

Connecting Isolated Social Multimedia Big Data

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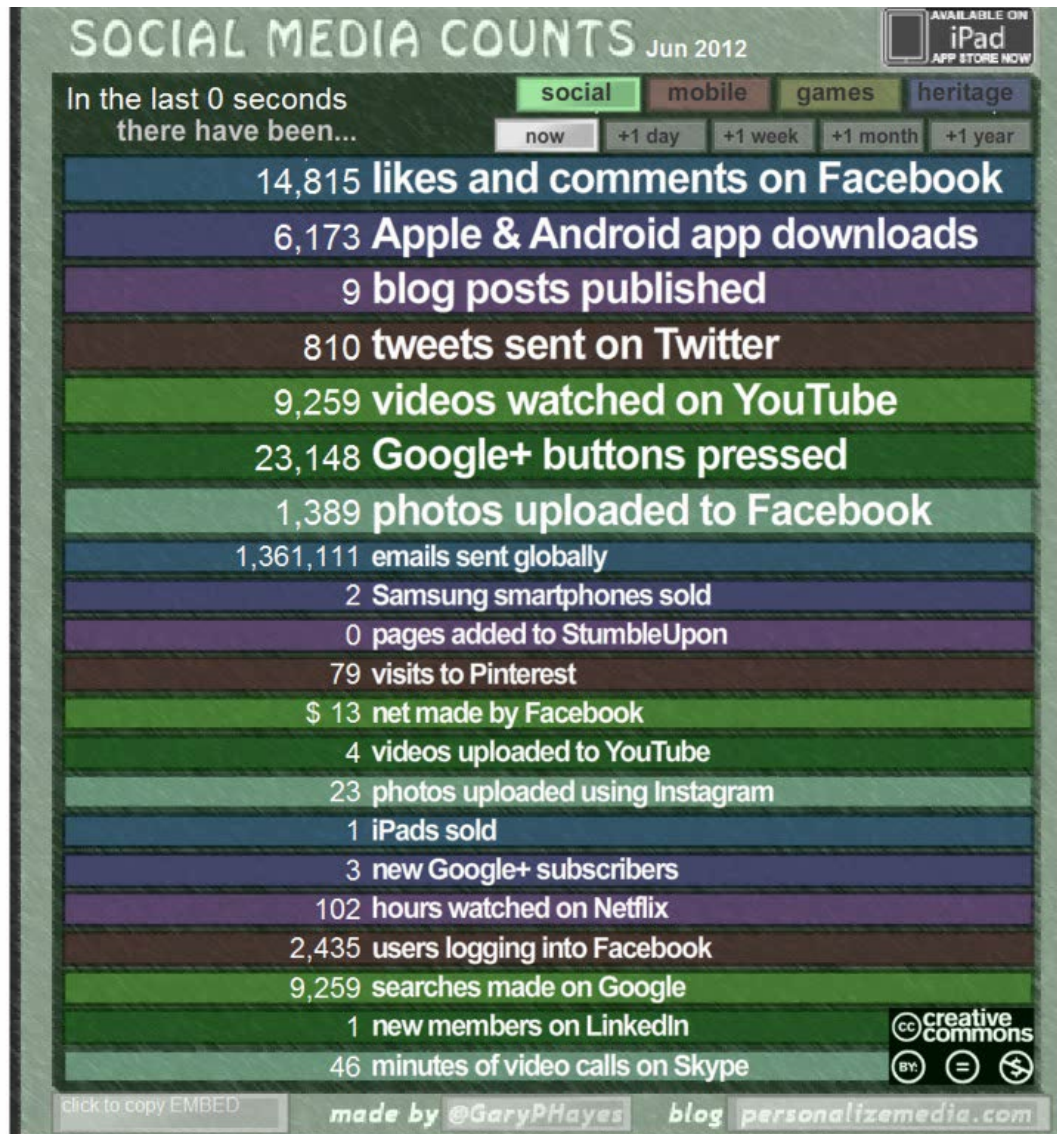
Outline

- Social Multimedia
- Social Multimedia Meet Big Data
- “User-centric” Cross-OSN Computing
- Future Directions

①

What is Social Multimedia?

Start from social media



Social Media Services



Multimedia is dominant in social media.



passively receive textual data

- ◆ Portal websites;
- ◆ Information is edited by professional editors, and for passive users.
- ◆ Constrained by the network conditions and capturing devices, **textual information dominates.**



actively obtain textual and little visual data

- ◆ Search engine, forums;
- ◆ Users mainly contribute to textual data;
- ◆ Constrained by the network conditions and capturing devices, **textual information dominates.**



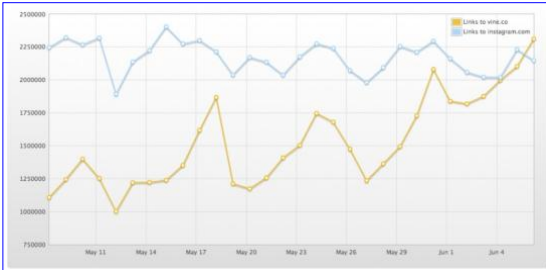
actively contribute, obtain and propagate rich multimedia data

- ◆ Micro-blogging, multimedia sharing websites, SNS;
- ◆ User-contributed becomes the main mechanism for data generation;
- ◆ Development in capturing devices and network transmission, **huge multimedia data are produced and consumed.**



Internet media roadmap

Multimedia is dominant in social media.



Twitter increases its support on multimedia content, and releases the 6-second video sharing app: Vine.



WeChat has attracted more than 300 million users in two years, which is tending to replace SMS.



actively contribute, obtain and propagate rich multimedia data

- ◆ Micro-blogging, multimedia sharing websites, SNS;
- ◆ User-contributed becomes the main mechanism for data generation;
- ◆ Development in capturing devices and network transmission, huge multimedia data are produced and consumed.

People are getting used to get access to information in the form of multimedia data.

capturing devices, textual information dominates.



Internet media roadmap

The “Social” trend in Multimedia



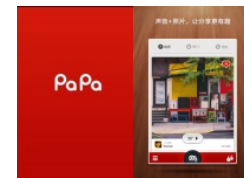
350 million photos are uploaded **daily** in November 2013 on **facebook**.



image tweet



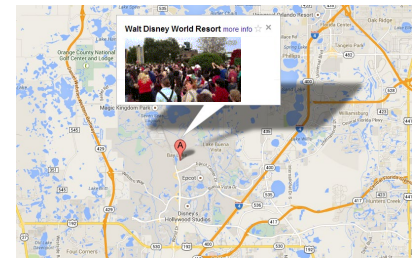
1.4 million minutes of chats are produced **every minute** on **skype**.



audio photo



100 hour videos are uploaded **every minute**, resulting in **2 billion** videos totally by the end of 2013 on **YouTube**.



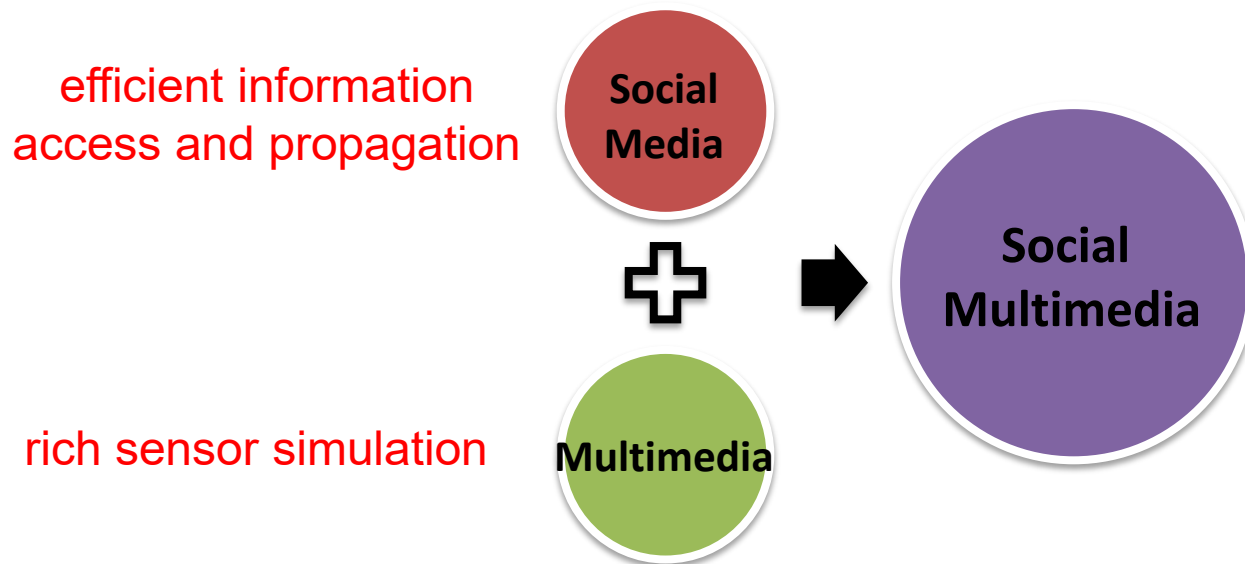
geo-tagged video

Social Multimedia

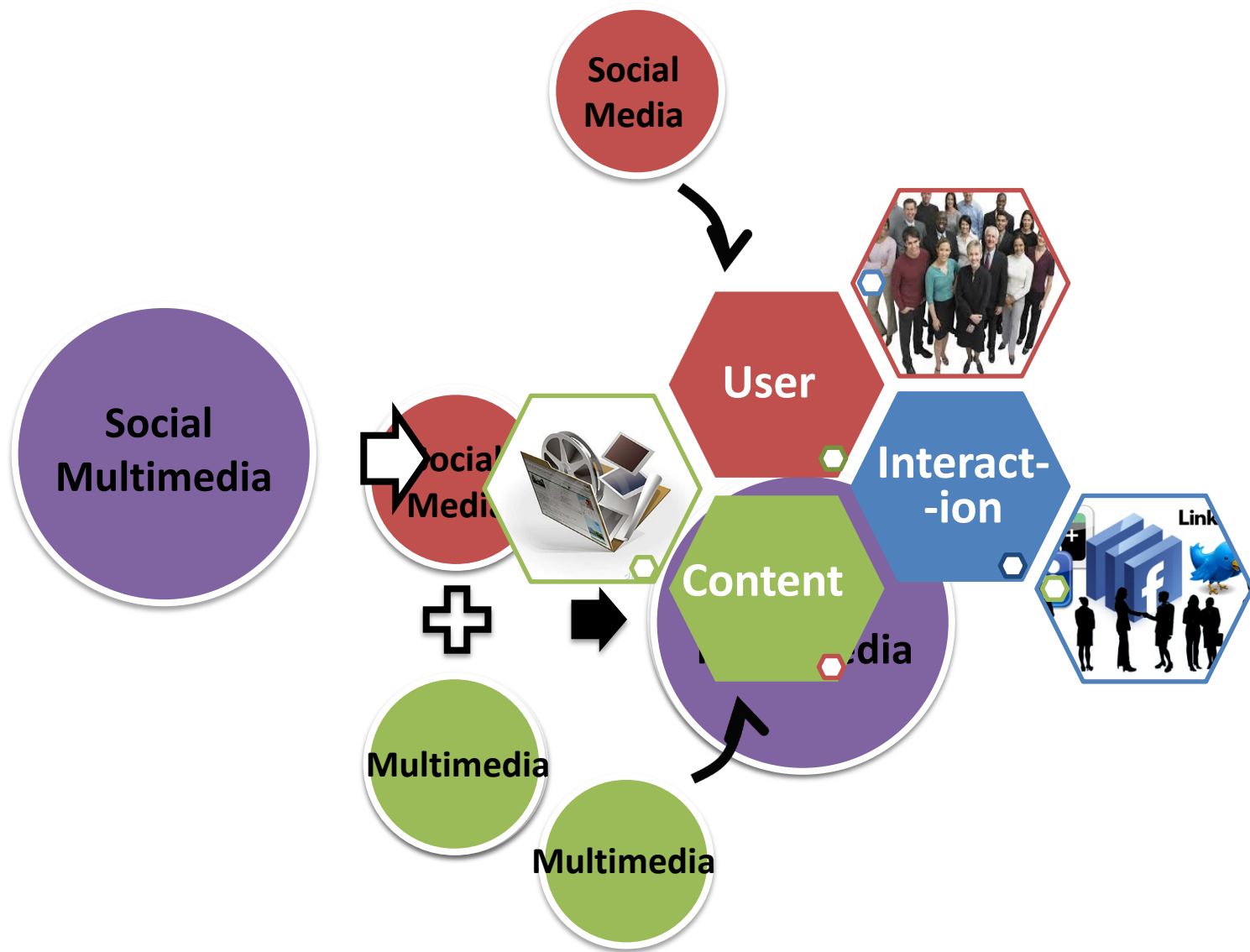
Definition:

“An online source of multimedia resources that fosters an environment of significant **individual participation** and that promotes **community curation, discussion** and **re-use** of content.”

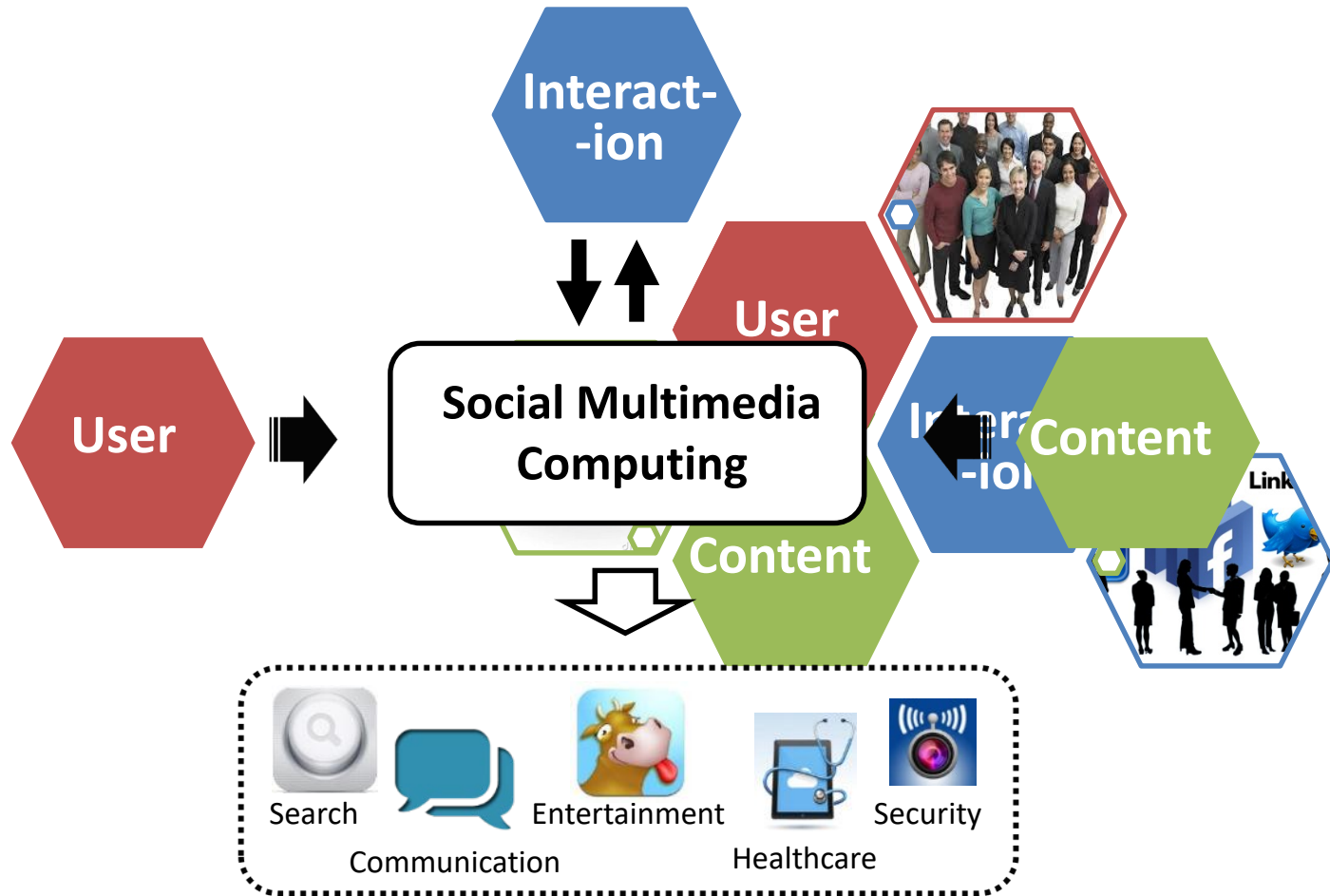
----- *Mor Naaman*



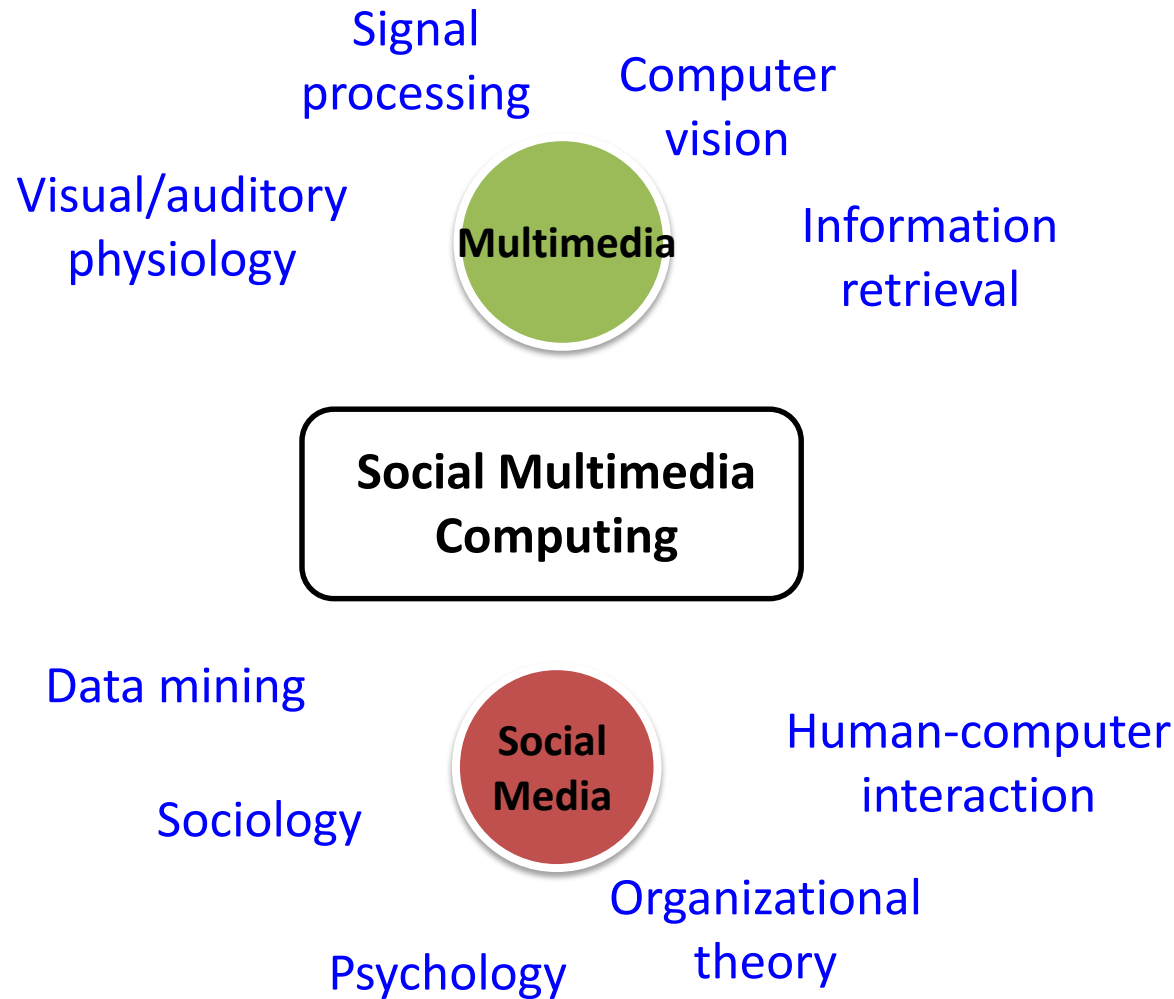
Social Multimedia



Social Multimedia Computing



Social Multimedia Computing



Content-centric V.S. User-centric

- ❑ The focus is multimedia CONTENT understanding and application
- ❑ Typical tasks include media content analysis, semantic classification, structured media authoring, etc.

Traditional Multimedia Computing

content-centric

- ❑ Heavily related to WEB1.0.
- ❑ Dominated by BROADCAST media developed by professional designers for PASSIVE users.

Web Multimedia Computing

user-centric

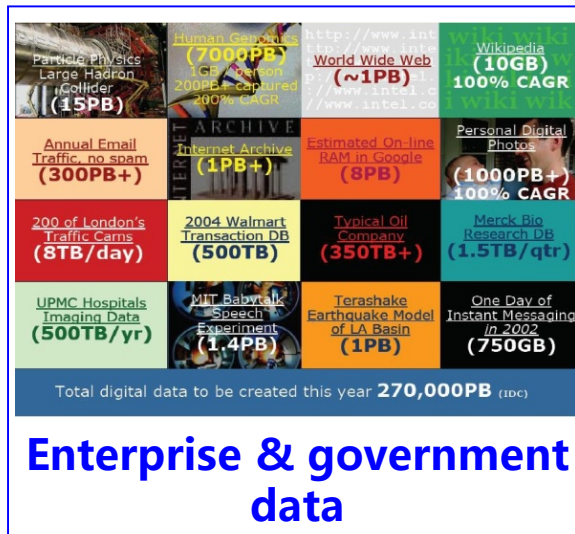
Social Multimedia Computing

- ❑ **From User:** User is the basic data collection source.
- ❑ **For User:** User is the ultimate information service consumer.

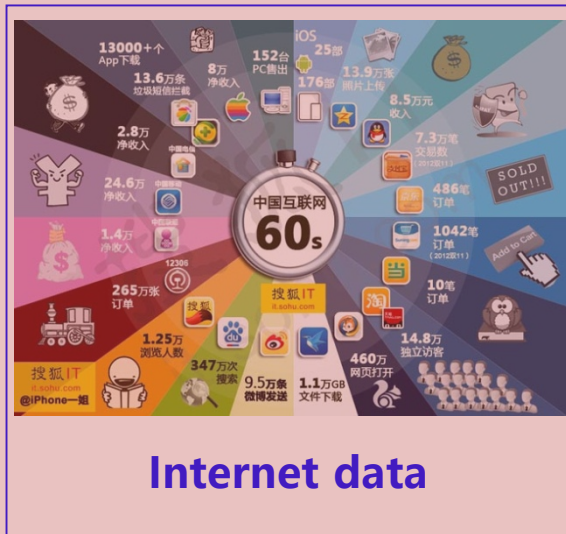
② Social Multimedia meets Big Data

Big Data & Social Multimedia

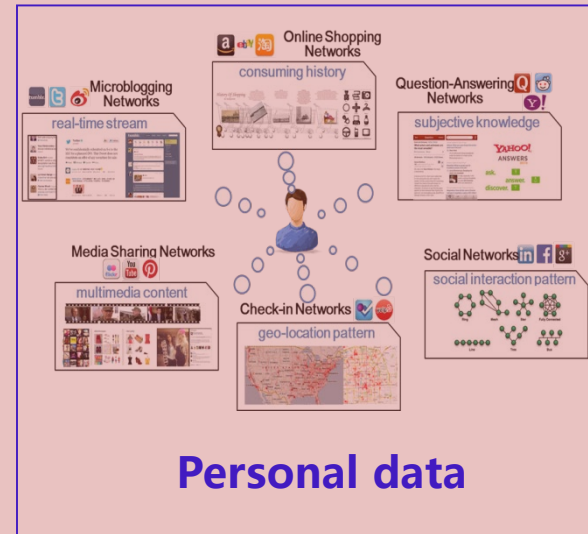
Big Data: any collection of data sets so **large and complex** that is **difficult to process using traditional techniques.** --- Wikipedia



According to IDC, in 5 years, the data storage will reach **18EB** (10^{18}), in fields of telecommunication, financial services, health care, public safety, transportation, education, etc.



BAT (Baidu, Alibaba, Tencent) possess data in the scale of **10EB** (10^{18}), and increase at a speed of **PB per day.**

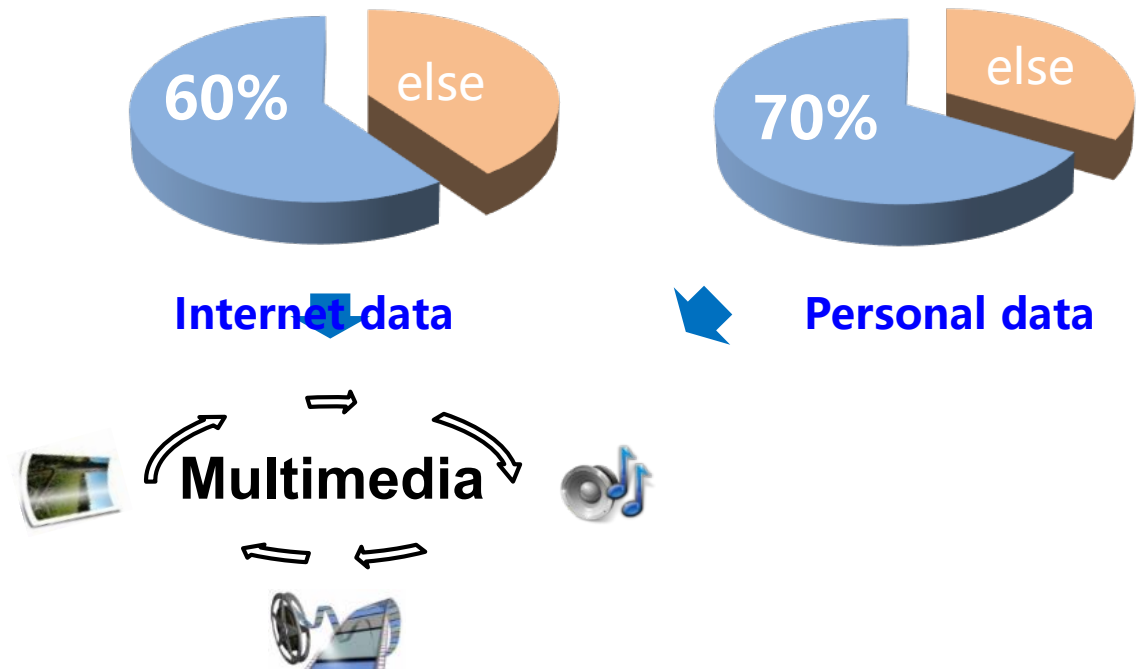


EMC2 estimated that an individual contributes to average **45 GB personal data** (public service, credit record, video surveillance, social media data, etc.)

Social Media

Big Data & Social Multimedia

Big Data: any collection of data sets so **large and complex** that is **difficult to process using traditional techniques.** --- Wikipedia



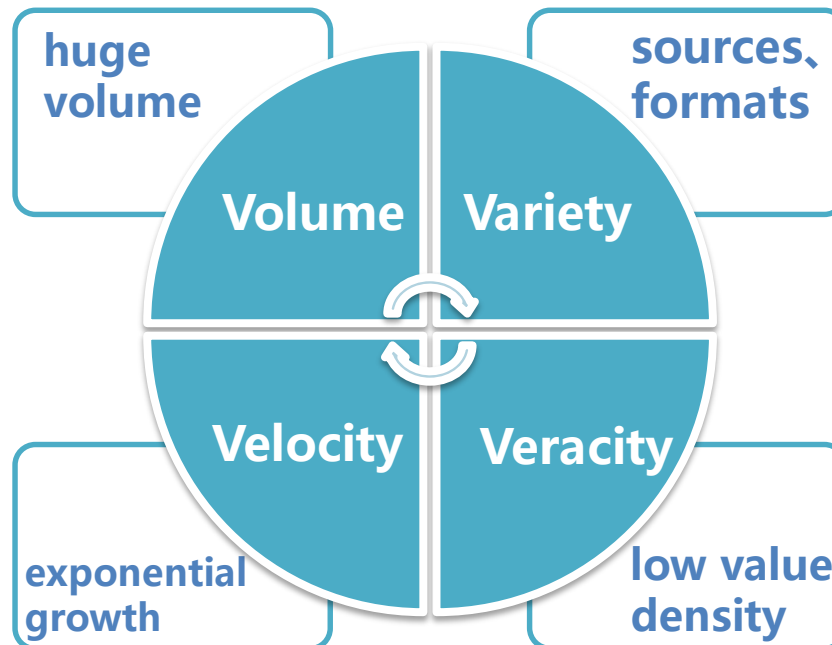
Big Data & Social Multimedia

■ Social Multimedia has significant big data “4V” characteristics:

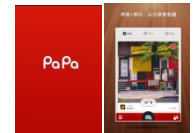
- ◆ YouTube: #[videos] > 2 billion;
- ◆ Facebook: #[pics] > 300 billion.



- ◆ YouTube: uploading 72 hour video per min.
- ◆ Skype: up to 1.4 million mins chat per min



- ◆ **source:** desktop/mobile, official/individual;
- ◆ **format:** traditional – photo/video/audio, new media-pic tweet/audio pic/geo-tagged media.



- ◆ **format:** 1 hour video with few semantics;
- ◆ **generation:** open environment -> low quality, duplicate data;
- ◆ **demands:** personalized



Big Data & Social Multimedia

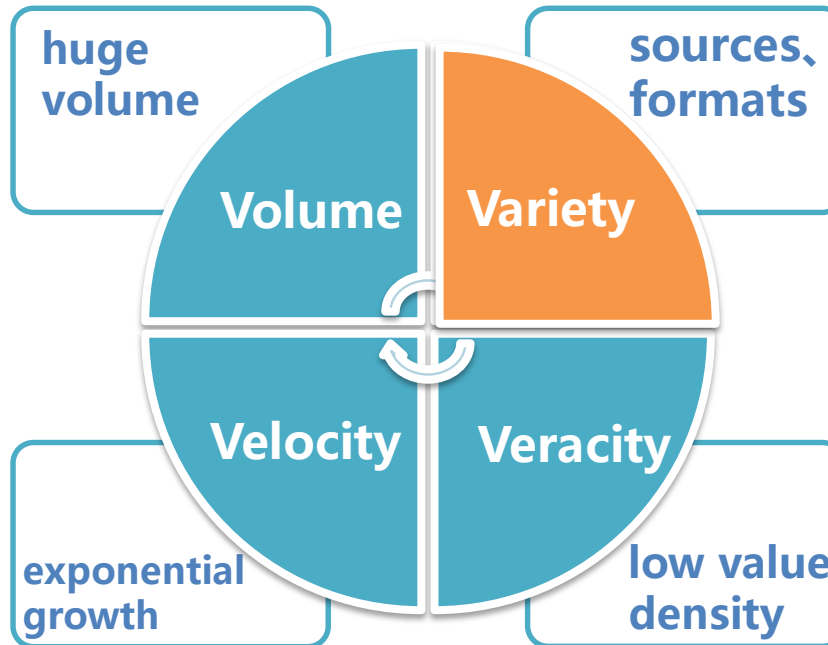
Social multimedia meets big data:
Not “Volume”, Not “Velocity”, But “Variety”.

capacity in data storage

- ◆ Facebook: # [pics] > 300 billion.

efficiency in data capture & computing

- ◆ Skype: up to 1.4 million mins chat per min



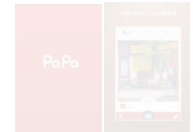
Complexity characteristics:



- ◆ source: desktop/mobile, official/individual:

complexity in data analysis

- ◆ format: text/html, photo/video, new media-pic tweet/audio pic/geo-tagged media.



data accuracy and quality

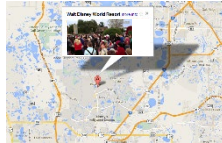
- ◆ format: 1 hour video
- ◆ generated in environment -> low quality, duplicate data; demands: personalized



Two Interpretations for “Variety”



Multiple
Modalities



Multiple
Sources

received extensive attentions in
the “small” data era

Two Interpretations for “Variety”

the heterogeneous data created
and consumed in various OSNs

(OSN: Online Social Network)



Multi-modal V.S. Multi-source

Multiple Modalities

Multiple Sources

Modality-oriented



Beyond-modality:
same-modal data in different OSNs will express very different characteristics.

Semantic-associated



Not necessarily semantic-associated:
the association patterns among different OSN data are more complex.

“Variety” in social multimedia big data:
Not “Multi-modal”, But “Multi-source”.

“Multisource”: Multi-OSN Comparison

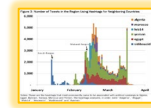
- Compare between multiple OSNs:
 - Characteristics of different online social networks (OSN).
 - degree distribution, clustering coefficient [Ahn et al. 2007],
 - degree centrality, shortest path [Magnani and Rossi, 2011];
 - User activity patterns in macro-level.
 - user tagging patterns [Guo et al. 2009];
 - user participation motivations [Choudhury and Sundaram, 2011].
 - Diffusion dynamics between OSNs.
 - cite and influence correlation [Leskovec et al. 2007];
 - diffusion and evolution patterns [Rodriguez et al. 2013];
 - jointly analyze network characteristics, user activity patterns, and diffusion dynamics [Kim et al. 2014]

Cross-OSN: Connecting Isolated Data

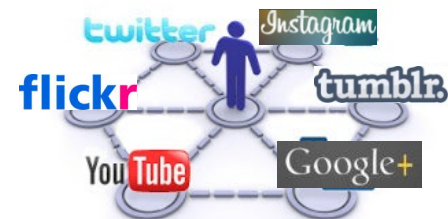
■ Exploring medium to connect isolated data :

- **Concept:** different perspectives for the same concept/event, e.g., the distribution and evolution of social events among Twitter, Facebook, etc.

Jasmine
Revolution



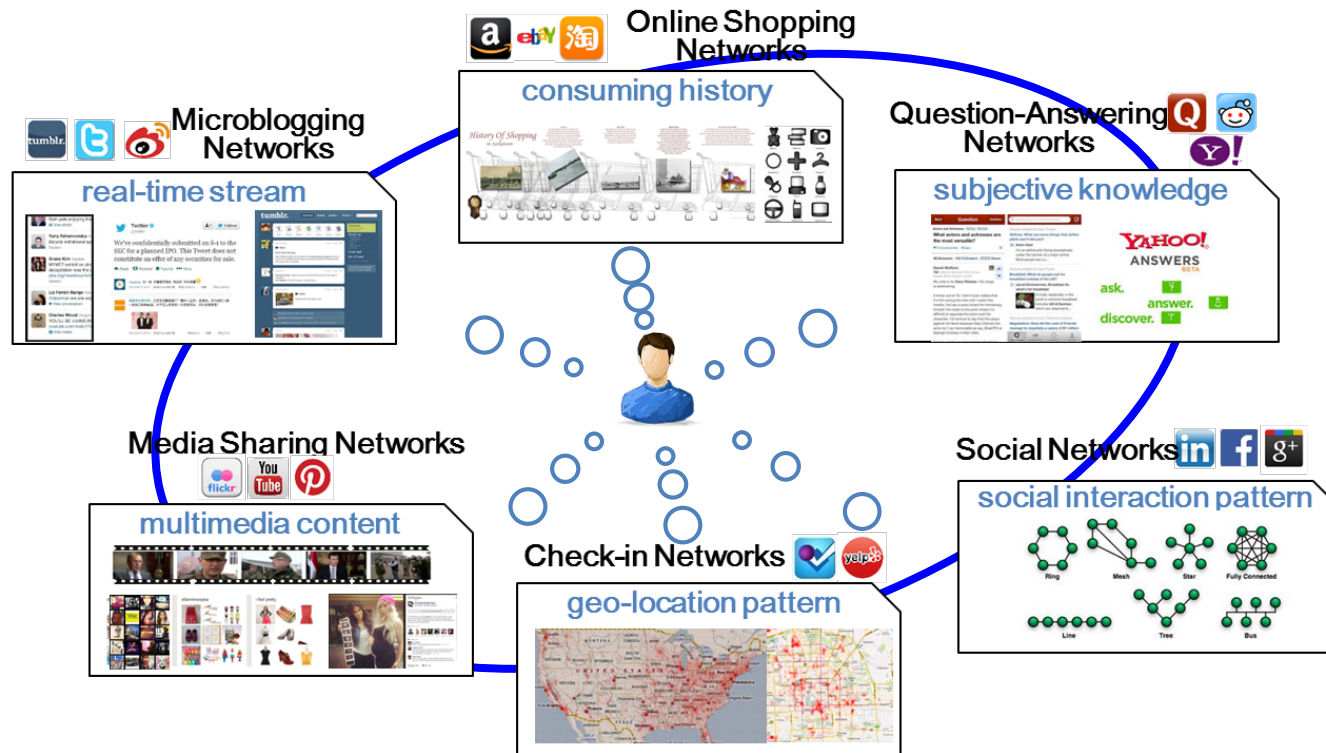
- **User:** different domains involved by the same individual, e.g., unique user registers and participates into several OSNs.



Consistent with the “**User-centric**” characteristic.

User-centric Solution

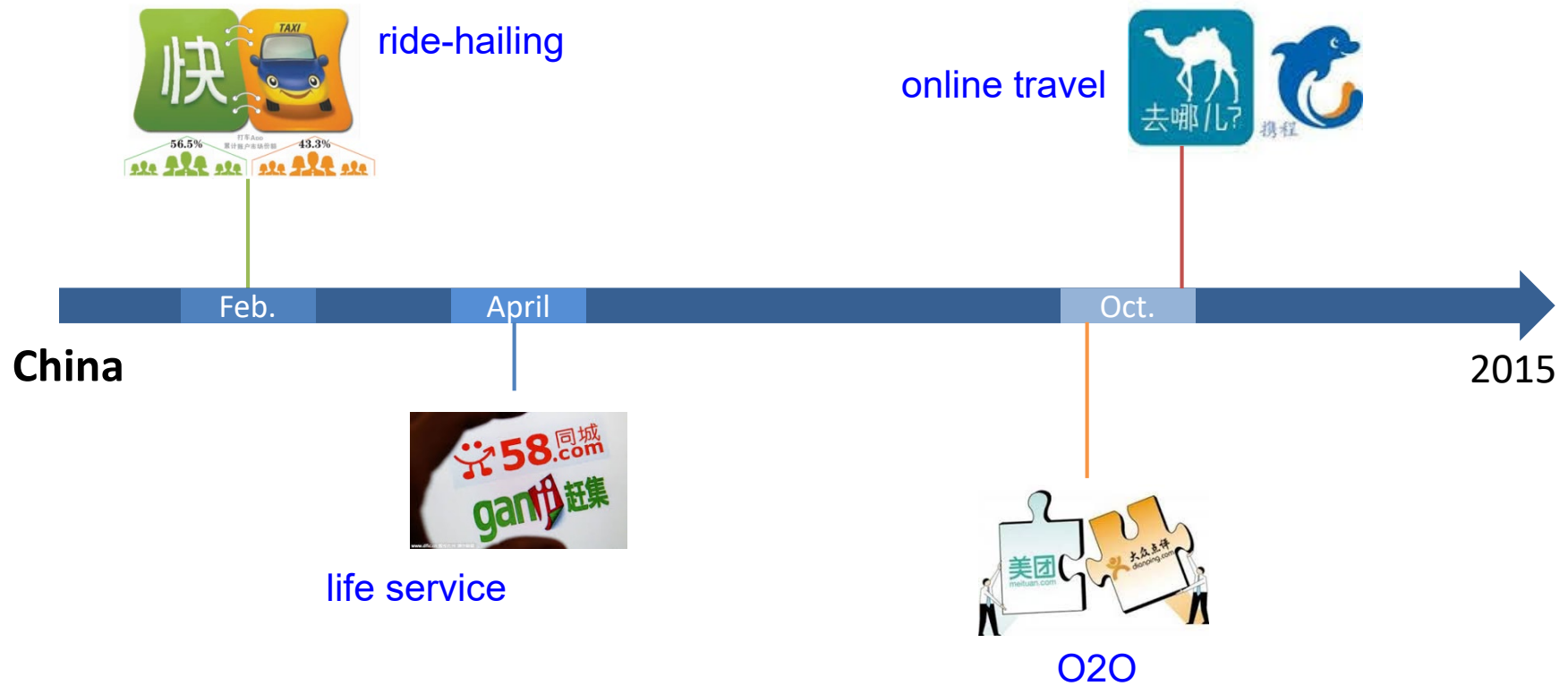
- Isolated heterogeneous data among different OSNs share the unique user space:



Global Web Index 2015 has reported that within the investigated 50 OSNs, each individual holds user accounts on an average of **5.54** OSNs, and actively participate in **2.82** OSNs. (overlapped users)

Cross-OSN is Happening Real World

- Horizontal cross-OSN cooperation: **maximize monopoly profits**



Cross-OSN is Happening Real World

- **Vertical** cross-OSN cooperation: **enhance upper & downstream**



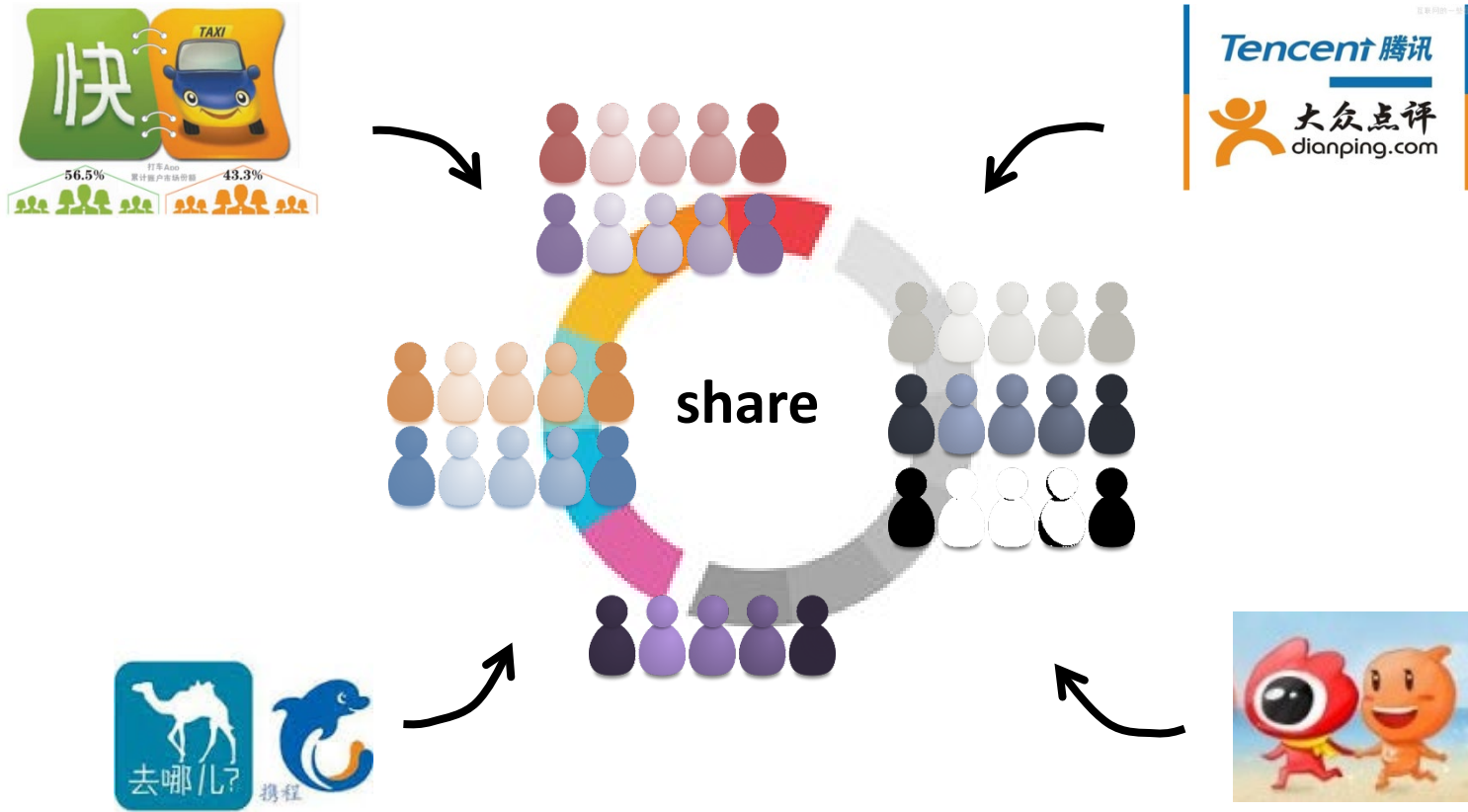
Cross-OSN is Happening Real World

➤ Vertical cross-OSN cooperation: enhance



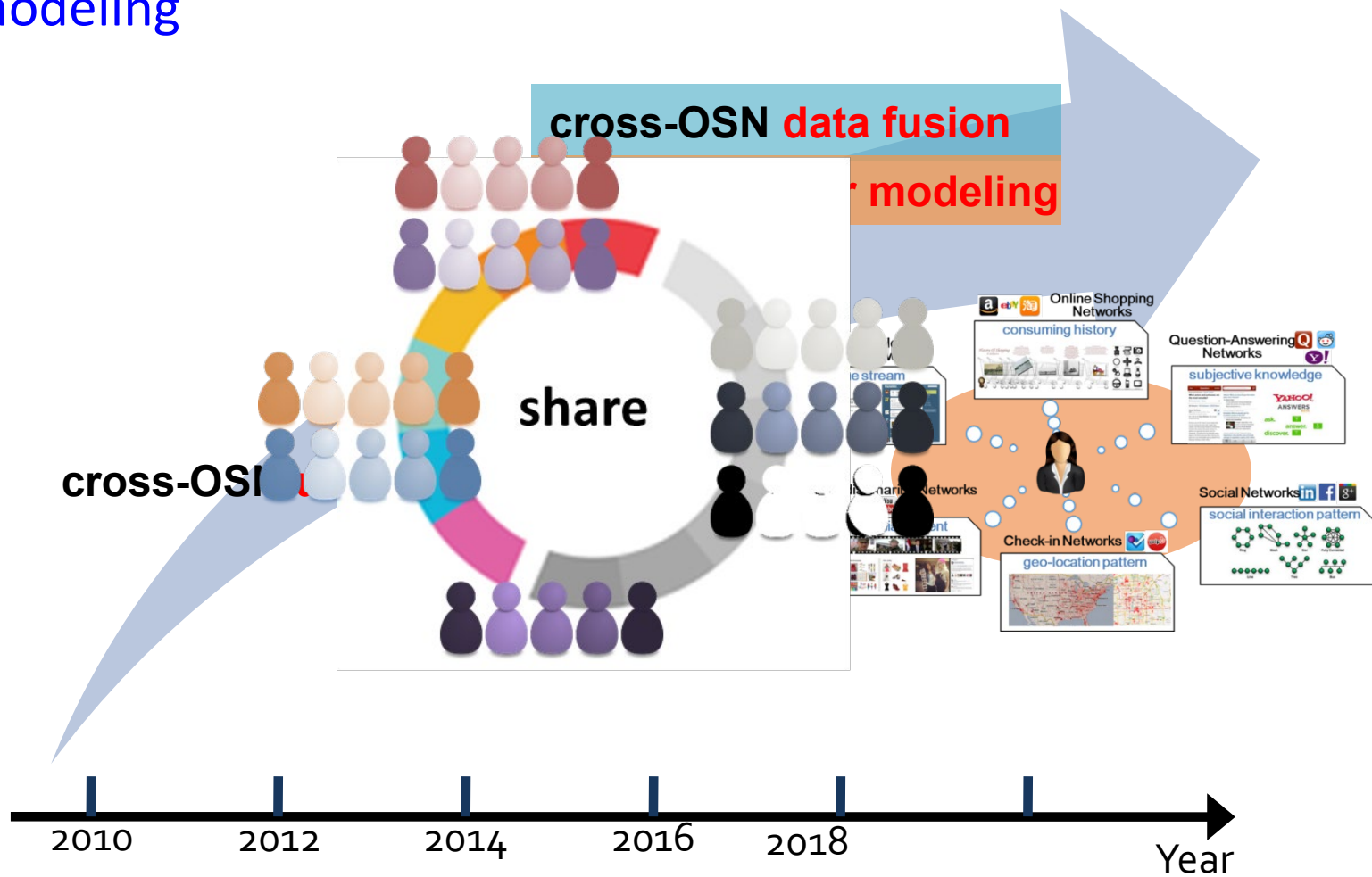
Cross-OSN Cooperation

- Current Cross-OSN “**shallow**” cooperation: **user sharing**



Cross-OSN Cooperation

- Upcoming cross-OSN “**deep**” cooperation: **data fusion & user modeling**



Cross-OSN in IT Giants



Isolated Data in IT Giants



The Next "Google"?

Portal

Search

Recomnd.

"All-web" Recommendation.

YAHOO!

Google



Data



User



③ “User-centric” Cross-OSN Computing

Fundamental Tasks

cross-OSN data fusion

To **understand the association among cross-OSN data** and explore the potentials of combining cross-OSN data in advanced social media applications

cross-OSN user modeling

To **combine the available user data on different OSNs** and construct an integrated online user profile for customized social media services

Challenges

cross-OSN data fusion

Cross-OSN knowledge gap:

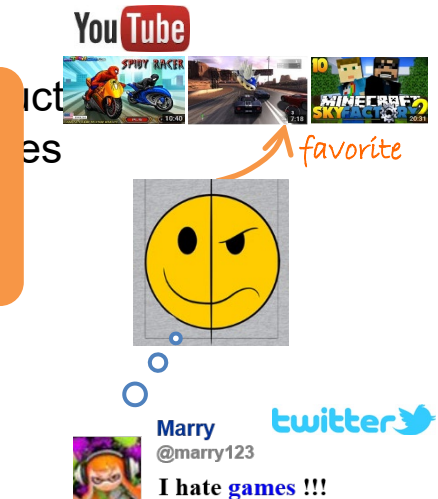
The heterogeneous data in different OSNs are distributed in different **domains**, **granularities** or **formats**, which are not readily to be directly fused.



cross-OSN user modeling

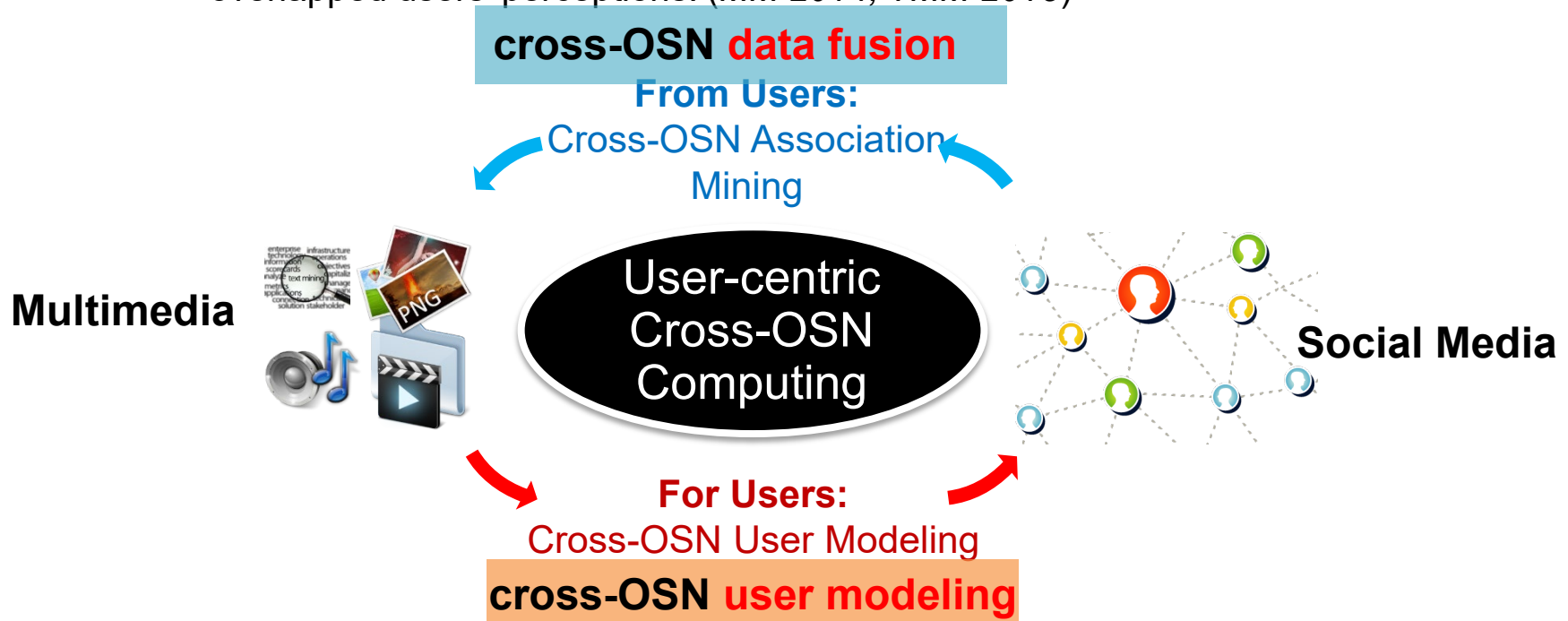
Cross-OSN intent gap:

The observed user activities in different OSNs may be **inconsistent** and even **contradict** with each other in representing their preferences.



User-centric Cross-OSN Research Paradigm

Mining the correlation between cross-OSN data based on overlapped users' perceptions. (*MM 2014; TMM 2015*)



Exploring cross-OSN characteristics and integrating distributed user data for comprehensive user understanding. (*ICME 2013; TOMM 2014, ICMR 2015, TMM 2015*)

Cross-OSN Overlapped User

- Identical user account among different social media services.



- Users are voluntary to disclose their accounts in multiple OSNs.

Google+

jitao sang

Worked at CASIA
Lived in Beijing

Links

Other profiles

twitter.com/chenev8023

cn.linkedin.com/pub/jitao-sang/32/637/399

about.me

jitao sang

Like + Email Me

twitter.com

facebook.com

plus.google.com

weibo.com

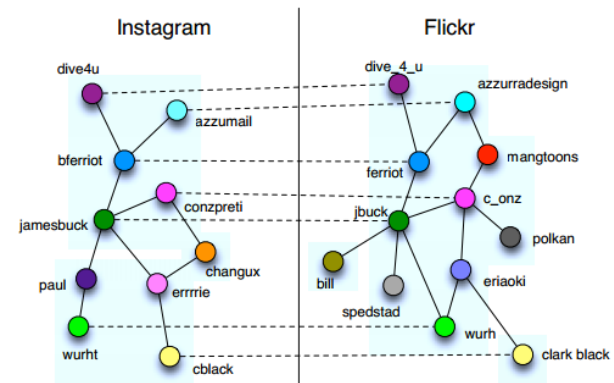
escience.cn

renren.com

cn.linkedin.com

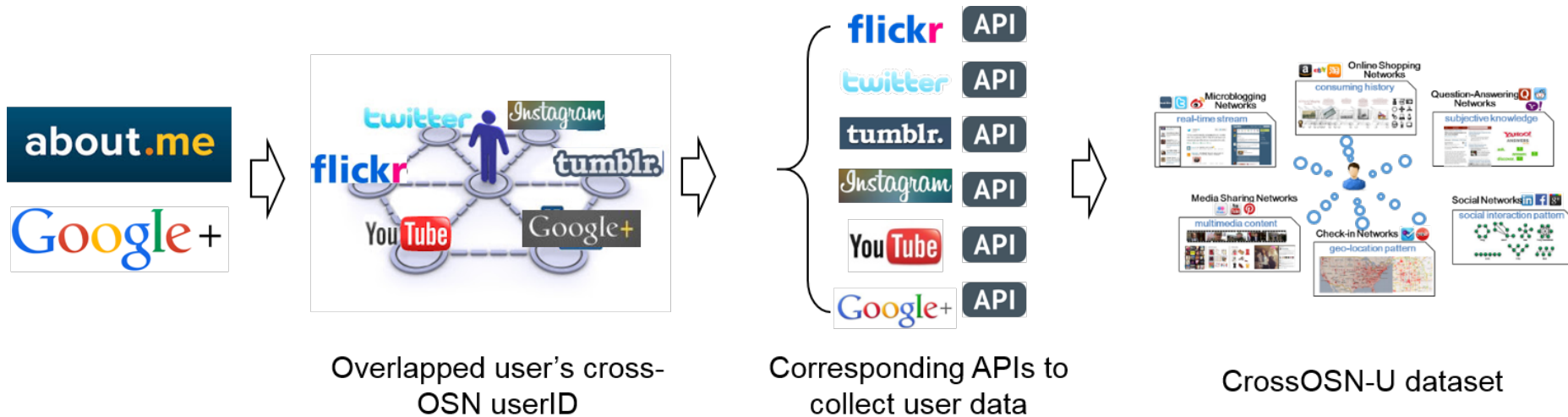
RG researchgate.net

- User account linkage mining is a separated research topic.



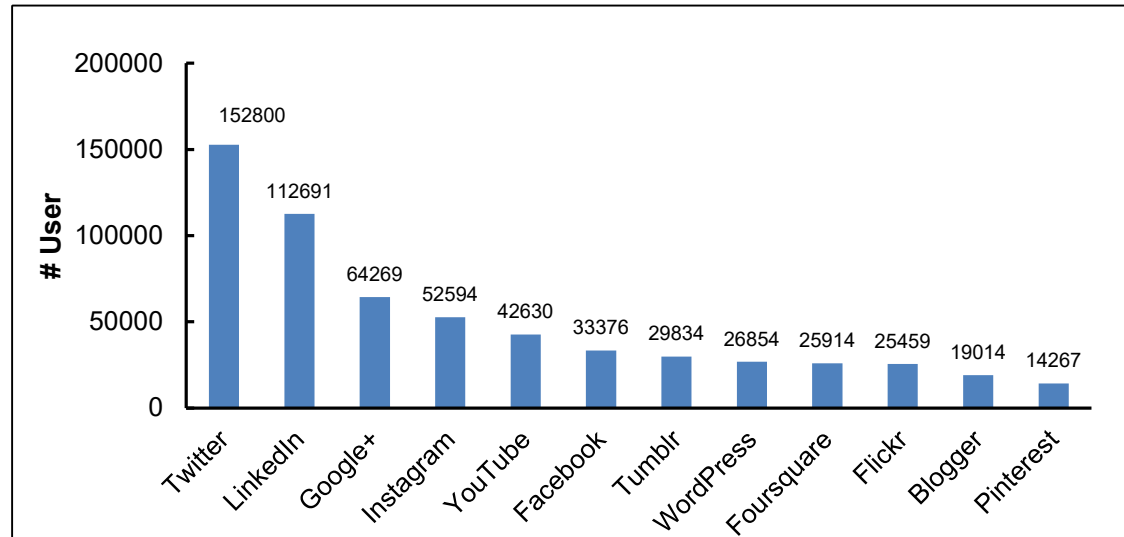
CrossOSN-U Dataset

CrossOSN-U: CASIA Cross-OSN dataset based on **overlapped Users**

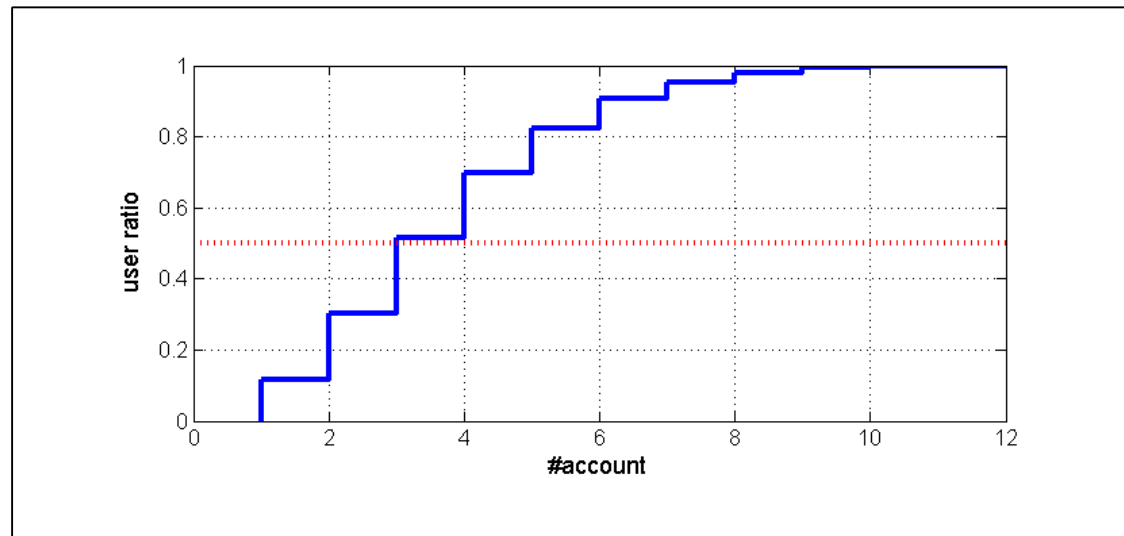


User-centric Cross-OSN Dataset

180,000 registered users in About.me.



Over 50% users share at least 4 accounts.



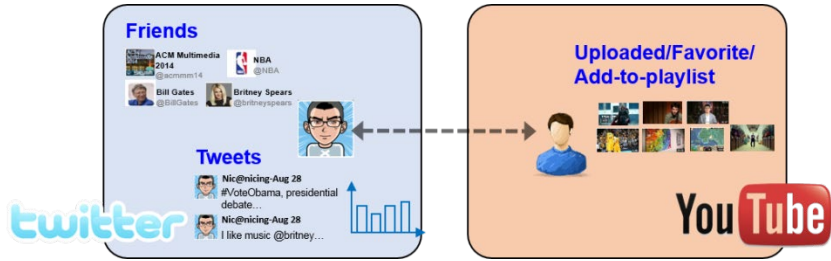
User-centric Cross-OSN Dataset

TABLE I
STATISTICS OF THE COLLECTED DATASET.

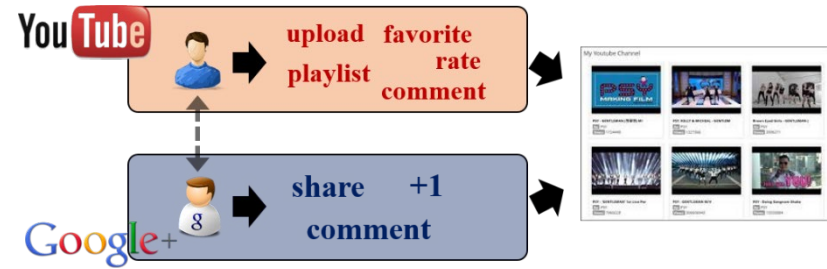
	Social Relation (M)	Social Activity (M)	
		created	consuming
Twitter	following:33.4; follower:25.1	tweet post: 70.8	retweet: 129.0
Google+	–	article post: 0.8; photo/album post: 2.5; video post: 0.1	article reshare: 1.9; photo/album reshare: 3.7; video reshare: 1.3
Instagram	following:6.3; follower:6.5	photo upload: 5.3	like: 13.8; comment: 3.2
Tumblr	–	(post) text: 4.5; photo: 3.9; audio: 0.3; video: 0.8	link: 1.8; quote: 1.1; reblog: 2.8
Flickr	contact: 0.8; groups: 0.6	upload photo: 7.3	favorite photo: 0.5
YouTube	–	upload video: 0.4; comment: 0.7	favorite: 0.3; play list: 17.1
sum	82.7	97.4	176.5



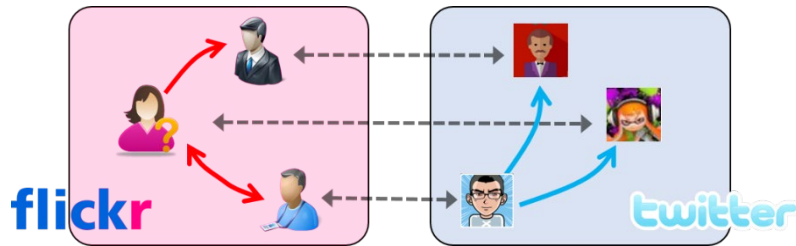
CrossOSN-U Dataset



CrossOSN-U: Hetero



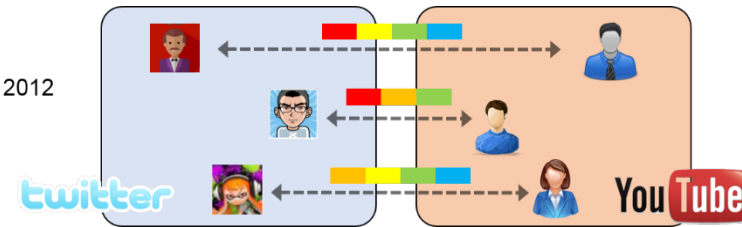
CrossOSN-U: Homo



CrossOSN-U: SN

Event List

- T1: US presidential election 2012
- ...
- T13: Iphone5 release
- ...

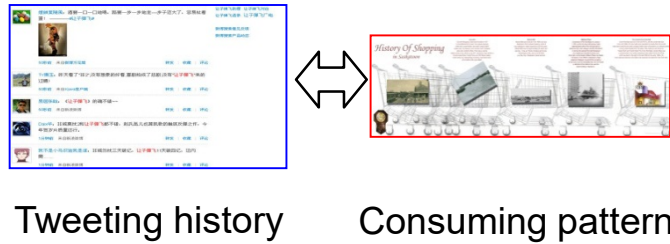


CrossOSN-U: Event

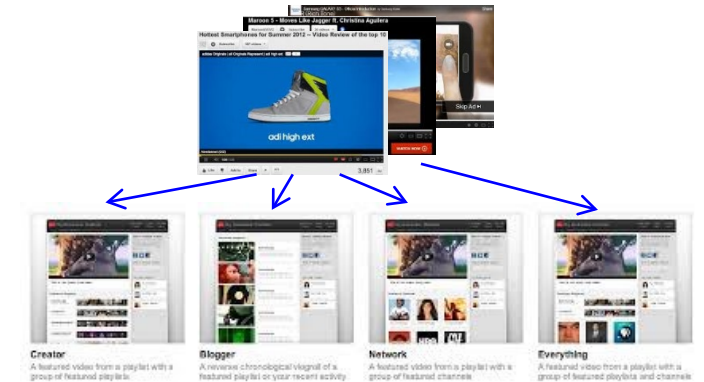
③-1 Cross-OSN Association Mining

Cross-OSN Association Pattern & Application

Association Pattern



Application



Crowdsourcing-based Knowledge Discovery



ESP: Collaboratively Image Labeling game



Player 1



guess: BOAT

guess: WATER

guess: RIVER

Score! Agreement on 'BOAT'.



Player 2

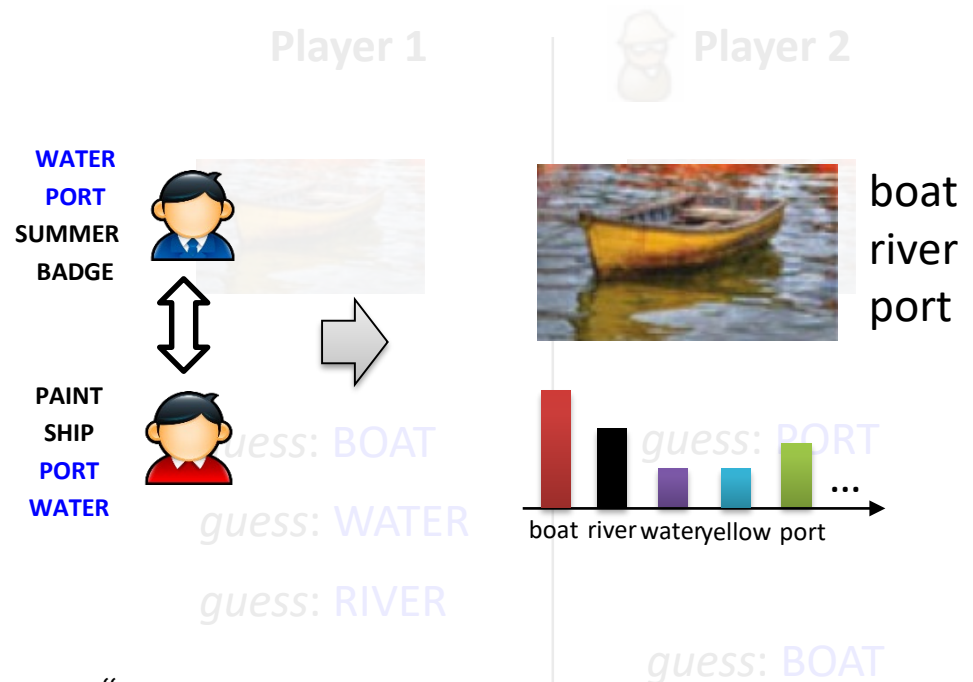
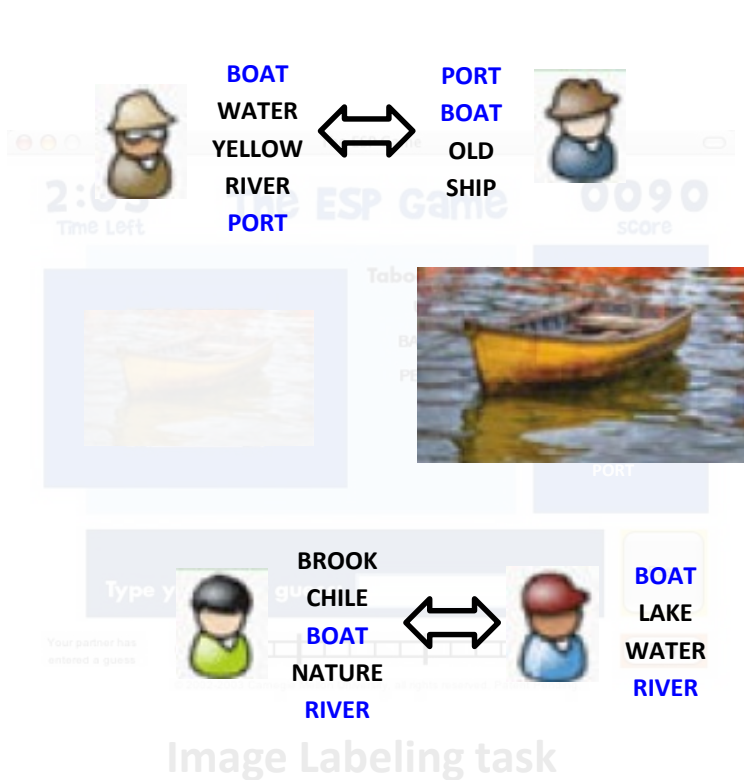


guess: PORT

guess: BOAT

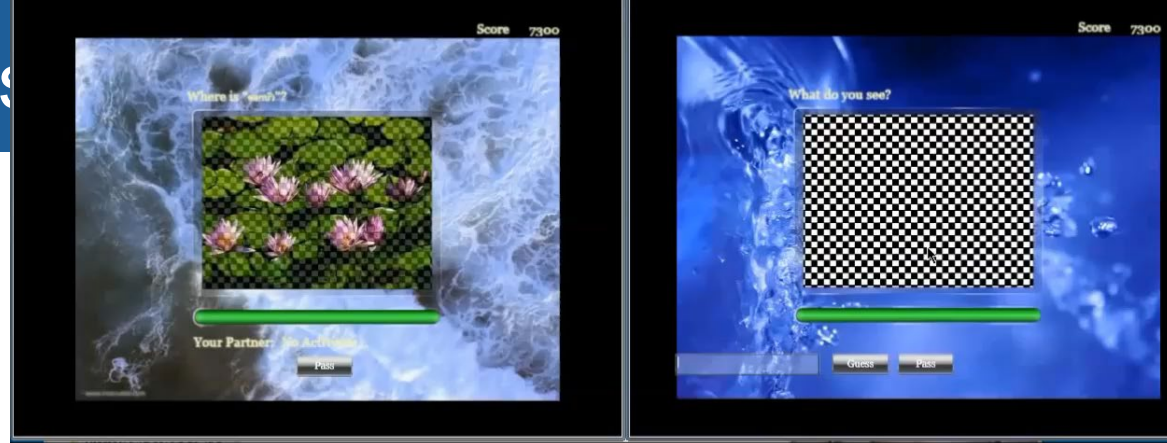
Score! Agreement on 'BOAT'.

Crowdsourcing-based Knowledge Discovery



“The string on which the two players agree is typically *a good label* for the image. Experimental evaluation indicates that a majority (85%) of the words would be useful for describing.” [Von Ahn and Dabbish 2004]

Crowdsourcing-based



PEEK : GUESS WHAT YOUR PARTNER IS REVEALING



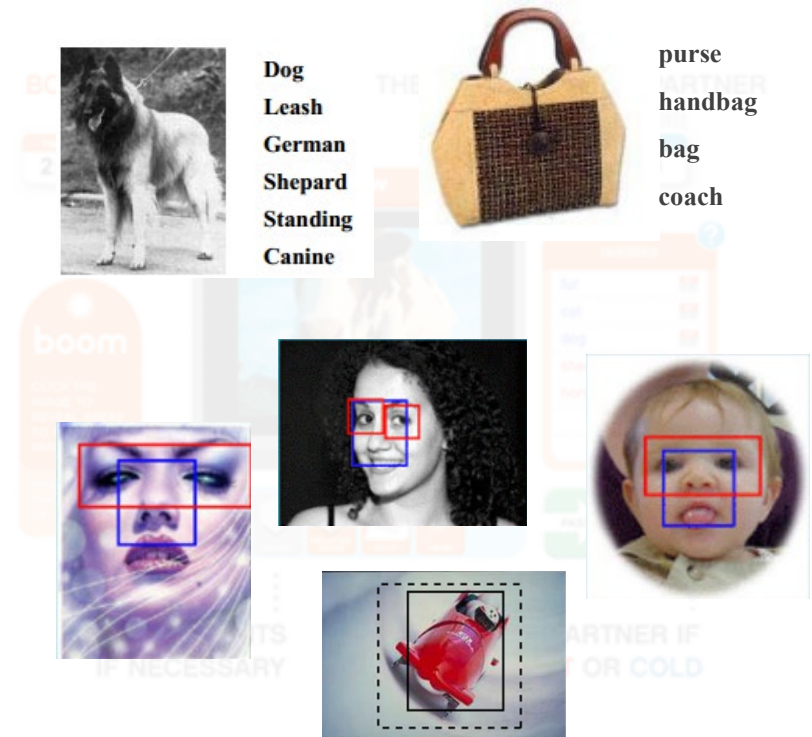
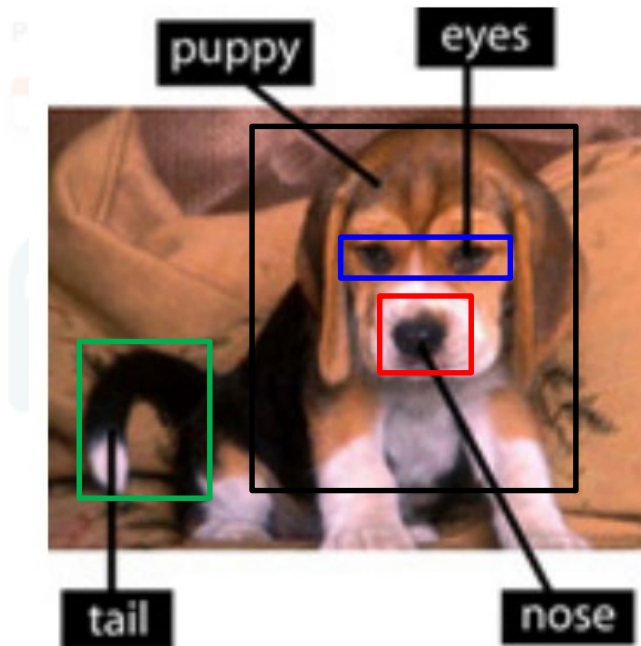
BOOM : REVEAL PARTS OF THE IMAGE TO YOUR PARTNER



Peekaboom: Boom gets an image along with a word related to it, and must reveal parts of the image for Peek to guess the correct word. Peek can enter multiple guesses that Boom can see.

Image Segmentation game

Crowdsourcing-based Knowledge Discovery



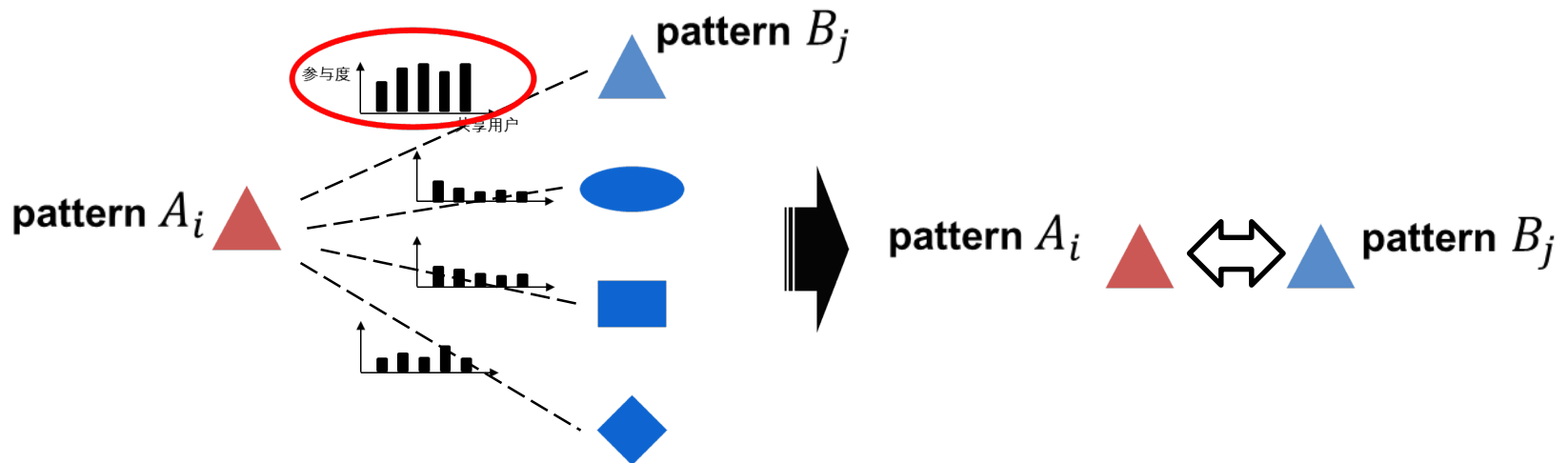
Peekaboom: Boom gets an image along with a word related to it, and must reveal parts of the image for Peek to guess the correct word. Peek can earn points for correct guesses. Image labels and object regions as by-product of collaboratively playing games.

Knowledge discovered:

association between **visual appearance** and **semantic concepts**.

Crowdsourcing Solution

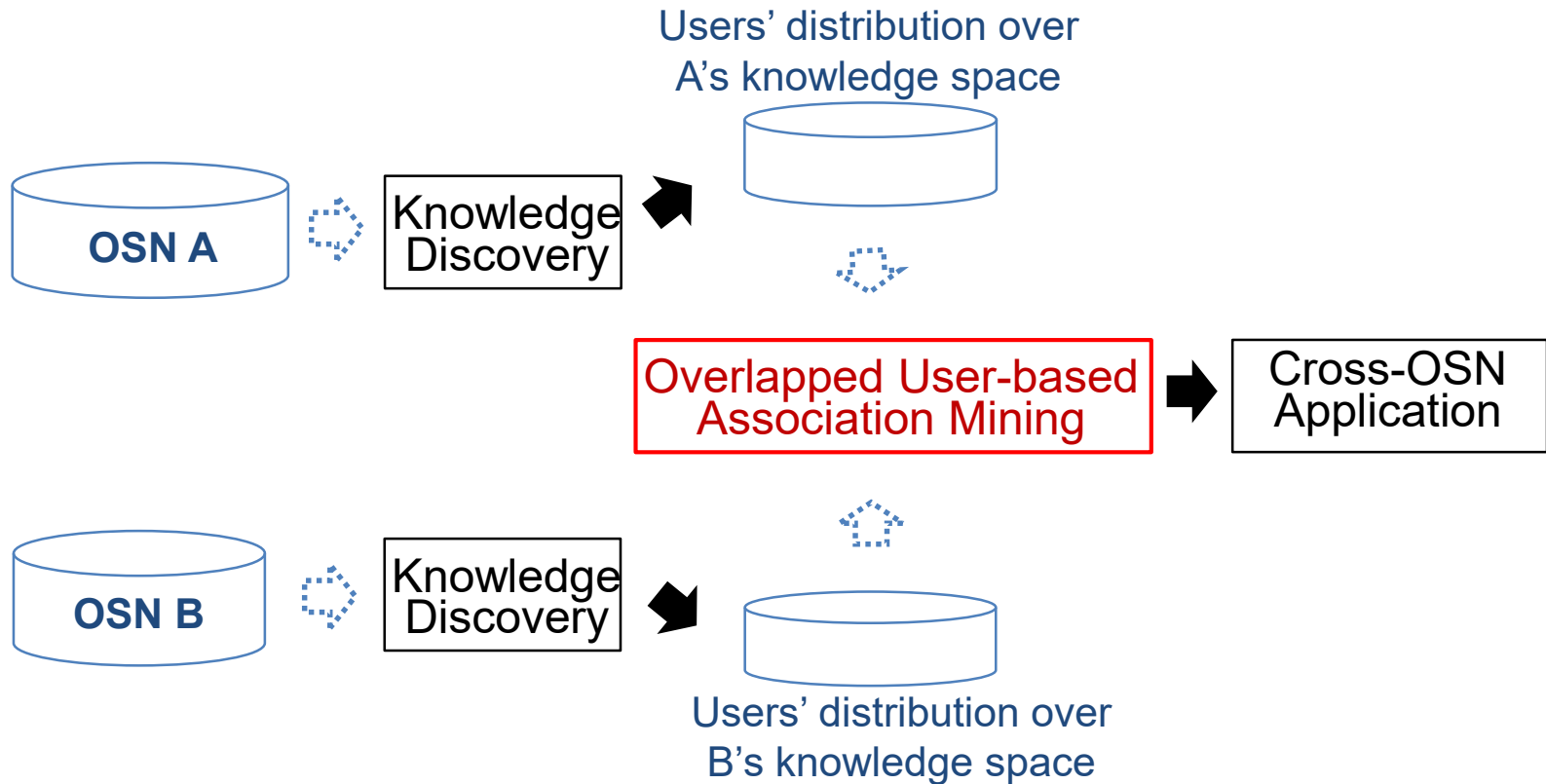
- **Assumption:** If abundant users heavily involve with pattern A_i in social media network A and pattern B_j in network B , it is very likely that pattern A_i and pattern B_j are closely associated.



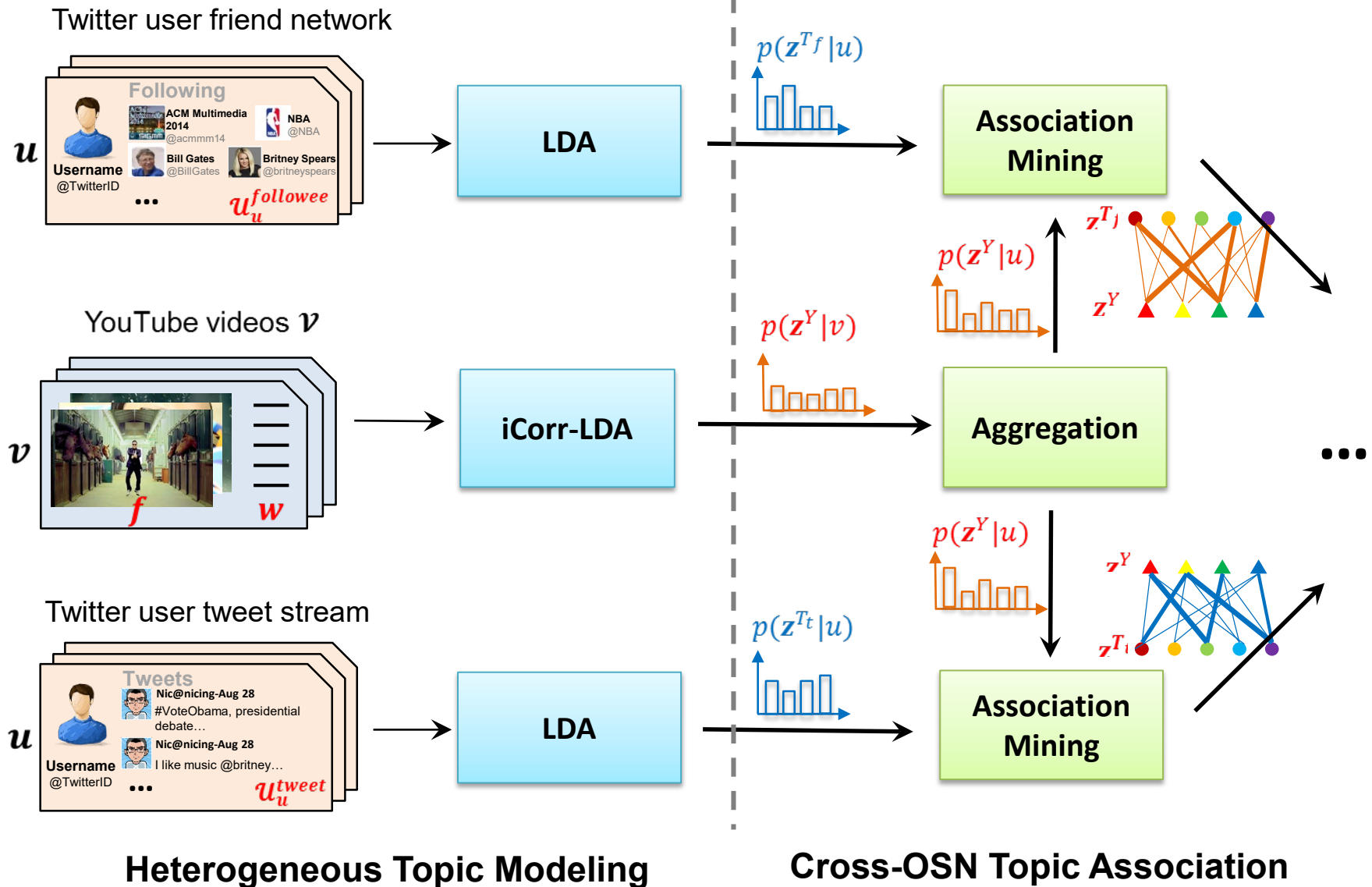
- We refer to this associated pattern pairs as “**crowd-perceptive correlated**”.



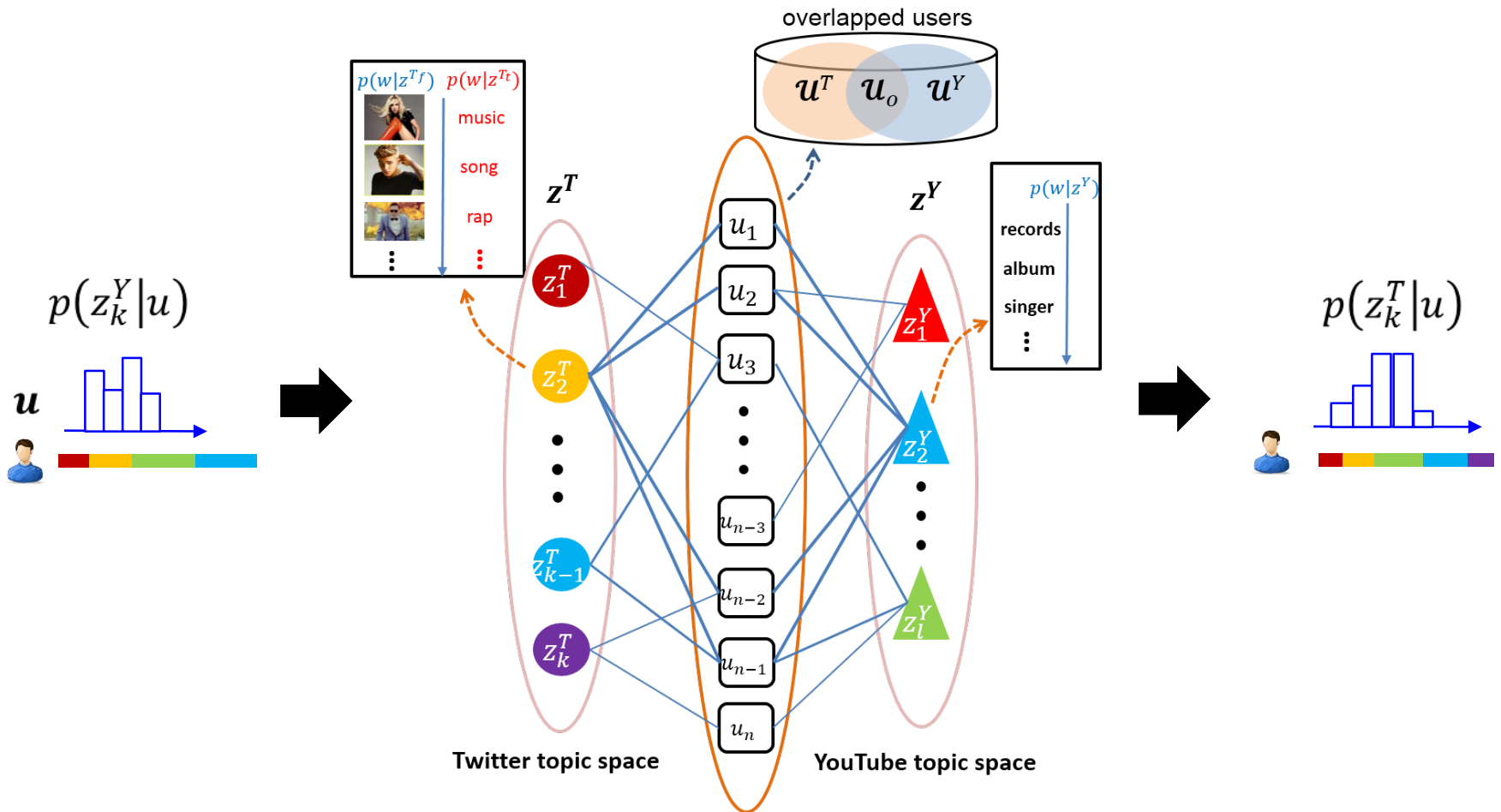
Framework



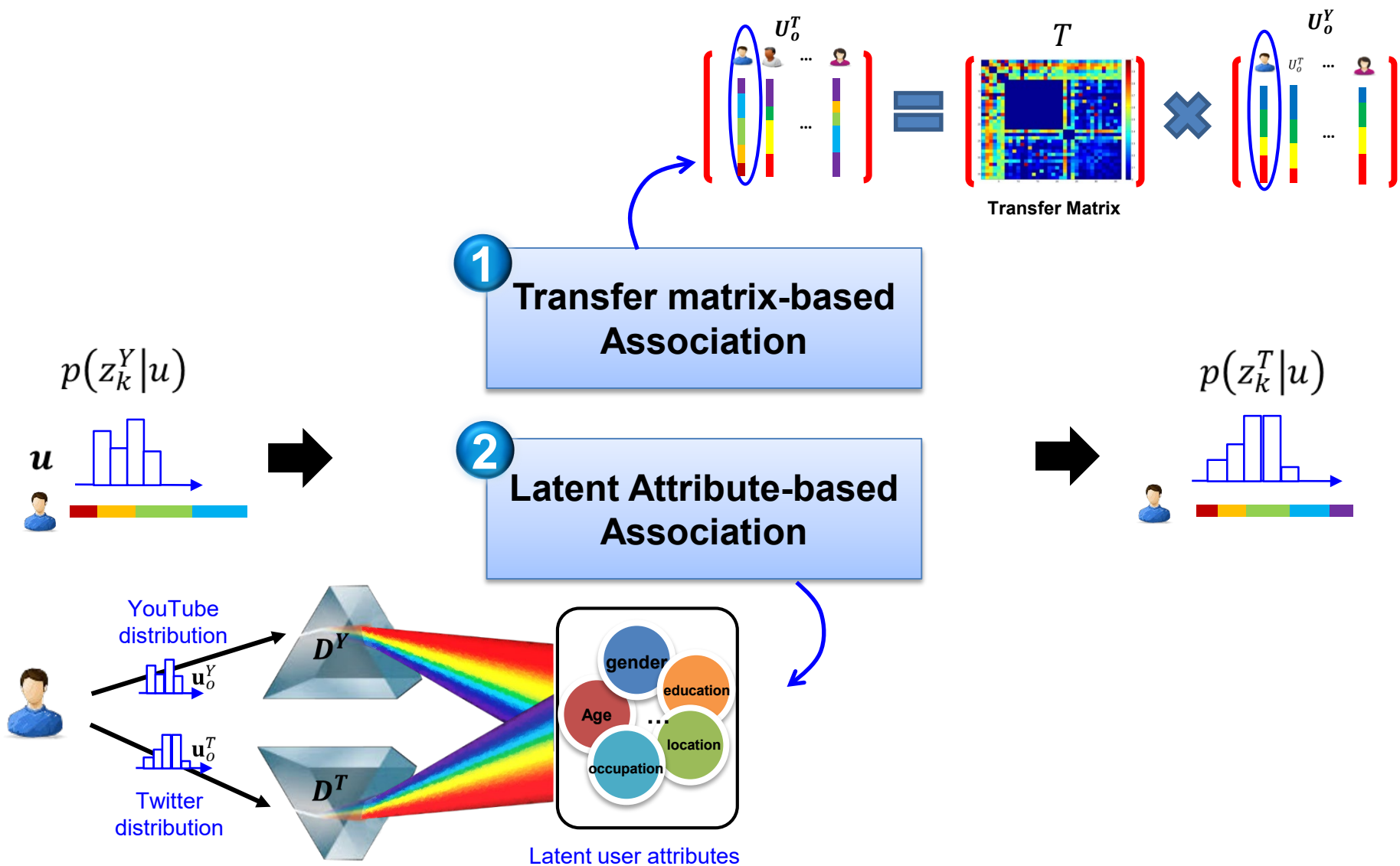
Framework



Cross-OSN Association Mining



Cross-OSN Association Mining



Association between Twitter Following & YouTube

game video

TABLE IV
VISUALIZATION OF DISCOVERED YouTube TOPICS.

game-related

Visualization of discovered Twitter topics

Topic	User	Location	#follower	Self description
#43	Markus Persson	Stockholm, Sweden	1,436,534	Hey, you! Play more games! Now!
	Steam		932,044	Steam. The Ultimate Online Game Platform.
	Humble Bundle	San Francisco, CA	192,764	News from the Humble Bundle
#38	Sascha Lobo	Berlin, Germany	161,099	Author, Internet.
	netzpolitik	Berlin, Germany	120,014	Entrepreneur, activist, organizer of @republica.
	Mario Sixtus	Berlin, Germany	60,542	Journalist, Photographer. Hier mehr oder weniger

semantic correlated



geographical correlated



Berlin popular users

Topic	Word	Video
Topic #1	gameplay xbox playstation gaming minecraft	<p>"Epic Mods - MW2 MOD IN CoD4"</p> <p>"HEXXIT COOP ep7 w/ Double"</p> <p>"Halo 4 Adrift Multiplayer Map"</p>
	history german berlin germany poetry	<p>"GEH STERBEN, DU OPFER!!!"</p> <p>"Syrien - Wahrheit ber das Massaker"</p> <p>"Volker Pispers - Einzeltater"</p>

German TV show

Association between Twitter Following & YouTube

famous actor


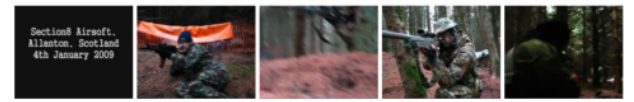




Table 4: Visualization of discovered Twitter followee topics.

Topic	Username	Location	Self-description
#57	Conan O'Brien	Los Angeles	The voice of the people. Sorry, people.
	Louis C.K.	New York City	I am a comedian and a person and a guy who is sitting here.
	Neil Patrick Harris	Hollywood	I act some. Dig variety acts, Pixar, puppets, theme parks and great meals.
	Steve Martin	-	From Jerk to proud Oscar winner! Oh, and a new CD with Edie Brickell is out now.
#58	Kevin Rudd	Australia	Former Prime Minister of Australia. Proud father of 3 great kids.
	Julia Gillard	Canberra, Australia	Official Twitter account of the 27th Prime Minister of Australia.
	ABC News	Australia	Latest news updates from the Australian Broadcasting Corp.
	Malcolm Turnbull	Sydney, Australia	Federal Member for Wentworth, Minister for Communications. Australian Parliament.

Australian official account

war & political

Table 3: Visualization of discovered YouTube topics.

Topic	Word	Video
#4	war gun syria iraq nuclear	<p>“Why US has no moral authority on Syrian chemical weapons?”</p> 
	Airsoft War L96 SNIPER Action M4 P90.	
	Assad Running Out of Time in Syria.	
#35	cat dog cute parody pet	<p>“CATS SCREAM YAWNS”</p> 
	Curious Rhodesian Ridgeback Dog Grumpy n Barking At Noises	
	Cat Bath Freak Out - says 'NO!' to bath	

cute animal

③-2 Cross-OSN User Modeling

How Cross-OSN User Modeling Works

new user
newly register with
empty history



view count

Cold-start & Sparsity: inadequate
user data in single-OSN.

Engine

light user

limited behavior
records



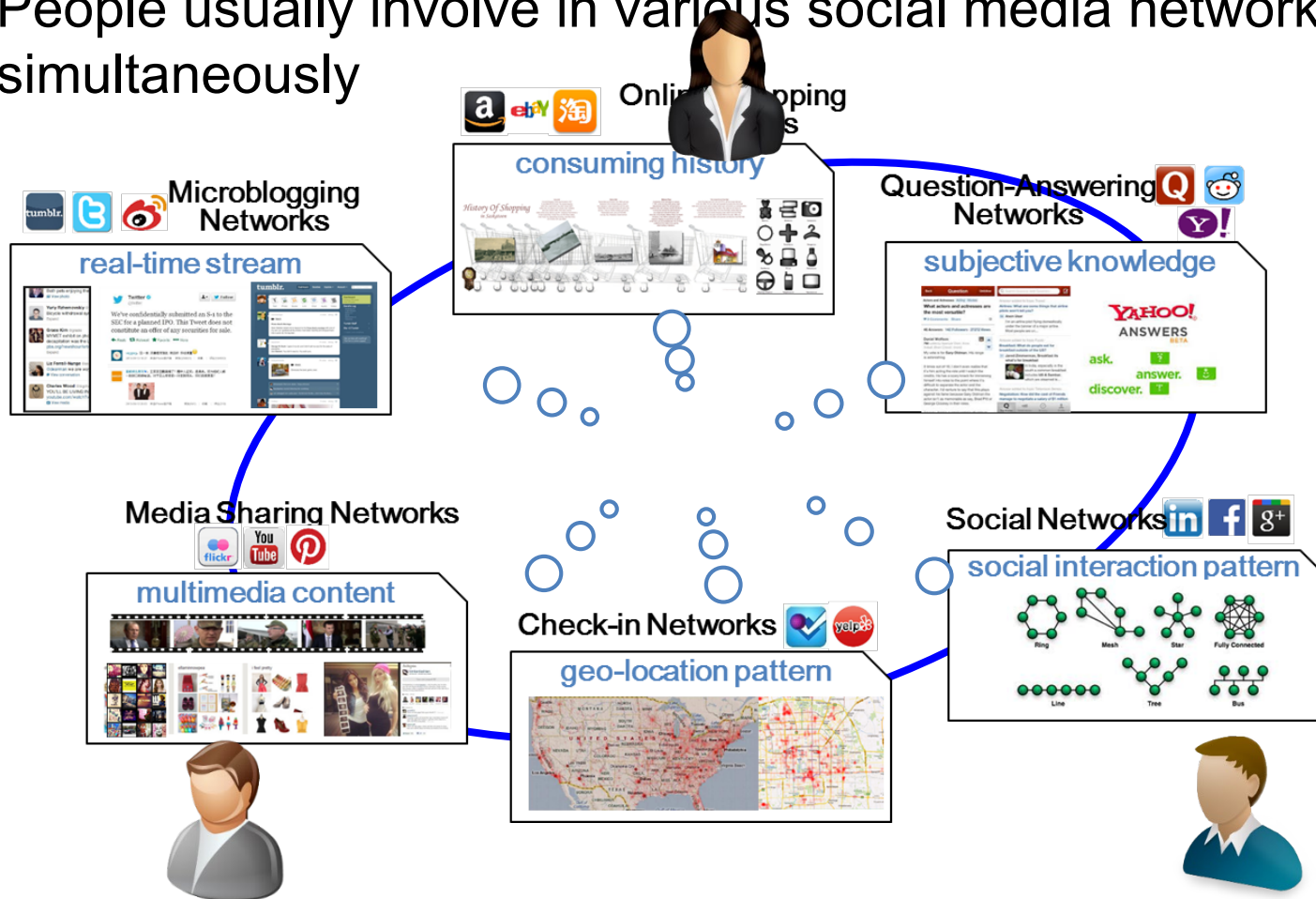
heavy user

frequent interaction



How Cross-OSN User Modeling Works

- People usually involve in various social media networks simultaneously



Toy Examples

YouTube

new user



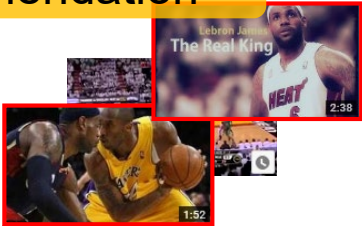
initial recommendation
more fine-grained
recommendation



light user



basketball



Recommender Engine



Marry @marry123 tweets
Anybody knows how **iphone 6 plus** functions? RT if you are a iOS fan.
Marry @marry123
I love new technology.



new technology lover



James fan



Mike @ michael tweets
Cheer up! @KingJames!
Mike @ michael
Overtime. LeBron has 42 points.



follow



Toy Examples

YouTube

heavy user

game				sport	
3	2	0	0	1	2



diverse & novel recommendation

Recommender Engine



follow



politics

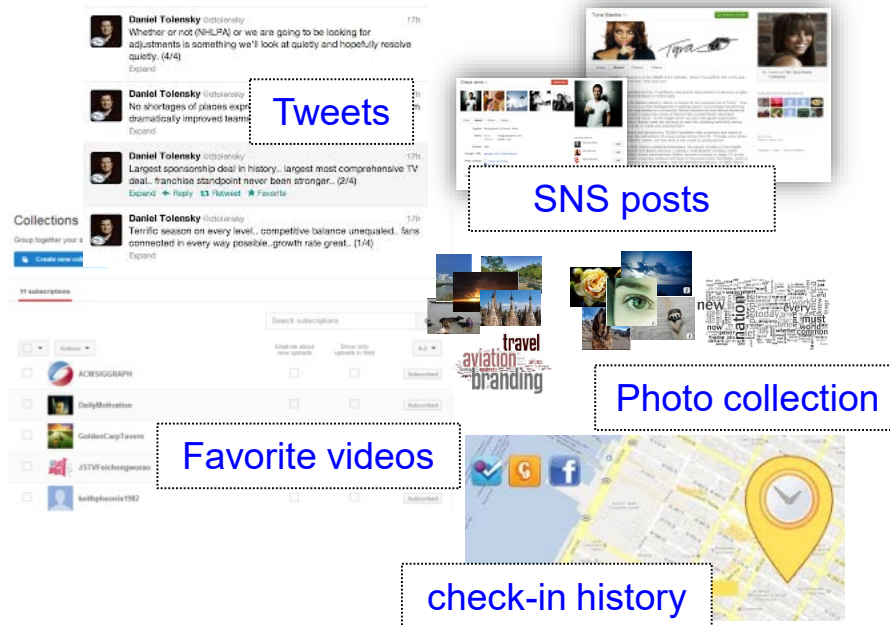


follow

Cross-OSN User Modeling:
exploit the user data on multiple OSNs for better user understanding and improved customized services.

Data-driven User Modeling

Social Multimedia Activities



Knowledge

Trending Topics

Interest Ontology

Association patterns

Occupation Distribution



User Models



Real-time Video Recommendation

Application:
Real-time Personalized video search
/recommendation



Key problem:
Dynamic Interest Modeling

Challenge:
Sparse user data in single
OSN, difficult to capture
the interest drifting

Long-term
interest

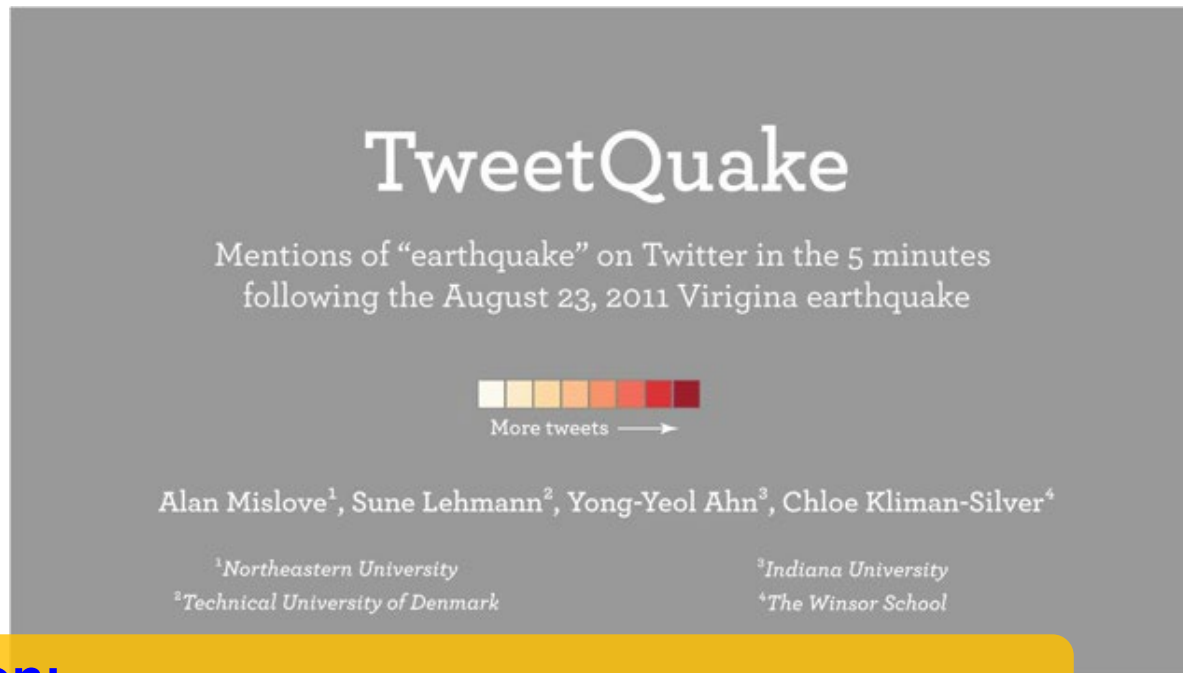
Stable and on general
topics, e.g., sports,
politics

Short-term
interest

Evolve with time, vulnerable
to transient events, e.g.,
focuses on FIFA World Cup
around July, 2014

Twitter is “Faster”

- Twitter has been recognized as an efficient platform for information sharing and spread.

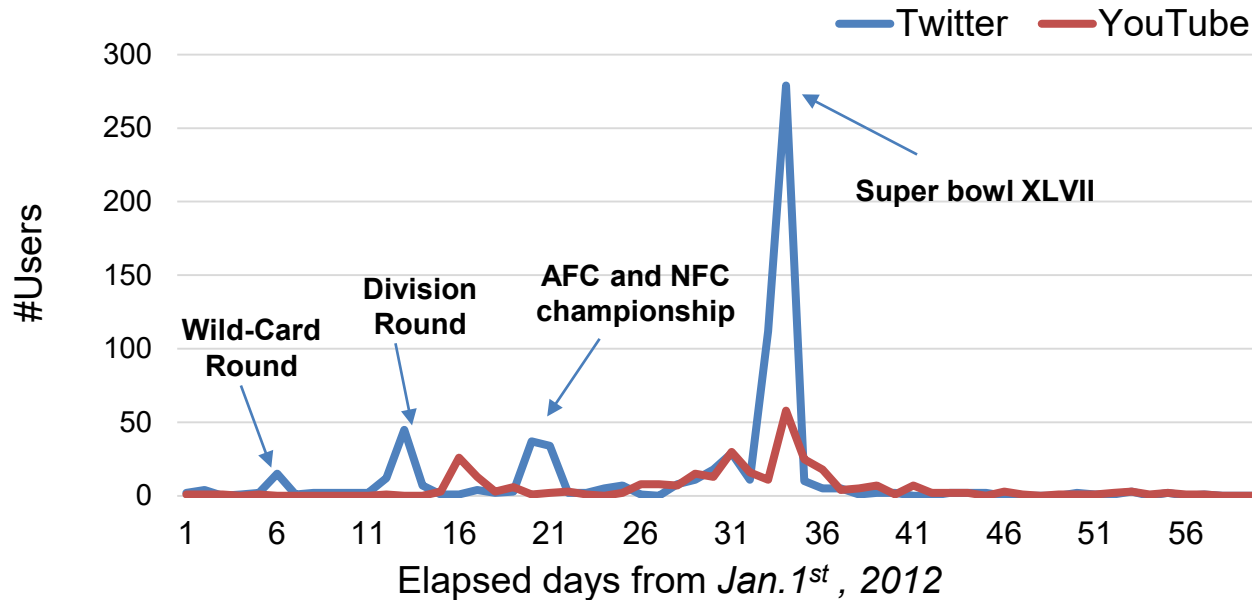


Motivation:

Can we leverage users' observed activities on Twitter to predict their interest drifting?

Cross-OSN Temporal User Behavior Analysis

- Twitter responses faster than YouTube in **macro** level



Cross-OSN Temporal User Behavior Analysis

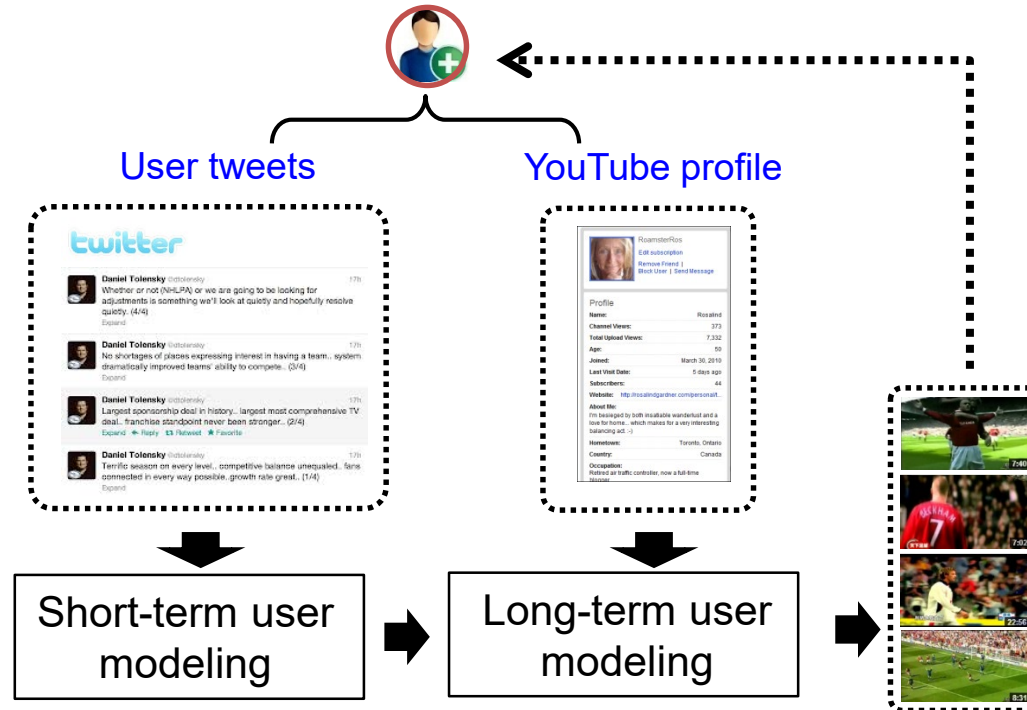
- Twitter responses faster than YouTube in **micro** level

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
#Twitter earlier votes	352	414	58	80	50	181	135	141	140	40
#YouTube earlier votes	169	188	24	35	28	169	84	80	52	22
The ratio	2.08	2.20	2.42	2.29	1.79	1.07	1.61	1.76	2.69	1.82
	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20
#Twitter earlier votes	480	155	177	48	107	45	181	61	48	42
#YouTube earlier votes	249	34	69	15	70	30	88	56	34	43
The ratio	1.93	4.56	2.57	3.2	1.53	1.5	2.06	1.09	1.41	0.98

Table 3. The number of user votes for “Twitter is earlier” and “YouTube is earlier” and their ratio on the topics in our trending topic list

Cross-OSN Recommendation Solution

- ❑ **Data analysis conclusion:** for specific user, his/her short-term interest change emerges first on Twitter
- ❑ **Basic idea:** exploit the Twitter behavior towards short-term interest modeling



Unified Recommendation

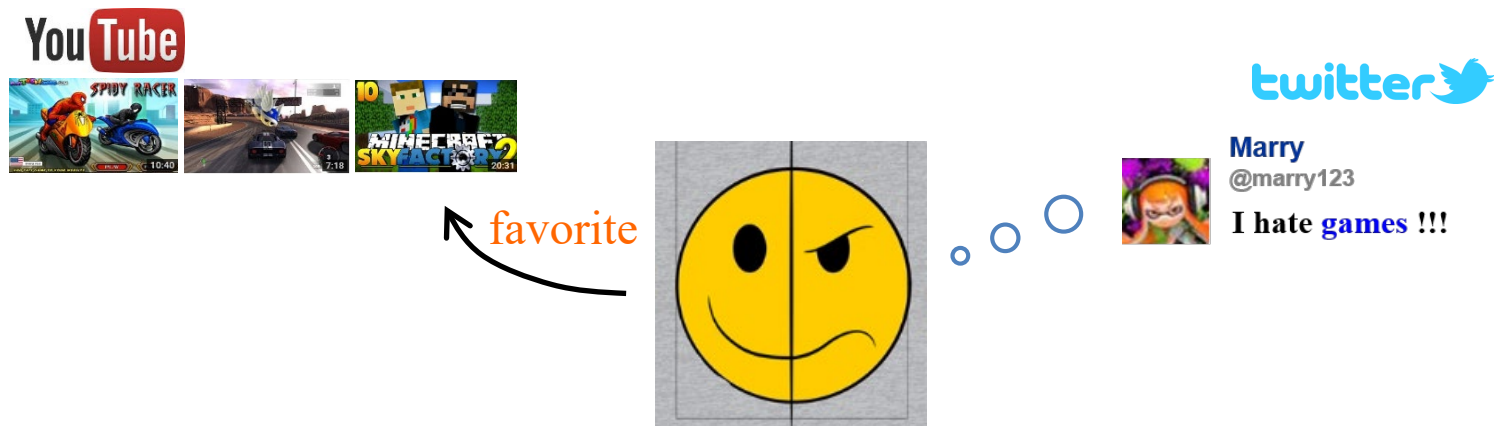


Cross-OSN Challenges

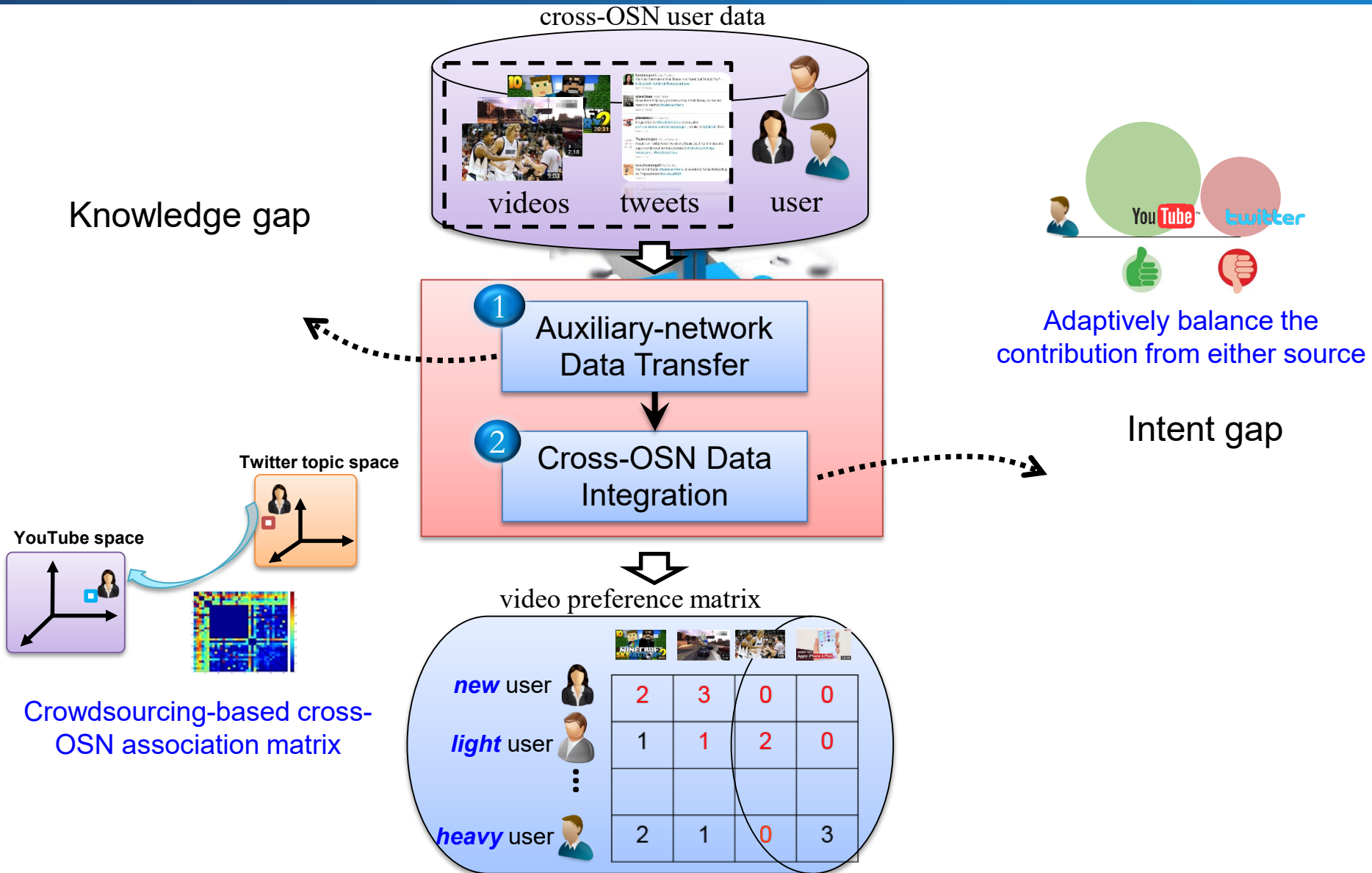
➤ Cross-OSN knowledge gap



➤ Cross-OSN intent gap



Unified Solution



Accuracy Performance Evaluation

➤ Baselines

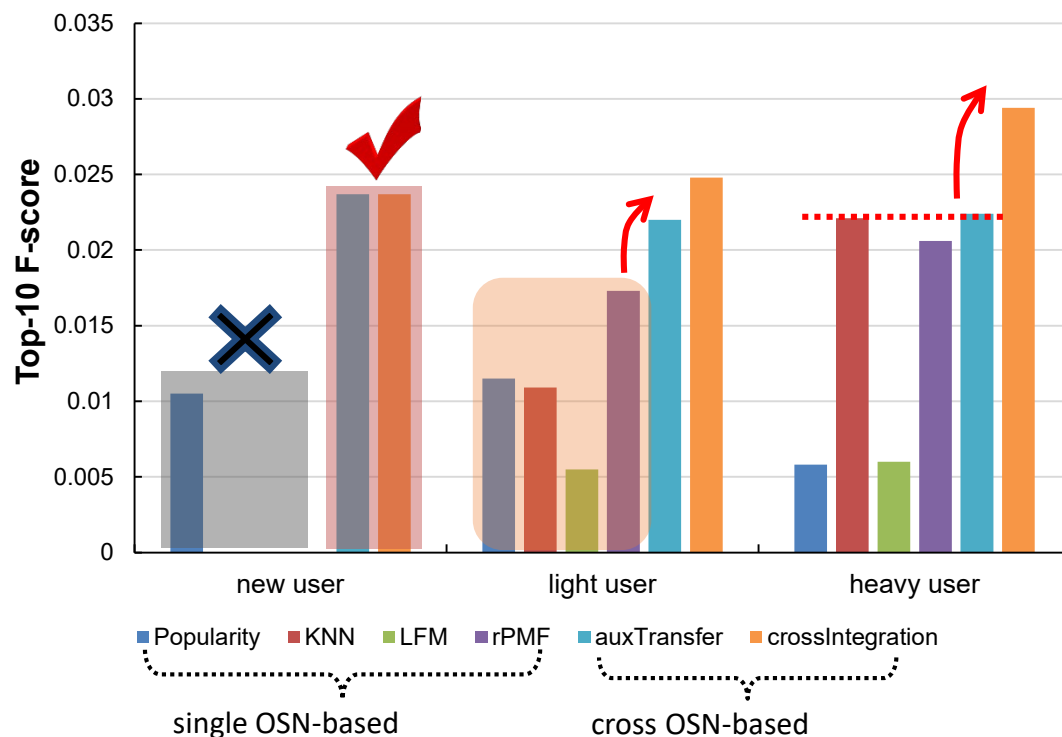
- *Popularity*: recommend according to the video view count
- *KNN*: Item-based KNN
- *LFM*: Latent Factor Model
- *rPMF*: Probabilistic MF method with video content Laplacian regularization

➤ Proposed approach

- *auxTransfer*: only considers stage 1
- *crossIntegration*: combines both stage 1 and stage 2

➤ Evaluation metrics

- Top-k precision, recall and F-score

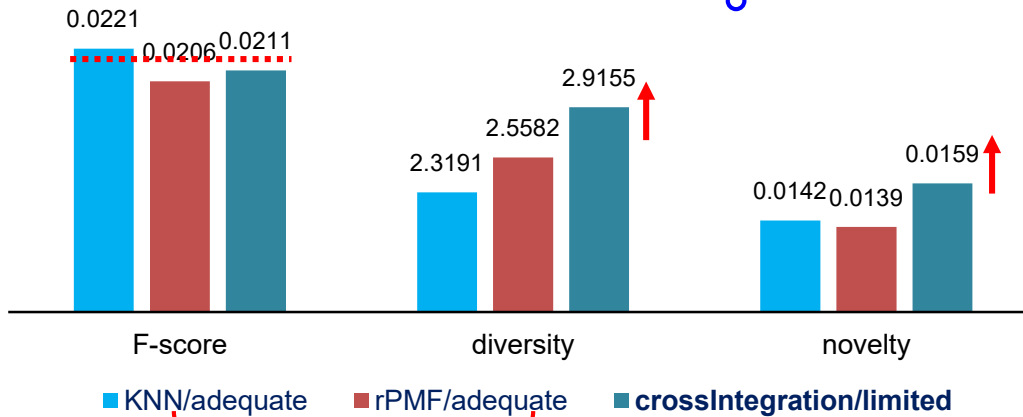


Advantage beyond Accuracy

- Limited *cross-OSN* data *V.S.* adequate *single-OSN* data

Recommender systems must provide not just accuracy, but also *usefulness*.

--JONATHAN L. HERLOCKER



$$diversity(u) = \left(\frac{\sum_{v_i \in \mathbf{V}_u^{rec}} \sum_{v_j \in \mathbf{V}_u^{rec}, v_i \neq v_j} sim(v_i, v_j)}{N_u^{pair}} \right)^{-1}$$

intra-list similarity by video content

$$novelty = \frac{\sum_{u \in \mathcal{U}^{test}} \log\left(\frac{|\mathcal{V}_u^{test}|}{|\mathcal{V}_u|}\right) \cdot novelty(u)}{\sum_{u \in \mathcal{U}^{test}} \log\left(\frac{|\mathcal{V}_u^{test}|}{|\mathcal{V}_u|}\right) \cdot \max(novelty(u))}$$

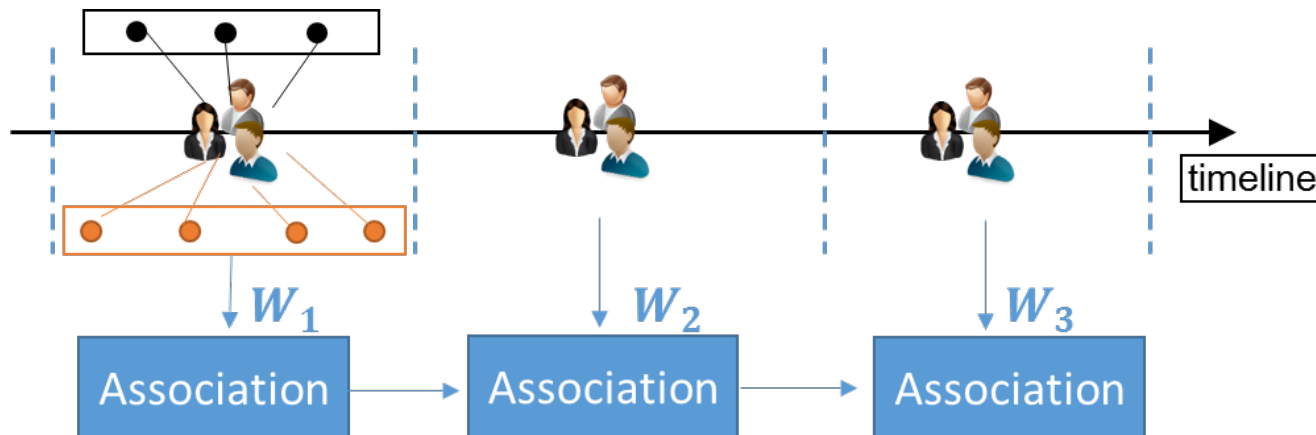
taking both the video popularity and user behavior sparsity into consideration

Exploiting cross-OSN user data contributes to understanding users' distributed interests towards serendipity recommendation.

Call for Action

Cross-OSN Association Mining

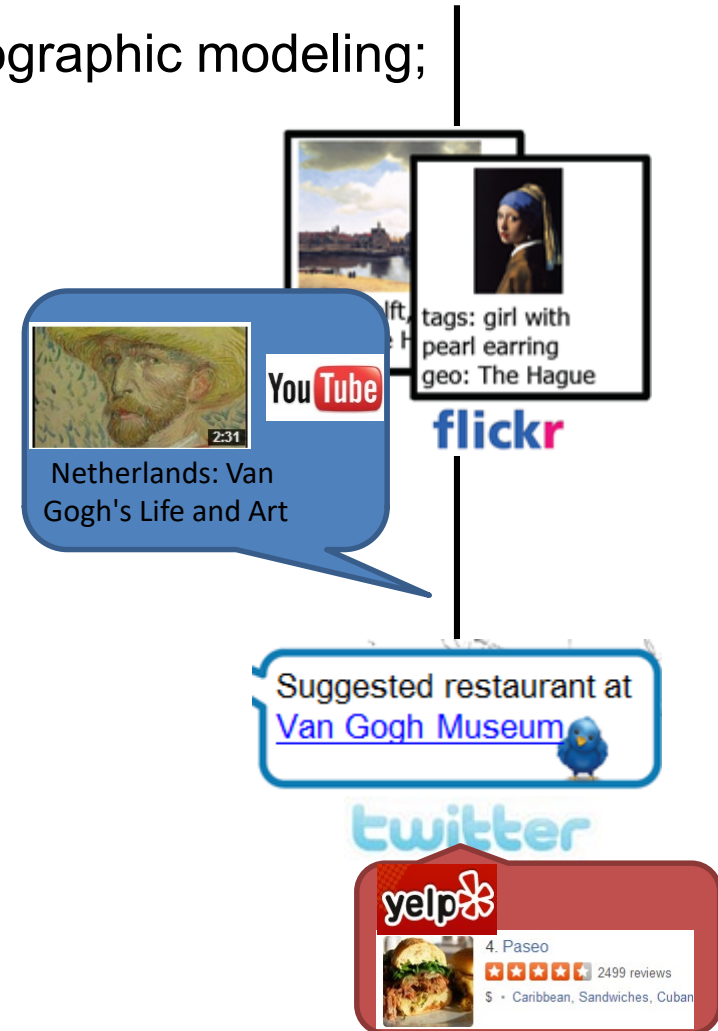
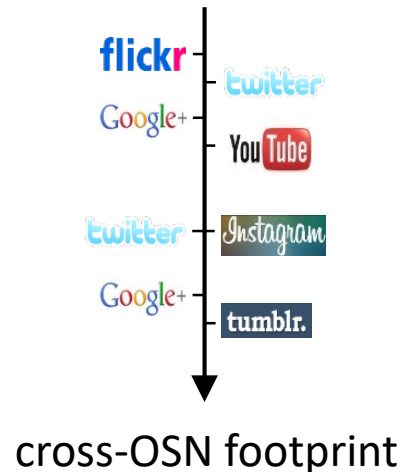
- Undirected & directed association patterns;
- One-to-many & many-to-many association patterns;
- Dynamic cross-OSN association patterns.



Call for Action

cross-OSN user modeling

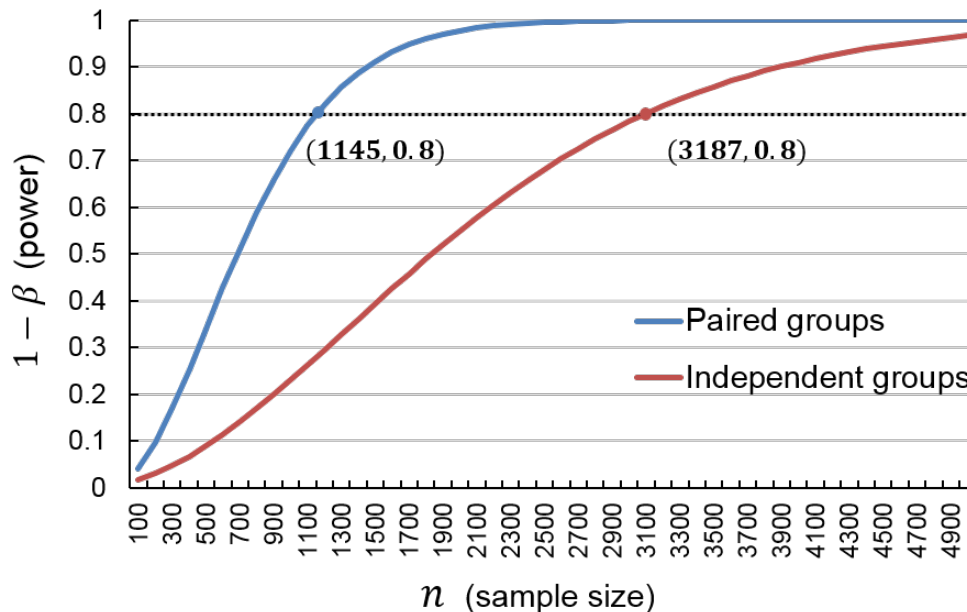
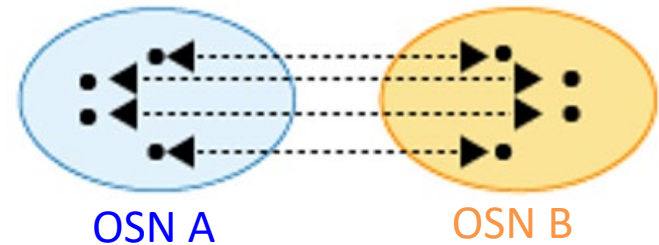
- Exploiting cross-OSN user data for demographic modeling;
- When #OSN>2...;
- Cross-OSN sequential user modeling & contextual recommendation.



④-1 Prospect: From Micro to Macro

Overlapped User-based Comparative Study

- Overlapped user is equivalent to the **paired sample** in **statistical analysis**: control the subject variable.



The paired statistical analysis is **more powerful with fewer samples** to prove a given difference between the study groups. (< half of #sample for the same statistical power)

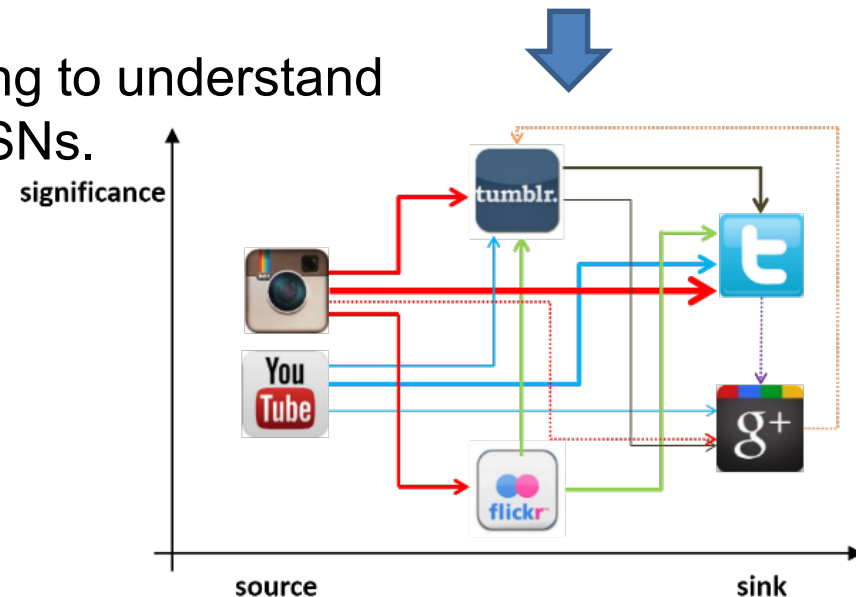
Cross-OSN Information Propagation Analysis

- **Cross-OSN sharing**: overlapped user multicasts his/her activity over different OSNs.



Time	Network	Content
26/05/2013 18:36:46	Twitter	my poolside jam... http://t.co/f2480xhw5u
27/05/2013 03:00:42	Instagram	I miss baby snuggles when the kids are away... :) I'm so blessed. #momlife
27/05/2013 03:00:44	Flickr	I miss baby snuggles when the kids are away... :) I'm so blessed. #momlife
27/05/2013 03:00:44	Twitter	I miss baby snuggles when the kids are away... :) I'm so blessed. #momlife @ home tweet home http://t.co/WioRNR6BjA
27/05/2013 21:02:02	Twitter	you just never know who or what's going to show up at a wedding ... ;)

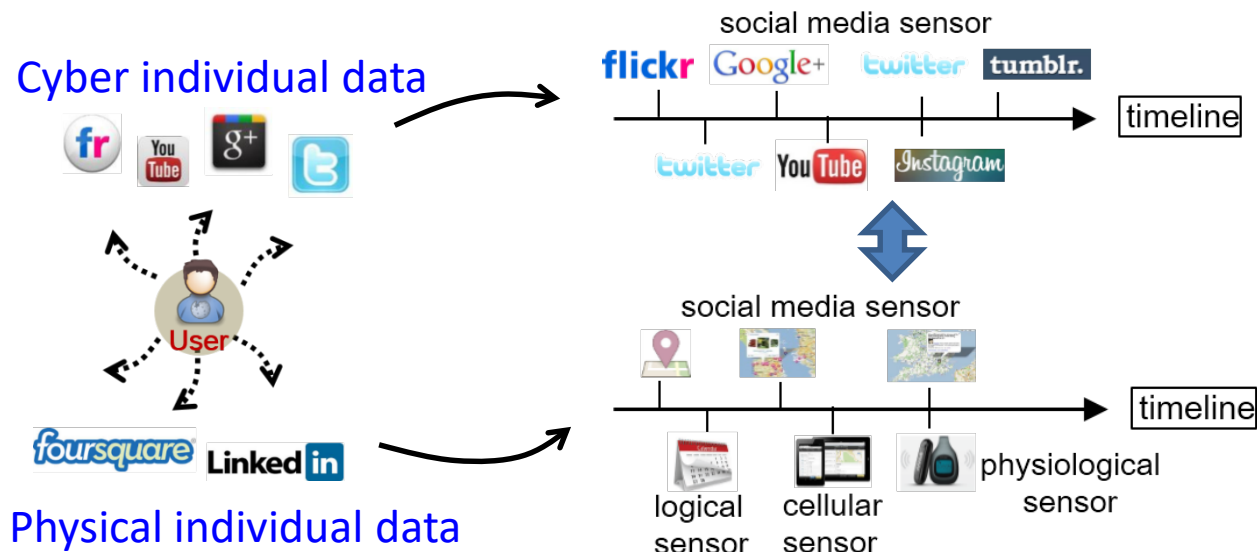
- Exploring the micro cross-OSN sharing to understand the **macro information flow** among OSNs.



④-2 Prospect: Cross-OSN to Cross-space

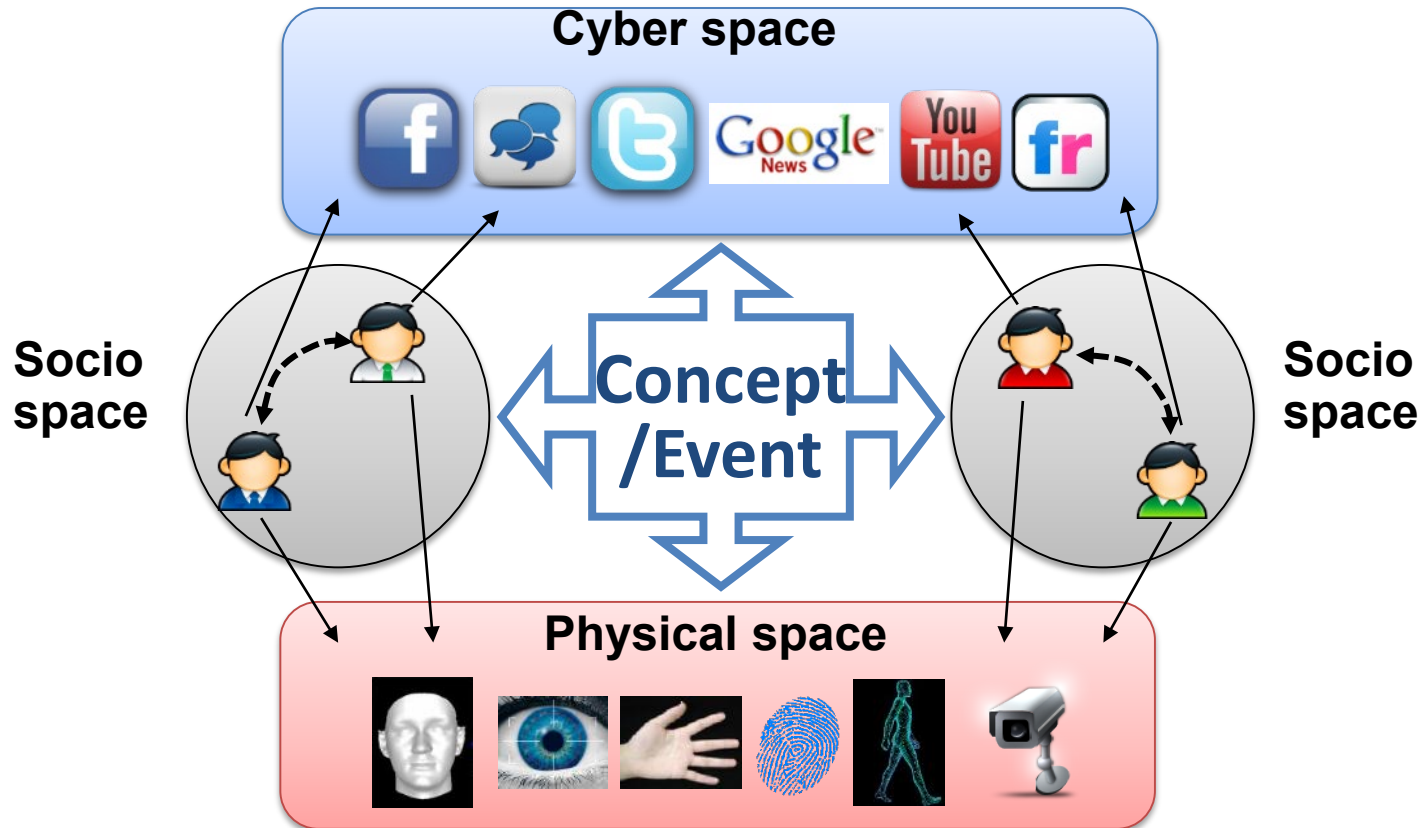
Cross-space Individual Data Alignment & Analysis

- Align between the cyber-physical data for the same individual to construct the **cross-space personal footprint**. (cyber & physical sensors)
- Potential applications in smart health, contextual recommendation, personal surveillance, etc.



User Connects Cyber to Physical

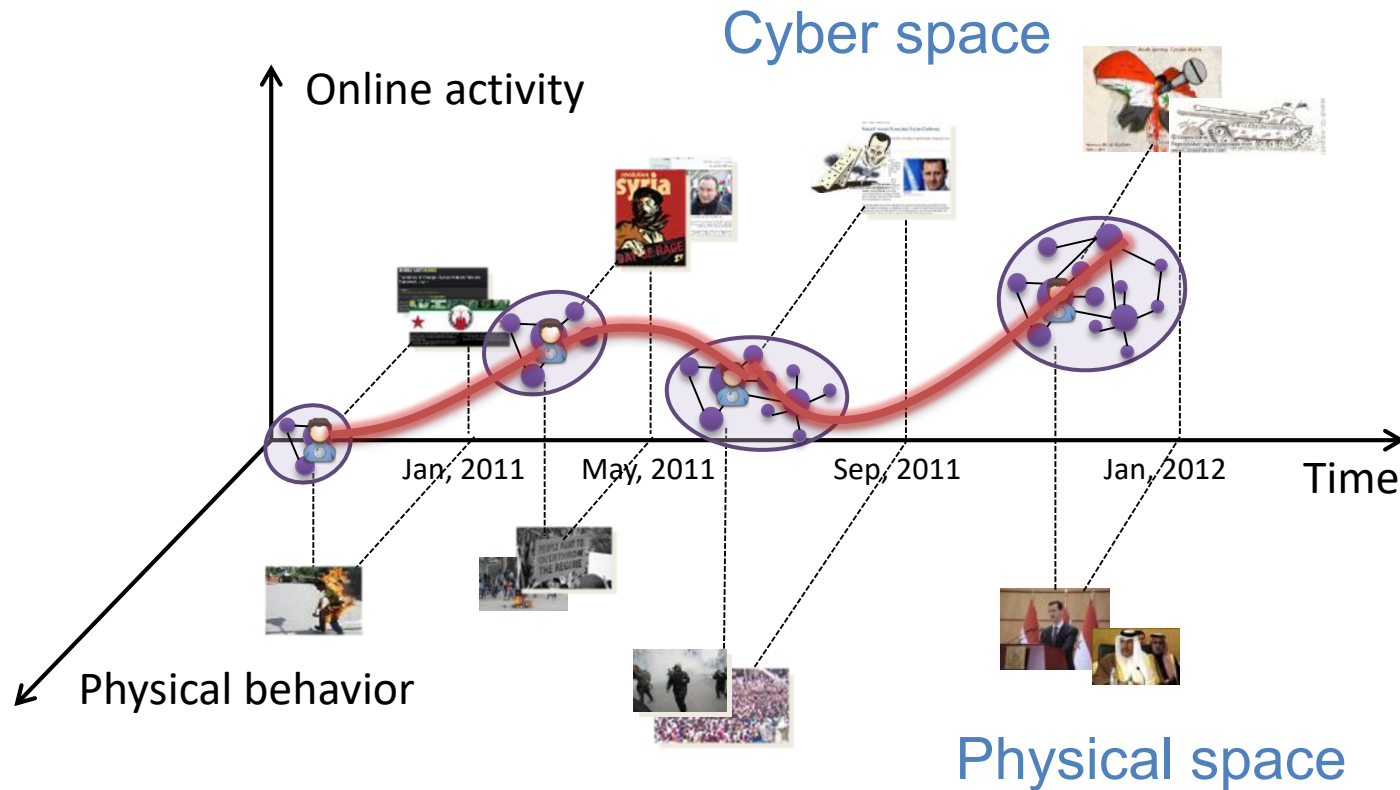
- **User** is key to bridge cyber with physical worlds.



Cyber-social-physical spaces

Cross-space Social Event Modeling

- Social event detection and tracking in cyber-social-physical spaces



Summary

- 
- **Background:**
BigData “4V” ➔ **Variety** ➔ **Multi-source** ➔ **Cross-OSN.**

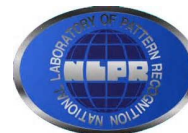
- 
- **Connecting Isolated Data:**
Cross-OSN **data fusion** & **user modeling.**

- 
- **Prospects:**
Micro to macro; Cross-OSN to cross-space.

Thank you.

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- Multimedia Computing Group,
National Lab of Pattern Recognition,
CASIA



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M. Yan, J. Sang, C. Xu, Mining Cross-network Association for YouTube Video Promotion, **ACM International Conference on Multimedia**, Orlando, FL, 3-7 Nov 2014, 557-566.

M. Yan, J.Sang, C.Xu, YouTube Video Promotion by Cross-network Association: @Britney to Advertise Gangnam style, **IEEE Transactions on Multimedia**, 2015, 17(8): 1248-1261.

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M. Yan, J.Sang, C.Xu, Unified YouTube Video Recommendation via Cross-network Collaboration, **ACM International Conference on Multimedia Retrieval**, 2015. **Best Student Paper**

J. Sang, Z. Deng, C. Xu, Cross-OSN User Modeling by Homogeneous Behavior Quantification and Local Social Regularization, **IEEE Transactions on Multimedia**, 2015, 17(12): 2259-2270.

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