Modeling Communication Dynamics During Extreme Events: The Case of the World Trade Center Disaster

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Communication and Coordination During Disasters

• A succinct summary of the situation:
  – “Many people trying to do quickly what they do not ordinarily do, in an environment with which they are not familiar.” (Tierney, 1985)
    • Demand for coordination escalates, as infrastructure degrades
    • Communication essential to prevent task interference, inappropriate risk assessment, suboptimal resource allocation

• Communication particularly critical during emergency phase
  – Hazards still present, immediate response required
  – Responders incompletely mobilized; central first responder role
Communication and the World Trade Center Disaster

- **Mass fatality event on 9/11/01**
  - Aircraft collision leading to large-scale structure fire and subsequent collapse
  - Largest response action in NY history
  - Over 2,900 dead, including 400+ emergency response personnel

- **The Port Authority Data Set**
  - Various transcripts, police reports, and other documents released by Port Authority of New York and New Jersey
  - Documents communication/coordination during WTC emergency phase
  - Present focus: networks from radio transcripts
Responder Radio
Communications at the WTC

- 17 radio transcripts from WTC, PA, Newark responders
  - Divided into partitions
  - Partitions contain transcribed transmissions
  - Transmissions contain identifiers, text
    - Some missing data due to inaudibility, redaction

- Used to construct multigraphs of interpersonal communication during WTC event
  - \((i,j)\) edge corresponds to a transmission from \(i\) to \(j\)

- MALE A: (Inaudible), escort unit, is that marked? (PAUSE)
- MALE B: Eighty-three, Central. (PAUSE) Eight-three, Central.
- MALE O: Eighty-three, go.
- MALE B: We’ve got an explosion in Tower Two, looks like, uh, at least the 96th floor. Uh, tell personnel follow directions of support personnel. They can come down West Broadway, and right to the facility. But make it as nice and clear as possible.
- MALE O: Okay, copy. (PAUSE)
- MALE C: CPD from eight-five, eight-one, Kenny.
- MALE O: Eight-five, eight-one, Kenny, go.
- MALE C: We’re, uh, headed towards the Trade Center. Could you advise us if the Battery Tower is providing emergency access for us?
Overview

- Aggregate Properties
  - Group Level
  - Position Level
- Relational Dynamics
  - Modeling Framework
  - Mechanisms and Effects
  - Findings
- Conclusion
Responder Heterogeneity at the Group Level

• Not all responders are alike
  – “Specialist” responders are trained and equipped to respond to crisis situations as part of their standard duties
    • Fire, EMS, police, security, etc.
  – “Non-specialist” responders lack special training/equipment
    • Bystanders, civilian volunteers, victims, etc.

• Does specialization affect communication network structure?
  – Coded WTC networks by responder type
    • 9 “specialist” networks, 8 “non-specialist” networks
The WTC Networks: A First Look

Specialist Responder Networks

Non-specialist Responder Networks
Aggregate Group-Level Findings

- Overall, WTC nets appear more “formal” than “informal”
  - Fairly high dyadic reciprocity, but non-negligible (path) hierarchy
  - Little clustering, but more than dyad census would predict; seems to reflect activity within coordinative “core”
  - Skewed degree distribution, fairly centralized structure

- Specialist/Nonspecialist networks surprisingly similar
  - Few significant differences, none substantively strong

- Some implications (theoretical and practical)
  - Situational context can dominate preparation in extreme events
  - Different groups may have similar emergency communication needs
  - Individual involvement in emergency communication may vary greatly
Position-Level Heterogeneity

- Practical as well as substantive importance
  - Usage patterns impact system design

- Starting point: heterogeneity in communication activity level
  - Very large differences in volume, number of partners
    - Volume and degree correlate strongly across networks (median 0.96, IQR 0.064)
  - Not power-law distributed, but long-tailed
    - BIC favors Yule over Poisson, but truth lies in between
A Closer Look: Identifying Coordinators

- Degree distribution implies strong role for coordinators
  - Structures held together by few key actors

- Identifying coordinators
  - Define as vertices with total degree, betweenness above respective 90% quantiles
  - Mediate connections among many alters
Coordination and Institutional Role

- Importance of coordination well-known among practitioners (e.g., Auf der Heide, 1989)
  - Response organizations include institutionalized coordinative roles, e.g., dispatchers, call desk operators

- Can coordination be explained via existing roles?
  - “Institutionalized” vs. “emergent” coordinators (a la Dynes, 1970)

- Coding from transcript content
  - Title includes “command,” “desk,” “operator,” “dispatch,” “manager,” “control,” or “base”
  - Responder identified with site (“Newark Airport”)
Specialist Coordinators by Institutional Status, WTC Data
Non-specialist Coordinators by Institutional Status, WTC Data
### Coordinators by Specialization and Status

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<thead>
<tr>
<th></th>
<th>Coordinators</th>
<th>Non-coordinators</th>
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<tr>
<td>Non-institutionalized</td>
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<td>1048</td>
</tr>
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</table>

#### Formal status
- Large majority (85%) of coordinators are emergent
  - Only 29% of institutionalized actors are coordinators!
- However, institutionalized actors over 3.4 times as likely to be coordinators ($\chi^2 p=6.2e-11$)
  - Base rate effect

#### Specialization
- No significant main effect for centralization ($\chi^2 p=0.131$)
- Test for three-way interaction w/formal status using loglinear model
  - No effect ($p=0.228$)
  - Side note: inst. actors 1.8 times as common in spec. networks ($\chi^2 p=0.004$)
Aggregate Position-Level Findings

• Substantial heterogeneity at position level
  – Networks are uniformly “hub-dominated,” with few responders doing most of the communication and coordination (both)

• Key role of emergent coordination
  – Overwhelming majority of coordinators emergent
  – Institutional status has real impact, but overwhelmed by base rates

• Motivation for dynamic modeling
  – How do coordinators emerge within the communication network?
  – Relative impact of endogenous processes vs. responder heterogeneity?
Overview

• Aggregate Properties
  – Group Level
  – Position Level

• Relational Dynamics
  – Modeling Framework
  – Mechanisms and Effects
  – Findings

• Conclusion
From Statics to Dynamics

- Aggregate analyses only take us so far
- The challenge: models which capture key processes, but which are inferentially tractable
  - Must capture processes such as clustering, reciprocity, attachment, etc.
  - Must allow principled (i.e., likelihood-based) inference from available data
- Our approach: relational event modeling
  - Treat communications as Poisson events, conditional on a (generally endogenous) rate structure
  - Compare to “actor oriented” models of Snijders et al. (2001)
Relational Event Model
Likelihood

- Hazard model, based on relational events
  - Let a be a transmission from sender \( s(a) \) to receiver \( r(a) \) at time \( \tau(a) \); let \( A_t=\{a_i:0 \leq \tau(a_i) \leq t\} \) be the time-ordered set of all transmissions from time 0 to time \( t \).
  - If transmissions arise independently conditional on time and event history, we have

\[
p(A_t) = \prod_{i=1}^{|A_t|} h(\tau(a_i) - \tau(a_{i-1})|s(a_i), r(a_i), A_{\tau(a_{i-1})}) \left( \prod_{j=1}^N \prod_{k=1}^N S(\tau(a_i) - \tau(a_{i-1})|j, k, A_{\tau(a_{i-1})}) \right) \times \left( \prod_{j=1}^N \prod_{k=1}^N S(t - \tau(a_i)|j, k, A_t) \right)
\]

- Where \( S \) is the survival function of the transmission process (i.e., \( 1-F(x) \)), \( h \) is the associated hazard function (i.e., \( f(x)/S(x) \)), and \( \tau(a_0)=0 \).
Event Model Likelihood: Piecewise Exponential Case

- **Natural simplifying assumption:** communications arise as Poisson process with piecewise constant rates
  - Intuition: each pair has a sending rate which is constant, given complete event history up to that point
    - Waiting times conditionally exponentially distributed
    - Rates change when events transpire, but not otherwise
- **Can use to implement event likelihood**
  - Let $s_i = s(a_i)$, $r_i = r(a_i)$, $\tau_i = \tau(a_i)$, $\lambda_{ijk} = \lambda(s_i, r_i, A_k)$; then
    
    $$ p(A_t) = \left( \prod_{i=1}^{N} \lambda_{s_i r_i \tau_{i-1}} \prod_{j=1}^{N} \prod_{k=1}^{N} \exp \left[ -\lambda_{jkt} \left( t - \tau_{i} \right) \right] \right) \left( \prod_{j=1}^{N} \prod_{k=1}^{N} \exp \left[ -\lambda_{jkt} \left( t - \tau_{|A_t|} \right) \right] \right) $$
The Problem of Uncertain Event Timing

• Likelihood of an event sequence depends on the detailed history
  – Problem: exact timing is generally uncertain for WTC transcripts, though order is known
  – What if we only have (temporally) ordinal data?

• Stochastic process theory to the rescue!
  – Thm: Let $X_1,\ldots, X_n$ be independent exponential r.v. w/rate parameters $\lambda_1,\ldots, \lambda_n$. Then the probability that $x_i = \min\{x_1,\ldots, x_n\}$ is $\lambda_i/(\lambda_1+\ldots+\lambda_n)$.
  – Implication: likelihood of ordinal data is a product of multinomial likelihoods
    • Identifies rate function up to a constant factor
Event Model Likelihood: Ordinal Data Case

- Using the above, we may write the likelihood of an event sequence $A_t$ as follows:

$$p(A_t) = \prod_{i=1}^{\left|A_t\right|} \left[ \lambda_{s,r_i \tau_{i-1}} \right]$$

$$= \prod_{i=1}^{\left|A_t\right|} \left[ \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} \lambda_{jk \tau_{i-1}}}{\lambda_{s,r_i \tau_{i-1}}} \right]$$

- Dynamics governed by rate function, $\lambda$

$$\lambda_{ijt} = \begin{cases} 
\exp \left( \lambda_0 + \theta^T u(i, j, A_t, X) \right) & i \neq j \\
0 & i = j 
\end{cases}$$

- Where $\lambda_0$ is an arbitrary constant, $\theta \in \mathbb{R}^p$ is a parameter vector, and $u: (i,j,A_t,X) \rightarrow \mathbb{R}^p$ is a vector of sufficient statistics.
Fitting the Event Model

- Given $A_t$ and $u$, how do we estimate $\theta$?
  - Parameters interpretable as logged rate multipliers (in $u$)
- We have $p(A_t | \theta)$, so can conduct likelihood-based inference
  - Find MLE $\theta^* = \arg \max_\theta p(A_t | \theta)$, e.g., using a variant Newton-Rapheson or other method
  - Can also proceed in a Bayesian manner
    - Posit $p(\theta)$, work with $p(\theta | A_t) \propto p(A_t | \theta)p(\theta)$
    - Some computational challenges when $N$ is large; tricks like MC quadrature needed to deal with sum of rates across dyads
Mechanisms and Effects

- Modeling the WTC dynamics is now a matter of choosing the sufficient statistics, $u$
  - Should incorporate behaviorally meaningful mechanisms, baseline effects

- A first cut: five basic effects
  - Primary interest: preferential attachment, persistence, fixed effects
  - “Controls”: recency, clustering

- Before fitting the models, we consider each in greater detail....
Explaining Hub Formation

• Two obvious classes of explanation
  – Preferential attachment
    • Exposure effects
    • Emergent specialization
  – Heterogeneity in base activity levels
    • Institutional role
    • The “latent safety” hypothesis

• Modeling the mechanisms
  – Past total degree effect
  – Fixed effects for communication activity
Persistence Effects

- **Inertia-like effect**: past contacts may tend to become future contacts
  - Unobserved relational heterogeneity
  - Availability to memory
  - (Compare with autocorrelation terms in an AR process)

- **Simple implementation**: fraction of previous contacts as predictor
  - Log-rate of \((i,j)\) contact adjusted by \(\theta d_{ij}/d_i\)
Recency/Ordering Effects

- Ordering of past contact potentially affects future contact
  - Reciprocity norms
  - Recency effects (salience)
- Simple parameterization: dyadic contact ordering effect
  - Previous incoming contacts ranked
    - Non-contacts treated as rank $\infty$
  - Log-rate of outgoing $(i,j)$ contact adjusted by $\theta(1/rank_{ji})$
Triadic/Clustering Effects

- Can also control for endogenous triadic mechanisms
  - Two-path effects
    - Past outbound two-path flows lead to/inhibit direct contact (transitivity)
    - Past inbound two-path flows lead to/inhibit direct contact (cyclicity)
  - Shared partner effects
    - Past outbound shared partners lead to/inhibit direct contact (common reference)
    - Past inbound shared partners lead to/inhibit direct contact (common contact)
Relational Dynamics at the WTC

- Given the above, we fit the relational event model to six transcripts from the WTC
  - PATH radio communications; Newark police, airport maintenance, and command post radio; NJ SPEN 2; and WTC police
  - Chosen b/c small size allows estimation of fixed effects

- MLEs, fit information obtained using previously mentioned effects
  - Approximate asymptotic standard errors, $p$-values using inverse of estimated information matrix at MLE
  - Model selection via BIC
# Model Selection

<table>
<thead>
<tr>
<th>Network</th>
<th>PATH Radio</th>
<th>Newark Maint</th>
<th>Newark Police</th>
<th>NJSPEN 2</th>
<th>Newark CPD</th>
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<td>FE</td>
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<tr>
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Parameter Estimates, Marginal Models

MLEs for Event Model Parameters, w/ Asymptotic 95% CIs

T-ISP
T-OSP
T-ITP
T-OPT
R
P
PA

PATH Radio
Newark Maint
Newark Police
NJSPEN 2
Newark CPD
WTC Police

\[ \hat{\theta} \]
Parameter Estimates, Marginal Models

MLEs for Event Model Parameters, w/Asymptotic 95% CIs

- T-ISP
- T-OSP
- T-ITP
- T-OPT
- PATH Radio
- Newark Maint
- Newark Police
- NJSPEN 2
- Newark CPD
- WTC Police
Parameter Estimates, Joint Model

MLEs for Event Model Parameters, w/Asymptotic 95% CIs

- T-ISP
- T-OSP
- T-ITP
- T-OPT
- R
- P
- PA

PATH Radio
Newark Maint
Newark Police
NJSPEN 2
Newark CPD
WTC Police
Parameter Estimates, Joint Model

MLEs for Event Model Parameters, w/ Asymptotic 95% CIs

T-ISP
T-OSP
T-ITP
T-OPT
R
P
PA

PATH Radio
Newark Maint
Newark Police
NJSPEN 2
Newark CPD
WTC Police

-20 -15 -10 -5 0 5

\( \hat{\theta} \)
Fixed Effects, Joint Model

PATH Radio

Newark Maint

Newark Police

NJSPEN 2

Newark CPD

WTC Police

z=0.09

z=0.793

z=0.625

z=0.166

z=1.753

z=1.471
Overview

• Aggregate Properties
  – Group Level
  – Position Level

• Relational Dynamics
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  – Findings

• Conclusion
Conclusion

- **Heterogeneity within networks**
  - All WTC networks fairly centralized
  - Distinct communication roles

- **Dynamic properties**
  - Dynamics driven largely by recency effects (reciprocity), differences in activity level
  - Triadic effects weak to nonexistent
    - Few opportunities in smaller data sets, so high uncertainty

- **Emergent coordination**
  - 85-90% of coordinators/hubs emergent
  - Little evidence for preferential attachment; latent heterogeneity more powerful
    - Heterogeneity not due to institutionalized coordinator status – "latent safety"?
  - Conjecture: intense demand during disaster overwhelms conventional role structure, responses are highly variable
    - Local context may provide missing element
Ongoing and Future Work

- **More Dynamics**
  - Efficient computation for large models

- **Content**
  - Tasks, locations, resources
  - Helping vs. communication (police reports)

- **Accuracy**
  - Relationship w/position, activity level

- **Interorganizational networks**
  - WTC, Katrina
  - Bridging the “meso-meso” gap