FeedMeter: Evaluating the Quality of Community-Driven Threat Intelligence

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Abstract: A sound understanding of the adversary in the form of cyber threat intelligence (CTI) is key to successful cyber defense. Various sources of CTI exist, however there is no state-of-the-art method to approximate feed quality in an automated and continuous way. In addition, finding, combining and maintaining relevant feeds is very laborious and impedes taking advantage of the full potential of existing feeds. We propose FeedMeter, a platform that collects, normalizes, and aggregates threat intelligence feeds and continuously monitors them using eight descriptive metrics that approximate the feed quality. The platform aims to reduce the workload of duplicated manual processing and maintenance tasks and shares valuable insights about threat intelligence feeds. Our evaluation of a FeedMeter prototype with more than 150 OSINT sources, conducted over four years, shows that the platform has a real benefit for the community and that the metrics are promising approximations of source quality. A comparison with a prevalent commercial threat intelligence feed further strengthens this finding.

1 INTRODUCTION

Threat information is defined by The National Institute of Standards and Technology (NIST) (Johnson et al., 2016) as "any information that can help an organization identify, assess, monitor, and respond to cyber-threats". This information is considered key to effectively defend against, react on, and detect attacks. To be applicable, this information must be transformed into *threat intelligence* which the NIST defines as "threat information that has been aggregated, transformed, analyzed, interpreted, or enriched to provide the necessary context for decision-making processes" (Johnson et al., 2016). One possibility to get threat intelligence is the use of Open-source intelligence (OSINT) sources, available in the Internet. The scope and the quality of OSINT sources vary heavily, making source selection difficult. In research, there have been numerous attempts (e.g., recently by (Griffioen et al., 2020, Li et al., 2019, Ramanathan et al., 2020)) to analyze the quality of CTI feeds using some of the criteria defined by the European Union Agency for Cybersecurity (ENISA) (Pawlinski et al., 2014). However, applicability of these studies are limited since they often only represent a snapshot for a given point in time, or their results cannot be verified due to use of closed source algorithms or data.

As shown in (Johnson et al., 2016, RSA, The Security Division of EMC, 2012, Sauerwein et al., 2017, Connolly et al., 2014) data from several threat intelligence sources has to be combined in order to get actionable information. While several sources for consolidated feeds exist, the aggregation process is often opaque, and their quality is unknown.

To address this problem, we propose **FeedMeter**, a platform for automated collection, normalization, aggregation, metadata-enrichment, and rating of various OSINT feeds. The collected feeds are la-

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beled according to their threat type and continuously and methodically rated using eight descriptive metrics. Together, these metrics approximate the five criteria defined by ENISA, *relevant*; *timely*; *accurate*; *complete*; and *ingestible* (Pawlinski et al., 2014). We apply seven already known metrics, based solely on feed statistics and OSINT data, and propose our own, called **DNS age** in addition. Our CTI platform performs the common, usually laborious tasks in source evaluation and makes individual searches for information sources and their evaluation much more efficient. The resulting main research questions in this study are:

1. *Can we aggregate, monitor, and evaluate OSINT CTI feeds continuously and automatically using only feed data and publicly available OSINT?*
2. *Can we define metrics that approximate the theoretical quality criteria of ENISA and result in an immediate operational benefit for the end-user?*
3. *Is the quality of OSINT CTI feeds good enough compared to commercial feeds?*

As our main contributions, we outline the proposed FeedMeter platform, build a prototype, and answer these questions. In Section 2 we describe key components of the proposed platform, some of the challenges and their mitigation, and define the descriptive metrics. Section 3 describes the used data sets ranging from OSINT feeds to a commercial feed for comparison purposes. Section 4 shows the key results. The data as well as the results are available on our interactive website [1], which can be used to evaluate our findings. In Section 5, we conclude that automatic monitoring of CTI feeds is possible and highlight the benefits and limitations of the proposed metrics regarding their usage as a quality approximation of the feeds. We show that using commercial CTI feeds can have advantages, but its quality is not fundamentally superior to OSINT feeds.

2 METHODOLOGY

An overview of FeedMeter is outlined in Figure 1. Different OSINT feeds are downloaded, validated, normalized, enriched with metadata, aggregated, and evaluated. The result is an aggregate feed that retains all information of its sources and contains additional metadata, such as the results of the continuously calculated metrics and user feedback from the community. Additional metadata from OSINT is added as well, where it can reduce individual collection and implementation efforts and provide a tangible advantage in dealing with threats, e.g. location data and DNS data. A significant benefit of the FeedMeter platform is the possibility to filter the aggregate feed and only query the parts relevant to one's threat model. However, compiling such an aggregate feed poses nontrivial challenges, primarily attributed to the very heterogeneous landscape of OSINT feeds and OSINT data sources. The following paragraphs describe the problems and approaches to solve them. Where this is not possible, we explain how to mitigate them.

2.1 Feed Aggregation

Update Intervals. In order to cope with different update intervals and strategies, we aggregated the feeds over a defined time interval. This results in periodic snapshots which can be compared to each other.
Data Formats. OSINT feed syntaxes are diverse with providers utilizing various data formats. For our analysis, we normalized the data to a set of predefined types, including IPv4/IPv6 addresses, subnets, Fully Qualified Domain Name (FQDNs), and URLs. Normalization efforts mostly consists of simple actions such as converting to lowercase or IPv6 address compression. Addressing several nontrivial cases are out of scope of this paper.
Semantic Meaning. Labels. are used to specify the meaning of different OSINT feeds and indicator. However, as criticized by (Metcalf and Spring, 2015, Li et al., 2019), there is no standardized set of labels. This normalization step is particularly challenging and generally has to be performed manually.

With FeedMeter we introduce an hierarchical taxonomy where child labels have a more confined and detailed meaning than their parent. This approach has the advantage that no information from the original label is lost. Additionally, the taxonomy can easily be extended and adapted as the threat landscape evolves. In this paper, we focus on the labels shown in Table 1.
Licensing. When aggregating feeds, we respected and preserved all license information by tagging them correspondingly so that potential users can select the feeds that correspond to their licensing needs.
Aggregation. We deduplicated and aggregated the normalized indicators while preserving all semantic meaning, origins, and relevant additional metadata provided by the sources. Additional metadata from other OSINT sources could be added during this step.

[1] https://osint-feed-analysis.site

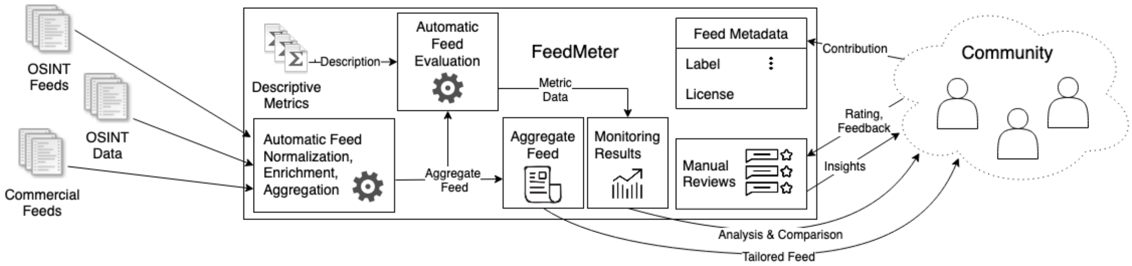


Figure 1: Architecture overview of FeedMeter.

Table 1: Overview of labels representing the semantic meaning of feeds.

Label	*Meaning*
Malware	C&C and malware distribution servers, hosts belonging to a botnet
Spam	Hosts distributing spam through emails or web forms
Phishing	Hosts sending phishing mails or serving phishing sites
Attacks	Origins of active attacks, such as port scanning, brute force attacks, exploitation attempts, etc.
Crime & Fraud	Other bad actors, unrelated to active attacks: cybercrime, fraud, etc.
Anonymization	Tor nodes, web proxies, VPN gateways, etc.
Cryptocurrency	Nodes in cryptocurrency networks and cryptojacking hosts
Info	Generic host or network information, such as routable and unroutable address spaces
Consolidation	Feeds consolidating other feeds with possibly many different labels
Reputation	Hosts serving porn, gambling, online pharmacy sites, etc.

2.2 Descriptive Metrics

ENISA (Pawlinski et al., 2014) proposed a set of theoretical quality criteria for the assessment of Threat Intelligence Feeds: relevance, timeliness, accuracy completeness and Ingestibility of the CTI. However, those criteria cannot simply be applied to an automated evaluation, since some are subjective and others require a ground truth.

In order to approximate those theoretical metrics, we selected seven metrics from previous work that can be calculated using only openly available data. Additionally, we propose a new metric called *DNS age*. Figure 2 shows an overview of the used metrics in the context of the theoretical quality criteria. To keep the figure concise, we only show the three theoretical criteria with the most relation to our metrics, relevance, completeness, and timeliness. The following paragraphs describe the rationale behind the selected metrics in detail.

Figure 2: Mapping of the proposed metrics to the three quality criteria, Relevance, Completeness, and Timeliness.

Feed Size. The feed size helps to understand the feed's coverage better. Even if the total number of entries needed for a feed for full coverage is unknown, more entries mean more coverage (assuming no false negatives).

Agility. The agility of the feed can give valuable insights into how the maintainer curates a feed and how frequently and to what extent something changes. Therefore, an addition and a removal metric is used. The first evaluates the timeliness of a feed. The second assesses the relevance and completeness of the feed and if additional post-processing is needed, like manually dropping entries according to a retention policy. To capture all the aspects of agility, we define 3 metrics for both types of updates: the *update frequency*, the *absolute update size*, and the *relative update size*

Uniqueness and Overlap. The uniqueness and the overlap of a feed give insight into its relevance: it might help decide if adding the feed is worth the effort, in both complexity and expenses. As pointed out in previous work (Metcalf and Spring, 2015, Li et al., 2019), a low overlap of two feeds means that each feed does not provide enough information about the threat landscape, and we are far from a complete threat feed.

Relative Timeliness. Relative timely feeds provide a time advantage for the establishment of preventive measures as compared to feeds that are less timely.
FeedRank. The FeedRank (Meier et al., 2018) provides insights into several quality dimensions: The contribution analysis helps to understand the relevance and completeness. The correlation part of FeedRank is an approximation of the accuracy (confirmation of entries) and the (relative) timeliness of a feed.
ASN and Country Distribution. While ASN and country distributions do not accurately represent the origin of threats, they can be used in the context of feed quality evaluation. Here, they show whether a feed is biased towards a certain ASN or country (e.g., due to sensors being present only in that part of the network). Organizations can use this information to make a determination whether a feed is relevant for their use case.
Entry Age and Retention. We define the following four key characteristics of the age distribution of a snapshot: the percentage of *fresh entries* (age $<$ 24h), the percentage of *recent entries* (age $<$ 7 days), the percentage of *stale entries* (age $>$ 60 days) and the *median* of the age distribution.

The age and retention give, like the agility, insights into how a list is curated and thus its relevance. Generally, a feed with many new entries is desirable to face upcoming threats. Still, stale entries can also be helpful due to recurring attacks or re-using of infrastructure by threat actors. The retention can also help identify if further post-processing is needed in employing a retention policy.
DNS Age. We propose the new metric *DNS age* and define it for FQDN and URL entries as the time between the first appearance of its Second Level Domains (SLD) in the DNS and the time it was added to the feed. We measure the DNS age in days since a higher resolution is hard to achieve for the DNS appearance. Since the combination of such DNS ages in the context of a feed is somewhat intricate, we have to define several sub-metrics. Either we can only analyze true SLD entries (*SLD* DNS age distribution), or we can look at all FQDNs, including sub-domains and also URLs. In the second case, we further want to distinguish if we analyze the DNS age of all new entries (*all* DNS age distribution) or just those entries that correspond to an SLD that has not been added to the feed since its DNS appearance (*first-seen* DNS age distribution). For example, a feed adds the FQDN “some.domain.com” and later adds “some-other.domain.com.” The *all* DNS age distribution includes the DNS age for both entry additions. Since they have the same SLD (domain.com), the *first-seen* DNS age distribution only includes the DNS age of the first entry addition. Besides analyzing the data series metrics for these distributions, we additionally define meaningful key metrics for them, listed in Table 2.

A high rate of fresh entries can attribute a feed to good timeliness. On the contrary, an increased number of stale entries does not imply low timeliness. A threat can also emerge from an FQDN registered a long time ago but not from an FQDN that is not present yet in the DNS. Not registered and expired entries can tell something about the accuracy and relevance of the feed. And finally, future entries can in some cases, e.g., for domain generation algorithm (DGA) feeds, give insight into how well the feeds can “predict the future,” namely if the listed entries are used in practice.

3 DATASETS

We collected, stored and aggregated more than 150 OSINT feeds, primarily threat information, from a variety of public intelligence sources between March 2018 and April 2022. The exact number of collected feeds fluctuated throughout this period as we added new sources or removed discontinued ones. Availability and reliability of these sources was inconsistent, and there were a few short outages in our own collection infrastructure, e.g., due to maintenance.

The nature of these feeds is very heterogeneous, both in the structure of the data as well as the process in which they are created. There are simple lists of indicators as well as labeled, metadata enriched, and well-structured databases, feeds manually maintained by individuals, community-driven databases, and automatically generated feeds. To be included in our body, the feeds had to be actively updated and provide one of the data types we wanted.

3.1 Collection, Normalization and Labeling

We downloaded the feeds according to the specification published by the feeds. For feeds without a specification we used an interval of 5 minutes. We performed the validation and normalization steps as well as the labeling as explained in Section 2.1.

3.2 Additional OSINT Data

For the computation of several metrics we need additional OSINT data, which we collected as follows:
Geolocation. We downloaded the free version of

Table 2: DNS age key metrics.

0-day entries	ratio of entries with DNS age $= 0$
fresh entries	ratio of entries with DNS age ≤ 3 days
recent entries	ratio of entries with DNS age ≤ 30 days
stale entries	ratio of entries with DNS age > 365 days
10% most recent entries	10th percentile DNS age
unknown entries	ratio of entries with DNS appearance before start of our DNS data collection
not registered entries	ratio of entries where SLD never in DNS zone
expired entries	ratio of entries where SLD previously in DNS zone but removed
future entries	ratio of entries where SLD added to DNS zone after entry added

the MaxMind database called GeoLite2 [2] every week from December 2019 to April 2022 and used it to look up and store the ISO 3166-1 country code of all IP addresses within the collected feeds.

Autonomous Systems. For ASN determination we used the BGP Routing Report [3] by Philip Smith which publishes border gateway protocol (BGP) routing table data from several geographical regions on a daily basis. We used the data from the London Internet Exchange (LINX), as it is the location geographically closest to us. During outages of this location we switched to the data collected in Brisbane, Australia.

Domain Name System. We downloaded the zone files of more than 1,000 TLDs on a daily basis from August 2019 to April 2022, including *.com*, the most prevalent TLD. We used the resulting data to build a comprehensive domain database to analyze the DNS age of FQDNs and URLs within the collected feeds.

3.3 Commercial Reference Feed

We were granted access to an aggregate feed by a prevalent commercial CTI provider for six months and downloaded it every 5 minutes from June 2019 to December 2019. The feed consists of entries labeled as either *spam and abuse*, *phishing*, *malware*, or *cracked sites* using a bit mask. The labels match with our taxonomy with the exception of *cracked sites* which is represented by our label *crime & fraud*.

3.4 Aggregation

We aggregated the collected and normalized feeds hourly, resulting in periodic snapshots of the entire indicator body. For feeds collected once per hour or more often, all data collected since the last aggregation was used. For feeds collected less often, the latest feed was used. Feeds for which we had more than one consecutive collection failure were not included.

[2]https://dev.maxmind.com/geoip/geolite2-free-geolocation-data?lang=en

[3]https://thyme.apnic.net/

For all feeds, a reference to the originating feeds including source labels and any additional metadata originating from the sources was preserved.

4 RESULTS

4.1 Automatic Metric Evaluation

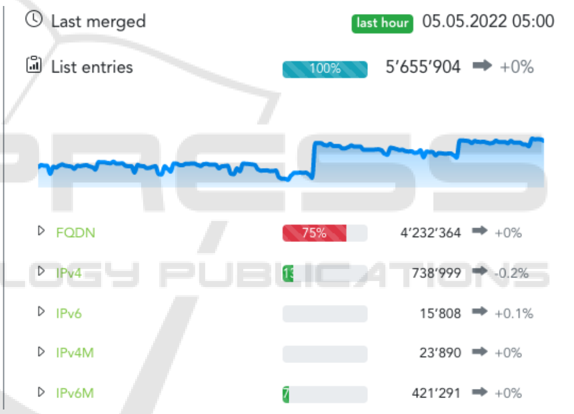


Figure 3: Screenshot of the threat feed live monitoring dashboard.

In parallel to collecting and aggregating OSINT threat feed data for four years, we set up and operated a platform to monitor and evaluate the feeds using the proposed metrics, called FeedMeter. FeedMeter shows our vision of a platform where the threat feed metadata can be analyzed in real-time but also be studied historically. Figure 3 shows an extract of the status dashboard of this platform. For the thorough analysis of the proposed metrics, we extracted different samples from the 4-year evaluation data. In doing so, we can also evaluate whether the findings for a metric in one evaluation period can be reproduced in a similar period at a later time. Table 3 gives an overview over the chosen samples, their evaluation periods, and for which kind of analysis in this work the sample was used for. Where not noted otherwise, we refer to the main sample in the results.

Table 3: Overview of the used evaluation samples.

Sample	*Period duration*	*Periods*	*Description*
Main sample	6 months	2020-10-01 - 2021-04-01 2021-10-01 - 2022-04-01	Main sample, all feeds all metrics except *DNS age*
DNS age sample	3 months	2020-09-01 - 2020-12-01 2021-04-01 - 2021-07-01 2021-12-01 - 2022-03-01	FQDN and URL feeds, *DNS age* only
Comparison sample	6 months	2019-06-23 - 2019-12-03	Period with access to the commercial feed to analyze OSINT vs. commercial feeds

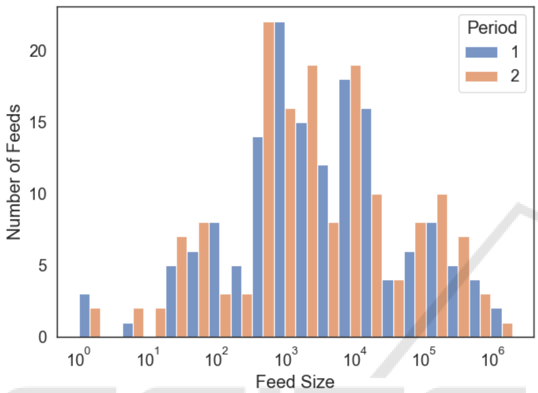


Figure 4: Median feed size distribution of the two main sample periods.

In the following, we show a small extract of the evaluation results. The full results can be studied on our results website [4].

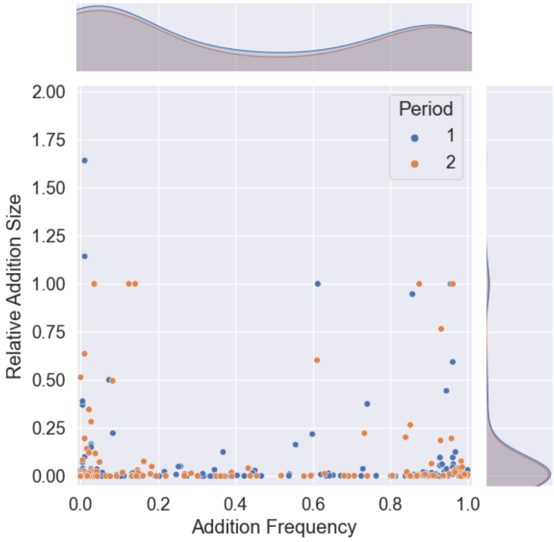
Feed Size. Figure 4 shows the median size distribution of the evaluated feeds that were active in both periods. The size varies substantially, from feeds with only a handful of entries to feeds with several hundreds of thousands. The analysis of the feed size variability shows that most of the feeds have a quite stable feed size.

Agility. To analyze the agility of the feeds, we look at the joint distribution of the update frequency and the relative update size for both additions and removals, as shown in Figure 5. A data point reflects the median value of the corresponding metric of one feed in a period. Note that the normalization of the update frequency is relative to their respective update interval. This can lead to a bias to the value claimed by the provider or chosen by us, if the update interval is higher than our aggregation interval of one hour, and has to be considered when evaluating the update frequency of a feed. As can be seen in the figure, most of the feeds are updated very regularly. 42% of the feeds add new entries in every second update or more and 36% of them remove entries in at least 50% of updates. However, more than half of them have an update interval $> 1h$. The analysis also uncovers feeds that rarely change. 13% of the feeds almost never add new entries and 15% of the feeds almost never remove entries. On the other hand, the distribution of the relative update sizes shows that most of the feeds change very few of their entries during an update. 70% of the feeds have relative addition sizes below 3%, and relative removal sizes below 5%. There were, however, feeds with a very high agility. Namely the feed *tracker.h3x.eu malware corpus*, an event feed with 24h update interval, delivered on the promise to only list entries from the last day and showed a complete change of the content in every update interval.

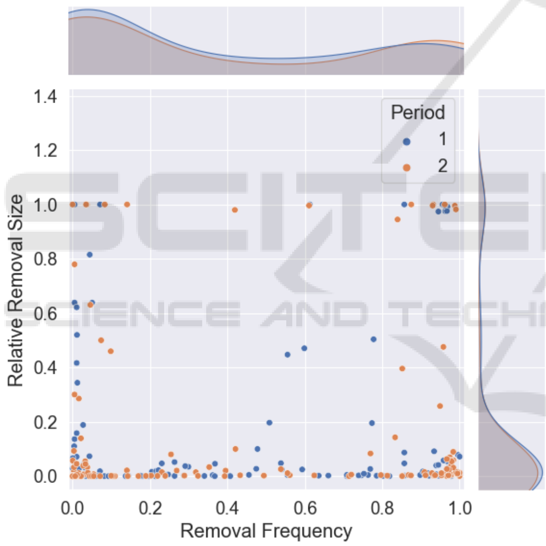
Uniqueness and Overlap. The overall uniqueness of all entries in the two evaluation periods is 77% and 78%. It has to be noted that there is some inherent overlap of several related feeds by the same feed provider (e.g. *blocklist.de SSH attackers* and *blocklist.de all attackers*) reducing the overall uniqueness by some percentages. Similarly to Li *et al.* (Li et al., 2019), we analyzed the relative overlap of the feeds, especially when looking at their labels. In contrast to their finding, we could not find any labels with significantly higher internal overlap or with significant cross-label overlap. The visualization of this grouped overlap matrix just confirmed our expectation that feed variants of the same provider have a high overlap. It also confirmed the labeling of the consolidation feeds. The feeds with this label consolidate entries with potentially very different labels in one feed. And, indeed, most of them overlap with many different feeds from all kinds of labels.

Relative Timeliness. For more than 60% of feeds, over 50% of the shared entries are untimely. The most prevalent examples were the two consolidation feeds of *missdeer blocklist* in which many of shared entries were untimely. Additionally, two of the *netlab.360.com* feeds included all of their entries in an untimely manner.

[4] https://osint-feed-analysis.site



(a) Feed addition agility.



(b) Feed removal agility.

Figure 5: Feed agility addition and removal distribution with the marginal frequency and relative size marginal distribution.

FeedRank. In Table 4, we list for both periods the top 3 for the contribution and the correlation metric. In general, we can see that feeds with a good contribution also have a good FeedRank. In contrast, the feeds with the best correlation cannot outweigh a mediocre contribution performance and end up in the upper-middle range of the FeedRank ranking.

By definition, FeedRank aims to provide a tamper resilient combination metric. However, our evaluation shows that large feeds are favored, and tampering attempts by including fake entries could be a problem. To efficiently detect tampering attempts, this metric alone is not enough. Nevertheless, to decide between two feeds in the same feed size order, the metric is considered accurate.

ASN and Country Distribution. To obtain reference distributions, we approximate the ratio of an ASN and a country by dividing the number of IPv4 addresses allocated by the total number of allocated IPv4 addresses for an ASN and a country, respectively. Table 5 lists all the ASNs that had a share of $> 10\%$ on at least two feeds in one of the evaluation periods. Many of them are known large service providers with a substantial share of several million IPv4 addresses. Still, high ratios far above the reference ratio like the ones in the max columns should be considered as an anomaly most likely originating in a network bias of the feed provider.

For the country distribution, we expect the US to dominate in the feeds since its ratio of allocated IPs is over 40%. Table 6 lists the prominent countries with at least two feeds having a country ratio of $> 10\%$ in a period. The US is confirmed to be listed very prominent by almost all IP feeds. The other prominent countries are also mostly represented according to their reference ratio as can be seen by the median ratios. But the very high maximum ratios again indicate that there might be a network bias in the underlying feed. Table 7 lists the most suspicious feeds for such a bias, with a median ratio of $> 40\%$ for one of the countries (except US).

Entry Age and Retention. Only 9 feeds had more than 50% fresh entries. Still, the freshness of the entries were substantial for 32 of the feeds with more than 50% recent entries. On the other hand, about half of the analyzed feeds contain more than 75% stale entries. In the case where threat indicators have long lifetime, such stale entries are legitimate and even desirable. In contrary, in the context of short-lived threats, stale entries can be seen as a sign of lacking curation. This is another important reason for proper labeling of CTI feeds, as the semantic meaning is important for the significance of indicators being stale.

Regarding retention, the times after which entries get removed from the feeds vary widely. There are what we call fast removers, 15 feeds where 90% of the removed entries are being removed in the first three days after being added. Another 25 feeds (40 in period 2) have at most 30 days retention for 90% of the removed entries. And there are the slow removers, 53 feeds (38 in period 2) in which more than half of the removed entries have a retention of over 100 days.

DNS Age. In our evaluation, which was done for this metric using the DNS sample as described in Ta-

Table 4: FeedRank table excerpt listing the top 3 (bold-faced) feeds for contribution and correlation in either period 1 (P1) or period 2 (P2), sorted by the average FeedRank.

Feed	*Contribution*		*Correlation*		*FeedRank*		
	P1	P2	P1	P2	P1	P2	Avg
blocklist.site porn	**1**	**1**	142	128	**1**	**1**	**1**
missdeer blocklist	**3**	4	10	13	**3**	4	3.5
abuse.ch URLhaus database	**2**	8	13	17	**2**	8	5
blocklist.site malware	5	**3**	78	67	5	5	5
Mitchell Krog - Ultimate Hosts File	8	**2**	128	121	9	**2**	5.5
aggregated hosts file by Steven Black	26	116	**3**	**1**	15	18	16.5
anti-webminer crypto	116	85	**1**	**2**	16	23	19.5
torproject.org exit addresses	83	24	**2**	6	20	19	19.5
phishing.army blocklist	40	29	4	**3**	23	22	22.5

Table 5: List of prominent ASN on IP threat feeds.

ASN	*Median*		*Max*		*# Feeds* > 10%		*Reference*
	P1	P2	P1	P2	P1	P2	
14061 DigitalOcean (US)	4%	3%	36%	57%	17	12	0.1%
45090 Shenzen Tencent Computer Systems (CN)	0%	0%	19%	21%	12	2	0.2%
16276 OVH (FR)	4%	1%	20%	20%	5	2	0.1%
4134 Chinanet (CN)	1%	1%	18%	18%	3	4	3.0%
14618 Amazon (US)	0%	0%	40%	39%	1	2	0.4%
4837 China Unicom (CN)	1%	1%	10%	31%	1	2	1.6%
24086 Viettel (VN)	0%	0%	0%	19%	0	2	0.0%
7552 Viettel (VN)	0%	0%	0%	12%	0	2	0.1%
12876 Online (FR)	0%	0%	12%	7%	2	0	0.0%
15169 Google (US)	0%	0%	11%	7%	2	0	0.4%

ble 3, we see that more than 70% of the added SLDs (for which the matching TLD zone file was available) were covered by our zone files. Looking at the SLDs in all added FQDN and URL entries, the coverage was even higher than 85% and thus we can conclude that we have a representative data set to evaluate the new metric.

One of the benefits of the new DNS age metric is the possibility to analyze the ratio of *not registered entries*. For the evaluated feeds, most of them had a ratio of not registered entries of below 5%. A higher ratio is most prominently visible on DGA feeds. It is, however, the intent of these feeds to list domains that were generated by an algorithm and that could potentially be used by a C2 server for communication. As only a few of these generated domains are actually used in practice, this high ratio of domains not in the DNS zone is expected. To be of any operational benefit, such a feed should still have a substantial part of its entries appearing in the DNS zone. Table 8 shows the largest DGA feeds and the DNS zone registration status of their new entries, comparing period 1 and period 3. *netlab.360.com dircrypt DGA list* has a high ratio of 86% registered entries in the first period, whereas in period 3 the ratio dropped significantly. Many added domains were expired or future entries. Also, *netlab.360.com matsnu DGA list* had a decent registered ratio of new entries in period 1 and a drop in period 3, whereas the other two feeds in the table show very low ratios of registered entries in all analyzed periods.

Looking at the *fresh* and *stale entries* on the feeds, we see that the phishing related feeds have a high ratio of *fresh* or even *0-day entries*. This is desirable in the context of rapidly changing and short-lived phishing campaigns, but could not be taken as granted for OSINT feeds. For the *stale entries*, we see that some feeds have a high number of added entries that were already added to the DNS zone more than a year ago, which can be a sign of untimely entries or for threats that are stable over a long period of time. In this case, ideally, it would have been listed from when it appeared in the DNS zone. Figure 6 visualizes the cumulative DNS age distribution of the feeds with mainly fresh and stale entries respectively. Feeds were added to Figure 6 (a) if the ratio of fresh

Table 6: List of prominent countries on IP threat feeds.

Country	*Median*		*Max*		*# Feeds* $> 10\%$		*Reference*
	P1	P2	P1	P2	P1	P2	
US	16%	22%	68%	67%	62	61	41%
CN	5%	10%	41%	49%	27	25	9%
DE	4%	6%	39%	26%	10	11	3%
FR	3%	3%	23%	21%	6	2	3%
RU	3%	4%	23%	21%	10	6	1%
IN	3%	3%	28%	13%	4	3	1%
BR	2%	2%	56%	17%	3	1	1%
NL	2%	3%	100%	20%	3	2	1%
GB	2%	3%	13%	40%	3	1	3%
VN	1%	2%	10%	31%	1	2	0%

Table 7: List of feeds with unnaturally prominent country.

Feed	*Country*	*Median ratio*	
		P1	P2
greensnow.co attack blocklist	CN	41%	21%
gpf-comics.com DNS blocklist IPv6	NL	100%	0%
gpf-comics.com DNS blocklist IPv6	CZ	0%	100%
charles.the-haleys.org SMTP attack list	BR	56%	17%
alienvault.com brute force list	CN	37%	49%
darklist.de Ips	CN	39%	43%

entries was > 0.3, and added to Figure 6 (b) if the ratio of stale and unknown entries was > 0.5. All the feeds in the figure have > 100 added entries covered by our DNS zone files during the evaluation period. *Unknown entries* are treated like stale entries in this figure. We do not know the exact DNS age of them but we know that they were in the DNS zone since we started to collect the data, and thus they must be older than all the other entries. For simplification, we used a placeholder age of 1000 days in the figure, resulting in a steep increase at age 1000 for many of the feeds. For this evaluation, we used the metric variant *first-seen* DNS age distribution and the data from period 2. In general, we see from the results that all three metric variants (*SLD*, *all*, and *first-seen*) produce comparable results and none of them seems to outperform the others. But depending on the use-case of an evaluation, one of the variants could still be preferable, due to some of its unique characteristics.

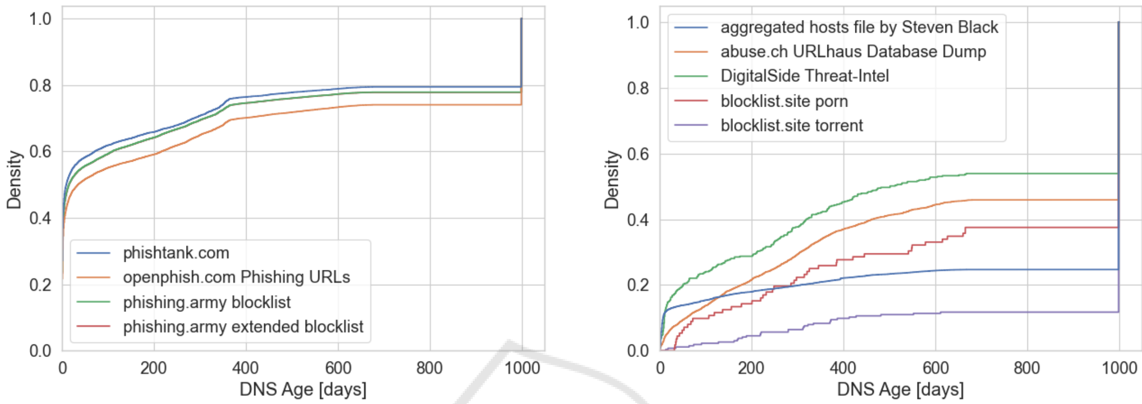
4.2 Comparison with Commercial Feed

To evaluate the proposed metrics further and to set the previous results in the context of the results of a professionally maintained feed, we analyze the comparison sample including the commercial feed in the following. The commercial feed contains only FQDN entries and renders the evaluation of ASN and country distribution obsolete. In general, the commercial feed showed promising results for most of the metrics. The feed size was large for its spam feed, comparably large for its phishing feed, but rather small for its malware and cracked sites feed. The agility of the feeds was good with frequent updates for all of the sub feeds except malware, and reasonably good update sizes. The uniqueness and overlap showed that the feed has a real benefit by providing data that no other feeds already contains. The high uniqueness of the feeds also renders the timeliness analysis obsolete. In the FeedRank evaluation, the contribution was the best of the analyzed feeds, whereas the correlation was negligible due to the lack of shared entries. Still, the overall and the large spam sub feed were ranked at the top of the FeedRank ranking. The results of the commercial feed regarding age and retention distribution are slightly worse than for the previous metrics. The age distribution shows 75% of *stale entries* and only 4% of *recent entries*. Evaluating the retention distribution, we see a big difference between the spam sub feed and the others. On the spam feed, 25% of the removed entries were on the feed for more the 116 days. In contrary, the median retention of malware, cracked sites and phishing were 3, 13, and 22 days respectively. This is likely due to a generally higher retention policy for spam entries.

If the age distribution results might be a sign for

Table 8: List of DGA feeds and the zone registration status of their new entries.

Feed	*Registered*		*Expired/Future*		*Not Registered*	
	P1	P3	P1	P3	P1	P3
netlab.360.com conficker DGA list	1%	1%	0%	1%	99%	99%
netlab.360.com dircrypt DGA list	86%	48%	14%	52%	0%	0%
netlab.360.com matsnu DGA list	33%	6%	2%	2%	65%	92%
netlab.360.com tofsee DGA list	0%	0%	0%	1%	100%	99%



(a) DNS age distribution of feeds with > 30% fresh entries.

(b) DNS age distribution of feeds with > 50% stale entries.

Figure 6: Cumulative DNS age distribution of feeds of chosen feeds.

untimely information on the commercial feed, the analysis of the DNS age, shows noteworthy results that suggests that at least what is added to the feed is timely and fresh information. As can be seen in Table 9, especially the spam and phishing sub feeds added many entries that were recently added to the DNS zone. The ratio of stale and not registered entries were low on all sub feeds.

The commercial feed showed good results in almost all metrics. Since we assume good quality of the commercial threat feed we conclude that the metrics are actually well suited to assess the quality of a threat feed.

5 DISCUSSION

5.1 Selected Metrics

Due to the lack of perfect knowledge and the often subjective nature of threat information, it is challenging to evaluate OSINT CTI feeds objectively and automatically. In this work, we can show that the eight selected metrics work reasonably well and are solid measures for feed quality in the real world. It is important to note that the significance of negative statements is generally much stronger. Feeds that are relatively untimely are indeed untimely, whereas relatively timely feeds are not necessarily timely in a global context. Other metrics show similar properties of favoring negative statements: domains not registered in the DNS zone are irrelevant, and the absence of additions is a lack of information about new threats. Positive statements are much harder to make, and even if some can be found, there will always be uncertainty without a ground truth. Despite these difficulties with positive statements, the metrics work well in a generalized context and even better for specific use-cases. For example, the evaluation results show that the DNS age metric works well for phishing detection, as the freshness of entries is high for some feeds. Using them in a platform like FeedMeter would result in a tangible benefit compared to today's state of OSINT CTI feed deployment.

5.2 Labeling

A feed can quickly become unfit for operational use, if the labeling of a feed does not provide enough detail. Additionally, normalizing the various labels used by different feed providers is laborious and challenging, especially for per-indicator labels. A platform such as FeedMeter could be a significant contributor to establishing a taxonomy, and we believe that our hierarchical approach, briefly described in Section 2.1, is a sound and extensible basis.

Table 9: DNS age results of the commercial feed.

Sub feed	*0-Day*	*Fresh*	*Recent*	*Stale*	*Not registered*
Spam	25%	37%	47%	0%	4%
Phishing	16%	30%	47%	0%	2%
Malware	1%	3%	12%	0%	0%
Cracked Sites	0%	2%	9%	0%	0%

5.3 Limitations

While we can show that the selected metrics do provide a tangible benefit, there are some questions our study does not answer. The high uniqueness and small overlap between the feeds confine its significance primarily to consolidation feeds and negatively impact the relative timeliness and FeedRank metrics. Perhaps it is an inherent property of the vast threat landscape, or it could simply root in our feed selection and implementation. Further work should handle the inclusion of additional sources, nontrivial normalization cases, unidirectional overlap checks (such as IP subnets and IP addresses), and the adjustment of FeedRank weights.

Our approach for building a corpus of DNS data is incomplete: not all registries provide access to their zone files, operators of country code top-level domains (ccTLD) in particular. Additionally, these zone files only contain information about SLDs but not third- and lower-level domains. Despite these limitations, the DNS age works well as a metric. We know that the data in the accessible zone files provides a full picture of its SLDs, whereas this is not certain with additional third-party data. Nonetheless, including additional sources in the future could be beneficial.

In our prototype, we only use descriptions by the feed provider to assign labels to entire feeds. However, some feeds contain additional metadata, such as malware names in the abuse.ch ThreatFox Database[5]. Mapping such metadata to more specific labels on a per-indicator basis is challenging, but could provide more detailed insight into the metrics and feeds.

The fourth limitation is the constricted comparison with commercial CTI feeds. We only compared the metrics of the OSINT feeds to a single commercial feed, which is a result of commercial feeds often being expensive. The feed used in this study was kindly provided to us free of charge. Further research into comparing the quality of OSINT and commercial CTI feeds and where they provide tangible benefits respectively would be advantageous.

[5]https://threatfox.abuse.ch/

6 RELATED WORK

The quality of CIT feeds is of high interest and has been studied intensively since the very beginning of using threat intelligence in the form of blocklists. In Section 2.2, we introduced the theoretical quality criteria defined by ENISA (Pawlinski et al., 2014). Caltagirone (Caltagirone, 2016a, Caltagirone, 2016b) and the NIST (Johnson et al., 2016) also define and discuss the fundamental quality properties of valuable threat intelligence and come to very similar criteria. These quality criteria have been studied extensively and applied in practice to existing CTI feeds by approximating them using proprietary or manually crafted reference data. Table 10 relates these studies to the quality criteria they studied and the threat type they focused on. Due to the limited practicability of these criteria, various new metrics have been introduced to approximate the quality of CTI in a more simple and reproducible manner. Metcalf and Spring studied the *overlap* (Metcalf and Spring, 2013) as well as the *feed size*, *uniqueness*, *intersection*, and *pairwise timeliness* (Metcalf and Spring, 2015) of CTI feeds. Pinto *et al.* (Pinto and Maxwell, 2014, Pinto and Sieira, 2015, Pinto and Maxwell,) formally defined the metrics *novelty*, *overlap*, *population*, *country and ASN distribution*, *aging*, and *uniqueness* and applied the metrics to several CTI feeds in two evaluation periods. Meier *et al.* (Meier et al., 2018) propose *FeedRank* and apply and evaluate it using a set of CTI feeds. The recent work of Li *et al.* (Li et al., 2019) had a very similar goal to our work regarding the requirements of suitable metrics. The proposed metrics *volume*, *contribution*, *latency*, *coverage*, and *accuracy* should be simple and reproducible using public data. The metrics are applied and evaluated using several IP and hash CTI feeds, and a longitudinal study a year later evaluates the stability of the metrics.

Other studies focused more on a high-level or multi-dimensional rating of CTI (Qiang et al., 2018),(Sauerwein et al., 2019),(Schlette et al., 2021).

Regarding automated monitoring of threat intelligence feeds, several pioneers have been sharing their platforms with the community. Makey (Makey, 2014)

Table 10: Overview of quality criteria studies for different threat types.

Threat type	*Completeness*	*Accuracy*	*Timeliness*
Spam	(Jung and Sit, 2004),(Ramachandran and Feamster, 2006),(Ramachandran et al., 2006),(Sinha et al., 2008),(Pitsillidis et al., 2012)	(Sinha et al., 2008)	(Ramachandran et al., 2006),(Pitsillidis et al., 2012)
Phishing	(Ludl et al., 2007),(Zhang et al., 2007),(Sheng et al., 2009),(Oest et al., 2019)	(Zhang et al., 2007),(Sheng et al., 2009)	(Sheng et al., 2009)
Malware	(Kührer et al., 2014)		(Kührer et al., 2014)
Various	(Pawliński et al., 2016)	(Pawliński et al., 2016)	(Pawliński et al., 2016)

monitored the *completeness* of public spam DNS blocklists (DNSBL) for 13 years by comparing their hits to SMTP logs of a mail server. The firewall software developer of FireHOL created a monitoring platform of OSINT CTI feeds (FireHOL,) and has maintained it since 2015. The platform includes several metrics we used in our work but only includes sources listing IP addresses. Also, to our knowledge, there has not been any scientific study of the platforms and the results they produce.

7 CONCLUSION

There is no state-of-the-art method to assess the quality of the numerous and heterogeneous OSINT threat intelligence feeds available. In this paper, we have proposed FeedMeter, a platform that collects, normalizes, and consolidates OSINT threat intelligence feeds into an aggregate feed. We introduced eight descriptive metrics for automated and continuous monitoring, evaluated them on a large corpus of more than 150 OSINT CTI feeds collected over four years, and made the data publicly accessible. Despite the small overlap of feeds in our data set and the resulting challenges in the uniqueness, relative timeliness, and FeedRank metrics, we were able to show the descriptive metrics' potential in helping find ones that are suitable or unsuitable for operational use. Predominantly negative assurance of unsuitability is a strength of some of the metrics. With the continuous and automated evaluation of these metrics, FeedMeter could provide a tangible benefit to end-users. We additionally collected a prevalent commercial CTI feed for six months and repeated the metrics evaluation on this feed. The results are very similar to a subset of OSINT feeds in our corpus, further reinforcing the previous findings, in both potential and limitations of these metrics. By providing the resulting aggregate feed retaining all source information, applying these metrics continuously, and making this information about them transparent, the FeedMeter platform reduces individual efforts and can make the Internet a more secure place.

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