



# Discovering Roles and Anomalies in Graphs: Theory and Applications

Part 1: Theory

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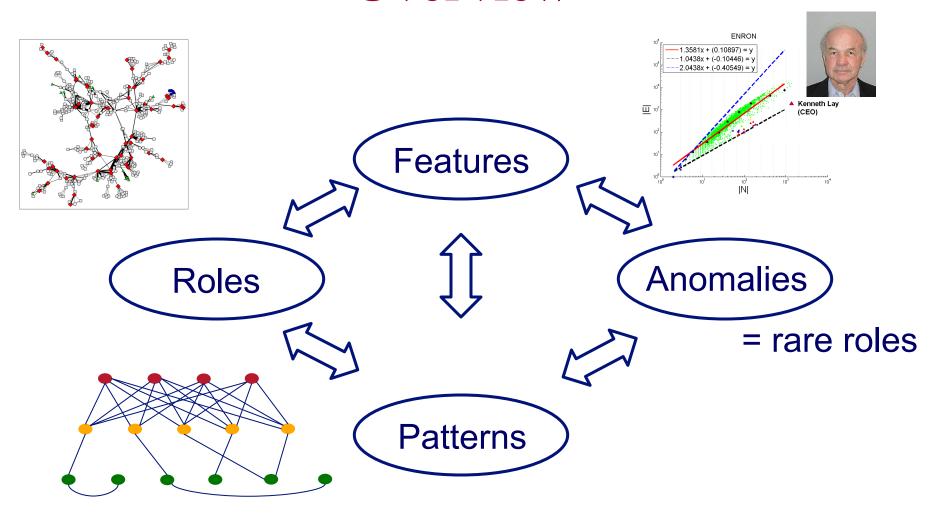
Christos Faloutsos (CMU)

SDM'12 Tutorial





#### **Overview**



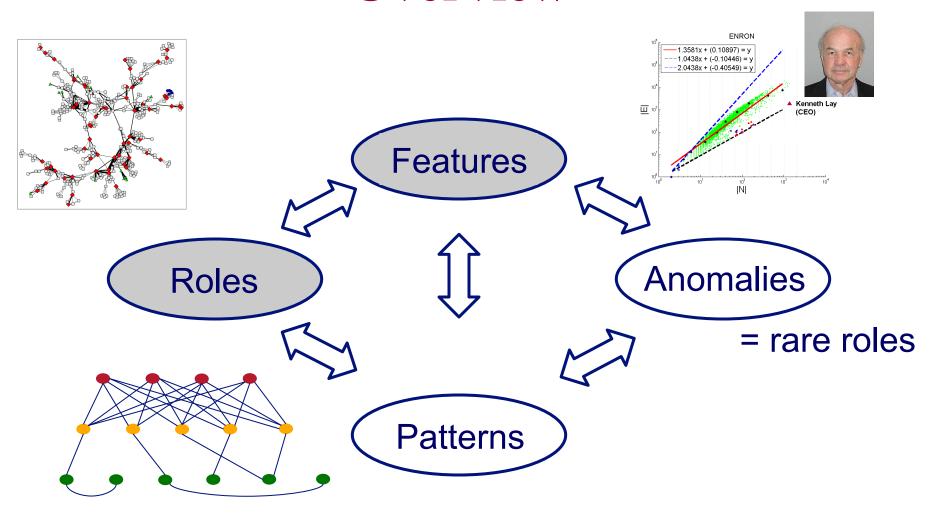
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#### **Overview**



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#### Roadmap

- What are roles
- Roles and communities



- Roles and equivalences (from sociology)
- Roles (from data mining)
- Summary





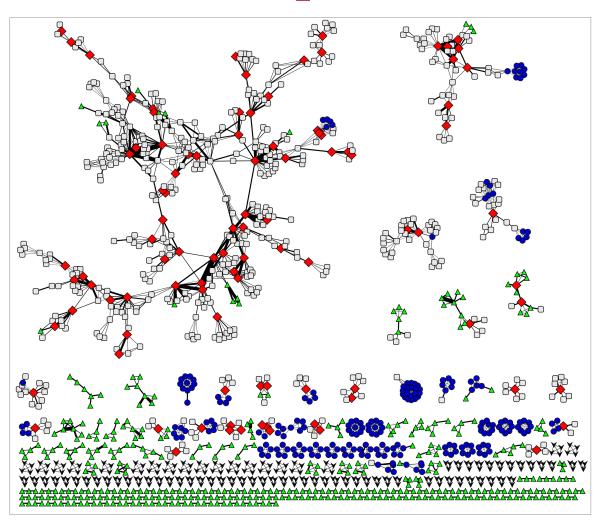
#### What are roles?

- "Functions" of nodes in the network
  - Think about roles of species in ecosystems
- Measured by structural behaviors
- Examples
  - centers of stars
  - members of cliques
  - peripheral nodes

**—** ...



# **Example of Roles**

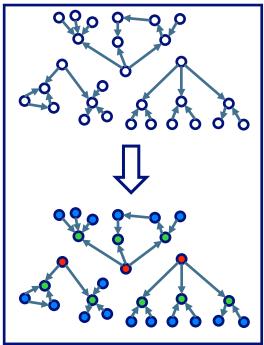


- centers of stars
- members of cliques
- ▲ peripheral nodes



# Why are roles important?

#### **Role Discovery**



- ✓ Automated discovery
- Behavioral roles
- ✓ Roles generalize

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
Identity resolution	Identify known individuals in a new network
Role transfer	Use knowledge of one network to make predictions in another
Network comparison	Determine network compatibility for knowledge transfer



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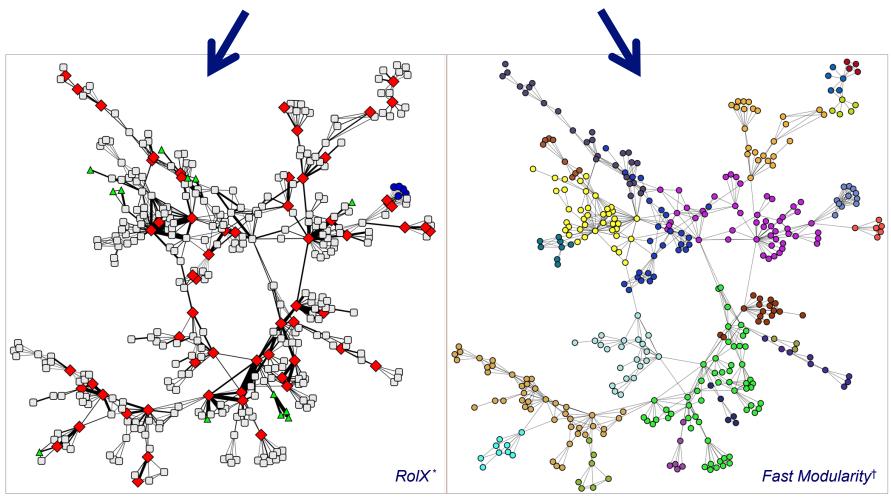


#### **Roles and Communities**

- Roles group nodes with similar structural properties
- Communities group nodes that are wellconnected to each other
- Roles and communities are complementary



# **Roles and Communities**



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





#### **Roles and Communities**

Consider the social network of a CS dept

- Roles
  - Faculty
  - Staff
  - Students
  - **—** ...

- Communities
  - AI lab
  - Database lab
  - Architecture lab

<del>-</del> ...



#### Roadmap

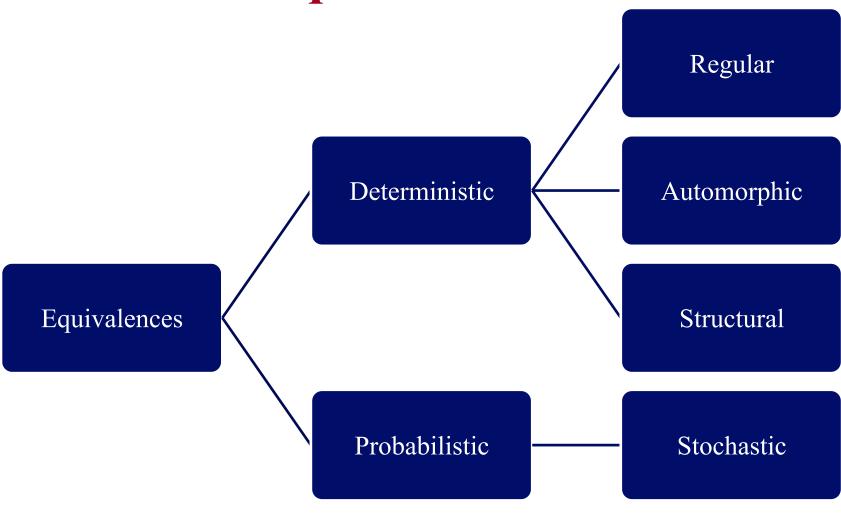
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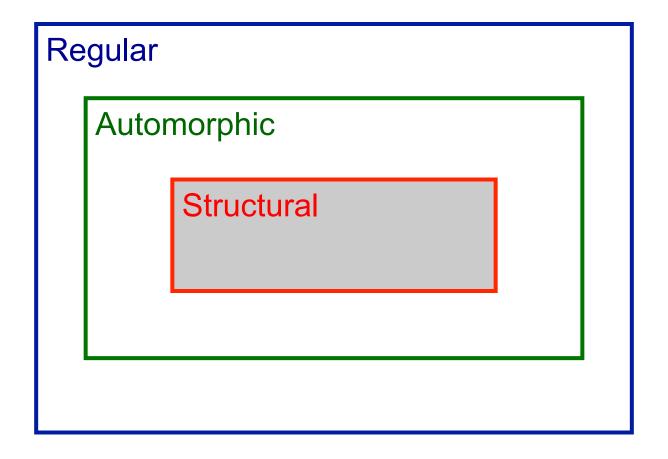
# **Equivalences**







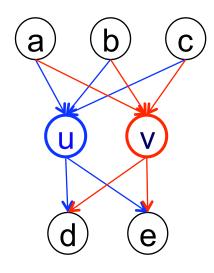
# Deterministic Equivalences





#### Structural Equivalence

- [Lorrain & White, 1971]
- Two nodes *u* and *v* are structurally equivalent if they have the same relationships to all other nodes
- Hypothesis: Structurally equivalent nodes are likely to be similar in other ways i.e., you are your friend



- Weights & timing issues are not considered
- Rarely appears in real-world networks





#### Structural Equivalence: Algorithms

- CONCOR (CONvergence of iterated CORrelations) [Breiger et al. 1975]
- A hierarchical divisive approach
  - 1. Starting with one or more sociomatrices (e.g. the adjacency matrix), repeatedly calculate Pearson correlations between rows (or columns) until the resultant correlation matrix consists of +1 and -1 entries
  - 2. Split the last correlation matrix into two structurally equivalent submatrices (a.k.a. blocks): one with +1 entries, another with -1 entries
- Successive split can be applied to submatrices in order to produce a hierarchy (where every node has a unique position)



#### Structural Equivalence: Algorithms

- STRUCUTRE [Burt 1976]
- A hierarchical agglomerative approach
  - 1. For each node *i*, create its ID vector by concatenating its row and column vectors from the adjacency matrix
  - 2. For every pair of nodes  $\langle i, j \rangle$ , measure the square root of sum of squared differences between the corresponding entries in their ID vectors
  - 3. Merge entries in hierarchical fashion as long as their difference is less than some threshold  $\alpha$



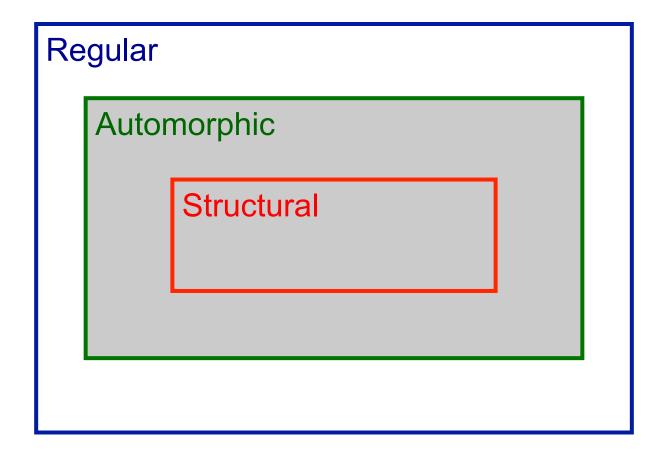
#### Structural Equivalences: Algorithms

- Combinatorial optimization approaches
  - Numerical optimization with tabu search [UCINET]
  - Local optimization [Pajek]
- Partition the sociomatrices into blocks based on a cost function that minimizes the sum of within block variances
  - I.e., minimize the sum of code cost within each block





# Deterministic Equivalences

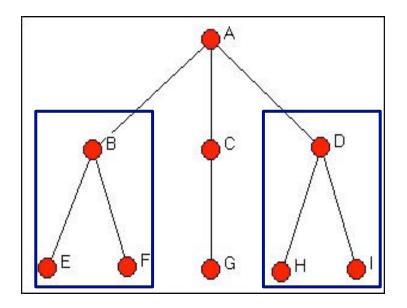






#### Automorphic Equivalence

- [Borgatti, et al. 1992; Sparrow 1993]
- Two nodes *u* and *v* are automorphically equivalent if all the nodes can be relabeled to form an isomorphic graph with the labels of *u* and *v* interchanged
  - Swapping u and v (possibly along with their neighbors)
    does not change graph distances
- Two nodes that are automorphically equivalent share exactly the same label-independent properties





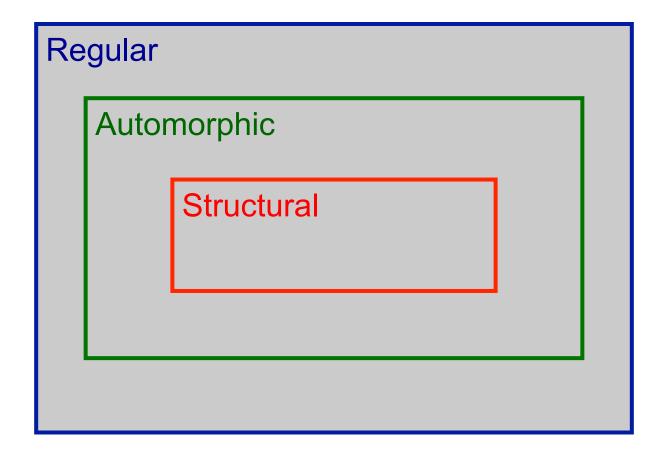
#### Automorphic Equivalence: Algorithms

- Sparrow (1993) proposed an algorithm that scales linearly to the number of edges
- Use numerical signatures on degree sequences of neighborhoods
- Numerical signatures use a unique transcendental number like  $\pi$ , which is independent of any permutation of nodes
- Suppose node *i* has the following degree sequence: 1, 1, 5, 6, and 9. Then its signature is  $S_{i,1} = (1 + \pi)(1 + \pi)(5 + \pi)(6 + \pi)(9 + \pi)$
- The signature for node *i* at k+1 hops is  $S_{i,(k+1)} = \Pi(S_{i,k} + \pi)$
- To find automorphic equivalence, simply compare numerical signatures of nodes





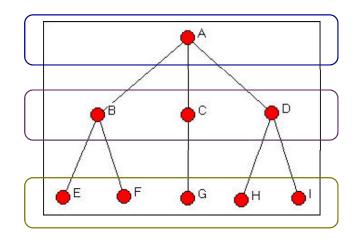
# Deterministic Equivalences





#### Regular Equivalence

- [Everett & Borgatti, 1992]
- Two nodes *u* and *v* are regularly equivalent *if* they are equally related to equivalent others



**President Motes** 

Faculty

**Graduate Students** 

Hanneman, Robert A. and Mark Riddle. 2005. Introduction to social network methods. Riverside, CA: University of California, Riverside ( published in digital form at http://faculty.ucr.edu/~hanneman/)



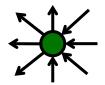
# Regular Equivalence

(continued)

- Basic roles of nodes
  - source



repeater



 $-\sin k$ 



- isolate



# Regular Equivalence (continued)

- Based solely on the social roles of neighbors
- Interested in
  - Which nodes fall in which social roles?
  - How do social roles relate to each other?
- Hard partitioning of the graph into social roles
- A given graph can have more than one valid regular equivalence set
- Exact regular equivalences can be rare in large graphs



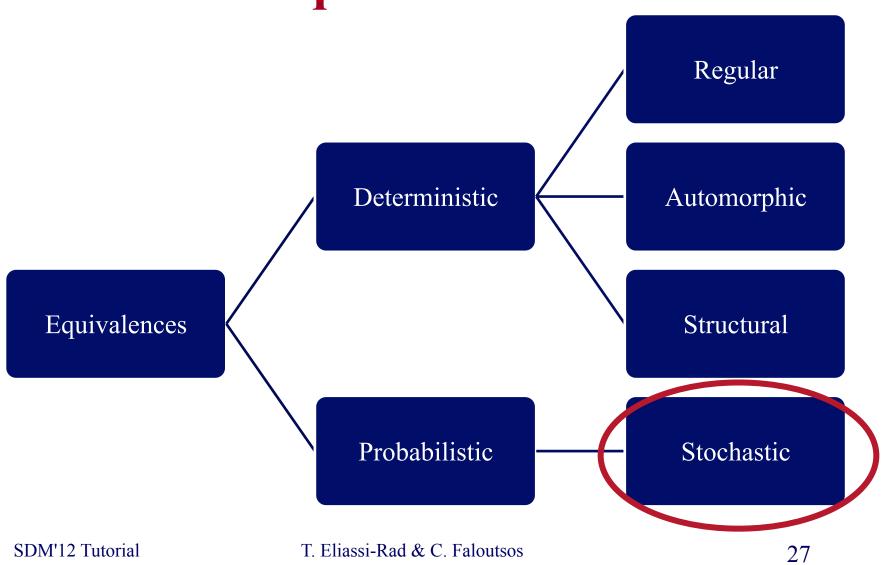


#### Regular Equivalence: Algorithms

- Many algorithms exist here
- Basic notion
  - Profile each node's neighborhood by the presence of nodes of other "types"
  - Nodes are regularly equivalent to the extent that they have similar "types" of other nodes at similar distances in their neighborhoods



# **Equivalences**



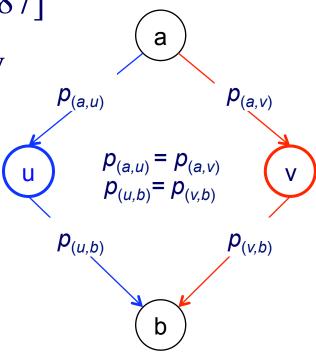


#### Stochastic Equivalence

• [Holland, et al. 1983; Wasserman & Anderson, 1987]

• Two nodes are stochastically equivalent if they are "exchangeable" w.r.t. a probability distribution

• Similar to structural equivalence but probabilistic





#### Stochastic Equivalence: Algorithms

- Many algorithms exist here
- Most recent approaches are generative [Airoldi, et al 2008]
- Some choice points
  - Single [Kemp, et al 2006] vs. mixed-membership [Koutsourelakis & Eliassi-Rad, 2008] equivalences (a.k.a. "positions")
  - Parametric vs. non-parametric models



# Roadmap

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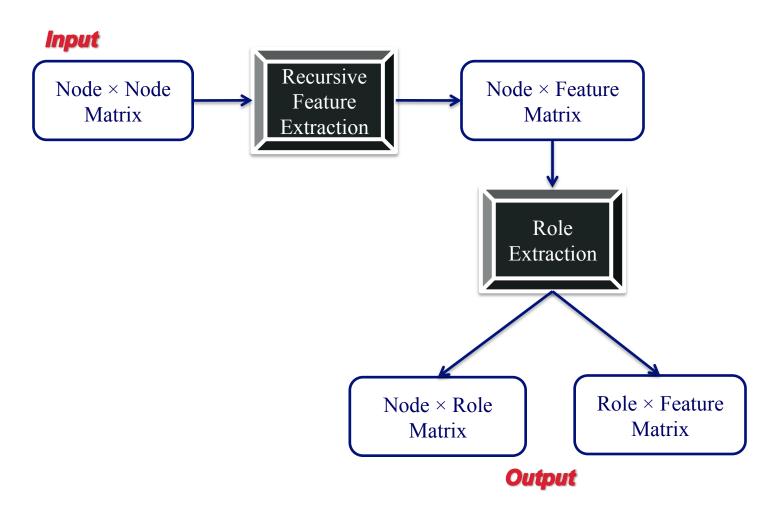


#### **RolX: Role eXtraction**

- Introduced by Henderson, et al. 2011b
- Automatically extracts the underlying roles in a network
  - No prior knowledge required
- Assigns a mixed-membership of roles to each node
- Scales linearly on the number of edges

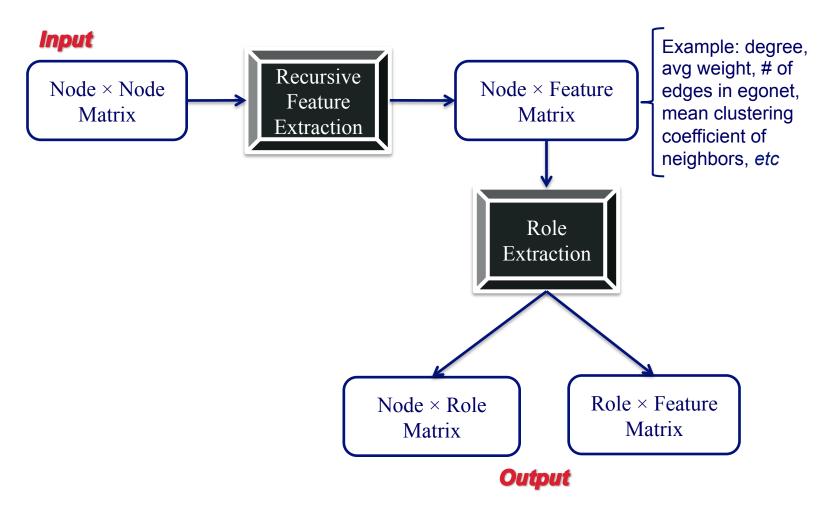


#### **RolX: Flowchart**





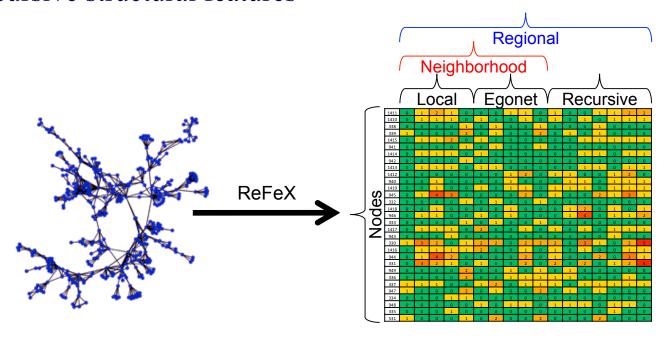
#### **RolX: Flowchart**





#### **Recursive Feature Extraction**

• ReFeX [Henderson, et al. 2011a] turns network connectivity into recursive structural features



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

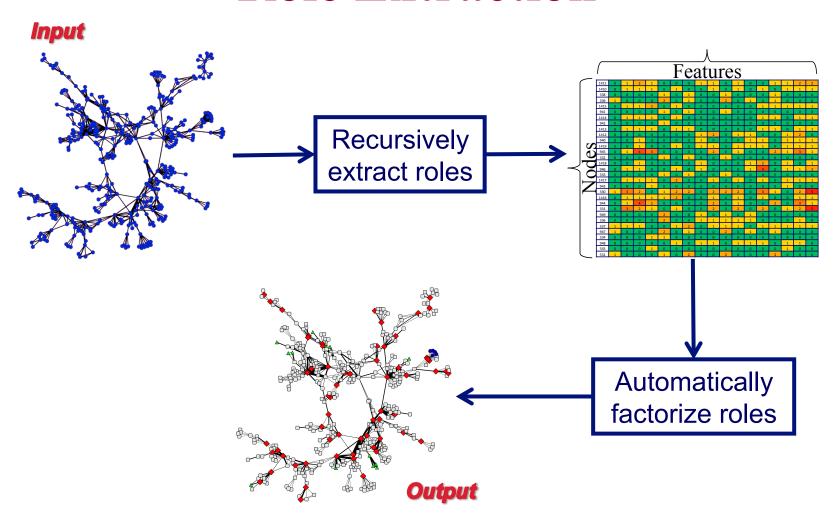


# **Propositionalisation (PROP)**

- [Knobbe, et al. 2001; Neville, et al. 2003; Krogel, et al. 2003]
- From multi-relational data mining with roots in Inductive Logic Programming (ILP)
- Summarizes a multi-relational dataset (stored in multiple tables) into a propositional dataset (stored in a single "target" table)
- Derived attribute-value features describe properties of individuals
- Related more to recursive structural features than structural roles

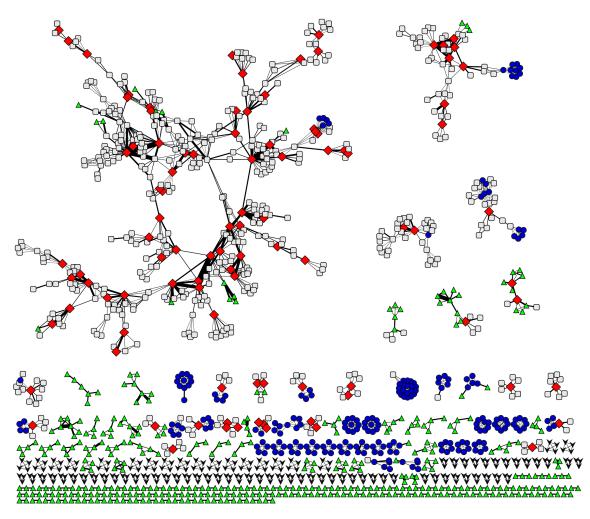


#### **Role Extraction**





## **Automatically Discovered Roles**

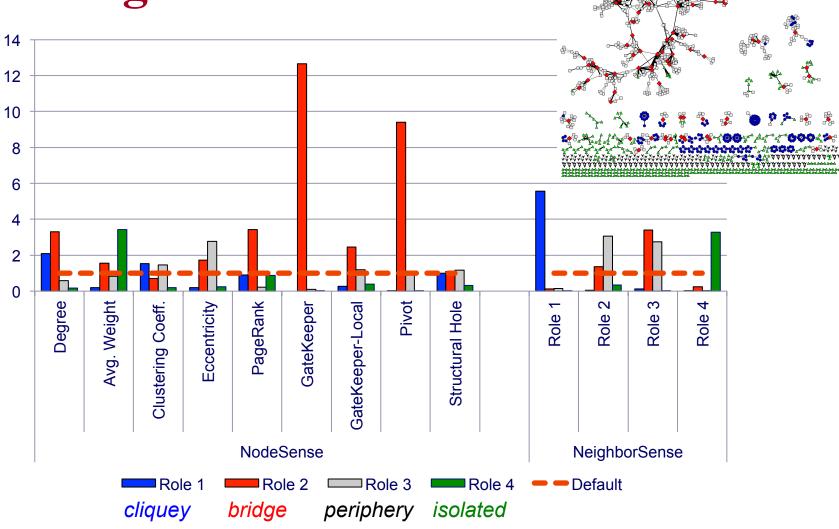


Network Science Co-authorship Graph [Newman 2006]





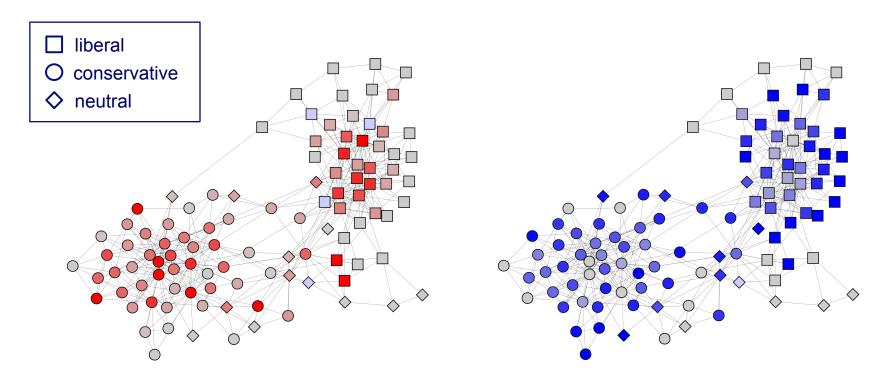
# **Making Sense of Roles**







## Mixed-Membership over Roles



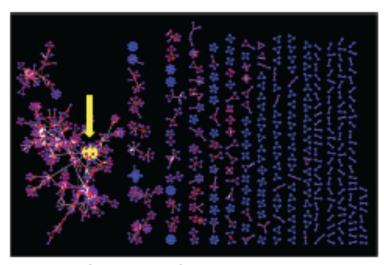
Bright red nodes are locally central nodes

Bright blue nodes are peripheral nodes

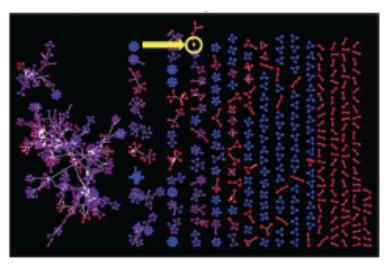
Amazon Political Books Co-purchasing Network [V. Krebs 2000]



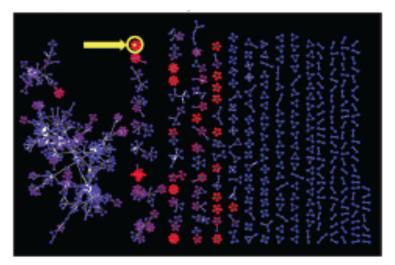
## **Role Query**



Node Similarity for M.E.J. Newman (*bridge*)



Node Similarity for J. Rinzel (*isolate*)

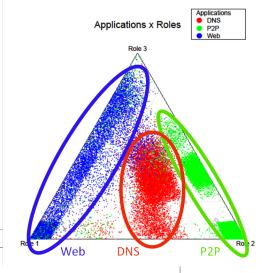


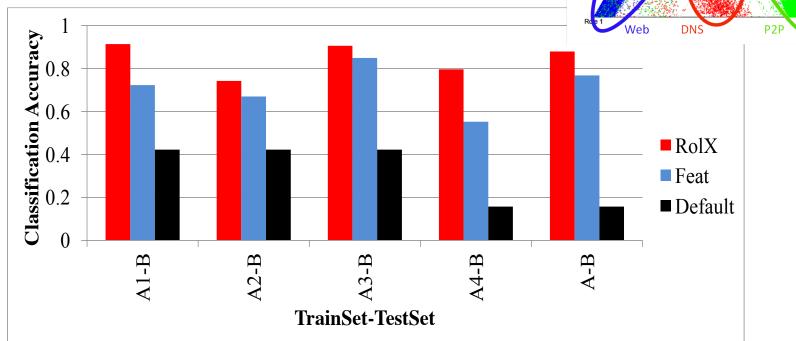
Node Similarity for F. Robert (*cliquey*)





# Roles Generalize across Disjoint Networks

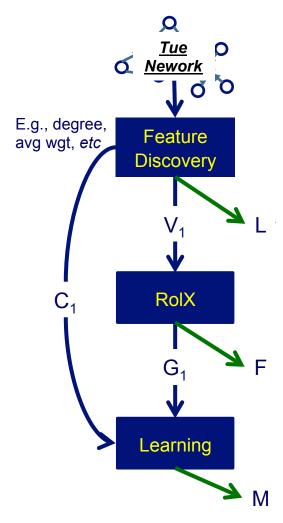






### Roles Generalize across Networks

Discovery Stage



V: (node × feature) matrix

G: (node × role) matrix

F: (role × feature) matrix

L: List of feature names

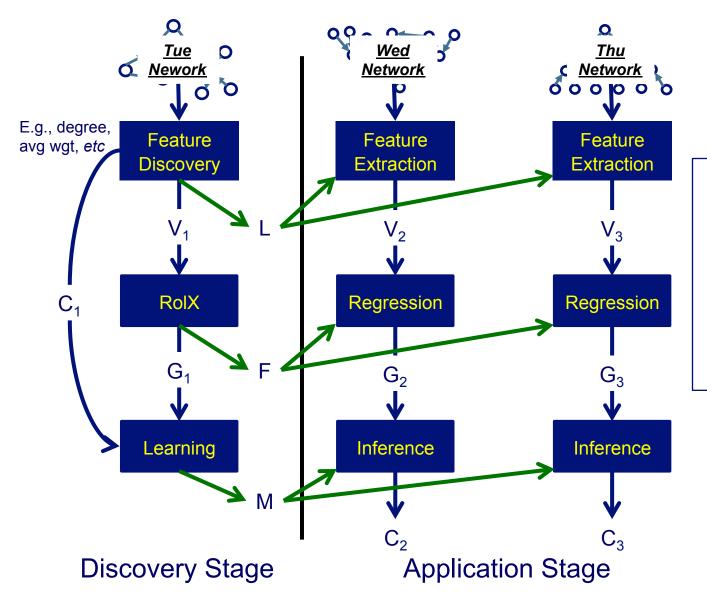
C: Class labels

M: model

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### Roles Generalize across Networks



V: (node × feature) matrix

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F: (role × feature) matrix

L: List of feature names

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## Roles: Regular Equivalence vs. RolX

	RolX	Regular Equivalence
Mixed-membership over roles	✓	
Fully automatic	✓	
Uses structural features	✓	
Uses structure	✓	<b>✓</b>
Generalizable across disjoint networks	✓	?
Scalable (linear on # of edges)	<b>√</b>	



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## Summary

#### Roles

- Structural behavior ("function") of nodes
- Complementary to communities
- Previous work mostly in sociology under equivalences
- Recent graph mining work produces mixedmembership roles, is fully automatic and scalable
- Can be used for many tasks: transfer learning, reidentification, node dynamics, etc





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- CMU: Leman Akoglu, Danai Koutra, Lei Li

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## **Back to Overview**

