

# Attackers vs AI: how AI detects cyber threats

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- Malware evolution
- Artificial Intelligence and Machine Learning applied to cybersecurity
- Common techniques used by attackers
- The infamous Wannacry ransomware
- The Astaroth malware family
- o Offensive Al

## Malware evolution





Source: IKARUS Software Security GmbH

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- The 2000s marked the transition from malware with either "noble" or "less-noble" purposes to:
  - recruit computers in a botnet in order to attack companies and organizations
  - industrial virtual espionage
  - mass surveillance
  - attack (h)ac(k)tivists
  - MaaS
- From single malicious software authors, now attackers are organized in cybercriminal organizations structured as companies



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## Malware evolution

The 2000s marked the transition from malware 0

Sources – On the left: freebeacon.com. Stolen F-35 Secrets Now Showing Up in China's Stealth Fighter, 2014. On the right:<sup>5</sup> guora.com. US F-35 compared to Chinese J-31, 2018.

in order to attack c









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- Given the huge amount of information to process and the failure of classic approaches:
  - analysis processes should be automated as much as possible
  - security analysts should be supported by tools enabling the identification of possible cyber threats
- Artificial Intelligence (AI) can back their analyses highlighting suspicious events that are worth to be investigated by analysts



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- Branch of artificial intelligence
- Allows an application to perform an activity without being explicitly programmed to do so by building a mathematical model
- Machine learning algorithms are responsible for creating mathematical models based on a data samples
- Differs from statistical approaches because:
  - there exist lots of statistical models able to make predictions, but accuracy is not one of their strengths

## ML for cybersecurity



- provides more predictional power at the cost of a less interpretable mathematical model
- needs for a data sample for model creation
- ML-driven investigations can leverage different approaches:
  - supervised
  - unsupervised
  - semi-supervised



 Classification is a typical example of supervised learning:

> Process for assigning an observation to a specific class on the basis of a labeled knowledge base, namely

- observation: bytes sent by a monitored machine → class: legit data transfer/data exfiltration
- observation: HTTP traffic → suspicious HTTP traffic/ legit HTTP traffic



## Overview on ML





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• Clustering is a typical example of unsupervised learning:

• Task of grouping similar observations, like

Overview on ML

• observation: DNS query  $\rightarrow$  similar to legit queries/similar to suspicious queries







11

- o DGA
- o IP Flux
- o Covert channel over DNS
- Covert channel over HTTP
- o Host/Port scan
- Encrypted communications
- o ...



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- Attributed<sup>1,2</sup> to the APT Lazarus Group:
  - a North Korean state-sponsored cyber threat group
  - active since 2009
  - responsible for many disruptive attacks (e.g., the wiper attack against Sony Pictures Entertainment)
- Wannacry samples use:
  - DGA
  - host/port scan

<sup>1</sup> WSJ.com. It's Official: North Korea Is Behind WannaCry. <u>https://www.wsj.com/articles/its-official-north-korea-is-behind-wannacry-1513642537</u>. <sup>2</sup> MITRE.org. Wannacry. <u>https://attack.mitre.org/software/S0366/</u>.



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- Exploitation of MS implementation of SMB protocol through Eternal Blue<sup>3</sup>
- Wannacry attempts to contact kill-switch domains to establish if it has to encrypt disk(s)
  - kill-switch domains are of the form www[.]iuqerfsodp9ifjaposdfjhgosurijfaewrwergwea[.] com<sup>4</sup>
  - Infected machines querying kill-switch domains are more active in the network with respect to healthy machines<sup>5</sup>
- Infected systems not able to contact kill-switch domains starts a reconnaissance phase and concurrently encrypt data

<sup>3</sup> MITRE.org. CVE-2017-0144. <u>https://cve.mitre.org/cgi-bin/cvename.cgi?name=cve-2017-0144</u>.
 <sup>4</sup> FireEye.com. Wannacry Ransomware Campaign: Threat Details and Risk Management. <u>https://www.fireeye.com/blog/products-and-services/2017/05/wannacry-ransomware-campaign.html</u>.
 <sup>5</sup> Cisco.com. The Hours of WannaCry. <u>https://umbrella.cisco.com/blog/the-hours-of-wannacry</u>.

The infamous Wannacry ransomware

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- Reconnaissance phase consists in
  - scanning random IPs for open TCP 445 ports<sup>6</sup>
    - about 25 IP addresses per second

to rapidly spread the infection

- Execution of Eternal Blue exploit to infect machines with open TCP 445 ports
- Reconnaissance and exploitation phase are run in parallel

<sup>6</sup> FireEye.com. Wannacry Ransomware Campaign: Threat Details and Risk Management. <u>https://www.fireeye.com/blog/products-and-services/2017/05/wannacry-ransomware-campaign.html</u>.

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 Kill-switch domains seem to be obtained from "someone smashed a few keys on the upper rows of the keyboard"<sup>7</sup>



Figure: Character distance and frequency of the kill-switch domain "iuqerfsodp9ifjaposdfjhgosurijfaewewergwea"

<sup>7</sup> Cisco.com. The Hours of WannaCry. <u>https://umbrella.cisco.com/blog/the-hours-of-wannacry</u>.





 However, kill-switch domains look like as algorithmically generated, also known as Domain Generated Algorithm



Figure: Character distance and frequency of the kill-switch domain "iuqerfsodp9ifjaposdfjhgosurijfaewewergwea"







- DNS query peaks in a specific time window are outliers that deviate from the usual query volume of a machine
- Outliers can be determined on the basis of the combination of statistical indicators which model deviations from machine usual DNS queries

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- Characterizing features of domains involved in DNS query peaks are extracted
- A clustering algorithm can be applied on extracted features to group similar domains
- Resulting clusters represent legitimate domains and possible different DGAs

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- Both cluster and lexical analyses establish the presence of possible algorithmically generated domains
- Resolutions of these domains increases the criticality level

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- Host and port scannings can be identified by
  - analyzing flags of connections between machines that represent
    - TCP and UDP pings, TCP ACK pings, and TCP SYN pings in case of host discovery
    - TCP and UDP scans and TCP SYN/NULL/FIN scans in case of port scans
  - collecting features about the number of destination machines (and ports) reached in a specific time interval
  - outliers in collected features describe likely scanning activities





- Astaroth<sup>8</sup> samples are trojans and steal information about
  - e-mails
  - e-commerce
  - banking accounts
- Attacks companies in Europe and Latin America since late 2017
- In July 2021, samples have been distributed in a Malspam campaign through mails containing an infected link





- The infected link provides access to a compressed Powershell script performing different infection stages:
  - creation of a support file specifying a C&C domain
  - HTTP connection to C&C to download an XML file containing
    - Javascript source code executed to download malicious DLLs
    - a compiler for guaranteeing persistence
- Downloaded DLLs extract sensitive information, later exfiltrated to either predetermined or algorithmically generated malicious domains
- Communications with the C&C are established through DGA and are both encrypted and in clear



## Detect covert channels over DNS with ML

• A covert channel is a technique to communicate, transfer or exfiltrate data using different protocols, after having exploited machines in a network<sup>9</sup>

COVERT CHANNEL OVER DNS	
Query DNS	⊥Date
c26f48940a185559ca2e5cbf35e10136.mifahfjheijjgfoosdspdsfjeummcsde.ga 🚯	Nov 21, 2021 23:43:03 ()
4b0ddc0f8956802871583519f0383b5b.mifahfjheijjgfoosdspdsfjeummcsde.ga 0	Nov 21, 2021 23:42:54 🟮
b389d4484a3df27544c79cd0e2ccc436.mifahfjheijjgfoosdspdsfjeummcsde.ga 0	Nov 21, 2021 23:42:51 0
f8db5951fcc6d67d9cba15cf0d1c4307.mifahfjheijjgfoosdspdsfjeummcsde.ga 3	Nov 21, 2021 23:42:42 🟮
4c0d1fa067186f2e5db94bffa7f05fb4.mifahfjheijjgfoosdspdsfjeummcsde.ga 🟮	Nov 21, 2021 23:42:38 🟮
3d7ef392f93b5155607a6eccf1ae3f13.mifahfjheijjgfoosdspdsfjeummcsde.ga 0	Nov 21, 2021 23:39:12 0

Figure: Examples of covert channel over DNS used by a sample belonging to the Astaroth malware family

<sup>9</sup> Saeli S., Bisio F., Lombardo P., and Massa D. (2020). DNS Covert Channel Detection via Behavioral Analysis: a Machine Learning Approach. MALWARE conference, 2020.

## Detect covert channels over DNS with ML



4

#### COVERT CHANNEL OVER DNS

c26f48940a185559ca2e5cbf35e10136.mifahfjheijjgfoosdspdsfjeummcsde.ga 🜖

b389d4484a3df27544c79cd0e2ccc436.mifahfjheijjgfoosdspdsfjeummcsde.ga 🟮

f8db5951fcc6d67d9cba15cf0d1c4307.mifahfjheijjgfoosdspdsfjeummcsde.ga 🟮

4c0d1fa067186f2e5db94bffa7f05fb4.mifahfjheijjgfoosdspdsfjeummcsde.ga 🕄

3d7ef392f93b5155607a6eccf1ae3f13.mifahfjheijjgfoosdspdsfjeummcsde.ga 0

4b0ddc0f8956802871583519f0383b5b.mifahfjheijjgfoosdspdsfjeummcsde.ga 🛚 🕂 🔶

Query DNS

#### Feature extraction:

- upper-lowercase ratio of DNS queries
- numbers-letters ratio of DNS queries
- o max length per level
- o hostname length

#### 0 ...

# Image: Date Nov 21, 2021 23:43:03 Image: Date Nov 21, 2021 23:42:54 Nov 21, 2021 23:42:54 Image: Date Nov 21, 2021 23:42:51 Image: Date Image: Date

Nov 21, 2021 23:39:12 🐧

## Detect covert channels over DNS with ML

- A one-class SVM classifier is trained with the features previously dicussed, periodically extracted from legit DNS queries
- Features extracted from real-time DNS queries are given in input to the SVM to test if they are legitimate or anomalous
- Suspicious DNS queries are then aggregated with other anomaly indicators to classify them as malicious, such as:
  - high number of unique requests/hostnames to/per domain
  - high query entropy
  - high distance of monograms and bigrams distributions of the query from dictionary ones





## Detect anomalies in encrypted communications with ML

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- Suspicious encrypted communications can be detected by analyzing and extracting features from exchanged secure protocol (e.g., HTTPS) messages
- The extraction phase processes SSL/TLS metadata and data contained in the fields of X.509 certificates to detect anomalies in a SSL/TLS handshake
- Suspicious connections are identified by combining unsupervised ML technique with JA3 hashes
- A JA3 hash is a client fingerprint of a SSL/TLS flow

```
"version" : "TLSv12",
"server_name" : "teams.microsoft.com",
"curve" : "secp384r1".
"subject" : "CN=teams.microsoft.com",
"issuer" : "CN=Microsoft RSA TLS CA 01.
            O=Microsoft Corporation, C=US",
"server cert chain" : [
  "md5" : "28211f1f8a50966b518ec39d3546d57d",
  "sha1" : "4a263f1f39dd526901987ecdb09e2d1297e2bc51".
  "x509" :
      "version" : 3.
      "key type" : "rsa".
      "key_alg" : "rsaEncryption",
      "key_length" : 2048,
      "sig_alg" : "sha256WithRSAEncryption",
      "not valid before" : 1606847889.0.
      "not_valid_after" : 1638383889.0,
      "subject" : "CN=teams.microsoft.com",
      "issuer" : "CN=Microsoft RSA TLS CA 01.
                  O=Microsoft Corporation, C=US",
"ja3" : "7f805430de1e7d98b1de033adb58cf46",
ia3s" : "0f14538e1c9070becdad7739c67d6363".
"cipher" : "TLS_ECDHE_RSA_WITH_AES_256_GCM_SHA384",
"machineDest" : "TEAMS_MICROSOFT_COM"
```

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## Offensive Al



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29



Source: Inovex.de. Robustifying Machine Perception for Image Recognition Systems: Defense Against the Dark Arts. 2019. <u>https://www.inovex.de/</u> <u>de/blog/machine-perception-face-recognition/</u>

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## Thanks for your attention

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