

Connectors, Mavens, Salesmen and More: An Actor-Based Online Social Network Analysis Method Using Tensed Predicate Logic

Joshua S. White, PhD

Department of Computer Science
State University of New York Polytechnic Institute

Jeanna N. Matthews, PhD

Department of Computer Science
Clarkson University

ASE SocialInformatics2014
December 16, 2014

Outline

Initial Motivation	3
Problem Questions	4
Actor Descriptions	6
Actor Identification Example: Liaison	7
Established Dataset	12
Actor Identification Example: Results	13
Conclusions	14
Future Work	15
Contact	17
Questions	18
Suplimental Material	19

Initial Motivation

Partially inspired by Gladwell's book, *The Tipping Point* [1], in which he discusses how life can be thought of as an epidemic. Some criticism exists as to Gladwell's rigor, however for our use it is about inspiration and motivation not accuracy.

The Books Key Points “for our purposes”

- Actors (Connectors, Mavens, Salesmen).
- Information spreads like disease.
- Ideas reach a tipping point (critical mass).

Let's Face It - Social Networks Are Fun

- We are a social species, that enjoy communicating and self adulation.

Problem Questions

- Are there information security applications for social network data-mining?
 - ✓ Can we detect malicious social network use?
 - ✓ Can we analyze the spread of a major malware campaign?
 - ☆ Can we detect phishing in near-real-time
- Can we determine how information spreads on these networks?
 - ☆ Can we determine if a user is unique?
 - ★ Is there a way of classifying users based on actor types?
 - ☆ Can we determine who the opinion leaders or influencers are?

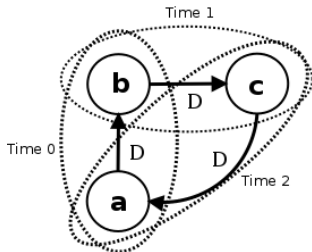
Actor Descriptions

- Isolate (Developmental Psychology) [27]
- Connector (Tipping Point) [1]
 - Star (Small World Problem) [26]
 - Bridge (The Hidden Organizational Chart) [2]
 - Liason (The Hidden Organizational Chart) [2]
- Maven (Tipping Point) [1]
- Salesmen (Tipping Point) [1]

Actor Identification Example: Liaison

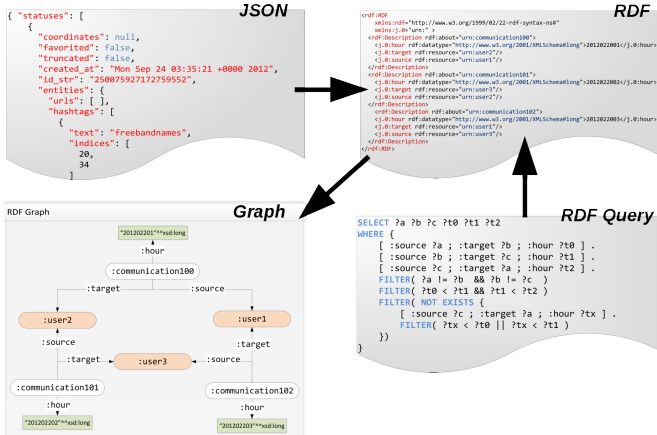
- Liaison: (Noun not Verb)
 - A person (b) who connects party 1 (a) and party 2 (c) through a requested introduction.
 - Like requesting for a first level contact on LinkedIn to introduce you to someone in their network
- Not all social networks have a special features like LinkedIn, we need to derive this relationship... Time is important!
- Previous methods did not take event sequence into account

Actor (b): Liaison - Logical



For the graph (a,b,c), It will at some time be the case that edge (a,b) exists and It will at some time be the case that edge (b,c) exists and It will at some time be the case that edge (c,a) exists and It has always been the case that edge (c,a) did not exist.

Actor Identification Example: Liaison



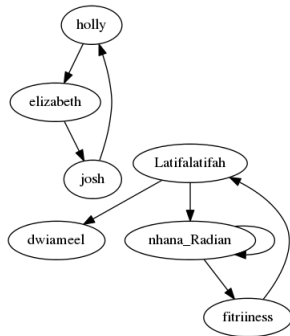
Actor Identification Continued

```
There were 2 liaisons found
#####
The Following Liaison (b) relationship was found:
-----
| (a) is: holly | (b) is: elizabeth | (c) is: josh |
-----

Slot      Communication      Edge      Hour
-----
t0 | First Communication | (a) --> (b) | 2012022001
t1 | Second Communication | (b) --> (c) | 2012022002
t2 | Third Communication | (c) --> (a) | 2012022003
-----

The Following Liaison (b) relationship was found:
-----
| (a) is: Latifalatifah | (b) is: nhana_Radian | (c) is: fitriiness |
-----

Slot      Communication      Edge      Hour
-----
t0 | First Communication | (a) --> (b) | 2012021904
t1 | Second Communication | (b) --> (c) | 2012021912
t2 | Third Communication | (c) --> (a) | 2012021922
-----
```

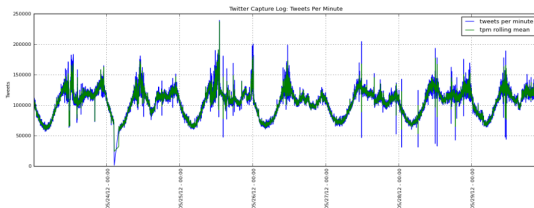


Actor Identification Sample Logics

Actor Type	Logic
Isolate	$\forall a [Isolate(a) \leftrightarrow \mathbf{G}[\forall b \neg edge(a,b)]]$ (1)
Connector: Star	$\forall a (Star(a) \leftrightarrow \neg \exists b (cent(b) > cent(a)))$ (2)
Connector: Bridge	$\forall b \left(Bridge(b) \leftrightarrow \exists c, e \left(\begin{array}{l} c \neq e \wedge edge'(b,c) \wedge edge'(b,e) \wedge \\ \forall x (edge'(b,x) \rightarrow (x = c \vee x = e)) \wedge \\ cent(b) > cent(c) \wedge cent(b) > cent(e) \end{array} \right) \right)$ (3)
Connector: Liaison (Prospective)	$\forall a, b, c (Liaison(a,b,c) \leftrightarrow \mathbf{F}(edge(a,b) \wedge \mathbf{F}(edge(b,c) \wedge \mathbf{F}(edge(c,a) \wedge \mathbf{H}\neg edge(c,a))))$ (4)
Connector: Liaison (Retrospective)	$\forall a, b, c (Liaison(a,b,c) \leftrightarrow \mathbf{P}(edge(c,a) \wedge \mathbf{H}\neg edge(c,a) \wedge \mathbf{P}(edge(b,c) \wedge \mathbf{P}edge(a,b))))$ (5)
Maven	$\forall m (Maven(m) \leftrightarrow \exists i, g \mathbf{F}(edge(i,m, msg) \wedge \mathbf{F}(edge(g,m) \wedge \mathbf{F}(edge(m,g, msg))))$ (6)
Salesman	$\forall s (Salesman(s) \leftrightarrow \exists i, g \mathbf{F}(edge(i,s, msg) \wedge \mathbf{F}(edge(s,g, msg) \wedge \mathbf{H}\neg edge(g,s))))$ (7)

Established Dataset

- In 2012 we collected 165 TB of Twitter Data (Uncompressed)
 - 175 Days Collected, 147 Full Days
 - * Estimated 45 Billion Tweets
 - Estimates place total Twitter traffic at 175 million tweets/day-2012
 - Daily collection rates between 50% and 80% of total traffic



Actor Identification Example: Results

- Remember those pretty plots from earlier?
- We take our entire dataset and filter it for 31 days between February 20th and March 20th, and for only #KONY2012 related Tweets

Query	Number of Records	Approach	Time
Edges	1,070,910	Conversion of CSV to RDF using Python	18 sec
Isolates	48,060	RDF file procd. w/Jena (8 thr.)	6.285 min
Liaisons	37,530	RDF file procd. w/RDFLib (1 thr.)	13.151 hr
Mavens	1,790	RDF file procd. w/RDFLib (8 thr.)	35.854 min
Salesmen	391	Serialized CSV-RDF procd. w/RDFLib (1 thr.)	13.159 hr
		Serialized CSV-RDF procd. w/RDFLib (8 thr.)	36.762 min

Conclusions

- We aimed to answer the following subset of questions when we started this portion of our work:
 - Can we come up with a way of classifying users based on actor types?
 - Can we determine who the opinion leaders or influencers are?
 - Can we determine how information spreads on these networks?

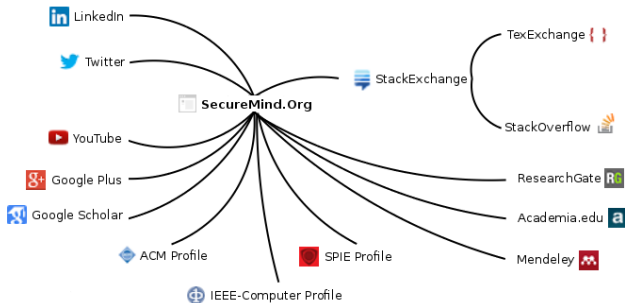
Future Work

- We have established a more permanent test facility and dataset location in the COSI (Clarkson Open Source Institute)
- We are pursuing the semantic side of social network analysis
 - Currently only one true SNA semantic ontology exists that is openly available and it's only on paper.
 - We are planning on rolling both the actor and event analysis into one approach which will be part of a new ontology
- We have grown our team to include a number of individuals affiliated with multiple institutions.
- We recently finished a project using machine learning to process URLs and web-pages on-mass to detect Phishing
- We recently finished a project that analyzed Twitter accounts for duplication, or single ownership

References

- [1] Gladwell, M. (2000). "The tipping point". Boston: Little, Brown and Company.
- [2] Allen, H. T. (1976). "Communication networks - The hidden organizational chart". The Personnel Administrator, 21(6), 31-35.
- [3] Arun Phadke, James Thorp. (1978). "Contracts and Influence". Social Networks, 1:1-48
- [4] Davis, A., et. al. (1941). "Deep South: A social Anthropological Study of Caste and Class". University of Chicago Press. Chicago, Ill.
- [5] Freeman, L. (2004) "The Development of Social Network Analysis: A Study in the Sociology of Science". BookSurge, LLC. North Charleston, SC.
- [6] Stanley Wasserman, Katherine Faust. (1994). "Social Network Analysis: Methods and Applications", Structural Analysis in the Social Sciences, 25 November 1994
- [7] Donald Triner. (2010). "Publicly Available Social Media Monitoring and Situational Awareness Initiative," Office of Operations Coordination and Planning: Department of Homeland Security, June 22 2010.
- [8] Juris, Jeffrey. (2012). "reflections on #Occupy Everywhere: Social media, public space, and emerging logics of aggregation". American Ethnologist, Vol 39, No. 2, pp. 259-279.
- [9] Steady, Caroline. (2011). "Social Media for Social Change: A Case Study of Social Media Use in the 2011 Egyptian Revolution". Capstone Project.
- [10] Stark, Rodney. (1987). "Deviant Places: A Theory of the Ecology of Crime". Criminology, 25: 893A-910.
- [11] Brett Stross-Gross, et al. (2011). "The underground economy of spam: a botmaster's perspective of coordinating large-scale spam campaigns." In Proceedings of the 4th USENIX conference on Large-scale exploits and emergent threats (LEET'11). USENIX Association, Berkeley, CA, USA, 4-4.
- [12] Taylor Dewey, et al. (2012). "The Impact of Social Media on Social Unrest in the Arab Spring". Stanford University - Defense Intelligence Agency Final Report.
- [13] Christian Sturm and Homay Amr. (2013). "The effects of (social) media on revolutions: perceptions from egypt and the arab spring". In Proceedings of the 15th international conference on Human-Computer Interaction: users and contexts of use - Volume Part II (HCI'13), Masaki Kirosu (Ed.), Vol. Part II. Springer-Verlag, Berlin, Heidelberg, 352-358.
- [14] Woods, Richard. (2010). "Privacy is Dead? Facebook's Mark Zuckerberg says privacy is dead. So why does he want to keep this picture hidden?". Times Newspapers Ltd.
- [15] Statistics Brain. (2013). "Facebook Statistics". Statistic Brain Research Institute, publishing at Statistic Brain. 6/23/2013. <http://www.statisticbrain.com/facebook-statistics/>
- [16] CBS News. (2012). "Twitter's censorship plan rouses global furor". Associated Press. January 27, 2012
- [17] Statistics Brain. (2013). "Twitter Statistics". Statistic Brain Research Institute, publishing at Statistic Brain. 5/7/2013. <http://www.statisticbrain.com/twitter-statistics/>
- [18] Bagley, Nick. (2012). "The Decline of Myspace: Future of Social Media." Dreamgrow Digital. 8/13/2012. <http://www.dreamgrow.com/the-decline-of-myspace-future-of-social-media/>
- [19] alton, Antony. "Temporal Logic". The Stanford Encyclopedia of Philosophy (Fall 2008 Edition). Edward N. Zalta (ed.)
- [20] Shea Bennett. "Just How Big Is twitter In 2012 [INFOGRAPHIC]". All Twitter - The Unofficial Twitter Resource, February 2013
- [21] Mallon, Shanna. (2012). "50 Facts about Social Media for Business". Straight North, LLC publishing at The Straight North Blog. Donners Grove, Ill.
- [22] D. Karaliskos, et al. (2010). "Social network addiction : a new clinical disorder?". European psychiatry : the journal of the Association of European Psychiatrists. volume 25, Page 855. DOI: 10.1016/S0924-9330(10)70846-4
- [23] Helms, R. Ignacio, et al. (2010). "Limitations of Network Analysis for Studying Efficiency and Effectiveness of Knowledge Sharing" Electronic Journal of Knowledge Management Volume 8 Issue 1 (pp53 - 68)
- [24] Dhar, Vaasant. (2013). "Data Science and Prediction." Communications of the ACM. Vol. 56 No 12, Pages 64-73. 10.1145/2500499
- [25] Sullivan, Darryn. (2011). "Why Second Chance Tweets MATter: After 3 Hours, Few Care About Socially Shared Links". Third Door Media Inc. Publishing as Search Engine Land.
- [26] Travers J., Milgram S. (1969) "An Experimental Study of the Small World Problem." Sociometry, Vol. 32, No. 4. pp. 425-443, doi:10.2307/2786545
- [27] Harist, A. W., Zaia, A. F., Bates, J. E., Dodge, K. A. and Pettit, C. S. (1997). "Subtypes of Social Withdrawal in Early Childhood: Sociometric Status and Associative Differences across Four Years". Child Development, 68: 2781A-2804. doi: 10.1111/j.1467-8624.1997.tb01940.x
- [28] Taylor, J. (2013). "Personal communication", August 12, 2013.
- [29] Galton, Antony. (2008). "Temporal Logic". The Stanford Encyclopedia of Philosophy. Edward N. Zalta (ed.). URL = <http://plato.stanford.edu/archives/fall2008/entries/logic-temporal/>.
- [30] Minker, Jack. (1982). "On indefinite databases and the closed world assumption". Lecture Notes in Computer Science, 6th Conference on Automated Deduction. Springer Berlin Heidelberg, pp. 292-308 doi:10.1007/BFb0000066
- [31] Jeremy J. Carroll, Ian Dickinson, Chris Dolin, Dave Reynolds, Andy Seaborne, and Kevin Wilkinson. (2004). "Jena: implementing the semantic web recommendations." In Proceedings of the 13th international World Wide Web conference on Al-
- ternate track papers & posters (WWW Alt'04). ACM, New York, NY, USA, 74-83. DOI:10.1145/1013367.1013381
- [32] Claudio Gutierrez, et al. (2005) "Temporal RDF". In Proceedings of the Second European conference on The Semantic Web: research and Applications (ESWC'05). Ausoncio Gomez-Perez and Jerome Euzenat (Eds.). Springer-Verlag, Berlin, Heidelberg, 93-107.
- [33] Andrew Page.(2012). "Know Your Meme: Kony 2012". <http://www.knowyourmeme.com/memes/events/kony-2012>
- [34] Goutam Kumar Saha. 2007. "Web ontology language (OWL) and semantic web." Ubiquity 2007, September, Article 1 (September 2007), 1 pages. DOI=10.1145/1295280.1295290 <http://doi.acm.org/10.1145/1295280.1295290>
- [35] John Guare, "Six Degrees of Separation," A Play, May 1990
- [36] Lada Adamic, et al. (2003). "A social network caught in the Web." First monday 8(6)
- [37] David Liben-Nowell, et al. (2005). "Geographic Routing in Social Networks," Proceedings of the National Academy of Sciences (PNAS), 102:11623-1162, 2005
- [38] Ravi Kumar, et al. (2006). "Structure and Evolution of Online Social Networks." In the Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'06), Philadelphia, PA.
- [39] Michelle Granov, Mark Newman. (2002). "Community structure in social and biological networks." Proceedings of the National Academy of Sciences (PNAS), 99(12):7821-7826.
- [40] Ceren Budak, et al. (2010). "Where the blog tip: connectors, mavens, salesmen and translators of the blogosphere." In Proceedings of the First Workshop on Social Media Analytics (SOMA '10). ACM, New York, NY, USA, 106-114. DOI=10.1145/1964858.1964873
- [41] Steven Levitt, Stephen J. Dubner. (2005) "Freakonomics: A Rogue Economist Explores the Hidden Side of Everything." New York: Morrow-Harper.
- [42] George Kelling, Catherine Coles. (1998). "Fixing Broken Windows: Restoring Order and Reducing Crime in Our Communities." January 20, 1998
- [43] Roe v. Wade, 410 U.S. 113 (1973)
- [44] Jonah Berger. (2013). "Contagious: Why Things Catch On." Simon and Schuster Publishing, March 5, 2013
- [45] R. S. Renfro. (2001). "Modeling and Analysis of Social Networks"; PhD thesis, Air Force Institute of Technology.
- [46] C. Clark. (2005). "Modeling and analysis of clandestine networks," Masters thesis, Air Force Institute of Technology.
- [47] J. T. Hamill. (2000). "Analysis of Layered Social Networks," PhD thesis, Air Force Institute of Technology.
- [48] G. Ertesz, F. Gandon, M. Buffa, O. Corby. (2009) "Semantic Social Network Analysis," Proceedings of the WebSci&A209. <http://journal.asascience.org/141/>

Contact



Questions

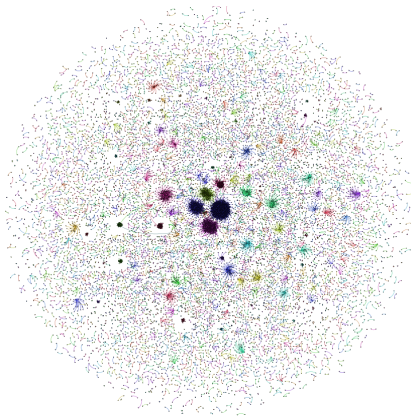
Questions?

Suplimental Material

- Twitter JSON Key Fields

profile_link_color	Coordinates	verified
In_reply_to_screen_name	Geo	time_zone
In_reply_to_status_id	text	statuses_count
In_reply_to_status_id_str	entities	Contributors
In_reply_to_user_id	place	protected
profile_background_color	contributors_enabled	truncated
profile_background_title	default_profile	retweeted
default_profile_image	description	id_translator
follow_request_sent	followers_count	location
friends_count	geo_enabled	favorites_count
profile_image_url_https	listed_count	following
profile_background_image_url	notifications	retweet_count
background_image_url_https	name	created_at
profile_image_url	lang	Favorited
sidebar_border_color	use_background_image	Id_str
sidebar_fill_color	screen_name	Created_at
profile_text_color	show_all_inline_media	Id
url	utc_offset	

- **BEK Infectious Account Visualization**

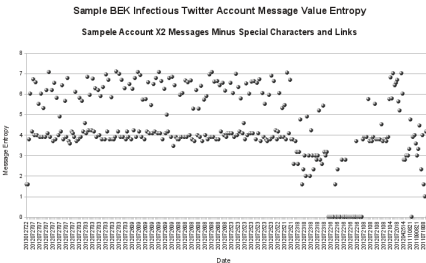
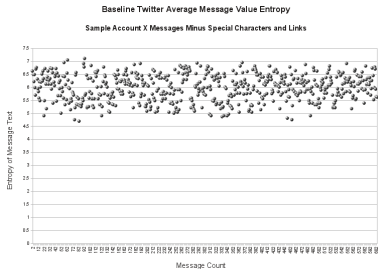


- Coalmine User Interface

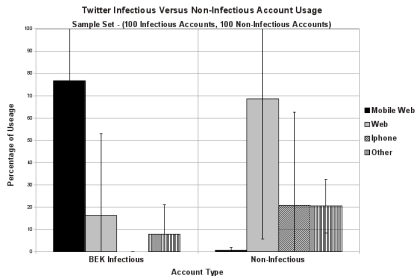
The screenshot displays the Coalmine User Interface. On the left, there is a 'Search Panel' with a 'History' section and a search criteria input field containing 'text:a* - text:RT*'. Below this is a 'Search Results: For' section with a list of search results. On the right, an 'Analysis Results Table [text:a* - text:RT*]' window is open, showing an 'Export' section with a table of results for 'Twitter(242449)'. The table has columns for 'user', 'created at', 'id str', and a text column. The text column contains various phrases, many of which are 'all of the lights'.

user	created at	id str	
CarlecJuarez94	Sun Mar 27 22:12:45 +0000 ...	52130966040037120	all of the lights
PVTanna_the	Sun Mar 27 16:42:00 +0000 ...	52047992801830400	That's what I am.
LeGraver	Sun Mar 27 16:45:45 +0000 ...	52048674431311872	We is the arsenal
cbe_stewiz	Sun Mar 27 16:58:31 +0000 ...	52051807758013536	all of the lights
_ImJustJosh	Sun Mar 27 23:21:46 +0000 ...	52140335640060217	All of the lights
-Hey_itsNina	Sun Mar 27 23:31:14 +0000 ...	52150719638991120	- is he autistic?
TeamVaria	Sun Mar 27 23:47:46 +0000 ...	52154879573114862	All of the lights
-Highskulchick	Mon Mar 20 00:03:24 +0000 ...	52150012601011200	All of the lights
WelcomeFirst	Sun Mar 27 22:46:12 +0000 ...	52139384643915777	All of the lights
QIDswiss	Sun Mar 27 23:06:37 +0000 ...	52144520690805784	Here she go again
frescoFiesco038	Sun Mar 27 23:12:30 +0000 ...	52146028014012480	all of the lights
ShowoffTolo	Sun Mar 27 16:49:20 +0000 ...	52049599912073904	@AyeeyAyo She Fell As
adamburger	Sun Mar 27 16:33:02 +0000 ...	52045474533879808	Does anyone know wh

- Malware Infection Vector Detection Continued



- Malware Infection Vector Detection Continued



Total Tweets Processed	6,531,319,202
Total Number of Unique Accounts	265,163,290

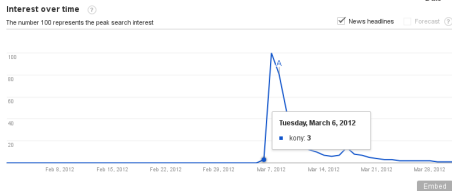
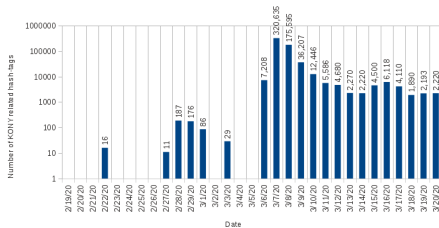
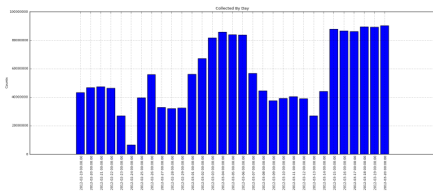
Number of Suspicious Accounts	729,609
Total Number of Suspicious Tweets	8,286,480
Calculated Percentage of Infectious Accounts	0.000275
Calculated Percentage of Infectious Tweets	0.127

Dataset Processing Time with Regex	22H 48M
Dataset Processing Time w/fig. 5.10 filter	23H 21M

Event Identification

- Still in the initial stages of this part of our work
- Given a general topic, “search term, hashtag,” we can identify most of the related content from the dataset
- We have a means for alerting on all new posts regarding that term
- We can dig historically through the data and trace the path that an idea took
- We can identify the influential individuals, “accounts,” that played a part in the information spread
- Our test case was the KONY2012 Event

Event Identification Continued



Event Identification Continued

- Top 10 Twitter Accounts, sending and receiving KONY2012 related Tweets

Directed @ Account Names	In-Degree	Origin Account Names	Out-Degree
tothekidswho	625	twittonpeace	47
Invisible	125	interhabernet	44
youtube	118	DailyisOut	44
helpspreadthis	95	MEDYA_TURK	42
justinbieber	83	haber_42	35
pretypinkprobz	48	gundem_haber	30
ninadobrev	48	twitofpeace	22
MeekMill	47	korkmazhaber	19
ladygaga	43	tarafsiz_haber	14
KendallJenner	39	Son_DakikaHaber	13

Event Identification Continued

- Top 10 Twitter Accounts, retweeting and being retweeted regarding KONY2012

Retweeting Accounts	In-Degree	Message Source	Out-Degree
MedyaKonya	8	Stop_____Kony	2642
twittonpeace	8	tothekidswho	753
haber_42	7	konyfamous2012	716
gudem_haber	7	Kony2012Help	615
korkmazhaber	7	stop_____kony	353
DailyisOut	7	WESTOPKONY	225
interhabernet	6	zaynmalik	221
KONYA_ZAMAN	6	iSayStopKony	127
konya_time	6	Stop_2012_Kony	80
konyagazetesi	5	Kony_Awareness	72