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System and method for identifying and preventing misappropriation using normalized request sequences

Abstract

Systems, computer program products, and methods are described herein for identifying and preventing misappropriation using normalized request sequences. The method includes receiving a sequence of two or more requests associated with a user. The method also includes comparing the sequence of two or more requests with one or more past sequence of two or more past requests. The method further includes determining whether the sequence of two or more requests were carried out by the user or the malfeasant actor. The determination is made based on a comparison of the sequence of two or more requests with at least one of the one or more past sequence of two or more past requests. The method also includes causing an escalation action to be executed in an instance in which the sequence of two or more requests was carried out by the malfeasant actor.

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Background/Summary

FIELD OF THE INVENTION

(1) Example embodiments of the present disclosure relate generally to identifying and preventing misappropriation, more particularly, to identifying and preventing misappropriation using normalized request sequences.

BACKGROUND

(2) Misappropriation access of data can be difficult to monitor and prevent in real-time. Current security methods still lack the ability to prevent all misappropriation access. Through applied effort, ingenuity, and innovation, many of these identified problems have been solved by developing solutions that are included in embodiments of the present disclosure, many examples of which are described in detail herein.

SUMMARY

(3) The following presents a simplified summary of one or more embodiments of the present disclosure, in order to provide a basic understanding of such embodiments. This summary is not an extensive overview of all contemplated embodiments and is intended to neither identify key or critical elements of all embodiments nor delineate the scope of any or all embodiments. Its sole purpose is to present some concepts of one or more embodiments of the present disclosure in a simplified form as a prelude to the more detailed description that is presented later.

(4) In an example embodiment, a system for identifying and preventing misappropriation using normalized request sequences is provided. The system includes at least one non-transitory storage device and at least one processing device coupled to the at least one non-transitory storage device. The at least one processing device is configured to receive a sequence of two or more requests associated with a user. The at least one processing device is also configured to compare the sequence of two or more requests with one or more past sequence of two or more past requests. The one or more past sequence of two or more past requests were associated with one of the user or a malfeasant actor. The at least one processing device is further configured to determine whether the sequence of two or more requests were carried out by the user or the malfeasant actor. The determination is made based on a comparison of the sequence of two or more requests with at least one of the one or more past sequence of two or more past requests. The at least one processing device is also configured to cause an escalation action to be executed in an instance in which the sequence of two or more requests was carried out by the malfeasant actor.

(5) In various embodiments, the escalation action includes a notification that the sequence of two or more requests was carried out by the malfeasant actor. In various embodiments, the escalation action includes limiting access of one or more computing devices associated with the malfeasant actor.

(6) In various embodiments, the at least one processing device is configured to train a training set for the user based on the one or more past sequence of two or more past requests. In various embodiments, the training set is updated based on the determination that the sequence of two or more requests were carried out by the user.

(7) In various embodiments, the one or more past sequence of two or more past requests were carried out by the user. In various embodiments, the one or more past sequence of two or more past requests were carried out by the malfeasant actor.

(8) In another example embodiment, a computer program product for identifying and preventing misappropriation using normalized request sequences is provided. The computer program product includes at least one non-transitory computer-readable medium having computer-readable program code portions embodied therein. The computer-readable program code portions include an executable portion configured to receive a sequence of two or more requests associated with a user. The computer-readable program code portions also include an executable portion configured to compare the sequence of two or more requests with one or more past sequence of two or more past requests. The one or more past sequence of two or more past requests were associated with one of

the user or a malfeasant actor. The computer-readable program code portions further include an executable portion configured to determine whether the sequence of two or more requests were carried out by the user or the malfeasant actor. The determination is made based on a comparison of the sequence of two or more requests with at least one of the one or more past sequence of two or more past requests. The computer-readable program code portions still further include an executable portion configured to cause an escalation action to be executed in an instance in which the sequence of two or more requests was carried out by the malfeasant actor.

(9) In various embodiments, the escalation action includes a notification that the sequence of two or more requests was carried out by the malfeasant actor. In various embodiments, the escalation action includes limiting access of one or more computing devices associated with the malfeasant actor.

(10) In various embodiments, the computer program product further includes an executable portion configured to train a training set for the user using the one or more past sequence of two or more past requests. In various embodiments, the training set is updated based on the determination that the sequence of two or more requests were carried out by the user.

(11) In various embodiments, the one or more past sequence of two or more past requests were carried out by the user. In various embodiments, the one or more past sequence of two or more past requests were carried out by the malfeasant actor.

(12) In still another example embodiment, a computer-implemented method for identifying and preventing misappropriation using normalized request sequences is provided. The method includes receiving a sequence of two or more requests associated with a user. The method also includes comparing the sequence of two or more requests with one or more past sequence of two or more past requests. The one or more past sequence of two or more past requests were associated with one of the user or a malfeasant actor. The method further includes determining whether the sequence of two or more requests were carried out by the user or the malfeasant actor. The determination is made based on a comparison of the sequence of two or more requests with at least one of the one or more past sequence of two or more past requests. The method also includes causing an escalation action to be executed in an instance in which the sequence of two or more requests was carried out by the malfeasant actor.

(13) In various embodiments, the escalation action includes a notification that the sequence of two or more requests was carried out by the malfeasant actor. In various embodiments, the escalation action includes limiting access of one or more computing devices associated with the malfeasant actor.

(14) In various embodiments, the method includes training a training set for the user using the one or more past sequence of two or more past requests. In various embodiments, the training set is updated based on the determination that the sequence of two or more requests were carried out by the user.

(15) In various embodiments, the one or more past sequence of two or more past requests were carried out by the user or the malfeasant actor.

(16) The features, functions, and advantages that have been discussed may be achieved independently in various embodiments of the present disclosure or may be combined with yet other embodiments, further details of which can be seen with reference to the following description and drawings.

Description

BRIEF DESCRIPTION OF THE DRAWINGS

(1) Having described certain example embodiments of the present disclosure in general terms above, reference will now be made to the accompanying drawings. The components illustrated in

the figures may or may not be present in certain embodiments described herein. Some embodiments may include fewer (or more) components than those shown in the figures.

(2) FIGS. 1A-1C illustrates technical components of an exemplary distributed computing environment for identifying and preventing misappropriation using normalized request sequences, in accordance with an embodiment of the present disclosure;

(3) FIG. 2 illustrates an exemplary machine learning (ML) subsystem architecture used for identifying and preventing misappropriation using normalized request sequences, in accordance with an embodiment of the present disclosure;

(4) FIG. 3 illustrates a process flow for identifying and preventing misappropriation using normalized request sequences, in accordance with an embodiment of the present disclosure; and

(5) FIG. 4 illustrates a process flow for training and updating a machine learning model for identifying and preventing misappropriation using normalized request sequences, in accordance with an embodiment of the present disclosure.

DETAILED DESCRIPTION OF EMBODIMENTS OF THE INVENTION

(6) Embodiments of the present disclosure will now be described more fully hereinafter with reference to the accompanying drawings, in which some, but not all, embodiments of the disclosure are shown. Indeed, the various inventions may be embodied in many different forms and should not be construed as limited to the embodiments set forth herein; rather, these embodiments are provided so that this disclosure will satisfy applicable legal requirements. Where possible, any terms expressed in the singular form herein are meant to also include the plural form and vice versa, unless explicitly stated otherwise. Also, as used herein, the term “a” and/or “an” shall mean “one or more,” even though the phrase “one or more” is also used herein. Furthermore, when it is said herein that something is “based on” something else, it may be based on one or more other things as well. In other words, unless expressly indicated otherwise, as used herein “based on” means “based at least in part on” or “based at least partially on.” Like numbers refer to like elements throughout.

(7) As used herein, an “entity” may be any institution employing information technology resources and particularly technology infrastructure configured for processing large amounts of data. Typically, these data can be related to the people who work for the organization, its products or services, the customers or any other aspect of the operations of the organization. As such, the entity may be any institution, group, association, financial institution, establishment, company, union, authority or the like, employing information technology resources for processing large amounts of data.

(8) As described herein, a “user” may be an individual associated with an entity. As such, in some embodiments, the user may be an individual having past relationships, current relationships or potential future relationships with an entity. In some embodiments, the user may be an employee (e.g., an associate, a project manager, an IT specialist, a manager, an administrator, an internal operations analyst, or the like) of the entity or enterprises affiliated with the entity. The user may also be an automated actor, such as processor.

(9) As used herein, a “user interface” may be a point of human-computer interaction and communication in a device that allows a user to input information, such as commands or data, into a device, or that allows the device to output information to the user. For example, the user interface includes a graphical user interface (GUI) or an interface to input computer-executable instructions that direct a processor to carry out specific functions. The user interface typically employs certain input and output devices such as a display, mouse, keyboard, button, touchpad, touch screen, microphone, speaker, LED, light, joystick, switch, buzzer, bell, and/or other user input/output device for communicating with one or more users.

(10) As used herein, an “engine” may refer to core elements of an application, or part of an application that serves as a foundation for a larger piece of software and drives the functionality of the software. In some embodiments, an engine may be self-contained, but externally-controllable

code that encapsulates powerful logic designed to perform or execute a specific type of function. In one aspect, an engine may be underlying source code that establishes file hierarchy, input and output methods, and how a specific part of an application interacts or communicates with other software and/or hardware. The specific components of an engine may vary based on the needs of the specific application as part of the larger piece of software. In some embodiments, an engine may be configured to retrieve resources created in other applications, which may then be ported into the engine for use during specific operational aspects of the engine. An engine may be configurable to be implemented within any general purpose computing system. In doing so, the engine may be configured to execute source code embedded therein to control specific features of the general purpose computing system to execute specific computing operations, thereby transforming the general purpose system into a specific purpose computing system.

(11) As used herein, “authentication credentials” may be any information that can be used to identify of a user. For example, a system may prompt a user to enter authentication information such as a username, a password, a personal identification number (PIN), a passcode, biometric information (e.g., iris recognition, retina scans, fingerprints, finger veins, palm veins, palm prints, digital bone anatomy/structure, and positioning (distal phalanges, intermediate phalanges, proximal phalanges, and the like)), an answer to a security question, a unique intrinsic user activity, such as making a predefined motion with a user device. This authentication information may be used to authenticate the identity of the user (e.g., determine that the authentication information is associated with the account) and determine that the user has authority to access an account or system. In some embodiments, the system may be owned or operated by an entity. In such embodiments, the entity may employ additional computer systems, such as authentication servers, to validate and certify resources inputted by the plurality of users within the system. The system may further use its authentication servers to certify the identity of users of the system, such that other users may verify the identity of the certified users. In some embodiments, the entity may certify the identity of the users. Furthermore, authentication information or permission may be assigned to or required from a user, application, computing node, computing cluster, or the like to access stored data within at least a portion of the system.

(12) It should also be understood that “operatively coupled,” as used herein, means that the components may be formed integrally with each other, or may be formed separately and coupled together. Furthermore, “operatively coupled” means that the components may be formed directly to each other, or to each other with one or more components located between the components that are operatively coupled together. Furthermore, “operatively coupled” may mean that the components are detachable from each other, or that they are permanently coupled together. Furthermore, operatively coupled components may mean that the components retain at least some freedom of movement in one or more directions or may be rotated about an axis (i.e., rotationally coupled, pivotally coupled). Furthermore, “operatively coupled” may mean that components may be electronically connected and/or in fluid communication with one another.

(13) As used herein, an “interaction” may refer to any communication between one or more users, one or more entities or institutions, one or more devices, nodes, clusters, or systems within the distributed computing environment described herein. For example, an interaction may refer to a transfer of data between devices, an accessing of stored data by one or more nodes of a computing cluster, a transmission of a requested task, or the like.

(14) As used herein, “determining” may encompass a variety of actions. For example, “determining” may include calculating, computing, processing, deriving, investigating, ascertaining, and/or the like. Furthermore, “determining” may also include receiving (e.g., receiving information), accessing (e.g., accessing data in a memory), and/or the like. Also, “determining” may include resolving, selecting, choosing, calculating, establishing, and/or the like. Determining may also include ascertaining that a parameter matches a predetermined criterion, including that a threshold has been met, passed, exceeded, and so on.

(15) The system provides a system to identify and prevent misappropriation access of data. Entities that secure data are constantly attempting to identify and prevent misappropriating actors from access data. However, common security methods, such as private keys, multi-level authentication, dual authentication, and/or the like, can be inadequate in identifying the misappropriation access in or near real-time in order to actually prevent the access. Various embodiments of the present disclosure are configured to identify and/or prevent misappropriation access in real or near real-time.

(16) Various embodiments of the present disclosure provide for identifying and preventing misappropriation using normalized request sequences. To do this, various embodiments use an AI machine learning engine to track requests for the data and determining, based on training of certain sequences of requests, whether the accessor is likely a malfeasant actor. For instance, the AI engine may be trained to look for requests regarding what data is requested (e.g., the accessing of specific account data right away, nominal request sequences of what is normally requested, and/or the like). The system then determines if said sequence of requests match up to a specific pattern of the alleged user or a malfeasant actor. Based on the comparison, the system is configured to determine whether the sequence of requests was made by the alleged user or a malfeasant actor. In an instance in which a malfeasant actor is potentially making the sequence of requests, an escalation action may be performed by the system. In some embodiments, the AI engine may additionally be trained using requests that come from certain locations, requests that come at certain times, and the like, to determine whether an accessor is bad.

(17) The present disclosure provides a technical solution to a technical problem. As described herein, the technical problem includes identifying and preventing misappropriation access in or near real-time. The technical solution allows for improved security without any substantial impairment to processing speed.

(18) FIGS. 1A-1C illustrate technical components of an exemplary distributed computing environment for identifying and preventing misappropriation using normalized request sequences, in accordance with an embodiment of the disclosure. As shown in FIG. 1A, the distributed computing environment **100** contemplated herein may include a system **130** (i.e., an entity system), an end-point device(s) **140**, and a network **110** over which the system **130** and end-point device(s) **140** communicate therebetween. FIG. 1A illustrates only one example of an embodiment of the distributed computing environment **100**, and it will be appreciated that in other embodiments one or more of the systems, devices, and/or servers may be combined into a single system, device, or server, or be made up of multiple systems, devices, or servers. Also, the distributed computing environment **100** may include multiple systems, same or similar to system **130**, with each system providing portions of the necessary operations (e.g., as a server bank, a group of blade servers, or a multi-processor system).

(19) In some embodiments, the system **130** and the end-point device(s) **140** may have a client-server relationship in which the end-point device(s) **140** are remote devices that request and receive service from a centralized server, i.e., the system **130**. In some other embodiments, the system **130** and the end-point device(s) **140** may have a peer-to-peer relationship in which the system **130** and the end-point device(s) **140** are considered equal and all have the same abilities to use the resources available on the network **110**. Instead of having a central server (e.g., system **130**) which would act as the shared drive, each device that is connect to the network **110** would act as the server for the files stored on it.

(20) The system **130** may represent various forms of servers, such as web servers, database servers, file server, or the like, various forms of digital computing devices, such as laptops, desktops, video recorders, audio/video players, radios, workstations, or the like, or any other auxiliary network devices, such as wearable devices, Internet-of-things devices, electronic kiosk devices, mainframes, or the like, or any combination of the aforementioned.

(21) The end-point device(s) **140** may represent various forms of electronic devices, including user

input devices such as personal digital assistants, cellular telephones, smartphones, laptops, desktops, and/or the like, merchant input devices such as point-of-sale (POS) devices, electronic payment kiosks, and/or the like, electronic telecommunications device (e.g., automated teller machine (ATM)), and/or edge devices such as routers, routing switches, integrated access devices (IAD), and/or the like.

(22) The network **110** may be a distributed network that is spread over different networks. This provides a single data communication network, which can be managed jointly or separately by each network. Besides shared communication within the network, the distributed network often also supports distributed processing. The network **110** may be a form of digital communication network such as a telecommunication network, a local area network (“LAN”), a wide area network (“WAN”), a global area network (“GAN”), the Internet, or any combination of the foregoing. The network **110** may be secure and/or unsecure and may also include wireless and/or wired and/or optical interconnection technology.

(23) It is to be understood that the structure of the distributed computing environment and its components, connections and relationships, and their functions, are meant to be exemplary only, and are not meant to limit implementations of the disclosure described and/or claimed in this document. In one example, the distributed computing environment **100** may include more, fewer, or different components. In another example, some or all of the portions of the distributed computing environment **100** may be combined into a single portion or all of the portions of the system **130** may be separated into two or more distinct portions.

(24) FIG. 1B illustrates an exemplary component-level structure of the system **130**, in accordance with an embodiment of the disclosure. As shown in FIG. 1B, the system **130** may include a processor **102**, memory **104**, input/output (I/O) device **116**, and a storage device **106**. The system **130** may also include a high-speed interface **108** connecting to the memory **104**, and a low-speed interface **112** (shown as “LS Interface”) connecting to low-speed expansion port **114** (shown as “LS Port”) and storage device **110**. Each of the components **102**, **104**, **108**, **110**, and **112** may be operatively coupled to one another using various buses and may be mounted on a common motherboard or in other manners as appropriate. As described herein, the processor **102** may include a number of subsystems to execute the portions of processes described herein. Each subsystem may be a self-contained component of a larger system (e.g., system **130**) and capable of being configured to execute specialized processes as part of the larger system.

(25) The processor **102** can process instructions, such as instructions of an application that may perform the functions disclosed herein. These instructions may be stored in the memory **104** (e.g., non-transitory storage device) or on the storage device **106**, for execution within the system **130** using any subsystems described herein. It is to be understood that the system **130** may use, as appropriate, multiple processors, along with multiple memories, and/or I/O devices, to execute the processes described herein.

(26) The memory **104** stores information within the system **130**. In one implementation, the memory **104** is a volatile memory unit or units, such as volatile random access memory (RAM) having a cache area for the temporary storage of information, such as a command, a current operating state of the distributed computing environment **100**, an intended operating state of the distributed computing environment **100**, instructions related to various methods and/or functionalities described herein, and/or the like. In another implementation, the memory **104** is a non-volatile memory unit or units. The memory **104** may also be another form of computer-readable medium, such as a magnetic or optical disk, which may be embedded and/or may be removable. The non-volatile memory may additionally or alternatively include an EEPROM, flash memory, and/or the like for storage of information such as instructions and/or data that may be read during execution of computer instructions. The memory **104** may store, recall, receive, transmit, and/or access various files and/or information used by the system **130** during operation.

(27) The storage device **106** is capable of providing mass storage for the system **130**. In one aspect,

the storage device **106** may be or contain a computer-readable medium, such as a floppy disk device, a hard disk device, an optical disk device, or a tape device, a flash memory or other similar solid state memory device, or an array of devices, including devices in a storage area network or other configurations. A computer program product can be tangibly embodied in an information carrier. The computer program product may also contain instructions that, when executed, perform one or more methods, such as those described above. The information carrier may be a non-transitory computer- or machine-readable storage medium, such as the memory **104**, the storage device **106**, or memory on processor **102**.

(28) The high-speed interface **108** manages bandwidth-intensive operations for the system **130**, while the low speed interface **112** manages lower bandwidth-intensive operations. Such allocation of functions is exemplary only. In some embodiments, the high-speed interface **108** (shown as “HS Interface”) is coupled to memory **104**, input/output (I/O) device **116** (e.g., through a graphics processor or accelerator), and to high-speed expansion ports **111** (shown as “HS Port”), which may accept various expansion cards (not shown). In such an implementation, low-speed interface **112** is coupled to storage device **106** and low-speed expansion port **114**. The low-speed expansion port **114**, which may include various communication ports (e.g., USB, Bluetooth, Ethernet, wireless Ethernet), may be coupled to one or more input/output devices, such as a keyboard, a pointing device, a scanner, or a networking device such as a switch or router, e.g., through a network adapter.

(29) The system **130** may be implemented in a number of different forms. For example, it may be implemented as a standard server, or multiple times in a group of such servers. Additionally, the system **130** may also be implemented as part of a rack server system or a personal computer such as a laptop computer. Alternatively, components from system **130** may be combined with one or more other same or similar systems and an entire system **130** may be made up of multiple computing devices communicating with each other.

(30) FIG. **1C** illustrates an exemplary component-level structure of the end-point device(s) **140**, in accordance with an embodiment of the disclosure. As shown in FIG. **1C**, the end-point device(s) **140** includes a processor **152**, memory **154**, an input/output device such as a display **156**, a communication interface **158**, and a transceiver **160**, among other components. The end-point device(s) **140** may also be provided with a storage device, such as a micro-drive or other device, to provide additional storage. Each of the components **152**, **154**, **158**, and **160**, are interconnected using various buses, and several of the components may be mounted on a common motherboard or in other manners as appropriate.

(31) The processor **152** is configured to execute instructions within the end-point device(s) **140**, including instructions stored in the memory **154**, which in one embodiment includes the instructions of an application that may perform the functions disclosed herein, including certain logic, data processing, and data storing functions. The processor may be implemented as a chipset of chips that include separate and multiple analog and digital processors. The processor may be configured to provide, for example, for coordination of the other components of the end-point device(s) **140**, such as control of user interfaces, applications run by end-point device(s) **140**, and wireless communication by end-point device(s) **140**.

(32) The processor **152** may be configured to communicate with the user through control interface **164** and display interface **166** coupled to a display **156**. The display **156** may be, for example, a TFT LCD (Thin-Film-Transistor Liquid Crystal Display) or an OLED (Organic Light Emitting Diode) display, or other appropriate display technology. The display interface **156** may comprise appropriate circuitry and configured for driving the display **156** to present graphical and other information to a user. The control interface **164** may receive commands from a user and convert them for submission to the processor **152**. In addition, an external interface **168** may be provided in communication with processor **152**, so as to enable near area communication of end-point device(s) **140** with other devices. External interface **168** may provide, for example, for wired communication

in some implementations, or for wireless communication in other implementations, and multiple interfaces may also be used.

(33) The memory **154** stores information within the end-point device(s) **140**. The memory **154** can be implemented as one or more of a computer-readable medium or media, a volatile memory unit or units, or a non-volatile memory unit or units. Expansion memory may also be provided and connected to end-point device(s) **140** through an expansion interface (not shown), which may include, for example, a SIMM (Single in Line Memory Module) card interface. Such expansion memory may provide extra storage space for end-point device(s) **140** or may also store applications or other information therein. In some embodiments, expansion memory may include instructions to carry out or supplement the processes described above and may include secure information also. For example, expansion memory may be provided as a security module for end-point device(s) **140** and may be programmed with instructions that permit secure use of end-point device(s) **140**. In addition, secure applications may be provided via the SIMM cards, along with additional information, such as placing identifying information on the SIMM card in a non-hackable manner.

(34) The memory **154** may include, for example, flash memory and/or NVRAM memory. In one aspect, a computer program product is tangibly embodied in an information carrier. The computer program product contains instructions that, when executed, perform one or more methods, such as those described herein. The information carrier is a computer- or machine-readable medium, such as the memory **154**, expansion memory, memory on processor **152**, or a propagated signal that may be received, for example, over transceiver **160** or external interface **168**.

(35) In some embodiments, the user may use the end-point device(s) **140** to transmit and/or receive information or commands to and from the system **130** via the network **110**. Any communication between the system **130** and the end-point device(s) **140** may be subject to an authentication protocol allowing the system **130** to maintain security by permitting only authenticated users (or processes) to access the protected resources of the system **130**, which may include servers, databases, applications, and/or any of the components described herein. To this end, the system **130** may trigger an authentication subsystem that may require the user (or process) to provide authentication credentials to determine whether the user (or process) is eligible to access the protected resources. Once the authentication credentials are validated and the user (or process) is authenticated, the authentication subsystem may provide the user (or process) with permissioned access to the protected resources. Similarly, the end-point device(s) **140** may provide the system **130** (or other client devices) permissioned access to the protected resources of the end-point device(s) **140**, which may include a GPS device, an image capturing component (e.g., camera), a microphone, and/or a speaker.

(36) The end-point device(s) **140** may communicate with the system **130** through communication interface **158**, which may include digital signal processing circuitry where necessary.

Communication interface **158** may provide for communications under various modes or protocols, such as the Internet Protocol (IP) suite (commonly known as TCP/IP). Protocols in the IP suite define end-to-end data handling methods for everything from packetizing, addressing and routing, to receiving. Broken down into layers, the IP suite includes the link layer, containing communication methods for data that remains within a single network segment (link); the Internet layer, providing internetworking between independent networks; the transport layer, handling host-to-host communication; and the application layer, providing process-to-process data exchange for applications. Each layer contains a stack of protocols used for communications. In addition, the communication interface **158** may provide for communications under various telecommunications standards (2G, 3G, 4G, 5G, and/or the like) using their respective layered protocol stacks. These communications may occur through a transceiver **160**, such as radio-frequency transceiver. In addition, short-range communication may occur, such as using a Bluetooth, Wi-Fi, or other such transceiver (not shown). In addition, GPS (Global Positioning System) receiver module **170** may provide additional navigation—and location-related wireless data to end-point device(s) **140**, which

may be used as appropriate by applications running thereon, and in some embodiments, one or more applications operating on the system **130**.

(37) The end-point device(s) **140** may also communicate audibly using audio codec **162**, which may receive spoken information from a user and convert it to usable digital information. Audio codec **162** may likewise generate audible sound for a user, such as through a speaker, e.g., in a handset of end-point device(s) **140**. Such sound may include sound from voice telephone calls, may include recorded sound (e.g., voice messages, music files, etc.) and may also include sound generated by one or more applications operating on the end-point device(s) **140**, and in some embodiments, one or more applications operating on the system **130**.

(38) Various implementations of the distributed computing environment **100**, including the system **130** and end-point device(s) **140**, and techniques described here can be realized in digital electronic circuitry, integrated circuitry, specially designed ASICs (application specific integrated circuits), computer hardware, firmware, software, and/or combinations thereof.

(39) FIG. 2 illustrates an exemplary machine learning (ML) subsystem architecture **200**, in accordance with an embodiment of the disclosure. The machine learning subsystem **200** may include a data acquisition engine **202**, data ingestion engine **210**, data pre-processing engine **216**, ML model tuning engine **222**, and inference engine **236**.

(40) The data acquisition engine **202** may identify various internal and/or external data sources to generate, test, and/or integrate new features for training the machine learning model **224**. These internal and/or external data sources **204**, **206**, and **208** may be initial locations where the data originates or where physical information is first digitized. The data acquisition engine **202** may identify the location of the data and describe connection characteristics for access and retrieval of data. In some embodiments, data is transported from each data source **204**, **206**, or **208** using any applicable network protocols, such as the File Transfer Protocol (FTP), Hyper-Text Transfer Protocol (HTTP), or any of the myriad Application Programming Interfaces (APIs) provided by websites, networked applications, and other services. In some embodiments, these data sources **204**, **206**, and **208** may include Enterprise Resource Planning (ERP) databases that host data related to day-to-day business activities such as accounting, procurement, project management, exposure management, supply chain operations, and/or the like, mainframe that is often the entity's central data processing center, edge devices that may be any piece of hardware, such as sensors, actuators, gadgets, appliances, or machines, that are programmed for certain applications and can transmit data over the internet or other networks, and/or the like. The data acquired by the data acquisition engine **202** from these data sources **204**, **206**, and **208** may then be transported to the data ingestion engine **210** for further processing.

(41) Depending on the nature of the data imported from the data acquisition engine **202**, the data ingestion engine **210** may move the data to a destination for storage or further analysis. Typically, the data imported from the data acquisition engine **202** may be in varying formats as they come from different sources, including RDBMS, other types of databases, S3 buckets, CSVs, or from streams. Since the data comes from different places, it needs to be cleansed and transformed so that it can be analyzed together with data from other sources. At the data acquisition engine **202**, the data may be ingested in real-time, using the stream processing engine **212**, in batches using the batch data warehouse **214**, or a combination of both. The stream processing engine **212** may be used to process continuous data stream (e.g., data from edge devices), i.e., computing on data directly as it is received, and filter the incoming data to retain specific portions that are deemed useful by aggregating, analyzing, transforming, and ingesting the data. On the other hand, the batch data warehouse **214** collects and transfers data in batches according to scheduled intervals, trigger events, or any other logical ordering.

(42) In machine learning, the quality of data and the useful information that can be derived therefrom directly affects the ability of the machine learning model **224** to learn. The data pre-processing engine **216** may implement advanced integration and processing steps needed to prepare

the data for machine learning execution. This may include modules to perform any upfront, data transformation to consolidate the data into alternate forms by changing the value, structure, or format of the data using generalization, normalization, attribute selection, and aggregation, data cleaning by filling missing values, smoothing the noisy data, resolving the inconsistency, and removing outliers, and/or any other encoding steps as needed.

(43) In addition to improving the quality of the data, the data pre-processing engine **216** may implement feature extraction and/or selection techniques to generate training data **218**. Feature extraction and/or selection is a process of dimensionality reduction by which an initial set of data is reduced to more manageable groups for processing. A characteristic of these large data sets is a large number of variables that require a lot of computing resources to process. Feature extraction and/or selection may be used to select and/or combine variables into features, effectively reducing the amount of data that must be processed, while still accurately and completely describing the original data set. Depending on the type of machine learning algorithm being used, this training data **218** may require further enrichment. For example, in supervised learning, the training data is enriched using one or more meaningful and informative labels to provide context so a machine learning model can learn from it. For example, labels might indicate whether a photo contains a bird or car, which words were uttered in an audio recording, or if an x-ray contains a tumor. Data labeling is required for a variety of use cases including computer vision, natural language processing, and speech recognition. In contrast, unsupervised learning uses unlabeled data to find patterns in the data, such as inferences or clustering of data points.

(44) The ML model tuning engine **222** may be used to train a machine learning model **224** using the training data **218** to make predictions or decisions without explicitly being programmed to do so. The machine learning model **224** represents what was learned by the selected machine learning algorithm **220** and represents the rules, numbers, and any other algorithm-specific data structures required for classification. Selecting the right machine learning algorithm may depend on a number of different factors, such as the problem statement and the kind of output needed, type and size of the data, the available computational time, number of features and observations in the data, and/or the like. Machine learning algorithms may refer to programs (math and logic) that are configured to self-adjust and perform better as they are exposed to more data. To this extent, machine learning algorithms are capable of adjusting their own parameters, given feedback on previous performance in making prediction about a dataset.

(45) The machine learning algorithms contemplated, described, and/or used herein include supervised learning (e.g., using logistic regression, using back propagation neural networks, using random forests, decision trees, etc.), unsupervised learning (e.g., using an Apriori algorithm, using K-means clustering), semi-supervised learning, reinforcement learning (e.g., using a Q-learning algorithm, using temporal difference learning), and/or any other suitable machine learning model type. Each of these types of machine learning algorithms can implement any of one or more of a regression algorithm (e.g., ordinary least squares, logistic regression, stepwise regression, multivariate adaptive regression splines, locally estimated scatterplot smoothing, etc.), an instance-based method (e.g., k-nearest neighbor, learning vector quantization, self-organizing map, etc.), a regularization method (e.g., ridge regression, least absolute shrinkage and selection operator, elastic net, etc.), a decision tree learning method (e.g., classification and regression tree, iterative dichotomiser 3, C4.5, chi-squared automatic interaction detection, decision stump, random forest, multivariate adaptive regression splines, gradient boosting machines, etc.), a Bayesian method (e.g., naïve Bayes, averaged one-dependence estimators, Bayesian belief network, etc.), a kernel method (e.g., a support vector machine, a radial basis function, etc.), a clustering method (e.g., k-means clustering, expectation maximization, etc.), an associated rule learning algorithm (e.g., an Apriori algorithm, an Eclat algorithm, etc.), an artificial neural network model (e.g., a Perceptron method, a back-propagation method, a Hopfield network method, a self-organizing map method, a learning vector quantization method, etc.), a deep learning algorithm (e.g., a restricted Boltzmann

machine, a deep belief network method, a convolution network method, a stacked auto-encoder method, etc.), a dimensionality reduction method (e.g., principal component analysis, partial least squares regression, Sammon mapping, multidimensional scaling, projection pursuit, etc.), an ensemble method (e.g., boosting, bootstrapped aggregation, AdaBoost, stacked generalization, gradient boosting machine method, random forest method, etc.), and/or the like.

(46) To tune the machine learning model, the ML model tuning engine **222** may repeatedly execute cycles of experimentation **226**, testing **228**, and tuning **230** to optimize the performance of the machine learning algorithm **220** and refine the results in preparation for deployment of those results for consumption or decision making. To this end, the ML model tuning engine **222** may dynamically vary hyperparameters each iteration (e.g., number of trees in a tree-based algorithm or the value of alpha in a linear algorithm), run the algorithm on the data again, then compare its performance on a validation set to determine which set of hyperparameters results in the most accurate model. The accuracy of the model is the measurement used to determine which set of hyperparameters is best at identifying relationships and patterns between variables in a dataset based on the input, or training data **218**. A fully trained machine learning model **232** is one whose hyperparameters are tuned and model accuracy maximized.

(47) The trained machine learning model **232**, similar to any other software application output, can be persisted to storage, file, memory, or application, or looped back into the processing component to be reprocessed. More often, the trained machine learning model **232** is deployed into an existing production environment to make practical business decisions based on live data **234**. To this end, the machine learning subsystem **200** uses the inference engine **236** to make such decisions. The type of decision-making may depend upon the type of machine learning algorithm used. For example, machine learning models trained using supervised learning algorithms may be used to structure computations in terms of categorized outputs (e.g., C_1, C_2 . . . C_n **238**) or observations based on defined classifications, represent possible solutions to a decision based on certain conditions, model complex relationships between inputs and outputs to find patterns in data or capture a statistical structure among variables with unknown relationships, and/or the like. On the other hand, machine learning models trained using unsupervised learning algorithms may be used to group (e.g., C_1, C_2 . . . C_n **238**) live data **234** based on how similar they are to one another to solve exploratory challenges where little is known about the data, provide a description or label (e.g., C_1, C_2 . . . C_n **238**) to live data **234**, such as in classification, and/or the like. These categorized outputs, groups (clusters), or labels are then presented to the system **130**. In still other cases, machine learning models that perform regression techniques may use live data **234** to predict or forecast continuous outcomes.

(48) It will be understood that the embodiment of the machine learning subsystem **200** illustrated in FIG. 2 is exemplary and that other embodiments may vary. As another example, in some embodiments, the machine learning subsystem **200** may include more, fewer, or different components. The machine learning subsystem **200** may be a part of the distributed computing environment **100**, as a part of the system **130**, the end unit(s) **140**, and/or as an individual component (e.g., a standalone device with processor, memory, and/or the like).

(49) FIG. 3 is a flow chart **300** that illustrates an example method of identifying and preventing misappropriation using normalized request sequences. The method may be carried out by various components of the distributed computing environment **100** discussed herein (e.g., the system **130**, one or more end-point devices **140**, etc). An example system may include at least one non-transitory storage device and at least one processing device coupled to the at least one non-transitory storage device. In such an embodiment, the at least one processing device is configured to carry out the method discussed herein.

(50) Referring now to Block **302** of FIG. 3, the method includes receiving a sequence of two or more requests associated with a user. The user as used in the present disclosure may be a person or automated computing device that is attempting to carry out the two or more requests. The request

may be any action that is related to a data request or interaction with data. The request may be associated with the user based on the computing device and/or an account being associated with a computer. The request may be transmitted (or masked to appear as being transmitted) by a computing device registered to the user. The request may be transmitted (or masked to appear as being transmitted) by a computing device logged into an account associated with the user. In various embodiments, the sequence of two or more requests is an ordered listing of the steps taken by the user (e.g., computing device associated with the user) to submit a given request for data or the like.

(51) The sequence of two or more requests associated with a user may be tracked using various computer tracking technology, such as metadata, key stroke tracking, and/or the like. The sequence of two or more requests associated with a user may be stored in a log and/or transmitted in real-time. The sequence of two or more requests associated with a user may include information relating to timing of each request (e.g., a timestamp), location of each request (e.g., location of computing device making said request), type of request, and/or the like. The type of request may include the data that is being requested.

(52) Referring now to Block **304** of FIG. 3, the method includes comparing the sequence of two or more requests with one or more past sequence of two or more past requests. The one or more past sequence of two or more past requests may include past sequences by the user, by other user, and/or by known malfeasant actors. A malfeasant actor may be any person or computing device that is attempting to make a request associated with a user that is not authorized to make a request for said user. While the term malfeasant actor may include intentional misappropriation, malfeasant actors may include other users that are not authorized to make requests for the user (e.g., a user being logged into the wrong account).

(53) The comparison of the sequence of two or more requests with one or more past sequence of two or more past requests may include a comparison of the data requested during a request in the past requests (e.g., the data requested is compared to past requests). For example, the size of the data requested may be compared to the previous request and large discrepancies may intend a malfeasant actor (e.g., a malfeasant actor may request more data than the intended actor). The type of requests may also be compared (e.g., a malfeasant actor may use admin requests while the user typically does not use such admin requests).

(54) In various embodiments, the one or more past sequence of two or more past requests may be a past sequence of the specific user. Each user of a service may have one or more past sequences stored that are used for comparison. For example, a user may carry out data requests in the same or similar ways across different requests (e.g., same location, same time, same order of operations, and/or the like). Such information on the data requests may be associated with the user and stored, such that a new sequence of two or more requests for a user can be compared to the stored sequences for similarities. In some instances, the system may have a threshold value for which the sequence of two or more requests and one or more past sequence of two or more past requests are similar. The level of the threshold value may be based on the level of security used. For example, higher security may require more similarities between the sequence of two or more requests and the one or more past sequence of two or more past requests than lower security. Based on the similarities, the system is configured to determine whether the sequence of two or more requests was carried out by the user.

(55) In various embodiments, the one or more past sequence of two or more past requests may be a past sequence of one or more malfeasant actors. Malfeasant actors may carry out misappropriation attacks in similar ways across multiple attacks. However, malfeasant actors are often difficult to determine before the misappropriation. However, known misappropriations can be used to prevent future misappropriations. Using the machine learning model discussed herein, the past sequence of known malfeasant actors can be compared to the one or more sequences of two or more requests to determine whether there are similarities between the sequence of two or more requests and the one

or more past sequence of two or more past requests. The system may have a threshold value, such that in an instance in which the similarity is above the threshold value, then the sequence is marked as being carried out by a malfeasant actor. The level of the threshold value may be based on the level of security used. For example, higher security may require less similarities between the sequence of two or more requests and the one or more past sequence of two or more past requests than lower security.

(56) In various embodiments, the one or more past sequence of two or more past requests may be past sequences by other similar users to the user. For example, human users may have generally similar actions, while computers attempting to act as a user may have completely different actions. As such, the one or more sequences of two or more requests may be compared to one or more past sequence of two or more past requests by other users.

(57) As discussed below in reference to FIG. 6, the one or more past sequence of two or more past requests may be generated using machine learning. For example, one or more machine learning models may be used to create a training set based on one or more past sequence of two or more past requests and the sequence of two or more requests are then compared to the training set.

(58) Referring now to Block 306 of FIG. 3, the method includes determining whether the sequence of two or more requests were carried out by the user or the malfeasant actor. The determination is made based on a comparison of the sequence of two or more requests with at least one of the one or more past sequence of two or more past requests. As discussed above, the system may have a threshold value in which in an instance in which the threshold value is met, the sequence is determined to be carried out by the user or a malfeasant actor. The confidence level may be based on the level of security desired.

(59) Referring now to Block 308 of FIG. 3, the method includes causing an escalation action to be executed in an instance in which the sequence of two or more requests was carried out by the malfeasant actor. The escalation action may be any action in response to the determination that the actions were carried out by the malfeasant actor with the intent to prevent such misappropriation. The escalation action may be causing a notification to be transmitted to a user and/or entity related to the data request to review the requests. For example, the user may receive a notification that requests were made on the user's behalf. In some instances, the escalation action may include user verification (e.g., a user may be asked to confirm that the user submitted said request). The user verification may be completed using two-factor authentication and/or the like.

(60) Additionally or alternatively, the escalation action may be proactive restriction of the data request. For example, the requests may be delayed or automatically rejected. In some instances, the requests may be delayed for review (e.g., review by user and/or entity related to the request). The escalation action may also include limiting access of one or more computing devices associated with the malfeasant actor. For example, a suspected malfeasant actor may have access to the network limited (e.g., limit the amount or type of requests available) or completely deactivating access (e.g., either temporary and/or permanent ban).

(61) FIG. 4 is a flow chart 400 that illustrates an example method of training and updating a machine learning model used in various embodiments for identifying and preventing misappropriation using normalized request sequences. The method may be carried out by various components of the distributed computing environment 100 (e.g., the system 130, one or more end-point devices 140, etc) and/or the machine learning subsystem 200. An example system may include at least one non-transitory storage device and at least one processing device coupled to the at least one non-transitory storage device. In such an embodiment, the at least one processing device is configured to carry out the method discussed herein.

(62) Referring now to Block 402 of FIG. 4, the method includes training a training set for the user based on the one or more past sequence of two or more past requests. The training set may be trained using the operations discussed above in reference to FIG. 2. Namely, the one or more past sequences of two or more past requests may be imported from the data acquisition engine 202 and

used to train the machine learning models. The machine learning models used may be any disclosed above.

(63) Referring now to Block **404** of FIG. **4**, the method includes using the training set to compare the sequence of two or more requests with one or more past sequence of two or more past requests shown in Block **304** of FIG. **3**. The training set may be used to compare the sequence of two or more requests with one or more past sequence of two or more past requests by inputting the sequence of two or more requests into the machine learning model for comparison with the one or more past sequence of two or more past requests. Based on the similarities, the system can determine whether the actions were carried out by the user or a malfeasant actor.

(64) Referring now to Block **406** of FIG. **4**, the method includes updating the training set based on the determination that the sequence of two or more requests were carried out by the user or the malfeasant actor, as shown in FIG. **3**. In an instance in which the one or more past sequence of two or more past requests were carried out by the user, the training set may be updated to include the sequence of two or more past requests in an instance in which the sequence of two or more requests were carried out by the user. In an instance in which the one or more past sequence of two or more past requests were carried out by the malfeasant actor, the training set may be updated to include the sequence of two or more past requests in an instance in which the sequence of two or more requests were carried out by the malfeasant actor.

(65) In some embodiments, additional reviews may be carried out before updating the training set based on the determination that the sequence of two or more requests were carried out by the user or the malfeasant actor. For example, a third party review of the sequence of two or more requests may be carried out to confirm that the determination was correct (e.g., a user may be asked to confirm that the requests were made by the user, or a manual review of the sequence may be completed). In various embodiments, the additional review may be used to improve the machine learning model.

(66) As will be appreciated by one of ordinary skill in the art, various embodiments of the present disclosure may be embodied as an apparatus (including, for example, a system, a machine, a device, a computer program product, and/or the like), as a method (including, for example, a business process, a computer-implemented process, and/or the like), or as any combination of the foregoing. Accordingly, embodiments of the present disclosure may take the form of an entirely software embodiment (including firmware, resident software, micro-code, and the like), an entirely hardware embodiment, or an embodiment combining software and hardware aspects that may generally be referred to herein as a “system.” Furthermore, embodiments of the present disclosure may take the form of a computer program product that includes a computer-readable storage medium having computer-executable program code portions stored therein. As used herein, a processor may be “configured to” perform a certain function in a variety of ways, including, for example, by having one or more special-purpose circuits perform the functions by executing one or more computer-executable program code portions embodied in a computer-readable medium, and/or having one or more application-specific circuits perform the function.

(67) It will be understood that any suitable computer-readable medium may be utilized. The computer-readable medium may include, but is not limited to, a non-transitory computer-readable medium, such as a tangible electronic, magnetic, optical, infrared, electromagnetic, and/or semiconductor system, apparatus, and/or device. For example, in some embodiments, the non-transitory computer-readable medium includes a tangible medium such as 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), a compact disc read-only memory (CD-ROM), and/or some other tangible optical and/or magnetic storage device. In other embodiments of the present disclosure, however, the computer-readable medium may be transitory, such as a propagation signal including computer-executable program code portions embodied therein.

(68) It will also be understood that one or more computer-executable program code portions for carrying out the specialized operations of the present disclosure may be required on the specialized computer include object-oriented, scripted, and/or unscripted programming languages, such as, for example, Java, Perl, Smalltalk, C++, SAS, SQL, Python, Objective C, and/or the like. In some embodiments, the one or more computer-executable program code portions for carrying out operations of embodiments of the present disclosure are written in conventional procedural programming languages, such as the “C” programming languages and/or similar programming languages. The computer program code may alternatively or additionally be written in one or more multi-paradigm programming languages, such as, for example, F#.

(69) It will further be understood that some embodiments of the present disclosure are described herein with reference to flowchart illustrations and/or block diagrams of systems, methods, and/or computer program products. It will be understood that each block included in the flowchart illustrations and/or block diagrams, and combinations of blocks included in the flowchart illustrations and/or block diagrams, may be implemented by one or more computer-executable program code portions. These computer-executable program code portions execute via the processor of the computer and/or other programmable data processing apparatus and create mechanisms for implementing the steps and/or functions represented by the flowchart(s) and/or block diagram block(s).

(70) It will also be understood that the one or more computer-executable program code portions may be stored in a transitory or non-transitory computer-readable medium (e.g., a memory, and the like) that can direct a computer and/or other programmable data processing apparatus to function in a particular manner, such that the computer-executable program code portions stored in the computer-readable medium produce an article of manufacture, including instruction mechanisms which implement the steps and/or functions specified in the flowchart(s) and/or block diagram block(s).

(71) The one or more computer-executable program code portions may also be loaded onto a computer and/or other programmable data processing apparatus to cause a series of operational steps to be performed on the computer and/or other programmable apparatus. In some embodiments, this produces a computer-implemented process such that the one or more computer-executable program code portions which execute on the computer and/or other programmable apparatus provide operational steps to implement the steps specified in the flowchart(s) and/or the functions specified in the block diagram block(s). Alternatively, computer-implemented steps may be combined with operator and/or human-implemented steps in order to carry out an embodiment of the present disclosure.

(72) While certain exemplary embodiments have been described and shown in the accompanying drawings, it is to be understood that such embodiments are merely illustrative of, and not restrictive on, the broad disclosure, and that this disclosure not be limited to the specific constructions and arrangements shown and described, since various other changes, combinations, omissions, modifications and substitutions, in addition to those set forth in the above paragraphs, are possible. Those skilled in the art will appreciate that various adaptations and modifications of the just described embodiments can be configured without departing from the scope and spirit of the disclosure. Therefore, it is to be understood that, within the scope of the appended claims, the disclosure may be practiced other than as specifically described herein.

Claims

1. A system for identifying and preventing misappropriation using normalized request sequences, the system comprising: at least one non-transitory storage device; and at least one processing device coupled to the at least one non-transitory storage device, wherein the at least one processing device is configured to: receive a sequence of two or more requests associated with a user; compare

the sequence of two or more requests with one or more past sequence of two or more past requests, wherein the one or more past sequence of two or more past requests were associated with one of the user or a malfeasant actor; determine whether the sequence of two or more requests were carried out by the user or the malfeasant actor, wherein the determination is made based on a comparison of the sequence of two or more requests with at least one of the one or more past sequence of two or more past requests; in an instance in which the sequence of two or more requests was carried out by the malfeasant actor, cause an escalation action to be executed, wherein the escalation action comprises limited access to computing devices associated with the malfeasant actor; and update a training set for a machine learning model for the normalized request sequences with the sequence of two or more requests associated with the user.

2. The system of claim 1, wherein the escalation action comprises a notification that the sequence of two or more requests was carried out by the malfeasant actor.

3. The system of claim 1, wherein the at least one processing device is configured to train a training set for the user based on the one or more past sequence of two or more past requests.

4. The system of claim 3, wherein the training set is updated based on the determination that the sequence of two or more requests were carried out by the user.

5. The system of claim 1, wherein the one or more past sequence of two or more past requests were carried out by the user.

6. The system of claim 1, wherein the one or more past sequence of two or more past requests were carried out by the malfeasant actor.

7. A computer program product for identifying and preventing misappropriation using normalized request sequences, the computer program product comprising at least one non-transitory computer-readable medium having computer-readable program code portions embodied therein, the computer-readable program code portions comprising: an executable portion configured to receive a sequence of two or more requests associated with a user, an executable portion configured to compare the sequence of two or more requests with one or more past sequence of two or more past requests, wherein the one or more past sequence of two or more past requests were associated with one of the user or a malfeasant actor; an executable portion configured to determine whether the sequence of two or more requests were carried out by the user or the malfeasant actor, wherein the determination is made based on a comparison of the sequence of two or more requests with at least one of the one or more past sequence of two or more past requests; an executable portion configured to cause an escalation action to be executed in an instance in which the sequence of two or more requests was carried out by the malfeasant actor, wherein the escalation action comprises limited access to computing devices associated with the malfeasant actor; and update a training set for a machine learning model for the normalized request sequences with the sequence of two or more requests associated with the user.

8. The computer program product of claim 7, wherein the escalation action comprises a notification that the sequence of two or more requests was carried out by the malfeasant actor.

9. The computer program product of claim 7, wherein the computer program product further comprises an executable portion configured to train a training set for the user using the one or more past sequence of two or more past requests.

10. The computer program product of claim 9, wherein the training set is updated based on the determination that the sequence of two or more requests were carried out by the user.

11. The computer program product of claim 7, wherein the one or more past sequence of two or more past requests were carried out by the user.

12. The computer program product of claim 7, wherein the one or more past sequence of two or more past requests were carried out by the malfeasant actor.

13. A computer-implemented method for identifying and preventing misappropriation using normalized request sequences, the method comprising: receiving a sequence of two or more requests associated with a user; comparing the sequence of two or more requests with one or more

past sequence of two or more past requests, wherein the one or more past sequence of two or more past requests were associated with one of the user or a malfeasant actor; determining whether the sequence of two or more requests were carried out by the user or the malfeasant actor, wherein the determination is made based on a comparison of the sequence of two or more requests with at least one of the one or more past sequence of two or more past requests; in an instance in which the sequence of two or more requests was carried out by the malfeasant actor, causing an escalation action to be executed, wherein the escalation action comprises limited access to computing devices associated with the malfeasant actor; and updating a training set for a machine learning model for the normalized request sequences with the sequence of two or more requests associated with the user.

14. The method of claim 13, wherein the escalation action comprises a notification that the sequence of two or more requests was carried out by the malfeasant actor.

15. The method of claim 13, further comprising training a training set for the user using the one or more past sequence of two or more past requests.

16. The method of claim 15, wherein the training set is updated based on the determination that the sequence of two or more requests were carried out by the user.

17. The method of claim 13, wherein the one or more past sequence of two or more past requests were carried out by the user or the malfeasant actor.
