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

Part III: Outline

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

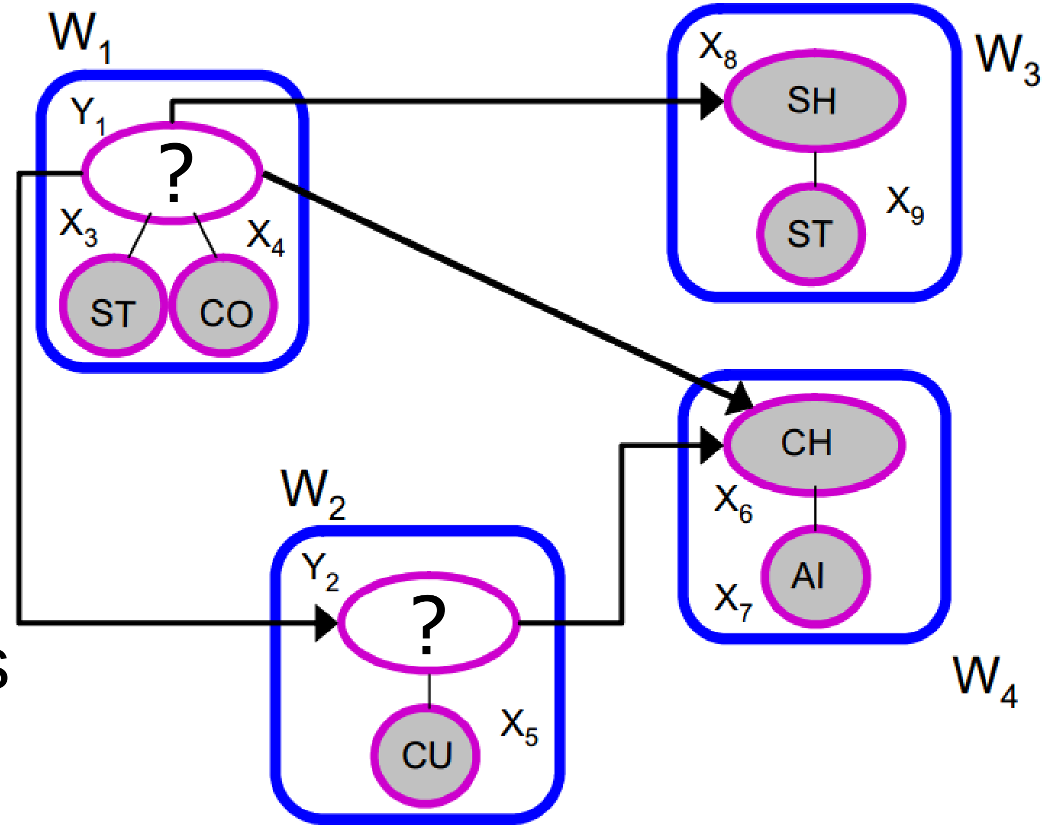
- Applications: **fraud and spam** detection
  - Online auction fraud
  - Accounting fraud
  - Fake review spam
  - Web spam

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

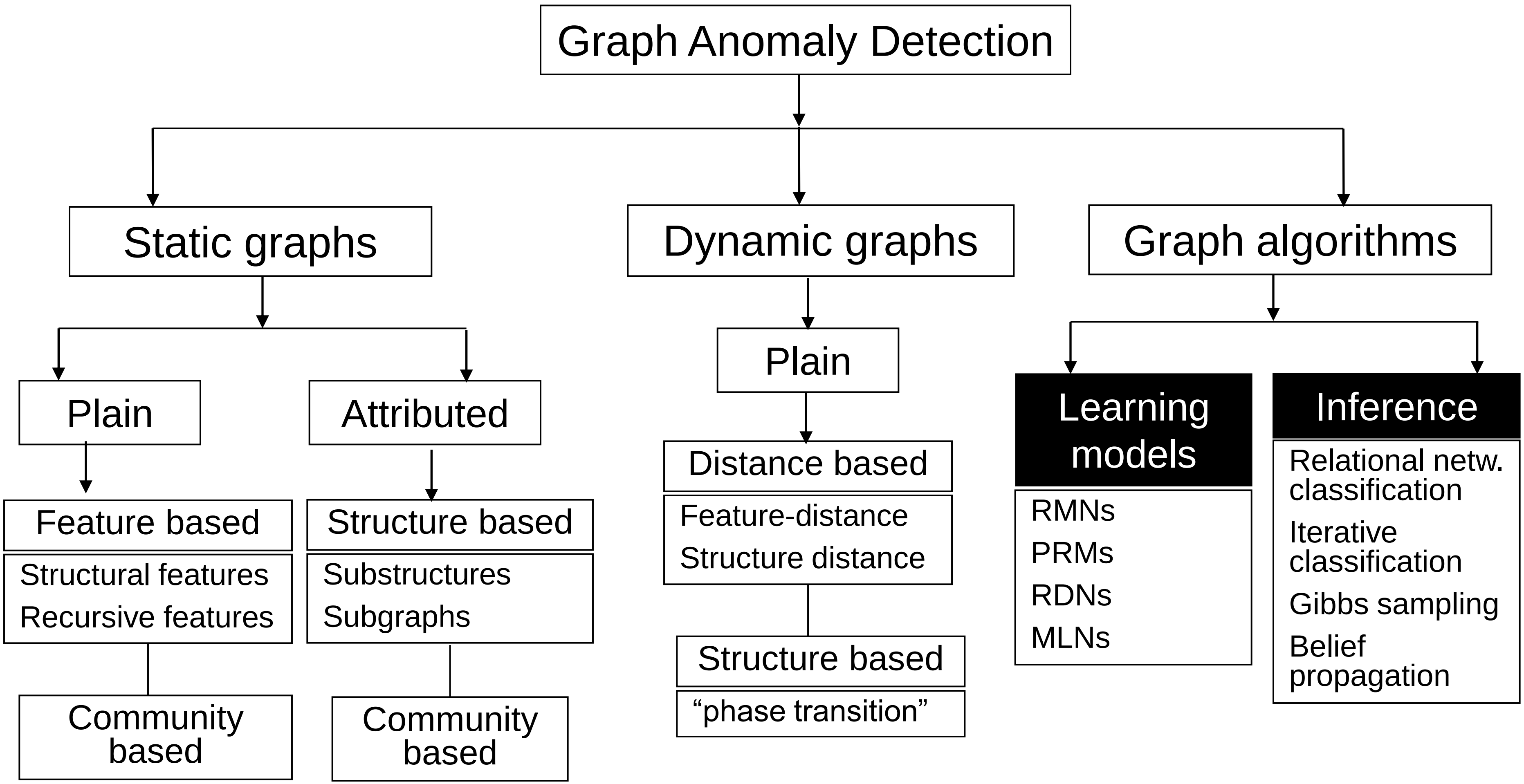


nodes; web pages, edges; hyperlinks, labels; SH or CH: student/course page; features nodes are keywords; ST: student, CO: course, CU: curriculum, AI: artificial intelligence

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
Dynamic graphs
Graph algorithms
Plain
Attributed
Feature based
Structural features
Recursive features
Community based
Structure based
Substructures
Subgraphs
Community based
Plain
Distance based
Feature-distance
Structure distance
Structure based
“phase transition”
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

(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

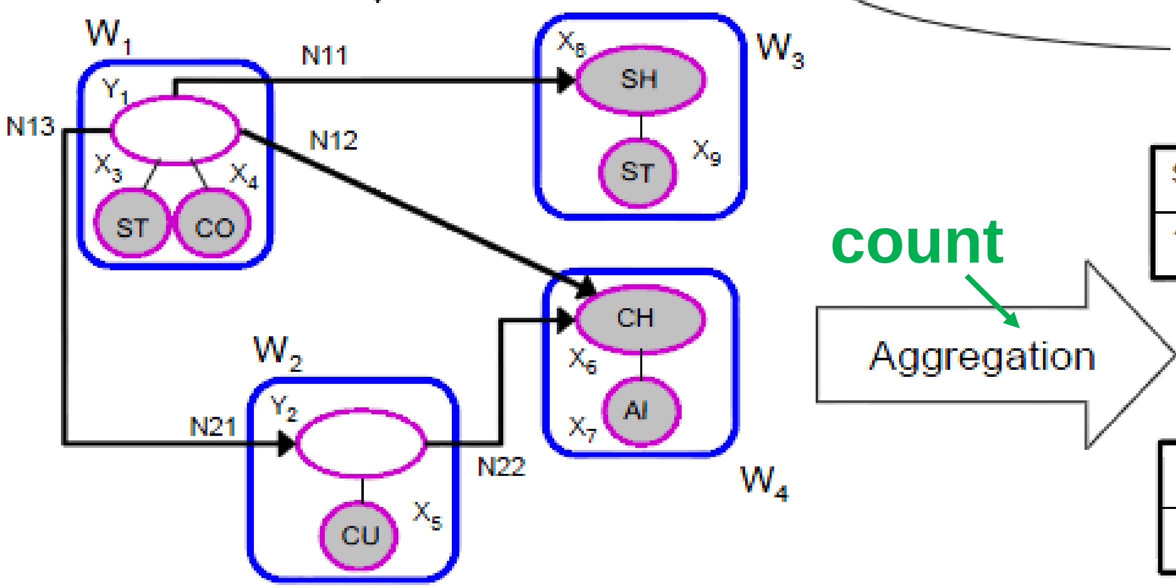
    Various #neighbors → **aggregation**
    - count
    - mode
    - proportion
    - mean
    - exists

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

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

NEIGHBOR LABELS →

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

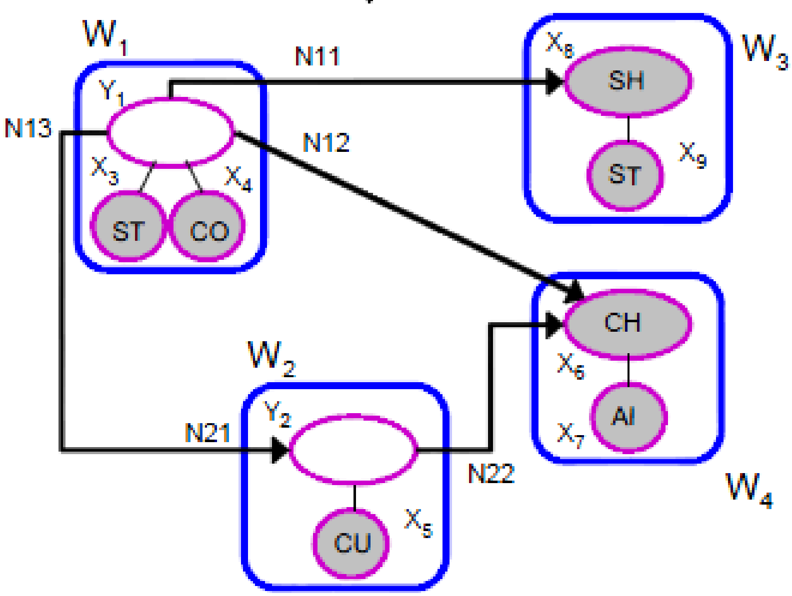
Note: convergence not guaranteed

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

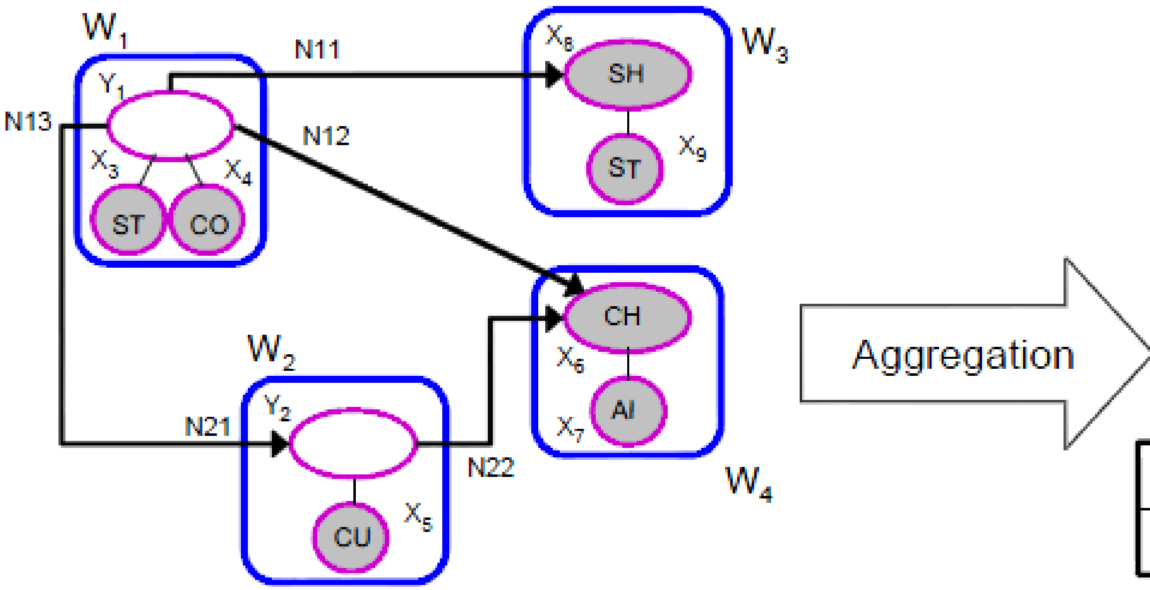
$a_1^{t=1}$

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

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

a'_2

NEIGHBOR LABELS →

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

Gibbs sampling

Bootstrap

Burn-in

Sample

- Main idea:
  - Convert each node Y_i to a flat vector a_i
  - Use local classifier $f(a_i)$ to compute best value for y_i
  - **Repeat B times** for each node Y_i
    - Reconstruct feature vector a_i
    - Update label to $f(a_i)$ (hard assignment)
  - **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**

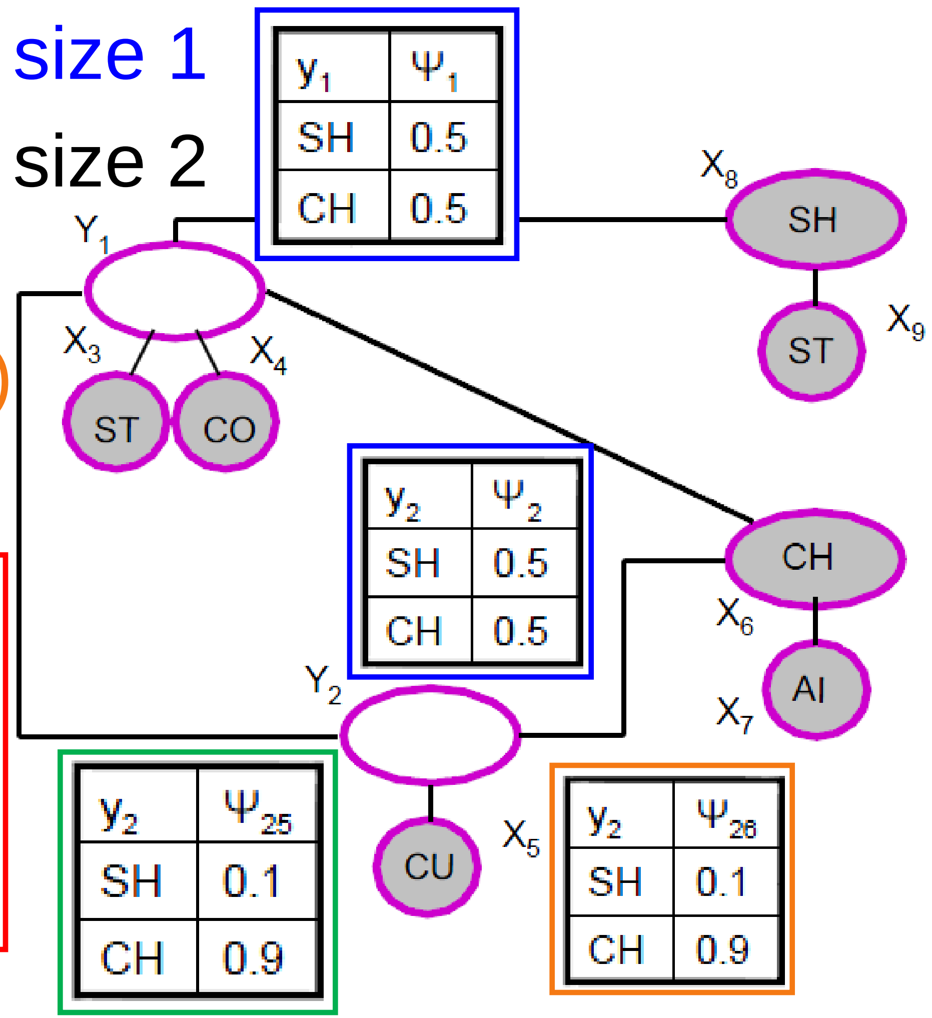
    Yedidia et al. '00

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)

For pairwise RMNs max clique size is 2



y_1	Ψ_1
SH	0.5
CH	0.5

y_2	Ψ_2
SH	0.5
CH	0.5

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_{25}
SH	0.1
CH	0.9

y_2	Ψ_{26}
SH	0.1
CH	0.9

pairwise Markov Random Field

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

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

Node labels as random variables

compatibility potentials (label-label)

"known" potential

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

prior belief (1-clique potentials)

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

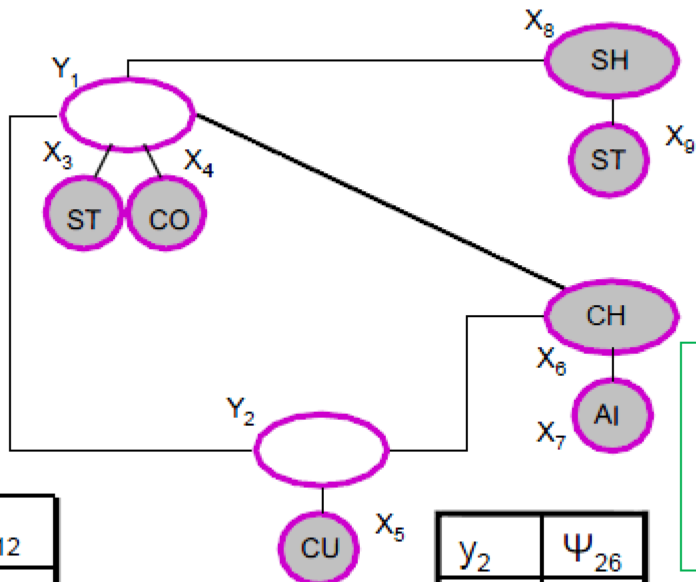
y_1	Ψ_{13}
SH	0.6
CH	0.4

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
- $P(y \mid x)$ 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 x_1) believe you (variable x_2) belong in these states with various likelihoods…"

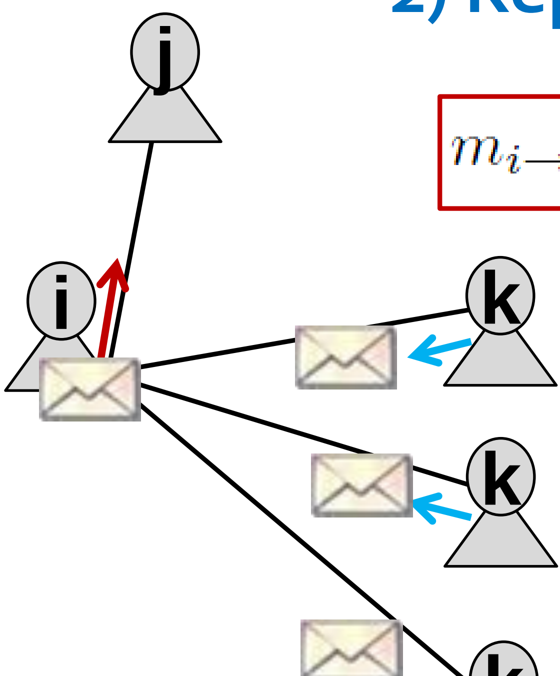
- When consensus reached, calculate belief

Loopy belief propagation

details

1) Initialize all messages to 1

2) Repeat for each node:

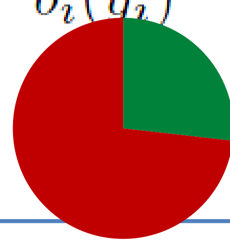


$$\boxed{m_{i\to j}(y_j)} = \alpha \sum_{y_i \in \mathcal{L}} \boxed{\psi_{ij}(y_i, y_j)} \boxed{\phi_i(y_i)} \boxed{\prod_{Y_k \in \mathcal{N}_i \cap \mathcal{Y} \setminus Y_j} m_{k\to i}(y_i)}, \quad \forall y_j \in \mathcal{L}$$

$$\boxed{m_{k\to i}(y_i)}$$

3) When messages "stabilize":

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



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CH	0.4

y_1	Ψ_{16}
SH	0.1
CH	0.9

y_1	Ψ_{18}
SH	0.8
CH	0.2

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

y_1	Φ_1
SH	0.0096
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y_1	Ψ_1
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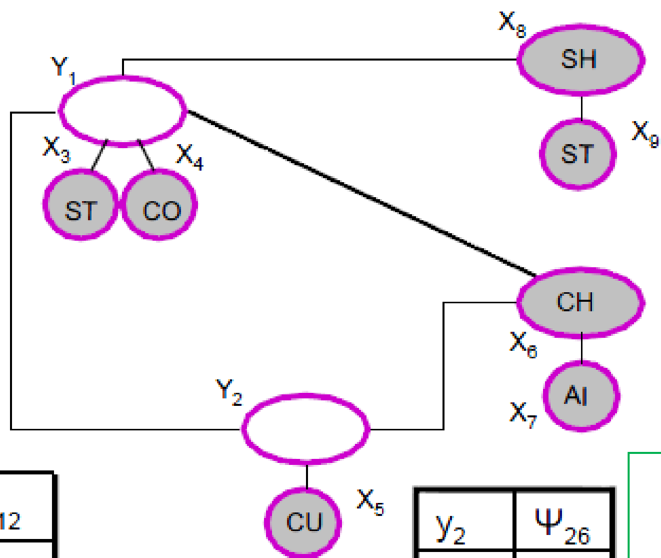
CH	0.5

y_1	Ψ_{14}
SH	0.4
CH	0.6

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

y_2	Φ_2
SH	0.005
CH	0.405



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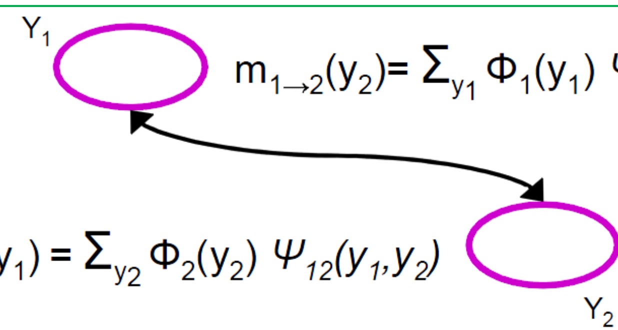
SH	CH	0.1
CH	SH	0.1
CH	CH	0.9

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



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

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

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

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

Loopy belief propagation

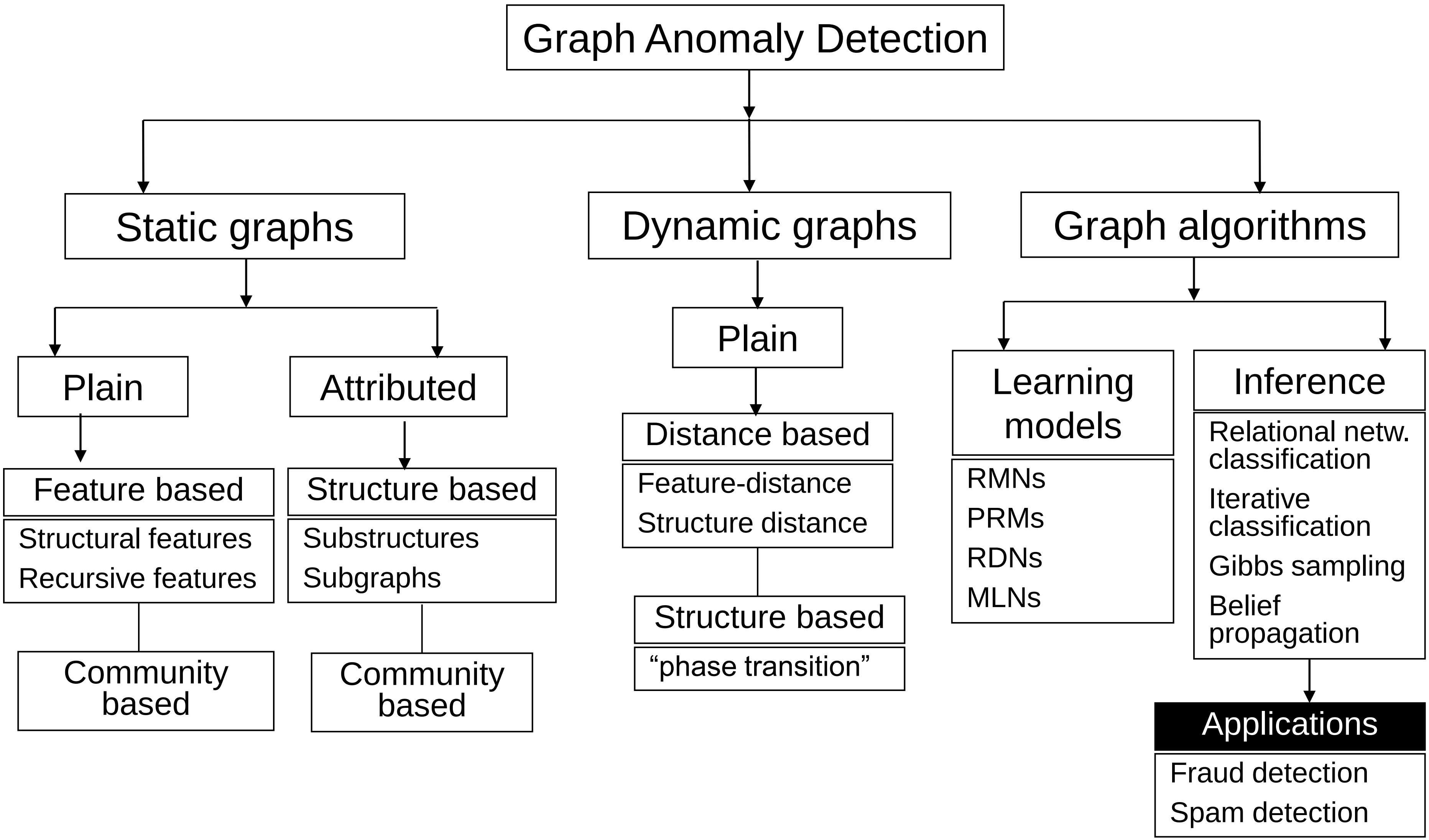
Advantages:

- 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



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Feature based
Structural features
Recursive features
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Structure based
“phase transition”
Learning models
RMNs
PRMs
RDNs
MLNs
Inference
Relational netw. classification
Iterative classification
Gibbs sampling
Belief propagation
Applications
Fraud detection
Spam detection

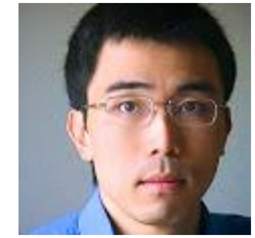
Part III: Outline

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

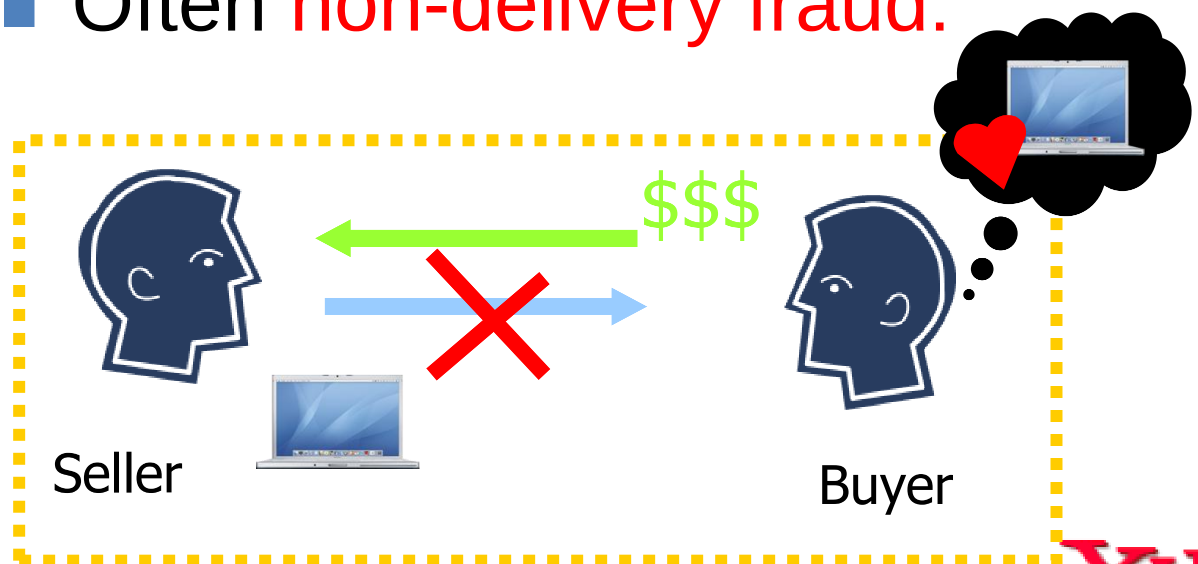
- Applications: **fraud and spam** detection
  - (1) Online auction fraud
  - (2) Accounting fraud
  - (3) Fake review spam
  - (4) Web spam

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:



Online auction fraud detection

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

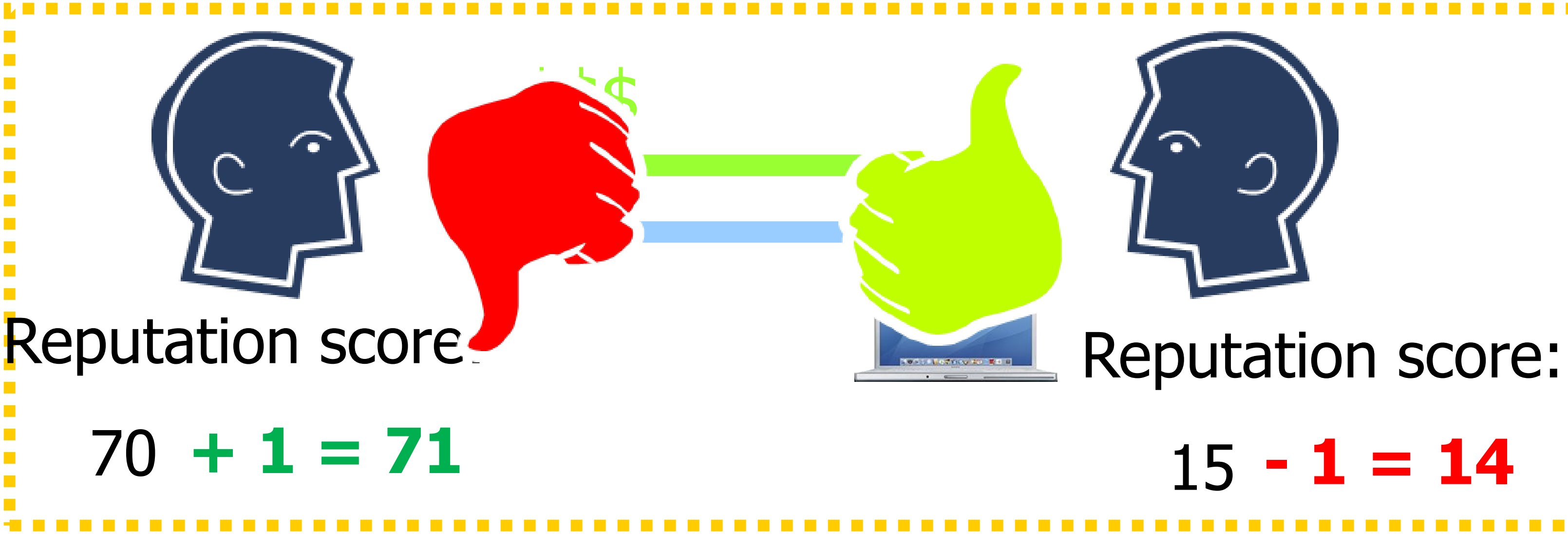
Easy to fake!

- Hard 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

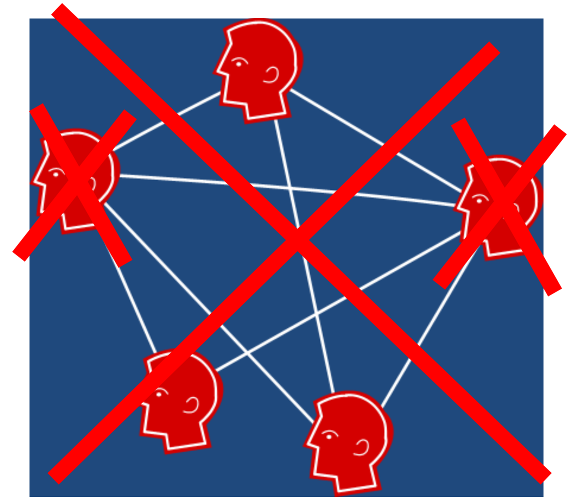


- Q: How do fraudsters game the feedback system?

Auction "roles"

- Do they boost each other's reputation?

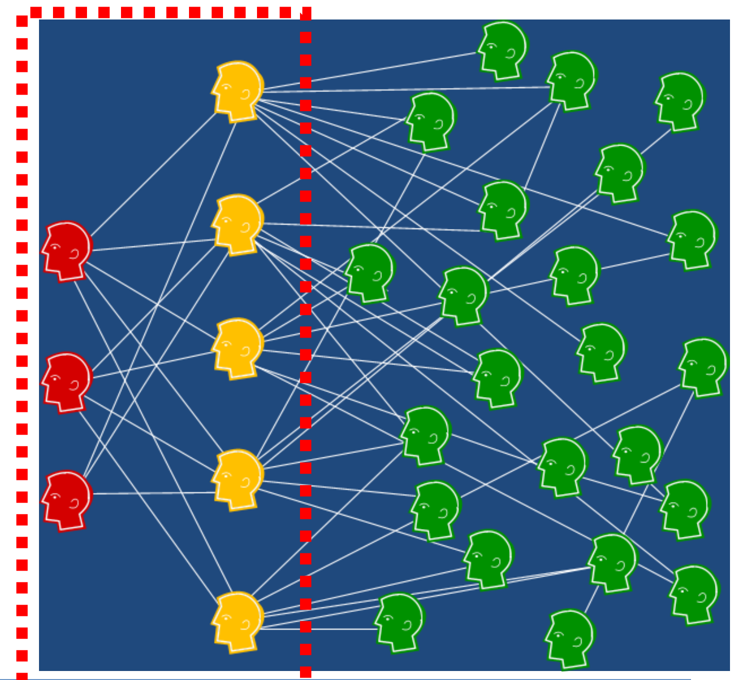
No, if one caught, all caught!



- They form near-bipartite cores (2 roles)

accomplice
  - trades w/ honest, looks legit

fraudster
  - trades w/ accomplice
  - fraud w/ honest

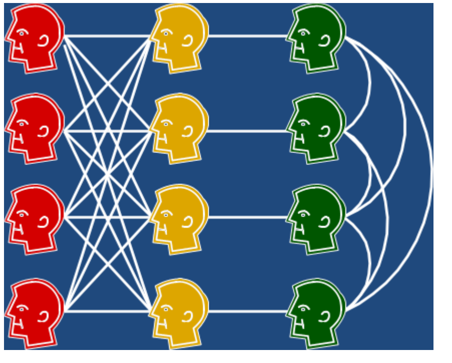


Chau+PKDD'06 modified with permission

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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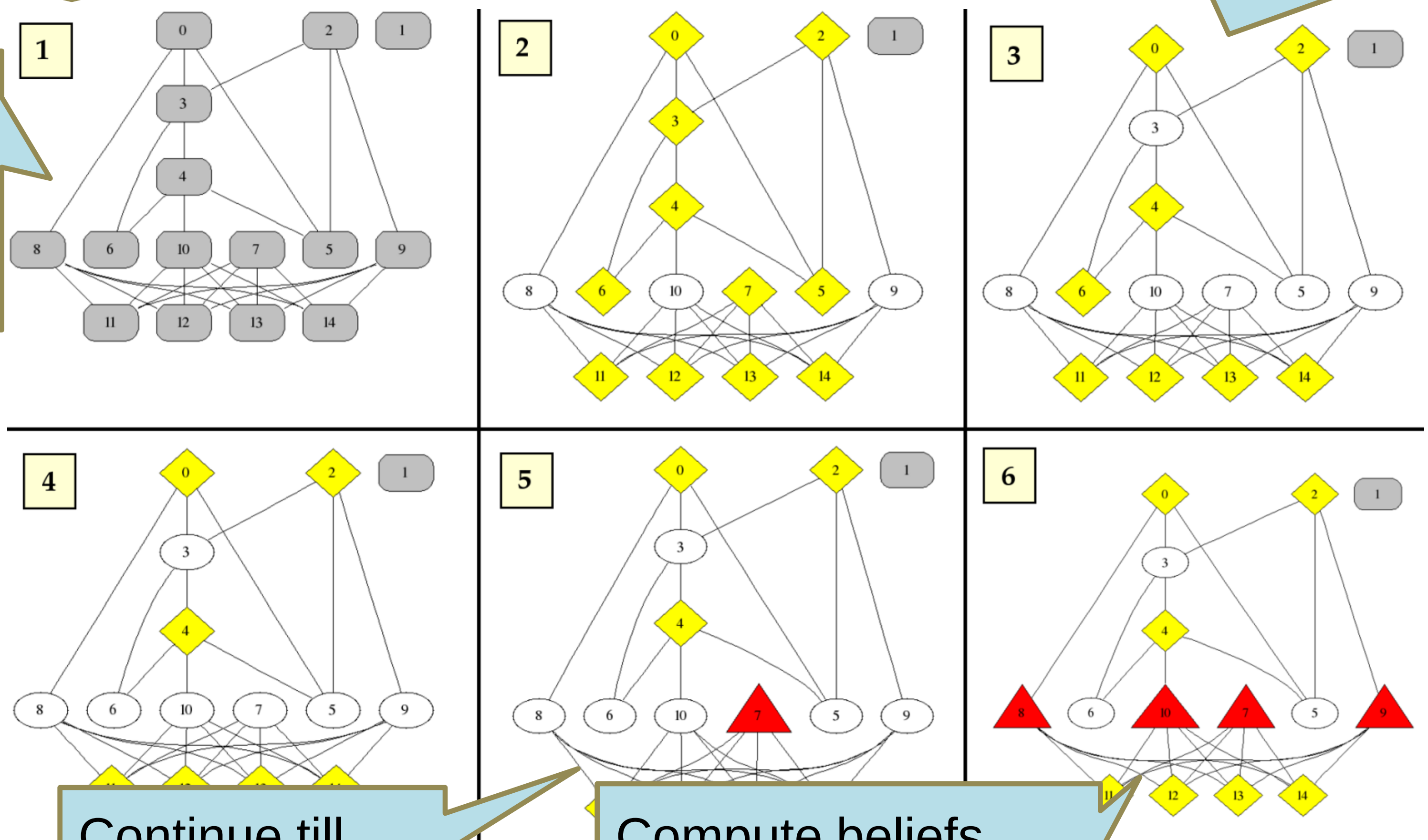
BP in action

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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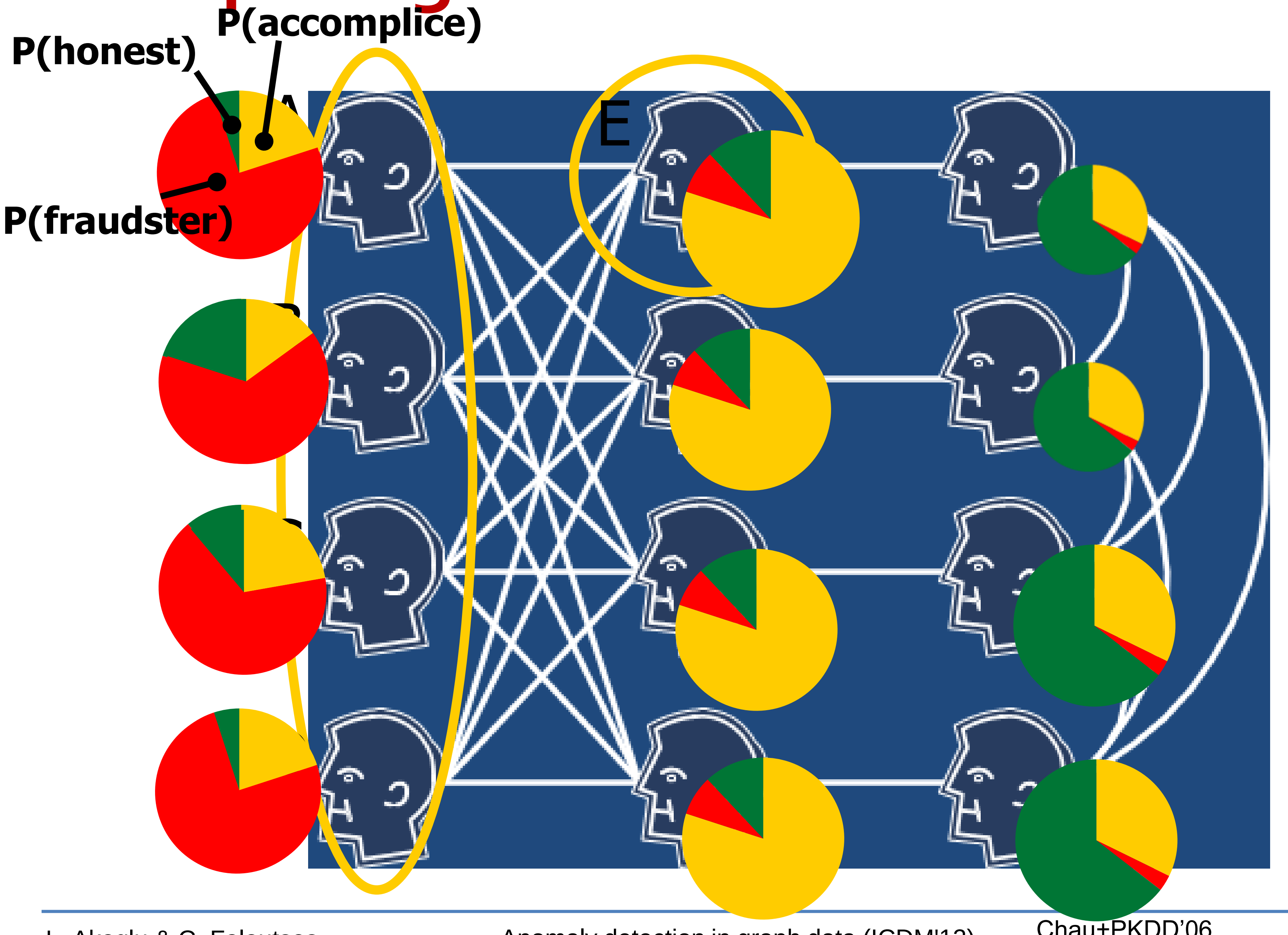
Computing beliefs → roles



Chau+PKDD'06
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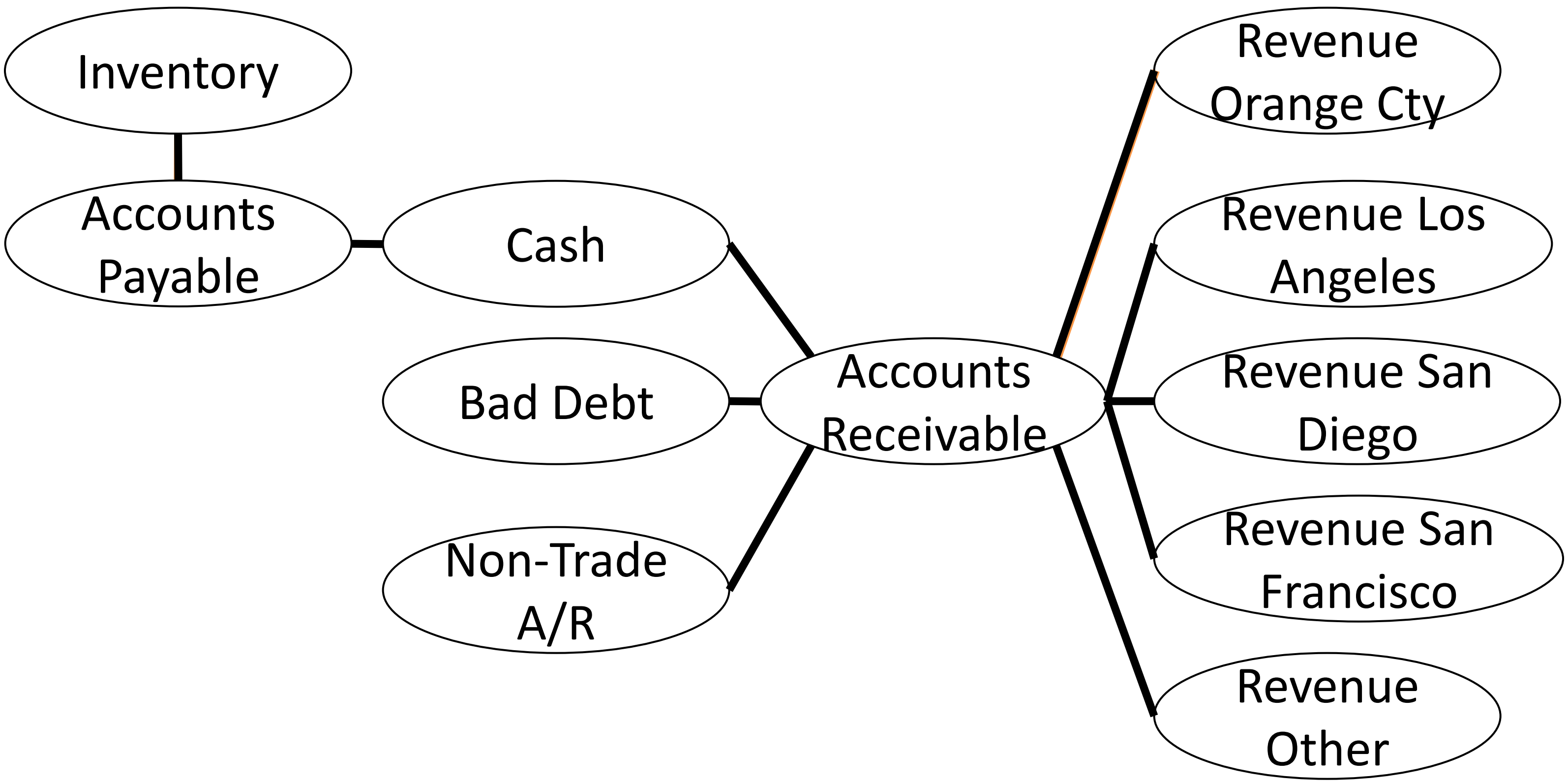
McGlohon et al. '09

(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

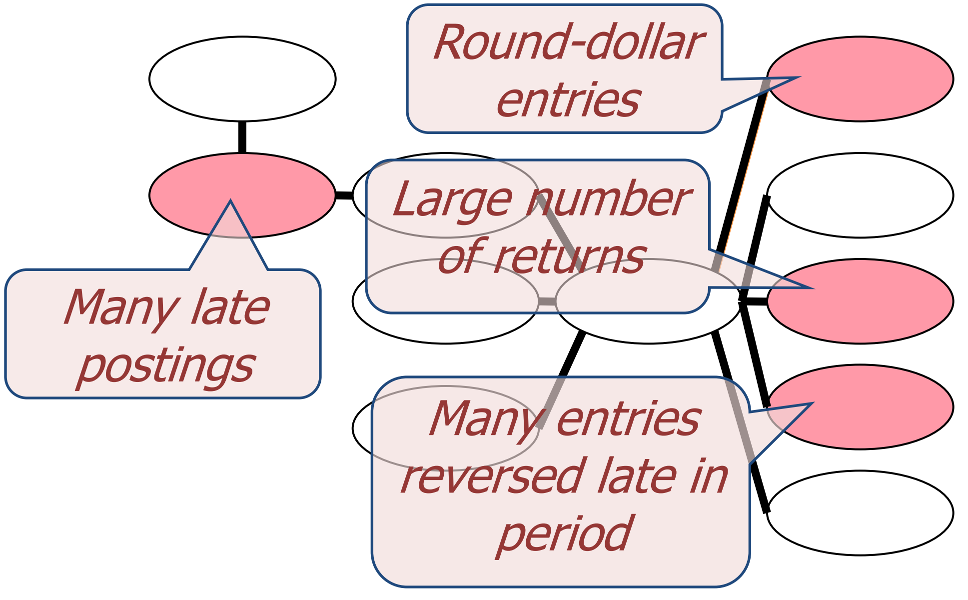
- Assume homophily ("guilt by association")

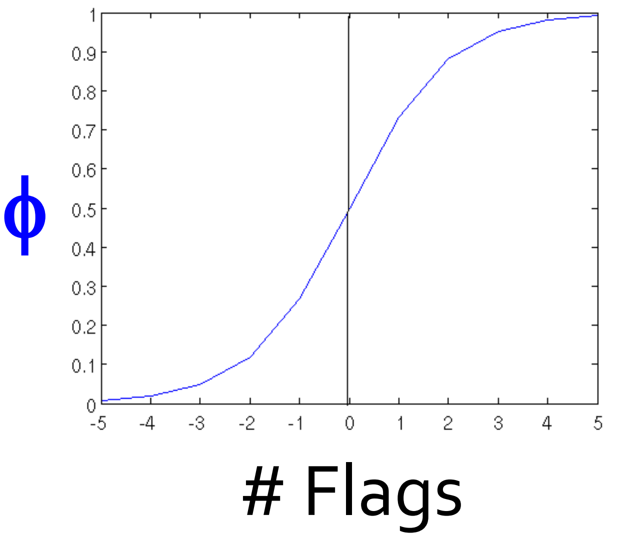
  compatibility potentials

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

Social Network Analytic Risk Evaluation

- Prior beliefs (noisy domain knowledge)



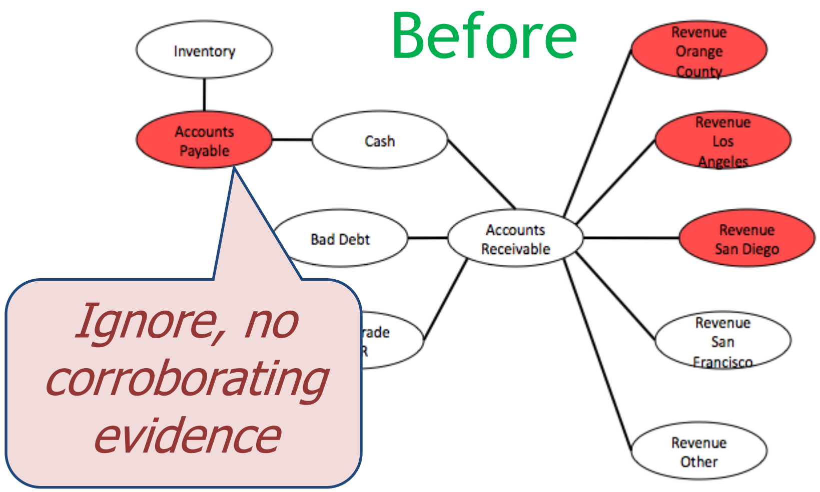


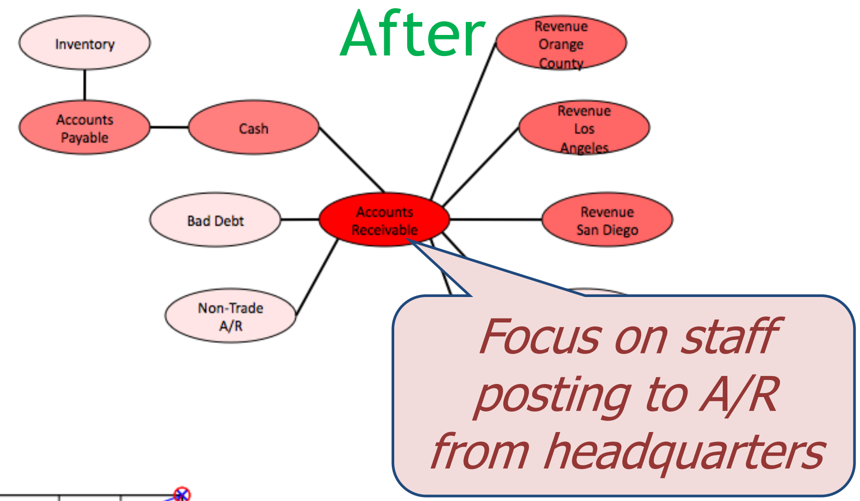
- Compatibility potentials (by homophily)

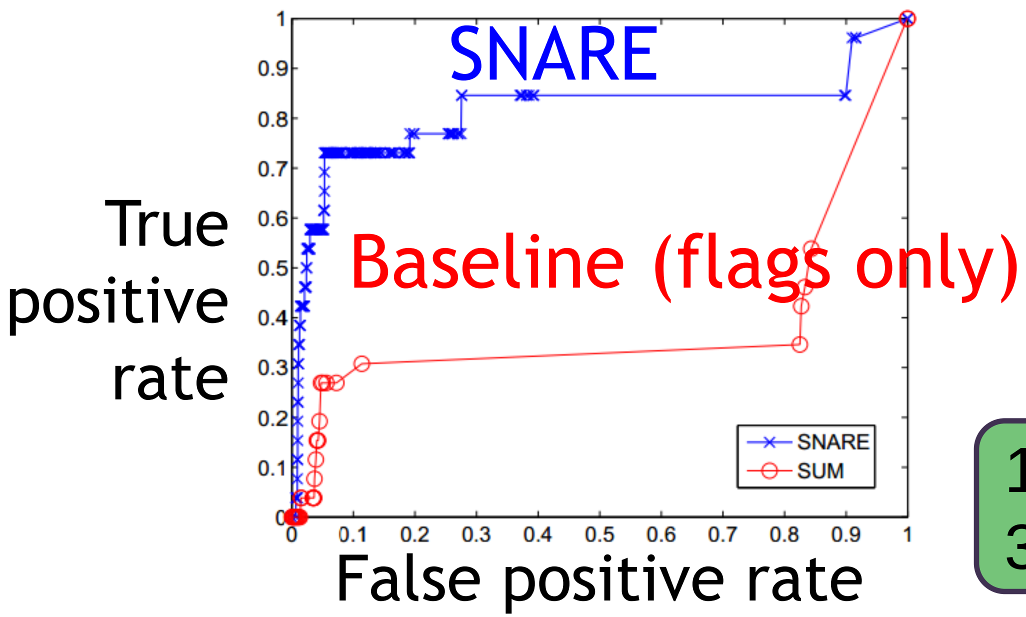
$\psi_{ij}(x_d, x_c)$	$v_i = x_{NR}$	$v_i = x_R$
$v_j = x_{NR}$	$1-\epsilon$	ϵ
$v_j = x_R$	ϵ	$1-\epsilon$

McGlohon+KDD'09 modified with permission

Social Network Analytic Risk Evaluation







1380 accounts
3820 transactions

McGlohon+KDD'09
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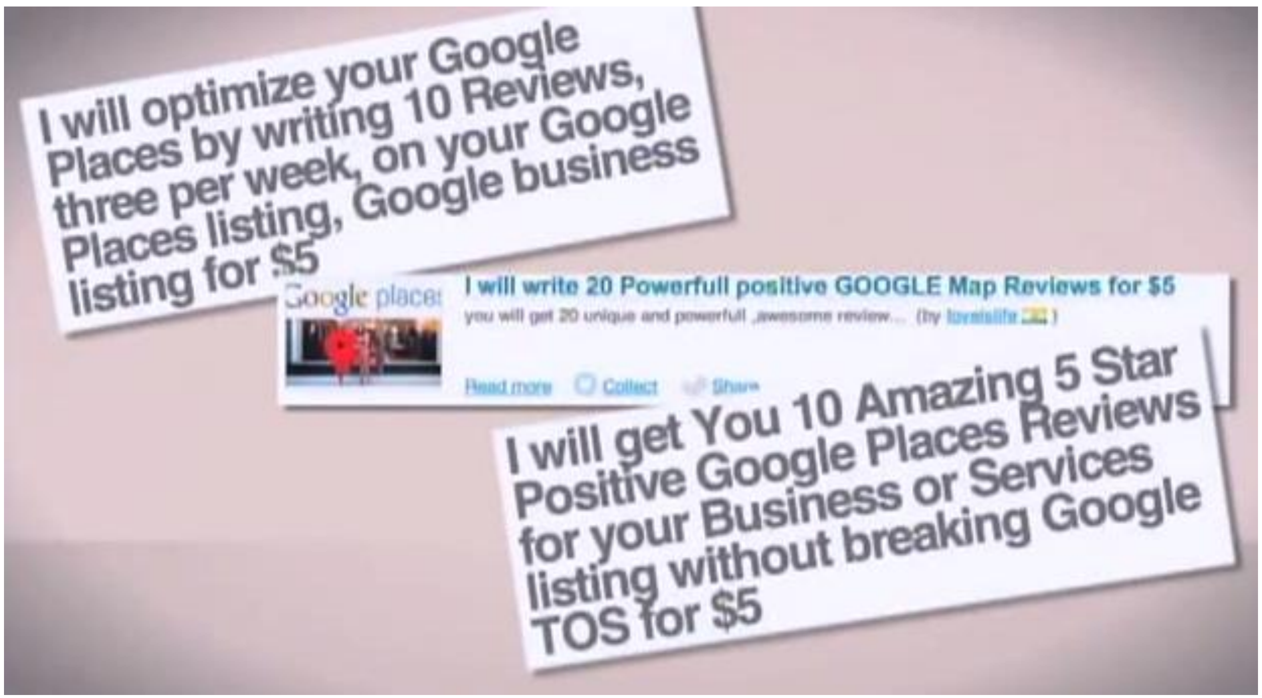
(3) Fake review spam

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



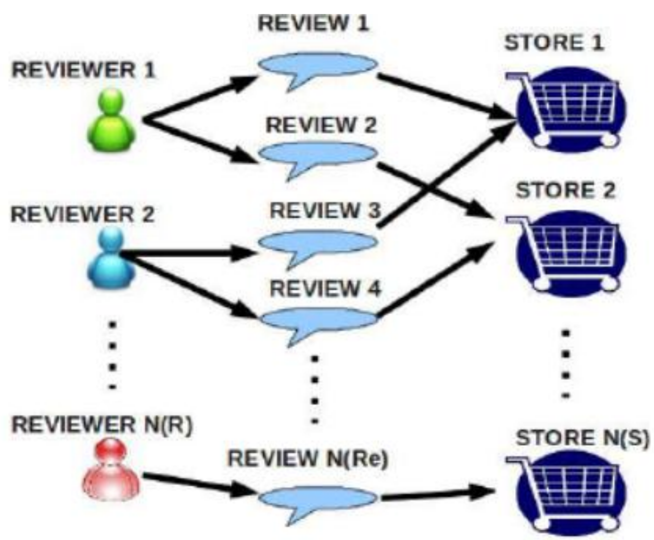
Fake review spam detection

- Behavioral analysis **[Jindal & Liu'08]**
  - individu... features, geographic locations, login times, ...ry, etc.

Easy to fake!

- Language a... **...tt et al.'11]**
  - use of superlatives, ...ny self-referencing, rate of misspell, many agreement words, …

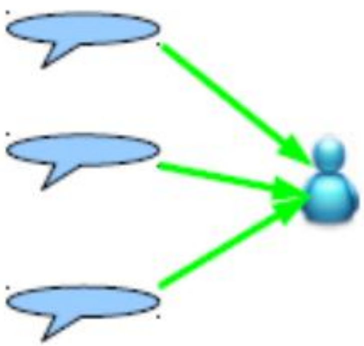
- Hard to fake: graph structure
- Capture relationships between reviewers, reviews, stores



[Wang et al. '11]

Graph-based detection

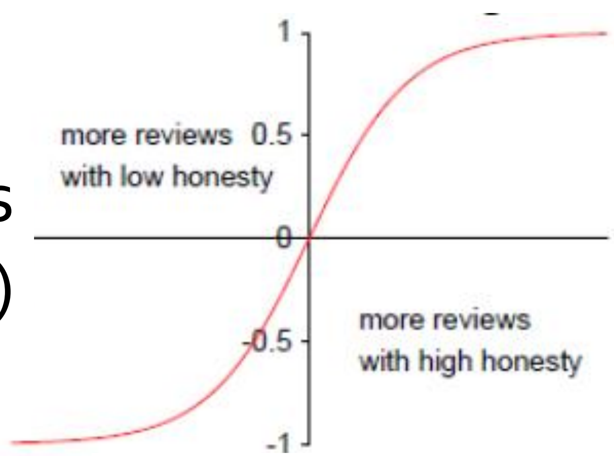
Reviewer r **trustiness** T(r)



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

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

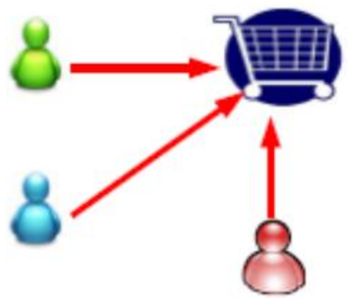
Trustiness T(r)



Honesty H_r

Graph-based detection

Store s **reliability** R(s)



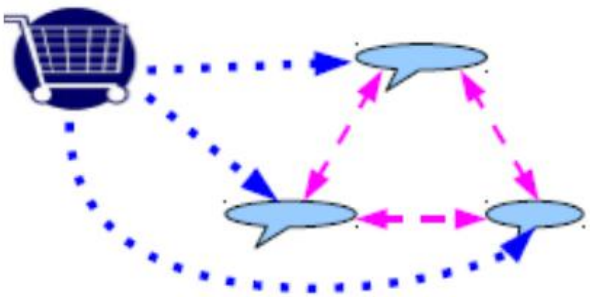
$$\theta = \sum_{v \in U_s, T(\kappa_v) > 0} T(\kappa_v)(\Psi_v - \mu)$$

review v rating

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

Graph-based detection

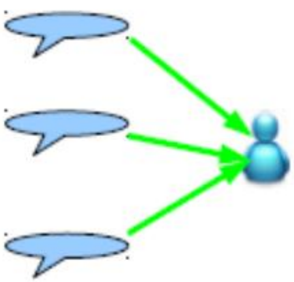
Review v **honesty** H(v)



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

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

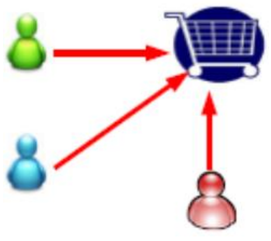
Graph-based detection



Reviewer r **trustiness** T(r)

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

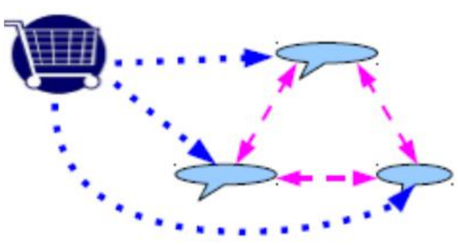
$$T(r) = \frac{2}{1+e^{-\underline{H_r}}} - 1$$



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)

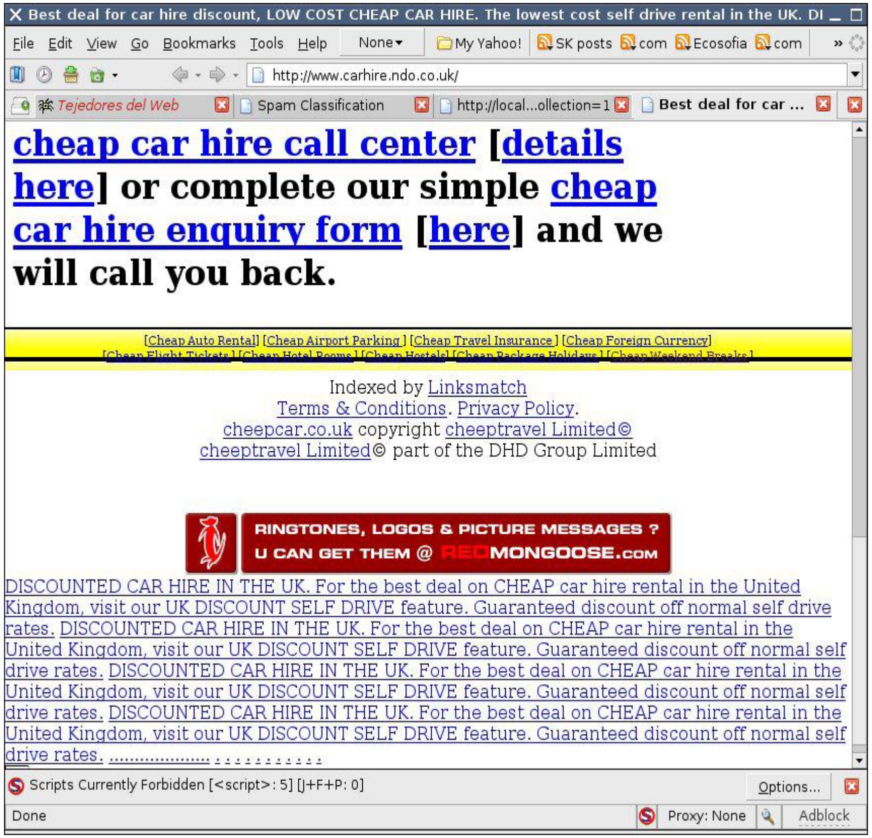
Part III: Outline

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

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

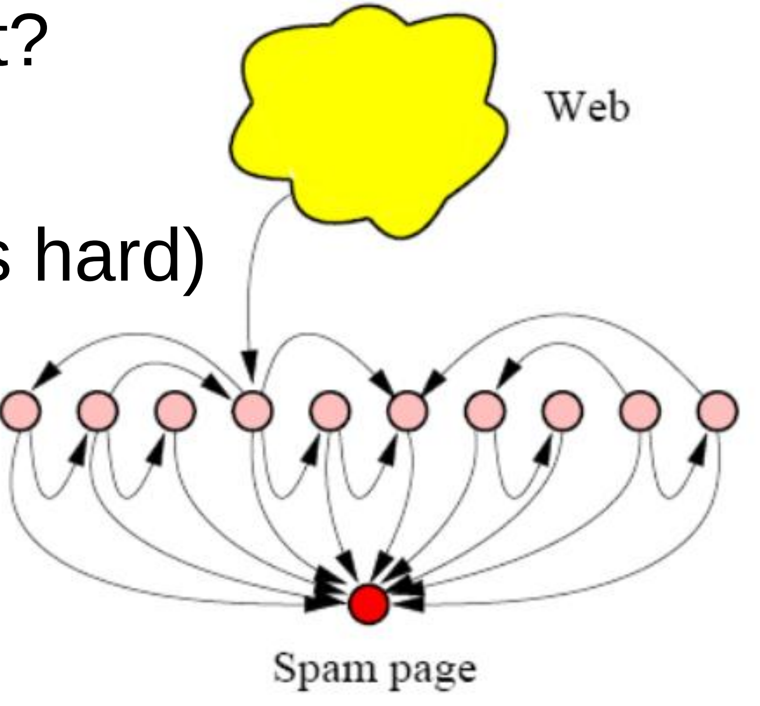
(4) Web spam

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

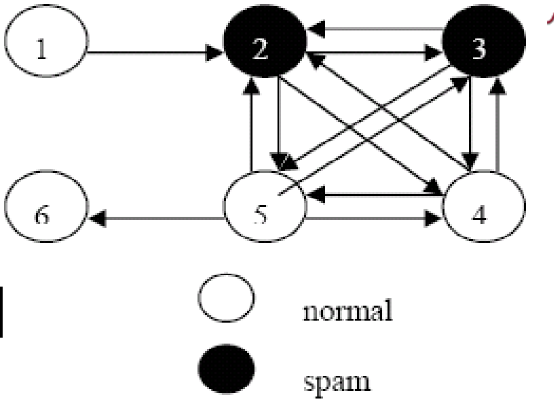


Web spam

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



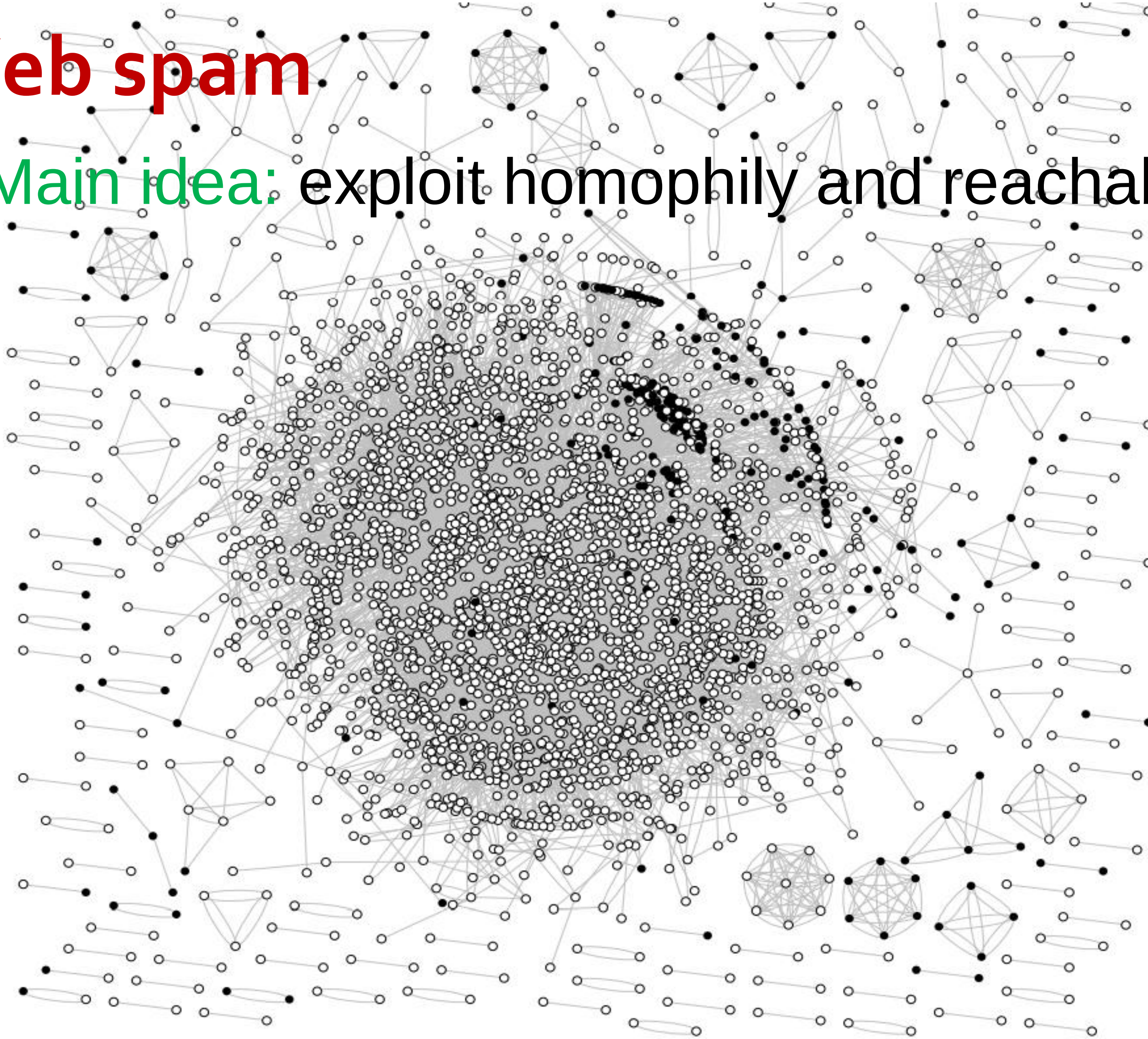
Web spam



- 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]**
  - …

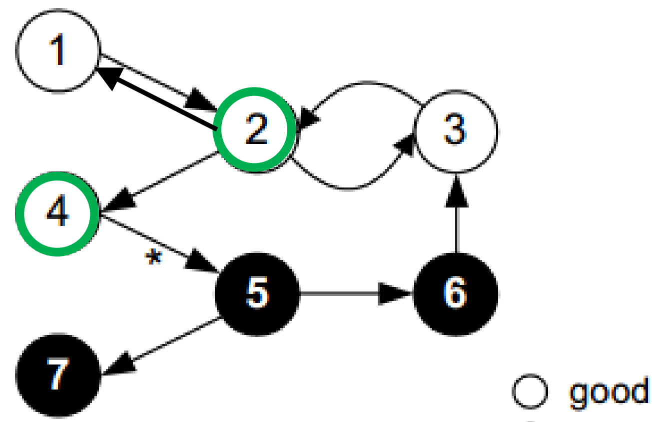
Web spam

- Main idea: exploit homophily and reachability



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:

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

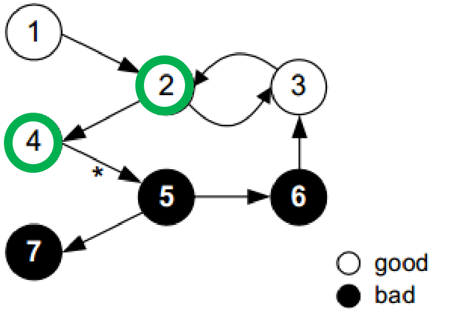
damping factor

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)

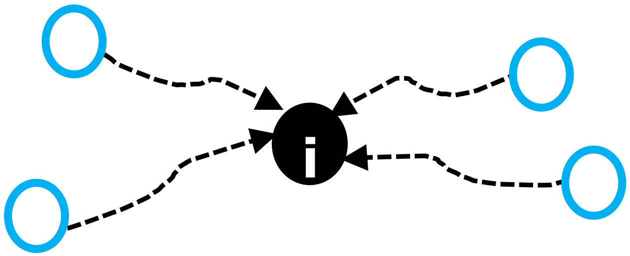


$$\mathbf{d} = \begin{bmatrix} 0, & \frac{1}{2}, & 0, & \frac{1}{2}, & 0, & 0, & 0 \end{bmatrix}$$

[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: $PPR_i(v) > 0$



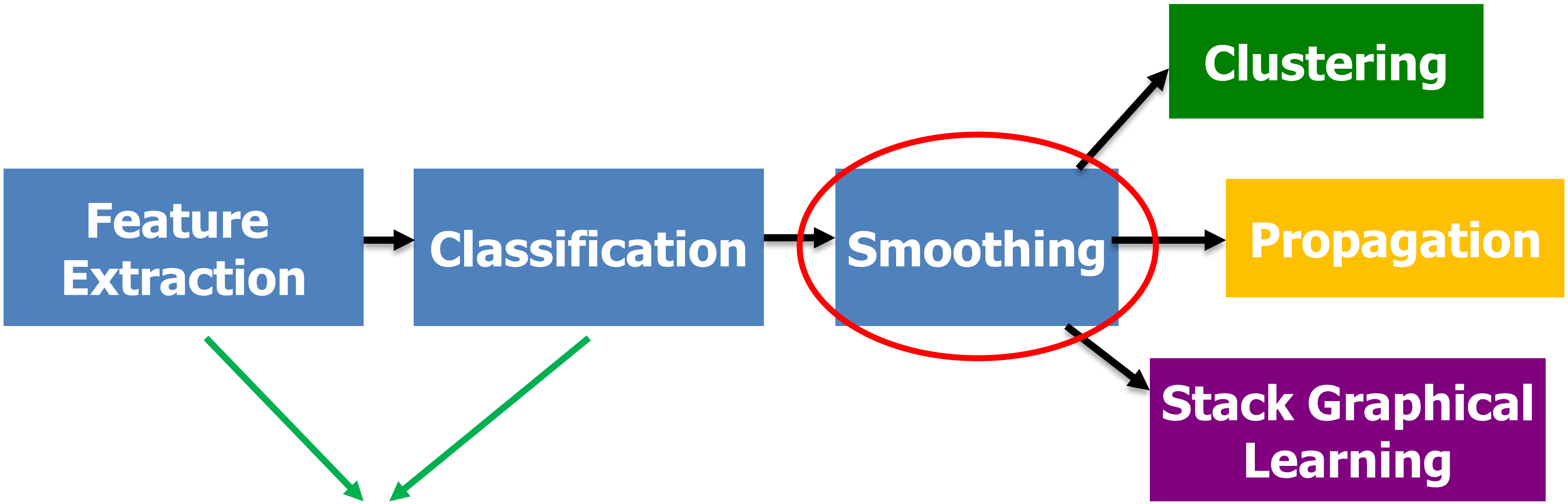
- For each page i
  - get PageRank scores of all supporters of i
  - test PageRank histogram for power law
  - calculate irregularity score s(i)
- SpamRank ← PPR($\vec{\mathbf{s}}$)

Note: 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

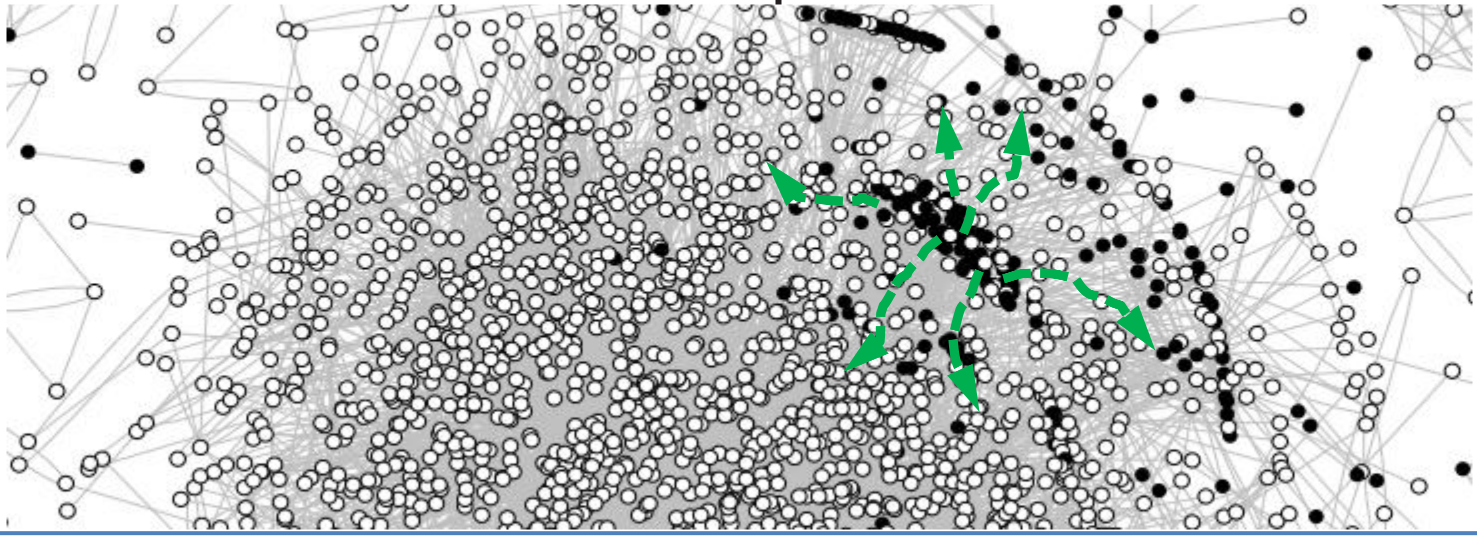
- Split graph into many clusters. (e.g. by METIS)
- If majority of nodes in cluster are spam, then all pages in cluster are spam.

	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)

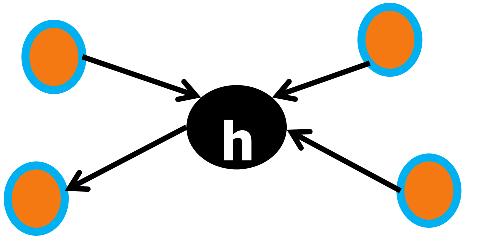
	Baseline	Fwds.	Backwds.	Both
True positive rate	78.7%	76.5%	75.0%	75.2%
False positive rate	5.7%	5.4%	4.3%	4.7%
F-Measure	0.723	0.716	**0.733**	0.724



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**

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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

- Anomalies in dynamic graphs
  - dynamic **attributed** graphs (definitions, formulations, real-world scenarios)
  - temporal effects: node/edge **history** (not only updates)
- Fraud/spam detection
  - 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

Q & A

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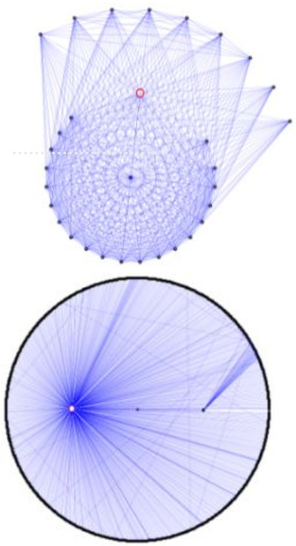
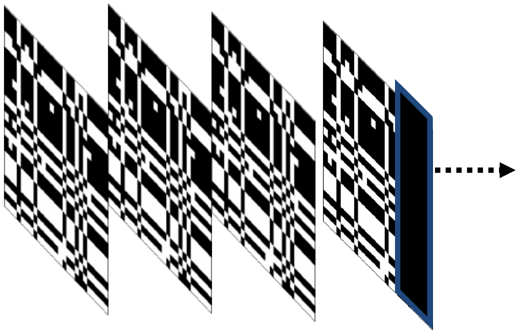
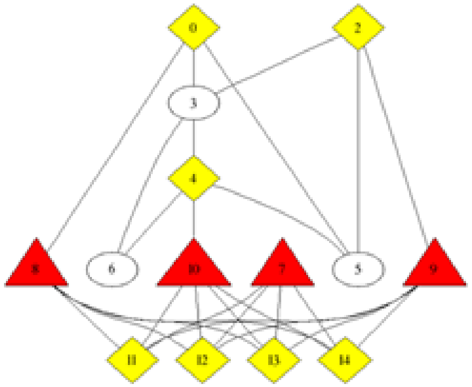


anomalies



events



fraud/spam