

Social Network Analysis for Science of Security



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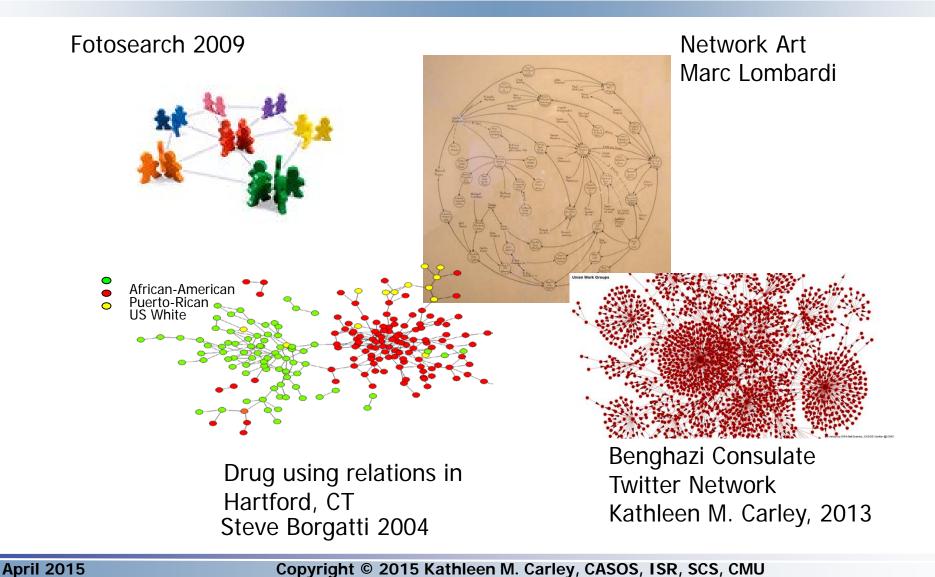




Center for Computational Analysis of Social and Organizational Systems http://www.casos.cs.cmu.edu/



Networks!

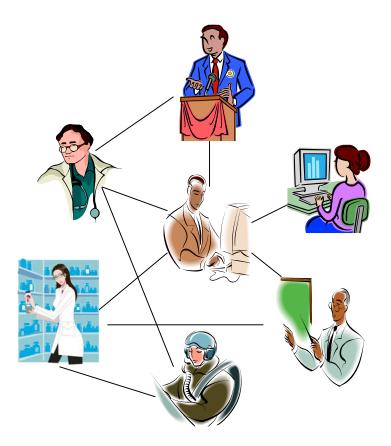






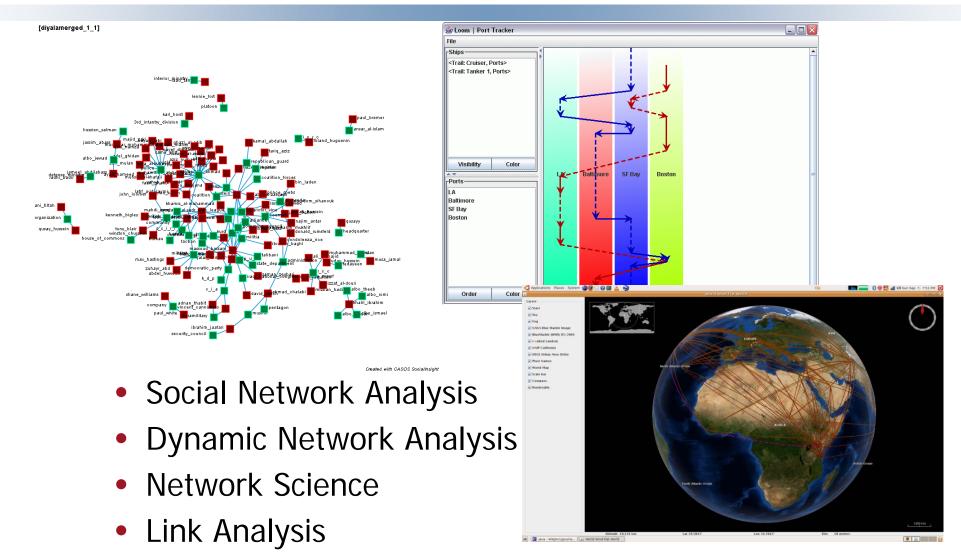
Social Networks

- A **social network** is a description of the social structure at a particular point in time in terms of the actors, mostly individuals or organizations and the links among them.
- A social network indicates the ways in which the actors are connected through various social familiarities ranging from casual acquaintance to close familiar bonds.

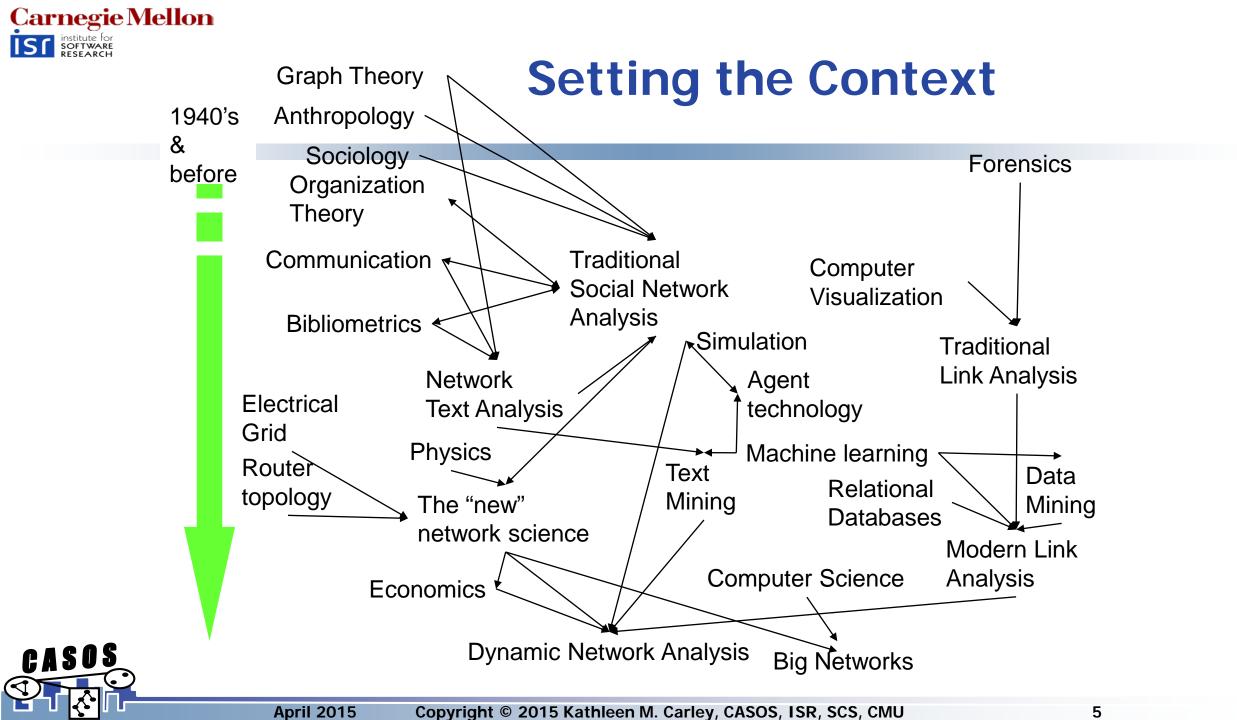




Carnegie Mellon Connecting the Dots and Trails to Predict and Explain Behavior

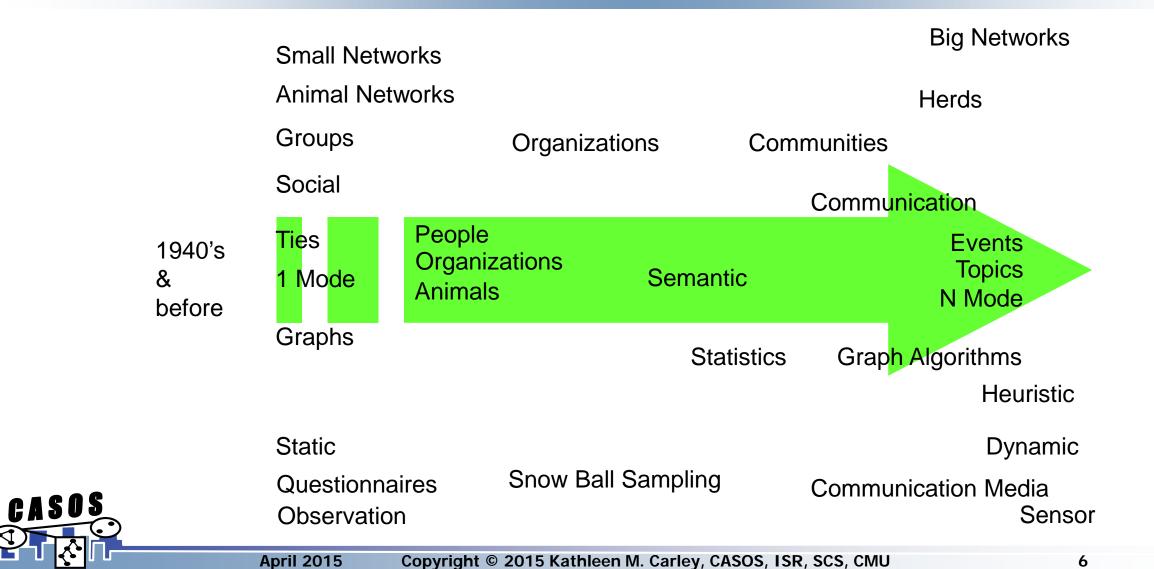








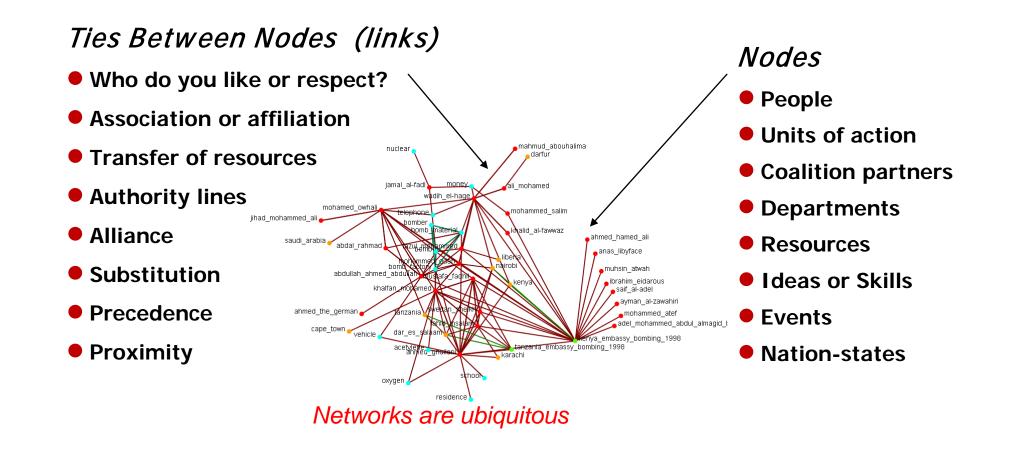
Evolutionary Themes





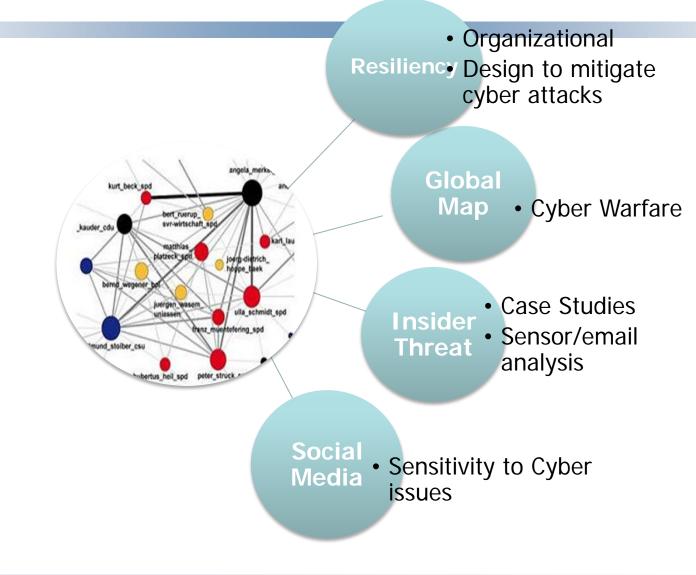
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What is a network?





Areas of Application

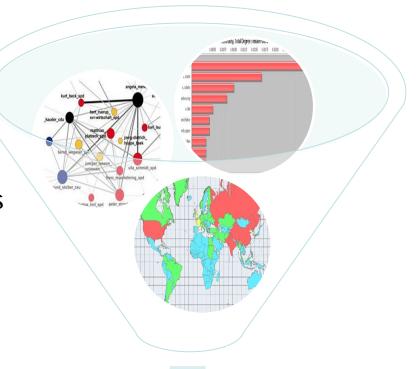




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Supporting Technologies

- Network Analytics
 - Graph metrics & algorithms
 - Statistical metrics & algorithms
 - Simulation
- Visual Analytics
- Text Analytics
- Machine Learning

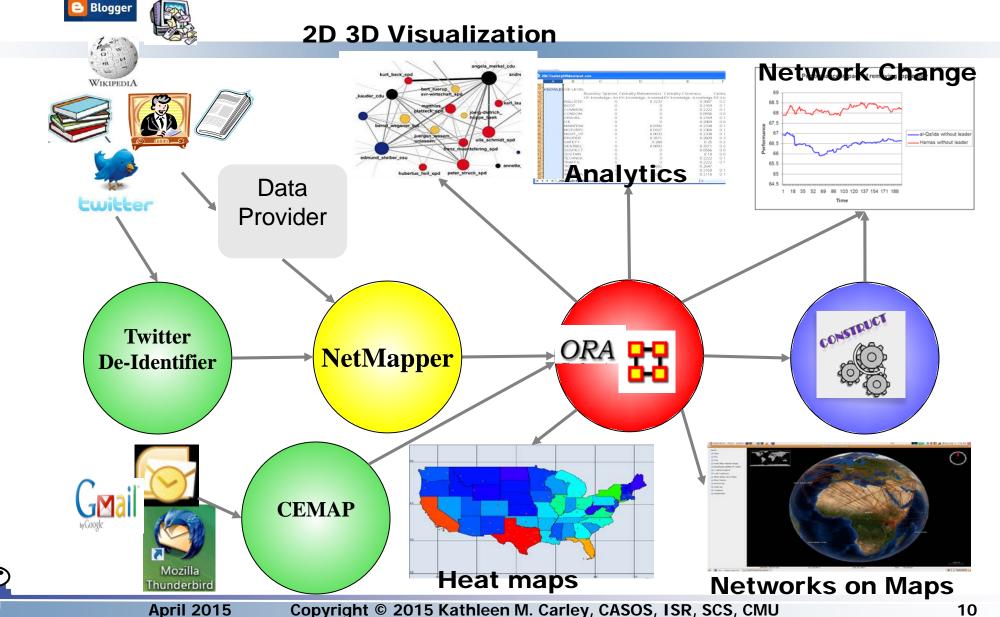


Analysis of who communicates, influences or did / will do what to whom - when, how, and why





Capabilities





The Network Perspective

Standard Statistics	Social Network Analysis	Dynamic Network Analysis	
Attributes	Relations	Relations + Attributes	$\begin{pmatrix} PA \\ 1 \\ GA \\ 2 \end{pmatrix} \qquad \qquad LA \\ 5$
Atomistic	Interdependence		GA T T T T T T T T T T T T T T T T T T T
Actors as independent	Actors constrained and enabled by links	Actors constrained and enabled by links	
Actor state matters	Actor state irrelevant	Actor state impacts perception of and use of links	NY NY LA A NY
•	HIV: Sexual contacts ar nusual cancers, traced by CDC		2 NY NY NY NY NY NY NY NY NY NY



Definitions

- Node
 - The entity of interest (point, entity,dot, <person>)
 - Mode aka Node type
- Link
 - relation, link, edge, connection, <friendship>
 - vary in strength (weight), direction, type, confidence (another weight)
 - Link type
- Ego-Network
 - The set of nodes directly connected to ego and the relations among them
- Social Network
 - A one-mode, one-link network from a single time
 - Nodes are generally people
- High-dimensional aka Meta-network
 - Multi-mode, multi-link network
 - Often geo-temporal
- Path

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 A path in a network between two nodes, such that no link or node is crossed twice



Simple SNA Measures

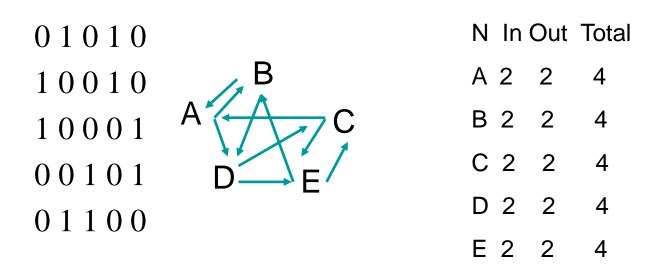
Measure	Definition	Meaning	Usage			
Degree Centrality	Node with the most connections	In the know	Identifying sources for intel; Reducing information flow			
Betweenness	Node in the most best paths Needs symmetric data	Connects groups	Typically has political influence, but may be too constrained to act			
Eigenvector Centrality	Node most connected to other highly connected nodes	Strong social capital	Identifying those who can mobilize others			
Closeness	Node that is closest to all other nodes	Rapid access to all information	Identifying sources to acquire/transmit information			
Betweenness - Centrality	High in betweenness but not degree centrality	Connects disconnected groups	Go-between; Reduction in activity by disconnecting groups			
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Degree Centrality

- Degree total number of edges/ nodes ego is connected to
- In Degree total number of nodes that send edge to ego
- Out Degree total number of nodes that receive edge from ego
- Sink 0 in degree; Source 0 out degree







Betweenness Centrality

- How often a node lies along the shortest path between two other nodes
- Computed as: $b_k = \sum_{i,j} \frac{g_{ikj}}{g_{ij}}$

- Index of potential for
 - gate-keeping, brokering, controlling the flow, and liaising between disparate parts of network – "connects groups"
- Indicates power, access to diversity of flows, potential for synthesizing
- Very "expensive" to compute



Closeness Centrality

- Measured as:
 - Sum of distances to all other nodes
 - Computed as marginals of symmetric geodesic distance matrix
- Closeness is an inverse measure of centrality
- Index of expected time until arrival for given node of whatever is flowing through the network
 - - Gossip network: central player hears things first





Eigenvector Centrality

- Node has high score if connected to many nodes that are themselves well connected
- Computed as:

$$\lambda v = Av$$

where A is adjacency network and V is eigenvector centrality. V is the principal eigenvector of A

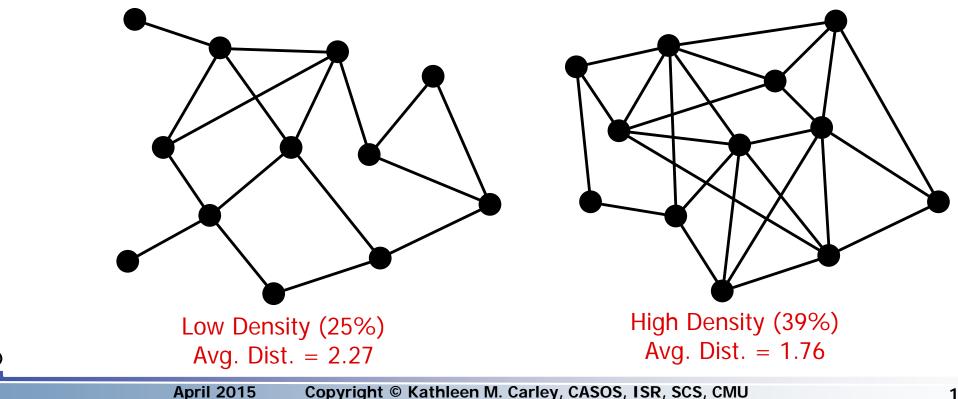
- Indicator of popularity, "in the know"
- Index of exposure, risk
- Tends to identify centers of large cliques
 - Often identified as leader of self-contained group
 - Leader of Leaders





Density

- Number of ties, expressed as percentage of the number of ordered/unordered pairs
- Number of ties / Number of possible ties
- If number of nodes = N and number of ties is M, then M/(N*(N-1)) if directed and M/((N*(N-1))/2) if undirected







Network Analytic Toolkits

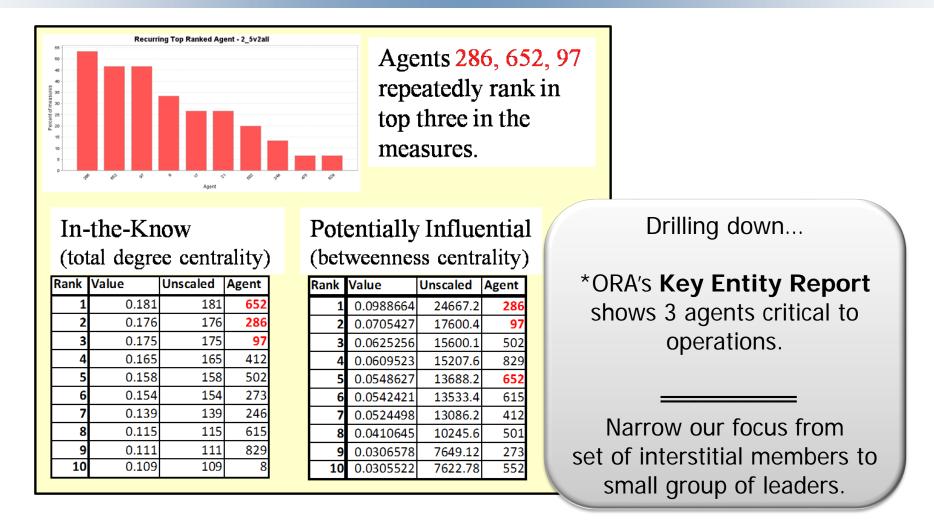
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Identify: Who are the Key Players? Or Locations, Resources ...



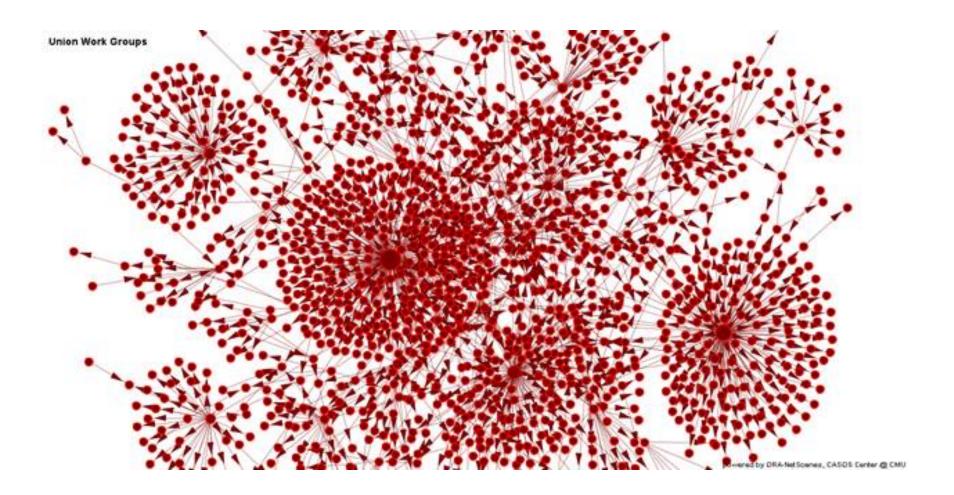


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Overall Tweet Network

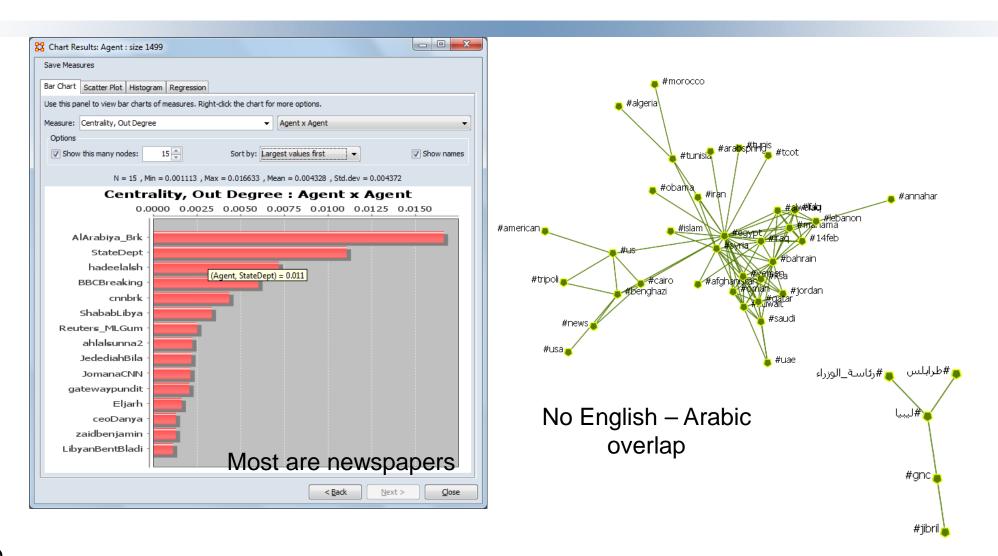
Note there are a few sources that are picked up







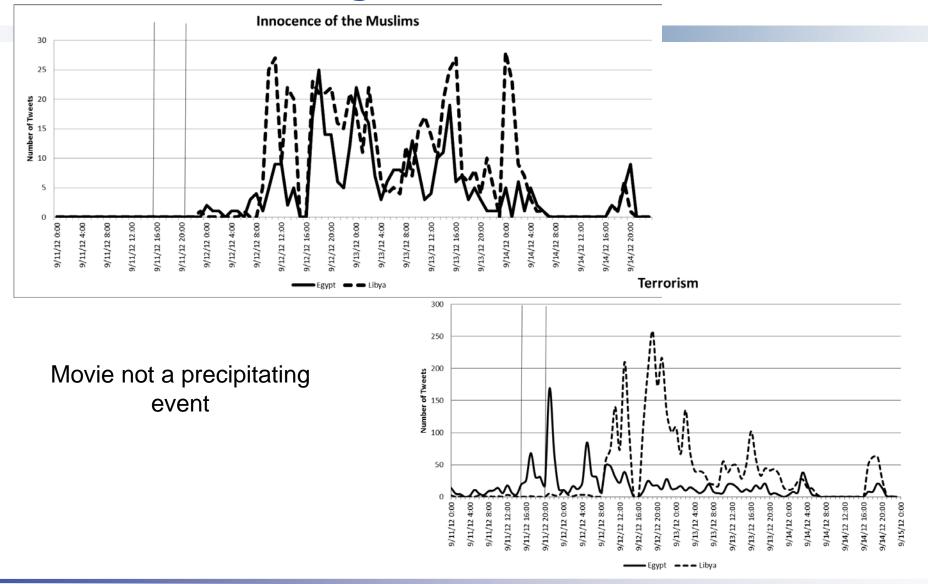
Retweeted Actors & Hashtags

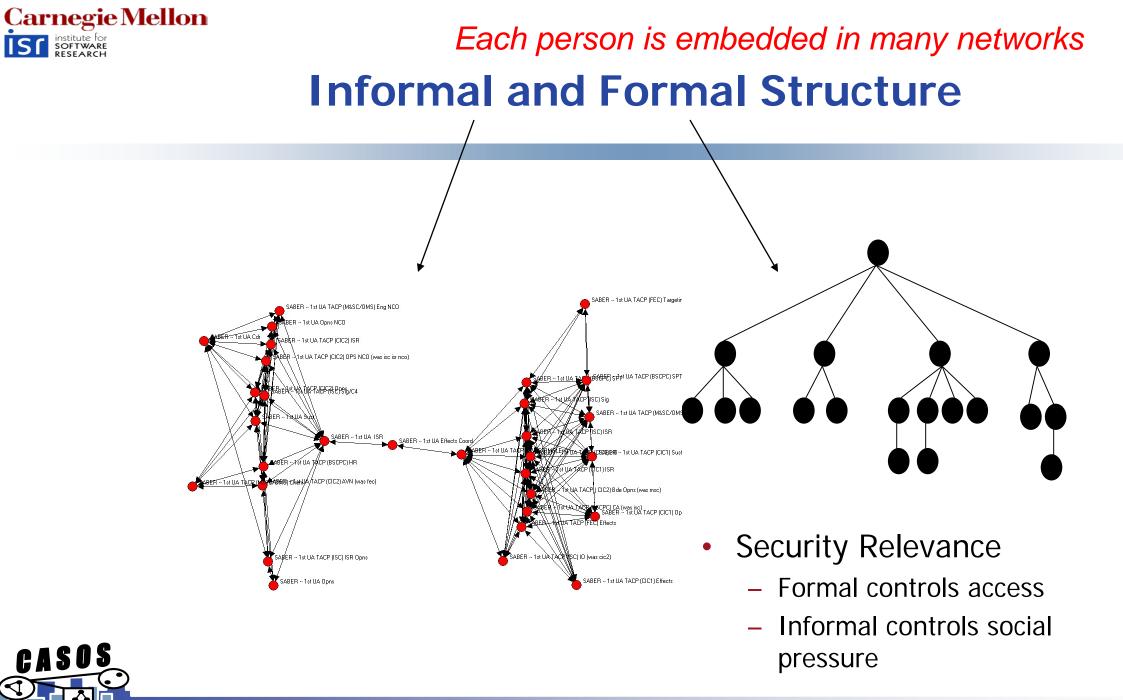


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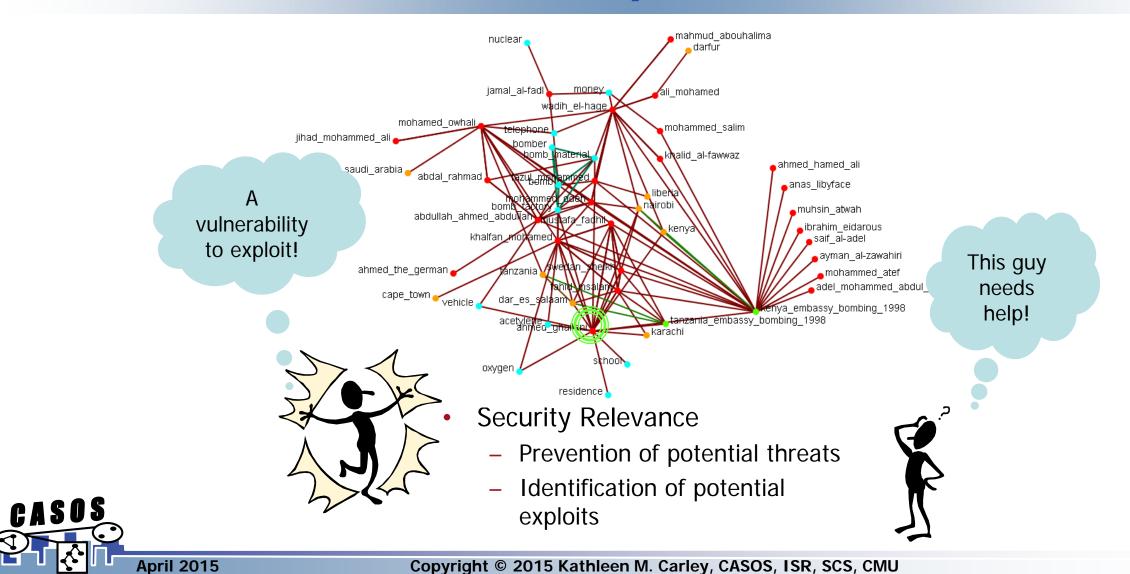


Benghazi Consulate





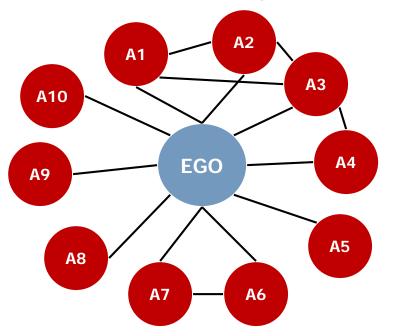
Carnegie Mellon Network Analysis Enables Management and Disruption





Ego Networks

A node's (ego's) set of alters, the connections of ego to alters, and the connections among the alters





Differences in Ego Networks Family for Drug Users

Friend **Cocaine User** Normal Person



Carnegie Mellon

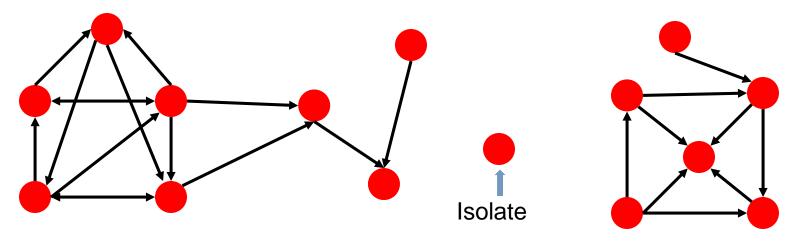
SOFTWARE RESEARCH

People with Different Roles have Different Networks



Terminology: Components

- A subgraph S of a graph G is a component if S is maximal and connected
- If G is a digraph, then
 - S is a weak component if it is a component of the underlying (undirected) graph
 - S is a strong component if for all dyads u,v in S, there is a path from u to v
- Finding components is the first step in analysis of large graphs
 - Analyze each component separately, or discard very small components







Grouping Algorithms

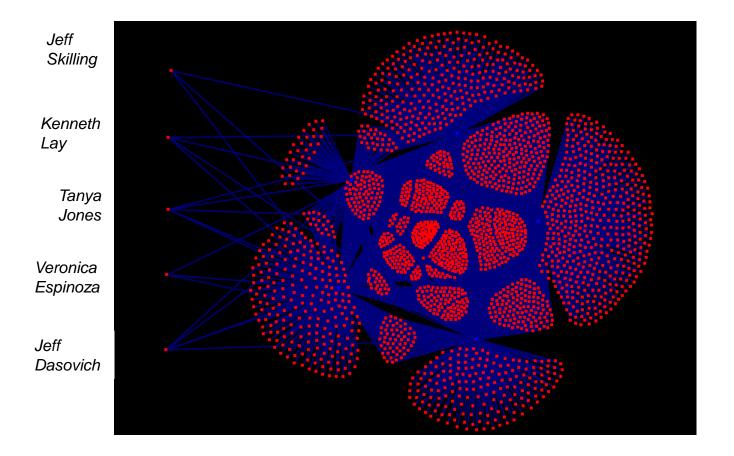
- Aka community detection
- All good at finding cliques
- All good at ignoring isolates
- Some notion of "cohesion"

	CONCOR	FOG	NEWMAN -GIRVIN	LOUVAIN	Johnson Hierarchi cal
Exclusive	yes	no	yes	yes	no
Overlappd	no	yes	no	no	yes
Bottom-up	no	yes	yes	yes	yes
Top-Down	yes	no	no	yes	no





Critical Actors are Interstitial





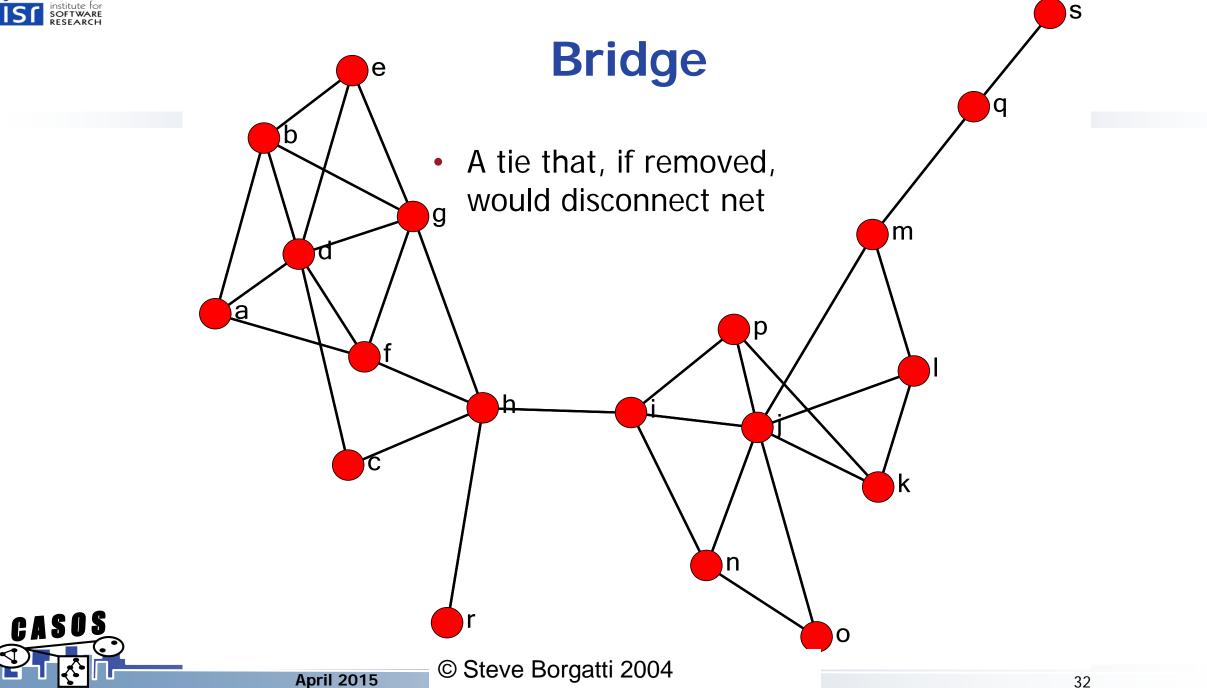


Insider Threat Example

- Extracted meta-networks from texts
- Semi-automated
- Data organized by year
- Coding is from perspective of "spy"
- Roles of actors coded
- Attributes of "spy" coded



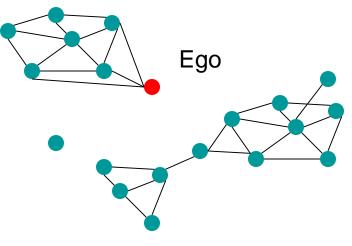




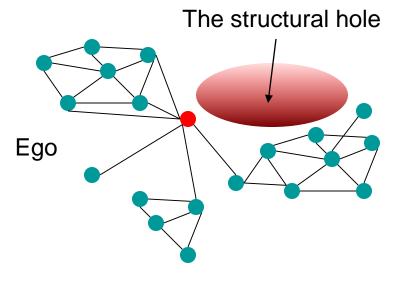


Structural Holes

Local Betweenness



Few structural holes



Many structural hole

Measured by: Burt's effective size Burt's constraint Everett & Borgatti's ego betweenness - This last is recommended



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Structural Holes

Robert took over James' job. Entrepreneurial Robert expanded the social capital of the job by reallocating network time and energy to more diverse contacts.

> It is the weak connections (structural holes) between Robert's contacts that provide his expanded social capital. Robert is more positioned at the crossroads of communication between social clusters within his firm and its market, and so is better positioned to craft projects and policy that add value across clusters.

Research shows that people like Robert, better positioned for entrepreneurial opportunity, are the key to integrating across functions and across the people of increasingly diverse backgrounds in today's flatter organizations. In research comparisons between managers like James and Robert, it is the people like Robert who get promoted faster, earn higher compensation, receive better performance evaluations, and perform more successfully on teams.

lames

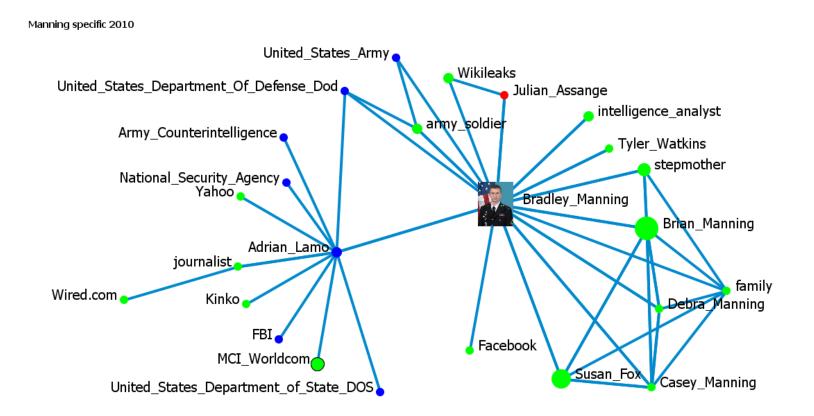


Slide from Ron Burt

Robert



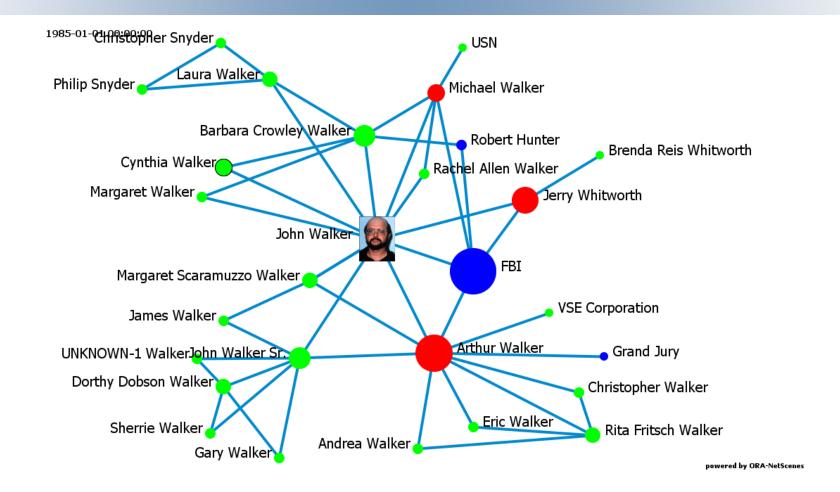
Manning – Lone Wolf example open-source



powered by ORA-NetScenes



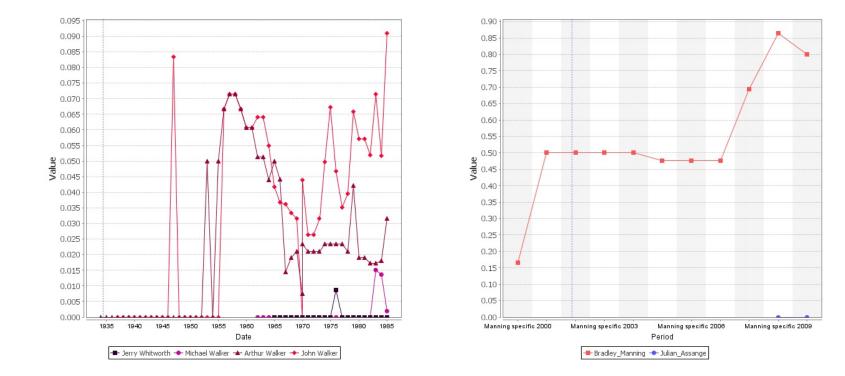
Carnegie Mellon Software Walker – Gang example Case records/searches (open-source)





Increasing betweenness during spy activities – insider starts connecting more individuals

Walker Case



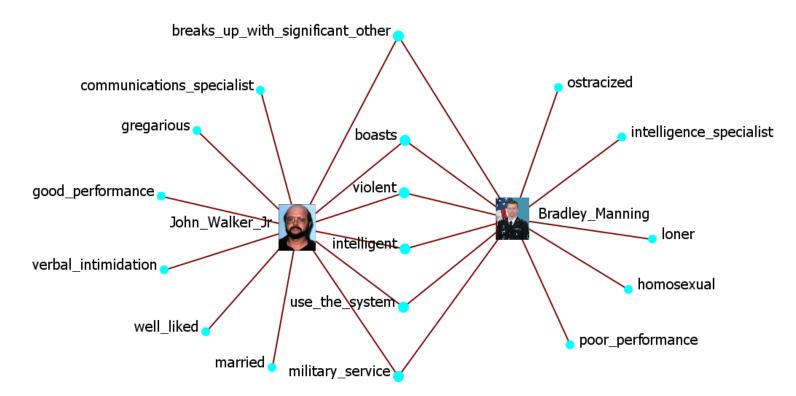
Manning Case



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Carnegie Mellon Characteristics shared and not shared by Walker and Manning

Manning Walker with attributes







Insiders examined have these characteristics

- Special characteristics
 - Boastful
 - Abusive or violent when provoked
 - Intelligent
 - Had or was in military service
 - Had broken up with significant other
 - Wanted to "use-the-system" for own gain
 - Wanted change (money/psych change)
- Access to classified material
- Increasing betweenness over time
- Increasing structural holes
- Disrupted family network tie strength with family decreased
- Irrelevant characteristics
 - Gender
 - Age
 - Loner/outgoing





Demos

• NetMapper

• ORA



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Enron – Network Anomaly Detection

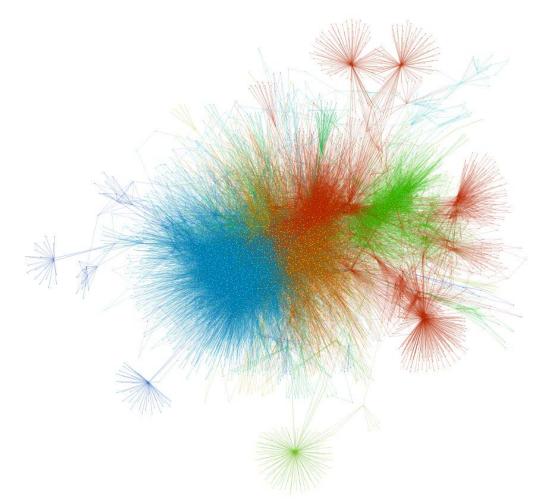
- Anomaly assessment
 - Can we identify insiders in an organization based on their recorded email habits?
 - Are different network features more useful for identification?
- Identify features of Enron "insider-threats" and compare with other Enron employees
 - Insiders Threats will show
 - greater connections outside than inside firm and that change may grow over time
 - Increasing betweenness prior to events
 - Structural holes prior to events
- Extracted meta-networks from email headers
 - Automated
- Data organized by year
- Segmented out the Enron insiders
- Data cleaning
 - Collapsed all email ids of same Enron insider into single person
- Machine learning algorithm to identify insiders





Enron 2001

All Enron Messages - Transformed

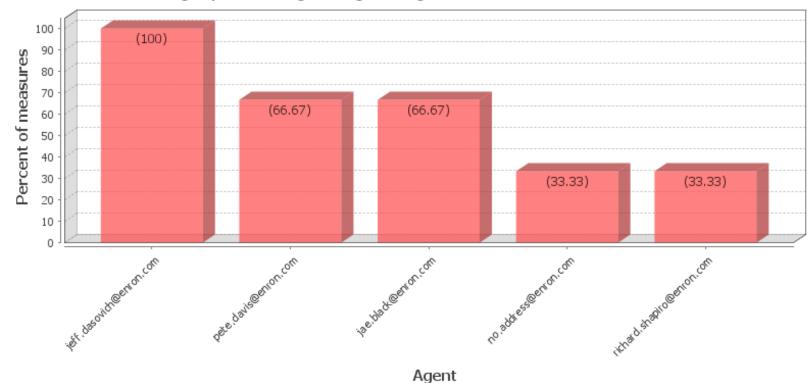






Enron Insiders are not top actors

Recurring Top Ranked Agent - Agent x Agent 2001 reduced - isolates removed

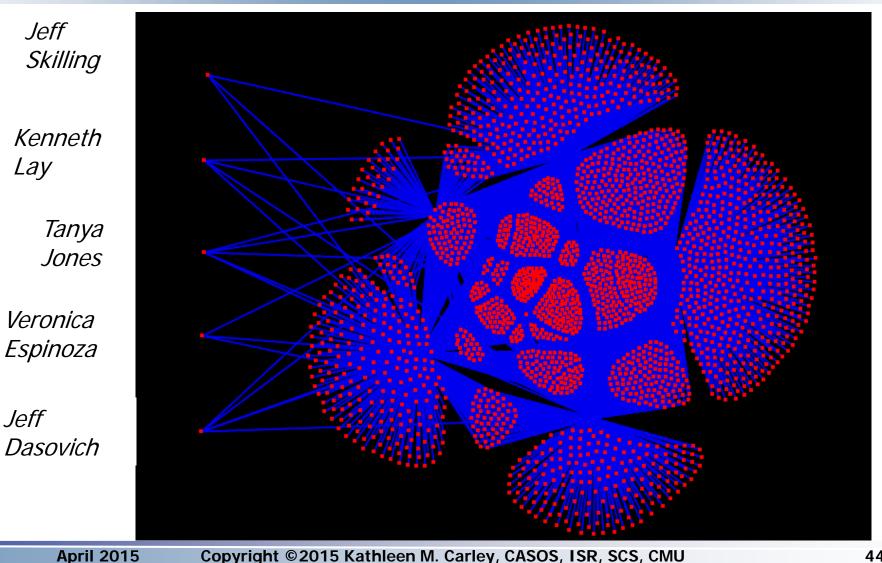






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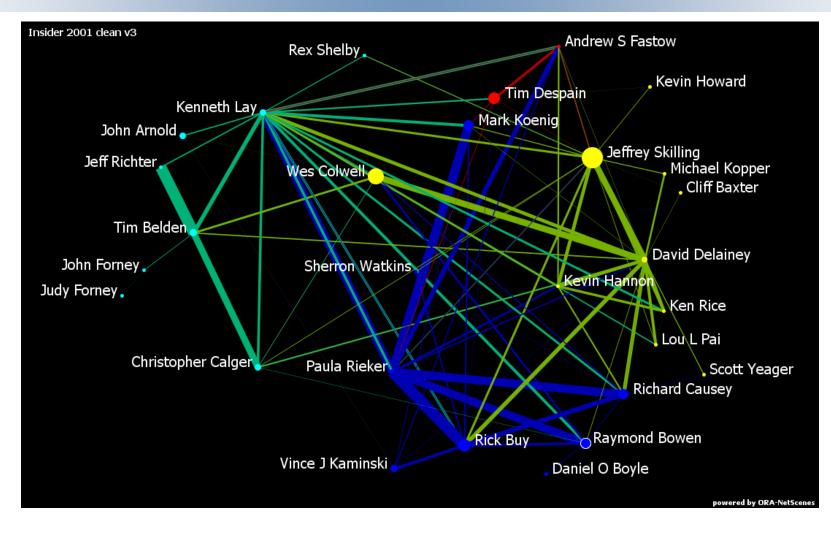
Critical Actors are Interstitial



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Enron "Insiders" – those accused – A densely connected sub-group



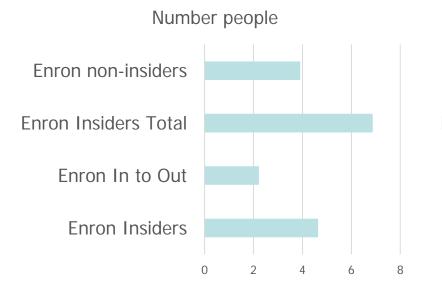


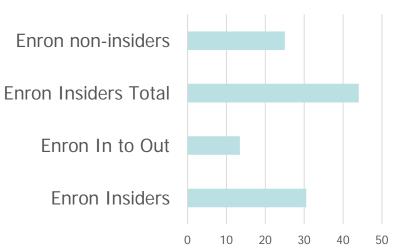


Enron Comparison of Insiders and non Insiders

Number of People Communicated with on Average

Number of Messages sent on Average





Number of Messages





Details on Machine Learning Setup

- Algorithm: JRIP, which is based on RIPPER (Cohen 1995)
 - Supervised Learning Algorithm
 - Scales linearly with training instances
 - Goal was to handle hundreds of thousands of examples quickly
 - Roughly a thousand instances a second with our data
- Data-Cleaning:
 - Nodes with multiple email addresses had been consolidated
 - Distribution Lists had been removed
- We use five-fold cross-validation to evaluate performance (and generate the ROC curve, later).
 - 20% used to build classifier, 80% tested, flipping through what each 20% is used to build the classifier.

Carnegie Mellon Definitions of Machine Learning Feature Groups

- Structural Features Node-level network measures describing the position of the node in the entire network
 - Snapshot: These node-level network measures for a single meta-network representing a period of time
 - Summaries: Numerical summaries of these node-level network features over multiple points in time. Count, Min, Max, Sum, Average, Median, StDev
- Message Ratios In-Degree and Out-Degree based on messages to employees and outsiders
 - Snapshot: These in-degree and out-degree for a single collection period
 - Multiple Snapshots: In-Degree and Out-Degree for multiple collection periods represented separately (May01, Oct01, etc)
 - Summaries: Numerical summaries of these ratios for multiple points in time for these nodes. Count, Min, Max, Sum, Average, Median, StDev



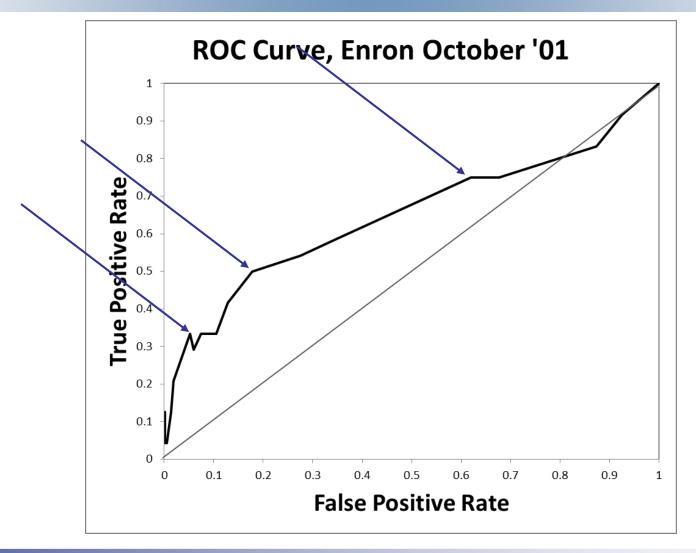
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Feature Creation Summary

- Method:
 - All nodes
 - Structural Features: Snapshot + Message Ratio: Multiple Snapshots
- Filtering down to only organizational members is not useful
 - Insiders look like other employees
 - Insiders do not look like external actors
- Internal vs External Ratio very useful!
- Summaries (e.g. cumulative sums or averages) add noise features
 - Network collection not regular in Enron corpus
 - Executives trained to delete emails



ROC Curve for October 2001





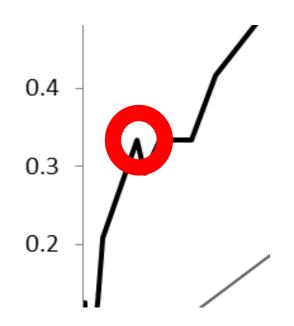
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Farnegie Mellon SRIP Features on the ROC Curve (Alphabetical Order)

- AuthorityCentrality_TO
- CliqueCount_TO
- ClusteringCoefficient_TO
- CognitiveSimilarity_TO
- ColumnGiniMeansDifference_TO
- Constraint_TO

CASOS

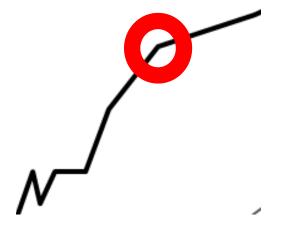
- CorrelationResemblance_TO
- InverseClosenessCentrality_BCC
- InverseClosenessCentrality_TO
- Oct2001_InDegree_TO_Internal
- May2001_InDegree_TO_ALL
- May2001_InDegree_TO_Internal
- WeakComponentMembers_BCC



33% True .05% False

Farnegie Mellon UNITED FILL FOR THE ROC Curve (Alphabetical Order)

- ColumnGiniMeansDifference_TO
- InverseClosenessCentrality_BCC
- InverseClosenessCentrality_TO
- Oct2001_InDegree_TO_Internal
- May2001_InDegree_TO_ALL
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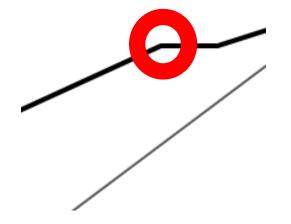


50% True 18% False



Farnegie Mellon STRIP Features on the ROC Curve (Alphabetical Order)

- ColumnGiniMeansDifference_TO
- May2001_InDegree_TO_ALL
- WeakComponentMembers_BCC



78% True 60% False





Findings on Insiders – those accused

- Are not "top" network actors
- Form a densely connected sub-group
- High level of in-group communication
- Low out-group communication
- Overall have many structural holes
- Part of a hidden network (BCC Weak component)
- Have long reach inside and out inverse closeness

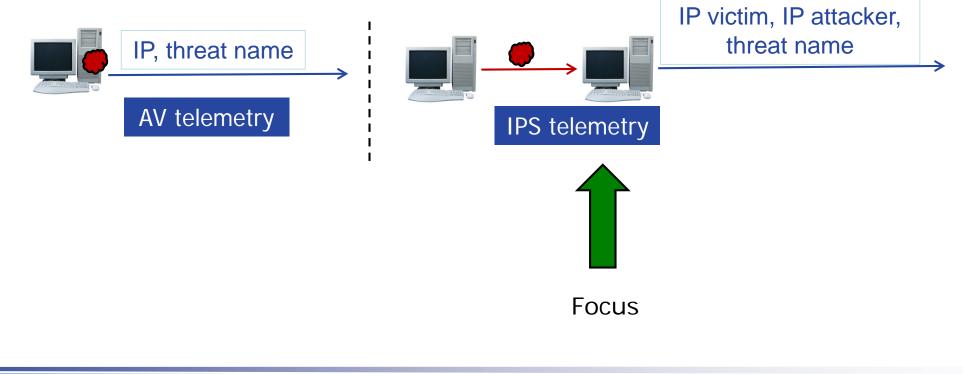




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Symantec's WINE telemetry data

- From ~10 million customer machines worldwide
- Use thesaurus for threat attributes
 - AV: type, IPS: type, infrastructure

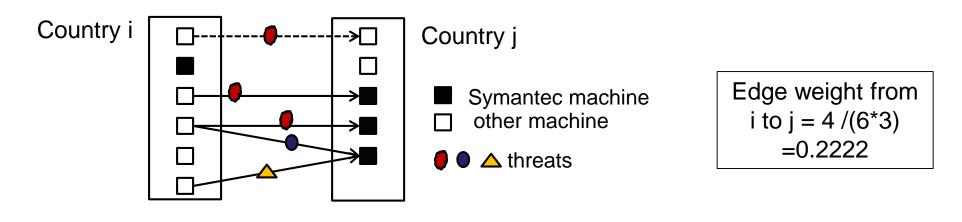




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Attack Network

- Cyber attack network
 - Avg # of attacks by a computer in country i on a computer in country j
 - (# of attacks by computers in country i on computers in country j)/
 (# of computers in i * # Symantec computers in j)
 - Total, infrastructure * type, (IPS)





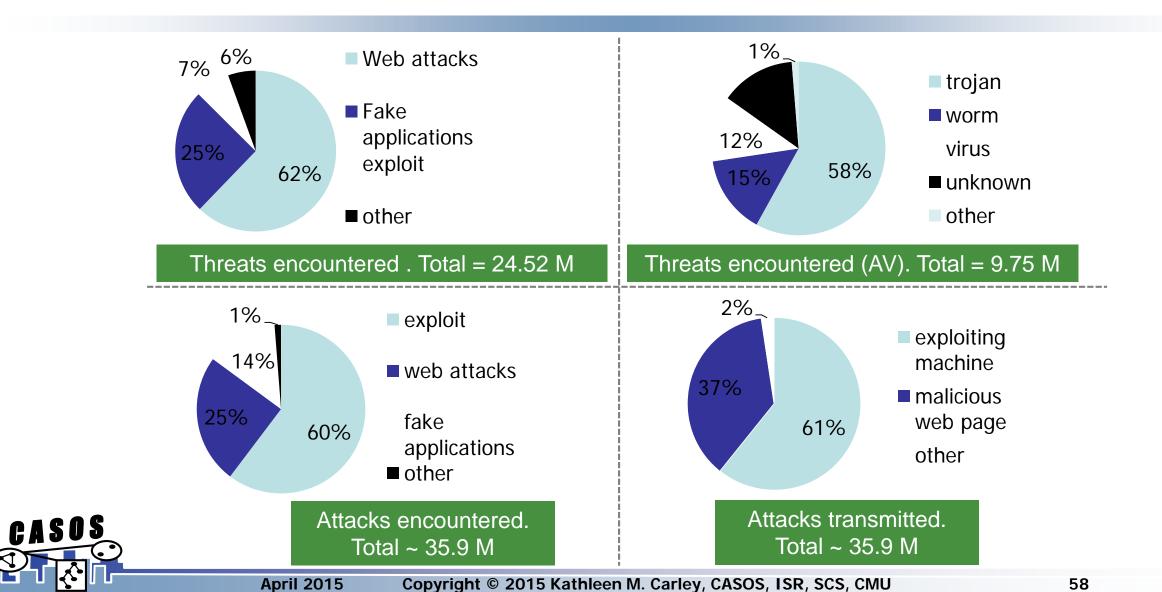
Non-Attack Data

- ICT development index
 - ICT development index [ITU 2010] that combines 11 indicators (fixed telephone lines per 100 inhabitants, mobile cellular telephone subscriptions per 100 inhabitants, international Internet bandwidth per Internet user(bits/s), % of households with a computer, % of households with Internet access, % of individuals using Internet, fixed broadband Internet subscriptions per 100 inhabitants, active mobile broadband subscriptions per 100 inhabitants, a
- Cyber Research
 - # cyber security papers during 2002-2011[SCOPUS]
- Region
 - Africa, Asia, Eastern European, Western European and others (includes US, Canada, N. Zealand), Latin America
- Corruption [transparency international]
 - Index of corruption in the public sector
 - High index value: low corruption
- Software piracy rate [Business software alliance]
 - Number of units of pirated software installed divided by total number of units of installed software
- GDP per capita [world bank]
- Alliance Network [correlates of war]
- Hostility Network network [Center for International Development & Conflict Management, Department of Peace and Conflict Research]



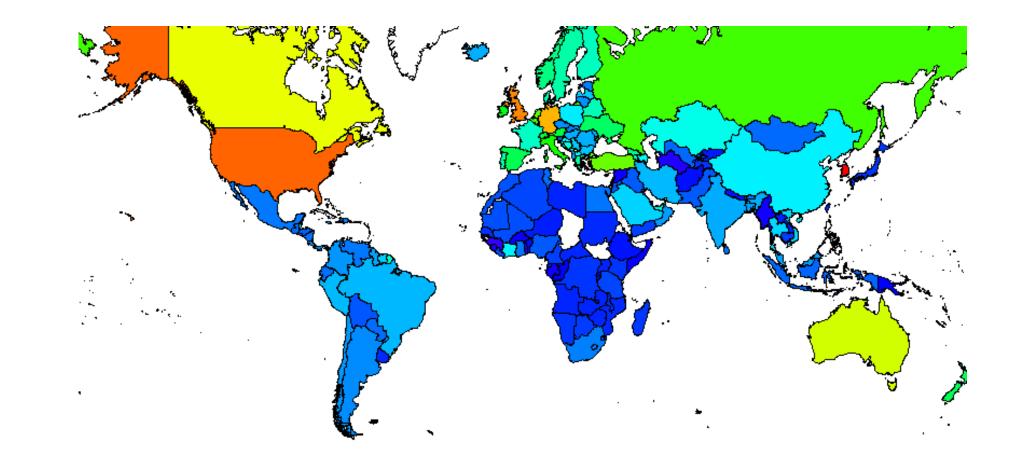


Relative Prevalence





Web Site Threats Encountered





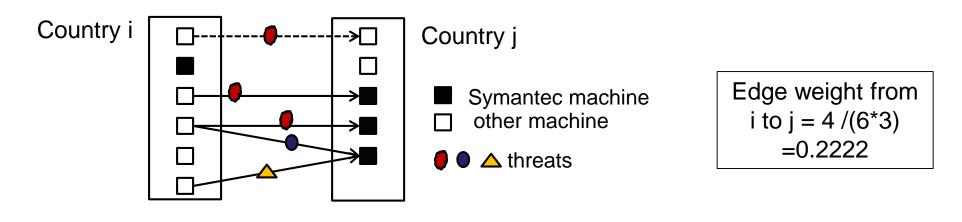
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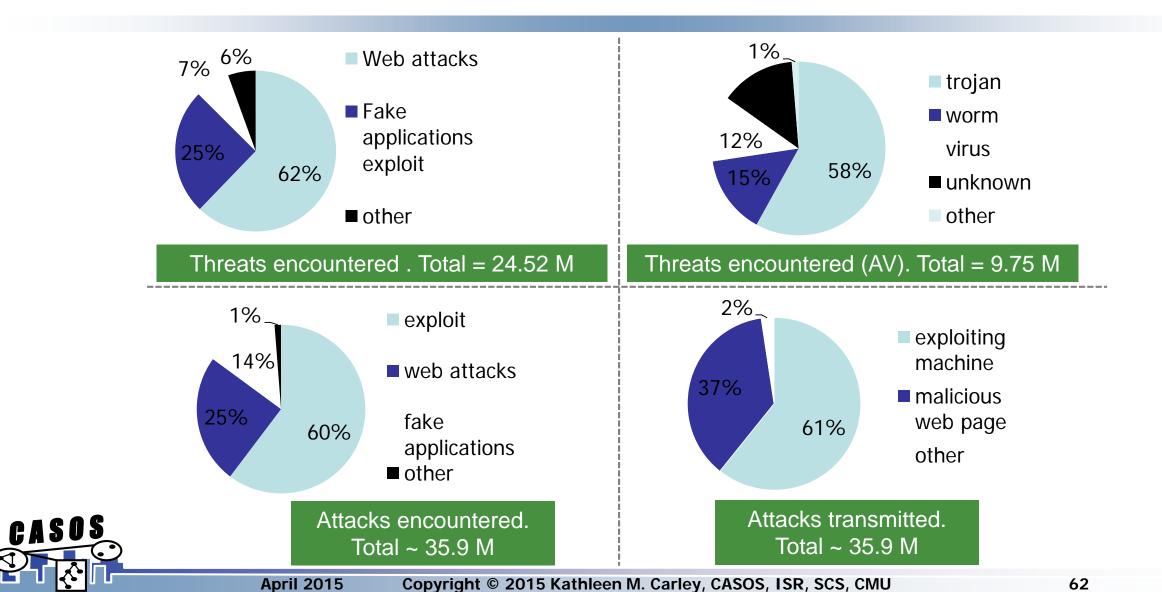
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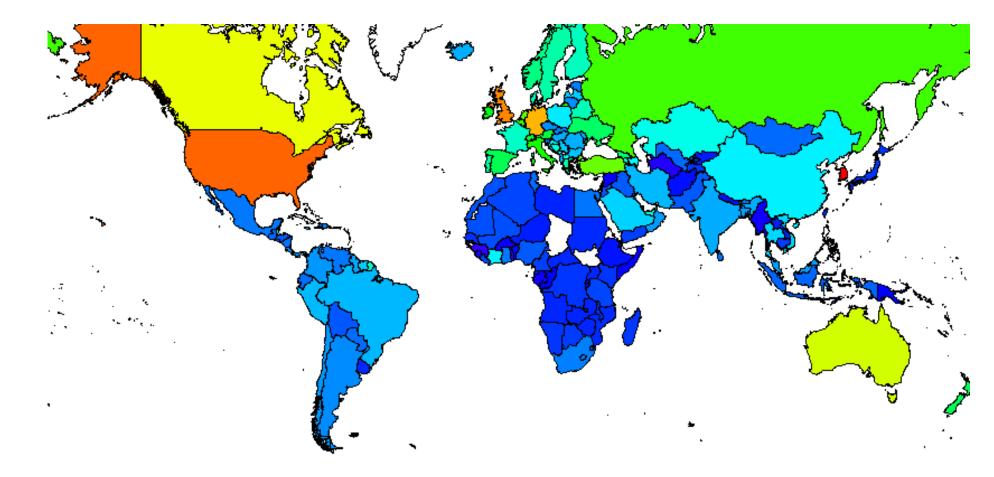


Relative Prevalence





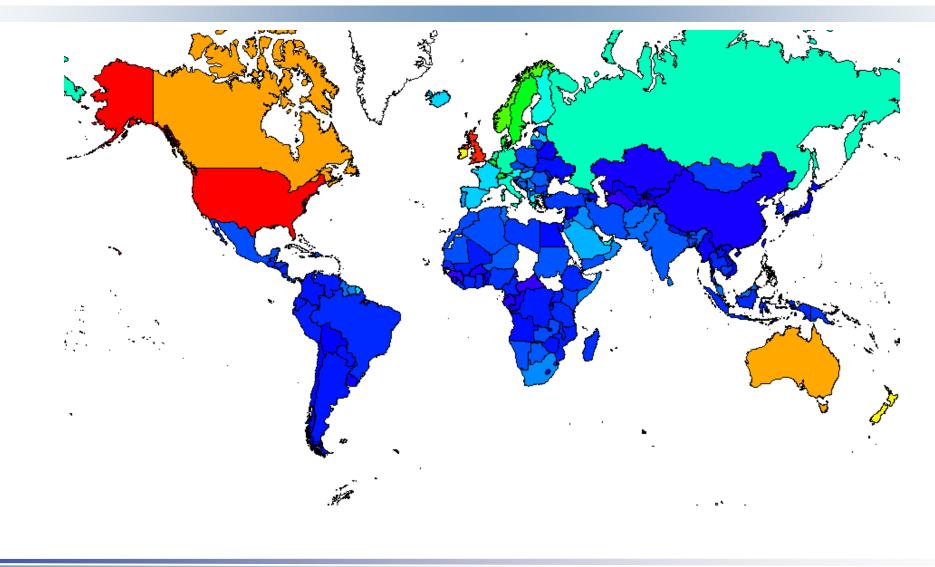
Web Site Threats Encountered







Fake Application Threats Encountered





Top Countries – Threats Encountered (IPS)

- Top countries for web attacks & fake applications
 - High ICT development
- Top countries for exploits
 - Middle ICT development

	All		Web attack		Fake application		Exploit	
Rank	country	value	country	value	country	value	country	value
1	United States	1.412	S. Korea	0.957	United States	0.424	Moldova	0.553
2	United Kingdom	1.34	United States	0.874	United Kingdom	0.409	India	0.369
3	Canada	1.199	United Kingdom	0.844	Canada	0.361	Latvia	0.309
4	Australia	1.164	Germany	0.805	Australia	0.359	Uruguay	0.284
5	S. Korea	1.058	Canada	0.727	Ireland	0.328	Ukraine	0.259
6	Germany	1.042	Australia	0.706	New Zealand	0.327	Taiwan	0.257
7	Ireland	0.97	Turkey	0.619	Norway	0.256	Bangladesh	0.24
8	Russia	0.942	Netherlands	0.608	Vatican	0.239	Mali	0.232
9	Italy	0.937	Russia	0.585	Sweden	0.217	Belarus	0.226
10	Moldova	0.869	Belgium	0.581	Belgium	0.212	Kazakhstan	0.223





Top Countries – Attacks Encountered (IPS)

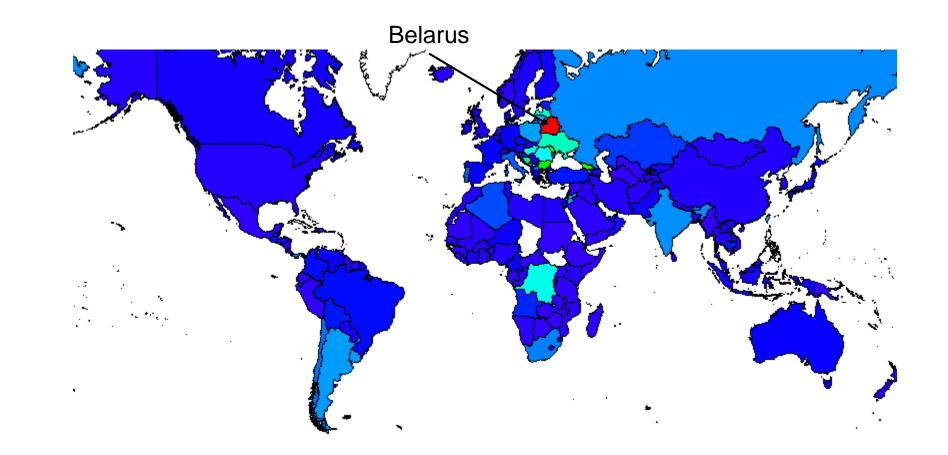
- Top countries for web attacks & fake applications
 - High ICT development
- Top countries for exploits
 - Middle ICT development

	All		Exploit		Web attacks		Fake application	
Rank	country	value	country	value	country	value	country	value
1	Moldova	28.77	Moldova	28.42	Germany	1.64	United States	0.92
2	India	16.56	India	16.22	S. Korea	1.64	United Kingdom	0.83
3	Taiwan	15.91	Taiwan	15.75	United States	1.29	Canada	0.76
4	Nicaragua	13.3	Nicaragua	13.02	United Kingdom	1.25	Australia	0.68
5	Latvia	13.05	Latvia	12.58	Netherlands	1.06	Ireland	0.59
6	Italy	11.13	Italy	10.09	Canada	0.99	New Zealand	0.56
7	Israel	10.1	Israel	9.54	Australia	0.99	Norway	0.46
8	Uruguay	8.41	Uruguay	8.23	Russia	0.83	Switzerland	0.4
9	Bosnia & Herzegovina	7.45	Bosnia & Herzegovina	6.86	Belgium	0.81	Belgium	0.38
10	Georgia	7.07	Georgia	6.54	Italy	0.79	Sweden	0.36





Exploits Transmitted – "Purportedly"



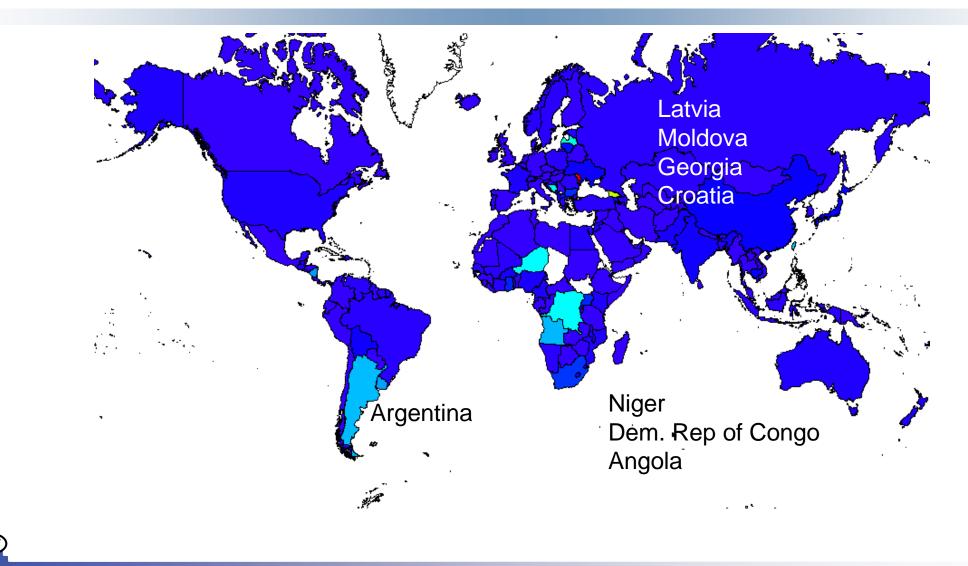


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CASOS

Exploits: Countries that act as wayports





Findings on Global Mapping

- Web Attacks Increasing
- Wayport countries
 - High corruption
 - Unsophisticated IT infrastructure
 - Include some in Russia sphere of influence
- Third world countries may be more susceptible to wide range of attacks

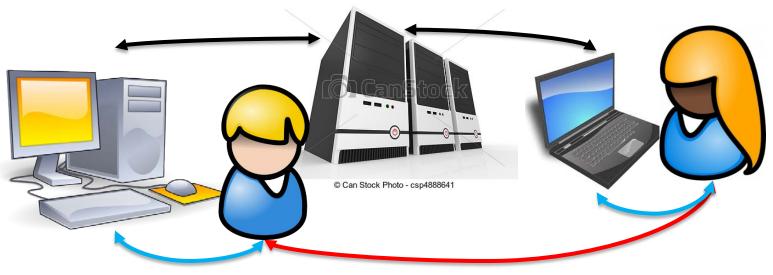




Resiliency

How should organizations be structured to mitigate the impact of cyber attacks?

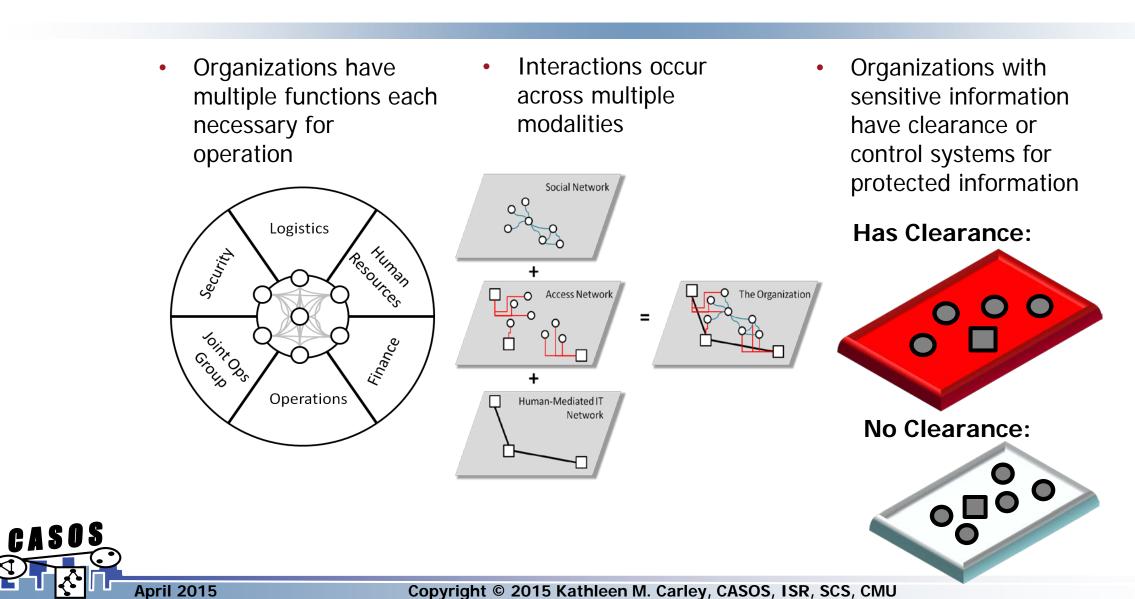
- Approach:
 - Empirically Grounded Computer Simulation
- Why are we unique:
 - Model both the human side and the information technology side



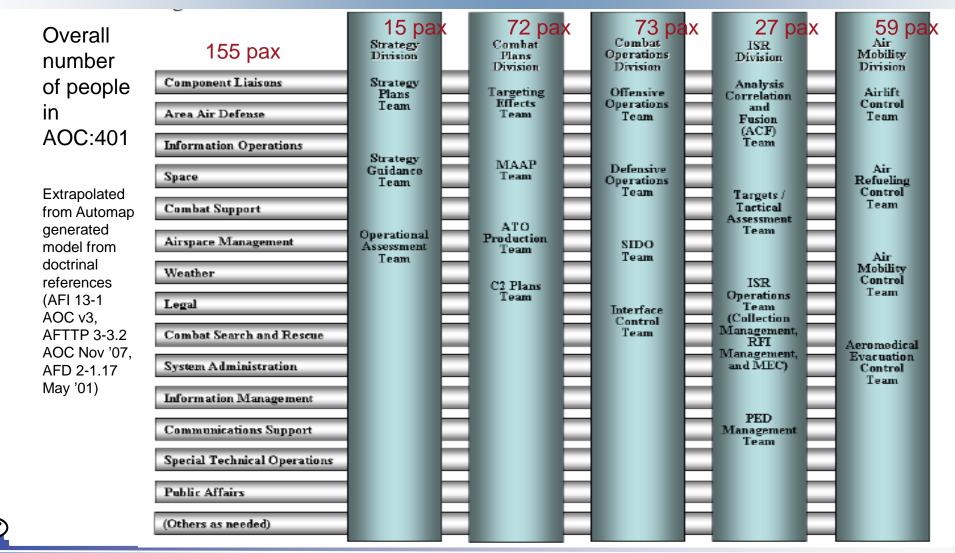




Modeling the Organization



USAF AOC – a cross between Divisions and Functional Areas

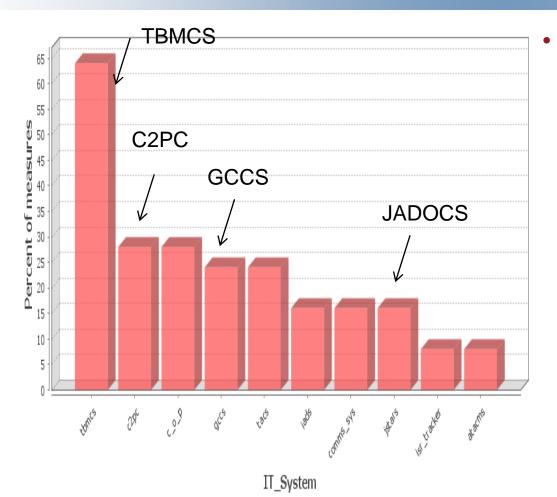


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Key Entities in USAF AOC



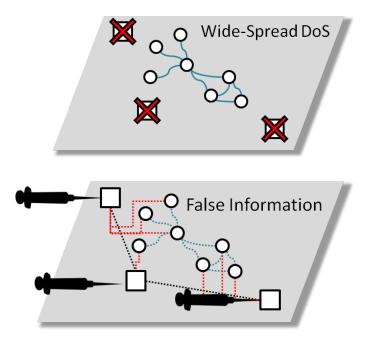
- For USAF Regional AOC
 - TBMCS, is in top 10 list
 ~60% of the agent-relevant
 measures (13 of 22) (Lanham et al, 2011b)
 - E.g., Betweeness Centrality (across all node pairs that have a shortest path containing *v*, the percentage that pass through *v*) (Freeman, 1979)





Most Attacks are Minimally Disruptive

- Our models have shown that most attacks cause minimal disruption to the organization's processes
- Supported by the empirical literature.
- We now focus on **severe** attacks and on attack combinations.







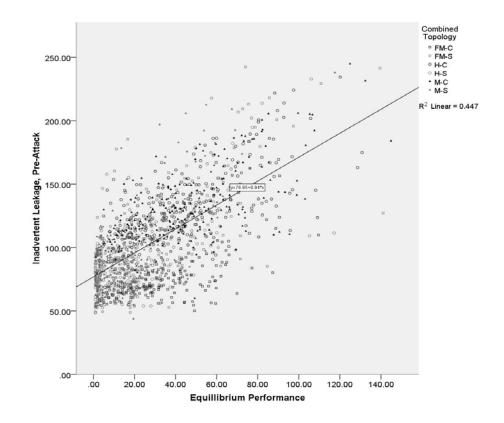
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Inadvertent Leaks

- Inadvertent leaks occur when proprietary or classified information is transferred to those who should not have access, s.t. the transfer may have occurred without explicit intent
- Inadvertent leaks are:
 - Inevitable

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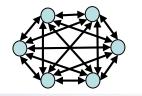
- More likely in higher performing organizations
- More likely in certain network topologies
- Prevention requires heedful interaction and acting as a high reliability organization





Topologies

- Social network people to people
 - Functional Mesh: members of each functional area may interact with each other
 - Hierarchy: 3-4 levels with each manager having 3-7 subordinates
 - Matrix: Hierarchy + cross-functional teams where members integact across functional areas
- IT Networks system to system
 - Stove-pipe: All Decision Support IT Systems are autonomous, and are not intended to be cross-linked with each other except through interaction with people.
 - Cloud: All Decision Support IT Systems are allowed to create cross-linkages as desired.







Attacks

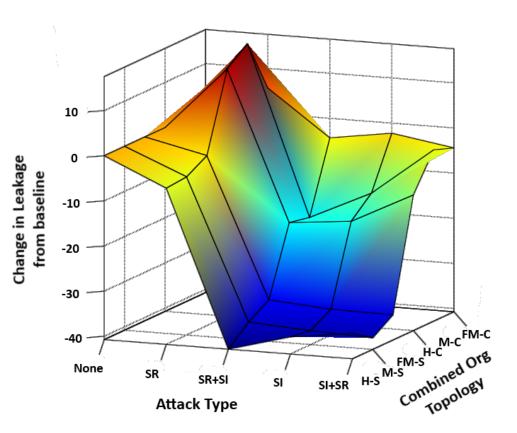
- No Attacks
- Reliability
 - Non-Severe IT support system is unavailable
 - Severe all IT support systems are unavailable
- Integrity
 - Non-Severe compromised IT system has ingested new non-relevant data
 - Severe introduce new non-relevant but interesting information to the organization through all IT systems
- Reliability & Integrity





Impact of Attacks and Topology

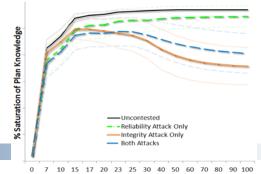
- Hierarchical Siloed organizations least prone to inadvertent leaks and performance will be least degraded by attacks
- Combined attacks most harmful
- Cloud is more conducive to inadvertent leaks







Illustrative Results



- Most organizations resilient to small and medium attacks
- Integrity attacks more devastating than DOS attacks
 - shown Air Operations Command (AOC).
- Resiliency is enhanced by redundancy
- Resiliency is increased by coordination
- When only a few systems face an integrity attack, key decision makers are less impacted than others
 - Possibly leading to feeling attack is not serious
 - Contributes to resiliency as key personnel are able to operate
- When many systems are attacked key decision makers are more impacted



Network Analytics

- Useful for insider threat
- Supports analysis of high dimensional networks
- Supports analysis of big data
- Supports social media analytics
- Valuable methodology for Science of Security



