Northeastern University
Network Science Institute

The Reasonable Effectiveness of Roles in Networks

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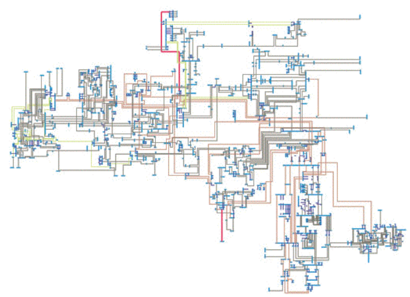
Supported by NSF, DTRA, DARPA, IARPA, DOE/LLNL & WaPo Labs

Complex Networks are Ubiquitous

Technological Networks

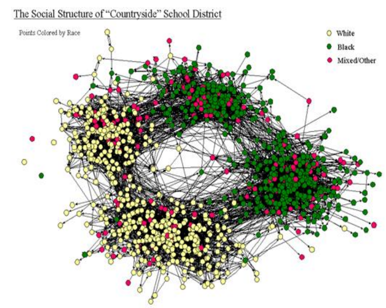
Internet

NY State Power Grid



Social Networks

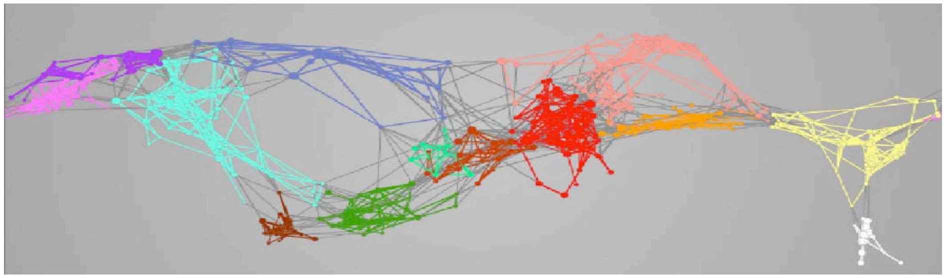
Friendship



HP Emails

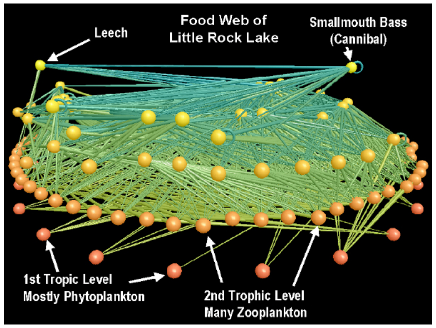
Information Networks

Map of Science

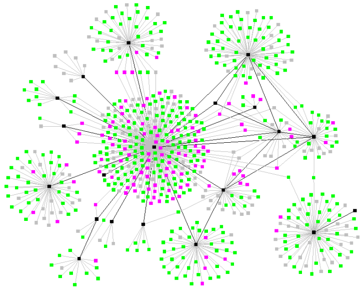


Biological networks

Food Web

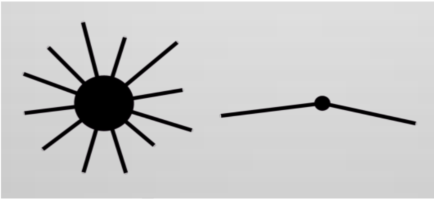
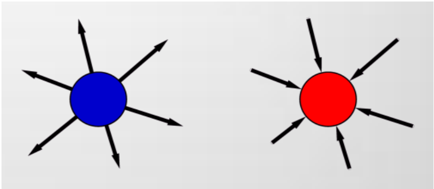
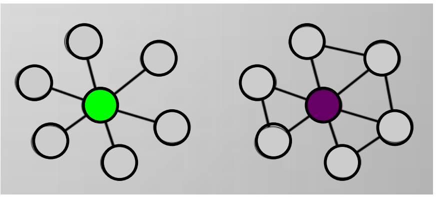
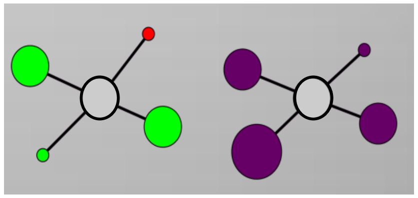


Contagion of TB

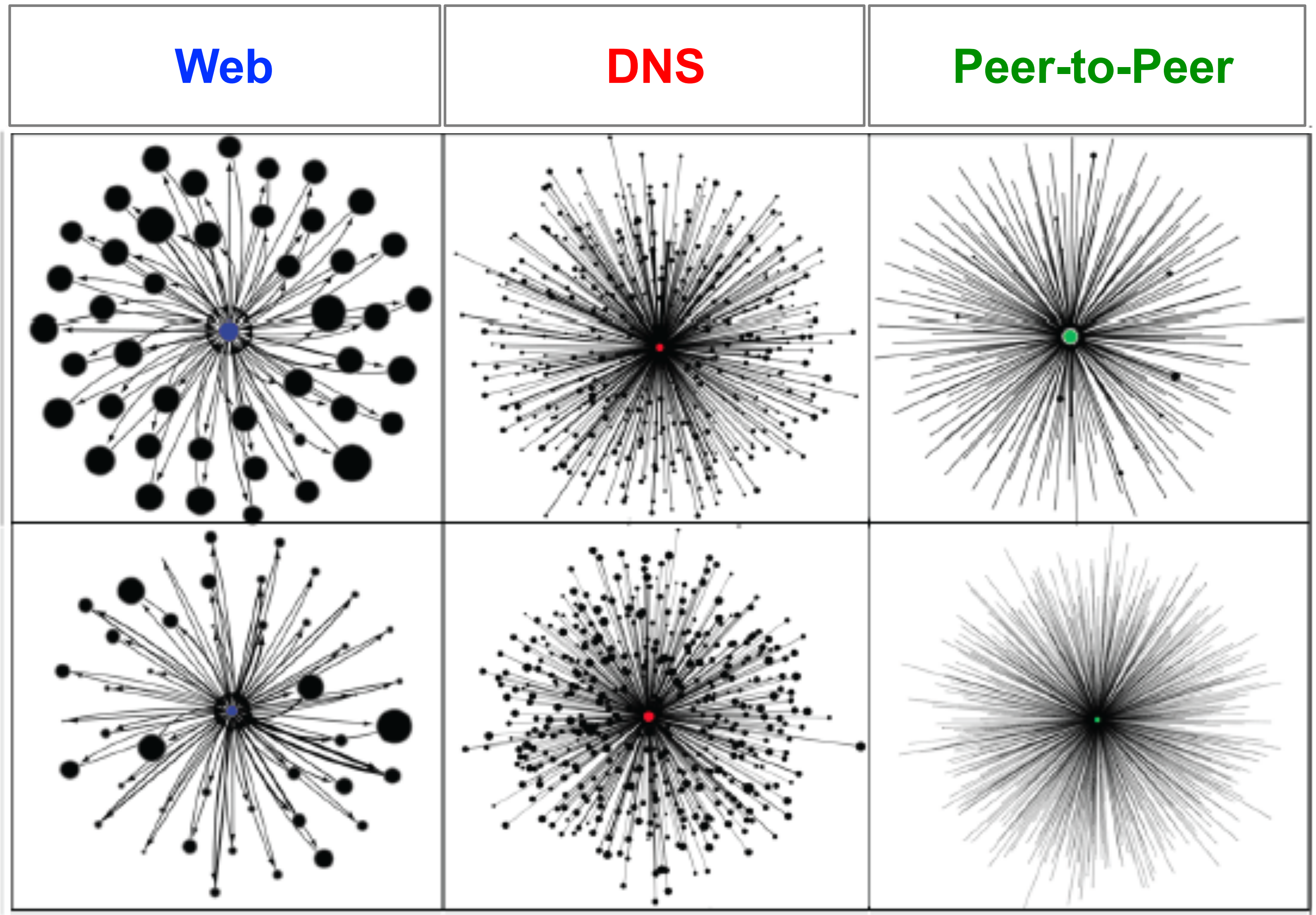


What are Roles?

- Functions of nodes in the network
  - Similar to functional roles of species in ecosystems
- Roles are defined in terms of structural behaviors
  - What is your connectivity pattern?
  - To what kinds of individuals are you connected?

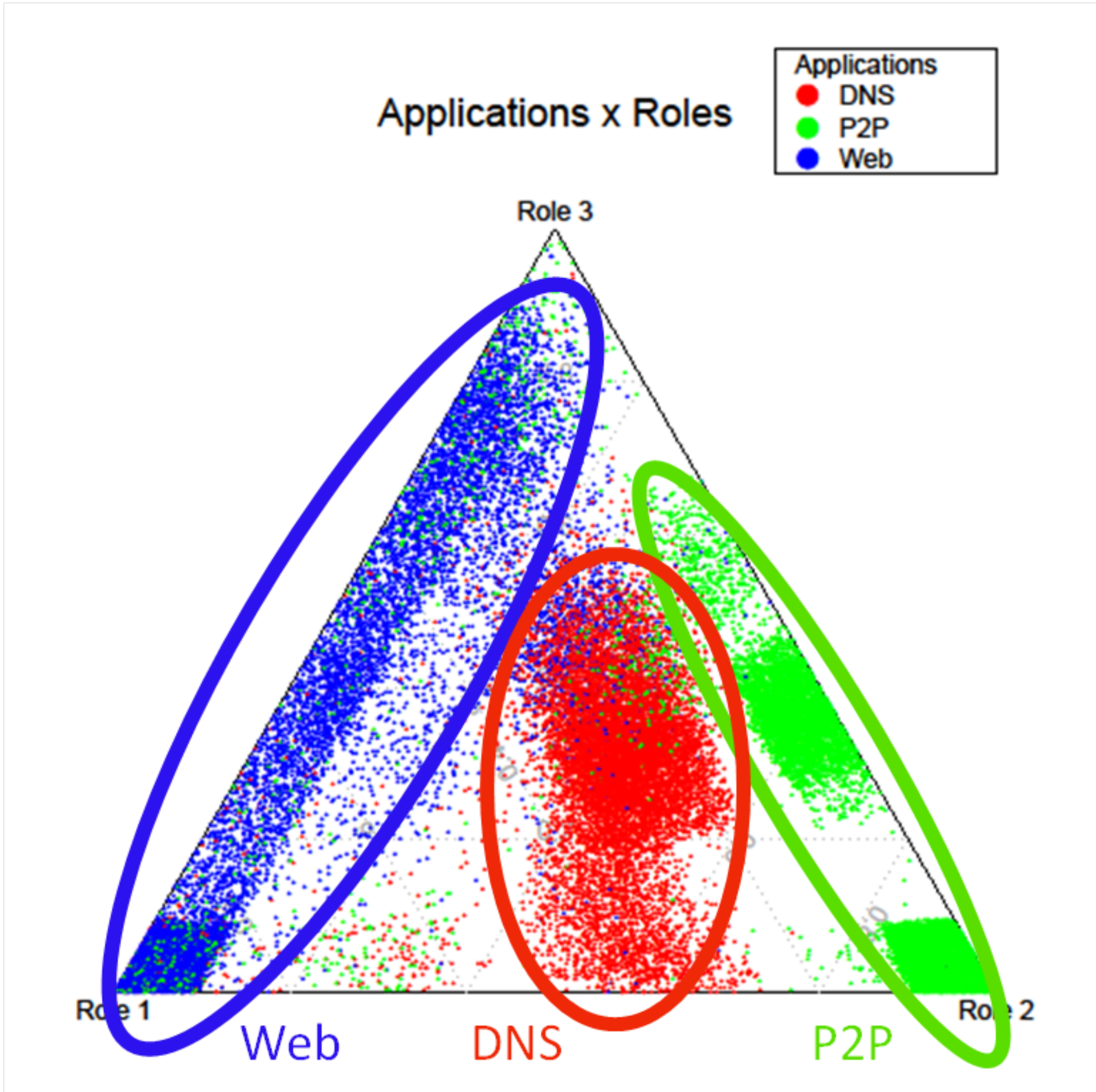
Example of Roles in an IP × IP Network



Node sizes indicate communication volume relative to the central node in each frame.

The types of neighbors that are connected to a given host are indicators of the host's role.

Each Node has a Mixture of Roles

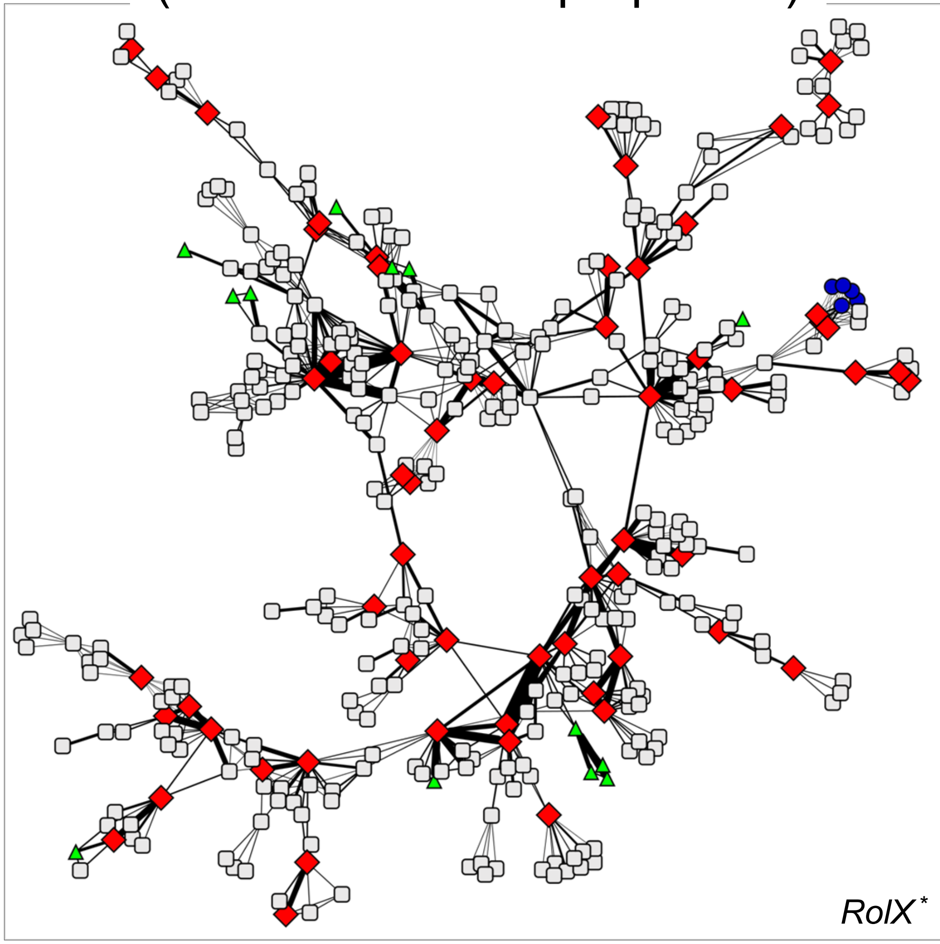


Research Questions

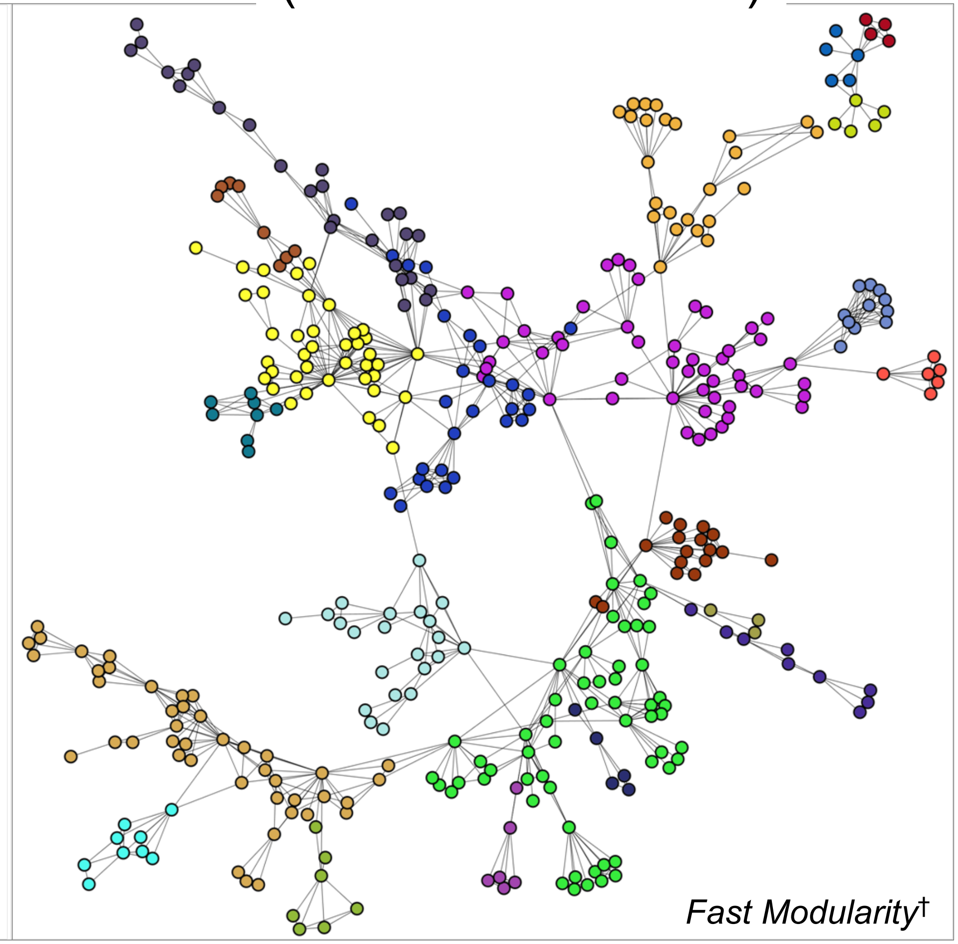
1. How are roles different from communities and from positions/equivalences (from sociology)?
2. Given a network, how can we automatically discover roles of nodes?
3. How can we make sense of these roles?
4. Are there good features that we can extract for nodes that indicate role-membership?
5. What are the applications in which these discovered roles can be effectively used?

Roles & Communities are Complementary

Roles
(similar structural properties)



Communities
(well-connectedness)

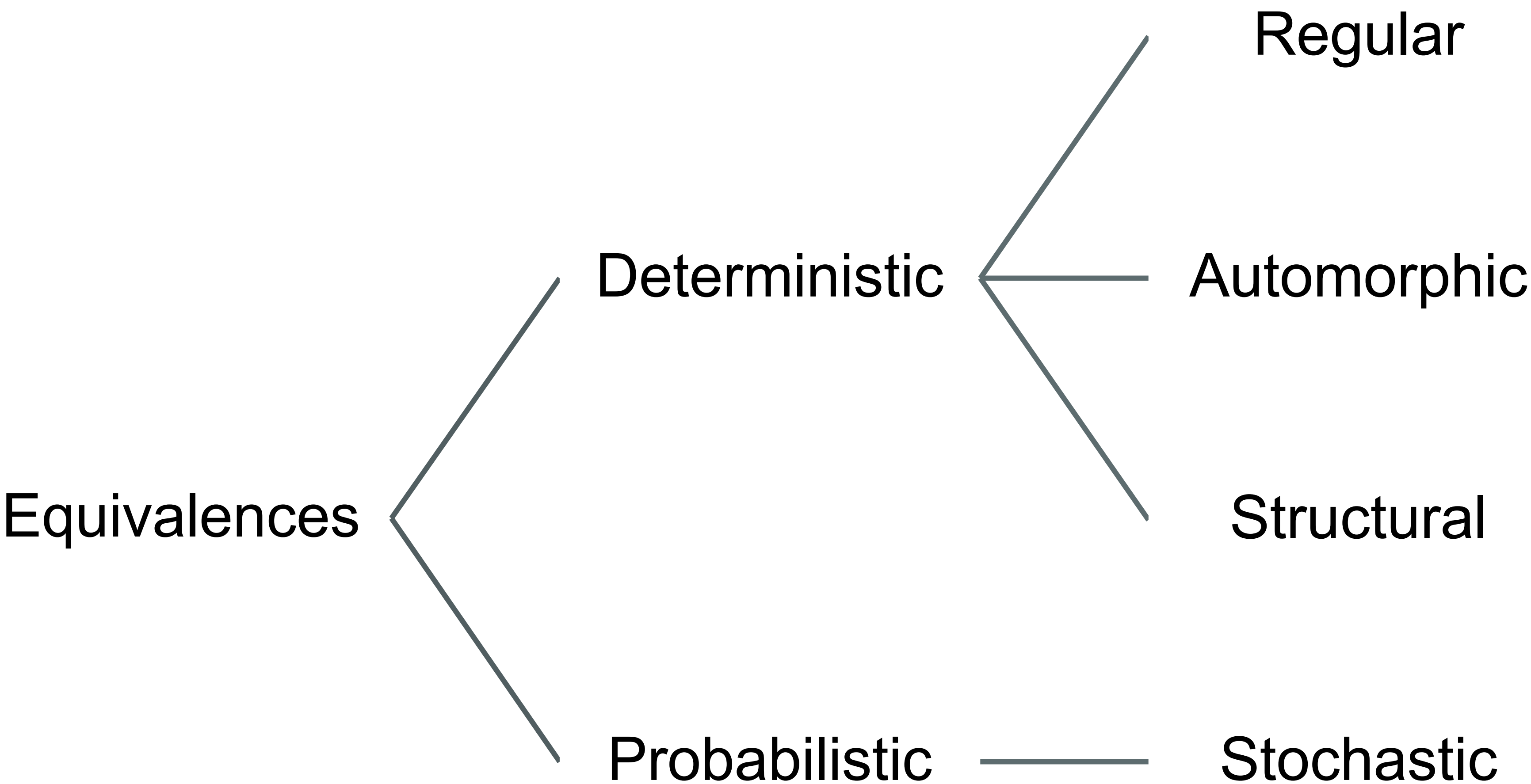


* Henderson, et al. 2012; † Clauset, et al. 2004

Roles are Similar to Positions from Sociology

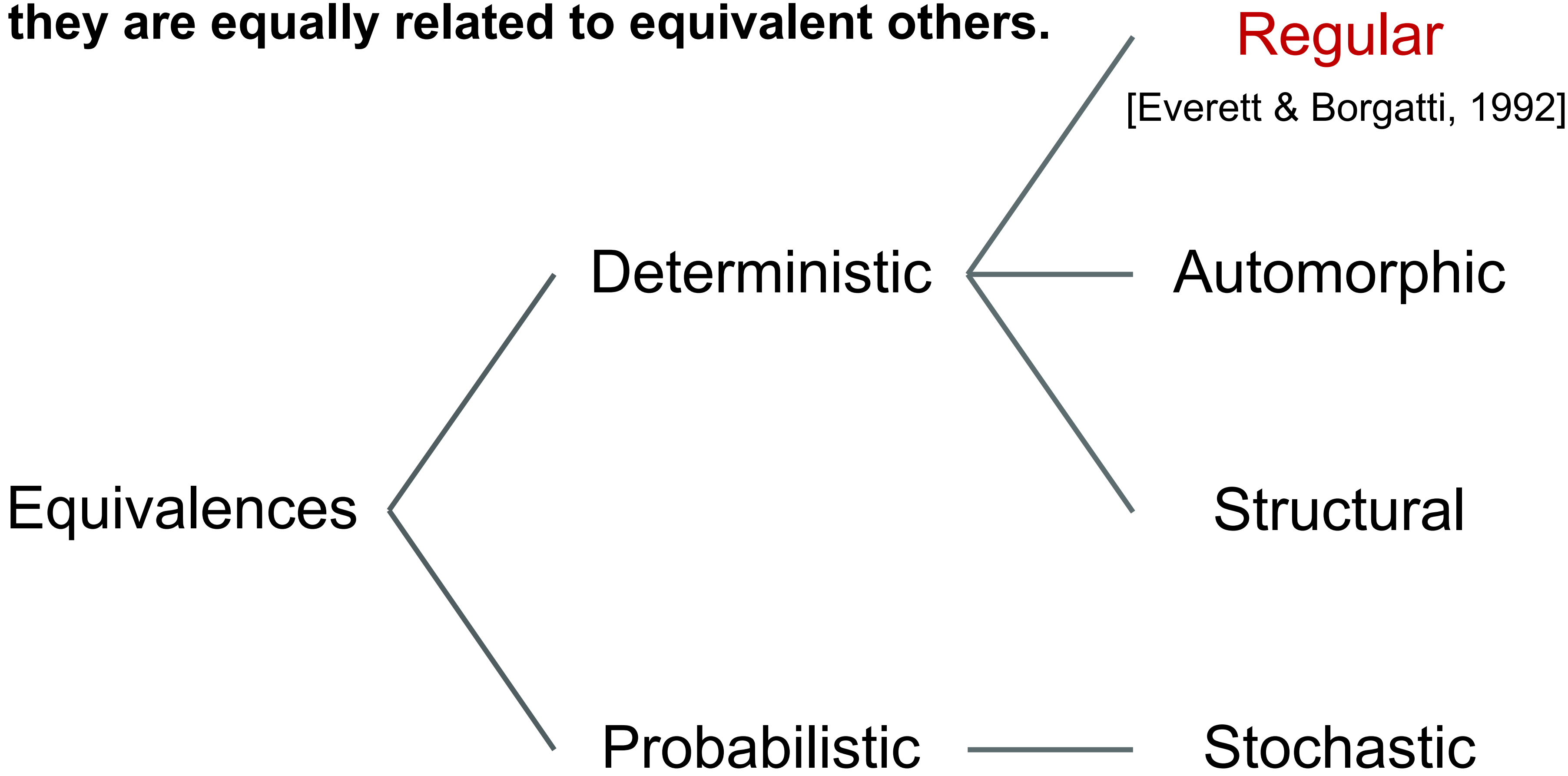
- Two nodes with the same position are in an equivalence relation
- Equivalence, Q, is any relation that satisfies these three conditions:
  - Transitivity: $(a,b), (b,c) \in Q \Rightarrow (a,c) \in Q$
  - Symmetry: $(a, b) \in Q$ if and only if $(b, a) \in Q$
  - Reflexivity: $(a, a) \in Q$

Taxonomy of Equivalences from Sociology



Roles find Regular Equivalences

Two nodes *u* and *v* are regularly equivalent if they are equally related to equivalent others.



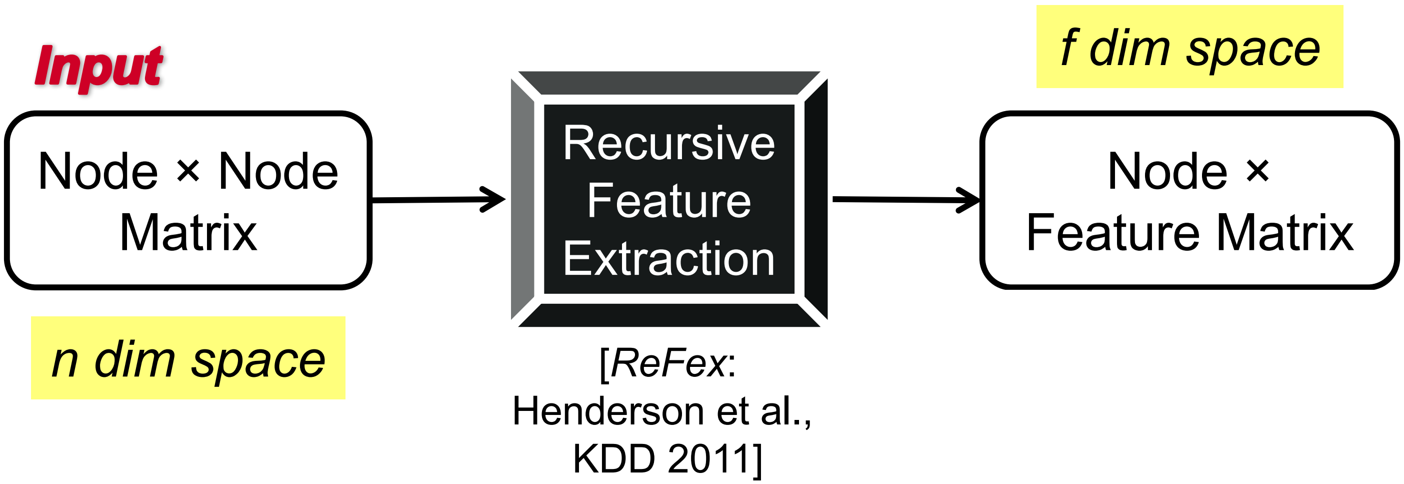
Finding Roles in a Network

Input

Node × Node
Matrix

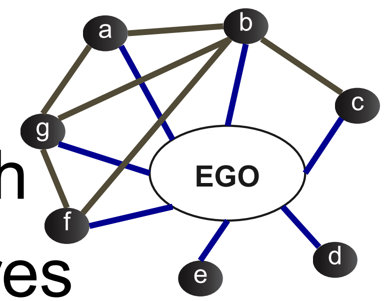
n dim space

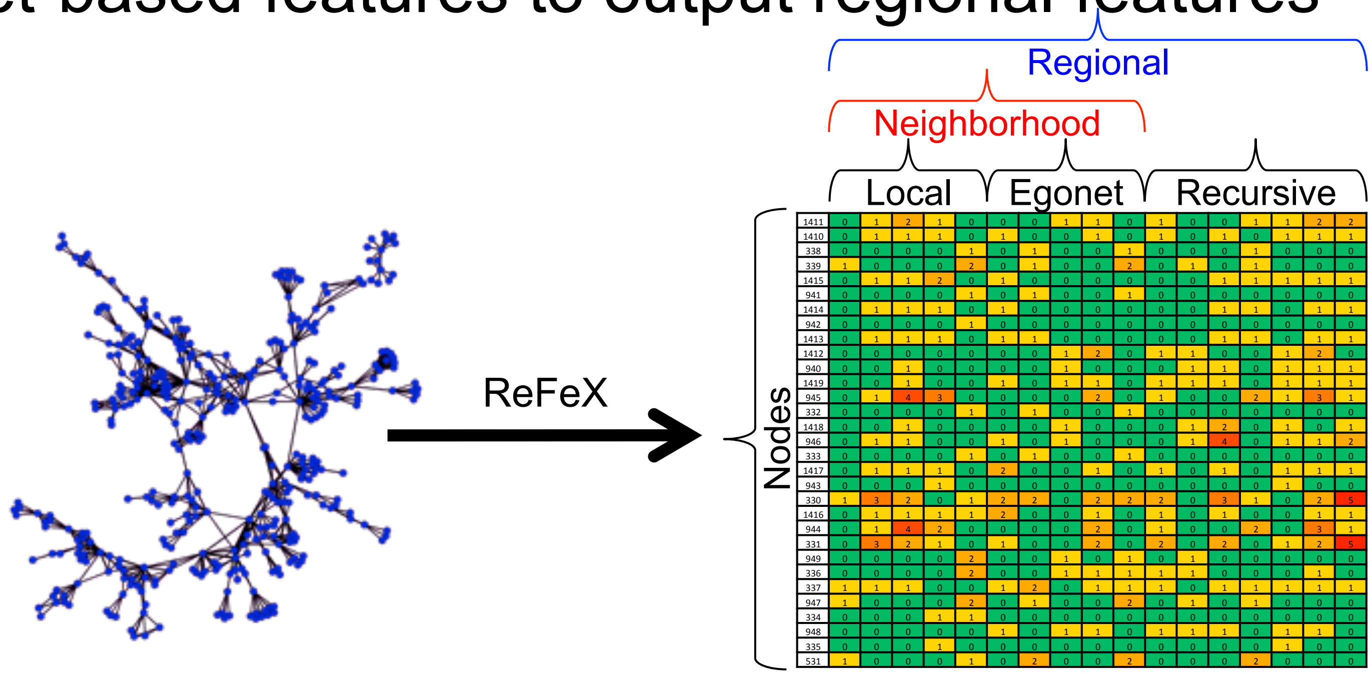
Finding Roles in a Network



ReFeX: Recursive Feature Extraction

- [Henderson *et al*., KDD 2011]
- Recursively combines node-based features with egonet-based features to output regional features





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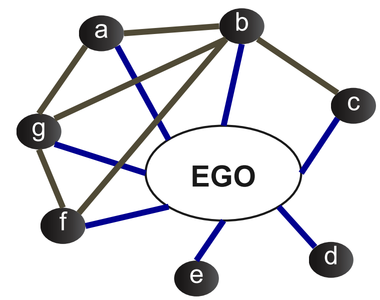
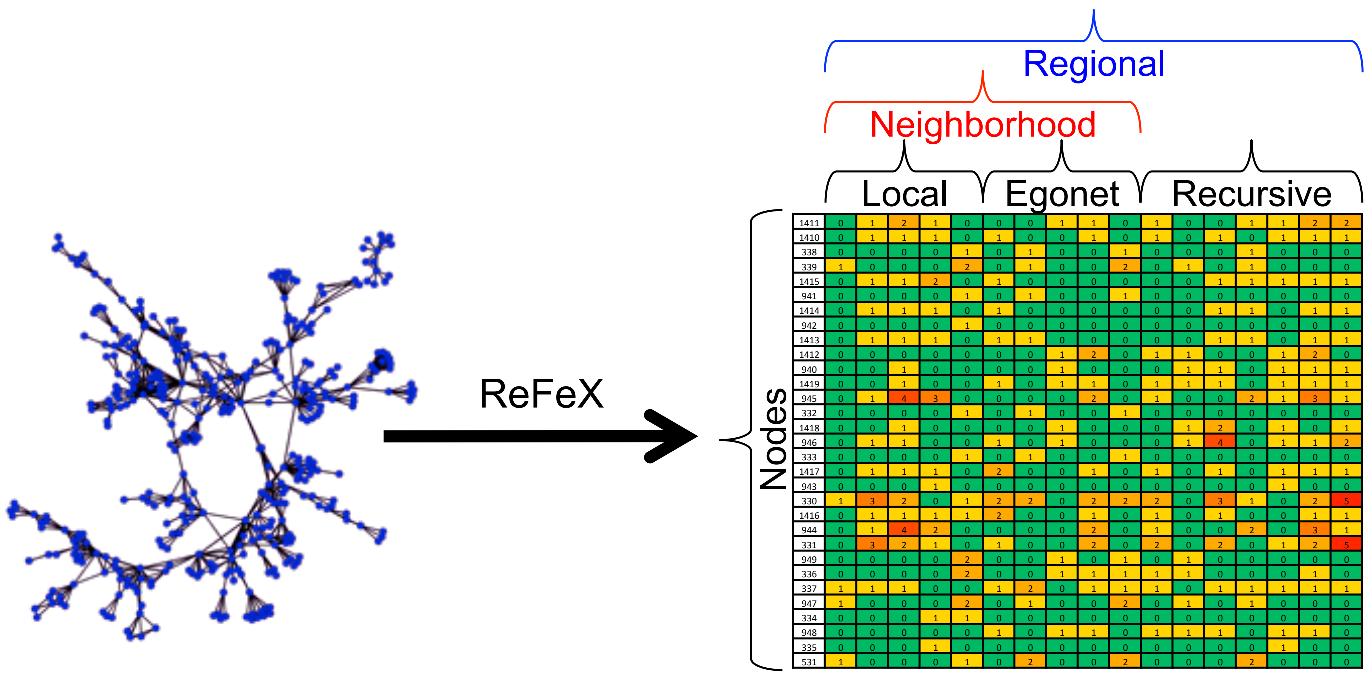
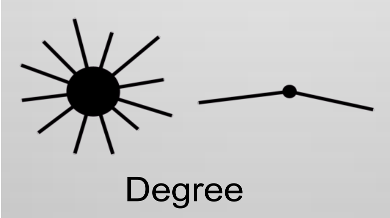


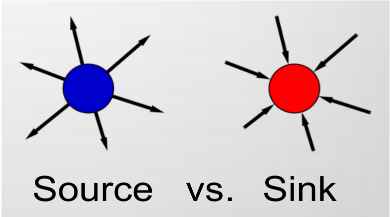


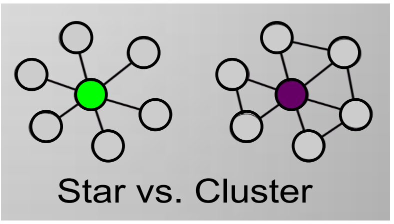
- Neighborhood features: What is your connectivity pattern?
- Recursive Features: To what kinds of nodes are you connected?

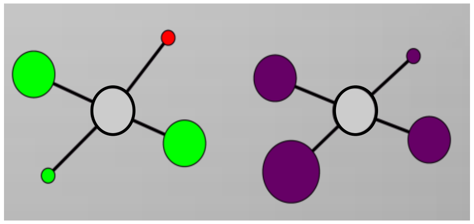
ReFeX: Structural Features

- Local
  - Essentially measures of the node degree
- Egonet
  - Computed based on each node's ego network
  - Examples
    - # of within-egonet edges
    - # of edges entering & leaving the egonet
- Recursive
  - Some aggregate (mean, sum, max, min, …) of another feature over a node's neighbors
  - Aggregation can be computed over any real-valued feature, including other recursive features









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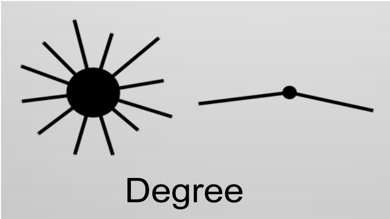

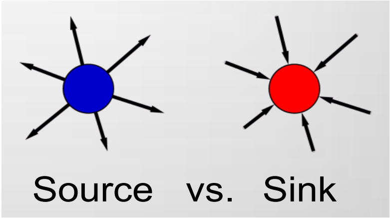

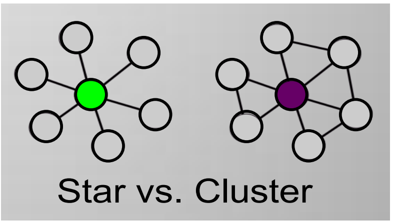

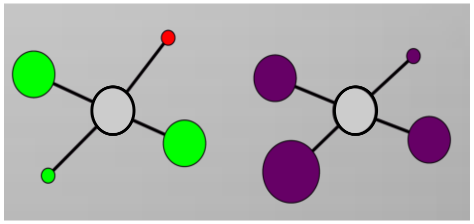

ReFeX: Structural Features

Regional

Neighborhood

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- Egonet
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  - Some aggregate (mean, sum, max, min, …) of another feature over a node’s neighbors
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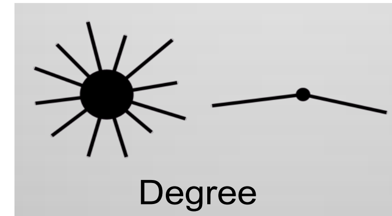

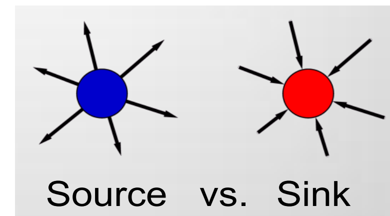

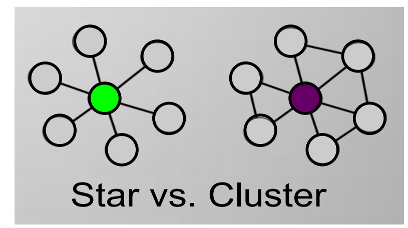

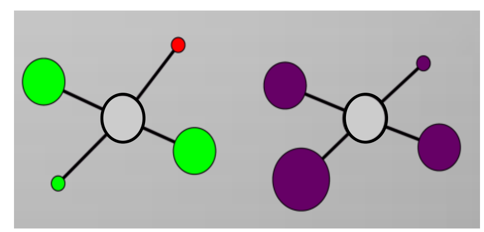

ReFeX (continued)

- Number of possible recursive features is infinite

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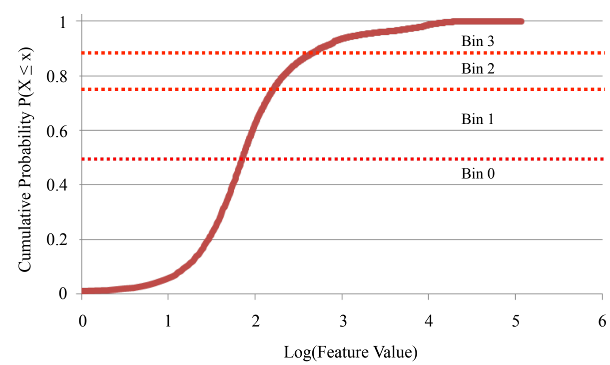
  - Feature values are mapped to small integers via vertical logarithmic binning
    - Log binning places most of the discriminatory power among sets of nodes with large feature values



ReFeX (continued)

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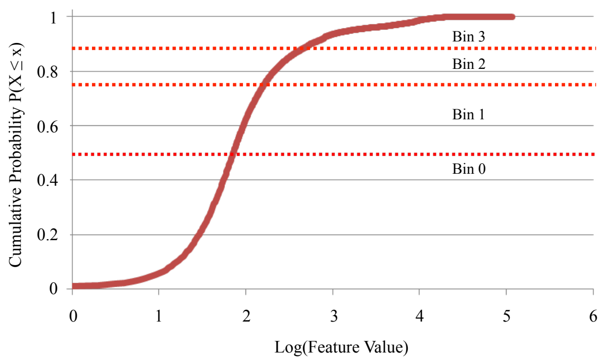
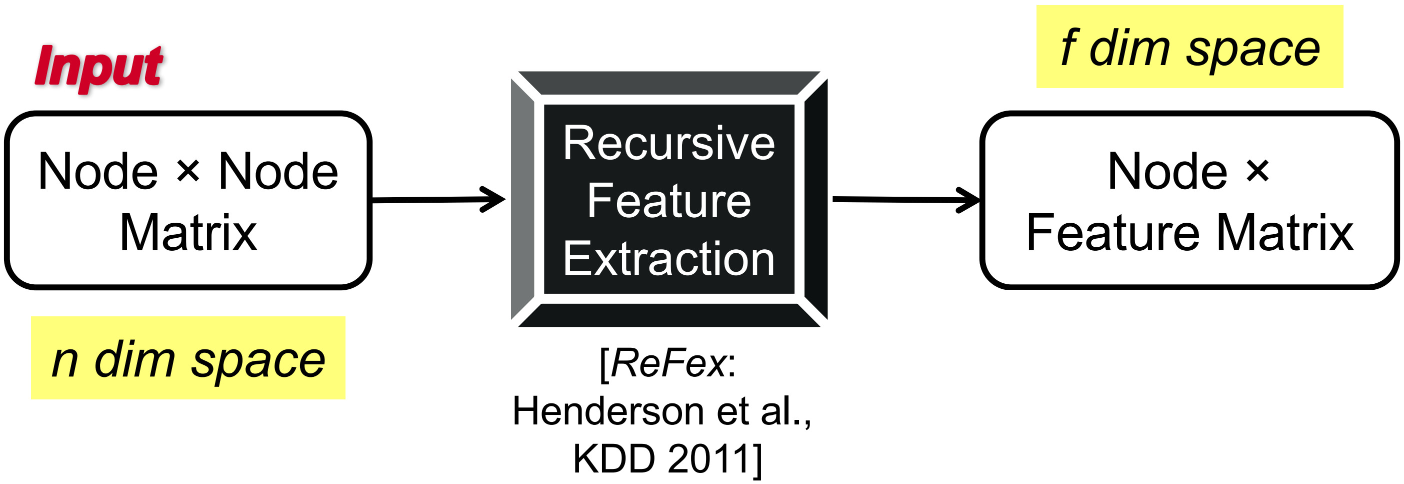


  - Look for pairs of features whose values never disagree by more than a threshold
    - A graph-based approach
    - Threshold automatically set
    - Details in the KDD'11 paper

Finding Roles in a Network



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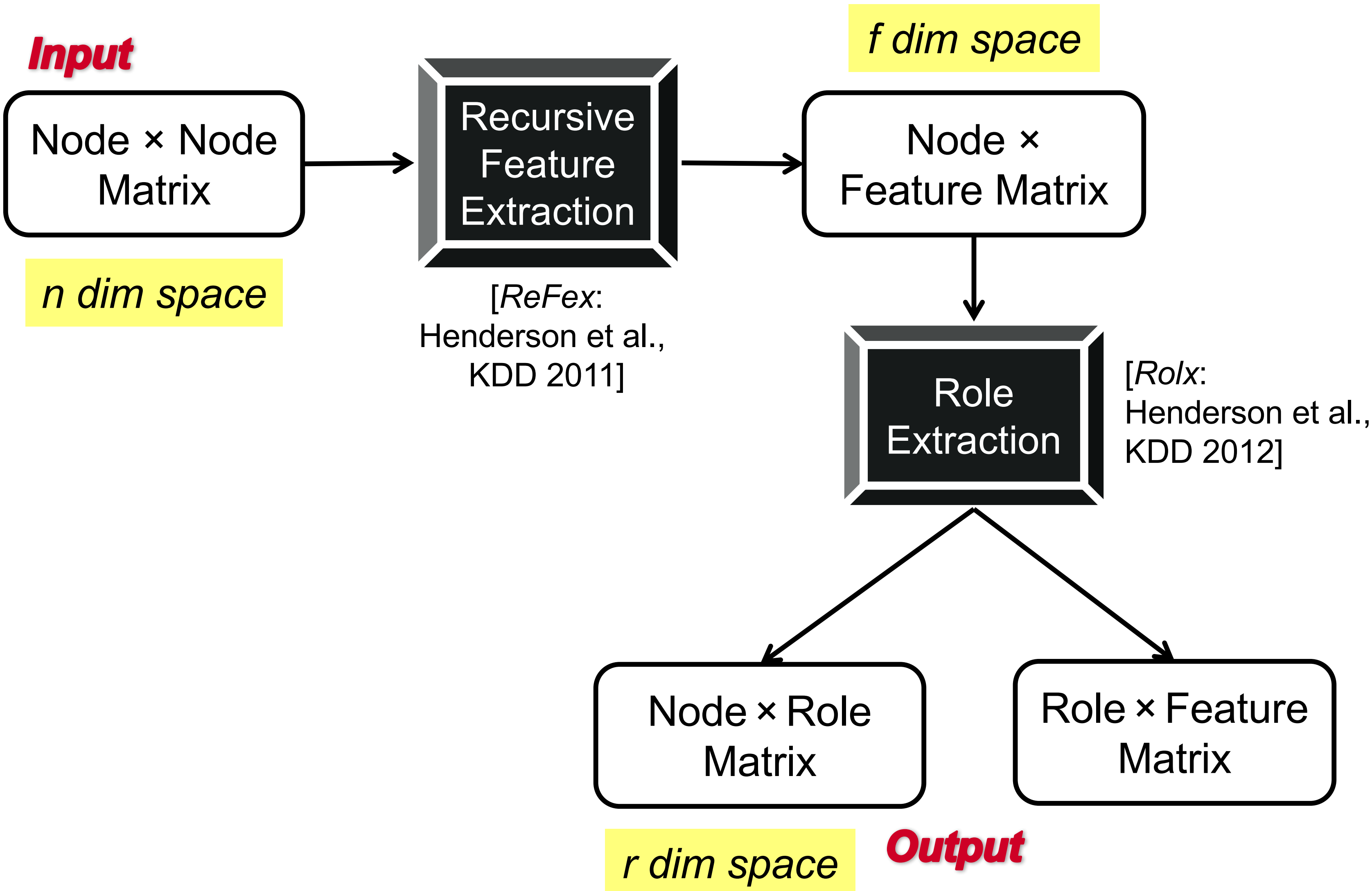

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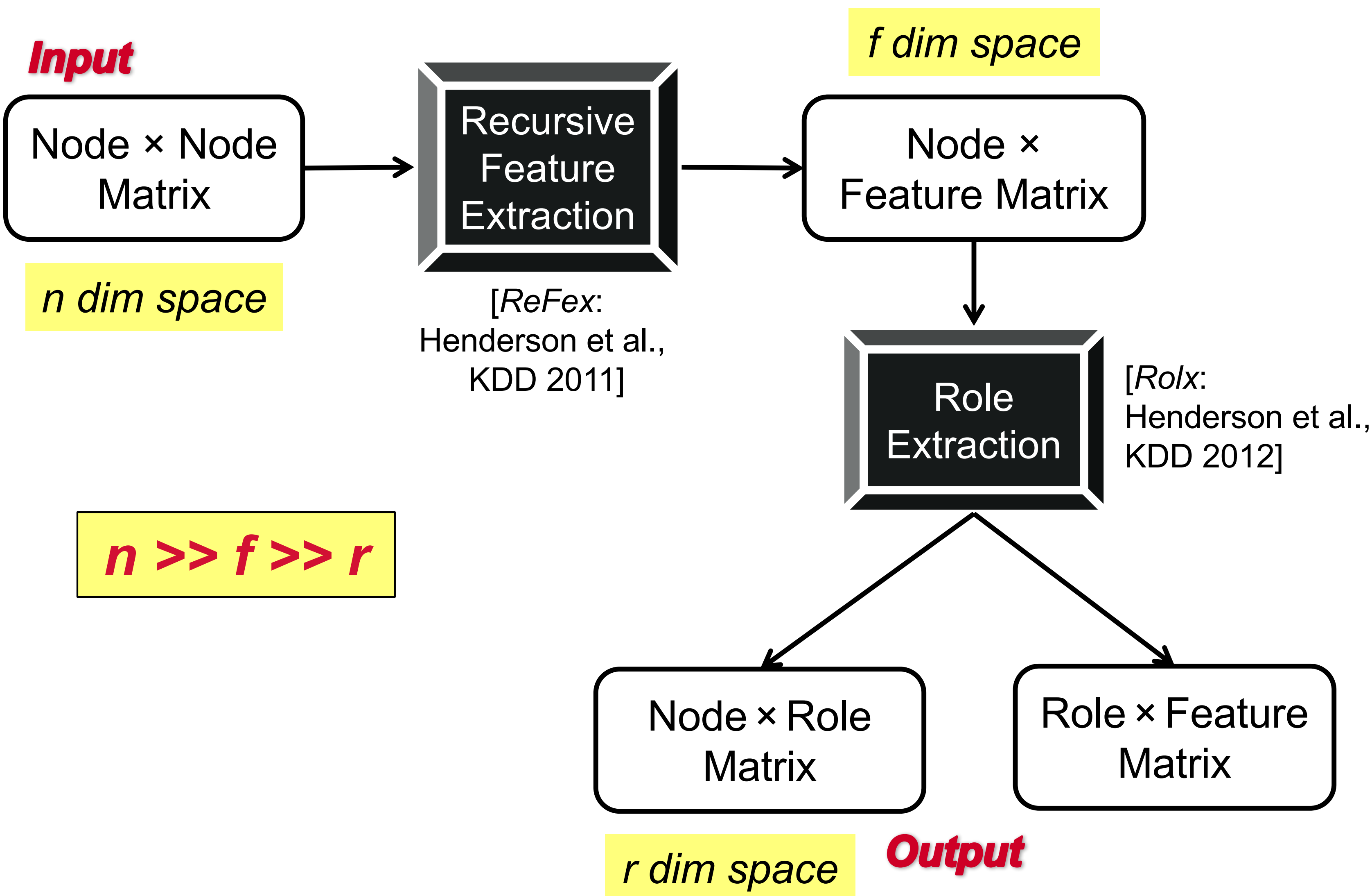
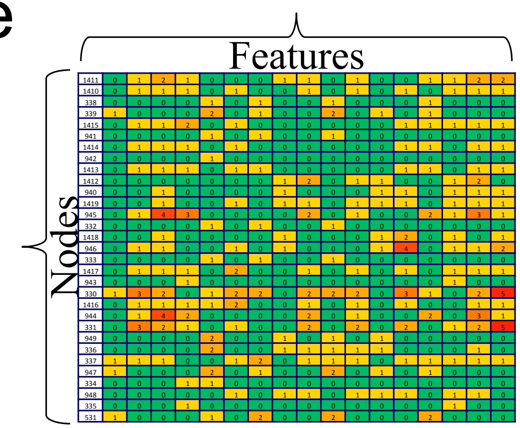


Role Extraction: Feature Grouping

- Soft clustering in the structural feature space
    - Each node has a mixed-membership across roles



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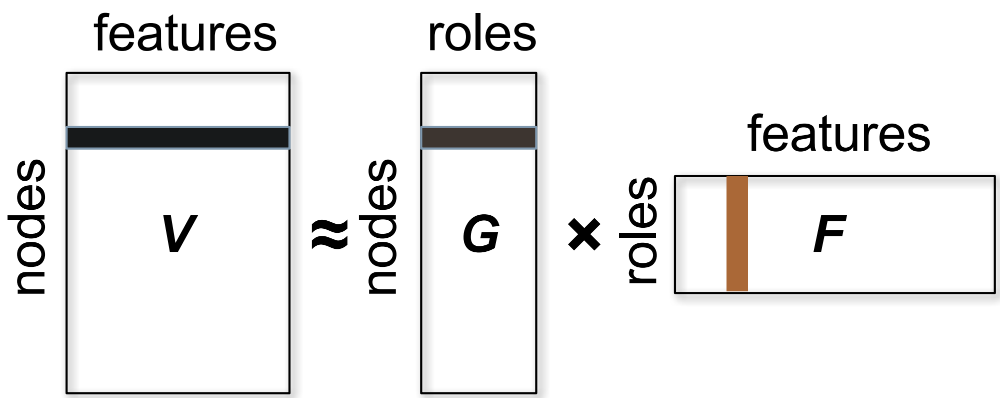
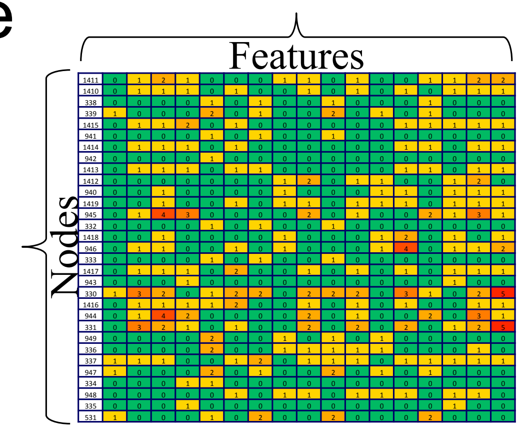
- Generate a rank r approximation of $V \approx GF$





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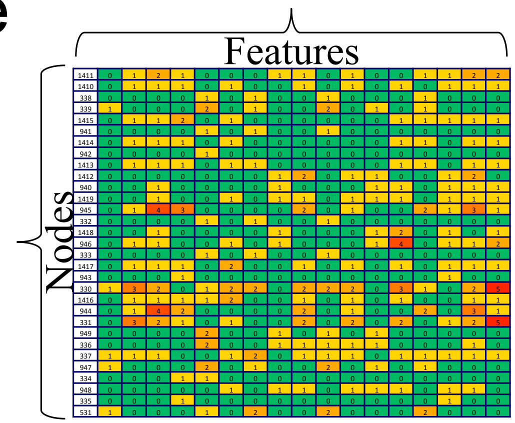

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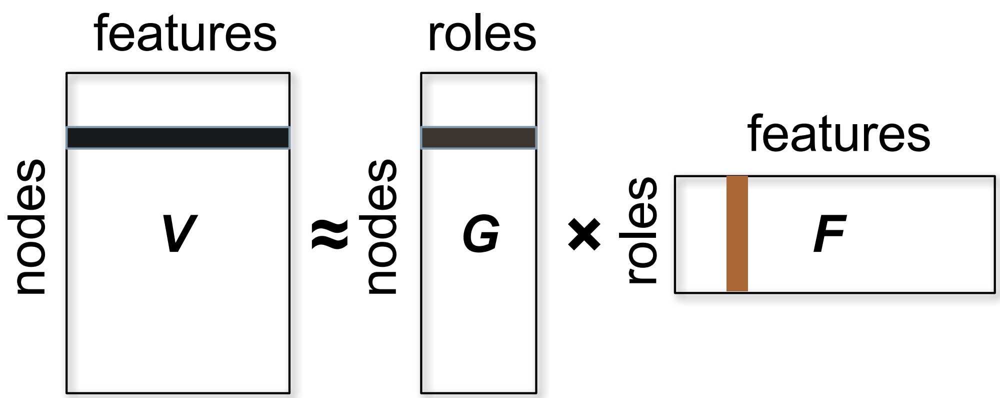

- RolX uses NMF for feature grouping
  - Computationally efficient
  - Non-negative factors simplify interpretation of roles and memberships

$$\boxed{\text{argmin}_{G,F}\|V - GF\|_{fro}, \text{s.t. } G \geq 0,\ F \geq 0}$$

Role Extraction: Model Selection

- Roles summarize behavior
  - Or, they compress the feature matrix, V

Role Extraction: Model Selection

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  - Or, they compress the feature matrix, V
- Use MDL to select the model size r that results in the best compression
  - L: description length
  - M: # of bits required to describe the model
  - E: cost of describing the reconstruction errors in $V - GF$
  - Minimize $L = M + E$

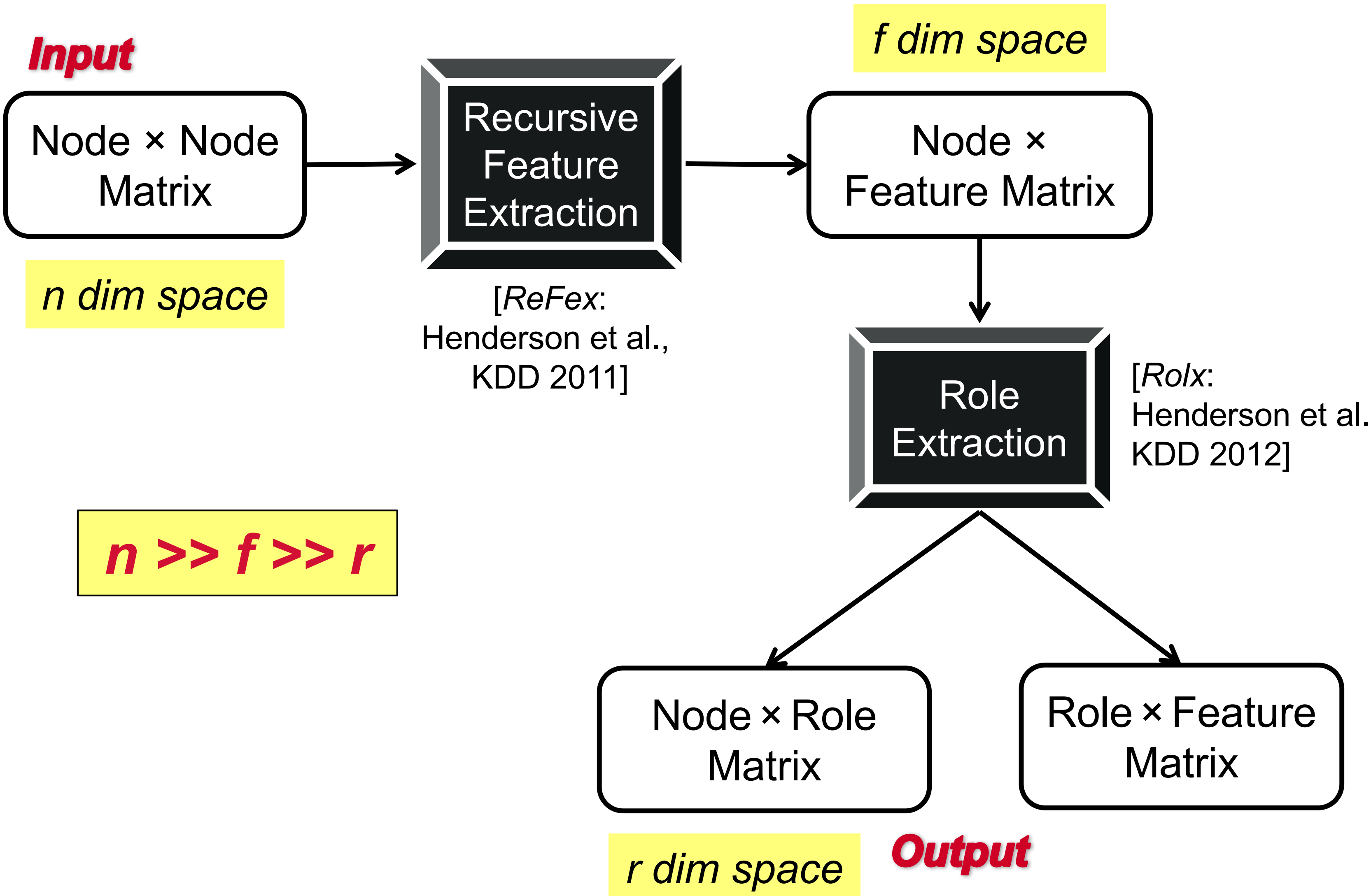
Role Extraction: Model Selection

- Roles summarize behavior
  - Or, they compress the feature matrix, *V*
- Use MDL to select the model size *r* that results in the best compression
  - *L*: description length
  - *M*: # of bits required to describe the model
  - *E*: cost of describing the reconstruction errors in *V* – *GF*
  - Minimize *L* = *M* + *E*
    - To compress high-precision floating point values, RolX combines Llyod-Max quantization with Huffman codes
    - Errors in *V-GF* are not distributed normally, RolX uses KL divergence to compute *E*

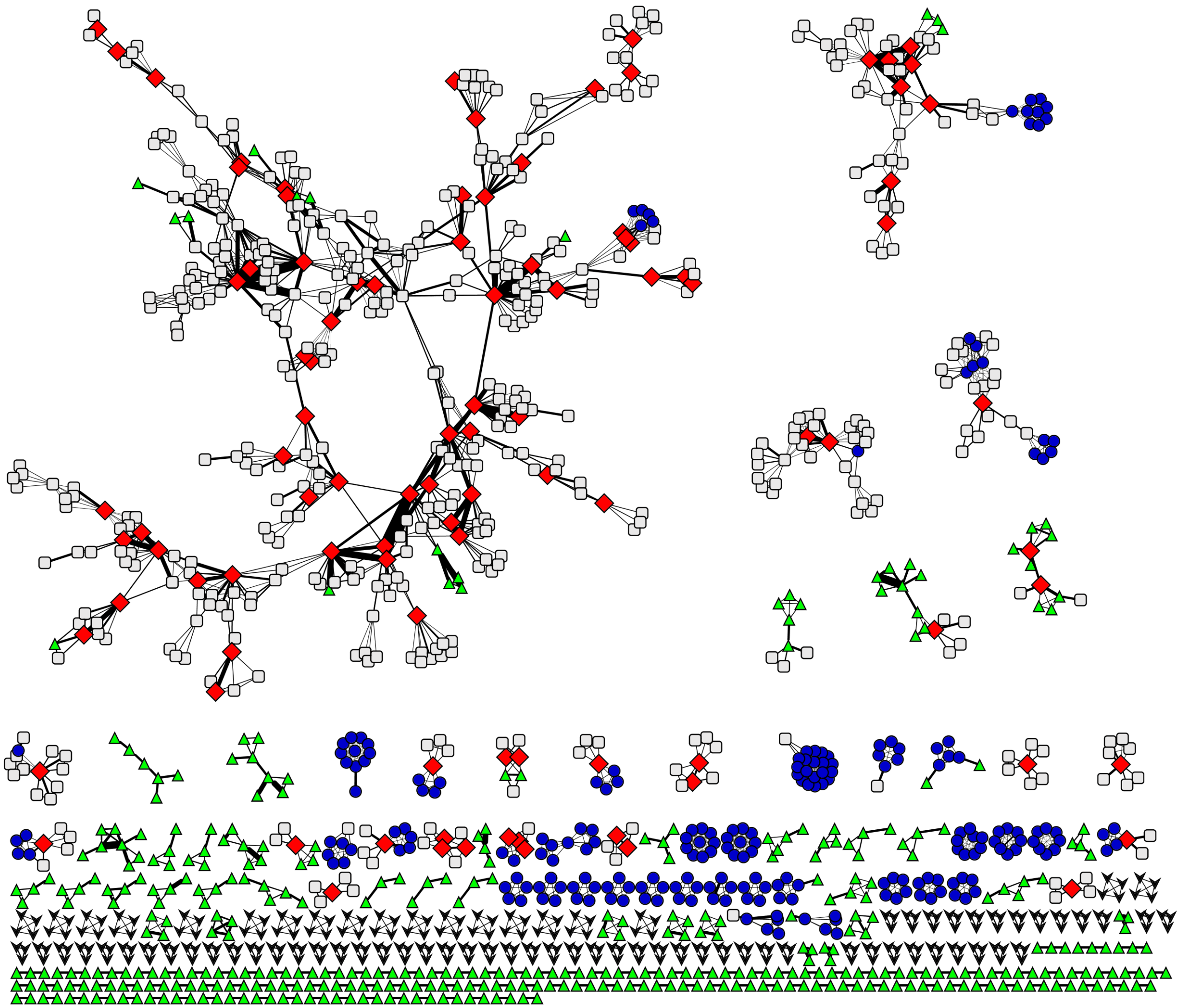
$$\boxed{M = \bar{b}r(n+f)}$$

$$\boxed{E = \sum_{i,j}\left(V_{i,j}\log\frac{V_{i,j}}{(GF)_{i,j}} - V_{i,j} + (GF)_{i,j}\right)}$$

Finding Roles in a Network



Automatically Discovered Roles



Network Science Co-authorship Graph
[Newman 2006]

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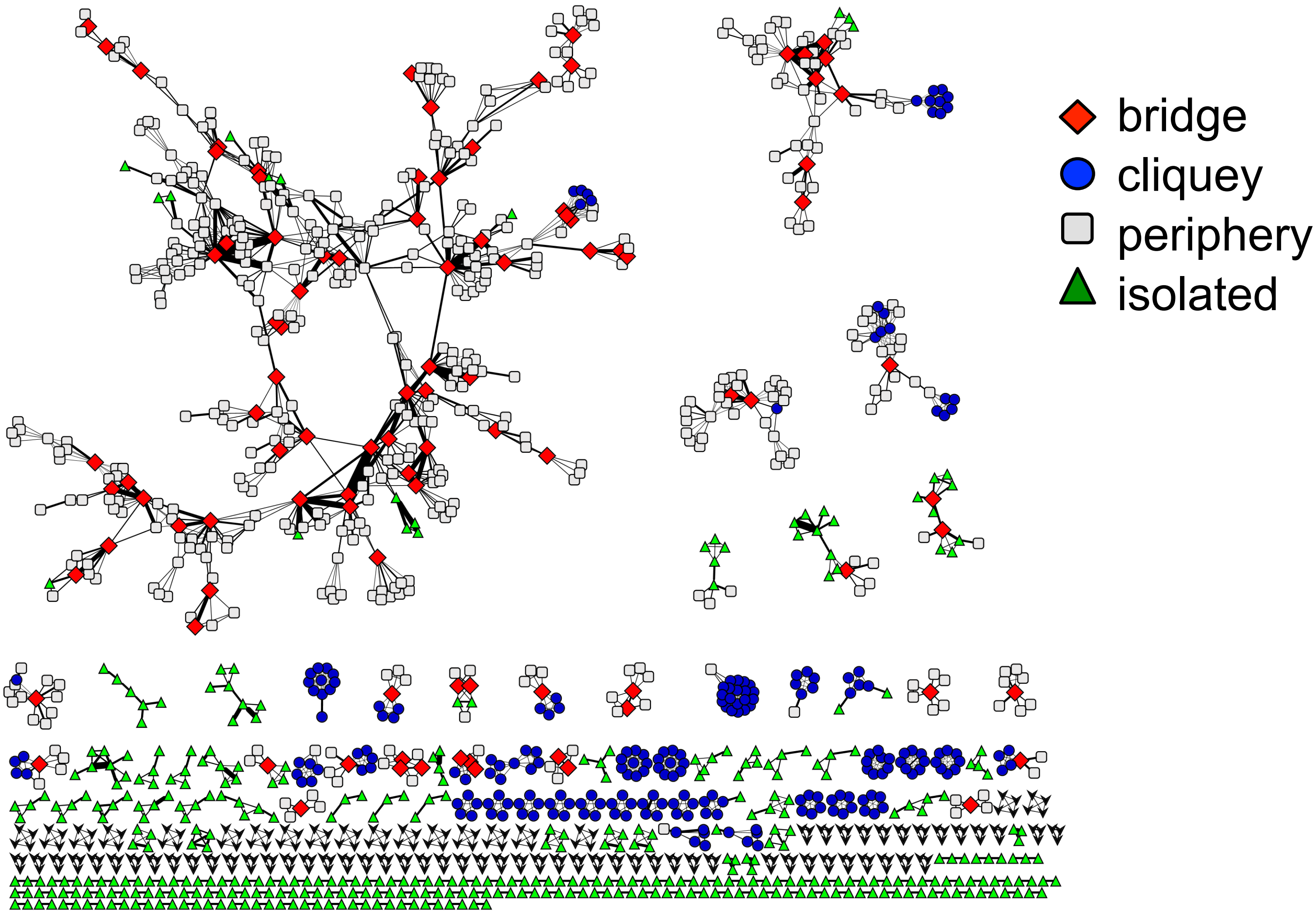

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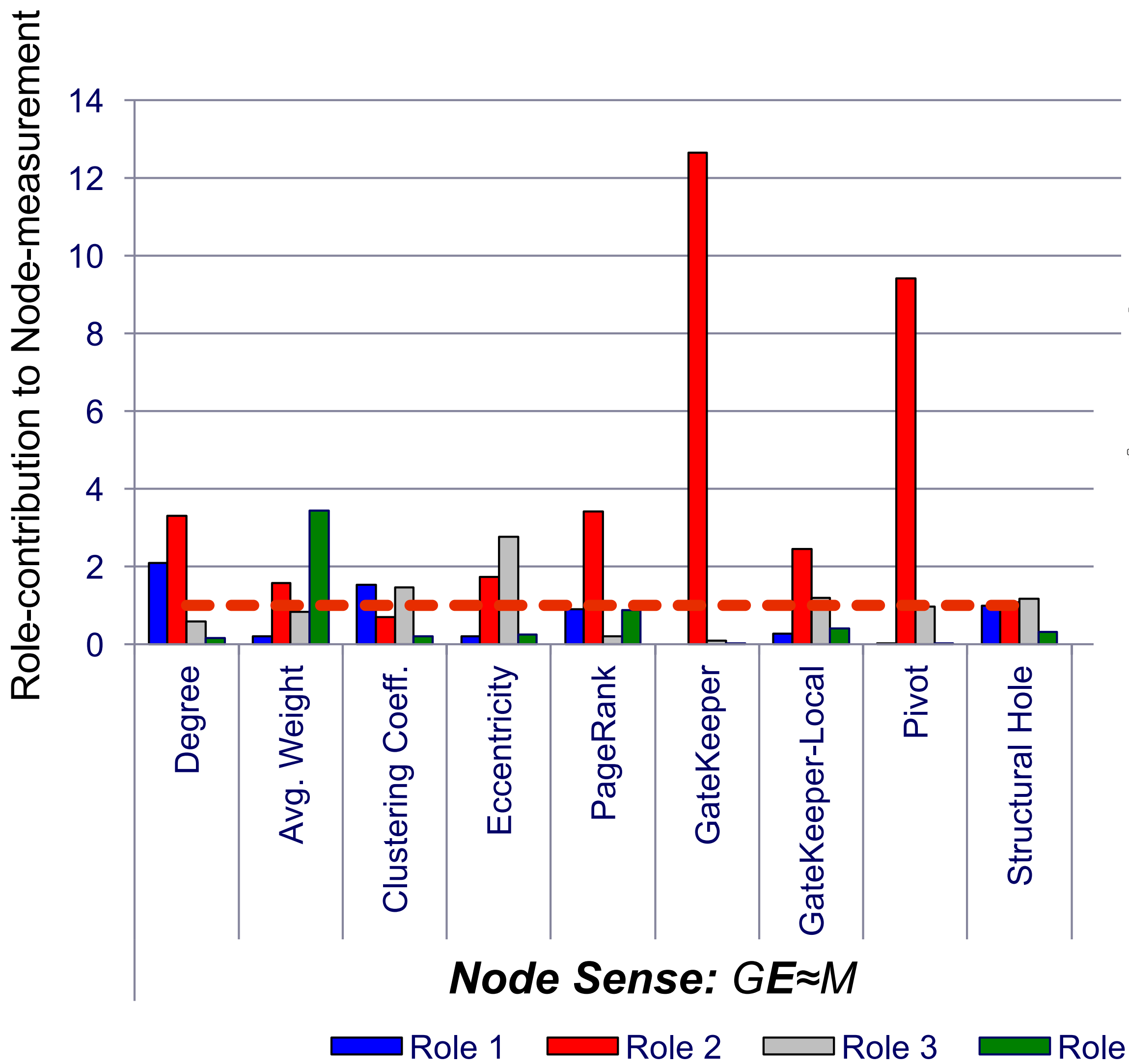
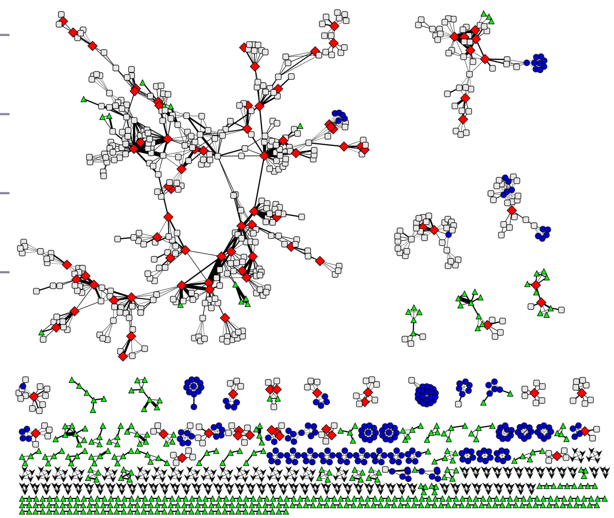
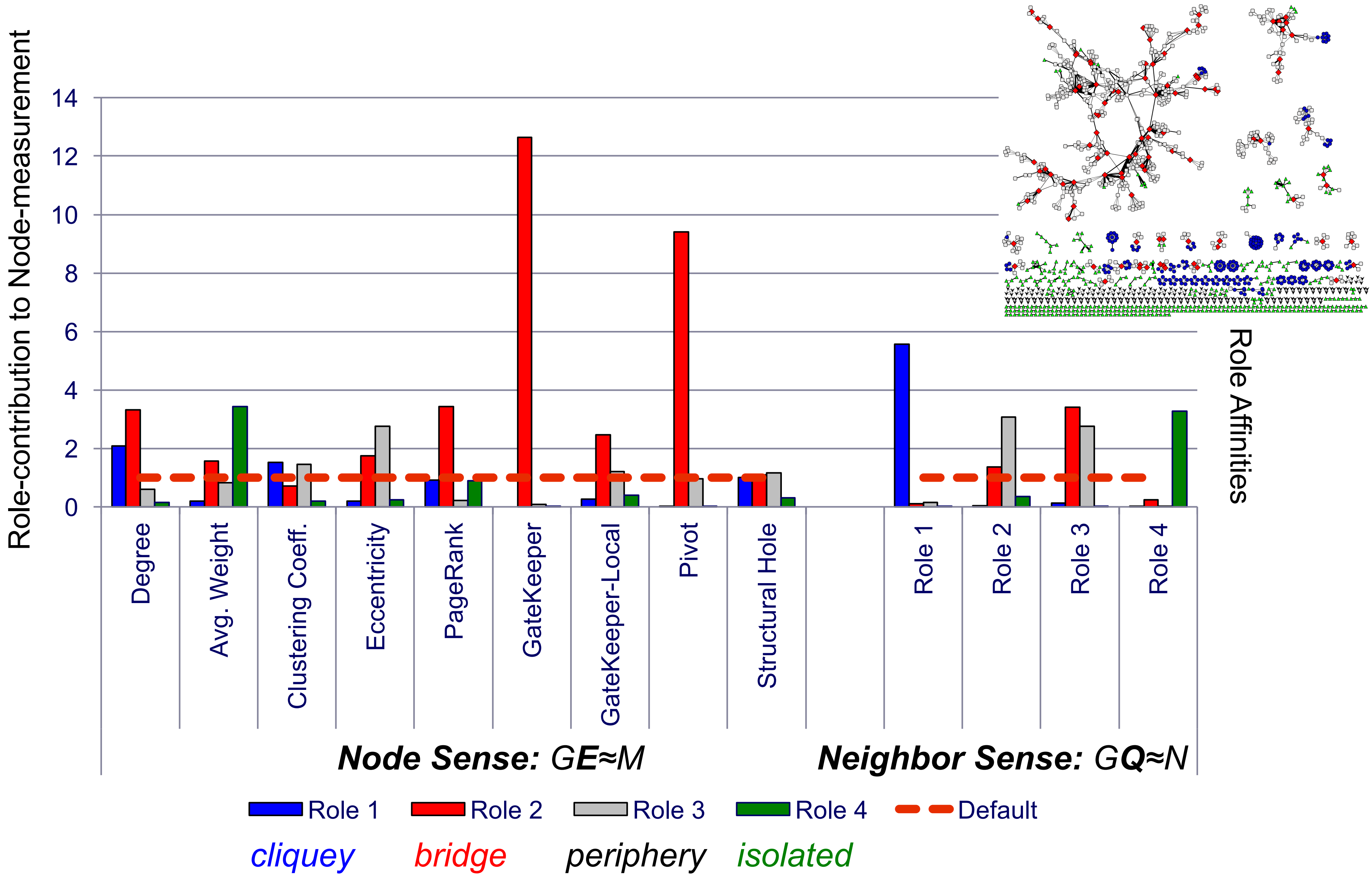
Making Sense of Roles





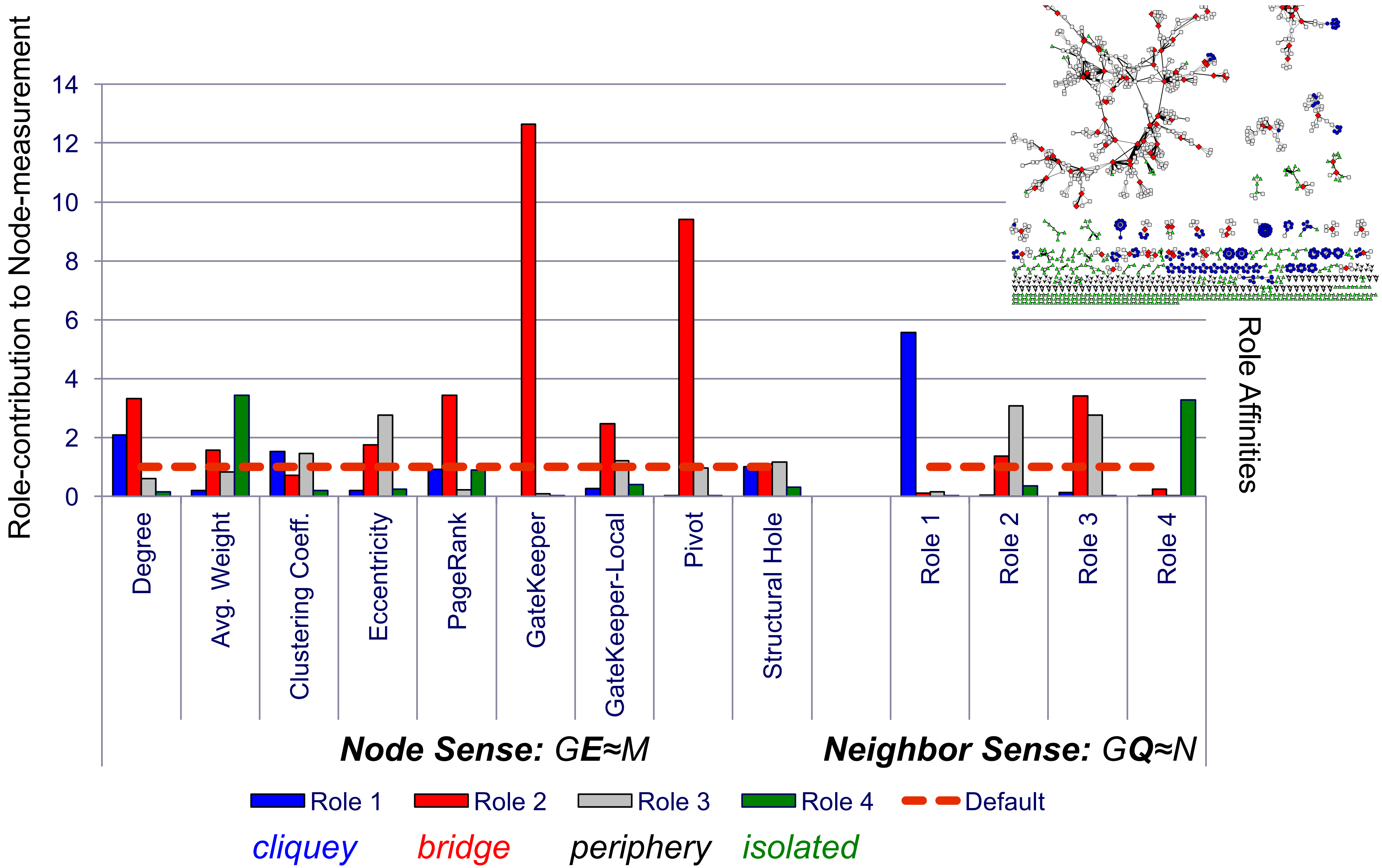
cliquey *bridge* *periphery* *isolated*

Making Sense of Roles



Making Sense of Roles

Topological measures & role homophily help interpret roles.



Applications of role discovery

Task	Use Case
Role query	Identify individuals with similar behavior to a known target
Role outliers	Identify individuals with unusual behavior
Role dynamics	Identify unusual changes in behavior
Re-identification	Identify individuals in an anonymized network
Role transfer	Use knowledge of one network to make predictions in another
Network comparison	Determine network compatibility for knowledge transfer
Exploration in role space	Exploratory analysis of network data in the role space
…	…

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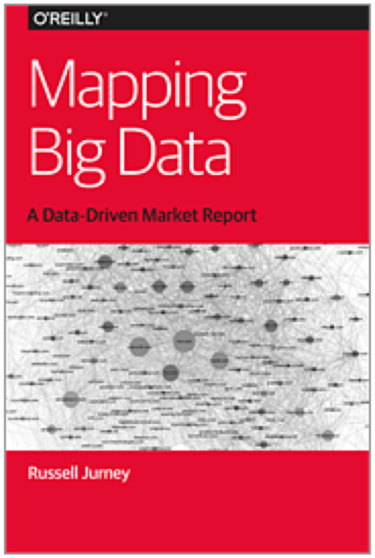


Mapping Big Data

A Data-Driven Market Report

By Russell Jurney

Publisher: O'Reilly
Released: September 2015

Description

To discover the shape and structure of the big data market, the San Francisco-based startup Relato took a unique approach to market research and created the first fully data-driven market report. Company CEO Russell Jurney and his team collected and analyzed raw data from a variety of sources to reveal a boatload of business insights about the big data space. This exceptional report is now available for free download.

Using data analytic techniques such as social network analysis (SNA), Relato exposed the vast and complex partnership network that exists among tens of thousands of unique big data vendors. The dataset Relato collected is centered around Cloudera, Hortonworks, and MapR, the major platform vendors of Hadoop, the primary force behind this market.

From this snowball sample, a 2-hop network, the Relato team was able to answer several questions, including:

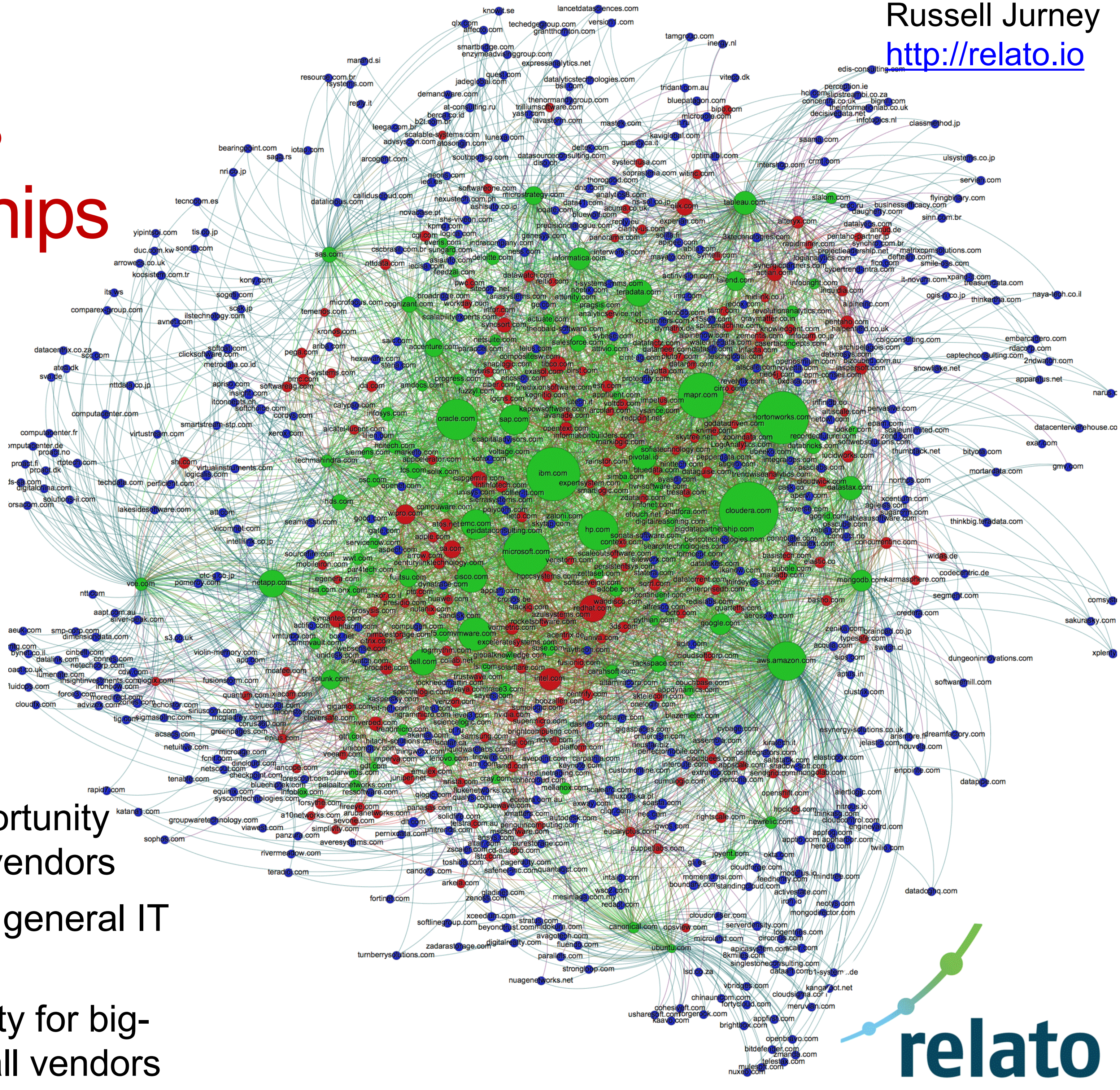
- Who are the major players in the big data market?
- Which is the leading Hadoop vendor?
- What sectors are included in this market and how do they relate?
- Which among the thousands of partnerships are most important?
- Who's doing business with whom?

Metrics used in this report are also visible in Relato's interactive web application, via a link in the report, which walks you through the insights step-by-step.

Russell Jurney is CEO of Relato, a San Francisco area startup that maps markets to drive sales and marketing. He is the author of Agile Data Science *and co-author of* Big Data for Chimps *(both O'Reilly). In addition, Russell is an Apache Committer on the Incubating DataFu project. Russell is a full stack engineer.*

Big data business partnerships

Russell Jurney
http://relato.io

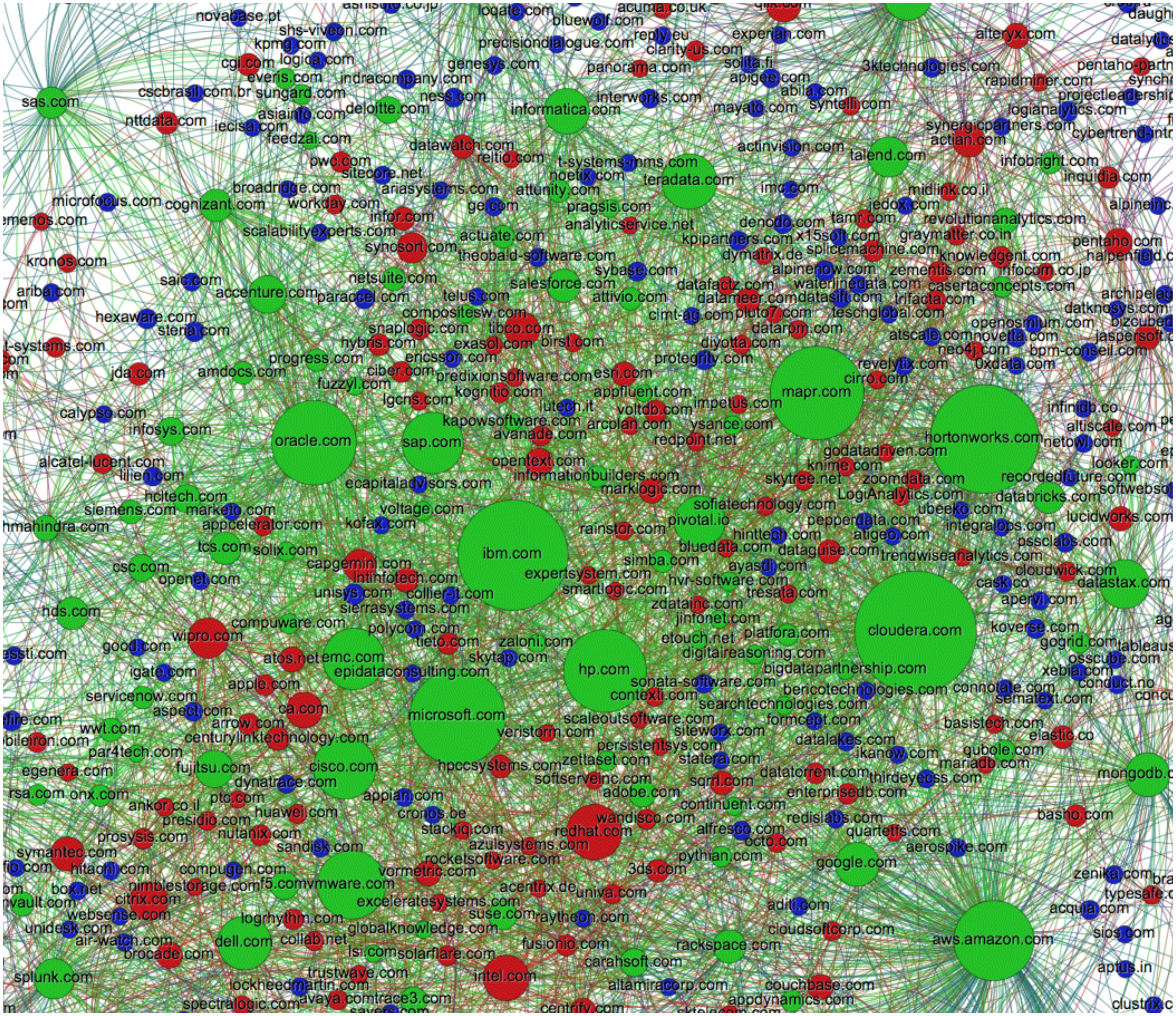


- **Green**: equal opportunity bridges; big-data vendors
- **Red**: middle-men; general IT vendors
- **Blue**: Strong affinity for big-data vendors; small vendors

relato

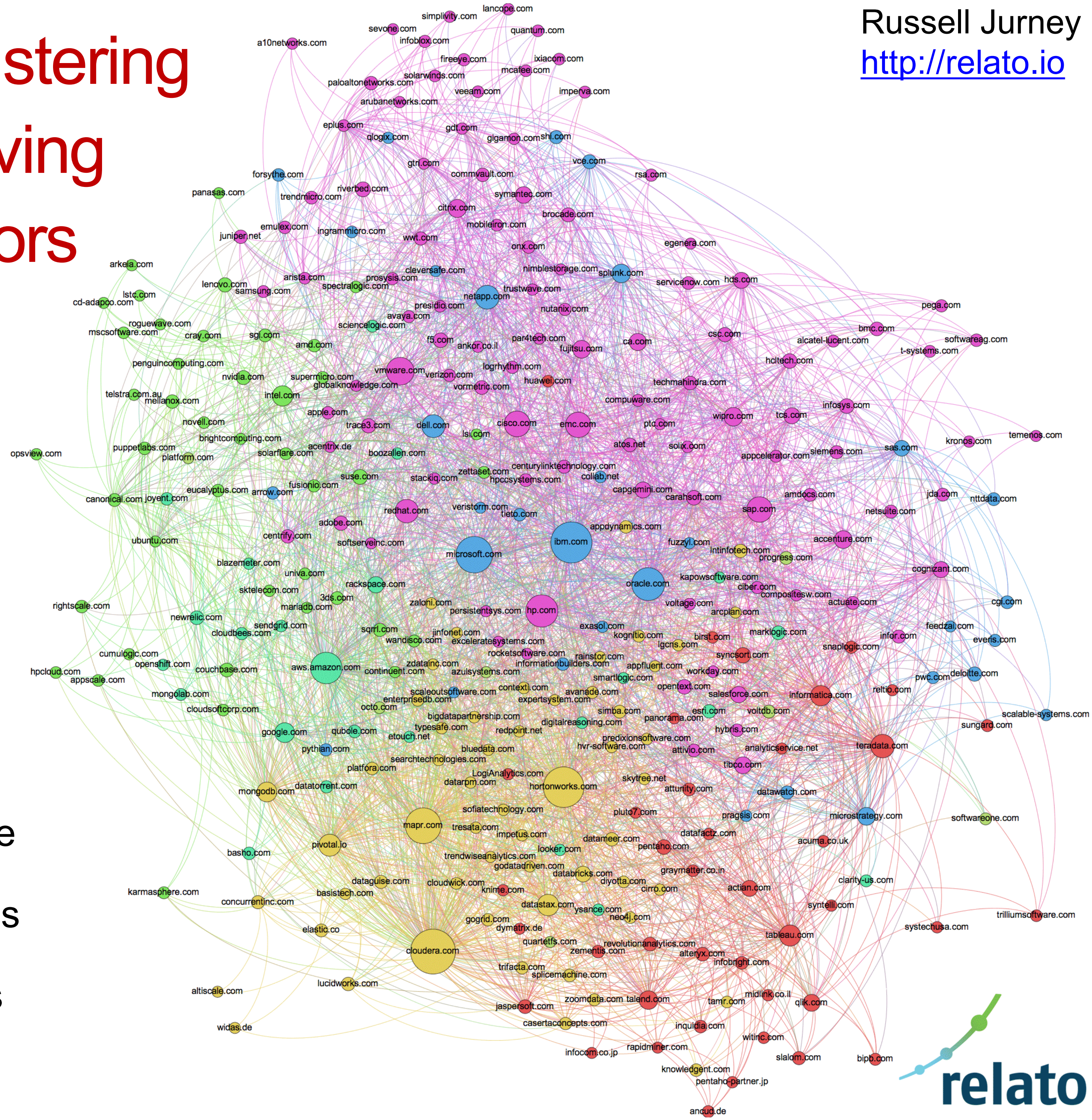
Russell Jurney
http://relato.io

Big-data business-partnerships



Louvain Clustering After Removing Small Vendors (Blue Role)

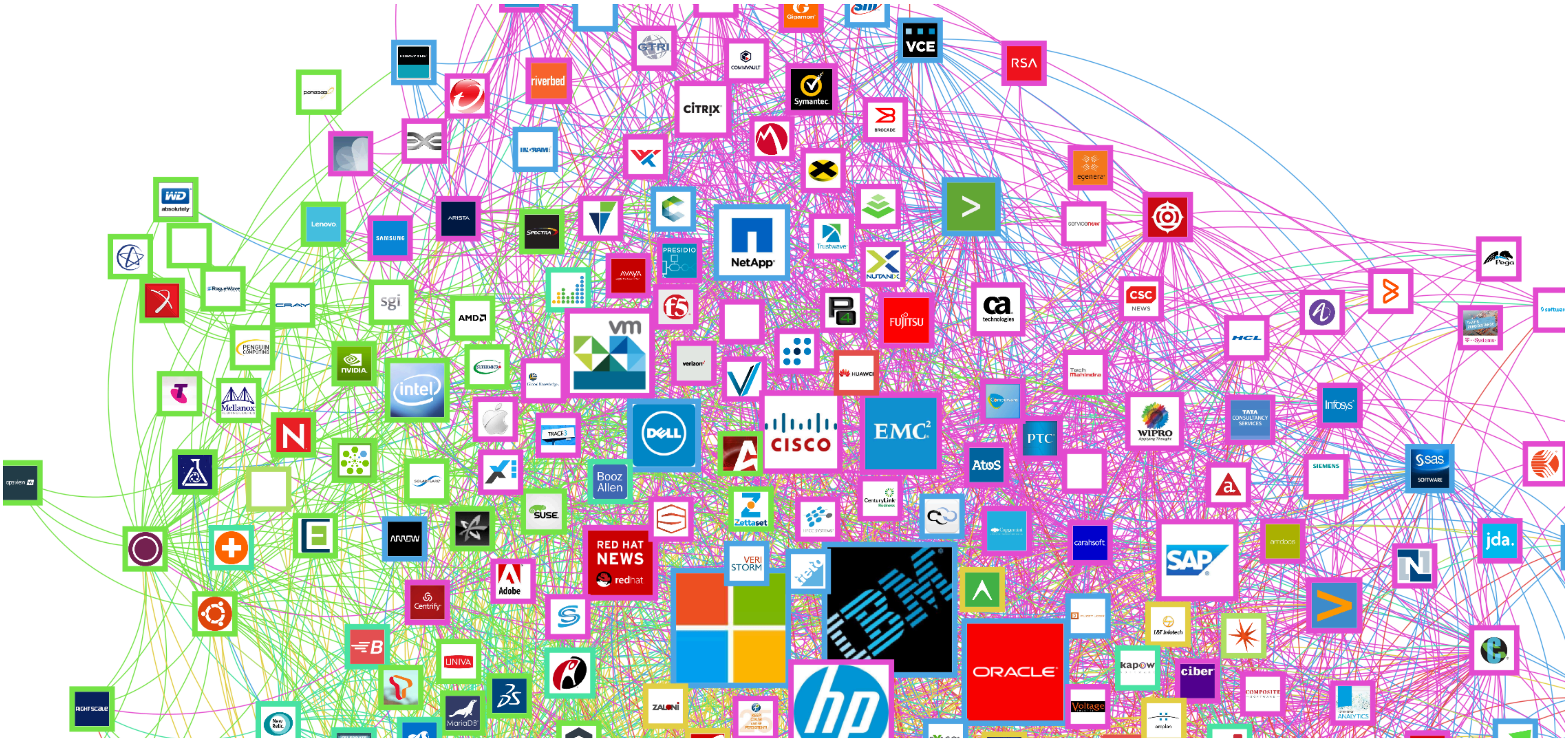
Russell Jurney
http://relato.io



- Analytics Software
- Cloud Computing
- Enterprise Software
- New Data Platforms
- Old Data Platforms
- Servers

An Interactive Market Map of the Big Data Space

- http://demo.relato.io/oreilly and http://demo.relato.io/public



Role Transfer = RolX + SL

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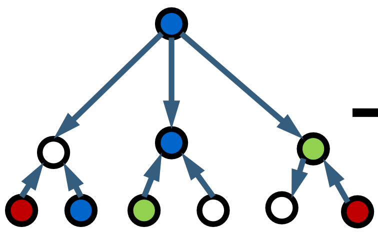


External Network

(1) RolX

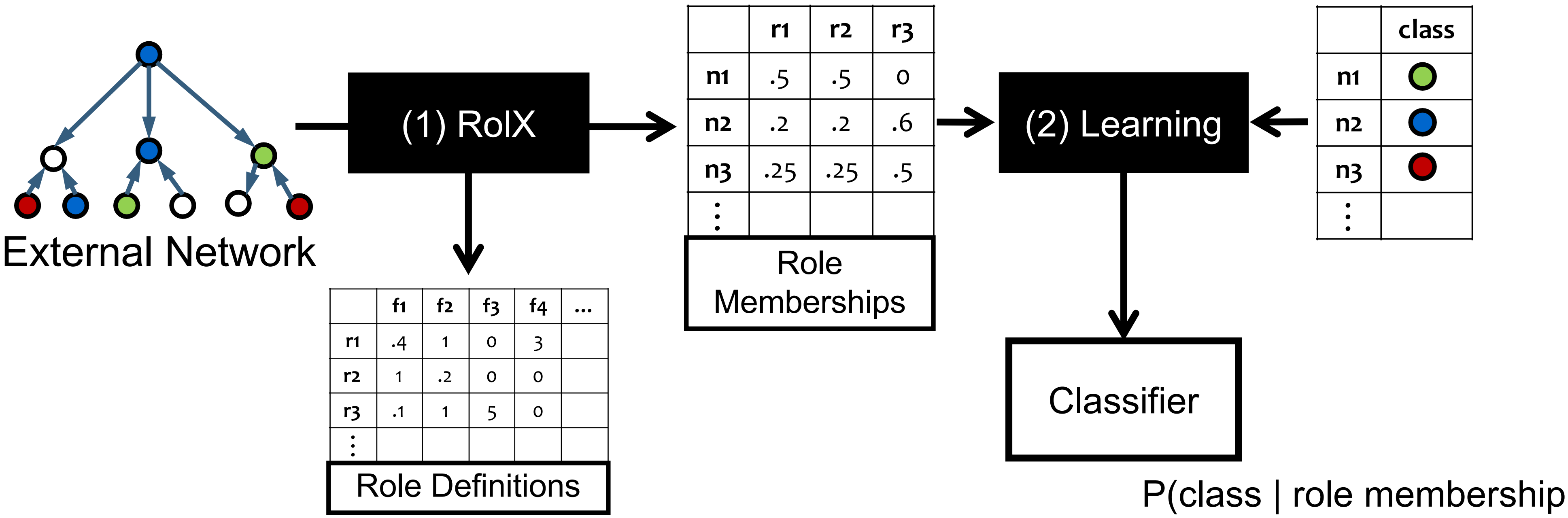
	r1	r2	r3
n1	.5	.5	0
n2	.2	.2	.6
n3	.25	.25	.5
⋮			

Role Memberships

	f1	f2	f3	f4	...
r1	.4	1	0	3	
r2	1	.2	0	0	
r3	.1	1	5	0	
⋮					

Role Definitions

Role Transfer = RolX + SL

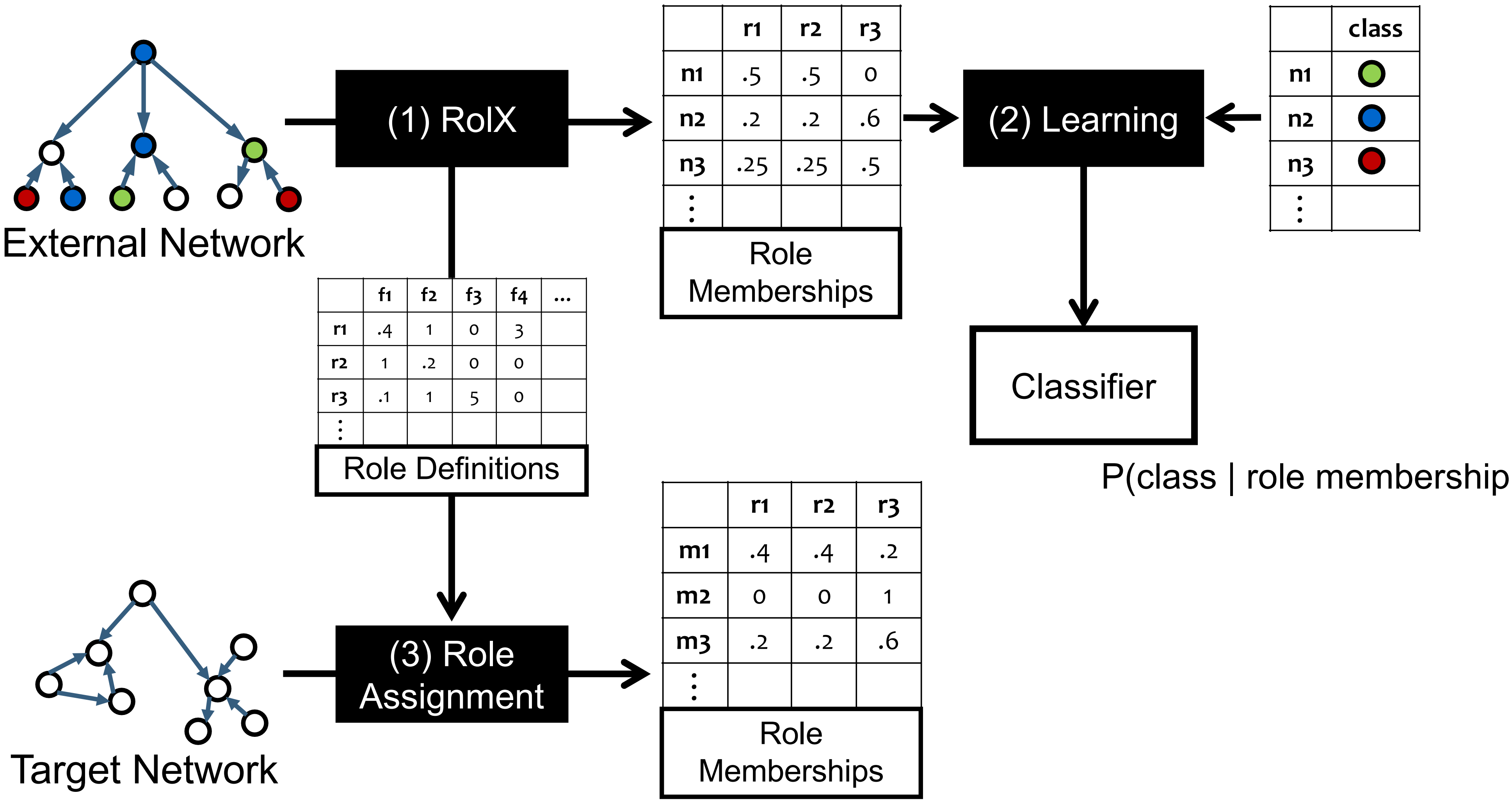


	f1	f2	f3	f4	...
r1	.4	1	0	3	
r2	1	.2	0	0	
r3	.1	1	5	0	
⋮					

	r1	r2	r3
n1	.5	.5	0
n2	.2	.2	.6
n3	.25	.25	.5
⋮			

	class
n1	
n2	
n3	
⋮	

Role Transfer = RolX + SL



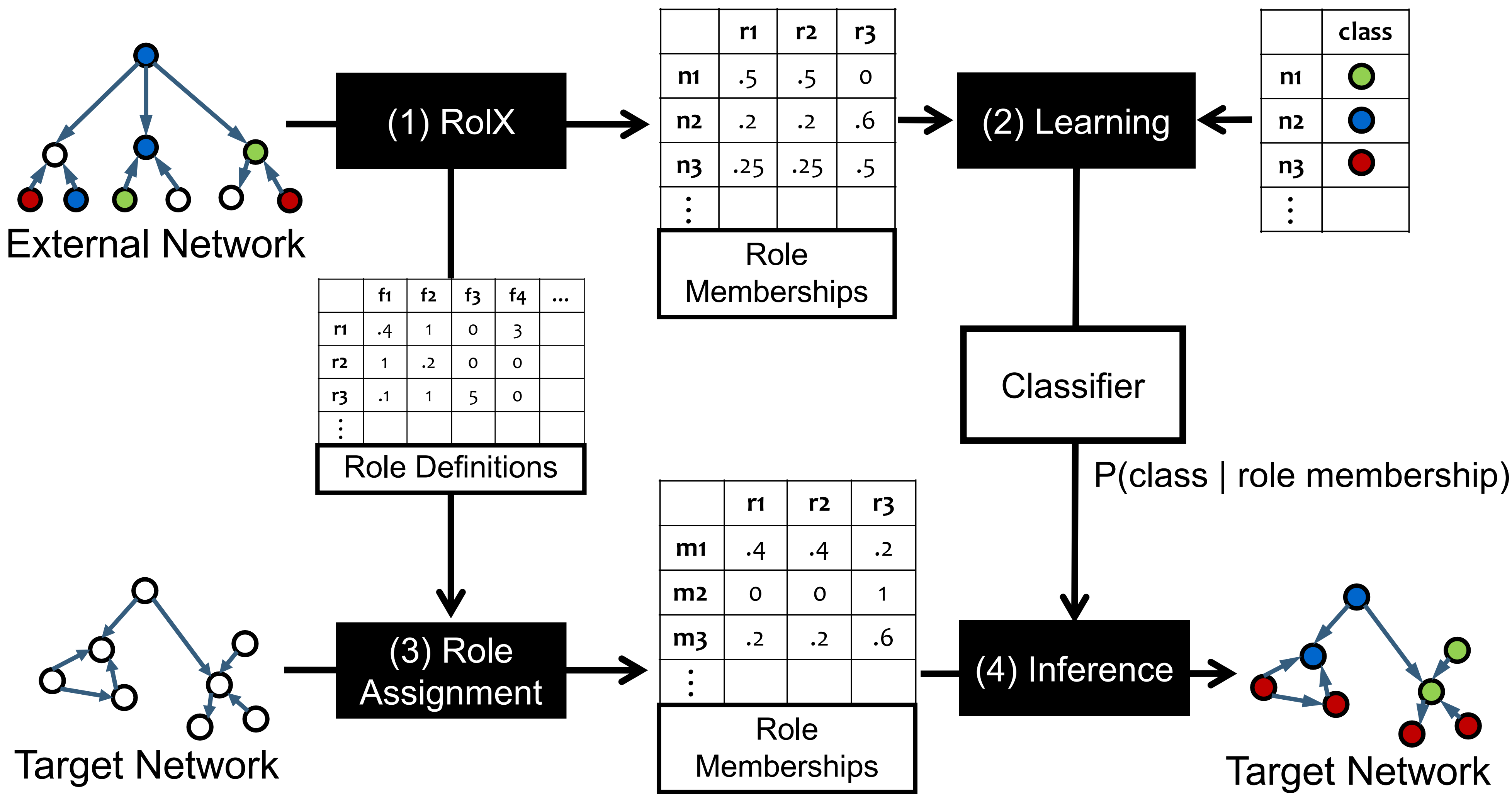
	r1	r2	r3
n1	.5	.5	0
n2	.2	.2	.6
n3	.25	.25	.5
⋮			

	class
n1	
n2	
n3	
⋮	

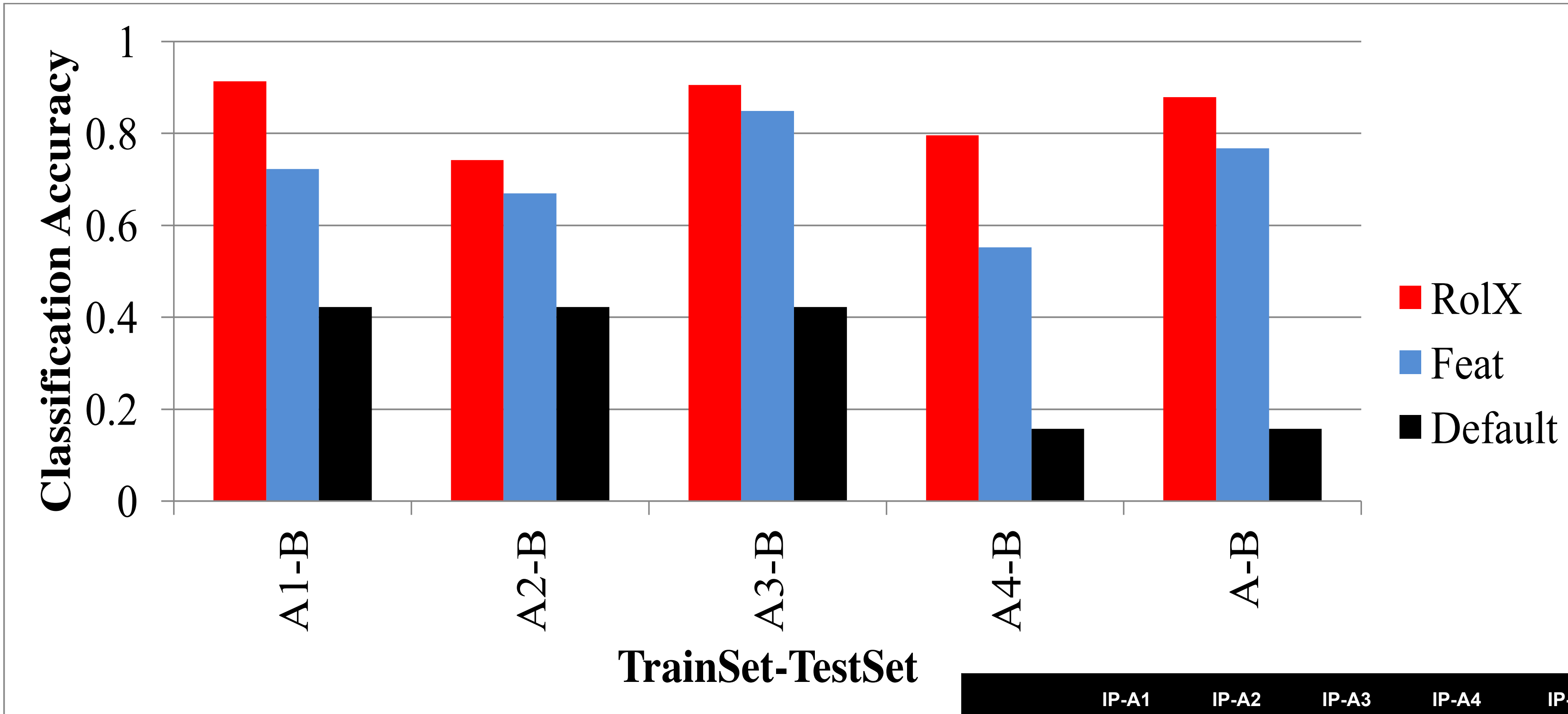
	f1	f2	f3	f4	...
r1	.4	1	0	3	
r2	1	.2	0	0	
r3	.1	1	5	0	
⋮					

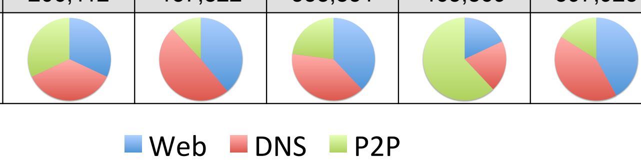
	r1	r2	r3
m1	.4	.4	.2
m2	0	0	1
m3	.2	.2	.6
⋮			

Role Transfer = RolX + SL



Roles Generalize Across Disjoint Networks



	IP-A1	IP-A2	IP-A3	IP-A4	IP-B
# Nodes	81,450	57,415	154,103	206,704	181,267
% labeled	36.7%	28.1%	20.1%	32.9%	15.3%
# Links	968,138	432,797	1,266,341	1,756,082	1,945,215
(# unique)	206,112	137,822	358,851	465,869	397,925
Class Distribu-tion					

2nd Generation Algorithms for Role Discovery

- GLRD: guided learning for role discovery
  - [Gilpin et al., KDD 2013]
- DBMM: dynamic behavioral mixed-membership model
  - [Rossi et al., WSDM 2013]
- RC-Joint: simultaneous detection of communities and roles
  - [Ruan & Parthasarathy, COSN 2014]
- Motif-Role-Fingerprints
  - [McDonnell et al., PLoS ONE 9(12), 2014]

- Dynamic inference of social roles in information cascades
  - [Choobdar et al., DMKD 29(5), 2015]
- MRD: multi-relational role discovery
  - [Gilpin et al., ArXiv 2016]
- DERM: dynamic edge role mixed-membership model
  - [Ahmed et al., ArXiv 2016]
- A combinatorial approach to role discovery
  - [Arockiasamy et al., ICDM 2016]
- …

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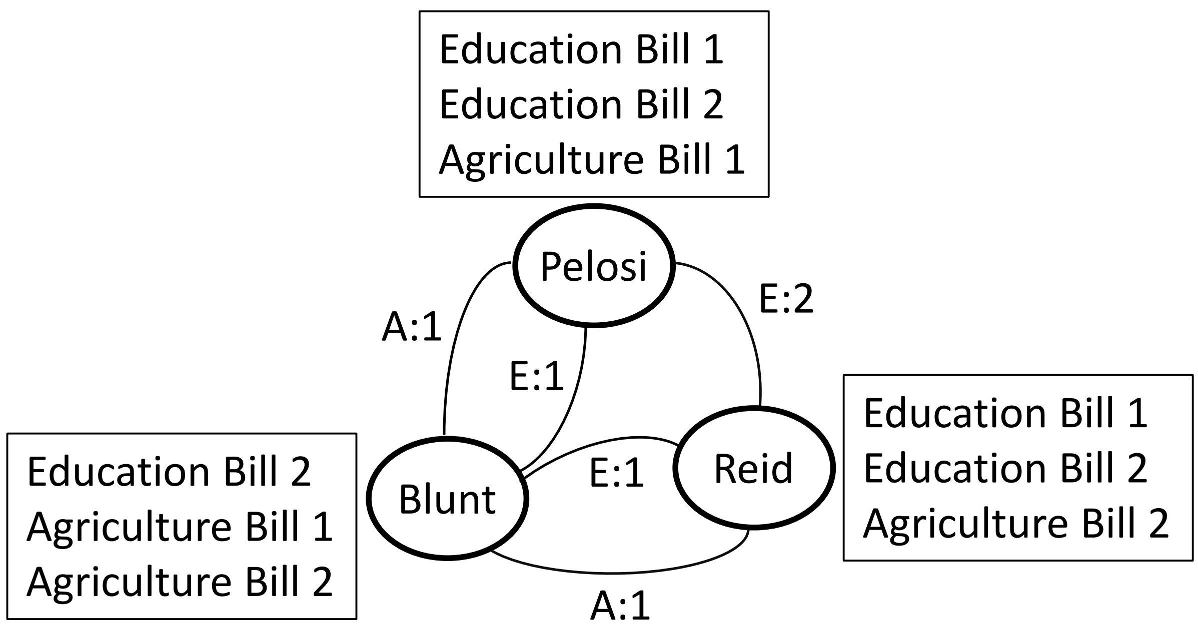
- …

Multi-relational Role Discovery (MRD)

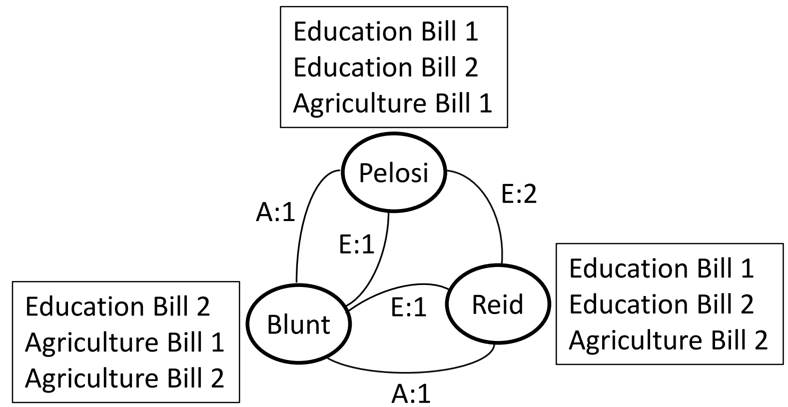
- Moving beyond simple networks
- Suppose you have a multi-relational networks
- Example: Congressional co-sponsorship data

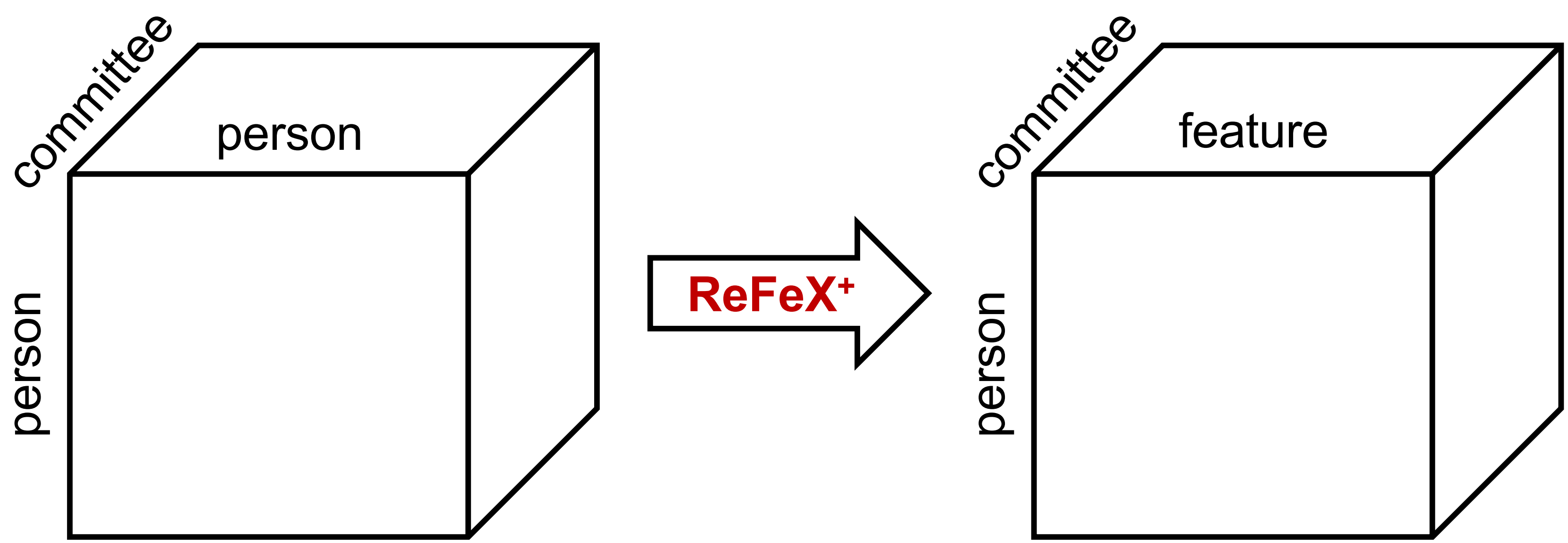


[Gilpin et al., ArXiv 2016]

No longer have an adjacency matrix

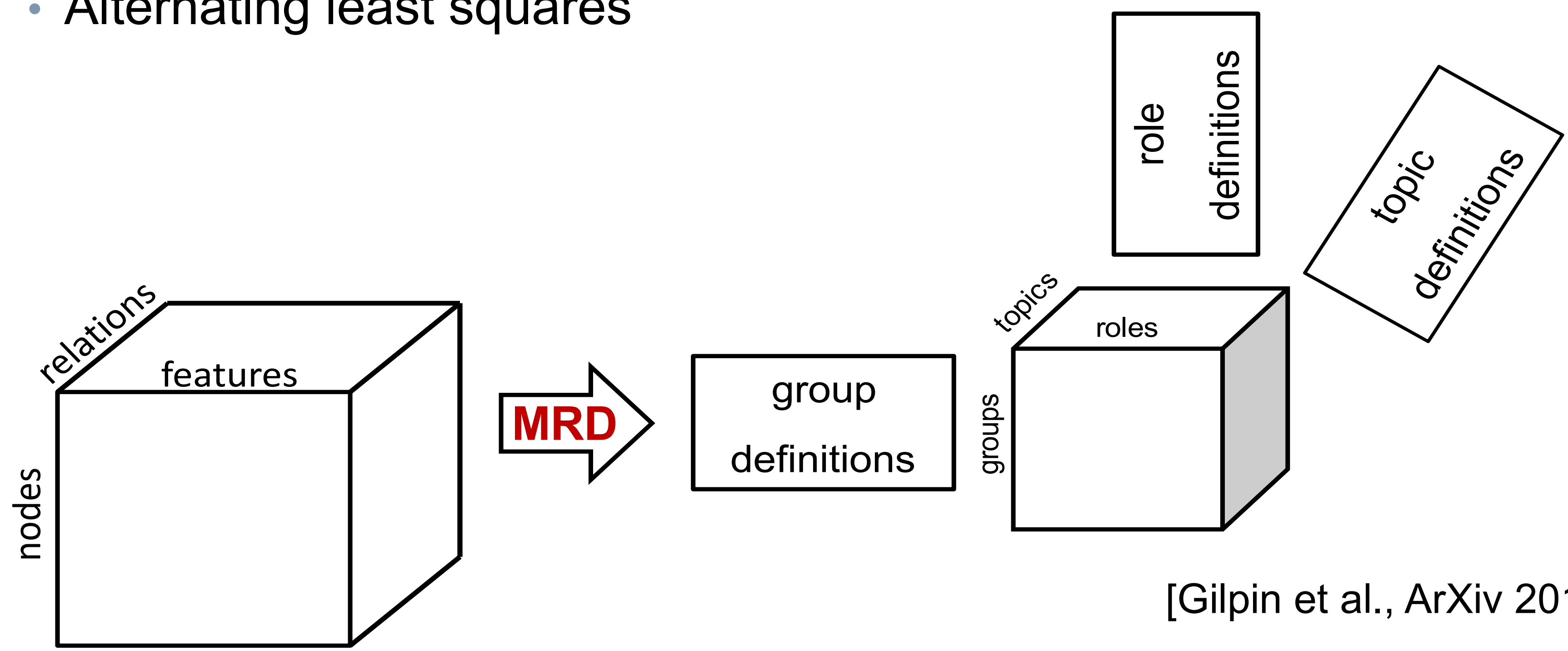
- We have a `person` × `person` × `committee` tensor
- Entry at (*i* , *j*, *k*) indicates how often congress-person *i* and *j* co-sponsored a bill that was sent to committee *k* for a particular congressional committee





Multi-relational Role Discovery (MRD)

- *Multi-relational Role Discovery* (MRD)
  - No orthogonality constraint on factors
  - Nonnegative Tucker decomposition
  - Alternating least squares
- The factor matrices are:
  - groups of features (*role* definitions)
  - groups of entities (*groups*)
  - groups of relations (*topics*)
- Tucker core



[Gilpin et al., ArXiv 2016]

Multi-relational Role Discovery (MRD)

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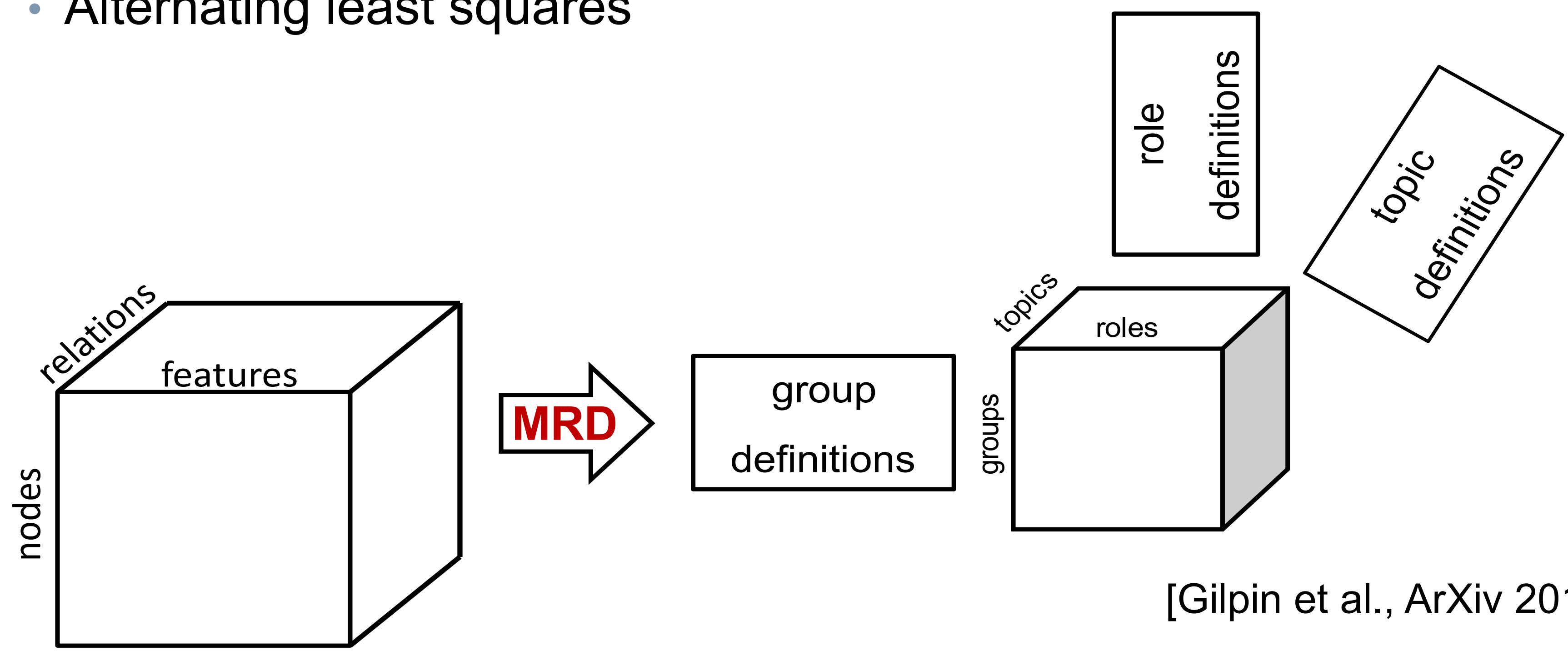
$$\begin{aligned} \underset{\mathbf{G},\mathbf{F},\mathbf{R},\mathcal{H}}{\text{argmin}} \quad & ||\mathcal{V} - \sum_i \sum_j \sum_k h_{ijk} * \mathbf{g_k} \circ \mathbf{f_k} \circ \mathbf{r_k}||_{Fro} \\ \text{subject to:} \quad & \mathbf{G} \geq \mathbf{0}, \mathbf{F} \geq \mathbf{0}, \mathbf{R} \geq \mathbf{0}, \mathcal{H} \geq \mathbf{0} \\ & g_i(\mathcal{H}) \leq d_{\mathcal{H}_i}, i = 1 \ldots t_{\mathcal{H}} \\ & \textit{where } g_i \textit{ is a convex function} \end{aligned}$$



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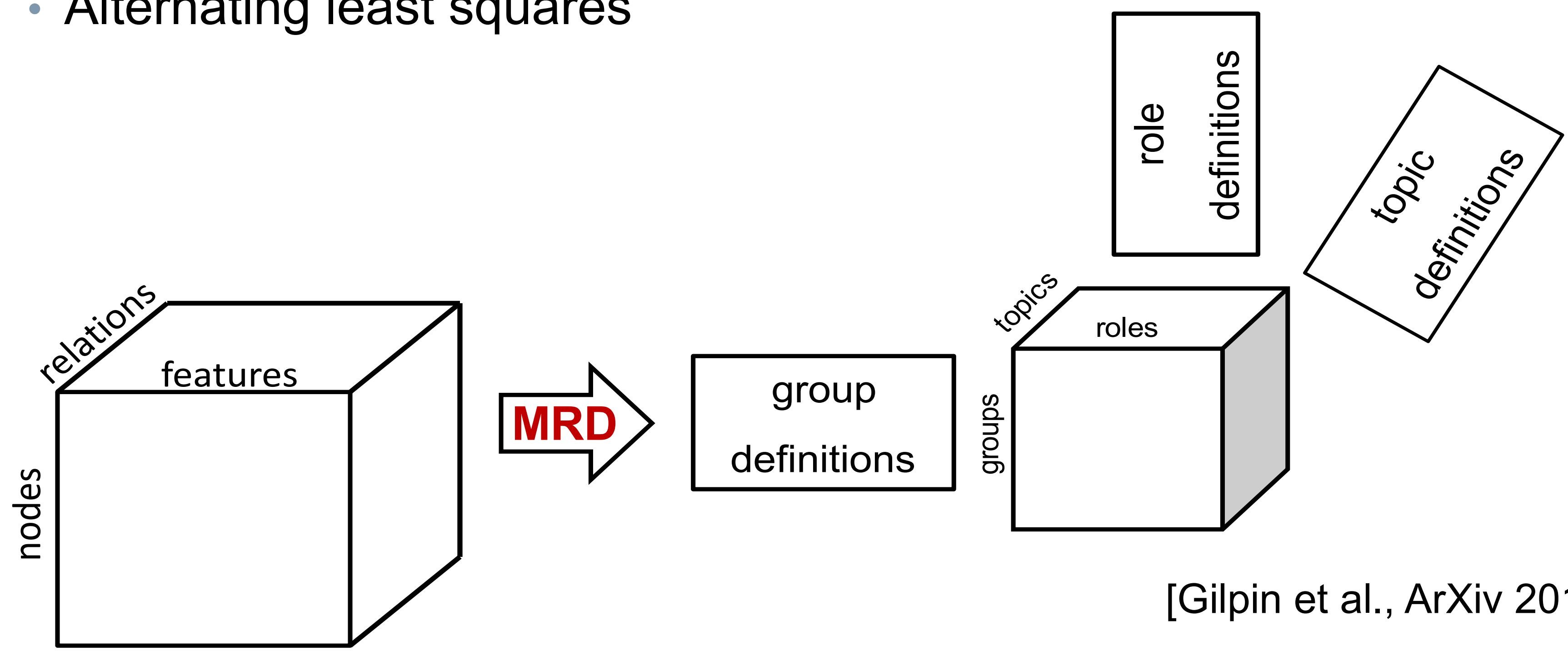


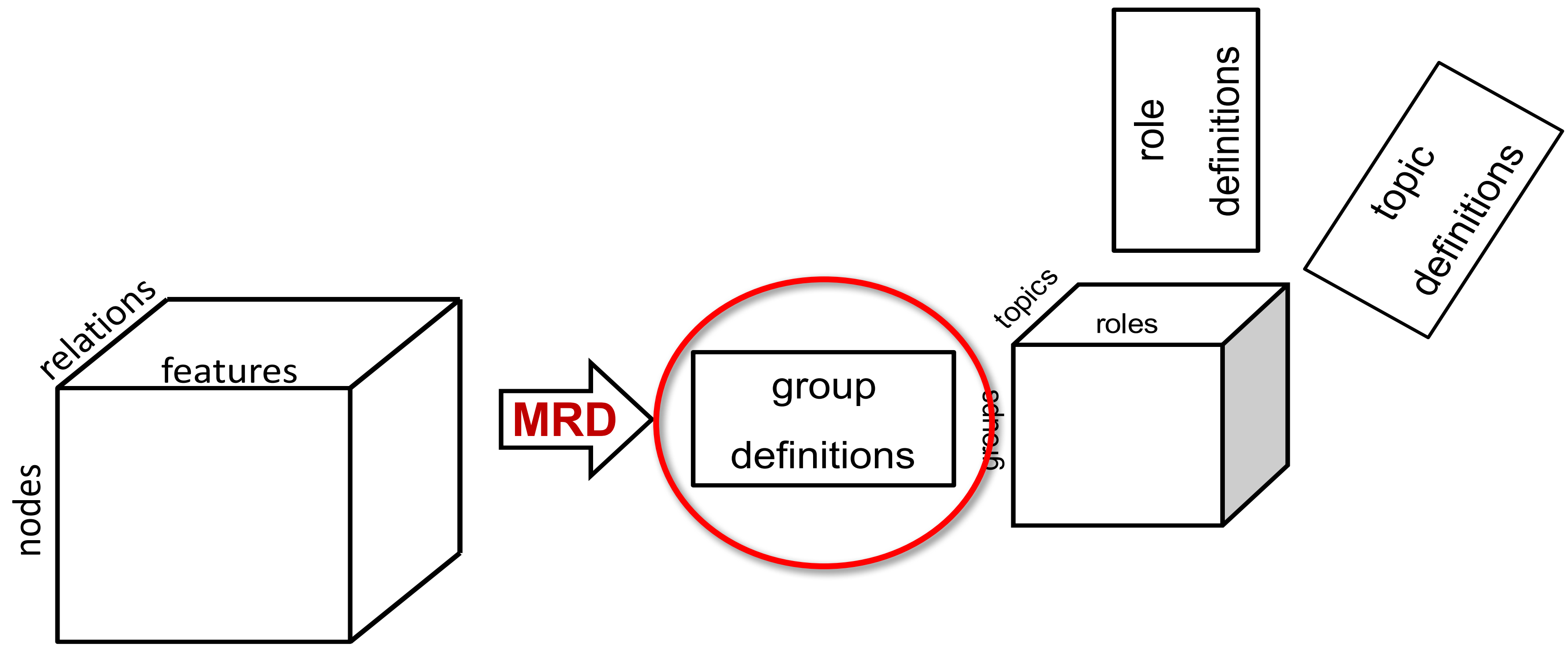
[Gilpin et al., ArXiv 2016]

Experiments

- Data from U.S. House of Representatives
- Bill co-sponsorship data from 1979 (the start of the 96^{th} Congress) to 2009 (the end of the 110^{th} Congress)
- 15 committees, for which there were legislation in each congress from 96^{th} to 110^{th}
- 110^{th} Congress (from 2007-09)
  - 453 representatives & 10,613 bills
  - Average degree in aggregated graph = 8.37
  - Median value of average degree across committee co-sponsorship graphs = 0.48

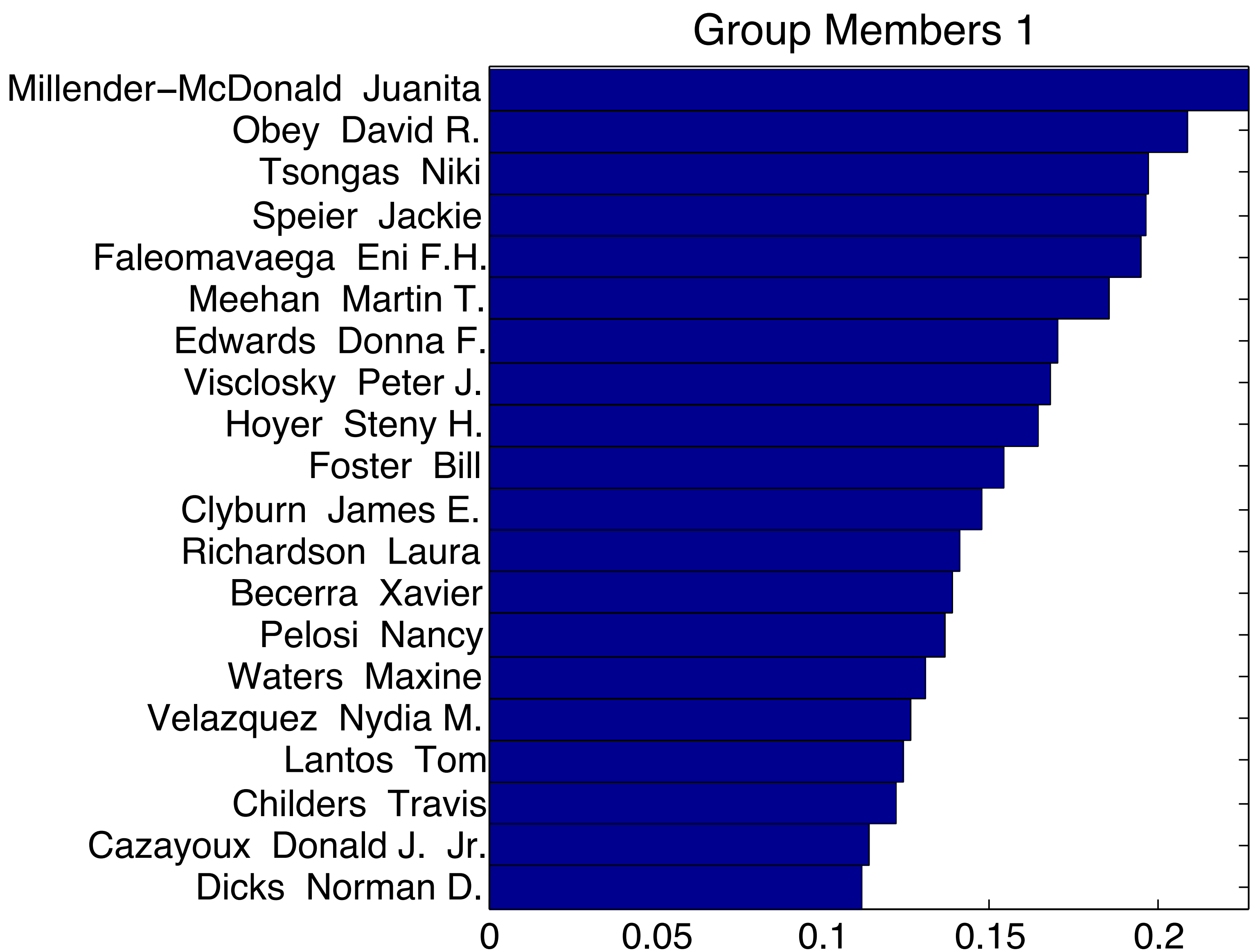
Sci & Tech
Judiciary
Ways & Means
VA
Small Business
Budget
Oversight & Gov't Reform
Agriculture
Appropriations
Rules
Natural Resources
Financial Services
Education & Labor
Transportation & Infrastructure
Energy & Commerce

Multi-relational Role Discovery (MRD)



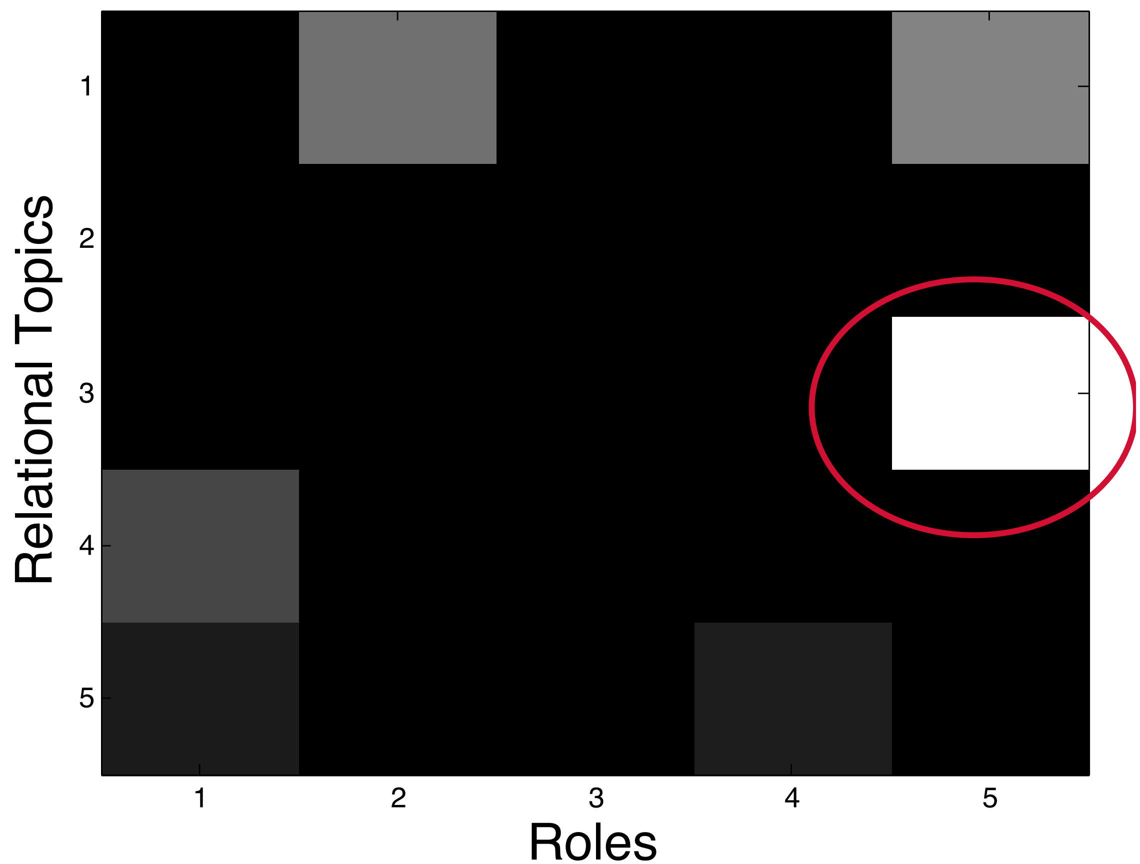
[Gilpin et al., ArXiv 2016]

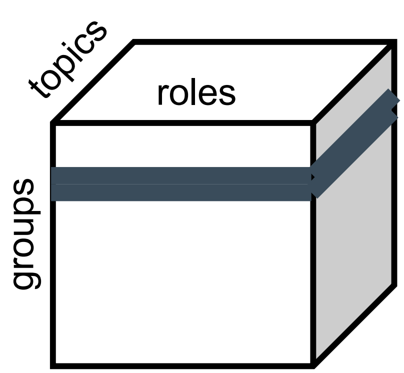
Groups of representatives



Group 1 of representatives

Name	Party	Exp
Millender-McDonald	D	11
Obey, David	D	38
Tsongas, Niki	D	0
Speier, Jackie	D	0
Faleomavaega, Eni	D	18
Meehan, Martin	D	14
Edwards, Donna	D	0
Visclosky, Peter	D	22
Hoyer, Steny	D	26
Foster, Bill	D	0





More insights into Group 1

Group 1

Name	Party	Exp
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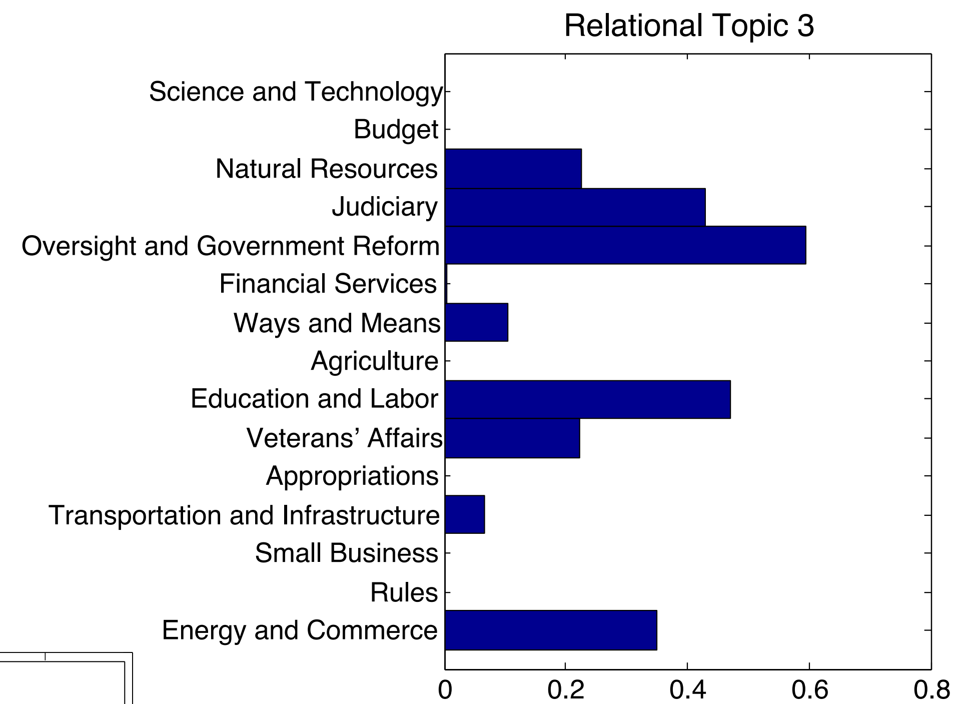
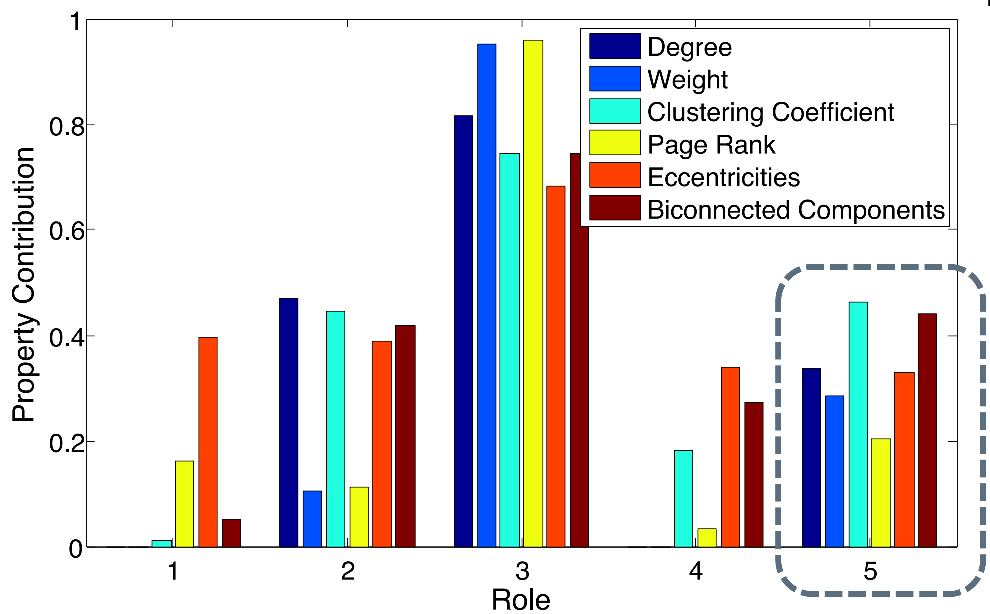


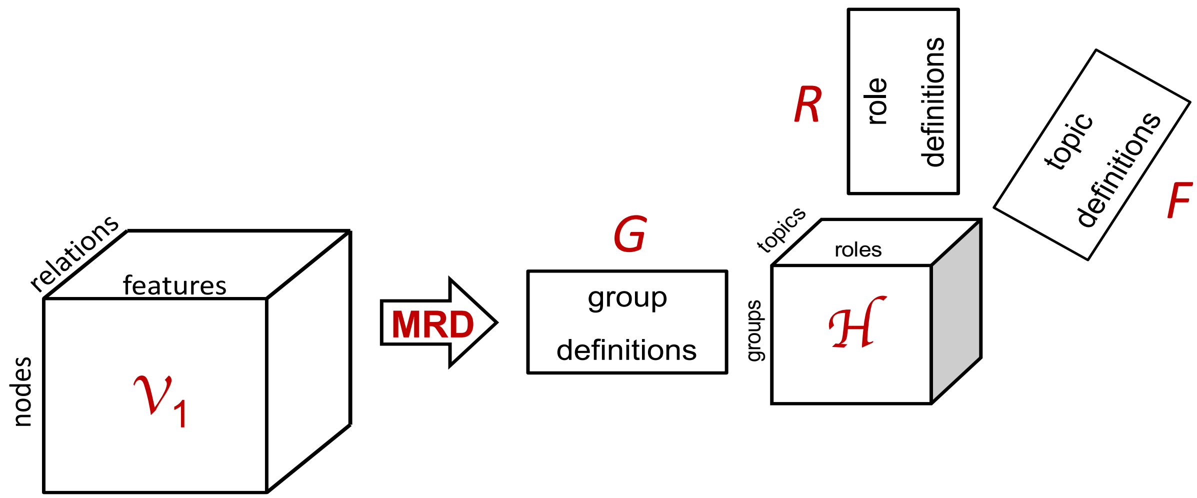


<u>Group 1</u>

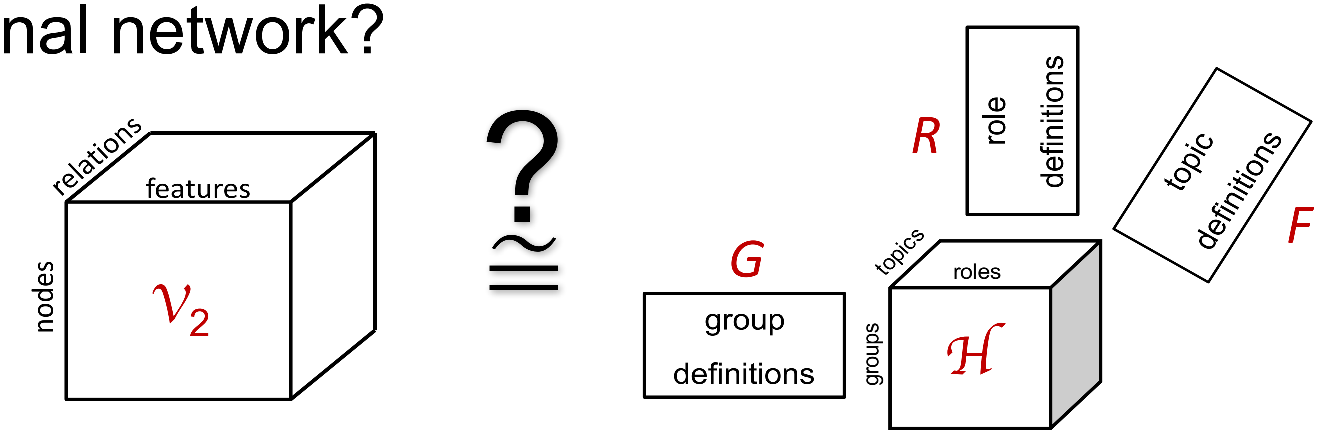
- Democrats; mostly not mid-career
- Active in oversight & gov't reform
- On the periphery, but lots of triangles

Role Transfer in MRD

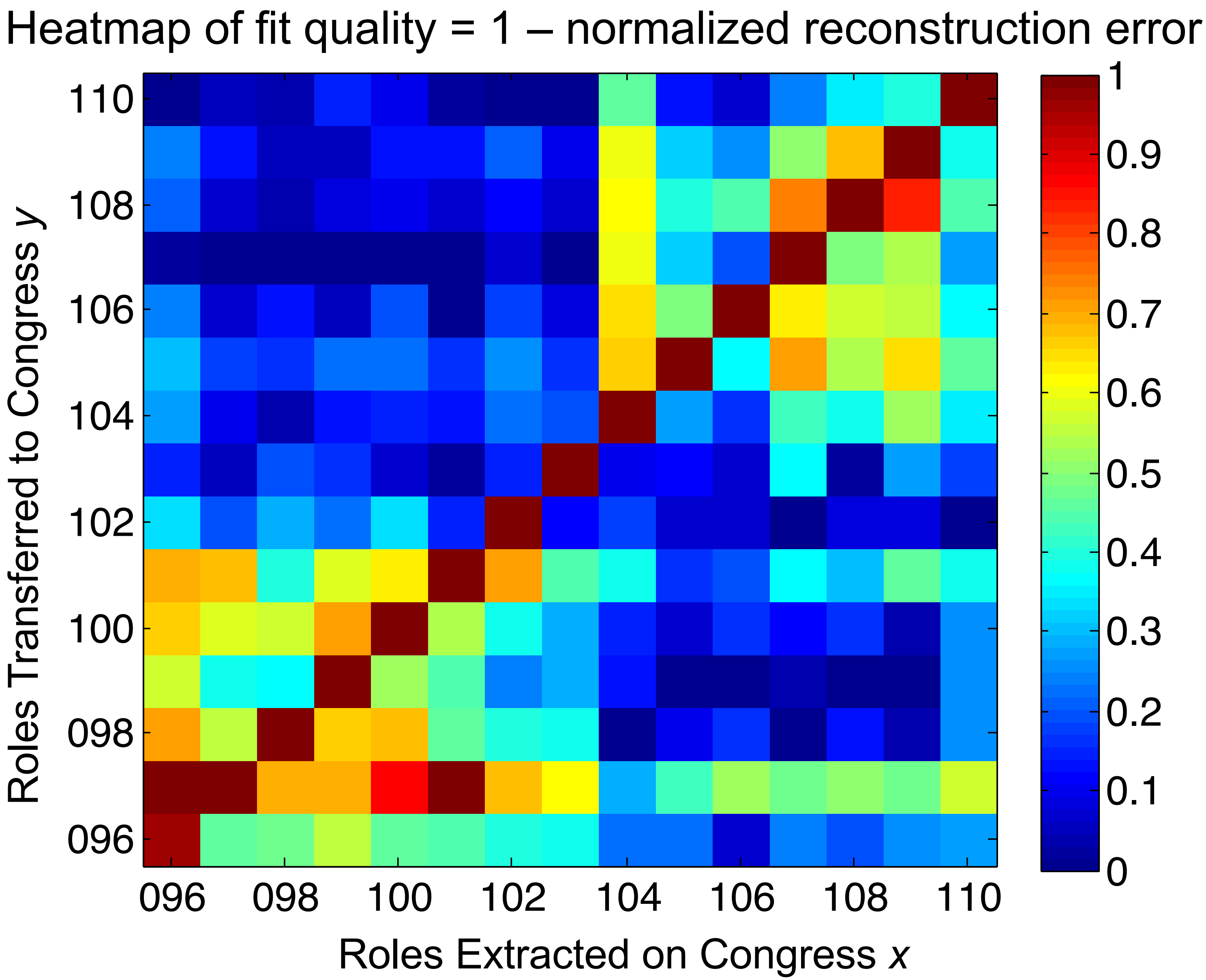
- Extract roles on one multi-relational network



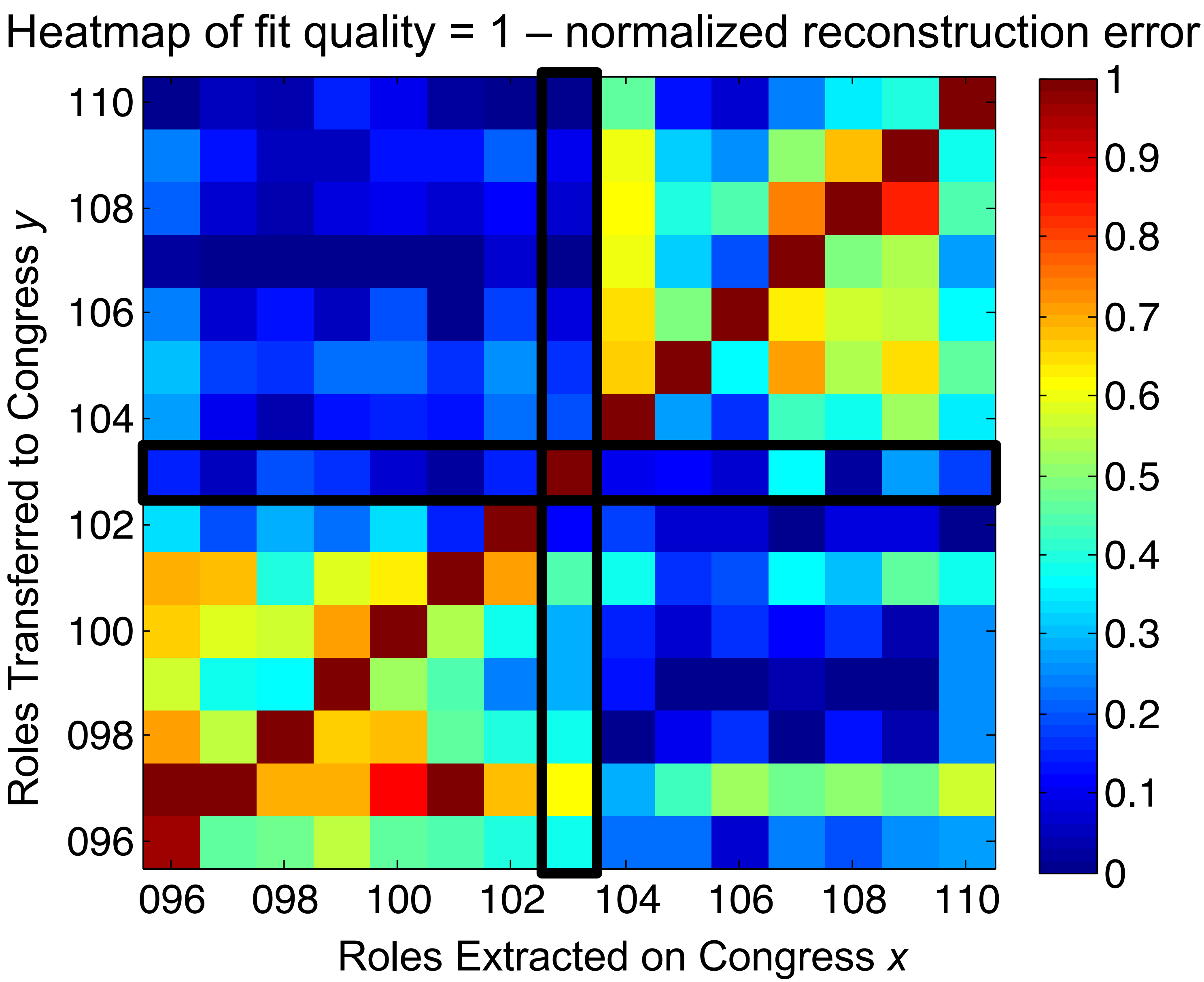
- How well do the extracted roles transfer to another multi-relational network?



Role Transfer on Multi-relational Networks



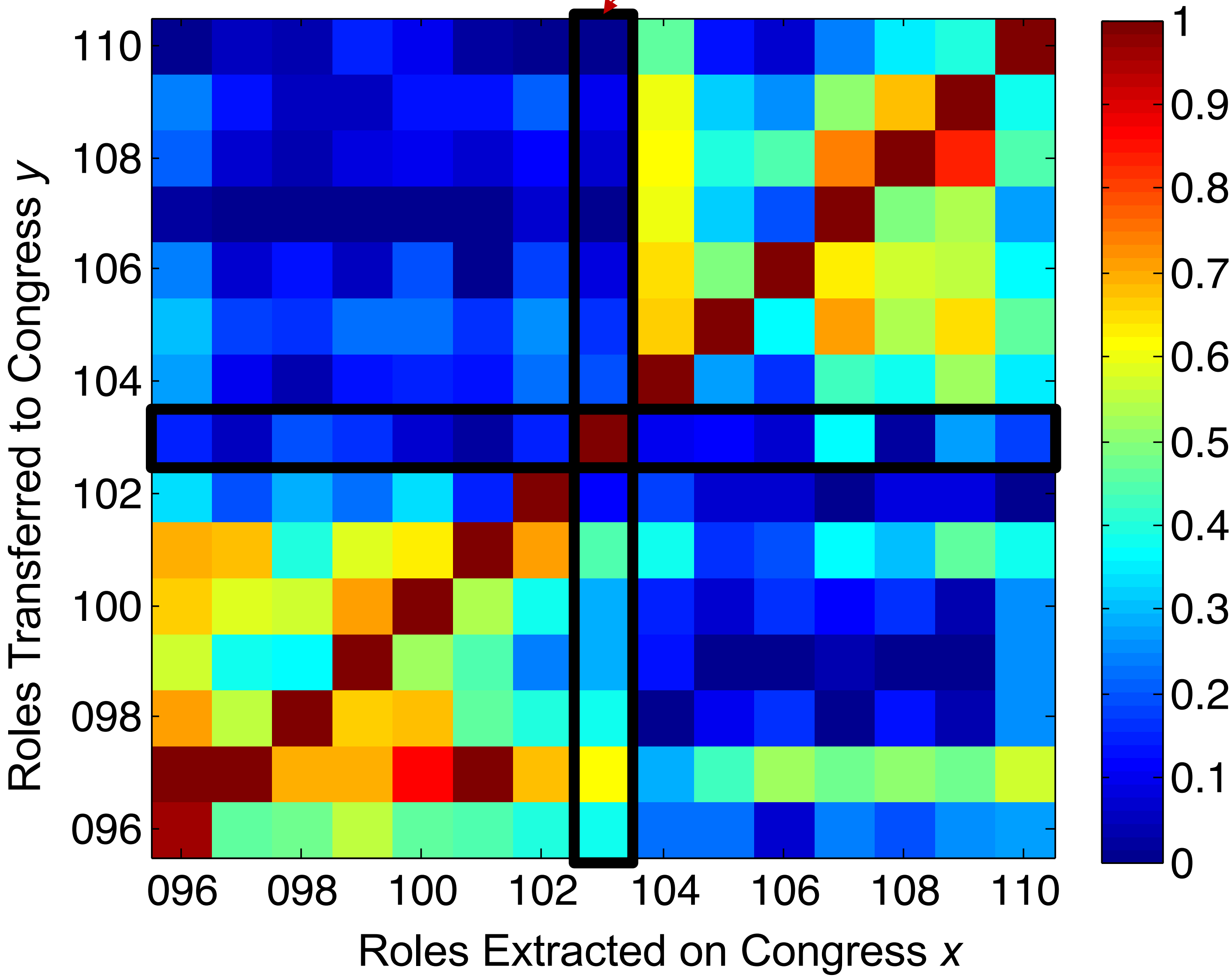
Role Transfer on Multi-relational Networks



Role Transfer

Hastert Rule: the Speaker will not allow a floor vote on a bill unless a majority of the majority party supports the bill.

Heatmap of fit quality = 1 – normalized reconstruction error



Why are Roles Effective in Many Applications?

- Encode complex behavior
- Map nodes into a useful lower dimensional space
- Generalize across networks

Lots more to do …

- An in-depth study on properties of these latent role spaces
- Information spread through roles
    - How roles affect influence & susceptibility?

Lots more to do …

- An in-depth study on properties of these latent role spaces
- Information spread through roles
  - How roles affect influence & susceptibility?
- Combining physics of networks (PoN) with the mining of graphs (MoG)
  - What are the functional roles in an ensemble of networks?
  - How do we incorporate functional roles from instances of networks into PoN models?

Papers, Tutorials, Code

- Papers at http://eliassi.org/pubs.html
- Tutorials at http://eliassi.org
- Open-source code at https://snap.stanford.edu/snap-2.3/
- Role discovery is joint work with
  - LLNL (Keith Henderson & Brian Gallagher)
  - CMU (Christos Faloutsos, Leman Akoglu et al.)
  - Google (Sugato Basu)
  - UC Davis (Ian Davidson et al.)

WOMAN IN COMPUTING

GHC: Grace Hopper Celebration of Women in Computing

- https://ghc.anitaborg.org
- Sponsored by
  - Anita Borg Institute for Women in Technology
  - Association for Computing Machinery (ACM)

Anita Borg

Telle Whitney

- Backstory from Wikipedia

"In 1994, Anita Borg and Telle Whitney founded the Grace Hopper Celebration of Women in Computing. With the initial idea of creating a conference by and for women computer scientists, Borg and Whitney met over dinner, with a blank sheet of paper, having no idea how to start a conference, and started to plan out their vision."

History of GHC

- https://ghc.anitaborg.org
- 1st GHC in June 1994, 500 technical women attended
- 2nd GHC in 1997
- Held annually since 2006
- 15K attended the opening of the GHC 2016
- There is also a GHC India since 2016

GHC 2016, Picture from NY Times
http://nyti.ms/2qNa998

CRA-W

- CRA-W: Computing Research Association - Committee on the Status of Women in Computing Research
- http://cra.org/cra-w/
- Established in 1991 by
  Nancy Leveson and Maria Klawe

NANCY LEVESON

MARIA KLAWE

- Mission: "To increase the success and participation of women in computing research and education at all levels."
- Known for their excellent career mentoring workshops
- Sponsors many conferences, programs, and projects
- Offers fellowships and awards

Women in Machine Learning (WiML)

- http://wimlworkshop.org/
- Idea started in NIPS 2005 when Hanna Wallach, Jenn Wortman Vaughan, Lisa Wainer, and Angela Yu shared a room
- Amy Greenwald helped Jenn, Hanna, and Lisa with the NSF proposal that funded the endeavor initially

Hanna Wallach

Jenn Wortman Vaughan

Amy Greenwald

WiML’s Mission from http://wimlworkshop.org/

Our mission is to enhance the experience of women in machine learning, and thereby…

Increase the number of women in machine learning

Help women in machine learning succeed professionally

Increase the impact of women in machine learning in the community and the world

WiML History

- 1st WiML in 2006
  - Co-located with GHC
  - Almost 100 participants (3 men!)
  - Nearly 60 student presenters
- 2008: GHC → NIPS
- WiML 2015:
  - Still co-located with NIPS
  - 265 registered participants (at capacity!)
  - 130 posters (200 submitted)

Women in Machine Learning

Diversity Matters

- The power of computation is constantly changing our daily lives
  - open-source movement: the best way to design software that will be useful to many [people of diverse backgrounds] is to see it to it that it is programmed by many
- Machine learning is so pervasive (big data, statistics, optimization, applied math, etc.) that it is all the more important that ML is diverse
- While WiML is of course about women, our efforts increase diversity need to reach beyond only (white) women to all underrepresented minorities and to people of all (or no) sexual orientations

Diversity Matters (cont.)

- BPDM: Broadening Participation in Data Mining
- http://www.dataminingshop.com/
- Started in 2012
- Mission: "To foster mentorship, guidance, and connections of minority and underrepresented groups in Data Mining, while also enriching technical aptitude and exposure."
- Workshop associated with data mining conferences, SIAM SDM and ACM KDD
- Provides scholarships to attend conferences

Brandeis Marshall

Caio Soares

The Pretty-Good Present

- CVPR 2016:
  - Organizers: 21 out of 26 organizers are women!
- ICML 2015:
  - Invited speakers: 1 out of 3 invited speakers were women
  - Tutorials: 2 out 6 tutorials were given by (sole) women
  - Board: 5 out of 23 members of the current IMLS board are women

The Not-So-Good Present

- AISTATS 2015:
  - Invited speakers: 0 out of 4 invited speakers were women
  - Orals: 0 (?) out of 27 contributed talks were given by women
  - Attendees: 14 out of 251 attendees were women
- COLT:
  - Invited speakers: Since 2004, 1 out of the 31 invited speakers have been women
  - Steering committee: 1 out of 10 on the steering committee is a woman

The Not-So-Good Present (cont.): NIPS 2015

- Participants: 3600 total; 13.7% women (~500); 2.9% didn't respond, 83.4% men
- Tutorials: 0 women
- Invited speakers: 1 woman out of 6 invited speakers
- Orals: 3 out of 15 papers included a woman; 4 out of 50 authors were women
- Symposia:
  - Deep Learning: 0/5 organizers are women; 0/23 PC members are women; 1/10 talks list a woman (but not clear who is actually giving the talk)
  - Societal Impacts: 0/3 organizers are women; 0/9 speakers are women
  - Brains, Minds, and Machines: 0/3 organizers are women; 0/7 speakers are women
- Boards: 0 out of 7 women on executive board; 3 out of 25 women on advisory board

KDD is no better. ☹

The Future

- There's still work to be done, but we **can** make a difference!
- We have a strong community and we can work together
- But we can't do it alone:
  - Recruit strong male allies who aren't afraid to speak up
  - Encourage ML conferences to appoint a "diversity chair"
- Remember, gender is only one part of diversity

What Can You Do?

- Speak up and take action
- Don’t get discouraged and don’t give up
- Seek out help when you need it
- Form support networks
- Promote your female friends and colleagues
  - Database of women in ML: https://sites.google.com/site/wimllist/

Thank You!

- Contact info
  - *tina@eliassi.org*
  - *@tinaeliassi*