Patterns and Linkages

Dr. Kathleen M. Carley

The CMU centers for:

Informed DEmocracy And Social cyber-security

Computational Analysis of Social and Organizational Systems

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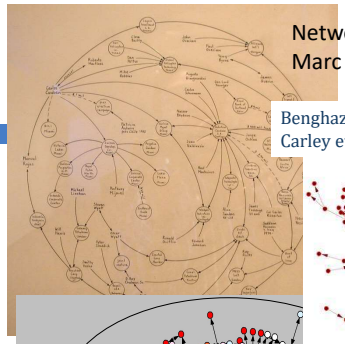
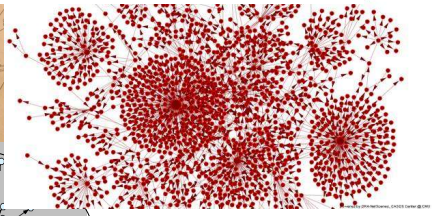
Networks!

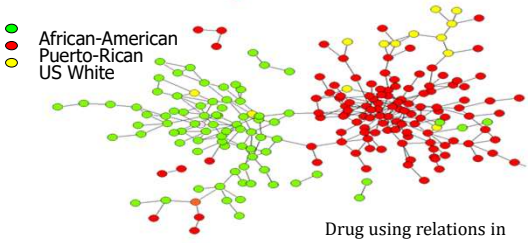


Network Art
Marc Lombardi

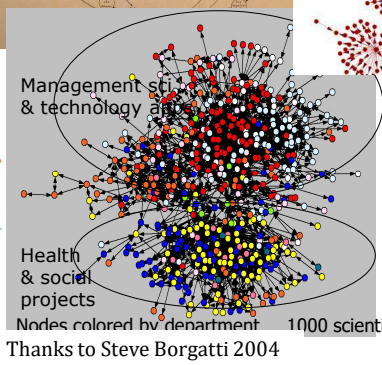
Benghazi Twitter Network 2012 – Kathleen M. Carley et al.



Fotosearch 2009



Drug using relations in Hartford, CT
Thanks to Steve Borgatti 2004



Thanks to Steve Borgatti 2004

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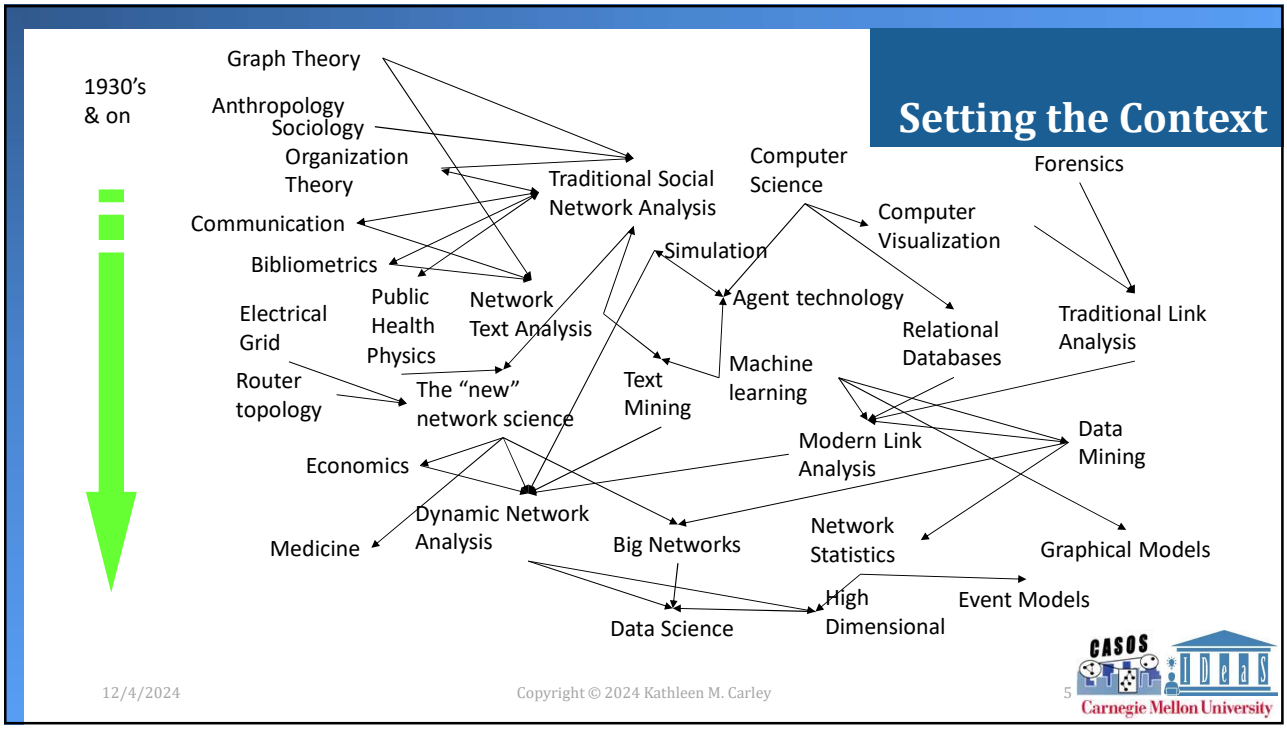
The Network Perspective

Consider
the complex web of connections & relationships between components
don't just analyze individual elements in isolation

- ❑Networks are everywhere and they are connected
- ❑Non-reductionist, holistic
- ❑Moves beyond formal structures (e.g. org-chart)
- ❑Emergent properties – patterns are embedded in the system
- ❑Systems thinking

Dartmouth 1975


Setting the Context
1930's & on
Graph Theory
Anthropology
Sociology
Organization Theory
Communication
Bibliometrics
Public Health Physics
Electrical Grid
Router topology
Network Text Analysis
The "new" network science
Traditional Social Network Analysis
Simulation
Text Mining
Computer Science
Agent technology
Machine learning
Computer Visualization
Relational Databases
Forensics
Traditional Link Analysis
Data Mining
Modern Link Analysis
Economics
Dynamic Network Analysis
Medicine
Big Networks
Network Statistics
Graphical Models
High Dimensional
Event Models
Data Science
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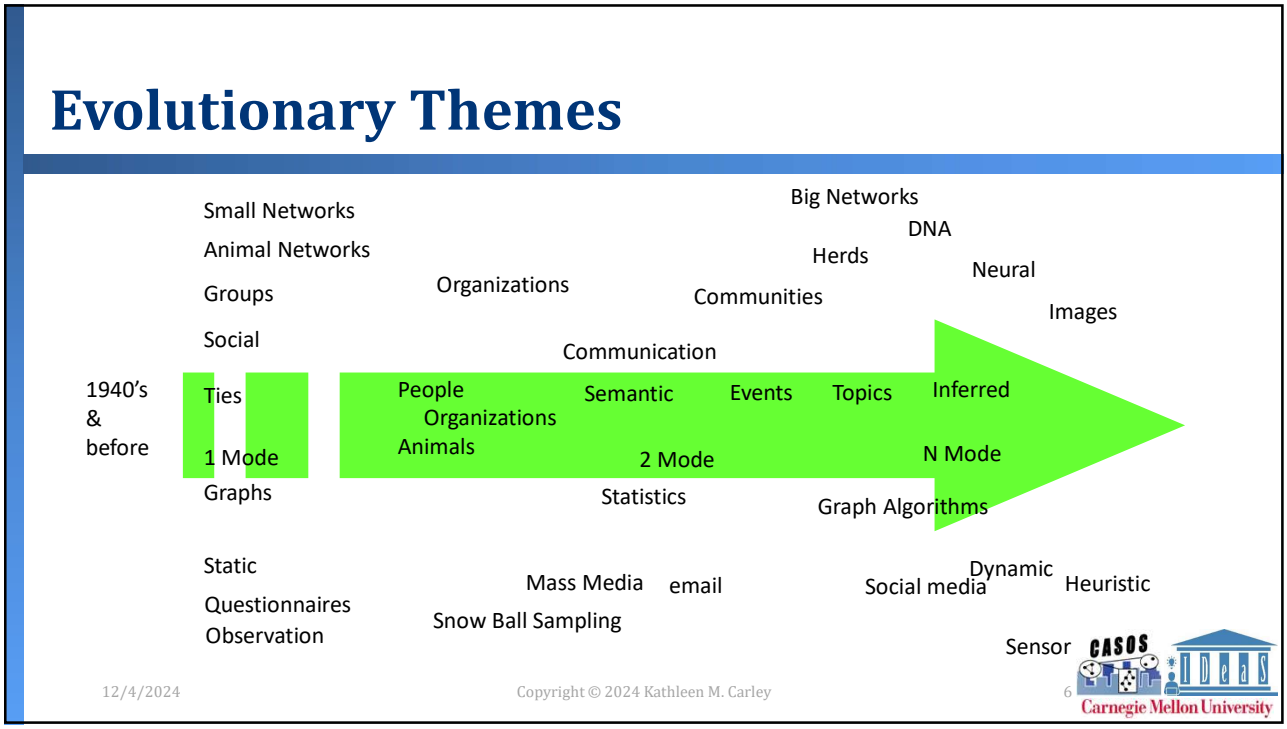
Evolutionary Themes
1940's & before
Small Networks
Animal Networks
Groups
Social
Ties
1 Mode
Graphs
Static
Questionnaires
Observation
Organizations
Communication
People
Organizations
Animals
Semantic
Events
Topics
Inferred
2 Mode
N Mode
Statistics
Graph Algorithms
Mass Media
email
Snow Ball Sampling
Big Networks
DNA
Herds
Neural
Communities
Images
Social media
Dynamic
Heuristic
Sensor
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Social Networks

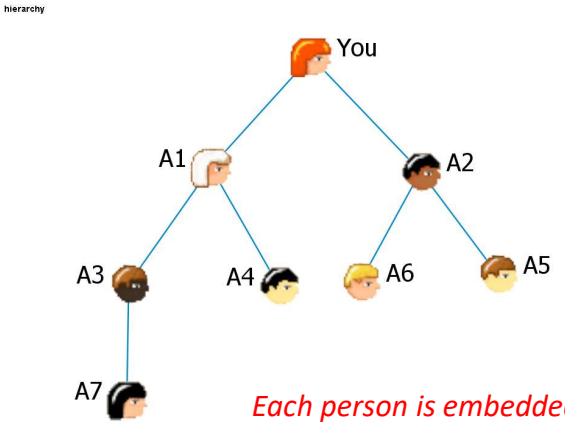
A **social network** is a description of the social structure at a particular point in time in terms of the actors, mostly individuals or organizations and the links among them.

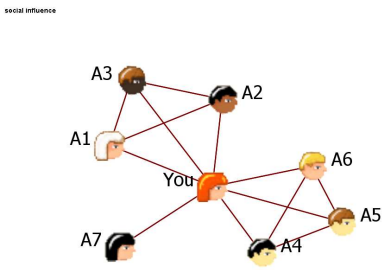
A social network indicates the ways in which the actors are connected through various social familiarities ranging from casual acquaintance to close familiar bonds.

Organization's have Formal and Informal Structures

Formal

Informal





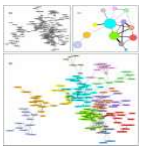
Each person is embedded in many networks

Illustrative Networks

Nodes have attributes that matter

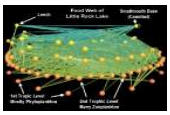
High School Dating

Physicist Collaborations

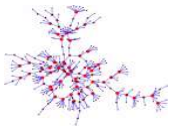


Contagion of TB

Fresh Water Food Web

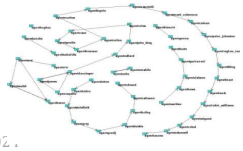


Sexual Contacts



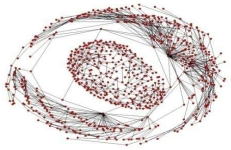
The Internet

Topic Network (Email)

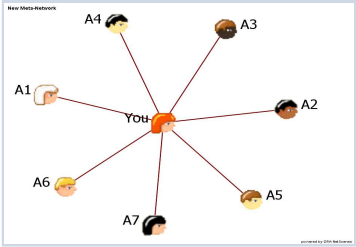
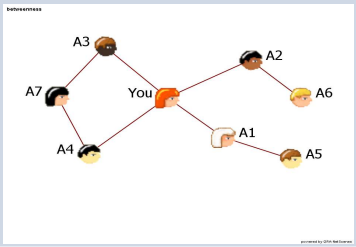
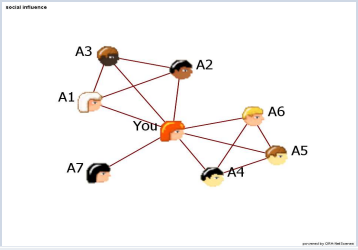


Email Profile

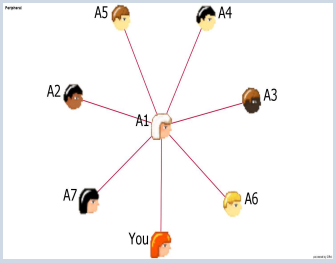
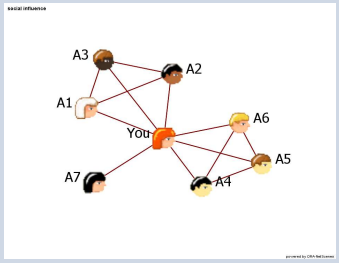
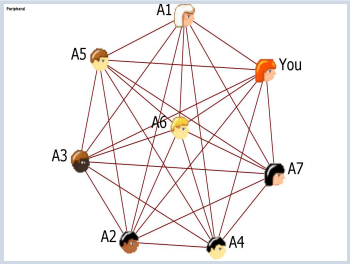
al Qaida 2004



Network Effects

Access	Control of Flows	Influence
		
The more people you are connected to the more you can know	The more you are on the path between people the more you can control	The more you are connected to others who are connected to each other the more influence (leverage) they have on you and you on them

Influence on You - Network Effects

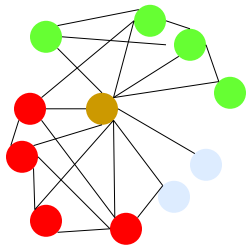
Super Spreader	Constraint	Echo Chamber
		
You are more likely to get information/resources from a super-spreader	The more you are between multiple groups the more constrained your actions – social influence	The more you are connected to others who are connected to each other the more influence they have on you – group think

Ego Network

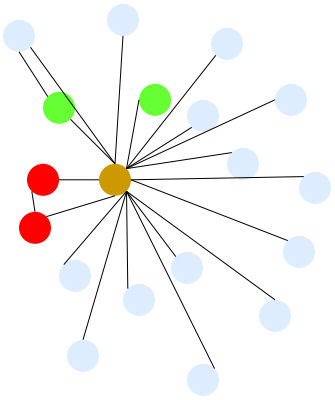
- Ego – the node you are examining
- Alters – the nodes directly connected to ego
- The set of ties directly to/from ego to/from an alter
- + (sometimes) the set of ties among ego's alters

Differences in Ego Networks for Drug Users

Normal Person



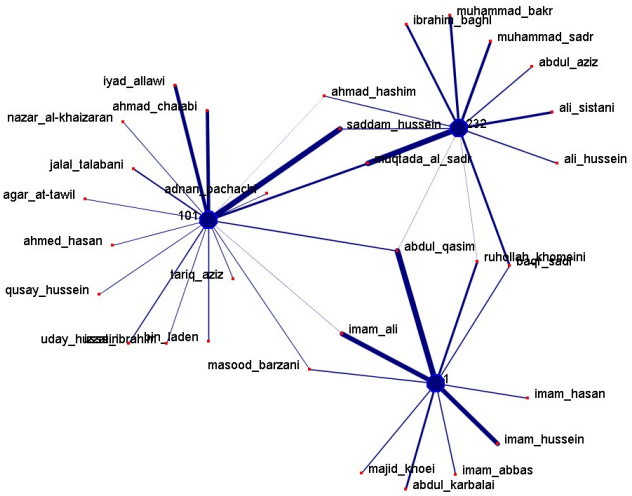
Cocaine User



Family
Work
Friend

People with Different Roles have Different Networks

Assess: How are they organized?



FOG (Fuzzy Group Clustering) shows suspicious entities organized into 5 groups w/shared members.

Interstitial members are likely to contain coordinators & leaders

Key Actors are Interstitial

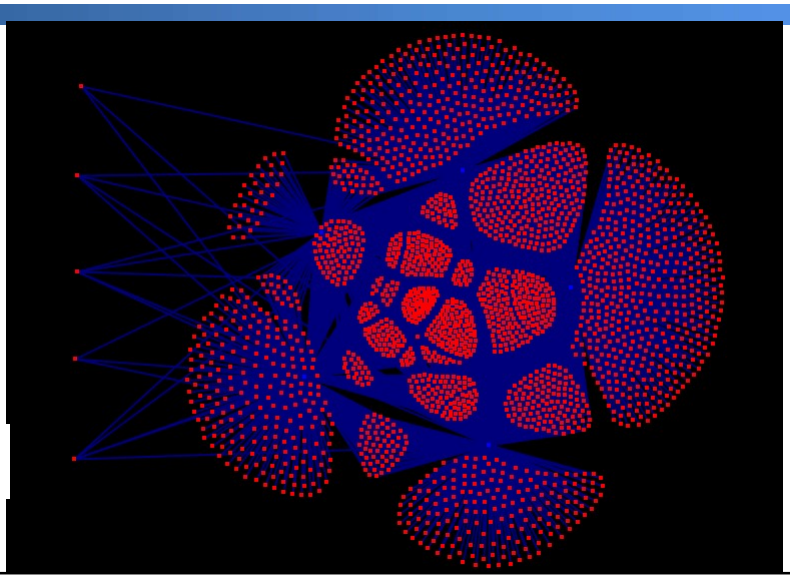
Jeff Skilling

Kenneth Lay

Tanya Jones

Veronica Espinoza

Jeff Dasovich



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Study of Social Networks

- Social network analysis = structural approach to understanding the world
- Incorporates statistical methods, mathematical modeling, simulation, machine learning, big data analytics, neural imaging

IC Relevance

- Distribution & exchange of resources
- Establishment of normative constraints
- Development of trust within a group/society
- Ideological contagion
- Diffusion of beliefs
- Evolution of organizational leadership, robustness and resilience
- Political stability
- Features and changes in narratives, rhetorical strategies

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Research Directions: Social Networks

Distinguish the effects of a network on people's attitudes and behaviors on network form and behaviors from the effects of people's attitudesation

Apply recent developments in statistical network analysis and dynamic network modeling to global dynamics

Conduct interdisciplinary work combining social network analysis with narrative analysis

Develop new dynamic network analytic methods, and conduct fundamental research on how human networks, such as social, knowledge, semantic, and task networks, adapt or evolve

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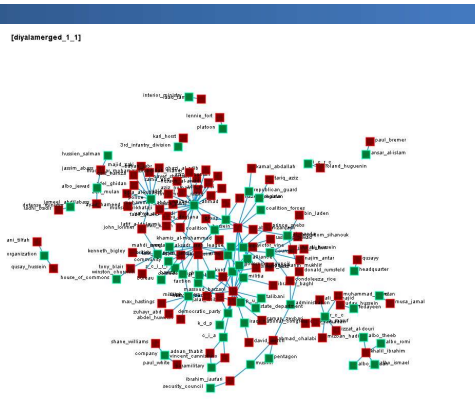
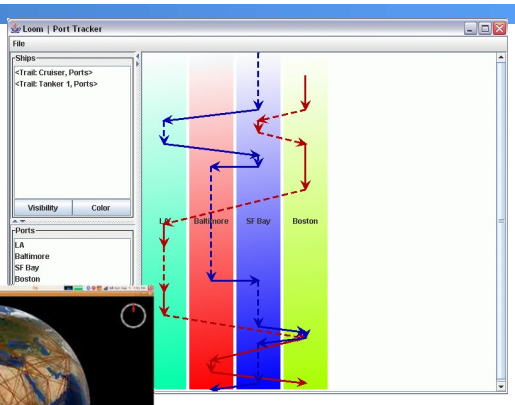
Network Science - Connecting the Dots and Trails to Predict and Explain Behavior





Identify Groups / Threats
Using Network and Geo-Spatial Information
How does space – constrain and enable networks

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Connect & Dis-Connect the Dots!

	Degree	Betweenness	Closeness
1	0.417 Mohamed Atta	0.334 Nawaf Alhazm	0.571 Mohamed Atta
2	0.389 Marwan Al-Shehhi	0.318 Mohamed Atta	0.537 Nawaf Alhazmi
3	0.278 Hani Hanjour	0.227 Hani Hanjour	0.507 Hani Hanjour
4	0.278 Nawaf Alhazmi	0.158 Marwan Al-Shehhi	0.500 Marwan Al-Shehhi

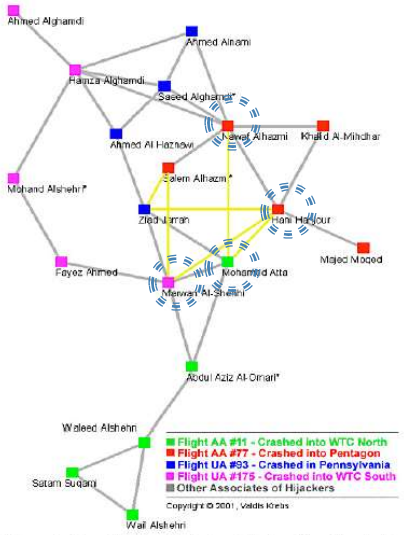


Figure 3 Trusted Prior Contacts + Meeting Ties [shortcuts]

Standard Social Network Measures

So – why is this hard?

- The Network
  - Vast quantities of data
  - Multi-mode – people, events, etc.
  - Multi-plex – many connections e.g. financial and authority
  - Geo-temporal
- The Information
  - Intentional misinformation – e.g., aliases
  - Inaccurate information – e.g., typos
  - Out-of-date information
  - Incomplete information
  - Inconsistent information
  - Varying levels of resolution in spatially and temporally
- The Dynamics
  - Learning
  - Individual changed – e.g. life course
  - Organizational changes – e.g., recruitment
  - Technology changes – e.g. what data can be collected
  - Daily activity…

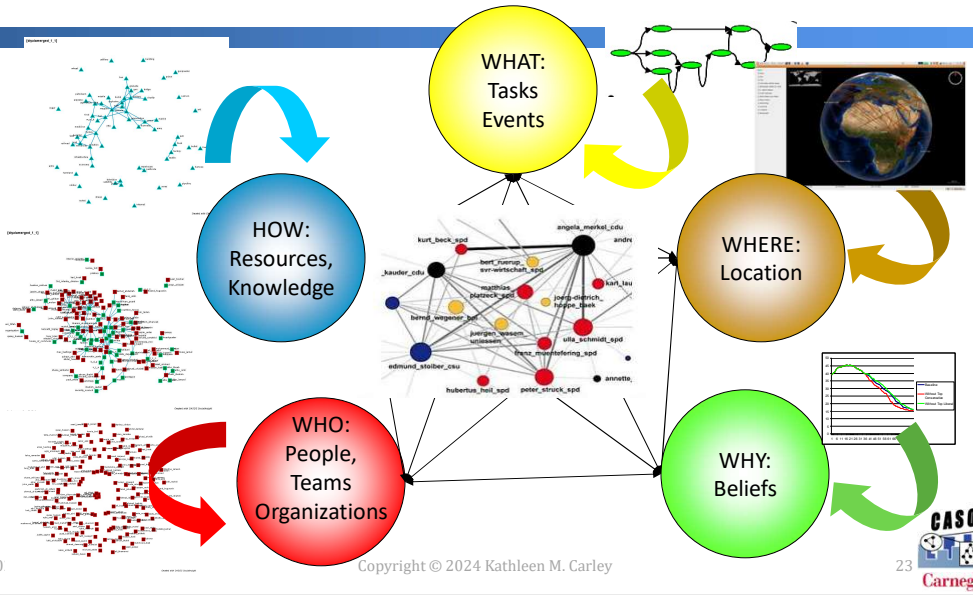
High Dimensional Networks are Common

Crime	Social Media
❑Crime scene data often includes	❑Who interacts with whom
❑Who is linked to whom	❑Who uses what words, hashtags, urls …
❑Who is at what event	❑What words, hashtags, urls co-occur in a message
❑What even is at what location	
❑Who is at what location	

High Dimensional Networks

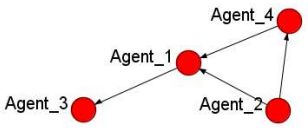
- ❑Critical for Understanding and Predicting
- ❑Have led to new insights
- ❑Require new methods
  - ❑From ego networks to sphere of influence
  - ❑From centrality to weighted multi-mode centrality
  - ❑From density to complexity
  - ❑New metrics for
    - ❑ Overlap/Uniqueness
    - ❑ Performance
    - ❑ Cognitive demand
    - ❑ Workload
  - ❑New Ensemble and MVMC methods for clustering
- ❑Initial versions of all new methods are in ORA-PRO and many in ORA-LITE

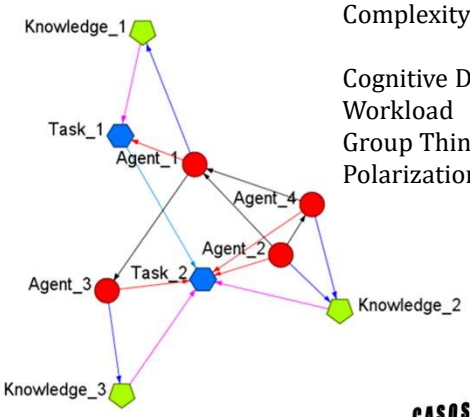
Networks form a Meta-Network



One Mode – High Dimensional

Degree
Density

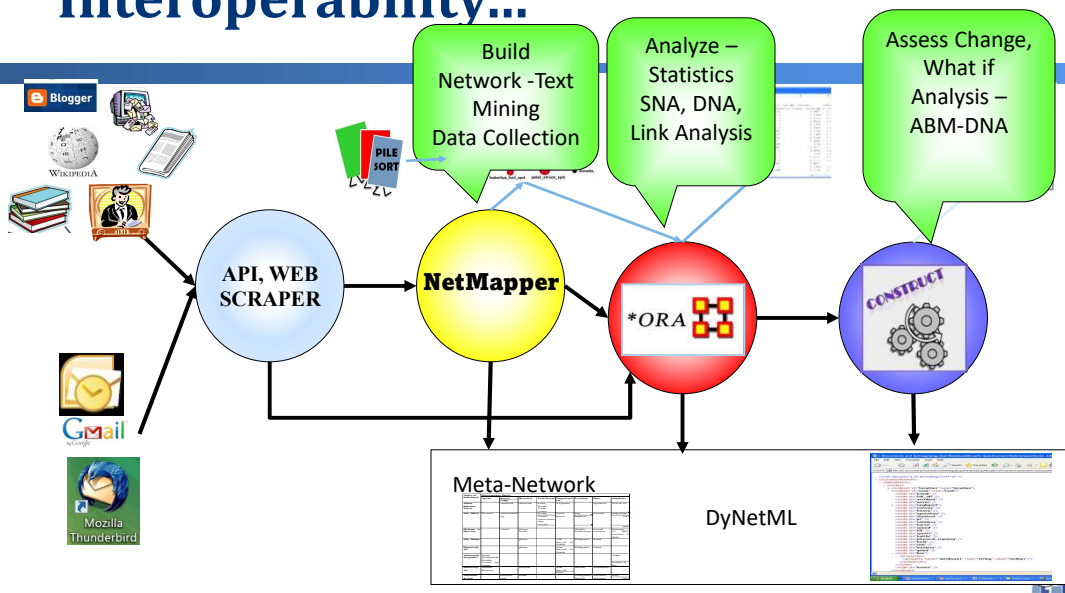




Sphere of Influence
Complexity

Cognitive Demand
Workload
Group Think
Polarization

Interoperability…

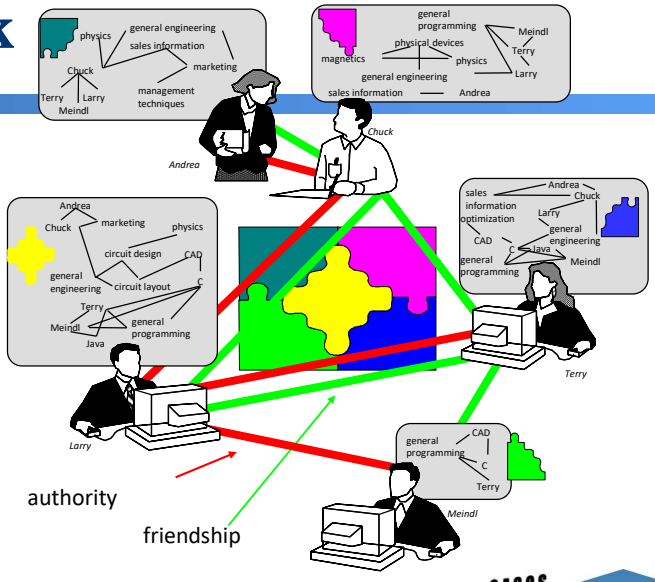


Networks Interlink

- Social networks
  - Who to whom
- Information networks
  - What to what
- Knowledge networks
  - Who to what

These can be inter-linked at either the individual, group, or corporate level.

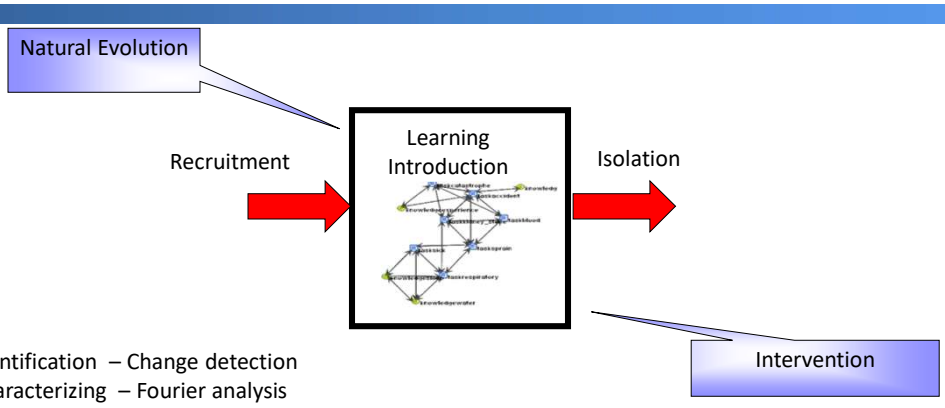
These can be inter-linked in terms of words, specific pieces of information, or general bodies of knowledge.



Duality of Nodes and Attributes

- Imagine twitter data
  - Who sends tweet mentioning whom using what hashtag
  - Part of the tweet meta-network
    - Tweeter x Tweeter network (traditional social network)
    - Tweeter x Hashtag network (bi-partite network
    - Hashtag x Hashtag network (co-use)
- Hashtags can be treated as nodes of type "knowledge"
- Hashtags can be treated as attributes of tweeter nodes

Change in Networks



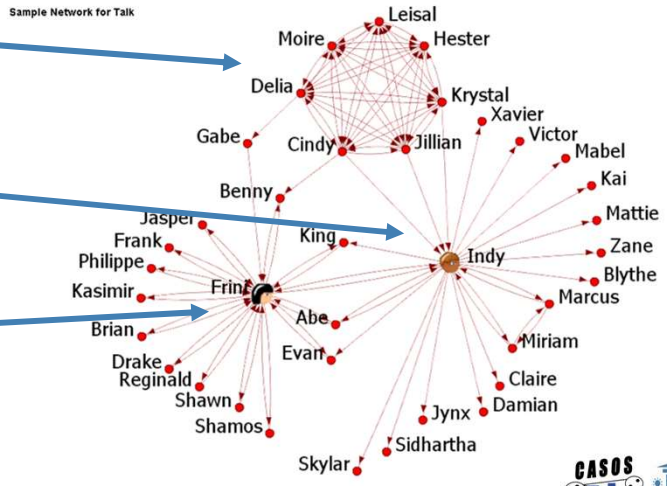
Identification – Change detection
Characterizing – Fourier analysis
Immediate Impact Assessment – Comparative statics – ORA
Near term Impact and forecasting – Simulation – Construct
Prediction – Machine Learning

Information Diffusion and Influence in Networks

Echo chamber
- creates feeling of group support
- within emotions escalate

Superspreader
- accepted as credible
- reaches large community

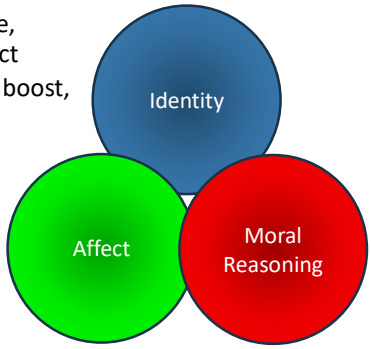
Superfriend
- bridges communities
- knows how to engage community



BEND Framework

WHO
- Influencers – e.g. superspreaders, superfriends, newsagencies
- Bots, Trolls, Cyborgs

Did What
- BEND maneuvers
- Shape narrative – engage, explain, excite, enhance, dismiss, distort, dismay, distract
- Shape community – back, build, bridge, boost, negate, neutralize, narrow, neglect



To Whom
- Community
- Individual

AI + Network Science

Impact
- Reach
- Echo-chamberness
- Polarization
- Hysteria
- …

Assessing Who is conducting a maneuver

Three Methods:

- ❑ Machine learning
- ❑ Listings
- ❑ Network science indicators

Categories of actors conducting maneuvers

- ❑ Bots
- ❑ Cyborgs
- ❑ Trolls
- ❑ News agencies
- ❑ Government actors
- ❑ Super-spreaders
- ❑ Super-friends
- ❑ Other influentials

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BEND: Narrative vs. Community Maneuvers

Narrative Maneuvers: Impact what is being said and how it is being said			**Community Maneuvers**: Alter who is connected to whom, the strength of those connections, and so alters who is influential and what groups exist		
Emotional Messaging	**Develop Narrative**	**Counter Narrative**	**Individual Centric**	**Make Groups**	**Unmake Groups**
Excite	Explain	Distort	Back	Build	Neutralize
Dismay	Engage	Dismiss	Negate	Bridge	Narrow
	Enhance	Distract		Boost	Neglect

Each is measurable using high dimensional network metrics

Most are difficult for analysts to spot without computer support

ORA-PRO, NetMapper & Bot-Huntresses support BEND

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BEND Maneuvers & Effects

- Maneuvers occur at message or platform level
- Short term effects can occur within 1-2 days
- Difficult for untrained people to identify
- Correct identification takes months of training
- Minimally trained people who use BEND metrics in ORA do as well or better than experts
- Metrics employ AI and network science
- Current metrics handle text, emoticons and emoji –and operate in over 40 languages

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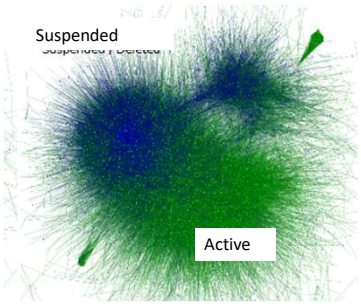
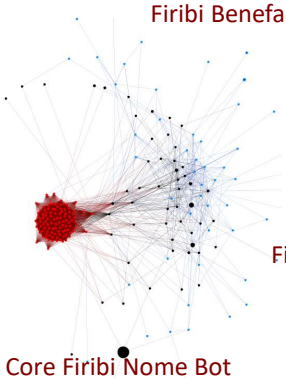
High Dimensional Social Influence: Bots Can Manipulate Topic-Groups

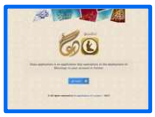
Syria Focused Extremist Topic Group "Dense Community"



Firibi Benefactor



Core Firibi Nome Bot



App Sign Up, solicits donations for children of Syria

Firibi Follower

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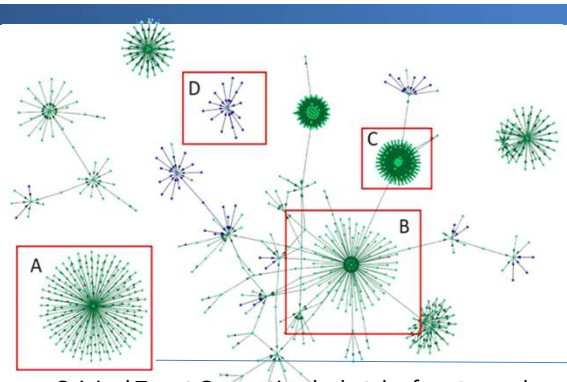
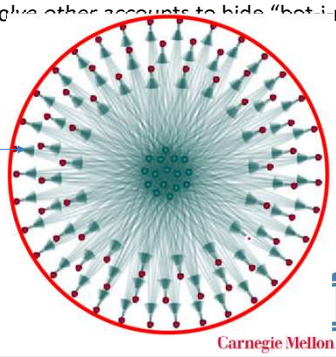
Chinese Covert Activity Network 2023



- ❑ Network 93% isolates
- ❑ 97% of agents appear to be bots
- ❑ Four distinct operations

A. Source Bots: amplified by other bots
B. OVERT amplifier: retweet isolated repeater bots
C. Periphery amplifier: round-robin
D. Covert Amplifier: will involve other accounts to hide "bot-i-ness"



1) Original Tweet Generation by batch of center nodes
2) Randomized Retweeting by Periphery Nodes
3) Amplification Iteration: every Periphery node will retweet each original tweet
4) Repeat with new batch of center nodes

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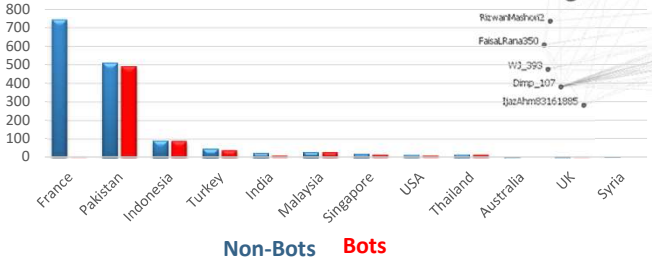
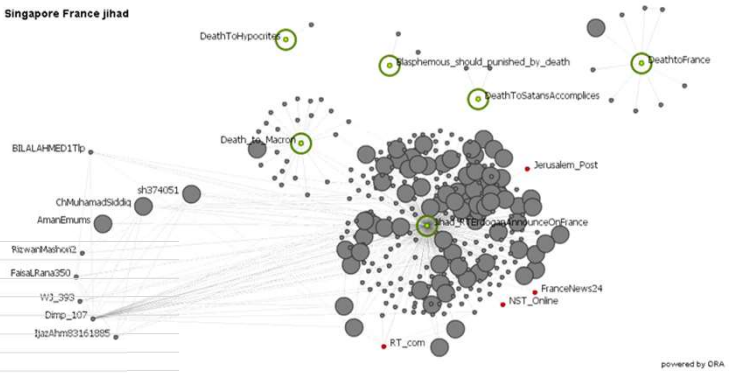
Users Tweeting Jihad

- Green circled nodes are hashtags related to Jihad
- All others are users
- Red users are news agencies
- Large nodes are bots
- Users on left from top to bottom are top 9 users who use Jihad hashtags – most frequent at top



Non-Bots Bots



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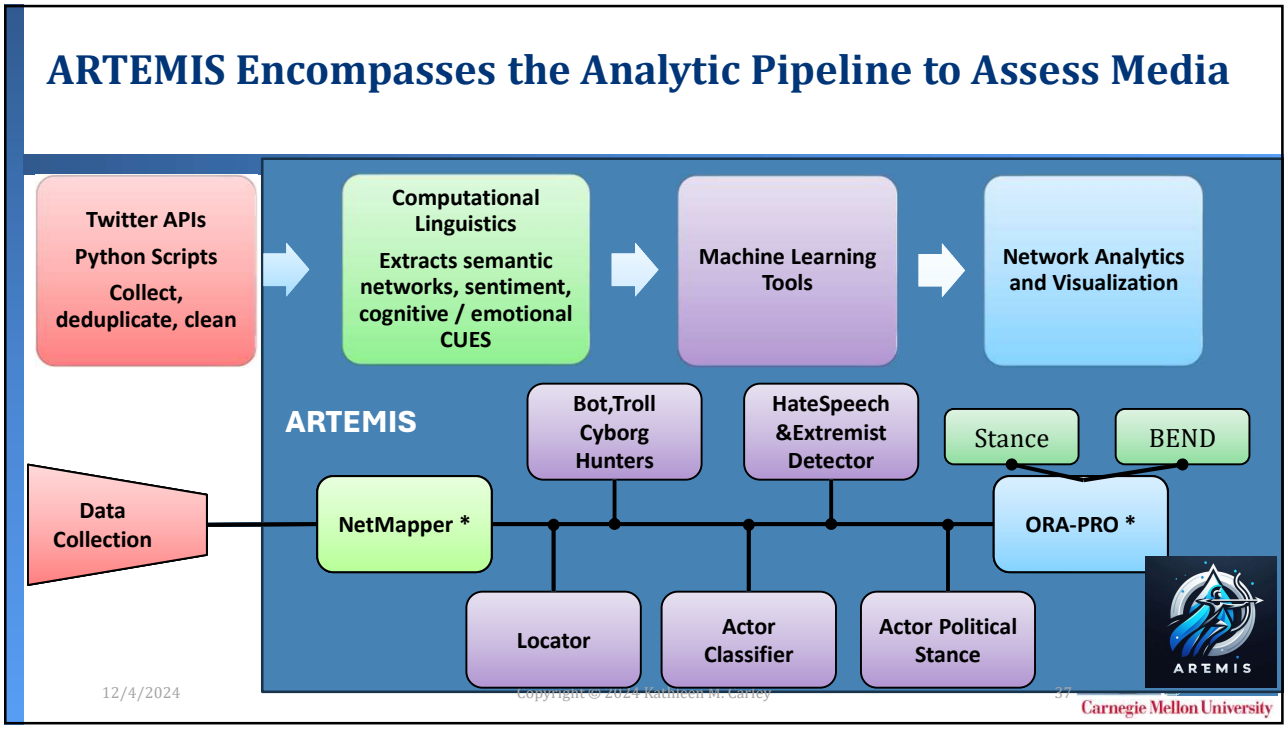
ARTEMIS Encompasses the Analytic Pipeline to Assess Media
Twitter APIs
Python Scripts
Collect, deduplicate, clean
Computational Linguistics
Extracts semantic networks, sentiment, cognitive / emotional CUES
Machine Learning Tools
Network Analytics and Visualization
ARTEMIS
Bot,Troll Cyborg Hunters
HateSpeech &Extremist Detector
Stance
BEND
Data Collection
NetMapper *
ORA-PRO *
Locator
Actor Classifier
Actor Political Stance
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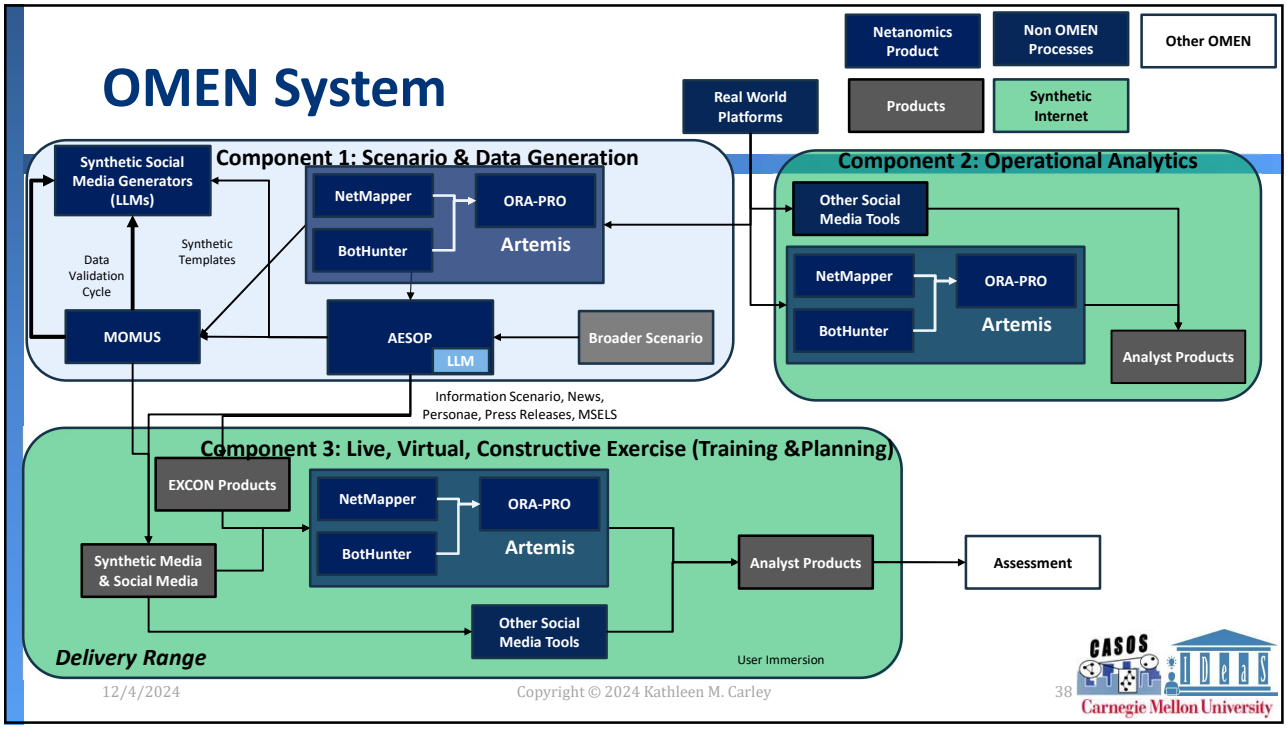
OMEN System
Netanomics Product
Non OMEN Processes
Other OMEN
Real World Platforms
Products
Synthetic Internet
Component 1: Scenario & Data Generation
Synthetic Social Media Generators (LLMs)
NetMapper
ORA-PRO
BotHunter
Artemis
Data Validation Cycle
Synthetic Templates
MOMUS
AESOP
LLM
Broader Scenario
Component 2: Operational Analytics
Other Social Media Tools
NetMapper
ORA-PRO
BotHunter
Artemis
Analyst Products
Information Scenario, News, Personae, Press Releases, MSELS
Component 3: Live, Virtual, Constructive Exercise (Training &Planning)
EXCON Products
NetMapper
ORA-PRO
BotHunter
Artemis
Synthetic Media & Social Media
Analyst Products
Assessment
Other Social Media Tools
Delivery Range
User Immersion
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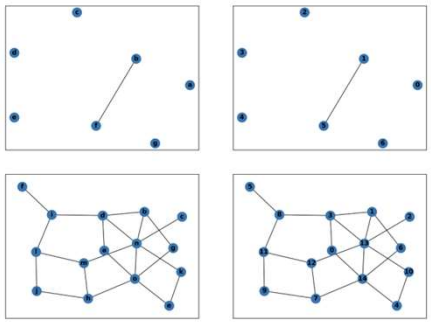
Counting – Assess degree

- Identify maximum degree
- Identify nodes with maximum degree

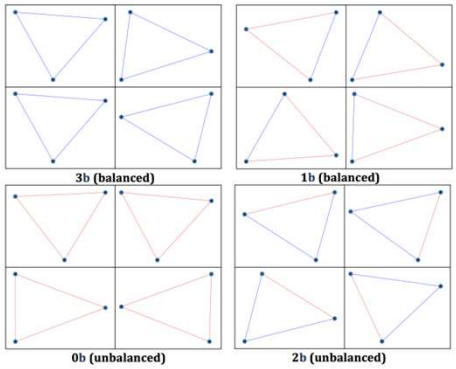


FAIL

Triadic balance - Assess Balance

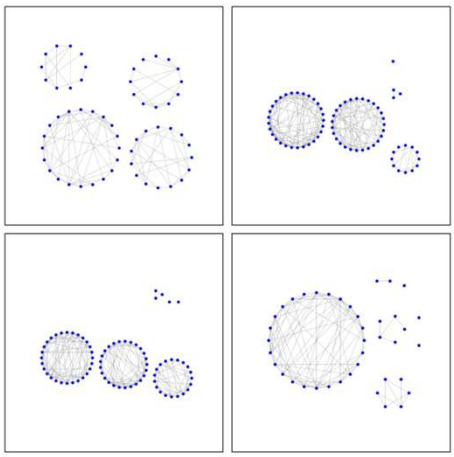
- Identify balanced triads

Mediocre



		Accuracy						
		3b	1b	b0	2b	balanced	unbalanced	overall
GPT4	No Definitions	0.70	**0.50**	0.80	0.37	**0.55**	0.46	**0.51**
	Definitions	**1**	0.20	0.90	0.47	0.40	0.58	0.49
LLaVa	No Definitions	0.10	0.23	0.80	0.73	0.20	0.75	0.48
	Definitions	0	0	**1**	**1**	0	**1**	0.50

Cluster Recognition – Assess components



- How many components
- How many isolates

		Components			Isolates		
		Accuracy	MAE	MSE	Accuracy	MAE	MSE
GPT4	No Definitions	**0.39**	**1.25**	**3.41**	**0.67**	**0.51**	**0.99**
	Definitions	0.37	1.45	4.97	0.64	0.58	1.3
LLaVa	No Definitions	0.03	59.79	23297.95	0.08	32.43	20652.51
	Definitions	0.05	2.81	10.57	0.17	1.27	2.23

FYI: Annual Summer Institute

- Purpose – education and community building in the CSS and COS areas
- Date – June 2024
- Location – CMU
- Eligibility – students, faculty, and people from industry from any where in the world
- Limited number of Scholarships available for minority and women - U.S. nationals, non CMU
- CMU – students, reduced rate

FYI: Another Network Class

Dynamic Network Analysis (Spring 2024)

- Course 17-801 (PhD), 17-685 (undergrad or masters), 19-640 (undergrad or masters)
- Hybrid
- Project based

Course provides

- Interdisciplinary perspective
- Considers social networks, dynamic networks, high-dimensional networks, geo-spatial networks
- A variety of application areas are covered – including health, terrorism, and social media

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For More Information

- Director Kathleen M. Carley - kathleen.carley@cs.cmu.edu
- IDeaS website - https://www.cmu.edu/ideas-social-cybersecurity/
- CASOS website – http://www.casos.cs.cmu.edu/
- Social Cybersecurity Working Group - http://social-cybersecurity.org
- Facebook: @IDeasCMU @CMU_CASOS
- Twitter: @IDeaSCMU @CMU_CASOS
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