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(54) # SYSTEM AND METHOD FOR DETECTING DICTIONARY-BASED DGA TRAFFIC

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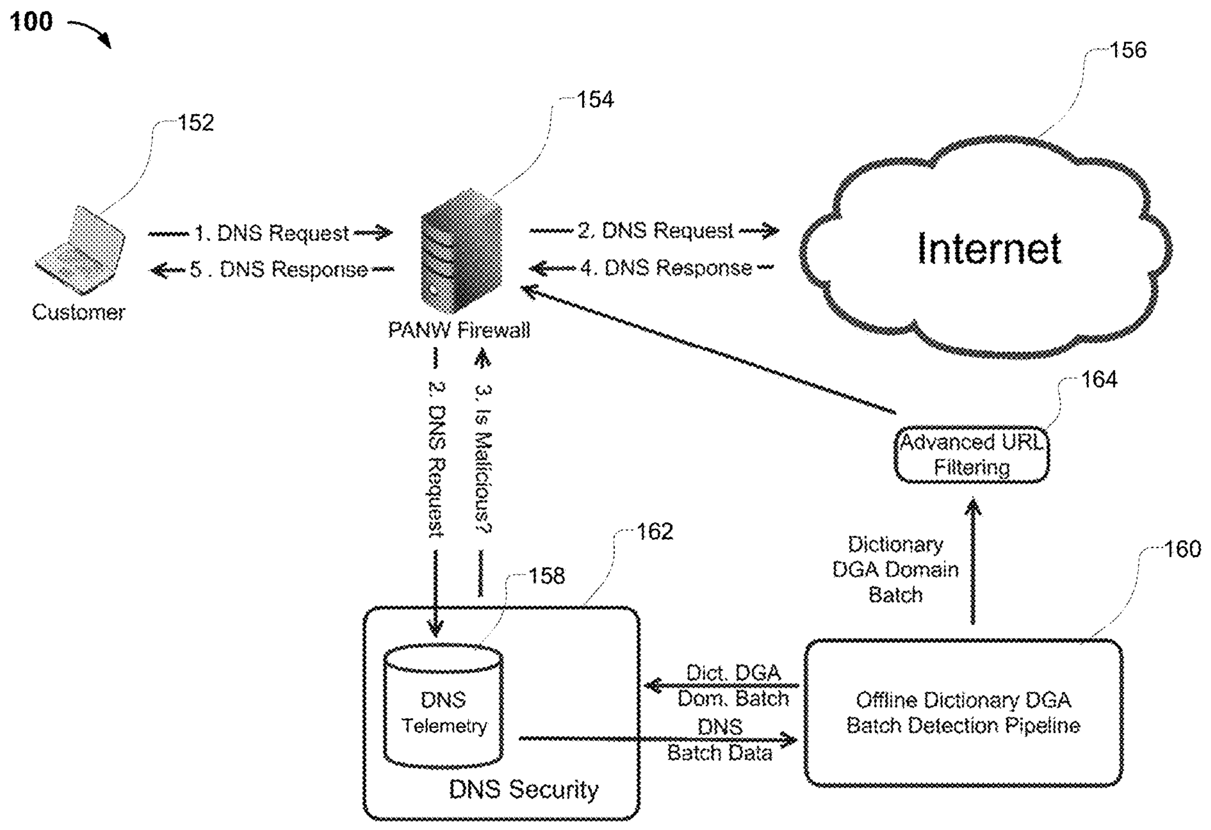
(57) **ABSTRACT**

A system and method for detecting dictionary-based DGA traffic is provided. A domain name system (DNS) stream is received. The DNS stream is classified using a per domain dictionary domain generation algorithm (DGA) classifier to generate candidate dictionary DGA domains with cluster information. The candidate dictionary DGA domains are filtered to generate a set of dictionary DGA domains. An action is performed based on a match with a monitored domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains.



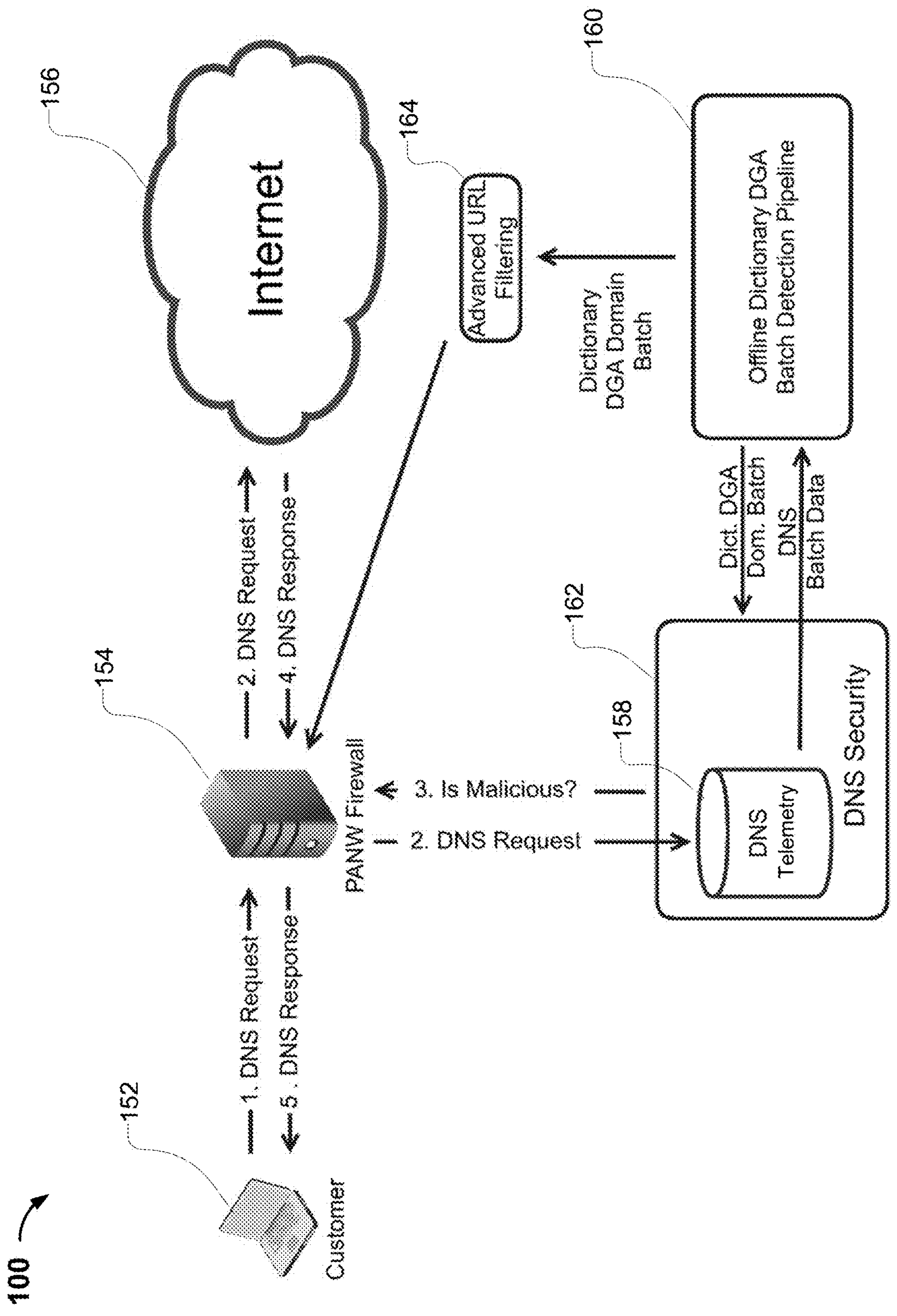

100
152
Customer
1. DNS Request
5. DNS Response
154
PANW Firewall
2. DNS Request
4. DNS Response
156
Internet
164
Advanced URL Filtering
160
Offline Dictionary DGA Batch Detection Pipeline
Dictionary DGA Domain Batch
Dict. DGA Dom. Batch
DNS Batch Data
162
158
DNS Telemetry
DNS Security
3. Is Malicious?
2. DNS Request

Figure 1A

intgmxdeadnxuyla.com (CryptoLocker)
axwscwsslmiagfah.com (CryptoLocker)
facebook.com
paloaltonetworks.com

Figure 1B

heavenpatternleader.net (Suppobox)
facebook.com
paloaltonetworks.com
shareleaderspace.net (Suppobox)

Figure 1C

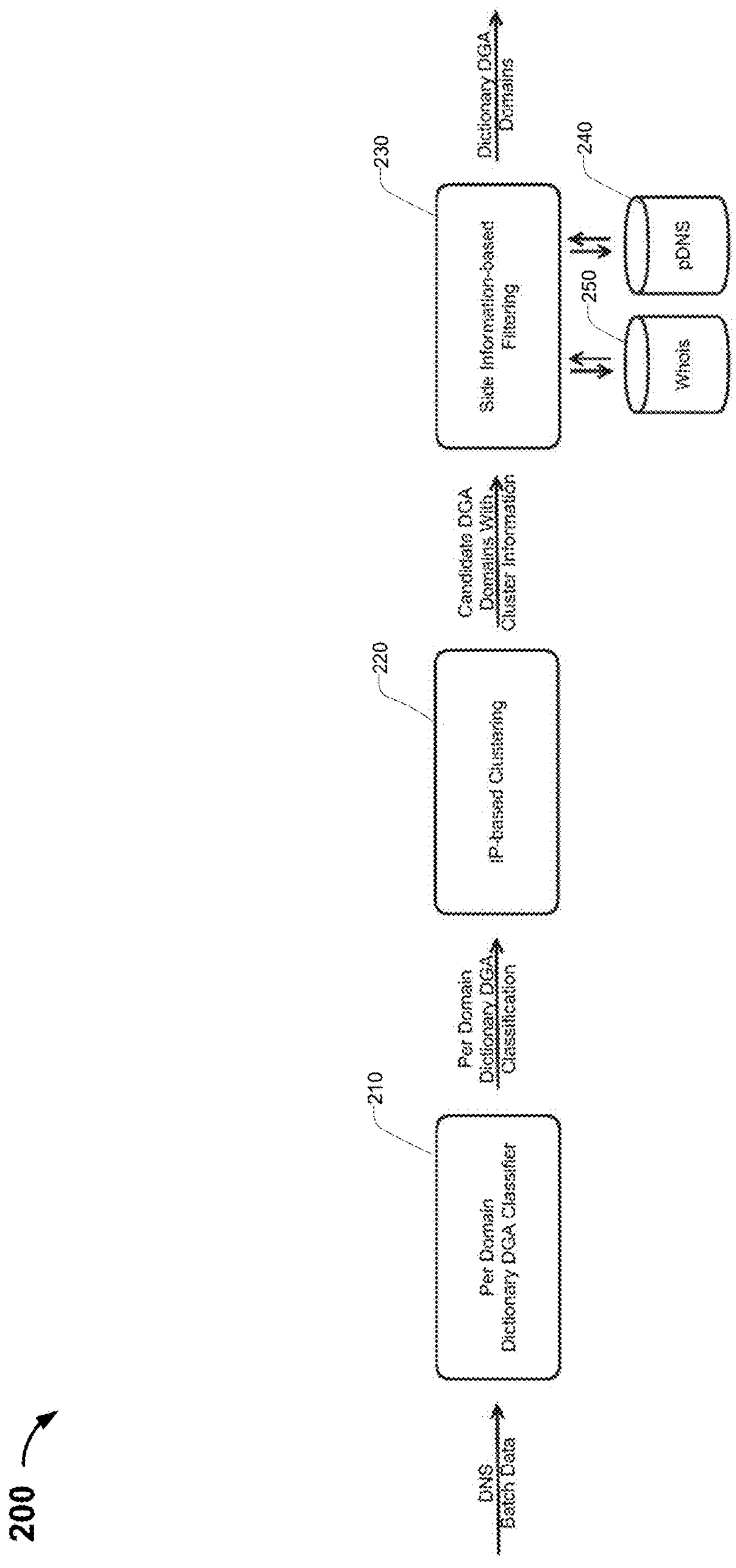

200
DNS Batch Data
210
Per Domain Dictionary DGA Classifier
Per Domain Dictionary DGA Classification
220
IP-based Clustering
Candidate DGA Domains With Cluster Information
230
Side Information-based Filtering
Dictionary DGA Domains
250
Whois
240
pDNS

Figure 2

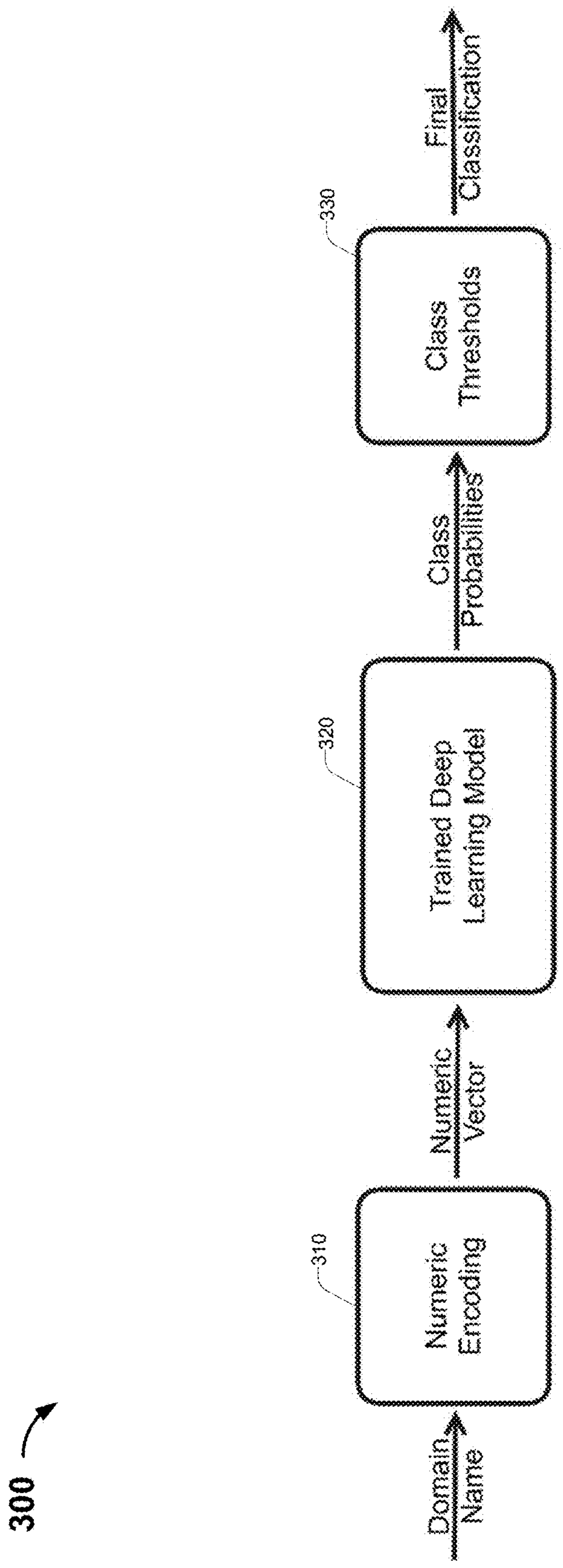

300
Domain Name
310
Numeric Encoding
Numeric Vector
320
Trained Deep Learning Model
Class Probabilities
330
Class Thresholds
Final Classification

Figure 3A

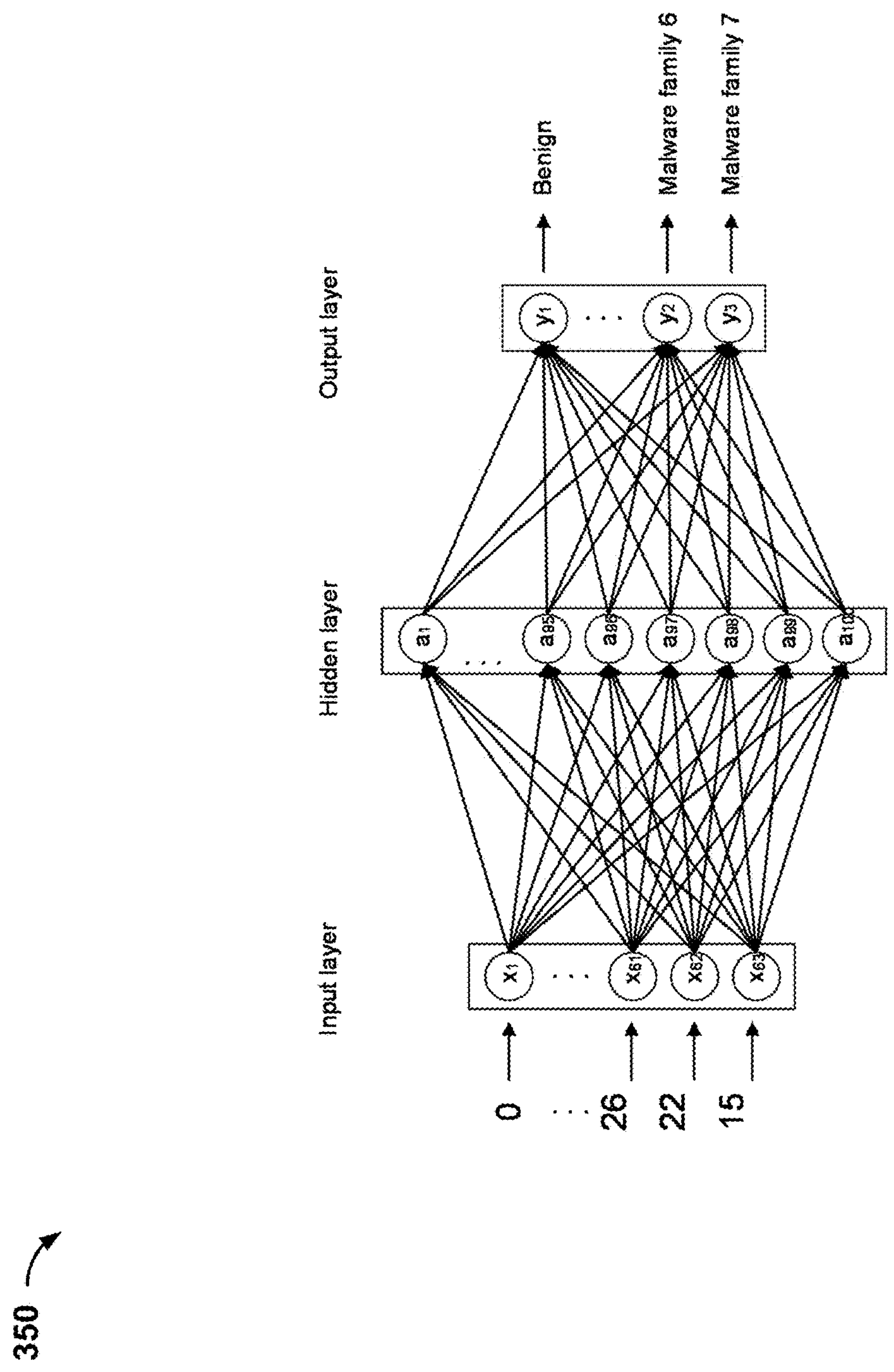

350
Input layer
Hidden layer
Output layer
0
26
22
15
x_1
x_{61}
x_{62}
x_{63}
a_1
a_{95}
a_{96}
a_{97}
a_{98}
a_{99}
a_{100}
y_1
y_2
y_3
Benign
Malware family 6
Malware family 7

Figure 3B

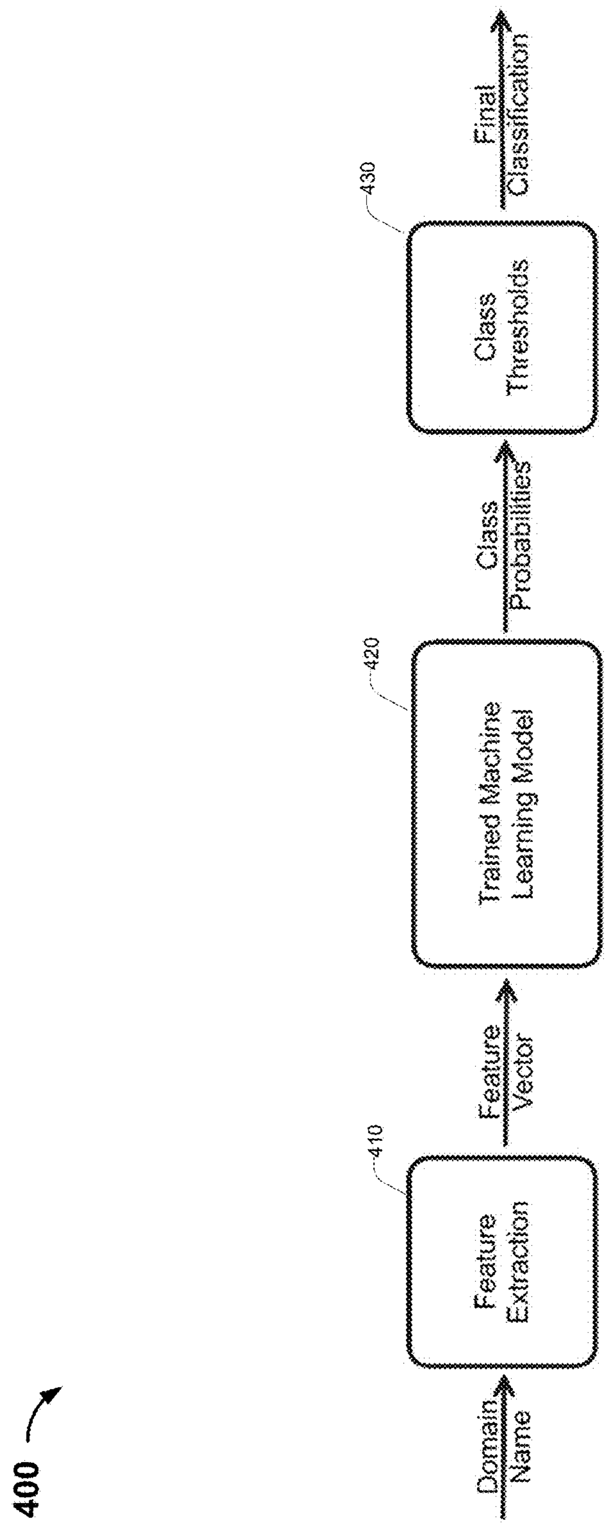

400
Domain Name
Feature Extraction
410
Feature Vector
Trained Machine Learning Model
420
Class Probabilities
Class Thresholds
430
Final Classification

Figure 4

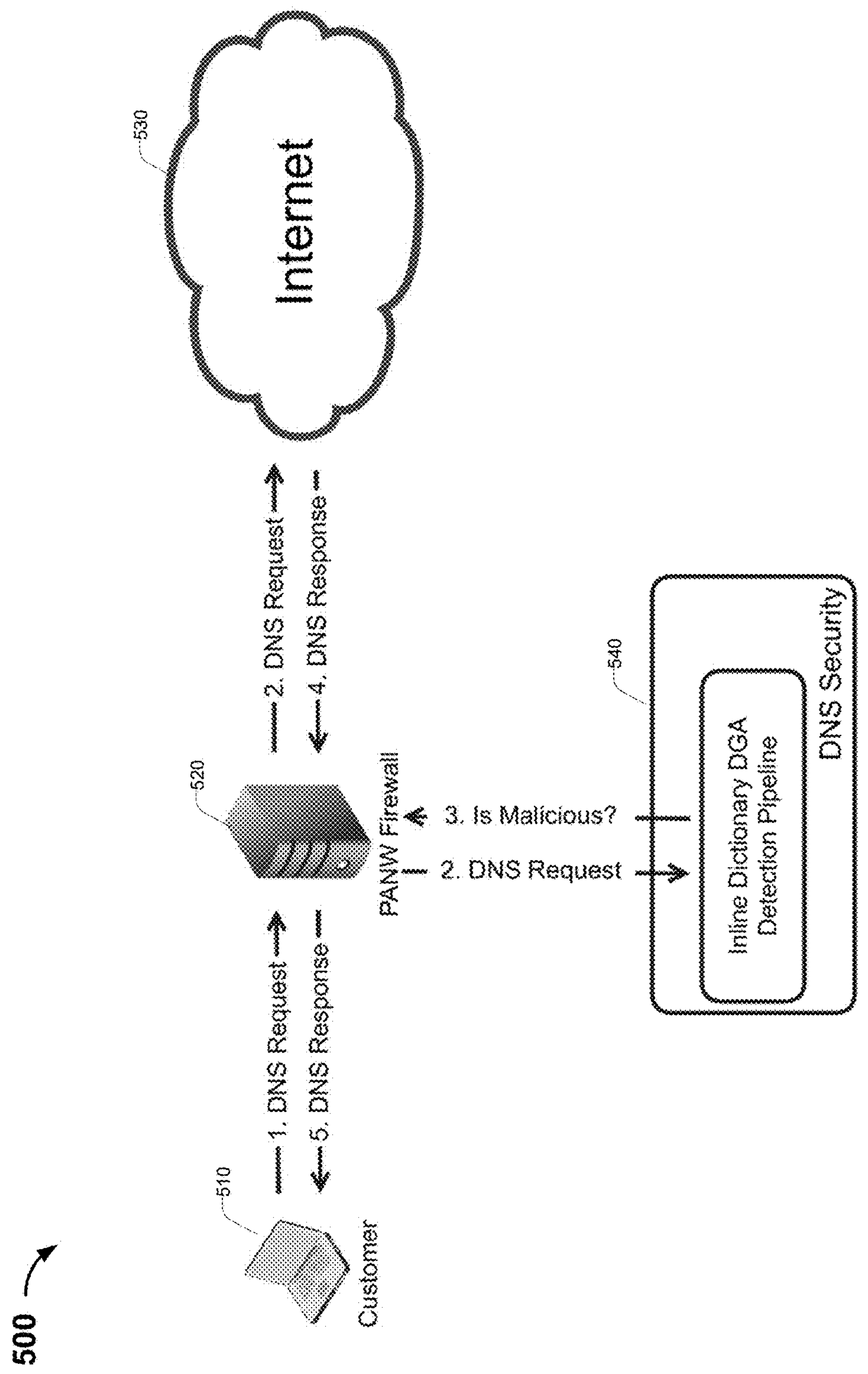

500
510
Customer
1. DNS Request
5. DNS Response
520
PANW Firewall
2. DNS Request
4. DNS Response
530
Internet
540
2. DNS Request
3. Is Malicious?
Inline Dictionary DGA Detection Pipeline
DNS Security

Figure 5

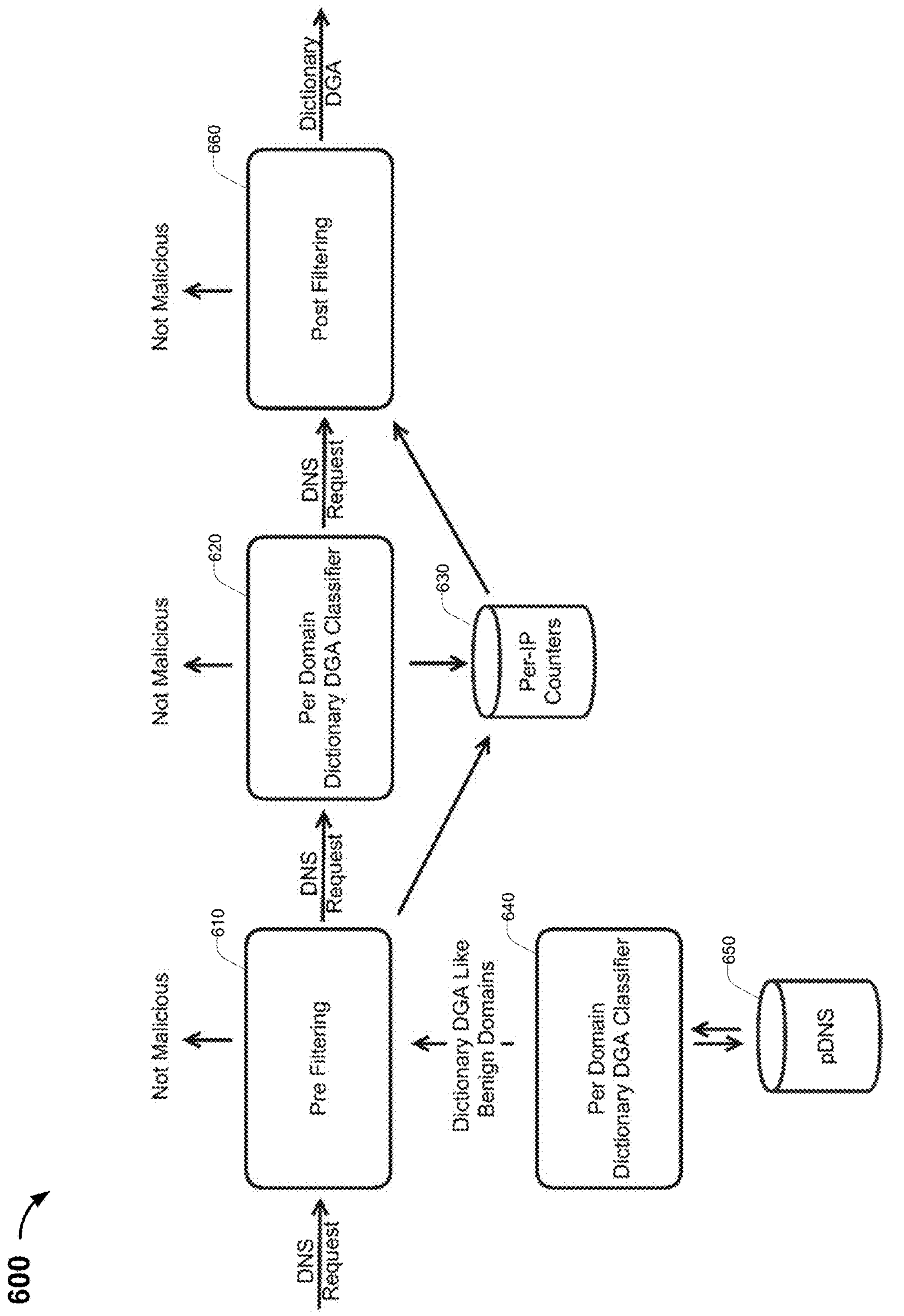

600
DNS Request
610
Pre Filtering
Not Malicious
DNS Request
620
Per Domain Dictionary DGA Classifier
Not Malicious
630
Per-IP Counters
DNS Request
660
Post Filtering
Not Malicious
Dictionary DGA
Dictionary DGA Like Benign Domains
640
Per Domain Dictionary DGA Classifier
650
pDNS

Figure 6

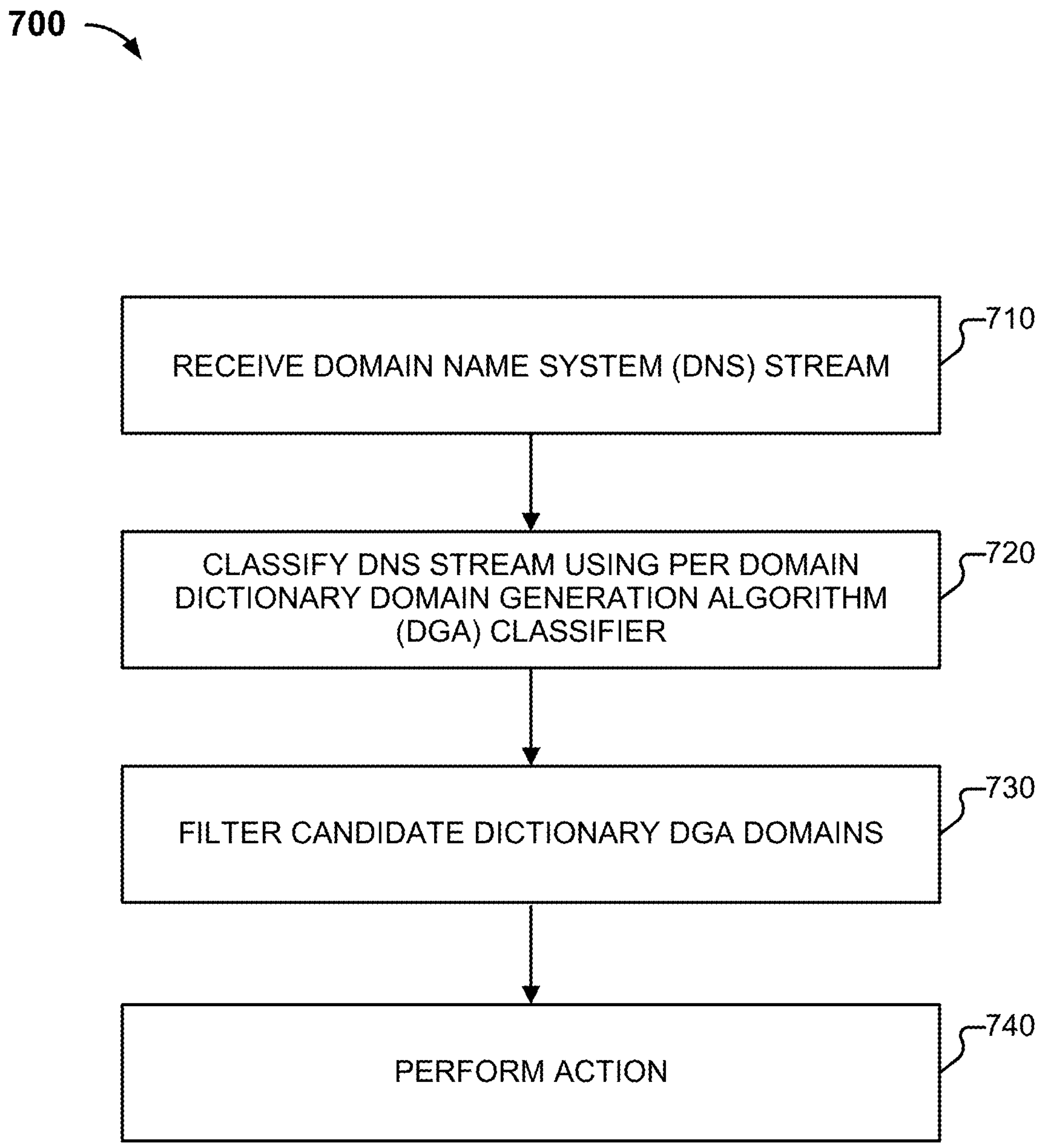

700
RECEIVE DOMAIN NAME SYSTEM (DNS) STREAM
710
CLASSIFY DNS STREAM USING PER DOMAIN DICTIONARY DOMAIN GENERATION ALGORITHM (DGA) CLASSIFIER
720
FILTER CANDIDATE DICTIONARY DGA DOMAINS
730
PERFORM ACTION
740

Figure 7

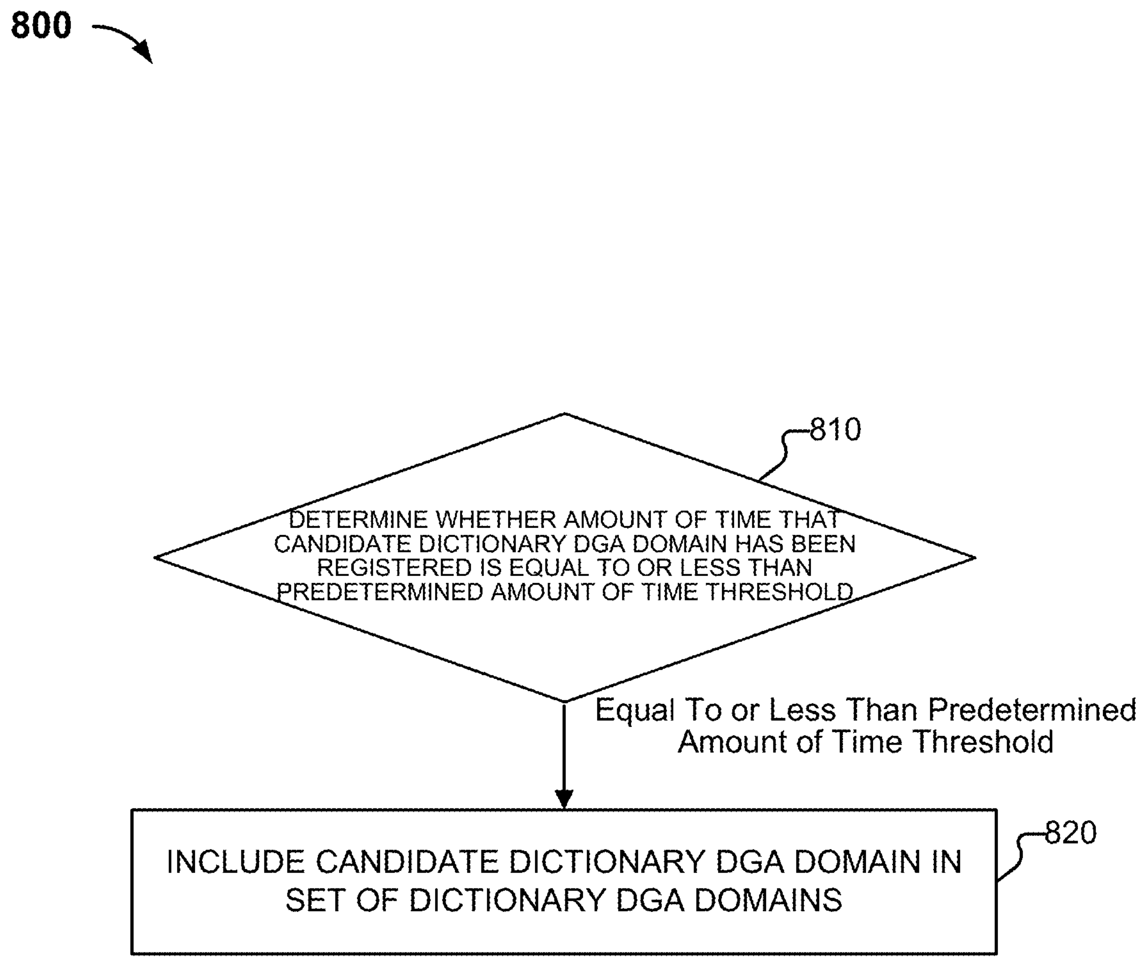

800
810
DETERMINE WHETHER AMOUNT OF TIME THAT CANDIDATE DICTIONARY DGA DOMAIN HAS BEEN REGISTERED IS EQUAL TO OR LESS THAN PREDETERMINED AMOUNT OF TIME THRESHOLD
Equal To or Less Than Predetermined Amount of Time Threshold
820
INCLUDE CANDIDATE DICTIONARY DGA DOMAIN IN SET OF DICTIONARY DGA DOMAINS

Figure 8

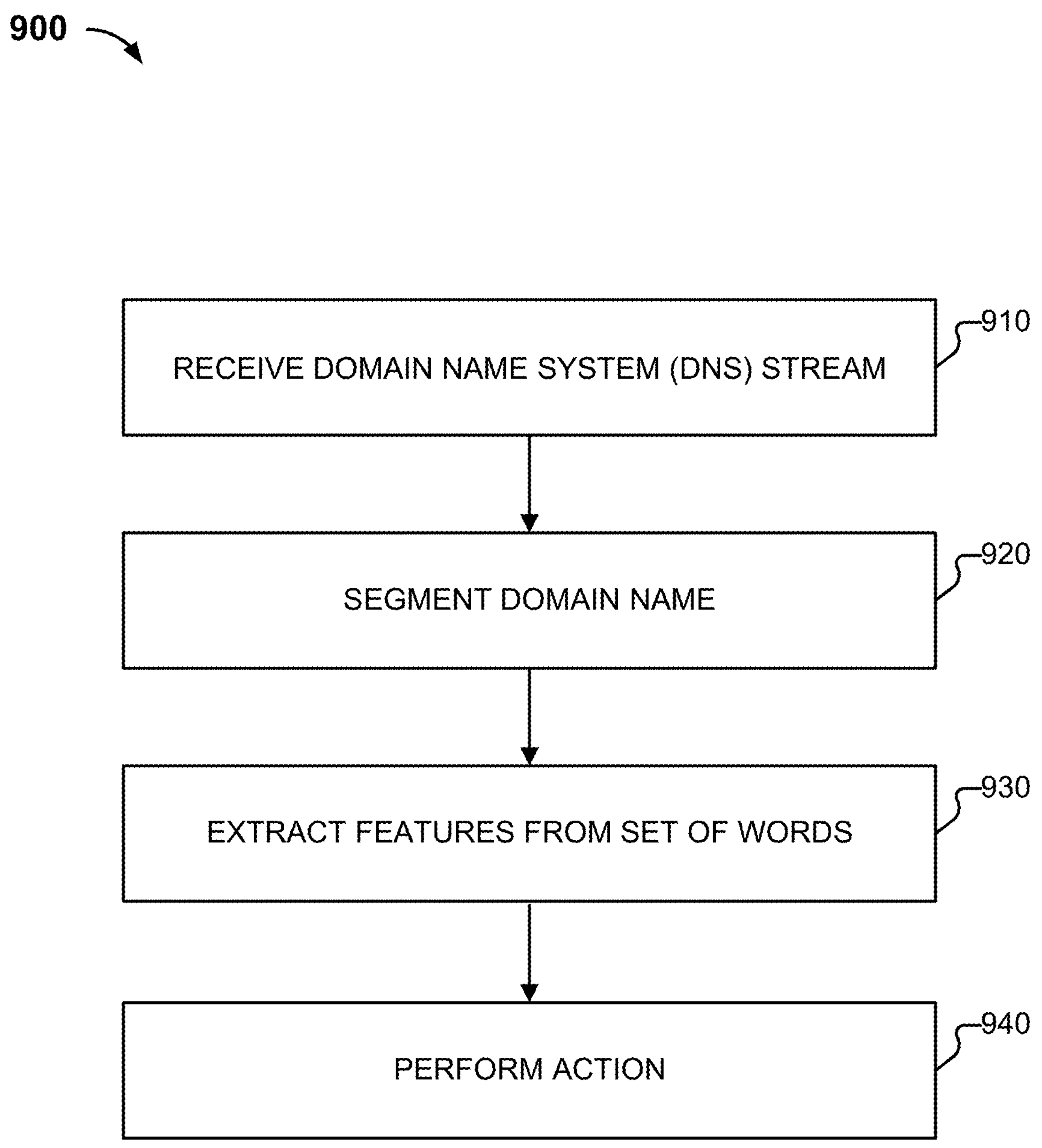

900
RECEIVE DOMAIN NAME SYSTEM (DNS) STREAM
910
SEGMENT DOMAIN NAME
920
EXTRACT FEATURES FROM SET OF WORDS
930
PERFORM ACTION
940

Figure 9

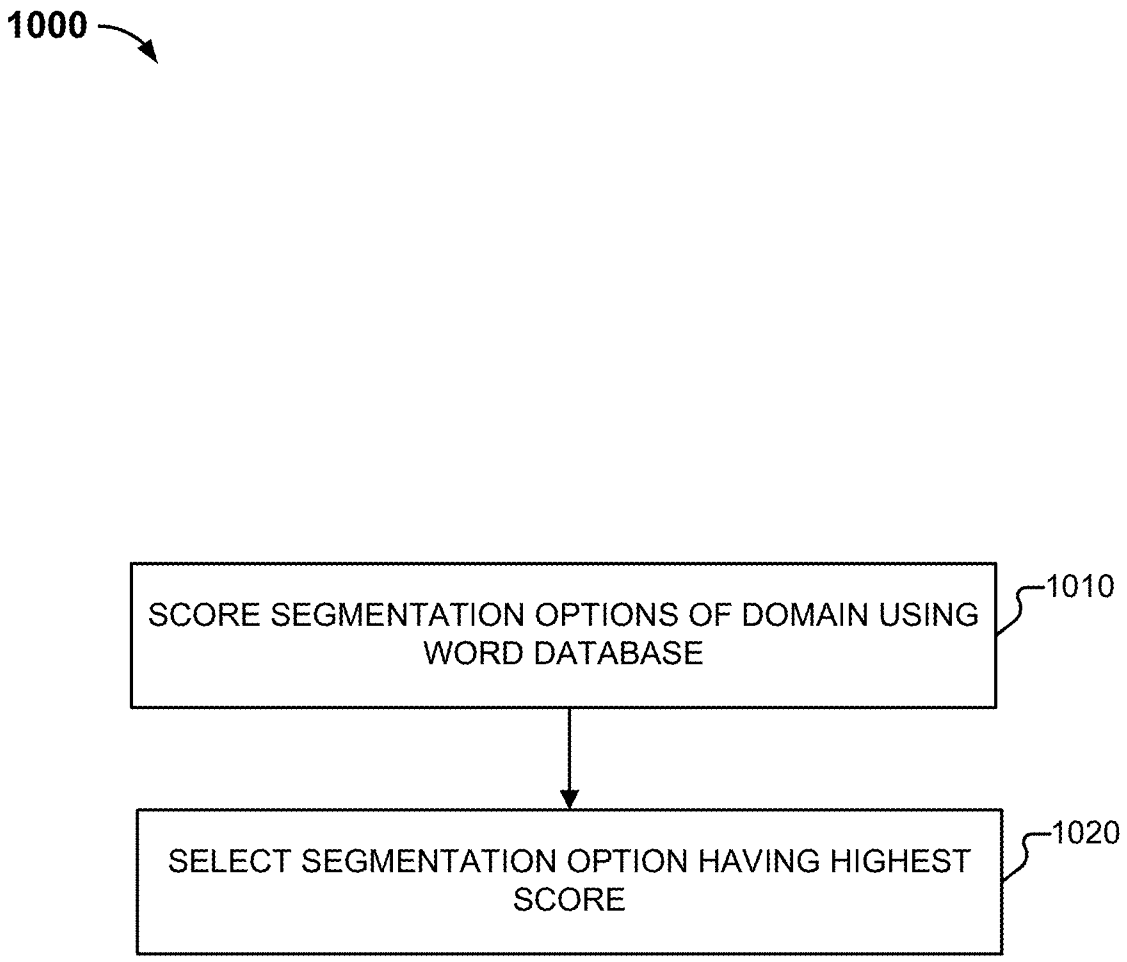

1000
SCORE SEGMENTATION OPTIONS OF DOMAIN USING WORD DATABASE
1010
SELECT SEGMENTATION OPTION HAVING HIGHEST SCORE
1020

Figure 10

SYSTEM AND METHOD FOR DETECTING DICTIONARY-BASED DGA TRAFFIC

BACKGROUND OF THE INVENTION

[0001] Malicious software (malware) generally refers to unwanted, hostile, or intrusive software that can be used to disrupt computer or network operations, collect private or sensitive information, or access private computer systems or networks. Malware can be in the form of executable code, scripts, active content, and other software. Example malware includes computer viruses, worms, Trojan horses, rootkits, keyloggers, spyware, adware, botnet command and control (C&C) related malware, and other unwanted, hostile, or intrusive software.

[0002] Security solutions (e.g., security devices or appliances, which can provide firewall solutions) can be used to safeguard against malware. For example, a firewall can identify and prevent the further spread of malware in a network.

[0003] A firewall generally protects networks from unauthorized access while permitting authorized communications to pass through the firewall. A firewall is typically implemented as a device or a set of devices, or software executed on a device, such as a computer or appliance, that provides a firewall function for network access. For example, firewalls can be integrated into operating systems of devices (e.g., computers, smart phones, tablets, or other types of network communication capable devices). Firewalls can also be integrated into or executed as software on servers, gateways, network/routing devices (e.g., network routers), or appliances (e.g., security appliances or other types of special purpose devices).

[0004] Firewalls typically deny or permit network transmission based on a set of rules. These sets of rules are often referred to as policies. For example, a firewall can filter inbound traffic by applying a set of rules or policies. A firewall can also filter outbound traffic by applying a set of rules or policies. Firewalls can also be capable of performing basic routing functions.

BRIEF DESCRIPTION OF THE DRAWINGS

[0005] Various embodiments of the invention are disclosed in the following detailed description and the accompanying drawings.

[0006] FIG. **1**A is a functional block diagram illustrating an architecture for detecting dictionary-based DGA traffic in accordance with some embodiments.

[0007] FIG. **1**B is an example of a list of domains generated by a compromised IP address.

[0008] FIG. **1**C is another example of a list of domains generated by a compromised IP address.

[0009] FIG. **2** is an example of a workflow for detecting dictionary-based DGA traffic.

[0010] FIG. **3**A is an example of a workflow for performing per domain deep learning dictionary DGA classification.

[0011] FIG. **3**B is an example of a neural network.

[0012] FIG. **4** is an example of a workflow for performing per domain machine learning dictionary DGA classification.

[0013] FIG. **5** is another functional block diagram illustrating an architecture for detecting dictionary-based DGA traffic in accordance with some embodiments.

[0014] FIG. **6** is another example of a workflow for detecting dictionary-based DGA traffic.

[0015] FIG. **7** is a flow diagram illustrating an embodiment of a process for detecting dictionary-based DGA traffic.

[0016] FIG. **8** is a flow diagram illustrating an embodiment of a process for filtering a candidate dictionary DGA domain.

[0017] FIG. **9** is a flow diagram illustrating another embodiment of a process for detecting dictionary-based DGA traffic.

[0018] FIG. **10** is a flow diagram illustrating an embodiment of a process for segmenting a domain name.

DETAILED DESCRIPTION

[0019] The invention can be implemented in numerous ways, including as a process; an apparatus; a system; a composition of matter; a computer program product embodied on a computer readable storage medium; and/or a processor, such as a processor configured to execute instructions stored on and/or provided by a memory coupled to the processor. In this specification, these implementations, or any other form that the invention may take, may be referred to as techniques. In general, the order of the steps of disclosed processes may be altered within the scope of the invention. Unless stated otherwise, a component such as a processor or a memory described as being configured to perform a task may be implemented as a general component that is temporarily configured to perform the task at a given time or a specific component that is manufactured to perform the task. As used herein, the term 'processor' refers to one or more devices, circuits, and/or processing cores configured to process data, such as computer program instructions.

[0020] A detailed description of one or more embodiments of the invention is provided below along with accompanying figures that illustrate the principles of the invention. The invention is described in connection with such embodiments, but the invention is not limited to any embodiment. The scope of the invention is limited only by the claims and the invention encompasses numerous alternatives, modifications and equivalents. Numerous specific details are set forth in the following description in order to provide a thorough understanding of the invention. These details are provided for the purpose of example and the invention may be practiced according to the claims without some or all of these specific details. For the purpose of clarity, technical material that is known in the technical fields related to the invention has not been described in detail so that the invention is not unnecessarily obscured.

[0021] Malicious software (malware) generally refers to unwanted, hostile, or intrusive software that can be used to disrupt computer or network operations, collect private or sensitive information, or access private computer systems or networks. Malware can be in the form of executable code, scripts, active content, and other software. Example malware includes computer viruses, worms, Trojan horses, rootkits, keyloggers, spyware, adware, botnet command and control (C&C) related malware, and other unwanted, hostile, or intrusive software.

[0022] Security solutions (e.g., security devices or appliances, which can provide firewall solutions) can be used to safeguard against malware. For example, a firewall can identify and prevent the further spread of malware in a network.

[0023] A firewall generally protects networks from unauthorized access while permitting authorized communications to pass through the firewall. A firewall is typically implemented as a device or a set of devices, or software executed on a device, such as a computer or appliance, that provides a firewall function for network access. For example, firewalls can be integrated into operating systems of devices (e.g., computers, smart phones, tablets, or other types of network communication capable devices). Firewalls can also be integrated into or executed as software on servers, gateways, network/routing devices (e.g., network routers), or appliances (e.g., security appliances or other types of special purpose devices).

[0024] Firewalls typically deny or permit network transmission based on a set of rules. These sets of rules are often referred to as policies. For example, a firewall can filter inbound traffic by applying a set of rules or policies. A firewall can also filter outbound traffic by applying a set of rules or policies. Firewalls can also be capable of performing basic routing functions.

[0025] A network domain generally refers to a domain that is identified by a domain name. A domain name typically includes an identification string (e.g., www.example-website.com) that defines a realm of authority or control for a domain on the Internet. Domain names are generally formed by rules and procedures of the Domain Name System (DNS). A domain name can be registered in the DNS as a domain name.

[0026] Network domains can be used in various networking contexts and application-specific naming and addressing purposes. For example, a domain name can be used to identify an Internet Protocol (IP) resource, such as a web site (e.g., a server hosting a web site), or any other service accessible via the Internet (e.g., a File Transfer Protocol (FTP) resource or other services accessible via the Internet).

[0027] A DNS service can be used to translate a domain name into an IP address. For example, when a user types in a domain name (e.g., an Internet or Intranet domain name), such as example.com, using a web browser, an authoritative DNS server can translate the domain name into an IP address, such as 172.16.254.1 (for IPv4) and 2001:db8:0:1234:0:567:8:1 (for IPv6). However, if a user attempts to perform a DNS lookup or host command on an unregistered or invalid domain name, such as examplefakedomain.com, then an error can be received indicating that such is a non-existing domain name, or in other words, that such is a non-existent domain (NXDOMAIN). Generally, an NXDOMAIN (e.g., an NXDOMAIN response received in response to a DNS query for a given domain name) is a condition or error that can be indicated for an Internet domain name that is unable to be resolved using the DNS servers (e.g., invalid domain name) or that the Internet domain name is not yet registered. In some cases, an NXDOMAIN can also be indicated due to a network or DNS server problem.

[0028] Network domains can also be used by malware. For example, malware can be distributed or propagated using a network domain, such as www.bad-malware-download-site.com. As another example, botnet C&C related malware can be associated with a network domain, such as www.botnet-site.com. Various commercial efforts as well as open project efforts exist to provide listings of network domains (e.g., bad/malware domains) that are known to be used to distribute or propagate malware. Some approaches use such network domain listings (e.g., bad/malware domain listings) to provide spoofed replies, in response to any requests to a network domain on such a listing, as a mechanism for preventing propagation of malware distribution.

[0029] Blackholing is a technique that can be used to send all traffic (e.g., network communications) to a network domain (e.g., DNS or IP address) to a null interface or non-existent server (e.g., sometimes referred to as a black hole). For example, an Internet Service Provider (ISP) can manage such blackholing for efficiency and to avoid affecting network connectivity. However, while blackholing may be efficient for certain types of severe network attacks, such an approach fails to allow for analysis of the traffic to the blackholed network domain.

[0030] Sinkholing generally refers to a technique for routing traffic (e.g., network communications) to a valid IP address. For example, a security device (e.g., a network device, which can be implemented using a server or appliance) associated with the valid IP address can receive the traffic that was directed (e.g., redirected) to the sinkholed IP address that is associated with the network domain. The security device that receives the traffic can analyze the traffic. Based on the analysis of the traffic, the security device can then perform an action (e.g., reject bad packets or perform some other action).

[0031] For example, malware, such as C&C malware and/or other types of malware, can generate many different network domains, such as by using Domain Generation Algorithms (DGAs). Generally, malware utilizes the DGA approach to generate many different domain names for detection evasion purposes and take-down evasion purposes. DGA-based malware can attempt to resolve multiple DGA domain names until the DGA-based malware locates a domain name that allows communication with a command and control server.

[0032] However, existing approaches fail to accurately and/or efficiently identify DGA behavior on a network (e.g., an enterprise IP-based network or other network). Also, existing approaches fail to determine whether a given host device that is sending DNS queries to non-existent network domains (e.g., NXDOMAINs) may be infected with DGA malware (e.g., including a previously new or not yet identified, known version of DGA malware executing on the host device).

[0033] What is needed are new and improved techniques for identifying and monitoring DGA behavior on a network.

[0034] Accordingly, techniques for Domain Generation Algorithm (DGA) behavior detection are provided.

[0035] In some embodiments, a system/method/computer program product for detecting dictionary-based DGA traffic includes receiving a domain name system (DNS) stream; classifying the DNS stream using a per domain dictionary domain generation algorithm (DGA) classifier to generate candidate dictionary DGA domains with cluster information; filtering the candidate dictionary DGA domains to generate a set of dictionary DGA domains; and performing an action based on a match with a domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains.

[0036] In some embodiments, the classifying of the DNS Stream includes classifying the DNS stream using a per domain deep learning dictionary DGA classifier to generate the candidate dictionary DGA domains with cluster information.

[0037] In some embodiments, the classifying of the DNS Stream includes classifying the DNS stream using a per domain machine learning dictionary DGA classifier to generate the candidate dictionary DGA domains with cluster information.

[0038] In some embodiments, the filtering of the candidate dictionary DGA domains includes determining whether an amount of time that a candidate dictionary DGA domain has been registered is equal to or less than a predetermined amount of time threshold; and in response to a determination that the amount of time that the candidate dictionary DGA domain has been registered is equal to or less than the predetermined amount of time threshold, including the candidate dictionary DGA domain in the set of dictionary DGA domains.

[0039] In some embodiments, the performing of the action includes generating an alert.

[0040] In some embodiments, the performing of the action includes blocking a response for the domain name.

[0041] In some embodiments, the performing of the action includes responding with a sinkhole IP address.

[0042] In some embodiments, the cluster information includes a source IP address of the one DNS request.

[0043] In some embodiments, the cluster information includes a source IP address of a firewall forwarding the one DNS request.

[0044] In some embodiments, a system/method/computer program product for detecting dictionary-based DGA traffic includes receiving a domain name system (DNS) stream, the DNS stream including a plurality of DNS requests; segmenting a domain name of one of the plurality of DNS requests into a set of words; extracting features from the set of words to generate a set of dictionary DGA domains using a classifier; and performing an action based on a match with a monitored domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains.

[0045] In some embodiments, the segmenting of the domain name includes scoring segmentation options of the domain name using a word database, the word database including a set of words and a set of corresponding frequencies, a frequency relating to a ratio the word appears in text; and selecting a segmentation option having a highest score.

[0046] In some embodiments, the segmenting of the domain name includes performing auxiliary natural language processing (NLP) on unselected segmentation options to optimize the results.

[0047] In some embodiments, the per domain dictionary DGA classifier includes a machine learning classifier.

[0048] In some embodiments, the per domain dictionary DGA classifier includes a deep neural network.

[0049] In some embodiments, the features include a part of speech, the part of speech including a noun, a verb, or both.

[0050] FIG. **1**A is a functional block diagram illustrating an architecture for detecting dictionary-based DGA traffic in accordance with some embodiments. In some embodiments, the architecture **100** includes a customer **152**, a Firewall **154**, The Internet **156**, DNS Telemetry Module **158**, an Offline Dictionary DGA Batch Detection Pipeline **160**, a DNS Security Module **162**, and An Advanced URL Filtering Module **164**.

[0051] In operation 1, the customer **152** sends a DNS request to the Firewall **154**.

[0052] In operation 2, the Firewall **154** forwards the DNS request to the Internet **156** so that the DNS request can be resolved, and also forwards the DNS request to the DNS Security Module **162**.

[0053] In some embodiments, the DNS Telemetry Module **158** of the DNS Security Module **162** forwards the DNS batch data to the Offline Dictionary DGA Batch Detection Pipeline **160** which provides Dictionary DGA Domain Batch information to the DNS Security Module **162** and the Advanced URL Filtering Module **164**.

[0054] In some embodiments, the Advanced URL Filtering Module **164** sends its output to the Firewall **154**.

[0055] In operation 3, the DNS Security Module **162** sends its output (malicious or benign) to the Firewall **154**.

[0056] In operation 4, the Firewall **154** received a DNS response from the Internet **156**.

[0057] In operation 5, based on the DNS response and the outputs of the DNS Security Module **162** and Advanced URL Filtering Module **164**, the Firewall **154** sends a DNS response to the customer **152**.

[0058] In some embodiments, the DNS response includes among other information whether the request was a non-existent (NX) request. The NX request count (NX count) can be used in cluster-based filtering. The NX count information is not always available in some network security architectures. Also, information related to DNS responses can be used for additional response data based clustering.

[0059] FIG. **1**B is an example of a list of domains generated by a compromised IP address. Malware that infected a host computer associated with the compromised IP address generates DNS requests using a DGA. As shown in the list of domains, the infected host computer was infected with the malware from the CryptoLocker family. Typically, identifying infected computers is not difficult because the DNS requests issued by the infected host computer are composed of random characters (or alphanumeric characters), e.g., intgmxdeadnxuyla.com and axwscwsslmiagfah.com, which are illegitimate domains. The list of domains also shows legitimate DNS traffic, e.g. facebook.com and paloaltonetworks.com.

[0060] FIG. **1**C is another example of a list of domains generated by a compromised IP address. The first generation of DGA generated domains were easily detectable because the domains were made up of random characters, a next generation of DGA was created called dictionary-based DGA. Because the dictionary-based DGA generates domains that are composed of dictionary words, the dictionary-based DGA generates domains that resemble legitimate domains. In this example, the malware family Suppobox generates domains such as, e. g., heavenpatternleader.net and shareleaderspace.net, which look like legitimate domains but are illegitimate domains. Also, the list of domains also shows legitimate DNS traffic, e.g. facebook.com and paloaltonetworks.com.

[0061] FIG. **2** is an example of a workflow for detecting dictionary-based DGA traffic. In the example, the workflow **200** is implementation of the Offline Dictionary DGA Batch Detection Pipeline **160** for FIG. **1**A and includes a Per Domain Dictionary DGA Classifier **210**, an IP-based Clustering Module **220**, a Side Information-based Filtering Module **230**, a passive DNS (pDNS) module **240**, and a Whois module **250**.

[0062] In some embodiments, the Per Domain Dictionary DGA Classifier **210** received the DNS batch data and outputs domains classified as dictionary DGA generated domains or benign domains. The classified domains are input to the IP-based Clustering Module **220**, which clusters the dictionary DGA generated domains to generate candidate DGA domains with statistical information about the cluster. The statistical information can include the number of malicious and benign DGA domains, the ratio of the number of malicious and benign DGA domains for each cluster, etc. In an example, the cluster is determined based on an IP address of the firewall that originated the DNS request. In another example, the cluster is determined based on a source IP address or other identifier of the customer/device that originated the DNS request.

[0063] In some embodiments, the candidate DGA domains are input into the Side Information-based Filtering Module **230**, the Side Information-based Filtering Module **230** accesses the Whois module **250** to confirm that the candidate domain has been registered for more than one year and has been regularly accessed as determined by the pDNS module **240**, and in the event that the candidate domain has been registered for more than one year or has been regularly accessed over time, the candidate domain is filtered out and the remaining candidate domains are output as Dictionary DGA domains.

[0064] The modules described above can be implemented as software components executing on one or more general purpose processors, as hardware such as programmable logic devices and/or Application Specific Integrated Circuits designed to perform certain functions or a combination thereof. In some embodiments, the modules can be embodied by a form of software products which can be stored in a nonvolatile storage medium (such as optical disk, flash storage device, mobile hard disk, etc.), including a number of instructions for making a computer device (such as personal computers, servers, network equipment, etc.) implement the methods described in the embodiments of the present invention. The modules may be implemented on a single device or distributed across multiple devices. The functions of the modules may be merged into one another or further split into multiple sub-modules.

[0065] FIG. **3**A is an example of a workflow for performing per domain deep learning dictionary DGA classification. In some embodiments, the workflow **300** is an implementation of the Per Domain Dictionary DGA Classifier **210** of FIG. **2** and includes a numeric encoding module **310**, a trained deep learning module **320**, and a class thresholds module **330**.

[0066] In some embodiments, the numeric encoding module **310** receives domain names as input, and outputs numeric vectors that are more suitable for trained deep learning models. For example, domain name example.com is translated into a fixed length numeric vector which is padded at the right with zeros so that the numeric vector reaches the maximum domain name length, and only the root portion of the domain name is used without the top-level domain (TLD). In this example, each letter of the root is translated to a numeric value, so "example" is translated to 15, 34, 11, 23, 26, 22, 15, which is padded by leading zeros to obtain the numeric vector.

[0067] In some embodiments, the numeric vectors are inputted into the trained deep learning module **320**, and outputs a numeric vector that corresponds to class probabilities. In some embodiments, the trained deep learning module **320** is a pre-trained deep neural network.

[0068] As an example, using seven malware families and one benign class, a vector of eight numerical values corresponding to a probability of each class are output. As an example, a vector [0.2, 0.01, 0.1, 0.3, 0.04, 0.25, 0.05, 0.05] is output. In the example, there is a 30% probability (0.3) that the fourth malware family exists and the benign class has a 5% probability (0.05) of existing.

[0069] In some embodiments, the class thresholds module **330** receives the class probabilities and selects a class based on a set of thresholds. For example, if the class thresholds module **330** wants to achieve a high precision in determining whether a domain is malicious then the class thresholds module **330** sets a low threshold, e.g. a 1% probability (0.01), for discarding the possibility that the domain is benign to avoid false positive. In the event that the received benign class probability is equal to or less than 0.01, the class thresholds module **330** ignores that class probability. In the event that the received benign class probability is more than 0.01, the class thresholds module **330** classifies the domain as benign even if there is a higher class probability for a malware family.

[0070] FIG. **3**B is an example of a neural network. In neural network **350**, vector x can be the input layer for our neural network (e.g., [0, 0, . . . 0, 15, 34, 11, 23, 26, 22, 15] representing the word "example"). The input layer is fed into the hidden layer. The output of the hidden layer is computed as $a=\sigma(W \cdot x+b)$. W can be a weight matrix of the hidden layer where each row represents a neuron and each value in a row can represent an importance of an input value for the neuron. As an example, the hidden layer has 100 neurons and the input layer includes 63 numeric inputs then the weight matrix is 100×63 matrix. The function a can be any nonlinear function, such as, for example, sigmoid, tanh, and ReLu functions. The nonlinear functions allow the neural network **450** to learn nonlinear functions between the input and output. The output layer can be similar to the hidden layer but the inputs of the output layer are the outputs of the hidden layer. If there are eight classes and a hundred neurons in the hidden layer then the weight matrix of the output layer is to be a 8×100 matrix.

[0071] The neural network **350** is one example, and other neural networks can be used to classify domains as dictionary DGA domains. The other neural networks can include more layers than in neural network **350** and can have different layers including recurrent neural network layers, convolutional neural network layers, Long Short-Term Memory (LSTM) layers, gated recurrent layers, transformer layers, dropout layers, etc. The other neural networks can use various word embeddings, regularization, multi-representation, different activation functions, different sizes for each layer, separately trained deep learning language model, word splitting, etc.

[0072] Some of the benefits of using a deep neural network in comparison to a machine learning technique is that there is no need for feature engineering, which can require a great deal of effort to properly implement because identifying optimal features can be difficult and the optimal features can change over time as malware families evolve and new malware families are identified.

[0073] FIG. **4** is an example of a workflow for performing per domain machine learning dictionary DGA classification. In some embodiments, the workflow **400** is an implementation of the Per Domain Dictionary DGA Classifier **210** of

FIG. **2** and includes a feature extraction module **410**, a trained machine learning model **420**, and a class thresholds module **430**.

[0074] In some embodiments, the feature extraction module **410** receives a domain name, extracts features from the domain name, and outputs a feature vector. In some embodiments, the domain name is segmented into a set of segmented words and the features are extracted from the set of segmented words.

[0075] In some embodiments, features include natural language processing (NLP) features, which fall into three categories: domain level features, meaningfulness-level features, and part-of-speech level features.

[0076] The domain level features can include, for example, domain length, total word pair count, etc.

[0077] The meaningfulness-level features can include, for example, a meaningful word count, a meaningful word ratio, a meaningful character ratio, etc.

[0078] In some embodiments, the meaningful-level features relate to meaningful pair count, meaningful pair ratio-enchant, meaningful pair ratio-google, character count of meaningful pair count, character count of total word pair count, meaningful character pair ratio, etc. As an example, the Enchant Library can be used to determine the meaningful word count and/or the meaningful character count. In another example, the Google trillion-word Corpus (Google Corpus) can be used to determine the meaningful word count and/or the meaningful character count.

[0079] Using the URL trainstationhellocup.com as an example, the URL is segmented using Google Corpus to obtain a set of words ["train", "station", "hello", "cup"]. In the example, the total pair count of words is three, which includes ("train", "station"), ("station", "hello"), and ("hello", "cup"). In the example, each of the three pairs is checked to determine whether there is a linguistic meaning. In the example, only the first pair is meaningful (has a linguistic meaning), so the meaningful pair count is one. The meaningful pair ratio is defined as the meaningful pair count divided by the total word pair count (the meaningful pair count/the total word pair count). The meaningful pair ratio is 1/3 (0.3333). The meaningful character pair ratio is a sub-feature obtained from the meaningful pair ratio, and is defined as: character count of the meaningful pair count divided by character count of the total word pair count (character count of the meaningful pair count/character count of the total word pair count).

[0080] Both the Enchant Library and the Google Corpus can be used to generate the meaningful-level features. For example, "meaningful pair ratio-enchant" and "meaningful pair ratio-google" are extracted meaningful-level features. Meaningful-level features extracted using Different corpus can have different weight in the NLP model. Because of the nature of URL naming convention, Internet based corpuses (e.g., Enchant Library and Google Corpus), which include more informal words, are given larger weights.

[0081] The part-of-speech level features can include, for example, a number of nouns included in the domain name, a number of verbs included in the domain name, etc.

[0082] In some embodiments, the part-of-speech level features include frequent part-of-speech (PoS) tagging count, frequent PoS tagging ratio, etc. For example, a word is determined to be either a noun or a verb.

[0083] In NLP, PoS tagging includes tagging each word with a PoS. For example, a word can be tagged as a noun, a verb, an adjective, an adverb, a "single character" (for example: "x"), an "Internet typographical error" (for example, fir instead of "for"), etc. The most frequently tagged PoS are collected for bi-grams. When a URL is received and segmented into a set of words, the words of the set of words are tagged using their PoS, and determined whether each bi-gram is a frequent PoS bi-gram (above a frequency threshold or a top ranked bi-gram). The frequent PoS tagging count relates to how many bi-grams appeared to be frequently used in the PoS bi-gram collections. The frequent PoS tagging ratio corresponds to a frequent part-of-speech (PoS) tagging count divided by a total PoS bi-gram count (a frequent PoS tagging count/total PoS bi-gram count).

[0084] In some embodiments, the part-of-speech level features score how the words in the URL correspond to frequently used PoS tagging patterns in natural languages. The part-of-speech level features can include frequent part-of-speech (PoS) tagging count, frequent PoS tagging ratio, etc. For example, a bi-gram ["beautiful", "flower"] from a URL is tagged as [adjective, noun], which matches the frequent PoS tagging pattern adjective+noun in the English language.

[0085] As an example, a domain name associated with a DNS request is segmented into various segmentation candidates, and each segmentation candidate is scored using a word database where the word database includes words and various frequencies of the words appearing in text. As an aspect, for each segmentation candidate, a score is determined using the word database. Google Corpus, which includes a trillions words, is an example of a word database.

[0086] As an example, "facebook" is segmented to ["f" "ace", "book"] or ["face", "book"] or ["facebook"]. The segments are scored using an NLP technique called "stupid backoff" based on each word's frequency appearing in the word database (e.g., Google Corpus). The highest scored segmentation candidate is the final segmentation result. In this example, the final segmentation result is ["facebook"] because "facebook" appears more frequently in the word database that any of the other segmentation candidates. As an aspect, the "stupid backoff" technique is an NLP smoothing technique used to calculate the probability of the various segmentation candidates. The "stupid backoff" technique takes into consideration that some high n-grams may be never collected in any corpus, so the "stupid backoff" technique typically uses an n−1 gram for the answer. The "stupid backoff" technique is a fast technique and typically yields good results as scoring is obtained from a real probability distribution via the NLP chain rule.

[0087] In some embodiments, the feature extraction module **410** also clusters segmented words using a Brown clustering technique to identify words that appear together less frequently. For example, "New York" is typically clustered together; however, "Carmel-by-the-Sea" is clustered together less frequently.

[0088] As an example, the Brown clustering technique is an NLP technique used to cluster related word together such as, for example, city names. Since some city names appear less frequently than some non-city names in the word database, when NLP features are generated for these words, the results can be less than ideal. To adjust for this occurrence, a different word database can be used and the Brown clustering technique can be performed to cluster related words together. As an example, ["New York", "Shanghai", "Carmel-by-the-Sea"] are part of the same cluster because the words of the cluster are all "places or cities." When a URL is received and segmented to output ["Carmel-by-the-Sea", "city"], even though the bi-gram can appear less frequently in the word database than other segmentation candidates, the Brown clustering technique is aware that the cluster relates to ["city name", "city"]. As a result, the Brown clustering technique borrows some points for ["Carmel-by-the-Sea", "city"] from ["New York", "City"] so more reasonable feature vectors can be produced and the ML models can better handle these feature vectors.

[0089] In some embodiments, the feature extraction module **410** uses pre-generated word clusters to help extract features. In some embodiments, word clusters are generated using the Brown clustering technique where related words are clustered together into the same node based on the context in which the related words occur in natural language. Words in the same node can share weights from the NLP models.

[0090] In some embodiments, the trained machine learning model **420** corresponds to a decision tree (DT) or a support vector machine (SVM) model, which can be trained using the samples found in Gozi or Matsnu families. After being trained, the trained machine learning model **420** is input with a feature vector and a vector that corresponds to class probabilities.

[0091] In some embodiments, the trained machine learning model **420** is trained using a set of training data. Gozi and/or Matsnu are examples of sets of training data that can be used to train the trained machine learning model **420**. Gozi is a set of training data (e.g., 105631 samples) where the support vector machine (SVM) is trained with the Alexa top 50K domains, and the decision tree (DT) is trained with the Alexa top 50K domains. In the example, Matsnu is a set of training data (e.g., 12666 samples) where the support vector machine (SVM) is trained with the Alexa top 50K domains and the decision tree (DT) is trained with the Alexa top 50K domains.

[0092] In some embodiments, class thresholds module **430** receives the vector and outputs a final classification.

[0093] Some of the benefits of using a machine learning technique in comparison to a deep learning technique such as a deep neural network include machine learning technique decisions are easier to understand than deep learning technique decisions because, for machine learning technique decisions, it can be inferred which features are used to make classification choices. The features from the machine learning technique are human made and meaningful as opposed to features from the deep learning technique where the features are automatically created to fit the task at hand and are harder to interpret. Also if the features are well crafted then there is no need for an architecture search as in case of the deep learning technique.

[0094] FIG. **5** is another functional block diagram illustrating an architecture for detecting dictionary-based DGA traffic in accordance with some embodiments. In some embodiments, the architecture **500** includes a customer **510**, a Firewall **520**, the Internet **530**, and an Inline Dictionary DGA Detection Pipeline **540**.

[0095] In operation 1, the customer **510** sends a DNS request to the Firewall **520**.

[0096] In operation 2, the Firewall **520** forwards the DNS request to the Internet **530** so that the DNS request can be resolved, and also forwards the DNS request to the Inline Dictionary DGA Detection Pipeline **540**. In some embodiments, the Inline Dictionary DGA Detection Pipeline **540** is included in a DNS security module.

[0097] In operation 3, the Inline Dictionary DGA Detection Pipeline **540** responds to the Firewall **520** with a verdict on whether the DNS request is malicious.

[0098] In operation 4, the Firewall **520** receives a DNS response from the Internet **530**. In some embodiments, the verdict of operation 3 is returned to the Firewall **520** before or about the same time as when the DNS response (operation 4) arrives at the Firewall **520**.

[0099] In operation 5, based on the verdict from the Firewall **520** and the DNS response, the Firewall **520** sends a DNS response to the customer **510**. For example, in addition, in the event that the Inline Dictionary DGA Detection Pipeline **540** determines that the DNS request is associated with a compromised customer computer, the Firewall **520** can generate an alert, block a response for the domain name, and/or respond with a sinkhole IP address.

[0100] FIG. **6** is another example of a workflow for detecting dictionary-based DGA traffic. In some embodiments, the workflow **600** is implemented by the Inline Dictionary DGA Detection Pipeline **540** of FIG. **5** and includes a pre filtering module **610**, a per domain dictionary DGA classifier **620**, a per-IP counters module **630**, a per domain dictionary DGA classifier **640**, a passive DNS (pDNS) module **650**, and a post filtering module **660**.

[0101] In workflow **600**, at regular time intervals (e.g., one day), the pre filtering module **610** determines an allowlist of domains that are likely benign or other non-DGA domains that would be classified as dictionary DGA domains by the per domain dictionary DGA classifier **640**. The per domain dictionary DGA classifier **640** obtains historical passive DNS queries from the pDNS module **650** and selects domain names with a DNS query pattern inconsistent with DGA domains (e.g., domains that have a long history of being included in DNS queries). Most of the selected domains are benign and some of the selected domains can be illicit or malicious but are unlikely to be DGAs. The domains classified as DGA by the per domain dictionary DGA classifier **640** can be selected for filtering. The per domain dictionary DGA classifier **640** outputs an allowlist used for prefiltering by the pre filtering module **610**. For all domains found in the allowlist, the pre filtering module **610** returns a benign verdict. Additionally, the pre filtering module **610** will increase a benign counter for the requesting customer's IP address in the per-ip counters module **630**.

[0102] Upon receiving a DNS request, the pre filtering module **610** determines whether the domain in the DNS request is in the allowlist of domains, and in the event that the domain is not present in the allow list, the DNS request is sent to the per domain dictionary DGA classifier **620**. In the event that the per domain dictionary DGA classifier **620** classifies the domain as benign, the per domain dictionary DGA classifier **620** returns a benign verdict and increases the benign per-ip counter of the per-ip counters module **630**. In the event that the per domain dictionary DGA classifier **620** finds the domain to be a dictionary DGA, the per domain dictionary DGA classifier **620** increases a counter for the malware family most likely to have generated the domain name in the per-ip counters module **630** and returns a verdict that the domain is a Dictionary DGA. In some embodiments, in the event that the per domain dictionary DGA classifier **620** finds the domain to be a dictionary DGA, the per domain dictionary DGA classifier **620** increases a counter for the malware family most likely to have generated the domain name of the per-ip counters module **630** and sends the domain to the post filtering module **660**. In some embodiments, the post filtering module **660** uses a set of rules based on a combination of the per-ip counters of the per-ip counters module **630** to select which domains have the final malicious dictionary DGA verdict. An example of the set of rules includes a minimum number of dictionary DGA queries seen from a customer IP address before the domains are started to be blocked. Another example of the set of rules includes a proportion of dictionary DGA domains seen in a specific time period. The set of rules are not limited to the examples above.

[0103] FIG. **7** is a flow diagram illustrating an embodiment of a process for detecting dictionary-based DGA traffic. In some embodiments, the process **700** is implemented by the Offline Dictionary DGA Batch Detection Pipeline **160** of FIG. **1**A and comprises:

[0104] In **710**, the pipeline receives a domain name system (DNS) stream.

[0105] In **720**, the pipeline classifies the DNS stream using a per domain dictionary domain generation algorithm (DGA) classifier to generate candidate dictionary DGA domains with cluster information.

[0106] In **730**, the pipeline filters the candidate dictionary DGA domains to generate a set of dictionary DGA domains.

[0107] In **740**, the pipeline performs an action based on a match with a monitored domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains.

[0108] FIG. **8** is a flow diagram illustrating an embodiment of a process for filtering a candidate dictionary DGA domain. In some embodiments, the process **800** is an implementation of operation **730** of FIG. **7** and comprises:

[0109] In **810**, the pipeline determines whether an amount of time that a candidate dictionary DGA domain has been registered is equal to or less than a predetermined amount of time threshold.

[0110] In **820**, in response to a determination that the amount of time that the candidate dictionary DGA domain has been registered is equal to or less than a predetermined amount of time threshold, the pipeline includes the candidate dictionary DGA domain in the set of dictionary DGA domains.

[0111] FIG. **9** is a flow diagram illustrating another embodiment of a process for detecting dictionary-based DGA traffic. In some embodiments, the process **900** is implemented by the Per Domain Dictionary DGA Classifier **210** of FIG. **2** and comprises:

[0112] In **910**, the classifier receives a domain name system (DNS) stream, wherein the DNS stream includes a plurality of DNS requests.

[0113] In **920**, the classifier segments a domain name of one of the plurality of DNS requests into a set of words.

[0114] In **930**, the classifier extracts features from the set of words to generate a set of dictionary DGA domains.

[0115] In **940**, the classifier performs an action based on a match with a monitored domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains.

[0116] FIG. **10** is a flow diagram illustrating an embodiment of a process for segmenting a domain name. In some embodiments, the process **1000** is an implementation of operation **920** of FIG. **9** and comprises:

[0117] In **1010**, the classifier scores segmentation options of the domain name using a word database. In some embodiments, the word database includes a set of words and a set of corresponding frequencies. In some embodiments, a frequency relates to a ratio the word appears in text.

[0118] In **1020**, the classifier selects a segmentation option having a highest score.

[0119] Although the foregoing embodiments have been described in some detail for purposes of clarity of understanding, the invention is not limited to the details provided. There are many alternative ways of implementing the invention. The disclosed embodiments are illustrative and not restrictive.

What is claimed is:

1. A system, comprising:
a processor configured to:
receive a domain name system (DNS) stream;
classify the DNS stream using a per domain dictionary domain generation algorithm (DGA) classifier to generate candidate dictionary DGA domains with cluster information;
filter the candidate dictionary DGA domains to generate a set of dictionary DGA domains; and
perform an action based on a match with a domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains; and
a memory coupled to the processor and configured to provide the processor with instructions.

2. The system of claim **1**, wherein the classifying of the DNS Stream comprises to classify the DNS stream using a per domain deep learning dictionary DGA classifier to generate the candidate dictionary DGA domains with cluster information.

3. The system of claim **1**, wherein the classifying of the DNS Stream comprises to classify the DNS stream using a per domain machine learning dictionary DGA classifier to generate the candidate dictionary DGA domains with cluster information.

4. The system of claim **1**, wherein the filtering of the candidate dictionary DGA domains comprises to:
determine whether an amount of time that a candidate dictionary DGA domain has been registered is equal to or less than a predetermined amount of time threshold; and
in response to a determination that the amount of time that the candidate dictionary DGA domain has been registered is equal to or less than the predetermined amount of time threshold, include the candidate dictionary DGA domain in the set of dictionary DGA domains.

5. The system of claim **1**, wherein the performing of the action comprises to generate an alert.

6. The system of claim **1**, wherein the performing of the action comprises to block a response for the domain name.

7. The system of claim **1**, wherein the performing of the action comprises to respond with a sinkhole IP address.

8. The system of claim **1**, wherein the cluster information includes a source IP address of the one DNS request.

9. The system of claim **1**, wherein the cluster information includes a source IP address of a firewall forwarding the one DNS request.

10. A system, comprising:

a processor configured to:

receive a domain name system (DNS) stream, wherein the DNS stream includes a plurality of DNS requests;

segment a domain name of one of the plurality of DNS requests into a set of words;

extract features from the set of words to generate a set of dictionary DGA domains; and

perform an action based on a match with a monitored domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains; and

a memory coupled to the processor and configured to provide the processor with instructions.

11. The system of claim **10**, wherein the segmenting of the domain name comprises to:

score segmentation options of the domain name using a word database, wherein the word database includes a set of words and a set of corresponding frequencies, wherein a frequency relates to a ratio the word appears in text; and

select a segmentation option having a highest score.

12. The system of claim **11**, wherein the segmenting of the domain name comprises to:

perform auxiliary natural language processing (NLP) on unselected segmentation options to optimize the results.

13. The system of claim **10**, wherein the per domain dictionary DGA classifier includes a machine learning classifier.

14. The system of claim **10**, wherein the per domain dictionary DGA classifier includes a deep neural network.

15. The system of claim **10**, wherein the features include a part of speech, the part of speech including a noun, a verb, or both.

16. A method, comprising:

receiving, using a processor, a domain name system (DNS) stream;

classifying, using the processor, the DNS stream using a per domain dictionary domain generation algorithm (DGA) classifier to generate candidate dictionary DGA domains with cluster information;

filtering, using the processor, the candidate dictionary DGA domains to generate a set of dictionary DGA domains; and

performing, using the processor, an action based on a match with a domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains.

17. A computer program product embodied in a non-transitory computer readable medium and comprising computer instructions for:

receiving a domain name system (DNS) stream;

classifying the DNS stream using a per domain dictionary domain generation algorithm (DGA) classifier to generate candidate dictionary DGA domains with cluster information;

filtering the candidate dictionary DGA domains to generate a set of dictionary DGA domains; and

performing an action based on a match with a domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains.

18. A method, comprising:

receiving, using a processor, a domain name system (DNS) stream, wherein the DNS stream includes a plurality of DNS requests;

segmenting, using the processor, a domain name of one of the plurality of DNS requests into a set of words;

extracting, using the processor, features from the set of words to generate a set of dictionary DGA domains; and

performing, using the processor, an action based on a match with a monitored domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains.

19. A computer program product embodied in a non-transitory computer readable medium and comprising computer instructions for:

receiving a domain name system (DNS) stream, wherein the DNS stream includes a plurality of DNS requests;

segmenting a domain name of one of the plurality of DNS requests into a set of words;

extracting features from the set of words to generate a set of dictionary DGA domains; and

performing an action based on a match with a monitored domain name of a monitored DNS request and a dictionary DGA domain of the set of dictionary DGA domains.

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