



# Evaluating Organizational Change

Geoffrey P Morgan

[gmorgan@cs.cmu.edu](mailto:gmorgan@cs.cmu.edu)

Dissertation-Related Work

# MOTIVATION AND OVERVIEW: EVALUATING ORG CHANGE



# Human organizations change all the time, and it's a big deal

- Hundreds of firms either specialize or have specific consulting departments for “organizational restructuring”
- 90% of companies with more than a 1000 employees has recently restructured (BCG, 2012)
- Lots and lots of mergers:
  - Major merger firms handled more than 1000+ mergers in the first half of 2013, for a total valuation of more than 400B (NYTimes, 2013)
  - In terms of valuation (NYTimes, 2013):
    - 40% Happened in the US
    - 60% happened in the rest of the World



# These changes rarely produce desired outcomes.

- Organizational restructuring failure rate is between 50 to 70%



- Merger failure – Estimates vary, but even the most conservative estimates suggest that merger success is a 50/50 proposition.



# Why do these efforts fail?

- Major reason is **Cultural Issues**
  - Lack of clarity in leadership
    - Shared values improve information transfer (Weick 1987)
    - Without shared values and knowledge, actors have difficulty communicating new goals (Wilson and Ferch 2005)
  - Lack of clarity in proposed direction (why is this change a good idea?)
    - Actors do not do tasks unless given reasons to identify with those tasks (Sheldon, Turban et al. 2003)
    - Guidance from management that ignores or contradicts functional work practice exposes the organization to significant risks (Nathanael and Marmaras 2006)
  - Incompatible corporate cultures



# We use surveys to use evaluate corporate culture

- Multi-National Merger and Acquisition has been dealing with this for some time (Shimizu, Hitt et al. 2004)
- But domestic merger analysis has also been looking at incompatible corporate culture as a source of failure (Epstein 2005) (Holt, Armenakis et al. 2007)
- Principally, **surveys** are used to evaluate corporate culture and then develop suggestions for intervention and remediation

# But, surveys of org culture are difficult to do well

- Fixed points in Time
- Limited employee exposure
  - Often, survey responders will be self-selected
  - Penetration below executive layer is rare
- Surveys can alarm employees
- Implicit demand characteristics (Orne 1962) can overwhelm

Is there another method we can use  
to supplement survey techniques?

# Organizations generate lots of data

*Already frequently leveraged*

*Frequently ignored*



Financials



Business Process Activity  
Tracking Systems

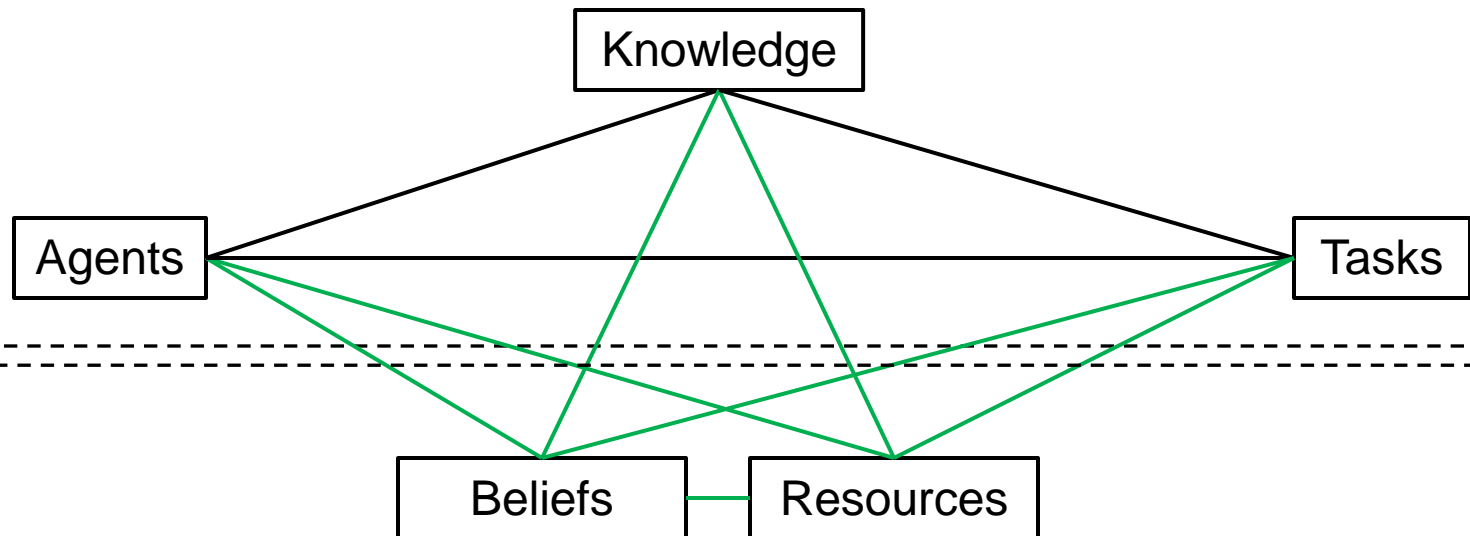
**Let's use this  
(awesome) data!**

Collaborative Wikis and  
Code Repositories



# Meta-networks as a representation of the organization

*PCANS (Krackhardt & Carley, 1998; Lee and Carley 2004; Cataldo, Herbsleb et al. 2008)*



*Importance established in review of organizational characteristics which contributes to resilience, Morgan & Carley, To be submitted*

# Meta-Networks are ways of representing many relationships

	Agents	Knowledge	Tasks
Agents	"Who Talks to Who"	"Who knows what"	"Who does what"
Knowledge		"What knowledge is linked to what"	"What must be known for each task"
Tasks	Typical PCANS semantics		"What tasks are related to what"

# DATA DESCRIPTION



# The (Very Excellent) Data

- Fortune 500 Company, purchased another large company
  - Wants to understand the integration process
  - Asked academic researchers if they wanted to help
- Allowed collection of email-server data for multiple months at two points in time
  - Collection Period 1: Right after merger announcement
  - Collection Period 2: A year later
  - Collection Period 3: Another year later
- Encouraged employees to participate in org surveys administered by research team

# Survey Data

- Survey was run on a sub-sample of employees. The survey collected various indices, including:
  - Organization Culture (Denison and Mishra 1995)
  - Job Satisfaction (Cammann, Fichman et al. 1983)
  - Commitment to the Organization (Allen and Meyer 1990)
  - Group Identification (van Dick, van Knippenberg et al. 2008)
  - Perceptions of Organizational Justice (Niehoff and Moorman 1993)
- 4849 People surveyed, Year 1
- 4915 People surveyed, Year 2
- 4300 People surveyed, Year 3
- ~11,000 People surveyed in total



# Email: Structured and Unstructured Elements

- As discussed over the week, email is interesting (and difficult) because it includes both structured data and unstructured data
- Structured Data
  - Timestamp
  - From
  - To, CC, BCC
- Unstructured Data
  - Subject
  - Body

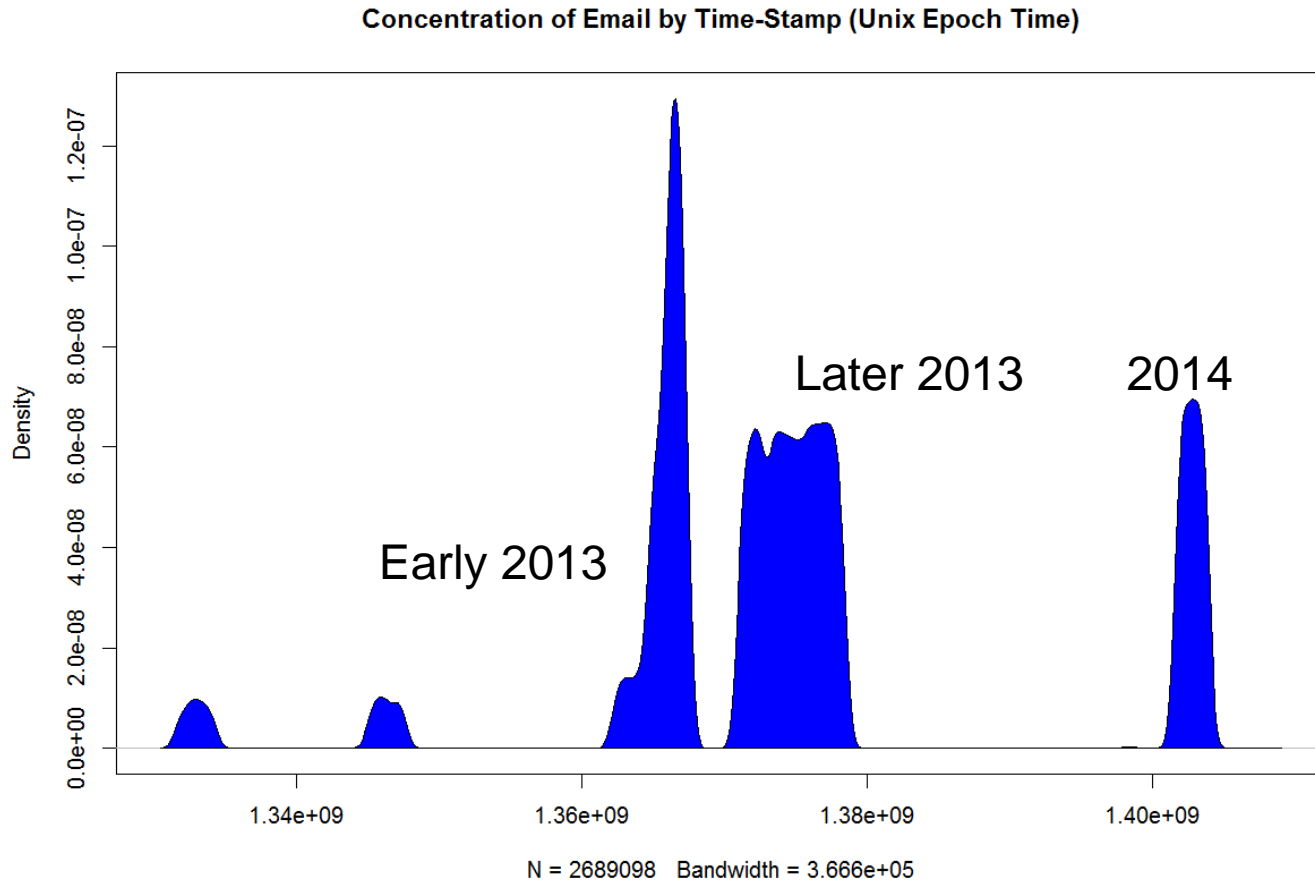


# Email Dataset

- Filtering:
  - English Emails (identified by Tika API)
  - Sent to a small group of people (less than 7)
  - At least one sender and receiver must have taken the survey in any of the three years
- After filtering to 'known actors' from surveys
  - Timeperiod 1 : 233k Emails
  - Timeperiod 2 : 700k Emails
  - Timeperiod 3 : 1M Emails
- Average Subject Length: 32 Characters
- Average Body Length:
  - Total Characters (includes replies): 2000 Characters
  - Novel\* Characters: 184 Characters

\* We wrote code to scrape off reply-chains

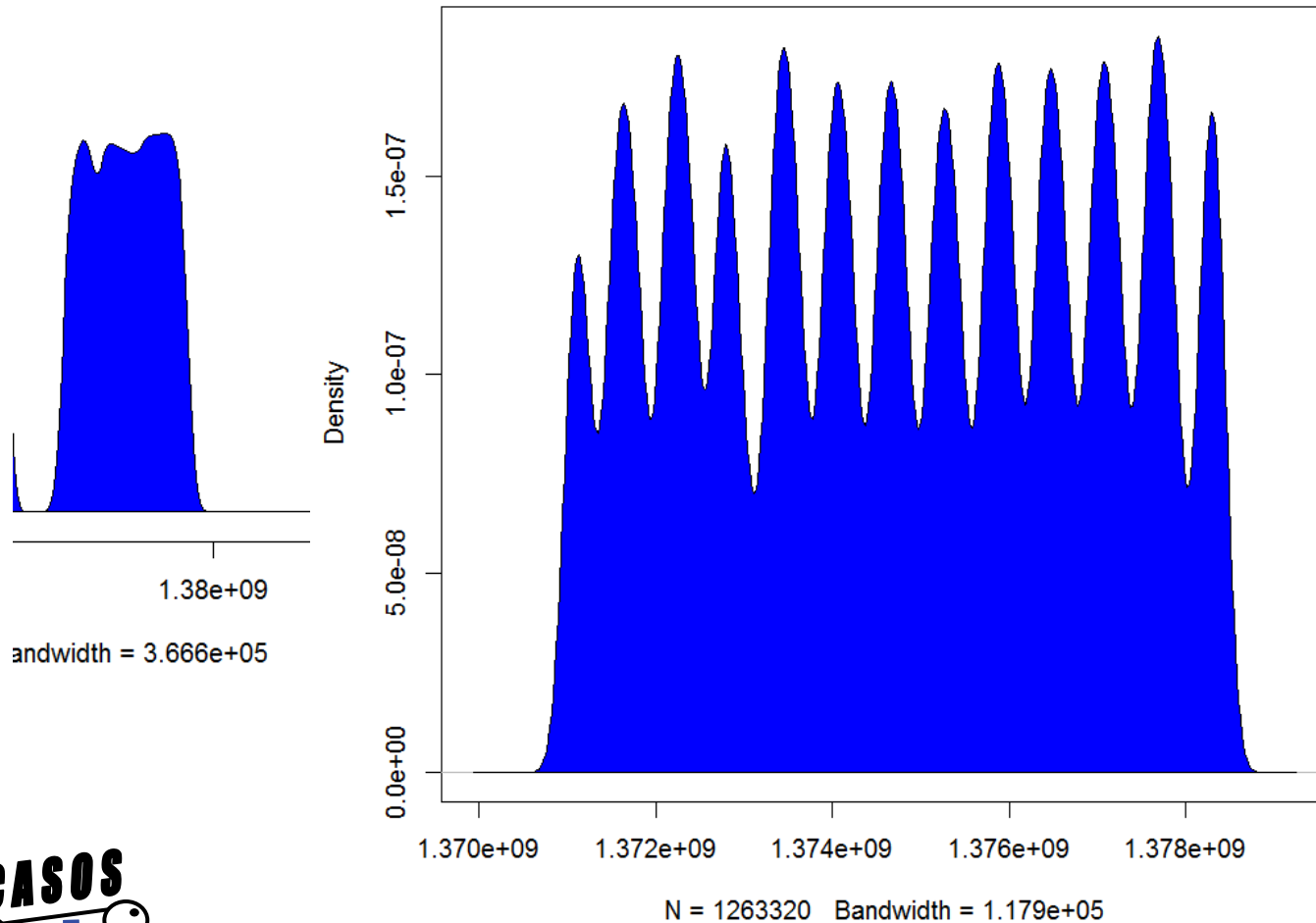
# Email Draws over Time



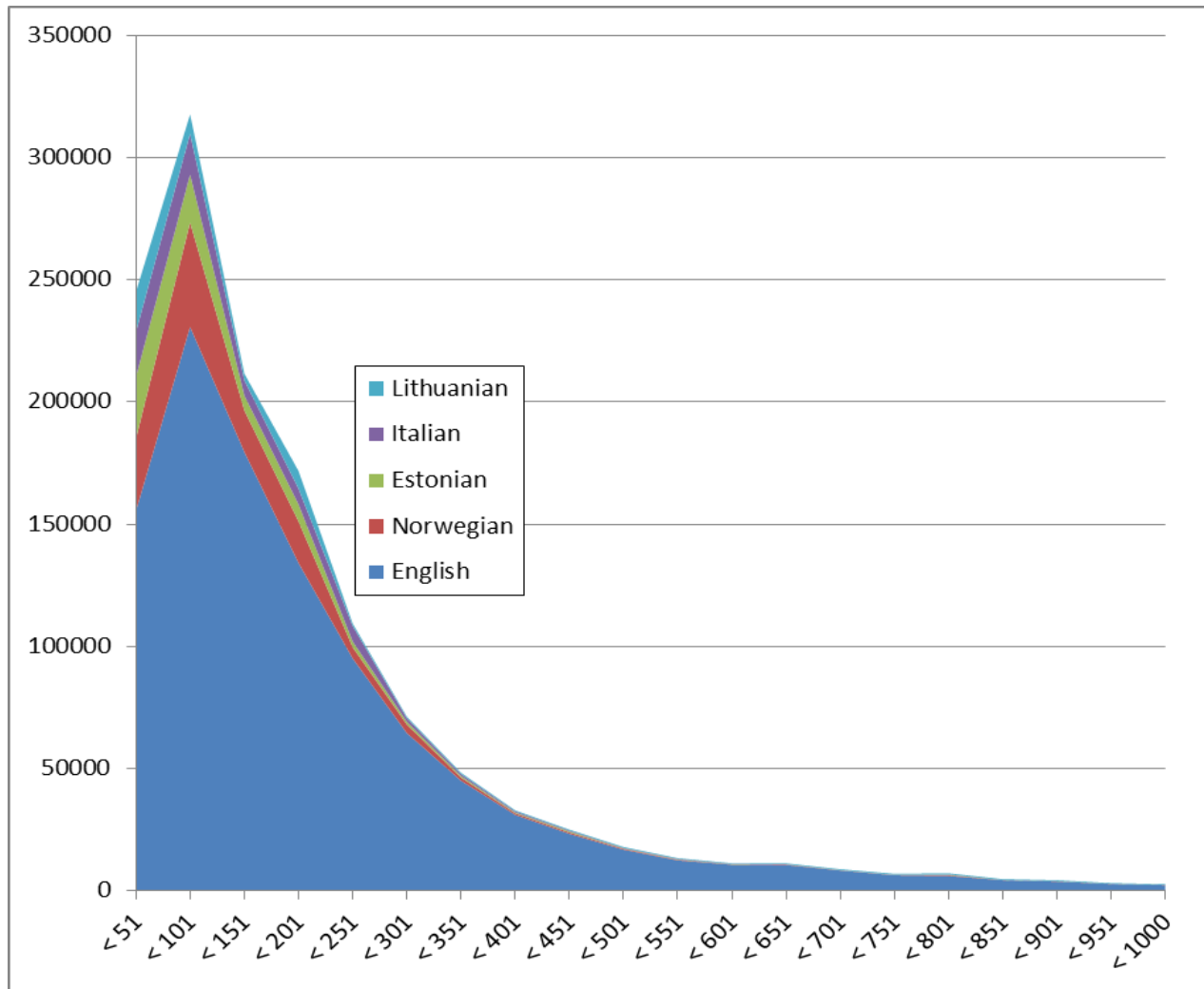


# Email Draws Show Expected Frequencies

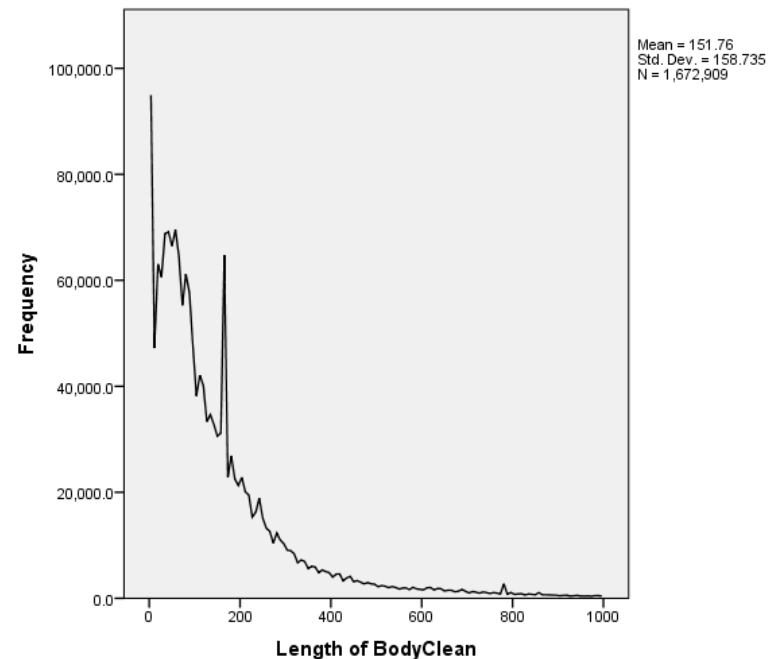
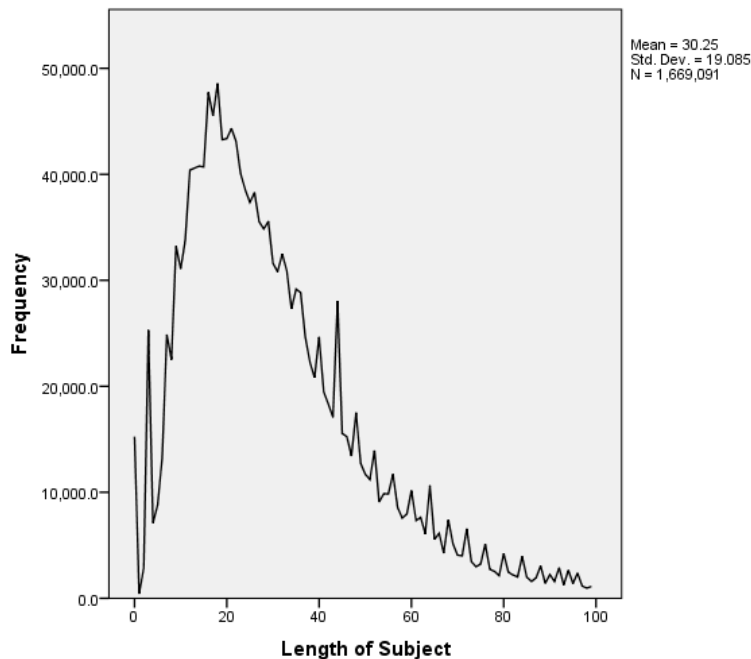
Concentration of Email by Time-Stamp (Unix Epoch Time)



# Distribution of Languages



# Distribution of Unstructured Content Lengths



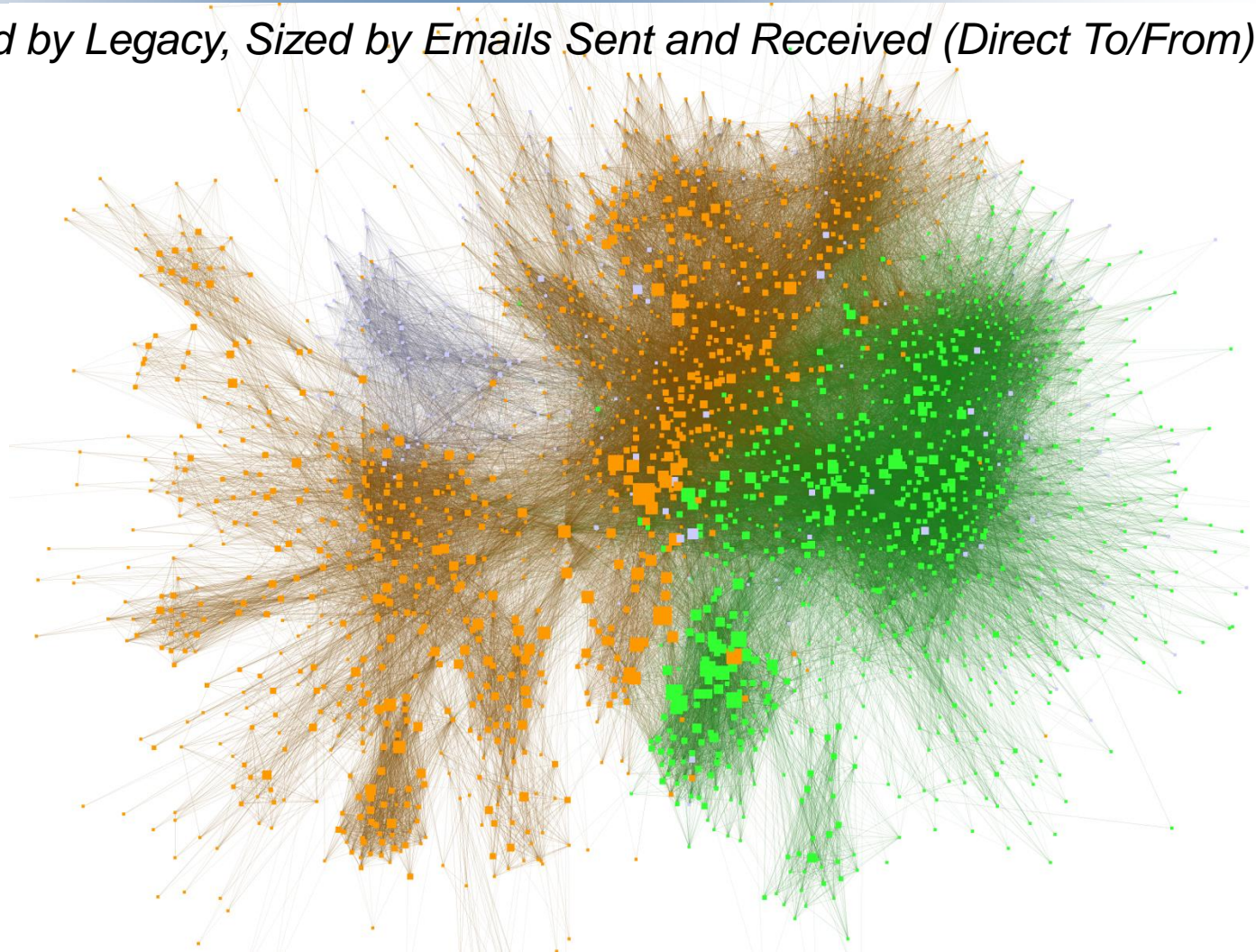
# Internal Email Interactions

*Employees - Colored by Legacy, Sized by Emails Sent and Received (Direct To/From)*

LuxuryCo

StandardCo

MergedCo



# WORKING WITH AND MEASURING CONTENT



# De-Identification

- Legal Requirement!
- Used Stanford NER (Named Entity Recognizer) to identify and then de-identify:
  - People
  - Locations
  - Organizations

# De-Identifying Entities Consistently in Unstructured Content

- First, identify and create anonymous mappings for all NER tokens
  - Replace proper names with tokens:
    - "Jean Paul" = "Name\_1"
    - "Abe Lincoln" = "Name\_2"
  - Replace locations with tokens:
    - "San Francisco" = "Location\_1"
    - "New York" = "Location\_2"
  - Replace organizations with tokens
    - "Bank of Omaha" = "Org\_1"
    - "IKEA" = "Org\_2"
- Replace all numeric characters with `#`
  - ###-###-#####
  - ##-###
  - ##,###



# Using Content as a Proxy for OrgCulture

- Every organization has its unique jargon, informed by the collective backgrounds and contributions of all members.
1. Can we identify words or tokens that are consistently and regularly associated with LuxuryCo and StandardCo?
  2. Is the overall language of LuxuryCo and StandardCo becoming more or less similar?



# Token Score

- For token  $t$  of all Tokens  $T$ , we have group  $A$ ,  $G$ , and a Prior  $P$
- We have two terms:
  - the token's odds score based on percentage appearance in the  $A$  and  $G$ 's documents, but we flatten out marginal cases
  - the token's appearance in  $A$  or  $G$  (depending on the odds ratio outcome) subtracted against the percentage appearance of the token in Prior  $P$

$$S(t) = flattenedOdds(t) * freq(t)$$

$$flattenedOdds(t) = \begin{cases} abs(odds(t)) > .1, odds(t) \\ else, 0 \end{cases}$$

$$odds(t) = \left( 1 - \left( \frac{1}{\left( \frac{|t_A|}{|T_A|} / \frac{|t_G|}{|T_G|} \right)} \right) \right) - .5$$

$$freq(t) = \begin{cases} odds(t) \geq 0, \max\left(\frac{|t_A|}{|T_A|} - \frac{|t_P|}{|T_P|}, 0\right) \\ odds(t) < 0, \max\left(\frac{|t_G|}{|T_G|} - \frac{|t_P|}{|T_P|}, 0\right) \end{cases}$$

$$odds(t) < 0, \max\left(\frac{|t_G|}{|T_G|} - \frac{|t_P|}{|T_P|}, 0\right)$$



# Example, "relax"

Group A uses "relax" 100 times in a corpus of 10,000 total word instances. Group B uses it 10 times in a corpus of 5,000 instances. The Prior P has the word 30 times out of 40,000 instances.

$$S(t) = .002775 = .3 * .00925$$

$$flattenedOdds(t) = .3 = abs(.3) > .1, .3 \text{ else, } 0$$

$$odds(t) = .3 = \left( 1 - \left( \frac{1}{\left( \frac{100}{10000} / \frac{10}{5000} \right)} \right) \right) - .5$$

$$freq(t) = .00925 = .3 \geq 0, \max \left( \frac{100}{10000} - \frac{30}{40000}, 0 \right)$$



# Difference Score

- We can sum the absolute value of the token scores to evaluate how different the two groups are in language after accounting for a prior

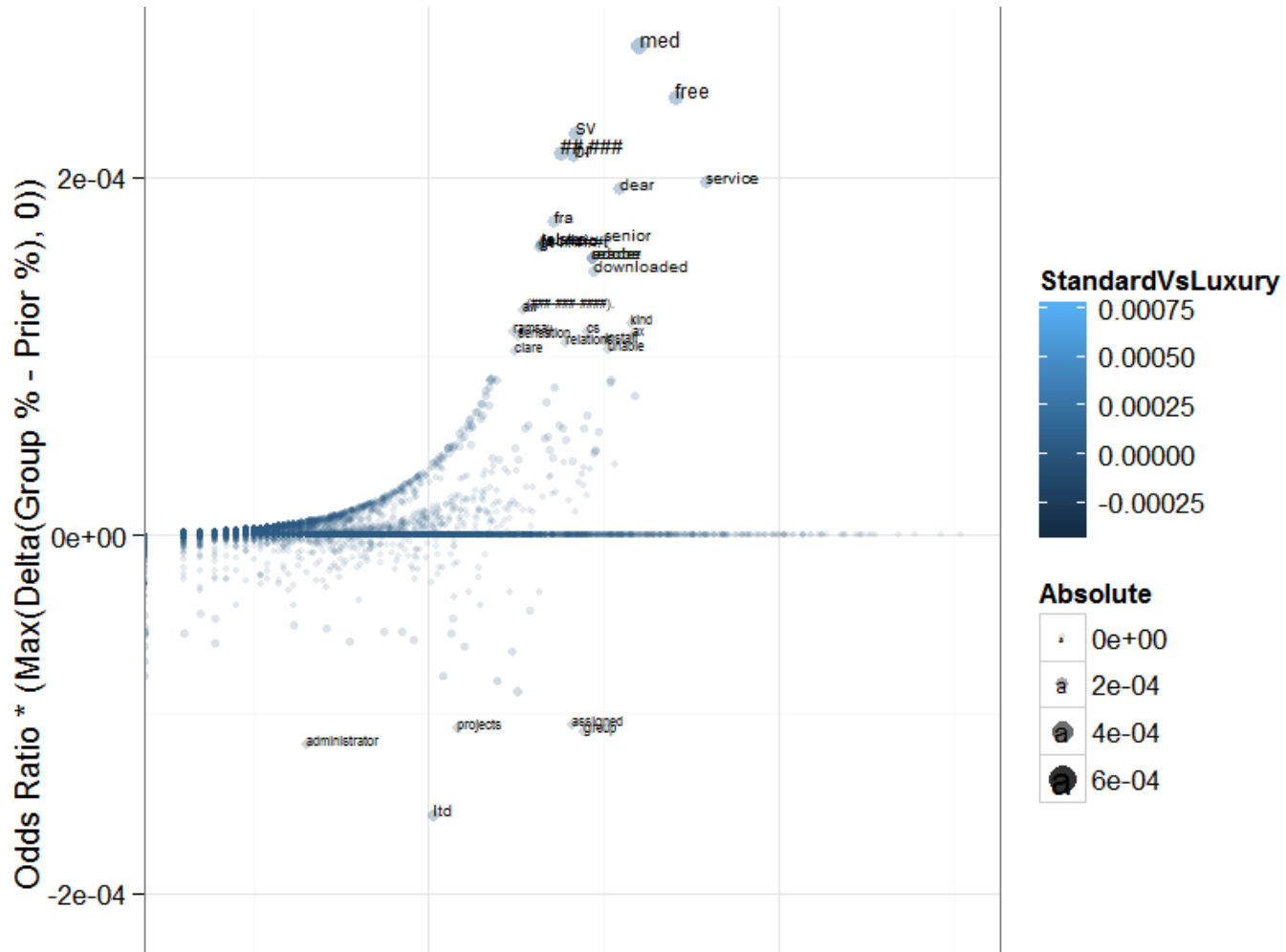
$$Score(T, A, G, P) = \sum_t s(t)$$

# Concerns/Limitations

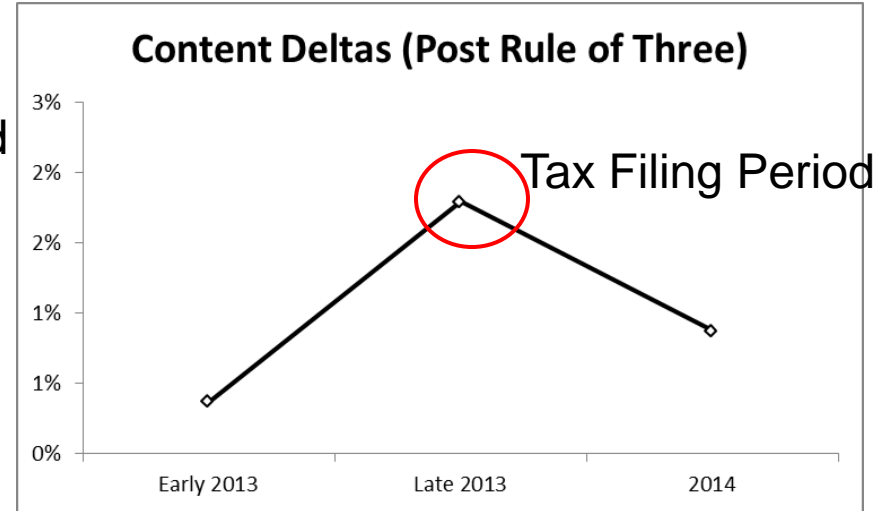
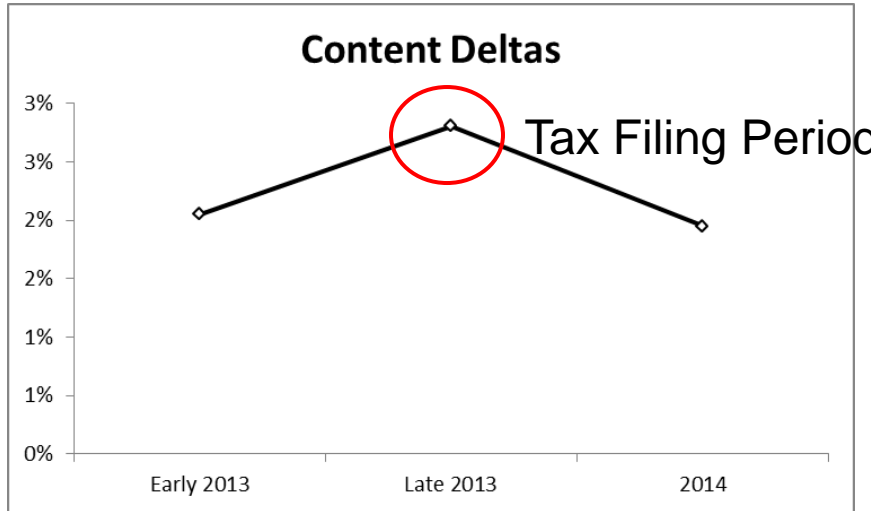
- Instead of an arbitrary threshold for flattening, maybe consider a transformation function
- The choice of Prior is important
  - I used a time sensitive prior from email senders who did not take the survey
- Cleaning the text corpus remains important
  - But the cleaning is **easier**
  - Focused on removing rare words
    - Why?
    - “Rule of 3” would generally resolve the issue
  - Removing very common (“the”, “a”, “an”) stop words may help



# Illustrative Graphic, Late 2013



# Overall Scores, Text Corpus



These charts *suggest* different things!

**Left:** Extant identities are mostly stable

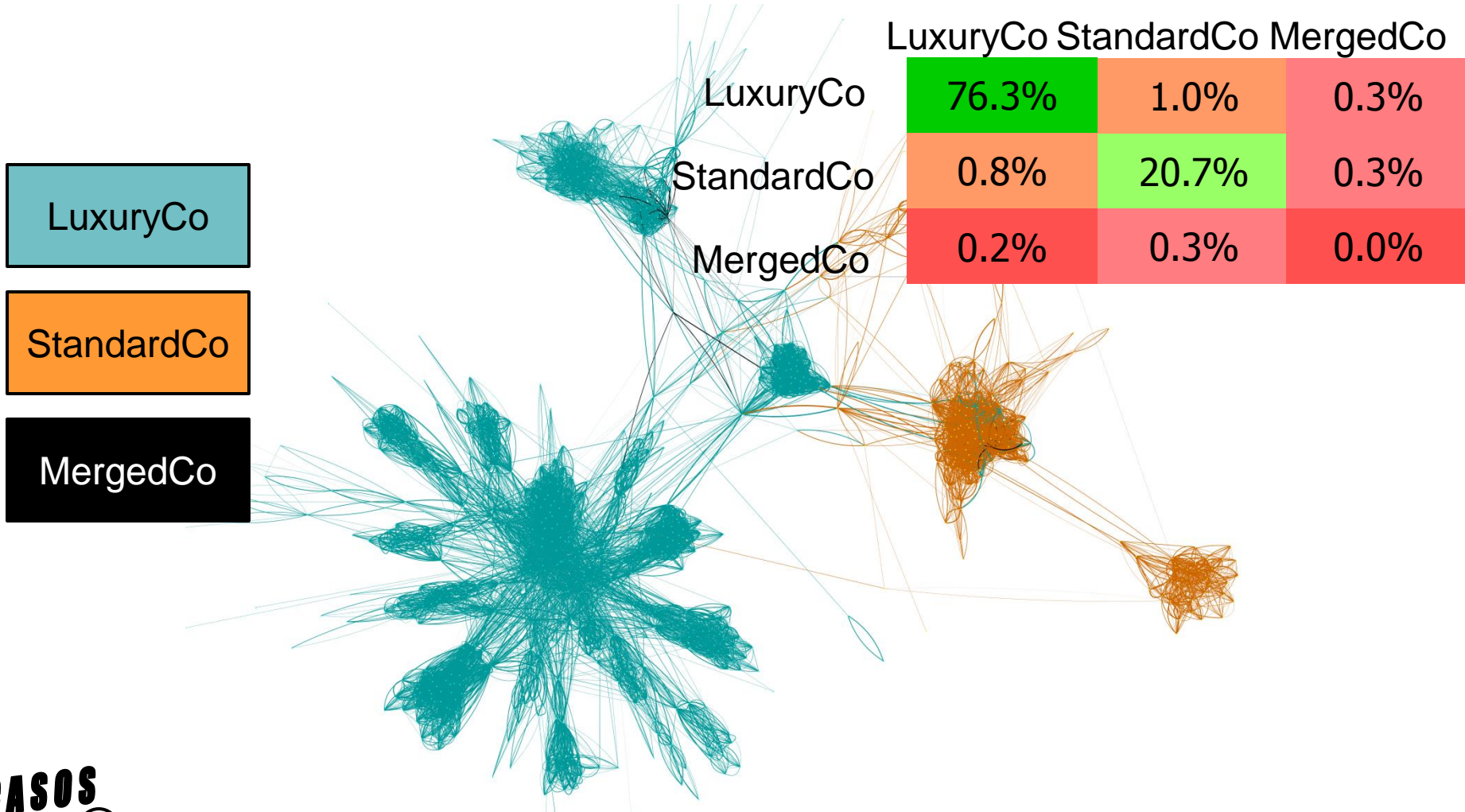
**Right:** Identities are differentiating in response to interaction with the other

CLEANING IS IMPORTANT

# STRUCTURAL COMPARISON



# Visualizations, Early 2013



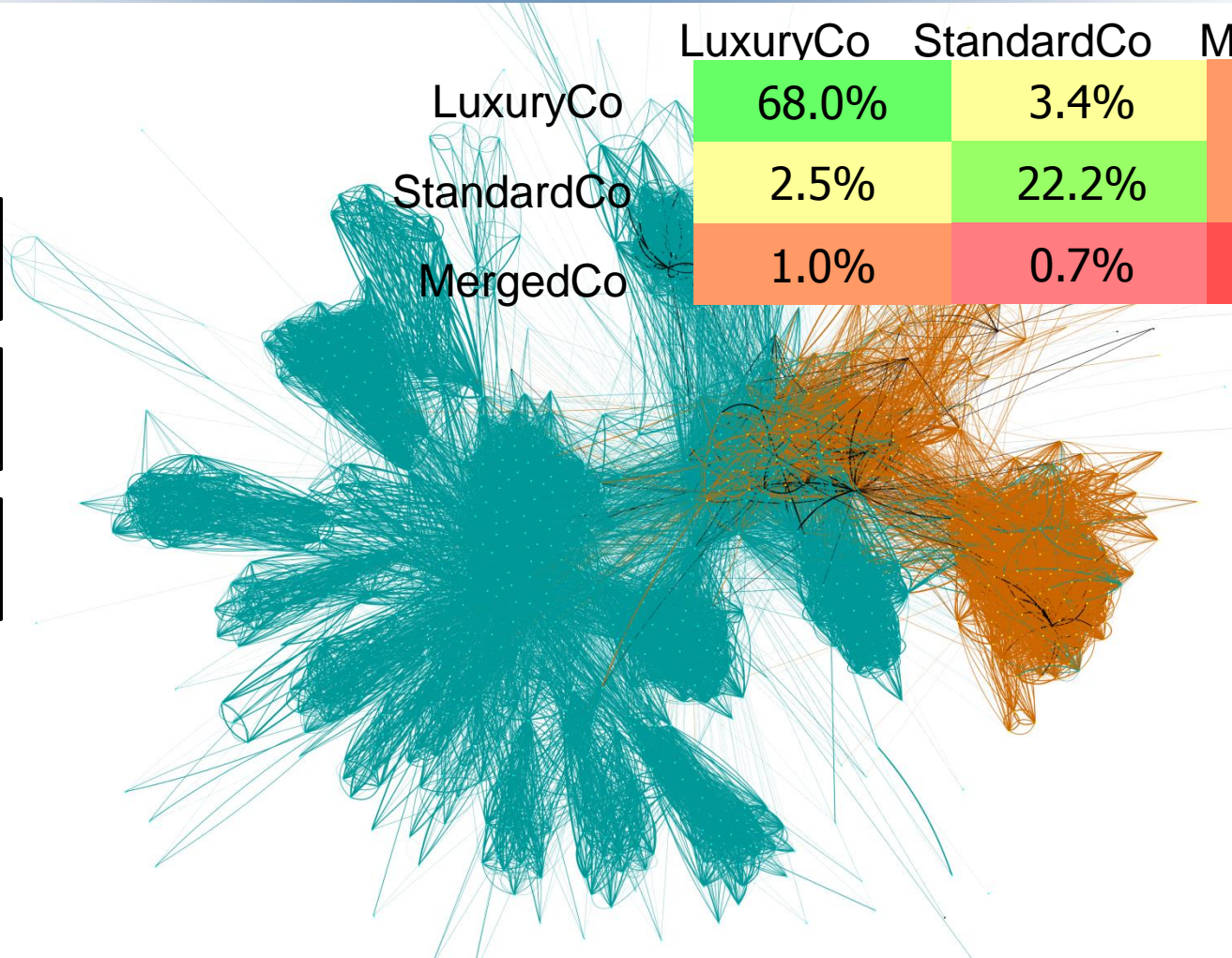


# Visualizations, Late 2013

LuxuryCo

StandardCo

MergedCo



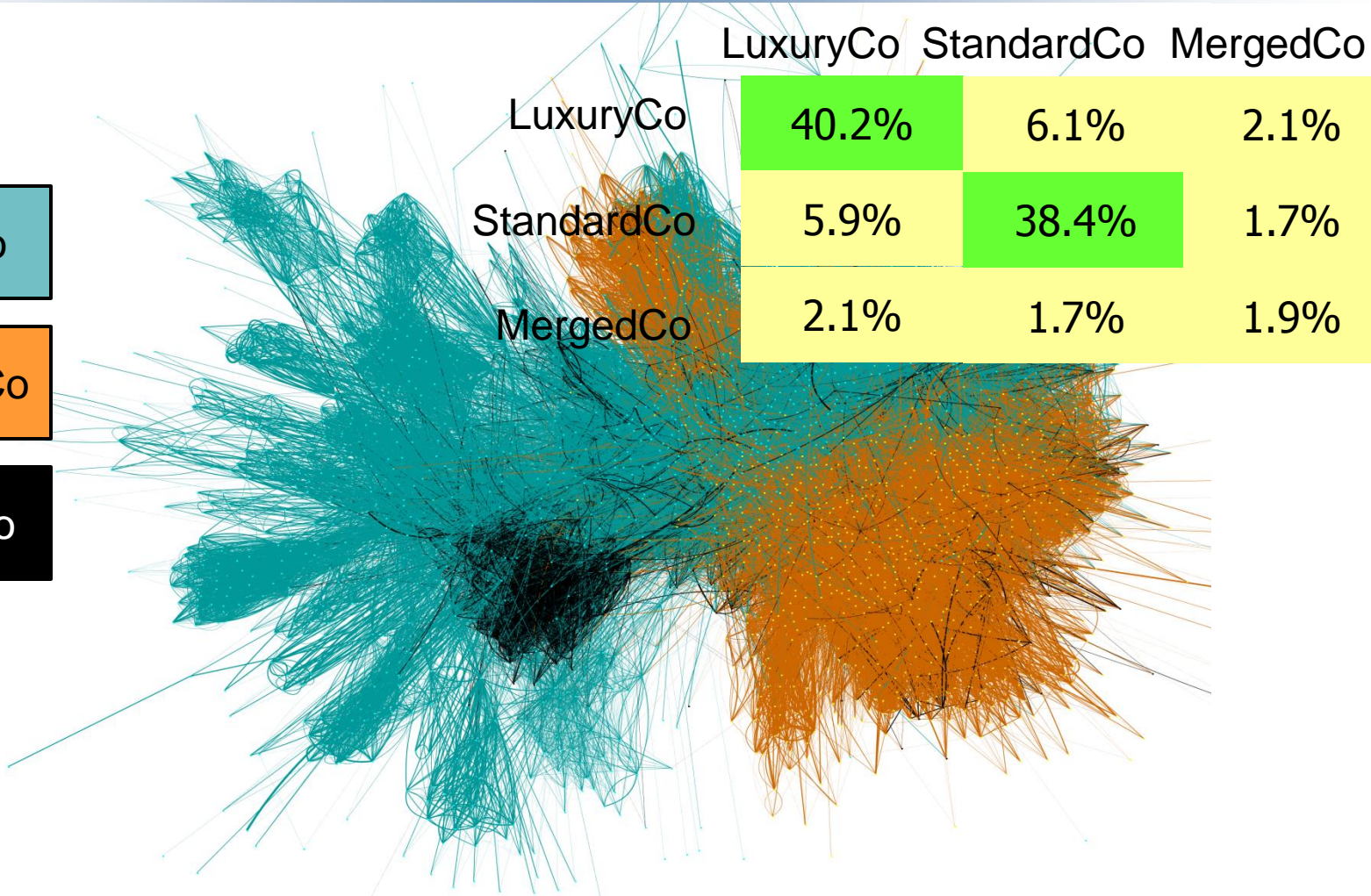
	LuxuryCo	StandardCo	MergedCo
LuxuryCo	68.0%	3.4%	1.2%
StandardCo	2.5%	22.2%	1.0%
MergedCo	1.0%	0.7%	0.1%

# Visualizations, 2014

LuxuryCo

StandardCo

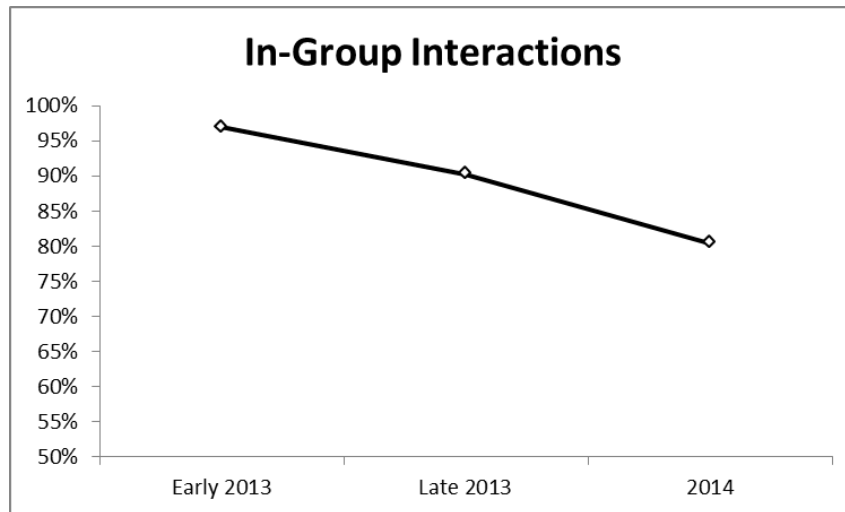
MergedCo



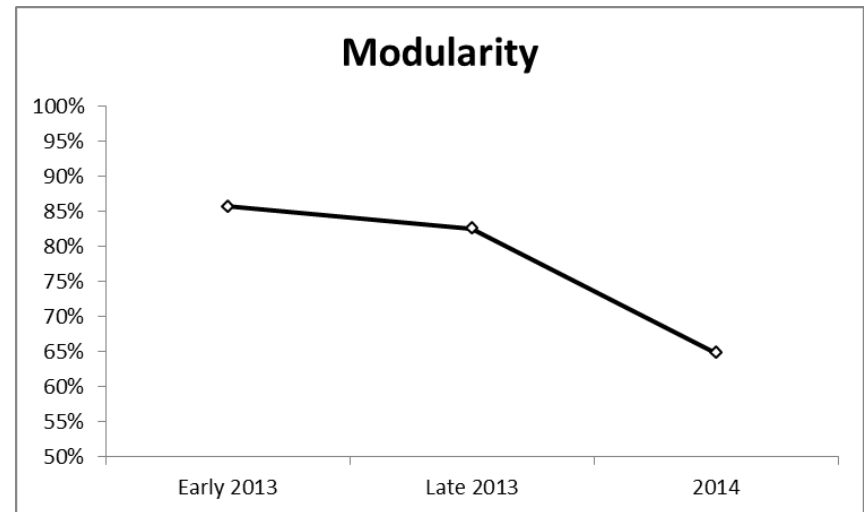
	LuxuryCo	StandardCo	MergedCo
LuxuryCo	40.2%	6.1%	2.1%
StandardCo	5.9%	38.4%	1.7%
MergedCo	2.1%	1.7%	1.9%

# Structural Measures

## In-Group Interaction

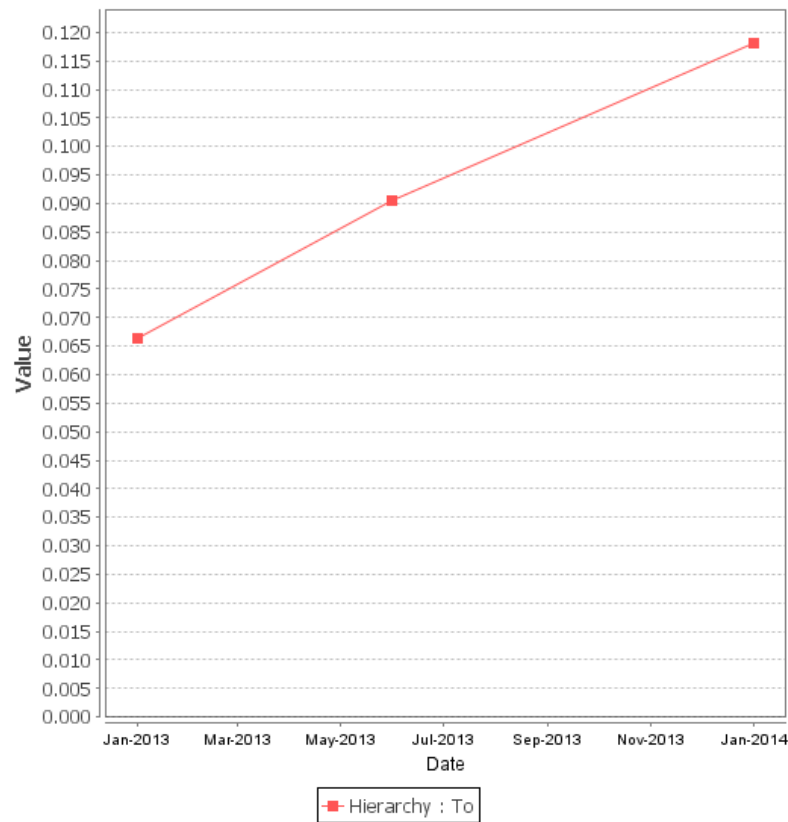


## Louvain Modularity



# Network-Level Measures

## Hierarchy



## Average Speed

