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A Novel Approach to Analyzing Online User Innovation Networks

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Outline of Presentation

- MCPC: How granular is the multiverse?
- Extant theory of social networks
- Research questions
- Structure and information flow in online networks
- Metrics from graph theory
- Network archetypes
- Empirical study
- Simulation of an online network
- Implications and further research

Mass Customization and Personalization: How Granular is the Multiverse?

- A goal of mass customization is to design for the requirements of the individual user [12].
- But what if the user community consists an online network of millions of users?
- How many customizations do you realize?
- Do you design for the needs of the lead users [16]?
- Or the trendsetters in the mainstream [11]?
- How do you identify who is important?
- How do you make your product more valuable to your user community?

Key Gaps in Extant Theory

- ***Extant theory on social capital and social networks[1]***
  - ***Is primarily based on connectivity***
  - ***Does not take possibility of preferential attachments into consideration.***
    - Does not show how influence within a network depends upon control of information flow.
    - A critical factor contributing to influence within a network may have been ignored.
    - A manager's perceived influence may not reflect actual influence.
    - Managers may choose incorrect channels to get things done.

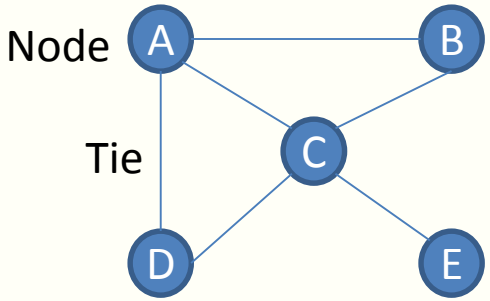
[1]e.g. Granovetter [10], Burt [5], Podolny [13], Coleman [6], Powell [14], Putnam [15]

Research Questions

- What are the best metrics and methods to determine the optimal locus of influence within a social network?
- How does one design a network that enhances or optimizes preferential attachments and information flow?
- How can the timing of surges in network performance be predicted in advance?
- Are there leading indicators?

About Network Structure and Information Flow

Borgatti [4]



- Human social networks can be represented as graphs.
- Nodes represent humans; ties represent relationships.
- Nodes that are directly connected by a tie are called neighbors.
- A ***path*** is a sequence of distinct nodes, with each node in the sequence being a neighbor of the preceding node.
- If information travels from the first node in the path to the last by following ties, then the number of ties that are traveled is the path's length.
- Multiple paths of varying lengths might lead from one node to another.
- The shortest path amongst such paths is called the ***geodesic***.

Serial Propagation (Borgatti, [4])

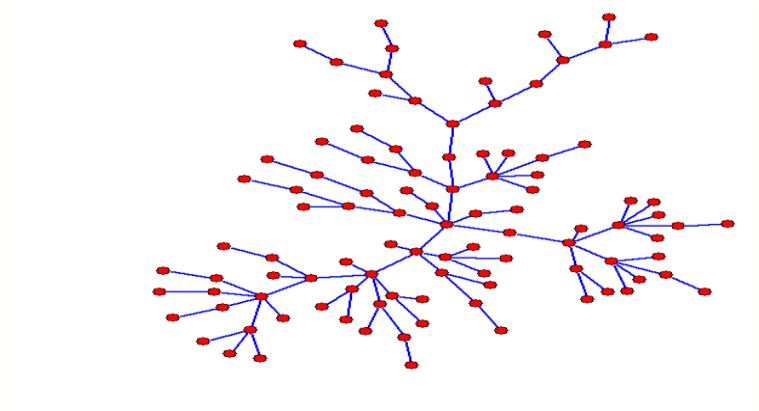
- Focus of this paper
- Propagation occurs by replicating what is at one node to multiple neighbors of the node one at a time.
- Example: gossip network amongst friends.
  - One person might pass the gossip to a friend, and then to another, and then to another.

Metrics for Measuring the Structure of Social Networks Based on Graph Theory

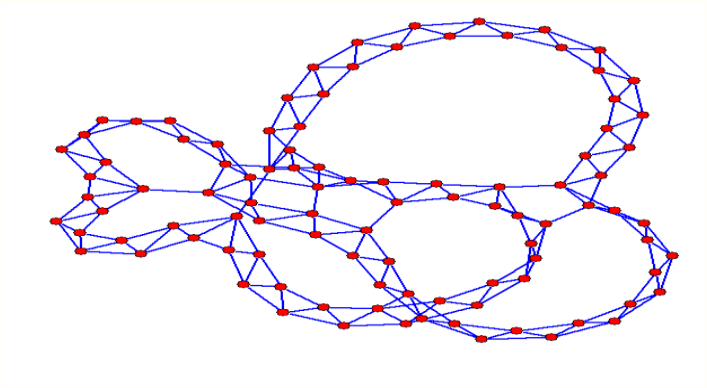
(Freeman, [7], [8])

- **Degree (communication activity)**:
  - The number of ties that are incident upon a node
- **Betweenness (communication control)**:
  - How often a node occurs on the shortest paths between other nodes?
- **Closeness (communication inefficiency)**:
  - Across how many nodes does the information have to travel to get from a given node to other reachable nodes in the network?
- **Eigenvector (importance of node)**: (Bonacich, [3])
  - connections to high-degree nodes contribute more to the score of the node in question than equal connections to low-degree nodes.
  - (Google's PageRank is a variant of the Eigenvector centrality measure.)

Network Archetypes



Scale Free Network (Albert & Barabási [1]; Goh *et al*. [9])



Small World Network (Watts & Strogatz [17])

Scale Free Networks:

- Exponentially distributed connections from each node outwards
- Uneven distribution means that some members are connected to a lesser / greater degree than others
- Greater degree of connection indicates a senior position in the network.
- *'Finding new friends on Facebook'*

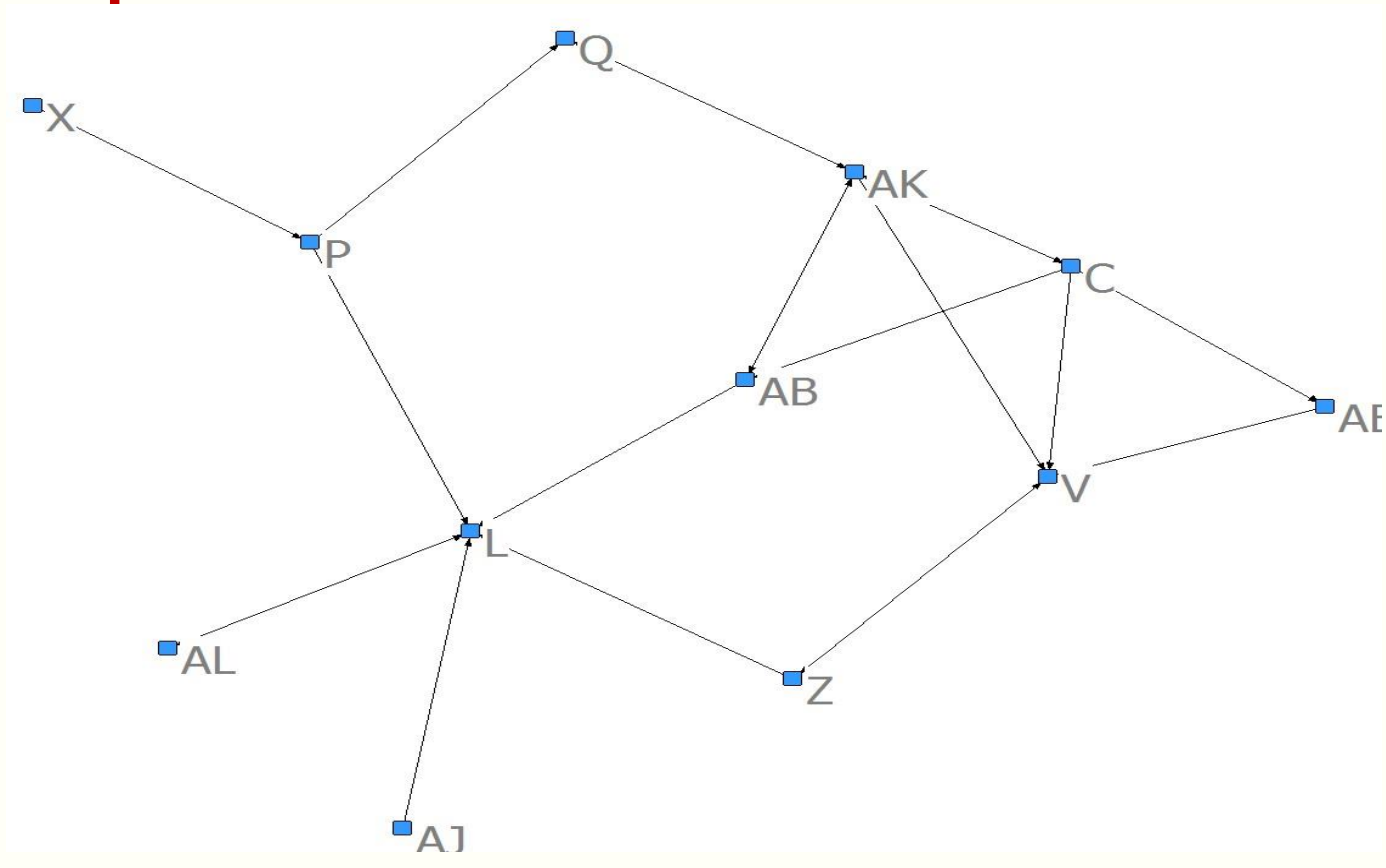
Small World Networks:

- Long distance connections are added at random to regular networks.
- Low path lengths between nodes
- High clustering coefficient (high levels of nodes' isolation)
- *'Reconnecting with old classmates on Facebook'*

Setting for Empirical Study:
the Intel Software Network

- For profit virtual network
- Purpose: to foster for profit peer production and open innovation within Intel's user communities.
- Ideal setting for study
  - Recent advances in Web2.0 technologies
    - are enabling for profit peer production and open innovation.
    - provide an elaborate record of the network's history including
      - network structure
      - information flow
  - Network exhibits hybrid structural characteristics.
    - Small world and scale free

Sample Network from Intel



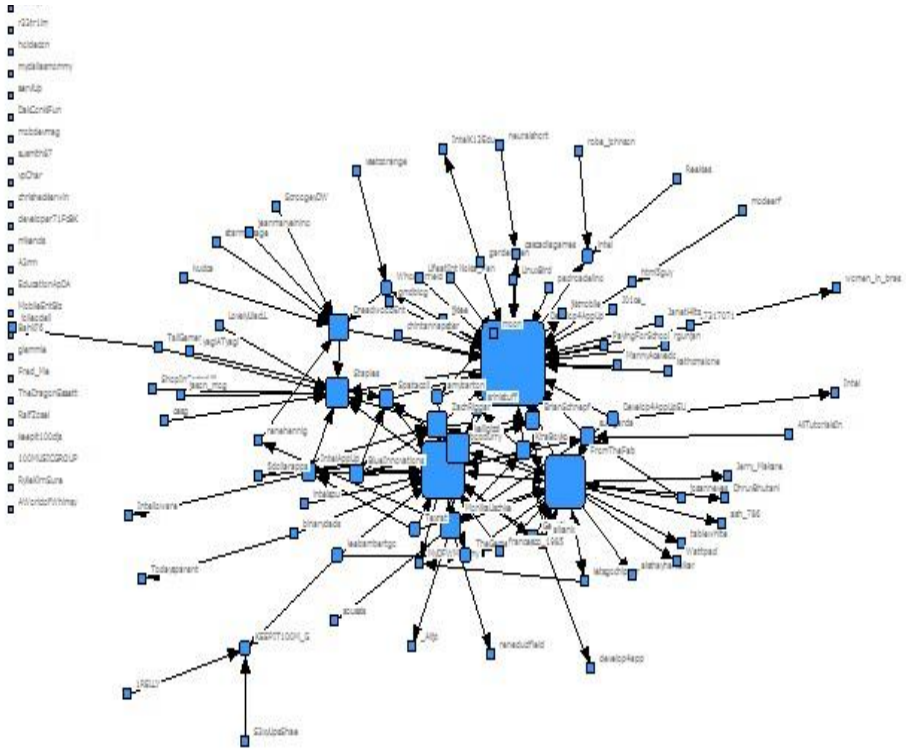
- Random sample of 12 nodes (users) and 15 ties (relationships)
- Serves as basis for comparing metrics

Comparing Measures of Influence

- All centrality measures seem to agree with each other to a certain extent.
  - For example, all centrality measures rank node **Q** around 8.
- The biggest disagreement in centrality measures occurs for node **C**.
  - Eigenvector centrality ranks node C at 1;
  - Degree centrality ranks it at 2-4;
  - Betweeness centrality ranks it at 7-8; and
  - Closeness centrality ranks it at 5-7.

Node	Degree Centrality	Between-ness Centrality	Closeness Centrality	Eigen-vector Centrality
AB	3.00 (5)	9.00 (3)	32.00 (2)	0.36 (4)
AE	2.00 (6-9)	0.00 (9-12)	43.00 (11)	0.27 (6)
AJ	1.00 (10-12)	0.00 (9-12)	40.00 (9-10)	0.09 (10-11)
AK	4.00 (2-4)	8.00 (4)	33.00 (3)	0.44 (2)
AL	1.00 (10-12)	0.00 (9-12)	40.00 (9-10)	0.09 (10-11)
C	4.00 (2-4)	5.00 (7-8)	35.00 (5-7)	0.46 (1)
L	5.00 (1)	27.50 (1)	30.00 (1)	0.28 (5)
P	3.00 (5)	13.50 (2)	35.00 (5-7)	0.16 (9)
Q	2.00 (6-9)	5.00 (7-8)	36.00 (8)	0.18 (8)
V	4.00 (2-4)	7.00 (5)	35.00 (5-7)	0.43 (3)
X	1.00 (10-12)	0.00 (9-12)	45.00 (12)	0.05 (12)
Z	2.00 (6-9)	6.00 (6)	34.00 (4)	0.22 (7)

Intel Software Network

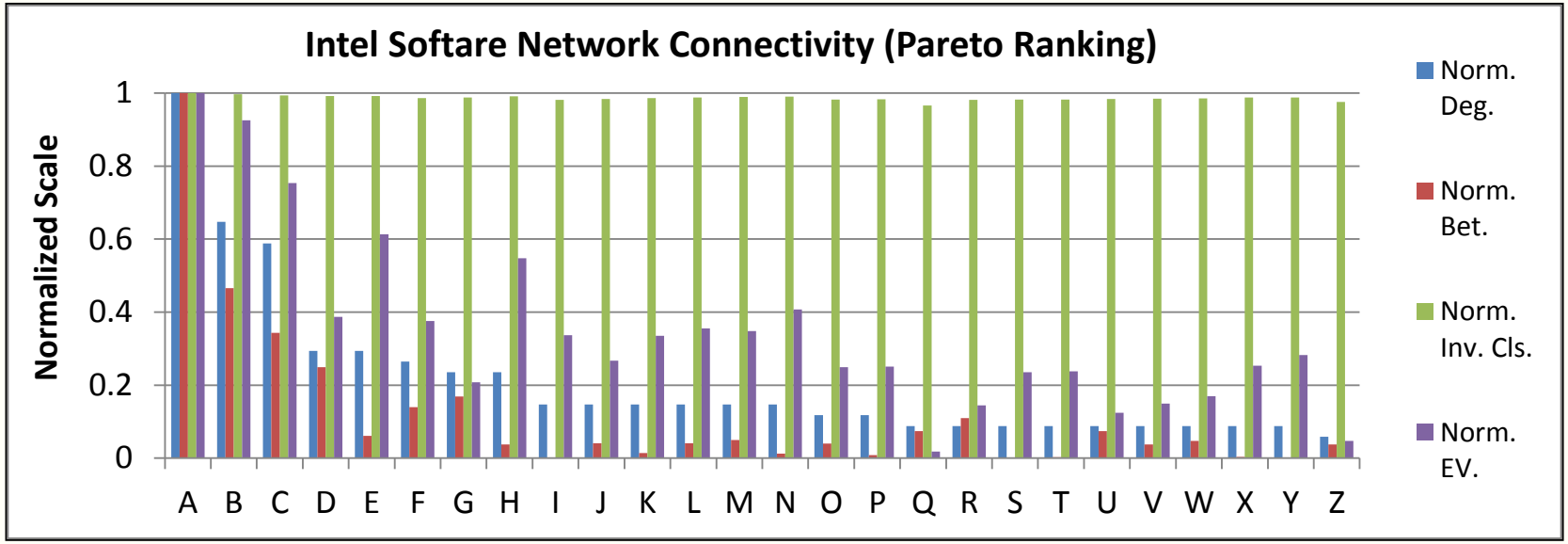


- Larger random sample
  - One week's Twitter traffic
  - 124 nodes
  - 89 connected
- Sparse sample
  - Total # of ties = 134
- More scale free than small world

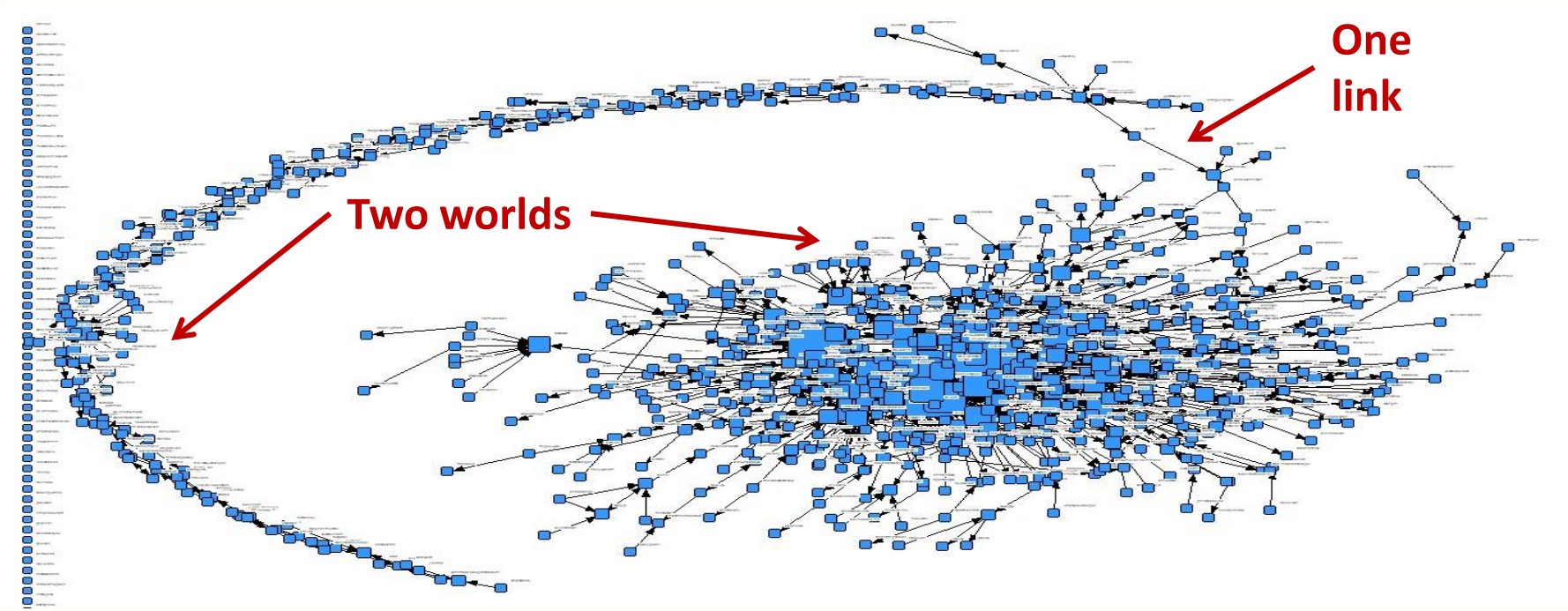
Connectivity of Intel Software Network

Intel Rank Correlation (Spearman's rho); N=124				
	Degree	Between-ness	Close-ness	Eigen-vector
Degree	1.000	0.787	-0.868	0.882
Betweenness	0.787	1.000	-0.647	0.671
Closeness	-0.868	-0.647	1.000	-0.964
Eigenvector	0.882	0.671	-0.964	1.000
Correlations are significant at the 0.01 level (2-tail)				

- Metrics disagree as connectivity decreases.
- Ranking varies from metric to metric.



VMWorld Software Conference

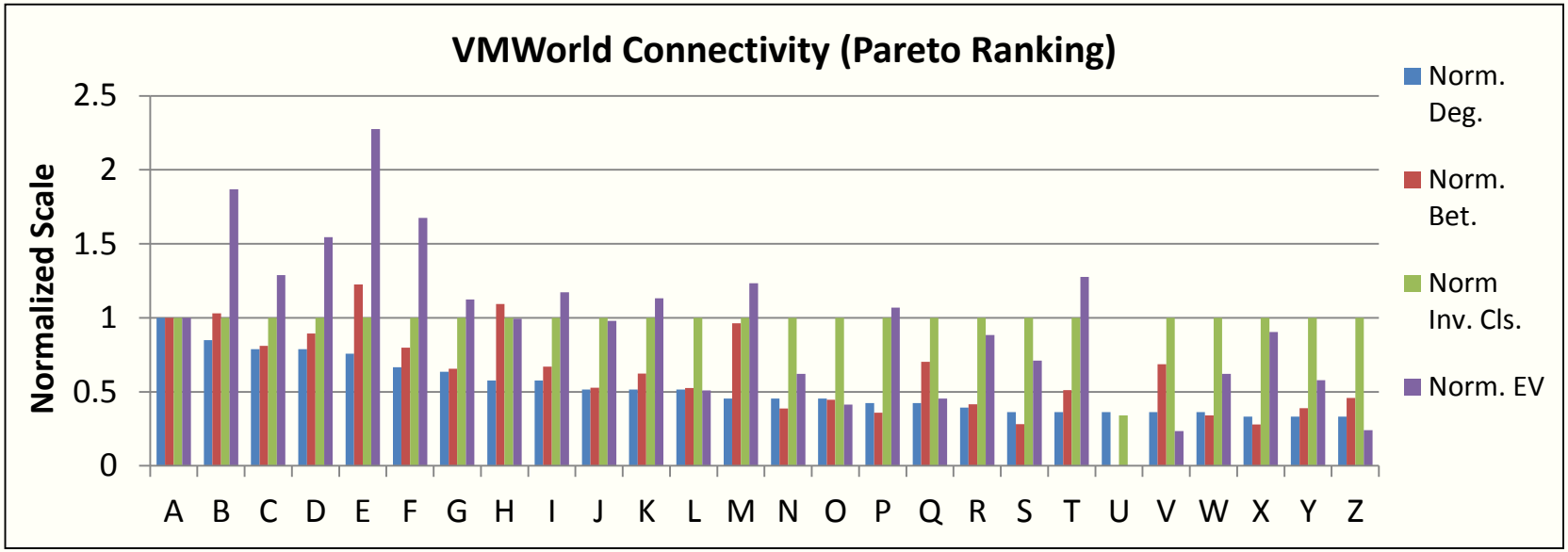


- Total Population: Two days' Twitter traffic;
  - 958 nodes; 868 connected
- Sparse sample -- # of ties =1044;
- More scale free than small world

Connectivity of the VMWorld Conference

VMWorld Rank Correlation (Spearman's rho); N=958				
	Degree	Between-ness	Close-ness	Eigen-vector
Degree	1.000	0.900	-0.706	0.618
Betweenness	0.900	1.000	-0.567	0.557
Closeness	-0.706	-0.567	1.000	-0.955
Eigenvector	0.618	0.557	-0.955	1.000
Correlations are significant at the 0.01 level (2-tail)				

- Metrics disagree as connectivity decreases.
- Ranking varies from metric to metric.



Tentative Conclusions and Questions

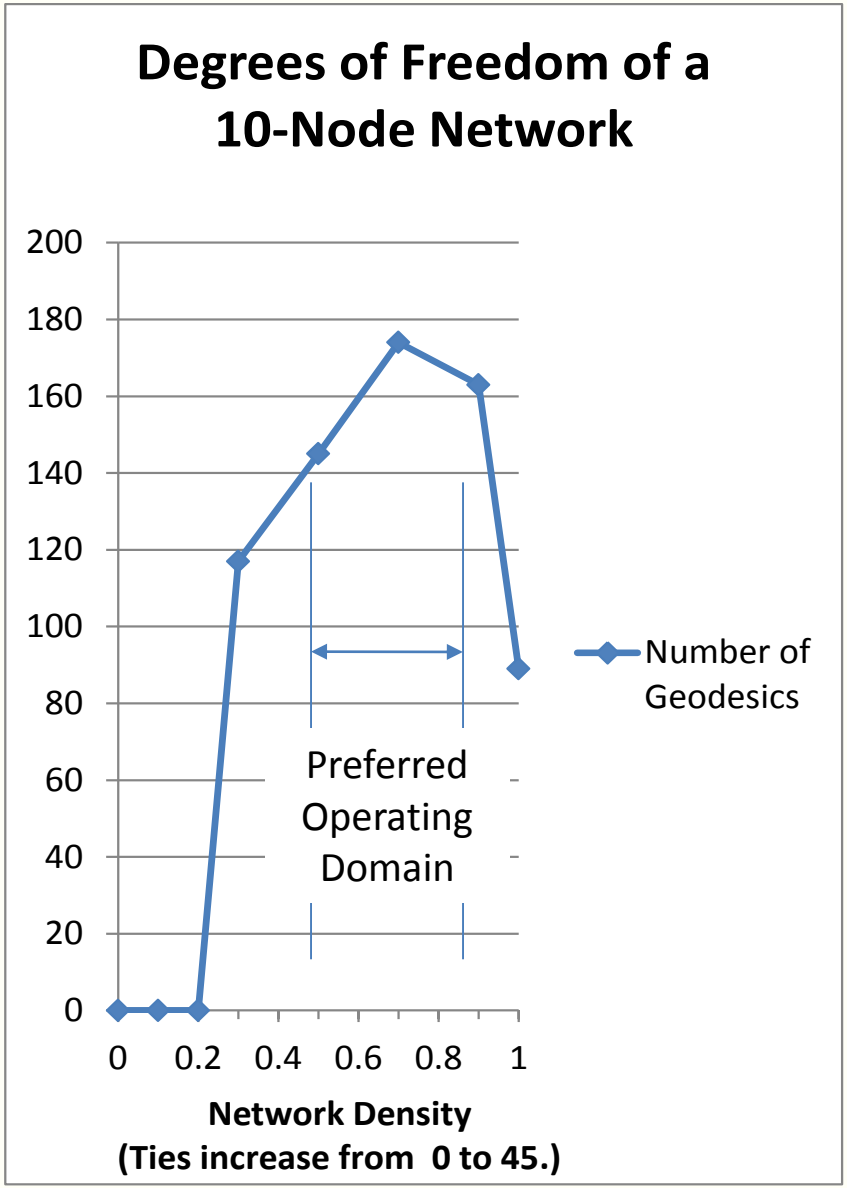
- The extent of influence within a social network may depend upon all of the above measures.
- To date no optimal measure for extent of influence has been identified.
- To identify true loci of influence, more research needs to be done.
- Specific questions:
  - Does the correlation between metrics decrease as network size increases?
  - What about network density?
  - What about information flow?

Simulation of a Small Network

- Number of geodesics as a function of network density
  - 10 nodes; up to 45 ties.
  - Randomly increase network density from 0 to 45/45.
  - *We assume freedom for information flow increases with number of geodesics.*

Finding : Optimal Operating Domain for Social Network

- Network too chaotic at low density.
  - Human activity below critical mass.
- Optimal domain for structure formation at intermediate level
  - Large number of geodesics
- Network performance deteriorates at high network density
  - Too many communication channels.
  - Fewer short communication channels
  - No 'small worlds'



Implications

- Human activity has no significant impact until ND hits critical mass.
- Surge in human activity follows.
- Activity peaks and deteriorates at high ND.
- Human activity within network is prerequisite to network performance.
- Surge in network performance likely to follow surge in human activity.
- ***Number of geodesics forecasts revolutions in network performance.***
- ***Intel is likely to know in advance when its network's performance will take off.***

Contributions and Work in Progress

- ***Contributions to date***
  - Demonstrate that current approaches are not well suited for determining the true loci of influence.
- ***Work in progress***
  - Developing methods of analysis that is based on preferential attachment and information flow.
  - Repeat benchmarking study

Upcoming Research

- Analyze structure of complete Intel network (>10,000 nodes)
  - Validate the current results of serial-geodesic flow
  - for undirected and unweighted (homogeneous tie strength) networks
  - with networks of multiple sizes and varying structure
  - (denser vs. less dense; scale free vs. small world).
- Content analysis
  - Analyze content of all messages sent within the Intel Software Network
  - Characterize context in which Intel's various user communities operate
  - Identify the interests of different user groups
- Apply approach to other settings
  - Validate the metrics for directed and weighted networks
  - Characterize the impact of preferential attachment
  - Assess the impact of various governance structures

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