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# Predicting Terror Attacks? A Network Story

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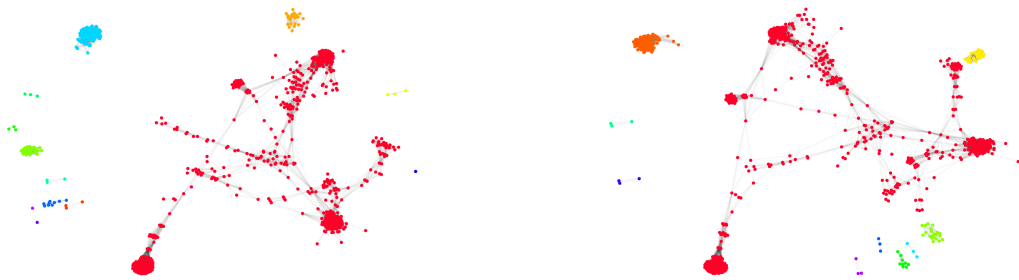
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## 1 Introduction

## 2 Exploring the Data

### 2.1 Relationships Dataset



(a) Terrorist relations graph, colouring by component ID

(b) Ten biggest components from the terrorist relation graph

Figure 1: *Graphs of the terrorist relations dataset*

## 2.2 Terror Attacks Dataset

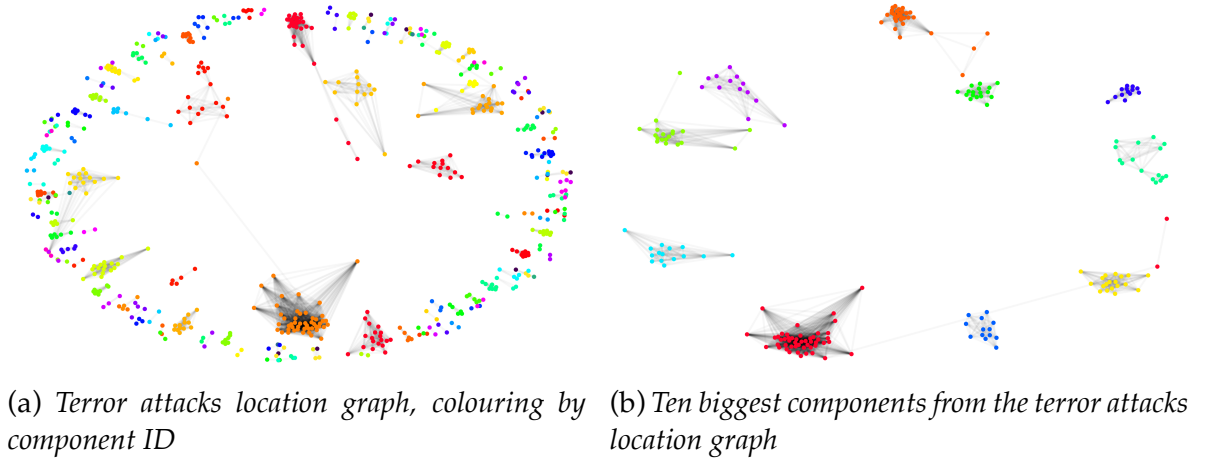


Figure 2: *Graphs from the terror attacks dataset*

The formation of the network implies a transitive relation between most of the nodes. Indeed, if for most nodes, take  $a$ ,  $b$  and  $c$  in the network, we have

$$a \sim b \text{ and } b \sim c \text{ then } a \sim c \quad (1)$$

Equivalently, if attack  $a$  took place close to  $b$ , and attack  $b$  took place close to  $c$ , then it is probable that attack  $a$  took place close to  $c$ .

## 3 Data Quality

### 3.1 Terror Attacks Dataset

Multiple issues regarding data quality have been found in this dataset:

**Breadth** The dataset comprises attacks ranging from 1969 to 1950 and spanning the entire globe. Simple and relevant explanations for the graph formation or properties are not likely to be found, since the mechanisms behind two different attacks can be entirely different.

**Structure** Half of the nodes are isolated, hence the topological information they carry in the graph is very limited. What is more, because of the transitivity relation described in Section 2.2, connected components are in most of the cases complete, hence isotropic.

**Reliability** Errors have been found in the data. For example nodes `Djibouti_Youth_Movement_19900927` and `Armed_Islamic_Group_19950711` have been connected, whereas the first attack took place in Djibouti [1] and the second one in Paris [2]. Hence algorithms using the data must tolerate some error in order to avoid overfitting.

## 4 Predictions

The algorithm used to predict the terror attack location is the following:

1. From the dataset, select the 10 biggest connected components (“component” in what follows).
2. Sort the dataset by date of terror attack.
3. At this point, a component represents a location, and the nodes are the terror attacks in chronological order.
4. Select one node per component that is strongly connected to the others, the “lead” node.
5. Find the lead node  $l^*$  that is the most strongly linked to the new node (i.e. the next terror attack).
6. The predicted location of the next terror attack is the location of the component  $l^*$  belongs to.

The determination of the lead node uses the features vector supplied with each node, and a weighting function  $w$ . Let  $w$  be the application that returns a weight for each pair of nodes  $(n_1, n_2)$  in the graph  $\mathcal{G}$ , defined as

$$w : \mathcal{G}^2 \rightarrow \mathbb{R}^+ \quad (2)$$

$$(n_1, n_2) \mapsto f(|n_1 - n_2|) \quad (3)$$

where

$$|n_1 - n_2| = \|\text{features}(n_1) - \text{features}(n_2)\|_2 \quad (4)$$

$\text{features}(n)$  is a binary features vector for each node  $n$  in  $\mathcal{G}$  and  $f : \mathbb{R}^+ \mapsto \mathbb{R}^+$  is the node distance weighting. Examples for  $f$  are given in Table 1.

For each connected component, the lead node is determined as described below.

*Algorithm 1: Finding the lead node of a connected component with weighted edges*

**Data:** Connected component  $C$

**Result:** Lead node  $n_l$

Initialise  $s(n)$  to zero.  $s$  is a dictionary mapping a score  $s(n)$  for each node  $n$

**for each edge  $e$  from  $C$  do**

    Let  $e = (n_1, n_2)$ ,  $w$  be the weight of  $e$

$s(n_1) \leftarrow s(n_1) + w$

$s(n_2) \leftarrow s(n_2) + w$

**end**

**return**  $n_l = \arg \max_{n \in C} s(n)$

Finally, the prediction algorithm is presented below.

*Algorithm 2: Finding the predicted location of the next terror attack*

**Data:** Set of connected components  $\{C_i^t\}, i = 1, \dots, 10$ , and the features vector of the next terror attack  $n_{t+1}$ , i.e.  $\text{feature}(n_{t+1})$ , at each timestep  $t$

**Result:** Location prediction  $p_t$  for time  $t + 1$  at time  $t$ , at each timestep  $t$

**for each timestep  $t$  do**

    Compute the lead component  $l(C_i^t)$  for each component  $C_i^t$

$p_t = \arg \max_{i=1, \dots, 10} w(n_{t+1}, l(C_i^t))$

**end**

**return**  $p_t$

## 4.1 Justification

- topology
- formation, not labelling
- robustness

## 4.2 Results

Table 1: *Prediction accuracy for different node distance weightings  $f$*

Weighting		Best skewness $\zeta$	Accuracy
Gaussian:	$f(d) = e^{-d^2/\zeta} - e^{-1/\zeta}$	0.01	50.5 %
Log-Exponential:	$f(d) = e^{-d} \log\left(\frac{1+\zeta}{d+\zeta}\right)$	0.1	50 %
Linear:	$f(d) = 1 - d$	N.A.	47 %
Square:	$f(d) = \begin{cases} 1 & d < \zeta \\ 0 & \text{otherwise} \end{cases}$	0.1	43 %

## 5 Conclusion

## References

- [1] Amnesty International Publications, 1 Easton Street, London, *Amnesty International Report 1991*, 1991.
- [2] L'Obs, "Attentats de 1995 : chronologie." [fr] Online. <https://bit.ly/2ASwNQP>, last checked 17 January 2019, October 2007.