DESCRIPTION

TITLE OF THE INVENTION

LEARNING DEVICE, LEARNING METHOD, AND LEARNING PROGRAM

Technical Field

[0001] The present invention relates to a learning device, a learning method, and a learning program.

Background Technology

[0002] In some cases, a machine learning model is used to learn the relationship between time series data collected by sensors, etc. that are installed in a chemical plant or the like, and the trained model is used to continuously calculate characteristic values that are difficult to detect or measure for signs of abnormalities.

[0003] For example, in the case of detecting signs of abnormalities, model training is performed to construct a model that detects abnormalities. Therefore, as conventional technology, there is known a technique that performs fuzzy regression analysis based on actual input and output values of multiple instrumentation devices, estimates estimated values of input and output values of a monitored instrumentation device, and displays the difference between the actual input and output values and the estimated values to perform abnormality detection (for example, see Patent Document 1).

Related Art Documents

Patent Documents

[0004] [Patent Document 1] Japanese Patent Application Laid-Open No. 2016-071456

SUMMARY

Problem to be Solved by the Invention

[0005] However, in the above-described conventional technology, it may be difficult to execute accurate inference in the case of data drift occurring in time series data. For example, in the case of maintenance work, etc. being performed on a data acquisition device or equipment targeted by the data acquisition device, data drift may occur in the acquired time series data. And, in the case of data drift occurring in time series data, the relationship between the time series data and the trained model changes, and therefore, it is difficult to perform accurate inference by inputting time series data after data drift to the model that has been trained to perform inference using time series data before drift. In addition, after data drift occurs in time series data, it may take time to accumulate learning data for retraining the model, making prompt model retraining difficult, and as a result, it becomes difficult to continue accurate inference.

Means for Solving the Problem

[0006] Therefore, in order to solve the above problem and achieve the objective, a learning device of the present invention includes: a correction amount calculation unit that calculates a correction parameter using first data included in a reference interval where an operation of equipment satisfies predetermined conditions among time series data before state change of the equipment, and second data included in the reference interval among time series data after state change of the equipment; and a data conversion unit that converts the time series data before state change of the equipment into learning data which is identical or similar to the time series data after state change of the equipment, using the correction parameter calculated by the correction amount calculation unit.

Effects of the Invention

[0007] The present invention achieves an effect of enabling execution of accurate

inference using time series data.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008]

FIG. 1 is a diagram illustrating the overall picture of processing performed by the learning device according to an embodiment.

FIG. 2 is a diagram showing an example of the configuration of the learning device according to the embodiment.

FIG. 3 is a table diagram showing an example of the time series data according to the embodiment.

FIG. 4 is a table diagram showing an example of the reference interval extraction conditions according to the embodiment.

FIG. 5 is a table diagram showing an example of the reference interval data according to the embodiment.

FIG. 6 is a table diagram showing an example of the converted data according to the embodiment.

FIG. 7 is a diagram showing an example of the learning process according to the embodiment.

FIG. 8 is a diagram showing an example of processing in the case of occurrence of multiple state changes according to the embodiment.

FIG. 9 is a flowchart showing an example of the procedure of the learning process according to the embodiment.

FIG. 10 is a hardware configuration diagram showing an example of the computer that realizes the functions of the learning device according to the embodiment.

DESCRIPTION OF THE EMBODIMENTS

[0009] Forms of embodying the present invention (hereinafter, "embodiments") will be described below with reference to the drawings. In the following description, common components are given the same reference numerals, and repeated descriptions will be omitted. Also, the description of the embodiments provided below is not intended to limit the learning device, learning method, and learning program according to the present invention.

[0010] <Introduction>

(Background)

In manufacturing equipment, etc., an abnormality sign detection system or the like may be constructed using a model that has learned the relationship between time series data acquired by sensors, etc. based on machine learning. Then, abnormality detection is performed based on the constructed model.

[0011] For manufacturing equipment, etc., periodic or sudden equipment maintenance such as equipment cleaning, sensor zero point adjustment, overhaul, and replacement with normal products may be implemented. In the case of implementing such maintenance, "data drift" may occur in which the relationship between time series data changes. Hereinafter, data drift may be simply referred to as "drift".

[0012] In the case of occurrence of the above-mentioned drift, the relationship between the time series data and the trained model changes, so it is difficult to perform accurate inference by inputting time series data after drift to the machine learning model that has been trained to perform inference using time series data before drift.

[0013] Therefore, in some cases, a method of collecting time series data as learning data from manufacturing equipment after maintenance and retraining the machine learning model is implemented. However, in order to properly execute retraining, it is required to

wait for accumulation of a sufficient amount of learning data, and it is difficult to continue inference in response to the occurrence of drift.

[0014] (Overview of Processing Performed by Learning Device 100)

Therefore, a learning device 100 according to the present embodiment solves the above-described problem by retraining a machine learning model using converted data that is converted so that time series data before state change of equipment (hereinafter may be referred to as "time series data before state change") can be considered as time series data after state change of equipment (hereinafter may be referred to as "time series data after state change") using a correction parameter in the case of drift occurring due to maintenance.

[0015] Here, a series of flows of processing of the learning device 100 will be described. FIG. 1 is a diagram illustrating the overall picture of processing performed by the learning device 100 according to an embodiment. The learning device 100 shown in FIG. 1 is an example of a computer that provides a technique for retraining a machine learning model using at least one of converted time series data before state change obtained by converting time series data before state change and time series data after state change as learning data. In the present embodiment, a form in which both "converted time series data before state change and time series data after state change" are used as learning data will be described, but the present invention is not limited thereto, and either one of "converted time series data before state change and time series data after state change" may be used as learning data.

[0016] Data included in a reference interval where an operation of equipment satisfies predetermined conditions among time series data before state change acquired from outside may hereinafter be simply referred to as "first data". In addition, data included in the reference interval where an operation of equipment satisfies predetermined conditions among time series data after state change acquired from outside may hereinafter be simply referred to as "second data". The above "reference interval" refers to an interval in which

target equipment performs identical or similar operation before and after state change, and corresponds to, for example, a data interval showing the same behavior or a data interval after stable operation of equipment.

[0017] First, the learning device 100 calculates a correction parameter based on first data extracted from the acquired time series data before state change and second data extracted from the acquired time series data after state change ((1) of FIG. 1). Next, the learning device 100 converts the time series data before state change to be identical or similar to the time series data after state change using the calculated correction parameter ((2) of FIG. 1).

[0018] The learning device 100 retrains a machine learning model using the converted time series data before state change that is converted based on the correction parameter and the time series data after state change as learning data ((3) of FIG. 1). The learning device 100 inputs the time series data after state change to the retrained machine learning model 10 to perform inference ((4) of FIG. 1). Then, the learning device 100 outputs inference results based on the retrained machine learning model as output data ((5) of FIG. 1).

[0019] As described above, the learning device 100 according to the present embodiment enables the machine learning model to be retrained using the time series data before state change converted based on the calculated correction parameter and the time series data after state change as learning data. As a result, the learning device 100 achieves an effect of enabling execution of accurate inference based on the retrained machine learning model even in the case of drift occurring in the time series data. Further, by using the converted time series data before state change and the time series data after state change as learning data, the learning device 100 achieves an effect of being able to construct a machine learning model that adapts to the latest state after state change while utilizing abundant learning data before state change.

[0020] <Description of Learning Device 100>

Detailed functions of the learning device 100 according to the present embodiment will be described below. FIG. 2 is a diagram showing an example of the configuration of the learning device 100 according to the embodiment.

[0021] As shown in FIG. 2, the learning device 100 includes a communication unit 110, a storage unit 120, and a control unit 130. The learning device 100 also includes an input unit (not shown) such as a keyboard and touch panel for receiving input from a user or the like, and a display unit (not shown) such as a display and printer for displaying results of information processing performed by the learning device 100 to the user or the like.

[0022] (Communication Unit 110)

The communication unit 110 performs communication related to output of time series data including time series data before state change, time series data after state change, first data, second data, and converted time series data before state change, inference results based on the machine learning model, and input of time series data related to equipment. The communication unit 110 is realized by a NIC (Network Interface Card) or the like. Then, the communication unit 110 is connected to a network in a wired or wireless manner as required, and can transmit and receive information bidirectionally.

[0023] (Storage Unit 120)

The storage unit 120 is realized by, for example, a RAM (Random Access Memory), a semiconductor memory element such as a flash memory, or a storage device such as a hard disk and optical disk. The storage unit 120 stores data and programs used for various processes to be performed by the control unit 130. In addition, as shown in FIG. 2, the storage unit 120 includes a time series data DB 121, a reference interval extraction condition DB 122, a reference interval data DB 123, converted data DB 124, and a machine learning model DB 125.

[0024] (Time Series Data DB 121)

The time series data DB 121 is a database that stores time series data collected by external data collection devices such as sensors. An example of time series data stored by the time series data DB 121 will be described here using FIG. 3. FIG. 3 is a table diagram showing an example of the time series data according to the embodiment.

[0025] The time series data DB 121 stores "No", which is information identifying data acquired in time series and included in the time series data, and the name of the acquired time series data in association with each other in a table format or the like as shown in FIG. 3. For example, as shown in FIG. 3, the time series data DB 121 stores time series data A "a" identified by No "1".

[0026] Further, as shown in FIG. 3, the time series data DB 121 can store multiple pieces of time series data such as time series data A, B, C, and so on. "a, b, c..." shown in the item of time series data A refer to data included in the target item, and may be information such as numerical values, text, and symbols, for example.

[0027] In addition, the data stored in the time series data DB 121 is not limited to data in table format shown in FIG. 3. For example, the time series data DB 121 can store measurement values obtained from multiple sensors, values calculated from sensor data, sequence numbers, flags representing the operating state of equipment, etc.

[0028] (Reference Interval Extraction Condition DB 122)

The reference interval extraction condition DB 122 is a database that stores reference interval extraction conditions, which are conditions for determining which interval of the time series data corresponds to a reference interval. An example of the reference interval extraction conditions stored by the reference interval extraction condition DB 122 will be described here using FIG. 4. FIG. 4 is a table diagram showing an example of the reference interval extraction conditions according to the embodiment.

[0029] The reference interval extraction condition DB 122 stores "reference interval

conditions", which are conditions for determining whether or not there is a reference interval, in association with "No" that is information for identifying individual records, in a table format or the like as shown in FIG. 4.

[0030] The individual reference interval conditions will be described below. For example, the reference interval extraction condition DB 122 stores "portion of operation performed during equipment start-up in continuous process" as the reference interval condition identified by No "1". The reference interval condition identified by No "1" is a condition that sets, as a reference interval, a data interval in which operations commonly executed during equipment operation start (start-up) are performed among continuous processes of equipment.

[0031] The reference interval extraction condition DB 122 stores "data for n cycles in continuous process of performing periodic operation" as the reference interval condition identified by No "2". The reference interval condition identified by No "2" is a condition that sets, as a reference interval, a data interval corresponding to "n cycles" among periodic operation in which the same operation is repeatedly executed in equipment processes.

[0032] The reference interval extraction condition DB 122 stores "data for n batches in batch process" as the reference interval condition identified by No "3". The reference interval condition identified by No "3" is a condition that sets, as a reference interval, a data interval corresponding to "n batches" among the batch process in equipment processes.

[0033] (Reference Interval Data DB 123)

The reference interval data DB 123 is a database that stores, as reference interval data, data extracted from the acquired time series data based on the reference interval conditions. An example of the reference interval data stored by the reference interval data DB 123 will be described here using FIG. 5. FIG. 5 is a table diagram showing an example of the reference interval data according to the embodiment.

[0034] The reference interval data DB 123 stores "No", which is information for identifying individual data included in the reference interval data, and the extracted reference interval data (for example, first data, second data, etc.) in association with each other in a table format or the like as shown in FIG. 5. For example, as shown in FIG. 5, the reference interval data DB 123 stores first data "a1" in association with identification by No "1".

[0035] Further, as shown in FIG. 5, the reference interval data DB 123 can store multiple pieces of time series data such as first data, second data, and so on. "a1, b1, c1..." shown in the item of the first data refer to data included in the target item, and may be information such as numerical values, text, and symbols, for example.

[0036] (Converted Data DB 124)

The converted data DB 124 is a database that stores converted time series data converted based on the correction parameter as converted data. An example of the converted data stored by the converted data DB 124 will be described here using FIG. 6. FIG. 6 is a table diagram showing an example of the converted data according to the embodiment.

[0037] The converted data DB 124 stores "No", which is information for identifying individual data included in the converted data, and the converted data in association with each other in a table format or the like as shown in FIG. 6. For example, as shown in FIG. 6, the converted data DB 124 stores time series data before state change (after conversion) "a2" in association with identification by No "1".

[0038] (Machine Learning Model DB 125)

The machine learning model DB 125 is a database that stores a machine learning model used to continuously calculate characteristic values that are difficult to detect or measure for signs of abnormalities and occurrence of abnormalities using time series data as input.

For example, in the present embodiment, the machine learning model DB 125 stores a machine learning model trained using time series data before state change and a retrained machine learning model.

[0039] The type of the machine learning model stored by the machine learning model DB 125 is not particularly limited. For example, the machine learning model DB 125 can store machine learning models trained based on supervised learning, unsupervised learning, reinforcement learning, etc., which are known technologies.

[0040] (Control Unit 130)

The control unit 130 is realized by a processor, a MPU (Micro Processing Unit), a CPU (Central Processing Unit), etc., executing various programs stored in the storage unit 120 using RAM as a working area. Additionally, the control unit 130 is realized by, for example, an IC (Integrated Circuit) such as an ASIC (Application Specific Integrated Circuit) and an FPGA (Field Programmable Gate Array).

[0041] As shown in FIG. 2, the control unit 130 includes an acquisition unit 131, an extraction unit 132, a correction amount calculation unit 133, a data conversion unit 134, an inference unit 135, a learning unit 136, and an output unit 137.

[0042] (Acquisition Unit 131)

The acquisition unit 131 acquires time series data collected based on equipment and sensors, etc. that monitor the equipment from a storage medium provided in the equipment and sensors, etc., or from an external information processing device or the like where the time series data is stored. Then, the acquisition unit 131 can store the acquired time series data in the time series data DB 121.

[0043] (Extraction Unit 132)

The extraction unit 132 can extract data of an interval corresponding to the "reference interval" as reference interval data from the time series data stored in the time series data

DB 121, and store the reference interval data in the reference interval data DB 123.

[0044] For example, the extraction unit 132 extracts data corresponding to the reference interval condition "portion of operation performed during equipment start-up in continuous process" stored in the reference interval extraction condition DB 122 from the time series data. Then, the extraction unit 132 can store data corresponding to the reference interval of the time series data before state change as "first data" and data corresponding to the reference interval of the time series data after state change as "second data" in the reference interval data DB 123.

[0045] (Correction Amount Calculation Unit 133)

The correction amount calculation unit 133 calculates a correction parameter using the first data and the second data extracted by the extraction unit 132. Specifically, the correction amount calculation unit 133 compares the first data and the second data to calculate the correction parameter. The calculation of the correction parameter based on comparison between the first data and the second data described above will be described below with specific examples.

[0046] For example, in the case of equipment state change occurring due to drift of the center position of data distribution, which is a predetermined reference point, the correction amount calculation unit 133 calculates the difference value between the center position of data distribution in the first data and the center position of data distribution in the second data as a correction parameter (correction value). For example, the correction amount calculation unit 133 compares the center positions of data distribution between the first data before state change due to maintenance and the second data after state change due to maintenance, and calculates the difference as a correction parameter (correction value).

[0047] Further, for example, in the case of equipment state change occurring due to calibration of the position of a zero point, which is a predetermined reference point, the

correction amount calculation unit 133 calculates the value changed by calibration as a correction parameter. The above example is a correction parameter used in the case of zero point variation of equipment (sensor) being corrected by maintenance. That is, the correction amount calculation unit 133 compares the zero point positions between the first data, which is time series data before state change due to maintenance, and the second data, which is time series data after state change due to maintenance, and calculates the difference as a correction parameter (correction value).

[0048] Here, the calculation of correction parameters in "the case of calibration based on bias being performed" and "the case of calibration based on gain and bias being performed" will be described.

[0049] Calibration based on bias can be expressed by formula (1), which is the correction function (correction method) shown below.

[0050] [Formula 1]

$$f(x) = x + b \quad \cdots (1)$$

f(x): correction function

x: time series data

b: correction parameter calculated from change in bias

[0051] In the case of calibration based on bias as described above being performed, the correction amount calculation unit 133 compares the average values of time series data before and after state change to calculate the correction parameter (for example, "b", etc.) included in the above formula (1). Specifically, the correction amount calculation unit 133 substitutes the average value of the first data (mean(X1)) and the average value of the second data (mean(X2)) into formula (2) shown below to calculate the correction parameter.

[0052] [Formula 2]

$$b = mean(X2) - mean(X1) \quad \cdots (2)$$

mean(X1): average value of first data

mean(X2): average value of second data

[0053] On the other hand, calibration based on gain and bias can be expressed by formula (3) shown below, which is a correction function (correction method).

[0054] [Formula 3]

$$f(x) = a * x + b \quad \cdots (3)$$

f(x): correction function

x: time series data

a: correction parameter calculated from change in gain

b: correction parameter calculated from change in bias

[0055] In the case of calibration based on gain and bias as described above being performed, the correction amount calculation unit 133 calculates correction parameters (for example, "a" and "b", etc.) based on values implemented in the correction that caused the state change.

[0056] For example, it is assumed that in the work that caused the state change, correction was performed so that the zero point became "+z" and the gain became "g times". In that case, the correction amount calculation unit 133 calculates the correction parameters "a" and "b" in formula (3) above based on the following formulas (4) and (5).

[0057] [Formula 4]

$$a = g \quad \cdots (4)$$

[Formula 5]

$$b = z \quad \cdots (5)$$

[0058] (Data Conversion Unit 134)

The data conversion unit 134 uses the correction parameters calculated by the correction amount calculation unit 133 to convert time series data before state change into

learning data that is identical or similar to time series data after state change. Then, the data conversion unit 134 can store the converted time series data before state change in the converted data DB 124.

[0059] Specifically, the data conversion unit 134 converts the time series data before state change using the correction parameters calculated by the correction amount calculation unit 133 and the correction formula, thereby converting the time series data before state change into data that is identical or similar to the time series data after state change.

[0060] For example, in the case of calibration based on bias being performed, the data conversion unit 134 can convert the time series data before state change into data that is identical or similar to the time series data after state change according to the above formula (1), using the correction parameter calculated based on the above formula (2) and the time series data x before state change.

[0061] Further, in the case of calibration based on gain and bias being performed, the data conversion unit 134 can convert the time series data before state change into data that is identical or similar to the time series data after state change according to the above formula (3), using the correction parameters calculated based on the above formulas (4) and (5) and the time series data x before state change.

[0062] (Inference Unit 135)

The inference unit 135 performs inference by inputting the latest time series data after state change that has not been used as learning data to a machine learning model retrained using the converted time series data before state change converted by the data conversion unit 134 and the time series data after state change as learning data.

[0063] For example, the inference unit 135 executes inference such as detection of signs of abnormalities or occurrence of abnormalities and calculation of characteristic values by inputting the time series data after state change to a machine learning model retrained using

the converted time series data before state change and the time series data after state change as learning data.

[0064] In the present embodiment, "inference" includes detection of signs of abnormalities and occurrence of abnormalities, calculation of characteristic values, etc. based on the input time series data.

[0065] (Learning Unit 136)

The learning unit 136 retrains a machine learning model that performs inference with the time series data after state change as input, using the time series data before state change converted by the data conversion unit 134 and the time series data after state change as learning data.

[0066] The learning unit 136 can also learn a machine learning model using only the converted time series data before state change, in addition to learning using the converted time series data before state change and the time series data after state change described above. For example, the learning unit 136 can use only the converted time series data before state change, only the time series data after state change, or both the converted time series data before state change and the time series data after state change as learning data.

[0067] (Output Unit 137)

The output unit 137 outputs the inference result from the inference unit 135 to an information processing device or the like operated by a target user.

[0068] (Example of Processing)

The learning process realized by the learning device 100 according to the present embodiment will be described below using FIG. 7 and FIG. 8. FIG. 7 shows an example of "retraining a machine learning model using the converted time series data before state change and the time series data after state change as learning data" as the first example. Further, FIG. 8 shows an example in regard to "the calculation of correction parameters and

the conversion process of time series data before state change in the case of occurrence of multiple state changes" as the second example.

[0069] (First Example)

First, the first example will be described using FIG. 7. FIG. 7 is a diagram showing an example of the learning process according to the embodiment. The first example is a case where the retraining process of a machine learning model by the learning device 100 is executed in the case of drift occurring due to implementation of equipment maintenance, making accurate inference difficult.

[0070] First, the learning device 100 (acquisition unit) acquires time series data (input data) collected by equipment and sensors, etc., and stores the time series data in the storage unit 120 (time series data DB) ((1) of FIG. 7).

[0071] The learning device 100 (correction amount calculation unit) extracts first data (data corresponding to the reference interval among time series data before state change due to maintenance) and second data (data corresponding to the reference interval among time series data after state change due to maintenance) from the time series data stored in the storage unit 120 (time series data DB) ((2) of FIG. 7).

[0072] The learning device 100 (correction amount calculation unit) calculates a correction parameter ((3) of FIG. 7). Specifically, the learning device 100 (correction amount calculation unit) compares the first data and the second data to calculate the correction parameter ((3-1) of FIG. 7).

[0073] The learning device 100 (data conversion unit) performs data conversion using the calculated correction parameter ((4) of FIG. 7). Specifically, the learning device 100 (data conversion unit) uses the correction parameter ((3-1) of FIG. 7) to convert the time series data before state change ((4-1) of FIG. 7) into data similar to the time series data after state change ((4-2) of FIG. 7).

[0074] The learning device 100 (learning unit) uses the converted time series data before state change and the time series data after state change as learning data to retrain the machine learning model and construct a retrained machine learning model 11 ((5) of FIG. 7).

[0075] The learning device 100 (inference unit) inputs the time series data after state change to the retrained machine learning model 11 to perform inference ((6) of FIG. 7). Then, the learning device 100 (output unit) outputs an inference result based on the retrained machine learning model 11 to the user or the like ((7) of FIG. 7).

[0076] (Second Example)

Next, the second example will be described using FIG. 8. FIG. 8 is a diagram showing an example of processing in the case of occurrence of multiple state changes according to the embodiment. FIG. 8 shows a first period to a third period. And, first maintenance is performed between the first period and the second period, and second maintenance is performed between the second period and the third period.

[0077] As shown in FIG. 8, even in the case where maintenance is performed multiple times during the target period, the learning device 100 can generate learning data by sequentially applying multiple correction parameters calculated for each state change based on respective maintenance.

[0078] Specifically, the learning device 100 (correction amount calculation unit) calculates the first correction parameter based on first data and second data included in a reference interval among time series data after the state has further changed from the state of the equipment related to the first data.

[0079] For example, the learning device 100 (correction amount calculation unit) calculates the first correction parameter using "first data" extracted from time series data related to the first period and "second data" extracted from time series data related to the second period ((1) of FIG. 8).

[0080] Specifically, the learning device 100 (correction amount calculation unit) calculates the second correction parameter based on second data and third data included in a reference interval among time series data after the state has further changed from the state of the equipment related to the second data.

[0081] Next, the learning device 100 (correction amount calculation unit) calculates the second correction parameter using "second data" extracted from time series data related to the second period and "third data" extracted from time series data related to the third period ((2) of FIG. 8).

[0082] Then, the learning device 100 (data conversion unit) converts the converted time series data before state change, which has been converted to be identical or similar to the time series data after state change, using the calculated second correction parameter and the correction formula, so that the converted time series data before state change becomes identical or similar to the time series data after the state has further changed from the state of the equipment related to the second data.

[0083] For example, the learning device 100 (data conversion unit) applies the first correction parameter ((1) of FIG. 8) to the time series data before state change to execute the first conversion process ((3-1) of FIG. 8). Next, the learning device 100 (data conversion unit) applies the second correction parameter ((2) of FIG. 8) to the time series data before state change after the first conversion to execute the second conversion process ((3-2) of FIG. 8). Then, the learning device 100 (data conversion unit) generates time series data before state change after the second conversion that has undergone the second conversion process ((3-3) of FIG. 8).

[0084] As described above, the learning device 100 makes it possible to further increase available learning data by calculating multiple correction parameters from respective reference interval data in the case of occurrence of multiple state changes, and sequentially

applying the correction parameters to the reference interval data.

[0085] (Processing Procedure)

The procedure of processing performed by the learning device 100 according to the present embodiment will be described below using FIG. 9. FIG. 9 is a flowchart showing an example of the procedure of the learning process according to the embodiment.

[0086] The learning device 100 stands by for processing until an event that may cause data drift (for example, periodic maintenance, etc.) occurs (No in S101). Then, in the case of an event that may cause data drift occurring (Yes in S101), the learning device 100 starts processing.

[0087] First, the acquisition unit 131 acquires time series data from outside (S102). Next, the extraction unit 132 extracts time series data before state change and time series data after state change as reference interval data from the time series data before and after state change stored in the time series data DB, as described above (S103).

[0088] The correction amount calculation unit 133 calculates a correction parameter using the extracted reference interval data (first data and second data) (S104). Next, the data conversion unit 134 converts the time series data before state change using the calculated correction parameter (S105).

[0089] The learning unit 136 retrains the machine learning model using the converted time series data before state change (S106). Next, the inference unit 135 executes inference based on the retrained machine learning model (S107). Next, the output unit 137 outputs an inference result based on the converted data (S108). Then, the learning device 100 ends the process.

[0090] (Effects)

The effects achieved by the learning device 100 according to the present embodiment will be described below. Conventionally, in the case where maintenance is performed on

equipment and sensors, etc. and causes drift, the relationship between time series data and the trained machine learning model changes, so there arises a problem that it is difficult to perform accurate inference using time series data before drift.

[0091] Therefore, the correction amount calculation unit 133 of the learning device 100 according to the present embodiment calculates a correction parameter using the first data and the second data. The data conversion unit 134 of the learning device 100 converts the time series data before state change into learning data that is identical or similar to the time series data after state change, using the correction parameter calculated by the correction amount calculation unit 133.

[0092] Through the processing described above, the learning device 100 of the present embodiment achieves an effect of enabling execution of accurate inference using time series data in which drift has occurred.

[0093] For example, in the case of drift occurring, the learning device 100 can retrain the machine learning model more quickly than conventional technology by retraining the machine learning model using data that has been corrected using the correction parameter so that data before drift can be considered as data after drift.

[0094] That is, the learning device 100 enables utilization of a large amount of data that already exists, and enables improvement of accuracy of the trained model as well as adaptation to the latest situation by using time series data in the current situation (after state change of the equipment) (for example, new operating conditions, etc.) as learning data.

[0095] As a result, even in the case of drift occurring due to equipment maintenance, etc., the learning device 100 can prepare learning data required for construction of the machine learning model immediately thereafter, thereby making it possible to quickly retrain the machine learning model, and continuously detect signs of abnormalities and occurrence of abnormalities and perform inference of characteristic values.

[0096] The learning device 100 also achieves the effects described below. The learning unit 136 retrains the machine learning model that performs inference with time series data before state change as input, by using time series data before state change converted using the correction parameter and time series data after state change as learning data.

[0097] Through the processing described above, the learning device 100 can retrain the machine learning model using learning data based on time series data before state change that has already been accumulated, even in situations immediately after equipment state change occurs and sufficient learning data has not been accumulated. Therefore, the learning device 100 achieves an effect of enabling execution of accurate inference using time series data in which drift has occurred, by responding quickly and appropriately to state change.

[0098] Through the processing described above, the converted time series data before state change and the time series data after state change can be treated as identical or similar, which enables these data to be used simultaneously as learning data. This achieves an effect of allowing the machine learning model to be adapted to a new state that changes the operating conditions in the equipment after state change.

[0099] The correction amount calculation unit 133 compares the first data and the second data, and calculates a difference value of a predetermined reference point as a correction parameter. The learning device 100 can calculate a correction parameter used to convert time series data before state change into data similar to time series data after state change, according to the occurrence factor of drift.

[0100] For example, in the case of equipment state change occurring due to calibration of the position of a zero point which is a predetermined reference point, the correction amount calculation unit 133 calculates the value changed by calibration as a correction parameter. Through the processing described above, the learning device 100 can calculate a correction

parameter for performing data conversion according to the event, even in the case of the zero point shifting due to equipment maintenance, etc.

[0101] Further, for example, in the case of equipment state change occurring due to drift of the center position of data distribution, which is a predetermined reference point, the correction amount calculation unit 133 calculates the difference value between the center position of data distribution in the first data and the center position of data distribution in the second data as a correction parameter. Through the processing described above, the learning device 100 can calculate a correction parameter for performing data conversion according to the event, even in the case of data median shifting due to equipment maintenance, etc.

[0102] As a result, the learning device 100 achieves an effect of realizing execution of accurate inference using time series data in which drift has occurred, by enabling appropriate response to various occurrence factors of drift.

[0103] In the case of calibrating the gain (magnification) and zero point of a measuring instrument by maintenance, the correction amount calculation unit 133 calculates a predetermined coefficient as a correction parameter from the adjustment amount of gain. Then, the data conversion unit 134 corrects the time series data after state change using the predetermined coefficient calculated from the adjustment amount of gain.

[0104] Through the processing described above, the learning device 100 can directly use calibration amounts such as gain and shift amount of the AD converter, etc. (for example, "ratio of values before and after calibration" in the case of gain, "difference before and after calibration" in the case of shift amount, etc.) as correction parameters. As a result, the learning device 100 enables efficient conversion of time series data.

[0105] The data conversion unit 134 converts time series data before state change into data that is identical or similar to time series data after state change using the correction

parameter calculated by the correction amount calculation unit 133 and the correction formula.

[0106] Through the processing described above, the learning device 100 enables prompt generation of learning data after occurrence of state change by converting time series data before state change to be similar to time series data after state change, even in the case of drift occurring due to equipment maintenance, etc. As a result, the learning device 100 can continue the inference for signs of abnormalities, occurrence of abnormalities, and characteristic values with minimal stoppage of equipment operation.

[0107] Specifically, the correction amount calculation unit 133 calculates the second correction parameter based on the time series data after state change and the third data included in the reference interval among time series data after the state has further changed from the state of the equipment related to the time series data after state change. The data conversion unit 134 converts the converted time series data before state change, which has been converted to be identical or similar to the time series data after state change, using the second correction parameter, thereby converting the converted time series data before state change to be identical or similar to the time series data after the state has further changed from the state of the equipment related to the second data.

[0108] By correcting the reference interval data based on multiple correction parameters according to state change in this way, the learning device 100 can generate learning data even in the case of equipment maintenance being performed multiple times. Therefore, the learning device 100 achieves an effect of enabling appropriate generation of learning data and retraining of machine learning model regardless of the timing and frequency of maintenance.

[0109] <Modification Example>

The following describes modification examples realized by the learning device 100

according to the present embodiment.

[0110] (Data, etc.)

The names used in the description of the above embodiment, such as before state change, after state change, first data, second data, correction parameter, inference result, and functional units of the learning device 100, steps, processes, and names of steps or processes, are merely examples, and can be changed arbitrarily.

[0111] Although the storage unit 120 of the learning device 100 according to the present embodiment is described as storing target data and information in a table format, the present invention is not limited thereto. For example, the storage unit 120 can store target data and information in formats such as predetermined file and image, in addition to a table format.

[0112] Although the time series data DB 121 is described as storing "No", which is information for identifying data acquired in time series and included in time series data, and the name of acquired time series data in association with each other in a table format or the like as shown in FIG. 3, for example, the table items or contents included in the target items are not limited to the contents shown in FIG. 3.

[0113] In addition, although the reference interval extraction condition DB 122 is described as storing "reference interval conditions", which are conditions for determining whether or not there is a reference interval, in association with "No" that is information for identifying individual records, in a table format or the like as shown in FIG. 4, the table items or contents included in the target items are not limited to the contents shown in FIG. 4.

[0114] Further, although the reference interval data DB 123 is described as storing "No", which is information for identifying individual data included in the reference interval data, and the extracted reference interval data (for example, first data, second data, etc.) in

association with each other in a table format or the like as shown in FIG. 5, the table items or contents included in the target items are not limited to the contents shown in FIG. 5.

[0115] Although the converted data DB 124 is described as storing "No", which is information for identifying individual data included in the converted data, and the converted data (for example, time series data after state change (after conversion)) in association with each other in a table format or the like as shown in FIG. 6, the table items or contents included in the target items are not limited to the contents shown in FIG. 6.

[0116] (Example of Data Used as Learning Data)

Although the learning device 100 is described as converting past time series data to be considered identical to current time series data and using "converted time series data before state change" and "time series data after state change" together as learning data, the data used as learning data is not limited to the above combination. For example, the learning device 100 can retrain the machine learning model using only "converted time series data before state change" as learning data without including time series data after state change.

[0117] (Application Fields, etc.)

The learning device 100 according to the present embodiment can be applied to various fields such as chemical plants, chemical processes, power plant equipment, machining processes (press, NC (Numerically Controlled) machine tools/MC (Machining Center)), semiconductor manufacturing processes, and water treatment equipment. Nevertheless, the application fields mentioned above are merely examples, and the application fields of the learning device 100 according to the present embodiment are not limited.

[0118] (Flowchart, etc.)

Each step in the flowchart, etc. may be performed in a different order within a range that does not cause contradiction, and there may be steps that are not performed. Also, conjunctions such as "next", "subsequently", "further", "at this time", and "at this point" in

the description of the flowchart do not limit the order or timing of performing the processes in the flowchart.

[0119] (Others)

Among the processes described in the above embodiments and modification examples, all or some of the processes described as being performed automatically can also be performed manually, or all or some of the processes described as being performed manually can also be performed automatically by known methods. In addition, the processing procedures, specific names, and information including various data and parameters shown in the above document and drawings can be changed arbitrarily except for cases specifically noted. For example, the various information shown in each drawing is not limited to the illustrated information.

[0120] Furthermore, each component of each device illustrated is functionally conceptual and does not necessarily need to be physically configured as illustrated. That is, the specific form of distribution and integration of each device is not limited to the form illustrated, and all or part thereof can be functionally or physically distributed and integrated in arbitrary units according to various loads, usage conditions, etc.

[0121] The above-described components include those that can be easily assumed by those skilled in the art, those that are substantially the same, and those within the so-called equivalent range. Furthermore, the embodiments and modification examples described above can be appropriately combined within a range that does not contradict the processing content.

[0122] In addition, the above-described "section, module, unit" can be interpreted as "means", "circuit", etc. For example, a control unit can be interpreted as a control means or a control circuit.

[0123] Several embodiments have been described in detail above based on the drawings,

but these are examples, and the present embodiment can be implemented in other forms with various modifications and improvements based on the knowledge of those skilled in the art, including the aspects described in the disclosure section of the invention.

[0124] <Hardware Configuration>

The learning device 100 according to the present embodiment is realized by, for example, a computer 1000 having a configuration as shown in FIG. 10. FIG. 10 is a hardware configuration diagram showing an example of the computer that realizes the functions of the learning device 100 according to the embodiment. The computer 1000 has a form in which a CPU 1100, a RAM 1200, a ROM 1300, an auxiliary storage device 1400, a communication I/F (interface) 1500, and an input/output I/F (interface) 1600 are connected by a bus 1800.

[0125] The CPU 1100 operates based on programs stored in the ROM 1300 or the auxiliary storage device 1400, and controls each unit. The ROM 1300 stores boot programs to be executed by the CPU 1100 when the computer 1000 starts up, programs dependent on the hardware of the computer 1000, etc.

[0126] The auxiliary storage device 1400 stores programs to be executed by the CPU 1100 and data to be used by such programs. The communication I/F 1500 receives data from other devices via a predetermined communication network NW (in the present embodiment, including wireless communication in a closed area) and sends the data to the CPU 1100, and transmits data generated by the CPU 1100 to other devices via the predetermined communication network NW. The CPU 1100 controls an output device such as a display and printer, and an input/output device 1700 such as a keyboard and mouse via the input/output I/F 1600. The CPU 1100 acquires data from the input/output device 1700 via the input/output I/F 1600. Additionally, the CPU 1100 outputs generated data to the input/output device 1700 via the input/output I/F 1600.

[0127] For example, in the case of the computer 1000 functioning as various devices according to the present embodiment, the CPU 1100 of the computer 1000 realizes the functions of the control unit by executing programs loaded on the RAM 1200.

Description of Reference Numerals

[0128]

100 learning device

110 communication unit

120 storage unit

121 time series data DB

122 reference interval extraction condition DB

123 reference interval data DB

124 converted data DB

125 machine learning model DB

130 control unit

131 acquisition unit

132 extraction unit

133 correction amount calculation unit

134 data conversion unit

135 inference unit

136 learning unit

137 output unit

CLAIMS

Claim 1:

A learning device, comprising:

a correction amount calculation unit that calculates a correction parameter using first data included in a reference interval where an operation of equipment satisfies predetermined conditions among time series data before state change of the equipment, and second data included in the reference interval among time series data after state change of the equipment; and

a data conversion unit that converts the time series data before state change of the equipment into learning data which is identical or similar to the time series data after state change of the equipment, using the correction parameter calculated by the correction amount calculation unit.

Claim 2:

The learning device according to claim 1, further comprising:

a learning unit that retrains a machine learning model which performs inference with the time series data before state change of the equipment as input, using the learning data.

Claim 3:

The learning device according to claim 1 or 2, wherein:

the correction amount calculation unit calculates the correction parameter by comparing the first data and the second data.

Claim 4:

The learning device according to claim 3, wherein:

in a case where state change of the equipment occurs due to calibration of a position of a zero point, the correction amount calculation unit calculates a value changed by the calibration as the correction parameter.

Claim 5:

The learning device according to claim 4, wherein:

in a case where state change of the equipment occurs due to drift of a center position of data distribution, the correction amount calculation unit calculates a difference value between a center position of data distribution in the first data and a center position of data distribution in the second data as the correction parameter.

Claim 6:

The learning device according to claim 1, wherein:

the data conversion unit converts the time series data before state change of the equipment to become data which is identical or similar to the time series data after state change of the equipment, using the correction parameter calculated by the correction amount calculation unit and a correction formula.

Claim 7:

The learning device according to claim 1, wherein:

the correction amount calculation unit calculates a second correction parameter based on the second data and third data which is included in the reference interval among time series data after the state has further changed from the state of the equipment related

to the second data, and

the data conversion unit converts converted time series data before state change of the equipment, which has been converted to be identical or similar to the time series data after state change of the equipment, using the second correction parameter and a correction formula, so that the converted time series data before state change of the equipment becomes identical or similar to time series data after the state has further changed from the state of the equipment related to the second data.

Claim 8:

A learning method, executed by a learning device, comprising:

a correction amount calculation step of calculating a correction parameter using first data included in a reference interval where an operation of equipment satisfies predetermined conditions among time series data before state change of the equipment, and second data included in the reference interval among time series data after state change of the equipment; and

a data conversion step of converting the time series data before state change of the equipment into learning data which is identical or similar to the time series data after state change of the equipment, using the correction parameter calculated by the correction amount calculation step.

Claim 9:

A learning program, causing a computer to execute:

a correction amount calculation procedure of calculating a correction parameter using first data included in a reference interval where an operation of equipment satisfies predetermined conditions among time series data before state change of the equipment, and

second data included in the reference interval among time series data after state change of the equipment; and

a data conversion procedure of converting the time series data before state change of the equipment into learning data which is identical or similar to the time series data after state change of the equipment, using the correction parameter calculated by the correction amount calculation procedure.