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Bartos et al.

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(45) **Date of Patent: Oct. 4, 2016**

(54) **IDENTIFYING THREATS BASED ON HIERARCHICAL CLASSIFICATION**

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G06F 21/55	(2013.01)
G06F 17/30	(2006.01)

(52) **U.S. Cl.**

CPC ***H04L 63/1416*** (2013.01); ***G06F 17/30861*** (2013.01); ***G06F 21/552*** (2013.01); ***H04L 63/1425*** (2013.01); ***H04L 63/1433*** (2013.01); *H04L 2463/142* (2013.01)

(58) **Field of Classification Search**

USPC 726/24, 2

See application file for complete search history.

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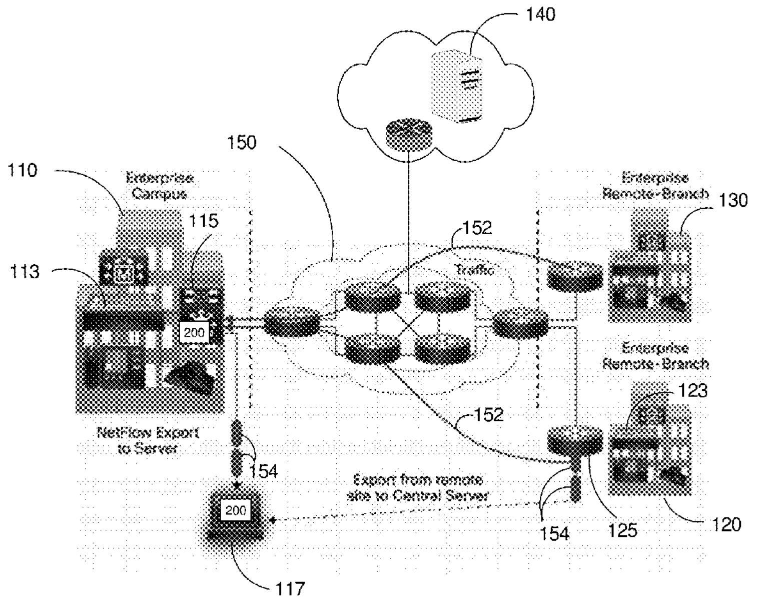
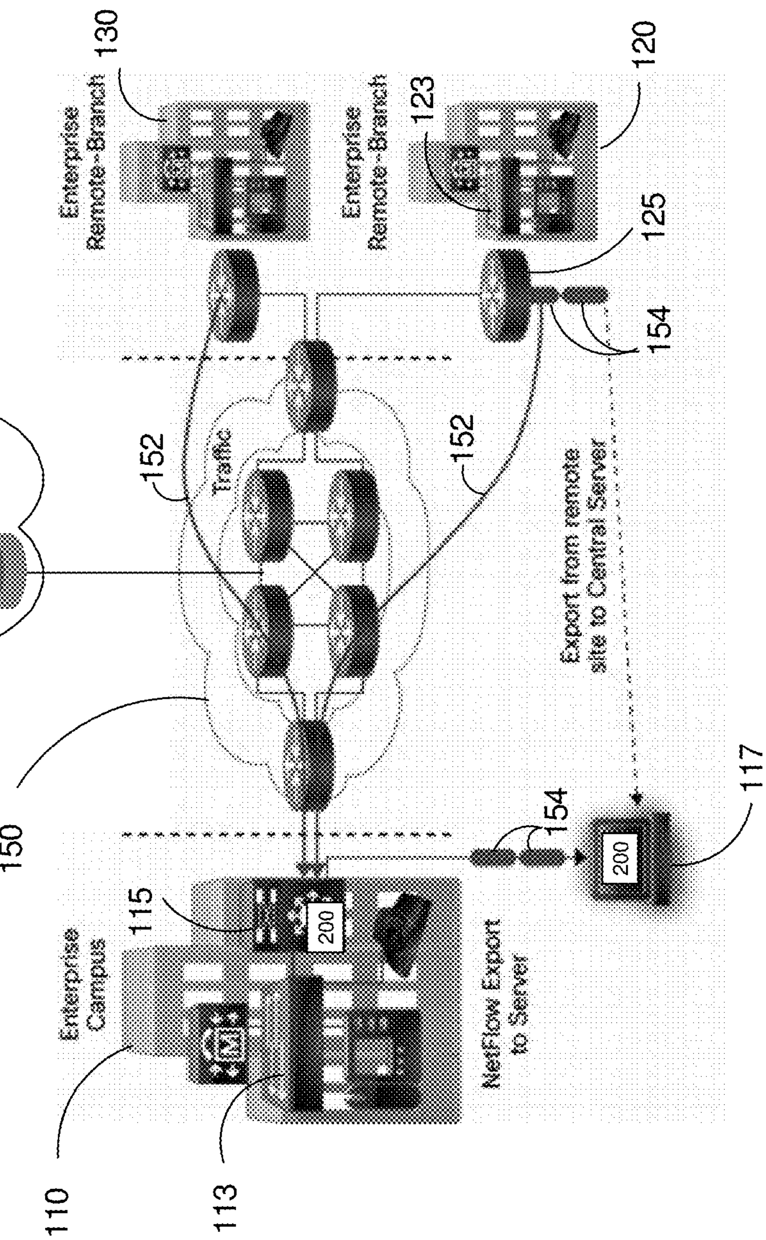
(57) **ABSTRACT**

A system and a method are disclosed for identifying network threats based on hierarchical classification. The system receives packet flows from a data network and determines flow features for the received packet flows based on data from the packet flows. The system also classifies each packet flow into a flow class based on flow features of the packet flow. Based on a criterion, the system selects packet flows from the received packet flows and places the selected packet flows into an event set that represents an event on the network. The system determines event set features for the event set based on the flow features of the selected packet flows. The system then classifies the event set into a set class based on the determined event set features. Based on the set class, the computer system may report a threat incident on an internetworking device that originated the selected packet flows.

20 Claims, 6 Drawing Sheets





140
130
Enterprise Remote–Branch
120
123
Enterprise Remote–Branch
125
154
152
Traffic
152
Export from remote site to Central Server
150
117
200
154
115
200
Enterprise Campus
NetFlow Export to Server
110
113

FIG. 1

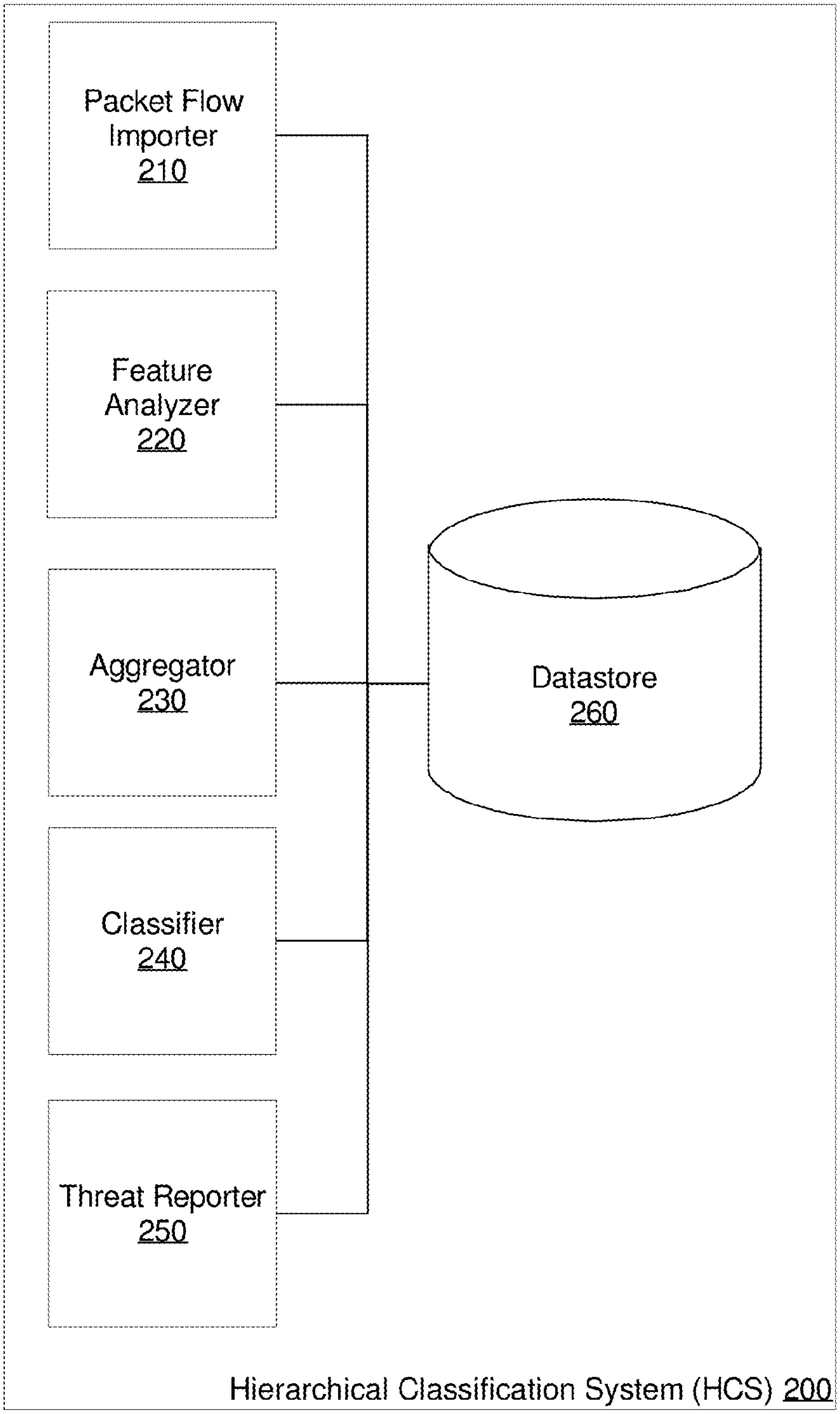
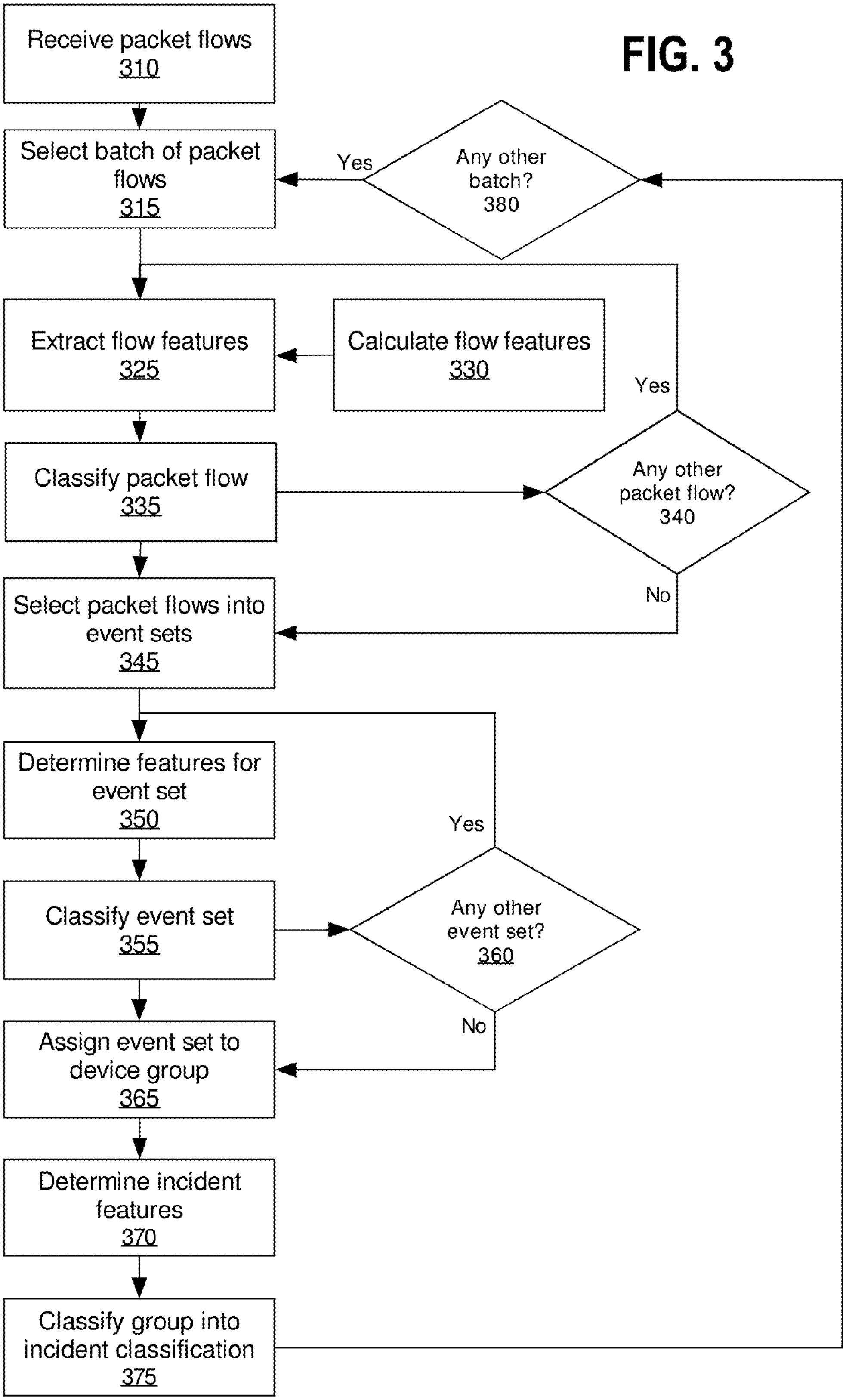

Packet Flow Importer 210
Feature Analyzer 220
Aggregator 230
Classifier 240
Threat Reporter 250
Datastore 260
Hierarchical Classification System (HCS) 200

FIG. 2

FIG. 3


Receive packet flows
310
Select batch of packet flows
315
Yes
Any other batch?
380
Extract flow features
325
Calculate flow features
330
Yes
Classify packet flow
335
Any other packet flow?
340
No
Select packet flows into event sets
345
Determine features for event set
350
Yes
Classify event set
355
Any other event set?
360
No
Assign event set to device group
365
Determine incident features
370
Classify group into incident classification
375

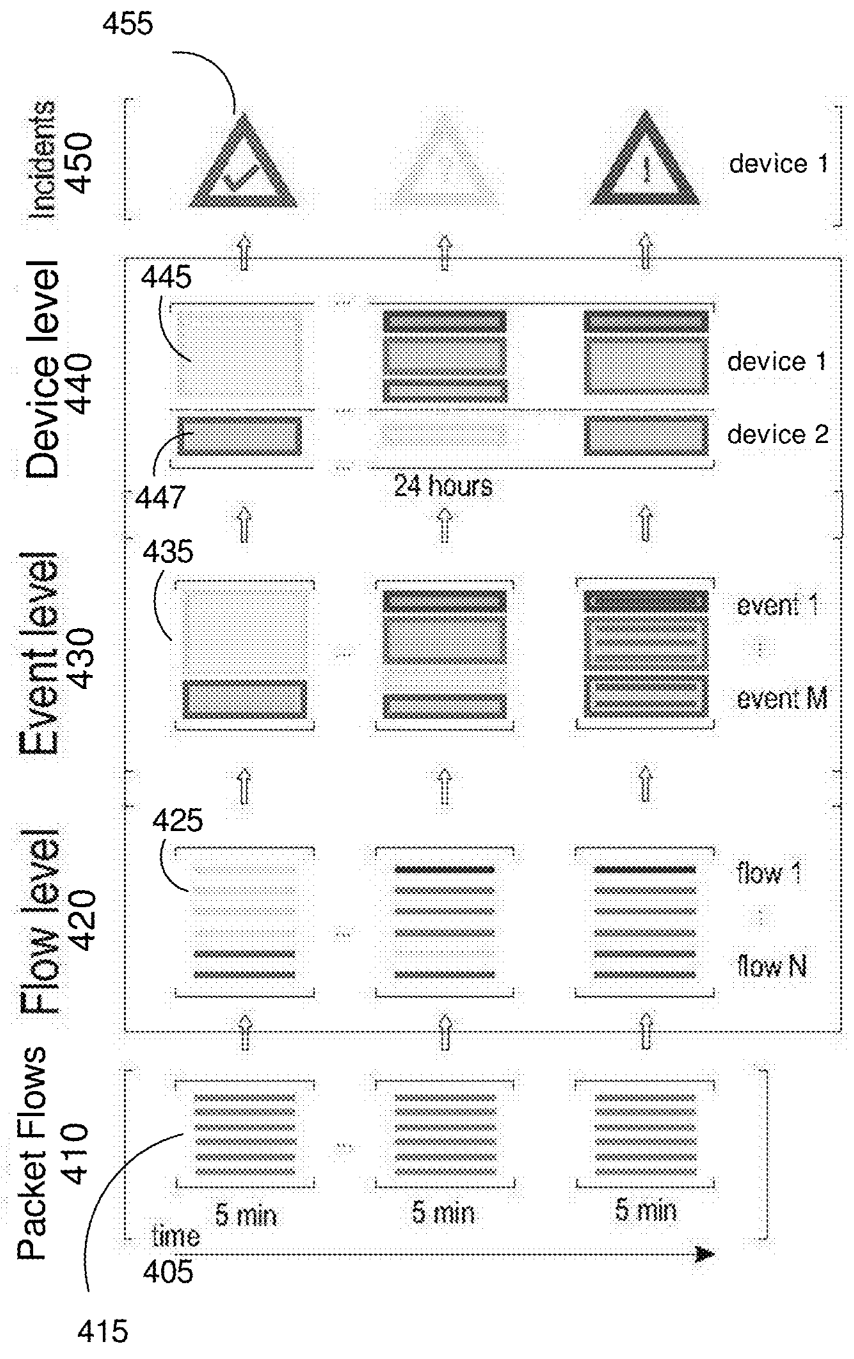

455
Incidents
450
device 1
Device level
440
445
device 1
device 2
447
24 hours
Event level
430
435
event 1
event M
Flow level
420
425
flow 1
flow N
Packet Flows
410
5 min
5 min
5 min
time
405
415

FIG. 4

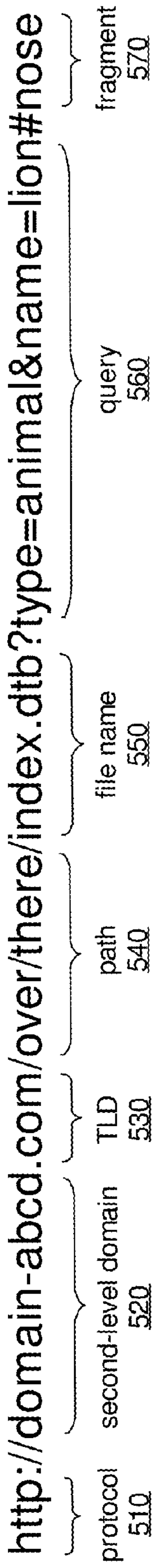
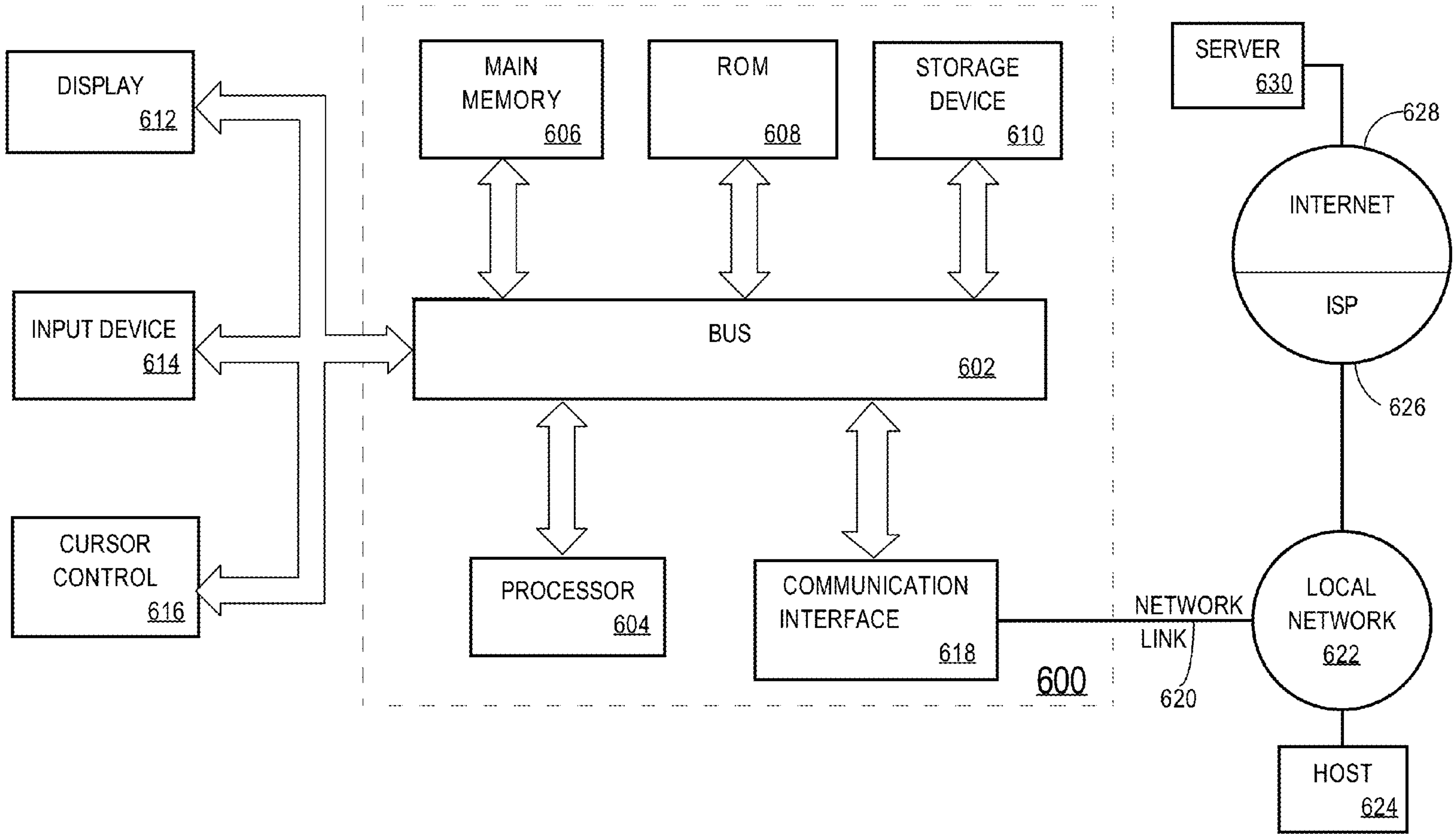

http://domain-abcd.com/over/there/index.dtb?type=animal&name=lion#nose
protocol 510
second-level domain 520
TLD 530
path 540
file name 550
query 560
fragment 570

FIG. 5

Fig. 6


DISPLAY
612
INPUT DEVICE
614
CURSOR
CONTROL
616
MAIN
MEMORY
606
ROM
608
STORAGE
DEVICE
610
BUS
602
PROCESSOR
604
COMMUNICATION
INTERFACE
618
600
NETWORK
LINK
620
LOCAL
NETWORK
622
HOST
624
INTERNET
ISP
626
628
SERVER
630

IDENTIFYING THREATS BASED ON HIERARCHICAL CLASSIFICATION

BENEFIT CLAIM

This application claims the benefit under 35 U.S.C. §119 (e) of provisional application 61/994,344, filed May 16, 2014, the entire contents of which is hereby incorporated by reference for all purposes as if fully set forth herein.

TECHNICAL FIELD

The present disclosure generally relates to improved methods, computer software and computer hardware in the field of security of computer networks. The disclosure relates more specifically to improved computer-based network security devices and computer-implemented techniques that can perform classifying threats in computer networks.

BACKGROUND

The approaches described in this section could be pursued, but are not necessarily approaches that have been previously conceived or pursued. Therefore, unless otherwise indicated herein, the approaches described in this section are not prior art to the claims in this application and are not admitted to be prior art by inclusion in this section.

Network security incidents are composed of several events, steps or actions that an attacker may take to compromise a targeted network and extract valuable intellectual property or personal data, or perform malicious reconfiguration operations. These steps may include scanning of potential targets, initial infection, library download, or communication with a command and control server.

Traditionally, signature-based security devices, firewalls, or anti-viruses are deployed to detect such threats. However, signature-based algorithms simply compare a byte sequence that has been detected to stored byte-sequences corresponding to known threats, which may be in a database. Thus, if a new threat has not yet been analyzed and recorded into the database, the signature based algorithm may not identify the new threat. Furthermore, if a threat has the ability to change, the signature-based algorithms may again fail to identify the threat because a current signature of the threat may be different than a stored signature of the same threat that was recorded earlier. Thus, polymorphic malware, zero-day attacks by threats that are novel or previously unseen, or other types of advanced persistent network threats are usually not detected or blocked by signature-based security algorithms.

BRIEF DESCRIPTION OF THE DRAWINGS

In the drawings:

FIG. **1** illustrates an example operating environment upon which an embodiment may be implemented.

FIG. **2** is a block diagram that illustrates an embodiment of a hierarchical classification system (HCS).

FIG. **3** is a flow diagram that depicts a process of hierarchically classifying packet flows into network threats, in an embodiment.

FIG. **4** depicts an example of packet flow classification on different levels of hierarchy, in an embodiment.

FIG. **5** depicts an URL string partition, in an embodiment.

FIG. **6** is a block diagram that illustrates a computer system upon which an embodiment of the system may be implemented.

DESCRIPTION OF EXAMPLE EMBODIMENTS

Identifying threats based on hierarchical classification is described. In the following description, for the purposes of explanation, numerous specific details are set forth in order to provide a thorough understanding of the present disclosure. It will be apparent, however, to one skilled in the art that the present disclosure may be practiced without these specific details. In other instances, well-known structures and devices are shown in block diagram form in order to avoid unnecessarily obscuring the present disclosure.

Embodiments are described herein according to the following outline:

1.0 GENERAL OVERVIEW

Identifying threats based on hierarchical classification is described. In an embodiment, a computer system receives a plurality of packet flows from a data network. Based on a criterion, the computer system selects packet flows from the plurality of packet flows and places the selected packet flows into a set. The computer system determines, for each packet flow in the set, a flow feature associated with that packet flow based on data from that packet flow, and classifies each packet flow into a flow class based on the flow feature. The computer system further determines set features for the set based on the flow features that are associated with the selected packet flows of the set. The computer system then classifies the set into a set class based on the determined set features. Based on the set class, the computer system may report a threat incident on an internetworking device associated with the selected packet flows. In other embodiments, the disclosure encompasses a method that carries out the foregoing steps using one or more computing devices.

In an embodiment, a hierarchical classification system (HCS) analyzes network packet flows with statistical and machine learning algorithms to identify and report novel security threat incidents from events on a computing device. As referred to herein, "packet flow" describes packet traffic that comprises network packets with the same source and destination internet addresses. In some embodiment, network packets of a packet flow may also have the same source port number, the same destination port number and the same protocol. The events are identified from the packet flows, classified, and combined into incidents based on automatically-recognized relationships. Since the system analyzes various features of network traffic on different levels of granularity, from packet flows to events to incidents, the system may correlate fast classifiers at the lower levels like the packet flow level with complex, more computationally intensive classifiers at the higher levels like incident level to help identify threats more effectively. At every level, the classifiers utilize statistical properties derived from the network traffic at the granularity that is specific to each level as well as information gained at the lower levels. The system then may classify network traffic starting with simple classifiers designed to process millions network connections per minute and ending with modeling the behavior of each potentially infected computing device. The resulting classification data may be used to facilitate more efficient, faster recognition of threats in networks and to initiate remediation efforts.

2.0 EXAMPLE OPERATING ENVIRONMENT

FIG. **1** illustrates an example operating environment upon which an embodiment may be implemented. In FIG. **1**, network traffic **152** between enterprise main campus **110** and enterprise remote branches **120**, **130** is depicted. The computer system **123** of branch **120** may initiate communication with computer system **113** of main campus **110** through a proxy device **125** that is connected to Internet **150**. Packet flows **154** of the network communication from computer system **123** are routed by internetworking devices in Internet **150** to a gateway computer system **115**. Once received by gateway computer system **115**, the communication is then routed to a destination main campus computer system **113**.

In an example of processing a network threat incident, computer system **140**, also connected to Internet **150**, may be a source of a network attack. The network attack may have been able to penetrate branch computer system **123**. Thus, the packet flows from computer system **123** to main campus computer system **113** may contain malicious network attack packets. In order to detect the network threat, HCS logic **200** may be part of gateway system **115**, in an embodiment. As the packet flows **154** are received by gateway system **115**, the HCS logic **200** may analyze the packet flows **154** using the techniques described herein.

In another embodiment, the HCS logic **200** may be in a separate computer system such as central server computer **117**. In this configuration, the HCS logic **200** may import packet flow log data or files ("logs") and analyze them rather than receiving packet flows **154** directly from network. For example, the HCS logic **200** may receive logs from gateway system **115** as well as other systems on the network, such as proxy **125**. The logs from proxy **125** may also contain the packet flows of the initial network attack by computer system **140** on computer system **123**, since the packet flows containing the attack should have passed through proxy **125**. Thus, using techniques described herein, the HCS logic **200** may detect the network threat incident on computer system **123** and also may trace the incident to the originating computer system **140**.

3.0 STRUCTURAL OVERVIEW

FIG. **2** depicts an embodiment of the HCS logic. In one embodiment, HCS logic **200** may comprise packet flow importer **210**, feature analyzer **220**, aggregator **230**, classifier **240**, threat reporter **250** and datastore **260**. For purposes of brevity, the terms packet flow importer **210**, feature analyzer **220**, aggregator **230**, classifier **240**, threat reporter **250** and datastore **260** are used and each such unit may be implemented, in various embodiments, using one or more computer programs or other software elements, one or more units of digital logic, a special-purpose computer, or other computing elements.

In an embodiment, the packet flow importer **210** may be configured to be coupled to a network interface to receive packet flows from network. Once received, the packet flows may be analyzed on-line or stored into the datastore **260** for future analysis. In an alternative embodiment, packet flow importer **210** may import log data such as log files that contain packet flow data. Such log files may be from various internetworking devices that the HCS logic **200** can access, such as proxy **125** or gateway system **115**. Packet flow importer **210** may analyze the imported log files to determine flow features before or after storing the packet flow data into datastore **260**. "Packet flow data," as used herein, is data that describes packet flow information or derives from packet flow information and typically comprises a five-tuple or other set of values that are common to all packets that are related in a flow, such as source address, destination address, source port, destination port, and protocol value.

In an embodiment, datastore **260** may be a data storage device and/or a database that has a particular database schema. Thus, packet flow importer **210** and other components of HCS logic **200**, using datastore **260**, may convert packet flow data to the particular database schema to store the data in the database of datastore **260**. In an alternative embodiment, datastore **260** may comprise a file system with one or more structured data files that may have various formats or schemas. For example, datastore **260** may store packet flow data in log files similar to or exactly matching log files received by packet flow importer **210**, while other data may be stored in XML files conforming to a particular schema. The exact type of datastore, schema, or combination of schemas are not critical.

In an embodiment, feature analyzer **220** is configured to determine features of packet flows or any aggregation of packet flows. Feature analyzer **220** may receive packet flow data from packet flow importer **210** or may select packet flow data from datastore **260** to perform analysis of the received packet flows. Feature analyzer **220** may first perform a basic analysis to extract native flow features. "Native flow feature" refers herein to a feature of a packet flow that is intrinsic to the packet flow and generally may be extracted from packet flow fields. A list of example native flow features is in Table 1 below. Using native flow features and other packet flow data, feature analyzer **220** may perform calculations to determine complex features. A "complex feature" refers herein to a feature of packet flow that may not be readily available from native flow fields of a packet flow. A complex feature may be calculated based on statistical features of one or more native flow features. Feature analyzer **220** may also determine other types of features such as event and incident features as described in more detail below. Feature analyzer **220** may retrieve the packet flow data necessary for calculations from datastore **260** or receive the data directly from other components of HCS logic **200**. Once calculated, feature analyzer **220** may store features into datastore **260**.

In an embodiment, aggregator **230** is configured to hierarchically aggregate packet flows into multiple hierarchical levels of sets and groups. Aggregator **230** may use various criteria to aggregate packet flows. Such criteria may include time periods, origin devices, events on the origin devices or any combination of thereof. Aggregator **230** may also use various features of packet flow data in the aggregation. Aggregator **230** may retrieve packet flow data for aggregations from datastore **260** or receive the data directly from other components of HCS logic **200**. Once aggregated, aggregator **230** may store the new aggregation into datastore **260**.

In an embodiment, classifier **240** is configured to classify packet flows, sets and groups of packet flows into categories and classifications. The classifications may include threat levels such as malicious, fault, possible policy violation, warning, legitimate and OK. The categories may include the type or behavior of network traffic that a packet flow or an aggregation of packet flows represents. Examples of categories may include multimedia streaming, rich site summary (RSS) feed, generated domain traffic and many others.

Classifier **240** may retrieve packet flow data for classification from datastore **260** or receive the data directly from other components of HCS logic **200**. Once classified, classifier **240** may store the classifications into datastore **260**.

In an embodiment, threat reporter **250** is configured to report classifications of packet flow data to computer display devices, which may be used by users of HCS logic **200**, in an embodiment. Threat reporter **250** may report the classifications for any level of aggregation from a single packet flow to a network incident. The reports may assist in the analysis of classifications and understanding of classification of previously undetected malware.

4.0 FUNCTIONAL DESCRIPTION

FIG. **3** is a flow diagram that depicts a process of hierarchically classifying packet flows into network threats, in an embodiment. At block **310**, packet flows are received by HCS logic, such as HCS logic (FIG. **1**, FIG. **2**). The HCS logic may then select all or part of the received packet flows for analysis and classification at block **315**. In a related embodiment, the HCS logic may periodically select a batch of received packet flows for analysis, where each batch contains packet flows corresponding to the selection period. Any timestamp associated with a packet flow may be used to determine whether the packet flow corresponds to the selection period. In one embodiment, such timestamp may be origination timestamp of the packet flow, and in another embodiment, it may be the timestamp of the receipt of the packet flow by the HCS logic or the timestamp the packet flow is recorded in a log file that the HCS logic has imported.

FIG. **4** depicts an example of packet flow classification on different levels of flow hierarchy, in an embodiment. In FIG. **4**, the HCS logic receives packet flows **410** either from a log file or network interface. The HCS logic then selects, for analysis, a particular batch **415** that corresponds to all the packet flows with timestamps within a particular time period, such as five minutes. The particular time period may vary in different embodiments or according to configuration data in the same embodiment. The HCS logic continues to select for analysis the next batch of packet flows until all packet flows in the log files have been analyzed. Alternatively, the HCS logic may continuously select batches of packet flows as new packet flows are received by the system, as depicted by batches on time axis **405** in FIG. **4**.

In an embodiment, the packet flow importer **210** of the HCS logic **200** may perform block **310** and store the received packet flows into datastore **260**.

4.1 Flow Level Analysis

The HCS logic may be configured to analyze and classify individual packet flows on packet flow level, in an embodiment. At block **325** of FIG. **3**, the HCS logic may extract native flow features of packet flows that provide the HCS logic with information to classify a packet flow. As described in Table 1, the process may extract intrinsic features such as flow duration or number of bytes transferred. In addition to intrinsic features, the native flow features may include protocol specific features. For example, HTTP header information may be extracted from HTTP protocol packet flows. Table 1 provides a sample of HTTP specific features, but other protocols and protocol features may be extracted for the analysis.

In another embodiment, the feature analyzer **220** of the HCS logic **200** may perform block **325** to extract native flow features of packet flows. Feature analyzer **220** may then store the extracted features in datastore **260** in association with the corresponding packet flows.

TABLE 1

Sample Native Flow Features

Feature Name	Description
URL	Origin or destination URL of the packet flow such as Host field in HTTP protocol.
Flow duration	Time duration between the first packet received in a flow till the last packed received in the flow
Client-server traffic size	Number of bytes transferred from client to server
Server-client traffic	Number of bytes transferred from server to client
User agent	Browser or application description related to the packet flow
Referrer	URL of the redirection that generated the packet flow.
MIME-type	Content type of packet flow.
Status	HTTP response status codes

4.2 Complex Features

In an embodiment, at block **330**, complex features of a packet flow may be calculated based on the native features of the packet flow. For example, the HCS logic **200** may apply a set of functions to native flow features to calculate complex features. In a related embodiment in which the extracted packet flows are using a protocol that utilizes an URL, such as HTTP protocol, statistical features may be calculated for each of the packet flow or a group/set of packet flows that contain the same URL information. The complex features are calculated by applying a set of functions on the URL string or any portion of the URL string.

FIG. **5** depicts a URL string partition, in an embodiment. A URL string may be decomposed into a protocol, domain, path, file name, file fragment and query strings. A protocol string, such as protocol **510**, may have values that denote various application protocols of packet flows, such as "http" for the HTTP protocol or "ftp" for the FTP protocol. Second-level domain string **520** in combination with top-level domain (TLD) **530** strings denote the domain name of a host computer that the URL string references. The actual network address of the host computer may be accessed by requesting the network address corresponding to second-level domain **520** and TLD **530** from a computer hosting a name resolution server, such as a DNS server. Path **540** and file name **550** strings denote the path to the file name on the host computer system to be invoked using the URL string. Query string **560** denotes the meta-data passed in to the file and fragment **570** denotes an index to a particular portion of the file.

In an embodiment, a URL string or a partition of the URL string as described above or any combination of partitions of the URL string may be used as an input string to calculate the values of one or more of the following complex features.

Length—describes the number of characters in the string, in an embodiment.

Consonant to vowel change ratio—describes the frequency of changes between consonants and vowels, in an embodiment. The equation below describes the ratio r_v, where $l(c_i)$ describes the length feature of the input string c_i.

$$r_v(c_i) = \frac{\text{number of changes from consonant to vowel}}{l(c_i)}$$

ASCII metric—describes whether the input string contains any characters that are in the UTF-8 character set but not in the ASCII character set, in an embodiment. The ASCII metric feature may be a Boolean value indicating whether any character outside of ASCII character set exists in the input string. The metric may have a value of FALSE when any character from the input string is outside the ASCII range of characters and may have a value of TRUE otherwise.

Maximum character occurrence ratio—describes the maximum number of the recurrence of a character in the input string as compared to the length of the string, in an embodiment. This ratio feature may be calculated by measuring a maximum number of recurrences of any character in the input string and by dividing the maximum number by the length of the input string.

Maximum character type occurrence ratio—describes the maximum number of the recurrence of a character type in the input string as compared to the length of the string, in an embodiment. An example of character type is a letter character, a capital letter character, a number character or a special character. In a related embodiment, this ratio feature may be calculated by measuring the maximum number of recurrences of any of the character types and dividing the maximum number by the length of the input string.

URL based form addressability—describes whether the input string contains URL addressable forms, in an embodiment. Special characters may be used as separators in URL addressable forms and views. Thus the repetitive occurrence of special characters may indicate that a page associated with the URL contains forms and views. In a related embodiment, the feature may be calculated by counting the number of occurrences of special characters such as '=' and '&'.

Popular trigram probability—describes whether trigrams within the input string are similar to those in well-known domain names, in an embodiment. An existing repository of well-known domains, such as the ALEXA service, may be used. In a related embodiment, the most popular trigrams in the domains of a domain repository may be ranked. Then, each of component trigrams from the input string may be compared to the ranked list of the most popular trigrams of the repository. If a component trigram matches, then a probability value is assigned to the component trigram based on the rank of the matched popular trigram. In this approach, a higher rank of the matched trigram results in assigning a greater probability value to the component trigram. To calculate the feature, an average may be taken of all probabilities assigned to the component trigrams of the input string. For example, a ranking of 1 to 1,000 is selected for trigrams in the repository. To rank all the repository trigrams, each trigrams probability may be calculated using the following equation:

$$p_t(t(A)) = \frac{\text{number of } t(A) \text{ occurrences in } \mathit{Alexa}}{\text{number of all trigrams in } \mathit{Alexa}},$$

where t(A) represents a trigram of domains in the repository.

Then a rank may be assigned to each domain trigram describing the trigram frequency. The rank may be described by:

$$\forall i,j \le |A| : p_t(t^{(i)}(A)) \ge p_t(t^{(j)}(A)) \Leftrightarrow i \le j,$$

where $p_t(t^{(i)}(A))$ denotes i-th most-frequent trigram from the repository, |A| is a number of trigrams in the repository, and $i \in \{1, \ldots, 1000\}$.

The ranking probability of each component trigram in the input string, t(d), may then be calculated as:

$$\hat{p}_t(t(d)) = \begin{cases} 1-(i-1)\cdot 10^{-4} & \exists\, i \le 1000 : t(d) = t^{(i)}(A) \\ 0 & \text{otherwise} \end{cases},$$

where $\hat{p}_t(t(d))$ is a ranking probability of t(d) component trigram in the input string. The feature may be calculated by averaging of all ranking probabilities $\hat{p}_t(t(d))$. In a related embodiment, highly ranked domain trigrams for long domains may be discarded to ensure that long domains, which are more likely to have popular trigrams, do not skew the probabilities.

Maximum adjacent trigram probability—describes the probability of locating adjacent popular trigram in the input string, in an embodiment. In a related embodiment, the feature may be calculated by calculating the probabilities of two adjacent trigrams based on the probabilities of component trigrams of the input string, as follows:

$$p_t(t_j(d), t_{j+1}(d)) = \frac{\hat{p}_t(t_j(d)) + \hat{p}_t(t_{j+1}(d))}{2},$$

Then the maximum of all the calculated probability values is computed to determine the feature:

$$m(d) = \max_j (p_t(t_j(d), t_{j+1}(d))).$$

Suspicious trigrams metric—describes the number of unpopular trigrams found in the input string, in an embodiment. In a related embodiment, the feature may be calculated by counting the number of component trigrams of the input string that have a value of zero for their respective ranking probability as calculated above:

$$n(d) = \text{number of trigrams with } \hat{p}_t(t(d)) = 0.$$

In a related embodiment, the feature analyzer **220** of HCS logic **200** may perform block **330** to calculate complex features of packet flows. Feature analyzer **220** may then store the complex features in datastore **260** in association with the corresponding packet flows.

4.3 Flow Level Classification

At block **335** of FIG. **3**, packet flows of a batch are classified. In an embodiment, packet flows may be classified into malicious (M), possible policy violation (PPV) and legitimate (L) packet flows. The classification is based on the calculated complex features and extracted native features that are compared to malicious network traffic properties.

For example, a malicious network traffic that originates from non-browser may not have the "user agent" field set in the HTTP headers of packets of the flow. In response, the

HCS logic **200** may analyze the "user agent" native flow feature of a packet flow and, if the field is missing or set to a value indicating a non-recognizable browser, then the HCS logic **200** may classify the packet flow as "malicious non-browser traffic" category and set the classification to "M." Similarly, the HCS logic **200** may examine the "MIME-type" native feature of a packet flow, and if the field is set to "application/x-bittorrent," then the packet flow may be categorized as "torrent tracker" and classified as "PPV." On the other hand, if the "MIME-type" native feature has value of "video/x-msvideo," then the HCS logic **200** may classify the packet flow in a "multimedia (audio/video streaming)" category with "L" as classification. In the examples above, for purposes of illustrating a clear example, only a single feature is used to classify a packet flow, however in practice multiple or all features of a packet flow are used to classify a packet flow.

In an embodiment, complex features may be used to determine whether a URL string representing the whole URL or a partition of the URL from a packet flow is statistically similar to a URL string from a malicious threat. For example, malicious network traffic may contain URL strings that are computer-generated. Identifying the existence of such a computer generated string in a URL of a packet flow may likely classify the packet flow as malicious (M). A URL string may be identified as computer generated, if the string has a statistically random distribution of characters. In a related embodiment, random distribution of characters in a URL string may be identified by analyzing maximum character/character type occurrence, consonant to vowel change ratio or any combination thereof. For example, if the consonant to vowel change ratio for a URL string is small, then the URL string may be computer generated, and thus, the packet flow with the URL string may be malicious.

In another embodiment, the URL string may be identified as originating from a malicious network threat if the URL string is determined to be statistically different from well-known URL strings. For example, most well-known URL strings are easy to pronounce and thus contain frequently used trigrams. In a related embodiment, complex features, such as popular trigram probability, maximum adjacent trigram probability, the suspicious trigrams metric or a combination thereof may represent the degree of statistical similarity of the URL string with a malicious URL string. For example, if the suspicious trigrams metric feature has a large value, then the packet flow containing the URL string may be classified as malicious.

In another embodiment, the HCS logic **200** may be configured to self-train based on known malicious and legitimate traffic on ranges of feature values that correspond respectively to malicious and legitimate packet flow feature values. In an embodiment, once the HCS logic **200** extracts or calculates features of a packet flow, the HCS logic may classify the packet flow based on a comparison of its features with the known ranges. Table 2 lists example classifications and categories for a packet flow based on its features, for an embodiment. In a related embodiment, a packet flow may be categorized into more than one category from Table 2.

TABLE 2

Classifications and categories for a packet flow

Classifier	Category
M	Data transfer through URL to computer-generated domain

TABLE 2-continued

Classifications and categories for a packet flow

Classifier	Category
M	Downloading file with multiple extensions
M	Data transfer through URL to raw IP address
M	Communication with generated domain
M	Data transfer through URL
M	Download of malicious executable file
M	Malicious non-browser traffic
M	Malicious repetitive requests
M	WPAD (Web Proxy Auto-discovery Protocol) misuse
PPV	Torrent user
PPV	Remote desktop
PPV	Torrent tracker
L	Proxy connect
L	Connection check
L	Streaming/downloading data
L	Upload data through body
L	Skype user
L	Flash
L	Multimedia (audio/video streaming)
L	Software update
L	RSS feed
L	File download

Block **340** of FIG. **3** indicates repeating blocks **325** through **335** associated with determining features of a packet flow and classifying the packet flow, for all packet flows in a batch. FIG. **4** depicts an example of the result of classifying packet flows, in an embodiment. A batch **415** of packet flows has been classified at flow level **420**. The packet flows **425** represents a classified batch of packet flows of batch **415**. The classification of each packet flow within packet flows **425** is represented by different shadings.

In a related embodiment, classifier **240** may perform block **340** and may then store the flow classifications in association with the corresponding packet flows in datastore **260**.

4.4 Event Description

At block **345** of FIG. **3**, packet flows of a batch are selected into an event set, in an embodiment. An event set may consist of packet flows that has been transmitted in response to an event on a computing device. Such event may represent one click of a user in a browser, or a single action of a malware item. Packet flows may be selected into an event set based on a criterion. According to one embodiment, the criterion for the selection of packet flows may be the proximity of their respective time stamps, and packet flows with same or similar timestamp may be grouped into a particular event set. In an alternative embodiment, packet flows may be grouped into a particular event set based on native features of the packet flows such as referrer. Other techniques for selecting packet flows into event sets may be implemented as described in U.S. patent application Ser. No. 14/519,160 filed on Oct. 21, 2014.

At block **350**, HCS determines event set features based on flow features of packet flows of an event set. The event set features may represent consistency, variability, and ranges of the flow features in the event set. The event set feature values may be determined by applying various functions to the flow feature values of the packet flows of the event set. In an embodiment, aggregation functions such as minimum, maximum, average, standard deviation, may be applied.

In an embodiment, values for a particular complex flow feature may be aggregated to determine an event set feature. For a particular complex feature, described in section 4.2, flow feature values of packet flows of an event set may be selected. Then, an aggregation function may be applied to the selected values to produce an event set feature. For example, a mean suspicious trigrams metric of an event set may be determined by averaging all the suspicious trigrams metric values of packet flows of the event set.

Similarly, a combination of aggregation functions may be used to derive an event set feature. An event set feature may be calculated by removing outlier flow feature values based on the standard deviation of the flow feature values. If a flow feature value is a number of standard deviations away, then the flow feature value may be designated as an outlier and not be used in calculation of an aggregation function to determine an event set feature. Continuing with the above example using the mean suspicious trigrams metric, a standard deviation based on all the suspicious trigrams metric flow feature values is first calculated; the flow feature values that are outside of three (3) standard deviations from the mean metric value are disregarded. An adjusted mean suspicious trigrams metric event set feature is then calculated based on the remaining flow feature values for the suspicious trigrams metric. However, the exact combination of aggregation functions is not critical.

In another embodiment, an event aggregation flow feature may be determined by selecting a common native flow feature. The value of the event aggregation flow feature may be determined based on identifying common native flow feature values of packet flows of an event set. The common feature values may be determined based on the percentage of flow features that have a same or similar value. For example, if a MIME-type native feature has value of "video/x-ms-video" for all packet flows in an event set, then an event set feature MIME-type is assigned to the value "video/x-ms-video".

At block **355** of FIG. **3**, an event set is classified into classes. Such classes may match packet flow classifications such as malicious (M), possible policy violation (PPV) and legitimate (L) events or may be more or less granular. In an embodiment, an event set may be classified based on event set feature by comparing event set features to known event properties. For example, an event set may be classified as malicious, if a known malware has same or similar feature values. The malware is determined to have the same or similar features when statistical analysis of known malware features substantially matches the event set features. Similarly, event set features may be compared to statistical properties of the legitimate network events to determine whether the event set represents a legitimate event.

In a related embodiment, an event set may be classified without comparison to known event properties. An event set feature may itself represent an anomaly in a network traffic because the event set feature may describe a discrepancy in flow feature values of packet flows of the event set. For example, continuing with the above example using the mean suspicious trigrams metric, if the standard deviation of suspicious trigrams metric values divided over the mean is below 1, then flow feature values for the metric have low variance. Thus, the mean suspicious trigrams feature of the event set may be precisely representative of all packet flows and may classify the event as a legitimate or malicious by itself.

In another embodiment, an event set may be classified based on flow classifications. An event set may be classified based on the number/percent of occurrences of different classifications within the classifications of packet flows that are selected into the event set. For example, if majority of packet flows selected in an event set have been classified as malicious, then the event set is classified as malicious. In another example, an event set may be classified based on the worst case scenario and thus, if any packet flows is classified as malicious in an event set, then the event set is classified as malicious.

In another embodiment, flow features of packet flows may be the basis for classifying an event set to which the packet flow belongs. When even set features do not yield a conclusive classification, an event set may be classified based on packet flow features. For example, if the majority of packet flows have various native flow features that are classified as malicious, then regardless of values for the respective event set features, the event set is classified as malicious.

At block **360** of FIG. **3**, blocks **350** and **355** for determining features of an event set and classifying the event set are repeated for all event sets, in an embodiment. FIG. **4** depicts an example of the result for selecting packet flows into event sets and classifying the event sets. Event level **430** depicts the selection of packet flows **425** into event sets **435** and the classification of event sets **435**. Each event set in event sets **435** is depicted by a rectangle, where the shading of rectangle corresponds to the classification of the corresponding event set. In an embodiment, with time **405**, other batches of packet flows are received and classified, new events sets are aggregated on event level **430** in accordance with blocks **350** and **355** of FIG. **3**, in an embodiment.

In alternative embodiments, numerous event levels may exist based on temporal aggregation of event sets and aggregation of the underlying packet flows of the event sets. For example, event sets may be aggregated into an hourly event set that comprises of all event sets that have packet flows with timestamps that are within a particular hour-long duration. Such higher level event sets may have features and classifications determined using the same techniques described herein.

In a related embodiment, aggregator **230** may perform block **345** to select packet flows into event sets. Feature analyzer **220** may perform block **350** to determine event set features and then, may store the event set features in datastore **260** in association with the corresponding event sets. Classifier **240** may perform block **355** to classify event sets into classifications and then, may store the event set classification into datastore **260** in associations with the corresponding event sets.

4.5 Incident Description

At block **365** of FIG. **3**, an event set is assigned to a device group based on an originating computing device and timestamp, in an embodiment. Each timestamp may be determined by the timestamps associated with the packet flows comprising the event set. The event sets from the same originating device or multiple originating devices with the same user may be selected based on the timestamps of the event steps. A device group for a particular time period may contain all event sets from the originating device(s) that are within the particular time period. Since each of the event sets represents an event on the originating device(s), a device group of event sets represents an incident on the originating device(s) during the particular time period. For example, an incident for past 24 hours may be represented by a device group that comprises event sets from the originating device(s) that have timestamps within past 24 hours from the current time. Similarly, other grouping of event sets into a device group may be performed in other embodiments to represent other incidents, however, the exact time period duration used to assign event sets to a device group is not critical to the techniques described herein.

At block **370**, incident features for a device group are determined, in an embodiment. Incident features of a device group may be determined similar to techniques described for event sets in section 4.4. Incident features of a device group may be calculated by statistically aggregating event set features of event sets of the group or flow features of packet flows of the event sets of the group. Thus, the incident features may similarly represent consistency, variability, and ranges of the event set features and the flow features corresponding to the events on a computing device during a particular time period.

At block **375**, a device group is classified into a particular incident classification, in an embodiment. The incident classifications may match event and packet flow classifications such as malicious (M), possible policy violation (PPV) and legitimate (L). In a related embodiment, a device group may have different incident classification which may be higher or lower granularity than the event set or flow classifications. For example, a device group may be classified into OK, warning, or fault incident classifications.

In an embodiment, a device group may be classified using techniques similar to an event set classification, such as those described in sections 4.3 and 4.4. The device group may be classified based on the determined device group features. In a related embodiment, a device group may be classified based on one or more event set features, event set classifications, flow features and packet flow classifications or combination thereof.

In an embodiment, at block **380**, blocks **315** through **375** may be repeated for new batches. Thus, new incidents may be generated based on new events received in the new batches following the same process of FIG. **3**. For example, FIG. **4** depicts receiving a new batch every 5 minutes and incidents **450** may be classified every 5 minutes based on the new packet flows received. Since incident classifications may be performed per originating device, event sets from **435** that originated at device **1** are selected into device group **445**, and event sets that originated at device **2** are selected into device group **447** on device level **440**. In an alternative embodiment, if device **1** and device **2** are determined to have the same user, the event sets from **435** may be selected into a single device group.

Incidents **450** comprise incidents, such as incident **455**, which have a time period duration of 24 hours and are created every 5 minutes. Incidents **450** are classified based on corresponding device groups and the device groups' event sets and packet flows. For example, incident **455** is classified based on device group **445** and based on event sets from event set **435** and packet flows from packet flows **425** from batch **415**. As new batches of packet flows are received, new incidents are created that, depending on time period, may or may not include previous incidents event sets and packet flows. Thus, the new incidents may have different classifications as depicted by incidents **450**.

In a related embodiment, aggregator **230** may perform block **365** to assign event sets to device groups and may store them in datastore **260**. Feature analyzer **220** may perform block **370** to determine incident features and then, may store the incident features in datastore **260** in association with the corresponding device groups or may directly pass the incident features to classifier **240**. Classifier **240** may perform block **375** to classify device groups into incident classes. Classifier **240** may then store the incident classifications into datastore **260** in associations with the corresponding device groups.

5.0 IMPLEMENTATION MECHANISMS

Hardware Overview

According to one embodiment, the techniques described herein are implemented by one or more special-purpose computing devices. The special-purpose computing devices may be hard-wired to perform the techniques, or may include digital electronic devices such as one or more application-specific integrated circuits (ASICs) or field programmable gate arrays (FPGAs) that are persistently programmed to perform the techniques, or may include one or more general purpose hardware processors programmed to perform the techniques pursuant to program instructions in firmware, memory, other storage, or a combination. Such special-purpose computing devices may also combine custom hard-wired logic, ASICs, or FPGAs with custom programming to accomplish the techniques. The special-purpose computing devices may be desktop computer systems, portable computer systems, handheld devices, networking devices or any other device that incorporates hard-wired and/or program logic to implement the techniques.

For example, FIG. **6** is a block diagram that illustrates a computer system **600** upon which an embodiment of the disclosure may be implemented. Computer system **600** includes a bus **602** or other communication mechanism for communicating information, and a hardware processor **604** coupled with bus **602** for processing information. Hardware processor **604** may be, for example, a general purpose microprocessor.

Computer system **600** also includes a main memory **606**, such as a random access memory (RAM) or other dynamic storage device, coupled to bus **602** for storing information and instructions to be executed by processor **604**. Main memory **606** also may be used for storing temporary variables or other intermediate information during execution of instructions to be executed by processor **604**. Such instructions, when stored in non-transitory storage media accessible to processor **604**, render computer system **600** into a special-purpose machine that is customized to perform the operations specified in the instructions.

Computer system **600** further includes a read only memory (ROM) **608** or other static storage device coupled to bus **602** for storing static information and instructions for processor **604**. A storage device **610**, such as a magnetic disk or optical disk, is provided and coupled to bus **602** for storing information and instructions.

Computer system **600** may be coupled via bus **602** to a display **612**, such as a cathode ray tube (CRT), for displaying information to a computer user. An input device **614**, including alphanumeric and other keys, is coupled to bus **602** for communicating information and command selections to processor **604**. Another type of user input device is cursor control **616**, such as a mouse, a trackball, or cursor direction keys for communicating direction information and command selections to processor **604** and for controlling cursor movement on display **612**. This input device typically has two degrees of freedom in two axes, a first axis (e.g., x) and a second axis (e.g., y), that allows the device to specify positions in a plane.

Computer system **600** may implement the techniques described herein using customized hard-wired logic, one or more ASICs or FPGAs, firmware and/or program logic which in combination with the computer system causes or programs computer system **600** to be a special-purpose machine. According to one embodiment, the techniques herein are performed by computer system **600** in response to processor **604** executing one or more sequences of one or more instructions contained in main memory **606**. Such instructions may be read into main memory **606** from another storage medium, such as storage device **610**. Execution of the sequences of instructions contained in main memory **606** causes processor **604** to perform the process steps described herein. In alternative embodiments, hardwired circuitry may be used in place of or in combination with software instructions.

The term "storage media" as used herein refers to any non-transitory media that store data and/or instructions that cause a machine to operation in a specific fashion. Such storage media may comprise non-volatile media and/or volatile media. Non-volatile media includes, for example, optical or magnetic disks, such as storage device **610**. Volatile media includes dynamic memory, such as main memory **606**. Common forms of storage media include, for example, a floppy disk, a flexible disk, hard disk, solid state drive, magnetic tape, or any other magnetic data storage medium, a CD-ROM, any other optical data storage medium, any physical medium with patterns of holes, a RAM, a PROM, and EPROM, a FLASH-EPROM, NVRAM, any other memory chip or cartridge.

Storage media is distinct from but may be used in conjunction with transmission media. Transmission media participates in transferring information between storage media. For example, transmission media includes coaxial cables, copper wire and fiber optics, including the wires that comprise bus **602**. Transmission media can also take the form of acoustic or light waves, such as those generated during radio-wave and infra-red data communications.

Various forms of media may be involved in carrying one or more sequences of one or more instructions to processor **604** for execution. For example, the instructions may initially be carried on a magnetic disk or solid state drive of a remote computer. The remote computer can load the instructions into its dynamic memory and send the instructions over a telephone line using a modem. A modem local to computer system **600** can receive the data on the telephone line and use an infra-red transmitter to convert the data to an infra-red signal. An infra-red detector can receive the data carried in the infra-red signal and appropriate circuitry can place the data on bus **602**. Bus **602** carries the data to main memory **606**, from which processor **604** retrieves and executes the instructions. The instructions received by main memory **606** may optionally be stored on storage device **610** either before or after execution by processor **604**.

Computer system **600** also includes a communication interface **618** coupled to bus **602**. Communication interface **618** provides a two-way data communication coupling to a network link **620** that is connected to a local network **622**. For example, communication interface **618** may be an integrated services digital network (ISDN) card, cable modem, satellite modem, or a modem to provide a data communication connection to a corresponding type of telephone line. As another example, communication interface **618** may be a local area network (LAN) card to provide a data communication connection to a compatible LAN. Wireless links may also be implemented. In any such implementation, communication interface **618** sends and receives electrical, electromagnetic or optical signals that carry digital data streams representing various types of information.

Network link **620** typically provides data communication through one or more networks to other data devices. For example, network link **620** may provide a connection through local network **622** to a host computer **624** or to data equipment operated by an Internet Service Provider (ISP) **626**. ISP **626** in turn provides data communication services through the world wide packet data communication network now commonly referred to as the "Internet" **628**. Local network **622** and Internet **628** both use electrical, electromagnetic or optical signals that carry digital data streams. The signals through the various networks and the signals on network link **620** and through communication interface **618**, which carry the digital data to and from computer system **600**, are example forms of transmission media.

Computer system **600** can send messages and receive data, including program code, through the network(s), network link **620** and communication interface **618**. In the Internet example, a server **630** might transmit a requested code for an application program through Internet **628**, ISP **626**, local network **622** and communication interface **618**.

The received code may be executed by processor **604** as it is received, and/or stored in storage device **610**, or other non-volatile storage for later execution.

6.0 EXTENSIONS AND ALTERNATIVES

In the foregoing specification, embodiments of the disclosure have been described with reference to numerous specific details that may vary from implementation to implementation. Thus, the sole and exclusive indicator of what is the disclosure, and is intended by the applicants to be the disclosure, is the set of claims that issue from this application, in the specific form in which such claims issue, including any subsequent correction. Any definitions expressly set forth herein for terms contained in such claims shall govern the meaning of such terms as used in the claims. Hence, no limitation, element, property, feature, advantage or attribute that is not expressly recited in a claim should limit the scope of such claim in any way. The specification and drawings are, accordingly, to be regarded in an illustrative rather than a restrictive sense.

What is claimed is:

1. A computer system comprising:

one or more network interfaces that are configured to couple to a data network and to receive a plurality of packet flows therefrom;

one or more hardware processors coupled to the one or more network interfaces;

an aggregator that is configured to select, based on a criterion, two or more selected packet flows from the plurality of packet flows and placing the selected packet flows into a set;

a feature analyzer that is configured to determine a plurality of flow features and a plurality of flow classes for the set at least by, for each packet flow in the set:

determining a corresponding flow feature, of the plurality of flow features, associated with that packet flow based on data from that packet flow and any combination of one or more of: URL data from that packet flow, flow duration of that packet flow, number of bytes transferred in that packet flow, type of that packet flow, status of that packet flow, referrer of that packet flow, timestamps associated with that packet flow, internet address of a computing device originating that flow, type of the computing device originating that packet flow, or status of the computing device originating that packet flow, and

classifying that packet flow into a flow class, of the plurality of flow classes, based on the corresponding flow feature;

the feature analyzer that is further configured to determine a set feature for the set based on the plurality of flow features that are associated with the selected packet flows of the set;

a classifier that is configured to classify the set into a set class based on the set feature; and a threat reporter that is configured to report, based on the set class, a threat incident on a computing device originating the selected packet flows.

2. The system of claim **1**, wherein the feature analyzer is further configured to determine the set feature by calculating an aggregate function of the plurality of flow features.

3. The system of claim **1**, wherein the classifier is further configured to determine the set class based on the plurality of flow classes for the set.

4. The system of claim **1**, wherein the criterion is based on the selected packet flows that are associated with a particular event on the computing device originating the selected packet flows.

5. The system of claim **4**, wherein the particular event is an action performed on the computing device originating the selected packet flows.

6. The system of claim **1**, wherein:

the aggregator is further configured to select, into a group, one or more sets of packet flows that include the set, based on temporal attributes or native features of particular packet flows of the one or more sets of packet flows that originated at the computing device;

the feature analyzer is further configured to determine a group feature for the group based on one or more set features corresponding to the one or more sets; and

the classifier is further configured to classify the group into a group class based on the group feature.

7. The system of claim **6**, wherein the feature analyzer is further configured to determine the group feature by calculating an aggregate function of the one or more set features.

8. The system of claim **6**, wherein the classifier is further configured to determine the group class based on any combination of one or more of:

the one or more set features,

particular one or more flow features corresponding to the particular packet flows of the one or more sets,

set classes that the one or more sets are classified into, or

particular flow classes that the particular packet flows are classified into.

9. The system of claim **6**, wherein the temporal attributes are timestamps of the particular packet flows.

10. The system of claim **9**, wherein the timestamps of the particular packet flows are within a particular time duration.

11. A method comprising:

receiving a plurality of packet flows from a data network;

selecting, based on a criterion, two or more selected packet flows from the plurality of packet flows and placing the selected packet flows into a set;

determining a plurality of flow features and a plurality of flow classes for the set, comprising, for each packet flow in the set:

determining a corresponding flow feature, of the plurality of flow features, associated with that packet flow based on data from that packet flow and any combination of one or more of: URL data from that packet flow, flow duration of that packet flow, number of bytes transferred in that flow, type of that packet flow, status of that packet flow, referrer of that packet flow, timestamps associated with that packet flow, internet address of a computing device originating that packet flow, type of the computing device originating that packet flow, or status of the computing device originating that packet flow, and

classifying that packet flow into a flow class, of the plurality of flow classes, based on the corresponding flow feature of the plurality of flow features;

determining a set feature for the set based on the plurality of flow features that are associated with the selected packet flows of the set;

classifying the set into a set class based on the set feature;

based on the set class, reporting a threat incident on a computing device originating the selected packet flows; and

wherein the method is executed by one or more computing devices.

12. The method of claim **11**, further comprising determining the set feature by calculating an aggregate function of the plurality of flow features.

13. The method of claim **11**, further comprising determining the set class based on the plurality of flow classes for the set.

14. The method of claim **11**, wherein the criterion is based on the selected packet flows that are associated with a particular event on the computing device originating the selected packet flows.

15. The method of claim **14**, wherein the particular event is an action performed on the computing device originating the selected packet flows.

16. The method of claim **11**, further comprising:

selecting, into a group, one or more sets of packet flows that include the set, based on temporal attributes or native features of particular packet flows of the one or more sets of packet flows that originated at the computing device;

determining a group feature for the group based on one or more set features corresponding to the one or more sets; and

classifying the group into a group class based on the group feature.

17. The method of claim **16**, further comprising determining the group feature by calculating an aggregate function of the one or more set features.

18. The method of claim **16**, further comprising determining the group class based on any combination of one or more of:

the one or more set features,

particular one or more flow features corresponding to the particular packet flows of the one or more sets,

set classes that the one or more sets are classified into, or

particular flow classes that the particular packet flows are classified into.

19. The method of claim **16**, wherein the temporal attributes are timestamps of the particular packet flows.

20. The method of claim **19**, wherein the timestamps of the particular packet flows are within a particular time duration.

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