Analysis on employees skill awareness network in a Manufacturing Company

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University of Florence

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Introduction

Skill awareness (R&D team); R. Cross and A. Parker, ”The Hidden Power of Social Networks.” Harvard Business School Press (2004).

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- Directed graph
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- New interpretation: 1842 edges; binary dyadic variable
- Three nodal categorical attributes, everyone with four levels

Introduction

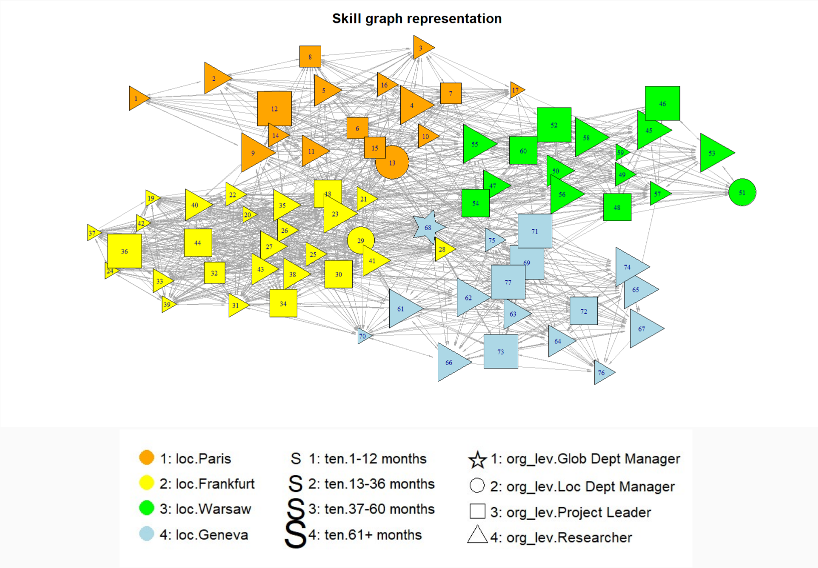

Figure 1: Graph representation of the data.

Network Statistics

Values to summarize information from the composition of the network

Network Statistics I

Density: In a probabilistic way, it can be seen as an estimate of the probability which two nodes are tied.

$$\rho = \frac{\sum_i \sum_j Y_{ij}}{n(n-1)} = \frac{m}{n(n-1)} = 0.315$$

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Transitivity: In a probabilistic way, it can be seen as the probability which two nodes are tied given that they are tied to a third one.

$$C = \frac{\#\text{triangles}}{\#\text{triangles} + \#\text{two stars}} = 0.648$$

Network Statistics II

Modularity: it is defined as the difference between the fraction of ties observed between nodes in the same category and the fraction of expected ties (based on the nodes degree) between nodes in the same category. A normalized measure:

$$r = \frac{\sum_{ij}(Y_{ij} - \frac{k_i k_j}{2m})\delta(c_i, c_j)}{2m - \sum_{ij} \frac{k_i k_j}{2m}\delta(c_i, c_j)}; \qquad \text{where:}$$

$$k_i = \deg(i), \qquad \delta(c_i, c_j) = \begin{cases} 1 & \text{if } c_i = c_j \\ 0 & \text{otherwise} \end{cases}$$

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$$r_{loc} = 0.527 \qquad r_{org\_lev} = -0.032 \qquad r_{tenure} = 0.125$$

Nodal Statistics

Values to summarize nodal information

Nodal Statistics - Measures of Centrality I

In- and Out-Degree Centrality: The measure for node i is the simple count of observed ties incoming in it or outgoing from it.

$$\tilde{\zeta}_i^{in-d} = \frac{\zeta_i^{in-d}}{n-1} \qquad \tilde{\zeta}_i^{out-d} = \frac{\zeta_i^{out-d}}{n-1}$$

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Min.	0.1316	0.0263
1st Qu.	0.2237	0.2105
Median	0.3158	0.3026
Mean	0.3148	0.3148
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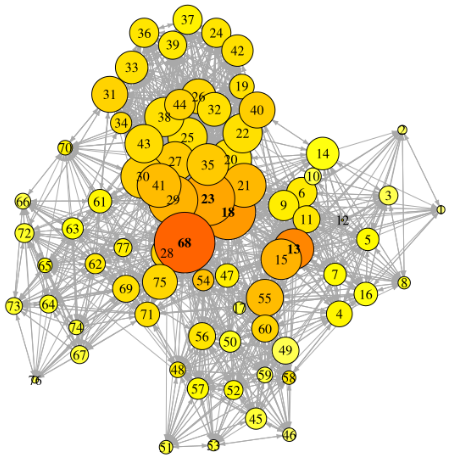

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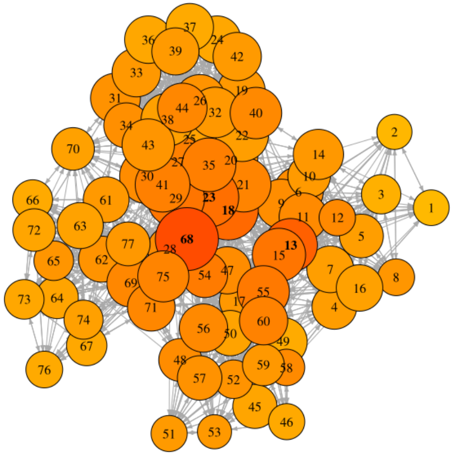

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Eigenvector Centrality: defines central a node that is connected to other central nodes.

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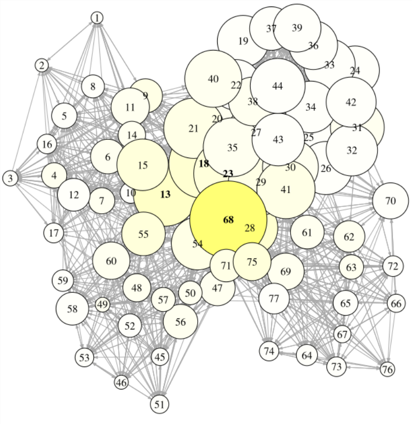

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Nodal Statistics

Centralization indexes:

Index	Formula	Value
CI^{in-d}	$\frac{\sum_i(\zeta_{max}^{in-d} - \zeta_i^{in-d})}{n-1}$	0.401
CI^{out-d}	$\frac{\sum_i(\zeta_{max}^{out-d} - \zeta_i^{out-d})}{n-1}$	0.401
CI^{in-c}	$\left[\sum_i \zeta_{max}^{in-d} - \zeta_i^{in-d}\right](n-1)$	0.214
CI^{out-c}	$\left[\sum_i \zeta_{max}^{in-d} - \zeta_i^{in-d}\right](n-1)$	0.208
CI^{b}	$\frac{\sum_i \zeta_{max}^{in-d} - \zeta_i^{in-d}}{(n-1)^2(n-2)}$	0.122

Models

Comparing different data generating process for our network

Simple Random Graph

Assumption:

$$Y_{ij} \overset{iid}{\sim} Bern(p)$$

Is number of edges ($\sum_{ij} y_{ij}$) fixed?

- No: $\implies$ Binomial Random Graph (BRG) $\in$ ERG family:

$\kappa(\mu)^{-1} = \prod_{ij} 1 + \exp\{\mu\}$.

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Simple Random Graph

Goodness of fit:

- Residual Deviance: 7290; (Null Deviance: 8113)
- MLE.LogLikelihood: -3644.975 (Null.LogLikelihood: -4056.297)
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Good simulations only for density ρ and modularity *organization level* r_{org}.

Non Homogeneous Binomial Random Graph

Relaxing Homogeneity Assumption:

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$$Y_{ij} \sim Bern(p_{ij})$$

According the model:

$$Y_{ij} = \mu + a_i + b_j + \epsilon_{ij}; \quad \Longrightarrow \quad E[Y_{ij}] = \mu + a_i + b_j = \mu_{ij}$$

ERGM form:

$$P(\boldsymbol{Y} = \boldsymbol{y}) = \kappa(\mu, \boldsymbol{a}, \boldsymbol{b})^{-1} \exp\left\{\mu y_{..} + \sum_i a_i y_{i.} + \sum_j b_j y_{.j}\right\}$$

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Results:

- $\hat{\mu}$ = -0.7779;
- Greater values of a_i and b_j for the Global Department Manager (vertex 68).

Non Homogeneous Binomial Random Graph

Goodness of fit:

- Residual Deviance: 6399; (BRG Residual Deviance: 7290)
- MLE.LogLikelihood: -3199.748 (MLE.LogLikelihood BRG: -3644.975)
- Number of parameters: $2(n-1)+1=153$ (BRG: 1)
- BIC: 7727 (BRG BIC: 7299)

Compared to BRG, good simulations also for centralization measures in-degree CI^{in-d}, out-degree CI^{out-d}, in-closeness CI^{in-c} and out-closeness CI^{out-c}.

P1 Model

Dyad Assumption:

$$D_{ij} = (Y_{ij}, Y_{ji}) \overset{ind}{\sim} Multinomial(p_{ij})$$

$$P(D_{ij} = d_{ij}) = P\left[(Y_{ij}, Y_{ji}) = (y_{ij}, y_{ji})\right] = \frac{e^{\mu_{ij} y_{ij} + \mu_{ji} y_{ji} + \gamma y_{ij} y_{ji}}}{1 + e^{\mu_{ij}} + e^{\mu_{ji}} + e^{\gamma + \mu_{ij} + \mu_{ji}}}$$

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$\mu_{ij} = \mu + a_i + b_j$ depends on popularity and sociability

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where: γ reciprocity parameter constant across dyads
$\mu_{ij} = \mu + a_i + b_j$ depends on popularity and sociability

Results (after few tries):

- $\hat{\mu} = -4.254$
- $\hat{\gamma} = 4.738$
- sender effects significant for numerous vertexes, mostly of Frankfurt
- receiver effects significant only for nodes 12, 13 and 54

P1 Model

Goodness of fit:

- Residual Deviance: 4965; (BRG Residual Deviance: 7290)
- MLE.LogLikelihood: -2482.381 (MLE.LogLikelihood BRG: -3644.975)
- Number of parameters: $2(n-1)+2=154$ (BRG: 1)
- BIC: 6301 (BRG BIC: 7299)

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Good simulations for μ, γ, r_{org}, In- and Out-Degree and In- and Out-Closeness.

Markov Model

Markov Assumption: two tie-variables are assumed to be independent unless they share a node.

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MCMC frequently did not converge: restricted choice of parameters.

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- $\widehat{nodefactor.org\_level.1}$ = 2.579 , (Global Manager)
  $\widehat{nodefactor.org\_level.2}$ = 0.457 (Local Manager);
  baseline: Project Leader and Researcher

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- $\widehat{\textit{nodefactor.tenure.1}}$ = -0.457 (1-12 months);
  baseline: 13-36, 37-60 and +61 months.

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- $\widehat{\textit{nodefactor.tenure.1}}$ = -0.457 (1-12 months);
  baseline: 13-36, 37-60 and +61 months.
- $\widehat{\textit{nodematch.location}}$ = 4.634;
  other two *nodematch* estimates not significant and removed.

Markov Model

Goodness of fit:

- Residual Deviance: 3765; (P1 Residual Deviance: 4965)
- MLE.LogLikelihood: -1882.63 (MLE.LogLikelihood P1: -2482.381)
- Number of parameters: 8 (P1: 154)
- BIC: 3835 (P1 BIC: 6301)

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- MLE.LogLikelihood: -1882.63 (MLE.LogLikelihood P1: -2482.381)
- Number of parameters: 8 (P1: 154)
- BIC: 3835 (P1 BIC: 6301)

Observations:

- Without nodal attributes as covariates BIC results equal to 7013.
- Passable simulations except for reciprocity, transitivity and eigenvector centrality.

Social Circuit Model

Extension of Markov Assumption:

$$Y_{ij} \not\perp Y_{kl} \quad \Longleftrightarrow \quad Y_{ik} = Y_{jl} = 1 \vee Y_{il} = Y_{jk} = 1$$

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MCMC frequently did not converge: models with alternating k-2 paths parameter σ_w not available

Social Circuit Model

Results: All parameters highly significant

- $\hat{\mu}$ = -8.042
- $\hat{\sigma}_2^{out}$ = 0.243, $\hat{\sigma}_3^{out}$ = -0.006;
  (other Markov typical configurations not available).
- $\widehat{\textit{nodefactor.location.2}}$ = -0.287 (Frankfurt);
  baseline: Paris, Geneva and Warsaw.
- $\widehat{\textit{nodefactor.org\_level.1}}$ = 2.484, (Global Manager)
  $\widehat{\textit{nodefactor.org\_level.2}}$ = 0.443 (Local Manager);
  baseline: Project Leader and Reasercher
- $\widehat{\textit{nodefactor.tenure.1}}$ = -0.446 (1-12 months);
  baseline: 13-36, 37-60 and +61 months.
- $\widehat{\textit{nodematch.location}}$ = 4.639;
  other two *nodematch* estimates not significant and removed.

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Social Circuit Model

Goodness of fit:

- Residual Deviance: 3758 (Markov Model Residual Deviance: 3765)
- MLE.LogLikelihood:-1878.84 (MLE.LogLikelihood Markov Model: -1882.63)
- Number of parameters: 10 (Markov Model: 9)
- BIC: 3836 (Markov Model BIC: 3835)

P1 model with attributes

Results:

- $\hat{\mu}$ = -2.941;
- $\hat{\gamma}$ = 2.548;
- $\widehat{\textit{nodefactor.location.2}}$ = 0.446 (Frankfurt);
  baseline: Paris, Geneva and Warsaw.
- $\widehat{\textit{nodefactor.org\_level.1}}$ = 1.879, (Global Manager)
  $\widehat{\textit{nodefactor.org\_level.2}}$ = 0.6103 (Local Manager);
  baseline: Project Leader and Reasercher
- $\widehat{\textit{nodefactor.tenure.1}}$ = -0.578 (1-12 months);
  baseline: 13-36, 37-60 and +61 months.
- $\widehat{\textit{nodematch.location}}$ = 2.750;
  other two *nodematch* estimates not significant and removed.

P1 model with attributes

Goodness of fit:

- Residual Deviance: 3686 (Markov Model Residual Deviance: 3765)
- MLE.LogLikelihood: -1842.802 (MLE.LogLikelihood Markov Model: -1882.63)
- Number of parameters: 7 (Markov Model: 9)
- BIC: 3746 (Markov Model BIC: 3835)

Model Choice

Model	BIC
SRG	7299
NH-SRG	7727
P1	6301
Markov	3835
Social	3836
P1 with attr.	3746

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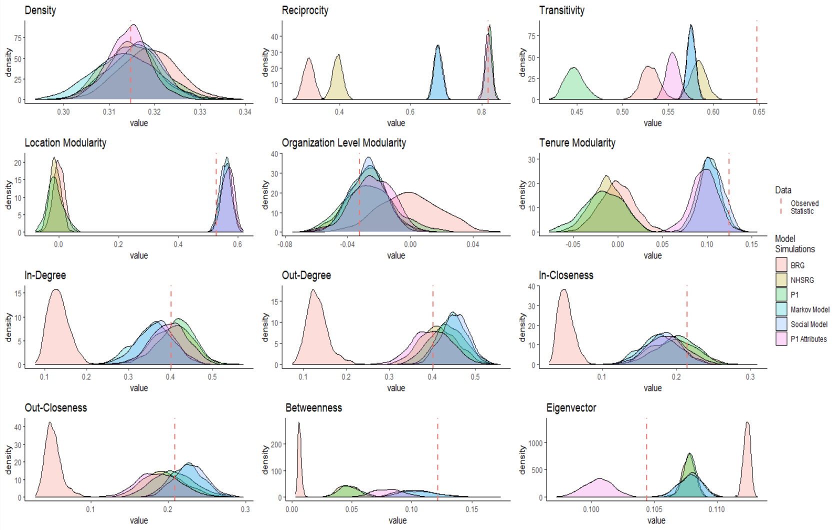
MCMC diagnostics: All parameters converged.

All Model Simulations



Conclusion

Final observations

Conclusion

Statistics:

- Quite dense network;
- High values of transitivity and reciprocity $\rightarrow$ tendency to form clusters within same location (due to modularity values);
- Not very centralized network;
- Very important node: the only global department manager.

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Models:

- Bad performance of simpler models (SRG and NH-SRG);
- Improvements with P1;
- Good performances with Social Circuit and Markov Model both with respect of BIC and fit in simulations;
- Best performance for P1 with attributes.

Thank you for the attention!