

Data-driven Country Safety Monitoring Terrorist Attack Prediction

Dimitris Spiliotopoulos and Costas Vassilakis
Department of Informatics and Telecommunications
University of the Peloponnese
Tripoli, Greece
dspilot@uop.gr, costas@uop.gr

Dionisis Margaritis
Department of Informatics and Telecommunications
University of Athens
Athens, Greece
margaris@di.uoa.gr

Abstract—Terrorism is a key risk for prospective visitors of tourist destinations. This work reports on the analysis of past terrorist attack data, focusing on tourist-related attacks and attack types in Mediterranean EU area and the development of algorithms to predict terrorist attack risk levels. Data on attacks in 10 countries have been analyzed to quantify the threat level of tourism-related terrorism based on the data from 2000 to 2017 and formulate predictions for subsequent periods. Results show that predictions on potential target types can be derived with adequate accuracy. Such results are useful for initiating, shifting and validating active terrorism surveillance based on predicted attack and target types per country from real past data.

Keywords—Data Analysis, Terrorist Attacks, Safety Perception, Risk Calculation, Threat Ranking

I. INTRODUCTION

“World’s safest countries for [year]”, is a commonly seen article title announcing global country safety indices, every year, from reputable sources. These are organisations devoted to global peace, such as The Organisation for Economic Co-operation and Development (OECD) that publishes the Better Life Index [1], and the Institute for Economics and Peace [2] that publishes the Global Terrorism Index (GTI) [3]; both publications rank countries for safety.

The country safety indices take into account several geopolitical factors as well as expert opinions based on very recent political events or even terrorist attacks on areas or nearby locations. Terrorism is one of the most impactful factors that affect the citizen perception of safety. According to Pain [4], inciting widespread fear among the global population is a key objective behind terrorism attacks. According to the Institute for Economics and Peace, global terrorism peaked in 2014, with an unprecedented increase of 80% between 2013 to 2014. While terrorist attacks had then receded to the levels of 2013, the attacks are still very widespread between countries. This is reflected by

incidents of terrorism happening in relatively low risk countries, maintaining terrorism as a key public fear factor for many countries.

Country safety indices utilize the global information on several aspects, including terrorism, to rank countries, however, that ranking alone, by design, is only an indication, which cannot be directly used in decision making processes by citizens, businesses and Local Enforcement Agencies (LEAs). Especially for LEAs, since the existing information is based on general parameters, such aggregated ranking scores are not as useful for counter-terrorism preparation. The usefulness lies in several activities that LEAs engage, one of those being the prediction of possible types of targets. That is also the case for groups of citizens. For example, for tourism, the groups of citizens that are concerned are the travelers and tourists, as well as businesses, such as tour operators, hotel managers and others. Risk perceptions and risk estimates clearly differ among these groups, hence an aggregated and uniform risk assessment is inherently of limited utility.

From the above, it is evident that deeper and more detailed analysis of terrorism data may lead to informative results on specific queries, like “how safe and from what type of terrorist attack is country X for us to visit?” and “how safe is country Y at the dates of my planned trip?”.

This work analyses the *Global Terrorism Database* (GTD) and country statistics to:

1. develop a method to visualise aspects of terrorism attacks for citizens, businesses and LEAs to qualitatively understand how attacks are perceived, their impact to society and business, and their usefulness to LEA preparedness,
2. measure predicted safety risk per country, factoring in time series data of past terrorist events, and a multitude of factors that relate to them, in order to produce accurate assessments of threat and safety from the impact of terrorism and
3. validate the prediction for level of terrorist threat ranking based on the specific query on tourism, utilising time, attack type and country information data analysis, as opposed to general terrorism risk level descriptors.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.

ASONAM '19, August 27–30, 2019, Vancouver, BC, Canada

© 2019 Copyright is held by the owner/author(s). Publication rights licensed to ACM.

ACM 978-1-4503-6868-1/19/08...\$15.00

<https://doi.org/10.1145/3341161.3343527>

The results show that safety ranking can be predicted from past years' data, enabling accurate country ranking based on queried aspects of impact. The deeper analysis of the data also reveals specifics that counter terrorism organisation can utilise through visualisation methods for better understanding targets per country based on time, fatality, types of targets and other factors that provide insight and aid preparedness.

The rest of the paper is structured as follows: section II overviews related work, while section III describes the dataset that was used. Section IV discusses the data analysis findings and section V presents the prediction algorithms. Section VI discusses the experimental results and finally, section VII concludes the paper and outlines future work.

II. RELATED WORK

Terrorism inspires fear which spans across citizens and visitors alike. Recent works studied the importance of safety on the attractiveness of tourist destinations, finding that safety is an important, marketable factor for tourist destinations [5]. That risk is calculated by potential visitors as a quality factor, which is as important as the natural beauty of the destination [6]. Tourism is a major source of income for tourist destination countries and terrorists know that targeting tourist destinations may force their respective governments to be involved in the international politics [7, 8, 9].

Targeting tourist destinations affects people that are directly involved in the tourist sector and businesses within the tourist industry, as well as a large portion of the economy partners that support that industry indirectly, such as food suppliers; in total, it affects countries' economies heavily [10, 11]. Moreover, it has been observed that terrorist attacks in one tourist destination have an effect on tourism for other tourist destinations, based on correlations of places, geography, politics and other factors [12].

Studies have found that there is different level of impact of terrorism attacks between places with high and low tourist activity. High tourist activity places are affected heavily in the short term but may recover over time based on factors such as media coverage (reports on life returning to normal, advertisements, tourist resilience to terrorism [13, 14]), while low activity places are greatly affected in the long term, resulting in the tourist operations going out of business [15, 16]. The effects of terrorist attacks on an area result in tourism decline and may take a period of six months to a year for the local tourism industry to recover [17], based on how the perception of safety by potential visitors is restored [18].

Tourists, as opposed to local population, develop expectations and make decisions on whether to visit a destination based on past experiences and general perception of what they expect to experience [19]. Due to that fact, tourists are easy targets to be affected by terrorism [20]. Another business that is also involved in tourism and terrorism is the media, which reports on the impact internationally [21].

The placement of this work lies between the deeper understanding of terrorism based on terrorism data and the support of the broad analytics that can be applied on big data. The latter synthesizes methods of forensics analytics, visualisations, communication and social network data. Counter-terrorism relies on

information availability and accurate predictive analytics to effectively monitor financial, communication and social data streams for traces of potential terrorism-related activities. The results of this work support those methods by showcasing and validating how past terrorism data can be utilised to aid the filtering or focus of the data streams under surveillance, may those be gathered through social networks [22-26] or other data sources, such as the IoT [27].

III. DATASET

Several datasets were considered for this work, including the GTD, introduced and maintained by the University of Maryland [28, 29], and the *Terrorist and Insurgent Organizations' Service Provision* (TIOS) v2.0 [30] that were among the largest and richest. The datasets have been evaluated for the purpose of this work based on criteria derived from the scope for this exploratory work.

The scope of the exploratory data analysis was to understand how terrorism attacks spun within the peak tourism period in Europe, in the location around the Mediterranean, over a specified period of time. The GTD was selected for this work based on the availability of information from 1970 to 2017 and the inclusion of data from several sources. The GTD dataset has been used in several studies since its introduction. It has been used to measure the effect of terrorism on investor sentiment and the stock market [31, 32], on country growth [33], and policy making [34, 35].

The GTD dataset was explored in its totality for consistency and missing information that would render it or parts of it unsuitable to use as is. More specifically, the raw and processed data entries were examined in pairs and checked for normalisation and descriptiveness. Although the full dataset was explored to understand the links between the types of information contained, we were mostly interested in the tourist-related data. We selected the Mediterranean region, which is a very popular destination area for tourists, especially during the summer. We also examined the *target type* and *attack type* data.

For the overall dataset, the main attack type and main target type are not independent, as confirmed by a chi-square test giving $\chi^2(168)=64,531$, $p<0.001$. The most frequent *attack type* is *bombing/explosion*. It was positively correlated (Pearson correlation) to *target types*: airports, $r(181689)=0.017$, $p<0.001$; business, $r(181689)=0.069$, $p<0.001$; educational institute, $r(181689)=0.010$, $p<0.001$; transportation, $r(181689)=0.060$, $p<0.001$; food/water supply, $r(181689)=0.015$, $p<0.001$; telecom, $r(181689)=0.017$, $p<0.001$, while other *target types* had either negative or no correlation. On the other hand, the second most frequent *attack type*, *armed assault*, mainly targeted LEAs such as police, $r(181689)=0.119$, $p<0.001$, and military, $r(181689)=0.163$, $p<0.001$.

According to the above findings, it was deduced that the dataset contained consistent data of adequate quantity and density. Therefore, it was deemed suitable for our task at hand.

The validation scenario selected for this work is the following: out of the total of the selected terrorism dataset entries, we extracted the data for the Mediterranean region EU countries of France, Spain, Italy, Greece, Serbia, Croatia, Cyprus, Malta,

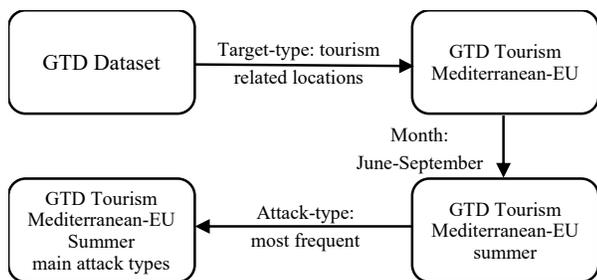


Fig. 1. The selection process for the tourism-related data subset.

Slovenia, as well as Turkey. From those we filtered the “tourist-related” attacks based on the target type values contained in the set {Business, Airports & Aircraft, Maritime, Private citizens & Property, Tourists, Transportation (other than Aviation)}. Then, we selected the events that occurred from June-September (Summer high season), for the years 2000-2017 for which the GTD started to include dense and continuous monitoring for the European region events. Then, we selected the four most frequent *attack types* (the four of them accounting for the 92.7% of the total number of attacks), resulting in the types of *bombing/explosion* (56.1%), *armed assault* (24.3%), *hostage taking (kidnapping)* (5.6%) and *facility/infrastructure attack* (13.1%) from the attack type category (Fig. 1).

IV. DATA ANALYSIS

In this section, we report on the country data that was analysed and the findings on the tourist-related attacks and the distribution of the attack types.

A. France

As depicted in Fig. 2, over the span of the 18 years (2000-2017), a very high proportion of the attacks in France were tourist-related.

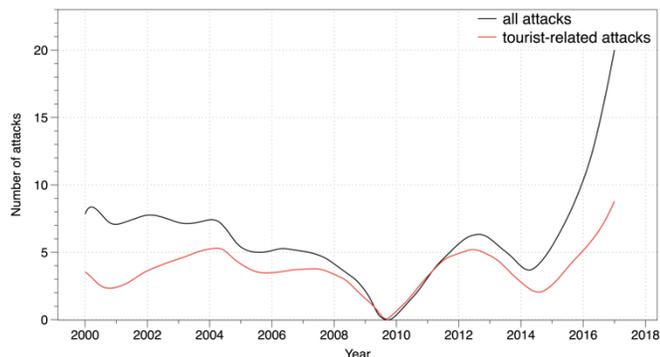


Fig. 2. Tourist-related vs. total number of attacks for France, 2000-2017.

Compared to its size and number of tourist destinations, France had a very low number of attacks, much lower than Turkey, Spain and Greece. As in the case of Turkey and Italy, the attacks increased significantly in the recent years, after an all-time low in 2010 (Fig. 2).

B. Spain

As in the case of France and Italy, the tourist-related attacks in Spain were also a large proportion of the total attacks.

However, contrary to France, the attacks have been significantly reduced from 2000 onwards to about 1/10th of their number over 18 years ago (Fig. 3).

Spain has the second highest number of tourist-related attacks from the countries examined. However, it has one of the lowest numbers of attacks, for its size and number of visitors, in the recent years.

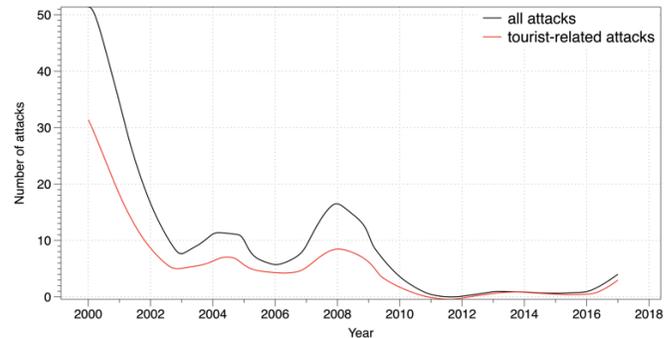


Fig. 3. Tourist-related vs. total number of attacks for Spain, 2000-2017.

C. Greece

The ratio of the tourist-related attacks over the total attacks is quite low, with less than 40% of the attacks been tourist-related.

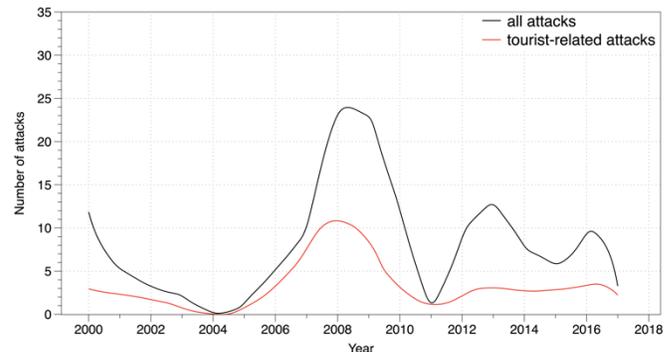


Fig. 4. Tourist-related vs total number of attacks for Greece, 2000-2017.

Greece, a country that battled domestic terrorism in the late 2000s, has seen the terrorist attacks peaking in 2009, after a period of nearly zero attacks around 2004. After the peak, the attacks have been reduced to very moderate numbers taking into account the number of tourist destinations and visitors (Fig. 4).

D. Italy

Traditionally, Italy has had very low numbers of total attacks, most of them tourist-related. Visually, Italy has an opposite distribution to Greece, with very low number of attacks in the late 2000s (Fig. 5).

Italy has a very low number of attacks, taking into account the size and visitors, much lower than Turkey, Greece and Spain and France.

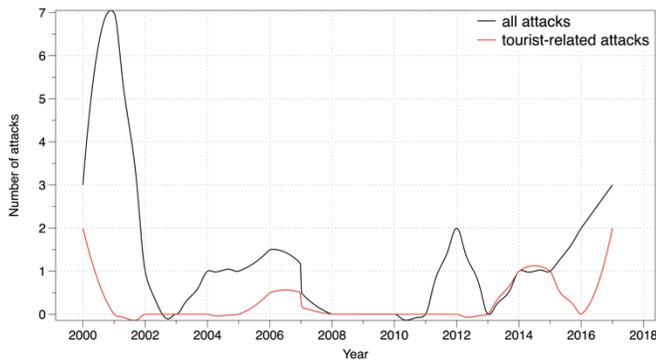


Fig. 5. Tourist-related vs total number of attacks for Italy, 2000-2017.

E. Turkey

Turkey had suffered the highest number of attacks between the countries of the Mediterranean examined.

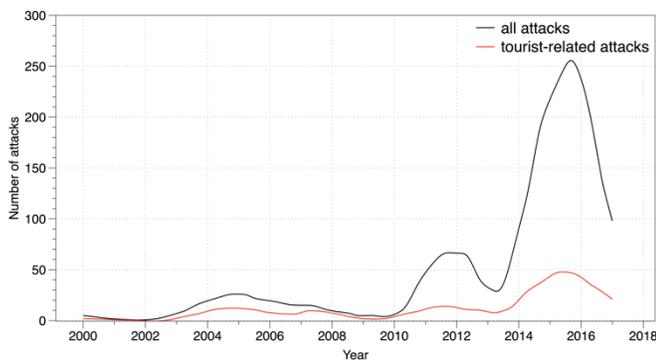


Fig. 6. Tourist-related vs. total number of attacks for Turkey, 2000-2017.

Total numbers show that it had more than five times the number of attacks of second-place Spain. Only a quarter of the attacks were tourist-related. The pattern is similar to France, with the attacks peaking in the recent years (Fig. 6).

F. Other Countries

The rest of the countries examined, Albania, Croatia, Serbia-Montenegro, Cyprus, Malta and Slovenia had a very low number (<6) tourist-related attacks in the 18-year span.

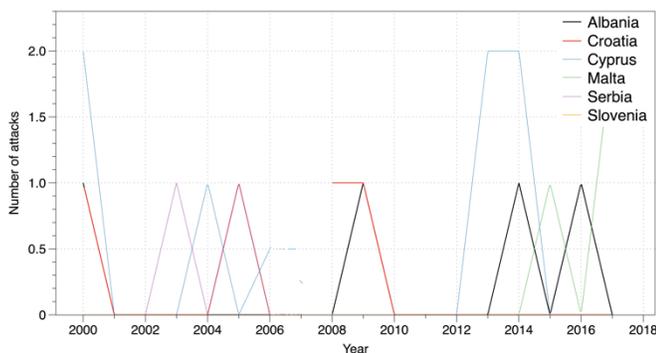


Fig. 7. Total attacks for the remaining examined countries, 2000-2017.

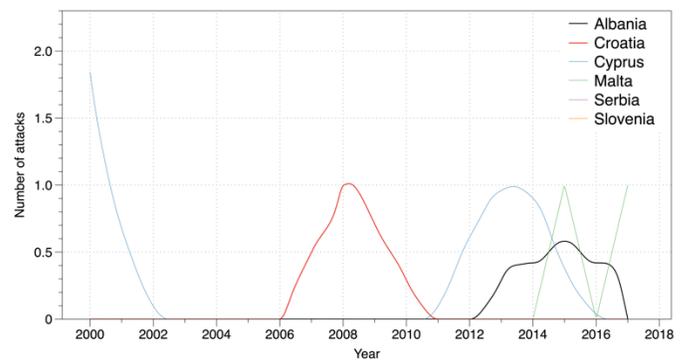


Fig. 8. Tourism-related attacks for the remaining examined countries, 2000-2017.

Fig. 7 shows the total number of attacks for the six, low terrorist activity countries in the Mediterranean EU region. To compare, Fig. 8 shows the tourist-related terrorist attacks for the same group of countries.

In our case these figures did not provide any new insight into the tourism-related attacks for the examined countries. In general, however, such analysis would reveal situations where low activity locations might stand out for specific periods of time.

G. Terrorist attack type

We used a topic modelling type of analysis similar to the works done in other domains [36] to spatially visualise the four major types of attacks that are related to tourism and their distribution per country.

Fig. 9 depicts how each of the five major countries (in red) relates to the *attack types* (in blue). The size for both the *attack types* and the countries is relevant to the number of attacks for each category. From Fig. 9, it can be seen that all countries except Greece have suffered mostly from *bombing* terrorist-related attacks. Greece had suffered attacks to *facilities/infrastructures* but also had its share of *bombings*, too. Turkey, on the other side, had suffered mostly *bombings* but also a significant portion of the attacks were *armed assaults*. One can see the difference of the number of tourist-related attacks per country in the graph. For LEAs, this is especially important to know and prepare accordingly to protect their respective countries' tourism.

V. PREDICTION ALGORITHMS

After analyzing the relations between *target type* and *attack type* of terrorist data for the countries in our case, this section focuses on the prediction regarding the increase/decrease of projected year attacks for the same countries, based on the data from the years before. The motivation was to be able to predict changes in the attacks, in order to enable better focus on surveillance and alertness from authorities and citizens.

Recommender systems is a major research area for prediction of values from earlier data. In the domain of product recommendation, past user rating for products are utilized to predict unknown rating values, and rating age can be exploited to substantially enhance recommendation quality, tackling phenomena like shift of interest [37, 38]. Similarly, terrorism-related measurements age can be exploited to substantially

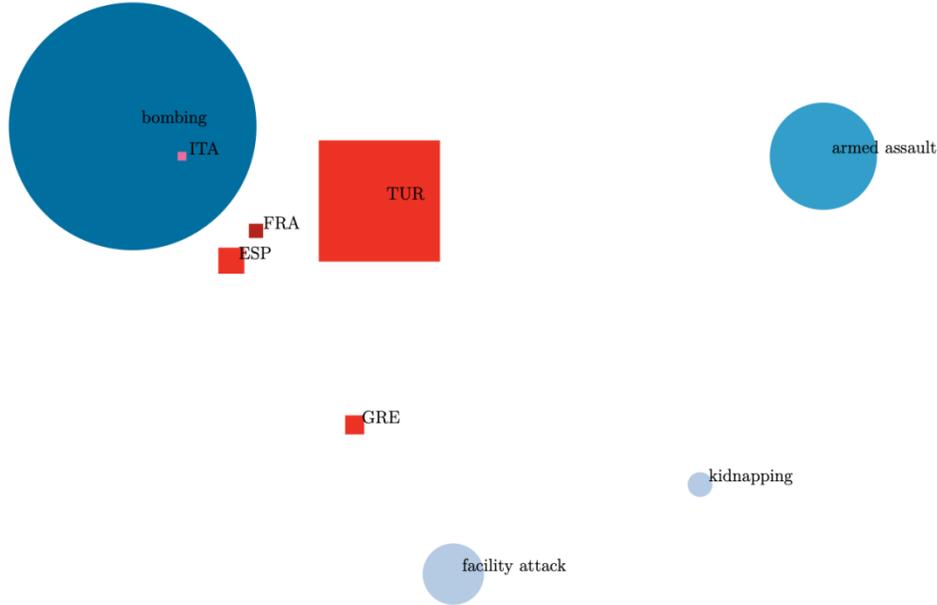


Fig. 9. Visualisation of tourism-related terrorist attack type per country.

enhance terrorist activity prediction accuracy, since, time series data of attacks on countries are dependent on the time distance from value of the target prediction time.

In the next subsections, we present algorithms for pruning and aging measurements, respectively, based on their oldness, under the rationale that aged measurements may not accurately reflect the current state of users regarding their preferences. These algorithms are adopted from the recommender systems research field [39, 40] and have proven to improve rating prediction quality. A combination algorithm is also examined, which prunes the dataset and subsequently applies measurement weighting.

A. The Aging Algorithm

The aging algorithm operates similarly to a prediction algorithm [41, 42], except for the fact that when computing a prediction, each measurement is assigned a weight, based on its age: recent measurements are assigned higher weights, while older measurements are assigned lower ones. This approach is based on the rationale that older measurements may not accurately reflect the current state of subjects, thus their importance in the final prediction is attenuated.

More specifically, in this paper, we have used the standard normalization function [39, 43] of weighting old measurements, i.e. computing the age-based weight $w(m_{c,y})$ for measuring $m_{c,y}$ concerning country c in year y .

In more detail, the weight of a measuring $m_{c,y}$ using the standard normalization function is:

$$w(m_{c,y}) = \frac{y(m_{c,y}) - \min(x)}{\max(x) - \min(x)}$$

where $y(m_{c,y})$ is the year of measuring $m_{c,y}$; $\min(x)$ and $\max(x)$ denote the minimum and the maximum year in the database, respectively, among measurements entered for country c . The exploration of alternative aging methods, such as the sigmoid function [44], will be a part of our future work.

Afterwards, the prediction of a future measuring $m_{c,y}$ is computed as:

$$m_{c,y} = \frac{\sum_{y' \in Y} (w(m_{c,y'}) * m_{c,y'})}{\sum_{y' \in Y} w(m_{c,y'})}$$

where Y is the set of all years that a measuring for country c exist in the database.

Furthermore, if the importance of the more recent measurements in the final prediction should be further amplified, the factor of $w^e(m_{c,y})$ ($e > 1$) can be used, in the last formula, instead of the $w(m_{c,y})$; in our experiments, reported in section VI, we explored different values for the parameter e .

B. The Pruning Algorithm

The pruning algorithm operates similarly to a standard prediction algorithm [40], however it applies a preprocessing step to the dataset: this step retains only the N more recent measurements per subject (country), dropping all older ones. Then, the prediction equals to the average of these N measurements (without using any weights); in our experiments, reported in section VI, we explored different values for the parameter N .

C. The combined algorithm

The combined algorithm synthesizes the aging and the pruning algorithm into a single bundle. More specifically, the combined algorithm initially performs the preprocessing step of the pruning algorithm to the dataset, retaining only the N more recent measurements per subject (country). In the prediction

formulation phase, it computes and utilizes a weight per measurement, based on the measurement's age, as described in subsection *A* of section *V*.

VI. EXPERIMENTAL RESULTS

In this section, we report on our experiments through which we compared: (i) the aging algorithm presented in section 5.A, (ii) the pruning algorithm presented in section 5.B, (iii) a plain prediction algorithm whose prediction value equals to the average of all past values and (iv) a plain prediction algorithm whose prediction value equals to the closest, as far as time is concerned, value. This value, for counter terrorism preparedness organizations such as LEAs, is interpreted as a way to ensure that the current year expected number of attacks remains the same as last year's, thus the surveillance and alert level remain unchanged.

For this comparison, we used the mean absolute percentage error (MAPE) metric, which is defined as

$$\text{MAPE} = \frac{100\%}{N} * \sum_{N} \frac{|A_i - P_i|}{|A_i|}$$

where A_i is the actual value of item i , P_i is the predicted one and N the number of the measurements. To compute the MAPE, we employed the standard "hide one" technique [44, 45]: for each country in the database we hid its last measuring and then predicted its value based on the values of other non-hidden measurements. The MAPE was therefore computed by considering all countries in the database. The reason that only the last measurement was hidden and predicted pertains to the fact that the value of each prediction should be computed using only measurements that existed in the database at the time the measurement to be predicted was submitted. Furthermore, the work in this paper aims towards data-driven assessment of projected alert level and raising or lowering the surveillance level per country.

The main reason for opting for the MAPE metric, instead of the mean average error (MAE) metric, which is the most common one, is that the number of attacks varies between the

countries data in our experiment; e.g. Spain has a number of 5 attacks in 2015-2017, while at the same period Turkey has more than 500, hence the use of the MAE metric would lead to unreliable results.

The dataset used in our experiments [29] consists of attack data, such as date, country, region and city that the attack took place, weapon type, target type, casualties, etc. Since this work focuses on tourism-related attacks during the summer period in the Mediterranean-European countries, the dataset's records taken into account fulfill the time (June–September) and space criteria, where the target type values are contained in the tourist-related set, as described in Section III.

In order to produce more reliable results, we split the experiment into two parts. In the first part, we aim at tuning the parameters of the two algorithms presented in section V, as well as their combinations (pruning and aging at the same time) settings. Then, the setting of each algorithm, achieving the minimum MAPE value in the first experiment, is "qualified" to the second experiment.

Specifically, in the first experiment, for each country, we dropped its last measurement (2017) from the database and tried to predict the (current-) last measurement (2016) based on the previous ones (2000-2015), while in the second experiment we tried to predict the dataset's last (2017) measurement, for each country, based on all its previous ones (2000-2016), however only for the setting proved to be optimal in the first experiment, for each algorithm, as well as their optimal combination.

A. Algorithm tuning

As described above, in the first experiment we tested different e and N parameter values (recall from the previous section that the e parameter is the one used in the exponent of the aging algorithm, while the N parameter is the one used in the pruning algorithm, determining how many measurements we must take into account), as well as their combinations. In total, more than 30 value combinations were examined, however, we report only on the most indicative ones, for conciseness purposes. Fig. 10 illustrates the MAPE observed in these cases.

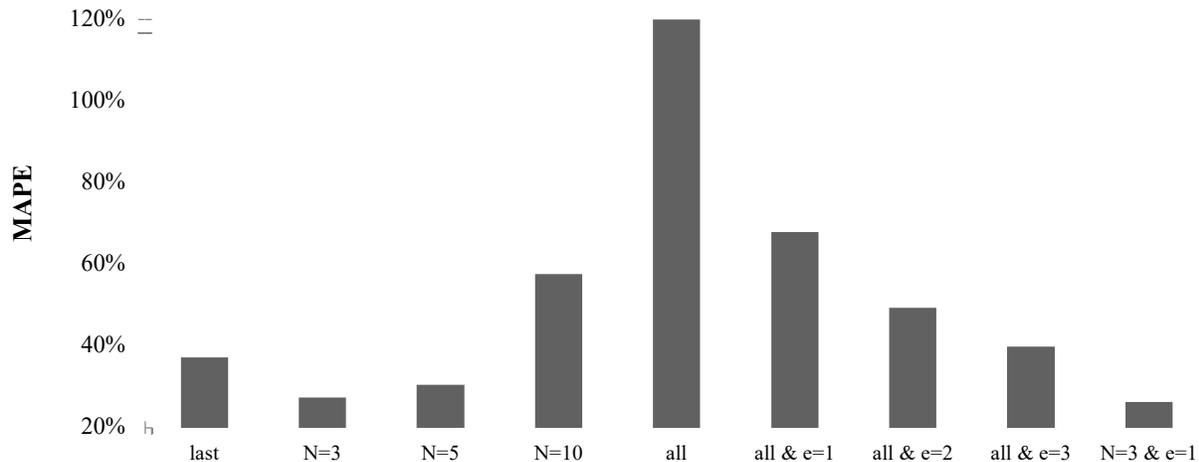


Fig. 10. Prediction MAPE under different e and N parameter values combinations, when trying to predict the 2016 attack incidents.

We can clearly see that the settings achieved the optimal results, for each algorithm, are the:

- $N=3$ (taking into account the 3 more recent measurements), for the pruning algorithm,
- $e=3$ (exponent factor set to 3) for the aging algorithm and
- $N=3$ and $e=1$, for the combination algorithm.

B. Performance evaluation

In the second experiment we tested the three settings qualified from the first experiment, along with the two plain prediction algorithms (average of past measurements and last measurement). Fig. 11 illustrates the MAPE observed in these five cases.

We can observe that the setting in which the last three measurements in the database are taken into account, per country, however without using any aging weights, is the one delivering the lowest prediction error (a deviation of 9.2 attacks, in absolute numbers). Specifically, this setting achieves a reduction of 32.8% (44.7% versus 66.5%) when compared to the one that takes into account the last (year's) measurement of each country (the deviation, in absolute numbers, is 12 attacks, in this case); hence the proposed algorithms achieve to improve prediction accuracy, facilitating the use of these predictions information or input for preparedness activities and possible alert status elevation from the authorities.

VII. CONCLUSION AND FUTURE WORK

In this paper, we have used past terrorist database information to analyse and visualise relations about tourism-related terrorist attacks. The past tourism-related attacks, when analysed and explored through the prism of *target types* and *attack types* can be a means to understand and predict near-future activity. This activity can be broken down to potential attack types and target types as well as visualise past trends to reveal potential targets and vulnerabilities. Moreover, such results can help visitors and citizens get an up-to-date, real view of risk, as well as help businesses and authorities plan on rebuilding safety and the perception of the people through resilience [46, 47].

Through informed, data-driven analysis, local and federal governments may prepare against targeted terrorist attacks that disrupt the operations, destabilise the countries and hinder the economy [48]. The influence of terrorism in the decisions of potential visitors, domestic or international is undeniable [49]. Authorities may use information and targeted terrorism predictions to shield against and ultimately prevent terrorism in tourist destinations [50]. The News may also use such information, to inform tourists, citizens and businesses on the real risks [51].

From the experimental results of this work, it was found that the optimal time window of attacks at a country, to be used in the prediction algorithm, is the last three years ($N=3$). Hence, this means that the observers of terrorist attack data, should optimally be taking the three-year time window into account when estimating the surveillance and alert preparation levels. This means that lower (or higher) numbers of recorded attacks in the year before the prediction is not by itself a reliable indicator for safety and risk levels.

Future work will focus on real-time predictions based on features from location, geographical and transport data, as well as social media streams. Social media can be mined and used to analyse sentiment of visitors, safety perception of actual tourists that have visited a location, as well as the perception of prospective visitors.

REFERENCES

- [1] The Organisation for Economic Co-operation and Development (OECD), <http://www.oecdbetterlifeindex.org/topics/safety/> (accessed 1 May, 2019).
- [2] Institute for Economics and Peace, <http://economicsandpeace.org/> (accessed May 31, 2019).
- [3] Global Terrorism Index (GTI), <http://globalterrorismindex.org/> (accessed May 31, 2019).
- [4] R. Pain, "Everyday Terrorism: Connecting Domestic Violence and Global Terrorism," *Progress in Human Geography*, vol. 38(4), pp. 531–550, 2014.
- [5] A. Gupta, "Terrorism and its Impact on Financial Performance: A Case of Tourism Industry," *International Journal of Financial Management*, vol. 1(4), pp. 46-52, 2011.
- [6] O.S. Goldman and M. Neubauer-Shani, "Does International Tourism Affect Transnational Terrorism?," *Journal of Travel Research*, vol. 56 (4), pp. 451–67, 2016.

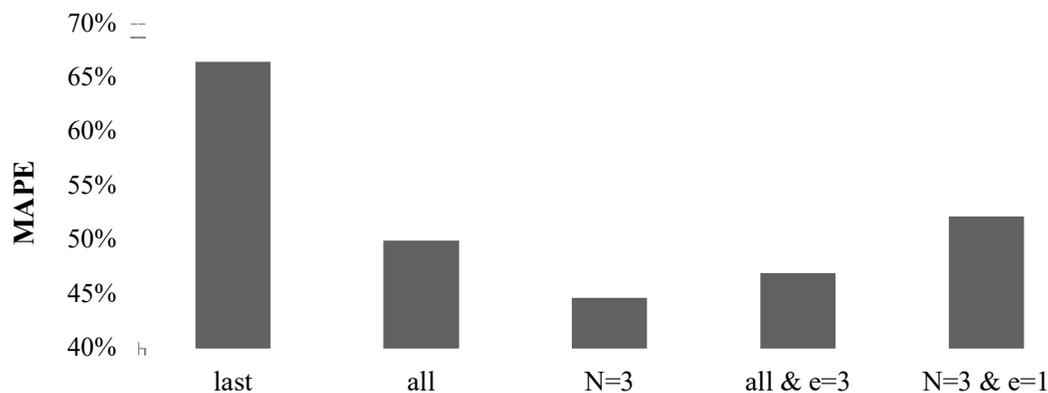


Fig. 11. Prediction MAPE under different e and N parameter values combinations, when trying to predict the 2017 attack incidents.

- [7] G. Fuchs, N. Uriel, A. Reichel and D. Maoz, "Vacationing in a Terror-Stricken Destination. Tourists' Risk Perceptions and Rationalizations", *Journal of Travel Research*, vol. 52(2), pp. 182-191, 2012.
- [8] M. Ranga and P. Pradhan, "Terrorism terrorizes tourism: Indian Tourism effacing myths?," *International Journal of Safety and Security in Tourism*, vol. 1(5), pp. 26-39, 2014.
- [9] C.E. Albu, "Tourism and Terrorism: a Worldwide Perspective," *CES Working Papers*, vol. 8(1), pp. 1-19, 2016.
- [10] M.E. Korstanje, "Preemption and terrorism. When the future governs," *Cultura*, vol. 10(1), pp. 167-184, 2013.
- [11] D. Meierrieks and T. Gries, "Causality between terrorism and economic growth," *Journal of Peace Research*, vol. 50(1), pp. 91-104, 2013.
- [12] J. Araña and C. León, "The Impact of Terrorism on Tourism Demand," *Annals of Tourism Research*, vol. 35(2), pp. 299-315, 2008.
- [13] N. Cavlek, "Tour operators and destination safety," *Annals of Tourism Research*, vol. 29(2), pp. 478-496, 2002.
- [14] A. Liu and S. Pratt, "Tourism's vulnerability and resilience to terrorism," *Tourism Management*, vol. 60, pp. 404-417, 2017.
- [15] K. Wolff and S. Larsen, "Can terrorism make us feel safer? Risk perceptions and worries before and after the July 22nd attacks," *Annals of Tourism Research*, vol. 44, pp. 200-209, 2014.
- [16] S. Larsen, W. Brun and T. Ogaard, "What tourists worry about. Construction of a scale measuring tourist worries," *Tourism Management*, vol. 30(2), pp. 260-265, 2009.
- [17] A. Pizam and A. Fleischer, "Severity versus Frequency of Acts of Terrorism: Which Has a Larger Impact on Tourism Demand?," *Journal of Travel Research*, vol. 40(3), pp.337-339, 2002.
- [18] S. Khan, "Gendered leisure: are women more constrained in travel for leisure?," *Tourismos: an international multidisciplinary journal of tourism*, vol. 6(1), pp. 105-121, 2011.
- [19] H. Seddighi and A. Theocharous, "A model of tourism destination choice: a theoretical and empirical analysis," *Tourism Management*, vol. 23(5), pp.475-487, 2002.
- [20] C. Seabra, S. Dolnicar, J. Abrantes and E. Kastenholz, "Heterogeneity in risk and safety perceptions of international tourists," *Tourism Management*, vol. 36, pp.502-510, 2013.
- [21] P. Burns, J. Lester and L. Bibbings, "Tourism and Visual Culture, Methods and Cases," vol. 2, CABI, 2010.
- [22] D. Margaris, C. Vassilakis and P. Georgiadis, "Query personalization using social network information and collaborative filtering techniques," *Future Generation of Computer Systems*, vol. 78, pp. 440- 450, 2018.
- [23] D. Margaris and C. Vassilakis, "Exploiting Rating Abstention Intervals for Addressing Concept Drift in Social Network Recommender Systems," *Informatics*, vol. 5(2), Article no. 21, 2018.
- [24] D. Antonakaki, D. Spiliotopoulos, C.V. Samaras, S. Ioannidis and P. Fragopoulou, "Investigating the Complete Corpus of Referendum and Elections Tweets," *Proceedings of the IEEE/ACM Conference on Advances in Social Networks Analysis and Mining*, pp. 100-105, 2016.
- [25] G. Schefbeck, D. Spiliotopoulos and T. Risse, "The Recent Challenge in Web Archiving: Archiving the Social Web," *Proceedings of the International Council on Archives Congress*, pp. 20-24, 2012.
- [26] D. Spiliotopoulos, E. Tzoannos, P. Stavropoulou, G. Kouroupetroglou and A. Pino, "Designing User Interfaces for Social Media driven Digital Preservation and Information Retrieval," *Proceedings of the 13th International Conference on Computers Helping People with Special Needs*, pp. 581-584, 2012.
- [27] D. Margaris and C. Vassilakis, "Exploiting Internet of Things Information to Enhance Venues' Recommendation Accuracy," *Service Oriented Computing & Applications*, vol. 11(4), pp. 393-409, 2017.
- [28] National Consortium for the Study of Terrorism and Responses to Terrorism (START), "Global Terrorism Database", <https://www.start.umd.edu/gtd> (accessed May 31, 2019).
- [29] G. LaFree and L. Dugan, "Introducing the global terrorism database," *Political Violence and Terrorism*, vol. 19, pp. 181-204, 2007.
- [30] L. Heger and F. Danielle, *Negotiating with Rebels: The Effect of Rebel Service Provision on Conflict Negotiations*. *Journal of Conflict Resolution*, vol. 61(6), pp. 1203-1229, 2017.
- [31] C. Chang and Y. Zeng, "Impact of Terrorism on Hospitality Stocks and the Role of Investor Sentiment," *Cornell Hospitality Quarterly*, vol. 52, pp. 165-175, 2011.
- [32] K. Drakos, "Terrorism Activity, Investor Sentiment, and Stock Returns," *Review of Financial Economics*, vol. 19, pp. 128-135, 2010.
- [33] R. Greenbaum, L. Dugan and G. LaFree, "The Impact of Terrorism on Italian Employment and Business Activity," *Urban Studies*, vol. 44, pp. 1093-1108, 2007.
- [34] C. Kollias, P. Messus, N. Mylonidis, and S. Paleologou, "Terrorism and the Effectiveness of security spending in Greece: Policy implications of some empirical findings," *Journal of Policy Modeling*, vol. 31, pp. 788-802, 2009.
- [35] G. LaFree and J. Hendrickson, "Build a criminal justice policy for terrorism," *Criminology and Public Policy*, vol. 6, pp. 781-790, 2007.
- [36] D. Antonakaki, D. Spiliotopoulos, C.V. Samaras, P. Pratikakis, S. Ioannidis and P. Fragopoulou, "Social media analysis during political turbulence," *PloS one*, vol. 12(10), pp. 1-23, 2017.
- [37] R. Dias and M. J. Fonseca, "Improving Music Recommendation in Session-Based Collaborative Filtering by Using Temporal Context," *Proceedings of the 25th IEEE International Conference on Tools with Artificial Intelligence*, pp. 783-788, 2013.
- [38] D. Margaris and C. Vassilakis, "Improving Collaborative Filtering's Rating Prediction Quality by Considering Shifts in Rating Practices," *Proceedings of the 19th IEEE International Conference on Business Informatics*, pp. 158-166, 2017.
- [39] D. Margaris and C. Vassilakis, "Pruning and Aging for User Histories in Collaborative Filtering," *Proceedings of the 7th IEEE Symposium Series on Computational Intelligence*, pp. 1-8, 2016.
- [40] D. Margaris and C. Vassilakis, "Enhancing User Rating Database Consistency through Pruning," *Transactions on Large-Scale Data- and Knowledge-Centered Systems*, vol. XXXIV, pp. 33-64, 2017.
- [41] C. Tofallis, "A better measure of relative prediction accuracy for model selection and model estimation," *Journal of the Operational Research Society*, vol. 66(8), pp. 1352-1362, 2015.
- [42] Y. Zhang and A. Haghani, "A gradient boosting method to improve travel time prediction," *Transportation Research Part C: Emerging Technologies*, vol. 58, pp. 308-324, 2015.
- [43] D. He and D. Wu, "Toward a robust data fusion for document retrieval," *Proceedings of the IEEE 4th International Conference on Natural Language Processing and Knowledge Engineering*, pp.1-8, 2008.
- [44] M.D. Ekstrand, J.T. Riedl and J.A. Konstan, "Collaborative Filtering Recommender Systems," *Foundations and Trends in Human-Computer Interaction*, vol. 4(2), pp. 81-173, 2011.
- [45] D. Margaris and C. Vassilakis, "Improving Collaborative Filtering's Rating Prediction Accuracy by Considering Users' Rating Variability," *Proceedings of the 4th IEEE International Conference on Big Data Intelligence and Computing*, pp. 1022-1027, 2018.
- [46] A. Cox, F. Prager, and A. Rose, "Transportation security and the role of resilience: A foundation for operational metrics," *Transport Policy*, vol. 18(2), pp. 307-317, 2011.
- [47] Z. Zemishlany, "Resilience and vulnerability in coping with stress and terrorism," *Israel Medical Association Journal*, vol. 14(5), pp. 307-309, 2012.
- [48] S. Sönmez, "Tourism, terrorism, and political instability," *Annals of Tourism Research*, vol. 25(2), pp. 416-456, 1998.
- [49] S. Sönmez and A. Graefe, "Influence of terrorism risk on foreign tourism decisions," *Annals of Tourism Research*. vol. 25(1), pp. 112-144, 1998.
- [50] A. Kılıçlar, A. Uşaklı, and A. Tayfun. "Terrorism prevention in tourism destinations: Security forces vs. civil authority perspectives," *Journal of Destination Marketing and Management*, vol. 8, pp. 232-246, 2018.
- [51] G. Kapuściński and B. Richards, "News framing effects on destination risk perception," *Tourism Management*, vol.57, pp. 234-244, 2016.