A Social Network Analysis of Emergent International Communities: A Global Discussion about the 2013-2014 Ukrainian Crisis

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To Sarah, John, Lila and Anna.

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ABSTRACT

A SOCIAL NETWORK ANALYSIS OF EMERGENT INTERNATIONAL COMMUNITIES: A GLOBAL DISCUSSION ABOUT THE 2013-2014 UKRAINIAN CRISIS

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Transnational global interactions observed through activities such as international voting measures, trade transactions and participations in alliances have historically provided researchers an opportunity to analyze international relations (IR) amongst national actors within the global power structure. In addition to these traditional macro-level global interactions, the recent emergence of social media has ushered in a new era of global connectivity amongst individual people throughout the world, thus enabling micro-level global interactions. This thesis provides a more holistic view of global international relations by capturing both macro-level and micro-level global interactions and viewing them as comparable networks. By using social network analysis (SNA) tools to detect emergent communities within networks, this thesis directly compared the community structure of two macro-level networks (United Nations General Assemble (UNGA) voting records and arms trade transaction networks) and one social media micro-level

network (e.g. Twitter). The UNGA macro-level voting network served as a measure of validation for this approach by properly showing East-West geopolitical divisions during the Cold War and a North-South socio-economic division following the Cold War. The micro-level Twitter network was created from tweets harvested from conversations about the Ukrainian crisis from the initial Euromaidan protests in November 2013 through June 2014, which included the annexation of Crimea by Russia. The community detection results for the micro-level Ukrainian Twitter network shared the greatest similarity (0.42 on a 0-1 scale) with the UNGA Cold War community results. This result suggests that Ukrainian citizens did not shed their historical cultural roots that aligned themselves with the Cold War East-West geopolitical structure. Additionally, a further analysis evaluating the level of cooperation between the NATO alliance and Ukraine showed that there exists very little evidence of cooperation between the two entities in either the micro-level or macro-level networks.

1. INTRODUCTION

1.1 Background and Motivation

The traditional study of international relations (IR) has focused on the transnational relationships that exist between actors within the global power structure. In the case of IR, actors are typically viewed as nations, international non-governmental organizations (NGOs), or other multi-national bodies such as the United Nations (UN) or participatory alliance systems such as the North Atlantic Treaty Organization (NATO). It is through this traditional state-level or higher macro-level actor paradigm that observable relationships such as trade, international voting and alliance participation emerge for researchers to comparatively study and analyze. The conclusions resulting from the analyses of these emergent global relationships provide a deeper understanding into the behavioral patterns of global actors and the evolution of the global power structure. The long-standing singular focus on macro-level actors in IR studies has led to recent criticism as to whether such a focus can accurately account for the increased interconnectedness of today's globalized world (Nye 2010; Kirshner 2008). Some criticisms have declared that traditional power structures are decaying at an alarmingly rapid pace and that this erosion is giving way to new entrants to the global power system (Naím 2014). As Singer previously argued, IR studies must recognize the level-of-analysis issues that arise when observing international relationships, since transactions can take place on a global, state or individual level (Singer 1961).

A primary catalyst behind the interconnectedness of today's globalized world has been the quantum advances in computing technologies in addition to the vast diffusion of global access to the Internet. The relatively low barrier to entry for gaining access to the Internet has made for new primary mechanisms for individual people to interact with each other throughout the world. Social media platforms such as Twitter and Facebook have enabled these global individual interactions and thus have played a major role in amplifying individual thoughts and desires to a global audience in nearly instantaneous fashion (Musser 2006). Such individual interactions have resulted in significant observable physical events such as the wave of Arab Spring protests that have enveloped many Middle Eastern nations since late 2010 (Howard and Parks 2012; Maamari and Zein 2014). The apparent success of the Arab Spring, driven by "grass roots" social media, as well as evidence of individual actors ultimately influencing state-level power structures, has called into question whether traditional IR methodologies, which typically focus on macro-level interactions, are inclusive enough to properly assess the complex interactions that define today's global environment. Earlier work by Mueller (2010) suggests that the increased reliance upon electronic communications made available by the Internet has resulted in global borderless communication, and, as a result, created new ways in which social relations are fostered.

Social network analysis (SNA) serves as one possible existing methodological approach to address Singer's level-of-analysis problem associated with traditional IR studies. SNA is a highly complementary methodology for studying international relations as it provides methods for measuring structural mechanisms of organization and hierarchy that exist in an international network (Hafner-Burton et al. 2009). Wasserman and Faust (1994), widely acknowledged as the preeminent modern SNA theorists, describe social network analysis (SNA) as analyzing relationships among social entities and recognizing the patterns resulting from those relationships that can then be used to answer social science research questions focusing on the political, economic or structural environments. The application of SNA, an existing methodological approach already used to analyze traditional IR networks, could offer such a framework to address varying levels of analysis, if adapted to account for individual actors. When viewing traditional macro-level international actors as nodes, and their relationships, or transactions, as edges, SNA has played a key part in analyzing the structure of global interactions as an interconnected network system. The recent rapid rise of social media use has not only empowered global individual actor interactions throughout the world, but also provided a whole new data source to specifically analyze these interactions. Robust data sets capturing the details of each individual social media interaction made in the cyber realm are readily available and accessible for use by researchers. By applying SNA methods to these new social media data sources, the level-of-analysis issue could possibly be overcome through the inclusion of individual-level interactions under such a common analytic framework application.

Previous research has successfully applied network analysis methods to understanding various levels of IR interactions. Noteworthy applicable works include global activism (Keck and Sikkink 1998), global trade (Smith and White 1992), global economic markets (Jackson and Wolinsky 1996) and state-level policymaking (Marsh and Rhodes 1992; Marsh and Smith 2000); however, no significant research has attempted to provide a holistic SNA approach to account for all levels of analysis. Promising recent research by Crooks et al. (2014) has attempted to bridge the IR level-of-analysis gap by developing methods to directly compare both macro- and micro-level networks, applying adapted SNA mechanisms to acquired social media data. Crooks et al. (2014) were able to construct "citizen-driven" networks from Twitter discussions involving the Syrian crisis as a representative example. They examined emergent communities from these citizen-driven networks against communities emerging from traditional government-driven networks developed from United Nations (UN) voting records and international arms trade transactions made available for the Stockholm International Peace Research Institute (SIPRI) dataset. The findings from Crooks et al. (2014) showed a clear misalignment between citizen-formed international networks and state-level networks formed by the Syrian government.

1.2 Overview of Approach

Recognizing the unique SNA applications presented by Crooks et al. (2014) in attempting to provide clarity to the complex evolving crisis in Syria since 2012, current researchers have much to gain from applying these proposed applications to other global crises. The study presented in this thesis attempts to replicate for the first time the development of the citizen-driven networks of Crooks et al. (2014) from social media data, and to apply this methodological framework to an entirely different global situation, using harvested Twitter conversations with key words associated with the current ongoing crisis in Ukraine[1]. Specifically, this research uses Crooks et al. (2014) as a road map to evaluate the macro-level (i.e. UN voting record and SIPRI arms trade) and micro-level (i.e. Twitter conversations) networks pertaining to the Ukrainian crisis, but significantly expands the time scale of observation to six months of tweets, while also providing a more in-depth examination of the Twitter data. Additionally, this study introduces a major extension by evaluating the structural characteristics of a key alliance network that exists in the ongoing conflict. The NATO alliance serves as the primary supporter of the current Ukrainian government and the observable network structures of the alliance could prove beneficial to evaluate. The emergent communities unfolding from the constructed networks provide an opportunity for a direct comparative analysis across the varying levels-of-analysis networks in relation to the Ukrainian crisis.

In relation to more traditional analytical data sources such as voting record and arms transfer datasets, social media data are significantly immature when it comes to use in academic work. This study acknowledges such criticism and will attempt to address it by conducting extensive analyses of the referenced social media data in addition to the aforementioned micro-level network analysis. It is the hope of the author that such an effort will place the data in better context and will provide the reader with a better understanding of the characteristics associated with the social media data, while adding to the growing corpus of academic work seeking to develop measures of validation for social media data.

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[1] The Ukrainian crisis, as discussed in this paper, describes the events unfolding in Ukraine since the beginning of the Euromaidan protests in November 2013 and extends the discussion through June 2014. As of this study's publishing date, the Ukrainian crisis continues to escalate, but any events occurring after June 2014 were not part of this analysis.

1.3 Research Questions

The comparative analysis approach for the various networks associated with the Ukrainian crisis seeks to provide insights into whether there exists any congruence between and within the different levels of analysis. Specifically, this study attempts to answer the following research questions: (1) To what degree do the emergent network communities match or overlap between the different networks associated with the Ukrainian crisis? (2) Do the actions of national-level actors participating in an existing global alliance such as NATO appear coordinated in response to the Ukrainian crisis? Any results could serve as a significant tool to add to a more holistic analysis and validation of global and national policymaking decisions in regard to this ongoing conflict.

1.4 Outline of the Thesis

The next chapter of this study will present relevant background information and supporting literature that is essential to understanding and implementing this study's proposed methodology. Chapter three focuses on the macro-level networks associated with the Ukrainian crisis by presenting the detailed procedures for constructing the networks and visualizing the resulting characteristics of the networks. Chapter four follows a similar format in regards to the creation and visualization of the micro-level Twitter network, but provides additional analyses to better familiarize the reader with the social media data used in this study. Chapter five presents the comparative network methodology used to directly compare the emergent network communities from the Ukrainian networks. Chapter six presents the findings of the NATO-specific network observations, while chapter seven concludes this paper with a summarization of the research findings as well as suggestions for future possible extensions of this study.

2. LITERATURE REVIEW

2.1 Introduction

The purpose of the following chapter is to provide a literature review to present essential theoretical foundations to provide the reader with a better understanding of the key components employed in the development and analysis of macro- and micro-level international networks in the subsequent methodology sections in each of the following chapters. Section 2.2 presents an overview of social network analysis (SNA) topics pertinent to this study. Section 2.3 presents some previous SNA applications in international relations works. Section 2.4 provides a necessary introduction to community detection methods in large-scale networks. Section 2.5, the last topic presented in this chapter, discusses using social media data for analysis. This review also attempts to provide explanatory elements justifying the validity of the chosen theoretical foundations and the resulting inclusion in this study's methodology. Given the robustness of many of the following topics, this review has been purposely selective in focusing on only those elements vital to the understanding of this study's intended area of focus.

2.2 Social Network Analysis Overview

> "Social network analysis is neither a theory nor a methodology. Rather, it is a perspective or a paradigm. It takes as its starting point the premise that social life is created primarily and most importantly by relations and the patterns they form." – Marin and Wellman (2011, 22)

The preceding quote by Marin and Wellman (2011) captures the true robustness of social network analysis (SNA) and its inherent ability to examine social relations, while also referencing the resounding difficulty in trying to explicitly define SNA as a traditional theory or methodology given its evolvement from multiple other theoretical disciplines. SNA's inherent ability to examine social relations can provide a glimpse into understanding how autonomous individuals can collectively combine to create functioning societies (Borgatti et al. 2009). This SNA overview section provides a basic context for the evolvement of SNA from other disciplines, the motivations behind the development of SNA, and explicit definitions for key SNA terms for the necessary development of this study's methodological focus of analyzing networks in the context of international relations. This section should ultimately arm any reader with a sufficient level of knowledge for understanding all SNA aspects employed throughout the remainder of the thesis.

The underlying concepts of SNA developed from a conglomeration of social theory and applications from formal mathematical, statistical and computing methodology (Wasserman and Faust 1994). Graph theory serves as the primary mathematical application foundation that appropriately represents a social network (Butts 2008; Cioffi-Revilla 2014; Wasserman and Faust 1994; Iacobucci 1994). Graph theory, originating in 1735 with Leonhard Euler's famous solution to the Königsberg's Bridge problem (Alexanderson 2006), focused on the structural relationships that exist between the entities that make up a graph. Entities, in the case of graph theory, are defined as nodes or vertices, while the linkages or connections between those nodes are defined as edges. The set of nodes and their edges comprise what is known as a graph. Figure 1 depicts a basic graph consisting of four generic nodes and their edges.

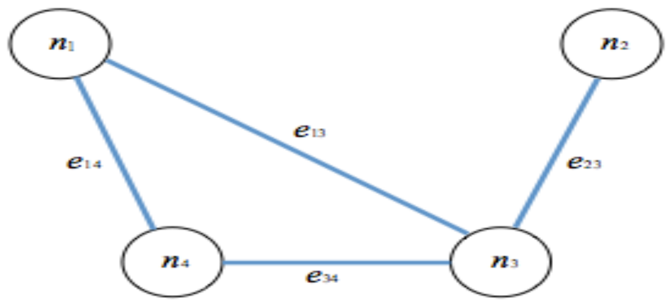

Figure 1. Simple graph ***G*** consisting of node set ***N***, where $N = \{n_1, n_2, n_3, n_4\}$ and edge set **E**, where $E = \{e_1, e_2, e_3, e_4\}$.

Graph theory lends itself to the direct application of mathematical algebraic operations to the entities (nodes and edges) comprising the structure of the graph. Specifically, the structural components of a graph can easily be observed and measured through matrix operations. In basic form, the simple graph depicted in Figure 1 can be translated into a matrix as observed in the following matrix equation, Equation 2.1, with the potential edges between all nodes serving as the referenced edge value between two nodes. The total number of direct connections a node has in a network is defined as a node's degree value.

$$\boldsymbol{G} = \begin{bmatrix} \boldsymbol{e_{11}} & \boldsymbol{e_{12}} & \boldsymbol{e_{13}} & \boldsymbol{e_{14}} \\ \boldsymbol{e_{21}} & \boldsymbol{e_{22}} & \boldsymbol{e_{23}} & \boldsymbol{e_{24}} \\ \boldsymbol{e_{31}} & \boldsymbol{e_{32}} & \boldsymbol{e_{33}} & \boldsymbol{e_{34}} \\ \boldsymbol{e_{41}} & \boldsymbol{e_{42}} & \boldsymbol{e_{43}} & \boldsymbol{e_{44}} \end{bmatrix} \qquad \text{(Equation 2.1)}$$

The following discussion presents a simple example to illustrate the extraction of node degree values from a given network. If one assumes that the referenced values in Equation 2.1 are measurements of degree, which is a direct edge connection between two nodes, then the resultant degree values in the matrix for the original simple network depicted in Figure 1 would be as follows in Equation 2.2:

$$\boldsymbol{G} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{1} & \mathbf{1} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} & \mathbf{0} \\ \mathbf{1} & \mathbf{1} & \mathbf{0} & \mathbf{1} \\ \mathbf{1} & \mathbf{0} & \mathbf{1} & \mathbf{0} \end{bmatrix} \qquad \text{(Equation 2.2)}$$

In this case, realized edges received an edge value of '1' to account for the connection between the two nodes, while unrealized values received a value of '0' given no edge existence between the two nodes. Figure 1 shows that Node 3 (n_3) shares a direct connection with three nodes (n_1, n_2, n_4); therefore, the degree value for Node 3 is 3. This same value can be obtained by adding a node's column or row degree values. This is a simplistic example to help the reader better understand basic matrix development from a simple network. Further explanation for specific characteristics associated with networks of greater complexity will be introduced with the analyzed networks presented in the specific methodology sections 3.2.2, 3.3.2 and 4.3.3, respectively.

Beyond the simple, but essential derivation of node degree values, SNA provides robust methods for determining other key network measurement metrics. These metrics are derived from the structural characteristics of a graph. The distribution of edges within a graph suggests two important structural characteristics for measurement: centrality, or importance, of the graph's nodes and the division of the graph or network into subgroups (Hafner-Burton et al. 2009). While the terms *graph* and *network* can and are used interchangeably, from this point forward in the study the term *network* will be used exclusively to avoid any ambiguities with terminology. Although there exist numerous centrality measures[2], this study's focus only requires the application and understanding of three centrality measures: degree centrality, closeness centrality and betweenness centrality. Definitions for these three centrality measures are as follows:

- *Degree Centrality* measures importance of a node by the sum of edges or linkages it has in relation to all other nodes within the network (Wasserman and Faust 1994). The more edges present on a node results in a higher degree measurement value, thus alluding to its greater relative importance in terms of access to other nodes throughout the network (Hafner-Burton et al. 2009).
- *Closeness Centrality* measures importance of a node by calculating the length of a path between a node and all other nodes within the network (Hafner-Burton et al. 2009). The shorter the length of a path between two nodes suggests a stronger or closer relationship between those nodes.
- *Betweenness Centrality* measures importance of a node by the sum of occurrences that the node's position falls between two non-adjacent nodes in a path within the network (Wasserman and Faust 1994). A higher betweenness value suggests that a node has greater influence in the graph since the paths

[2] Interested readers of other centrality measures and their associated characteristics can reference Wasserman and Faust (1994) and Borgatti, Everett, and Johnson (2013).

connecting the non-adjacent nodes are entirely dependent on the node located between them.

The structural characteristics of a network create an important opportunity to identify possible sub-groups that may exist within a network based upon measures of similarity or cohesion. Measurements indicating sub-group levels of cohesion are dependent upon the density of edges between two nodes or if a node's set of edges are similar to another node's set of edges (Hafner-Burton et al. 2009). The detection of cohesive sub-groups, or communities, allows for the direct comparative analysis between the structural characteristics of identified sub-groups and also between these sub-groups and the overall macro-level network in its entirety. Specific community detection methods will be discussed at length in Section 2.4 of this literature review. Essentially, the structure of networks provides an opportunity to classify different levels of analysis, while also offering a framework to extend the analysis between and among all identified levels within a network (Snijders and Stokman 1987; Maoz 2012).

The derivation of SNA concepts from multiple existing methodologies provides a robust platform for appropriately representing and analyzing social networks. Since social interactions of any kind can be reduced to a set of actors, or nodes, and the connected relationships, or edges, between those actors, the translation of social networks from the formalized mathematical foundations of graph theory is cogent. Given the ubiquity of social networks in the social sciences disciplines, it appears logical to implement SNA techniques to further the understanding of such disciplines, and in the case of this study, international relations.

2.3 International Relations Applications of SNA

The pervasive connectedness of today's globalized world provides incredible potential for applying and analyzing international relations (IR) through the established global networks. Maoz (2012) describes global international networks as truly complex systems due to their inherent structural properties and thus declares that SNA is eminently suited for capturing, analyzing and modeling this complexity. Recalling Singer's (1961) previous level-of-analysis issue with traditional IR studies, IR studies, now more than ever, must account for the increasing connectedness of today's world and provide a holistic analysis that includes observing international relationships that occur at the global, state and individual level. Traditional global interactions such as trading and voting patterns within international governing bodies such as the UN have been the focus of the majority of most SNA applications to IR studies. This is due to the historical view that international power or influence solely resides among macro-level actors and the simple fact that validated datasets capturing voting and trader histories have been readily available from reliable sources (e.g. UN voting records, international trade data). The recent emergence of large-scale social media use throughout the world provides a relatively new opportunity to develop and analyze networks at the individual level. Readily accessible social media datasets, along with advanced computing technologies, make possible the application of SNA techniques to these individual networks.

The international system can be described as networks consisting of actors as nodes and the global international relations or activities of these actors within the overall international network as edges. The ease of reducing international networks into a "node-edge" paradigm provides a common baseline reference for analyzing the various types and levels of international networks. Establishing such a baseline measurement reference is key to setting conditions for directly comparing international networks with previously introduced network measurements such as centrality and cohesion and for detecting emergent communities. The relative ease of deconstructing an international network into nodes and edges should not take away, however, from the overall complexity associated with international systems. There is an incredibly wide range of possible types of actors as nodes and transactions as edges that exist within the construct of international relations. Therefore, it is prudent to provide some examples describing the various types of nodes and edges that exist at the different levels of analysis in the international network. The following presented examples are not entirely exhaustive of all SNA applications within the IR domain, but they should provide the reader with sufficient context to understand the deconstruction of the presented international networks into key SNA components within this study's methodology sections.

Macro-level networks have been the primary focus for most of the literature examining IR through the lens of SNA (Cao 2012; Cranmer et al. 2012; Marsh and Smith 2000; Jackson and Wolinsky 1996; Smith and White 1992). Most of these macro-level SNA-focused IR works focus on trade, membership and voting patterns in intergovernmental organizations and diplomatic exchanges (Hafner-Burton et al. 2009). In the specific case of international voting patterns, which is entirely pertinent to this study's macro-level network analysis, the identification of voting patterns dominated the earliest IR works analyzing UN voting records (Lijphart 1963; Russett 1966; Rai 1972), but they exclusively used statistical methods in those studies, not SNA. Lijphart (1963) discussed the relative validation successes of those early statistics-based works' ability to replicate certain East-West patterns that existed in the pre-Soviet collapse world, while acknowledging their biggest weakness to be their inability to satisfactorily identify precise voting blocs. Given the strength of SNA to evaluate network structure as a result of its emergence from graph theory, Hafner-Burton et al. (2009) extended the idea of a basic matrix formulation into the concept of an affiliation matrix where an actor's membership in a certain group allows for the potential emergence of bloc or community identification within a network. Two recent studies (Macon et al. 2012; Häge and Hug 2013) viewed UN voting records as affinity matrices and determined that the existence of high agreement amongst all voting members results in skewed assumptions of voting blocs. Macon et al. (2012), the only SNA-focused application of the two, attempted to overcome this agreement bias by identifying validated voting blocs through the use of community detection algorithms.

Until recently, the examination of international networks at the individual level has been quite sparse. The recent rapid advances in networked computing technology along with the emergence of pervasive global social media has effectively provided researchers a new opportunity to examine large-scale human networks interacting via the Internet. Previous network studies were limited to groups of tens to hundreds of individuals due to the burdensome collection methods, but the digital data traces left by online social interactions provide data on a scale of tens of millions of individuals with nearly zero latency in acquisition time (Kleinberg 2008). Java et al. (2007) conducted a social network analysis of tweets aggregated to the continental levels, but limited the scope of their work to comparing the observed network statistics of each intra-continental social network as opposed to a global intercontinental social network. Leskovec and Horvitz (2008) created and analyzed a social network comprised of approximately 30 billion instant message conversations over the course of one month with the purpose of observing global communication flows. Lauterbach et al. (2009) analyzed the international trust network of patrons interacting on the global hospitality website Couchsurfing.com. The most relevant works with a primary focus on IR prior to Crooks et al. (2014) was the "bottom-up" view of international alignments garnered through the international network of email flow by State et al. (2013) and the identification and mapping of global virtual polycentric communities formed around issues of national interest by Stefanidis et al. (2013).

2.4 Community Detection in Large-Scale Networks

One of the primary benefits that result from applying a SNA approach to the analysis of international networks is the emergence of the sub-network, or community, structures that exist within a network. In networks, the concept of a community is synonymous with the terms module, class, group and cluster (Radicchi et al. 2004). Communities are defined as locally dense sub-networks of nodes that share similar attributes within a larger network that is sparse as a whole (Lambiotte 2010). Nodes that share similar attributes tend to form communities since they have a higher chance to share an edge or connection than random nodes in the overall network (Lancichinetti et al. 2011). For example, UN members that share higher voting affinity values have a greater chance of belonging to the same community since they share more connections.

In the case of trade networks, nations that have more direct trade connections will have a greater chance of belonging to the same community. The ability to detect communities in networks allows for the discovery of relationships within the structure of the network that are not readily apparent. Community identification becomes much harder as the size of the network grows. Social media datasets can sometimes scale to 10^7 edge observations, which makes it impossible to determine communities without the assistance of a community detection algorithm.

There exist an incredible range of community detection algorithms to assist in identifying communities within networks. Fortunato (2010) provides an extensive overview of the current corpus of community detection algorithms. This work is a foundational piece that describes the essential common components of all community detection algorithms and provides a construct for evaluating such algorithms. In order to choose the right community detection algorithm within a network, a researcher must truly understand the characteristics of the network being analyzed and the compatibility of applying an algorithm to that network. Since the computational complexity associated with large-scale networks makes finding exact communities an NP-hard problem, community detection algorithms are not precise measurements, but optimized solutions (Fortunato 2010).

For the given purpose of evaluating international networks at both the macro- and micro-levels with the goal of identifying community structures aggregated at the country-level, this study will implement the Louvain method for modularity community detection developed by Blondel et al. (2008). Although harvested tweets provide granularity at the individual user level, it is necessary to aggregate tweets to the country-level in order to directly compare the individual actors of the micro-level network to the state actors of the macro-level networks. The Louvain method finds high modularity partitions of large networks representing a complete hierarchical community structure of the entire network in a short computational time (Blondel et al. 2008). The method follows a two-step iterative process that focuses on binding communities based on the weighted edges of nodes in the network. The advantage of applying the Louvain method to this study is that it can properly partition large-scale networks in an extremely fast manner and, more importantly, the process is self-regulating in terms of the final number of detected communities within the overall network. This is extremely important since the resulting number of detected communities is truly an emergent product of the algorithm as opposed to a pre-determined partition size that most other community detection algorithms employ. In contrast to the Louvain method, Lambiotte et al. (2010) describes the slower modularity optimization algorithms as insufficient in determining communities in an empirical network since the pre-determined number of detected communities results in the oversight of intermediate hierarchical partitions.

2.5 Using Social Media Data for Analysis

In August 2014, the total number of active user accounts across all social media platforms in the world surpassed 2 billion accounts for the first time (Kemp 2015). The pervasive and ever-increasing global use of social media platforms is resulting in the production of incredible troves of user-created data (Croitoru et al. 2014). Social media users that produce these large amounts of social media data, both actively and passively, can be considered to be human sensors that detect, observe and transmit information about events taking place throughout the world. Stefanidis et al. (2011) classifies geospatial information derived from these human sensors as ambient geospatial information (AGI). AGI is highly pertinent to this study given the necessity of geospatial data to construct the comparative micro-level Twitter network and will be further discussed in Section 4.2.

The vast quantity, along with ease of accessibility for researchers, makes social media data a logical area of focus for possible academic and commercial endeavors. Given the aforementioned effect on the Arab Spring and their use as messaging platforms for other global events, social media have come to play a major role as a real-time information source for significant events (Crooks et al. 2013; Zhao et al. 2014). Although social media may play an obvious major role as a timely source of information, their role as an acceptable and valid source for research is certainly debatable given their relative youth and lack of standardized practices in comparison to other validated data sources (Croitoru et al. 2014). Therefore, research that uses social media data, such as this study, must be deliberate in describing the detailed processes employed in using such data. This is not only a good principle to follow in order to provide clarity for the reader, but also allows for replication, extensibility and the possibility of adding to any eventual standardized practices that might develop in social media research.

While social media has been presented in a generic fashion so far in this study, it is necessary to make note of the vast array of different social media platforms that currently exist. Although social media use continues to grow in a dramatic fashion throughout the entire globe, the social media platforms of choice by users appear to follow somewhat of a regional focus for certain areas of the world. Figure 2, created by Cosenza (2015) using Alexa social media traffic data, provides a global map depicting the top social media platforms by country as of December 14, 2014. Facebook appears to hold an expansive global reach, but it is significant to note that social media users in China and Russia, two nations with historical international geo-political power and large populations, choose QZone and VKontakte, respectively, over Facebook as the most popular social media platform. The primary purpose behind this brief introduction to the global array of social media platforms is to show that research based on social media data must take into account the global reach and participation of specific platforms when researching certain social media topics of interest.

Figure 2. Most popular social media platforms by country as of December 14, 2014 (Cosenza 2015).

Although the proliferation of social media might be considered a recent phenomenon, there exists a growing corpus of work that is providing unique frameworks for harnessing the data provided by social media transactions. Recognizing the difficulty in transforming social media data into real world knowledge, Lu et al. (2013) present a case study attempting to classify the degree to which geolocated social media data can serve as a potential proxy for a corresponding physical community. This ‘cyber-to-physical’ framework (Croitoru et al. 2015) has the potential to serve as a verification mechanism for properly using social media data and to help take a holistic approach to explain social phenomenon given the increased creation of cyber connections and blurred lines with the physical world. Croitoru et al. (2013) created a social media agnostic platform for harvesting and ingesting data from different types of social media sources. Their work highlights the source-independent components that are common among many social media: entry, author, geolocation, time, narrative and source components. By creating an interface that incorporates social media data from multiple platform sources, this work makes possible the ability to capture a more total conversation in the cyber world and overcome any biases generated by participation rates associated with certain social media platforms.

2.6 Summary

The preceding literature review chapter provided essential theoretical foundations necessary to explaining the methodology applied in this study. This purposely selective discussion of fairly robust topics was intentional and meant to provide the reader with basic conceptual understanding. The referenced sources are the preeminent works in their respective fields and can serve as avenues for more in-depth discussions on the presented topics.

3. MACRO-LEVEL NETWORKS

3.1 Introduction

In accordance with the framework set forth by Crooks et al. (2014) for directly comparing both top-down and bottom-up international networks, this chapter specifically introduces the methodological and analytical processes employed to examine the macro-level networks developed in Sections 3.2.2 and 3.3.2. The macro-level network results presented in Sections 3.2.3 and 3.3.3 of this chapter will serve as the comparative basis for the Twitter micro-level network results, which are revealed later in Chapter 4. The macro-level networks included in this study have been sufficiently calibrated in academia and their inclusion is meant to provide a validated comparative basis against which to judge the Twitter micro-level network. The stated purpose of Chapters 3 and 4 is to bridge the IR level-of-analysis gap by employing methods to directly compare both macro- and micro-level international networks through the application of adapted SNA mechanisms to acquired international datasets.

The outline of this chapter presents the UN voting record and SIPRI arms trade networks separately by providing introductions to the data in Sections 3.2.1 and 3.3.1, detailed processes describing the network development methodology in Sections 3.2.2 and 3.3.2, visualized results and a subsequent analysis for each macro-level network in Sections 3.2.3 and 3.3.3. The study places a major emphasis on visualized results in an effort to best illustrate the story that the resulting data is trying to tell. Although both macro-level networks follow similar developmental methodologies, there exist significant differences in the peculiarities of each dataset and network construction mechanisms to warrant introducing them separately in this chapter. Additionally, this process supports the author's intention to provide transparency to the reader in presenting this work.

An epochal analysis of each network, in accordance with the epochs defined by Crooks et al. (2014), allows for empirical evidence validation of observed international patterns during the associated discrete periods. Table 1 provides the naming convention that will be used throughout the rest of this study for each of the epochs. Although Ukraine, the focus nation of this study, did not regain its status as an independent entity until the end of the cold war (i.e. Post-Cold War 1990-2000), the observance of the international networks during the Cold War period is still entirely relevant to validate the observed international patterns of that epoch.

Table 1. Epochs of consideration for analysis of all networks.

Epoch	Nomenclature	Period Start	Period End
1	Cold War	1950	1989
2	Post-Cold War	1990	2000
3	Post-9/11	2001	2013*

* Accounts for UN votes through 2012 and SIPRI transactions through 2013

3.2 UN Voting Network

The following sections in Section 3.2 present the first of two macro-level networks created and analyzed in this study: the UN voting record network. The sections are presented in a specified order to walk the reader through the entire process from data collection to analysis of the results. The final results will present visualizations and key metrics of the networks created from historical voting records of the UN that will serve as the basis for comparison against the other networks generated in this study.

3.2.1 UN Voting Network Data

The United Nations General Assembly (UNGA) is the preeminent global consortium for nation-states and the arena for global policy decisions. Although the topics and issues debated at the UN can be complex in nature, the process by which nations make their voices heard is especially quite simple. In fact, the underlying voting structure of the UNGA is quite conducive to social network modeling. A recent effort by Strezhnev and Voeten (2013) has produced a database capturing the voting results for all UN measures from the creation of the UN through 2012. This database has become a gold standard for observing UN voting patterns and has been used as the basis for studies spanning many academic disciplines (Macon et al. 2012; Crooks et al. 2014; Dreher et al. 2014; Bailey et al. 2013; Campos and Gassebner 2013; Carnegie 2014; Fuchs and Gehring 2013). A single vote by a member nation receives an individual entry in the database. The attributes of each entry include: session number, date of vote, resolution descriptor, vote choice (i.e. yes, no, abstain, absent) and 15 separate naming conventions of the voting nation. By using this extensive and highly vetted UN voting records database, all recorded votes throughout the history of the UN are conveniently accessible in a comma-separated value spreadsheet. This allows for easy extraction of the voting parameters that are necessary to create the actual UN voting record network as described in the next section.

3.2.2 UN Voting Network Methodology

The UN voting network is based on the "node-edge" paradigm with all countries represented as nodes and their votes for a specific UN resolution represented as an edge. Similarly to Crooks et al. (2014), the developed voting network follows the methodology put forth by Macon et al. (2012) by excluding resolutions receiving unanimous votes. The exclusion of unanimous votes recognizes the bias Macon et al. (2012) observed towards agreement that exists in UN voting measures as shown in Figure 3 and hopes to serve as a differentiating mechanism to hedge against this agreement bias.

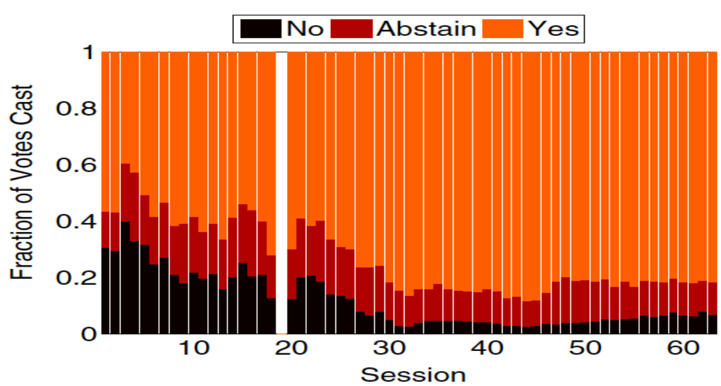

Figure 3. UN voting agreement bias observed from 1946 to 2008 (Source: Macon et al. 2012).

The process for creating edges between nations in the UN voting network involves extracting all positively voting countries for each given UN resolution. A positive vote equates to a "Yes" entry by a nation for a given resolution. A negative vote classifies all other votes, which includes explicit "No" votes and abstentions. Therefore, the creation of an edge results between all positively voting nations for a given resolution and the edge is subsequently assigned an edge weight value of 1, while all negative voting nations create no edge for the resolution. This process is repeated for all historical UN votes, and an overall "affinity" score, the cumulative edge weight between two nations divided by the total number of resolutions, will result between all countries. A higher affinity value between two countries implies a higher congruence in voting behavior than those country pairs that have a lower affinity score. Normalization of the UN data already exists as each nation is allowed to only vote once per general assembly measure and all votes are equal in weight.

As previously demonstrated in Section 2.2 of the literature review, the "node-edge" paradigm of a social network relationship is easily represented in matrix format. For the given UN voting network development description above, let G represent a network with node set N, the list of all nations of length x, where $N = \{n_1, n_2, \dots, n_{x-1}, n_x\}$. The resulting edges between all nations would populate the edge list E, where $E = \{e_{11}, e_{12}, \dots, e_{xx}\}$. A shared positive vote between two nations is non-directional; therefore, the UN voting network is an undirected network. The following matrix summarizes the UN voting network in matrix format.

$$G = \begin{bmatrix} e_{11} & \cdots & e_{1x} \\ \vdots & \ddots & \vdots \\ e_{x1} & \cdots & e_{xx} \end{bmatrix} \qquad \text{(Equation 3.1)}$$

Following the completion of the realized UN voting networks for each epoch, the community detection algorithm is employed to extract emergent communities from the networks. The cumulative edge weight attribute computed for each nation pair serves as the primary mechanism upon which the Louvain community detection algorithm determines the resulting communities in a given network. The Louvain method automatically segregates those nations that share higher affinity scores and assigns them to an identifiable international community sub-network. The emergent sub-networks detected by the Louvain method are entirely self-regulated by the method instance, so no predetermined number of sub-networks will result and the final number is truly an emergent result of the employed method. The UN voting network community results in Section 3.2.3 will serve as the primary input parameter for directly comparing the other observed networks in Chapter 5.

3.2.3 UN Voting Network Analysis Results

The UN voting network results seek to not only provide the reader with the descriptive statistics associated with the voting networks but to also heavily incorporate visualizations to aid in the subsequent analysis. The section begins with the presentation of the derived UN voting networks in epochal order beginning with the Cold War epoch. The section concludes with a specific analysis and discussion of international voting affinity results and narrows the focus to historical Ukrainian voting affinity and community affiliations within the final two UN voting epochs. The Ukrainian-specific results will serve as a primary input to the Chapter 7 NATO discussion.

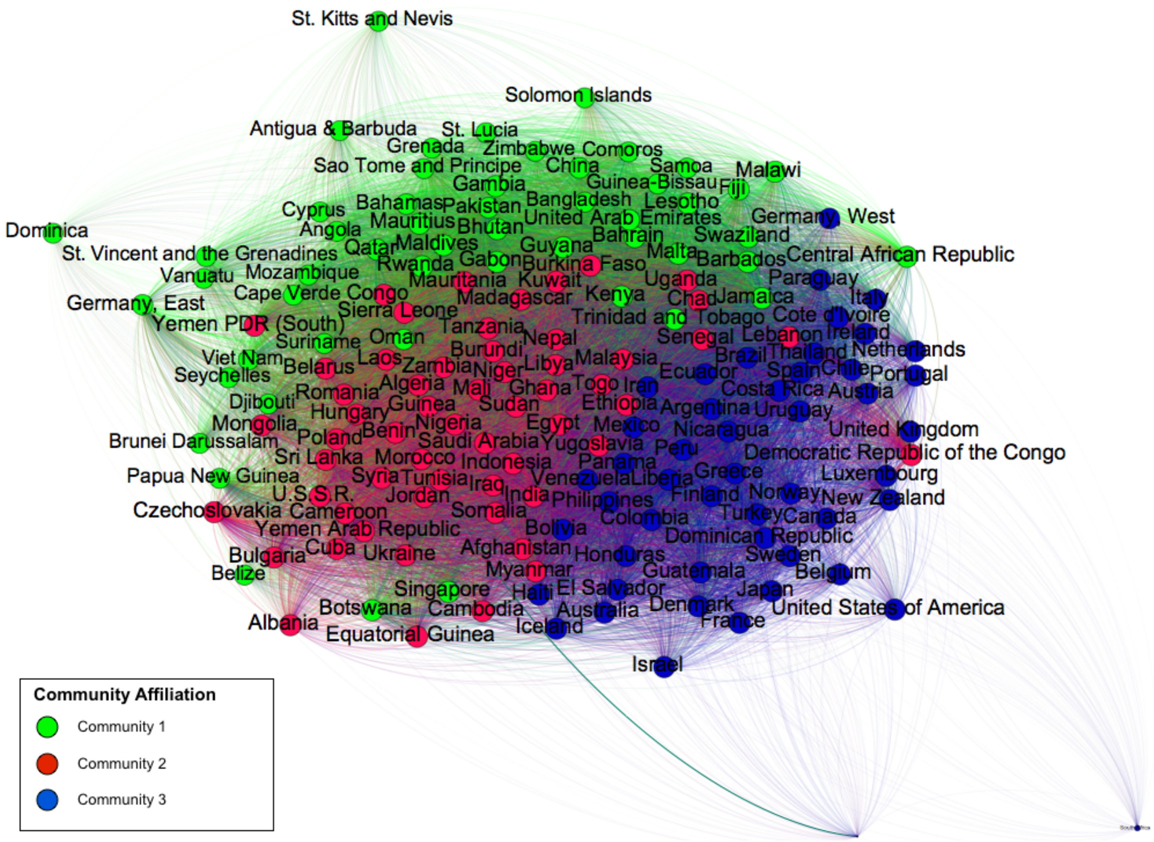

Figure 4. Cold War (1950-1989) UN voting record network visualization diagram.

Figure 4 displays the UN voting network visualization diagram that captures the international voting affinities among UN member nations during the Cold War epoch. The colored clusters, which follow the Brewer palette recommendations for optimizing sensory perception of qualitative data visualizations (Brewer et al. 2003), signify the three distinct emergent communities of the network resulting from the application of the Louvain community detection algorithm. Figure 5 and Figure 6 present the UN voting network visualization diagrams for the remaining two epochs. The actual national membership list for each community, along with all other networks in this study, is available in Appendix A: Community Tables. These network visualizations do provide the reader with a consolidated view of community clusters in relation to one another, but they do not truly capture the geospatial relationship that exists with the explicit geographic boundaries associated with each country node. A geospatial visualization of network communities recognizing this relationship for each of the epochs will follow later in this section.

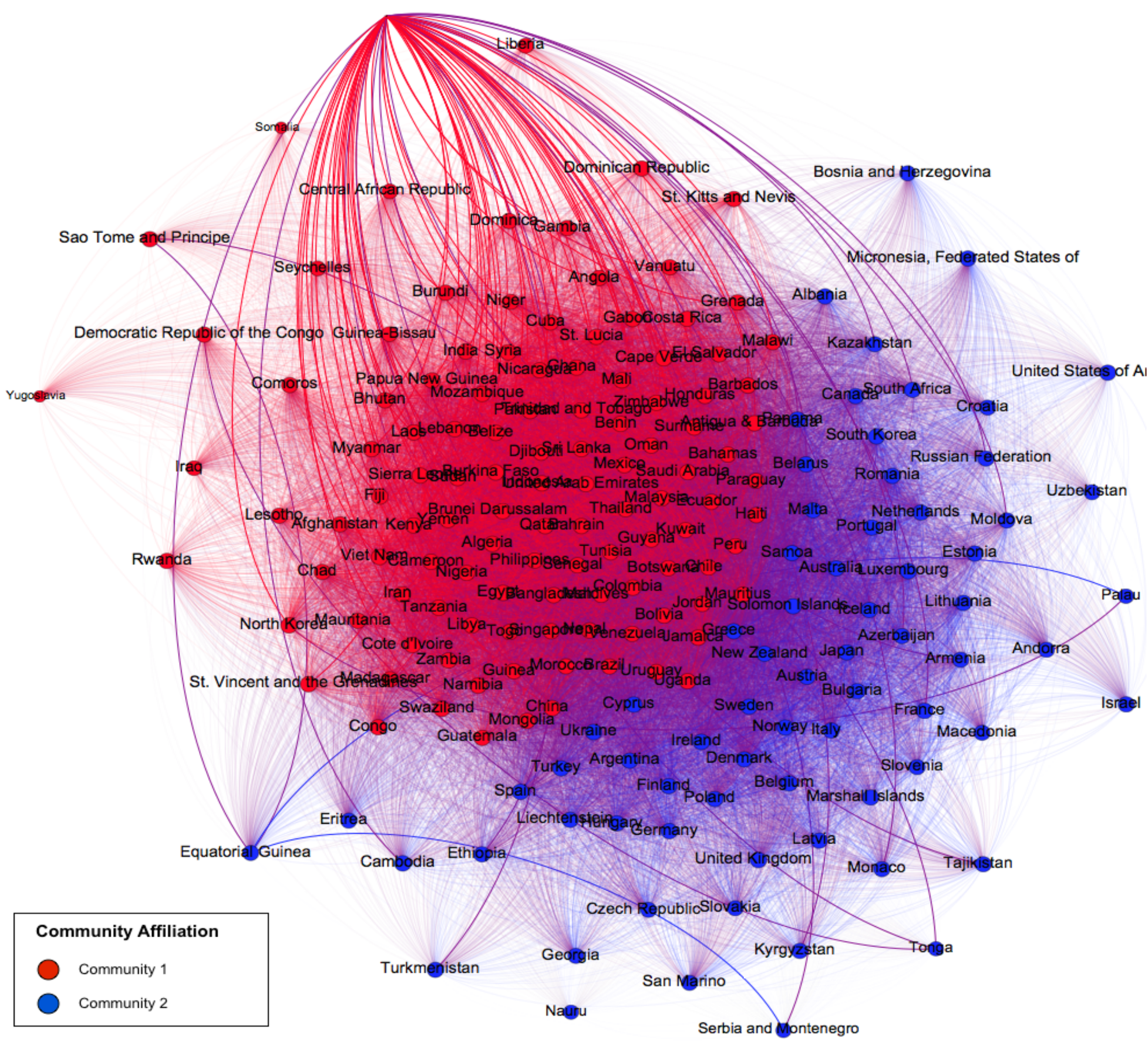

Figure 5. Post-Cold War (1990-2000) UN voting record network visualization diagram.

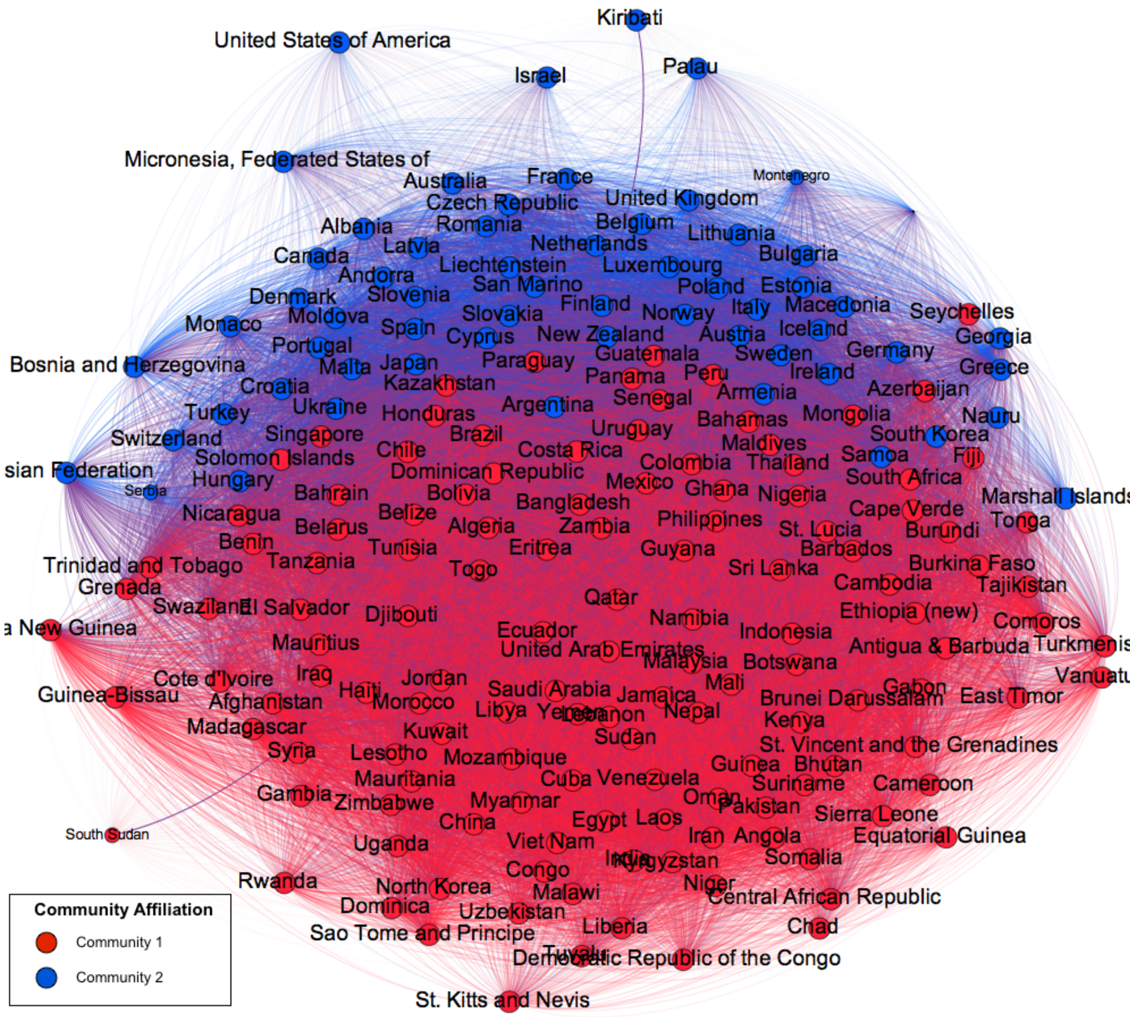

Figure 6. Post-9/11 (2001-2012) UN voting record network visualization diagram.

The Cold War epoch network identified three distinct communities, while the Post-Cold War and Post-9/11 epochs each identified two communities. Recalling the previous voting agreement bias shown in Figure 3, most of the nations are shown in tight agreement clusters in all three network graphs due to the gravity component of the network visualization layout algorithm[3]. The gravity component pulls nodes closer

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[3] The open-source network visualization tool, GEPHI, served as the sole generator of the network diagrams throughout the study. It is available at https://gephi.github.io (Bastian et al. 2009).

together based on a country's weight degree value. Additionally, the country node sizes, which are proportionally sized to represent the degree value for each country, are relatively uniform, except for the represented countries that were only UN voting members for limited periods during the observed epoch.

The visualized geospatial results of the networks provided in the Figure 7 maps validate the number of emergent communities in each of the epochal UN voting networks. The top map depicting the global community structure during the Cold War period shows a clear East-West divide between Community 1 and Community 2. Additionally, Community 3 prominently shows a group comprised of China and mostly sub-Saharan African countries. This serves as evidence of the Sino-African influence driven by post-WWII Chinese government foreign policy measures meant to establish a Chinese sphere of influence in Africa (Muekalia 2004). The middle and lower maps representing the immediate Post-Cold War and Post-9/11 epochs show the major transition from the formerly dominant geo-political East-West divide to the currently existing North-South global geographic division based on socio-economic differences between countries (Lloyd et al. 2009). These results are consistent with the macro-level observations made by both Macon et al. (2012) and Crooks et al. (2014) in their respective UN voting network studies. The ability to validate UN voting network patterns against historical empirical evidence, along with cross-validated results from other academic works, allows for a greater level of confidence in applying SNA techniques for analyzing macro-level international relations.

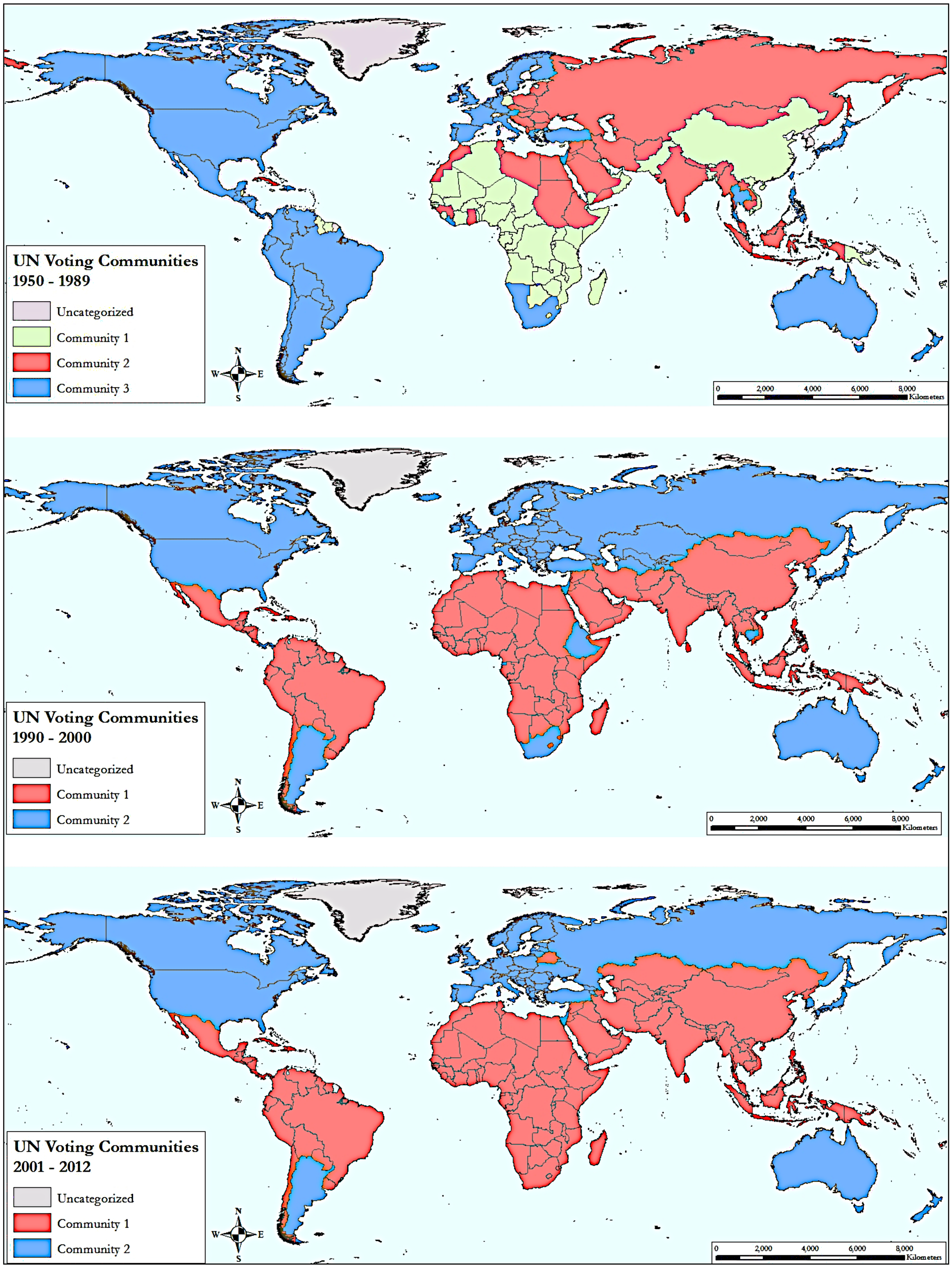


Figure 7. Global emergent community maps for UN voting networks in all three observed epochs.

Table 2. Evolution of Ukrainian UN voting affinity values.

Country	Affinity with Ukraine (1990 - 2000)	Country	Affinity with Ukraine (2001 - 2012)
Chile	73.82%	Chile	65.05%
Kuwait	73.19%	Peru	64.81%
Bolivia	73.19%	Mexico	64.12%
Guyana	73.06%	Argentina	63.66%
Singapore	72.55%	Uruguay	63.54%
Brazil	72.55%	Malta	62.96%
Maldives	72.55%	Costa Rica	62.73%
Botswana	72.43%	Guatemala	62.73%
Venezuela	72.30%	Cyprus	62.73%
Peru	72.30%	Maldives	62.73%
Mexico	72.17%	Austria	62.27%
Colombia	71.92%	Brazil	62.27%
Tunisia	71.66%	Ireland	62.27%
Philippines	71.66%	New Zealand	62.15%
United Arab Emirates	71.54%	Paraguay	62.04%
Avg. all nations w/Ukraine	54.62%	Avg. all nations w/Ukraine	52.62%
Avg. between all nations	*47.55%*	*Avg. between all nations*	*54.90%*

Although Ukraine has fallen exclusively within the ‘North’ community during its tenure as a UN member, the relative strength tying Ukraine to that community is not observable unless one views the actual Ukrainian affinity values with other countries. Table 2 provides a detailed reference that captures the evolution of the Ukrainian affinity values over time. The table provides a list of the top-15 affinity values between Ukraine and other nations, along with the averages for all Ukrainian and worldwide affinity values. The results show that only 27% of the original top-15 countries remain in the current top-15. Additionally, the average affinity value Ukraine shares with the rest of the world previously exceeded the global average, whereas now, even though its average has only slightly dipped from the previous epoch, it has now fallen below the world average. This drop in average affinity during a time when global affinity has become more prevalent, as well as the variability in Ukraine's closest affinity partners, suggest Ukraine has had trouble establishing a consistent international identity since it regained independence from the Soviet Union.

3.3 SIPRI Arms Trade Network

This section introduces the second macro-level network incorporated into this study: the SIPRI arms trade network. The presentation of this network follows the same format of the previously introduced UN voting network. This section will not only provide the specific characteristics of the SIPRI arms trade network but will also reference key differences between the developments of both the SIPRI arms trade and UN voting networks.

3.3.1 SIPRI Arms Trade Network Data

Similarly to the geo-political UN voting record network, the arms trade transaction network is based on a highly respected database that is widely used in academia. The Stockholm International Peace Research Institute (SIPRI) arms trade dataset provides detailed transfer records for all reported international arms trade transactions from 1950 through 2013 (SIPRI, 2014). SIPRI openly concedes and estimates that its database accounts for 90% of major conventional weapons trades. Garcia points to the lack of data made available by some countries, most notably China, as the reason why SIPRI cannot account for all major global arms transactions (Garcia 2014). Given that the SIPRI data only date back to 1950, this SIPRI inaugural year serves as the initial year of the Cold War epoch in this study even though the creation of the UN and resolution votes precede the earliest tracked SIPRI arms trades.

SIPRI provides arms trade data between supplier and recipient countries in two distinct formats: raw trade registers and trend indicator values (TIV). Raw trade registers provide the date, weapon systems and weapon systems value attributes for each order agreement between the supplier and recipient countries. Additional raw trade registers capture the actual delivery of those orders according to the same order attributes. Unfortunately, there exist numerous issues for using raw trader register data for an analysis. First, the raw data values are absolute and make no attempt at normalization. This results in highly skewed biases towards nations more active in the arms trade environment. Additionally, there is great ambiguity associated with linking initial orders to actual deliveries. The database attempts to provide explicit explanation for each transaction, but it fails in regards to tracking initiated orders projected to take place over multiple decades and the actual deliveries that take place. The creation of the TIV metric overcomes both of these issues. TIVs represent a normalized statistical parameter for actual weapon deliveries executed between two nations. According to SIPRI (2014), the TIV seeks to represent the transfer of military resources as opposed to just the financial value of the transactions. The common value metric is a result of comparing size and performance characteristics of a weapon against all other available weapons. This study solely used TIV metrics to determine an associated value for an arms trade between two nations. The SIPRI database portal provides a user-friendly application programming interface (API) to extract arms trade data in multiple formats, which enables great compatibility for use of the data in a scientific computing environment.

Unlike the undirected network classification affixed to the UN voting network, the SIPRI arms trade network must be classified as a directed network. This is due to the observable flow of weapons between supplier and recipient nations in an arms trade. The social network translation of an arms trade allows for the connection or edge between the two nations to be viewed as an out-degree transaction for the supplier nation and an in-degree transaction for the recipient nation.

3.3.2 SIPRI Arms Trade Network Methodology

The arms trade network also follows the “node-edge” paradigm with all countries executing arms trades represented as nodes and edges represented as arms trade transactions between two countries. The weight of the directed edge between the two countries is assigned the aforementioned TIV valuation for each realized trade transaction. The entire arms trade transaction network incorporates all transactions between nations in the SIPRI database from 1950 through 2013. This temporal range exceeds the available UN voting records thru date of 2012, but is fair to include in the comparison as the additional year falls into the currently defined Post-9/11 epoch. The inclusion of more recent data also provides a better temporal association with the ongoing Ukrainian crisis. The timing of this study allowed for the inclusion of two additional years of arms trade transactions beyond that of Crooks et al.’s SIPRI arms trade network study. SIPRI provides arms trade data on rebel and separatists groups, but those transactions are beyond the scope of this social network study. Similarly to the UN voting network, the resulting affinity scores between all countries represents an observable strength of cooperation through arms trades. A higher affinity score is representative of countries with greater trade relations, while a lower score represents countries with lesser trade relations.

Following the creation of the SIPRI arms trade networks for each epoch, the Louvain community detection algorithm is applied to detect emergent arms trade communities in the same fashion as it was applied to the UN voting networks in Section 3.2.3. The derived weighted degree of each network edge serves as the primary value for the Louvain community detection algorithm to determine sub-networks within the arms trade transaction network. The resulting communities within the arms trade networks provide the key comparative metric to directly compare against the UN voting network communities in Chapter 5.

3.3.3 SIPRI Arms Trade Network Analysis Results

The directional flow of global arms trades allows for the evaluation of different network perspectives than the previously discussed undirected UN voting networks. The directionality of trade allows not only for the classification of country nodes as participants in the trade network, but also differentiates between partners who are exporters and importers. The corresponding total weighted degree of each nation provides a metric for gross arms trade market transactions, while the in-degree and out-degree weights signify import and export sub-classifications respectively. The resulting directed network diagrams created below from the SIPRI arms dataset exhibit a somewhat dissimilar level of modularity, or total emergent communities, across the different epochs in comparison to the UN voting networks. There does, however, exist a certain level of similarity in some community memberships that mirrors the geo-political East-West divide discovered in the Cold War UN voting network.

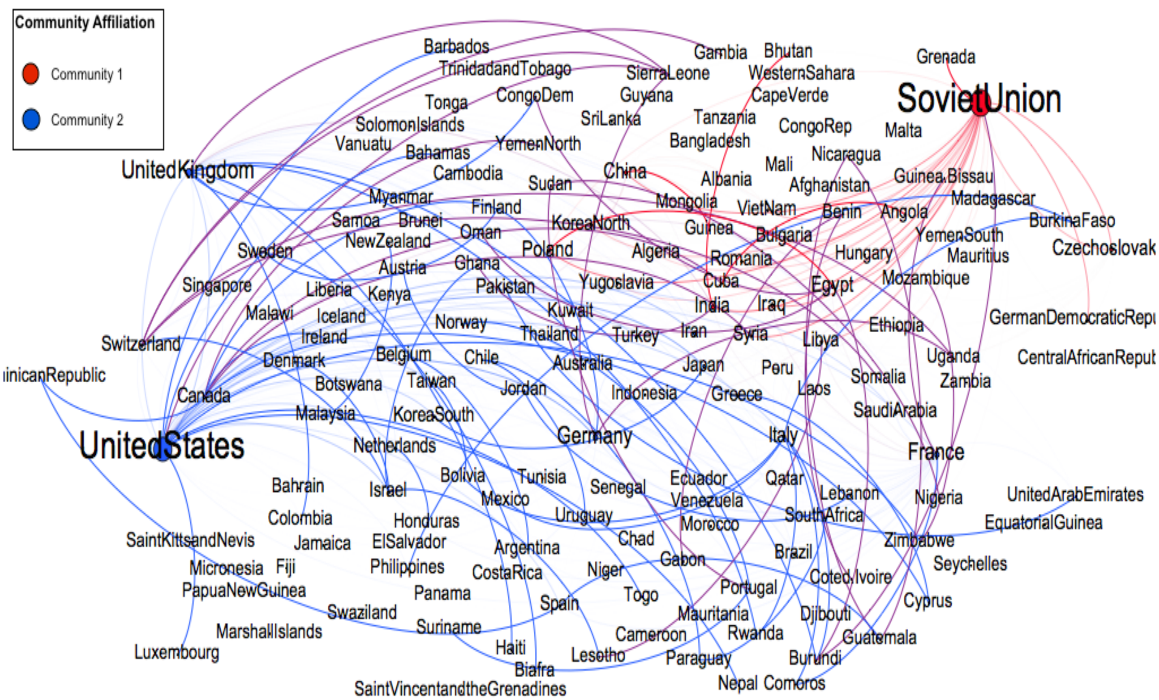


Figure 8. Cold War (1950-1989) SIPRI arms trade network visualization diagram.

Figure 8, along with Figures 9 and 10, provide visualization results depicting the arms trade networks for each epoch. The arms trade network visualizations show much greater disparity between the node sizes and edge weights viewed in the UN voting network. This is due to the directed nature of the arms trade networks and the ability to capture export, import and total trade transactions. The text and node size of a country is based on total weighted degree. Thicker edges between nodes represents greater trade volume, while a larger node and text size represents a greater level of participation in the trade network. The color scheme represents a country's community affiliation given the community detection results. The Cold War epoch arms trade network detected two distinct communities within the network driven by two primary countries, the United States and the Soviet Union. Following the end of the Cold War and the dissolution of the Soviet Union, the United States and the resulting Russian Federation continued to serve as the dominate key nodes throughout the global arms market, but the results show the number of detected communities increasing to four in each of the final two epochs. This increased fractionalization in the global arms markets is a result of the volatility created by the end of the Cold War and the uncertainty associated with Soviet-Russian global interactions (Brzoska 2014).

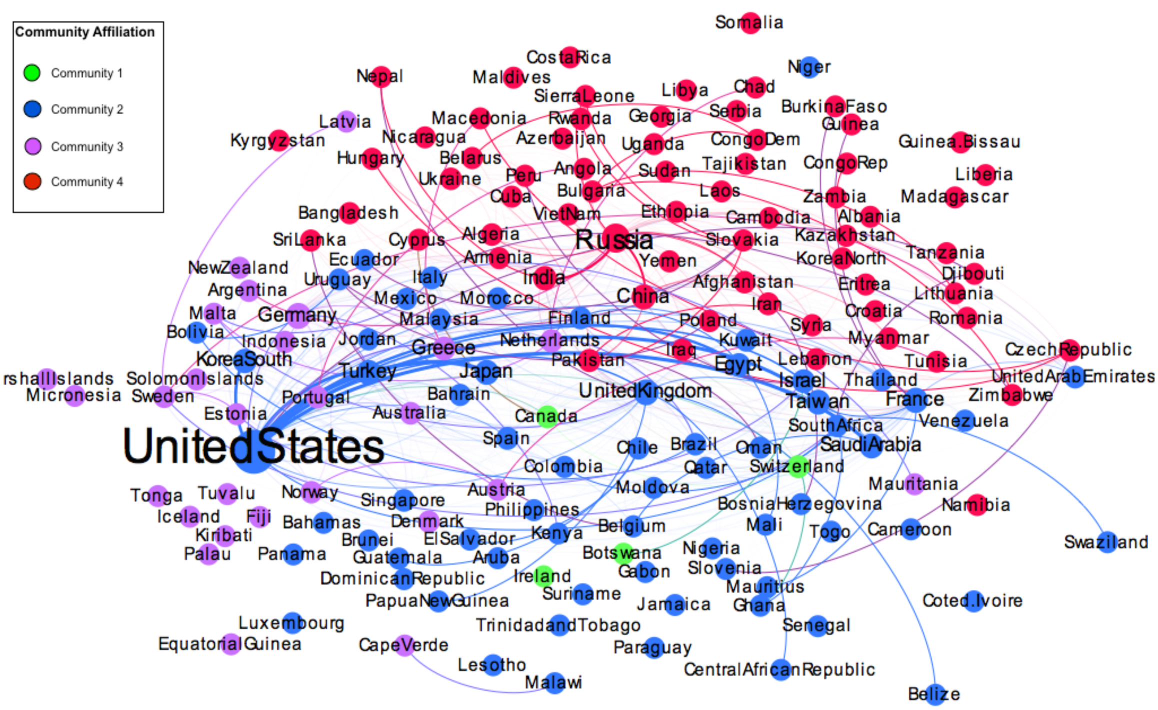


Figure 9. Post-Cold War (1990-2000) SIPRI arms trade network visualization diagram.

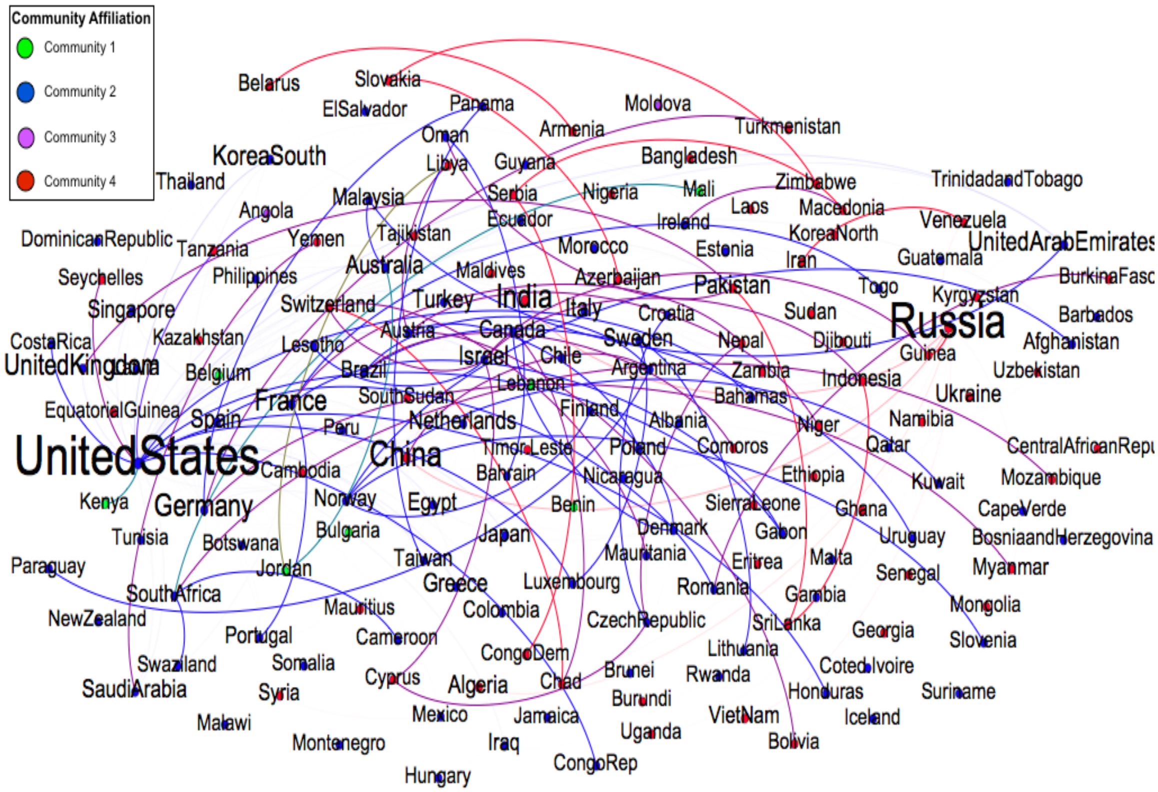


Figure 10. Post-9/11 (2001-2013) SIPRI arms trade network visualization diagram.

As previously demonstrated with the UN voting networks, the geospatial visualized results of the networks provided below in Figure 11 help impart a geographical context to the analysis discussion. The top map accurately captures the prominent existence of the geo-political East-West divide with a concrete bipolar color pattern throughout the globe. Unlike the Sino-African community seen in the Cold War UN voting network map shown in Figure 7, the SIPRI Cold War does not capture a direct Chinese arms trade influence in Africa. This might speak to general political and economic differences that exist between a voting and trade network, but might be more so the result of Garcia's (2014) aforementioned comment regarding the lack of available Chinese arms trade data from that era. Pierre (1982) gives further credence to the fact that

Chinese arms trades did occur in Africa during the Cold War in his discussion of East-West power competitions in Africa.

The diluted Soviet influence seen in the immediate Post-Cold War era map (middle) and the consolidation and capture of new community members by Russia in the Post-9/11 map (bottom) are truly driven by the Russian arms export market share. Table 3 allows for the observation of total degree metrics from all created trade networks by showing a summarized market share by country in terms of the total transfers, imports and exports. Clearly, there exists a substantial Post-Cold War drop from 37.3% to 15.8% in Russian export market participation, while the United States and other Western powers gain market share. Russia prevents further export share decline in the Post-9/11 epoch and actually returns to 26.4% of the total export market, but fractionalization persists with four emergent communities in the global arms trade marketplace.

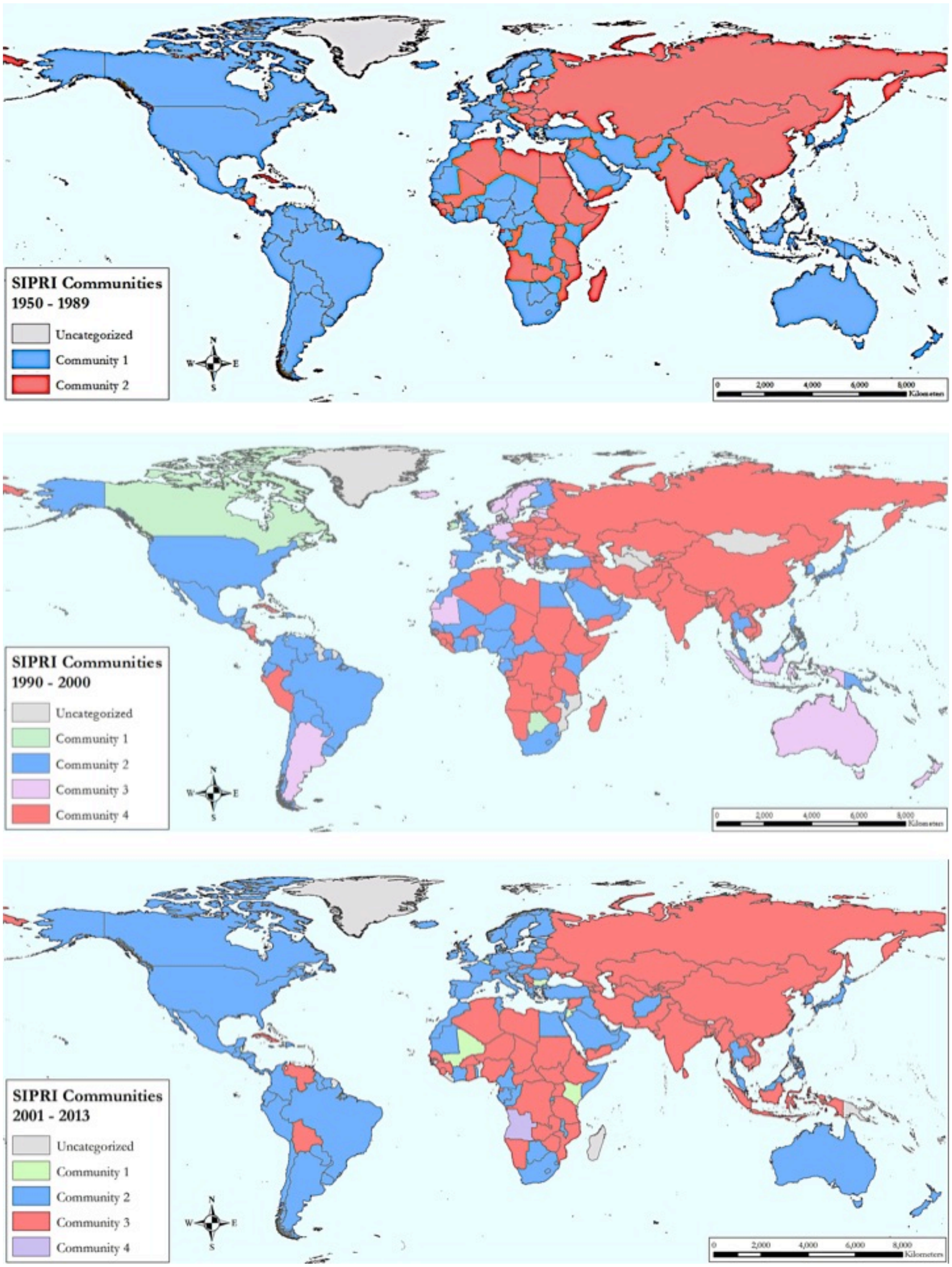


Figure 11. Global emergent community maps for SIPRI arms trade networks for all epochs.

Table 3. Overview of global arms transfers key participants during all epochs.

	Cold War		Post-Cold War		Post-9/11	
	% World Transfers	*(rank)*	% World Transfers	*(rank)*	% World Transfers	*(rank)*
Russia*	19.90%	*(1)*	14.85%	*(2)*	13.30%	*(2)*
United States	17.68%	*(2)*	25.55%	*(1)*	16.31%	*(1)*
United Kingdom	5.18%	*(3)*	4.39%	*(4)*	3.41%	*(7)*
France	3.82%	*(4)*	3.65%	*(5)*	3.70%	*(6)*
Germany	3.62%	*(5)*	4.51%	*(3)*	4.31%	*(5)*
China	2.58%	*(6)*	3.49%	*(6)*	6.52%	*(3)*
India	2.58%	*(7)*	2.66%	*(12)*	5.47%	*(4)*
Iraq	1.89%	*(8)*	0.14%	*(68)*	0.56%	*(38)*
Poland	1.86%	*(9)*	0.31%	*(44)*	0.79%	*(28)*
Italy	1.78%	*(10)*	1.08%	*(20)*	1.76%	*(15)*
Ukraine	-	-	0.59%	*(35)*	1.08%	*(26)*

	Cold War		Post-Cold War		Post-9/11	
	% World Imports	*(rank)*	% World Imports	*(rank)*	% World Imports	*(rank)*
India	5.15%	*(1)*	5.26%	*(6)*	10.87%	*(1)*
Germany	4.26%	*(2)*	1.78%	*(16)*	0.81%	*(36)*
Iraq	3.76%	*(3)*	0.28%	*(62)*	1.12%	*(25)*
Egypt	3.37%	*(4)*	4.03%	*(7)*	2.48%	*(12)*
Iran	3.26%	*(5)*	2.00%	*(14)*	0.85%	*(35)*
Japan	3.18%	*(6)*	6.19%	*(4)*	1.72%	*(16)*
Poland	3.16%	*(7)*	0.36%	*(53)*	1.24%	*(20)*
Syria	2.94%	*(8)*	0.64%	*(37)*	0.70%	*(39)*
China	2.87%	*(9)*	3.77%	*(9)*	9.30%	*(2)*
Libya	2.62%	*(10)*	0.00%	*(135)*	0.05%	*(98)*
Ukraine	-	-	0.00%	*(T-162)*	0.00%	*(T-162)*

	Cold War		Post-Cold War		Post-9/11	
	% World Exports	*(rank)*	% World Exports	*(rank)*	% World Exports	*(rank)*
Russia*	37.33%	*(1)*	15.79%	*(2)*	26.44%	*(2)*
United States	33.03%	*(2)*	48.37%	*(1)*	29.28%	*(1)*
United Kingdom	8.82%	*(3)*	6.29%	*(5)*	4.55%	*(5)*
France	6.31%	*(4)*	6.44%	*(4)*	7.13%	*(4)*
Germany	2.97%	*(5)*	7.15%	*(3)*	7.80%	*(3)*
China	2.29%	*(6)*	3.15%	*(6)*	3.73%	*(6)*
Italy	1.61%	*(7)*	1.27%	*(8)*	2.36%	*(7)*
Switzerland	0.80%	*(8)*	0.95%	*(11)*	1.07%	*(13)*
Netherlands	0.79%	*(9)*	1.83%	*(7)*	2.22%	*(8)*
Canada	0.58%	*(10)*	0.49%	*(15)*	0.99%	*(14)*
Ukraine	-	-	1.17%	*(9)*	2.15%	*(10)*

Note: Russia* is used as the reference name for the Soviet Union to account for the Cold War data column.

Ukraine exhibits very unique characteristics in the global arms trade network. Although it consistently falls within the same community as Russia, Ukraine acts solely as an arms exporter and receives no imports. Even so, Table 3 shows how Ukraine emerged as a top-10 weapons exporter immediately upon gaining its independence following the end of the Cold War. Further, Ukraine dramatically expands its portfolio of trading partners between the Post-Cold War and Post-9/11 epochs. Figure 12 below captures this expansion by visualizing Ukraine's ego network during both periods. Ukraine, whose ego is being evaluated, is situated in the middle of each network diagram. The node and text sizes have been intentionally kept uniform to allow for ease in recognizing all members of the ego network. The edge weights are the differentiating factor as the edge thickness represents the volume of trade between nodes, with greater thickness representing higher volume. The color scheme allows for the identification of community affiliation within the ego network. An ego network captures all neighbors, or directly connected nodes, of a particular node and the links amongst those neighbors. In this case, Ukraine's ego network captures all countries that it exports arms to and the direct trading partners of those countries that receive exports from Ukraine. The Ukrainian ego networks not only expand in partner volume, but also transcend community boundaries by transacting with all communities in the Post-9/11 network. Section 6.3 presents a further analysis of Ukraine's expansive arms trade export network and the implications associated with the current ongoing crisis.

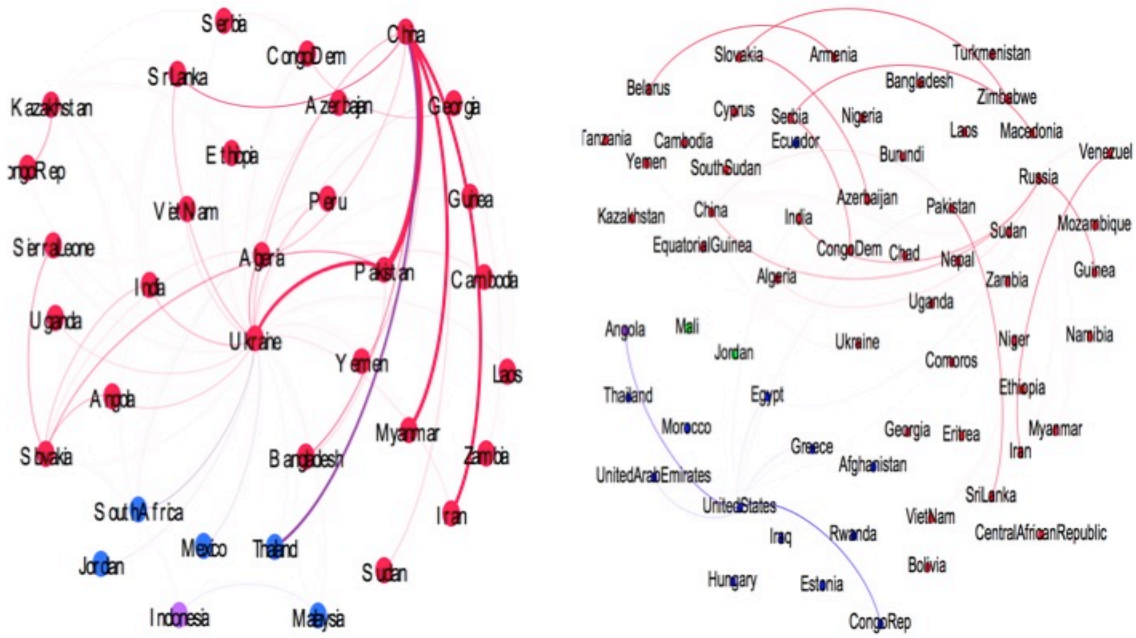


Figure 12. Network visualizations of all arms transfers within Ukraine's ego networks: (left) Post-Cold War epoch (right) Post-9/11 epoch.

3.4 Summary

This chapter presented the findings associated with the two macro-level networks of interest in this study. By incorporating highly vetted sources such as the UN voting and SIPRI arms databases, the study attempted to provide a validation mechanism for the SNA processes employed. The presented network results successfully resembled verified empirical evidence associated with UN voting patterns and historical arms transfers. This attainment of verification and validation is essential to providing a proper baseline to compare the resulting Twitter micro-level network in the following chapter.

4. MICRO-LEVEL TWITTER NETWORK

4.1 Introduction

The recent emergence and massive global use of social media has ushered in a new era of transnational connectivity between individuals. This new digital method of connecting individuals throughout the world transcends traditional physical geographic boundaries and allows near real-time conversations to take place in a cyber world. The digital nature of these social media conversations also leaves a digital data footprint, giving researchers a rich data source for analyzing social media transactions (Croitoru et al. 2014; Zhao et al. 2014; Crooks et al. 2013). The pervasive use of social media and the diffusion of information are undeniable, but much work remains to be done in regards to validating this new source of data for use in analytical studies. It is the intent of this chapter to provide one possible example for using social media-generated data, specifically Twitter, by developing a network that captures micro-level individual social media interactions that can be compared to pre-existing global networks. The micro-level network created in this study is the Ukrainian retweet conversation network, which captures global connections created by individual retweet conversations of the Ukrainian crisis from the initial protests in the fall of 2013 through the Russian annexation of Crimea in late spring of 2014. Retweets are a very specific tweet form that implies a special, concerted connection between Twitter users (Conover et al. 2011; boyd et al. 2010; Suh et al. 2010). Section 4.3 provides the methodology for developing the micro-level network in a fashion similar to the macro-level network methodologies presented in Sections 3.2.2 and 3.3.2, but it includes a more robust analysis of the Twitter data due to the relative immaturity of using such a dataset in academic research.

4.2 Ukraine Twitter Data

The data used to create the Ukrainian retweet conversation network originated from harvested Twitter conversations containing one of the 19 keywords listed in Table 4. The chosen keywords, which include people, events and locations, all focus on the most common themes associated with the ongoing unrest in Ukraine starting in November 2013. Table 4 provides the language of origin and the explicit meaning for each keyword in order to better explain their associated context with the ongoing Ukrainian crisis. The GeoSocial system platform (Croitoru et al. 2013) served as the interface mechanism to extract tweets from the Twitter API. The compiled database captured 27,479,233 total tweets from November 2013 through June 2014, of which, 13,344,545 (48.6%) were retweets. The specified collection period included key events such as the initial Euromaidan protests, official resignations of several high-ranking Ukrainian government officials and the Russian incursion and subsequent annexation of the Crimean Peninsula.

Table 4. Keyword filter list used for harvesting tweets associated with the Ukrainian crisis.

Keyword	Language	Purpose
ukraine	English	Country of interest
euromaidan	English	Official anti-Ukrainian government protest name beginning November 2013
євромайдан	Ukrainian	Official anti-Ukrainian government protest name beginning November 2013
maidan	English	Short-form of official protest name
майдан	Russian / Ukrainian	Short-form of official protest name
kiev	English	Capital city of Ukraine
киев	Russian	Capital city of Ukraine
pro-eu	English	Protests viewed as pro-European Union
berkut	English	Ukrainian special force police agents
беркут	Ukrainian	Ukrainian special force police agents
ianoukovitch	French	Former Ukraine President Viktor Yanukovych
yanukoviç	French / Turkish / Tartar	Former Ukraine President Viktor Yanukovych
yanukovic	English	Alternate English spelling of Yanukovych
yanukovych	English	English spelling of former Ukraine President Viktor Yanukovych
titushky	English	Ukrainian undercover mercenary police agents
titushko	English	Vidam Titushko is a famous Ukraine athlete; surname inspired the naming of the Titushky agents
spetsnaz	English	Common term associated with military special forces units in former Soviet countries
specnaz	English	Alternative common spelling of spetsnaz
львов	Russian	Russian spelling of Lviv, which is a major Ukrainian city in west Ukraine

Although the GeoSocial system harvest returned 16 associated data attributes for each tweet, this study focused primarily on the following tweet attributes: author name, time of tweet, location (if provided) and the actual text message. A tweet author's name can be attributed to a certain location if the harvested tweet contains location information. Location information can come in the form of geographic coordinates provided directly by a Twitter user via GPS-enabled device location services or through a location-describing toponym. The tweets used in this study consisted of 146,864 tweets (1.3%) with precise GPS-provided coordinates and 10,886,805 tweets (39.6%) contained toponym-derived coordinates. The total combined geolocation tweet count was

11,033,689 (40.2%). The relatively low volume (1.3%) of geolocated tweets with precise coordinates is consistent with other tweet databases sourced from the Twitter API (Morstatter et al. 2013; Valkanas et al. 2014; Crooks et al. 2014). In terms of retweets in this data set, 39.5% contained geolocation information. As previously mentioned in Section 2.5, Stefanidis et al. (2011) classify geolocation information derived from passive social media users as ambient geospatial information (AGI). The toponym-derived coordinates from the tweets are a prime example of obtaining AGI from passive social media users. A reliability test for derived coordinates was conducted on the tweets containing both precise and derived coordinates, which was the entire precise coordinate tweet corups. The test resulted in the toponym-derived coordinates matching precise coordinates at a rate of 95.6% at the country level.

4.3 Ukraine Twitter Network Methodology

The development of the micro-level Ukrainian retweet conversation network is similar to the network construction methodologies employed for the macro-level networks in Chapter 3. Prior to the introduction of the network development specifics, this section will also provide extensive spatial, temporal and content analyses of this study's Twitter data. The purpose of these additional layers of analyses is to provide the reader with a greater foundational understanding the data used to construct the resulting Ukraine retweet conversation network. Unlike the previously introduced macro-level network data sources used in this study, these Twitter data are unique to this study and they do not have a historical precedence of use or empirical validation.

Biases associated with social media data are an additional consideration this study must address. Valkanas et al. (2014) observed an inherent English language bias in their Twitter study data due to the overall user base of Twitter. Twitter provides sparse demographic data associated with its user base, but does acknowledge in its most recent annual report that users from the United States account for 28.9% of the entire Twitter population (Twitter 2014). Twitter (2014) further acknowledges challenges in capturing a total global user base due to the blocking of Twitter use by countries such as China. Figure 13 provides an interesting visualization created by Leetaru et al. (2013) that captures a global Twitter participation bias. The visualization uses NASA man-made light imagery to show Twitter usage rates by shading the visible light red to indicate higher concentrations of Twitter users and blue to indicate lower concentrations. An additional source of bias associated with Twitter data can emanate from the types of users involved in a tweet conversation and the volumes at which they tweet. Beyond ordinary individual users, core Twitter user account types include accounts for organizations and new media (De Choudhury et al. 2012). In some cases, these types of accounts can be managed by a bot and produce an abnormally high volume of tweets that could potentially skew the context of a conversation (Gerlitz and Rieder 2013). It is important to carry forward these known biases and acknowledge the possibility of others for the remainder of this analysis. The following in-depth look at time, spatial, and content characteristics of the Ukraine tweet conversation data seeks to provide the reader with a holistic examination of the employed data.

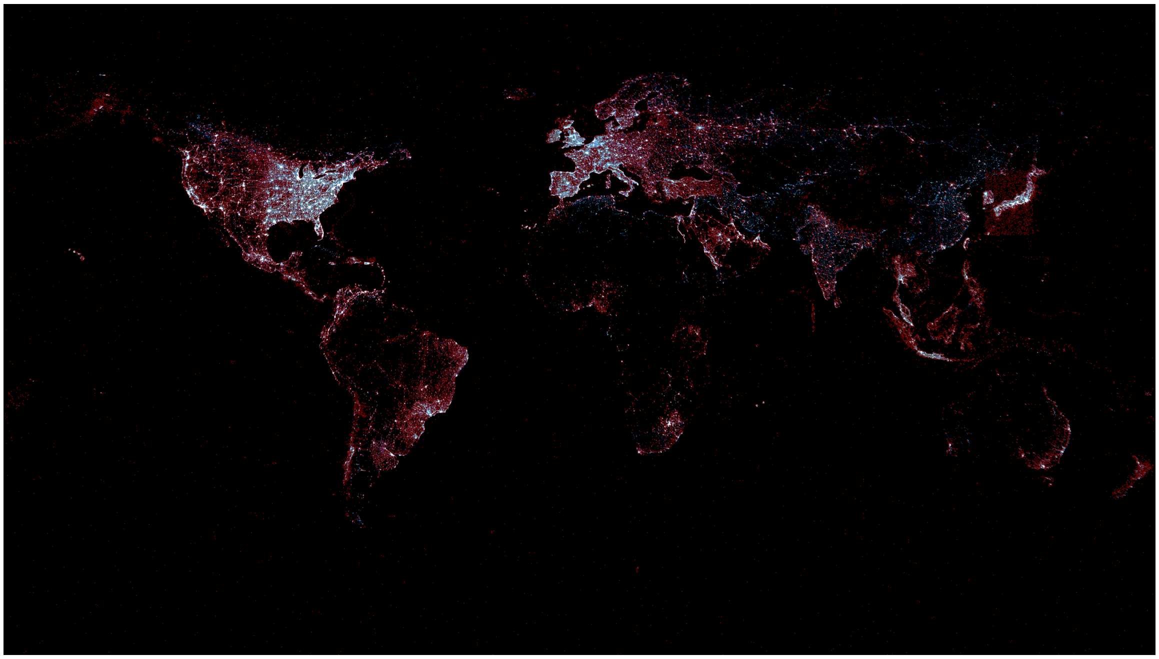


Figure 13. Global Twitter participation heat map for tweets from 23 October 2012 to 30 November 2012 integrated with NASA imagery (Leetaru et al. 2013).

4.3.1 Temporal and Spatial Analysis

The associated time stamp and geolocation information of the Ukraine conversation tweets are two primary attributes of interest in this study. These two attributes contribute to separate temporal and spatial analyses, as well as combined spatio-temporal analyses. The inclusion of time information is essential to the Ukraine conversation tweet corpus since it serves as the primary indicator for meeting the time range considered in this study. Geolocation information is necessary for inclusion in the independent spatial analysis and retweet network analysis but not the spatio-temporal analysis.

The independent temporal analysis of this study provides a time-series of all tweets in the Ukraine tweet conversation corpus, thus enabling the detection of the key events associated with the ongoing Ukrainian crisis between November 2013 and June 2014. By viewing the tweets in a time series plot, one observes the key events that are accompanied by spikes in tweet volume. An associated key event spike suggests a deviation from the normal conversation pattern in the tweet environment for a given period.

The independent spatial analysis seeks to simply observe the differences in volume between tweets with and without geolocation information. It is important to understand the proportion of the conversation with geolocation and to attempt to decipher whether it is sufficient in representing the entire tweet conversation. This analysis observes the global geographical dispersion of all tweets with geolocation. Additionally, the analysis includes a discussion of the geolocation characteristics of the Ukraine tweet conversation corpus.

Finally, a combined observation of tweet geolocation attributes over time concludes the temporal and spatial analysis section. Tracking the level of geolocated tweets in proportion to the overall tweet corpus verifies whether the proportion remains consistent throughout the analysis. As mentioned previously, the observed proportions must sufficiently represent the overall tweet corpus.

4.3.2 Content Analysis

The content analysis conducted in this study seeks to validate that the harvested tweets are contextually tied to keywords associated with the Ukrainian crisis. This analysis employs natural language processing tools to extract keywords from the Ukraine tweet conversation corpus. The resulting top keywords should be synonymous with the key events of the Ukrainian crisis. Furthermore, content analysis allows for the observation of conversation phase transitions in the tweet corpus over time. Specifically, this analysis examines the emergent keywords during two distinct two-month periods in isolation: (1) the initial Euromaidan protests (2) the Crimea annexation. The content analysis results should be observably different given the associated narrative changes with these separate events. Finally, the overall content analysis captures the different languages in the resulting key word lists. The observance of languages associated with user populations other than English, given the acknowledgement of Twitter user population bias, could suggest increased participation of minority populations.

4.3.3 Retweet Network Analysis

The Ukrainian retweet conversation network focuses on capturing transnational linkages that result when an original tweet message is "retweeted" in a conversation. The notion of a retweet implies a relationship between two authors: the original tweet author and the retweet author. The importance of a retweet has been highlighted in numerous works (boyd et al. 2010; Freelon et al. Preprint; Conover et al. 2011; Suh et al. 2010). In keeping with the "node-edge" paradigm for constructing the Ukrainian Twitter network, the countries of the tweet and retweet authors represent nodes, while the retweet linkage between the two authors is the edge. Therefore, the geolocation data for each author of a retweet conversation must be provided to ensure the retweet edge can be included in the overall Ukraine retweet conversation network. The decision to aggregate the nodes to the country-level allows for the future comparative analysis between the micro- and macro-level networks.

Since the retweet author initiates the retweet act of an original author's tweet, a retweet is also directional in nature, thus classifying the Ukraine retweet conversation network as a directed network. An observed retweet edge between countries is assigned a value of 1 in keeping with the similar weighting system of the previously mentioned macro-level networks in Section 3.2.2. The resulting affinity scores between countries suggest a connectivity metric, with a higher affinity score constituting a greater number of tweet conversation connections between two countries. The Louvain community detection algorithm references the edge weights, which are the cumulative affinity scores, to detect the emergent communities of this micro-level retweet network (Blondel et al. 2008). The resulting emergent communities from the Ukraine retweet conversation network provide the final key comparative metric to directly evaluate all the study's derived networks in Chapter 5.

4.4 Ukraine Twitter Network Analysis Results

The following section begins by providing results from the robust analysis of the overall harvested tweet data used in this chapter and concludes with the results of the Ukraine retweet conversation network analysis. The rigorous testing of the tweet data source seeks to provide a certain level of comfort with the data and attempts to serve as a validation measure. Although no tweet sample meets the empirical validation standards of the macro-level networks data sources in this study, it is an essential effort to provide as much transparency as possible with the use of such a relatively untested data source.

4.4.1 Temporal and Spatial Analysis Results

The results of the independent spatial analysis are shown in Figure 14. This map plots the 11,033,689 tweets with geolocation data from the harvested tweet sample. As is obvious from the map, the Ukrainian Twitter conversation spans the entire globe and is not limited to any specific geographic locales. It is important to note the global extent of the conversation, but beyond this simplistic observation, the map below serves little more than to verify the populated zones throughout the globe that have access to social media. Nearly identical geographic distributions of large geolocated Twitter datasets are seen in Crooks et al. (2014) and Varol et al. (2014), even though those social media analyses are examining completely different subjects.

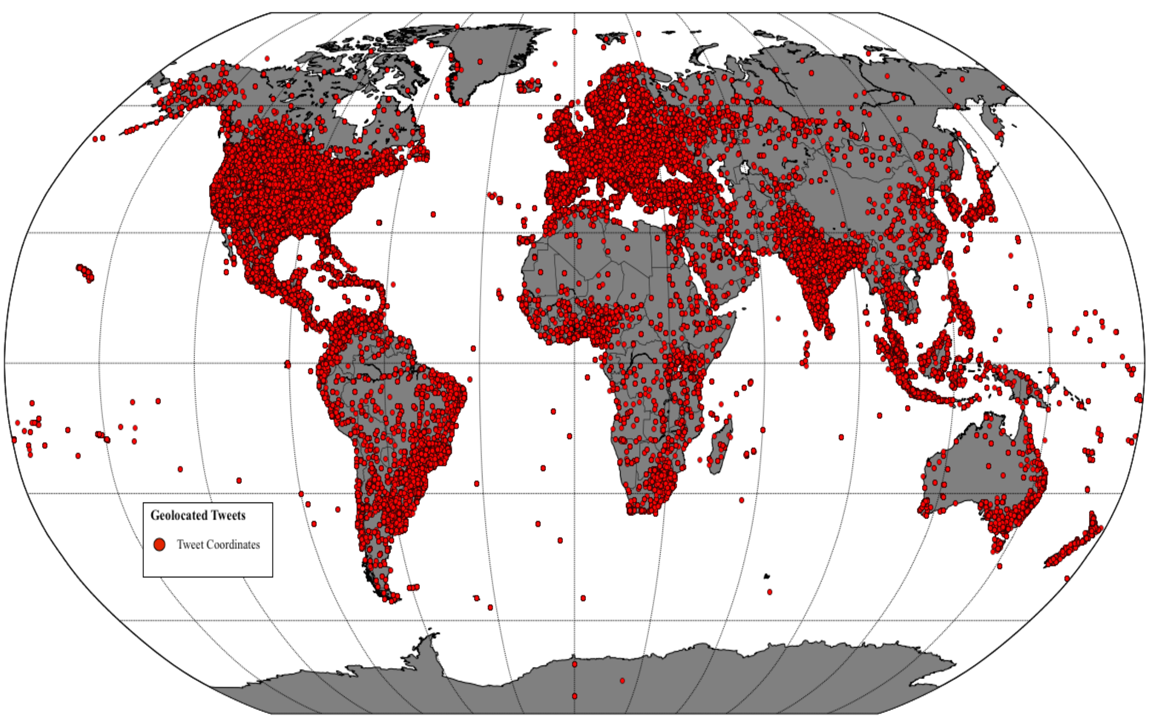


Figure 14. Global distribution of all harvested Ukraine-related tweets with geolocation data from November 2013 through June 2014.

Figure 15 provides a different global distribution perspective of all tweets with geolocation information by differentiating between tweets with precise and derived coordinate data. Tweets with precise coordinates are represented in blue, while derived coordinates are shown in green. Given the much larger volume of tweets with derived coordinates, the blue precise tweets are plotted over the derived green tweets. The intent of the map is to ascertain any coverage differences between the two sources of geolocation information. The results display no major differences between the two sources, with minimal additional coverage shown by tweets with derived coordinates.

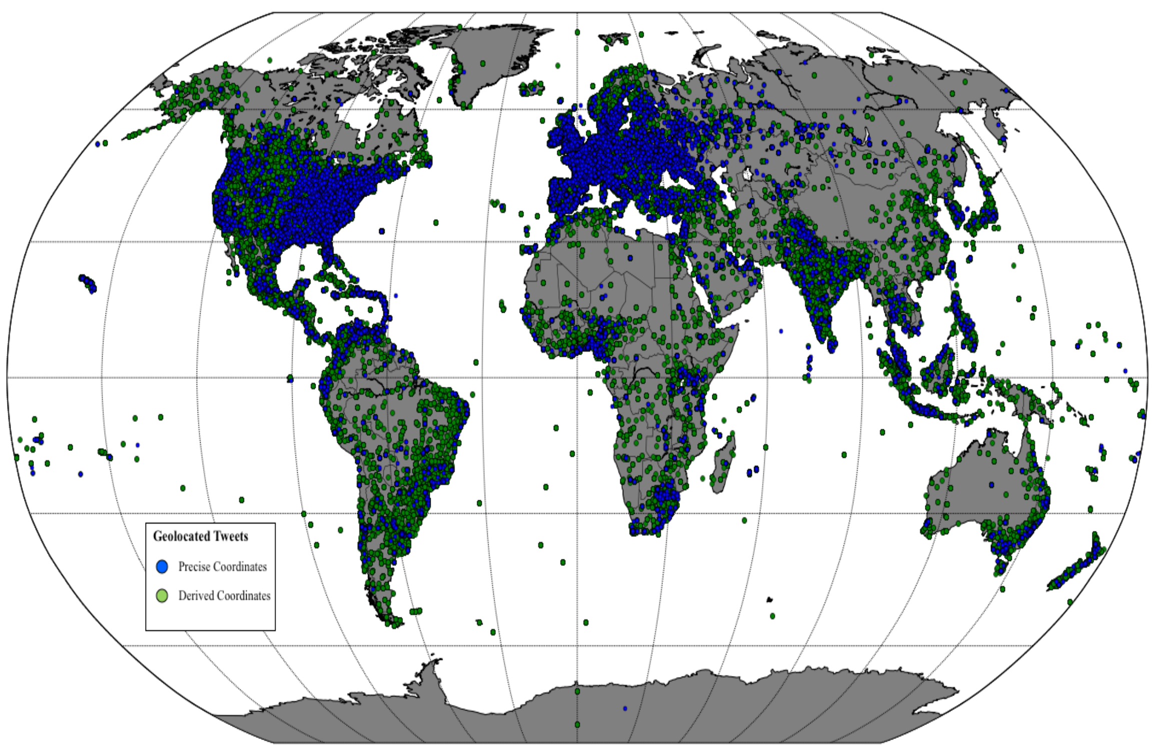


Figure 15. Global distribution of all harvested geolocated Ukraine-related tweets with precise and derived geographic coordinates from November 2013 through June 2014.

Figure 14 and Figure 15 provided map visualizations depicting the global reach of the Ukrainian Twitter conversation. The high volume of 11,033,689 tweets with geolocation information resulted in severe overplotting issues when viewing all tweets individually on the map and failed to capture a true density estimate for specific areas. Figure 16 provides a thematic global map capturing individual country total tweet counts as a percentage of the total global tweet conversation with an increasing shade darkness representing a higher percentage of global tweet contributions. The resulting country participation rates show the United States dominating the total conversation, with Ukraine and Great Britain as the next top tweet contributors.

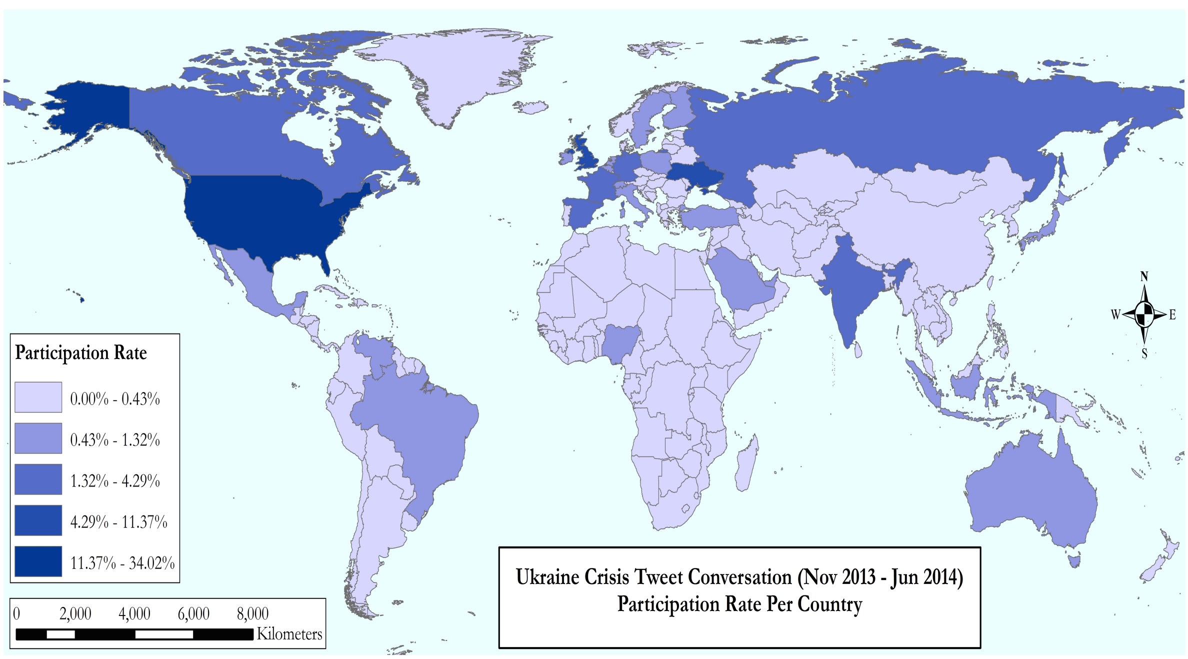


Figure 16. Ukraine tweet conversation participation rate per country from November 2013 through June 2014.

The independent temporal analysis sought to observe the Ukrainian Twitter conversation over time and detect any abnormal volume changes. Evidence of abrupt volume changes suggests the occurrence of a significant event. Figure 18 below depicts the time series of regular tweets and retweets from November 2013 through June 2014. The conversation pattern does indeed show significant peaks associated with the most prominent events of the Ukrainian crisis. The first two spikes correspond with the initiation of the Euromaidan protests beginning in late November 2013 and the Ukrainian government's aggressive attempts to enforce anti-protest laws in late January 2014. The largest spike occurs in late February 2014, which corresponds with the February 23rd dissolution of the Ukrainian government, including the resignation of President Viktor Yanukovych. A spike detecting the Russian invasion and subsequent annexation of Crimea quickly follows the spike detecting the government dissolution.

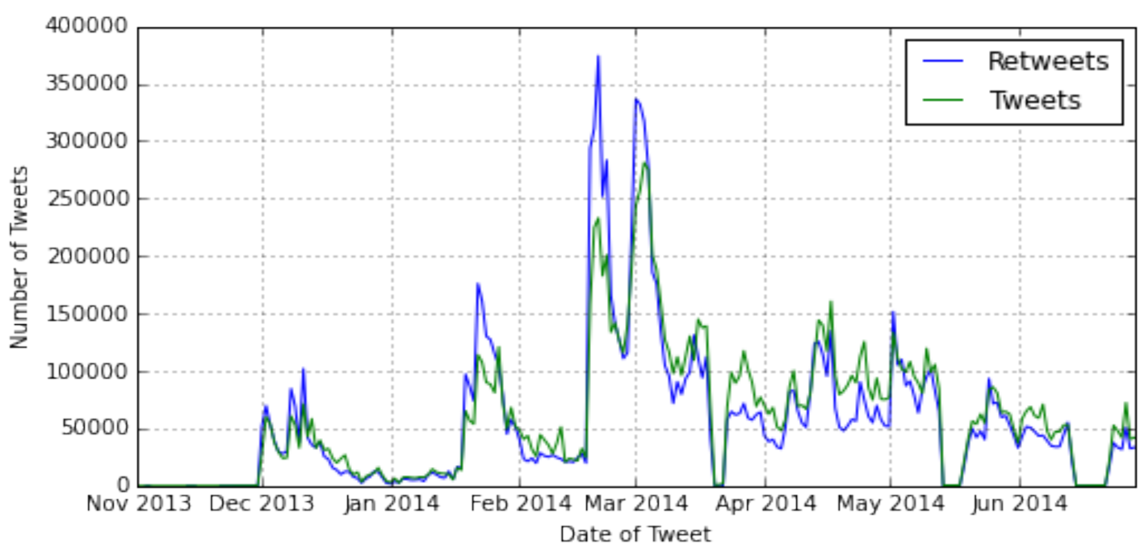


Figure 17. Time series of Ukrainian crisis-related tweets and retweets from November 2013 through June 2014.

Additionally, an interesting pattern of this time series emerges over the focus period. The volume of normal tweets typically outnumbers the retweet volume during the ongoing conversation, but during significant events this conversation pattern reverses course and retweets far outnumber normal tweets. This inverse relationship between normal tweet and retweet levels during significant events suggests that Twitter users are seeking more information about the event than is currently available to them. Twitter users satisfy this demand by connecting with other users that are providing information about the event, thus leading to the increased propagation of the ongoing event of interest through retweets. Figure 18 presents the retweet ratio for the Ukrainian tweet conversation over time, which captures the number of retweets versus total tweets.

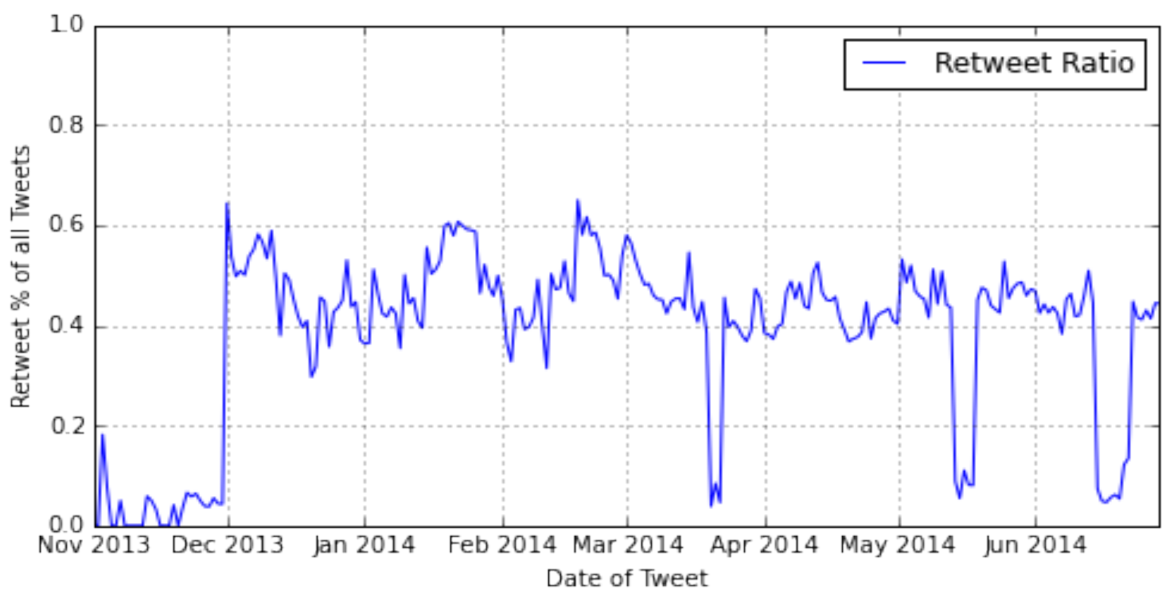


Figure 18. Ratio of retweets versus total Ukrainian crisis-related tweets from November 2013 through June 2014.

As previously mentioned in Section 4.3, it is imperative to understand the proportion of geolocated tweets in the tweet corpus over time. Figure 19 depicts the volume of tweets with and without geolocation information over time. The observable pattern for both volumes is consistent throughout the time series. Tweets without geolocation information consistently outnumber geolocated tweets. This volume differential holds true even during events of significance when tweet volumes are high, unlike the reversal of volumes observed between retweets and tweets during significant events. The consistent proportionality between tweets with and without geolocation information over time suggests that neither is dominating the pattern of the Twitter discussion. The precipitous drops in volume observed in mid-March, mid-May and mid-June can be attributed to the fact that the tweet-collecting server was down for maintenance.

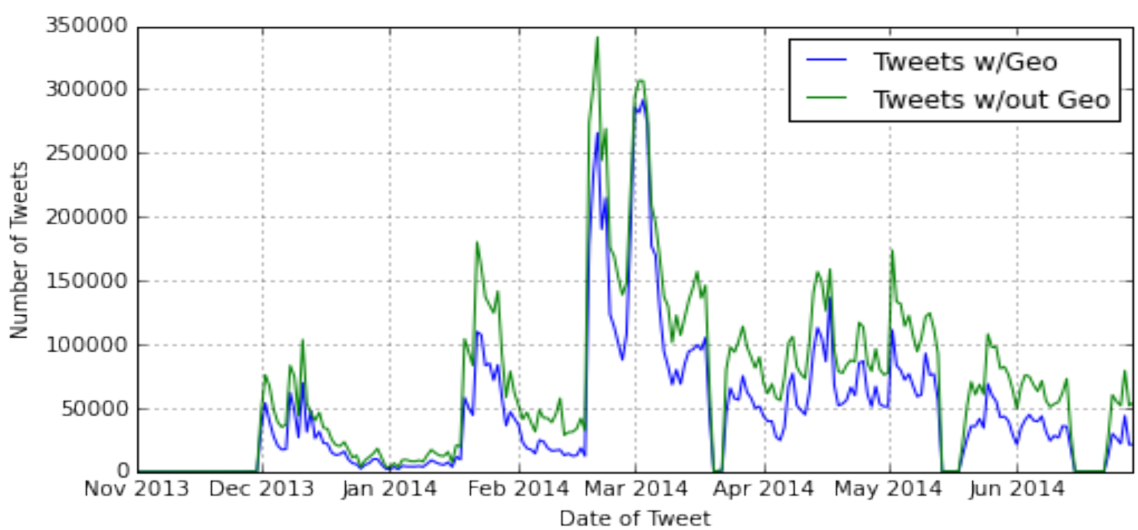


Figure 19. Time series of Ukrainian crisis-related tweets with and without geolocation information from November 2013 through June 2014.

4.4.2 Tweet Content Analysis Results

The following content analysis discussion begins with the presentation of the natural language processing results for the two key periods of interest followed by a direct comparison of the two periods. The key period analyses provide separate top-20 keyword results for tweets with and without geolocation information. This differentiation between geolocated and non-geolocated tweets provides a clear format to observe any contextual differences between the types of tweets. The final direct comparison of the two-month conversation periods associated with the initial Euromaidan protests and the annexation of Crimea allows for the observance of a conversation phase transition between these two prominent events.

Table 5. Keyword list results from content analysis of Euromaidan conversations (November – December 2013).

Euromaidan (Tweets w/ geolocation)			Euromaidan (Tweets w/o geolocation)		
Total Words: 14,387,257			*Total Words: 22,188,554*		
ukraine	317,089	2.20%	ukraine	393,000	1.77%
kiev	157,748	1.10%	євромайдан	368,007	1.66%
євромайдан	142,152	0.99%	euromaidan	228,652	1.03%
euromaidan	130,897	0.91%	kiev	175,688	0.79%
protesters	50,898	0.35%	евромайдан	93,959	0.42%
police	41,176	0.29%	Євромайдан	70,741	0.32%
майдан	35,117	0.24%	protesters	62,421	0.28%
protests	33,682	0.23%	dbnmjr	59,625	0.27%
eu	32,461	0.23%	russia	51,263	0.23%
евромайдан	30,691	0.21%	police	48,280	0.22%
russia	30,375	0.21%	киев	45,575	0.21%
lenin	27,714	0.19%	eu	44,928	0.20%
януковичсрачка	25,143	0.17%	майдан	42,565	0.19%
Євромайдан	24,610	0.17%	Евромайдан	39,912	0.18%
protest	21,915	0.15%	protests	35,451	0.16%
ukrainian	21,241	0.15%	Україна	33,940	0.15%
dbnmjr	20,667	0.14%	live	30,111	0.14%
maidan	20,107	0.14%	львов	27,409	0.12%
riot	18,333	0.13%	lenin	25,300	0.11%
president	17,696	0.12%	protest	23,604	0.11%

Table 5 presents the top-20 keyword lists derived from the approximately 36.5 million words mined from the initial Euromaidan protest Twitter conversations from November to December 2013. The keyword results for both geolocated and non-geolocated tweets show clear congruence with a keyword direct match of 75%. The resulting five mismatches can be attributed to different spelling patterns or different language characters for the same words. The geolocation and non-geolocation keyword lists include non-English text at a rate of 25 and 35% respectively. The generalized theme of the consolidated lists suggests a geographic focus on Ukraine itself, with mention of the EU and Russia, and an event-specific focus on the Euromaidan protests.

The content analysis results of the Crimea annexation conversations from March to April 2014 are presented in Table 6. There exists a 75% match between the geolocation and non-geolocation lists, with 'ukraine' emerging as the clear top word in both lists. This two-month period observed approximately 220 million total words, which is six times the volume of words observed in the Euromaidan tweet corpus. The resulting mismatched words between the geolocation and non-geolocation words show a completely different dynamic than the Euromaidan conversation. The geolocated tweet list contains only two non-English words, while the non-geolocated tweets have eight total non-English words among the top-20 keywords. Recalling the previously mentioned user base Twitter base, one might see this as evidence of English language users dominating the geolocation conversation. These initial content analysis results can also be viewed as highly skewed due to the inclusion of keywords listed in Table 4 used to initially harvest the tweets. Additionally, evidence of a conversation phase transition is clear between these two lists. Although ‘ukraine’ emerges as the clear top keyword in all lists, a noticeable transition towards Crimea takes place, with the inclusion of foreign intervention possibilities, given the mention of ‘obama’ and ‘us’ in the lists.

Table 6. Keyword list results from content analysis of Crimea annexation conversations (March – April 2014).

Crimea Annexation (Tweets w/ geolocation)			Crimea Annexation (Tweets w/o geolocation)		
Total Words: 114,950,719			*Total Words: 105,258,865*		
ukraine	3,552,531	3.09%	ukraine	2,327,389	2.21%
russia	779,530	0.68%	euromaidan	774,933	0.74%
kiev	702,796	0.61%	kiev	602,794	0.57%
crimea	483,179	0.42%	євромайдан	450,556	0.43%
euromaidan	473,543	0.41%	russia	448,648	0.43%
putin	380,963	0.33%	Євромайдан	363,404	0.35%
russian	349,111	0.30%	Майдан	258,686	0.25%
obama	244,995	0.21%	crimea	255,323	0.24%
crisis	239,250	0.21%	Киев	235,270	0.22%
us	214,611	0.19%	putin	234,311	0.22%
president	204,754	0.18%	russian	197,594	0.19%
news	188,691	0.16%	Евромайдан	167,780	0.16%
yanukovych	156,502	0.14%	майдан	166,758	0.16%
євромайдан	155,567	0.14%	crisis	141,315	0.13%
military	143,349	0.12%	евромайдан	141,012	0.13%
eu	142,748	0.12%	yanukovych	139,020	0.13%
Євромайдан	141,923	0.12%	president	138,259	0.13%
war	129,495	0.11%	obama	133,164	0.13%
troops	124,008	0.11%	news	127,050	0.12%
ukrainian	118,818	0.10%	Украина	126,246	0.12%

Table 7. Keyword list results without search words of Euromaidan conversations (November – December 2013).

Euromaidan (Tweets w/ geolocation)			Euromaidan (Tweets w/o geolocation)		
Total Words: 14,387,257			*Total Words: 22,188,554*		
protesters	50,898	0.35%	евромайдан	93,959	0.42%
police	41,176	0.29%	protesters	62,421	0.28%
protests	33,682	0.23%	dbnmjr	59,625	0.27%
eu	32,461	0.23%	russia	51,263	0.23%
евромайдан	30,691	0.21%	police	48,280	0.22%
russia	30,375	0.21%	eu	44,928	0.20%
lenin	27,714	0.19%	Евромайдан	39,912	0.18%
януковичсрачка	25,143	0.17%	protests	35,451	0.16%
Євромайдан	24,610	0.17%	Україна	33,940	0.15%
protest	21,915	0.15%	live	30,111	0.14%
ukrainian	21,241	0.15%	lenin	25,300	0.11%
dbnmjr	20,667	0.14%	protest	23,604	0.11%
riot	18,333	0.13%	ukrainian	23,218	0.10%
president	17,696	0.12%	video	22,276	0.10%
opposition	16,061	0.11%	president	21,914	0.10%
statue	14,451	0.10%	класс	19,457	0.09%
news	14,065	0.10%	onedirslaytion	19,443	0.09%
people	13,750	0.10%	tukvasociopat	18,690	0.08%
Евромайдан	13,594	0.09%	львова	17,986	0.08%
putin	13,545	0.09%	ukrainian	23,218	0.10%

Table 7 and Table 8 provide keyword lists for the Euromaidan and Crimea annexation conversations without the inclusion of the original search words used to initially harvest the Ukrainian tweet conversation. Original search words accounted for 33% and 38% of the initial top keywords in the Euromaidan and Crimea annexation conversations, respectively. Removing the original search words allows for the observation of more emergent word patterns beyond the original search words. The results show similar English language dominance in both conversations, with a greater amount of non-English words observed in tweets without geolocation. The resulting keywords of the Euromaidan period conversations provide great context that captures the initial unrest associated with the Euromaidan protests. The Crimea annexation conversation continues to show an observable conversation transition to the Russian annexation of Crimea.

Table 8. Keyword list results without search words of Crimea annexation conversations (March – April 2014).

Crimea Annexation (Tweets w/ geolocation) *Total Words: 114,950,719*			Crimea Annexation (Tweets w/o geolocation) *Total Words: 105,258,865*		
crimea	483,179	0.42%	russia	448,648	0.43%
putin	380,963	0.33%	crimea	255,323	0.24%
russian	349,111	0.30%	putin	234,311	0.22%
obama	244,995	0.21%	russian	197,594	0.19%
crisis	239,250	0.21%	Евромайдан	167,780	0.16%
us	214,611	0.19%	crisis	141,315	0.13%
president	204,754	0.18%	евромайдан	141,012	0.13%
news	188,691	0.16%	president	138,259	0.13%
military	143,349	0.12%	obama	133,164	0.13%
eu	142,748	0.12%	news	127,050	0.12%
war	129,495	0.11%	Украина	126,246	0.12%
troops	124,008	0.11%	us	125,858	0.12%
ukrainian	118,818	0.10%	ЄвроМайдан	122,099	0.12%
un	109,865	0.10%	euromaydan	103,158	0.10%
people	106,176	0.09%	eu	95,857	0.09%
protesters	100,640	0.09%	protesters	90,078	0.09%
breaking	96,908	0.08%	military	87,721	0.08%
u.s.	82,167	0.07%	war	85,181	0.08%
world	78,405	0.07%	un	82,277	0.08%
police	75,619	0.07%	Янукович	81,873	0.08%

The tag clouds in Figure 20 capture the top-100 keywords for the total Twitter conversations associated with the Euromaidan period (top) and the Crimea annexation period (bottom) without showing any differentiation between tweets with geolocation data. The clouds clearly capture the conversation phase transition between the two different conversations. The words shown in the Euromaidan cloud clearly focus on the protests and the immediate Ukrainian geographic area. The Crimea annexation cloud shows the evolution from a focus on the protests to words capturing the annexation of Crimea. Additionally, the Crimea annexation word cloud captures the diffusion of the Ukrainian crisis from a regional conversation to a global conversation. This is evident with the numerous references to the United States, to include President Obama and Secretary of State Kerry.

(a) Euromaidan

(b) Crimea Annexation

Figure 20. Tag clouds of top keywords from tweet conversations during (a) Euromaidan protests (b) Crimea annexation.

Table 9 provides a list of the top-20 Twitter authors contributing to the Ukrainian crisis Twitter conversation from November 2013 through June 2014. A majority of the author names are associated with a major news agency or blog user type account. Of particular interest, LowMaintainLife, the only author accounting for more than 1% of all tweets, is actually a Russian propaganda bot account presenting a positive spin on Russian activities associated with the Ukrainian crisis.

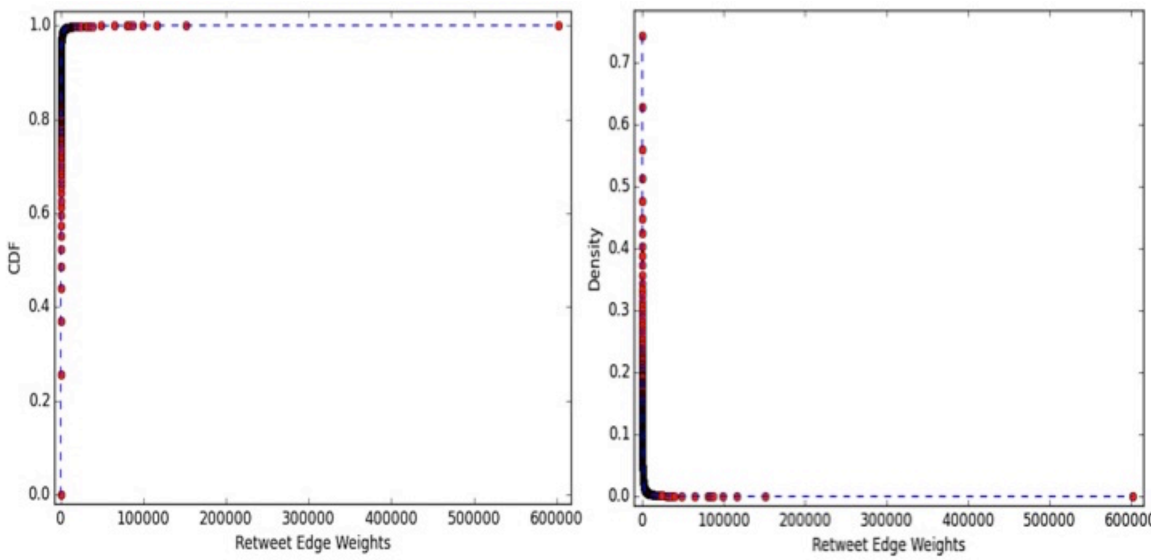
Table 9. Top contributing Twitter author names for the Ukrainian tweet conversation (November 2013 – June 2014)

Tweet Author	*# of Tweets*	*% of Total Tweets*
LowMaintainLife	37,902	1.06%
BrianBrownNet	35,446	0.99%
HauteLifestyle	25,975	0.73%
FroodyWisco	15,406	0.43%
EastOfBrussels	14,530	0.41%
EuroMaydan	14,059	0.39%
GiterDoneNews	13,011	0.37%
EuromaidanPR	11,631	0.33%
GORussiaNews	11,229	0.32%
BlueMarbleTimes	10,281	0.29%
AndrijUKR	9,966	0.28%
ComGromov	9,824	0.28%
EBPOMOCKBA	9,724	0.27%
EventsUa	9,696	0.27%
Cyber_Cossack	9,000	0.25%
Catherina_News	8,434	0.24%
Andimko	8,349	0.23%
LevMartin	8,172	0.23%
HelenHide	8,110	0.23%
Christian_bss	7,423	0.21%
Dbnmjr	7,388	0.21%
FidaSyahadah	7,342	0.21%
HCMess	7,130	0.20%
Dim_Serebro	7,077	0.20%
Lionardo518	7,011	0.20%

4.4.3 Ukraine Retweet Network Analysis Results

This section presents the network analysis results for the Ukraine retweet conversation network. Unlike the data sources used in creating the macro-level networks of this study, the raw harvested Twitter data source does not have any predetermined means of normalization. This is highly problematic given the known bias of the Twitter user database, a bias, that became immediately apparent upon observing the network characteristics of the initially created Ukraine retweet conversation network. The bias showed a complete domination of the United States in the overall Ukraine retweet conversation. The top retweet edge weight of the network is a US-to-US node pair with an edge weight four times the size of the next highest retweet edge weight. Additionally, a United States node is present in six of the retweet network's top ten weighted edge pairs. The total effect on the entire retweet network is not completely apparent until directly observing the cumulative distribution function (CDF) and corresponding probability density function (PDF) of the retweet edge weights.

The CDF (Φ) and PDF allow for the direct observation of the retweet edge weights without binning. Figure 21 shows the CDF and PDF plots capturing the distribution of the edge weight densities in the retweet network. Both plots show a highly skewed retweet edge weight distribution that follows a many-some-rare pattern of the distribution with a primary share of minimal weights. The dominant US-to-US node edge weight appears in isolation in the tail of both distributions at approximately 600,000 retweets. The second closest edge weight pair is at just 151,627, with a remaining super majority of edge weights falling precipitously below this value.



(a) CDF (b) PDF

Figure 21. CDF and PDF empirical distributions for retweet edge weight distribution between country nodes in Ukrainian retweet conversation network.

In order to account for the highly skewed retweet edge weight distribution and attempt to reduce the United States domination of the conversation, the logarithm of edge weight values replaced the raw edge weight values to effectively reduce the scaling effect. The resulting LOG-LOG plot of the complementary cumulative distribution function (CCDF), which is simply the complement of the CDF, for the edge weights is shown in Figure 22. Observation of the CCDF in LOG-LOG space is a primary visual test procedure when evaluating heavy tail distributions for evidence of a power law. This is a common practice for attempting to detect power law evidence in empirical datasets (Cioffi-Revilla 2014; Clauset et al. 2009). Although the retweet edge CDF and PDF show a highly skewed, fat tail distribution, the results of the CCDF LOG-LOG plot rule out classifying the retweet edge weight distribution as a power law distribution. The observance of power law evidence is significant given the scale-free properties indicative of a power law and the fact that power law distributions are observable in many naturally occurring phenomenon (Clauset et al. 2007).

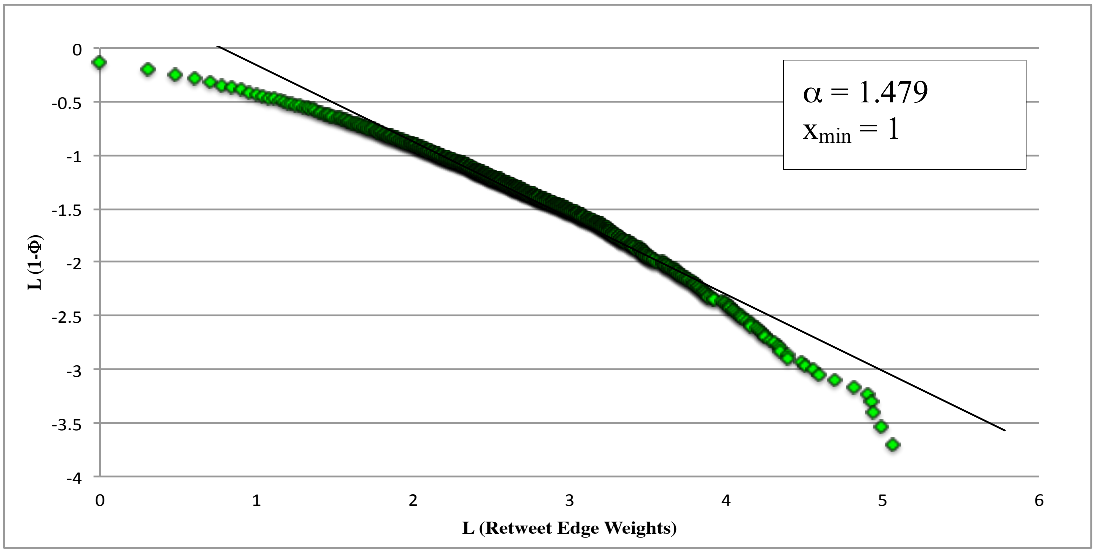


Figure 22. CCDF empirical distribution in LOG-LOG space for the retweet edge weights of the Ukraine retweet conversation network.

Upon normalization of the retweet edge weights of the network, the resulting network characteristics were able to support the application of the Louvain community detection method to detect modularity in the retweet network. Figure 23 depicts the network visualization diagram of the Ukraine retweet conversation network partitioned by community. The community detection algorithm recognized four distinct communities in the network. Total retweet edge weight serves as the scaling parameter of the corresponding node size. It is immediately apparent that a few nations operate as the prominent voices in the network, with most of the nations serving a minor role. The community sizes are pretty evenly distributed within the first three communities with populations of 75, 64 and 60, respectively. Community 4 appears to be an outlier community as it consists of only two islands nations, Palau and Tokelau. Appendix A: Community Tables provides complete community lists of the detected retweet network communities.

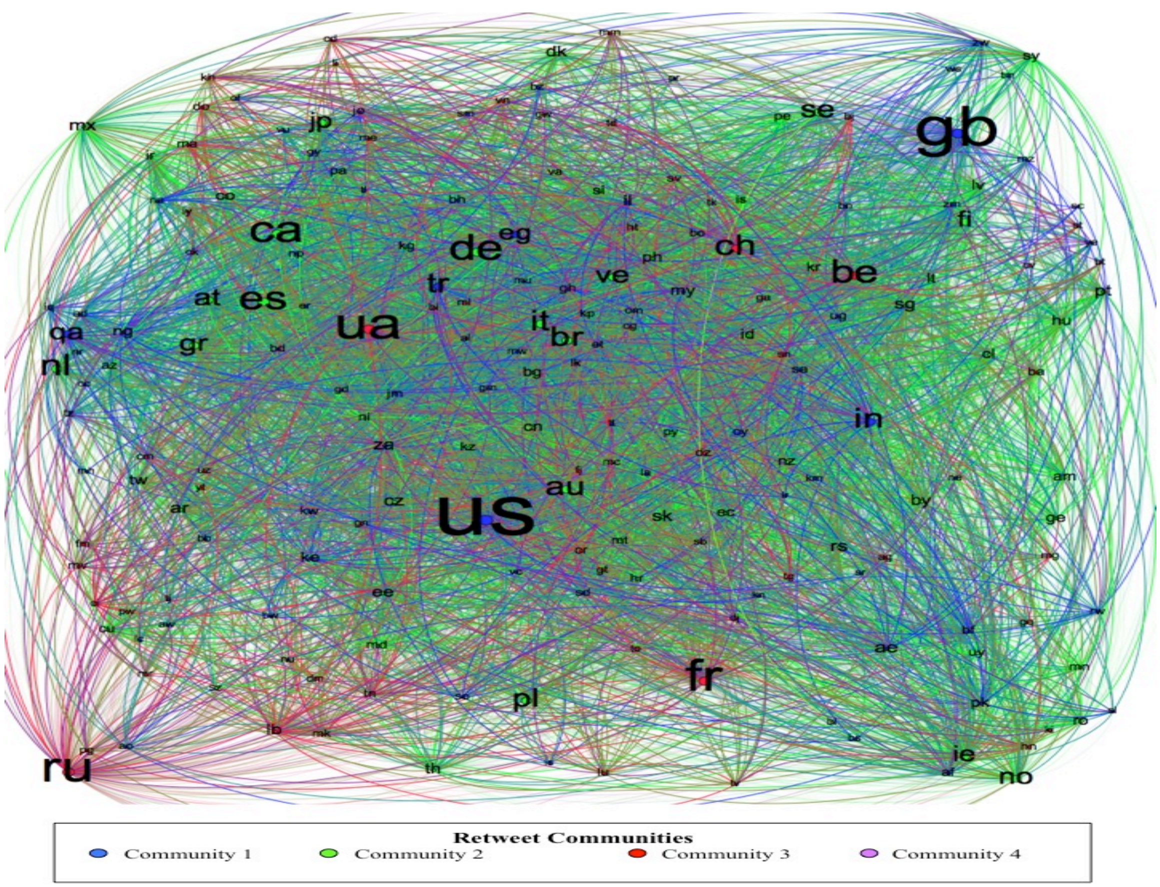


Figure 23. Ukrainian retweet conversation network visualization diagram for harvested retweets from November 2013 through June 2014.

The spatial visualization of the retweet network community results in Figure 24 provides a geographical context to the network's community structure. The resulting community dynamics are interesting given the distribution of the prominent voices in the retweet network. Western Europe, along with the United States, have been the primary supporters of the current push towards a more democratized Ukrainian government (NATO 2015; Diuk 2014), yet the United States and Great Britain are isolated in a different community than the majority of primary Western European countries. Additionally, Ukraine falls into the same community as with Russia and France. This result appears in contrast to the ongoing political dynamics of the Ukrainian crisis, given that the massive protests and subsequent government changes have been anti-Russian and pro-Western in nature. This might suggest the cultural relationship that exists between Russian and Ukrainian citizens is stronger than political affiliation. Finally, the community alignment of France with Russia captures the current debate associated with recent arms trade agreements between those two nations (Birnbaum 2014).

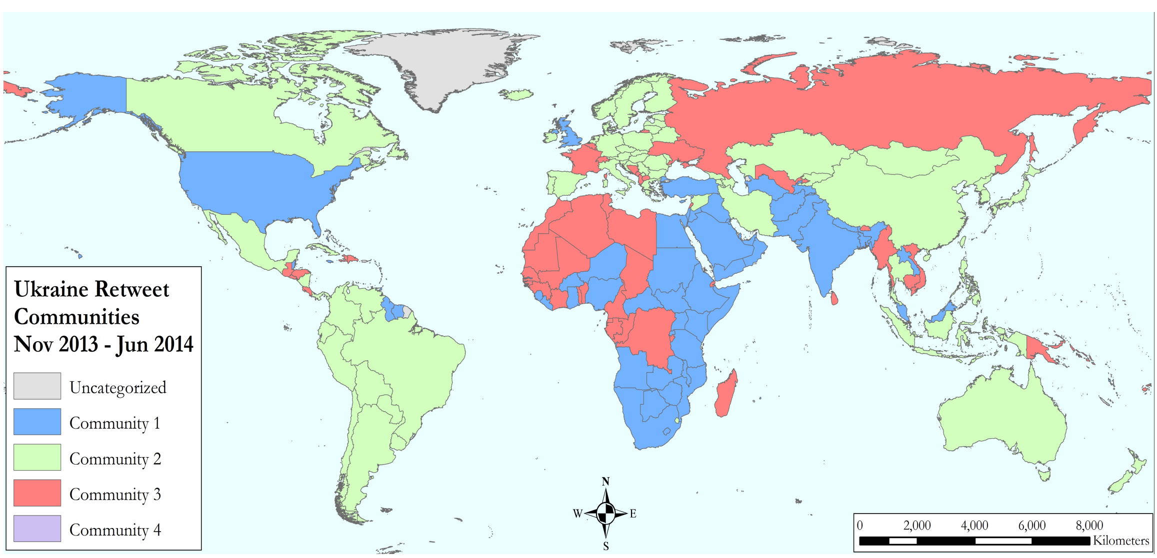


Figure 24. Global emergent community map results for Ukraine retweet conversation network from November 2013 through June 2014.

Given the previous revelation of the United States domination of the overall retweet conversations and observations resulting for the community membership analysis, it is important to better understand the flow of communication within the Ukraine retweet conversation network. Figure 25 provides a visualization of the most prominent retweet countries in the overall network. This map depicts transnational linkages between countries that represent the 20 highest retweet edge weights of the retweet network. The terminal points of each radial signify the geographical centroids of the country nodes comprising the retweet edge. The color of the radial link signifies the nation from which the retweet originates. Nine countries represent at least one node in the top 20 edges, with the United States appearing as a node in 12 of the edge pairs. The United States, Great Britain and Canada have contributed the most to the propagation of original Ukraine tweets about the crisis with the highest retweet edge weights shared with Ukraine. A surprising outcome of this analysis is the inclusion of Venezuela in the top retweet edge weight values. This is due to protests taking place against the Venezuelan Maduro government during the same period (Mundo and Cristobal 2015).

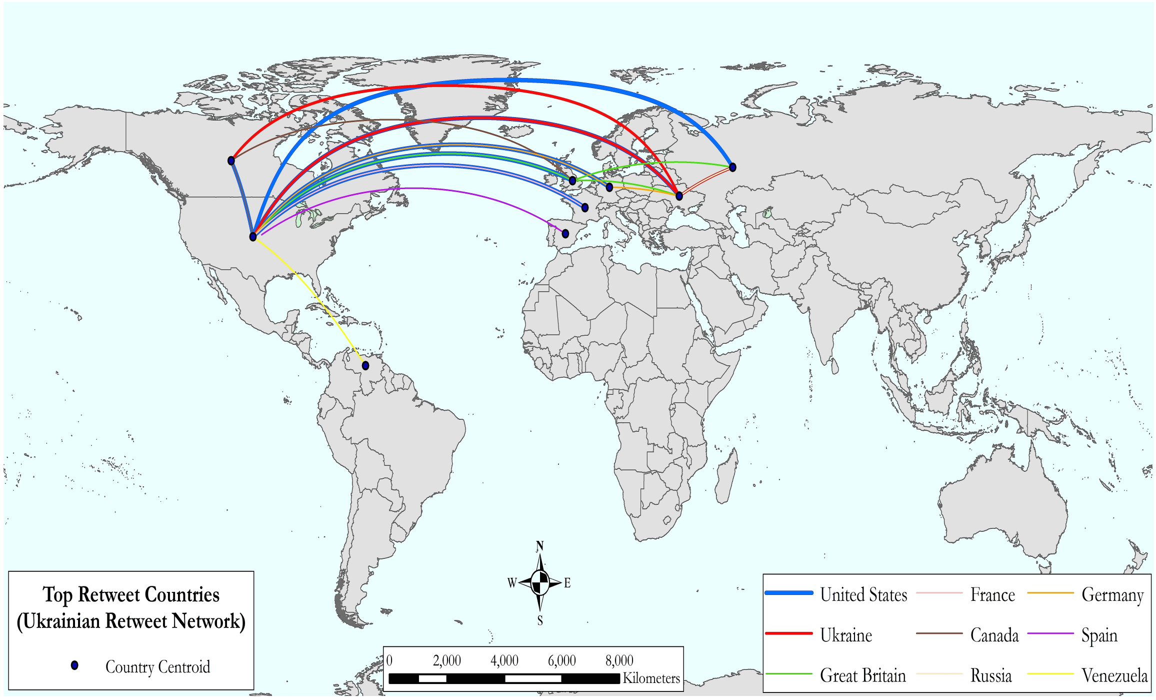


Figure 25. Most prominent retweet countries in the overall Ukrainian retweet conversation network.

4.5 Summary

This chapter provided the necessary background, methodology and analysis associated with the micro-level network of this study. In contrast to the macro-level networks presented in Chapter 3, this chapter provided a more extensive analysis of the referenced source data used to create the micro-level network. The relative immaturity of social media use in traditional analytical studies requires additional efforts to develop a better understanding of the data. In this case, the Twitter data showed evidence of bias given the United States' saturation of the Ukraine retweet conversation network. This recognition allowed for an attempt to normalize the data and produce community detection results, thus enabling the direct comparison of this micro-level network against the traditional macro-level networks in Chapter 5.

5. ANALYTICAL FRAMEWORK FOR COMPARING NETWORKS

5.1 Introduction

The emergent communities that unfolded from the constructed networks in Chapters 3 and 4 provide an opportunity for a direct comparative analysis across the varying levels-of-analysis networks in relation to the Ukrainian crisis. This chapter presents this network comparative analysis and the results serve as the primary evidence to answer the first research question posed in Section 1.3: to what degree do the emergent network communities match or overlap between the different networks associated with the Ukrainian crisis? The direct comparative metric applied to measure similarity between network communities is the Jaccard similarity coefficient. The final conclusions presented in this chapter hope to add to the conversation started by Lu et al. (2013) by evaluating the level at which the cyber micro-level network and can possibly serve as a proxy to the physical macro-level networks in this IR-focused study.

5.2 Comparative Network Methodology

The calculated Jaccard similarity coefficient serves as the primary statistical measure for comparing the likeness of the developed networks and the associated emergent community sub-networks in the study. It is a widely used similarity measure for extracting information in network studies (Salton and McGill 1986). In this case, the Jaccard similarity coefficient calculation provides a direct measure of similarity between all network communities on 0 to 1 scale, with a value of 1 representing an exact similarity. The formal calculation between two given communities, A and B, as shown below in Equation 5.2, divides the set intersection $|A \cap B|$ by the set union $|A \cup B|$.

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \qquad \text{(Equation 5.2)}$$

The network comparative analysis calculated the Jaccard similarity coefficient between all possible network community pairs by epoch. The resulting maximum similarity value for a given pair served as the final measure of similarity between the two networks. The results and subsequent analysis are presented in the following section.

5.3 Network Comparison Results

The consolidated maximum value results of the iterative Jaccard similarity coefficient calculations between all epochal network community pairs are presented in Table 10. An additional reference table located in Appendix B: Jaccard Similarity Values provides the Jaccard similarity results for all network community pairs. The analysis of these results begins with the general observation of trends resulting from the direct comparison of the UN voting and SIPRI arms trade macro-level network communities. The analysis concludes with the comparison of the micro-level Ukraine retweet conversation network communities against the macro-level network community results.

Table 10. Consolidated Jaccard similarity scores between the communities of all networks.

	UN 1950-1989	UN 1990-2000	UN 2001-2012	SIPRI 1950-1989	SIPRI 1990-2000	SIPRI 2001-2013	Ukraine Retweets
UN 1950-1989	1.000	0.556	0.514	0.423	0.326	0.398	0.418
UN 1990-2000	0.556	1.000	0.852	0.484	0.346	0.313	0.417
UN 2001-2012	0.514	0.852	1.000	0.473	0.342	0.400	0.415
SIPRI 1950-1989	0.423	0.484	0.473	1.000	0.504	0.424	0.303
SIPRI 1990-2000	0.326	0.346	0.342	0.504	1.000	0.512	0.259
SIPRI 2001-2013	0.398	0.313	0.400	0.424	0.512	1.000	0.320
Ukraine Retweets	0.418	0.417	0.415	0.303	0.259	0.320	1.000

The overall results of the macro-level community similarity analysis strongly agree with Crooks et al.'s (2014) observed results. All but one of the maximum similarity values is in agreement. The sole outliers in this study include much higher maximum similarity values associated with the SIPRI 2001-2013 networks. This discrepancy might be due to the use of updated SIPRI data that included an additional two years of the most recent global arms trades.

The general trend in the UN network over time shows how the dissolution of the Soviet Union resulted in a maximum similarity value of 0.556 with the immediate post-Cold War epoch, but similarity dramatically rises to a level of 0.852 between the Post-Cold War and Post-9/11 epochs. The results of Macon et al. (2012) shown in Figure 3 corroborate this UN increased affinity over time assertion. The SIPRI similarity values remain relatively stable over time in comparison to the volatility seen with UN similarity values over time. This might be an artifact of the differences that exist between a political and economic market system. It is much easier to change a voting stance then it is to change a manufacturing development process, therefore less volatility could be a reasonable expectation for the SIPRI network similarity values. Root (2013) contends, however, that global manufacturing is diffusing rapidly and this will continue to result in the increased dispersion of influence in global macro-level networks such as UN voting and arms trade networks. The most prominent observation between the direct comparison of the UN and SIPRI networks is consistent observation that the maximum community similarity values are aligned with the same epoch.

The micro-level community similarity measures in relation to the macro-level produced some surprising results. Ukraine retweet conversation network communities produced an average similarity value of 0.417 with the UN voting network communities, with the maximum shared similarity with the UN voting Cold War epoch. This value is not much different than the UN-to-SIPRI average similarity value of 0.458. The SIPRI communities produced an average shared value of only 0.294 with the retweet network communities. Overall, the average similarity value between the all macro-level network and the retweet network communities was 0.355. This value shows some level of similarity and is much higher than the 0.27 average similarity value observed in Crooks et al.'s (2014) analysis comparing the same UN voting and SIPRI arms trade network communities to the Syrian retweet network communities. The conclusion of this analysis shows that there does indeed exist some agreement between the macro-level UN voting network and the micro-level Ukraine retweet network. The fact that the highest similarity exists between current retweet conversations and Cold War era voting patterns suggest that Ukraine might not have shed its historical cultural roots that align with the Cold War "East-West" geo-political structure.

5.4 Summary

This chapter presented the results of the direct comparative analysis of the macro-level and micro-level networks in this study. By using the Jaccard similarity coefficient, the emergent network communities were evaluated and compared across epochs. The macro-level network results showed empirically validated results consistent with previous works. The comparison of the micro-level communities to the macro-level communities showed a much greater similarity between the Ukraine retweet and UN voting communities as opposed to the SIPRI arms trade communities. The fact that the retweet network's most similar macro-level community came from the UN voting Cold War epoch might suggest a cultural linkage that transcends current macro-level political assumptions.

6. NATO

6.1 Introduction

The NATO alliance, which was created to counter the growing power of the Soviet Union following WWII, has been the most prolific international body to publicly support the Euromaidan protests in Ukraine, while simultaneously acting in an aggressive political manner to vocally denounce and punish through sanctions the Russian actions of annexing the Crimean peninsula away from Ukraine. NATO's actions and the consistent public dialogue pushed forth by its member nations' heads of state, leads the casual observer to believe that NATO's efforts are in the best interest of the Ukrainian people, but recent polling efforts of the Ukrainian citizens suggest otherwise. An April 2014 poll by the Razumkov Center indicates that 41.6% of Ukrainians remain opposed to Ukraine joining the NATO military alliance, while only 36% agree that joining the NATO alliance is in the best interest of Ukraine even after the Russian annexation of Crimea (Williams 2014). The following chapter seeks to gain a greater understanding of NATO's relationship with Ukraine and attempts to answer whether the actions of NATO appear coordinated in response to the Ukrainian crisis. This analysis begins by providing pertinent background information about the NATO alliance, followed by an examination of Ukraine's relational network ties with NATO members in the Post-9/11 networks previously discussed in this study. The examination focuses on the Post-9/11 epoch due to it being the most recent period to evaluate the most current NATO-Ukraine relations.

6.2 NATO Background

The NATO alliance, formerly created in April 1949 with 12 original charter members, currently consists of 28 member nations. The map provided in Figure 26 shows the current member nations highlighted in blue, along with Ukraine referenced in red. NATO has progressively extended its membership base since its inception, but increased its overall growth rate by including 13 additional countries after the end of the Cold War. The most recent additions to the alliance used to be entities of the former Soviet Union, so the spread of NATO has had an eastward geographical projection towards Russia. Ukraine consistently is mentioned as a possible candidate for future NATO expansion efforts (Taylor 2014). This eastward encroachment into former Soviet Union areas of influence has been a key source of contention between the Russian Federation and the NATO alliance (NATO 2015).

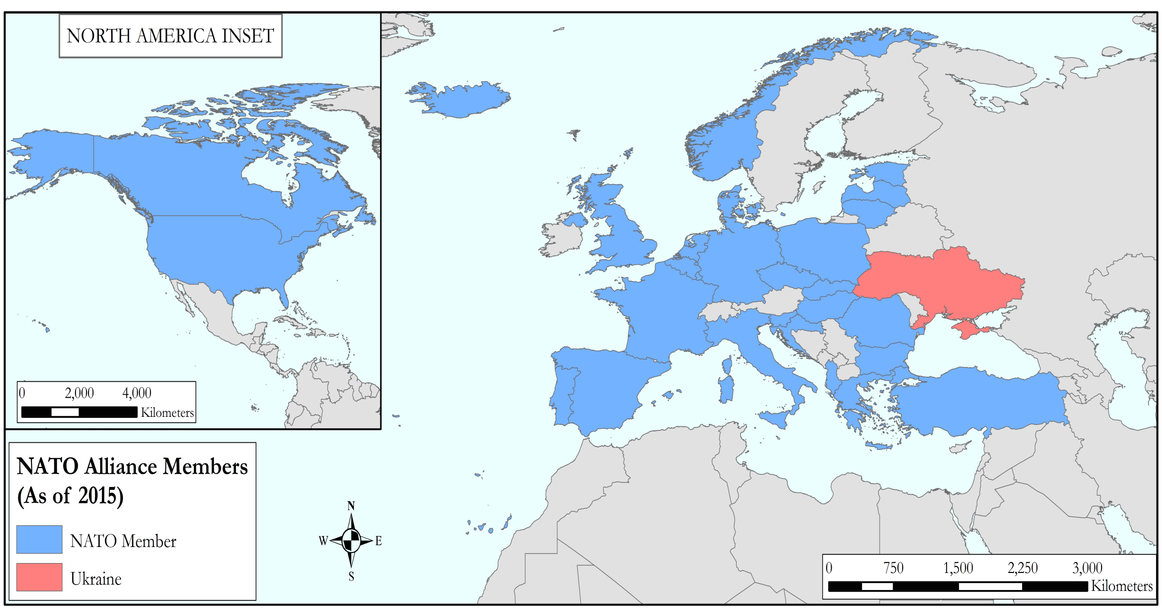


Figure 26. Map of NATO alliance members as of March 2015.

6.2 NATO-Ukraine UN Voting Network Analysis

This section extends the previous UN voting network results in Section 3.2.3 by directly focusing on Ukraine's voting affinity and emergent community membership with NATO member nations during the Post-9/11 epoch. Ukraine held an average affinity value of 52.6% with the rest of the world's countries during the Post-9/11 epoch, while the global affinity average between all countries was slightly higher at 54.9%. Given NATO's persistent eastward expansion into nations that were former entities of the Soviet Union, it could be reasonably assumed that NATO would have a higher UN voting affinity with Ukraine. This is not the case though, as Ukraine has only a 56.3% average voting affinity with NATO members, which is only slightly higher than its average with the rest of the world.

The UN voting network emergent community results of the Post-9/11 epoch provide an additional opportunity to view Ukraine's network relations with NATO country members. Table 11 provides a convincing argument of alignment between Ukraine and all NATO members given that they all fall into the same emergent community. These results require closer observation though and might not appear to mean anything more than a socio-economic relational indication. This is due to the discussion in Section 3.2.3 of the current "North-South" partitioning of the world in the UN voting pattern between nations according to social economic status. Therefore, these combined UN voting affinity and community results do not provide a clear indication of current support between NATO members and Ukraine.

Table 11. UN voting network community membership for NATO members and Ukraine (Post-9/11 Epoch).

Community 2			
Albania	France	Lithuania	Slovakia
Belgium	Germany	Luxembourg	Slovenia
Bulgaria	Greece	Netherlands	Spain
Canada	Hungary	Norway	Turkey
Croatia	Iceland	Poland	***Ukraine***
Czech Republic	Italy	Portugal	United Kingdom
Denmark	Latvia	Romania	United States of America
Estonia			

6.3 NATO-Ukraine SIPRI Arms Trade Network Analysis

The extension of the SIPRI arms trade network analysis in Section 3.3.3 by focusing on NATO-Ukraine arms trade transactions produces little evidence of cooperation between the two entities. Recall that Ukraine functions solely as an arms exporter in the global arms market. During the Post-9/11 epoch, Ukraine only supplied arms to four NATO member countries: Greece, Hungary, Slovakia and the United States. This amounted to just 8.1% of Ukraine's arms trade network partners and accounted for only 2.2% of the Ukraine's total export volume. Ukraine's top arms trade partners, China and Russia, account for 7.9 and 2.4 times the total NATO volume respectively.

The results of any cooperative signals from the shared community membership also appear to be severely insignificant. Table 12 shows that Ukraine shares a common community membership with only Slovakia, while a great majority of NATO members belong to one common community.

Table 12. SIPRI arms trade network community membership for NATO members and Ukraine (Post-9/11 Epoch).

Community 2		Community 3	Community 4
Albania	Lithuania	Slovakia	Belgium
Canada	Luxembourg	***Ukraine***	Bulgaria
Czech Republic	Netherlands		
Denmark	Norway		
Estonia	Poland		
Finland	Portugal		
France	Romania		
Germany	Slovenia		
Greece	Spain		
Hungary	Turkey		
Iceland	United Kingdom		
Italy	United States		
Latvia			

6.4 NATO-Ukraine Retweet Conversation Network Analysis

The extension of the original Ukraine retweet conversation network analysis in Section 4.4.3 provides the most promising evidence for the possible detection of signs of cooperation between NATO and Ukraine during the Post-9/11 epoch. The top three nations responsible for spreading the Ukrainian social media conversation by retweeting tweets originating in Ukraine were the United States, Great Britain and Canada. Additionally, six NATO members accounted for at least one of the node pairs in the top-20 weighted edges in the overall retweet network. Those six members were the United States, Great Britain, Canada, France, Germany and Spain. The high-ranking retweet statuses of these NATO members in the overall Ukraine retweet conversation network must be put into proper context though in order to derive a positive relationship with Ukraine.

Table 13 provides such context by listing the community membership status for each NATO country and Ukraine in the retweet network. The results show that Ukraine only shares a community with four NATO members, of which, only France was one of the prominent NATO retweet members previously mentioned. This finding requires further investigation that might require an analysis that incorporates the detection of tone within the tweet corpus. Additionally, the lack of shared community membership could just be an artifact of the English language bias observed in the Twitter user base.

Table 13. Retweet conversation network community membership for NATO members and Ukraine (Post-9/11 Epoch).

Community 1	Community 2		Community 3
Turkey	Bulgaria	Latvia	Albania
United Kingdom	Canada	Lithuania	Belgium
United States of America	Croatia	Netherlands	France
	Czech Republic	Norway	Luxembourg
	Denmark	Poland	***Ukraine***
	Estonia	Portugal	
	Germany	Romania	
	Greece	Slovakia	
	Hungary	Slovenia	
	Iceland	Spain	
	Italy		

6.5 Summary

This chapter sought to observe network relationships between the NATO alliance and Ukraine during the Post-9/11 epic. NATO has positioned itself as a prominent international figure in the current ongoing Ukrainian crisis with a self-proclaimed intention of seeking out the best interests for the Ukrainian people. Recent polling data suggested that the Ukrainian people were not fully supportive of NATO, which appears in contrast to NATO's stated intentions. The results of this chapter discovered little evidence of cooperative characteristics within the UN voting, SIPRI arms trade and

Ukraine retweet conversation networks. Recent works by Mearsheimer (2014) and Müllerson (2014) point out this observable disconnect between the positive media messaging platform put forth by NATO members in regards to supporting Ukraine and the inherent lack of observable actions justifying such claims. This disconnect appears to be an example of a failure of the marketplace of ideas (Thrall 2007). NATO members have persistently provided a messaging campaign that Russia is the sole instigator of the Ukrainian crisis and effectively drowned out any debate that NATO has played a complicit role in the crisis by not providing consistent levels of cooperation with Ukraine.

7. SUMMARIZED RESULTS AND CONCLUSION

This final chapter provides a summary of the key research findings observed throughout the study. Following an overview of the key results in Section 7.1, the chapter presents future research opportunities to possibly extend this study and contribute to research in additional domains of focus in Section 7.2. The chapter closes with the final concluding comments of the study in Section 7.3.

7.1 Overview of Research Findings

The primary motivation behind this study sought to replicate and extend the recent work of Crooks et al. (2014) that created a more holistic global international relations network framework by accounting for the inclusion of increasing individual interactions made through social media. In the case of this study, Twitter conversations discussing the ongoing Ukrainian crisis served as the source for the individual global interactions used to create a micro-level network to compare directly against traditional global macro-level networks. The resulting similarity measures between the emergent communities in each network served as the primary evidence to answer the study's first research question: To what degree do the emergent network communities match or overlap between the different networks associated with the Ukrainian crisis? The extended portion of the study sought to directly analyze the network relationships between Ukraine and the NATO alliance and attempted to answer the research question:

Do the actions of national-level actors participating in an existing global alliance such as NATO appear coordinated in response to the Ukrainian crisis?

The observed results from the macro-level network analysis presented in Chapter 3 accurately captured the geo-political communities generally associated with UN voting blocs and global arms trade partnerships during each of the evaluated epochs. The emergent UN voting network communities discovered during the Cold War epoch spatially display a clear, predominantly bipolar East-West divide as shown by Figure 7. The observable evidence following the end of the Cold War shows the UN voting networks evolving into today's North-South socio-economic global divide. The SIPRI arms trade network community results follow a similar pattern with a bipolar East-West divide during the Cold War epoch, but display greater fracture with more emergent communities in the Post-Cold War and Post-9/11 epochs. These macro-level results were strongly aligned with Crooks et al.'s findings except for a resulting deviation associated with the arms trade network during the Post-9/11 epoch, which could be attributed to the use of a more recent SIPRI database in this study.

The study conducted a robust initial analysis of the Twitter data used to create the micro-level retweet network. The additional temporal, spatial and content analyses of the Ukrainian retweet data provided a better foundational understanding of the social media data characteristics. The results of these additional analyses allowed for the positive detection of the key events associated with the crisis, along with observing the phase conversation change between the Euromaidan and Crimea annexation events, which were the two most significant events to occur during the period under scrutiny. The community detection results for the final Ukrainian conversation retweet network proved to be very structured with four defined communities.

The Chapter 5 network comparison results, which were based on the calculated Jaccard similarity coefficients between the emergent network communities across all epochs, proved to be quite revealing. The Cold War to Post-Cold War UN network similarity transformation showed a distinct drop in maximum similarity following the end of the Cold War with a 0.556 shared similarity. The similarity dramatically increased to a more agreeable 0.852 similarity between the Post-Cold War and Post-9/11 periods, which is in align with Crooks et al.'s results. In contrast, the Ukrainian retweet network showed a much higher level of similarity with the macro-level networks then Crooks et al.'s Syrian retweet network. Specifically, the Ukraine retweet network showed a shared an average similarity value of 0.417 with the UN voting network, which was not much lower than the 0.458 average similarity value between the UN voting and SIPRI arms trade networks.

The final analysis conducted in this study sought to evaluate the network relational characteristics between the NATO alliance and Ukraine. The results showed a clear misalignment between NATO and Ukraine given the lack of cooperative evidence between the two entities. Ukraine lacked shared community membership with a vast majority of NATO members across epochs, while also showing only near average UN voting affinity values. Ukraine, an export-only arms trader, conducted total trades with NATO members that accounted for only 2.2% of Ukraine's total exports. The results of the micro-level retweet network also showed signs of misalignment between NATO and the Ukrainian people given that Ukraine belonged to a network community with only four NATO members, of which, France being the only significant member of the retweet edge network.

7.2 Considerations for Future Research

As mentioned previously in Section 2.5, the recent emergence of social media and the corresponding access to their generated data allows for an incredible research opportunity to gain insights into the global connectivity enabled by social media platforms. In order for significant research to exist and receive acceptance amongst the established fields of academia, much work must be done to show how the analysis of social media can contribute to the overall marketplace of research. The relative immaturity of this new lens through which to view human interaction requires research efforts such as the contributions of this study, but also many others. The following discussion provides some additional areas of consideration for extending this study and for also using its methods in a whole new domain of interest.

Although a dominant social media platform, Twitter is just one of many social media options consumers have throughout the world. Given the self-proclaimed issues Twitter faces in reaching a completely global market, this study could be significantly bolstered by including the missing social media voices of the Ukrainian conversation that might exist in other social media platforms. Russian citizens, for example, do use Twitter, but Vkontakte is the primary social media service of choice in Russia. The Russian voice in the Ukrainian conversation is entirely relevant given Russia's annexation of Crimea and continued support to Pro-Russian supporters within Ukraine. Additionally, China has no voice in this study since the Chinese government prohibits the use of Twitter and its citizens use Weibo for their primary social media platform. Therefore, it would be prudent to combine Twitter, Weibo and Vkontakte conversations to better capture a more complete global discussion about the Ukrainian crisis conversation.

An additional possible extension to the social media analysis of this study would be to analyze whether tweets can serve as a true detection mechanism for significant events before the actual events take place. The time series analysis shown in Figure 18 properly detected the major events associated with the Ukraine crisis with major tweet volume spikes. Additionally, the volume of retweets surpassed tweet volumes only during periods when major events took place. There might exist a tipping point prior to this retweet-tweet volume swap associated with major events that could be an early indicator of a pending event. This tipping point could be further strengthened through an additional simultaneous observation of increased event logs from an event database such as GDELT (2015) for a given geographical area.

The comparative framework put forth in this study provides numerous extension possibilities from a network analysis point of view. First, by simply viewing different subcomponent classifications of data associated with this study's existing networks, such as arms trades limited to certain weapon systems (i.e. aircraft, field artillery, etc.) or UN voting resolutions limited to certain issues (i.e. Israeli-Palestinian conflict, climate change, etc.), one may gain additional insights into global network dynamics associated with more specific topics of interest. Furthermore, creating new global networks through the incorporation of entirely new datasets provides even more network comparison opportunities. For example, readily available international trade data from Centre d'Etudes Prospectives et d'Informations Internationales (CEPII 2015) captures the international bilateral flows of goods in 147 different product categories since 1967. This dataset provides a more comprehensive view of global trade than just the specific arms trade data used in this study. The inclusion of a broader trade dataset allows for the examination of more international global connections, since not all nations participated in the global arms trade.

The traditional macro-level networks examined in this study provided evidence of the growing complexity of international relations in the world since the end of the Cold War. The bipolarity that existed during the Cold War has given way to a certain period of uncertainty associated with the distribution of global power. This growing complexity and uncertainty is resulting in a new need to examine implications associated with global conflict. Specifically, the rapid diffusion of technology and reliance upon the Internet has ushered in a new era of persistent conflict in the cyber realm. One of the primary issues associated with cyberwarfare is its relative lack of rules and norms in comparison to traditional modes of warfare. Simply put, it is extremely difficult to identify and contest an enemy threat that operates in a cyber realm that has no physical geographic limitations. A recent article suggests identifying geopolitical cyberwarfare enemies might be made easier by closely monitoring the customers of the few large cybersecurity companies that exist in the marketplace (Yadron 2015). The article suggests that the cybersecurity industry has become highly provincial with the national powers aligning with specific companies and creating cyber-blocs of power. The theory put forth in this article could be tested with the methodological concepts put forth in this study. The arms trade transaction network could be modified to capture global cybersecurity service transactions. Additionally, social media harvests could capture all associated social media transactions between cybersecurity companies and individuals in a similar fashion to the development of the Ukrainian retweet network. Community detection methods could then be employed to observe any resulting community structure that might identify any potential cyber-blocs of power.

7.3 Conclusion

This study has added to the growing corpus of recent works seeking to understand any benefits that might be gained from using the readily available data created from global social media interactions. The ubiquity of social media participation today has ushered in an incredible opportunity for individuals to connect throughout the world. The ability to capture this level of interaction is essential to providing a more holistic view of global international relations as traditional sources of power continue to face uncertain challenges.

APPENDIX A: COMMUNITY TABLES

The following appendix provides community membership table references for each network in this study by epoch.

A.1 UN Voting Network Community Tables

Table 14. UN Cold War voting network communities (1950 – 1989).

Community 1		Community 2	Community 3	
Algeria	Madagascar	Afghanistan	Argentina	South Africa
Angola	Malawi	Albania	Australia	Spain
Antigua & Barbuda	Maldives	Belarus	Austria	Sweden
Bahamas	Mali	Bulgaria	Belgium	Taiwan
Bahrain	Malta	Cambodia	Bolivia	Thailand
Bangladesh	Mauritania	Cuba	Brazil	Turkey
Barbados	Mauritius	Czechoslovakia	Canada	United Kingdom
Belize	Mozambique	Egypt	Chile	United States of America
Benin	Niger	Ethiopia	Colombia	Uruguay
Bhutan	Nigeria	Ghana	Costa Rica	Venezuela
Botswana	Oman	Guinea	Denmark	
Brunei Darussalam	Pakistan	Hungary	Dominican Republic	
Burkina Faso	Papua New Guinea	India	Ecuador	
Burundi	Qatar	Indonesia	El Salvador	
Cameroon	Rwanda	Iran	Finland	
Cape Verde	Samoa	Iraq	France	
Central African Republic	Sao Tome and Principe	Jordan	Germany, West	
Chad	Senegal	Laos	Greece	
China	Seychelles	Lebanon	Guatemala	
Comoros	Sierra Leone	Libya	Haiti	
Congo	Singapore	Malaysia	Honduras	
Cote d'Ivoire	Solomon Islands	Mongolia	Iceland	
Cyprus	Somalia	Morocco	Ireland	
Dem. Rep. of the Congo	St. Kitts and Nevis	Myanmar	Israel	
Djibouti	St. Lucia	Nepal	Italy	
Dominica	St. Vincent & Grenadines	Poland	Japan	
Equatorial Guinea	Suriname	Romania	Liberia	
Fiji	Swaziland	Saudi Arabia	Luxembourg	
Gabon	Tanzania	Sri Lanka	Mexico	
Gambia	Togo	Sudan	Netherlands	
Germany, East	Trinidad and Tobago	Syria	New Zealand	
Grenada	Uganda	Tunisia	Nicaragua	
Guinea-Bissau	United Arab Emirates	U.S.S.R.	Norway	
Guyana	Vanuatu	Ukraine	Panama	
Jamaica	Viet Nam	Uruguay	Paraguay	
Kenya	Yemen	Yugoslavia	Peru	
Kuwait	Zambia		Philippines	
Lesotho	Zimbabwe		Portugal	

Table 15. UN Post-Cold War voting network communities (1990 – 2000).

Community 1			Community 2	
Afghanistan	Ghana	North Korea	Albania	Malta
Algeria	Grenada	Oman	Andorra	Marshall Islands
Angola	Guatemala	Pakistan	Argentina	Micronesia
Antigua & Barbuda	Guinea	Papua New Guinea	Armenia	Moldova
Bahamas	Guinea-Bissau	Paraguay	Australia	Monaco
Bahrain	Guyana	Peru	Austria	Nauru
Bangladesh	Haiti	Philippines	Azerbaijan	Netherlands
Barbados	Honduras	Qatar	Belarus	New Zealand
Belize	India	Rwanda	Belgium	Norway
Benin	Indonesia	Sao Tome and Principe	Bosnia and Herzegovina	Palau
Bhutan	Iran	Saudi Arabia	Bulgaria	Panama
Bolivia	Iraq	Senegal	Cambodia	Poland
Botswana	Jamaica	Seychelles	Canada	Portugal
Brazil	Jordan	Sierra Leone	Croatia	Romania
Brunei Darussalam	Kenya	Singapore	Cyprus	Russian Federation
Burkina Faso	Kiribati	Somalia	Czech Republic	Samoa
Burundi	Kuwait	Sri Lanka	Denmark	San Marino
Cameroon	Laos	St. Kitts and Nevis	Equatorial Guinea	Serbia and Montenegro
Cape Verde	Lebanon	St. Lucia	Eritrea	Slovakia
Central African Republic	Lesotho	St. Vincent & Grenadines	Estonia	Slovenia
Chad	Liberia	Sudan	Ethiopia	Solomon Islands
Chile	Libya	Suriname	Finland	South Africa
China	Madagascar	Swaziland	France	South Korea
Colombia	Malawi	Syria	Georgia	Spain
Comoros	Malaysia	Tanzania	Germany	Sweden
Congo	Maldives	Thailand	Greece	Tajikistan
Costa Rica	Mali	Togo	Hungary	Tonga
Cote d'Ivoire	Mauritania	Trinidad and Tobago	Iceland	Turkey
Cuba	Mauritius	Tunisia	Ireland	Turkmenistan
Dem. Rep. of the Congo	Mexico	Uganda	Israel	Ukraine
Djibouti	Mongolia	United Arab Emirates	Italy	United Kingdom
Dominica	Morocco	Uruguay	Japan	United States of America
Dominican Republic	Mozambique	Vanuatu	Kazakhstan	Uzbekistan
Ecuador	Myanmar	Venezuela	Kyrgyzstan	
Egypt	Namibia	Viet Nam	Latvia	
El Salvador	Nepal	Yemen	Liechtenstein	
Fiji	Nicaragua	Yugoslavia	Lithuania	
Gabon	Niger	Zambia	Luxembourg	
Gambia	Nigeria	Zimbabwe	Macedonia	

Table 16. UN Post-9/11 voting network communities (2001 – 2012).

Community 1			Community 2	
Afghanistan	Gambia	Papua New Guinea	Albania	Romania
Algeria	Ghana	Paraguay	Andorra	Russian Federation
Angola	Grenada	Peru	Argentina	Samoa
Antigua & Barbuda	Guatemala	Philippines	Armenia	San Marino
Azerbaijan	Guinea	Qatar	Australia	Serbia
Bahamas	Guinea-Bissau	Rwanda	Austria	Slovakia
Bahrain	Guyana	Sao Tome and Principe	Belgium	Slovenia
Bangladesh	Haiti	Saudi Arabia	Bosnia and Herzegovina	South Korea
Barbados	Honduras	Senegal	Bulgaria	Spain
Belarus	India	Seychelles	Canada	Sweden
Belize	Indonesia	Sierra Leone	Croatia	Switzerland
Benin	Iran	Singapore	Cyprus	Turkey
Bhutan	Iraq	Solomon Islands	Czech Republic	Ukraine
Bolivia	Jamaica	Somalia	Denmark	United Kingdom
Botswana	Jordan	South Africa	Estonia	United States of America
Brazil	Kazakhstan	South Sudan	Finland	
Brunei Darussalam	Kenya	Sri Lanka	France	
Burkina Faso	Kuwait	St. Kitts and Nevis	Georgia	
Burundi	Kyrgyzstan	St. Lucia	Germany	
Cambodia	Laos	St. Vincent & Grenadines	Greece	
Cameroon	Lebanon	Sudan	Hungary	
Cape Verde	Lesotho	Suriname	Iceland	
Central African Republic	Liberia	Swaziland	Ireland	
Chad	Libya	Syria	Israel	
Chile	Madagascar	Tajikistan	Italy	
China	Malawi	Tanzania	Japan	
Colombia	Malaysia	Thailand	Kiribati	
Comoros	Maldives	Togo	Latvia	
Congo	Mali	Tonga	Liechtenstein	
Costa Rica	Mauritania	Trinidad and Tobago	Lithuania	
Cote d'Ivoire	Mauritius	Tunisia	Luxembourg	
Cuba	Mexico	Turkmenistan	Macedonia	
Dem. Rep. of the Congo	Mongolia	Tuvalu	Malta	
Djibouti	Morocco	Uganda	Marshall Islands	
Dominica	Mozambique	United Arab Emirates	Micronesia	
Dominican Republic	Myanmar	Uruguay	Moldova	
East Timor	Namibia	Uzbekistan	Monaco	
Ecuador	Nepal	Vanuatu	Montenegro	
Egypt	Nicaragua	Venezuela	Nauru	
El Salvador	Niger	Viet Nam	Netherlands	
Equatorial Guinea	Nigeria	Yemen	New Zealand	
Eritrea	North Korea	Zambia	Norway	
Ethiopia	Oman	Zimbabwe	Palau	
Fiji	Pakistan		Poland	
Gabon	Panama		Portugal	

A.2 SIPRI Arms Trade Network Community Tables

Table 17. SIPRI Cold War arms trade network communities (1950 – 1989).

Community 1			Community 2	
Argentina	Guyana	Papua New Guinea	Afghanistan	Somalia
Australia	Haiti	Paraguay	Albania	U.S.S.R.
Austria	Honduras	Peru	Algeria	Sudan
Bahamas	Iceland	Philippines	Angola	Syria
Bahrain	Indonesia	Portugal	Bangladesh	Tanzania
Barbados	Iran	Qatar	Benin	Uganda
Belgium	Ireland	Rwanda	Bhutan	Viet Nam
Bolivia	Israel	Samoa	Bulgaria	Yemen
Botswana	Italy	Saudi Arabia	Cambodia	Yugoslavia
Brazil	Jamaica	Senegal	CapeVerde	Zambia
Brunei	Japan	Seychelles	China	
Burkina Faso	Jordan	Singapore	Congo	
Burundi	Kenya	Solomon Islands	Cuba	
Cameroon	Kuwait	South Africa	Czechoslovakia	
Canada	Lebanon	South Korea	Egypt	
Centra lAfrican Republic	Lesotho	Spain	Equatorial Guinea	
Chad	Liberia	Sri Lanka	Ethiopia	
Chile	Luxembourg	St. Kitts and Nevis	Gambia	
Colombia	Malawi	St. Vincent & Grenadines	Germany, East	
Comoros	Malaysia	Suriname	Grenada	
Costa Rica	Marshall Islands	Swaziland	Guinea	
Cote d'Ivoire	Mauritania	Sweden	Guinea-Bissau	
Cyprus	Mauritius	Switzerland	Hungary	
Dem. Rep. of Congo	Mexico	Taiwan	India	
Denmark	Micronesia	Thailand	Iraq	
Djibouti	Morocco	Togo	Laos	
Dominican Republic	Myanmar	Tonga	Libya	
Ecuador	Nepal	Trinidad and Tobago	Madagascar	
El Salvador	Netherlands	Tunisia	Mali	
Fiji	New Zealand	Turkey	Malta	
Finland	Niger	United Arab Emirates	Mongolia	
France	Nigeria	United Kingdom	Mozambique	
Gabon	Norway	United States	Nicaragua	
Germany, West	Oman	Uruguay	North Korea	
Ghana	Pakistan	Vanuatu	Poland	
Greece	Panama	Venezuela	Romania	
Guatemala		Zimbabwe	Sierra Leone	

Table 18. SIPRI Post-Cold War arms trade network communities (1990 – 2000).

Community 1	Community 2		Community 3	Community 4	
Botswana	Aruba	Malaysia	Argentina	Afghanistan	Liberia
Canada	Bahamas	Mali	Australia	Albania	Libya
Ireland	Bahrain	Mauritius	Austria	Algeria	Lithuania
Switzerland	Belgium	Mexico	Cape Verde	Angola	Macedonia
	Belize	Moldova	Denmark	Armenia	Madagascar
	Bolivia	Morocco	Equatorial Guinea	Azerbaijan	Maldives
	Bosnia and Herzegovina	Niger	Estonia	Bangladesh	Myanmar
	Brazil	Nigeria	Fiji	Belarus	Namibia
	Brunei	Oman	Germany	Bulgaria	Nepal
	Cameroon	Panama	Greece	Burkina Faso	Nicaragua
	Centra lAfrican Republic	Papua New Guinea	Iceland	Cambodia	North Korea
	Chile	Paraguay	Indonesia	Chad	Pakistan
	Colombia	Philippines	Kiribati	China	Peru
	Cote d'Ivoire	Qatar	Latvia	Congo	Poland
	Dominican Republic	Saudi Arabia	Malta	Costa Rica	Romania
	Ecuador	Senegal	Marshall Islands	Croatia	Russia
	Egypt	Singapore	Mauritania	Cuba	Rwanda
	El Salvador	Slovenia	Micronesia	Cyprus	Serbia
	Finland	South Africa	Netherlands	Czech Republic	Sierra Leone
	France	South Korea	New Zealand	Dem. Rep. of Congo	Slovakia
	Gabon	Spain	Norway	Djibouti	Somalia
	Ghana	Suriname	Palau	Eritrea	Sri Lanka
	Guatemala	Swaziland	Portugal	Ethiopia	Sudan
	Israel	Taiwan	Solomon Islands	Georgia	Syria
	Italy	Thailand	Sweden	Guinea	Tajikistan
	Jamaica	Togo	Tonga	Guinea-Bissau	Tanzania
	Japan	Trinidad and Tobago	Tuvalu	Hungary	Tunisia
	Jordan	Turkey		India	Uganda
	Kenya	United Arab Emirates		Iran	Ukraine
	Kuwait	United Kingdom		Iraq	Viet Nam
	Lesotho	United States		Kazakhstan	Yemen
	Luxembourg	Uruguay		Kyrgyzstan	Zambia
	Malawi	Venezuela		Laos	Zimbabwe
				Lebanon	

Table 19. SIPRI Post-9/11 arms trade network communities (2001 – 2013).

Community 1	Community 2		Community 3		Community 4
Angola	Afghanistan	Kuwait	Algeria	Mauritius	Belgium
Moldova	Albania	Latvia	Armenia	Mongolia	Benin
	Argentina	Lesotho	Azerbaijan	Mozambique	Bulgaria
	Australia	Lithuania	Bangladesh	Myanmar	Jordan
	Austria	Luxembourg	Belarus	Namibia	Kenya
	Bahamas	Malawi	Bolivia	Nepal	Lebanon
	Bahrain	Malaysia	BurkinaFaso	Niger	Mali
	Barbados	Malta	Burundi	Nigeria	
	BosniaandHerzegovina	Mauritania	Cambodia	Pakistan	
	Botswana	Mexico	CentralAfricanRepublic	Russia	
	Brazil	Montenegro	Chad	Senegal	
	Brunei	Morocco	China	Serbia	
	Cameroon	Netherlands	Comoros	Seychelles	
	Canada	NewZealand	CongoDem	SierraLeone	
	CapeVerde	Nicaragua	Cyprus	Slovakia	
	Chile	Norway	Djibouti	SouthSudan	
	Colombia	Oman	EquatorialGuinea	SriLanka	
	CongoRep	Panama	Eritrea	Sudan	
	CostaRica	Paraguay	Ethiopia	Switzerland	
	Coted.Ivoire	Peru	Georgia	Syria	
	Croatia	Philippines	Ghana	Tajikistan	
	CzechRepublic	Poland	Guinea	Tanzania	
	Denmark	Portugal	India	Timor.Leste	
	DominicanRepublic	Qatar	Indonesia	Turkmenistan	
	Ecuador	Romania	Iran	Uganda	
	Egypt	Rwanda	Kazakhstan	Ukraine	
	ElSalvador	SaudiArabia	KoreaNorth	Uzbekistan	
	Estonia	Singapore	Kyrgyzstan	Venezuela	
	Finland	Slovenia	Laos	VietNam	
	France	Somalia	Libya	Yemen	
	Gabon	SouthAfrica	Macedonia	Zambia	
	Gambia	Spain	Maldives	Zimbabwe	
	Germany	Suriname			
	Greece	Swaziland			
	Guatemala	Sweden			
	Guyana	Taiwan			
	Honduras	Thailand			
	Hungary	Togo			
	Iceland	TrinidadandTobago			
	Iraq	Tunisia			
	Ireland	Turkey			
	Israel	UnitedArabEmirates			
	Italy	UnitedKingdom			
	Jamaica	UnitedStates			
	Japan	Uruguay			
	KoreaSouth				

A.3 Retweet Network Community Tables

Table 20. Ukraine retweet conversation network communities (November 2013 – June 2014).

Community 1		Community 2		Community 3		Community 4
Afghanistan	Mozambique	Argentina	Netherlands	Albania	Mali	Palau
Andorra	Namibia	Armenia	New Zealand	Algeria	Mauritania	Tokelou
Angola	Nauru	Australia	Nicaragua	Antigua & Barbuda	Mayotte	
Aruba	Nepal	Austria	North Korea	Belgium	Micronesia	
Bahamas	Niger	Azerbaijan	Norway	Benin	Monaco	
Bahrain	Nigeria	Belarus	Panama	Bhutan	Montenegro	
Bangladesh	Niue Island	Bolivia	Paraguay	Bosnia and Herzegovina	Morocco	
Barbados	Oman	Brazil	Peru	Burundi	Myanmar	
Belize	Pakistan	Bulgaria	Philippines	Cambodia	Papua New Guinea	
Botswana	Puerto Rico	Canada	Poland	Cameroon	Russian Federation	
Brunei Darussalam	Qatar	Chile	Portugal	Cape Verde	Sao Tome and Principe	
Burkina Faso	Rwanda	China	Romania	Chad	Senegal	
Central African Rep	Samoa	Colombia	Serbia	Congo	Solomon Islands	
Cocos Islands	San Marino	Croatia	Singapore	Cook Islands	Sri Lanka	
Comoros	Saudi Arabia	Cuba	Slovakia	Costa Rica	Switzerland	
Cyprus	Seychelles	Czech Republic	Slovenia	Cote d'Ivoire	Togo	
East Timor	Sierra Leone	Denmark	South Korea	Dem. Rep. Congo	Tonga	
Egypt	Somalia	Ecuador	Spain	Djibouti	Tunisia	
Eritrea	South Africa	Estonia	Swaziland	Dominica	Tuvalu	
Ethiopia	St. Kitts and Nevis	Finland	Sweden	Dominican Republic	Ukraine	
Gambia	St. Lucia	Georgia	Syria	El Salvador	Uzbekistan	
Ghana	St. Vincent & Grenadines	Germany	Taiwan	Equatorial Guinea	Viet Nam	
Grenada	Sudan	Greece	Thailand	Fiji		
Guyana	Suriname	Hungary	Uruguay	France		
India	Tajikistan	Iceland	Vatican City	Gabon		
Iraq	Tanzania	Indonesia	Venezuela	Guatemala		
Israel	Trinidad and Tobago	Iran		Guinea		
Jamaica	Turkey	Ireland		Guinea-Bissau		
Jordan	Turkmenistan	Italy		Haiti		
Kenya	Uganda	Japan		Honduras		
Kuwait	United Arab Emirates	Kazakhstan		Kiribati		
Laos	United Kingdom	Kyrgyzstan		Lebanon		
Lesotho	United States of America	Latvia		Libya		
Liberia	Vanuatu	Lithuania		Liechtenstein		
Malawi	Yemen	Malta		Luxembourg		
Malaysia	Zambia	Mexico		Macedonia		
Marshall Islands	Zimbabwe	Moldova		Madagascar		
Mauritius		Mongolia		Maldives		

APPENDIX B: JACCARD SIMILARITY VALUES

	UA1	UA2	UA3	UB1	UB2	UC1	UC2	SA1	SA2	SB1	SB2	SB3	SB4	SC1	SC2	SC3	SC4	TC1	TC2	TC3	TC4
UA1	1.000	-	-	***0.556***	0.034	***0.514***	0.023	0.329	0.242	0.013	0.235	0.062	0.182	0.115	0.161	0.219	0.013	0.398	0.029	0.250	0.000
UA2	-	1.000	-	0.195	0.091	0.190	0.067	0.089	0.339	0.000	0.063	0.016	0.321	0.081	0.095	0.238	0.000	0.133	0.111	0.118	0.000
UA3	-	-	1.000	0.138	0.290	0.138	0.305	***0.423***	0.011	0.040	***0.326***	0.190	0.036	0.162	***0.398***	0.018	0.000	0.051	***0.418***	0.092	0.000
UB1	***0.556***	0.195	0.138	1.000	-	***0.852***	0.006	***0.484***	0.262	0.008	***0.346***	0.036	0.305	0.138	0.250	***0.313***	0.008	0.401	0.139	0.285	0.000
UB2	0.034	0.091	0.290	-	1.000	0.079	0.770	0.230	0.082	0.027	0.140	0.269	0.209	0.132	0.261	0.154	0.014	0.113	***0.417***	0.129	0.000
UC1	***0.514***	0.190	0.138	***0.852***	0.079	1.000	-	***0.473***	0.250	0.007	0.327	0.053	***0.342***	0.123	0.241	***0.400***	0.007	***0.415***	0.159	0.297	0.000
UC2	0.023	0.067	0.305	0.006	0.770	-	1.000	0.225	0.060	0.050	0.136	0.284	0.145	0.169	0.270	0.061	0.017	0.081	0.398	0.113	0.000
SA1	0.329	0.089	***0.423***	***0.484***	0.230	***0.473***	0.225	1.000	-	0.036	***0.504***	0.161	0.106	0.185	***0.424***	0.146	0.000	***0.303***	0.270	0.207	0.000
SA2	0.242	0.339	0.011	0.262	0.082	0.250	0.060	-	1.000	0.000	0.018	0.042	0.373	0.083	0.085	0.236	0.021	0.162	0.110	0.152	0.000
SB1	0.013	0.000	0.040	0.008	0.027	0.007	0.050	0.036	0.000	1.000	-	-	-	0.061	0.029	0.000	0.000	0.013	0.030	0.016	0.000
SB2	0.235	0.063	***0.326***	***0.346***	0.140	0.327	0.136	***0.504***	0.018	-	1.000	-	-	0.169	0.441	0.066	0.015	***0.259***	0.204	0.136	0.000
SB3	0.062	0.016	0.190	0.036	0.269	0.053	0.284	0.161	0.042	-	-	1.000	-	0.115	0.131	0.023	0.000	0.010	0.213	0.103	0.000
SB4	0.182	0.321	0.036	0.305	0.209	***0.342***	0.145	0.106	0.373	-	-	-	1.000	0.065	0.098	***0.512***	0.015	0.203	0.202	0.200	0.000
SC1	0.115	0.081	0.162	0.138	0.132	0.123	0.169	0.185	0.083	0.061	0.169	0.115	0.065	1.000	-	-	-	0.104	0.159	0.098	0.000
SC2	0.161	0.095	***0.398***	0.250	0.261	0.241	0.270	***0.424***	0.085	0.029	0.441	0.131	0.098	-	1.000	-	-	0.172	***0.320***	0.134	0.000
SC3	0.219	0.238	0.018	***0.313***	0.154	***0.400***	0.061	0.146	0.236	0.000	0.066	0.023	***0.512***	-	-	1.000	-	0.243	0.155	0.173	0.000
SC4	0.013	0.000	0.000	0.008	0.014	0.007	0.017	0.000	0.021	0.000	0.015	0.000	0.015	-	-	-	1.000	0.013	0.015	0.000	0.000
TC1	0.398	0.133	0.051	0.401	0.113	***0.415***	0.081	***0.303***	0.162	0.013	***0.259***	0.010	0.203	0.104	0.172	0.243	0.013	1.000	-	-	-
TC2	0.029	0.111	***0.418***	0.139	***0.417***	0.159	0.398	0.270	0.110	0.030	0.204	0.213	0.202	0.159	***0.320***	0.155	0.015	-	1.000	-	-
TC3	0.250	0.118	0.092	0.285	0.129	0.297	0.113	0.207	0.152	0.016	0.136	0.103	0.200	0.098	0.134	0.173	0.000	-	-	1.000	-
TC4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	-	-	1.000

REFERENCES

Alexanderson, Gerald. 2006. “About the Cover: Euler and Königsberg’s Bridges: A Historical View.” *Bulletin of the American Mathematical Society* 43 (4): 567–73. doi:10.1090/S0273-0979-06-01130-X.

Bailey, Michael, Anton Strezhnev, and Erik Voeten. 2013. “Estimating Dynamic State Preferences from United Nations Voting Data.” *Available at SSRN 2330913*. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2330913.

Bastian, Mathieu, Sebastien Heyman, and Mathieu Jacomy. 2009. “Gephi: An Open Source Software for Exploring and Manipulating Networks.” In *Proceedings of the Third International Conference on Weblogs and Social Media*. San Jose. doi:10.13140/2.1.1341.1520.

Birnbaum, Michael. 2014. “European Countries Are Selling Arms to Russia While Condemning It over Ukraine.” *The Washington Post*, June 16. http://www.washingtonpost.com/world/europe/european-countries-are-selling-arms-to-russia-while-condemning-it-over-ukraine/2014/06/16/6ad20143-ffce-4b45-a063-bea132fa0123_story.html.

Blondel, Vincent D., Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. 2008. “Fast Unfolding of Communities in Large Networks.” *Journal of Statistical Mechanics: Theory and Experiment* 2008 (10): P10008. doi:10.1088/1742-5468/2008/10/P10008.

Borgatti, Stephen P., Martin G. Everett, and Jeffrey C. Johnson. 2013. *Analyzing Social Networks*. 1 edition. Los Angeles i.e. Thousand Oaks, Calif.; London: SAGE Publications Ltd.

Borgatti, Stephen P., Ajay Mehra, Daniel J. Brass, and Giuseppe Labianca. 2009. “Network Analysis in the Social Sciences.” *Science* 323 (5916): 892–95. doi:10.1126/science.1165821.

boyd, danah, Scott Golder, and Gilad Lotan. 2010. “Tweet, Tweet, Retweet: Conversational Aspects of Retweeting on Twitter.” In *2010 43rd Hawaii International Conference on System Sciences (HICSS)*, 1–10. doi:10.1109/HICSS.2010.412.

Brewer, Cynthia A., Geoffrey W. Hatchard, and Mark A. Harrower. 2003. "ColorBrewer in Print: A Catalog of Color Schemes for Maps." *Cartography and Geographic Information Science* 30 (1): 5–32. doi:10.1559/152304003100010929.

Brzoska, Michael. 2014. "Defence Industry Restructuring and Consolidation in Europe." In *The Global Arms Trade: A Handbook*, edited by Andrew T. H. Tan, 2nd ed., 221–34. London: Routledge.

Butts, Carter T. 2008. "Social Network Analysis: A Methodological Introduction." *Asian Journal of Social Psychology* 11 (1): 13–41. doi:10.1111/j.1467-839X.2007.00241.x.

Campos, Nauro F., and Martin Gassebner. 2013. "International Terrorism, Domestic Political Instability, and the Escalation Effect." *Economics & Politics* 25 (1): 27–47.

Cao, Xun. 2012. "Global Networks and Domestic Policy Convergence: A Network Explanation of Policy Changes." *World Politics* 64 (03): 375–425. doi:10.1017/S0043887112000081.

Carnegie, Allison. 2014. "States Held Hostage: Political Hold-Up Problems and the Effects of International Institutions." *American Political Science Review* 108 (01): 54–70.

CEPII. 2015. "Centre d'Etudes Prospectives et d'Informations Internationales (CEPII)." www.cepii.fr.

Cioffi-Revilla, Claudio. 2014. *Introduction to Computational Social Science: Principles and Applications*. 2014 edition. London ; New York: Springer.

Clauset, Aaron, Cosma Rohilla Shalizi, and M. E. J. Newman. 2009. "Power-Law Distributions in Empirical Data." *SIAM Review* 51 (4): 661–703. doi:10.1137/070710111.

Clauset, Aaron, Maxwell Young, and Kristian Skrede Gleditsch. 2007. "On the Frequency of Severe Terrorist Events." *The Journal of Conflict Resolution* 51 (1): 58–87.

Conover, Michael D., Jacob Ratkiewicz, Matthew Francisco, Bruno Goncalves, Filippo Menczer, and Alessandro Flammini. 2011. "Political Polarization on Twitter." In *Fifth International AAAI Conference on Weblogs and Social Media*. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/view/2847.

Cosenza, Vincenzo. 2015. “World Map of Social Networks.” Accessed March 24. http://vincos.it/world-map-of-social-networks/.

Cranmer, Skyler J., Bruce A. Desmarais, and Elizabeth J. Menninga. 2012. “Complex Dependencies in the Alliance Network.” *Conflict Management and Peace Science* 29 (3): 279–313. doi:10.1177/0738894212443446.

Croitoru, Arie, Andrew Crooks, Jacek Radzikowski, and Anthony Stefanidis. 2013. “Geosocial Gauge: A System Prototype for Knowledge Discovery from Social Media.” *International Journal of Geographical Information Science* 27 (12): 2483–2508. doi:10.1080/13658816.2013.825724.

Croitoru, Arie, Andrew Crooks, Jacek Radzikowski, Anthony Stefanidis, Ranga Vatsavai, and Nicole Wayant. 2014. “Geoinformatics and Social Media.” In *Big Data: Techniques and Technologies in Geoinformatics*, edited by Hassan Karimi, 207–32. CRC Press. http://www.crcnetbase.com.mutex.gmu.edu/doi/abs/10.1201/b16524-12.

Croitoru, Arie, N. Wayant, A. Crooks, J. Radzikowski, and A. Stefanidis. 2015. “Linking Cyber and Physical Spaces through Community Detection and Clustering in Social Media Feeds.” *Computers, Environment and Urban Systems*. Accessed March 15. doi:10.1016/j.compenvurbsys.2014.11.002.

Crooks, Andrew, Arie Croitoru, Anthony Stefanidis, and Jacek Radzikowski. 2013. “#Earthquake: Twitter as a Distributed Sensor System.” *Transactions in GIS* 17 (1): 124–47. doi:10.1111/j.1467-9671.2012.01359.x.

Crooks, Andrew, David Masad, Arie Croitoru, Amy Cotnoir, Anthony Stefanidis, and Jacek Radzikowski. 2014. “International Relations State-Driven and Citizen-Driven Networks.” *Social Science Computer Review* 32 (2): 205–20. doi:10.1177/0894439313506851.

De Choudhury, Munmun, Nicholas Diakopoulos, and Mor Naaman. 2012. “Unfolding the Event Landscape on Twitter: Classification and Exploration of User Categories.” In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, 241–44. CSCW ’12. New York, NY, USA: ACM. doi:10.1145/2145204.2145242.

Diuk, Nadia. 2014. “Finding Ukraine.” *Journal of Democracy* 25 (3): 83–89. doi:10.1353/jod.2014.0041.

Dreher, Axel, Matthew Gould, Matthew D. Rablen, and James Raymond Vreeland. 2014. “The Determinants of Election to the United Nations Security Council.” *Public Choice* 158 (1-2): 51–83.

Fortunato, Santo. 2010. “Community Detection in Graphs.” *Physics Reports* 486 (3–5): 75–174. doi:10.1016/j.physrep.2009.11.002.

Freelon, Deen, Mark Lynch, and Sean Aday. Preprint. “Online Fragmentation in Wartime: A Longitudinal Network Analysis of Tweets about Syria, 2011-2013.” *ANNALS of the American Academy of Political and Social Science*, 1–24.

Fuchs, Andreas, and Kai Gehring. 2013. “The Home Bias in Sovereign Ratings.” *University of Heidelberg Department of Economics Discussion Paper Series*, no. 552. http://papers.ssrn.com/sol3/Papers.cfm?abstract_id=2370374.

Garcia, Denise. 2014. “Global Norms on Arms: The Significance of the Arms Trade Treaty for Global Security in World Politics.” *Global Policy* 5 (4): 425–32. doi:10.1111/1758-5899.12182.

GDELT Project. 2015. “GDELT Database.” http://gdeltproject.org.

Gerlitz, Carolin, and Bernhard Rieder. 2013. “Mining One Percent of Twitter: Collections, Baselines, Sampling.” *M/C Journal* 16 (2). http://journal.media-culture.org.au/index.php/mcjournal/article/view/620.

Hafner-Burton, Emilie M., Miles Kahler, and Alexander H. Montgomery. 2009. “Network Analysis for International Relations.” *International Organization* 63 (3): 559–92.

Häge, Frank, and Simon Hug. 2013. “Consensus Voting and Similarity Measures in IOs.” In . Barcelona.

Howard, Philip N., and Malcolm R. Parks. 2012. “Social Media and Political Change: Capacity, Constraint, and Consequence.” *Journal of Communication* 62 (2): 359–62. doi:10.1111/j.1460-2466.2012.01626.x.

Iacobucci, Dawn. 1994. “Graphs and Matrices.” In *Social Network Analysis*, edited by Faust, Katherine Wasserman, Stanley, 92–166. Structural Analysis in the Social Sciences. New York: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511815478.005.

Jackson, Matthew O., and Asher Wolinsky. 1996. “A Strategic Model of Social and Economic Networks.” *Journal of Economic Theory* 71 (1): 44–74. doi:10.1006/jeth.1996.0108.

Java, Akshay, Xiaodan Song, Tim Finin, and Belle Tseng. 2007. “Why We Twitter: Understanding Microblogging Usage and Communities.” In *Proceedings of the*

9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis, 56–65. WebKDD/SNA-KDD ’07. New York, NY, USA: ACM. doi:10.1145/1348549.1348556.

Keck, Margaret E., and Kathryn Sikkink. 1998. *Activists beyond Borders: Advocacy Networks in International Politics*. Ithaca, NY: Cornell University Press.

Kemp, Simon. 2015. “Digital, Social & Mobile in 2015.” *We Are Social*. January 21. http://wearesocial.net/tag/sdmw/.

Kirshner, Jonathan. 2008. “Globalization, American Power, and International Security.” *Political Science Quarterly* 123 (3): 363–89.

Kleinberg, Jon. 2008. “The Convergence of Social and Technological Networks.” *Commun. ACM* 51 (11): 66–72. doi:10.1145/1400214.1400232.

Lambiotte, Renaud. 2010. “Multi-Scale Modularity in Complex Networks.” *arXiv:1004.4268 [cond-Mat, Physics:physics]*, April. http://arxiv.org/abs/1004.4268.

Lancichinetti, Andrea, Filippo Radicchi, José J. Ramasco, and Santo Fortunato. 2011. “Finding Statistically Significant Communities in Networks: e18961.” *PLoS One* 6 (4). doi:http://dx.doi.org.mutex.gmu.edu/10.1371/journal.pone.0018961.

Lauterbach, Debra, Hung Truong, Tanuj Shah, and Lada Adamic. 2009. “Surfing a Web of Trust: Reputation and Reciprocity on CouchSurfing.Com.” In *Proceedings of the 2009 International Conference on Computational Science and Engineering - Volume 04*, 346–53. CSE ’09. Washington, DC, USA: IEEE Computer Society. doi:10.1109/CSE.2009.345.

Leetaru, Kalev, Shaowen Wang, Guofeng Cao, Anand Padmanabhan, and Eric Shook. 2013. “Mapping the Global Twitter Heartbeat: The Geography of Twitter.” *First Monday* 18 (5). http://firstmonday.org/ojs/index.php/fm/article/view/4366.

Leskovec, Jure, and Eric Horvitz. 2008. “Planetary-Scale Views on an Instant-Messaging Network.” *arXiv:0803.0939 [physics]*, March. http://arxiv.org/abs/0803.0939.

Lijphart, Arend. 1963. “The Analysis of Bloc Voting in the General Assembly: A Critique and a Proposal.” *The American Political Science Review* 57 (4): 902–17. doi:10.2307/1952608.

Lloyd, Paulette, Matthew C. Mahutga, and Jan De Leeuw. 2009. “Looking Back and Forging Ahead: Thirty Years of Social Network Research on the World-System 1.” *American Sociological Association* XV (1): 48–85.

Lu, Xu, Arie Croitoru, Jacek Radzikowski, Andrew Crooks, and Anthony Stefanidis. 2013. “Comparing the Spatial Characteristics of Corresponding Cyber and Physical Communities: A Case Study.” In *Proceedings of the 6th ACM SIGSPATIAL International Workshop on Location-Based Social Networks*, 11–14. LBSN ’13. New York, NY, USA: ACM. doi:10.1145/2536689.2536805.

Maamari, Bassem E., and Hala El Zein. 2014. “The Impact of Social Media on the Political Interests of the Youth in Lebanon at the Wake of the Arab Spring.” *Social Science Computer Review* 32 (4): 496–505. doi:10.1177/0894439313512777.

Macon, Kevin T., Peter J. Mucha, and Mason A. Porter. 2012. “Community Structure in the United Nations General Assembly.” *Physica A: Statistical Mechanics and Its Applications* 391 (1–2): 343–61. doi:10.1016/j.physa.2011.06.030.

Maoz, Zeev. 2012. “How Network Analysis Can Inform the Study of International Relations.” *Conflict Management and Peace Science* 29 (3): 247–56. doi:10.1177/0738894212443341.

Marin, Alexandra, and Barry Wellman. 2011. “The SAGE Handbook of Social Network Analysis.” In *The SAGE Handbook of Social Network Analysis*, edited by John Scott and Peter J. Carrington, 11–22. London: SAGE.

Marsh, David, and R. A. W. Rhodes. 1992. *Policy Networks in British Government*. Oxford: Clarendon Press.

Marsh, David, and Martin Smith. 2000. “Understanding Policy Networks: Towards a Dialectical Approach.” *Political Studies* 48 (1): 4.

Mearsheimer, John J. 2014. “Why the Ukraine Crisis Is the West’s Fault: The Liberal Delusions That Provoked Putin.” *Foreign Affairs* 93: 77.

Morstatter, Fred, Jürgen Pfeffer, Huan Liu, and Kathleen M. Carley. 2013. “Is the Sample Good Enough? Comparing Data from Twitter’s Streaming API with Twitter’s Firehose.” *arXiv:1306.5204 [physics]*, June. http://arxiv.org/abs/1306.5204.

Muekalia, Domingos Jardo. 2004. “Africa and China’s Strategic Partnership.” *African Security Review* 13 (1): 5–11. doi:10.1080/10246029.2004.9627264.

Mueller, Milton L. 2010. *Networks and States: The Global Politics of Internet Governance*. Cambridge: MIT Press.

Müllerson, Rein. 2014. “Ukraine: Victim of Geopolitics.” *Chinese Journal of International Law* 13 (1): 133–45. doi:10.1093/chinesejil/jmu011.

Mundo, Arturo Wallace BBC, and San Cristobal. 2015. “San Cristobal: The Birthplace of Venezuela’s Protests.” *BBC News*. Accessed March 27. http://www.bbc.com/news/world-latin-america-26477526.

Musser, John. 2006. *Web 2.0: Principles and Best Practices*. O’Reilly Media, Inc. http://proquest.safaribooksonline.com.mutex.gmu.edu/0596527691.

Naím, Moises. 2014. *The End of Power: From Boardrooms to Battlefields and Churches to States, Why Being In Charge Isn’t What It Used to Be*. Reprint edition. Basic Books.

NATO. 2015. “The Ukraine Crisis and NATO-Russia Relations.” *NATO Review*. Accessed March 27. http://www.nato.int/docu/review/2014/Russia-Ukraine-Nato-crisis/Ukraine-crisis-NATO-Russia-relations/EN/index.htm.

Nye, Joseph S., Jr. 2010. “The Future of American Power: Dominance and Decline in Perspective.” *Foreign Affairs* 89 (6): 2–12.

Pierre, Andrew J. 1982. *The Global Politics of Arms Sales*. Princeton University Press.

Radicchi, Filippo, Claudio Castellano, Federico Cecconi, Vittorio Loreto, Domenico Parisi, and Giorgio Parisi. 2004. “Defining and Identifying Communities in Networks.” *Proceedings of the National Academy of Sciences of the United States of America* 101 (9): 2658–63.

Rai, Kul B. 1972. “Foreign Policy and Voting in the UN General Assembly.” *International Organization* 26 (03): 589–94. doi:10.1017/S0020818300003027.

Root, Hilton L. 2013. *Dynamics among Nations: The Evolution of Legitimacy and Development in Modern States*. Cambridge, Massachusetts: The MIT Press.

Russett, Bruce M. 1966. “Discovering Voting Groups in the United Nations.” *The American Political Science Review* 60 (2): 327–39. doi:10.2307/1953359.

Salton, Gerard, and Michael J. McGill. 1986. *Introduction to Modern Information Retrieval*. New York, NY, USA: McGraw-Hill, Inc.

Singer, J. David. 1961. “The Level-of-Analysis Problem in International Relations.” *World Politics* 14 (1): 77–92. doi:10.2307/2009557.

Smith, David A., and Douglas R. White. 1992. “Structure and Dynamics of the Global Economy: Network Analysis of International Trade 1965-1980.” *Social Forces* 70 (4): 857–93. doi:10.2307/2580193.

Snijders, Tom A. B., and Frans N. Stokman. 1987. “Extensions of Triad Counts to Networks with Different Subsets of Points and Testing Underlying Random Graph Distributions.” *Social Networks* 9 (3): 249–75. doi:10.1016/0378-8733(87)90022-0.

State, Bogdan, Patrick Park, Ingmar Weber, Yelena Mejova, and Michael Macy. 2013. “The Mesh of Civilizations and International Email Flows.” *arXiv:1303.0045 [physics]*, February. http://arxiv.org/abs/1303.0045.

Stefanidis, Anthony, Amy Cotnoir, Arie Croitoru, Andrew Crooks, Matthew Rice, and Jacek Radzikowski. 2013. “Demarcating New Boundaries: Mapping Virtual Polycentric Communities through Social Media Content.” *Cartography and Geographic Information Science* 40 (2): 116–29. doi:10.1080/15230406.2013.776211.

Stefanidis, Anthony, Andrew Crooks, and Jacek Radzikowski. 2011. “Harvesting Ambient Geospatial Information from Social Media Feeds.” *GeoJournal* 78 (2): 319–38. doi:10.1007/s10708-011-9438-2.

Stockholm International Peace Research Institute. 2014. “Stockholm International Peace Research Institute (SIPRI) Database.” *Stockholm International Peace Research Institute*. http://www.sipri.org/databases.

Strezhnev, Anton, and Erik Voeten. 2013. “United Nations General Assembly Voting Data.” http://hdl.handle.net/1902.1/12379.

Suh, B., Lichan Hong, P. Pirolli, and Ed H. Chi. 2010. “Want to Be Retweeted? Large Scale Analytics on Factors Impacting Retweet in Twitter Network.” In *2010 IEEE Second International Conference on Social Computing (SocialCom)*, 177–84. doi:10.1109/SocialCom.2010.33.

Taylor, Adam. 2014. “That Time Ukraine Tried to Join NATO — and NATO Said No.” *The Washington Post*, September 4. http://www.washingtonpost.com/blogs/worldviews/wp/2014/09/04/that-time-ukraine-tried-to-join-nato-and-nato-said-no/.

Thrall, A. Trevor. 2007. “A Bear in the Woods? Threat Framing and the Marketplace of Values.” *Security Studies* 16 (3): 452–88. doi:10.1080/09636410701547915.

Twitter. 2014. "Twitter Annual Financial Report." https://investor.twitterinc.com/annuals.cfm.

Valkanas, George, Ioannis Katakis, Dimitrios Gunopulos, and Antony Stefanidis. 2014. "Mining Twitter Data with Resource Constraints." In *Proceedings of the 2014 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT) - Volume 01*, 157–64. WI-IAT '14. Washington, DC, USA: IEEE Computer Society. doi:10.1109/WI-IAT.2014.29.

Varol, Onur, Emilio Ferrara, Christine L. Ogan, Filippo Menczer, and Alessandro Flammini. 2014. "Evolution of Online User Behavior During a Social Upheaval." *arXiv:1406.7197 [physics]*, 81–90. doi:10.1145/2615569.2615699.

Wasserman, Stanley, and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*. 1 edition. New York: Cambridge University Press.

Williams, Carol. 2014. "Russian Aggression Driving Ukrainians toward EU, NATO." *Los Angeles Times*, May 14. http://www.latimes.com/world/europe/la-fg-ukraine-russia-eu-nato-20140514-story.html.

Yadron, Danny. 2015. "When Cybersecurity Meets Geopolitics." *WSJ Blogs - Digits*. March 23. http://blogs.wsj.com/digits/2015/03/23/when-cybersecurity-meets-geopolitics/.

Zhao, Liang, Feng Chen, Jing Dai, Ting Hua, Chang-Tien Lu, and Naren Ramakrishnan. 2014. "Unsupervised Spatial Event Detection in Targeted Domains with Applications to Civil Unrest Modeling." *PLoS ONE* 9 (10). doi:10.1371/journal.pone.0110206.

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