Identifying Trends and Investigating Predictive Power in the Global Conflict Network

Wesley C. Olmsted
wolmsted@stanford.edu

Abstract

Conflicts on both the small-scale and large-scale lead to heavy loss of life and damages in the affected areas. Studies have been done on peace science and the factors that contribute to risk of conflict. In this paper, I use network analysis to model these conflicts between various groups. From this analysis, I will provide insights on victimized groups, conflict trends over time, and the most violent perpetrators. I also will demonstrate the predictive power of the network structure in identifying unknown armed aggressors.

1 Introduction

The global conflict network now operates at a massive scale because of many non-state players. There are conflicts that span country borders creating a vast network. Conflict networks present an interesting antithesis to social networks. In this paper, I will explore the nature of the global conflict network. I will use static and temporal techniques to identify the major motifs and trends that have changed over time. I will also place all the insights into qualitative context to better understand the actors that are most active in the network.

On top of this analysis, I will demonstrate that the network structure is valuable in identifying unknown aggressors. Oftentimes when there is an attack, no one will claim responsibility, but from the network structure along with other attributes of the attack we can make classifications of the unknown actor. This model can be extremely valuable so that the international community can hold the aggressors accountable for their actions.

2 Related work

2.1 Sharma et al., A complex network analysis of ethnic conflicts and human rights violations [1]

This paper focuses on ethnic conflicts and humans rights violations. The data they use is gathered from the GDELT Event Database, which contains articles from all over the world that can be queried by keywords. Sharma et al. constructed the graph by creating undirected edges between two actors involved in an event [1].

One of the key insights Sharma et al. provide is the systematic removal of the highest degree actors. They show how the percentage of actors present in the largest cluster decrease drastically at removal of less than 10% of nodes [1].

This paper was valuable in describing the structure of a conflict network in a way not many papers have. It helped illustrate the key way to make the most impact in violent clusters by removing the players with the highest degrees. The authors did not seem to take into account aggressors vs. victims, however. For example, one of their samples was, ”Serb forces were engaged in ethnic cleansing in Kosovo against the majority Albanian population of the province, according to the US government.” [1] In this case, it would be more difficult to identify the aggressor and victim because it would require some natural language processing, but using a directed graph seems to be a better option. Having ”Serb forces” as one node directed towards ”Albanian population” would help us have more insights in the network.

2.2 Campbell et al., Triangulating War: Network Structure and the Democratic Peace [2]

This paper focuses of the notion of democratic peace, meaning that “jointly democratic states do not go to war, but democratic states are not monadically less likely to engage in conflict.” [2] It attempts to show that this notion is not necessarily true because previous analysis has viewed conflict as being purely dyadic. Campbell et al. back up the claims by performing network analysis on state behavior. They also mention previous papers that support the notion of conflict graphs rarely showing triadic closure behavior since node i and j, which are engaged in a conflict with node k, would not engage in conflict with each other as it would interfere with their conflict with k [3]. One of the main hypotheses of the paper is that there are many mixed-regime two-stars, meaning there are frequent instances of two democratic states engaging in conflict with an autocratic state. These mixed two-stars are then calculated as:

$$\mathbf{h}_{MTS}(N) = \Sigma_{i>j>k}^{N}(N_{ij}D_iA_j)(N_{jk}A_jD_k)$$

where $\mathbf{h}_{MTS}(N)$ is the sum of all instances of the mixed two-star. N_{ij} refers to a state i in conflict with state, D_i refers to if i is a democratic state, and A_j refers to if j is an autocratic state. N_{jk} refers to a state i in conflict with state, A_j refers to if j is an autocratic state, and D_k refers to if k is a democratic state [2]. The paper concludes that once you account for the tendency of like-regime states with common enemies not to fight one another, “the effect of the democratic peace not only vanishes, but jointly democratic dyads seem to be more conflict prone than mixed dyads.” [2]

The main contribution of this paper is to show that an isolated, qualitative view of inter-state conflicts does not paint the true nature of conflict. The need for allies to share the burden of the cost of war exceeds the “force” of any kind of democratic peace. Showing the statistical significance of certain motifs in the conflict graph was illustrated well through comparison with different variations of random graph models. Overall, the study was well executed, but it seems that the focus could have been better served to also examine conflicts that do not have state players or have mixed state and non-state players.

2.3 Datta et al., Extracting Inter-community Conflicts in Reddit [4]

This paper takes a look at subreddits in a conflict network by investigating individual players displaying aggressive behavior in subreddits that are not their normal social home. The graph is set up with subreddits as nodes and directed edges as conflict. Each individual on reddit has social homes in subreddits where they post norm-compliant posts (upvoted posts). There is a certain threshold of 10 comments they must post in order to be a part of the social home [4]. For a certain amount of individuals from a given social home that post downvoted comments in other subreddits, a directed edge is drawn from the agressors’ subreddit to the victim subreddit.

The paper also goes into detail of a co-conflict graph, where the authors analyze the nature of individual agitators that share commonly attacked subreddits. An undirected edge is drawn between subreddit A and B if the set of agitators that have commonly attacked subreddits Jaccard coefficient is positive. The resulting graph is very disconnected because agitators tend to only misbehave in one subreddit. Datta et al. then performed community detection with the Louvain algorithm and displayed the strongest communities based on μ-score. The strongest communities tend to be about politics, sports, and video games [4]. Most interestingly, the paper delves into the shift of aggression over time. They created a monthly conflict graph and measured how many times a subreddit shifts its number one aggression from month to month. On average, subreddits changed 6.91 times over the year [4].

This paper does a good job creating a conflict graph in a unique way. Taking downvotes into account to create a conflict graph out of a social network helps to identify where aggressors tend to spend their time. By performing community detection and looking at changes over time, they present a holistic view of conflict.

3 Dataset

The dataset is from the Armed Conflict Location & Event Data Project (ACLED) [5]. The dataset ranges from 1997 to 2018. It contains conflicts between all non-state and state players ranging from mortar strikes against civilians in Syria to private security engaging with local tribes in Kenya. Each row of data contains the date of the conflict, type of conflict (battle, remote violence, violence against civilians, etc.), actors in the conflict, region, and number of fatalities. The dataset also contains 247,427 instances of conflict since 1997.

4 Approach

4.1 Graph construction

The graph is constructed as a partially directed, weighted graph. Each edge is weighted by the number of fatalities caused by it. If there are no fatalities in the conflict, we weight the edge as 0.1 so that we are using a nonzero weight. This graph can have multiple edges between nodes due to different conflicts. For motif detection, however, we use an unweighted graph with only at most one directed edge from node a to b and one from b to a. Edges are directed from the attacking group to the defending group. For this reason, civilians will not have any outgoing edges. There are more edges than instances of conflicts because some instances have multiple actors involved. Both graphs contain 9,599 nodes. The weighted graph contains 296,182 edges, and the unweighted graph contains 26,245 edges.

4.2 Static measurements

Before analyzing the graph temporally, I gathered static measurements on individual nodes and the underlying motif structure. These statistics include: out-degree, in-degree, pagerank centrality, betweenness centrality, HITS centrality, and 3-node motif counts. When working with motif counts, we need to compare with a null model in order to determine statistical significance.

4.2.1 Ranking by degree

Some of the simplest and most valuable measures in this conflict graph are out-degree and in-degree. From the weighted graph out-degrees, we can see the actors that are the most aggressive. From the in-degrees, we can see which actors have the most fatalities from attackers. On top of the simple in and out degrees, we can subtract $out - in$, which tells us how much actors are attacking over being attacked. $in - out$ shows us how much actors are being attacked over attacking others.

4.2.2 Pagerank centrality

To measure which actors are at the middle of conflict we can use centrality to find key players. Centrality can help to tell us which groups should receive the most aid if they are victims and can tell us which groups cause the most unrest in a region. We use the pagerank algorithm to determine each node's centrality. The pagerank algorithm is as follows [6]:

$$r_j = \Sigma_{i \to j} \beta \frac{r_i}{d_i} + (1 - \beta) \frac{1}{n}$$

Where r_i is the pagerank of node i, d_i is the weighted out-degree of node i, and β is a probability that we jump to another node.

4.2.3 Betweenness Centrality

Besides, pagerank centrality, betweenness centrality is a useful measure for determining the players that end up linking the subsects of conflict. Betweenness centrality is calculated by seeing how many shortest paths pass through each node.

$$c_{bet}(x) = \Sigma_{y,z \neq qx, \sigma_{yz} \neq 0} \frac{\sigma_{yz}(x)}{\sigma_{yz}}$$

Where σ_{yz} is the total number of shortest paths between nodes y and z, and $\sigma_{yz}(x)$ is the total number of shortest paths between nodes y and z that pass through x.

4.2.4 HITS Centrality

Hubs and authorities are a good way of understanding the aggressor and victim dynamic of the conflict network. Hubs with directed edges towards authorities can be thought of as aggressors, and authorities with inwards edges can be thought as the victims. We can use this simple iterative method to find the hubs and authorities.

$$c_{aut}(x) = \Sigma_{y \to x} c_{hub}(y)$$

$$c_{hub}(x) = \Sigma_{x \to y} c_{aut}(y)$$

$c_{hub}(x)$ is the hub value of node x and $c_{aut}(x)$ is the authority value of node x. We ran this method for 20 iterations.

4.3 Partially directed configuration model

The problem with using a standard configuration model to compare is that it only takes into account in and out degrees. We also need to take into account the undirected degrees. The conflict graph contains many undirected edges because violence is often reciprocated between two parties. We wanted to make sure we can accurately depict the difference between two parties engaged in conflict versus one party engaging with a nonviolent party. Our conflict graph contains about 28% undirected edges, which means the conflict is reciprocated 28% of the time. In order to create an accurate configuration model, we built on a partially directed graph model proposed by Spricer et al. [7] The algorithm for creating the model in our context of bidirectional edges is shown in Algorithm 1, where $G(V, E)$ is the graph G with vertices V and edges E.

Algorithm 1 Create partially undirected configuration model [7]

procedure PARTIALLYUNDIRECTEDNULLMODEL
    input $G(V, E)$
    $D \leftarrow$ initialized matrix of size $(|V|, 3)$
    $G_{null} \leftarrow$ initialized graph with $V_{null} = V$ and no edges
    for $i \leftarrow 0, ..., |V| - 1$ **do**
        $D[i, 0] \leftarrow d_i$ for out degree
        $D[i, 1] \leftarrow d_i$ for in degree
        $D[i, 2] \leftarrow d_i$ for undirected degree
    while $\Sigma_i D[i, 2] > 0$ **do**
        $m \leftarrow$ random i in $|V|$ where $D[i, 2] > 0$
        $n \leftarrow$ random j in $|V|$ where $D[j, 2] > 0$
        if $m = n$ **then**
            continue
        $E_{null} \leftarrow E_{null} \cup (m, n)$
        $E_{null} \leftarrow E_{null} \cup (n, m)$
        $D[m, 2] \leftarrow D[m, 2] - 1$
        $D[n, 2] \leftarrow D[n, 2] - 1$
    while $\Sigma_i(D[i, 0] + D[i, 1]) > 0$ **do**
        $m \leftarrow$ random i in $|V|$ where $D[i, 0] > 0$
        $n \leftarrow$ random j in $|V|$ where $D[j, 1] > 0$
        if $m = n$ **then**
            continue
        $E_{null} \leftarrow E_{null} \cup (m, n)$
        $D[m, 0] \leftarrow D[m, 0] - 1$
        $D[n, 1] \leftarrow D[n, 1] - 1$

4.4 Motif detection

In order to have a better understanding of the structure of the conflict network, we counted 3-node motifs using the ESU algorithm and compared the results with the null model discussed earlier.

The Z-scores were calculated by creating 10 samples of the null model and calculating the mean and standard deviation of each motif count. Then the Z-score was as follows:

$$Z_i = \frac{N_i^{real} - \bar{N}_i^{null}}{std(N_i^{null})}$$

4.5 Temporal motif detection

Since this dataset spans 21 years, it would be valuable how motifs change from year to year in the network. There might be trends over time that would show the changing nature of how conflict is conducted. In order to do this, we created 21 separate networks, one for each year from 1997 to 2018. Then we use the same null model and motif detection as discussed earlier. To account for differing sizes of these annual graphs, we used the network significance profile:

$$SP_i = \frac{Z_i}{\sqrt{\Sigma_j Z_j^2}}$$

Where SP is a vector of the normalized Z-scores.

4.6 Unidentified aggressor classification model

This dataset contains many instances of attacks by unknown groups. In order to address this problem and hold aggressors accountable, we can attempt to identify them using a classification model. We eliminated samples of unidentified groups from the dataset so we had reliable labels. The resulting dataset contains 168,194 samples. To capture the network features, we used Node2Vec for each node. On top of capturing the network features, this also drastically reduces the dimensionaltiy of the feature vector. If we did not use Node2Vec, we would need a one-hot vector to represent the victim of the attack, which would have dimension of 9,599. Instead using Node2Vec, we represent each node with a 128-dimensional vector. We used p = 1 and q = 1 to accurately capture both structure and neighborhoods of each node. Besides the node vectors, we concatenated the location of the attack in terms of latitude and longitude, country (as a one-hot vector), type of interaction (ie: remote violence), fatalities, and timestamp. The labels corresponded to the id of the actor in the graph. The dataset was divided up into train, dev, and test with a 80/10/10 split. It was also ordered temporally because the identification would be time-sensitive so having attack data from the future would introduce bias.

4.6.1 Classifier

We used a feedforward neural network as our main classifier. The network contiains 5 fully connected layers with a relu activation function. For an optimizer, we used an Adam optimizer, and for the dropout rate we used 0.1. We then optimized through 10 epochs of the data and used the weights that had the best dev accuracy from each iteration. To compare the classifier, we also instituted a Naive Bayes and Logistic regression classifier.

5 Results and discussion

5.1 Static measurements

This dataset contains many attacks by unidentified groups so for the sake of analysis, we omit these groups and focus on known ones. First, we gathered the in and out degrees of all nodes and recorded the top 5 in each category. The results are shown in Table 1. One major thing to notice is the groups with the highest out-degrees are not necessarily the aggressors. A high out degree for example in the case of AMISOM (African Union Mission to Somalia), which is an operation approved by the UN security council, can be attributed to a large amount of successful strikes. On the other hand, a high in-degree means that the group is taking on heavy losses from attacks. So oftentimes, civilians as well as violent aggressors have high in-degrees because they are targeted frequently.

The results for the out-in degrees and in-out degrees is displayed in Table 2. The highest out – in degrees mainly come from organized groups carrying out strikes on specific violent targets. For

	Group	Out-degree
1	Military Forces of Afghanistan (2004-)	74126
2	Military Forces of Yemen (2016-)	64467
3	Taliban	38706
4	Al Shabaab	29103
5	AMISOM (2007-)	24477

	Group	In-degree
1	Military Forces of Yemen (2012-)	66419
2	Taliban	53442
3	Islamic State (Iraq)	51745
4	Civilians (Nigeria)	43103
5	Al Shabaab	42584

Table 1: Groups with highest out and in degrees

example, AMISOM is fighting against Al Shabaab and the Global Coalition Against Daesh is fighting against ISIL. Not surprisingly, civilians make up the the most of in – out degrees. Interestingly, The war in Yemen is accurately reflected in these degree rankings. The Military Forces of Yemen (2016-) is also known as the Supreme Political Council who began challenging the existing regime in 2015 and has led to immense amounts of violence in the region. According to these numbers, the Military Forces of Yemen (2012-) or the Hadi regime have faced the heaviest attacks.

	Group	Out – In
1	Military Forces of Yemen (2016-)	59583
2	Military Forces of Afghanistan (2004-)	43636
3	AMISOM	24463
4	Global Coalition Against Daesh	21702
5	Military Forces of Ivory Coast (2000-2011)	19130

	Group	In – Out
1	Military Forces of Yemen (2012-)	65878
2	Civilians (Nigeria)	43103
3	Civilians (Syria)	42220
4	Islamic State (Iraq)	37914
5	Civilians (Somalia)	31780

Table 2: Groups with highest out – in and in – out degrees

For the pagerank centrality, the term d_i, which is the weighted out-degree of node i, dampens the pagerank so it would seem that civilian groups would have the highest pagerank. This is generally the case in Table 3. The one exception is the Islamic State (Syria), which means that they are engaged with many large players in the region. This kind of fighting on all fronts hits at a large amount of infighting between groups.

Betweenness centrality is an interesting measure because it can show which groups bridge together different regions of conflicts. Most conflicts tend to contained locally so nodes with high centrality are most often bridge nodes between regions. The betweenness centrality also shows that civilians are often these bridge nodes between other aggressive groups. There is one violent group in Al Shabaab with high betweenness centrality meaning that Al Shabaab is in conflict with various regional opponents.

	Group	Pagerank
1	Civilians (Somalia)	0.0093
2	Civilians (Democratic Republic of Congo)	0.0079
3	Civilians (Nigeria)	0.0078
4	Civilians (India)	0.0072
5	Islamic State (Syria)	0.0068

	Group	Betweenness
1	Civilians (Somalia)	2824915
2	Civilians (India)	2569817
3	Civilians (Pakistan)	1985836
4	Civilians (Nigeria)	1736069
5	Al Shabaab	1551730

Table 3: Groups with highest pagerank and betweenness centrality

One of the best measures of centrality for the conflict graph is HITS shown in Table 4. Most of the time, hubs and authorities accurately fill roles of aggressive groups and victimized groups. Due to the recursive nature, the highest authority scores are all civilians because they are at the center of most conflicts. This also in turn means that the hubs are the most violent in targeting civilians. We can see that three main conflicts are responsible for these high centrality scores: the Syrian Civil War, Sudanese Civil Wars, and Somali Civil War.

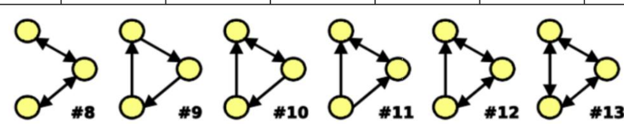
	Group	Hub		Group	Authority
1	Al Shabaab	0.1808	1	Civilians (Somalia)	0.2445
2	Military Forces of Sudan (1989-)	0.1700	2	Civilians (Sudan)	0.2173
3	Military Forces of Syria (2000-)	0.1507	3	Civilians (Syria)	0.1368
4	Military Forces of South Sudan (2011-)	0.1206	4	Civilians (Democratic Republic of Congo)	0.1316
5	Islamic State (Syria)	0.1077	5	Civilians (South Sudan)	0.1280

Table 4: Groups with highest hub and authority scores

5.2 Motif detection

The resulting Z-scores are shown in Figure 1. Interestingly enough, based on literature triadic closure was quite infrequent because it makes little sense to engage with an enemy of an enemy [2]. Our findings show that the 12th motif where two actors are engaged with each other and one is aggressive toward the other is one of the most statistically significant Z-scores. The previous works tend to focus more on inter-state conflict so this might be a relatively new phenomenon with conflicts on the smaller scale. Also, noteworthy motifs are ones that contain a node with no out edges and only in edges. This would most likely signify civilian targeting. For example, motifs 4 through 6 have a node that is targeted by two other nodes. These 3 nodes appear often with statistical significance so we can assume that civilians are often involved in small skirmishes regardless if they are targeted on purpose. Motif 5 is the most significant motif and is interesting because there is no reciprocated aggression. It seems that one actor is targeting civilians directly and the other is attacking both with the violence towards civilians potentially being incidental.

0.9399	1.250	-15.70	13.35	115.7	68.04	-29.83



59.38	28.48	-1.400	56.61	88.22	-0.288

Figure 1: Z-Scores of 3-node motif counts

5.3 Temporal motif detection

Normalized Z-scores from 1997 to 2018 are shown in Figure 2. From first glance, it does not seem that any motif steadily increases or decreases over the years. Most tend to change sporadically from year to year. One of the most interesting motifs is motif 13, which is not very statistically significant until 2016 where it spikes quite heavily. Motif 13 is a triangle motif where all actors have shown aggression to all others in the triangle. This motif is usually not very common, but in 2016, there is a serious change in the conflict network, which has led to this becoming more prevalent. This potentially could have arisen out of more intervention in the Syrian Civil War, and the sheer amount of different players involved in the conflict. The three-way conflict motif suggests that there are groups with the same enemies and goals that are fighting among themselves. Many Islamic militant groups differ on ideology and this leads to infighting and a more decentralized power struggle. Overall, some spikes are anomalies and provide a starting point for more investigation into major conflicts during that year.

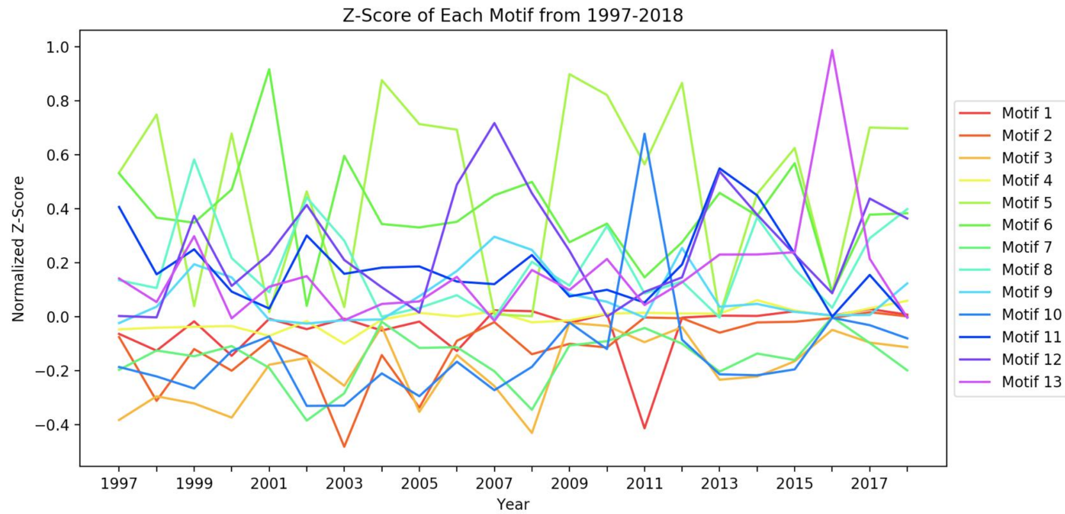


Figure 2: Normalized Z-Scores of 3-node motif counts from 1997-2018

5.4 Aggressor classification

The neural network classifier was significantly more accurate than the Naive Bayes and Logistic regression classifiers. With 72% accuracy the neural network classifier is extremely successful considering there are 9,599 possible labels. The classifier still struggles with similar groups that operate in the same regions. For example, one incorrectly classified sample was an attack against the Afghanistan military, which was classified as the Taliban. The correct label was the Islamic State (Afghanistan). This introduces a problem with the model because these hard identifications are often the most valuable. Overall, this model is best used for identification at scale or in conjunction with proper qualitative investigation.

Classifier	Accuracy
Naive Bayes	0.0511
Logistic regression	0.0781
Neural network	0.720

Table 5: Test set accuracy

6 Conclusion and future work

The main value of this project is the applications combined with real-world context. One caveat to consider is that this dataset does not contain indirect fatalities. Famine in Yemen, for example, is one of the largest crises in the world, but it is not reflected in these numbers. Quantitative data on specific actors in the network can lead to prioritizing in peacekeeping missions or aid to violent regions. The methods for identifying trends in motifs can help increase the depth to how we investigate small-scale conflicts. Node2Vec provides a powerful method of using network features to help solve a difficult problem in identifying aggressive actors. It also provides a way of dimensionality reduction necessary for complicated models. For future work, this predictive model could be expanded on. For example, we could use natural language processing from news articles as part of the feature space. Also, more hyperparameter tuning would benefit the model. Predictive models using edge detection could also be valuable in identifying at-risk civilians. Overall, network analysis provides us both macro and micro insights on the nature of modern conflict.

Github link: https://github.com/wolmsted/conflict-network-analysis

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