# *Predicting Terror Attacks?*
# A Data Story

Axel Nilsson, Nicolas Bollier, Elias Le Boudec, Enea Figini
Team 29

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# 1 Introduction

Analysing terror organisations and predicting terror attacks is a subject of interest for national security organisations. From data on terrorist relationships and terror attacks, this project aims to assess whether terrorist relationships can be viewed as a social network, and to try to predict terror attacks locations from some known features.
To help reaching these goals, graph theory and data analysis tools are used, as part of the course *A Network Tour Of Data Science* at EPFL.

# 2 Exploring the Data

The data consists of two datasets: a relationships dataset describing relations between terrorists, and a terror attacks dataset documenting terror events by location and organisation.

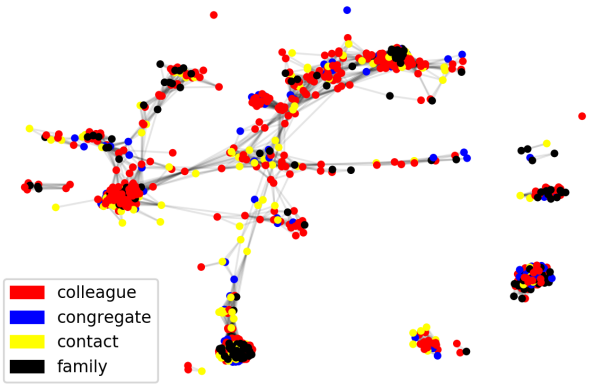
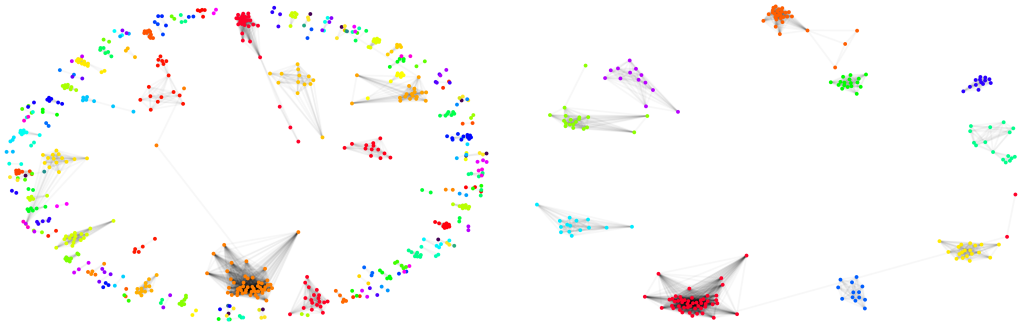



Figure 1: *Relationships dataset graph. The colouring of each node is related to its type of relation.*

The relationships dataset represents the line graph of a network of relationships between terrorists. Each node represents a relationship between two terrorists. Two nodes are connected if they share a common terrorist. The label of each node relates to the nature of the relation between the two terrorists. It is an element from {family, congregate, colleague, contact}.
The terror attacks graph is built by connecting to nodes (terror attacks) if they share a common location. An other graph can be built by also connecting two terror attacks if they are perpetrated by the same organisation. This graph is not studied here.
Multiple issues have been found in this dataset:



(a) *Terror attacks location graph, colouring by component ID*

(b) *Ten biggest components from the terror attacks location graph*

Figure 2: *Graphs from the terror attacks dataset*

**Broadness** The dataset comprises attacks ranging from 1969 to 2005 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, the construction of the graph implies a transitive relation inside connected components. Indeed, let $a$, $b$ and $c$ be terror attacks from the same connected component. Let "$a \sim b$" mean that terror attacks $a$ and $b$ took place close to each other. Then

$$\text{If } (a \sim b \text{ and } b \sim c) \text{ then probably } a \sim c \tag{1}$$

This property translates into connected component that are almost complete – hence bearing little topological information.

**Reliability** As expected, 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 [3] and the second one in Paris [4]. Hence algorithms using the data must tolerate some error in order to avoid overfitting.

**Incompleteness** The dataset has been constructed from publicly available sources [1]. Because of the sensitivity of the data behind terrorist attacks and relationships, some of it is classified, making the dataset incomplete.
Further properties of the graphs are discussed below.

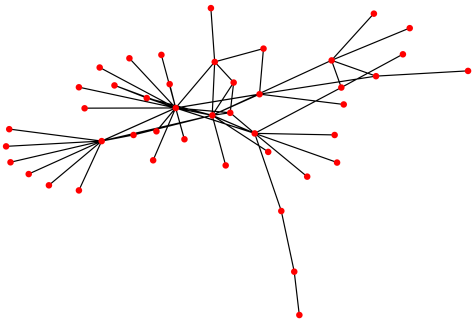
# 3 Terrorist Relationships as a Social Network?

In this section, the proprieties of the line graph as a relational network is explored. As [1] mentions, an organisation needs interpersonal connection to function and

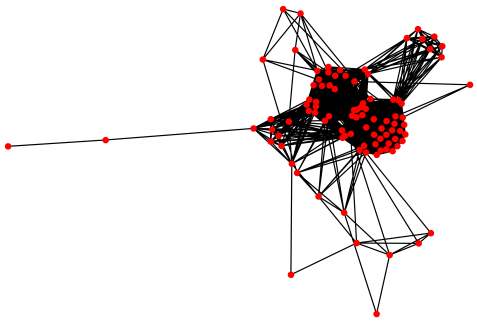
studying the structure of the social organisation could yield valuable insight.
[2] found that on the basis of a study of an online social network, a social network could be well approximated by the line graph of a scale free network. If that propriety can be verified by our dataset,
Social sciences studies have shown that social/relationship networks have the particularities of homophily and transitivity. Logically if $a$ & $b$ are friends and $c$& $b$ are also, the it is more likely that $a$ & $c$ are friends than not. This mathematically translates to:

$$a \sim b \text{ and } b \sim c \text{ then } a \sim c \tag{2}$$

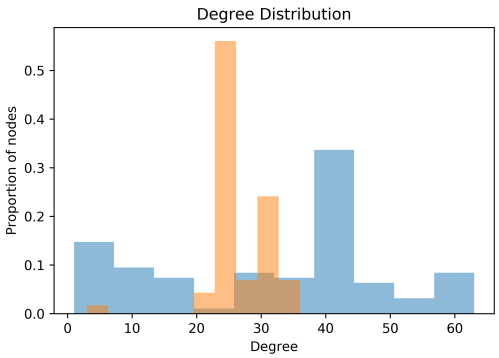
As a first research question we will try to verify that our dataset derives from a scale-free network, implying that the graph that generated the relationship dataset have proprieties similar to social networks. By creating a scale-free network and making its line graph, we compared the degree distribution of the relationship dataset we were able to show that.



(a) *Scale free network*



(b) *Line graph of scale free network*




(c) *Comparison of the degree distribution of the two line graphs. In blue, the created line graph and in orange the degrees of the relationships graph*

Figure 3: *Comparison of a scale free network and the terrorist relationships network.*

# 4 Predicting Terror Attack Location

The goal of this part is to predict the location of a terror attack based on its features and the history of previous attacks. The algorithm used for prediction 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 $l^\star$ 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 $l^\star$ 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

$$w : \mathcal{G}^2 \to \mathbb{R}^+ \tag{3}$$
$$(n_1, n_2) \mapsto f(|n_1 - n_2|) \tag{4}$$

where:

$$|n_1 - n_2| = \|\text{features}(n_1) - \text{features}(n_2)\|_2 \tag{5}$$

features$(n)$ is a binary features vector for each node $n$ in $\mathcal{G}$ and $f : \mathbb{R}^+ \to \mathbb{R}^+$ is the node distance weighting. Examples for $f$ are given in Table 1 on page 5.
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 $\{C_i^t\}$, $i = 1, \ldots, 10$, and the features vector of the next terror attack $n_{t+1}$, i.e. features$(n_{t+1})$, at each timestep $t$

**Result:** Location prediction $p_t$ at each timestep $t$

**for** *each timestep* $t$ **do**

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

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

**end**

## 4.1 Justification

The design of prediction algorithm is motivated by the following aspects:

- The labels are taken into account by weighting the edges. This allows to completely ignore label signals on the graph and simplify the analysis.
- The determination of one lead node per component allows to smoothen local variations inside a component, thus making the prediction algorithm more robust.
- The choice of one lead component per component is justified by the fact that connected components are almost complete.

## 4.2 Results

Running the algorithm aforementioned on the terror attacks dataset yields a prediction accuracy around $\frac{1}{2}$ (see Table 1 below), i.e. half of the predicted location is correct.

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

Analysing the terrorist relationships graphs showed that the network does not correspond to a scale-free network, which is typical for social networks.

The prediction algorithm yields reasonable results, given the flaws contained in the data and the compromises that had to be made (removal of isolated nodes, selection of a lead node).

# References


[1] B. Zhao, P. Sen, and L. Getoor, "Entity and Relationship Labeling in Affiliation Networks," *Proceedings of the 23rd International Conference on Machine Learning*, 2006.

[2] M. Krawczyk, L. Muchnik, A. Mańka-Krasoń, and K. Kułakowski, "Line graphs as social networks," *Physica A: Statistical Mechanics and its Applications*, vol. 390, pp. 2611–2618, July 2011.

[3] Amnesty Internation Publications, 1 Easton Street, London, *Amnesty Internation Report 1991*, 1991.

[4] L'Obs, "Attentats de 1995 : chronologie." [fr] Online. https://bit.ly/2ASwNQP, last checked 17 January 2019, October 2007.