Social Media

Social media is the social interaction among people in which they create, share or exchange information and ideas in virtual communities and networks.

-------- *Wikipedia*

Social Media

social media panorama

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.

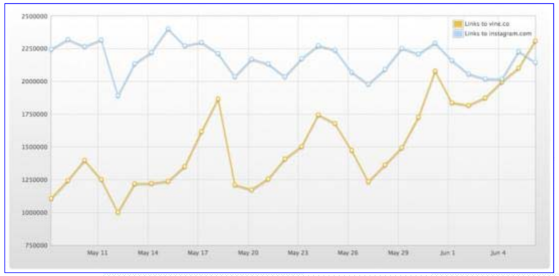
Portal Era | Search Era | Mobile Internet / Social Media Era

1996 1999 2005 2007 2009 2011

WEB 1.0 | WEB 2.0

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.

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

capturing devices, textual information dominates.

actively contribute, obtain and propagate rich multimedia data

- Micro-blogging, multimedia sharing websites, SNS；
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Portal Era | Search Era | Social Media Era | Mobile Internet

1996 1999 2005 2007 2009 2011

WEB 1.0 | WEB 2.0

Internet media roadmap

"Social" trend in multimedia

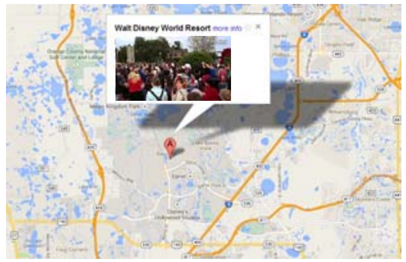
350 million photos are uploaded **daily** in November 2013 on facebook

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

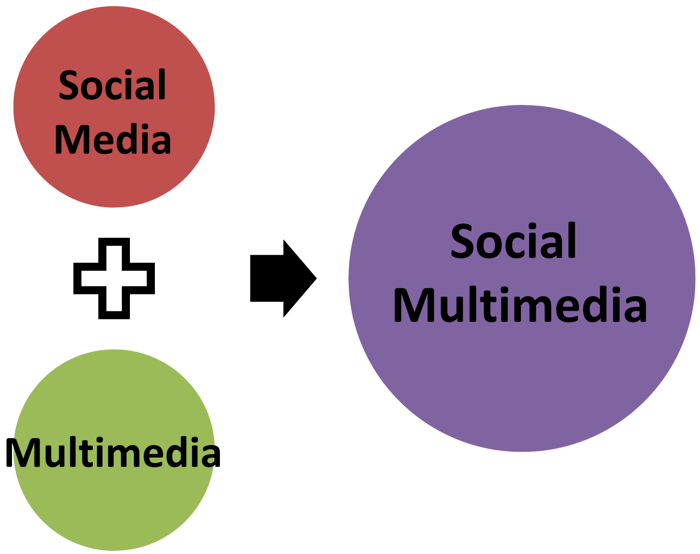
Definition:

"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."

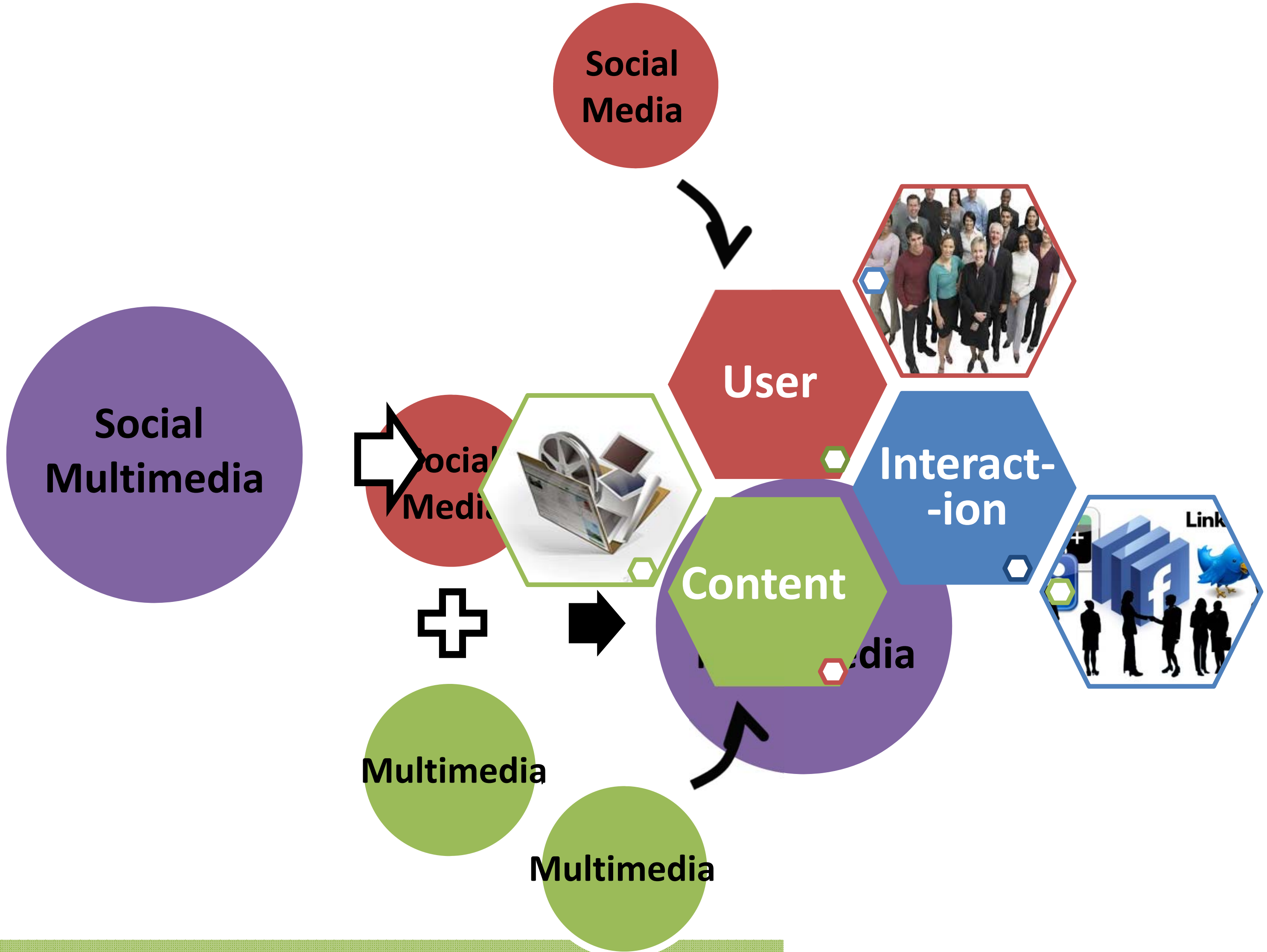
----- *Mor Naaman*

efficient information access and propagation

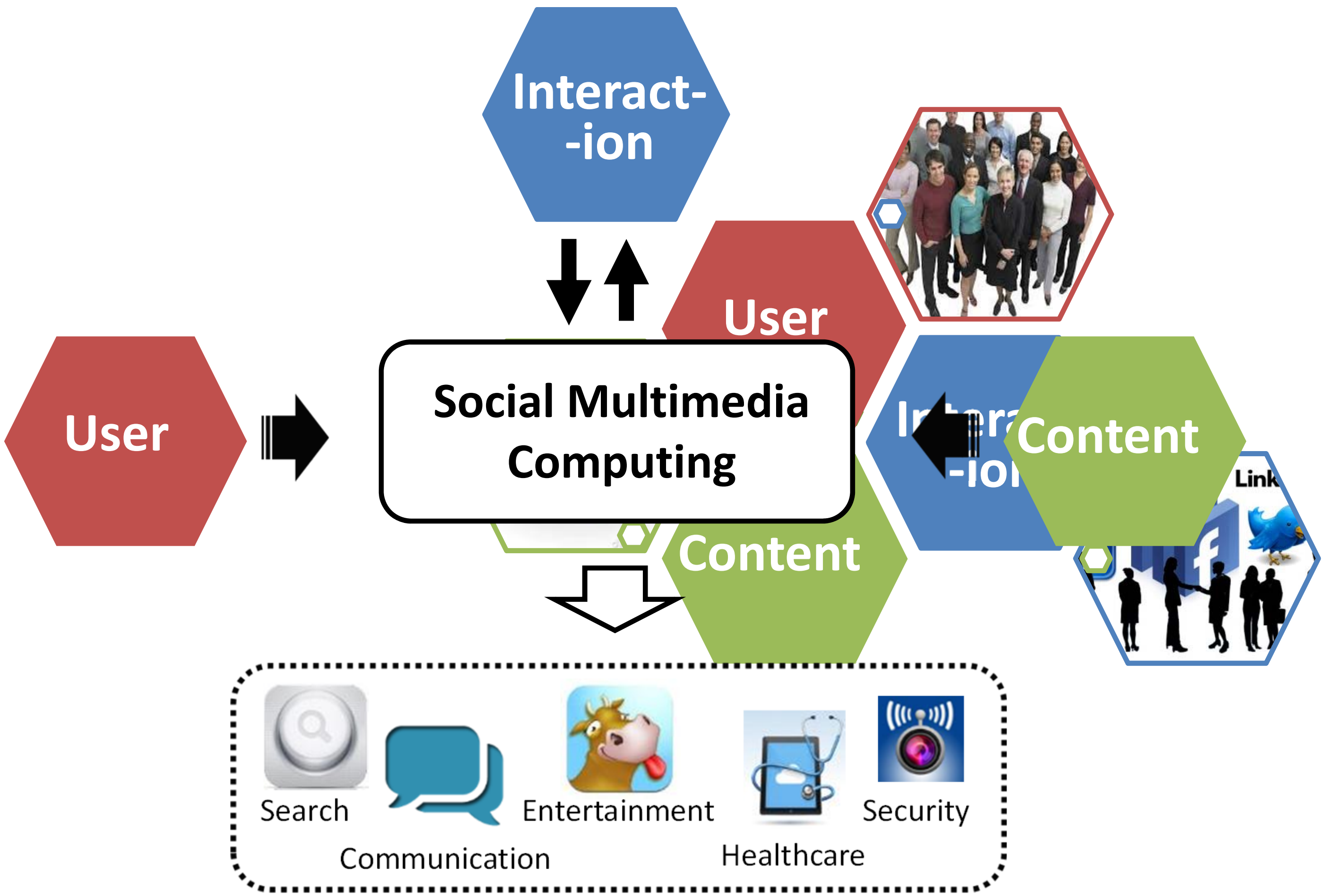
rich sensor simulation



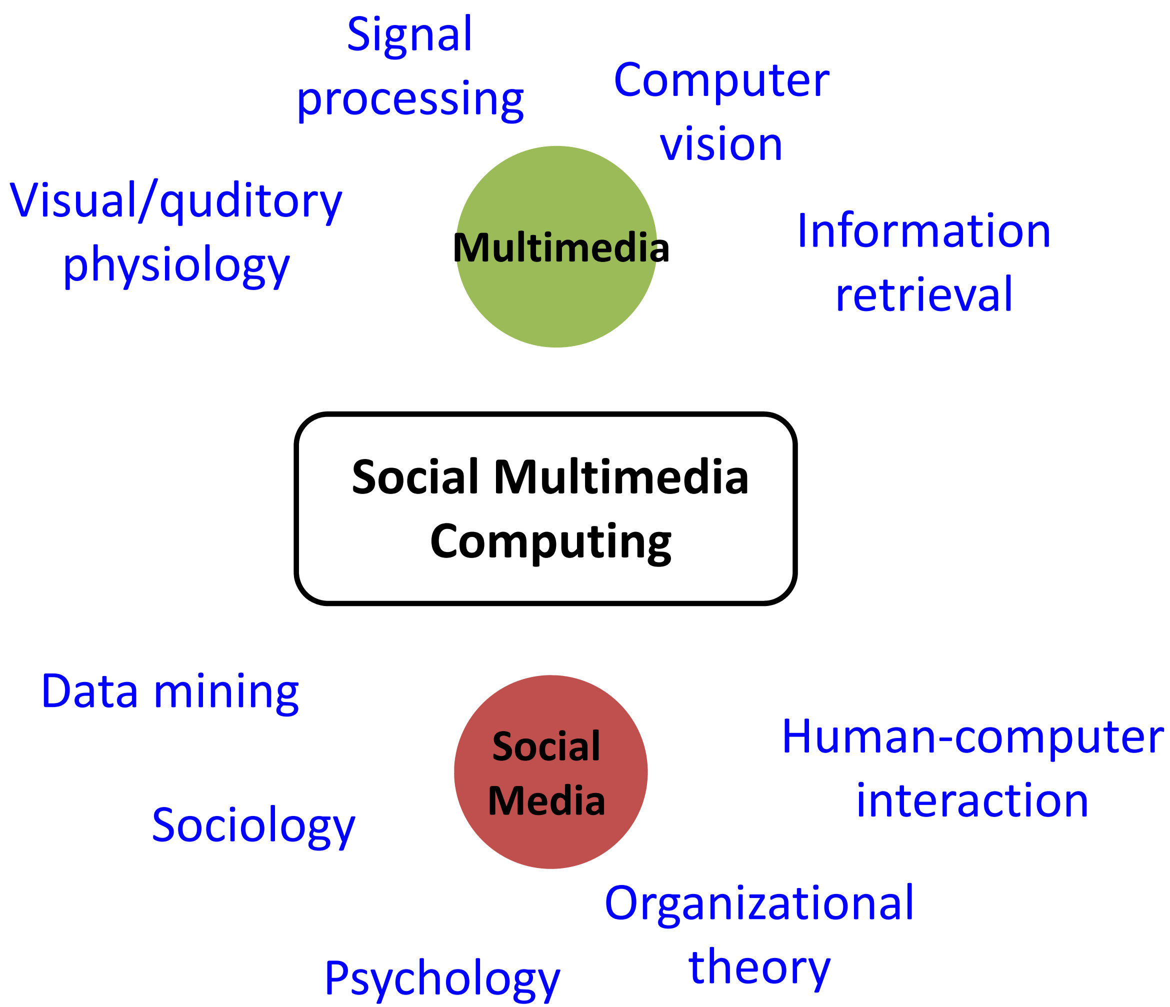
Social Multimedia



Social Multimedia Computing



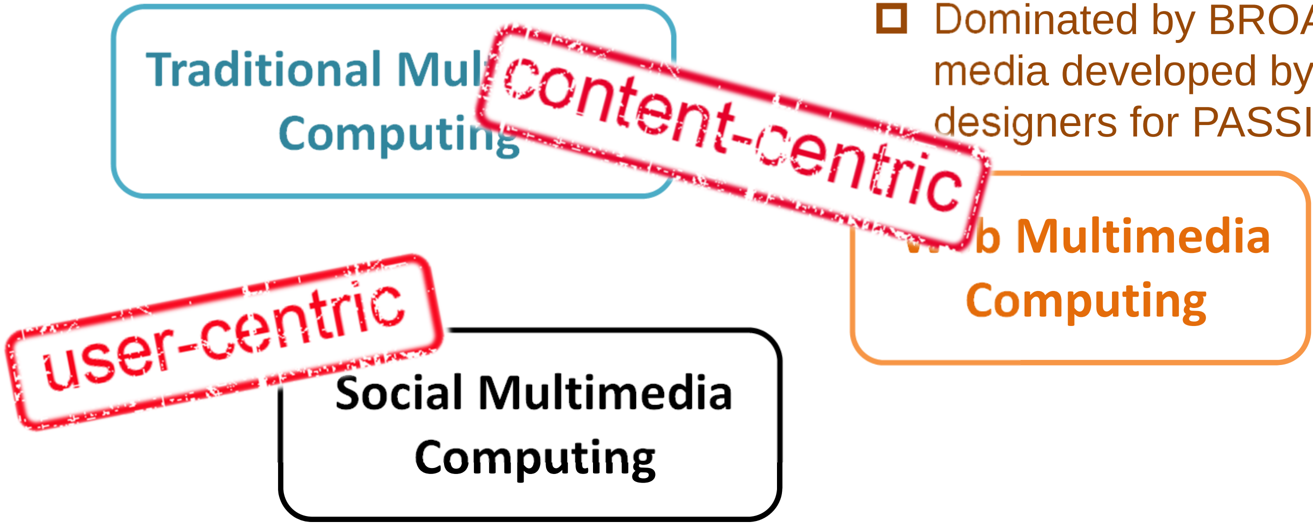
Social Multimedia Computing



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.

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



- **From User**: User is the basic data collection unit.
- **For User**: User is the ultimate information service target.

semantic gap

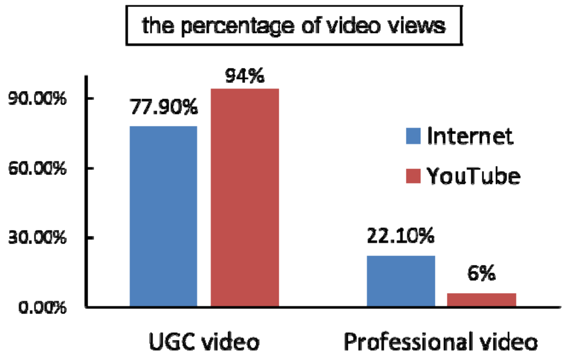
intent gap

User is the basic data collection unit.


IN 60 SECONDS...
1 NEW DEFINITION IS ADDED ON urban
1,600+ READS ON Scribd.
13,000+ HOURS MUSIC STREAMING ON PANDORA
12,000+ NEW ADS POSTED ON craigslist
New Craigslist Ads
370,000+ MINUTES VOICE CALLS ON skype
98,000+ TWEETS
20,000+ NEW POSTS ON tumblr.
THE LARGEST SOCIAL READING PUBLISHING COMPANY!!
320+ NEW twitter ACCOUNTS
100+ NEW LinkedIn ACCOUNTS
13,000+ iPhone APPLICATIONS DOWNLOADED
1 associatedcontent NEW ARTICLE IS PUBLISHED
QUESTIONS ASKED ON THE INTERNET...
100+ Answers.com
40+ YAHOO! ANSWERS
6,600+ NEW PICTURES ARE UPLOADED ON flickr
600+ NEW VIDEOS
YouTube
25+ HOURS TOTAL DURATION
70+ DOMAINS REGISTERED
50+ WORDPRESS DOWNLOADS
60+ NEW BLOGS
168 MILLION EMAILS ARE SENT
694,445 SEARCH QUERIES
1,700+ Firefox DOWNLOADS
695,000+ facebook STATUS UPDATES
1,500+ BLOG POSTS
79,364 WALL POSTS
510,040 COMMENTS
Google
Google Search
GO-Globe.com web technologies

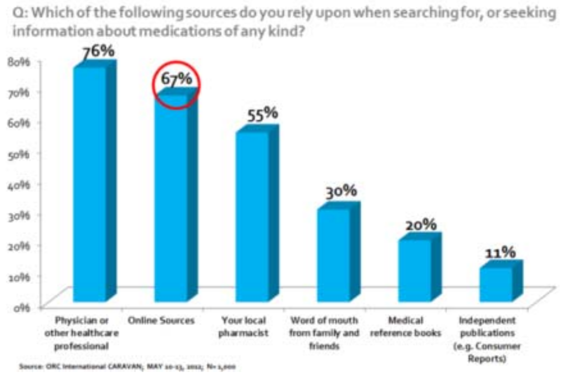
UGC is dominant

UGC videos make up 4/5 of total video views.



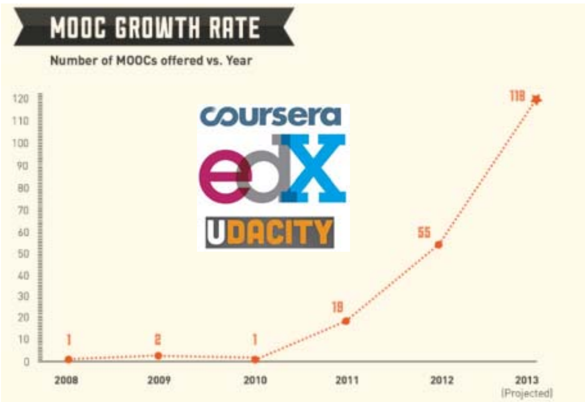
(source: AccuStream.com)

Consumers rely more on UGC for info about medications.



2012-2013 witnesses a boosting rise of MOOC in online education.

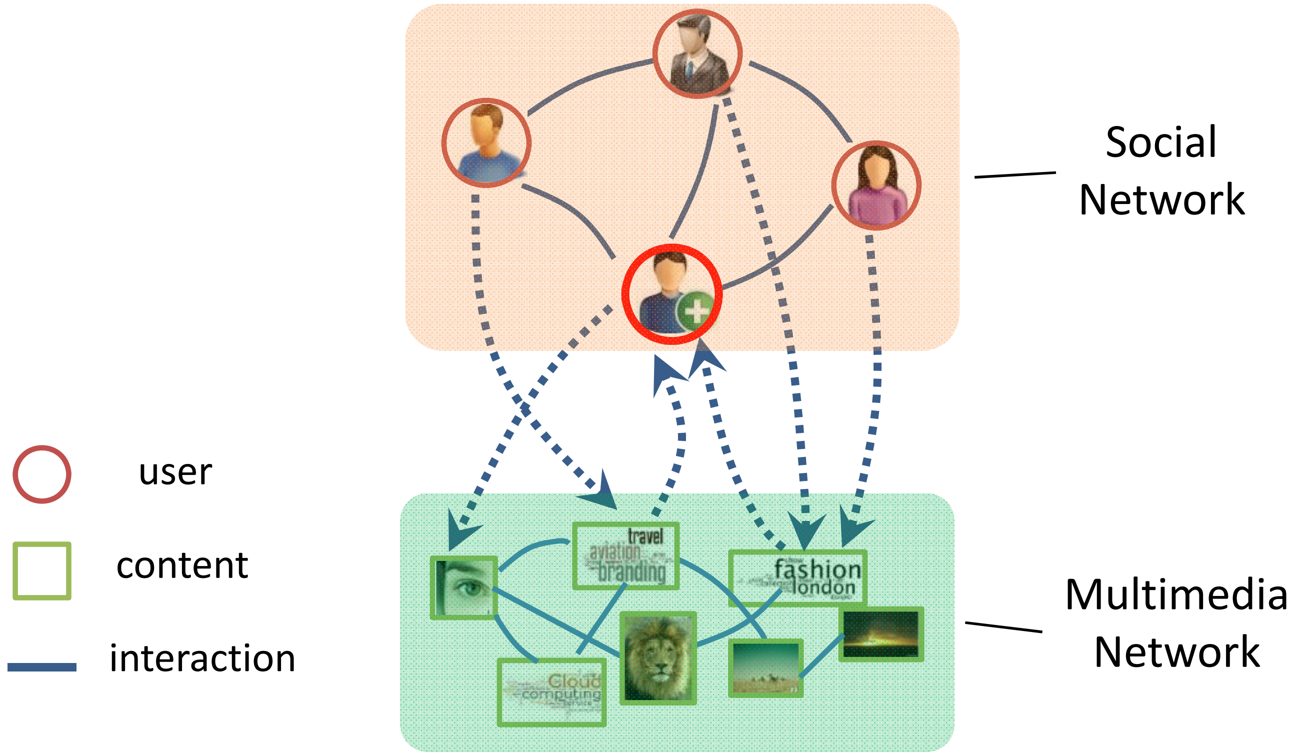
(MOOC: Massive Open Online Courses)



(source: Infographics)

the Role of User in Social Multimedia

- User serves as bridges between social network and multimedia network:



User is the basic data collection unit

- Each user is analog to a data sensor

see
listen
think

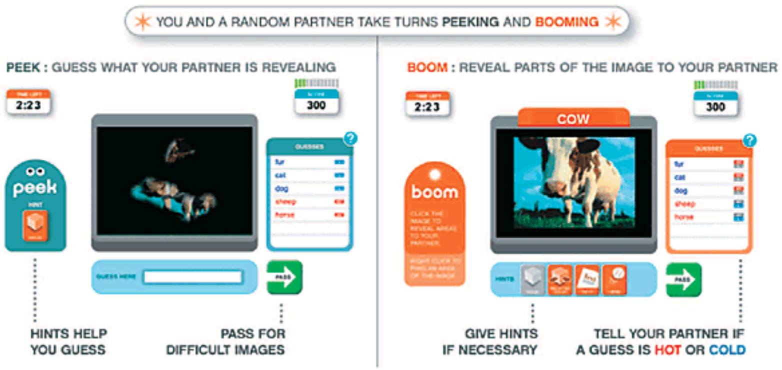
speak
feel

✓ EMC^2 estimates that each person contributes to 45GB social media data on average.

- User collaboration leads to crowded knowledge/intelligence

[ESP games]

✓ Image label
✓ Image segmentation

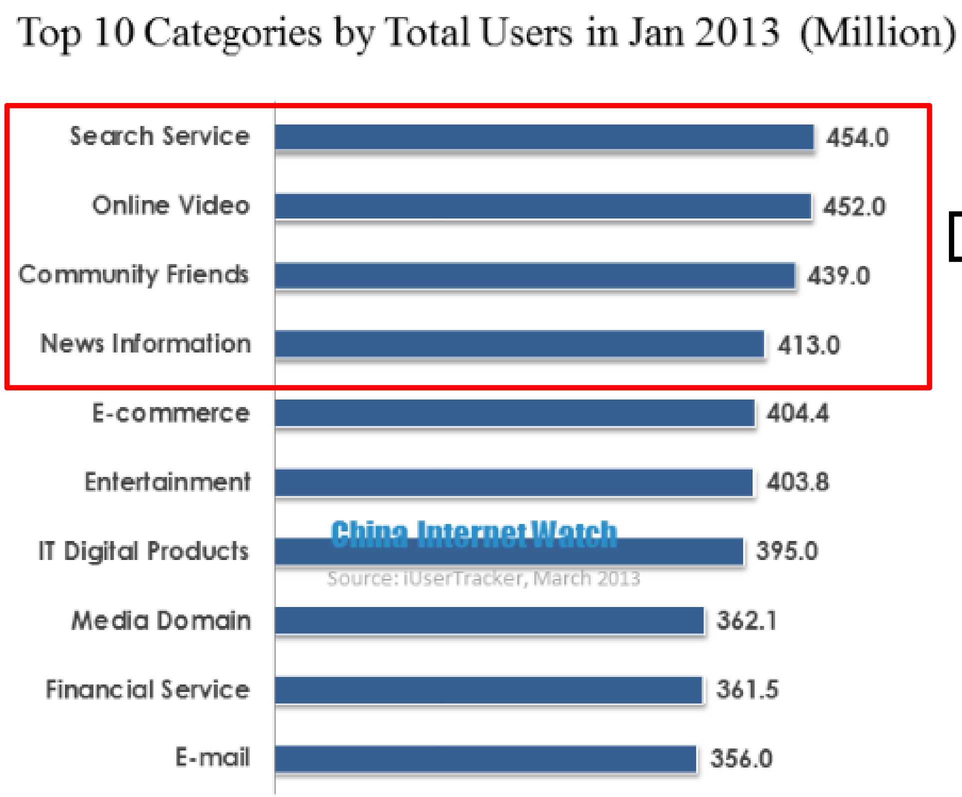


[WAZE]

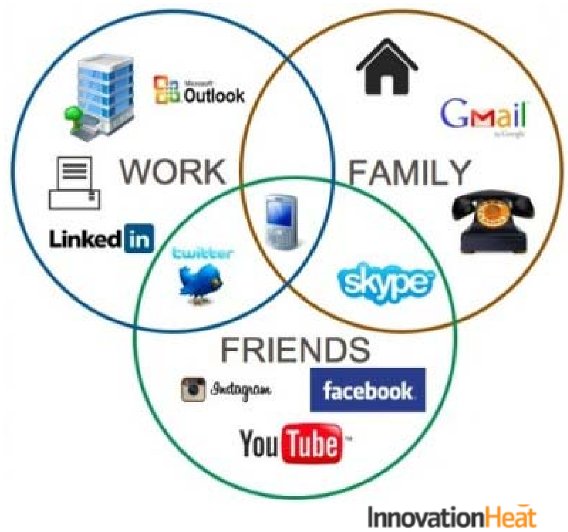
User is the ultimate information service target.

User is the information service target.

- Social multimedia tends to be consumerized :

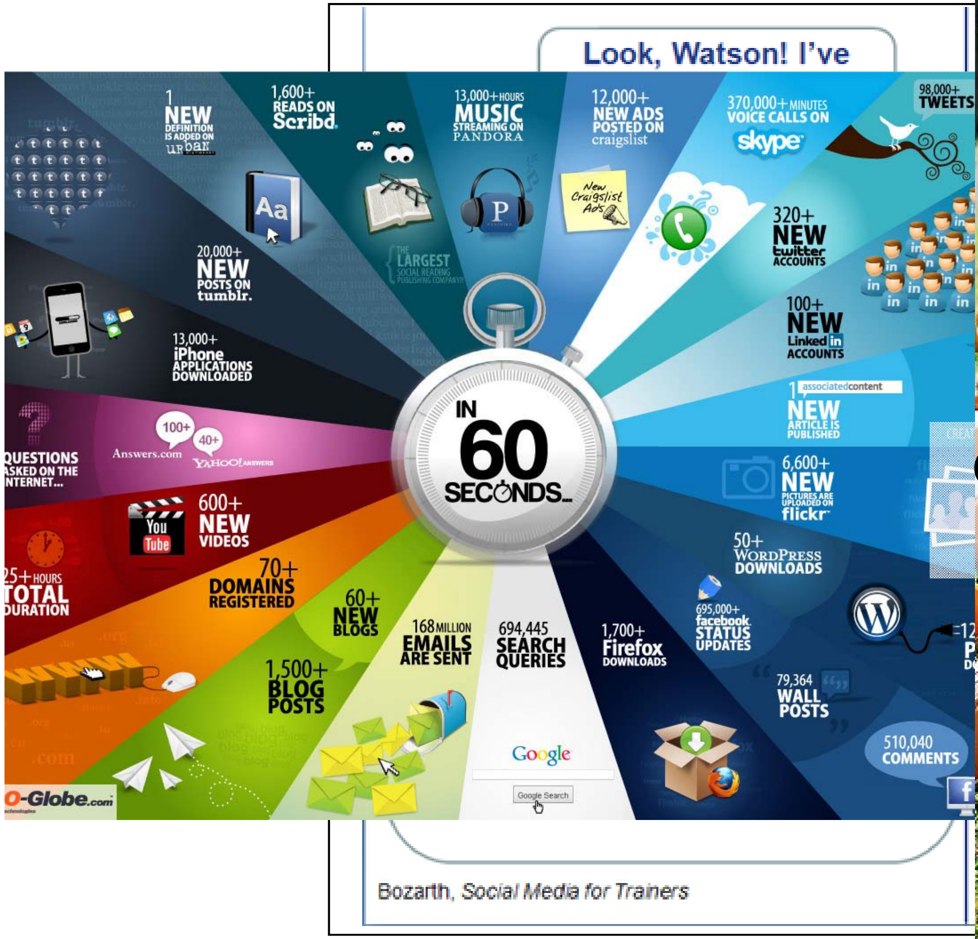


Information Service



User is the information service target.

- Information explosion: Opportunity V.S. Challenge to information services.



User is the information service target.

- Personalization stands out for solution:

Rank results considering web history and +1 statistics

Douban FM: personalized music listening channel.

22

User is the information service target.

- Understanding user intents and preferences is key to personalized services.

Information Overload

User Modeling

Personalized Service

User-centric Social Multimedia Computing

User-centric Social Multimedia Computing

***From Users*:**

User-perceptive Multimedia Analysis

Social -> Multimedia

***On Users*:**

User Modeling based on Social Multimedia Activity

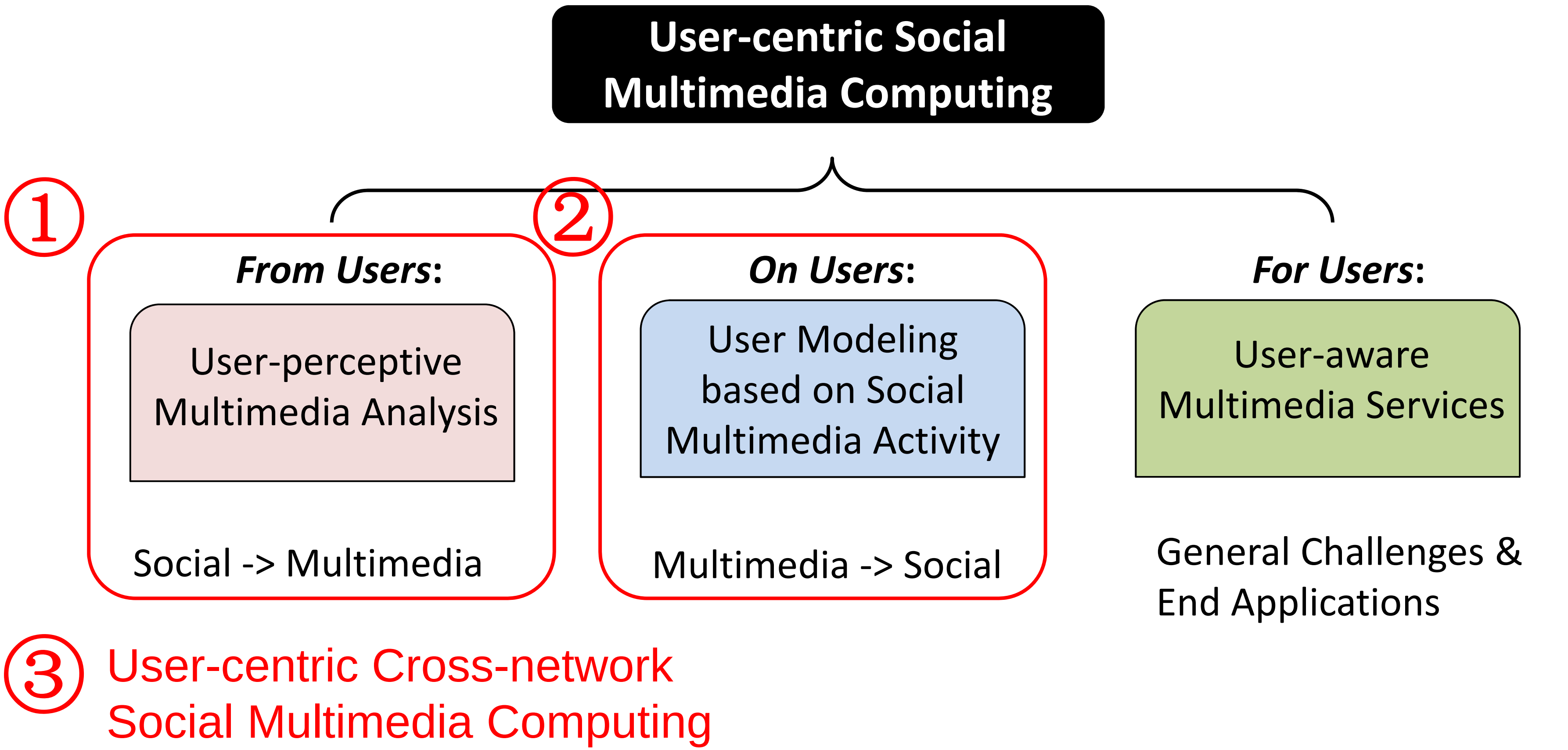
Multimedia -> Social

***For Users*:**

User-aware Multimedia Services

General Challenges & End Applications

User-centric Social Multimedia Computing

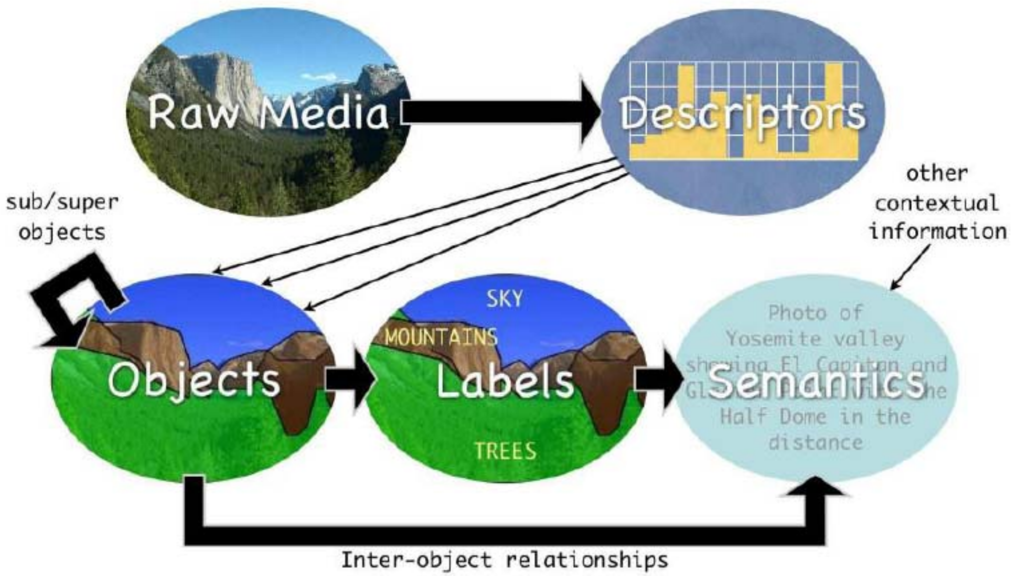


More background & context:

- Springer book: "User-centric Social Multimedia Computing".

Semantic Gap

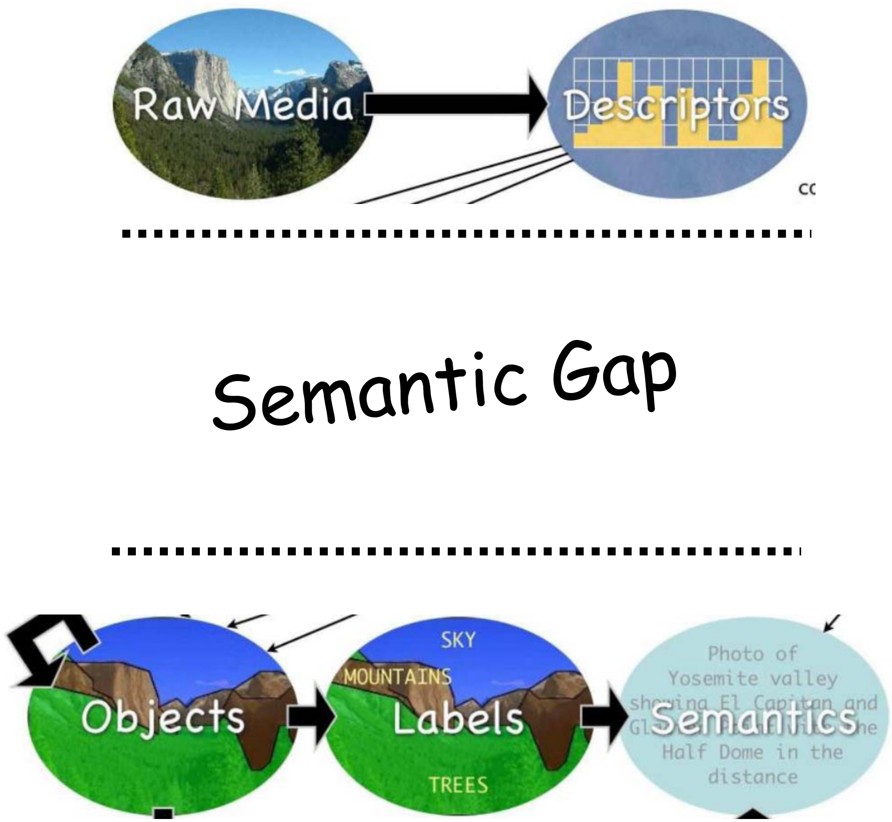
Semantic gap indicates the lack of coincidence between the information extracted from low-level representations (e.g., color, contour, audio pattern) and the high-level interpretations (e.g., object, emotion).



Hare et al. (2006) . Bridging the semantic gap in multimedia information retrieval: Top-down and bottom-up approaches.

Crowd Wisdom bridges Semantic Gap

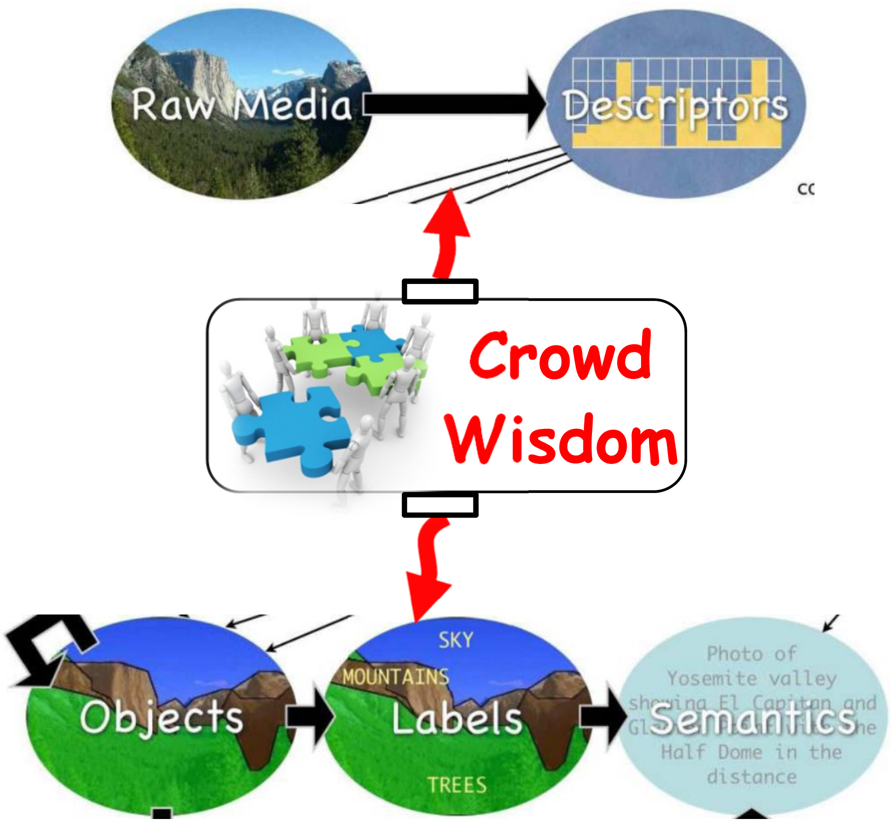
low-level representation



high-level interpretation

Crowd Wisdom bridges Semantic Gap

low-level representation



high-level interpretation

waze

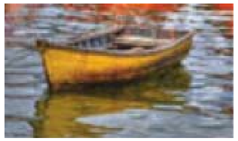
amazon mechanical turk
Artificial Artificial Intelligence

Wikipedia
The Free Encyclopedia

ESP Game

Image Labeling game

Player 1



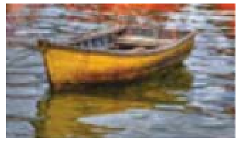
guess: BOAT

guess: WATER

guess: RIVER

Score! Agreement on 'BOAT'.

Player 2

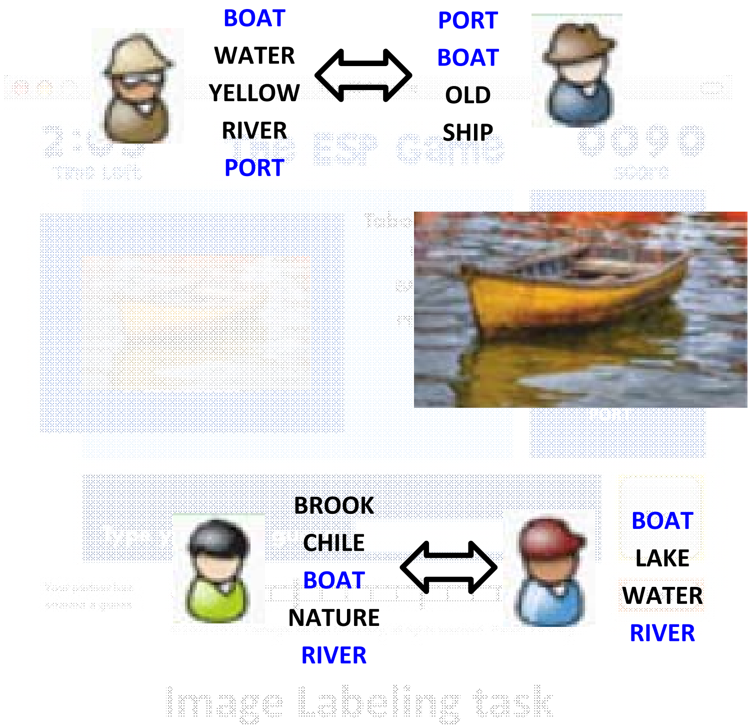


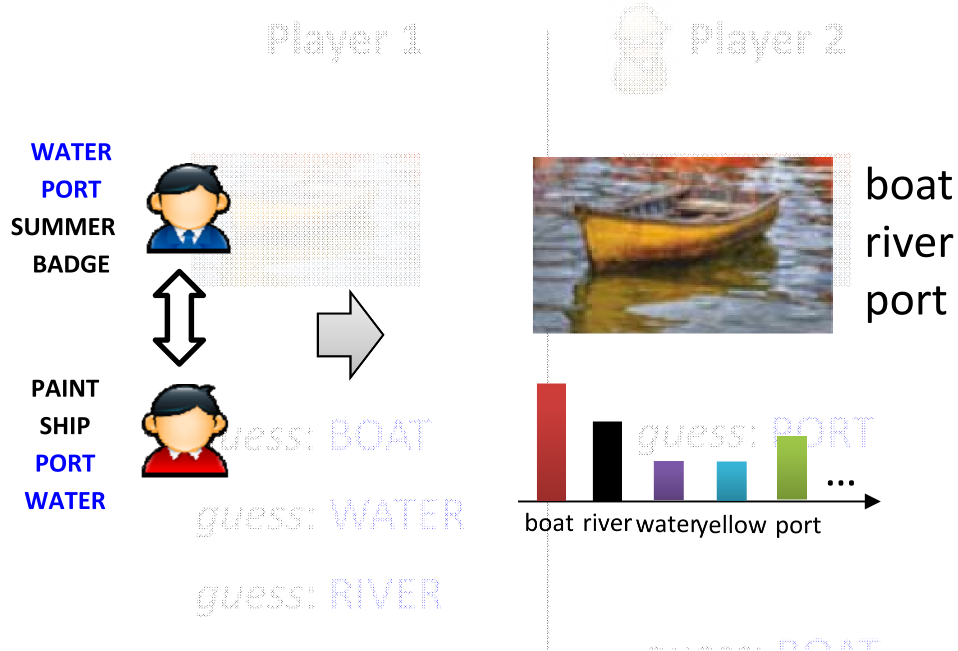
guess: PORT

guess: BOAT

Score! Agreement on 'BOAT'.

ESP Game





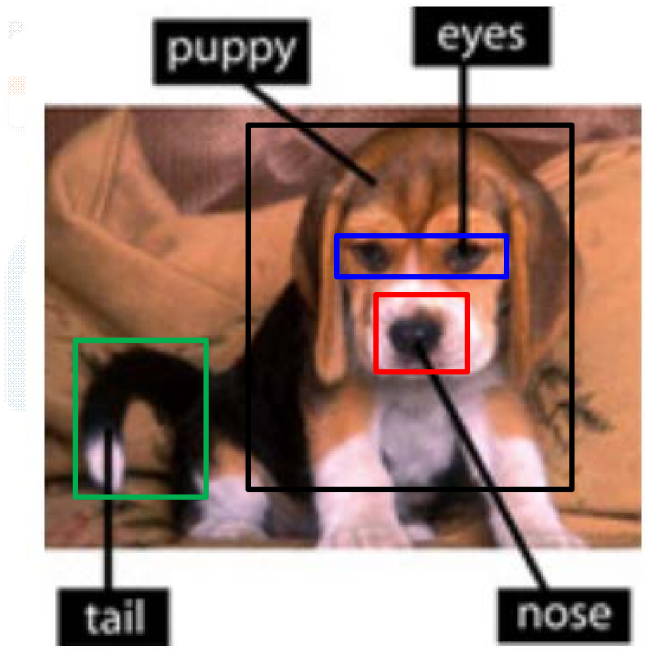
"The string on which the two players agree is typically *a good label* *for the image.*
Experimental evaluation indicates that a majority *(85%)* *of the words would be useful for describing*. " [Von Ahn and Dabbish 2004]

ESP Game

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

ESP Game



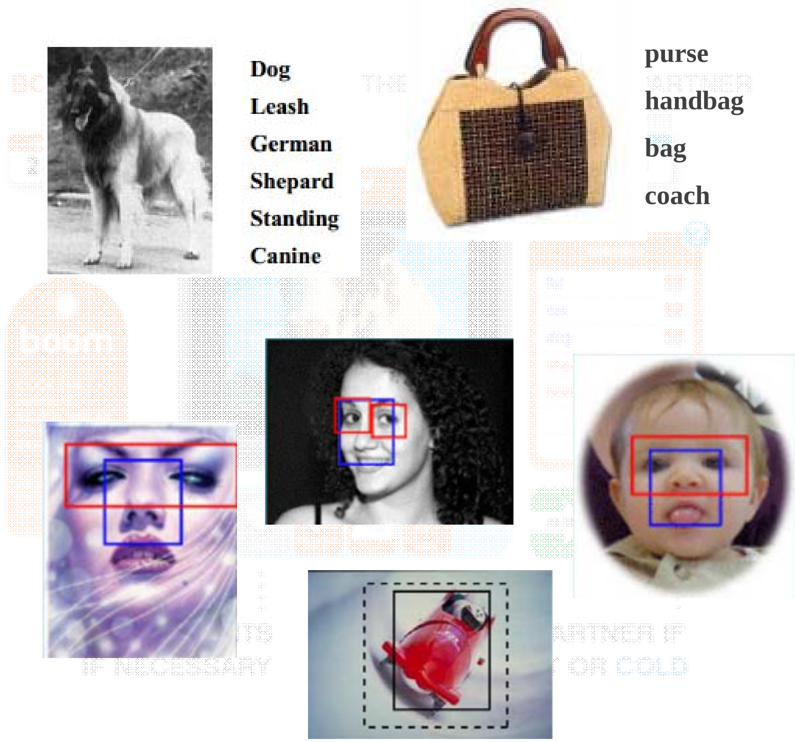


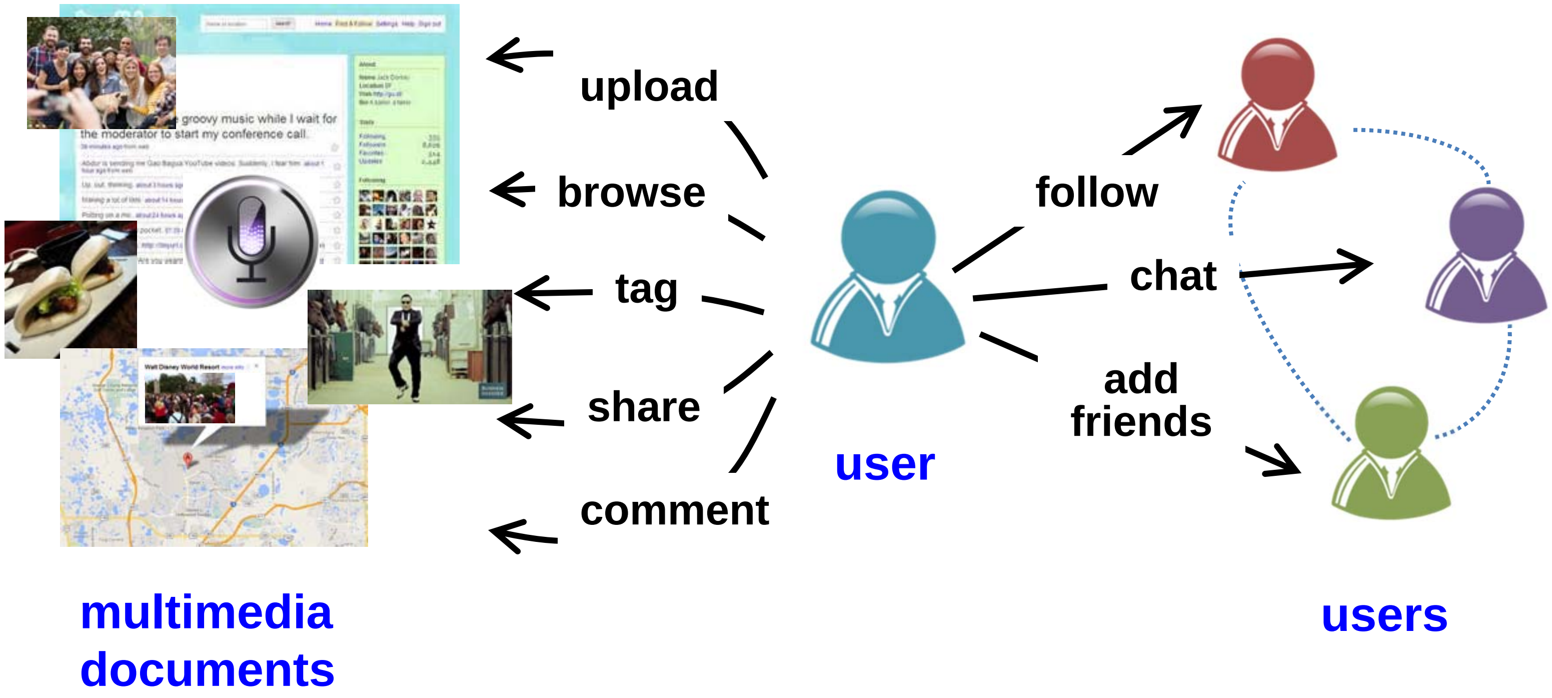
Image labels and object regions as
by-product of collaboratively playing games.

ESP Game

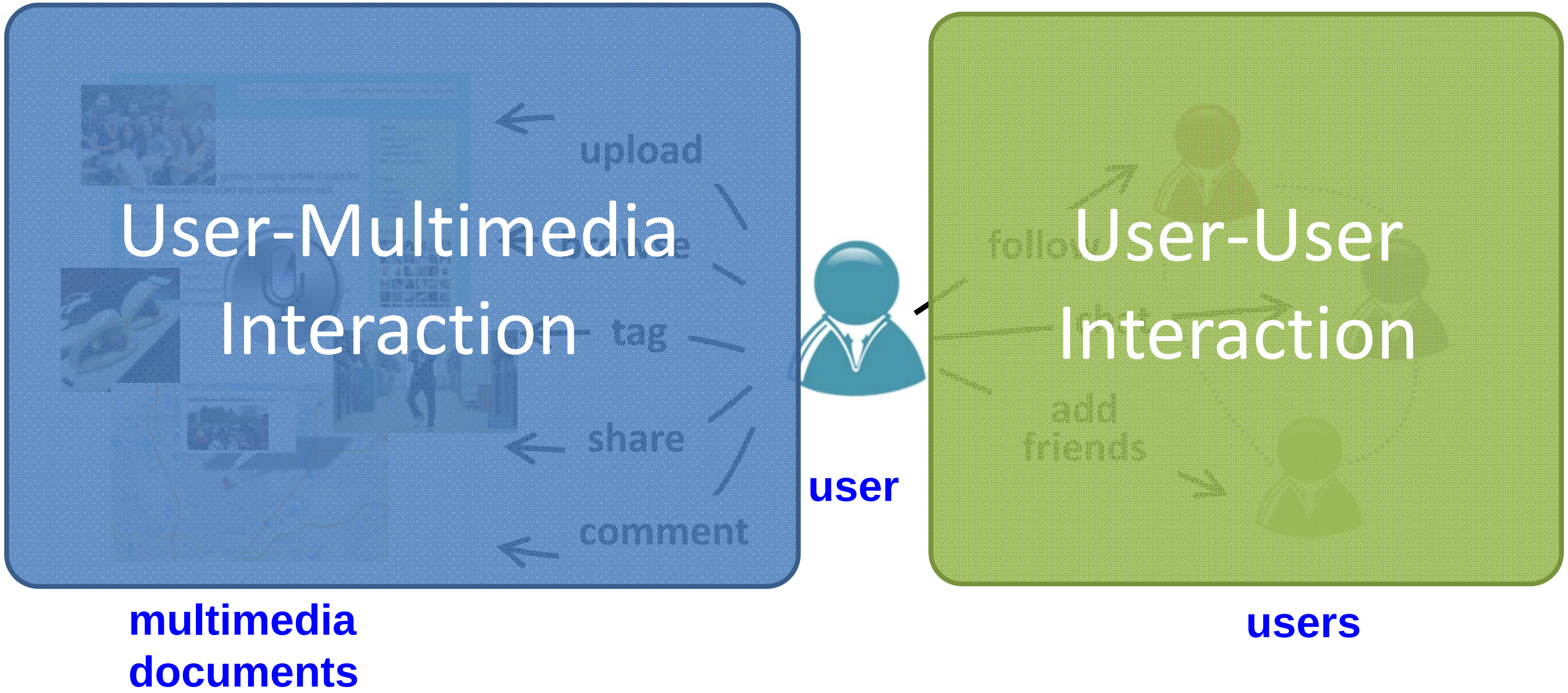
Luis Von Ahn

Learning a language while translating the web

User Participation in Social Multimedia



User Participation in Social Multimedia



Categorization of Related Work

User-Multimedia Interaction

User-User Interaction

Categorization of Related Work

User Usage Data

UGC Metadata

User-User Interaction

User Usage data-based Multimedia Analysis

User Usage Data

User usage Data

User-User Interaction

User Usage data-based Multimedia Analysis

User Usage Data

User usage Data

User-User Interaction

Browsing behavior-based

[Simon and Seitz, 2008; Borghol et al. 2012; Pinto et al. 2013; Yao et al. 2013; Chrysoula and Konstantinos, 2014]

Social endorsement-based

[Lappas et al. 2011; Jin et al. 2011]

Comment-based

[De Choudhury et al. 2009; Potthast et al. 2010; Filippova and Hall 2011; Eickhoff et al. 2013; Siersdorfer et al. 2010; Yamamoto and Nakamura 2013; He et al. 2014; Fang et al. 2014]

User Usage data-based Multimedia Analysis

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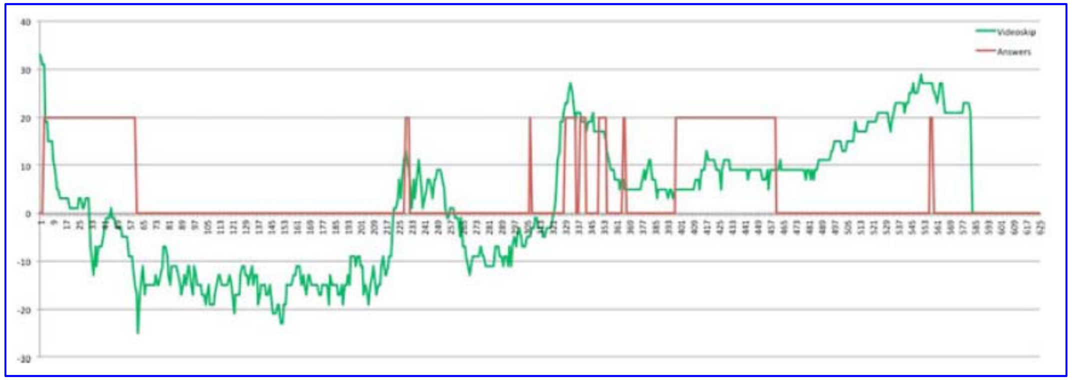
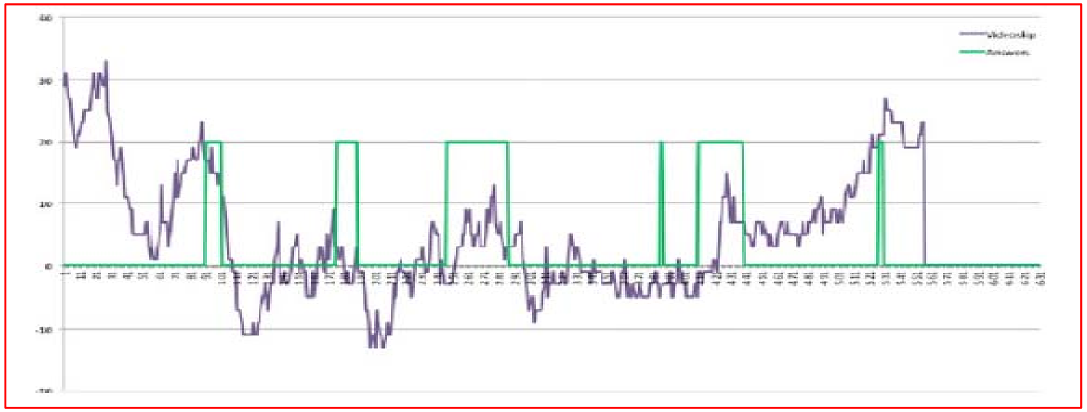
Browsing behavior-based Video summarization

user interface



documentary video



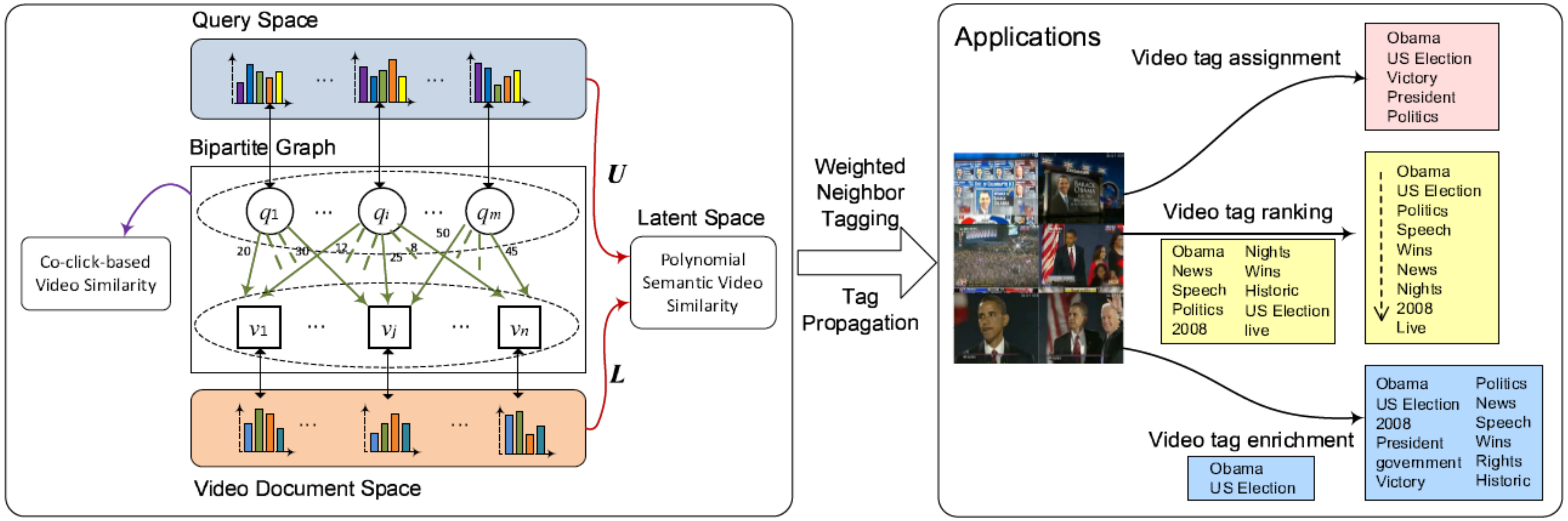
lecture video

[Chrysoula and Konstantinos, 2014] Gkonela, Chrysoula and Chorianopoulos, Konstantinos. VideoSkip: event detection in social web videos with an implicit user heuristic. *Multimedia Tools and Applications, 2014.*

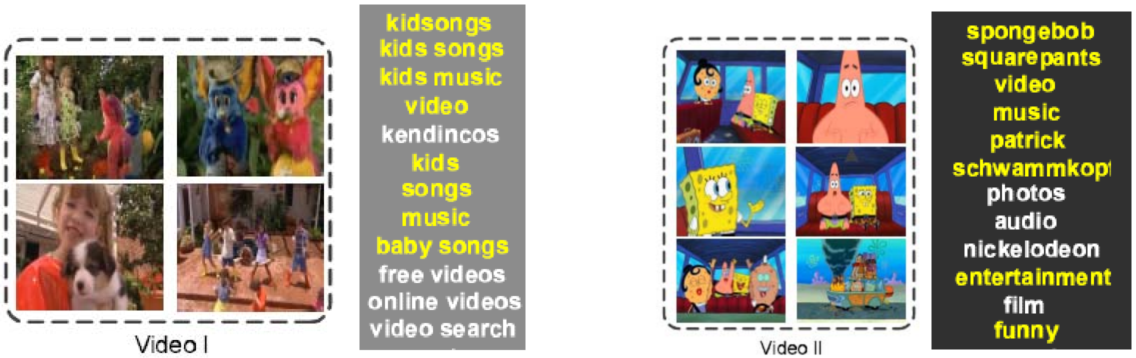
(Ionian University, Greece)

Browsing behavior-based Video Annotation

The framework



Tag assignment results

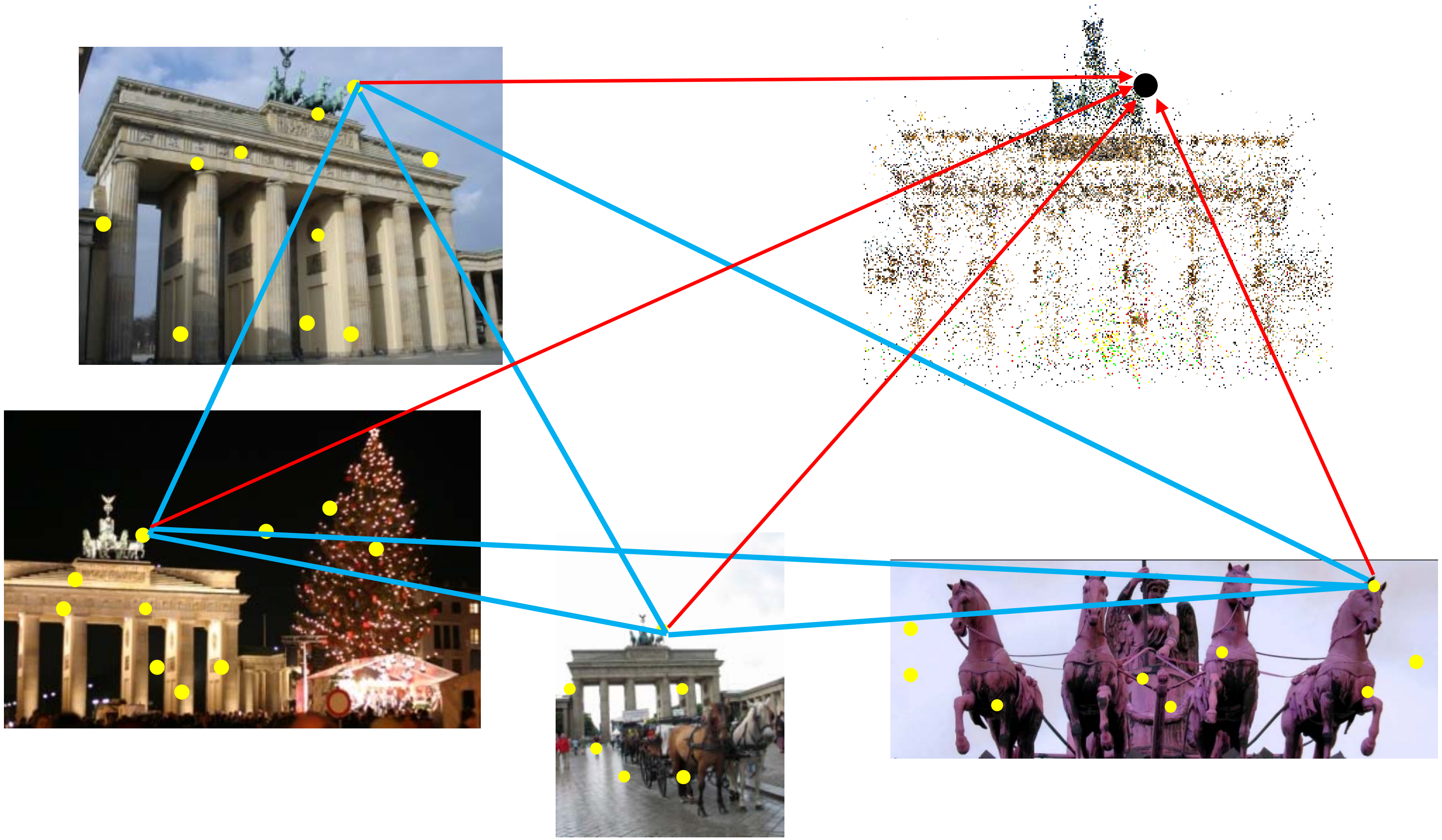


[Yao et al. 2013] Ting Yao, Tao Mei, Chong-Wah Ngo, Shipeng Li: Annotation for free: video tagging by mining user search behavior. *ACM Multimedia 2013.* (Microsoft Research Asia)

Browsing behavior-based Image Segmentation

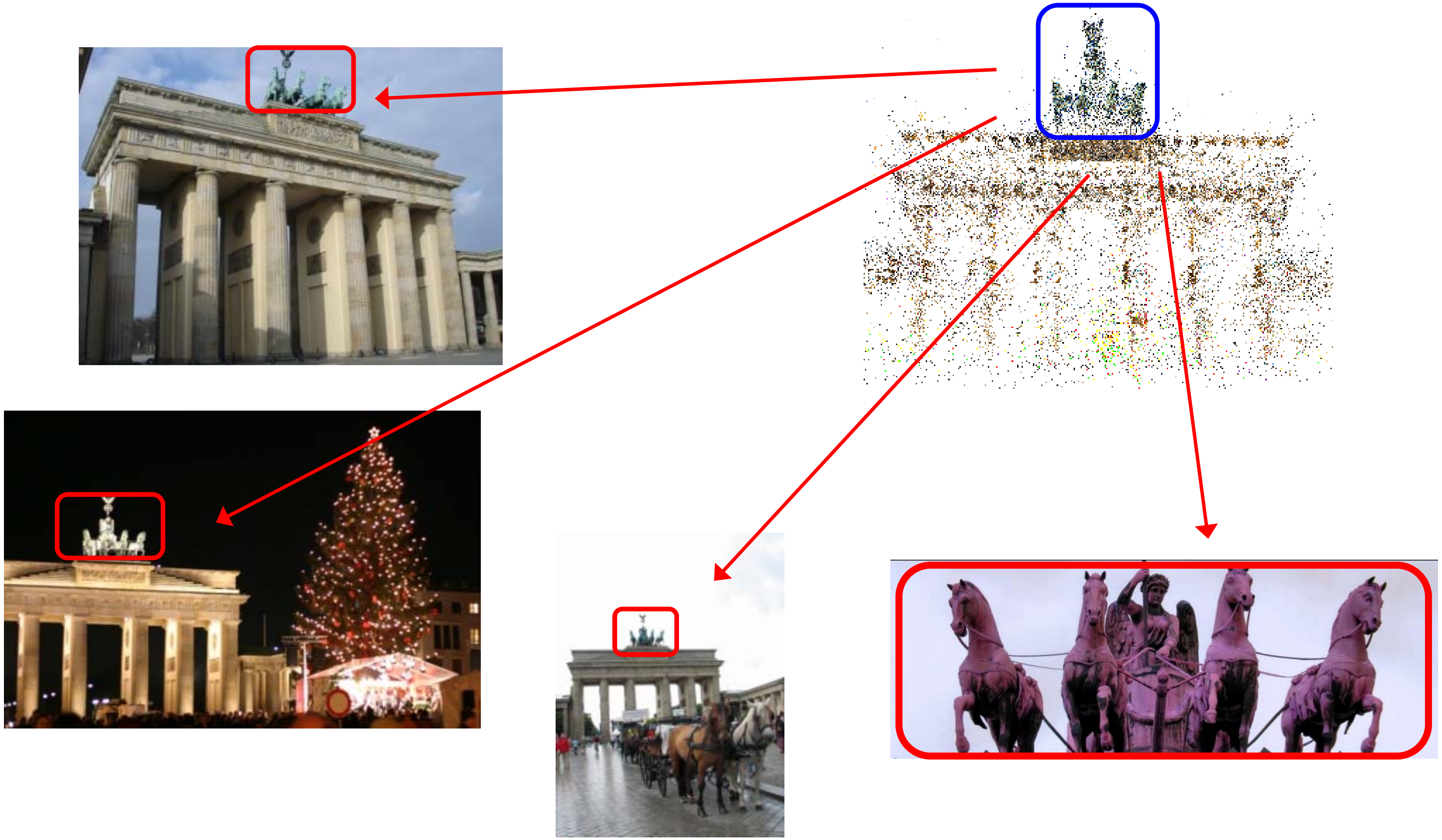
[Simon and Seitz, 2008] Simon, Ian, and Steven M. Seitz. Scene segmentation using the wisdom of crowds. *ECCV 2008.* (University of Washington)

Browsing behavior-based Image Segmentation



[Simon and Seitz, 2008] Simon, Ian, and Steven M. Seitz. Scene segmentation using the wisdom of crowds. *ECCV 2008.*

Browsing behavior-based Image Segmentation



[Simon and Seitz, 2008] Simon, Ian, and Steven M. Seitz. Scene segmentation using the wisdom of crowds. *ECCV 2008.*

Browsing behavior-based Image Segmentation

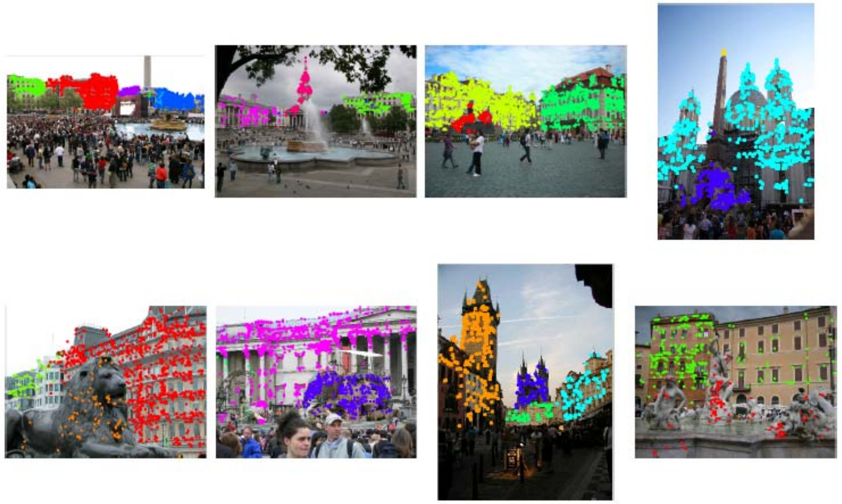


Image segmentation results

Tag-to-region results

[Simon and Seitz, 2008] Simon, Ian, and Steven M. Seitz. Scene segmentation using the wisdom of crowds. *ECCV 2008.*

User Usage data-based Multimedia Analysis

User Usage Data

User usage Data

User-User Interaction

Browsing behavior-based

[Borghol et al. 2012; Pinto et al. 2013; Yao et al. 2013; Chrysoula and Konstantinos, 2014]

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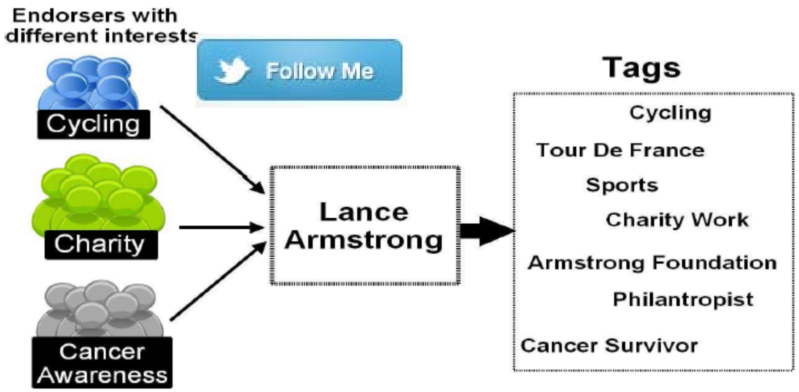
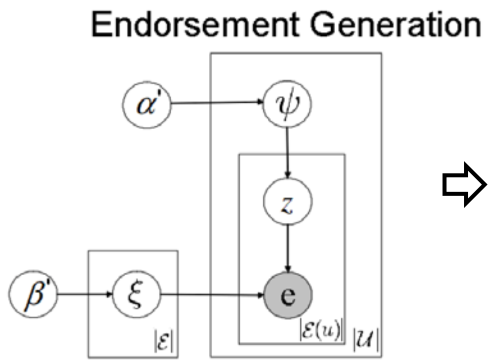
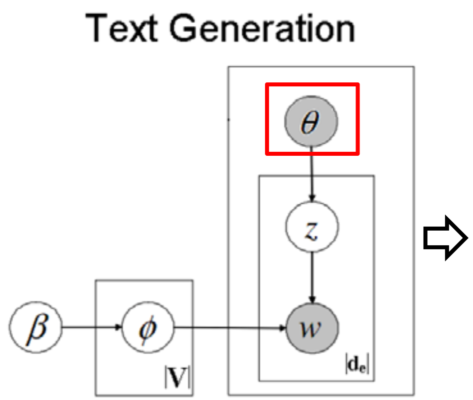
Endorsement-based Multimedia Annotation





entity-topic distribution θ

descriptive labels for each entity

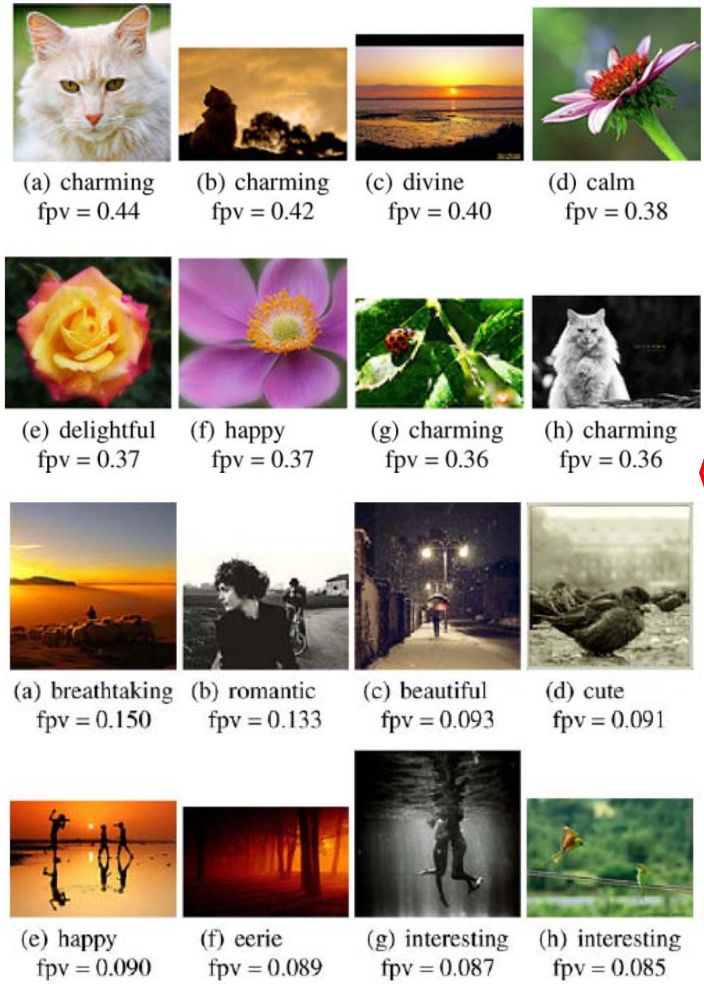


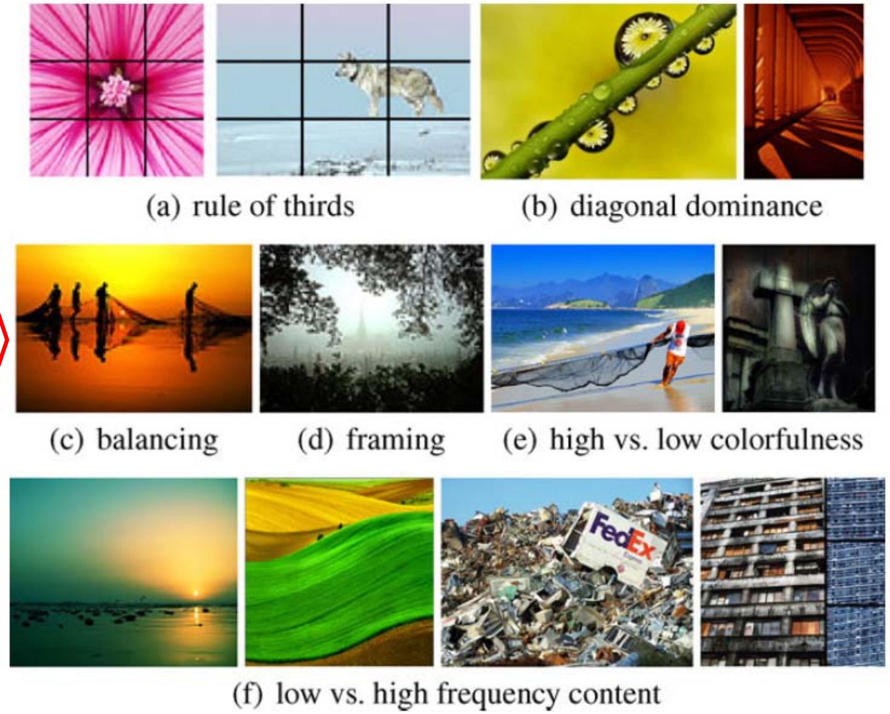
topic-word distribution

[Lappas et al. 2011] Theodoros Lappas, Kunal Punera, and Tamas Sarlos. Mining Tags Using Social Endorsement Networks. *SIGIR 2011.* (Yahoo! Research)

Endorsement-based Aesthetic Analysis

Flickr images with high “fav” rate





Principals of photographic composition

[Christian and Kersting, 2013] Bauckhage, Christian, and Kristian Kersting. "Can Computers Learn from the Aesthetic Wisdom of the Crowd?." *KI-Künstliche Intelligenz* (University of Bonn, Germany)

User Usage data-based Multimedia Analysis

User Usage Data

User usage Data

User-User Interaction

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[Yu et al. 2003; Borghol et al. 2012; Pinto et al. 2013]

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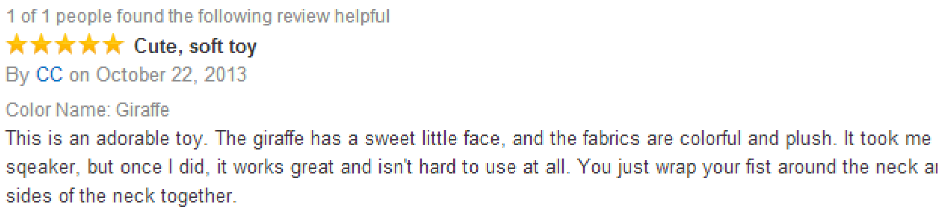
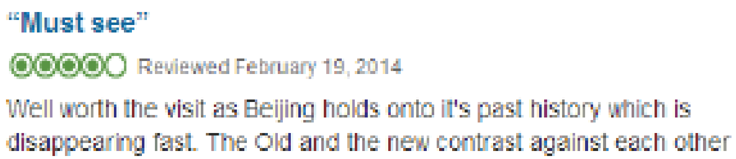
[Fang et al. 2014] Quan Fang, Changsheng Xu, and **Jitao Sang**. Word-of-Mouth Understanding: Entity-Centric Multimodal Aspect-Opinion Mining in Social Media. *TMM, accept with minor.*

Background: UGC Aspect-Opinion Mining

Product review


1 of 1 people found the following review helpful
★★★★★ **Cute, soft toy**
By CC on October 22, 2013
Color Name: Giraffe
This is an adorable toy. The giraffe has a sweet little face, and the fabrics are colorful and plush. It took me sqeaker, but once I did, it works great and isn't hard to use at all. You just wrap your fist around the neck ai sides of the neck together.

Trip summary


"Must see"
Reviewed February 19, 2014
Well worth the visit as Beijing holds onto it's past history which is disappearing fast. The Old and the new contrast against each other

Video comments

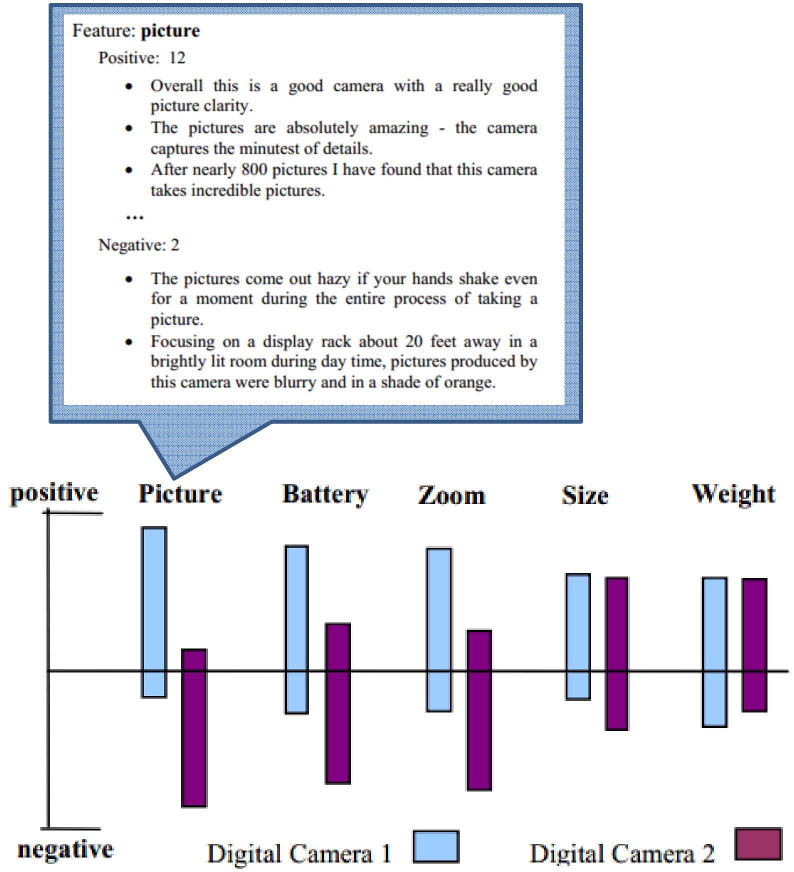
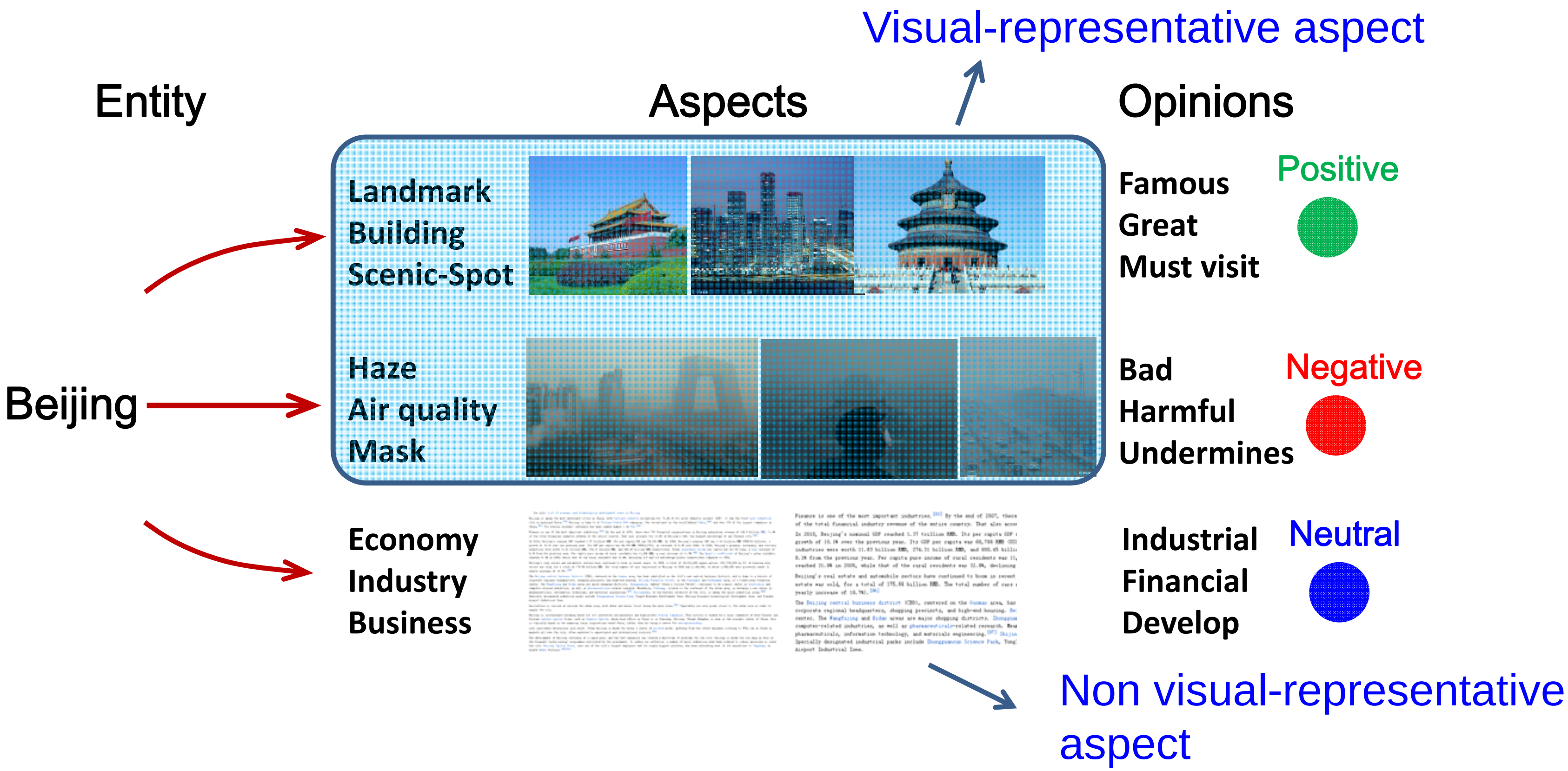


Figure 1: Visual comparison of consumer opinions on two products.

Aspect-opinion summarization

(Prof. Bing Liu, University of Illinois at Chicago, USA)

Motivation: Aspects are Multi-modal

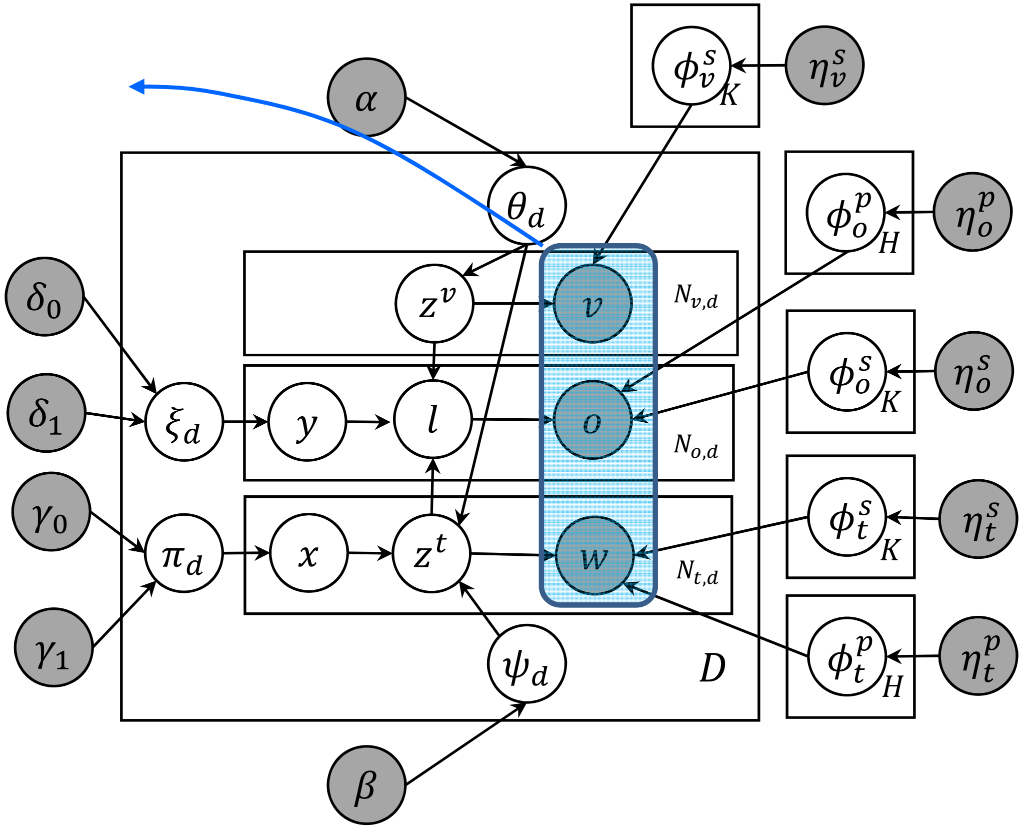


The example of multimodal aspects and opinions for "Beijing".

Multimodal Aspect-Opinion Mining (mmAOM)

Inputs:

- visual features
- opinion words
- aspect words



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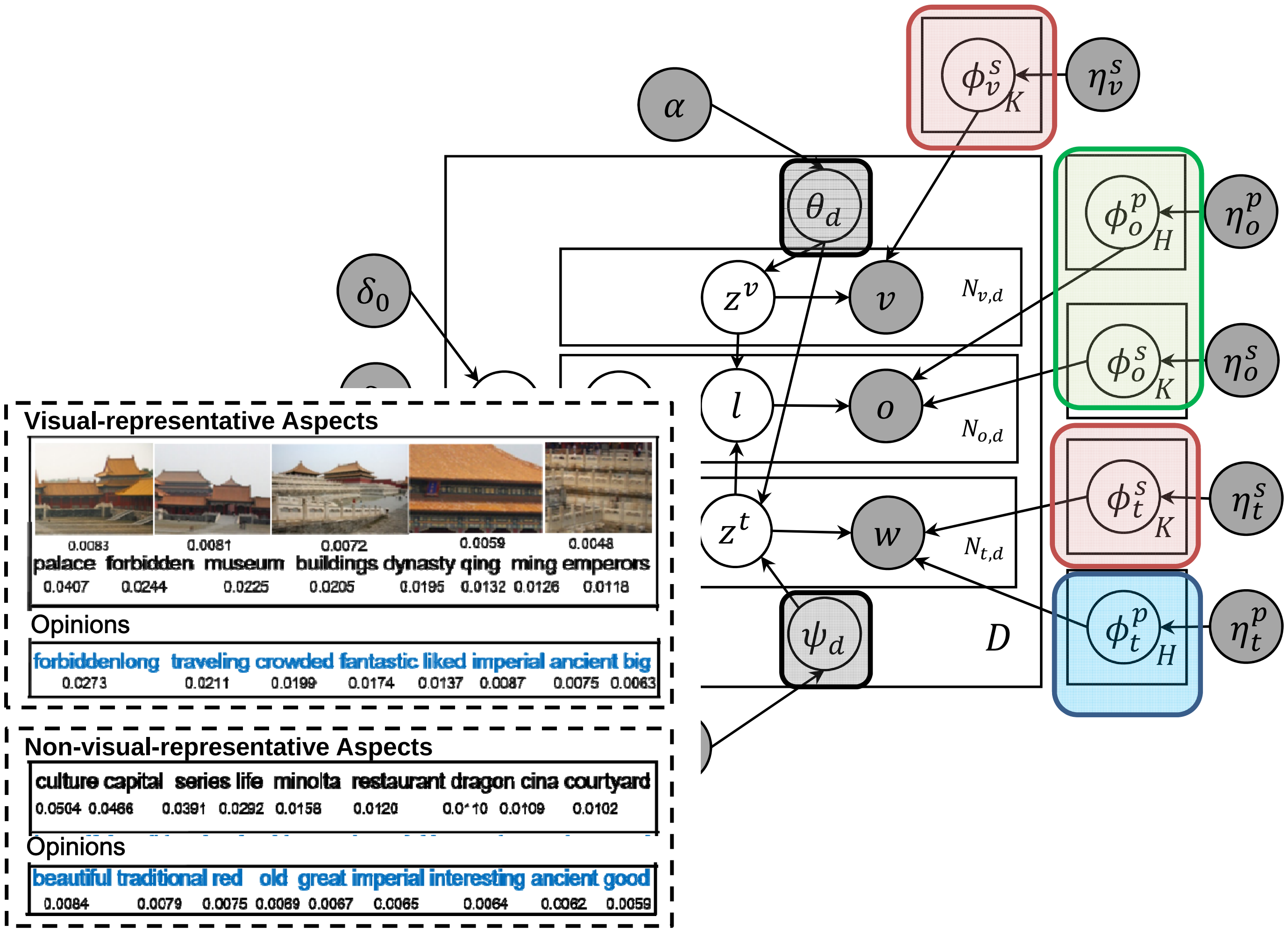
Multimodal Aspect-Opinion Mining (mmAOM)

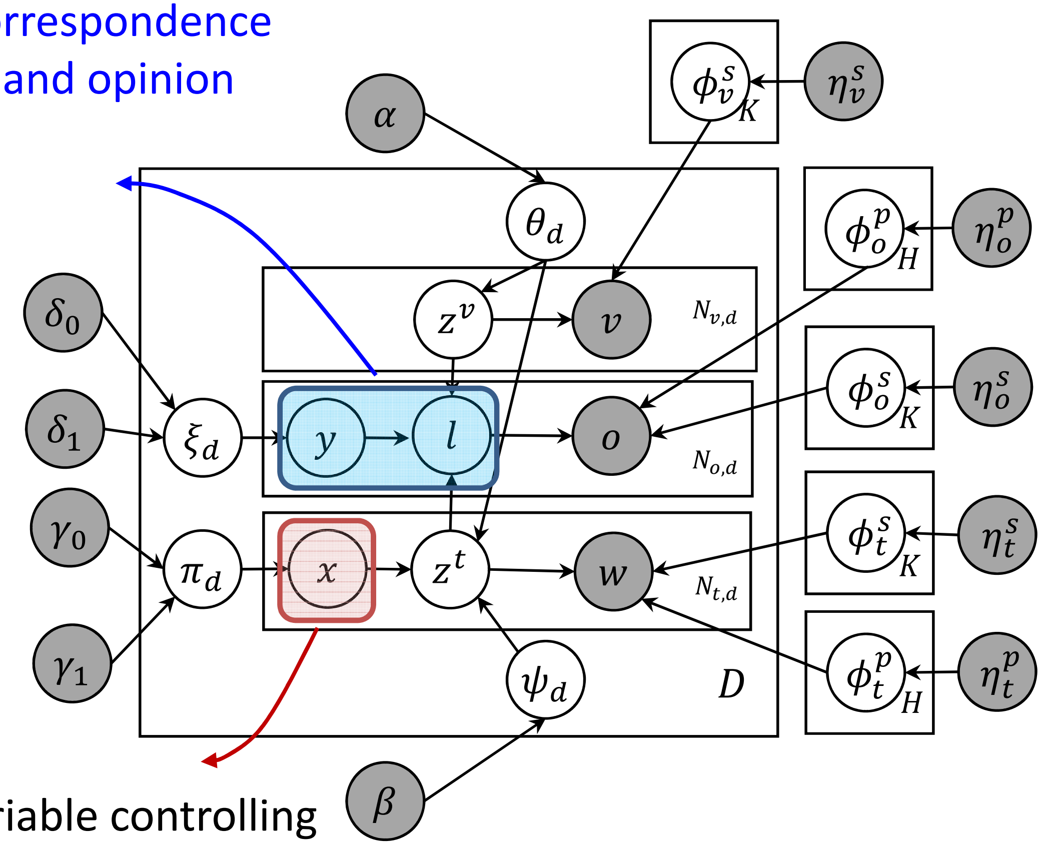


Outputs:

- Document-aspect distributions
- Visual-representative aspect topics
- Non.. aspect topics
- Opinion topics

Multimodal Aspect-Opinion Mining (mmAOM)

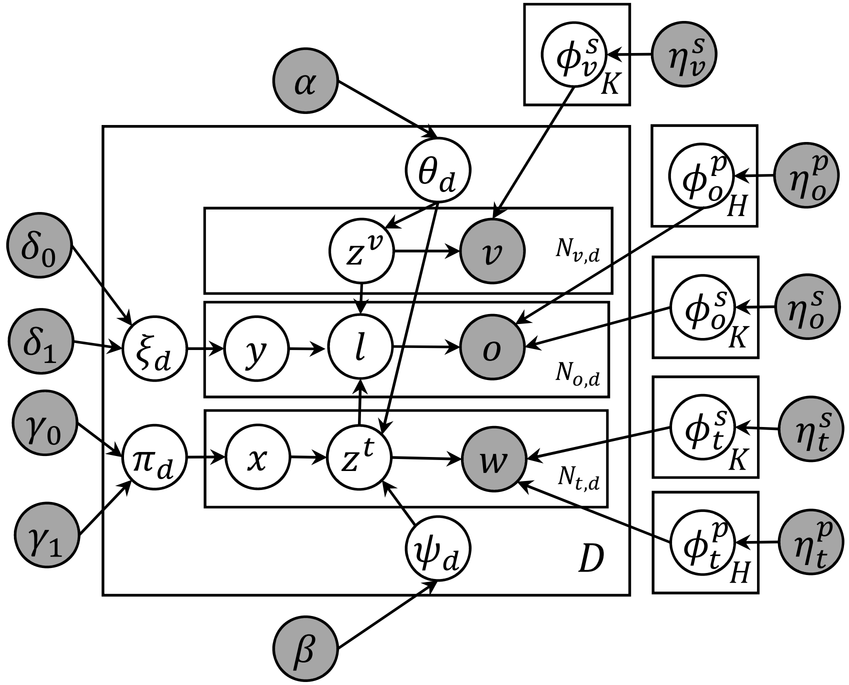
Switch and index variables controlling the correspondence between aspects and opinion words.



Switch binary variable controlling the generation of aspect words from visual-representative or non visual-representative aspects.

Multimodal Aspect-Opinion Mining (mmAOM)

1. For each visual-representative aspect including textual aspect z^w and visual aspect z^v, draw a multinomial distribution over aspect words, $\phi_t^s \sim Dir(\eta_w^s)$ and $\phi_v^s \sim Dir(\eta_v^s)$.
2. For each non-visual-representative aspect z^w, draw a multinomial distribution over aspect words, $\phi_t^p \sim Dir(\eta_w^p)$.
3. Draw a multinomial opinion word distribution for each aspect z, $\phi_o^s \sim Dir(\eta_o^s)$ for each z_s, $\phi_o^p \sim Dir(\eta_o^p)$ for each z_p.
4. For each document d,
   - Draw a multinomial distribution over visual-representative aspects, $\theta_d \sim Dir(\alpha)$.
   - Draw a multinomial distribution over non-visual-representative aspects, $\psi_d \sim Dir(\beta)$.
   - For each textual aspect word w in d,
     - Toss a coin x_{di}: $bernoulli(x_{di}) \sim beta(\gamma_0, \gamma_1)$.
     - if $x_{di} = 0$, draw a non-visual-representative aspect $z_{di}^w \sim Multi(\psi_d)$.
     - if $x_{di} = 1$, draw a visual-representative aspect $z_{di}^w \sim Multi(\theta_d)$.
     - Draw a word $w_{di} \sim Multi(\phi_{z_{di}^w})$ from z_{di}^w-specific word distribution.
   - For each visual aspect word v in d,
     - $x_{di} = 1$.
     - Draw a visual-representative aspect $z_{di}^v \sim Multi(\theta_d)$.
     - Draw a word $v_{di} \sim Multi(\phi_{z_{di}^v})$ from z_{di}^v-specific word distribution.



- For each opinion word o in d,
  - Toss a coin y_{di}: $bernoulli(y_{di}) \sim beta(\delta_0, \delta_1)$.
  - if $y_{di} = 0$, draw an opinion $l_{di}^o \sim \text{Uniform}(z_{w_1}^p, z_{w_2}^p, \ldots, z_{w_{n_p}^p})$.
  - if $y_{di} = 1$, draw an opinion $l_{di}^o \sim \text{Uniform}((z_{w_1}^s, z_{v_1}^s), (z_{w_2}^s, z_{v_2}^s), \ldots, (z_{w_{n_s}}^s, z_{v_{n_s}}^s))$.
  - Draw an opinion word o_{di} from the opinion-word distribution: $o_{di} \sim Multi(\phi_{l_{di}^o})$.

Experiments: Ability to Describe the Observation

TABLE IV
PERPLEXITY OF ASPECT IDENTIFICATION FOR DIFFERENT MODELS.

Model	Beijing	London	Paris	New York	Steve Jobs	Nelson Mandela	Nike	Adidas
LDA	4993.58	5694.98	6947.25	8499.195	11966.82	5416.84	1816.68	2499.61
Corr-LDA	4986.46	5691.35	6912.31	8497.80	11824.82	5395.62	1806.01	2467.90
mmLDA	4980.31	5589.10	6871.38	8582.67	11846.54	5326.64	1786.92	2418.32
AOM	4969.83	5638.24	6879.11	8459.18	11717.81	5307.19	1784.94	2397.06
smmAOM	4872.13	5567.49	6818.81	8437.78	11589.24	5356.91	1791.02	2391.39
mmAOM	**4576.41**	**5337.36**	**6685.72**	**8404.65**	**9799.83**	**5069.63**	**1714.74**	**2377.67**

TABLE V
PERPLEXITY OF OPINION PREDICTION FOR DIFFERENT MODELS.

Model	Beijing	London	Paris	New York	Steve Jobs	Nelson Mandela	Nike	Adidas
LDA	3375.14	3224.36	4089.48	4575.86	4473.20	2195.60	1277.39	1336.32
Corr-LDA	3419.90	3282.99	4112.34	4564.50	4378.37	2200.09	1280.15	1334.56
mmLDA	3316.57	3280.56	4179.48	4295.62	4272.32	2140.15	1276.61	1335.57
AOM	3309.18	3264.10	4063.24	3868.69	4430.71	2128.96	1286.49	1321.85
smmAOM	3267.21	3235.73	4021.02	3849.76	4459.90	2055.20	1270.11	1304.78
mmAOM	**3202.22**	**3088.97**	**3769.14**	**3653.71**	**4172.85**	**1935.42**	**1188.50**	**1261.19**

Experiments: the Aspect-Opinion for Brand

Adidas

aspect

opinion

VR #1

0.0258 0.0135 0.0117 0.0098

forfun vivo circo finland fotos voador people face men game

0.0417 0.0370 0.0356 0.0329 0.0297 0.0244 0.0242 0.0218 0.0195 0.0190

better play pretty running looking watching saying cushioning like

0.0545 0.0416 0.0287 0.0183 0.0157 0.0131 0.0106 0.0080 0.0054

VR #12

0.0252 0.0218 0.0169 0.0136 0.0134 0.0101

shoes collection sale air sneakers sky asics max vintage

0.0930 0.0508 0.0478 0.0457 0.0439 0.0410 0.0407 0.0398 0.0380

new white shiny socken voetbal kicks played black good blue

0.0280 0.0246 0.0231 0.0197 0.0197 0.0186 0.0134 0.0122 0.0107 0.0105

NVR #3

match world cup fifa official football soccer brazil brazuca

0.0597 0.0576 0.0575 0.0453 0.0386 0.0369 0.0333 0.0316 0.0300

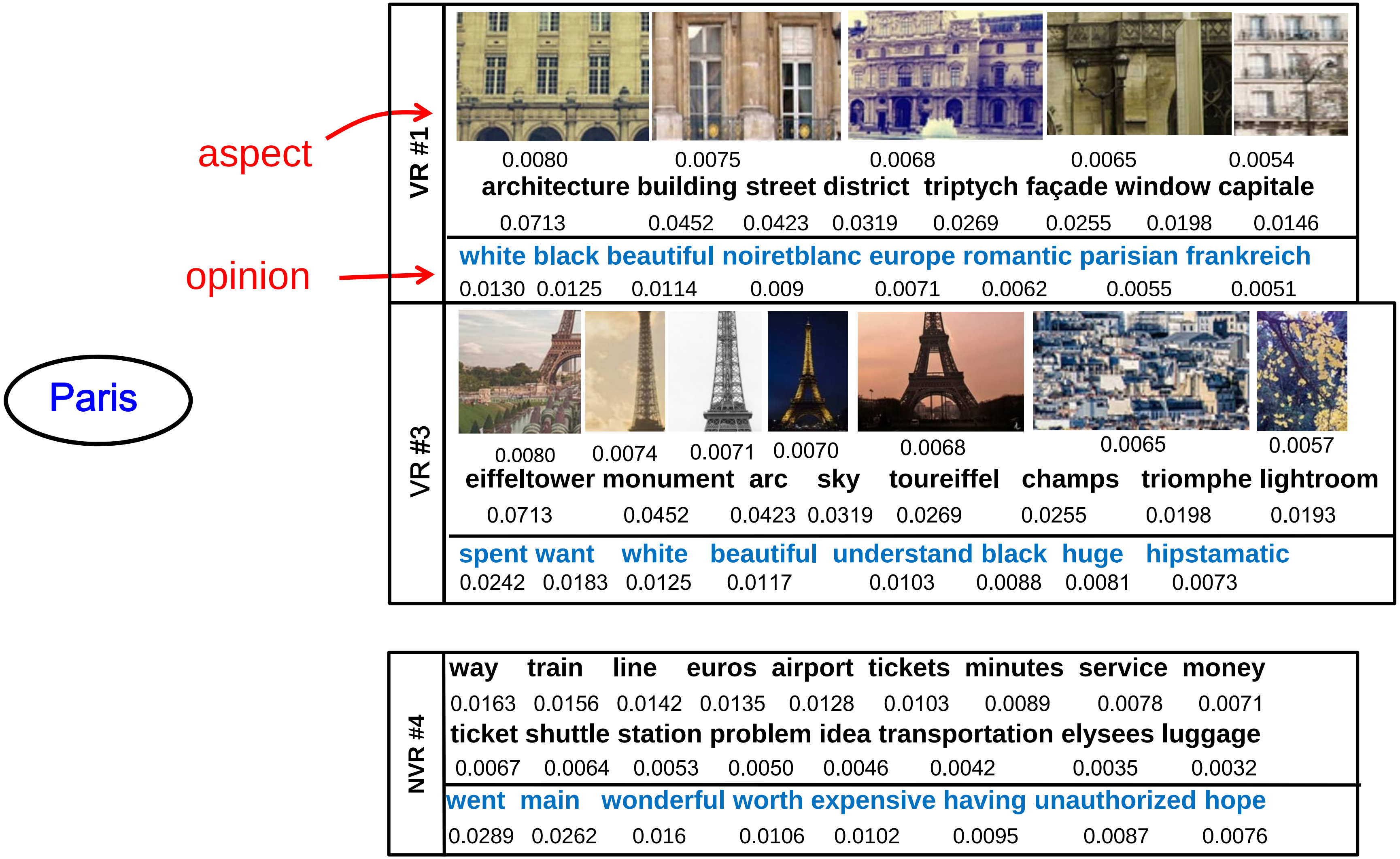
design property ykyeco fussball ballon tango dark opening

0.0183 0.01831 0.0151 0.0135 0.0124 0.0110 0.0107 0.0103

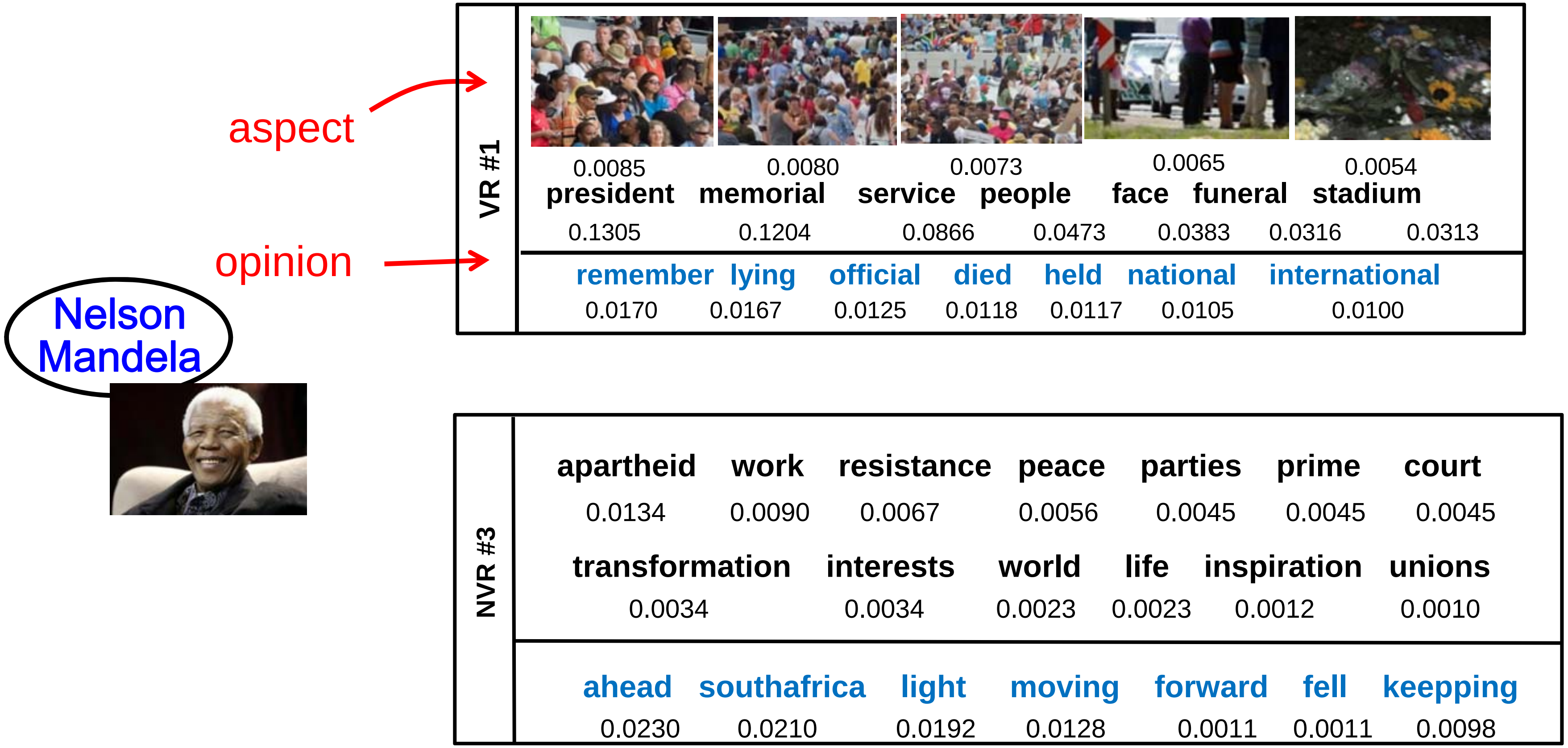
official ride big issued pelota tango wanted working took

0.0304 0.0258 0.0235 0.0165 0.0142 0.0119 0.0118 0.0095 0.0072

Experiments: the Aspect-Opinion for Location



Experiments: the Aspect-Opinion for Celebrity



Application: Multimodal Aspect-Opinion Retrieval

- **mmMOM also outputs:**
  - dependency between visual aspects and textual aspects
  - dependency between (multimodal) aspects and opinions

W→VD

Query: shoes collectionsale air sneakers

Results:

Application: Multimodal Aspect-Opinion Retrieval

- **mmMOM also outputs:**
  - dependency between visual aspects and textual aspects
  - dependency between (multimodal) aspects and opinions

V→W

Query:

Results: soccer sneaker socks shorts player

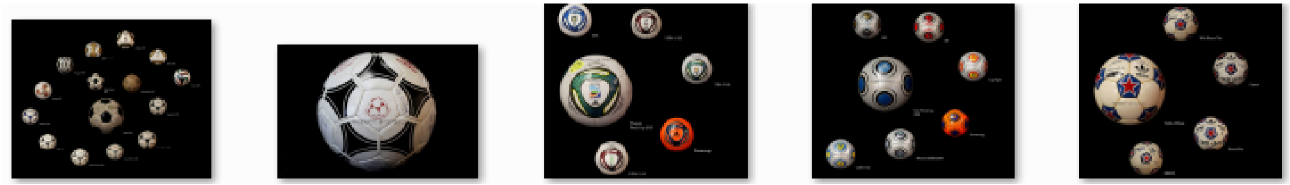
Application: Multimodal Aspect-Opinion Retrieval

- **mmMOM also outputs:**
  - dependency between visual aspects and textual aspects
  - dependency between (multimodal) aspects and opinions

W→O, V→O, W+V→O

Ball match world cup fifa official football

Aspect query:

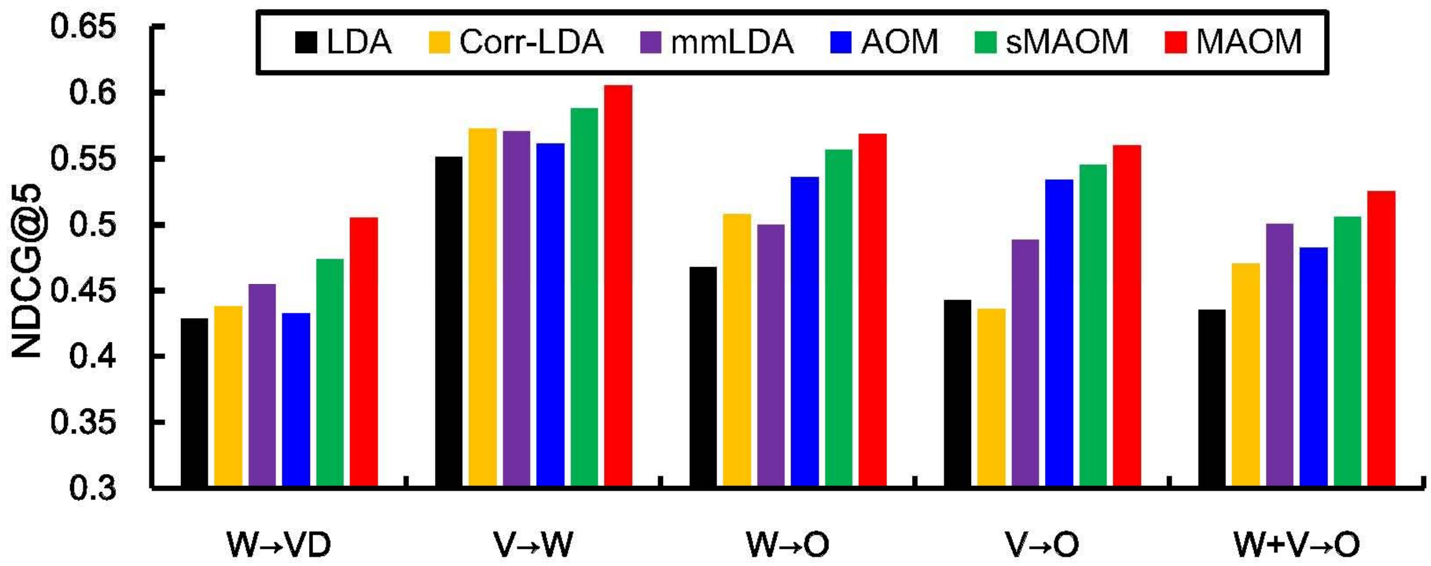


Opinion: New good get like better

Application: Multimodal Aspect-Opinion Retrieval

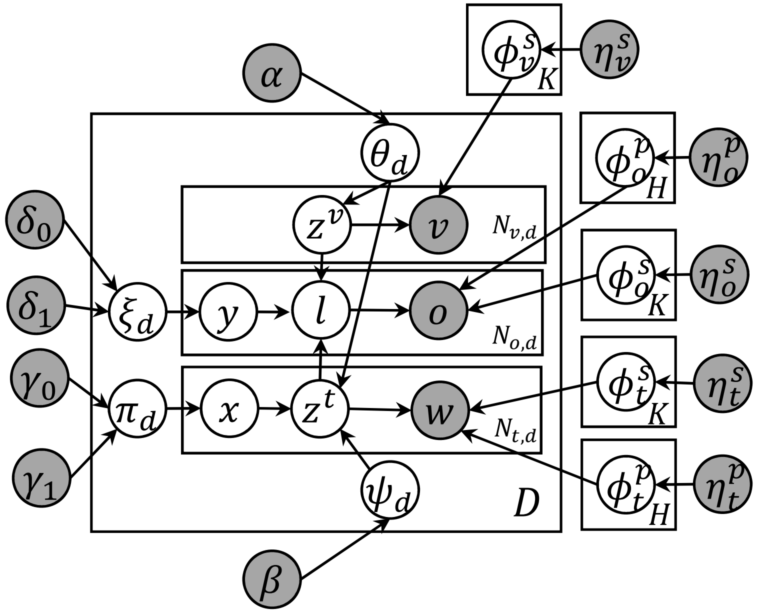
- **mmMOM also outputs:** **W→VD V→W**
  - dependency between visual aspects and textual aspects
  - dependency between (multimodal) aspects and opinions

W→O, V→O, W+V→O



Limitations of mmMOM

- Different entities cannot share the aspect or opinion topic spaces.
- The association between the aspect and opinion is loose. (sample by l)
- The interpretability of the derived topic representation is unsatisfactory.



User Metadata-based Multimedia Analysis

User Usage Data

UGC Metadata

User-User Interaction

User Metadata-based Multimedia Analysis

User Usage Data

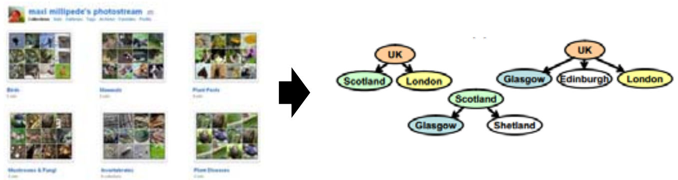
UGC Metadata

User-User Interaction

Individual: tag processing

[Liu et al. 2009; Zhu et al. 2010; Sang et al. 2011; Liu et al. 2012a; Sang et al. 2012a]

Collection: ontology construction



[Helic and Strohmaier 2010; Plangprasopchok et al. 2010; Sang and Xu 2011; Sang and Xu 2012a]

City dynamics: geo-tag mining

[Ye et al. 2011; Cranshaw et al. 2012; Fang et al. 2013a; Fang et al. 2013b]

User Metadata-based Multimedia Analysis

UGC Metadata

UGC Metadata

User-User Interaction

Individual:
tag processing

[Liu et al. 2009; Zhu et al. 2010; Sang et al. 2011; Liu et al. 2012a; Sang et al. 2012a]

- Xian-Sheng Hua. "Image and Video Tagging in the Internet Era," *Summer school on Social Media Retrieval.*

- Meng Wang, Bingbing Ni, Xian-Sheng Hua, Tat-Seng Chua. "Assistive Tagging: A Survey of Multimedia Tagging with Human-Computer Joint Exploration," *ACM Computing Surveys*

City dynamics: geo-tag mining

[Ye et al. 2011; Cranshaw et al. 2012; Fang et al. 2013a; Fang et al. 2013b]

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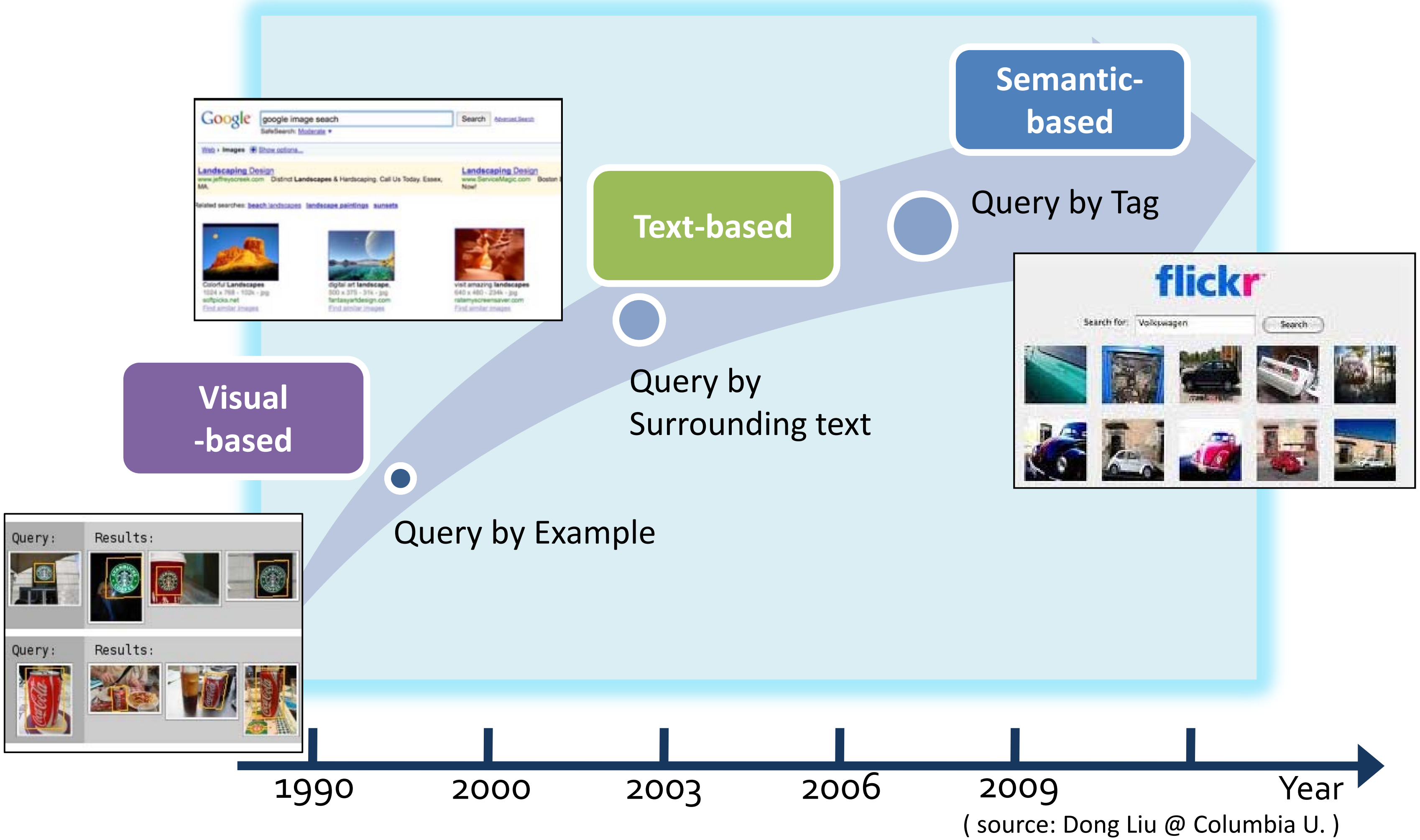
[Sang et al. 2011] Jitao Sang, Jing Liu, Changsheng Xu: Exploiting user information for image tag refinement. *ACM Multimedia* 2011.

[Sang et al. 2012a] Jitao Sang, Changsheng Xu, and Jing Liu. User-Aware Image Tag Refinement via Ternary Semantic Analysis. *IEEE Transactions on Multimedia* 14, 3-2 (2012).

Background: Multimedia Search Roadmap



Multimedia search roadmap

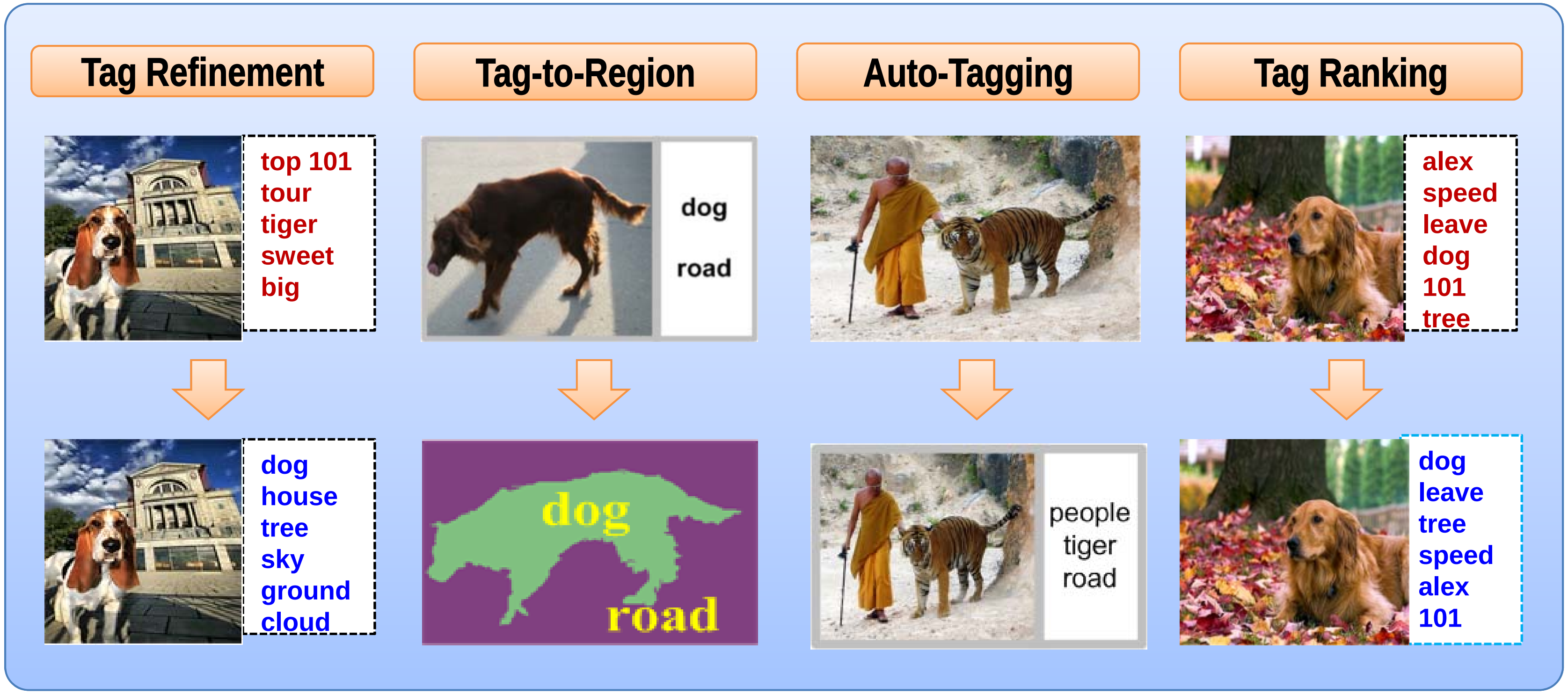
Background: UGC Tag Issues

- **UGC tags are helpful, but they are:**
  - ✓ Noisy
  - ✓ Subjective
  - ✓ Incomplete
  - ✓ Coarsely labeled

aeroplane
MSRC-355
sky
Canon 50D
building
favorite
grass
cool

Imprecise Tags	
Subjective Tags	
Missing Tags	sky building grass

Background: Social Tag Processing

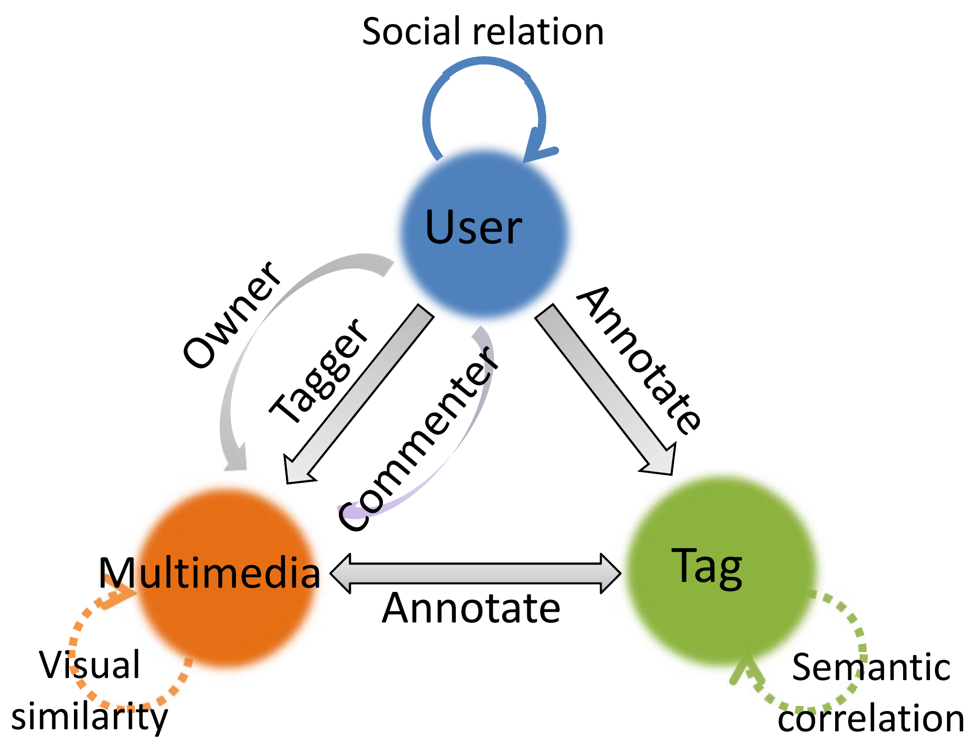


(source: Dong Liu @ Columbia U.)

Exploit the relations between Tag and Multimedia.

Motivation: Counting User In

- **Social multimedia sharing ecosystem**



Motivation: Counting User In

IMAGES | TAGS | USERS

TAG REFINEMENT
WEB IMAGE RETRIEVAL

$\leq 40\, papers$

IMAGE + TAG
* *Tag_relevance* X.Li et al. [2010]
* *Tag propagation* M. Guillaumin et al. [2009]
* *Simple label transfer* A. Makadia et al. [2008]..

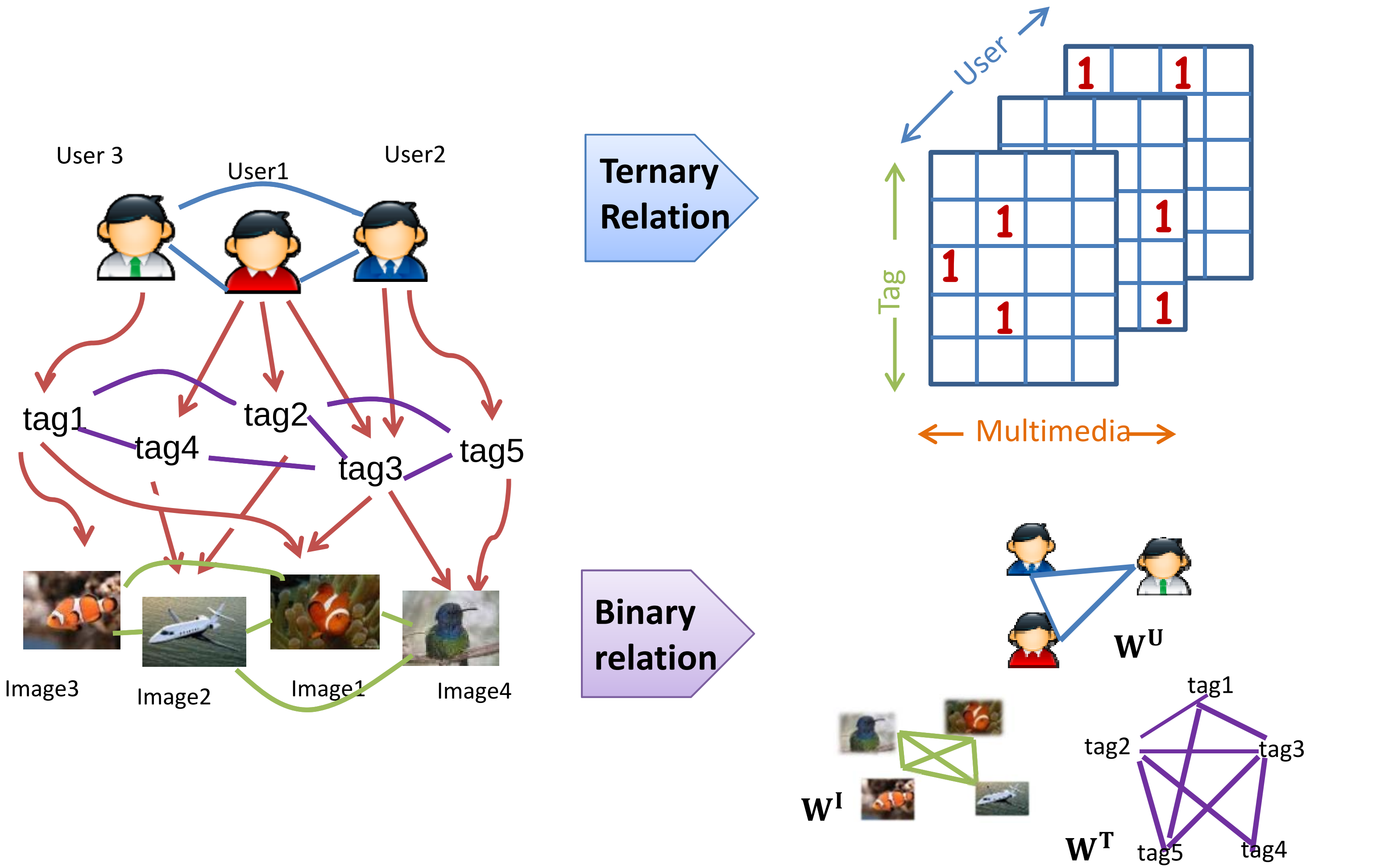
VIDEO + TAG
* *Tag localization* L. Ballan et al. [2011].....

IMAGE + TAG + USER
* *Tensor factorization* J. Sang et al. [2012]

- Alberto del Bimbo, panel talk on Cross media analysis and mining, ACM Multimedia 2013.

Ranking based Multi-correlation Tensor Factorization (RMTF)

- **Raw ternary and binary relation construction:**



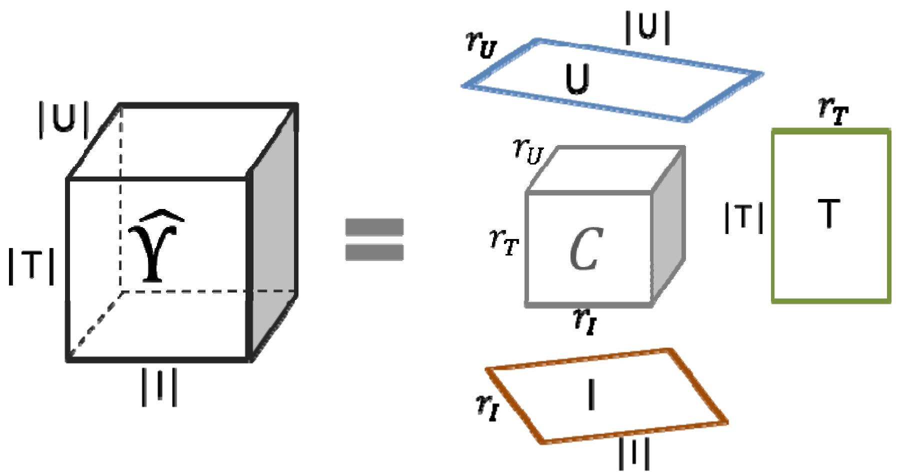
Ranking based Multi-correlation Tensor Factorization (RMTF)

- **Regularized Tensor Reconstruction:**

$$\min_{U,I,T,\mathcal{C}} g = \sum_{(\tilde{u},\tilde{i})\in\mathbb{P}_{\mathbb{O}}} \left(\sum_{t^{+}\in\mathbb{T}^{+}_{\tilde{u},\tilde{i}}} \sum_{t^{-}\in\mathbb{T}^{-}_{\tilde{u},\tilde{i}}} f(\hat{y}_{\tilde{u},\tilde{i},t^{-}} - \hat{y}_{\tilde{u},\tilde{i},t^{+}}) \right) + \alpha(tr(U^{\top}L_{U}U) + tr(I^{\top}L_{I}I) + tr(T^{\top}L_{T}T))$$
$$+ \beta\left(\|U\|_F^2 + \|I\|_F^2 + \|T\|_F^2 + \|C\|_F^2\right)$$

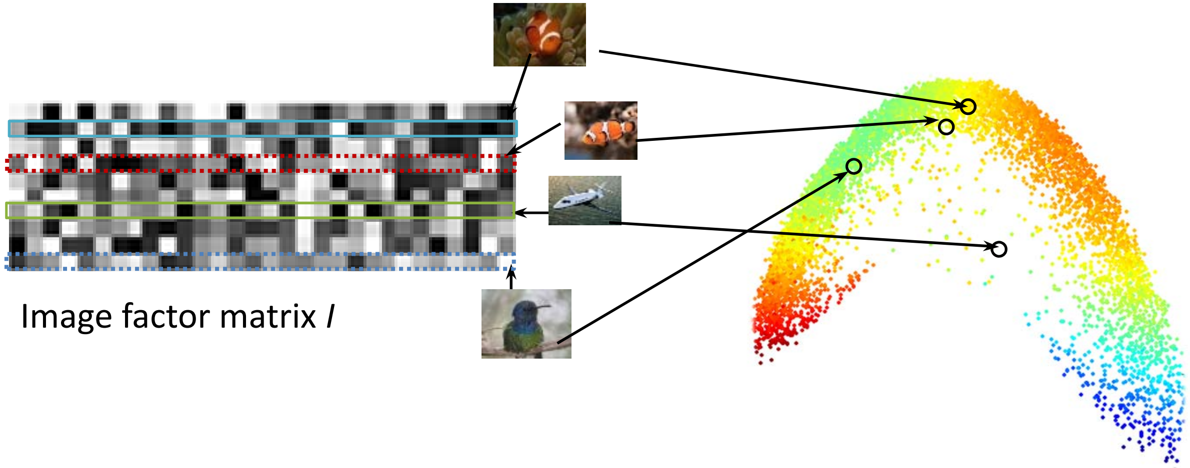
Ranking-based Tensor decomposition

binary relation regularization



Ranking based Multi-correlation Tensor Factorization (RMTF)

- **The derived factor matrices define latent subspaces:**



- **Exploiting factor matrices to obtain improved binary or ternary relations :**

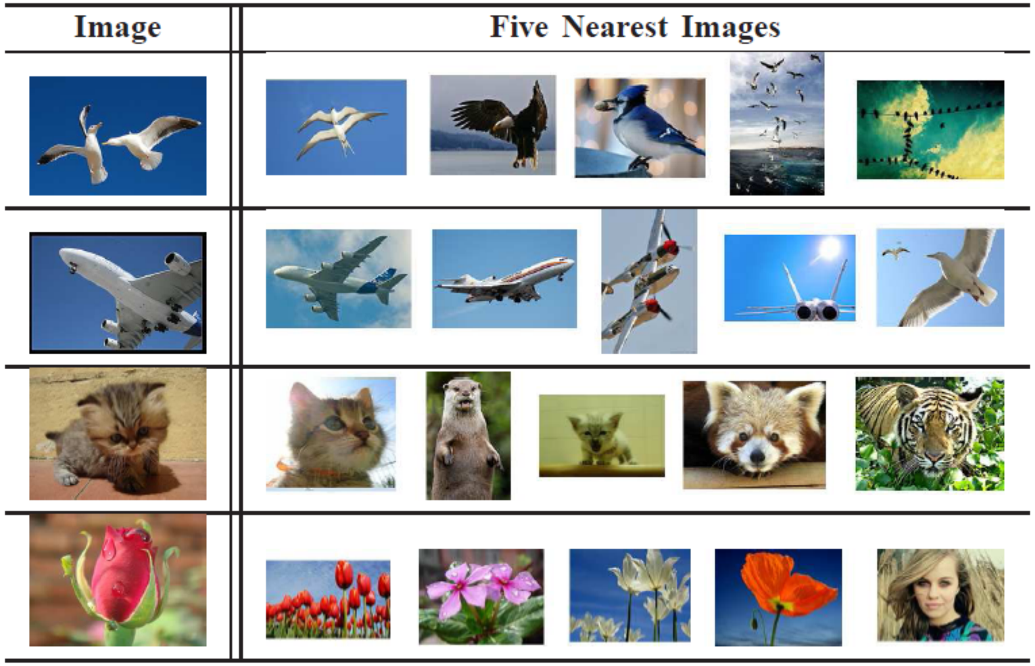
$$T_I = C \times_t T \times_u \mathbf{1}_{r_U}{}^T$$ map tag representation to image subspace

$$X^{IT} = I \cdot T_I$$ calculate the correlation between tag and image in the unique image subspace

$$Top(i,K) = \max_{t \in \mathbb{T}}{}^K X_{i:}^{IT}$$ obtain the top K tags according to the derived correlation

Experiments: Tag and Image Subspace

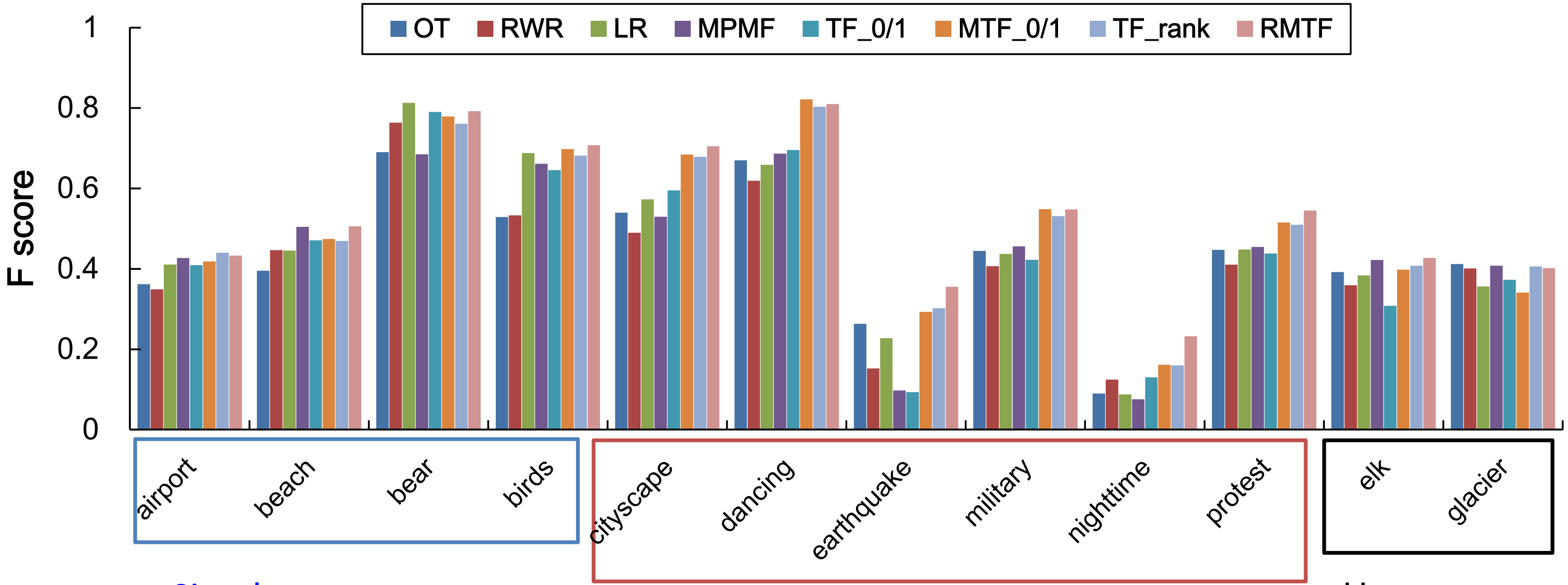
Selected Tag	Five Nearest Tags
cat	grass, animal, pet, dog, vacation
flower	blooms, butterfly, nature, spring, blossoms
airplane	aircraft, travel, planes, photographer, airport
buddhist	buddha, religion, buddhism, thailand, ancient



Experiments: Tag Refinement Evaluation

- **F-score on NUS-wide, 3,000 users, 120,000 pictures, 81 concepts:**

	OT	RWR	TRVSC	M-E Graph	LR	MPMF	TF_0/1	MTF_0/1	TF_rank	RMTF
F-score	0.477	0.475	0.490	0.530	0.523	0.521	0.515	0.542	0.531	**0.571**

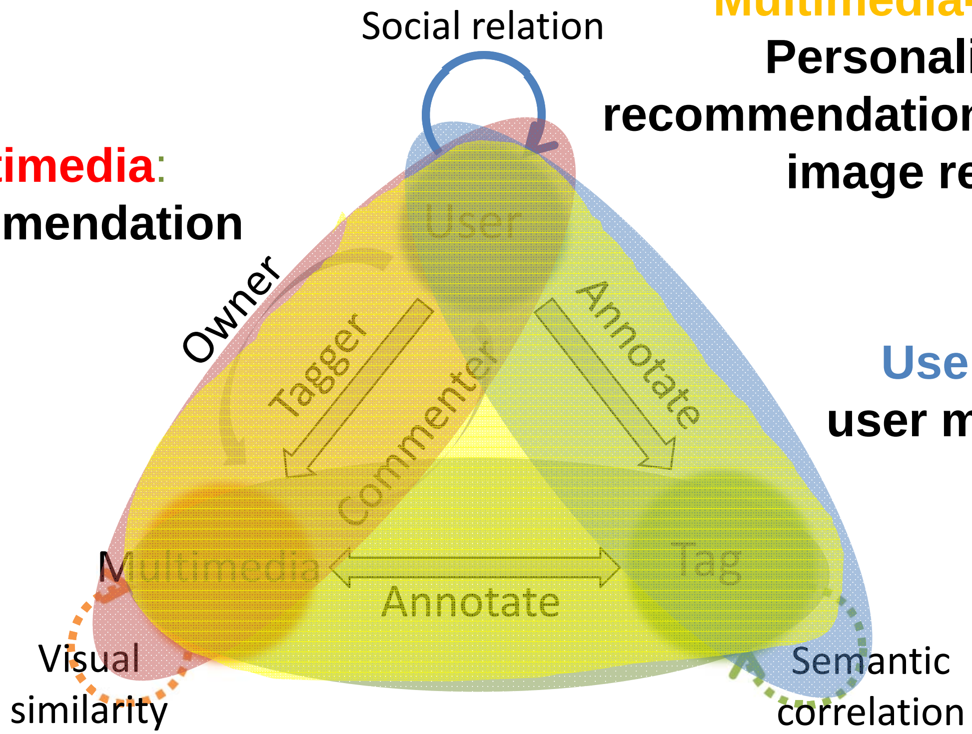


Simple concepts

Abstract/complex concepts

Uncommon concepts

Extensions: Different Factor Combinations



Multimedia-User-Tag: Personalized tag recommendation/ personalized image retrieval

User-Multimedia: image recommendation

User-Tag: user modeling

Multimedia-Tag: social tag processing

User Metadata-based Multimedia Analysis

UGC Metadata

Individual: tag processing

[Liu et al. 2009; Zhu et al. 2010; Sang et al. 2011; Liu et al. 2012a; Sang et al. 2012a]

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User-User Interaction

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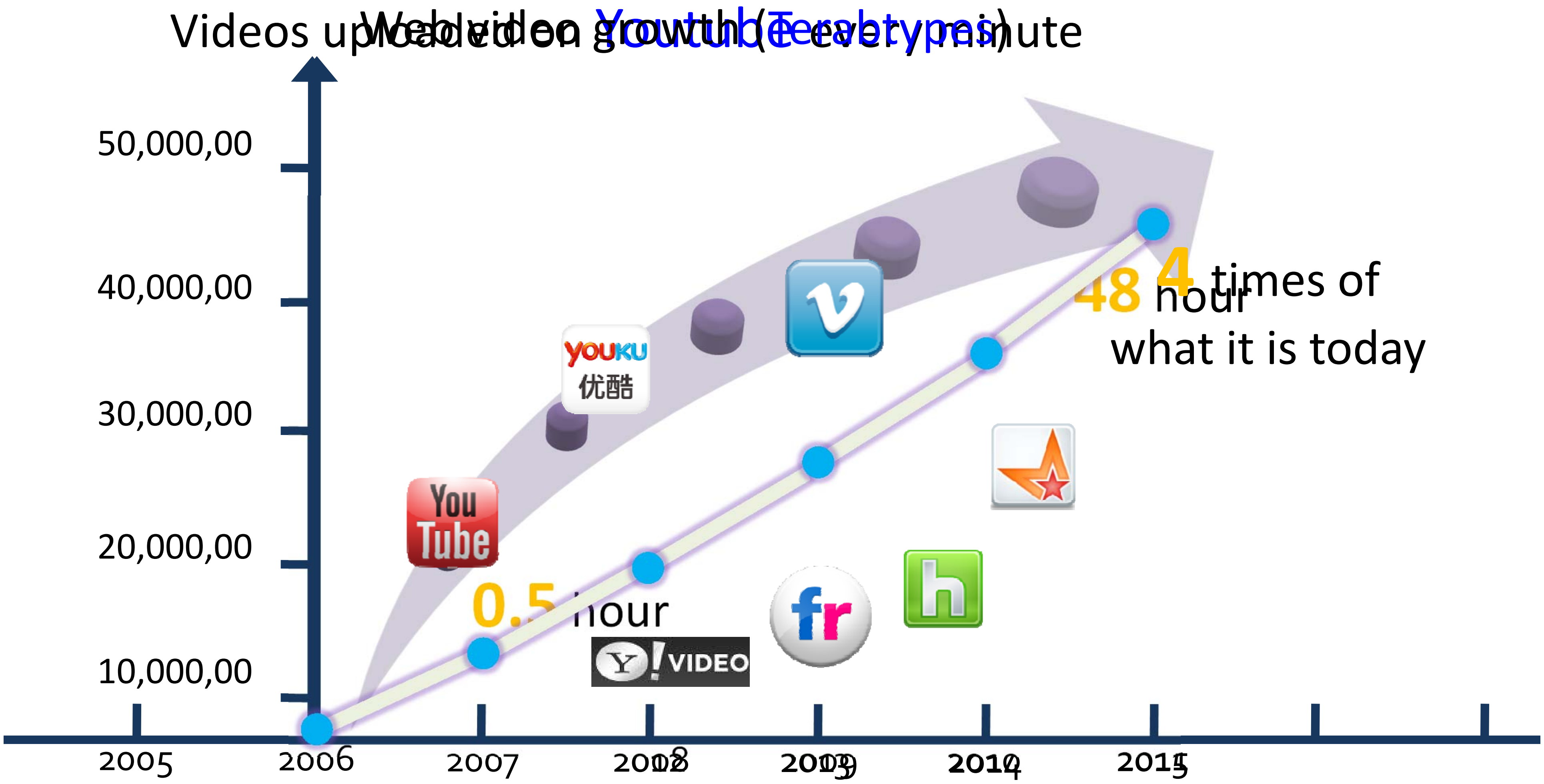
[Sang and Xu 2011] Jitao Sang and Changsheng Xu. Browse by chunks: Topic mining and organizing on web-scale social media. *TOMCCAP 2011*.

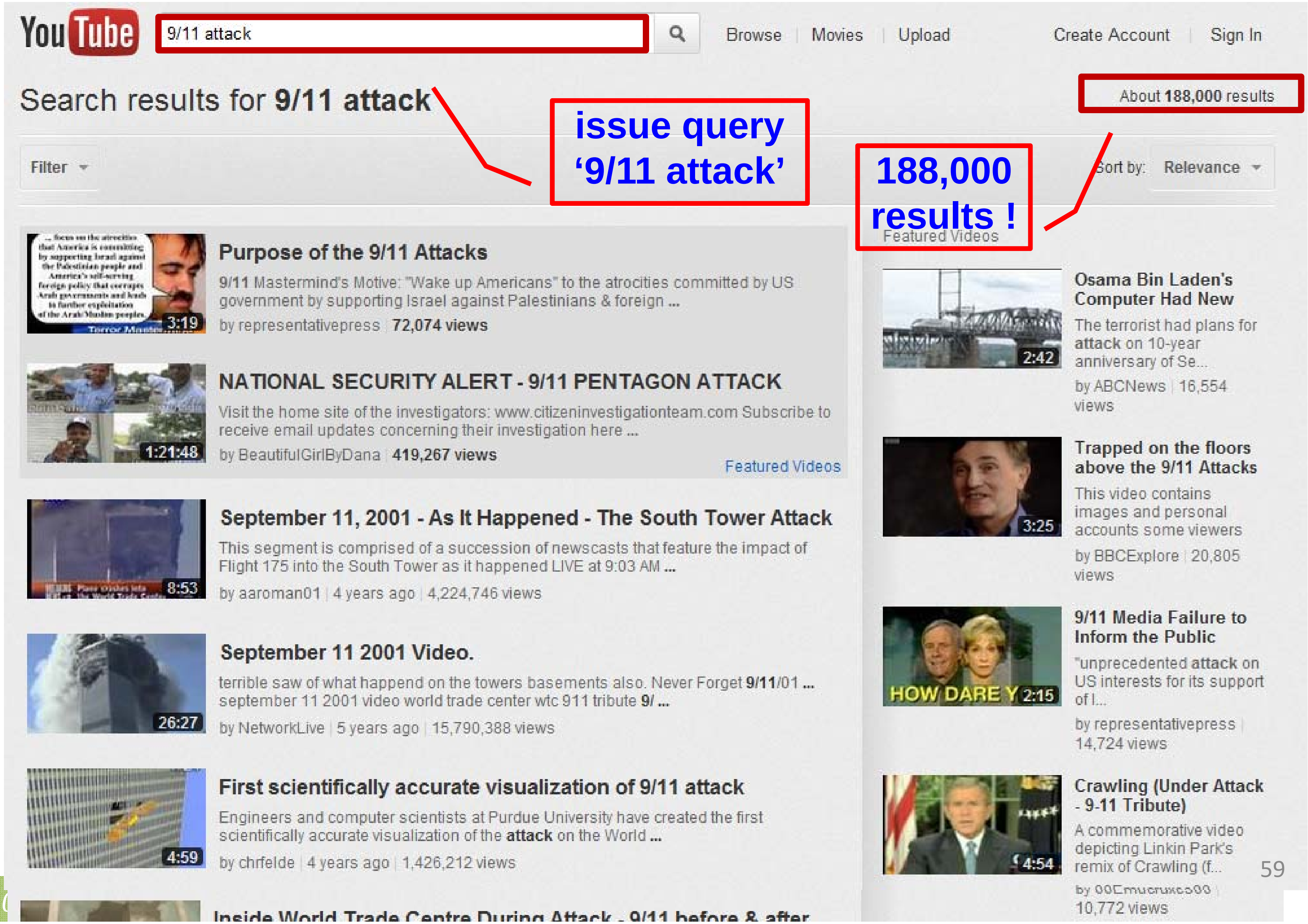
[Sang and Xu 2012a] Jitao Sang and Changsheng Xu. Faceted Subtopic Retrieval: Exploiting the Topic Hierarchy via a Multi-modal Framework. *Journal of Multimedia, 2012*.

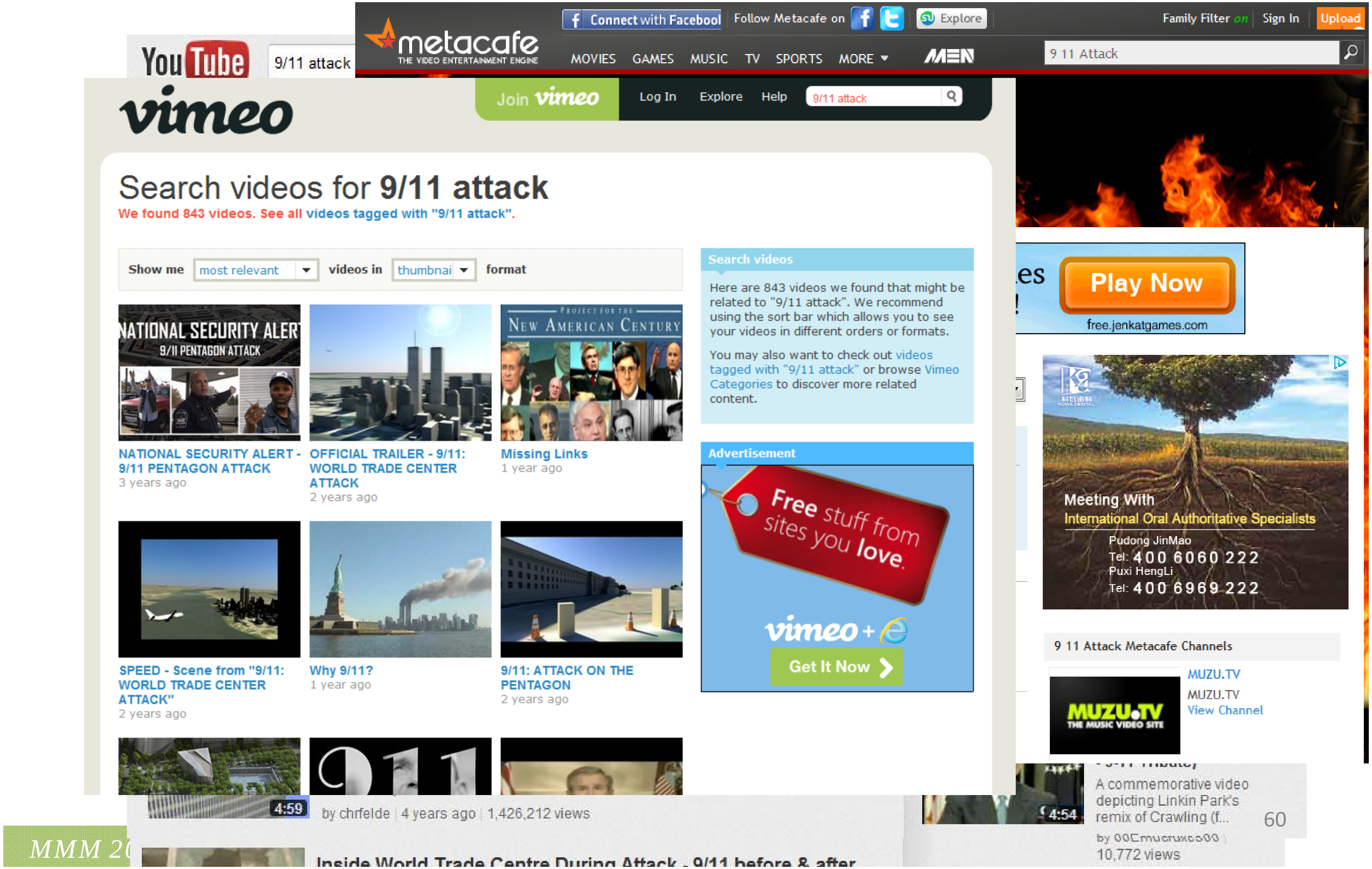
Background: Web Video is Boosting



Source: Cisco.com

Background: List-based Organization




You Tube
9/11 attack
metacafe
THE VIDEO ENTERTAINMENT ENGINE
Connect with Facebook
Follow Metacafe on
Explore
Family Filter on
Sign In
Upload
MOVIES GAMES MUSIC TV SPORTS MORE
9 11 Attack
vimeo
Join vimeo
Log In
Explore
Help
9/11 attack
Search videos for 9/11 attack
We found 843 videos. See all videos tagged with "9/11 attack".
Show me most relevant videos in thumbnail format
NATIONAL SECURITY ALERT - 9/11 PENTAGON ATTACK
3 years ago
OFFICIAL TRAILER - 9/11: WORLD TRADE CENTER ATTACK
2 years ago
Missing Links
1 year ago
SPEED - Scene from "9/11: WORLD TRADE CENTER ATTACK"
2 years ago
Why 9/11?
1 year ago
9/11: ATTACK ON THE PENTAGON
2 years ago
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Here are 843 videos we found that might be related to "9/11 attack". We recommend using the sort bar which allows you to see your videos in different orders or formats.
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International Oral Authoritative Specialists
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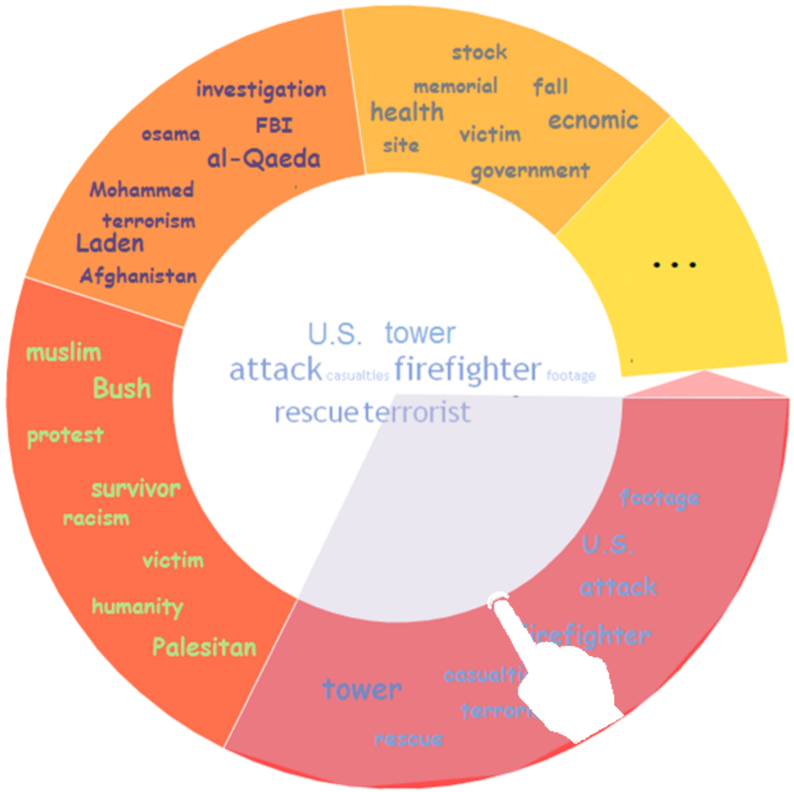
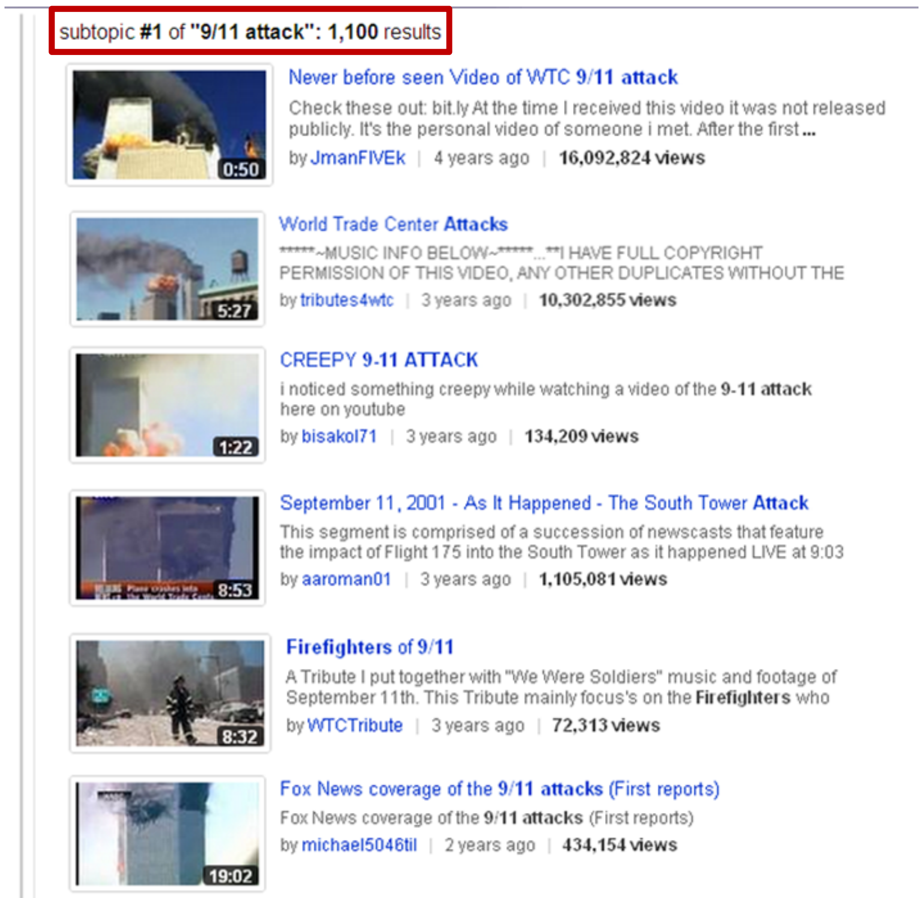
Tel: 400 6060 222
Puxi HengLi
Tel: 400 6969 222
9 11 Attack Metacafe Channels
MUZU.TV
MUZU.TV
View Channel
4:59
by chrfelde 4 years ago 1,426,212 views
Inside World Trade Centre During Attack - 9/11 before & after
4:54
A commemorative video depicting Linkin Park's remix of Crawling (f...
10,772 views
60
MMM 20

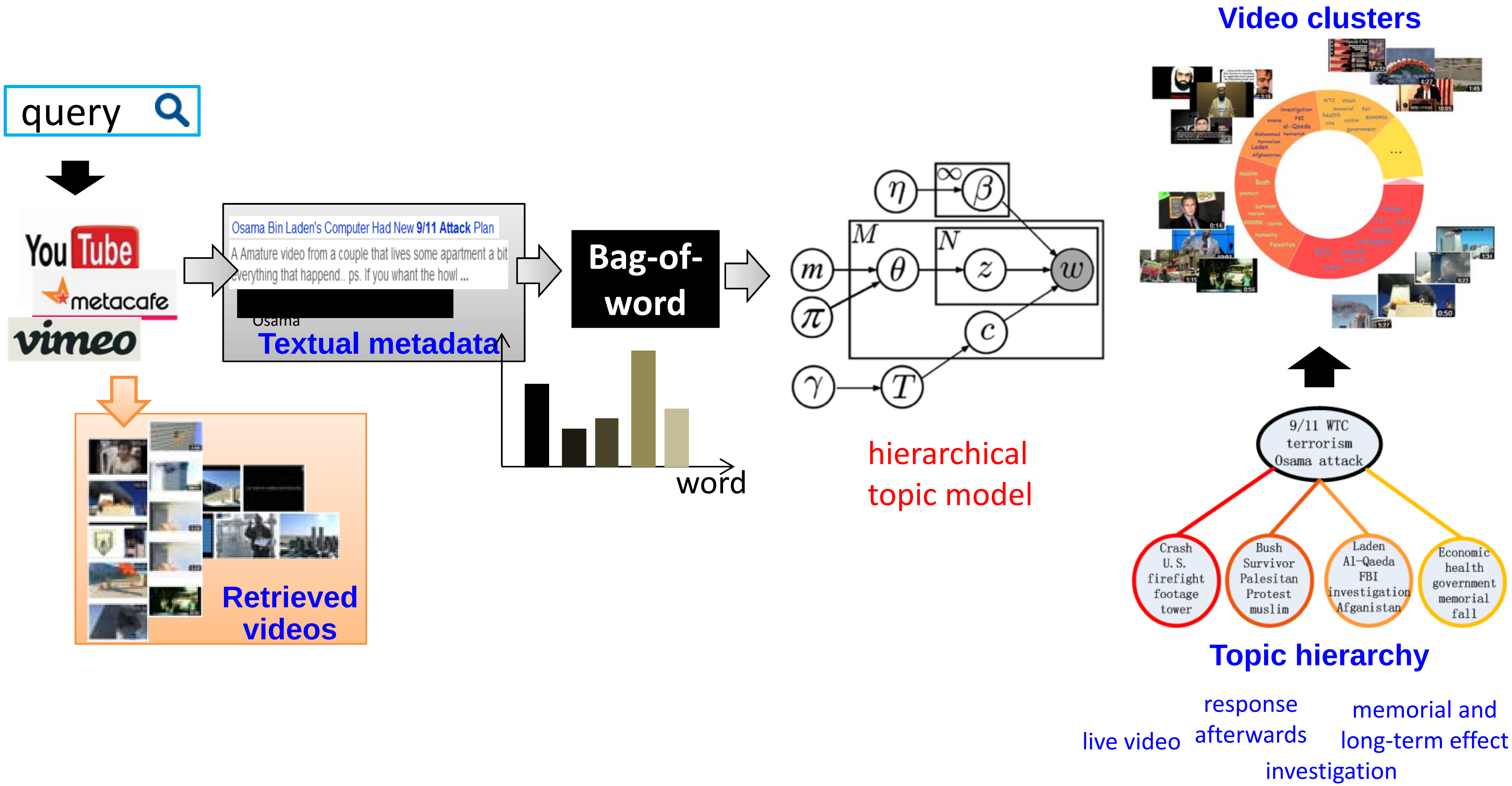
Motivation: Cluster-based Organization

User Interface: Hierarchical Semantics-based

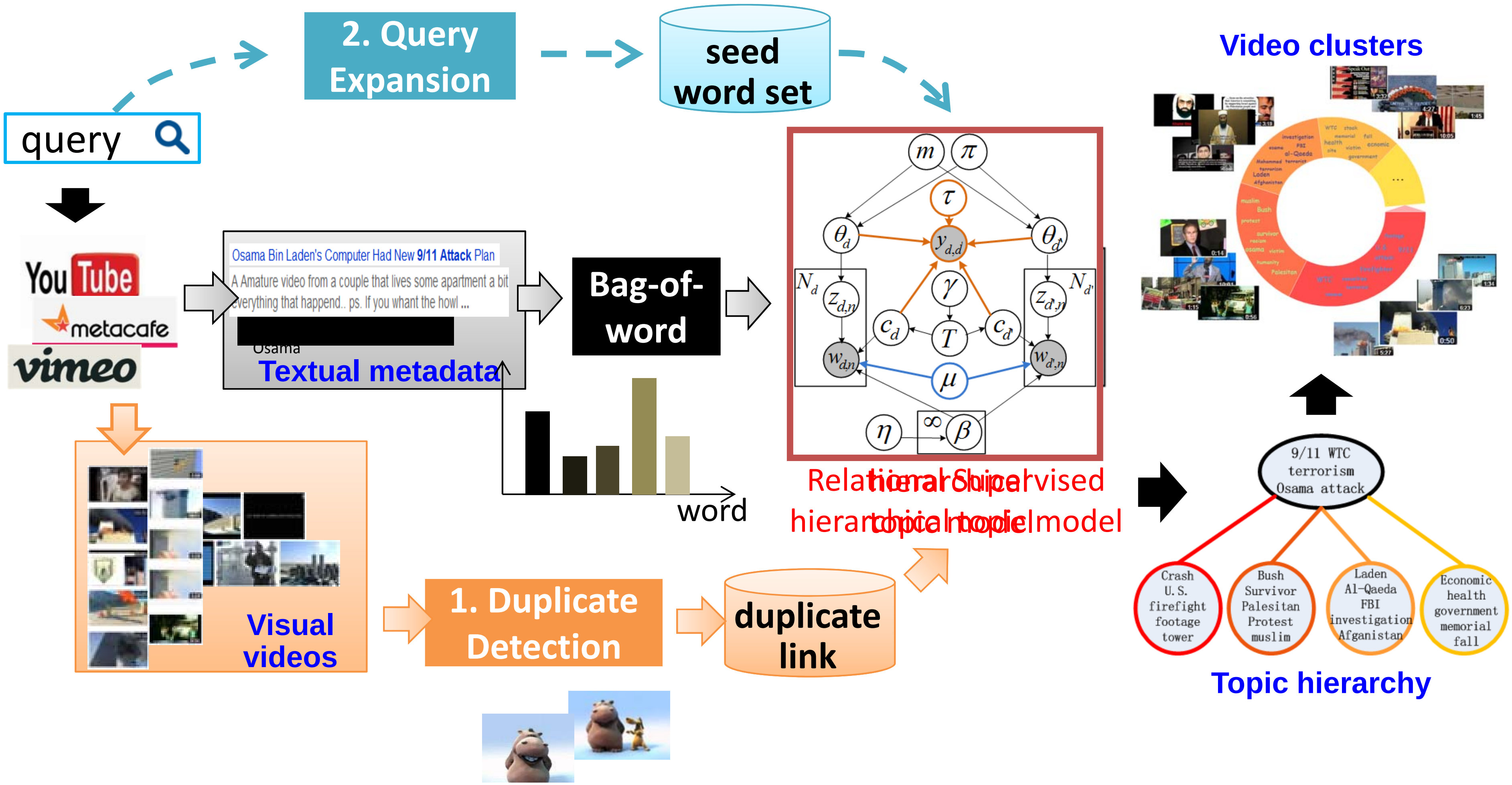




Relational Supervised hLDA (RShLDA)



Relational Supervised hLDA (RShLDA)

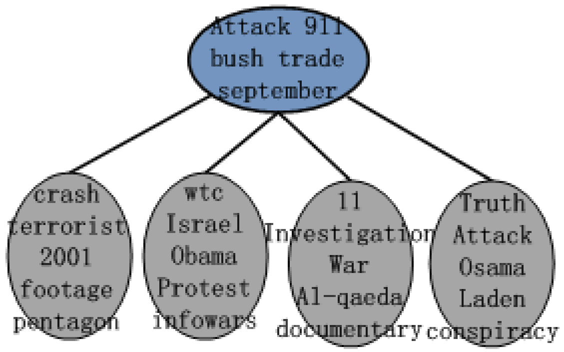


Experiments: Semantic and Video Clusters

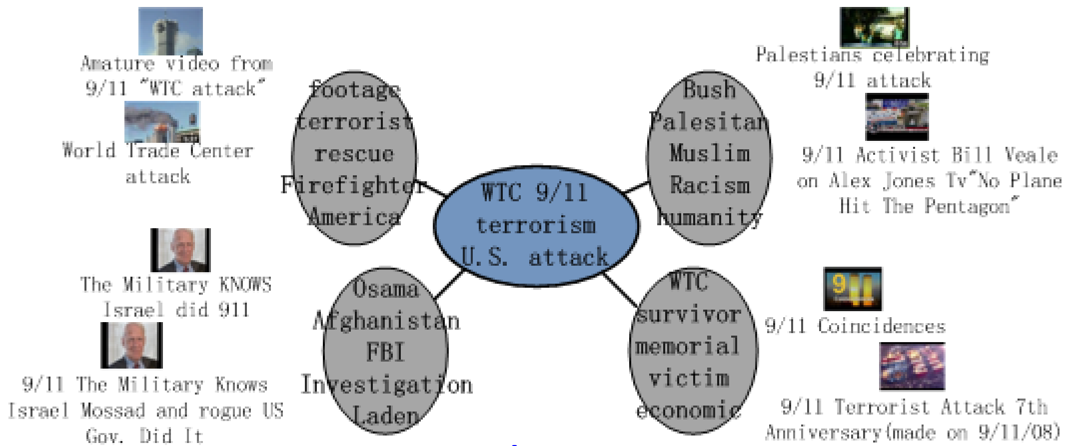
- **'9/11 attack':**

LDA

ShLDA

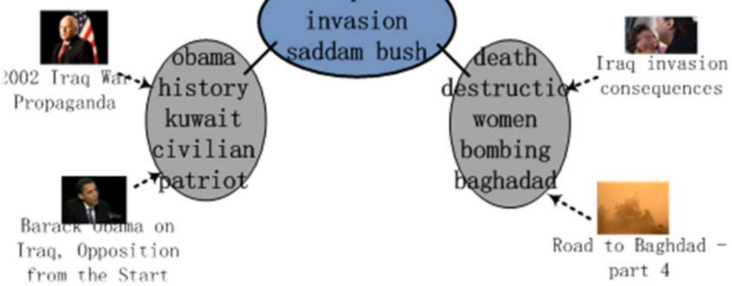


hLDA

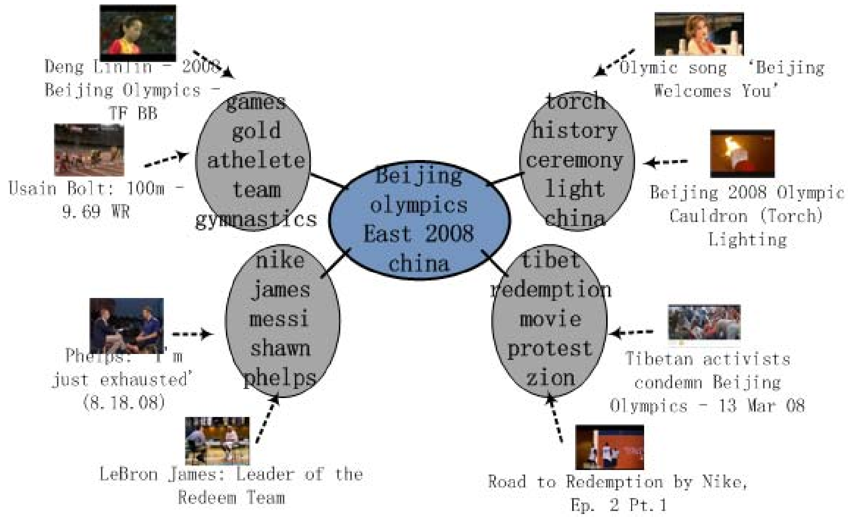


RShLDA

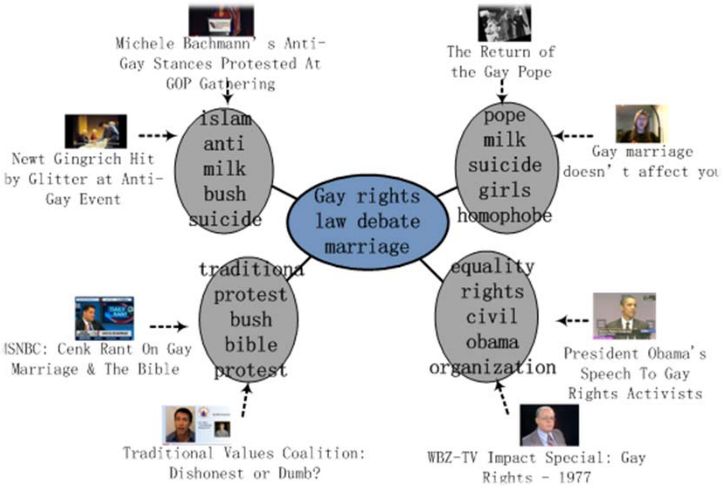
Experiments: Semantic and Video Clusters



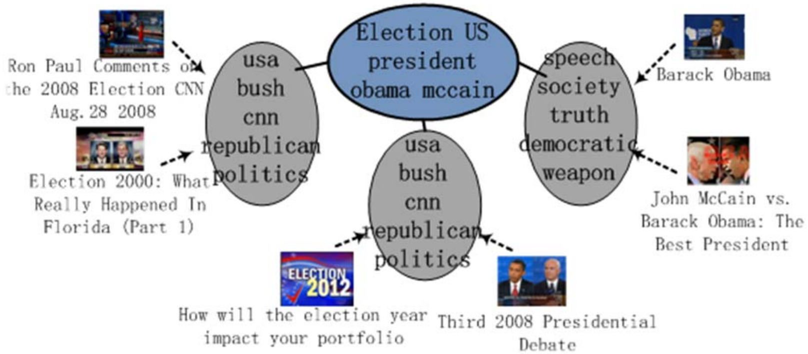
Query: Iraq War Invasion



Query: Beijing Olympics



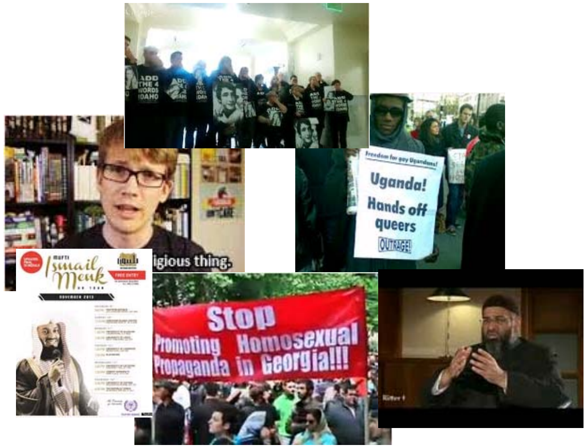
Query: gay rights



Query: US president election

Extension: Ideological Video Clusters

Query: gay rights



Cluster	Ratio	Opinion Words	Representative Comments
#1	42%	right equal civil evolution bible	"We have the right to love anyone. We as normal as 'normal' people, ..."
		free homosexual society life milk	"If someone chooses to be gay, it is his life and his own decision..."
#2	58%	god religion islam bush hell	"If you actually look deeply into a religion, it is almost impossible..."
		bad family traditional society protest	"Feelings are just feelings. Being gay is unnatural. I can list hundreds of .."

User Metadata-based Multimedia Analysis

UGC Metadata

Individual: tag processing

[Liu et al. 2009; Zhu et al. 2010; Sang et al. 2011; Liu et al. 2012a; Sang et al. 2012a]

UGC Metadata

Collection: ontology construction

- Jiebo Luo, Dhiraj Joshi, Jie Yu, Andrew Gallagher. "Geotagging in multimedia and computer vision—a survey".

- Yan-Tao Zheng, Zheng-Jun Zha, Tat-Seng Chua. "Research and applications on georeferenced multimedia: a survey."

User-User Interaction

City dynamics: geo-tag mining

[Ye et al. 2011; Cranshaw et al. 2012; Fang et al. 2013a; Fang et al. 2013b]

User Metadata-based Multimedia Analysis

UGC Metadata

UGC Metadata

User-User Interaction

- **Individual:** tag processing — [Liu et al. 2009; Zhu et al. 2010; Sang et al. 2011; Liu et al. 2012a; Sang et al. 2012a]
- **Collection:** ontology construction — [Helic and Strohmaier 2010; Plangprasopchok et al. 2010; Sang and Xu 2011; Sang and Xu 2012a]
- **City dynamics:** geo-tag mining — [Ye et al. 2011; Cranshaw et al. 2012; Fang et al. 2013a; Fang et al. 2013b]

[Fang et al. 2013a] Quan Fang, **Jitao Sang**, Changsheng Xu, Ke Lu. Paint the City Colorfully: Location Visualization from Multiple Themes. *MMM 2013*. Best Student Paper.

Background: Huge Photo Online

flickr 8 billion images

facebook 250 billion images

16 billion images

200 million images a day

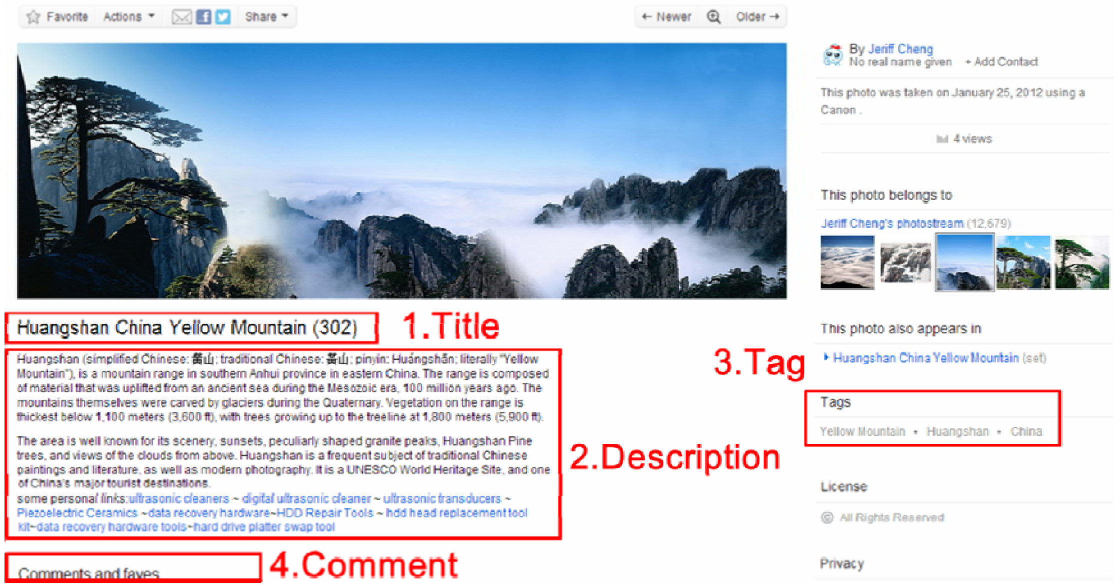
150 billion images

350 million images a day

Background: Geo-tagged Photo

Motivation: Geographical & Semantic

- Besides position, rich textual metadata is associated.



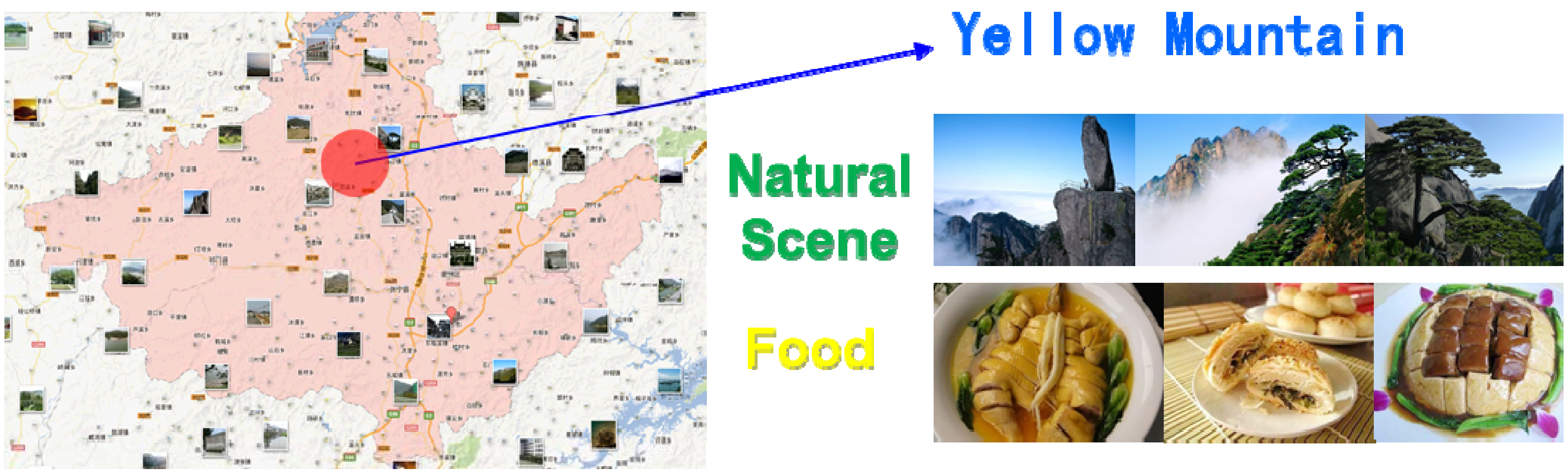
- This work exploits user-generated content to organize photos both geographically and semantically, and facilitate location visualization from multiple theme.

Motivation: Geographical & Semantic

- The visualization scheme is two-level:
  - ✓ **POI visualization**

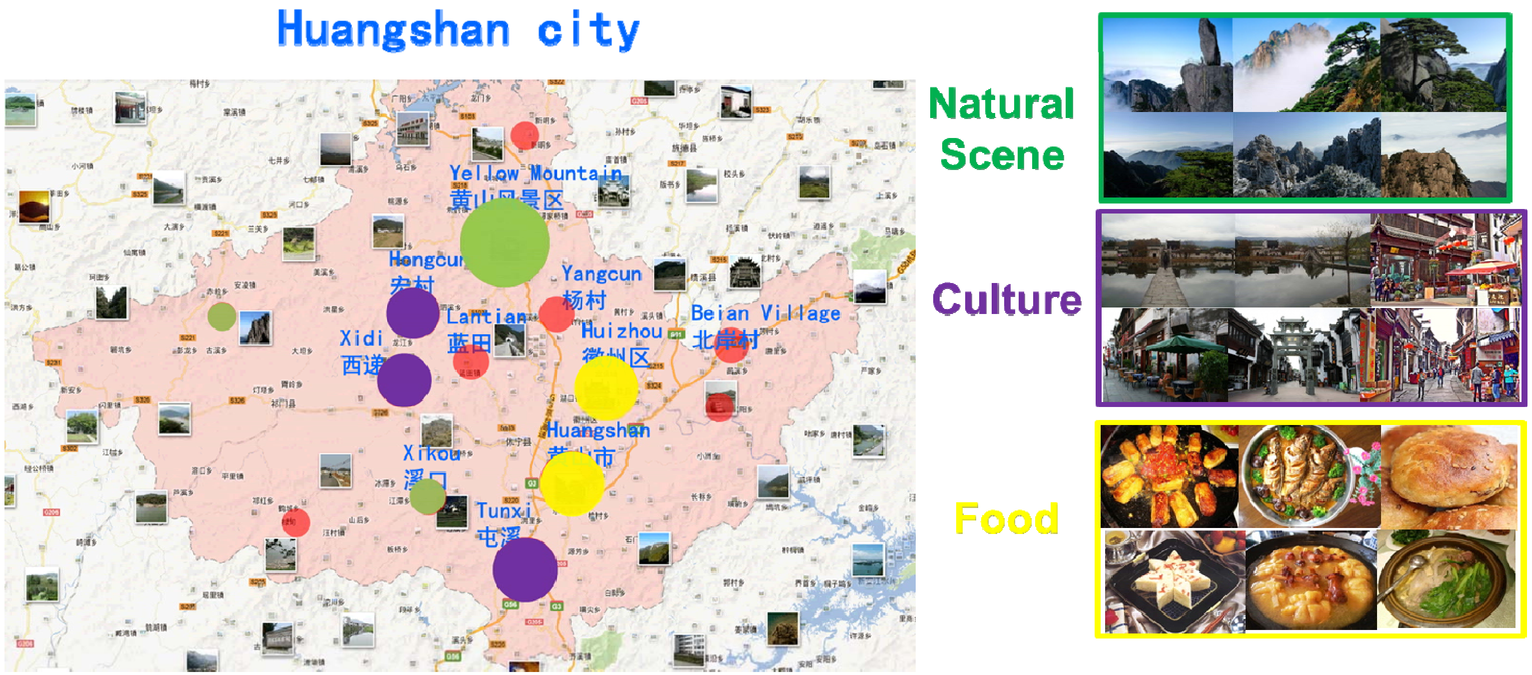
  POI - Point of Interest, a highly photographed place

  Theme - representative pattern or interesting topic

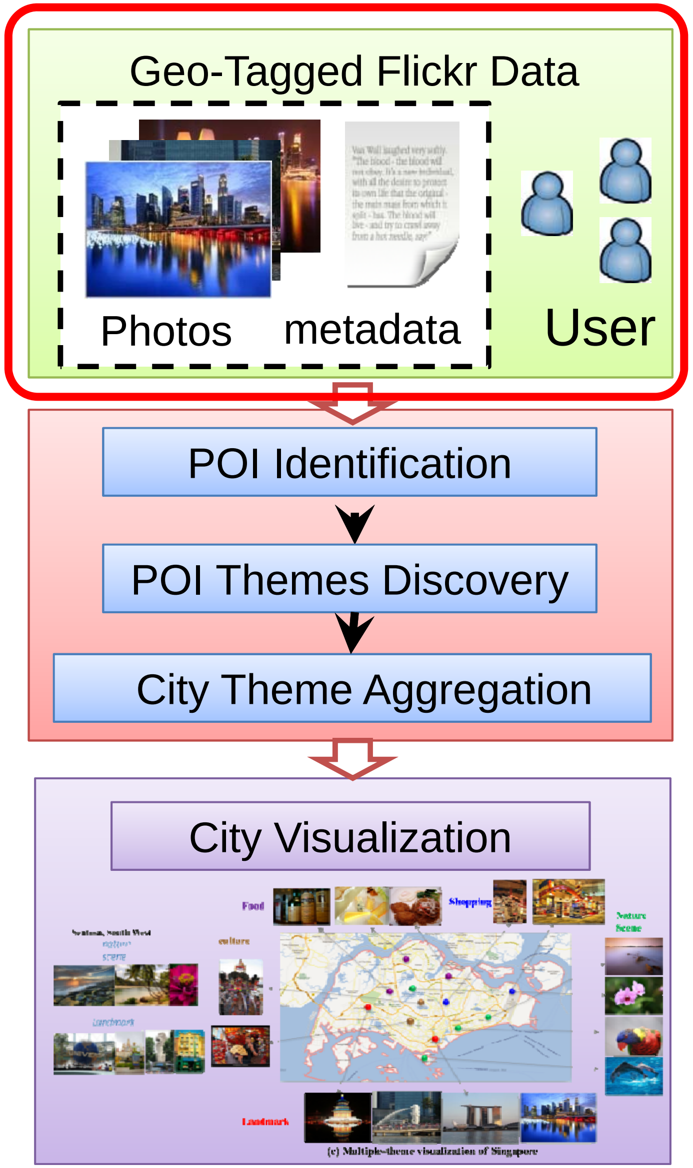


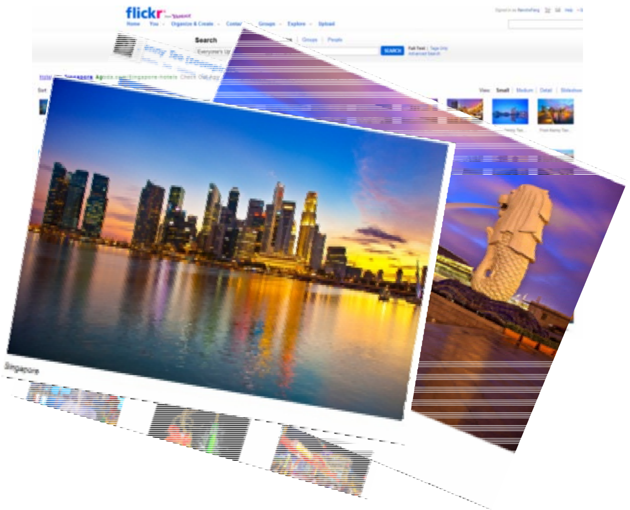
Motivation: Geographical & Semantic

- The visualization scheme is two-level:
  - ✓ **POI visualization**
  - ✓ **City visualization**
    - the summarized city themes,
    - the representative POIs and exemplary photos for each theme.



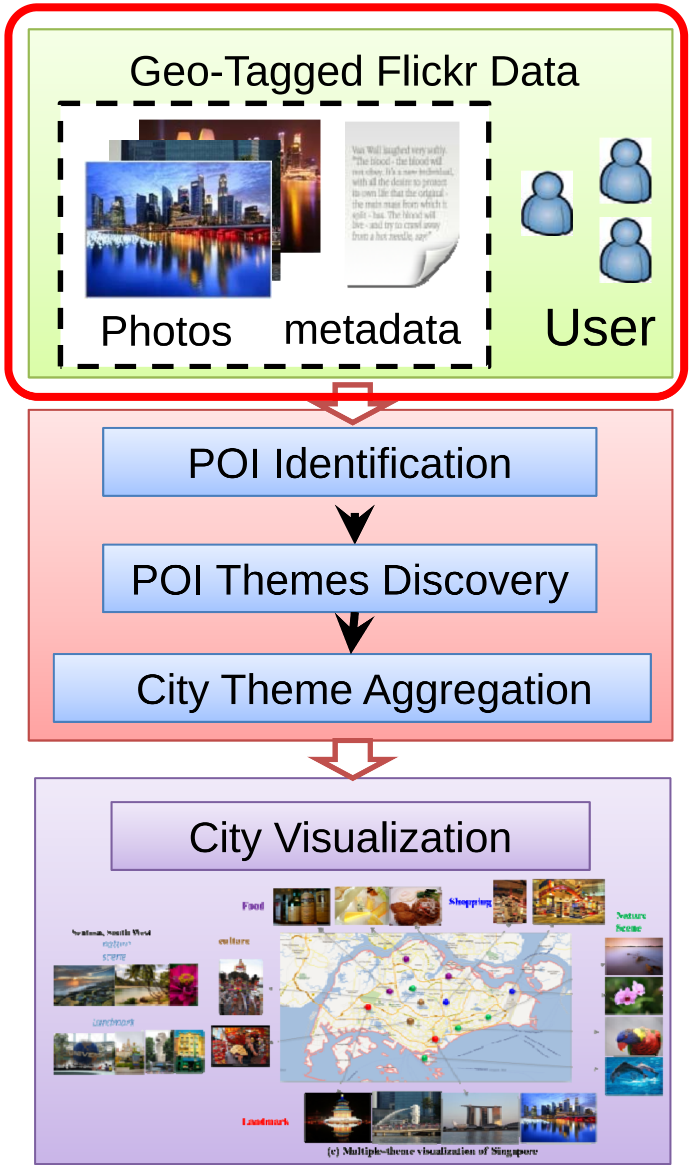
POI-City Visualization



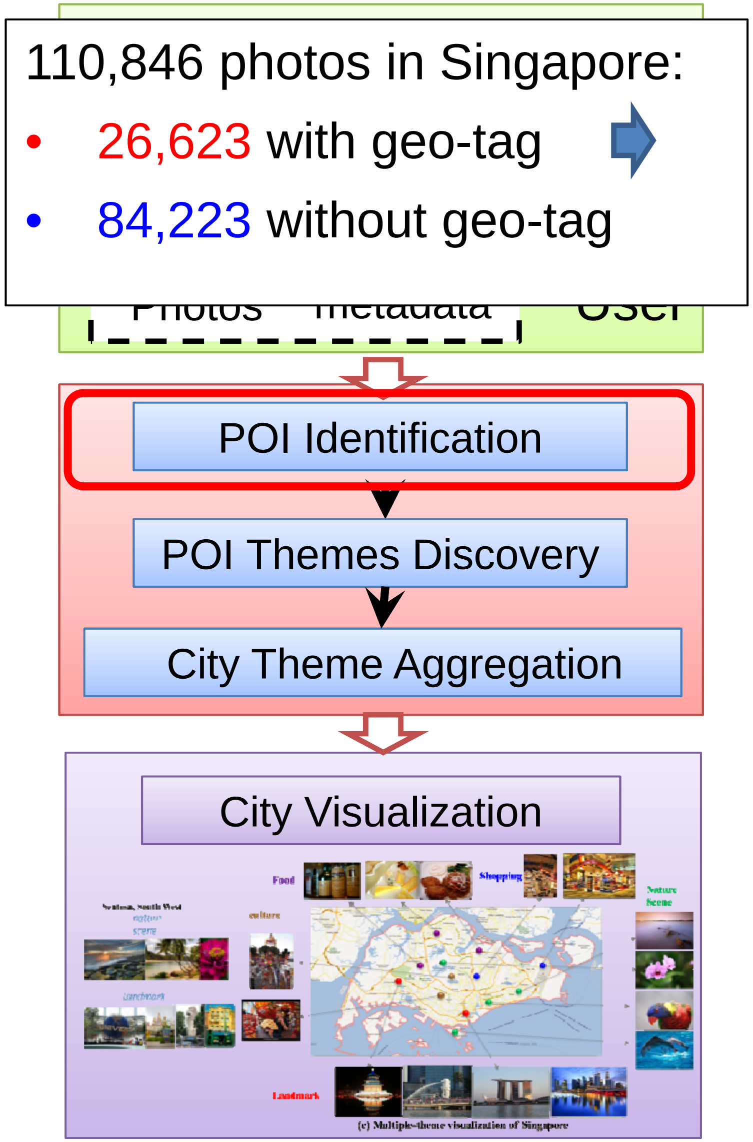


- Singapore as the running example.
- 110,846 photos, 26,623 geo-tagged photos, from 9,044 users in flickr
- Photo and associated text metadata.

POI-City Visualization



POI-City Visualization

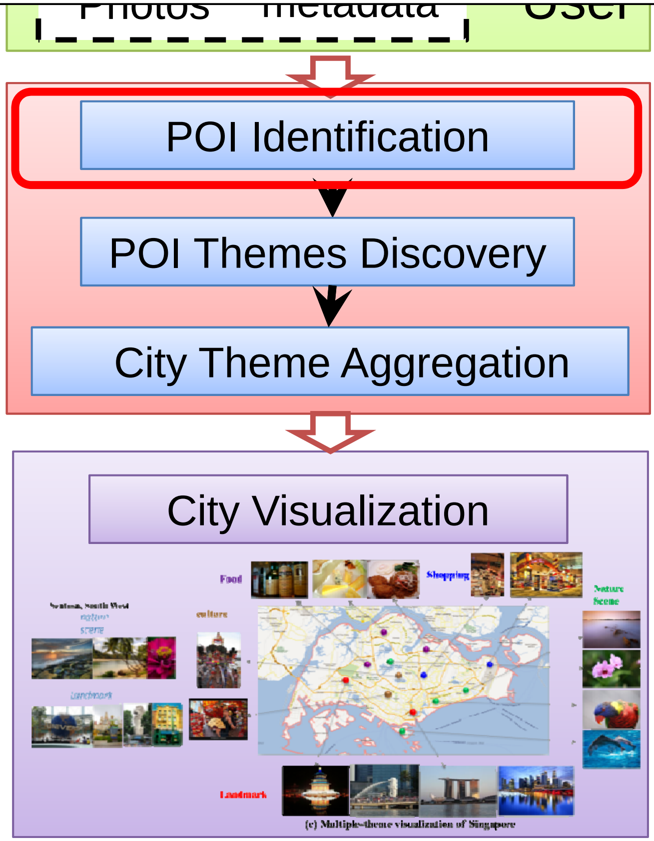


- POI detection: detect highly photographed places from geo-tagged photos.

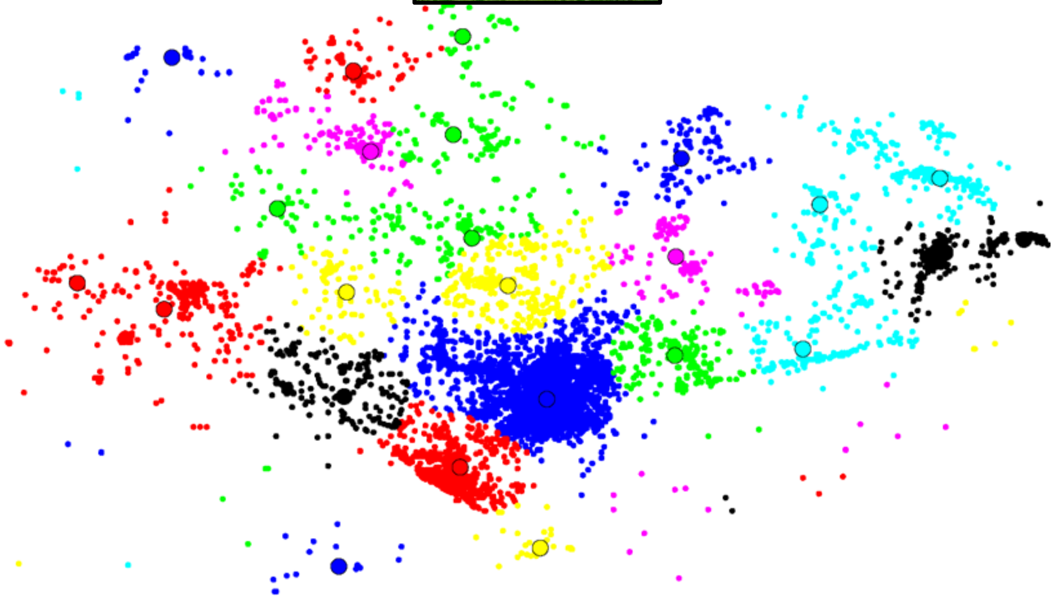
POI-City Visualization

110,846 photos in Singapore:

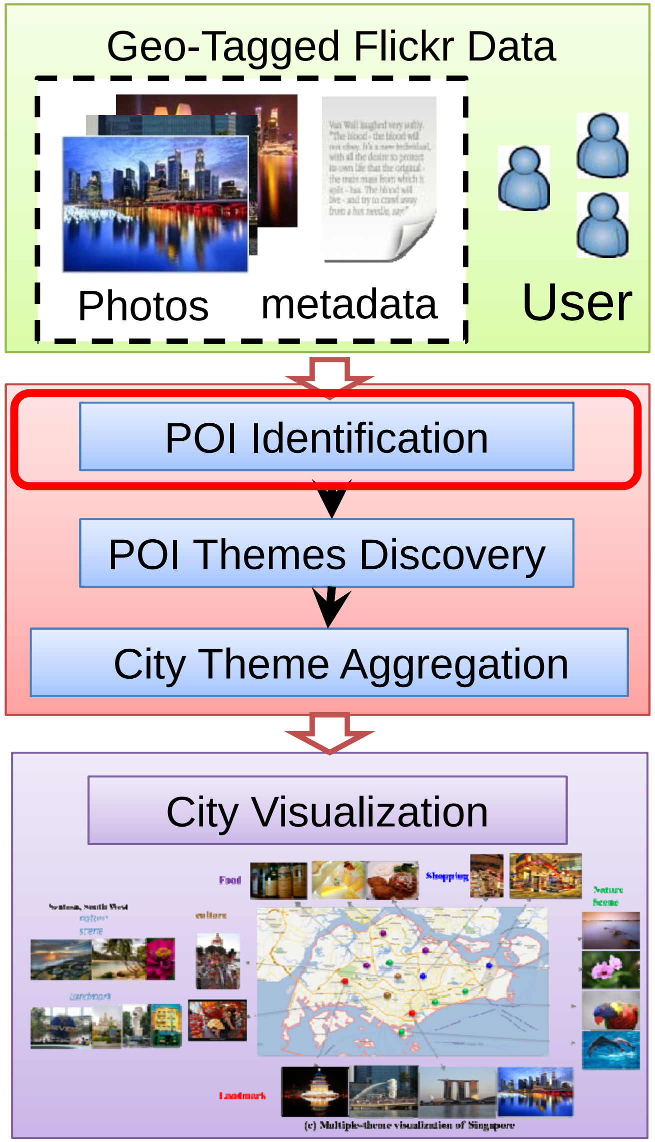
- 26,623 with geo-tag
- 84,223 without geo-tag



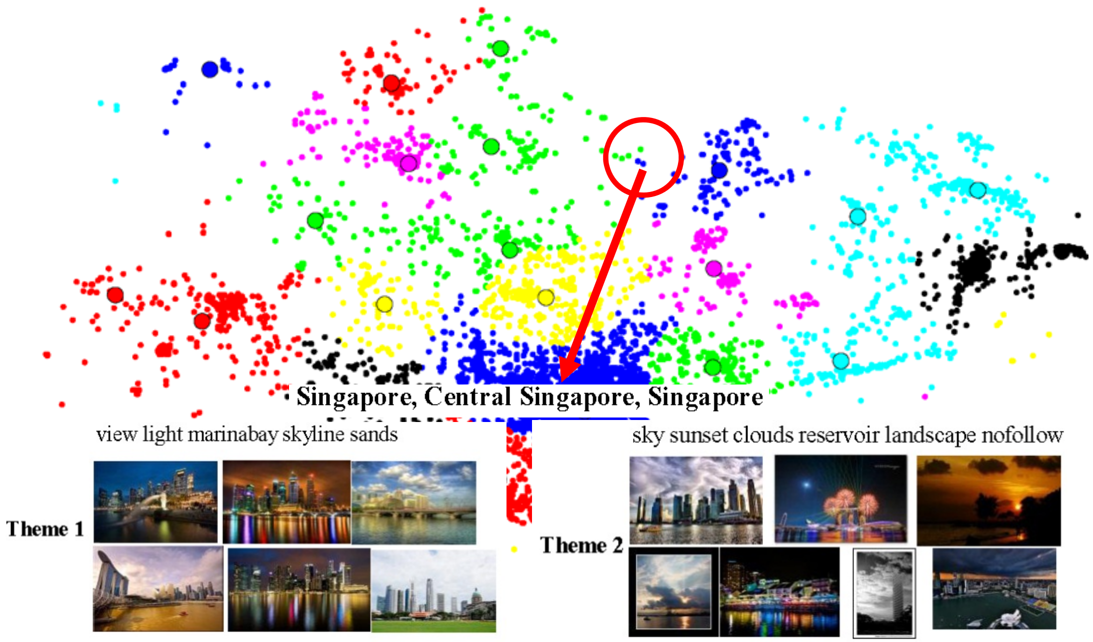
- POI estimation: assign non geo-tagged photos to the detected POIs.



POI-City Visualization

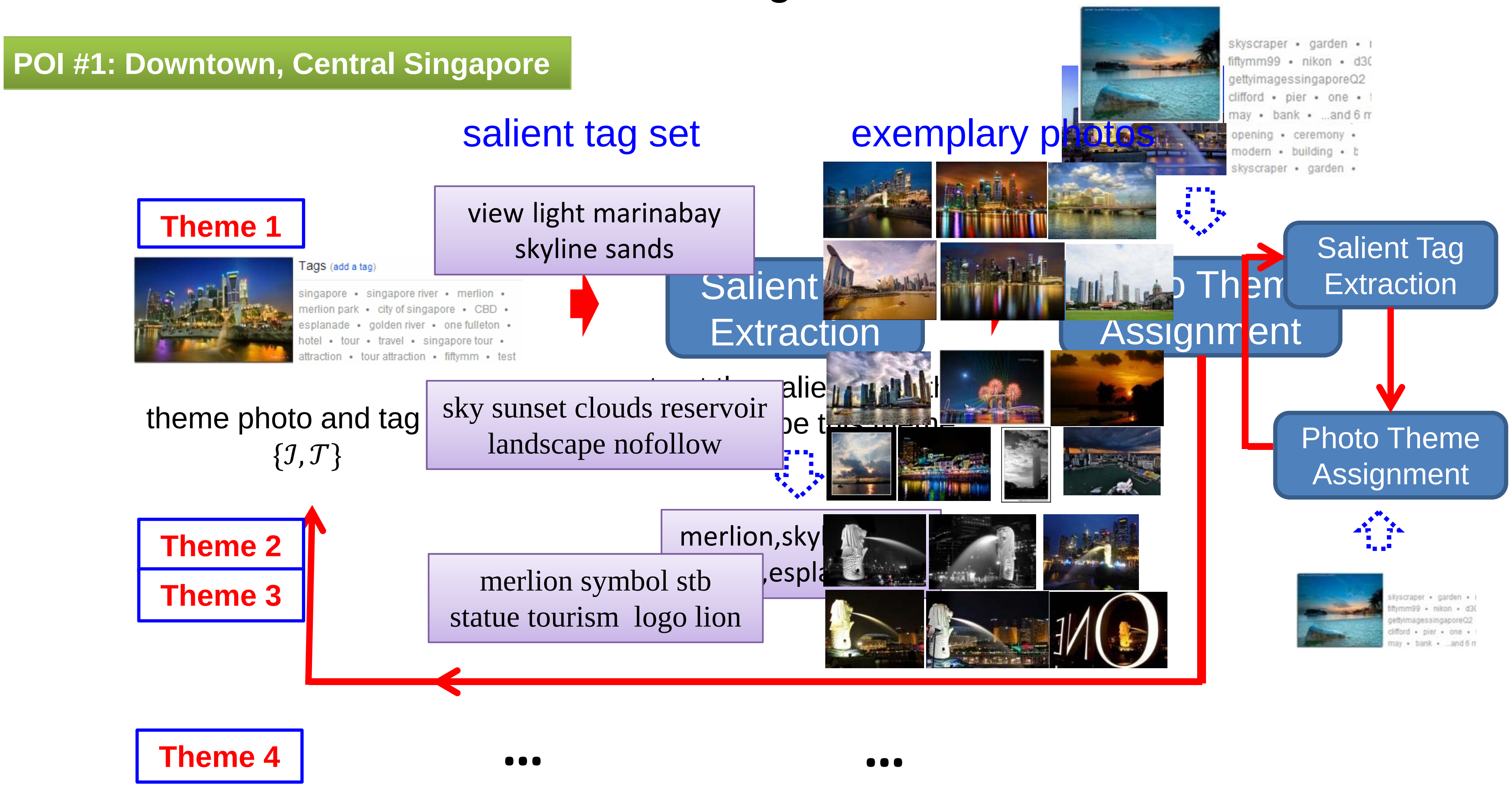


- POI Theme: represented by salient tag set and exemplary photos.

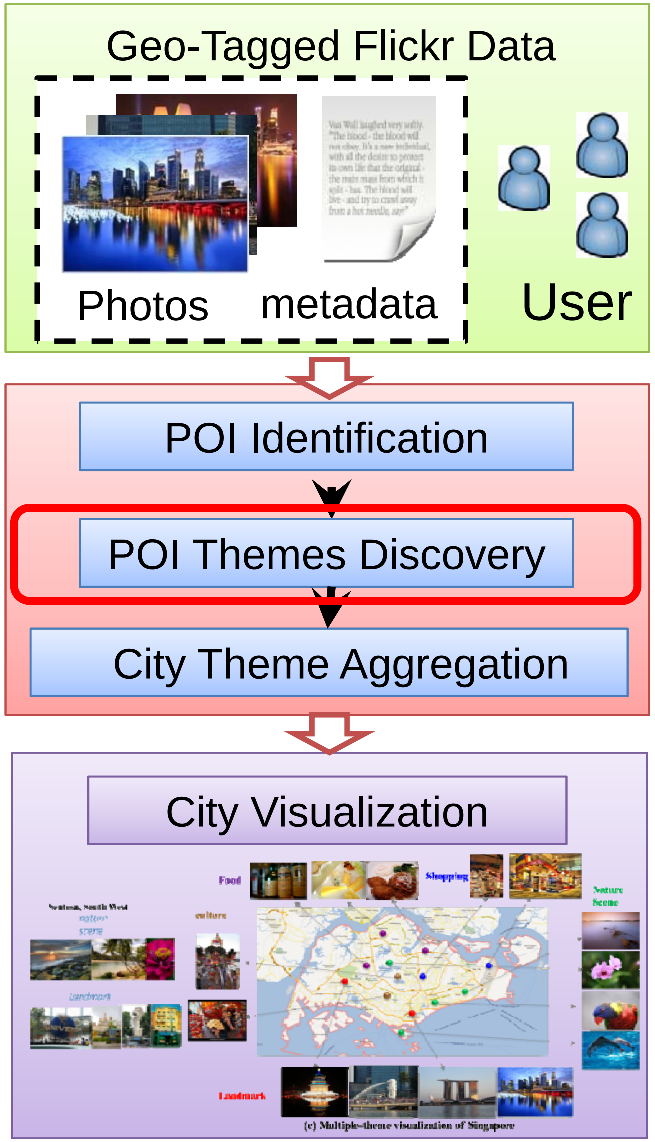


POI Theme Discovery

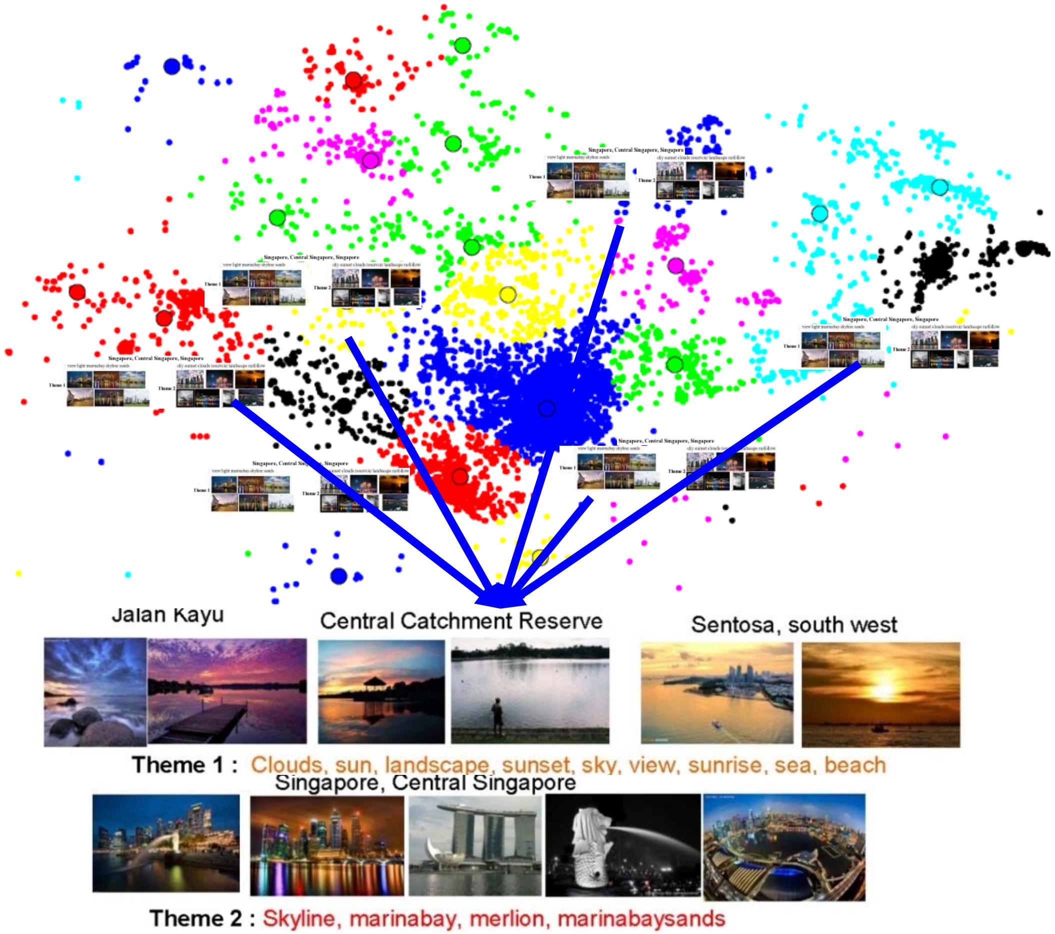
- Challenges: visual variance & tag noise;
- Solution: incremental learning-based method.



POI-City Visualization



- City Theme: representative pattern or interesting topic at city level.



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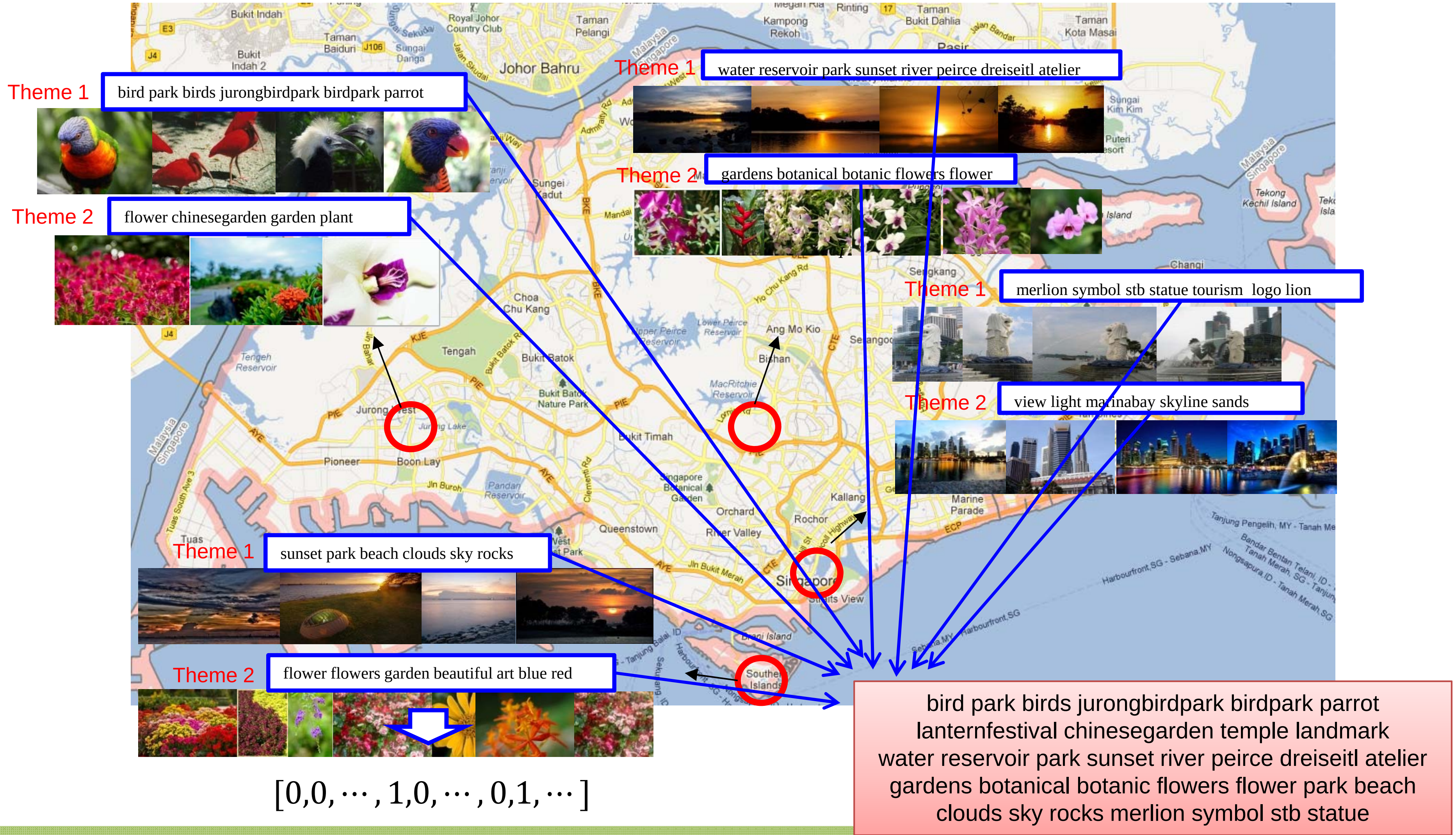
City Theme Aggregation

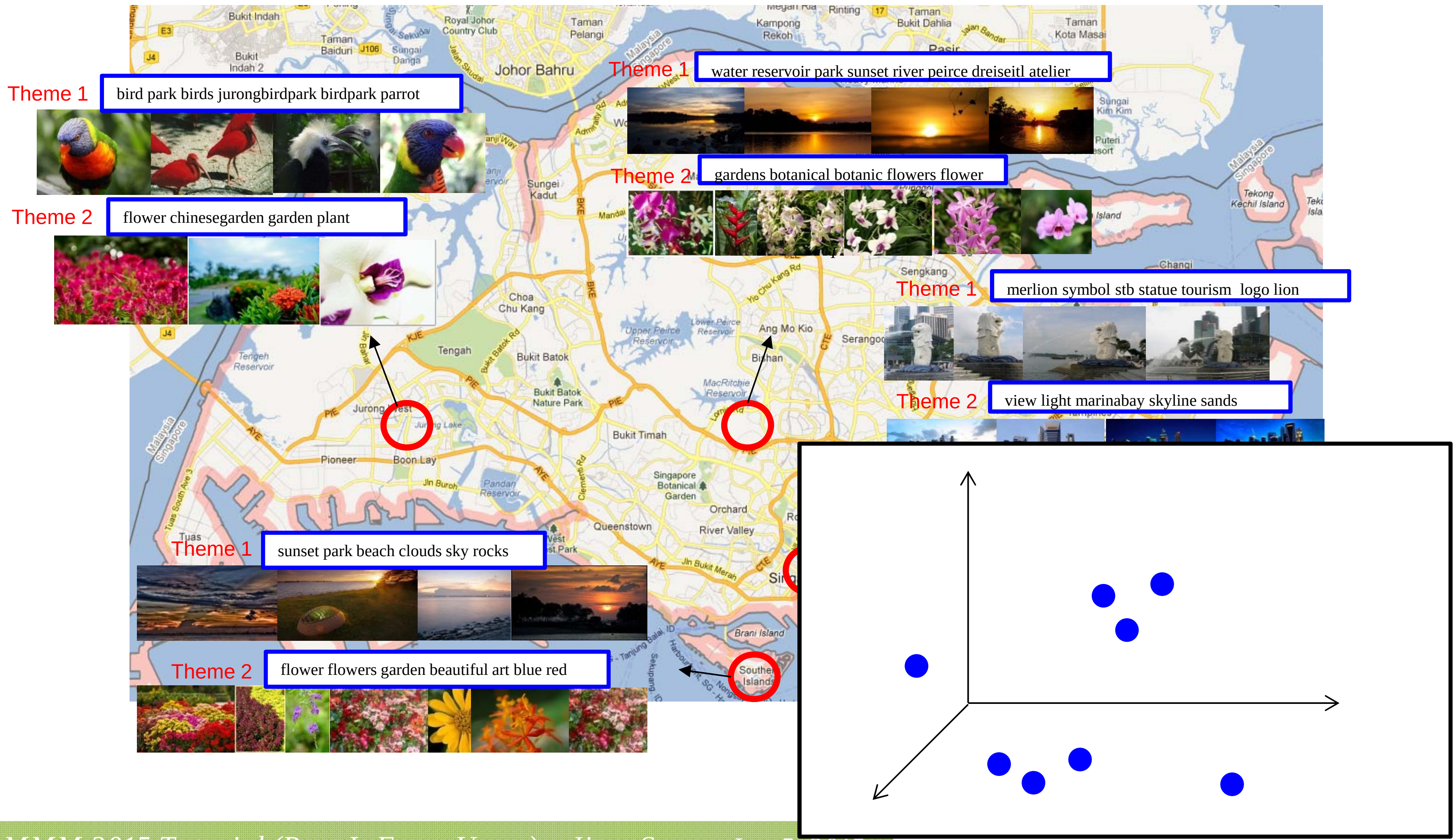
- Fuse salient tags in POI themes to construct a tag vocabulary $V = \{t_d\}_{d=1}^{D}$.



$[0,0,\cdots,1,0,\cdots,0,1,\cdots]$

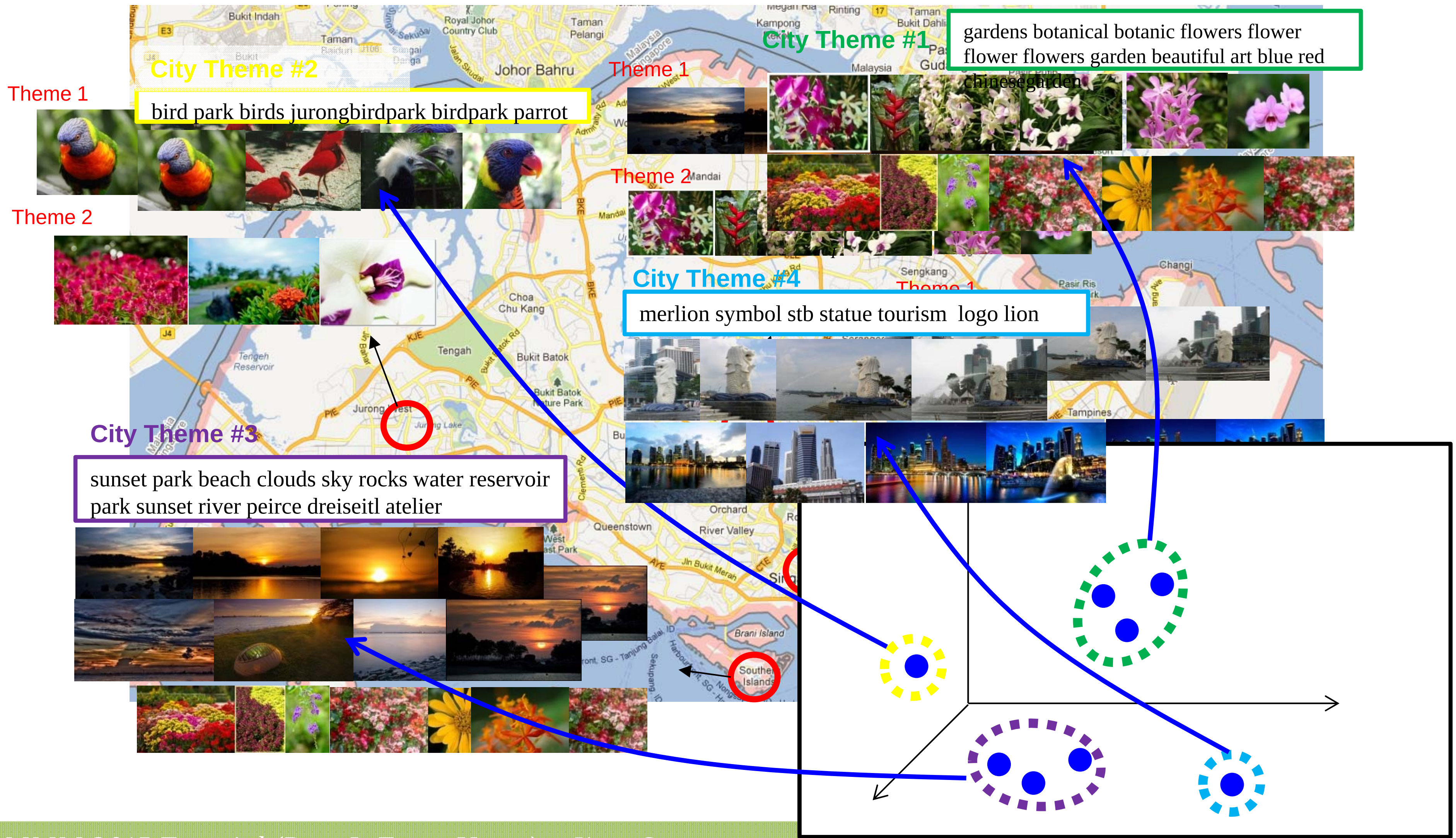
City Theme Aggregation

- Locate each POI theme onto the vocabulary space ;

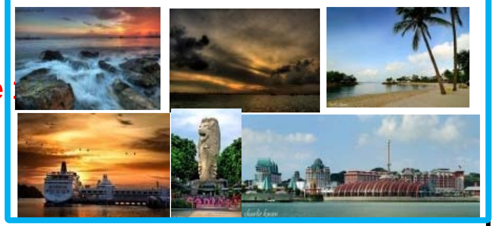
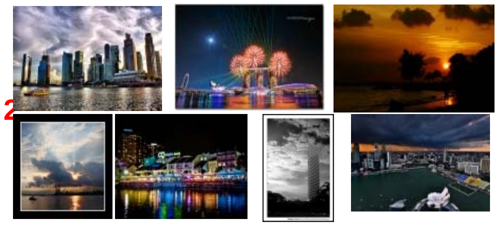
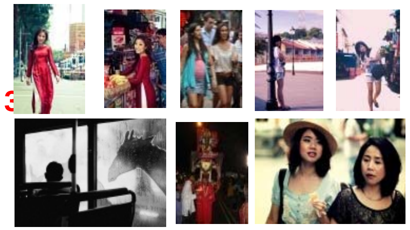


City Theme Aggregation

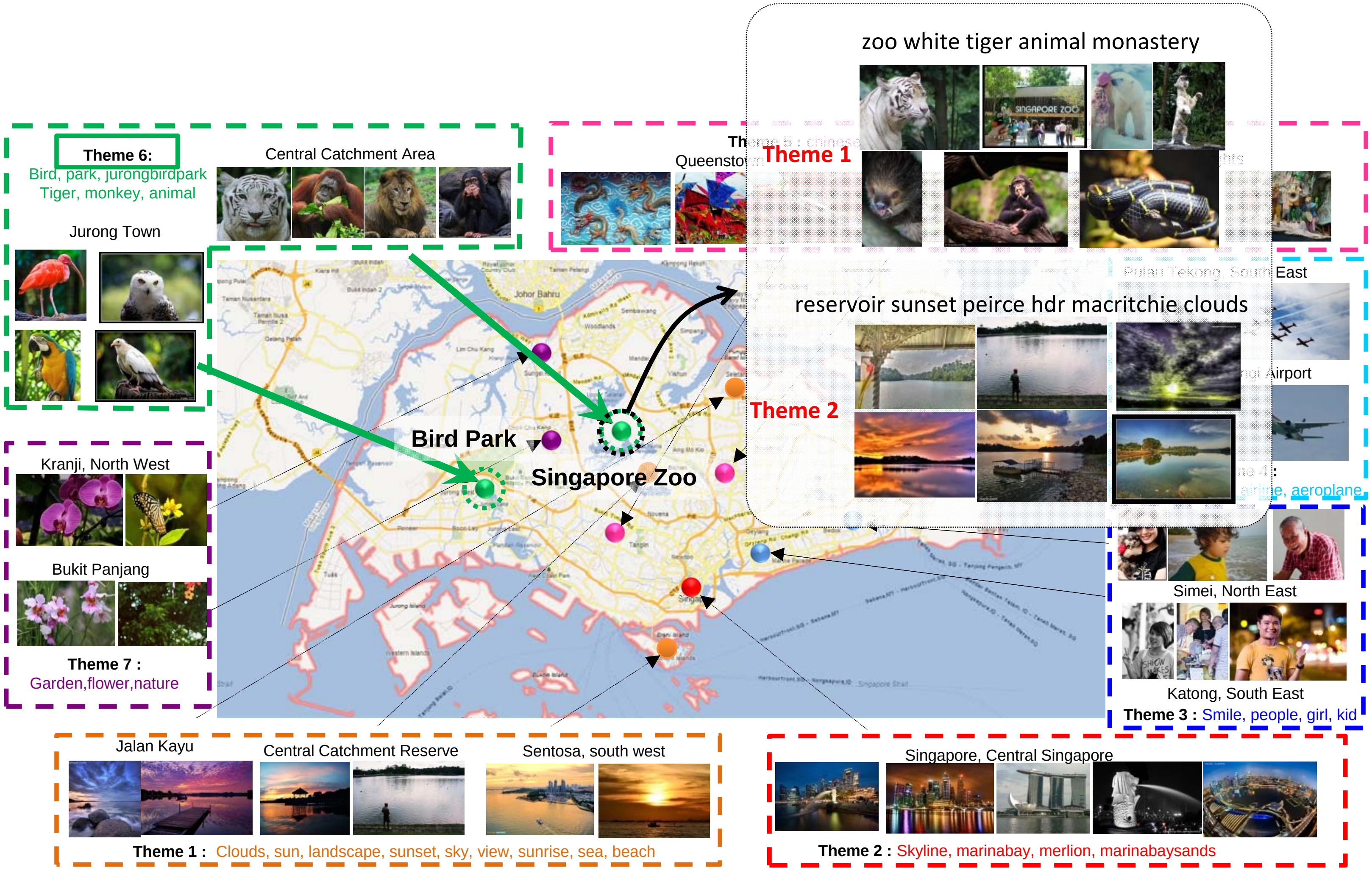
- Aggregate the POI themes into k clusters;



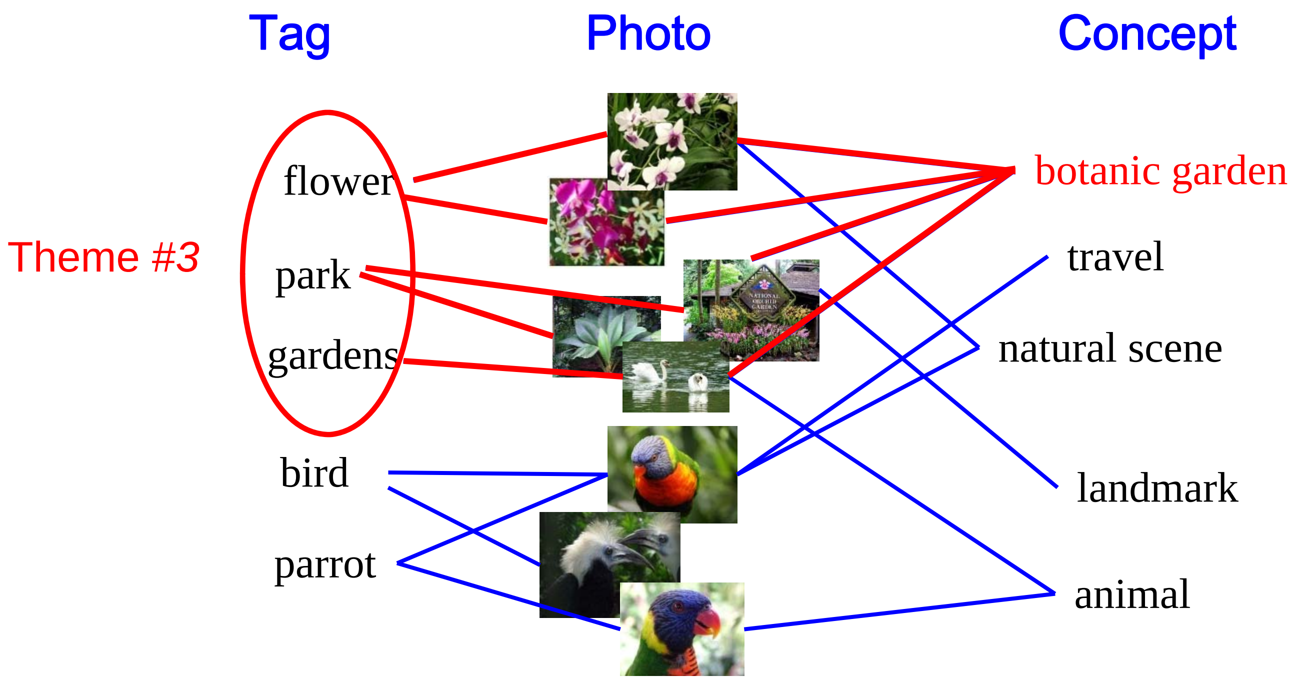
Experiments: POI Theme Visualization

Downtown, Central Singapore	Central Catchment Reserve	Sentosa, South West, Singapore
Theme 1: view light marinabay skyline sands 	Theme 1: reservoir sunset peirce hdr macritchie clouds 	Theme 1: sunset park beach clouds sky rocks merlion 
Theme 2: sky sunset clouds reservoir landscape nofollow 	Theme 2: zoo white tiger animal monastery gene 	Theme 2: food braise meal cuisine restaurant lunch 
Theme 3: merlion symbol stb statue tourism logo 	Theme 3: megan kavadi lady goddess kali girls 	Theme 3: flower flowers garden beautiful art blue red 

Experiments: City Visualization



Extension: Topic Labeling



Extension: Topic Labeling

flickr

Theme 1 :

Clouds, sun, landscape, sunset, sky, view, sunrise, sea, beach

Theme 2 :

Skyline, marinabay, merlion, marinabaysands

Theme 3 :

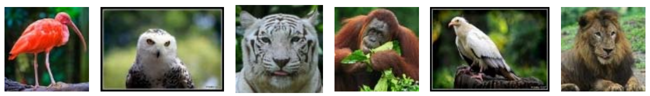
Smile, people, girl, kid

Theme 5 :

chinese, india, temple, chinatown, murugan

Theme 6:

Bird, park, jurongbirdpark Tiger, monkey, animal



Contents [hide]

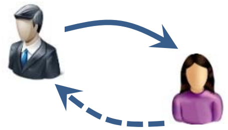
User-User Interaction-based Multimedia Analysis

User Usage Data

UGC Metadata

User-User Interaction

- **Microscopic**



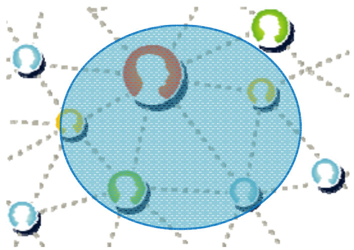
connect in *LinkedIn*

add friend in *Facebook*

follow in *Twitter*

subscribe in *Youtube*

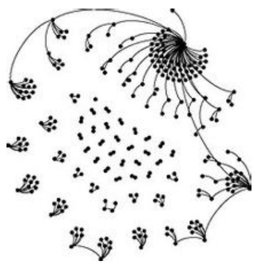
- **Mesoscopic**



Douban group

Flickr group

- **Macroscopic**



Microblogging propagation pattern

User-User Interaction-based Multimedia Analysis

User Usage Data

UGC Metadata

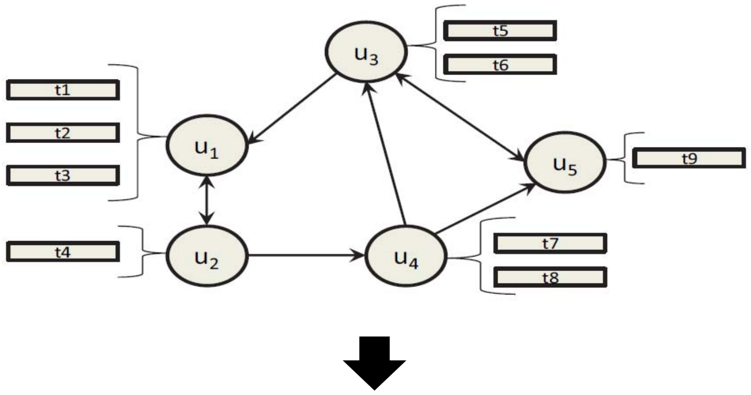
User-User Interaction

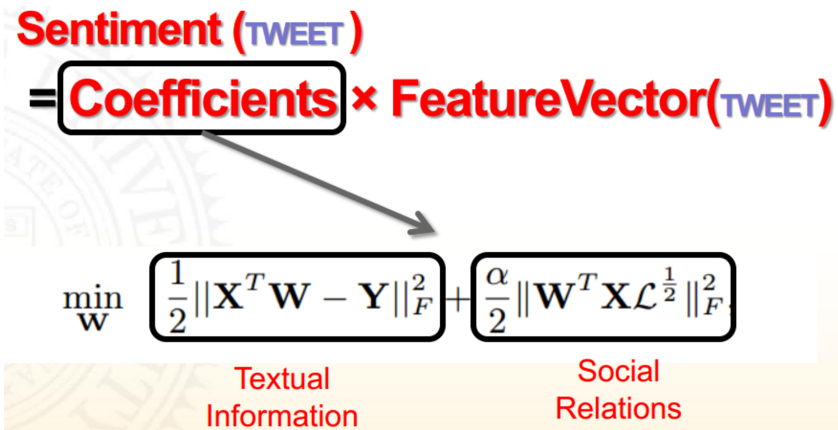
- Microscopic Interaction-based — [Sang et al. 2012a;Hu et al. 2013; Trevisiol et al. 2013]
- Mesoscopic Interaction-based — [Ulges et al. 2011; Liu et al. 2013; Liu et al. 2014]
- Macroscopic Interaction-based — [Li et al. 2013; Yu et al. 2014; Abisheva et al. 2014]

Microscopic Interaction-based Sentiment Analysis

Sentiment Consistency

Emotional Contagion

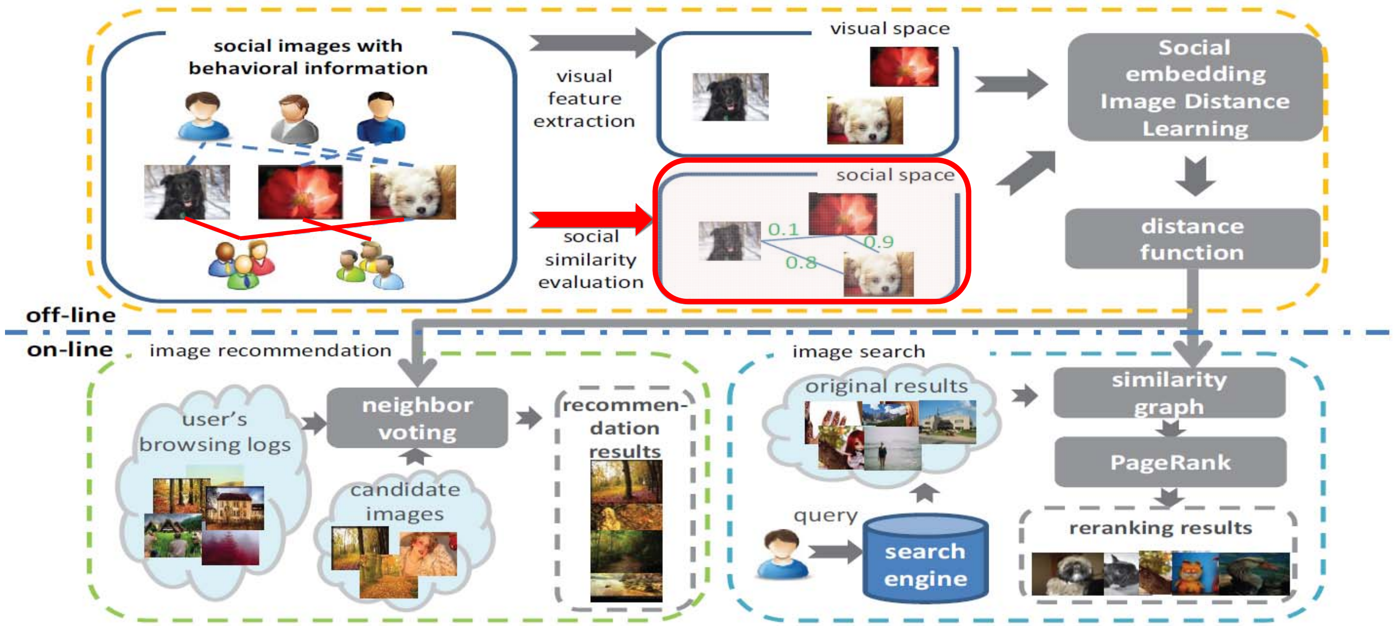




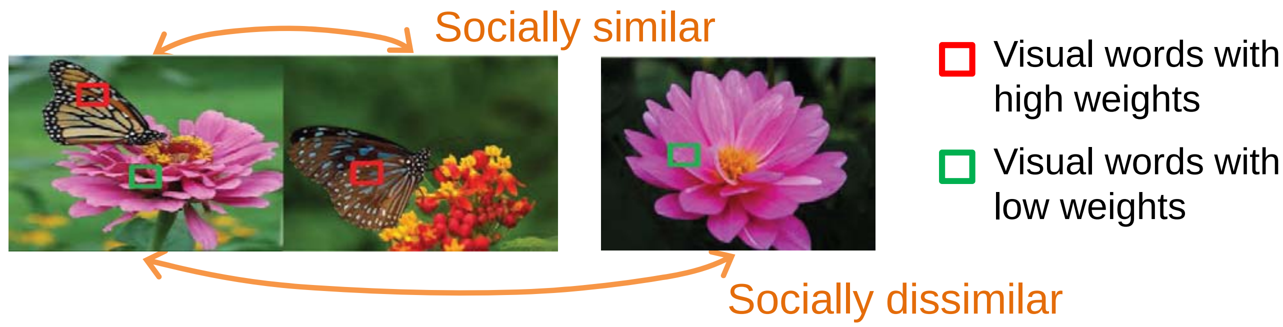
[Hu et al., 2013] Xia Hu, Lei Tang, Jiliang Tang, and Huan Liu. Exploiting social relations for sentiment analysis in microblogging. *WSDM 2013*. (Arizona State University)

Mesoscopic Interaction-based Metric Learning

Framework illustration



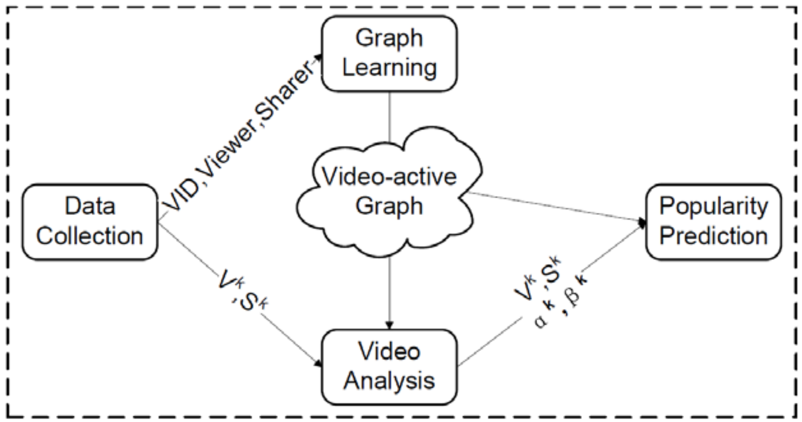
Weights of visual words



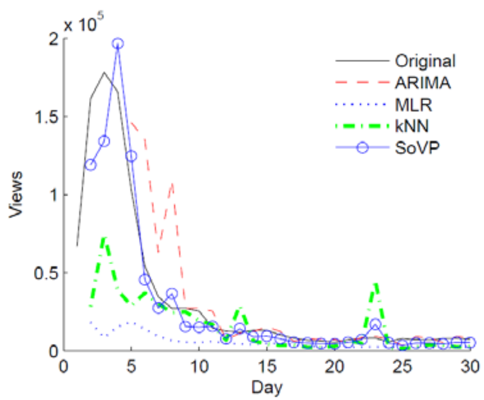
[Liu et al., 2014] Shaowei Liu, Peng Cui, Wenwu Zhu, Shiqiang Yang, Qi Tian. Social Embedding Image Distance Learning. *ACM Multimedia*, 2014. (Tsinghua University)

<u>Macroscopic</u> Interaction-based Popularity Analysis

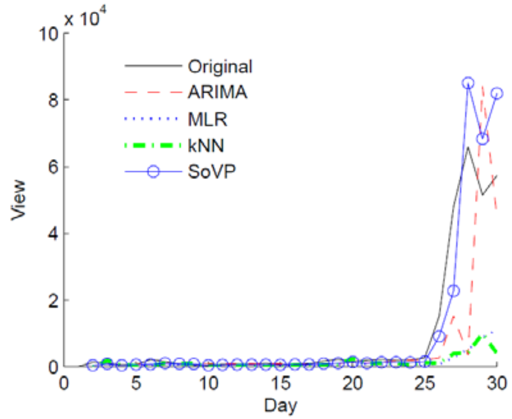
Illustration of a video propagation through social network



Propagation-based popularity prediction (SoVP)



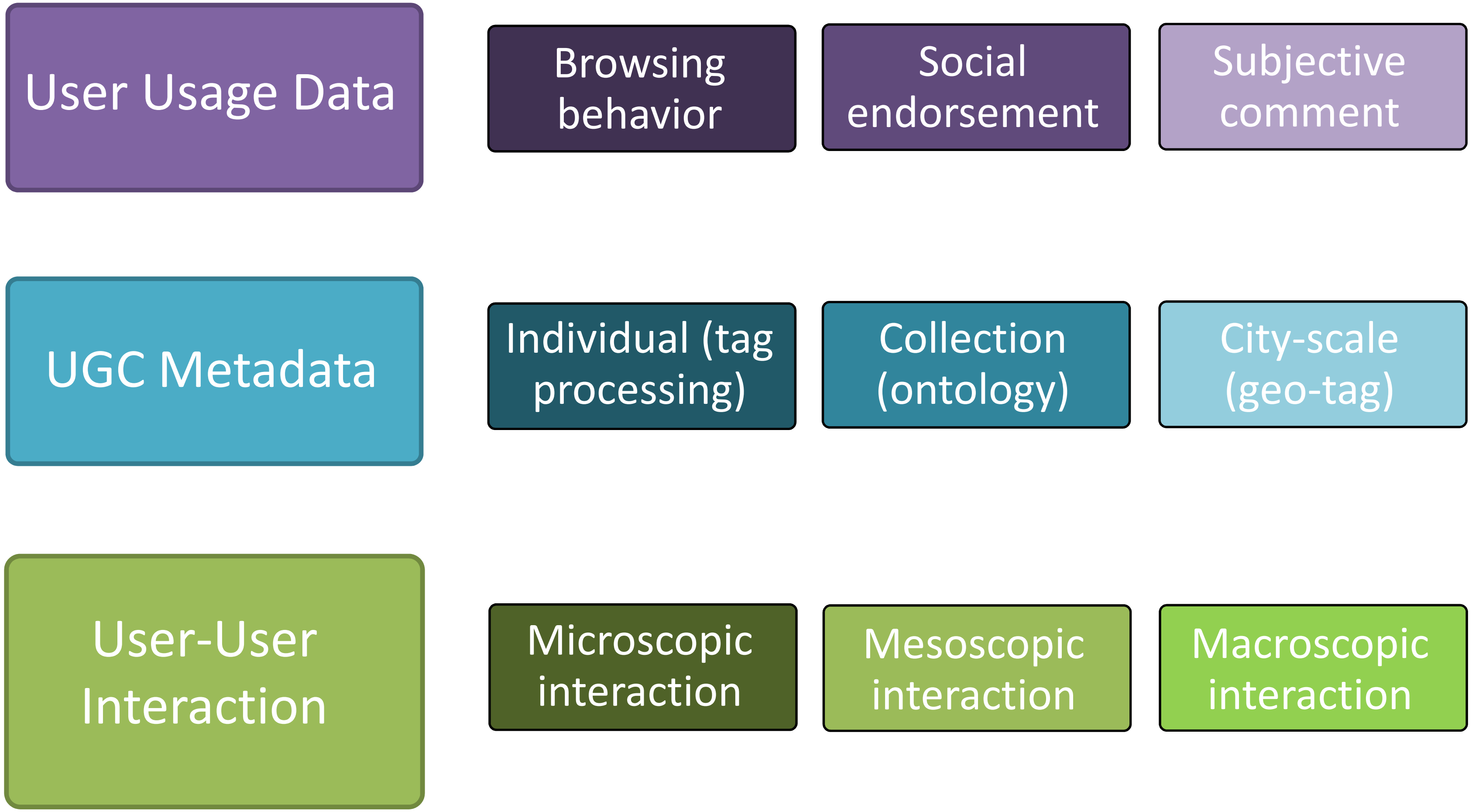
video #1

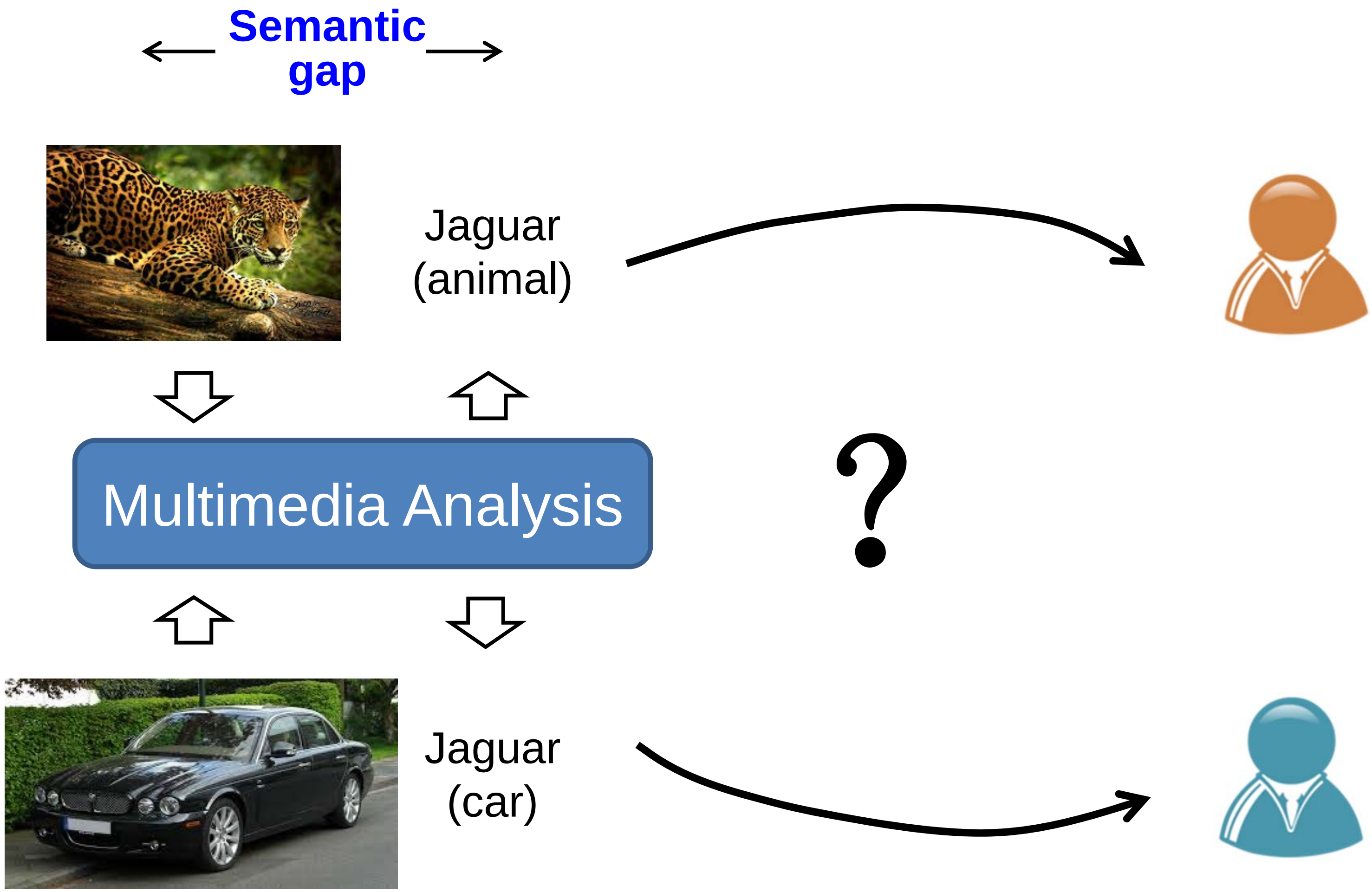


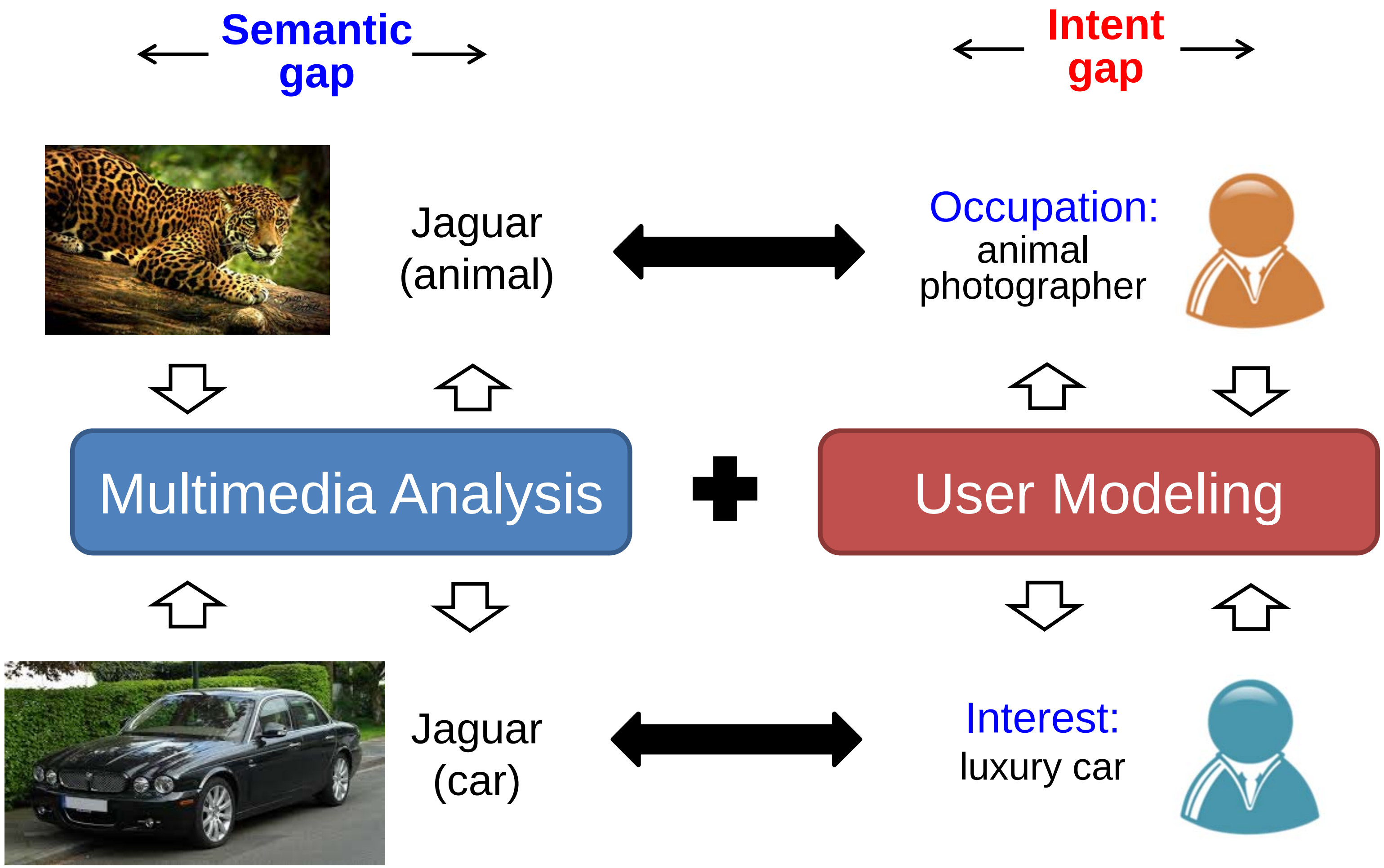
video #2

[Li et al., 2013] Haitao Li, Xiaoqiang Ma, Feng Wang, Jiangchuan Liu, Ke Xu. <u>On Popularity Prediction of Videos Shared in Online Social Networks</u>. *CIKM 2013*. (Simon Fraser University)

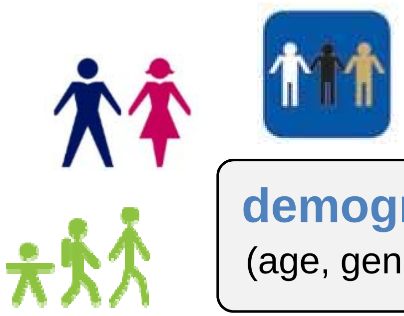
Summary: User-perceptive Multimedia Analysis



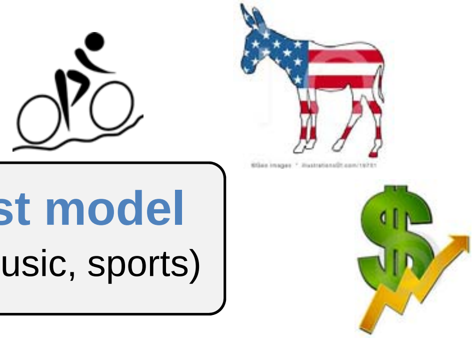

Semantic gap
Jaguar (animal)
Multimedia Analysis
?
Jaguar (car)


Semantic gap
Intent gap
Jaguar (animal)
Occupation:
animal photographer
Multimedia Analysis
User Modeling
Jaguar (car)
Interest:
luxury car

Generalized User Models



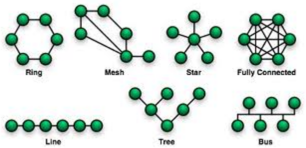
demographic model
(age, gender, occupation)



interest model
(politics, music, sports)

social status model
(friends, influence, propagation)

consuming model
(electronics, beauty, clothing,)



mobility model
(Point-of-Interest)

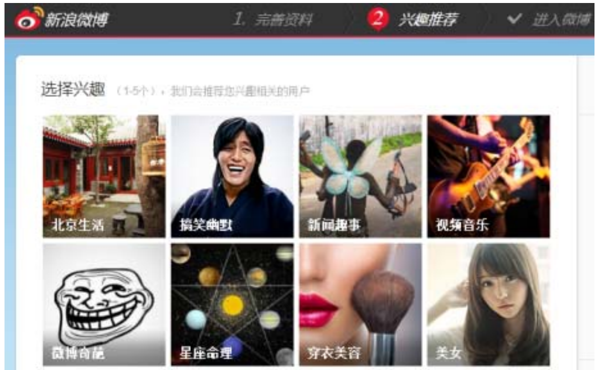
emotion model
(optimistic, positive negative)

…

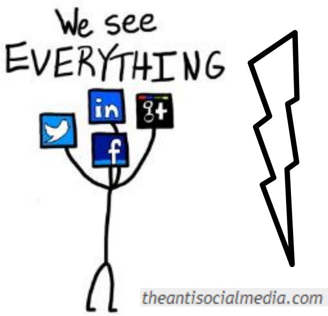
Shortage of User Information

✓ Registration: not troubling to provide the details.

✓ Choosing from lists: the taxonomy is arbitrary.



✓ Privacy issues.



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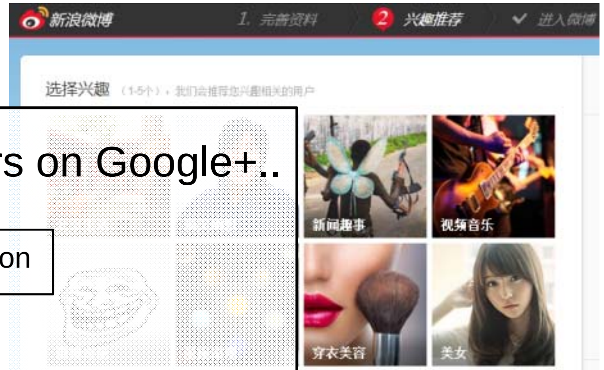
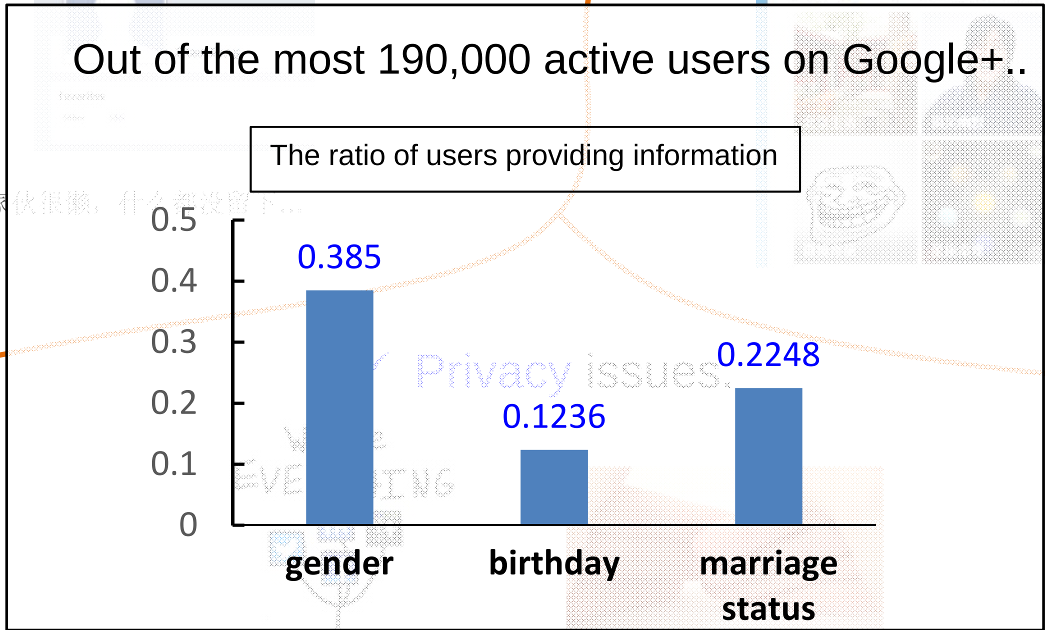
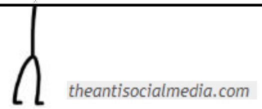


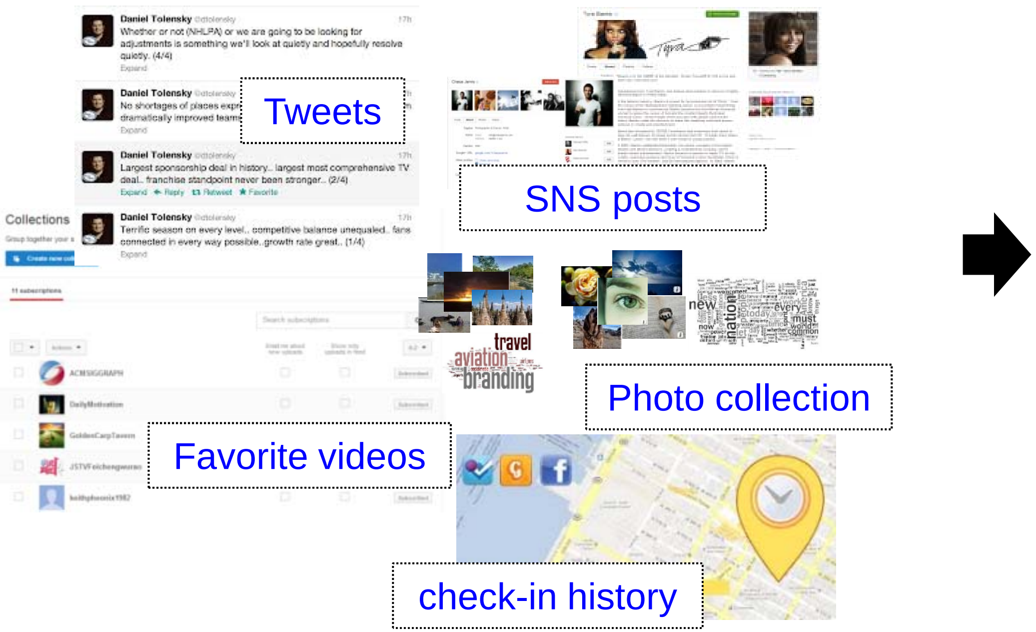




Extensive Social Multimedia Activities

Social Multimedia Activities

User Models



Categorization of Related Work

Demographics	[Hu et al. 2007; Jones et al. 2007; Otterbacher 2010; Pennacchiotti and Popescu 2011; Ying et al. 2012; Bi et al. 2013; Fang et al. 2014a]
Interests	[Koren 2010; Xiong et al. 2010; Koenigstein et al. 2011; Bennett et al. 2012; Yuan et al. 2013; Deng et al. 2014]
Social Status	[Anagnostopoulos et al. 2008; Crandall et al. 2008; Xiang et al. 2010; Zhuang et al. 2011; Sang and Xu 2012; Fang et al. 2014b]
Others	Mobility model [Li et al. 2012; Yamaguchi 2013; Ahmed et al. 2013] Emotion [Tang et al. 2012; Damian et al. 2013; Gao et al. 2014] Consuming model [Zhang and Pennacchiotti 2013; Zhang et al. 2014]

Demographics Modeling from SMA

Demographics

Interests

Social Status

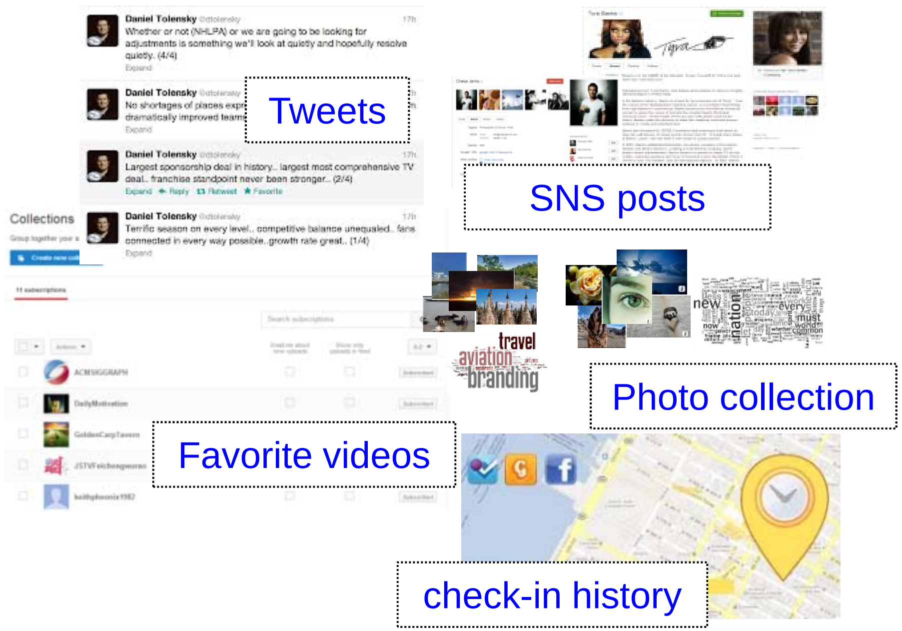
Others

[Hu et al. 2007; Jones et al. 2007; Otterbacher 2010; Pennacchiotti and Popescu 2011; Ying et al. 2012; Bi et al. 2013; Fang et al. 2014a]

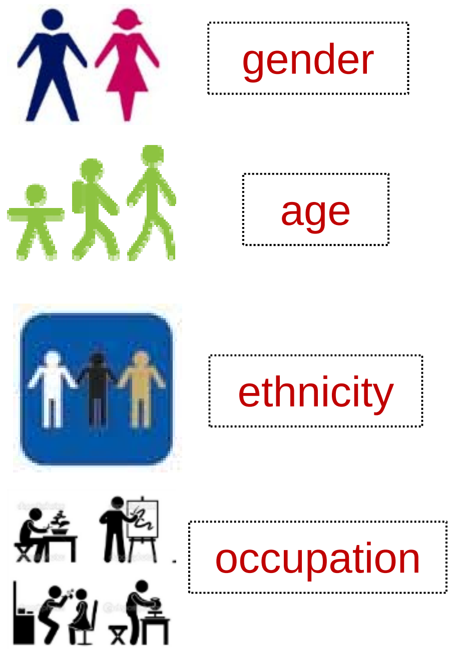
[Fang et al. 2014a] Quan Fang, **Jitao Sang**, and Changsheng Xu. UserCube: Exploiting Interaction with Multimedia Information for Relational User Attribute Inference. *Submitted for publication.*

Background: Demographic Attribute Inference

Social Multimedia Activities



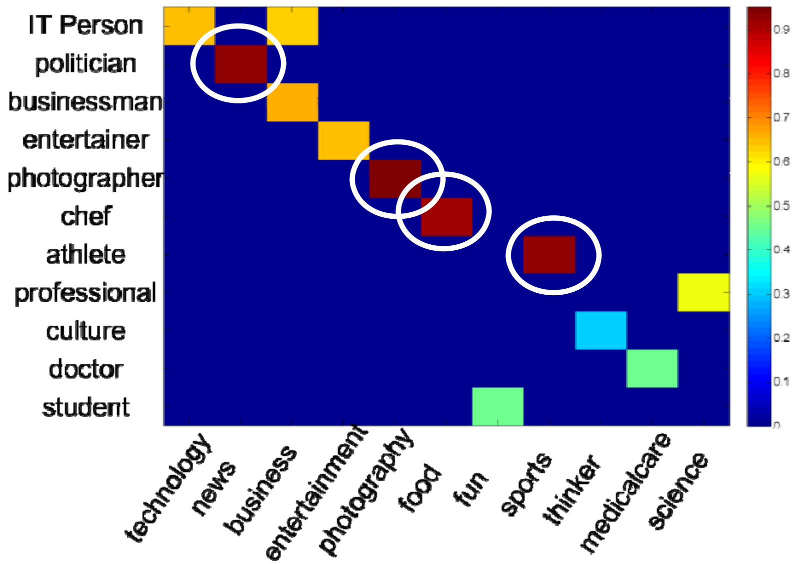
Demographic Attributes



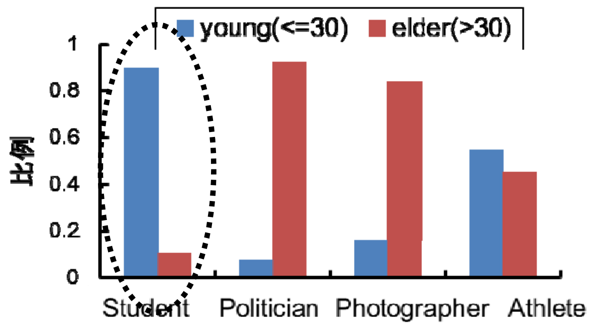
User attributes are predicted independently.

Motivation: Attributes are Connected

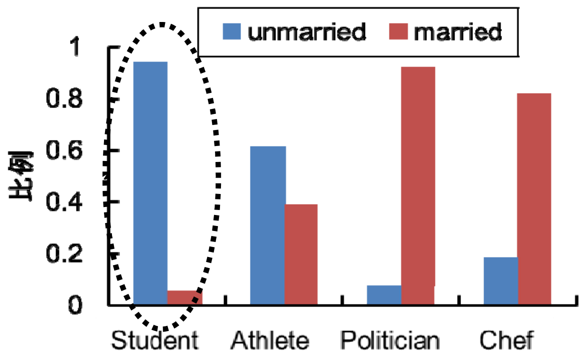
- User attributes have positive or negative intra-relations.



Occupation v.s. **Interests**



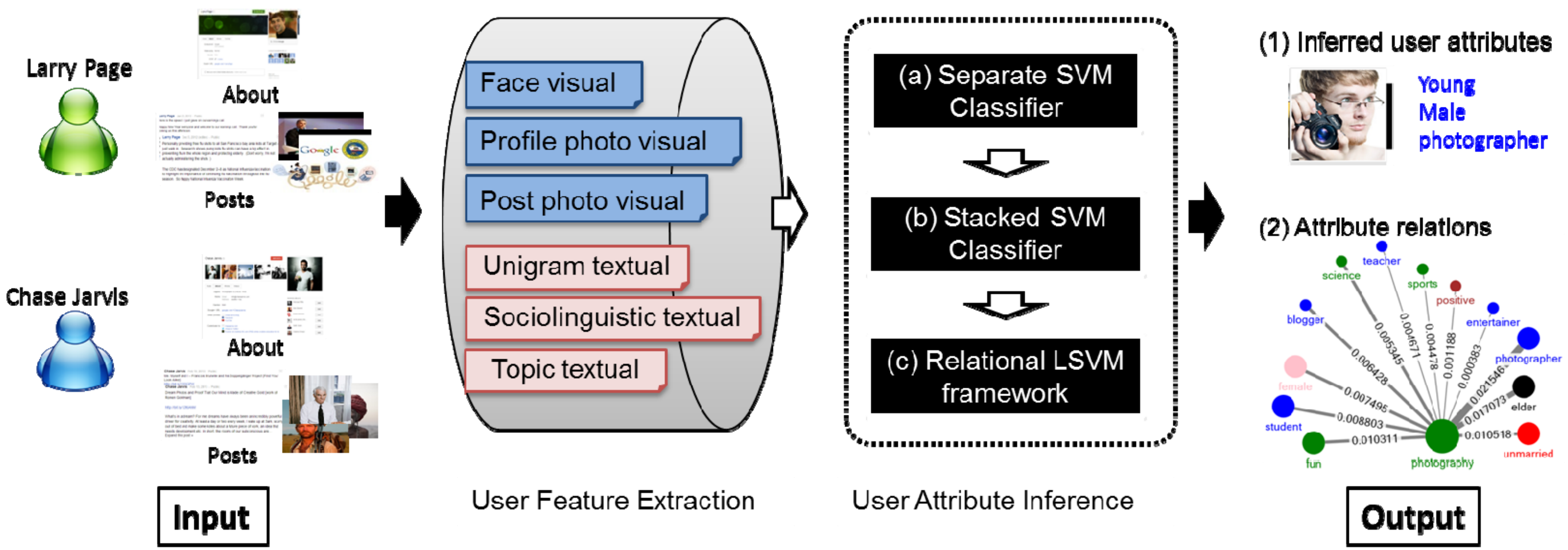
Age v.s. **Occupation**



Marriage v.s. **Occupation**

(Statistics based on *100 million* Google+ users.)

Relational User Attribute Inference



Relational User Attribute Inference

- Separate SVM classifier training for each user feature:

Feature				Classifier
Face visual	→	Train	→	SVM-Face
Profile photo visual	→		→	SVM-ProfilePhoto
Post photo visual	→		→	SVM-PostPhoto
Unigram textual	→		→	SVM-unigram
Sociolinguistic textual	→		→	SVM-sociolinguistic
Topic textual	→		→	SVM-topic-based

- Stacked SVM classifier fusion for individual attribute estimation :

(SVM-Face, SVM-ProfilePhoto, SVM-PostPhoto, SVM-unigram, SVM-sociolinguistic, SVM-topic-based) → Fusion → Stacked SVM

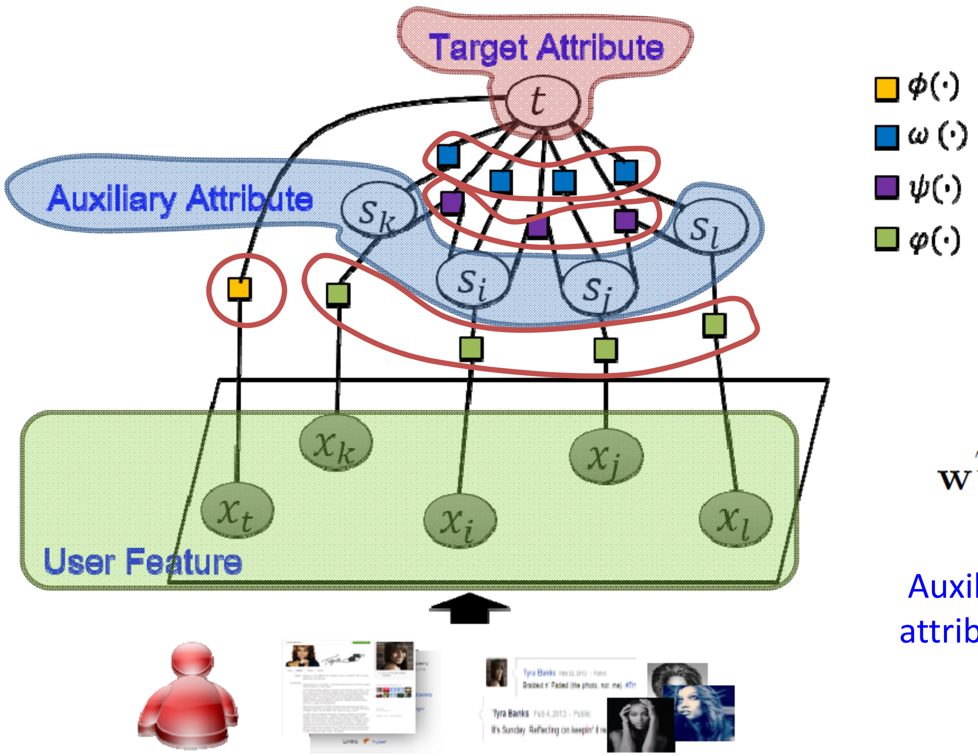
X

$\mathcal{H}$

female	age<30	unmarried
0.83	0.65	0.91

Relational User Attribute Inference

- Relational Latent SVM framework for enhancement



User feature vector

Stacked SVM model for each attribute

$$\mathbf{w}^T\mathbf{\Phi}(\mathbf{x},\mathbf{h},t) = \boxed{\alpha^T\phi(\mathbf{x},t) + \sum_{i\in\mathcal{H}}\beta^T\varphi(\mathbf{x},h_i)}$$
$$+ \boxed{\sum_{i\in\mathcal{H}}\gamma^T\omega(h_i,t) + \sum_{(i,k)\in\mathcal{E}}\eta^T\psi(h_i,h_k)}$$

Auxiliary attributes

Target attribute

Attribute relations

Experiments: Attribute Example

- Define 6 types of attributes and their optional values:

Attribute Name	Attribute Values
Gender	1-Male; 2-Female
Age	1-Young($\leq$30); 2-Elder($\geq$30)
Relationship	1-Unmarried; 2-Married
Occupation	1-Student(St); 2-Information Technology Person (IT), Software Engineer, Geek; 3-Entertainer, Musician, Actor, Comedian, Model, TV show host; 4-Writer, Journalist, Blogger, Editor, TV news host, Critics Lawyer; 5-Politician; 6-Sports star, Athlete; 7-Business man, Economist, Entrepreneur, Market strategist, Financiers; 8-Scientist, Professional, Researcher, Expert; 9-Photographer Traveler; 10-Doctor, Dentist, Pharmacist, Beautician ; 11-Chef, Eater, Cook; 12-Engineer, Specialist, Designer; 13-Teacher; 14-Artist, Religious people, Culture Writer, Designer, Author, Critic; 15-Other
Interest	1-Technology, Information, Internet; 2-News, Politics,military, Society; 3-Economy, Business Manage Strategy; 4-Entertainment, Music, Movie, Fashion; 5-Photography, Travel; 6-Food&Drink; 7-Daily things, Lives life living, Fun interest, Personal Stuff; 8-Sports, Exercise, Body-Building; 9- Thinker, ideas religion culture literature art; 10-Health, Medical care, Treatment,Makeup; 11-Science, Knowledge; 12-Other
Sentiment Orientation	1-Positive (fantastic, great, elated, bouncy, jubilant, excited, cheerful, ecstatic); 2-Negative (annoyed, aggravated, bad, pain, embarrassed, bored, anxious, crazy, depressed, scared, sick, angry, sad, score); 3-Neutral (normal, awake, calm, working, blank, report, news, fact)

Experiments: Attribute Inference Evaluation

Table 2: The statistics of our collected Google+ data

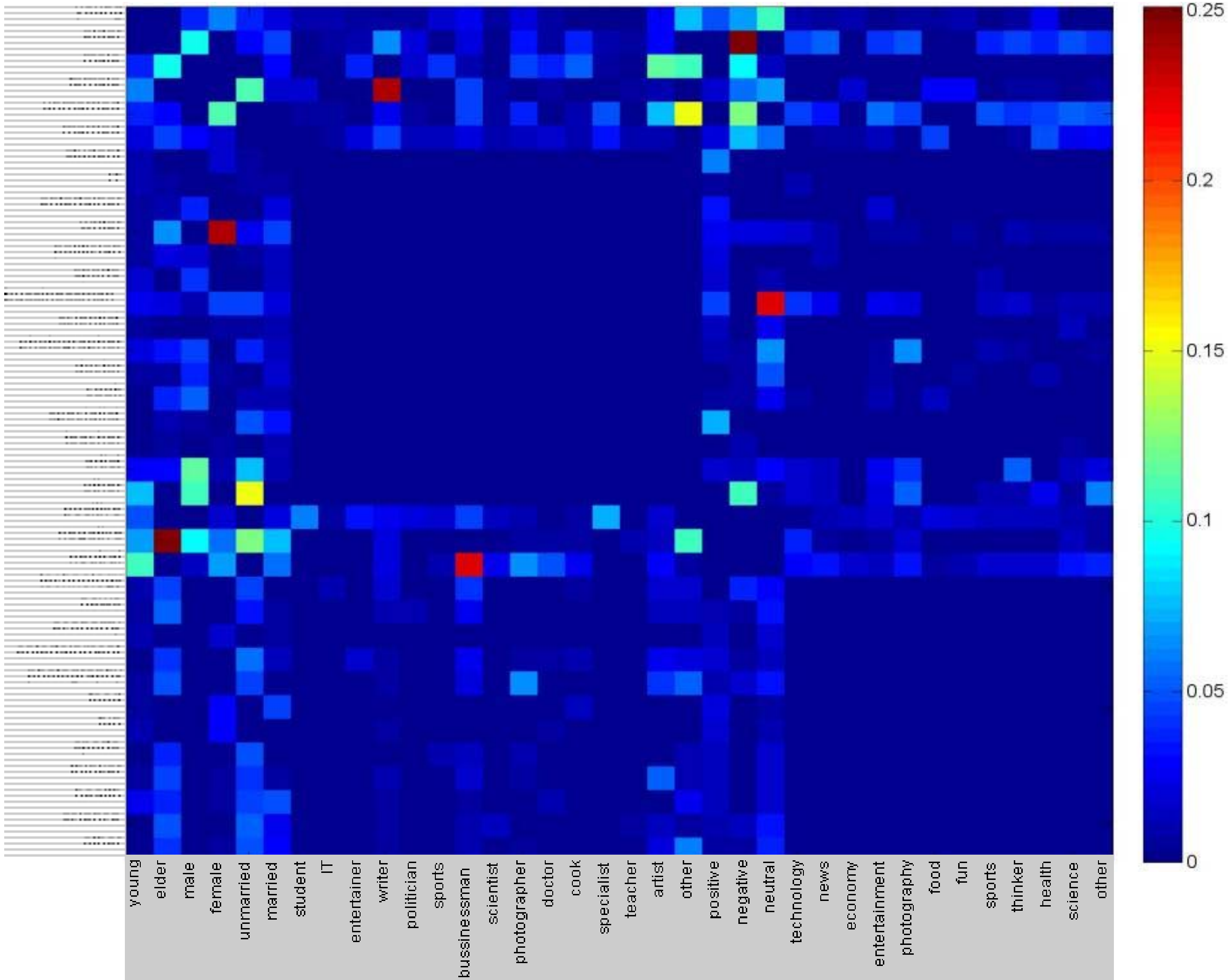
#Users	2,548	#Profile Photos	2,548
#Posts	846,339	#Post Photos	88,988
#Attached Objects	333,331		

Table 4: Performance comparison of different methods for user attribute inference.

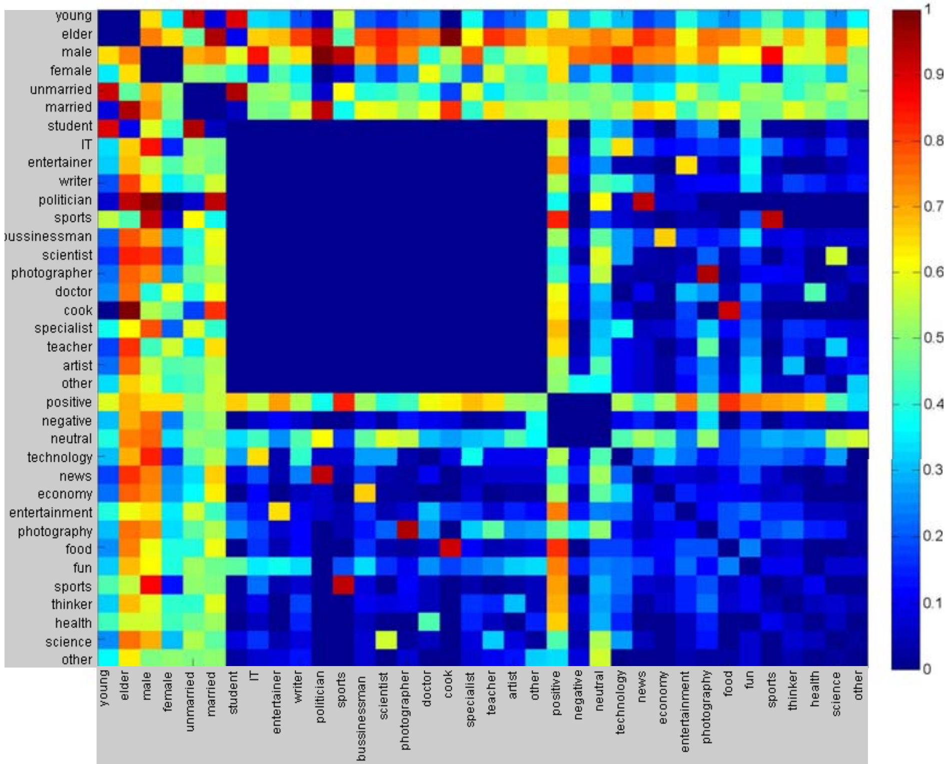
	Age	Gender	Relationship	Occupation	Interest	Sentiment Orientation
SVM-Face	0.6194	0.7607	0.5835	0.0741	0.5005	0.3398
SVM-ProfilePhoto	0.5422	0.7185	0.5181	0.0776	0.5002	0.3579
SVM-PostPhoto	0.5047	0.6276	0.5193	0.1098	0.5215	0.3671
SVM-unigram	0.5989	0.7239	0.5899	0.2329	0.5490	0.4002
SVM-sociolinguistic	0.5972	0.7123	0.6081	0.2002	0.5501	0.3922
SVM-topic-based	0.5264	0.5768	0.5376	0.0798	0.5037	0.3333
Stacked SVM	0.6054	0.7856	0.6114	0.2373	0.5980	0.4096
Relational LSVM	**0.7278**	**0.7986**	**0.6240**	**0.2507**	**0.6172**	**0.4106**

Experiments: Attribute Relation Results

- The derived user attribute relations:

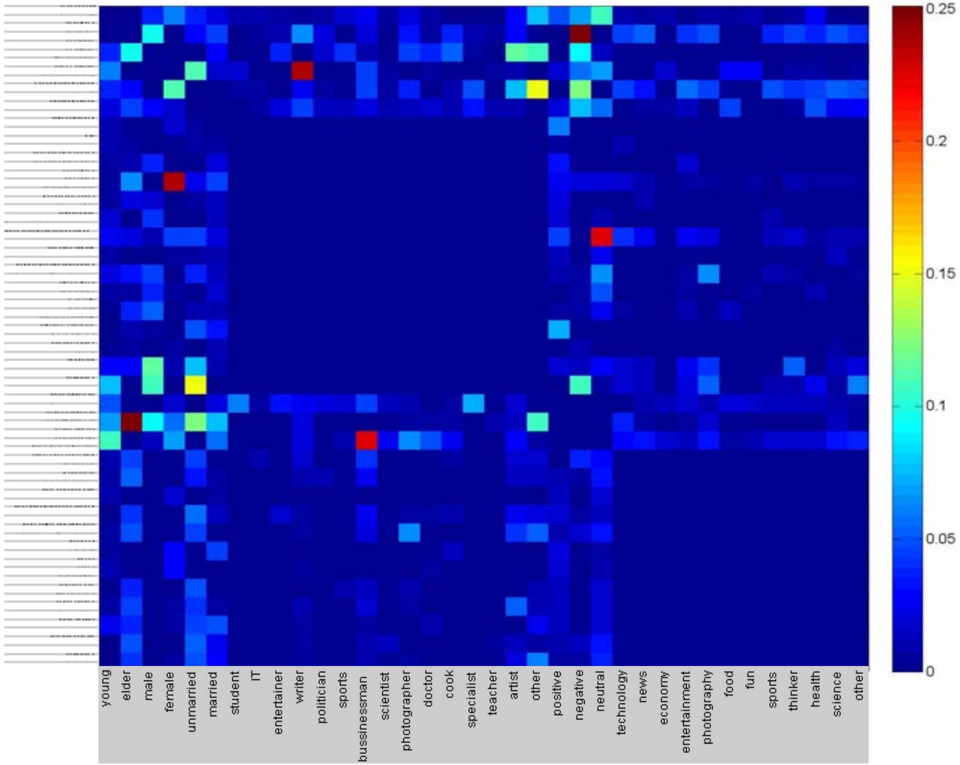


Experiments: Attribute Relation Results



(a)

the attribute relation In the labeled dataset

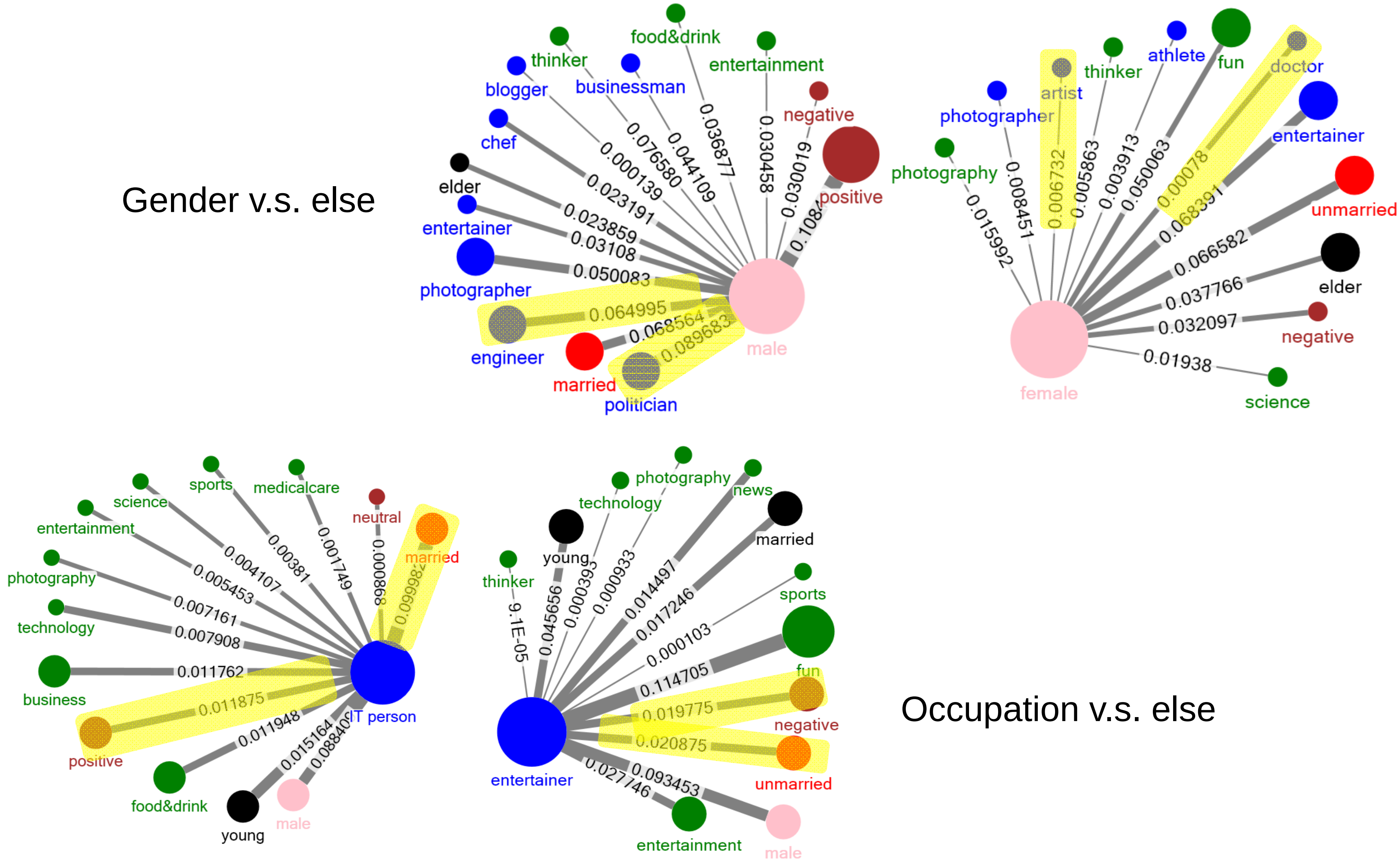


(b)

the derived user attribute relations

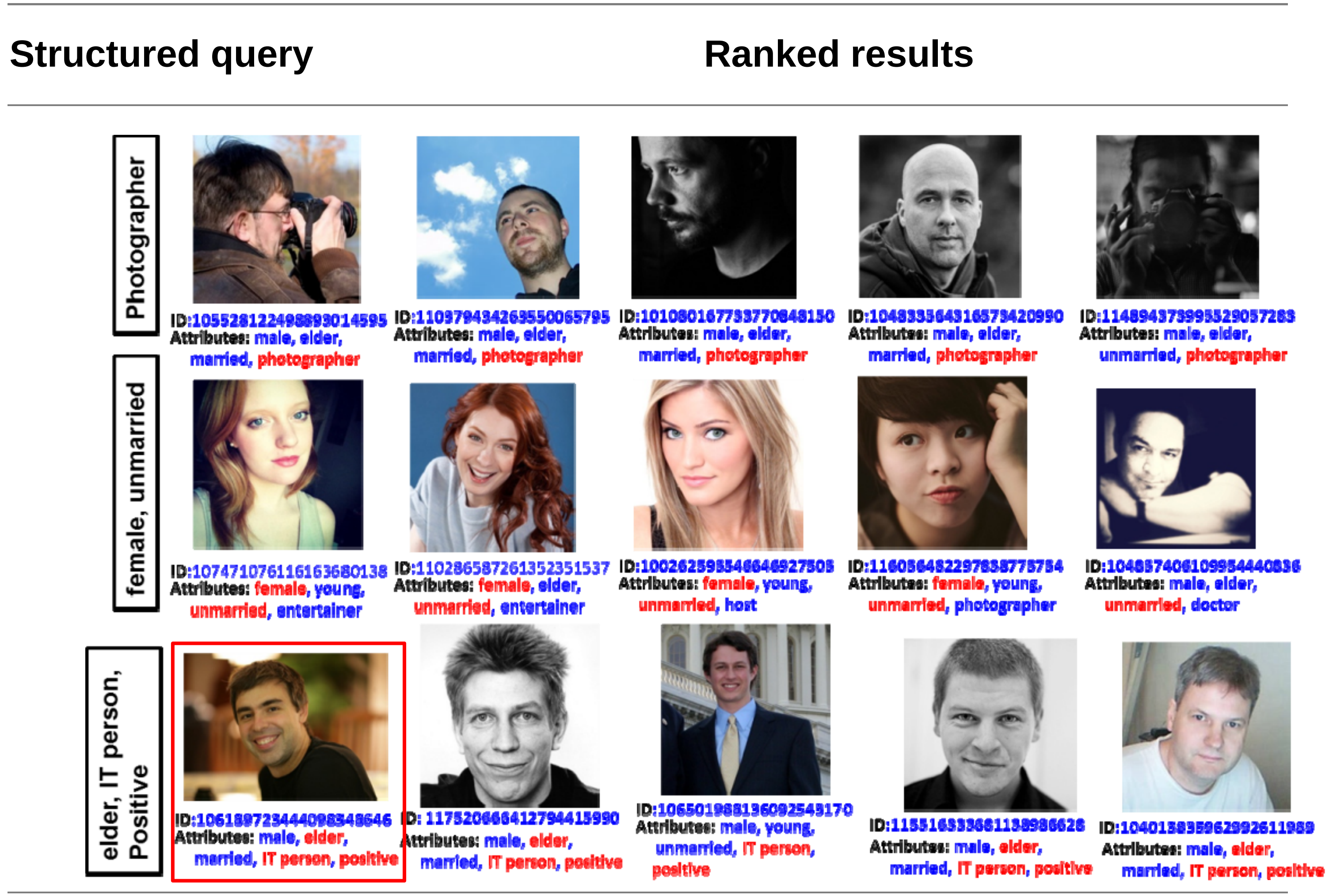
Experiments: Attribute Relation Results

Gender v.s. else



Occupation v.s. else

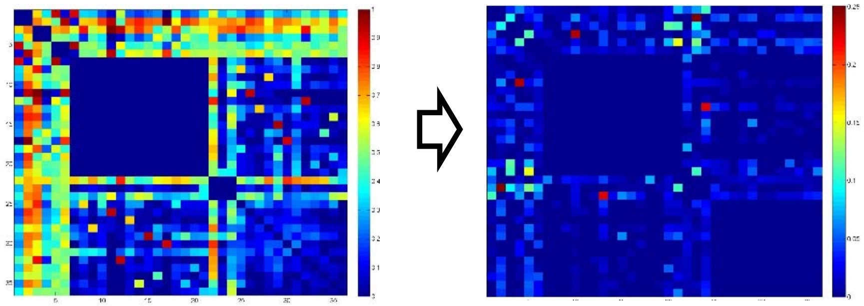
Application: Structural Attribute-based User Retrieval



Extensions

- Attribute-based user retrieval:
  - Formulated as a ranking problem;
  - Consider social context (graph) information.

- The observed attribute relation as supervision:
  - First refine the observed attribute relation matrix;
  - Fix the attribute relation as supervision, to improve attribute inference performance.



User Interest Modeling from SMA

Demographics

Interests

[Koren 2010; Xiong et al. 2010; Koenigstein et al. 2011; Wang et al. 2012; Bennett et al. 2012; Yuan et al. 2013; Deng et al. 2014]

Social Status

Others

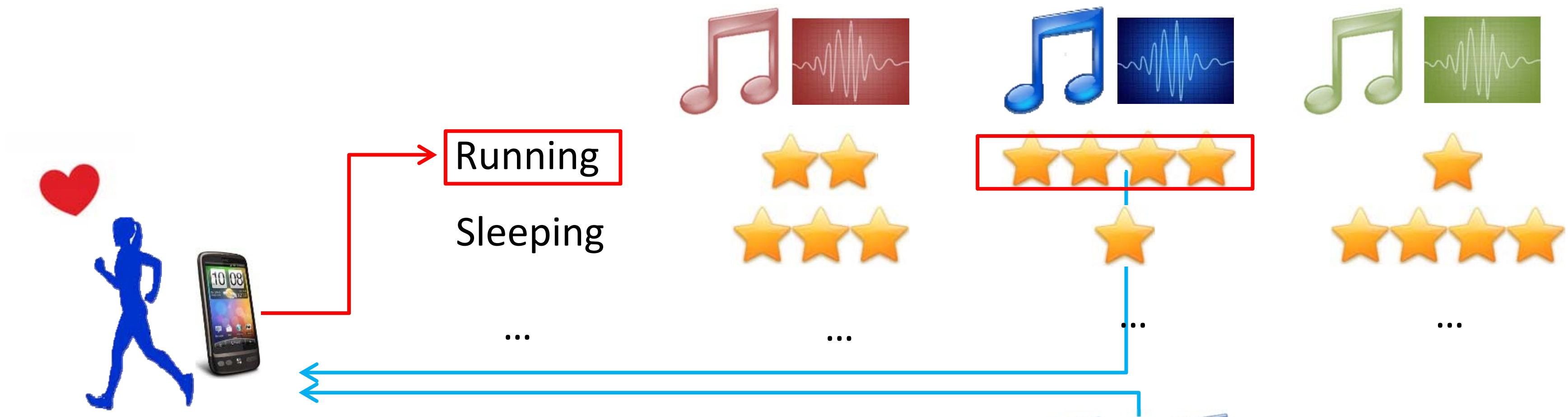
User Interest Modeling: Dynamics & Context

Girlfriend

Sleepsong

[Wang et al. 2012] Xinxi Wang, David Rosenblum, Ye Wang: Context-aware mobile music recommendation for daily activities. *ACM Multimedia 2012*: 99-108. (National University of Singapore)

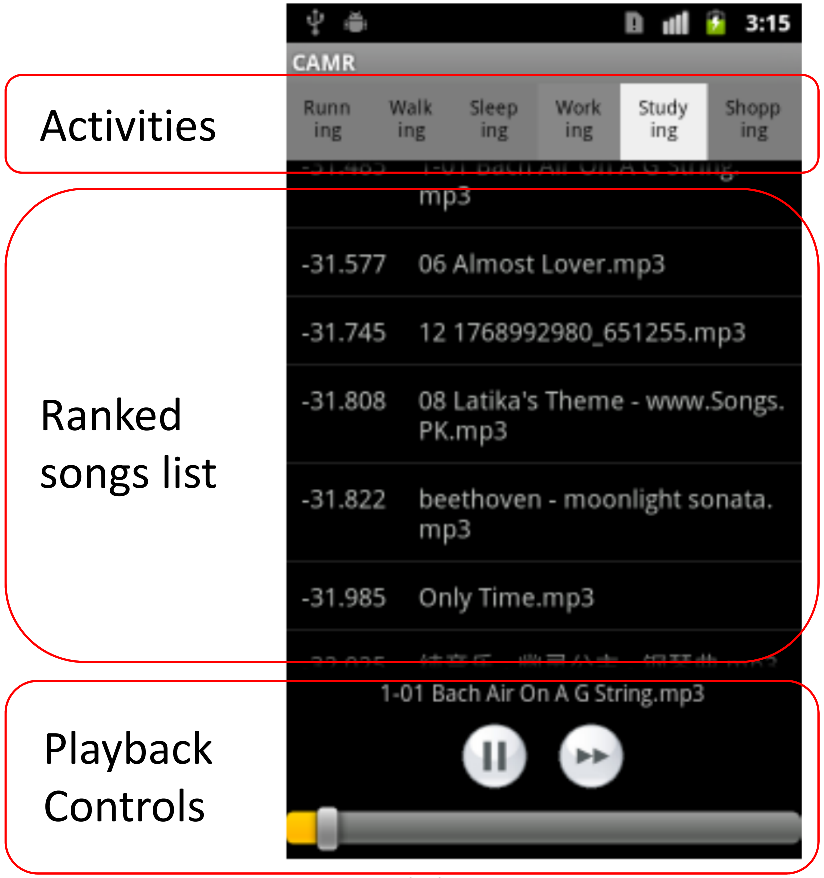
User Interest Modeling: Dynamics & Context



- Audio content analysis
- Sensor based activity detection
- Personalization and adaptation

[Wang et al. 2012] Xinxi Wang, David Rosenblum, Ye Wang: Context-aware mobile music recommendation for daily activities. *ACM Multimedia 2012*: 99-108.

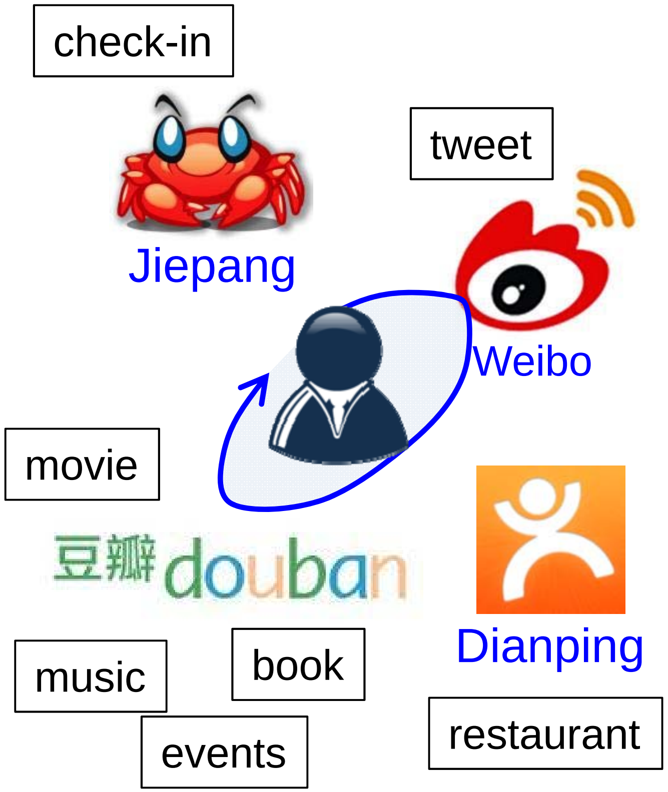
User Interest Modeling: Dynamics & Context

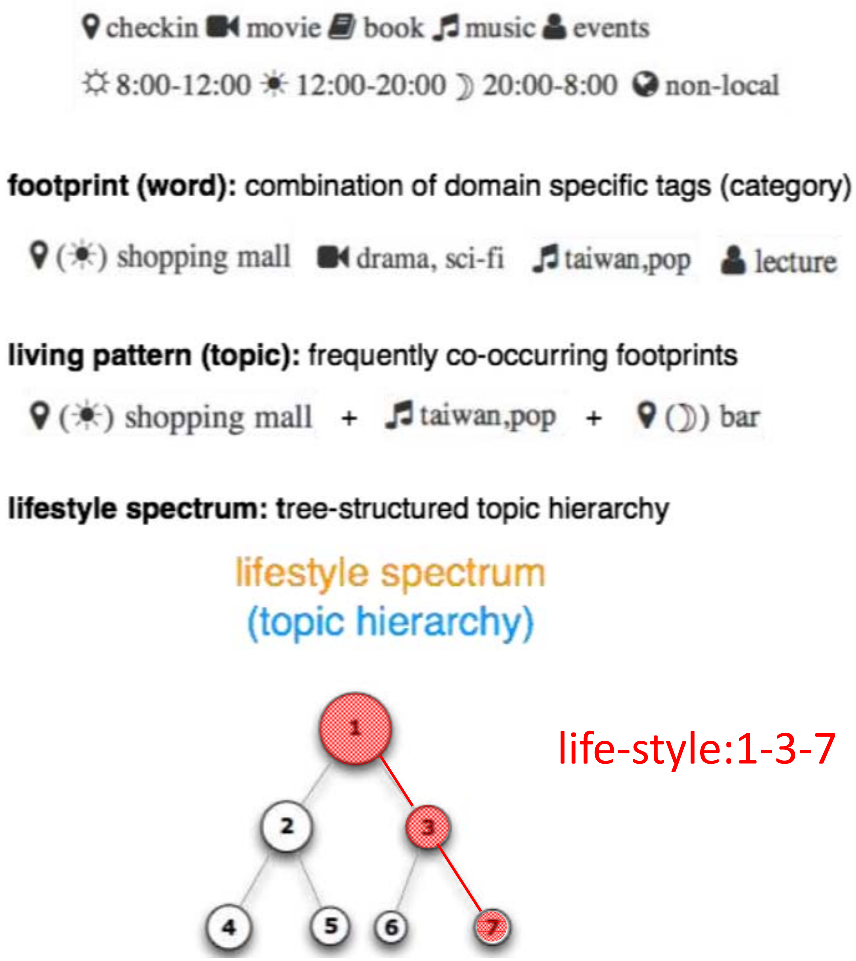


(a) auto mode

[Wang et al. 2012] Xinxi Wang, David Rosenblum, Ye Wang: Context-aware mobile music recommendation for daily activities. *ACM Multimedia 2012*: 99-108.

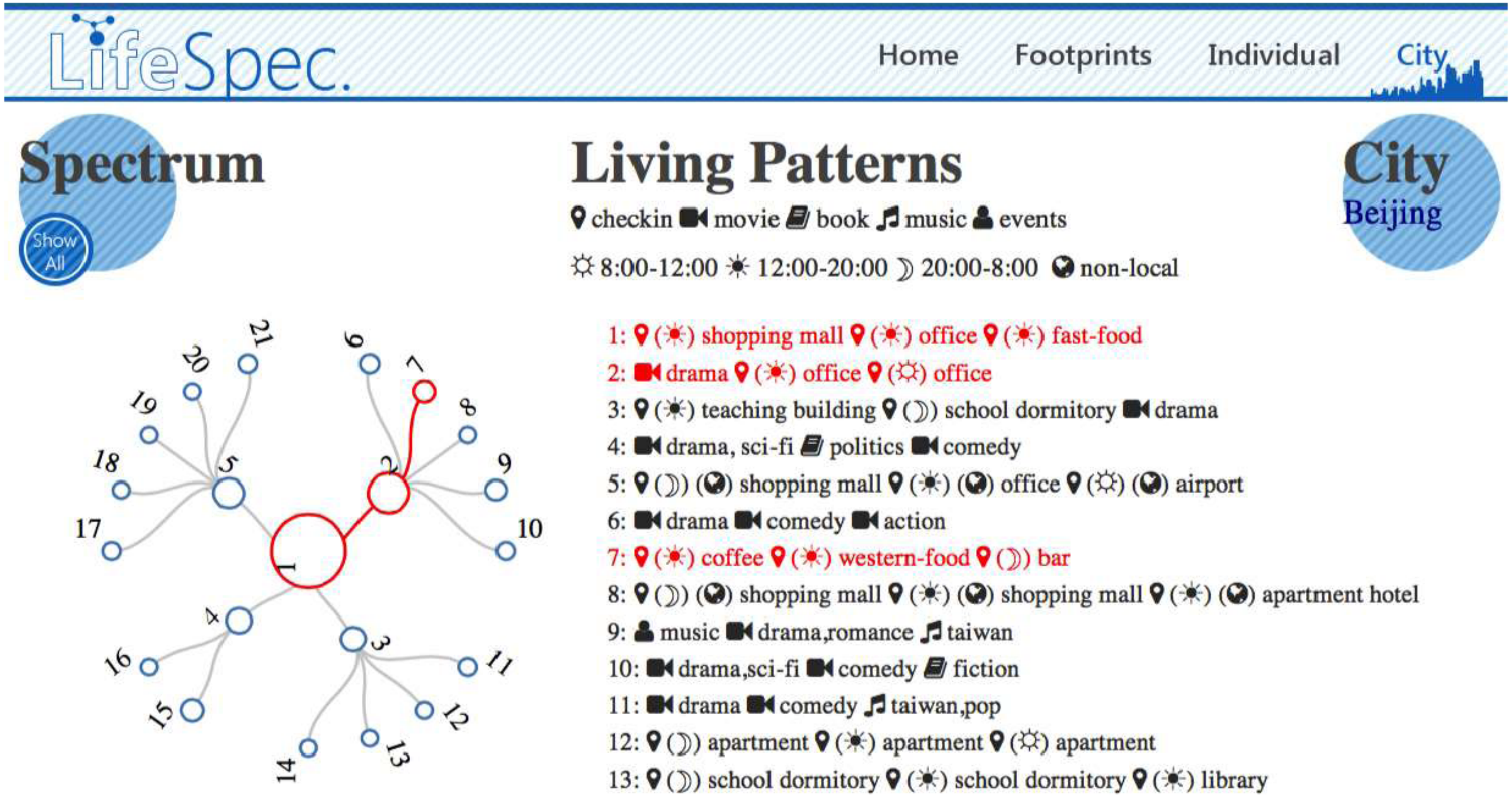
User Interest Modeling: Life Styles





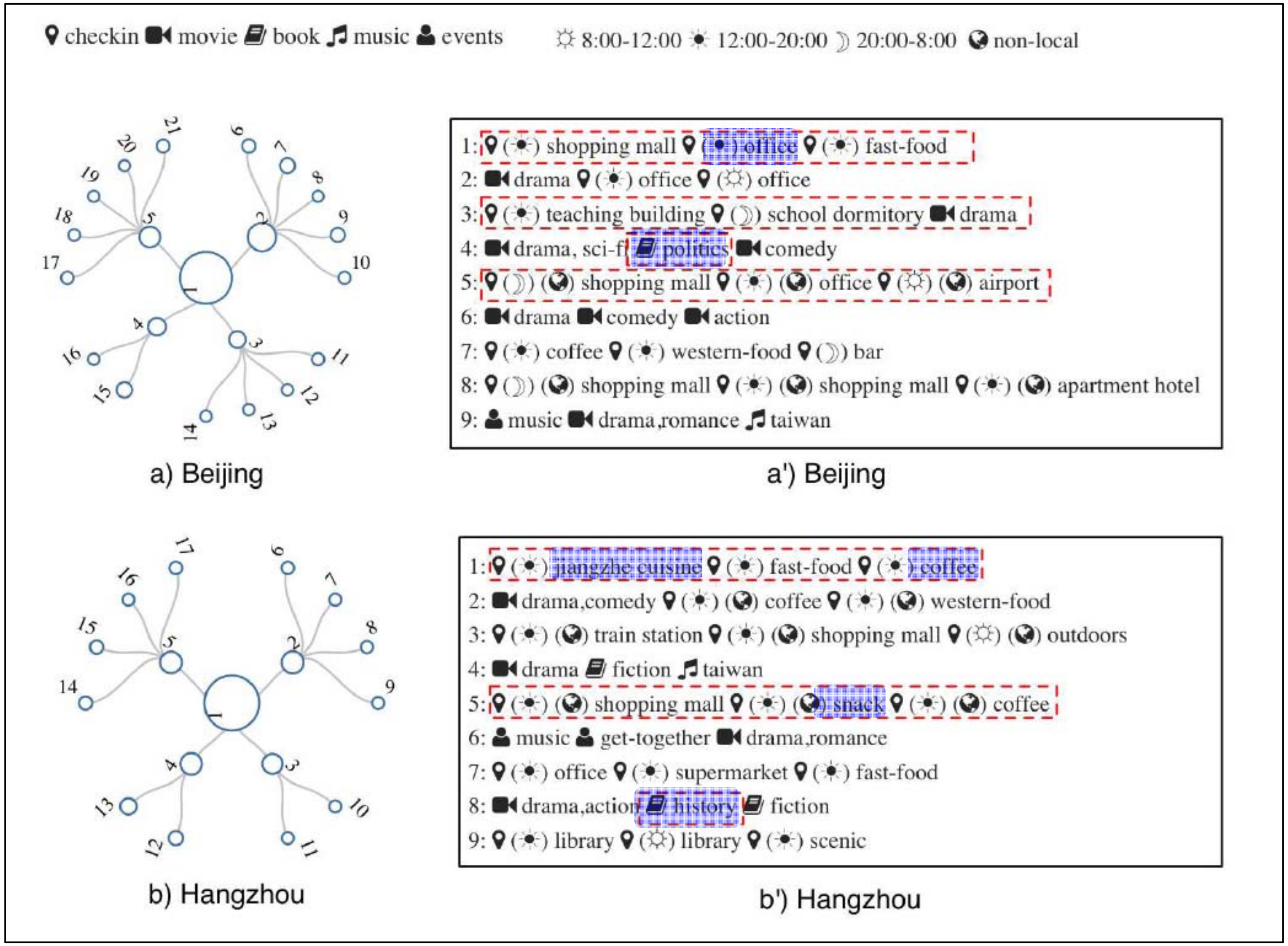
[Yuan et al. 2013] Nicholas Jing Yuan, Fuzheng Zhang, Defu Lian, Kai Zheng, Siyu Yu, Xing Xie, We Know How You Live: Exploring the Spectrum of Urban Lifestyles. *COSN 2013*. (Microsoft Research Asia)

User Interest Modeling: Life Styles



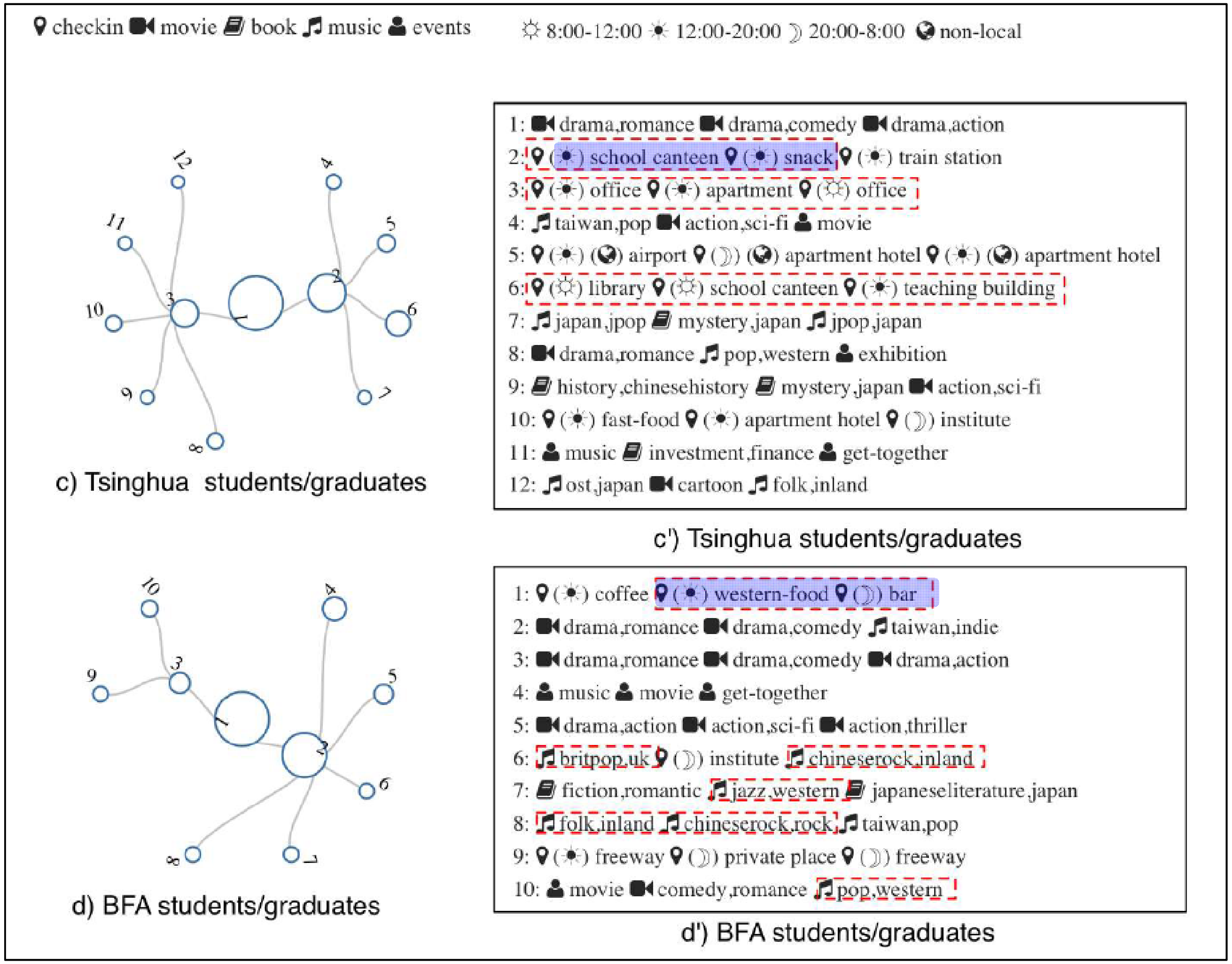
[Yuan et al. 2013] Nicholas Jing Yuan, Fuzheng Zhang, Defu Lian, Kai Zheng, Siyu Yu, Xing Xie, <u>We Know How You Live: Exploring the Spectrum of Urban Lifestyles</u>. *COSN 2013*. (Microsoft Research Asia)

User Interest Modeling: Life Styles



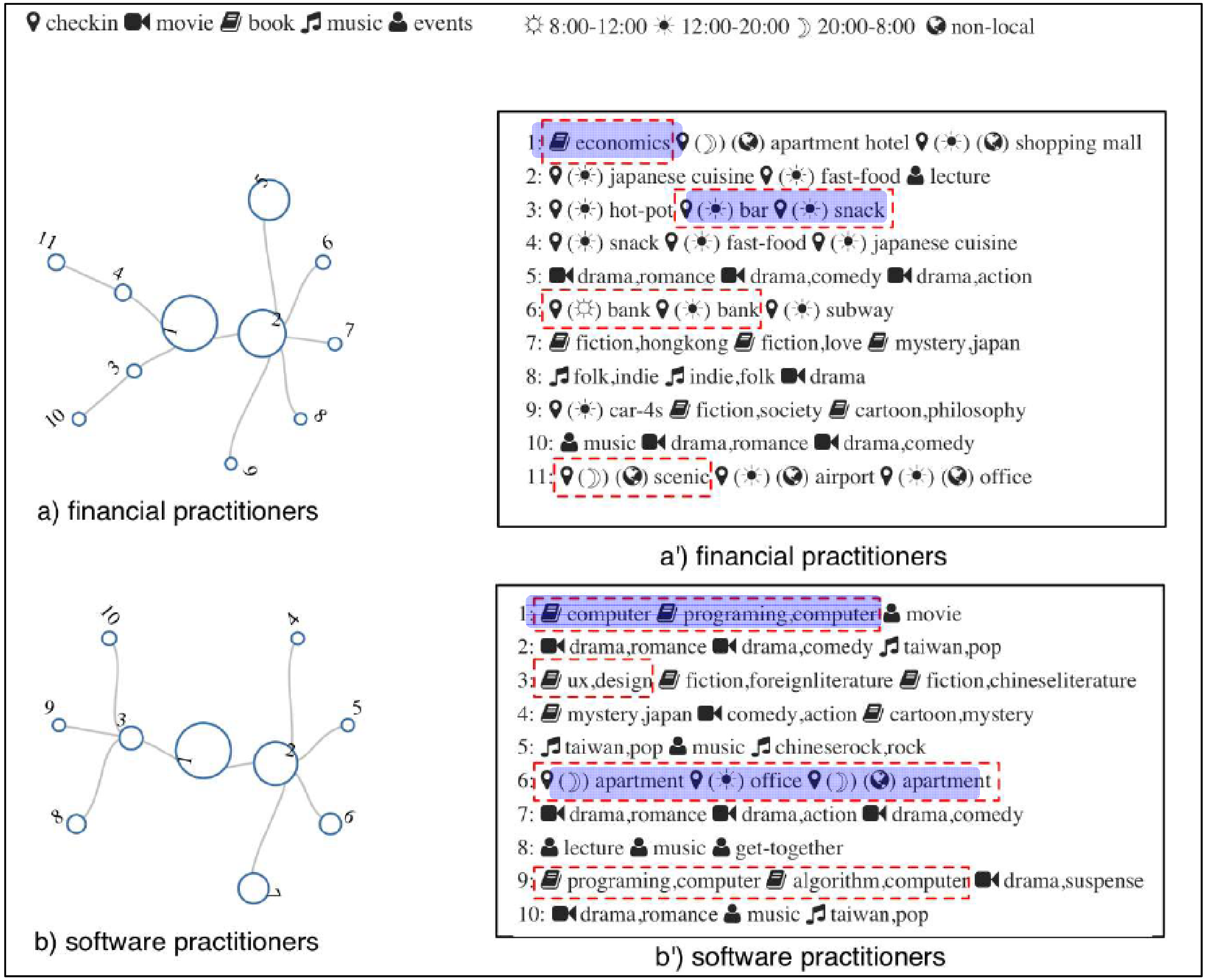
[Yuan et al. 2013] Nicholas Jing Yuan, Fuzheng Zhang, Defu Lian, Kai Zheng, Siyu Yu, Xing Xie, We Know How You Live: Exploring the Spectrum of Urban Lifestyles. *COSN 2013*.

User Interest Modeling: Life Styles



[Yuan et al. 2013] Nicholas Jing Yuan, Fuzheng Zhang, Defu Lian, Kai Zheng, Siyu Yu, Xing Xie, We Know How You Live: Exploring the Spectrum of Urban Lifestyles. *COSN 2013*.

User Interest Modeling: Life Styles



[Yuan et al. 2013] Nicholas Jing Yuan, Fuzheng Zhang, Defu Lian, Kai Zheng, Siyu Yu, Xing Xie, We Know How You Live: Exploring the Spectrum of Urban Lifestyles. *COSN 2013*.

Background: Understanding Social Influence

Psychology

Human Dynamics for persuasion and stress

Influence is **Quantitative**

Social Science

Information flow and social network evolution

Mechanism underlying **Homophily**:

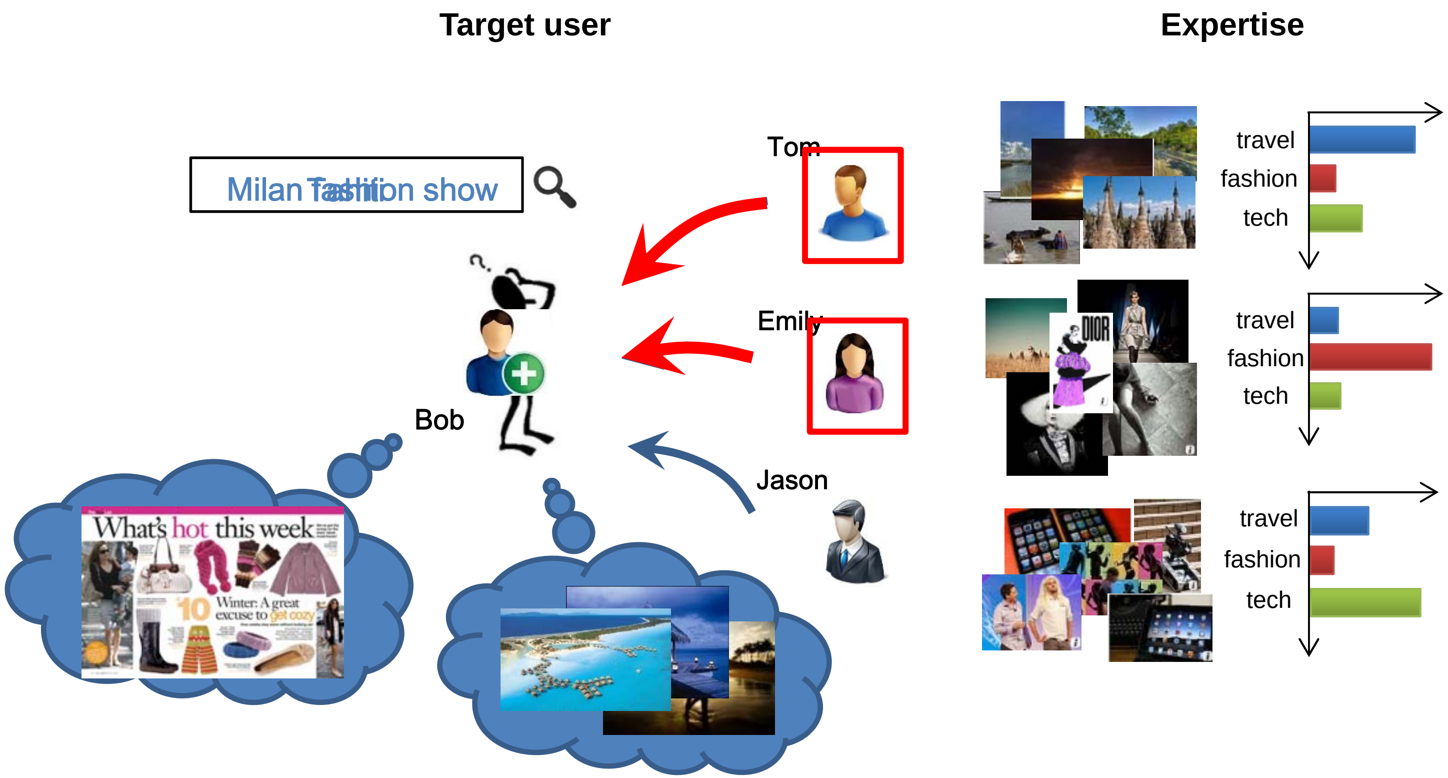
Influence is **Qualitative**

Social Multimedia Computing

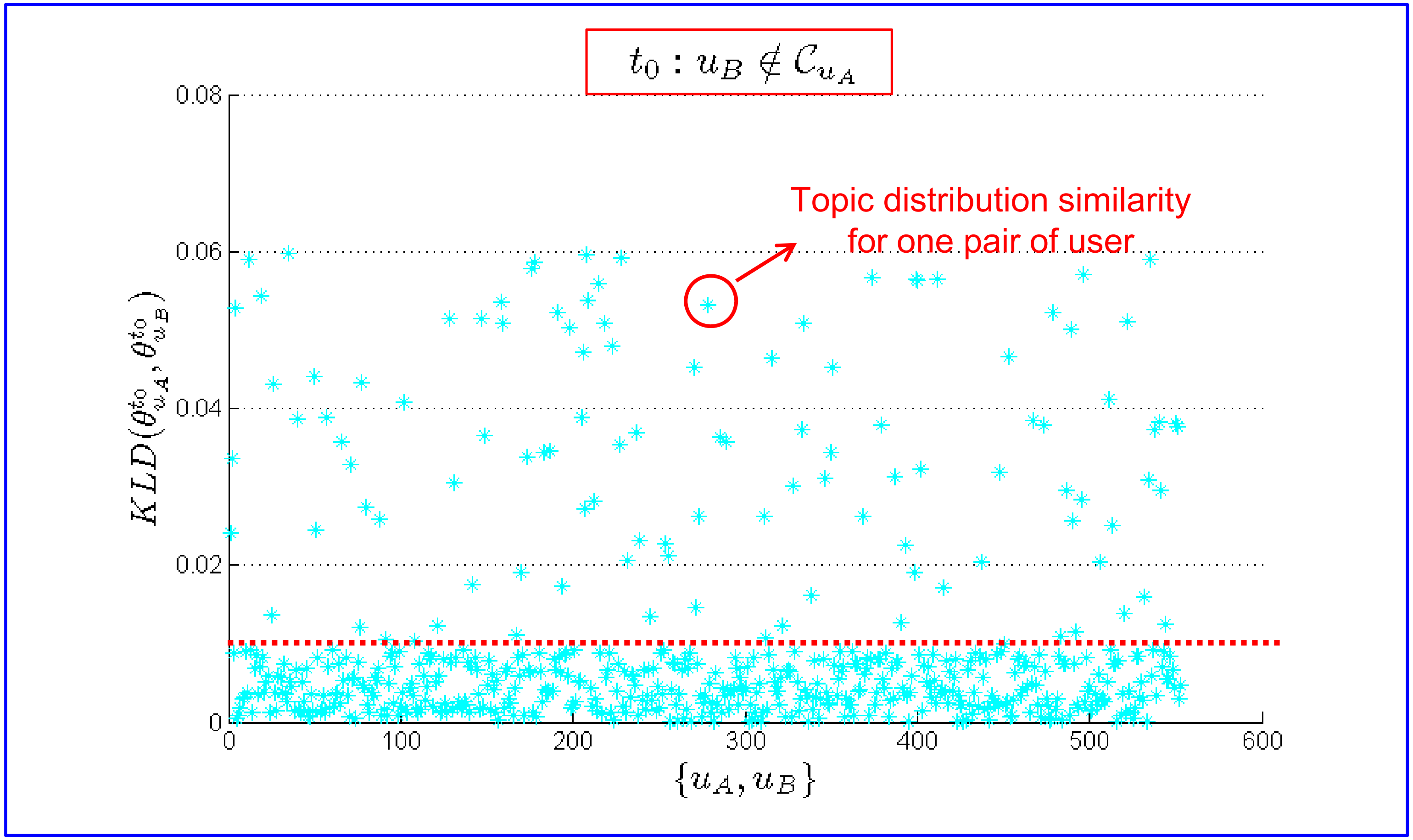
Affection on behaviors, preferences or decisions

Is influence **Quantitative** or **Qualitative?**

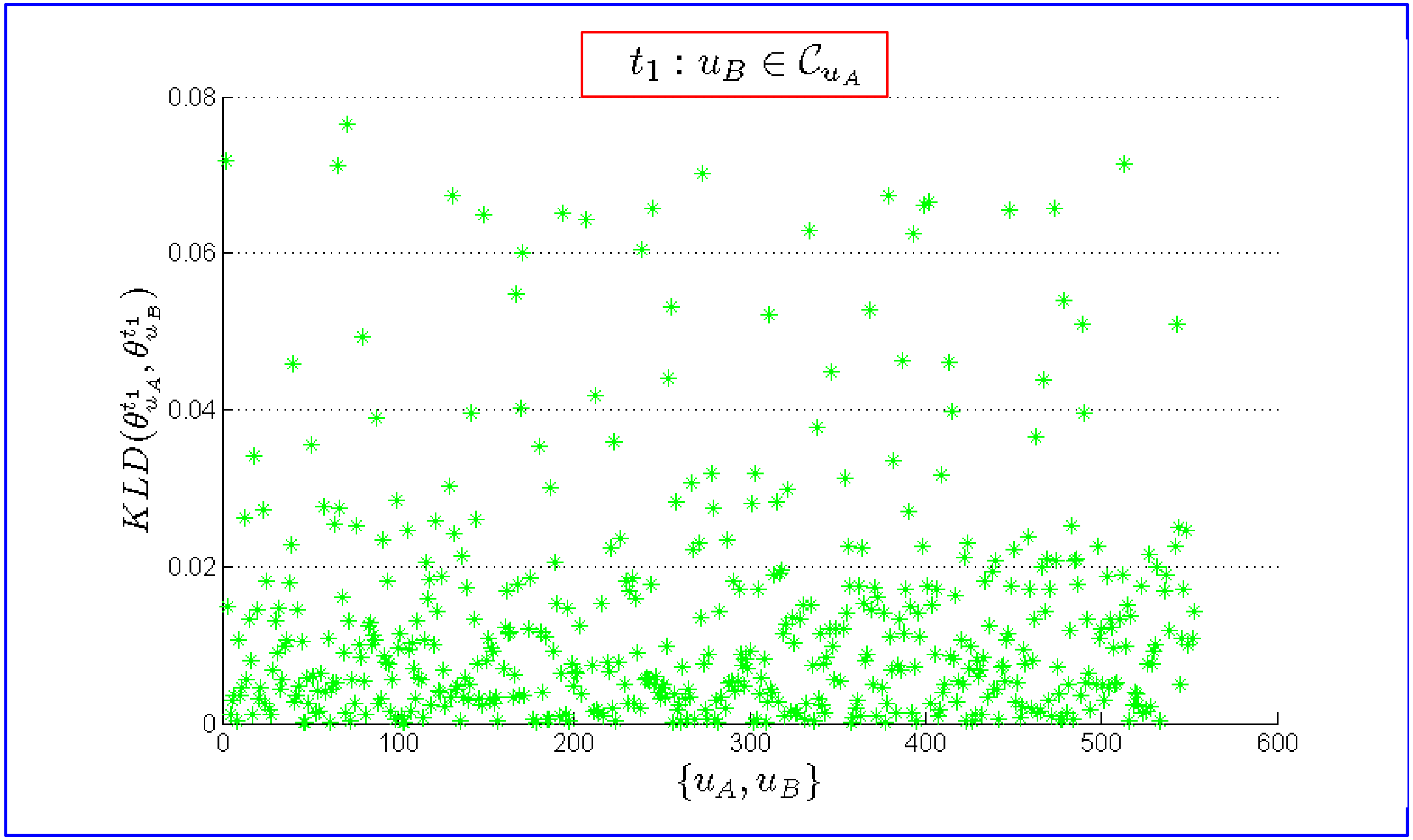
Motivation: Social Influence is Topic-sensitive



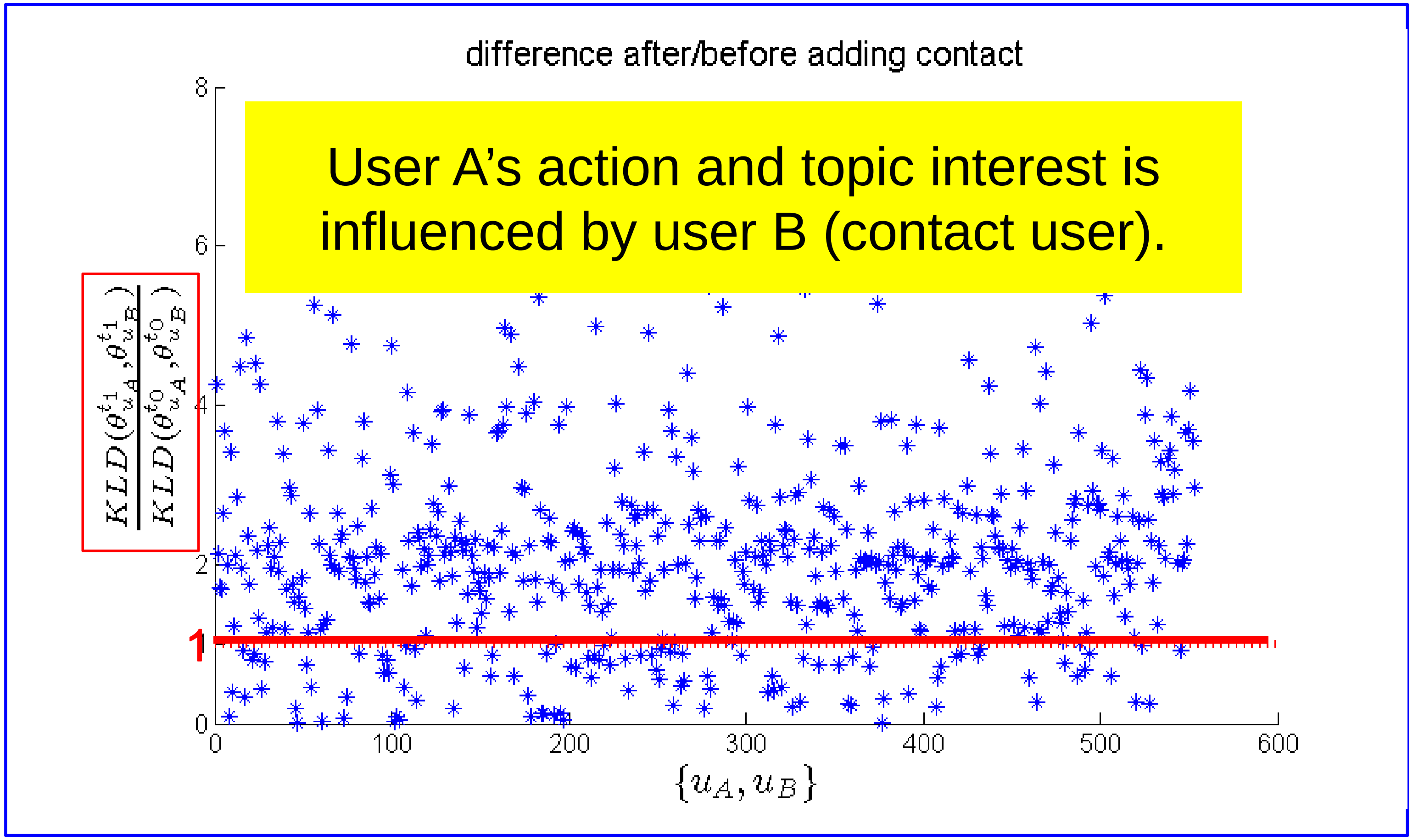
Data Analysis: User Interest Evolvement



Data Analysis: User Interest Evolvement



Data Analysis: User Interest Evolvement



Assumption: UGC Generative Process

- User interest evolvement data analysis:

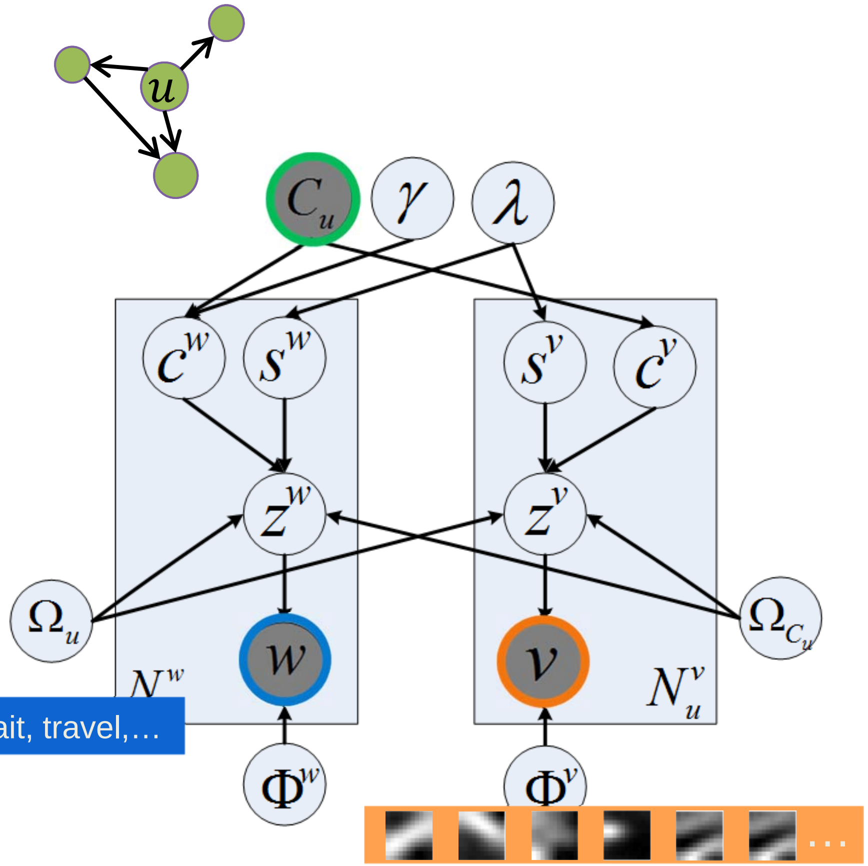
User A's action and topic interest is influenced by user B (contact user).

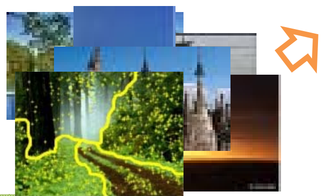
- Two ways to uploading and tagging:
  - Innovative: created based on own interest
  - Influenced: affected by contact users

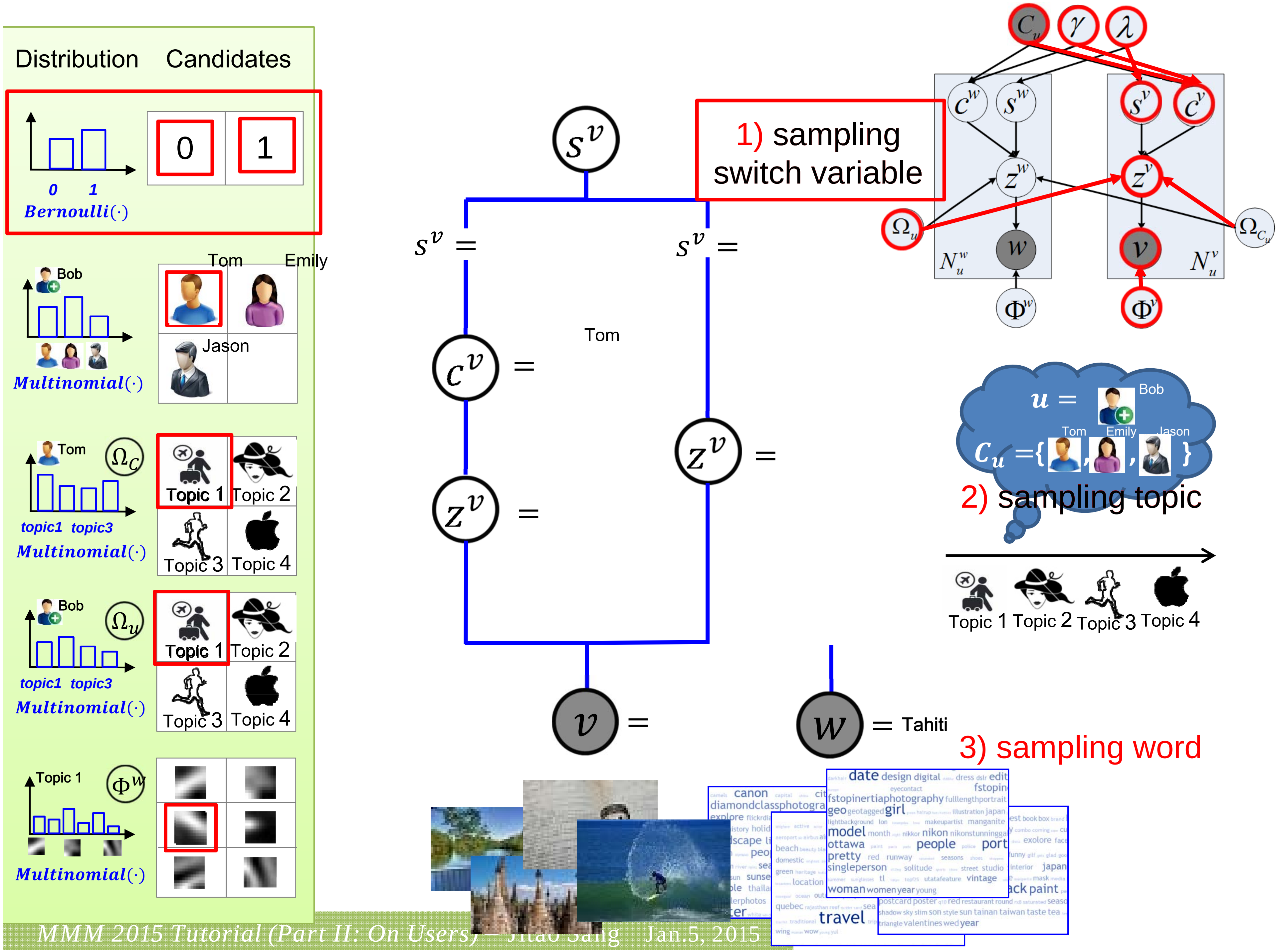
Solution: Multi-modal Topic-sensitive Influence Model (mmTIM)

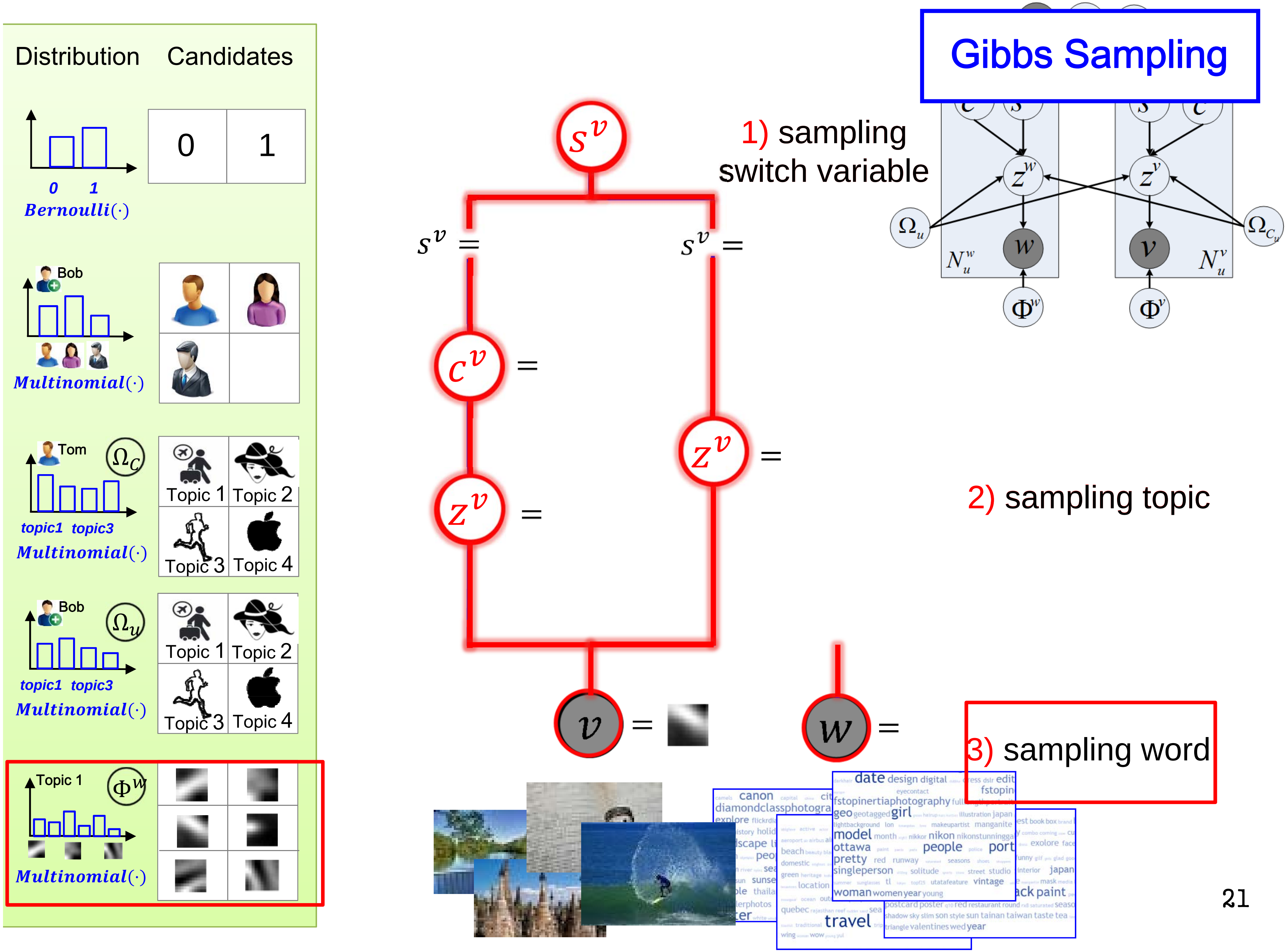
- Observations
  - Contact network C_u
  - User annotated tags $\boldsymbol{w}$
  - User uploaded images $\mathbf{v}$

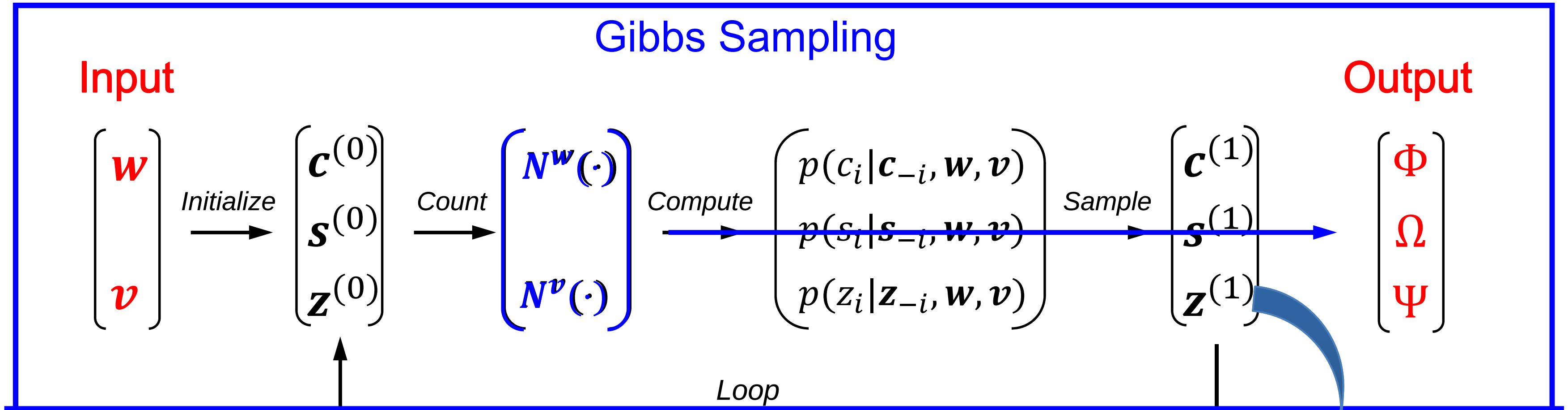
travel, fashion, portrait, travel,…






Distribution
Candidates
0
1
Bernoulli(·)
0
1
Bob
Tom
Emily
Jason
Multinomial(·)
Tom
topic1 topic3
Multinomial(·)
Topic 1
Topic 2
Topic 3
Topic 4
Bob
topic1 topic3
Multinomial(·)
Topic 1
Topic 2
Topic 3
Topic 4
Topic 1
Multinomial(·)
1) sampling switch variable
Tom
=
=
= Tahiti
2) sampling topic
u =
Bob
Tom
Emily
Jason
Topic 1
Topic 2
Topic 3
Topic 4
3) sampling word
canon
diamondclassphotogra
date design digital
fstopinertiaphotography
geo geotagged girl
model
ottawa
people
pretty
singleperson
woman women year
travel


Gibbs Sampling
Distribution
Candidates
0
1
Bernoulli(·)
Bob
Multinomial(·)
Tom
topic1 topic3
Multinomial(·)
Topic 1
Topic 2
Topic 3
Topic 4
Bob
topic1 topic3
Multinomial(·)
Topic 1
Topic 2
Topic 3
Topic 4
Topic 1
Multinomial(·)
s^v
$s^v =$
$s^v =$
$c^v =$
$z^v =$
$z^v =$
$v =$
$w =$
1) sampling switch variable
2) sampling topic
3) sampling word
Ω_C
Ω_u
Φ^w
Φ^v
N_u^w
N_u^v



Topic-word distribution

$$\Phi_{t,j} = \frac{N^W_{Z,W}(Z_t, w_j) + \alpha_{\Phi^w}}{N^W_Z(Z_t) + |W|\alpha_{\Phi^w}}$$

User-topic distribution

$$\Omega_{m,t} = \frac{N^W_{U,S,Z}(U_m, 1, Z_t) + N^v_{U,S,Z}(U_m, 1, Z_t) + \alpha_\Omega}{N^W_{U,S}(U_m, 1) + N^v_{U,S}(U_m, 1) + T\alpha_\Omega}$$

Topic-sensitive influence strength

$$\Psi_{m1,m2}(t) = \frac{N^w{}_{U,C,S,Z}(U_{m2}, U_{m1}, 0, Z_t) + N^v{}_{U,C,S,Z}(U_{m2}, U_{m1}, 0, Z_t) + \alpha_\gamma}{N^w{}_{U,S,Z}(U_{m2}, 0, Z_t) + N^v{}_{U,S,Z}(U_{m2}, 0, Z_t) + |C_{U_{m2}}|\alpha_\gamma}$$

Experiments

- Dataset:
  - ✓ 3,372 users (crawl their contact relationship)
  - ✓ 30,108 unique tags
  - ✓ 124,099 uploaded pictures
  - ✓ 5,000 MSER visual words
- #Topic = 20

Experiments: Case Study

- Illustration of Discovered Topics:

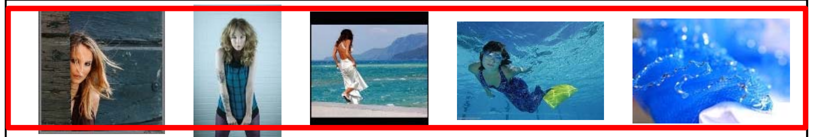
Topic #2

travel	vacation	landscape	trip	architecture
0.01433	0.01163	0.00867	0.00681	0.00645

0.3757	0.3453	0.2657	0.2481	0.1755

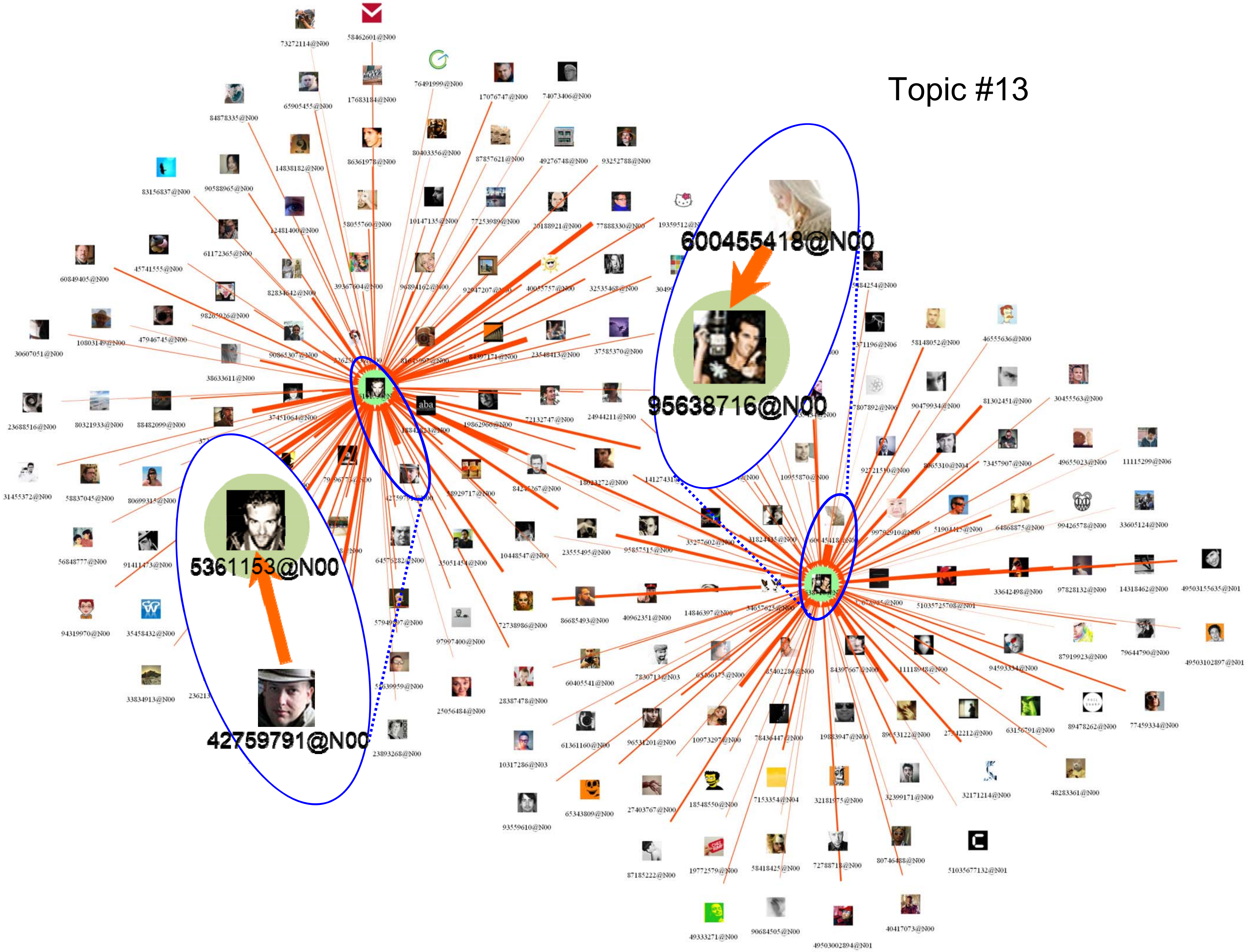
Topic #13

fashion	portrait	model	dress	style
0.01213	0.00702	0.00552	0.00486	0.00461

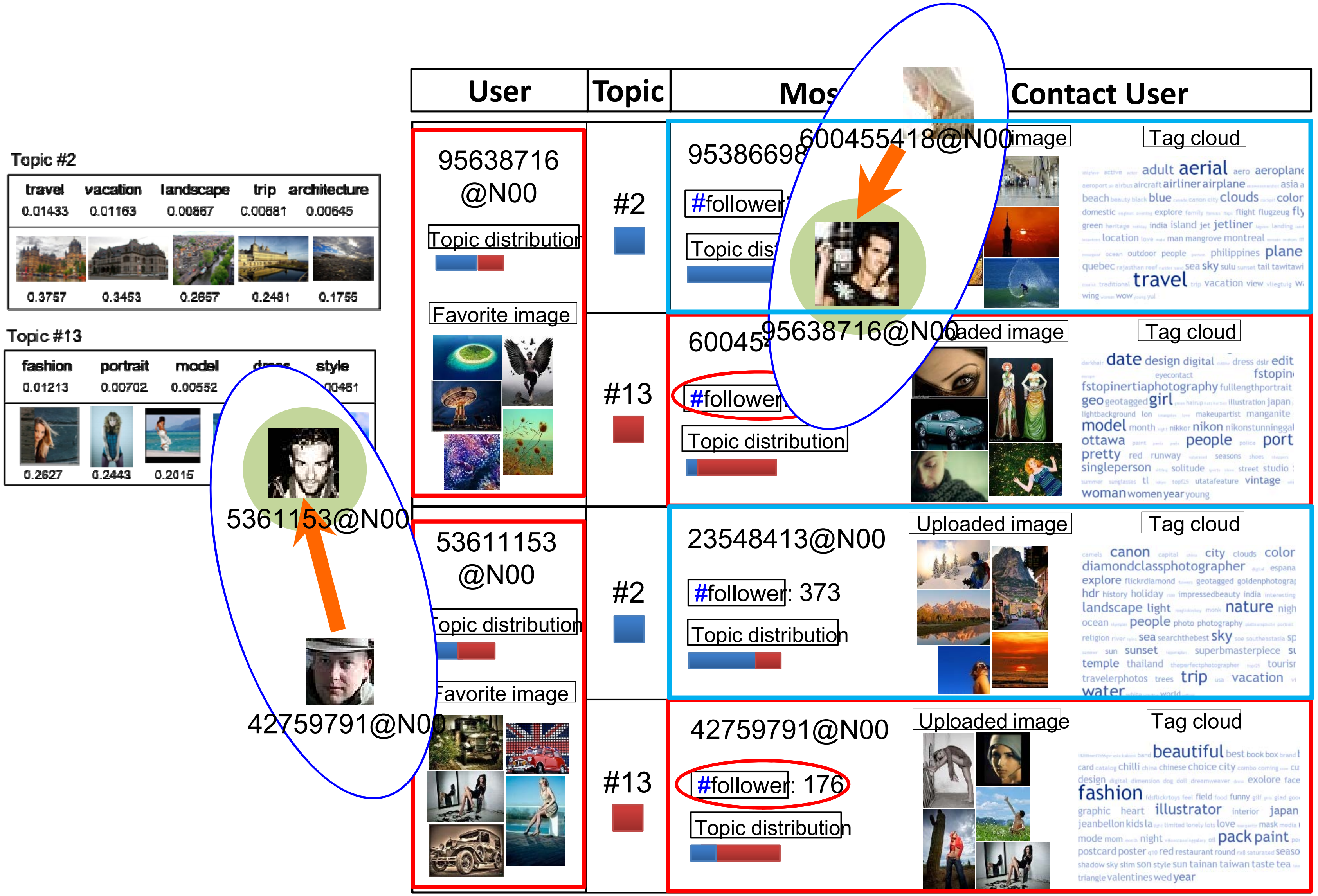


0.2627	0.2443	0.2015	0.1578	0.1204

Topic #13



Experiments: Case Study

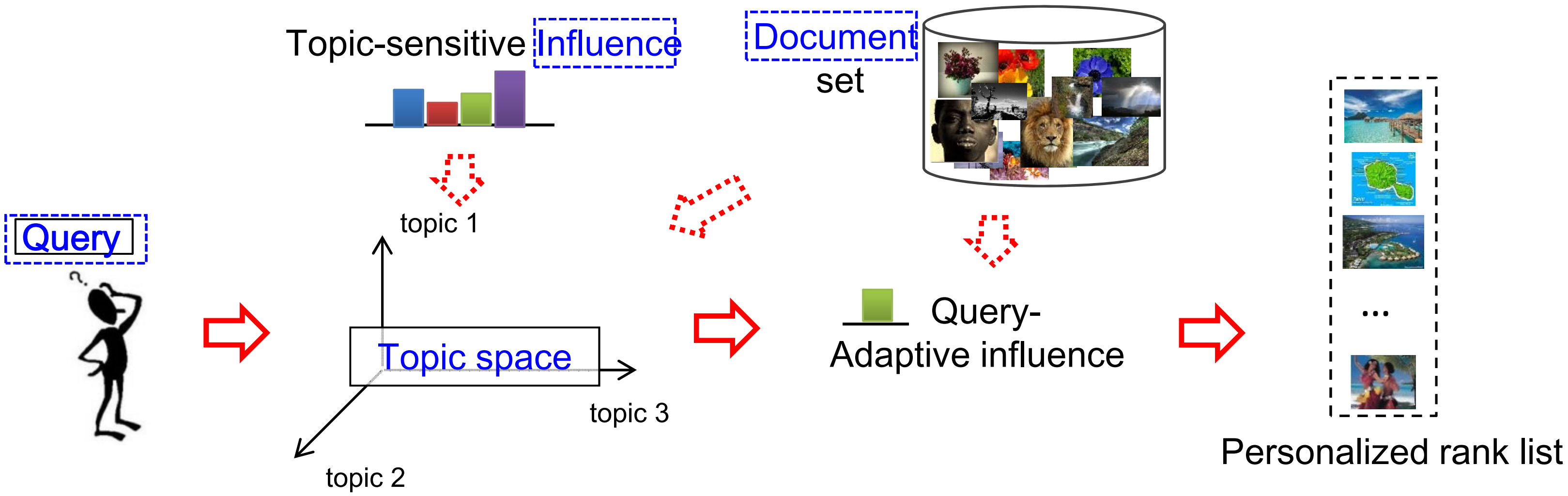


Application 1: Personalized Image Retrieval

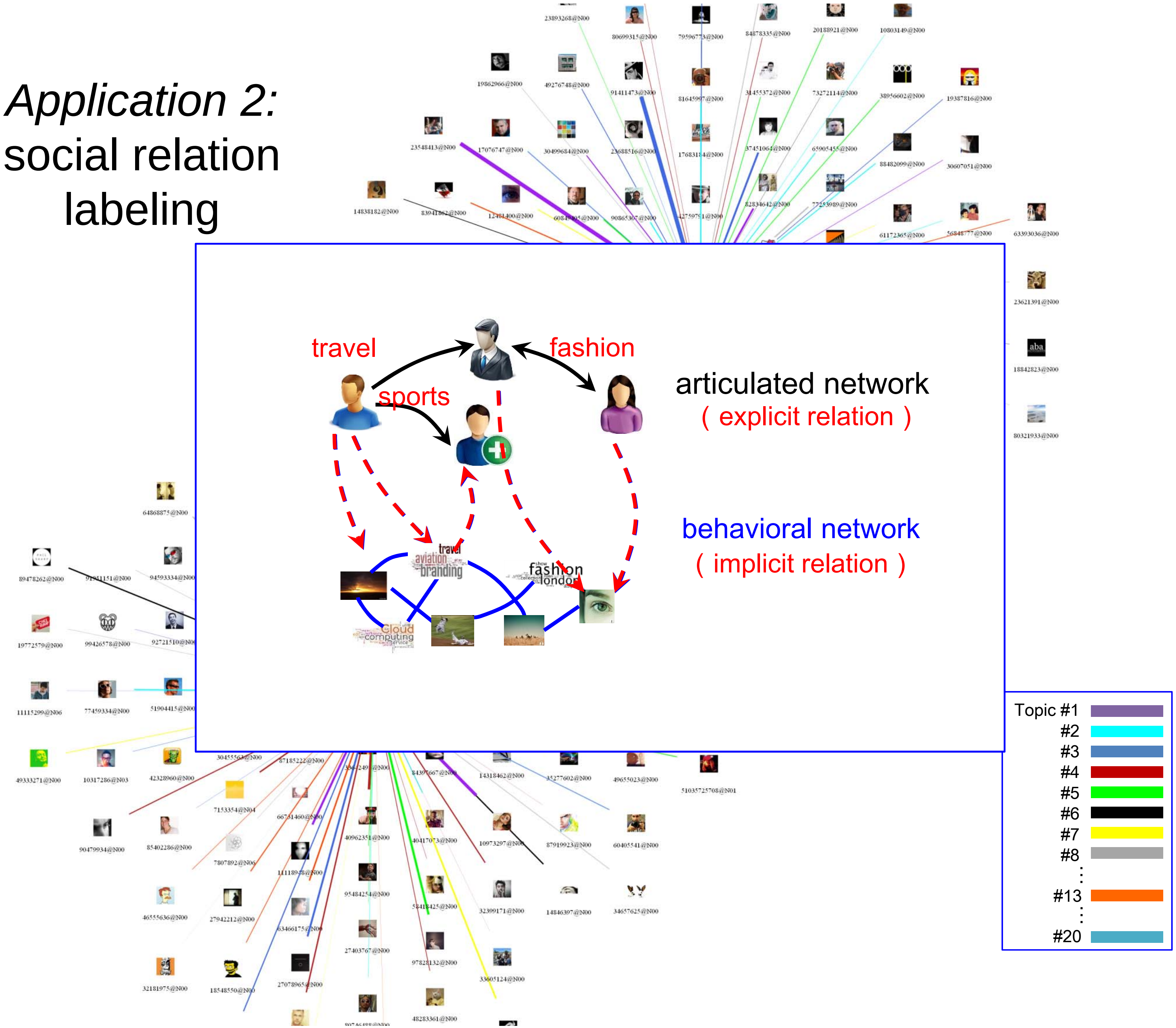
- Basic idea:

  Social-related users' preference can help understand the searcher's preference.

- Query ⇨ influence ⇨ ranked results

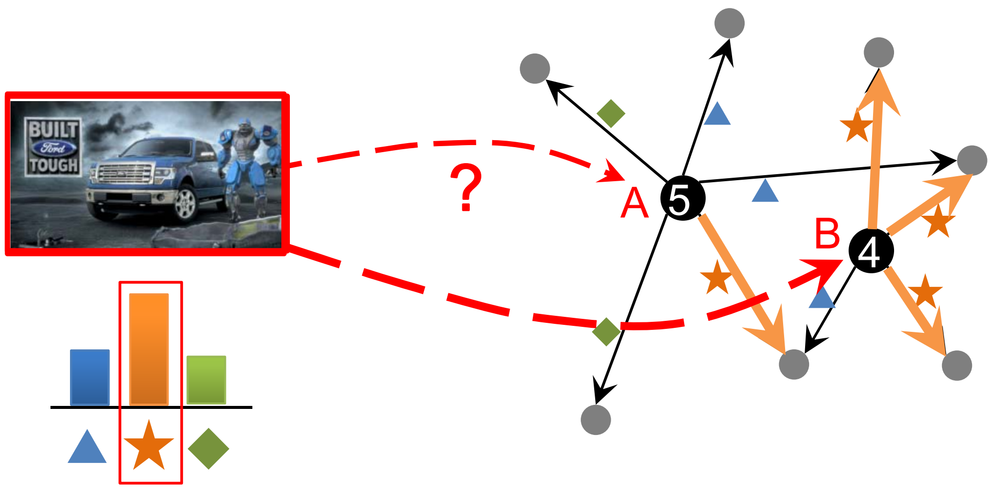


Application 2:
social relation labeling

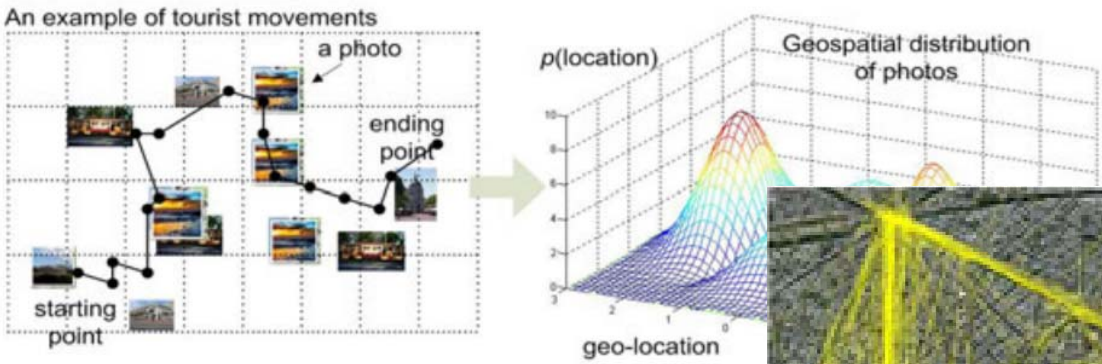


Application 3: Social Media Marketing

- Topic-aware social multimedia marketing:



User Mobility Pattern Modeling

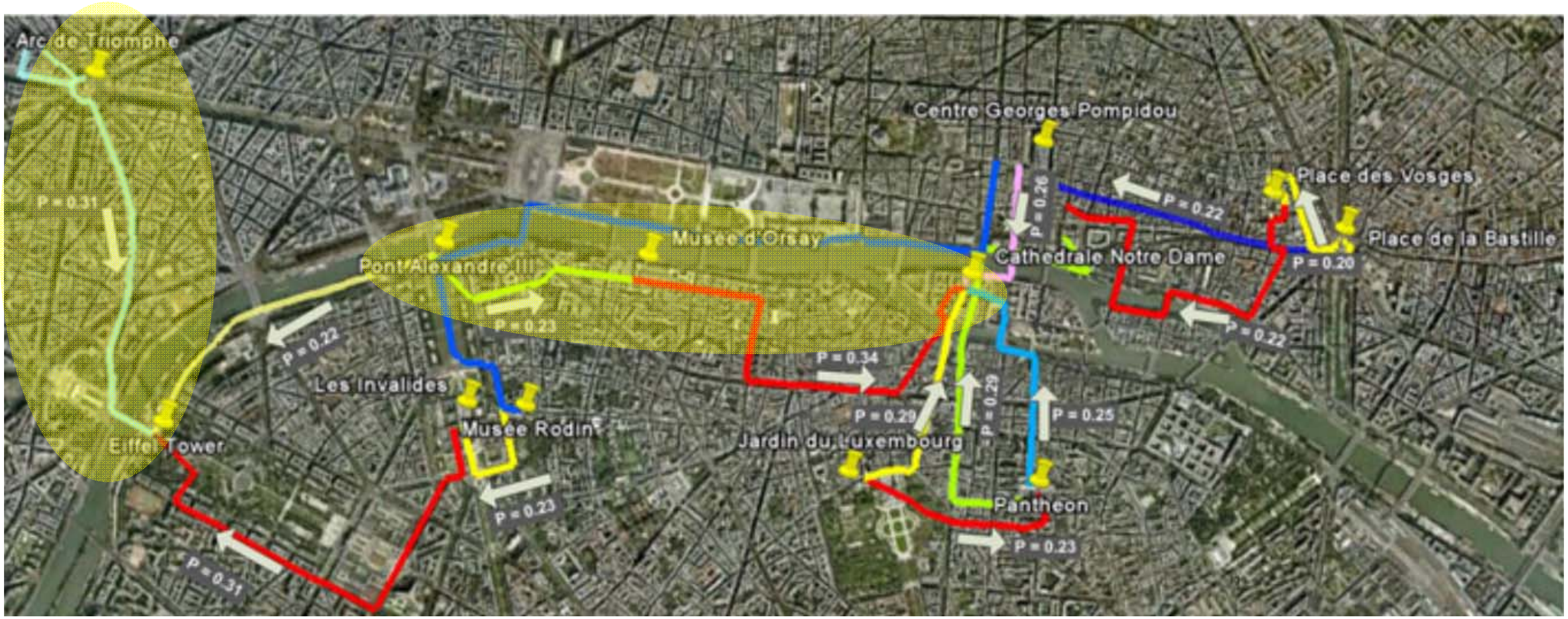


a tourist movement trajectory

Tourist travel trails in Paris

[Zheng et al. 2012] Yan-Tao Zheng, Zheng-Jun Zha, Tat-Seng Chua: Mining Travel Patterns from Geotagged Photos. *ACM TIST 2012*. (National University of Singapore)

User Mobility Pattern Modeling

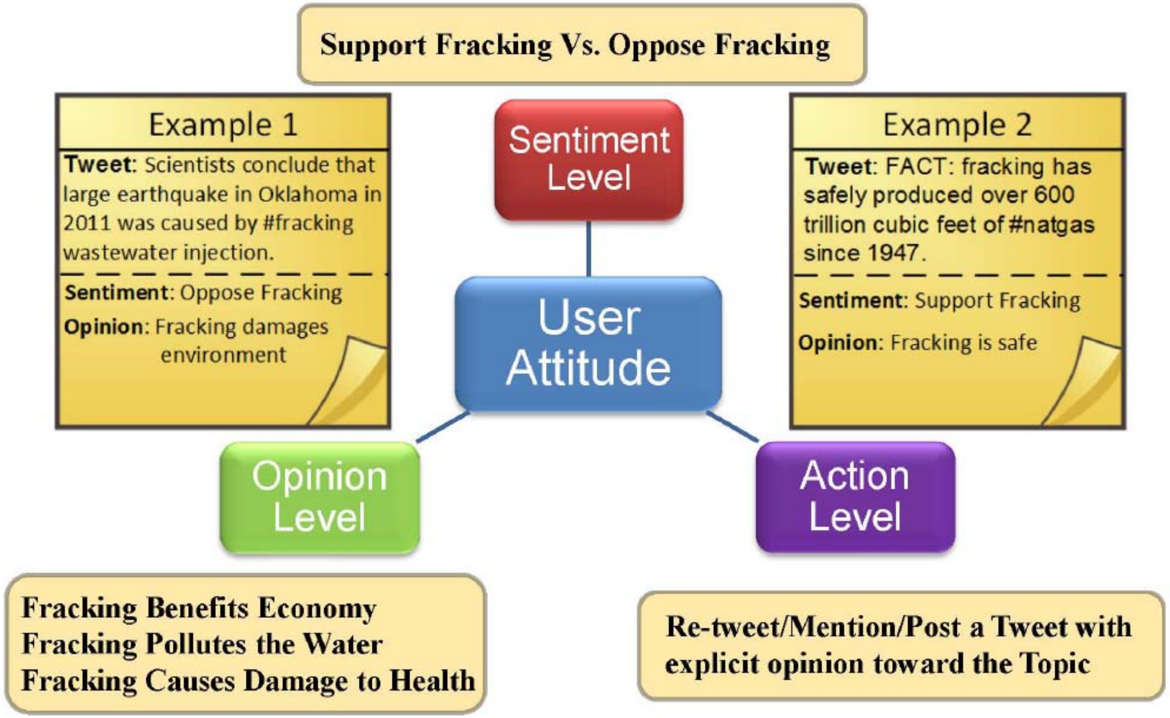


Significant traffic transition pattern among Region of Attractions, in Paris

[Zheng et al. 2012] Yan-Tao Zheng, Zheng-Jun Zha, Tat-Seng Chua: Mining Travel Patterns from Geotagged Photos. *ACM TIST 2012*.

User Emotion Modeling

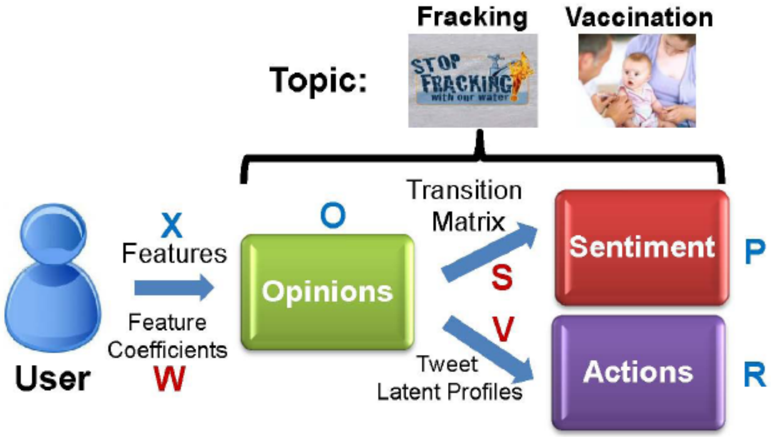
- Sentiment, opinion, and action are inter-related:



[Gao et al. 2014] Huiji Gao, Jalal Mahmud, Jilin Chen, Jeffrey Nichols, Michelle X. Zhou: Modeling User Attitude toward Controversial Topics in Online Social Media. *ICWSM 2014.*

(Arizona State University & IBM Research)

User Emotion Modeling



between item and topic

between opinion and topic

$$\min_{\mathbf{W}\geq 0,\mathbf{S}\geq 0,\mathbf{V}\geq 0} \|\boxed{\mathbf{R} - \mathbf{F}(\mathbf{W},\mathbf{X})\mathbf{V}^\top}\|_F^2 + \lambda\|\boxed{\mathbf{F}(\mathbf{W},\mathbf{X}) - \mathbf{O}}\|_F^2$$

$$+ \eta\|\boxed{\mathbf{F}(\mathbf{W},\mathbf{X})\mathbf{S} - \mathbf{P}}\|_F^2 + \varphi\|\mathbf{W}\|_1$$

$$+ \alpha(\|\mathbf{W}\|_F^2 + \|\mathbf{V}\|_F^2 + \|\mathbf{S}\|_F^2)$$

$$s.t. \quad \mathbf{F}(\mathbf{W},\mathbf{X}) = \mathbf{X}\mathbf{W}^\top.$$

between sentiment and opinion

[Gao et al. 2014] Huiji Gao, Jalal Mahmud, Jilin Chen, Jeffrey Nichols, Michelle X. Zhou: Modeling User Attitude toward Controversial Topics in Online Social Media. *ICWSM 2014*.

User Consuming Pattern Modeling

Table 1: Example of User Information.

Name	Anonymous
Gender	Male
Age group	35-44
Facebook likes (*Category*)	Beatles (*Musician/band*) iPhone 5 (*Electronics*) Starbucks (*Food/beverage*) Walt Disney Studios (*Movie*)
eBay purchases (*Meta-category*)	iPhone 4S (*Electronics*) Beatles T-shirt (*Clothing*) Beatles Mug (*Collectibles*)

Table 2: Statistics of Our Dataset.

Users	13,619
Facebook categories	214
Facebook pages	1,373,984
Facebook likes	4,165,690
eBay categories	35
eBay purchases	628,753

Table 3: Examples of Correlated Categories.

eBay Category	Facebook Category	χ
Computers/Tablets	Computers/technology	52.0
Computers/Tablets	Software	51.9
Music	Record label	95.5
Music	Musical Instrument	67.1
Travel	Bags/luggage	7.9
Travel	Book Genre	5.9
Jewelry & Watches	Jewelry/watches	63.6
Jewelry & Watches	Health/beauty	13.4
Cell Phones	Telecommunication	67.2
Cell Phones	Electronics	46.1

[Zhang and Pennacchiotti 2013a] Yongzheng Zhang, Marco Pennacchiotti: Predicting purchase behaviors from social media. *WWW 2013*. (Ebay)

[Zhang and Pennacchiotti 2013b] Yongzheng Zhang, Marco Pennacchiotti: Recommending branded products from social media. *RecSys 2013*

User Consuming Pattern Modeling

Table 2: Statistics of Our Dataset.

Users	9,398
Brands	4,445
Facebook categories	214
Facebook pages	1,373,984
Facebook likes	4,165,690
eBay meta-categories	9
eBay branded purchases	174,190

Table 3: Examples of Correlated Brands.

Purchased brands	Liked brands	*pmi*
Victoria's Secret	Paul Frank	1.35
	Soda	1.32
	Designer Skin	1.29
	Too Faced	1.24
	Derek Heart	1.23
HTC	Sony Ericsson	1.62
	HTC	1.50
	Galaxy	1.17
	T-mobile	1.12
	Monster	1.10
Pottery Barn	Talbots	3.46
	Banana Republic	2.32
	MAC	1.84
	Bath & Body Works	1.61
	Vera Bradley	1.58
Nike	Supreme	3.02
	Air Jordan	2.67
	NBA	2.44
	59Fifty	2.17
	New Era	2.07

[Zhang and Pennacchiotti 2013a] Yongzheng Zhang, Marco Pennacchiotti: Predicting purchase behaviors from social media. *WWW 2013*.

[Zhang and Pennacchiotti 2013b] Yongzheng Zhang, Marco Pennacchiotti: Recommending branded products from social media. *RecSys 2013*

Summary: User Modeling from SMA

Demographics

Interests

Social Status

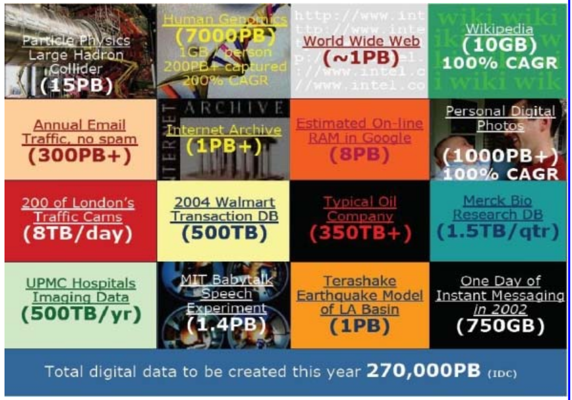
Mobility

Emotion

Consuming Model

Big Data & Multimedia

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



Enterprise & government data

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.

Internet data

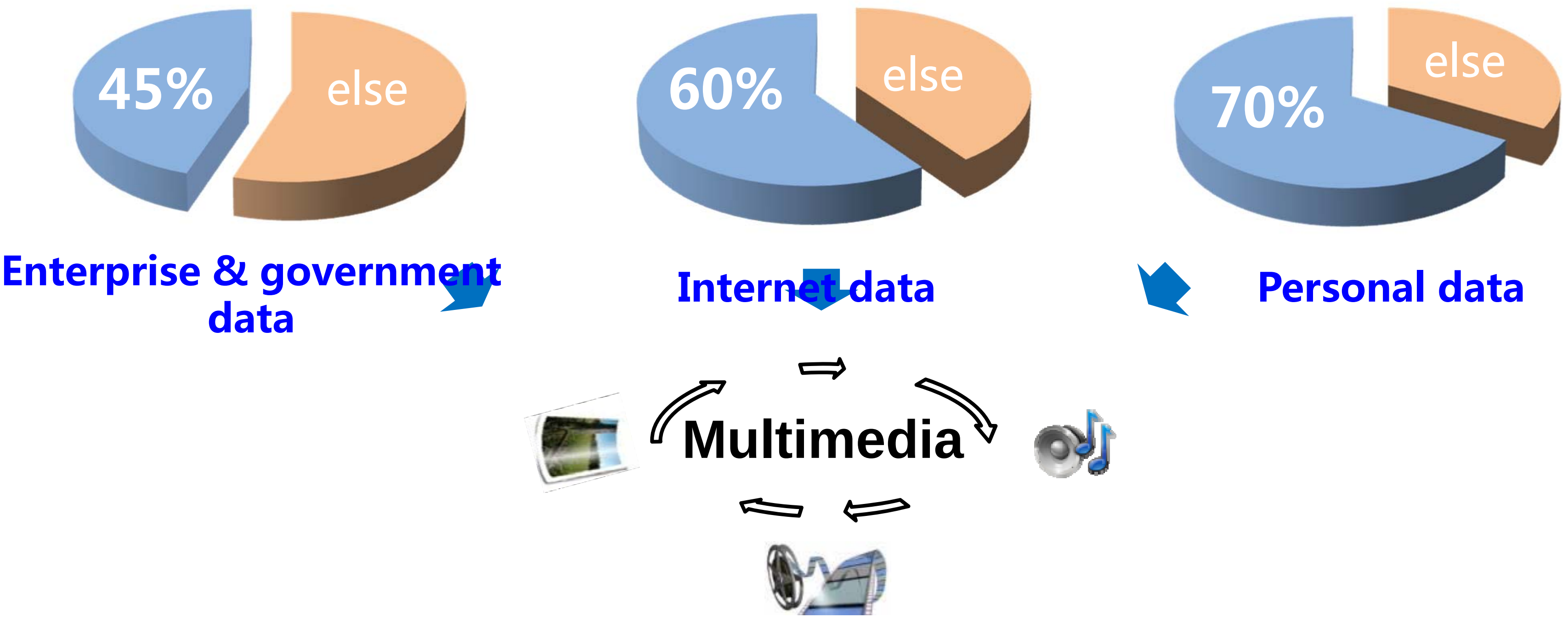
BAT（Baidu、Alibaba、Tencent）possess data in the scale of 10EB（10^{18}）, and increase at a speed of PB per day.

Personal data

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

Big Data & Multimedia

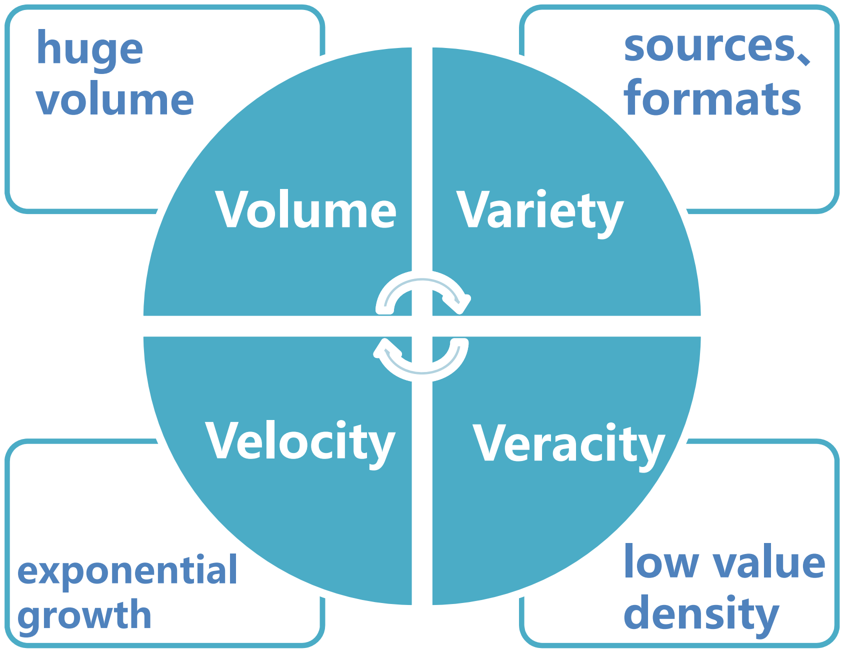
Big Data：any collection of data sets so large and complex that is difficult to process using traditional techniques. --- Wikipedia



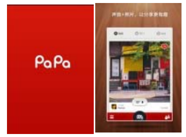
Big Data & Social Multimedia

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

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



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



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

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

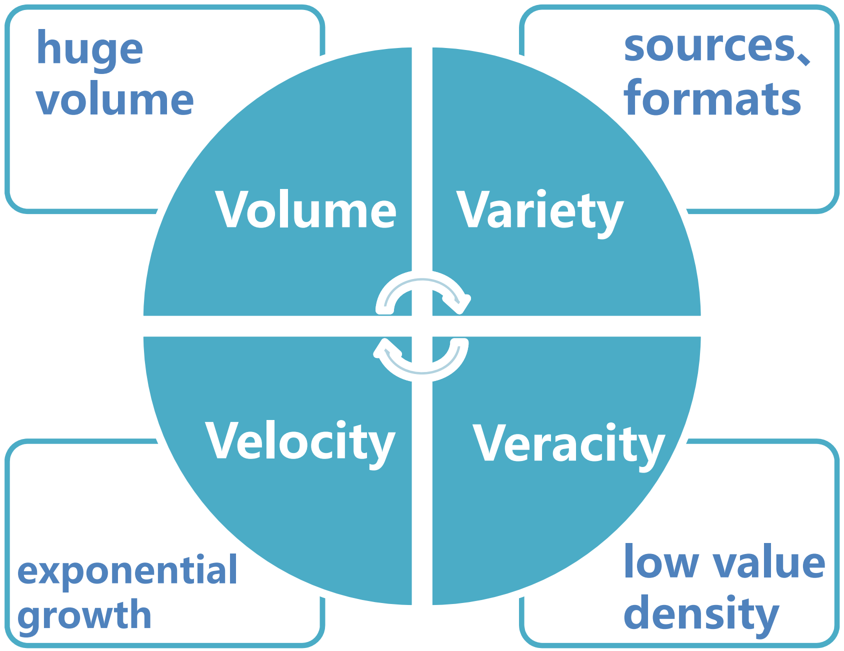
demands：personalized

Big Data & Social Multimedia

Social Multimedia has significant big data characteristics:

capacity in data storage

complexity in data analysis



efficiency in data capture & computing

data accuracy and quality

“Variety” in Social Multimedia

received extensive attentions in the “small” data era

"Variety" in Social Multimedia

beyond multiple modalities:

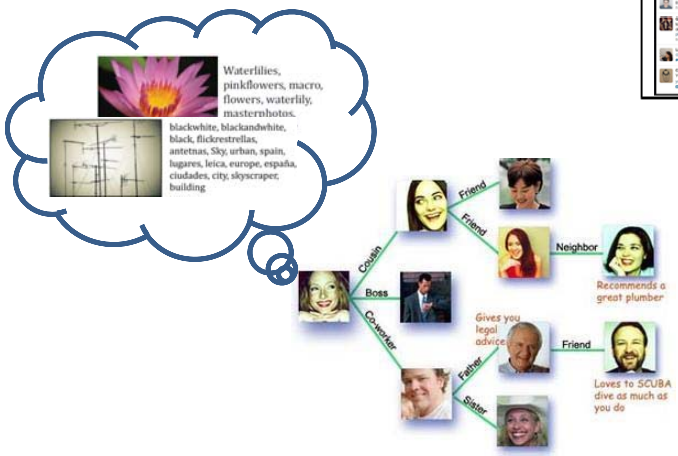
the heterogeneous data created and consumed in various social media networks

- same modality, different information

YouTube upload favorite playlist rate

Google+ share comment +1

- Content + Context.



“Variety” in Social Multimedia

the heterogeneous data created and consumed in various social media networks

beyond multiple modalities

“Multisource” in Social Multimedia

- Macro-level analysis:
  - Characteristics of different social media networks.
    - degree distribution, clustering coefficiency [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 social media networks.
    - 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]

"Multisource" in Social Multimedia

- Micro-level analysis and applications:

  - **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 social media websites.

User-centric Solution

- Heterogeneous data among different social media networks share the unique user space:

Cross-network User Account Collection

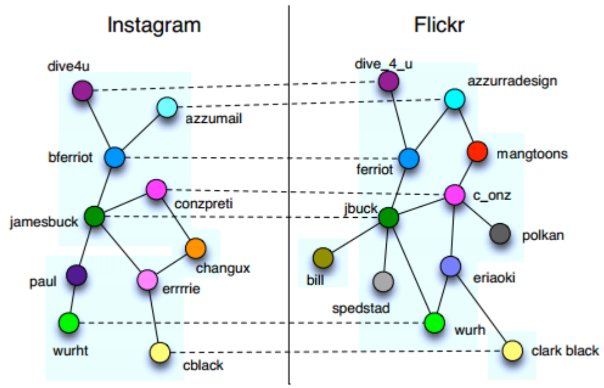
- Identical user account among different social media services.

Google account: Google+, YouTube

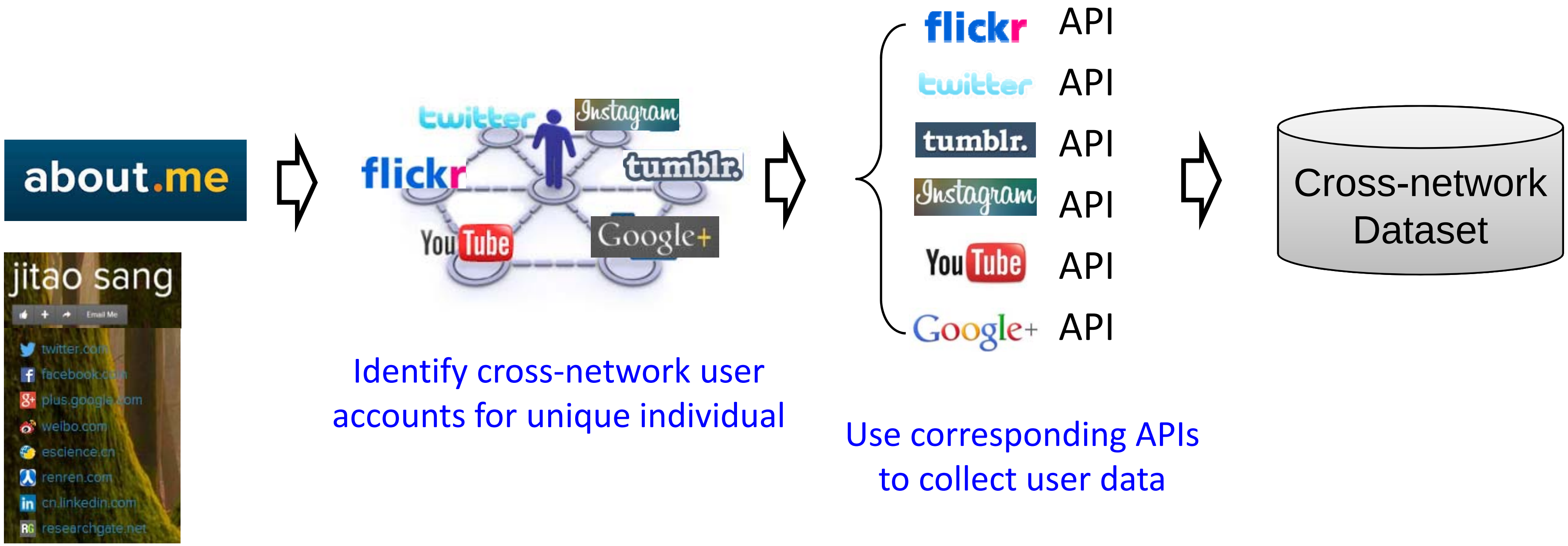
Tencent account

- Users are voluntary to discover their accounts in multiple networks.

- User account linkage mining is a separated research topic.

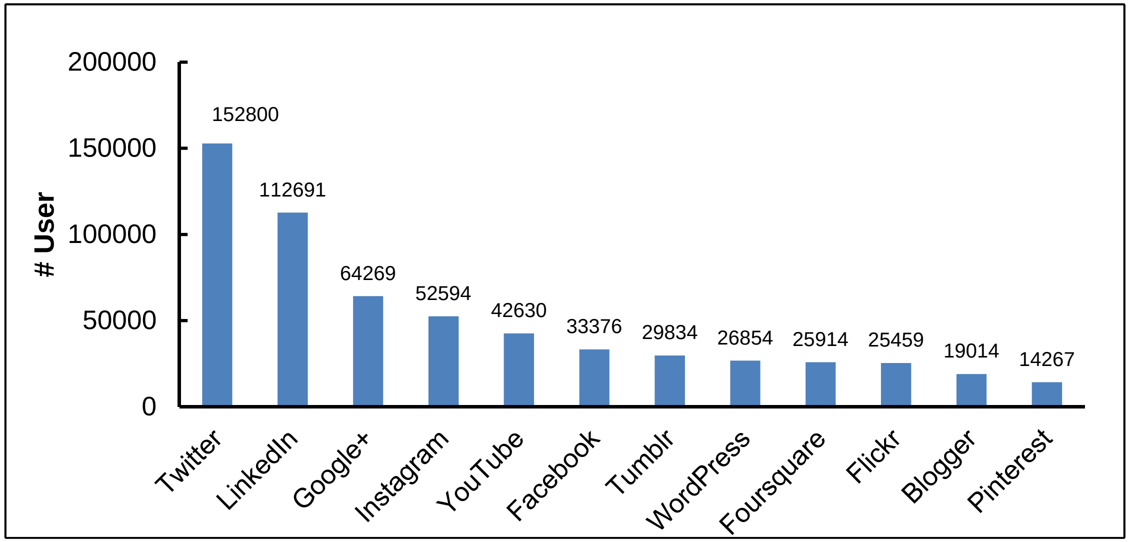


User-centric Cross-network Dataset

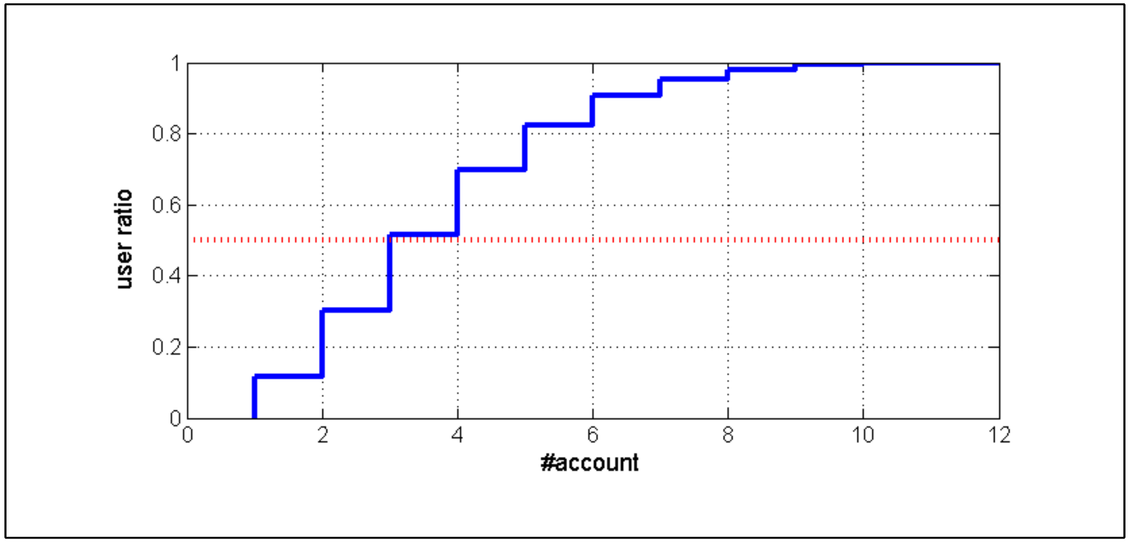


User-centric Cross-network Dataset

180,000 registered users in About.me.



Over 50% users share at least 4 accounts.



User-centric Cross-network 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

User-centric Cross-network Social Multimedia Computing

User-centric Cross-network Social Multimedia Computing

***From Users*:**

Cross-network Knowledge Association Mining

Mining the correlation based on overlapped users' perceptions.

***On Users*:**

Cross-network User Modeling

Integrating heterogeneous user data for comprehensive user understanding.

***For Users*:**

Cross-network Collaborated Multimedia Applications

Exploring user-centric cross-network characteristics to design collaborated solutions.

User-centric Cross-network Social Multimedia Computing

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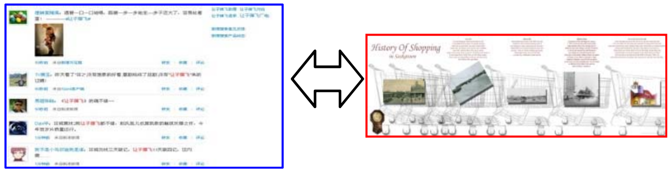
Ming Yan, **Jitao Sang**, and Changsheng Xu. Mining Cross-network Association for YouTube Video Promotion . *ACM Multimedia, 2014*.

Background: Heterogeneous Knowledge Association

Heterogeneous Knowledge Association

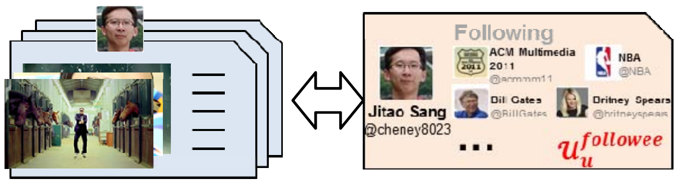
Cross-network Application



UGC behavior ,
e.g., tweeting history

Consuming
pattern

Targeted advertising



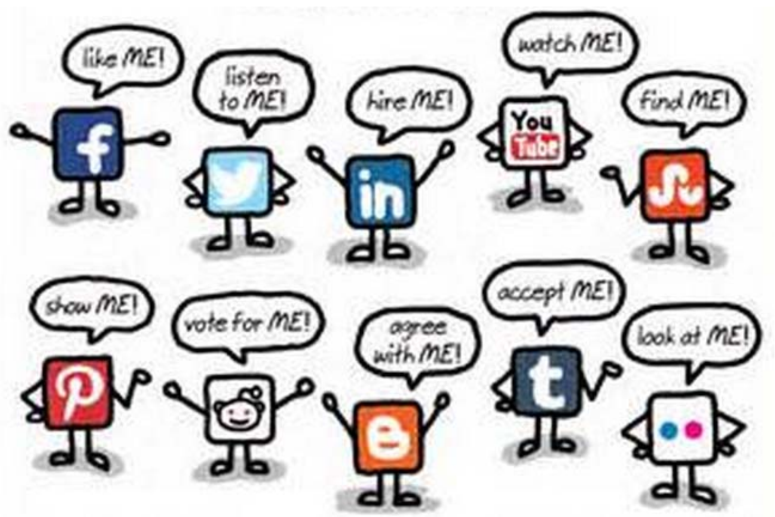
Video browsing
behavior

Following
social network

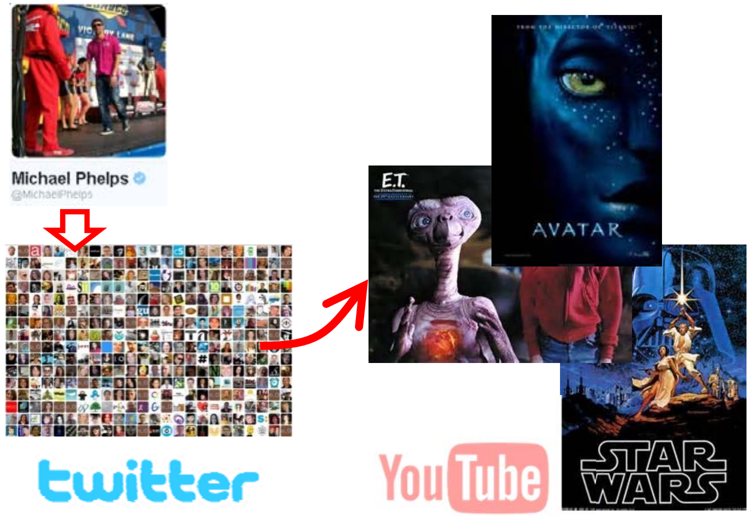
Cross-network video promotion

Challenge: Cross-network Knowledge Gap

- No explicit association exists between different social media networks.



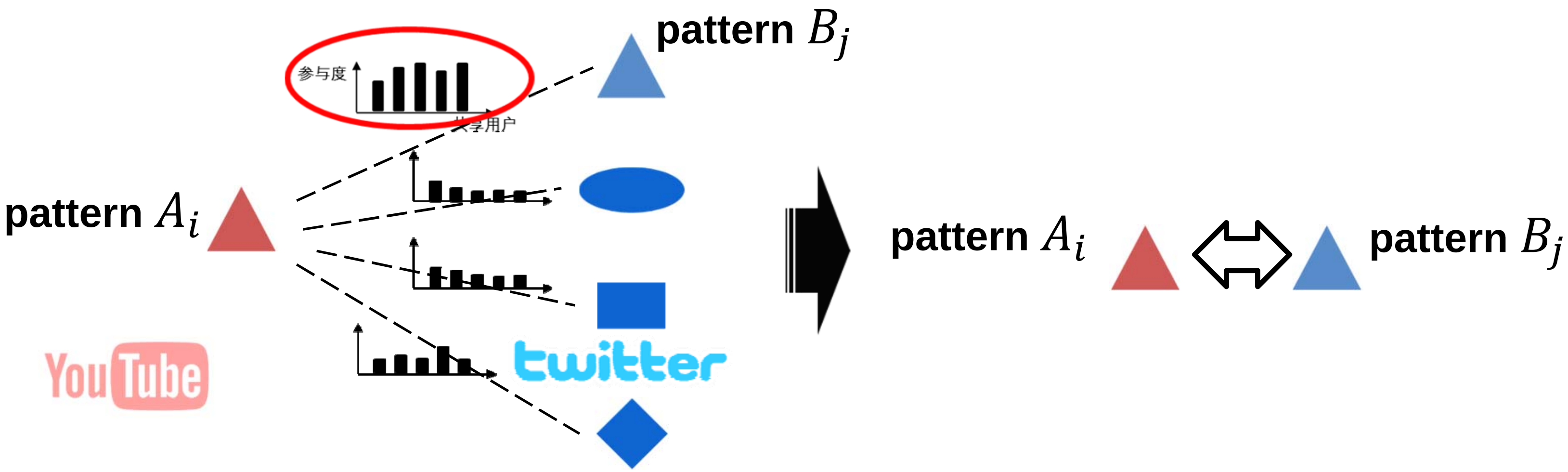
- The association is not necessarily semantic-based.



Traditional semantic-based solution cannot address all scenarios. A data-driven cross-network association mining solution is needed.

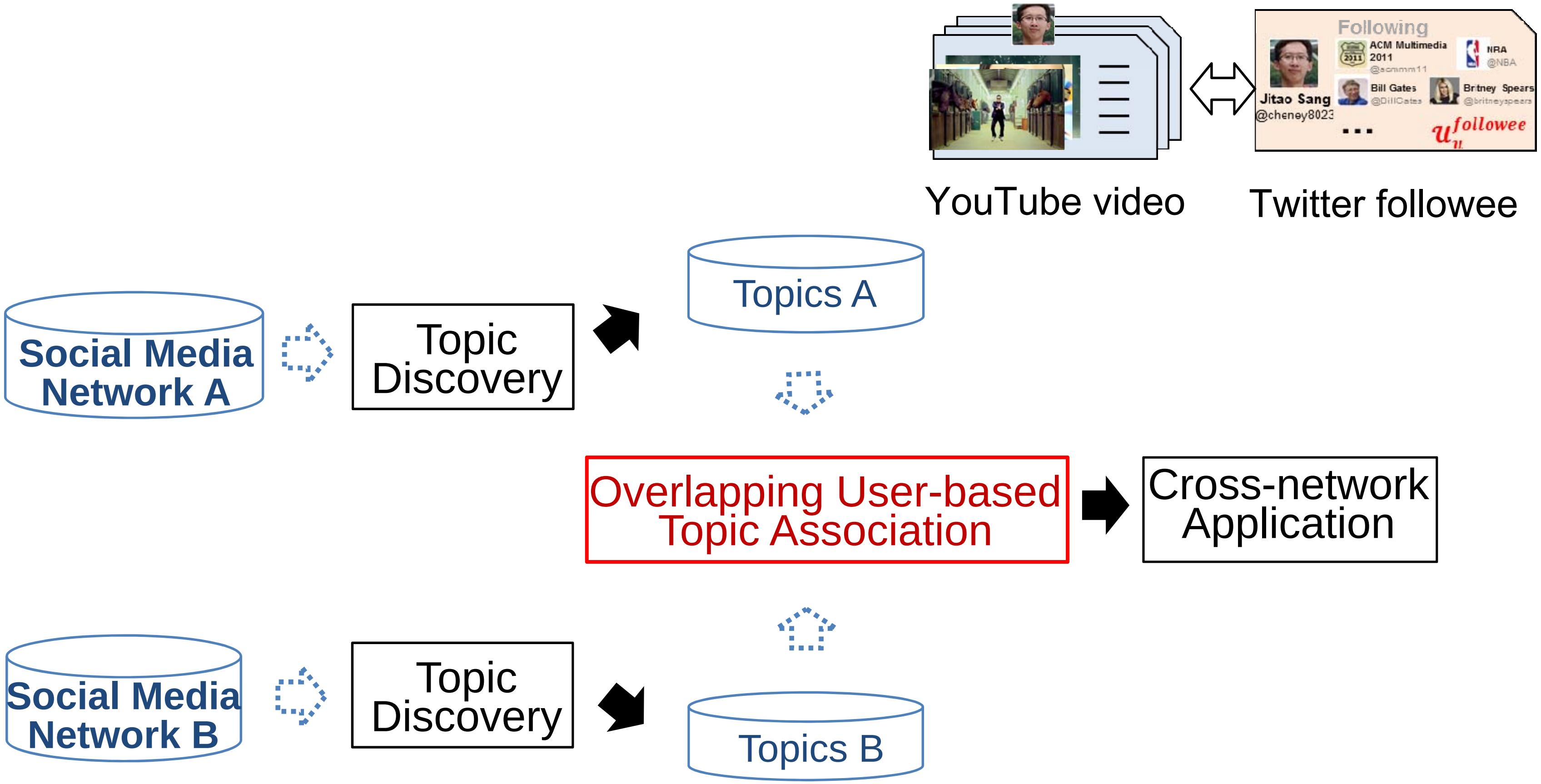
Motivation: Overlapping User Collaboration

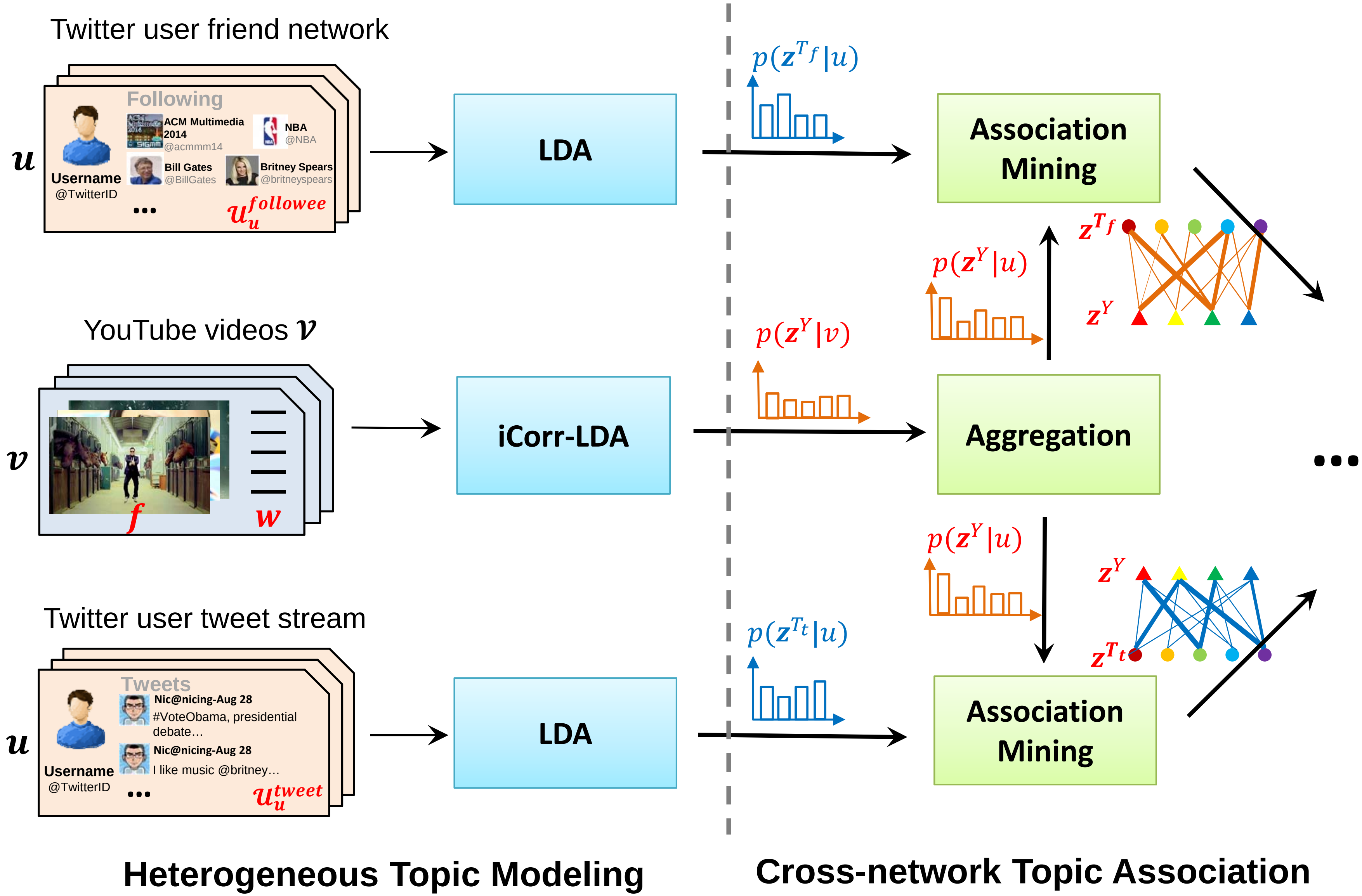
- **Assumption**: If abundant users heavily involve with pattern A_i in social media network A and pattern B_j in network B, it is very likely that pattern A_i and pattern B_j are closely associated.



- We refer to this associated pattern pairs as "crowd-perceptive correlated".

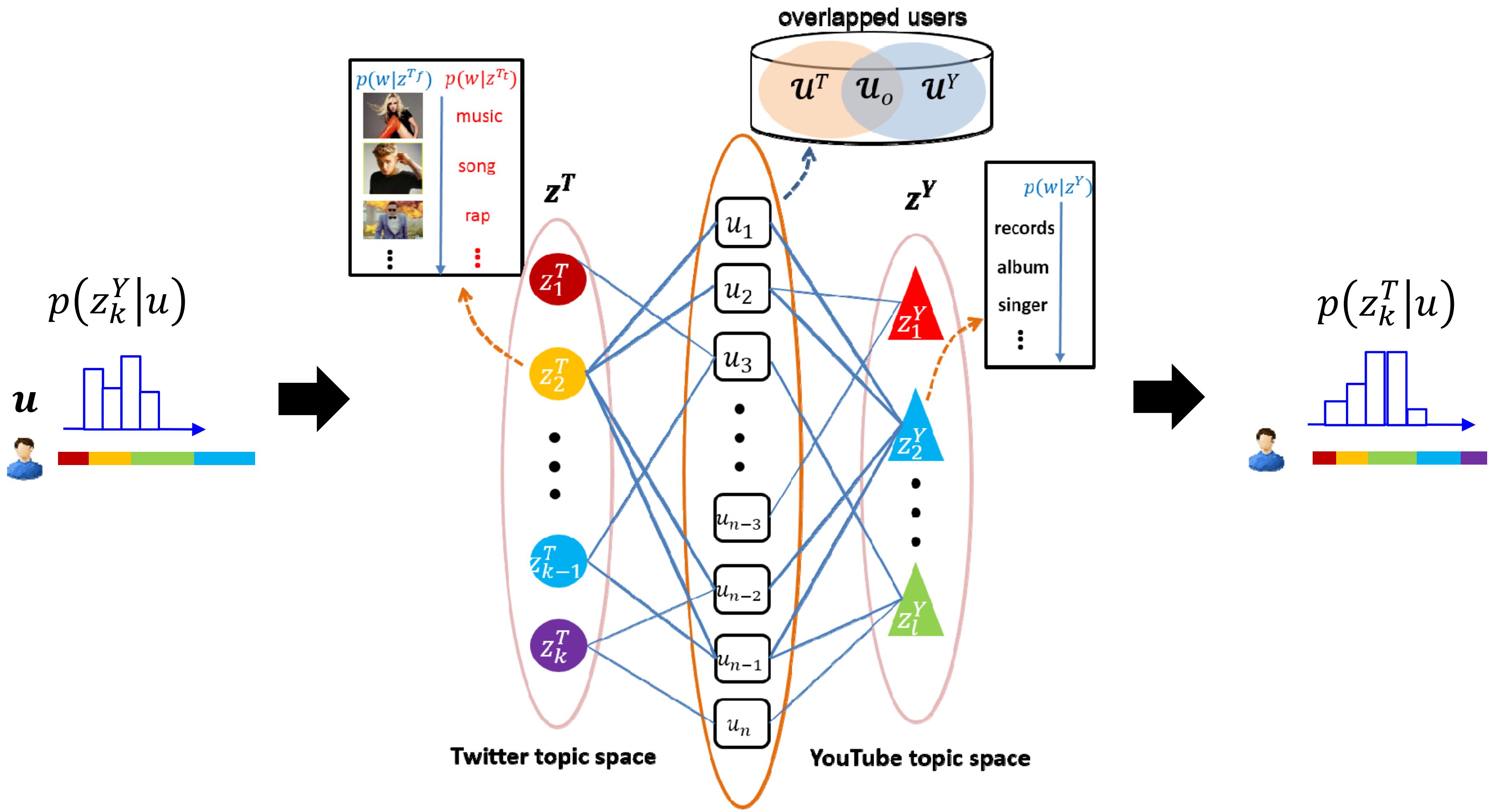
Cross-network Knowledge Association Mining



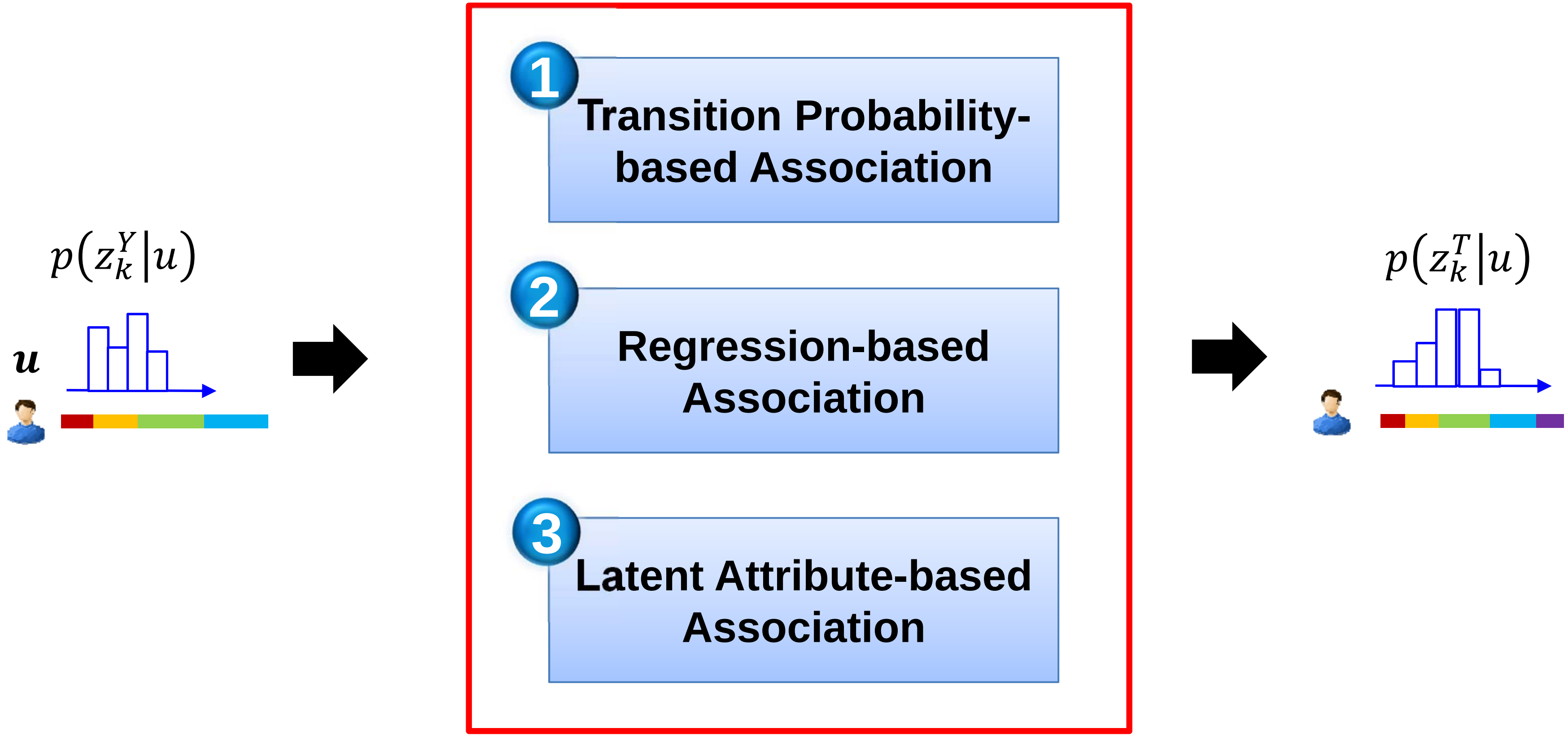


Twitter user friend network
Following
ACM Multimedia 2014 @acmmm14
NBA @NBA
Bill Gates @BillGates
Britney Spears @britneyspears
Username @TwitterID
u
$u_u^{followee}$
LDA
YouTube videos v
v
f
w
iCorr-LDA
Twitter user tweet stream
Tweets
Nic@nicing-Aug 28
#VoteObama, presidential debate…
Nic@nicing-Aug 28
I like music @britney…
Username @TwitterID
u_u^{tweet}
LDA
$p(\boldsymbol{z}^{T_f}|u)$
$p(\boldsymbol{z}^{Y}|v)$
$p(\boldsymbol{z}^{T_t}|u)$
$p(\boldsymbol{z}^{Y}|u)$
$p(\boldsymbol{z}^{Y}|u)$
Association Mining
Aggregation
Association Mining
$\boldsymbol{z}^{T_f}$
$\boldsymbol{z}^{Y}$
$\boldsymbol{z}^{Y}$
$\boldsymbol{z}^{T_t}$
…
Heterogeneous Topic Modeling
Cross-network Topic Association

Cross-network Topic Association Mining



Cross-network Topic Association Mining

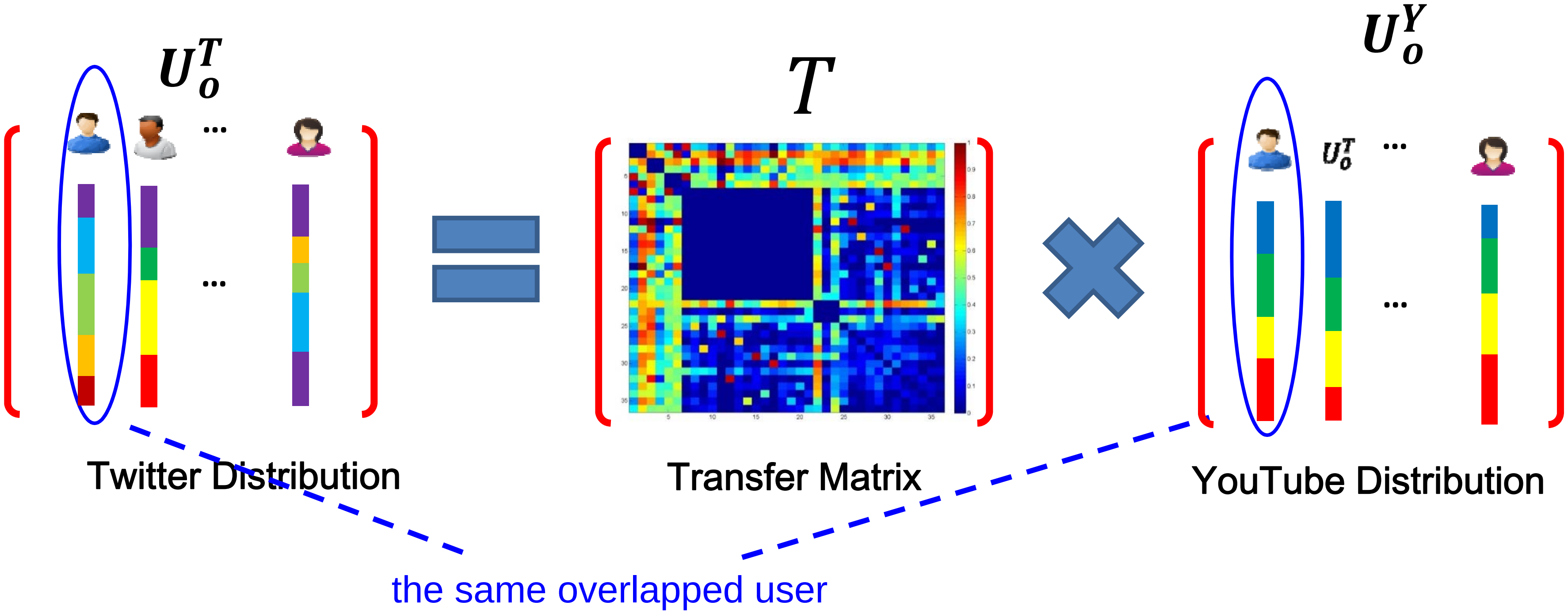


Cross-network Topic Association Mining

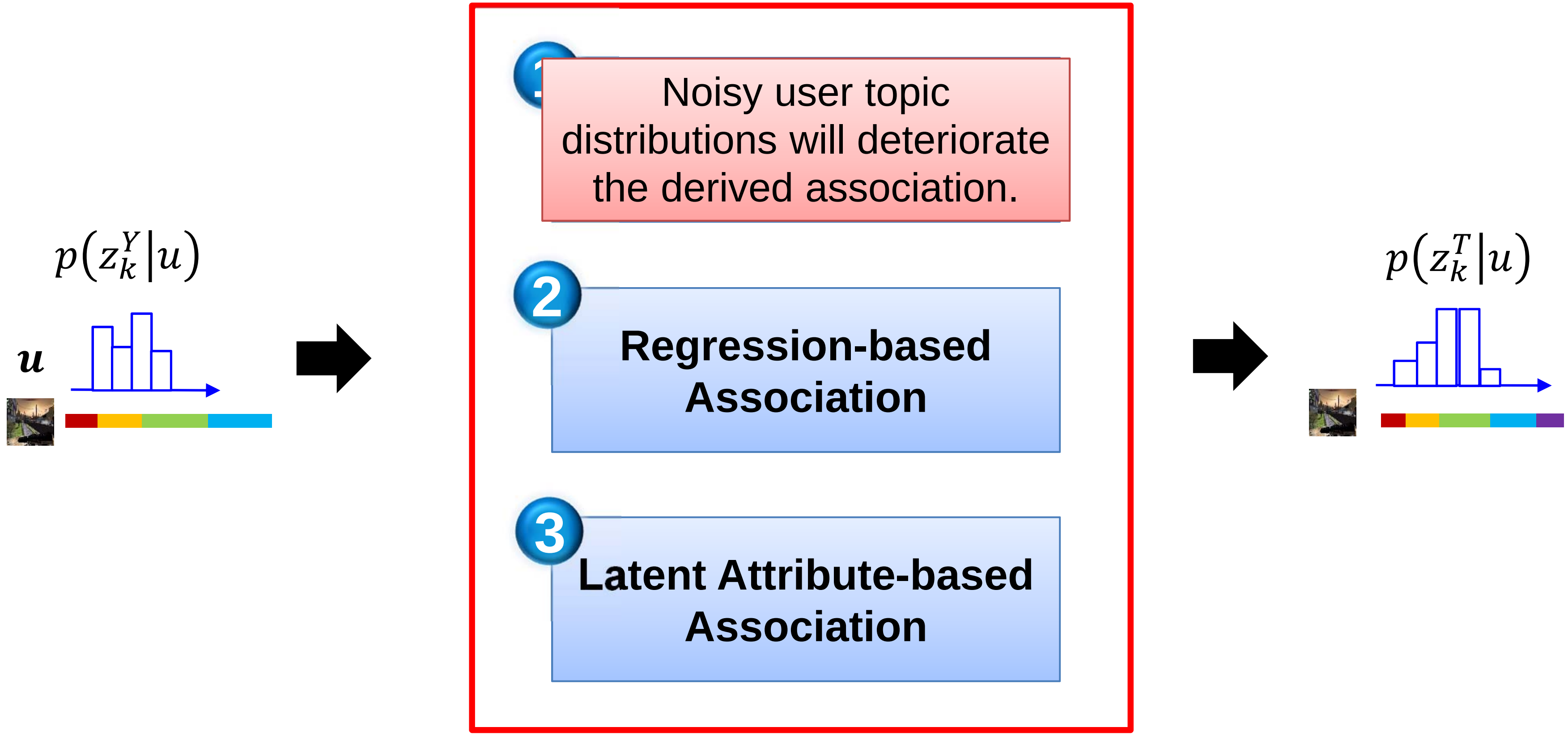
1 Transition Probability-based Association

over all the overlapped users

$$T_{ij} = p\left(z_j^T \middle| z_i^Y\right) = \sum_{\boxed{u \in \mathcal{U}_o}} p(z_j^T|u) \cdot p(u|z_i^Y)$$



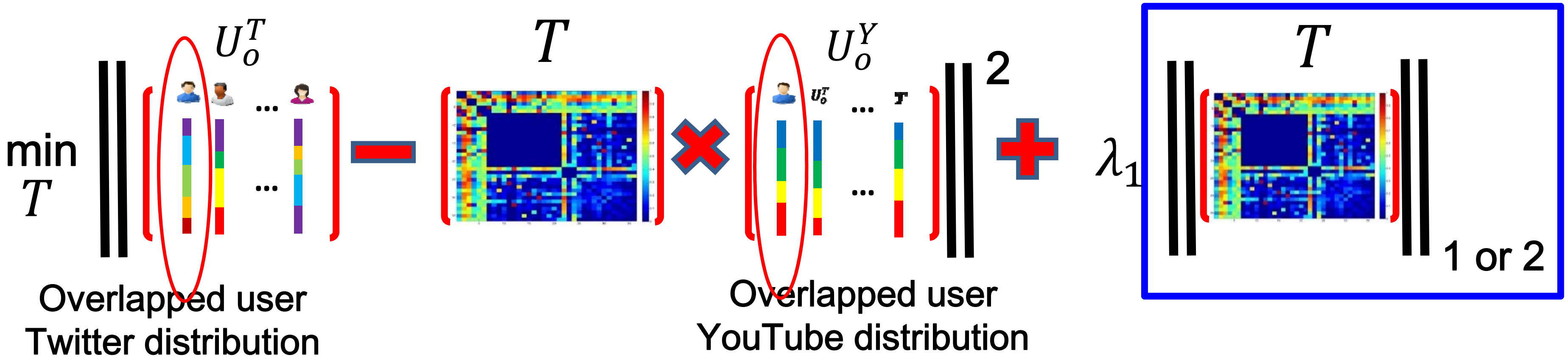
Cross-network Topic Association Mining



Cross-network Topic Association Mining

2 Regression-based Association

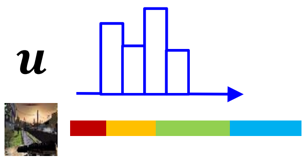
1 norm: Lasso problem
2 norm: ridge regression problem



Cross-network Topic Association Mining

$p(z_k^Y|u)$

$\boldsymbol{u}$

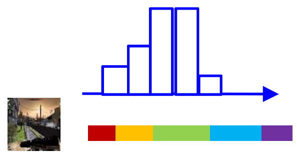


Noisy user topic distributions will deteriorate the derived association.

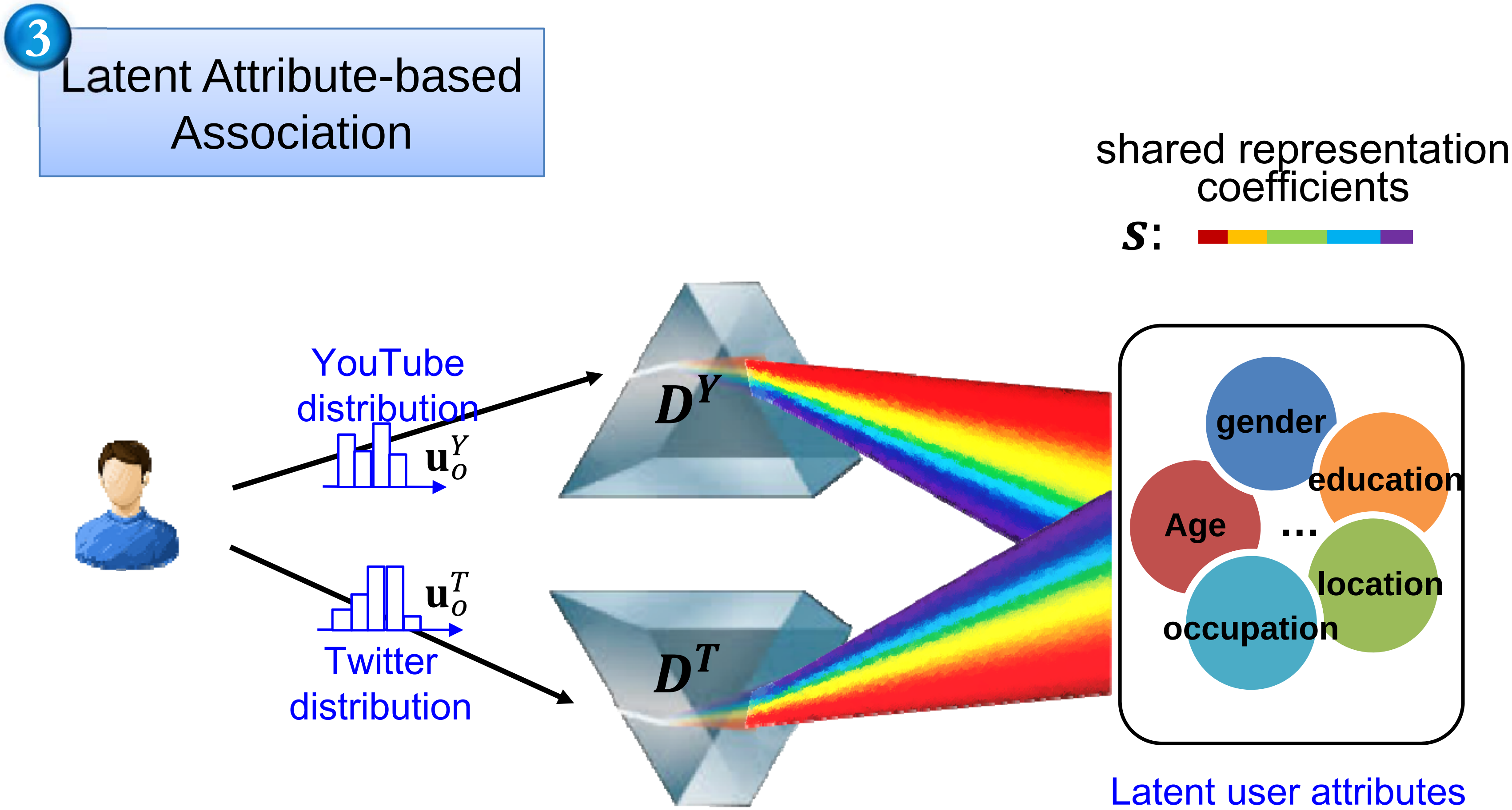
(1) Non-linear association is not allowed.
(2) Non-overlapped users are not exploited.

3 **Latent Attribute-based Association**

$p(z_k^T|u)$



Cross-network Topic Association Mining



Cross-network Knowledge Association Mining

3 Latent Attribute-based Association

Not only coupled to unique user attributes over the overlapped users, but minimizing the reconstruction error over all the non-overlapped users.

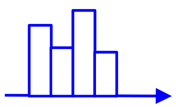
$$\min_{D^Y, D^T, S^Y, S^T} ||U^Y - D^Y S^Y||_2^2 + ||U^T - D^T S^T||_2^2 + \lambda_3 ||S_o||_1 + \lambda_4 ||S_{non}^Y||_1 + \lambda_5 ||S_{non}^T||_1$$

$$s.t. ||\boldsymbol{d}^Y|| \leq 1, ||\boldsymbol{d}^T|| \leq 1, \forall d \in D$$

$U^Y = [U_o^Y, U_{non}^Y]$,
$U^T = [U_o^T, U_{non}^T]$;
$S^Y = [S_o, S_{non}^Y]$,
$S^T = [S_o, S_{non}^T]$.

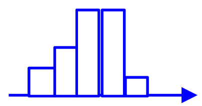
D^Y, D^T: base vector in latent attribute space;
S: shared latent user attribute representation.

$\boldsymbol{D^Y}$ $\boldsymbol{D^T}$



$\boldsymbol{u}^Y$

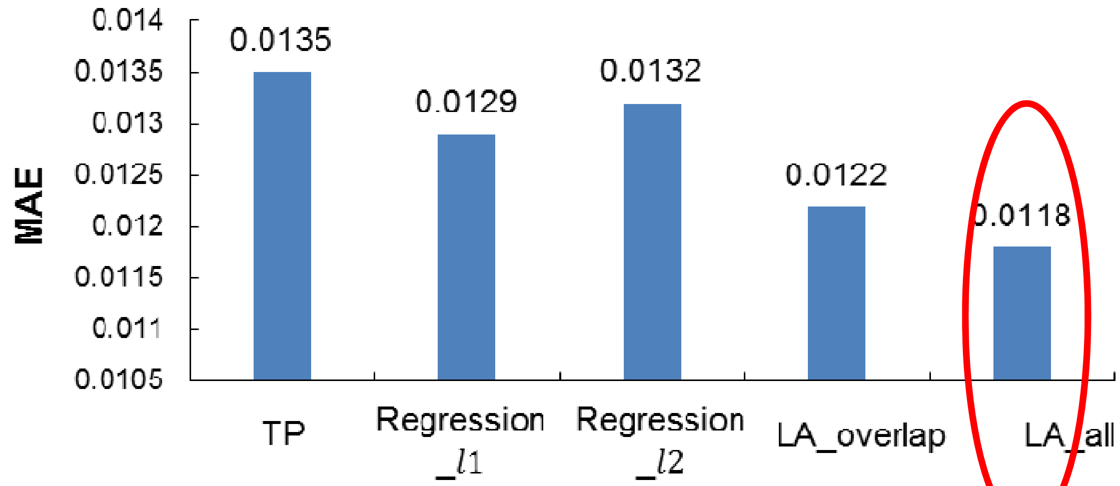
$$s^* = \min_{s} ||\boldsymbol{u}^Y - D^Y s||_2^2 + \lambda ||s||_1$$
$$\boldsymbol{u}^T = D^T s^*$$



$\boldsymbol{u}^T$

Experiments: Cross-network Topic Association

- Quantitatively calculate Mean Absolute Error (MAE) over half of the overlapped users.



prediction error over all topics in Twitter topic space

$$MAE = \frac{\sum_{u \in \mathcal{U}_{test}} \sum_{k=1}^{K^T} |\hat{u}_k^T - u_k^T|}{|\mathcal{U}_{test}| \cdot K^T}$$

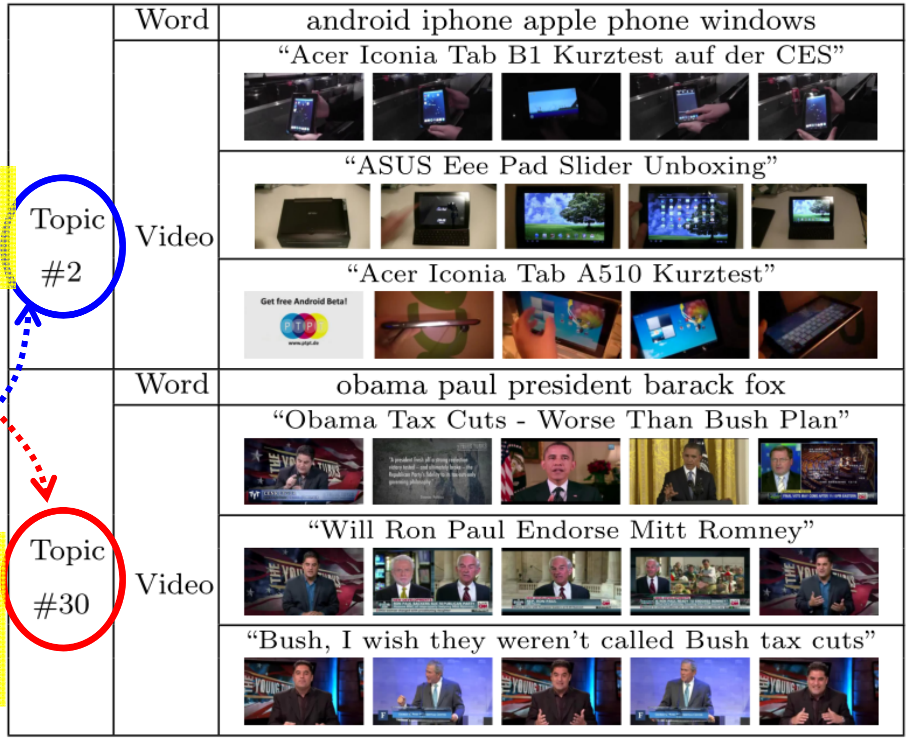
Experiments: Association Mining between Twitter Tweet & YouTube Video

TABLE III
VISUALIZATION OF DISCOVERED TWITTER TWEET SEMANTIC TOPICS IN TWITTER SEMANTIC-BASED TOPIC SPACE.

Topic	The top-5 probable tweet words in terms of $p(w\|z^{T_t})$				
#12	people	news	government	vote	state
#57	google	android	apple	phone	windows
#3	game	team	cup	win	WorldCup

digital devices

US presidential election



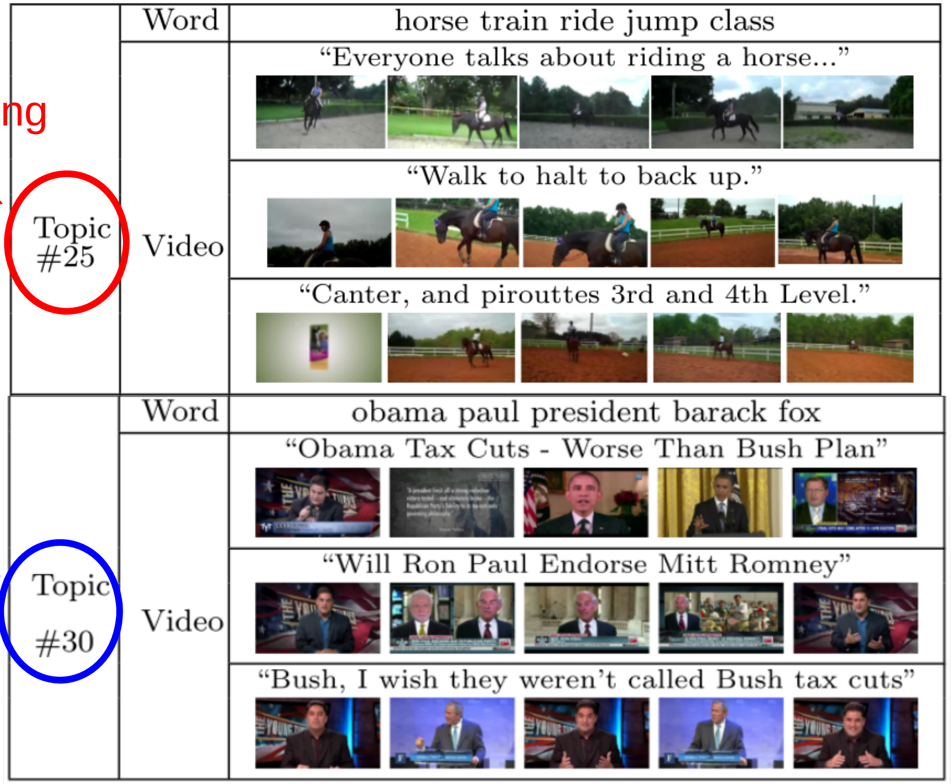
Experiments: Association Mining between Twitter Tweet & YouTube Video

social media marketing

Topic	Top-5 probable words				
#59	social	marketing	business	search	brand
#13	drinking	beer	brew	ale	craftbeer

beer

horse riding



US presidential debate

Experiments: Association Mining between Twitter Network & YouTube Video

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.
	netzpo--litik	Berlin, Germany	120,014	Entrepreneur, activist, organizer of @republica.
	Mario Sixtus	Berlin, Germany	60,542	Journalist, Photographer. Hier mehr oder weniger

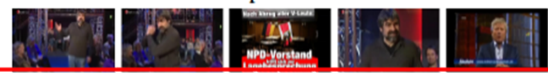
semantic correlated

geographical correlated

Berlin popular followees

game video

TABLE IV
VISUALIZATION OF DISCOVERED YOUTUBE TOPICS.

Topic #1	Word	gameplay xbox playstation gaming minecraft
	Video	"Epic Mods - MW2 MOD IN CoD4" 
		"HEXXIT COOP ep7 w/ Double" 
		"Halo 4 Adrift Multiplayer Map" 
Topic #17	Word	history german berlin germany poetry
	Video	"GEH STERBEN, DU OPFER!!!" 
		"Syrien - Wahrheit ber das Massaker" 
		"Volker Pispers - Einzeltater" 

German TV show

Experiments: Association Mining between Twitter Network & YouTube Video

famous actor

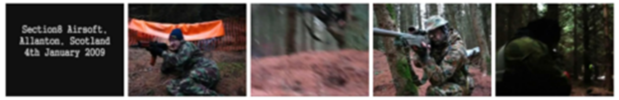
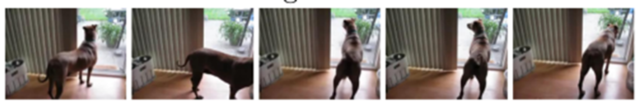
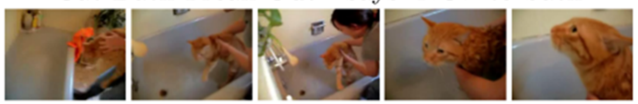
Table 4: Visualization of discovered Twitter followee topics.

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

cute animal

User-centric Cross-network Social Multimedia Computing

User-centric Cross-network Social Multimedia Computing

***From Users*:**

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Integrating heterogeneous user

***For Users*:**

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Exploring user-centric cross-
vork characteristics to design collaborated solutions.

YouTube	upload 0.20	favorite 1.25	playlist 0.35	rate 0.30
Google+	share 1	comment 0.08	+1 0.37	

Zhengyu Deng, **Jitao Sang**, and Changsheng Xu. Cross-network User Modeling with Local Social Regularization. *Submitted for publication*.

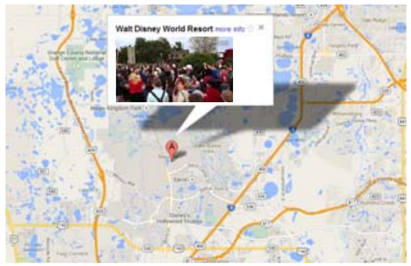
Background: User Data are Heterogeneous

- Heterogeneity is beyond modalities.

tagged photo

audio photo

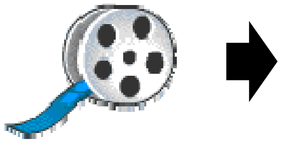
image tweet



geo-tagged video

Background: User Data are Heterogeneous

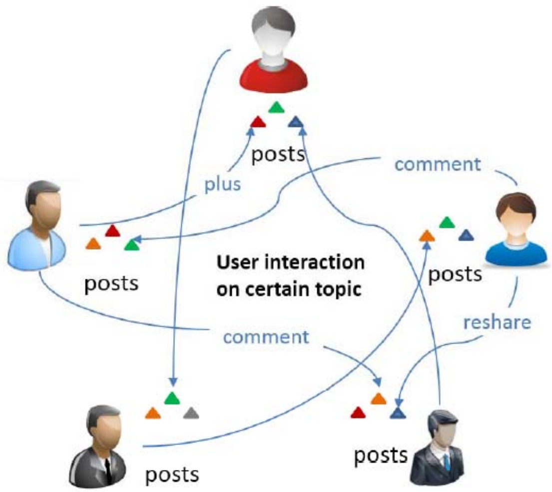
- Heterogeneity is obvious within the same modality.



YouTube upload favorite playlist rate

Google+ share comment +1

- Complex social interactions aggravate the heterogeneity.



Motivation: Integrating Heterogeneous Data

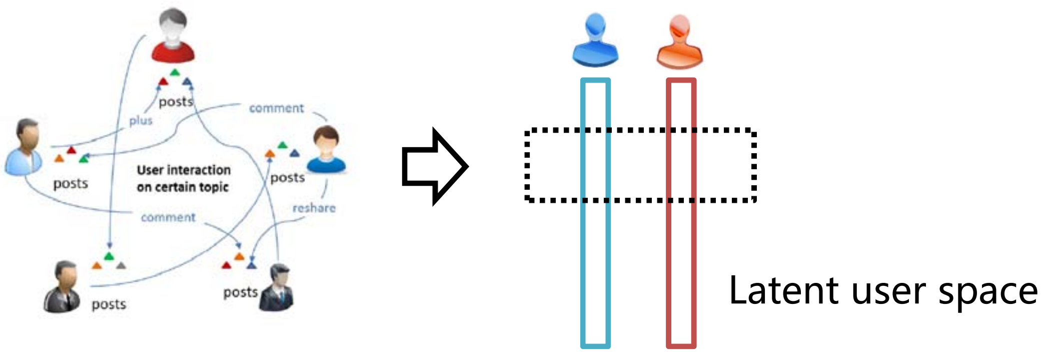
- How to unify different behaviors?

Cross-network user behavior quantification

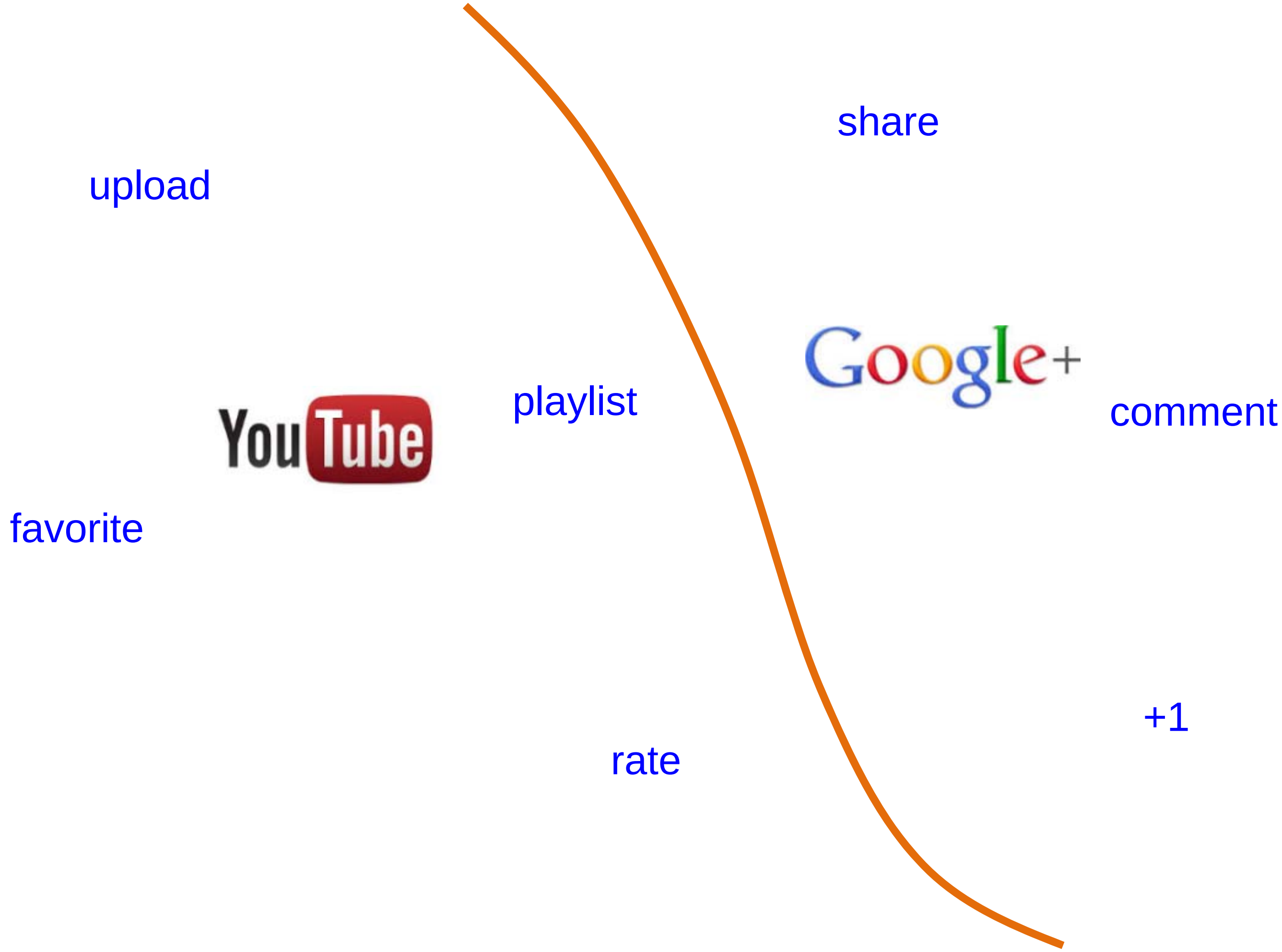
YouTube	upload 0.20	favorite 1.25	playlist 0.35	rate 0.30
Google+	share 1	comment 0.08	+1 0.37	

- How to integrate social relation with behaviors?

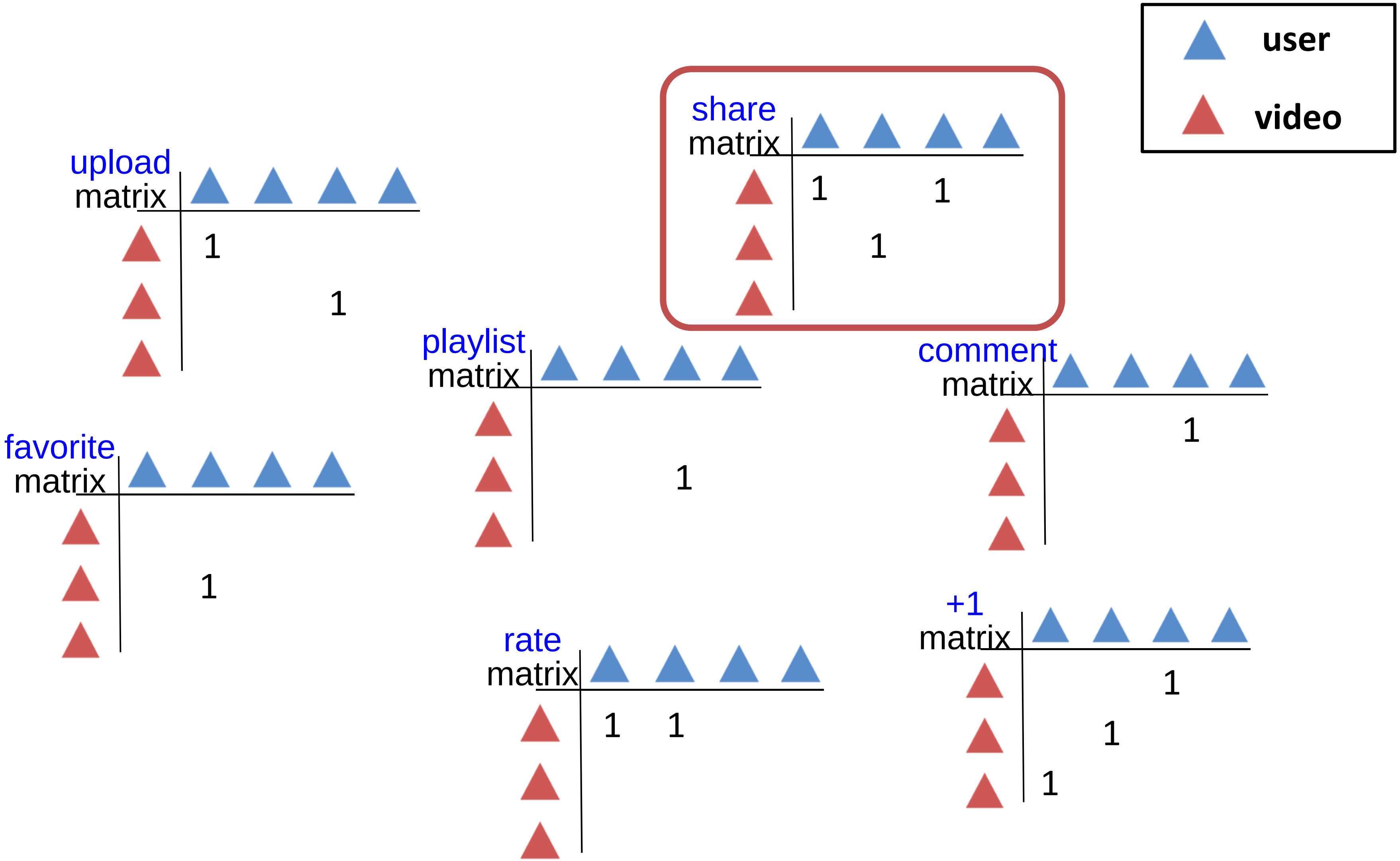
Collaborative filtering with local social regularization



Cross-network user behavior quantification



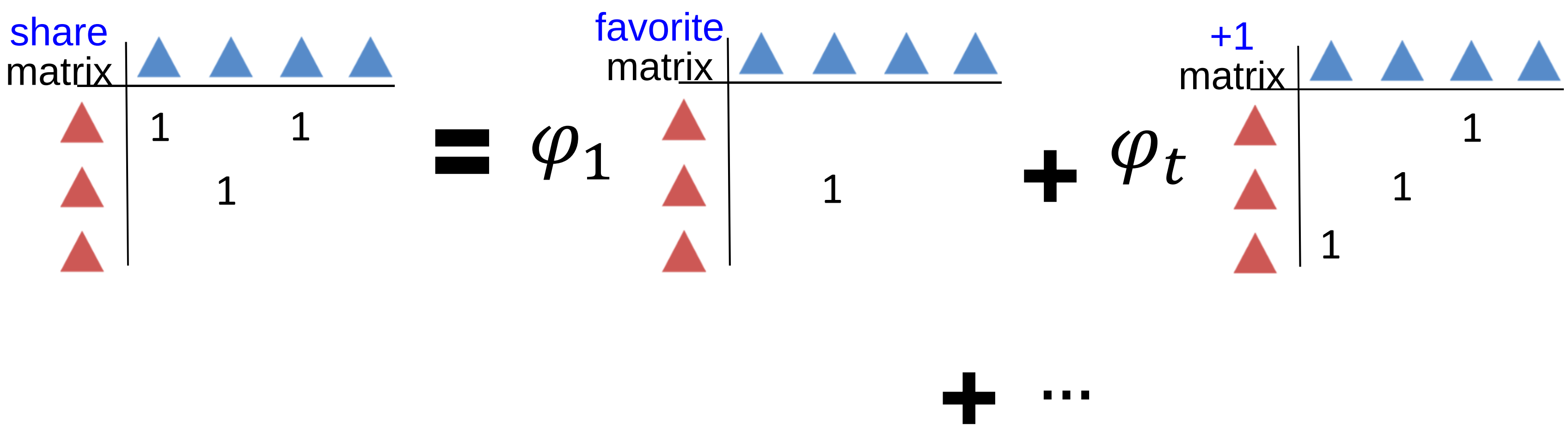
Cross-network user behavior quantification



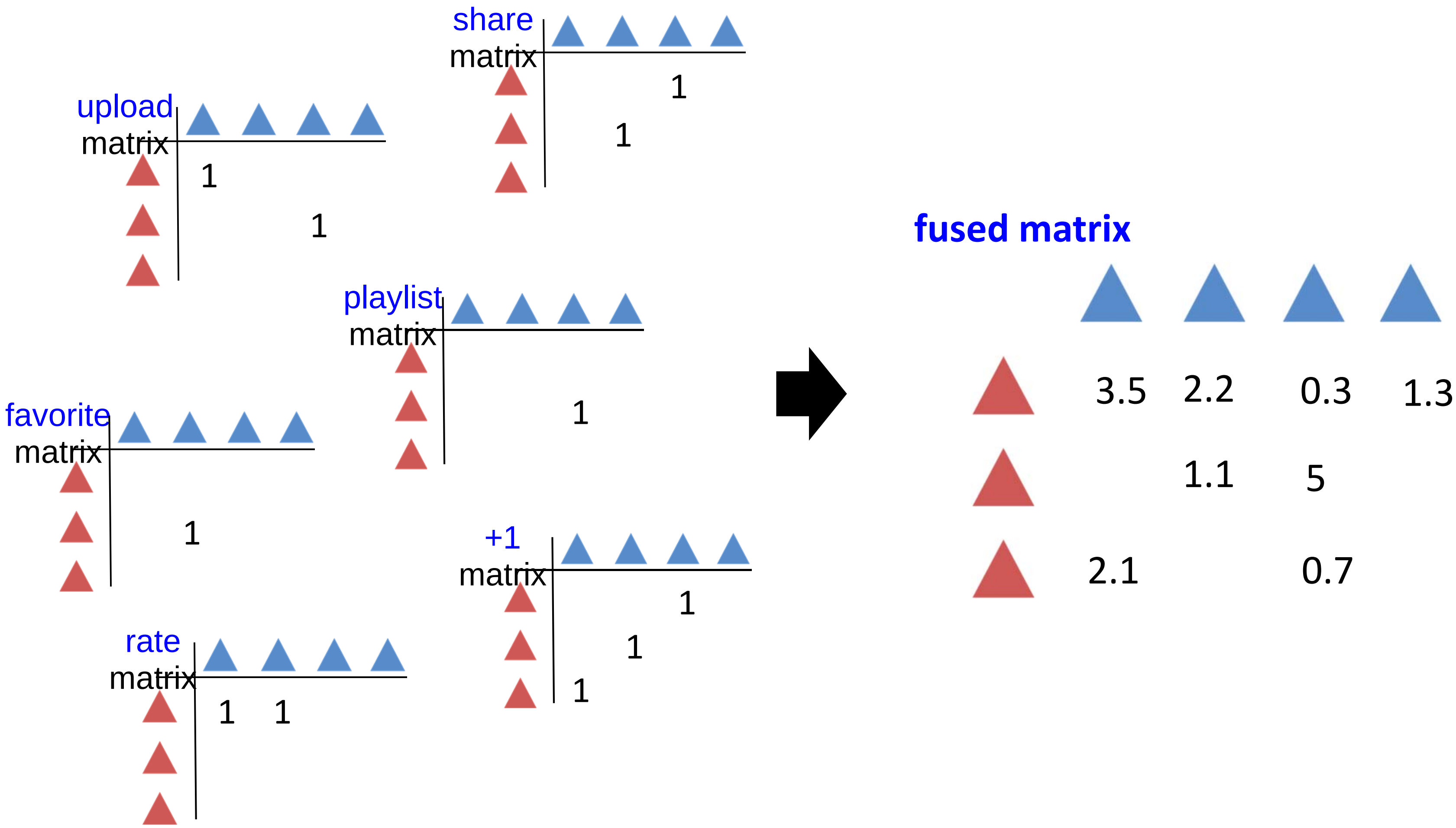
Cross-network user behavior quantification

- Multiple-kernel learning:

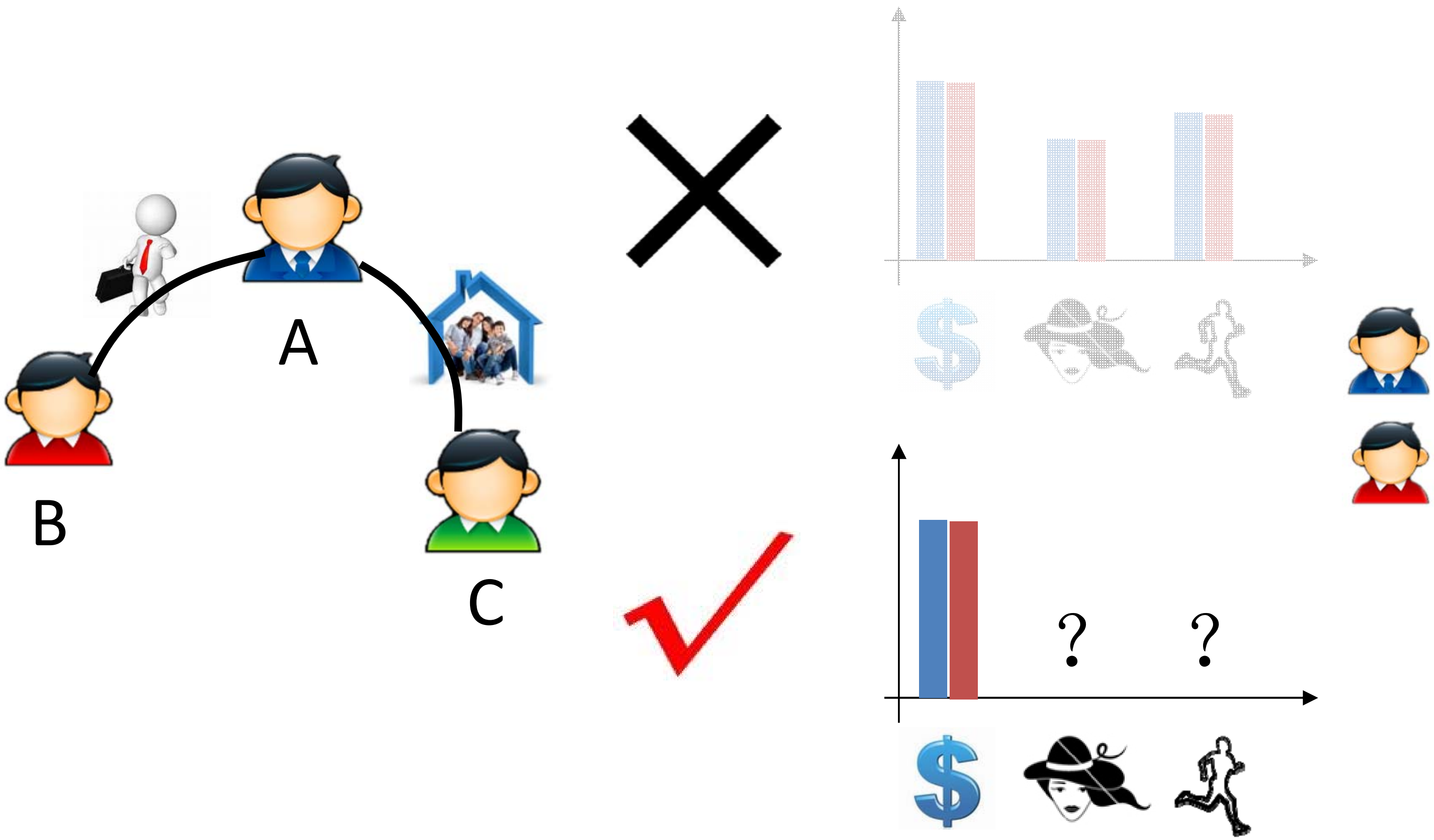
$$\mathbf{A}_s = \sum_{t=1}^{N_k} \varphi_t * \mathbf{A}_t$$



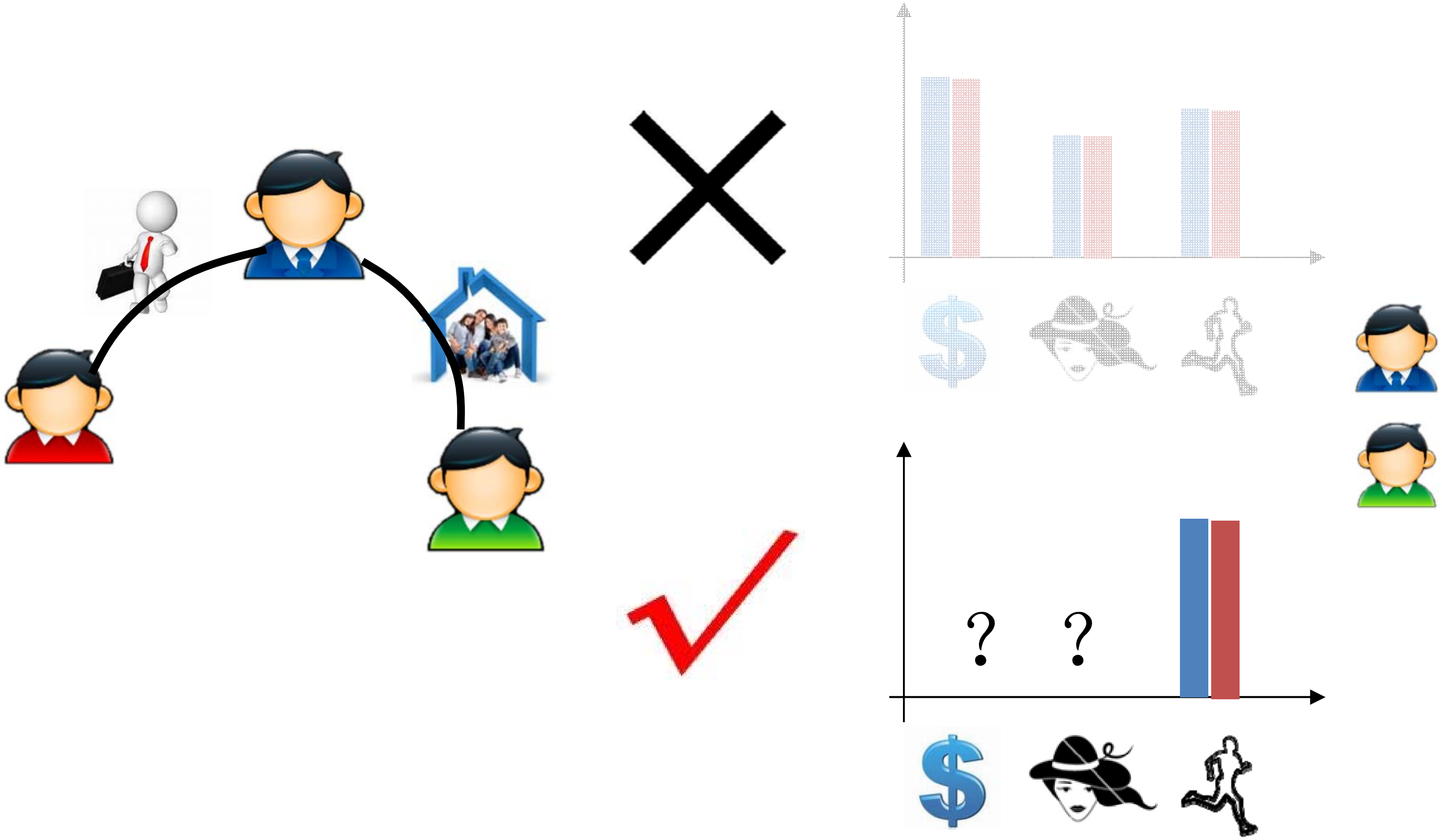
Cross-network user behavior quantification



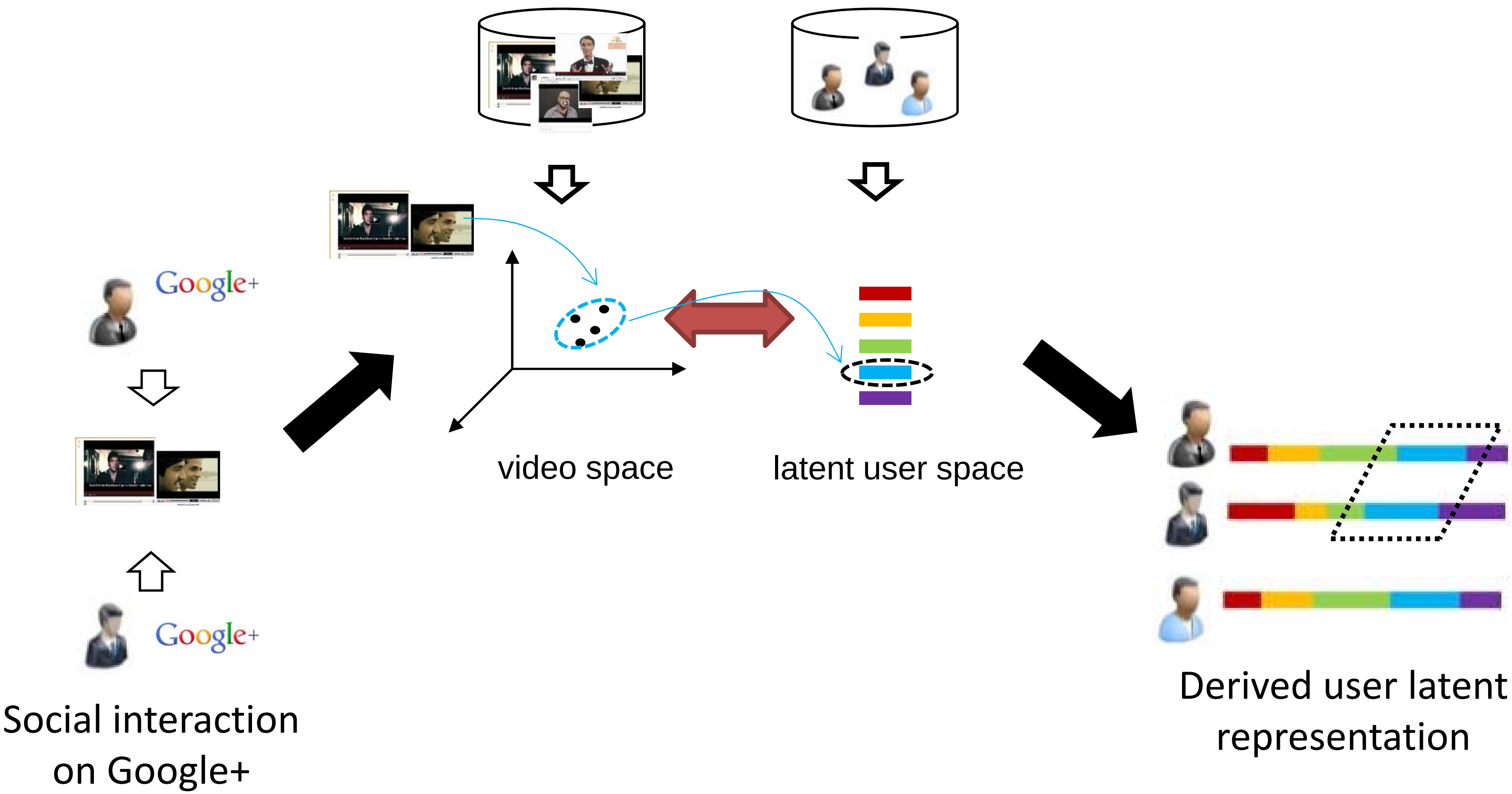
Collaborative filtering with local social regularization



Collaborative filtering with local social regularization



Collaborative filtering with local social regularization



Experiments: Evaluation on Video Recommendation

TABLE V

THE LINEAR PARAMETERS OBTAINED BY MKL

favor	upload	play	comm	rate	+1
0.2162	0.1895	0.0968	0.1211	0.1114	0.3559

TABLE VIII

THE PERFORMANCE COMPARISON OF DIFFERENT STRATEGIES BY MAE

Training data	Metrics	PMF	SocMF1	SocMF2	MFCML	MFCMS	GSocMFCML	GSocMFCMS	LSocMFCML	LSocMFCMS
90%	MAE	0.2362	0.2255	0.2289	0.2405	0.2337	0.2304	0.2273	0.2218	**0.2205**
	Improve	6.65%	2.22%	3.67%	8.32%	5.65%	4.30%	2.99%		
70%	MAE	0.239	0.2377	0.2308	0.2483	0.2343	0.2448	0.2304	0.2332	**0.2272**
	Improve	4.94%	4.42%	1.56%	8.50%	3.03%	7.19%	1.39%		
50%	MAE	0.2542	0.2382	0.2474	0.2513	0.2522	0.253	0.2395	0.253	**0.2373**
	Improve	6.65%	0.38%	4.08%	5.57%	5.91%	6.21%	0.92%		
30%	MAE	0.2695	0.2594	0.2682	0.2672	0.2612	0.2668	0.2572	0.2685	**0.2535**
	Improve	5.94%	2.27%	5.48%	5.13%	2.95%	4.99%	1.44%		
10%	MAE	0.286	0.285	0.2868	0.2854	0.2716	0.2869	0.2683	0.2873	**0.2657**
	Improve	7.10%	6.77%	7.36%	6.90%	2.17%	7.39%	0.97%		

User-centric Cross-network Social Multimedia Computing

User-centric Cross-network Social Multimedia Computing

***From Users*:**

Cross-network Knowledge Association Mining

Mining the correlation based on overlapped users’ perceptions.

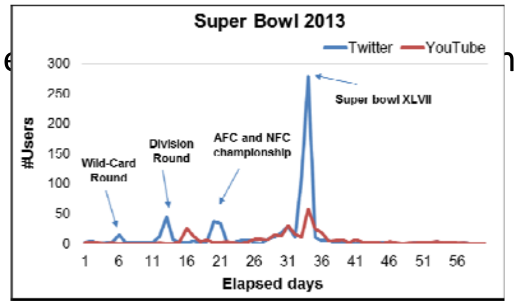
***On Users*:**

Cross-network User Modeling

Integrating heterogeneous user data for comprehensive user understanding.

***For Users*:**

Cross-network Collaborated Multimedia Applications



Zhengyu Deng, Ming Yan, **Jitao Sang**, Changsheng Xu. Twitter is Faster: Personalized Time-aware Video Recommendation from Twitter to YouTube , *TOMCCAP*, 2014.

Challenge: Sparsity in Personalization

Application：
Real-time Personalized video search /recommendation

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

Key problem：
Dynamic Interest Modeling

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

Motivation: Twitter is Faster

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

"Virginia earthquake" tweets heat map (08/23/2011)

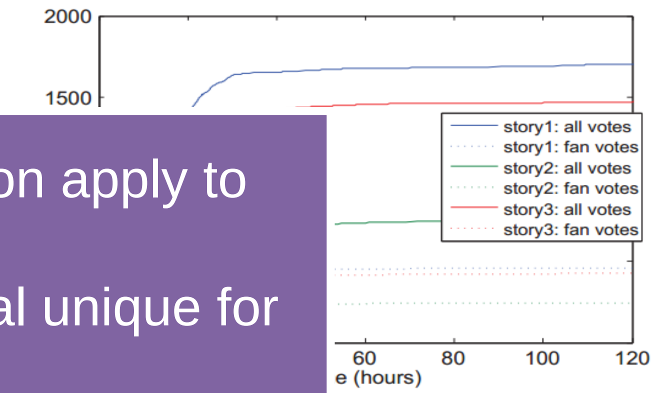
Motivation: Twitter is Faster

- **Twitter is faster than many social media services**
  - Twitter is faster than Wikipedia.

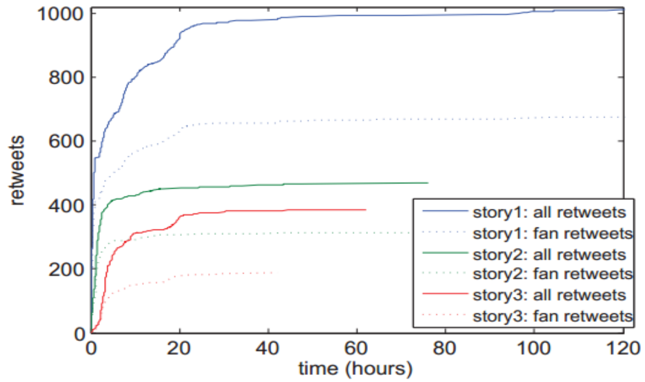
Latency (Hours)		Mean Distance	Standard deviation
Lagging			
	-3		
	-2		
	-1		
Equal			
	0		
Leading			
	1		
	2		

Table 1: Mean and stand... between Twitter first-stories and neare... page titles.

  - Twitter is faster than Digg.



Digg



(b) Twitter

- ✓ Will this conclusion apply to micro-level?
- ✓ Is the time interval unique for different topics?

Data Analysis: Statistics

- The examined 22 trending events.

Topic	Topic	Topic
1. US presidential election 2012	9. Samsung Galaxy S III	17. google glasses
2. gangnam style	10. Michael Jackson	18. call me maybe
3. super bowl 2013	11. Christmas 2012	19. Spider Man
4. Olympic 2012	12. Google Nexus 4 release	20. Skyfall
5. Justin Bieber	13. Iphone 5 release	21. End of the World 2012
6. star wars film	14. Call of Duty: Black Ops II	22. Whitney Houston
7. The Dark Knight Rises	15. Doctor Who TV Series	
8. Minecraft Game	16. Prometheus	

Table 1. The final selected trending topic list

- The involved user number for each event.

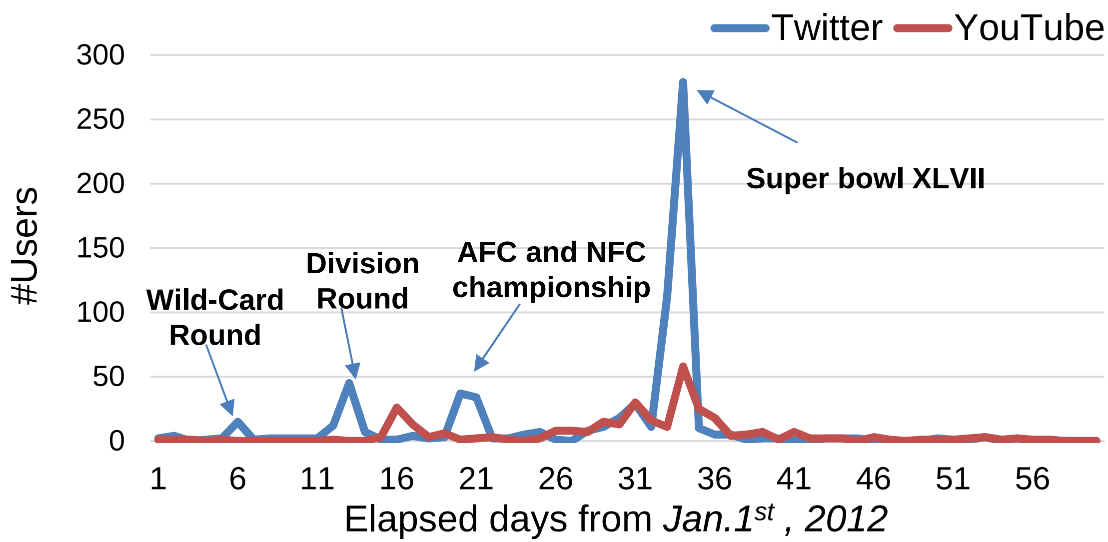
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Twitter	2908	3850	1107	1376	1071	2385	2251	857	1164	519
YouTube	949	1181	239	310	405	1171	638	572	458	321
Both Two	521	602	82	115	78	350	219	221	192	62

	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20
Twitter	4155	1434	2708	890	1114	791	1704	897	951	1254
YouTube	1270	361	497	174	586	231	658	508	264	249
Both Two	729	189	246	63	177	75	269	117	82	85

Table 2. The user number who have referred to each of the selected trending topics

Data Analysis: Cross-network Temporal User Behavior Analysis

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



Data Analysis: Cross-network Temporal User Behavior Analysis

- Twitter responses faster than YouTube in **individual** 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

Data Analysis: Cross-network Temporal User Behavior Analysis

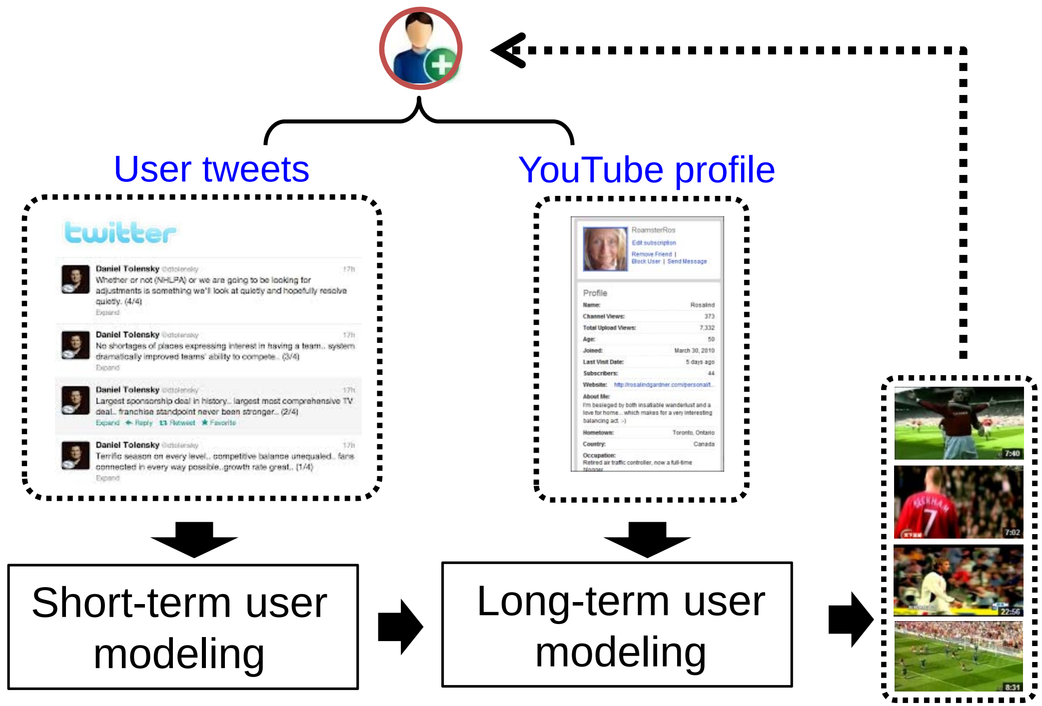
- The cross-network temporal dynamic characteristic is **topic-sensitive**

Category	Celebrity	Technology	Movie	Game	Sport
The ratio	1.87	3.27	1.31	2.48	2.35

Table 4. The user vote ratio between Twitter and YouTube on different categories

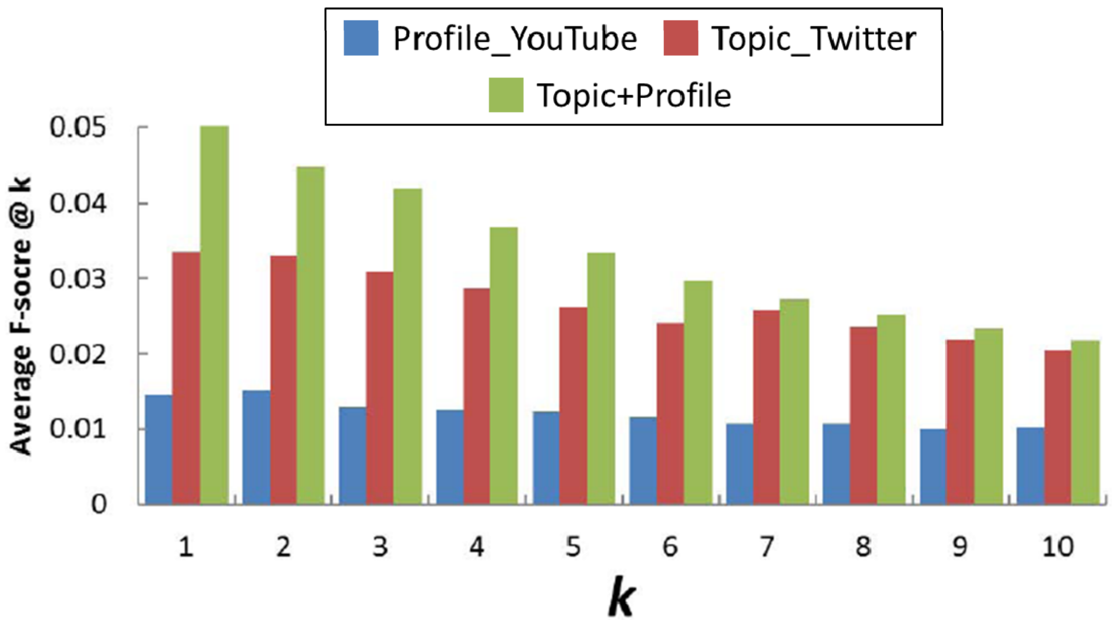
Cross-network Collaborated Video Recommendation

- **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



Cross-network Collaborated Video Recommendation

- Dataset: evaluate on 10 of the 22 trending events.
- Ground-truth: user's favorite videos on YouTube.
- Baselines: only considering user interested topics on Twitter, or profiles on YouTube.



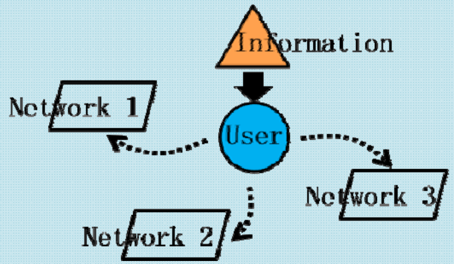
User-centric Cross-network Social Multimedia Computing

Cross-network Knowledge Association

Mining the correlation based on overlapped users' perceptions.

MM 2014
TMM under review

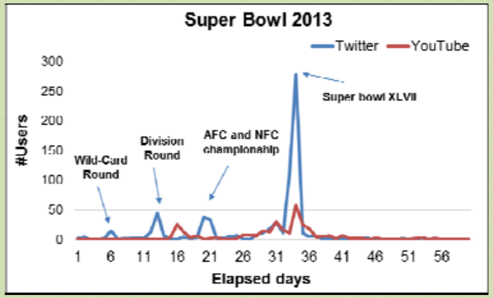
Cross-network User Modeling



Integrating heterogeneous user data for comprehensive user understanding.

ICME 2013
TMM under review

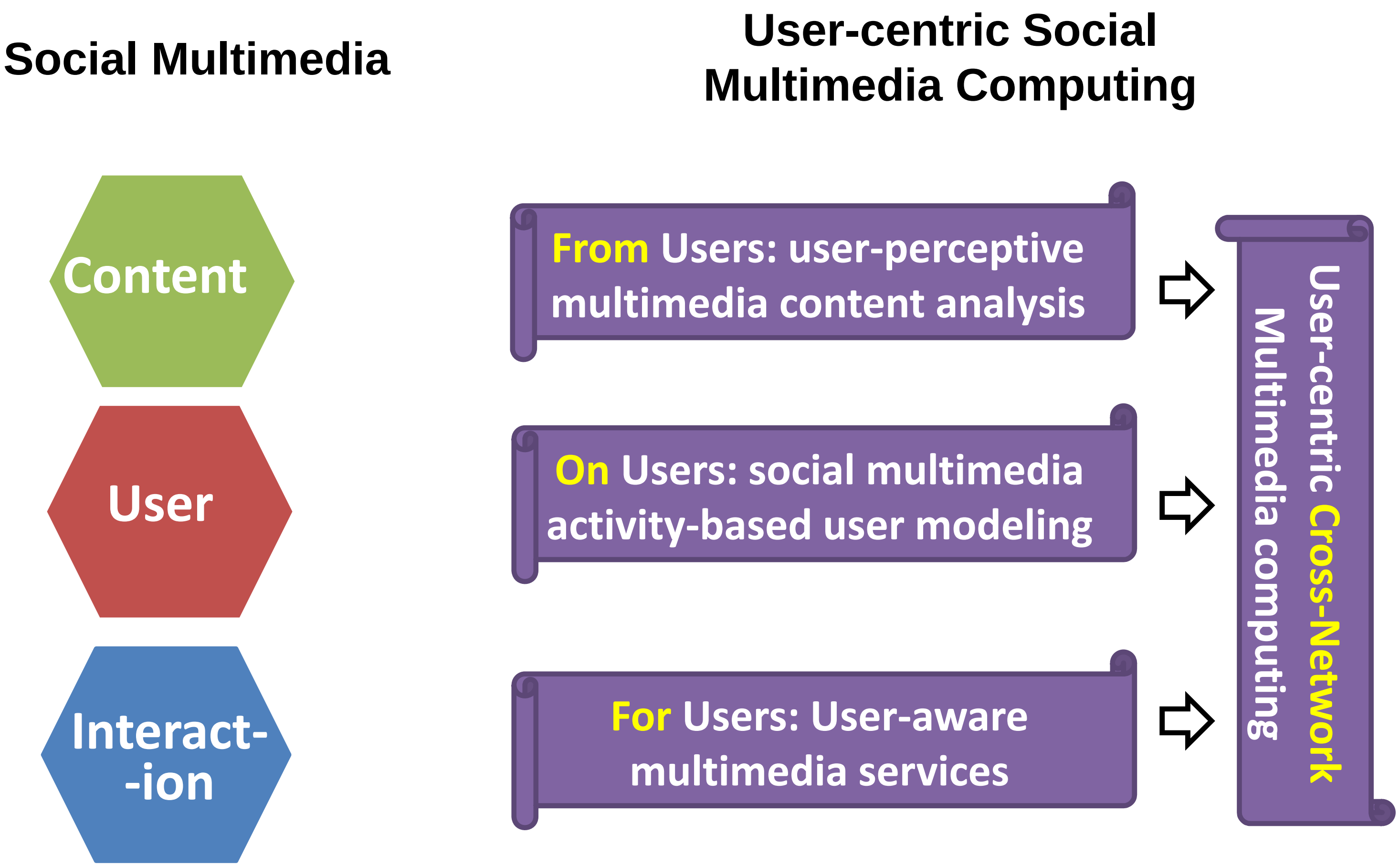
Cross-network Collaborated Multimedia Applications



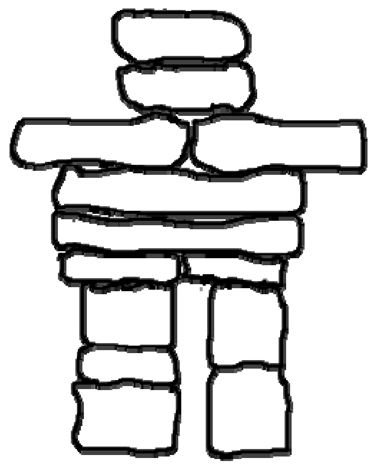
Exploring user-centric cross-network characteristics to design collaborated solutions.

ICME 2013
ICIAP 2013, TOMCCAP
TKDE under review

Summary


Social Multimedia
User-centric Social Multimedia Computing
Content
User
Interact-
-ion
From Users: user-perceptive multimedia content analysis
On Users: social multimedia activity-based user modeling
For Users: User-aware multimedia services
User-centric Cross-Network Multimedia computing

Practical Challenges



Lack of Benchmark Dataset

- Large-scale benchmark dataset on respective multimedia, user, and social network, but none including all of them.

IMAGENET

- Due to the problem variety, most researches conduct experiments on the self-collected dataset.

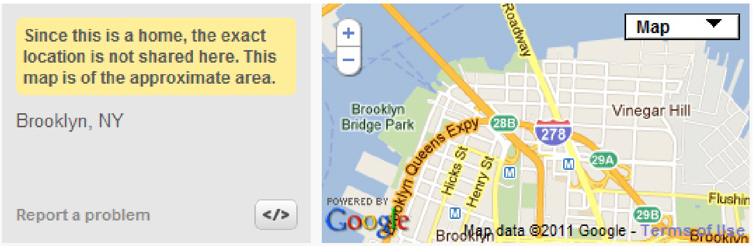
- The lack of benchmark dataset discourages the follow-ups of other researchers and the progress of new problems.

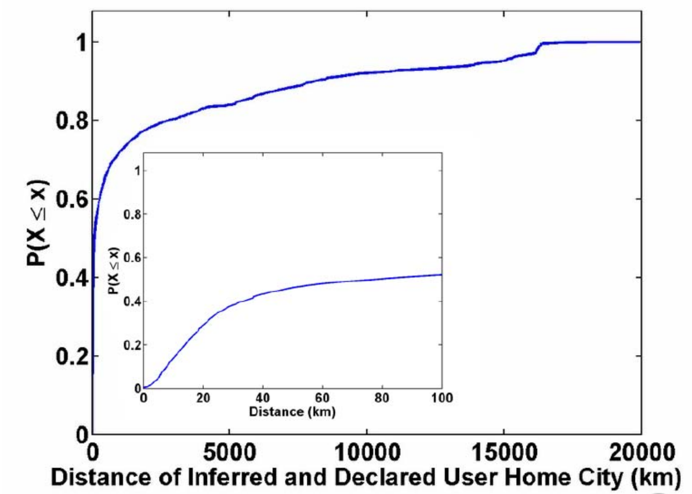
Evaluation Dilemma

- User ground-truth intent and demands are difficult to obtain in open network environment, especially for the personalized information services.
- Existing data-driven evaluation strategies are either unable to reflect real intent/preferences or limited in scale (e.g., favorite record as indication of preference).

Privacy

- Privacy breach: learn the private information of an individual from the publicly available user data.





(“We know where you live.” LBSN 2012.)

Privacy

- Privacy breach: learn the private information of an individual from the publicly available user data.
- Data anonymization is not adequate to preserve privacy: social media data exhibit rich dependencies.

What Revealing Search Data Reveals

AOL posted, but later removed, a list of the Web search inquiries of 658,000 unnamed users on a new Web site for academic researchers. An in
with one of those unnamed users, Thelma Arnold, combined with her data reveal what she was searching for, why and on which Web sites.

A sample of Thelma Arnold's search data released by AOL

4417749	swing sets	2006-04-24	15:39:30	4	http://www.byoswingset.com
4417749	swing sets	2006-04-24	15:39:30	9	http://www.buychoice.com
4417749	swing sets	2006-04-24	15:39:30	10	http://www.creativeplaythings.com
4417749	swing sets	2006-04-24	15:39:30	5	http://www.childlife.com
4417749	swing sets	2006-04-24	15:39:30	6	http://www.planitplay.com
4417749	that do not shed	2006-04-28	9:05:54	2	http://www.gopetsamerica.com
4417749	dog who urinate on everything	2006-04-28	13:24:07	6	http://www.dogdaysusa.com
4417749	walmart	2006-04-28	14:07:32	1	http://www.walmart.com
4417749	womens underwear	2006-04-28	14:12:28	10	http://www.bizrate.com
4417749	jcpenny	2006-04-28	14:16:05		
4417749	jcpenny	2006-04-28	14:16:49	1	http://www.jcpenney.com
4417749	tortus and turtles	2006-04-29	13:12:47		
4417749	manchester terrier	2006-05-02	9:05:31	1	http://www.manchesterterrier.com
4417749	delta	2006-05-02	11:49:26		
4417749	fingers going numb	2006-05-02	17:35:47		
4417749	dances by laura	2006-05-02	17:59:32		
4417749	dances by lori	2006-05-02	17:59:57		
4417749	single dances	2006-05-02	18:00:18	1	http://solosingles.com
4417749	single dances in atlanta	2006-05-02	18:01:13		
4417749	single dances in atlanta	2006-05-02	18:01:50		
4417749	dry mouth	2006-05-06	16:49:14	2	http://www.mayoclinic.com
4417749	dry mouth	2006-05-06	16:49:14	8	http://www.wrongdiagnosis.com
4417749	tyroid	2006-05-06	16:55:34		
4417749	thyroid	2006-05-06	16:55:44		
4417749	competitive market analysis of homes in lilburn	2006-05-14	12:14:52		
4417749	competitive market analysis of homes in lilburn	2006-05-14	12:16:17		
4417749	competitive market analysis of homes in lilburn	2006-05-14	12:16:43		

Why the search

"I was thinking ab
my grandchildren"

"I was looking for

"A woman was in
[public] bathroom
She was going tho
divorce. I thought
was a place called
by Lori,' for single

"I wanted to find o
my house was wor

Louis Rosenfeld LLC

AOL Searcher #4417749

Thelma Arnold
- 62-year old widow
- Lilburn, GA resident

Interests
- 60 single men
- aameetings in georgia
- plastic surgeons in gwinnett county
- applying to west point
- bipolar
- panic disorders
- yerba mate
- shedless dogs
- movies for dogs
- new zealand real estate

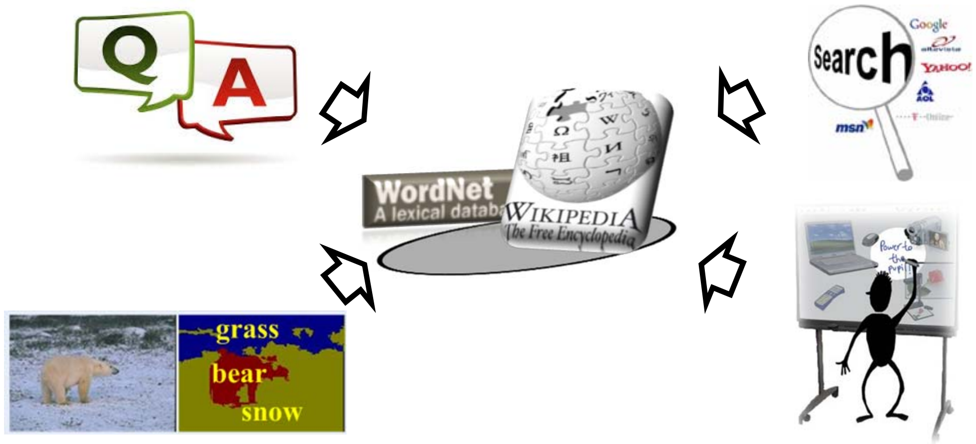
NY Times, August 9, 2006: "A Face Is Exposed for AOL Searcher No. 4417749"

 3

Promising Topics

From Users: Knowledge Base Construction

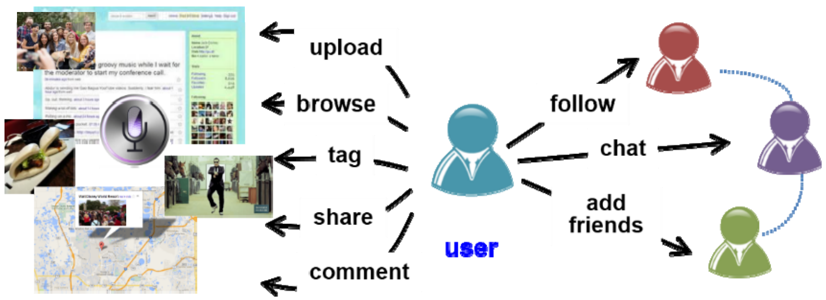
- Social multimedia involves with rich multimedia information and complicated user and community social information.
- To facilitate user services as well as pursue multimedia understanding, it is of particular significance to construct social multimedia knowledge base that: (1) connects between heterogeneous data, and (2) integrates user awareness/perception.



On Users: Heterogeneous Data Integration

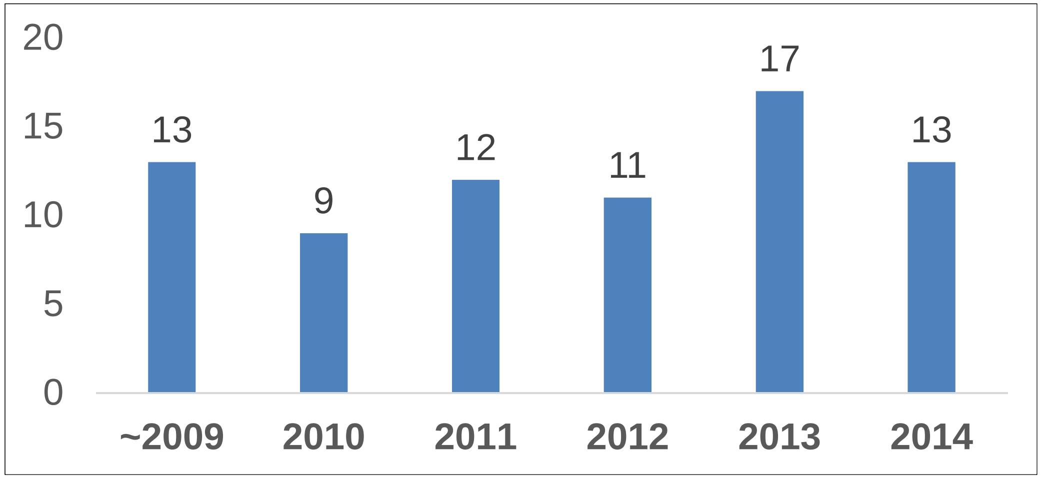
- **User-MM + User-User**: Social media users interact with each other, (e.g., adding friends, joining in interest groups), and with multimedia content, (e.g., sharing, annotation, commenting).

- **Cross-network:** Users data are distributed on various social media networks, e.g., acquiring news via Twitter, sharing videos via YouTube, and chatting with friends via Facebook.



For Users: Unified Theoretical Framework

- Social multimedia computing is still in the primary stage.



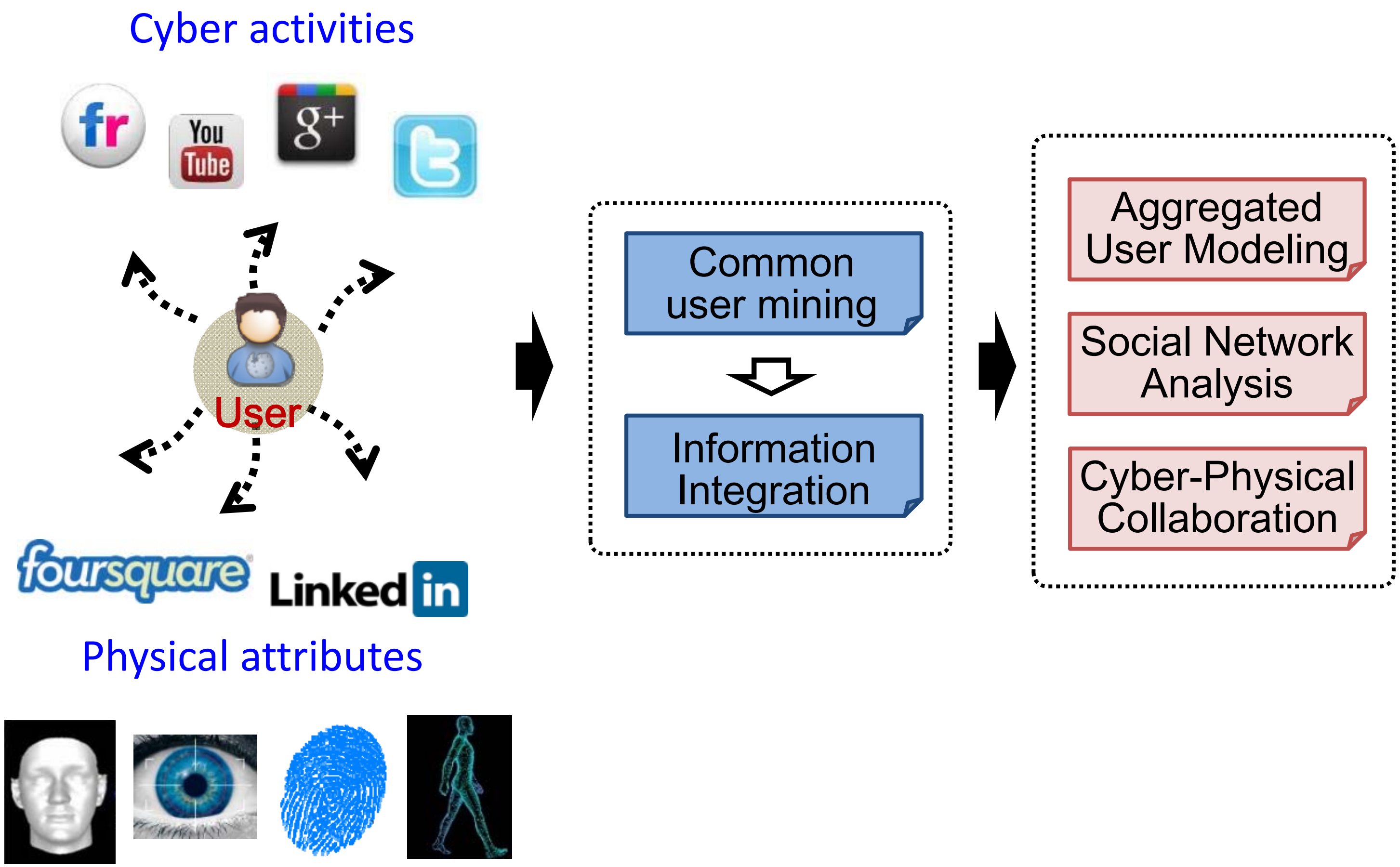
- It is a promising research line to refer to classical theoretical work from information retrieval, multimedia analysis and social network analysis, to develop the theoretical framework for social multimedia computing.

The Prospects

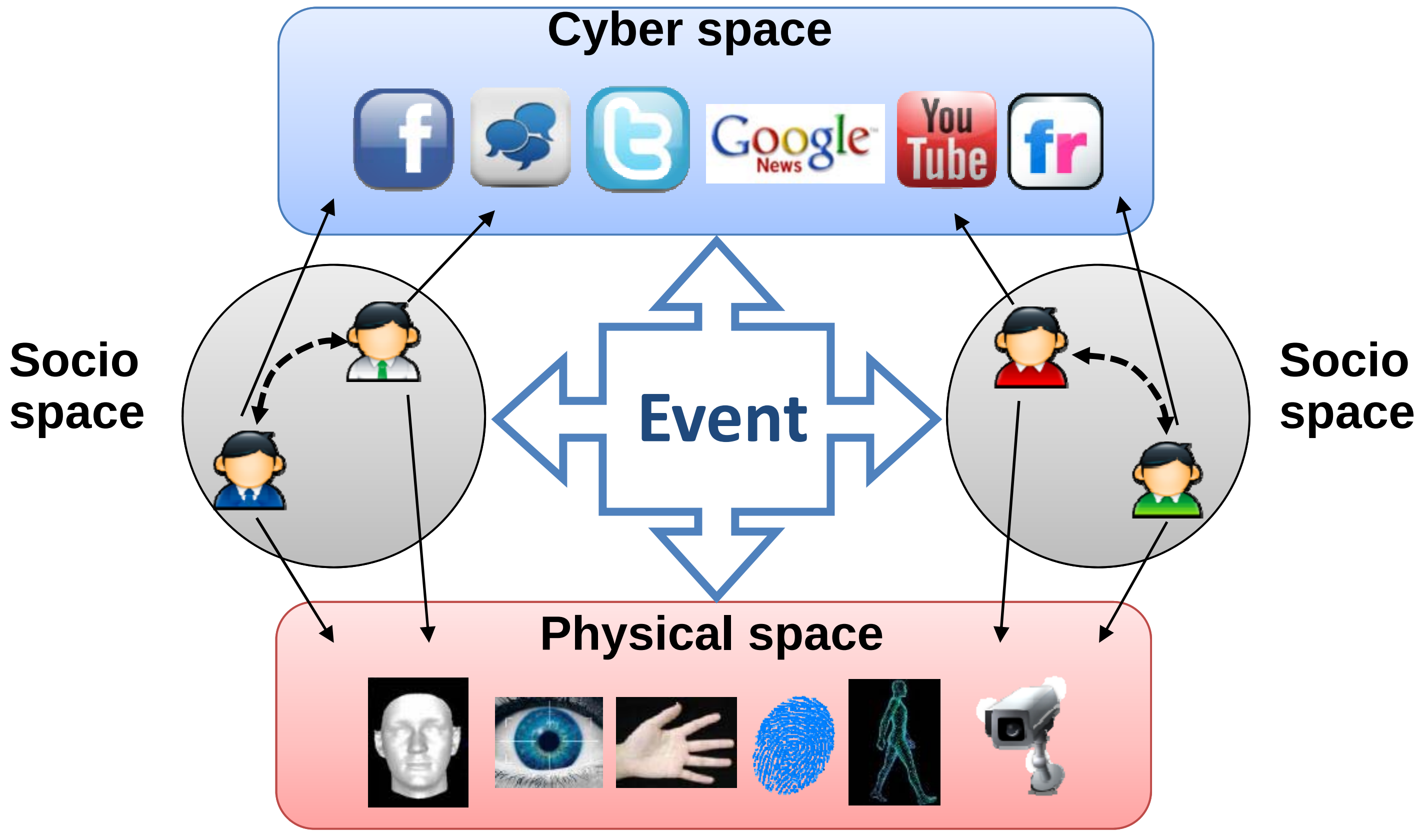
User connects cyber to the physical worlds.

User-centric Cyber-Physical Association and Collaboration

- Overlapping user-based cyber-physical collaboration.



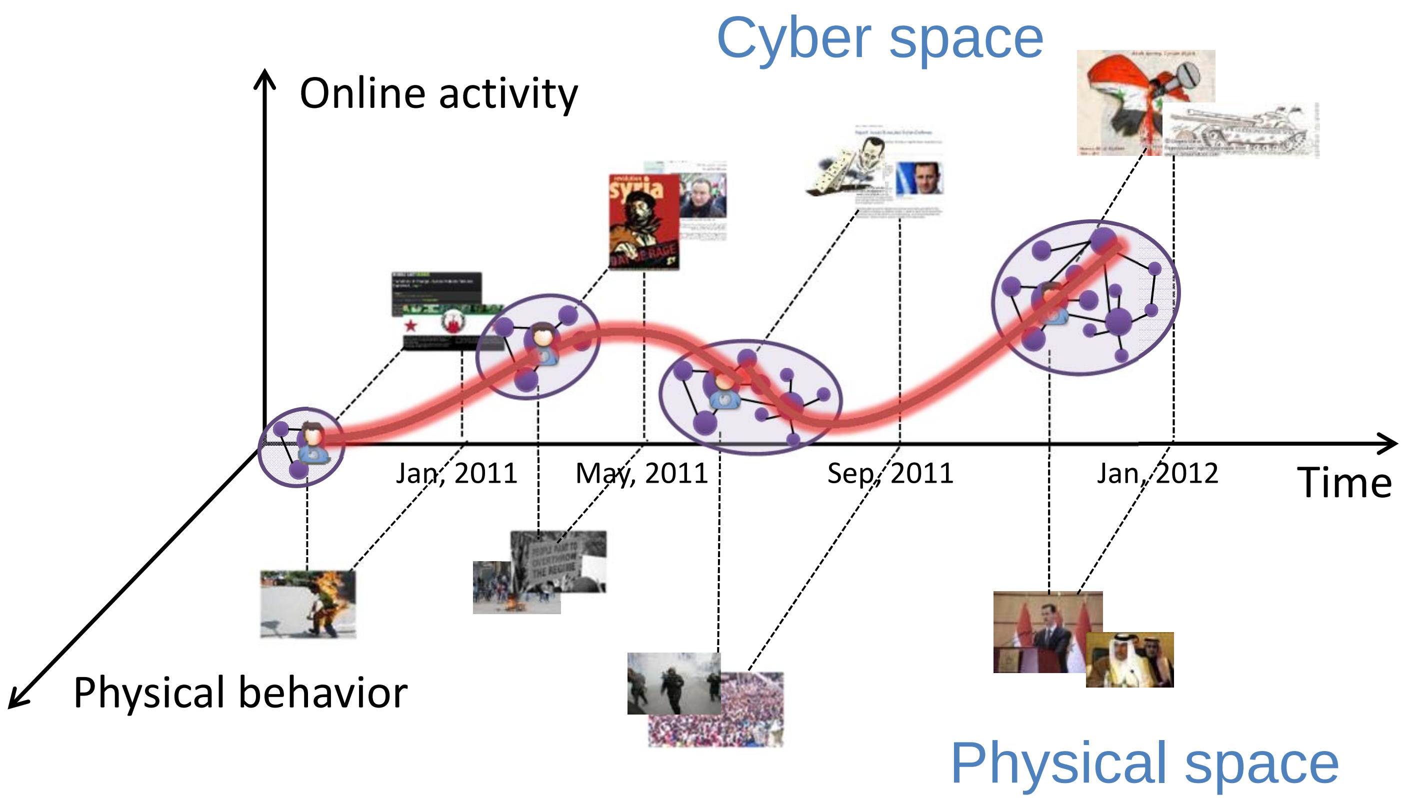
Cyber-Social-Physical Spaces



Cyber-social-physical spaces

Cyber-Social-Physical Computing

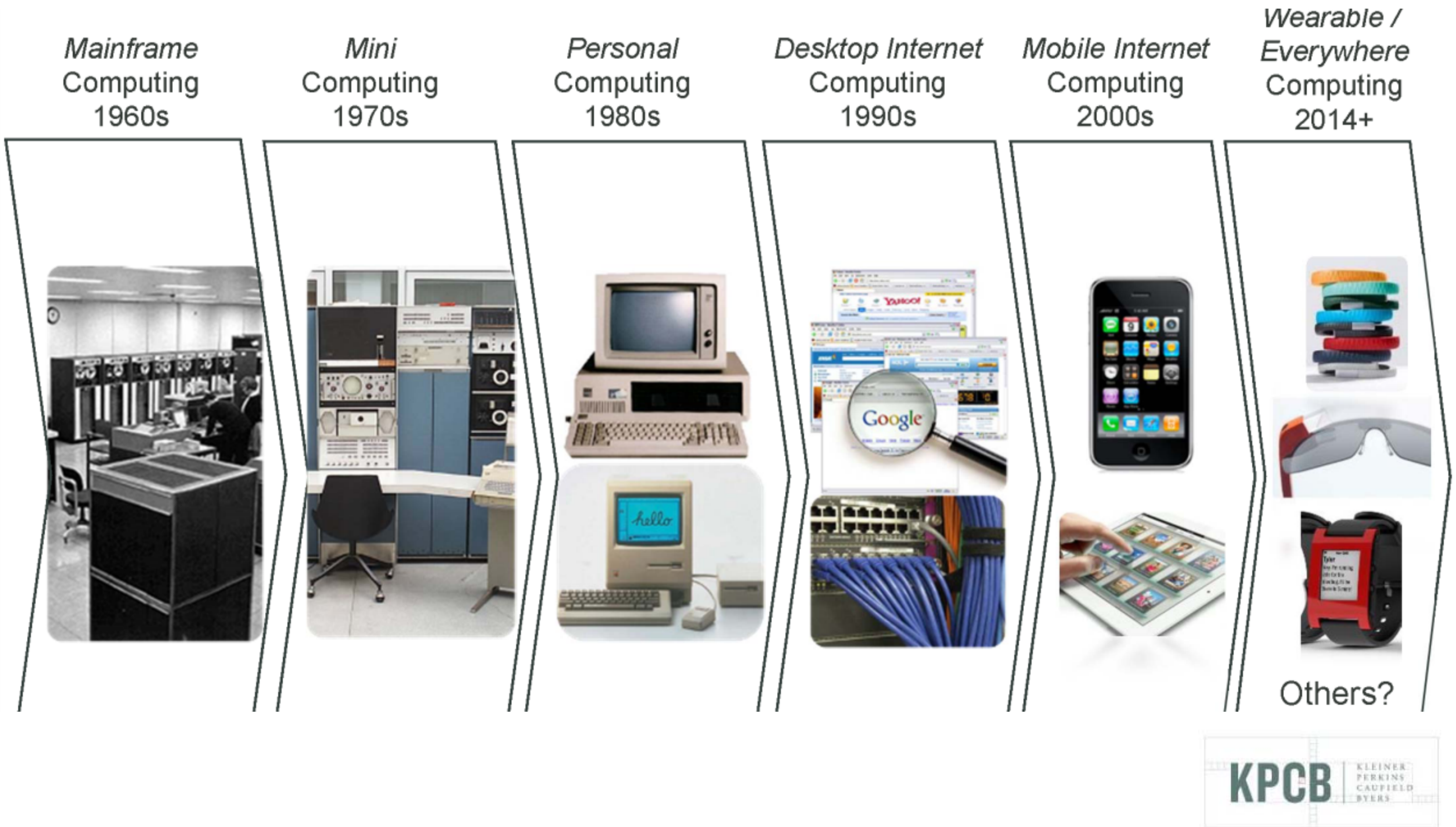
- Social event detection and tracking in cyber-social-physical spaces.



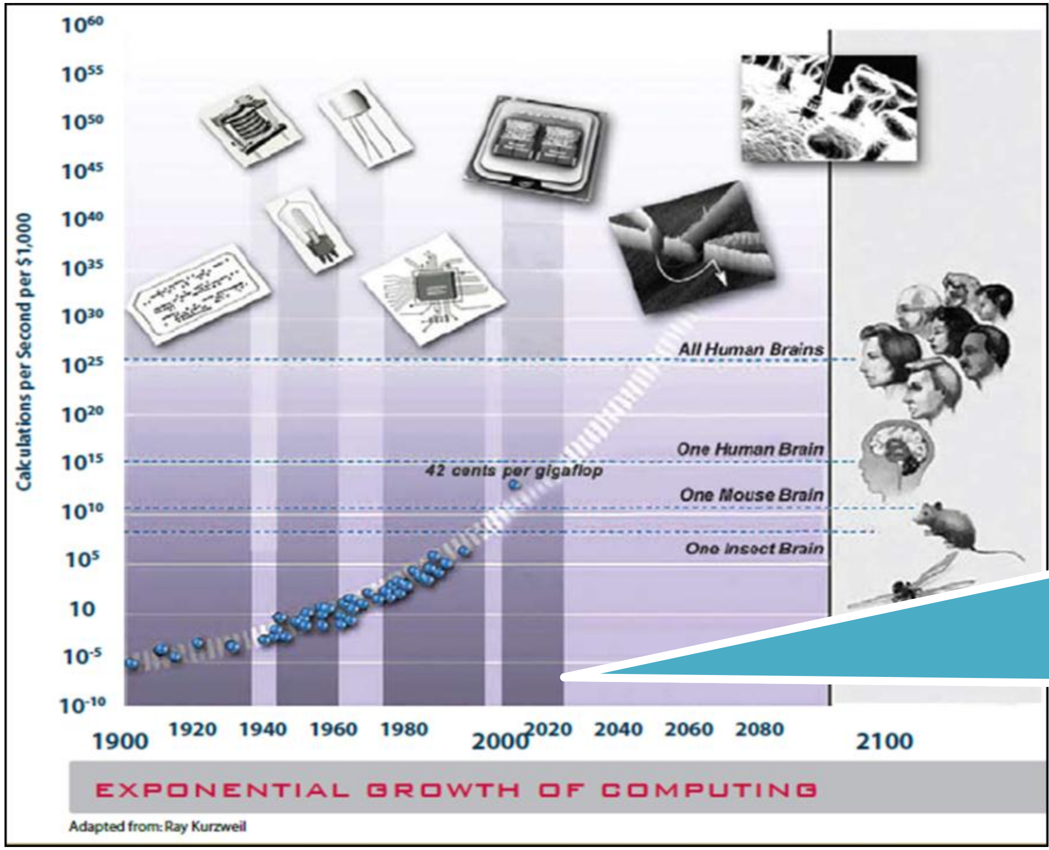
User will be the fundamental computing terminal.

Designed by Ken Sakamura

Computing is tending decentralized



Individual computational capability has significantly increased



Social Multimedia + Pervasive Computing

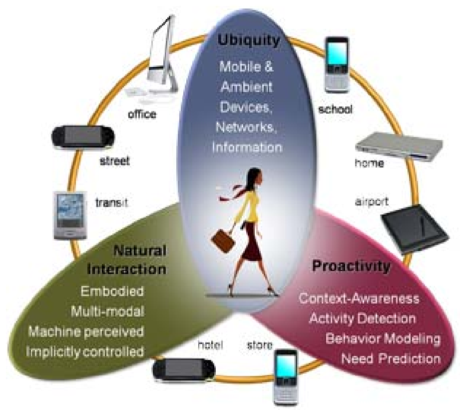
Social Multimedia Computing

content understanding

user modeling

Internet of Things

Pervasive Computing



application scenario

resource allocation

Take Home Message

- User is the basic data collection unit.
- User is the ultimate information service target.
- User connects cyber to the physical worlds.
- User will be the fundamental computing terminal.