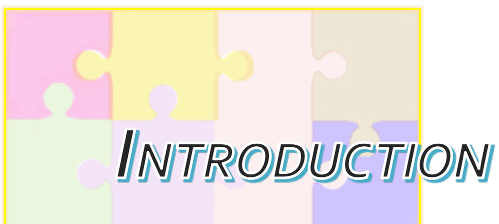
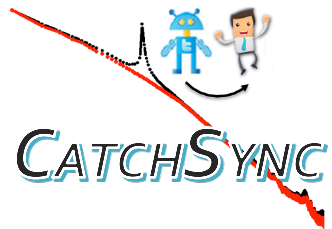
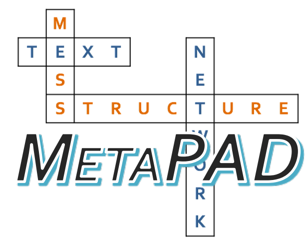
Data-Driven Behavioral Analytics with Networks







Meng Jiang
University of Illinois at Urbana-Champaign
mjiang89@gmail.com   2130 SC

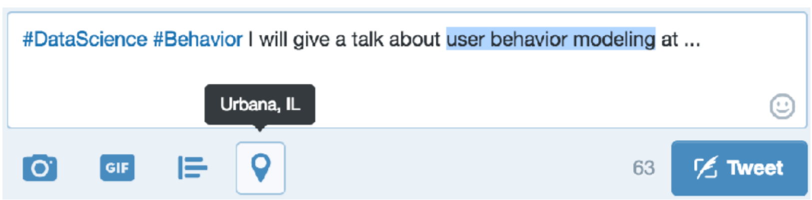
http://www.meng-jiang.com

Behavior and “Behavior Networks”

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

Social behaviors

Tweeting behaviors



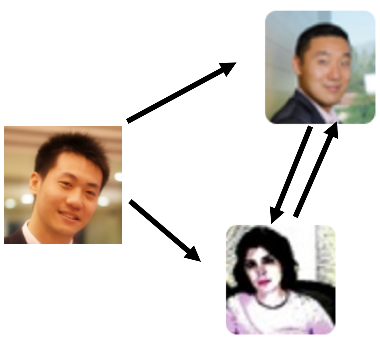
Paper-publishing behaviors

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

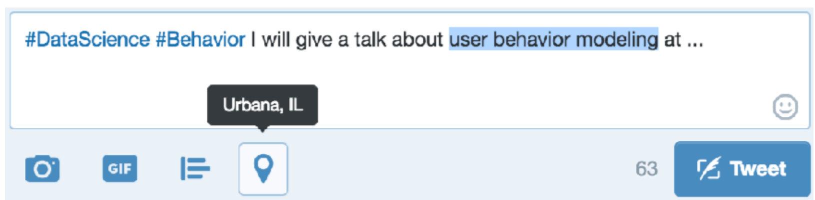
Behavior and “Behavior Networks”

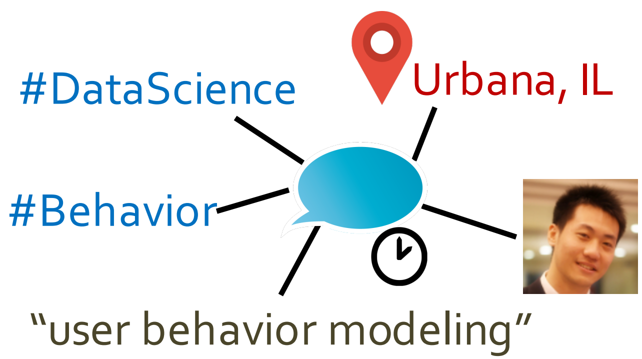
Interaction of individuals with themselves and with their environment. — Wikipedia

Social behaviors



Tweeting behaviors



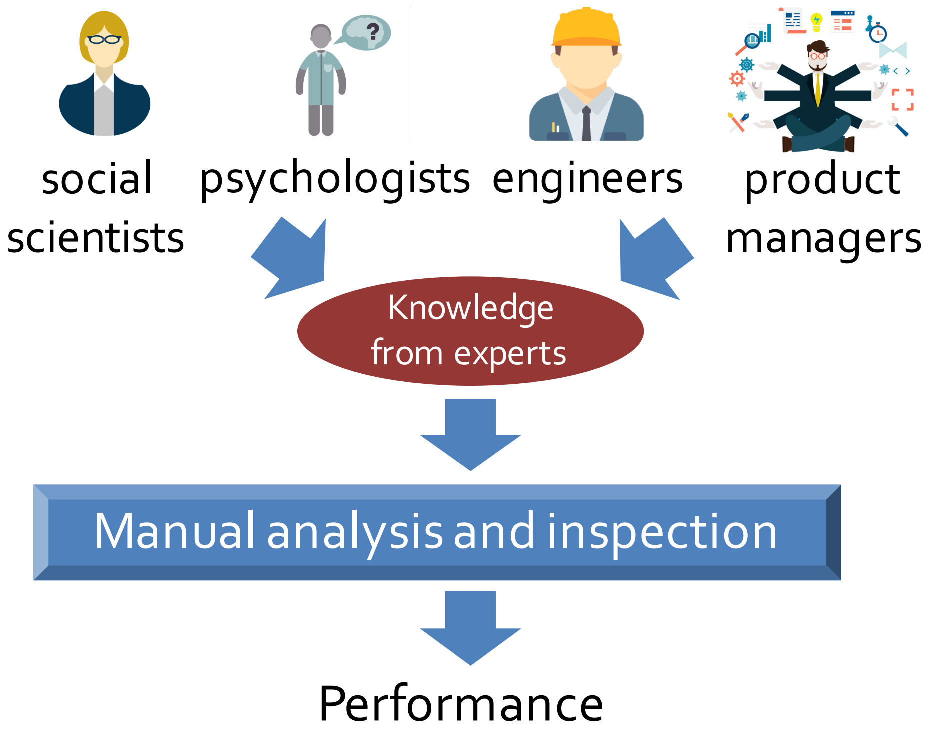


Paper-publishing behaviors

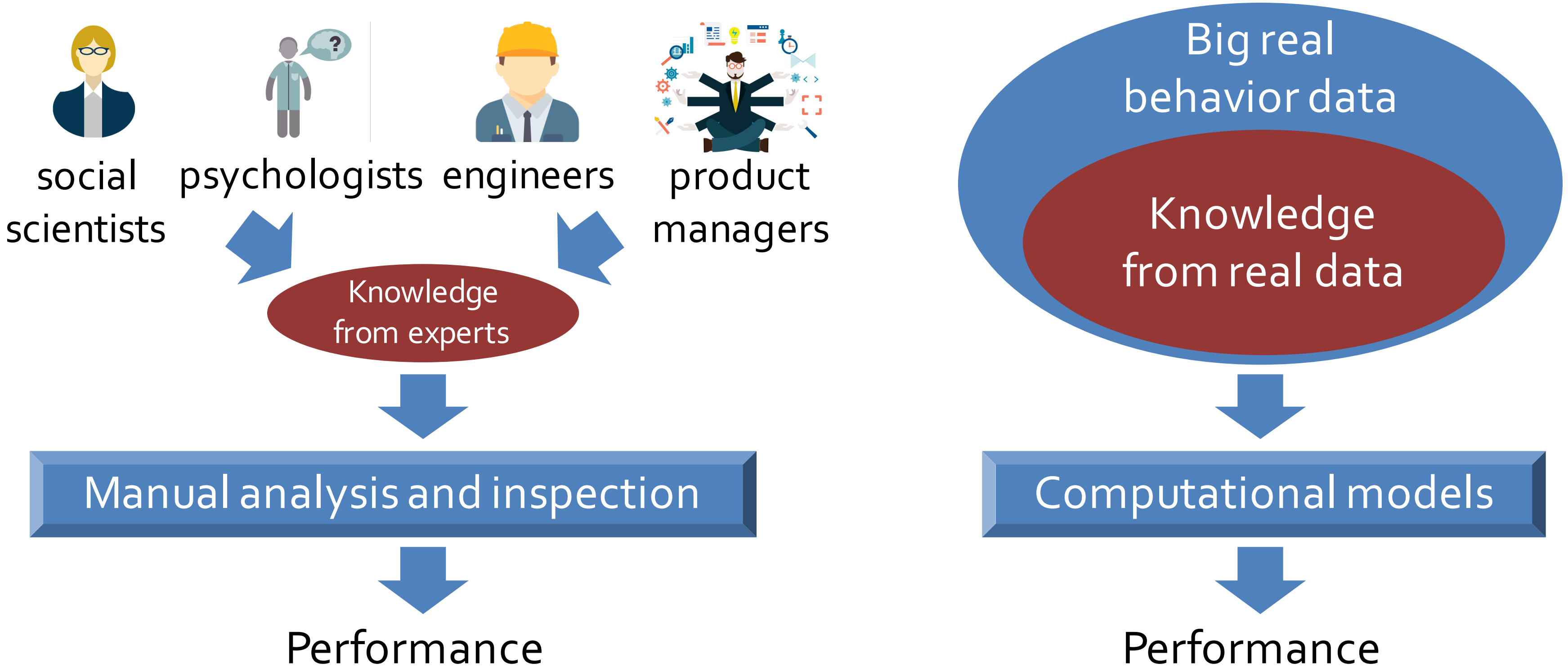
Meng Jiang, **Christos Faloutsos**, and **Jiawei Han**. “CatchTartan: **Representing** and **Summarizing Dynamic Behaviors**.” In **SIGKDD 2016**.

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

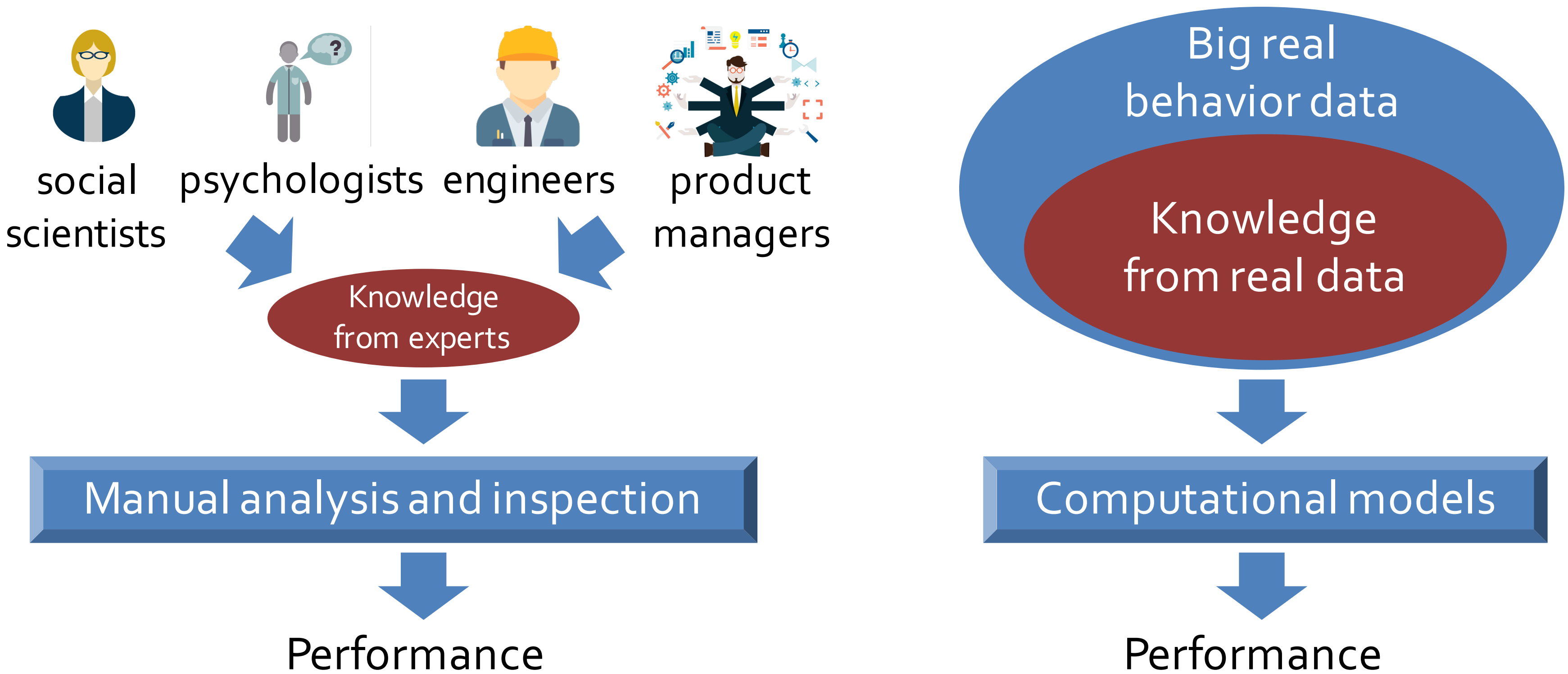
Data-Driven Behavioral Analysis



Data-Driven Behavioral Analysis



Data-Driven Behavioral Analysis



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

Behavior Modeling

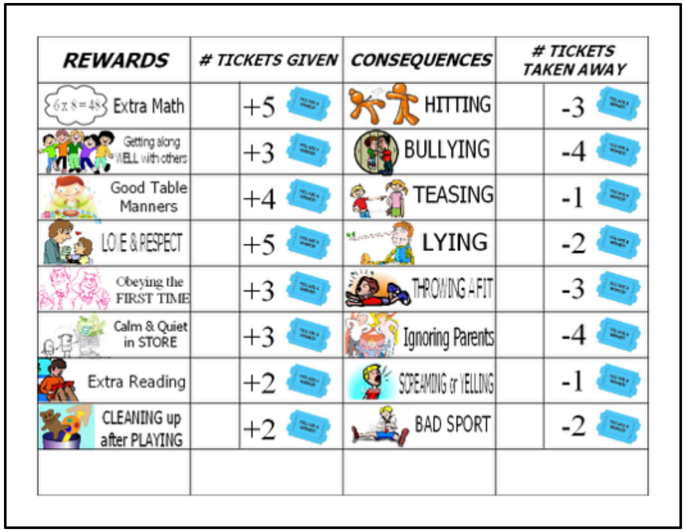
Research Topics in Behavior Modeling

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

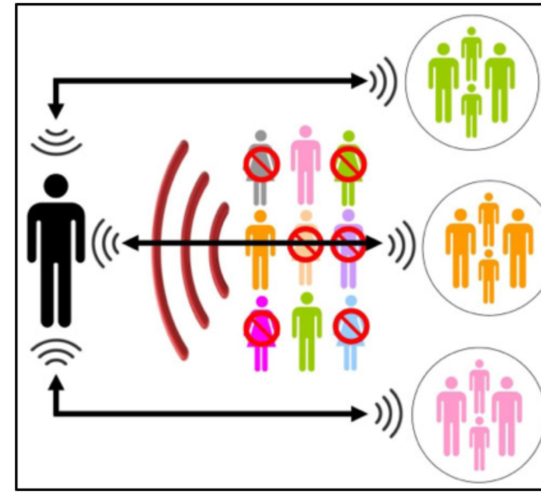


REWARDS	# TICKETS GIVEN	CONSEQUENCES	# TICKETS TAKEN AWAY
Extra Math	+5	HITTING	-3
Getting along WELL with others	+3	BULLYING	-4
Good Table Manners	+4	TEASING	-1
LOVE & RESPECT	+5	LYING	-2
Obeying the FIRST TIME	+3	THROWING A FIT	-3
Calm & Quiet in STORE	+3	Ignoring Parents	-4
Extra Reading	+2	SCREAMING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

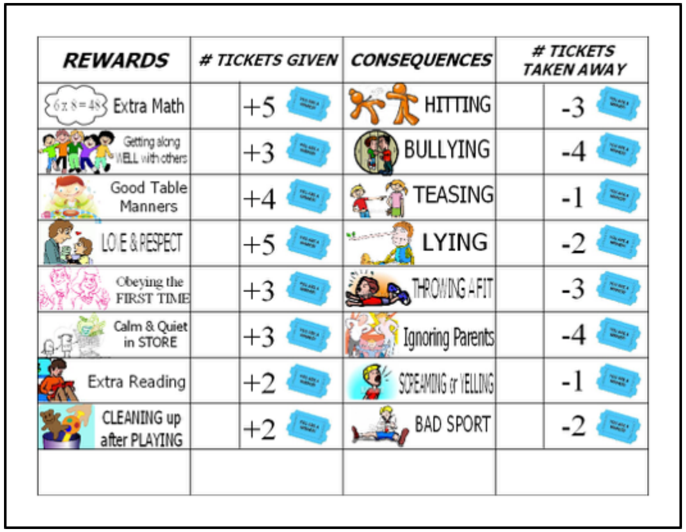
1. Behavior intentions

2. Social contexts

Behavior Modeling



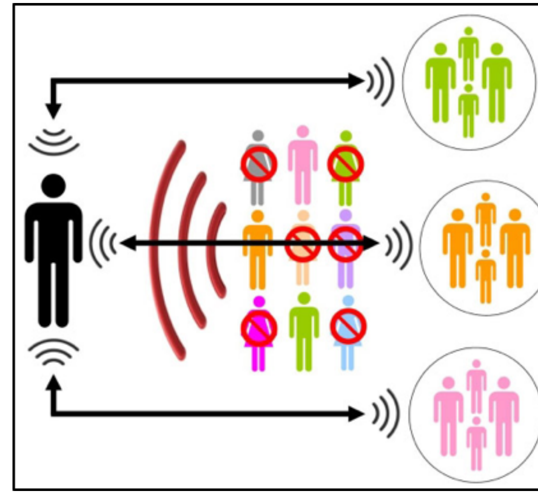
Research Topics in Behavior Modeling



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

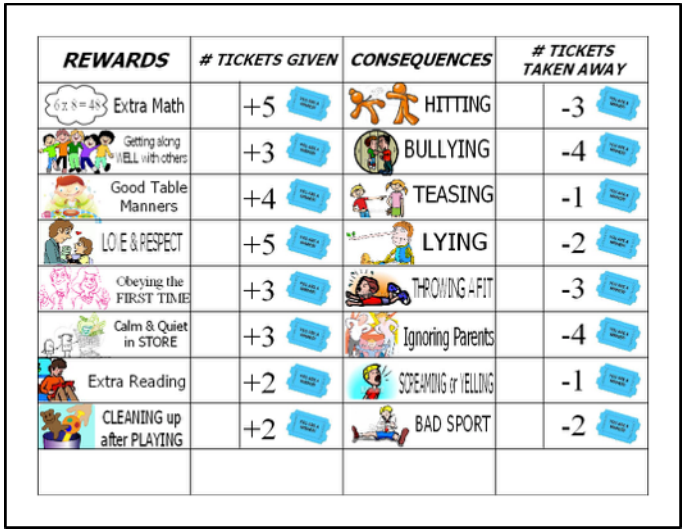
2. Social contexts



Behavior Modeling

3. Spatiotemporal contexts

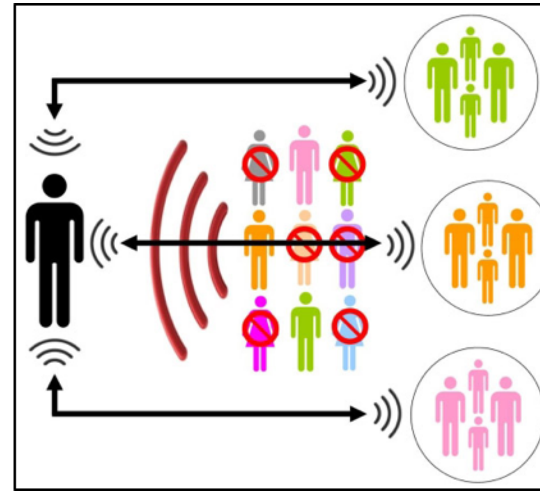
Research Topics in Behavior Modeling



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

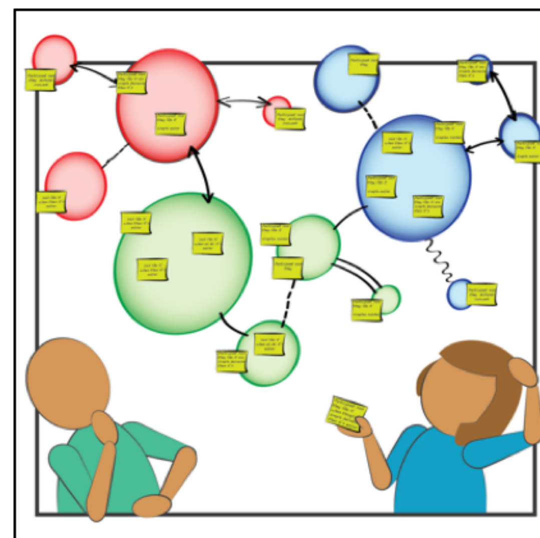
2. Social contexts



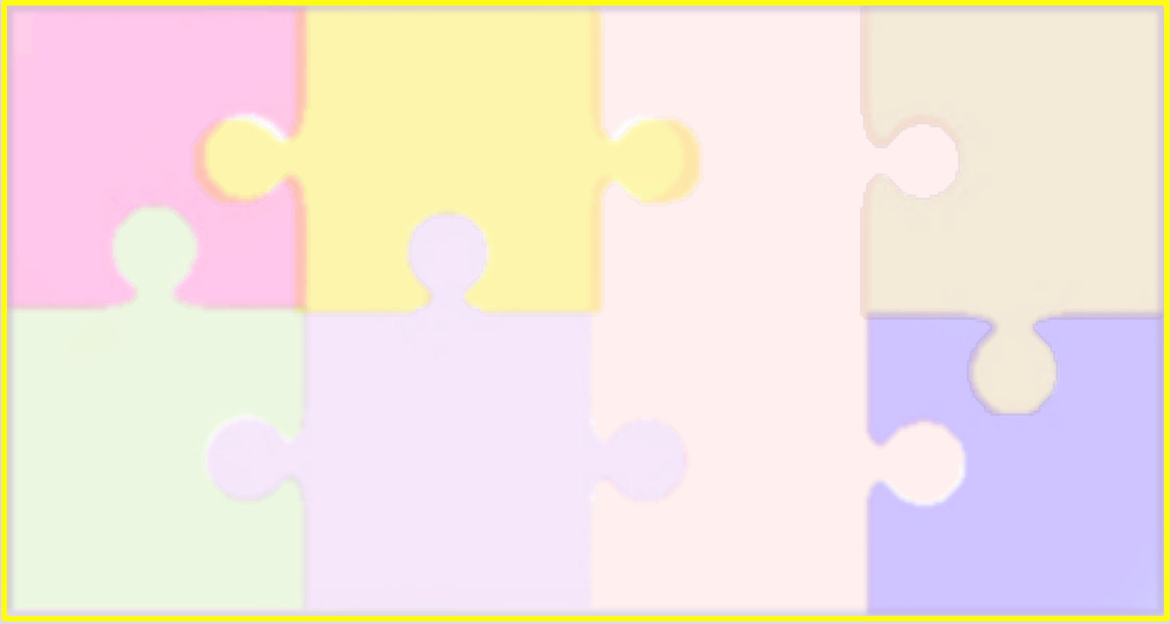
Behavior Modeling

3. Spatiotemporal contexts

4. Behavior content



My Research "Area"



My Research “Area”

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

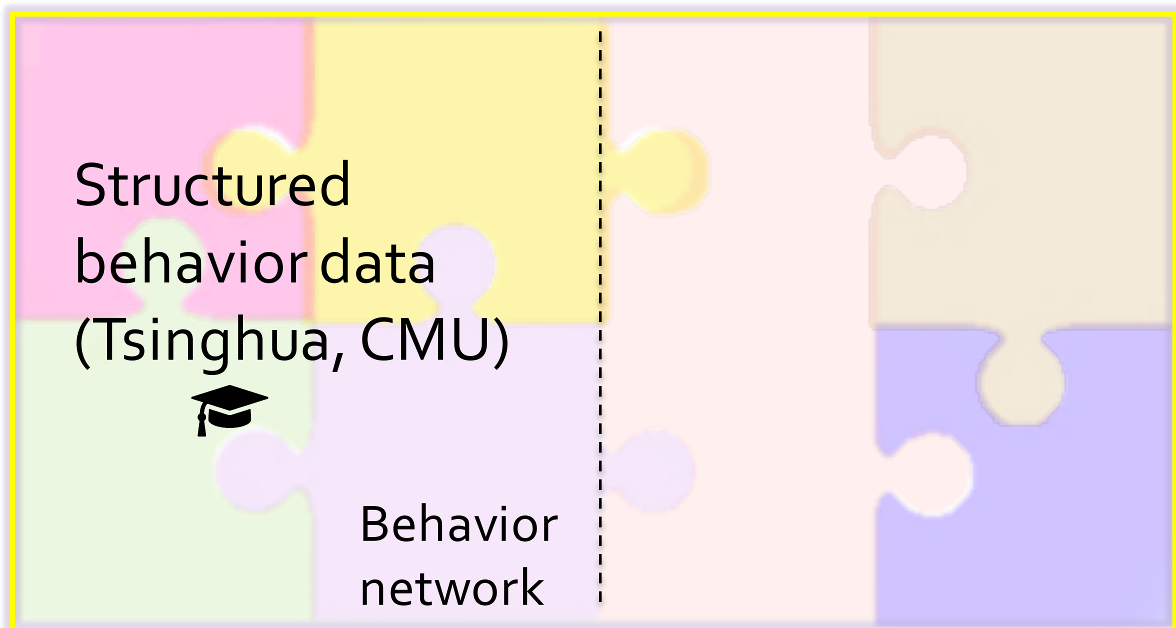
My Research "Area"

Social contexts

Spatiotemporal contexts

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

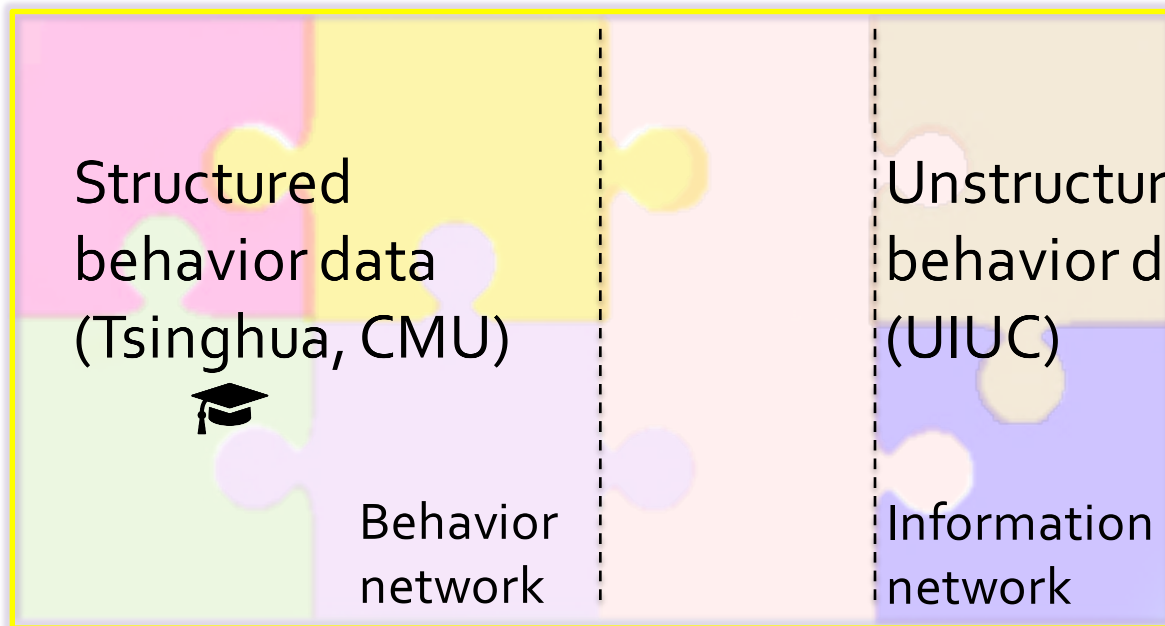


My Research "Area"

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

Social contexts | Spatiotemporal contexts | Behavioral content



My Research “Area”

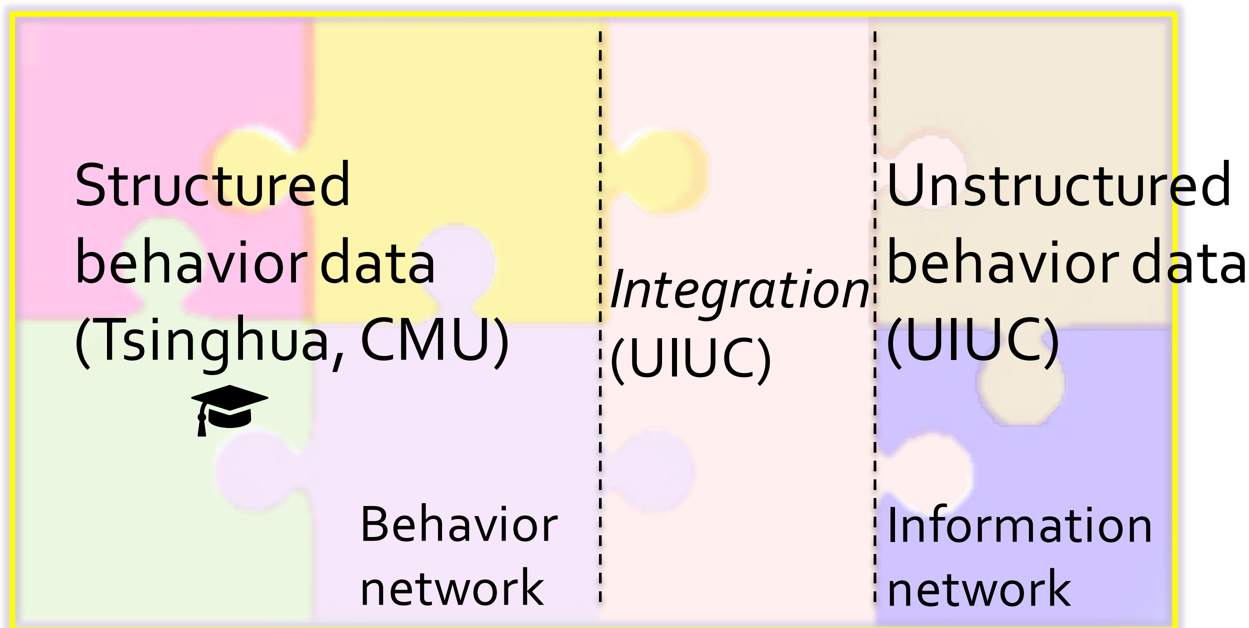
Social contexts

Spatiotemporal contexts

Behavioral content

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

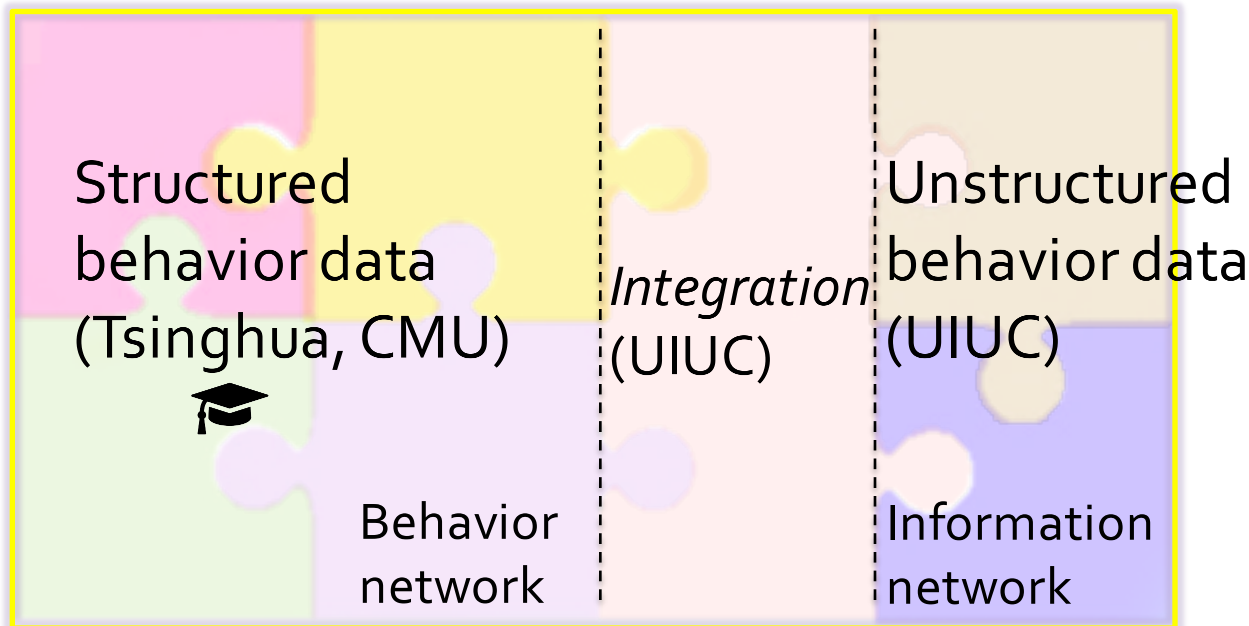


My Research "Area"

Social contexts | Spatiotemporal contexts | Behavioral content

Intelligence: Behavior prediction and recommendation

Trustworthiness: Suspicious behavior detection



Ask good **Q**uestions.

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

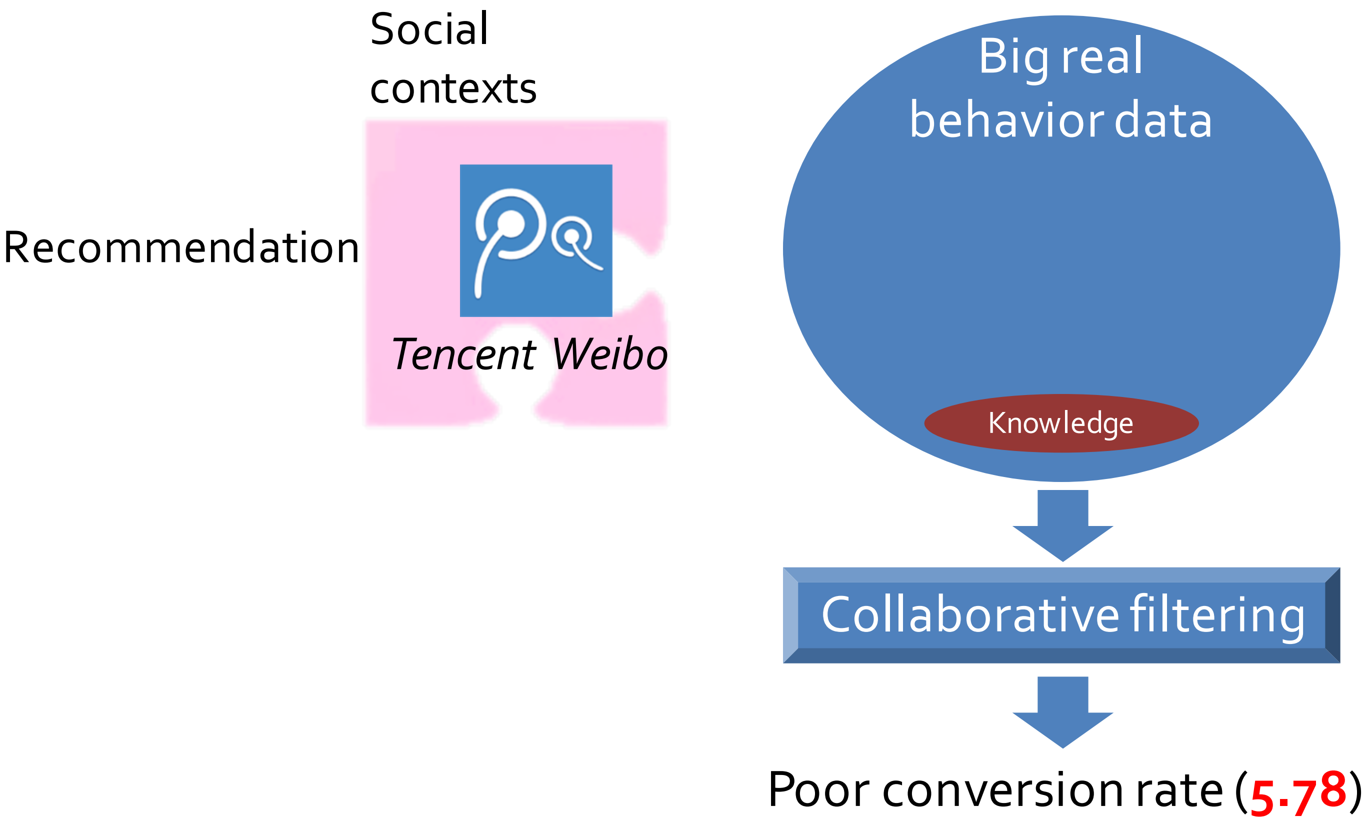
Propose good **S**olutions.

Q1: A Social Recommender System

Social
contexts

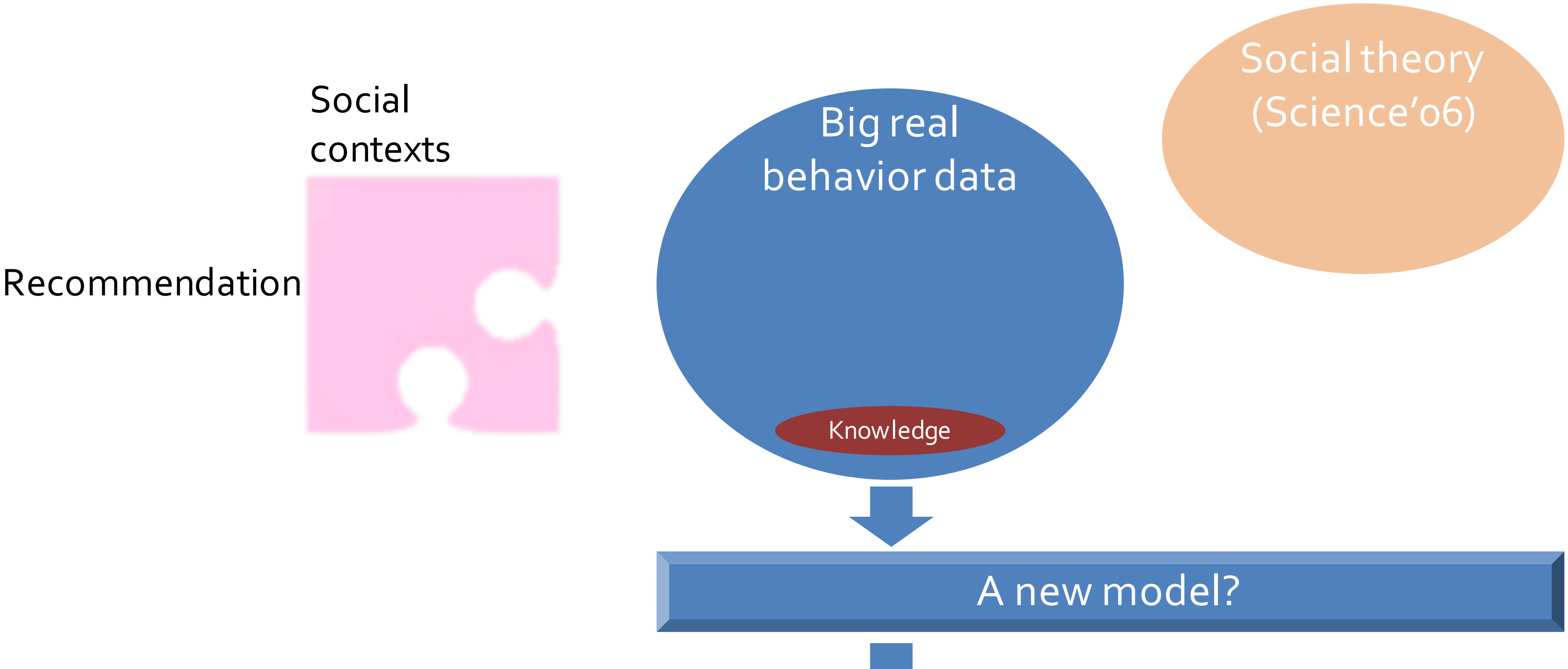
Recommendation

Q1: A Social Recommender System



Collaborative filtering for recommenders [Breese et al. UAI'98; Herlocker et al. CSCW'00; Koren et al. KDD'08 Computer'09; Liu et al. SIGIR'08; Yao et al. CIKM'14; Bogdanov et al. Social Network Analysis and Mining, 2014.]

M1: Knowledge from Social Theories



"... Differences between **independent**
and **social influence conditions** are significant ..."

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

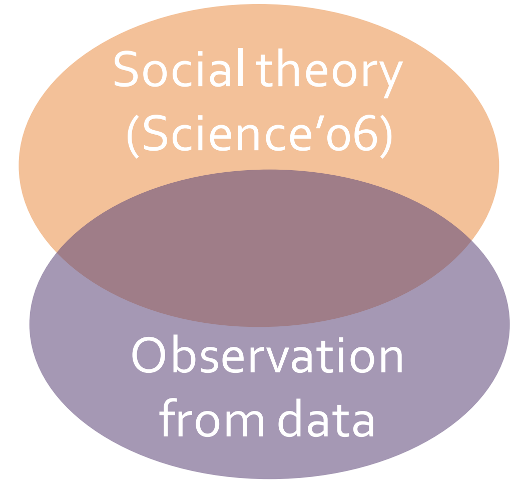
M1: Knowledge from Social Theories

Social contexts

Recommendation

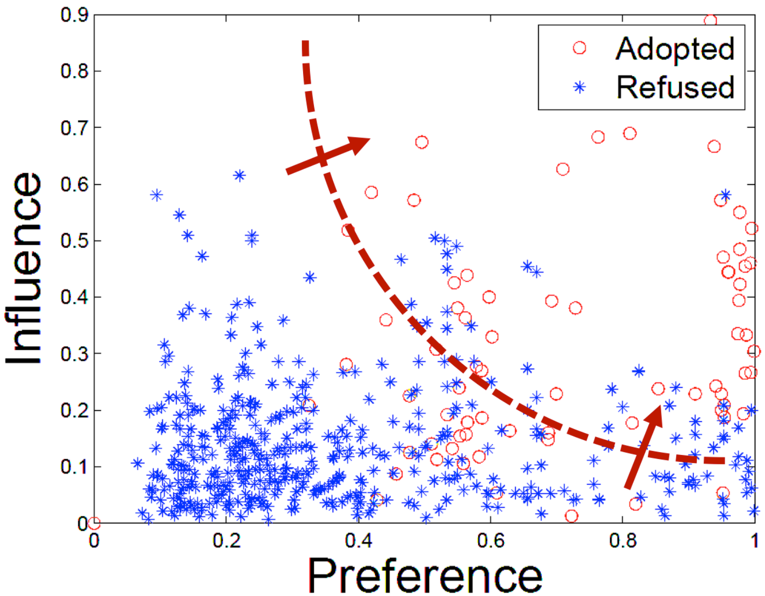
Big real behavior data

Knowledge

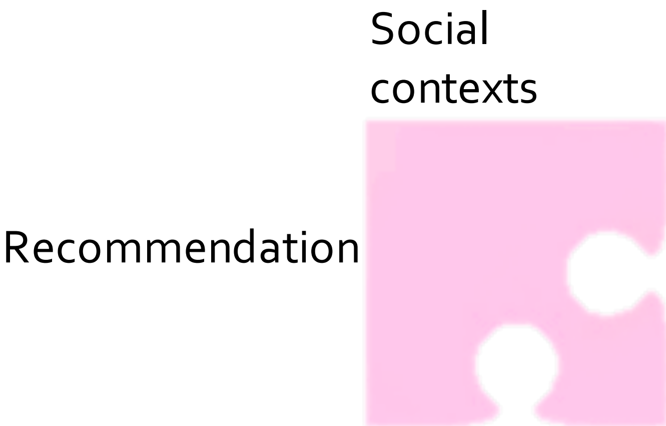


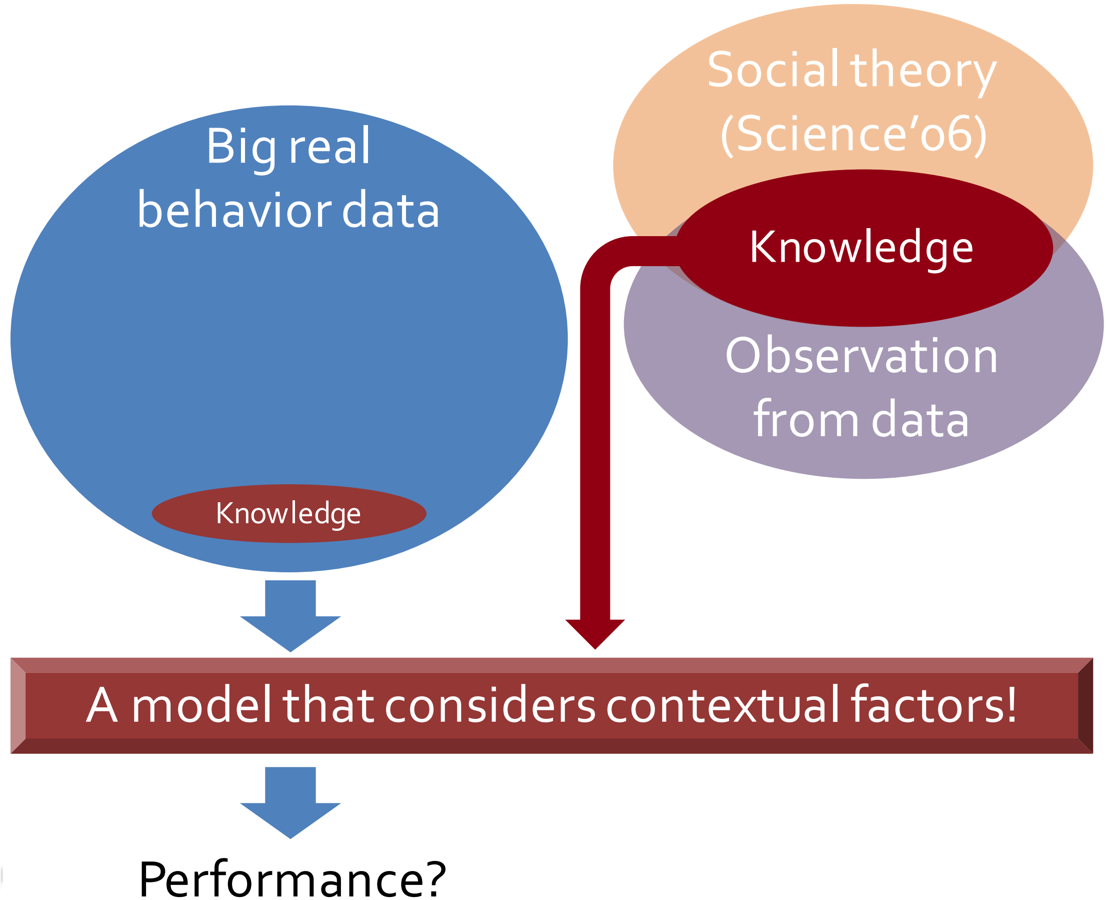
A new model?

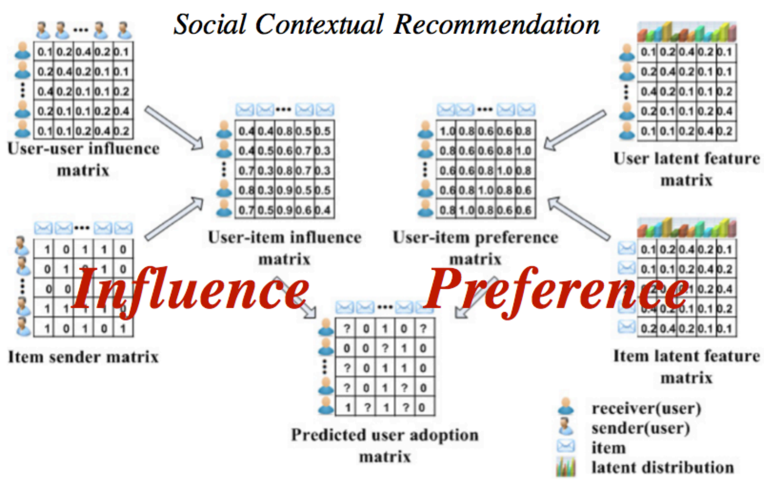
Performance?



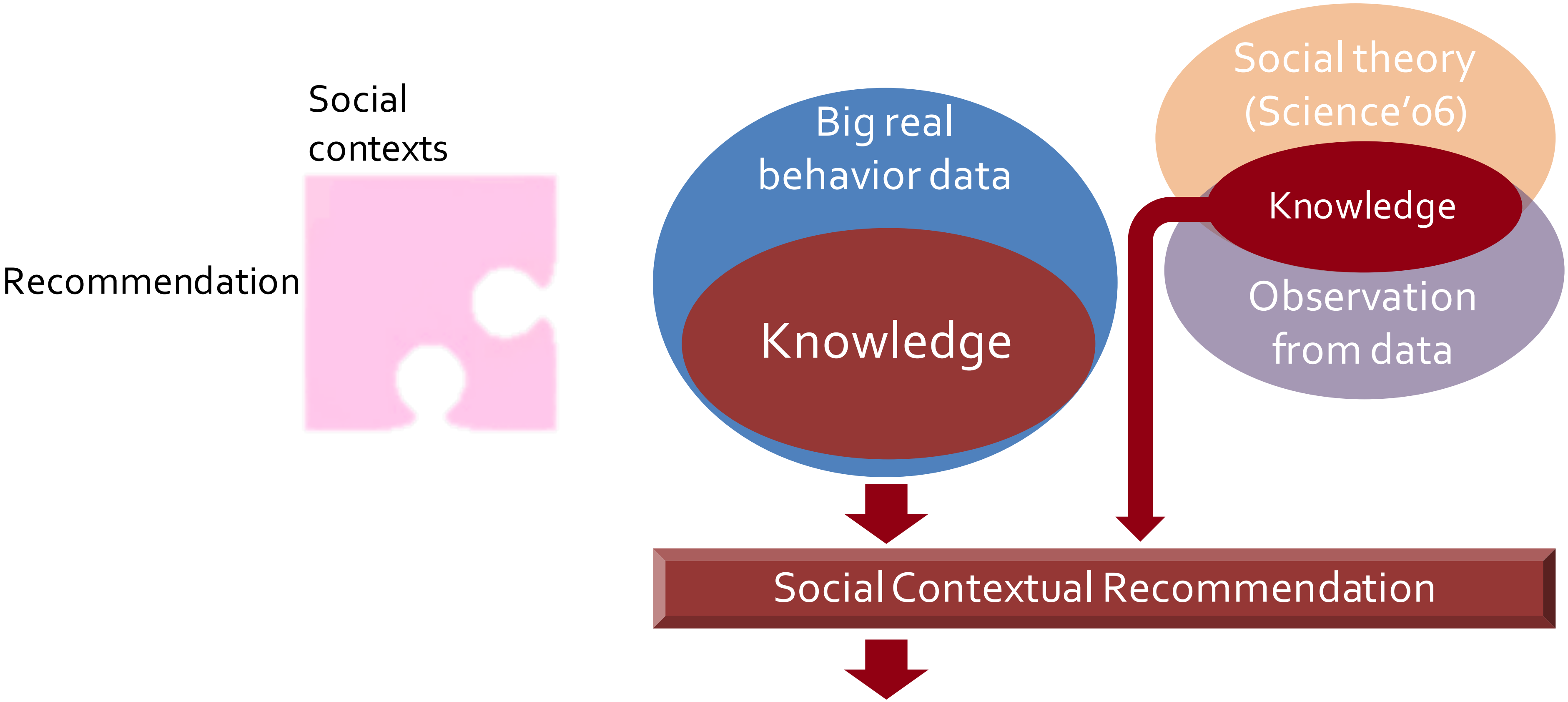
M1: Knowledge from Social Theories







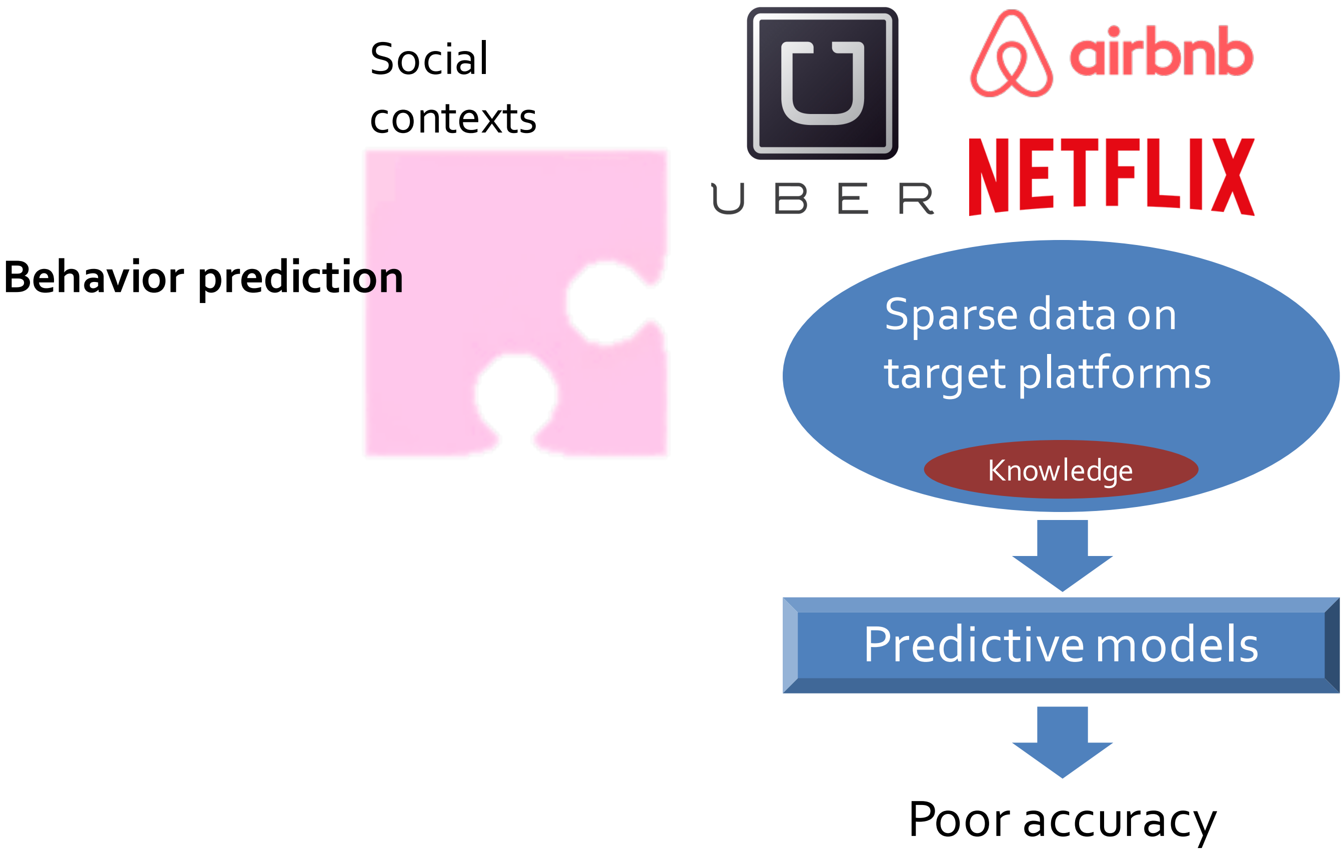
M1: Knowledge from Social Theories



Higher conversion rate (**8.27, relatively +43%**)

S1: CIKM'12: cited by **133**, ranked at the **3rd** of 146 accepted papers; TKDE'14: cited by **44**.

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]

Q2: Leveraging Social Data for Prediction

Social contexts

Behavior prediction

Sparse data on target platforms

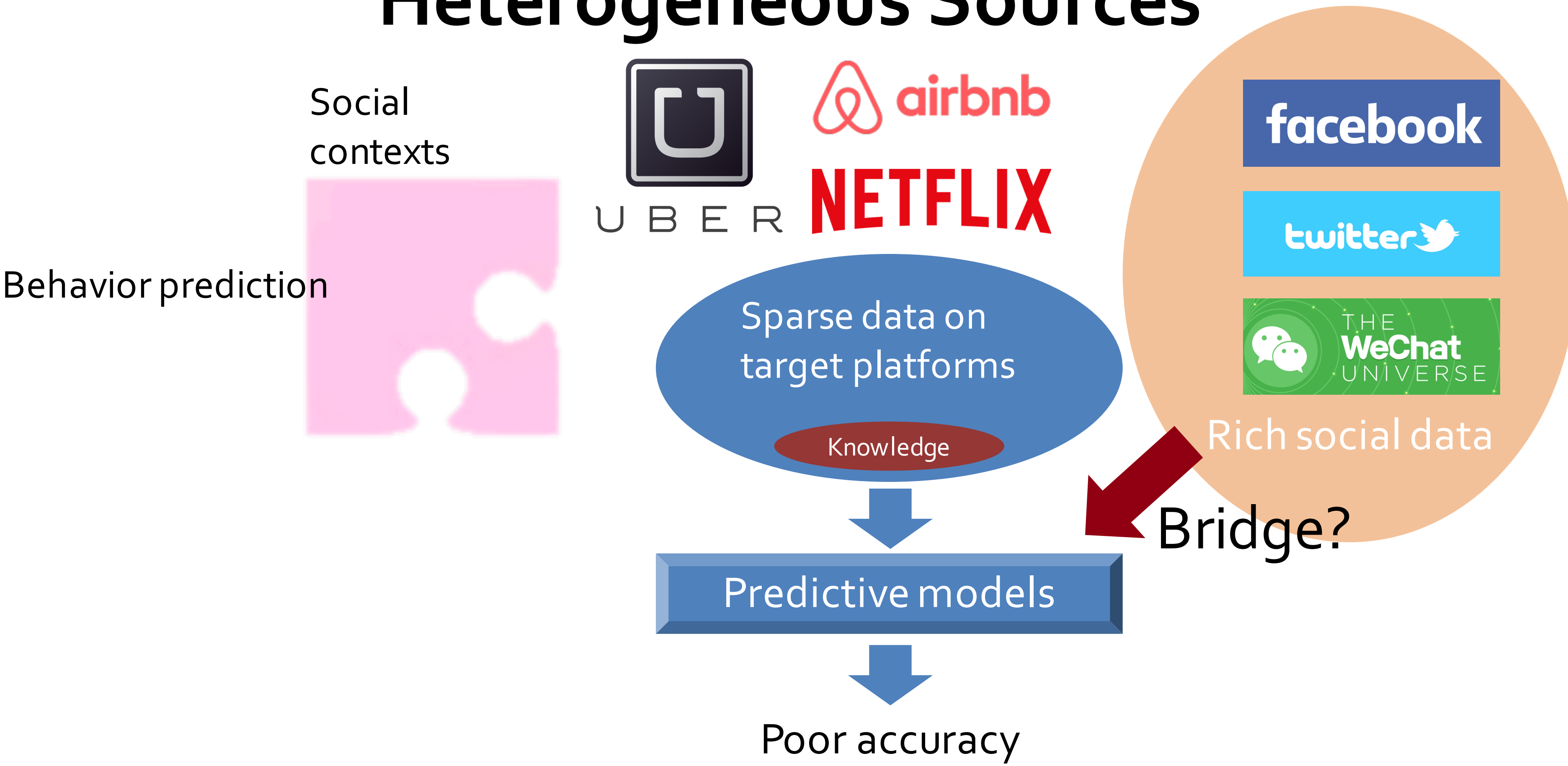
Knowledge

Predictive models

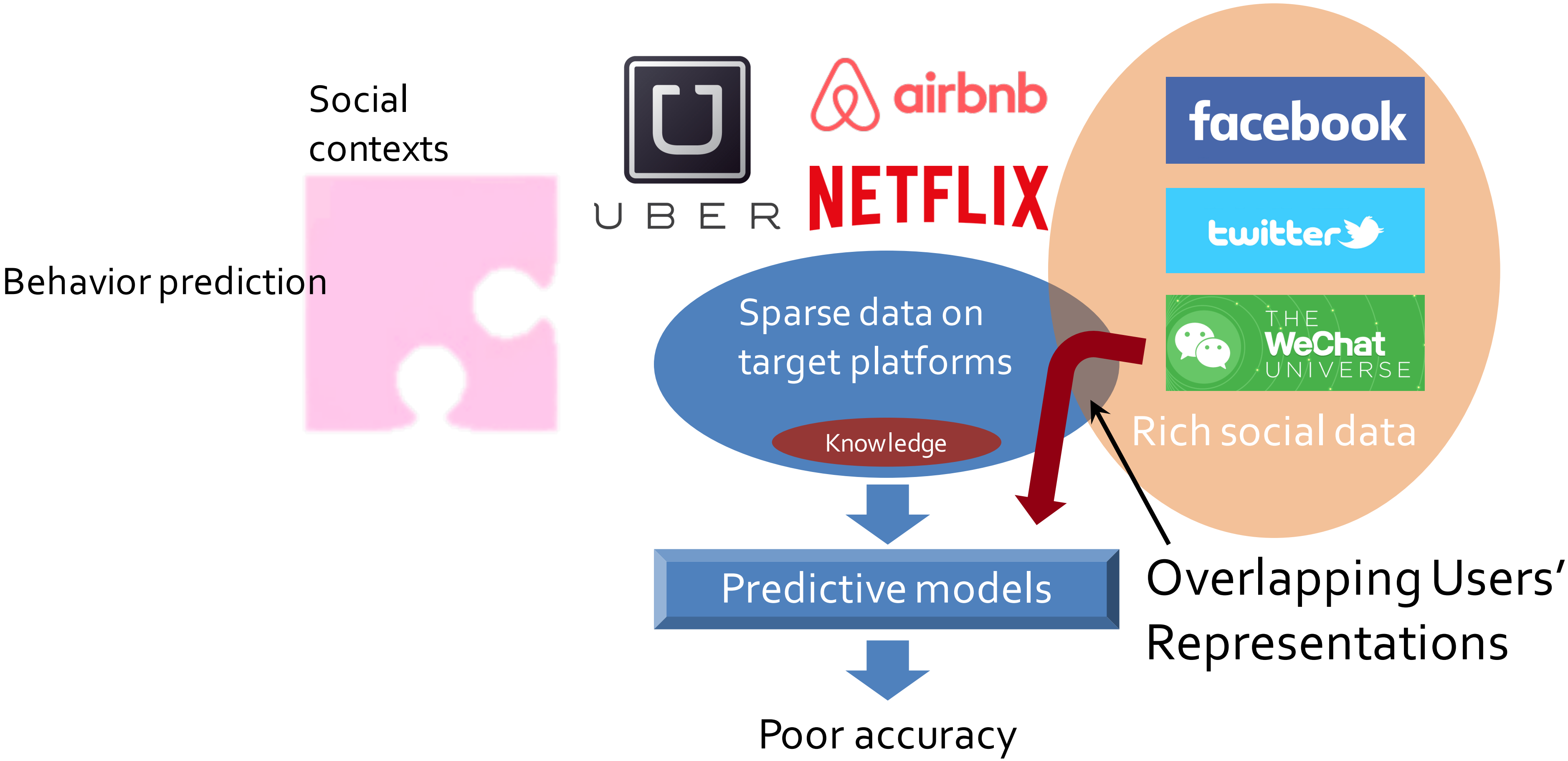
Poor accuracy

Rich social data

M2: Knowledge Transfer from Heterogeneous Sources



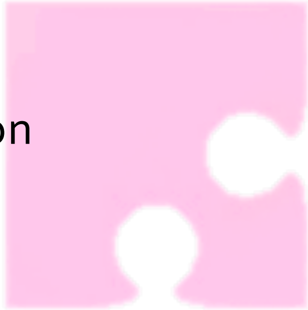
M2: Knowledge Transfer from Heterogeneous Sources



M2: Knowledge Transfer from Heterogeneous Sources

Social contexts

Behavior prediction



~50K users

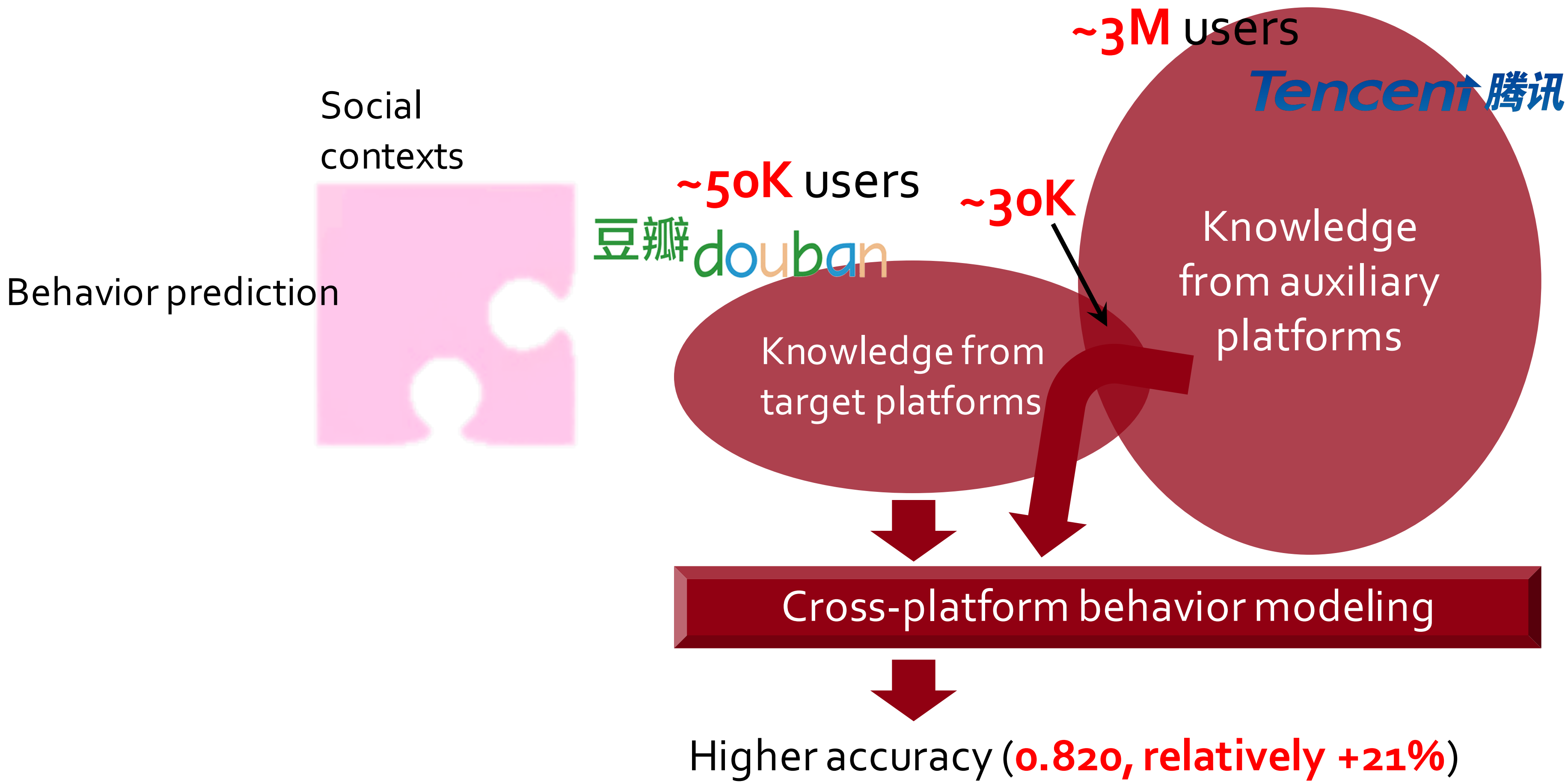
豆瓣douban

Knowledge from target platforms

Predictive models

Poor accuracy (**0.676**)

M2: Knowledge Transfer from Heterogeneous Sources



S2: CIKM'12: cited by **53**, ranked at the **9th** of 146 accepted papers; TKDE'15: cited by **14**; AAAI'16: invited by NIPS-CrowdML'16.

Q3: Catching Social Link Farming

Social contexts

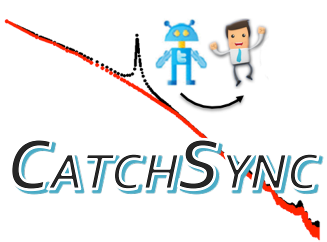
Suspicious behavior detection

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

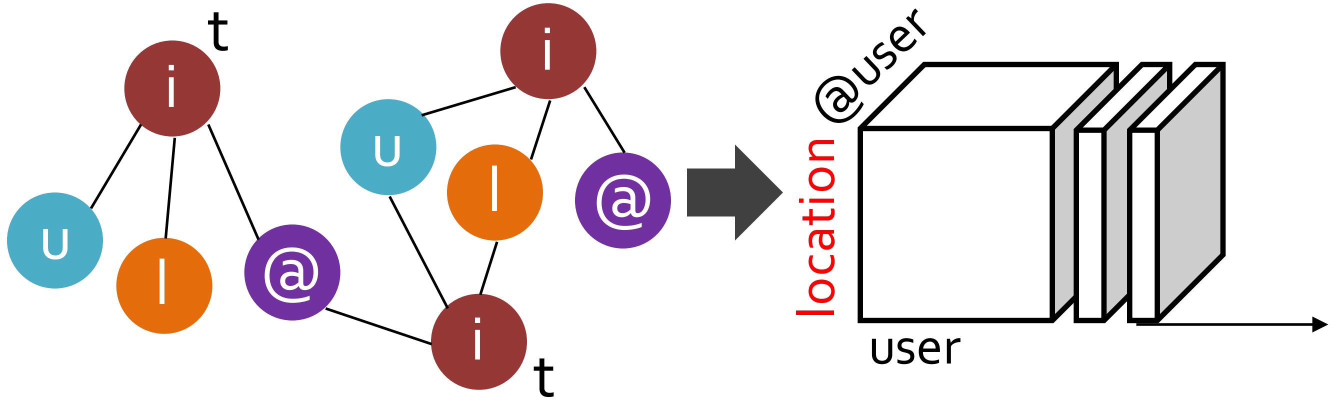
S3: 

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!



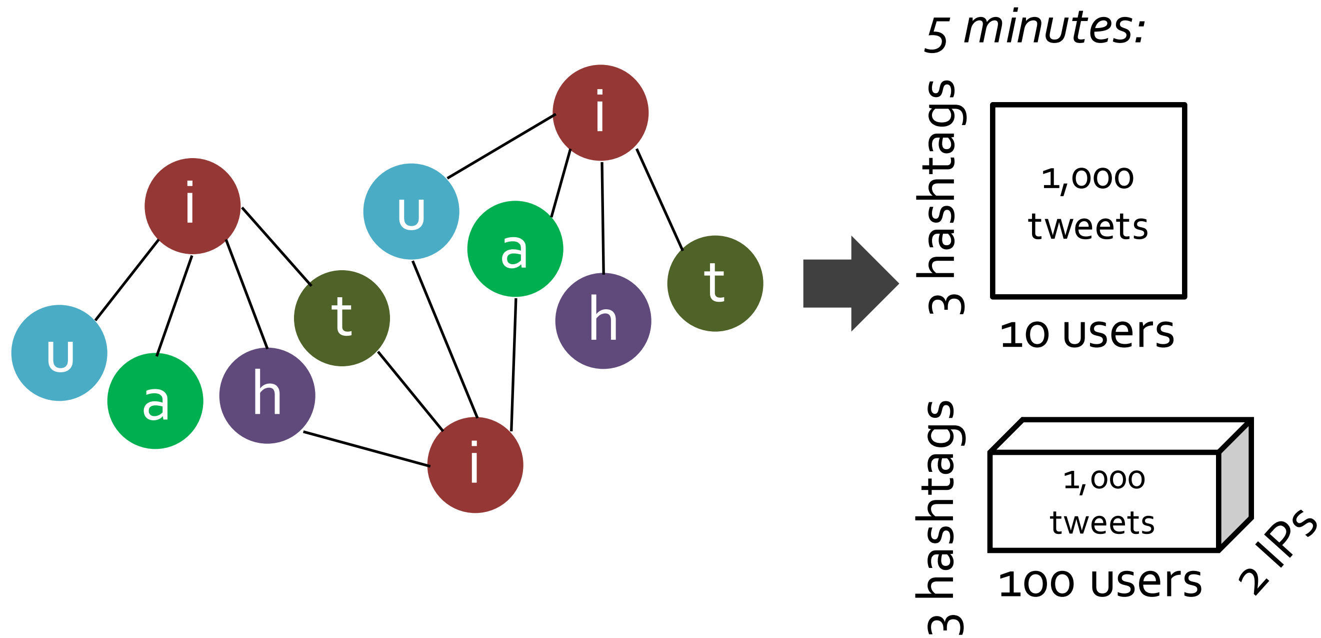
M4-1: Incremental tensor decomposition: Approximation based on tensor perturbation theory. We proved bound guarantees of errors.

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 **21**.

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 **20**; TKDE'16.

Q5: Knowledge from Behavioral Content

From Words, Topics, to Networks

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

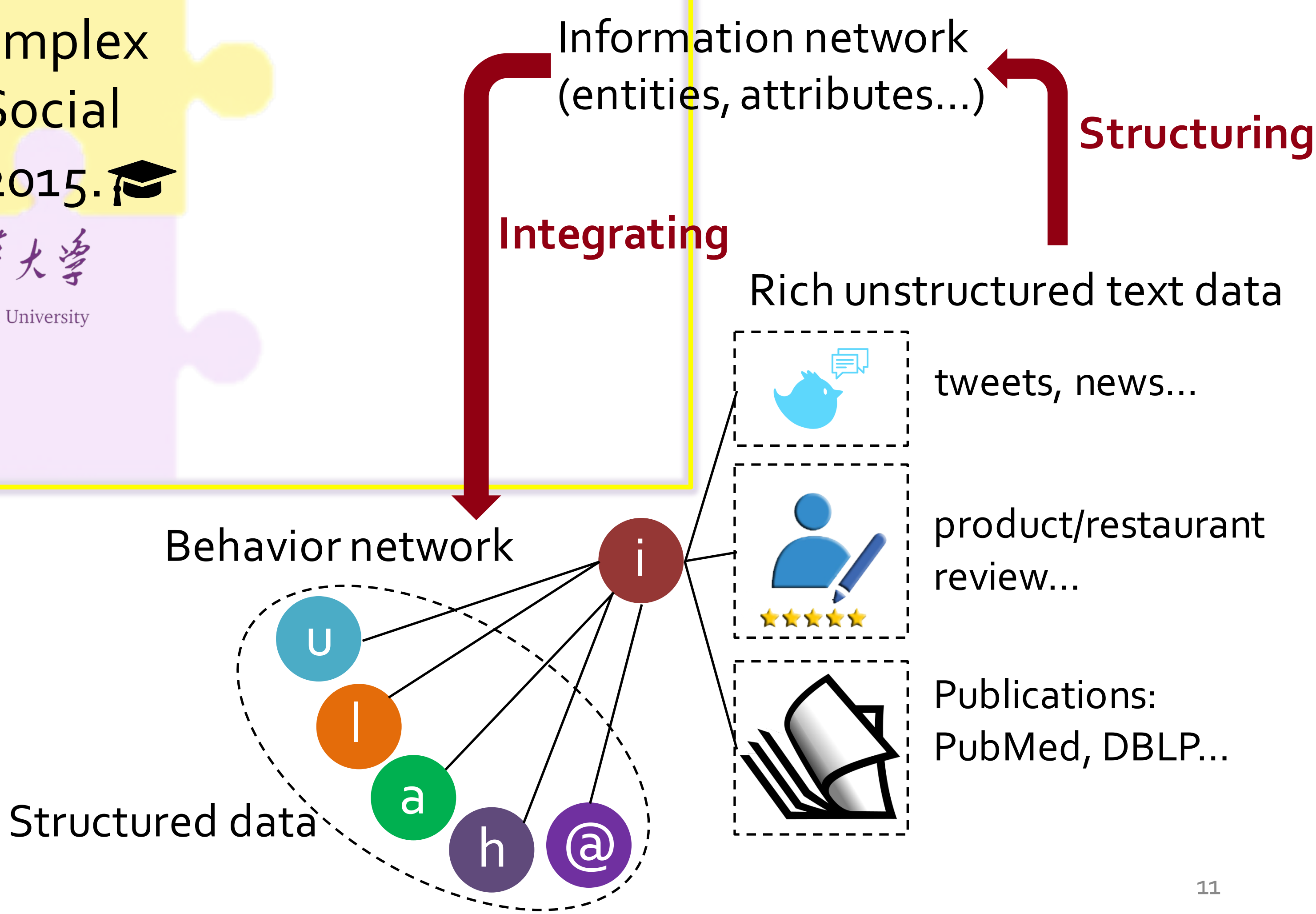
清華大學
Tsinghua University

Q5: Knowledge from Behavioral Content

From Words, Topics, to Networks

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

Tsinghua University



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

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

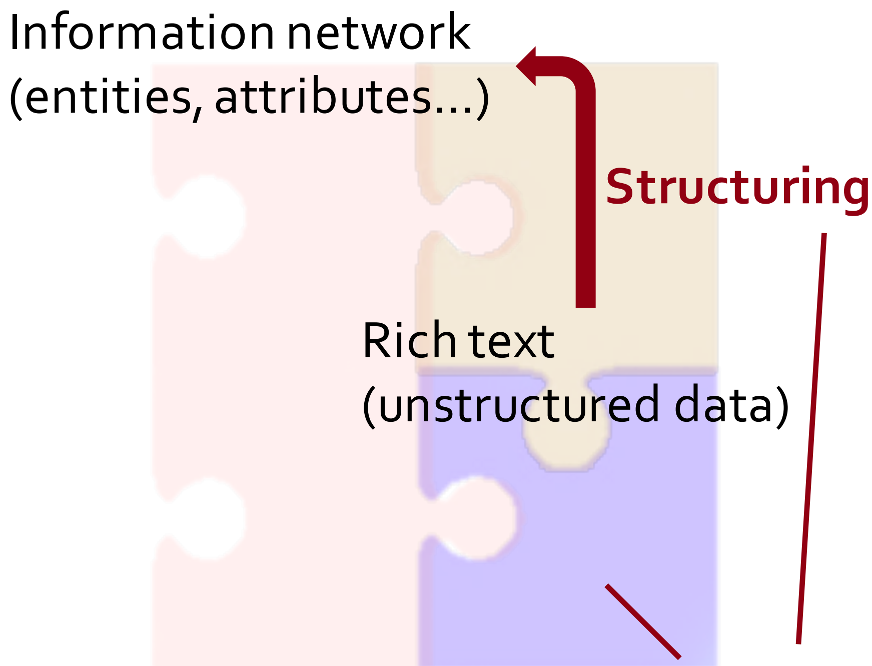
Q'5-1. Who has studied the biggest number of datasets of large scale?

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?

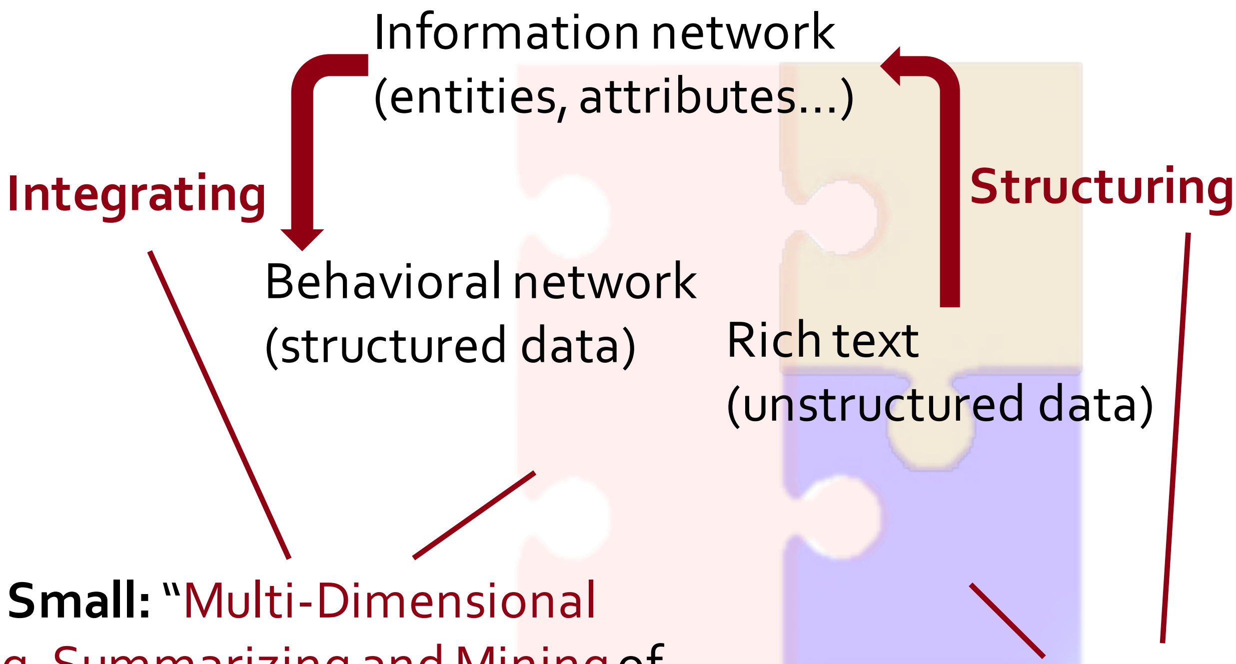
Sorry, I don't have answers now… But…

S5: Multiple Proposal Writing and Papers



1. Submitted to **NSF III: Medium:** Collaborative: "StructNet: Constructing and Mining Structure-Rich Information Networks for Scientific Research". (Submitted Oct 16)
2. Submitted to **KDD'17:** "Meta Pattern-Driven Attribute Discovery from Massive Text Corpora".

S5: Multiple Proposal Writing and Papers



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. Submitted to **NSF III: Medium:** Collaborative: "StructNet: Constructing and Mining Structure-Rich Information Networks for Scientific Research". (Submitted Oct 16)

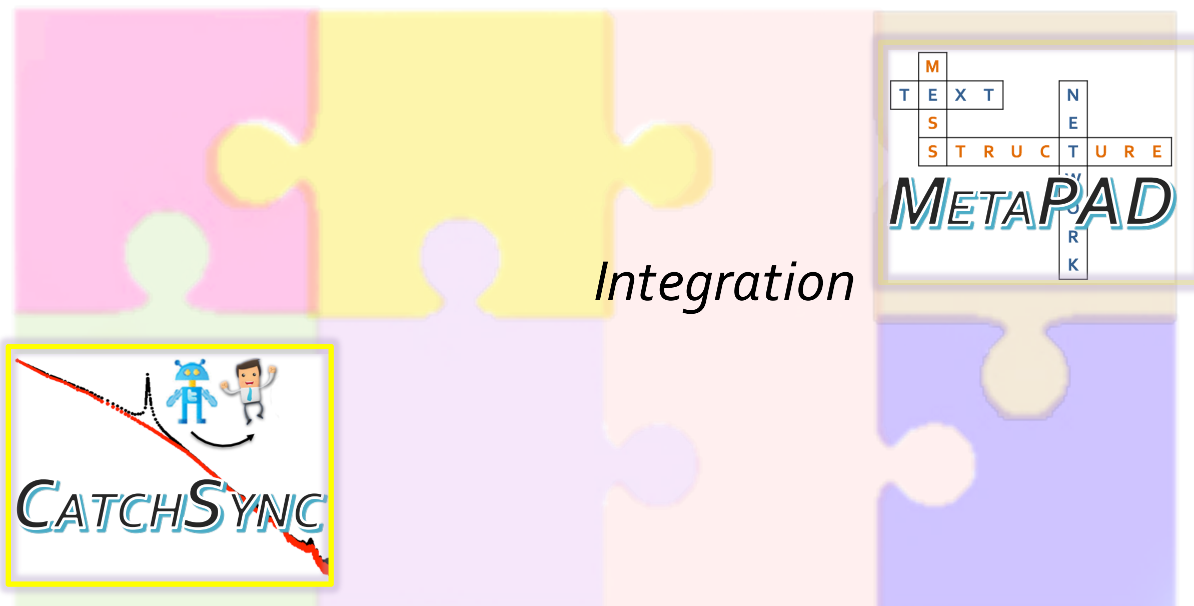
2. Submitted to **KDD'17:** "Meta Pattern-Driven Attribute Discovery from Massive Text Corpora".

Outline

Social contexts | Spatiotemporal contexts | Behavioral content

Intelligence: Behavior prediction and recommendation

Trustworthiness: Suspicious behavior detection



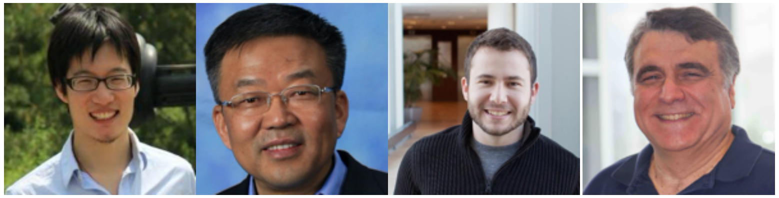
CatchSync: Catching Synchronized Behavior in Large Directed Graphs

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

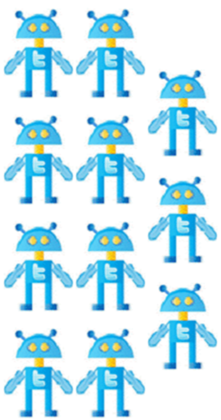
Alex Beutel, and Christos Faloutsos (CMU)

ACM SIGKDD 2014 Best Paper Finalist

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



Q3: Catching Zombie Followers



"Your best followers!"
"Delivery within 1-2 days"

Q3: Catching Zombie Followers

engineers

product managers

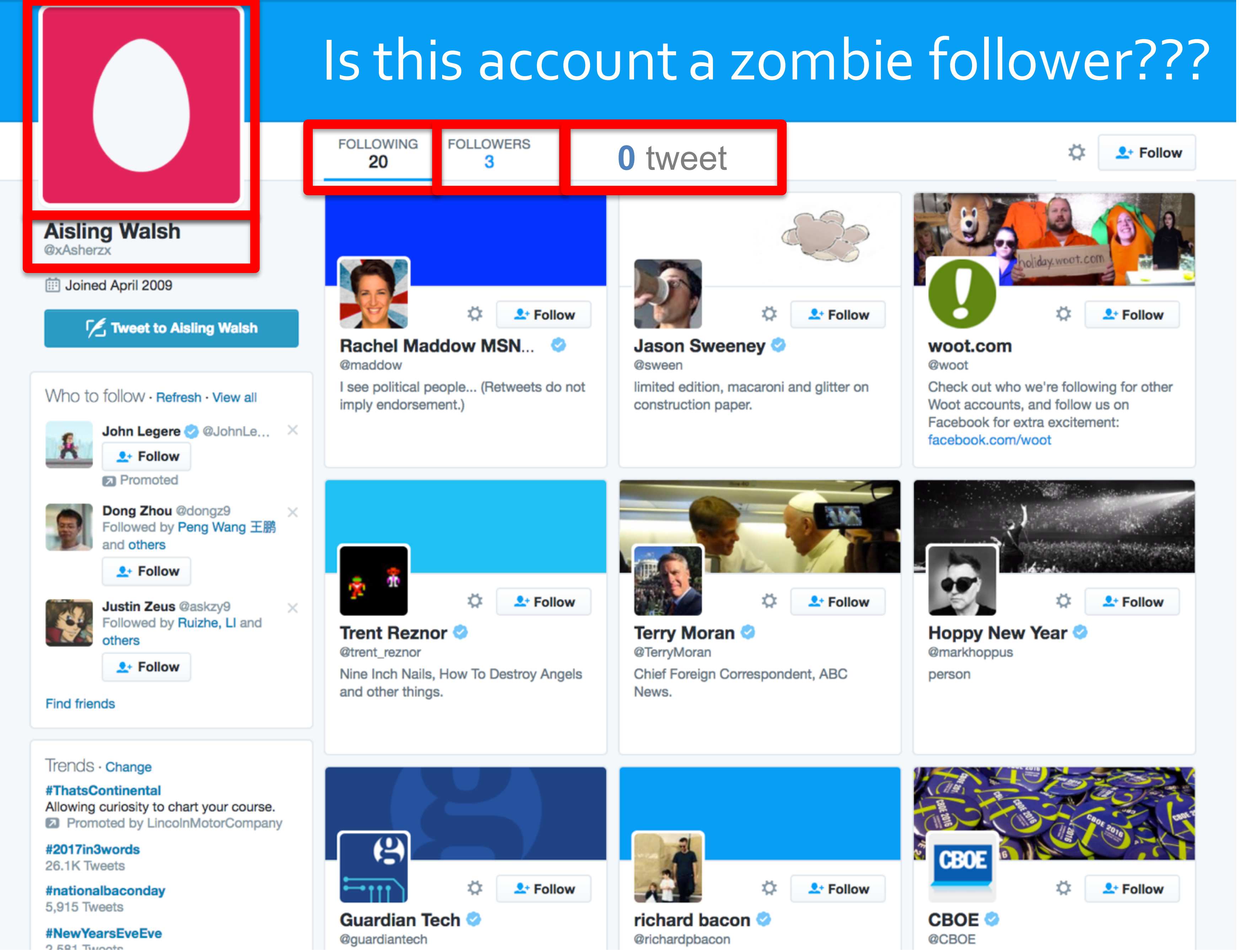
Knowledge from manual inspection: #followees, #followers, #tweets, #hashtags, #urls...

Learning models (classifiers)

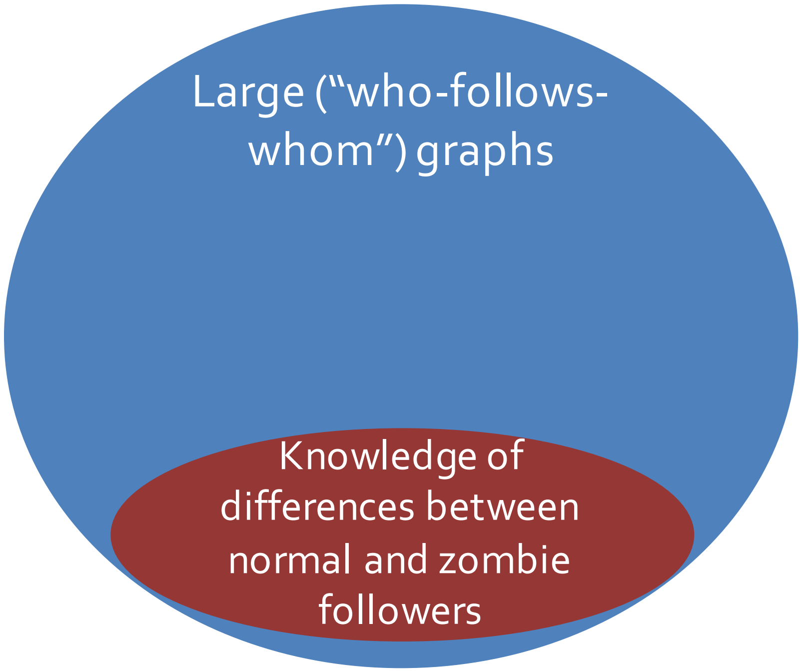
Poor accuracy
(**serious complaints** from users)

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???



Our Methodology (M1)



Our Methodology (M1)

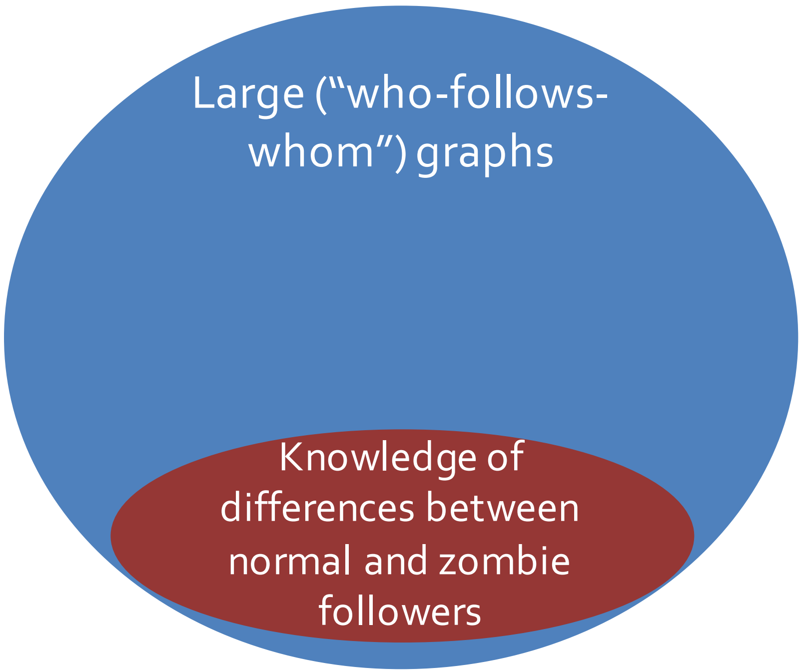
Large ("who-follows-whom") graphs

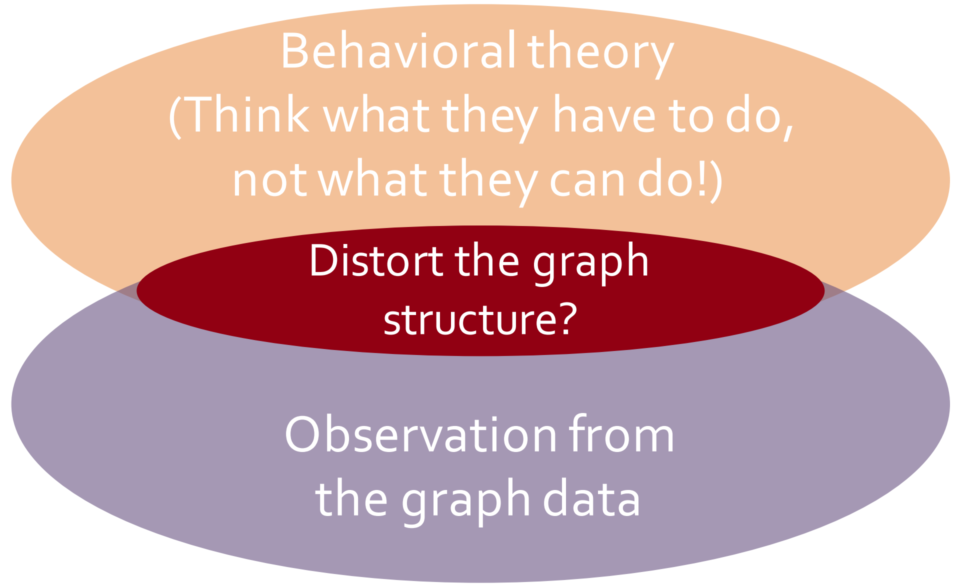
Knowledge of differences between normal and zombie followers

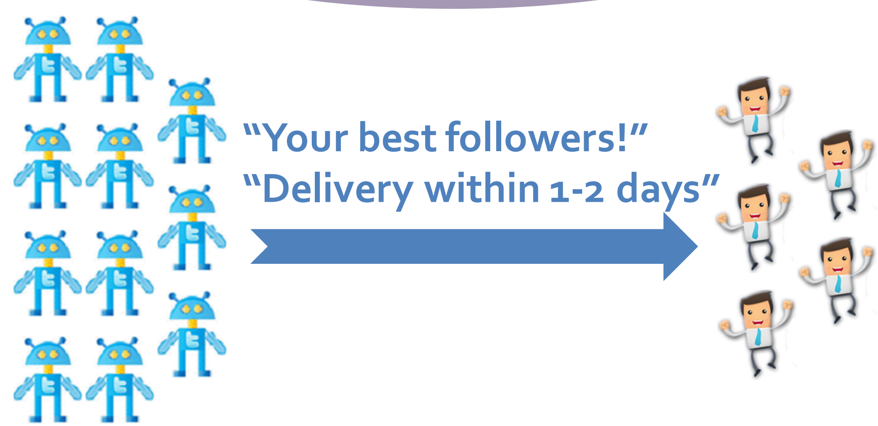
Behavioral theory
(Think what they have to do, not what they can do!)

Consistently Connecting to Customers

Our Methodology (M1)

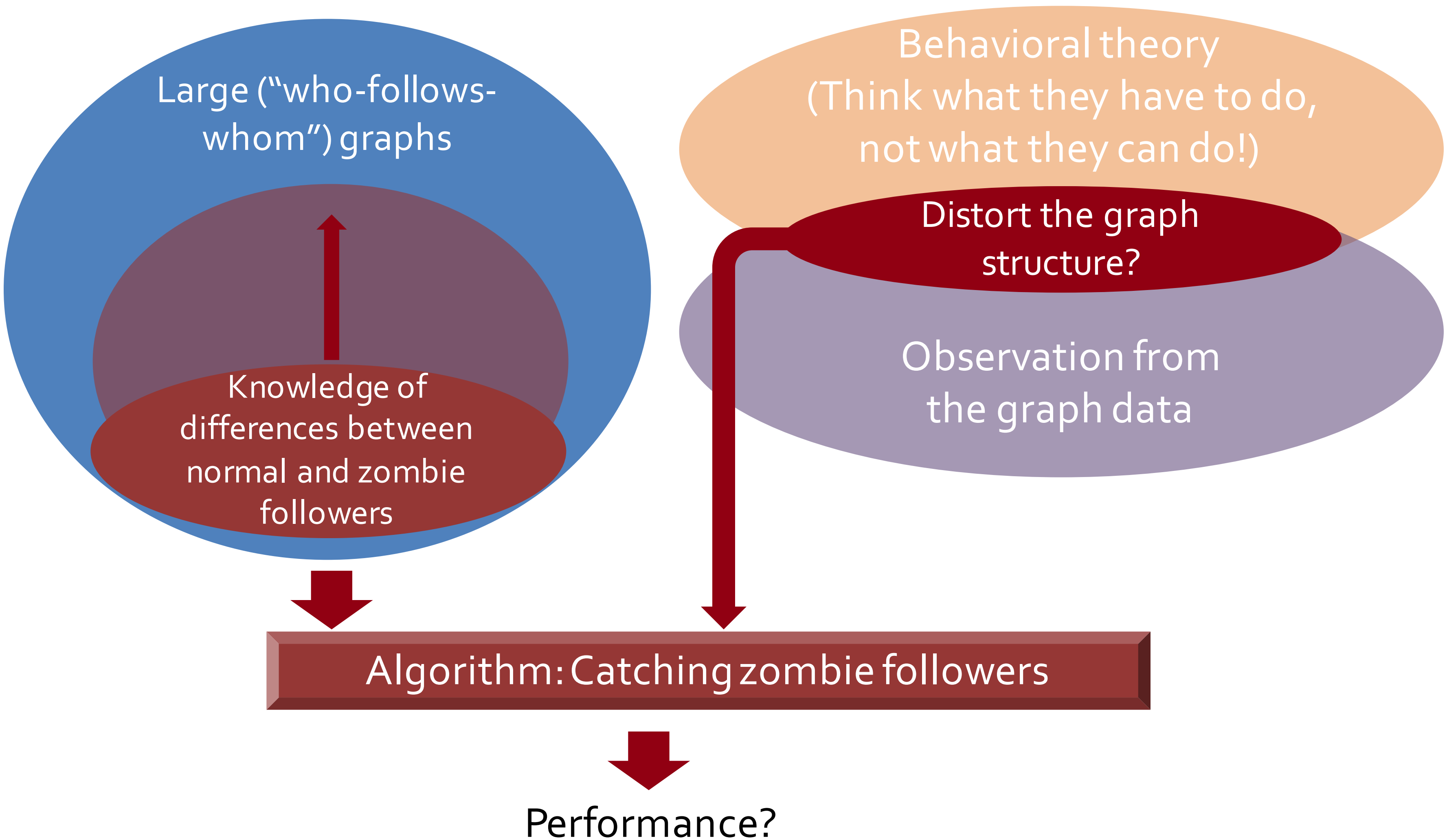






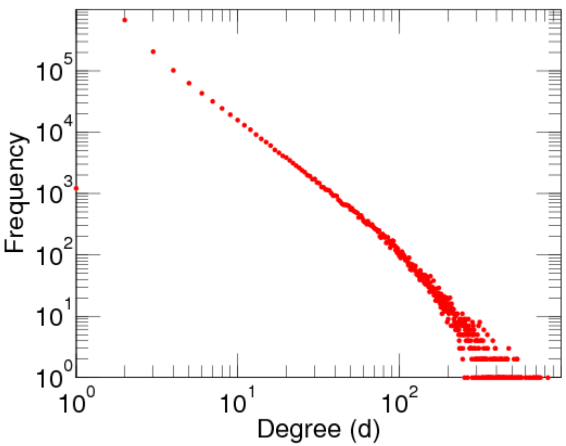
Consistently Connecting to Customers

Our Methodology (M1)

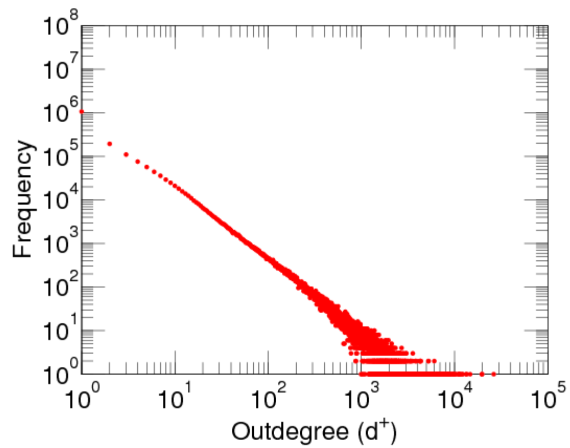


Out-Degree Distributions: Power Law Expected

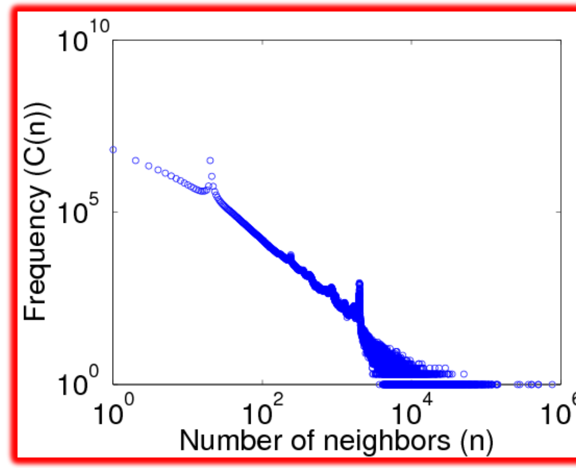
DBLP
Author-publication



Flickr
User-user



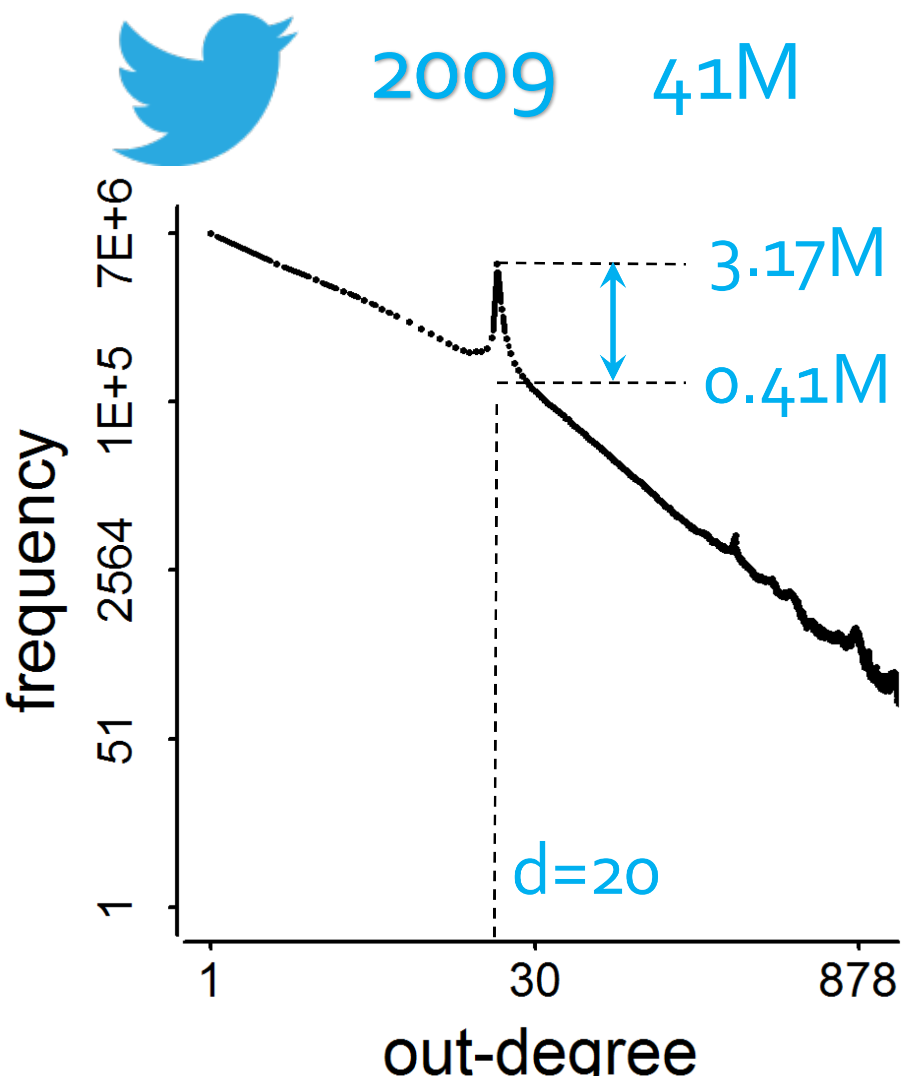
Twitter
Who-follows-whom

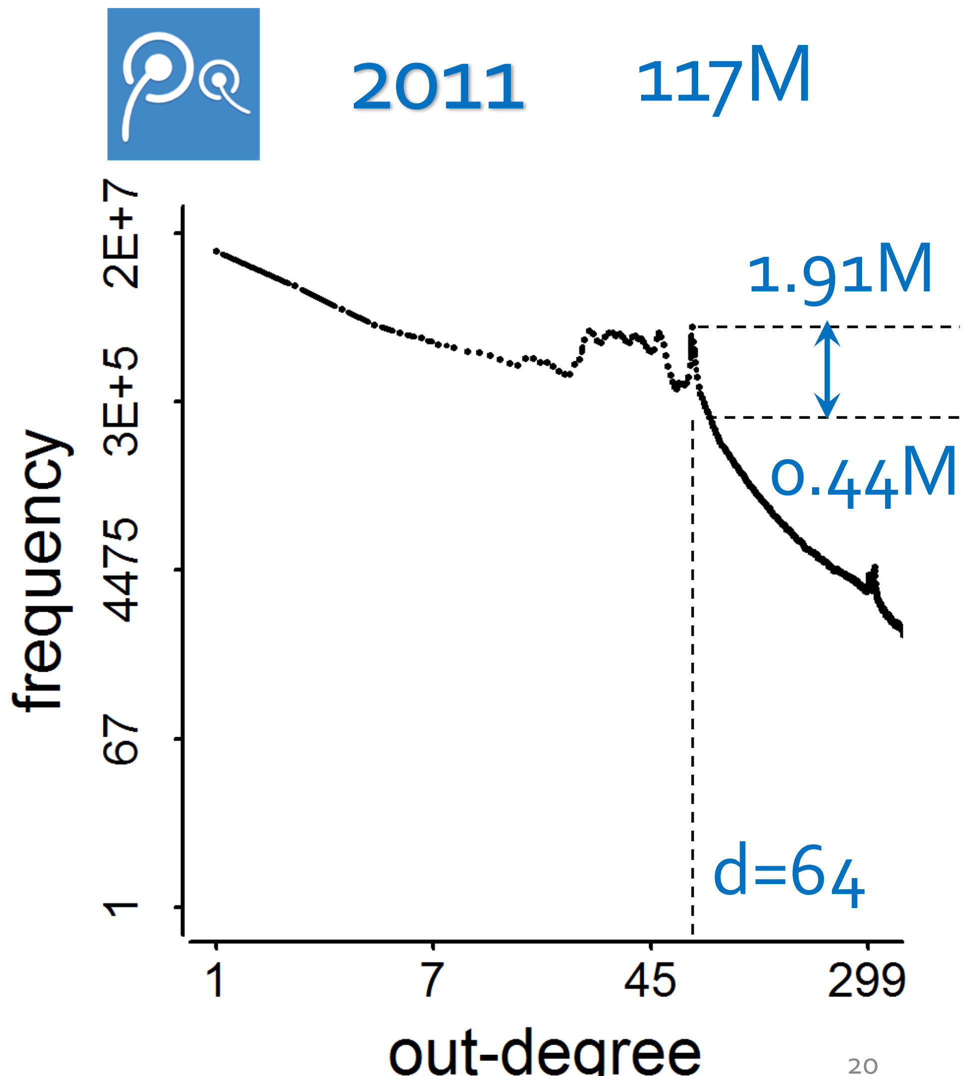


[konect.uni-koblenz.de/networks/]

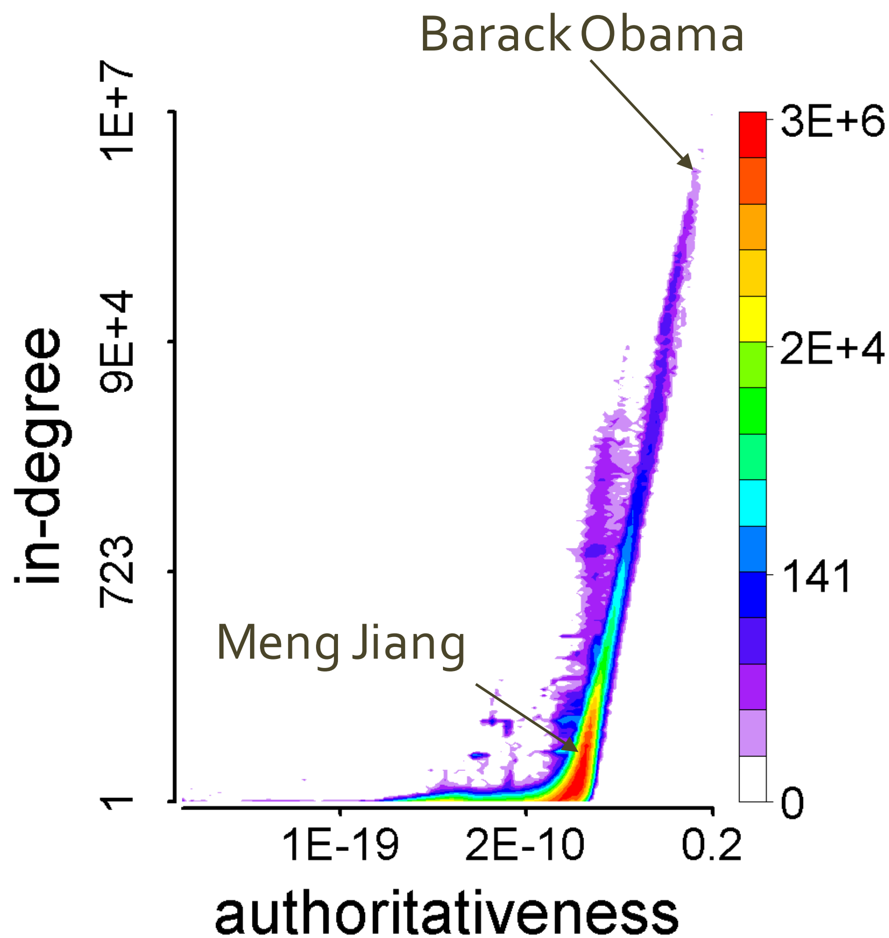
Power-law distributions in networks [Faloutsos et al. SIGCOMM’99; Chung et al. PNAS’02]

Spikes!


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

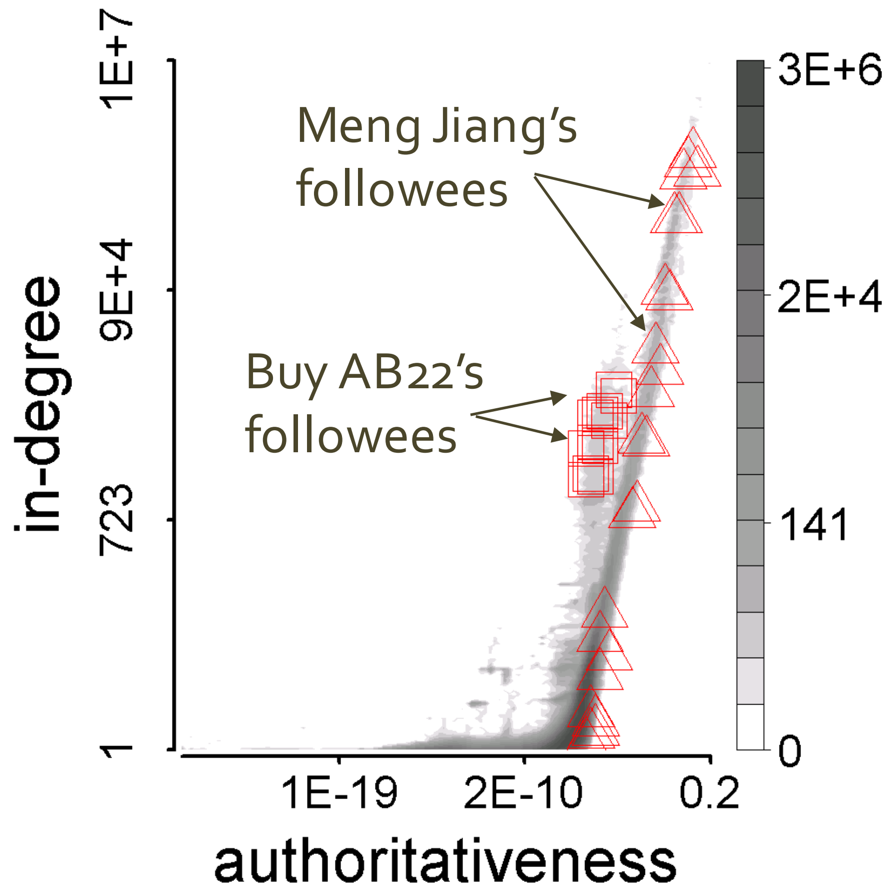

2011
117M
2E+7
3E+5
4475
67
1
frequency
1.91M
0.44M
d=64
1
7
45
299
out-degree

How We/They Connect to Our/Their Followees

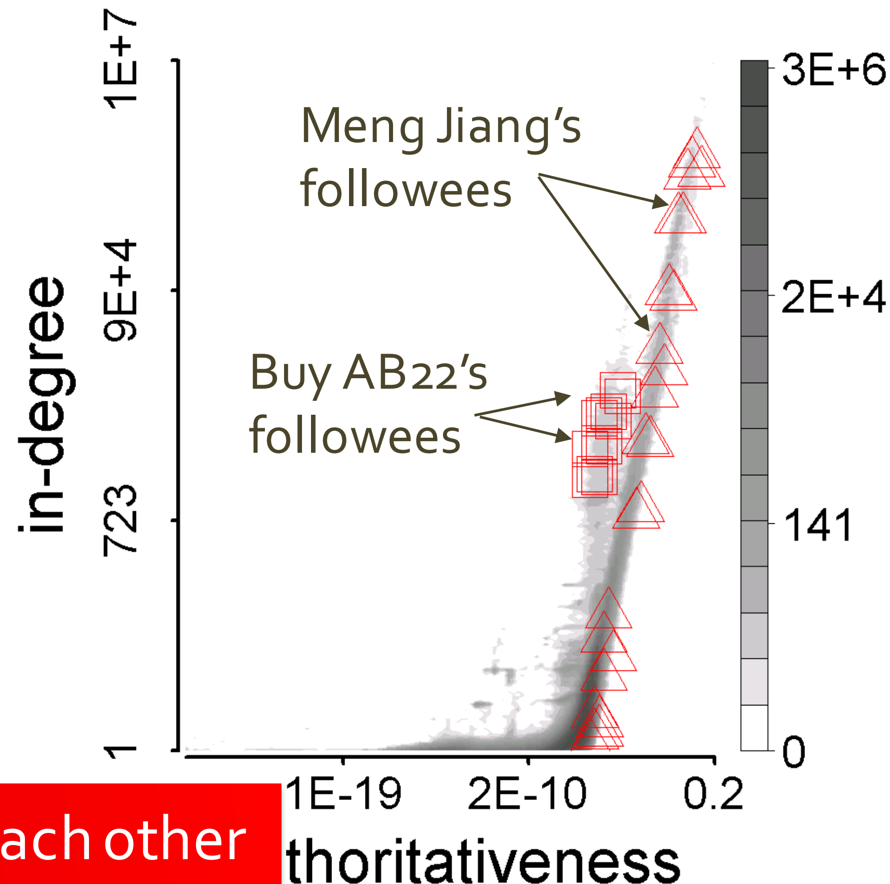


The HITS algorithm. Kleinberg. "Authoritative sources in a hyperlinked environment." JACM'99.

How We/They Connect to Our/Their Followees



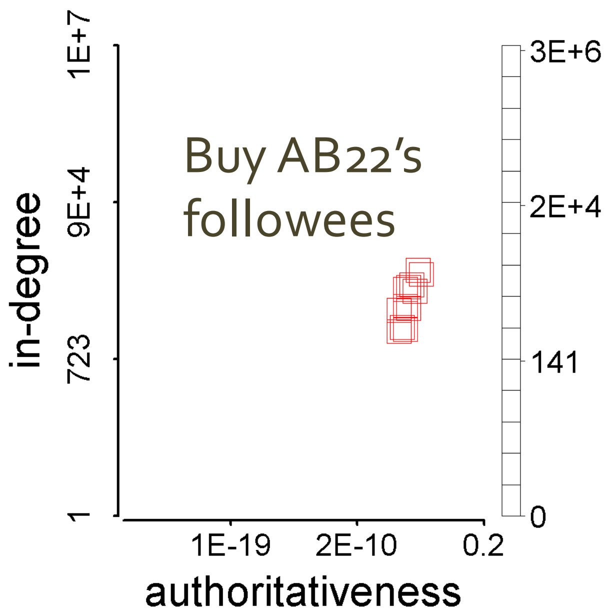
How We/They Connect to Our/Their Followees



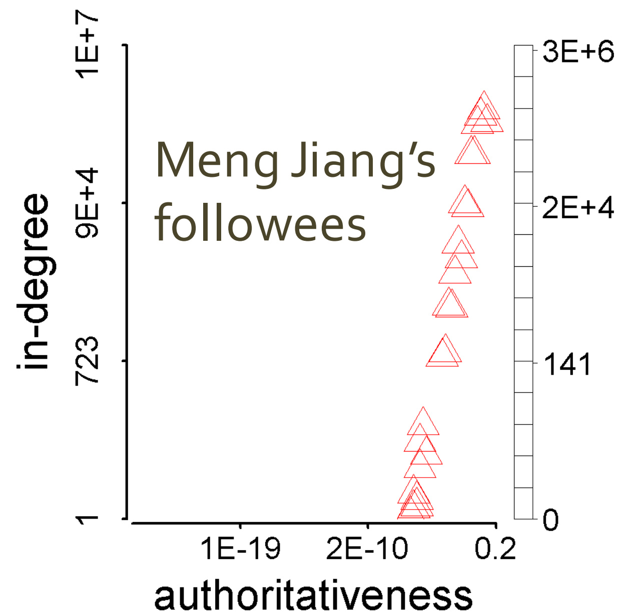
Synchronized: too similar with each other
Abnormal: too different from the majority

Definition: Synchronicity

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

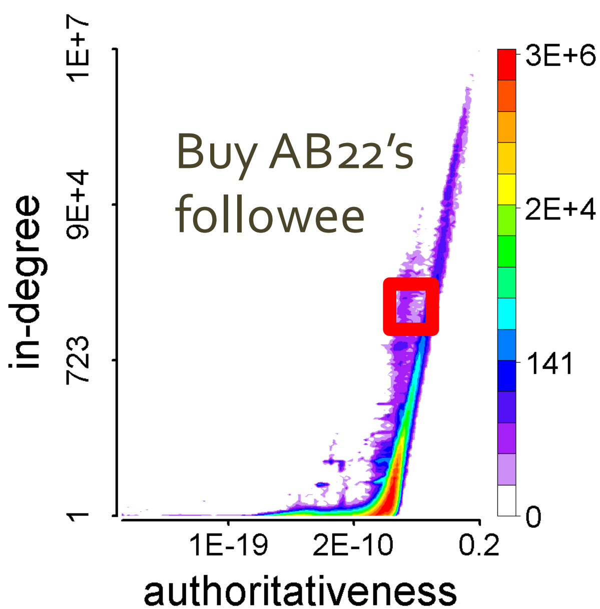


>

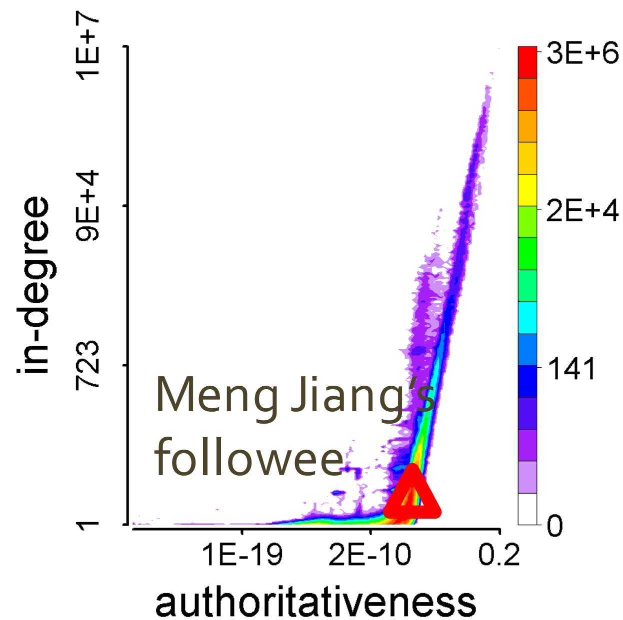


Definition: Normality

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



$<$



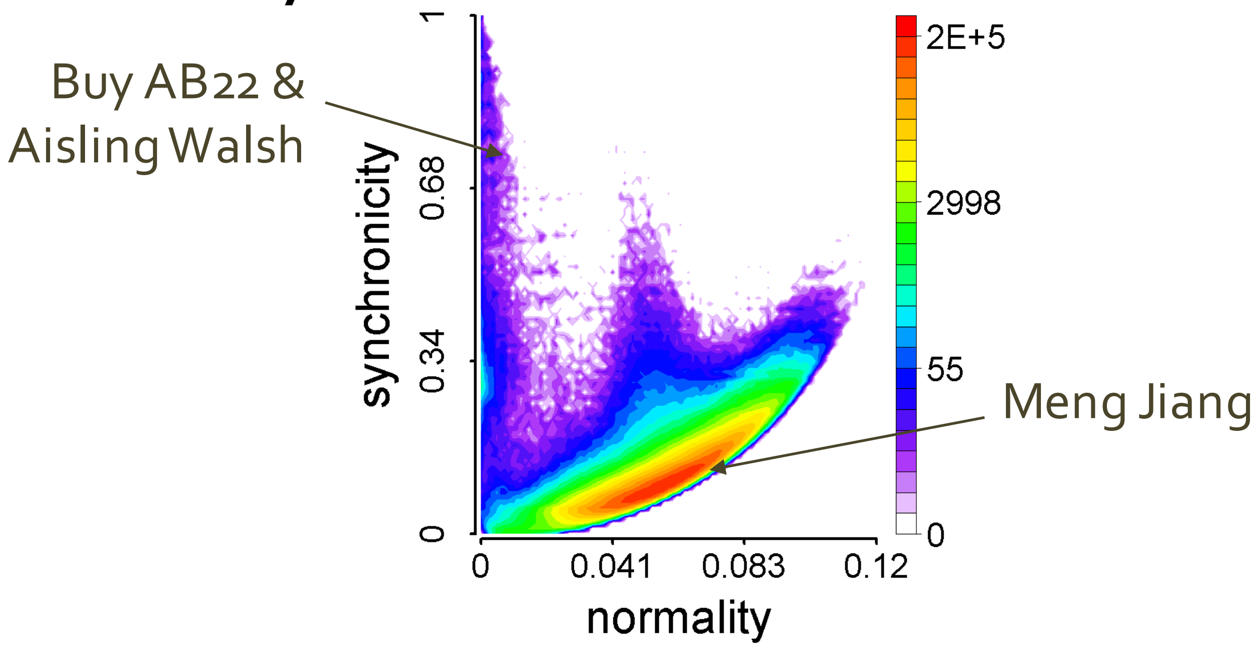
When is the Synchronicity Too High?

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

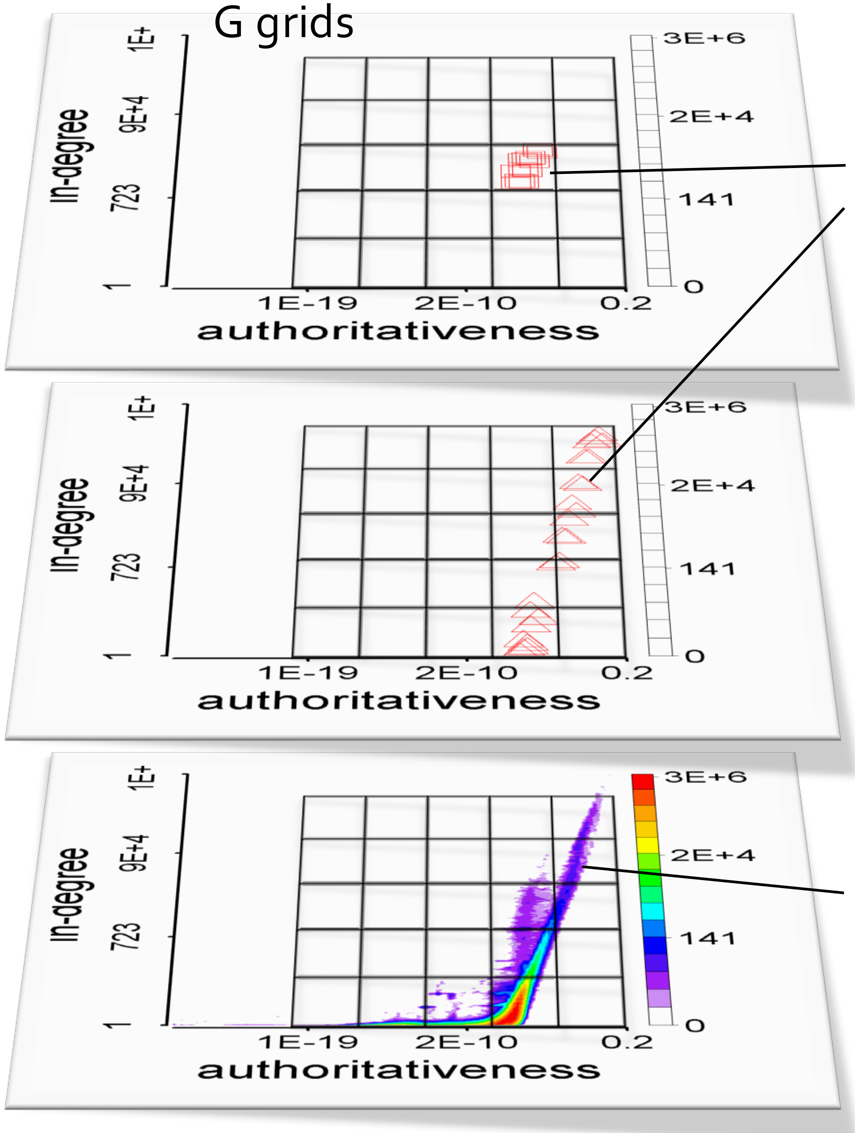
Theorem:

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

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

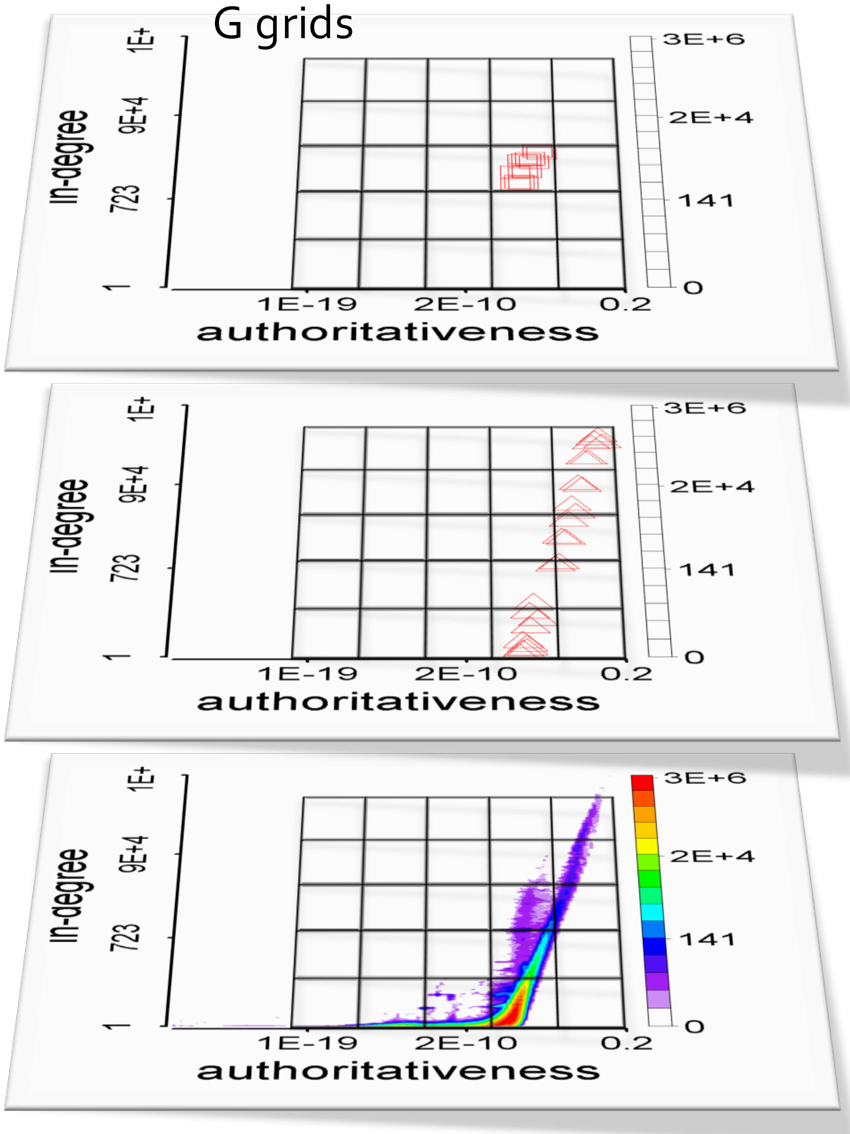
$$s_{min} = \sum (fp_g/F)\ (fp_g/F) = \sum f_g^2$$

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:

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

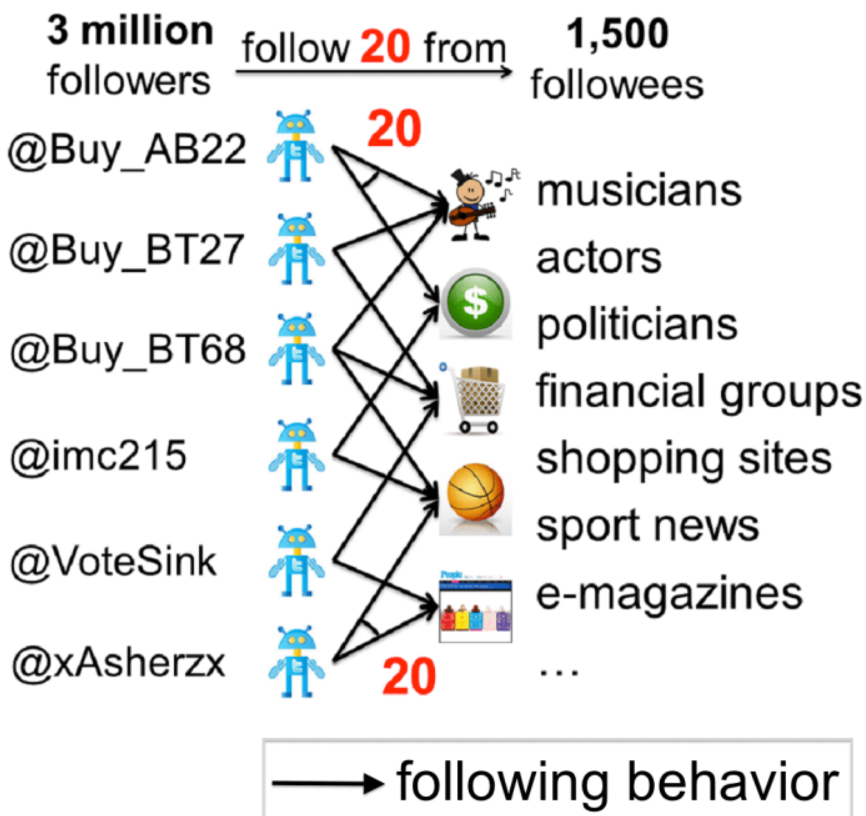
$$\begin{cases} 2 + \lambda G + \mu = 0 & \leftarrow \sum \\ 2n + \lambda + \mu s_b = 0 & \leftarrow \times b_g \sum \\ 2 s_{min} + \lambda + \mu n = 0 & \leftarrow \times f_g \sum \end{cases}$$

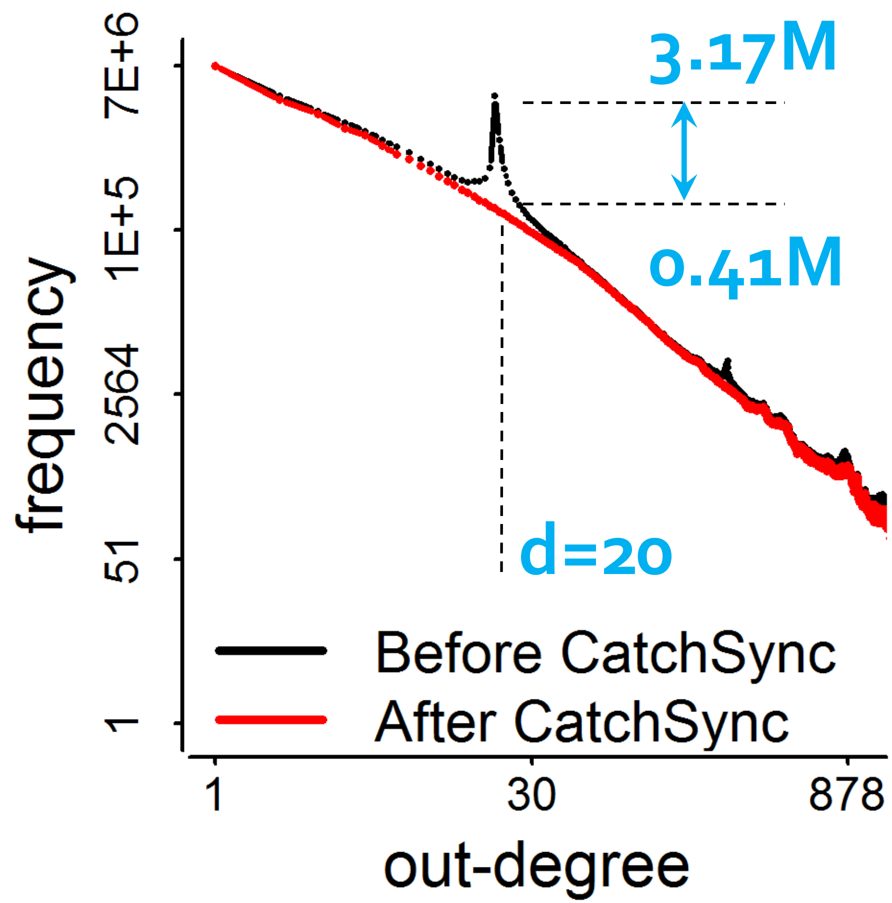
where $s_b = \sum b_g^2$.

Therefore,

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

The Distribution was Recovered!





Impact

- Cited by **44**. 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 **32**.
  - Cited by *KDD'16 Best Research Paper*: the authors (B. Hooi *et al*.) provided theoretical bounds to prevent the camouflage.

Outline

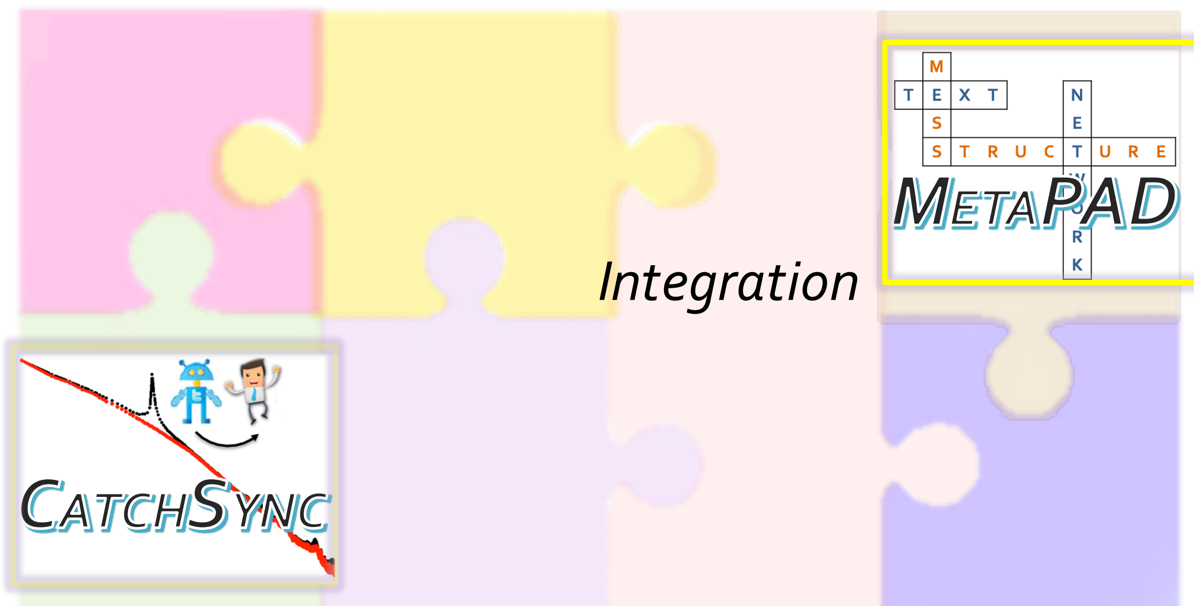
Social contexts

Spatiotemporal contexts

Behavioral content

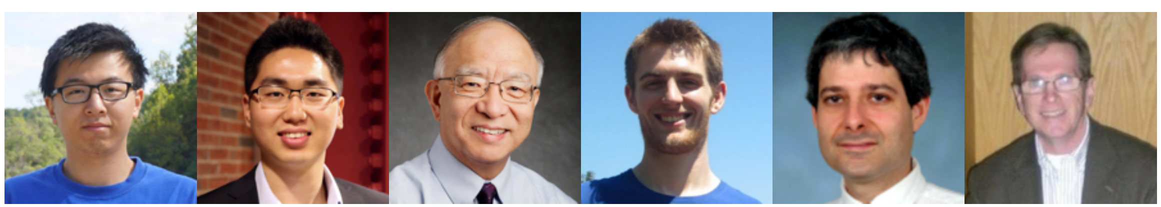
Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

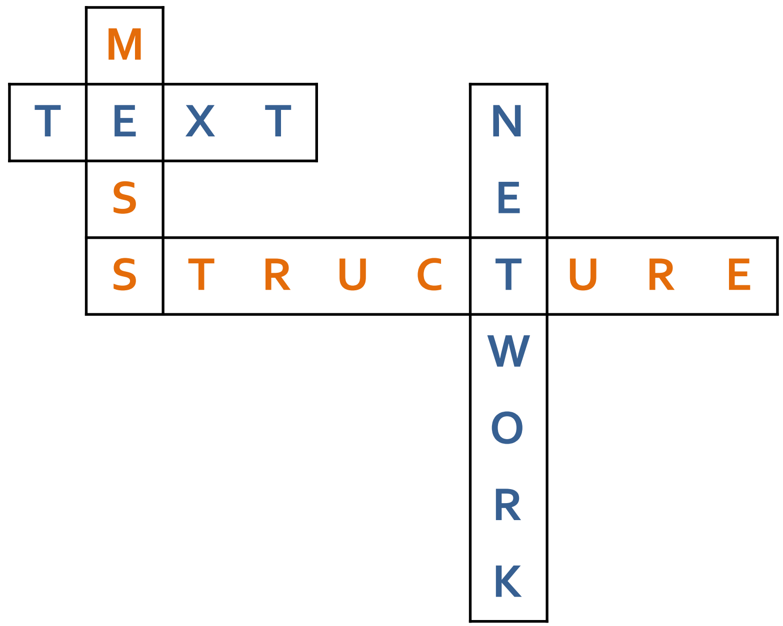


MetaPAD: Meta Pattern-driven Attribute Discovery from Massive Text Corpora

Joint work with Jingbo Shang, Xiang Ren, Jiawei Han (UIUC),
Taylor Cassidy, Lance Kaplan, and Timothy Hanratty (US Army Research Lab)
Submitted to ACM SIGKDD'17

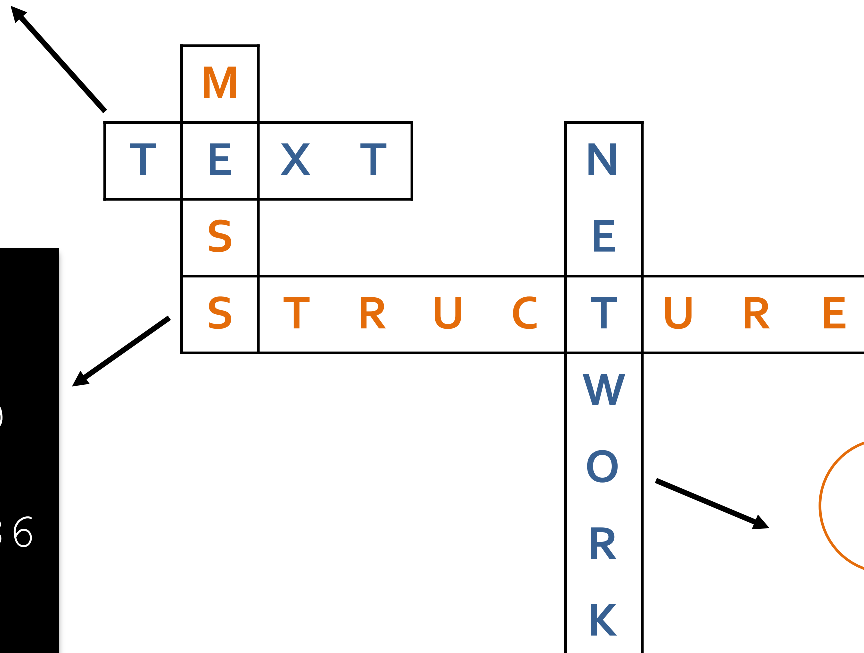


Motivation

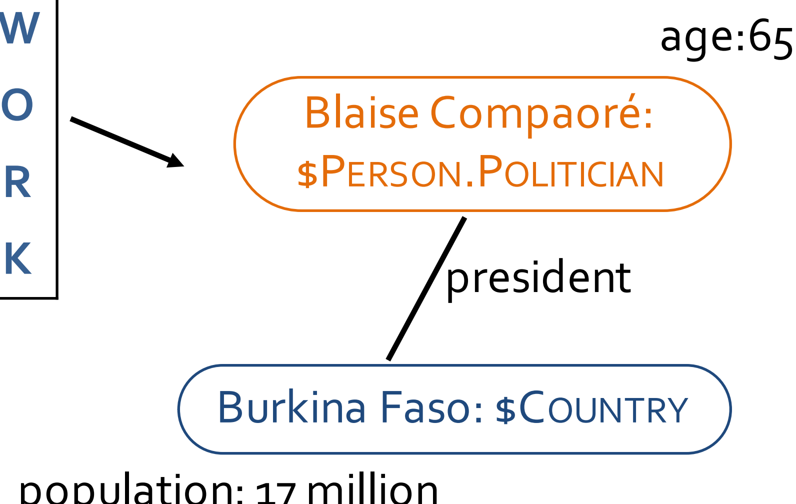


Motivation

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




```
was,13897
…
president,2769
…
government,1886
…
blaise,42
…
compaore,15
…
```



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

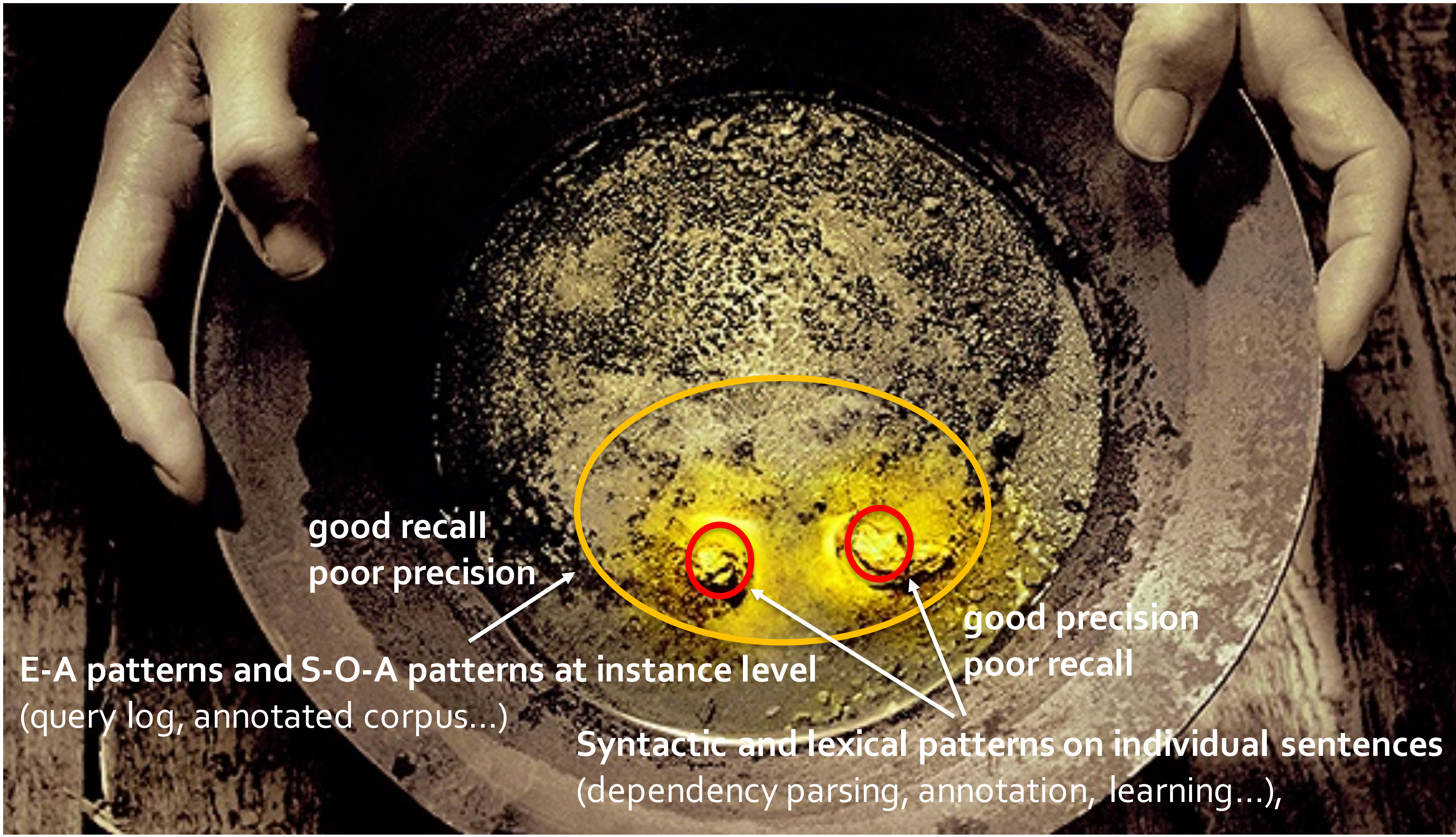
"Barack Obama, President of U.S., " ➡ "O, A of S,", "S A O"

Annotated corpus: Domain limited and expensive

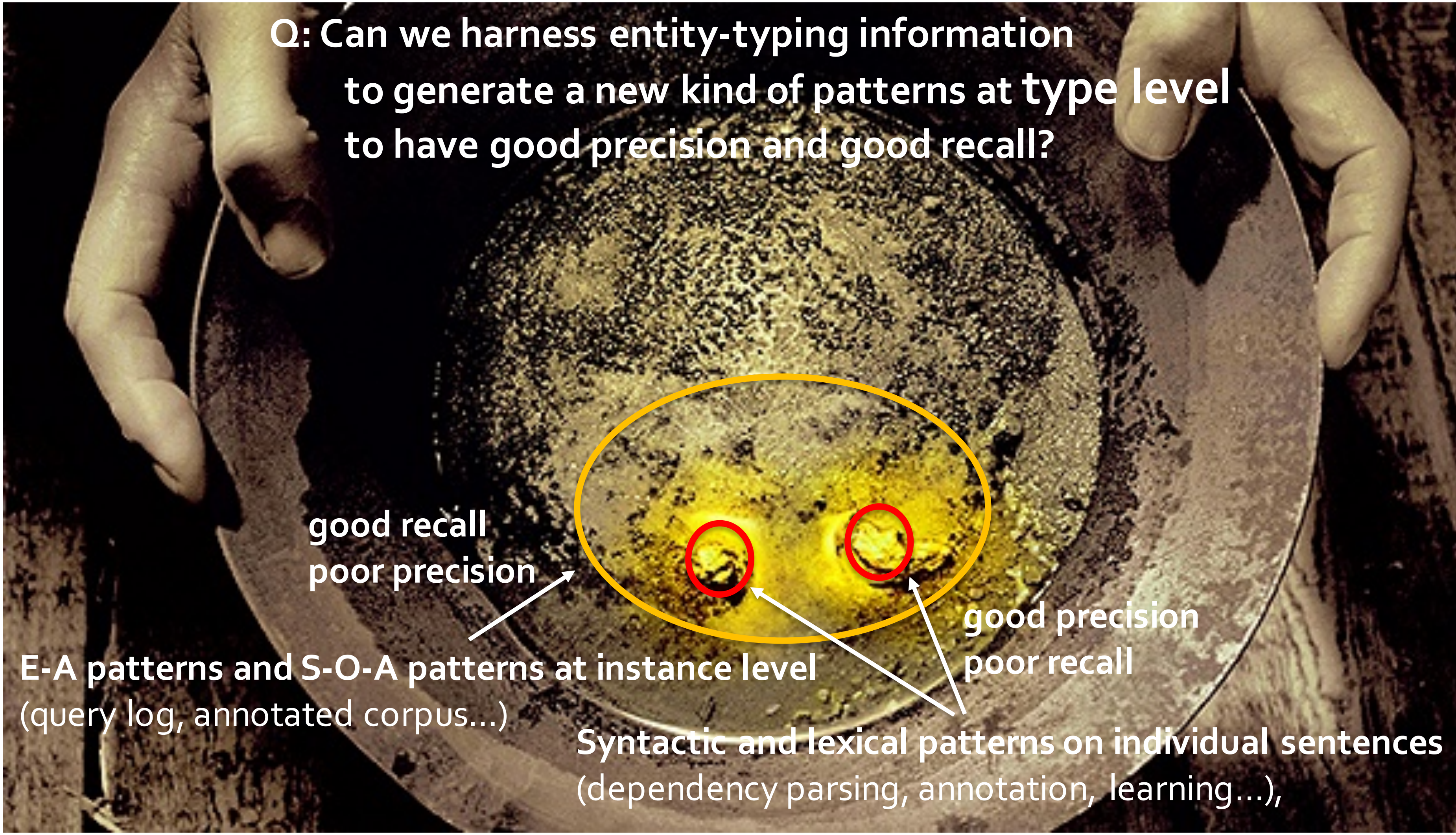
Input: "...Sunday night, Burkina Faso..." and the "A, E" pattern

Output: ⟨\$COUNTRY, Sunday night⟩ ☹

Triple Extraction from Data



Triple Extraction from Data



Our Methodology (M5)

(#1) “President Blaise Compaoré’s government of Burkina Faso was founded…”

⟨$COUNTRY, {president}, $POLITICIAN⟩

⟨Burkina Faso, {president}, Blaise Compaoré⟩

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)

(#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⟩

frequency↑↑

Group synonymous patterns by <u>massive</u> triples

⟨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…”
(#3) “U.S. President Barack Obama visited …”

Meta patterns:

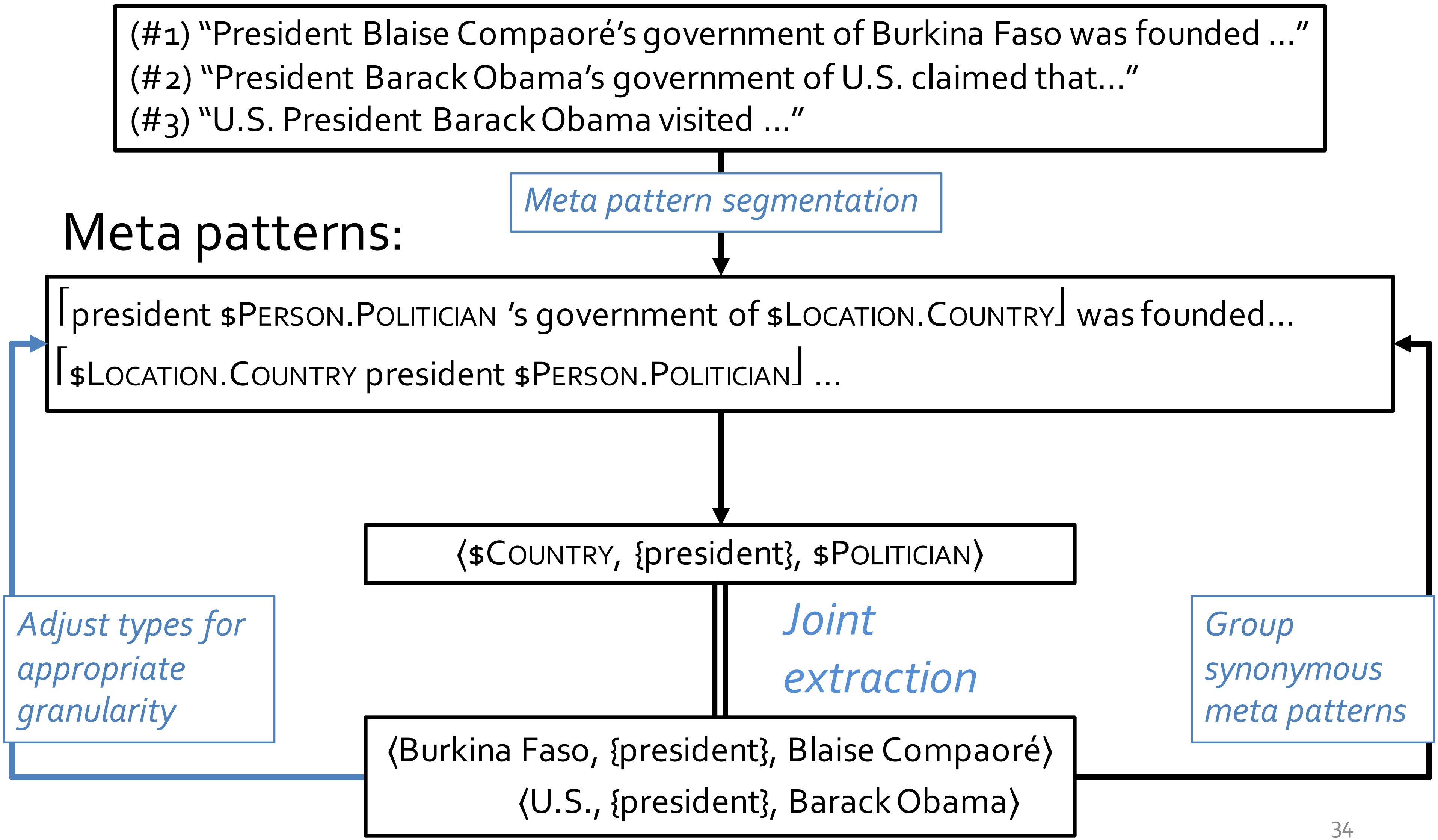
⌈president $PERSON.POLITICIAN ’s government of $LOCATION.COUNTRY⌋ was founded…
⌈$LOCATION.COUNTRY president $PERSON.POLITICIAN⌋ …

⟨$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)

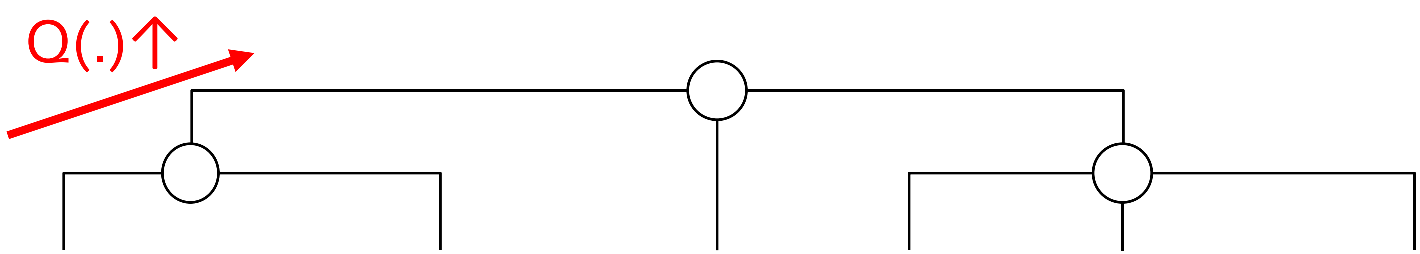
"president $PERSON.POLITICIAN 's government of $LOCATION.COUNTRY was founded …"

Meta-Pattern Quality Assessment and Segmentation

A rich set of features:

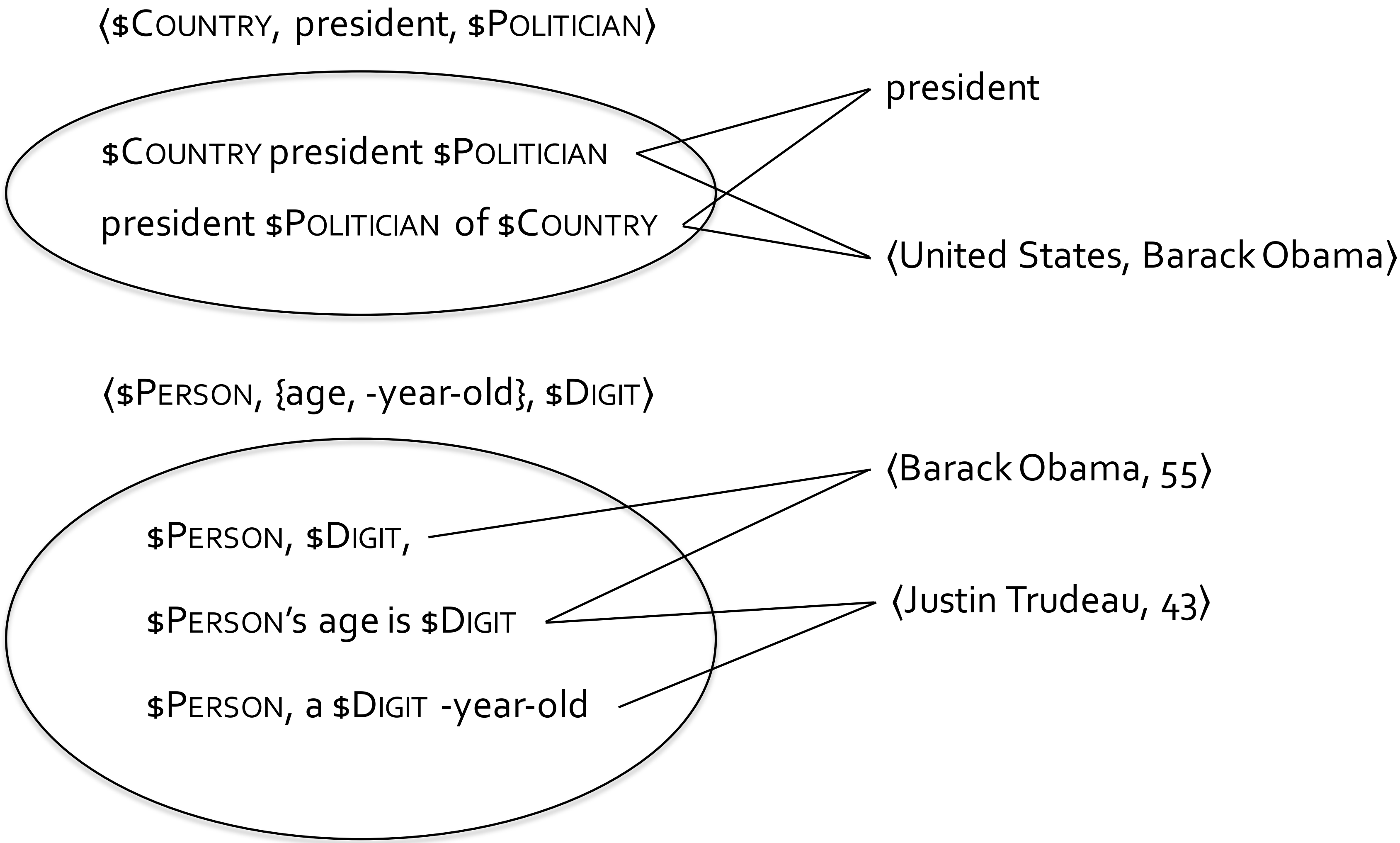
- ✓ Frequency
- ✓ Concordance: “$PERSON ’s wife”
- ✓ Completeness: “$COUNTRY president” vs “$COUNTRY president $POLITICIAN”
- ✓ Informativeness: “$PERSON and $PERSON ” vs “$PERSON ’s wife, $PERSON”

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



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

Grouping Synonymous Patterns



Adjusting Types in Meta Patterns for Appropriate Granularity

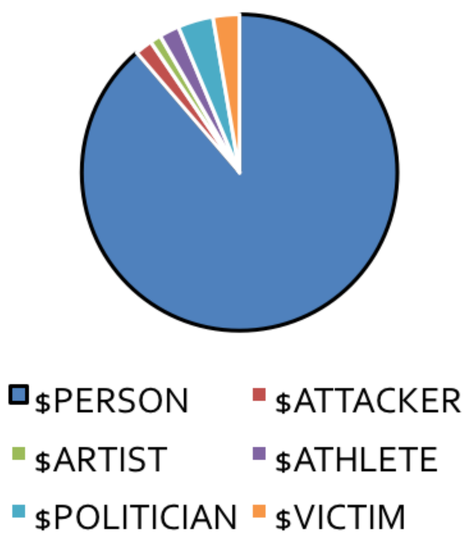
$PERSON, $DIGIT,

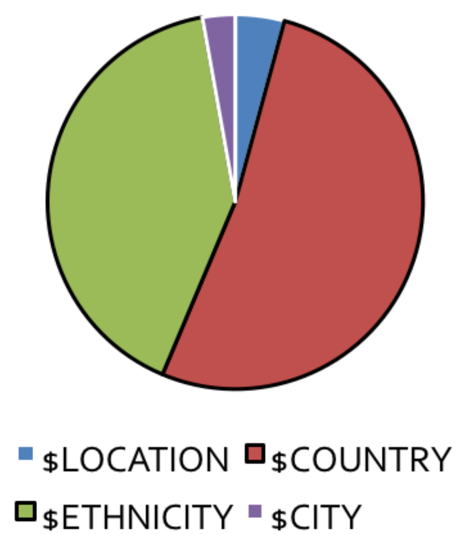
$PERSON's age is $DIGIT

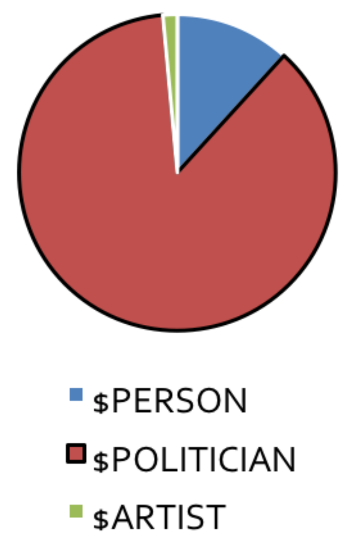
$PERSON, a $DIGIT -year-old

$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 ... President \$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

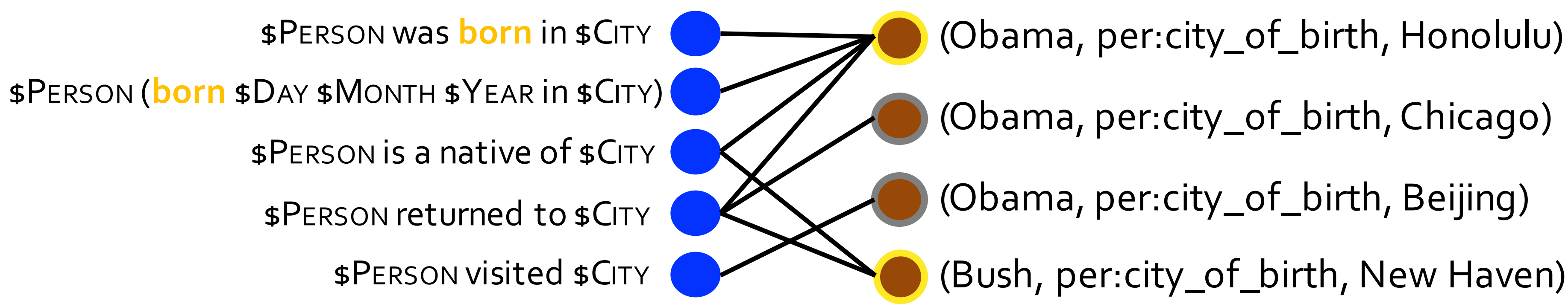
Meta patterns	Entity	Attribute value
\$TREATMENT was used to treat \$DISEASE \$DISEASE using the \$TREATMENT \$TREATMENT has been used to treat \$DISEASE \$TREATMENT of patients with \$DISEASE …	zoledronic acid therapy	Paget's disease of bone
	bisphosphonates	osteoporosis
	calcitonin	Paget's disease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

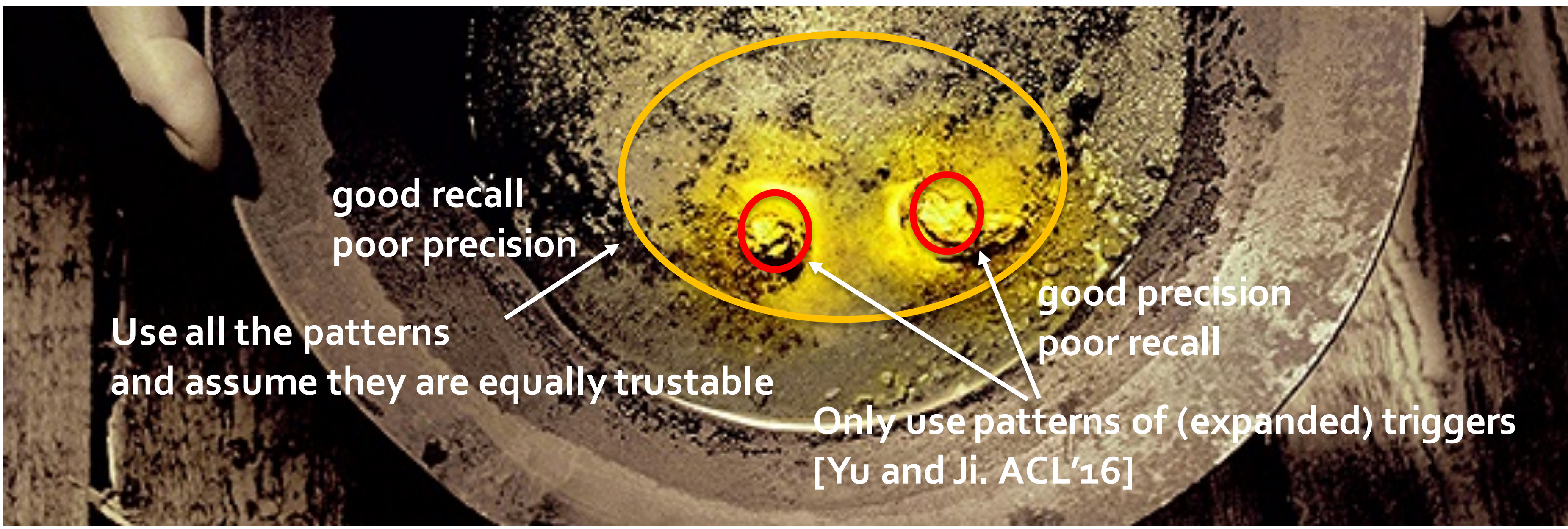
Meta patterns	Entity	Attribute value
\$BACTERIA was resistant to \$ANTIBIOTICS \$BACTERIA are resistant to \$ANTIBIOTICS \$BACTERIA is the most resistant to \$ANTIBIOTICS … \$BACTERIA, particularly those resistant to \$ANTIBIOTICS	corynebacterium striatum BM4687	gentamicin
	corynebacterium striatum BM4687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

Experimental Results

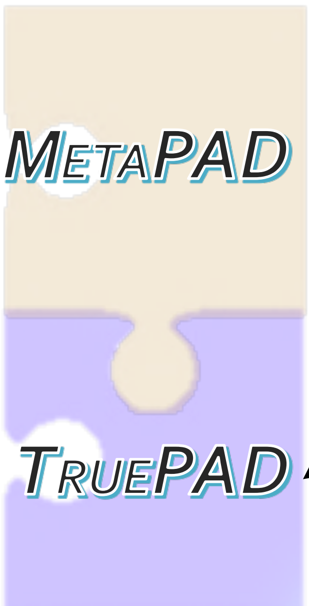
F1 score	⟨entity type, attribute name⟩	⟨entity, attribute name, attribute value⟩
Baselines		Stanford's OpenIE: 0.035
		AI2's Ollie: 0.131
	Biperpedia: 0.324	Google's ReNoun: 0.309
+Segmentation	+40.0%	+19.4%
+Type Adjustment	+6.5%	+15.0%
+Synonymous	+2.6%	
All	0.495 **relatively +52.9%**	0.424 **relatively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

On-going: Reliable Attribute Discovery



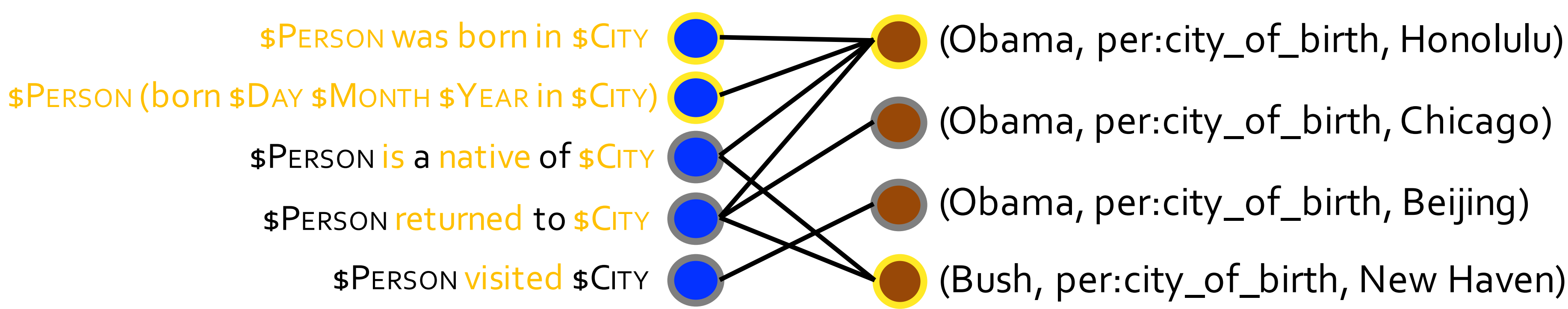


On-going: Reliable Attribute Discovery



Modeling the **reliability** of extractors:

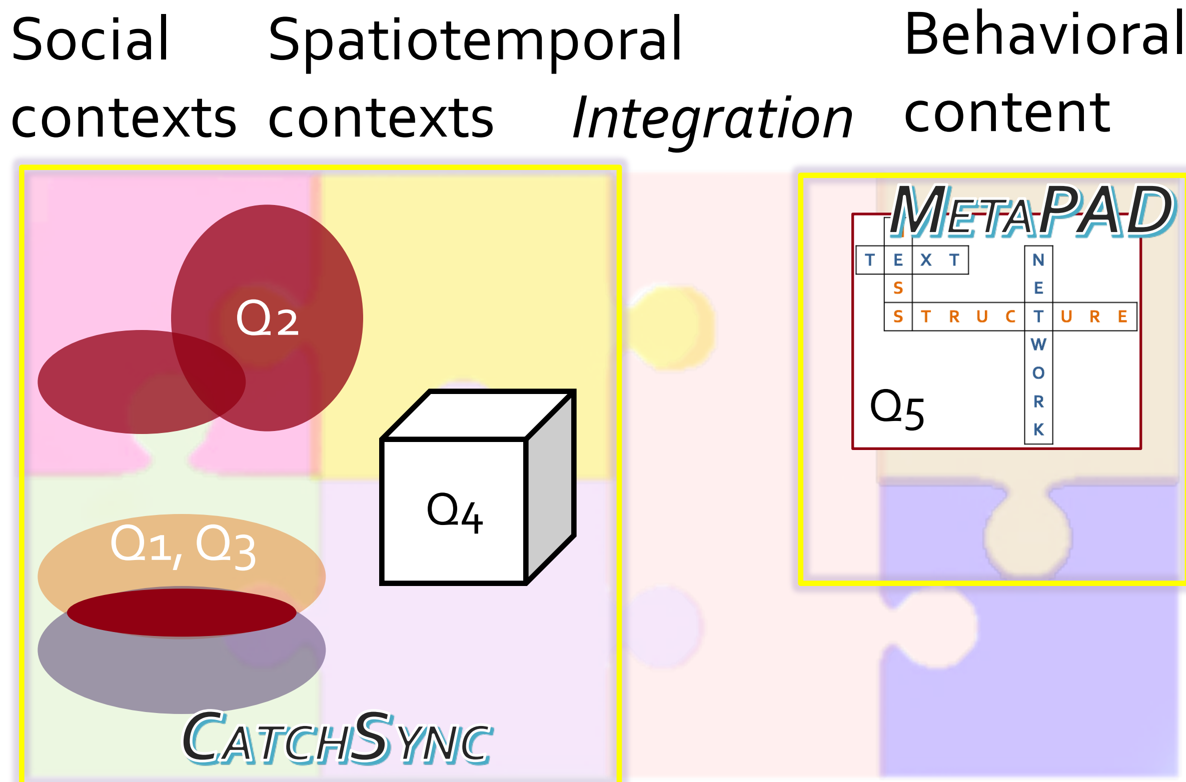
- Not every extraction is 100% correct.
- The meta patterns are not equally trustable.



Summary

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

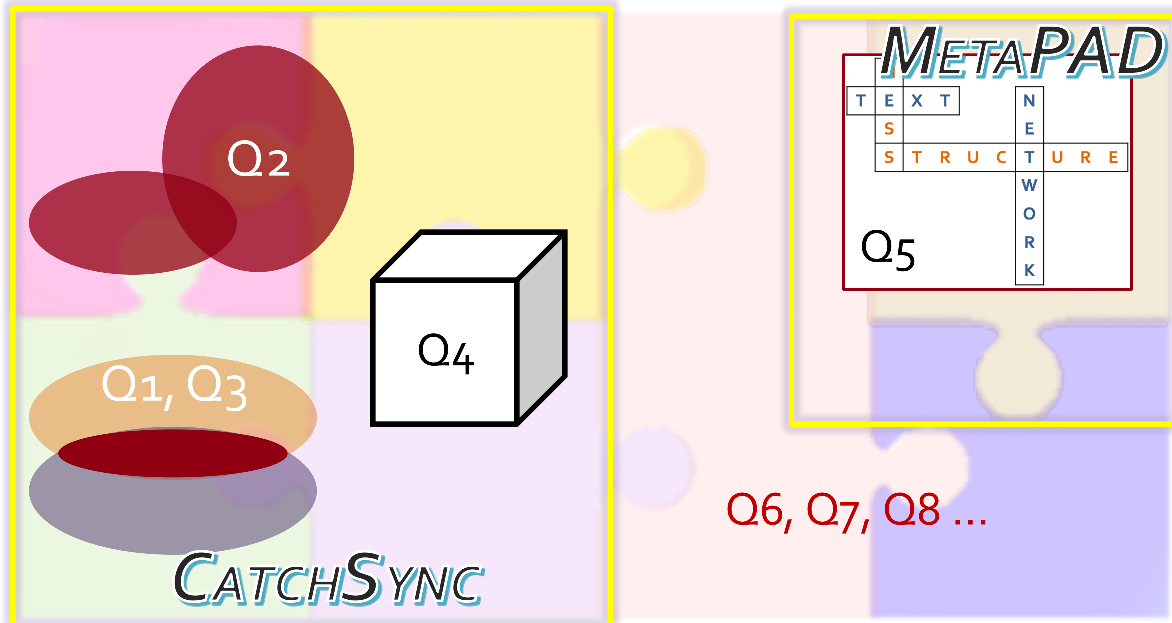


Summary

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

Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

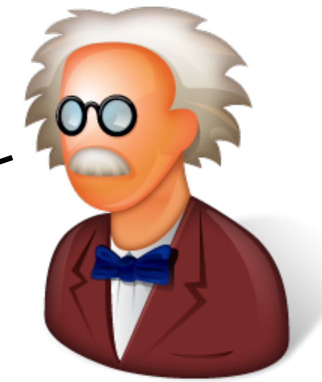


"Data-Driven Approaches for Reliable Information Extraction"
"Data Science in Data Science"
"Principles in Structured and Unstructured Data Integration"…

Data Science in Data Science

Show me your data.
I have great tools.
I know what you are doing.

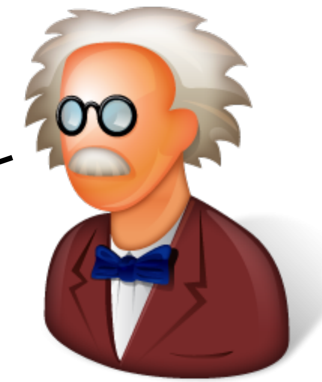
Show me your papers.
Give me your tools.
I should be able to know
what you are doing
and if you are lying to me…



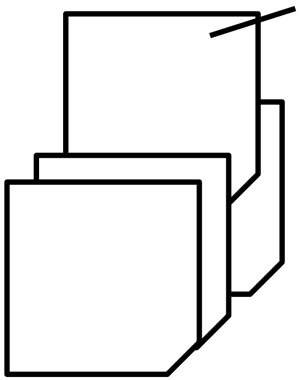
Data Science in Data Science

Show me your data.
I have great tools.
I know what you are doing.

Show me your papers.
Give me your tools.
I should be able to know
what you are doing
and if you are lying to me…



Type	Entity
$PROBLEM	summarization
$OBJECT	behavior
$OBJECT	event
$DATASET	twitter
$DATASET	dblp
$METHOD	minimum_description_length



My paper
on behavior
summarization
(KDD'16)

224 KDD'15 papers
206 KDD'16 papers

Tools: From one paper to all?

Type	Entity
$PROBLEM	?
$DATASET	?
$CONCEPT	?
$METHOD	?

Start …

Entity name detection and typing

Meta pattern generation

$Problem	summarization
$Object	behavior
$Object	event

Iteration 1: E to M

Entity name detection and typing

Meta pattern generation

$PROBLEM	summarization
$OBJECT	behavior
$OBJECT	event

$PROBLEM result (5)
$PROBLEM performance (3)
$PROBLEM problem (3)
method for $OBJECT $PROBLEM (2)
problem of $OBJECT $PROBLEM (1)

"... shows the summarization result ..."
"... evaluate the summarization performance ..."
"... address the summarization problem ..."
"... method for behavior summarization ..."
"... problem of behavior summarization ..."

x2

Iteration 1: M to E

Entity name detection and typing

Meta pattern generation

$PROBLEM	summarization
$OBJECT	behavior
$OBJECT	event
$PROBLEM	**detection**

$PROBLEM result (5)
$PROBLEM performance (3)
$PROBLEM problem (3)

"… shows the detection result …"
"… evaluate the detection performance …"
"… address the detection problem …"

x2

Iteration 2: E to M

Entity name detection and typing → **Meta pattern generation**

$PROBLEM	summarization
$OBJECT	behavior
$OBJECT	event
$PROBLEM	detection

…
$PROBLEM performance
evaluate the $PROBLEM performance (7)
address the $PROBLEM problem (14)
method for $OBJECT $PROBLEM (8)
problem of $OBJECT $PROBLEM (6)
…

"… evaluate the detection performance …" "… evaluate the summarization performance …"
"… address the detection problem …" "… address the summarization problem …"
"… method for behavior summarization …" "… method for event detection …"
"… problem of behavior summarization …" "… problem of event detection …"

Iteration 2: M to E

Entity name detection and typing

Meta pattern generation

$PROBLEM	summarization
$OBJECT	behavior
$OBJECT	event
$PROBLEM	detection
$OBJECT	**community**
$OBJECT	**anomaly**
$OBJECT	**outlier**
$OBJECT	**entity**
$OBJECT	**object**

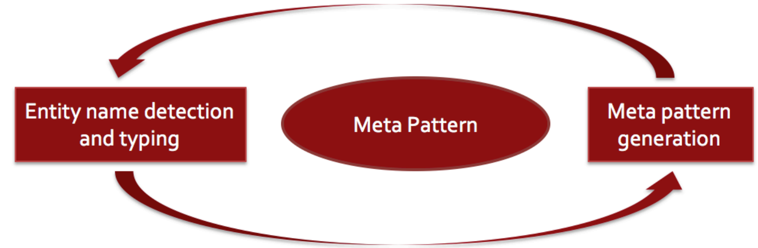
…
method for $OBJECT $PROBLEM
problem of $OBJECT $PROBLEM
…

"… *method for community detection* …"
"… *problem of anomaly detection* …"
"… *method for outlier detection* …"
"… *method for entity detection* …"
"… *problem of object detection* …"

x2

Results

A piece of code written on Feb 18, 2017



Result 1: Popular $PROBLEMs

$OBJECT $PROBLEM	$CONCEPT $PROBLEM	$METHODFEATURE $PROBLEM
anomaly detection (235)	influence maximization (187)	convex optimization (111)
link prediction (192)	pattern mining (137)	ensemble clustering (103)
topic modeling (143)	graph clustering (86)	random sampling (82)
community detection (132)	dimensionality reduction (86)	semi-supervised clustering (72)
outlier detection (83)	matrix completion (72)	bayesian optimization (58)
event forecasting (68)	similarity search (65)	hierarchical clustering (48)
risk prediction (61)	influence analysis (53)	hierarchical classification (44)
job recommendation (57)	principal_component analysis (48)	linear classification (39)
text mining (51)	social_network analysis (47)	bayesian inference (34)
spam detection (51)	evolution influence (45)	stochastic optimization (30)
text classification (49)	subgraph mining (33)	joint optimization (30)
trajectory prediction (48)	entity recognition (32)	context-aware recommendation (20)
...	...	...

Results

Result 1: Popular $PROBLEMs

$OBJECTFEATURE $OBJECT $PROBLEM	$CONCEPTFEATURE $CONCEPT $PROBLEM
spatial item recommendation (18)	collective evolution inference (36)
local event recommendation (14)	top-k similarity search (24)
spatial event forecasting (4)	social influence analysis (21)
spatial event detection (2)	frequent pattern mining (21)
discriminative topic modeling (2)	sequential pattern mining (15)
discriminative feature representation (2)	frequent itemset mining (12)
local context analysis (1)	inductive matrix completion (11)
discriminative feature mining (1)	multi-domain graph clustering (8)
temporal community detection (1)	frequent subgraph mining (8)
inner cluster optimization (1)	dynamic tensor analysis (7)
local anomaly detector (1)	dense subgraph detection (7)
temporal anomaly mining (1)	online influence maximization (7)
spatial anomaly detection (1)	item-based collaborative filtering recommendation (6)
suspicious behavior detection (1)	dense subgraph mining (6)
	dynamic graph summarization (6)
	legislative influence detector (3)
	distant-supervised entity recognition (3)
	... x2

Results

Result 2: Read Dr. Jiawei Han's KDD 15-16 papers

FaitCrowd: Fine Grained Truth Discovery for Crowdsourced Data Aggregation

Fenglong Ma[1], Yaliang Li[1], Qi Li[1], Minghui Qiu[2], Jing Gao[1], Shi Zhi[3]
Lu Su[1], Bo Zhao[4], Heng Ji[5], and Jiawei Han[3]

$CONCEPTFEATURE $OBJECT $PROBLEM	fine_grained truth discovery
$PROBLEM question $OBJECT	modeling question content
$METHODFEATURE $METHOD to estimate $CONCEPT	probabilistic graphical_model to estimate source_reliability
$METHODFEATURE approach to discovering $OBJECT from $CONCEPTFEATURE data	bayesian approach to discovering truth from conflicting data
$METHOD can significantly reduce the $METRIC	faitcrowd can significantly reduce the error_rate
$DIGIT $DATASETFEATURE datasets	2 real-world datasets
$METHODFEATURE $CONCEPT	gaussian distribution
$CONCEPTFEATURE $CONCEPT	posterior distribution

Results

Result 2: Read Dr. Jiawei Han's KDD 15-16 papers

ClusType: Effective Entity Recognition and Typing by Relation Phrase-Based Clustering

Xiang Ren† Ahmed El-Kishky† Chi Wang‡ Fangbo Tao† Clare R. Voss * Heng Ji ♯ Jiawei Han†

$MethodFeature $ConceptFeature $Problem	multi-view relation_phrase clustering
$MethodFeature $Problem problem	joint optimization problem
$MethodFeature $ConceptFeature $Concept $Method	joint non-negative matrix factorization
$Digit % enhancement in $Metric on the $DatasetSource	58.3 % enhancement in f_score on the yelp
$Digit $DatasizeUnit are annotated	3000 tweets are annotated
$Digit $Datasizeunit	302875 tweets
$Year $DatasetSource dataset	2014 yelp dataset

Results

Result 2: Read Dr. Jiawei Han's KDD 15-16 papers

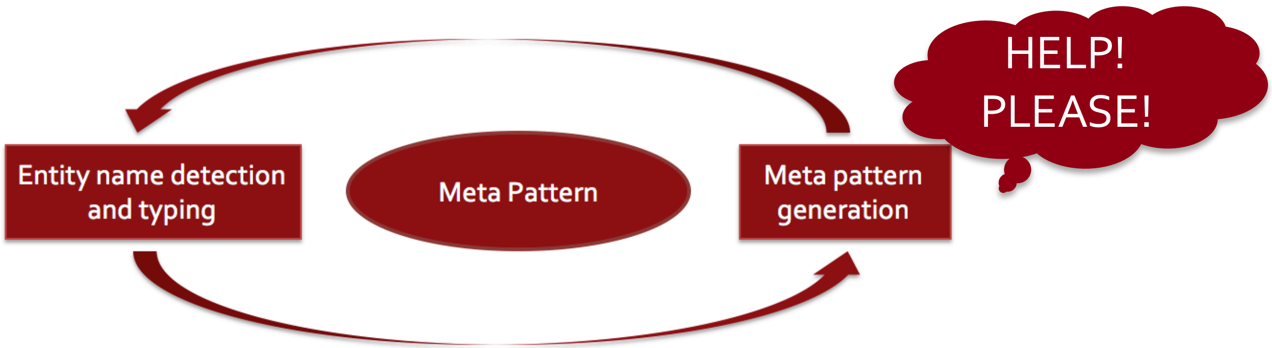
Label Noise Reduction in Entity Typing by Heterogeneous Partial-Label Embedding

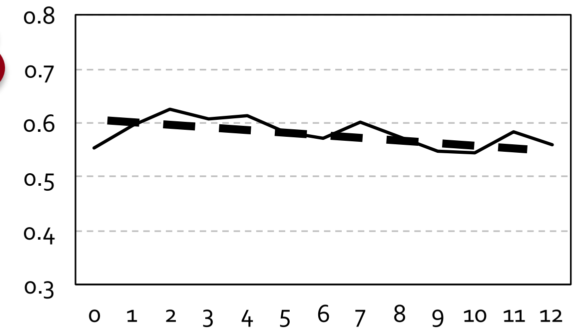
Xiang Ren[†*] Wenqi He[†*] Meng Qu[†] Clare R. Voss[‡] Heng Ji[♯] Jiawei Han[†]

$CONCEPTFEATURE $CONCEPT	heterogeneous graph
$CONCEPTFEATURE $CONCEPT	margin-based loss
$METHODFEATURE $PROBLEM problem	joint optimization problem
$CONCEPTFEATURE $CONCEPT	partial-label loss
$CONCEPTFEATURE $CONCEPT	homogeneous graph
$CONCEPTFEATURE $CONCEPT assumption	mutual exclusion assumption
$METHODFEATURE $PROBLEM	hierarchical classification
$DATASET and $DATASET datasets	bbn and ontonotes datasets
$DATASET and $DATASET datasets	ontonotes and bbn datasets

X2

Future Directions





Tasks and Problems

- Entity resolution
- Phrase mining
- Attribute discovery
- Truth finding
- Mining functions: Prediction, ranking…

Data

- Annotation on more papers
- Data Science Ontology
- Knowledge Bases
- Computer Science
- PubMed …

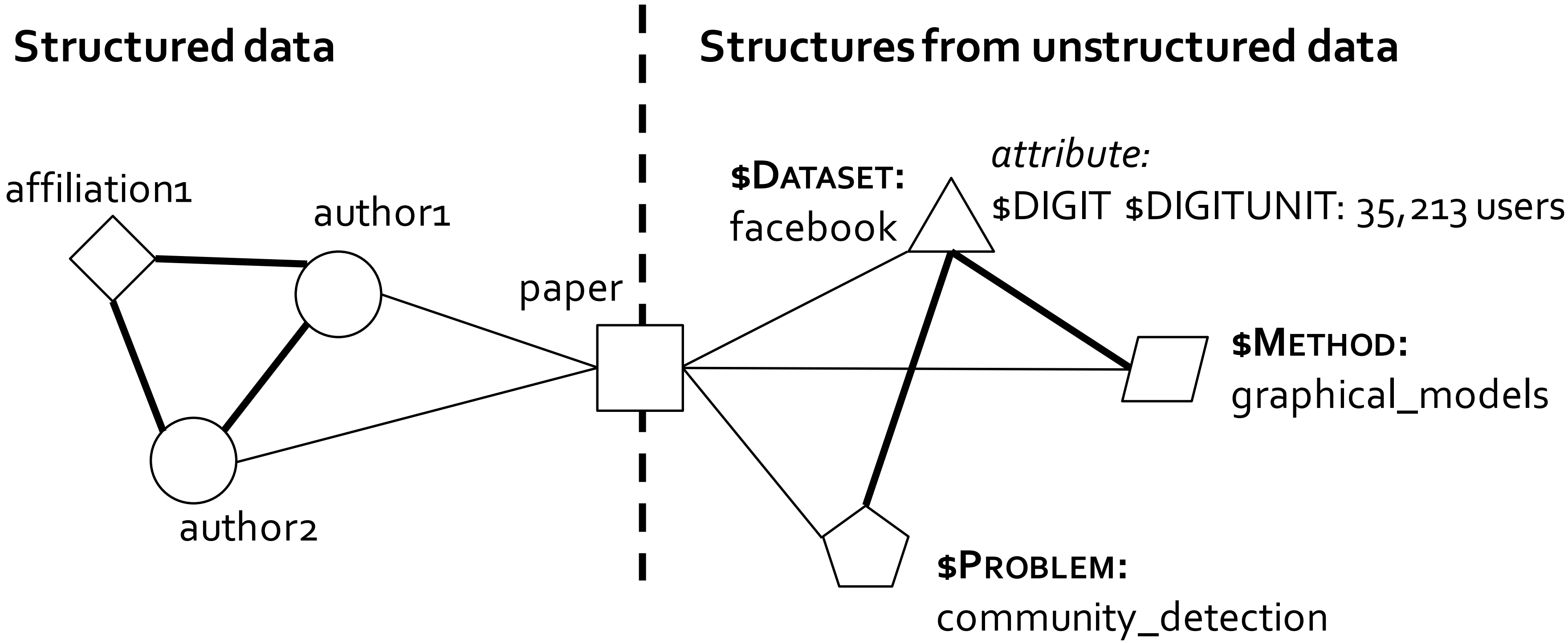
Technologies

- NLP:
  POS tagging
  Dependency parsing
  Information extraction
  (Slot filling, statement extraction, aspect mining …)
  …
- Machine learning and AI
- Crowdsourcing

x2

Integrating Structured Data and Unstructured Data

- Q: Who has studied the largest number of datasets for community detection?



Integrating Structured Data and Unstructured Data

- Q: Residents of which state support what policy of which politician?

Structured data: Social spatiotemporal information

Structures (entities, attributes, relations) from unstructured data

	User	Location (geo-tagged)			$PERSON.POLITICIAN		$POLICY		Sentiment
	…	…	Pennsylvania	…	Donald Trump	Hillary Clinton	Immigration	Gun-control	…
t1									
t2									+
t3									
t4									+

Integrating Structured Data and Unstructured Data

- Q: Residents of which state support what policy of which politician?

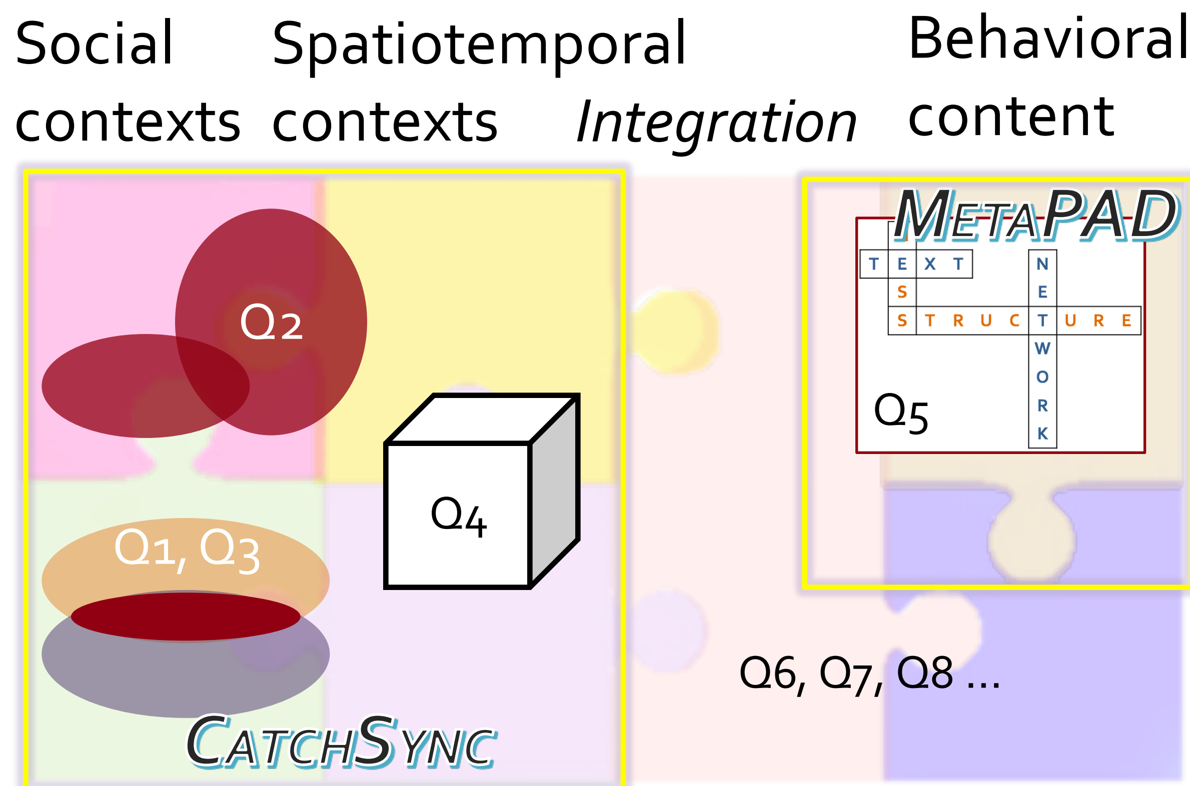
Structured data: Social spatiotemporal information

Structures (entities, attributes, relations) from unstructured data

	User	Location (geo-tagged)			$PERSON.POLITICIAN		$POLICY		Sentiment
	…	…	Pennsylvania	…	Donald Trump	Hillary Clinton	Immigration	Gun-control	…
t1									
t2									+
t3									
t4									+

Exploring principles of data integration for in-depth behavioral analysis (and many other applications)

Summary



Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

Expedition!!!

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

References

Yao, Tong, Yan, Xu, Zhang, Szymanski, and Lu. Dual-regularized one-class collaborative filtering. ACM International Conference on Information and Knowledge Management (CIKM), 2014.

Bogdanov, Busch, Moehlis, Singh, and Szymanski. Modeling individual topic-specific behavior and influence backbone networks in social media. Social Network Analysis and Mining, 4, 2014.

Yu and Ji. Unsupervised Person Slot Filling based on Graph Mining. ACL, 2016.

Breese, Heckerman, and Kadie. Empirical analysis of predictive algorithms for collaborative filtering. In UAI, pages 43–52, 1998.

Hu, Koren, and Volinsky. Collaborative filtering for implicit feedback datasets. In International Conference on Data Mining (ICDM), pages 263–272, 2008.

Koren. Factorization meets the neighborhood: A multifaceted collaborative filtering model. ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD), 2008.

Koren, Bell, and Volinsky. Matrix factorization techniques for recommender systems. Computer, 2009.

Liu and Yang. Eigenrank: A ranking-oriented approach to collaborative filtering. International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2008.

Liu, Zhao, and Yang. Probabilistic latent preference analysis for collaborative filtering. ACM International Conference on Information and Knowledge Management (CIKM), 2009.

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

Herlocker, Konstan, and Riedl. Explaining collaborative filtering recommendations. ACM Conference on Computer Supported Cooperative Work (CSCW), 2000.

References

Sarwar, Karypis, Konstan, and Riedl. Item-based collaborative filtering recommendation algorithms. International conference on World Wide Web (WWW), 2001.

Burke. Hybrid recommender systems: Survey and experiments. User modeling and user-adapted interaction, 2002.

Ma, Zhou, Lyu, and King. Improving recommender systems by incorporating social contextual information. ACM Transactions on Information Systems (TOIS), 2011.

Ma. King, and Lyu. Learning to recommend with explicit and implicit social relations. ACM Transactions on Intelligent Systems and Technology (TIST), 2011.

Tang, Hu, and Liu. Social recommendation: a review. Social Network Analysis and Mining, 2013.

Han, Zhang, Ghalwash, Vucetic, and Obradovic. Joint Learning of Representation and Structure for Sparse Regression on Graphs. SIAM International Conference on Data Mining (SDM), 2016.

Egele, Stringhini, Kruegel, and Vigna. COMPA: Detecting Compromised Accounts on Social Networks. The Network and Distributed System Security Symposium (NDSS), 2013.

Yang, Wilson, Wang, Gao, Zhao, and Dai. Uncovering social network sybils in the wild. ACM Transactions on Knowledge Discovery from Data (TKDD), 2014.

Viswanath, Bashir, Crovella, Guha, Gummadi, Krishnamurthy, and Mislove. Towards detecting anomalous user behavior in online social networks. USENIX Security Symposium (USENIX Security), 2014.

Faloutsos, Faloutsos, and Faloutsos. On power-law relationships of the internet topology. ACM SIGCOMM computer communication review, 1999.

Chung, and Lu. The average distances in random graphs with given expected degrees. Proceedings of the National Academy of Sciences, 2002.

References

Kleinberg. Authoritative sources in a hyperlinked environment. Journal of ACM, 1999.

Hooi, Song, Beutel, Shah, Shin, and Faloutsos. Fraudar: Bounding graph fraud in the face of camouflage. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2016.

Angeli, Premkumar, and Manning. Leveraging linguistic structure for open domain information extraction. Linguistics, 2015.

Schmitz, Bart, Soderland, and Etzioni. Open language learning for information extraction. Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP), 2012.

Gupta, Halevy, Wang, Whang, and Wu. Biperpedia: An ontology for search applications. Proceedings of the VLDB Endowment (VLDB), 2014.

Halevy, Noy, Sarawagi, Whang, and Yu. Discovering Structure in the Universe of Attribute Names. International Conference on World Wide Web (WWW), 2016.

Yahya, Whang, Gupta, and Halevy. ReNoun: Fact Extraction for Nominal Attributes. Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP), 2014.

Liu, Shang, Wang, Ren, and Han. Mining quality phrases from massive text corpora. ACM SIGMOD International Conference on Management of Data (SIGMOD), 2015.

Ren, El-Kishky, Wang, Tao, Voss, and Han. Clustype: Effective entity recognition and typing by relation phrase-based clustering. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2015.

My **First-Author** Papers (cited by 403/609; including 3 KDDs, 3 TKDEs)

Jiang, Cui, Yang, Wang, Zhu, and Yang. Social Contextual Recommendation. **CIKM**, 2012.

Jiang, Cui, Wang, Yang, Zhu, and Yang. Social Recommendation across Multiple Relational Domains. **CIKM**, 2012.

Jiang, Cui, Beutel, Faloutsos, and Yang. Inferring Strange Behavior from Connectivity Pattern in Social Networks. **PAKDD**, 2014. (**Oral**)

Jiang, Cui, Wang, Xu, Zhu, and Yang. FEMA: Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery. **KDD**, 2014.

Jiang, Cui, Beutel, Faloutsos, and Yang. CatchSync: Catching Synchronized Behavior in Large Directed Graphs. **KDD**, 2014. (**Best paper finalist**)

Jiang, Beutel, Cui, Hooi, Yang, and Faloutsos. A General Suspicious Metric for Dense Blocks in Multimodal Data. **ICDM**, 2015.

Jiang, Cui, Yuan, Xie, and Yang. Little is Much: Bridging Cross-Platform Behaviors through Overlapped Crowds. **AAAI**, 2016.

Jiang, Faloutsos, and Han. CatchTartan: Representing and Summarizing Dynamic Multicontextual Behaviors. **KDD**, 2016. (**Oral**)

Jiang, Cui, Wang, Zhu, and Yang. Scalable Recommendation with Social Contextual Information. **TKDE**, 2014.

Jiang, Cui, Chen, Wang, Zhu, and Yang. Social Recommendation with Cross-Domain Transferable Knowledge. **TKDE**, 2015.

Jiang, Cui, Beutel, Faloutsos, and Yang. Inferring Lockstep Behavior from Connectivity Pattern in Large Graphs. **KAIS**, 2015.

Jiang, Cui, Beutel, Faloutsos, and Yang. Catching Synchronized Behaviors in Large Networks: A Graph Mining Approach. **TKDD**, 2016.

Jiang, Beutel, Cui, Hooi, Yang, Faloutsos. Spotting Suspicious Behaviors in Multimodal Data: A General Metric and Algorithms. **TKDE**, 2016.

Jiang, Cui, Faloutsos. Suspicious Behavior Detection: Current Trends and Future Directions. **IEEE Intelligent Systems**, 2016.

Collaborative Papers

Liu, Tang, Han, **Jiang**, Yang. Mining Topic-Level Influence in Heterogeneous Networks. **CIKM**, 2010.

Liu, Zhu, **Jiang**, Han, Sun, Yang. Mining Diversity on Social Media Networks. **MTA**, 2012.

Gui, Liu, Tao, **Jiang**, Norick, Han. Large-Scale Embedding Learning in Heterogeneous Event Data. **ICDM**, 2016.

Kuang, **Jiang**, Cui, Yang. Steering Social Media Promotions with Effective Strategies. **ICDM**, 2016.

Kuang, Cui, Li, **Jiang**, Yang, Wang. Treatment Effect Estimation with Data-Driven Variable Decomposition. **AAAI**, 2017.

Tutorials

Jiang, Cui. **Behavior Modeling** in Social Networks: From Micro to Macro. **ICDM**, 2015. (50+ audience, $700 honorarium)

Jiang, Cui, Han. Data-Driven **Behavioral Analytics**: Observations, Representations and Models. **CIKM**, 2016. (70+ audience, $360 honorarium)

Book Chapters

Jiang, Cui. **Mining User Behaviors** in Large Social Networks. In Big Data in Complex and Social Networks, Chapman and Hall/CRC Big Data Series, 2016.

Jiang. **Behavior Modeling** in Social Networks. In Encyclopedia of Social Network Analysis and Mining, 2nd edition, Springer, 2016.

Acknowledgement

NSF

NSFC
National Natural Science Foundation of China

清华大学 TSINGHUA UNIVERSITY 1911

Carnegie Mellon University

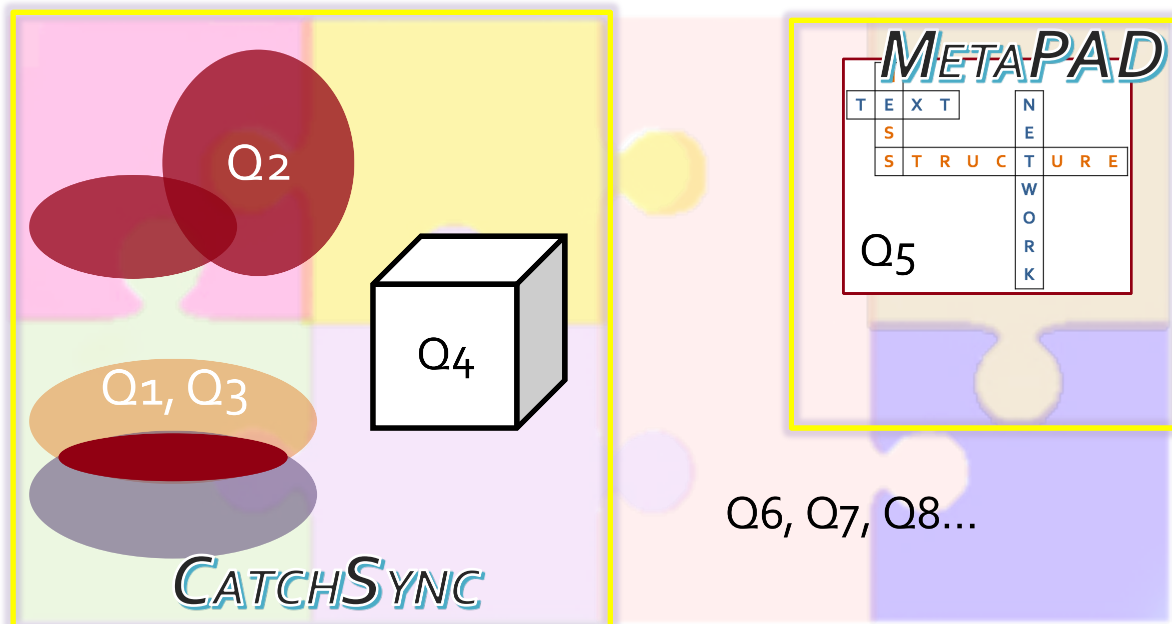
UNIVERSITY OF MARYLAND 1856

Microsoft Research 微软亚洲研究院

Tencent 腾讯

Summary

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



Intelligence:
Behavior prediction and recommendation

Trustworthiness:
Suspicious behavior detection

Expedition!!!

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

Backup: 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

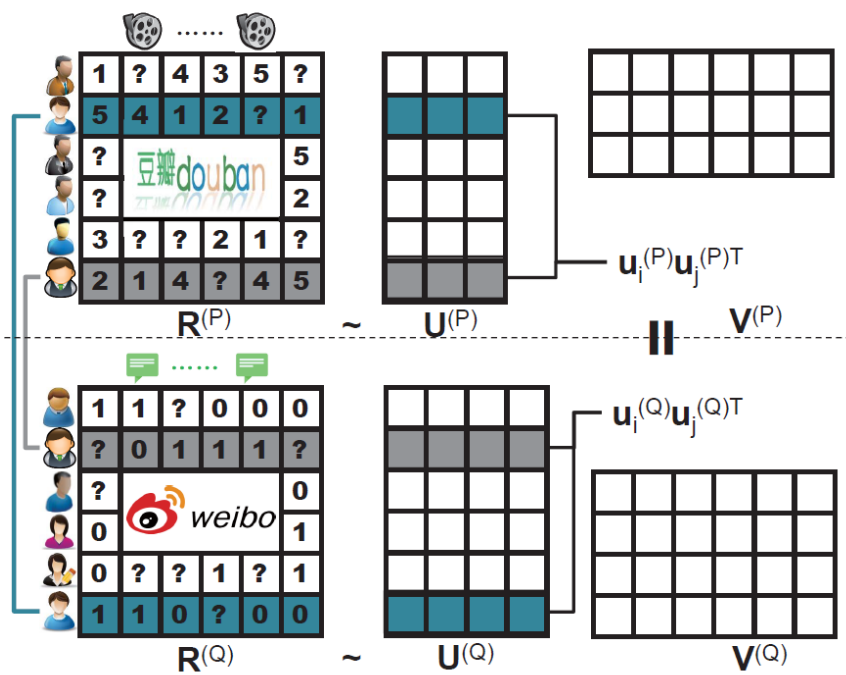
- Gradient descent method

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

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

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

Backup: S2: Cross-Platform Behavior Modeling



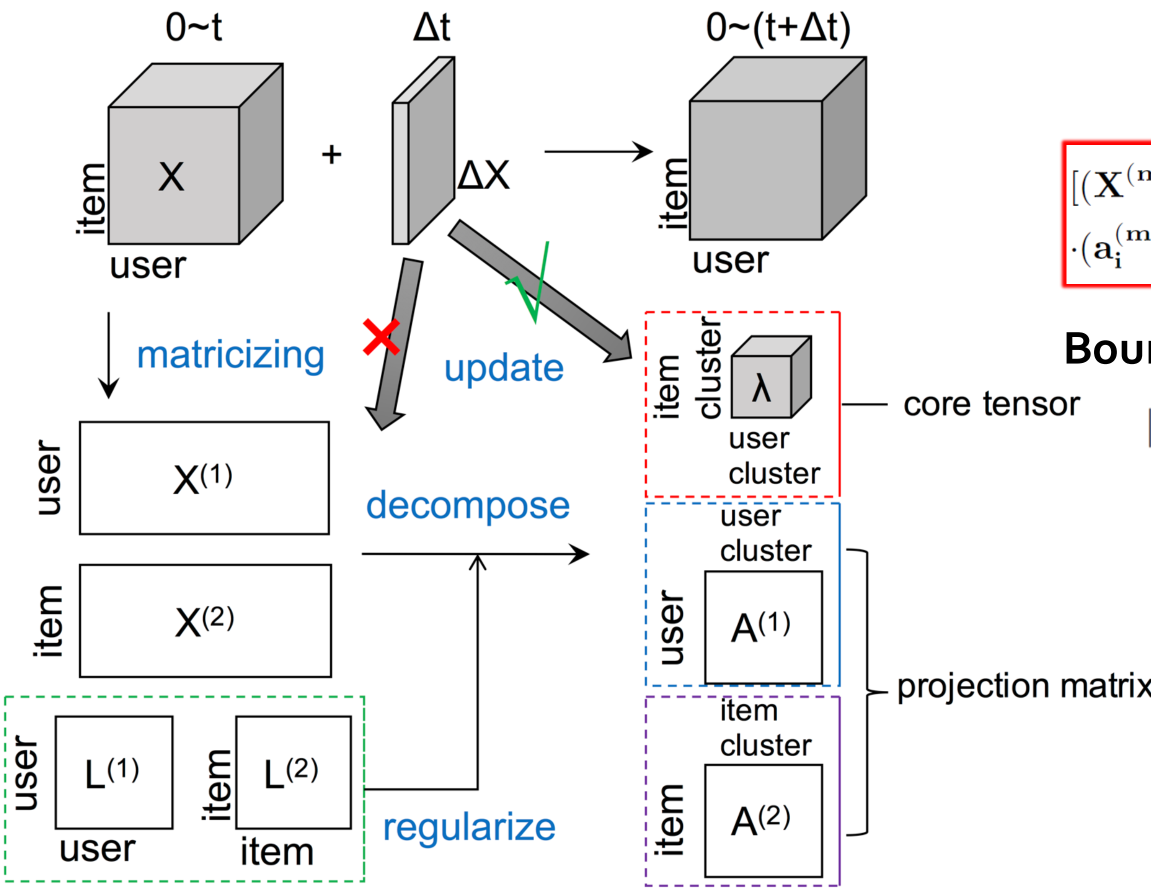
Target platform

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)

Backup: S4-1: Flexible Evolutionary Multifaceted Analysis



Tensor perturbation theory:

$$\boxed{\begin{aligned}&[(\mathbf{X}^{(m)} + \Delta\mathbf{X}^{(m)})(\mathbf{X}^{(m)} + \Delta\mathbf{X}^{(m)})^{\top} + \mu^{(m)}\mathbf{L}^{(m)}]\\ &\cdot(\mathbf{a}_i^{(m)} + \Delta\mathbf{a}_i^{(m)}) = (\lambda_i^{(m)} + \Delta\lambda_i^{(m)})(\mathbf{a}_i^{(m)} + \Delta\mathbf{a}_i^{(m)})\end{aligned}}$$

Bounds (guarantee for approximation):

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

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

Backup: S4-2: Evaluating Suspiciousness across Dimensions