Predicting Terror Attacks?
A Network Story

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1 Introduction

Exploring the dataset "Terror Attacks" led to formulating the following question: is it possible to predict the location of a terrorist attack given a list of features of this attack?
The goal of this project is to answer this question using data analysis tools provided by the course "*A Network Tour Of Data Science*".

2 Exploring the Data

2.1 Relationships Dataset

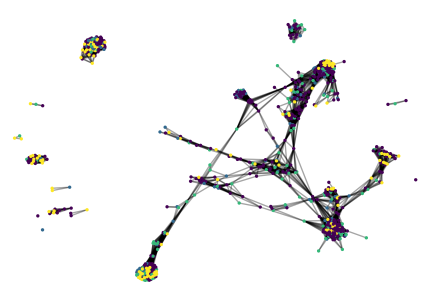
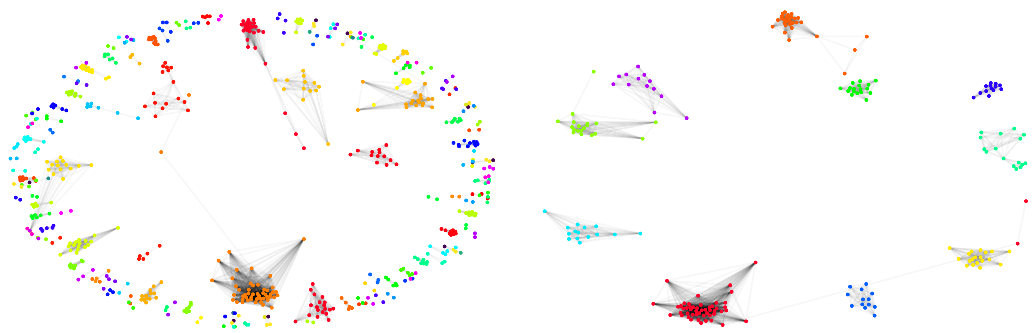


Figure 1: *Terrorist relation dataset graph, colouring the relation type*

The nodes of the network are relations between terrorists. These nodes are connected together if the relations share one individual.

2.2 Terror Attacks Dataset



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

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

Figure 2: *Graphs analysed in the project*

The nodes of the network are terrorist attacks. These nodes are connected together if the attacks were located in places that are close. Thus, 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

$$a \sim b \text{ and } b \sim c \text{ then } a \sim c \tag{1}$$

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 Terrorist Relations Dataset

3.2 Terror Attacks Dataset

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

Broadness 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 [**?**] and the second one in Paris [**?**]. 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:
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

$$w: \mathcal{G}^2 \to \mathbb{R}^+ \tag{2}$$

$$(n_1, n_2) \mapsto f(|n_1 - n_2|) \tag{3}$$

where

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

$$\text{features}(n) \text{ is a binary features vector for each node } n \text{ in } \mathcal{G} \tag{5}$$

$$f: \mathbb{R}^+ \mapsto \mathbb{R}^+ \text{ is a decreasing function} \tag{6}$$

Examples for f are given in Table 1.

Algorithm 1: *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. 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

Algorithm 2: *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 $n_l = \arg\max_{n \in C} s(n)$

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

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

5 Conclusion

Section 3.2 explains that the "Terror Attacks" dataset contains flaws that make it difficult to analyze.
However, the results in Table 1 show that predicting the location of an attack with its features is feasible even though the prediction is not very efficient. This result suggests that there is a link between the location of an attack and its characteristics (such as the type of the attack).