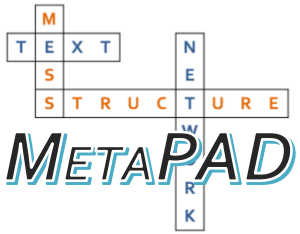
Data-Driven Behavioral Analytics with Networks



Meng Jiang
University of Notre Dame

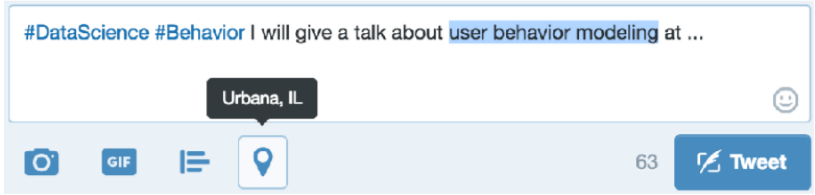
http://www.meng-jiang.com

Behavior and "Behavior Networks"

Interaction of individuals with themselves and with their environment. —Wikipedia

Social behaviors

Tweeting behaviors



Paper-publishing behaviors

Meng Jiang, **Christos Faloutsos**, and **Jiawei Han**. "CatchTartan: **Representing** and **Summarizing Dynamic Behaviors**." In **SIGKDD 2016**.

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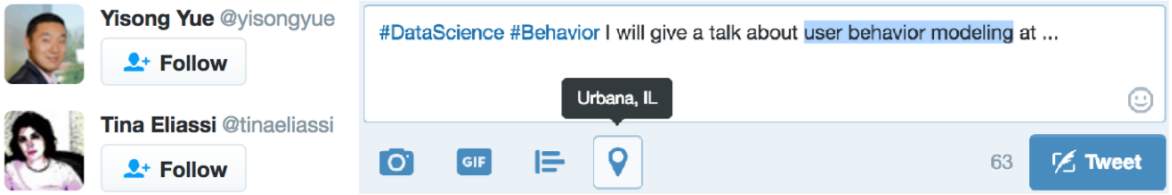
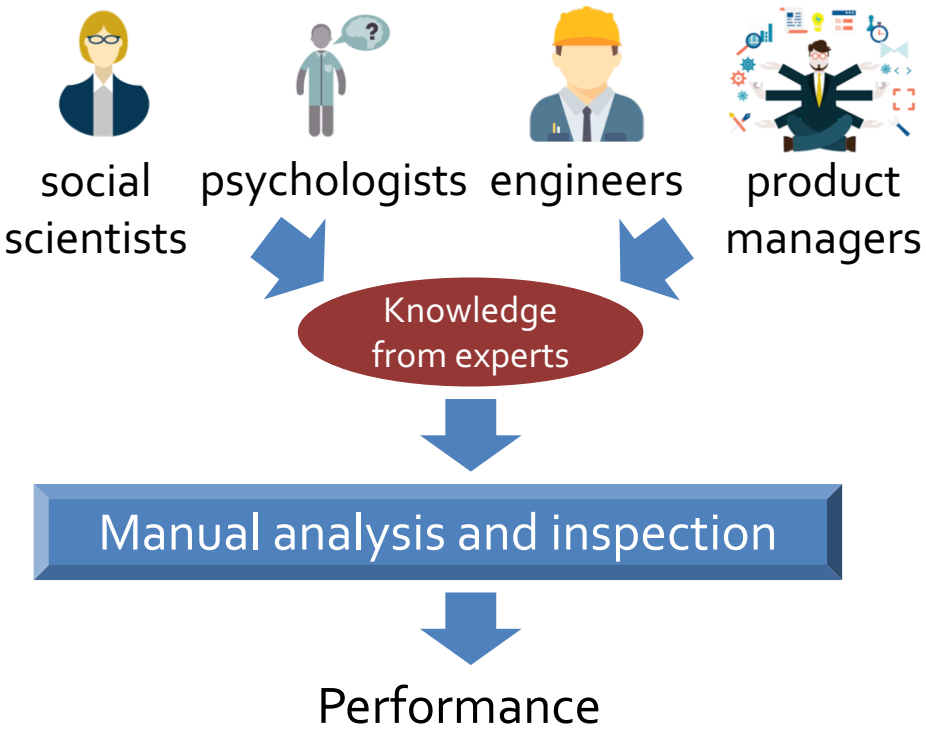


Paper-publishing behaviors

Meng Jiang, **Christos Faloutsos**, and **Jiawei Han**. "CatchTartan: **Representing** and **Summarizing Dynamic Behaviors**." In **SIGKDD 2016**.

Applications: prediction, recommendation, fraud detection, spam detection…

Data-Driven Behavioral Analysis



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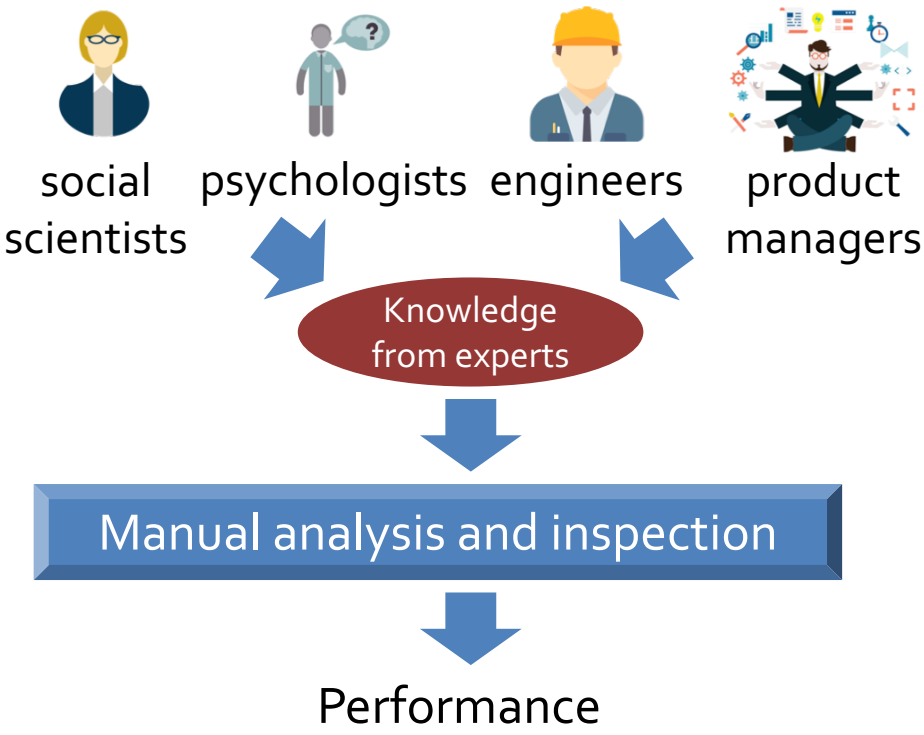


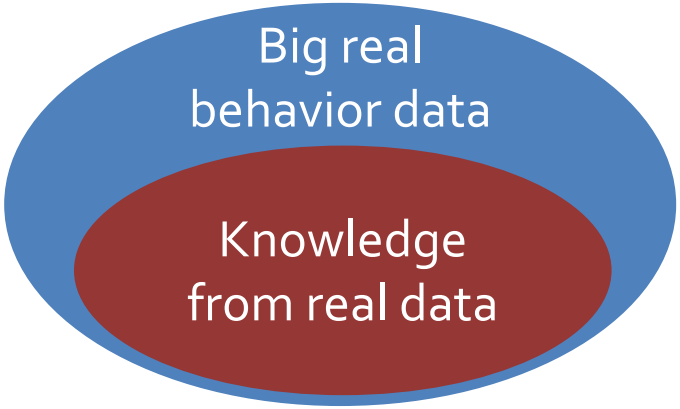
Data-Driven Behavioral Analysis

social scientists | psychologists | engineers | product managers

Knowledge from experts

Manual analysis and inspection

Performance



Computational models

Performance

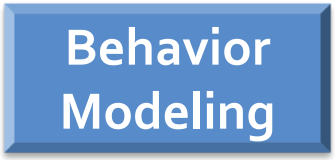
Data, knowledge, intelligence, and trustworthiness.

(User behavior modeling)

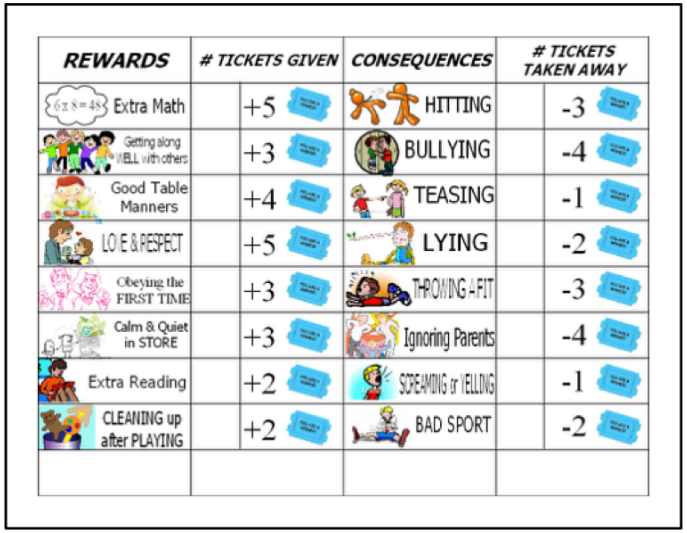
Basic Research Areas

- 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

Research Topics in Behavior Modeling



Research Topics in Behavior Modeling

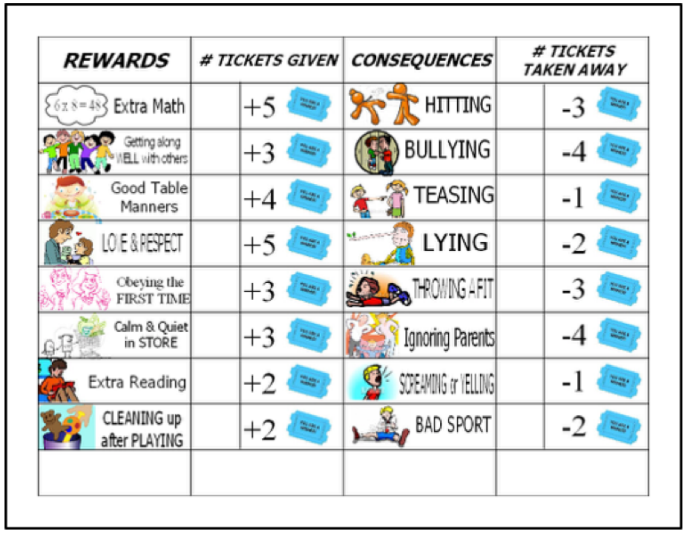


REWARDS	# TICKETS GIVEN	CONSEQUENCES	# TICKETS TAKEN AWAY
Extra Math	+5	HITTING	-3
Getting along WELL with others	+3	BULLYING	-4
Good Table Manners	+4	TEASING	-1
LOVE & RESPECT	+5	LYING	-2
Obeying the FIRST TIME	+3	THROWING A FIT	-3
Calm & Quiet in STORE	+3	Ignoring Parents	-4
Extra Reading	+2	SCREAMING or YELLING	-1
CLEANING up after PLAYING	+2	BAD SPORT	-2

1. Behavior intentions

Behavior Modeling

Research Topics in Behavior Modeling



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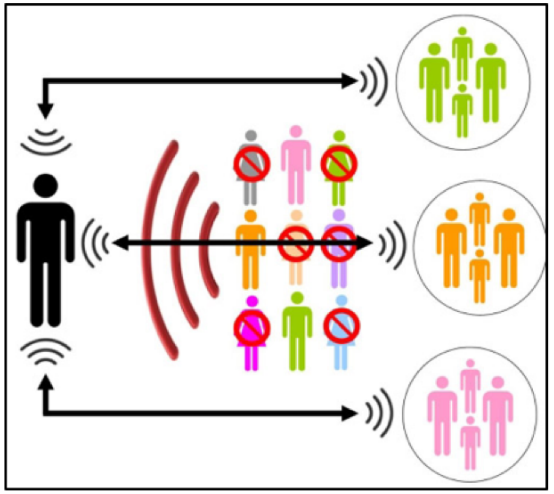
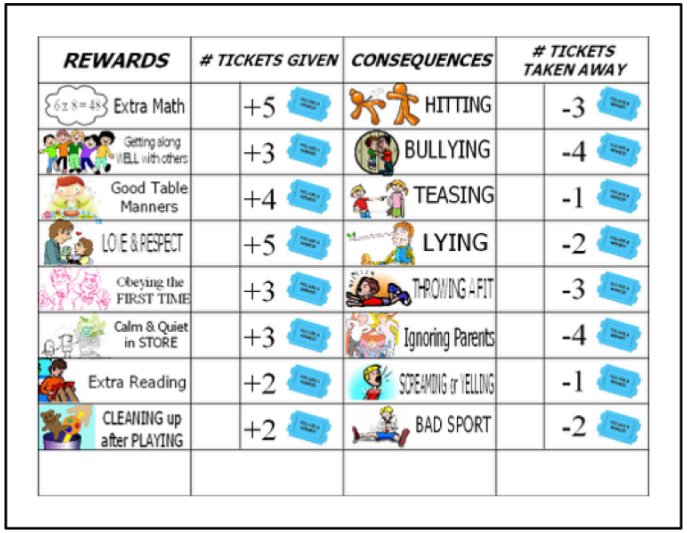
1. Behavior intentions

2. Social contexts

Behavior Modeling



Research Topics in Behavior Modeling



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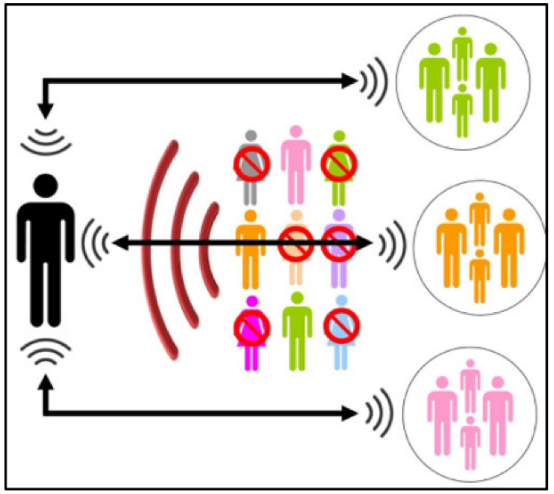
1. Behavior intentions

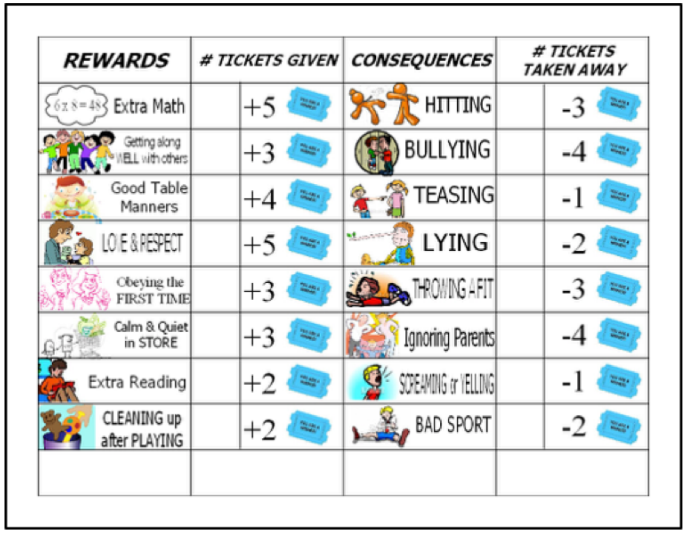


2. Social contexts

Behavior Modeling

3. Spatiotemporal contexts

Research Topics in Behavior Modeling



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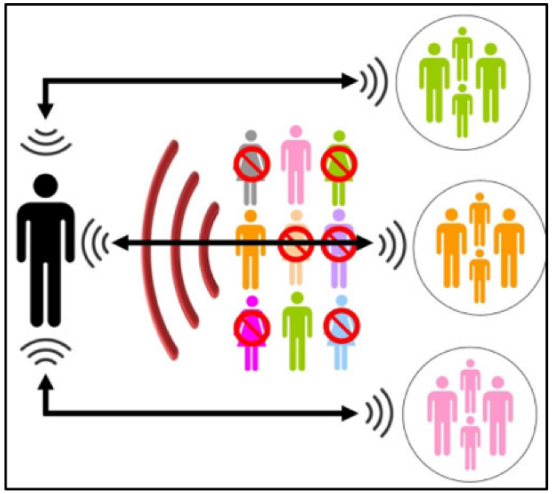
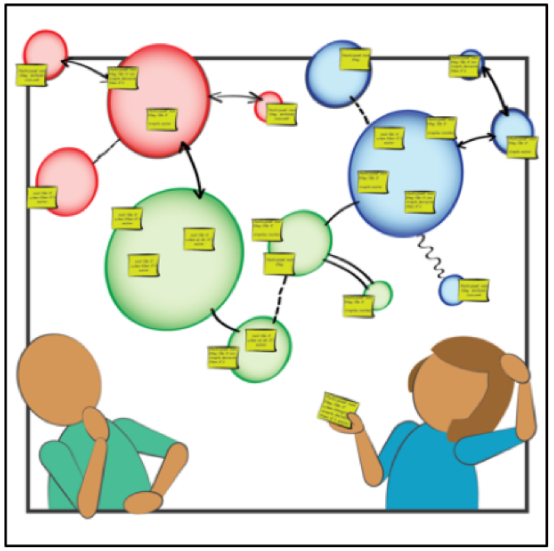


2. Social contexts

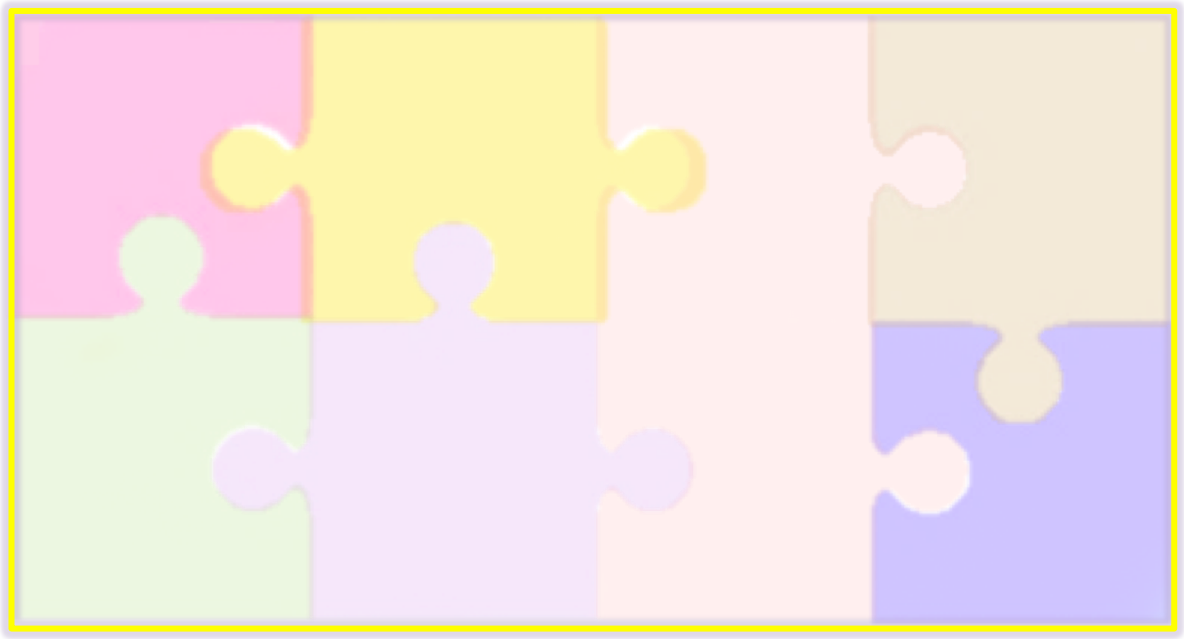
Behavior Modeling

3. Spatiotemporal contexts

4. Behavior content



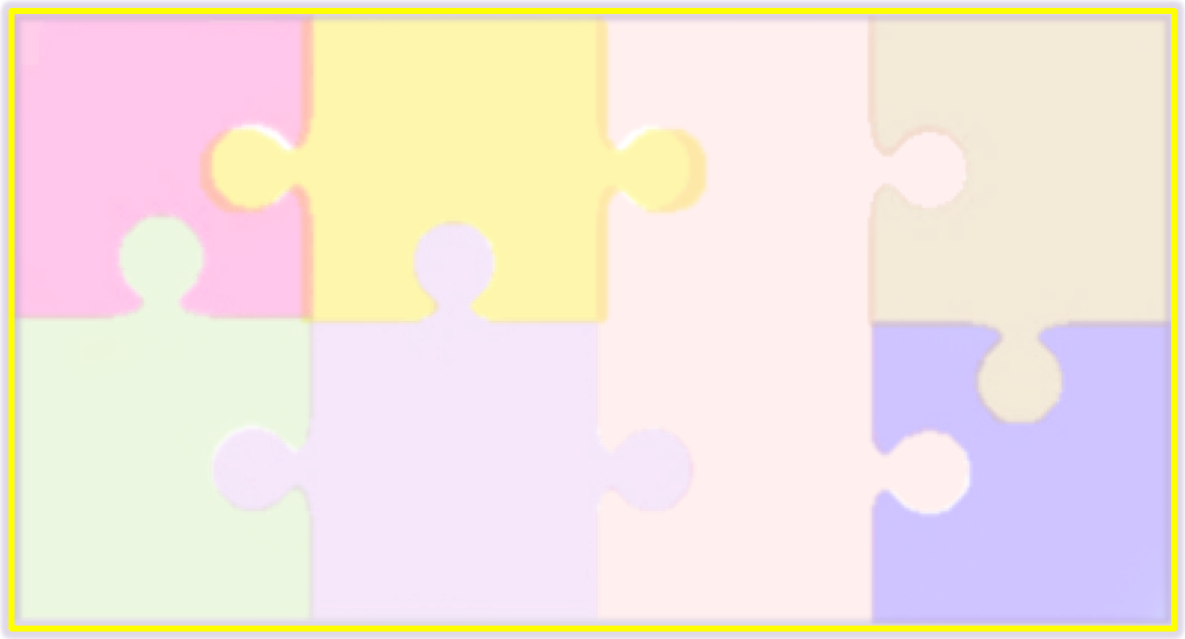
My Research "Area"



My Research "Area"

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection



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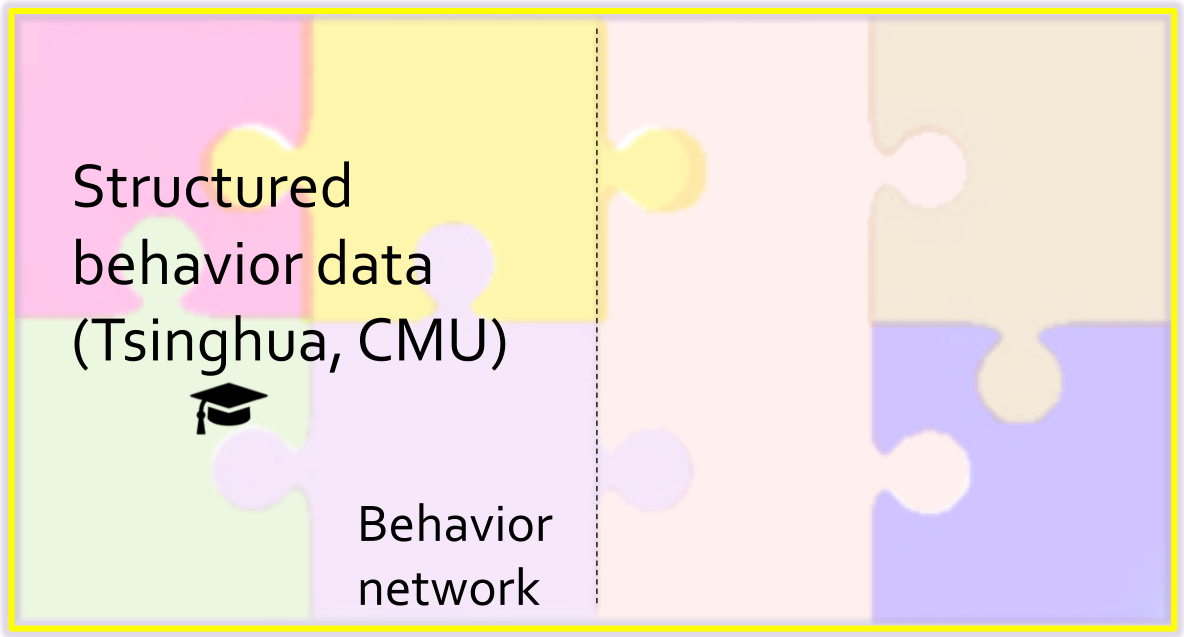

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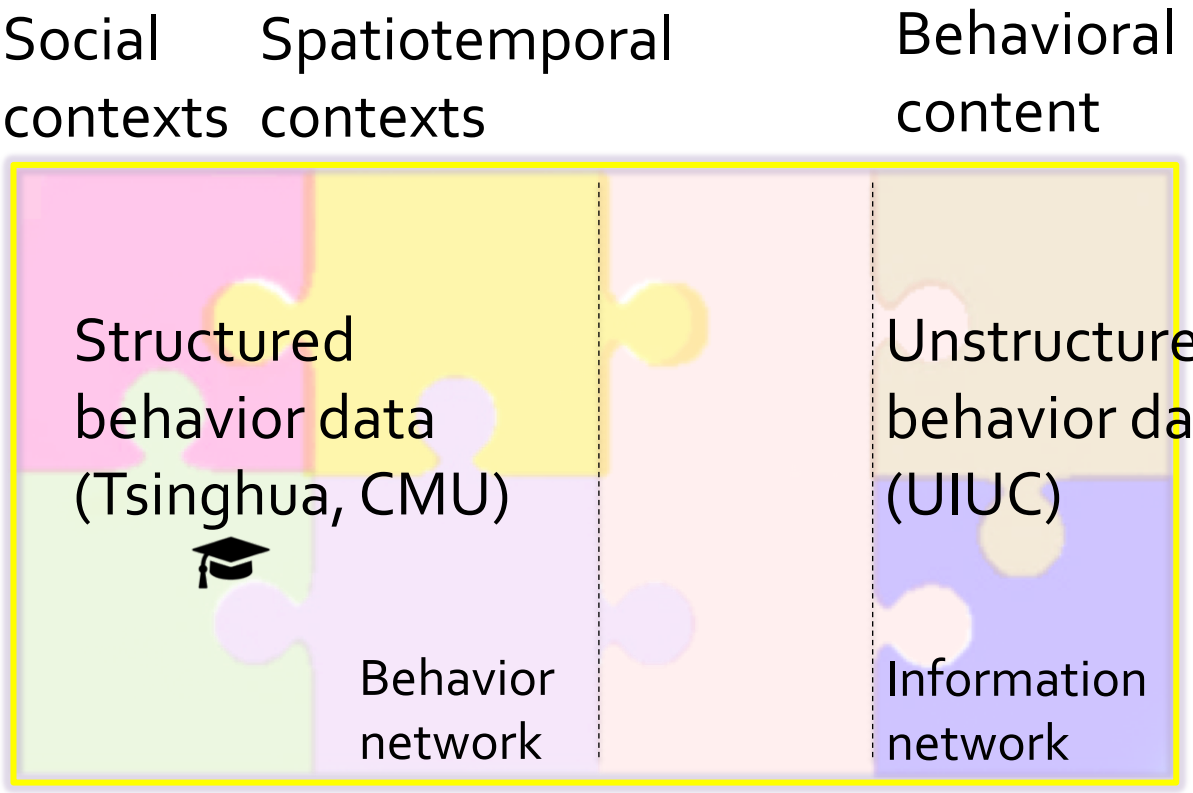

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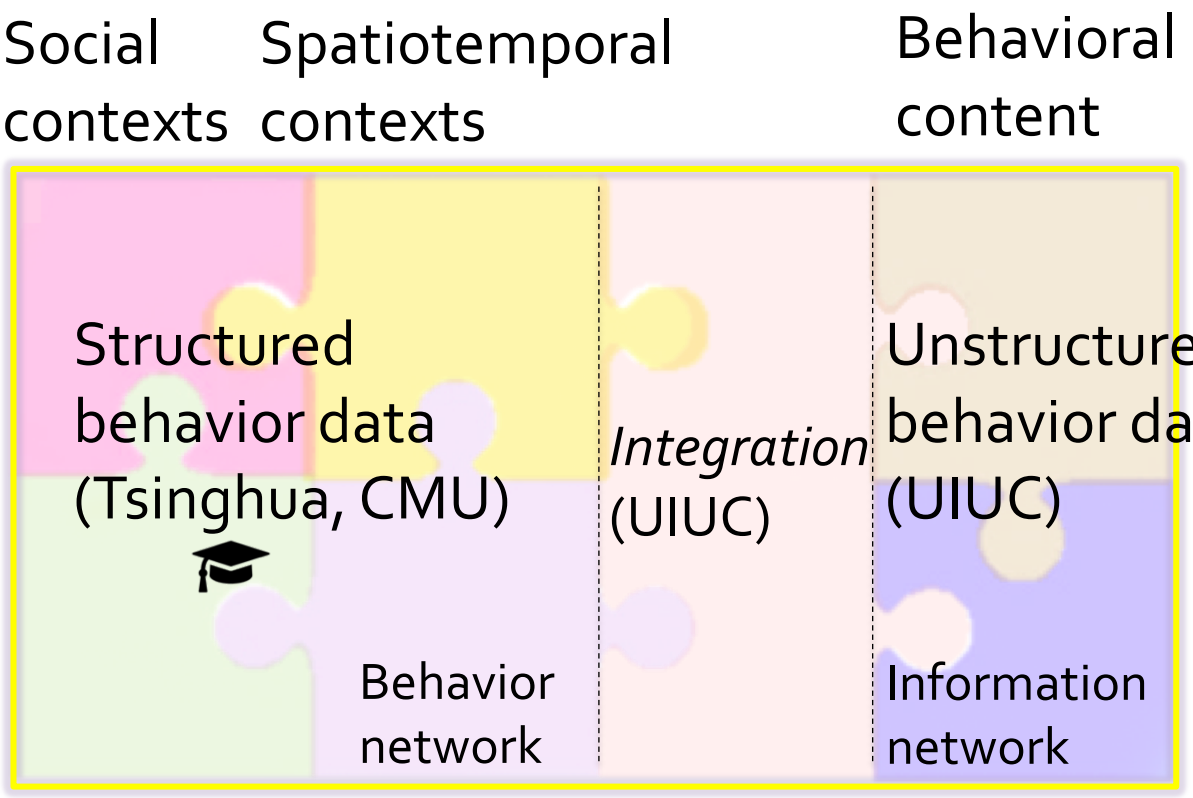

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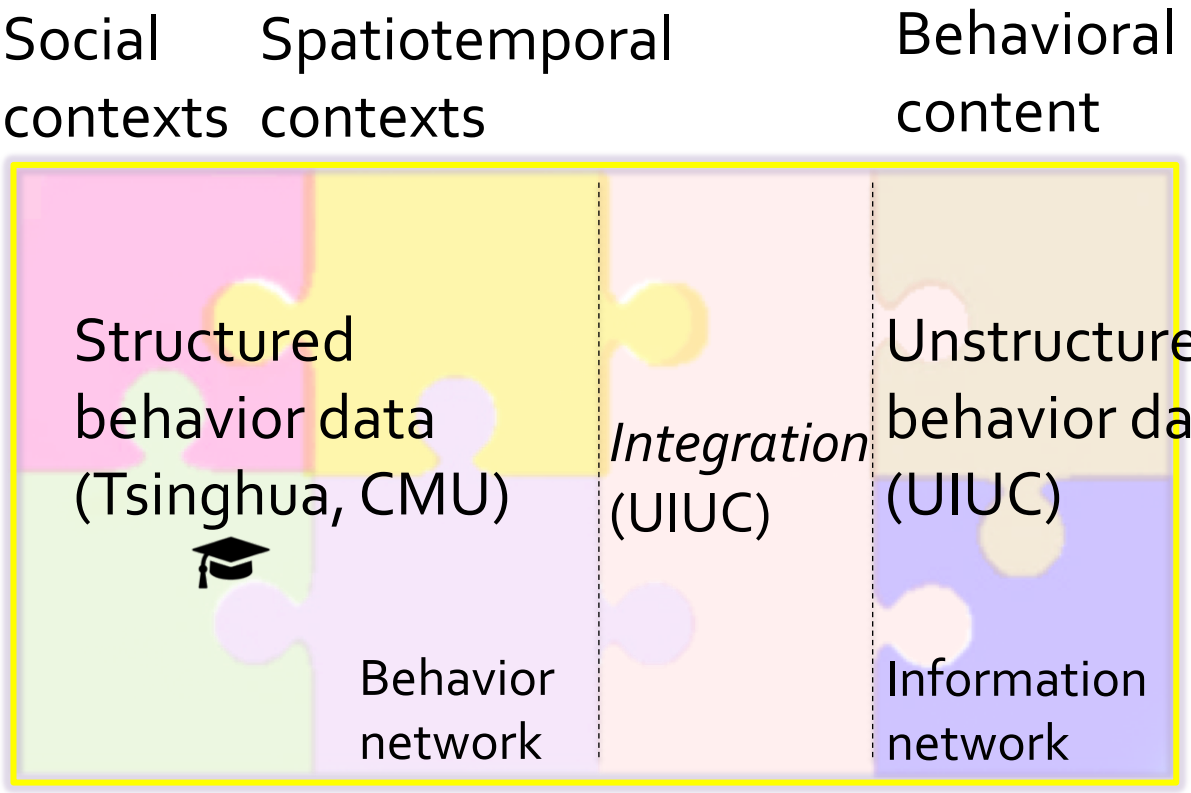


Ask good **Q**uestions.

Find good Data-Driven **M**ethodologies.

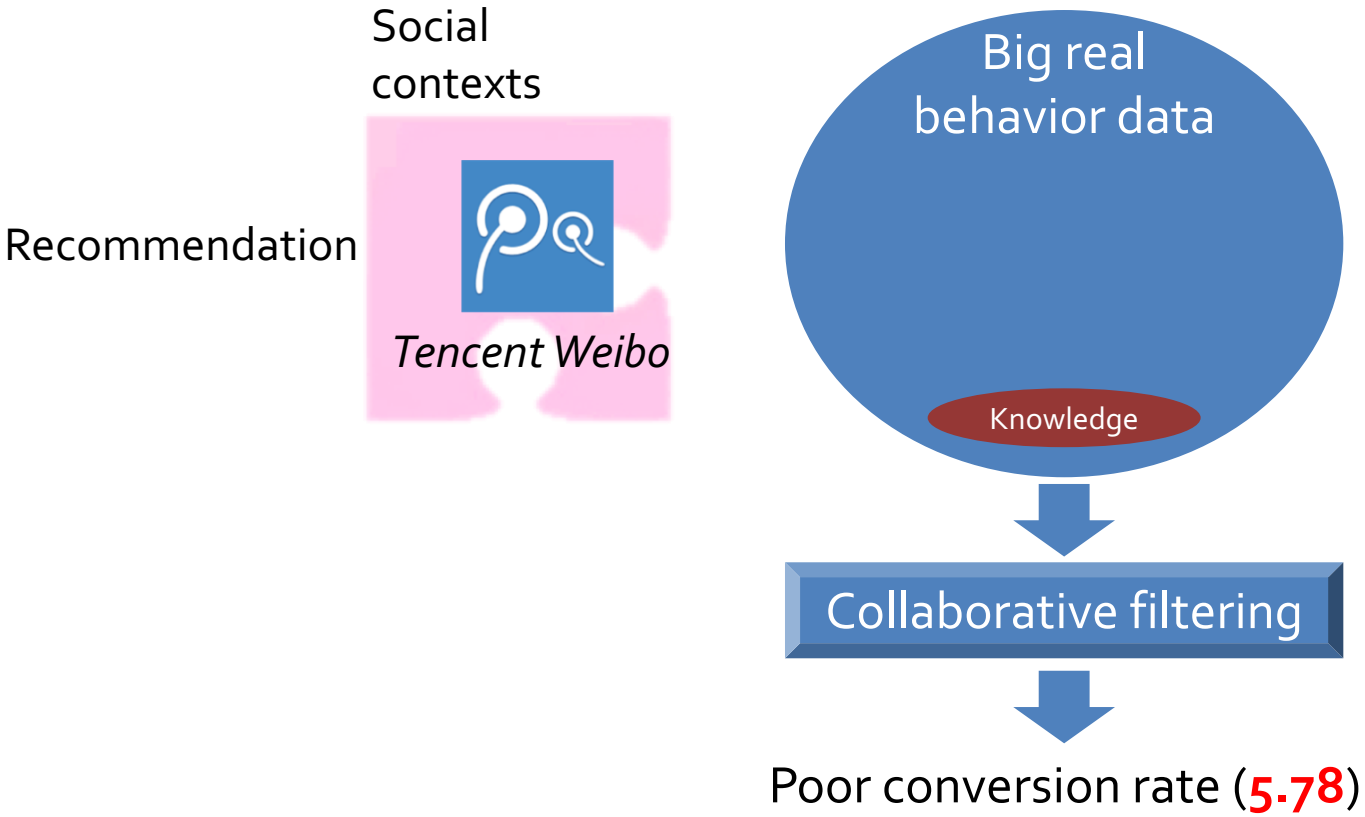
Propose good **S**olutions.

Q1: A Social Recommender System

Social contexts

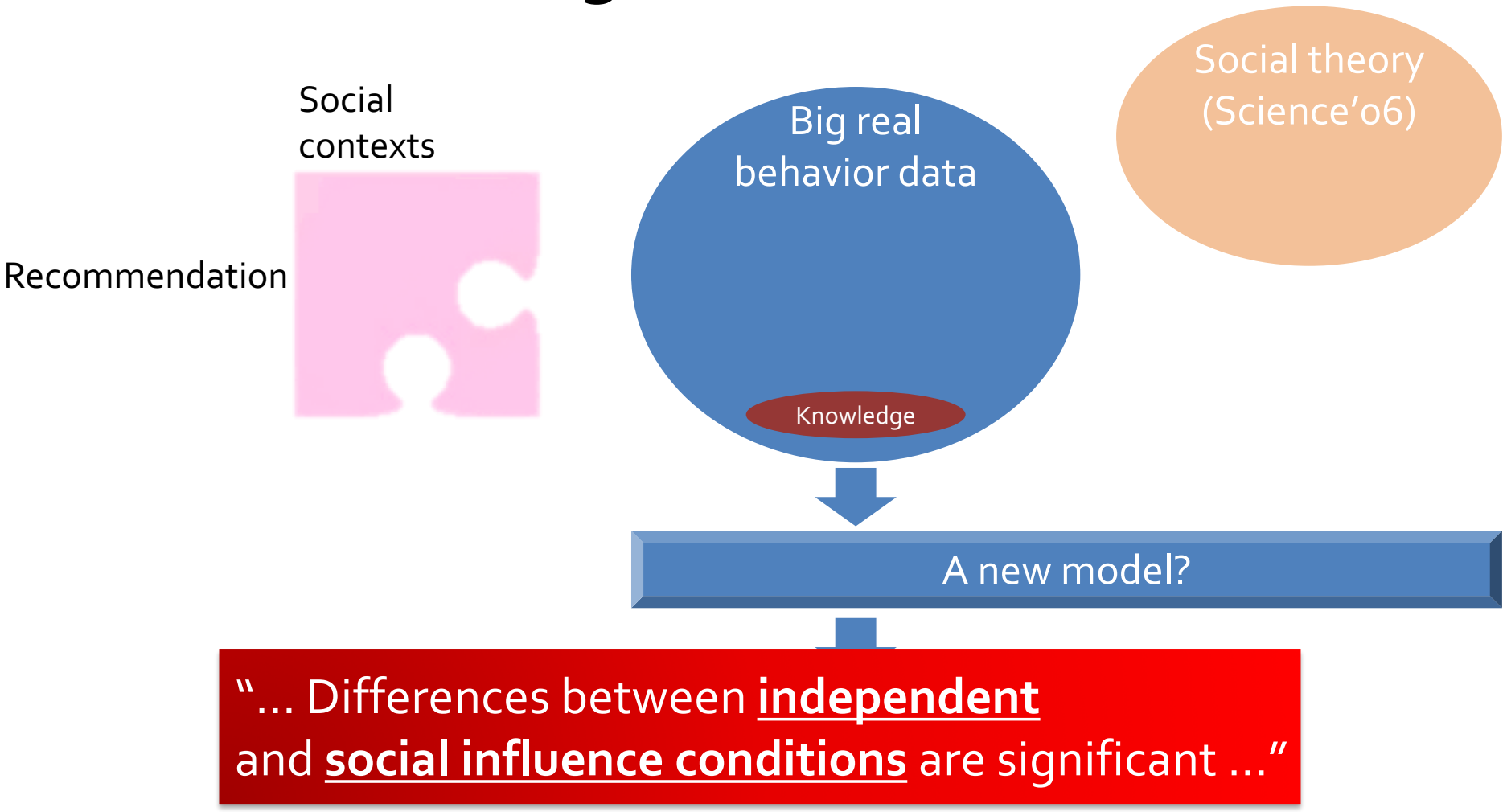
Recommendation

Q1: A Social Recommender System



Collaborative filtering for recommenders [Breese et al. UAI'98; Getoor and Sahami WEBKDD'99; Herlocker et al. CSCW'00, TOIS'04; Koren et al. KDD'08 Computer'09; Liu et al. SIGIR'08]

M1: Knowledge from Social Theories

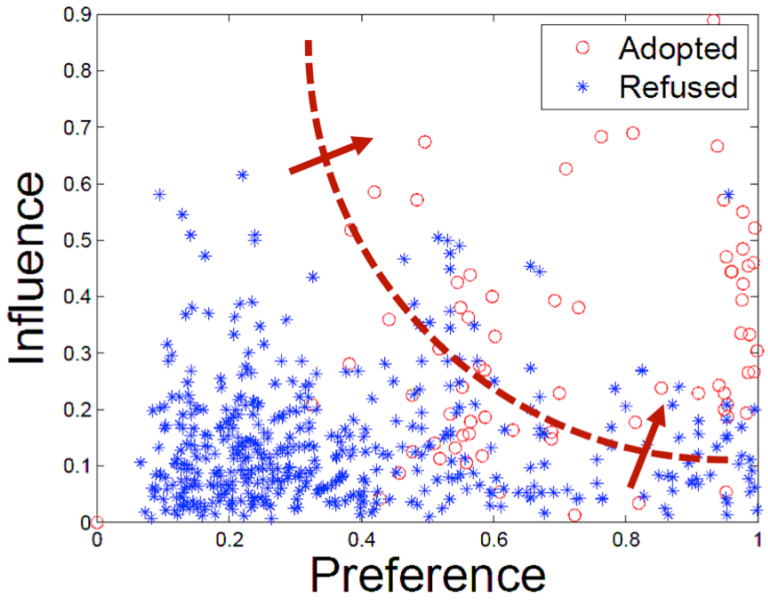


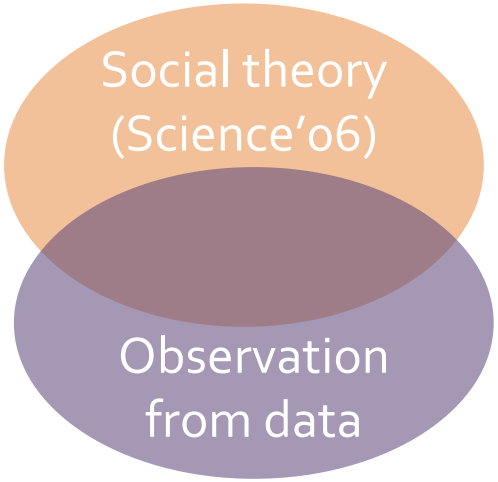
Salganik, Dodds, and Watts. "Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market." Science, Vol. 311, 2006.

M1: Knowledge from Social Theories

Social contexts

Recommendation





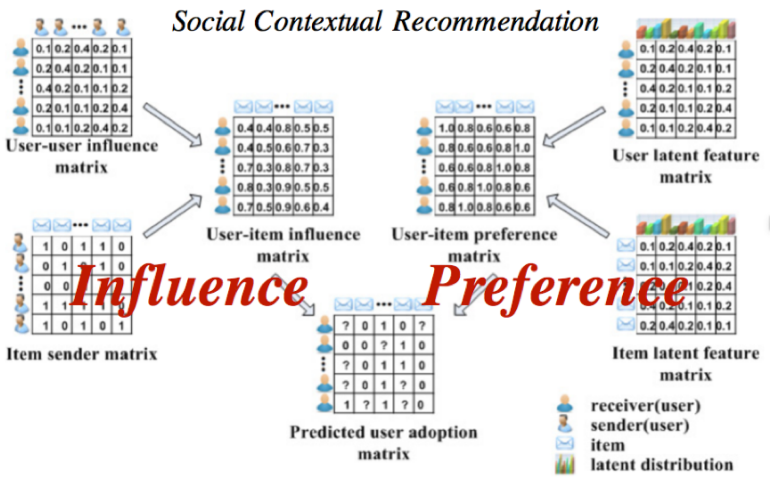
A new model?

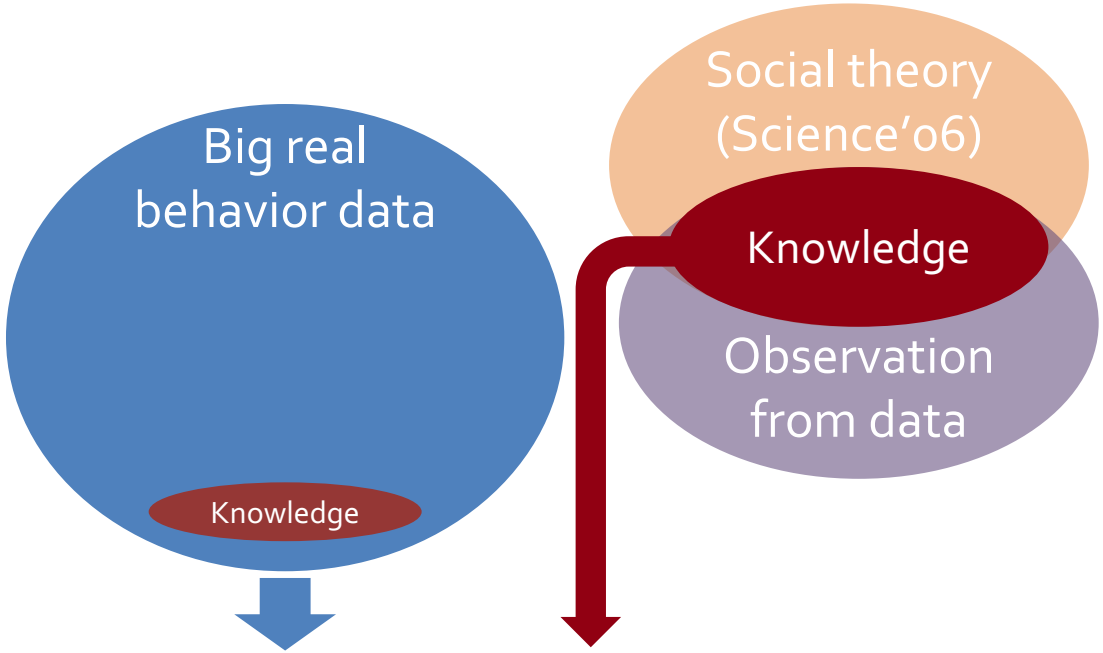
Performance?

M1: Knowledge from Social Theories

Social contexts

Recommendation

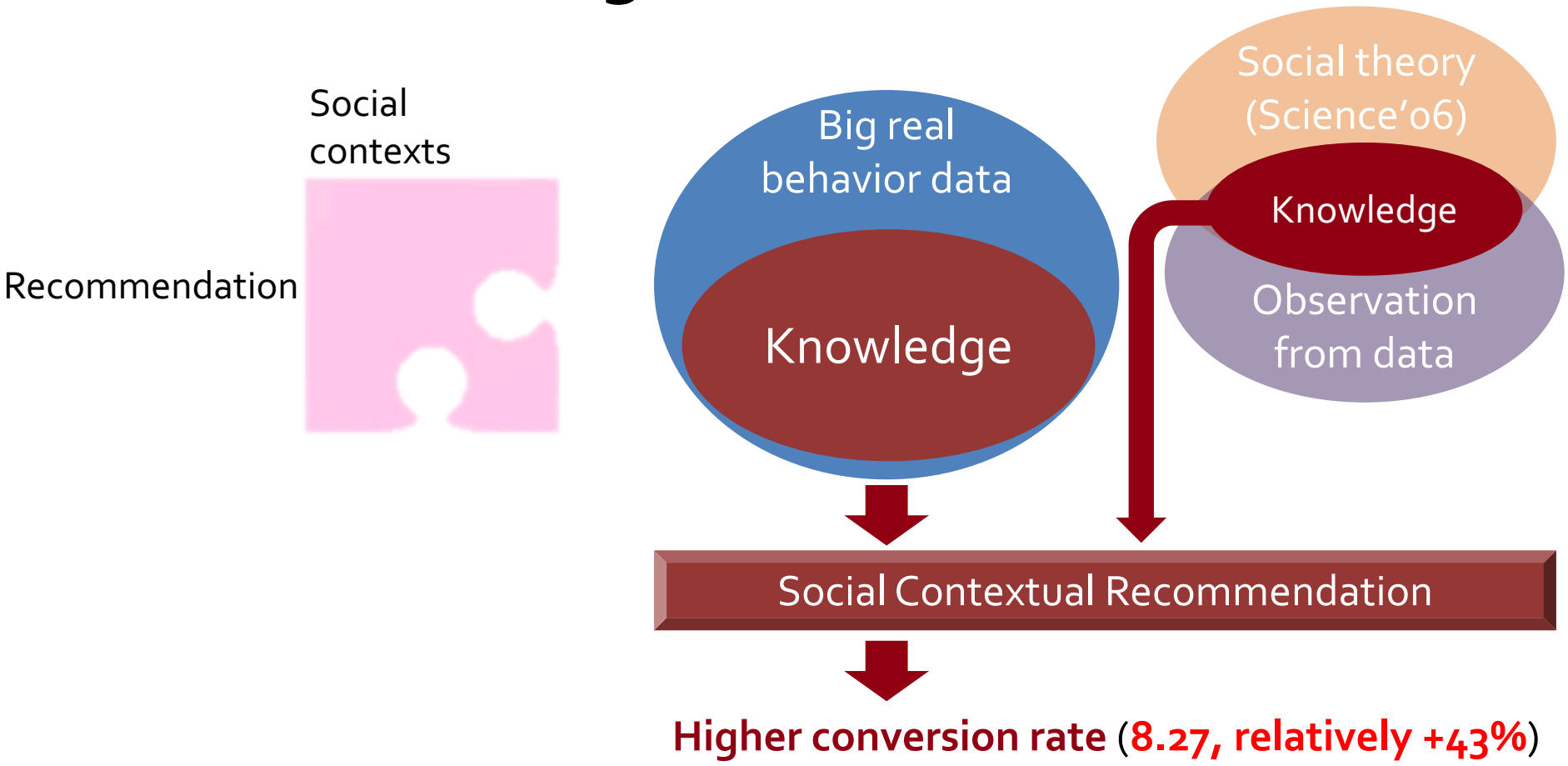




A model that considers contextual factors!

Performance?

M1: Knowledge from Social Theories



S1: CIKM'12: cited by **211**; TKDE'14: cited by **82**.

S1: Social Contextual Recommendation

- Optimization

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 user-user interaction

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

social relation

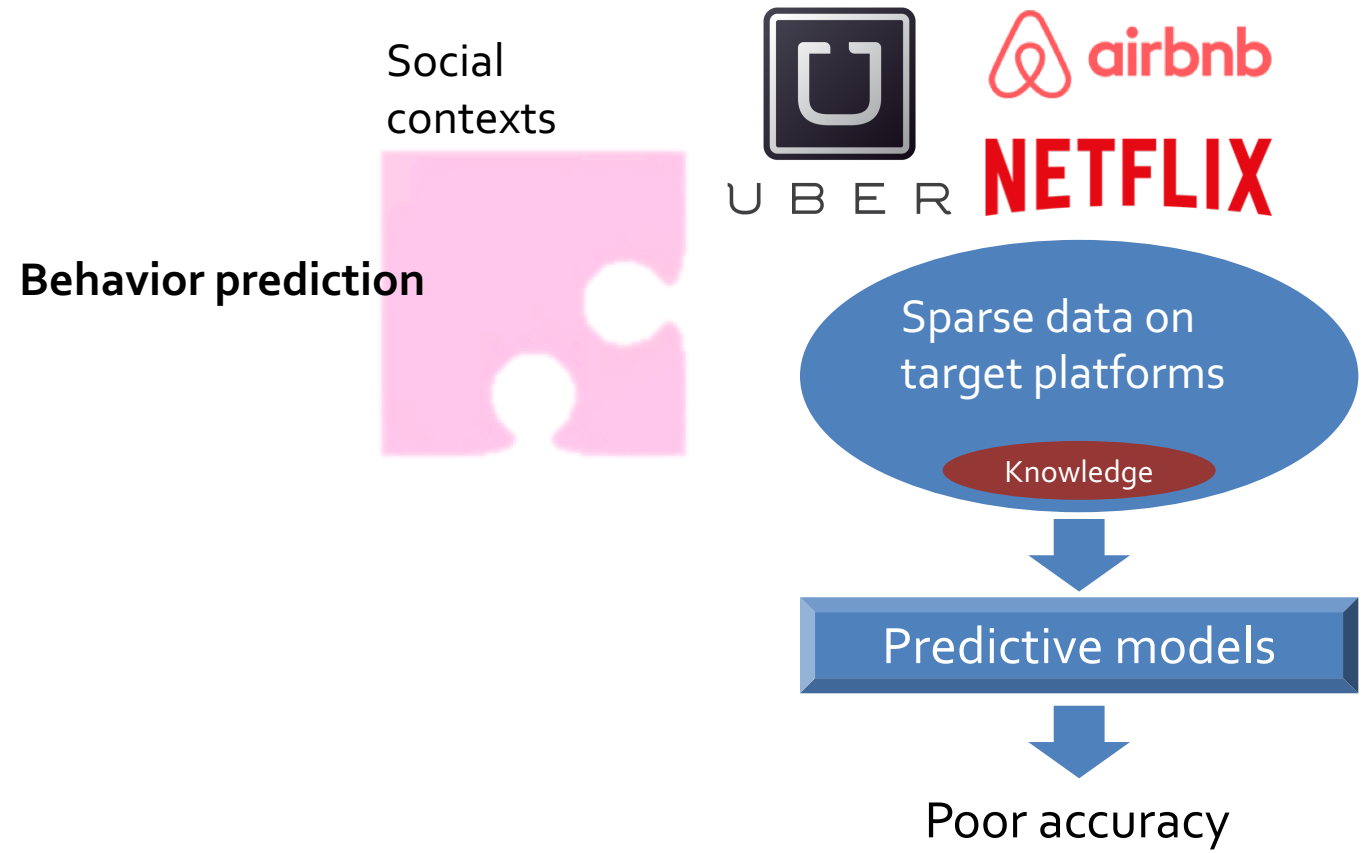
item content

avoid overfitting

- Gradient descent method

$$\begin{aligned}\frac{\partial\mathcal{J}}{\partial\mathbf{S}} &= 2\Big(-\mathbf{R}(\mathbf{G}\odot\mathbf{V}^\top\mathbf{U})+(\mathbf{S}\mathbf{G}^\top\odot\mathbf{U}^\top\mathbf{V})\mathbf{G}\\ &\quad+\gamma(\mathbf{S}-\mathbf{F})+\delta\mathbf{S}\Big)\\ \frac{\partial\mathcal{J}}{\partial\mathbf{U}} &= 2\Big(-\mathbf{V}\mathbf{R}^\top+\mathbf{V}(\mathbf{G}\mathbf{S}^\top\odot\mathbf{V}^\top\mathbf{U})-2\alpha\mathbf{U}\mathbf{W}\\ &\quad+2\alpha\mathbf{U}\mathbf{U}^\top\mathbf{U}+\eta\mathbf{U}\Big)\\ \frac{\partial\mathcal{J}}{\partial\mathbf{V}} &= 2\Big(-\mathbf{U}\mathbf{R}+\mathbf{U}(\mathbf{S}\mathbf{G}^\top\odot\mathbf{U}^\top\mathbf{V})-2\beta\mathbf{V}\mathbf{C}\\ &\quad+2\beta\mathbf{V}\mathbf{V}^\top\mathbf{V}+\lambda\mathbf{V}\Big)\end{aligned}$$

Q2: Leveraging Social Data for Prediction



Data sparseness [Herlocker et al. CSCW'00; Sarwar et al. WWW'01; Burke UM&UAI'02; Ma et al. TOIS'11 TIST'11; Tang et al. Soc. Netw. Anal. Min.; Xue et al. VLDB'15; Han and Obradovic et al. SDM'16]

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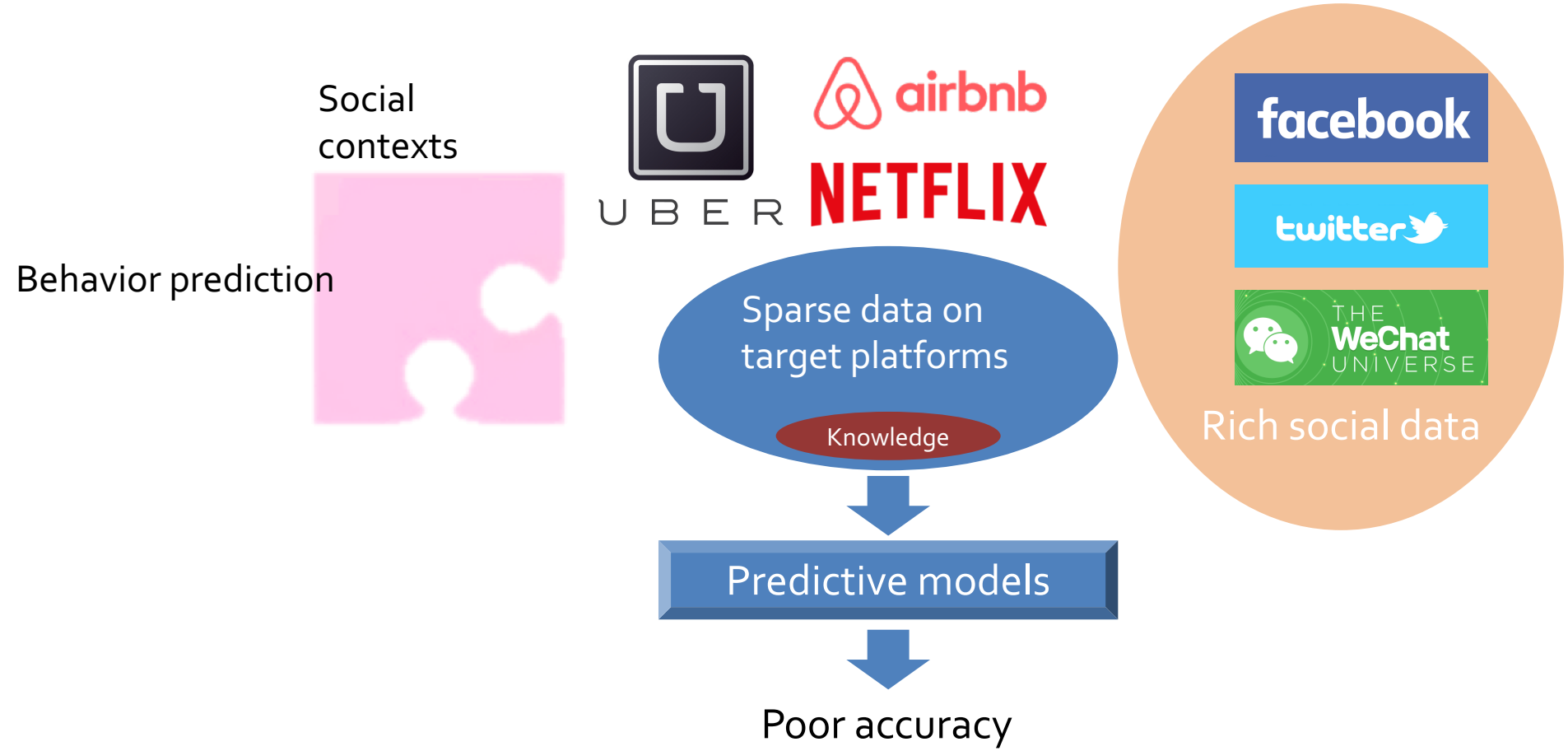
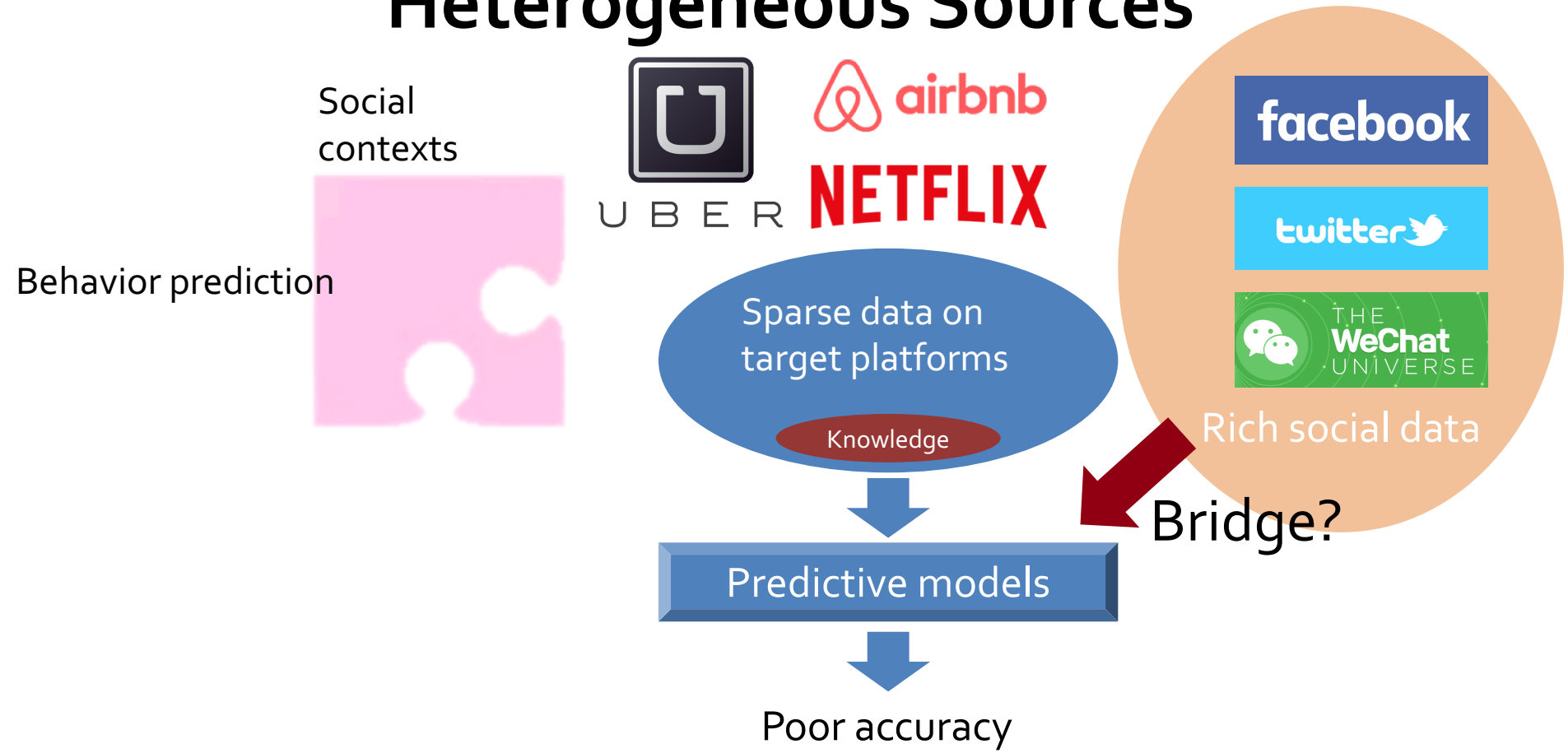


M2: Knowledge Transfer from Heterogeneous Sources



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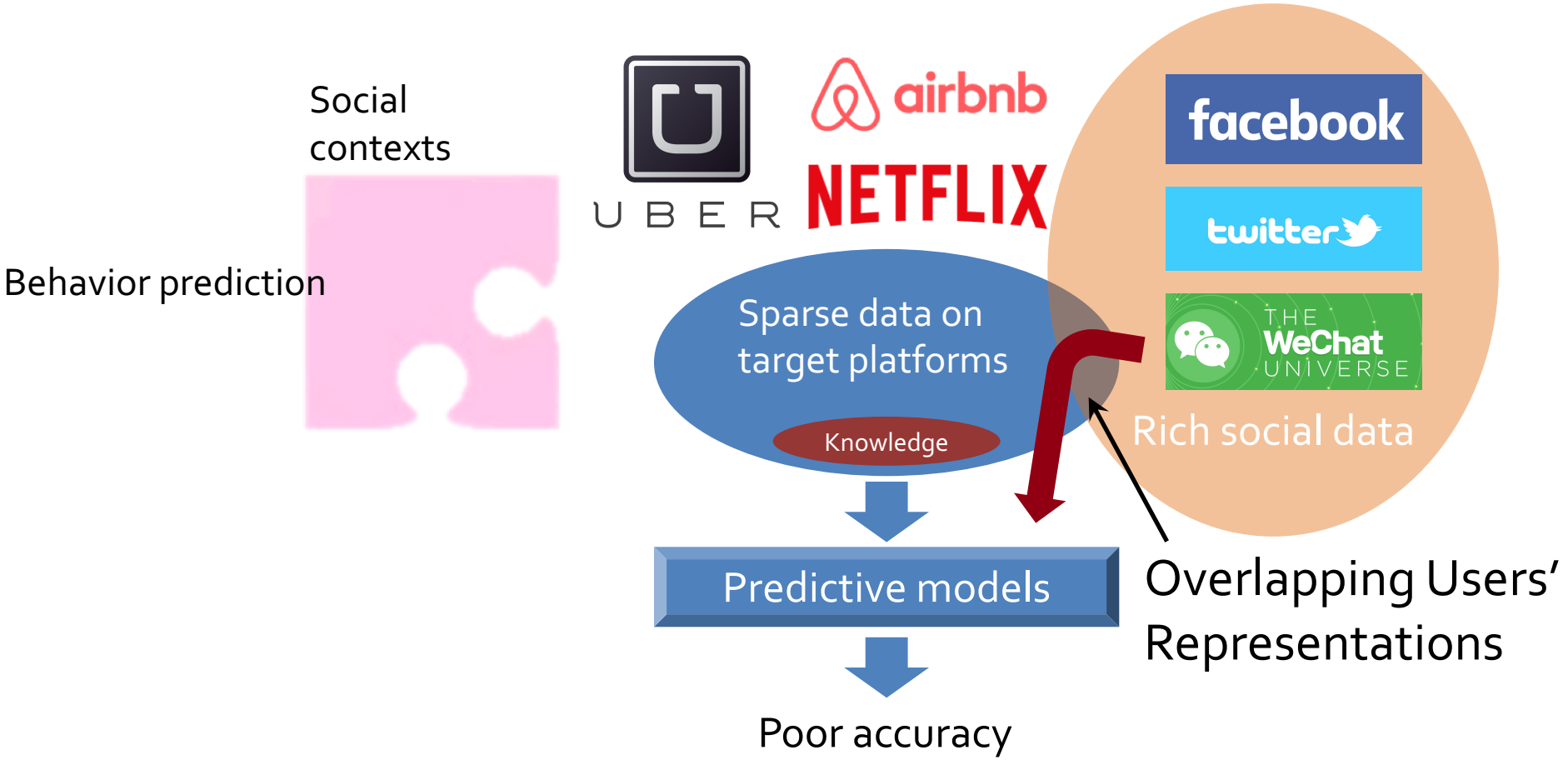

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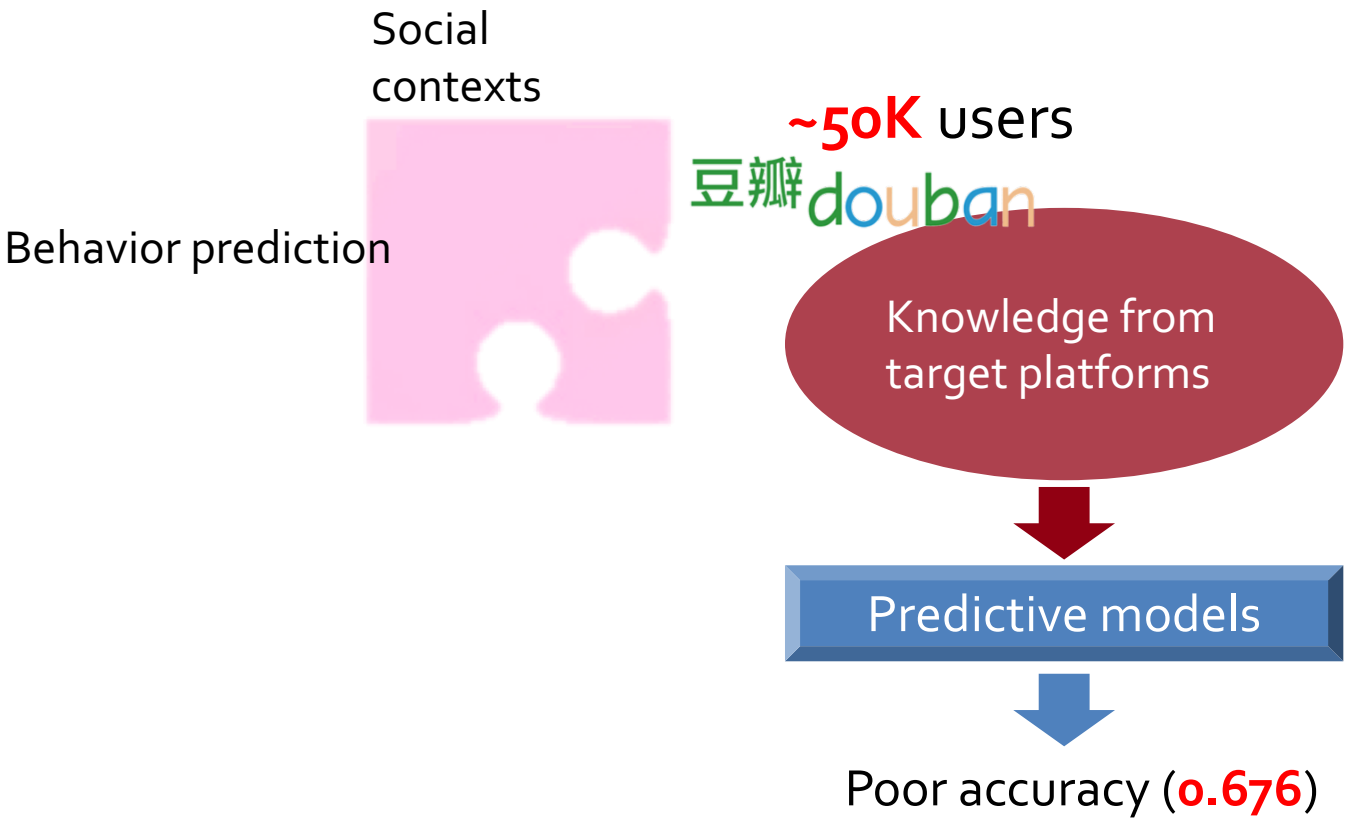

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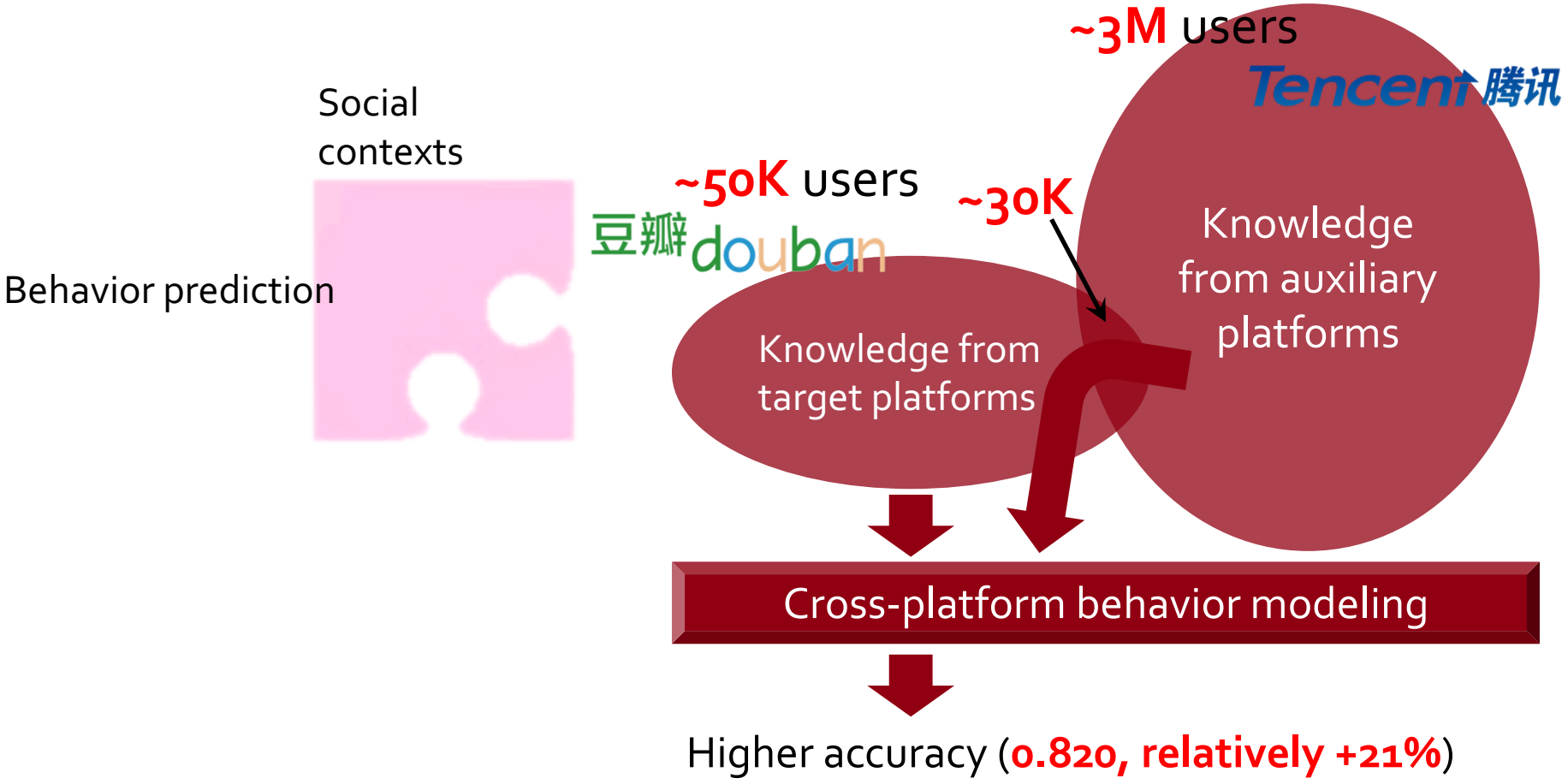
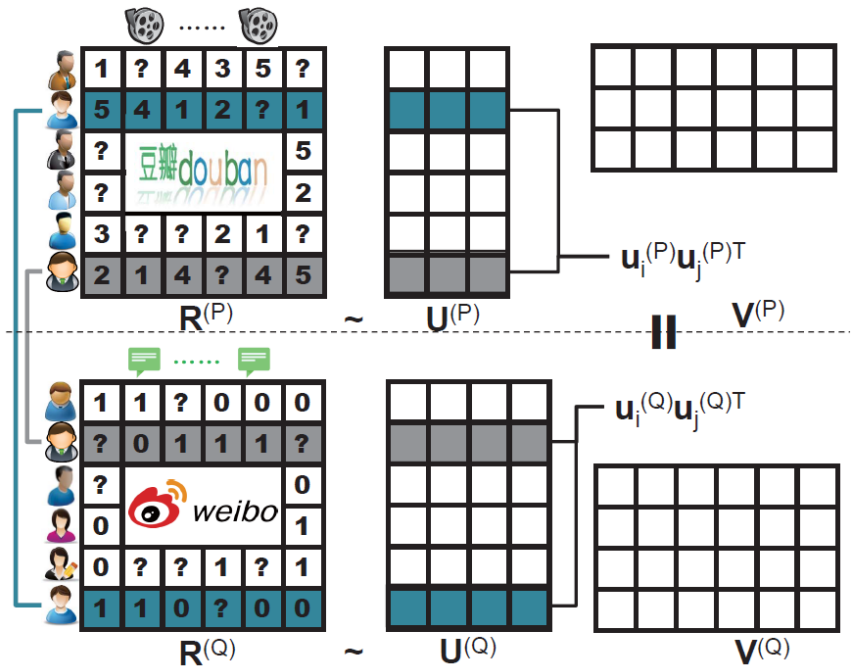


S2: CIKM'12: cited by **72**; TKDE'15: cited by **44**; AAAI'16: cited by **13**.

S2: Cross-Platform Behavior Modeling



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)

Q3: Catching Social Link Farming

Social contexts

Suspicious behavior detection

Meng Jiang, Peng Cui, and Christos Faloutsos. "Suspicious behavior detection: current trends and future directions." **IEEE Intelligent Systems**, 2016. (Survey paper)

Q3: Catching Social Link Farming

Social contexts

Suspicious behavior detection

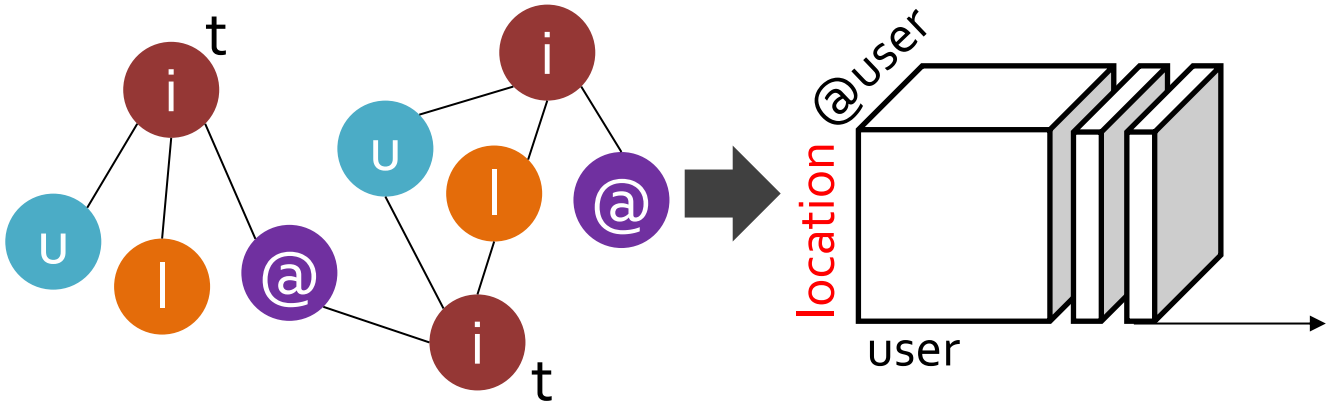
S3: CatchSync

KDD'14 best paper finalist

Q4: Knowledge from Spatiotemporal Information
M4: Tensor Methods for Modeling Multiple Dimensions

Spatiotemporal contexts

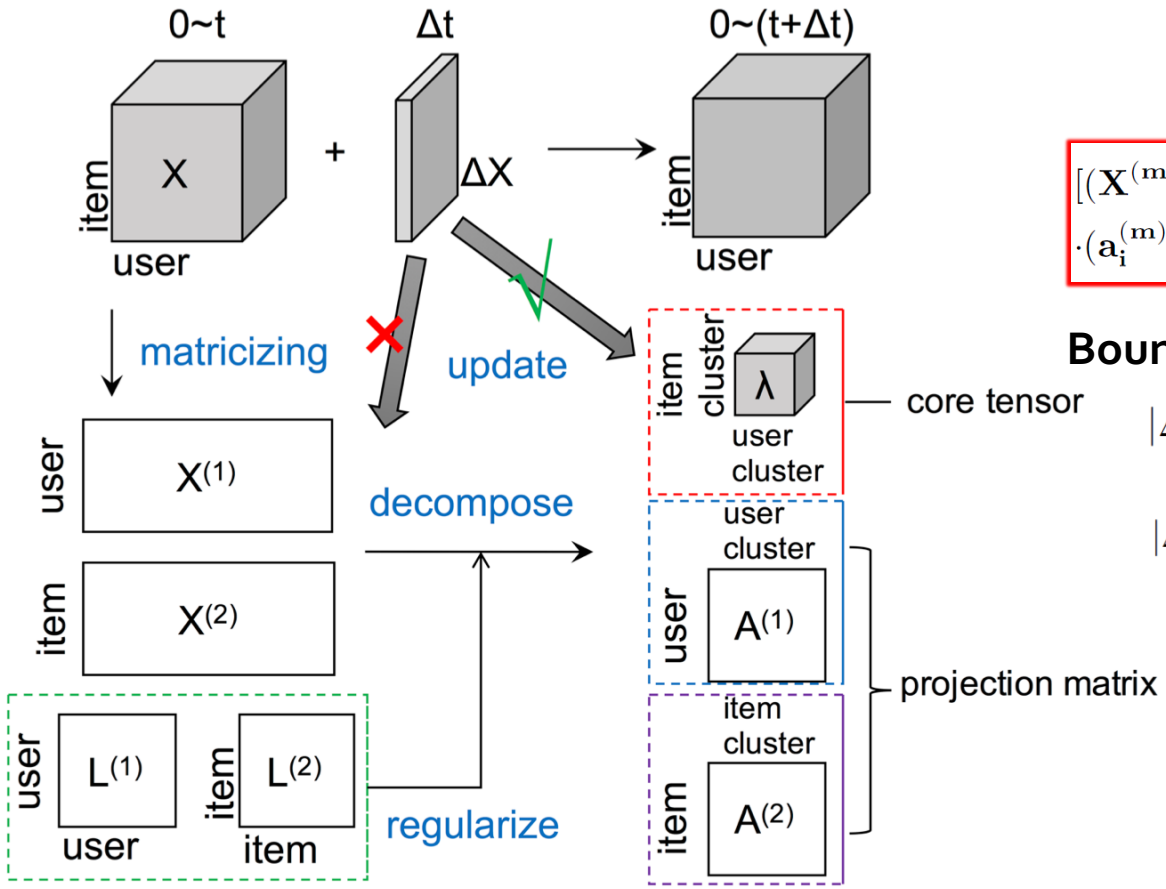
Q4-1: Who-@-whom prediction: High complexity!



M4-1: Incremental tensor decomposition: Approximation based on tensor perturbation theory. We proved bound guarantees of errors.

S4-1: RMSE reduced from **1.120** to **0.894** (**relatively -20.2%**); running time reduced from **25 hours** to **51 minutes**. KDD'14: cited by **28**.

S4-1: Flexible Evolutionary Multifaceted Analysis



Tensor perturbation theory:

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

Bounds (guarantee for approximation):

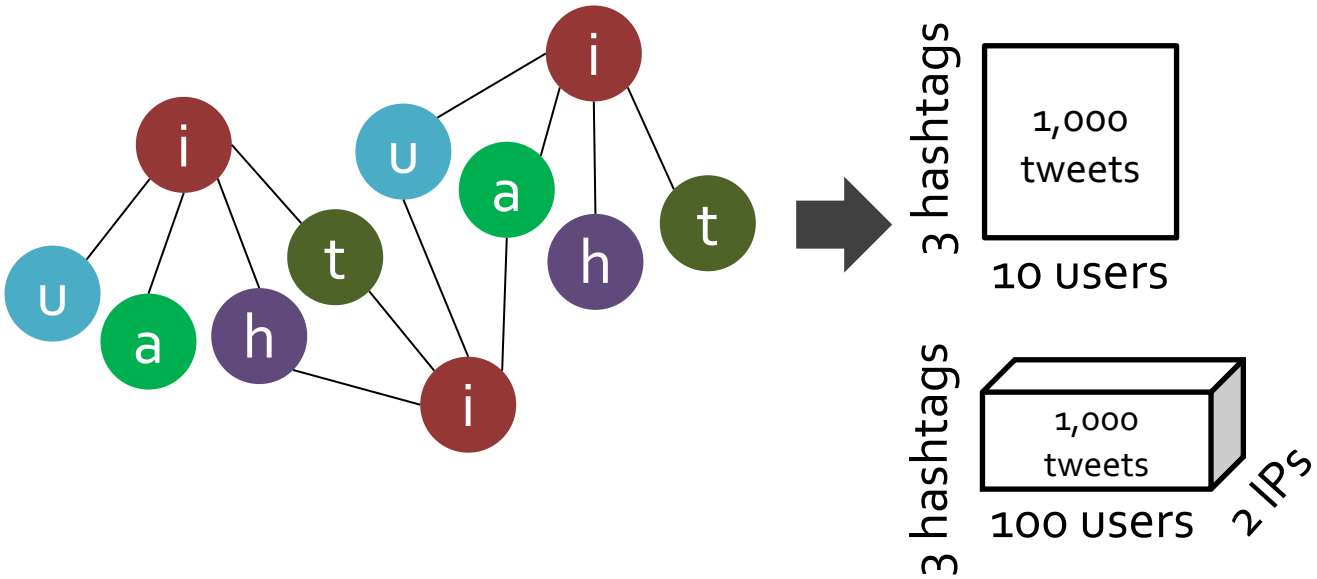
$$|\Delta\lambda_i^{(m)}|\leq 2(\lambda^{\max}_{\mathbf{X}^{(\mathbf{m})\top}\mathbf{X}^{(\mathbf{m})}})^{\frac{1}{2}}\|\Delta\mathbf{X}^{(\mathbf{m})}\|_2$$

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

Q4: Knowledge from Spatiotemporal Information
M4: Tensor Methods for Modeling Multiple Dimensions

Spatiotemporal contexts

Q4-2: Spam detection: Evaluating suspiciousness?

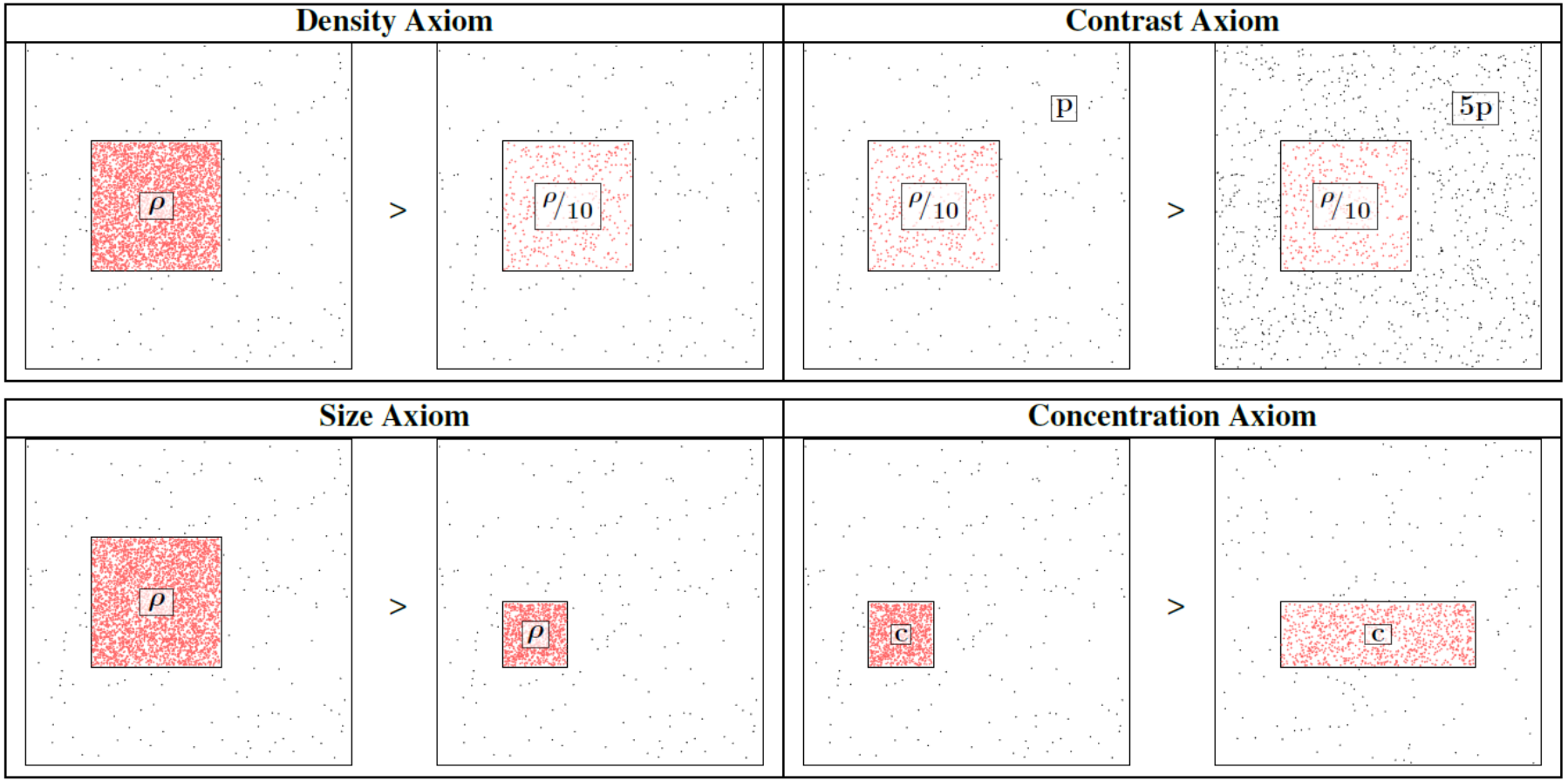


M4-2: Proposed a principled suspiciousness metric.

S4-2: Detected ~6M hijacking tweets of 3 hashtags by ~600 users from ~300 IP addresses in ~40 days.

ICDM'15: cited by **42**; TKDE'16: cited by **8**.

S4-2: Evaluating Suspiciousness across Dimensions



Q5: Knowledge from Behavioral Content

From Words, Topics, to Networks

"Modeling Complex Behaviors in Social Media", July 2015. 🎓

清華大學

Tsinghua University

Q5: Knowledge from Behavioral Content

From Words, Topics, to Networks

"Modeling Complex Behaviors in Social Media", July 2015.

清華大學 Tsinghua University

Information network (entities, attributes…)

Structuring

Integrating

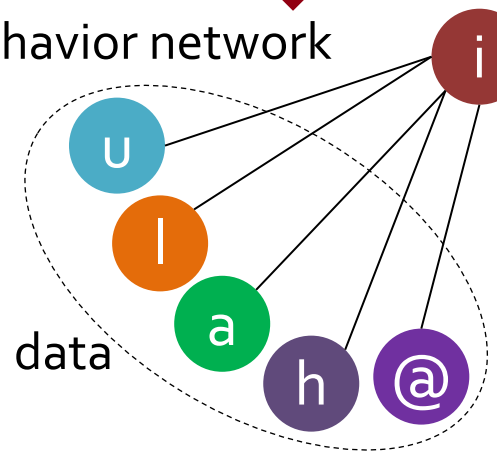
Rich unstructured text data

tweets, news…

product/restaurant review…

Publications: PubMed, DBLP…

Behavior network



Structured data

Q5': Entity and Attribute Discovery

Given full **text** of all the Data Science publications

Q'5-1. Who has studied the biggest number of datasets of large scale?

Q'5-2. Who study truly big data, and who always claim their work is on big data but their datasets are not big at all?

Q'5-3. For a dataset and a problem, who are the experts? How can we organize a team to solve the problem?

Q5': Entity and Attribute Discovery

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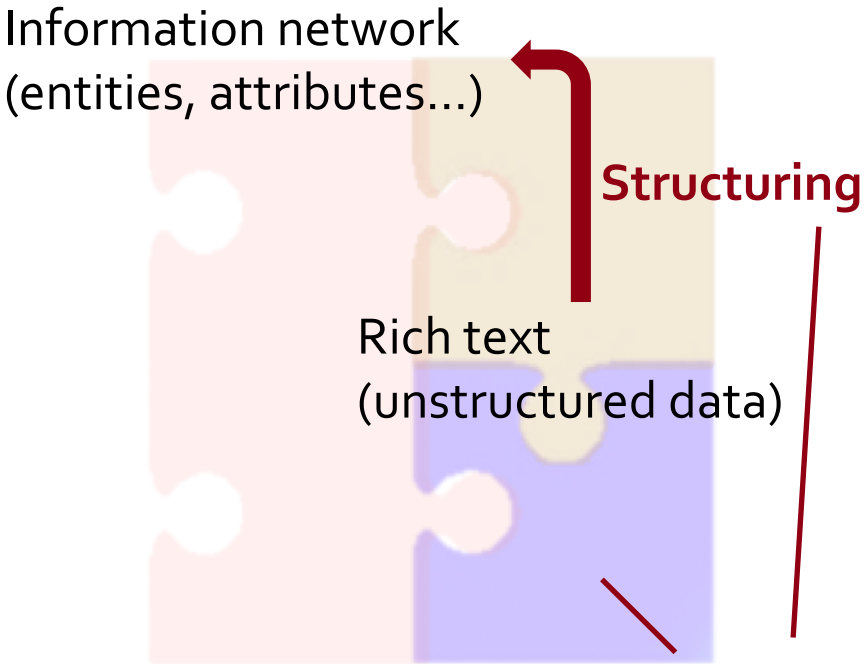
Q'5-3. For a dataset and a problem, who are the experts? How can we organize a team to solve the problem?

Sorry, I don't have answers now… But…

S5: Multiple Proposal Writing and Papers



1. **NSF III: Medium:** Collaborative: "StructNet: Constructing and Mining Structure-Rich Information Networks for Scientific Research". (Funded 2017)
2. **KDD'17:** "Meta Pattern-Driven Attribute Discovery from Massive Text Corpora". (Accepted)

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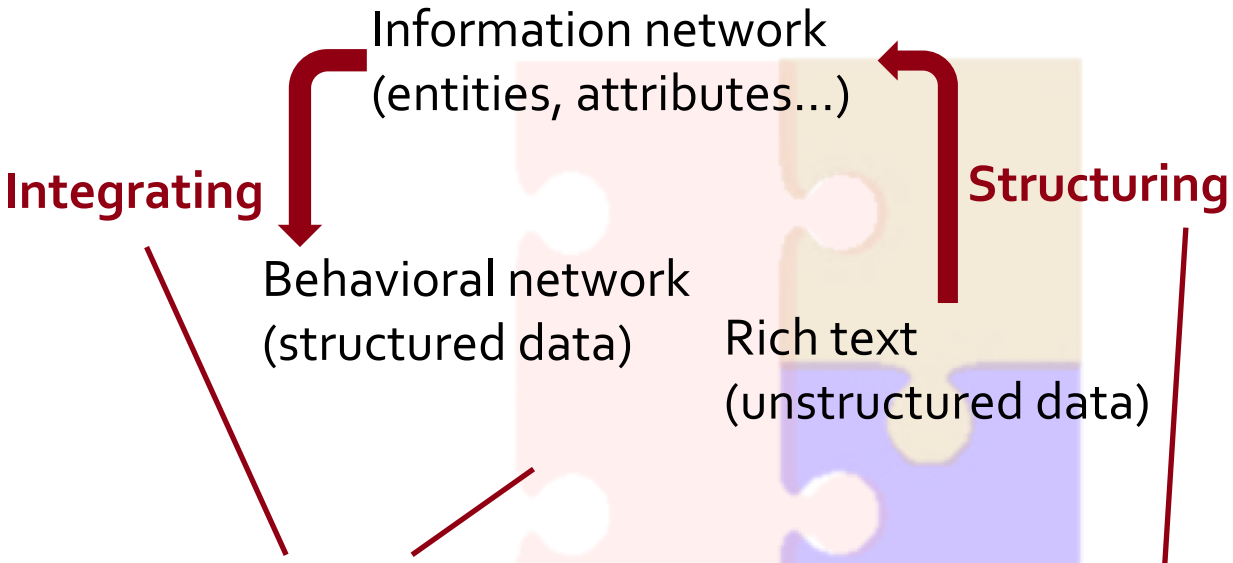


3. **NSF III: Small:** "Multi-Dimensional Structuring, Summarizing and Mining of Social Media Data", NSF IIS 16-18481. Jiawei Han, PI. (Submitted Nov 15, funded Aug 16)

4. **KDD'16:** "CatchTartan: Representing and Summarizing Dynamic Multicontextual Behaviors". **Oral** (Acc. = 8.9%).

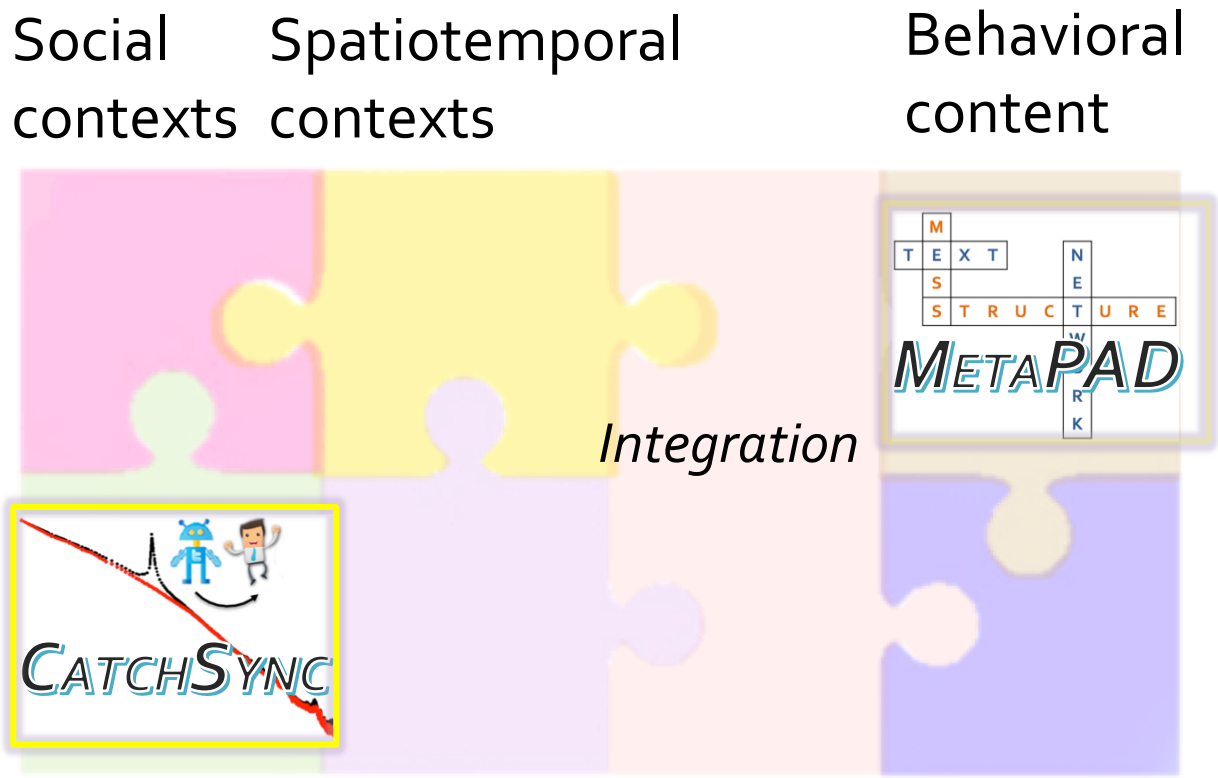
1. **NSF III: Medium:** Collaborative: "StructNet: Constructing and Mining Structure-Rich Information Networks for Scientific Research". (Funded 2017)

2. **KDD'17:** "Meta Pattern-Driven Attribute Discovery from Massive Text Corpora". (Accepted)

Outline

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection



CatchSync: Catching Synchronized Behavior in Large Directed Graphs

Joint work with Peng Cui, Shiqiang Yang (Tsinghua),

Alex Beutel, and Christos Faloutsos (CMU)

ACM SIGKDD 2014 Best Paper Finalist

(among **151** accepted research papers, **1,036** submissions)

Q3: Catching Zombie Followers

Q3: Catching Zombie Followers

engineers

product managers

Knowledge from manual inspection: #followees, #followers, #tweets, #hashtags, #urls…

Learning models (classifiers)

Poor accuracy
(**serious complaints** from users)

Fake account detection [Egele and Stringhini et al. NDSS'13; Yang and Wilson et al. TKDD'14; Viswanath and Bashir et al. USENIX Security Symposium'14]

Is this account a zombie follower???

Aisling Walsh
@xAsherzx

Joined April 2009

Tweet to Aisling Walsh

FOLLOWING 20 | FOLLOWERS 3 | 0 tweet

Follow

Who to follow · Refresh · View all

John Legere @JohnLe... Follow Promoted

Dong Zhou @dongz9 Followed by Peng Wang 王鹏 and others Follow

Justin Zeus @askzy9 Followed by Ruizhe, LI and others Follow

Find friends

Trends · Change

#ThatsContinental
Allowing curiosity to chart your course.
Promoted by LincolnMotorCompany

#2017in3words
26.1K Tweets

#nationalbaconday
5,915 Tweets

#NewYearsEveEve

Rachel Maddow MSN... Follow
@maddow
I see political people... (Retweets do not imply endorsement.)

Jason Sweeney Follow
@sween
limited edition, macaroni and glitter on construction paper.

woot.com Follow
@woot
Check out who we're following for other Woot accounts, and follow us on Facebook for extra excitement: facebook.com/woot

Trent Reznor Follow
@trent_reznor
Nine Inch Nails, How To Destroy Angels and other things.

Terry Moran Follow
@TerryMoran
Chief Foreign Correspondent, ABC News.

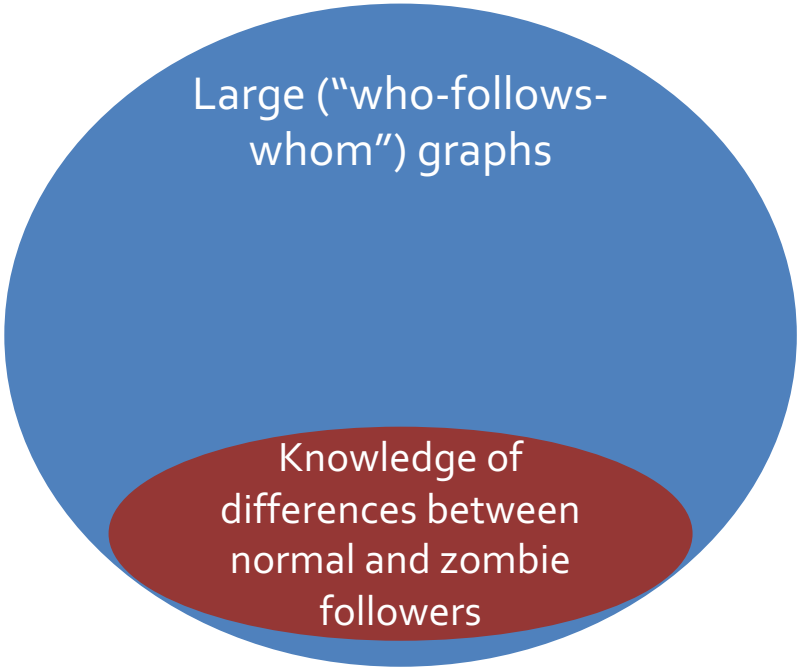
Hoppy New Year Follow
@markhoppus
person

Guardian Tech Follow
@guardiantech

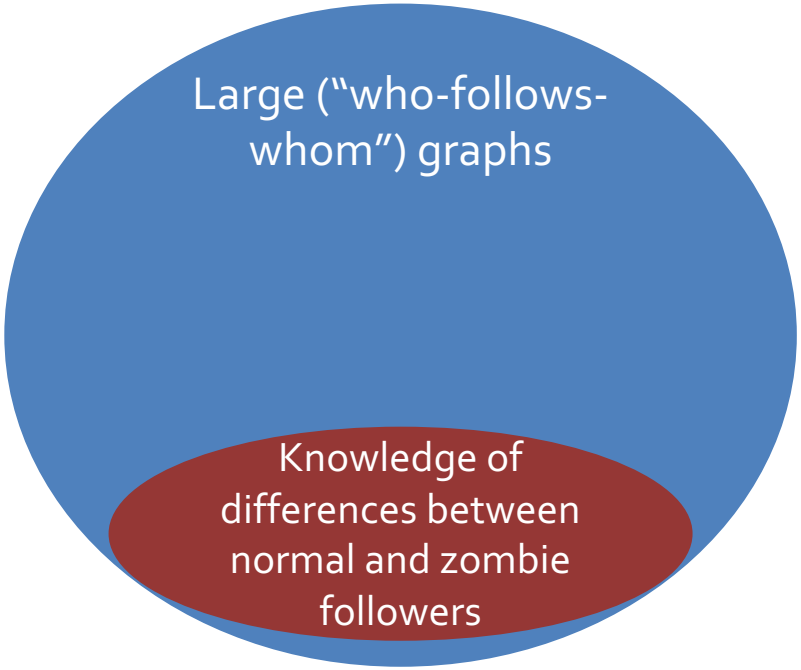
richard bacon Follow
@richardpbacon

CBOE Follow
@CBOE

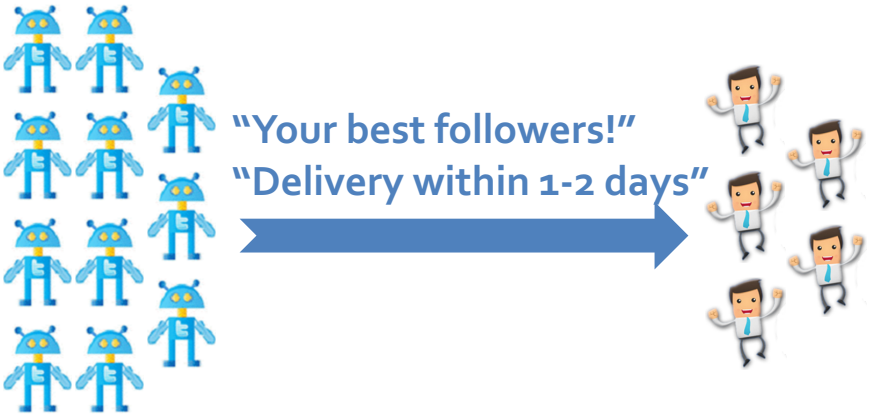
Our Methodology (M1)



Our Methodology (M1)

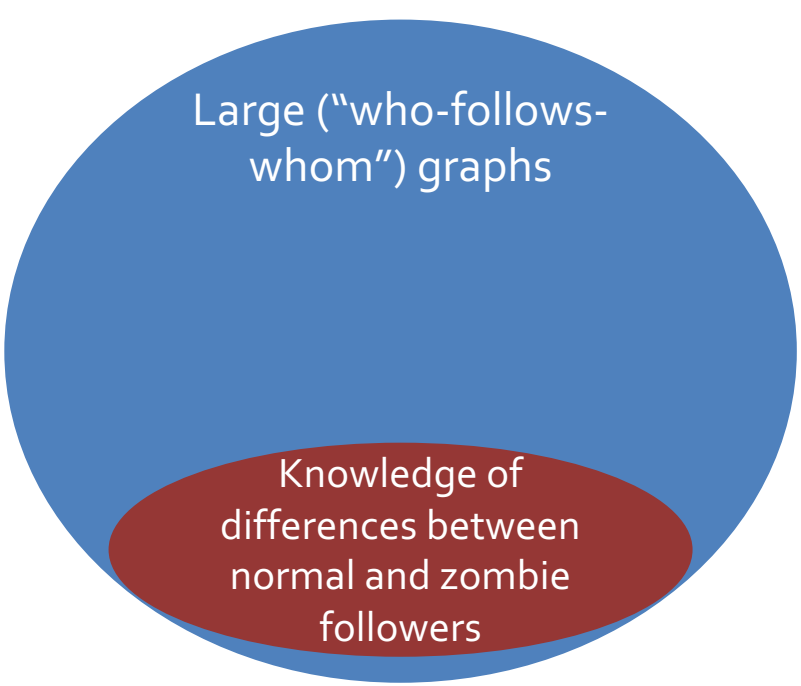


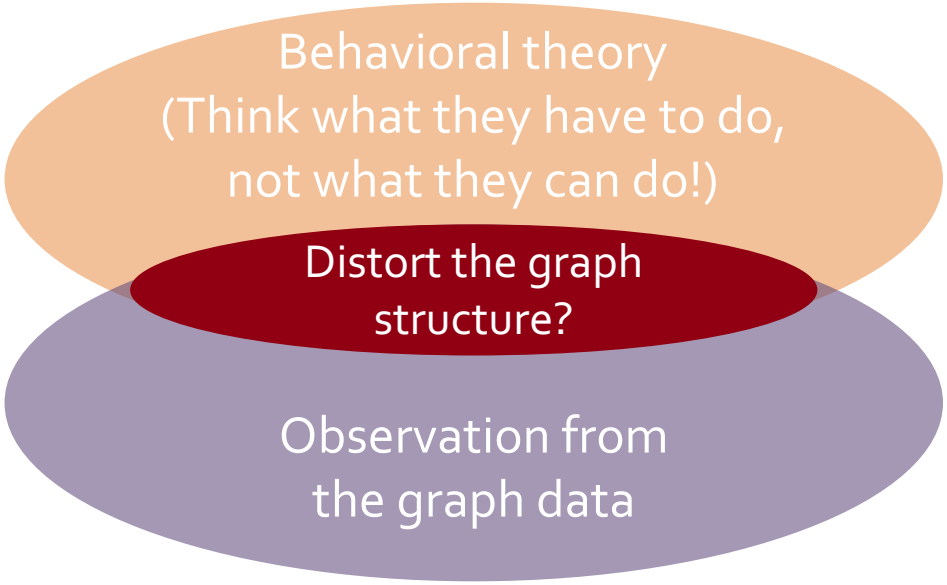
Behavioral theory
(Think what they have to do, not what they can do!)



Consistently Connecting to Customers

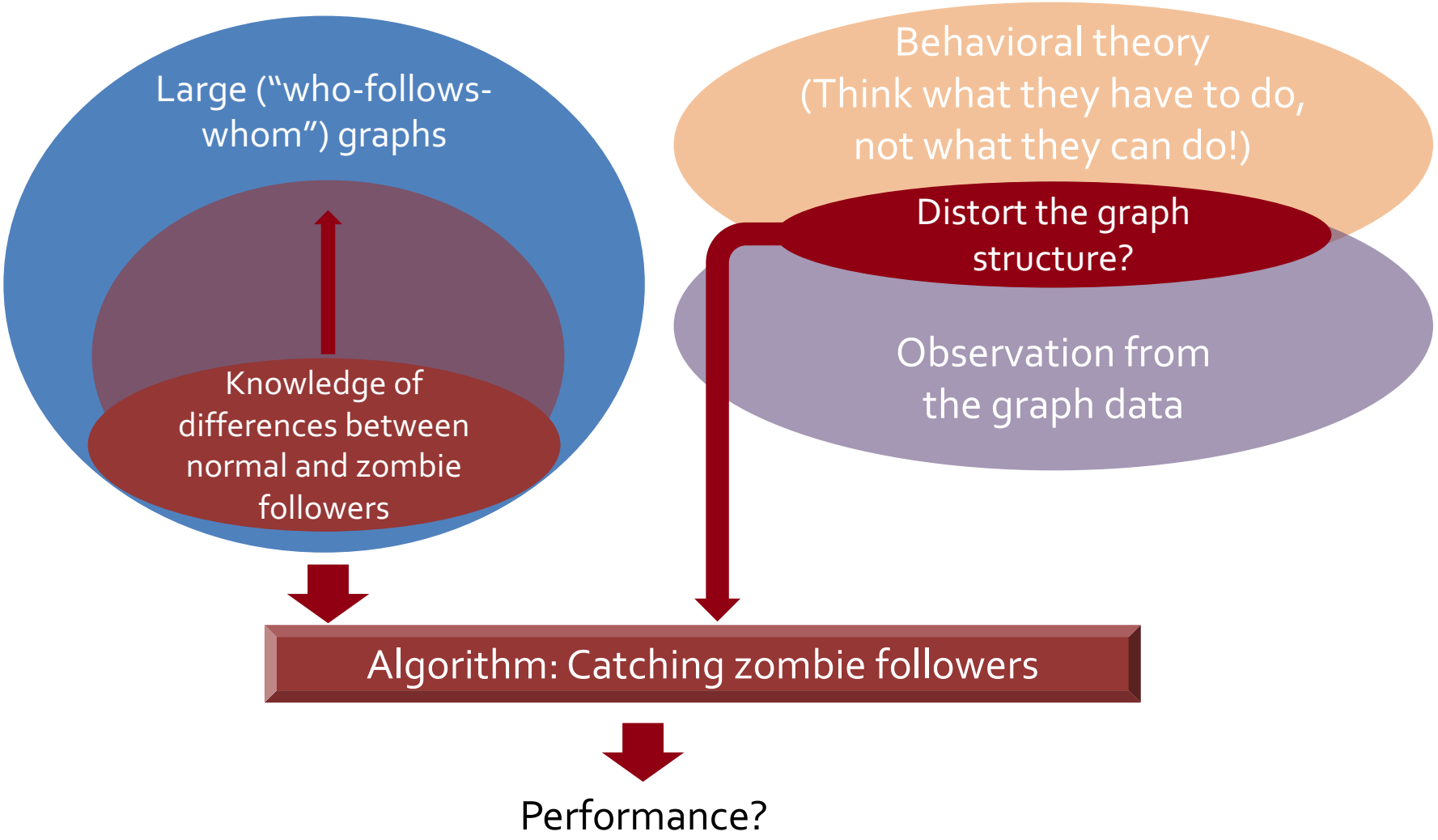
Our Methodology (M1)





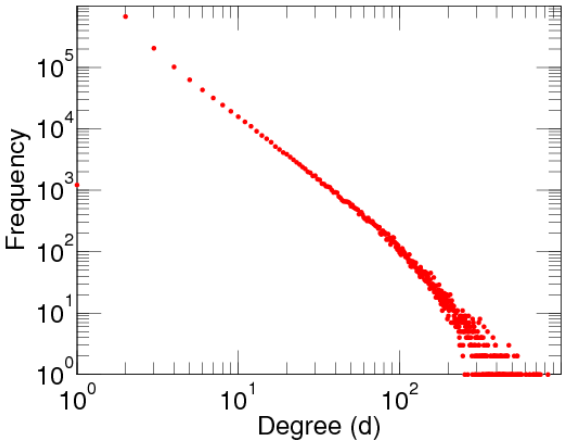
Consistently Connecting to Customers

Our Methodology (M1)

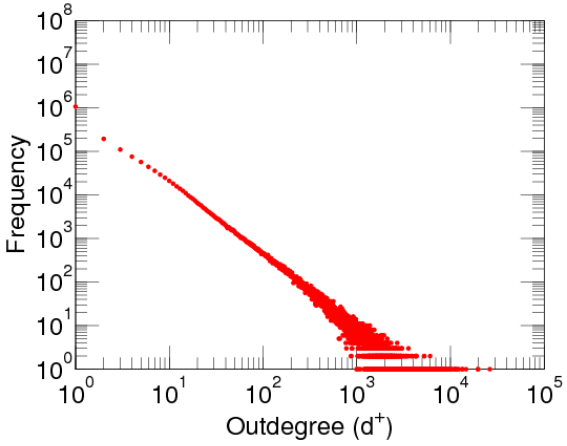


Out-Degree Distributions: Power Law Expected

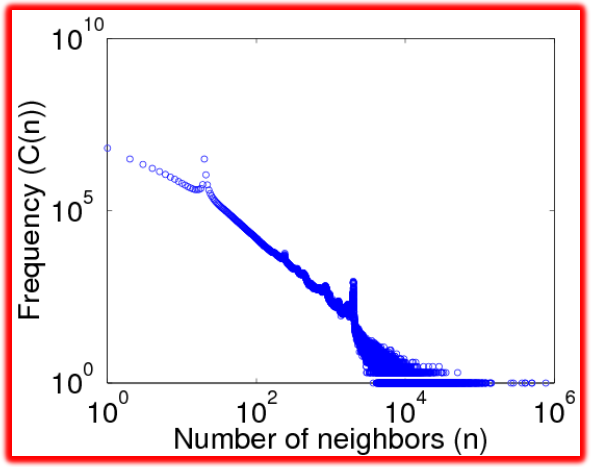
DBLP
Author-publication



Flickr
User-user



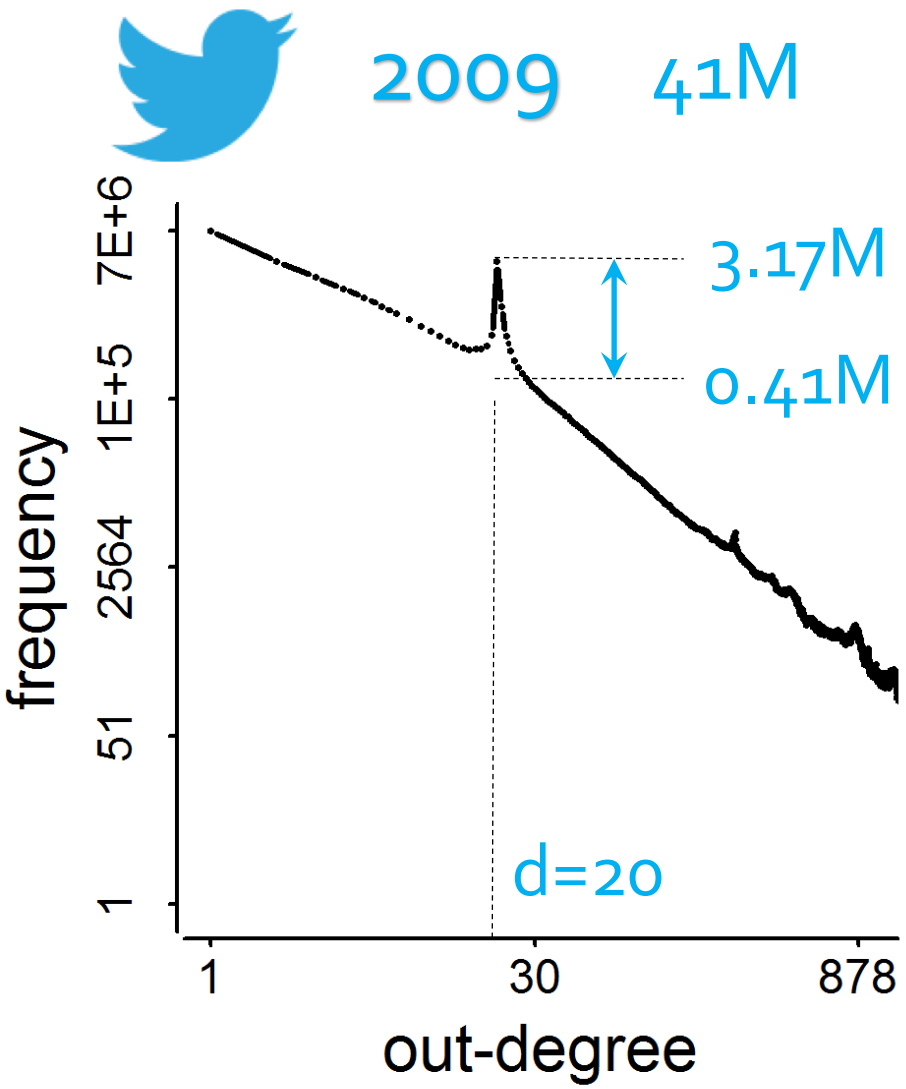
Twitter
Who-follows-whom

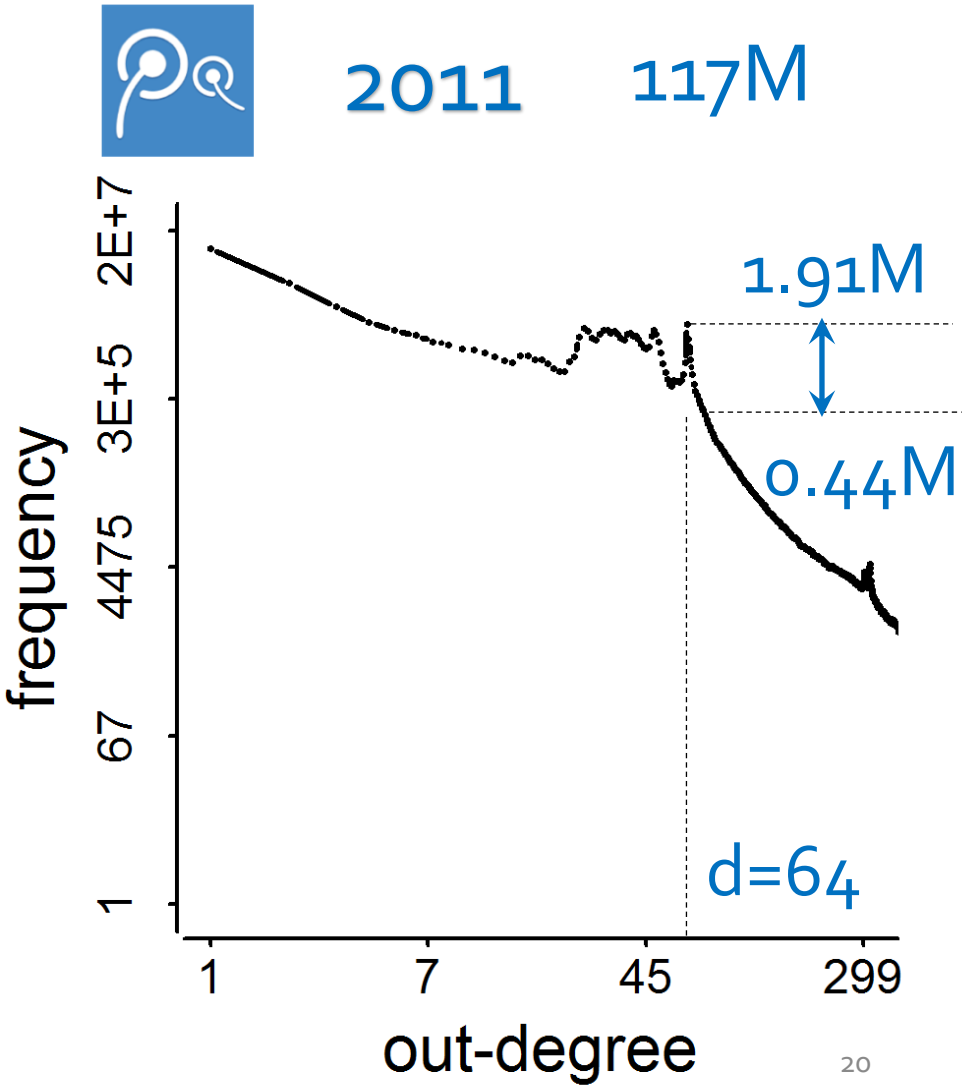


[konect.uni-koblenz.de/networks/]

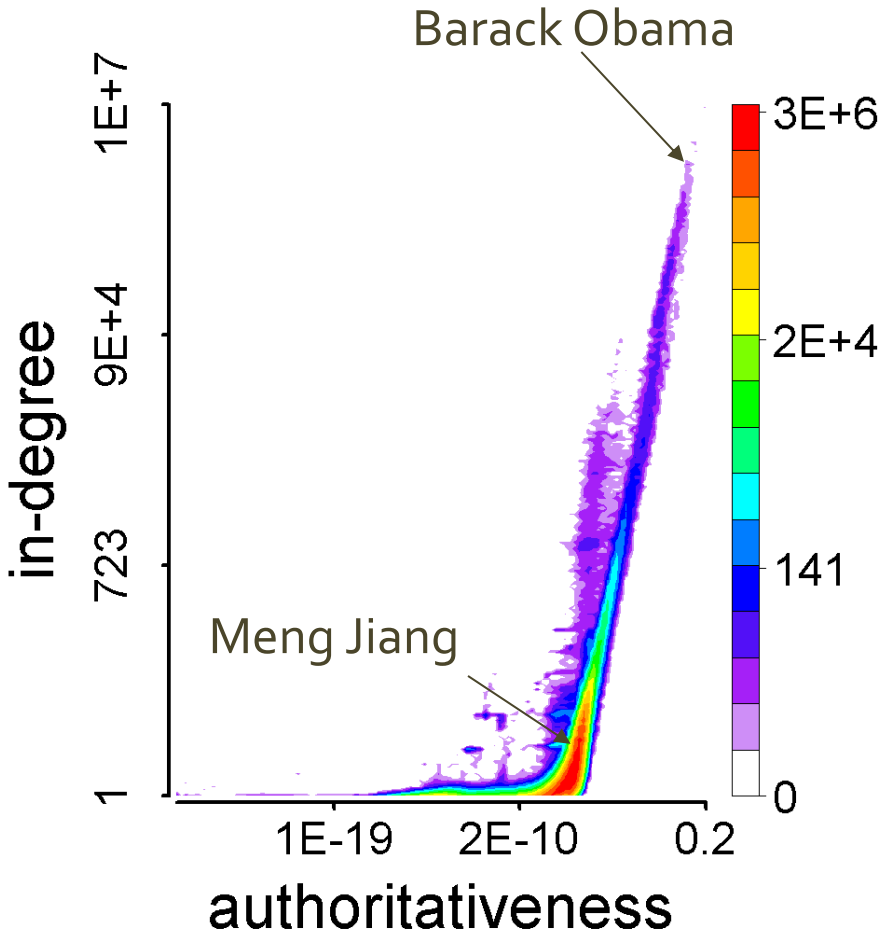
Power-law distributions in networks [Faloutsos et al. SIGCOMM'99; Chung et al. PNAS'02]

Spikes!


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

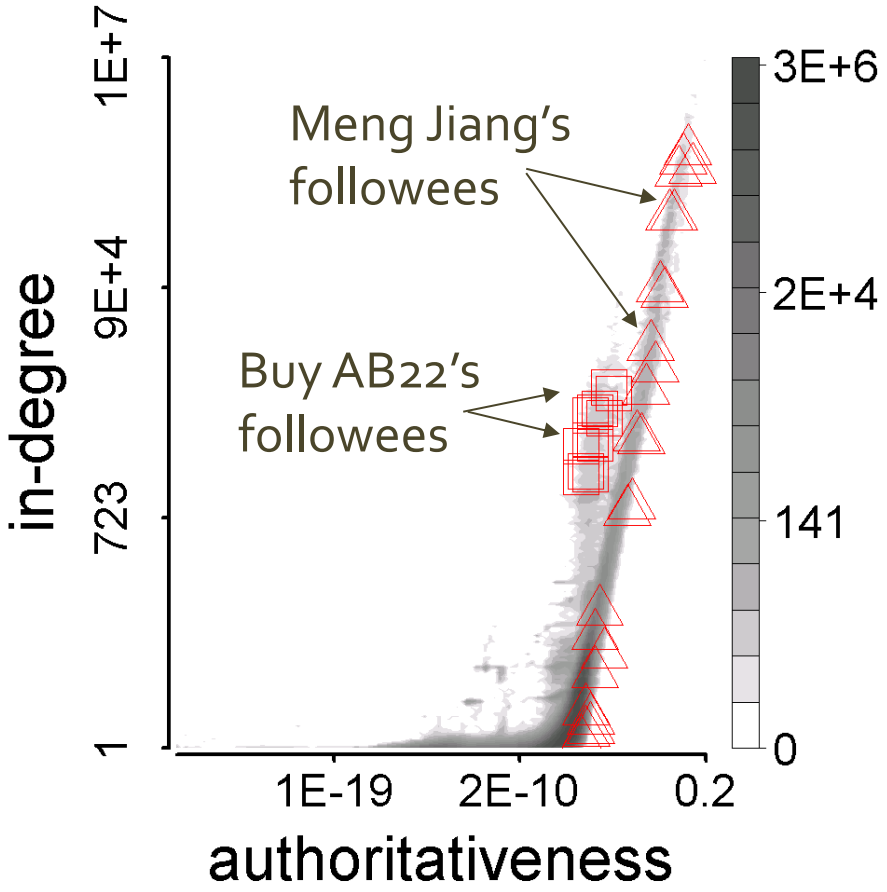

2011
117M
1.91M
0.44M
d=64
frequency
2E+7
3E+5
4475
67
1
1
7
45
299
out-degree

How We/They Connect to Our/Their Followees



The HITS algorithm. Kleinberg. "Authoritative sources in a hyperlinked environment." JACM'99.

How We/They Connect to Our/Their Followees



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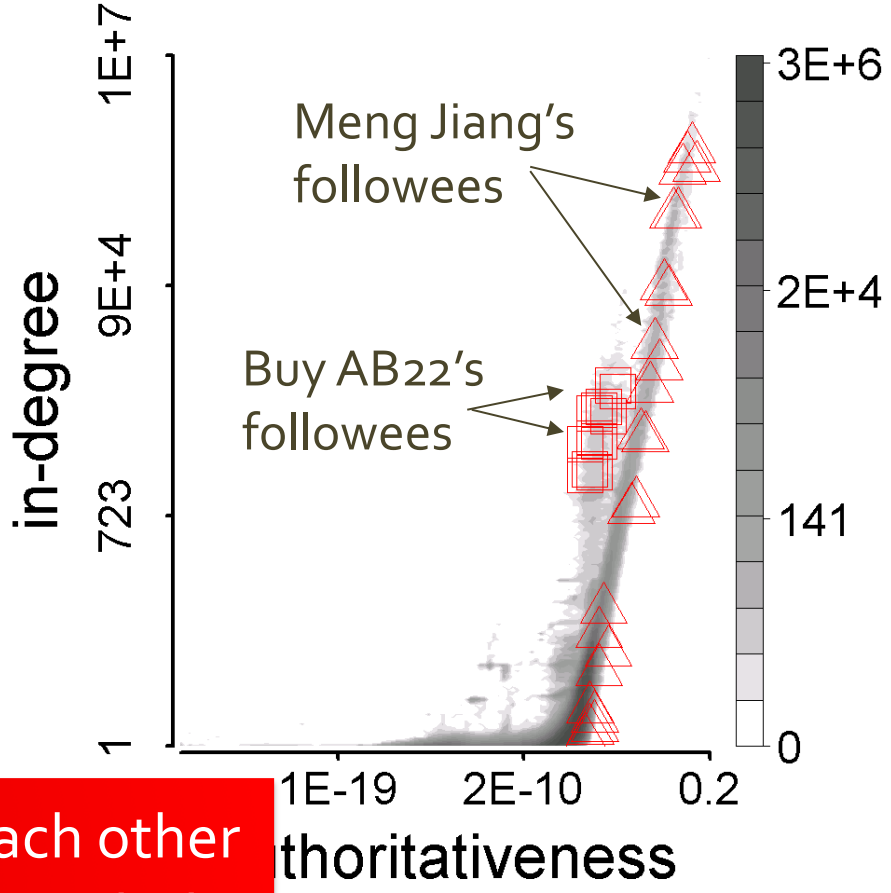
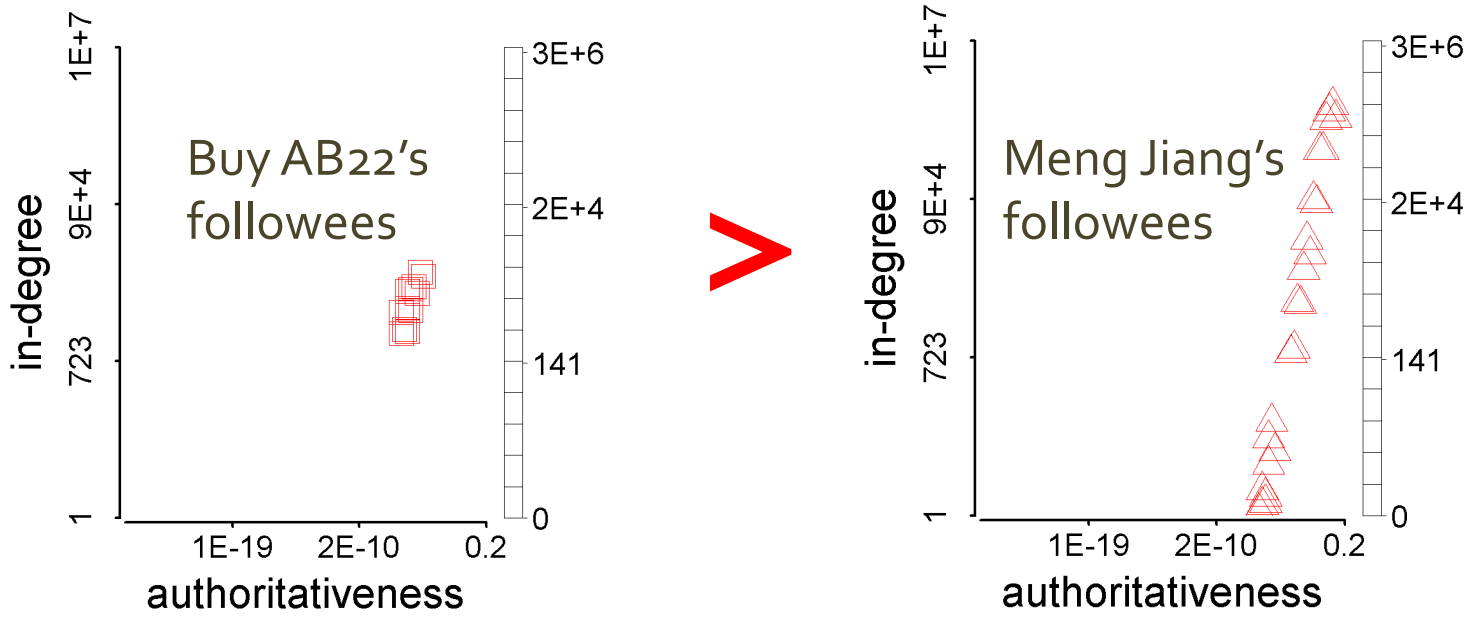


Synchronized: too similar with each other
Abnormal: too different from the majority

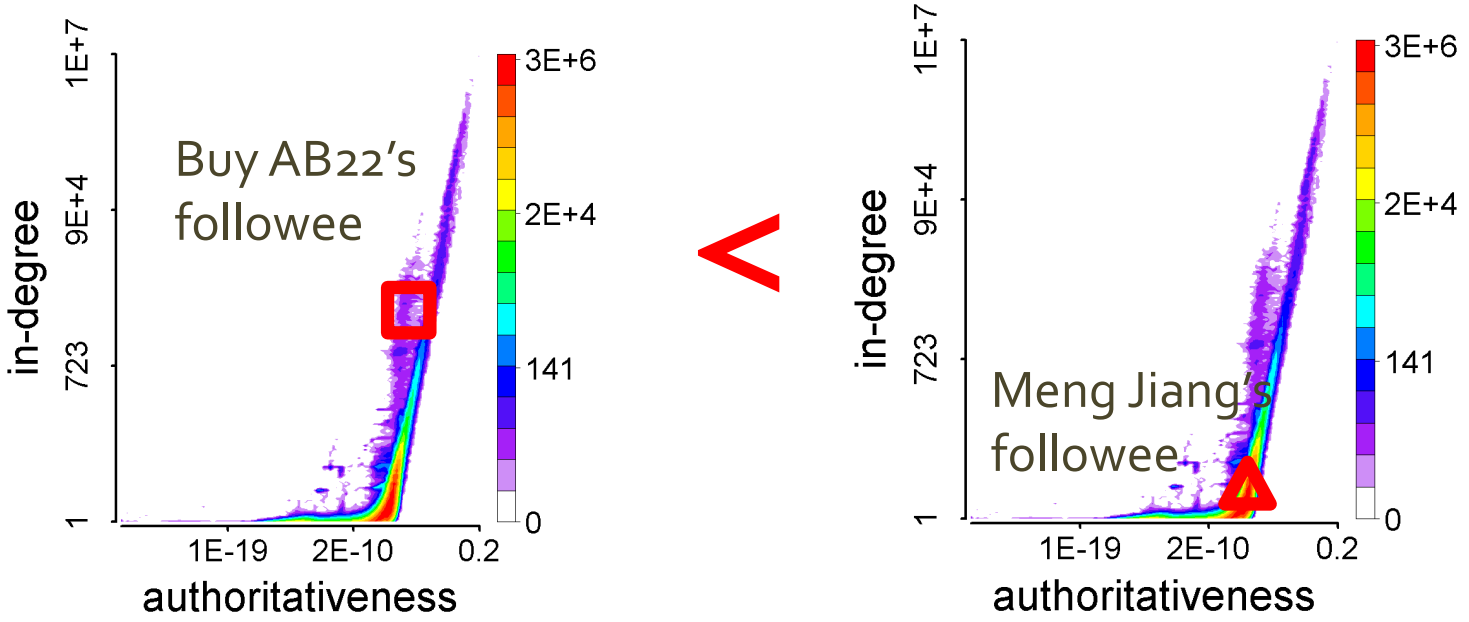
Definition: Synchronicity

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



Definition: Normality

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



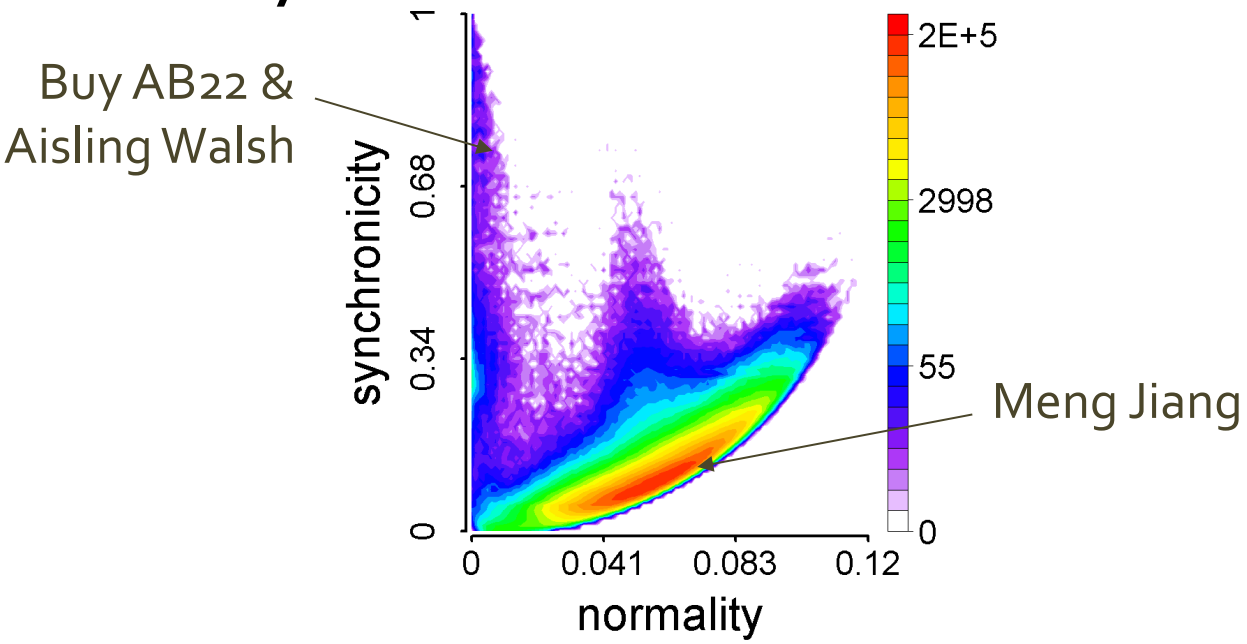
When is the Synchronicity Too High?

Problem: Given a normality value (n) of a follower, find the minimal synchronicity value (s_{min}).

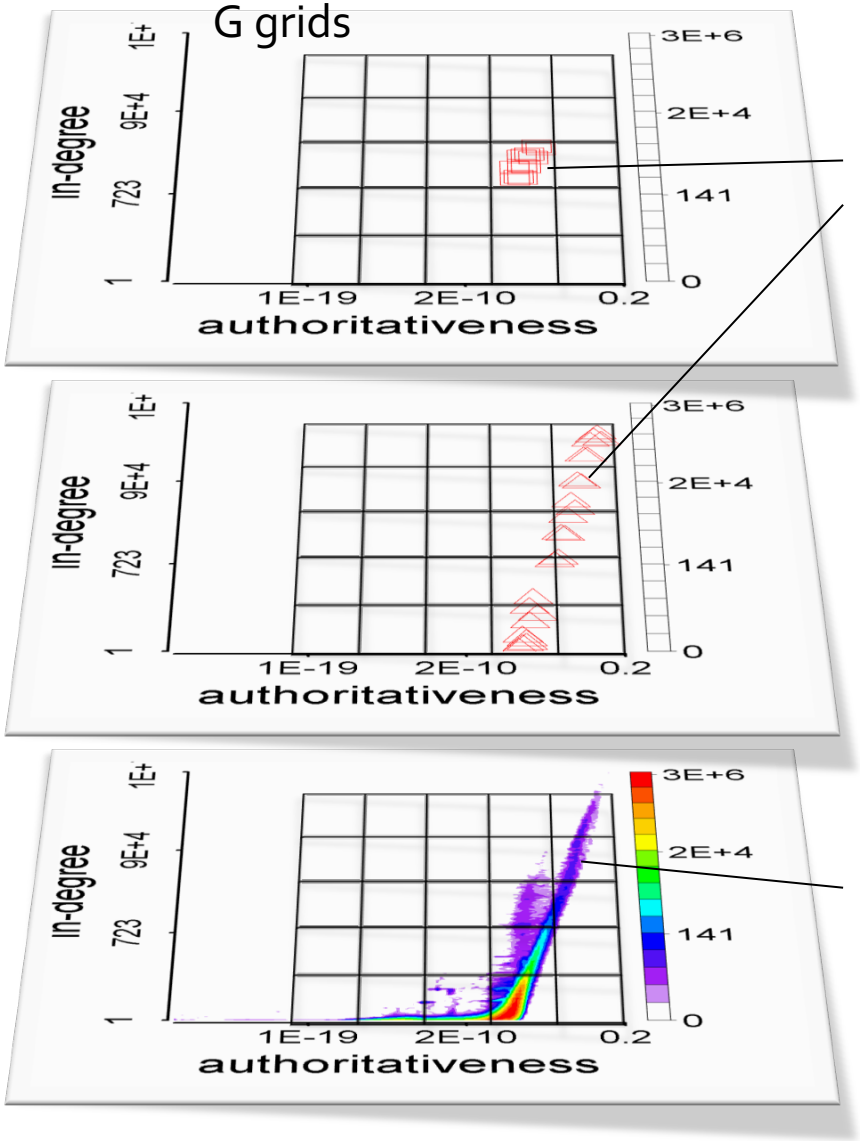
Theorem:

$$s_{min} = \frac{-G\,n^2 + 2\,n - s_b}{1 - G\,s_b}$$ *(parabolic lower limit)*

Our CatchSync:



Proof



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

$s_{min} = \sum (fp_g/F)\,(fp_g/F) = \sum f_g^2$

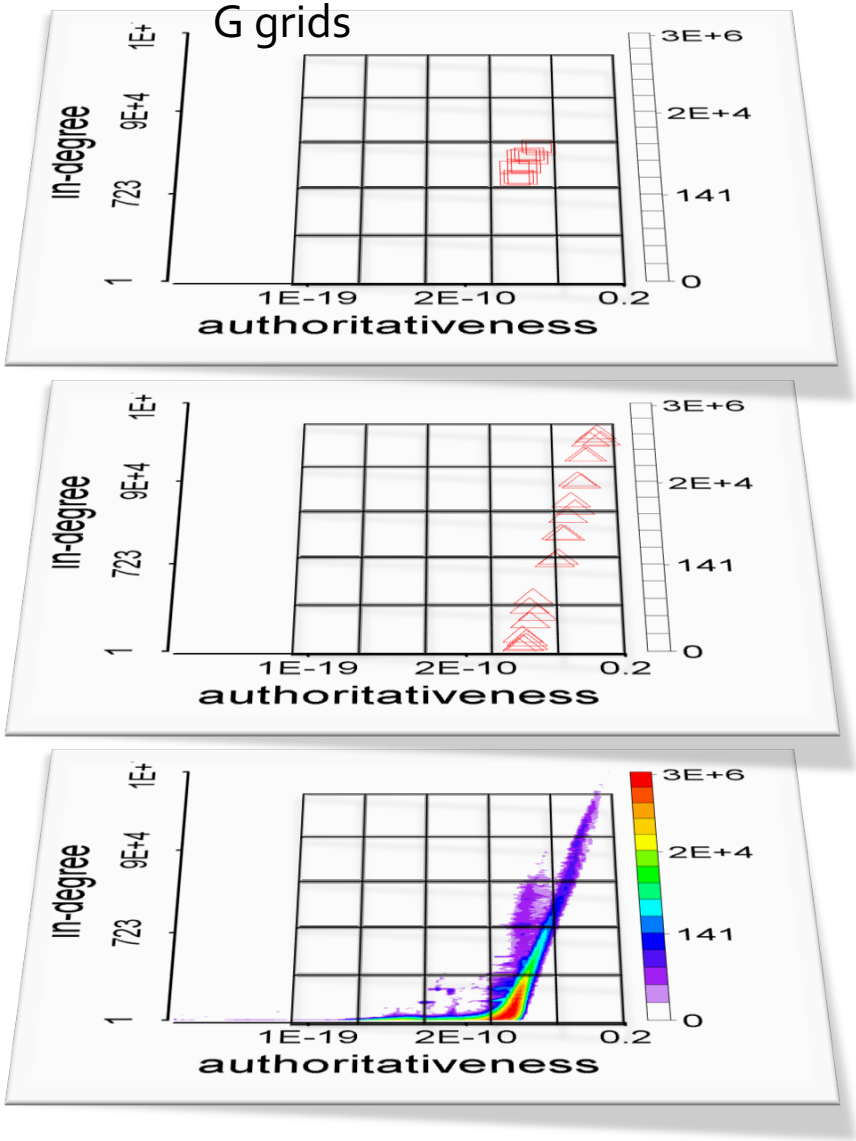
where

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

bp_g: #background points in grid g

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

Proof



Lagrange multiplier:

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

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

Lagrange function:

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

Gradients:

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

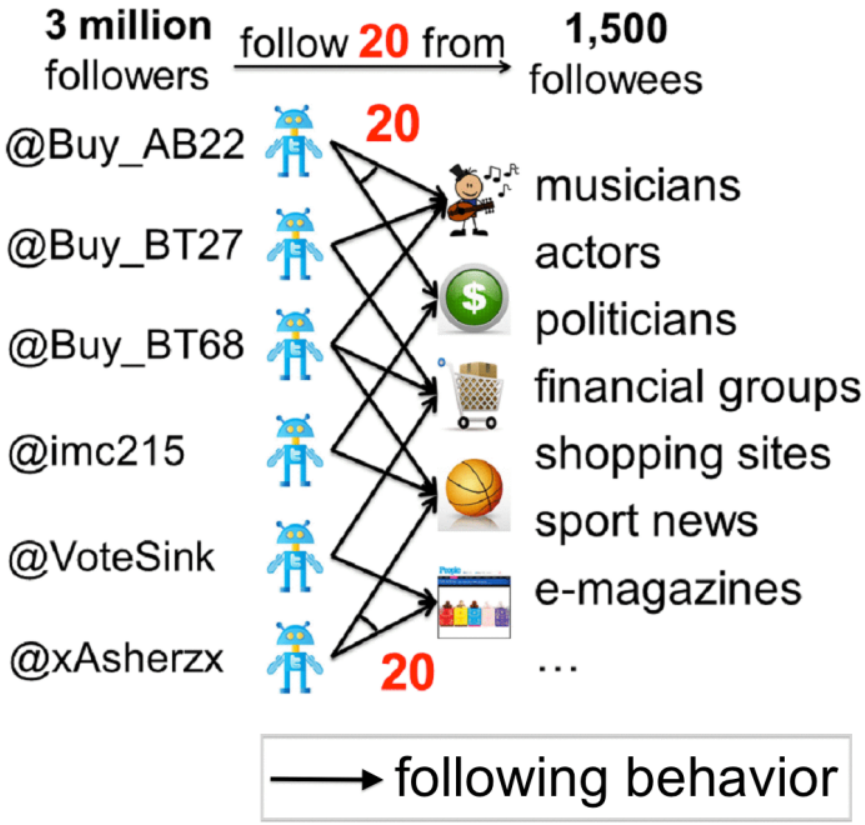
$$\begin{cases} 2 + \lambda G + \mu = 0 & \times \sum \\ 2n + \lambda + \mu s_b = 0 & \times b_g \sum \\ 2 s_{min} + \lambda + \mu n = 0 & \times f_g \sum \end{cases}$$

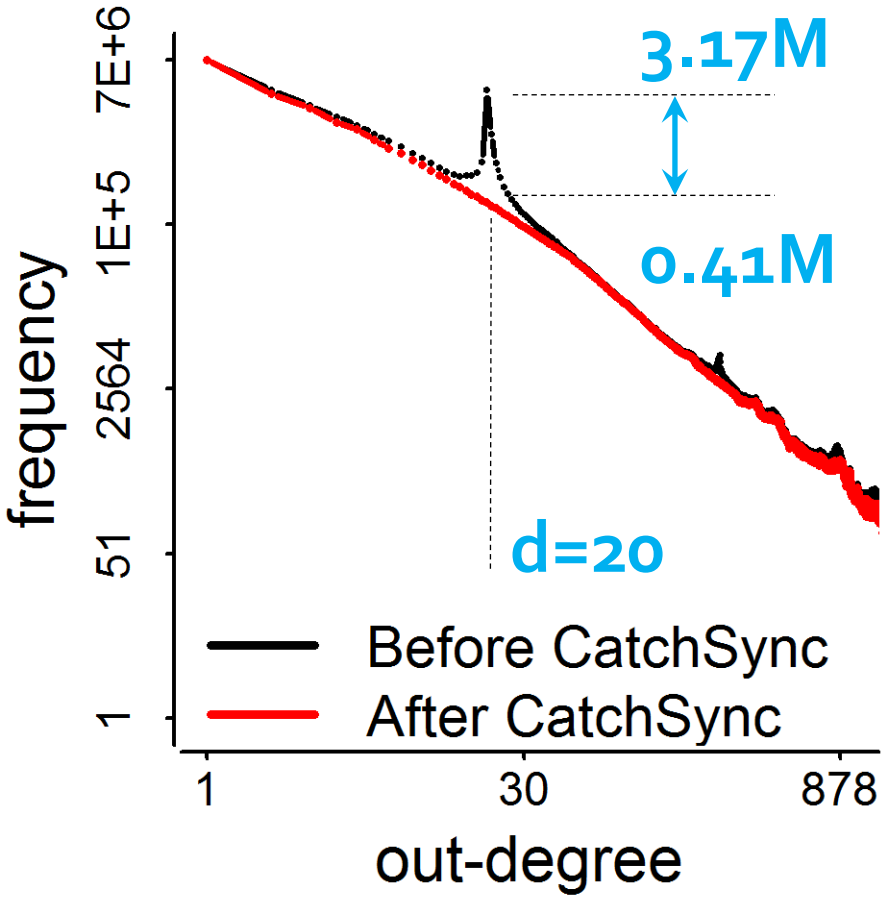
where $s_b = \sum b_g^2$.

Therefore,

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

The Distribution was Recovered!





Impact

- Cited by **76**; WWW'14: cited by **21**. TKDD'16: cited by **21**. Synchronized behavior in cyber attacks.
  - ACM SIGSAC Conference on **Computer and Communications Security** (CCS), 2015 : two papers
  - **Network and Distributed System Security** Symposium (NDSS), 2016: one paper
  - The 31st Annual **Computer Security Applications** Conference (ACSAC), 2015: one paper
  - IEEE Transactions on **Information Forensics and Security** (TIFS), 2016: one paper
  - International Journal of **Digital Crime and Forensics** (IJDCF), 2016: one paper
  - …

Impact

- Cited by **76**; WWW'14: cited by **21**. TKDD'16: cited by **21**. Synchronized behavior in cyber attacks.
- 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
- Endless games! First proposed **Camouflage** in PAKDD'14.
  - Cited by **47**.
  - Cited by *KDD'16 Best Research Paper*: the authors (B. Hooi *et al.*) provided theoretical bounds to prevent the camouflage.

Outline

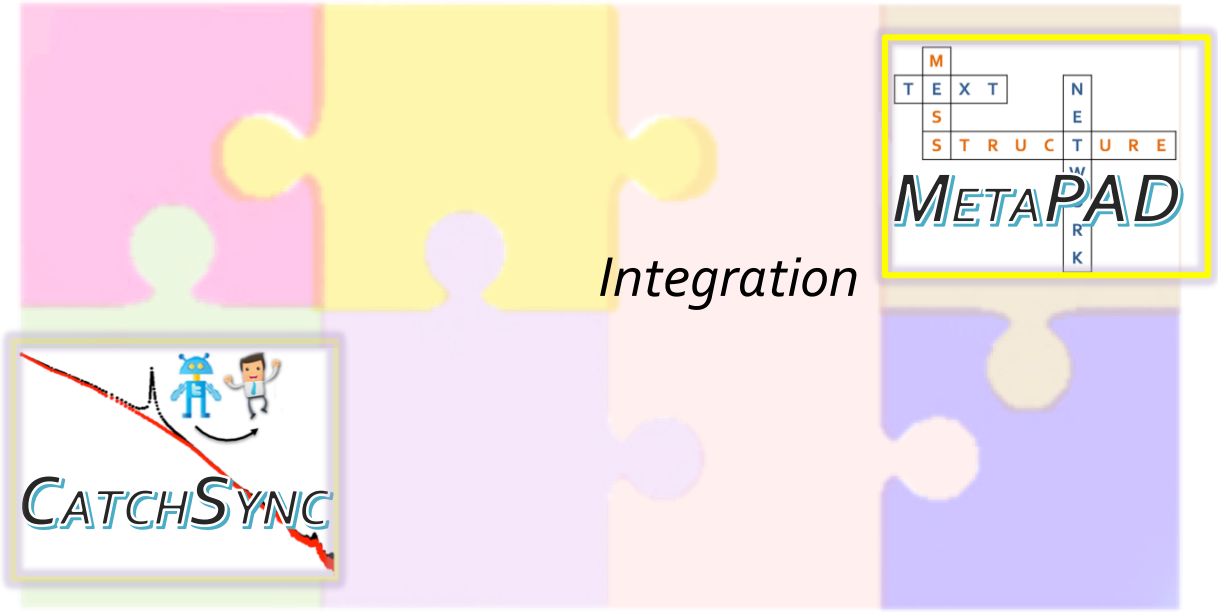
Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

Social contexts

Spatiotemporal contexts

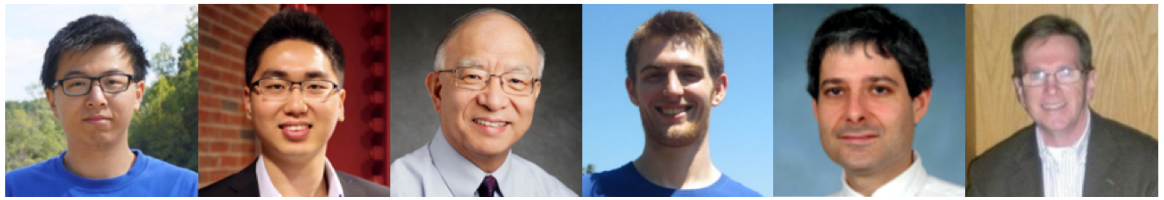
Behavioral content



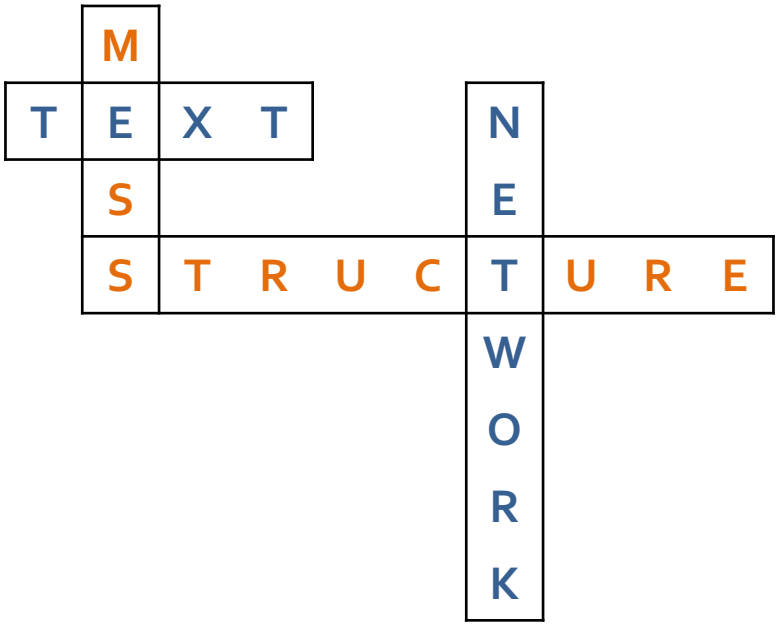
MetaPAD: Meta Pattern-driven Attribute Discovery from Massive Text Corpora

Joint work with Jingbo Shang, Xiang Ren, Jiawei Han (UIUC),
Taylor Cassidy, Lance Kaplan, and Timothy Hanratty (US Army Research Lab)

ACM SIGKDD 2017

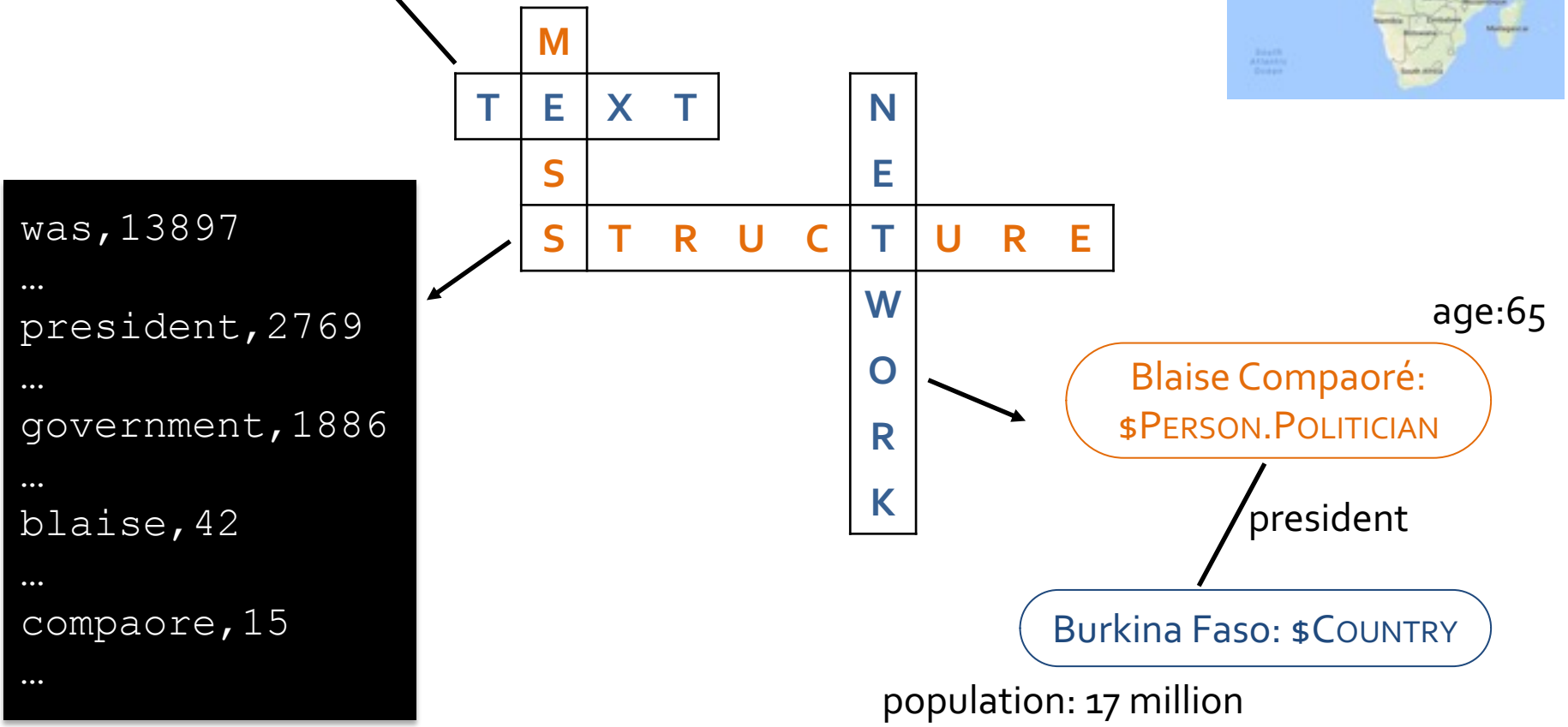


Motivation



Motivation

Given a sentence "President Blaise Compaoré's government of **Burkina Faso** was founded…", …



Q'5: Attribute Discovery

Given a text corpus,

Task 1: ⟨entity, attribute name, attribute value⟩

⟨Burkina Faso, president, Blaise Compaoré⟩

⟨Burkina Faso, population, 17 million⟩

⟨Blaise Compaoré, age, 65⟩

Instance-level

Task 2: ⟨entity type, attribute name⟩

⟨$COUNTRY, president⟩

⟨$COUNTRY, population⟩

⟨$PERSON, age⟩

Type-level

Literature: Task 1

Stanford OpenIE [ACL'15], AI2's Open IE-Ollie [EMNLP'12]:

Learn syntactic and lexical patterns of expressing relations

Ignore entity-typing information!

Input: "President Blaise Compaoré**'s** government of Burkina Faso was founded…"

Output: ⟨President Blaise Compaoré, **have**, government of Burkina Faso⟩ ☹

Literature: Task 2

Google's Biperpedia+ARI [VLDB'14, WWW'16], ReNoun [EMNLP'15]:

"president of united states" → "A of E", "E 's A", "E A", "A, E"

Query log: Highly constrained and unavailable

"Barack Obama, President of U.S., " → "O, A of S,", "S A O"

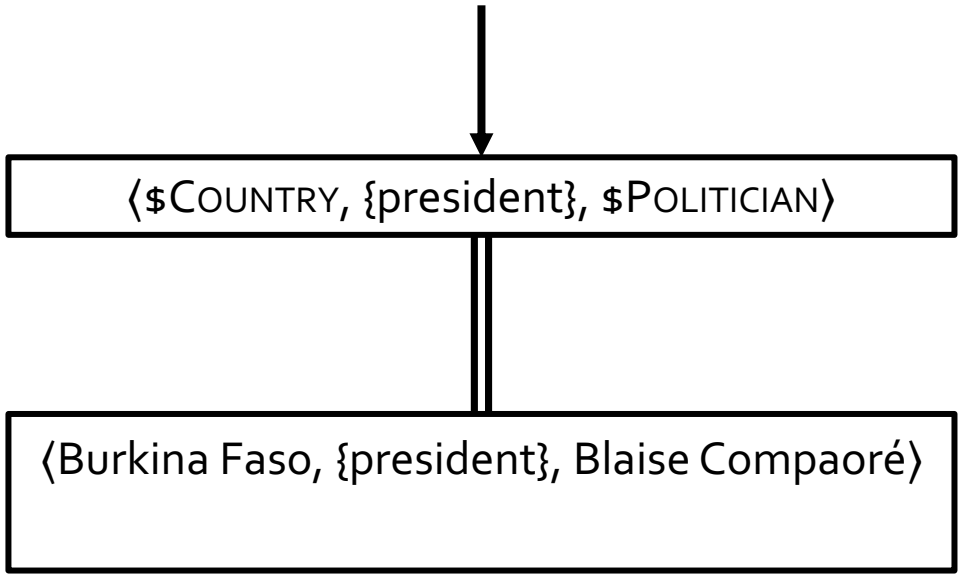
Annotated corpus: Domain limited and expensive

Input: "…Sunday night, Burkina Faso…" and the "A, E" pattern

Output: ⟨$COUNTRY, Sunday night⟩ ☹

Our Methodology (M5)

(#1) "President Blaise Compaoré's government of Burkina Faso was founded…"



Our Methodology (M5)

(#1) "President Blaise Compaoré's government of Burkina Faso was founded …"
(#2) "President Barack Obama's government of U.S. claimed that…"

Meta patterns:

⌈president $PERSON.POLITICIAN 's government of $LOCATION.COUNTRY⌋ …

Generate patterns with massive instances in the data

⟨$COUNTRY, {president}, $POLITICIAN⟩ frequency↑

⟨Burkina Faso, {president}, Blaise Compaoré⟩
⟨U.S., {president}, Barack Obama⟩

Our Methodology (M5)

(#1) "President Blaise Compaoré's government of Burkina Faso was founded …"
(#2) "President Barack Obama's government of U.S. claimed that…"

Meta patterns:

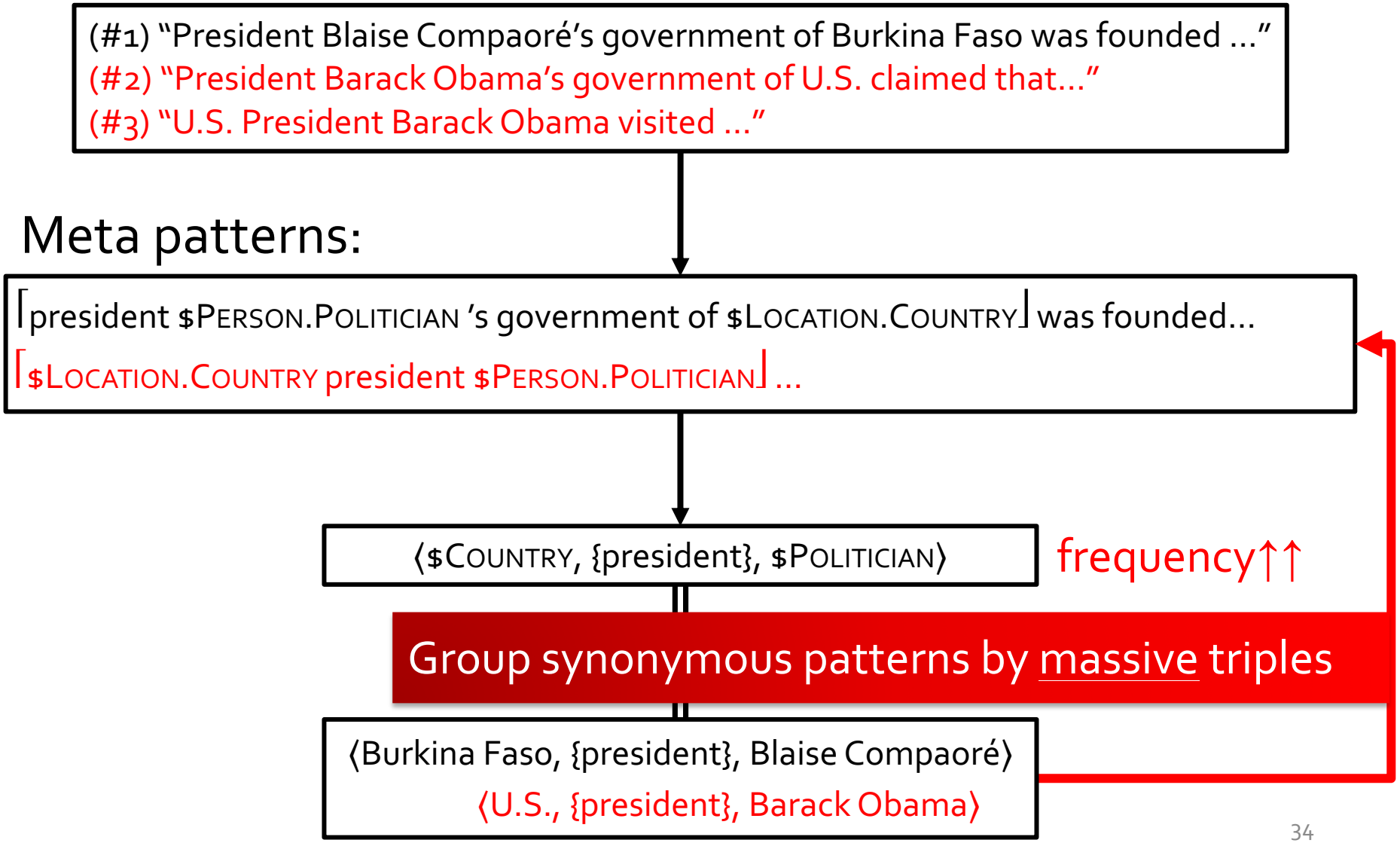
⌈president $PERSON.POLITICIAN 's government of $LOCATION.COUNTRY⌋ …

⟨$COUNTRY, {president}, $POLITICIAN⟩

Generate massive triples by matching the meta patterns

⟨Burkina Faso, {president}, Blaise Compaoré⟩
⟨U.S., {president}, Barack Obama⟩

Our Methodology (M5)



Our Methodology (M5)

(#1) "President Blaise Compaoré's government of Burkina Faso was founded …"
(#2) "President Barack Obama's government of U.S. claimed that…"
(#3) "U.S. President Barack Obama visited …"

Meta patterns:

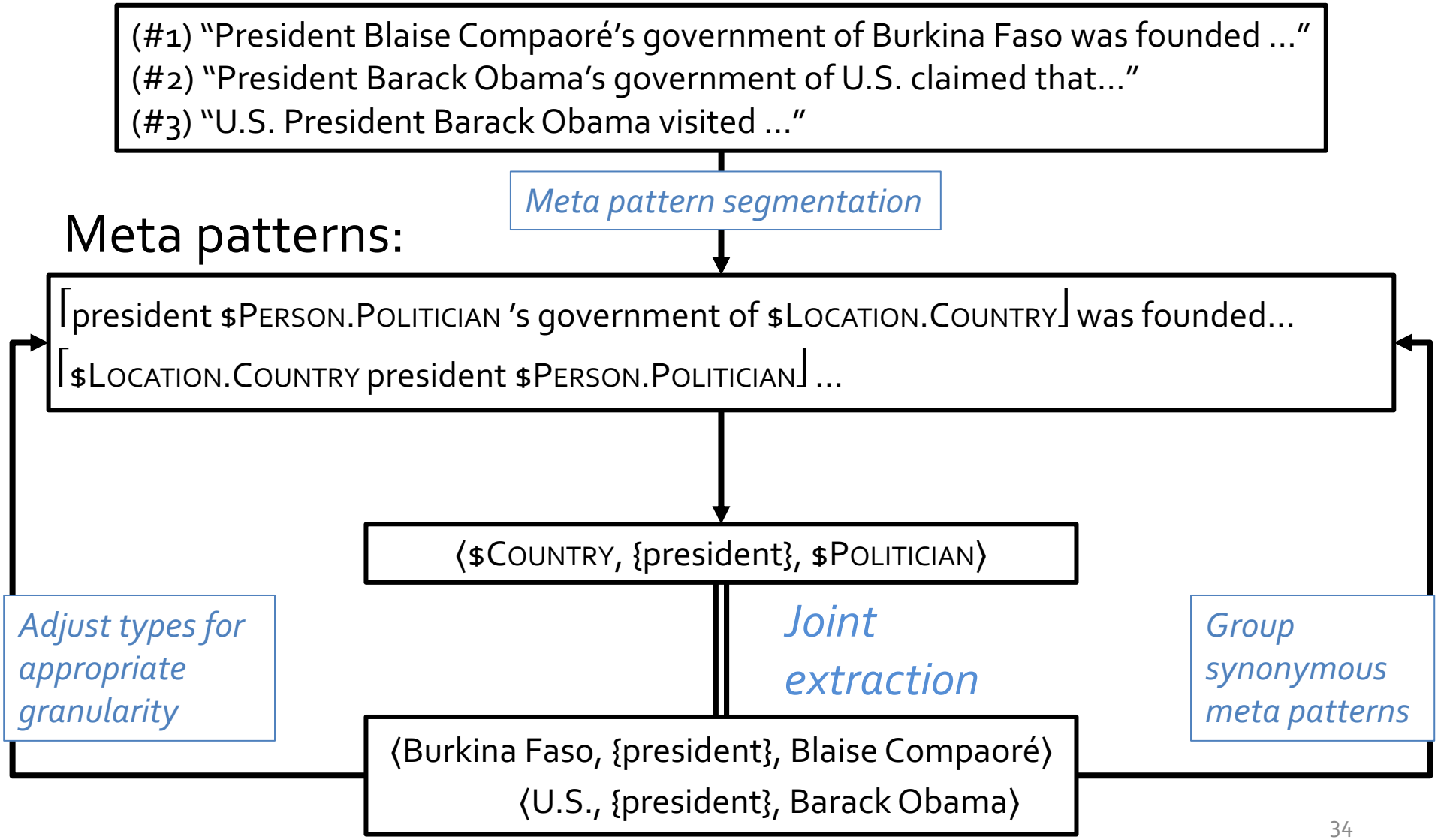
⌈president $PERSON.POLITICIAN 's government of $LOCATION.COUNTRY⌋ was founded…
⌈$LOCATION.COUNTRY president $PERSON.POLITICIAN⌋ …

⟨$COUNTRY, {president}, $POLITICIAN⟩

Adjust entity types in meta patterns for appropriate granularity with triples

⟨Burkina Faso, {president}, Blaise Compaoré⟩
⟨U.S., {president}, Barack Obama⟩

Our Meta-Pattern Methodology



Our Meta-Pattern Methodology

(#1) "President Blaise Compaoré's government of Burkina Faso was founded …"
(#2) "President Barack Obama's government of U.S. claimed that…"
(#3) "U.S. President Barack Obama visited …"

Meta pattern segmentation

Meta patterns:

⌈president $PERSON.POLITICIAN 's government of $LOCATION.COUNTRY⌋ was founded…
⌈$LOCATION.COUNTRY president $PERSON.POLITICIAN⌋ …

No heavy annotation required
No domain knowledge required
No query log required

if we can recognize and type the entities in the same manner…

Adjust type appropriate granularity

up onymous meta patterns

⟨Burkina Faso, {president}, Blaise Compaoré⟩
⟨U.S., {president}, Barack Obama⟩

Han's Group Strength in Text Mining

"President Blaise Compaoré's government of Burkina Faso was founded …"

Phrase mining (SegPhrase by Liu and Han et al. SIGMOD'15)

"president blaise_compaoré 's government of burkina_faso was founded …"

Entity recognition and typing with Distant Supervision (ClusType by Ren and Han et al. KDD'15)

"president $PERSON 's government of $LOCATION was founded …"

Fine-grained typing (PLE by Ren and Han et al. KDD'16)

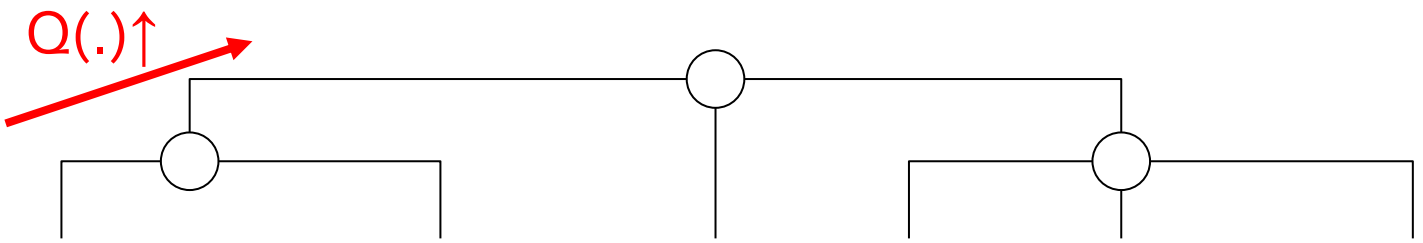
"president $PERSON.POLITICIAN 's government of $LOCATION.COUNTRY was founded …"

Meta-Pattern Quality Assessment and Segmentation

A rich set of features:

- ✓ Frequency
- ✓ Concordance: "$PERSON 's wife"
- ✓ Completeness: "$COUNTRY president" vs "$COUNTRY president $POLITICIAN"
- ✓ Informativeness: "$PERSON and $PERSON " vs "$PERSON 's wife, $PERSON"

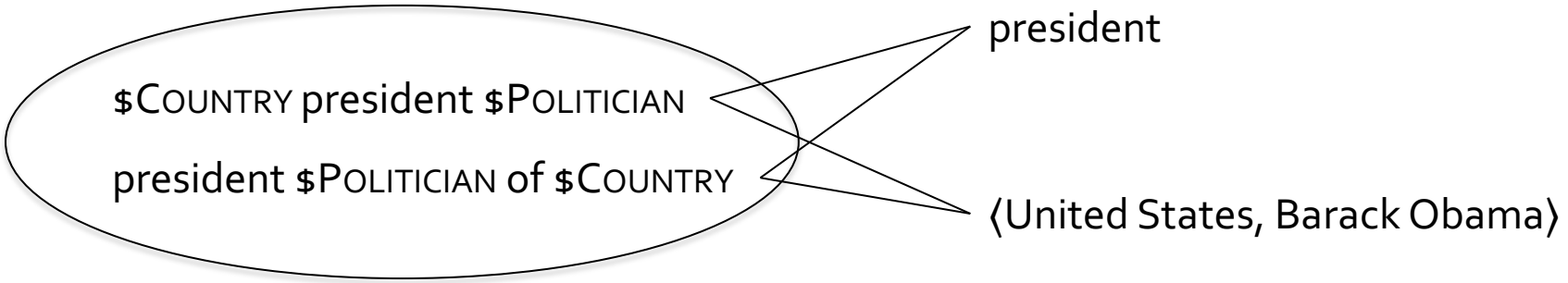
Regression Q(.): random forest with only 300 labels



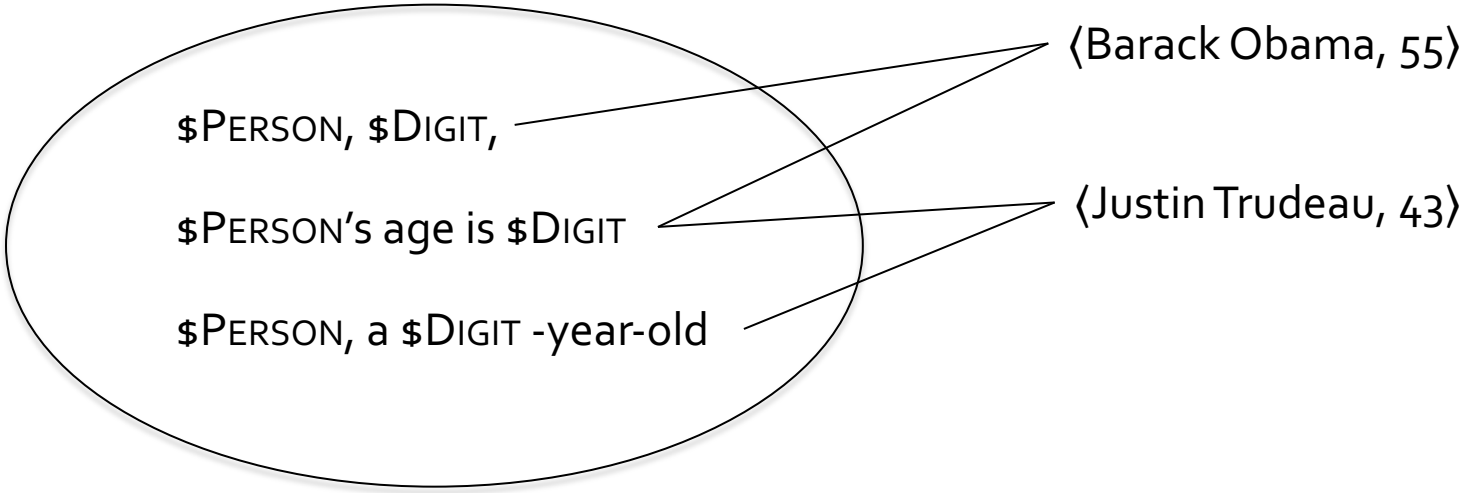
president $PERSON.POLITICIAN 's government of $LOCATION.COUNTRY

Grouping Synonymous Patterns

⟨$COUNTRY, president, $POLITICIAN⟩



⟨$PERSON, {age, -year-old}, $DIGIT⟩



Adjusting Types in Meta Patterns for Appropriate Granularity

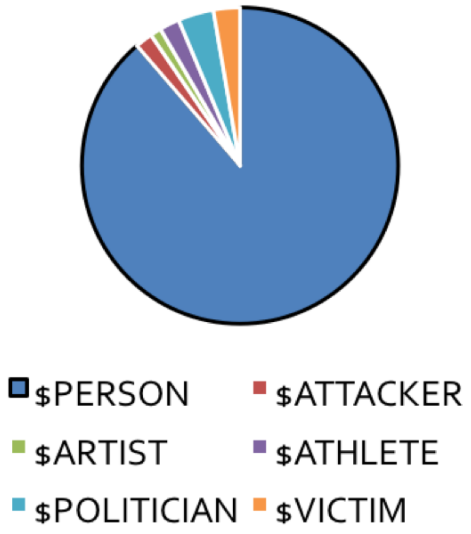
$PERSON, $DIGIT,

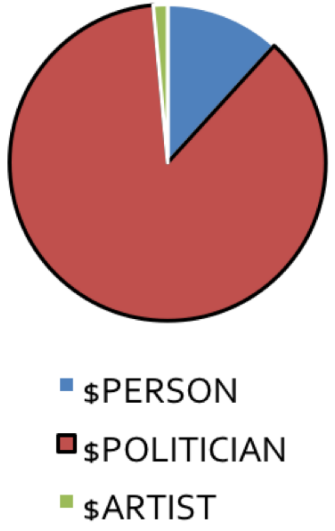
$PERSON's age is $DIGIT

$PERSON, a $DIGIT -year-old

$COUNTRY president $POLITICIAN

president $POLITICIAN of $COUNTRY





Results in General Domain

Meta patterns	Entity	Attribute value
$COUNTRY President $POLITICIAN $COUNTRY's president $POLITICIAN President $POLITICIAN of $COUNTRY ... $POLITICIAN's government of $COUNTRY	United States	Barack Obama
	Russia	Vladimir Putin
	France	Francois Hollande
	...	...
	Burkina Faso	Blaise Compaoré

Meta patterns	Entity	Attribute value
$COMPANY CEO $PERSON $COMPANY chief executive $PERSON $PERSON, the $COMPANY CEO, ... $COMPANY former CEO $PERSON $PERSON, the $COMPANY former CEO,	Apple	Tim Cook
	Facebook	Mark Zuckerberg
	Hewlett-Packard	Carly Fiorina
	...	...
	Infor	Charles Phillips
	Afghan Citadel	Roya Mahboob

Results in Biomedical Domain

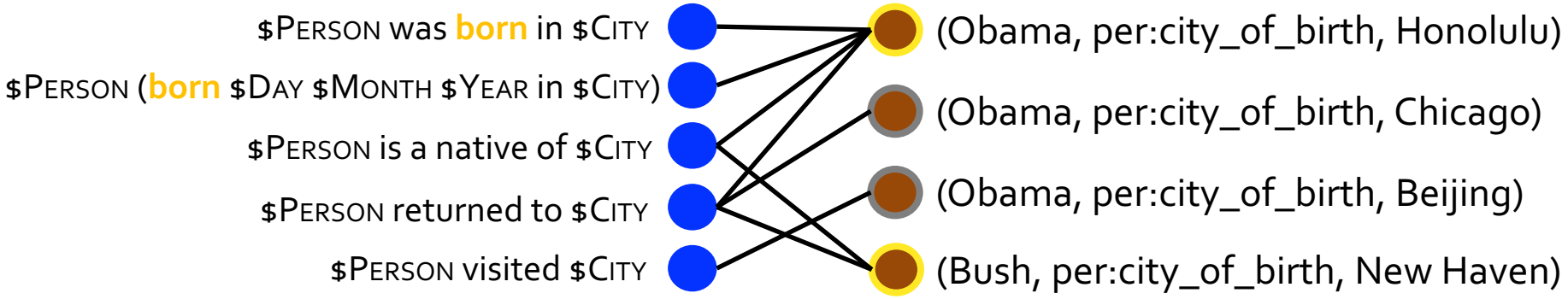
Meta patterns	Entity	Attribute value
$TREATMENT was used to treat $DISEASE $DISEASE using the $TREATMENT $TREATMENT has been used to treat $DISEASE $TREATMENT of patients with $DISEASE …	zoledronic acid therapy	Paget's disease of bone
	bisphosphonates	osteoporosis
	calcitonin	Paget's disease of bone
	calcitonin	osteoporosis
	…	…

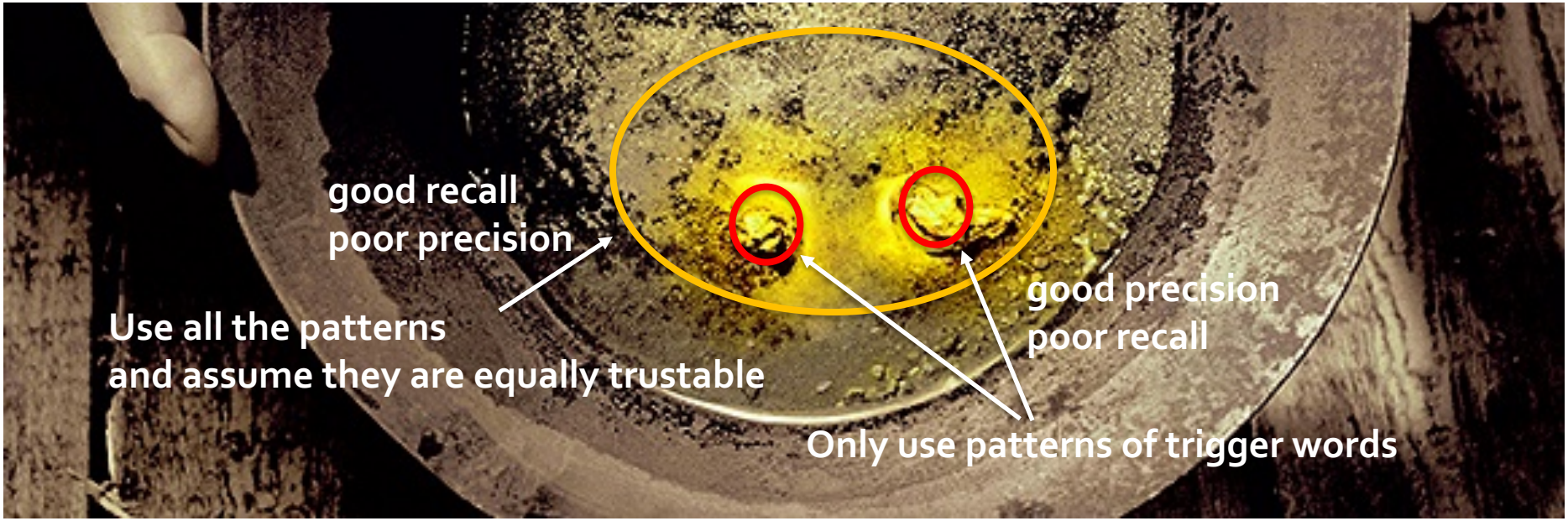
Meta patterns	Entity	Attribute value
$BACTERIA was resistant to $ANTIBIOTICS $BACTERIA are resistant to $ANTIBIOTICS $BACTERIA is the most resistant to $ANTIBIOTICS … $BACTERIA, particularly those resistant to $ANTIBIOTICS	corynebacterium striatum BM4687	gentamicin
	corynebacterium striatum BM4687	tobramycin
	methicillin-susceptible S aureus	vancomycin
	multidrug-resistant enterobacteriaceae	gentamicin
	…	…

Experimental Results

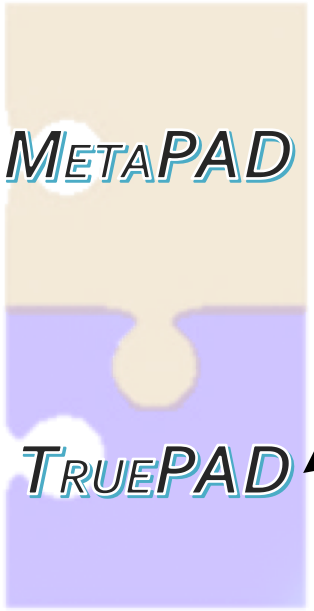
F1 score	⟨entity type, attribute name⟩	⟨entity, attribute name, attribute value⟩
Baselines		Stanford's OpenIE: 0.035
		AI2's Ollie: 0.131
	Biperpedia: 0.324	Google's ReNoun: 0.309
+Segmentation	+40.0%	+19.4%
+Type Adjustment	+6.5%	+15.0%
+Synonymous	+2.6%	
All	0.495 **relatively +52.9%**	0.424 **relatively +37.3%**

On-going: Reliable Attribute Discovery



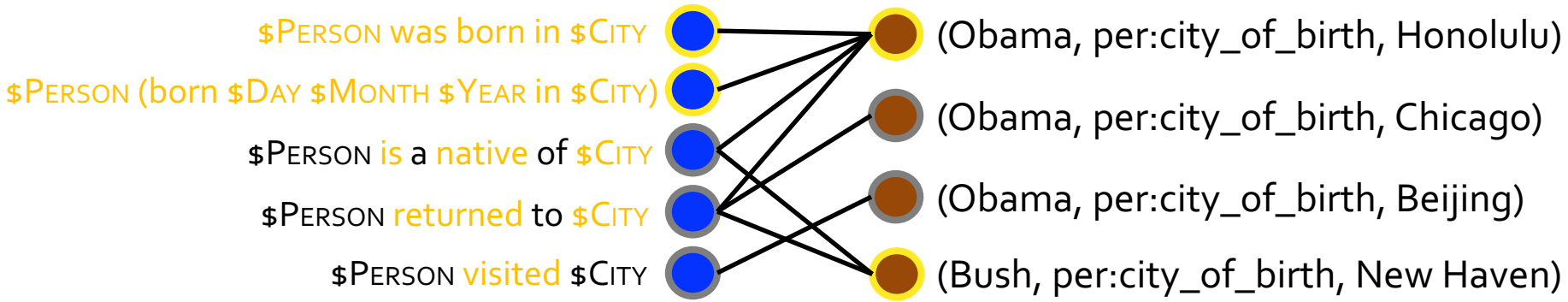


On-going: Reliable Attribute Discovery



Modeling the **reliability** of extractors:

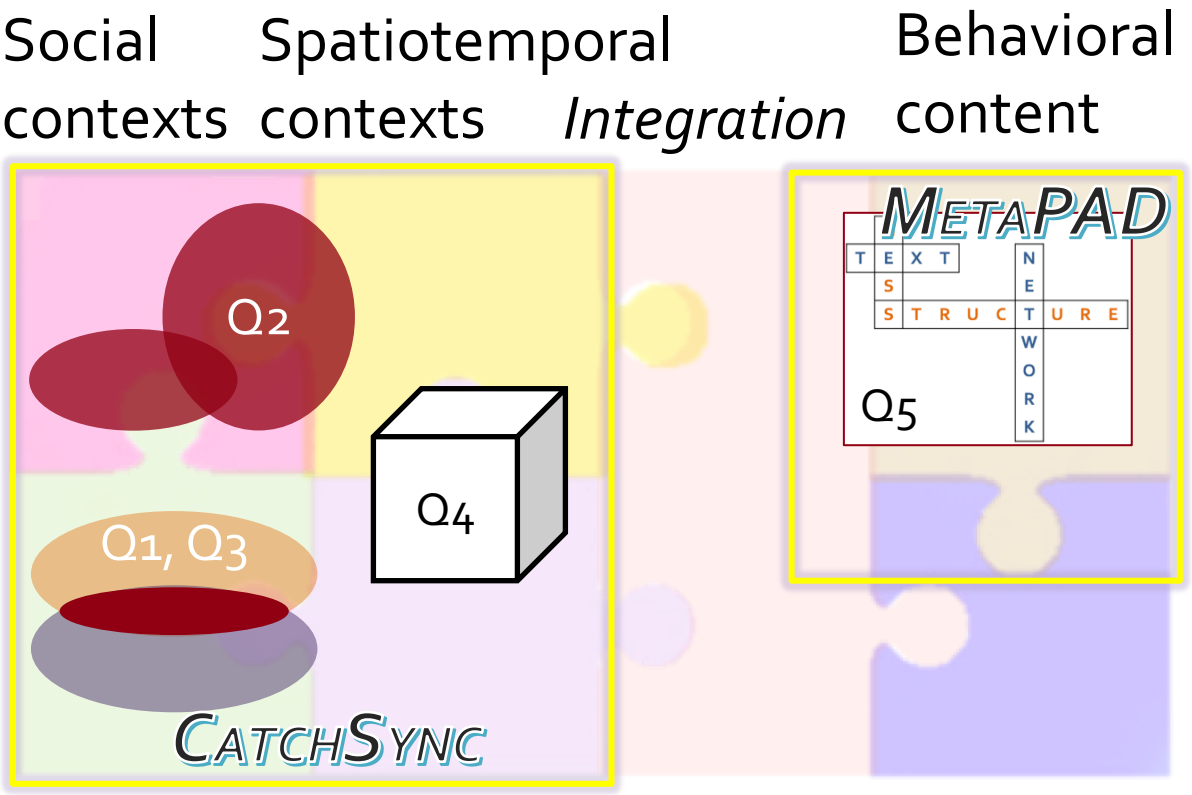
- Not every extraction is 100% correct.
- The meta patterns are not equally trustable.



Summary

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

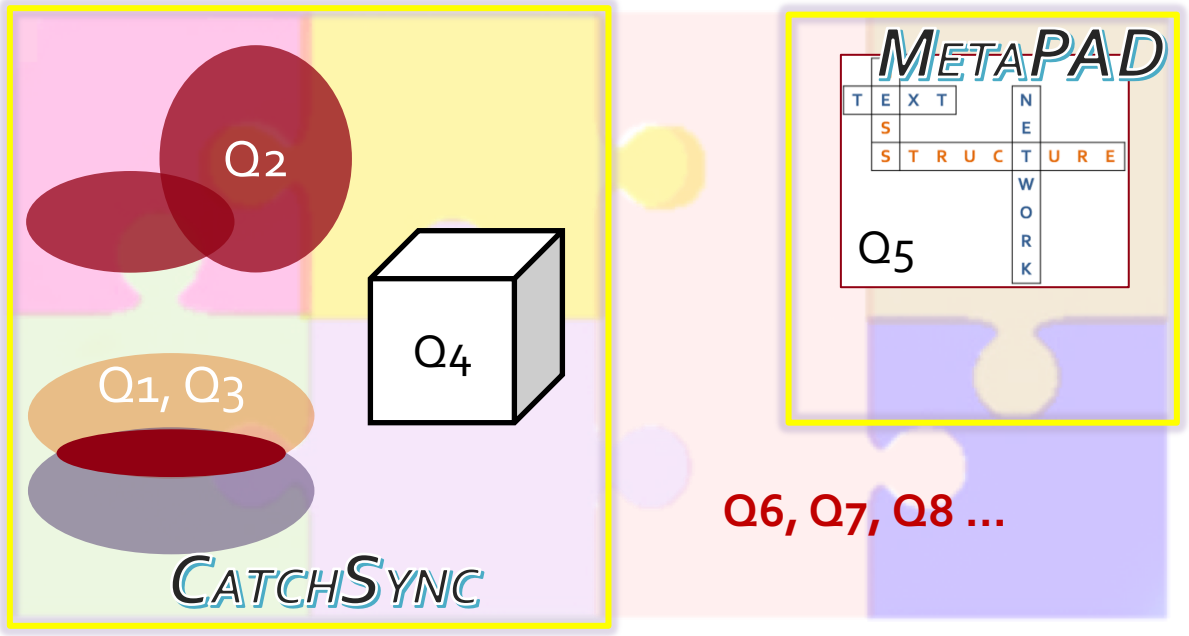


Summary

Social contexts | Spatiotemporal contexts | *Integration* | Behavioral content

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection



Expedition!!!

- ❑ Data sciences + ML, AI, NLP, CyberSecurity …
- ❑ Interdisciplinary research: Sociology, Psychology …
- ❑ Transformative technologies: Change the games ☺

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