourth analysis results to obtain a final disaster recovery score (i.e., the third analysis result). In one example, when calculating the average, the mean processing may include average processing, weighted average processing, and/or other statistical processing.

[00138] In particular, the method can be explicitly combined with a univariate polynomial scaling function and/or an adjustable scaling coefficient and/or multiple scaling functions corresponding to multiple ranges. In the equipped multiple disaster recovery models, one or more disaster recovery models may be equipped with multiple analysis result ranges. The configuration of multiple analysis result ranges for a single disaster recovery model here does not mean that the primary model is only equipped with one disaster recovery model, but refers to the configuration of multiple analysis result ranges for one of the disaster recovery models itself.

[00139] In some embodiments, scaling strategies and/or other disaster recovery configurations can be updated. Such updates include, for example, updates through the model management module (scaling configuration module). Automated testing and verification may

also be performed on the updated scaling strategies and/or other disaster recovery configurations, with verification results returned.

[00140] In some embodiments is provided a method 800 for detecting whether there is a change or update to the scaling strategy, depicted as a flow chart in FIG. 8, as follows:

[00141] Step S801: Real-time monitoring of updates to the scaling strategy.

[00142] Step S802: In a positive determination that an update is detected, retrieve historical data for the primary model and disaster recovery model corresponding to the updated scaling strategy.

[00143] As mentioned, the scaling strategy characterizes the stretch or contraction ratio between the first analysis result range of the primary model and the second analysis result range of the disaster recovery model. Based on the scaling strategy, historical operational data for the primary model and disaster recovery model involved in the scaling strategy can be retrieved accordingly.

[00144] Step S803: Performing scaling test processing using the historical data of the disaster recovery model based on the updated scaling strategy to obtain a third test analysis result.

[00145] After obtaining the historical data of the disaster recovery model corresponding to the updated scaling strategy, the analysis results in the historical data of the disaster recovery model may be stretched or contracted according to the updated scaling strategy to generate a new third test analysis result.

[00146] Step S804: Verifying the effectiveness of the update to the scaling strategy based on the historical data of the primary model and the third test analysis result, and return the verification result.

[00147] After obtaining the new third test analysis result, the system compares and verifies the new third test analysis result with the historical analysis results in the historical data of the primary model to evaluate the effectiveness of the new scaling strategy. In an example, the error between the third test analysis result and the historical analysis results in the historical data of the primary model can be verified. When the error is less than a preset error threshold, the verification result indicates that the scaling strategy is effective; otherwise, it indicates that the scaling strategy is ineffective. In a specific example, suppose the scaling strategy involves one primary model and three corresponding disaster recovery models, with a preset error threshold of 5%. Testing is conducted based on historical requests A, B, C, where the historical analysis results in the primary model's historical data are {70, 80, 90}. After applying the updated scaling strategy to the three disaster recovery models, the third test analysis results

obtained are {63, 72, 81}. The error calculations are: {(65-63)/65, (75-72)/75, (85-81)/85} ≈ {3.08%, 4.00%, 4.71%}, all less than the error threshold of 5%. Therefore, the verification result indicates that the scaling strategy is effective.

[00148] According to another aspect of the present disclosure there is provided a method 900, depicted in the flowchart of FIG. 9, comprising the steps of:

[00149] Step S901: obtaining a first dataset for input into a first data analysis model;

[00150] Step S902: determining, based on at least one of the first dataset and a first analysis result of the first data analysis model, whether the first data analysis model is in a first condition;

[00151] wherein in a positive determination that the output of the first data analysis model meets the first condition;

[00152] Step S903: obtaining a second dataset for input into a second data analysis model to obtain a second analysis result;

[00153] Step S904: processing the second analysis result based on a scaling strategy to obtain a third analysis result; and

[00154] Step S905: replacing the first analysis result with the third analysis result.

[00155] The methods described herein may be performed and the various processing or computation units and the devices and computing entities described herein may be implemented by one or more circuits. In an embodiment, a "circuit" may be understood as any kind of a logic implementing entity, which may be hardware, software, firmware, or any combination thereof. Thus, in an embodiment, a "circuit" may be a hard-wired logic circuit or a programmable logic circuit such as a programmable processor, e.g. a microprocessor. A "circuit" may also be software being implemented or executed by a processor, e.g. any kind of computer program, e.g. a computer program using a virtual machine code. Any other kind of implementation of the respective functions which are described herein may also be understood as a "circuit" in accordance with an alternative embodiment.

[00156] While the disclosure has been particularly shown and described with reference to specific embodiments, it should be understood by those skilled in the art that various changes in form and detail may be made therein without departing from the spirit and scope of the disclosure as defined by the appended claims. The scope of the disclosure is thus indicated by the appended claims and all changes which come within the meaning and range of equivalency of the claims are therefore intended to be embraced.

CLAIMS

1. A server apparatus, the server apparatus comprising a processor, the processor configured to:

obtain a first dataset for input into a first data analysis model;

determine, based on at least one of the first dataset and/or a first analysis result of the first data analysis model, whether the first data analysis model is in a first condition;

wherein in a positive determination that an output of the first data analysis model meets the first condition;

obtain a second dataset for input into a second data analysis model to obtain a second analysis result;

process the second analysis result based on a scaling strategy to obtain a third analysis result; and

replace the first analysis result with the third analysis result.

2. The server apparatus of claim 1, wherein the scaling strategy comprises a ratio between a first possible range of the first analysis result and a second possible range of the second analysis result.

3. The server apparatus of claim 2, wherein the second possible range is smaller than the first possible range.

4. The server apparatus of any one of claims 1 to 3, wherein the scaling strategy comprises at least one scaling function, and wherein the at least one scaling function is a univariate polynomial function or a linear function.

5. The server apparatus of any one of claims 1 to 4, wherein the first condition is an abnormal condition.

6. The server apparatus of claim 5, wherein the processor is further configured to determine whether the first dataset contains missing data.

7. The server apparatus of claim 4, wherein the at least one scaling function comprises a first scaling function associated with a first range of the second analysis result, and a second scaling function associated with a second range of the second analysis result.

8. The server apparatus of claim 7, wherein the processor is further configured to monitor one or more changes to the second scaling function.

9. The server apparatus of any one of the preceding claims, wherein the processor is configured to obtain a plurality of first dataset and a plurality of second data analysis models, each of the plurality of first dataset corresponding to one of the plurality of second data analysis models.

10. The server apparatus of any one of the preceding claims, wherein the processor is configured to perform scaling test processing using a historical dataset of the second data analysis model based on an updated scaling strategy to obtain a third test analysis result.

11. The server apparatus of any one of the preceding claims, wherein the second data analysis model is a data disaster recovery model.

12. The server apparatus of any one of the preceding claims, wherein the first data analysis model is a scoring model.

13. A method, the method comprises:

obtaining a first dataset for input into a first data analysis model;

determining, based on at least one of the first dataset and a first analysis result of the first data analysis model, whether the first data analysis model is in a first condition;

wherein in a positive determination that an output of the first data analysis model meets the first condition;

obtaining a second dataset for input into a second data analysis model to obtain a second analysis result;

processing the second analysis result based on a scaling strategy to obtain a third analysis result; and

replacing the first analysis result with the third analysis result.

14. The method of claim 13, wherein processing the second analysis result based on the scaling strategy further comprises defining at least one scaling function, wherein the at least one scaling function is a univariate polynomial function or a linear function.

15. The method of claim 14, further comprises defining a first scaling function associated with a first range of the second analysis result, and defining a second scaling function associated with a second range of the second analysis result.

16. The method of claim 15, further comprises monitoring one or more changes to the second scaling function.

17. The method of any one of claims 13 to 16, wherein the first condition is an abnormal condition.

18. A disaster recovery system, the disaster recovery system arranged in data or signal communication with a main data analysis model, the disaster recovery system comprising a processor configured to:

detect a first dataset for input into the main data analysis model;

determine, based on at least one of the first dataset and/or a first analysis result of the main data analysis model, whether the main data analysis model is in an abnormal condition; wherein in a positive determination that the main data analysis model is in the abnormal condition;

obtain a second dataset for input into a disaster recovery model to obtain a second analysis result;

process the second analysis result based on a scaling strategy to obtain a third analysis result; and

replace the first analysis result with the third analysis result.

19. The disaster recovery system of claim 18, wherein the processor is configured to monitor, on a real-time basis, whether main data analysis model is in the abnormal condition.

20. A non-transitory computer-readable medium storing computer executable code comprising instructions for processing data according to the method of claims 1 to 17.