Decaying Indicators of Compromise

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Abstract—The steady increase in the volume of indicators of compromise (IoC) as well as their volatile nature makes their processing challenging. Once compromised infrastructures are cleaned up, threat actors are moving to other target infrastructures or simply changing attack strategies. To ease the evaluation of IoCs as well as to harness the combined analysis capabilities, threat intelligence sharing platforms were introduced in order to foster collaboration on a community level. In this paper, the open-source threat intelligence platform MISP is used to implement and showcase a generic scoring model for decaying IoCs shared within MISP communities matching their heterogeneous objectives. The model takes into account existing meta-information shared along with indicators of compromise, facilitating the decision making process for machines in regards to the validity of the shared indicator of compromise. The model is applied on common use-cases that are normally encountered during incident response.

Keywords—Indicators of Compromise, Decay functions, Information Sharing, Incident Response

I. INTRODUCTION

Information sharing platforms nowadays have become an important tool in fighting active threats and a precious source of information about the actual indicator of compromise landscape. One of these platforms is MISP [25], an open source threat intelligence sharing platform that enables various actors from private or public IT-communities to share a wide range of their information, may this be IoCs, malware or other relevant data about existing threats. A particularity of MISP is that it broke with the traditional ‘single producer multiple consumer’ paradigm that can commonly be observed in other threat intelligence platforms and rather implements a peer to peer architecture. Due to this, each participating member can produce, enhance or consume information and give feedback on information produced by others. Pieces of information can be transferred along multiple nodes between partners. Hence, the data quality and the trust of the data source is not always certain. To provide a reliability and credibility measure to data providers, some data interaction models are applied, as for example taxonomies.

By giving data context, such as descriptions or adding attributes, raw data becomes precious information for others. Data is volatile and thus becomes outdated or even invalid, as for example, compromised machines get cleaned up or reused, IP addresses can change or domain names can be deleted. Therefore a model is proposed which uses the existing shared pool of data, matching the various, diverse objectives of community members, such as operational network security or threat intelligence along with community defined metrics and classifications to scope the lifecycle of IoCs for various use-cases.

The paper is organized as follows, section [II] discusses relevant approaches focussing on threat intelligence collection, processing and sharing. Section [II] introduces to MISP and describes this platform in general and its data interaction models. In section [V] attribute scoring methods are introduced to the reader. Since the research is still ongoing, some future work and conclusions will be presented in section [V].

II. RELATED WORK

Sharing indicators of compromise within a community can have a direct impact on the reaction times to an actual threat. Research in cybersecurity shows that information sharing within a community is one of the key factors to accurate incident response, as shown in the study of [11]. Recurring problems with information sharing include the fact that it is a collective effort based on a give-and-take approach [10]. Another major concern is the quality of information, especially when it comes to achieving low false positive rates. Having reliable information is a major concern in information sharing as described in article [6], where a concept of knowledge management is introduced to assess requirements for information sharing tools. The authors of [4] describe similar requirements by identifying challenges for threat intelligence platforms, as for example privacy or quality control approaches. For this, the authors of article [15] introduce an assessment approach for malware threat levels referring to scoring and weighting factors. Other authors, such as those in article [27] apply a data mining approach to identify similarity metrics in statistical relations for shared information. A data-driven visualisation approach is presented in article [11], which evaluates content from news and social media based on emotions to increase the added value of information.

Event detection and evaluation are complex tasks, where in intrusion detection it is often referred to as threshold-based methods for triggering alarms, such as presented in articles [12] [17]. Threshold-based detection are considered as reliable and is often applied in statistics, data mining or game-theoretical evaluation approaches [2] [9] [15] [20]. Beside the evaluation techniques of data, the data itself provides a large amount of information, such as IP-addresses, protocols,
timestamps, etc, that play a major role in information sharing and a lot of evaluation techniques are investigated [8] [13] [26].

In the area of IoC tracing and evaluation, various approaches exist, from analysing technical articles or blog entries to the deep analysis of samples to extract IoC information. Technical focus is given in [22], where malware samples are evaluated in order to output IoCs by analysing traffic information. In article [21] IoCs are automatically extracted from different sources, such as reports, articles, etc. and evaluated using convolutional neural networks to correlate data with other indicators in order to set up rules to be deployed in a network. A similar idea was presented in article [14] that studies technical articles and blog entries, but here, natural language processing schemes are applied to evaluate data and to identify decay times for observed IoCs in text appearances.

III. BACKGROUND AND DATA INTERACTION TECHNIQUES IN MISP

The MISP software is introduced in this section with the focus on the features used in the scoring model presented in section IV. For a detailed description of the design and implementation of MISP, we refer the reader to article [25]. MISP is an open-source threat information sharing platform, where information on all kinds of threats can be shared within communities or subsets of community members. Such pieces of information are typically include indicators of compromise such as IP addresses and file hashes, but also other types of indicators such as financial indicators can be shared within communities or a subset of them.

Users can decide on the granularity of information they wish to disclose in MISP by sharing only some subsets of the information package. The sharing level can also be set, using the following levels: organisation only, the current community, directly inter-connected communities, managed distribution lists via "sharing groups", or simply all available communities. With the distribution level set to organisation only, the information is kept exclusively for the organisation of the information producer. Community only allows the sharing of information among all members of the given MISP instance. Data marked as connected communities will be made available to all users of the given MISP instance along with all members of any MISP that has a direct link to the current instance. For more complex sharing scenarios, sharing groups allow users to create reusable or ad-hoc groups, including a list of defined, involved partners. Popular examples for sharing groups are organisations grouped by business sectors such as actors within the telecom sector or financial sector. Information can also travel through $N$ hops such as the connected communities and their connected communities etc when the sharing level is set to all. Hence, MISP uses a peer to peer architecture. Three methods of synchronization exist between connected MISP instances: push, pull and cherry pick. In the last method, administrators can manually pick the events from a connected MISP instance they want to share within their own community.

In MISP shared events can be populated with one of 140 different types of attributes (destination IP addresses, file hashes) as well as a list of community developed object templates, combining clusters of linked attributes into logical containers.

Attributes themselves can be defined as a tuple of (category, type, value), conveying both direct actionable data as well as its associated context. Additional contextual information such as the date, threat level, description, organisation, and higher level information such as that on threat actors among others can also be attached to events. Consumers have the possibility to create proposals, which pending the producer’s validation can become attributes. Communication between participants can happen through the built-in discussion system. Events can be filtered according to the various taxonomies described via the standard format defined in the IETF document [7].

A taxonomy in MISP is based on the machine-tag approach with triple-tags for representing semantic information. The method was introduced by Flickr for the geolocation of pictures [24]. The triple-tag syntax is a simple expression that has a namespace, a predicate and a value, as shown in the following example: \{nato: classification = 'NU'\}, this means that nato is the namespace, classification is the predicate and 'NU' the value.

The public repository with MISP taxonomies includes 47 different taxonomies for the domains of law enforcement, computer security incident response team (CSIRT) classifications, intelligence and many more. Each community can define their own taxonomy explaining the growing of used taxonomies. Intrusion detection systems can also import the latest signatures from MISP and integrate them in their detection rule set. Some intrusion detection systems can be instrumented to sent a REST (REpresentational State Transfer) request towards MISP with feedback about its detections. This feedback is called sighting. Thus, knowledge can be gathered about the validity, freshness of an information or its impact. A typical example is an IP address of a compromised website distributing malware or acting as command and control server which is cleaned up after a while. In MISP the concept of detection and sighting is applicable for almost all kind of attributes. Hence, it can be used by host intrusion detection systems capable of detecting malicious files. Accounting software was also observed capable of fetching bank accounts of money mules from MISP for warning accountants in case of wire transfers towards those. These automated mechanisms are possible due to the API (Application Programming Interface) that is heavily used by third parties. At the moment of writing 28 known tools are capable of interacting with MISP such as Splunk, McAfee, TheHive®.

The main reason to present the approach of sightings and taxonomies in this section is that they play a major role as parameters in the scoring model presented in section IV.

IV. SCORING INDICATORS OF COMPROMISE

To illustrate the challenges within MISP communities and the need for a scoring model for attributes, this section will highlight some numbers extracted from our community we operate for the private sector [5].

In its early operation in 2012, the users knew each other and the trust and data quality was granted in an implicit way. In January 2018, this community contains 1646 users

1. https://github.com/MISP/misp-taxonomies
2. http://www.misp-project.org/tools/
from 845 organizations and it is almost impossible that each user knows each other, such that there is no explicit trust. The more, the objectives from each user are different. Users consuming events for operational security including blocking actions do not want to have false positives. People performing threat intelligence activities by correlating indicators of various threat actors want to have a maximum of indicators and even want information about false positives as they give indications about the dynamics between threat actors and defenders. Hence, these organizations need reliable historical data. The correlation feature of MISP is a major driving incentive for sharing information. Producers see whether other organizations encountered the same threats. At the time of writing, the users shared 8686 events having 1048405 attributes. 260896 correlations are found giving the users incentives to share information. They can find out if other organizations were also targeted. The data interaction methods start to grow as 54347 proposals are active and 407 discussion posts are created. This community includes 8 sighting sources ranging from incident response systems to honeypots giving both indications about the freshness of information. In total 10219 sightings were recorded including 30 confirmed false positives.

The lifetime of the various available attributes are not homogeneous. For example, machines cleaned, IP addresses changes up, IP addresses or domain names are traded and get used in different fashions over time. Hence, each attribute has its own decay function. File hashes usually tend not to vary over time. Nevertheless, a shared file hash can be declared as false positive over time by organizations with distinct trust bases. IP addresses. In case, the IP is given up, it could become a IP address of a different organization. Therefore, the decay rate of the IP should be low in the first hours, but should go faster the more time passes. The first time activities from this IP are sighted, the better chances are that the threat actors are still active or are executing follow up operations. When this IP address is shared among a community targeted by the threat actors, more and more members can take measures, such as blocking the IP address. Hence, the attack becomes ineffective forcing threat actors to use other IP addresses. In case, the IP is given up, it could be reassigned to a legitimate customer of the Internet service provider leading to collateral damage due to the blocking actions of this IP.

Information about threats are produced in a collaborative manner using the data annotation and interaction techniques described in section II. Tags can be added to events by producers and are defined in a taxonomy. Some taxonomies enable to express their confidence or reliability of a source regarding a given piece of information they are attached to. Consumers get this information and have different levels of trust in the producers.

The $basescore_a$ for an attribute is defined in equation 1.

$base_score ∈ [0, 100]$. It represents the score of an attribute before taking into account its decay. It is composed of its weighted applied tags and its source confidence.

The weights of the applied taxonomies are defined at predicate level of each taxonomy and represent its acceptance within a community. For instance, if tags from the taxonomy with the namespace admiralty-scale and with the predicate source-reliability are hardly used, it gets a low weight. However, if within the same taxonomy tags with the predicate information-credibility are regularly used, it gets a higher weight.

The source confidence can also be influenced by an additional parameter called $\omega_{sc}$. This parameter takes into account more subtle trust evaluations. For example, it could be that an organization has a good image and a good reputation but due to some circumstances within a given time frame, the trust in this organization is decreased. A practical example is an organization that was compromised or taken over by the attacking party.

$$base_score_a = \text{weight}_x \cdot \text{tags} + \omega_{sc} \cdot \text{source confidence} \quad (1)$$

The $base_score_a$ is defined in equation 1 with

- $\forall \text{weight}_x ∈ [0, 100], \forall \omega_{sc} ∈ [0, 100], \text{weight}_x + \omega_{sc} = 100$, $\text{weight}_x = 100$ or $\omega_{sc} = 100$, a mean to adjust the focus either on the tags or on the source confidence. As little research on the trust rebalancing and trust evolution of organizations in distributed threat sharing is done, the $\omega_{sc}$ parameter is set to $100 - \text{weight}_x$ and is considered as future work implying further research.

- $\text{tags} ∈ [0, 1]$ is the score derived from the taxonomies and is defined in equation 2

- $\text{source confidence} ∈ [0, 1]$, is the confidence given to the source that published the attribute. The $\text{source confidence}$ parameter in equation 1 gives a possibility to influence the $base_score$, which should be a number between 0 and 100. Each source between 1 and N has its $source confidence$ level. In case a source is fully trusted the $source confidence$ is set to 1. If there is no trust, the source level is set to 0. The user could also set intermediate values, which could give an estimate on how reliable the source is. The learning of the confidence of a source based on

The scoring model for IoCs

Hence, a model of scores per attribute is selected including the following conditions:

- The base score of an attribute ($a$), called $base_score_a$, is a weighting of the confidence of its source and its linked taxonomies ($x$). It is the initial value of the life cycle of an indicator. To this value, the score is reset upon a new sighting.

- The elapsed time of an attribute was seen first and seen last.

- The end-time of an attribute $\tau_a$ represents the time at which the overall score should be 0.

- The decay rate $\delta_a$ represents the speed at which the overall score is decreasing over time. The decay speed is variable over time as motivated in the following example:

  The decay rate of the IP should be low in the first hours, but should go faster the more time passes. The first time activities from this IP are sighted, the better chances are that the threat actors are still active or are executing follow up operations. When this IP address is shared among a community targeted by the threat actors, more and more members can take measures, such as blocking the IP address. Hence, the attack becomes ineffective forcing threat actors to use other IP addresses. In case, the IP is given up, it could
its produced information over time is subject to future research.

The relevant taxonomies are summarized in Table I.

The MISP taxonomy includes also a confidence level that is set to ‘Confidence cannot be evaluated’. This special confidence level cannot be mapped to a numerical value. One possibility is to introduce the concept of ‘undefined’.

Once a value is undefined, the base score cannot be computed and becomes undefined. At the end, the overall score would be undefined and by this, cancel other scoring factors defined in tags. Hence, when the confidence level is “Confidence cannot be evaluated”, it will be ignored.

The score derived from the taxonomies is defined in equation 2, where \( G \) is the number of defined taxonomy groups and \( T \) the number of used taxonomy per group. The weights are defined at predicate level in the taxonomies and should be integer numbers between 0 and 100.

\[
tags = \frac{\sum_{j=1}^{G} \sum_{i=1}^{T} taxonomy_i \cdot weight_i}{\sum_{j=1}^{G} \sum_{i=1}^{T} 100 \cdot weight_i} \tag{2}
\]

The idea is to decrease the base score over time. When it reaches zero, the related indicator can be discarded. A first idea to express the overall score could be to use equation 3.

\[
\text{score}_a = \text{base}_{-}\text{score} - \delta_a (T_t - T_{t-1}) \tag{3}
\]

where,

- \( \text{base}_{-}\text{score}_a \in [0, 100] \) is described in equation 1
- \( \delta_a \in [0, +\infty) \) represents the decay rate, or expressed as the speed at which the score of an attribute decreases over time.
- \( T_t \) and \( T_{t-1} \) are timestamps. \( T_t \) represents the current time and \( T_{t-1} \) represents the last time this attribute received from a sightings. It is assumed that \( T_t > T_{t-1} \).

Figure 1 shows the decay of the score of an attribute with a base_score of 80 and a decay rate \( \delta_a \) of 2.

An evaluation of the parameters shows that neither the end-time nor the variable decay rate can be controlled. Indeed, by fixing the decay rate, the end-time cannot be specified of the score of an attribute. In the same mind, even if the decay rate is controlled by the constant \( \delta_a \), the decay is fixed over time.

To address the latter point, an exponential degression could be considered as shown in equation 4.

\[
\text{score}_a = \text{base}_{-}\text{score} \cdot e^{-\delta_a \cdot t} \tag{4}
\]

In this case a variable decay rate can be used. The slope in figure 2 is high at the beginning and lower as time passes. However, the decay rate cannot be significantly influenced. This expression cannot be used to have a slow decay at the beginning followed by a rapid degression. A behavior that can, for example, be found in dynamic IP address allocation by threat actors as previously described in this section. Moreover, the time at which the overall score of the attribute should be 0 is entirely defined by the decay rate. So, manipulating the slope as well as the end-time at the same time is still not possible. Furthermore, it can be observed that the choice of the parameter \( \delta_a \) will essentially range between 0 and 1 due to the tendency of the exponential degression to rapidly tend to 0.

The final score is defined in equation 5 capturing the conditions stated previously.

\[
\text{score}_a = \text{base}_{-}\text{score} \cdot \left( 1 - \left( \frac{t}{\tau_a} \right)^{\frac{1}{\delta_a}} \right) \tag{5}
\]

with
Fig. 3. \( \text{score}_a = \text{base}\_\text{score} \cdot \left(1 - \left(\frac{t}{\tau_a}\right)^{\frac{1}{\delta_a}}\right) \) for a fixed \( \tau_a \) of 7 days.

- \( \delta_a \in ]0, +\infty) \), the decay speed.
- \( \tau_a \in ]0, +\infty) \), the end-time or time needed such that \( \text{score}_a = 0 \). The end-time can be told by an expiration sighting, where an organization knows when an indicator will be expired. An example is the grace time: an Internet service provider gives a grace time to customers to fix their machine until disconnecting them or law enforcement agencies seizing the equipments. It can also be derived from existing regular sightings, where organizations provided data about sightings from the past.
- \( t = T_t - T_{t-1} \), is an integer > 0

This polynomial function has two advantages over the exponential one. First, the end-time with \( \tau_a \) can be easily controlled. Second, the direction direction of the cavity of the slope can also be controlled. A fast depression at the beginning can be obtained followed by a slow depression along with the complete opposite. An example for a different decay rate \( \delta_a \) can be seen in figure 3. It can be seen that the greater \( \delta_a \) is, the faster the overall score decreases at the beginning. The more, the closer \( \delta_a \) is to zero, the slower the overall score will decrease at the start. The score is 0 for all decay rate for the specified \( \tau_a \).

The parameters can be easily fine tuned which is an additional advantage. A value can be set for each type of attribute by performing a statistical analysis on an existing dataset or users could set their own values via a dedicated interface.

Two examples are shown how the score in equation 5 can be used. The first example is an attribute for a compromised IP address being part of a botnet. The attribute of a shared event in MISP belongs to the category Network activity with its type ip-dest, meaning the destination IP address of a compromised webservice hosting an exploitkit distributing malware. Some organizations spotted it and started to share information about it. Abuse teams are informed to cleanup the compromised systems. The IP address is encoded in publicly available blacklists. The threat actors might notice the detection too and start to move their exploitkit to another webservice. If we assume that the Internet service provider gives a customer 1 week time to fix the webservice. If it is not fixed within this time frame, the IP of the webservice will be null-routed, meaning that it will not be accessible any more. Hence, \( \tau_a = 7 \cdot 24 \) hours. Under the hypothesis that the typical blacklists take 48 hours to be applied in proxy servers or browsers, the overall score should be halved after 2 days. Hence, \( \delta_a = 0.55 \). Finally, if the base score of the attribute is calculated to be \( \text{base}\_\text{score} = 80 \) (based on the taxonomies and source confidence), equation 5 becomes:

\[
\text{score}_a = 80 \cdot \left(1 - \left(\frac{t}{7 \cdot 24}\right)^{\frac{1}{0.55}}\right)
\]

where \( t \) is the time between now and the last sighting, expressed in hours. A plot of the decay is represented in figure 4.

The second example is the hash of a malware. If the hash is not a false positive and a confirmed malware it says a malware and should not be decayed. However, some host intrusion detection systems cannot handle million of hashes. It could be considered that the attribute will not have any value after 2 months, with a rather slow decay if this is the expected time to destroy the attacking infrastructure. \( \tau_a = 2 \cdot 30 \) days and \( \delta_a = 0.3 \). It is also supposed that the base score is the same as the previous example: \( \text{base}\_\text{score} = 80 \). We have:

\[
\text{score}_a = 80 \cdot \left(1 - \left(\frac{t}{2 \cdot 30}\right)^{\frac{1}{0.3}}\right)
\]

and the resulting plot can be seen in figure 5.

V. Future Work and Conclusions

This paper presents a work in progress for a scoring approach for evaluating the decay methods of indicators of compromise that are shared within threat intelligence platforms. The model is designed for the peer to peer threat intelligence platform MISP taking into account existing data annotations and data interaction methods. Taxonomies attached to attributes are used in order to get information about reliability and confidence organizations have in a given information source. Each member organization can produce or consume information, even consume information from multiple hops.
away. The precondition in this case is that an information consumer trusts the information provider. Since the MISP platform grew organically from a handful interconnected MISP instances, where members from the various communities knew and trusted each other, to a large interconnected community having lots of MISP instances in place. By this, nowadays, it is not unlikely that a given information transits more MISP instances and only little information known about the source and its producer. This is a major drawback, because fake information can be shared for harming an organization or to disrupt the sharing communities. To counter this, another future work will be the investigation of distributed information sharing with game theoretical approaches, where detailed adversary models for peer to peer threat sharing will be studied. Future research activities include the study of various models for the source confidence. Here, evaluations will focus most probably on the different machine learning techniques. For this, the model presented in section IV in this paper has to be fully operational in order to collect data about sharing behaviours.

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