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Zheng, Quan; Skillicorn, David; Walther, Olivier

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Signed Directed Social Network Analysis Applied to Group Conflict

Q. Zheng and D.B. Skillicorn School of Computing, Queen's University
O. Walther, University of Southern Denmark

***Abstract*—Real-world social networks contain relationships of multiple different types, but this richness is often ignored in graph-theoretic modelling. We show how two recently developed spectral embedding techniques, for directed graphs (relationships are asymmetric) and for signed graphs (relationships are both positive and negative), can be combined. This combination is particularly appropriate for intelligence, terrorism, and law-enforcement applications. We illustrate by applying the novel embedding technique to datasets describing conflict in North-West Africa, and show how unusual interactions can be identified.**

I. Introduction

Modelling real-world social networks requires accounting for the fact that the edge connecting a pair of nodes often implies, simultaneously, multiple properties of the relationship between them. Table I shows how relationship properties map to graph edge properties. Most analysis focuses on the symmetric case, partly because the algorithmics to handle the other cases is still being developed.

Intelligence and law-enforcement applications, in particular, are characterized by asymmetric relationships (command-and-control or flow of information) and by relationships with both allies and foes. Understanding the social dynamics of a group, or the ecosystem of interactions among groups requires social network analysis for networks in which the edges are both signed *and* directed.

Signed networks have always been problematic to model because, while an edge with a positive weight can be imagined as "pulling" the nodes it connects closer together, an edge with a negative weight must (somehow) "push" the nodes it connects apart. "Pull" is naturally transitive, but "push" is not – proverbially the enemy of my enemy is my friend, but in practice the enemy of my enemy is often also my enemy. Furthermore, the balance between the relative effects of positive and negative relationships must be determined.

Directed networks are difficult to model for more technical reasons. Spectral graph models, which embed graphs into geometric spaces where distance reflects dissimilarity, work for symmetric adjacency matrices. The standard approach to embedding directed graphs maps an asymmetric matrix to a symmetric one via a mechanism that creates three additional issues, all problematic both from a performance and an accuracy perspective [2]: estimating the importance of each node by computing the principal left eigenvector of a matrix representing the graph, which is expensive; adding a constant ε matrix to the graph to address reducibility, which makes the matrix dense; and embedding almost-isolated nodes too close to the center, which creates a misleading sense of their importance to the network.

In this paper we take two newly developed spectral graph embedding techniques, one for signed networks [8] and one for directed networks [7] and show how they can be combined into a single technique that can be used to embed directed, signed networks. Properties of the network can be understood from visualizations; we also define a measure that highlights nodes with unusual roles. We apply this new technique to a small well-studied dataset, the Sampson Monastery data, and to a substantial dataset of interactions collected by the Armed Conflict Location and Event Data (ACLED) Project. This project collects data about incidents of political violence in Africa.

II. Spectral embedding

The strategy for embedding based on both sign and direction is to take the information implicit in the network edges (direction and sign) and encode it by introducing multiple versions for each node. In the first step, each node is replaced by two versions, one coding for its inward edges and the other for its outward edges. The edges connecting these versions are undirected, since the directional information is coded in the pattern of connections. This is then repeated by creating multiple versions of these nodes, one connected to the positive edges and one to the negative edges. Each node of the original graph is therefore replaced by four versions with these connections: incoming negative edges, outgoing negative edges, incoming positive edges, and outgoing positive edges. The edges of the original graph are connected to these nodes in the obvious way. The four versions of each node are then connected to each other by an undirected 4-clique whose edges weights are the sum of (the absolute values of) the incident weight of the original version of the node.

Let P be the directed adjacency matrix representing the positive edges; N the directed adjacency matrix representing the negative edges (so both matrices containing only non-negative entries); DP_{in} and DN_{in} the indegrees of the two adjacency matrices, and DP_{out} and DN_{out} their outdegrees.

Relationship	Edge property
Symmetric	Undirected
Asymmetric	Directed
Qualitatively different	Typed
Positive or negative	Signed

TABLE I: Relationship and edge properties

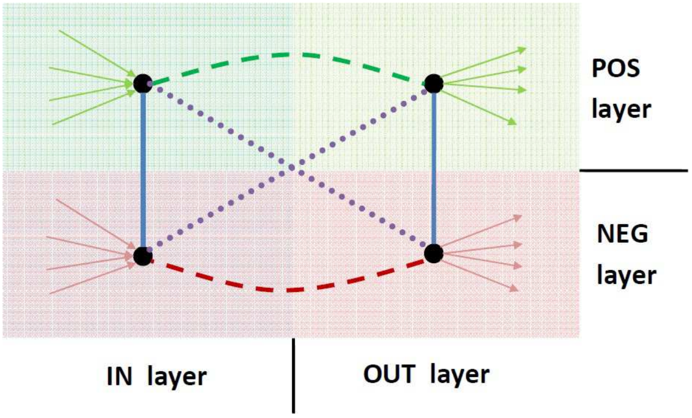

Fig. 1: Replication of each node first into positive and negative versions and then into in and out versions

The weights on the edges joining the new versions of the ith node will be the sum of the ith entries of these vectors. Let D be the matrix with these weights on the diagonal.

Define a matrix in which the four versions are connected in a clique as shown in Figure 1. First, each node is duplicated and the positive edges connected to one copy and the negative edges to the other. Then each of these nodes is duplicated and the incoming edges connected to one and the outgoing edges to the other. Finally, a clique is added to connect the four versions of each original node.

More formally, define the adjacency matrix for the graph that captures the signed structure of the network by:

$$W = \begin{bmatrix} P+D & D \\ D & -N+D \end{bmatrix} \quad (1)$$

If the network contains n nodes, then W is a $2n \times 2n$ matrix, but the added pieces are only diagonals (so linear in n) and, if P and N are sparse, then so is W.

We now take into account the signed structure of the network. The intuition here is that positive edges should cause their endpoints to be embedded close to one another, while negative edges should cause their endpoints to be embedded far apart.

Let $bigD$ be the $2n \times 2n$ matrix:

$$bigD = \begin{bmatrix} 0 & D \\ D & 0 \end{bmatrix}$$

and then define a $4n \times 4n$ matrix:

$$X = \begin{bmatrix} bigD & W \\ W' & bigD \end{bmatrix} \quad (2)$$

Equation 1 adds the horizontal (dashed) edges in Figure 1 by the entries added to the major diagonal submatrices, and adds the vertical (solid) edges by the submatrices on the minor diagonal. Equation 2 adds the diagonal (dotted) (dotted) edges in Figure 1.

Embeddings cannot be done directly from adjacency matrices since well-connected nodes correspond to matrix rows with many non-zero entries, which causes them to be embedded far from the origin, rather than centrally as desired. Conventionally, an adjacency matrix is converted to one of a number of Laplacian matrices which are then turned into embeddings via an eigendecomposition.

Previous work [8] has shown that there are two Laplacians that faithfully represent the balance of positive versus negative edge weights. Here we build on the simpler of the two.

Let $\overline{DP}$ and $\overline{DN}$ be the matrices whose diagonals are the row sums of the absolute values of the positive and negative entries of X respectively. Let $\overline{D}$ be the sum of $\overline{DP}$ and $\overline{DN}$. Then the desired Laplacian matrix is

$$L_{sns} = \overline{D}^{-1}(\overline{DP} - \overline{DN} - X)$$

Although L_{sns} is much larger than P and N, the extra pieces are either diagonals or transposes. The matrix remains sparse if P and N are.

If V is the matrix of the eigenvectors of L_{sns} then the network is embedded in k dimensions by treating the k smallest eigenvectors as coordinates for each point [1].

This embedding has the property that positively connected nodes are placed close to one another, and negatively connected nodes are placed far from one another – but the local edge lengths have been moderated by the emergent global structure of all of the edges (as well as the projection into a smaller number of dimensions). Thus the embedding has integrated local information into a globally consistent ensemble representing similarity and dissimilarity. There are now four versions of each node of the original graph, so embeddings can become cluttered.

For positive edges it should be the case that:

$$embedded\ length \propto 1/edge\ weight$$

and for negative edges:

$$embedded\ length \propto edge\ weight$$

Whenever the embedded length of an edge deviates from these expectations, it signals that the global structure of the graph is distorting the local environment. Places where this occurs are likely to be parts of the social network of particular interest.

Each of the four versions of an original node are connected to one another by edges of the same weight. They should therefore be embedded at similar distances from one another, all things being equal.

The positive-positive edge connecting versions of the same node is long when the individual has positive connections *from* one set of participants but positive connections *to* a largely disjoint set of other participants. In other words, this edge is long when there is net flow of positivity across the individual.

The negative-negative edge in an embedding is short when the individual has negative connections from many diverse other participants (that is, negativity comes from many different directions). This is because negative edges tend to “push”

[1] One eigenvector with eigenvalue 0 represents the trivial embedding in which each node is placed at the same location and is ignored as usual; however, it can appear at any point in the eigenvalue spectrum since eigenvalues range from -2 to $+2$. Furthermore, it is possible (though unlikely) that another eigenvalue is 0, even for a connected graph, because positive and negative values cancel one another out, so care is needed in this region of the spectrum.

nodes outwards; this push is effectively stronger when most of the outward force is aligned, that is it comes from a set of nodes that are embedded in relatively the same direction. Thus an individual whose embedded negative-negative edge is short can be thought of as transmitting negativity between a variety of different subgroups.

III. Application

Signed, directed social network datasets are rare, not because they do not exist in the real world, but because ways to analyze them have not been available.

To illustrate the embedding, we first apply it to the Sampson dataset (derived from Sampson's 1969 unpublished doctoral thesis; we use the data available from the UCINET repository), a collection of 18 monks who were asked for opinions about their relationships over a period of time in which the group was disintegrating. The monks were asked about who influenced them positively and negatively, who they esteemed or despised, and who they praised or blamed, but almost all of the analysis has focused on the like/dislike ratings. Almost any technique applied to the matrix produces four clusters that agree with those that Sampson originally postulated (for example, [3]).

Our embedding of this network produces the same four clusters; but what we add is the ability to see the net like and dislike experienced by each individual. The full embedding contains $4 \times 18 = 72$ points, so the rendering is cluttered. We show the the positive-positive edges and the negative-negative edges corresponding to each individual separately, in Figures 2 and 3. The names in these figures are colored based on the groups previously observed; the group shown in magenta has been called the "outlier" or "fringe" group since they do not form a tight cluster.

The positive-positive edges are all short. From this we conclude that there is a strong clique structure, with liking being almost entirely a within-subgroup relationship. The negative edges show more variability. Individuals such as *bonaven* or *winf* appear to be disliked from all directions; whereas individuals such as *albert* and *boni* are involved in much more focused dislike.

We also compute the normalized embedded edge lengths for these edges. Deviations from the mean indicate nodes with different patterns of positivity or negativity:

1) High positive normalized edge length – focused positive feeling (set of those liked is disjoint from those who like);
2) Low positive normalized edge length – diffuse positive feeling (likes those who like in return);
3) High negative normalized edge length – focused negative feeling;
4) Low negative normalized edge length – diffuse negative feeling (set of those disliked is disjoint from those who dislike).

In most situations, cases 1 and 4 will be surprising – it is much more conventional to be mutually liked by friends, and to be disliked by a few.

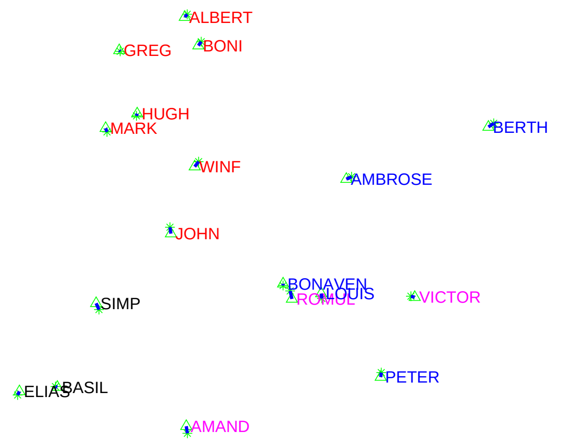

Fig. 2: Embedded graph showing positive-positive edges

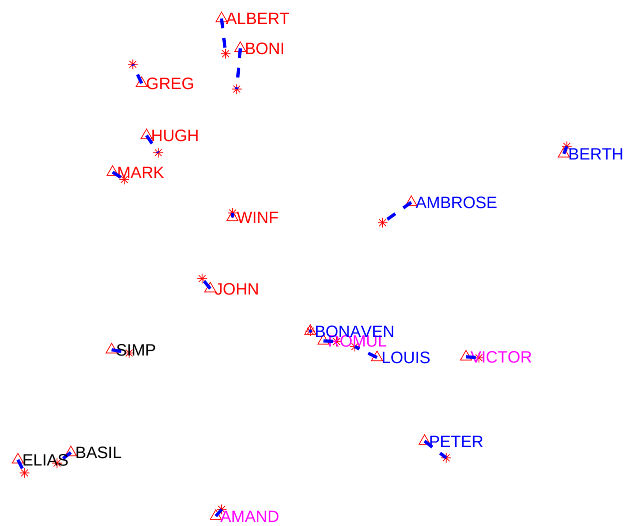

Fig. 3: Embedded graph showing negative-negative edges

Table II shows these edge lengths for each of the monks. PETER stands out with both positive-positive and negative-negative values that are well above the mean. As expected of the leader of the "Young Turks" PETER has discrepancies between those he likes and those who like him (so he mediates the flow of positivity); and is disliked in a relatively focused way.

We now turn to a more significant real-world dataset, the ACLED (Armed Conflict Location & Event Data Project – acleddata.com), a dataset of political violence events in Africa from 1997 to the present. Subsets of this dataset were converted to directed signed social networks as follows: each record describes an attack by group A on group B, possibly with A assisted by some other group C and group B assisted by some other group D. This record results in a negative directed edge from A to B, and positive directed edges from C to A and/or from D to B. Multiple attacks or collaborations increase the edge weights accordingly. There can be (and are!) both

Name	pos-pos	neg-neg
ROMUL	0.07	0.11
BONAVEN	0.03	0
AMBROSE	0.09	0.52
BERTH	0.15	0.18
PETER	0.17	1.00
LOUIS	0.07	0.34
VICTOR	0.10	0.32
WINF	0.09	0.06
JOHN	0.15	0.30
GREG	0.05	0.76
HUGH	0.03	0.31
BONI	0.06	0.53
MARK	0.08	0.27
ALBERT	0.05	0.46
AMAND	0.12	0.15
BASIL	0.06	0.54
ELIAS	0.08	0.29
SIMP	0.13	0.32
Mean	0.087	0.360
STD	0.041	0.247

TABLE II: Product of edge length and reciprocal of edge weight; deviations from average indicate nodes with unusual neighborhoods

positive and negative edges between the same pair of actors.

Algeria, Libya, Nigeria

We begin by looking at particular countries with a complex insurgent landscape, both because at the scale of a single country visualizations of the social network are small enough that they can be understood directly, and because there are interesting and practical intelligence benefits to comparing these countries to one another.

Because there are four version of the node corresponding to each group, these figures can quickly become cluttered. We display the positive and negative segments of the embedded social network separately, but with the same orientation and scale so that they can be compared visually. We remove groups that only participate in negative interactions – most of these are pairs of groups that attack only each other, and so are readily understood by analysts. The embedded position of each node is determined by both the "pull" of the other nodes to which it is connected positively, and the "push" of the other nodes to which it is connected negatively, but both "pull" and "push" are directional, that is asymmetric. The blue edges represent the embedded positive and negative in-to-out edges respectively – the longer such a positive edge and the shorter such a negative edge, the more net flow of that kind passes "through" the original node.

Algeria. Figures 4 and 5 show the ecosystem of groups in that country. The negative edges show clearly the separation of bad actors and good actors: radical groups such as GIA, GSPC, and AQIM on the left, and police, military, and civilians on the right [2]. Nodes that are not directly connected are embedded close together when they see the same landscape in the rest of the graph; this is often a signal that they are similar, but concealing their similarity. In this case, AQIM and GSPC are

[2]A limitation of the dataset coding is that, while "GIA" is a well-defined group, "civilians" is a placeholder for a number of different groups at different times.

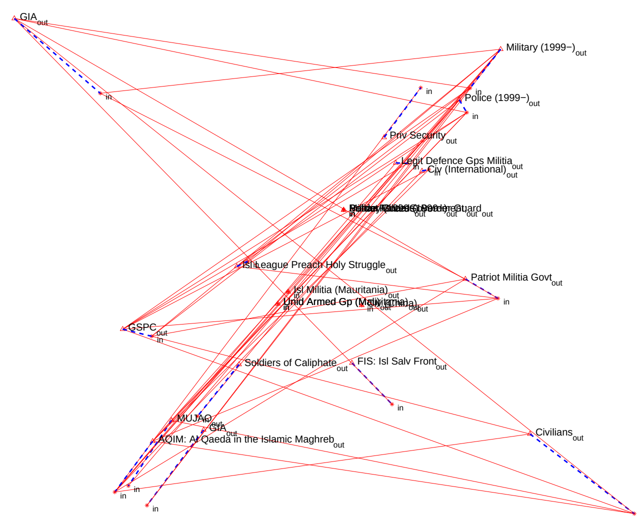

Fig. 4: Negative relationships among Algerian groups

unconnected and embedded close together but, in this case, it is because AQIM is a rebranding of GSPC. Differences in strategy are also clearly visible: AQIM, GSPC, and MUJAO tend to target government forces while GIA tends to target civilians. (At the end of the 1990s, the Armed Islamic Group (GIA) lost popular support in Algeria because of its massive atrocities against civilians; the situation was so bad that several GIA commanders decided to create their own, more moderate, Islamic groups, such as GSPC.)

Groups such as, in this figure, the Islamic Salvation Front are folded in towards the middle of the picture because they have a negative relationship with only one other group, GIA. It would be tempting to think of the natural position of such groups as even more peripheral, but their potential relationship to all other groups need not be negative just because of their one known negative relationship, and the more central placement reflects this.

The positive relationships (Figure 5) contain a surprise, since they show that GIA has some indirect positive relationships with the government, even though they attack civilians. The good actors have extensive alliances amongst themselves, and the entire positive social network occupies less space than the negative one (the two figures are to the same scale). There is also a cross-border threat revealed in the relationship between AQIM and MUJAO with Mauritanian groups.

Libya. The relationships in Libya are, as expected, more complex with many combinations of both positive and negative relationships between the same subset of groups. Figure 6 shows the two main axes of negative relationships: between Al Qaeda and military special forces, and between Ansar al Sharia (and some related groups) and military and civilians. Figure 7 shows this latter axis in greater detail. The positive relationships are shown in Figure 8. There are several examples of positive relationships between groups who are, at the same time, closely associated with groups that have negative relationships – a messy ecosystem indeed.

Nigeria. The structure in Nigeria is simpler because it is dominated by Boko Haram, which is opposed to almost every

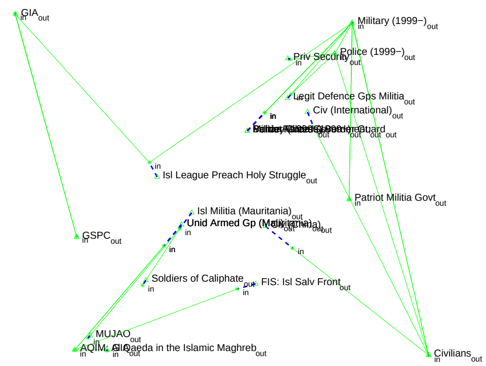

Fig. 5: Positive relationships among Algerian groups

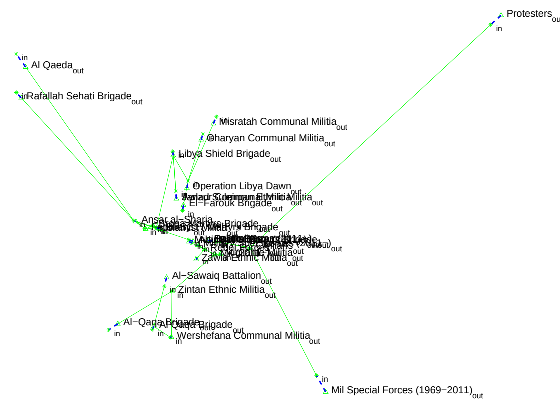

Fig. 8: Positive relationships among Libyan groups

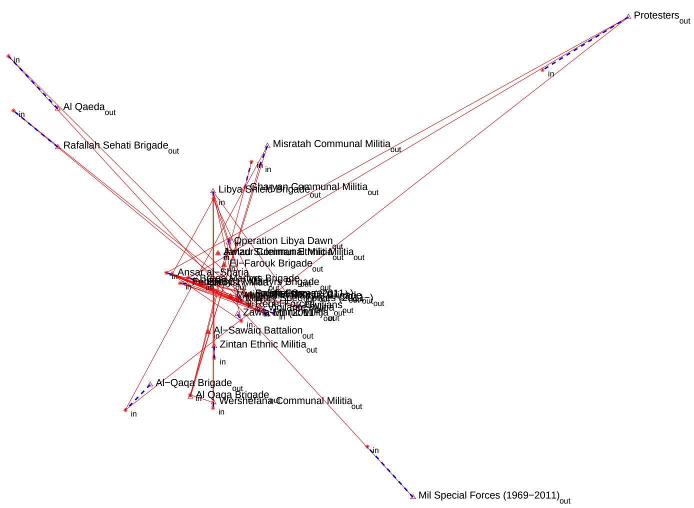

Fig. 6: Negative relationships among Libyan groups

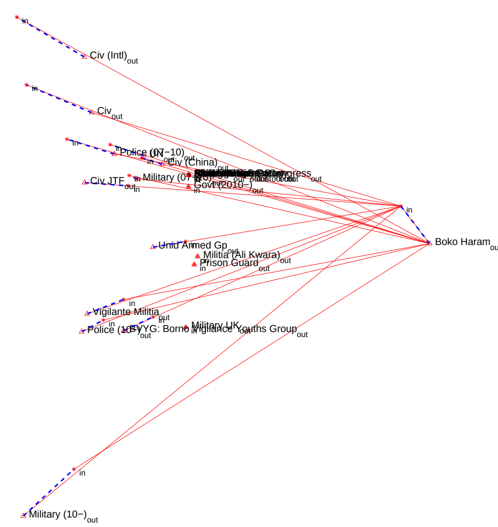

Fig. 9: Negative relationships among Nigerian groups

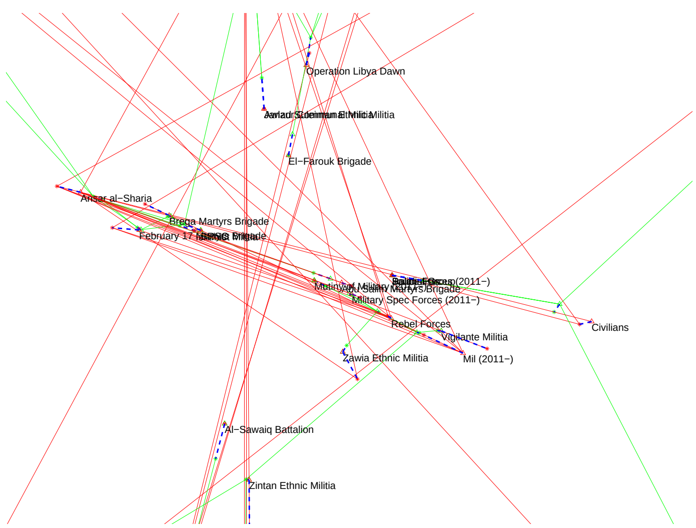

Fig. 7: Zoomed in positive and negative relationships among Libyan groups

other actor in the country. Figure 9 shows this clearly; note the relatively long dashed edge between the in and out versions of the Boko Haram node, signalling that negative relationships connect to groups that are similar in their position in the social network. The positive relationships are shown in Figure 10. Both of the positive relationships to Boko Haram are of intelligence interest. First, they clearly enjoy some support from civilians; second, they are supported by an Unidentified Armed Group suggesting that they are capable or willing to act under a false flag. Note how far separated the civilian groups are from the police and military post-2010, a situation that did not hold for these groups at an earlier time.

This country by country analysis shows that visualizations are able to show significant relationships: subsets of groups that are primarily in opposition to one another, subsets that are allies, and groups whose relationships to everyone else are unusual.

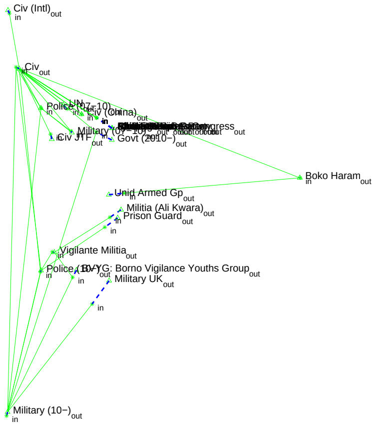

Fig. 10: Positive relationships among Nigerian groups

The entire North West Africa ecosystem

We now scale up this analysis to include 21 countries in North-West Africa. This is important because many groups operate across national borders, and a country-by-country analysis therefore misses significant interactions. We also choose two subsets of incidents, those involving incidents in which radical groups participated, and all incidents coded as violent. For each set of records, we select a large connected component of groups. (As expected, there are small sets of groups that interact only with one another, and we ignore these.) These subsets have previously been examined from a geographical perspective [9].

This much larger set of incidents can still be visualized but it is more challenging, especially as strong negative relationships tend to occupy the more significant dimensions in the embedding.

Figure 11 shows the interaction structure of the negative edges of a 173-node connected component derived from radical incidents; Figure 12 shows the corresponding negative edges.

The presence of groups with only or primarily negative edges to others forces embeddings in which the first few dimensions capture this oppositional structure, at the expense of details about other groups, which are all embedded close to the origin. For example, the negative edge weight between node 127 (GIA) and node 49 (Civilians (Algeria)) is 309, while the mean positive edge weight in this entire subgraph is 5.2 and the mean negative edge weight is 12.9.

The answer given by this approach to the question of how to consider the enemy of my enemy is this: if X has enemy Y, and Y has enemy Z, then the edge from Y to Z is *orthogonal* to that from X to Y. In other words, the best way to model the putative transitivity of negative edges is by orthogonality. This reveals the hidden assumption that we, as humans, tend to make: that such graphs ought somehow to be planar.

If we eliminate groups that are only connected to the rest by negative edges, we are left with 111 groups. The embeddings

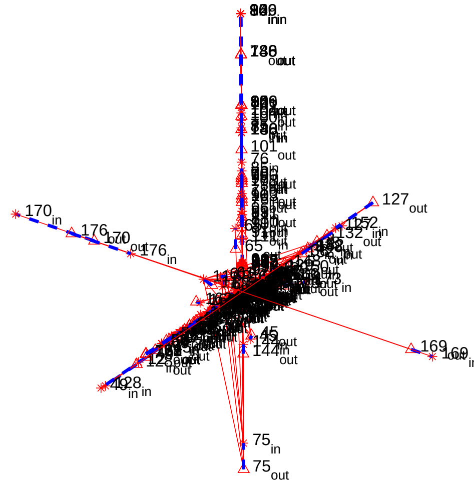

Fig. 11: 173 embedded groups involved in incidents with radical groups showing negative edges

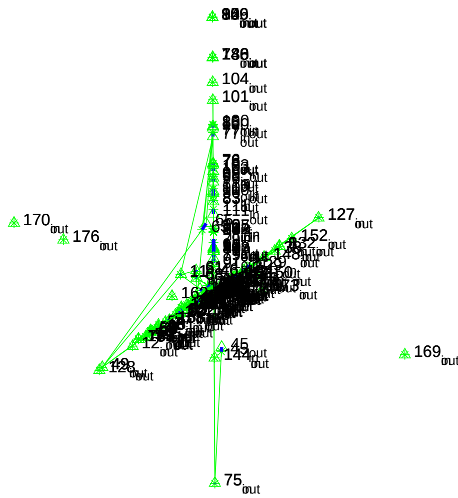

Fig. 12: 173 embedded groups involved in incidents with radical groups showing positive interactions

of their negative and positive structure is shown in Figures 13 and 14. Structures more complex than simply opposition now become visible in both the positive and negative substructure.

Finally, we select a subset of those groups that are connected to at least ten other groups. The relationships among these 16 groups are shown in Figures 15 and 16. These break into a small number of positively connected components (i.e. collaborating groups) that are united into a single structure by their negative edges. At this granularity, the lengths of the embedded extra edges become visible; for example, node 13 (Ansar al Sharia) has almost no net positive flow (so has mutual positive relationships with the same groups) but a substantial net negative one. The directed social network is important here since Ansar al Sharia has been the aggressor against several different categories of groups including civilians, rebels, the Libyan government, and external groups, including the 2012

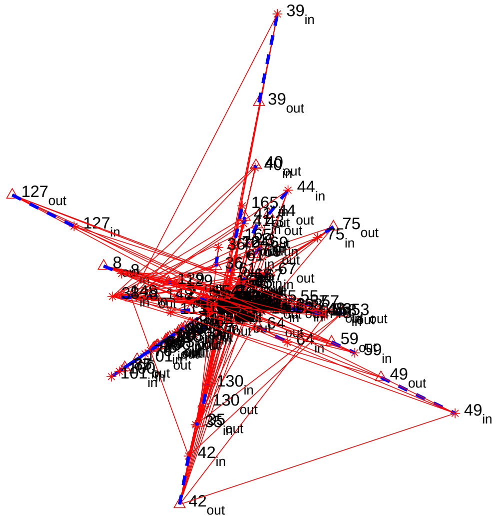

Fig. 13: 111 embedded groups involved in incidents with radical groups showing negative edges

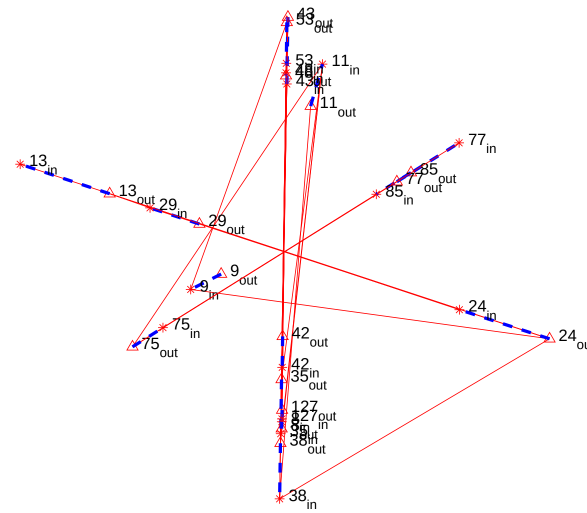

Fig. 15: 16 embedded groups involved in incidents with radical groups showing negative edges

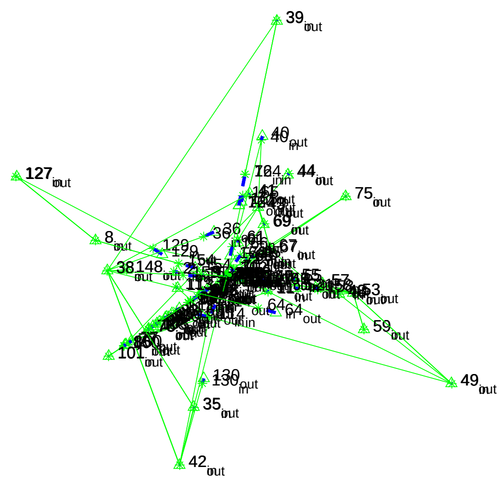

Fig. 14: 111 embedded groups involved in incidents with radical groups showing positive edges

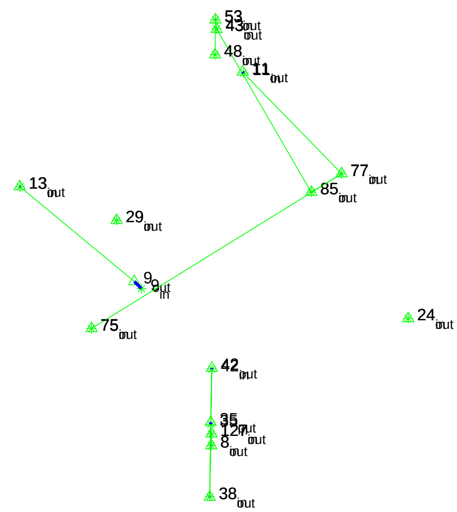

Fig. 16: 16 embedded groups involved in incidents with radical groups showing positive edges

attack against the U.S. Consulate in Benghazi, but has also been the target of violence from the Libyan government and external groups. These visualizations give some insights into the complex and shifting alliances and divisions among groups.

The visualizations are useful but become hard to interpret for large numbers of nodes or complex structure. Computing the normalized edge lengths for the extra edges between versions of the same node focuses attention on those that are unusual. This is shown in Table III. First, it is clear that the negative edges are much longer than the positive ones, as expected; there are more negative relationships, and they are quite focused. Second, the nodes that have substantial net flow can be highlighted. For example, node 77 (Civilians (Nigeria)) has unusually high normalized edges length in both columns. The figures show why: this node is connected in interesting ways to one set of nodes by positive edges e.g. 11 (Civilians (international)), and to a completely different set of nodes by negative edges (75 Boko Haram, and 85 Military Forces of Nigeria 2010–). Notice that there are both positive and negative edges connecting all three of these groups. The nodes highlighted here are all among the most important actors of the Northern Nigeria conflict, which opposes Boko Haram to both the Nigerian government and to Nigerian civilians. As Walther and Leuprecht show [9], Boko Haram is successful despite having virtually no friends. (The same can be said of ISIS.)

The subset of groups associated with violent action contains 1895 members. We select the subset of those connected to at least 20 others, resulting in a subset of 65 nodes. The negative and positive embeddings are shown in Figures 17 and 18. Again, constellations of groups in mutual opposition are

Node	Name	pos-pos	neg-neg
8	GSPC	0.023	1.621
9	Al Qaeda	0.033	0.167
11	Civ (international)	0.054	1.102
13	Ansar al-Sharia	0.048	13.981
24	Mil Forces Libya	0	14.402
29	Libya Shield Brigade	0	0.242
35	Ansar Dine	0.512	7.805
38	AQIM	0.166	29.832
42	MUJAO	0.290	1.309
43	Mil Forces France	0.104	10.157
48	Police (Algeria, 1999–)	0.007	0.438
53	Mil Forces (Algeria, 1999–)	0.087	29.877
75	Boko Haram	0.252	67.301
77	Civ (Nigeria)	0.372	92.177
85	Mil Forces (Nigeria, 2010–)	0.124	26.307
127	Mil Forces (Algeria 1994-99)	0.010	1.221
Mean		0.130	18.621
Std		0.152	26.492

TABLE III: Normalized length of embedded edges for the 16 radical groups

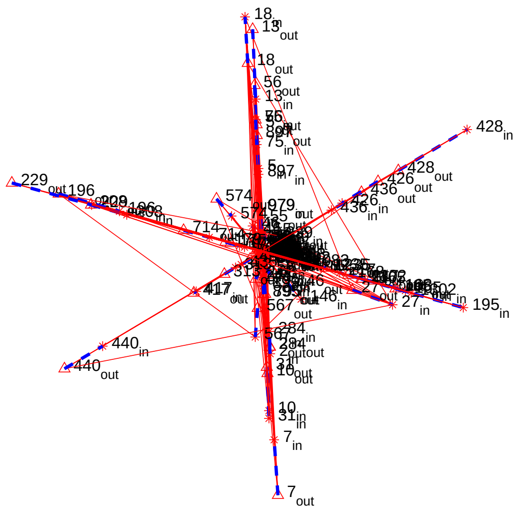

Fig. 17: 65 embedded groups involved in violent incidents showing negative edges

clearly visible, but there are also some interesting (primarily negative) relationships that connect the arms of the clusters. Note especially the strongly focused negativity between groups 195 (Unidentified Armed Group, Nigeria) and 196 (Niger Delta Defence and Security Council).

Table IV shows the normalized edge lengths for some of the groups that either have anomalous values or are visible in the embeddings. The magnitude of the values for Unidentified Armed Group (Nigeria) is a strong red flag, since it signals both that there is a major player in the conflicts in this region, and that it remains unidentified (although the earlier analysis for Nigeria was suggestive).

IV. Related work

Almost all work on signed networks has built on social balance theory, the idea that certain triads in social networks are much less likely to occur than others. For example, it is likely that two people who like each other will dislike a third, but not that two people who dislike one another will

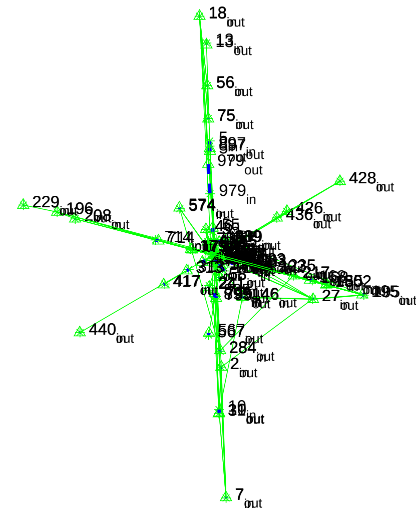

Fig. 18: 65 embedded groups involved in violent incidents showing positive edges

Nodes	Name	pos-pos	neg-neg
7	Mil Forces (Algeria, 1999–)	0.965	32.222
10	Police (Algeria, 1999–)	3.116	28.987
13	Rioters (Algeria)	0.410	21.711
18	AQIM	0.173	33.436
27	Civ (international)	0.165	10.338
31	Civ (Mali)	0.082	18.816
46	Unident Armed Group (Libya)	0.282	39.813
56	MUJAO	0.065	9.961
195	Unident Armed Group (Nigeria)	3.555	182.398
196	Niger Delta Def and Sec Council	0.067	109.039
229	Farmers Militia (Cameroon)	0.016	25.653
426	RUF	0.035	5.485
428	RPG (Guinea)	0.162	65.025
440	Union for the New Republic	0.254	45.255
Mean		0.331	13.319
Std		0.649	28.373

TABLE IV: Normalized edge lengths for selected nodes in the 65-node violent subset

like a third. There are more possible triads when the edges are directed, but the same kind of intuitive arguments can be made. There is also a edge-creation (and weight) bias because there is a natural return on investment in effort put into a positive relationship, but not for effort put into a negative relationship. (This shows how unusual the social network or ecosystem of these violent groups really is.)

A number of approaches have constructed objective functions derived from social balance and then used heuristic optimization techniques to find good clusters in networks (e.g. [4]). There has also been some work on signed edge prediction [1]. All of this work considers the edges to be undirected. Everett and Borgatti [5] develop ways to model negatively weighted edges (including when the edges are directed) using the complement of the positive graph. However, this approach does not include *both* negative and positive edge weights in the same model.

Leskovec *et al.* [6] looked at the way in which signed (and directed) social networks evolved in online communities and pointed out discrepancies from what social balance theory would predict. There are therefore questions about whether models derived from social balance can accurately model real-world data.

In adversarial settings, social balance theory may have some explanatory role for groups with a positive social orientation, but probably not for insurgent, anarchist, or corrupt groups.

V. Discussion and conclusions

Most real-world social networks contain relationships that are negative (dislike) as well as positive (like); and most relationships are asymmetric so that neither positivity nor negativity is necessarily reciprocated with the same intensity. Social network analysis techniques must be able to model this level of richness to address many real-world domains, especially those associated with national security (military, intelligence, counterterrorism) and law enforcement. The workhorse of social network analysis, spectral embedding, has struggled to model such networks because it, in the end, requires a symmetric matrix representation of the graph. We have shown how rich edge properties can be captured by creating multiple versions of each node, and preserving edge semantics in the connection patterns among these versions. Techniques to embed signed graphs and directed graphs have been combined to allow signed, directed networks to be embedded in a mathematically plausible way. While it is not possible to validate the construction directly, since it is not clear what the 'right answer' should be, we have illustrated the practical application of the approach using a small well-studied dataset, and some larger datasets where the understanding gained has practical value for understanding and intervention in ongoing North-West African regional violence.

References

[1] K.-Y. Chiang, C.-J. Hsieh, N. Natarajan, I.S. Dhillon, and A. Tewari. Prediction and clustering in signed networks: A local to global perspective. *Journal of Machine Learning Research*, 15:1177–1213, 2014.

[2] F.R.K. Chung. Lectures on spectral graph theory. www.math.ucsd.edu/~fan/research/revised.html, 2006.

[3] P. Doreian, V. Batagelj, and A. Ferligoj. *Generalized Blockmodeling*. Cambridge University Press, 2005.

[4] P. Doreian and A. Mrvar. Partitioning signed social networks. *Social Networks*, 31:1–11, 2009.

[5] M.G. Everett and S.P. Borgatti. Networks containing negative ties. *Social Networks*, 38:111–120, 2014.

[6] J. Leskovec, D. Huttenlocher, and J. Kleinberg. Signed networks in social media. In *CHI2010*, 2010.

[7] ———. Spectral embedding of directed networks. 2015.

[8] ———. Spectral embedding of signed networks. 2015.

[9] O. Walther and C. Leuprecht. Mapping and deterring violent extremist networks in north-west africa. Technical report, Department of Border Region Studies Working Papers 4, 2015.