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On Recommending Safe Travel Periods to High Attack Risk Destinations

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

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

***Abstract*— Terrorism is a major disincentive to tourism. It affects both a country or area's tourists as well as local residents and staff. On the one hand, the prospective tourist is likely to avoid traveling to a high-risk country due to safety concerns, and thus lose the opportunity to visit it, while, on the other hand, the tourism of the country would decline. This work solves the above-mentioned problem by (1) showing that reasonably safe visits to high-risk countries can be predicted with high precision, using limited information, including data on attacks and fatalities from recent years, which is widely available, and (2) creating an algorithm that recommends these periods to potential travellers. The findings of this work would be useful for tourists, citizens, businesses and operators, as well as related stakeholders.**

Keywords—Terrorist Attacks, Safety Perception, Tourism, Risk Calculation, Safety Prediction, Recommendations

I. INTRODUCTION

Travelling agencies and individual travellers, nowadays, take into account terrorist attack reports before planning a trip abroad, in order to make sure that they are planning on visiting a safe destination. The term "safe destination" is used to denote cities, regions or countries that crime is not likely to happen [1].

Perceived destination safety is dependent on the recent past events, where both the frequency and severity of such events is recorder and hence measurable. Stakeholders that can use such information may include:

- countries and prospective visitors: they may utilize such information to gradually build trust between countries and visitors for tourism viability [2];
- businesses: such as tour operators, hotel managers, restaurants, bar/clubs, etc.;
- authorities: they may use this information by examining the relatively unsafe time periods and prepare accordingly to not only shield against but also prevent terrorism in tourist destinations [3] and
- the News: in order to inform tourists, citizens and businesses on safety [4].

Since terrorism is a targeted act, past data may prove useful for the derivation of patterns that create the terrorism attack footprint for a specific country. Fig. 1 depicts the frequency of recorded attacks and fatalities for Thailand in 2017, by analysing the data found in Global Terrorism Database (GTD) [5].

In this figure we can observe that there are periods of time that the terrorism activity is (sometimes much) lower (shown in blue in Fig. 1), rather than having a uniform terrorist activity over time in a year. Therefore, a service which recommends statistically low terrorism activity seasons, for someone to travel, would be more than desirable.

Towards this direction, previous work utilized past terrorism information, found in GTD and, more specifically, the number of tourism-related attacks, attack types and target types, in order to estimate the number of attacks a country may suffer in the following years, targeting at upgrading a country's safety measures and vice-versa [6]. More specifically, the two main findings of that work were:

1. the tourism-related attack patterns mostly followed the general attack patterns, and
2. the number of attacks of the last 3 years proved to be a simple yet effective predictor for the following year's attack number.

This paper extends the aforementioned work by presenting an algorithm which recommends statistically low terrorism activity periods, for a traveller, to visit high terrorist activity countries and hence elevating the state-of-the-art in this research subject from safety evaluation to active safe period recommendation. The experimental results show that the presented algorithm achieves to recommend low-risk attack visiting time slots for the majority of the countries applied.

It has to be mentioned that the presented recommendation algorithm (1) requires only basic information (target type and date of the attack, number of fatalities, etc.), hence it is applicable to most cases, and (2) can be enriched with additional input data that affect the terrorist attack events of a city, region or country, such as political, economic and social information.

The rest of the paper is structured as follows: section 2 overviews related work, while section 3 reports on the algorithm prerequisites that are used in our work. Section 4 presents the proposed recommendation algorithm. Section 5 evaluates the

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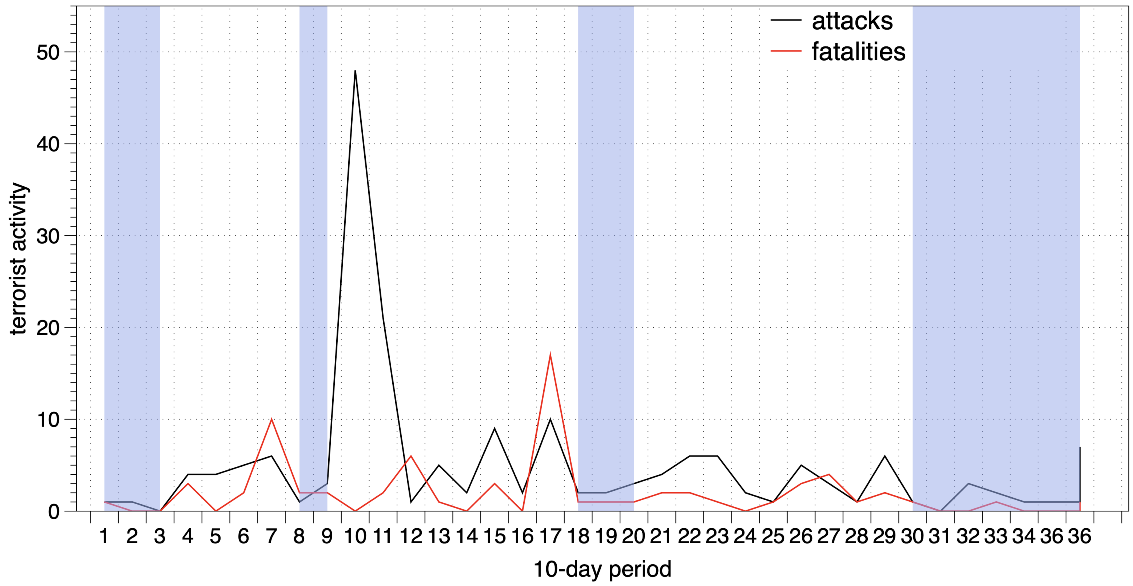

Fig. 1. Terrorist activity in Thailand in 2017 (source: GTD).

proposed algorithm and, finally, section 6 concludes the paper and outlines future work.

II. Related Work

As terrorism inspires fear, which spans across citizens and visitors alike, terrorism and tourism are negatively correlated with each other, in the literature [4,7,8].

Prior studies considered the role of protection in the appeal of travellers' worries, finding that well-being is an important and appealing consideration for holiday destinations [9]. This risk is regarded by prospective tourists as a quality factor which is as important as the attractiveness of the destination [10]. The travel industry is a significant source of income for tourist destinations and terrorists know that targeting tourist destinations may result in engaging the targeted countries into international politics [11,12].

Targeting the tourism sector impacts people who are directly active in the tourism sector and companies within the tourism market, as well as a significant portion of the economic partners that tacitly support the tourism industry, such as local producers; generally, the ecosystems of countries are heavily affected [13], [14]. Furthermore, it has been noted that acts of terrorism in one tourist destination have an impact on the tourism in several other destinations on the basis of locations, geopolitics, world affairs as well as other indicators [15].

Studies also indicate that there is a variation in the degree of effect of terrorist threats between upper and lower tourist activity locations [16]. High tourist activity destinations are strongly impacted in the short term but may rebound over time on the basis of conditions such as media attention, such as back-to-normal-life headlines, promotion, and visitor perseverance to threats [17,18]. On the other hand, low activity areas are negatively affected in the long term, the outcome being that the tourist industry ends up going out of business [19,20]. The consequence of terrorist attacks on the region is the downturn in tourism. This could take six months to a year for the local tourist economy to recuperate [21], depending on the rate that the safety perception of potential tourists is regained [22].

Tourists, in contrast to the local community, establish preferences and determine whether to visit a place based on previous experience and a general understanding of what they expect to encounter [23]. As such, vacationers are prime terrorism targets [24]. The media, which report on the international impact, are also associated in tourism and terrorism [25].

With the recent rise in terrorist attacks, anticipating potential terrorist attacks is an important goal of governments and communities. Public opinion is increasingly endorsing measures aimed at preventing and defending people from terrorism [26]. Understanding the dynamics of terrorism is a crucial move in anticipating terrorist attacks [27]. Several studies use machine learning, statistics and big data analytics to identify trends and forecast terrorist attacks [28-32]. Xia and Guo [33] utilized the GTD data to build a terrorism knowledge graph. Yang et al. [34] built a model to predict the lethality of terrorist attacks and tested it using the GTD data. All of the above works aim to predict terrorist activity, such as high levels of terrorist violence or incidents and associated metrics, such as fatalities. Recently, the work in Spiliotopoulos et al. [6] utilized past terrorism limited information, such as the number of tourism-related attacks, types of targets and forms of attacks, for predicting the number of attacks that a country may sustain in the years ahead, suggesting that a prediction of terrorist attacks is realistic.

None of the above listed works explore the aspect of prediction of safer periods from terrorism. Thus, prospective travellers cannot utilise the information to be guided accordingly when planning to visit a place. The prospective visitor would benefit from knowing an anticipated period of predicted safety, particularly for countries that have had a considerable number of terrorist attacks in the past years.

This article advances the state-of-the-art on the prediction of terrorism activity by examining trends of terrorist attacks in order to suggest reasonably secure travel times to high-risk destinations. Being able to recommend low activity time periods is a unique service to travellers and tourism businesses to attract visitors.

The results of the study reflect the assertion that very minimal evidence from past terrorism data can be used to establish recommendations for timeframes that are more likely to be safe (higher anticipated safety) for high-risk terrorist attack destinations. Apart from the apparent immediate effect on visitor choice of a safer travel time, such information may be used to filter time-series data such as social media data streams or surveillance data, may those be gathered through social networks [35-37] or other data sources, such as the IoT [38], [39], to focus on specific points in time.

III. Algorithm Prerequisites

The study of the GTD by Spiliotopoulos et al. [6] was based on tourism. It used a subset of GTD data containing information related to tourism. As an example, Fig. 2 juxtaposes the tourist-related attacks with the total volume of attacks in France (top) and Spain (bottom) over the course of 18 years (2000-2017).

A rather substantial percentage of the attacks in France and Spain were linked to tourism, i.e. the incidents affected areas where visitors will be, rather than targeting empty government facilities in isolated areas. Nevertheless, it was also demonstrated that the trends of tourism-related attacks largely followed the trends of general attacks.

The prediction algorithm performed well for the tourist data subset. Since the pattern of the tourist data is similar to the pattern of the full dataset, we opted to use the full data to validate the proposed algorithm.

The second finding of the work by Spiliotopoulos et al. [6] was the predictor data range. The results of that work showed that the data (tourist-related) of the last 3 years, and more specifically the accumulated attack number, is a simple, yet effective and reliable predictor. That result was derived by using pruning techniques for enhancing prediction accuracy in recommender systems [40,41].

The proposed algorithm is therefore designed to use the GTD data for the last 3 years. No additional information or data source shall be considered for the purpose of this study.

The purpose of this work is to create a recommender using very limited information (number of attacks and time) that can be easily obtained from the GTD or similar commonly available source. The proposed algorithm is therefore optimized for stand-alone, broad-based use and is highly scalable due to limited knowledge requirements. The proposed method, however, can

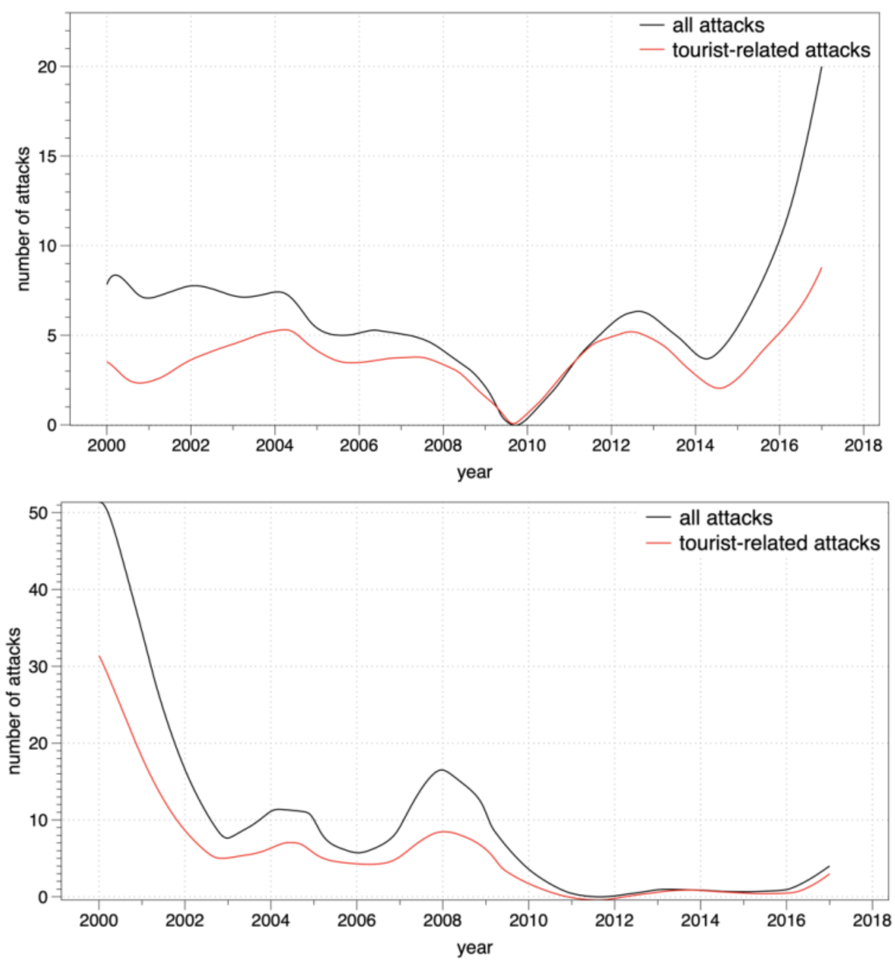

Fig. 2. Tourist-related vs. total number of attacks for France (top) and Spain (bottom), 2000-2017.

also be combined with other works that use multi-source data or enriched intelligence for enhanced accuracy and reliability.

IV. Prediction Algorithm

The aim of this work is to design an algorithm to predict safe periods for travel to a country, based on the limited information described in the previous sections. Tourism statistics show a variation of the number of days that visitors spend per country. Eurostat reports that for the EU-28 the number of days span from 1.4 to 20.8, with an average of 6.1 days per visitor [42]. Therefore, a 10-day window for safe timeslot prediction is a suitable baseline for our work.

The operation of the algorithm is divided in 2 phases, described in the following paragraphs.

A. Phase 1—histogram creation

In the first phase, the algorithm populates a histogram array regarding the number of incidents (attacks) that have occurred in each period of the year for all countries. Periods of years correspond to a duration equal to one third of month (BEGINNING, MIDDLE, END), thus totalling to 36 periods per year. It takes as input the set of countries, and the incident dataset (that have occurred in the last three years, following the work in Spiliotopoulos et al. [6]. Each incident has a "date" field, indicating when the incident occurred and a "country" field, designating the country. It gives as output the array of histograms, indexed by the country.

B. Phase 2—online operation:

In the second phase, the algorithm generates a recommendation for the safest period of the year to visit a country. It takes as input the country for which the recommendation will be generated, and the array of histograms computed. It gives as output the recommended period of the year, computed as the period with the fewest incidents

The idea behind the presented algorithm is to create a total of 36 10-day slots (three per month, marking the start, middle and end of each month) and recommend the period corresponding to the slot having the smallest number of accumulated attacks over the last 3 years.

In the next section, we assess the performance of the aforementioned recommendation algorithm, in terms of predicting safe visiting periods for high terrorist attack risk countries.

V. Experimental Results

In this section, we report on the experiments that were designed to measure the accuracy of the proposed algorithm on recommending safe periods for visiting countries with high terrorism attack risk. More specifically, from the GTD dataset, we selected the 40 countries that have had the most attacks over the last years. The list of the 40 countries includes Iraq, Egypt, USA, Israel, Turkey and France.

Since (1) the GTD dataset contains attacks until 2017, and (2) based on the work in Spiliotopoulos et al. [6], taking into account the attacks of the last three years proved to be the optimal predictor for the volume of attacks that will happen in the next year, we store in a separate file the attacks that occurred between 2014 and 2016, for the aforementioned 40 countries, targeting at recommending a relatively safe period for the year 2017, for each of the 40 countries. The real data for year 2017 is then used to assess the quality of the recommendation, i.e. whether the algorithm achieved to recommend a period with 'few' incidents.

In order to provide a better service for the potential visitors, we adjust the algorithm to recommend a total of two periods (instead of just one), as alternative option recommendation for the period of visit.

In this experiment, we use the following evaluation metrics for the periods recommended by our algorithm:

1. The number of the incidents that took place in the proposed period, when compared to the average attack number per period per country (#attacks in 2017 / 36). This metric will be denoted as RNoI (Relative Number of Incidents). A recommendation is considered successful when its RnoI value is less than 100.0% (i.e.

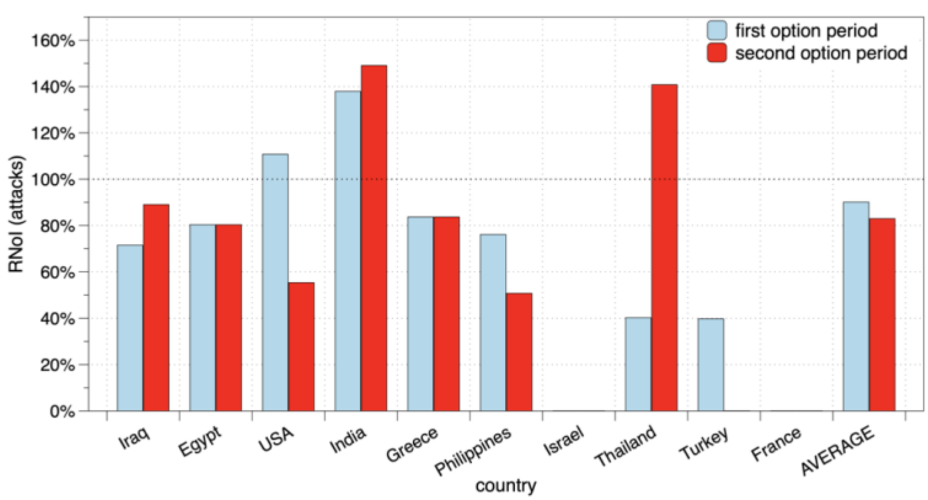

Fig. 3. RNoI results for primary and secondary predictions.

less than the average number of attacks per 10-day period).

2. The normalized number of incidents (denoted as NNoI) that occurred in the proposed period; normalization is performed using min-max normalization formula, according to which the normalized number for incidents for country c and period per is computed as $\mathrm{NNoI(per, c)} = \frac{NI(per,c) - \min_p NI(p,c)}{\max_p NI(p,c) - \min_p NI(p,c)}$, where NI(per,c) denotes the number of incidents that occurred in country *c* during period *per* and *p* the set of all (36) periods. A recommendation is considered successful when its NNoI value is less than 0.5.

3. The quartile that the recommended period belongs to, for each country. A recommendation is considered successful when a period belongs to either Q1 (very successful) or Q2 (successful).

In the remainder of this section, we present and discuss the results obtained from applying the algorithm presented above to the 40 countries, using the three aforementioned metrics.

Fig. 3 illustrates the results of the experiments, regarding the RNoI metric for 10 indicative cases (10 countries out of the 40 ones tested). The average value of the all the countries tested in our experiment is also included. It has to be mentioned that, within the 10 indicative cases, we opt to include countries with high tourism activity, such as France (no. 1), United States (no. 3) and Turkey (no. 6) in the international tourism arrival list, according to the Eurostat [42].

We can observe that the average number of the RNoI value of the 40 countries is 86.5% (90% for the first recommended period and 83% for the second), while for the 66.3% of the 80 recommendations produced (40 countries X 2 recommendations per country), the RNoI value was found to be less than 100% (indicating a successful recommendation).

Furthermore, we can clearly see that for the cases of France and Israel, the proposed algorithm achieved to recommend two periods with zero attacks for both, despite the number of attacks those countries had in 2017, 77 and 401 attacks respectively.

More specifically, in the case of France, the proposed algorithm recommended, as safe visiting periods, the middle and the end of February, i.e. the 5th and 6th 10-day period of the year (as indicated in Fig. 4).

Moreover, in the case of Turkey, a country where 1058 attacks occurred in 2017, the proposed algorithm achieves to recommend periods with only 12 attacks and 0 attacks, for the first and second recommendation, respectively. Considering that the average number of attacks in a 10-day period is 29.39 (i.e. 1058/36), these recommendations are deemed as very successful.

Fig. 5 illustrates the two periods proposed for visiting Turkey (end of February and middle of November, corresponding to the 6th and 32nd 10-day period of the year), along with a graph depicting the number of attacks and fatalities throughout the year.

Fig. 6 illustrates the results of NNoI metric, for the same 10 indicative cases, including the average value for all countries tested in our experiment.

We can observe that the average NNoI value of the 40 countries tested is 25.9%, while in the 87.5% of the (80) recommendations generated, the relative number is less than 50% (indicating a successful recommendation). Furthermore, considering the 10 countries illustrated in Fig. 6, only the two recommendations for India are categorized as not successful, hence overall the algorithm is deemed accurate, using this metric, as well. A deeper investigation of the reasons that have led to the formulation of the two non-successful recommendations will be performed in our future work.

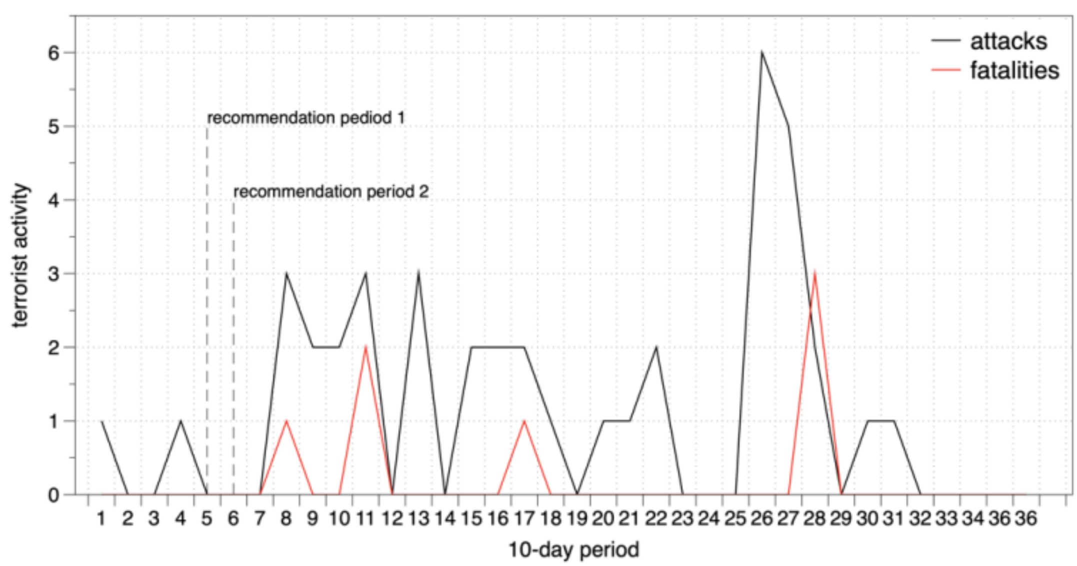

Fig. 4. Recommended periods of safety for France.

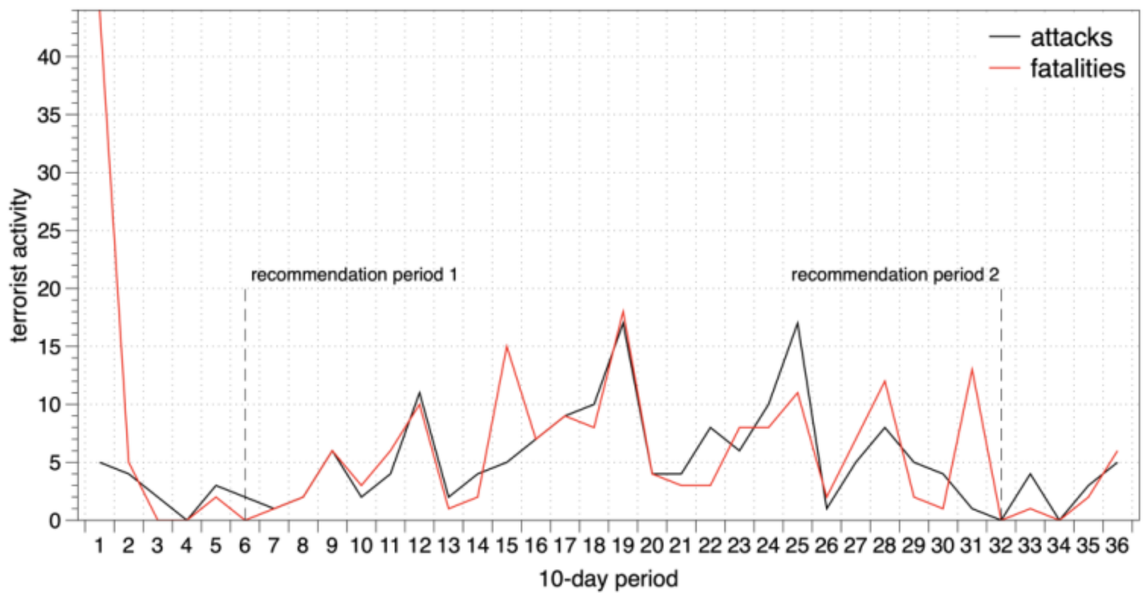

Fig. 5. Recommended periods of safety for Turkey.

Fig. 7 illustrates the results of the evaluation under the third metric, i.e., the quartile that each recommended period belongs to, for the same 10 indicative cases. The average value for all countries considered in our experiment is included.

Finally, Fig. 8 presents the aggregate results for all recommendations generated (80 in total = 40 countries X 2 recommendations per country).

We can observe that more than 2/3 of the recommendations (68.70%) are considered successful (Q1 and Q2), while only the 18.70% belongs to the Q4, meaning that the recommendation is considered very unsuccessful, actually recommending a period with high attack risk to the visitors. The investigation and handling of this phenomenon is part of our future work, as well. At country level, we can see that only 3 out of the 20 cases that Fig. 7 presents are categorized in Q4, however 8 of them are categorized in Q1, while all the others in Q2.

VI. Conclusion And Future Work

In this work, a recommendation algorithm that produces secure travel times over a 10-day span, without season limitations, has been introduced. This algorithm uses GTD data from past years, concerning past terrorist attack information, to predict future terrorist activity. The recommendations produced are useful for both visitors and locals to access a real view of risk and safety and also beneficial for industries and governments to prepare to restore safety and the perception of people through resilience [43,44].

The proposed algorithm is capable of operating with limited knowledge, in our case the number of attacks of the last three years, implementing the proposition of the work by Spiliotopoulos et al. [6]. It is a straightforward and reliable recommender that can be easily applied in many situations, from pilgrims visiting a spiritual site to a football team on their way to a friendly game.

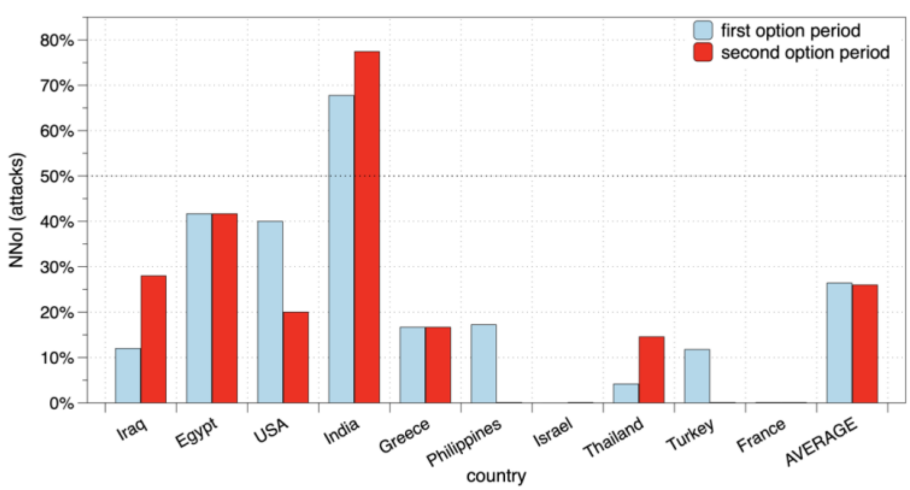

Fig. 6. NNoI results for primary and secondary predictions.

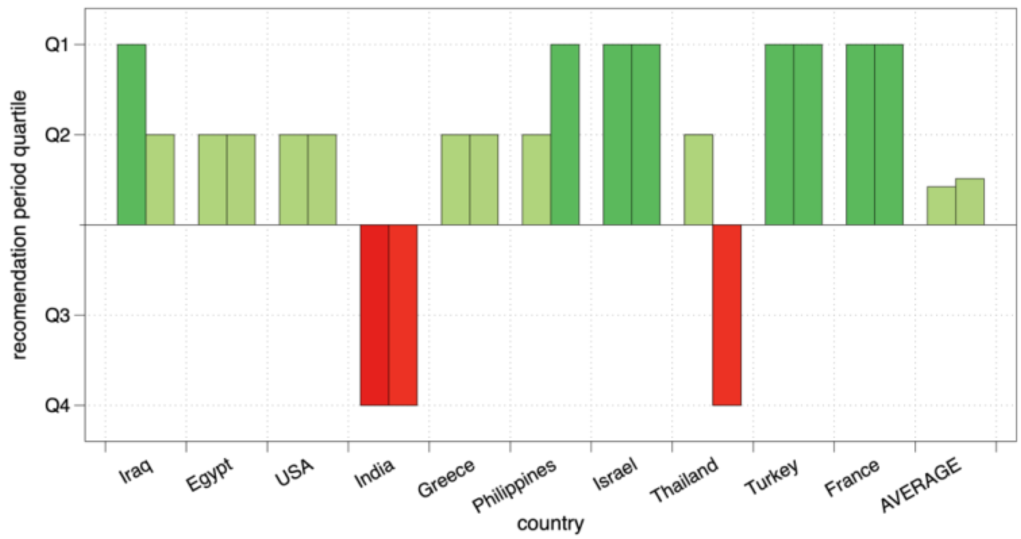

Fig. 7. Recommended period success for various countries when classifying the number of attacks into quartiles. For each country, the left value is the first recommended period and the right value is the second recommended period

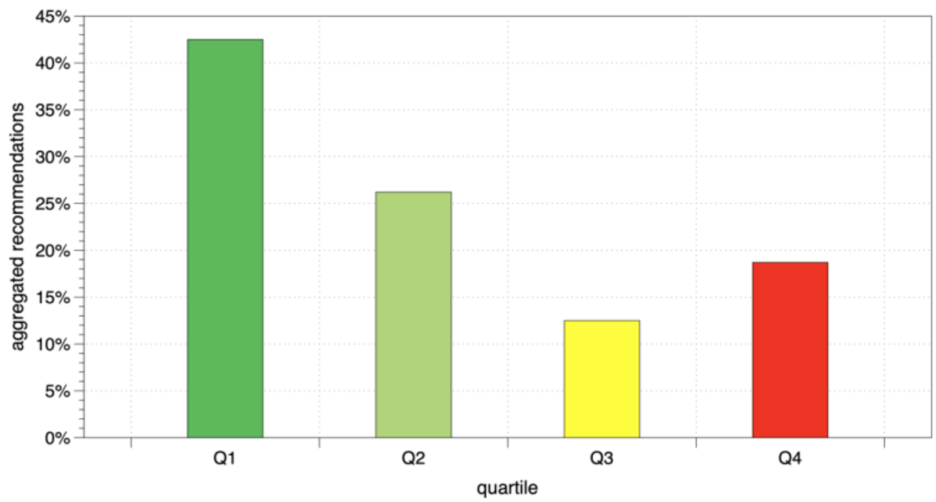

Fig. 8. Aggregated recommendations into quartiles for all countries.

The algorithm was experimentally validated using the data from the 40 most-attacked countries in the 2014-2016 timespan. The results of the evaluation indicated that, for the majority of cases, the 10-day periods of predicted safety were regarded to have been an accurate illustration. The algorithm was evaluated using three assessment metrics, the relative number of incidents, the normalized number of incidents, and the statistical quartile of the recommendation. In all cases, at least the 2/3 of the recommendations were considered successful, by all three metrics, at the same time. Furthermore, in 42.5% of the cases, the recommended 10-day visiting period was considered very successful, since the number of attacks/fatalities was extremely low, for that country, or even zero (as in the case of France).

Our future work will focus on utilising social network streams, location features, transport and geographical data for real-time predictions [45-48]. Geolocation, multimedia and text content can also be analysed [49-52] for the sentiment of local citizens and visitors for modelling their perception of safety, worry or fear, towards a prospective visit to a country.

References

[1] S. F. Sönmez and A. R. Graefe, "Influence of terrorism risk on foreign tourism decisions," *Ann. Tour. Res.*, 1998.

[2] S. F. Sönmez, "Tourism, terrorism, and political instability," *Ann. Tour. Res.*, 1998.

[3] A. Kılıçlar, A. Uşaklı, and A. Tayfun, "Terrorism prevention in tourism destinations: Security forces vs. civil authority perspectives," *J. Destin. Mark. Manag.*, 2018.

[4] G. Kapuściński and B. Richards, "News framing effects on destination risk perception," *Tour. Manag.*, 2016.

[5] G. LaFree and L. Dugan, "Introducing the Global Terrorism Database," *Terror. Polit. Violence*, vol. 19, no. 2, pp. 181–204, Apr. 2007.

[6] D. Spiliotopoulos, C. Vassilakis, and D. Margaris, "Data-driven country safety monitoring terrorist attack prediction," in *Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, 2019, pp. 1128–1135.

[7] A. Samitas, D. Asteriou, S. Polyzos, and D. Kenourgios, "Terrorist incidents and tourism demand: Evidence from Greece," *Tour. Manag. Perspect.*, vol. 25, pp. 23-28., 2018.

[8] S. A. Asongu, J. Nnanna, N. Biekpe, and P. N. Acha-Anyi, "Contemporary drivers of global tourism: evidence from terrorism and peace factors," *J. Travel Tour. Mark.*, vol. 36, no. 3, pp. 345–357, Mar. 2019.

[9] G. Walters, A. Wallin, and N. Hartley, "The Threat of Terrorism and Tourist Choice Behavior," *J. Travel Res.*, 2019.

[10] O. S. Goldman and M. Neubauer-Shani, "Does International Tourism Affect Transnational Terrorism?," *J. Travel Res.*, vol. 56, no. 4, pp. 451–467, Apr. 2017.

[11] C. E. Albu, "Tourism and Terrorism: A Worldwide Perspective," *CES Work. Pap.*, vol. 8, no. 1, pp. 1–19, 2016.

[12] G. Fuchs, N. Uriely, A. Reichel, and D. Maoz, "Vacationing in a Terror-Stricken Destination: Tourists' Risk Perceptions and Rationalizations," *J. Travel Res.*, vol. 52, no. 2, pp. 182–191, 2013.

[13] M. E. Korstanje, "Terrorists Tend to Target Innocent Tourists," *Int. J. Cyber Warf. Terror.*, vol. 5, no. 3, pp. 45–54, Jul. 2015.

[14] D. Meierrieks and T. Gries, "Causality between terrorism and economic growth," *J. Peace Res.*, vol. 50, no. 1, pp. 91–104, Jan. 2013.

[15] J. E. Araña and C. J. León, "The impact of terrorism on tourism demand," *Ann. Tour. Res.*, vol. 35, no. 2, pp. 299–315, Apr. 2008.

[16] S. A. Asongu, J. I. Uduji, and E. N. Okolo-Obasi, "Tourism and insecurity in the world," *Int. Rev. Econ.*, vol. 66, no. 4, pp. 453–472, Dec. 2019.

[17] N. Cavlek, "Tour operators and destination safety," *Ann. Tour. Res.*, vol. 29, no. 2, pp. 478–496, Apr. 2002.

[18] A. Liu and S. Pratt, "Tourism's vulnerability and resilience to terrorism," *Tour. Manag.*, vol. 60, pp. 404–417, 2017.

[19] K. Wolff and S. Larsen, "Can terrorism make us feel safer? Risk perceptions and worries before and after the July 22nd attacks," *Ann. Tour. Res.*, vol. 44, pp. 200–209, Jan. 2014.

[20] S. Larsen, W. Brun, and T. Øgaard, "What tourists worry about – Construction of a scale measuring tourist worries," *Tour. Manag.*, vol. 30, no. 2, pp. 260–265, Apr. 2009.

[21] A. Pizam and A. Fleischer, "Severity versus Frequency of Acts of Terrorism: Which Has a Larger Impact on Tourism Demand?," *J. Travel Res.*, vol. 40, no. 3, pp. 337–339, Feb. 2002.

[22] S. Khan, "Gendered leisure: are women more constrained in travel for leisure?," *Tour. an Int. Multidiscip. J. Tour.*, vol. 6, no. 1, pp. 105–121, 2011.

[23] H. R. Seddighi and A. L. Theocharous, "A model of tourism destination choice: a theoretical and empirical analysis," *Tour. Manag.*, vol. 23, no. 5, pp. 475–487, Oct. 2002.

[24] C. Seabra, S. Dolnicar, J. L. Abrantes, and E. Kastenholz, "Heterogeneity in risk and safety perceptions of international tourists," *Tour. Manag.*, vol. 36, pp. 502–510, Jun. 2013.

[25] S. Marschall, "'Personal memory tourism' and a wider exploration of the tourism−memory nexus," *J. Tour. Cult. Chang.*, vol. 10, no. 4, pp. 321–335, Dec. 2012.

[26] T. S. Rai, "Predicting future terror attacks," *Science (80-.).*, vol. 366, no. 6467, pp. 834 LP – 835, Nov. 2019.

[27] M. Hao, D. Jiang, F. Ding, J. Fu, and S. Chen, "Simulating Spatio-Temporal Patterns of Terrorism Incidents on the Indochina Peninsula with GIS and the Random Forest Method," *ISPRS Int. J. Geo-Information*, vol. 8, no. 3, p. 133, Mar. 2019.

[28] X. Meng, L. Nie, and J. Song, "Big data-based prediction of terrorist attacks," *Comput. Electr. Eng.*, vol. 77, pp. 120–127, 2019.

[29] H. Mo, X. Meng, J. Li, and S. Zhao, "Terrorist event prediction based on revealing data," in *2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA)(*, 2017, pp. 239–244.

[30] J. Troian, T. Arciszewski, and T. Apostolidis, "The dynamics of public opinion following terror attacks: Evidence for a decrease in equalitarian values from Internet Search Volume Indices," *Cyberpsychology J. Psychosoc. Res. Cybersp.*, vol. 13, no. 3, Jul. 2019.

[31] F. Ding, Q. Ge, D. Jiang, J. Fu, and M. Hao, "Understanding the dynamics of terrorism events with multiple-discipline datasets and machine learning approach," *PLoS One*, vol. 12, no. 6, p. e0179057, Jun. 2017.

[32] P. Agarwal, M. Sharma, and S. Chandra, "Comparison of Machine Learning Approaches in the Prediction of Terrorist Attacks," in *2019 Twelfth International Conference on Contemporary Computing (IC3)*, 2019, pp. 1–7.

[33] T. Xia and Y. Gu, "Building Terrorist Knowledge Graph from Global Terrorism Database and Wikipedia," in *2019 IEEE International Conference on Intelligence and Security Informatics (ISI)*, 2019, pp. 194–196.

[34] Y. Yang, A. R. Pah, and B. Uzzi, "Quantifying the future lethality of terror organizations," *Proc. Natl. Acad. Sci.*, vol. 116, no. 43, pp. 21463–21468, Oct. 2019.

[35] M. Aivazoglou *et al.*, "A fine-grained social network recommender system," *Soc. Netw. Anal. Min.*, vol. 10, no. 1, p. 8, Dec. 2020.

[36] D. Margaris, C. Vassilakis, and D. Spiliotopoulos, "Handling uncertainty in social media textual information for improving venue recommendation formulation quality in social networks," *Soc. Netw. Anal. Min.*, vol. 9, no. 1, p. 64, Oct. 2019.

[37] W. Deng, Y. Shi, Z. Chen, W. Kwak, and H. Tang, "Recommender system for marketing optimization," *World Wide Web*, pp. 1–21, Nov. 2019.

[38] C. Vassilakis *et al.*, "A Semantic Mixed Reality Framework for Shared Cultural Experiences Ecosystems," *Big Data Cogn. Comput.*, vol. 4, no. 2, p. 6, Apr. 2020.

[39] D. Margaris and C. Vassilakis, "Exploiting Internet of Things information to enhance venues' recommendation accuracy," *Serv. Oriented Comput. Appl.*, vol. 11, no. 4, pp. 393–409, 2017.

[40] D. Margaris and C. Vassilakis, "Enhancing User Rating Database Consistency Through Pruning," *Trans. Large-Scale Data- Knowledge-Centered Syst. XXXIV, Lect. Notes Comput. Sci.*, vol. 10620, pp. 33–64, Oct. 2017.

[41] D. Margaris and C. Vassilakis, "Improving collaborative filtering's rating prediction quality in dense datasets, by pruning old ratings," in *Proceedings - IEEE Symposium on Computers and Communications*, 2017, pp. 1168–1174.

[42] Eurostat, "Tourism Statistics," *https://ec.europa.eu/eurostat/statistics-explained/index.php/Tourism_statistics (accessed 21 June 2020)*, 2017.

[43] A. Cox, F. Prager, and A. Rose, "Transportation security and the role of resilience: A foundation for operational metrics," *Transp. Policy*, vol. 18, no. 2, pp. 307–317, Mar. 2011.

[44] S. Maguen, A. Papa, and B. T. Litz, "Coping with the threat of terrorism: A review," *Anxiety, Stress. Coping*, vol. 21, no. 1, pp. 15–35, Jan. 2008.

[45] D. Spiliotopoulos, D. Margaris, and C. Vassilakis, "Data-Assisted Persona Construction Using Social Media Data," *Big Data Cogn. Comput.*, vol. 4, no. 3, p. 21, Aug. 2020.

[46] D. Margaris, A. Kobusinska, D. Spiliotopoulos, and C. Vassilakis, "An Adaptive Social Network-Aware Collaborative Filtering Algorithm for Improved Rating Prediction Accuracy," *IEEE Access*, vol. 8, no. 1, pp. 68301–68310, 2020.

[47] D. Margaris, D. Spiliotopoulos, and C. Vassilakis, "Social Relations versus Near Neighbours: Reliable Recommenders in Limited Information Social Network Collaborative Filtering for Online Advertising," in *Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2019)*, 2019, pp. 1160–1167.

[48] D. Margaris, C. Vassilakis, and P. Georgiadis, "Recommendation information diffusion in social networks considering user influence and semantics," *Soc. Netw. Anal. Min.*, 2016.

[49] D. Margaris, C. Vassilakis, and D. Spiliotopoulos, "What makes a review a reliable rating in recommender systems?," *Inf. Process. Manag.*, vol. 57, no. 6, p. 102304, Nov. 2020.

[50] D. Margaris, D. Spiliotopoulos, C. Vassilakis, and G. Karagiorgos, *A user interface for personalized web service selection in business processes*, vol. 12427 LNCS. 2020.

[51] E. Makri, D. Spiliotopoulos, C. Vassilakis, and D. Margaris, "Human behaviour in multimodal interaction: main effects of civic action and interpersonal and problem-solving skills," *J. Ambient Intell. Humaniz. Comput.*, Mar. 2020.

[52] D. Margaris, C. Vassilakis, and P. Georgiadis, "Knowledge-Based Leisure Time Recommendations in Social Networks," in *Current Trends on Knowledge-Based Systems*, 2017, pp. 23–48.