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(54) OPTIMIZATION OF TIME-SERIES ANOMALY DETECTION

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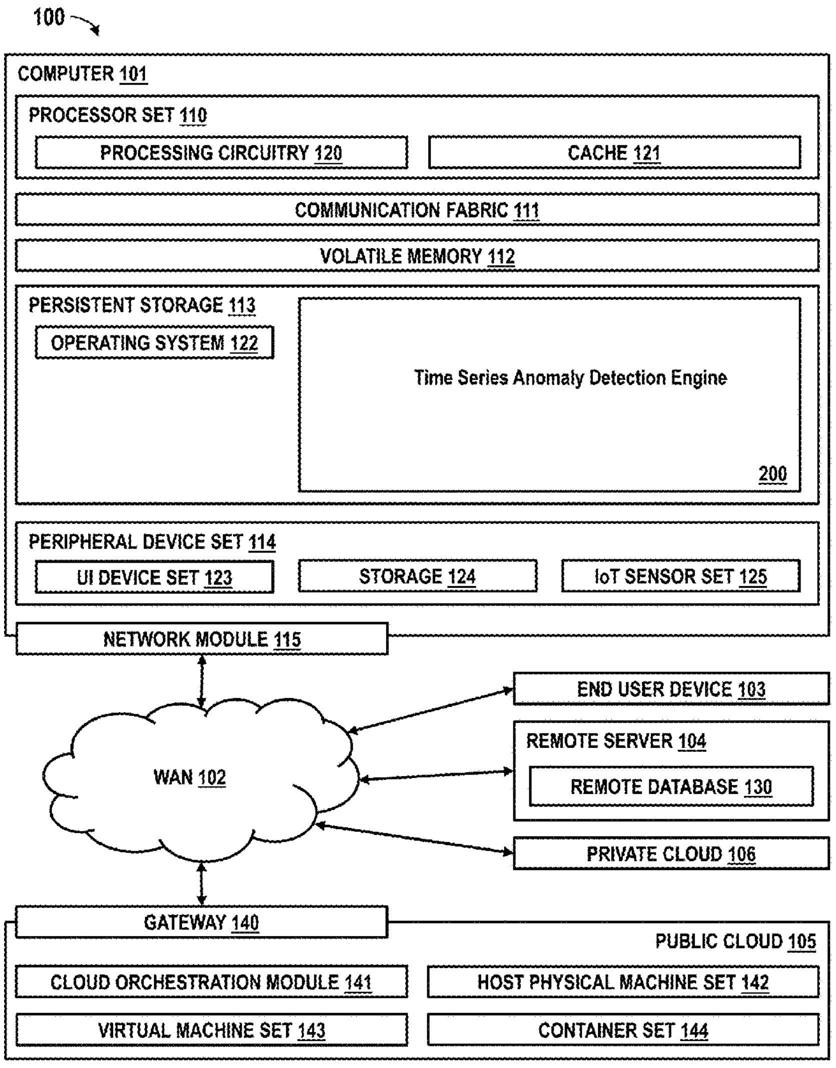
(57) ABSTRACT

An approach to time-series data point anomaly detection is presented. Data point anomalies in time-series data can cause a cascade of incorrect predictions in a time-series data prediction model. Presented herein is an approach to decompose a time-series training data set into elementary components, such as seasonal, trend and residual. The approach determines one or more confidence intervals for elementary components of data points including level shift, variance, and outlier. From these confidence intervals, new data points are analyzed and identified as anomaly data points. The approach also prevents anomaly data points from being incorporated into a time series data prediction model, reducing prediction error in the prediction model.



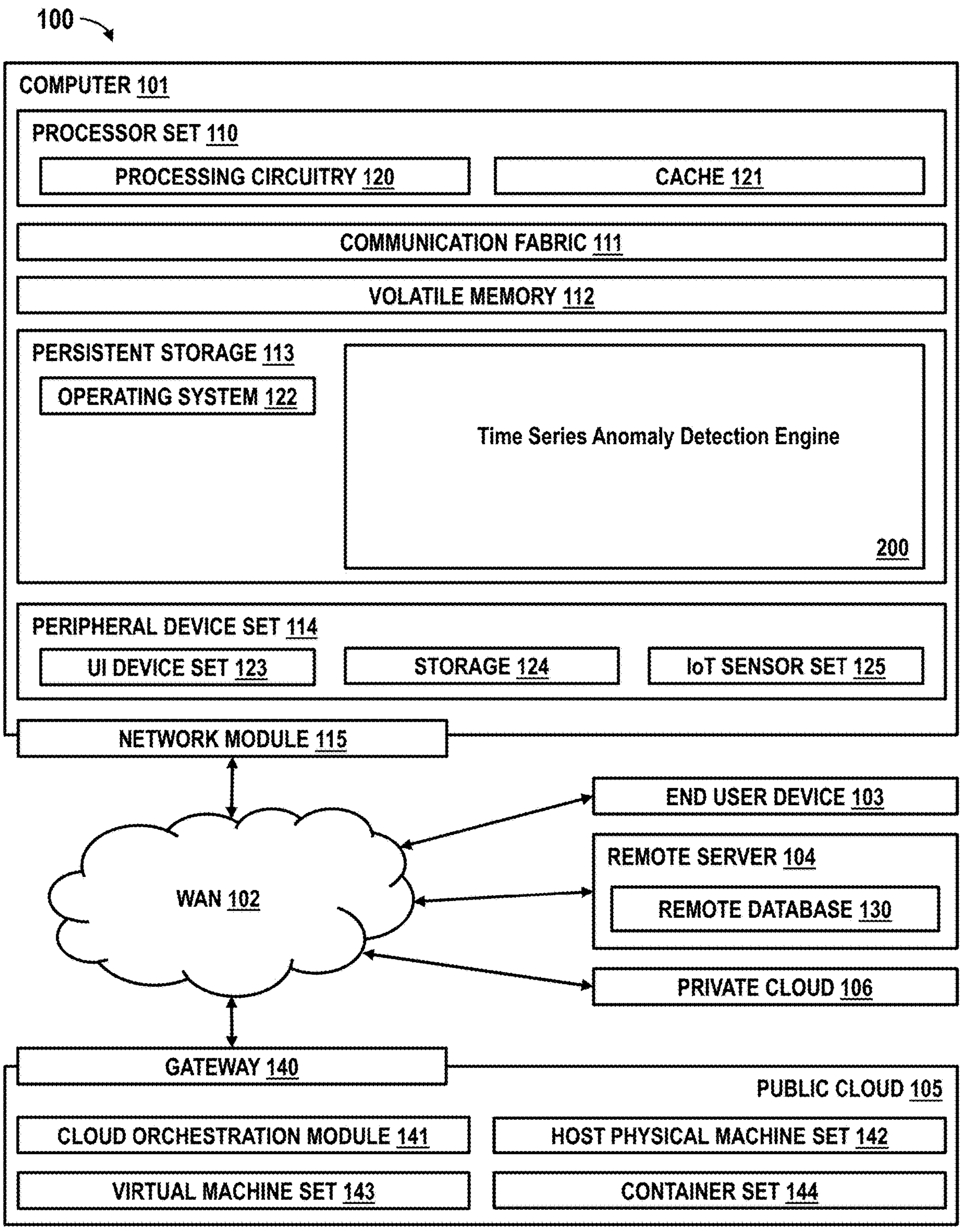

100
COMPUTER 101
PROCESSOR SET 110
PROCESSING CIRCUITRY 120
CACHE 121
COMMUNICATION FABRIC 111
VOLATILE MEMORY 112
PERSISTENT STORAGE 113
OPERATING SYSTEM 122
Time Series Anomaly Detection Engine
200
PERIPHERAL DEVICE SET 114
UI DEVICE SET 123
STORAGE 124
IoT SENSOR SET 125
NETWORK MODULE 115
END USER DEVICE 103
REMOTE SERVER 104
REMOTE DATABASE 130
WAN 102
PRIVATE CLOUD 106
GATEWAY 140
PUBLIC CLOUD 105
CLOUD ORCHESTRATION MODULE 141
HOST PHYSICAL MACHINE SET 142
VIRTUAL MACHINE SET 143
CONTAINER SET 144

FIG. 1

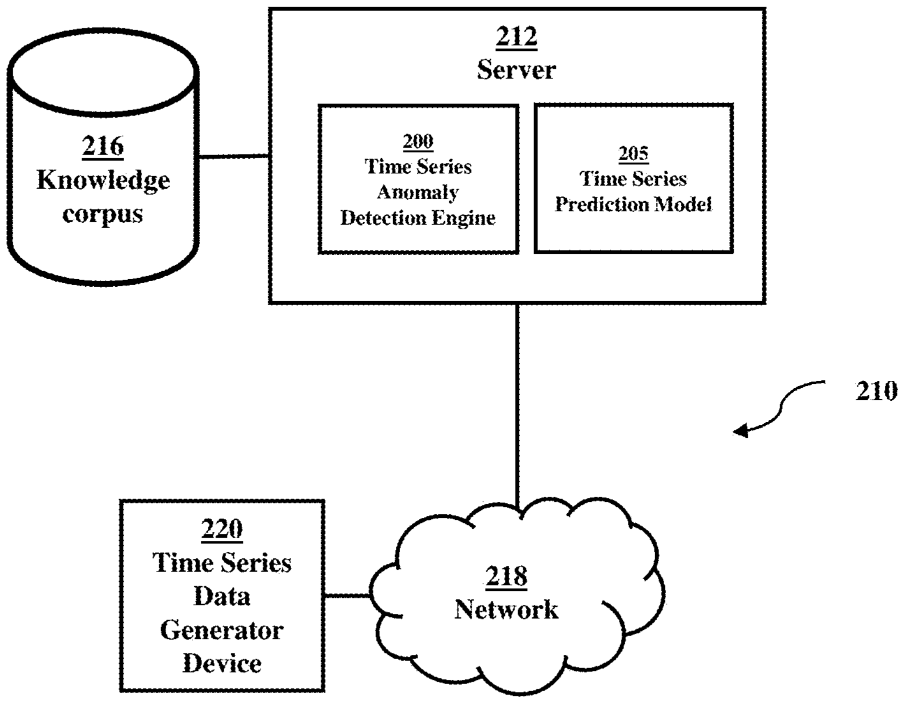

212
Server
200
Time Series Anomaly Detection Engine
205
Time Series Prediction Model
216
Knowledge corpus
210
220
Time Series Data Generator Device
218
Network

FIG. 2A

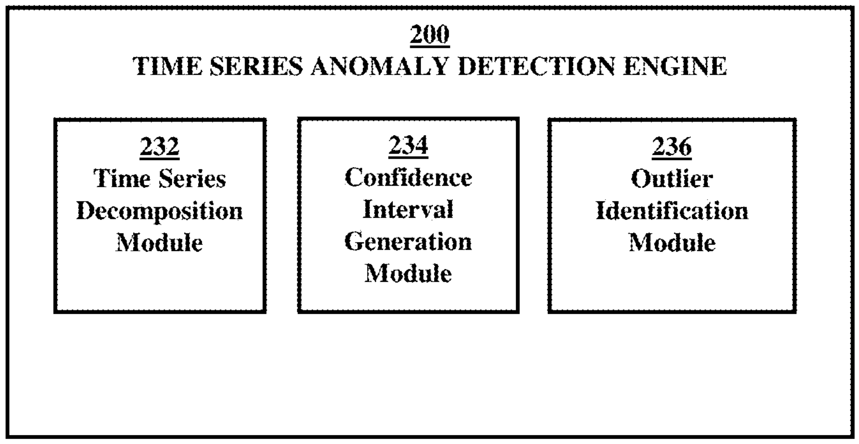

200
TIME SERIES ANOMALY DETECTION ENGINE
232
Time Series Decomposition Module
234
Confidence Interval Generation Module
236
Outlier Identification Module

FIG. 2B

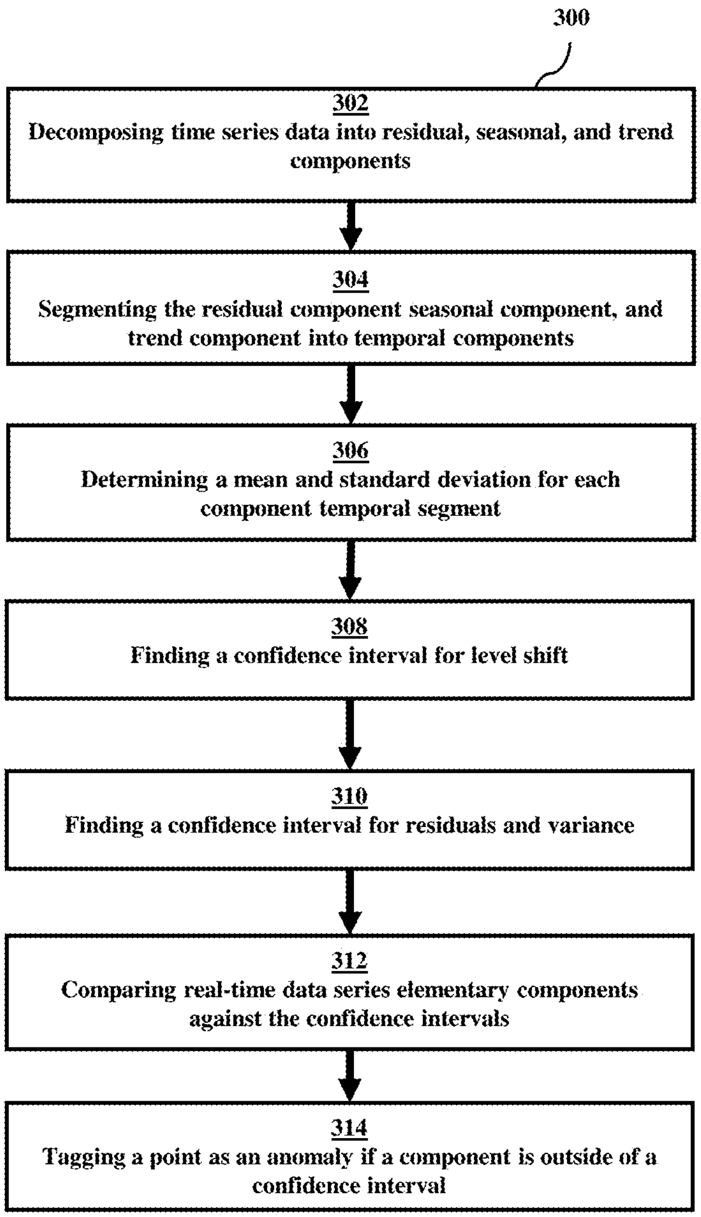

300
302
Decomposing time series data into residual, seasonal, and trend components
304
Segmenting the residual component seasonal component, and trend component into temporal components
306
Determining a mean and standard deviation for each component temporal segment
308
Finding a confidence interval for level shift
310
Finding a confidence interval for residuals and variance
312
Comparing real-time data series elementary components against the confidence intervals
314
Tagging a point as an anomaly if a component is outside of a confidence interval

FIG. 3

OPTIMIZATION OF TIME-SERIES ANOMALY DETECTION

BACKGROUND

[0001] The present invention relates to artificial intelligence and machine learning, and more specifically, to time-series data anomaly detection.

[0002] A time-series dataset are points of some value arranged in chronological order. The data point is comprised of the independent variable which is the time variable and the dependent variable which is the phenomenon being measured. Sensors (e.g., internet of things, etc.) or similar measuring devices typically produce a data sequence or time-series data. Time-series data can also come from financial markets, crop or husbandry yields, sun exposure, electrical usage, network traffic and even wildlife populations. When sensors operate properly, the variation in data points are generally within an expected range.

[0003] In its simplest terms time-series prediction is a task where an initial set of elements in a series is provided and the number of future elements in the series are predicted based on the initial set. Time-series forecasting occurs when you make scientific predictions based on historical time stamped data. Involves building models through historical analysis and using them to make observations and drive future strategic decision-making.

SUMMARY

[0004] In one aspect of the present invention, a method, a computer program product, and a system includes: segmenting a residual component and a trend component of a time-series dataset based on a time value; classifying a first data point of the time-series dataset as an anomaly; determining whether the first data point is within an outlier confidence interval; responsive to a determination the first data point is within the outlier confidence interval, labelling the first data point as a non-outlier; determining whether the first data point is within a level shift confidence interval for a residual segment containing the first data point; responsive to a number of data points of the time-series dataset being labeled as non-outlier data points exceeding a threshold value, calculating a mean difference between a first trend segment corresponding to the residual segment and a second trend segment, which immediately precedes the first trend segment; determining whether the mean difference between the first trend segment and the second trend segment is within a level shift confidence interval; responsive to the mean difference being within the level shift confidence interval, computing a variance difference between the first trend segment and the second trend segment; and responsive to the variance difference being within a variance confidence interval, removing the anomaly classification of the first data point.

BRIEF DESCRIPTION OF THE DRAWINGS

[0005] FIG. **1** is a block diagram depicting an exemplary computing environment, in accordance with an embodiment of the invention.

[0006] FIG. **2**A is a block diagram depicting time-series anomaly detection system **210**, in accordance with an embodiment of the invention.

[0007] FIG. **2**B is a block diagram depicting time-series anomaly detection engine **200**, in accordance with an embodiment of the invention.

[0008] FIG. **3** is a block diagram depicting a method for time-series anomaly detection **300**, in accordance with an embodiment of the invention.

DETAILED DESCRIPTION

[0009] In time-series data prediction models, anomaly detection of incoming data points is an important activity. Training of a time-series prediction model can be a semi-supervised task. The time-series prediction model can quickly determine if it is abnormal when a new input is received, based on the prior historical data and the time at which the new input corresponds. However, upon receiving this abnormal data point the entire model is then adjusted based on the abnormal data point. Thus, future data points predicted by the model, based on the abnormal data point, are then more likely to be abnormal and trigger false positives, until more data points are received to correct the initial abnormal data point. Embodiments of the present invention recognize the advantages of a time-series prediction model determining if a received data point is an abnormal data point. Further, in time-series data prediction, immediate prediction in response to an incoming data point is not typically necessary, thus allowing for a determination of whether the predictions based on the data point are likely to trigger a cascade of false positives.

[0010] In an embodiment, a time-series model prediction result can be adjusted to provide a more accurate and trustworthy result, resistant to abnormal or outlier data points. The embodiment can train a semi-supervised anomaly detection model trained with historical time-series training dataset and analyze the training dataset, thus exploiting traits and through decomposing the training dataset into a trend component, a seasonal component, and a residual component. The components may be analyzed to generate one or more confidence intervals for different abnormal data points, based on explored traits of the time-series dataset. Upon the time-series model receiving abnormal time-series dataset, the generated predictions can be compared against the confidence interval to determine if the generated predictions are false-positives.

[0011] In an embodiment, time-series decomposition can obtain the trend component, the seasonal component, and the residual component. In the time-series decomposition, a time series (X_t) of length n can be decomposed in the following manner,

$$X_t = TC_t + S_t + I_t$$

where TC_t is the trend cycle component, S_t is the seasonal component, and I_t is the residual component.

[0012] The trend component can be obtained by centering a moving average (X_t), based on a moving window size (l). The method to generate the trend component depends on whether l is even or odd. If l is even, then the trend component can be generated as follows:

$$TC_t = \left\{ \frac{X_{t-1/2} + X_{t+1/2}}{2l} + \frac{1}{l}\left(\sum_{j=t-[l/2]}^{t+l/2-1}, X_j \right), t = \frac{l}{2} + 1, \ldots , n - \frac{l}{2}; \right.$$

If l is odd the trend component can be generated as follows:

$$TC_t = \left\{ \frac{1}{l}\left(\sum_{j=t-[l/2]}^{t+l/2-1}, X_j \right), t = \left|\frac{l}{2}\right| + 1, \ldots , n - \left|\frac{l}{2}\right|; \right.$$

where |x| is the largest integer that is not greater than x. In an embodiment, the window size (l) can be specified. However, if the window size is not specified, the default rules may be utilized, where if the period of seasonality is s>1 and n>3s, then l=s and if s=1, but n≥3s, then l=3 for 6≤n≤10, and l=5 for n>10.

[0013] In an embodiment, the seasonal-irregular component can be obtained in the following manner:

$$SI_t = X_t - TC_t$$

further, the seasonal component can be obtained by averaging the seasonal-irregular component for each season:

$$S_{k+js} = \frac{\sum_{t\equiv k(mod\ s)} SI_t}{\text{the number of nonmissing in the summation}}$$

where k=1,2, . . . , s, j is non-negative integer such that 1≤k+js≤n, where t≡k(mod s) means that t and k have the same remainder after division by s. Therefore, the adjusted seasonal component will be

$$AdjS_t = S_t - \frac{\sum_{j=1}^{s} S_j}{s}, t = 1, 2, \ldots , n$$

and the seasonal factors are defined as: SF_k=$AdjS_t$ and k=1,2, . . . , s.

In an embodiment, if s>1 and n≥3s, the residual component can be obtained via

$$I_t = SI_t - AdjS_t$$

if s=1, but n≥3s, the residual component can be obtained via,

$$I_t = X_t - TC_t$$

[0014] In an embodiment, the trend component can be utilized to generate a confidence interval for a level shift. The trend cycle component can be segmented into multiple segments, which corresponding to one or more data points within a given time series. A mean value can be found from the data points within for each segment. Differences can be found between the mean values of each segment against the adjacent segments. Using the differences of the mean values the standard deviation of the mean differences can be calculated. The confidence interval can be generated based on the mean value and the standard deviation. In one embodiment the mean difference can be found via

$$\text{Mean}_{diff} = \sum_{i=1}^{n-1} \frac{Diff_i}{(n-1)}$$

in an embodiment, the standard deviation of the difference can be found via

$$sd(diff) = \sqrt{\frac{\sum_{i=1}^{n-1} (diff_i - \text{mean}_{diff})^2}{(n-2)}}$$

using the standard deviation, a confidence interval can be determined where the interval is provided by [Mean_{diff}−Csd (diff), Mean_{diff}+Csd(diff)], where C is a threshold value (e.g., 0.1 to 0.5).

[0015] Various aspects of the present disclosure are described by narrative text, flowcharts, block diagrams of computer systems and/or block diagrams of the machine logic included in computer program product (CPP) embodiments. With respect to any flowcharts, depending upon the technology involved, the operations can be performed in a different order than what is shown in a given flowchart. For example, again depending upon the technology involved, two operations shown in successive flowchart blocks may be performed in reverse order, as a single integrated step, concurrently, or in a manner at least partially overlapping in time.

[0016] A computer program product embodiment ("CPP embodiment" or "CPP") is a term used in the present disclosure to describe any set of one, or more, storage media (also called "mediums") collectively included in a set of one, or more, storage devices that collectively include machine readable code corresponding to instructions and/or data for performing computer operations specified in a given CPP claim. A "storage device" is any tangible device that can retain and store instructions for use by a computer processor. Without limitation, the computer readable storage medium may be an electronic storage medium, a magnetic storage medium, an optical storage medium, an electromagnetic storage medium, a semiconductor storage medium, a mechanical storage medium, or any suitable combination of the foregoing. Some known types of storage devices that include these mediums include: diskette, hard disk, random access memory (RAM), read-only memory (ROM), erasable programmable read-only memory (EPROM or Flash memory), static random access memory (SRAM), compact disc read-only memory (CD-ROM), digital versatile disk (DVD), memory stick, floppy disk, mechanically encoded device (such as punch cards or pits/lands formed in a major surface of a disc) or any suitable combination of the foregoing. A computer readable storage medium, as that term is used in the present disclosure, is not to be construed as storage in the form of transitory signals per se, such as radio waves or other freely propagating electromagnetic waves, electromagnetic waves propagating through a waveguide, light pulses passing through a fiber optic cable, electrical signals communicated through a wire, and/or other transmission media. As will be understood by those of skill in the art, data is typically moved at some occasional points in time during normal operations of a storage device, such as during access, de-fragmentation or garbage collection, but this does not render the storage device as transitory because the data is not transitory while it is stored.

[0017] Now with reference to FIG. **1**. FIG. **1** depicts Computing environment **100**. Computing environment **100** contains an example of an environment for the execution of at least some of the computer code involved in performing the inventive methods, such as time-series anomaly detection engine **200**. In addition to time-series anomaly detection engine **200**, computing environment **100** includes, for example, computer **101**, wide area network (WAN) **102**, end user device (EUD) **103**, remote server **104**, public cloud **105**, and private cloud **106**. In this embodiment, computer **101** includes processor set **110** (including processing circuitry **120** and cache **121**), communication fabric **111**, volatile memory **112**, persistent storage **113** (including operating system **122** and time-series anomaly detection engine **200**, as identified above), peripheral device set **114** (including user interface (UI) device set **123**, storage **124**, and Internet of Things (IOT) sensor set **125**), and network module **115**. Remote server **104** includes remote database **130**. Public cloud **105** includes gateway **140**, cloud orchestration module **141**, host physical machine set **142**, virtual machine set **143**, and container set **144**.

[0018] COMPUTER **101** may take the form of a desktop computer, laptop computer, tablet computer, smart phone, smart watch or other wearable computer, mainframe computer, quantum computer or any other form of computer or mobile device now known or to be developed in the future that is capable of running a program, accessing a network or querying a database, such as remote database **130**. As is well understood in the art of computer technology, and depending upon the technology, performance of a computer-implemented method may be distributed among multiple computers and/or between multiple locations. On the other hand, in this presentation of computing environment **100**, detailed discussion is focused on a single computer, specifically computer **101**, to keep the presentation as simple as possible. Computer **101** may be located in a cloud, even though it is not shown in a cloud in FIG. **1**. On the other hand, computer **101** is not required to be in a cloud except to any extent as may be affirmatively indicated.

[0019] PROCESSOR SET **110** includes one, or more, computer processors of any type now known or to be developed in the future. Processing circuitry **120** may be distributed over multiple packages, for example, multiple, coordinated integrated circuit chips. Processing circuitry **120** may implement multiple processor threads and/or multiple processor cores. Cache **121** is memory that is located in the processor chip package(s) and is typically used for data or code that should be available for rapid access by the threads or cores running on processor set **110**. Cache memories are typically organized into multiple levels depending upon relative proximity to the processing circuitry. Alternatively, some, or all, of the cache for the processor set may be located "off chip." In some computing environments, processor set **110** may be designed for working with qubits and performing quantum computing.

[0020] Computer readable program instructions are typically loaded onto computer **101** to cause a series of operational steps to be performed by processor set **110** of computer **101** and thereby effect a computer-implemented method, such that the instructions thus executed will instantiate the methods specified in flowcharts and/or narrative descriptions of computer-implemented methods included in this document (collectively referred to as "the inventive methods"). These computer readable program instructions are stored in various types of computer readable storage media, such as cache **121** and the other storage media discussed below. The program instructions, and associated data, are accessed by processor set **110** to control and direct performance of the inventive methods. In computing environment **100**, at least some of the instructions for performing the inventive methods may be stored in time-series anomaly detection engine **200** in persistent storage **113**.

[0021] COMMUNICATION FABRIC **111** is the signal conduction path that allows the various components of computer **101** to communicate with each other. Typically, this fabric is made of switches and electrically conductive paths, such as the switches and electrically conductive paths that make up buses, bridges, physical input/output ports and the like. Other types of signal communication paths may be used, such as fiber optic communication paths and/or wireless communication paths.

[0022] VOLATILE MEMORY **112** is any type of volatile memory now known or to be developed in the future. Examples include dynamic type random access memory (RAM) or static type RAM. Typically, volatile memory **112** is characterized by random access, but this is not required unless affirmatively indicated. In computer **101**, the volatile memory **112** is located in a single package and is internal to computer **101**, but, alternatively or additionally, the volatile memory may be distributed over multiple packages and/or located externally with respect to computer **101**.

[0023] PERSISTENT STORAGE **113** is any form of non-volatile storage for computers that is now known or to be developed in the future. The non-volatility of this storage means that the stored data is maintained regardless of whether power is being supplied to computer **101** and/or directly to persistent storage **113**. Persistent storage **113** may be a read only memory (ROM), but typically at least a portion of the persistent storage allows writing of data, deletion of data and re-writing of data. Some familiar forms of persistent storage include magnetic disks and solid state storage devices. Operating system **122** may take several forms, such as various known proprietary operating systems or open source Portable Operating System Interface-type operating systems that employ a kernel. The code included in block **200** typically includes at least some of the computer code involved in performing the inventive methods.

[0024] PERIPHERAL DEVICE SET **114** includes the set of peripheral devices of computer **101**. Data communication connections between the peripheral devices and the other components of computer **101** may be implemented in various ways, such as Bluetooth connections, Near-Field Communication (NFC) connections, connections made by cables (such as universal serial bus (USB) type cables), insertion-type connections (for example, secure digital (SD) card), connections made through local area communication networks and even connections made through wide area networks such as the internet. In various embodiments, UI device set **123** may include components such as a display screen, speaker, microphone, wearable devices (such as goggles and smart watches), keyboard, mouse, printer, touchpad, game controllers, and haptic devices. Storage **124** is external storage, such as an external hard drive, or insertable storage, such as an SD card. Storage **124** may be persistent and/or volatile. In some embodiments, storage **124** may take the form of a quantum computing storage device for storing data in the form of qubits. In embodiments where computer **101** is required to have a large amount of storage (for example, where computer **101** locally stores and manages a large database) then this storage may be provided by peripheral storage devices designed for storing very large amounts of data, such as a storage area network (SAN) that is shared by multiple, geographically distributed computers. IoT sensor set **125** is made up of sensors that can be used in Internet of Things applications. For example, one sensor may be a thermometer and another sensor may be a motion detector.

[0025] NETWORK MODULE **115** is the collection of computer software, hardware, and firmware that allows computer **101** to communicate with other computers through WAN **102**. Network module **115** may include hardware, such as modems or Wi-Fi signal transceivers, software for packetizing and/or de-packetizing data for communication network transmission, and/or web browser software for communicating data over the internet. In some embodiments, network control functions and network forwarding functions of network module **115** are performed on the same physical hardware device. In other embodiments (for example, embodiments that utilize software-defined networking (SDN)), the control functions and the forwarding functions of network module **115** are performed on physically separate devices, such that the control functions manage several different network hardware devices. Computer readable program instructions for performing the inventive methods can typically be downloaded to computer **101** from an external computer or external storage device through a network adapter card or network interface included in network module **115**.

[0026] WAN **102** is any wide area network (for example, the internet) capable of communicating computer data over non-local distances by any technology for communicating computer data, now known or to be developed in the future. In some embodiments, the WAN **102** may be replaced and/or supplemented by local area networks (LANs) designed to communicate data between devices located in a local area, such as a Wi-Fi network. The WAN and/or LANs typically include computer hardware such as copper transmission cables, optical transmission fibers, wireless transmission, routers, firewalls, switches, gateway computers and edge servers.

[0027] END USER DEVICE (EUD) **103** is any computer system that is used and controlled by an end user (for example, a customer of an enterprise that operates computer **101**) and may take any of the forms discussed above in connection with computer **101**. EUD **103** typically receives helpful and useful data from the operations of computer **101**. For example, in a hypothetical case where computer **101** is designed to provide a recommendation to an end user, this recommendation would typically be communicated from network module **115** of computer **101** through WAN **102** to EUD **103**. In this way, EUD **103** can display, or otherwise present, the recommendation to an end user. In some embodiments, EUD **103** may be a client device, such as thin client, heavy client, mainframe computer, desktop computer and so on.

[0028] REMOTE SERVER **104** is any computer system that serves at least some data and/or functionality to computer **101**. Remote server **104** may be controlled and used by the same entity that operates computer **101**. Remote server **104** represents the machine(s) that collect and store helpful and useful data for use by other computers, such as computer **101**. For example, in a hypothetical case where computer **101** is designed and programmed to provide a recommendation based on historical data, then this historical data may be provided to computer **101** from remote database **130** of remote server **104**.

[0029] PUBLIC CLOUD **105** is any computer system available for use by multiple entities that provides on-demand availability of computer system resources and/or other computer capabilities, especially data storage (cloud storage) and computing power, without direct active management by the user. Cloud computing typically leverages sharing of resources to achieve coherence and economics of scale. The direct and active management of the computing resources of public cloud **105** is performed by the computer hardware and/or software of cloud orchestration module **141**. The computing resources provided by public cloud **105** are typically implemented by virtual computing environments that run on various computers making up the computers of host physical machine set **142**, which is the universe of physical computers in and/or available to public cloud **105**. The virtual computing environments (VCEs) typically take the form of virtual machines from virtual machine set **143** and/or containers from container set **144**. It is understood that these VCEs may be stored as images and may be transferred among and between the various physical machine hosts, either as images or after instantiation of the VCE. Cloud orchestration module **141** manages the transfer and storage of images, deploys new instantiations of VCEs and manages active instantiations of VCE deployments. Gateway **140** is the collection of computer software, hardware, and firmware that allows public cloud **105** to communicate through WAN **102**.

[0030] Some further explanation of virtualized computing environments (VCEs) will now be provided. VCEs can be stored as "images." A new active instance of the VCE can be instantiated from the image. Two familiar types of VCEs are virtual machines and containers. A container is a VCE that uses operating-system-level virtualization. This refers to an operating system feature in which the kernel allows the existence of multiple isolated user-space instances, called containers. These isolated user-space instances typically behave as real computers from the point of view of programs running in them. A computer program running on an ordinary operating system can utilize all resources of that computer, such as connected devices, files and folders, network shares, CPU power, and quantifiable hardware capabilities. However, programs running inside a container can only use the contents of the container and devices assigned to the container, a feature which is known as containerization.

[0031] PRIVATE CLOUD **106** is similar to public cloud **105**, except that the computing resources are only available for use by a single enterprise. While private cloud **106** is depicted as being in communication with WAN **102**, in other embodiments a private cloud may be disconnected from the internet entirely and only accessible through a local/private network. A hybrid cloud is a composition of multiple clouds of different types (for example, private, community or public cloud types), often respectively implemented by different vendors. Each of the multiple clouds remains a separate and discrete entity, but the larger hybrid cloud architecture is bound together by standardized or proprietary technology that enables orchestration, management, and/or data/application portability between the multiple constituent clouds. In this embodiment, public cloud **105** and private cloud **106** are both part of a larger hybrid cloud.

[0032] With reference now to FIG. **2**. FIG. **2** is a block diagram of time-series anomaly detection system **210** in accordance with an embodiment of the invention. Shown in time-series anomaly detection system **210** is server **212**. Operational on server **212** is time-series anomaly detection engine **200** and time-series prediction model **205**. Knowledge corpus **216** is shown stored on server **212**. Also shown in time-series anomaly detection system **210** is network **218**, time-series data generator device **220**. Server **212** is shown in communication with time-series data generator device **220** via network **212** but may also be directly connected to server **212**.

[0033] Time-series prediction model **205** is a computer model which can predict future data points in a time series. This is also known as forecasting. In an embodiment, time-series prediction module **205** can be an artificial intelligence or machine learning model trained with one or more historical datasets of time-series data points. Time-series prediction model **205** can be trained in a semi-supervised manner without anomalies to accurately learn the expected behavior of the time-series data. In an embodiment, time-series prediction model **205** can predict one or more (e.g., 2, 3, n . . . n+1) future data points for real time received time series. In an embodiment, time-series prediction model **205** utilizes a sliding window with a stride of one time segment. This allows time-series prediction model **205** to build a context window and predict or forecast one or more data points in the immediate future. Time-series prediction model **205** can be based on a single forecasting method or a combination of forecasting methods, for example, autoregression, moving average, vector autoregression, simple exponential smoothing, and seasonal autoregressive moving average. Time-series prediction model **205** can be based on a deep learning design architecture for example, recurrent neural network, long short term memory, multi-layer perceptron. Time-series prediction model **205** can also be based on a machine learning model, for example, XGBoost, Random Forest, etc.

[0034] Knowledge corpus **216** is a database which can store historical time-series data points. In an embodiment, knowledge corpus **216** can incorporate newly received data from time-series data generator device **220** into the historical time-series data points into a human readable format. Knowledge corpus **216** can be a database or similar data structure which can retain data points or similar information from a device which records time-series events.

[0035] Time-series data generator device **220** is one or more devices capable of data points in a time based format. For example, time-series data generator device **220** may be a thermometer coupled with a clock. In this example, the thermometer may take temperature readings continuously or at predefined intervals. In another example, time-series data generator device **220** can be a network traffic monitor capable of monitoring data packets uploaded and downloaded at a specific point in an telecommunications system or within a local area network. In another example, time-series data generator may be a program which monitors the frequency and amounts of deposits and withdraws in a financial technology system. In yet another example, time-series data generator device **220** may monitor electricity usage associated with an electrical grid. Other examples of time-series data generator device **220**.

[0036] FIG. **2**B is a block diagram of time-series anomaly detection engine **200**, in accordance with an embodiment of the invention. Shown on anomaly detection engine **200** is time-series decomposition module **232**, confidence interval generation module **234**, and outlier modification module **236**.

[0037] Time-series decomposition module **232** is a computer module that can decompose time-series data into its elementary components. In an embodiment, time-series decomposition module **232** can receive a set of time-series data points from a historical dataset or real-time time-series data points from a device such as time-series data generator device **220**. Time-series decomposition module can decompose the time-series data points into component parts. The component parts can be a trend cycle component, a seasonal cycle component, and a residual cycle component. A trend component may indicate a general increase, decrease, or static pattern over time or the general long term direction. A seasonal component is related to systematic reoccurring patterns (e.g., temperature is a calendar related movement). A residual component is an unsystematic short term fluctuation in a time-series dataset.

[0038] Confidence interval generation module **234** is a computer module that can generate a confidence interval associated with each elementary component of a time-series dataset. In an embodiment, confidence interval generation module **234** can receive the output of times series decomposition module **232** (i.e., the trend component, seasonal component, and residual component). A confidence interval can be generated based on intervals associated with the time-series data points. For example, confidence interval generation module **234** can generate a confidence interval of a level shift associated with a trend component. In another example, confidence interval generation module **234** can generate a confidence interval of residual values. In another embodiment, confidence interval generation module **234** can generate a confidence interval of variance associated with a residual value.

[0039] In an embodiment, confidence interval generation module **234** can generate a confidence interval of an outlier from a residual component. Confidence interval generation module **234** can segment the residual component data points into equal temporal segments. Confidence interval generation module **234** can find the mean value for each individual segment. Confidence interval generation module **234** can find the difference between the mean of each adjacent temporal segment. Confidence interval generation module **234** can find the mean of the differences between adjacent temporal segments and determine a standard deviation. Confidence interval generation module **234** can find a confidence interval of the outlier based on the mean and standard deviation. In an embodiment, the confidence interval can have the mean as the midpoint of the confidence interval plus or minus a multiple of the standard deviation (e.g., 1, 2, n . . . n+1). In another embodiment, the confidence interval can have the mean as the midpoint of the confidence interval plus or minus a constant, times the generated standard deviation. The constant can be predetermined or dynamically determined.

[0040] In an embodiment, confidence interval generation module **234** can generate a confidence interval of a level shift from a trend component. Confidence interval generation module **234** can segment the trend component data points into equal temporal segments. Confidence interval generation module **234** can find the mean value for each individual segment. Confidence interval generation module **234** can find the difference between the mean of each adjacent temporal segment. Confidence interval generation module **234** can find the mean of the differences between adjacent temporal segments and determine a standard deviation. Confidence interval generation module **234** can find a confidence interval of the outlier based on the mean and standard deviation. In an embodiment, the confidence interval can have the mean as the midpoint of the confidence interval plus or minus a multiple of the standard deviation (c.g., 1, 2, n . . . n+1). In another embodiment, the confidence interval can have the mean as the midpoint of the confidence interval plus or minus a constant, times the generated standard deviation. The constant can be predetermined or dynamically determined.

[0041] In an embodiment, confidence interval generation module **234** can generate a confidence interval of variance from a residual component. Confidence interval generation module **234** can segment the residual component data points into equal temporal segments. Confidence interval generation module **234** can find the variance value for each individual segment. Confidence interval generation module **234** can find the difference between the variance of each adjacent temporal segment. Confidence interval generation module **234** can find the mean of the variance differences between adjacent temporal segments and determine a standard deviation. Confidence interval generation module **234** can find a confidence interval of the outlier based on the mean and standard deviation of the variance differences. In an embodiment, the confidence interval can have the mean as the midpoint of the confidence interval plus or minus a multiple of the standard deviation (e.g., 1, 2, n . . . n+1). In another embodiment, the confidence interval can have the mean as the midpoint of the confidence interval plus or minus a constant, times the generated standard deviation. The constant can be predetermined or dynamically determined.

[0042] Outlier identification module **236** is a computer module that can identify outlier data points in time-series data. In an embodiment, outlier identification module **236** can receive, as input, a confidence interval value generated by confidence interval generation module **234** and a time-series data point components of real-time time-series data decomposed by time-series decomposition module **236**. Outlier identification module **236** can analyze a decomposed real-time data point component in comparison to a confidence interval (e.g., a level shift, variance, and outlier). If outlier identification module **236** determines the decomposed real time data point is outside of one or more of the confidence intervals, outlier identification module **236** will identify or tag that data point as an anomaly. The type of anomaly corresponds to the confidence interval which the data point does not fall within. For example, the tags can be level shift, variance, and/or outlier.

[0043] Upon identifying or tagging the data point as an anomaly, outlier identification module **236** can signal or cause time-series prediction model to ignore the data point in its prediction or forecasting consideration. In an embodiment, outlier identification module **236** may send the expected mean value to for the data point at that time to prevent time-series prediction model from basing its future predictions on an anomaly data point. In an embodiment, outlier identification module can keep a running list of identified anomaly data points. If multiple anomaly data points are detected in succession, outlier identification module **236** can send the identified anomaly data points to time-series prediction model **205** with instructions to include the data points in its predictions to prevent incorrect predictions or drift.

[0044] With reference now to FIG. **3**. FIG. **3** is flowchart **300** depicting the steps of time-series data anomaly detection. At step **302**, Decomposing time-series data into a residual, seasonal, and a trend component. At step **304**, segmenting the residual component and the trend component into equal temporal components. At step **306**, determining a mean for each temporal segment and a standard deviation for the difference of the mean between each adjacent temporal segment for the residual component and trend component. At step **308**, finding a confidence interval for level shift based on the mean and standard deviation trend component. At step **310**, finding a confidence interval for outlier and a confidence interval for variance based on the mean and standard deviation residual component. At step **312**, compare the elementary components of a real-time data series point against the corresponding confidence intervals. At step **314**, responsive to an elementary component being outside a confidence interval, tagging the data point as an anomaly.

[0045] The descriptions of the various embodiments of the present invention have been presented for purposes of illustration, but are not intended to be exhaustive or limited to the embodiments disclosed. Many modifications and variations will be apparent to those of ordinary skill in the art without departing from the scope and spirit of the described embodiments. The terminology used herein was chosen to best explain the principles of the embodiments, the practical application or technical improvement over technologies found in the marketplace, or to enable others of ordinary skill in the art to understand the embodiments disclosed herein.

What is claimed is:

1. A computer-implemented method comprising:

segmenting a residual component and a trend component of a time-series dataset based on a time value;

classifying a first data point of the time-series dataset as an anomaly;

determining whether the first data point is within an outlier confidence interval;

responsive to a determination the first data point is within the outlier confidence interval, labelling the first data point as a non-outlier;

determining whether the first data point is within a level shift confidence interval for a residual segment containing the first data point;

responsive to a number of data points of the time-series dataset being labeled as non-outlier data points exceeding a threshold value, calculating a mean difference between a first trend segment corresponding to the residual segment and a second trend segment, which immediately precedes the first trend segment;

determining whether the mean difference between the first trend segment and the second trend segment is within the level shift confidence interval;

responsive to the mean difference being within the level shift confidence interval, computing a variance difference between the first trend segment and the second trend segment; and

responsive to the variance difference being within a variance confidence interval, removing the anomaly classification of the first data point.

2. The computer-implemented method of claim **1**, further comprising:

predicting one or more time-series data points for the time-series dataset based at least in part on the first data point, wherein the anomaly classification of the first data point has been removed.

3. The computer-implemented method of claim **1**, further comprising:

training a semi-supervised anomaly detection model, wherein the semi-supervised anomaly detection model is based on trait exploration of a historical time-series training dataset.

4. The computer-implemented method of claim **3**, further comprising:

decomposing the historical time-series training dataset into a historical residual component;

segmenting the historical residual component into historical residual segments;

computing mean values for the historical residual segments;

finding a difference between the mean values of adjacent historical residual segments;

computing a mean difference based on the difference between the mean values of adjacent historical residual segments;

computing a standard deviation based on the mean difference; and

generating an outlier confidence interval, wherein a maximum of the outlier confidence interval is the mean difference increased by the standard deviation and multiplied by a threshold, and a minimum of the outlier confidence interval is the mean difference reduced by the standard deviation and multiplied by the threshold.

5. The computer-implemented method of claim **3**, further comprising:

decomposing the historical time-series training dataset into a historical trend component;

segmenting the historical trend component into historical trend segments;

computing mean values for the historical trend segments;

finding a difference between the mean values of adjacent historical trend segments;

computing a mean difference based on the difference between the mean values of adjacent historical trend segments;

computing a standard deviation based on the mean difference; and

generating a level shift interval, wherein a maximum of the level shift interval is the mean difference increased by the standard deviation and multiplied by a threshold, and a minimum of the level shift interval is the mean difference reduced by the standard deviation and multiplied by the threshold.

6. The computer-implemented method of claim **3**, further comprising:

decomposing the historical time-series training dataset into a historical residual component;

segmenting the historical residual component into historical residual segments;

computing variances for the historical residual segments;

finding a difference between the variances of adjacent historical residual segments;

computing a variance difference based on the difference between the variance values of adjacent historical residual segments;

computing a standard deviation based on the variance difference; and

generating a historic variance confidence interval, wherein a maximum of the historic variance confidence interval is the variance difference increased by the standard deviation and multiplied by a threshold, and a minimum of the historic variance confidence interval is the variance difference reduced by the standard deviation and multiplied by the threshold.

7. The computer-implemented method of claim **1**, wherein the time-series dataset is associated with electricity generation.

8. A computer system comprising:

a processor set; and

a computer-readable storage medium having program instructions stored therein;

wherein:

the processor set executes the program instructions that cause the processor set to perform a method comprising:

segmenting a residual component and a trend component of a time-series dataset based on a time value;

classifying a first data point of the time-series dataset as an anomaly;

determining whether the first data point is within an outlier confidence interval;

responsive to a determination the first data point is within the outlier confidence interval, labelling the first data point as a non-outlier;

determining whether the first data point is within a level shift confidence interval for a residual segment containing the first data point;

responsive to a number of data points of the time-series dataset being labeled as non-outlier data points exceeding a threshold value, calculating a mean difference between a first trend segment corresponding to the residual segment and a second trend segment, which immediately precedes the first trend segment;

determining whether the mean difference between the first trend segment and the second trend segment is within the level shift confidence interval;

responsive to the mean difference being within the level shift confidence interval, computing a variance difference between the first trend segment and the second trend segment; and

responsive to the variance difference being within a variance confidence interval, removing the anomaly classification of the first data point.

9. The computer system of claim **8**, wherein the program instructions further cause the processor set to perform a method comprising:

predicting one or more time-series data points for the time-series dataset based at least in part on the first data point, wherein the anomaly classification of the first data point has been removed.

10. The computer system of claim **8**, wherein the program instructions further cause the processor set to perform a method comprising:

training a semi-supervised anomaly detection model, wherein the anomaly detection model is based on trait exploration of a historical time-series training dataset.

11. The computer system of claim **10**, wherein the program instructions further cause the processor set to perform a method comprising:

decomposing the historical time-series training dataset into a historical residual component;

segmenting the historical residual component into historical residual segments;

computing mean values for the historical residual segments;

finding a difference between the mean values of adjacent historical residual segments;

computing a mean difference based on the difference between the mean values of adjacent historical residual segments;

computing a standard deviation based on the mean difference; and

generating an outlier confidence interval, wherein a maximum of the outlier confidence interval is the mean difference increased by the standard deviation and multiplied by a threshold, and a minimum of the outlier confidence interval is the mean difference reduced by the standard deviation and multiplied by the threshold.

12. The computer system of claim **10**, wherein the program instructions further cause the processor set to perform a method comprising:

decomposing the historical time-series training dataset into a historical trend component;

segmenting the historical trend component into historical trend segments;

computing mean values for the historical trend segments;

finding a difference between the mean values of adjacent historical trend segments;

computing a mean difference based on the difference between the mean values of adjacent historical trend segments;

computing a standard deviation based on the mean difference; and

generating a level shift interval, wherein a maximum of the level shift interval is the mean difference increased by the standard deviation and multiplied by a threshold, and a minimum of the level shift interval is the mean difference reduced by the standard deviation and multiplied by the threshold.

13. The computer system of claim **10**, wherein the program instructions further cause the processor set to perform a method comprising:

decomposing the historical time-series training dataset into a historical residual component;

segmenting the historical residual component into historical residual segments;

computing variances for the historical residual segments;

finding a difference between the variances of adjacent historical residual segments;

computing a variance difference based on the difference between the variance values of adjacent historical residual segments;

computing a standard deviation based on the variance difference; and

generating a historic variance confidence interval, wherein a maximum of the historic variance confidence interval is the variance difference increased by the standard deviation and multiplied by a threshold, and a minimum of the historic variance confidence interval is the variance difference reduced by the standard deviation and multiplied by the threshold.

14. The computer system of claim **8**, wherein the time-series data is associated with electricity generation.

15. A computer program product comprising a computer-readable storage medium having a set of instructions stored therein which, when executed by a processor, cause the processor to perform a method comprising:

segmenting a residual component and a trend component of a time-series dataset based on a time value;

classifying a first data point of the time-series dataset as an anomaly;

determining whether the first data point is within an outlier confidence interval;

responsive to a determination the first data point is within the outlier confidence interval, labelling the first data point as a non-outlier;

determining whether the first data point is within a level shift confidence interval for a residual segment containing the first data point;

responsive to a number of data points of the time-series dataset being labeled as non-outlier data points exceeding a threshold value, calculating a mean difference between a first trend segment corresponding to the residual segment and a second trend segment, which immediately precedes the first trend segment;

determining whether the mean difference between the first trend segment and the second trend segment is within a level shift confidence interval;

responsive to the mean difference being within the level shift confidence interval, computing a variance difference between the first trend segment and the second trend segment; and

responsive to the variance difference being within a variance confidence interval, removing the anomaly classification of the first data point.

16. The computer program product of claim **15**, further causing the processor to perform a method comprising:

predicting one or more time-series data points for the time-series dataset based at least in part on the first data point, wherein the anomaly classification of the first data point has been removed.

17. The computer program product of claim **15**, further causing the processor to perform a method comprising:

training a semi-supervised anomaly detection model, wherein the anomaly detection model is based on trait exploration of a historical time-series training dataset.

18. The computer program product of claim **17**, further causing the processor to perform a method comprising:

decomposing the historical time-series training dataset into a historical residual component;

segmenting the historical residual component into historical residual segments;
computing mean values for the historical residual segments;
finding a difference between the mean values of adjacent historical residual segments;
computing a mean difference based on the difference between the mean values of adjacent historical residual segments;
computing a standard deviation based on the mean difference; and
generating an outlier confidence interval, wherein a maximum of the outlier confidence interval is the mean difference increased by the standard deviation and multiplied by a threshold, and a minimum of the outlier confidence interval is the mean difference reduced by the standard deviation and multiplied by the threshold.

19. The computer program product of claim **17**, further causing the processor to perform a method comprising:
decomposing the historical time-series training dataset into a historical trend component;
segmenting the historical trend component into historical trend segments;
computing mean values for the historical trend segments;
finding a difference between the mean values of adjacent historical trend segments;
computing a mean difference based on the difference between the mean values of adjacent historical trend segments;
computing a standard deviation based on the mean difference; and
generating a level shift interval, wherein a maximum of the level shift interval is the mean difference increased by the standard deviation and multiplied by a threshold, and a minimum of the level shift interval is the mean difference reduced by the standard deviation and multiplied by the threshold.

20. The computer program product of claim **17**, further causing the processor to perform a method comprising:
decomposing the historical time-series training dataset into a historical residual component;
segmenting the historical residual component into historical residual segments;
computing variances for the historical residual segments;
finding a difference between the variances of adjacent historical residual segments;
computing a variance difference based on the difference between the variance values of adjacent historical residual segments;
computing a standard deviation based on the variance difference; and
generating the variance confidence interval, wherein a maximum of the variance confidence interval is the variance difference increased by the standard deviation and multiplied by a threshold, and a minimum of the variance confidence interval is the variance difference reduced by the standard deviation and multiplied by the threshold.

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