Social Network Analysis to Combat Terrorism: 2015 Paris Attacks

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Abstract A series of attacks shook Paris in the year 2015. They were well-coordinated attacks by the terrorist organization ISIL. An in-depth analysis of the attacks is presented in this chapter. This work is divided into several stages and every stage progresses into the next stage by adding more information useful for the upcoming stage. Initially, data about terrorists is gathered from newspapers and online bulletins. The collected data is then transformed into a network which is created using an adjacency matrix. Strength of the relationship between the involved terrorists is also factored in while creating the network. To gather insight into this network, centrality measures are calculated. This analysis brought forward interesting facts such as who were the most important person(s) in the network and removing which person(s) would cripple the network. The final phase of this process was a Twitter analysis of the Paris attacks based on four keywords related to the attack. This further revealed a few facts which were unreported in major newspapers. Some conclusions and understanding of the attacks after an in-depth data analysis of Paris attacks are also reported.

1 Introduction

The 2015 Paris attacks were a series of coordinated terrorist attacks that occurred on Friday, November 13, 2015, in Paris, France, and the city's northern suburb, Saint-Denis [1]. The attacks started with three suicide bombers wearing suicide vests striking outside the Stade de France stadium in Saint-Denis while there was

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an ongoing soccer match between France and Germany. The attack at the stadium was followed by various bombings and shootings across the city at various cafés and restaurants. Also, three terrorists entered the Bataclan theatre during a concert and started shooting randomly at people in the theatre. The attack at Bataclan caused the highest number of causalities. Hostages were then taken at the Bataclan theatre followed by a standoff between the police and the terrorists. The standoff ended with all the attackers being shot down by the police.

130 people were killed in the Paris attacks, 89 of whom were killed at the Bataclan. Out of 352 people injured, 99 were critically injured [2]. The horrific incident was a series of seven attacks by nine terrorists. Eight terrorists were killed and one was captured by the police.

On November 14, ISIL—the so-called Islamic State of Iraq and the Levant—claimed responsibility for the attacks. The attacks, as claimed in the video, were an act of retaliation by ISIL on the French Government for their airstrikes on Syria and Iraq [3].

Figure 1 shows the locations of the attacks on a map of Paris. French police raided an apartment early on November 18 in the northern Paris suburb of Saint-Denis, a few miles from where the suicide bomb attacks at the Stade de France took place. Three people died, including Abdelhamid Abaaoud, a 28-year-old Belgian man who is suspected of planning the Paris attacks, and his 26-year-old cousin Hasna Aitboulahcen [4].

The aim of the study described in this chapter is to analyze Paris attacks in a scientific way and draw lessons which may help to avoid future similar disasters. For this purpose, we employ social network construction and analysis in the process. Indeed, as homeland security is concerned, social network analysis may be considered as a mathematical modelling technique for connecting the dots and using science and statistics to fight criminology and terrorism [5]. The research on social network analysis (SNA) to combat terrorism has propelled since the occurrence of September 11, 2001, attacks in New York, USA. Since then, there has been an increased research interest to gather insights into terror organizations but there is still room for further research to yield great insights (such as importance, power, influence, behavior) which can predict and possibly prevent a terror attack. Thus, the objective of this research paper is to gather information about the terrorist network of Paris attacks from some of the publicly available datasets and create useful insights based on node measures, network closures, and Twitter analysis. The target is to draw some conclusions which may guide investigators to may be pre-act and avoid disasters by better handling and coping with similar cases.

The rest of this chapter is organized as follows. Section 2 briefly covers related work. Section 3 describes the methodology applied in this study; it also includes results which show the importance of various terrorists who participated in Paris attacks. Section 4 reports analysis results of tweets related to Paris attacks; and finally some conclusions are presented.

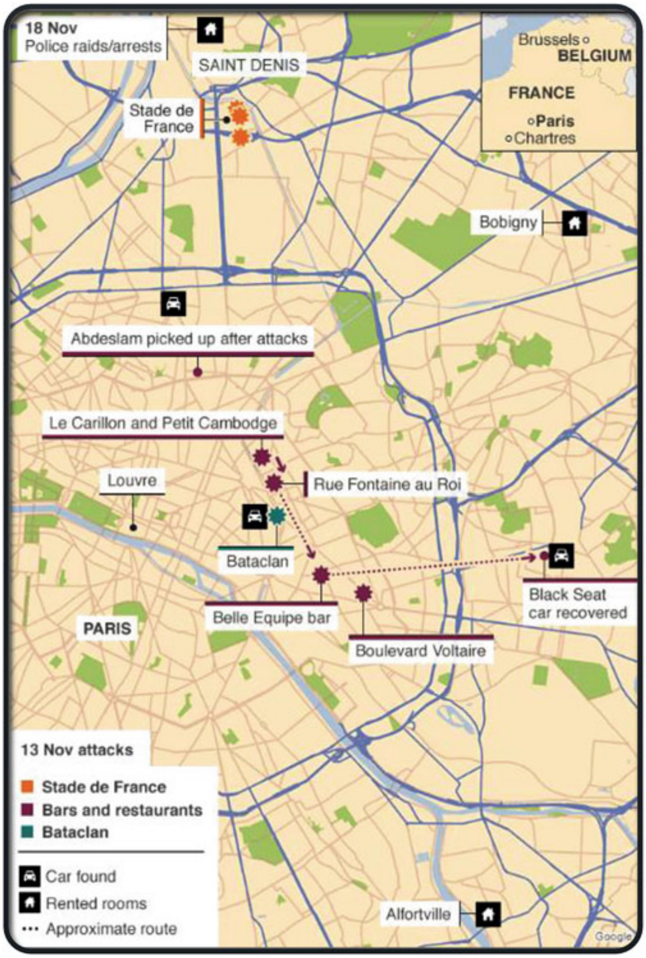


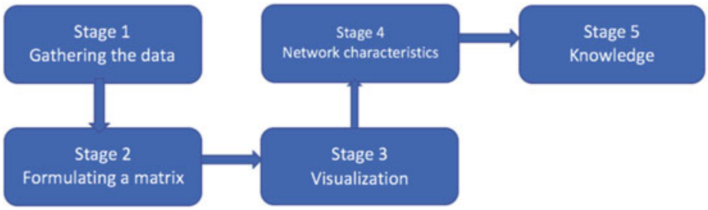
Fig. 1 Map of Paris showing attack locations and other key information

2 Related Work

There has been a constant battle against terrorism and many articles have been published by various research groups and contributed towards the growing research to combat terrorism. For instance, Koschade [6] attempted to advance the growing literature on social network analysis and terrorism studies through a social network analysis of the Jemaah Islamiyah cell that was responsible for the Bali bombings in 2002. The aim of his research was to understand the communication within and structure of such cells and assist to predict the outcomes of terrorist cells. A general introduction to social network analysis (SNA) as an analytical tool for the study of adversary networks can be found in [7] where the authors reviewed some theoretical and key concepts, highlighted functional applications, and presented a tentative protocol for data handling and coding when dealing with adversary networks. The work described in [8] provides an overview of the history of social network analysis and its use in terror-related research. Advantages of social network analysis for the study of terrorism and related fields, as well as its main, relevant methodological tools and concepts, by using pertinent and intelligible examples were discussed by Arie et al. [9]. This work also outlined how SNA provides important information about characteristics of group structure (and how this structure influences members' motives, behaviors, and outcome of their actions), recruitment processes, evolution, and division of political and social power among members. A case study on the so-called global Islamist terrorist network is provided by Medina [10]; he utilized traditional social network, as well as small-world, and scale-free analyses to characterize this system on individual, network, and systemic levels. From a social network perspective, the study in [11] investigated the impact of expatriate social network characteristics on psychological well-being in the terrorism-endangered environment of Afghanistan, India, and Pakistan. One of the key aims of a social network analysis of a terrorist network is to identify key players. Lindelauf et al. [12] introduced a game theoretic approach to identify key players in terrorist networks. The main advantage of this approach is that it incorporates both network structure and nonnetwork features. Concepts such as group cohesion, adhesion, and alternative network mappings derived from node removal are discussed in [13], inspired by the data analysis of the 9/11 hijacker network developed by Valdis Krebs from open sources.

3 Methodology

The following figure shows the five stages into which the first phase of the work described in this chapter has been divided. The second phase is the Twitter analysis of the Paris attacks. The five stages of the first phase are described further in this section.



Stage 1: Gathering the Data

In the data-gathering stage, information was gathered from articles and reports on Paris attacks published by major newspapers and websites starting from November 2015 till the date this chapter was completed. For this stage, we have been able to come up with a list of 21 terrorists who were either actively or passively involved in the attacks. By active participation, we mean terrorists who wore suicide vests and blew themselves up or terrorists who shot down people at Bataclan. Passive participation involves people who were not present at the scene; these may include drivers, recruiters, bomb makers, etc. Here is the list of all the 21 terrorists:

1. Bilal Hadfi
2. Ahmad al-Mohammed
3. M al Mahmod
4. Chakib Akrouh
5. Abdelhamid Abaaoud
6. Brahim Abdeslam
7. Omar Ismail Mostefai
8. Samy Aminour

Active Participation

9. Foued Mohamed-Aggad
10. Salah Abdeslam
11. Mohamed Abrini
12. Hasna Ait Boulahcen
13. Fabien Clain
14. Mehdi Nemmoude
15. Mourad Fares
16. Jawad Bendaoud
17. Mohammed Amri
18. Hamza Attouh
19. Abraimi Lazer
20. Abou Isleym

Passive Participation

21. Gelal Attar

The first 9 terrorists in the list are those who had an active participation in the attacks whereas the remaining 12 terrorists are those who had a passive participation. This list will now act as a dataset to form an adjacency matrix to define the relationships between these terrorists. The outcome will feed the following stages in the process.

Stage 2: Formulating a Matrix

A suspect/terrorist may have many contacts—both accidental and intentional [14]—but not all terrorists have the same strength of relationships with other terrorists. As data comes in, a picture of the terrorist organization slowly comes into focus [14]. Some share very strong bonds being family members, whereas others share a weak bond if they communicated just once over a phone call. A weighted adjacency matrix is created based on the strength of the relationships as follows:

Weight 1 corresponds to a very weak relationship, weight 2 corresponds to an intermediate relationship, and weight 3 corresponds to a very strong relationship between terrorists.

The adjacency matrix is a 21 $\times$ 21 matrix with terrorist names forming rows and columns of the matrix, and the strength of the relationship on a scale of 1–3 is used to decide on values of the entries in the matrix. The matrix has been appended at the end of the chapter.

Stage 3: Visualization

In this stage, we visualize the data by creating a network from the adjacency matrix. This has been done using R. Nodes in the network correspond to terrorists who were involved in the attacks and edges exist between terrorists sharing a relationship—weak or strong. Also, each edge is marked with a strength based on the weight matrix shown in Table 1.

Terrorist networks are very secretive and focus primarily on being clandestine than being efficient. These networks rely on moderators to act as a bridge between people who exist in the network. Moderators are not an actual part of the network, but appear briefly in the network during meetings and briefings. During the short duration of their presence, they act as a means of communication between other members of the group and then vanish until the next meeting. Therefore, the graph we obtained is a sparse network and the actors involved are not well connected with each other even after being in the same team. Most people who were involved did not know each other before the attacks. They were brought into contact only for the attack, and are therefore connected only through Jihadist recruiters in the network.

Table 1 Weight matrix

Weight	Type of interaction
1	Single text/transaction/phone call
2	Drove/recruiter
3	Family/prison mates/lived together

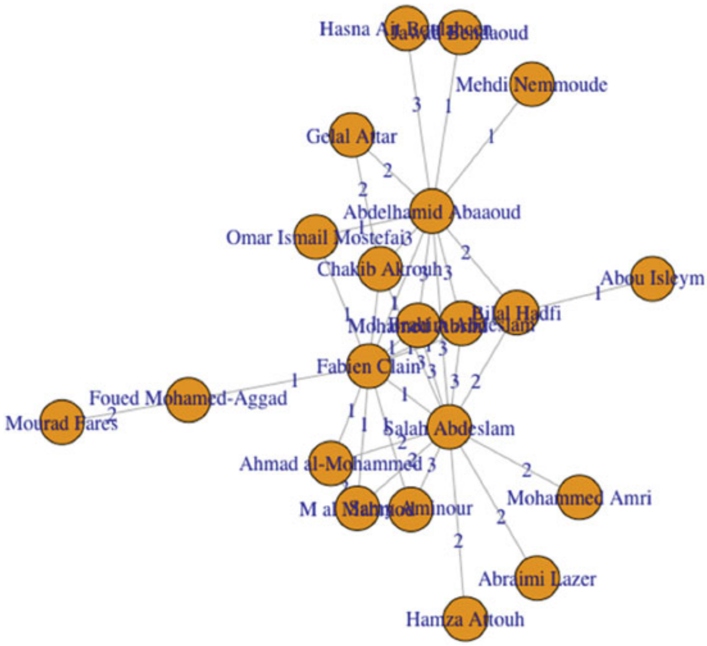


Fig. 2 Network of terrorists involved in the Paris attacks

In the network shown in Fig. 2, Abdelhamid Abaaoud, Salah Abdeslam, and Fabien Clain are the most densely connected terrorists. Newspaper reports claimed that Abdelhamid Abaaoud was the mastermind of this attack and our network supports this claim. Once we have the centrality measures for all the nodes, we should be able to explain and justify why Salah Abdeslam and Fabien Clan are densely connected in the network.

Stage 4: Network Characteristics

In this stage, we used NetDriller [15] and calculated the centrality measures for the graph created in the previous stage. This helped us to answer some implicit questions about the network which are not so evident from just looking at the facts. The four centrality measures which we have calculated are the following:

- *Degree Centrality*

It is defined as the number of links incident upon a node, i.e., the number of ties that a node has.

Table 2 Degree centrality

Degree centrality	
Node name	Score
Salah Abdeslam	12
Fabien Clain	11
Abdelhamid Abaaoud	11
Chakib Akrouh	4
Bilal Hadfi	4
M al Mahmod	3
Ahmad al-Mohammed	3
Brahim Abdeslam	3
Mohamed Abrini	3
Gelal Attar	2
Hasna Ait Boulahcen	2
Omar Ismail Mostefai	2
Samy Aminour	2
Jawad Bendaoud	2
Foued Mohamed-Aggad	2
Abou Isleym	1
Mohammed Amri	1
Abraimi Lazer	1
Mourad Fares	1
Hamza Attouh	1

- *Betweenness Centrality*

Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes.

- *Closeness Centrality*

Closeness centrality of a node is the average length of the shortest paths between the node and all other nodes in the graph.

- *Eigenvector Centrality*

Eigenvector centrality is a measure of the influence of a node in a network.

Tables 2–5 show these four centrality measures, respectively, for all terrorists. These measures helped us to fill the voids and answer questions which are not evident from a superficial study. We will now discuss these findings in the next stage.

Table 3 Betweenness centrality

Betweenness centrality	
Node name	Score
Salah Abdeslam	73
Abdelhamid Abaaoud	70.5
Fabien Clain	62.5
Bilal Hadfi	19
Foued Mohamed-Aggad	19
Chakib Akrouh	5
Gelal Attar	0
Abou Isleym	0
Hasna Ait Boulahcen	0
Mohammed Amri	0
Abraimi Lazer	0
Omar Ismail Mostefai	0
M al Mahmod	0
Mourad Fares	0
Ahmad al-Mohammed	0
Samy Aminour	0
Hamza Attouh	0
Brahim Abdeslam	0
Mehdi Nemmoude	0
Jawad Bendaoud	0

Table 4 Closeness centrality

Closeness centrality	
Node name	Score
Salah Abdeslam	0.689655
Fabien Clain	0.689655
Abdelhamid Abaaoud	0.666666
Bilal Hadfi	0.54054
Chakib Akrouh	0.526315
Brahim Abdeslam	0.51282
Mohamed Abrini	0.51282
Omar Ismail Mostefai	0.465116
M al Mahmod	0.465116
Ahmad al-Mohammed	0.465116
Samy Aminour	0.454545
Foued Mohamed-Aggad	0.434782
Gelal Attar	0.416666
Hasna Ait Boulahcen	0.416666
Mohammed Amri	0.416666
Abraimi Lazer	0.416666
Hamza Attouh	0.416666
Jawad Bendaoud	0.416666
Mehdi Nemmoude	0.408163
Abou Isleym	0.357142

Table 5 Eigenvector centrality

Eigenvector centrality	
Node name	Score
Salah Abdeslam	0.166666
Abdelhamid Abaaoud	0.152777
Fabien Clain	0.152777
Bilal Hadfi	0.055555
Chakib Akrouh	0.055555
Brahim Abdeslam	0.041666
Mohamed Abrini	0.041666
M al Mahmod	0.041666
Ahmad al-Mohammed	0.041666
Foued Mohamed-Aggad	0.027777
Samy Aminour	0.027777
Omar Ismail Mostefai	0.027777
Hasna Ait Boulahcen	0.027777
Jawad Bendaoud	0.027777
Gelal Attar	0.027777
Mohammed Amri	0.013888
Abraimi Lazer	0.013888
Hamza Attouh	0.013888
Mehdi Nemmoude	0.013888
Abou Isleym	0.013888

Stage 5: Knowledge Discovery

Network characteristics in terms of centrality measures reveal a lot of information about the terrorists who were involved in Paris attacks. Salah Abdeslam, Fabien Clan, and Abdelhamid Abaaoud have the highest centrality measures across all four parameters. These results are consistent with the fact that Abdelhamid Abaaoud, who was killed at Saint-Denis by the French police 5 days after the attack, was the mastermind of Paris attacks. Although he does not have the highest value in our calculations he is placed among the top three in each of the centrality measures. Abdelhamid Abaaoud not being on top in the centrality measures can be attributed to some missing or incorrect data which is common in a clandestine network analysis. Salah Abdeslam is the terrorist who has the highest centrality measures across all four parameters. He was arrested by French police during the attacks and is still in custody. According to the centrality measures, he was well connected within the network and can provide intelligence related to the attacks and the attackers which will be useful to understand the dynamics of this network in terms of evolution of the network by the addition of new members or the formation of new relationships between existing members.

Bataclan attackers, even if the death toll was the highest, seem to have had a much more peripheral role in the operation. Salah Abdeslam also had an important role in coordinating the different attacks [17]. Also, several links between Abdeslam and the suspected Paris attacks' mastermind, Abdelhamid Abaaoud, emerged in the days after the attacks [18]. Fabien Clan is believed to be one of the recruiters for Paris attacks and is the third most important person according to the centrality measures. He is also the voice in the video which was released by ISIL after the attacks claiming responsibility for the attacks. Although he was not directly involved in the attacks he had strong connections with most of the people who were involved in the attacks. Early detection of a person like Fabien Clan could have disrupted the entire network and possibly could have prevented an attack of this destructive magnitude.

4 Twitter Analysis

The following analysis was performed on a machine running Windows 7, 64-bit operating system, and having 8 GB of RAM.

In [16], Moujahid gave an overview of how text mining can be performed using Twitter streaming API and Python. He used Twitter data as an example to compare the popularity of three programming languages, Python, Javascript, and Ruby, and to retrieve links to programming tutorials. Some parts of this work are inspired from Adil's article.

For this phase, python is used for the analysis of tweets which are extracted from a dataset containing twitter IDs of tweets corresponding to the four keywords—#parisattacks, #Bataclan, #paris, and #porteouverte. Hydrating the tweets gave us 6.5 million tweets. These tweets formed the basis for our analysis. To be able to predict an attack, the time when the tweets about the attack start rolling in is of utmost importance. Therefore, we extracted the timestamp for all the tweets as our most important feature to work with.

Since we know that the first attack (from the series of attacks) occurred at 9:16 PM on July 14, we construct a timeline starting from 8 PM on July 14 until 1 AM on July 15. Each one of the 6.5 million tweets is then mapped to this timeline based on the time when the tweet was received. Figure 3 shows the timeline with the corresponding number of tweets for every second within the chosen time period.

Although the attacks started at 9:16 PM, there is an absence of significant number of tweets between 8 PM and 9:30 PM. The magnitude of the tweets started increasing from 9:30 PM onwards and reached a maximum around 10:15 PM. There is a steady number of tweets after that till 12:30 AM after which the number of tweets starts decreasing again. This is shown graphically in Fig. 3 in which the height of the histogram at any time is proportional to the number of tweets at that time.

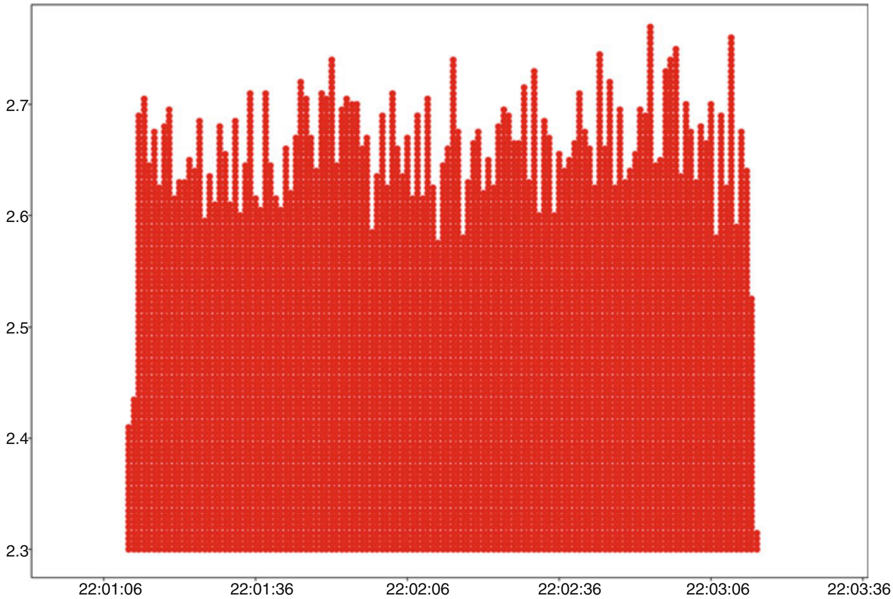


Fig. 3 Tweet timeline for Paris attacks

This work can be an essential cornerstone for an early detection system for a terrorist attack. Although predicting an attack of this magnitude is impossible based solely on twitter data because of the highly secretive nature of terrorist organizations, an early detection system is a need of the hour. An early detection system can detect an attack just a few minutes after any occurrence so that any subsequent occurrences can be avoided or tacked with the gained intelligence. The results and observations highlighted in this chapter about the terrorist network of Paris attacks can be used to base such a model on. The organization and working of any terrorist network will not be much different from the terrorist network explained in this chapter as all these organizations have the same goal and work according to a similar principle.

Appendix 1: Adjacency matrix

	Bilal Hadfi	Ahmad al-Mohammed	M al Mahmod	Chakib Akrouh	Abdelhamid Abaaoud	Brahim Abdeslam	Omar Ismail Mostefai	Samy Aminour	Foued Mohamed-Aggad	Salah Abdeslam
Bilal Hadfi	0	0	0	0	2	0	0	0	0	2
Ahmad al-Mohammed	0	0	2	0	0	0	0	0	0	2
M al Mahmod	0	2	0	0	0	0	0	0	0	2
Chakib Akrouh	0	0	0	0	3	0	0	0	0	3
Abdelhamid Abaaoud	2	0	0	3	0	3	1	0	0	3
Brahim Abdeslam	0	0	0	0	3	0	0	0	0	0
Omar Ismail Mostefai	0	0	0	0	1	0	0	0	0	0
Samy Aminour	0	0	0	0	0	0	0	0	0	3
Foued Mohamed-Aggad	0	0	0	0	0	0	0	0	0	0
Salah Abdeslam	2	2	2	3	3	3	0	3	0	0
Mohamed Abrini	0	0	0	0	3	0	0	0	0	3
Hasna Ait Boulahcen	0	0	0	0	3	0	0	0	0	0
Fabien Clain	1	1	1	1	1	1	1	1	1	1
Mehdi Nemmoude	0	0	0	0	1	0	0	0	0	0
Mourad Fares	0	0	0	0	0	0	0	0	2	0
Jawad Bendaoud	0	0	0	0	1	0	0	0	0	0
Mohammed Amri	0	0	0	0	0	0	0	0	0	2
Hamza Attouh	0	0	0	0	0	0	0	0	0	2
Abraimi Lazer	0	0	0	0	0	0	0	0	0	2
Abou Isleym	1	0	0	0	0	0	0	0	0	0
Gelal Attar	0	0	0	2	2	0	0	0	0	0

	Mohamed Abrini	Hasna Ait Boulahcen	Fabien Clair	Mehdi Nemmoude	Mourad Fares	Jawad Bendaoud	Mohammed Amri	Hamza Attouh	Abraimi Later	Abou Isleym	Gelal Attar
Bilal Hadfi	0	0	1	0	0	0	0	0	0	1	0
Ahmad al-Mohammed	0	0	1	0	0	0	0	0	0	0	0
M al Mahmod	0	0	1	0	0	0	0	0	0	0	0
Chakib Akrouh	0	0	1	0	0	0	0	0	0	0	2
Abdelhamid Abaaoud	3	3	1	1	0	1	0	0	0	0	2
Brahim Abdeslam	0	0	1	0	0	0	0	0	0	0	0
Omar Ismail Mostefai	0	0	1	0	0	0	0	0	0	0	0
Samy Aminour	0	0	1	0	0	0	0	0	0	0	0
Foued Mohamed-Aggad	0	0	1	0	2	0	0	0	0	0	0
Salah Abdeslam	3	0	1	0	0	0	2	2	2	0	0
Mohamed Abrini	0	0	1	0	0	0	0	0	0	0	0
Hasna Ait Boulahcen	0	0	0	0	0	1	0	0	0	0	0
Fabien Clain	1	0	0	0	0	0	0	0	0	0	0
Mehdi Nemmoude	0	0	0	0	0	0	0	0	0	0	0
Mourad Fares	0	0	0	0	0	0	0	0	0	0	0
Jawad Bendaoud	0	1	0	0	0	0	0	0	0	0	0
Mohammed Amri	0	0	0	0	0	0	0	0	0	0	0
Hamza Attouh	0	0	0	0	0	0	0	0	0	0	0
Abraimi Lazer	0	0	0	0	0	0	0	0	0	0	0
Abou Isleym	0	0	0	0	0	0	0	0	0	0	0
Gelal Attar	0	0	0	0	0	0	0	0	0	0	0

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