Analyzing Escalations in Militarized Interstate Disputes using Motifs in Temporal Networks

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Abstract. We present a temporal network analysis of militarized interstate dispute (MID) data from 1992 to 2014. MIDs progress through a series of incidents, each ranging from threats to uses of military force by one state to another. We model these incidents as a temporal conflict network, where nodes denote states and directed edges denote incidents. We analyze temporal motifs or subgraphs in the conflict network to uncover the patterns by which different states engage in and escalate conflicts with each other. We find that different types of temporal motifs appear in the network depending on the time scale being considered (days to months) and the year of the conflict. The most frequent 3-edge temporal motifs at a 1-week time scale correspond to different variants of two states acting against a third state, potentially escalating the conflict. Temporal motifs with reciprocation, where a state acts in response to a previous incident, tend to occur only over longer time scales (e.g. months). We also find that both the network's degree and temporal motif distributions are extremely heavy tailed, with a small number of states being involved in many conflicts.

Keywords: Temporal Motifs, Dynamic Networks, Militarized Incidents, International Conflicts, Conflict Networks, Conflict Escalation, Motif Distribution.

1 Introduction

Militarized interstate disputes (MIDs) are conflicts between (sovereign) states that are not full-scale wars [1]. Each dispute can be broken down into a series of smaller incidents, which provide us with additional information about the progression of the dispute. By analyzing past data on such incidents, we may discover some insights about how they escalate and de-escalate over time.

Incidents in MIDs can be modeled as a conflict network [2]. Each node in the network is a state, and each temporal edge is an incident, such as a threat, display, or use of force one state directs toward another. We include the temporal dimension in this network to analyze how disputes and international relations change over time.

A variety of analysis methods have been developed for temporal networks [3], including centrality measures [4], temporal community structures [5], and generative models [6, 7]. In this paper, we use *temporal motifs* [8] to extract information from MIDs. In a temporal or dynamic network, temporal motifs are defined as sequences of

edges that complete within a time interval. Fig. 1 shows an example of temporal motifs in a conflict network. The main reason to use temporal motifs to analyze incidents in MIDs is to identify patterns of escalations of disputes at different time scales.

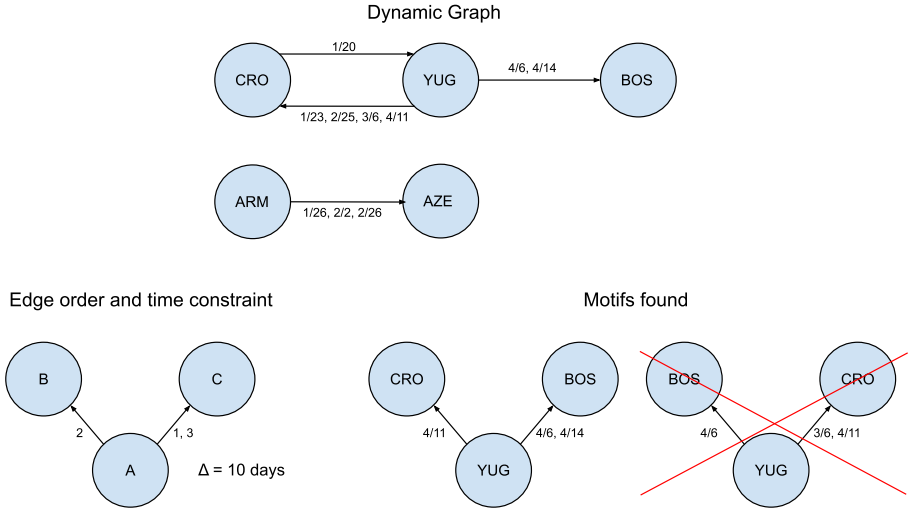


Fig. 1. Given a temporal network (top) and a temporal motif of interest (bottom left), we find one such instance of the motif (bottom right). The other crossed out one is not an instance despite matching the correct order of edges because the completion time exceeds the time limit of 10 days from first edge to last edge.

We present an analysis of MID data from 1992 to 2014 using temporal motifs on conflict networks constructed from incidents. Our main findings are as follows:

- A variety of temporal motifs appear, depending on the time scale we consider. We observe primarily non-reciprocal motifs over short times (e.g. 1 week), indicating that target states generally do not quickly escalate a conflict in response to an incident. Reciprocal motifs are more frequent over longer times (e.g. several months).
- The number of temporal motifs observed in a year is only moderately correlated with the number of incidents. Since temporal motifs denote rapid escalations of conflict, this indicates that lots of conflicts do not escalate quickly over time.
- Both the distribution of the number of incidents and the number of temporal motifs over the states are extremely heavy tailed, although they are better explained by alternative distributions, such as a stretched exponential, rather than a power law.

2 Materials and Methods

Data Description. We use the dataset MID 5.01 [1] compiled by the Correlates of War project. We use the incident-level data (MIDIP), which provides the date of each incident in a dispute from 1992 to 2014. Each incident represents a threat, display, or

use of force one state directs toward another. We construct a temporal network from the incidents using states as nodes and directed timestamped edges from the state that takes the action (side A) to the state that is the target (side B) using the start date of each incident. The dataset contains 156 states; 4,482 incidents; and 5,136 edges. (The number of edges is higher than the number of incidents because some incidents involve more than 2 states.) The MID data also contain short narrative descriptions of the incidents that are used to code the incident-level data.

The time resolution in the dataset is at the level of 1 day. Some of the incidents that happen on the same day may possibly happen one after another—for such actions, the dataset provides the temporal ordering of the incidents, but not the exact time. We assign each incident a time so that all incidents on that day are equally spaced; for example, a day with 1 incident is assigned the time of 12:00 UTC, while a day with 2 incidents is assigned the times of 8:00 and 16:00 UTC.

Temporal Motifs. There are many definitions of temporal motifs present in the literature [3]. We conduct our analysis using the Python package DyNetworkX [9] to enumerate temporal motifs according to the definition from [8]. For a subgraph in the network to match a temporal motif, it needs to have the correct ordering of edges, and the time difference between the first and last edges needs to be within the completion time δ (e.g. 10 days in Fig. 1). However, there is no need for the edges to be consecutive—there may be another edge that occurs between edges in the temporal motif. Also, since we impute the exact time during the day of an incident, our temporal motif counts are an estimate of the actual counts that would be obtained given the actual incident timestamps.

We first calculate all possible 2 or 3-node, 3-edge temporal motifs, which are shown in Fig. 2(a), with maximum completion time δ of 7 days. We choose these small motifs primarily for ease of interpretation. By using this short time period, we focus on rapid escalations between countries rather than long-term changes. After that, we calculate these motifs with different completion time intervals of [0, 3], (3, 7], (7, 30], and (30, 120] days to analyze the escalations at different level of intensities. In addition to counts of different motifs, we also analyze the frequency of different temporal motifs by state and by role (red, green, or blue node) in the motif.

While many incidents involve a single state on side A and a single state on side B, some incidents have multiple states on a side. For example, a group of 4 allied countries (side A) may decide to take joint action targeting another state (side B). This would be represented by 4 temporal edges (from the 4 different side A states to the side B state) at the exact same time. Having such edges at the same time destroys the notion of order for temporal motifs, which do not account for simultaneous edges. To not lose these simultaneous edges, which will in turn impact our motif counts, we added a small Gaussian noise (mean of 0, standard deviation of 1 second) to each of the timestamps. This creates a unique ordering of the edges, so that they now appear in temporal motifs; however, the ordering is artificial and dependent on the noise values. We average results over 10 different networks generated with different random noise values to mitigate the artificial ordering.

Degree and Motif Distributions. The degree distribution is one of the most fundamental properties of a network. The degree distribution for many types of networks are heavy tailed and often claimed to follow a power law; however, recent findings suggest that alternative heavy-tailed distributions may be a better fit [10].

We consider the degree distribution of the temporal network, which is a distribution of the number of incidents that a particular state has been involved in (either on side A or B). This is also the weighted degree distribution of a static network aggregated over time. (The unweighted degree distribution of the aggregated network is less interesting because the maximum degree is limited by the 156 states.) We next consider the distribution of participations in temporal motifs, which we call the *motif distribution*, in a manner analogous to a degree distribution. The motif distribution is a distribution over the number of times a state is involved in any temporal motif in any of the three roles.

We analyze degree and motif distributions using the Python package powerlaw [11], which fits both power law distributions and other heavy-tailed distributions. We use the likelihood ratio test proposed by Clauset et al. [12] for direct comparison of two candidate distributions. We compare the fit of a power law distribution with the exponential, log-normal, stretched exponential (Weibull), and truncated power law alternative distributions for both the degree and motif distributions.

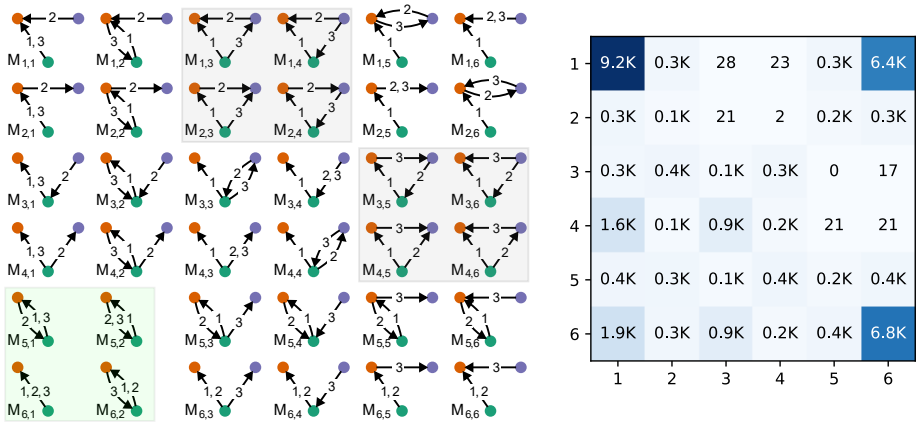
3 Results

We first present the observed frequencies for all temporal motifs with a maximum completion time of 7 days over the entire data trace. We then examine several motifs that appear frequently (Section 3.1), motif frequencies for different completion times (Section 3.2), and distributions of motifs over time and states (Section 3.3). Code to reproduce all results in this paper can be found at the following GitHub repository: `https://github.com/IdeasLabUT/Temporal_Motifs_MIDs`.

Fig. 2(b) shows the count of all 2 or 3-node and 3-edge temporal network motifs with a maximum completion time of 7 days from the constructed network. The average total motif count is about 33,000 with standard deviation of 18 (due to the Gaussian noise added to the timestamps). The dominant motif counts we found are, in decreasing order:

1. $M_{1,1}$, $M_{1,6}$, and $M_{6,6}$: 2 states initiate 3 incidents in total with the same target state.
2. $M_{6,1}$: 1 state initiates 3 incidents in a row with the same target state.
3. $M_{4,1}$, $M_{4,3}$, and $M_{6,3}$: 1 state initiates 3 incidents in a row with 2 other target states.

The triangle motifs do not frequently appear, likely because it is unusual to have cyclical relationships between countries in the context of international conflicts. Moreover, the prominent motifs we listed out above are not reciprocated. They all show one side initiating incidents to another state without getting any immediate retaliation. Examples of reciprocated motifs are $M_{1,2}$, $M_{1,5}$, and $M_{2,6}$, all of which appear to have very low counts compared to the prominent non-reciprocated ones. We discuss reciprocated motifs further in Section 3.2 when we vary the motif completion time.



(a) (b)

Fig. 2. (a) All possible temporal motifs with 2 or 3 nodes and 3 edges (figure credit: [8]). Green and grey shaded boxes denote 2-node and triangle motifs, respectively. We denote the green, red, and blue nodes as roles 1, 2, and 3, respectively. (b) Temporal motif counts with a maximum completion time of 7 days for each of the 2 or 3-node, 3-edge motifs. Counts are averaged over 10 networks with Gaussian noise added to each timestamp for each temporal motif type.

3.1 Motifs of Interest

We looked further into the prominent motifs to determine which states are most involved in each motif and in which roles in the motifs. For all motifs in Fig. 2(a), role 1 means the green node, role 2 means the red node, and role 3 means the blue node. States are denoted by their 3-letter codes from the Correlates of War project [13].

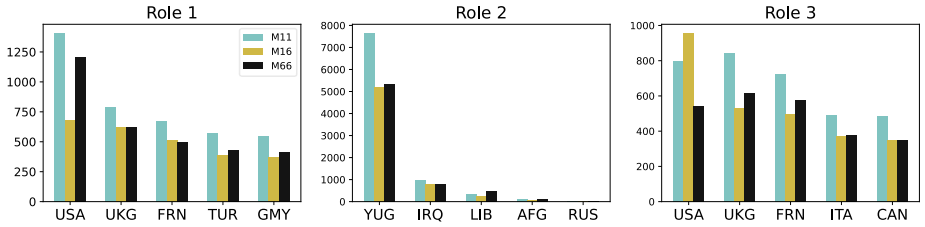


Fig. 3. Motifs $M_{1,1}$, $M_{1,6}$, and $M_{6,6}$ (2 states initiate incidents towards 1 target state)

Motifs $M_{1,1}$, $M_{1,6}$, and $M_{6,6}$ (many to one). We can see from Fig. 3 that Yugoslavia[1] is the most frequent participant in these motifs. It has high counts in role 2 of $M_{1,1}$, $M_{1,6}$, and $M_{6,6}$, which shows that it was on side B of many incidents initiated by other

[1] Yugoslavia and Serbia may be conflated in this data set. There is no COW country code for Serbia, despite it being mentioned in some of the narratives.

states. The most frequent participant in roles 1 and 3 is the USA, which was involved in two main disputes that created these types of motifs: a dispute with Yugoslavia, where Germany, Turkey, the Netherlands, and Greece among others were also on side A with the USA; and a dispute with Iraq, where the United Kingdom and France among others were also on side A with the USA.

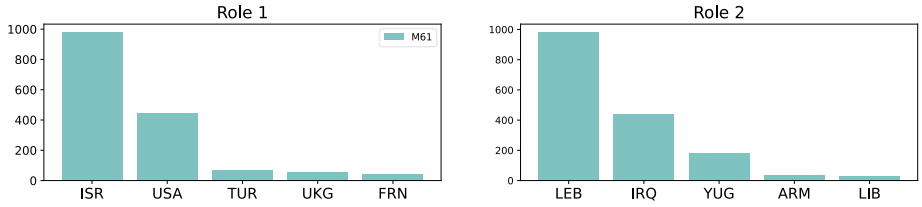


Fig. 4. Role of each country in Motif $M_{6,1}$ (1 state initiates 3 incidents towards a target state)

Motif $M_{6,1}$ (one to one 3 times). From Fig. 4 we can see that the main participants in motif $M_{6,1}$ are Israel dominating role 1, and Lebanon dominating role 2. The edges that Israel directs toward Lebanon account for about 11% of the total incidents from 1992 to 2014. On the other hand, the proportion of edges in the opposite direction is only 0.5%, which implies that Lebanon rarely retaliates against Israel. This can also be illustrated by the low count of $M_{5,1}$, $M_{5,2}$, and $M_{6,2}$, which represent balanced reciprocity between the 2 countries. Most incidents appear to be Israeli attacks on Hezbollah guerillas in southern Lebanon, with the Lebanese not getting involved as frequently.

The next most frequent participants in motif $M_{6,1}$ are the USA in role 1 and Iraq in role 2. Many incidents involved a show of force building up to the USA's invasion of Iraq. Other states also participated in this dispute, which shows up in other motifs such as the many-to-one motifs discussed previously.

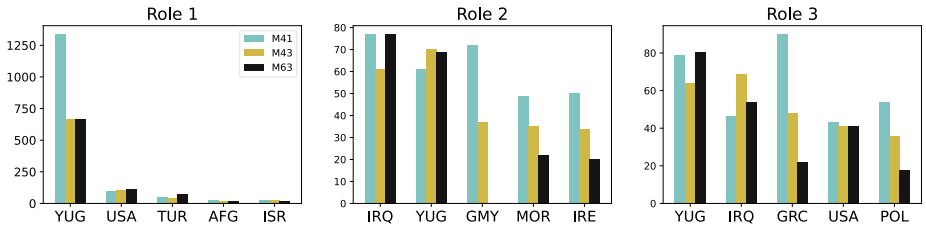


Fig. 5. Motifs $M_{4,1}$, $M_{4,3}$, and $M_{6,3}$ (1 state initiates incidents towards 2 target states)

Motifs $M_{4,1}$, $M_{4,3}$, and $M_{6,3}$ (one to many). From Fig. 5, the most frequent participant in these motifs is again Yugoslavia, and this time, in role 1, which shows that it initiated incidents towards many other target states. Unlike the case of Israel and Lebanon for motif $M_{6,1}$, only about 3% of the total edges in the network have Yugoslavia on either side of the one-to-many and many-to-one motifs. Even though Yugoslavia isn't

involved in as many total incidents as Israel or Lebanon, when it is involved, it tends to escalate fast and bring in many other countries. By digging further into when the one-to-many and many-to-one motifs occur, we find that most of them are only in 1999 and 2000, which is shown in Fig. 6.

From the narratives for these actions, we find that they are the result of conflicts between Yugoslavia and Kosovo. These conflicts had interventions from the North Atlantic Treaty Organization (NATO), which increases the motif counts for Yugoslavia substantially. We note that the incidents involving NATO tend to be joint threats from its member countries. As we discussed earlier, these joint threats are coded as having the same timestamps, which the temporal motif counting algorithm ignores. With the noise we added to each time stamp, these incidents now have random orderings, so they are included in our motif counts.

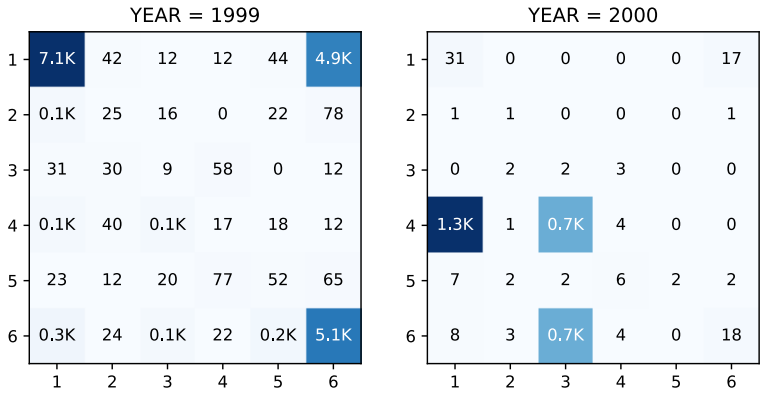


Fig. 6. Temporal motifs in 1999 and 2000, with completion window $\delta = 7$ days

Moreover, these motifs all lack reciprocity, which shows that there was not much immediate retaliation from the state on side B. If there were, other motifs such as $M_{1,2}$ or $M_{4,2}$ should also occur frequently. The fact that Yugoslavia was the center of these 2 groups of motifs shows that it took a while for Yugoslavia to retaliate back (side A) in 2000 after being on side B in 1999, as we can see in Fig. 6.

3.2 Temporal Motif Distributions at Different Completion Times

The smaller the completion time, the more rapid we find the escalation to be. Fig. 7 shows the temporal motif distribution at different completion time intervals. We can notice that the one-to-many motifs $M_{4,1}$, $M_{4,3}$, and $M_{6,3}$ fade away in relative frequency as the completion time gets longer. This shows that this behavior can only occur when a state escalates quickly, and single-handedly engaging in conflicts with many other states over a long time period is not an ideal tactic. However, the opposite is possible, which is also illustrated in Fig. 7, as the many-to-one motifs $M_{1,1}$, $M_{1,6}$, and $M_{6,6}$ remain dominant as the completion time increases.

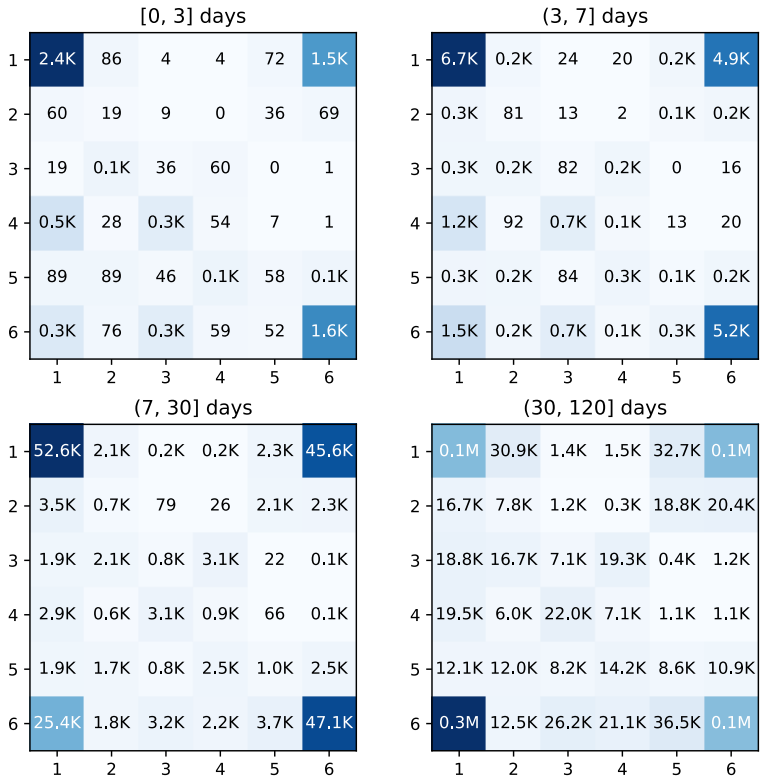


Fig. 7. Temporal motifs for different completion time intervals δ

Another interesting observation is that reciprocated motifs, particularly $M_{1,2}$, $M_{1,5}$, and $M_{2,6}$, begin to appear more frequently as we increase the completion time. For completion time between 30 and 120 days, $M_{1,2}$ and $M_{1,5}$ appear even more frequently than the one-to-many motifs, which indicates that reciprocation by a target (side B) state to an action from a side A state tends to happen more slowly than continued escalation from the side A state.

Finally, we observe that motif $M_{6,1}$, which denotes one state against another 3 times, increases significantly in frequency for longer completion time. Indeed, it becomes the most frequent motif for completion time between 30 and 120 days.

3.3 Motif Distributions Over Time and States

In the context of MIDs, temporal motifs represent escalations whereas edges represent separate conflict incidents. They represent different things, which can reveal more insights when we analyze them together. An analysis over the raw number of edges (incidents) can help us get the context that those motifs are in.

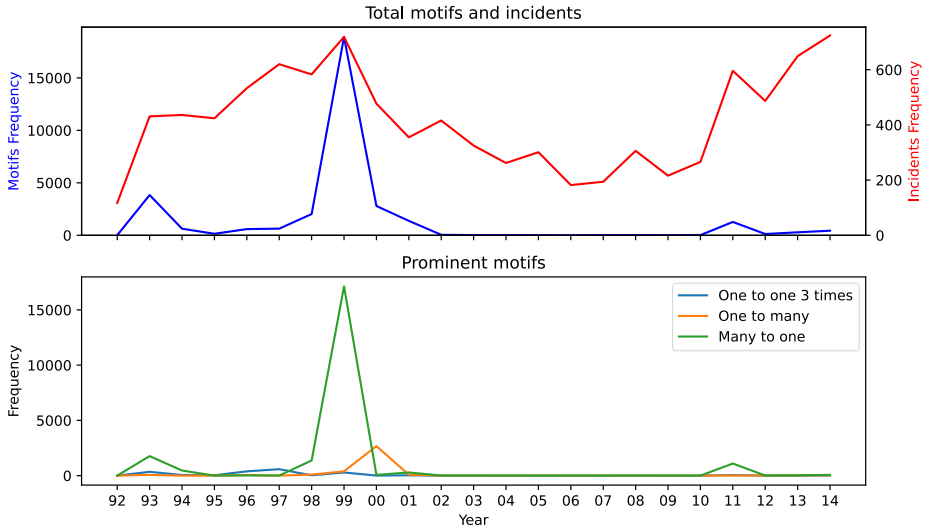


Fig. 8. (Top) Distribution of all 3-edge temporal motifs (with a completion time of 7 days) vs. raw edges (incidents) over years. (Bottom) Distributions of prominent motifs over years.

Distributions Over Time. Fig. 8 shows the distribution of temporal motifs and raw edges over the timeline of the dataset. We can notice that they have some correlation with each other, with correlation coefficient of 0.44. This is somewhat expected because more edges tend to lead to more motifs. However, in many years, that is not the case as one can see in Fig. 8. From 1994 to 1998 and 2011 to 2014, even though there were a lot of incidents, the number of temporal motifs (at a 1-week time scale) remains very low. This implies that those incidents happened over a long period and don't constitute any type of rapid escalations. Moreover, we can observe that there are spikes in the trend of temporal motifs, particularly the many-to-one motifs in 1999 and the one-to-many motifs in 2000. If we exclude those two years, the many-to-one motifs are still among the most frequent, while the one-to-many motifs are not. Indeed, the most prominent motif type can be different in each year and different from the aggregated results over the entire data trace shown in Fig. 2(b). On the other hand, the trend of raw edges over time is more gradual. This can be explained by how one escalation tends to lead to another in a short time period then fades away altogether. Both trends show that interstate conflicts were less intense from 2002 to 2011 when there was a low number of incidents and almost no escalations.

Distributions Over States. We find that both the degree and temporal motif distributions have heavy tails, with a few states dominating the counts, as shown in Fig. 9. The exponential distribution is a particularly bad fit for both the degree and motif distributions due to its lack of heavy tails. However, after fitting different heavy-tailed distributions to the data, we find that neither the degree nor motif distributions are best explained by a true power law distribution. They are better fit by either a

lognormal, stretched exponential, or truncated power law distribution as shown by the statistics in Table 1.

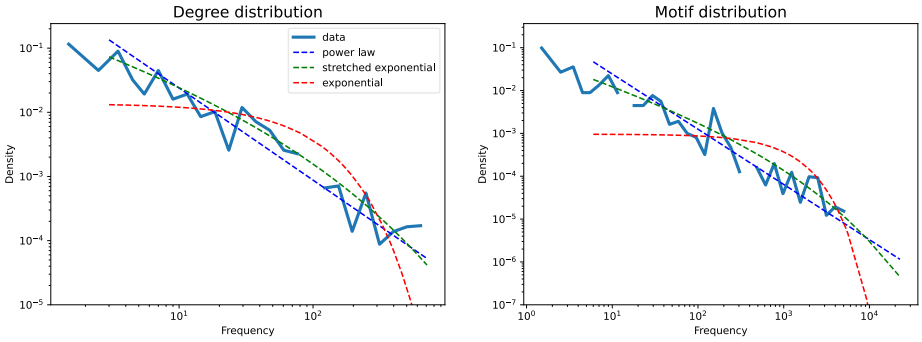


Fig. 9. Degree and temporal motif distributions (solid lines) in the network on a log-log scale. Both distributions are quite heavy tailed, as indicated by the poor fit of the exponential distribution compared to a power law or stretched exponential (dashed lines).

Table 1. Summary of likelihood ratio tests for degree and motif distributions. While both the degree and motif distributions are heavy tailed, they are better explained by alternative heavy-tailed distributions rather than a power law.

	Degree distribution			**Motif distribution**		
Distribution	*Preferred to PL?*	*p-value*	*Parameter estimate*	*Preferred to PL?*	*p-value*	*Parameter estimate*
Power law (PL)	–	–	$\hat{\alpha} = 1.44$	–	–	$\hat{\alpha} = 1.29$
Exponential	No	0.013	$\hat{\lambda} = 0.013$	No	0.023	$\hat{\lambda} = 0.001$
Log-normal	Yes	< 0.001	$\hat{\beta} = 0.37$	Yes	< 0.001	$\hat{\beta} = 0.35$
Stretched exponential	Yes	< 0.001	$\hat{\sigma} = 1.98$	Yes	< 0.001	$\hat{\sigma} = 2.38$
Truncated power law	Yes	< 0.001	$\hat{\alpha} = 1.06$	Yes	< 0.001	$\hat{\alpha} = 1.00$

The parameter estimates in Table 1 suggest that both the degree and motif distributions in the MID incident network are extremely heavy tailed. For example, the estimated power law scaling parameter $\hat{\alpha}$ values of 1.44 and 1.29 are smaller than the typical range of $2 < \alpha < 3$, indicating heavier tails [12]. Furthermore, the motif distribution has an even heavier tail than the degree distribution, indicating that a small number of states are involved in a large number of conflict escalations.

4 Conclusion

In this paper, we illustrated how temporal motifs can be beneficial in analyzing militarized interstate disputes (MIDs). By representing escalations between states as tem-

poral motifs, we investigated their intensities and patterns. We found that, somewhat surprisingly, there are not many reciprocated motifs at short time scales. Instead, there are mainly motifs that show that one state initiates actions towards a single target multiple times and disputes between one state with many other targets. We identified key participants, such as Israel, Lebanon, Yugoslavia, and the USA, for each role in those motifs. By varying the completion time, we found that motifs representing one state acting against many other targets only occurred frequently in short completion times, while motifs representing reciprocated actions only occurred frequently in long completion times. We also demonstrated the difference between using temporal motif counts, which show rapid escalations, and raw edge counts, which represent incidents without rapid escalations, over time to analyze conflicts. Both the temporal motif and degree distributions over the states are extremely heavy tailed, with just a few states dominating the counts.

A potential limitation of this analysis concerns the accuracy of the dataset. A study in 2012 found that there may be flaws within the dataset [14]. Furthermore, states change over time as a result of conflict but may be coded the same way in the dataset, such as Yugoslavia. Even though the country ceased to exist in 1992, there are still edges in the years after that. The narrative for a 1999 incident uses the name Yugoslavia in the description, whereas the 2013 one uses the name Serbia (even though that incident is still coded as YUG in the dataset). Moreover, Serbia is not in the dataset. Hence, we suspect that Yugoslavia and Serbia may be conflated.

Another limitation is that we ignore the different types of incidents, which range from threats to use of military force. A potential avenue for future work involves modeling these different types of incidents as multi-layer conflict networks, which could be analyzed using multi-layer temporal motifs [15].

Acknowledgments. This material is based upon work supported by the National Science Foundation grants IIS-1755824, DMS-1830412, and IIS-2047955. We would like to thank the University of Toledo's Office of Undergraduate Research for providing funding for Hung Do through the Undergraduate Summer Research and Creative Activities Program (USRCAP).

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