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(54) USING THREAD PATTERNS TO IDENTIFY ANOMALOUS BEHAVIOR

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CPC ***G06F 21/552*** (2013.01); ***G06F 9/45558*** (2013.01); *G06F 2009/45587* (2013.01); *G06F 2221/034* (2013.01)

(58) **Field of Classification Search**
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See application file for complete search history.

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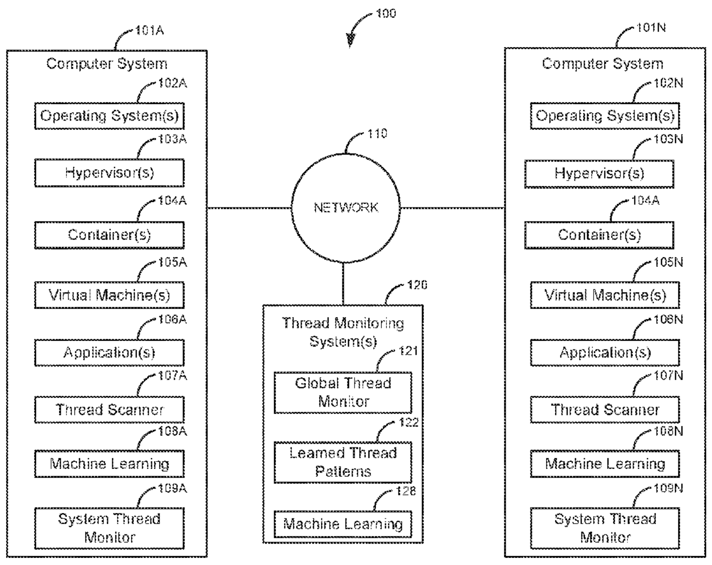
(57) **ABSTRACT**

Thread information generated by one or more computing systems is captured. A thread pattern is identified from the captured thread information. The thread pattern is compared to a learned thread pattern. An anomaly is identified in the thread pattern based on a variance from the learned thread pattern. In response to identifying the anomaly in the thread pattern, an action is taken based on the anomalous thread pattern. For example, a user may be notified. The thread patterns may be extended to compare between operating systems, hypervisors, containers, and/or virtual machines.

20 Claims, 8 Drawing Sheets



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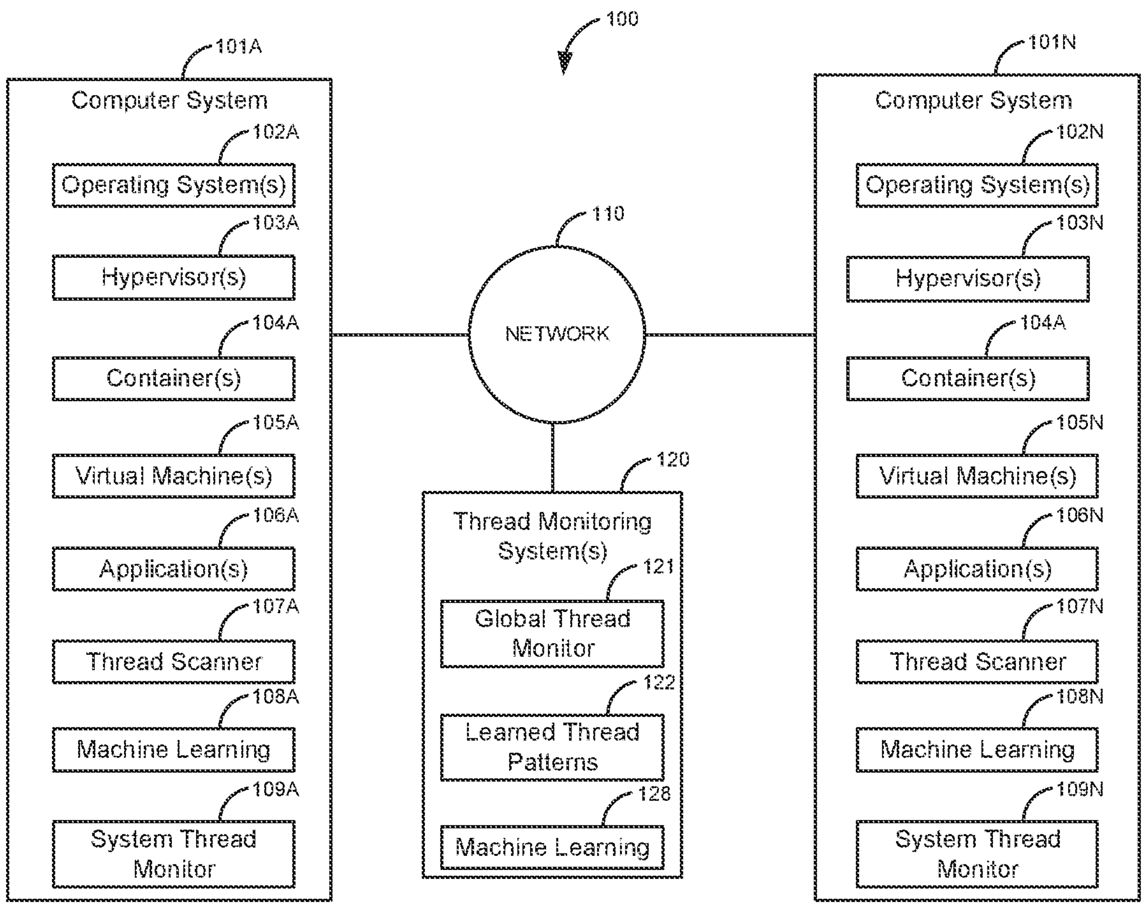
100
101A
Computer System
102A
Operating System(s)
103A
Hypervisor(s)
104A
Container(s)
105A
Virtual Machine(s)
106A
Application(s)
107A
Thread Scanner
108A
Machine Learning
109A
System Thread Monitor
110
NETWORK
120
Thread Monitoring System(s)
121
Global Thread Monitor
122
Learned Thread Patterns
128
Machine Learning
101N
Computer System
102N
Operating System(s)
103N
Hypervisor(s)
104A
Container(s)
105N
Virtual Machine(s)
106N
Application(s)
107N
Thread Scanner
108N
Machine Learning
109N
System Thread Monitor

FIG. 1

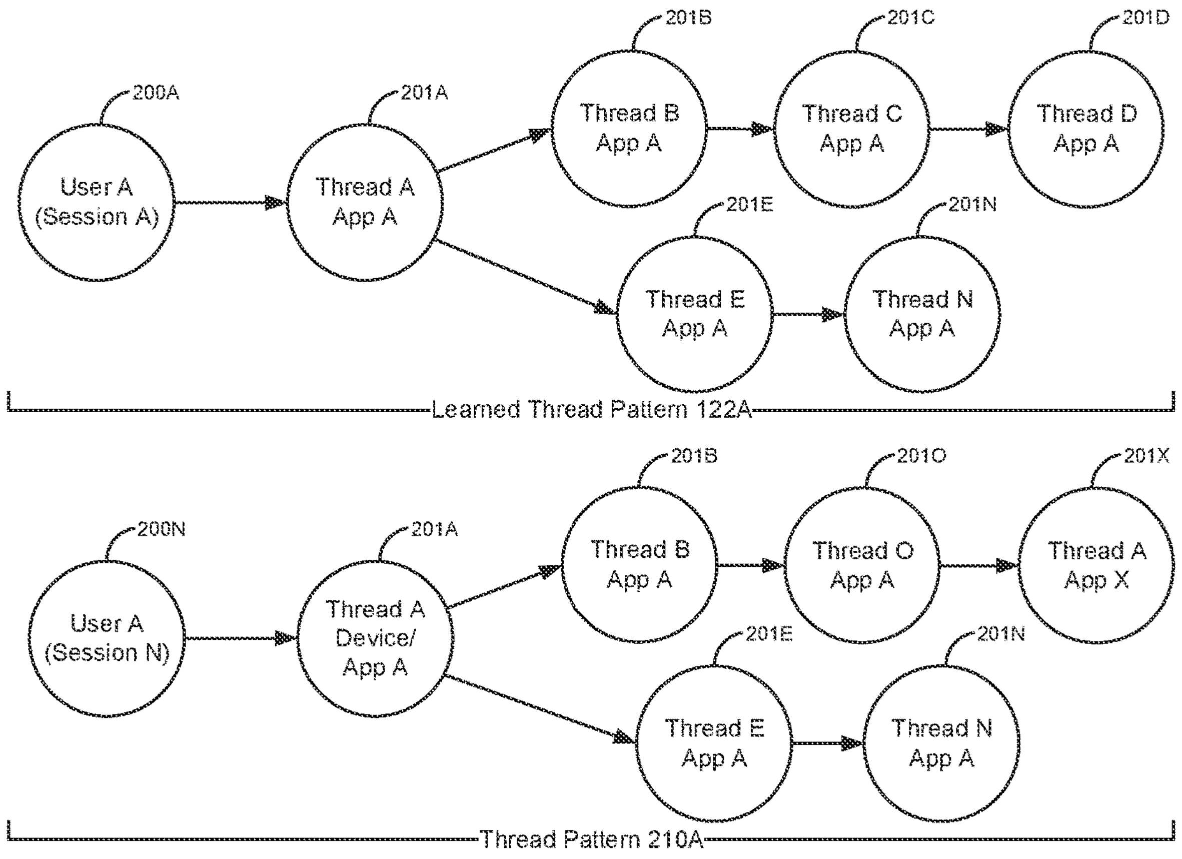
200A
User A (Session A)
201A
Thread A App A
201B
Thread B App A
201C
Thread C App A
201D
Thread D App A
201E
Thread E App A
201N
Thread N App A
Learned Thread Pattern 122A
200N
User A (Session N)
201A
Thread A Device/ App A
201B
Thread B App A
201O
Thread O App A
201X
Thread A App X
201E
Thread E App A
201N
Thread N App A
Thread Pattern 210A

FIG. 2

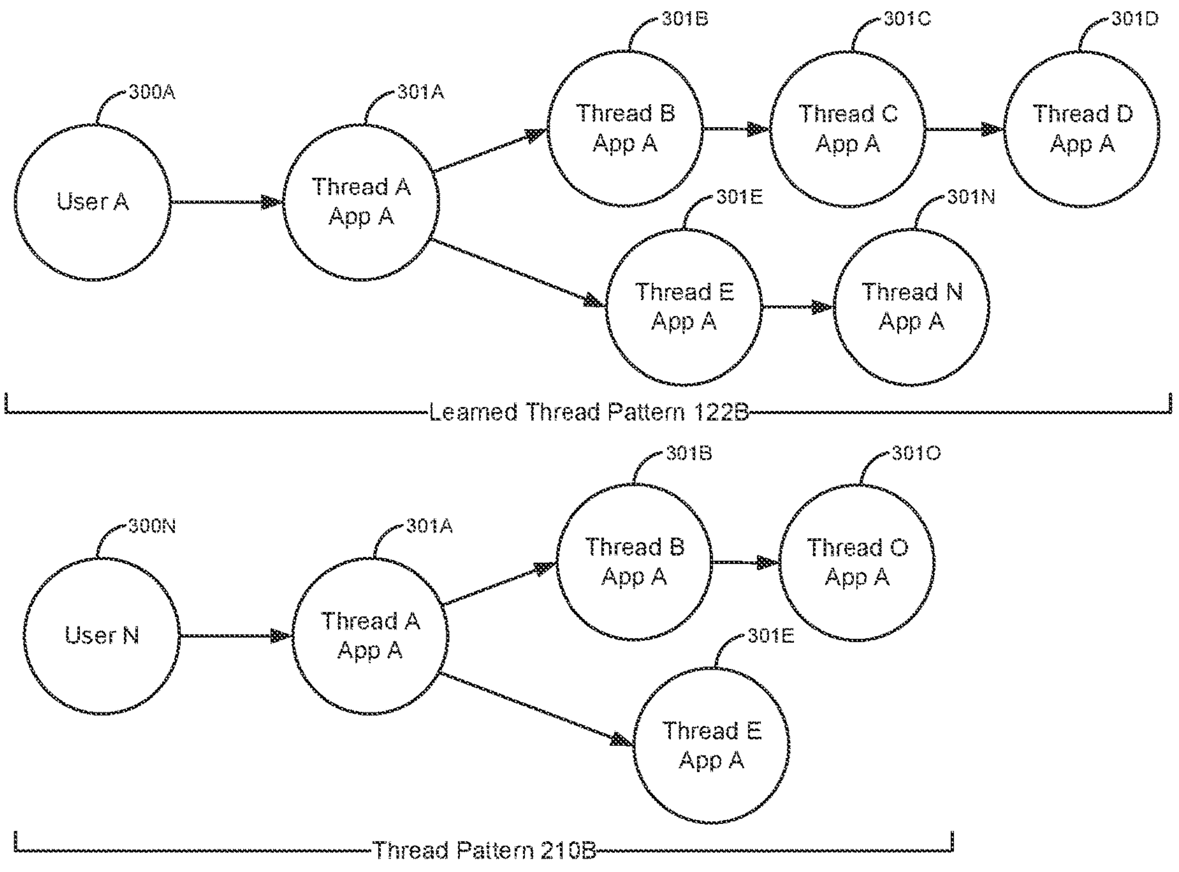
300A
User A
301A
Thread A App A
301B
Thread B App A
301C
Thread C App A
301D
Thread D App A
301E
Thread E App A
301N
Thread N App A
Learned Thread Pattern 122B
300N
User N
301A
Thread A App A
301B
Thread B App A
301O
Thread O App A
301E
Thread E App A
Thread Pattern 210B

FIG. 3

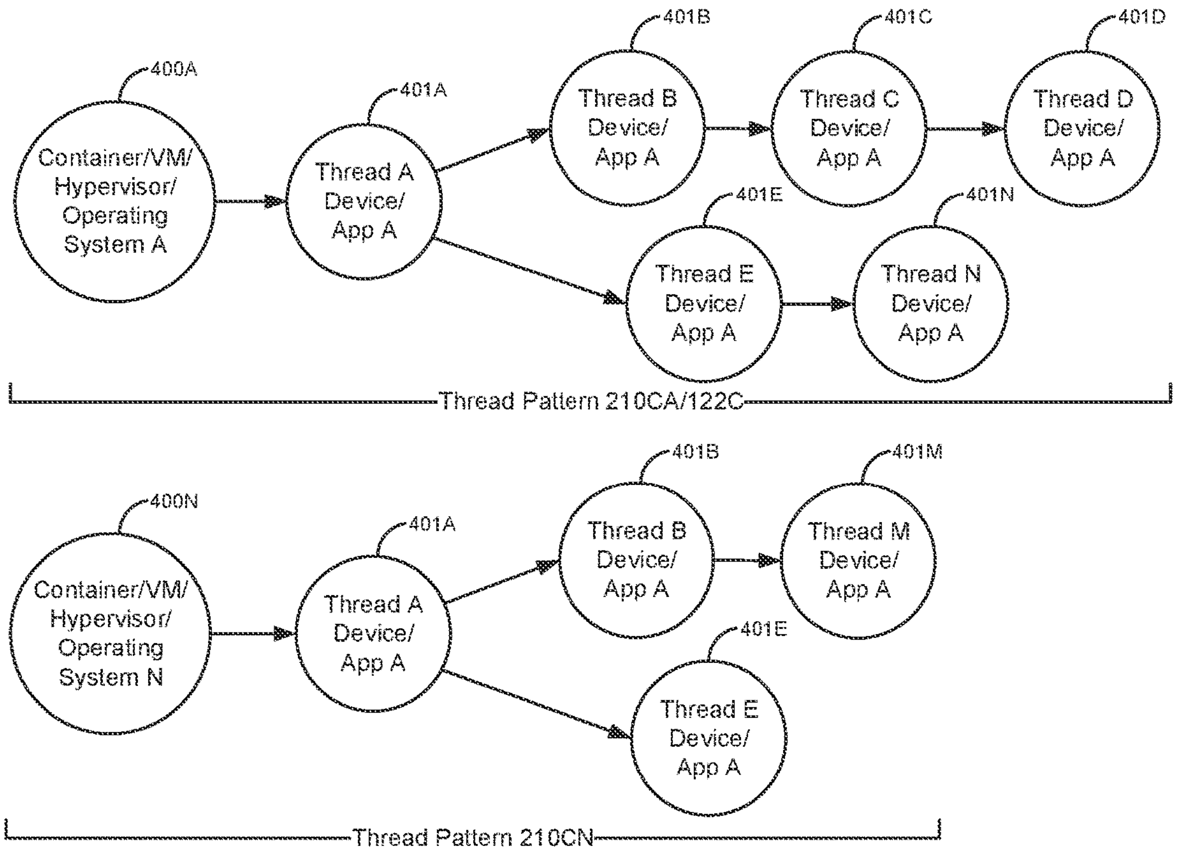
400A
Container/VM/ Hypervisor/ Operating System A
401A
Thread A Device/ App A
401B
Thread B Device/ App A
401C
Thread C Device/ App A
401D
Thread D Device/ App A
401E
Thread E Device/ App A
401N
Thread N Device/ App A
Thread Pattern 210CA/122C
400N
Container/VM/ Hypervisor/ Operating System N
401A
Thread A Device/ App A
401B
Thread B Device/ App A
401M
Thread M Device/ App A
401E
Thread E Device/ App A
Thread Pattern 210CN

FIG. 4

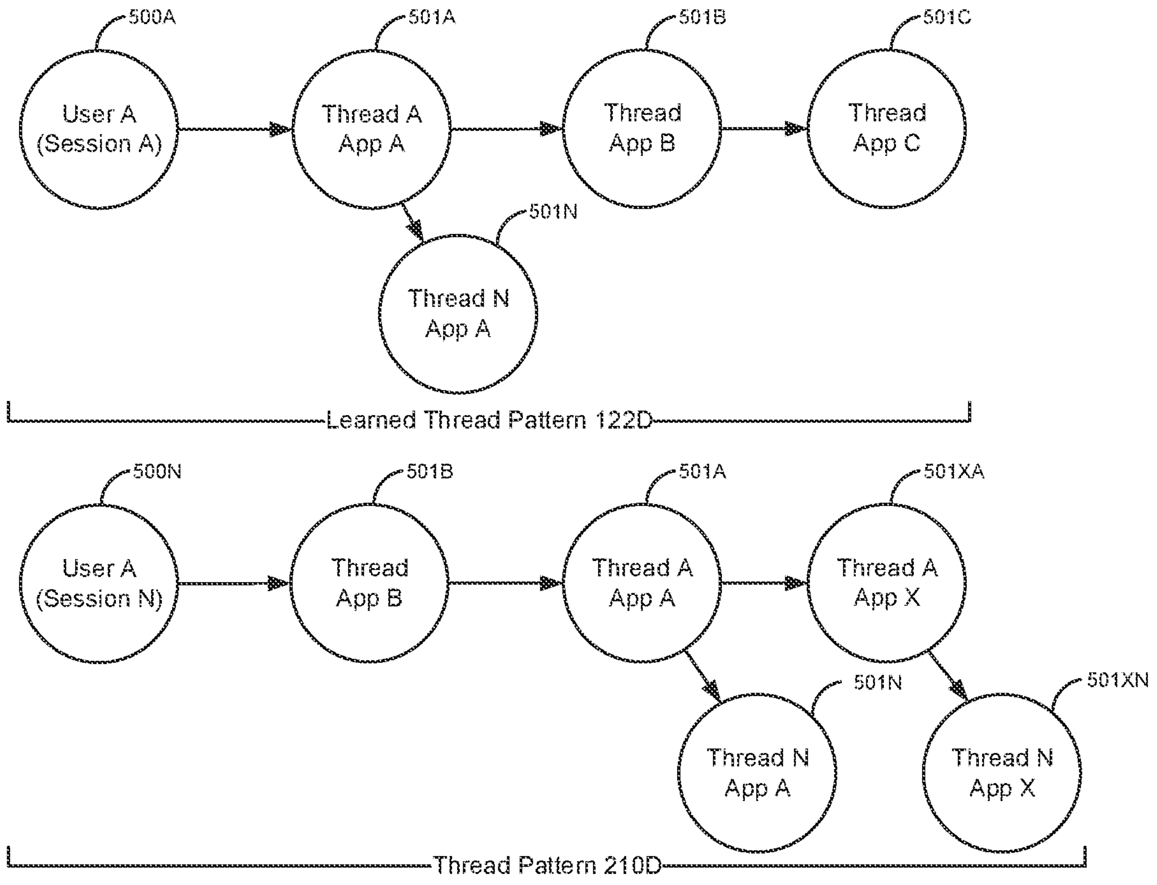
500A
User A (Session A)
501A
Thread A App A
501B
Thread App B
501C
Thread App C
501N
Thread N App A
Learned Thread Pattern 122D
500N
User A (Session N)
501B
Thread App B
501A
Thread A App A
501XA
Thread A App X
501N
Thread N App A
501XN
Thread N App X
Thread Pattern 210D

FIG. 5

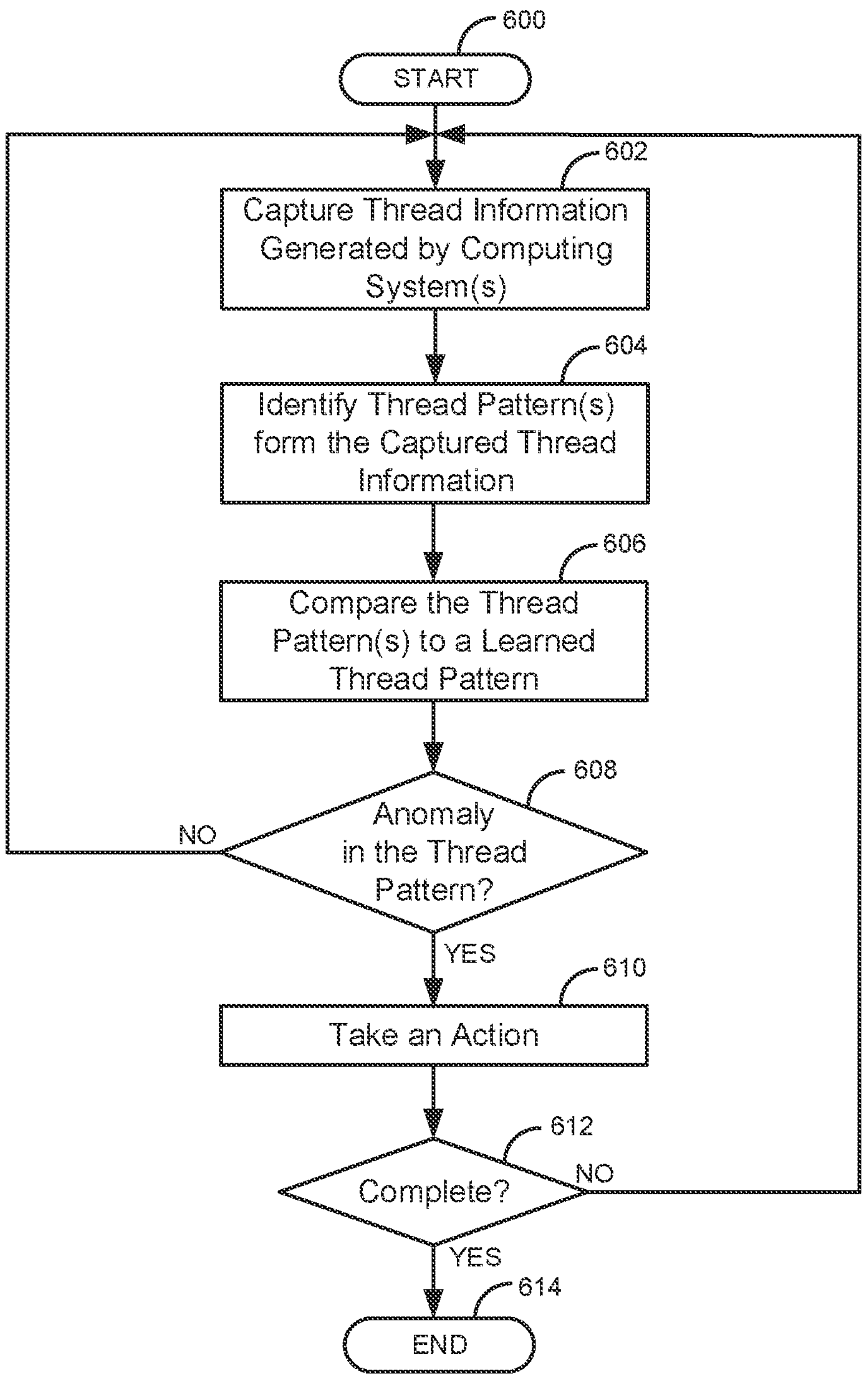
600
START
602
Capture Thread Information Generated by Computing System(s)
604
Identify Thread Pattern(s) form the Captured Thread Information
606
Compare the Thread Pattern(s) to a Learned Thread Pattern
608
Anomaly in the Thread Pattern?
NO
YES
610
Take an Action
612
Complete?
NO
YES
614
END

FIG. 6

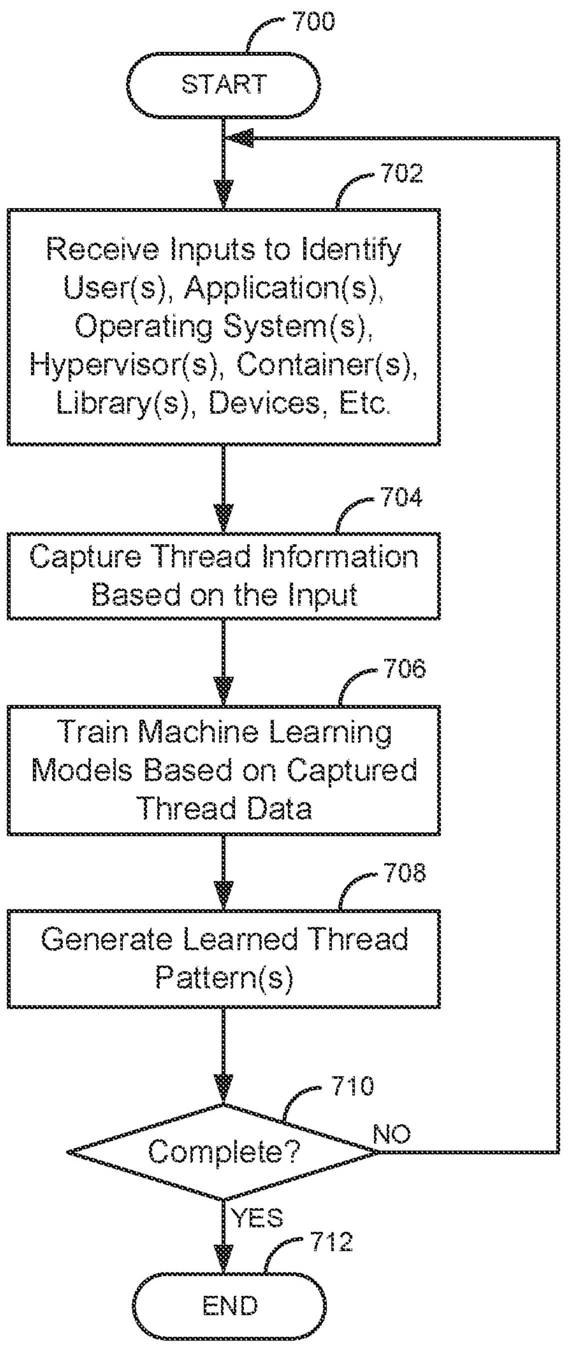
700
START
702
Receive Inputs to Identify User(s), Application(s), Operating System(s), Hypervisor(s), Container(s), Library(s), Devices, Etc.
704
Capture Thread Information Based on the Input
706
Train Machine Learning Models Based on Captured Thread Data
708
Generate Learned Thread Pattern(s)
710
Complete?
NO
YES
712
END

FIG. 7

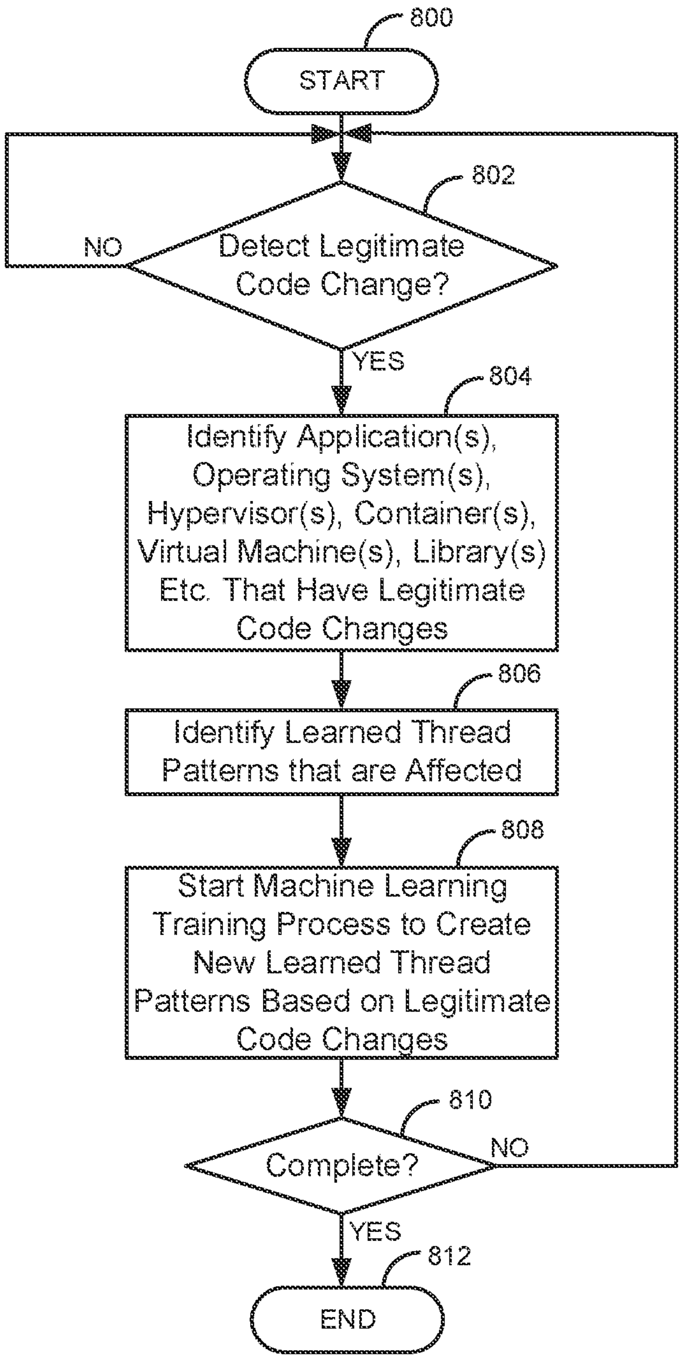
800
START
802
Detect Legitimate Code Change?
NO
YES
804
Identify Application(s), Operating System(s), Hypervisor(s), Container(s), Virtual Machine(s), Library(s) Etc. That Have Legitimate Code Changes
806
Identify Learned Thread Patterns that are Affected
808
Start Machine Learning Training Process to Create New Learned Thread Patterns Based on Legitimate Code Changes
810
Complete?
NO
YES
812
END

FIG. 8

USING THREAD PATTERNS TO IDENTIFY ANOMALOUS BEHAVIOR

FIELD

The disclosure relates generally to anomaly detection and particularly to identifying anomalous behavior based on thread patterns.

BACKGROUND

Identification of malicious attacks and malware are an ongoing issue in computer networks/computer systems. As malicious attacks/malware evolve, identification of new types has always been difficult to detect. Typically, it may require multiple malware detection processes and techniques to identify a new type of malicious attack/malware.

SUMMARY

These and other needs are addressed by the various embodiments and configurations of the present disclosure. The present disclosure can provide a number of advantages depending on the particular configuration. These and other advantages will be apparent from the disclosure contained herein.

In one embodiment, thread information generated by one or more computing systems is captured. A thread pattern is identified from the captured thread information. The thread pattern is compared to a learned thread pattern. An anomaly is identified in the thread pattern based on a variance from the learned thread pattern. In response to identifying an anomaly in the thread pattern, an action is taken based on the anomalous thread pattern. For example, a user may be notified.

In another embodiment, first thread information generated by at least one of a first operating system, a first hypervisor, a first virtual machine, and a first container is captured. Second thread information generated by at least one of a second operating system, a second hypervisor, a second virtual machine, and a second container is captured. A first thread pattern based on the first thread information is created. A second thread pattern based on the second thread information is created. The first thread pattern is compared to the second thread pattern. An anomaly in the first thread pattern is identified based on a variance from the second thread pattern. In response to identifying the anomaly in the first thread pattern based on the variance from the second thread pattern, an action is taken.

The phrases "at least one", "one or more", "or," and "and/or" are open-ended expressions that are both conjunctive and disjunctive in operation. For example, each of the expressions "at least one of A, B and C", "at least one of A, B, or C", "one or more of A, B, and C", "one or more of A, B, or C", "A, B, and/or C", and "A, B, or C" means A alone, B alone, C alone, A and B together, A and C together, B and C together, or A, B and C together.

The term "a" or "an" entity refers to one or more of that entity. As such, the terms "a" (or "an"), "one or more" and "at least one" can be used interchangeably herein. It is also to be noted that the terms "comprising," "including," and "having" can be used interchangeably.

The term "automatic" and variations thereof, as used herein, refers to any process or operation, which is typically continuous or semi-continuous, done without material human input when the process or operation is performed. However, a process or operation can be automatic, even

though performance of the process or operation uses material or immaterial human input, if the input is received before performance of the process or operation. Human input is deemed to be material if such input influences how the process or operation will be performed. Human input that consents to the performance of the process or operation is not deemed to be "material."

Aspects of the present disclosure may take the form of an entirely hardware embodiment, an entirely software embodiment (including firmware, resident software, micro-code, etc.) or an embodiment combining software and hardware aspects that may all generally be referred to herein as a "circuit," "module" or "system." Any combination of one or more computer readable medium(s) may be utilized. The computer readable medium may be a computer readable signal medium or a computer readable storage medium.

A computer readable storage medium may be, for example, but not limited to, an electronic, magnetic, optical, electromagnetic, infrared, or semiconductor system, apparatus, or device, or any suitable combination of the foregoing. More specific examples (a non-exhaustive list) of the computer readable storage medium would include the following: an electrical connection having one or more wires, a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), an optical fiber, a portable compact disc read-only memory (CD-ROM), an optical storage device, a magnetic storage device, or any suitable combination of the foregoing. In the context of this document, a computer readable storage medium may be any tangible medium that can contain or store a program for use by or in connection with an instruction execution system, apparatus, or device.

A computer readable signal medium may include a propagated data signal with computer readable program code embodied therein, for example, in baseband or as part of a carrier wave. Such a propagated signal may take any of a variety of forms, including, but not limited to, electromagnetic, optical, or any suitable combination thereof. A computer readable signal medium may be any computer readable medium that is not a computer readable storage medium and that can communicate, propagate, or transport a program for use by or in connection with an instruction execution system, apparatus, or device. Program code embodied on a computer readable medium may be transmitted using any appropriate medium, including but not limited to wireless, wireline, optical fiber cable, RF, etc., or any suitable combination of the foregoing.

The terms "determine," "calculate" and "compute," and variations thereof, as used herein, are used interchangeably, and include any type of methodology, process, mathematical operation, or technique.

The term "means" as used herein shall be given its broadest possible interpretation in accordance with 35 U.S.C., Section 112(f) and/or Section 112, Paragraph 6. Accordingly, a claim incorporating the term "means" shall cover all structures, materials, or acts set forth herein, and all of the equivalents thereof. Further, the structures, materials or acts and the equivalents thereof shall include all those described in the summary, brief description of the drawings, detailed description, abstract, and claims themselves.

The preceding is a simplified summary to provide an understanding of some aspects of the disclosure. This summary is neither an extensive nor exhaustive overview of the disclosure and its various embodiments. It is intended neither to identify key or critical elements of the disclosure nor to delineate the scope of the disclosure but to present selected concepts of the disclosure in a simplified form as an introduction to the more detailed description presented below. As will be appreciated, other embodiments of the disclosure are possible utilizing, alone or in combination, one or more of the features set forth above or described in detail below. Also, while the disclosure is presented in terms of exemplary embodiments, it should be appreciated that individual aspects of the disclosure can be separately claimed.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a block diagram of a first illustrative system for using thread patterns to identify anomalous user behavior.

FIG. **2** is a block diagram of a thread pattern and a learned thread pattern that compares threads of a user accessing an application.

FIG. **3** is a block diagram of a thread pattern and a learned thread pattern that compares threads of different users accessing an application.

FIG. **4** is a block diagram of a thread pattern and a learned thread pattern that compares threads between operating systems, hypervisors, containers, virtual machines, and/or applications.

FIG. **5** is a block diagram of a thread pattern and a learned thread pattern that compares threads of user sessions.

FIG. **6** is a flow diagram of a process for using thread patterns to identify anomalous user behavior.

FIG. **7** is a flow diagram of a process for generating learned thread pattern(s) based on machine learning.

FIG. **8** is a flow diagram of a process for detecting code changes to regenerate learned thread patterns.

In the appended figures, similar components and/or features may have the same reference label. Further, various components of the same type may be distinguished by following the reference label by a letter that distinguishes among the similar components. If only the first reference label is used in the specification, the description is applicable to any one of the similar components having the same first reference label irrespective of the second reference label.

DETAILED DESCRIPTION

FIG. **1** is a block diagram of a first illustrative system **100** for using thread patterns to identify anomalous user behavior. The first illustrative system **100** comprises computer systems **101**A-**101**N, a network **110**, and a thread monitoring system(s) **120**.

The computer systems **101**A-**101**N can be or may include any device that can communicate on the network **110**, such as a Personal Computer (PC), a telephone, a video system, a cellular telephone, a Personal Digital Assistant (PDA), a tablet device, a notebook device, a smart phone, a server, a firewall, proxy server, an embedded device, and/or the like. As shown in FIG. **1**, any number of computer systems **101**A-**101**N may be connected to the network **110**, including only a single communication system **101**.

The computer systems **101**A-**101**N further comprise operating system(s) **102**A-**102**N, hypervisor(s) **103**A-**103**N, virtual machines **105**A-**105**N, application(s) **106**A-**106**N, thread scanners **107**A-**107**N, machine learning **108**A-**108**N, and system thread monitors **109**A-**109**N. The operating system(s) **102**A-**102**N may comprise any known operating systems **102**, such as, Microsoft Windows®, Linux®, Android®, iOS®, and/or the like.

The hypervisor(s) **103**A-**103**N may be any know hypervisor **103**, such as Kernel-Based Virtual Machine (KVM), Red Hat® Enterprise Virtualization, Xen/Citrix XenServer, Microsoft® Windows Server 2012 Hyper-V, VMware vSphere, and/or the like. The containers **104**A-**104**N contain various application(s) **106**A-**106**N that are executed by the operating system(s) **102**A-**102**N.

The virtual machine(s) **105**A-**105**N can be any known type of virtual machine **105**. The virtual machines **105**A-**105**N may run various application(s) **106**.

The application(s) **106**A-**106**N can be any type of application, such as, a web server, a financial application, a database, a word processing application, a network application, an embedded application (e.g., a printing application in a printer), an authentication service, a security application, and/or the like. The application(s) **106**A-**106**N may be executed directly by the operating system(s) **102**A-**102**N, may be executed in the container(s) **104**A-**104**N, may be executed by the virtual machines **105**A-**105**N, and/or the like.

The thread scanners **107**A-**107**N can be any process/application that can capture thread information for the computer systems **101**A-**101**N. The thread scanners **107**A-**107**N may capture data in various ways, such as, using a thread dump, a thread capture program, a Java thread dump, using multi-device thread dumps, and/or the like.

The machine learning **108**A-**108**N may comprise various types of machine learning, such as, supervised machine learning, semi-supervised machine learning, unsupervised machine learning, reinforcement learning, and/or the like. The machine learning **108**A-**108**N is used to generate the learned thread patterns **122**. The machine learning **108**A-**108**N is used to learn over time how the thread patterns of the various components **102**-**106** are related and to learn variance tolerances. For example, variance tolerances may be timing between threads, how often specific threads occur, order of threads, and/or the like.

The system thread monitors **109**A-**109**N use the machine learning **108**A-**108**N to generate the learned thread patterns **122**. The system thread monitors **109**A-**109**N may work with the global thread monitor **121** to monitor thread patterns of all the computer systems **101**A-**101**N on the network **110**. In one embodiment, the system thread monitors **109**A-**109**N may be self-contained and not work with the thread monitoring system **120**(*s*)/global thread monitor **121**. Although not shown in FIG. **1**, the learned thread patterns **122** may be stored locally on the computer systems **101**A-**101**N.

The network **110** can be or may include any collection of communication equipment that can send and receive electronic communications, such as the Internet, a Wide Area Network (WAN), a Local Area Network (LAN), a packet switched network, a circuit switched network, a cellular network, a combination of these, and the like. The network **110** can use a variety of electronic protocols, such as Ethernet, Internet Protocol (IP), Hyper Text Transfer Protocol (HTTP), Web Real-Time Protocol (Web RTC), and/or the like. Thus, the network **110** is an electronic communication network configured to carry messages via packets and/or circuit switched communications.

The thread monitoring system(s) **120** is used to capture global thread information from the computer systems **101**A-**101**N. The thread monitoring system(s) **120** comprises the global thread monitor **121**, the learned thread patterns **122**, and machine learning **128**. The global thread monitor **121** may capture thread information received from the system thread monitors **109**A-**109**N to create the learned thread patterns **122** using the machine learning **128**.

For a large organization there may be many independent instances of the thread monitoring system **120**. In one embodiment, there could also be a hierarchy of thread monitoring systems **120**, that share aggregated information (e.g., statistics about different thread patterns seen in a local thread monitoring area/network **110**); this allows for a global management console where one could check if an unexpected thread pattern is seen in one monitoring area/network **110** has been seen/not seen in other areas before.

The thread monitoring systems **120** at a higher level in the hierarchy may not possess the thread patterns from their leaf nodes (e.g., the system thread monitors **109**), but rather summaries of the thread patterns that have been encountered at different leaves (or sub-leaves). One scalable approach would be to use Bloom Filters i.e., each thread monitoring system at the leaf (lowest) level of the hierarchy could summarize the thread patterns it observed over the last observation period, and then record that in a Bloom Filter. It could also build statistical summaries of the thread patterns seen over the past observation period and send those to its parent. At the parent one could analyze the statistics for anomalies. One could also monitor for the spread of anomalous patterns over time. The Bloom Filters may make such a check more efficient to do across a large number of monitored servers.

In another embodiment, the thread monitoring systems **120** may run in a peer-to-peer application. Similar to the hierarchical system, the organization's thread monitoring systems **120** may be broken into groups, cells, and/or the like. Summary information could be shared between the groups via a peer-to-peer protocol so that groups learn about patterns for other groups and can leverage that information to decide if some new patterns are anomalous. A benefit of using a number of small groups is that there is a higher probability of a local administrator knowing what is "normal" for systems they administer, so labeling of patterns can be determined more easily. This can be used in a collaborative environment of where a group of enterprises (e.g., different corporations) could cooperate with each other to sharer thread information.

The learned thread patterns **122** may be thread patterns of the computer systems **101**A-**101**N, may be a composite of the learned thread patterns **122** of the computer system **101**A-**101**N, and/or the like. For example, a composite learned thread pattern **122** may comprise thread patterns of a client/server application **106** or applications **106** that interact with each other. A composite learned thread pattern **122** may be thread pattern of two or more of the components **102**-**106** along with other components (e.g., shared libraries)/computer systems **101**A-**101**N/devices.

The machine learning **128** may be the same type of machine learning **128** as the machine learning **108**A-**108**N. Alternatively, the machine learning **128** may be different from the machine learning **108**A-**108**N. The machine learning **128** may also identify composite thread variances.

FIG. **2** is a block diagram of a thread pattern **210**A and a learned thread pattern **122**A that compares threads of a user accessing an application **106**. The learned thread pattern **122**A is a learned thread pattern **122** based on the machine learning **108**/**128**. The learned thread pattern **122**A is a thread pattern of how a user is accessing the application **106**A that is learned by the machine learning **108**/**128** over time. For example, the machine learning **108**/**128** may be a supervised machine learning process. The learned thread pattern **122**A comprises a user session node **200**A and threads **201**A-**201**N.

The thread pattern **210**A is a current thread pattern of how a user is accessing the application **106**A. The thread pattern **210**A comprises a user session node **200**N and threads **201**A-**201**B, **201**E, **201**N, **2010**, and **201**X.

The thread pattern **210**A for session N is compared to the learned thread pattern **122**A (e.g., learned from sessions A-M) to identify any potential variances. For example, as shown in FIG. **2**, in session N, instead of thread **201**C being created by thread **201**B, thread **2010** is created, which in turn, launches thread **201**X for application X (e.g., a virus). This can be flagged as an anomaly and potential use of malware.

FIG. **2** is an example of where the learned thread patterns **122**/thread patterns **210** are tracked using a Graph Neural Network (GNN). In the GNN, the user sessions **200**/threads **201** are nodes. The links between each node **200**/**201** may have associated information. For example, the link from the user session nodes **200**A/**200**N may have a username, a login time, and/or the like. The links for the threads **201** may have information such as, function calls where the thread **201** was created, stack size when the thread **201** was created/ended, a heap size of when the thread **201** was created/ended, memory usage while the thread **201** was active, timestamps/time periods of threads **201**, resource loads, other concurrently running applications **106**, and/or the like.

The node/link information may also be used when comparing the thread pattern **210**A to the learned thread pattern **122**A to identify variances. The comparison may use thresholds when identifying a malicious thread pattern based on one or more of these factors. For example, if the memory usage is dramatically different for a thread **201** of the thread pattern **210**A versus the learned thread pattern **122**A, this may indicate a malicious behavior or some other issue with the thread **201**/application **106**.

FIG. **3** is a block diagram of a thread pattern **210**B and a learned thread pattern **122**B that compares threads **201** of different users accessing an application **106**. In FIG. **3** the learned thread pattern **122**B comprises user node **300**A and threads **301**A-**301**N. The thread pattern **210**B comprises user node **300**N, threads **301**A-**301**B, **301**E, and **3010**.

The application **106** may be the same application **106** or different instances of the same application **106**. For example, if there are 100 users, and 99 of the 100 users have similar learned thread patterns **122** (or groups of learned thread patterns **122**), the thread pattern **210**B for user N can be flagged as a potentially anomalous thread pattern because thread **301**B creates thread **3010** instead of threads **301**C/**301**D. The users may be a group of users who are part of a group that perform similar functions. For example, the group may be software engineers of project X, network analysts for company Y, engineering managers for company Z, and/or the like. The users may be on different devices or the same device (e.g., a server). This process can be applied to web servers where a thread is spun off when a user accesses the web server.

In one embodiment, where unsupervised machine learning is used, the process can look for patterns that are different from the others. In this embodiment, it doesn't require comparison to a known good baseline pattern.

The process can be used to detect a group attack. For example, if a group of users suddenly started having similar anomalous thread patterns **210** versus the learned thread pattern **122** for the group, this may indicate a group attack or where a group of users/bots are working on concert to perform a malicious activity.

FIG. **4** is a block diagram of a thread pattern **210**CN and a learned thread pattern **122**C that compares threads **401** between operating systems **102**, hypervisors **103**, containers **104**, virtual machines **105**, and/or applications **106**. FIG. **4** comprises thread pattern **210**CA (a real-time thread pattern) or the leaned thread pattern **122**C to thread pattern **210**CN (a real-time thread pattern). The thread pattern **210**CA/leaned thread pattern **122**C comprises a container/VM (virtual machine)/hypervisor/operating system node **400**A, and thread nodes **401**A-**401**N. The thread pattern **210**CN comprises a container/VM (virtual machine)/hypervisor/operating system node **400**N and threads **401**A-**401**B, **401**E, and **401**M.

Instead of comparing at a user level (although it could also be extended to the user level as well) like described in FIGS. **2-3**, the process of FIG. **4** compares at an operating system level, a hypervisor level, a virtual machine level, a container level, and/or the like. For example, a cloud service may provide for multiple tenants where each tenant's application **106** is provided in a separate container **104** or virtual machine **105**.

The operating system **102**/hypervisor **103**/container **104**/virtual machine **105** thread patterns **210**A/**210**N may be compared to each other in real-time/semi-real time, within time periods, against previous thread patterns of the same component **102-106**, and/or the like. In one embodiment, a learned thread pattern **122**C may be used to compare against the thread pattern **210**CN. For example, if the hypervisor **103**A's/container **104**A's learned thread pattern **122**C varies from the hypervisor **103**N's/container **104**N's thread pattern **210**CN, it would be flagged as a potential anomaly.

In FIG. **4**, the variance is that instead of thread **401**B creating threads **401**C/**401**D as shown in the thread pattern **210**CA/learned thread pattern **122**C, the thread **401**M is created. Also, thread **401**N is not created in the thread pattern **210**CN. In this example, there are multiple variances.

The thread patterns **210**/learned thread patterns **122** may be a composite thread pattern. For example, the thread patterns **210**/learned thread patterns **122** may be across an operating system **102**/hypervisor **103**, and the corresponding containers **104** that are being run by the hypervisor **103**. The process can learn thread patterns **122** of how a hypervisor **103** creates a container **104** and then the threads that are run in the container **104**. In one embodiment, the thread pattern may be a tree GNN where the root is the operating system **102**/hypervisor **103** and the branches are the threads of each container **104** instantiated by the hypervisor **103**. The tree GNN could further include individual user thread patterns of the container **104** to provide a composite view. This can be extended even further to include applications **106** that are running in each of the containers **104**.

The thread patterns **210**/**122** may be across multiple containers **104**/virtual machines **105**. For example, a thread in container **104** may instantiate a new container **104** or access a process in another container **104**. An example would be an authentication micro service in a first container **104** that instantiates or allows access to a second container **104** once a user logs in. In this example, the thread pattern **210**/**122** would include those in the authentication micro service container **104** and then those in the second container **104** as a single user thread pattern **210**/**122**.

The user/operating system **102**/hypervisor **103**/container **104**/virtual machine **105** thread patterns may be monitored for common unusual changes that may indicate some type of group attack or Denial-of-Service (DoS) attack. For example, a DoS attack may be detected where there are new user threads **401** that all have the same pattern where typically a user pattern has a learned variance that is different. In this case, there is a large group of identical threads that would be identified and the anomaly/variance.

FIG. **5** is a block diagram of a thread pattern **210**D and a learned thread pattern **122**D that compares threads of user sessions. FIG. **5** comprises learned thread pattern **122**D and thread pattern **210**D. The learned thread pattern **122**D comprises a session node **500**A, and threads **501**A-**501**N. The thread pattern **210**D comprises session node **500**N and threads **501**A-**501**B, **501**N, **501**XA, and **501**XN.

The thread patterns **210**D/**122**D are based on a user session. For example, a user logs into their personal computer **101** and then accesses various applications **106**, executes various commands (e.g., shell scripts), and/or the like. Although shown for various applications **106**, the process of FIG. **5** may apply to the container level, the virtual machine level, the hypervisor level, the operating system level, and/or the like.

As the user does various activities that generates threads **501**, such as, logging in, launching an application **106**, entering command line commands, this information is captured in the learned thread pattern **122**D. The learned thread pattern **122**D may also comprise concurrent threads/non-concurrent threads. The anomalies may be at the application level where groups of application-level threads are captured and stored off for comparison. For example, even though for session N, where the thread for the application **106**B comes before the threads for the application **106**A, based on rules/learning, this would not likely be considered an anomaly because the thread patterns for applications **106**A/**106**B are similar. The difference is that the threads **501**A/**501**N/**501**B for applications **106**A and **106**B are transposed (this may also be learned over time). However, the threads for application X (**501**XA and **501**XN) would be considered an anomaly because application X has never been used previously by user A. In other words, there may be different rules/learned rules for different types of anomalies/variances and the threshold required to trigger a potentially anomalous event. Other patterns may be where a thread **501** is left running after the user logs out where this did not happen previously. Other factors may include the time a thread is active.

In another embodiment, which would be useful in the situation where there are thread monitoring systems **120** distributed around an organization, only one person needs to investigate the anomaly and label it, then all other thread monitoring systems could benefit from that label. The point of this is to try and either reduce false positives or to reduce the number of unknown activities/thread patterns detected.

The user thread patterns **210**D/learned thread patterns **122**D may be across different devices (e.g., computer systems **101**A-**101**N). For example, a user may login to computer system **101**A and then do a remote login to computer system **101**B from computer system **10**A. These two thread patterns may be combined into a composite thread pattern between the two computer systems **101**A/**101**B (e.g., a user has compromised computer system **101**A and is now trying to compromise the computer system **101**B). The composite thread pattern may be analyzed for anomalies. The thread pattern would be different if the user logged into computer system **101**A and computer system **101**B separately because there is a relationship between the computer system **101**A/**101**B because of the remote login which would be indicated by the GNN.

Any of the above processes may be combined. For example, individual user threads may be compared between containers **104**/virtual machines **105**. The detection of threads can be accomplished at the kernel level using a daemon.

The thread pattern comparison may consider a context. For example, the learned thread patterns **122** where a user is logged on remotely versus locally may be different. Other context factors may be location, time of day, access device, IP address, login level/role (e.g., accessing different functionality of an application **106** based on login level/role) and/or the like.

This process could use a learned thread pattern repository that can be accessed by different entities. For example, the learned thread patterns **122** for application **106**A in company A may be uploaded to a central repository for use another company/entity who is also using application **106**A. The machine learning process in the central repository can then be used to identify learned thread patterns **122** more quickly.

FIG. **6** is a flow diagram of a process for using thread patterns **122**/**210** to identify anomalous user behavior. Illustratively, the computer systems **101**A-**101**N, the operating system(s) **102**A-**102**N, the hypervisor(s) **103**A-**103**N, the container(s) **104**A-**104**N, the virtual machine(s) **105**A-**105**N, the application(s) **106**A-**106**N, the thread scanners **107**A-**107**N, the machine learning **108**A-**108**N, the system thread monitors **109**A-**109**N, the thread monitoring system **120**(*s*), the global thread monitor **121**, and the machine learning **128** are stored-program-controlled entities, such as a computer or microprocessor, which performs the method of FIGS. **6**-**8** and the processes described herein by executing program instructions stored in a computer readable storage medium, such as a memory (i.e., a computer memory, a hard disk, and/or the like). Although the methods described in FIGS. **6**-**8** are shown in a specific order, one of skill in the art would recognize that the steps in FIGS. **6**-**8** may be implemented in different orders and/or be implemented in a multi-threaded environment. Moreover, various steps may be omitted or added based on implementation.

The process starts in step **600**. The thread scanner(s) **107** capture, in step **602**, thread information generated by the computer system(s) **101**. The thread capture of step **602** may be based on one or more rules. The thread monitor(s) **109** and/or the global thread monitor **121** identify the thread patterns **210** from the captured thread information in step **604**. The thread monitor(s) **109** and/or the global thread monitor **121** compare the thread pattern(s) **210** to the learned thread pattern **122** in step **606**. The comparison could also be between real-time thread patterns. The thread monitor(s) **104** and/or the global thread monitor **121** determine, in step **608**, if there is an anomaly/variance. If there is not an anomaly/variance in step **608**, the process goes back to step **602**.

Otherwise, if there is an anomaly/variance in step **608**, the thread monitor(s) **109** and/or the global thread monitor **121** take an action in step **610**. The action may be any action related to the anomaly/variance. For example, the action may be blocking one or more threads, notify a user, shutting down a container **104**, shutting down an application **106**, shutting down a virtual machine **105**, quarantining an application **106**, blocking a thread, restricting resources (e.g., limiting memory, limiting CPU cycles give to an application **106**, etc.), and/or the like.

The process determines, in step **612**, if the process is complete. If the process is not complete in step **612**, the process goes back to step **602**. Otherwise, the process ends in step **614**.

FIG. **7** is a flow diagram of a process for generating learned thread pattern(s) **122** based on machine learning

108/**128**. The process starts in step **700**. The thread scanner(s) **107** receive inputs to identify user(s), application(s) **106**, operating system(s) **102**, hypervisor(s) **103**, container(s) **104**, library(s), computer system(s) **101**, device(s), etc. The input of step **702** is used to determine which thread information to capture and what thread patterns **210**/learned thread patterns **122** to capture/compare. The thread scanner(s) **107** capture the thread information based on the input in step **704**. The thread information is input into the machine learning **108**/**128**, in step **706**, to train the machine learning algorithms. The learned thread patterns **122** are then generated in step **708**.

The process determines, in step **710**, if the process is complete. If the process is not complete in step **710**, the process goes back to step **702**. Otherwise, the process ends in step **712**.

FIG. **8** is a flow diagram of a process for detecting code changes to regenerate learned thread patterns **122**. The process starts in step **800**. The system thread monitor(s) **109** detect if there are any legitimate code changes in step **802**. Step **802** may differentiate between legitimate code changes and illegitimate code changes. For example, legitimate code changes may be made based on an administered patch and/or installation. This may include a search for any kinds of malware before the installation. If a legitimate code change is not detected in step **802**, the process of step **802** repeats.

Otherwise, if a legitimate code change is detected in step **802**, the system thread monitor(s) **109** identify any application(s) **106**, operating system(s) **102**, hypervisors **103**, container(s) **104**, virtual machine(s) **105**, libraries, etc. that have legitimate code changes in step **804**. The system thread monitor(s) **109**/global thread monitor **121** identify the learned thread patterns **122** that are affected in step **806**. The system thread monitor(s) **109**/global thread monitor **121** restart the machine learning training process to create new learned thread patterns **122** based on the legitimate code changes in step **808**.

The process determines, in step **810**, if the process is complete. If the process is not complete in step **810**, the process goes back to step **802**. Otherwise, the process ends in step **812**.

In an embodiment that is designed to address the problem of false positives (i.e., too many actions to take), a risk scoring model is designed that takes advantage of context about the monitored computer systems **101**A-**101**N and the statistics generated about the thread patterns. For instance, a never-before-seen thread pattern from a popular application is likely a higher priority issue than a seldomly-seen thread pattern from an unpopular application.

To make the system more scalable, the global thread monitor **121** may break the thread activity into fixed "chain lengths" (e.g., FIG. **2** shows a chain length of 4 on the top: A→B→C→D), then give each of those a unique identifier and repeat the process. E.g., for chain link 4, A→B→C→D→A→B→C→D would be broken into A→B→C→D and A→B→C→D. if a="A→B→C→D" then the chain could be summarized as a+a.

In this embodiment, the summary statistics could be kept on individual computer systems **101**A-**101**N or in hierarchical nodes. For example, over a time window W count the number of occurrences of each computer system **101**A-**101**N or chain. The summary could be passed up the hierarchy so that probability distributions could be calculated, then when something is deemed an anomaly by other means, check the probability distribution to see how rare it is.

Examples of the processors as described herein may include, but are not limited to, at least one of Qualcomm® Snapdragon® **800** and **801**, Qualcomm® Snapdragon® **610** and **615** with 4G LTE Integration and 64-bit computing, Apple® A7 processor with 64-bit architecture, Apple® M7 motion coprocessors, Samsung® Exynos® series, the Intel® Core™ family of processors, the Intel® Xeon® family of processors, the Intel® Atom™ family of processors, the Intel Itanium® family of processors, Intel® Core® i5-4670K and i7-4770K 22 nm Haswell, Intel® Core® i5-3570K 22 nm Ivy Bridge, the AMD® FX™ family of processors, AMD® FX-4300, FX-6300, and FX-8350 32 nm Vishera, AMD® Kaveri processors, Texas Instruments® Jacinto C6000™ automotive infotainment processors, Texas Instruments® OMAP™ automotive-grade mobile processors, ARM® Cortex™-M processors, ARM® Cortex-A and ARM926EJ-S™ processors, other industry-equivalent processors, and may perform computational functions using any known or future-developed standard, instruction set, libraries, and/or architecture.

Any of the steps, functions, and operations discussed herein can be performed continuously and automatically.

However, to avoid unnecessarily obscuring the present disclosure, the preceding description omits a number of known structures and devices. This omission is not to be construed as a limitation of the scope of the claimed disclosure. Specific details are set forth to provide an understanding of the present disclosure. It should however be appreciated that the present disclosure may be practiced in a variety of ways beyond the specific detail set forth herein.

Furthermore, while the exemplary embodiments illustrated herein show the various components of the system collocated, certain components of the system can be located remotely, at distant portions of a distributed network, such as a LAN and/or the Internet, or within a dedicated system. Thus, it should be appreciated, that the components of the system can be combined in to one or more devices or collocated on a particular node of a distributed network, such as an analog and/or digital telecommunications network, a packet-switch network, or a circuit-switched network. It will be appreciated from the preceding description, and for reasons of computational efficiency, that the components of the system can be arranged at any location within a distributed network of components without affecting the operation of the system. For example, the various components can be located in a switch such as a PBX and media server, gateway, in one or more communications devices, at one or more users' premises, or some combination thereof. Similarly, one or more functional portions of the system could be distributed between a telecommunications device(s) and an associated computing device.

Furthermore, it should be appreciated that the various links connecting the elements can be wired or wireless links, or any combination thereof, or any other known or later developed element(s) that is capable of supplying and/or communicating data to and from the connected elements. These wired or wireless links can also be secure links and may be capable of communicating encrypted information. Transmission media used as links, for example, can be any suitable carrier for electrical signals, including coaxial cables, copper wire and fiber optics, and may take the form of acoustic or light waves, such as those generated during radio-wave and infra-red data communications.

Also, while the flowcharts have been discussed and illustrated in relation to a particular sequence of events, it should be appreciated that changes, additions, and omissions to this sequence can occur without materially affecting the operation of the disclosure.

A number of variations and modifications of the disclosure can be used. It would be possible to provide for some features of the disclosure without providing others.

In yet another embodiment, the systems and methods of this disclosure can be implemented in conjunction with a special purpose computer, a programmed microprocessor or microcontroller and peripheral integrated circuit element(s), an ASIC or other integrated circuit, a digital signal processor, a hard-wired electronic or logic circuit such as discrete element circuit, a programmable logic device or gate array such as PLD, PLA, FPGA, PAL, special purpose computer, any comparable means, or the like. In general, any device(s) or means capable of implementing the methodology illustrated herein can be used to implement the various aspects of this disclosure. Exemplary hardware that can be used for the present disclosure includes computers, handheld devices, telephones (e.g., cellular, Internet enabled, digital, analog, hybrids, and others), and other hardware known in the art. Some of these devices include processors (e.g., a single or multiple microprocessors), memory, nonvolatile storage, input devices, and output devices. Furthermore, alternative software implementations including, but not limited to, distributed processing or component/object distributed processing, parallel processing, or virtual machine processing can also be constructed to implement the methods described herein.

In yet another embodiment, the disclosed methods may be readily implemented in conjunction with software using object or object-oriented software development environments that provide portable source code that can be used on a variety of computer or workstation platforms. Alternatively, the disclosed system may be implemented partially or fully in hardware using standard logic circuits or VLSI design. Whether software or hardware is used to implement the systems in accordance with this disclosure is dependent on the speed and/or efficiency requirements of the system, the particular function, and the particular software or hardware systems or microprocessor or microcomputer systems being utilized.

In yet another embodiment, the disclosed methods may be partially implemented in software that can be stored on a storage medium, executed on programmed general-purpose computer with the cooperation of a controller and memory, a special purpose computer, a microprocessor, or the like. In these instances, the systems and methods of this disclosure can be implemented as program embedded on personal computer such as an applet, JAVA® or CGI script, as a resource residing on a server or computer workstation, as a routine embedded in a dedicated measurement system, system component, or the like. The system can also be implemented by physically incorporating the system and/or method into a software and/or hardware system.

Although the present disclosure describes components and functions implemented in the embodiments with reference to particular standards and protocols, the disclosure is not limited to such standards and protocols. Other similar standards and protocols not mentioned herein are in existence and are considered to be included in the present disclosure. Moreover, the standards and protocols mentioned herein, and other similar standards and protocols not mentioned herein are periodically superseded by faster or more effective equivalents having essentially the same functions. Such replacement standards and protocols having the same functions are considered equivalents included in the present disclosure.

The present disclosure, in various embodiments, configurations, and aspects, includes components, methods, processes, systems and/or apparatus substantially as depicted and described herein, including various embodiments, subcombinations, and subsets thereof. Those of skill in the art will understand how to make and use the systems and methods disclosed herein after understanding the present disclosure. The present disclosure, in various embodiments, configurations, and aspects, includes providing devices and processes in the absence of items not depicted and/or described herein or in various embodiments, configurations, or aspects hereof, including in the absence of such items as may have been used in previous devices or processes, e.g., for improving performance, achieving ease and\or reducing cost of implementation.

The foregoing discussion of the disclosure has been presented for purposes of illustration and description. The foregoing is not intended to limit the disclosure to the form or forms disclosed herein. In the foregoing Detailed Description for example, various features of the disclosure are grouped together in one or more embodiments, configurations, or aspects for the purpose of streamlining the disclosure. The features of the embodiments, configurations, or aspects of the disclosure may be combined in alternate embodiments, configurations, or aspects other than those discussed above. This method of disclosure is not to be interpreted as reflecting an intention that the claimed disclosure requires more features than are expressly recited in each claim. Rather, as the following claims reflect, inventive aspects lie in less than all features of a single foregoing disclosed embodiment, configuration, or aspect. Thus, the following claims are hereby incorporated into this Detailed Description, with each claim standing on its own as a separate preferred embodiment of the disclosure.

Moreover, though the description of the disclosure has included description of one or more embodiments, configurations, or aspects and certain variations and modifications, other variations, combinations, and modifications are within the scope of the disclosure, e.g., as may be within the skill and knowledge of those in the art, after understanding the present disclosure. It is intended to obtain rights which include alternative embodiments, configurations, or aspects to the extent permitted, including alternate, interchangeable and/or equivalent structures, functions, ranges, or steps to those claimed, whether or not such alternate, interchangeable and/or equivalent structures, functions, ranges, or steps are disclosed herein, and without intending to publicly dedicate any patentable subject matter.

What is claimed is:

1. A system comprising:

a microprocessor; and

a computer readable medium, coupled with the microprocessor and comprising microprocessor readable and executable instructions that, when executed by the microprocessor, cause the microprocessor to:

capture thread information generated by one or more computing systems;

identify a thread pattern from the captured thread information;

compare the thread pattern to a learned thread pattern comprising comparing a user session thread pattern of a first user using a plurality of applications to a learned session thread pattern of the first user using the plurality of applications and wherein machine

learning is used to filter out variances that have a similar usage pattern, but in a different order;

identify an anomaly in the thread pattern based on a variance from the learned thread pattern; and

in response to identifying the anomaly in the thread pattern, take an action based on the anomaly in the thread pattern.

2. The system of claim **1**, wherein comparing the thread pattern to the learned thread pattern comprises at least one of:

comparing a thread pattern of the first user using a first application to a learned thread pattern of the first user using the first application;

comparing the thread pattern of the first user using the first application to a learned thread pattern of a second user using the first application;

comparing a thread pattern of a first operating system to a learned thread pattern of the first operating system;

comparing a thread pattern of a first container running the first application to a learned thread pattern of a second container running the first application;

comparing a thread pattern of the first operating system running the first container running the first application to a learned thread pattern of the first operating system running the first container running the first application;

comparing a thread pattern of a first hypervisor running a first virtual machine to a learned thread pattern of a second hypervisor running the first virtual machine;

comparing a thread pattern of the first virtual machine running the first application to a learned thread pattern of a second virtual machine running the first application;

comparing a thread pattern of the first virtual machine running the first application to a learned thread pattern of the first virtual machine running the first application;

comparing a user session thread pattern of the first user using a plurality of applications to a learned session thread pattern of the first user using the plurality of applications; and

comparing a user session thread pattern of the first user using a plurality of applications to a learned session thread pattern of the second user using the plurality of applications.

3. The system of claim **1**, wherein the learned thread pattern is a composite learned thread pattern and wherein the composite learned thread pattern comprises at least one of:

a composite learned thread pattern between a plurality of communication systems;

a composite learned thread pattern of an operating system and an application;

a composite learned thread pattern of the operating system and a hypervisor;

a composite learned thread pattern of the operating system, the hypervisor, and a container;

a composite learned thread pattern of the operating system, the hypervisor, the container, and the application; and

a composite learned thread pattern of a virtual machine and the application.

4. The system of claim **1**, wherein comparing the thread pattern to the learned thread pattern is completed using a Graph Neural Network.

5. The system of claim **1**, wherein identifying the anomaly in the thread pattern based on the variance from the learned thread pattern comprises looking at associated thread information comprising at least one of:

a function call used to start a thread in the thread pattern;

a stack size when the thread in the thread pattern was used;

a heap size when the thread in the thread pattern was used;

a memory usage when the thread in the thread pattern was used;

a timestamp when the thread in the thread pattern was used;

a time period when the thread in the thread pattern was used;

a load on a resource; and

other concurrently running applications.

6. The system of claim **1**, wherein the thread pattern comprises a plurality of thread patterns of a plurality of users and wherein identifying the anomaly in the thread pattern based on the variance from the learned thread pattern comprises: identifying a plurality of anomalies based on the plurality of thread patterns of the plurality of users, and wherein the plurality of anomalies are used to identify a group attack.

7. The system of claim **1**, wherein taking the action based on the anomaly in the thread pattern comprises one or more of: blocking one or more threads, notify a user, shutting down a container, shutting down an application, shutting down a virtual machine, quarantining an application, and restricting a resource.

8. The system of claim **1**, wherein the machine readable and executable instructions further cause the microprocessor to:

detect a legitimate change in code in at least one of an application, an operating system, a hypervisor, a container, a virtual machine, and a library; and

in response to detecting the legitimate change in the code in at least one of the application, the operating system, the hypervisor, the container, the virtual machine, and the library, use machine learning to generate a new learned thread pattern.

9. The system of claim **1**, wherein capturing the thread information generated by the one or more computing systems comprises capturing thread information for a plurality of computing systems on a plurality of networks and the capturing is done by a hierarchy of thread monitoring systems or a group of peer-to-peer thread monitoring systems.

10. A method comprising:

capturing, by a microprocessor, thread information generated by one or more computing systems;

identifying, by the microprocessor, a thread pattern from the captured thread information;

comparing, by the microprocessor, the thread pattern to a learned thread pattern comprising comparing a user session thread pattern of a first user using a plurality of applications to a learned session thread pattern of the first user using the plurality of applications and wherein machine learning is used to filter out variances that have a similar usage pattern, but in a different order;

identifying, by the microprocessor, an anomaly in the thread pattern based on a variance from the learned thread pattern; and

in response to identifying the anomaly in the thread pattern, taking an action based on the anomaly in the thread pattern.

11. The method of claim **10**, wherein comparing the thread pattern to the learned thread pattern comprises at least one of:

comparing a thread pattern of the first user using a first application to a learned thread pattern of the first user using the first application;

comparing the thread pattern of the first user using the first application to a learned thread pattern of a second user using the first application;

comparing a thread pattern of a first operating system to a learned thread pattern of the first operating system;

comparing a thread pattern of a first container running the first application to a learned thread pattern of a second container running the first application;

comparing a thread pattern of the first operating system running the first container running the first application to a learned thread pattern of the first operating system running the first container running the first application;

comparing a thread pattern of a first hypervisor running a first virtual machine to a learned thread pattern of a second hypervisor running the first virtual machine;

comparing a thread pattern of the first virtual machine running the first application to a learned thread pattern of a second virtual machine running the first application;

comparing a thread pattern of the first virtual machine running the first application to a learned thread pattern of the first virtual machine running the first application;

comparing the user session thread pattern of the first user using a plurality of applications to a learned session thread pattern of the first user using the plurality of applications; and

comparing the user session thread pattern of the first user using a plurality of applications to a learned session thread pattern of the second user using the plurality of applications.

12. The method of claim **10**, wherein the learned thread pattern is a composite learned thread pattern and wherein the composite learned thread pattern comprises at least one of:

a composite learned thread pattern between a plurality of communication systems;

a composite learned thread pattern of an operating system and an application;

a composite learned thread pattern of the operating system and a hypervisor;

a composite learned thread pattern of the operating system, the hypervisor, and a container;

a composite learned thread pattern of the operating system, the hypervisor, the container, and the application; and

a composite learned thread pattern of a virtual machine and the application.

13. The method of claim **10**, wherein comparing the thread pattern to the learned thread pattern is completed using a Graph Neural Network.

14. The method of claim **10**, wherein identifying the anomaly in the thread pattern based on the variance from the learned thread pattern comprises looking at associated thread information comprising at least one of:

a function call used to start a thread in the thread pattern;

a stack size when the thread in the thread pattern was used;

a heap size when the thread in the thread pattern was used;

a memory usage when the thread in the thread pattern was used;

a timestamp when the thread in the thread pattern was used;

a time period when the thread in the thread pattern was used;

a load on a resource; and

other concurrently running applications.

15. The method of claim **10**, wherein the thread pattern comprises a plurality of thread patterns of a plurality of users and wherein identifying the anomaly in the thread pattern based on the variance from the learned thread pattern comprises: identifying a plurality of anomalies based on the plurality of thread patterns of the plurality of users, and wherein the plurality of anomalies are used to identify a group attack.

16. The method of claim **10**, wherein taking the action based on the anomaly in the thread pattern comprises one or more of: blocking one or more threads, notify a user, shutting down a container, shutting down an application, shutting down a virtual machine, quarantining an application, and a restricting resource.

17. The method of claim **10**, further comprising:

detecting a change in legitimate code in at least one of an application, an operating system, a hypervisor, a container, a virtual machine, and a library; and

in response to detecting the change in the legitimate code in at least one of the application, the operating system, the hypervisor, the container, the virtual machine, and the library, using machine learning to generate a new learned thread pattern.

18. A system comprising:

a microprocessor; and

a computer readable medium, coupled with the microprocessor and comprising microprocessor readable and executable instructions that, when executed by the microprocessor, cause the microprocessor to:

capture first thread information generated by at least one of a first operating system, a first hypervisor, a first container, and a first virtual machine;

capture second thread information generated by at least one of a second operating system, a second hypervisor, a second container, and a second virtual machine;

create a first thread pattern based on the first thread information;

create a second thread pattern based on the second thread information;

compare the first thread pattern to the second thread pattern comprising comparing a user session thread pattern of a first user using a plurality of applications to a learned session thread pattern of the first user using the plurality of applications and wherein machine learning is used to filter out variances that have a similar usage pattern, but in a different order;

identify an anomaly in the first thread pattern based on a variance from the second thread pattern; and

in response to identifying the anomaly in the first thread pattern based on the variance from the second thread pattern, taking an action.

19. The system of claim **18**, wherein comparing the user session thread pattern to the learned session thread pattern is completed using a Graph Neural Network.

20. The system of claim **18**, wherein identifying the anomaly in the first thread pattern based on the variance from the learned session thread pattern comprises looking at associated thread information comprising at least one of:

a function call used to start a thread in the first thread pattern;

a stack size when the thread in the first thread pattern was used;

a heap size when the thread in the first thread pattern was used;

a memory usage when the thread in the first thread pattern was used;

a timestamp when the thread in the first thread pattern was used;

a time period when the thread in the first thread pattern was used;

a load on a resource; and

other concurrently running applications.

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