Part III: Graph-based spam/fraud detection algorithms and apps

Part III: Outline

- ➡ Algorithms: **relational learning**
  - Collective classification
  - Relational inference

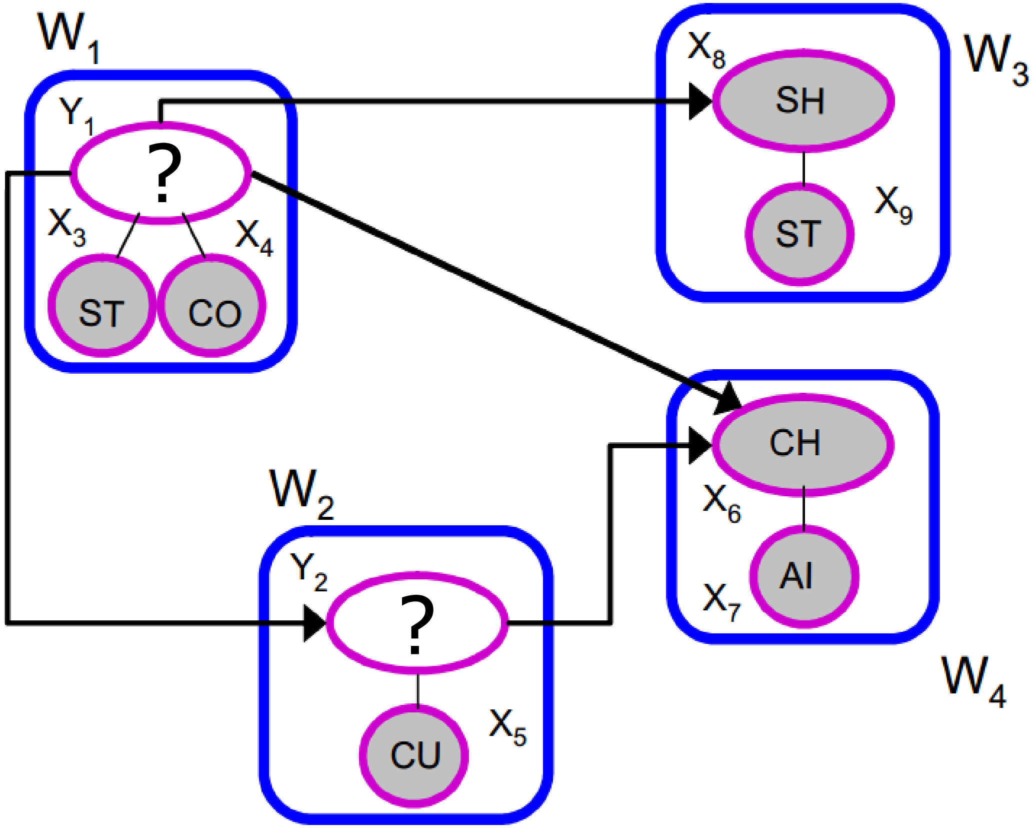
- Applications: **fraud and spam** detection
  - Online auction fraud
  - Accounting fraud
  - Fake review spam
  - Web spam

Collective classification (CC)

- Anomaly detection as a classification problem
  - spam/non-spam email, malicious/benign web page, fraud/legitimate transaction, etc.
- Often **connected** objects → guilt-by-association
- Label of object *o* in network may depend on:
  - Attributes (features) of *o*
  - Labels of objects in *o*'s neighborhood
  - Attributes of objects in *o*'s neighborhood
- CC: simultaneous classification of interlinked objects using above correlations

Problem sketch

- Graph (V, E)
- Nodes as variables
  - X: observed
  - Y: TBD
- Edges
  - observed relations
- **Goal:** label Y nodes

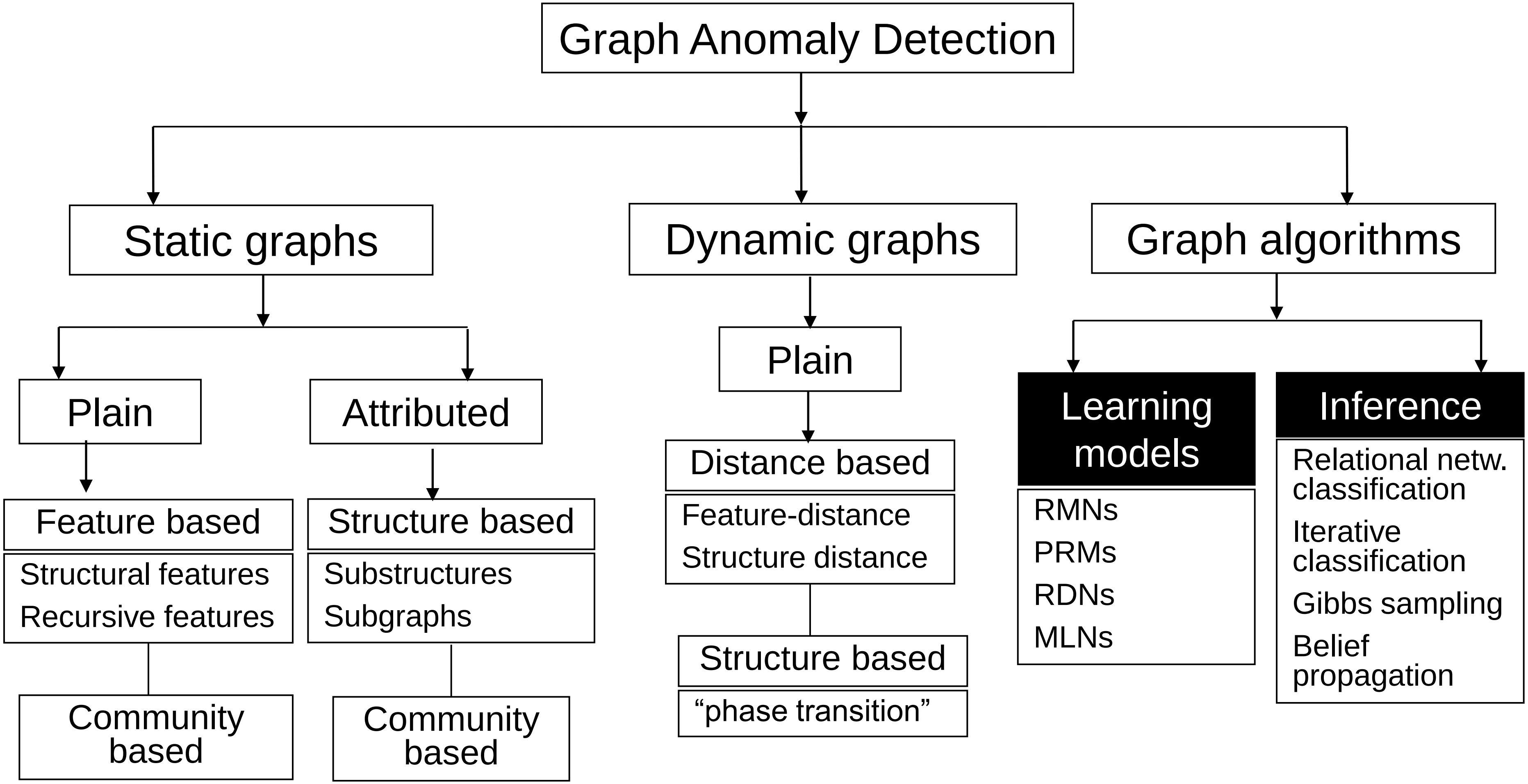


nodes; web pages, edges; hyperlinks, labels; SH or CH: student/course page; features nodes are keywords; ST: student, CO: course, CU: curriculum, AI: artificial intelligence

Collective classification applications

- Document classification Chakrabarti+'98, Taskar+'02
- Part of speech tagging Lafferty+'01
- Link prediction Taskar+'03
- Optical character recognition Taskar+'03
- Image/3Ddata segmentation Anguelov+'05, Chechetka+'10
- Entity resolution in sensor networks Chen+'03
- Spam and fraud detection Pandit+'07, Kang+'11

Taxonomy



Graph Anomaly Detection

Static graphs

Plain

Feature based

Structural features

Recursive features

Community based

Attributed

Structure based

Substructures

Subgraphs

Community based

Dynamic graphs

Plain

Distance based

Feature-distance

Structure distance

Structure based

“phase transition”

Graph algorithms

Learning models

RMNs

PRMs

RDNs

MLNs

Inference

Relational netw. classification

Iterative classification

Gibbs sampling

Belief propagation

Collective classification models

- Relational Markov Networks (RMNs)

  Taskar, Abbeel, Koller'03

- Relational Dependency Networks (RDNs)

  Neville&Jensen'07

- Probabilistic Relational Models (PRMs)

  Friedman, Getoor, Koller, Pfeffer+'99

- Markov Logic Networks (MLNs)

  Richardson&Domingos'06

Collective classification inference

- Exact inference is **NP hard** for arbitrary networks
- Approximate inference techniques **[in this tutorial]**
    - ➡ **Relational classifier**

      Macskassy&Provost'03,07
    - **Iterative classification alg. (ICA)**

      Neville&Jensen'00, Lu&Getoor'03, McDowell+'07
    - **Gibbs sampling IC**

      Gilks et al. '96
    - **Loopy belief propagation**

      Yedidia et al. '00

Note: All the above are iterative

Macskassy&Provost'03

(prob.) Relational network classifier

- "A simple relational classifier"
- Class probability of Y_i is a weighted average of class probabilities of its neighbors
- **Repeat** for each Y_i and label c

$$P(Y_i = c) = \frac{1}{Z} \sum_{(Y_i,Y_j)\in E} w(Y_i,Y_j) P(Y_j = c)$$

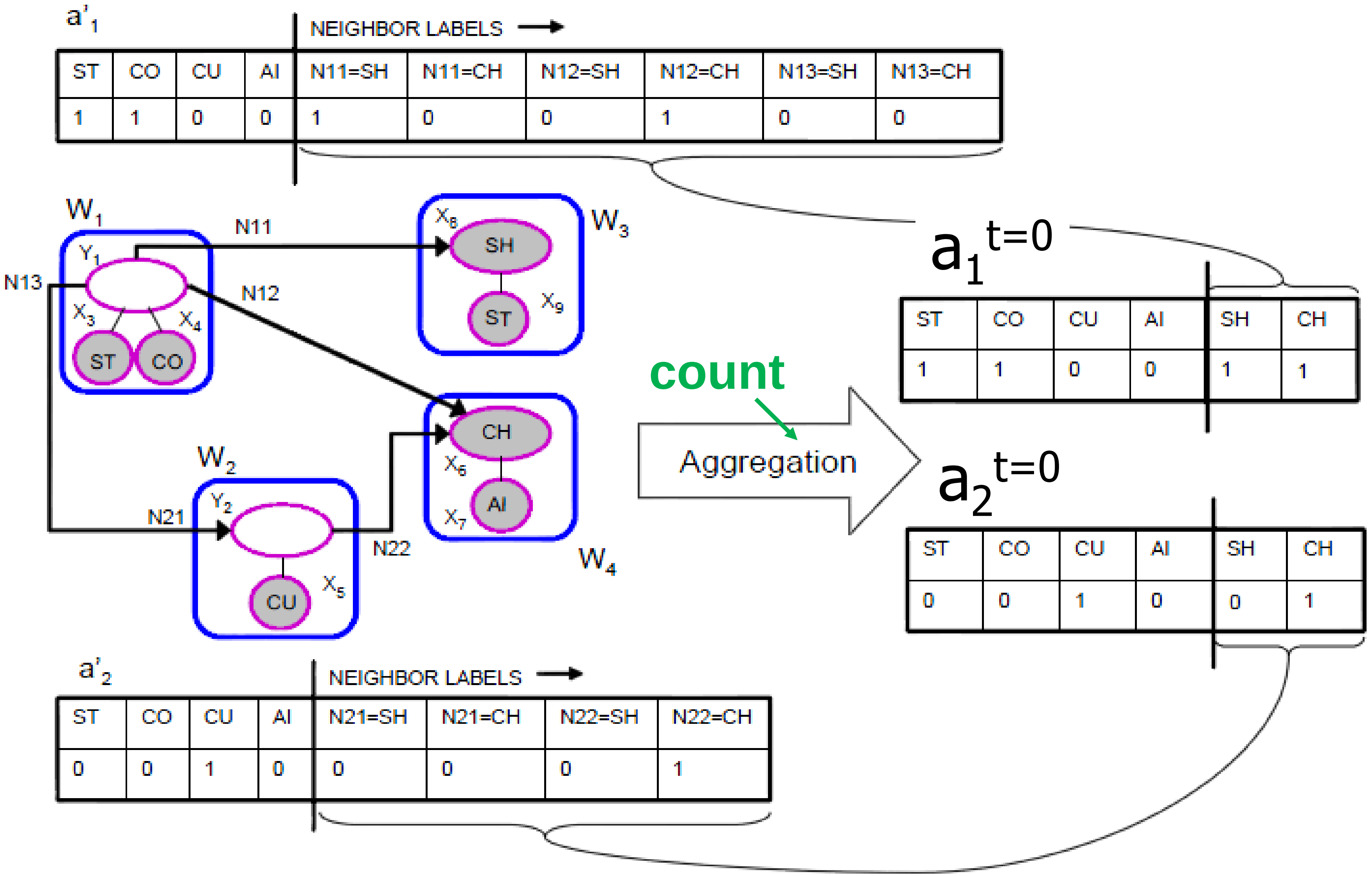
- pRN challenges:
  - Convergence not guaranteed
  - Some initial class probabilities should be biased or no propagation
  - Cannot use attribute info

Iterative classification

- Main idea: classify node Y_i based on its attributes as well as neighbor set N_i's labels
  - Convert each node Y_i to a flat vector a_i

    Various #neighbors → **aggregation**
    - count
    - mode
    - proportion
    - mean
    - exists

Iterative classification



a'_1

ST	CO	CU	AI	N11=SH	N11=CH	N12=SH	N12=CH	N13=SH	N13=CH
1	1	0	0	1	0	0	1	0	0

NEIGHBOR LABELS →

$a_1^{t=0}$

ST	CO	CU	AI	SH	CH
1	1	0	0	1	1

$a_2^{t=0}$

ST	CO	CU	AI	SH	CH
0	0	1	0	0	1

a'_2

NEIGHBOR LABELS →

ST	CO	CU	AI	N21=SH	N21=CH	N22=SH	N22=CH
0	0	1	0	0	0	0	1

Iterative classification

- Main idea: classify Y_i based on N_i

Bootstrap

  - Convert each node Y_i to a **flat vector** a_i
    - Various #neighbors → **aggregation**
  - **Use** local classifier f(a_i) (e.g., SVM, kNN, …) to compute best value for y_i

IC

  - **Repeat** for each node Y_i
    - **Reconstruct** feature vector a_i
    - **Update** label to f(a_i) (hard assignment) $\operatorname{argmax}_{l\in\mathcal{L}} f$
  - Until class labels stabilize or max # iterations

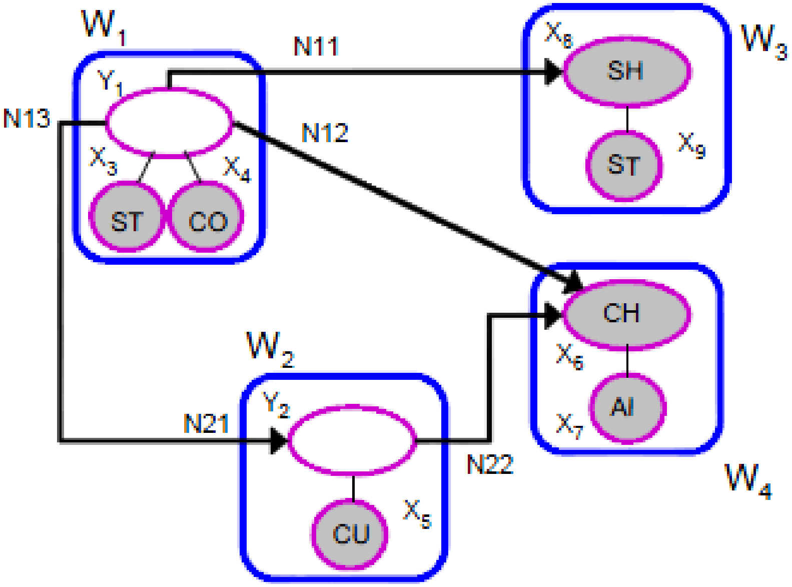
Note: convergence not guaranteed

Iterative classification

a'_1

NEIGHBOR LABELS →

ST	CO	CU	AI	N11=SH	N11=CH	N12=SH	N12=CH	N13=SH	N13=CH
1	1	0	0	1	0	0	1	0	**1**



$f(a_2^{t=0})=CH$

Aggregation →

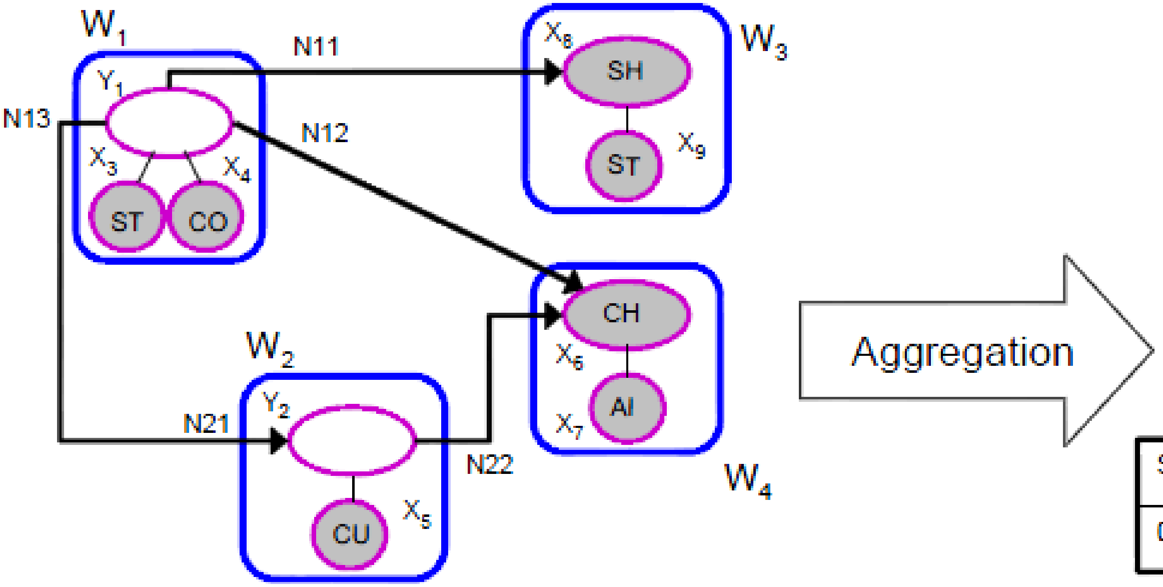
$a_1^{t=1}$

ST	CO	CU	AI	SH	CH
1	1	0	0	1	**2**

$f(a_1^{t=1})=SH$

Iterative classification

$f(a_1^{t=1})=SH$



$a_2^{t=1}$

ST	CO	CU	AI	SH	CH
0	0	1	0	1	1

a'_2

NEIGHBOR LABELS →

ST	CO	CU	AI	N21=SH	N21=CH	N22=SH	N22=CH
0	0	1	0	1	0	0	1

$f(a_2^{t=1})=CH$

Gibbs sampling

- Main idea:

Bootstrap

  - ❑ Convert each node Y_i to a flat vector a_i
  - ❑ Use local classifier $f(a_i)$ to compute best value for y_i

Burn-in

  - ❑ **Repeat B times** for each node Y_i
    - Reconstruct feature vector a_i
    - Update label to $f(a_i)$ (hard assignment)

Sample

  - ❑ **Repeat S times** for each node Y_i
    - Sample y_i from $f(a_i)$
    - Increase count $c(i, y_i)$ by 1
  - ❑ Assign to each Yi label $y_i \leftarrow \text{argmax}_{l \in \mathcal{L}} c[i, l]$

IC and GS challenges

- Feature construction for local classifier f
  - f often needs fixed-length vector
  - choice of aggregation (avg, mode, count, …)
  - choice of relations (in-, out-links, both)
  - choice of neighbor attributes (all?, top-k confident?)
- Local classifier f
  - requires training
  - choice of classifier (LR, NB, kNN, SVM, …)
- Node ordering for updates (random, diversity based)
- Convergence
- Run time (many iterations for GS)

Collective classification inference

- Exact inference is **NP hard** for arbitrary networks
- Approximate inference techniques **[in this tutorial]**
  - ❑ **Relational classifier**

    Macskassy&Provost'03,07
  - ❑ **Iterative classification alg. (ICA)**

    Neville&Jensen'00, Lu&Getoor'03, McDowell+'07
  - ❑ **Gibbs sampling IC**

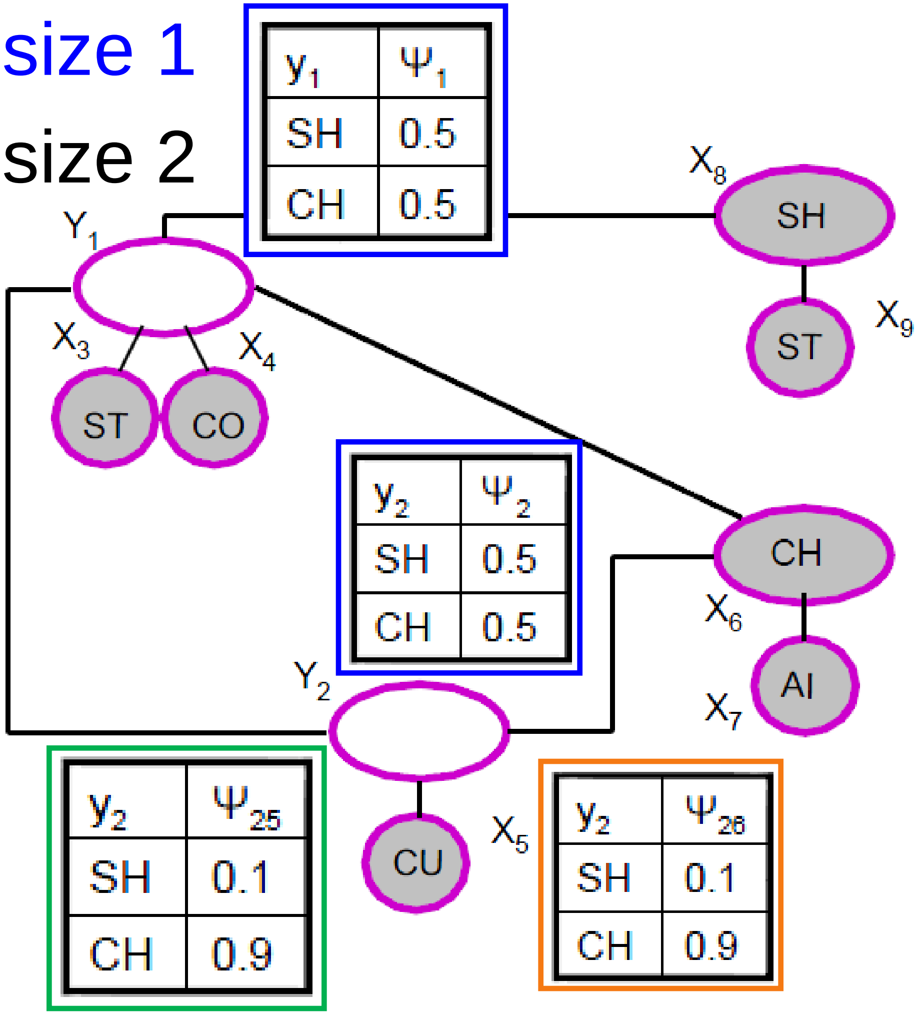
    Gilks et al. '96
  - ➡ **Loopy belief propagation**

    Yedidia et al. '00

Note: All the above are iterative

Relational Markov Nets

- Undirected dependencies
- Potentials on cliques of size 1
- Potentials on cliques of size 2
  - (label-attribute)
  - (label-observed label)
  - (label-label)



y_1	Ψ_1
SH	0.5
CH	0.5

y_2	Ψ_2
SH	0.5
CH	0.5

y_2	Ψ_{25}
SH	0.1
CH	0.9

y_2	Ψ_{28}
SH	0.1
CH	0.9

For pairwise RMNs max clique size is 2

y_1	y_2	Ψ_{12}
SH	SH	0.9
SH	CH	0.1
CH	SH	0.1
CH	CH	0.9

pairwise Markov Random Field

- For an assignment ***y*** to all unobserved **Y**, pMRF is associated with probability distr:

$$P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \prod\nolimits_{Y_i \in \mathcal{Y}} \phi_i(y_i) \prod\nolimits_{(Y_i,Y_j)\in E} \psi_{ij}(y_i, y_j)$$

Node labels as random variables

compatibility potentials (label-label)

“known” potential

$$\phi_i(y_i) = \psi_i(y_i) \prod\nolimits_{(Y_i,X_j)\in E} \psi_{ij}(y_i)$$

prior belief (1-clique potentials)

observed potentials (label-observed label) (label-attribute)

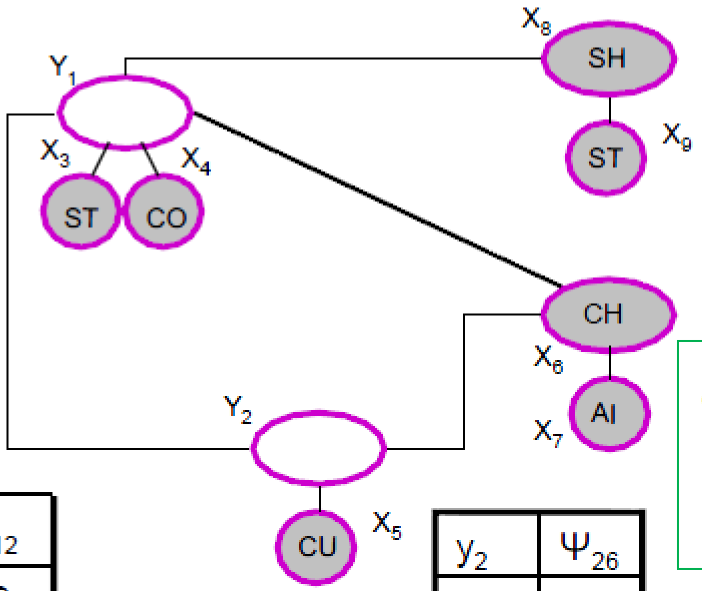
y_1	Ψ_{13}
SH	0.6
CH	0.4

y_1	Ψ_{16}
SH	0.1
CH	0.9

y_1	Ψ_{18}
SH	0.8
CH	0.2

y_1	Ψ_1
SH	0.5
CH	0.5

y_1	Ψ_{14}
SH	0.4
CH	0.6



y_1	y_2	Ψ_{12}
SH	SH	0.9
SH	CH	0.1
CH	SH	0.1
CH	CH	0.9

y_2	Ψ_2
SH	0.5
CH	0.5

y_2	Ψ_{26}
SH	0.1
CH	0.9

y_2	Ψ_{25}
SH	0.1
CH	0.9

$\Phi_1 = \Psi_1 * \Psi_{13} * \Psi_{14} * \Psi_{16} * \Psi_{18} =$

y_1	Φ_1
SH	0.0096
CH	0.0216

$\Phi_2 = \Psi_2 * \Psi_{25} * \Psi_{26} =$

y_2	Φ_2
SH	0.005
CH	0.405

pMRF interpretation

- Defines a joint pdf of all unknown labels
- P(y | x) is the probability of a given world y
- Best label y_i for Y_i is the one with highest marginal probability
- Computing one marginal probability $P(Y_i = y_i)$ requires summing over exponential # terms
- #P problem → approximate inference → loopy belief propagation

Loopy belief propagation

- Invented in 1982 [Pearl] to calculate marginals in Bayes nets.
- Also used to estimate marginals (=beliefs), or most likely states (e.g. MAP) in MRFs
- Iterative process in which neighbor variables “talk” to each other, passing **messages**

“I (variable *x1*) believe you (variable *x2*) belong in these states with various likelihoods…”

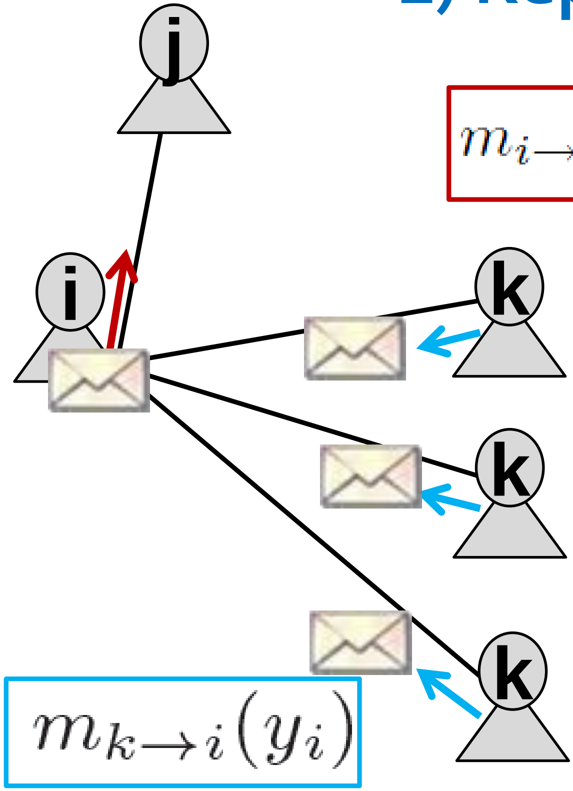
- When consensus reached, calculate belief

Loopy belief propagation

details

1) Initialize all messages to 1

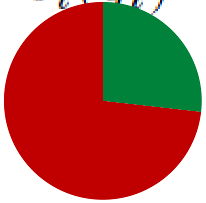
2) Repeat for each node:



$$\boxed{m_{i\to j}(y_j)} = \alpha \sum_{y_i\in\mathcal{L}} \boxed{\psi_{ij}(y_i, y_j)}\boxed{\phi_i(y_i)} \boxed{\prod_{Y_k\in\mathcal{N}_i\cap\mathcal{Y}\setminus Y_j} m_{k\to i}(y_i),} \quad \forall y_j \in \mathcal{L}$$

3) When messages "stabilize":

$$b_i(y_i) = \alpha\boxed{\phi_i(y_i)}\boxed{\prod_{Y_j\in\mathcal{N}_i\cap\mathcal{Y}} m_{j\to i}(y_i),} \quad \forall y_i \in \mathcal{L}$$



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SH	0.1
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SH	0.8
CH	0.2

$\Phi_1 = \Psi_1 {}^* \Psi_{13} {}^* \Psi_{14} {}^* \Psi_{16} {}^* \Psi_{18} =$

y_1	Φ_1
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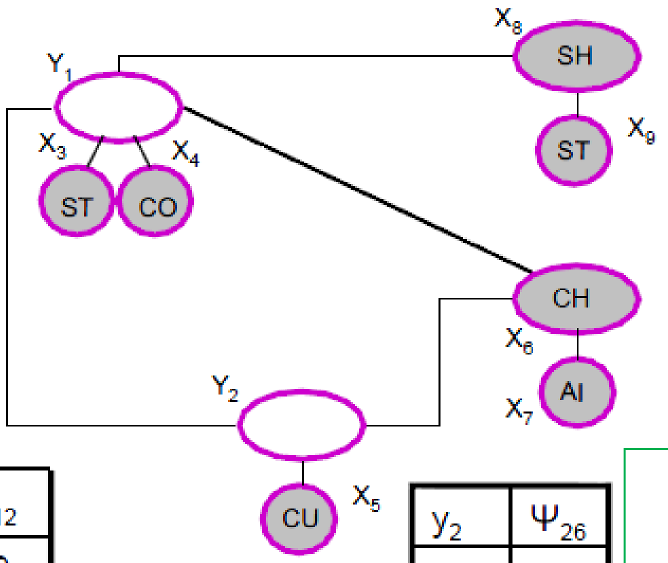


$\Phi_2 = \Psi_2 {}^* \Psi_{25} {}^* \Psi_{26} =$

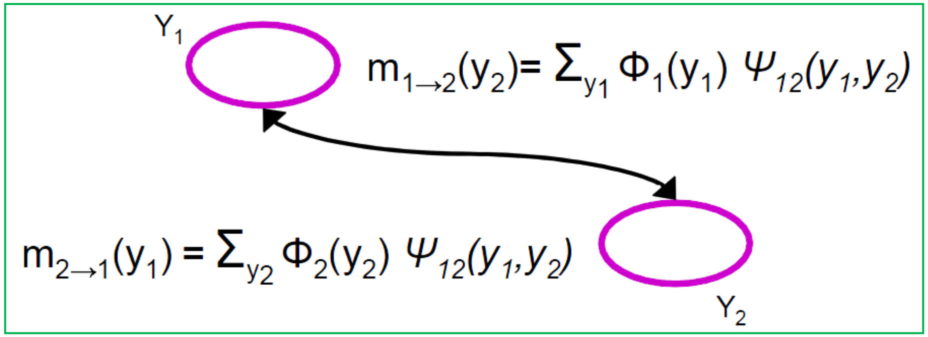
y_2	Φ_2
SH	0.005
CH	0.405

y_1	y_2	Ψ_{12}
SH	SH	0.9
SH	CH	0.1
CH	SH	0.1
CH	CH	0.9

y_2	Ψ_2
SH	0.5
CH	0.5

y_2	Ψ_{26}
SH	0.1
CH	0.9

y_2	Ψ_{25}
SH	0.1
CH	0.9



$m_{1\to2}(y_2) = \Sigma_{y_1} \Phi_1(y_1)\ \Psi_{12}(y_1,y_2)$

$m_{2\to1}(y_1) = \Sigma_{y_2} \Phi_2(y_2)\ \Psi_{12}(y_1,y_2)$

$m_{1\to2}(SH) = (0.0096*0.9+0.0216*0.1) / (m1 \to 2(SH) + m1 \to 2(CH)) \sim 0.35$

$m_{1\to2}(CH) = (0.0096*0.1+0.0216*0.9) / (m1 \to 2(SH) + m1 \to 2(CH)) \sim 0.65$

Loopy belief propagation

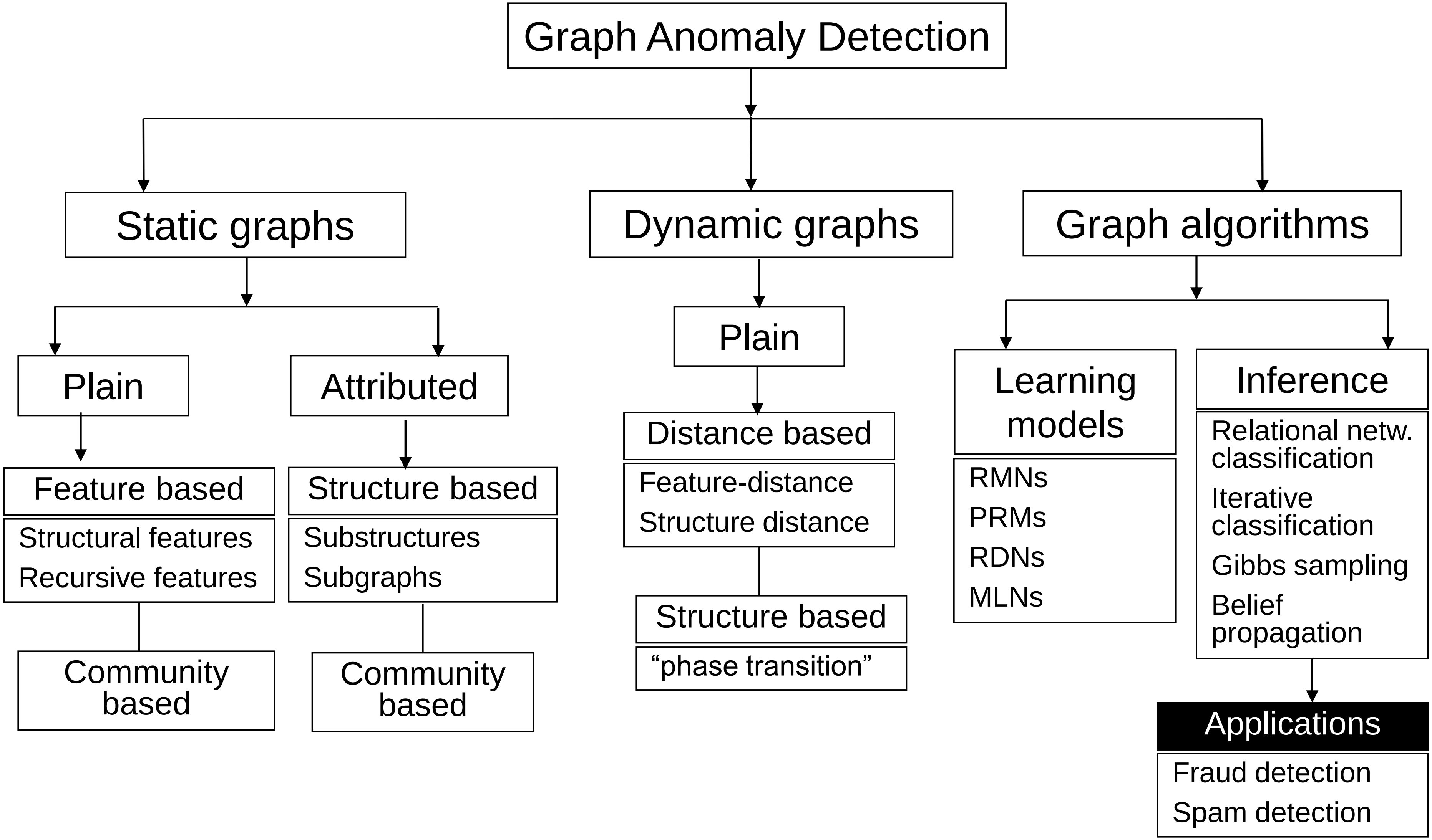
Advantages:

- Easy to program & parallelize
- General: can apply to any graphical model w/ any form of potentials (higher order than pairwise)

Challenges:

- Convergence is not guaranteed (when to stop)
    - esp. if many closed loops
- Potential functions (parameters)
    - require training to estimate
    - learning by gradient-based optimization: convergence issues during training

Taxonomy



Graph Anomaly Detection

Static graphs

Plain

Feature based

Structural features

Recursive features

Community based

Attributed

Structure based

Substructures

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Distance based

Feature-distance

Structure distance

Structure based

“phase transition”

Graph algorithms

Learning models

RMNs

PRMs

RDNs

MLNs

Inference

Relational netw. classification

Iterative classification

Gibbs sampling

Belief propagation

Applications

Fraud detection

Spam detection

Part III: Outline

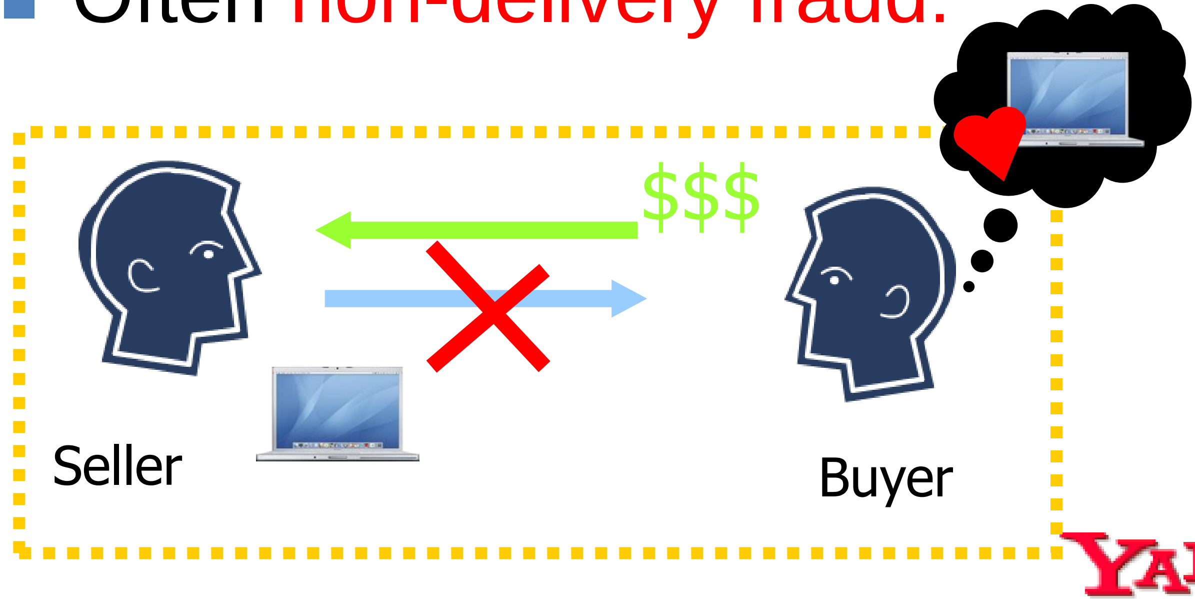
- Algorithms: **relational learning**
  - Collective classification
  - Relational inference

- Applications: **fraud and spam** detection
  - (1) Online auction fraud
  - (2) Accounting fraud
  - (3) Fake review spam
  - (4) Web spam

Chau et al. '06

(1) Online auction fraud

- Auction sites: attractive target for fraud
- 63% complaints to Federal Internet Crime Complaint Center in U.S. in 2006
- Average loss per incident: = **$385**
- Often non-delivery fraud:



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Auctions

Chau+PKDD'06
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Online auction fraud detection

- Insufficient solution:
  - Look at individual features, g[illegible]ns, login times, session history, etc.

Easy to fake!

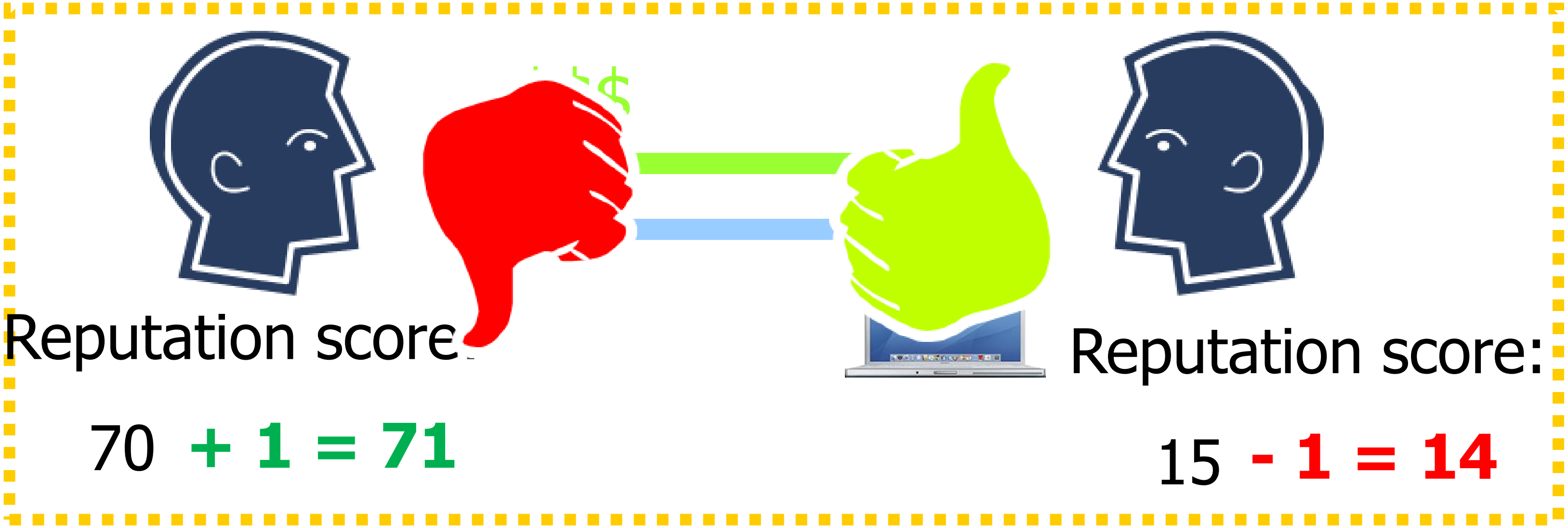
- Harder to fake: graph structure
- Capture relationships between users

- Q: How do fraudsters interact with other users and among each other?

  → in addition to buy/sell relations, there is a feedback mechanism

Feedback mechanism

- Each user has a **reputation score**
- Users rate each other via feedback



Reputation score

70 **+ 1 = 71**

Reputation score:

15 **- 1 = 14**

- Q: How do fraudsters game the feedback system?

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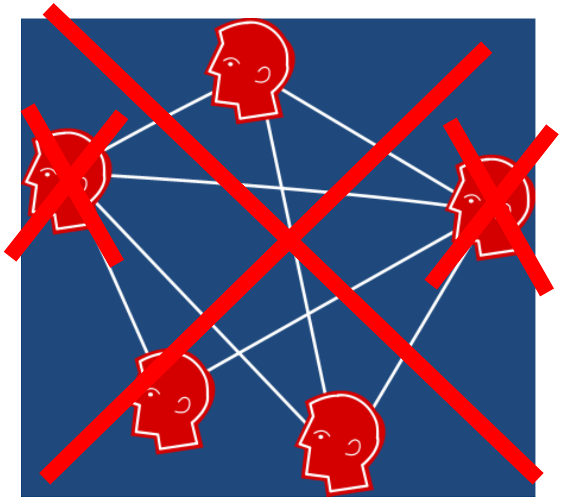
Auction “roles”

- D they boost each o tation?

No, if one caught, all caught!



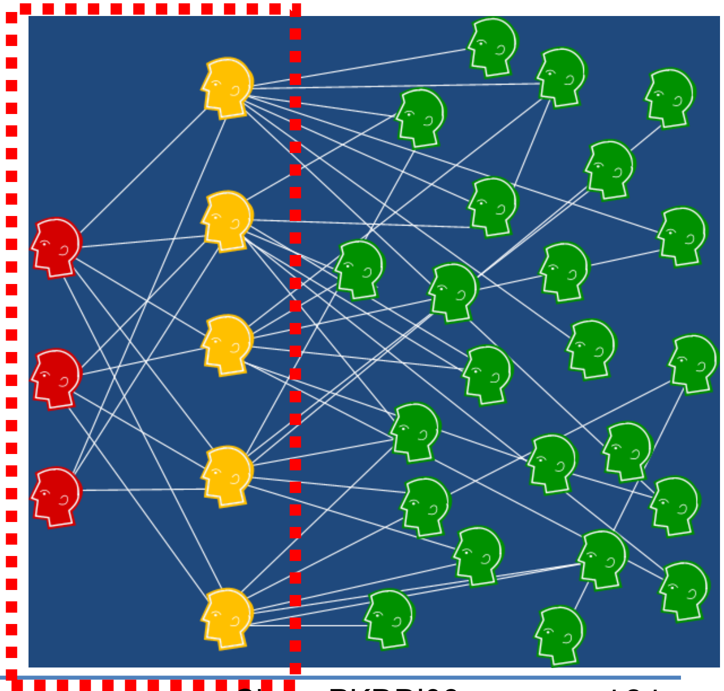
- They form near-bipartite cores (2 roles)

accomplice

- trades w/ honest, looks legit

fraudster

- trades w/ accomplice
- fraud w/ honest



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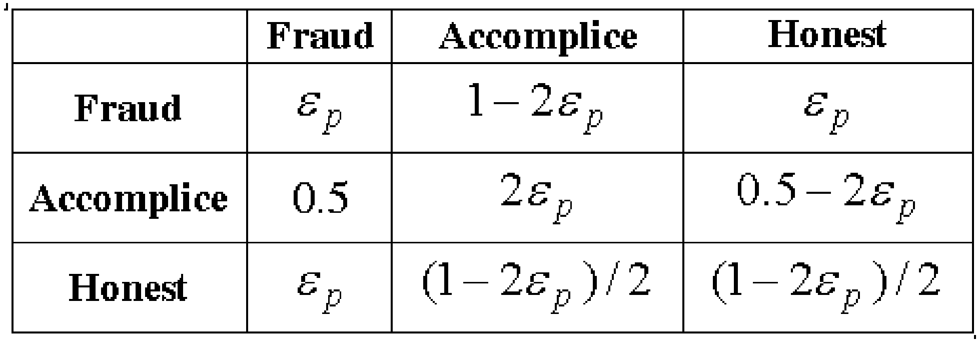
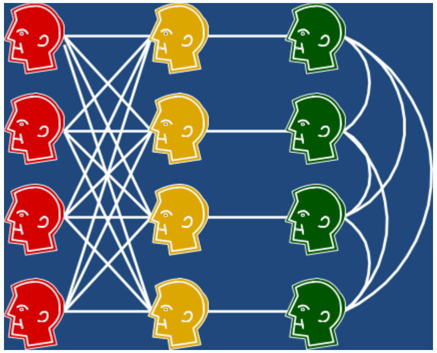
Detecting online fraud

- How to find near-bipartite cores? How to find roles (honest, accomplice, fraudster)?
  - Use Belief Propagation!
- **How to set BP parameters (potentials)?**
  - prior beliefs: prior knowledge, unbiased if none
  - compatibility potentials: by insight



	Fraud	Accomplice	Honest
Fraud	ε_p	$1-2\varepsilon_p$	ε_p
Accomplice	0.5	$2\varepsilon_p$	$0.5-2\varepsilon_p$
Honest	ε_p	$(1-2\varepsilon_p)/2$	$(1-2\varepsilon_p)/2$



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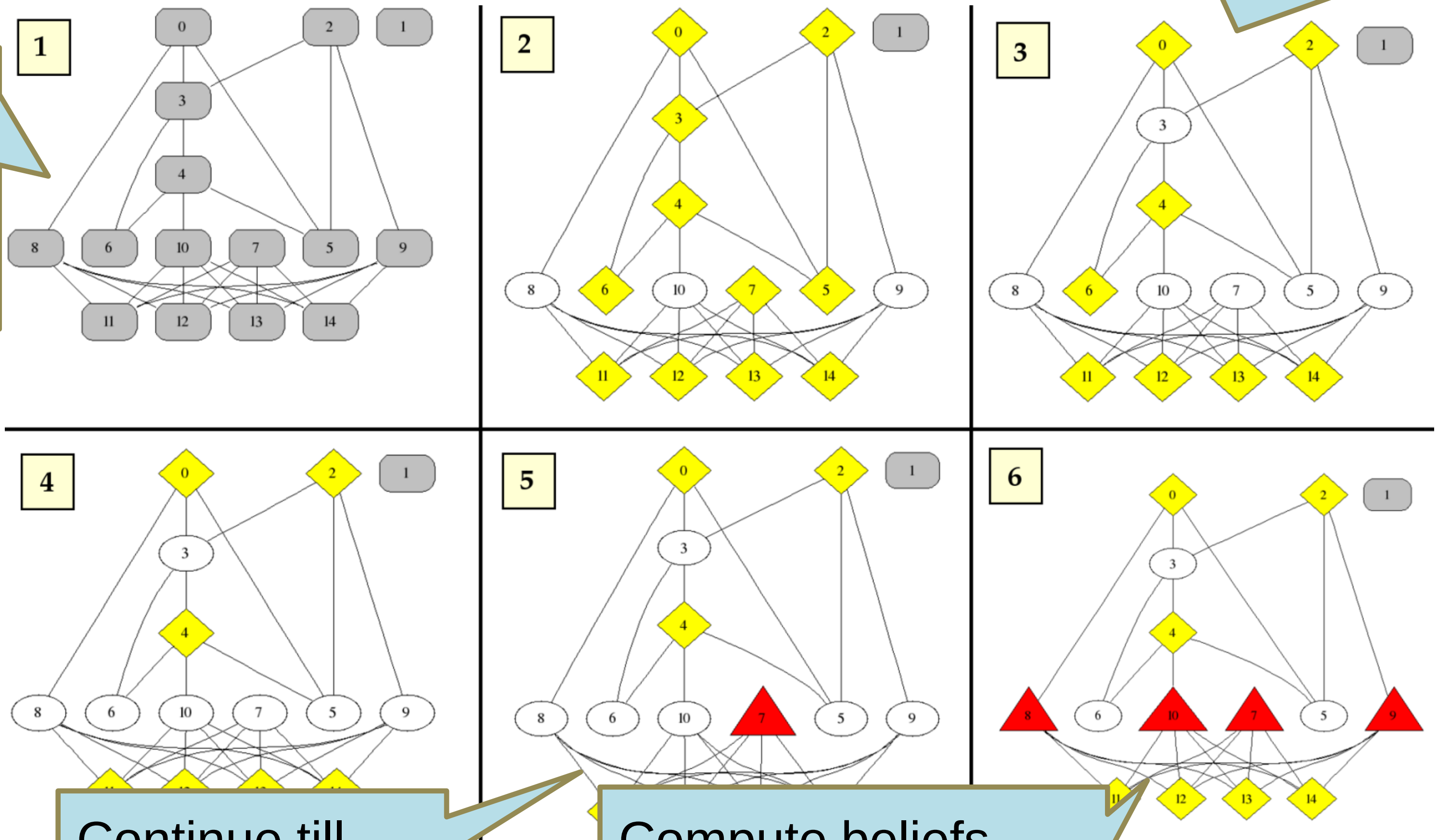
BP in action

Initialize prior beliefs of fraudsters to P(f)=1

At each iteration, for each node, compute messages to its neighbors

Initialize other nodes as unbiased



Continue till “convergence”

Compute beliefs, use most likely state

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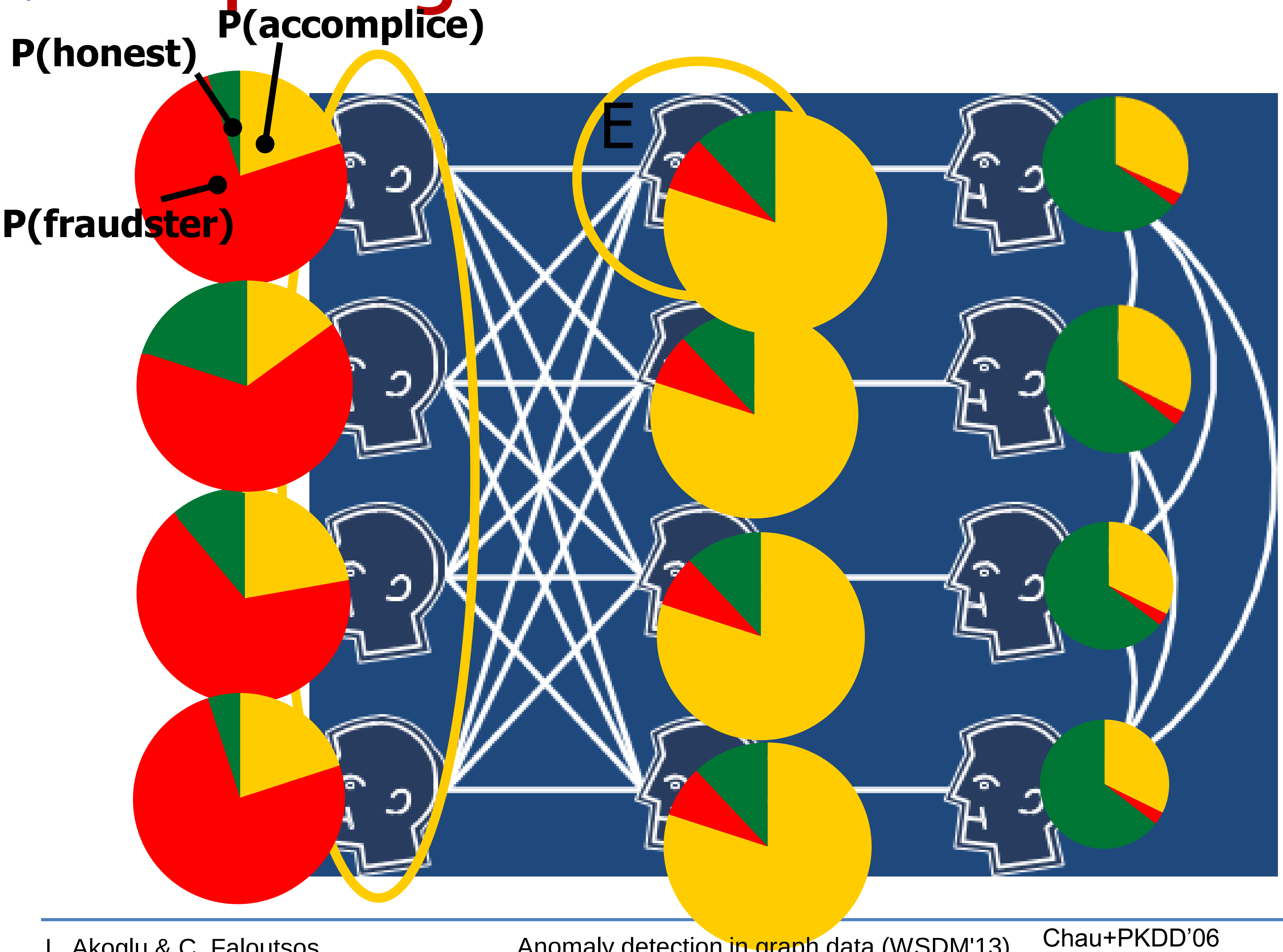
Computing beliefs → roles



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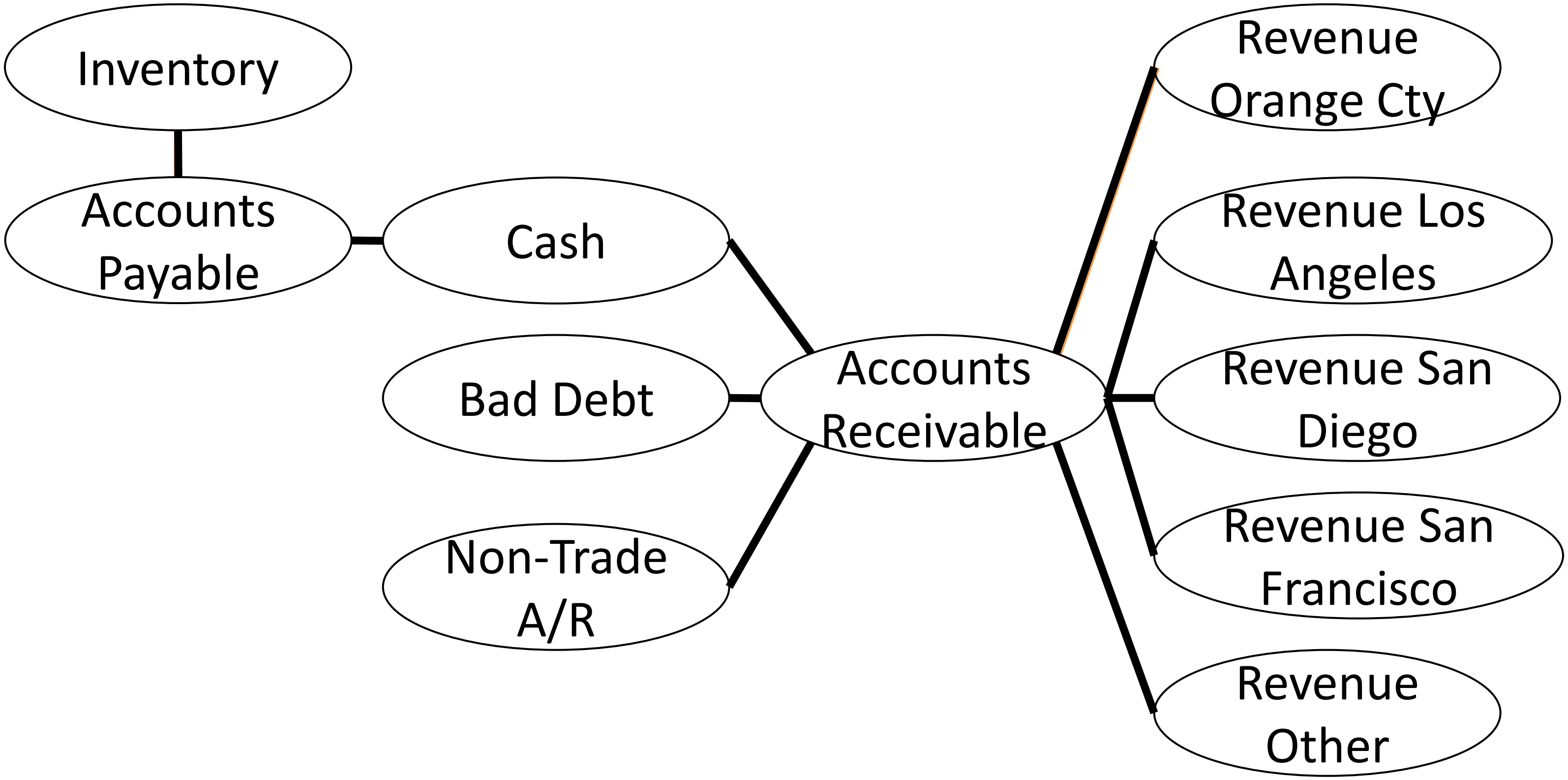
McGlohon et al. ’09

(2) Accounting fraud

- Problem: **Given** accounts and their transaction relations, **find** most risky ones



Accounting fraud detection

- Domain knowledge to flag certain nodes

  prior beliefs

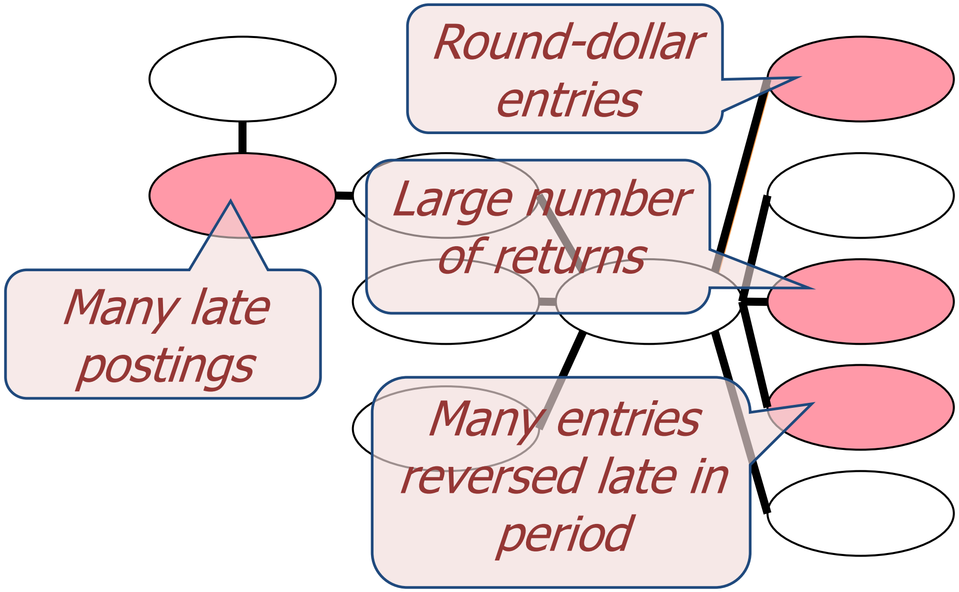
- Assume homophily ("guilt by association")

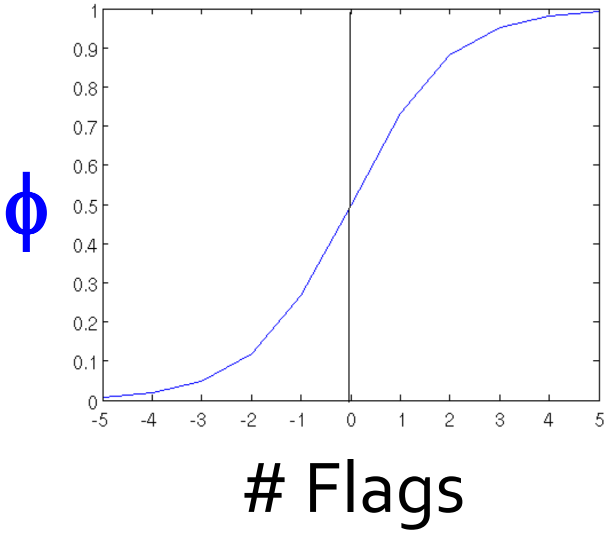
  compatibility potentials

- Use **belief propagation**
  - 2 states (risky R, normal NR)
- final beliefs → end risk scores

Social Network Analytic Risk Evaluation

- Prior beliefs (noisy domain knowledge)





- Compatibility potentials (by homophily)

$\psi_{ij}(x_d, x_c)$	$v_i = x_{NR}$	$v_i = x_R$
$v_j = x_{NR}$	$1 - \epsilon$	ϵ
$v_j = x_R$	ϵ	$1 - \epsilon$

McGlohon+KDD'09
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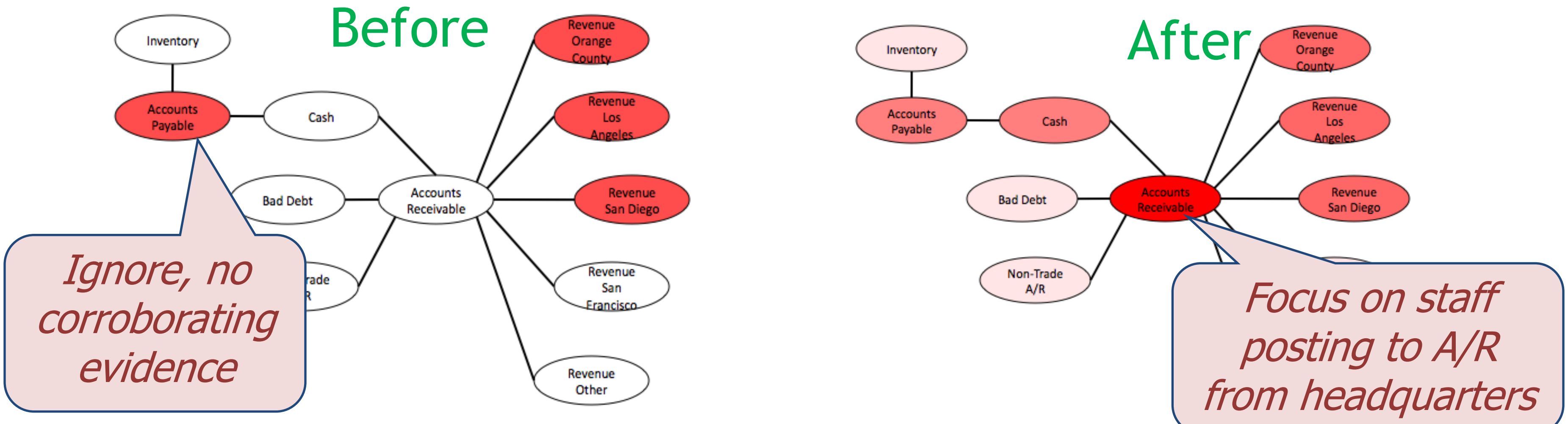
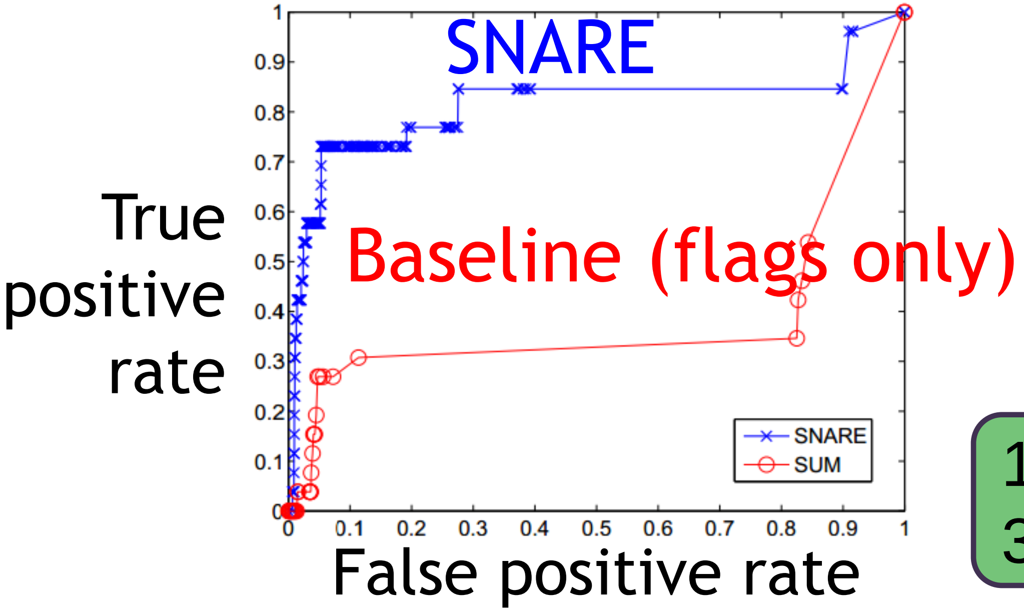
Social Network Analytic Risk Evaluation



Ignore, no corroborating evidence

Focus on staff posting to A/R from headquarters



1380 accounts
3820 transactions

McGlohon+KDD'09
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(3) Fake review spam

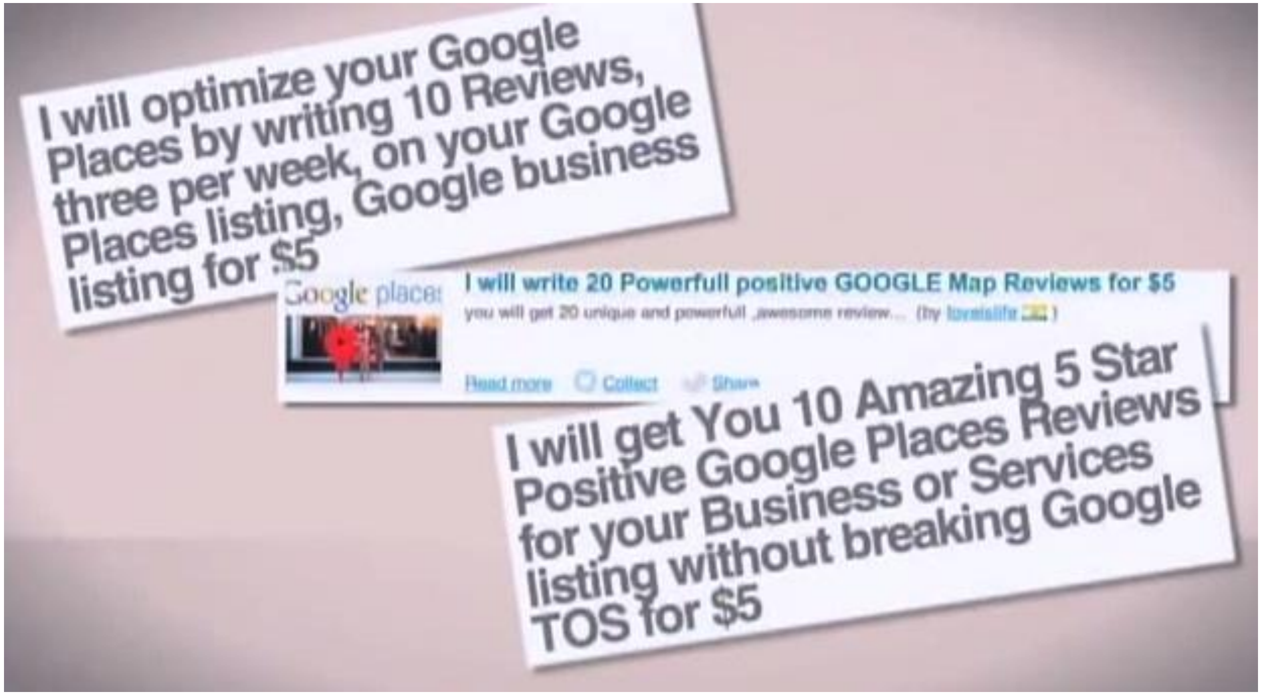
- Review sites: attractive target for spam
- Often hype/defame spam
- Paid spammers

Google

yelp

tripadvisor®

amazon



I will optimize your Google Places by writing 10 Reviews, three per week, on your Google Places listing, Google business listing for $5

Google places

I will write 20 Powerfull positive GOOGLE Map Reviews for $5

you will get 20 unique and powerfull ,awesome review... (by loveislife)

Read more Collect Share

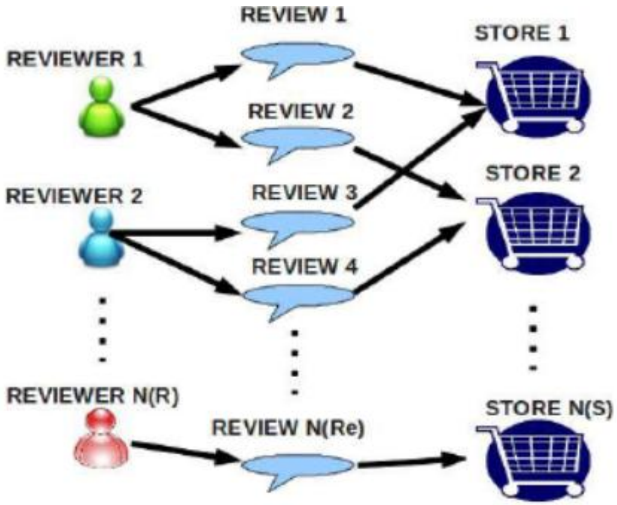
I will get You 10 Amazing 5 Star Positive Google Places Reviews for your Business or Services listing without breaking Google TOS for $5

Fake review spam detection

- Behavioral analysis [Jindal & Liu'08]
  - individual features, geographic locations, login times, [illegible]ry, etc.
- Language a[illegible] [[illegible]tt et al.'11]
  - use of superlatives, many self-referencing, rate of misspell, many agreement words, …

Easy to fake!

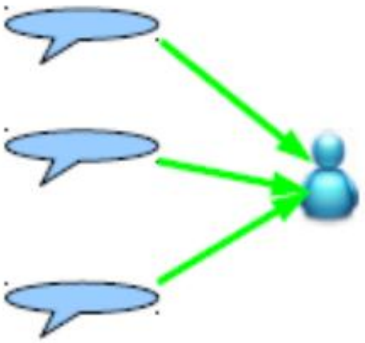
- Harder to fake: graph structure
- Capture relationships between reviewers, reviews, stores



[Wang et al. '11]

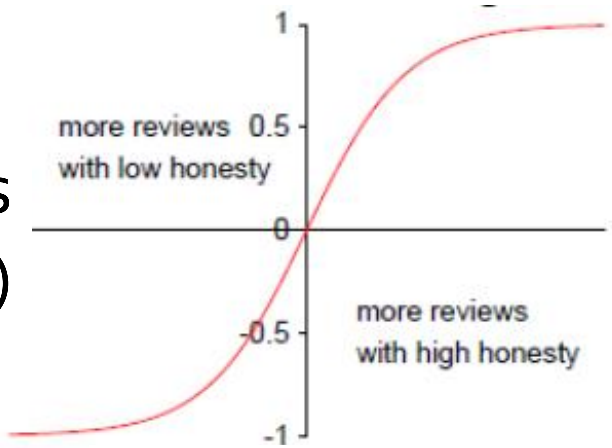
Graph-based detection

Reviewer r **trustiness** T(r)



$$H_r = \sum_{i=1}^{n_r} H(\alpha_r^i)$$

$$T(r) = \frac{2}{1+e^{-H_r}} - 1$$



Trustiness T(r)

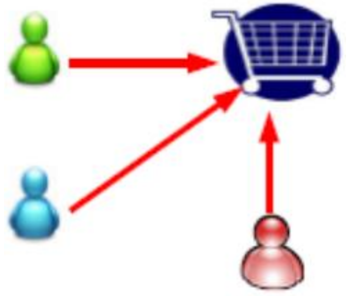
Honesty H_r

Graph-based detection

Store s **reliability** R(s)

$$\theta = \sum_{v \in Us, T(\kappa_v) > 0} T(\kappa_v)(\Psi_v - \mu)$$

review v rating

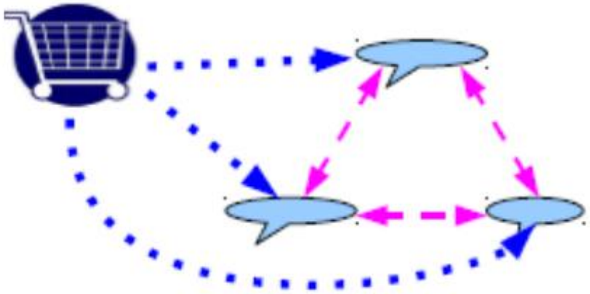


$$R(s) = \frac{2}{1 + e^{-\theta}} - 1$$

Trustiness
Honesty
Agreement
Reliability

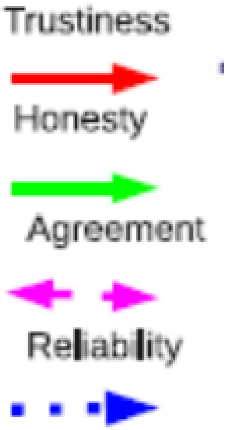
Graph-based detection

Review v **honesty** H(v)

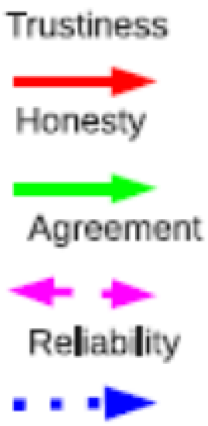


$$A(v,\Delta t) = \sum_{i\in S_{v,a}} T(\kappa_i) - \sum_{j\in S_{v,d}} T(\kappa_j)$$

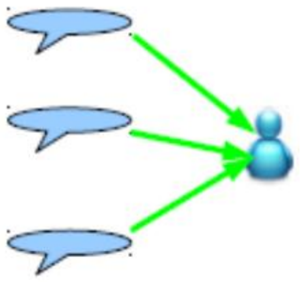
$$H(v) = | R(\Gamma_v) | A_n(v,\Delta t)$$



Graph-based detection



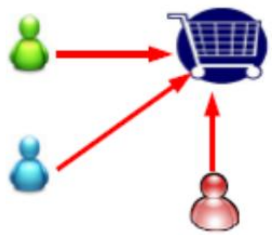
Reviewer r trustiness T(r)



$$\underline{H_r} = \sum_{i=1}^{n_r} H(\alpha_r^i)$$

$$T(r) = \frac{2}{1+e^{-\underline{H_r}}} - 1$$

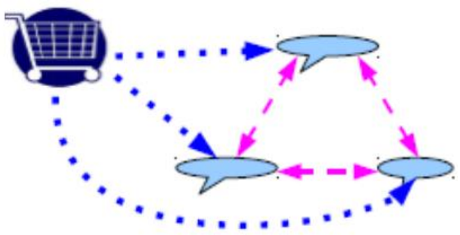
Store s reliability R(s)



$$\theta = \sum_{v \in Us, T(\kappa_v)>0} \underline{T(\kappa_v)}(\Psi_v - \mu)$$

$$R(s) = \frac{2}{1+e^{-\theta}} - 1$$

Review v honesty H(v)



$$A(v,\Delta t) = \sum_{i \in S_{v,a}} \underline{T(\kappa_i)} - \sum_{j \in S_{v,d}} \underline{T(\kappa_j)}$$

$$H(v) = \underline{|R(\Gamma_v)|}\, A_n(v,\Delta t)$$

Graph-based detection

- Algorithm: iterate trustiness, reliability, and honesty scores in a mutual recursion
  - similar to Kleinberg's HITS algorithm
  - **non-linear** relations

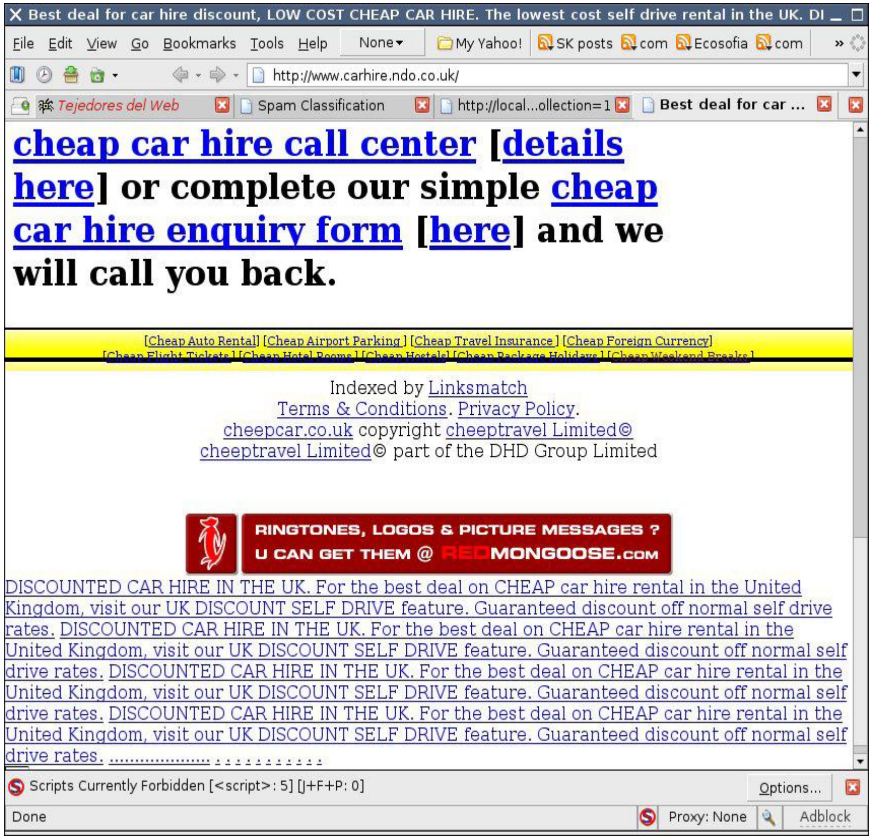
- Challenges:
  - Convergence not guaranteed
  - Cannot use attribute info
  - Parameters: agreement time window Δt, review similarity threshold (for dis/agreement)

Part III: Outline

- Algorithms: **relational learning**
  - Collective classification
  - Relational inference
- Applications: **fraud and spam** detection
  - Online auction fraud
  - Accounting fraud
  - Fake review spam
  - Web spam

(4) Web spam

- **Spam pages:** pages designed to trick search engines to direct traffic to their websites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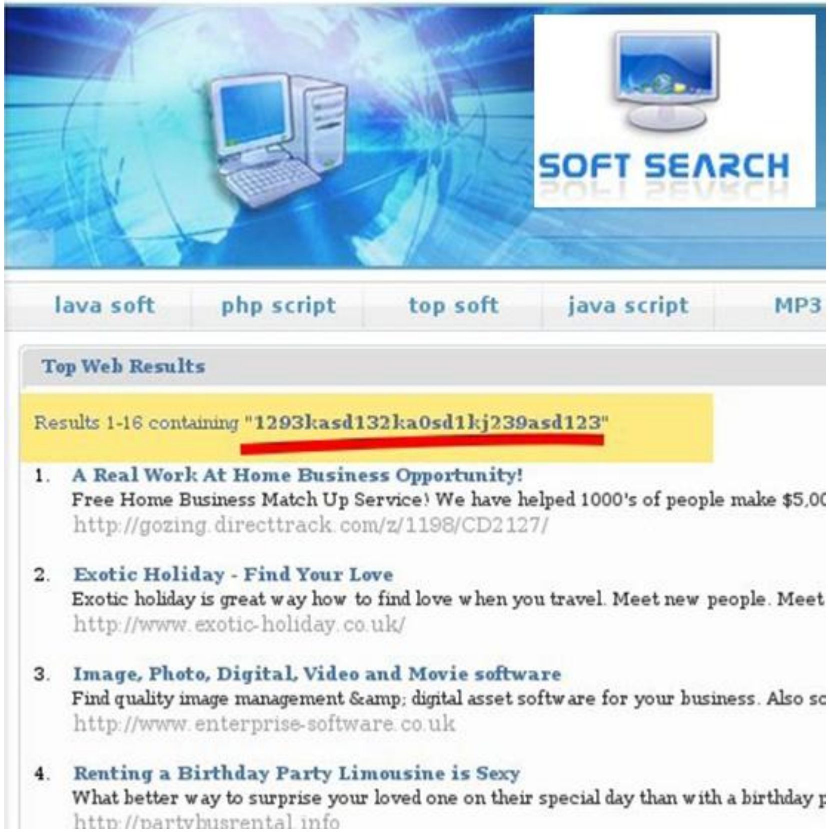


Top Web Results

Results 1-16 containing "1293kasd132ka0sd1kj239asd123"

1. A Real Work At Home Business Opportunity!
Free Home Business Match Up Service! We have helped 1000's of people make $5,0C
http://gozing.directtrack.com/z/1198/CD2127/

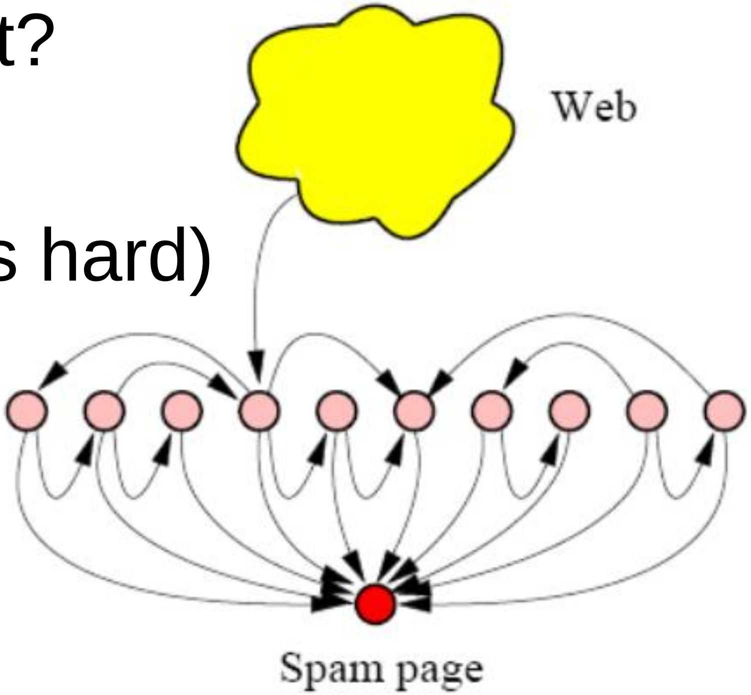
2. Exotic Holiday - Find Your Love
Exotic holiday is great way how to find love when you travel. Meet new people. Meet
http://www.exotic-holiday.co.uk/

3. Image, Photo, Digital, Video and Movie software
Find quality image management &amp; digital asset software for your business. Also sc
http://www.enterprise-software.co.uk

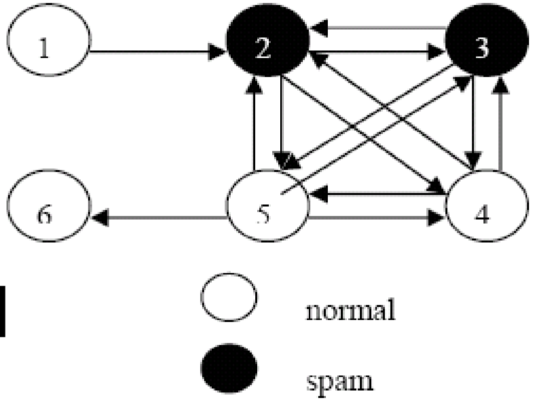
4. Renting a Birthday Party Limousine is Sexy
What better way to surprise your loved one on their special day than with a birthday p
http://partybusrental.info

Web spam

- Challenges:
  - pages are not independent
  - what features are relevant?
  - small training set
  - noisy labels (consensus is hard)
  - content very dynamic



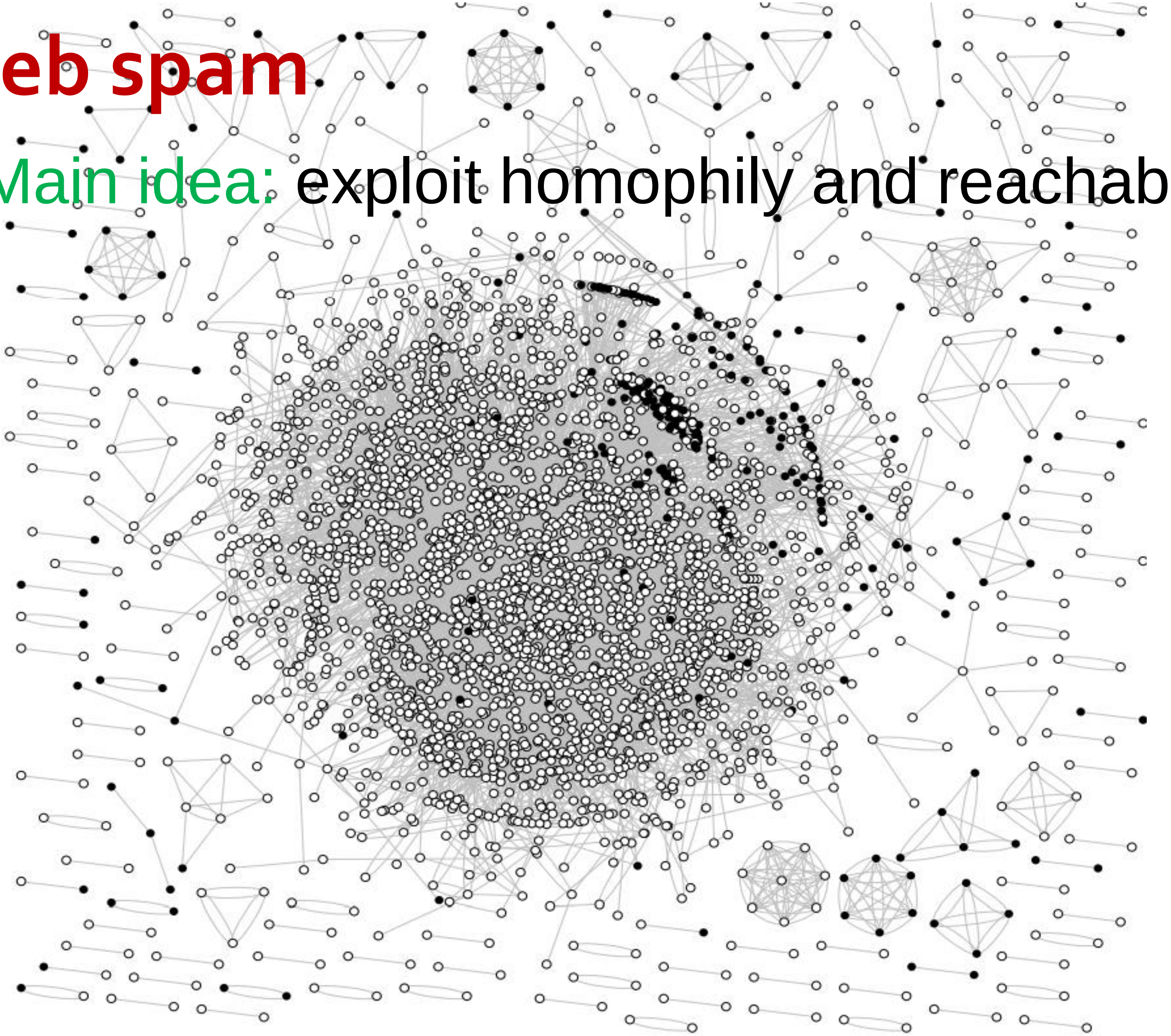
Web spam



- Many **graph-based** solutions
  - TrustRank **[Gyöngyi et al. '04]**
  - SpamRank **[Benczur et al. '05]**
  - Anti-trustRank **[Krishnan et al. '06]**
  - Propagating trust and distrust **[Wu et al. '06]**
  - Know your neighbors **[Castillo et al. '07]**
  - Guilt-by-association **[Kang et al. '11]**
  - …

Web spam

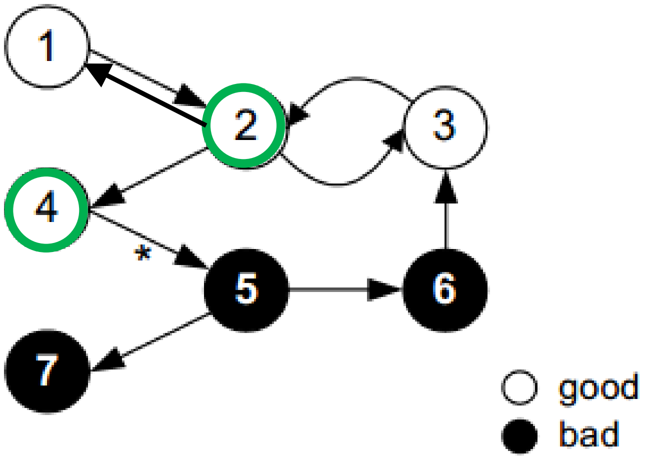
- Main idea: exploit homophily and reachability



[Gyöngyi et al. '04]

TrustRank: combating web spam

- Main steps:
  - Find seed set S of "good" pages (e.g. using oracle)
  - Compute trust scores by biased (personalized) PageRank from good pages



- Intuition: spam pages are hardly reachable from trustworthy pages
  - Hard to acquire direct inlinks from good pages

TrustRank mathematically

details

- Remember PageRank score of a page p:

$$\mathbf{r}(p) = \alpha \cdot \sum_{q:(q,p)\in\mathcal{E}} \frac{\mathbf{r}(q)}{\omega(q)} + (1-\alpha)\cdot\frac{1}{N}$$

- In closed form:

$$\mathbf{r} = \alpha \cdot \mathbf{T} \cdot \mathbf{r} + (1-\alpha)\cdot\frac{1}{N}\cdot\mathbf{1}_N \qquad \mathbf{T}(p,q) = \begin{cases} 0 & \text{if } (q,p)\notin\mathcal{E}, \\ 1/\omega(q) & \text{if } (q,p)\in\mathcal{E}. \end{cases}$$

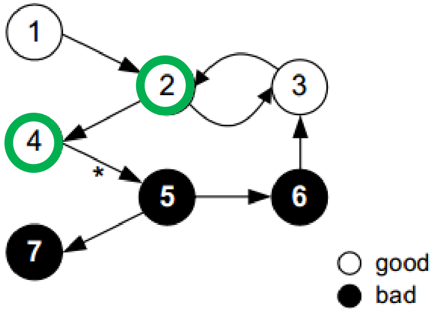
damping factor

Transition matrix

- Personalized PageRank:

$$\mathbf{r} = \alpha \cdot \mathbf{T} \cdot \mathbf{r} + (1-\alpha)\cdot\mathbf{d}$$

1/|S| for S nodes of interest (seeds)

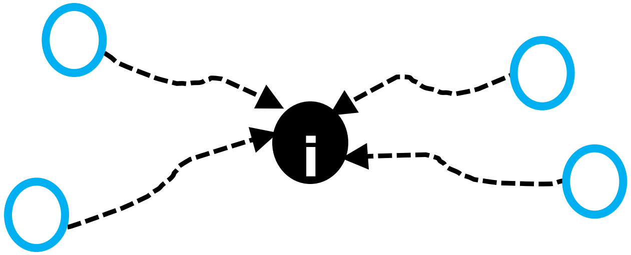


$$\mathbf{d} = [0, \ \tfrac{1}{2}, \ 0, \ \tfrac{1}{2}, \ 0, \ 0, \ 0]$$

[Benczur et al. '05]

SpamRank: link spam detection

- Intuition: PageRank distribution of "good" set of supporters should be power law (as in entire Web)
  - Page v is a supporter of page i if: $PPR_i(v) > 0$



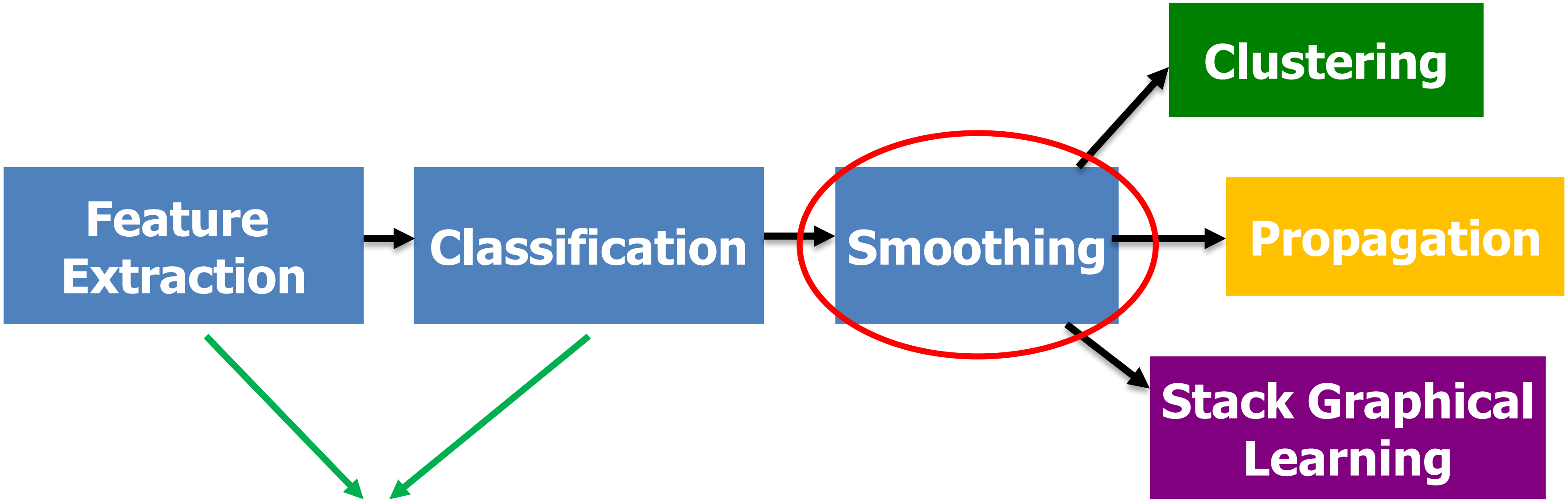
- For each page i
  - get PageRank scores of all supporters of i
  - test PageRank histogram for power law
  - calculate irregularity score s(i)
- SpamRank ← PPR($\vec{s}$)

Advantage: no user labeling (as for TrustRank)

[Castillo et al. '07]

"Know your neighbors"

- Graph-based techniques can help improve feature-based classifiers

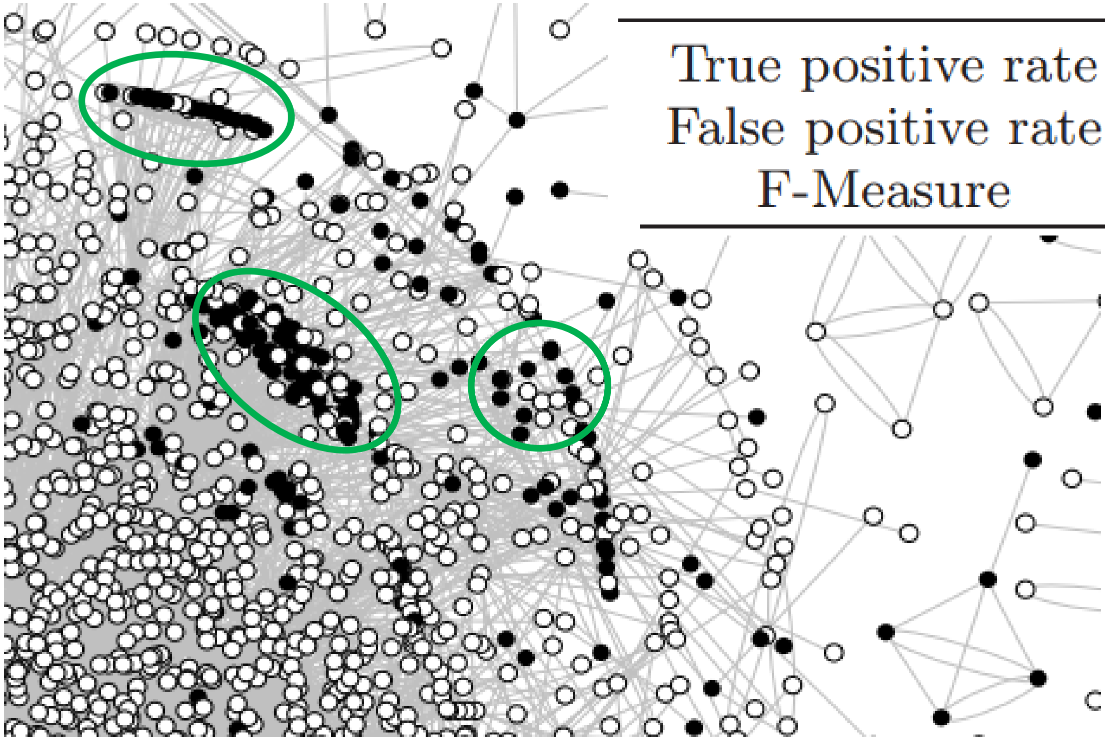


  - *Graph features*: reciprocity, assortativity, TrustRank, PageRank, …
  - *Content features*: fraction visible text, compression rate, entropy of trigrams, …

Smoothing –clustering

- Split graph into many clusters. (e.g. by METIS)
- If majority of nodes in cluster are spam, then all pages in cluster are spam.

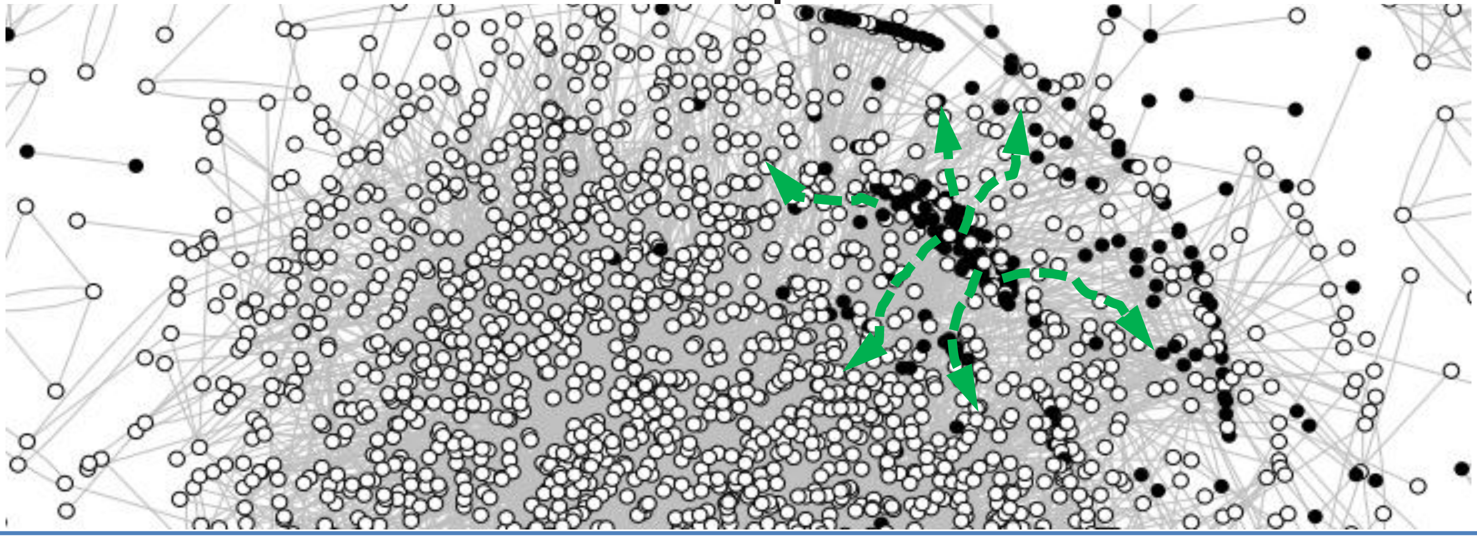
	Baseline	Clustering
True positive rate	78.7%	76.9%
False positive rate	5.7%	5.0%
F-Measure	0.723	**0.728**



Smoothing –propagation

- Propagate predictions using random walks.
- PPR($\vec{s}$); s(i): spamicity score by baseline classifier (backward and/or forwards steps)

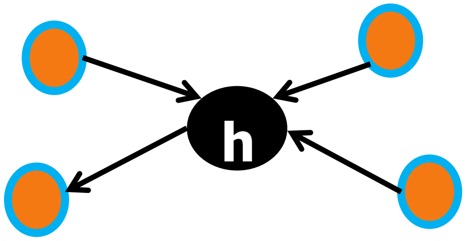
	Baseline	Fwds.	Backwds.	Both
True positive rate	78.7%	76.5%	75.0%	75.2%
False positive rate	5.7%	5.4%	4.3%	4.7%
F-Measure	0.723	0.716	**0.733**	0.724



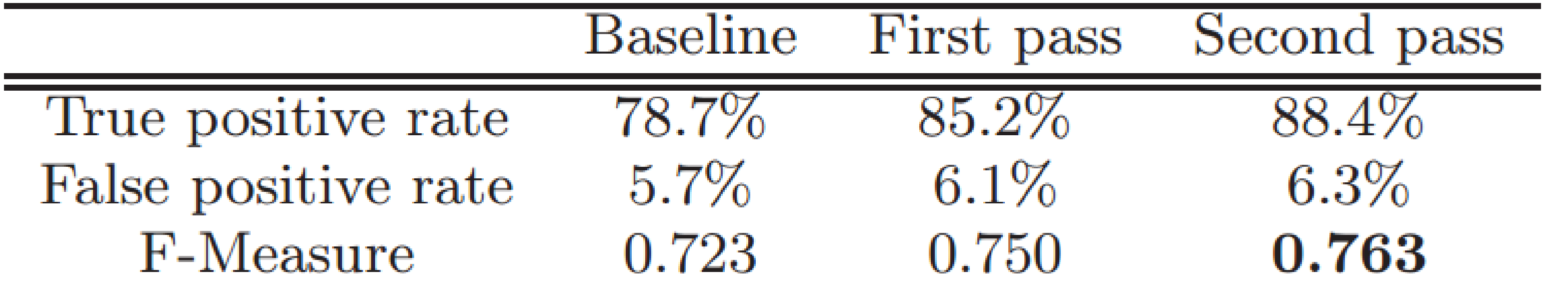
Smoothing –stacked learning

- Create additional features by combining predictions for related nodes
  - e.g., avg. spamicity score *p* of neighbors *r(h)* of *h*

$$f(h) = \frac{\sum_{g \in r(h)} p(g)}{|r(h)|}$$



  - similar to pRN classifier by Macskassy&Provost
  - can repeat, although 1-2 steps add most gain



	Baseline	First pass	Second pass
True positive rate	78.7%	85.2%	88.4%
False positive rate	5.7%	6.1%	6.3%
F-Measure	0.723	0.750	**0.763**

Part III: References (alg.s and app.s)

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Tutorial Outline

- Motivation, applications, challenges
- **Part I:** Anomaly detection in **static** data
  - Overview: Outliers in **clouds of points**
  - Anomaly detection in **graph data**
- **Part II:** Event detection in **dynamic** data
  - Overview: Change detection in **time series**
  - Event detection in **graph sequences**
- **Part III:** Graph-based **algorithms and apps**
  - Algorithms: **relational learning**
  - Applications: **fraud and spam** detection

Conclusions

- Graphs are powerful tools to detect
  - **Anomalies**
  - **Events**
  - **Fraud/Spam**

  in complex real-world data (attributes, (noisy) side information, weights, …)
- Nature of the problem highly dependent on the application domain
- Each problem formulation needs a different approach

Open challenges: research

- Anomalies in dynamic graphs
  - dynamic **attributed** graphs (definitions, formulations, real-world scenarios)
  - temporal effects: node/edge **history** (not only updates)
- Fraud/spam detection: system perspective
  - adversarial **robustness**
  - **cost** (to system in measurement , to adversary to fake, to user in exposure)
  - detection **timeliness** and other system design aspects; e.g. dynamicity, latency

Open challenges: practice

- What makes the results better in practice?
  - better priors?
  - better parameter learning?
  - more data?
  - …
- Graph construction
  - If no network, what to use to build one?
  - If one network,
    - more latent edges? (e.g. review similarity)
    - less edges? (e.g. domain knowledge)
  - If more than one network, how to exploit all?

Q & A

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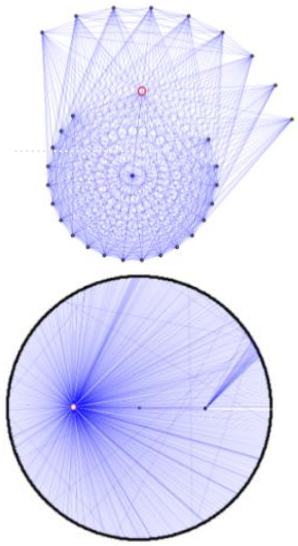
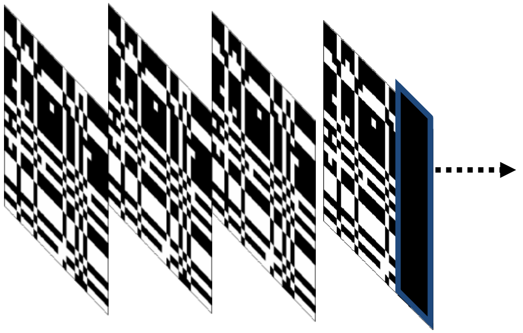
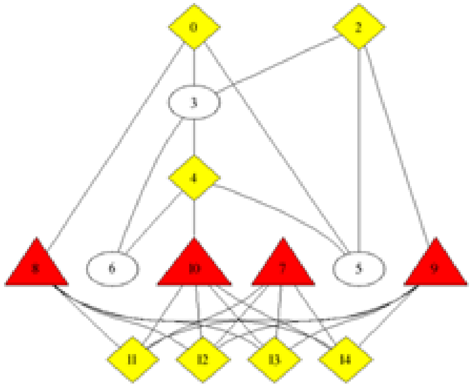


anomalies



events



fraud/spam