



Calhoun: The NPS Institutional Archive

Theses and Dissertations

Thesis Collection

2012-06

Battle of Narratives

Ruth, Lars

Monterey, California. Naval Postgraduate School

<http://hdl.handle.net/10945/7409>



Calhoun is a project of the Dudley Knox Library at NPS, furthering the precepts and goals of open government and government transparency. All information contained herein has been approved for release by the NPS Public Affairs Officer.

Dudley Knox Library / Naval Postgraduate School
411 Dyer Road / 1 University Circle
Monterey, California USA 93943

<http://www.nps.edu/library>



**NAVAL
POSTGRADUATE
SCHOOL**

MONTEREY, CALIFORNIA

THESIS

BATTLE OF NARRATIVES

by

Lars Ruth

June 2012

Thesis Advisor:

S. F. Everton

Second Reader:

H. Rothstein

Approved for public release; distribution is unlimited

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE			<i>Form Approved OMB No. 0704-0188</i>
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.			
1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE June 2012	3. REPORT TYPE AND DATES COVERED Master's Thesis	
4. TITLE AND SUBTITLE Battle of Narratives			5. FUNDING NUMBERS
6. AUTHOR(S) Lars Ruth			8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			10. SPONSORING/MONITORING AGENCY REPORT NUMBER
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB Protocol number _____N/A_____.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited			12b. DISTRIBUTION CODE
13. ABSTRACT (maximum 200 words) In this thesis, I analyze narratives from a network point of view using Social Network Analysis (SNA) software and methods. A narrative is a network of semantic meanings that can be coded and analyzed as such. In a competitive environment, such as politics, narratives are a means by which to influence people to act. To analyze a narrative's effectiveness, I use the 2008 Presidential Election campaigns of Senators John McCain and Barack Obama as a case study to evaluate their narratives in relation to their success. I generate a series of semantic networks of the two campaigns. I then estimate a series of SNA metrics and compare these to the approval ratings of the two candidates. I hypothesize that the degree of centralization and the cohesiveness of a candidate's narrative will be positively associated with the candidate's approval ratings, all else being equal. This hypothesis is confirmed in the analysis.			
14. SUBJECT TERMS Semantic Network, Narrative, Social Network Analysis, verbal communication, nonverbal communication, AutoMap, ORA			15. NUMBER OF PAGES 73
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT UU

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited

BATTLE OF NARRATIVES

Lars Ruth
Commander, German Navy
Dipl. Paed. Helmut Schmidt Universitaet, 1997

Submitted in partial fulfillment of the
requirements for the degree of

**MASTER OF SCIENCE IN
INFORMATION OPERATIONS**

from the

**NAVAL POSTGRADUATE SCHOOL
June 2012**

Author: Lars Ruth

Approved by: Prof. Sean F. Everton
Thesis Advisor

Dr. Hy Rothstein
Second Reader

Dr. John Arquilla
Chair, Department of Defense Analysis

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

In this thesis, I analyze narratives from a network point of view using Social Network Analysis (SNA) software and methods. A narrative is a network of semantic meanings that can be coded and analyzed as such. In a competitive environment, such as politics, narratives are a means by which to influence people to act. To analyze a narrative's effectiveness, I use the 2008 Presidential Election campaigns of Senators John McCain and Barack Obama as a case study to evaluate their narratives in relation to their success. I generate a series of semantic networks of the two campaigns. I then estimate a series of SNA metrics and compare these to the approval ratings of the two candidates. I hypothesize that the degree of centralization and the cohesiveness of a candidate's narrative will be positively associated with the candidate's approval ratings, all else being equal. This hypothesis is confirmed in the analysis.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

I.	INTRODUCTION.....	1
A.	MEANING DEPENDS ON CONTEXT	2
B.	NARRATIVES ARE SEMANTIC NETWORKS.....	3
C.	NETWORK ANALYSIS	4
II.	THEORETICAL FRAMEWORK	7
A.	NARRATIVES AS MEANS FOR POLITICAL COMPETITION	7
B.	RESEARCH QUESTION	10
C.	HYPOTHESIS.....	11
D.	SOFTWARE TO PROCESS TEXT TO NETWORKS AND ANALYZE THEM.....	12
1.	Processing Text to Networks with AutoMap.....	12
2.	Analyzing Networks with ORA	13
D.	METHODS	14
E.	DATA	17
III.	FINDINGS	21
A.	THE VERBAL AND NONVERBAL NETWORKS ASSESSED BY SNA.....	21
1.	SNA: Verbal Communication Networks	21
2.	SNA: Verbal and Nonverbal Communication Networks	33
B.	ANSWERING THE RESEARCH QUESTION.....	36
C.	VALIDATING THE HYPOTHESIS	37
IV.	OPEN QUESTIONS AND WAY AHEAD	39
	LIST OF REFERENCES.....	41
APPENDIX A	DATA OF NETWORKS	47
APPENDIX B	DATA GENERATION AND PRESENTATION.....	49
	INITIAL DISTRIBUTION LIST	53

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF FIGURES

Figure 1.	Direct versus indirect approach to decision	8
Figure 2.	Famous PQs by Tim Groseclose. Source: http://www.timgroseclose.com/famous-pqs/	9
Figure 3.	Narratives and their components	14
Figure 4.	Differences in approval rates over time for Obama versus McCain 2008 (Value _{Obama} / Value _{McCain} = Difference)	18
Figure 5.	Differences in approval rates over time September time frame	19
Figure 6.	Differences in approval rates over time January time frame	19
Figure 7.	Differences in approval rates over time June time frame	19
Figure 8.	Obama’s January Unidirectional Semantic Network with Frequency of Concepts Equal to or Greater than Two.....	23
Figure 9.	Unidirectional semantic Network, January time frame, Barack Obama, all nodes	23
Figure 10.	Obama’s June Bidirectional Semantic Network with frequency of Concepts Equal to or Greater than Two.....	25
Figure 11.	McCain’s June Bidirectional Semantic Network with Frequency of Concepts Equal to or Greater than Two.....	26
Figure 12.	Barack Obama’s September Bidirectional Semantic Network with with Frequency of Concepts Equal to or Greater than Two	27
Figure 13.	John McCain’s September Bidirectional Semantic Network with with Frequency of Concepts Equal to or Greater than Two	27
Figure 14.	Degree Centralization resulting from Semantic Network Report without debate	29
Figure 15.	Clustering Coefficient resulting from Semantic Network Report without the debate	30
Figure 16.	Clustering Coefficient resulting from Standard Network Analysis without debate	30
Figure 17.	Degree Centralization without debate.....	31
Figure 18.	Clustering Coefficient with debate	31
Figure 19.	Degree Centralization with debate.....	32
Figure 20.	Clustering Coefficient with debate	32
Figure 21.	Clustering Coefficient delta between Obama and McCain.....	35
Figure 22.	Degree Centralization delta between Obama and McCain	35
Figure 23.	Degree Centralization and Clustering Coefficient in comparison	37

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF TABLES

Table 1.	Political Issues for campaigns.....	15
Table 2.	Concept list Obama’s January speeches	22
Table 3.	Measurements Obama and McCain bidirectional semantic networks – June..	25
Table 4.	Measurements bidirectional semantic networks without debate September 2008.....	28
Table 5.	Measurements bidirectional semantic networks with debate September 2008.....	28
Table 6.	Obama and McCain nonverbal networks’ metrics.....	34
Table 7.	Data of semantic networks without nonverbal data compared to those with nonverbal data (inclusive).....	47

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

CASOS	Computational Analysis Of Social And Organizational Systems
DL	Delete List
DyNetML	Interchange Format for Rich Social Network Data
IED	Improvised Explosive Device
NATO	North Atlantic Treaty Organization
SAO	Subject – Action – Object sequence
SNA	Social Network Analysis
CL/T	Thesaurus

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

A narrative can be mapped as a network of semantic meanings. To the degree that a narrative is effective depends on the specific characteristics of the network itself, which can be analyzed using the tools of social network analysis (SNA). This thesis analyzes the verbal and nonverbal communications of Senators John McCain and Barack Obama during the 2008 U.S. Presidential Election campaign. More precisely, the semantic content of their communications is coded as a series of semantic networks that are then analyzed using SNA and compared to the candidates' approval ratings and finds that the degree of centralization and cohesiveness of a candidate's narrative is positively associated with the candidate's approval ratings.

The thesis demonstrates that verbal and nonverbal data can be integrated into a coherent semantic network, that the measurements taken identify differences that support the outcome of the competition, and that SNA provides an approach for analyzing the semantic content of a network. It also provides evidence that SNA is a method that has the potential to analyze, predict and shape the effectiveness of narratives.

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

First of all, I want to thank Prof. Sean F. Everton whose introduction to this topic offered me a whole new view of the world. Without his patience, advice, and outstanding support this thesis would have never been possible.

Secondly, I want to thank Prof. Rothstein for his support throughout the time at the NPS. His honest and supportive attitude helped me to accomplish my studies as a foreign national.

I also want to thank my wonderful wife and children. They are the best part of my life.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

The narrative “Change we can believe in”¹ is more convincing than “Country first.”²

The struggle between, at least, two competitors for the survival of their respective objective could generally be seen as a “battle.” One competitor’s success is the other’s loss. Battles can be fought with all sorts of means on all kinds of terrain. The phrase, “Battle of Narratives” implies that the “weapons” of choice are ideas.

A narrative is seen and used as a means to shape the recipient’s perceptions, opinions and behavior. The influence a narrative has on this mental terrain is critical.

In most cases behavior is also influenced by unrelated variables that do not originate through a narrative. Behavior that is the direct effect of a narrative is the subject of this thesis. It is generally agreed that carefully constructed and disseminated information can and does influence the behavior of recipients. It is also true that an actor will also be influenced by his experiences, beliefs, knowledge and other cognitive and perceptual components.

What makes one narrative more convincing than another? Particular topics resonate differently with different audiences. Freedom will resonate with most; religion with some; individualism with others. Nevertheless, competitors can knit together a variety of ideas in ways that produce unique narratives that resonate with a particular target audience.

As we will see, the way that competitors construct their narratives can be mapped as semantic networks where various ideas are seen as being linked (or not linked) together. In turn, these narratives can be evaluated for their effectiveness by comparing

¹ Wikipedia. Wikipedia. December 3, 2011, accessed March 12, 2011. http://en.wikipedia.org/wiki/Barack_Obama_presidential_campaign, 2008. This is a regularly updated Webpage with references to other pages belonging to Barack Obama, the Democratic Party and others, but, for the sake of showing the slogan of the 2008 presidential campaign, this specific site was sufficient.

² John McCain. *McCain Palin*. 2008, accessed January 20, 2012, <http://web.archive.org/web/20081103005023/http://www.johnmccain.com/Calendar>. There are multiple sites showing the slogan, but, on their own campaign homepage, John McCain and Sarah Palin use this slogan repeatedly.

them to how the target audience responds to the narrative. Indeed, the mapping and subsequent evaluation of semantic networks functions as the centerpiece of this thesis. In particular, it maps and evaluates the semantic networks of two candidates in a highly contested political campaign, the 2008 U.S. Presidential campaign between Barack Obama and John McCain.

In the political domain of Western democracies, candidates compete with one another for the vote of their respective country's citizens. The election of the President of the United States is an example of this. In this thesis, the 2008 U.S. Presidential Election campaign between Barack Obama and John McCain is used as a case study. Their narratives will be quantitatively analyzed. Thus, the effectiveness of each candidate's narrative can be evaluated with relative ease.

A. MEANING DEPENDS ON CONTEXT

Communication is a way to convey information with meaning. Words have two types of meaning: conceptual and associative. Conceptual meaning refers to grammatical value within a language,³ while associative meaning describes a composite of various modes of language usage that draw on certain mental connections. In general, meaning does not exist in an axiomatic way but is generated by the contextual environment of symbols in both verbal and nonverbal communications.⁴

The anthropological structuralist, Claude Levi Straus said that meaning exists above the isolated elements of language. He also criticized the traditional linguistics and traditional anthropologists, saying that their error "was to consider the terms, and not the

³ See also Alice Mwhaki, "Meaning as use: A functional view of Semantics and Pragmatics," *Swahili Forum* 11 (2004): 127-139, 130. Connotative meaning refers to "the real-world value a speaker associates with an expression"³ and which already reflects the traded values and norms of the communication context. Social meaning refers to the meaning of language used "(...) to establish and regulate social relations and to maintain social roles."³ Affective meaning refers to the language content related by and representing the speaker's attitudes and feelings often negative in nature.³ And collocative meaning refers to reoccurring meaning of a lexeme when combined with others. The lexeme lends or extends meaning in similar ways to co-located language components.³

⁴ Jeff Speaks, "Theories of Meaning," *The Stanford Encyclopedia of Philosophy* (Summer 2011 Edition, Edited by E. N. Zalta, San Francisco, June 21, 2011.

relations between the terms.”⁵ Following Strauss’ argument, meaning, requires that the observer focuses on things such as relationships and social order within the respective systems rather than only on the words or components. Meaning is constructed by the relationship within a system. Similarly, McGee⁶ and Lippmann⁷ highlight the importance of context and relationship for semantic meaning.

Both approaches see the meaning of language and other communication, verbal and nonverbal, as constructed or influenced by the context of other communication means and symbols. In other words, the semantic entities’ relationships and context give meaning to the communications.

B. NARRATIVES ARE SEMANTIC NETWORKS

In order to be able to analyze narratives, the term first must be defined in a way that adequately represents the concept. Aristotle, Tomashevski and Chatman agree that a narrative is constructed by sequential and causal events and see written texts as the means to tell a story. It is not, however, only through written texts, but also through other means of communication that narratives have meaning.

Narratives are analyzed in various ways. Franzosi demonstrates a method for getting “from words to numbers”⁸ to harvest data that can subsequently be analyzed

⁵ Claude-Levi Strauss, *Structural Anthropology*, Translated by Claire Jacobson and Brooke Grundfest Schoepf, (Perseus Books, 1963), position 66 (14%).

⁶ Michael Calvin McGee, "The "Ideograph": A link between Rhetoric and Ideology," *The Quarterly Journal Of Speech* 66, no. 1 (02 1980): 1-16, 14. “[a]n ideograph, however, is always understood in its relation to another;...”

⁷ Walter Lippmann, *Public Opinion*, (New York: Harcourt, Brace and Company, 1922), 66. “(...) language is by no means a perfect vehicle of meanings. (...) There is no certainty whatever that the same word will call out exactly the same idea in the reader’s mind as it is in the reporter’s.”

⁸ Roberto Franzosi, *Quantitative Narrative Analysis*, Series: Quantitative Applications in the Social Sciences, 07-162, SAGE, (Thousand Oaks 2010), 3, 8.

statistically.⁹ Flockhart focuses on a narrative's effect on a recipient.¹⁰ Nye¹¹ conceptualizes soft power similar to the way Flockhart conceptualizes narratives. He also acknowledges the existence of power that ends up influencing a recipient or an audience through attraction.¹²

In absence of an all-inclusive- definition, this thesis defines the term narrative in the following way:

A narrative is a holistic combination of a subject's verbal and nonverbal communication activities, whose semantic meanings form a network whose properties reveal the principles and values of one's cause.

C. NETWORK ANALYSIS

Social network analysis (SNA)¹³ is a collection of theories and methods that assumes that the behavior of actors (whether individuals, groups or organizations) is affected by their ties to other actors in the networks in which they are embedded.¹⁴ Rather than viewing actors as unaffected by those around them, SNA assumes that interaction patterns affect what actors say, believe, and how they act. A primary goal of SNA is to develop metrics that help analysts gain a better understanding of a particular network's structural features.

⁹ Jana Diesner and Kathleen M. Carley, *AutoMap 1.2 - Extract, analyze, represent, and compare mental models from texts*. CASOS Technical Report (Pittsburgh: Carnegie Mellon University, 2004), 1.

¹⁰ Trine Flockhart, Towards a strong NATO narrative: From a 'practice of talking' to a 'practice of doing': *International Politics*, (2012), www.palgrave-journals.com/ip/, accessed December 07, 2011, 80. Narratives "are more than simply 'stories.' Narratives describe the history, purpose and achievements of a collective entity, such as NATO, and they contribute in the process towards its unity and facilitate its continuous transformation. A strong narrative is a narrative, which supports ontological security by supporting the social identity of the agent in question and by being constitutive of identity."

¹¹ Joseph S. Nye, *Soft Power - The Means to success in World Politics*, (New York: Perseus Book Group, 2004), 6. "Soft Power is a power that is able to exert influence through argument and attraction: "in behavioral terms soft power is attractive power."

¹² Joseph S. Nye, *Soft Power - The Means to success in World Politics*, (New York: Perseus Book Group, 2004), 55. On page 55 he includes verbal and nonverbal communication in the overall concept.

¹³ The abbreviation SNA is not to be misunderstood as "Semantic Narrative Analysis," since "Social Network Analysis" is the title that is the one most prominently used. Semantic Narrative Analysis is a form of analysis specifically focusing on meaning of communication's semantic components – lexemes – that occur as signal. See Michael Calvin McGee, "The "Ideograph," A link between Rhetoric and Ideology," *The Quarterly Journal Of Speech* 66, no. 1 (February 1980): 1-16, 12.

¹⁴ Sean Everton. *Disrupting Dark Networks*, (New York and Cambridge 2012) Cambridge University Press, 3-4.

Just as the social networks can be analyzed by mapping ties between actors, semantic networks can be analyzed by mapping connections between semantic components. As Carley and Palmquist note:

Mental models are internal representations. Language is the key to understanding mental models,.... Mental models can be represented as networks of concepts. The meaning of a concept for an individual is embedded in its relations to other concepts in the individual's mental model, and the social meaning of a concept is not defined in a universal sense but rather through the intersection of individuals' mental models.¹⁵

In other words, the mental models are the objects of research, and the integral parts of the network are the semantic components.

Before moving forward, it is critical to distinguish between content and semantic analysis. As the names suggest, content analysis counts the number of words and the re-occurrence of phrases. It does not explain the relationship among the content's entities.¹⁶ Semantic analysis utilizes the tools of SNA to translate and categorize texts into semantic networks. The techniques used to interpret social networks can be applied to identify semantic patterns and relationships. These patterns and relationships may reveal how and why specific behavior is generated.¹⁷

The analysis of social networks provides researchers with metrics that can capture the overall structure and important aspects of networks, such as density, fragmentation, and centrality. Thus, it enhances the understanding of the network's structure and effectiveness. With this data, researchers can not only gain an understanding of the internal functions of a network, but also find ways to increase or decrease a network's effectiveness.

Semantic networks share the properties and characteristics of social networks. Measurements such as centrality and brokerage, and algorithms that detect cohesive

¹⁵ Kathleen Carley and Michael Palmquist, "Extracting, Representing, and Analyzing Mental Models." *Social Forces*, (The University of North Carolina Press) 70, no. 3 (March 1992): 601-636, 602.

¹⁶ Kathleen Carley and Michael Palmquist, "Extracting, Representing, and Analyzing Mental Models," *Social Forces*, (The University of North Carolina Press) 70, no. 3 (March 1992): 601-636, 605.

¹⁷ Reginald L. Hobbs, *Creating the Semantic Battlespace: Narrative Structure for Information Fusion*, Research, Computational & Information Sciences Directorate, Army Research Laboratory (Adelphi: US Army, 2006), 3, 5. This study informs on narratives' capability to convey complex information.

subgroups inform SNA about the network's characteristics and functions.¹⁸ Semantic concepts can be treated just like any other node within networks and, thus, can be measured the very same way. To summarize: a narrative can be represented as a semantic network. Analyzing narratives as semantic networks using SNA tools is the topic of this thesis.

¹⁸ De Nooy, Wouter, Andrej Mrvar, and Vladimir Batagelj, *Exploratory Social Network Analysis with Pajek* (New York: Cambridge University Press, 2005), 131. The betweenness centrality of a vertex is the proportion of all geodesics between pairs of other vertices that include this vertex.

II. THEORETICAL FRAMEWORK

A. NARRATIVES AS MEANS FOR POLITICAL COMPETITION

In a democratic political system, a core principal is the right to vote. Voting represents a decision-making process. A country's citizens seldom make decisions on specific courses of action, but instead leave such decisions up to their elected officials. This is true at the federal level in the United States and in about half of its constituent states.¹⁹ Other countries, such as Switzerland,²⁰ do have a long tradition of factual voting where the society directly decides on various political courses of action.

While the outcome of a vote reflects this will of the majority at the time of an election, individual citizens go through a decision-making process before they vote. Asked to make a choice, individuals seek information in order to make an informed one. In those cases where it comes to decisions in general, individuals take known facts, weigh the likely outcome of a particular decision, and choose the one they favor.²¹ When they have to choose a representative or delegate who will make decisions on their behalf, voters are confronted with another set of issues. Instead of deciding about a singular issue where factual information informs their decision-making process, they have to predict what the potential representative or delegate's future decisions will be and vote for the individual they believe will most likely to make decisions with which they will agree. The difference is that one is direct and the other indirect. Direct, in this context, means

¹⁹ Wikipedia, *Wikipedia*. (04.03.2012), http://en.wikipedia.org/wiki/Referendum#United_States , accessed March 04, 2012. In case of a referendum or an initiative the voters do not vote on personnel matters only, but also on courses of action. In those cases, they do need information on the topic itself and less on a person that should or should not decide on their behalf. (Wikipedia, Wikipedia 2012)

²⁰ Direct Democracy - Geschichte Schweiz Direct Democracy Switzerland's Referendums <http://direct-democracy.geschichte-schweiz.ch/switzerlands-system-referendums.html>, accessed March 07, 2012.

²¹ Thomas C. Schelling, *Arms And Influence* (London: Yale University Press, 2008), pages 36-43, 229. Schelling supports the rational actor theory that sees an actor who is in full control making a rational choice between given options. Other theories like Expectancy Theory and Attribution Theory (Heider) also introduce ways to calculate the most probable choice and the mental process behind it from an individual's perspective. Victor Vroom introduced a formula to calculate the outcome with his Expectancy Theory (Motivational Force = Expectancy x Instrumentality x sum of Valences]. Leadership-Central.com. Leadership-central.com Expectancy Theory of Motivation - Victor Vroom (2012), <http://www.leadership-central.com/expectancy-theory-of-motivation.html#axzz1pW7k5AJg>, accessed February 13, 2012.

that voters have to make a choice on a single matter. Indirect, in this context, means that voters have to choose an elected representative who best represents their interests.

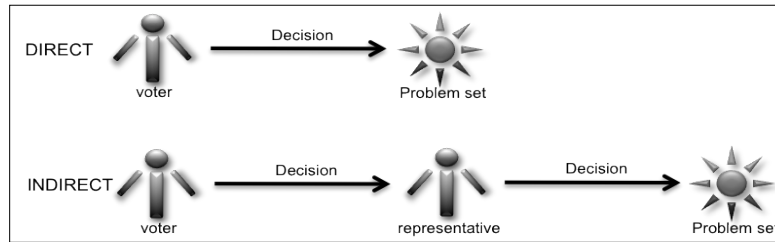


Figure 1. Direct versus indirect approach to decision

In the case of the latter there is no single issue to be decided upon; rather, there is a slate of candidates from whom voters must choose the one who they think will most likely make decisions they will support. This requires voters to gather all kinds of information about the candidates in order to select the one who best reflects their interests. This is a complex process and might not necessarily be easy for the average voter. Of course, some things are beyond the control of both voters and candidates. Some highly anticipated issues may never come up and other unanticipated issues will, e.g., who would have thought about decisions regards a “Global War On Terror” (GWOT) on September 10, 2001? Another problem is that voters can never know the candidates’ intrinsic motivation with regards to particular decision-making situations.

This means voters have to make some informed assumptions. They need to ascertain the candidates’ beliefs, values, previous actions, opinions, collaborations, and promises. If they can do all this, they will possess a holistic view of the candidates, at least from their perspective. This ‘holistic view’ can be seen as candidates’ narratives, which have developed over time and continue to morph with their on-going communication activities.

Candidates, especially those who have a long political history, do have records of actions that identify their individual narratives.²² This is illustrated by Groseclose and Milyo, who drew on past statements and voting records in order to calculate a “Political Quotient”²³ of various politicians (see Figure 2), which measures where various politicians align on the liberal-conservative spectrum.²⁴ Not surprisingly, prior to the 2008 elections, John McCain’s actions and words identified him as a conservative, and Barack Obama’s actions and words identified him as a liberal. So why did they campaign?²⁵ They did because it was crucial for both of them to frame their existing

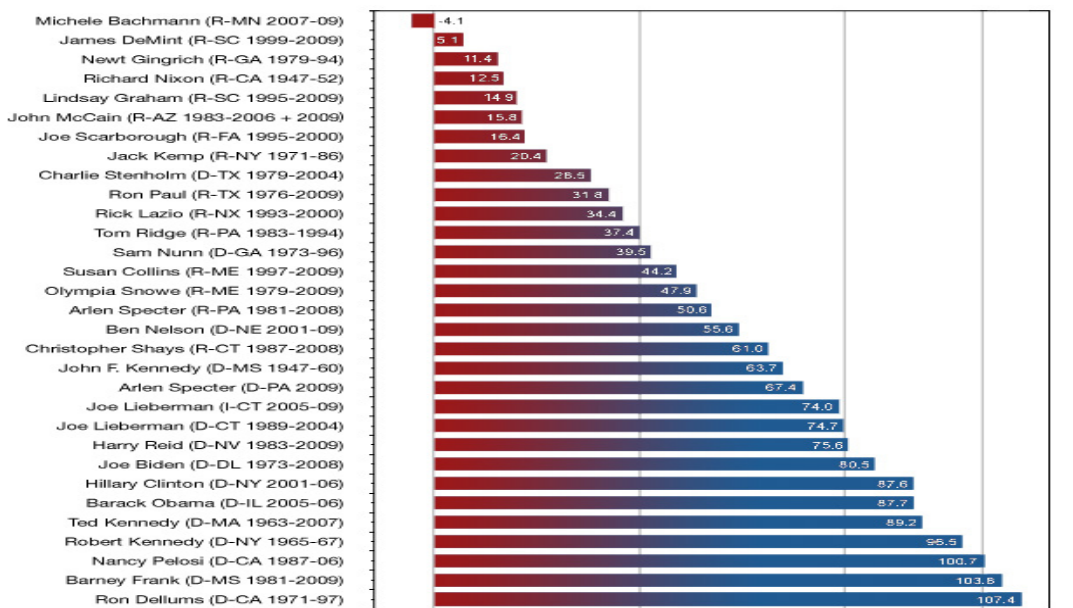


Figure 2. Famous PQs by Tim Groseclose. Source: <http://www.timgroseclose.com/famous-pqs/>

²² Tim Groseclose and Jeff Milyo, *A Measure of Media Bias*, (Los Angeles, December 2004). Stephen J. Dubner, *Freakonomics*, (February 16, 2012), <http://www.freakonomics.com/2012/02/16/how-biased-is-your-media/>, accessed February 28, 2012.

²³ Stephen J. Dubner, *Freakonomics*, (February 16, 2012), <http://www.freakonomics.com/2012/02/16/how-biased-is-your-media/>, accessed 28.02.2012 and Tim Groseclose and Jeff Milyo, *A Measure of Media Bias*, (Los Angeles, December 2004) and Tim Groseclose, *Tim Groseclose*, Word Press. <http://www.timgroseclose.com/famous-pqs/>, accessed March 02, 2012.

²⁴ Tim Groseclose and Jeff Milyo, *A Measure of Media Bias*, (Los Angeles, December 2004). "...To calculate average scores, for each member we note all of his or her scores for the seven-year period for which we recorded adjusted scores (1993-1999). Then we calculated the average over these years." See the earlier version of the very same paper Tim Groseclose and Jeff Milyo, *A Measure of Media Bias*, (Chicago, Los Angeles, September 2003), 6 (footnote 5), 7.

²⁵ A.S. Hornby, A.P. Cowie, and A C Gimson, *Oxford Advanced Learners Dictionary of Current English*, (Berlin, Cornelsen and Oxford University Press, 1984), 718. "Reputation[is] the general opinion about a character, qualities, etc of sb or sth,..."

narratives in ways that resonated with potential voters as well as convince them that their future actions will, if elected, match voters' interests and beliefs. Campaigning is designed to enhance the voters' knowledge and personal subjective narrative about the respective candidate. The goal is to shape the voters' internal representation of the candidate's narrative in a favorable way in order to make them vote for the respective candidate.

For voters some topics are more important than are others. For example, for some, social security and taxes are very important while gun control and LGBT are not. For others, just the opposite is true. All such topics can be seen in relation to each candidate and to each other. Every candidate needs to somehow signal his or her preferences and most likely choices. They do so through their personal narratives, which are more than simply a list of preferences and favored topics, but also how these preferences and topics relate to one another. As this thesis noted earlier, the semantic representation of these preferences and topics can be mapped and analyzed in ways similar to how social networks are mapped and analyzed. In this thesis, the candidates' communication activities are analyzed as networks using the tools of SNA and then compared to their effectiveness as measured by the candidates' approval ratings.

B. RESEARCH QUESTION

Whether a narrative can be seen as a network of semantic meaning and be mapped and analyzed using the tools of social network analysis is this thesis's overall research question. Here, two narratives are analyzed and compared to a known outcome. An overriding assumption is that the two narratives are semantically distinguishable from one another and that the winning narrative (i.e., Barack Obama's) will display features that made it more effective than the losing narrative (i.e., John McCain's). An important question is this: Can the difference between the two narratives be captured using SNA tools?

This question focuses on the identification of SNA metrics that are able to quantify a successful narrative in terms of its effectiveness while integrating verbal and nonverbal communication elements belonging to the same narrative. Of course, in a political

competition there are other variables that influence the election's outcome. The candidates' age, sex appeal, party affiliation, running mates, the state of the economy, and in this case the public perception of the sitting President's performance, all have an impact on the election's outcome. Nevertheless, these additional factors are not the focus of this thesis. Rather, it is the structure of the two candidates' narratives and how this structure is associated with the election's outcome.

C. HYPOTHESIS

SNA analyzes the relationship and pattern of social networks and uses measurements that capture the characteristics of specific networks. The same criteria can be used to analyze semantic networks. Semantic network analysis categorizes a narrative's verbal components into semantic concepts, and the relations between such concepts allow the narrative to be quantified as a semantic network, which is then analyzable using SNA. Building upon research that has found that a network's topography (i.e., its degree of centralization, cohesion, etc.) is correlated with its effectiveness,²⁶ this thesis researcher expects winning narratives to exhibit higher rates of cohesion and centralization than do losing narratives. Why? Because the degree to which decision-makers are confronted with a multitude of variables influencing their decisions, their decisions will increasingly depend on their understanding of the variables' interdependencies. And the more these different concepts are knit together in a network and presented in a coherent way, the more likely that it will resonate with voters.

While a number of SNA metrics exist that capture these dimensions of a network, in this thesis, centralization and cohesion will be operationalized using the degree centralization and average clustering coefficient metrics, respectively. Degree centralization measures the extent that a network centers on a single actor (here, a

²⁶ See Sean F. Everton 2012. "Network Topography, Key Players and Terrorist Networks." *Connections* 31(1):1-8; Sean F. Everton. *Disrupting Dark Networks*. Chapter 6. (Cambridge and New York 2012) Cambridge University Press. Bernice A. Pescosolido, and Sharon Georgianna. 1989. "Durkheim, Suicide, and Religion: Toward a Network Theory of Suicide." *American Sociological Review* 54(1):33-48; Brian Uzzi. 1996. "The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect." *American Sociological Review* 61(4):674-98; Brian Uzzi and Jarrett Spiro. 2005. "Collaboration and Creativity: The Small World Problem." *American Journal of Sociology* 111(2):447-504.

concept), while the average clustering coefficient captures the extent to which nodes are embedded in tightly knit clusters. Finally, the effectiveness of winning narratives will be distinguished from the effectiveness of losing narratives using candidate approval rates. Admittedly, this is not a perfect measure since approval ratings are undoubtedly a function of other factors, such as those mentioned above. However, it is reasonable, in this research context, to assume that the available data of verbal and nonverbal communication offers enough content to analyze the networks and identify correlations between network metrics and approval ratings.

Hypothesis: The level of centralization and cohesion of a political candidate's narrative's semantic network will be positively associated with the candidate's voter approval ratings.

D. SOFTWARE TO PROCESS TEXT TO NETWORKS AND ANALYZE THEM

Capturing a narrative's semantic network requires software that is up to the task. For the generation of semantic network data containing the semantic concepts as nodes, it uses AutoMap. For the analysis of that network data and its graphic representation, it uses ORA. Dr. Kathleen Carley, a social network analyst who uses SNA tools and methods to analyze oral and written texts, has developed both.²⁷ The programs are described in more detail below.

1. Processing Text to Networks with AutoMap

AutoMap is software designed and developed to analyze text and generate semantic networks. It is a text-mining tool that generates network files that are designed to work seamlessly with ORA (see description below). "The software enables the extraction of information from texts using Network Text Analysis methods. (...)

²⁷ See Kathleen M. Carley 1993. "Coding Choices for Textual Analysis: A Comparison of Content Analysis and Map Analysis." *Sociological Methodology* 23:75-126 and Kathleen M. Carley and Michael Palmquist. 1992. "Extracting, Representing, and Analyzing Mental Models." *Social Forces* 70(3):601-36.

AutoMap also offers a variety of techniques for pre-processing Natural Language.”²⁸ It also includes content analysis features as well as relational analysis of semantic content. AutoMap’s unique approach is to measure the relative distance between semantic concepts in the texts. This is different from other tools that are designed for content analysis only.

AutoMap was designed to extract meaning from texts by analyzing the frequencies and covariance of terms, concepts, and themes and the relations between them in the form of network maps. When the nodes of these network maps are concepts, AutoMap provides a snapshot of the mental map of a text’s author. When the nodes are people communicate with, organizations they join, or resources at their disposal, Auto Map reveals the structure of social and organizational systems. Proximity in the text of certain types of words is AutoMap’s key organizing principle and its basis for analysis.²⁹

For this thesis, AutoMap 3.0.8 is used which provides all necessary tools needed to generate semantic networks from the available communication.

2. Analyzing Networks with ORA

“ORA is a risk assessment tool for locating individuals or groups that are potential risks given social, knowledge and task network information.”³⁰ ORA provides the user with a wide array of possible processing, analyzing, and visualizing networks. It is designed to work with the network data produced by AutoMap. It also offers multiple analytical tools for the semantic analysis. All of the speeches were analyzed in the way described above. While the latest version is 2.3.6, this thesis uses ORA 2.3.2 because the data processing and report generation for semantic networks does not function as well as they do in previous versions. Moreover, the 2.3.2 version includes all the tools needed for this analysis.

²⁸ (CASOS), Computational Analysis Of Social And Organizational Systems, *CASOS Automap*, (2011), <http://www.casos.cs.cmu.edu/projects/automap/>, accessed September 1, 2011.

²⁹ Roberto Franzosi, *Quantitative Narrative Analysis*, Series: Quantitative Applications in the Social Sciences, 07-162, SAGE, (Thousand Oaks 2010), 67. Even if Franzosi on page 6 says that AutoMap belongs to a family of computer software based on the SAO structure, he now argues for the unique relational aspect AutoMap provides, and which makes it very useful for this thesis.

³⁰ CASOS; Computational Analysis of Social and Organizational Systems, *CASOS*, (2012), <http://www.casos.cs.cmu.edu/projects/automap/>, accessed November 15, 2011).

D. METHODS

To generate semantic networks from text, the latter must undergo a simplification process. Specifically, semantic components must be assembled into groups, or categories.³¹ A text's most basic *semantic component* is a word. The meaning of each word can vary across contexts and its meaning can also change as words are combined. In order to generate a measurable semantic network, one must assign words with similar meaning to a broader semantic concept.³²

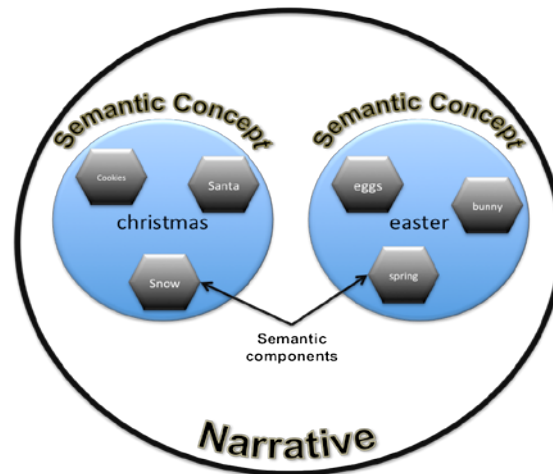


Figure 3. Narratives and their components

Semantic concepts are a group of words with similar meaning and within a specific context. Consequently, an initial and crucial step is to identify and define the concepts that will be used in the analysis.³³ As depicted in the simplified example in Figure 3, the overall narrative (*holidays*) contains the semantic concepts (*Christmas* and *Easter*),

³¹ Roberto Franzosi, *Quantitative Narrative Analysis*, Series: Quantitative Applications in the Social Sciences, 07-162, SAGE, (Thousand Oaks 2010), 67. Franzosi notes page 6 that AutoMap belongs to a family of computer software that AutoMap helps capture the relational aspects of texts, which makes it useful for this thesis.

³² Kathleen Carley and Michael Palmquist, *Extracting, Representing, and Analyzing Mental Models in: Institute for Software Research, Paper 40, (1992), 608.*

³³ The list of concepts is called Thesaurus in AutoMap and contains the components found in texts and the concepts they should be represented by, i.e., the word I as component will be represented by the broader concept Barack_Obama.

which contain semantic components (*eggs*, *Santa Claus*, and *snow*). Concept generation is an important, if not the most important, step in mapping the semantic network of a narrative.

In this thesis candidates' speeches are the texts from which the semantic components are identified, while the key political issues serve as semantic concepts. For this analysis, the topics that were initially identified as most salient were:³⁴

Table 1. Political Issues for campaigns

Each candidate sees these topics differently, but both have to present their views on them in ways that voters understand the candidate's most likely course of action with regards to each topic. Of course, each candidate may want to emphasize additional concepts to the voters, such as *Change*, *Leadership*, or *Unite*, which Barack Obama used to enhance his narrative.³⁵

AuoMap helps categorize components with the right concepts. The coding for this analysis recognized positive and negative mood of concepts and integrated them whenever possible. When this categorization is coded correctly, the occurrences of different concepts in a repeating constellation form an understanding of the meaning and its importance.³⁶ For example if *health care* is always close to and similarly used as *financial_loss*, it takes on a different connotation than if it regularly appears with *family*.

³⁴ Cable News Network (CNN), *CNN Politics.com*, CNN Election Center 2008, (2008), <http://www.cnn.com/ELECTION/2008/issues/>, accessed October 1, 2011.

³⁵ Kathleen Carley and Michael Palmquist, *Extracting, Representing, and Analyzing Mental Models*, Institute for Software Research, Paper 40, (1992), 611.

³⁶ Kathleen Carley et al., *AutoMap User's Guide 2010*, (Pittsburg 2010), p. 20. In AutoMap that distance is called Adjacency of Concepts. It is also represented in the Window Size defined when creating a semantic network from the preprocessed text.

Or again, if *military* is used with *financial_loss*, its contextual meaning will be different than if it is used with *national security*.³⁷

One of the most important steps to generate a semantic network is to preprocess, simplify and clean the text. The two functions available in AutoMap that facilitate this are the “Delete List” (DL) and the “Concept List/Thesaurus” (CL/T) (Wei, et al. 2011). The thesaurus defines semantic components that are categorized into broader semantic concepts, which then form the basis of the semantic network.³⁸ The delete list supplements this process by identifying the irrelevant words, or the “noise,” to the analysis.³⁹ The same delete list and thesaurus were applied to all texts.⁴⁰

The resulting text was used to generate unidirectional and bidirectional semantic networks, concept networks, and concept lists. A bi-directional network takes into account ties between concepts regardless of the order they appear in a text, while unidirectional networks only takes into account ties between concepts that only occur in “reading direction,” that is from left to right. However, since humans are able to link semantic meaning in both directions this thesis analyzes bi-directional networks. Moreover it uses a window size of two semantic entities and restricted the complete context to a single concept. “The window size determines the span in which connections will be made. The larger the window size, the more connections within that window.”⁴¹ In other words, a connection is made between concepts within a window. If the window size is two, then only two concepts will be linked. The window will subsequently shift to

³⁷ Roberto Franzosi, *Quantitative Narrative Analysis*, Series: Quantitative Applications in the Social Sciences, 07-162, SAGE, (Thousand Oaks 2010), 64. Franzosi points out that the reoccurrence of the same event in text cannot be counted as a reoccurrence in reality. This is true for his Narrative Analysis, but is different in the case of Semantic Analysis, since the reoccurrence of phrases and words does have influence on the recipients reaction to it.

³⁸ The thesauri used for each candidate both contain approximately 2,000 concepts. It is very important to note that this step is crucial for identifying combinations of words that will alter a concept’s meaning. For example, the Clinton_Global_Initiative is a concept of its own. The semantic components Clinton, global, and initiative, however, could serve as separate semantic components and could be assigned to different concepts, such as Democratic Party, globalization, leadership etc.

³⁹ There were 22 steps of preprocessing applied to each text. These steps included the repeated application of T and DL.

⁴⁰ The only variation was candidate specific coding e.g., I would be coded as either John_McCain or Barack_Obama depending on who is the communicator.

⁴¹ See AutoMap’s “Help” section.

the next concept in the sentence and create another link between the two concepts, which is a process that repeats until the end of the text.

E. DATA

In gathering data, some circumstances were of critical importance. One, the data had to be available. Second, they had to be of a social setting and period of time that decreased the possibility of misinterpretation by the coder. Third, the communication activities had to be directly related to competition and not for other purposes, such as supporting an overall party purpose or similar. Fourth, the competition's outcome had to be known, clear, reliable, and representative. Those four critical propositions had been matched perfectly by the presidential campaigns of the two candidates. Both competed from January 2008 until the election in November 2008. Throughout the year 2008 there had been various activities in which the two candidates participated and delivered numerous speeches. Still, the amount of available data is quite large, so this thesis focused on time frames when significant changes occurred in the approval rates of the two candidates.⁴² Three time frames were identified from surveys that exhibited more change than average: the 27th January 2008 to 03rd February 2008, 09th June 2008 to 19th June 2008, and finally 09th September 2008 to 30th September 2008. Henceforth, these time frames will be referred to as "January," "June," and "September," respectively. Within these time frames, available transcripts of speeches and other verbal communications were selected. Obama's and McCain's speeches are available on the Internet on "asksam" and other homepages.⁴³ The Presidential debate transcript was accessed from the New York Times.⁴⁴ Nonverbal communication for this thesis was derived from the candidates'

⁴² In order to avoid biases and unintended influences of small sample sizes or political affiliation of the survey company, this thesis researcher needed to compare multiple surveys taken at approximately the same time. Different surveys (264) for the year 2008 from 01st January to 03rd were located. Also, November was executed by a total of 27 agencies, companies, and organizations. The average approval rating for each candidate on every single day in 2008 from January, 1st to November, 3rd was calculated.

⁴³ ASKSAM TM, Making Information Useful, <http://www.asksam.com/ebooks/releases.asp?file=Obama-Speeches.ask>, accessed October 1, 2011. ProCon.org, ProCon.org 2008 Election, (October 3, 2009), <http://2008election.procon.org/view.resource.php?resourceID=1568#mccain>, accessed December 17, 2011.

⁴⁴ The New York Times, The New York Times - Election 2008, (December 22,2011), <http://elections.nytimes.com/2008/president/debates/transcripts/first-presidential-debate.html>, accessed January 5,

voting history as well as from the general understanding of what liberal and conservative values are and what action and attitudes are associated with them. Sources for this type of data were websites that collect and list voting activities, liberal and Democrat values, and conservative and Republican values. The data from these sources were in written form and were assembled into two documents, one for each candidate, and then coded using the same software and processes as was used for the coding of the verbal communication data.⁴⁵ The combination of both, the verbal and the nonverbal communication networks, represent the complete dataset and network for both candidates. They included all data. This researcher called them the *inclusive* networks.

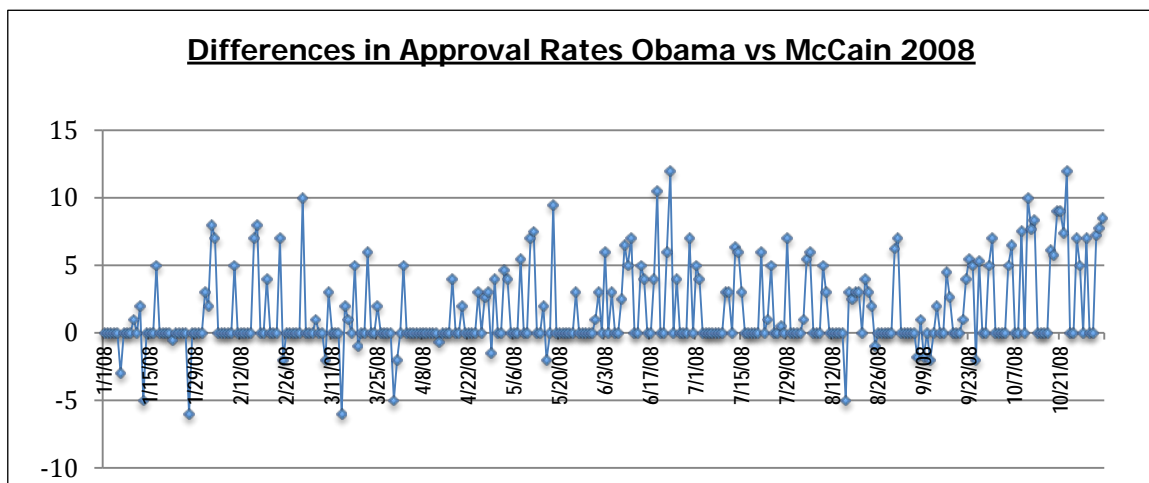


Figure 4. Differences in approval rates over time for Obama versus McCain 2008
(Value_{Obama} / Value_{McCain} = Difference)

2012. Nonverbal data was also accessed via Internet resources. For further insight in the sources of data, see the bibliography.

⁴⁵The only difference was that the thesaurus for that coding had to be enhanced by some concepts that had not been developed already. Voted YES, for example had to be coded as support, while Voted NO had to be coded as oppose. Also, some titles of voting topics had to be transferred into concepts that already existed, such as Roe vs. Wade (abortion) or same-sex-marriage (LGBT).

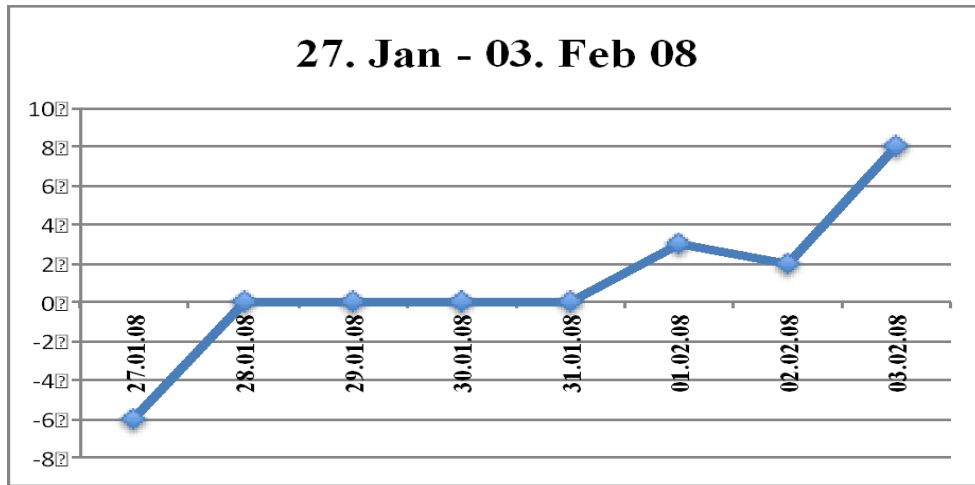


Figure 6. Differences in approval rates over time January time frame

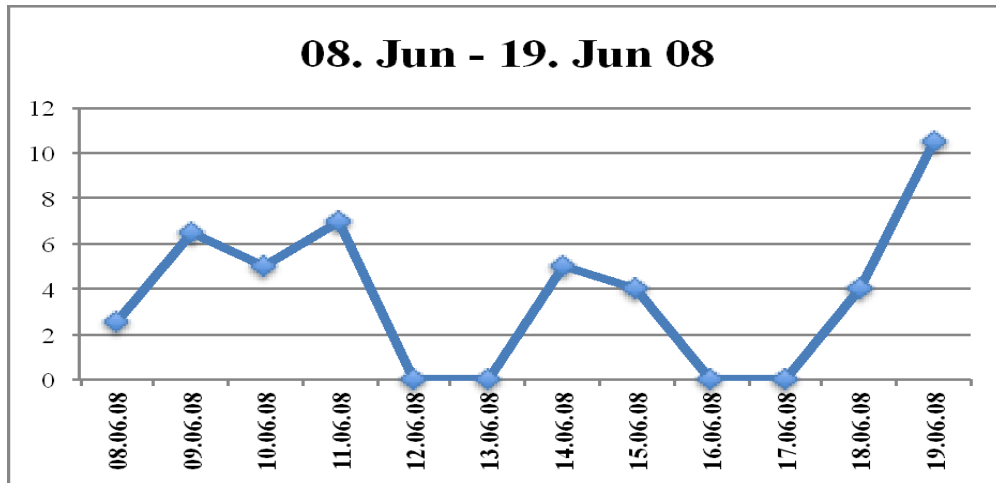


Figure 7. Differences in approval rates over time June time frame

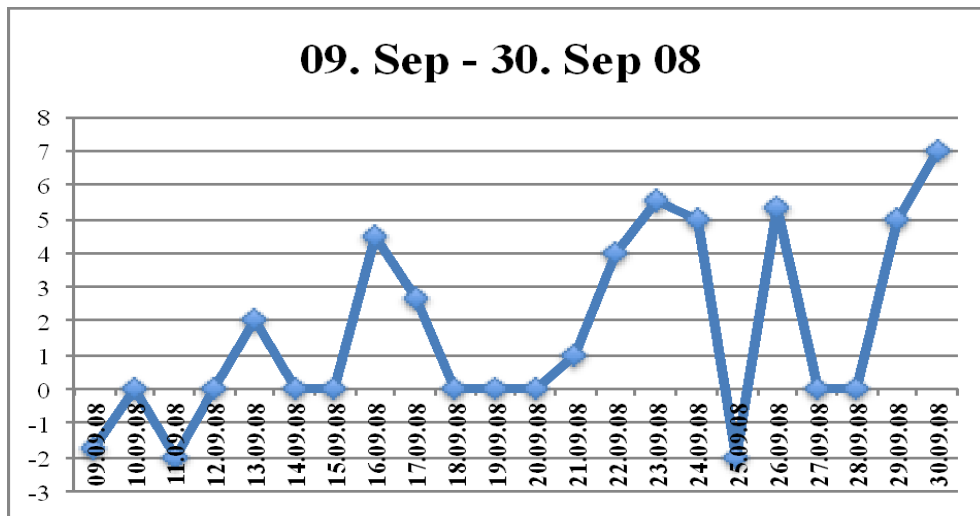


Figure 5. Differences in approval rates over time September time frame

THIS PAGE INTENTIONALLY LEFT BLANK

III. FINDINGS

After collecting the data available for both candidates, a series of semantic networks were generated. These can be divided into two groups of networks: One only includes verbal communication; the other includes both verbal and nonverbal communication. The resulting semantic networks are analyzed both visually and with standard SNA metrics. The verbal communication-based networks are analyzed first; the all-inclusive networks are analyzed second.

A. THE VERBAL AND NONVERBAL NETWORKS ASSESSED BY SNA

1. SNA: Verbal Communication Networks

The verbal communication of Barack Obama and John McCain includes the speeches they delivered to U.S. audiences during the campaign. Concept lists of the most important topics for all speeches show differences in the issues addressed. For example, the most central concepts in Barack Obama's speeches are presented in Table 2. Not surprisingly, the most central semantic concept was `barack_obama`. The other next important concepts are `change`, `unite`, `family`, and `usa`.⁴⁶

In January, Barack Obama gave four speeches on the 28th, 29th, and 30th, one of which was in response to President Bush's State of the Union address. While Obama might have had the opportunity to decide independently about the speeches' contents for the other three speeches, in one he had to respond to one given by someone else. This fact seems not to alter the speech's consistency, but responding to topics reduces the freedom to address whatever issues might fit better to the preplanned communication activity and the resulting narrative.

⁴⁶ See Sean F. Everton. *Disrupting Dark Networks*, (New York and Cambridge 2012) Cambridge University Press, 355-58 "Betweenness centrality measures the extent to which each actor lies on the shortest path between all other actors in a network." Degree centrality is the degree of how much an actor "equals the number of lines incident with it. More simply, it is the count of the number of an actor's ties." "Eigenvector Centrality assumes that ties to central actors are more important than ties to peripheral actors and thus weights each actor's summed connections to others by their(i.e., the others) centrality scores. With an undirected network, eigenvector centrality scores are the same as hubs and authority scores."

The semantic network of Obama’s speeches from this time period (Figure 8) is highly interconnected. Fortunately, ORA allows analysts to remove, or hide, relatively unimportant concepts by setting a frequency threshold at which concepts are included in the network. Table 9 depicts the same semantoc network except that it only includes concepts that occur more than twice. This results in a clearer picture of the network.

Degree	Betweenness	Eigenvector
change (.223)	barack_obama (.193)	barack_obama -1.000
barack_obama (.219)	change (.179)	future (.859)
unite (.203)	unite (.163)	unite (.762)
future (.161)	future (.104)	family (.737)
family (.147)	family (.098)	change (.736)
usa (.133)	usa (.089)	usa (.396)
financial_gain (.112)	no_change (.065)	president (.269)
democratic_party (.100)	financial_gain (.061)	leadership (.242)
no_change (.093)	economy (.050)	economy (.229)
american_population (.086)	democratic_party (.048)	democratic_party (.225)
leadership (.081)	american_population (.040)	american_population (.199)
economy (.075)	john_mccain (.036)	audience (.192)
financial_loss (.070)	financial_loss (.031)	financial_gain (.166)
working_middleclass (.070)	leadership (.030)	education (.160)
john_mccain (.061)	working_middleclass (.029)	no_change (.141)
audience (.060)	security_risk (.029)	own (.128)
education (.056)	education (.024)	health_care (.127)
health_care (.054)	audience (.022)	believe (.126)
republican_party (.054)	health_care (.017)	success (.115)
security_risk (.053)	president (.016)	john_mccain (.110)
president (.049)	republican_party (.015)	possible (.106)

Table 2. Concept list Obama’s January speeches

The degree centralization of the January bidirectional network 0.607. While not a perfect measure, the larger a network’s centralization, the more likely the network centers around a single actor or node (in this case a concept).

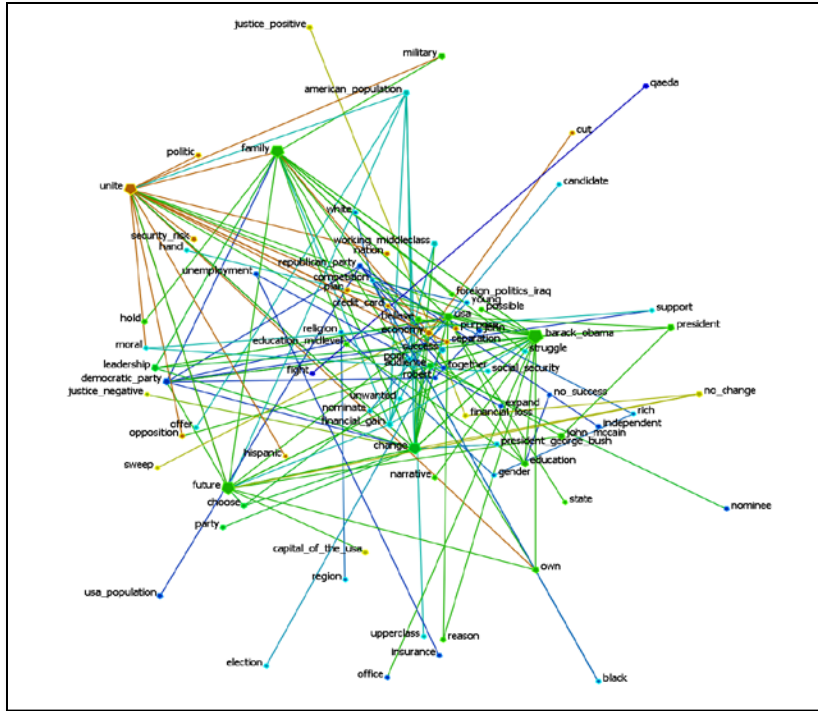


Figure 8. Obama's January Unidirectional Semantic Network with Frequency of Concepts Equal to or Greater than Two

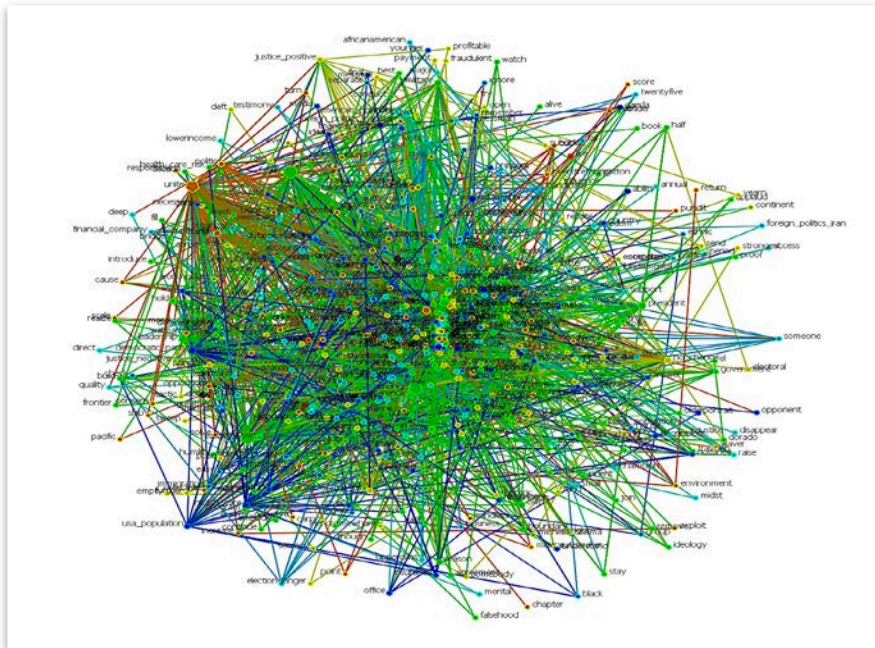


Figure 9. Unidirectional semantic Network, January time frame, Barack Obama, all nodes

The clustering coefficient for the two networks were 0.355/0.299.⁴⁷ For effective communication, it appears to be crucial to communicate symbols (e.g., “condensation symbols”) that are distinct from concepts. Concepts are overall categories, whereas Symbols are specific concepts that have high values in degree centrality, betweenness, and consensus.⁴⁸

John McCain did not have any communication events in the January timeframe. Thus his measurements are zero in all cases which raises the question: Why did Barack Obama not have 100% approval ratings during this time? And the obvious answer is that McCain had a preexisting narrative that already appealed to a portion of the population.

In the June time frame, both candidates had communication events from which semantic networks can be derived. Obama delivered four speeches while John McCain delivered three, all of which were analyzed as before. Because it is more parsimonious and probably more interesting to focus on the full picture rather than analyzing the individual speeches, they were combined and analyzed in an aggregate.

Looking at Figure 10, Obama’s network looks more complex than McCain’s and appears to be knit together more tightly.⁴⁹ As one can see, the name Barack Obama is linked to specific concepts: *barack_obama*, *family*, *future*, and *education*. These are the most central concepts in one group. *Unite*, *change*, *economy*, and *leadership* form another, and finally *financial_loss*, *financial_gain*, *working_middleclass*, and *health_care* form a third group. The clustering in John McCain’s speeches is different: *John_mccain*, *believe*, and *audience* form one group, while the most central concepts are *economy*, *usa*, *future*, and *financial_gain* in a second group. Finally, the concept *unite* also ranks high in eigenvector centrality. Moreover, the results presented in Table 3 suggest that Obama’s semantic network is more centralized, displays a higher level of clustering, and includes a

⁴⁷ The clustering coefficient describes the density of each nodes ego network, which means the density of each semantic concept’s network in that case. Two levels of clustering coefficient are possible: the node level (each semantic concept’s network) and the complete network’s average node level density. The clustering coefficient seems to be interesting when it comes to importance of a semantic concept and it’s embeddedness in the whole narrative. See also Wei et al., Handling Weighted, Asymmetric, Self-Looped, and Disconnected Networks in ORA, CMU-ISR-11-113, (Pittsburgh 2011), 19-20.

⁴⁸ Kathleen Carley and David Kaufer, "Condensation Symbols: Their Variety and Rhetorical Function in Political Discourse," *Philosophy and Rhetoric* 26, no. 3 (1993), 201-226.

⁴⁹ The frequency thresholds for Networks 3 and 4 are set to 2.1. In other words, the network includes only the concepts that appear more than twice within the text, which is one method to reduce the “noise” and focus on relatively more frequent concepts.

Thus, we need to turn to metrics in order to compare the two networks. These are presented in Table 4. Obama's speeches are once again more centralized and tightly knit than McCain's. The difference in the use of symbols do not appear to be significantly different from one another, however. When the debate is included in the network (Table 5), there is little change except that McCain now uses symbols at a higher rate.

	Obama	McCain
Nodes	100	100
Edges	100	100
Centrality	0.1	0.1
Clustering	0.1	0.1
Path Length	0.1	0.1
Symbol Use	0.1	0.1

Table 4. Measurements bidirectional semantic networks without debate September 2008

	Obama	McCain
Nodes	100	100
Edges	100	100
Centrality	0.1	0.1
Clustering	0.1	0.1
Path Length	0.1	0.1
Symbol Use	0.1	0.1

Table 5. Measurements bidirectional semantic networks with debate September 2008

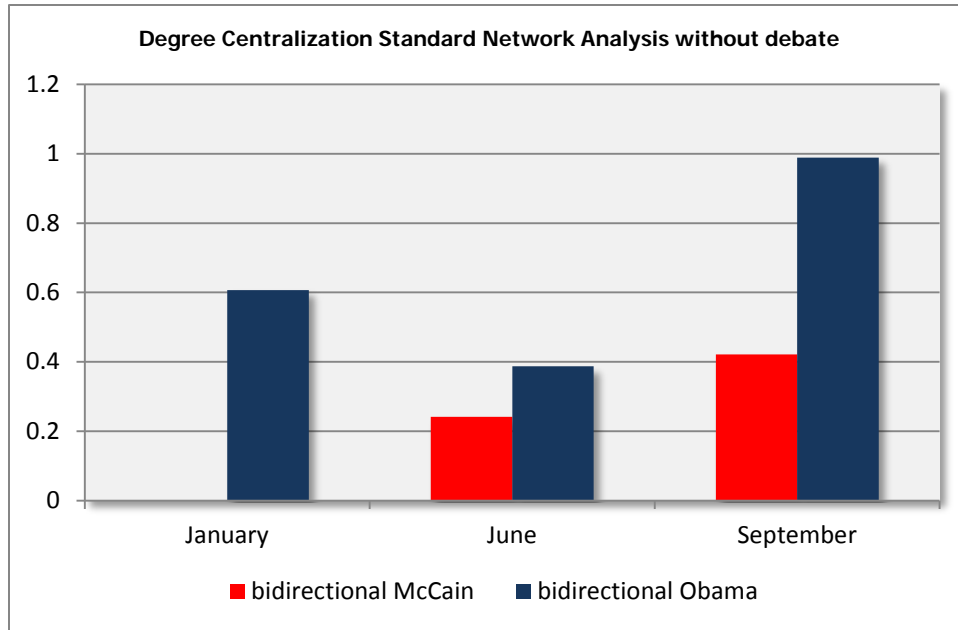


Figure 14. Degree Centralization resulting from Semantic Network Report without debate

When the measurements are compared over time, the differences between Obama’s and John McCain’s semantic networks become more obvious. The degree centralization in both bi- and unidirectional networks are different and for the bidirectional networks the difference is most significant.⁵⁰ The clustering coefficient results suggest that Obama’s semantic network (and consequently his narrative) was the more cohesive of the two.

⁵⁰ As noted earlier, the reason why there are no results for McCain in the January time frame is because of the lack of communication events by McCain.

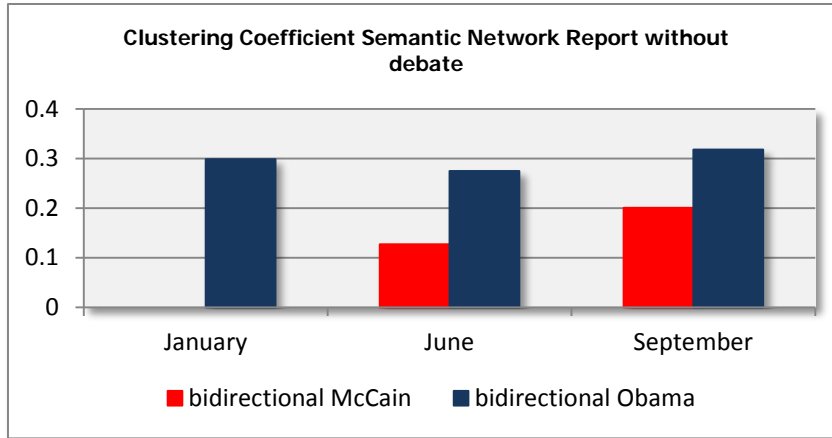


Figure 15. Clustering Coefficient resulting from Semantic Network Report without the debate

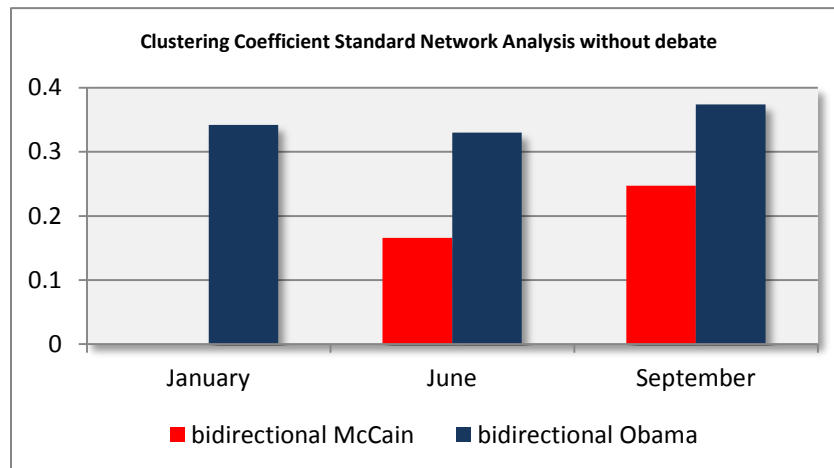


Figure 16. Clustering Coefficient resulting from Standard Network Analysis without debate

Degree centralization (Figures 17 and 18) is one measurement that seems to show a significant difference between both networks involved, with and without debate. Without the debate, the differences are substantial. When the debate is included, the differences decrease. Looking at the difference in the clustering coefficient (Figures 19 and 20) over time is also interesting. Whether the debate is included or not, Obama's speeches appear to be more cohesive although McCain's speeches were far more cohesive in September than they were in June.

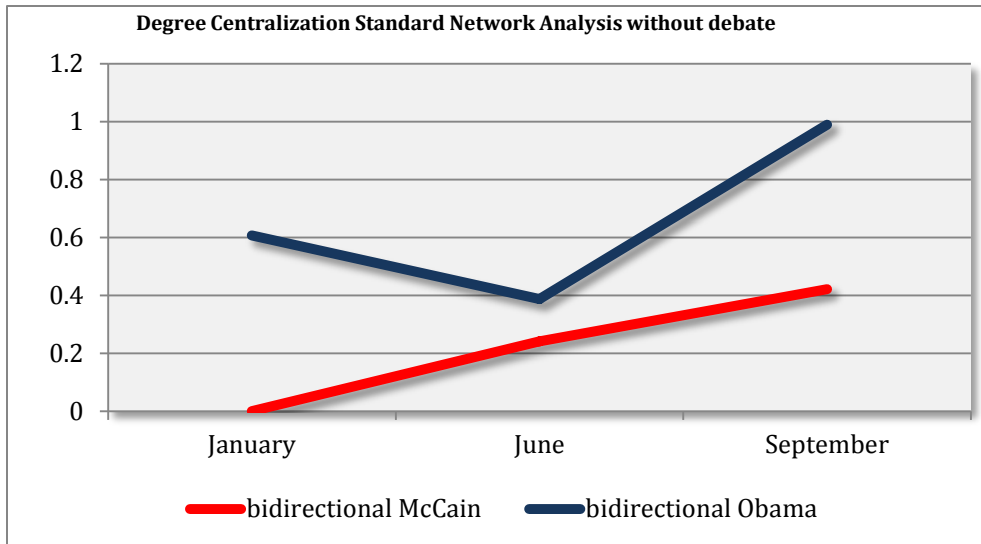


Figure 17. Degree Centralization without debate

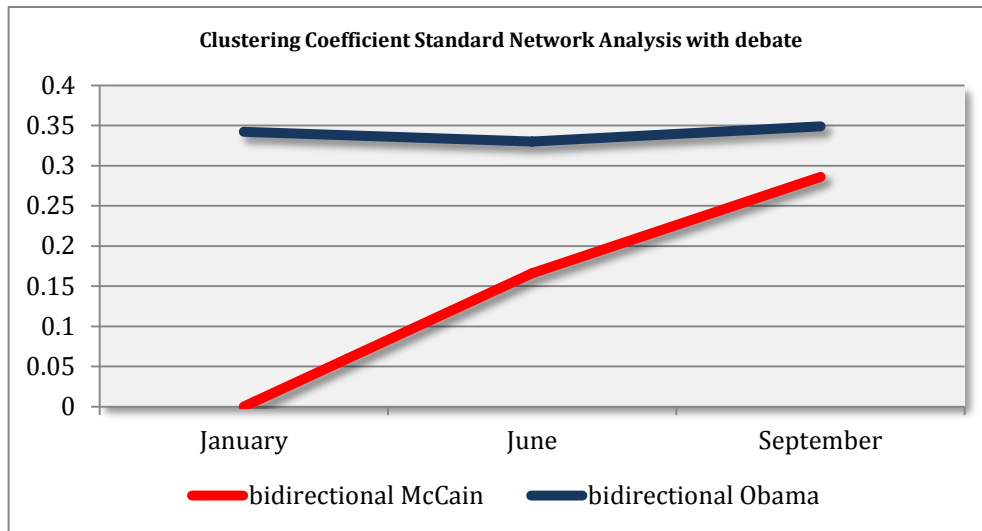


Figure 18. Clustering Coefficient with debate

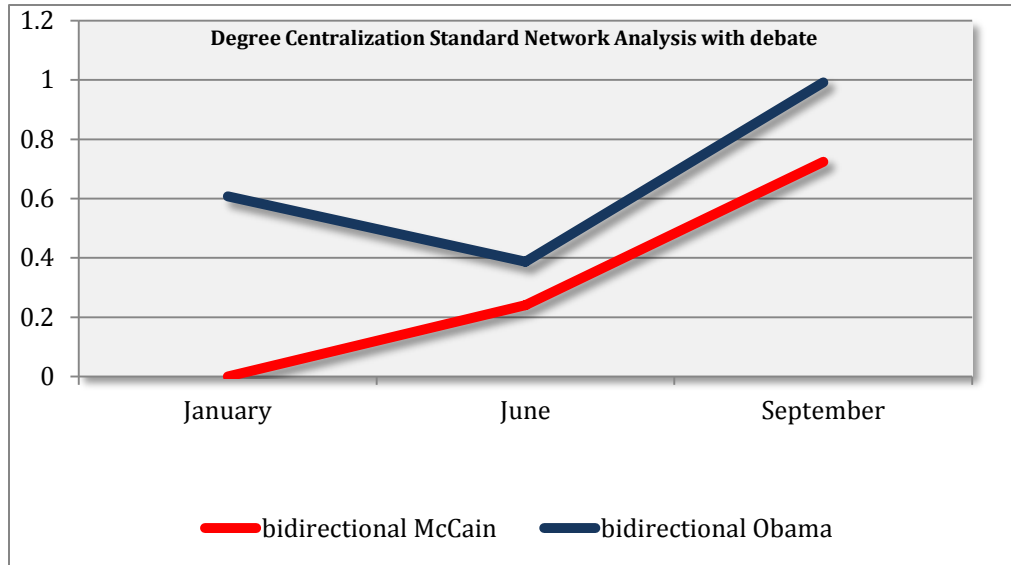


Figure 19. Degree Centralization with debate

Overall it seems reasonable to state that the Obama narrative shows strong evidence that the differences between both networks with regard to their degree centralization, their clustering coefficient, their variation in symbols and ordinary words, as well as buzz words, are positively associated with the candidate's approval levels, suggesting that, at least in part, Obama's narrative resonated more with American voters than did McCain's.

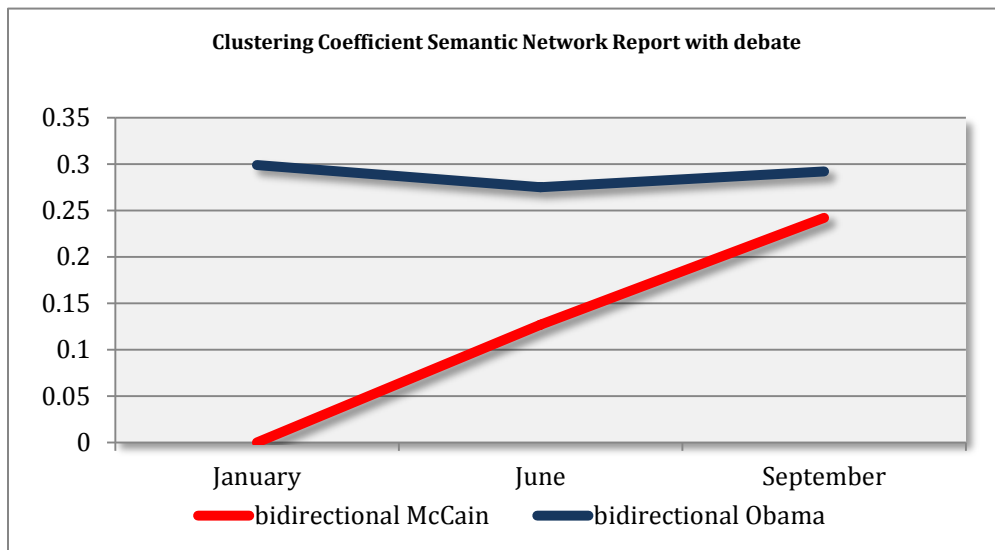


Figure 20. Clustering Coefficient with debate

As mentioned above, this chapter was only intended to show the results generated by the coding of verbal communication events. The debate's nature, having some similarities with the traditional speaking events, but also showing nonverbal aspects, such as the interaction, aggressiveness, or reactivity, sets it apart from the pure verbal communication, if something like this existed at all. Nevertheless, the closeness of the debate's action to the verbal communication led to its integration and as a result the findings of the verbal communication have been altered, respectively. The following sections examine the integration of nonverbal communication into the overall networks.

2. SNA: Verbal and Nonverbal Communication Networks

In the previous section it was noted that in the January time frame John McCain had no communication activities, but did not suffer under any form of great disparity of approval rates. Indeed, his approval ratings were actually higher than Obama's in January. This changed over the course of the campaign, but it indicates that McCain already had a well-developed narrative at the time. To compare this, the nonverbal communication networks for McCain and Obama were coded, analyzed, and compared. This comparison shows that both nonverbal networks look similar and have similar values for critical measures, such as centralization and clustering. The missing information still is how this data combines with the verbal communication. Does it improve the values and does it increase or reduce differences between both inclusive networks?

Obama	McCain
Standard Network Analysis	
Betweenness 0.140	Betweenness 0.190
Degree Centralization 0.152	Degree Centralization 0.151
Clustering Coefficient 0.134	Clustering Coefficient 0.127
Semantic Network Report	
Clustering Coefficient 0.108	Clustering Coefficient 0.074
Number of concepts 819	Number of concepts 813
Symbol 147	Symbol 135
Symbol Percent 17.950	Symbol Percent 16.160

Table 6. Obama and McCain nonverbal networks' metrics

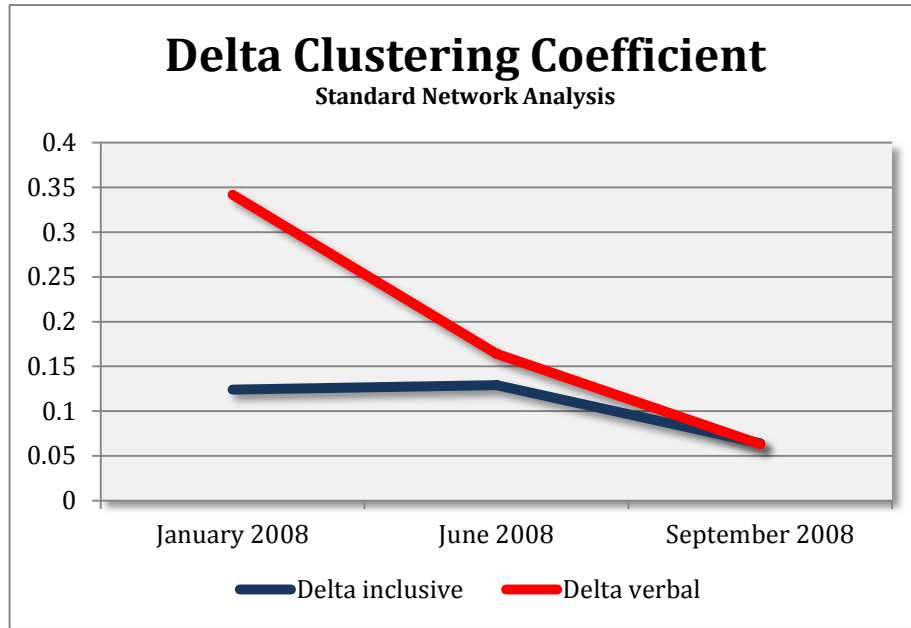


Figure 21. Clustering Coefficient delta between Obama and McCain

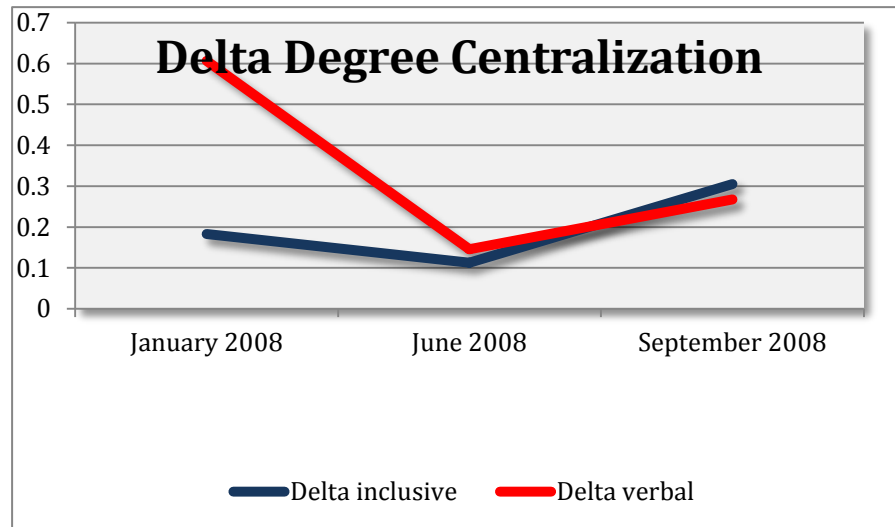


Figure 22. Degree Centralization delta between Obama and McCain

The January time frame is particularly interesting since Obama competes in this time with a historical and already existing network and adds his verbal activity to it. It turns out that significant differences between the two networks were present in January although the differences are not as great as before. For example, the difference (i.e.,

delta) between the clustering coefficient scores (Figure 21) of the two candidates' sets of semantic networks drops from 0.342 to 0.124 and the difference in degree centralization drops from 0.607 to 0.183 (see Figure 22). In other words, by including the nonverbal semantic networks with the verbal semantic networks, the degree to which Obama's semantic network is more centralized and clustered than McCain's is less than it is when only comparing the verbal semantic networks of the two candidates. Nevertheless, Obama's semantic networks were more centralized and clustered than were McCain's throughout the campaign, suggesting that semantic networks that are more centralized and cohesive may be more effective than less centralized and cohesive semantic networks. Of course, as noted above, the difference between the candidates' narratives is almost certainly not the only factor in determining an election's outcome. The candidates' age, sex appeal, party affiliation, running mates, the state of the economy, and so on all have impact on the election's outcome. Nevertheless, the results of this analysis are suggestive.

B. ANSWERING THE RESEARCH QUESTION

This thesis's research question was whether a verbal and nonverbal communication in political competition could be captured and analyzed using social network analysis. And while the process of prepping the text proved to be extensive and required significant attention to detail, the generation of semantic networks and their subsequent analysis using SNA was not only possible but it also provided interesting insights into the 2008 Presidential election. These insights, namely the comparison of semantic network topography, carried directly into the primary topic at hand: the battle of narratives. The addition of nonverbal communication such as beliefs, values, and actions provided another key element to examining this topic. Thus, the answer is yes, verbal and nonverbal data can be used to generate semantic networks that can be analyzed using the tools of social network analysis and capture differences between competing networks if such differences exist.

C. VALIDATING THE HYPOTHESIS

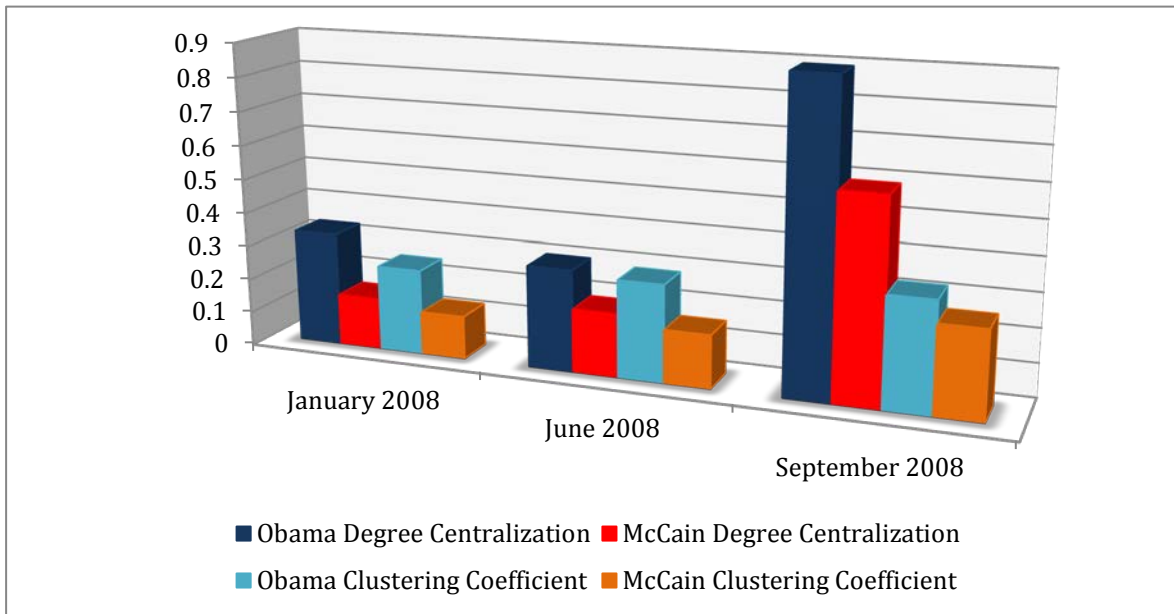


Figure 23. Degree Centralization and Clustering Coefficient in comparison

This thesis's primary hypothesis was this: Are semantic networks that are more cohesive and centralized more effective than semantic networks that are less cohesive and centralized. To test this hypothesis, the verbal communication data of two presidential candidates from three time periods were used to generate a series of semantic networks. These networks were then enhanced by including nonverbal communication. Both sets of networks were then analyzed using SNA, comparing their level of centralization and cohesiveness to the approval ratings of the candidates. It was discovered that Barack Obama's verbal and nonverbal communication networks were more centralized and more cohesive than were John McCain's over the course of the campaign and that during this time Obama generally enjoyed higher approval ratings than did McCain. It is also true that Obama's lead increased over time and he was eventually elected President, suggesting that his semantic network was more effective than McCain's.⁵¹

⁵¹ This is not to suggest that the only determining factor in the outcome were the two candidates' verbal and nonverbal communications. Other factors, many of which were identified earlier, undoubtedly came into play as well.

Furthermore, it appears likely that the measurements' accuracy increases when the semantic networks include both verbal and nonverbal communication. It provides higher explanatory and prediction value than a network that is solely based on the coding of verbal communication. This was demonstrated using the January time frame when McCain had no major communication events and Obama did, but McCain began January with a slight lead over Obama. Moreover, when the nonverbal communications were included in the analysis, the differences between Obama and McCain's metrics declined and perhaps better indicated that effectiveness of their competing narratives.

IV. OPEN QUESTIONS AND WAY AHEAD

The case study has focused on the political competition between two candidates. Before analyzing a more complex scenario, it might be necessary to integrate current personal action into the narrative as nonverbal communication. Due to its high level of complexity, for this thesis it was impossible to categorize all individual nonverbal communication, such as appearance, gesture, mimic, and other physical attributes into the data. A sociological and psychological set of data-categorization that would lead to adequate coding and network generation would have to be developed in advance in order to do something like this. It would be interesting to apply the approach outlined in this thesis in a cross-cultural setting. This would entail identifying semantic meanings of communication across culturally different audiences, which would be no easy task.

In the case study analyzed in this thesis, two individual communicators engaged with an audience to make their cases. In a more complex situation, it might be necessary to identify specific communicators for specific semantic concepts, e.g., a military leader talking about religious issues might be inadequate due to the misfit of verbal and nonverbal communication. Identification of the different effects of different communicators and channels of communication on the semantic meaning could be analyzed. In this case study, McCain may have been perceived as much more adequate and reliable with regard to the semantic concept *military* while in the tweeting, emailing, and grass-roots-fundraising Obama might have been perceived more adequate for the concept *information_technology*. The basic questions have been answered by supporting the hypothesis, but the addition of real world complexity has yet to be done.

PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

- AskSam. *askSam making information useful - eBooks and Databases*. 2011. <http://www.asksam.com/ebooks/releases.asp?file=Obama-Speeches.ask> (accessed 11 30, 2011).
- Barbasi, Albert-Laszlo. *Bursts: The Hidden Patterns Behind Everything We Do*. New York: Penguin Group, 2010.
- . *Linked - The New Science of Networks*. Cambridge: Perseus Publishing, 2002.
- Brafman, Ori, and Rod A. Beckstrom. *The Starfish And The Spider - The unstoppable power of leaderless organizations*. New York: Penguin Group, 2006.
- Campbell, Nick. "How Speech Encodes Affect and Discourse Information - Conversational Gestures." In *Fundamentals of Verbal and Nonverbal Communication and the Biometric Issue*, by Anna Espositos, Maja Bratanic, Eric Keller and Maria Marinaro, 103-114. Amsterdam: IOS Press, 2007.
- Carley, Kathleen, and David Kaufer. "Condensation Symbols: Their Variety and Rhetorical Function in Political Discourse." *Philosophy and Rhetoric* 26, no. 3 (1993): 201-226.
- Carley, Kathleen, and Michael Palmquist. "Extracting, Representing, and Analyzing Mental Models." *Social Forces* (The University of North Carolina Press) 70, no. 3 (March 1992): 601-636.
- Carley, Kathleen. "Coding Choices for Textual Analysis: A Comparison of Content Analysis and Map Analysis." *Sociological Methodology* 23 (1993): 75-126.
- Carley, Kathleen, Dave Columbus, Mike Bigrigg, and Frank Kunkel. "CASOS Automap Software." *Automap User's Guide 2010*. Pittsburgh: Carnegie Mellon University, June 15, 2011.
- CASOS, Computational Analysis Of Social And Organizational Systems. CASOS Automap. 2011. <http://www.casos.cs.cmu.edu/projects/automap/> (accessed September 01, 2011).
- CASOS, Computational Analysis of Social and Organizational Systems. Computational Analysis of Social and Organizational Systems. 2011. <http://www.casos.cs.cmu.edu/projects/ora/index.php> (accessed September 15, 2011).
- CASOS; Computational Analysis of Social and Organizational Systems. CASOS. 2012. <http://www.casos.cs.cmu.edu/projects/automap/> (accessed 11 15, 2011).

- . CASOS. 2012. <http://www.casos.cs.cmu.edu/terrorism/projects.php> (accessed 11 15, 2011).
- Christakis, Nicholas A., and James H. Fowler. *Connected. 2nd Ebook Edition January 2011*. New York: Back Bay Books / Little, Brown and Company, 2009.
- Cline, Lawrence E. "Pseudo Operations And Counterinsurgency: Lessons From Other Countries." <http://www.carlisle.army.mil/ssi>. Strategic Studies Institute, June 2005.
- CNN Cable News Network. "CNN Election Center." CNN Politics.com. 2008.
- Daniel, Donald C., and Katherine L. Herbig. "Propositions on Military Deception." In *Strategic Military Deception*, by Donald C. Daniel and Katherine L. Herbig, 3-30. New York: Pergamon Press, 1979.
- De Nooy, Wouter, Andrej Mrvar, and Vladimir Batagelj. *Exploratory Social Network Analysis with Pajek*. New York: Cambridge University Press, 2005.
- Democratic National Corporation. Democrats.org. 2012. <http://www.democrats.org/> (accessed 01 22, 2012).
- Diesner, Jana, and Kathleen M. Carley. AutoMap 1.2 - Extract, analyze, represent, and compare mental models from texts. CASOS Technical Report, Pittsburg: Carnegie Mellon University , 2004.
- Direct Democracy - Geschichte Schweiz. Direct Democracy Switzerland's Referendums. <http://direct-democracy.geschichte-schweiz.ch/switzerlands-system-referendums.html> (accessed 03 07, 2012).
- Dubner, Stephen J. *Freakonomics*. 02 16, 2012. <http://www.freakonomics.com/2012/02/16/how-biased-is-your-media/> (accessed 02 28, 2012).
- Everton, Sean F. *Disrupting Dark Networks*. Monterey: pre published version, 2012.
- . *Tracking, Destabilizing and Disrupting Dark Networks with Social Network Analysis*. Monterey: Naval Postgraduate School, 2010.
- . Network "Topography, Key Players and Terrorist Networks." *Connections* 31(1) 2012:1-4..
- Flockhart, Trine. "Towards a strong NATO narrative: From a 'practice of talking' to a 'practice of doing'." *International Politics*, www.palgrave-journals.com/ip/ (Ltd., Macmillan Publishers) 49, no. 1 (01 2012): 78-97.

- Fowler, C. A., and R. F. Nesbit. "Tactical Deception in Air-Land Warfare." *Journal of Electronic Defense* 18, no. 6 (June 1995): 37-44 and 76-79.
- Franzosi, Roberto. *Quantitative Narrative Analysis*. Los Angeles: SAGE Publications, 2010.
- Goffman, Erving. *Behavior in Public Places - Notes On The Social Organization Of Gatherings*. New York: The Free Press, 1963.
- Groseclose, Tim. Tim Groseclose . *Word Press*. <http://www.timgroseclose.com/famous-pqs/> (accessed 03 02, 2012).
- Groseclose, Tim, and Jeff Milyo. *A Measure of Media Bias*. Los Angeles, 12 2004.
- . *A Measure of Media Bias*. Chicago, Los Angeles, 09 2003.
- Heuer, Richards J. "Cognitive Factors in Deception and Counterdeception." In *Strategic Military Deception*, by Donald C. Daniel and Katherine L. Herbig, 31-69. New York: Pergamon Press, 1979.
- Hobbs, Reginald L. *Creating the Semantic Battlespace: Narrative Structure for Information Fusion*. Research, Computational & Information Sciences Directorate, Army Research Laboratory, Adelphi: U.S. Army, 2006.
- Hornby, A S, A P Cowie, and A C Gimson. *Oxford Advanced Learners Dictionary of Current English*. Berlin: Cornelsen and Oxford University Press, 1984.
- Jajko, Walter. "Deception: Appeal for Acceptance; Discourse on Doctrine; Preface to Planning." *Comparative Strategy* 21, no. 5 (2002): 351-363.
- Knoke, David, and Song Yang. *Social Network Analysis - Second Edition*. 2nd Edition. Sage Publications Inc., 2008.
- Latimer, John. *Deception in War*. New York: Overlook Press, 2001.
- Leadership Central. *Expectancy Theory of Motivation*. 2010-2012. <http://www.leadership-central.com/expectancy-theory-of-motivation.html#axzz1pW7k5AJg> (accessed 02 13, 2012).
- Leadership-Central.com. Leadership-central.com Expectancy Theory of Motivation - Victor Vroom . 2012. <http://www.leadership-central.com/expectancy-theory-of-motivation.html#axzz1pW7k5AJg> (accessed 02 13, 2012).
- Lippmann, Walter . *Public Opinion*. New York: Harcourt, Brace and Company, 1922.

- McCain, John. McCain Palin. 2008.
<http://web.archive.org/web/20081103005023/http://www.johnmccain.com/Calendar/> (accessed 01 20, 2012).
- McGee, Michael Calvin. "The "Ideograph": A Link Between Rhetoric and Ideology." *The Quarterly Journal of Speech*. 1. Vol. 66. EBSCO Publishing, 02 1980.
- Mwihaki, Alice. "Meaning as use: A functional view of Semantics and Pragmatics." *Swahili Forum* 11 (2004): 127-139.
- Nye, Joseph S. . *Soft Power - The Means to success in World Politics*. New York: Perseus Book Group, 2004.
- OnTheIssues & the SpeakOut Foundation. OnTheIssues. 1999-2008.
http://www.issues2000.org/John_McCain.htm (accessed February 23, 2012).
- Pescosolido, Bernice A. and Giorgianna, Sharon. "Durkheim, Suicide, and Religion: Toward a Network Theory of Suicide." *American Sociological Review* Vol. 54, No. 1 (February 1989): 33-48.
- ProCon.org. ProCon.org 2008 Election. 03 10, 2009.
<http://2008election.procon.org/view.resource.php?resourceID=1568#mccain> (accessed 12 17, 2011).
- Republican National Committee. GOP.com. 2012.
<http://www.gop.com/index.php/issues/issues/> (accessed February 2012).
- Schelling, Thomas C. *Arms And Influence*. London: Yale University Press, 2008.
- Schulz von Thun, Friedemann. *Miteinander Reden 1 Stoerungen und Klaerungen*. Hamburg: Rowohlt, 1993.
- .—— *Miteinander Reden 2 - Stile, Werte und Persoenlichkeitsentwicklung*. Hamburg: Rowohlt, 1993.
- Speaks, Jeff. "Theories of Meaning." *The Stanford Encyclopedia of Philosophy (Summer 2011 Edition)*. Edited by Edward N. Zalta. San Francisco, 06 21, 2011.
- Strauss, Claude-Levi. *Structural Anthropology. Translated by Claire Jacobson and Brooke Grundfest Schoepf*. Perseus Books, 1963.
- StudentNewsDaily. StudentNewsDaily.com. 2005.
<http://www.studentnewsdaily.com/conservative-vs-liberal-beliefs/> (accessed March 07, 2012).

- Times, The New York. *The New York Times - Election 2008*. 12 22, 2011.
<http://elections.nytimes.com/2008/president/debates/transcripts/first-presidential-debate.html> (accessed 01 5, 2012).
- Uzzi, Brian. “The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect.” *American Sociological Review* 61(4) 1996: 674-698.
- Uzzi, Brian and Spiro, Jarrett. “Collaboration and Creativity: The Small World Problem.” *American Journal of Sociology* 111(2): 447-504.
- Weber, Robert Philip. *Basic Content Analysis*. Second Edition. London: SAGE Publications, 1990.
- Wei, Wei, Juergen Pfeffer, Jeffrey Reminga, and Kathleen M. Carley. Handling, *Weighted, Assymmetric, Self-Looped, and Disconnected Networks in ORA*. Technical report, Center for the Computational Analysis of Social and Organizational Systems, Pittsburgh: Carnegie Mellon University, 2011.
- Wikipedia. Wikipedia. 12 03, 2011.
http://en.wikipedia.org/wiki/Barack_Obama_presidential_campaign,_2008 (accessed 12 03, 2011).
- . Wikipedia. 02 10, 2012.
http://en.wikipedia.org/wiki/Elections_in_the_United_States (accessed 02 10, 2012).
- . Wikipedia. 03 04, 2012. http://en.wikipedia.org/wiki/Referendum#United_States (accessed 03 04, 2012).
- Zunshine, Lisa. *Why We Read Fiction Theory of Mind and the Novel. Theory and Interpretation of Narrative Series*. Edited by James Phelan and Peter J. Rabinowitz. Ohio: The Ohio State University, 2006.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX A DATA OF NETWORKS

Harunk Obama

Standard Network Analysis						
Time Series	Network	Dating	Programation	Dimension	Degree Centrality	Characteristics Path Length
2008	Networks in network	0.006	0.007	0.14	0.133	4.362
January 2008	Individuals in network	0.005	0.006	0.097	0.134	0.114
June 2008	Individuals in network	0.004	0.005	0.064	0.1	3.503
September 2008	Individuals in network	0.004	0.003	0.044	0.3	3.764
January 2009	Individuals in network	0.011	0.01	0.128	0.207	3.316
June 2009	Individuals in network	0.006	0.005	0.131	0.237	3.313
September 2009	Individuals in network	0.004	0.007	0.114	0.243	3.784

John Mc Cain

Standard Network Analysis						
Time Series	Network	Dating	Programation	Dimension	Degree Centrality	Characteristics Path Length
2008	Networks in network	0.004	0.004	0.16	0.131	4.006
January 2008	Individuals in network	0.004	0.004	0.133	0.137	0.117
June 2008	Individuals in network	0.004	0.003	0.107	0.136	4.186
September 2008	Individuals in network	0.004	0.003	0.107	0.206	3.213
January 2009	Individuals in network	0	0	0	0	0
June 2009	Individuals in network	0.005	0	0.264	0.241	3.662
September 2009	Individuals in network	0.004	0.003	0.193	0.234	3.266

* Individuals in the same network do not overlap and verbal data are combined to a single semantic network.

Semantic Network Report

Charactering Coefficient	Number of words	Ordinary Words	Sum Word	Symbol	Symbol Percent
0.102	216	134	43	147	17.026
0.104	1143	131	33	146	11.236
0.108	1343	150	57	133	10.636
0.17	2424	243	113	146	11.046
0.106	371	27	17	143	13.106
0.135	1051	117	24	133	11.336
0.163	1653	154	71	146	11.746

Semantic Network Report

Charactering Coefficient	Number of words	Ordinary Words	Sum Word	Symbol	Symbol Percent
0.094	213	162	43	133	12.206
0.11	1446	126	29	103	10.736
0.107	1741	247	97	106	11.306
0	0	0	0	0	0
0.137	633	164	20	174	14.006
0.143	1724	360	74	133	12.116

Table 7. Data of semantic networks without nonverbal data compared to those with nonverbal data (inclusive)

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX B DATA GENERATION AND PRESENTATION

Visualization

The SNA of the semantic networks can easily be presented in graphics and tables, but the interpretation of the data needs a closer look and, thus, will be added to most data in tables and graphics. All graphical representations had been done by highlighting nodes in a specific way. For example, the node sizes vary in terms of eigenvector centrality, which is a measure that is based on the assumption “that ties to central actors are more important than ties to peripheral actors and [it] thus weights each actor’s summed connections to others by their (i.e., the others) centrality scores.”⁵² The choice to represent nodes this way resulted from the understanding that meaning of semantic concepts depends on the context. That is, if semantic concepts are connected to central nodes, that supports the understanding that they are in an already important or in some way central context. Eigenvector centrality together with degree and betweenness centrality will be used to help identify central actors of networks, which is what the semantic analysis in this case tries to achieve.⁵³ This assumption is illustrated by the size of the concepts, Barack_Obama and John_McCain, which are usually greater than less central semantic concepts (e.g., see Table 1). Another way to visualize the networks is to color code nodes based on how they cluster (or don’t cluster) together. For this we use a Newman Group clustering algorithm, which has been shown to do a good job at identifying clusters within more complex networks. The algorithm detects the likelihood that a dense community, with less dense links to the outside of itself, is separated from the rest of the complex network. The groups that result from this analysis are likely to indicate a semantic context, which can be seen, such as Newman groups with “more ties within and fewer ties between groups than would be expected in a random graph of the

⁵² Sean F Everton, *Disrupting Dark Networks*, pre-published version as personal deliverable from Prof. Everton to the author of this thesis (Monterey, 2012), 358.

⁵³ Sean F Everton, *Disrupting Dark Networks*, pre-published version as personal deliverable from Prof. Everton to the author of this thesis (Monterey, 2012), 225.

same size with the same number of ties.”⁵⁴ That represents a specific kind of meaning for related semantic concepts, e.g., financial_loss used in context with Health_care, family, housing_market and then probably belonging to the same group. Finally, an additional technique used to improve the graphics’ clarity was to hide isolated nodes and nodes that occurred only once and less, or twice and less.. On other occasions, also for reasons that should help improve the visual clarity different layouts, have been chosen.

Unidirectional vs bidirectional networks

AutoMap offers the opportunity to generate either unidirectional or bidirectional networks. The difference is that links point in one (uni) or two (bi) directions. This thesis researcher coded the networks both ways in order to be able to compare the outcomes. From a semantic point of view the bidirectional network is more likely to represent semantic meaning. While reading direction (i.e., left to right) and listening direction (i.e., past to present) is unidirectional, the understanding and interpretation of the written and spoken word is not. There is no significant difference in understanding whether someone says or writes *the perfect choice is John McCain* or *John McCain is the perfect choice*. In terms of coding semantic networks, it does, however, make a difference. For example, in the first example, *John McCain* would not be linked to *perfect choice* in a unidirectional network, but would in the second. Or, to take another example, compare *the perfect choice is John McCain and Obama fails to while Obama fails John McCain is the perfect choice*. With a window size of 2 concepts and the DL deleting the words *is*, *the*, *while*, and *and*, in a unidirectional network the concept “*John McCain*” would be connected with *Obama* in the former, or *perfect* in the latter sentence configuration. In the bidirectional network, he would be connected to either *perfect*, *choice*, *obama*, *fails* or *Obama*, *fails*, *perfect*, *choice*. Clearly, in a bidirectional network, more of a semantic concept’s surrounding context is taken into account. Therefore, network representation of the semantics involved improves with bidirectional coding.

⁵⁴ Sean F Everton, *Disrupting Dark Networks*, pre-published version as personal deliverable from Prof. Everton to the author of this thesis (Monterey, 2012), 360.

The Semantic Network Report in ORA

This thesis research ran two of ORA's reports, the Standard Network Analysis and Semantic Network reports, to obtain relevant network metrics. ORA's Semantic Network Report generates 4 different network outputs listing the concepts that appear in 25%, 50%, 75%, and 100% of the loaded networks (i.e., the 100% network only lists the concepts that appear in all of the loaded networks, which can be interpreted as the relatively most important concepts).⁵⁵ The report also calculates a clustering coefficient similar to the Standard Network Analysis Report. This report, however, calculates the coefficient for each of the four networks separately and, then, provides the average of these coefficients as the final output. This leads to different estimates in the coefficient.

The semantic network report also generates a list of concepts grouped with reference to their types within the context. Among others, there are ordinary words (low degree centrality, low betweenness, and low consensus), buzzwords (low degree centrality, high betweenness, and low consensus), and symbols (high degree centrality, high betweenness, and high consensus).

If separate speeches in any given time frame were not combined, a visual comparison of Obama and McCain's 75% bidirectional networks provides analytical advantages over the other three. Specifically, the 75% networks are less complex than the 25% and 50% networks, but they provide a sufficient number of nodes for this analysis. The 25% and 50% contain a significantly greater number of nodes than the 75% and 100% nodes. The sheer number of nodes, however, makes a visual interpretation of the network difficult whereas the 100% network is simply too sparse for meaningful analysis. Consequently, this thesis research initially compared the 75% networks, but finally formed a union of the networks in the specific time frame and analyzed the respective 100%, while hiding isolates and less often reoccurring concepts for visual clarity.

⁵⁵ See also the help section in ORA "semantic network."

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
Ft. Belvoir, Virginia
2. Dudley Knox Library
Naval Postgraduate School
Monterey, California