



Terrorist Social Network Analysis: Past, Present, and Future

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Talk Outline

- STONE Shaping Terrorist Organization Network Efficacy [joint with A. Mannes, F. Spezzano]
 - Quantifying Terror Network Lethality
 - Predicting Successors of a Removed Terrorist
 - Identifying Who to Remove
- Social Media Analytics of ISIL Activity [ongoing]
- WORK IN PROGRESS
- Twitter [joint with S. Kumar]
- YouTube [joint with M. Albanese]
- The Upcoming Threat Landscape
 - Next 2-4 Years: Bots, Ransomware, Banking Trojans, Bitcoin & Cryptocurrencies
 - 4-10 Years: ICS/SCADA, IoT Attacks



Goal of STONE

Maximally degrade the lethality of a terror network





- No metrics to measure lethality of terror networks
- No models to predict number of attacks by a terror group





How STONE Works – 4 Broad Problems to Solve

Predictive Model to Measure Lethality of a Terror Network (predict number of attacks)

Predict
successors of a
"removed"
(captured, killed,
etc.) terrorist

Predict new possible networks when a terrorist is removed

Identify who to remove from the network to minimize expected lethality of the resulting network

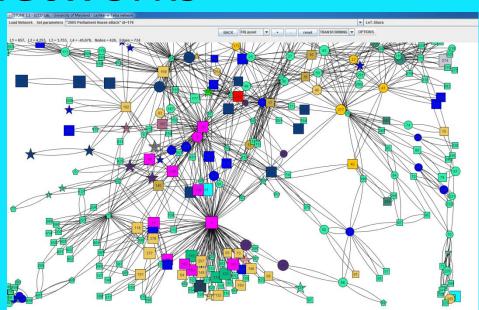


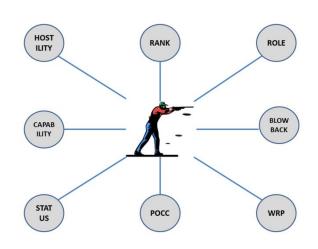


Terror Networks

Consists of

- Nodes people, events
- Edges connect nodes. Edges labeled with relationships.
- A <u>rank</u> labeling each node specifying how important the node is within the hierarchy
- A list of properties for each node with discrete and numeric values, e.g.
 - Role of the node in the organization
 - Clustering coefficient how "tightly connected" is the node to its neighbors
 - Blowback level level of blowback if the node is removed
 - Hostility Level including support for carrying out terror attacks
 - Competence in carrying out terrorist acts
 - Whether the individual is dead/otherwise removed from network/alive and active







Correlated Measure L4

Person P1 removed

Person P2 removed

Predictive regression model is highly accurate.

- 0.83 Pearson Correlation Coefficient for LeT network.
- 0.8 for AQ network

Network N1 A1 Attacks Network N2 A2 Attacks

- We have different networks as people are removed from the network.
- Initially, we have network N1 and during this time, A1 attacks occur. Network N1 has properties L1(1), L2(1), and L3(1).
- When person P1 was removed, we have a new network N2 and during the time N2 existed, there were A2 attacks. Network N2 has properties L1(2), L2(2), L3(3).
- We build a regression model to predict number of attacks from historical data about the L1(i)'s, L2(i)'s and L3(i)'s.





What Happens when a terrorist is removed from the network?

Influence Influence Influence Influential? Nho is most influential? Palit on top of Google's Built on top also rithm Page Rank also rithm

Connectedness

- Who belongs to a tightly knit network?
- Builds on top of clustering coefficients in social networks



Vertex Successor Prediction

First define a set of candidates to replace node r. Must have overlapping skills and must be at or below r's rank.

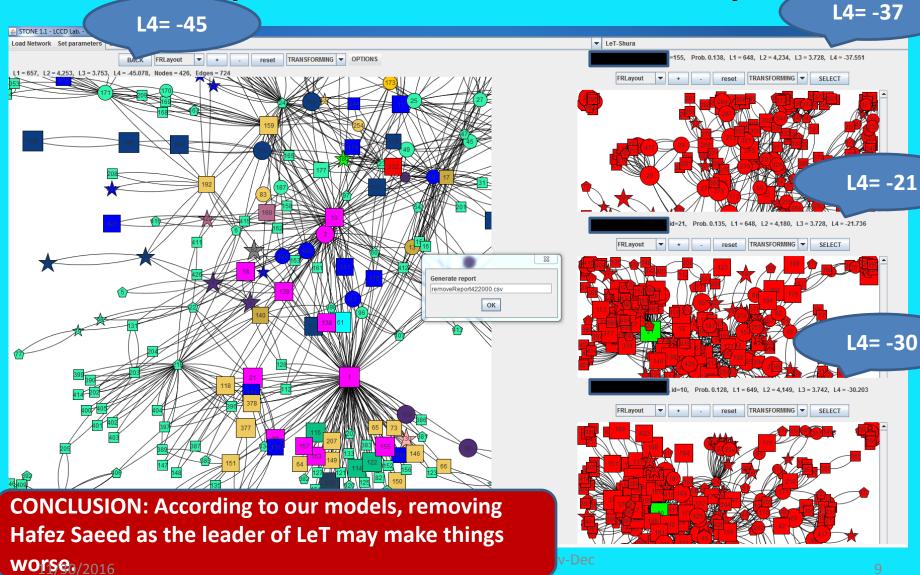
How does node v's influence change if node r is removed? Define WRP(v,r) – the weighted PageRank of v, assuming r is removed.

How do v's total ensemble of properties (incl. influence) qualify him as a successor to r? Define rv(v), the relative value of v as a successor.

Probability of v as a replacement for r is the ratio of his relative value to the total relative value of all candidates.



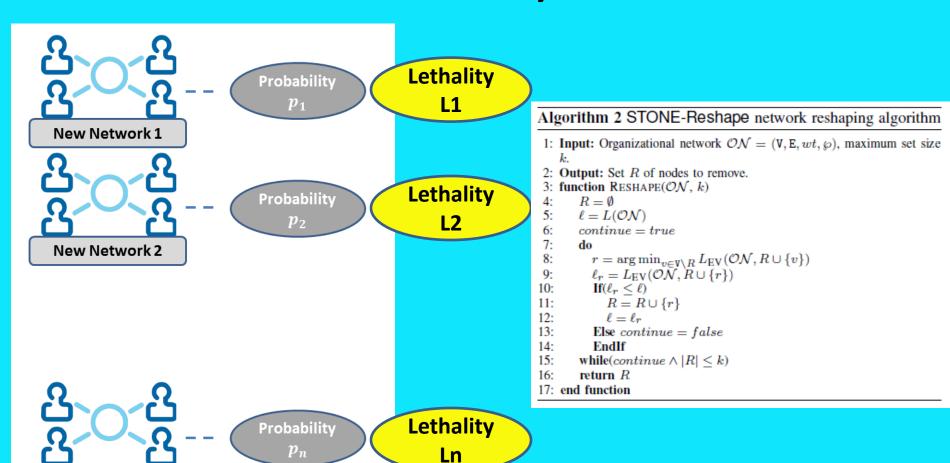
Replacement Probability







Pictorially.....



New Network n





Verification & Validation

- Tested and validated predictions on 4 terror networks: Al-Qaeda, Hamas, Hezbollah, Lashkar-e-Taiba.
- Predicting successor: In 80% of the cases, one of the top 3 predictions was the actual successor. This number not only includes terrorist leaders but lower level operatives as well.



Forecast: Hezbollah - Successor of Hassan Nasrallah





Pick #1
Hashem Saf
al-Din



Hussein al-Khalil



Pick #3 Naim Qassem

- CTED Meeting - Nov-Dec



Pick #4 Muhammed Yazbek



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The Art of the Possible

Bots

Use bots to:

- influence opinion
- crush/overwhelm dissent
- expend adversary's resources

2015 DARPA Bot Challenge



Identify Influencers

Key influencers not determined by followers or friends
Topic specific influencers
Diffusion Centrality

2014 India Election



Diffusion Model

Predict # of supporters on a topic Predict # of opponents over time Identify viral spread

2014 India Election

Identify Malicious Actors

Online Marketplace fraud [Flipkart]
SMS fraud
Fake information [Wikipedia]
Fake accounts
Online trolls







ISIL Twitter Data



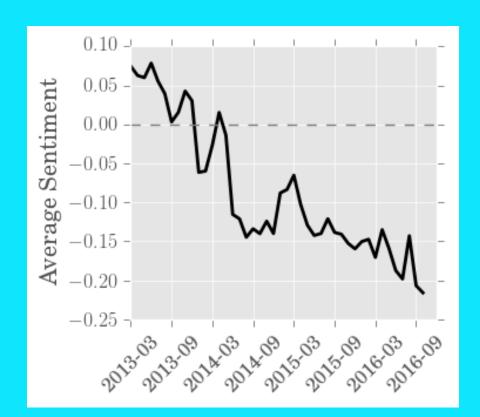
- Time frame (March 2013-Oct 2016)
- ~1.4M ISIL-related tweets
- ~737K Twitter users
- ~4K geo-tagged tweets
- Purpose
 - Dissemination of Ideology
 - Recruiting
 - Dissemination of Instructions
 - Command, Control, Communication
 - And more.....

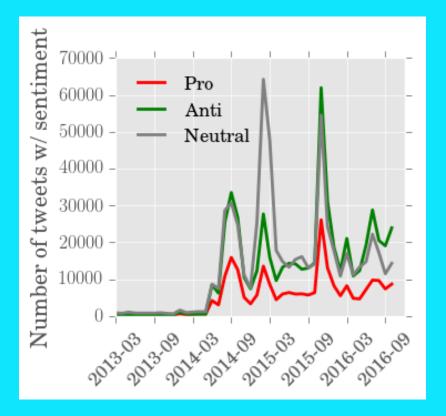




Twitter Sentiment Toward ISIL











Twitter Sentiment Toward ISIL





TIME FRAME	MOST SENTIMENT IN FAVOR OF ISIL (in decreasing order)
Mar-Sep 2013	Hungary, Germany, Malaysia, Chile, Indonesia
May-Oct 2016	Thailand, Tunisia, Ireland, Malaysia, UK, Indonesia

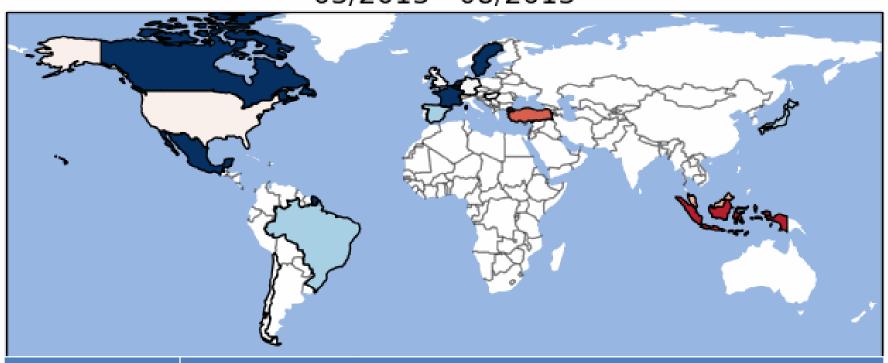




Fraction of ISIL Supporters on Twitte



03/2013 - 08/2013



TIME FRAME	MOST FRACTION OF SUPPORTERS FOR ISIL (in decreasing order)
Mar-Sep 2013	Indonesia, Turkey, Malaysia, USA, Germany
May-Oct 2016	Indonesia, Ireland, Thailand, Tunisia, Turkey, Malaysia, UK [all tied]



8.0

0.7



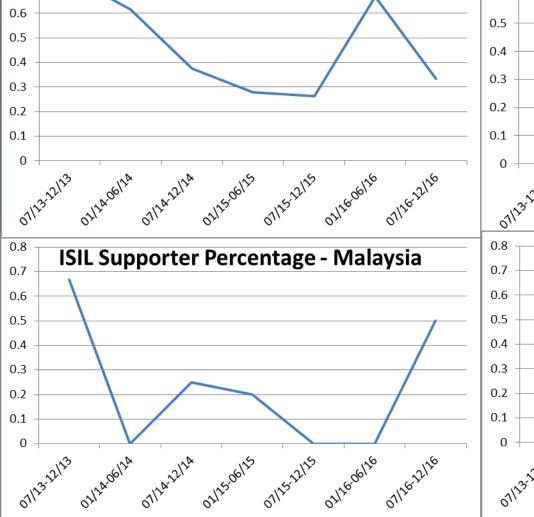
ISIL Supporter Percentage - USA

ISIL Supporter Percentage in

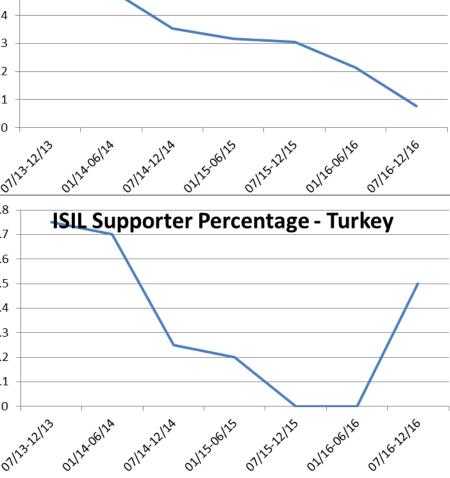
Selected Countries

0.6





ISIL Supporter Percentage - UK







YouTube Data

- Total videos crawled: 1,320,039
- Total users examined: 1,850,763
 - Number of users who uploaded videos: 16,048
- Total comments: 4,109,724
 - posted by 972,705 distinct users

Interactions among users:

- 423,513 subscriptions to other users' content
- 2,237,422 friendships
- 1,913,858 "commenting" interactions

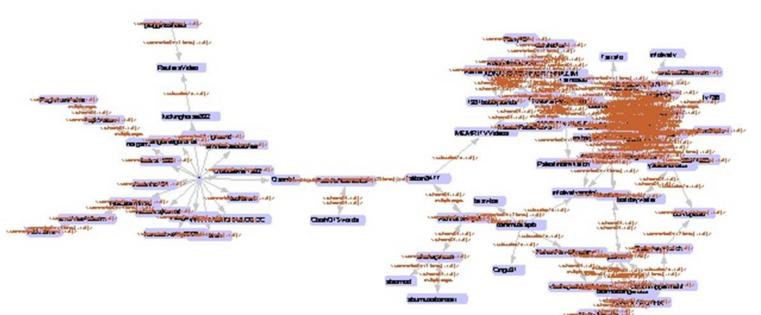




YouTube Data

 Relationships between YouTube users sympathetic to a given terrorist group: Except for a small number of isolated users, there is a large cluster of highly connected users, and several smaller satellite clusters of moderately connected users





11/30/2016





YouTube Data



- Our system determined that YouTube user andrea22borman must be extremely relevant to Hezbollah
- Andrea Borman is allegedly romantically linked to a senior Hezbollah operative







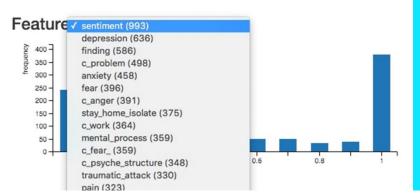
Next Steps

WORK IN PROGRESS

- Predict how support for or emotion about a terror group will spread through an online social network.
 Develop optimal countermessaging schemes.
- Who are the key influencers in the social network?

Sentimetrix has developed such diffusion modeling techniques in other domain (political tracking, health care) and predicted spread and key influencers.





Volume	Sentiment	Influencers	Forecast	Word Cloud	Hash Tags
Screen Name	Followers	Tweets	Topic(s)	Status	Score
SqnLdrHusain	5047	94	bjp		0.00004421
newsxonline	890646	217	bjp	News Organization	0.00004346
yumroni	6970	79	bjp	Potential Bot	0.00004229
SukhSandhu	389061	56	bjp	Potential Bot	0.00004176
jiya043	8081	54	bjp		0.00004118
dilipvamanan	39764	186	bjp		0.00004040
STForeignDesk	15347	38	bjp		0.00003987
ItsShrishti	20161	33	bjp		0.00003975
AmeyaKambli	6372	35	bjp		0.00003952
dot_lawyer	10746	23	bjp		0.00003951
AlSalamanty	2716	42	bjp		0.00003929
AbhayIndia	89762	113	bjp		0.00003879

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Next 2-4 Years: Terrorist Financing

SMS-Fraud

FakeInstaller JiFake OpFake



Bitcoin

Payment channel!

Also hacked, e.g.

Mt. Gox

Poloniex





Ransomware

Locky CryptoLocker Wirelocker



Banking Trojans

Carbanak Cobalt Dridex Dyre OpFake





Next 5-10 Years: Terrorist Attacks

ICS-SCADA Threats

- Stuxnet hits Iranian nuclear centrifuges
- German steel mill hit in 2014
- Havex RAT targets Object Linking
 & Embedding for Process Control used in turbines, pumps etc
- Blacken targets uses of GE's Cimplicity SCADA software

IoT-based Threats

- In October 2016, a Mirai based IoT attack brought down Dyn, a provider to Reddit, Twitter, Netflix,...
- In Sep 2016, researchers at Tencent successfully showed how the Tesla could be hacked, allowing them to gain some control over the brakes.





Conclusion

- Terrorist groups (esp. ones with state support) will find new and innovative ways to carry out their activities and attacks.
- Social media will be increasingly leveraged through the use of
 - Bots, fake accounts, social media fraud, malware distribution
- Cyberattacks will be used in the next several years for everything from:
 - Financing
 - Physical attacks
- Cryptocurrencies will be increasingly used



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