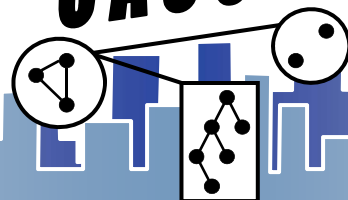


CASOS



Dynamic Network Analysis: Management and Intervention

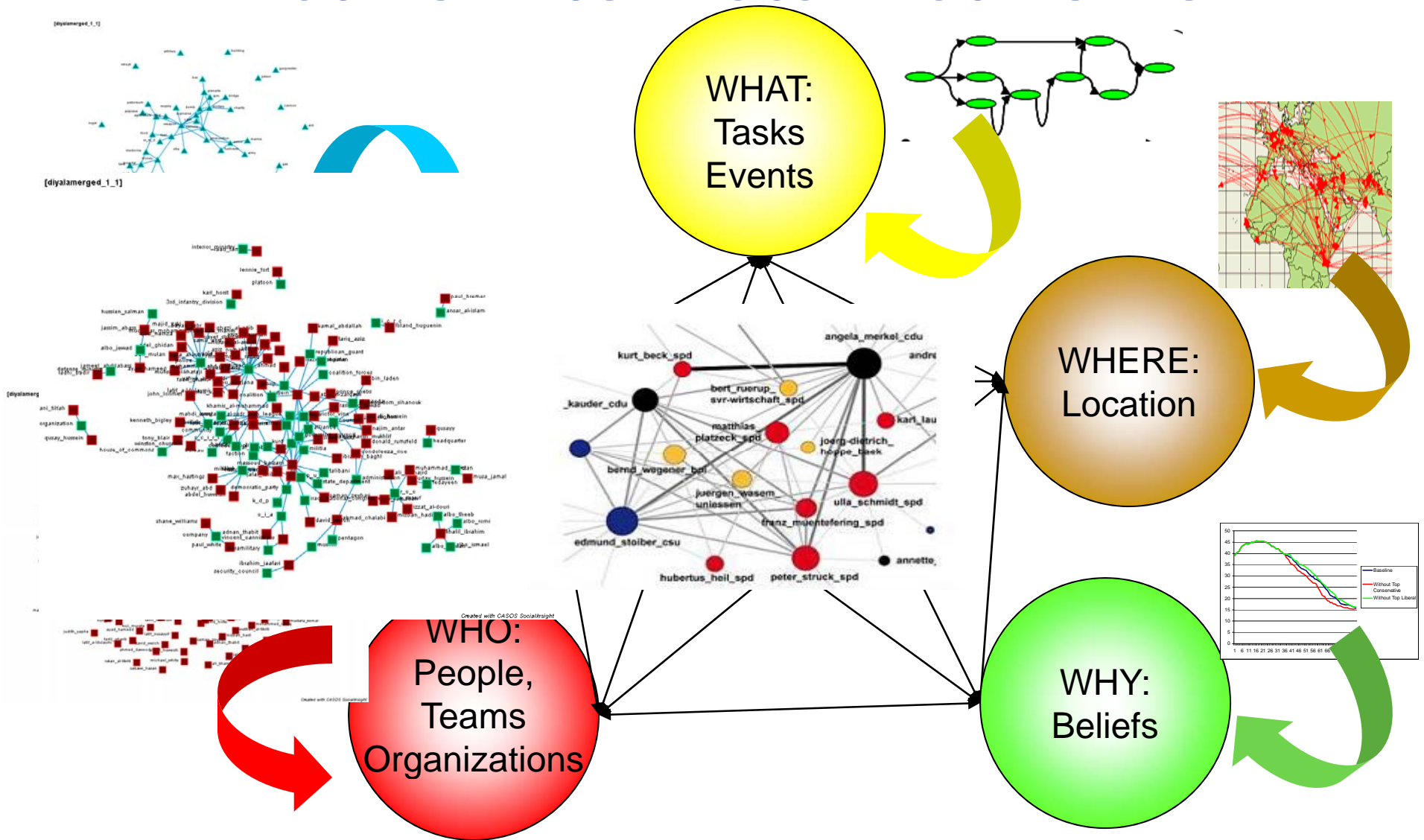
Prof. Kathleen M. Carley

kathleen.carley@cs.cmu.edu

PCANS

	People	Resources	Tasks
People Relation	Social Network <i>Who knows who</i>	Skills Network <i>Who knows what</i>	Assignment Network <i>Who does what</i>
Resources Relation			Commitment Network <i>What resource is needed for what tasks</i>
Tasks Relation			Precedence Network <i>Which tasks must be done before which</i>

Network to Meta-Networks



Interconnection Among Networks

- To understand groups/organization need a meta-network perspective
 - Social network is NOT ENOUGH
 - Need to move beyond single mode networks
- Connections among networks drive/determine
 - Adaptivity / evolution of single mode networks
 - Enable prediction of missing data
 - Provide basis for process analysis

Connectivity Logics and Concerns

- Homophily based interaction
- Expertise based interaction
- Co-work based interaction
- Congruence
 - The need for match
- Task analytics
 - Resource needs
 - Knowledge needs
 - Personnel needs

The Power of Meta-Networks

Illustrative Examples

1. Organizational Performance
 - Public Health
2. Identification and Disruption of Groups
 - Gangs and border control
3. Identification of Key Actors
 - Missing Information and key terrorists
4. Geo-Spatial Networks
 - Drug interdiction
 - Hidden Ports

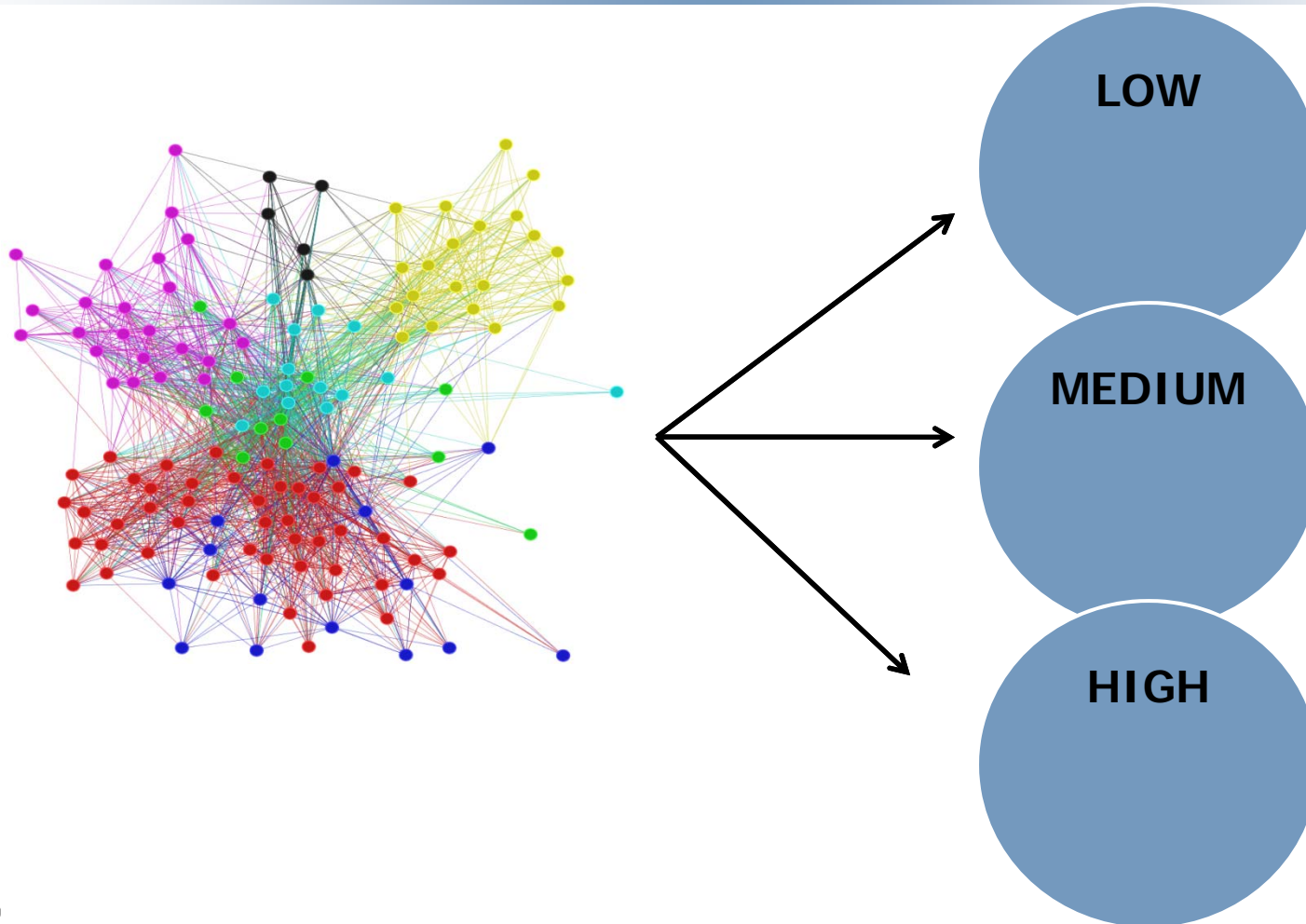
1: Organizational Performance



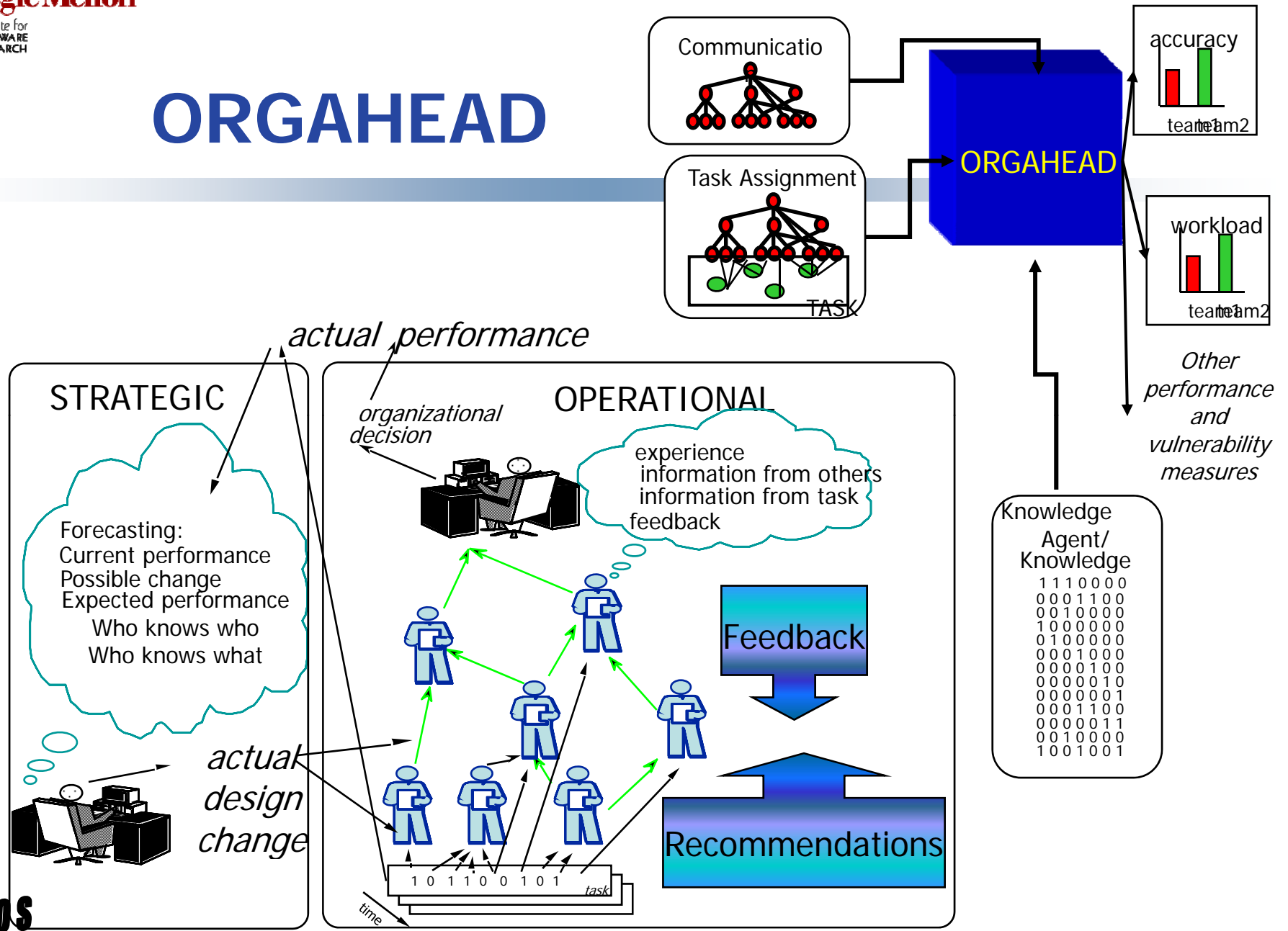
Formal Network

Informal Network

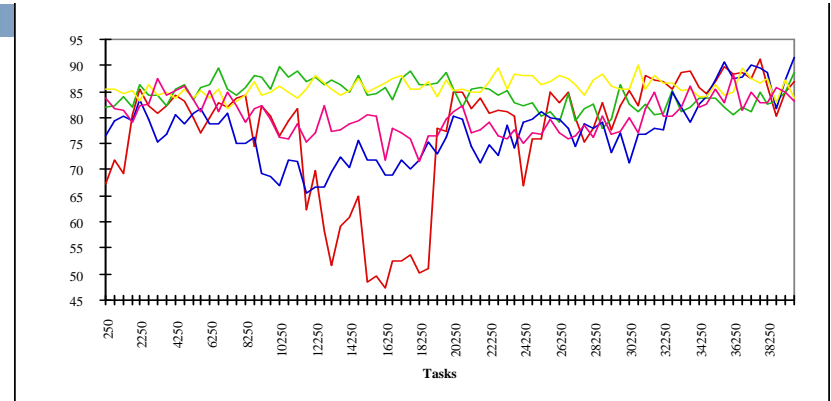
Impact of Social Structure on Performance



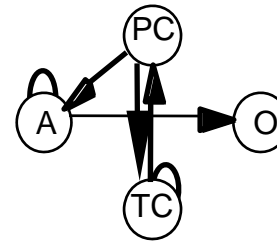
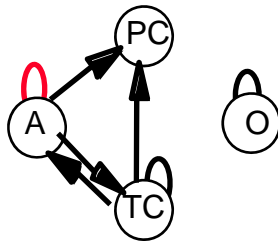
ORGAHEAD



Learning Clashes and Patterns of Change

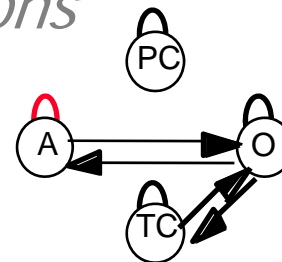
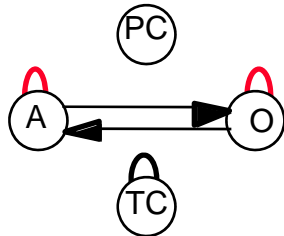


High Performance Organizations



A = augment
 O = transfer out
 PC = redesign
 TC = retask

Low Performance Organizations



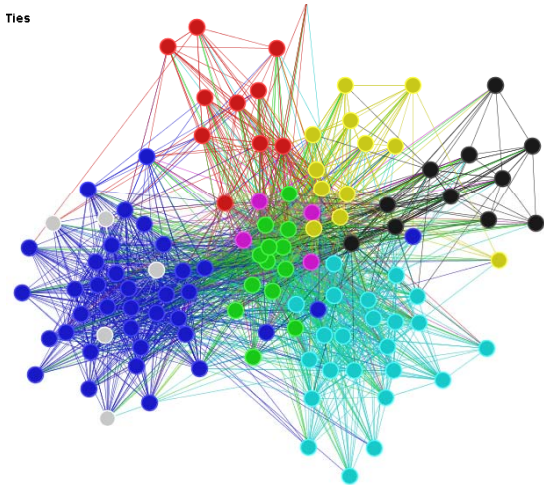
With different technologies these patterns and sets of actions change

CHANGE

Time

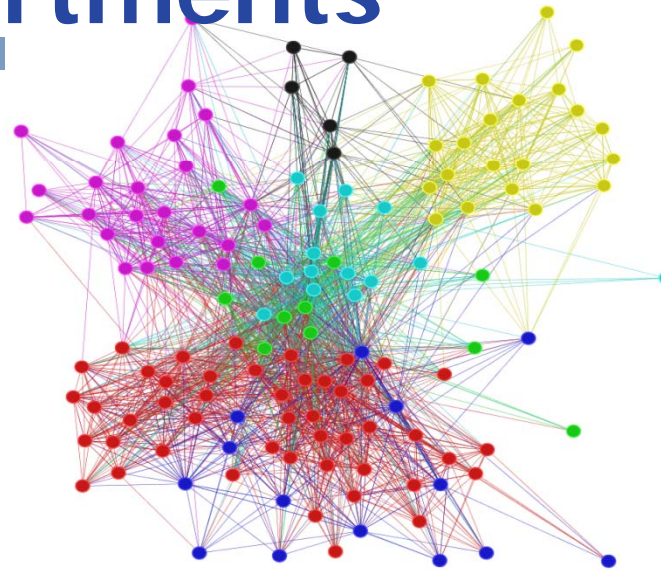


Four Illustrative Health Departments



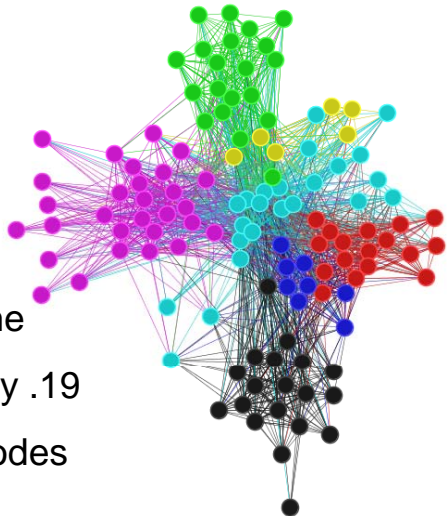
Champaign
 Density .24
 115 nodes

powered by O

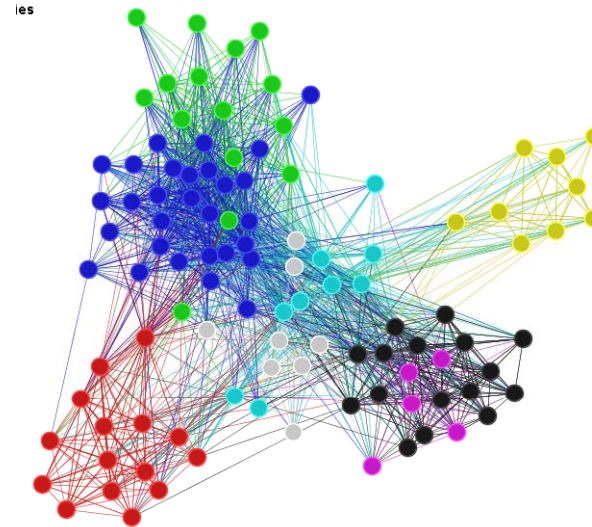


Coconino
 Density .16
 136 nodes

BroomeCountyAllTies



Broome
 Density .19
 122 nodes



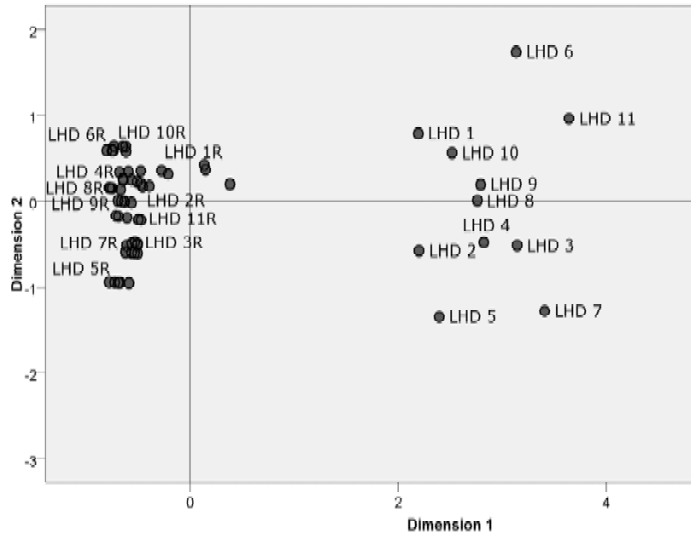
Missoula
 Density .21
 106 nodes

powered by ORA,

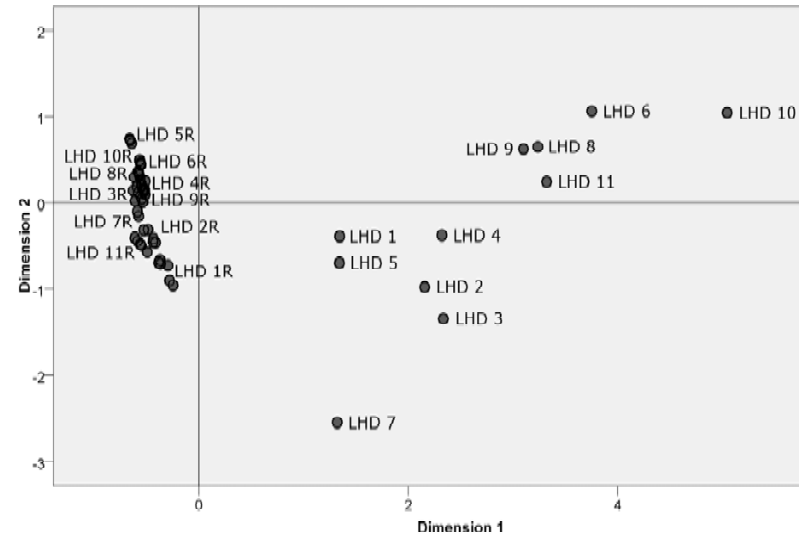
Health Department Structures



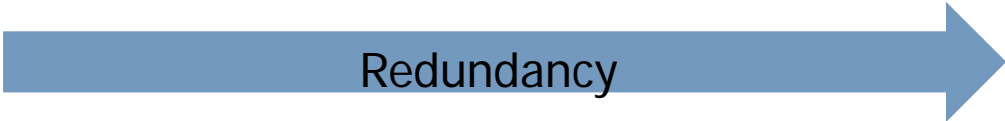
a. All ties networks



b. Strongest ties networks



† Centralization, complexity, percent silos, plus task, knowledge, and resource redundancy. Density was excluded because it was used to generate random network sets



Public Health: Common Structure is NOT about the Social Network

Diversity in authority and communication

- Centralization
 - CV 50.20
 - Mean .25
- Silos
 - CV 49.00
 - Mean .01
- Average Betweenness
 - CV 41.02
 - Mean .01

Similarity in coordination and grouping

- Clustering Coefficient
 - CV 15.23
 - Mean .53
- Task Assignment Redundancy
 - CV 11.58
 - Mean .30
- Resource Availability Redundancy
 - CV 13.71
 - Mean .42



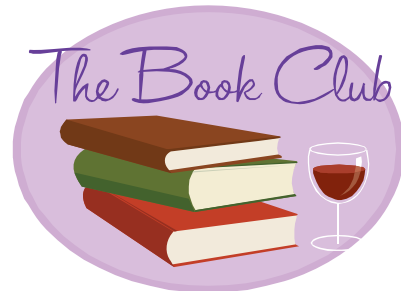
Impact of Silos

- Local efficiency
- Minimized training
- But ...

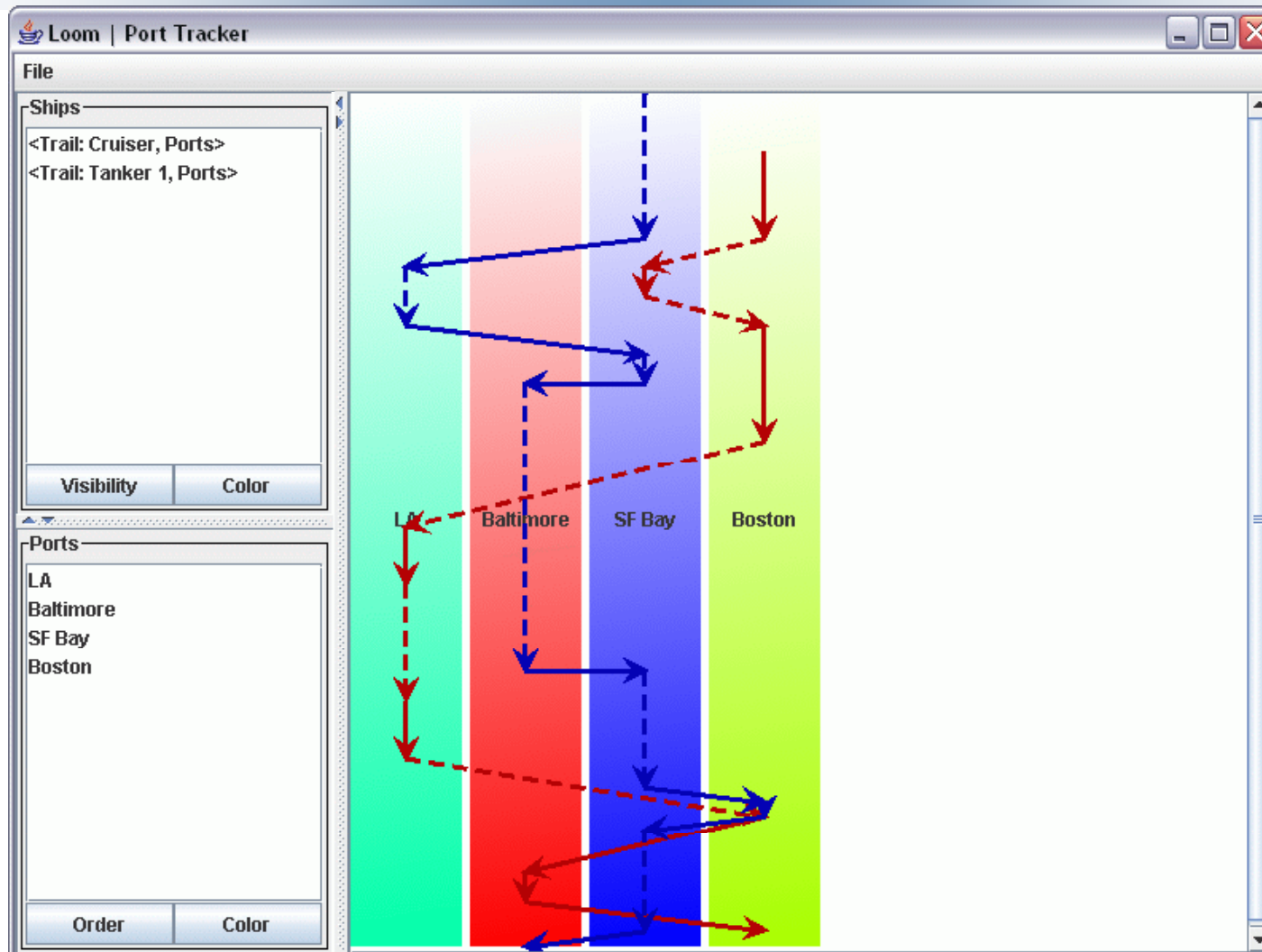
- What happens when people retire????
 - Level of silos increases
 - Lack of redundancy means real loss of skills!

- Informing health departments led to restructuring!

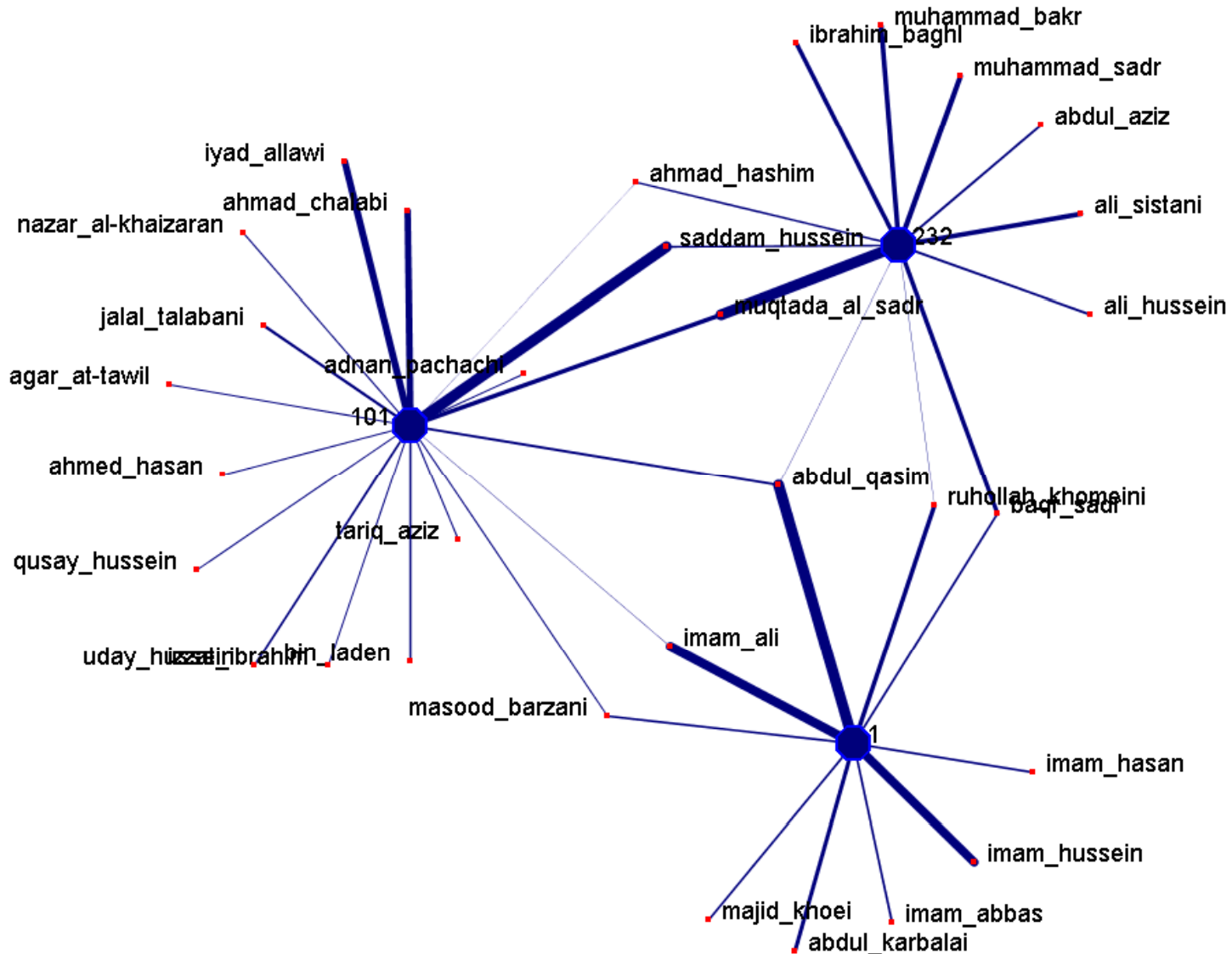
2: Identification and Disruption of Groups



Trails: How are Things Moving?



FOG: Fuzzy Groups on Central Core

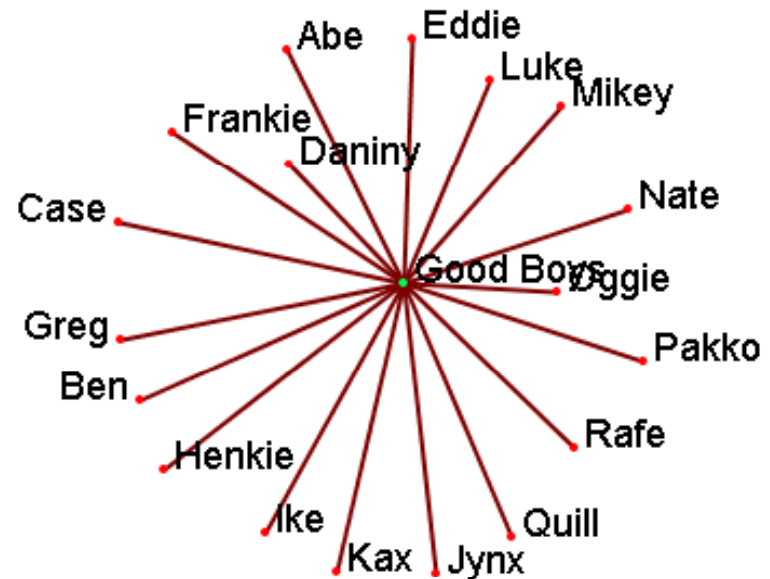


Example 2

A Tale of Two Gangs

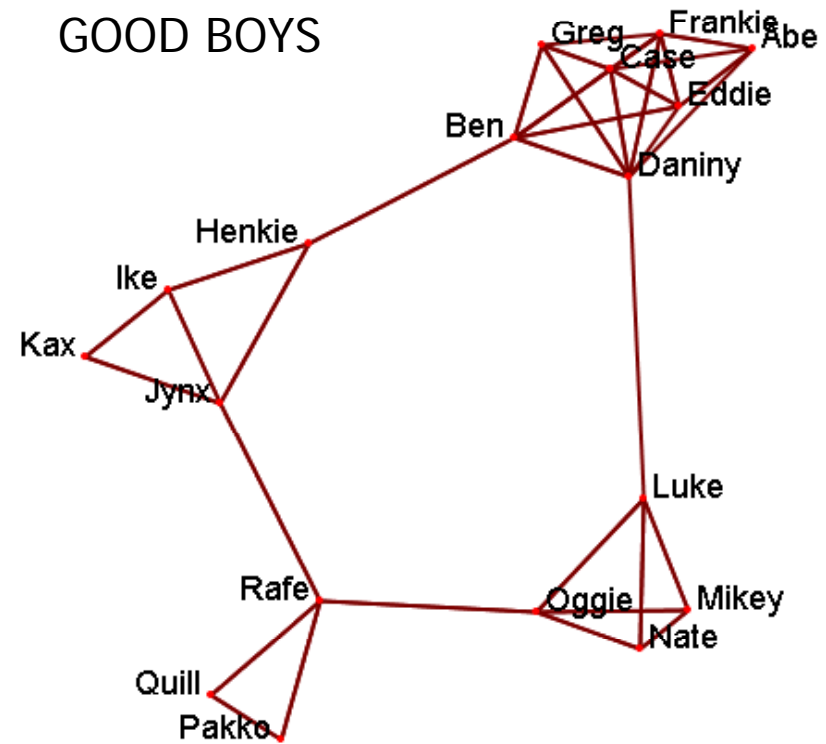
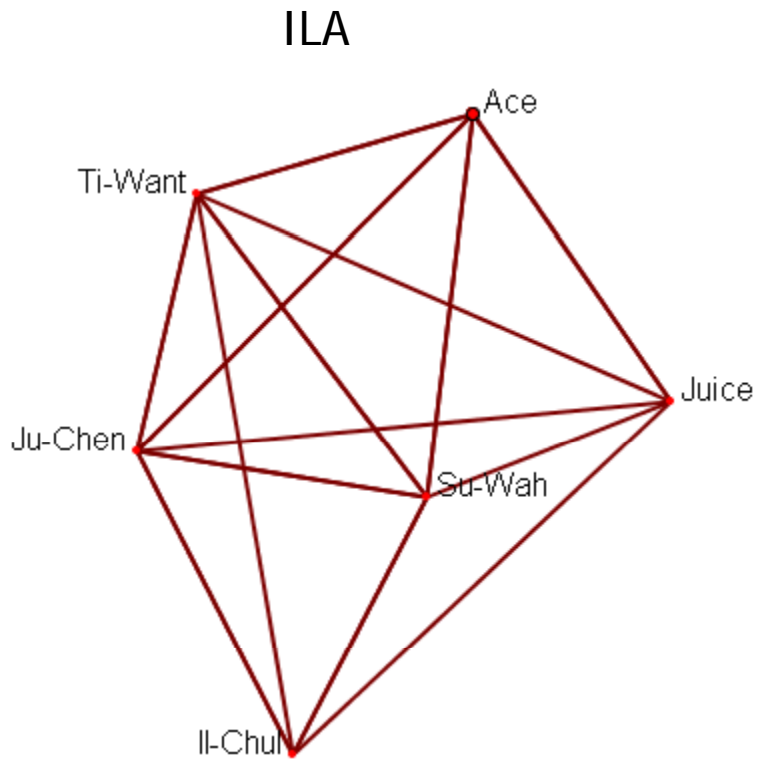


Two Gangs



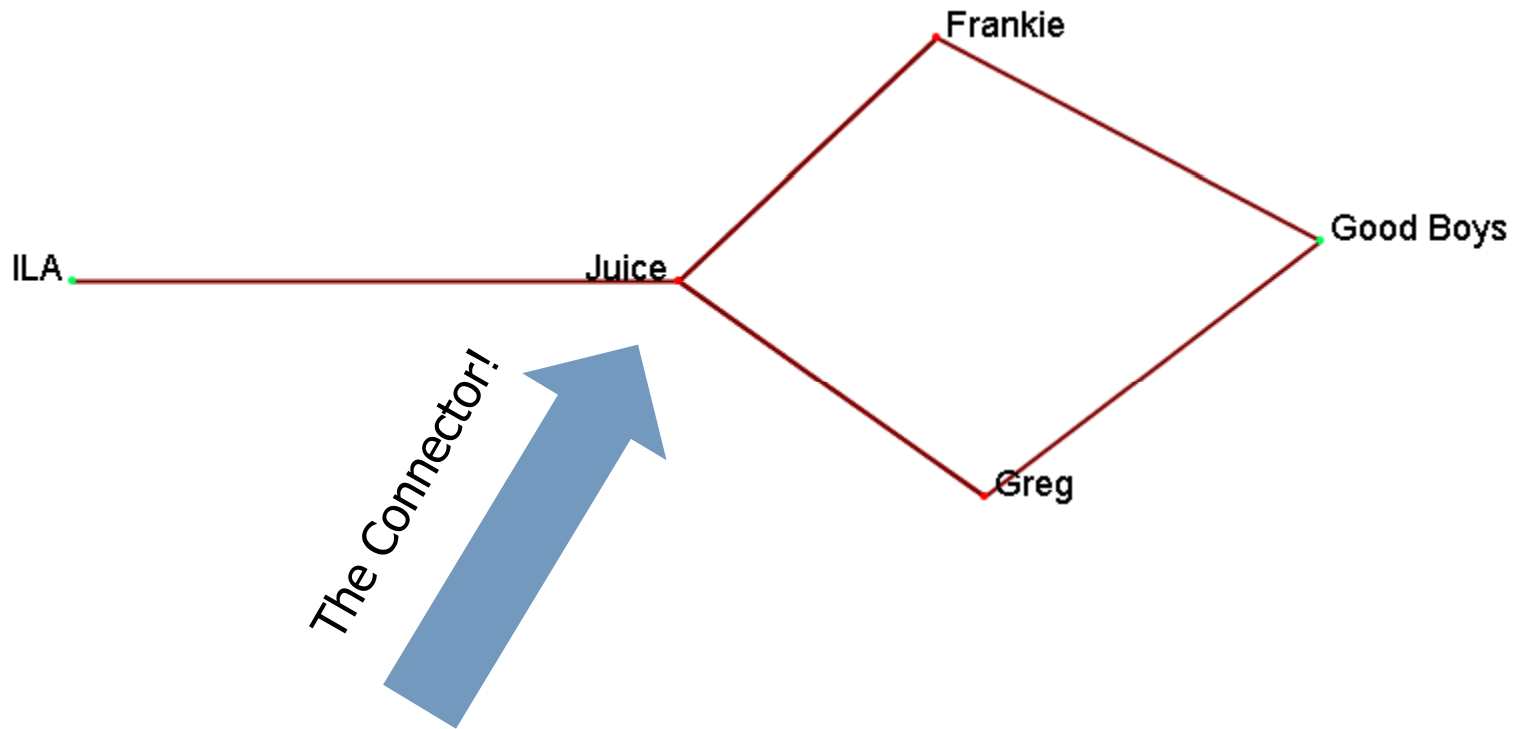
Notice – there are two gangs with very different members

Internal Structure

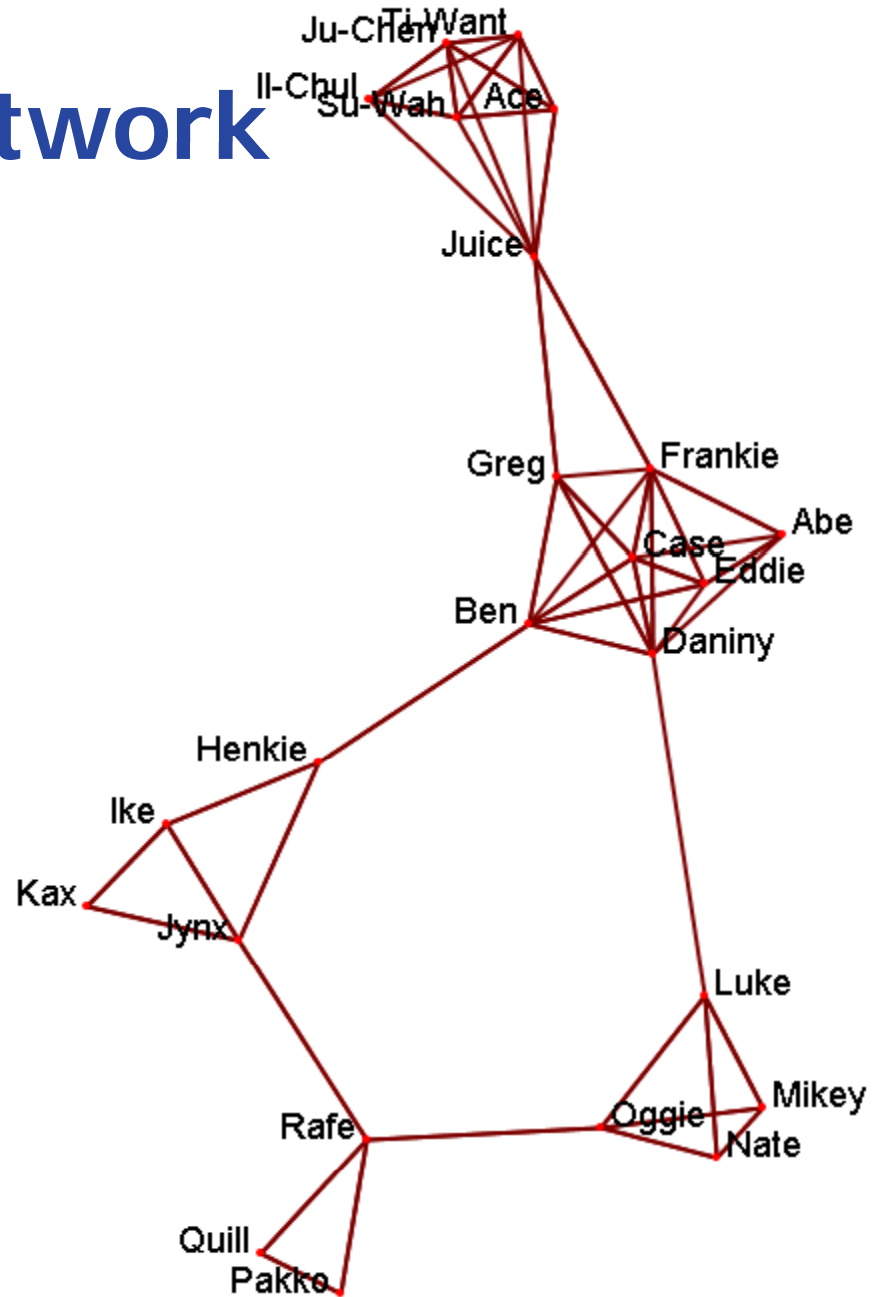


Notice – the two gangs have different structures
Derived from case files and co-presence

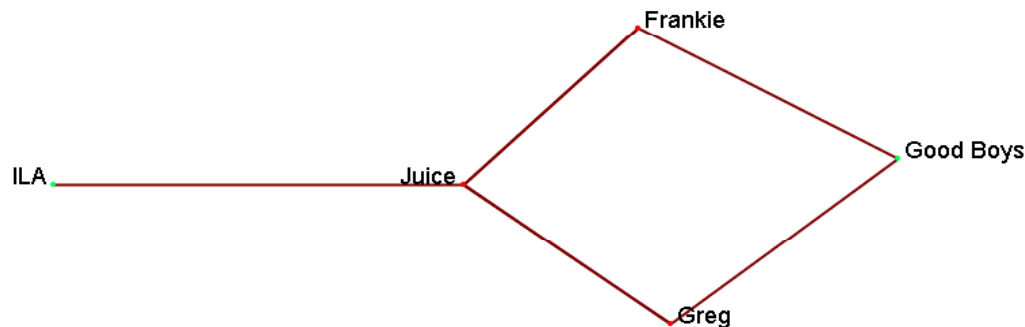
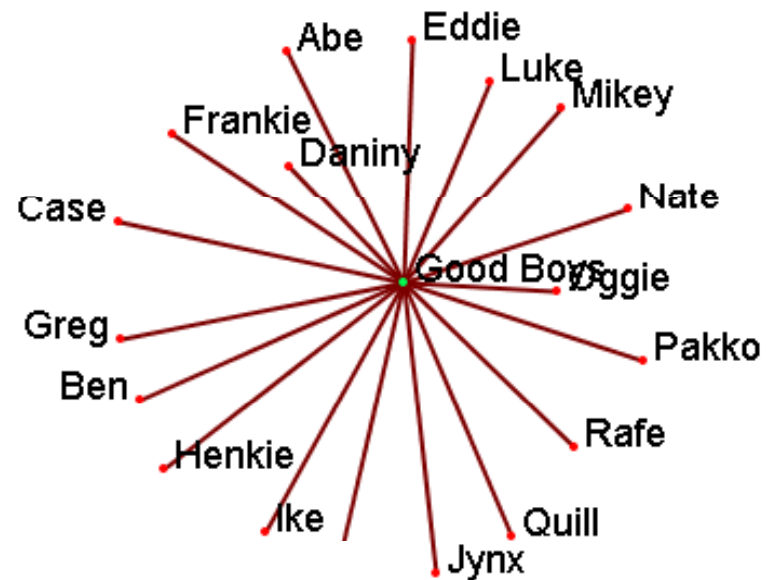
Are the gangs connected? Yes!



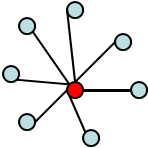
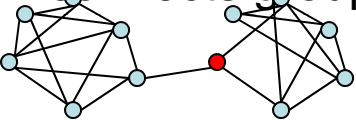
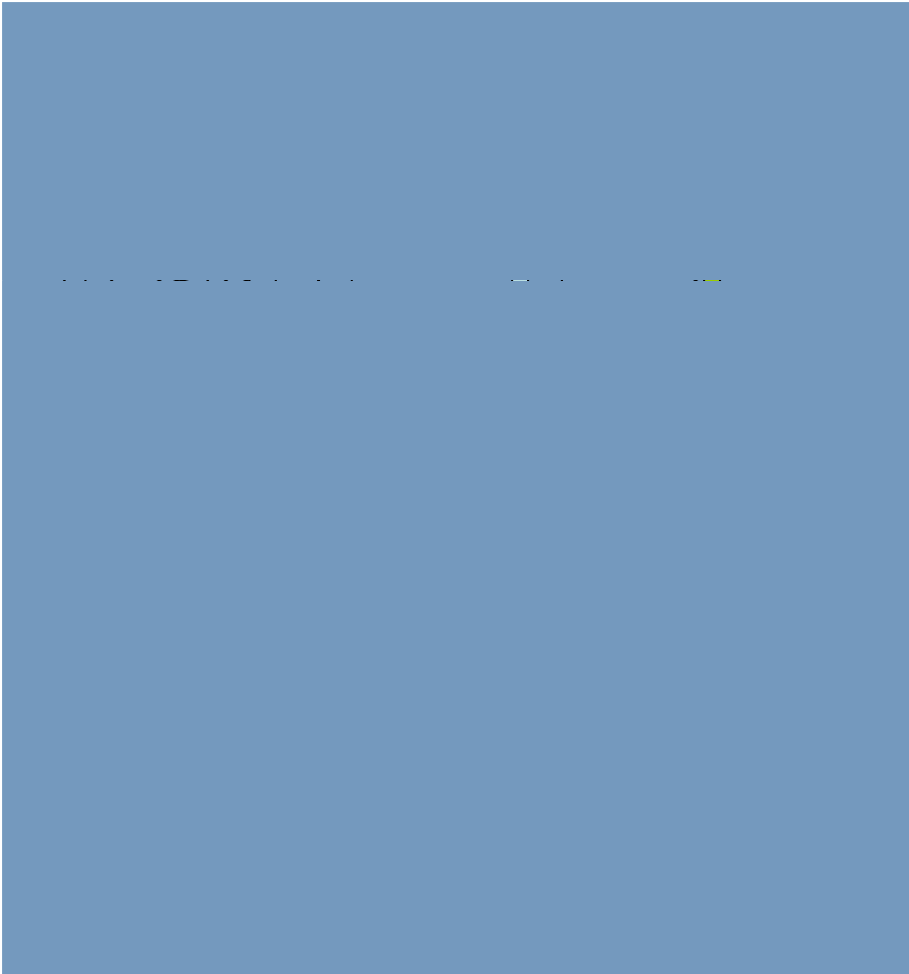
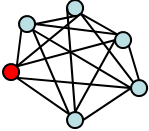
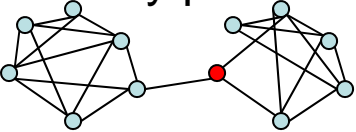
Overall Gang Network



From Gang Membership to Key Bridge



Meta-Network KEY ACTORS

<p>Degree Centrality in the know</p> 	<p>High Betweenness and not Degree</p> <p>connects groups</p> 	
<p>Eigenvector central core</p> 	<p>Betweenness many paths</p> 	



Immediate Impact - Prediction

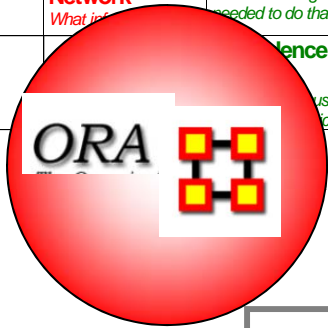
- *What if ? Remove top 5 emergent leaders*
- Change in performance
 - Anticipated drop – 4% percentage difference
- Change in information diffusion
 - Anticipated increase – 67% percentage difference
- New emergent leaders
 1. 0.0174 said_mortazavi
 2. 0.0137 kamal_kharazi
 3. 0.0127 reza_asefi
 4. 0.0120 morteza_sarmadi
 5. 0.0100 hashemi_shahroudi
- Value of “lowest” old emergent leader was .0246

Immediate
Impact

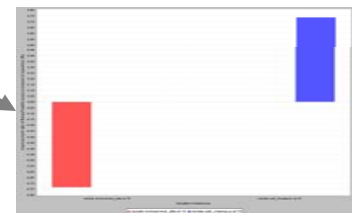
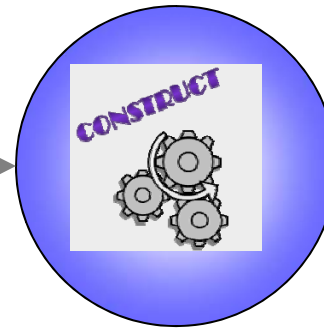


Forecast - from Patterns to Prediction

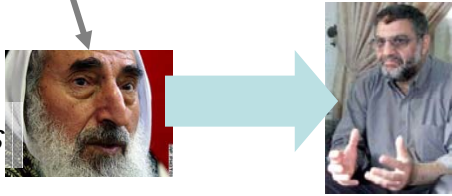
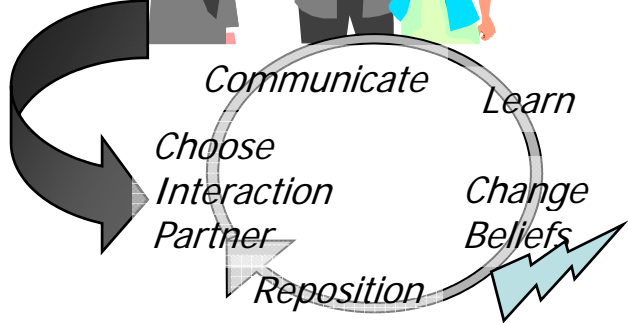
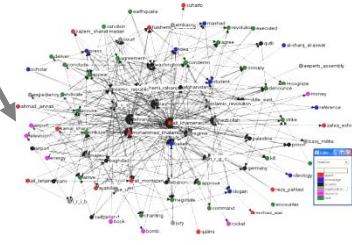
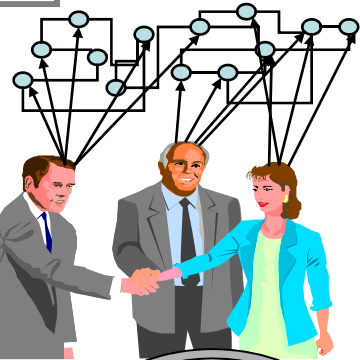
	People	Knowledge	Tasks
People Relation	Social Network <i>Who knows who</i>	Knowledge Network <i>Who knows what</i>	Assignment Network <i>Who does what</i>
Knowledge Relation		Information Network <i>What info is needed to do that task</i>	Needs Network <i>What knowledge is needed to do that task</i>
Tasks Relation			Precedence <i>What must be done first</i>



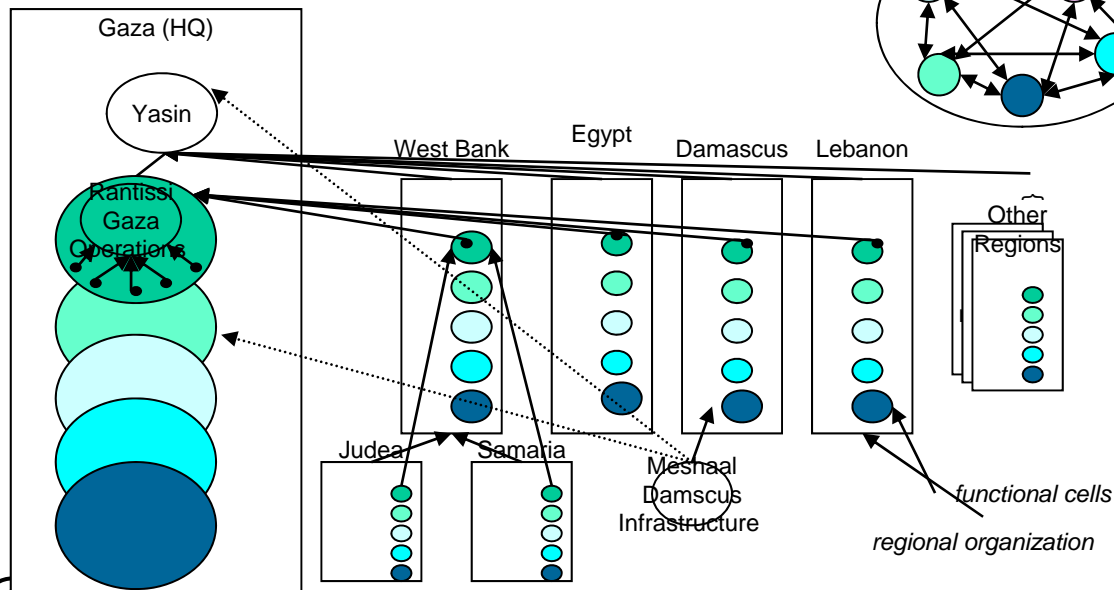
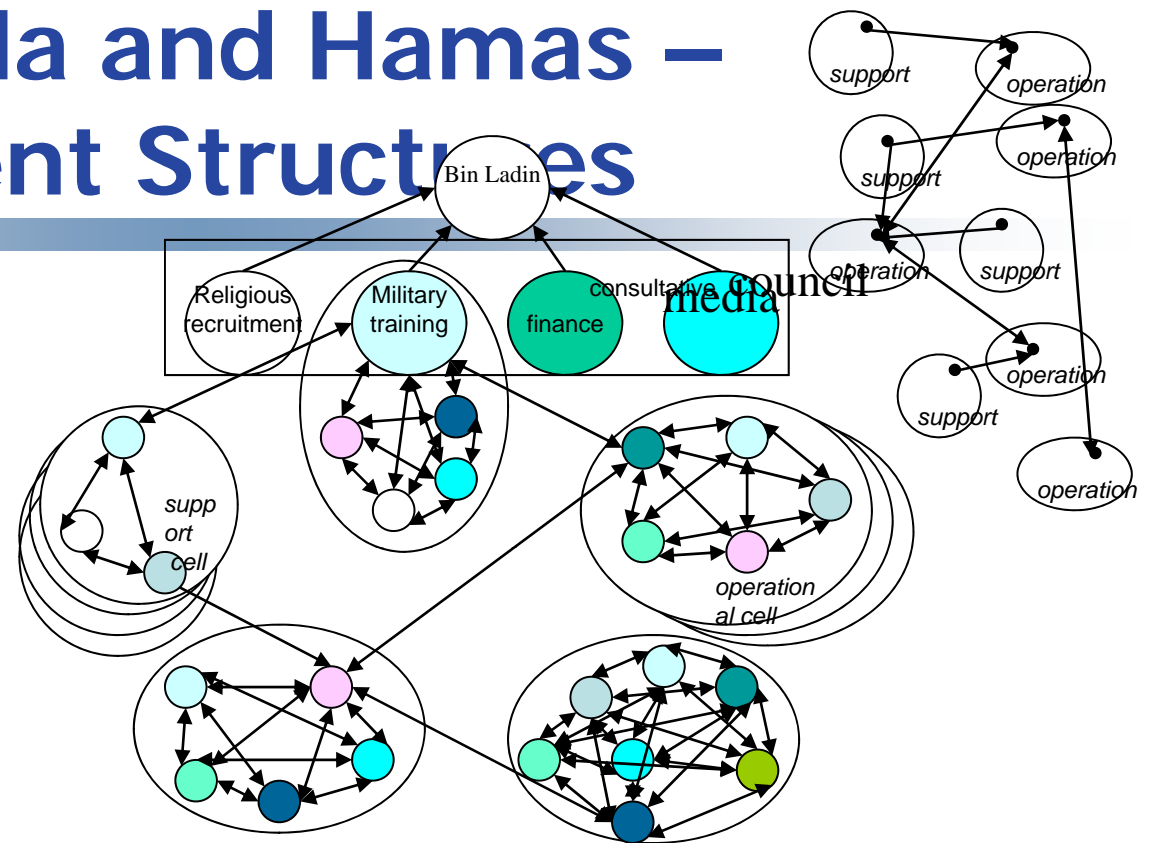
Near Term Impact Report



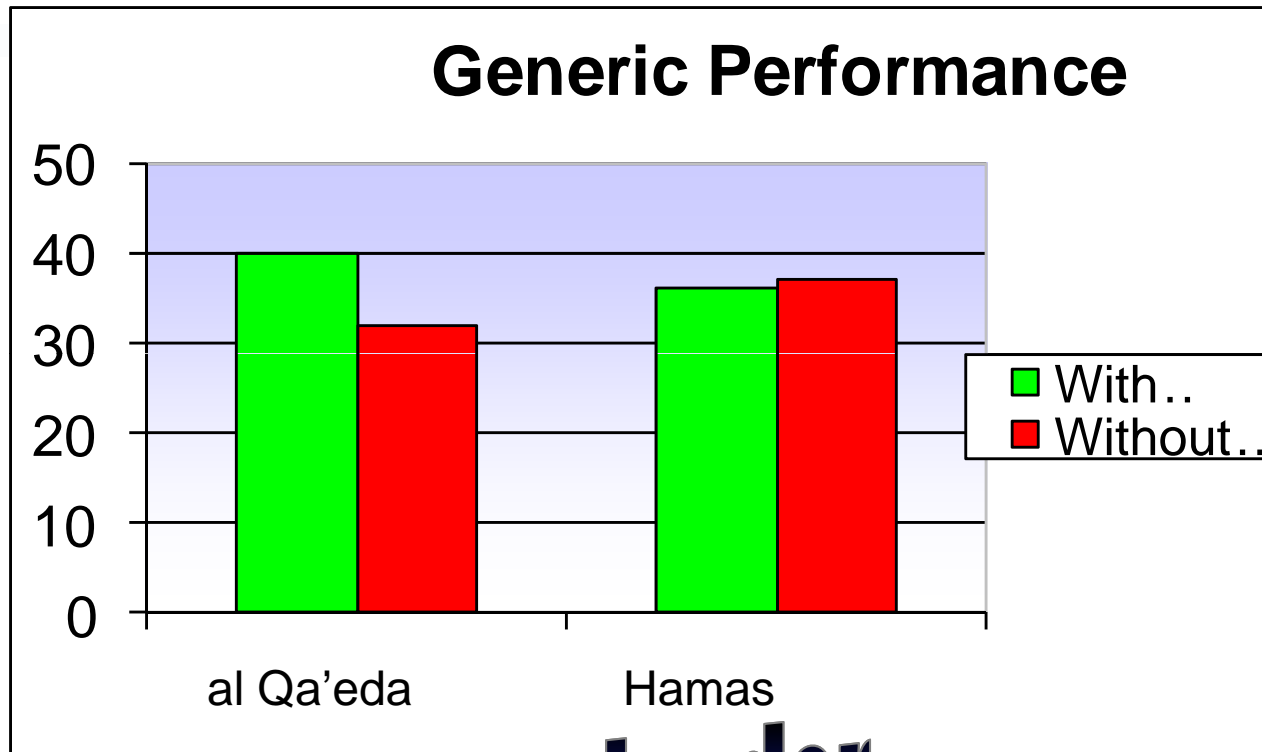
Knowledge Level	Boundary Spanner	Centrality	Betweenness	Centrality	Closeness	Centra
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	0	0	0	0	0	0
10	0	0	0	0	0	0
11	0	0	0	0	0	0
12	0	0	0	0	0	0
13	0	0	0	0	0	0
14	0	0	0	0	0	0
15	0	0	0	0	0	0
16	0	0	0	0	0	0
17	0	0	0	0	0	0
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99	0	0	0	0	0	0
100	0	0	0	0	0	0



al-Qa'eda and Hamas – Different Structures



What If Analysis



Bin Laden



al-Zawahiri



Yassin

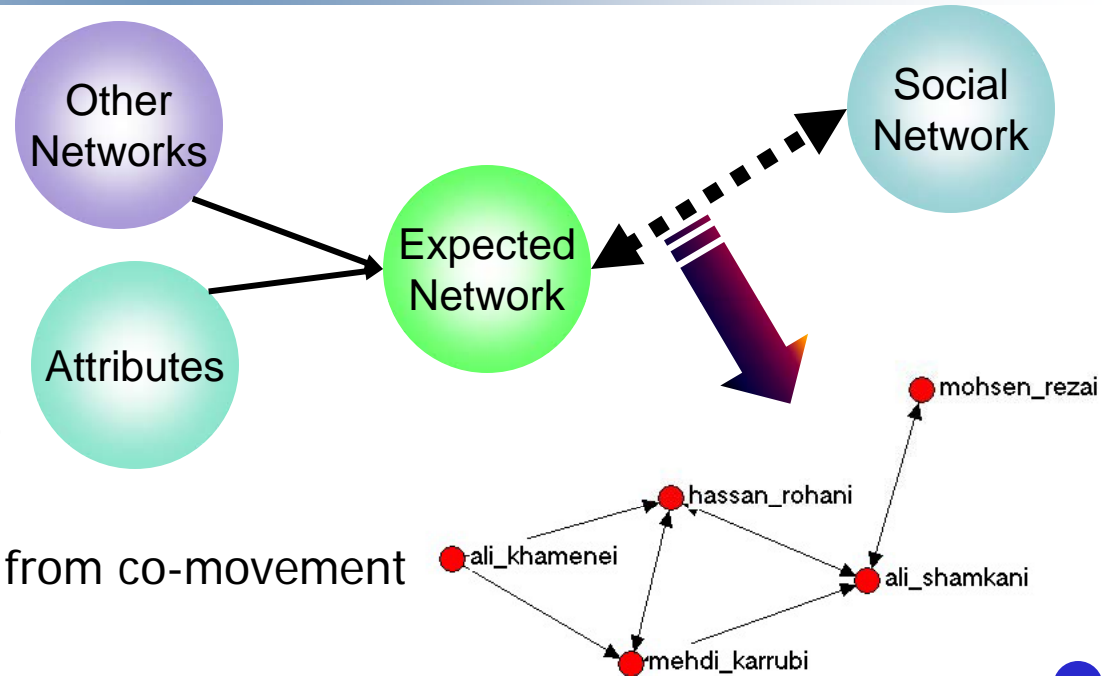


New Emergent Leader

Estimating possible missing data or errors

E.g., Who Should be Interacting?

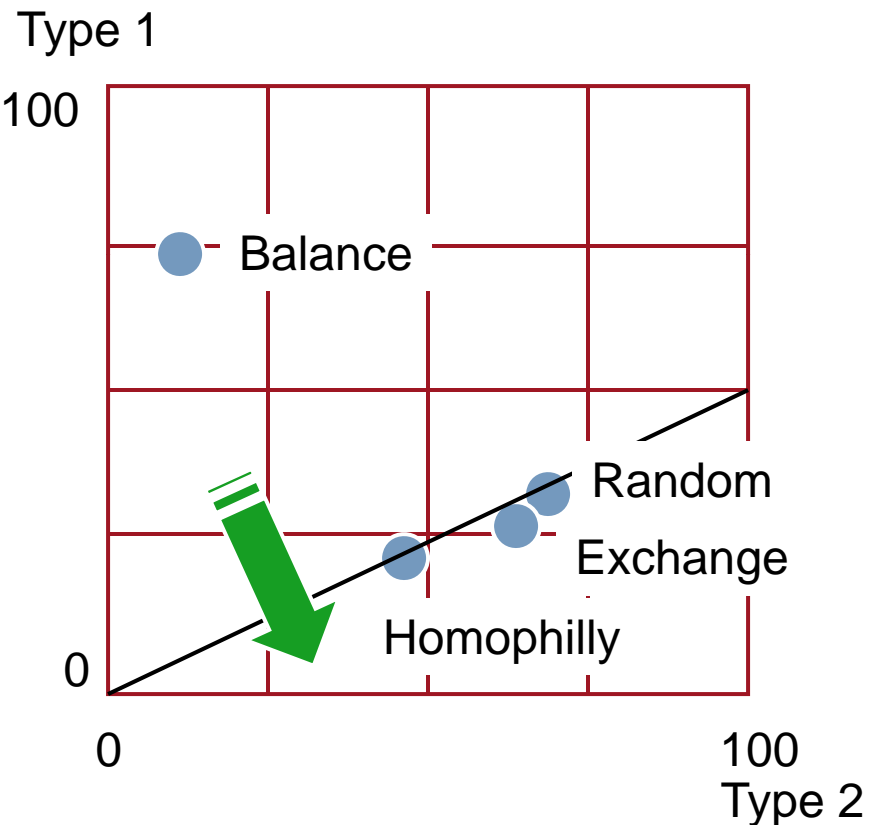
- Interaction Logics –
 - Similarity
 - Expertise
 - Shared experience/local
- Social Logics
 - Inheritance of social beliefs
- Spatio-Temporal
 - Estimate potential network from co-movement and co-presence
- Static –
 - Estimate potential network from attributes and other networks
- Dynamic –
 - Simulate network evolution – learning and communication logics



Meta-Network data or attributes can be used to predict possible missing data

Edge inference based on meta-network theories works best!

- Type 1:
 - Predicted no edge but there is an edge
- Type 2:
 - Predicted an edge but there is no edge



But – no theory is great – Type 2 twice as likely as type 1

Integration

- Each of the logics generates an indication of whether there is a missing link
- These need to be combined
- Next step is creating a Bayesian update system for combining alternative inferences
 - Challenge – culturally sensitive
 - Challenge – node/edge type sensitive



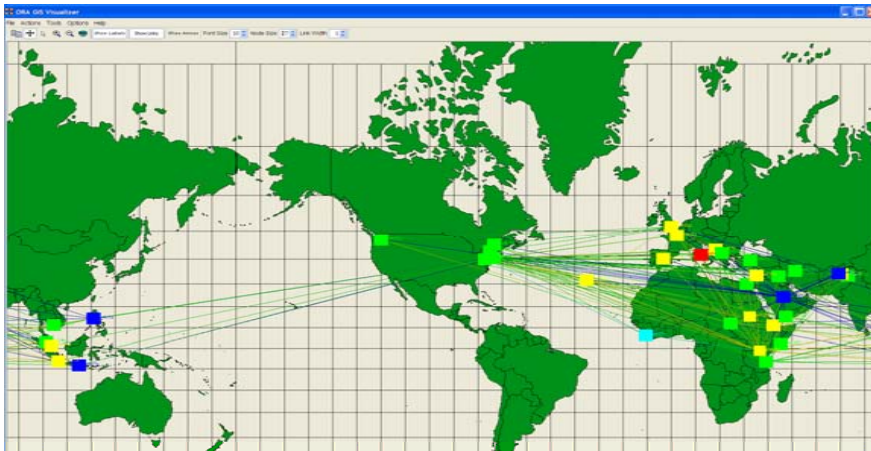
Impact of Inference - Illustration



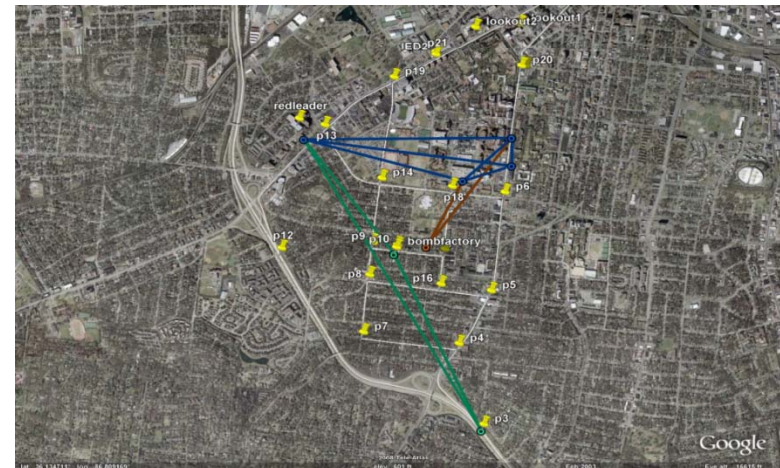
Metric	Base Data	With Inferred Edges
Probable Leader	Bin Laden	Bin Laden (stronger)
Leader of Sub-group	Khalfan Mohamed	Wadih el-Hage
Links disconnected groups	Mohamed Owahali	Abdullah Ahmed Abdullah
Density	.07	.37
Fragmentation	.61	0
Generic Performance	.23	.32



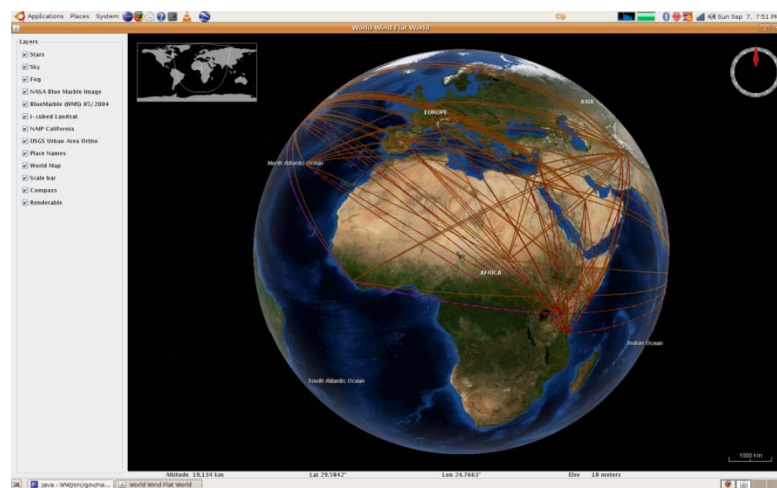
4: Geo-Spatial Networks



ArcGIS



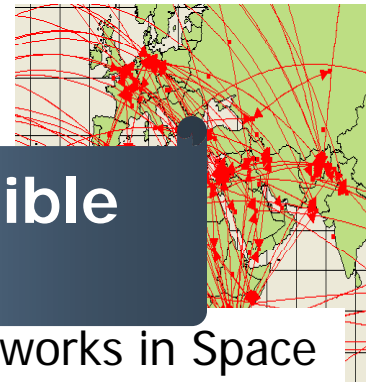
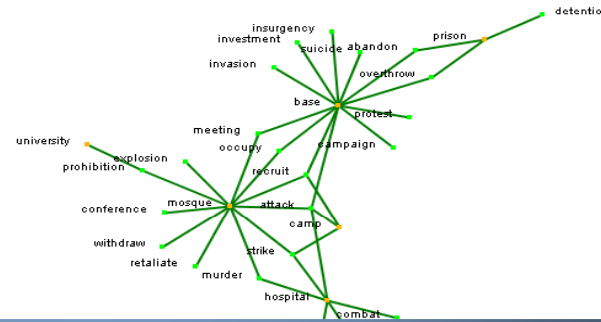
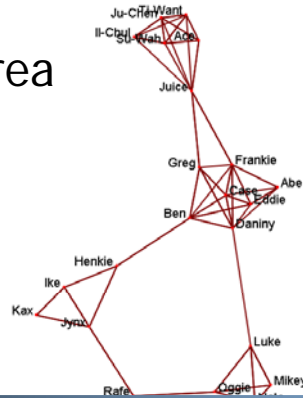
Google Earth



NASA WWJ

Geo-Enabled Network Analysis

Networks In an Area



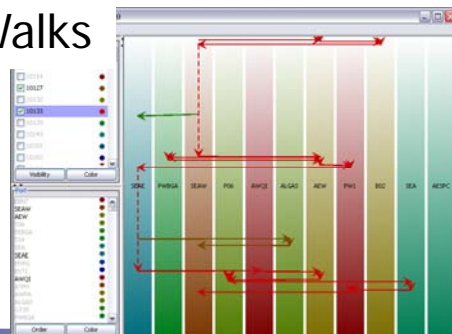
Layering Networks on Maps is Possible
 Geo-constraints on Networks

Visualizing Networks in Space

Information Loss Tracking

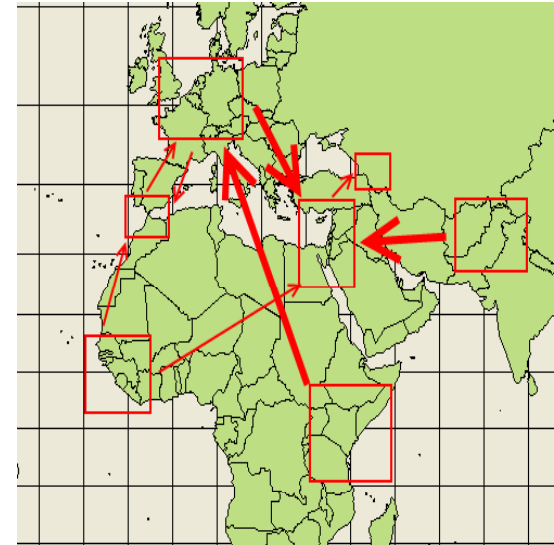
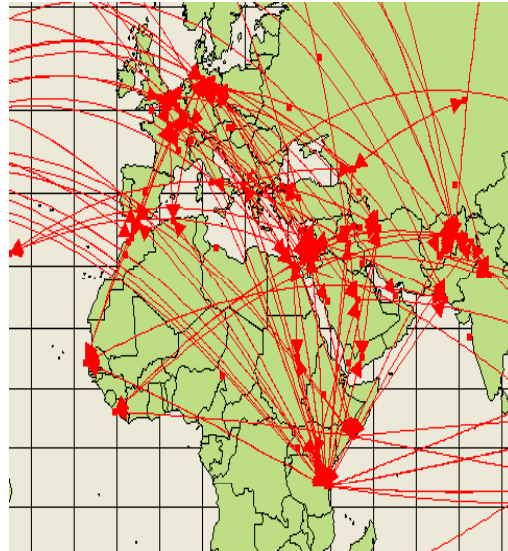


Walks

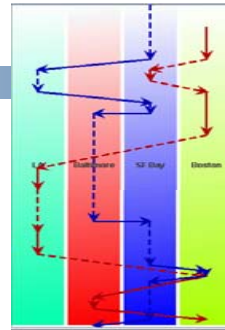


Implementing Geo-Spatial Network Resolution

- Want to combine nearby Locations into useful Places
- Density-Based Clustering (DBSCAN)
 - Single parameter: desired density
 - Computationally efficient
 - Deals well with outliers

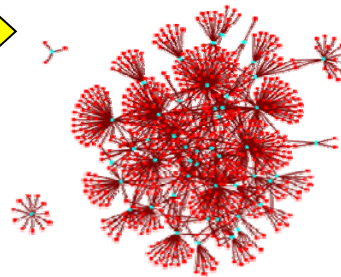
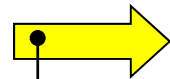


Merchant Marine Vessels

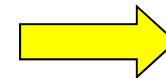


Trail Format

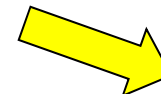
What Ship is Where When



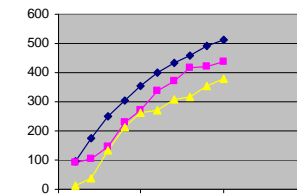
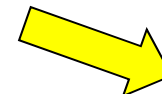
Relational Format
 Co-work, Owner-Links



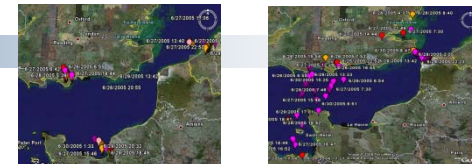
Network Analysis
 e.g., Critical Actors



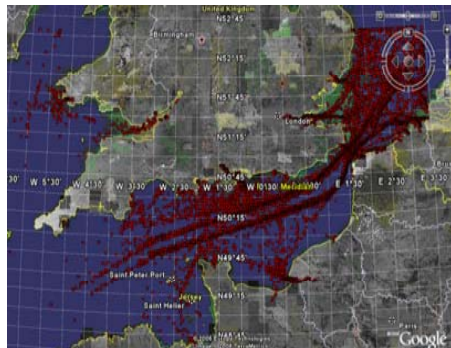
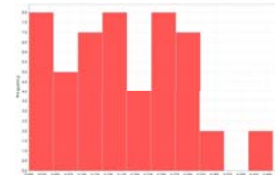
Inferred Locations
 e.g., Hidden Ports



Intervention Analysis
 e.g., Assess COA



Behavioral Clustering
 e.g. – Offshore Meetings



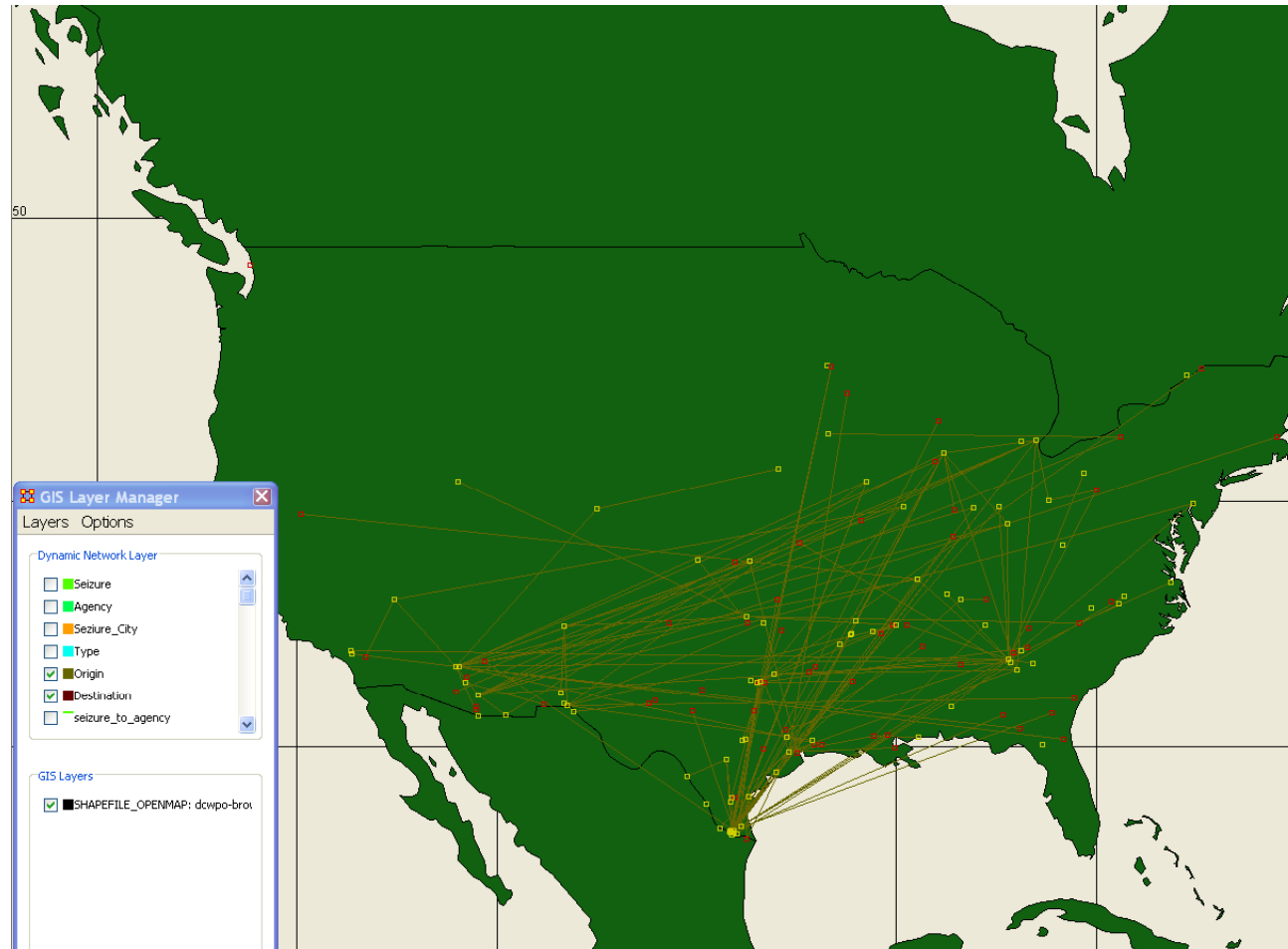
Spatial/Temporal Data
 e.g. AIS, Boarding Reports

ML Algorithms for
 Entity / Relation
 Inference

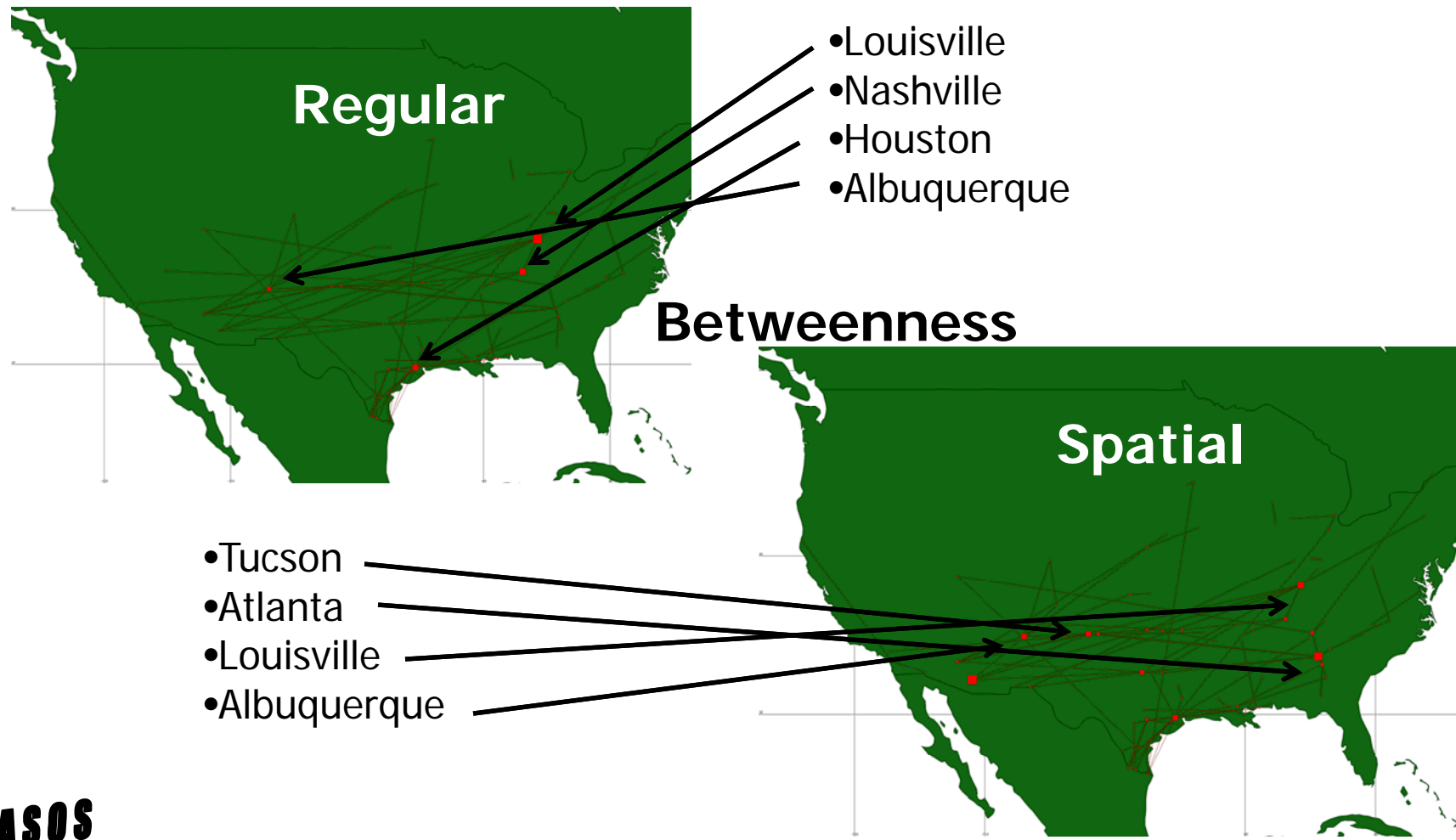
Geo-Temporal Blocking
 for creating snapshots



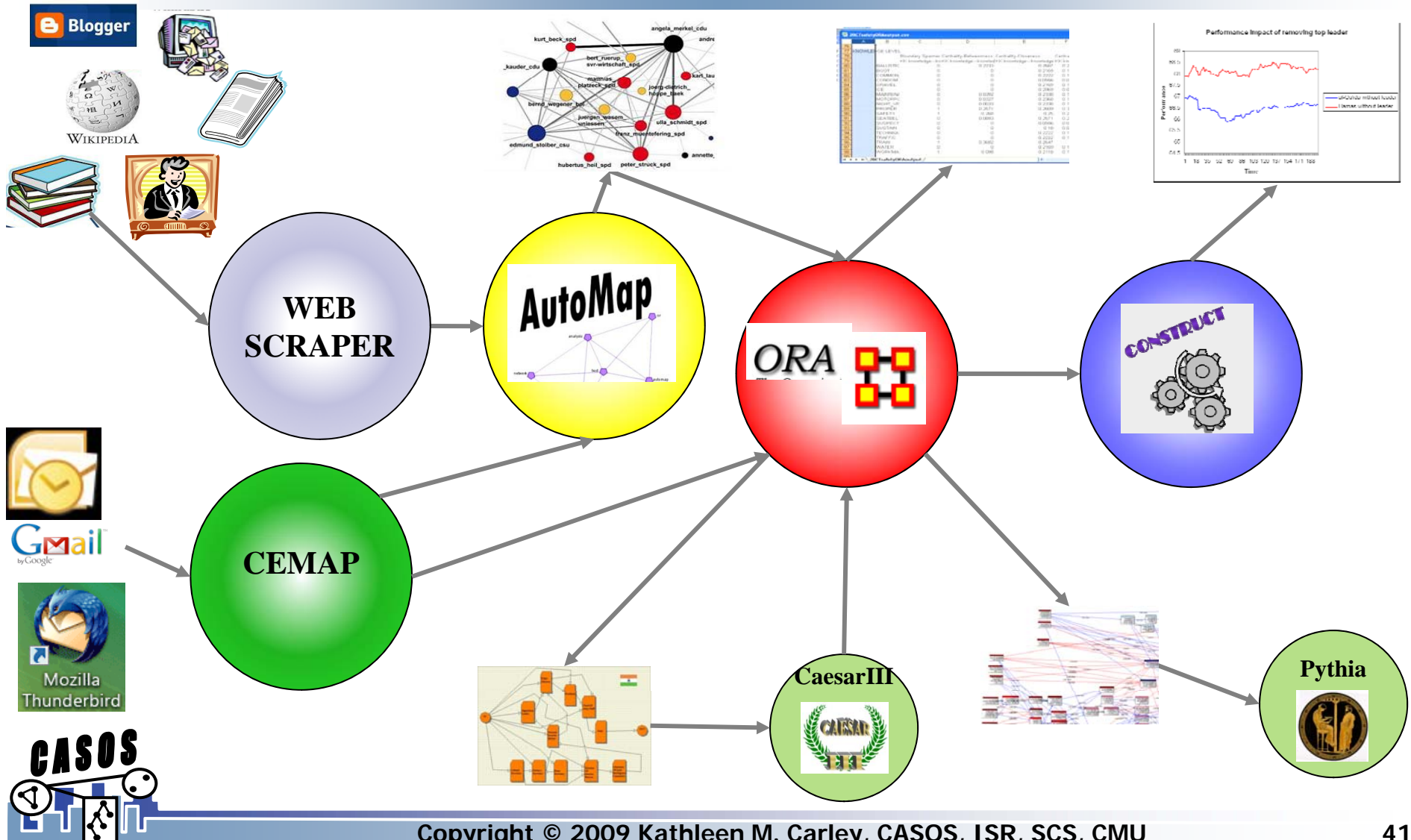
Drug Seizure: Origins to Destinations



Drug Seizures



A Useful Workflow



A look toward the future

- Focusing on simple network models is misleading
- Need a meta-network approach
 - But – pick networks based on problem
 - And – need specialized role metrics for these meta-network data
- Key areas
 - Communication + social networks
 - Geo-spatial + social + resource networks