Social Network Under Stress

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In collaboration with Brian Uzzi and Jon Kleinberg
Social Network Temporal Dynamics
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Temporal dynamics of networks:

Short diameter, densification, clustering, heavy tail degree distribution, ... [Leskovec et al. 2007, Barabasi et al. 1999, Kossinets et al. 2009, ...]
Social Network Temporal Dynamics

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Short diameter, densification, clustering, heavy tail degree distribution, ... [Leskovec et al. 2007, Barabasi et al. 1999, Kossinets et al. 2009, ...]

Useful for:
• Link prediction
• Detecting influential nodes
• Finding communities
Social Network Temporal Dynamics

t=1
Social Network Temporal Dynamics

$t=1$

$t=2$
Social Network Temporal Dynamics
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Hedge Fund Data

Instant Messages (IM):
• Full record of IMs: content, sender, recipient, timestamp
• 182 internal decision makers, 8646 outside contacts
• 22 Million IMs
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Stock Trading:
• Full record of all transactions: stock, price, number of stocks, type of transaction (Buy, Sell), timestamp
• 600K trades
• 2008 – 2012
In This Talk

Market Movements (Shocks)

Social Network
In This Talk

Market Movements
(Shocks)

Social Network

Trading
In This Talk

Market Movements (Shocks)

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Trading

Performance
In This Talk

Market Movements (Shocks)

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Emotional and Cognitive Content
In This Talk

Market Movements (Shocks)

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Emotional and Cognitive Content
Measures

**Shock**: Change in price of stock $s$ on day $d$

% change: $(\text{closing} - \text{opening}) / \text{opening}$
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For each stock $s$ and day $d$, generate network $G(s,d)$ among employees who mention $s$
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• Size (Nodes, edges)
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Network’s features:
• Size (Nodes, edges)
• Density (Clustering, tie strength)
• Openness (Border edges)
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• Size (Nodes, edges)
• Density (Clustering, tie strength)
• Openness (Border edges)
Turtled-up network
Turtled-up network

Open network
Theoretical Expectations

Networks may turtle-up during shocks:

- Trust (Granovetter 1985, Coleman 1988)
- Expertise knowledge, repeated information channels (Coleman 1990)
- Threat rigidity (Staw 1981)
Theoretical Expectations

Networks may turtle-up during shocks:

- Trust [Granovetter 1985, Coleman 1988]
- Expertise knowledge, repeated information channels [Coleman 1990]
- Threat rigidity [Staw 1981]

Networks may open-up during shocks:

- New information through weak ties [Granovetter 1973]
- Diverse information from different groups (structural holes) [Burt 92]
Num of nodes | Past: Ratio of num. nodes in $G(s,d)$ and mean num. nodes in $G(s,d')$ for $d' < d$. 
Findings: Size

Shocks → More nodes and edges

**Num of nodes | Past:** Ratio of num. nodes in $G(s,d)$ and mean num. nodes in $G(s,d')$ for $d' < d$. 
Findings: Clustering Coefficient

Clustering coefficient of a node $n$: the ratio of the existing and possible number of edges among the neighbors of $n$. 
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C = 4/10

Shocks $\rightarrow$ Higher Clustering coefficient
Tie strength: \((x,y)\) is \(k\)-strong, if \(y\) is among the top \(k\%\) most frequent connections of \(x\)
Findings: Tie Strength

Tie strength: \((x,y)\) is \(k\)-strong, if \(y\) is among the top \(k\%\) most frequent connections of \(x\)
Findings: Openness

Border edges: involve an outside contact
Findings: Openness

Shocks ➔ More border edges

Border edges: involve an outside contact
Networks “Turtle-up” During Shocks

• Higher clustering
• Stronger edges
• More internal communication

Consistent with theories of:
• Trust
• Expertise knowledge, repeated information channels
• Threat rigidity
**LIWC Categories**

**Linguistic Inquiry Word Count (LIWC):** text analysis tool, which identifies words that belong to various categories.

<table>
<thead>
<tr>
<th>Affective Processes</th>
<th>Cognitive Processes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Positive</strong></td>
<td><strong>Insight</strong></td>
</tr>
<tr>
<td>Love, nice</td>
<td>Think, Consider</td>
</tr>
<tr>
<td><strong>Negative</strong></td>
<td><strong>Causation</strong></td>
</tr>
<tr>
<td>Hurt, ugly</td>
<td>Because, Hence</td>
</tr>
<tr>
<td><strong>Anxiety</strong></td>
<td><strong>Discrepancy</strong></td>
</tr>
<tr>
<td>Worried, fearful</td>
<td>Should, Could</td>
</tr>
<tr>
<td><strong>Anger</strong></td>
<td><strong>Tentative</strong></td>
</tr>
<tr>
<td>Hate, kill</td>
<td>Maybe, Guess</td>
</tr>
<tr>
<td><strong>Sadness</strong></td>
<td><strong>Certainty</strong></td>
</tr>
<tr>
<td>Crying, sad</td>
<td>Always, Never</td>
</tr>
<tr>
<td></td>
<td><strong>Inhibition</strong></td>
</tr>
<tr>
<td></td>
<td>Block, Constrain</td>
</tr>
<tr>
<td></td>
<td><strong>Inclusive</strong></td>
</tr>
<tr>
<td></td>
<td>With, Include</td>
</tr>
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<tr>
<td></td>
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</tbody>
</table>
Price Changes vs. Emotions

Positive price changes \(\rightarrow\) Higher positive emotions
Price Changes vs. Emotions

Positive price changes ➞ Higher positive emotions
Negative price changes ➞ Higher negative emotions

Emotions are asymmetric with respect to price change.
Price changes $\rightarrow$ Higher cognitive language

Cognitive processes are asymmetric with respect to price change.
Predicting Sentiment and Cognition

Task: For a fixed stock $s$ and day $d$, predict if IMs that mention $s$ on day $d$ contain more words in the category than average.
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Network variables are more predictive of type of content than price changes.
Predicting Stock Trading
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**Task:** Predict whether a stock that has not been traded for \( k \) weeks will be traded.
Network variables are more predictive of type of sudden stock trading than price changes.

Task: Predict whether a stock that has not been traded for $k$ weeks will be traded.
Conclusions

• Relationship between stock market shocks and social network structure

• Competing hypotheses: turtle up vs. open network structure

• Communication “turtles-up” during shocks.

• Network structure is predictive of trading, performance, and emotional and cognitive content.

• Stock market changes do not improve prediction accuracy.
Network variables are more predictive of performance than price changes.

**Suboptimal trade:** Worse price than the worst price the next day.

**Task:** For a fixed stock $s$ traded on day $d$, predict if it’s suboptimal.

**N-serial trades:** A trade of stock $s$ that has occurred for at least $N$ consecutive days.