Data-Driven Behavioral Analytics: Observations, Representations and Models

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http://www.meng-jiang.com/tutorial-cikm16.html

Tutorial in CIKM 2016, October 24, Indianapolis, IN

What is Behavior?

- *Definition*. **Interactions** made by **individuals** in conjunction with **themselves** or their **environment**. (*Wikipedia*)

Behavioral Analysis

- *Significance*. What can we discover from behavioral data?
  - *Ex*. Given every phone call/message between military leaders, scientists, businesspersons, find…

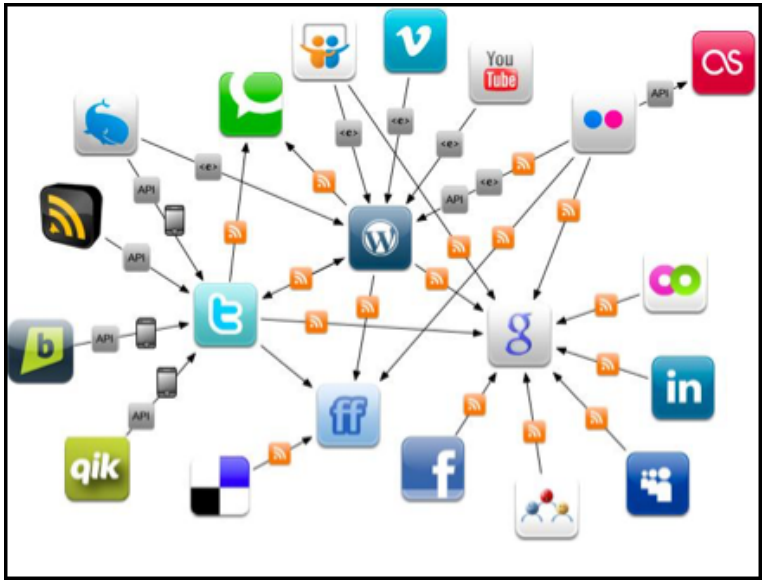
Observations	Who, what, where, when, why, how… (scientific view)
Representations	Graph, network, matrix, tensor… (mathematical view)
Models	Prediction, recommendation, anomaly detection… (application view)

Why Behavioral Analysis Today?

- *Today*. The human behaviors are broadly recorded in an unprecedented level. Insights of sciences and society?

Physical World

Online Applications



Basic Research Areas

- Six Disruptive Basic Research Areas
  - Engineered Materials (metamaterials and plasmonics)
  - Quantum Information and Control
  - Cognitive Neuroscience
  - Nanoscience and Nanoengineering
  - Synthetic Biology
  - Computational Modeling of Human and Social Behavior

VI. Computational Models of Human Behavior

A fundamental understanding and predictive capability of human behavior dynamics from individuals to societies.

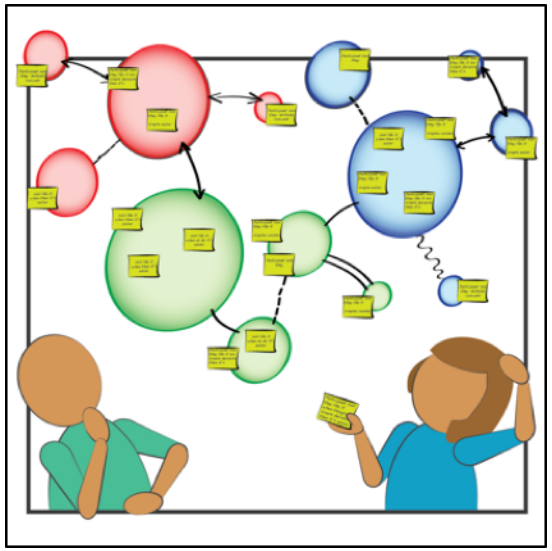
- ***Enabled capabilities***
  - *Predictive models supporting strategic, operational, and tactical decision making and planning*
  - *Real time cultural situational awareness*
  - *Immersive training and mission rehearsal*
  - *Cross cultural coalition building*
- ***Key research challenges:***
  - *Conflicting theories*
  - *Data management and fusion*
  - *Mathematical complexity*
  - *Validation of models*


RESEARCH ARTICLES

Costly Punishment Across Human Societies

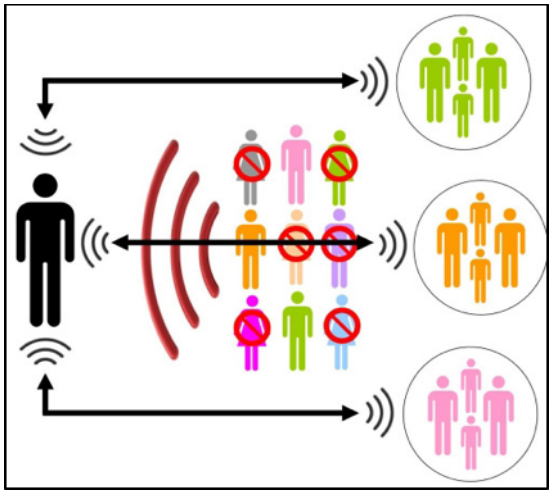
- ***Measures of success***
  - *Early success of simple models*
  - *Success of social network analysis*
  - *Prediction of crowd tipping points*

Challenges in Behavioral Analysis



Content
(preference)

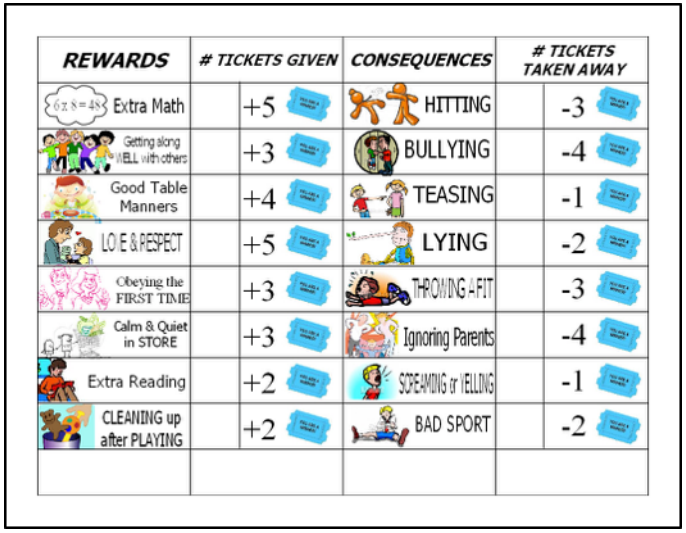
Social context
(influence)



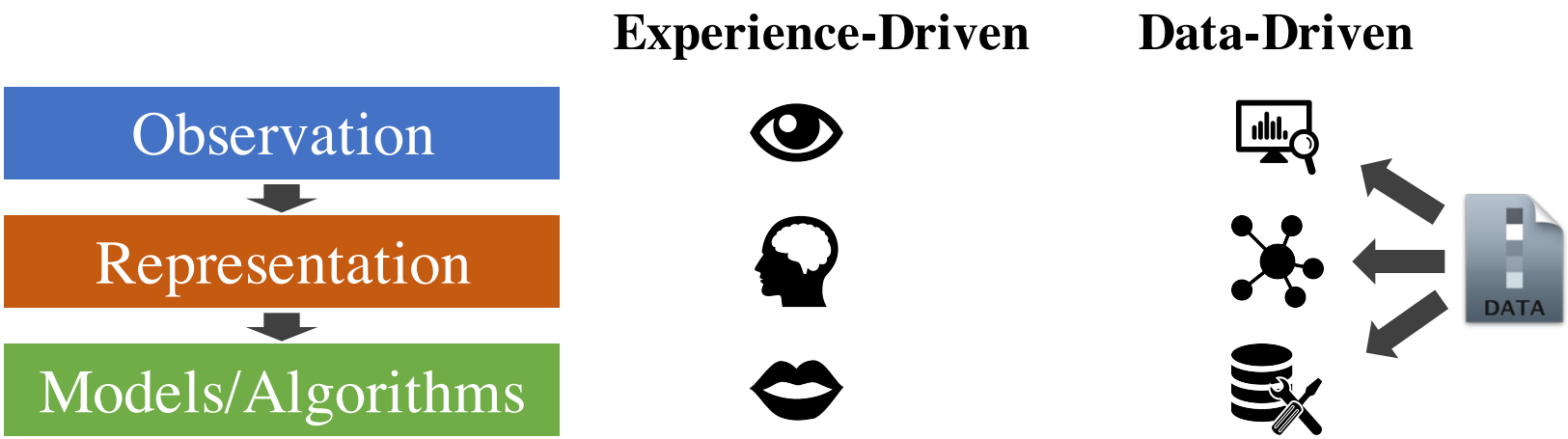
Behavioral Analysis

Spatiotemporal context

Intention
(suspiciousness)

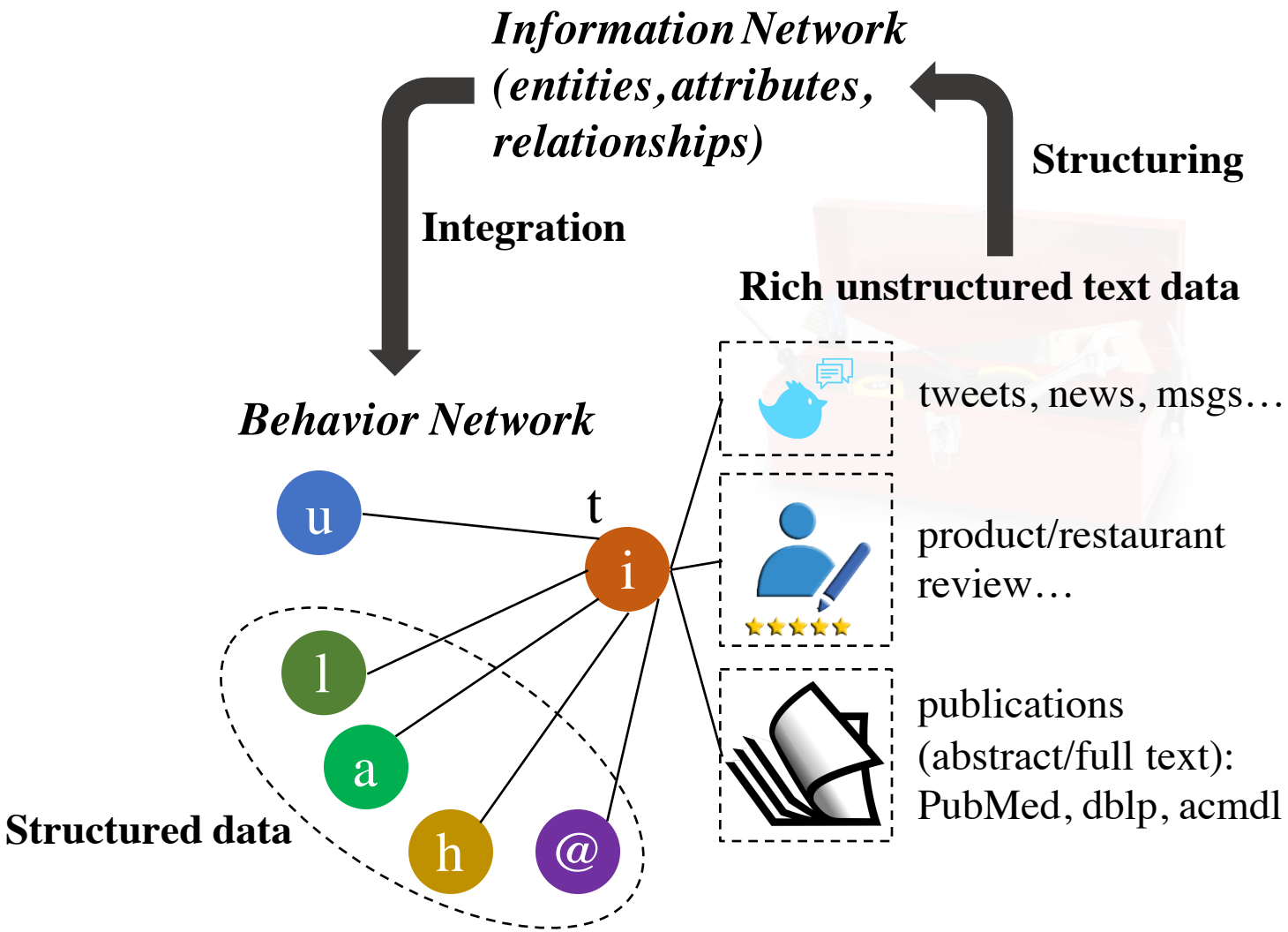


Methodology: Why Data-Driven?



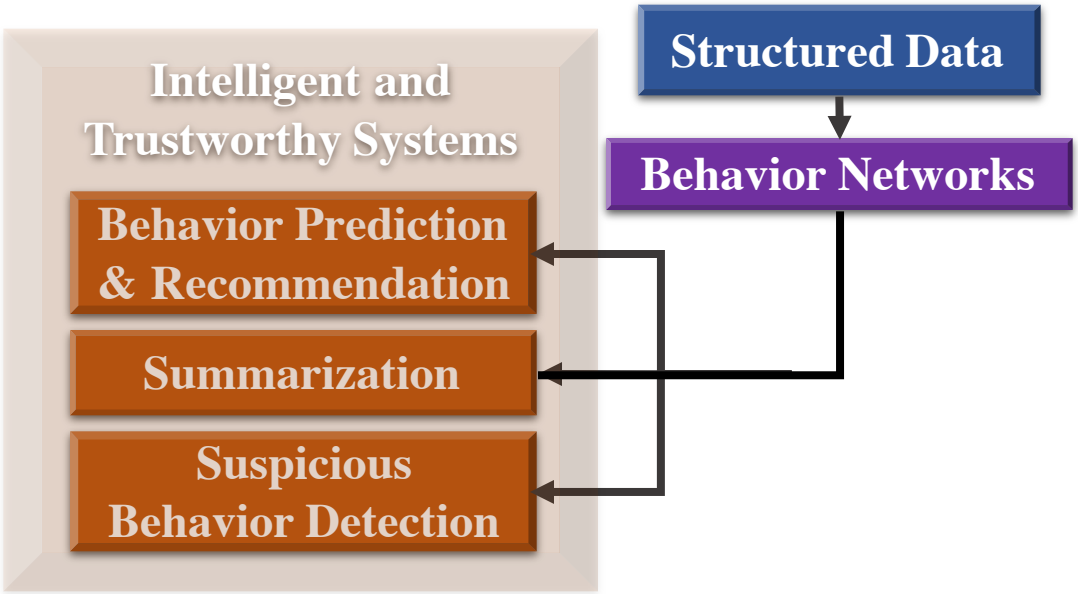
- *Applications*. Recommender systems, fraud/spam detection.
- *Representation*. **B**ehavior **N**etwork for interaction.
  - **Nodes:** users/authors, items (*e.g.*, products, tweets, papers), *etc*.
  - **Links:** (interaction) following, purchasing, tweeting, publishing, *etc*.
  - **Node attributes:** user profiles, item properties/features, *etc*.
  - **Link attributes:** similarity, distance, weight, *etc*.

Data to Network to Knowledge



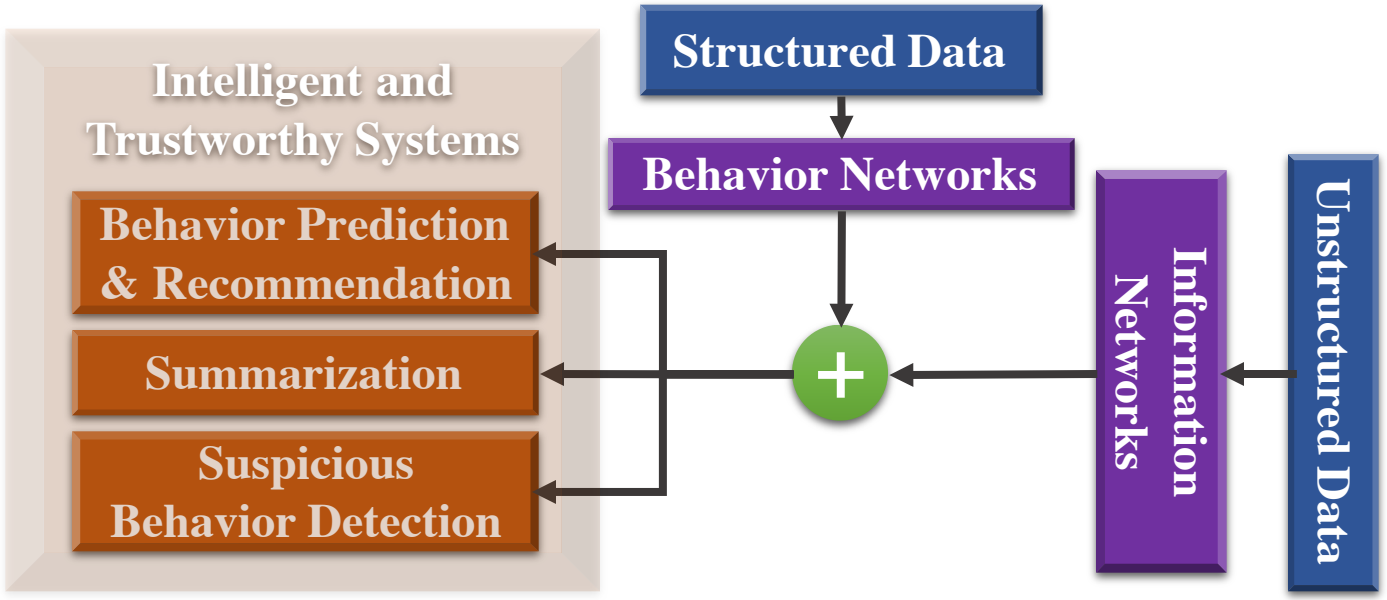
Outline: Data-Driven Behavioral Analytics

- Mining **behavior networks** with **social and spatiotemporal contexts** to support intelligent and trustworthy systems
  - Mining for **behavior prediction and recommendation**
  - Mining for **suspicious behavior detection**



Outline: Data-Driven Behavioral Analytics

- Mining **behavior networks** with **social and spatiotemporal contexts** to support intelligent and trustworthy systems
  - Mining for **behavior prediction and recommendation**
  - Mining for **suspicious behavior detection**
- Structuring behavioral content and integrating behavioral analysis with **information networks**

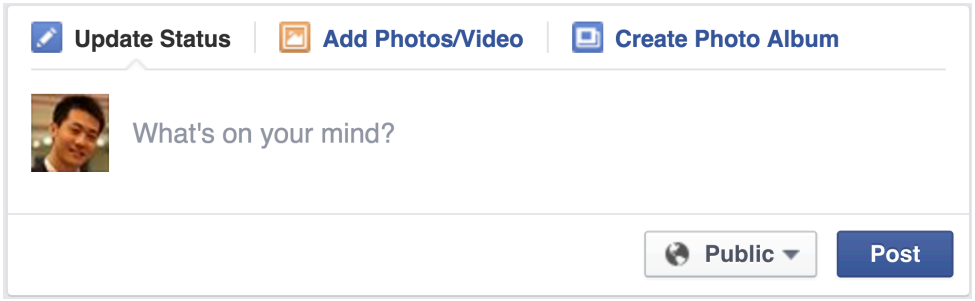


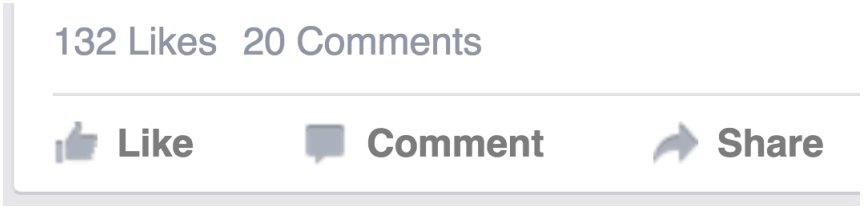
I. Mining behavior networks with social and spatiotemporal contexts

I.1. Behavior prediction and recommendation

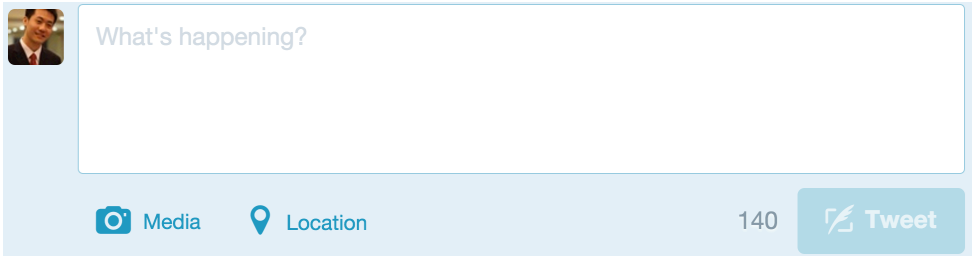
Behavior in Social Networks

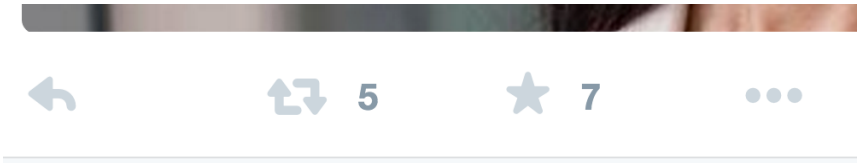
- **Facebook:** Post, Like, Comment, Share



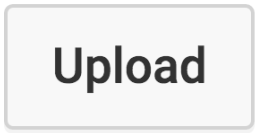


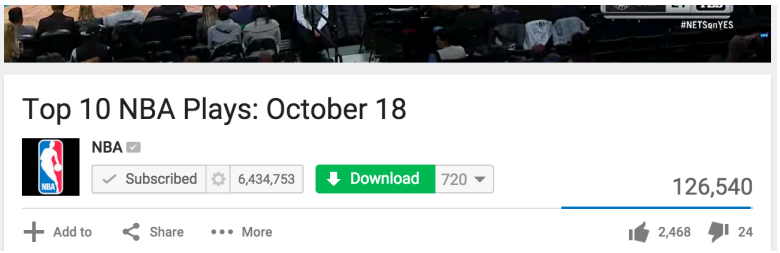
- **Twitter:** Post, Reply, Retweet, Favorite





- **YouTube:** Upload, Subscribe, Download, Share, Comment

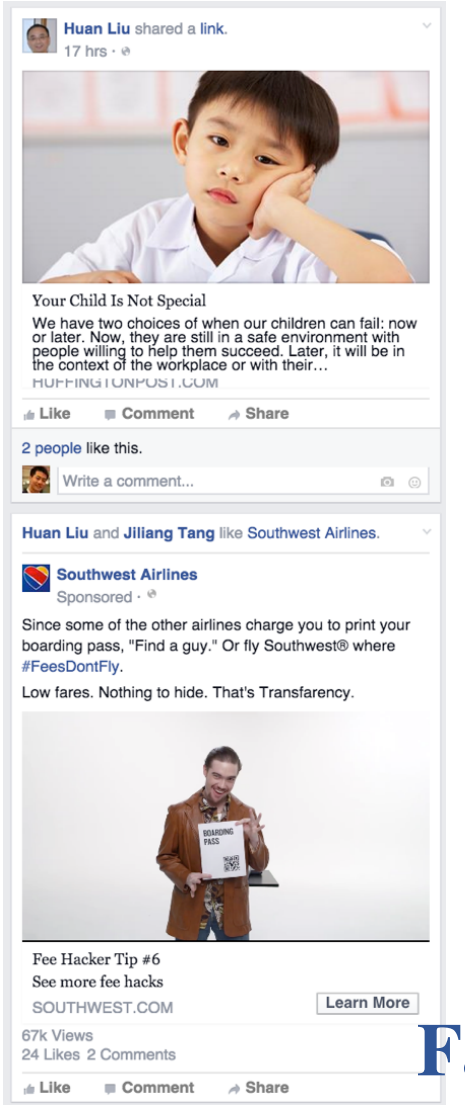




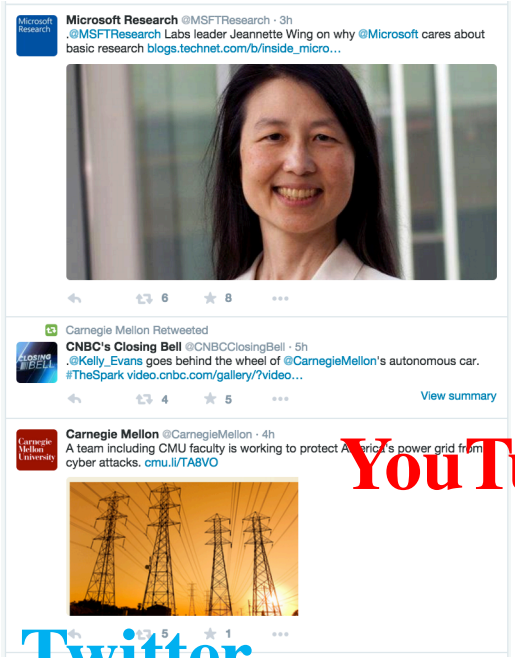
Behavior in Social Networks

Like
Reply
Share
Favorite
Retweet
Comment
Subscribe
Download
Add to
Send
Pin it
Visit
……

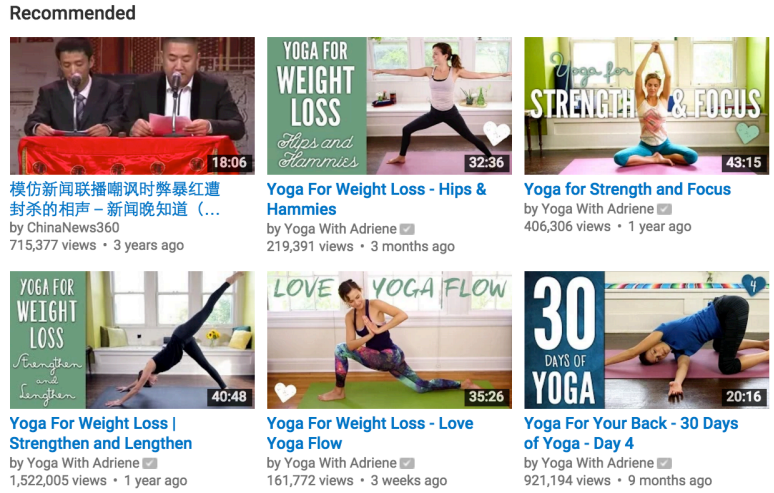
Social Recommender Systems



Facebook



Twitter



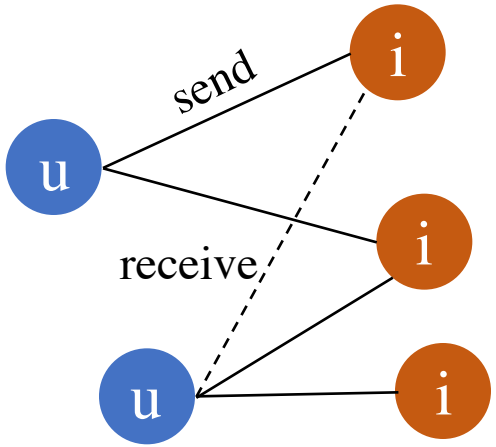
YouTube

Pinterest

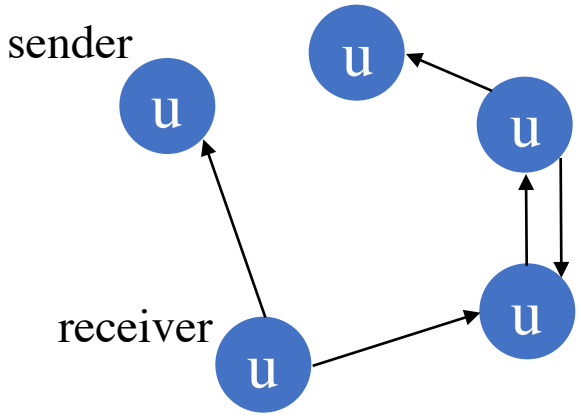
Social Recommender Systems

- April 20, 2011: **Tencent Weibo** visited Tsinghua University
  - Low *conversion rate* (< 6%): #retweets per feed request
  - Can we build a ***social recommender system***?
  - **Given**

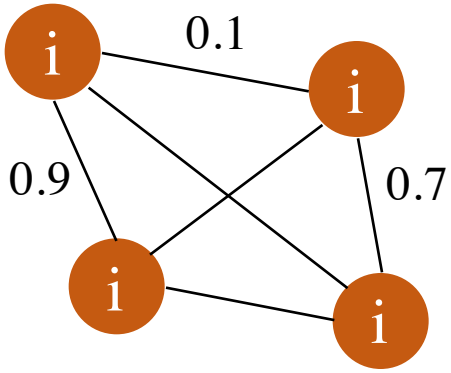
User-item behavior network



User-user social network



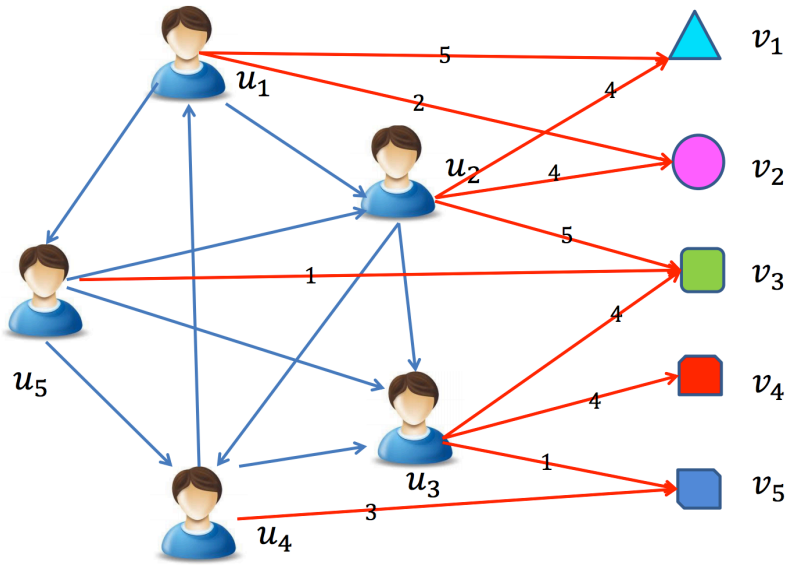
Content similarity (topic level) [Blei *et al.*]



- **Predict** which tweet/item a user will retweet.

Traditional Recommender Systems

- Assumed that users are independent and identically distributed (user-movie, user-book, *etc*.)



	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

Traditional Recommender Systems

- Content-based recommender (e.g., TF-IDF)
  - For textual information (e.g., news, documents)
  - *Limitation:* limited content analysis, over-specialization
- Collaborative filtering based recommender
  - Memory-based CF (e.g., PCC, similarity)
  - Model-based CF (e.g., factorization based)
  - *Limitation:* data sparsity, cold-start problem
- Hybrid recommender system

Tang et al. **Social Recommendation: A Review.** *Social Network Analysis and Mining*, 2013. Springer.

Matrix Factorization (MF) based CF

- Low-rank MF on the user-item rating matrix ***R***
- User preference vector ***U***
- Item characteristic vector ***V***

R

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

Koren. **Factorizatoin Meets the Neighborhood: A Multifaceted Collaborative Filtering Model.** *KDD*, **2008**.

Matrix Factorization (MF) based CF

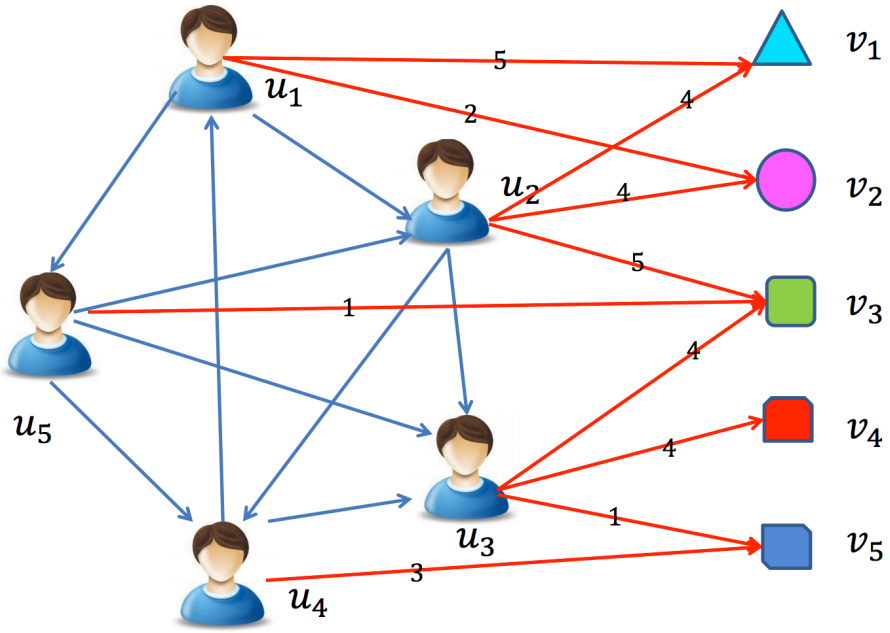
- Low-rank MF on the user-item rating matrix ***R***
- User preference vector ***U***
- Item characteristic vector ***V***
- Observed weight matrix ***W***

$$\min_{\mathbf{U},\mathbf{V}} \sum_{i=1}^{n}\sum_{j=1}^{m} \mathbf{W}_{ij}(\mathbf{R}_{ij} - \mathbf{U}_i\mathbf{V}_j^\top)^2 + \alpha(\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2)$$

avoid over-fitting,
controlled by the parameter

Social Recommendation

Social relations

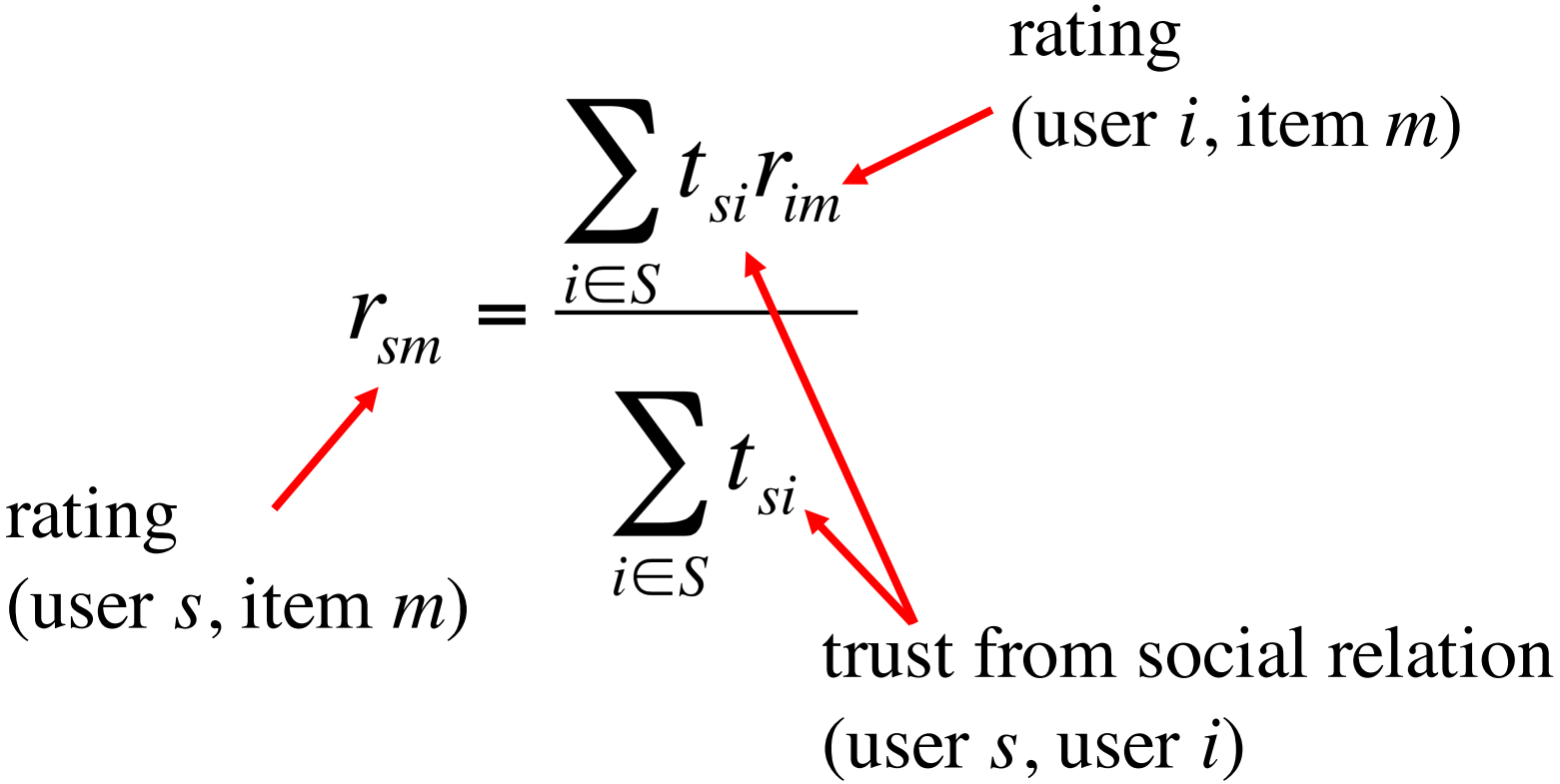


	u_1	u_2	u_3	u_4	u_5
u_1	0	1	0	0	1
u_2	0	0	1	1	0
u_3	0	0	0	0	0
u_4	1	0	1	0	0
u_5	0	1	1	1	0

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

Memory based Social Recommender

- **TidalTrust**



Golbeck. **Personalizing applications through integration of inferred trust values in semantic web-based social networks.** *Semantic Network Analysis Workshop*, 2005.

Memory based Social Recommender

- **MoleTrust**

average rating (user a)

rating (user u, item i)

average rating (user u)

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u=1}^{k} w_{a,u}(r_{u,i} - \bar{r}_u)}{\sum_{u=1}^{k} w_{a,u}}$$

predicted rating (user a, item i)

trust from social relation (user a, user u)

Massa et al. **Trust-aware recommender systems.** *RecSys*, 2007.

Memory based Social Recommender

- **TrustWalker**

similarity measure (item i, item j)

$$P(Y_{u,i} = j) = \frac{sim(i,j)}{\sum_{l \in RI_u} sim(i,l)}$$

probability of user u's random walk from item i to item j

Pearson correlation of (item i, item j)

$$sim(i,j) = \frac{1}{1 + e^{-\frac{|UC_{i,j}|}{2}}} \times corr(i,j)$$

common user set of (item i, item j)

Jamali et al. **TrustWalker: A Random Walk Model for Combining Trust-based and Item-based Recommendation.** *KDD*, 2009.

Model based Social Recommender

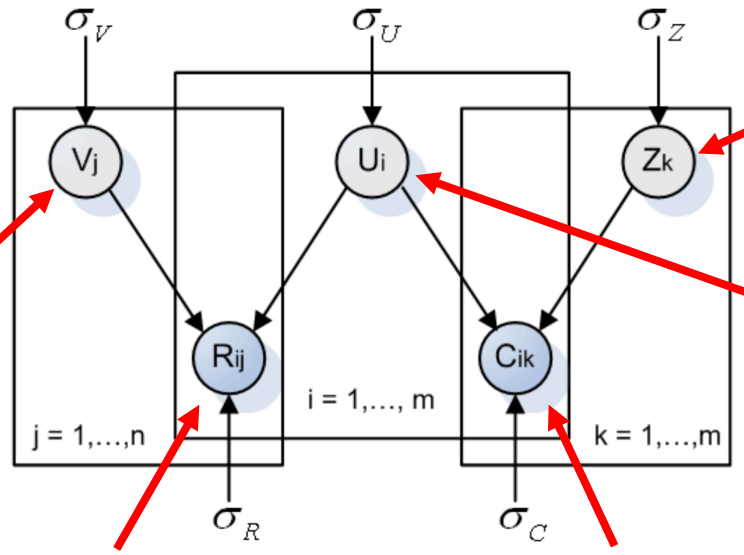
- Optimization methods such as gradient based methods can be applied to find a well-worked optimal solution.
- MF has a nice probabilistic interpretation with Gaussian noise.
- MF is very flexible and allows us to include prior knowledge.

$$\begin{aligned} & \textit{Social Recommendation CF} \\ = \; & \textit{Basic CF} + \textit{Social Information Model} \end{aligned}$$

Tang et al. **Social Recommendation: A Review.** *Social Network Analysis and Mining*, 2013. Springer.

Model based Social Recommender

- **SoRec**



factor vector

item vector

user vector

R: user-item rating matrix

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

C: user-user social matrix

	u_1	u_2	u_3	u_4	u_5
u_1	0	1	0	0	1
u_2	0	0	1	1	0
u_3	0	0	0	0	0
u_4	1	0	1	0	0
u_5	0	1	1	1	0

Ma et al. **Social Recommendation Using Probabilistic Matrix Factorization.** *CIKM*, 2008.
Improving Recommender Systems by Incorporating Social Contextual Information. *TIS*, 2011.

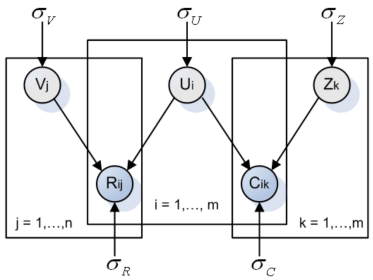
Model based Social Recommender

- SoRec

$$p(C|U,V,\sigma_R^2) = \prod_{i=1}^{m}\prod_{j=1}^{n}\mathcal{N}\left[\left(r_{ij}|g(U_i^T V_j),\sigma_R^2\right)\right]^{I_{ij}^R}$$

R

Gaussian distribution



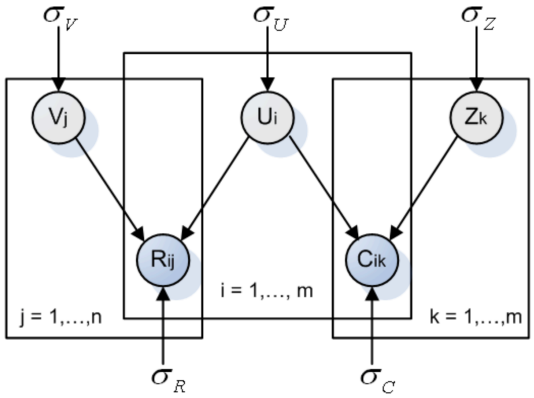
Logistic function

Observed

$$p(C|U,Z,\sigma_C^2) = \prod_{i=1}^{m}\prod_{k=1}^{m}\mathcal{N}\left[\left(c_{ik}|g(U_i^T Z_k),\sigma_C^2\right)\right]^{I_{ik}^C}$$

Model based Social Recommender

- **SoRec**



behavioral term

social term

$$\mathcal{L}(R,C,U,V,Z) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}(r_{ij}-g(U_i^T V_j))^2+\frac{\lambda_C}{2}\sum_{i=1}^{m}\sum_{k=1}^{m} I_{ik}^{C}(c_{ik}^{*}-g(U_i^T Z_k))^2$$

$$+\frac{\lambda_U}{2}\|U\|_F^2+\frac{\lambda_V}{2}\|V\|_F^2+\frac{\lambda_Z}{2}\|Z\|_F^2, \qquad (9)$$

regularization terms

Model based Social Recommender

- **SoRec**

Gradient Descent Methods

deviate of Logistic function

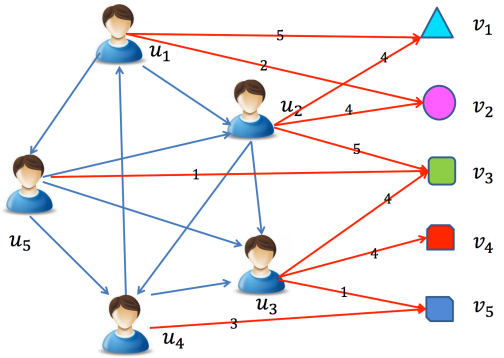
$$\frac{\partial \mathcal{L}}{\partial U_i} = \sum_{j=1}^{n} I_{ij}^R g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij}) V_j + \lambda_C \sum_{j=1}^{m} I_{ik}^C g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^*) Z_k + \lambda_U U_i,$$

$$\frac{\partial \mathcal{L}}{\partial V_j} = \sum_{i=1}^{m} I_{ij}^R g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij}) U_i + \lambda_V V_j,$$

$$\frac{\partial \mathcal{L}}{\partial Z_k} = \lambda_C \sum_{i=1}^{m} I_{ik}^C g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^*) U_i + \lambda_Z Z_k, \quad (10)$$

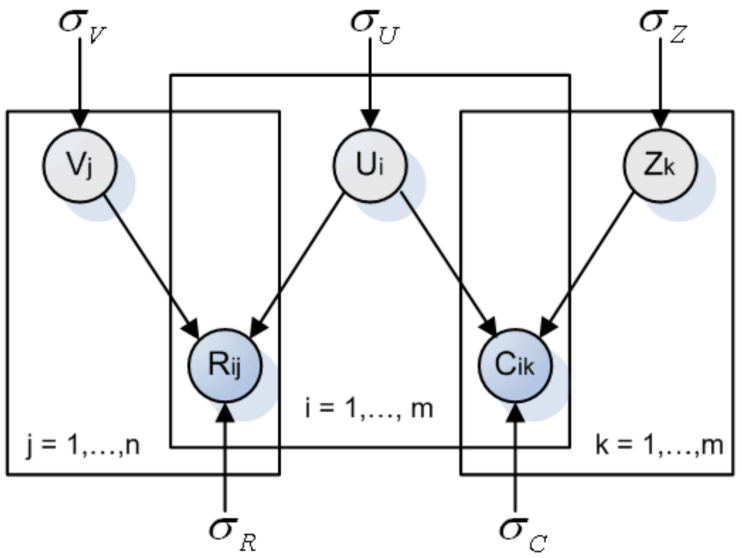
Model based Social Recommender

SoRec



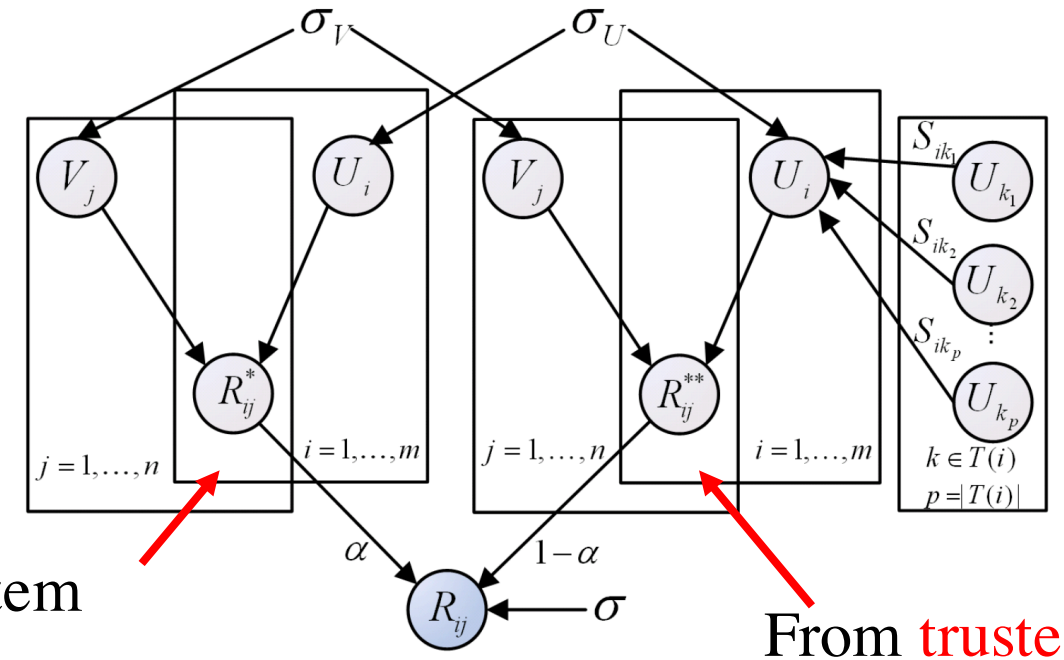
	u_1	u_2	u_3	u_4	u_5
u_1	0	1	0	0	1
u_2	0	0	1	1	0
u_3	0	0	0	0	0
u_4	1	0	1	0	0
u_5	0	1	1	1	0

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?



Model based Social Recommender

- Replacing social with trust
- **"Social Trust" Ensemble** for Epinion data



From user-item matrix

From trusted friends

Operation "plus"

Ma et al. **Learning to Recommend with Social Trust Ensemble.** *SIGIR*, 2009.
Learning to Recommend with Explicit and Implicit Social Relations. *TIST*, 2011.

Model based Social Recommender

- "Social Trust" Ensemble

From user-item matrix

From trusted friends

$$\mathcal{L}(R,S,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}(R_{ij} - g(\alpha U_i^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j))^2 + \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2, \quad (13)$$

Model based Social Recommender

- "Social Trust" Ensemble

Gradient Descent Methods

$$\frac{\partial \mathcal{L}}{\partial U_i} = \alpha \sum_{j=1}^{n} I_{ij}^R g'(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) V_j$$
$$\times (g(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) - R_{ij})$$
$$+ (1-\alpha) \sum_{p \in \mathcal{B}(i)} \sum_{j=1}^{n} I_{pj}^R g'(\alpha U_p^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(p)} S_{pk} U_k^T V_j)$$
$$\times (g(\alpha U_p^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(p)} S_{pk} U_k^T V_j) - R_{pj}) S_{pi} V_j + \lambda_U U_i,$$

$$\frac{\partial \mathcal{L}}{\partial V_j} = \sum_{i=1}^{m} I_{ij}^R g'(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j)$$
$$\times (g(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) - R_{ij})$$
$$\times (\alpha U_i + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T) + \lambda_V V_j, \qquad (14)$$

Model based Social Recommender

- **SoReg**

Average-based regularization:

Regularize with the average of friends' tastes

$$\min_{U,V} \mathcal{L}_1(R,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2$$

$$+ \frac{\alpha}{2}\sum_{i=1}^{m} \|U_i - \frac{\sum_{f\in\mathcal{F}^+(i)} Sim(i,f) \times U_f}{\sum_{f\in\mathcal{F}^+(i)} Sim(i,f)}\|_F^2,$$

$$+ \frac{\lambda_1}{2}\|U\|_F^2 + \frac{\lambda_2}{2}\|V\|_F^2. \quad (8)$$

Information loss: Friends may have diverse tastes!!!

Ma et al. **Recommender Systems with Social Regularization.** *WSDM*, 2011.

Model based Social Recommender

- **SoReg**

Individual-based regularization:
Regularize with friends individually

$$\min_{U,V} \mathcal{L}_2(R,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2$$

$$+ \frac{\beta}{2}\sum_{i=1}^{m}\sum_{f\in\mathcal{F}^+(i)} Sim(i,f)\|U_i - U_f\|_F^2$$

$$+ \lambda_1\|U\|_F^2 + \lambda_2\|V\|_F^2. \quad (11)$$

Related Work

	Behavior	Content	Social	Trust
Collaborative filtering (CF) [Herlocker *et al*. TOIS; Koren KDD]	✔			
Content-based filtering with CF [Balabanovic *et al*.; Liu *et al*. CIKM;]	✔	✔		
SoRec [Ma *et al*. CIKM, TIS] SoReg [Ma *et al*. WSDM]	✔		✔	
Trust-based methods [Massa *et al*. RecSys; Jamali *et al*. KDD; Ma *et al*. SIGIR, TIST]	✔			✔

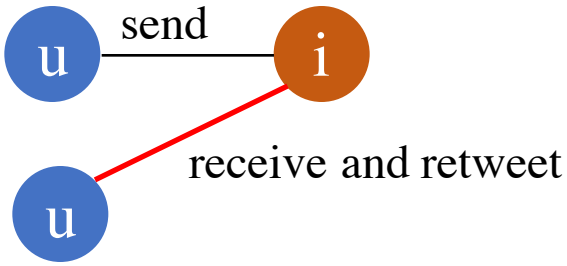
- **Q:** What are the **factors** of users' decisions on retweeting? Can we **observe** them from the data? How to **integrate** the information for accurate prediction?

Observation: Social Contextual Factors

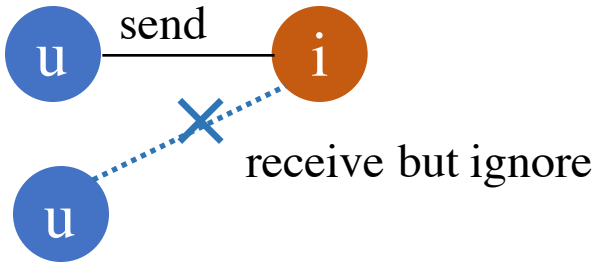
- Will Michelle Obama share this message?
- Please list your reasons.

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012.
Social Recommendation with Contextual Information. *TKDE*, 2014.

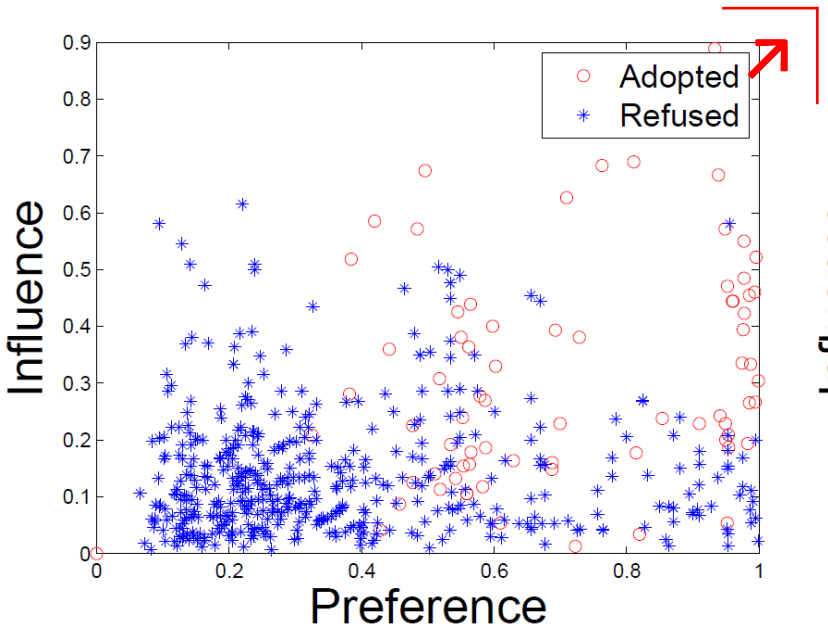
Observation: Social Contextual Factors



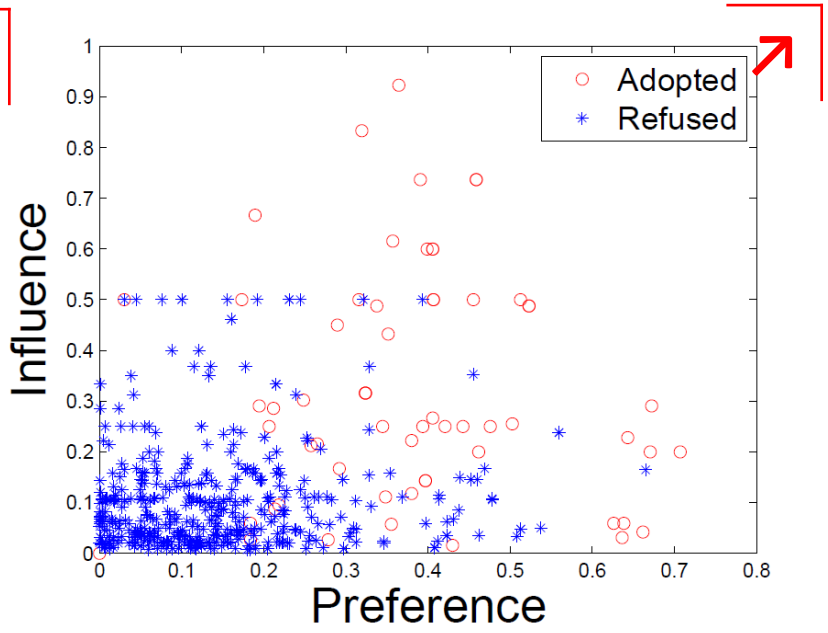
adopted



refused

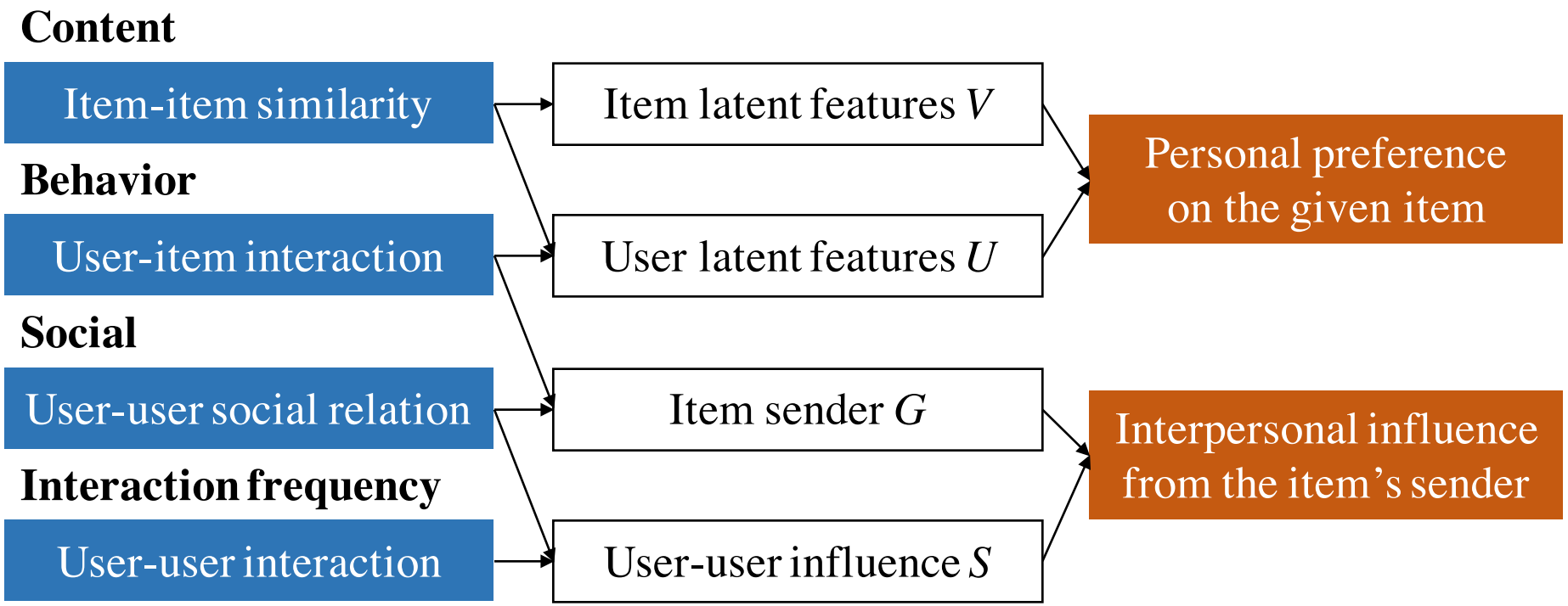


China's Facebook: Renren

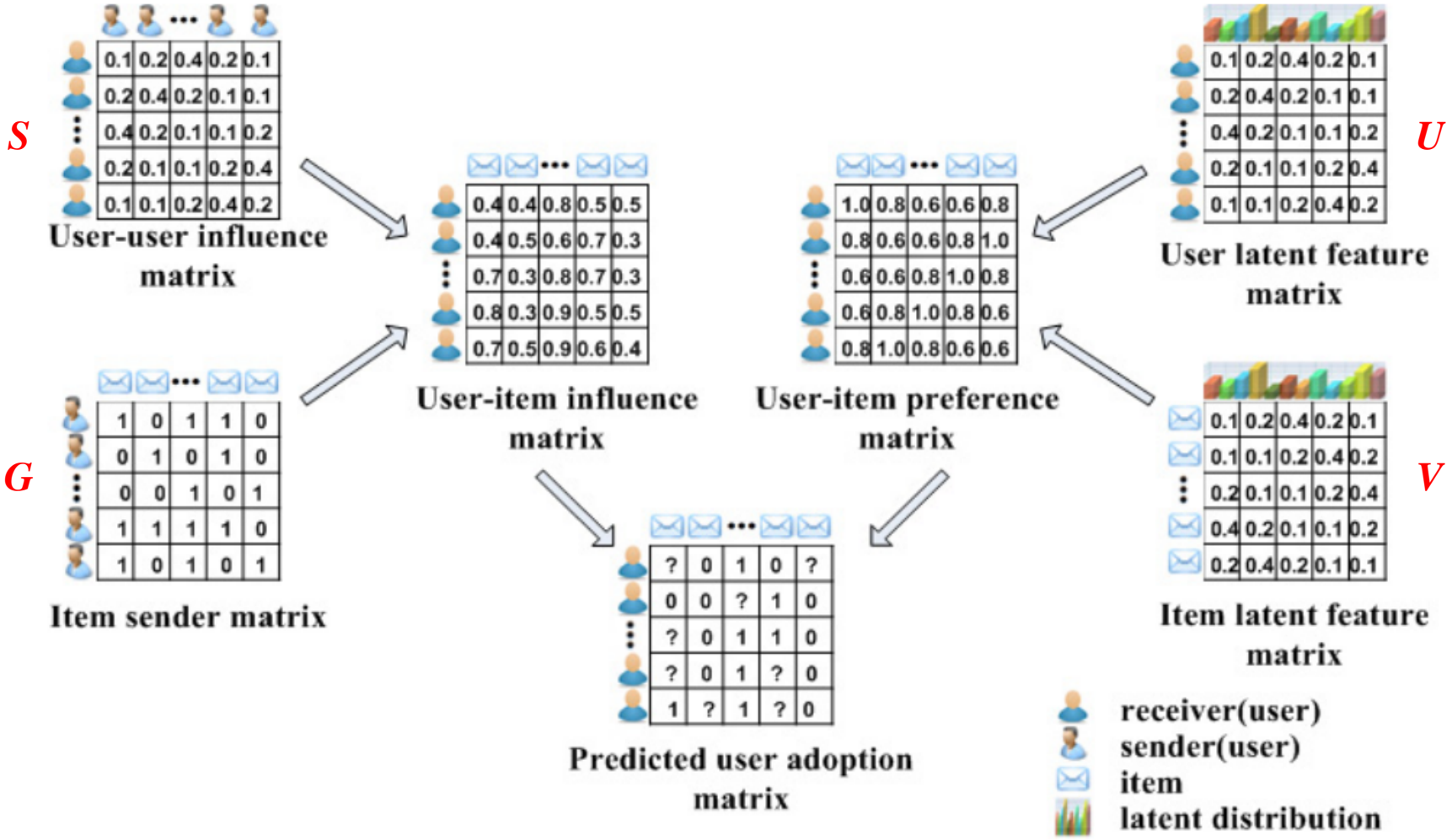


China's Twitter: Tencent Weibo

Representation: From Contextual Information to Contextual Factors



Model: ContextMF



Model: ContextMF

behavior influence preference

$$P(\mathbf{R}|\mathbf{S},\mathbf{U},\mathbf{V},\sigma_R^2)=\prod_{i=1}^{M}\prod_{j=1}^{N}\mathcal{N}(\mathbf{R}_{ij}|\mathbf{S}_i\mathbf{G}_j^\top\odot\mathbf{U}_i^\top\mathbf{V}_j,\sigma_R^2)$$

behavior interaction frequency/trust

item content

$$\mathcal{J}=||\mathbf{R}-\mathbf{S}\mathbf{G}^\top\odot\mathbf{U}^\top\mathbf{V}||_F^2+\alpha||\mathbf{W}-\mathbf{U}^\top\mathbf{U}||_F^2$$
$$+\beta||\mathbf{C}-\mathbf{V}^\top\mathbf{V}||_F^2+\gamma||\mathbf{S}-\mathbf{F}||_F^2$$
$$+\delta||\mathbf{S}||_F^2+\eta||\mathbf{U}||_F^2+\lambda||\mathbf{V}||_F^2$$

social relation

Model: ContextMF

- Gradient descent method

$$\frac{\partial \mathcal{J}}{\partial \mathbf{S}} = 2\Big(-\mathbf{R}(\mathbf{G} \odot \mathbf{V}^\top \mathbf{U}) + (\mathbf{S}\mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V})\mathbf{G} + \gamma(\mathbf{S} - \mathbf{F}) + \delta \mathbf{S}\Big)$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{U}} = 2\Big(-\mathbf{V}\mathbf{R}^\top + \mathbf{V}(\mathbf{G}\mathbf{S}^\top \odot \mathbf{V}^\top \mathbf{U}) - 2\alpha \mathbf{U}\mathbf{W} + 2\alpha \mathbf{U}\mathbf{U}^\top \mathbf{U} + \eta \mathbf{U}\Big)$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{V}} = 2\Big(-\mathbf{U}\mathbf{R} + \mathbf{U}(\mathbf{S}\mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V}) - 2\beta \mathbf{V}\mathbf{C} + 2\beta \mathbf{V}\mathbf{V}^\top \mathbf{V} + \lambda \mathbf{V}\Big)$$

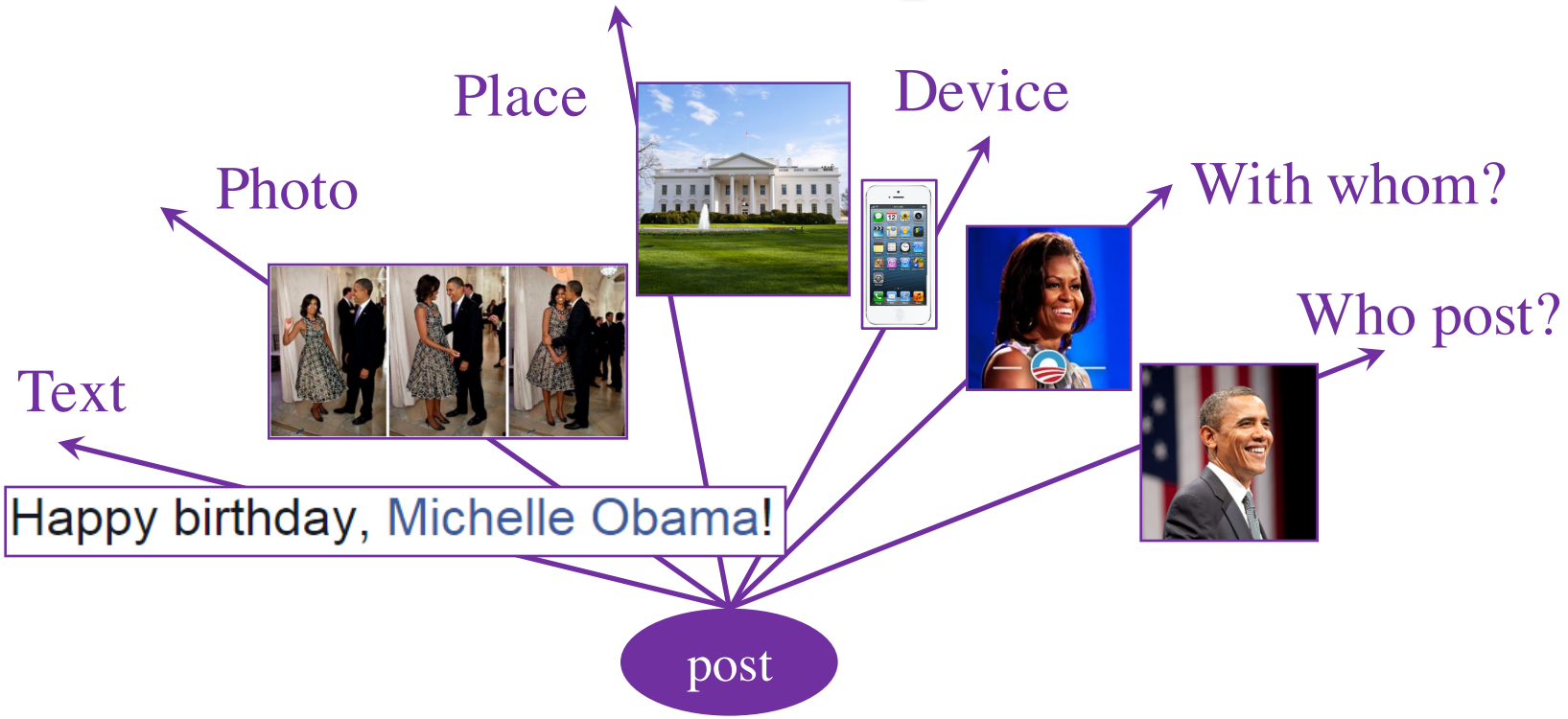
Experimental Results

Method	MAE	RMSE	$\hat{\tau}$	$\hat{\rho}$
Renren Dataset				
Content-based [1]	0.3842	0.4769	0.5409	0.5404
Item CF [25]	0.3601	0.4513	0.5896	0.5988
FeedbackTrust [22]	0.3764	0.4684	0.5433	0.5469
Influence-based [9]	0.3859	0.4686	0.5394	0.5446
SoRec [19]	0.3276	0.4127	0.6168	0.6204
SoReg [20]	0.2985	0.3537	0.7086	0.7140
Influence MF	0.3102	0.3771	0.6861	0.7006
Preference MF	0.3032	0.3762	0.6937	0.7036
Context MF	**0.2416**	**0.3086**	**0.7782**	**0.7896**
Tencent Weibo Dataset				
Content-based [1]	0.2576	0.3643	0.7728	0.7777
Item CF [25]	0.2375	0.3372	0.7867	0.8049
FeedbackTrust [22]	0.2830	0.3887	0.7094	0.7115
Influence-based [9]	0.2651	0.3813	0.7163	0.7275
SoRec [19]	0.2256	0.3325	0.7973	0.8064
SoReg [20]	0.1997	0.2962	0.8390	0.8423
Influence MF	0.2183	0.3206	0.8179	0.8258
Preference MF	0.2111	0.3088	0.8384	0.8453
Context MF	**0.1514**	**0.2348**	**0.8570**	**0.8685**

vs. SoReg [TIST'11]	Renren	Tencent Weibo
MAE	↓19.1%	↓24.2%
RMSE	↓12.8%	↓20.7%
Kendall's	↑9.82%	↑2.1%
Spearman's	↑10.6%	↑3.1%

- **Deployed** in Weibo News Feed. Improved conversion rate from 5.78% to 8.27% (relatively **43%**).
- #citations = **149**

Observation: Spatial Context



Jan. 18
Birthday party
@ White house

Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

Observation: Temporal Context

Photo

Text

Happy birthday, Michelle Obama!

post

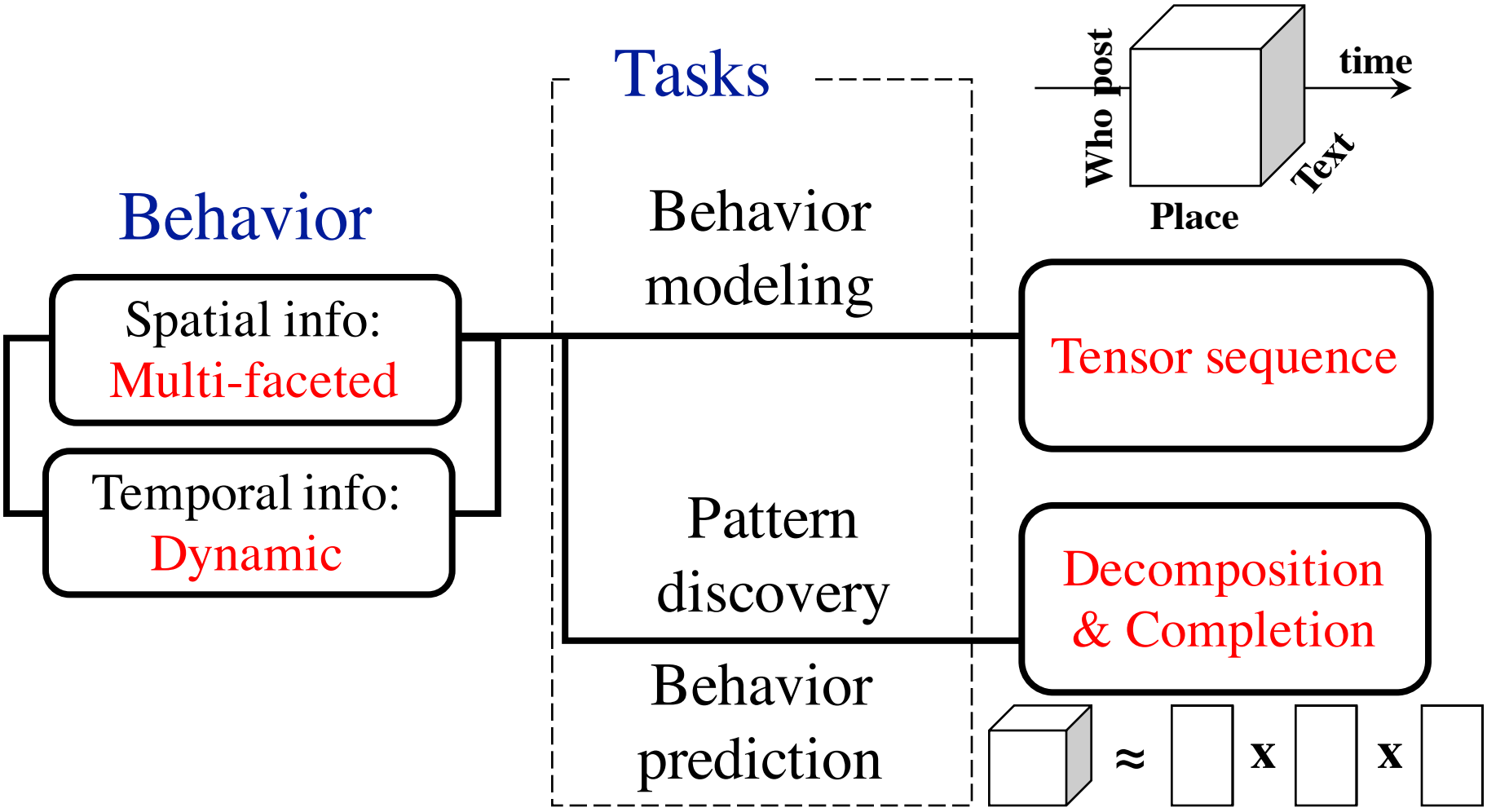
post

time

Jan. 18
Birthday party
@ White house

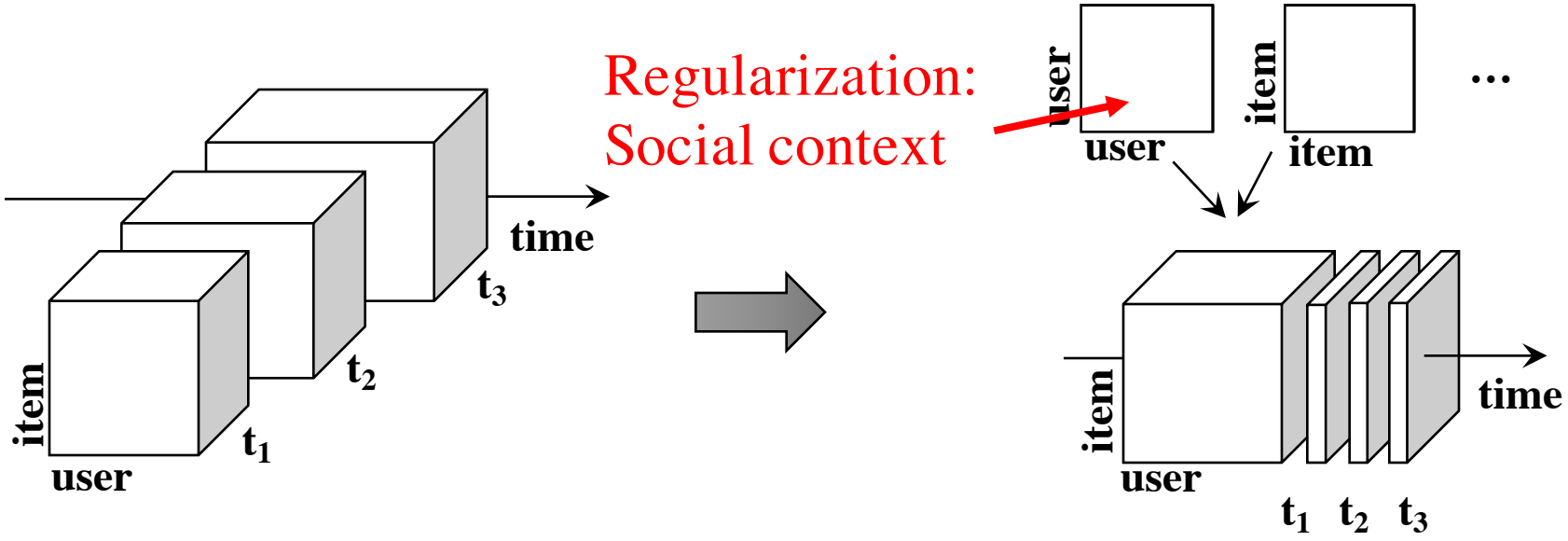
March 17
St. Patrick's Day
@ Bar

Representation: Tensor Sequence



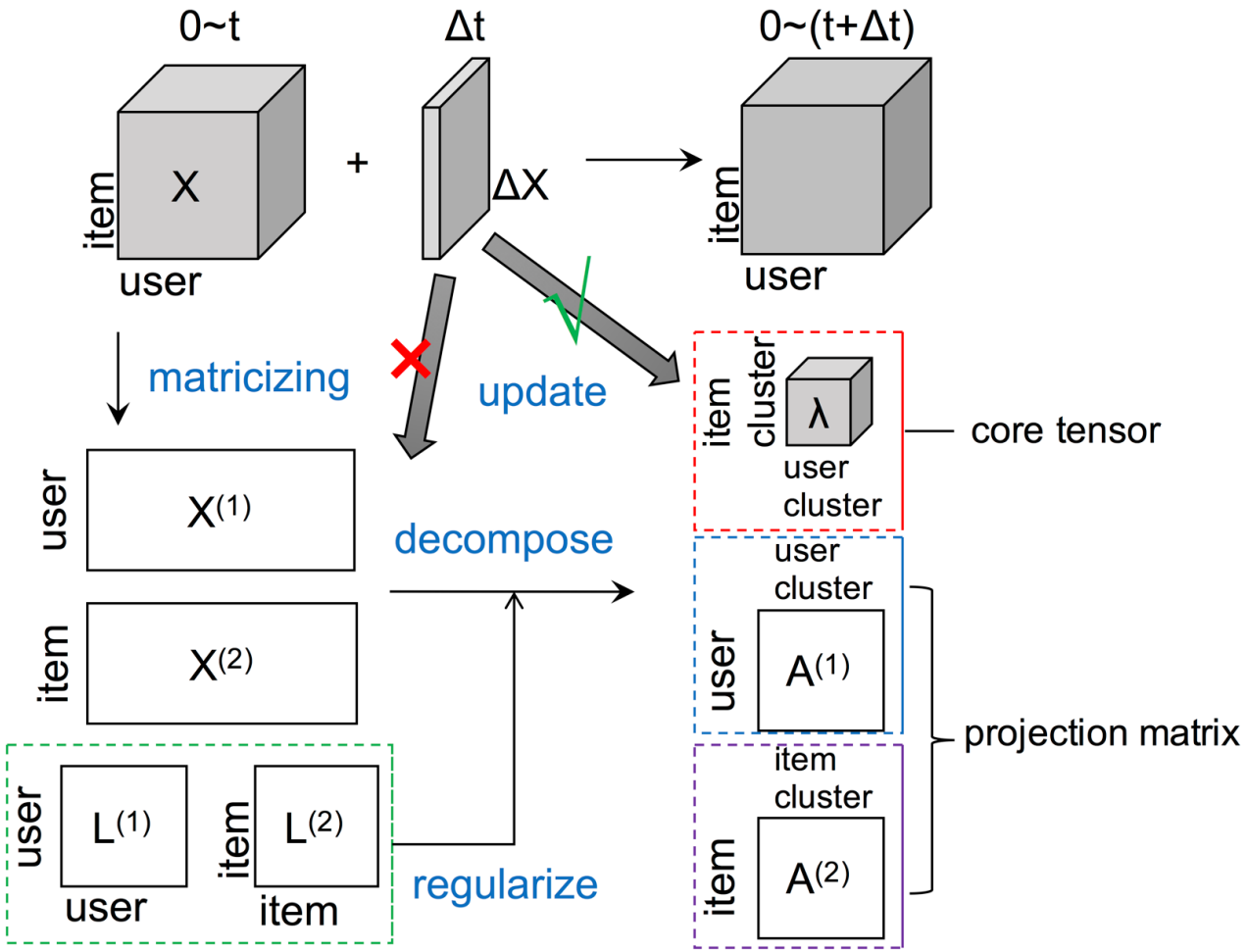
Challenges: Sparsity and Complexity

- Addressing sparsity: *Flexible regularization with auxiliary data*
- Addressing high complexity: *Incremental updates for projection matrix*



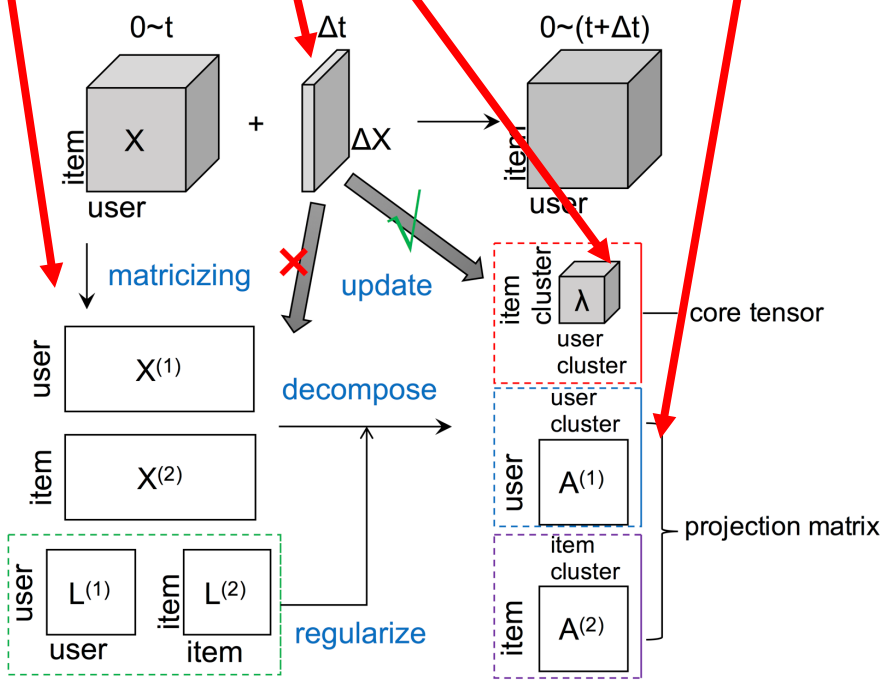
Model: FEMA

Flexible Evolutionary Multi-faceted Analysis



Tensor Perturbation Theory

$$[(\mathbf{X}^{(\mathbf{m})} + \Delta\mathbf{X}^{(\mathbf{m})})(\mathbf{X}^{(\mathbf{m})} + \Delta\mathbf{X}^{(\mathbf{m})})^{\top} + \mu^{(m)}\mathbf{L}^{(\mathbf{m})}]$$
$$\cdot(\mathbf{a_i}^{(\mathbf{m})} + \Delta\mathbf{a_i}^{(\mathbf{m})}) = (\lambda_i^{(m)} + \Delta\lambda_i^{(m)})(\mathbf{a_i}^{(\mathbf{m})} + \Delta\mathbf{a_i}^{(\mathbf{m})})$$



Algorithm: FEMA

Approximation

Require: $\mathcal{X}_t, \Delta\mathcal{X}_t, \mathbf{A}_t^{(m)}|_{m=1}^{M}, \lambda_t^{(m)}|_{m=1}^{M}$
  for $m = 1, \ldots, M$ **do**
    for $i = 1, \ldots, r^{(m)}$ **do**
      Compute $\Delta\lambda_{t,i}^{(m)}$ using
      $\Delta\lambda_i^{(m)} = \mathbf{a}_i^{(m)\top}(\mathbf{X}^{(m)}\Delta\mathbf{X}^{(m)\top} + \Delta\mathbf{X}^{(m)}\mathbf{X}^{(m)\top})\mathbf{a}_i^{(m)}$
      and compute
      $\lambda_{t+1,i}^{(m)} = \lambda_{t,i}^{(m)} + \Delta\lambda_{t,i}^{(m)}$;
      Compute $\Delta\mathbf{a}_{t,i}^{(m)}$ using
      $\Delta\mathbf{a}_i^{(m)} = \sum_{j\neq i} \frac{\mathbf{a}_j^{(m)\top}(\mathbf{X}^{(m)}\Delta\mathbf{X}^{(m)\top} + \Delta\mathbf{X}^{(m)}\mathbf{X}^{(m)\top})\mathbf{a}_i^{(m)}}{\lambda_i^{(m)} - \lambda_j^{(m)}}\mathbf{a}_j^{(m)}$
      and compute
      $\mathbf{a}_{t+1,i}^{(m)} = \mathbf{a}_{t,i}^{(m)} + \Delta\mathbf{a}_{t,i}^{(m)}$ and $\mathbf{A}_{t+1}^{(m)} = \{\mathbf{a}_{t+1,i}^{(m)}\}$;
    end for
  end for
  $\mathcal{Y}_{t+1} = (\mathcal{X}_t + \Delta\mathcal{X}_t)\prod_{m=1}^{M} \times_{(m)} \mathbf{A}_{t+1}^{(m)\mathbf{T}}$;
  return $\mathbf{A}_{t+1}^{(m)}|_{m=1}^{M}, \lambda_{t+1}^{(m)}|_{m=1}^{M}, \mathcal{Y}_{t+1}$

Bound Guarantee

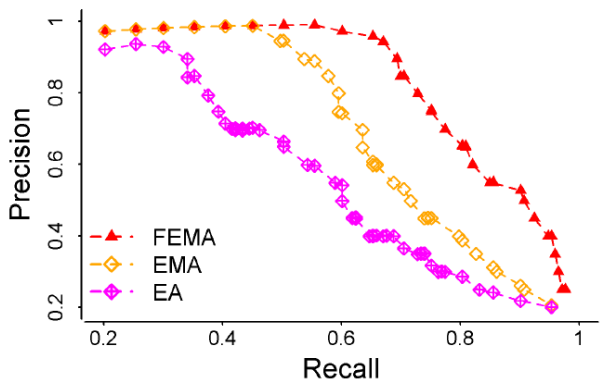
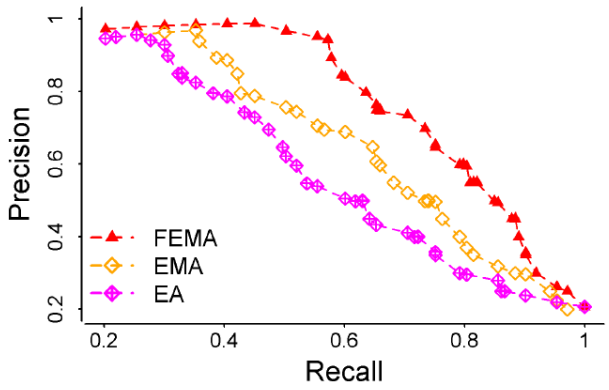
core tensor

$$|\Delta\lambda_i^{(m)}| \leq 2(\lambda^{\max}_{\mathbf{X}^{(m)\top}\mathbf{X}^{(m)}})^{\frac{1}{2}}\|\Delta\mathbf{X}^{(m)}\|_2$$

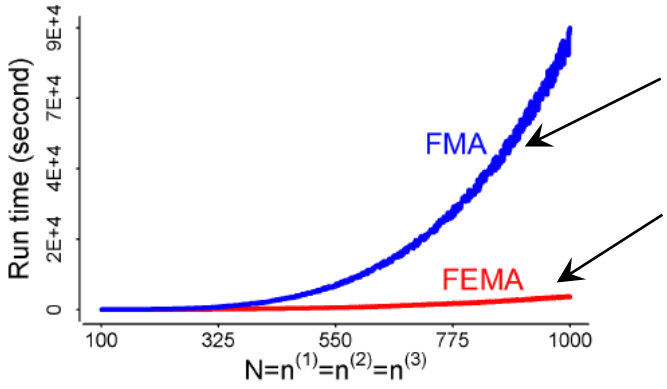
$$|\Delta\mathbf{a}_i^{(m)}| \leq 2\|\Delta\mathbf{X}^{(m)}\|_2 \sum_{j\neq i} \frac{(\lambda^{\max}_{\mathbf{X}^{(m)\top}\mathbf{X}^{(m)}})^{\frac{1}{2}}}{|\lambda_i^{(m)} - \lambda_j^{(m)}|}$$

projection matrix

Results: FEMA > EMA > EA

	Microsoft Academic Search		Tencent Weibo mentions "@"	
	MAE	RMSE	MAE	RMSE
FEMA X L	**0.735**	**0.944**	**0.894**	**1.312**
EMA X	0.794	1.130	0.932	1.556
EA X	0.979	1.364	1.120	1.873
Precision vs Recall				

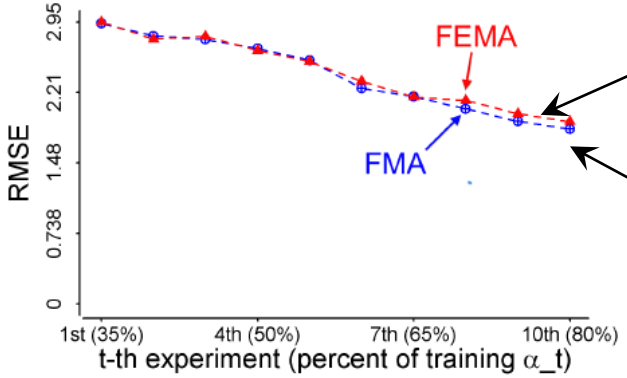
Results: Efficiency



Re-decomposition:
Re-compute projection matrices

Evolutionary analysis:
Use ΔX to update λ and a

Time vs Num. objects N



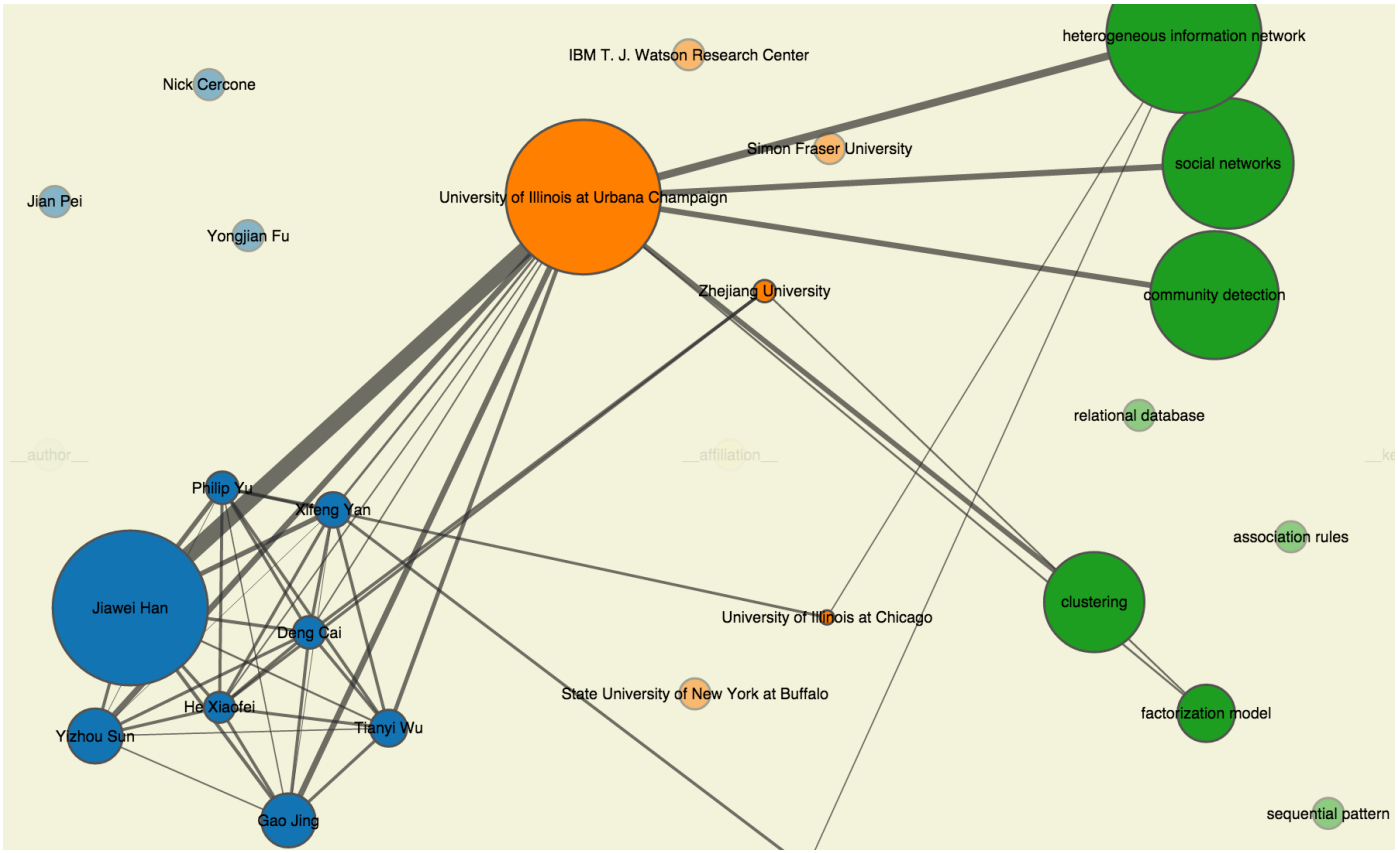
Evolutionary analysis:
Use ΔX to update λ and a

Re-decomposition:
Re-compute projection matrices

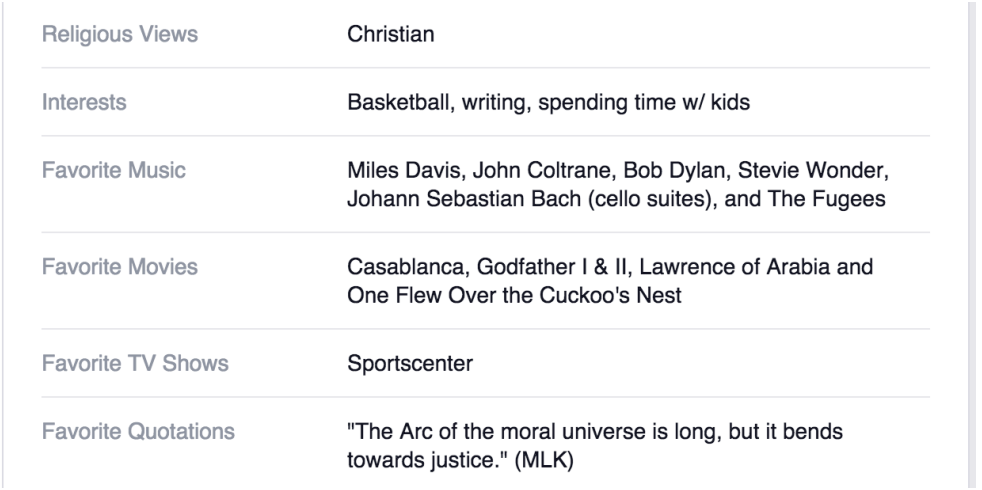
The loss is small.

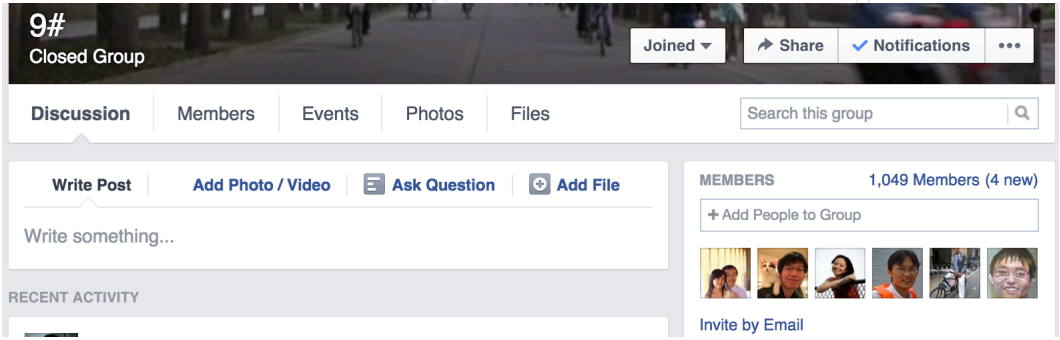
Demo: Author@Affiliation#Keyword

http://www.meng-jiang.com/demos/fema/mas/



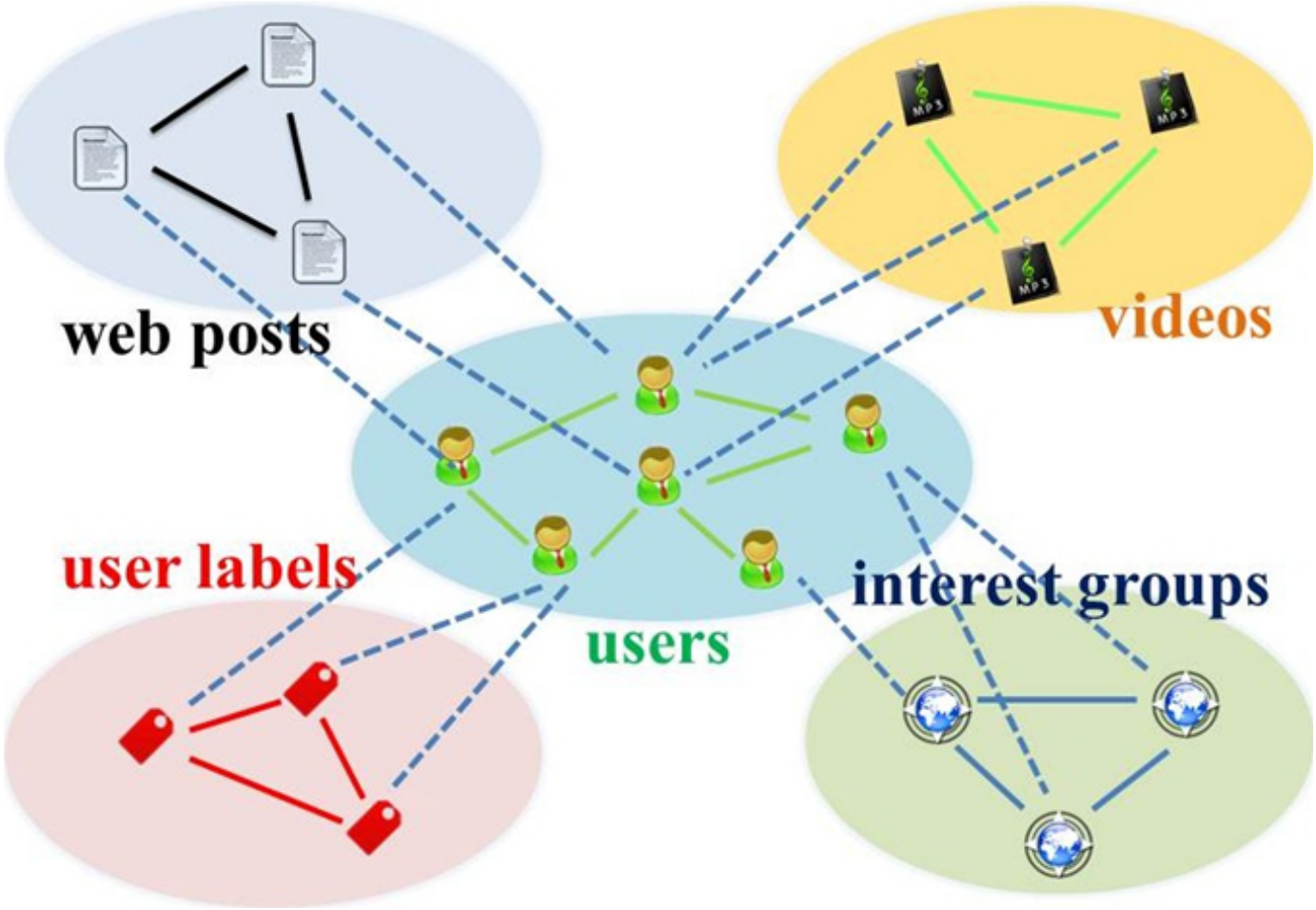
Observation: Multiple Domains



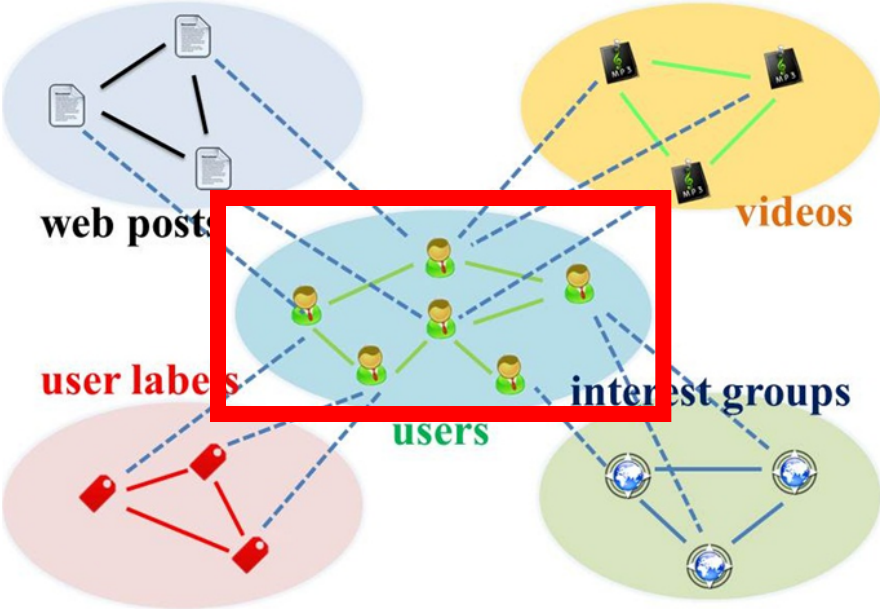


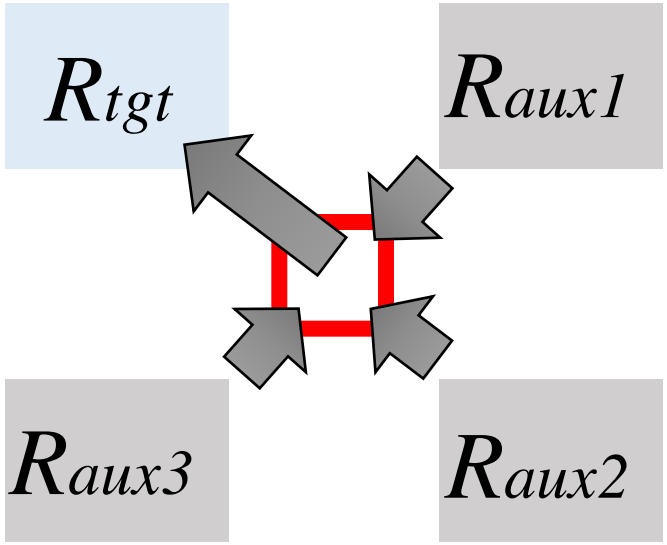
Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012.
Social Recommendation with Cross-Domain Transferable Knowledge. *TKDE*, 2015.

Representation: Star-Structured Graph



Representation: Social Bridge

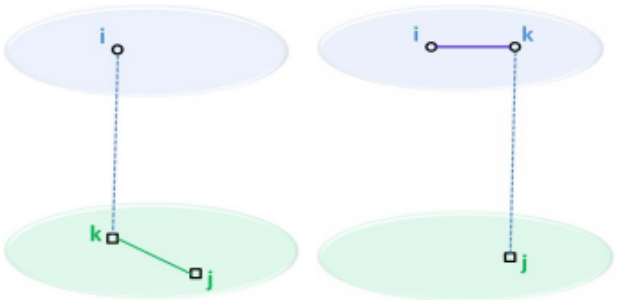




Bridge: Tie strength

Algorithm: Hybrid Random Walk

- Updating cross-domain links



(a) Route 1 (b) Route 2

$$p_{ij}^{(\mathcal{UP})^+} = \delta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UP})^+} + (1-\delta) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^+} r_{kj}^{(\mathcal{P})}$$

$$p_{ij}^{(\mathcal{UP})^-} = \delta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UP})^-} + (1-\delta) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^-} r_{kj}^{(\mathcal{P})}$$

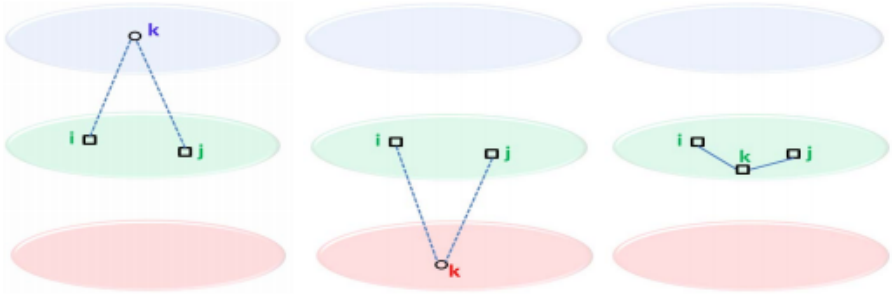
$$p_{ij}^{(\mathcal{UT})^+} = \eta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UT})^+} + (1-\eta) \sum_{t_k \in \mathcal{T}} p_{ik}^{(\mathcal{UT})^+} r_{kj}^{(\mathcal{T})}$$

$$\mathbf{P}^{(\mathcal{UP})^+}(t+1) = \delta \mathbf{R}^{(\mathcal{U})}(t) \mathbf{P}^{(\mathcal{UP})^+}(t) + (1-\delta) \mathbf{P}^{(\mathcal{UP})^+}(t) \mathbf{R}^{(\mathcal{P})}$$

$$\mathbf{P}^{(\mathcal{UP})^-}(t+1) = \delta \mathbf{R}^{(\mathcal{U})}(t) \mathbf{P}^{(\mathcal{UP})^-}(t) + (1-\delta) \mathbf{P}^{(\mathcal{UP})^-}(t) \mathbf{R}^{(\mathcal{P})}$$

$$\mathbf{P}^{(\mathcal{UT})^+}(t+1) = \eta \mathbf{R}^{(\mathcal{U})}(t) \mathbf{P}^{(\mathcal{UT})^+}(t) + (1-\eta) \mathbf{P}^{(\mathcal{UT})^+}(t) \mathbf{R}^{(\mathcal{T})}$$

- Updating within-domain links

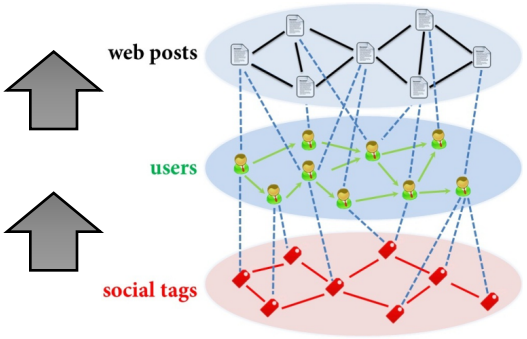


(a) Route 1 (b) Route 2 (c) Route 3

$$r_{ij}^{(\mathcal{U})} = \tau^{(\mathcal{P})} (\mu \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^+} p_{jk}^{(\mathcal{UP})^+} + (1-\mu) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^-} p_{jk}^{(\mathcal{UP})^-}) + \tau^{(\mathcal{T})} \sum_{t_k \in \mathcal{T}} p_{ik}^{(\mathcal{UT})^+} p_{jk}^{(\mathcal{UT})^+} + \tau^{(\mathcal{U})} \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} r_{kj}^{(\mathcal{U})} \quad (12)$$

$$\mathbf{R}^{(\mathcal{U})}(t+1) = \tau^{(\mathcal{P})} (\mu \mathbf{P}^{(\mathcal{UP})^+}(t) \mathbf{P}^{(\mathcal{UP})^+}(t)^T + (1-\mu) \mathbf{P}^{(\mathcal{UP})^-}(t) \mathbf{P}^{(\mathcal{UP})^-}(t)^T) + \tau^{(\mathcal{T})} \mathbf{P}^{(\mathcal{UT})^+}(t) \mathbf{P}^{(\mathcal{UT})^+}(t)^T + \tau^{(\mathcal{U})} \mathbf{R}^{(\mathcal{U})}(t) \mathbf{R}^{(\mathcal{U})}(t)^T \quad (13)$$

Results



Comparing with Random Walk with Restarts Models

Algorithm	MAE	Precision	Recall	F1	Kendall's $\hat{\tau}$
HRW	**0.227±1.5e-3**	**0.711±1.3e-3**	0.921±1.4e-3	**0.802±1.1e-3**	**0.792±2.5e-3**
BRW-R_U-P (TrustWalker)	0.276±1.1e-3	0.657±7.6e-4	**0.935±9.8e-4**	0.772±7.6e-4	0.774±1.6e-3
BRW-R_U	0.282±5.3e-3	0.655±4.0e-3	0.921±1.2e-2	0.765±7.7e-3	0.725±2.8e-3
BRW-W_U-P	0.292±1.1e-3	0.666±7.0e-4	0.900±5.2e-4	0.765±6.6e-4	0.725±8.5e-4
BRW-W_U (ItemRank)	0.318±1.4e-3	0.671±1.5e-3	0.713±2.4e-3	0.691±1.2e-3	0.661±2.2e-3
BRW-P	0.438±2.6e-4	0.571±3.4e-4	0.499±4.2e-4	0.532±3.2e-4	0.606±2.3e-4

Comparing with Social Recommendation Baselines

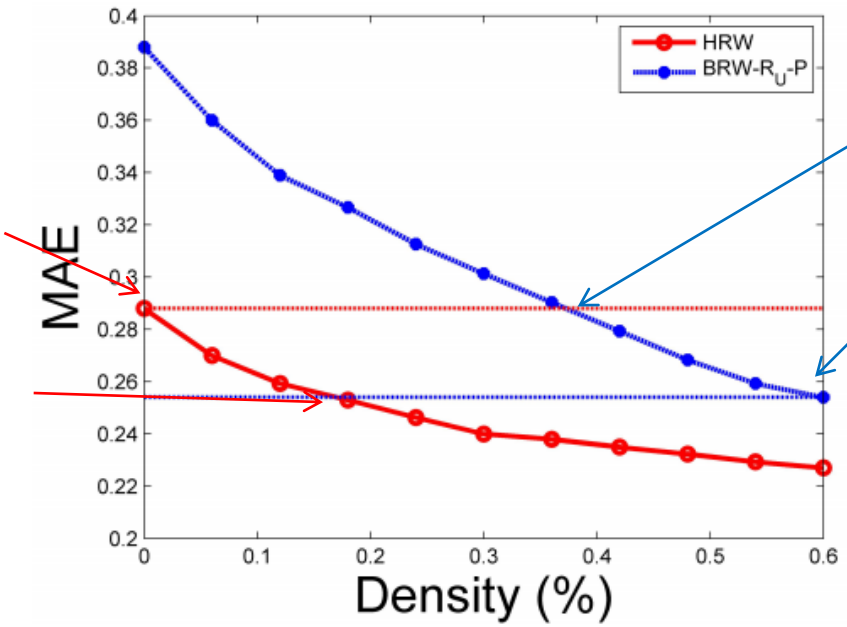
Algorithm	MAE	Precision	Recall	F1	Kendall's $\hat{\tau}$
HRW	**0.227±1.5e-3**	**0.711±1.3e-3**	0.921±1.4e-3	**0.802±1.1e-3**	**0.792±2.5e-3**
BRW-R_U-P (TrustWalker) [10]	0.276±1.1e-3	0.657±7.6e-4	0.935±9.8e-4	0.772±7.6e-4	0.774±1.6e-3
BRW-W_U (ItemRank) [8]	0.318±1.4e-3	0.671±1.5e-3	0.713±2.4e-3	0.691±1.2e-3	0.661±2.2e-3
MCF [5]	0.352±2.3e-4	0.592±1.8e-3	**0.951±6.0e-4**	0.730±1.3e-3	0.582±4.3e-4
CF [22]	0.506±3.4e-4	0.552±1.5e-3	0.589±7.2e-4	0.570±1.0e-3	0.540±5.2e-4

Results: Insight

- Knowledge transfer from auxiliary domains improves cold-start users' behavior prediction
  - Using aux. (label) data, saving ***60-70%*** tgt. (post) data

0 user-post
100% user-label

18% user-post
100% user-label



35% user-post
0 user-label

60% user-post
0 user-label

Observation: Multiple Platforms

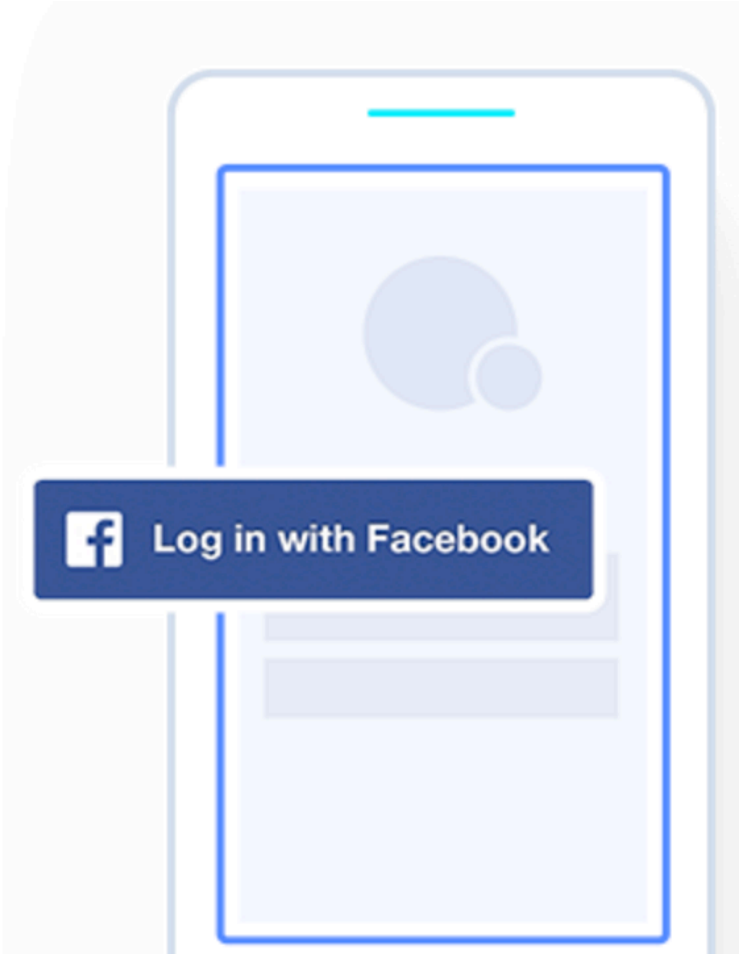
Jiang et al. **Little is Much: Bridging Cross-Platform Behaviors through Overlapped Crowds.** *AAAI*, 2016.

Observation: Cross-Platform

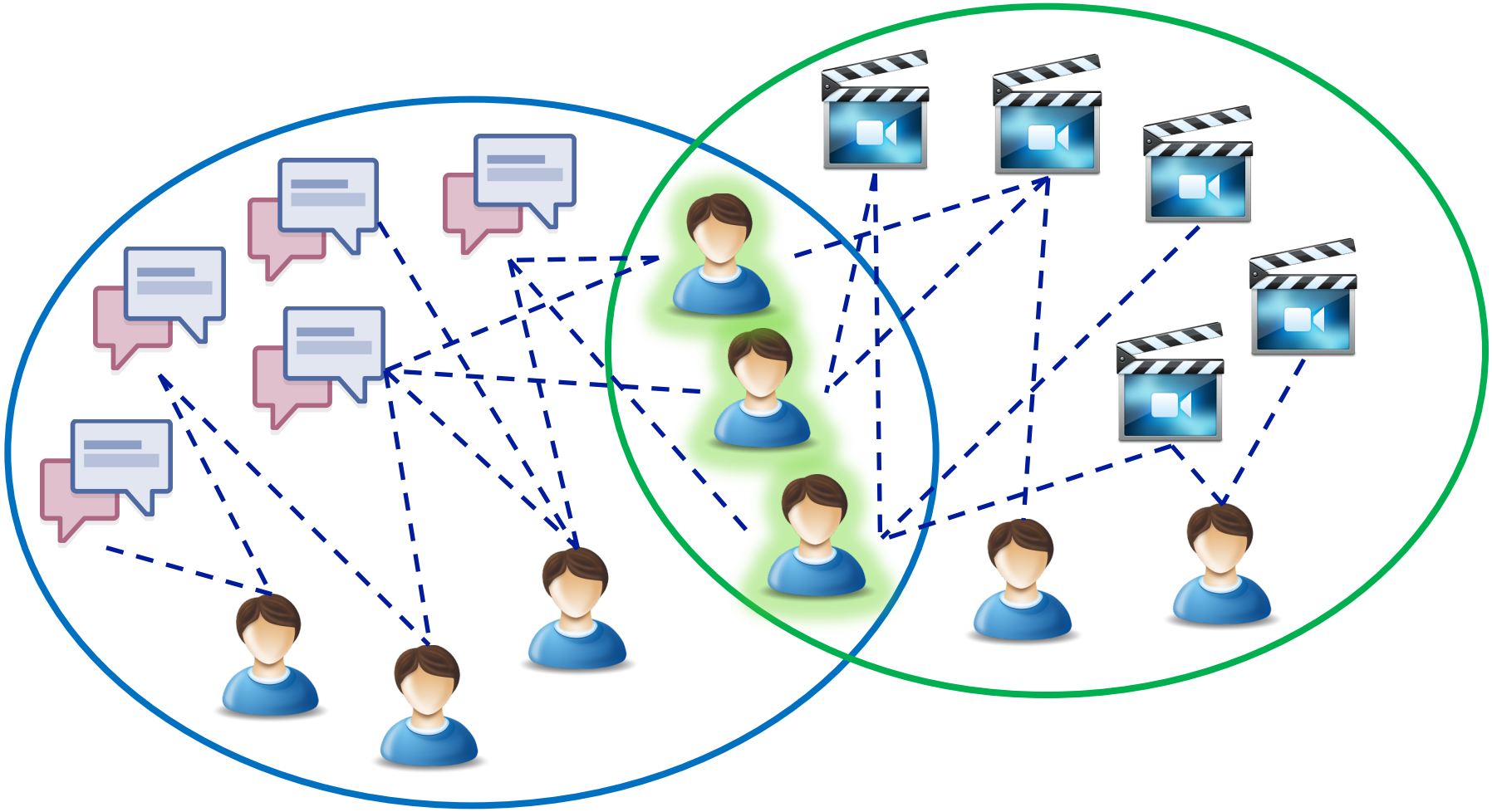
Add Facebook Login to Your App or Website

Facebook Login for Apps is a secure, fast and convenient way for people to log into your app or website.

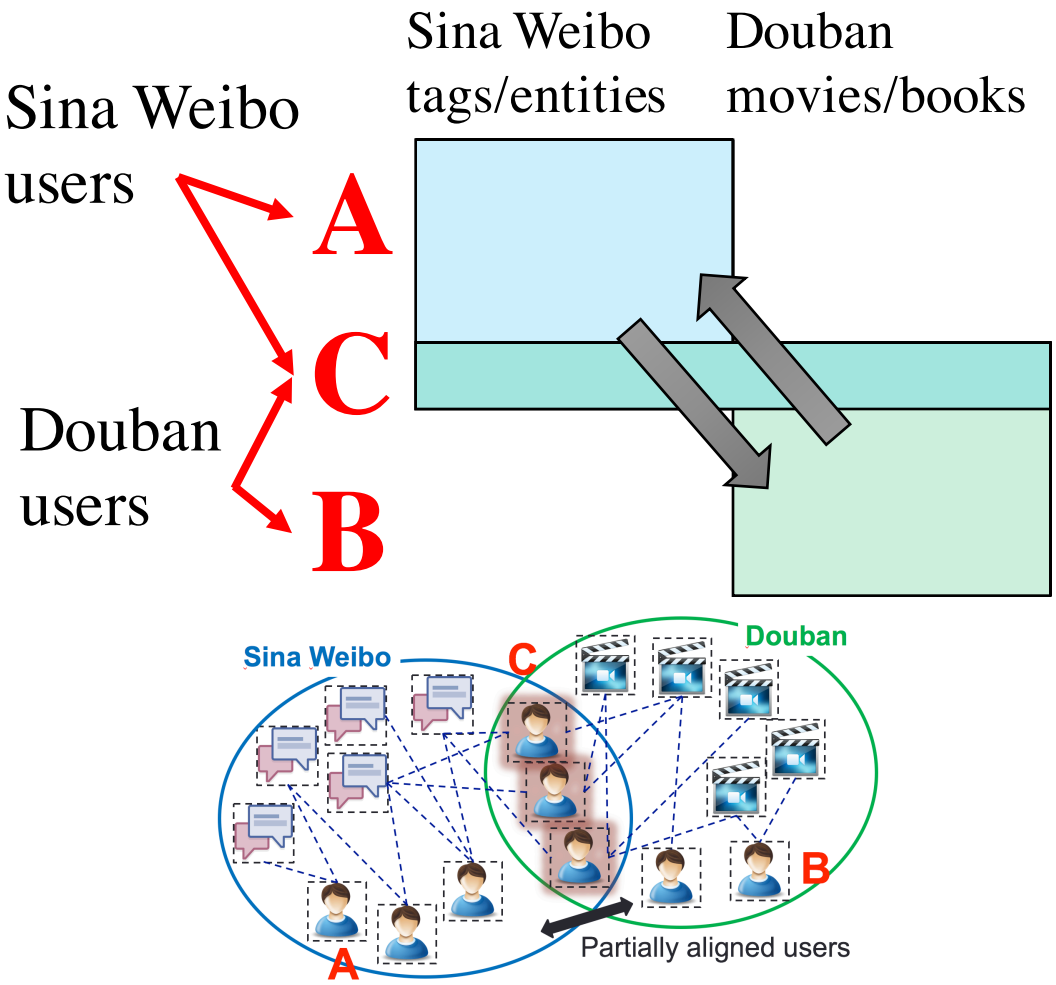
- iOS
- Android
- Websites or mobile websites
- More platforms



Observation: Partially Overlapped Crowds



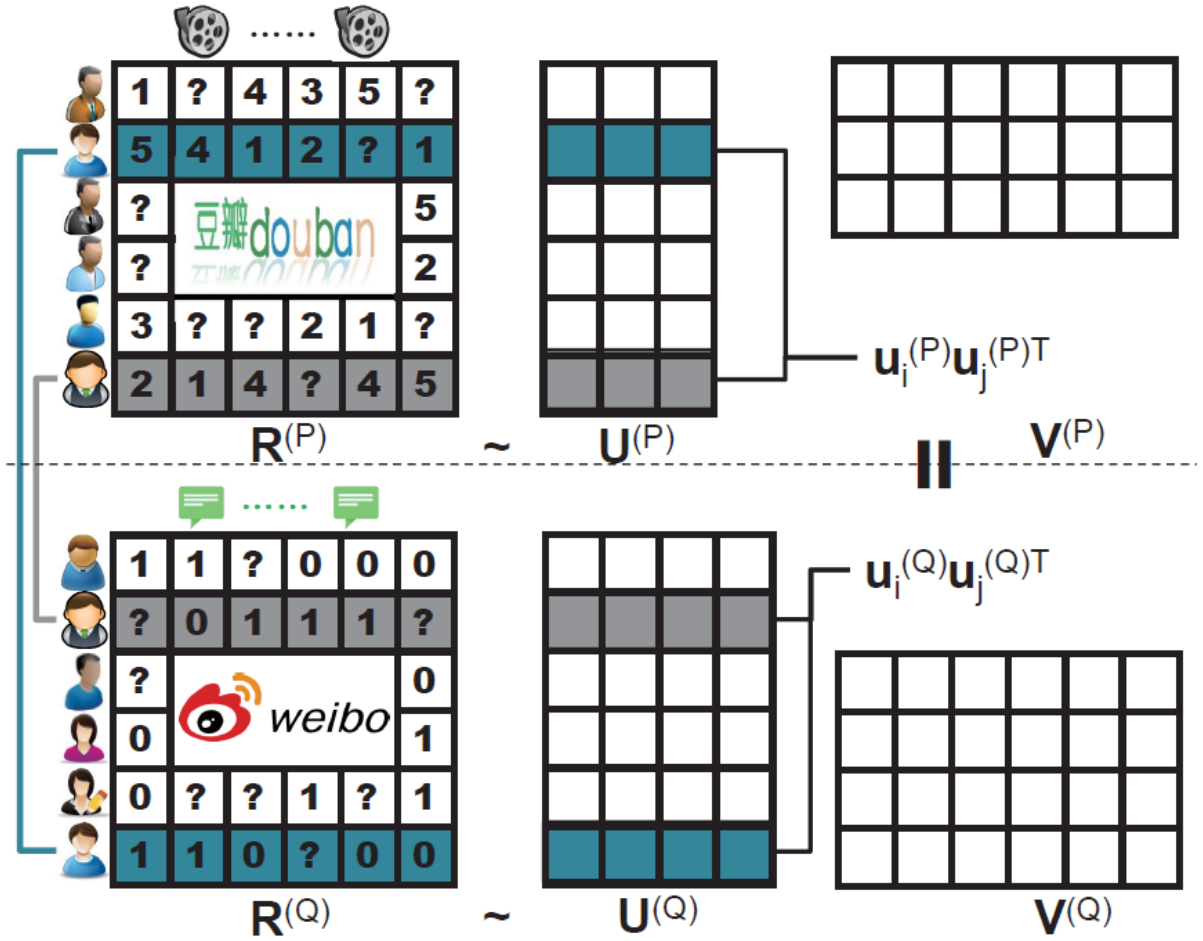
Representation: When NO Transfer



User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A	Auxiliary platform data!	
C	**0.779**	**0.805**
B	1.439	0.640

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	0.429	0.464
C	**0.267**	**0.666**
B	Auxiliary platform data!	

Algorithm: XPTrans



Algorithm: XPTrans

- Input
  - Tgt./Aux. platform P/Q;
  - Behavior data R(P)/R(Q);
  - Observation W(P)/W(Q);
  - Overlapping indicator W(P,Q),
- Output
  - User latent representation U(P)/U(Q);
  - Item latent representation V(P)/V(Q);
  - Missing values in R(P)

- Objective function

Target platform

Auxiliary platform

$$\mathcal{J} = \sum_{i,j} W_{i,j}^{(P)} \left(R_{i,j}^{(P)} - \sum_{r} U_{i,r}^{(P)} V_{r,j}^{(P)} \right)^2 + \lambda \sum_{i,j} W_{i,j}^{(Q)} \left(R_{i,j}^{(Q)} - \sum_{r} U_{i,r}^{(Q)} V_{r,j}^{(Q)} \right)^2 + \mu \sum_{i_1,j_1,i_2,j_2} W_{i_1,j_1}^{(P,Q)} W_{i_2,j_2}^{(P,Q)} \left(A_{i_1,i_2}^{(P)} - A_{j_1,j_2}^{(Q)} \right)^2$$

Overlapping user similarity (Pair-wise regularization)

Results: Leveraging Auxiliary Platform Data

NO Transfer

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A	Auxiliary platform data!	
C	0.779	0.805
B	**1.439**	**0.640**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.429**	**0.464**
C	0.267	0.666
B	Auxiliary platform data!	

Transfer via the Same Latent Space

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A		
C	0.757	0.811
B	**1.164 (-19%)**	**0.702 (+9.7%)**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.411 (-4.2%)**	**0.487 (+5.0%)**
C	0.256	0.681
B		

Results: Leveraging Different Latent Spaces

Transfer via the Same Latent Space

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A		
C	0.757	0.811
B	**1.164**	**0.702**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.411**	**0.487**
C	0.256	0.681
B		

Transfer via Different Latent Spaces

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A		
C	0.715	0.821
B	**0.722 (-38%)**	**0.820 (+17%)**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.374 (-11%)**	**0.533 (+12%)**
C	0.236	0.705
B		

Results: Where Amazing Happens

NO Transfer

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A	Auxiliary platform data!	
C	0.779	0.805
B	**1.439**	**0.640**

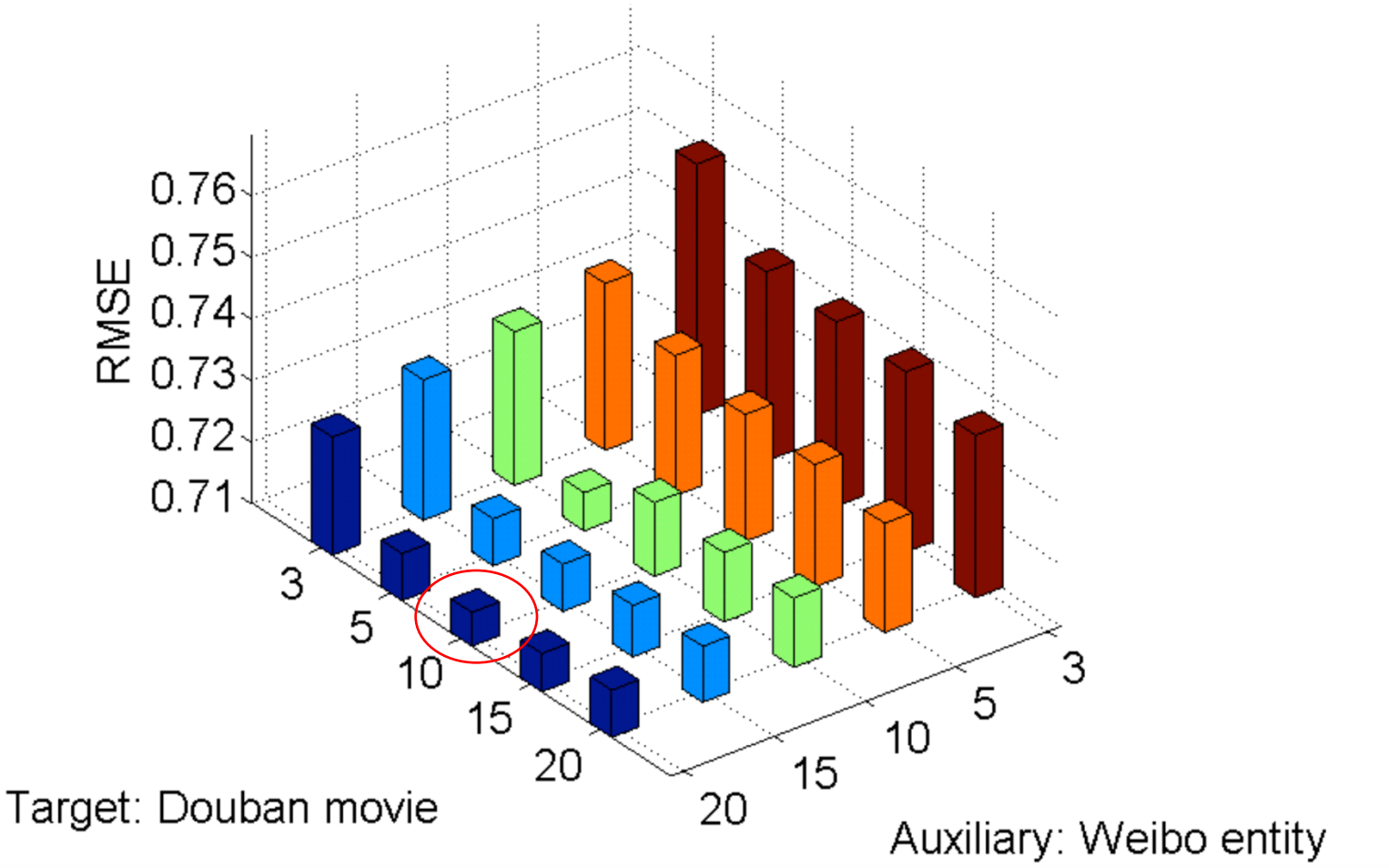
User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.429**	**0.464**
C	0.267	0.666
B	Auxiliary platform data!	

Transfer via Different Latent Spaces

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A		
C	0.715	0.821
B	**0.722**	**0.820**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.374**	**0.533**
C	0.236	0.705
B		

Results: Different Sizes of Latent Spaces



Summary

- Like, Reply, Share, Retweet, Favorite, Comment …
- Memory based social recommenders
  - TidalTrust, MoleTrust, TrustWalker
- Model based social recommenders
  - SoRec, "Social Trust" Ensemble, SoReg
- **Observations, Representations, Models**
  - **ContextMF:** Social contexts (preference & influence)
  - **FEMA:** Spatiotemporal contexts (multidimensional)
  - **HybridRW:** Cross-domain behavior modeling
  - **XPTrans:** Cross-platform behavior modeling

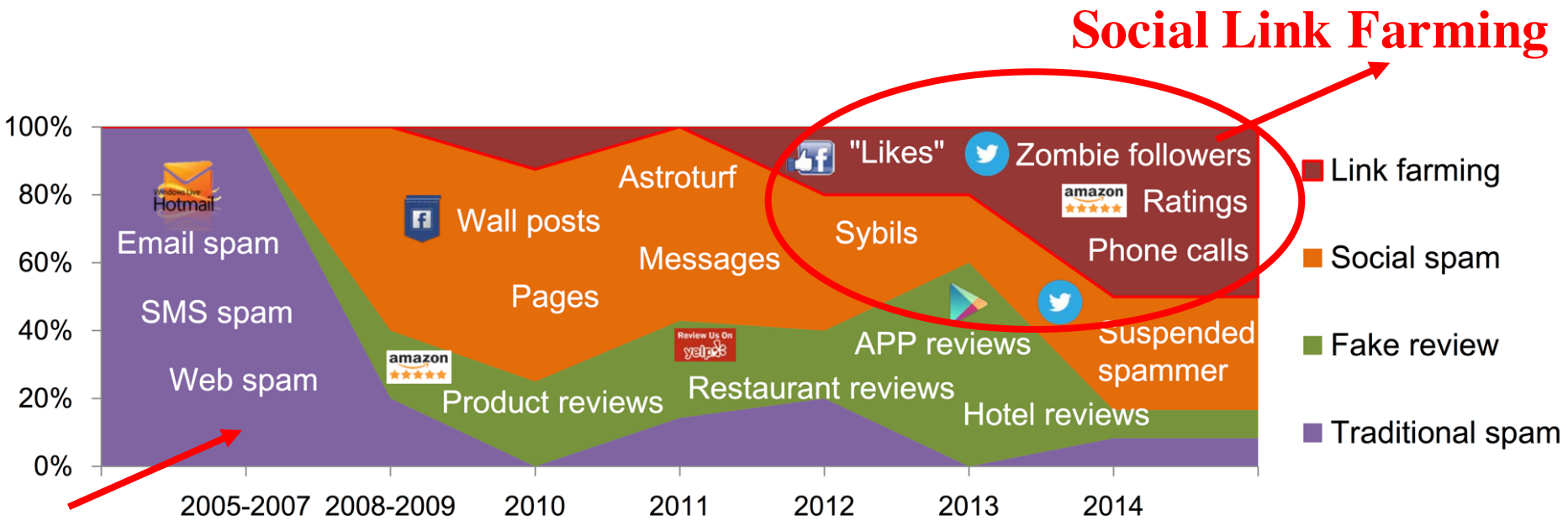
I. Mining behavior networks with social and spatiotemporal contexts

I.2. Suspicious behavior detection

Ill-gotten Facebook Likes

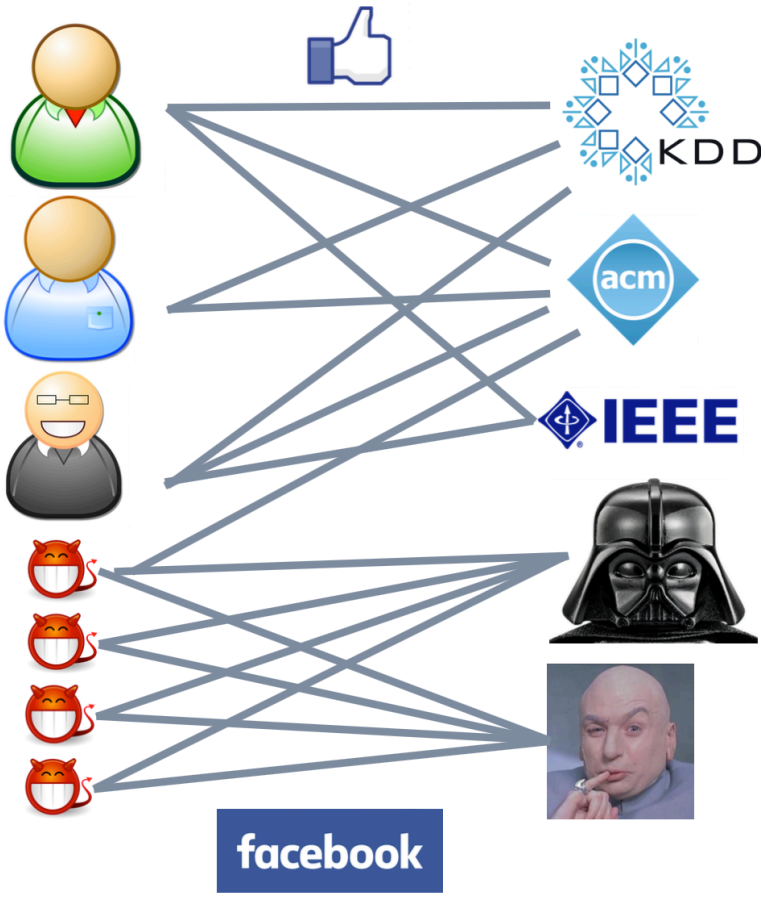
25,000 Facebook Likes	50,000 Facebook Likes	100,000 Facebook Likes	200,000 Facebook Likes
$265	$525	$1,000	$1,750
Lifetime Replacement Warranty	Lifetime Replacement Warranty	Lifetime Replacement Warranty	Lifetime Replacement Warranty
Dedicated 24/7 Customer Service	Dedicated 24/7 Customer Service	Dedicated 24/7 Customer Service	Dedicated 24/7 Customer Service
100% Risk Free, Try Us Today	100% Risk Free, Try Us Today	100% Risk Free, Try Us Today	100% Risk Free, Try Us Today
Order starts within 24 - 48 hours	Order starts within 24 - 48 hours	Order starts within 24 -48 hours	Order starts within 24 -48 hours
Order completed within 22 days	Order completed within 35 days	Order completed within 35 days	Order completed within 35 days

Suspicious Behavior Detection



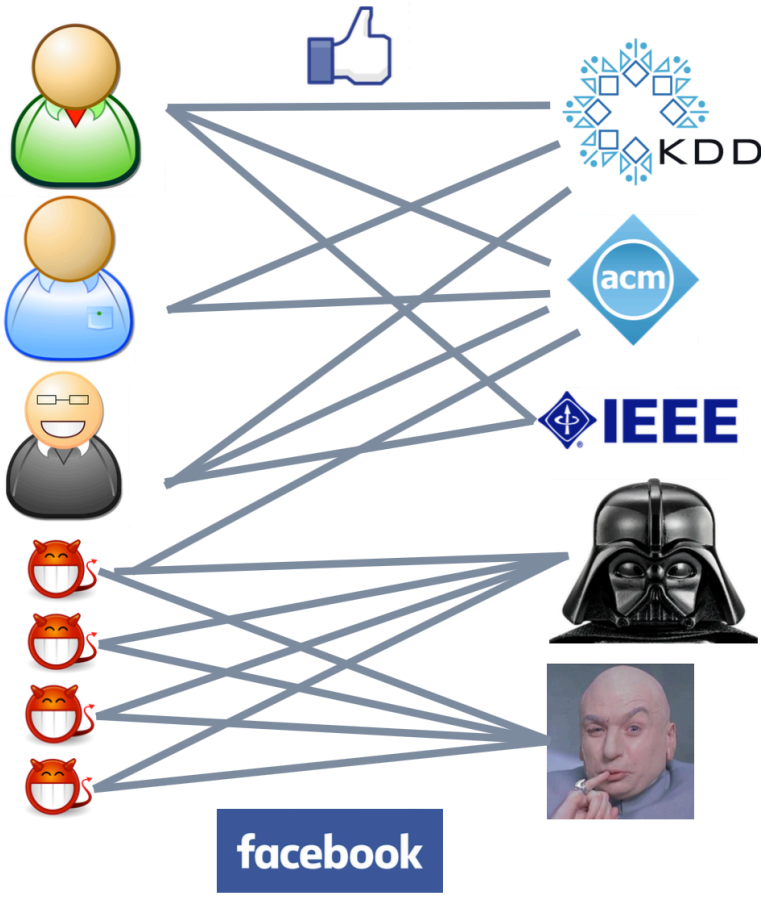
Meng Jiang, Peng Cui and Christos Faloutsos.
Suspicious Behavior Detection: Current Trends and Future Directions.
IEEE Intelligent Systems (ISSI), 2016.

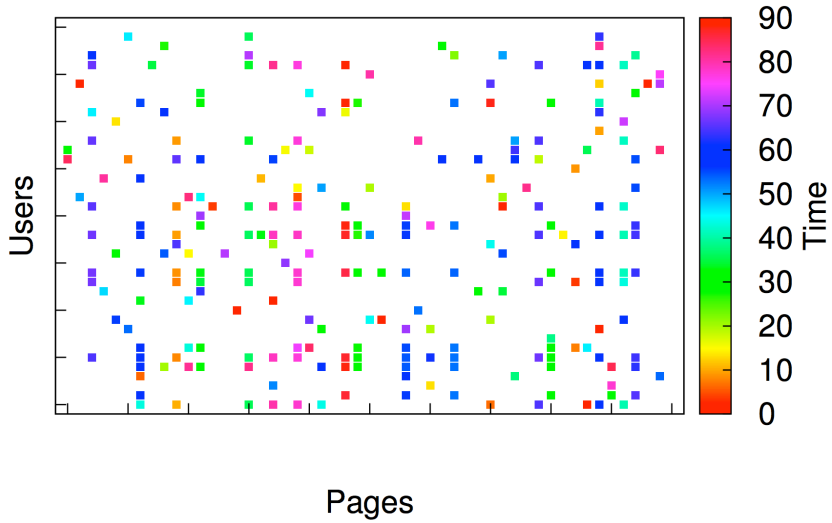
Ill-gotten Facebook Likes



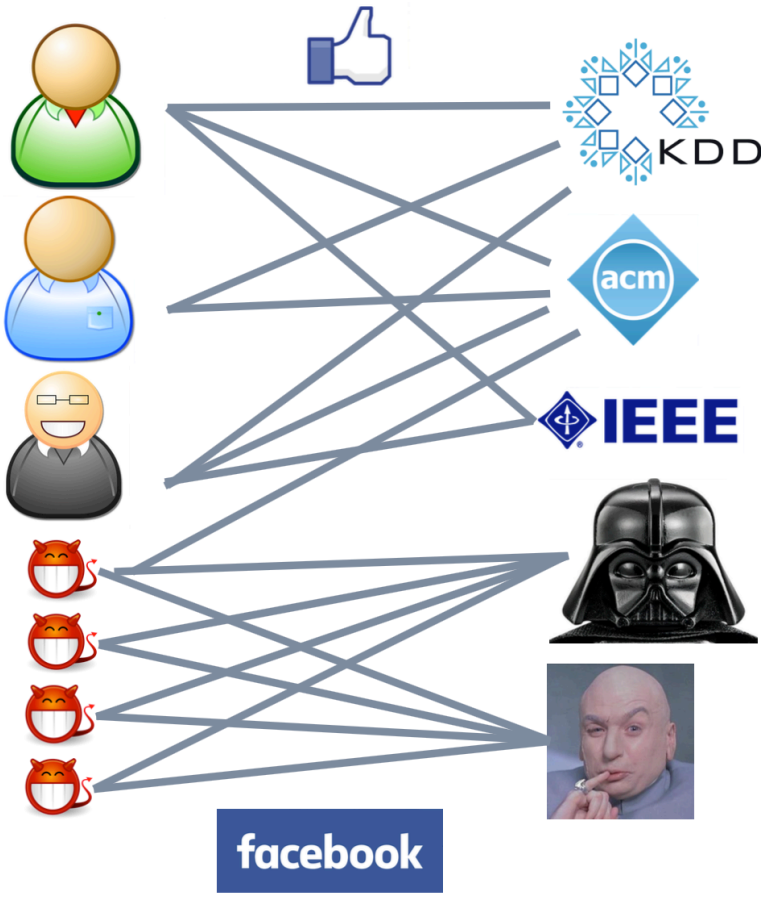
Beutel et al. **CopyCatch: Stopping Group Attacks by Spotting Lockstep Behavior in Social Neworks.** *WWW*, 2013.

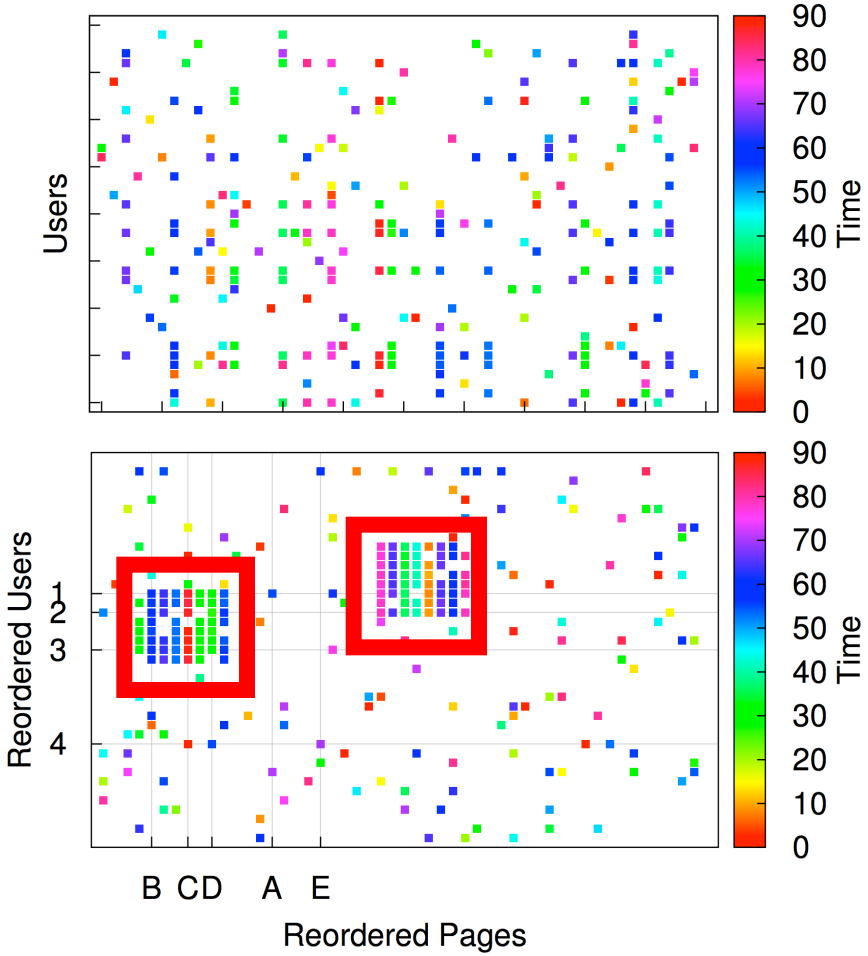
Observation: Graphical View





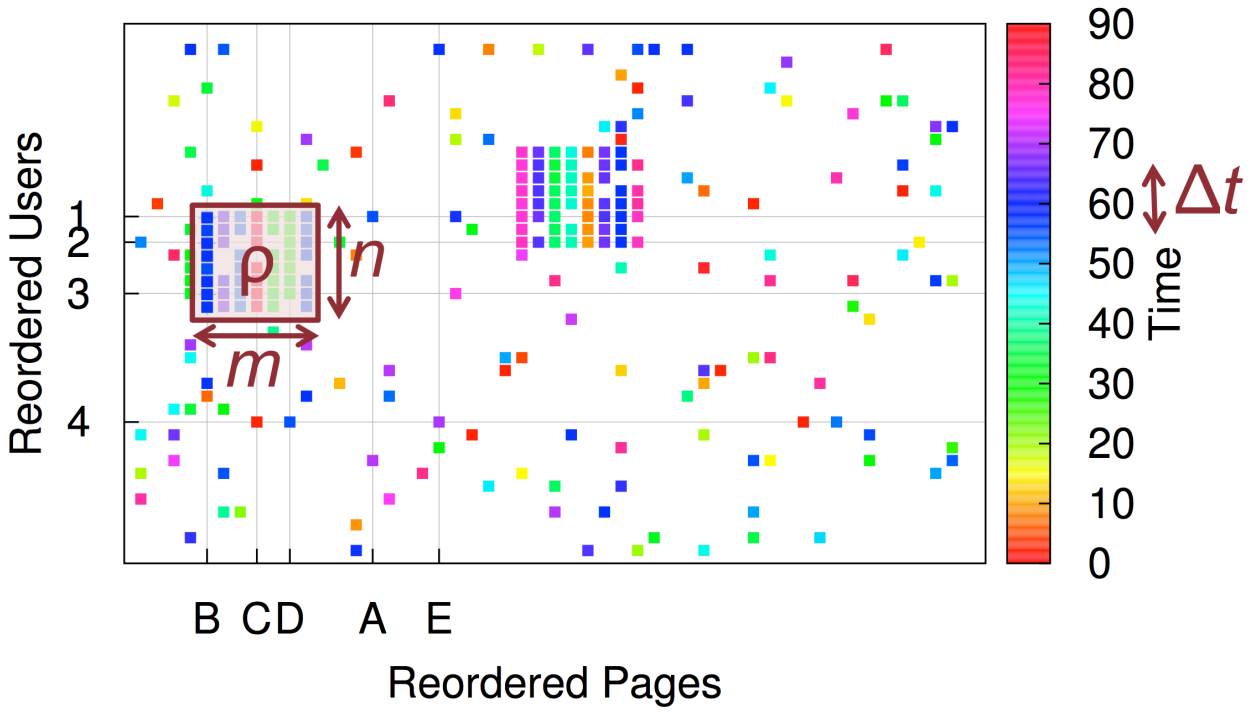
Observation: Reorder Matrix



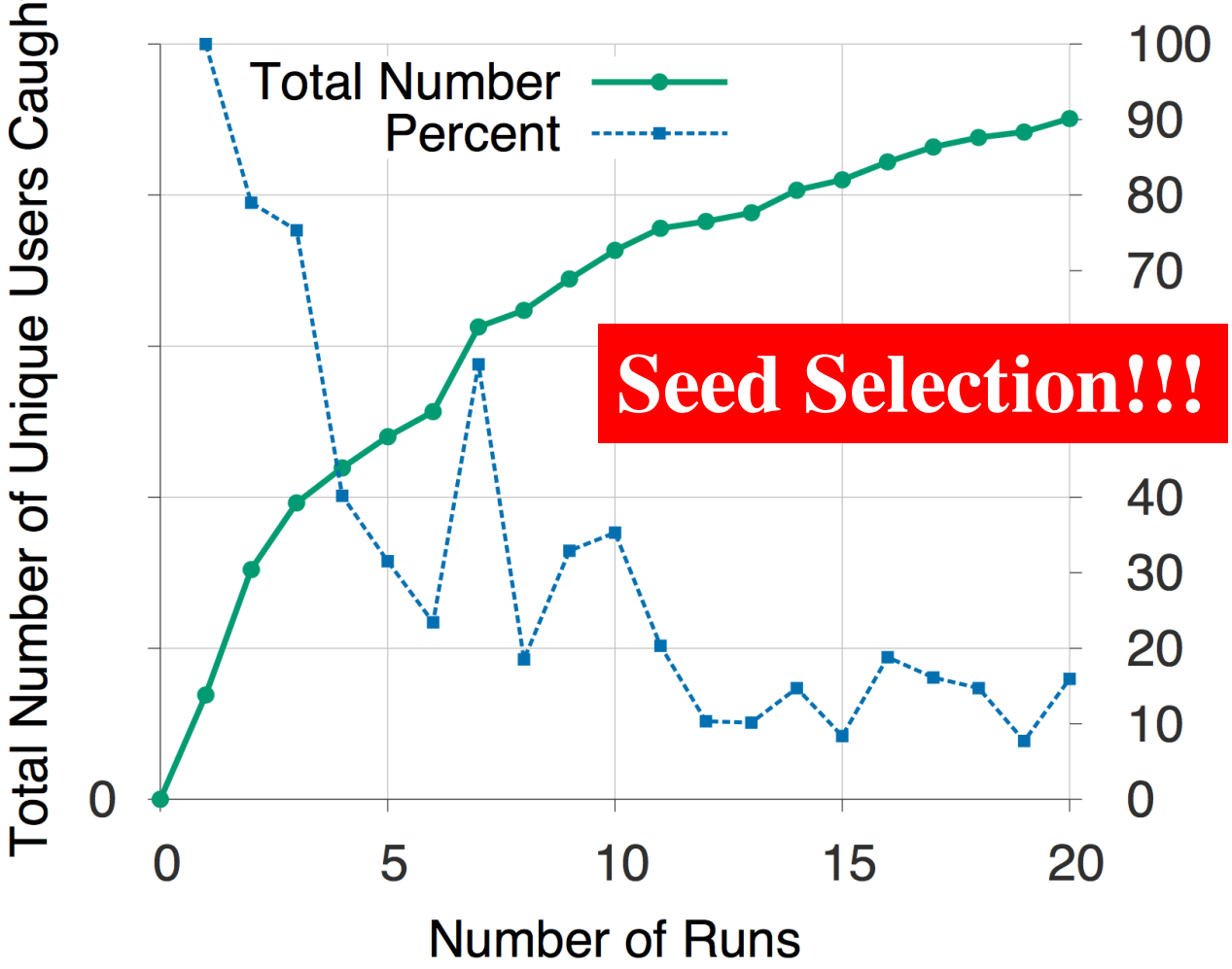


Algorithm: Seed + Search

- **CopyCatch**
  - "Near Bipartite Core": n users, m Pages, ϱ, Δt



Experimental Result

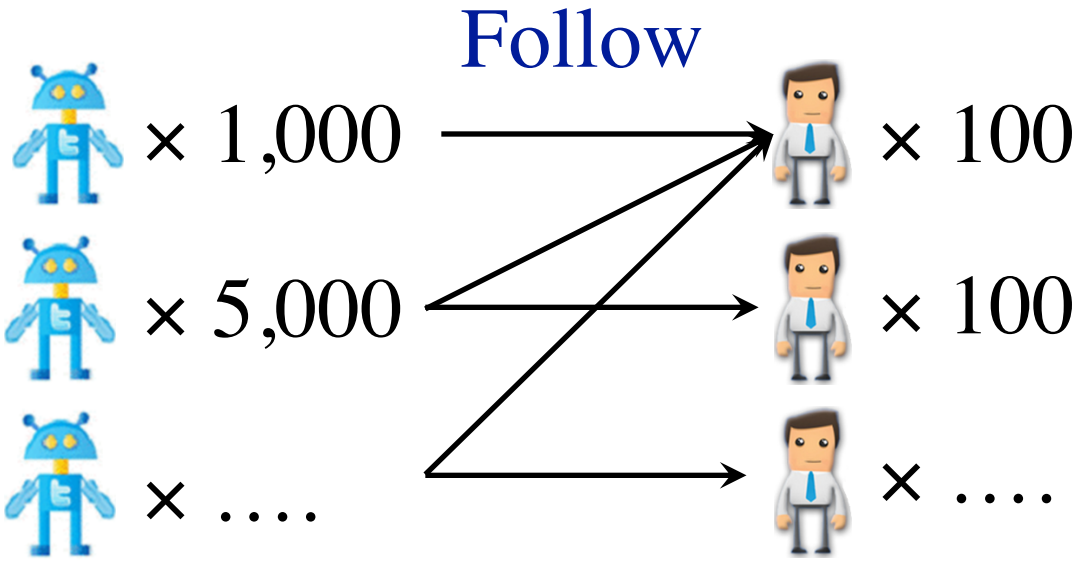


Serious Problem in Weibo

Experience-driven approaches:

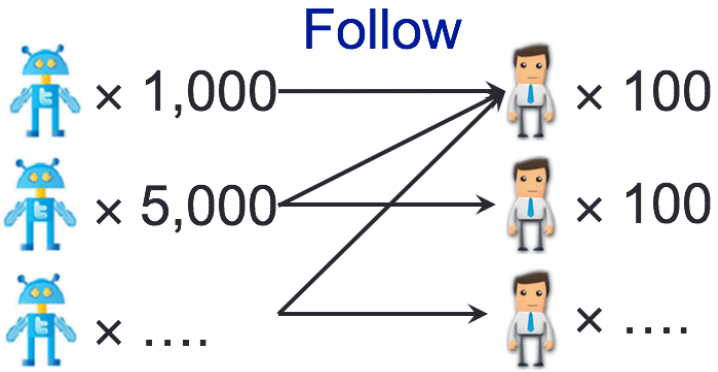
features of #followees, #hashtags, #URLs…

Zombie Followers

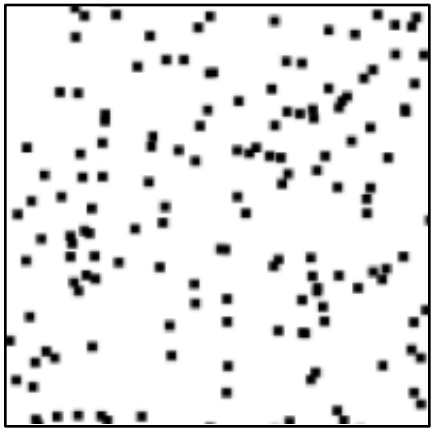


Jiang et al. **Inferring Strange Behavior from Connectivity Pattern in Social Networks.** *PAKDD*, 2014.

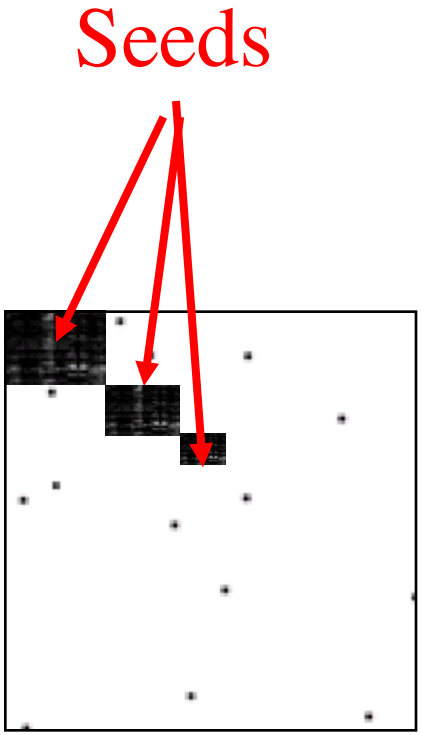
Observation: Reorder Matrix



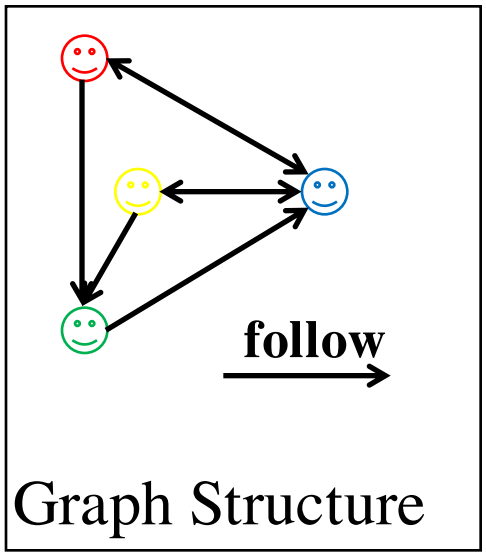
Given

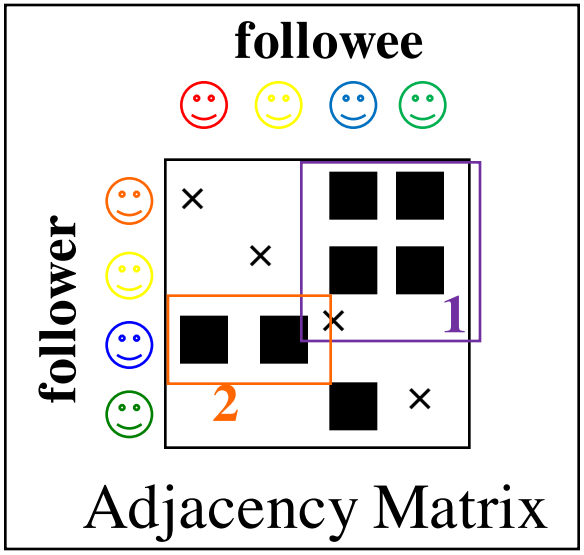


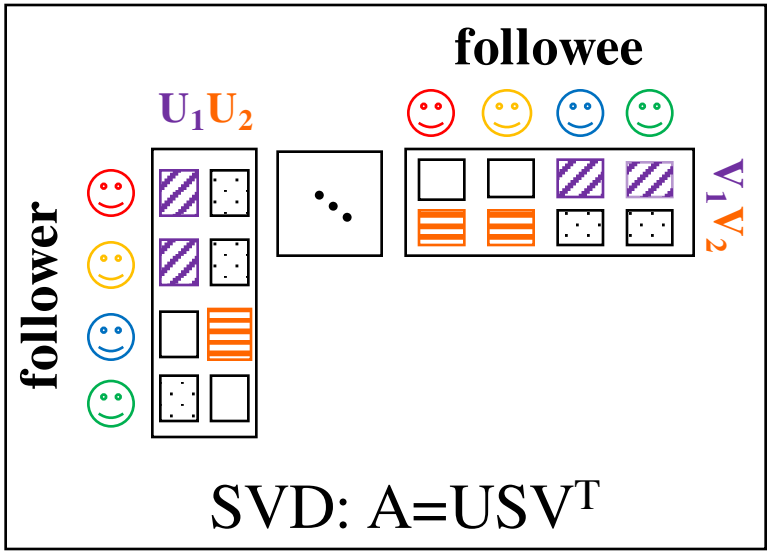
Reorder



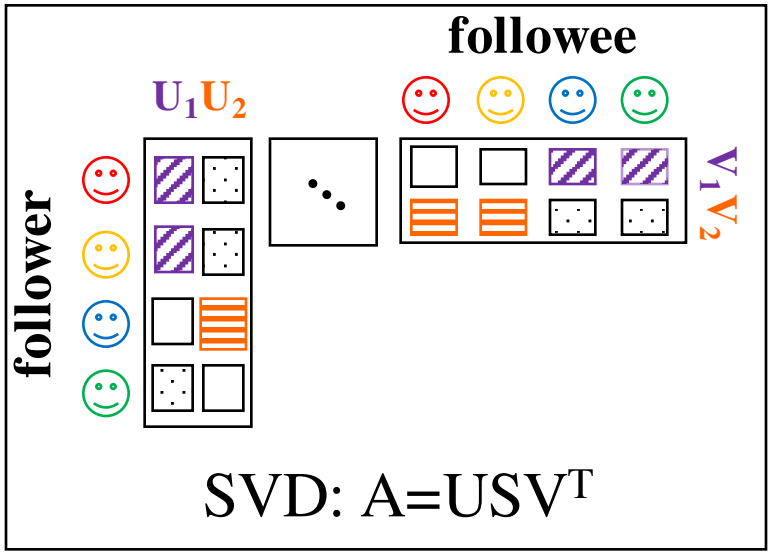
Representation: SVD Reminder



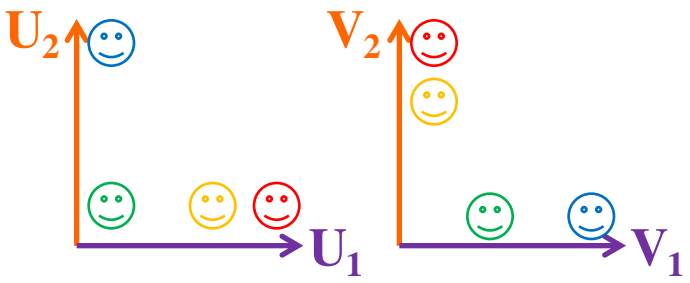




Representation: Spectral Subspace



Pairs of singular vectors:

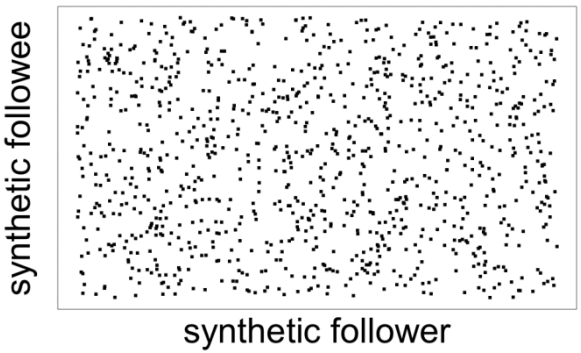


"Spectral Subspace Plot"

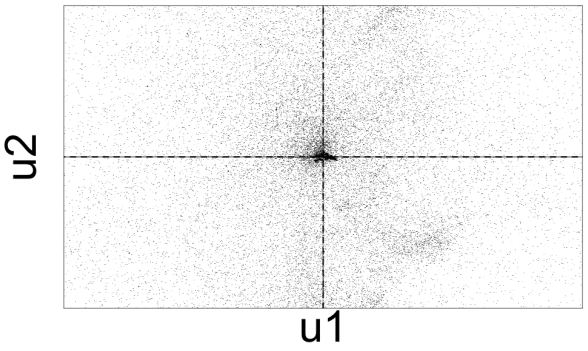
Spectral Subspace Plot: Case #0

- NO lockstep behavior: Scatter

Adjacency Matrix



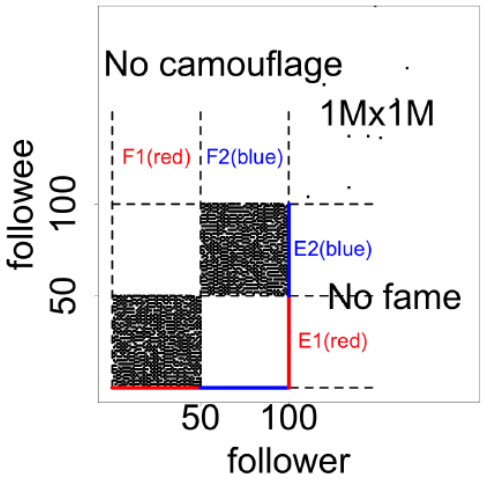
Spectral Subspace Plot



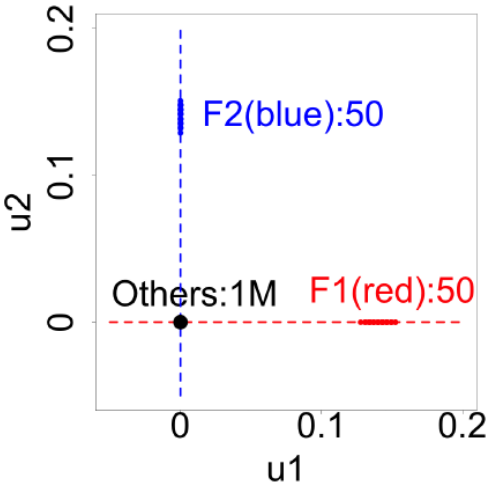
Spectral Subspace Plot: Case #1

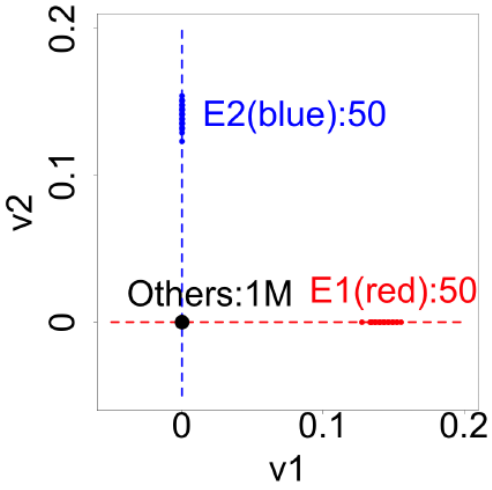
- Non-overlapping lockstep: "Rays"

Adjacency Matrix



Spectral Subspace Plot



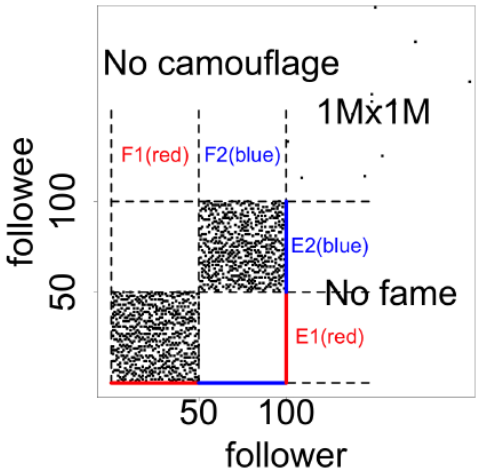


Rule 1 (short "rays"): two blocks, high density (90%), no "camouflage", no "fame"

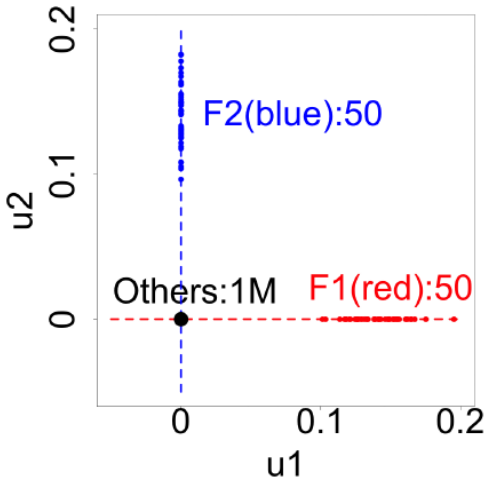
Spectral Subspace Plot: Case #2

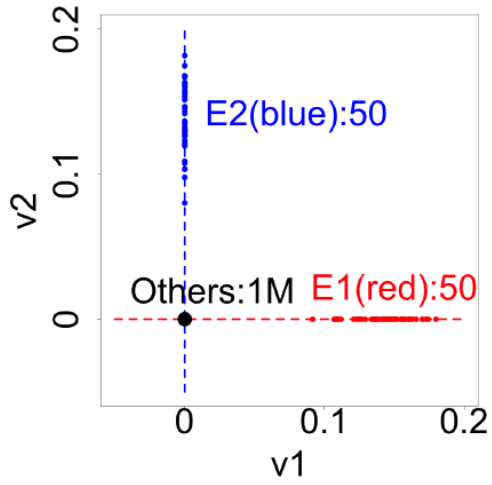
- Non-overlapping: Low density, Elongation

Adjacency Matrix



Spectral Subspace Plot



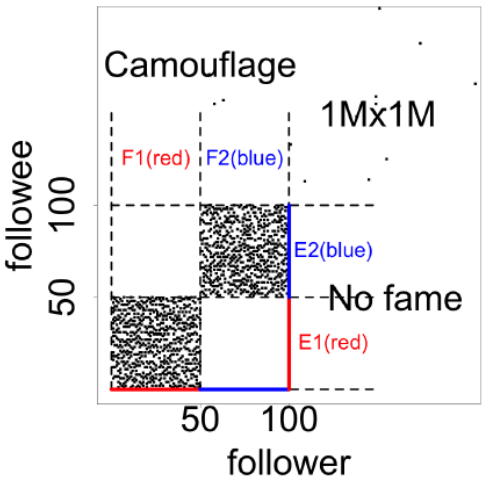


Rule 2 (long "rays"): two blocks, low density (50%), no "camouflage", no "fame"

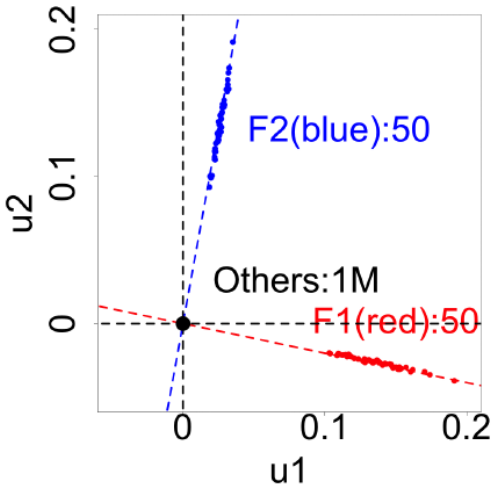
Spectral Subspace Plot: Case #3

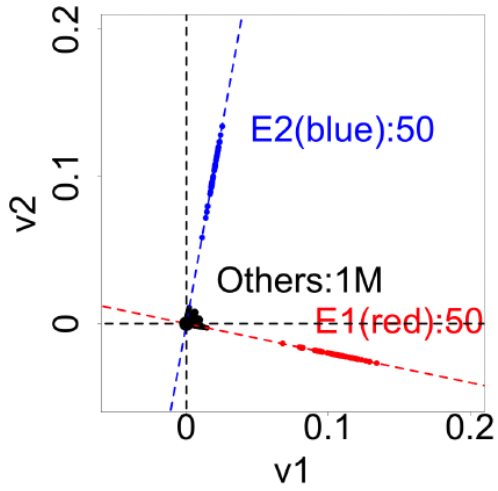
- Non-overlapping: Camouflage/Fame, Tilting

Adjacency Matrix



Spectral Subspace Plot



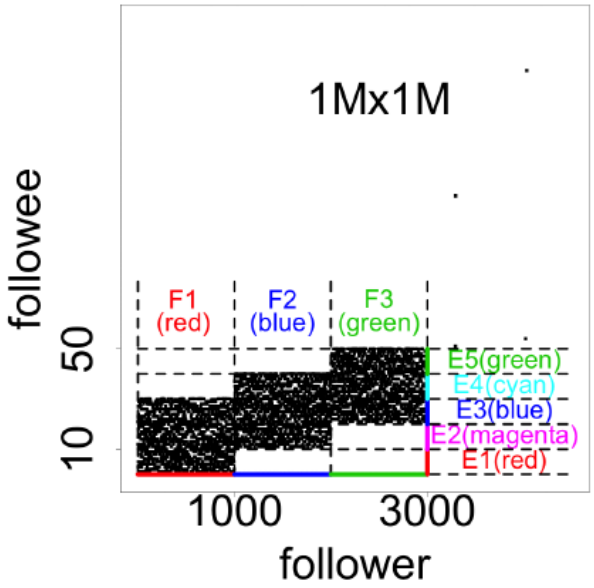


Rule 3 (tilting "rays"): two blocks, with "camouflage", no "fame"

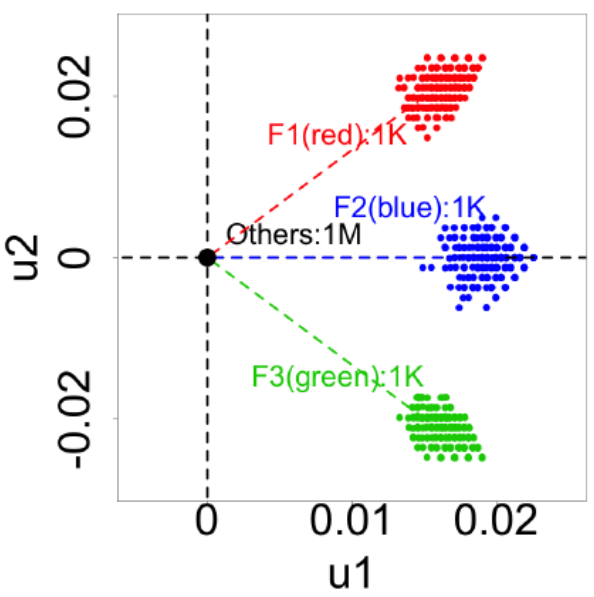
Spectral Subspace Plot: Case #4

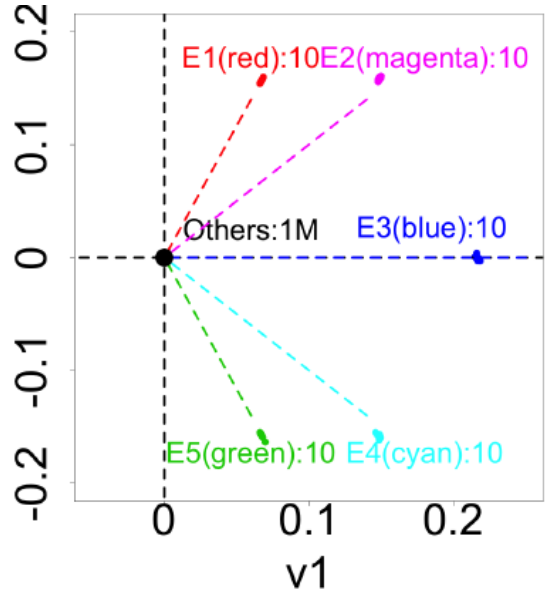
- Overlapping: "Staircase", "Pearls"

Adjacency Matrix



Spectral Subspace Plot





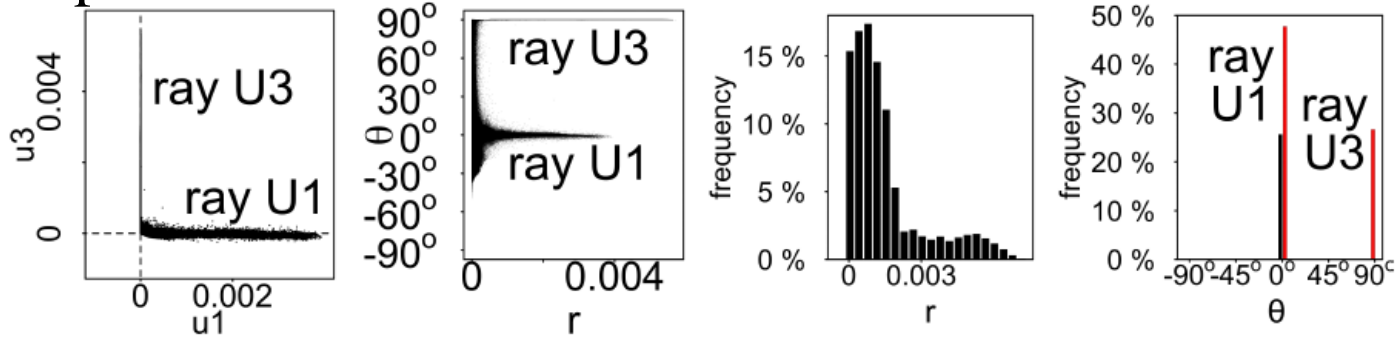
Rule 4 ("pearls"): a "staircase" of three partially overlapping blocks.

Algorithm: Reading & LockInfer

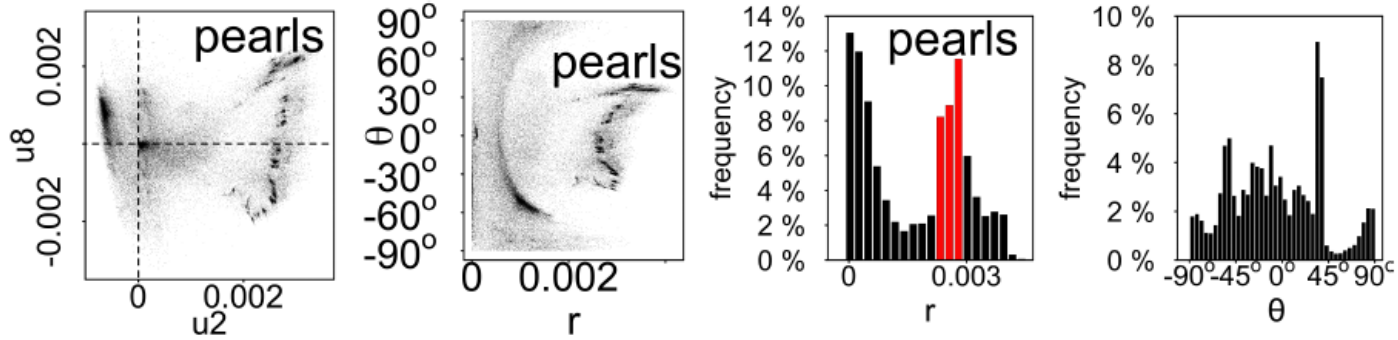
Spectral Subspace Plot

Polar Coordinate Transform

Histograms



"rays" show two apparent spikes on θ frequency at 0^o and 90^o

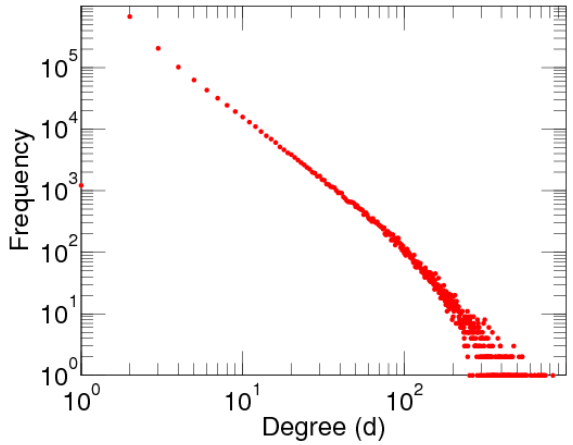
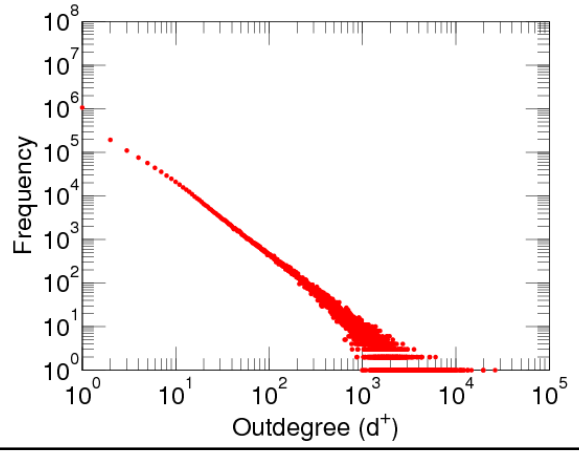
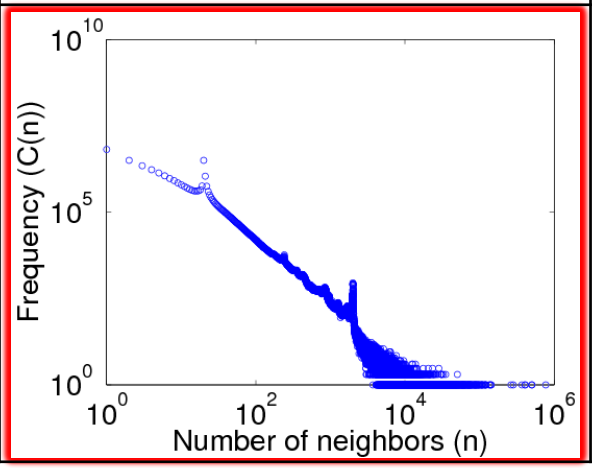


"pearls" show a spike on r frequency at a much-greater-than-zero value

High precision but low recall!!!

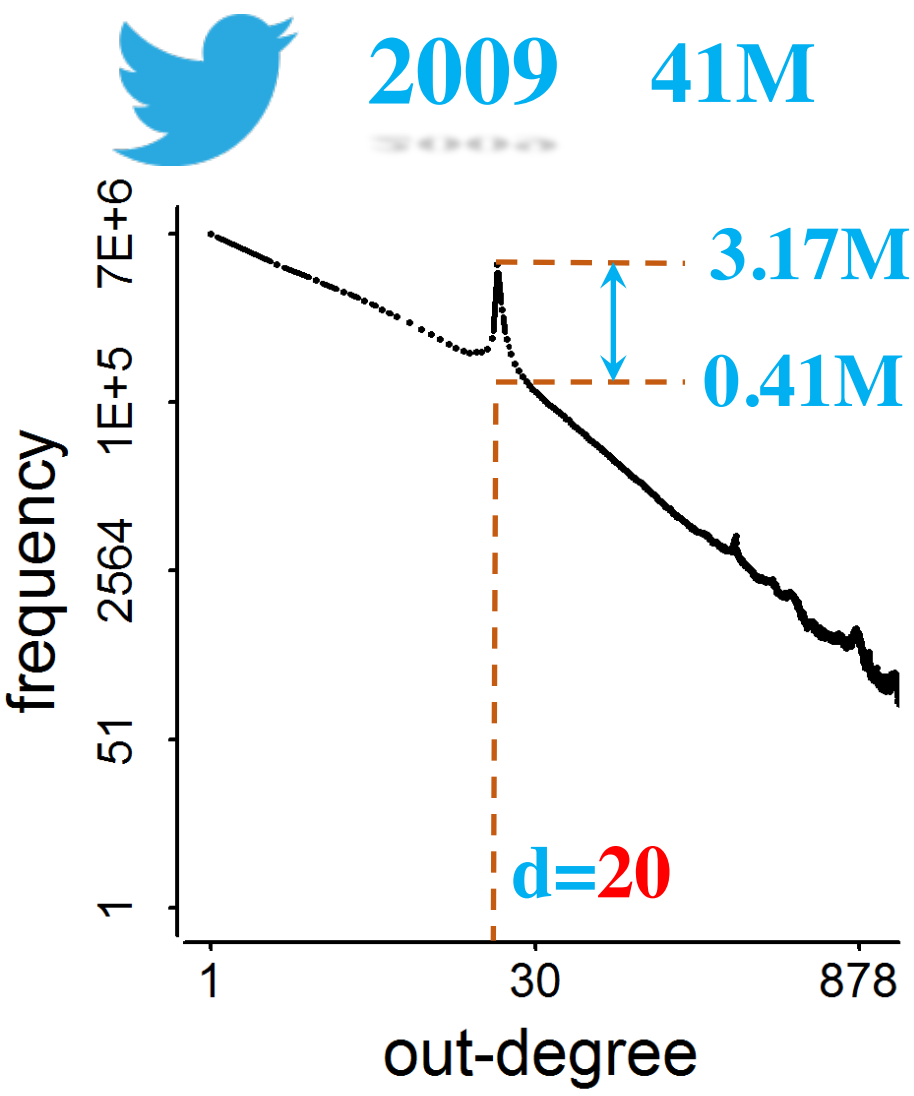
Out-Degree Distributions

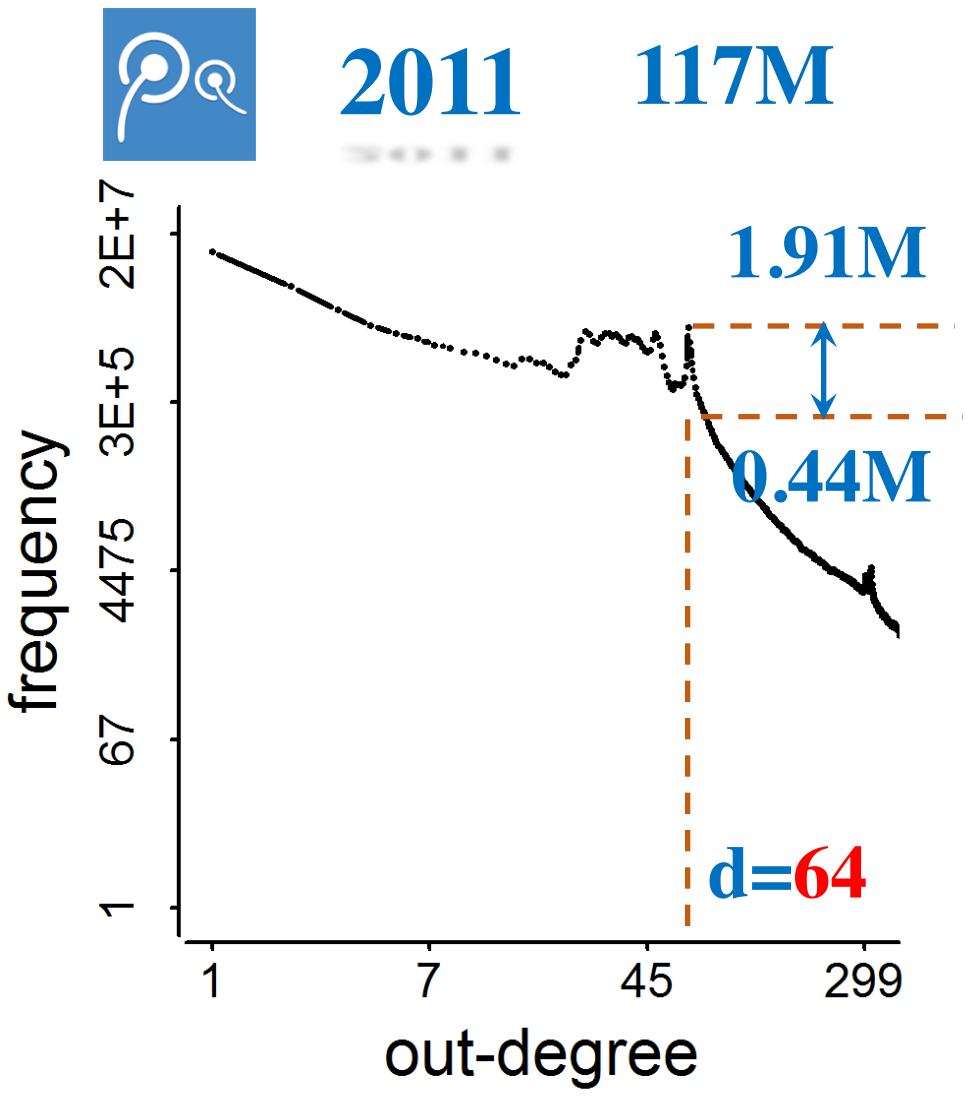
- **Power-law distribution** [Faloutsos *et al*. SIGCOMM; Broder *et al*. Computer Networks; Chung *et al*. PNAS]

DBLP **Author**-publication	**Flickr** **User**-user	**Twitter** **Who**-follows-whom
		

[konect.uni-koblenz.de/networks/]

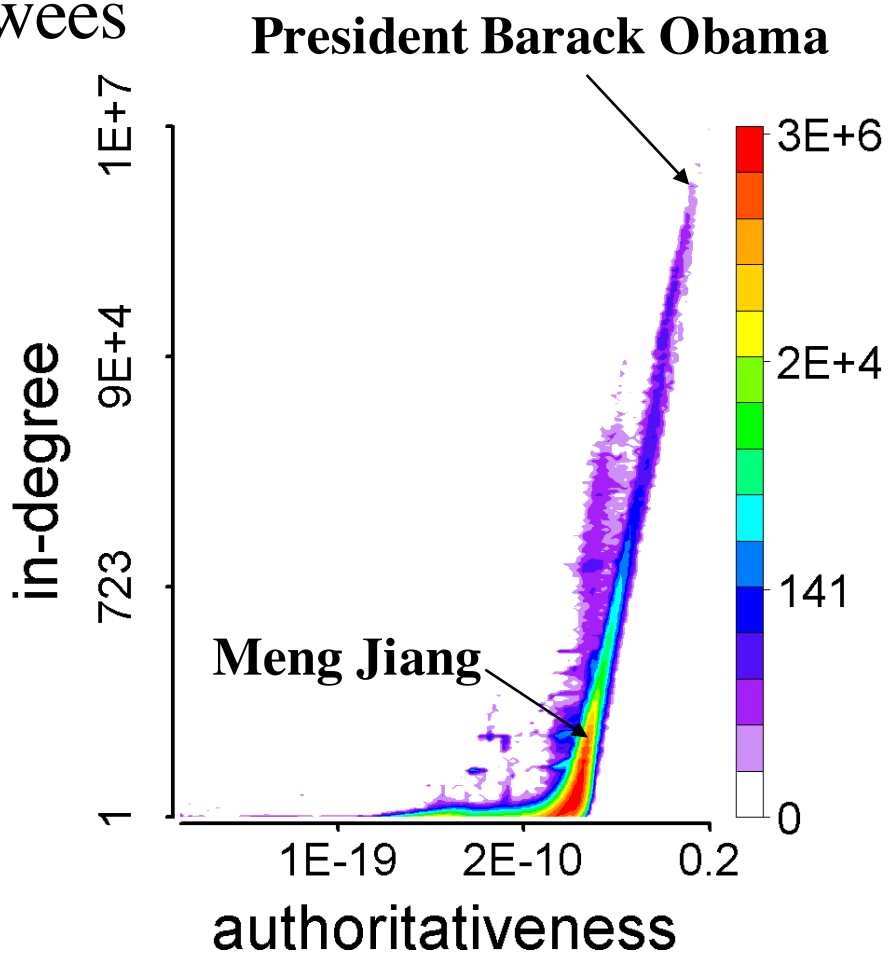
Spikes!


2009
41M
3.17M
0.41M
d=20
frequency
7E+6
1E+5
2564
51
1
1
30
878
out-degree


2011
117M
1.91M
0.44M
d=64
frequency
2E+7
3E+5
4475
67
1
1
7
45
299
out-degree

Observation: How They Behave

- Feature space of followees [Kleinberg. JACM]



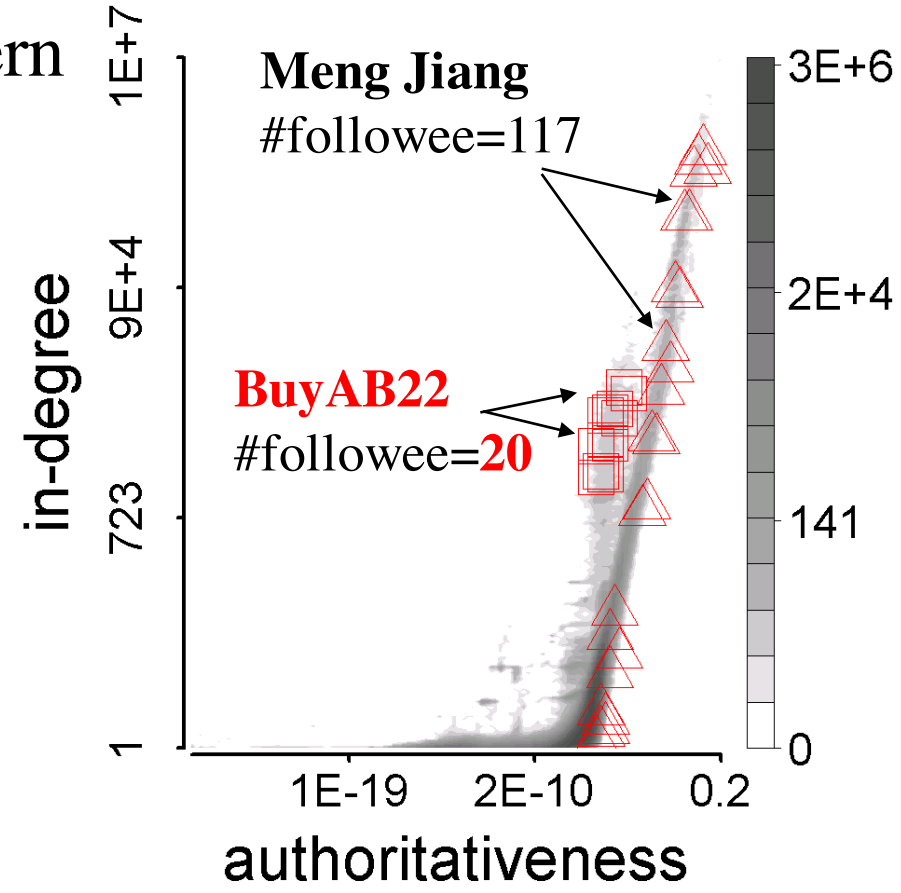
Observation: How They Behave

- Who are their followees?
- Their behavioral pattern
  - **Synchronized**

Similar with each other

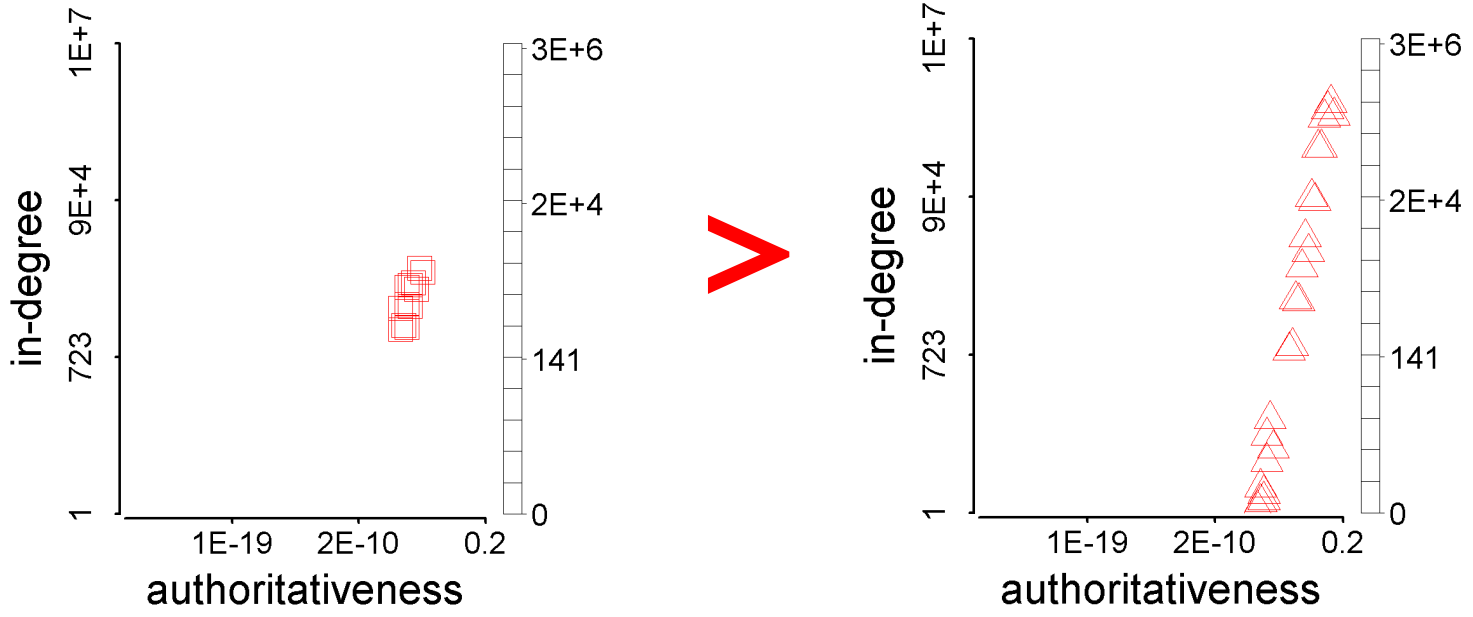
  - **Abnormal**

Different from the majority



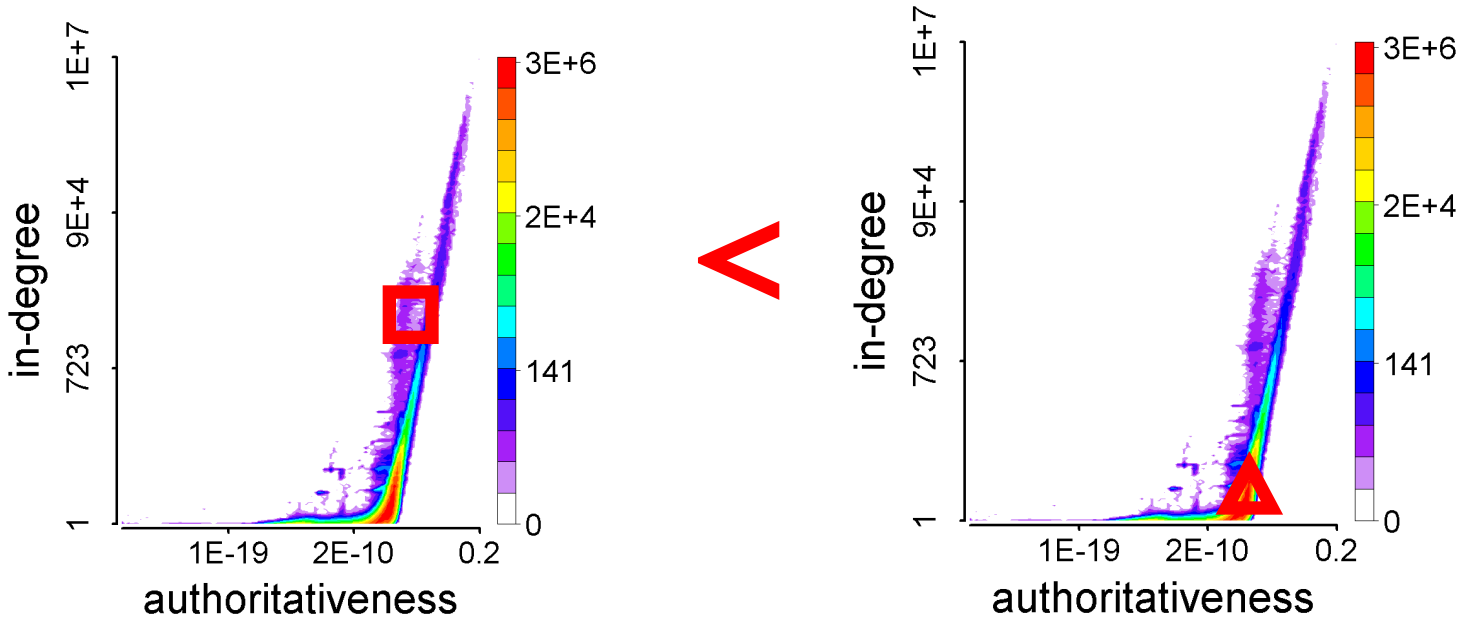
Represent Synchronicity

$$sync(u) = \frac{\sum_{(v,v') \in \mathcal{F}(u) \times \mathcal{F}(u)} \mathbf{p}(v) \cdot \mathbf{p}(v')}{d(u) \times d(u)}$$

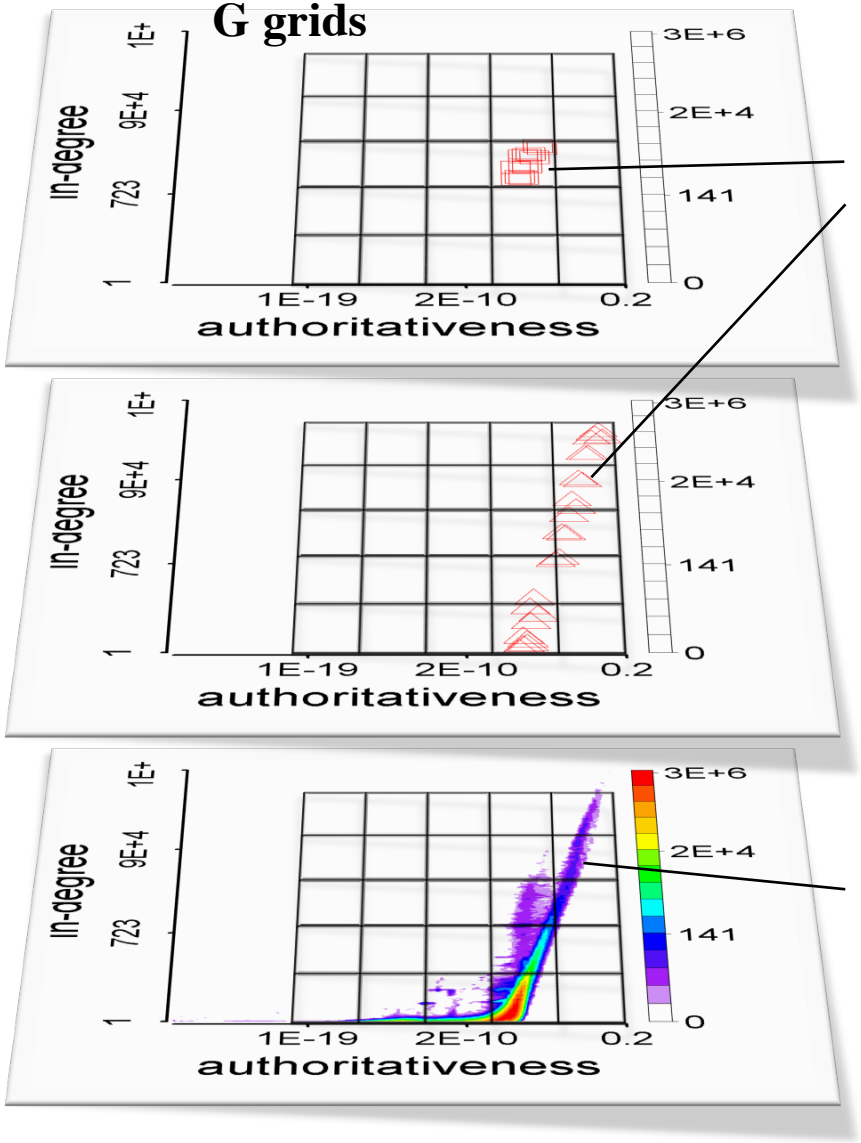


Represent Normality

$$norm(u) = \frac{\sum_{(v,v') \in \mathcal{F}(u) \times \mathcal{U}} \mathbf{p}(v) \cdot \mathbf{p}(v')}{d(u) \times N}$$



Theorem: Synchronicity vs. Normality



fp_g: #foreground points in grid **g**

$\sum fp_g = F = d(u)$ (#followees of **u**)

Given normality

$$n = \sum(fp_g/F)\,(bp_g/B) = \sum f_g b_g,$$

find minimal synchronicity

$$s = \sum(fp_g/F)\,(fp_g/F) = \sum f_g^2$$

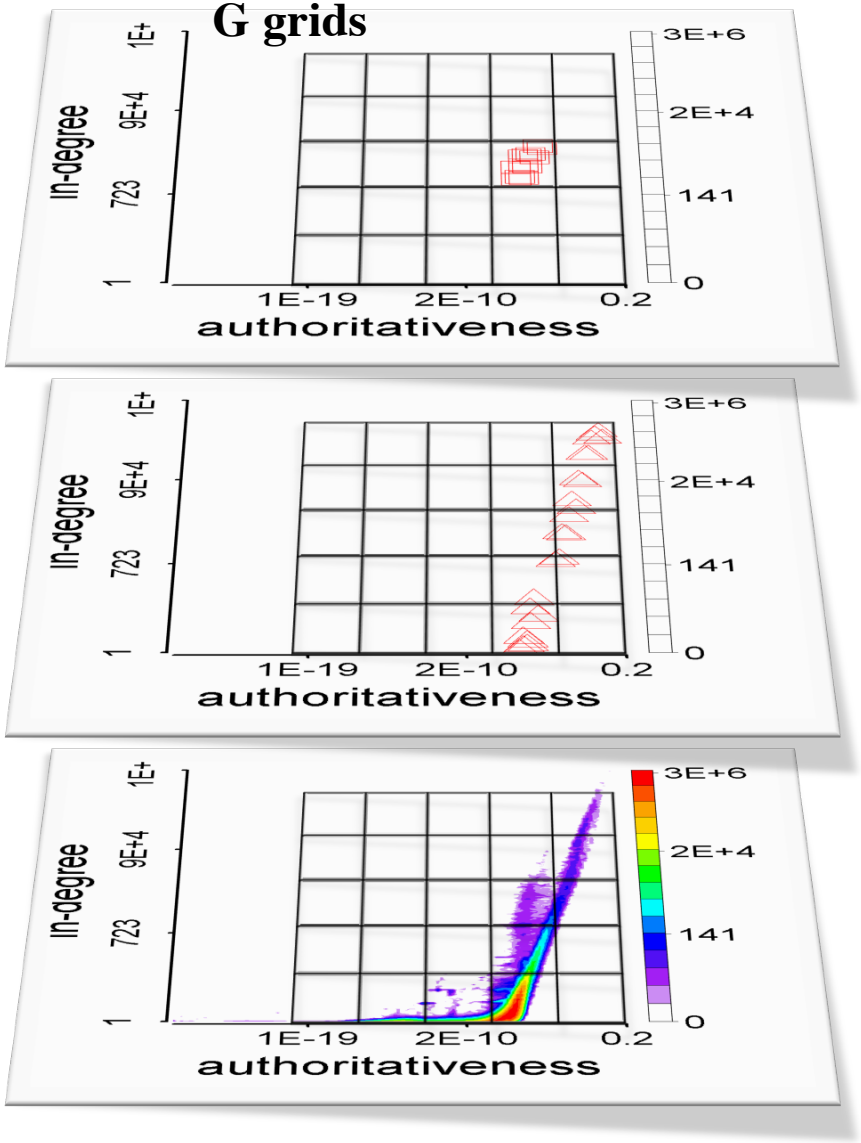
where

$$\sum f_g = 1, \sum b_g = 1$$

bp_g: #background points in grid **g**

$\sum bp_g = B = N$ (#all users)

Theorem: Synchronicity vs. Normality



Solution.

Lagrange multiplier:

minimize $s(f_g) = \Sigma f_g^2$

subject to $\Sigma f_g = 1, \Sigma f_g b_g = n$

Lagrange function:

$F(f_g, \lambda, \mu) = (\Sigma f_g^2) + \lambda(\Sigma f_g - 1) + \mu(\Sigma f_g b_g - n)$

Gradients:

$$\begin{cases} \nabla_{f_g} F = 2 f_g + \lambda + \mu b_g = 0 \\ \nabla_{\lambda} F = \Sigma f_g - 1 = 0 \\ \nabla_{\mu} F = \Sigma f_g b_g - n = 0 \end{cases}$$

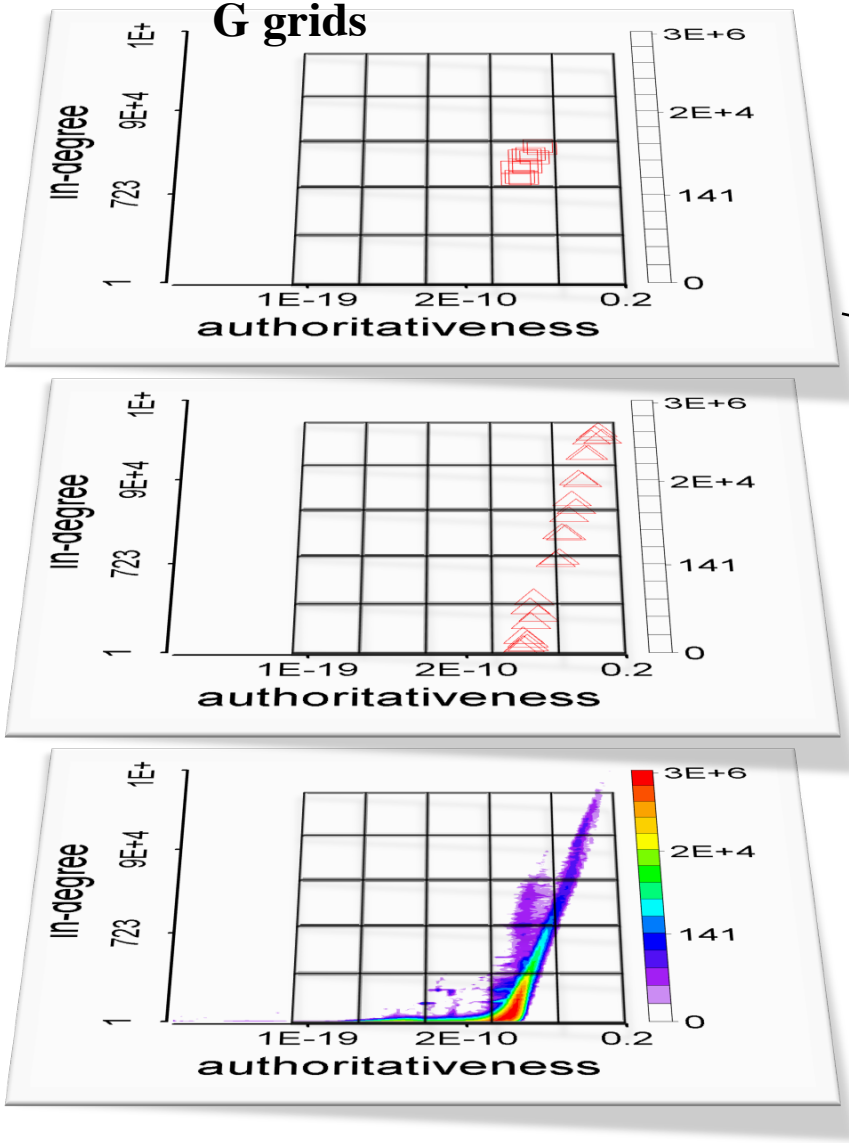
$$\begin{cases} 2 + \lambda G + \mu = 0 \quad (\Sigma) \\ 2 n + \lambda + \mu s_b = 0 \quad (\times b_g\ \Sigma) \\ 2 s_{min} + \lambda + \mu n = 0 \quad (\times f_g\ \Sigma) \end{cases}$$

where $s_b = \Sigma b_g^2$.

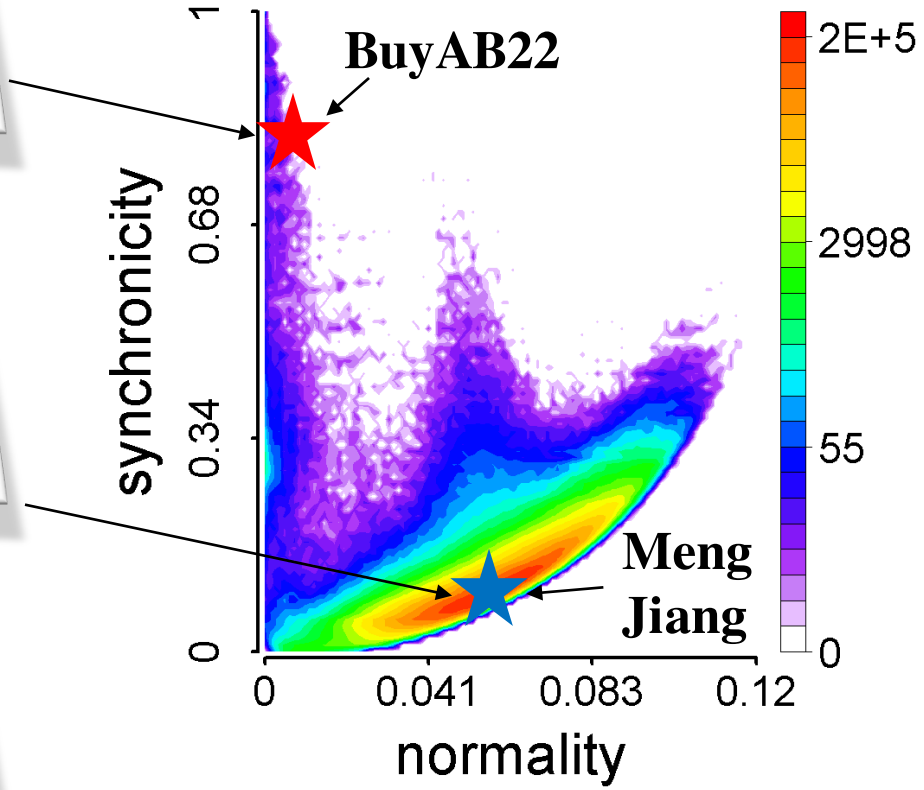
Therefore,

$$s_{min} = \frac{-G n^2 + 2 n - s_b}{1 - G s_b}$$

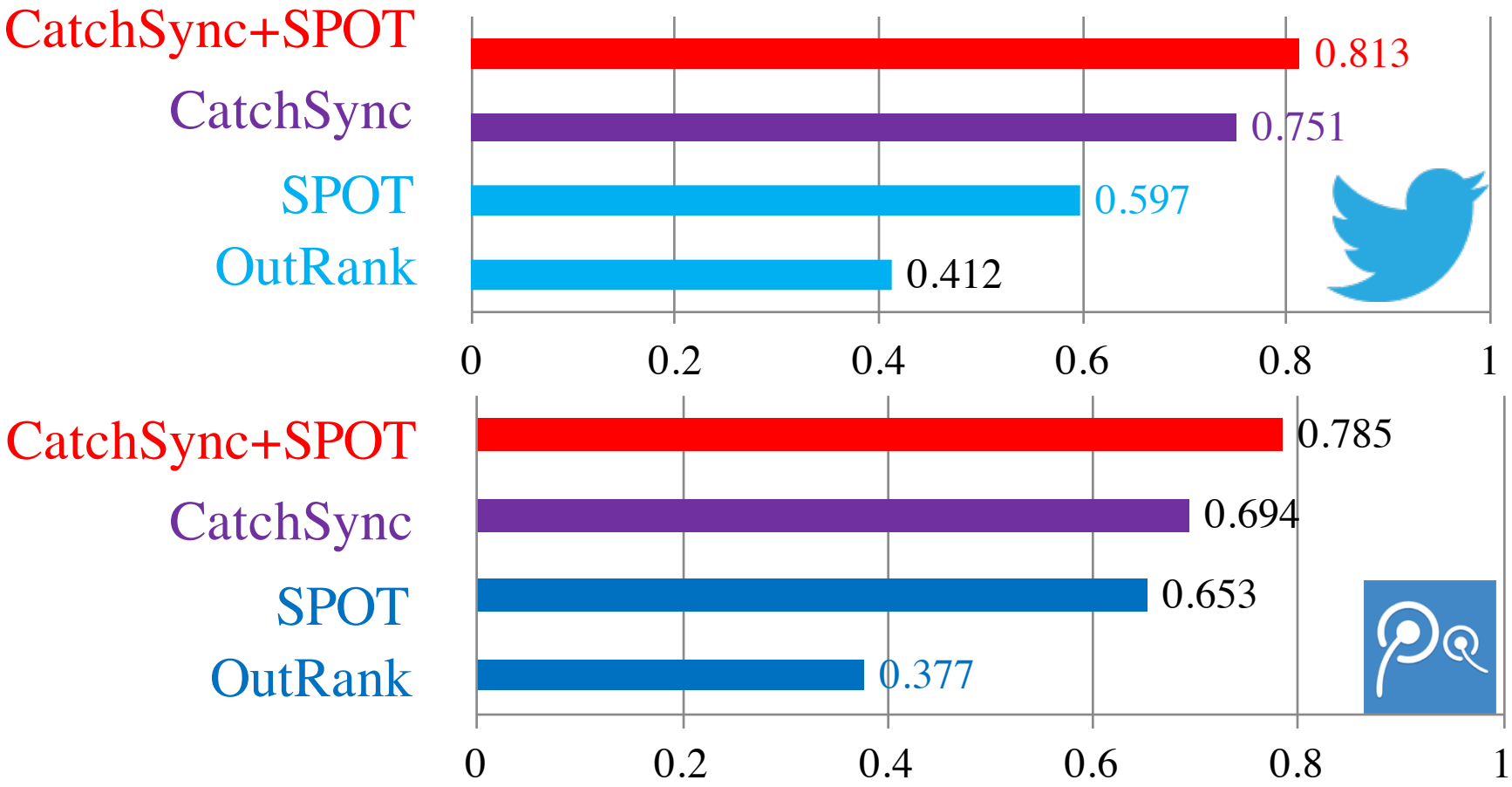
CatchSync Algorithm



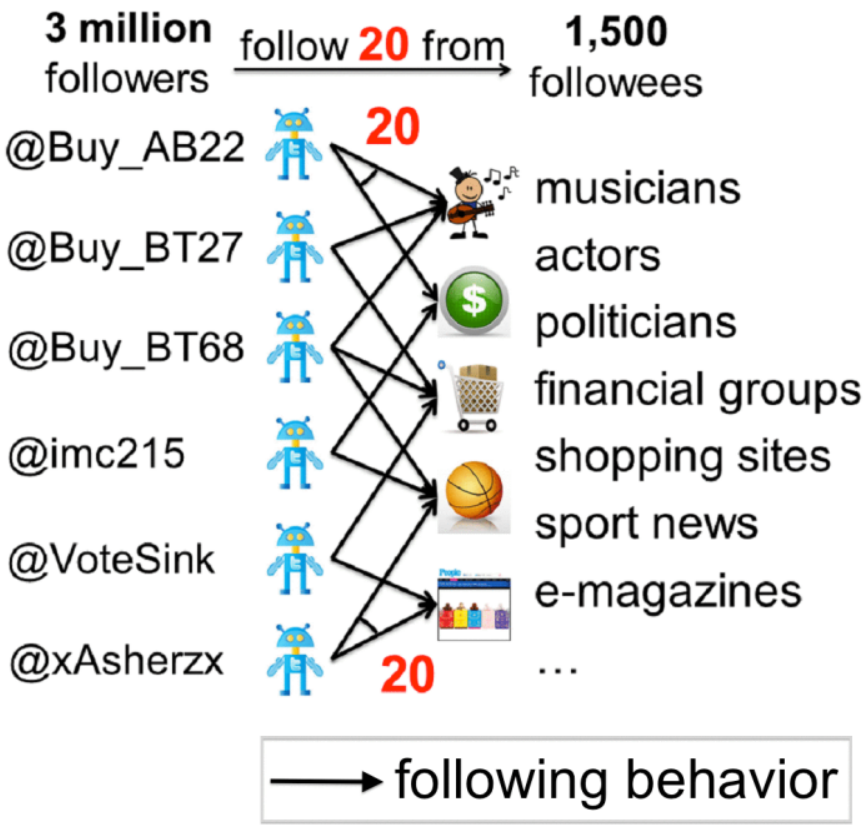
$$s_{min} = \frac{-G\,n^2 + 2\,n - s_b}{1 - G\,s_b}$$

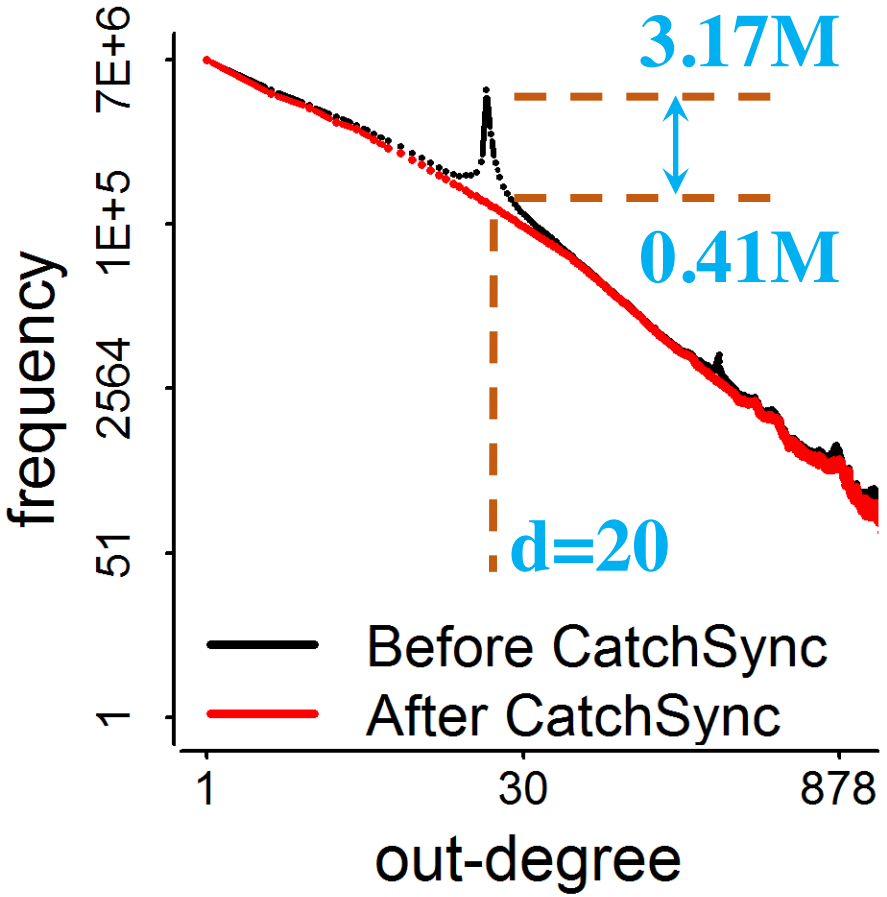


Experimental Results



Experimental Results





Impact

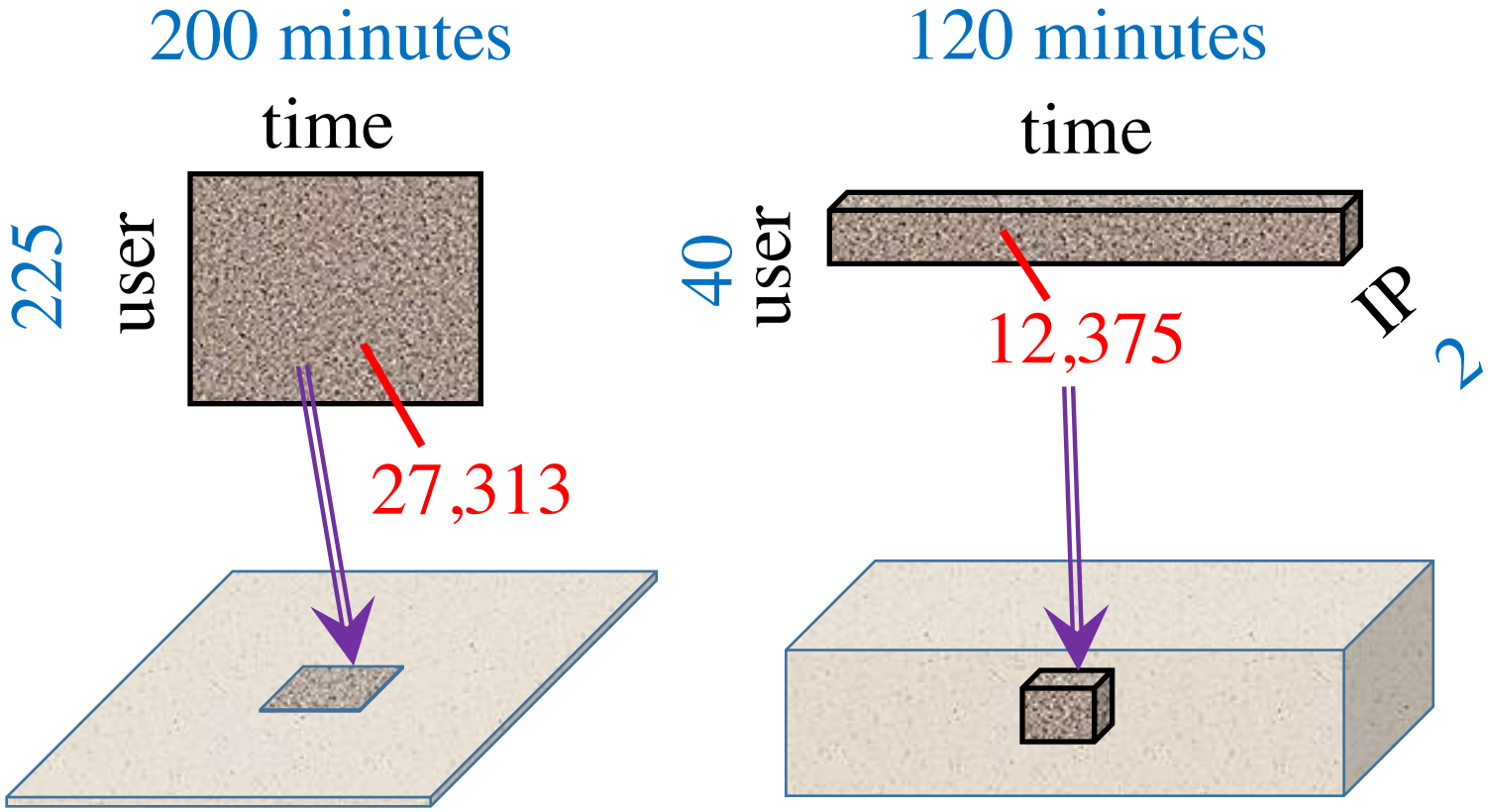
- **M. Jiang**, P. Cui, A. Beutel, C. Faloutsos and S. Yang. "CatchSync: Catching Synchronized Behavior in Large Directed Graphs" in **KDD'14 Best Paper Finalist**, Aug 2014. (#citations = **36**)
- Taught in
  - **CMU 15-826:** Multimedia Databases and Data Mining
  - **UMich EECS 598:** Graph Mining and Exploration at Scale
  - **ASONAM'16 Tutorial:** "Identifying Malicious Actors on Social Media" by S. Kumar, F. Spezzano, V.S. Subrahmanian
- Deployed in Weibo? Unfortunately, in July 2014…

Observation: Spatiotemporal Contexts

Dataset	Dimension/Mode				Mass
Weibo's Retweeting	User	Root ID	IP	Time (min)	#retweet
	29.5M	19.8M	27.8M	56.9K	211.7M
Weibo's Trending (Hashtag)	User	Hashtag	IP	Time (min)	#tweet
	81.2M	1.6M	47.7M	56.9K	276.9M
Network attacks (LBNL)	Src-IP	Dest-IP	Port	Time (sec)	#packet
	2,345	2,355	6,055	3,610	230,836

Jiang et al. **A General Suspiciousness Metric for Dense Blocks in Multimodal Data.** *ICDM*, 2015.

Dense Block Indicates Suspiciousness

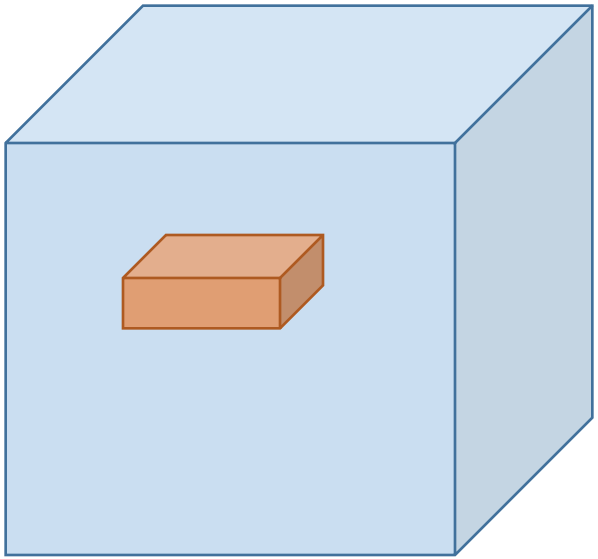


Q: Which is more suspicious?

We need a metric to evaluate the suspiciousness.

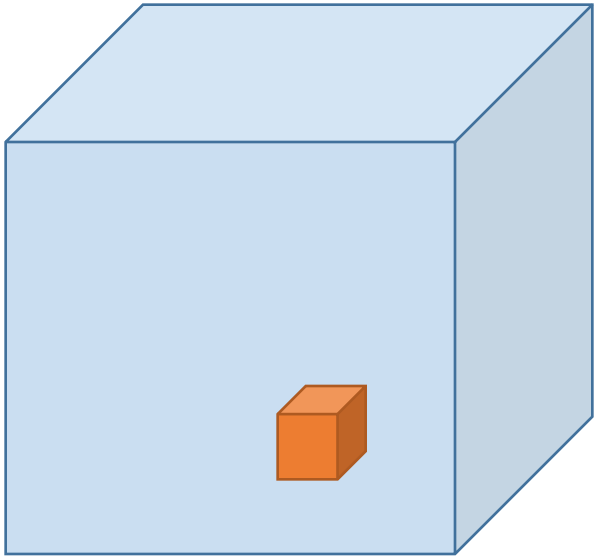
Criteria for Suspiciousness Metric

What properties are required of a good metric?



$N_1 \times N_2 \times N_3$

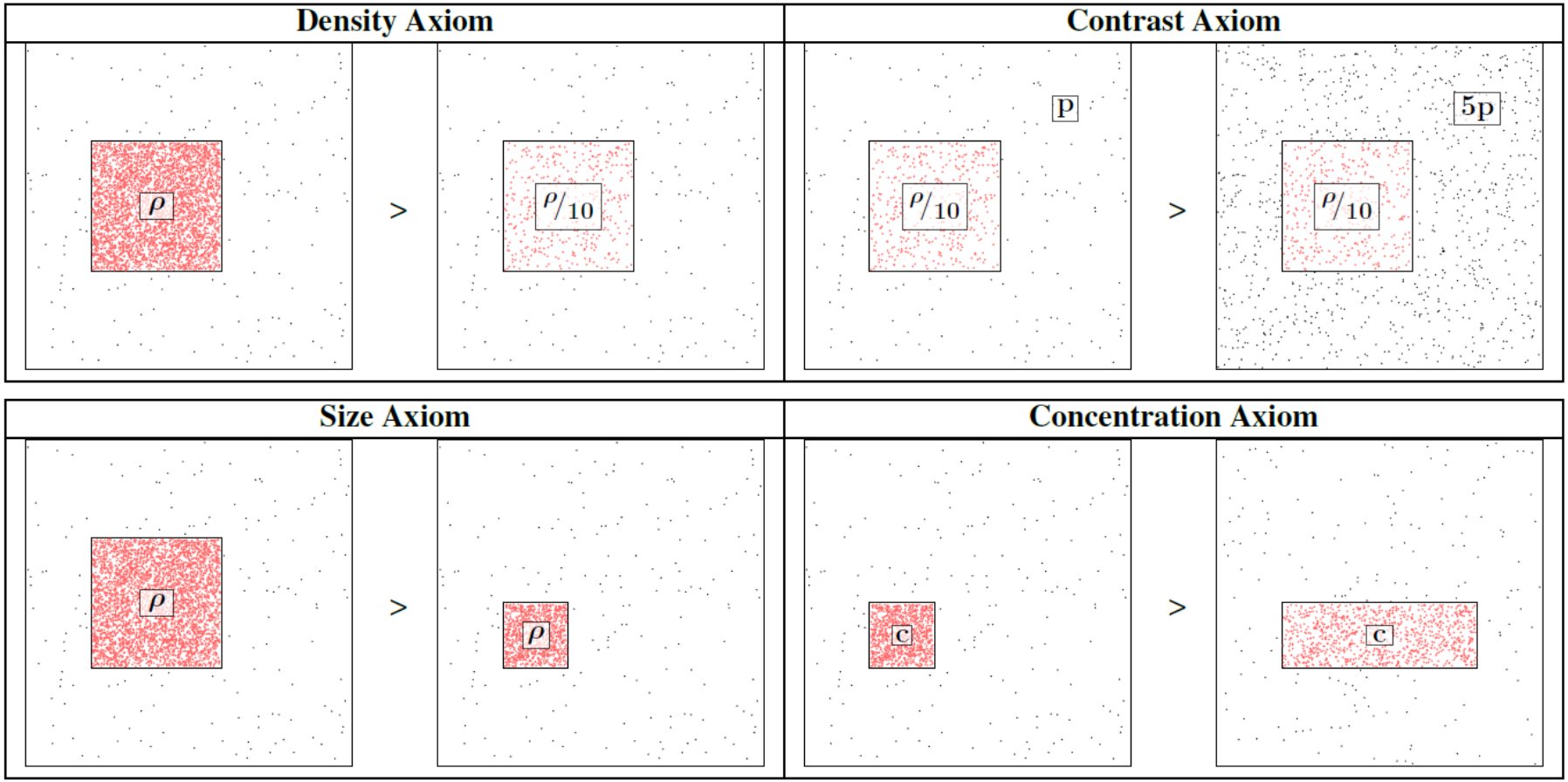
Count data with total "mass" C



$f\left(\begin{array}{c} n_1 \times n_2 \times n_3 \\ \text{mass } c \\ \text{density } \varrho \end{array}\right)$ vs $f\left(\begin{array}{c} n'_1 \times n'_2 \times n'_3 \\ \text{mass } c' \\ \text{density } \varrho' \end{array}\right)$

Axioms: 1 to 4

$$c_1 > c_2 \iff f(\mathbf{n}, c_1, \mathbf{N}, C) > f(\mathbf{n}, c_2, \mathbf{N}, C)$$

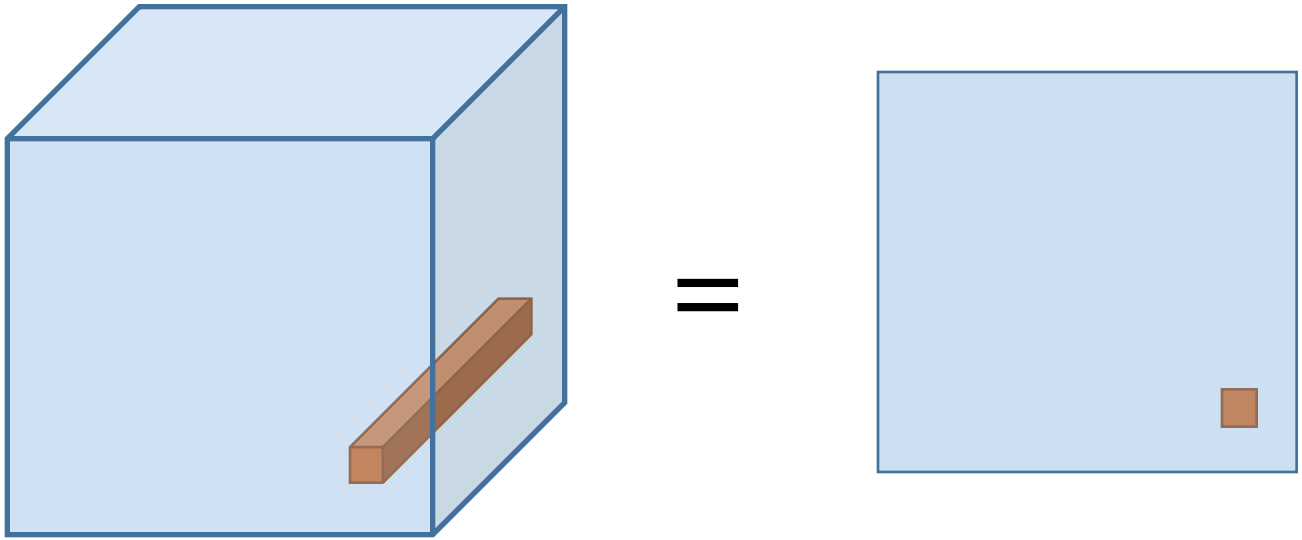


$$p_1 < p_2 \iff \hat{f}(\mathbf{n}, \rho, \mathbf{N}, p_1) > \hat{f}(\mathbf{n}, \rho, \mathbf{N}, p_2)$$

Axiom 5: Cross Dimensions

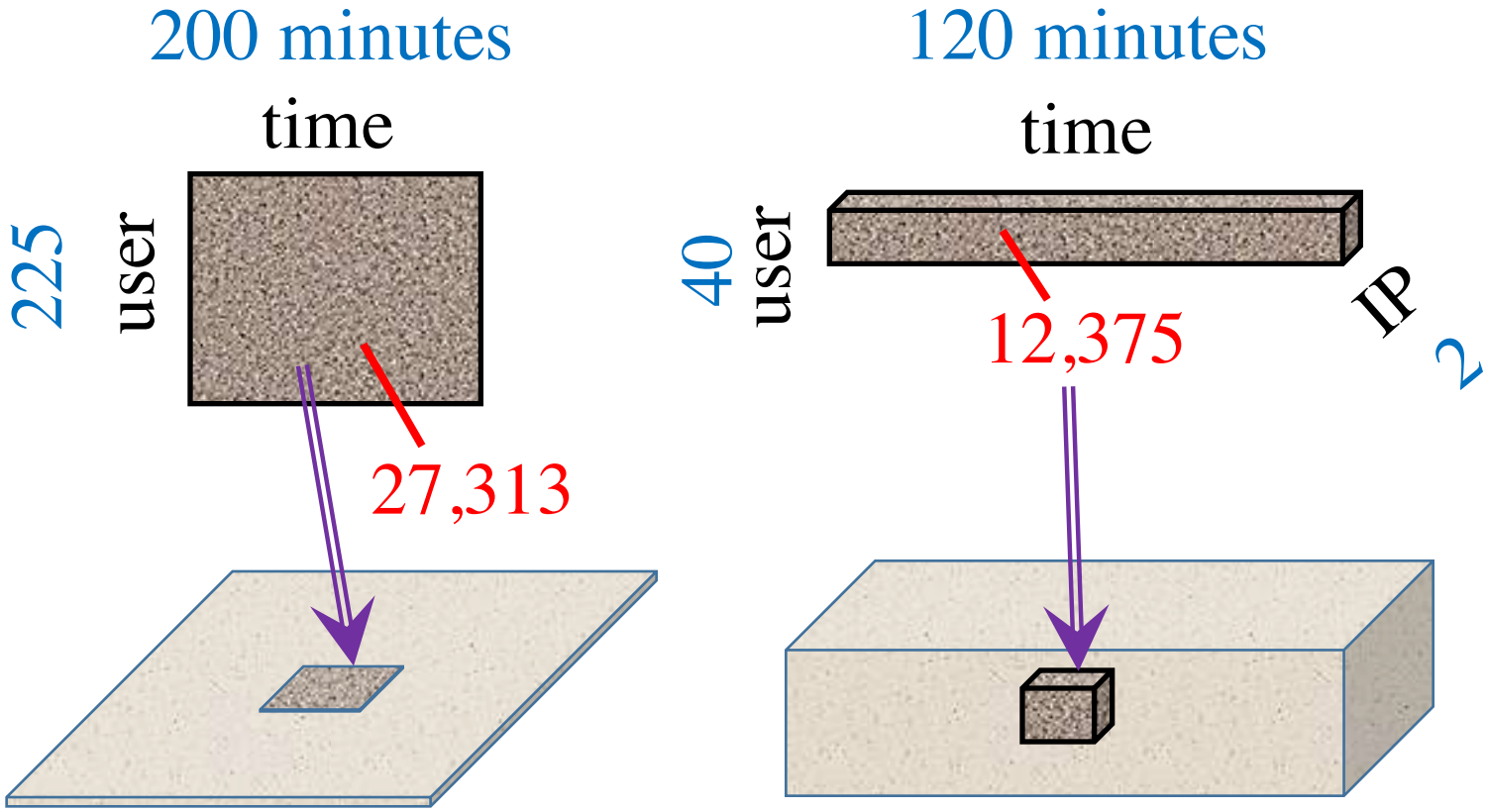
$$f_{K-1}\left([n_k]_{k=1}^{K-1}, c, [N_k]_{k=1}^{K-1}, C\right) = f_K\left(([n_k]_{k=1}^{K-1}, N_K), c, [N_k]_{k=1}^{K}, C\right)$$

Not including a mode is the same as including all values for that mode.



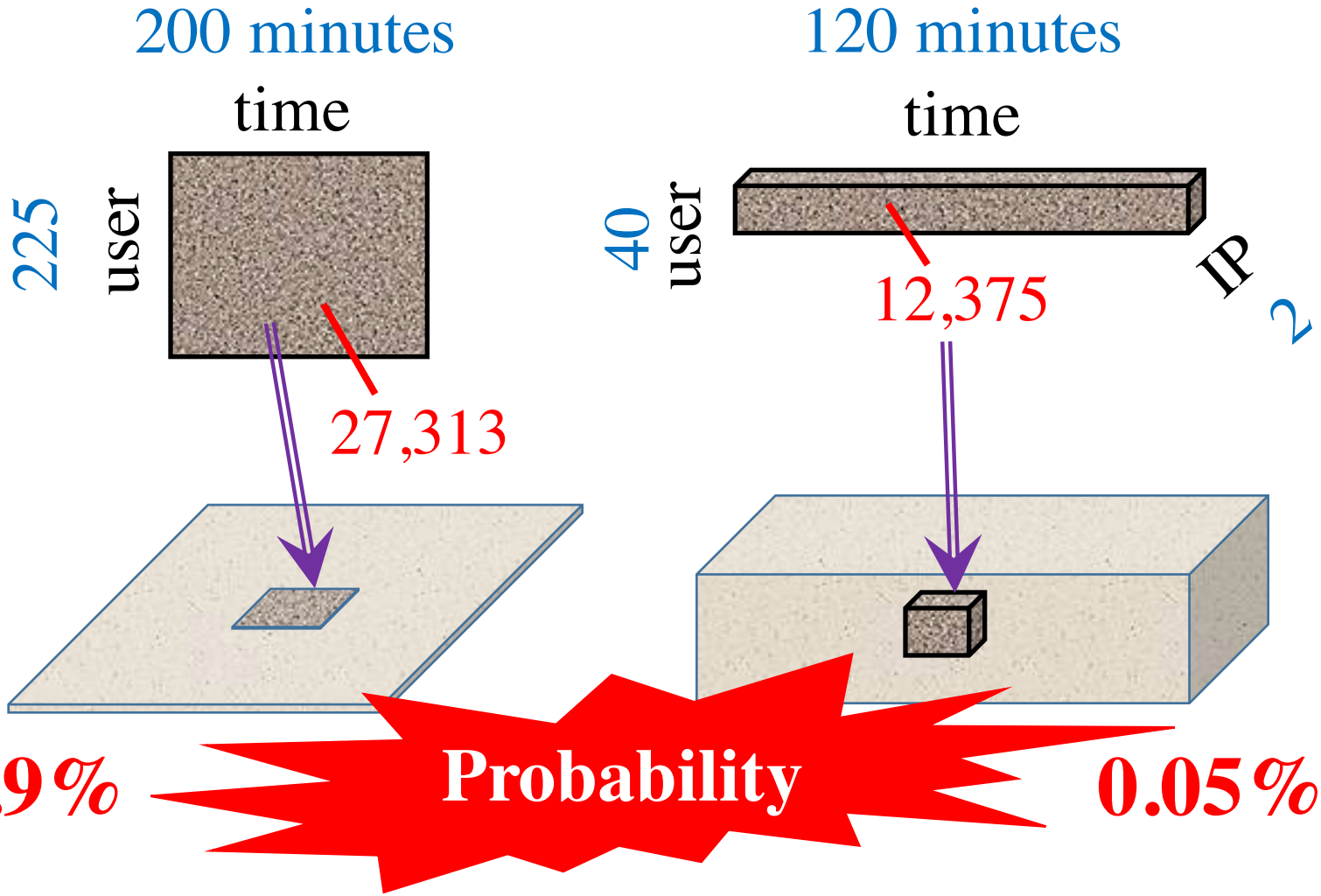
- New information (more modes) can only make our blocks more suspicious

Scoring the Suspiciousness



Q: Which is more suspicious?

Scoring the Suspiciousness



A General Suspiciousness Metric

- Negative log likelihood of block's probability

$$f(n, c, N, C) = -\log\left[Pr(Y_n = c)\right]$$

Lemma *Given an $n_1 \times \cdots \times n_K$ block of mass c in $N_1 \times \cdots \times N_K$ data of total mass C, the suspiciousness function is*

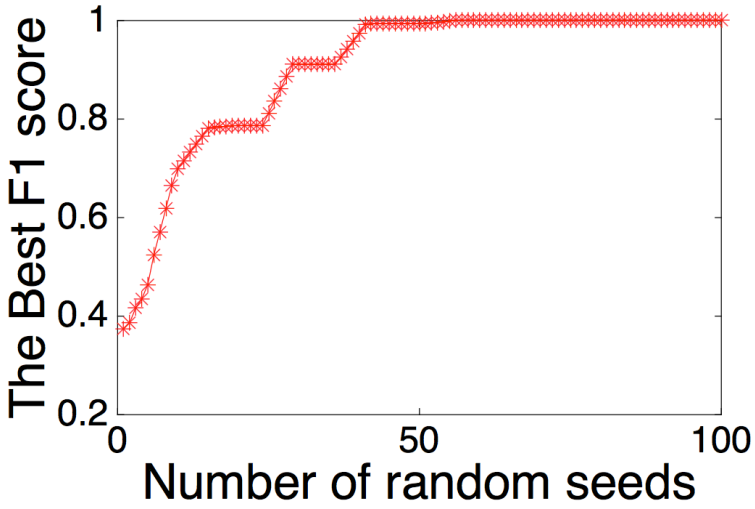
$$f(\mathbf{n}, c, \mathbf{N}, C) = c(\log \frac{c}{C} - 1) + C \prod_{i=1}^{K} \frac{n_i}{N_i} - c \sum_{i=1}^{K} \log \frac{n_i}{N_i}$$

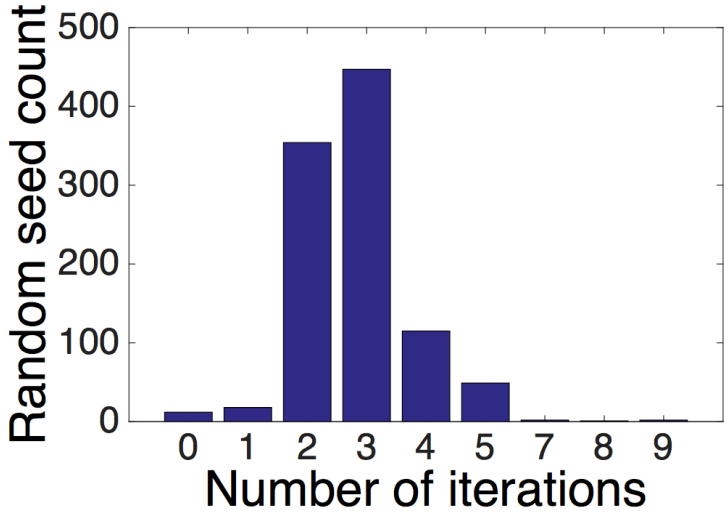
Using ρ as the block's density and p is the data's density, we have the simpler formulation

$$\hat{f}(\mathbf{n}, \rho, \mathbf{N}, p) = \left(\prod_{i=1}^{K} n_i\right) D_{KL}(\rho || p)$$

CrossSpot Algorithm

- Local search to maximize the metric
  - Start with seed blocks
  - Parameter-free: iteratively update the blocks
  - Scalable: parallelize to multiple machines





Advantages

	Method	Scores Blocks	Axioms: Density 1	Size 2	Concentration 3	Contrast 4	Multi-modal 5
Metrics	**SUSPICIOUSNESS**	✔	✔	✔	✔	✔	✔
	Mass	✓	✓	✗	✗	✗	✓
	Density	✓	✓	✗	✓	✗	✗
	Average Degree [9]	✓	✓	✗	✗	✗	N/A
	Singular Value [10]	✓	✓	✓	✓	✗	✗
Methods	**CROSSSPOT**	✔	✔	✔	✔	✔	✔
	Subgraph [30, 10, 36]	✓	✓	✓	✓	✗	N/A
	CopyCatch [6]	✓	✓	✓	✓	✗	N/A
	EigenSpokes [31]	✗	N/A				
	TrustRank [14, 8]	✗	N/A				
	BP [28, 1]	✗	N/A				

Results: Dense Block Detection

- Synthetic data
  - 1,000×1,000×1,000 of 10,000 random data
  - Block#1: 30×30×30 of 512 3 modes
  - Block#2: 30×30×1,000 of 512 2 modes
  - Block#3: 30×1,000×30 of 512 2 modes
  - Block#4: 1,000×30×30 of 512 2 modes

	Recall				Overall Evaluation		
	Block #1	Block #2	Block #3	Block #4	Precision	Recall	F1 score
HOSVD (r=20)	93.7%	29.5%	23.7%	21.3%	**0.983**	0.407	0.576
HOSVD (r=10)	91.3%	24.4%	18.5%	19.2%	0.972	0.317	0.478
HOSVD (r=5)	85.7%	10.0%	9.5%	11.4%	0.952	0.195	0.324
CrossSpot	**100%**	**99.9%**	**94.9%**	**95.4%**	0.978	**0.967**	**0.972**

Results: Tweeting Hashtags

User × hashtag × IP × minute	Mass c	Suspiciousness
582 × 3 × 294 × **56,940**	5,941,821	111,799,948
188 × 1 × 313 × **56,943**	2,344,614	47,013,868
75 × 1 × 2 × 2,061	689,179	19,378,403

User ID	Time	IP address (city, province)	Tweet text with hashtag
USER-D	11-18 12:12:51	IP-1 (Deyang, Shandong)	**#Snow#** the Samsung GALAXY SII QQ Service customized version...
USER-E	11-18 12:12:53	IP-1 (Deyang, Shandong)	**#Snow#** the Samsung GALAXY SII QQ Service customized version...
USER-F	11-18 12:12:54	IP-2 (Zaozhuang, Shandong)	**#Snow#** the Samsung GALAXY SII QQ Service customized version...
USER-E	11-18 12:17:55	IP-1 (Deyang, Shandong)	**#Li Ning - a weapon with a hero#** good support activities!
USER-F	11-18 12:17:56	IP-2 (Zaozhuang, Shandong)	**#Li Ning - a weapon with a hero#** good support activities!
USER-D	11-18 12:18:40	IP-1 (Deyang, Shandong)	**#Toshiba Bright Daren#** color personality test to find out your sense...
USER-E	11-18 17:00:31	IP-2 (Zaozhuang, Shandong)	**#Snow#** the Samsung GALAXY SII QQ Service customized version...
USER-D	11-18 17:00:49	IP-2 (Zaozhuang, Shandong)	**#Toshiba Bright Daren#** color personality test to find out your sense...
USER-F	11-18 17:00:56	IP-2 (Zaozhuang, Shandong)	**#Li Ning - a weapon with a hero#** good support activities!

Results: Network Attacks

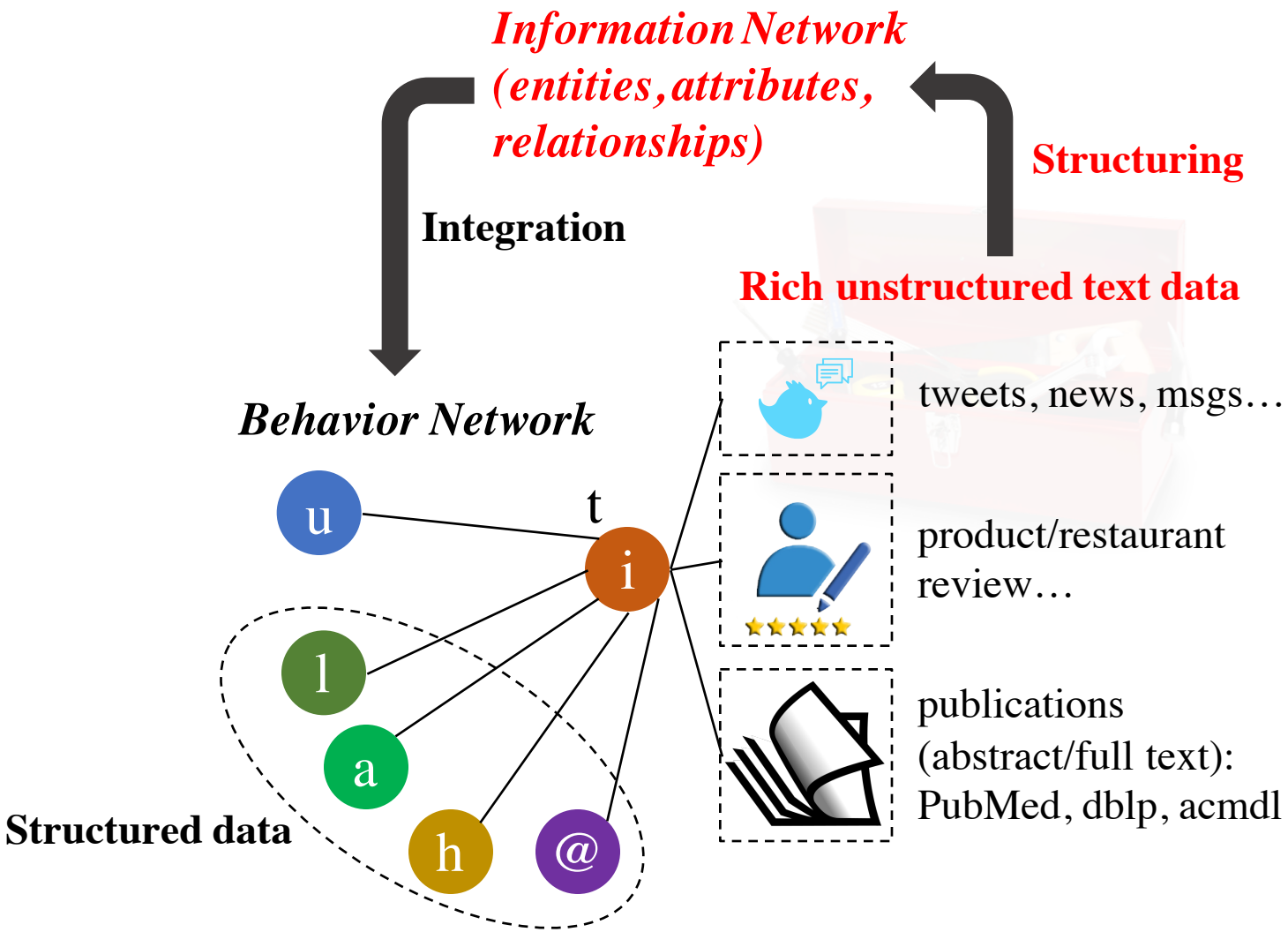
	#	Src-IP × dst-IP × port × second	Mass c	Suspiciousness
CROSSSPOT	1	411 × 9 × 6 × **3,610**	47,449	552,465
	2	533 × 6 × 1 × **3,610**	30,476	400,391
	3	5 × 5 × 2 × **3,610**	18,881	317,529
	4	11 × 7 × 7 × **3,610**	20,382	295,869
HOSVD	1	15 × 1 × 1 × 1,336	4,579	80,585
	2	1 × 2 × 2 × 1,035	1,035	18,308
	3	1 × 1 × 1 × 1,825	1,825	34,812
	4	1 × 13 × 6 × 181	1,722	29,224

Summary

- Ill-gotten Facebook Likes, Zombie Followers
- **Observations, Representations, Models**
  - **CopyCatch:** Catching ill-gotten Likes by core search
  - **LockInfer:** Adding seed selection before search
  - **CatchSync:** Catching smart zombie followers with high recall (recovering power-law distributions)
  - **CrossSpot:** Defining suspiciousness across dimensions

II. Structuring behavioral content and integrating behavioral analysis with information networks

Data to Network to Knowledge

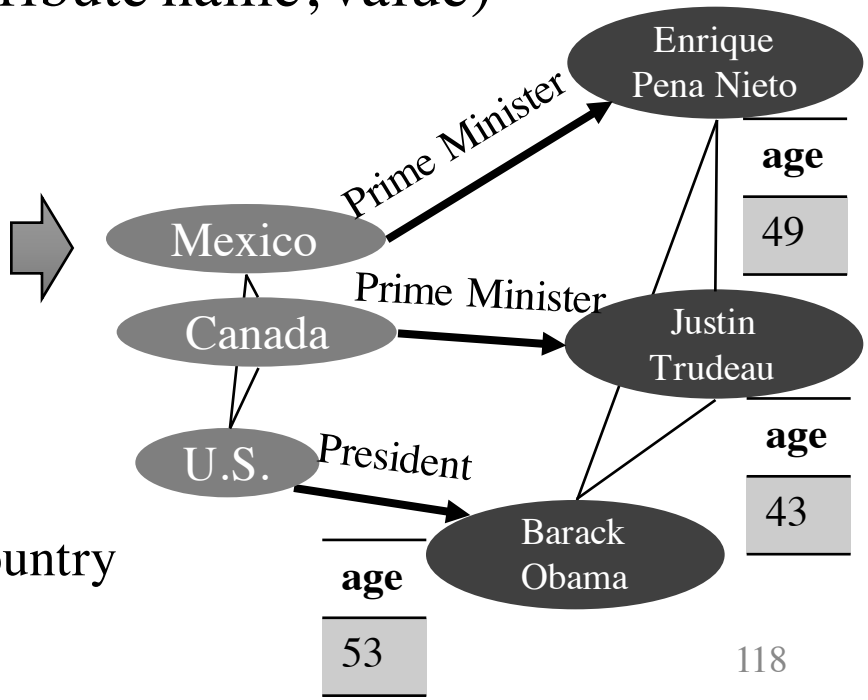


Construction of Heterogeneous Information Networks from Text

Philosophy: Not extensive "labeling" but exploring the power of massive text corpora!

- Mining phrases (the minimal semantic units)
- Entity recognition and typing
- Attribute discovery (entity, attribute name, value)

…here by **Canada Prime Minister Justin Trudeau, 43**, the so-called #APEChottie…of **Mexico's Enrique Pena Nieto, 49**, … **United States President Barack Obama, 53**, who…



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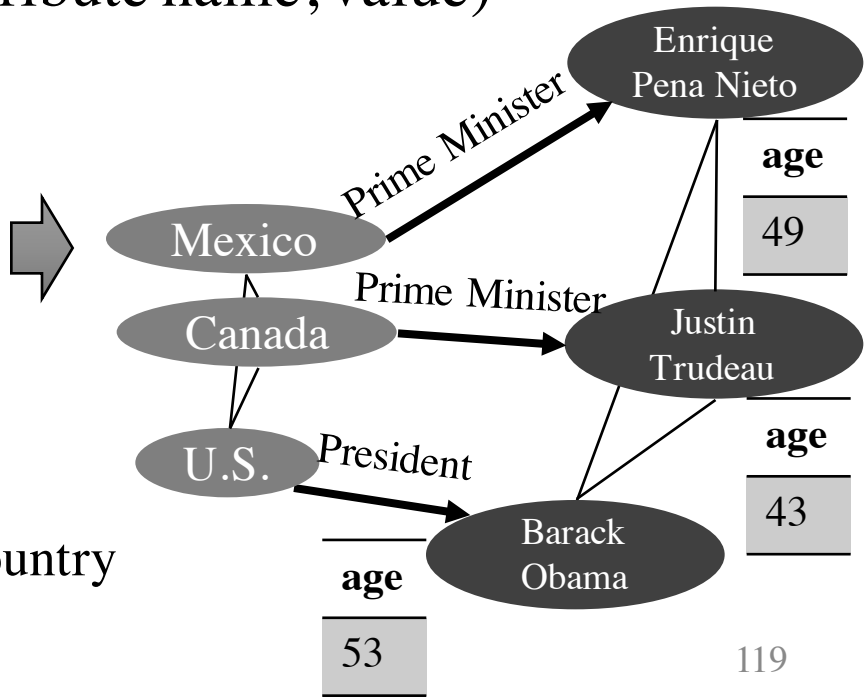


Why Mining Phrases?

- **Unigrams** are *ambiguous but* **phrases** are natural, *unambiguous* semantic units
  - Ex.: "United" vs. United States, United Airline, United Parcel Service
- Mining semantically meaningful phrases
  - Transform text data from *word granularity* to *phrase granularity*
  - Enhance the power at manipulating unstructured data using information networks
- Phrase mining: Most NLP methods may need annotation and training
  - Annotate hundreds of documents as training data
  - Train a supervised model based on part-of-speech features
  - ? Limitations: High annotation cost
  - ? May not be scalable to domain-specific, dynamic, emerging applications
    - ? Scientific domains, query logs, or social media, e.g., Yelp, Twitter
- Minimal/no training but making good use of massing corpora

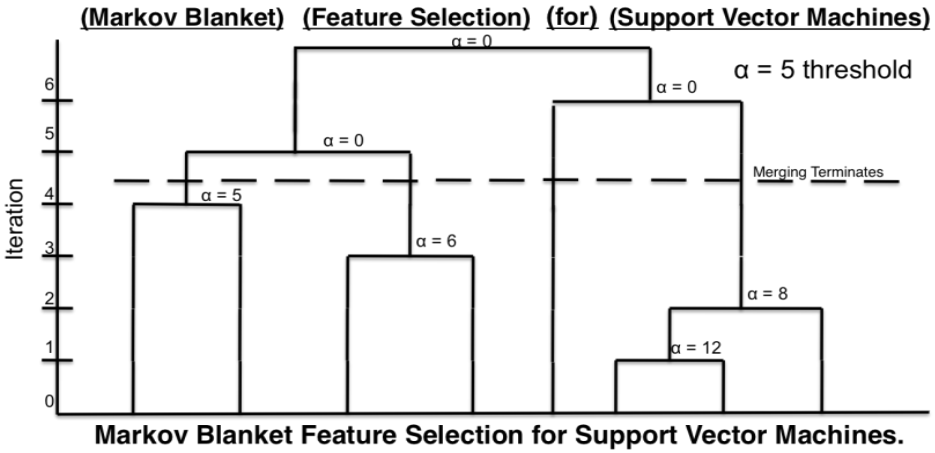
Strategies for Phrase Mining

- Strategy 1: Simultaneously inferring phrases and topics
  - Bigram topical model [Wallach'06], topical n-gram model [Wang, et al.'07], phrase discovering topic model [Lindsey, et al.'12]
  - High model complexity: Tends to overfitting; High inference cost: Slow
- Strategy 2: Post topic modeling phrase construction
  - Label topic [Mei et al.'07], TurboTopic [Blei & Lafferty'09], KERT [Danilevsky, et al.'14]
  - Words in the same phrase may be assigned to different topics
    - Ex. … knowledge discovery using least squares support vector machine …
- **Our solution 1: ToPMine** [El-kishky, et al., VLDB'15]
  - First Phrase Mining then Topic Modeling (No training data at all)
- **Our solution 2: SegPhrase+** [Liu, et al., SIGMOD'15]
  - Integrating phrase mining and document segmentation (with minimal training data)

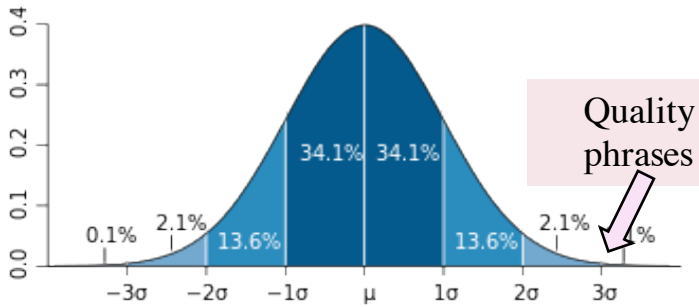
ToPMine: The Overall Phrase Mining Framework

- **ToPMine** [El-Kishky et al. VLDB'15]
  - First phrase construction, then topic mining
  - Contrast with KERT: First topic modeling, then phrase mining
- **The ToPMine Framework:**
  - Perform frequent ***contiguous pattern*** mining to extract candidate phrases and their counts
  - Perform agglomerative merging of adjacent unigrams as guided by a significance score—This segments each document into a ***"bag-of-phrases"***
  - The newly formed bag-of-phrases are passed as input to PhraseLDA, an extension of LDA, that constrains all words in a phrase to each sharing the same latent topic

Phrase Mining: Frequent Pattern Mining + Statistical Analysis



Markov Blanket Feature Selection for Support Vector Machines.



Based on significance score [Church et al.'91]:

$$\alpha(P_1, P_2) \approx (f(P_1 \bullet P_2) - \mu_0(P_1, P_2)) / f(P_1 \bullet P_2)^{1/2}$$

[Markov blanket] [feature selection] for [support vector machines]
[knowledge discovery] using [least squares] [support vector machine] [classifiers]
…[support vector] for [machine learning]…

Phrase	Raw freq.	True freq.
[support vector machine]	90	80
[vector machine]	95	0
[support vector]	100	20

What Kind of Phrases are of "High Quality"?

- Judging the quality of phrases
  - **Popularity**
    - "information retrieval" vs. "cross-language information retrieval"
  - **Concordance**
    - "powerful tea" vs. "strong tea"
    - "active learning" vs. "learning classification"
  - **Informativeness**
    - "this paper" (frequent but not discriminative, not informative)
  - **Completeness**
    - "vector machine" vs. "support vector machine"

ToPMine: Experiments on Yelp Reviews

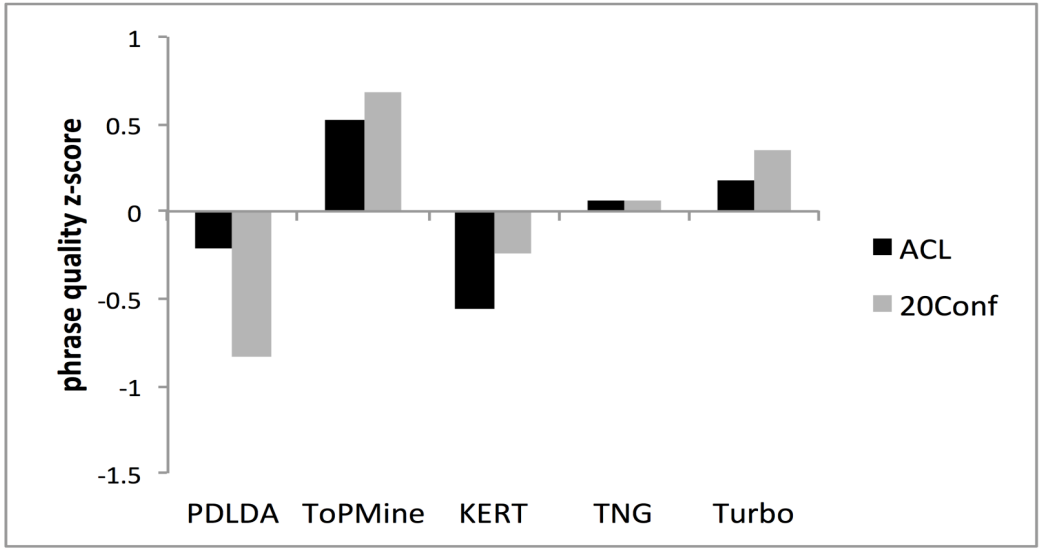
	Topic 1	*Topic 2*	*Topic 3*	*Topic 4*	*Topic 5*
unigrams	coffee	food	room	store	good
	ice	good	parking	shop	food
	cream	place	hotel	prices	place
	flavor	ordered	stay	find	burger
	egg	chicken	time	place	ordered
	chocolate	roll	nice	buy	fries
	breakfast	sushi	place	selection	chicken
	tea	restaurant	great	items	tacos
	cake	dish	area	love	cheese
	sweet	rice	pool	great	time
n-grams	ice cream	spring rolls	parking lot	grocery store	mexican food
	iced tea	food was good	front desk	great selection	chips and salsa
	french toast	fried rice	spring training	farmer's market	food was good
	hash browns	egg rolls	staying at the hotel	great prices	hot dog
	frozen yogurt	chinese food	dog park	parking lot	rice and beans
	eggs benedict	pad thai	room was clean	wal mart	sweet potato fries
	peanut butter	dim sum	pool area	shopping center	pretty good
	cup of coffee	thai food	great place	great place	carne asada
	iced coffee	pretty good	staff is friendly	prices are reasonable	mac and cheese
	scrambled eggs	lunch specials	free wifi	love this place	fish tacos

ToPMine: Faster and Generating Better Quality Phrases

Running time of different algorithms

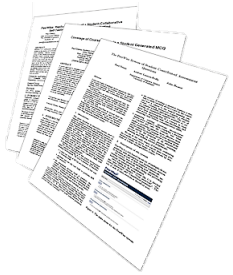
Method	*sampled dblp titles (k=5)*	*dblp titles (k=30)*	*sampled dblp abstracts*	*dblp abstracts*
PDLDA	3.72(hrs)	~20.44(days)	1.12(days)	~95.9(days)
Turbo Topics	6.68(hrs)	>30(days)*	>10(days)*	>50(days)*
TNG	146(s)	5.57 (hrs)	853(s)	NA†
LDA	**65(s)**	3.04 (hrs)	353(s)	13.84(hours)
KERT	68(s)	3.08(hrs)	1215(s)	NA†
ToP-Mine	67(s)	**2.45(hrs)**	**340(s)**	**10.88(hrs)**

Phrase quality measured by z-score



SegPhrase: From Raw Corpus to Quality Phrases and Segmented Corpus

Raw Corpus



+ A small set of labels or a general KB

Quality Phrases

Segmented Corpus

Document 1
Citation recommendation is an interesting but challenging research problem in data mining

Document 2
In this study, we investigate the problem in the context of heterogeneous information networks using data mining technique.

Document 3
Principal Component Analysis is a linear dimensionality reduction technique commonly used in machine learning applications.

Input Raw Corpus → **Quality Phrases** ↔ **Segmented Corpus**

Phrase Mining **Phrasal Segmentation**

Integrating phrase mining with phrasal segmentation

J. Liu et al. **Mining Quality Phrases from Massive Text Corpora.** SIGMOD, 2015 (**won Grand Prize in Yelp Dataset Challenge**).

Experiments: Interesting Phrases Generated
(From the Titles and Abstracts of SIGMOD)

Query	SIGMOD	
Method	**SegPhrase+**	**Chunking (TF-IDF & C-Value)**
1	data base	data base
2	database system	database system
3	relational database	query processing
4	query optimization	query optimization
5	query processing	relational database
…	…	…
51	sql server	database technology
52	**relational data**	database server
53	data structure	**large volume**
54	**join query**	performance study
55	web service	web service
…	…	…
201	**high dimensional data**	**efficient implementation**
202	location based service	sensor network
203	xml schema	**large collection**
204	**two phase locking**	**important issue**
205	deep web	frequent itemset
…	…	…

Only in SegPhrase+

Only in Chunking

Mining Quality Phrases in Multiple Languages

- Both ToPMine and SegPhrase+ are extensible to mining quality phrases in multiple languages
  - SegPhrase+ on Chinese (From Chinese Wikipedia)
  - ToPMine on Arabic (From Quran Fus7a Arabic)(no preprocessing)
    - Experimental results of Arabic phrases:

      اورفڪ → Those who disbelieve

      مسبر الله نمحرلا ميحرلا → In the name of God the Gracious and Merciful

Rank	Phrase	In English
…	…	…
62	首席_执行官	CEO
63	中间_偏右	Middle-right
…	…	…
84	百度_百科	Baidu Pedia
85	热带_气旋	Tropical cyclone
86	中国科学院_院士	Fellow of Chinese Academy of Sciences
…	…	…
1001	十大_中文_金曲	Top-10 Chinese Songs
1002	全球_资讯网	Global Info Website
1003	天一阁_藏_明代_科举_录_选刊	A Chinese book name
…	…	…
9934	国家_戏剧_院	National Theater
9935	谢谢_你	Thank you
…	…	…

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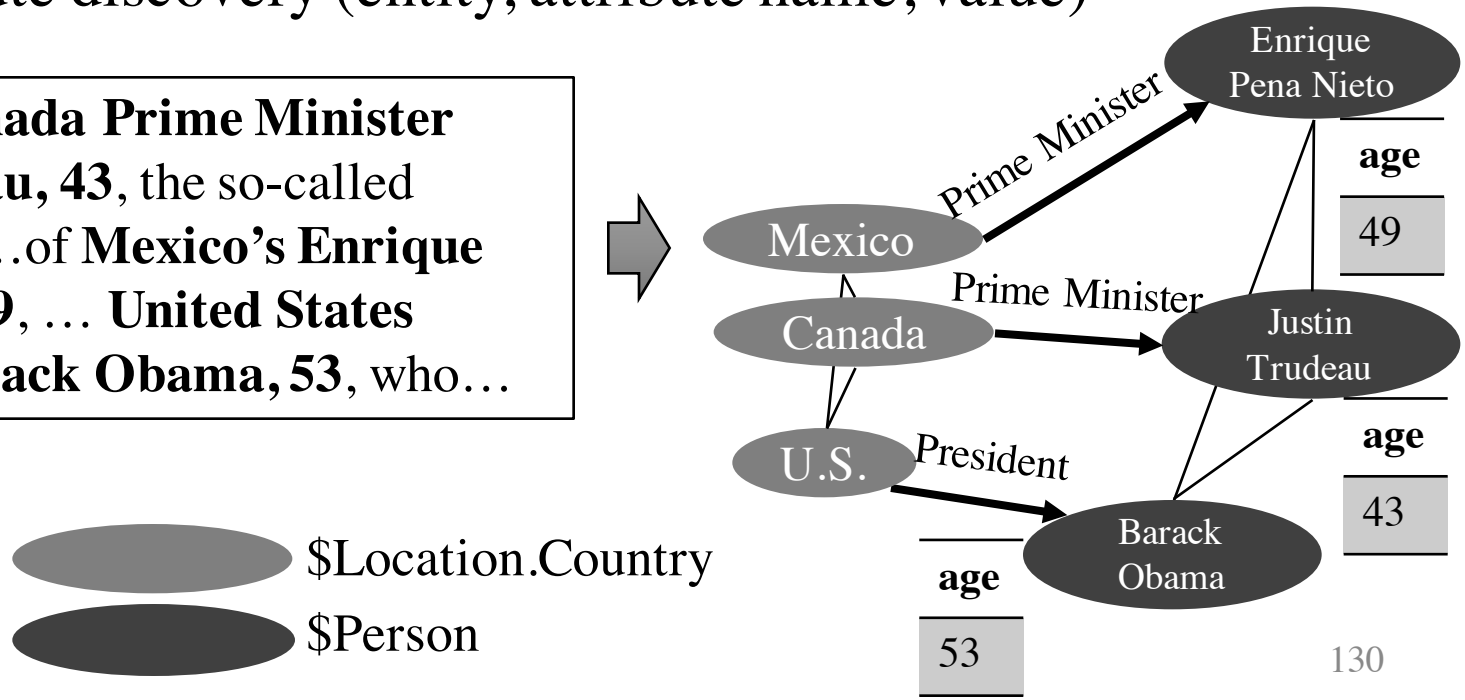


Why Entity Recognition and Typing from Massive Corpora?

- Traditional named entity recognition systems are designed for major types (e.g., PER, LOC, ORG) and general domains (e.g., news)
  - Require additional steps to adapt to new domains/types
  - Expensive human labor on annotation
    - 500 documents for entity extraction; 20,000 queries for entity linking
  - Unsatisfying agreement due to various granularity levels and scopes of types
- Entities obtained by entity linking techniques have *limited* coverage and freshness
  - > 50% unlinkable entity mentions in Web corpus [Lin et al., EMNLP'12]
  - > 90% in our experiment corpora: tweets, Yelp reviews, …
- A new approach: ClusType: Entity Recognition and Typing by Relation Phrase-Based Clustering [Ren, et al., KDD 2015]
  - Recognizing entity mentions of target types with minimal/no human supervision and with no requirement that entities can be found in a KB (distant supervision)

Recognizing Typed Entities

Identifying token span as entity mentions in documents and labeling their types

Target Types

- FOOD
- LOCATION
- JOB_TITLE
- EVENT
- ORGANIZATION
- …

The best BBQ I've tasted in Phoenix! I had the pulled pork sandwich with coleslaw and baked beans for lunch. ... The owner is very nice. …

Plain text

The best BBQ:Food I've tasted in Phoenix:LOC ! I had the [pulled pork sandwich]:Food with coleslaw:Food and [baked beans]:Food for lunch. … The owner:JOB_TITLE is very nice. …

Text with typed entities

FOOD → yelp

LOCATION → Google Maps

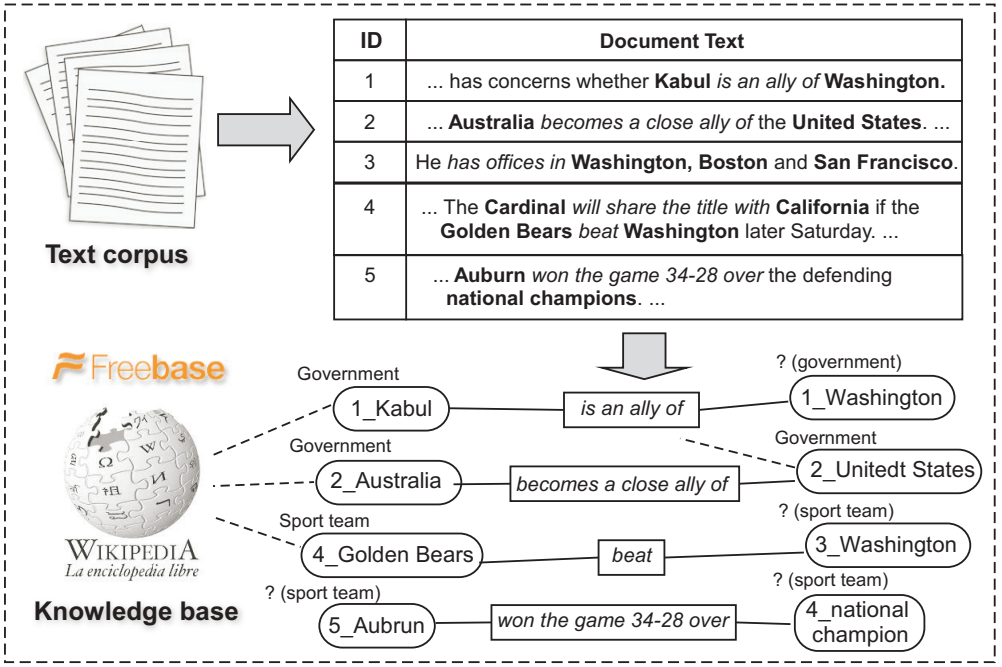
EVENT → twitter

Enabling structured analysis of unstructured text corpus

ClusType: A Distant Supervision Framework

Problem: *Distantly-supervised entity recognition in a domain-specific corpus*

- Given: (1) a domain-specific corpus *D*, (2) a knowledge base (e.g., Freebase), (3) a set of target types (*T*) from a KB
- Detect candidate entity mentions in D, and categorize each candidate mention by target types or Not-Of-Interest (NOI)

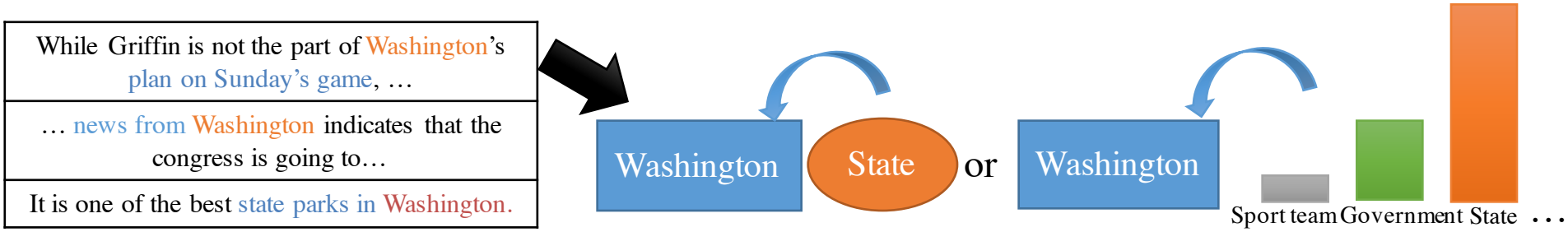


Solution:

- Detect entity mentions from text
- Map candidate mentions to KB entities of target types
- Use confidently mapped {mention, type} to infer types of remaining candidate mentions

Entity Recognition and Typing: Challenges and Solutions

- Challenge 1: Domain Restriction: Extensive training, use general-domain corpora, not work well on specific, dynamic or emerging domains (*e.g.*, tweets, Yelp reviews)
  - Solution: Domain-agnostic phrase mining: Extracts candidate entity mentions with minimal linguistic assumption (e.g., only use POS tagging)
- Challenge 2: Name ambiguity: Multiple entities may share the same surface name
  - Solution: Model each mention based on its surface name and context



- Challenge 3: Context Sparsity: There are many ways to describe the same relation
  - Solution: cluster *relation phrase*, infer synonymous relation phrases

Sentence	Freq.
The magnitude 9.0 quake **caused widespread devastation in [Kesennuma city]**	12
… tsunami that **ravaged [northeastern Japan]** last Friday	31
The resulting tsunami **devastate [Japan]**'s northeast	244

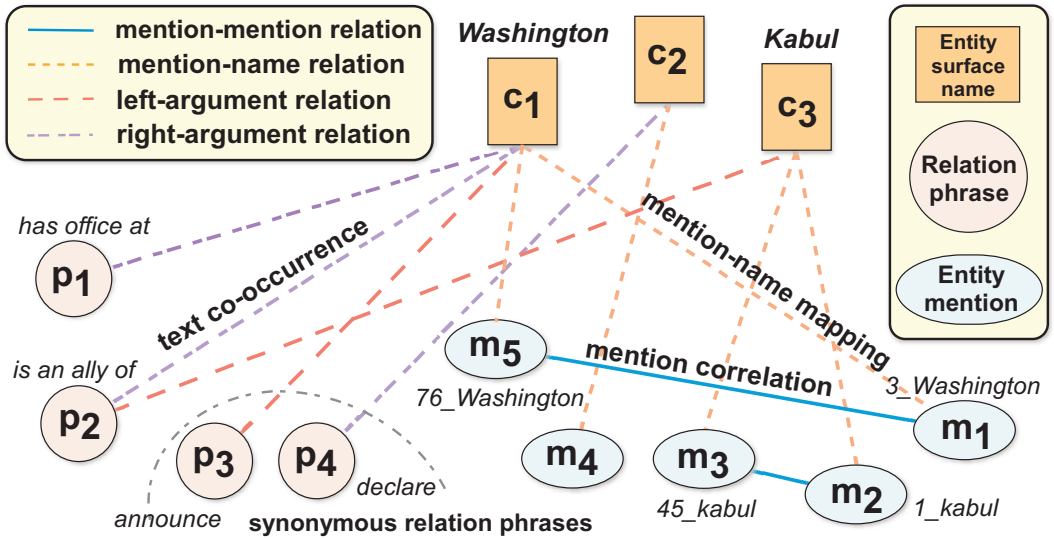
The ClusType Framework: Phrase Segmentation and Heterogeneous Graph Construction

- POS-constrained phrase segmentation for mining candidate entity mentions and relation phrases, simultaneously
- Construct a heterogeneous graph to represent available information in a unified form

Entity mentions are kept as individual objects **to be disambiguated**

Linked to entity surface names & relation phrases

Weight assignment: The more two objects are likely to share the same label, the larger the weight will be associated with their connecting edge

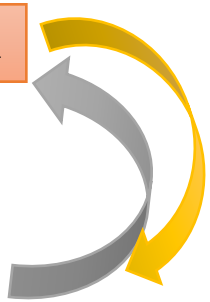


The ClusType Framework: Mutual Enhancement of Type Propagation and Relation Phrase Clustering

- With the constructed graph, formulate a graph-based semi-supervised learning of two tasks jointly:

Type propagation on heterogeneous graph

Derived entity argument types serve as **good feature** for clustering relation phrases



Multi-view relation phrase clustering

Propagate type information among entities bridges via synonymous relation phrases

Mutually enhancing each other; leads to quality recognition of unlinkable entity mentions

ClusType: A General Framework Overview

- **Candidate Generation**
  - Perform phrase mining on a POS-tagged corpus to extract candidate entity mentions and relation phrases
- **Construction of Heterogeneous Graphs**
  - Construct a heterogeneous graph to encode our insights on modeling the type for each entity mention
  - Collect seed entity mentions as labels by linking extracted mentions to the KB
- **Relation Phrase Clustering**
  - Estimate type indicator for unlinkable candidate mentions with the proposed type propagation integrated with relation phrase clustering on the constructed graph

Candidate Generation

- Phrase mining incorporating both *corpus-level statistics* and *syntactic constraints*
  - **Global significance score**: Filter low-quality candidates; **generic POS tag patterns**: remove phrases with improper syntactic structure
  - Extend ToPMine to partition corpus into segments which meet both significance threshold and POS patterns → candidate entity mentions & relation phrases

Relation phrase: Phrase that denotes a unary or binary relation in a sentence

Pattern	Example
V	disperse; hit; struck; knock;
P	in; at; of; from; to;
V P	locate in; come from; talk to;
VW*(P)	caused major damage on; come lately

V-verb; P-prep; W-{adv | adj | noun | det | pron}
W* denotes multiple W; (P) denotes optional.

Experiment: Entity detection: Performance comparison between our method and an NP chunker

Method	NYT		Yelp		Tweet	
	Prec	Recall	Prec	Recall	Prec	Recall
Our method	**0.469**	**0.956**	**0.306**	**0.849**	0.226	**0.751**
NP chunker	0.220	0.609	0.296	0.247	**0.287**	0.181

Recall is most critical for this step,since later we cannot detect the misses (i.e., false negatives)

Type Inference: A Joint Optimization Problem

$$\mathcal{O}_{\alpha,\gamma,\mu} = \mathcal{F}(\mathbf{C}, \mathbf{P}_L, \mathbf{P}_R) + \mathcal{L}_\alpha\big(\mathbf{P}_L, \mathbf{P}_R, \{\mathbf{U}^{(v)}, \mathbf{V}^{(v)}\}, \mathbf{U}^*\big) + \Omega_{\gamma,\mu}(\mathbf{Y}, \mathbf{C}, \mathbf{P}_L, \mathbf{P}_R). \quad (2)$$

$$\mathcal{F}(\mathbf{C}, \mathbf{P}_L, \mathbf{P}_R) = \sum_{i=1}^{n}\sum_{j=1}^{l} W_{L,ij} \left\| \frac{\mathbf{C}_i}{\sqrt{D^{(\mathcal{C})}_{L,ii}}} - \frac{\mathbf{P}_{L,j}}{\sqrt{D^{(\mathcal{P})}_{L,jj}}} \right\|_2^2 + \sum_{i=1}^{n}\sum_{j=1}^{l} W_{R,ij} \left\| \frac{\mathbf{C}_i}{\sqrt{D^{(\mathcal{C})}_{R,ii}}} - \frac{\mathbf{P}_{R,j}}{\sqrt{D^{(\mathcal{P})}_{R,jj}}} \right\|_2^2$$

Type propagation between entity surface names and relation phrases

Mention modeling & mention correlation

$$\Omega_{\gamma,\mu}(\mathbf{Y}, \mathbf{C}, \mathbf{P}_L, \mathbf{P}_R) = \big\|\mathbf{Y} - f(\Pi_{\mathcal{C}}\mathbf{C}, \Pi_L\mathbf{P}_L, \Pi_R\mathbf{P}_R)\big\|_F^2 + \frac{\gamma}{2}\sum_{c\in\mathcal{C}}\sum_{i,j=1}^{M_c} W^{(c)}_{ij} \left\| \frac{\mathbf{Y}_i}{\sqrt{D^{(c)}_{ii}}} - \frac{\mathbf{Y}_j}{\sqrt{D^{(c)}_{jj}}} \right\|_2^2 + \mu\|\mathbf{Y} - \mathbf{Y}_0\|_F^2$$

$$\mathcal{L}_\alpha\big(\mathbf{P}_L, \mathbf{P}_R, \{\mathbf{U}^{(v)}, \mathbf{V}^{(v)}\}, \mathbf{U}^*\big) = \sum_{v=0}^{d} \beta^{(v)} \big(\|\mathbf{F}^{(v)} - \mathbf{U}^{(v)}\mathbf{V}^{(v)T}\|_F^2 + \alpha\|\mathbf{U}^{(v)}\mathbf{Q}^{(v)} - \mathbf{U}^*\|_F^2\big). \quad (3)$$

Multi-view relation phrases clustering)

ClusType: Experiment Setting

- Datasets: 2013 New York Times news (~110k docs) [event, PER, LOC, ORG]; Yelp Reviews (~230k) [Food, Job, …]; 2011 Tweets (~300k) [event, product, PER, LOC, …]
- Seed mention sets: < 7% extracted mentions are mapped to Freebase entities
- Evaluation sets: manually annotate mentions of target types for subsets of the corpora
- Evaluation metrics: Follows named entity recognition evaluation (Precision, Recall, F1)
- Compared methods
  - **Pattern**: Stanford pattern-based learning; **SemTagger**:bootstrapping method which trains contextual classifier based on seed mentions; **FIGER**: distantly-supervised sequence labeling method trained on Wiki corpus; **NNPLB**: label propagation using ReVerb assertion and seed mention; **APOLLO**: mention-level label propagation using Wiki concepts and KB entities;
  - **ClusType-NoWm**: ignore mention correlation; **ClusType-NoClus**: conducts only type propagation; **ClusType-TwpStep**: first performs hard clustering then type propagation

Comparing ClusType with Other Methods and Its Variants

Performance comparison on three datasets in terms of Precision, Recall and F1 score

Table 5: Performance comparisons on three datasets in terms of Precision, Recall and F1 score.

Data sets	NYT			Yelp			Tweet		
Method	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Pattern [9]	0.4576	0.2247	0.3014	0.3790	0.1354	0.1996	0.2107	0.2368	0.2230
FIGER [16]	0.8668	0.8964	0.8814	0.5010	0.1237	0.1983	**0.7354**	0.1951	0.3084
SemTagger [12]	0.8667	0.2658	0.4069	0.3769	0.2440	0.2963	0.4225	0.1632	0.2355
APOLLO [29]	0.9257	0.6972	0.7954	0.3534	0.2366	0.2834	0.1471	0.2635	0.1883
NNPLB [15]	0.7487	0.5538	0.6367	0.4248	0.6397	0.5106	0.3327	0.1951	0.2459
ClusType-NoClus	0.9130	0.8685	0.8902	0.7629	0.7581	0.7605	0.3466	0.4920	0.4067
ClusType-NoWm	0.9244	0.9015	0.9128	0.7812	0.7634	0.7722	0.3539	**0.5434**	0.4286
ClusType-TwoStep	0.9257	0.9033	0.9143	0.8025	0.7629	0.7821	0.3748	0.5230	0.4367
ClusType	**0.9550**	**0.9243**	**0.9394**	**0.8333**	**0.7849**	**0.8084**	0.3956	0.5230	**0.4505**

- **vs. FIGER**: Effectiveness of our candidate generation and type propagation
- **vs. NNPLB** and **APOLLO**: ClusType utilizes not only semantic-rich relation phrase as type cues, but also cluster synonymous relation phrases to tackle context sparsity
- **vs.** our **variants**: (i) models mention correlation for name disambiguation; and (ii) integrates clustering in a mutually enhancing way

Comparing on Trained NER System

- Compare with Stanford NER, which is trained on general-domain corpora including ACE corpus and MUC corpus, on three types: PER, LOC, ORG

F1 score comparison with trained NER

Table 6: F1 score comparison with trained NER.

Method	NYT	Yelp	Tweet
Stanford NER [6]	0.6819	0.2403	0.4383
ClusType-NoClus	0.9031	0.4522	0.4167
ClusType	**0.9419**	**0.5943**	**0.4717**

[6] J. R. Finkel, T. Grenager and C. Manning. Incorporating non-local information into information extraction systems by Gibbs sampling. In ACL'05.

- ClusType and its variants outperform Stanford NER on both dynamic corpus (NYT) and domain-specific corpus (Yelp)
- ClusType has lower precision but higher Recall and F1 score on Tweet → Superior recall of ClusType mainly come from domain-independent candidate generation

Example Output and Relation Phrase Clusters

Example output of ClusType and the compared methods on the Yelp dataset

ClusType	SemTagger	NNPLB
The best **BBQ:Food** I've tasted in **Phoenix:LOC** ! I had the **[pulled pork sandwich]:Food** with **coleslaw:Food** and **[baked beans]:Food** for lunch. ...	The best BBQ I've tasted in **Phoenix:LOC** ! I had the pulled **[pork sandwich]:LOC** with **coleslaw:Food** and **[baked beans]:LOC** for lunch. ...	The best **BBQ:Loc** I've tasted in **Phoenix:LOC** ! I had the pulled pork **sandwich:Food** with coleslaw and baked **beans:Food** for **lunch:Food**. ...
I only go to **ihop:LOC** for **pancakes:Food** because I don't really like anything else on the menu. Ordered **[chocolate chip pancakes]:Food** and a **[hot chocolate]:Food**.	I only go to ihop for pancakes because I don't really like anything else on the menu. Ordered **[chocolate chip pancakes]:LOC** and a **[hot chocolate]:LOC**.	I only go to ihop for pancakes because I don't really like anything else on the menu. Ordered chocolate chip pancakes and a hot chocolate.

- **Extracts more mentions and predicts types with higher**

Example relation phrase clusters and corpus-wide frequency from the NYT dataset

ID	Relation phrase
1	recruited by (5.1k); employed by (3.4k); want hire by (264)
2	go against (2.4k); struggling so much against (54); run for re-election against (112); campaigned against (1.3k)
3	looking at ways around (105); pitched around (1.9k); echo around (844); present at (5.5k);

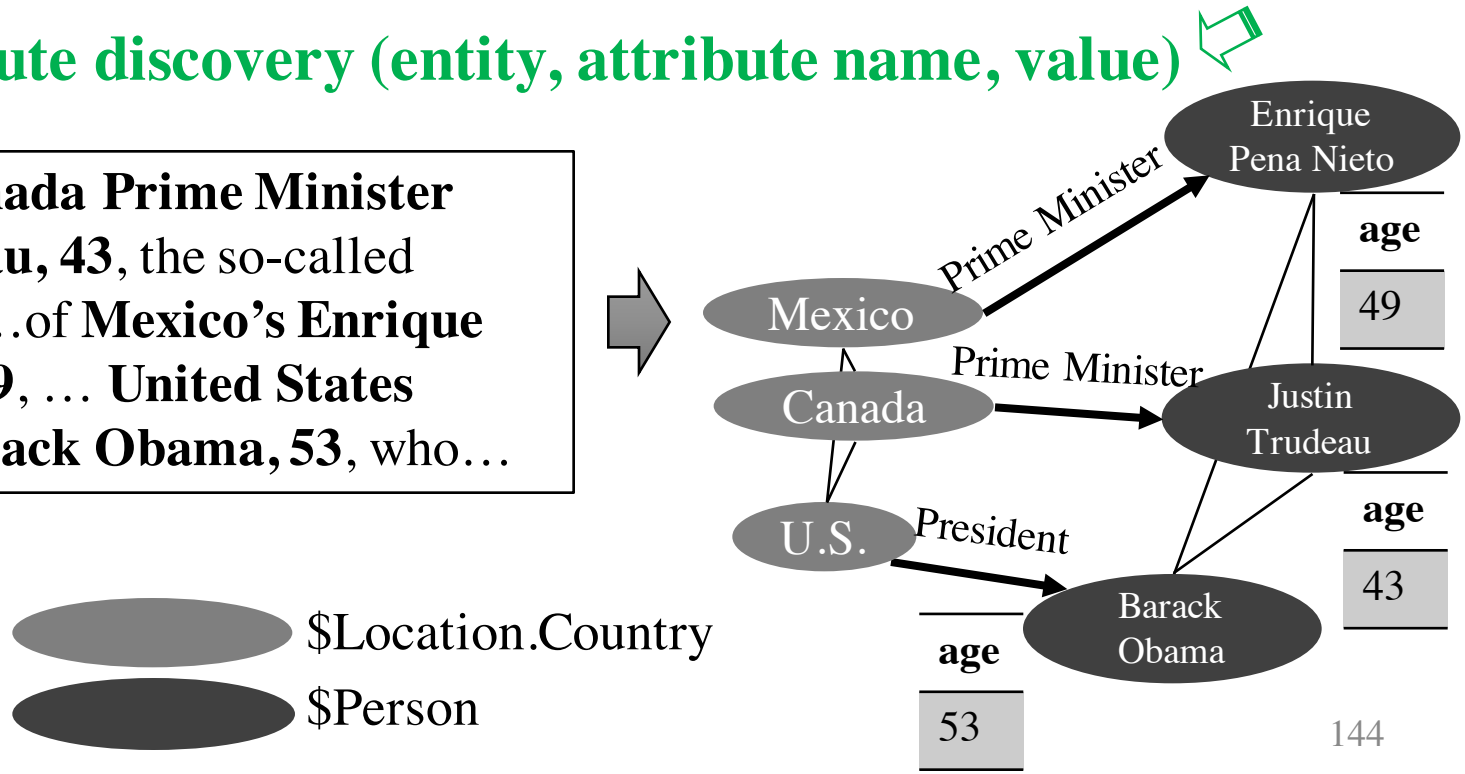
- Not only synonymous relation phrases, but also both sparse and frequent relation phrase can be clustered together
- → boosts sparse relation phrases with type information of frequent relation phrases

Construction of Heterogeneous Information Networks from Text

Philosophy: Not extensive "labeling" but exploring the power of massive text corpora!

- Mining phrases (the minimal semantic units)
- Entity recognition and typing
- **Attribute discovery (entity, attribute name, value)**

…here by **Canada Prime Minister Justin Trudeau, 43**, the so-called #APEChottie…of **Mexico's Enrique Pena Nieto, 49**, … **United States President Barack Obama, 53**, who…



Attributed Network Construction

- *Automatic* Attribute discovery: Given a class (*e.g.*, $Country)
  - **Feature** as a characteristic (*e.g.*, "population")
    - Value: the feature value (*e.g.*, $Digit or NULL)
  - **Relationship** with another class (*e.g.*, "prime minister")
    - Value: the other class (*e.g.*, $Person.Politician.PrimeMinister)
- Google's [VLDB'14, WWW'16] based on **fact-seeking** queries
  - Challenge 1: (Class, Attribute name, **Attribute value**)
  - Challenge 2: Just text documents (news, tweets, etc.). **NO query**.

"canada prime minister", "trudeau age",
"united states president", "obama age",
"mexico prime minister" …

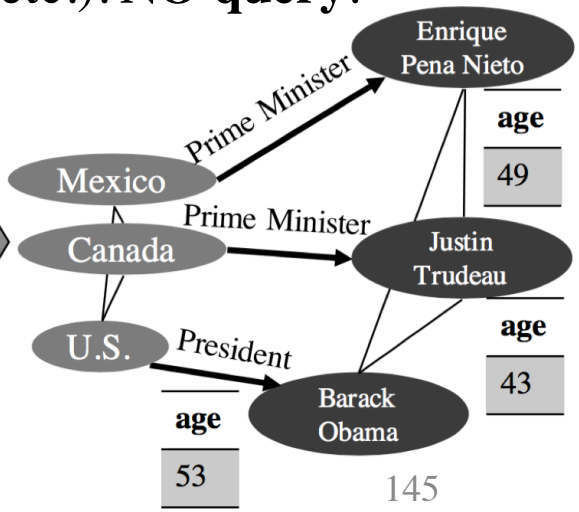
Unfortunately, we don't have the query data.

…here by **Canada Prime Minister Justin Trudeau, 43**, the so-called #APEChottie…of **Mexico's Enrique Pena Nieto, 49**, … **United States President Barack Obama, 53**, who…

Fortunately, we have large text corpus.

	Canada	Mexico
Prime Minister	Justin Trudeau	Enrique Pena Nieto

	Justin Trudeau	Enrique Pena Nieto	Barack Obama
age	43	49	53



Related Work

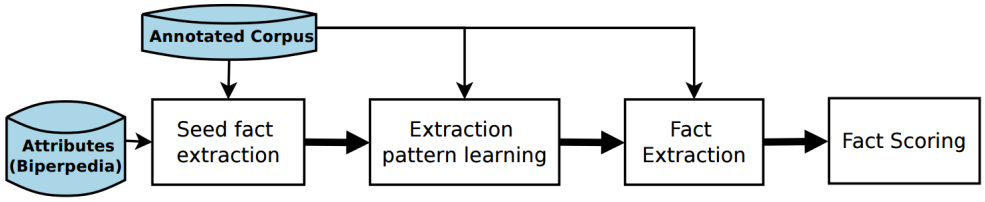
	Data source (√: available and unlimited with web crawler)	**Supervision level** (√: distant or unsupervised for massive data)	**Attribute discovery**		
			Fine-grained classes	Attribute names	Attribute values
CO-EM [6]	×, product description	?, semi-supervised	×	√	√
SE+R [2]	×, query log	?, weakly	×	√	×
DVSQ† [23]	×, query log	√, unsupervised	√	√	×
CAE† [22]	×, query log	√, unsupervised	√	√	×
WSIEQ† [20]	×, query log	?, weakly	√	√	×
HCAE† [21]	×, query log	?, weakly	√	√	×
WSEST† [24]	×, query log+HTML table	?, weakly	√	√	×
KNEXT [29]	√, text corpus	×, supervised	√	√	×
FAR [12]	×, HTML table	×, supervised	√	√	√
TYPICALITY [13]	×, query log+HTML table	×, supervised	√	√	×
BIPERPEDIA‡ [7]	×, query log+HTML table	√, distant	√	√	×
RENOUN‡ [30]	√, text corpus	×, supervised	√	×	√
ARI‡ [8]	×, query log	√, distant	√	√	×
UPSF [33]	√, text corpus	√, unsupervised	×	×	√
MetaPAD	**√, text corpus**	**√, distant**	√	√	√

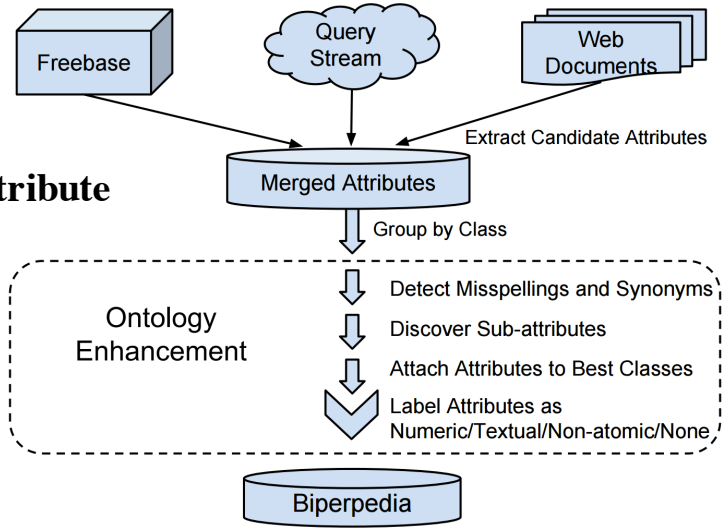
†These related papers were published by Dr. Marius Paşca et al., Google Inc. from 2007 to 2008.

‡These related papers were published by Dr. Alon Halevy et al., Google Inc. from 2014 to 2016.

Google's Approaches on Attribute Extraction

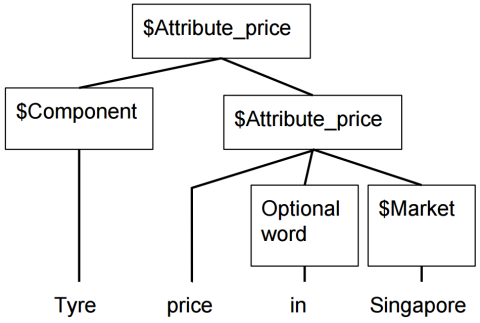
- Given Google's **query log**, web text and knowledge bases
  - "Obama wife name"… "Japan asian population", "Brazil female latino population", "Princeton economist"…
  - "Obama's wife, Michelle Obama, is a lawyer...", "Princeton economist Paul Krugman was awarded…"…
  - Obama: *$Person, $President*; Japan, Brazil: *$Location, $Country*; Princeton: *$Organization, $University*…
- Biperpedia (VLDB'14): **Attribute Name Extraction** from query log
  - $Person: wife name, daughter name
  - $Country: asian population, female latino population
  - $University: economist
- ReNoun (EMNLP'14): **Fact Extraction for Noun Phrase Attribute**
  - (Obama, wife, Michelle Obama)
  - (Princeton, economist, Paul Krugman)



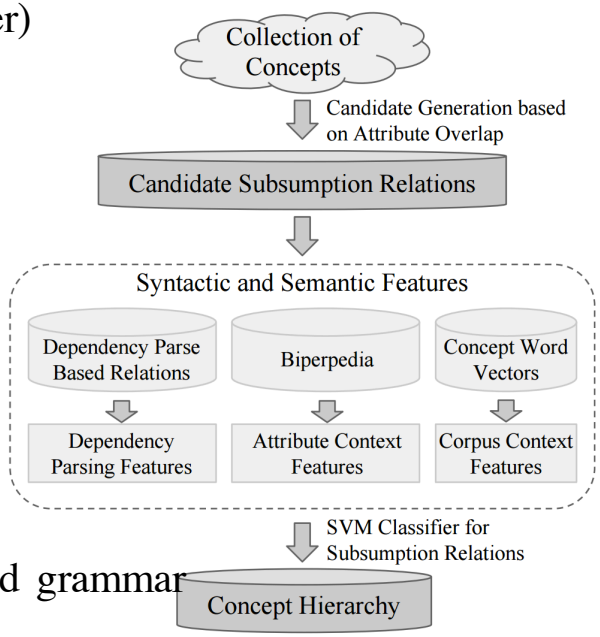


Google's Approaches on Attribute Extraction

- Latte (WebDB'15 Best Paper): **Concept (Type) Hierarchy Extraction** with attribute features
  - {country, address, zip code}: $University (sub) - $Location (super)
  - {online payment, non profit, tax return}: $University (sub) - $Organization (super)
  - {daughter name, wife name, age}: $President (sub) - $Person (super)




```
$Attribute_price ::= price
$Attribute_price ::= $Market $Attribute_price
$Attribute_price ::= $Attribute_price in $Market
$Attribute_price ::= $Component $Attribute_price
$Market          ::= Singapore | USA | Dubai | London | ...
$Component       ::= battery | bumper | tyre | door | ...
```



- ARI (WWW'16): **Attribute Name Structure Extraction** with rule-based grammar
  - Long-tail distribution of attribute names
  - $Person: $FamilyMember (name) - daughter, wife, mother, daughter name, wife name
  - $Country: ($Gender) ($Ethnicity) population - asian population, female latino population

Data-Driven: Meta Pattern Mining

- **Meta Pattern:** a sequence of *class symbols*, *words*, *phrases* and *punctuation marks* that appear contiguously in the text, and serves as a whole semantic unit.

News:

…he's gotten older and grayer, and he's been eclipsed at an Asian economic forum here by **Canada Prime Minister Justin Trudeau, 43**, the so-called #APEChottie… He's also the youngest leader at the Asia Pacific Economic Cooperation forum, six years the junior of **Mexico's Enrique Pena Nieto, 49**, … **Obama, 53**, who becomes the elder statesman…

→ **1. $Person, $Digit,**
2. $Location.Country Prime_Minister $Person.Politician.PrimeMinister

Tweets:

…Protestors march to **Gordon Square** for **12** -year-old **Tamir Rice**...

→ **1. protestors march to $Location.Square**
2. $Digit -year-old $Person.Victim

PubMed abstract:

… **Endocarditis** caused by **Streptococcus pneumoniae**… **Pericarditis** due to **Neisseria meningitidis** …

→ **$Cardiovasular_Diseases caused by $Bacteria**
$Cardiovasular_Diseases due to $Bacteria

MetaPAD Framework

Integrated Data-Driven Text Mining

Meta Pattern Mining

Attribute Extraction from Meta Patterns

… Canada Prime Minister Justin Trudeau …
… Barack Obama , 53, …

Quality phrase mining (SegPhrase, SIGMOD'15)

… Canada **Prime_Minister Justin_Trudeau** …
… **Barack_Obama** , 53, …

Entity recognition and typing with distant supervision (ClusType, KDD'15)

… **$Location** Prime_Minister **$Person** …
… **$Person** , **$Digit** , …

Fine-grained typing (PLE, KDD'16)

… **$Country** Prime_Minister **$PrimeMinister**…
… **$President**, **$Digit** , …

MetaPAD Framework

Integrated Data-Driven Text Mining

↓

Meta Pattern Mining

↓

Attribute Extraction from Meta Patterns

Quality Meta-Pattern Classifier

- **Frequency**
  - *"prime_minister $PrimeMinister" vs "young $PrimeMinister"*
- **Completeness**
  - *"$Country prime_minister $PrimeMinister" vs "$Country prime_minister"*
- **Informativeness**
  - *"$Person 's brother , $Person ," vs "$Person and $Person"*
- **Coverage**
  - *"$Person 's signature healthcare law": only "Barack Obama"*
- **Classifier: Random forest**

MetaPAD Framework

Integrated Data-Driven Text Mining

↓

Meta Pattern Mining

↓

Attribute Extraction from Meta Patterns

…xxx **$Country** Prime_Minister **$PrimeMinister** xxx…
…xxx **$President** , **$Digit** , xxx…

Quality Meta-Pattern Classifier

$Location Prime_Minister **$Person**
$Person, **$Digit** ,

$Country Prime_Minister **$PrimeMinister**
$President , **$Digit** ,

Synonym Meta-Pattern Detection
(1) Shared instances (2) J.W. similar words

$Location Prime_Minister **$Person**
$Location PM **$Person**
Prime_Minister **$Person** of **$Location**

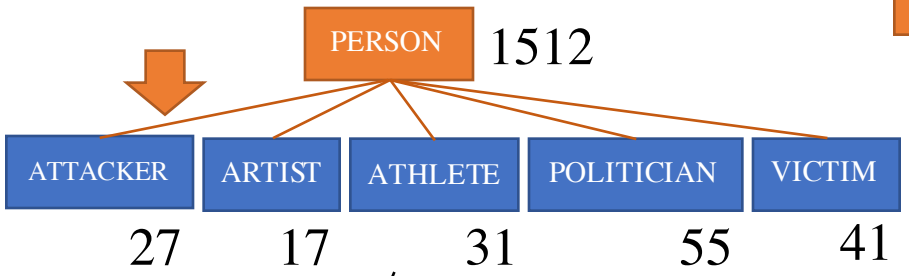
$Person , **$Digit** ,
$Person , a **$Digit** -year-old
$Person , age **$Digit**

Re-typing for Appropriate Granularity

$Country Prime_Minister **$PrimeMinister**
$Person , **$Digit** ,

Top-Down Re-Typing for Granularity

_____, a $Digit -year-old

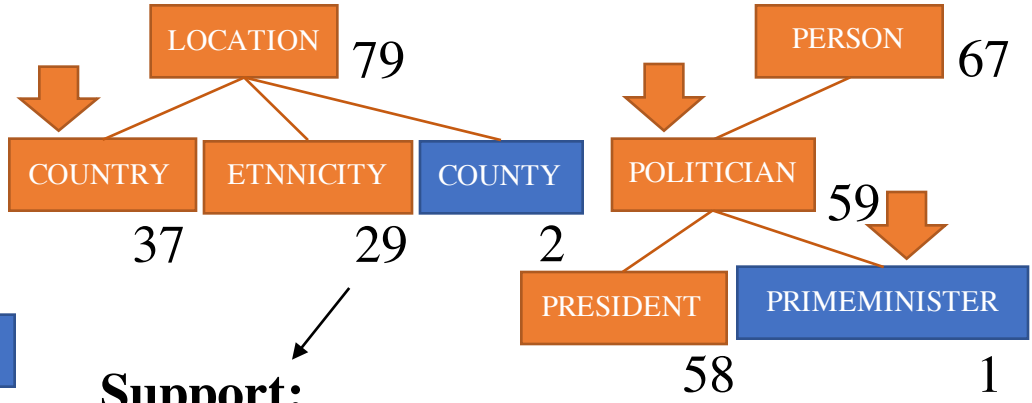


Graininess:

α=(27+17+…+41)/1512

small (< 0.8), stop going down

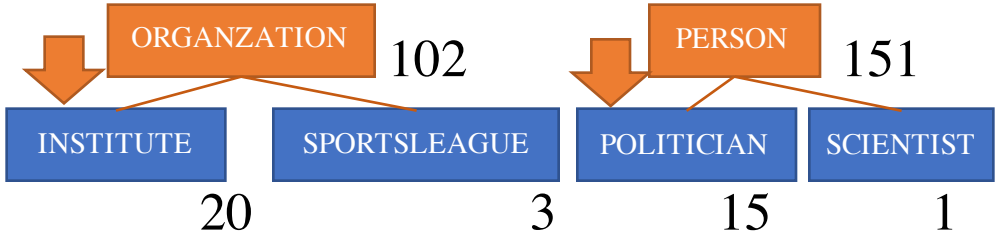
_____ President _____



Support:

β=29/max(37,29,2)

big (> 0.1), keep $Ethnicity



Similar for Bottom-Up…

Experimental Results

Class=$PERSON (METAPAD: 10,361 names, 4,839 pairs)		
Name:BIPERPEDIA	**(Name, -)**	**(Name, Value Type)**
Mr.	Dr.	(-year-old,$DIGIT)
Dr.	Mr.	(president,$ORGANIZATION)
president	president	(spokesman,$ORGANIZATION)
wife	director	(director,$ORGANIZATION)
-year-old	spokesman	(wife,$PERSON)
death	chief	(chairman,$ORGANIZATION)
coach	professor	(governor,$USSTATE)
love	head	(spokeswoman,$ORGANIZATION)
son	coach	(leader,$ORGANIZATION)
...	...	...
code case homicide	staff sergeant	(told reporters,$WEEKDAY)
snow pants	army chief	(board member,$ORGANIZATION)
fellow director	basketball coach	(hack,$COMPANY)

Class=$COUNTRY (METAPAD: 1,132 names, 3,930 pairs)		
Name:BIPERPEDIA	**(Name, -)**	**(Name, Value Type)**
president	president	(ambassador,$COUNTRY)
people	government	(president,$PRESIDENT)
government	war	(visit,$PERSON)
capital	border	(dead,$DIGIT)
visit	volcano	(prime minister,$PRIMEMINISTER)
economy	sanctions	(senator,$SENATOR)
prime minister	ambassador	(embassy,$COUNTRY)
part	earthquake	(condemn,$ORGANIZATION)
leaders	capital	(district judge,$PERSON)
...	...	...
nuclear dossier	volcano eruption	(protests,$NEWSAGENCY)
similar box	security	(-magnitude earthquake,$DIGIT)
episcopal oversight	parliament	(second biggest,$ORGANIZATION)

Class=$INSTITUTE (METAPAD: 402 names, 198 pairs)		
Name:BIPERPEDIA	**(Name, -)**	**(Name, Value Type)**
professor	professor	(professor,$PERSON)
students	students	(law professor,$PERSON)
president	graduate	(political science professor,$PERSON)
campus	law professor	(student,$PERSON)
law professor	campus	(grad,$PERSON)
graduate	degree	(signee,$PERSON)
director	dean	(economics professor,$PERSON)
study	faculty	(basketball coach,$PERSON)
researchers	expert	(finance professor,$PERSON)
...	...	...
foul	commitment	(class,$YEAR)
socialism speech	dorm	(superintendent,$PERSON)
good summary	program	(-year-old student,$DIGIT $PERSON)

Class=$BASKETBALLPLAYER (METAPAD: 58 names, 40 pairs)		
Name:BIPERPEDIA	**(Name, -)**	**(Name, Value Type)**
guard	forward	(points,$DIGIT)
star	points guard	(center,$TEAMNAME)
game	game	(freshman,$SPORTSLEAGUE)
forward	freshman	(forward,$TEAMNAME)
career	center	(point guard,$TEAMNAME)
teammate	get better	(all-star,$SPORTSLEAGUE)
point guard	basketball player	(games,$DIGIT)
points	full highlights	(rebounds,$DIGIT)
season	jumper	(ast,$DIGIT)
...	...	...
understudy	retirement	(PG,$TEAMNAME)
birthday boy	shoes	(career earnings,$DIGIT $DIGITUNIT)
injury meme	suspended without pay	(sue,$PERSON)

Experimental Results

Class=$Location; Value Type=$Month,$Day,$Year		
#	Meta Patterns	
1	$Location $Month $Day, $Year	
2	$Country, $Weekday, $Month $Day, $Year	
3	$Location on $Month $Day, $Year	
#	Entity	Attribute Value
1	Pearl Harbor	December 7, 1941
2	Green Bay	Sunday, Jan 11, 2015
3	Malta[1]	Friday, Nov 27, 2015
...	...	...
5862	Beijing[2]	October 11, 2013
5863	Finland[3]	April 8, 2015

Class=$Organization; Name="ceo"		
#	Meta Patterns	
1	$Organization CEO $Person	
2	$Company CEO $Businessperson	
3	$Organization's $Person	
#	Entity	Attribute Value
1	Apple	Tim Cook
2	Facebook	Mark Zuckerberg
3	Hewlett-Packard	Carly Fiorina
...	...	...
765	Boston Medical Center	Kate Walsh
766	Association of Private Sector Colleges and Universities	Steve Gunderson

Class=$Person; Name="-year-old"[7]		
#	Meta Patterns	
1	$Digit-year-old $Person	
2	$Person, $Digit,	
3	$Person, a $Digit-year-old	
#	Entity	Attribute Value
1	Tamir Rice	12
2	Bobbi Kristina Brown	21
3	Michael Brown	18
...	...	...
4993	Jay Nixon	58
4994	Xanana Gusmao	68

Class=$Person; Name="president"; Value Type=$Ethnicity		
#	Meta Patterns	
1	$Ethnicity President $President	
2	$Ethnicity leader $President	
3	$Ethnicity government of President $President	
#	Entity	Attribute Value
1	Vladimir Putin	Russian
2	Francois Hollande	French
3	Raul Castro	Cuban
...	...	...
254	Mohammed Morsi	Egyptian
255	Klaus Iohannis	Romanian

[1]Commonwealth Heads of Government Meeting. [2]UCI World Tour of Beijing. [3]Finnish parliamentary election begins.

Experimental Results

F1 score	WPB ('10, 100M)	CNA ('97-'10, 200M)	APR ('15, 200M)	TWT ('15, 1GB)
Total (vs Biperpedia -q)	↑67.7%	↑48.3%	↑189.5%	↑208.0%
w/ Meta pattern classifier	↑30.1%	↑27.0%	↑127.1%	↑195.6%
w/ Granularity	↑20.8%	↑15.6%	↑17.3%	↑3.1%
w/ Integrated text mining techs	↑13.8%	↑9.3%	↑13.0%	↑0.8%

$Cardiovasular_Diseases due to $Bacteria
$Cardiovasular_Diseases caused by $Bacteria

$Bacteria	$Cardiovascular_Diseases
Streptococcus pneumoniae	Endocarditis
Neisseria meningitidis	Pericarditis
Haemophilus paraphrophilus	Endocarditis
Proteus	Endocarditis
Listeria monocytogenes	Pericarditis
Corynebacterium	Endocarditis
Actinomyces	Endocarditis
Coxiella	Endocarditis
Pasteurella pneumotropica	Endocarditis
Cardiobacterium	Endocarditis

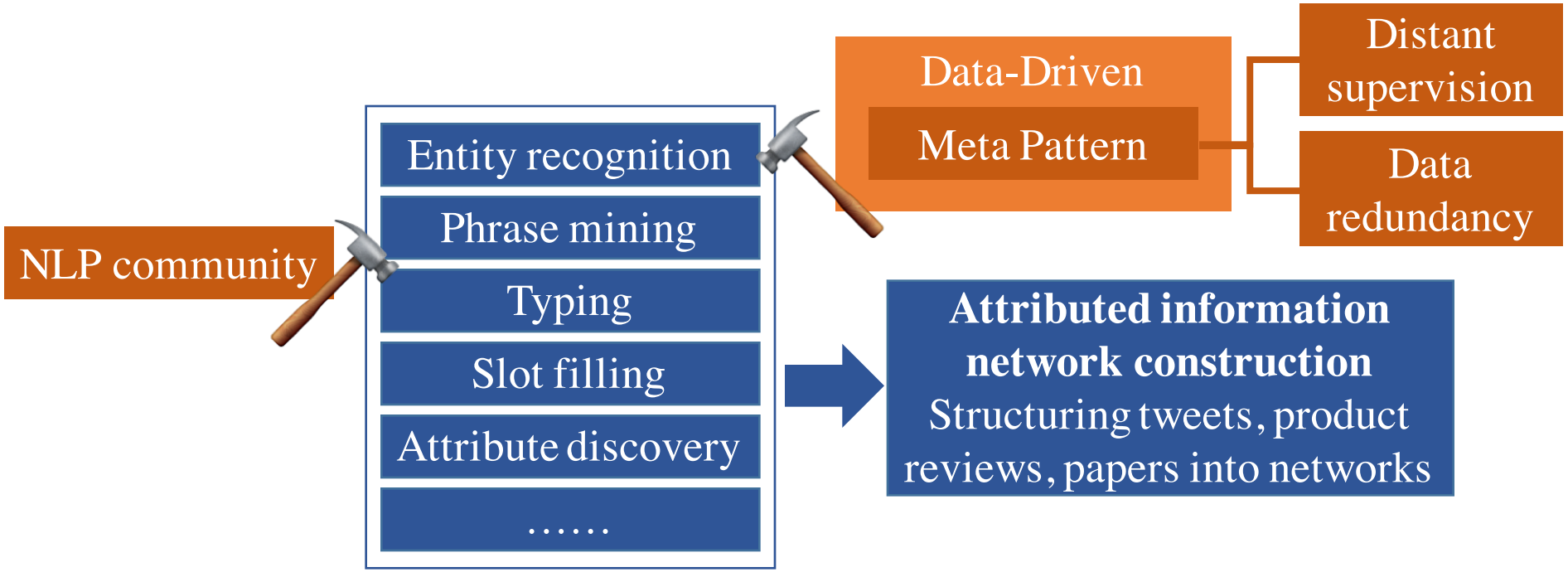
$Enzymes_and_Coenzymes inhibitor $Chemical

$Chemical	$Enzymes_and_Coenzymes
chelerythrine	protein kinase C
fondaparinux	Factor Xa
calphostin C	protein kinase C
bisindolylmaleimide	protein kinase C

$Diagnosis : $Digit +/- $Digit kg/m ($Digit)

$Diagnosis	$Digit $Digit $Digit
BMI	(31.0 , 6.4 , 2)
BMI	(26 , 4 , 2)
body mass index	(27 , 6 , 2)

Meta Pattern: Data-Driven Approaches for NLP Tasks

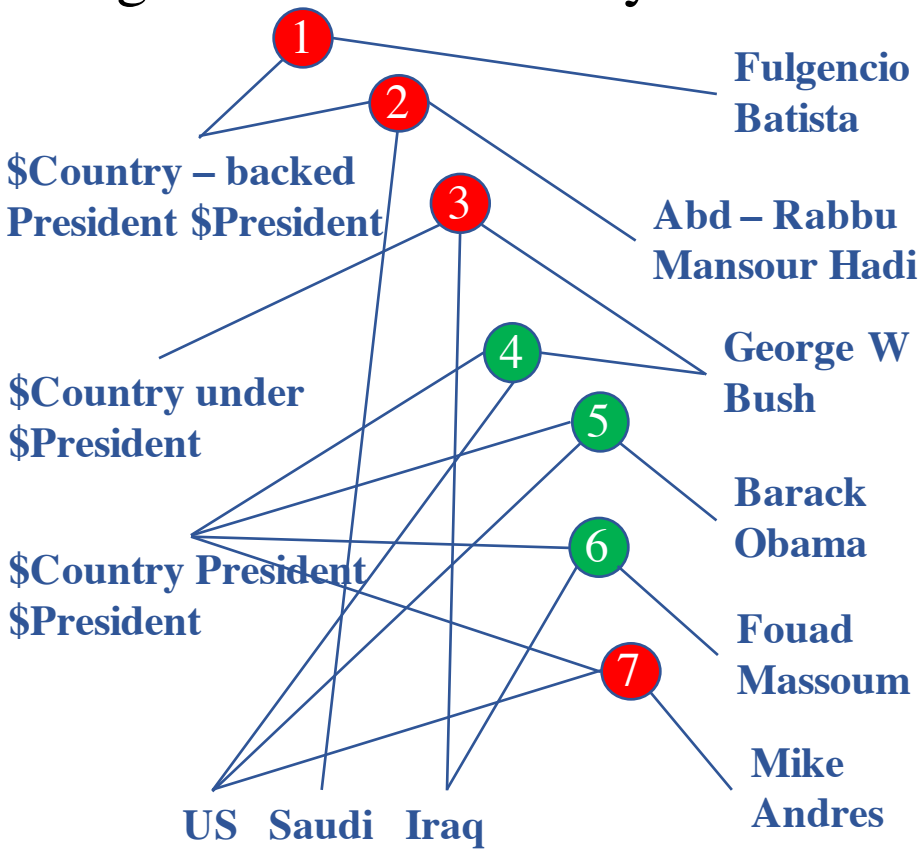


Finding Truth when Structuring

- Find trustworthy facts by modeling "source" reliability

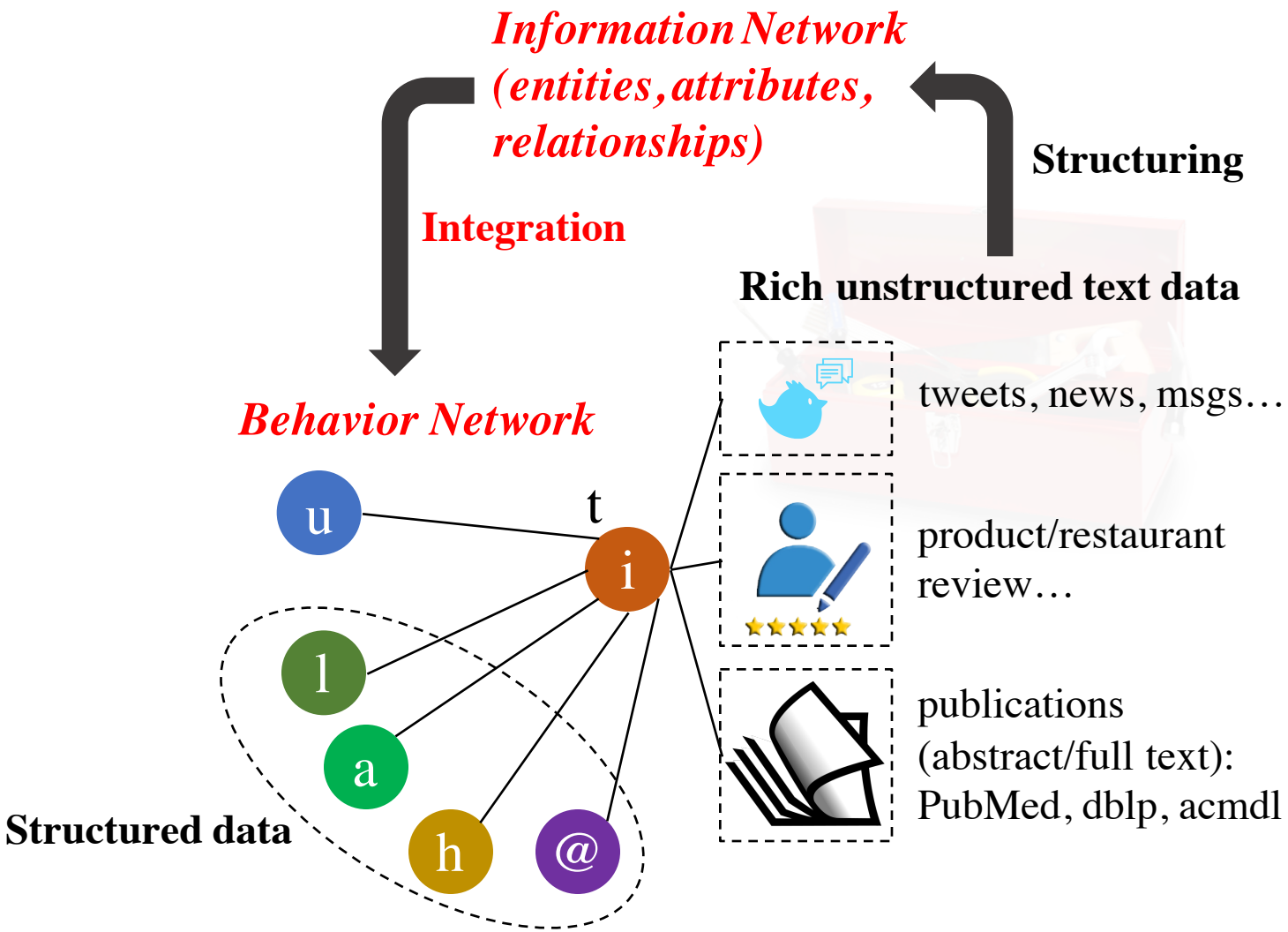
($Country, president, $President) : 0.829

Meta Pattern	Acc. (FP/P)
$Country 's President $President	0.984 (1/61)
President $President of $Country	1.000 (0/24)
$Country 's President $President ,	1.000 (0/16)
" $Country President $President	1.000 (0/7)
…	…
President $President said $Country	0.833 (1/6)
$Country President $President	0.807 (16/83)
$Country , President $President	0.650 (7/20)
$Country - backed President $President	0.500 (3/6)
$Country under $President	0.500 (1/2)



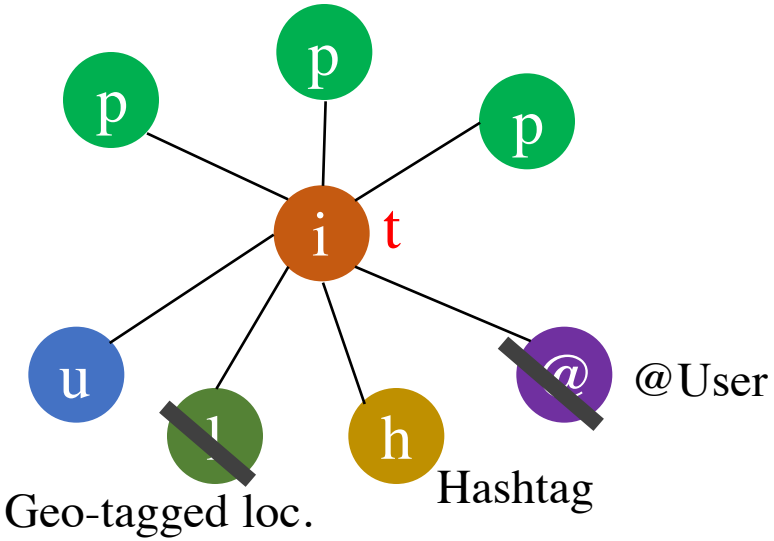
1. …Fidel Castro and his brother Raul led winning a revolution toppling ***US - backed President Fulgencio Batista*** .
2. …control of the country and at reinstating ***Saudi - backed President Abd - Rabbu Mansour Hadi*** .
3. …was profoundly forward - leaning and outspoken about the importance of invading ***Iraq under George W Bush*** .
7. …better delivering on those expectations , " McDonald 's ***US President Mike Andres*** said in the announcement .

Data to Network to Knowledge



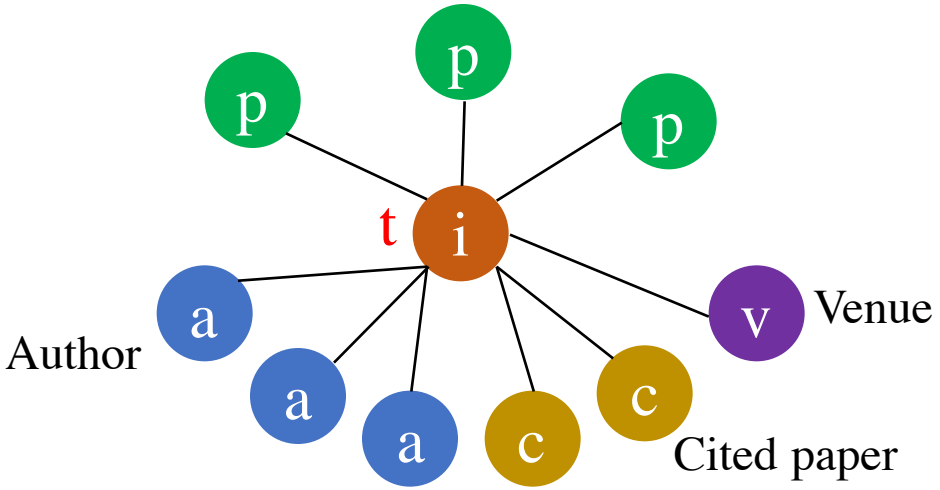
Bring Phrases to Behavior Modeling

- Tweeting behavior
  - Event **summary**



20:03:09 @ebekahwsm
this better be the best halftime show ever in the history of halftimes shows. ever. #SuperBowl

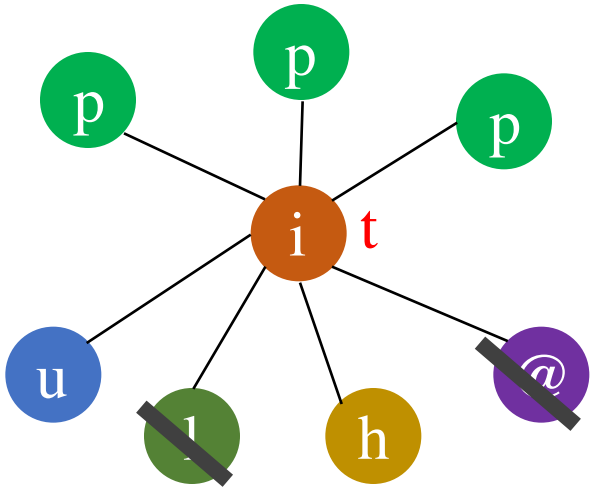
- Paper-publishing behavior
  - Research trend **summary**



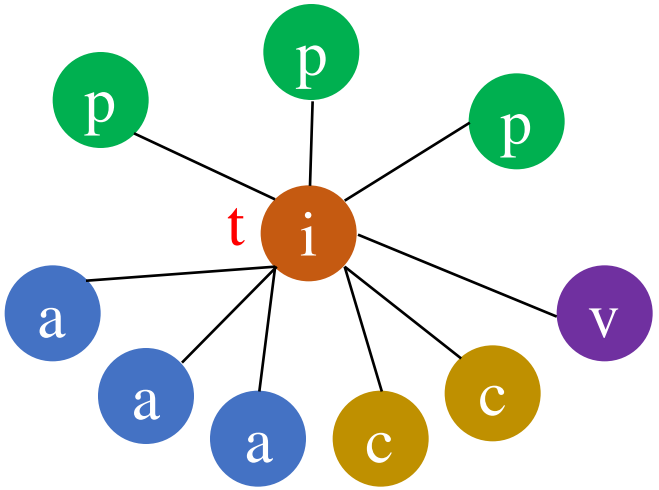
2009 P. Melville, W. Gryc, R. Lawrence, "Sentiment analysis of blogs by combining lexical knowledge with text classification", KDD'09. Refs: p81623, p84395…

Tensor Fails

- Tweeting behavior
  - Event **summary**



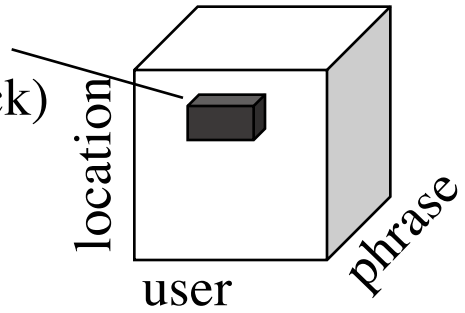
- Paper-publishing behavior
  - Research trend **summary**



Q: How to represent and summarize **dynamic multi-contextual** behaviors?

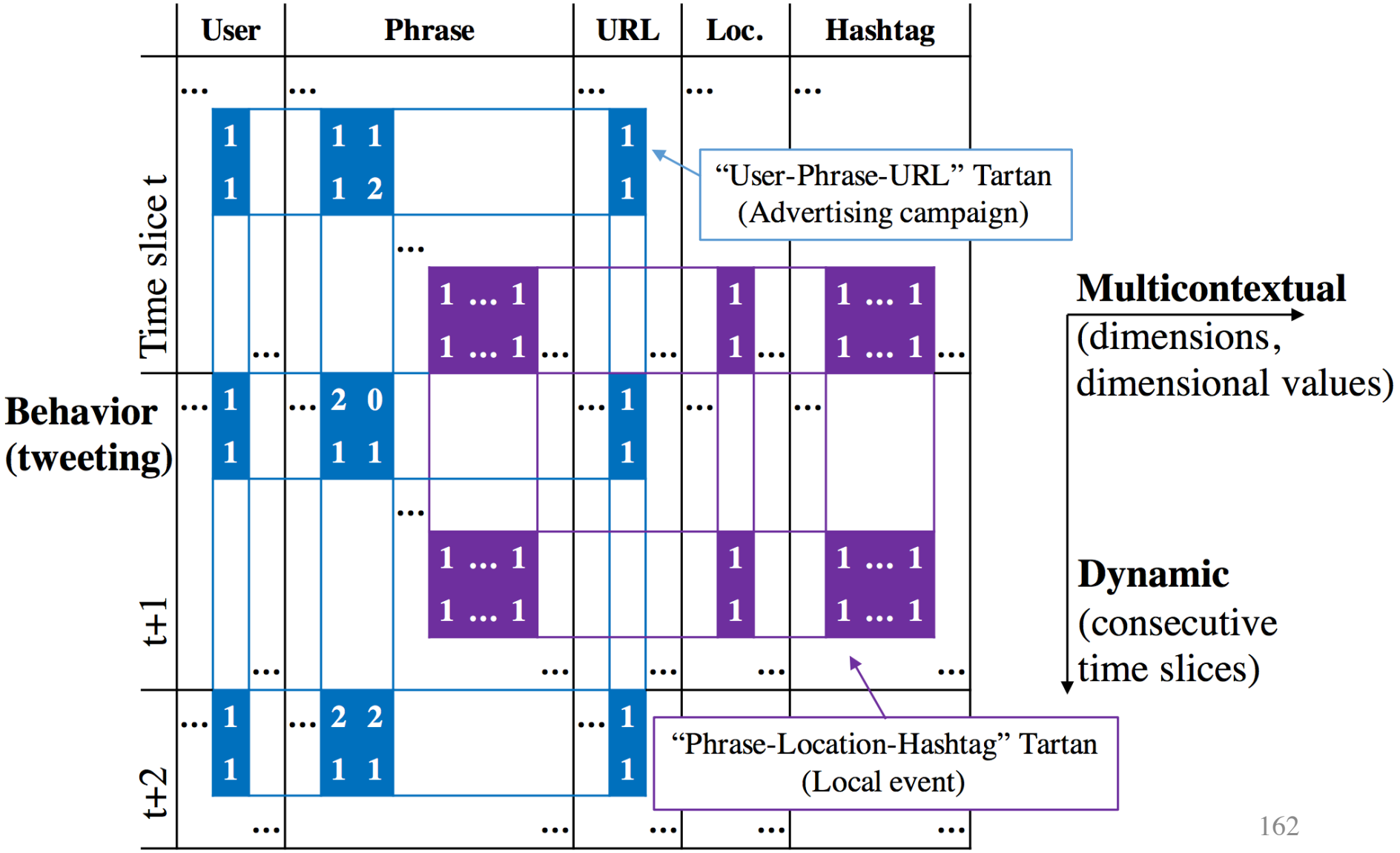
A set of values in dimensions (*one-guaranteed value*, *empty value*, *multi-values*)

summary
(dense block)

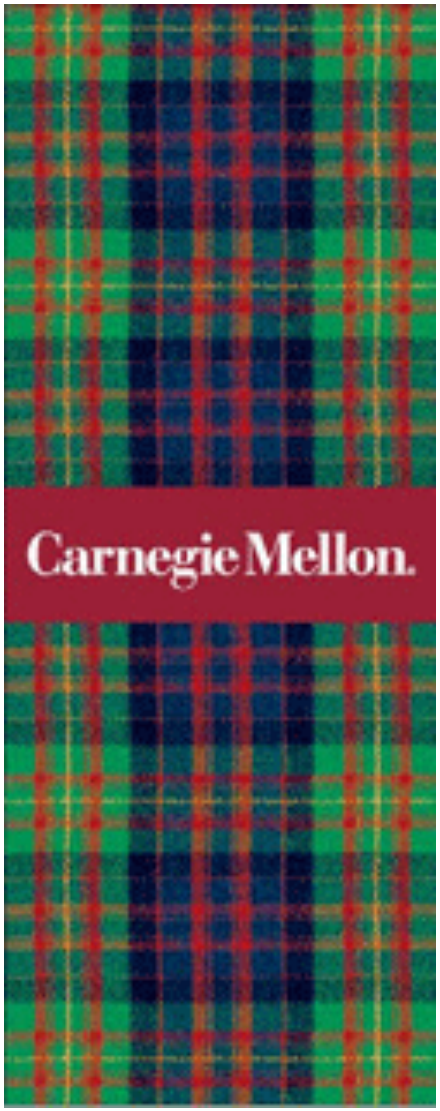


✔ ✘ ✘

Two-Level Matrix and "Tartan"



CMU Tartans


Carnegie Mellon.

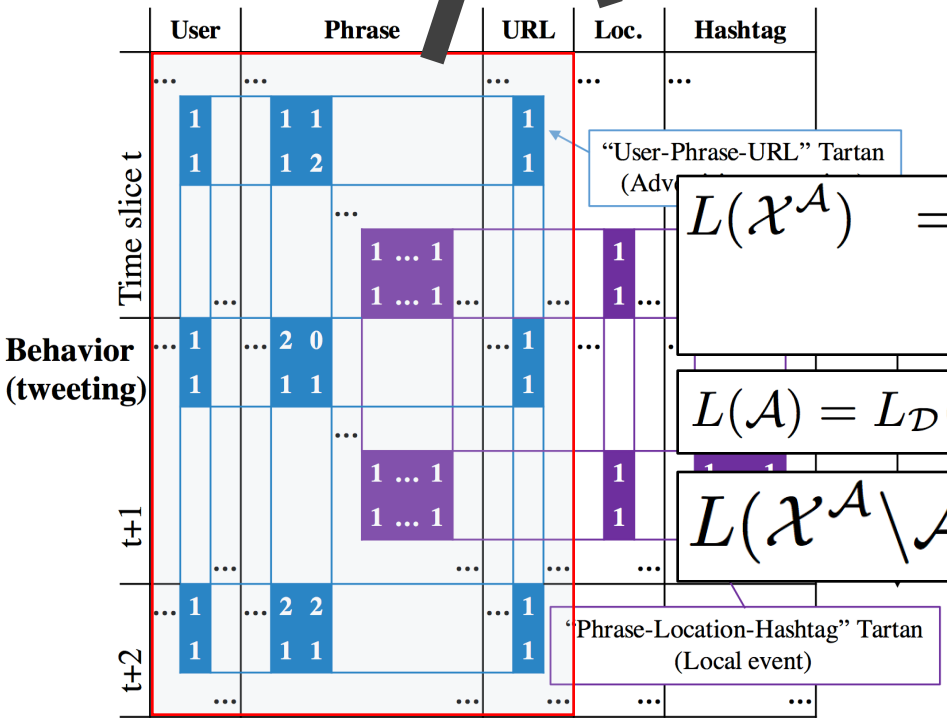

GO TARTANS!

CARNEGIE MELLON UNIVERSITY
PITTSBURGH PENNSYLVANIA 1900

Optimize with MDL Principle

- *Maximize* the number of bits by encoding the Tartan

$$f(\mathcal{A}, \mathcal{X}) = L(\mathcal{X}^{\mathcal{A}}) - L(\mathcal{A}) - L(\mathcal{X}^{\mathcal{A}} \backslash \mathcal{A}).$$

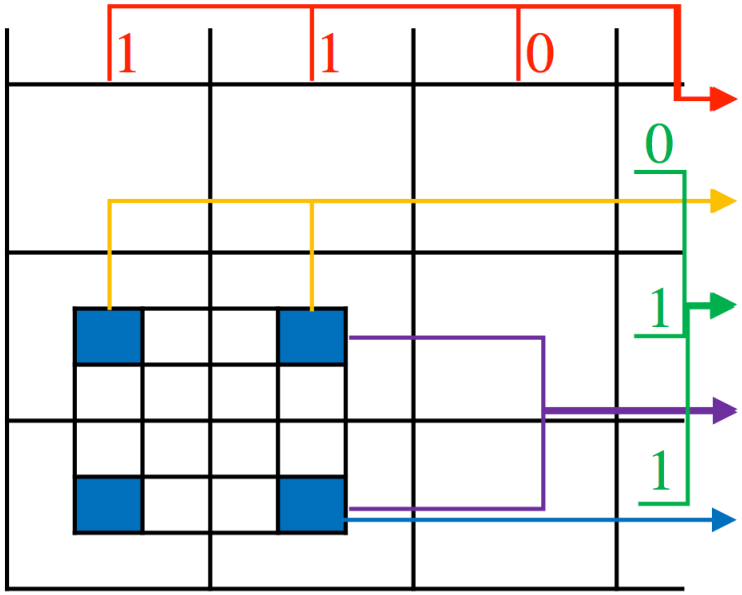


$$L(\mathcal{X}^{\mathcal{A}}) = g(V + C, C) + L_{\mathcal{D}}(\mathcal{A}) + L_{\mathcal{T}}(\mathcal{A}) + \sum_{d \in \mathcal{D}} \log^* N_d + \sum_{t \in \mathcal{T}} \log^* E^{(t)}.$$

$$L(\mathcal{A}) = L_{\mathcal{D}}(\mathcal{A}) + L_{\mathcal{V}}(\mathcal{A}) + L_{\mathcal{T}}(\mathcal{A}) + L_{\mathcal{B}}(\mathcal{A}) + L_{\mathcal{A}}(\mathcal{A}).$$

$$L(\mathcal{X}^{\mathcal{A}} \backslash \mathcal{A}) = g(V + C - v - c, C - c);$$

Encoding Tartan: Dimensions



Encoding the dimensions

Encoding the dimensional values

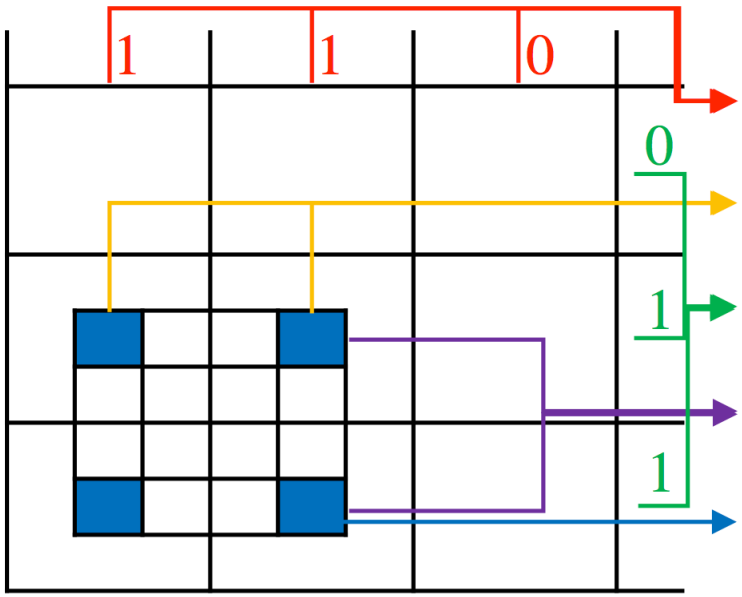
Encoding the time slices

Encoding the behaviors

Encoding the entries in the Tartan

$$H_{\mathcal{D}}(X) = -\sum_{x\in\{0,1\}} P(X=x)\log P(X=x)$$
$$= -\left(\frac{D^{\mathcal{A}}}{D}\log\frac{D^{\mathcal{A}}}{D} + \frac{D-D^{\mathcal{A}}}{D}\log\frac{D-D^{\mathcal{A}}}{D}\right).$$
$$L_{\mathcal{D}}(\mathcal{A}) = \log^* D + \log^* D^{\mathcal{A}} + D\cdot H_D(X)$$
$$= \log^* D + \log^* D^{\mathcal{A}} + g(D, D^{\mathcal{A}}),$$

Encoding Tartan: Dimensional Values



Encoding the dimensions

Encoding the dimensional values

Encoding the time slices

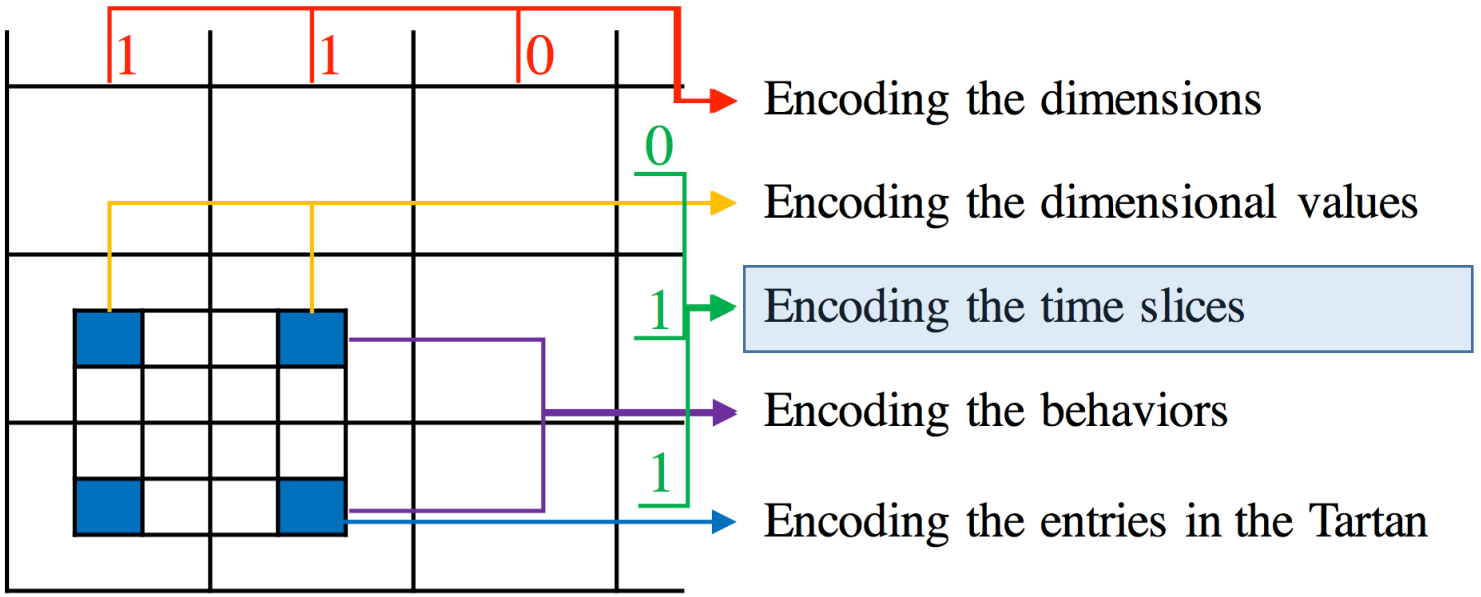
Encoding the behaviors

Encoding the entries in the Tartan

$$H_{\mathcal{V}_d}(X) = -\left(\frac{n_d}{N_d}\log\frac{n_d}{N_d} + \frac{N_d - n_d}{N_d}\log\frac{N_d - n_d}{N_d}\right).$$

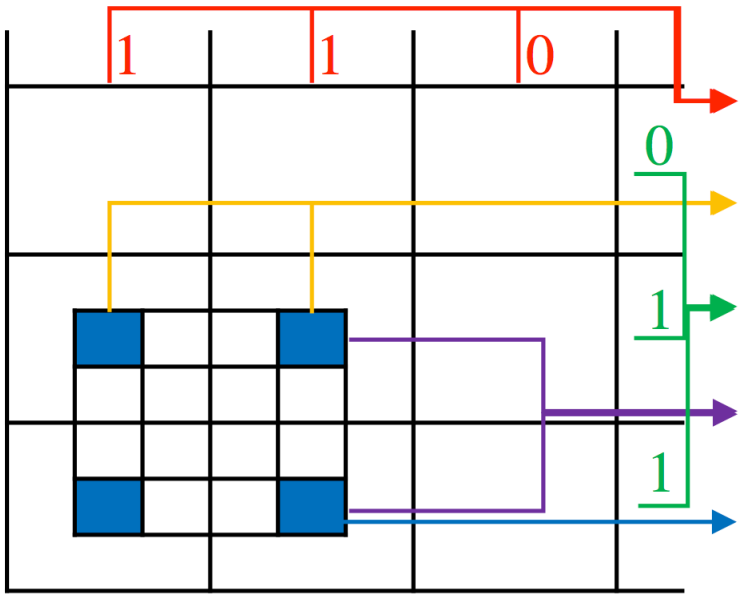
$$L_{\mathcal{V}}(\mathcal{A}) = \sum_{d\in\mathcal{D}}\left(\log^* N_d + \log^* n_d + g(N_d, n_d)\right).$$

Encoding Tartan: Time Slices



$$L_{\mathcal{T}}(\mathcal{A}) = \log^* T + \log^* T^{\mathcal{A}} + \log^* t_{start}$$

Encoding Tartan: Behaviors



Encoding the dimensions

Encoding the dimensional values

Encoding the time slices

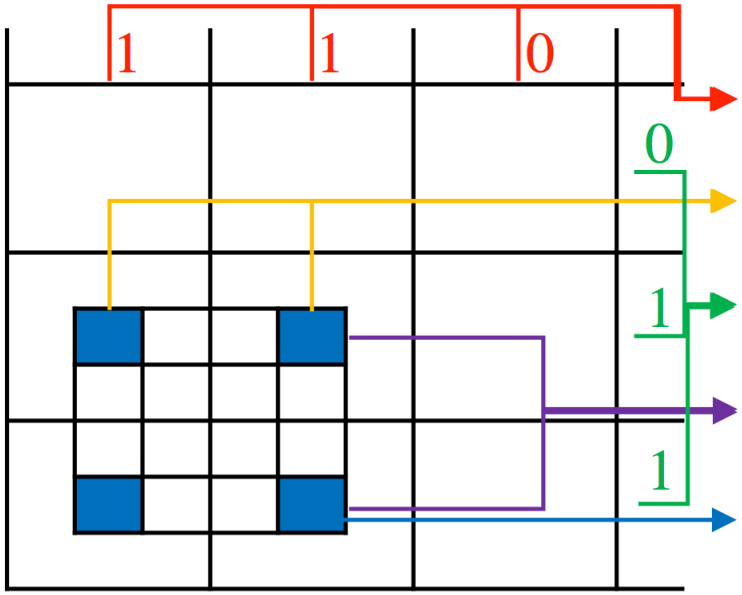
Encoding the behaviors

Encoding the entries in the Tartan

$$H_{\mathcal{B}^{(t)}}(X) = -\left(\frac{e^{(t)}}{E^{(t)}} \log \frac{e^{(t)}}{E^{(t)}} + \frac{E^{(t)}-e^{(t)}}{E^{(t)}} \log \frac{E^{(t)}-e^{(t)}}{E^{(t)}}\right).$$

$$L_{\mathcal{B}}(\mathcal{A}) = \sum_{t \in \mathcal{T}} \left(\log^* E^{(t)} + \log^* e^{(t)} + g(E^{(t)}, e^{(t)})\right).$$

Encoding Tartan: Entries



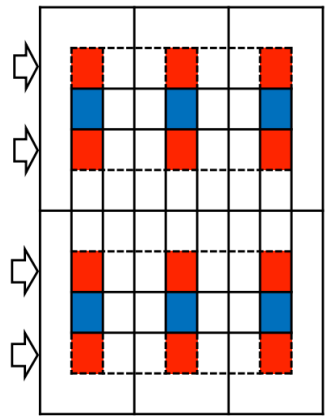
$$v = \left(\sum_{d\in\mathcal{D}} n_d\right)\left(\sum_{t\in\mathcal{T}} e^{(t)}\right).$$

$$c = \sum_{d\in\mathcal{D},t\in\mathcal{T}} \sum_{b\in\mathcal{B}^{(t)},i\in\mathcal{V}_d} \mathcal{X}_d^{(t)}(b,i).$$

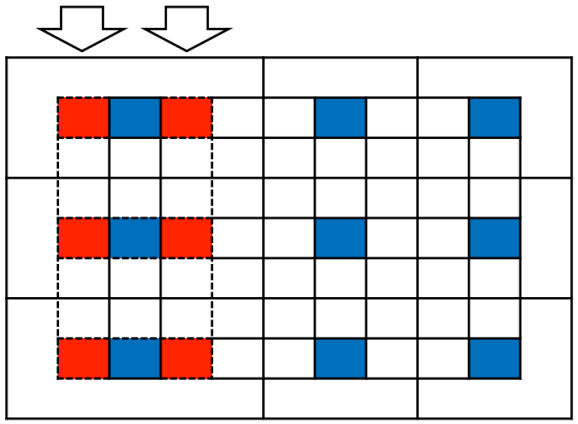
$$H_{\mathcal{A}}(X) = -\left(\frac{c}{v+c}\log\frac{c}{v+c} + \frac{v}{v+c}\log\frac{v}{v+c}\right).$$

$$L_{\mathcal{A}}(\mathcal{A}) = (v+c)H_{\mathcal{A}}(X) = g(v+c,c).$$

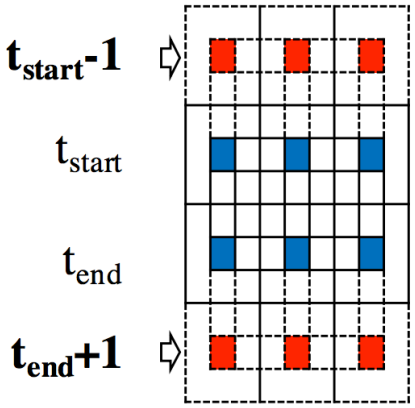
Greedy Search for the Local Optimum



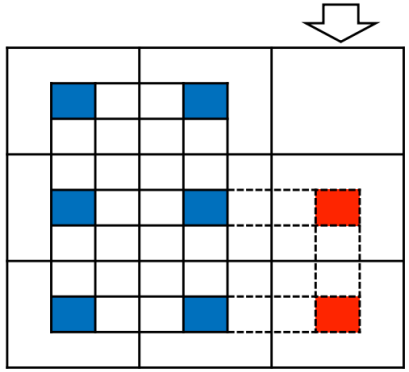
(a) Update the set of behaviors.



(b) Update the set of values.



(c) Update the consecutive time slices.



(d) Update the set of dimensions.

Time complexity:

$$\mathcal{O}(\sum_d N_d \log N_d + \sum_t E^{(t)} \log E^{(t)})$$

Experimental Results

- DM/ML research trend summaries with DBLP data

1997 2000 2003 2006 2009 2012

Author	Venue	Keyword	Cited	#Paper
76 Cheng-xiang Zhai Hui Fang S. Kambhampati	**7** SIGIR VLDB TKDE	**7** "information retrieval" "data integration" "text classification"	**68** p56743[1] p62995 p76869	**32** 2003- 2007

[1] "A language modeling approach to information retrieval"

Venue	Keyword	#Paper
5 ICML NIPS …	**6** "reinforcement learning" "machine learning"	**40** 1997- 2002

Author	Venue	Cited	#Paper
6 Jiawei Han Xifeng Yan	**1** SIG- MOD	**1** p76095[2]	**22** 2004- 2010

[2] "Frequent subgraph discovery"

Venue	Keyword	#Paper
3 ICDM AAAI TKDE	**1** "anomaly detection"	**25** 2005- 2013

Author	Venue	Keyword	#Paper
27 C. Faloutsos J. Pei P. S. Yu X. Lin C. Aggarwal…	**6** KDD ICDM ICDE TKDE …	**12** "large graphs" "data streams" "evolving data" "evolving graphs" …	**70** 2006- 2013

Author	Venue	Keyword	Cited	#Paper
12 Ryen White Hang Li Tie-Yan Liu Zhaohui Zheng…	**5** SIGIR WWW WSDM CIKM…	**3** "web search" "click-through data" "sponsored search"	**12** p82630[3] p116290 p103899 p106191…	**32** 2006- 2013

[3] "Optimizing search engines using clickthrough data"

Author	Venue	Keyword	#Paper
8 Qiang Yang Dou Shen Sinno Pan…	**3** KDD PAKDD AAAI	**6** "transfer learning" "data mining" "localization models"	**17** 2007- 2010

Experimental Results

- Event summaries with Super Bowl 2013 tweets

16:30 – 17:00

16:30:31 My prediction Ravens 34 Niners 31
16:30:57 Ready for the big game :D, my prediction 24-20 SF #SuperBowl
16:31:14 My prediction for superbowl.. 48.. Jets over Bears 17-13 Mark Sanchez MVP
16:32:24 I predict Baltimore Ravens will win 27 to 24 or 25 or 26. Basically it will be a close game.

"my prediction"

user	phrase	hashtag	URL	3,397 tweets
(3,325)	226	(0)	(0)	

Tartan #1: (1 dim) 16:30-17:30

17:30 – 18:00

17:30:51 RT @LMAOTWITPICS: Make Your Prediction. Retweet For 49ers http://t.co/KKksEist
17:31:01 RT @LMAOTWITPICS: Make Your Prediction. Retweet For 49ers http://t.co/KKksEist
17:31:16 RT @LMAOTWITPICS: Make Your Prediction. Retweet For 49ers http://t.co/KKksEist
17:31:19 RT @LMAOTWITPICS: Make Your Prediction. Retweet For 49ers http://t.co/KKksEist

"make your prediction"

user	phrase	RT @user	URL	196 tweets
(196)	4	1	1	

Tartan #2: (3 dims) 17:00-18:00

18:00 – 18:30

18:55:03 RT @49ers: Kaepernick is sacked on 3rd and goal. #49ers K David Akers makes 36-yard FG. Baltimore leads 7-3 with 3:58 left in 1st Qtr. #SB47
18:55:04 RT @49ers: Kaepernick is sacked on 3rd and goal. #49ers K David Akers makes 36-yard FG. Baltimore leads 7-3 with 3:58 left in 1st Qtr. #SB47
18:55:44 RT @Ravens: David Akers is good from 36 yards to make the score 7-3 Ravens. Nice job by the defense to tighten up in the red zone.

"7-3", "1st Qtr"

user	phrase	RT @user	URL	215 tweets
(213)	21	3	(0)	

Tartan #3: (2 dims) 18:30-19:30

19:00 – 19:30

20:20:01 RT @ExtraGrumpyCat: No Superbowl halftime show will ever surpass this. http://t.co/0VSy7Cv6
20:20:02 RT @WolfpackAlan: No Superbowl halftime show will ever surpass this. http://t.co/6BlloPXs
20:20:04 RT @ExtraGrumpyCat: No Superbowl halftime show will ever surpass this. http://t.co/0VSy7Cv6
20:20:05 RT @WolfpackAlan: No Superbowl halftime show will ever surpass this. http://t.co/6BlloPXs

"halftime show"

user	phrase	RT @user	URL	617 tweets
(617)	11	4	4	

Tartan #4: (3 dims) 20:00-21:00

20:00 – 20:30

20:20:47 (Manhattan, NY)..and every one of those girls took #ballet #Beyonce #superbowl
20:22:01 (New York, NY) I have the biggest lady boner for Beyonce #BeyonceBowl #DestinyBowl #DestinysChild #SuperBowl
20:24:32 (Manhattan, NY) No one can ever top that performance by Beyonce. EVER. #Beyonce #superbowl #halftimeshow

"beyonce", #beyonce, #superbowl, #DestinysChild

location	phrase	hashtag	URL	166 tweets
2	55	17	(0)	

Tartan #5: (3 dims) 20:00-21:00

21:00 – 21:30

21:44:42 Ahora si pff #49ers 23-28 #Ravens
21:44:44 Baltimore #Ravens 28-23 San Francisco #49ers
21:44:50 FG Akers #49ers 23-28 #Ravens 3Q 3:10 #SuperBolwXLVII #SuperBowl #NFL

"28-23", #49ers, #Ravens

user	phrase	hashtag	URL	653 tweets
(650)	69	11	(0)	

Tartan #6: (2 dims) 21:00-22:00

22:00

22:42:27 Congratulations Ravens!!!!
22:42:43 Congratulations Ray Lewis and the Ravens.
22:42:43 Game over.! Ravens won ray got his retirement ring now all y'all boys and girls go to sleep .!
22:42:52 "@LetThatBoyTweet: Game over. Ravens win the Super Bowl."

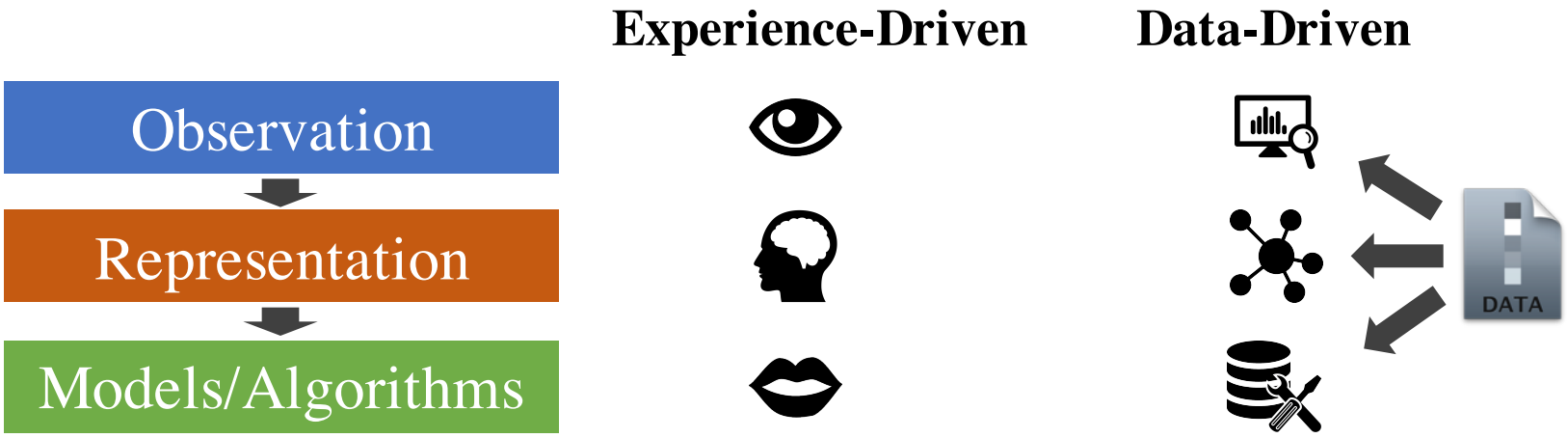
"congratulations", "game over"

user	phrase	hashtag	URL	1,950 tweets
(1942)	248	(0)	(0)	

Tartan #7: (1 dim) 22:00-23:30

Summary

- Structuring text into heterogeneous information networks
- **Observations, Representations, Models**
  - **ToPMine/SegPhrase:** Quality phrase mining
  - **ClusType:** Entity recognition and typing
  - **MetaPAD:** Data-driven automatic attribute discovery for attributed network construction
    - Integrating text mining techniques
    - **Meta Pattern** Mining
- Integrating phrases into behavioral analysis
- **Observations, Representations, Models**
  - **CatchTartan:** Dynamic multicontextual. Tensor fails.

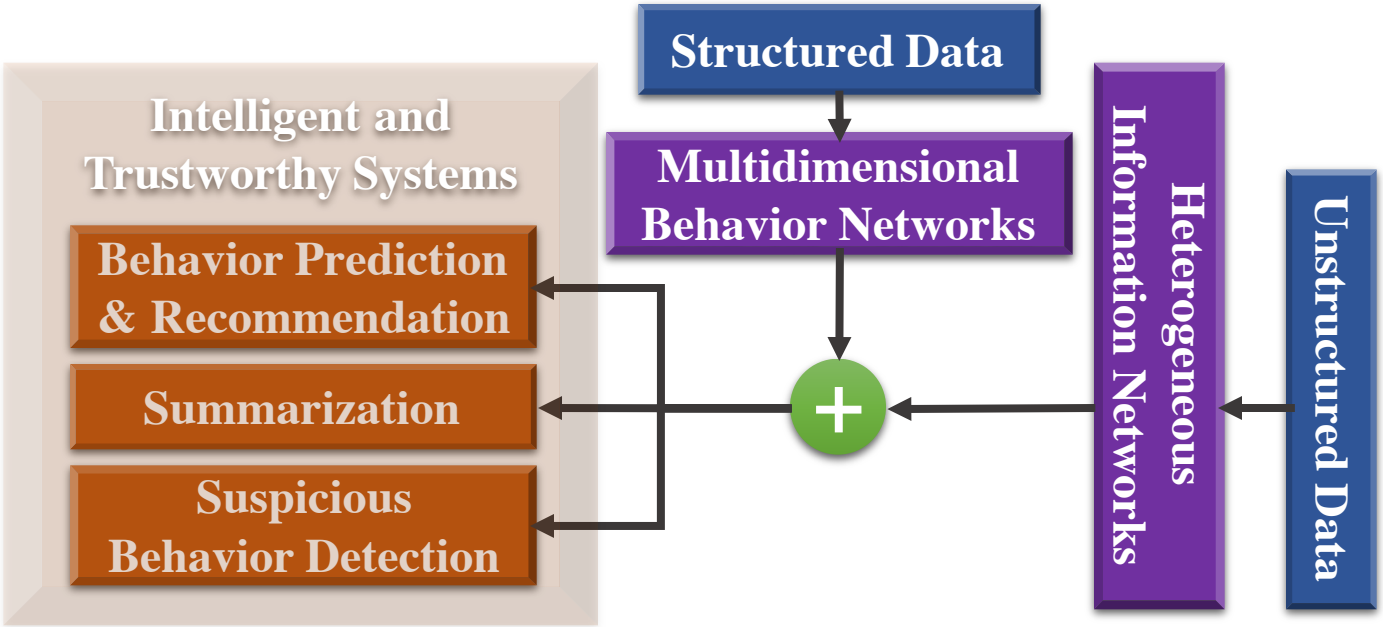


Conclusion

Data-Driven Behavioral Analytics

Data-Driven Behavioral Analytics

- Mining **behavior networks** with **social and spatiotemporal contexts** to support intelligent and trustworthy systems
  - Mining for **behavior prediction and recommendation**
  - Mining for **suspicious behavior detection**
- Structuring behavioral content and integrating behavioral analysis with **information networks**



Acknowledgement

NSF
NSFC
National Natural Science Foundation of China
Carnegie Mellon University
Microsoft Research
微软亚洲研究院
Tencent 腾讯

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Thank you!

Data-Driven Behavioral Analytics: Observations, Representations and Models