РАЗДЕЛ II
СЕТЕВОЙ АНАЛИЗ СТРУКТУРНЫХ ТРАНСФОРМАЦИЙ В СОВРЕМЕННОМ МИРЕ

PART II
NETWORK ANALYSIS OF STRUCTURAL TRANSFORMATIONS IN THE CONTEMPORARY WORLD

K. M. Carley

POLITICAL EVOLUTION AND REVOLUTION: A NETWORK ASSESSMENT OF SUDAN AND ARAB SPRING POWER TRANSFORMATIONS

The past few years have seen an upsurge in revolution and change at the nation-state level. As such political upheaval occurs, different individuals emerge as leaders and existing leaders may move out of focus. Social network analysis can be used to help us understand these political upheavals, identify emerging leaders, and assess factors that influence these changes. Data for such analyses can be extracted from on-line news and from social media. This paper demonstrates this process for Sudan and the Arab Spring. Findings indicate the need for a meta-network dynamic perspective that can identify secondary actors who serve as the emergent leaders and powers behind the thrones. In addition, to the extent that revolutionary activity requires coordination, social media is valuable due to early signaling; but, to the extent that revolutionary motivation requires understanding, traditional media is also valuable due to its in-depth coverage.

Keywords: *Dynamic network analysis, social network analysis, political elite, Arab Spring, emergent leader, Sudan, networks of concepts.*

К. М. Карли

ПОЛИТИЧЕСКАЯ ЭВОЛЮЦИЯ И РЕВОЛЮЦИЯ: СЕТЕВОЙ АНАЛИЗ ТРАНСФОРМАЦИЙ ВЛАСТИ В СУДАНЕ И В ХОДЕ АРАБСКОЙ ВЕСНЫ

Последние годы характеризуются множеством революций и изменений на уровне национальных государств. В результате политических сдвигов возникают новые политические лидеры, а существующие лидеры часто утрачивают популярность. Анализ социальных сетей может *быть использован для того, чтобы понять эти политические сдвиги, идентифицировать возникающих лидеров и оценить факторы, влияющие на изменения. Данные для анализа могут быть извлечены из онлайн-новостей и социальных медиа. Отраженные в статье результаты анализа событий в Судане и Арабской весны показывают необходимость применения метасетевого динамического подхода, который позволяет выявить акторов второго плана, оказывающихся как новыми лидерами, так и «серыми кардиналами». Кроме того, выясняется, что в динамике революционной активности социальные медиа играют лишь роль средства раннего оповещения об акциях, тогда как долгосрочное развитие революционных настроений подразумевает использование более глубоко воздействующих традиционных медиа.*

Ключевые слова: *динамический анализ сетей, анализ социальных сетей, политическая элита, «Арабская весна», возникающий лидер, Судан, сети концептов.*

Introduction

Political turmoil and state instability are growing concerns. Examples of such instability are the ongoing separation of Southern Sudan from Sudan, and the revolutions and warfare in the Middle East. As such events occur, a number of political elites — politicians, celebrities, political critics, and so on, play a role in the political transformation. Some members of these elites are leaders of the countries in question, others are insurgents or revolutionaries, and still others are peacekeepers. Importantly, these individuals are connected and the connections among them influence overall outcomes. Indeed, social networks are ubiquitous and underlie much individual, social and political behavior. These networks, particularly those of the political elite, are relevant to societal level transformations such as that occurring in Sudan and the Arab Spring.

Herein, the political instability in the Sudan and the Arab Spring are assessed by examining changes in the social networks and the meta-network for each of the countries separately. This paper provides an overview of two large projects examining evolution and revolution using a meta-network approach. High level results are presented. To attain these results, first, AutoMap is used to extract the networks by time period and country. Then ORA is used to visualize and assess changes in these networks. In the case of Sudan, all data is derived from the Sudan Tribune Review and Lexis Nexus. Hundreds of thousands of documents from 2000 to the present were used. These data are analyzed by year. In the case of the Arab Spring, hundreds of thousands of news articles and tweets are assessed. These are categorized by country and by month. Only tweets related to Syria are discussed here.

Data-to-Model and Dynamic Network Analysis

Traces of Sudan and Arab Spring political elite networks appear in newspapers and social media. Multiple technologies are needed for extracting, analyzing, and forecasting change in these political elite networks from these data sources. For the results presented here, the CASOS tool suite was used. First AutoMap was used to extract the networks from newspaper and Twitter data. Then ORA was used to analyze the data and assess change. AutoMap (Carley et al 2012a) is text-mining software that, using semantic and syntactic information in conjunction with pre-defined thesauri, extracts key entities and the relations among them, i.e., networks, from texts. Aspects of this approach are referred to as network text analysis (Diesner and Carley 2005). ORA (Carley et al. 2012b) is a network analysis package that uses statistical and graph-theoretic techniques to assess social and meta-networks and their changes through time. There are many ways in which ORA supports network analysis: 1) identification of key nodes and groups; 2) comparisons of two different networks; 3) statistical change detection on sequences of networks; 4) trail analysis for examining networks through time and space; 5) agent-based simulations for forecasting network change; and 6) comparative statics for assessing the impact of a change in a network. This process of moving from web-scraped texts to automated network extraction to dynamic network analysis is referred to as the data-to-model process and involves numerous steps for cleaning and processing the data (Carley et al. 2012c).

The data-to-model process extracts not just the social network (people and the connections among them) but also the full meta-network (Carley 2002). In a meta-network there are multiple types of nodes (multiple entity classes). The data herein was coded with the classes: agents, organizations, locations, knowledge, resources and tasks. In a meta-network there are multiple types of relations. In general, for each pair of entity classes there are one or more node classes. For example, there are two-mode networks such as agents by tasks, and one-mode networks such as agents by agents (the social network).

A key feature of a meta-network is that it enables network analysis to be conducted through time and space. This is often referred to as dynamic network analysis. Dynamic network analysis is an analytical approach that compliments mainstream statistics. Whereas statistical analysis focused on understanding the distribution of data elements that are independent and identically distributed; dynamic network analysis focuses on assessing data elements that have relations to each other forming a network. Due to these relations, often referred to as row-column dependencies, network elements such as the nodes and the links cannot be treated as independent. Since the nodes are highly dependent one on another, standard statistical assumptions do not hold. With dynamic network analysis, the focus shifts from aggregate measures of performance for a collection of people to the performance implied by the structure of relations among these people. With a dynamic network analysis model, the researcher can identify key people, tasks, ideas and locations, hidden groups and changes in these over time. Standard social network metrics (Wasserman and Faust 1994) can be applied in a meta-network to all one-mode and two-mode networks.

Sudan

The Sudan is a country in Africa made up of distinct ethnic groups and multiple types of climatic zones. The country is faced with internal dissension, genocide in

Darfur, changing political conditions, and increased desertification (Deng 2006). The president of Sudan is Omar Hassan Ahmad Al-Bashir. In 2004 there was international recognition of genocide, leading to the UN sanctioning an autonomous Southern Sudan in 2005. John Garang was the vice president of Sudan, was to become the president of Southern Sudan, but then died in a plane accident in 2005. In 2005 the government of Southern Sudan was formed and Salva Kiir Mayardit became the president and Reik Machar became the vice president. Ali Osman Taha became the vice president of Sudan. In 2010 the referendum for a separate Southern Sudan was passed. The data here covers this period of political evolution from 2000 to 2010.

Who are the key players? That is, across this decade who has been critical? We answer this by using social network metrics. These are presented in a series of tables. In Tables 1 through 5 the actors are color coded to indicate region of the world and political affiliation. The actors in gray, with black lettering, are part of the United Nations peacekeeping force, the United States or related leaders. Those actors in light gray, with black lettering, are from the Middle East or Africa. Those actors in dark gray, with white lettering, are from Southern Sudan and those actors in white, with black lettering, are from Sudan.

Table 1 shows the political leaders of Sudan using the standard social network metrics for power and influence. These are degree centrality, betweenness centrality, and eigenvector centrality. Degree centrality measures how many others the actor is connected to. Betweenness centrality measures the number of critical paths through the actor. Eigenvector centrality measures the extent to which the actor is highly connected to others who themselves are highly connected. These are three classic measures used to identify individuals with power in the social network. Not surprisingly, Bashir is the top ranked actor in all three measures. It is important to note that with these metric — most of the actors are leaders of countries. Two exceptions stand out — Ocampo and Keith Richards. Luis Moreno Ocampo was the first Prosecutor of the International Criminal Court , and served from June 2003 to June 2012. Keith Richards of the Rolling Stones was a strong proponent for peace and worked against genocide in Darfur.

The trouble with these actors is that it didn't take network analysis to tell us they were important. The strength of network analysis is to go beyond what is obvious. In this case, the goal is to ask who has the power behind the throne. To that end different network metrics are valuable. Three secondary actors of interest that can be assessed by network analysis are the power behind the throne (those connected to the top leader who have the most connections to others, gatekeepers (high betweenness and low degree centrality) and latent leaders (those who take over if the top leader is removed). These secondary actors are shown in Table 2. They key thing to note is that while numerous individuals from Southern Sudan show up, not one appears from Sudan. This suggests that the Sudan has a monolithic government run by a single individual; whereas, Southern Sudan has a more distributed government. The fact that all latent leaders are from outside the Sudan suggests that there is not a strong body of leaders within Sudan and Southern Sudan to prevent new conflict and further atrocities. One side note: Abu-Ahmed appears to be an error and not an actual specific actor.

Table 1

Political elite in the Sudan across all time periods

Rank	Degree	Betweenness	Eigenvector
1	omar_al_bashir	omar_al_bashir	omar_al_bashir
2	john_garang	john_garang	salva_kiir_mayardit
3	george_w_bush	george_w_bush	john_garang
4	salva_kiir_mayardit	salva_kiir_mayardit	luis_moreno_ocampo
5	yoweri_museveni	mustafa_fadhil	ali_osman_taha
6	ali_osman_taha	saddam_hussein	george_w_bush
7	joseph_kony	keith_richards	yoweri_museveni
8	kofi_annan	barack_obama	hosni_mubarak
9	barack_obama	ali_osman_taha	joseph_kony
10	hosni_mubarak	usama_bin_laden	thabo_mbeki

Table 2

Secondary actors in the Sudan

Rank	Power Behind the Throne	Gatekeeper	Latent Leader
1	luis_moreno_ocampo	peter_longole_kuma	kofi_annan
2	john_garang	john_terry	hosni_mubarak
3	hosni_mubarak	martin_odwar	bill_clinton
4	idriss_deby_itno	nyachigak_nyashiluk	ban_ki_moon
5		betty_ogwaro	yoweri_museveni
6		john_wol_makec	luis_moreno_ocampo
7		mark_john	tony_blair
8		nawaq_alhazmi	idriss_deby_itno
9		ahmed_abu	thabo_mbeki
10		aloysius_emor_ojetuk	ibrahim_khalil

A final type of secondary actor is the emergent leader (Table 3). The emergent leader is the individual who is very busy — e.g., that is highly connected to other actors, knowledge, resource and tasks, has to negotiate with others for knowledge and resources needed to do tasks, has to coordinate on task completion, and so on. Earlier studies have shown that actors with these characteristics tend to tell others what to do and serve as informal and emergent leaders. Notice that if the top level of leaders were removed, no person in Sudan or Southern Sudan would remain on the list. Rather a number of leaders of African countries emerge as potential power players (Zenawi, Mbeki, Mugabe). This result shows the power of using meta-network metrics that take into account more than the social network.

Table 3

Emergent leaders before and after removal of top incumbents

Rank	Emergent Leader — Before	Emergent Leader After
1	omar_al_bashir	yoweri_museveni
2	george_w_bush	joseph_kony
3	john_garang	barack_obama
4	salva_kiir_mayardit	kofi_annan
5	yoweri_museveni	luis_moreno_ocampo
6	Joseph kony	tony_blair
7	barack_obama	meles_zenawi
8	kofi_annan	thabo_mbeki
9	luis_moreno_ocampo	robert_mugabe
10	tony_blair	usama_bin_laden

In related work (Van Holt et al. 2012) we examined the relation of the ethnic groups to peace and conflict. In these networks — we have information on the number of ties across time to biomes, to livestock, and to environmental terms. For example, the more articles that talked about the relation of an ethnic group to livestock the higher the number of ties. We also considered the sheer number of environmental terms that were connected to the ethnic groups. The results are summarized in Figure 1. We found that ethnic groups at peace were strongly tied to distinct biomes. In contrast, those involved in conflict, that conflict is more severe the more the ethnic group is tied to livestock, environmental issues, and a variety of environmental issues. This result demonstrates how going beyond the social network to looking at the meta-network provides new insight into political revolution. In Figure 1, the bolder the line the stronger the relationship.

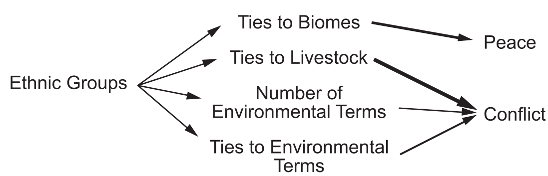

Figure 1. Meta-network factors leading to conflict and peace

The Arab Spring

The Arab Spring began on December 18, 2010 when a Tunisian merchant set fire to himself after his goods were confiscated. By January 2011, the Tunisian president had fled to Saudi Arabia. On January 25, 2011 protests broke out in Egypt leading to the government being overthrown on February 11, 2011. In Libya the protests started on February 15, 2011 — and by August 23, 2011 the government was overthrown — but by all-out internal warfare. Numerous explanations for the Arab Spring have been offered (Anderson 2011). We take a network analytic approach (for a more detailed assessment see: Pfeffer and Carley 2012a).

Now let us consider the way in which social networks can help us understand the Arab Spring. In Figure 2, we see the first four months of activity. Purple is for revolution & protest, while red is for warfare & conflict. The darker the color the more concern and articles there are for that country on that topic. As can be seen, the region is in a low state of conflict and protest; but then over time revolution breaks out in Tunisia, Algeria and Egypt, spreads to Libya and so on — and then Libya converts to all out warfare.

Figure 2. Spread of revolution through the Arab Spring

A key question is why are the profiles so different for Libya and Egypt? The network text analysis reveals that in both countries there is a spike in the number of actors reported in the news as the revolution ensues. In other words, the number of political elite brought to the attention of the public increases at the onset of the revolution. In both cases, the incumbent leader is the top actor in degree centrality until they are deposed. In both cases, there is high volatility in the gatekeepers (those high in betweenness and low in degree centrality).

Some of the network differences in Libya and Egypt are captured in the network statistics in Table 4. In this case, the incumbent is in white. The actors in green are part of the United Nations peacekeeping force, the United States or related leaders. Those in yellow are from the Middle East. One key finding is that the lists of top actors contain no revolutionaries. Indeed, to find the revolutionaries one needs to a) remove world leaders not in the Middle East, b) remove television-cinema personalities, and c) examine secondary actors.

As noted, the top person in degree centrality, the leader, tends to be the incumbent in both countries. Over time, the person holding this position tends to be consistent. The top gatekeeper, the person high in betweenness and low in degree centrality, changes with each month. Different world leaders take on the position and the occasional businessman and news broadcaster. It is likely that change occurs in the gatekeepers as change occurs in the issue of interest. That is, different actors champion different causes and bring together different groups based on the topic they are championing. Thus, for both countries the pattern of change in key actors is similar.

Table 4

Top leaders in Egypt and Libya

	Egypt		Libya	
Month	**Leader Degree Centrality**	**Gatekeeper Betweenness-Degree**	**Leader Degree Centrality**	**Gatekeeper Betweenness-Degree**
July 10	Hosni Mubark	Michael Hayden	Barack Obama	Prince Philip
Aug 10	Barack Obama	Asif Ali Zardari	Alex Salmond	Peter Mandelson
Sep 10	Mahmoud Abbas	Dmitry Medvedev	Alex Salmond	Ben Cardin
Oct 10	Hosni Mubark	Dmitry Medvedev	Mahmoud Abbas	Lee Myung-Bak
Nov 10	Hosni Mubark	Muammar Gaddafi	Nicholas Sarkozy	Benjamin Netanyahu
Dec 10	Hosni Mubark	John Kerry	Muammar Gaddafi	Sadam Hussein
Jan 11	Hosni Mubark	Thaddeus McCotter	Muammar Gaddafi	Kim Jong Il
Feb 11	Hosni Mubark	Wolfgang Schaeuble	Muammar Gaddafi	Francois Fillon
Mar 11	Hosni Mubark	Bill Nelson	Muammar Gaddafi	Stephen Colbert
Apr 11	Hosni Mubark	Angela Merkel	Muammar Gaddafi	Caroline Spelman
May 11	Barack Obama	Dick Cheney	Muammar Gaddafi	Christiane Amanpour
Jun 11	Barack Obama	Conan O'Brien	Muammar Gaddafi	Kevin McCarthy
Jul 11	Hosni Mubark	Tzipora Livini	Muammar Gaddafi	Prince William
Aug 11	Hosni Mubark	Joe Biden	Muammar Gaddafi	Dalai Lama
Sep 11	Barack Obama	Mark Zuckerberg	Muammar Gaddafi	Al Gore

Now consider the role of networks of concepts — not people. We find that over the course of the Arab Spring that as the revolution begins it is presaged by an increase in conversational complexity. That is, more topics are discussed and the density of connections among topics increases. Further, as coverage of the revolution increases, coverage of terrorists and terror groups decreases. This suggests that revolutionary activity creates a space where terrorists could engage in subversive activity relatively undetected.

Going further, the concepts related to "topics" highest in degree centrality and betweenness centrality for each of the countries are examined. "Topics" are those concepts representing issues rather than people, organizations or locations. Illustrative topic concepts include religion, oil and gas, and international relations. In both Egypt, prior to the revolution, top degree centrality concepts included oil & gas, religion, international relations, economics, and politics, and the elections. In Libya, prior to the revolution, top degree centrality concepts included oil & gas, international relations, wiki-leaks, sports, terrorism and economics.

It is after the revolutions begin that striking differences appear. In Egypt, "protest and demonstrations" is the number one concept in degree centrality, then religion, then international relations. When Mubarak resigns, his resignation becomes the third concept. Whereas, in Libya, the number one concept in degree centrality is "war & conflict", international relations is second and rebellion insurgence third. What this shows is that the conversation about revolution in Libya was, right from the start, much more violent. Where the Egyptian revolution was framed in terms of demonstrations and protestors, the Libyan revolution was framed in terms of war and insurgents.

We can go beyond identifying key terms to talk about the impact of the messages being constructed. The theory of communicative reach is a network analysis theory of rhetorical power (Carley and Kaufer 1993). Concepts that are high in either betweenness or degree centrality or in both of these measures, take on special rhetorical roles such that messages or articles that use those concepts will reach more people. Concepts high in both are symbols used mainly for asserting or garnering agreement. Concepts high in degree but low in betweenness are stereotypes — evoking a large common image. In contrast, concepts high in betweenness but low in degree are buzzwords — terms that are easily evoked or evoke other images, but for which there is little agreement on meaning. In Figure 3 we see the top terms that are high in one or more of these dimensions prior to and after the revolution for Egypt. Figure 4 is a similar assessment for Libya.

Contrasting Figures 3 and 4, we see that in Egypt protests became symbolic, whereas in Libya war became symbolic. In Egypt the elections remained a stereotypical image to which numerous other issues were linked. Peace and terrorism, which had been buzzwords prior to the revolution, became irrelevant during it — leaving economics as the only term used to link disconnected topics. In Libya, the elections, economics, religion and terrorism became buzzwords during the revolution that were easily evoked or which evoked numerous other discussions. Whereas sports, which had been a high stereotype prior to the revolution, became irrelevant during the revolution. These differences suggest a more cohesive argument in Egypt than Libya, the potential for greater disagreement in Libya due to the vacuousness of arguments centering on multiple buzzwords.

One issue that has repeatedly raised its head in the Arab Spring is the role of social media. Many have argued that Twitter and Facebook drove these revolutions (Khamis and Vaughn 2012) or at least impacted the outcomes (Zhuo et al. 2011). Our work suggests that social media was not a cause but a facilitator. Moreover, it was more of a tool used by the educated in large cities, than in the population at large. A critical issue, however, hinges on whether information is spreading faster via social media and so fomenting the revolution simply through this speed of communication.

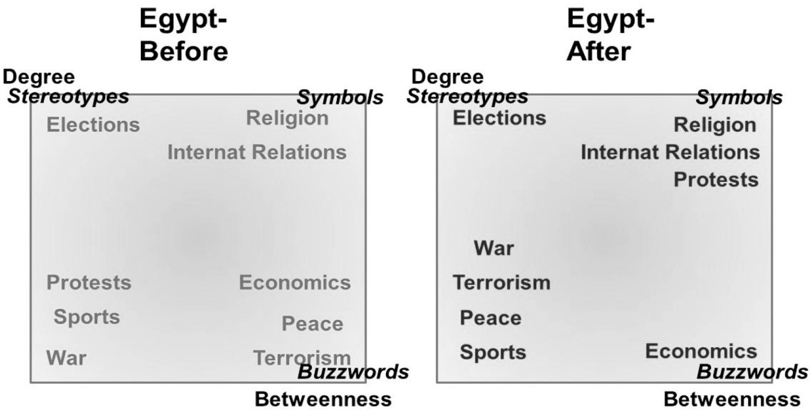

Figure 3. Change in communicative reach of critical concepts for Egypt

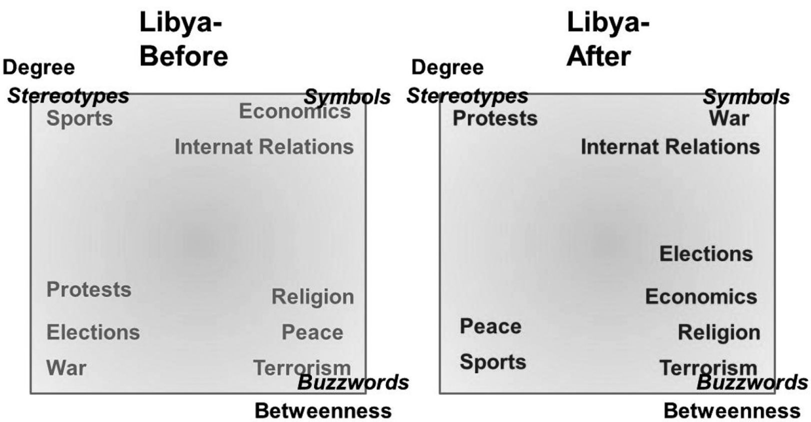

Figure 4. Change in communicative reach of critical concepts for Libya

Of these social media, Twitter in particular is interesting from a social network perspective. The Twitter network itself is a communication network. In related work we have found that Twitter networks are distinct from social networks in that the

Twitter networks have a preponderance of stars, thus many more stars and far less reciprocity than seen in actual social networks. In a related study we examined the role of social media in Syria (Pfeffer and Carley 2012b). We found that across time there was no correlation between the highs and lows of Twitter coverage and newspaper coverage. However, if you focus in on specific events then there is a correlated pattern. Specifically, for human initiated events such as the mass demonstration near the Homs city center in Syria, information on the event spreads by Twitter about 1 day prior to the spread of information by newspapers. However, for the more detailed follow-up stories and information, news leads Twitter. To the extent that revolutionary activity requires coordination, social media is valuable due to early signaling; but to the extent that revolutionary motivation requires understanding, traditional media is valuable due to in-depth coverage.

Discussion

This paper has presented an overview of two extensive projects that used network analysis to understand evolution and revolution in political systems. Social networks and indeed full meta-networks connecting who, what, when, where, why, and how were extracted from on-line open source data. Using news media, tags from news media, and Twitter, we were able to gain insight into the key actors and changes in the networks over time.

A key limitation of this work is that only English-language texts were used. However, even with this limitation we find new and critical insights into these politically transformative events. A critical feature of this work is that we are extracting the networks using a mixed initiative (human and computer) approach. The strength of this approach is that huge volumes of data can be processed. The weakness of this approach is that even with human review, some core concepts and some actors are missed. However, more importantly, relations among these entities may be missed and those found are not segregated by type; that is, relations such as talked about and worked together cannot be distinguished. Future work to improve entity extraction will be valuable. Even more valuable will be work on relation typing.

The analyses we conducted were of the political elites. This means that media stars and politicians in other countries show up, even in social networks associated with a specific country. Thus, for example, the American Presidents show up as key actors in most countries. Additional insights could be gained by removing all actors not from the country in question, and then examining how the country-only networks evolve. Future researchers might take this approach.

Despite these limitations, key insights were made. At a methodological level, this work demonstrates the importance of using two-mode and meta-network level multi-mode metrics as they facilitate identifying secondary actors. As noted, primary key actors in political elite networks are likely to be just the known top leaders. To get at the important but more hidden actors, secondary actors need to be considered. The two-mode and multi-mode metrics support finding such secondary actors.

In cases of state stability like the Sudan, these secondary actors may form coalitions allowing successful change. External actors with undue influence are often identifiable as secondary actors. Finally there is more volatility in these secondary positions than in the primary key actors. Thus political analysts would want to continually monitor the secondary actors.

In the case of the onset of revolution, secondary actors play a critical role. Secondary actors may serve as emergent leaders and so during the revolution effect change despite not having a formal position in the power structure. Revolutionaries, particularly in a social media coordinated revolution, may be difficult to identify without extreme data cleaning. And, as in the case of ongoing state stability, during revolutionary periods secondary actors are highly volatile. The frequency of change in secondary actors over the 10 month time period for all 18 countries is 0.9; whereas the frequency of change in primary actors is 0.3. Further, this high frequency of change appears related to change in issues of import. This suggests that these secondary actors may be gaining and losing power as the political conversation switches among topics.

These and many other questions can be addressed using network analytics. In general, the key is to move beyond just the social network and to consider the meta-network. The second key is to consider change in these networks.

References

Anderson L. Demystifying the Arab Spring: Parsing the Differences Between Tunisia, Egypt and Libya // Foreign Affairs. 2011. Vol. 90. No 8. Pp. 48–54.

Carley K.M., Kaufer D. Semantic Connectivity: An Approach for Analyzing Semantic Networks // Communication Theory. 1993. Vol. 3. No 3. Pp. 183–213.

Carley K.M. Smart Agents and Organizations of the Future // The Handbook of New Media / Ed. by L. Lievrouw and S. Livingstone. Thousand Oaks, CA: Sage, 2002.

Carley K.M., Columbus D., Azoulay A. AutoMap User's Guide 2012. Carnegie Mellon University, School of Computer Science, Institute for Software Research, Technical Report, CMU-ISR-12-106, 2012a.

Carley K.M., Reminga J., Storrick J., Columbus D. ORA User's Guide 2012. Carnegie Mellon University, School of Computer Science, Institute for Software Research, Technical Report, CMU-ISR-12-105, 2012b.

Carley K.M., Bigrigg M., Diallo B. Data-to-Model: A Mixed Initiative Approach for Rapid Ethnographic Assessment, Computational and Mathematical Organization Theory, 2012c. Vol. 18. No 3. Pp. 300–327.

Deng F.M. A Nation in Turbulent Search of Itself // Annals of the American Academy of Political Social Science. 2006. Vol. 603. No 1. Pp. 155–162.

Diesner J., Carley K.M. Revealing Social Structure from Texts: Meta-Matrix Text Analysis as a novel method for Network Text Analysis // Causal Mapping for Information Systems and Technology Research: Approaches, Advances, and Illustrations. Harrisburg, PA: Idea Group Publishing, 2005.

Khamis S., Vaughn K. 'We Are All Khaled Said': The potentials and limitations of cyberactivism in triggering public mobilization and promoting political change // Journal of Arab & Muslim Media Research, 2012. Vol. 4. No 23. Pp. 145–163.

Pfeffer J., Carley K.M. Rapid Modeling and Analyzing Networks Extracted from Pre-Structured News Articles // Computational and Mathematical Organization Theory. 2012a. Vol. 18. No 3. Pp. 280–299.

Pfeffer J., Carley K.M. Social Networks, Social Media, Social Change // Advances in Design for Cross-Cultural Activities. Part II / Ed. by D. D. Schmorrow, D.M. Nicholson. Boca Raton, FL: CRC Press, 2012b. Pp. 273–282.

Van Holt T., Johnson J.C., Brinkley J., Carley K.M., Caspersen J. Structure of ethnic violence in Sudan: an automated content, meta-network, and geospatial analytical approach // Computational and Mathematical Organization Theory. 2012. Vol. 18. No 3. Pp. 340–355.

Wasserman S., Faust K. Social Network Analysis: Methods and Applications. Cambridge: Cambridge University Press, 1994.

Zhuo X., Wellman B., Yu, J. Egypt: The First Internet Revolt? // Peace Magazine. 2011. Vol. 27. No 3. Pp. 6–10.