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15-826: Multimedia Databases and Data Mining

Lecture #28: Graph mining - Belief propagation

Christos Faloutsos

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Must-read material

- Danai Koutra, Tai-You Ke, U. Kang, Duen Horng Chau, Hsing-Kuo Kenneth Pao, and Christos Faloutsos. *Unifying guilt-by-association approaches: theorems and fast algorithms.* ECML/PKDD'11, Athens, Greece. (new)

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Main outline

- Introduction
- Indexing
- Mining
  - Graphs – patterns
  - ➡ Graphs – generators and tools
  - Association rules
  - …

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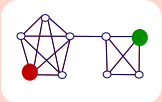
Detailed outline

- Graphs – generators
- Graphs – tools
  - Community detection / graph partitioning
  - ➡ 'Belief Propagation' & fraud detection
    - Motivation - Basics
    - Fast, linear approximation (FaBP)
    - Latest: zooBP
    - Success stories
  - Influence/virus propagation & immunization



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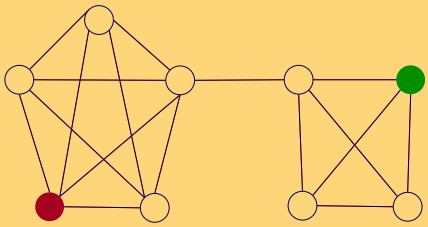
Problem

- What color, for the rest?
  - Given homophily (/heterophily etc)?



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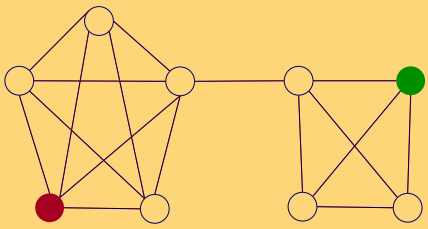
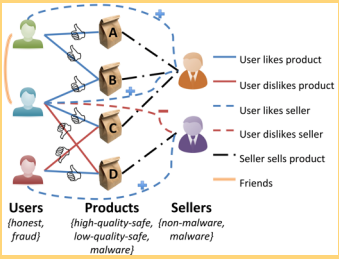
Short answer:

- What color, for the rest?
- A: Belief Propagation ('zooBP')



www.cs.cmu.edu/~deswaran/code/zoobp.zip



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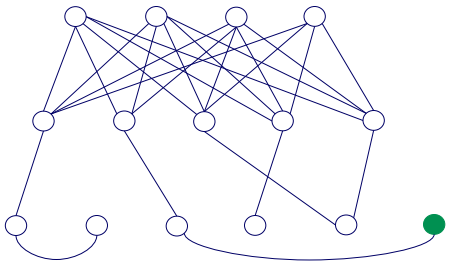
E-bay Fraud detection


w/ Polo Chau &
Shashank Pandit, CMU
[PKDD'06][WWW'07]



Detecting Fraudulent Personalities in Networks of Online Auctioneers. *Duen Horng (Polo) Chau, Shashank Pandit, and Christos Faloutsos. (PKDD) 2006*

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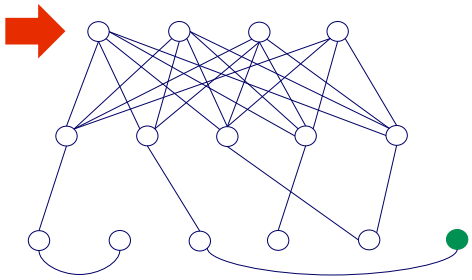
E-bay Fraud detection



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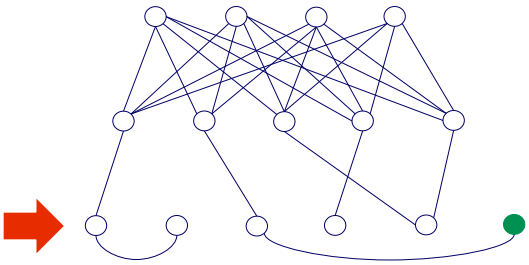
E-bay Fraud detection



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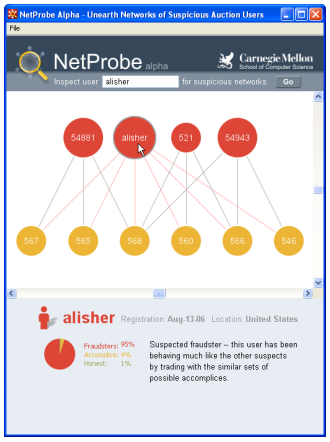
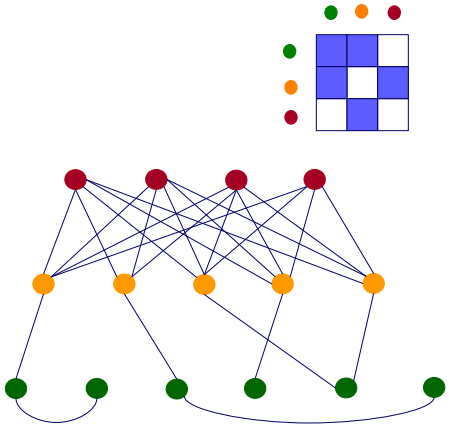
E-bay Fraud detection - NetProbe





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Prof. Danai Koutra
U. Michigan

Background

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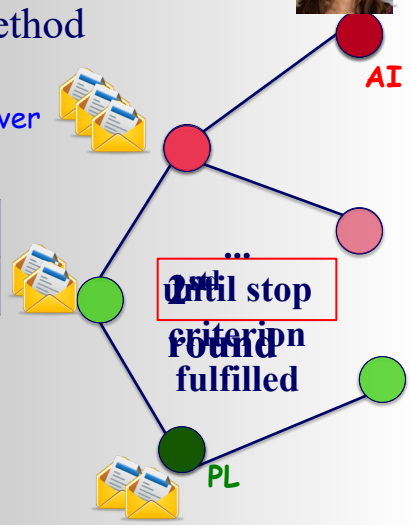
Belief Propagation

- Iterative message-based method
- "Propagation matrix":
  - Homophily

class of receiver

class of sender

	0.9	0.1
	0.1	0.9



[Pearl '82][Yedidia+ '02] … [Gonzalez+ '09][Chechetka+ '10]

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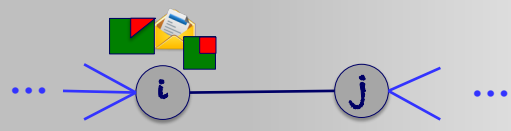
Belief Propagation Equations

message(i –> j) ≈ belief(i) □ homophily strength

	0.9	0.1
	0.2	0.8



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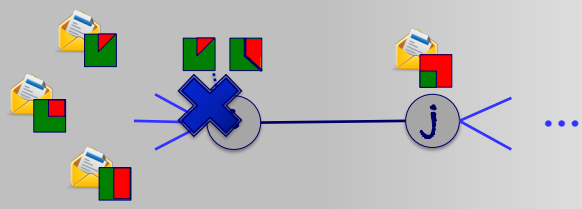
Belief Propagation Equations

belief of i

$$b_i(x_i) \propto \phi_i(x_i) \cdot \prod_{j \in N(i)} m_{ij}(x_i)$$

prior belief

messages from neighbors



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Background

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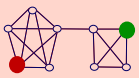
Roadmap

- Introduction – Motivation
- Part#1: Graphs
  - …
  - P1.5: belief propagation
    - Basics
    - Fast, linear approximation (FaBP)
    - Latest: zooBP



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Unifying Guilt-by-Association Approaches: Theorems and Fast Algorithms

Danai Koutra
U Kang
Hsing-Kuo Kenneth Pao
Tai-You Ke
Duen Horng (Polo) Chau
Christos Faloutsos

ECML PKDD, 5-9 September 2011, Athens, Greece

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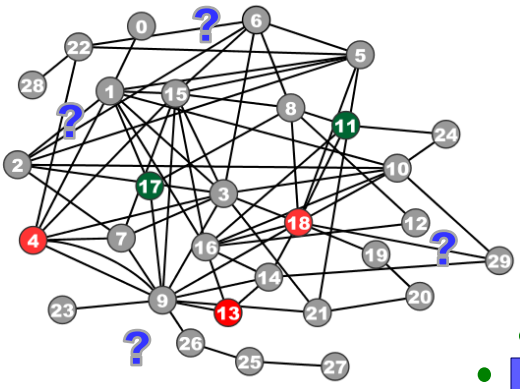
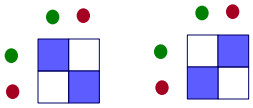
Problem Definition: GBA techniques



Given: Graph; & few labeled nodes
Find: labels of rest (assuming network effects)



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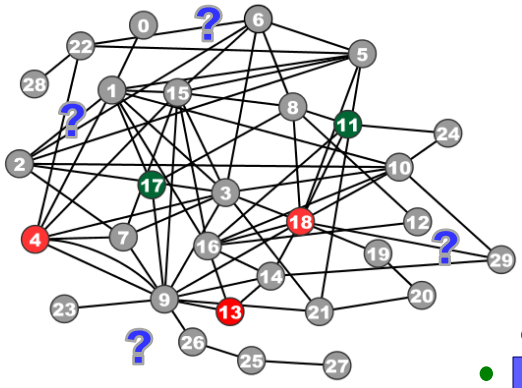
Problem Definition: GBA techniques



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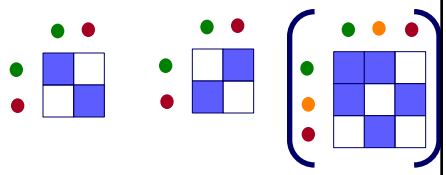

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BP vs. Linearized BP

DETAILS

Original [Yedidia+]:

Belief Propagation

$$m_{ij}(x_j) \leftarrow \sum_{x_i} \phi_i(x_i) \cdot \psi_{ij}(x_i, x_j) \cdot \prod_{n \in N(i) \setminus j} m_{ni}(x_i)$$

$$b_i(x_i) \leftarrow \phi_i(x_i) \cdot \prod_{j \in N(i)} m_{ij}(x_i)$$

non-linear

- Closed-form formula?
- Convergence?

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BP vs. Linearized BP

DETAILS

Original [Yedidia+]: **Our proposal:**

Belief Propagation

$$m_{ij}(x_j) \leftarrow \sum_{x_i} \phi_i(x_i) \cdot \psi_{ij}(x_i, x_j) \cdot \prod_{n \in N(i) \setminus j} m_{ni}(x_i)$$

$$b_i(x_i) \leftarrow \phi_i(x_i) \cdot \prod_{j \in N(i)} m_{ij}(x_i)$$

Linearized BP

BP is approximated by

$$[\mathbf{I} + a\mathbf{D} - c'\mathbf{A}]\, \mathbf{b}_h = \phi_h$$

$$\begin{bmatrix} 1 & & \\ & 1 & \\ & & 1 \end{bmatrix} \quad \begin{bmatrix} d1 & & \\ & d2 & \\ & & d3 \end{bmatrix} \quad \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad ? \quad \begin{bmatrix} 0 \\ -10^{-2} \\ 10^{-2} \end{bmatrix}$$

non-linear linear

- ✓ Closed-form formula?
- ✓ Convergence?

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Are they related?

- RWR (Random Walk with Restarts)
  - google's pageRank ('*if my parents are important, I'm important, too*')
- SSL (Semi-supervised learning)
  - minimize the differences among neighbors
- BP (Belief propagation)
  - send messages to neighbors, on what you believe about them

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Are they related? YES!

- RWR (Random Walk with Restarts)
  - google's pageRank ('*if my parents are important, I'm important, too*')
- SSL (Semi-supervised learning)
  - minimize the differences among neighbors
- BP (Belief propagation)
  - send messages to neighbors, on what you believe about them

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DETAILS

Correspondence of Methods

$\mathbf{p} = (1-c)/n \; [\mathbf{I} - c\,\mathbf{B}]^{-1} \; \vec{e}$

Method	Matrix		Unknown		known
RWR	$[\mathbf{I} - c\,\underline{\mathbf{A}}\mathbf{D}^{-1}]$	$\times$	$\mathbf{x}$	$=$	$(1-c)\mathbf{y}$
SSL	$[\mathbf{I} + a(\mathbf{D} - \underline{\mathbf{A}})]$	$\times$	$\mathbf{x}$	$=$	$\mathbf{y}$
FABP	$[\mathbf{I} + a\,\mathbf{D} - c'\underline{\mathbf{A}}]$	$\times$	$\mathbf{b_h}$	$=$	$\phi_\mathbf{h}$

$$\begin{bmatrix} 1 & & \\ & 1 & \\ & & 1 \end{bmatrix} \quad \begin{bmatrix} d1 & & \\ & d2 & \\ & & d3 \end{bmatrix} \quad \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad \begin{bmatrix} ? \end{bmatrix} \quad \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

adjacency matrix — final labels/ beliefs — prior labels/ beliefs

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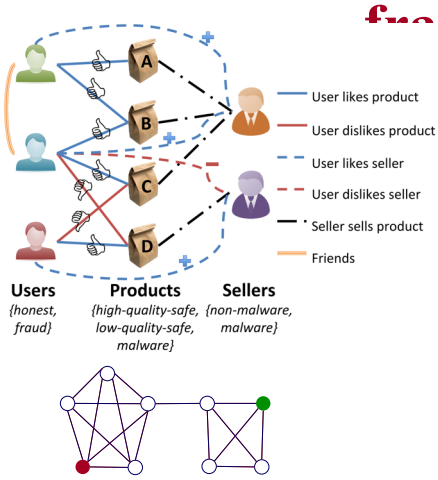
Problem: e-commerce ratings fraud



- **Given** a **heterogeneous** graph on users, products, sellers and positive/negative ratings with "seed labels"
- **Find** the top *k* most fraudulent users, products and sellers

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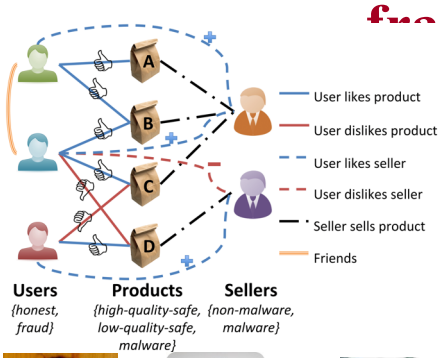
Problem: e-commerce ratings fraud



- **Given** a **heterogeneous** graph on users, products, sellers and positive/negative ratings with "seed labels"
- **Find** the top *k* most fraudulent users, products and sellers

Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, "*ZooBP:* Belief Propagation for Heterogeneous Networks", VLDB 2017

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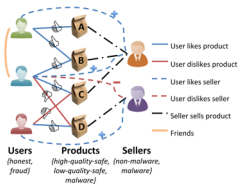
Problem: e-commerce rating fraud

DETAILS



Theorem 1 (ZooBP). *If* $\mathbf{b}, \mathbf{e}, \mathbf{P}, \mathbf{Q}$ *are constructed as described above, the linear equation system approximating the final node beliefs given by BP is:*

$$\mathbf{b} = \mathbf{e} + (\mathbf{P} - \mathbf{Q})\mathbf{b} \qquad (\text{ZooBP}) \qquad (10)$$

Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, "*ZooBP:* Belief Propagation for Heterogeneous Networks", VLDB 2017

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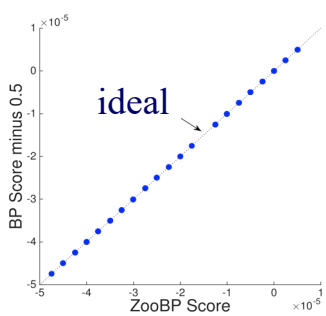
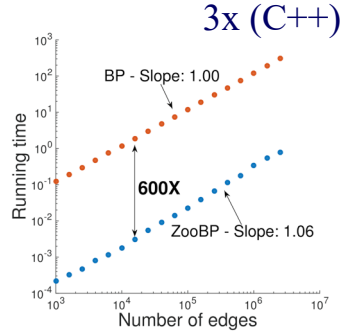
ZooBP: features

Fast; convergence guarantees.

600x (matlab)
3x (C++)



Near-perfect accuracy



linear in graph size

Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, "*ZooBP:* Belief Propagation for Heterogeneous Networks", VLDB 2017

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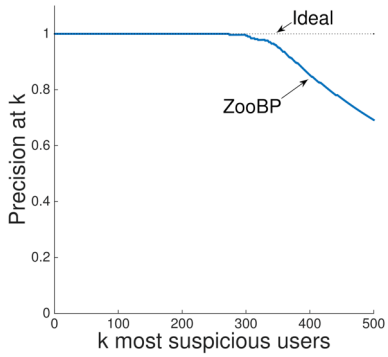
Flipkart

ZooBP in the real world



- Near 100% precision on top 300 users (Flipkart)
- Flagged users: suspicious
  - 400 ratings in 1 sec
  - 5000 good ratings and no bad ratings

Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, "*ZooBP:* Belief Propagation for Heterogeneous Networks", VLDB 2017

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ZooBP: code etc

http://www.cs.cmu.edu/~deswaran/code/zoobp.zip

Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, "*ZooBP:* Belief Propagation for Heterogeneous Networks", VLDB 2017

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Other 'success stories'?

- Accounting fraud
- Malware detection

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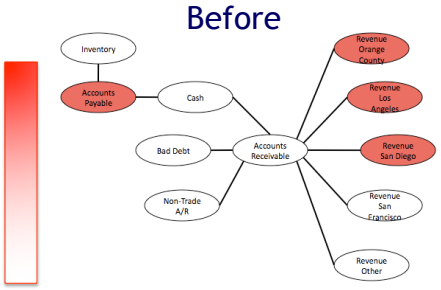
Network Effect Tools: SNARE

- Some accounts are sort-of-suspicious – how to combine weak signals?

Before



Mary McGlohon, Stephen Bay, Markus G. Anderle, David M. Steier, Christos Faloutsos: *SNARE: a link analytic system for graph labeling and risk detection*. KDD 2009: 1265-1274

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PATENT PENDING

Polonium: Tera-Scale Graph Mining and Inference for Malware Detection

SDM 2011, Mesa, Arizona

Polo Chau
Machine Learning Dept

symantec.

Carey Nachenberg
Vice President & Fellow

symantec.

Jeffrey Wilhelm
Principal Software Engineer

symantec.

Adam Wright
Software Engineer

Prof. Christos Faloutsos
Computer Science Dept

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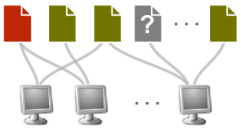
Polonium: The Data

60+ terabytes of data *anonymously* contributed by participants of worldwide *Norton Community Watch* program

- 50+ million machines
- 900+ million executable files



Constructed a machine-file bipartite graph (0.2 TB+)

- 1 billion nodes (machines and files)
- 37 billion edges

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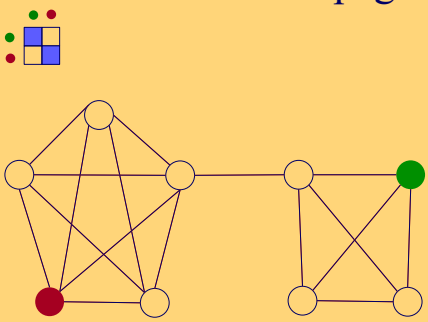
Short answer:

- What color, for the rest?
- A: Belief Propagation ('zooBP')



www.cs.cmu.edu/~deswaran/code/zoobp.zip