SERC DOCTORAL STUDENT FORUM 2023 | NOVEMBER 14, 2023

Unveiling Knowledge Structures within Organizations with a Novel Weighting Method

JD Caddell

STEVENS INSTITUTE OF TECHNOLOGY 1870

SYSTEMS ENGINEERING RESEARCH CENTER

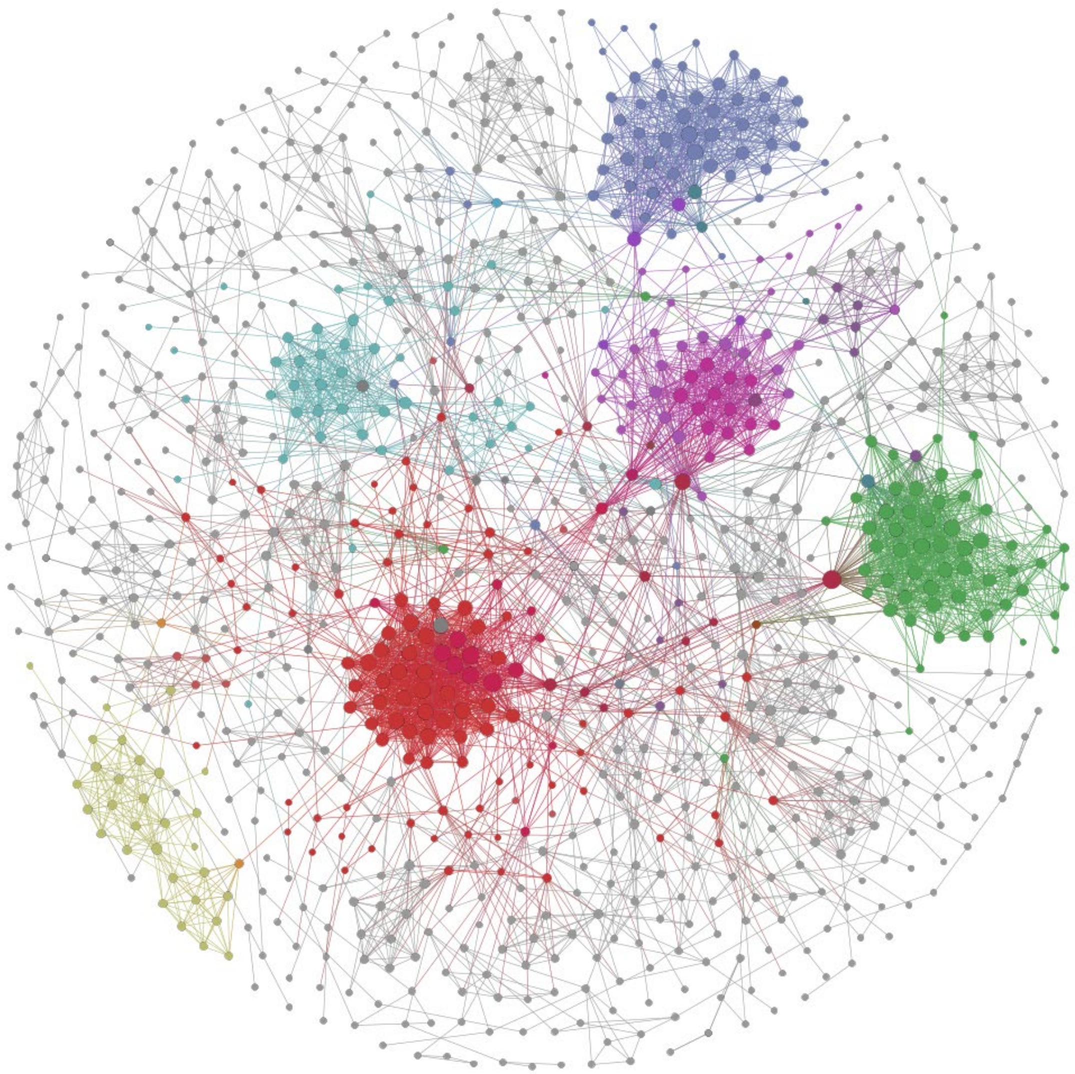
15 YEARS

SYSTEMS ENGINEERING RESEARCH CENTER • CELEBRATING 15 YEARS • 2008-2023

Agenda

- Research Questions
- Literature Review
- Method
- Case
- Results
- Limitations and Conclusion

Social Networks, Knowledge, and Observation



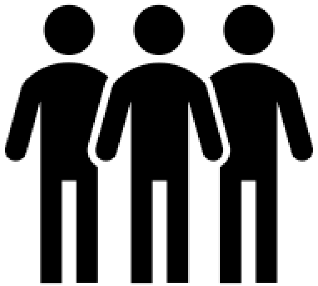
- How do we elicit knowledge networks in non-invasive manners?
- How do we weight these knowledge networks for insight?

What's Been Done?

- Data Collection for Elicitation of Knowledge Networks
  - ➢ Surveys
  - ➢ Interviews
  - ➢ Patents
  - ➢ Citations
  - ➢ Observational Study
- Quantifying Knowledge
- Assigning Weight to Relationships
- Analyzing Structure and Flow

https://hd.media.mit.edu/badges/

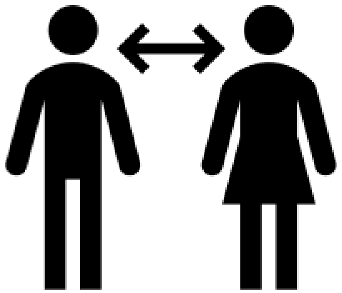
Characterizing Work Histories to Reveal Knowledge Structures



Collect Individual Work Histories

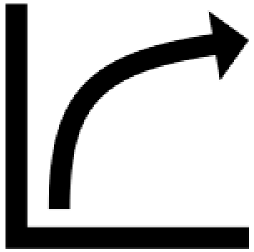
Individual work histories contain several fields like most Resumes and CVs:

- Title/Role
- Assigned Team
- Dates of Employment



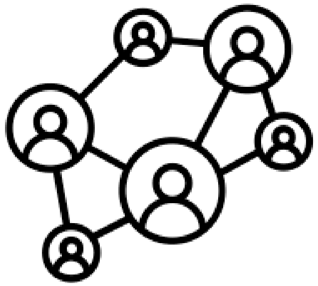
Determine Overlaps Between Members

Overlaps are determined by calculating the number of days on the same teams at the same time. This, along with the last time the two members overlapped, is derived from the work history.



Weight Edges

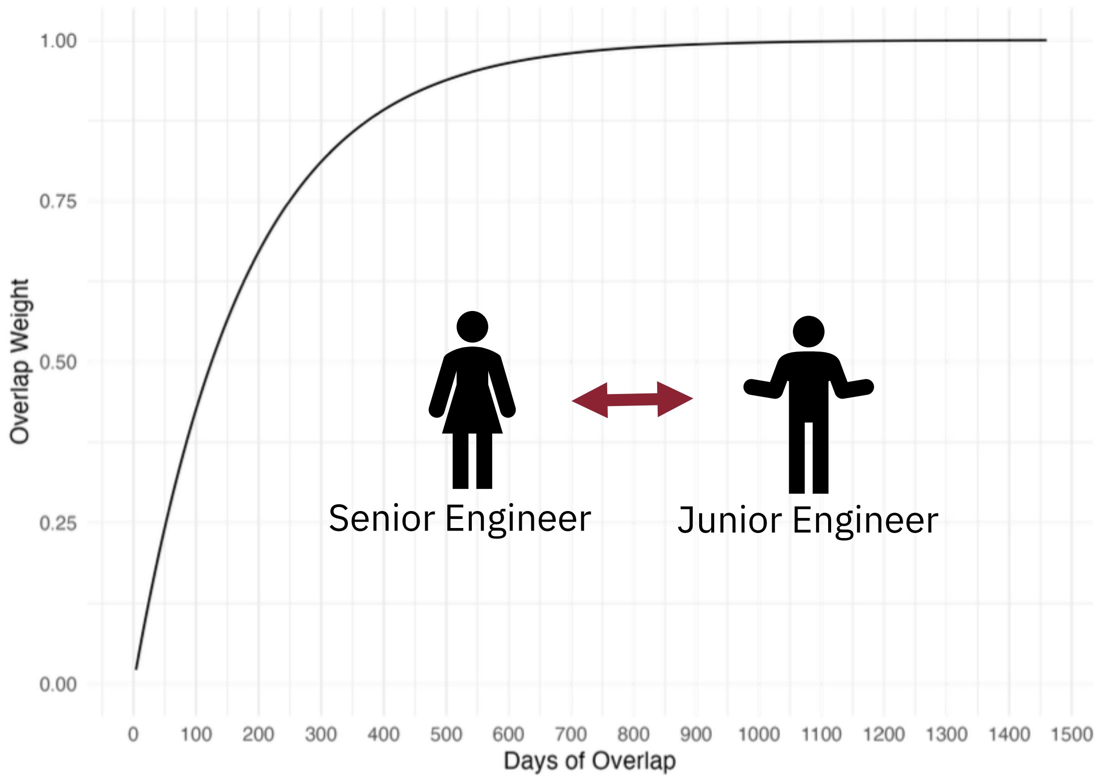
Edges between members are calculated by weighting the total time of overlap, time since last overlap, knowledge held by an individual, and the difference between the experience of the two members. The weight is meant to model the access to quality information or knowledge.

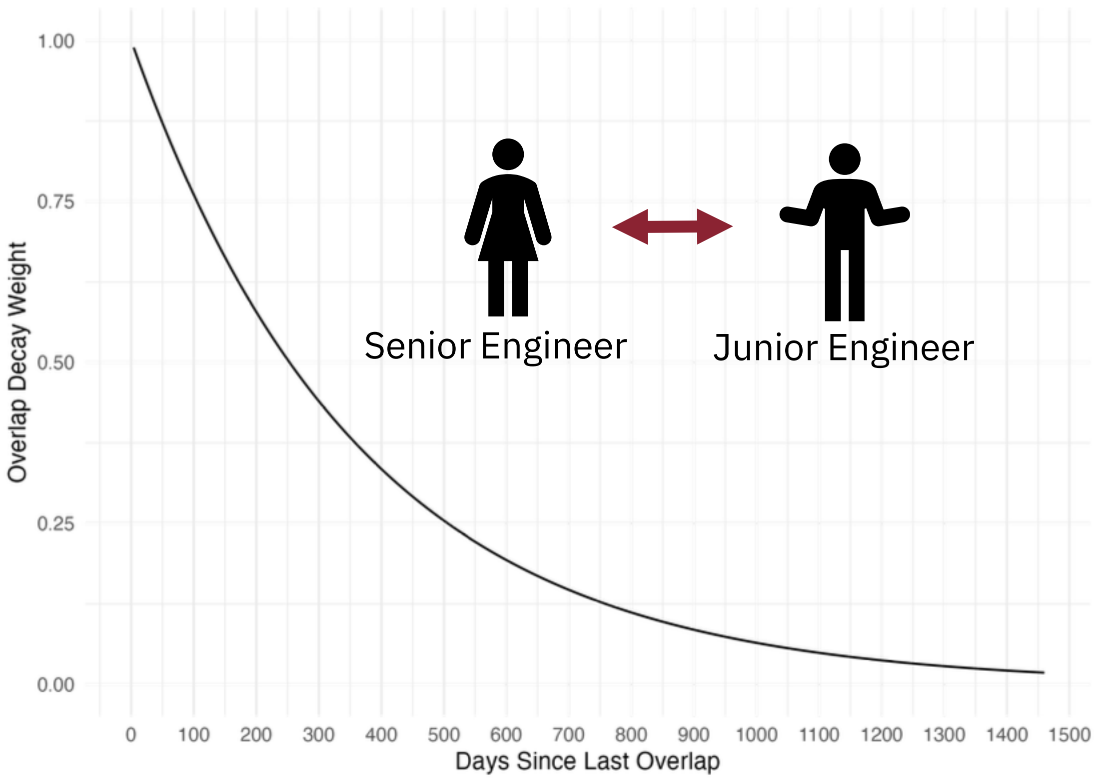


Analyze Network

Key metrics are extracted from the graph to better understand the current knowledge structures.

Overlap Weighting

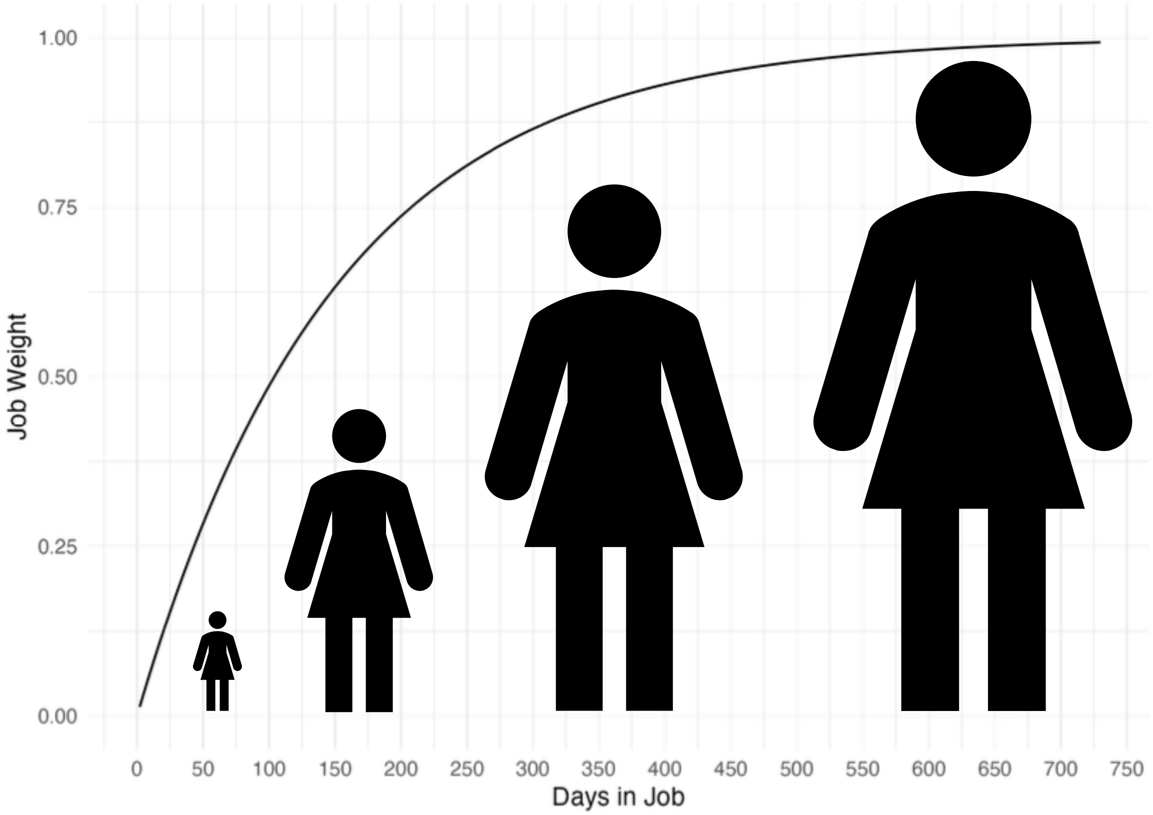




$$Overlap_{weight}(Overlap_{days}, \lambda_{overlap}) = 1 - e^{-\lambda_{overlap} Overlap_{days}}$$

$$Overlap_{decay}(Overlap_{gap}, \lambda_{decay}) = e^{-\lambda_{overlap} Overlap_{gap}}$$

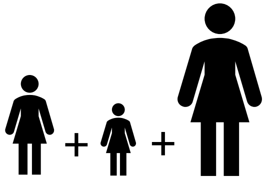
Job and Person Weighting



$$Job_{weight,i}(DaysInJob_i, \lambda_{job}) = 1 - e^{-\lambda_{job} DaysInJob_i}$$

- As a person accumulates time in a position, they develop knowledge specific to that role.
- We can model a person's knowledge as the sum of their acquired role

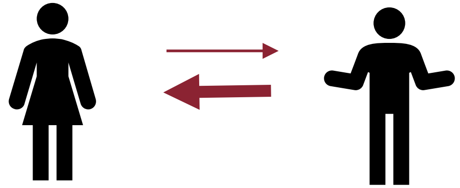
$$Person(Job_{weight}) = \sum_{i=1}^{n} Job_{weight,i}$$



= Person's Knowledge

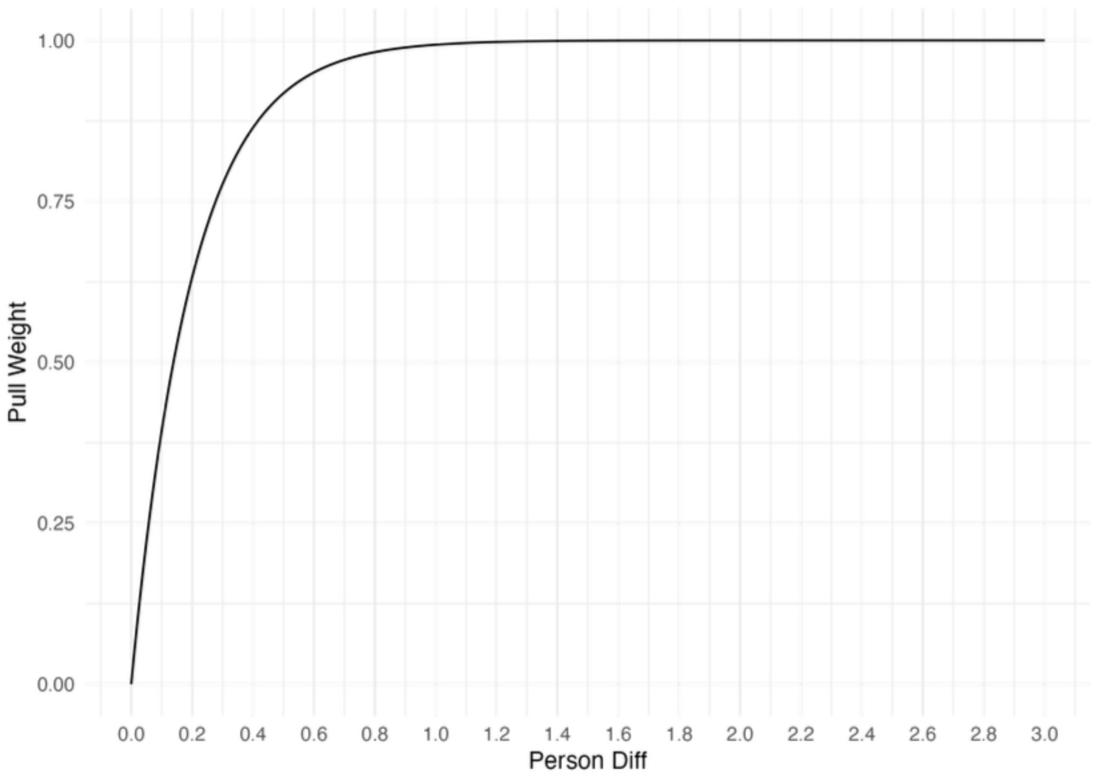
Knowledge Absorption

- Knowledge absorption is limited by differences between members
- Once a threshold is overcome, the ability to pull knowledge increases rapidly



Senior Engineer Junior Engineer

$$Person_{difference,(a,b)}(\theta, Person_a, Person_b) = max\left\{0, \frac{Person_a}{Person_b} - \theta\right\}$$



$$Pull_{weight,a}(\theta, \lambda_{diff}, Person_{difference,(a,b)}) = 1 - e^{-\lambda_{diff} Person_{difference,(a,b)}}$$

Final Edge Weights

$$\overbrace{Edge_{weight}}^{\text{Knowledge Available to A from B}} = \underbrace{Overlap_{weight} \times Overlap_{decay}}_{\text{Strength of the Relationship}} \times \underbrace{Person_B}_{\text{B's Knowledge}} \times \overbrace{Pull_{weight}}^{\text{A's Ability to Absorb B's Knowledge}}$$

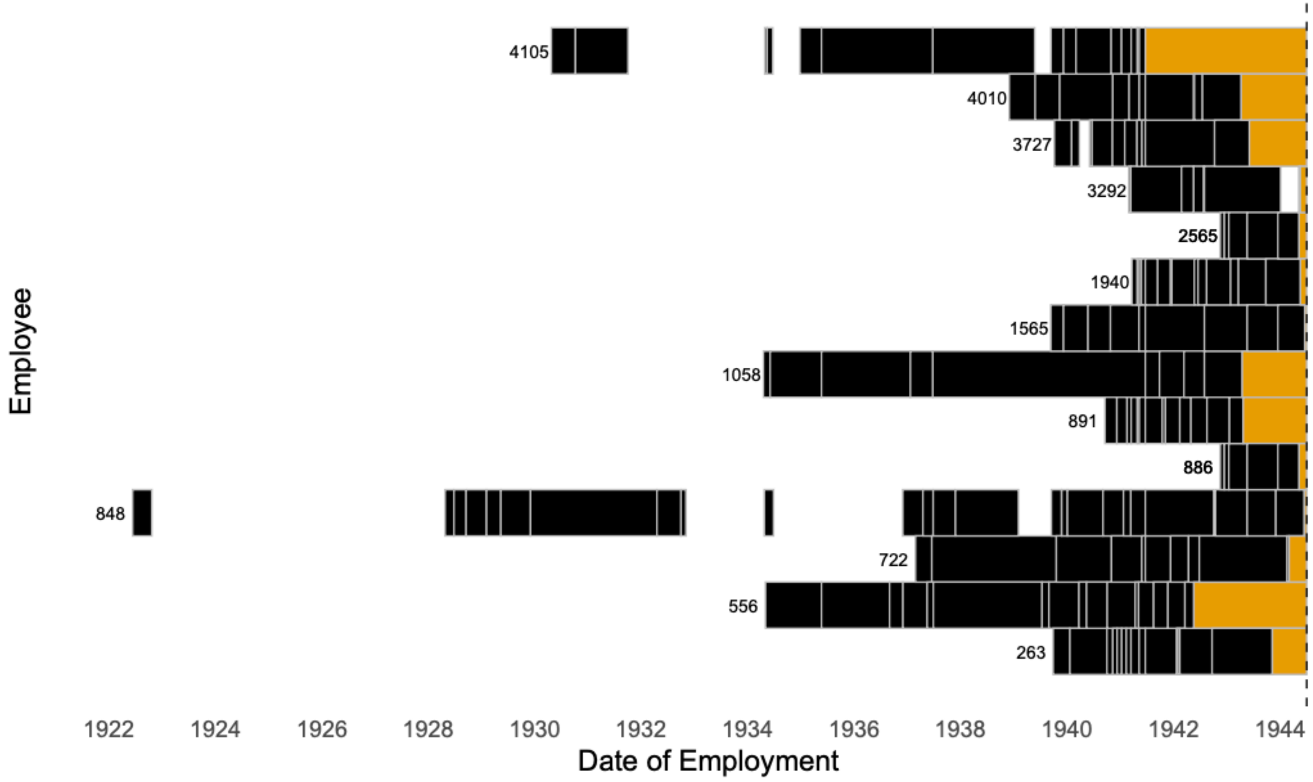
With this construction we can now examine:

- Knowledge of members and organizations
- The amount of anticipated knowledge flow
- Flow betweenness (node level and graph level)

Case Implementation

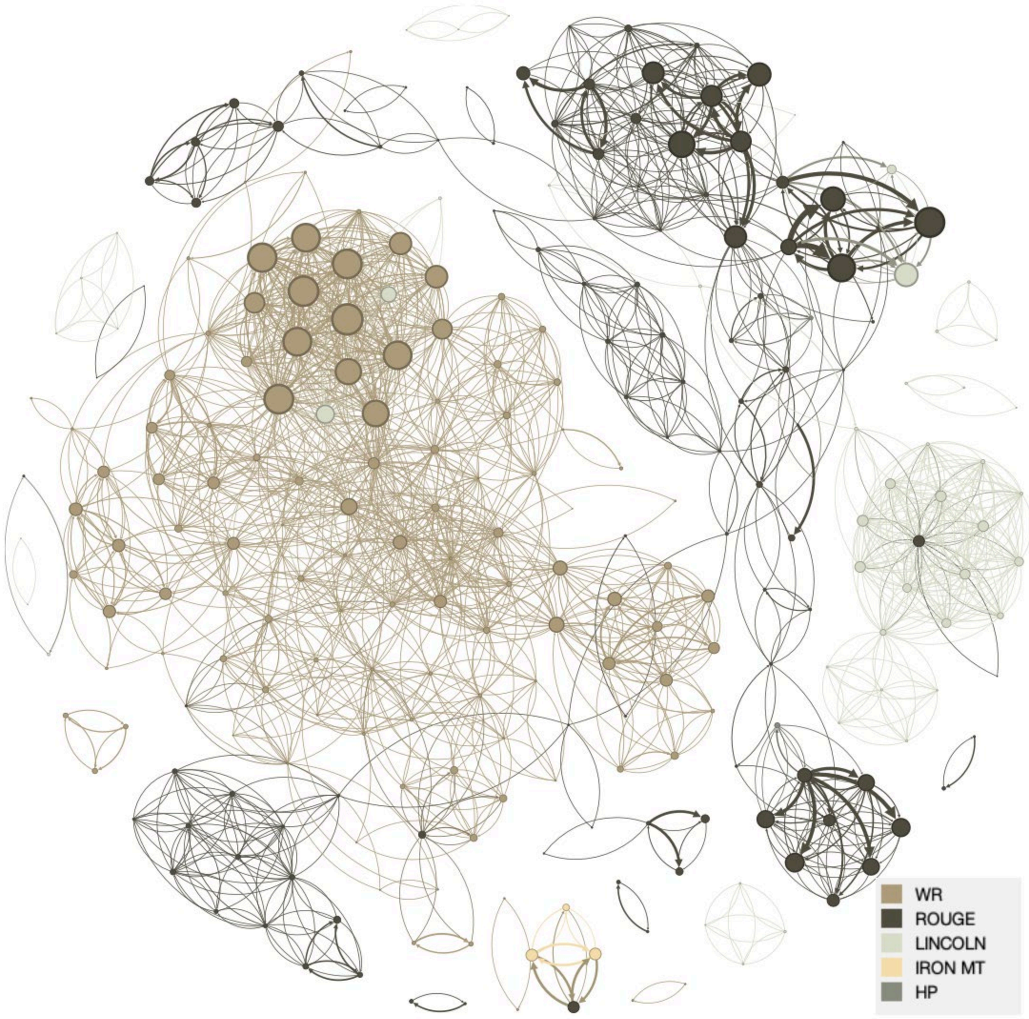
Ford Motor Company

- 4,144 hourly employees from 1918-1947, Detroit area
- 5 different plants
- Role level data (start, stop, role, team …)



Results

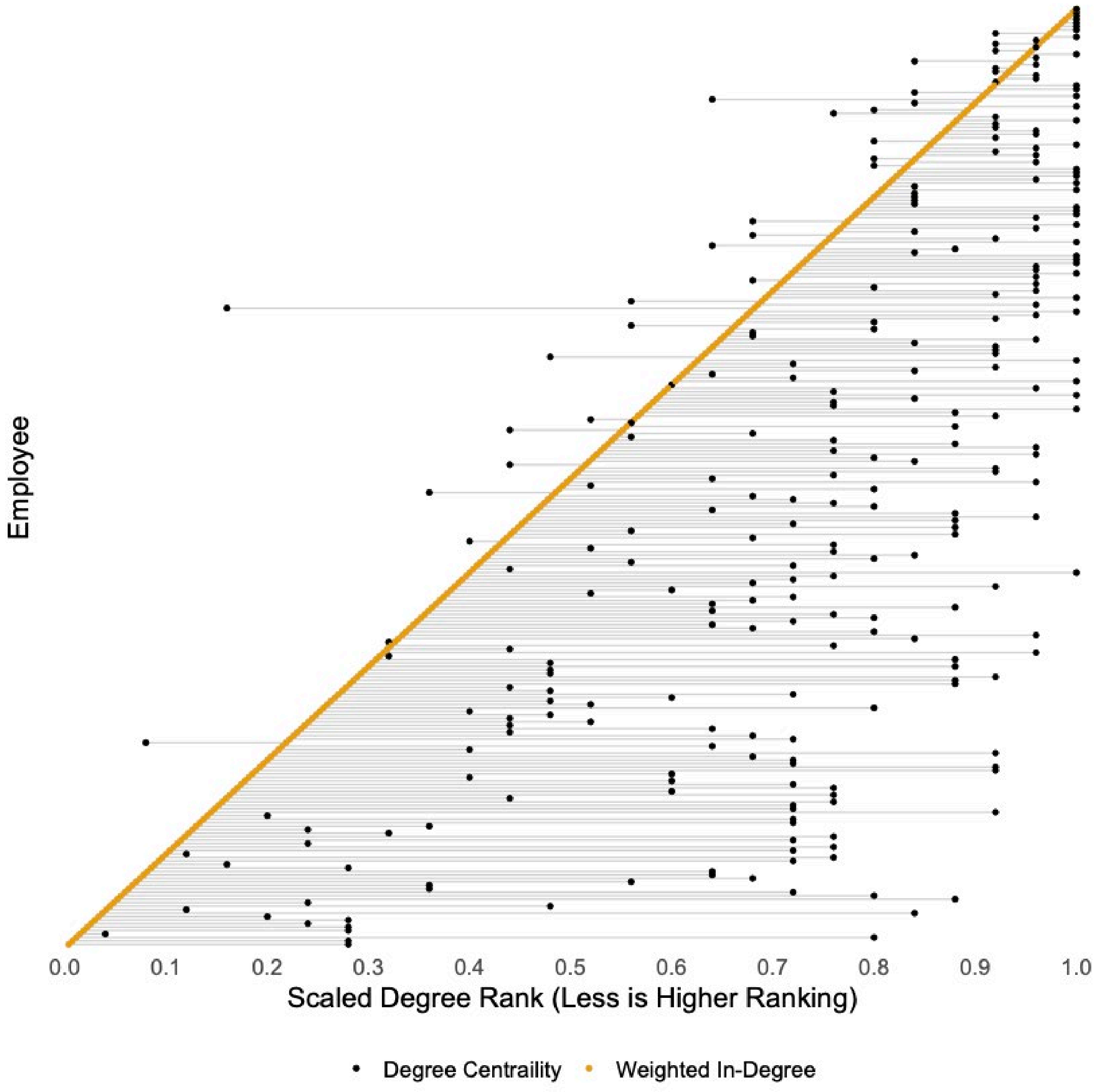
- Rouge retains a more established knowledge network (higher weights, lower flow betweenness)
- Lincoln is more dependent on a small set of nodes, with a relatively inexperienced workforce
- WR has lower mean weights than Rouge, but similar weighting for current roles



Plant	Employees	Network Weight	Mean Employee Weight	Mean Job Weight	Graph Flow Betweenness
HP	4	21.15	5.29	0.78	0.000
IRON MT	4	7.78	1.95	0.70	0.178
LINCOLN	46	57.49	1.25	0.59	0.193
ROUGE	103	311.59	3.03	0.77	0.078
WR	113	235.46	2.08	0.76	0.112

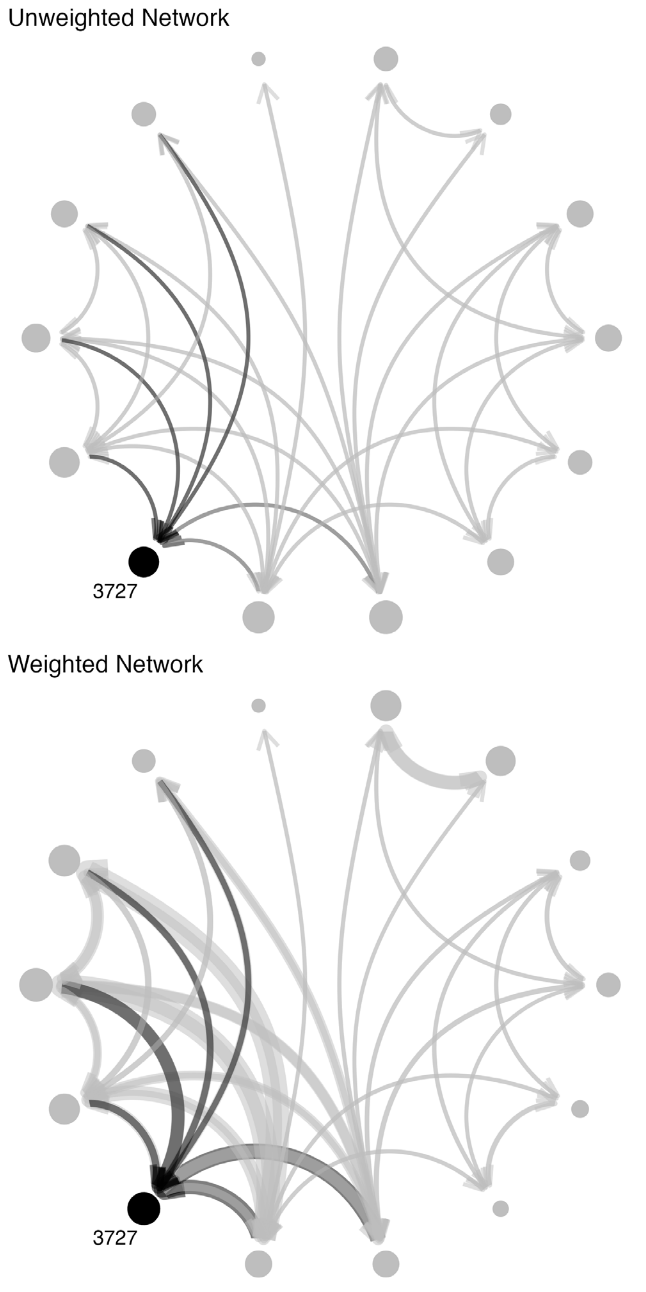
But is this different?

- Comparison of weighted In-Degree differs greatly from standard degree centrality.
- Deviations off the diagonal represent relative difference in metrics.



Comparing Ego Nets

Employee ID	Flow Betweenness	Degree
3727	0.28	6
4105	0.27	8
1565	0.27	5
848	0.23	7
3292	0.08	4
1940	0.06	4
4010	0.03	4
556	0.03	4
891	0.02	3
263	0.02	3
1058	0.00	2
722	0.00	1
2565	0.00	6
886	0.00	3



Limitations .... and Conclusion

- Doesn't capture the nature of relationships (peer-peer, leader-follower …)
- All overlaps are assumed positive
- Relationship strength returns to full immediately upon rejoining of members
- Knowledge is treated as a single dimension
- Additive method of person knowledge is simplistic
- Growth of individuals is devoid of the context they find themselves (Path Dependence of Trust)

- Presents a novel approach to non-intrusive elicitation of knowledge networks and flexible weighting according to the defined parameters of an organization
- Method exposes insights missed by more traditional methods
- With such a method, organizations can continuously observe and even predict changes to their knowledge network structure

Thank you

Stay connected with SERC Online:

Email the presenter: JD Caddell

jcaddell@stevens.edu

Email the advisor: Associate Professor Roshanak Nilchiani

rnilchia@stevens.edu