Learning from Others' Mistakes: An Analysis of Cyber-security Incidents

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Abstract: Cyber security incidents can have dramatic economic, social and institutional impact. The task of providing an adequate cyber-security posture to companies and organisations is far far from trivial and need the collection of information about threats from a wide range of sources. One such a source is history in the form of datasets containing information about past cyber-security incidents including date, size, type of attacks, and industry sector. Unfortunately, there are few publicly available datasets of this kind that are of good quality. The paper reports our initial efforts in building a large datasets of cyber-security incidents that contains around 14,000 entries by merging a collection of four publicly available datasets of different size and provenance. We also perform an analysis of the combined dataset, discuss our findings, and discuss the limitations of the proposed approach.

1 INTRODUCTION

Cyber security incidents, such as intentional attacks or accidental disclosures, can have serious economic, social and institutional effects. The average total cost for companies and institutions spans from \$7.35 millions in the U.S. to \$1.52 million in Brazil, with a notable relation between the cost of the data breach and the number of lost records (Ponemon Institute, 2017). In this context, data about past cyber security incidents can give an insight on potential vulnerabilities and attack types, thus helping to prevent them, provided that the data are available and have enough quality. Commercial reports on security incidents and data breaches can be easily retrieved; for example, (statista, 2018) is a well known online service that reports the annual number of data breaches and exposed records in the U.S. from 2005 to 2018. While these reports are potentially interesting, the lack of transparency on their generation method, as well as their (intended) non-academic audience, makes it difficult to use them in scientific work. On the other hand, academic works that take a quantitative approach to the analysis of data breaches are less numerous. In (Edwards et al., 2016), authors analyse data from the Privacy Rights Clearinghouse (PRC), and draw the conclusion that publicly reported data breaches in the USA have not increased significantly over the past 10 years, either in frequency or in size. (Wheatley et al., 2016) combined two different datasets, DataLossDB (currently unmaintained as public dataset) and the mentioned PRC, finding divergent trends between US and non-US firms. (Xu et al., 2018) also uses the PRC dataset to analyse whether the data breaches caused by cyber attacks are increasing, decreasing, or stabilising. (Romanosky, 2016) reports to have analysed a commercial dataset of 300,000 observations about corporate loss events, having extracted a subset of around 15,000 observations about cybersecurity incidents out of it. As this last work confirms, having access to a commercial dataset seems to be a necessity since publicly available datasets are limited in size (up to 5,000 events) and this reduces the effectiveness of several data analysis techniques.

To overcome this data availability limitation, in this paper we follow the intuition of (Wheatley et al., 2016), investigating on the possibility to combine multiple publicly available datasets to obtain a larger one, capable to support statistically grounded analysis of security incidents. Specifically, the paper reports on two main activities. First, we present the undertaken methodology, highlighting in particular the encountered issues, limitations and workarounds. Second, we analyse the generated dataset with respect to the yearly trend, the target business sector, the type of attack and the magnitude of the attack, with the

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twofold objective of extracting useful information and evaluate the methodology used to generate the data.

The paper is structured as follow: Section 2 describes the methodology undertaken to collect data and merge them into a single dataset. Section 3 presents the statistical analysis of the generated data and the produced results. Section 4 discusses the results with respect to the objectives and concludes the paper, outlining the future challenges.

2 METHODOLOGY

Information about cyber-security incidents are reported every day on the media, but a systematic access to the sources is problematic because is distributed across a large number of websites and is described in natural language. Fortunately, there are initiatives that aggregate news about cyber-security incidents from third party sites as part of a professional work, making them available on-line as structured datasets. To have a wider coverage of the incidents' reports, we further aggregate four databases into a larger one. However, the datasets adopt different structures and are based on different classifications on key variables, such as the type of attacks or the economic sector of the firms affected. For this reason, the first step of this work aimed at developing a method to overcome the technical and conceptual discrepancies between different sources. Below, we report our method, which consists of three main steps: Identification and Collection (Section 2.1); Mapping and Selection (Section 2.2); and Redundancy Elimination (Section 2.3). We conclude (Section 2.4) with a description of the main features of the combined dataset.

2.1 Identification and Collection

We consider in particular four datasets of cyber-security incidents derived from four websites, detailed in Table 1: **PRC**: Privacy Rights Clearinghouse — a U.S. -based nonprofit organisation for privacy awareness and protection of individuals, maintaining a collections of data-breaches. **ITRC**: The Identity Theft Resource Center — a U.S.-based nonprofit organisation, whose mission is to help victims of identity crimes (e.g., identity theft, scams, and frauds), provides a collection of data-breaches on yearly basis. **BLI**: The Data Breach Level Index — a website sponsored by Gemalto (which also offers cyber-security solutions), contains datasets of publicly disclosed data-breaches as well as related statistics with graphical representations. **IiB**: The 'Information is Beautiful' website — which offers visual representation of data about different phenomena ranging from infectuous diseases to cyber-security incidents.

Looking at column 'Description' in Table 1, the four datasets appear quite heterogeneous. They are made available in different formats (CSV, PDF or HTML), the number of categories associated to incidents varies from 6 to 14, the number of incidents greatly differ—ranging from few hundreds to several thousands—as well as their time span. . Additional sources of heterogeneity emerge as soon as we take a closer look. First, consider column 'Attack types' of Table 1; two observations are in order: (a) PRC, BLI, and IiB consider several types of attacks while ITRC focuses just on one type and (b) the three used classifications differ in the number and types of classes of attacks. Then, consider column 'Organization types' of Table 1; the main remark is that PRC and ITRC use (different) classifications while BLI and IiB does not. Finally, observe that BLI also contains a classification of the attackers.

On the other hand, a lesser degree of heterogeneity is detectable on other domains, where the fields present a similar or identical schema or at least some conceptual similarity. For these reasons, harmonising them into a single dataset looks challenging but feasible, and potentially useful.

2.2 Mapping and Selection

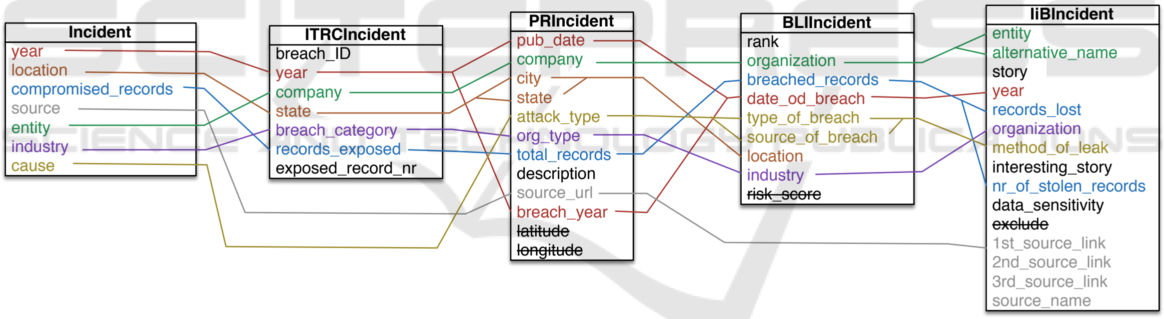
Given the difference and similarities illustrated above, we combine the four datasets into a single pool containing all the incidents in each dataset with the following 7 categories: *Year*; *Location*; *Compromised Records*; *Source*; *Entity*; *Industry*; and *Cause*. Table 2 shows the mapping from the original categories to the harmonised ones. On the left-end side, our dataset schema is reported ("Incident"), while the coloured lines define the mapping of each field to the source datasets. As concern the year of the incident, the information source, the target entity, its location, and the number of compromised records, the mapping is straightforward, because the values in such categories are homogenous across the four datasets,. Much of the effort is needed to harmonise the type of organisation (*Industry*) and the type of attack (*Cause*). More precisely, we need to perform the following two activities (1) mapping the original codings and translating into two homogeneous classifications and (2) checking the homogeneity of the resulting dataset and selecting one or more sub-sets that show some internal coherence.

Data Mapping. A critical work has been the reconciliation of the attack types — i.e., the *cause*

Table 1: Descrition of the four datasets.

ID	Description	Attack types	Organization types
PRC	www.privacyrights.org/data-breaches Format: CSV Number of attributes: 12 Number of entries: 4,413 Time range: 2005-2017 Impact: number of records	1. Payment Card Fraud 2. Hacking or Malware 3. Insider 4. Physical Loss 5. Portable Device 6. Stationary Device 7. Unintended Disclosure 8. Unknown	1. Bus.-Financial and Insurance Services 2. Bus.-Other 3. Bus.-Retail/Merchant-Including Online Retail 4. Educational Institutions 5. Government & Military 6. Healthcare, Med. Providers & Med. Insurance Services 7. Nonprofits 8. Unknown
ITRC	www.idtheftcenter.org/data-breaches Format: set of PDF files Number of attributes: 6 Number of entries: 5,924 Time range: 2005-2017 Impact: number of records	1. Identity theft	1. Banking/Credit/Finance 2. Business 3. Educational 4. Government/Military 5. Medical/Healthcare
BLI	breachlevelindex.com/data-breach-library Format: set of HTML pages Number of attributes: 9 Number of entries: 7,878 Time range: 2013-2018 Impact: risk score	1. Identity Theft 2. Account Access 3. Financial Access 4. Existential Data 5. Nuisance	1. Education 8. Insurance 2. Entertainment 9. Non-profit 3. Financial 10. Retail 4. Government 11. Social Media 5. Healthcare 12. Technology 6. Hospitality 13. Other 7. Industrial
IiB	informationisbeautiful.net/visualization worlds-biggest-data-breaches-hacks Format: Google sheet Number of attributes: 14 Number of entries: 292 Time range: 2004-2017 Impact: number of records	1. accidentally published 2. hacked 3. inside job 4. lost/stolen device or media 5. poor security	1. academic 9. media 2. app 10. military 3. energy 11. retail 4. financial 12. tech 5. gaming 13. telecoms 6. government 14. transport 7. healthcare 15. web 8. legal

Table 2: Redefinition of the data breach incident report.



field. While for some source categories the mapping was straightforward (e.g., Inside jobs), others made it difficult to produce a coherent and shared taxonomy of attacks. For example, BLI has two fields, "Type of breach" and "Source of breach", which report information about what kind of data has been accessed (e.g., Financial data, Existential data) and the source of the breach (e.g., Malicious insider, Hacktivist, State sponsored); PRC has a dedicated category for payment card frauds, and differentiates various types of physical losses; ITRC puts in the same category physical losses and employee errors, while Improper Disposal is kept separated from an Accidental disclosure. We ended up with a custom classification, which attempts to minimise the number of categories. Specifically, the following categories have been identified: (i) two main categories for intentional disclosures: malicious attacks coming form inside (Insider job) and from outside (Hacking or Malware); (ii) one category for unintentional disclosures (Unintended disclosure); (iii) one category for physical losses (Lost / Stolen device or media, which can be hardly differentiated in practice); (iv) one residual category for other unmapped incidents (Other / Unknown). Attack types from the source datasets are assigned to one of these categories according to a case-by-case evaluation.

Another field that required reconciliation was the type of attacked organisation — i.e., the *Industry* field. Source datasets classify organisations according to differente taxonomies and with different level of granularity. A complete manual reclassification was therefore needed. We ended up defining a custom classification, which tries to optimise the coverage and equal distribution of the source categories. The adopted classification consists in the following macro business sectors: (i) Education & Healthcare; (ii) Financial services; (iii) Industrial production; (iv) Information & Technology; (v) Standard commercial activities; (vi) Other privately-held businesses; (vii) Public administration; (viii) Non-profit; (ix) Other.

Data Selection. At the end of the data mapping step, we derived a single dataset containing 16,997 rows. After an analysis of the entries, it resulted that the largest number of incidents concerned organisations or companies located in North America (either USA or Canada). Specifically, 15,293 incidents occurred to organisations/companies in North America, corresponding to more than 90% of the total. This is probably due to two factors: (a) the dataset were taken from online services located in USA, and (b) these countries (USA and Canada) are subject to laws and regulations containing mandatory requirements for the notification of security breaches since 2004/2005. We hence decided to limit our analyses only to incidents happened in North America.

2.3 Redundancy Elimination

Despite showing some internal coherence, the dataset obtained after mapping and selection shows some redundancy. There are several sources of redundancy, that we describe below together with the techniques that we use to detect and eliminate them.

Duplicated Events. First, redundancy refers to a security incident reported more than once. Duplicate cases could be easily removed, but an issue emerges on the actual definition of "duplicate". In some cases two rows reported a security incident in the same year, concerning the same entity, but only in one case the number of compromised records was known. A check on a sample of original incident URL sources suggested that these instances referred actually to the same events. Such cases were removed, maintaining the records reporting the number of compromised records only. The trickiest case referred to records with similar entity names. Different sources reported the same incident recording the entity name with different acronyms, shortcuts, legal specifications and mistakes. We hence identified an additional set of potential duplicates. Here is a list of possible cases:

Differently Decorated Names. Differences could be related to partial omissions, typically concerning legal specification (e.g. "Google" and "Google, inc."). In this case the two names were unified through a simple catalog of pattern templates.

Similar Names. A more problematic set of cases was due to entity names that were actually similar but no precise detection rule could be defined. These cases involved typically spelling or punctuation mistakes (e.g. "HOMECARE OF MID-MISSOURI INC." and "HOME CARE OF MID MISSOURI", or "COHN HANDLER STURM" and "COHN HANDLES STURM"). These are basically singletons, and therefore defining pattern matching for all the instances would have resulted in a huge but useless effort. To overcome this problem, an algorithm has been applied to spot similar entities.

The algorithm proceeded by comparing all the possible $(n(n-1))/2$ pairs of entities, assigning to each pair a score, calculated using their Jaro-Winkler distance. A manual identification of the duplicates was performed below the threshold of 0.18, a threshold identified after manual tests as the one minimising both false positives and false negatives.

False Positives. were a major issue in the activity of similarities identification. Particularly problematic was the case of entities sharing part of the name but indicating different institutions (e.g. "University of ..."). This phenomenon had to be contrasted with cases of true positives, such as different branches of a same organisation, such as territorial units (e.g."7eleven' York", "7eleven Baltimora").

False Negatives. As for false positives, also false negatives involve the use of human knowledge and cannot be easily translated into clear-cut rules. For example, "Google" and "Alphabet", in which the latter is the new corporate name of the first; or "UNIVERSITY OF CALIFORNIA LOS ANGELES" and "UCLA", where the latter is an acronym for the first.

Once the algorithm has generated the list of candidate duplicates, a manual pass allowed us to identify false positives. To deal with them, a further catalogs of patterns have been defined, a white list, listing candidate duplicates. More difficult was to deal with false negatives. So far, they are added to a third pattern catalog, the black list, whenever they are identified.

Legal Entities. A last issue concern the legal setting of reported entities. Companies and public administrations can be articulated in hierarchies of controlled companies. Controlled companies can have legal personality, and therefore their own name, which in some cases may differ completely from the original. If the same security breach is reported multiple times and using different names (of the controller and controlled company), this is not easily identifiable in an automatic way.

2.4 Merged Dataset

The merged dataset, as resulting from the described process, contains 14.820 entries. We can not claim that it is fully duplicate-free, but duplicates also existed in the source datasets, accounting for around 7% of the total, on average, and this makes our work comparable with the literature. We also inherit other aspects of the source datasets: firstly, the dataset contains only attacks reported to authorities, which do not include foiled or unreported attacks; secondly, there are many salient information (such as technologies used by firms and public administration departments) about which nothing is known. Finally, our mapping of categories of attacks and organisation remains somehow arbitrary, but unfortunately arbitrariness also affects the source dataset, as none of the publisher adopted an official classification, assigning rather their own.

3 DATA ANALYSIS

We start our preliminary inspection of the data by plotting the trends of the number of cyber attacks, the number of firms involved and a measure of the damage they caused over the period 2008-2017 (Figures 1-2).

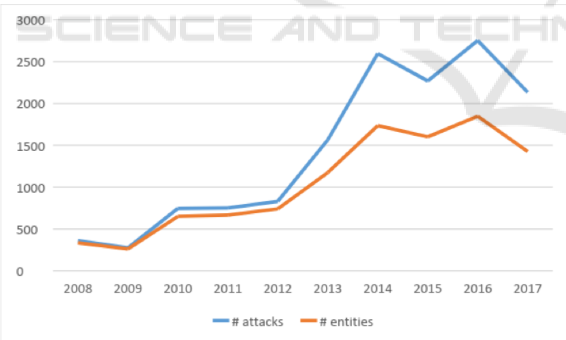


Figure 1: Yearly reported number of cyber attacks and entities involved - 2008/2017.

As Figure 1 shows, the reported number of attacks constantly increased from 2008 onwards. The number almost tripled from 2009 to 2010 passing from 275 to 746 events and, after two years of relative stability, sharply increased again from 2012 to 2013, and since then remained stable. As concern the number of entities subject to attacks, we can observe that from 2012 onwards their number is steadily lower than the number of attacks, indicating that a significant fraction of entities received multiple attacks in the same year. Figure 2 reports, for the same time-span, the median number of compromised records. In this case there is no clear-cut trend as in Figure 1. However, it is worth noticing that the last three years rank among the highest of the period considered. This evidence contradicts the optimistic forecasts produced by the predictive model of (Edwards et al., 2016), according to which we should have observed a reduction in the level of damage caused by the attacks, both in median terms and considering extreme events.

The figure also shows that cyber-attacks can be extremely harmful for private and public organisations: the median number of compromised records varies from 600 up to over 1,400.

The following tables break down the information on the number of attacks by year and sector (Table 3) and their relative significance (Table 4). According to Table 3), the sector mostly damaged by cyber-attackers is health and education (45%). Sectors such as public administration, financial services, standard commercial activities account for 11-13% of reported attacks each. At the bottom of the ranking stand information and technology (5.5%), industrial production (0.9%) and no-profit (0.8%). For a residual 10% of attacks the activity sector was not coded in the original source. The ranking depicted above is constantly evolving: health and educational organizations' quota is decreasing from the period 2010-2012 (values around 55%) to the 36.6% registered in 2017. The same relative reduction is found for public administration, whose quota decreased steadily from 20% (in 2008) to today's 6%. Conversely, the sectors of finance, industrial production, information and technology and standard commercial activities see for the same period an increasing trend.

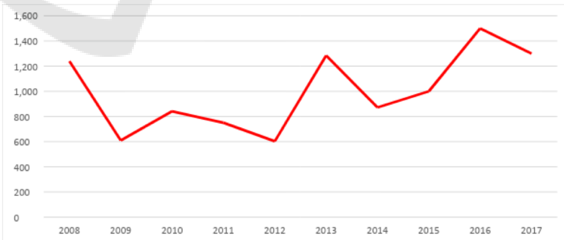


Figure 2: Median yearly number of compromised records - 2008/2017.

These figures alone, though, cannot provide a meaningful picture of the exposure of activities to cyber-attacks. For this reason we calculated the odds of being target of a cyber attack by sector and year. Odds ratios describe the relative risk of being attacked in relations to the sector in which the firm operates.[1]

[1] Odds are computed by dividing the proportion of year-by-sector firms attacked by the corresponding proportion of

The situation is depicted in Table 4. Industry and other commercial activities have a very low incidence rate all throughout the period, probably given the small relevance of personal data storage in their activity. Health and education firms show a very high but declining trend in the odds of being attacked, passing from a high value of 5.7 to 4.1. As predictable, financial services are a relatively common target for cyber-attackers (odds ratios around 3/4 for all the period considered), as well as information and technology, whose odds of being attacked skyrocketed since 2013.

Table 3: Attack by year and sector. Percentages.

Year	Industrial production	Information and technology	Financial services	Education & Healthcare	Other commercial activities	Undefined privately-held	Public administration	Non-profit	Unknown	Total
2008	0.0	0.6	12.2	43.6	8.1	0.0	20.3	0.3	15.0	**100**
2009	0.0	1.8	9.5	50.9	4.7	0.0	19.6	0.0	13.5	**100**
2010	0.0	0.7	13.1	55.1	11.4	0.0	13.7	0.0	6.0	**100**
2011	0.0	0.8	7.1	56.9	11.1	0.0	11.7	0.4	12.1	**100**
2012	0.1	1.7	8.7	54.3	12.6	0.0	10.8	2.4	9.4	**100**
2013	0.1	6.1	12.2	48.2	10.9	0.0	11.1	0.5	11.1	**100**
2014	0.0	4.5	11.1	53.3	10.9	2.5	11.7	0.2	5.7	**100**
2015	0.0	5.5	15.3	37.1	13.9	5.8	12.2	0.1	10.1	**100**
2016	1.8	9.1	13.4	40.0	15.6	4.3	9.5	1.5	4.8	**100**
2017	3.8	7.6	15.1	36.6	16.1	10.7	5.7	1.7	2.8	**100**
Total	**0.9**	**5.5**	**12.7**	**45.1**	**13.0**	**3.8**	**10.8**	**0.8**	**7.4**	**100**

Table 4: Relative risk for a firm of being attacked, by sector.

YEAR	Industrial production	Information and technology	Financial services	Education & Healthcare	Other commercial activities
2008	0.0	0.3	4.5	5.7	0.2
2009	0.0	0.9	3.4	6.2	0.1
2010	0.0	0.3	4.1	5.3	0.2
2011	0.0	0.2	2.3	5.9	0.2
2012	0.0	0.4	3.0	5.4	0.3
2013	0.0	2.3	3.5	5.0	0.2
2014	0.0	1.9	3.2	5.3	0.2
2015	0.0	2.4	4.6	4.4	0.3
2016	0.1	3.3	3.9	4.3	0.3
2017	0.2	2.7	4.1	4.1	0.3

Table 5 illustrates the attacks by type. The trends depicted show the rapidly changing geography of the way cyber-attacks are conducted: an increasing majority of attacks are conducted via hacking and malware, along with the diffusion of online tools to work and store data. At the same time, all other attack types are losing importance: stolen devices or media pass from 48.9% in 2008 to a residual 1.5%; inside jobs and unintended disclosure show a similar, even though less spectacular, decrease, both falling under 10% during the last year. The "other /unknown" category is currently the modal one and we conjecture that this data has two different explanations: the first refers to the ability of cyber attackers. The smoother is the attack, the more difficult it is to identify, and then report, its actual cause. The second one refers to the quality of the data. A part of it may be in fact attributable to sloppiness in reporting the attacks. We have indirect evidence of it when cross-tabulating the sector with the type of attack (Table 6): the rising category "undefined privately held businesses" (perhaps another example of sloppiness) is the one for which most of the attacks are of unknown origin. As concern the rest of the sectors, it is interesting to notice how hacking and malware represents by far the main problem in all the sectors except from health and education, where unintended disclosure and stolen devices are a big issue, and public administration, which sees various sources of attacks.

active firms in USA. Values equal to 1 mean that exposure is in line with the sector size; values greater than 1 mean over-exposure; values comprised from 0 to 1 mean the contrary.

Table 5: Type of attack by year (percentage).

Year	Hacking or Malware	Inside job	Stolen device or media	Poor security	Unintended disclosur	Other / Unknown	Total
2008	16.1	8.6	48.9	0.0	22.5	3.9	100
2009	19.3	10.9	46.9	0.0	19.3	3.6	100
2010	14.9	13.1	52.4	0.0	13.9	5.6	100
2011	21.8	12.3	45.5	0.3	14.4	5.7	100
2012	30.1	10.8	38.5	0.0	15.3	5.3	100
2013	44.3	15.3	15.3	0.1	21.3	3.6	100
2014	41.1	11.2	6.7	0.1	17.2	23.8	100
2015	45.1	9.6	4.0	0.1	16.3	24.9	100
2016	50.0	5.1	2.9	0.0	13.7	28.2	100
2017	42.5	4.0	1.5	0.1	9.2	42.9	100
Total	**39.9**	**9.2**	**13.8**	**0.1**	**15.4**	**21.6**	**100**

Table 6: Type of attack by sector (percentage).

Sector/Type of attack	Hacking or Malware	Inside job	Stolen device or media	Poor security	Unintended disclosure	Other / Unknown	Total
Industrial production	53.4	3.0	0.8	0.8	3.8	38.4	100
Information and Technology	65.5	2.7	0.5	0.3	10.3	20.8	100
Financial services	41.8	10.1	7.7	0.0	14.4	26.1	100
Education & Healthcare	32.2	9.7	22.3	0.1	18.3	17.5	100
Other commercial activities	59.5	8.5	4.5	0.0	7.0	20.5	100
Undefined privately-held businesses	2.2	0.0	0.0	0.0	0.2	97.6	100
Public administration	29.4	14.2	11.0	0.1	25.9	19.3	100
Non-profit	51.3	5.0	10.1	0.0	6.7	26.9	100
Unknown	62.5	9.6	12.4	0.0	12.5	3.1	100
Total	**39.9**	**9.2**	**13.8**	**0.1**	**15.4**	**21.6**	**100**

4 DISCUSSION AND CONCLUSION

The paper reports our initial efforts in building a large dataset of cyber-security incidents by merging a collection of four publicly available datasets of different size and provenance, overcoming the lack of publicly available datasets of substantial size observed in previous research (Romanosky, 2016).

By analysing the resulting dataset with standard statistical techniques, our work confirms the generally observed rapidity with which the phenomenon of cyber-attacks is evolving. While incidents caused by malicious outsiders passed from 16% to 50% in a time-span of just five years, other leading causes of data breaches such as malicious insiders and unintended disclosures lost most of their importance in the same period. There may be multiple causes underlying this trend. On the one hand, the decreasing relevance of unintended disclosures and malicious insiders may be the result of the adoption of better security procedures and awareness programs by companies and organisations. On the other hand, remote attacks are more and more widespread because of the explosion of personal and sensitive data available online resulting from the digitalisation of many aspects of our lives. These factors seem to confirm the idea that organisations and companies should take a holistic approach and tune their cyber-security postures according to a variety of sources about threats and countermeasures including cyber-intelligence information about current threats provided by, e.g., national or international Computer Emergency Response Teams (CERTs). It is thus not surprising that the forecasts about the size of 2015 and 2016 data breaches contained in (Edwards et al., 2016) remain partly unachieved.

Concerning the limitations of our approach, two issues must be considered. The first is related to the coverage of data and is shared with previous work (e.g., (Romanosky, 2016)). Since the four datasets used to build ours are based on public notifications to authorities, it is unclear whether the data are representative of the overall phenomenon of cyber-attacks or not. We draw this consideration from the comparison of two figures. In our dataset, the share of private USA companies and organisations involved in security breaches amounts to minuscule figures, namely 0.02% (or less) per year. An official report based on a representative UK sample highlights that 67% of medium-large firms have suffered from cyber-attacks in 2016 (Klahr et al., 2017). The corresponding number for Italy in the same period, based on another national representative survey, is 43% (Biancotti, 2017). We are currently gathering additional sources of information to understand to what extent our analyses reflects actual trends operating in the overall population of US firms and organization. The second issue to be considered is the remarkable amount of effort required to make the merged dataset coherent and uniform. The result is apparently worth the effort; a database derived from publicly available information that is comparable in size to that used in (Romanosky, 2016), which is privately owned and contains around 15,000 descriptions of data breaches. However, we acknowledge that the relevance of the results depends on the quality of the generated dataset, which in turn depends on the quality of the method used to join the source datasets: it must be able to eliminate redundancies and consistently map the source categorisations into one which is general enough to accommodate those used in the initial datasets and—at the same time—not too coarse to loose precision and significance in the analysis phase. To tackle this issue, our future efforts will be devoted to reach a high-level of automation of the various steps of the methodology by developing a toolkit for automatically collecting, tidying, mapping, and merging datasets of cyber-security incidents. The main benefit of developing such a toolkit is flexibility along two dimensions. First, it will be possible to experiment with different taxonomies for the types of attacks and economic sectors to better identify which option minimises the loss of precision and coherence when merging different datasets. Ultimately, this would reduce the level of arbitrariness in the data manipulations besides those imposed by the publishers of the original datasets. The second dimension is a tighter integration with the data analysis phase: depending on the results of the latter, we can decide to investigate some features of the component datasets and use the results to fine-tune some aspects of the collection, selection, mapping, and redundancy elimination steps. The flexibility deriving from a high-level degree of automation of the methodology will also simplify the inclusion of new datasets, increase the size of the merged dataset, and possibly make the application of a wider range of data analysis techniques.

The present work has revealed some preliminary results and interesting potentialities, but it has also highlighted issues and limitations. This raises an important observation. As stated in Section 1, several surveys and statistical reports are available online, mostly from private companies. Since the issues we reported depend only partially from our approach, it should be argued that the reports available online suffer the same limitations and issues. This calls for a deeper scientific exploration of the available data, to better evaluate the quality of the dataset and make transparent and questionable the results.

In short, our future work will focus to make "learning from others' mistakes" possible for a wide range of professionals involved in managing cybersecurity (such as technologists, insurers, or policy makers) by providing adequate tool support to the methodology described in this work and perform more extensive investigations about the datasets considered here and others that will be made available to us. As a firs concrete step to promote the use of our datasets and methodology, we provide pointers to the on-line datasets and the merged one, plus additional material, at the following address: https://sites.google.com/fbk.eu/ fbk-cybersec-flagship-project.

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