Hashtag-centric Immersive Search on Social Media

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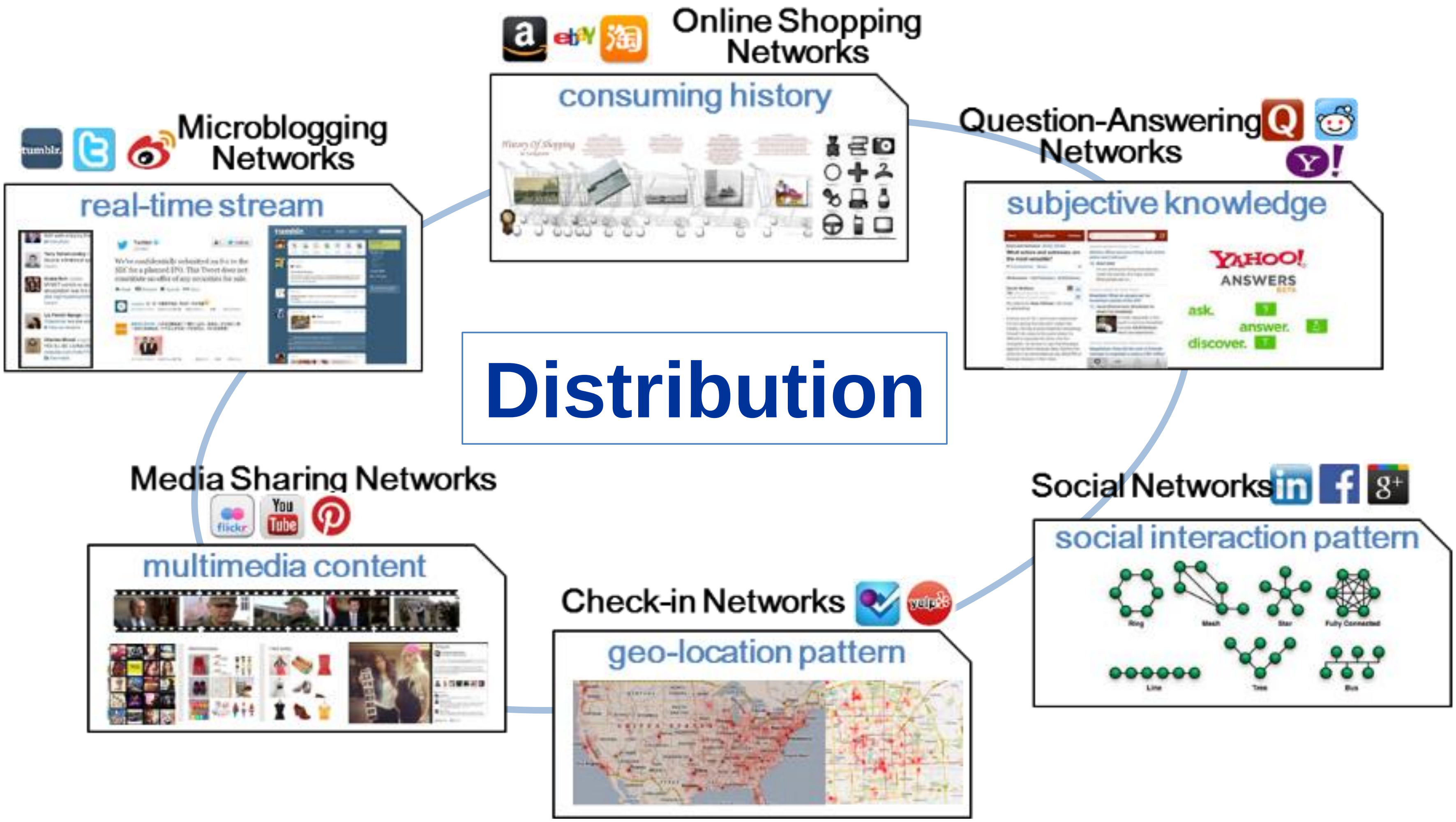
Outline

1. Motivation
2. Data Analysis
3. Solution
4. Experiment
5. Discussion

Outline

1 **Motivation**

Information: Multi-modality → Multi-source

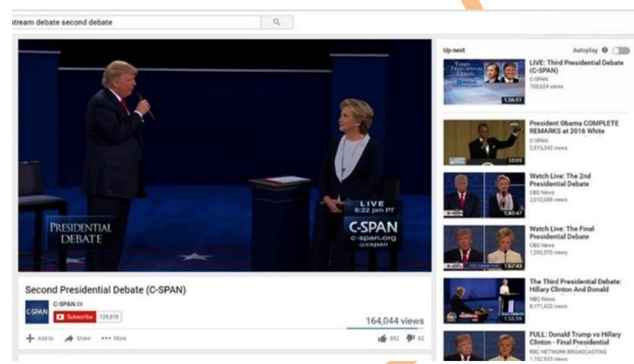


Information: Multi-modality ⟶ Multi-source

Access

ELECTION 2016

twitter



YouTube

Instagram

Immersive Information Access

Portal era → **Search era** → **Social media**

Portal era	Search era	Social media
All-web Passive index	**All-web** Active query	**Single OSN?** (Online Social Network)

Immersive Information Access

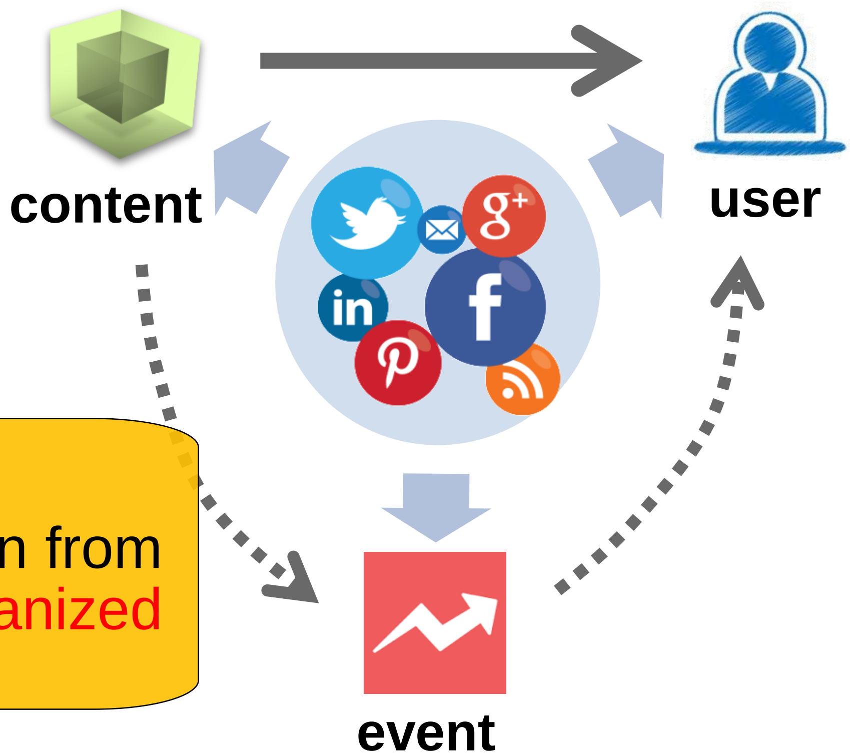
Portal era
All-web
Passive index

Search era
All-web
Active query

Social media
Cross-OSN
Immersive Service

YAHOO!

Google

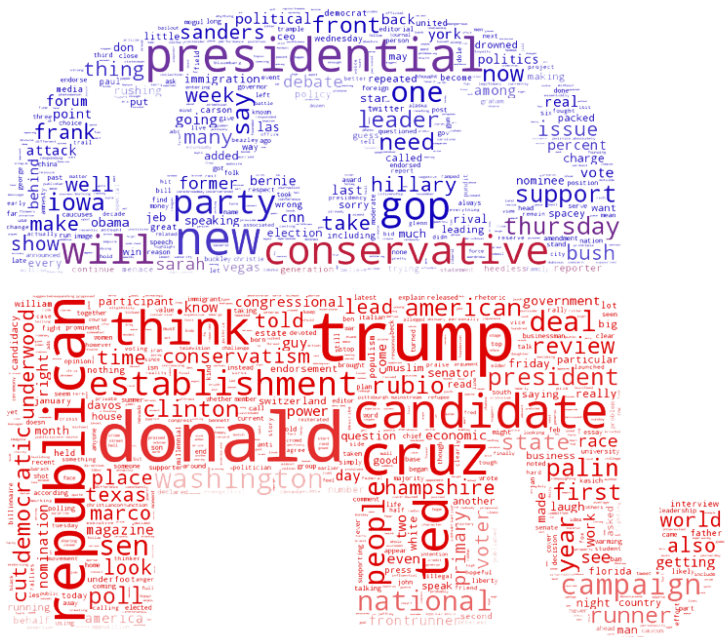


Cross-OSN search:
Given a query, the related information from different OSNs are aggregated, organized and demonstrated as search results.

Challenge: Relevance & Organization

1 **Relevance**
Noisy and biased results

2 **Organization**
Different modalities + search options



Election 2016

twitter

flickr

YouTube

relevance **interest** **#view**

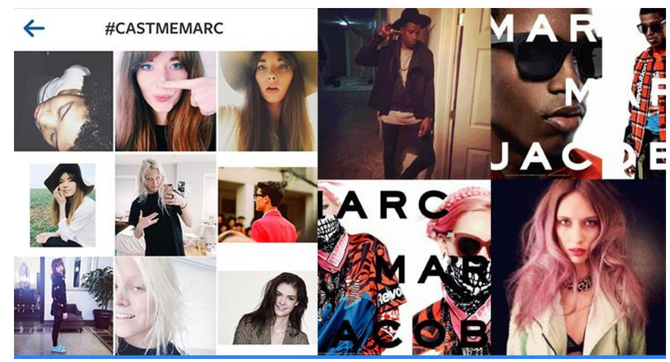
Hashtag: UGC Annotation + Management

1 Relevance
Noisy and biased results

2 Organization
Different search options + modalities

User-annotated

Management



naturally **cross-OSN**

Motivation:
We exploit hashtag as bridge for cross-OSN information integration and demonstration.

Outline

2 **Data Analysis**

Data Collection

Google Trends → 347 Queries → twitter / flickr / YouTube

Examples:

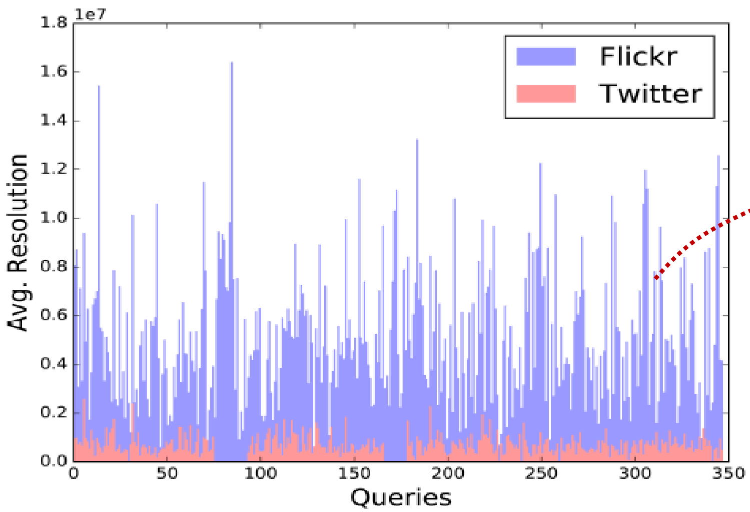
Election 2016	MLB
Overwatch	Arsenal
Halloween	Pokemon
Nobel Prize	Presidential debate

Question :

- What's the advantage of integrating different OSN search results? → **Single-OSN search comparison**
- How people use hashtag across different OSNs? → **Cross-OSN hashtag usage analysis**

Single-OSN Search Comparison: Information Richness

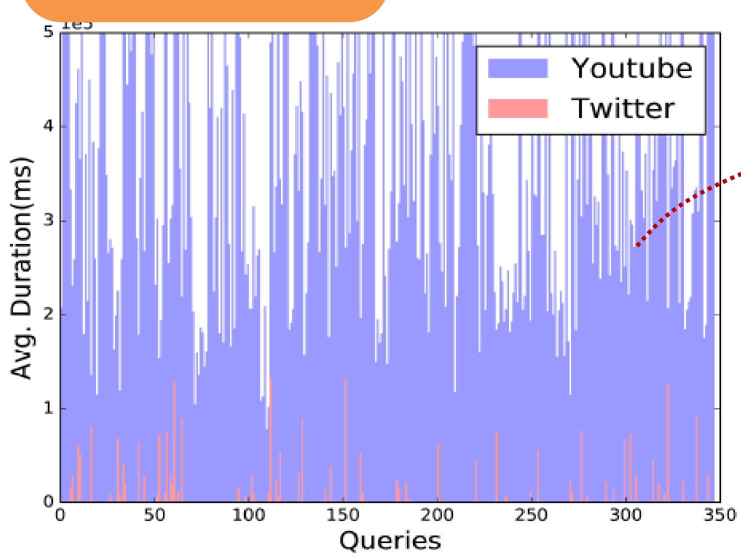
1 **Image Resolution**



480*360

900*853

2 **Video Duration**

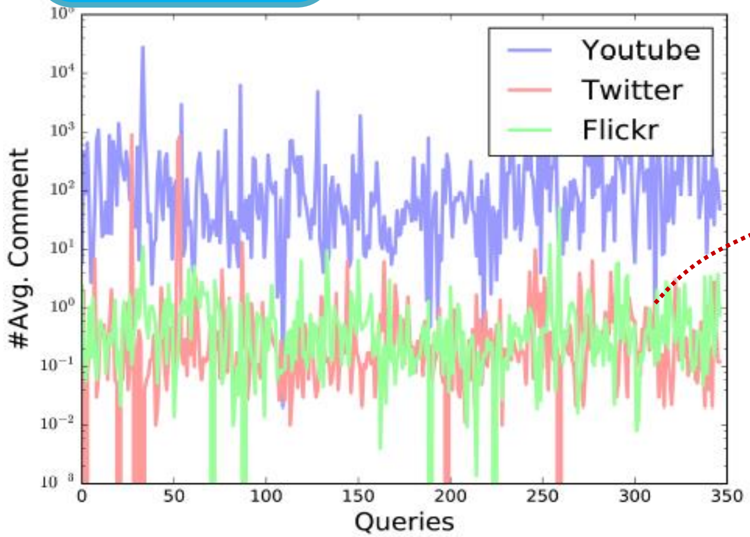


31s

21m47s

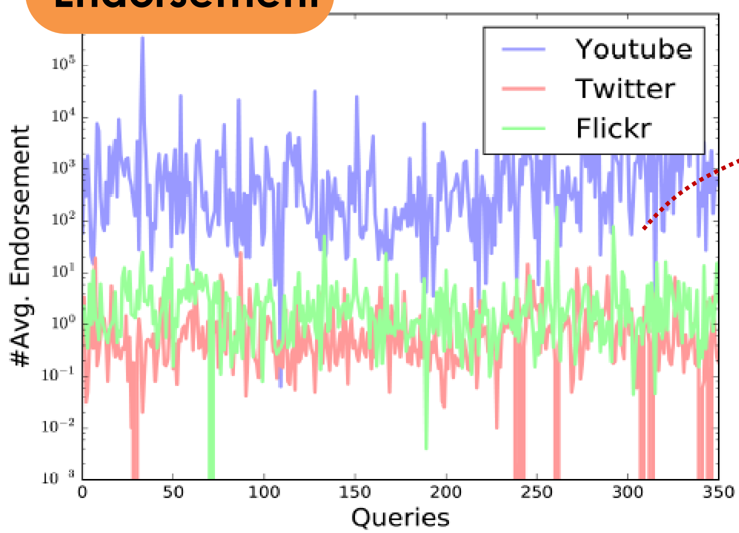
Single-OSN Search Comparison: User interaction

1 **Comments**



2 retweet **34 comment**

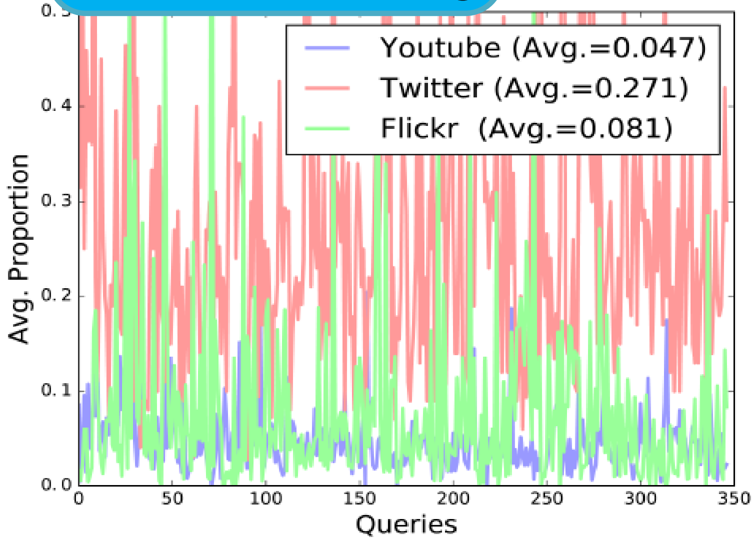
2 **Endorsement**



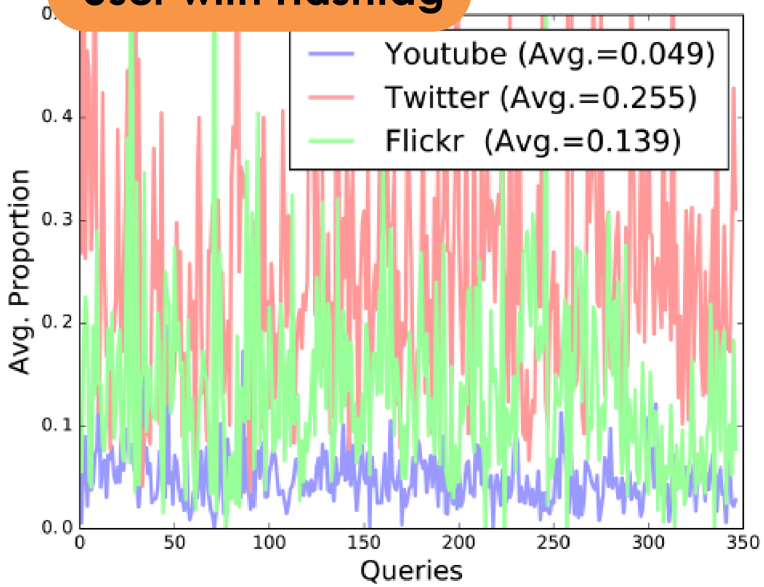
20 favorites **243 likes**

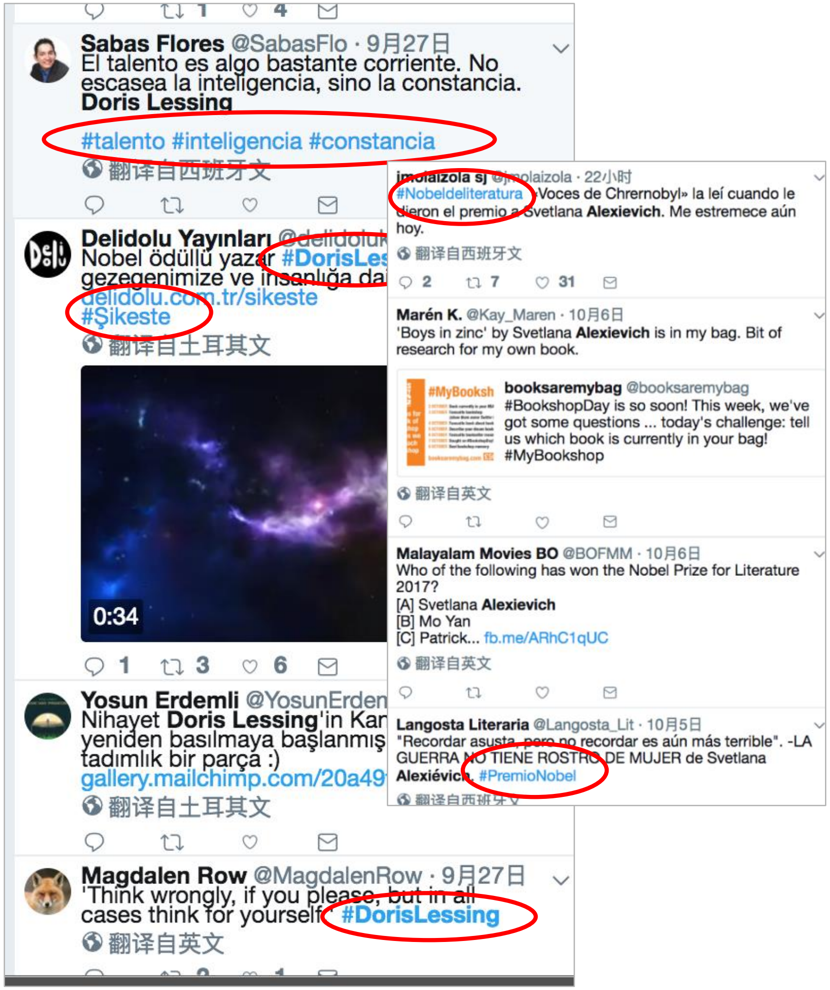
Cross-OSN Hashtag Usage Analysis: Popularity

1 **Result with Hashtag**



2 **User with Hashtag**





Cross-OSN Hashtag Usage Analysis: Diversity (1)

#Unique Hashtag (per query)

YouTube	Twitter	Flickr
17.77	28.42	27.61

Hashtag from search result of "Arsenal" (Partially)

Twitter	Flickr	YouTube
#EPL	#AlwaysTimeForCakevia	#afc
#RealMadrid	#alexanderhleb	#LIVE
#CristianoRonaldo	#wilshere	#Ludogorets
#AFC	#manchest	#PES2017
#Arsenal	#London	#MarqueeMatchups
#soccer	#MUFC	#EPL
#COYG		#COYG
#FootballNews		#SFC

Cross-OSN Hashtag Usage Analysis: Diversity (2)

NFr score of cross-OSN lists μ_1, μ_2

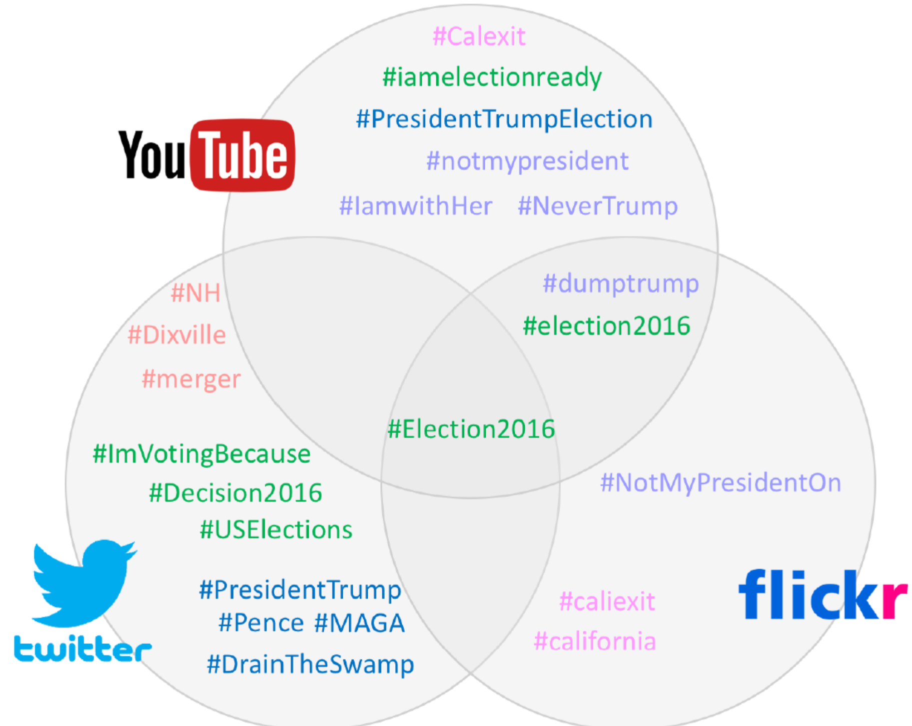
YouTube&Flickr	Twitter&YouTube	Flickr&YouTube
0.1006	0.0857	0.0375

$$NFr(\mu_1, \mu_2) = 1 - \frac{Fr^{|S|}(\mu_1, \mu_2)}{max \quad Fr^{|S|}}$$

$$Fr^{|S|}(\mu_1, \mu_2) = \sum_{i=1}^{|S|} |\mu_1(i) - \mu_2(i)|$$

$Fr^{|S|}$ equals $1/2|S|^2$ when $|S|$ is even

$Fr^{|S|}$ equals $1/2(|S| + 1)(|S| - 1)$ when $|S|$ is odd



Hashtags from search result of "Election 2016" from different OSNs

Data Observations

Single-OSN search comparison
- Information Richness
- User Interaction

Necessity
- Guarantee a better multi-modal search experience
- Enable more advanced features like social interaction

Cross-OSN hashtag usage analysis
- Popularity Analysis
- Diversity Analysis

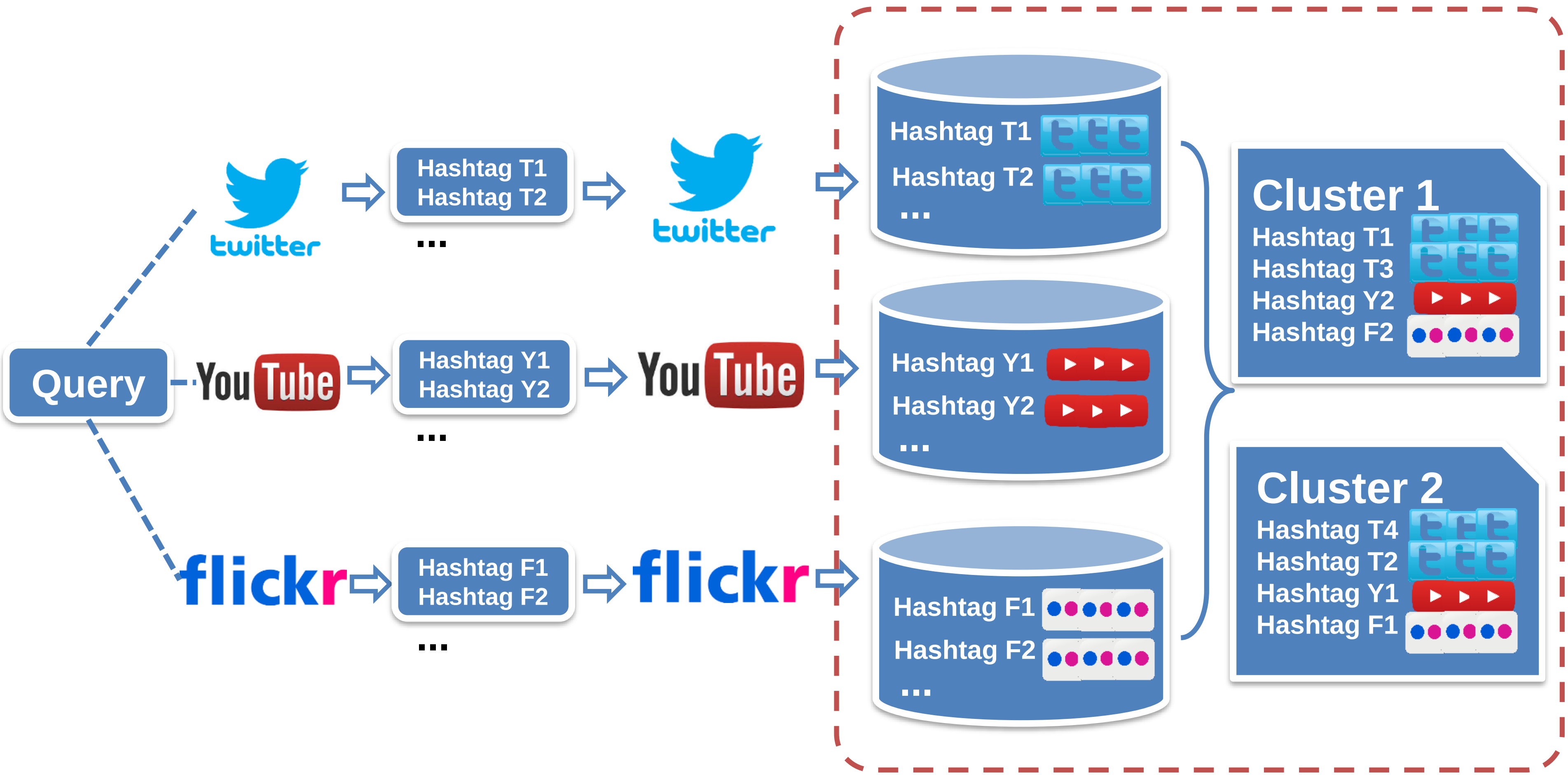
Feasibility
- Hashtag is widely used across different OSNs.

Inspiration to Solution
- **Multiple hashtag** → fine-grained semantic exploration;
- **OSN-distinctive hashtag** →higher topic level for integration.

Outline

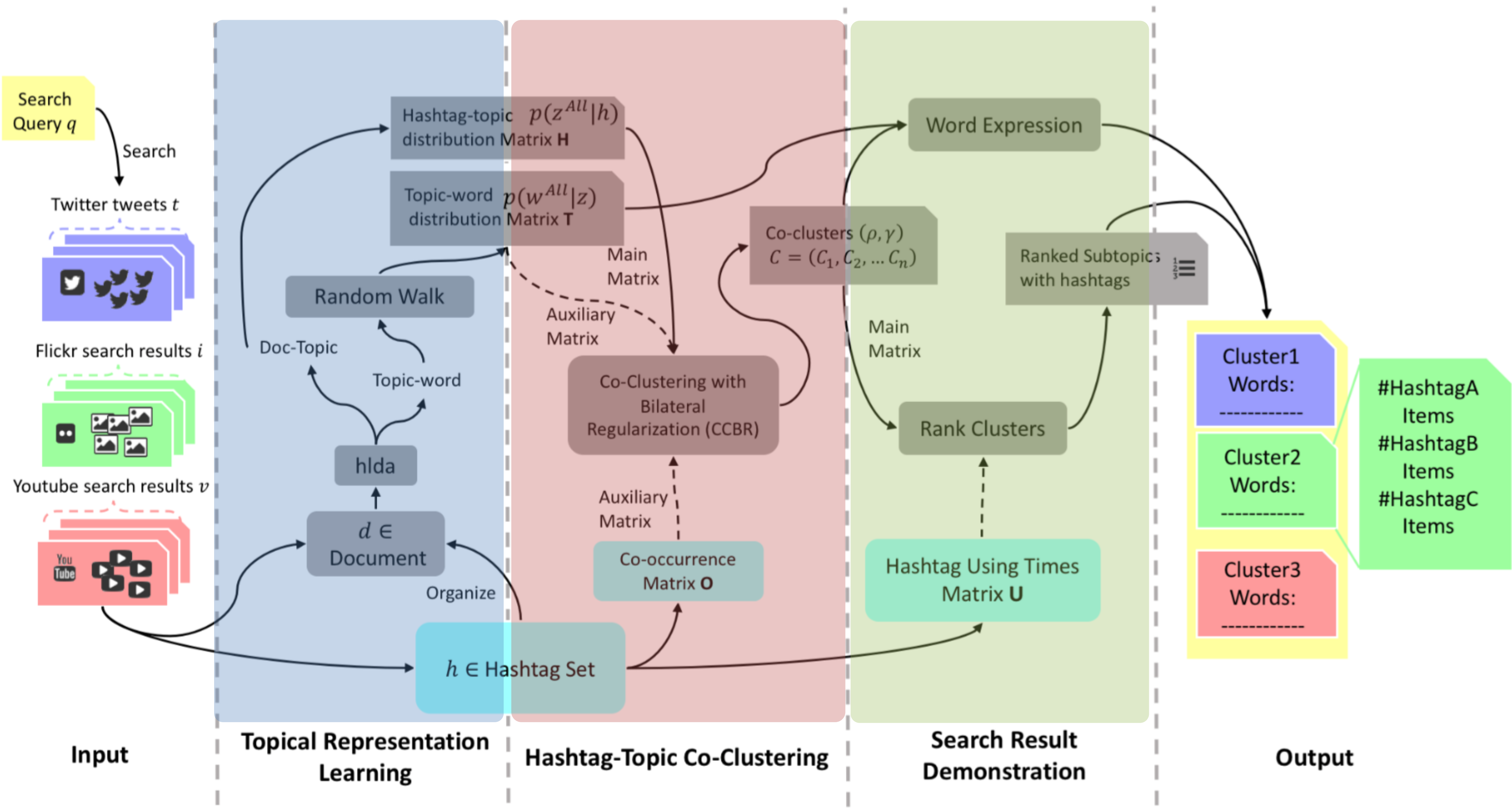
3 **Solution**

Data Flowchart

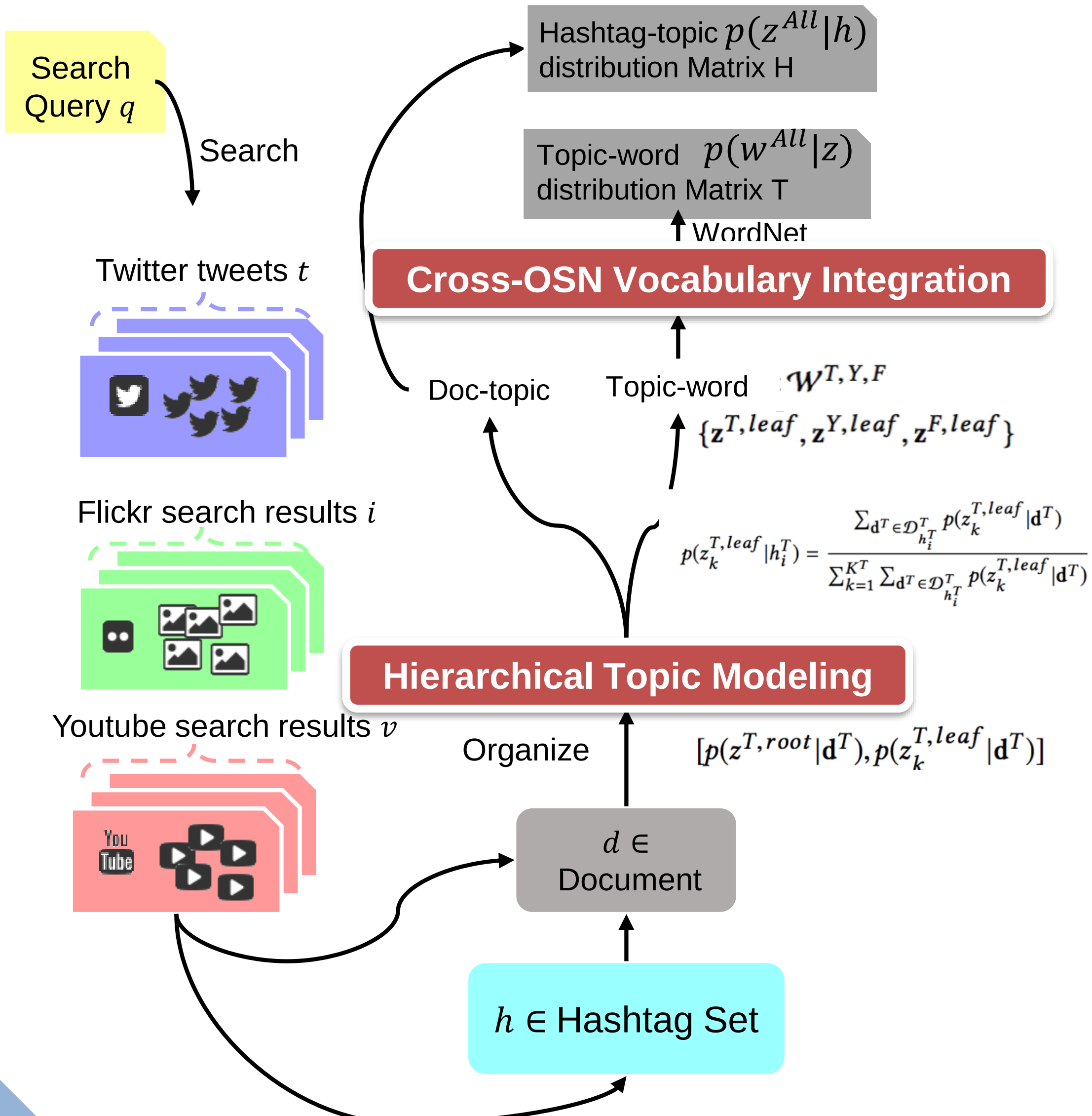


Hashtag Clustering

Solution Framework



Stage 1: Topical Representation Learning



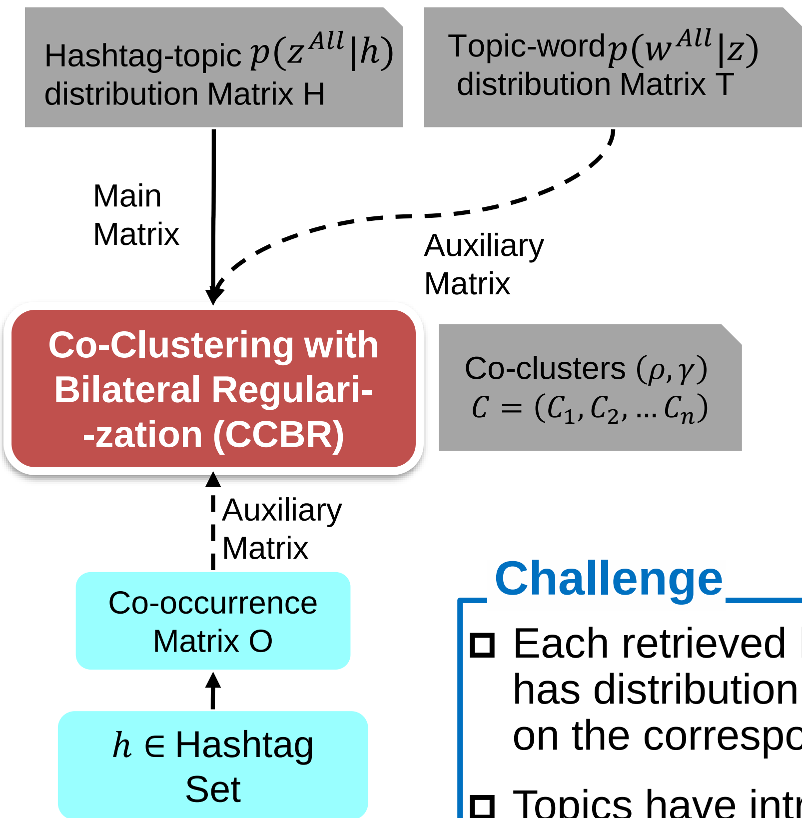
Challenge

- How to explore the fine-grained semantics under the same query topic?
- How to connect the biased vocabulary sets from different OSNs?

Solution

- **Hierarchical Topic Modeling**: utilize hLDA to represent each hashtag over the **subtopics** of the corresponding OSN $\{z^{T,leaf}, z^{Y,leaf}, z^{F,leaf}\}$
- **Cross-OSN Vocabulary Integration**: conduct random walk to propagate the subtopic relevance and obtain a **cross-OSN topic space** z^{All}

Stage 2: Hashtag-Topic Co-Clustering



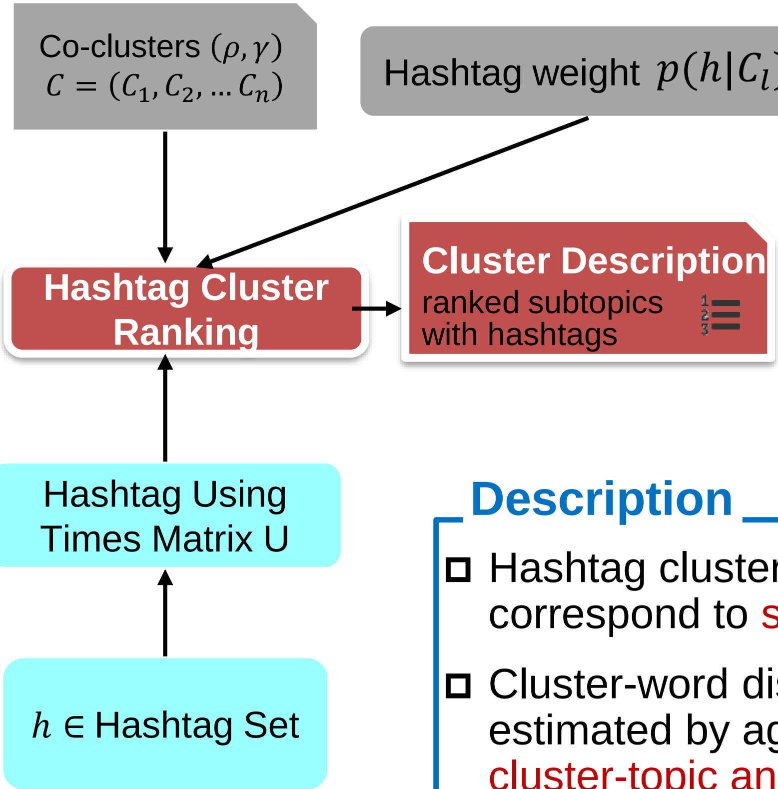
Challenge

- Each retrieved hashtag only has distribution over the topics on the corresponding OSN.
- Topics have intra-relation both within OSN and cross OSNs.

Solution

- **Hashtag-topic Co-Clustering:** cluster cross-OSN hashtags and topics simultaneously;
- **Co-Clustering with Bilateral Regularization (CCBR)**
  ① Regularizing **topic semantic relation** for column/topic clustering: topic-hashtag involvement + topic-word distribution;
  ② Regularizing **hashtag co-occurrence** for row/hashtag clustering: hashtags that co-occurring in the same item have high probability to contribute to the same subtopic.

Stage 3: Search Result Demonstration



Description

- Hashtag cluster is expected to correspond to subtopics.
- Cluster-word distribution is estimated by aggregating the cluster-topic and topic-word distribution.

$$p(w|C_l) = \sum_{z^t \in z^{all}} p(z^t|C_l) \cdot p(w|z^t)$$

Organization

- **Cluster - Hashtag - Item**
- Items within unique hashtag are organized **chronologically.**
- Hashtags within unique cluster are organized via **cluster-hashtag weight** $p(h|C_l)$.
- Cluster Ranking:
  ① Popularity constrain: cluster with more hashtag-annotated items in the search result set should be ranked higher;
  ② Smooth constrain: clusters with similar semantic relation deserve close ranks.

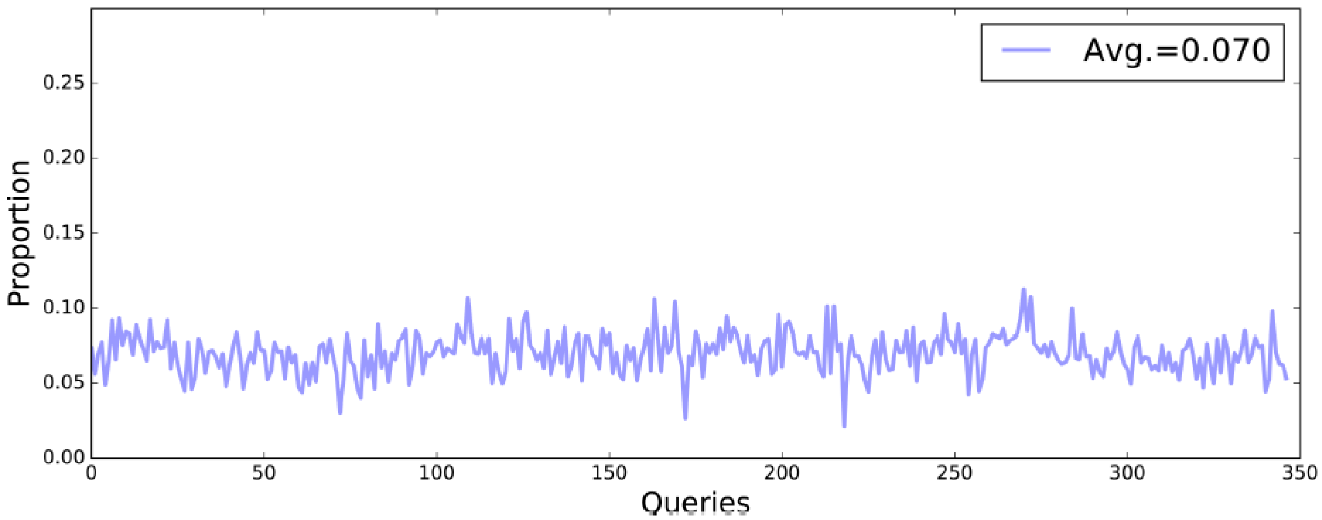
$$\kappa_{ij} = exp\left(-\frac{\sum_{z^t \in z^{all}} (p(z^t|C_i) - p(z^t|C_j))^2}{2\sigma^2}\right)$$

Outline

4 **Experiments**

Vocabulary overlap proportion.

It is shown only about **7%** vocabulary is shared between the three OSNs, which validates the necessity for random walk-based vocabulary integration.



Results of Topical Representation Learning

Derived topics for query "Election 2016".

- The discovered topics have a wide coverage.
- Random walk connects between different vocabulary spaces and enhances the topic representation with cross-OSN words.

Platform	Topic
Twitter	ranks,states,worldpolitics,meet ...
	published,newsletter, history,online,...
Flickr	million,trump,election,votes,riches...
	nation,people,language,americanelection...
Youtube	trump,donald,live,rally,presidenttrump,...
	country,children, feel,hold, citizens,...

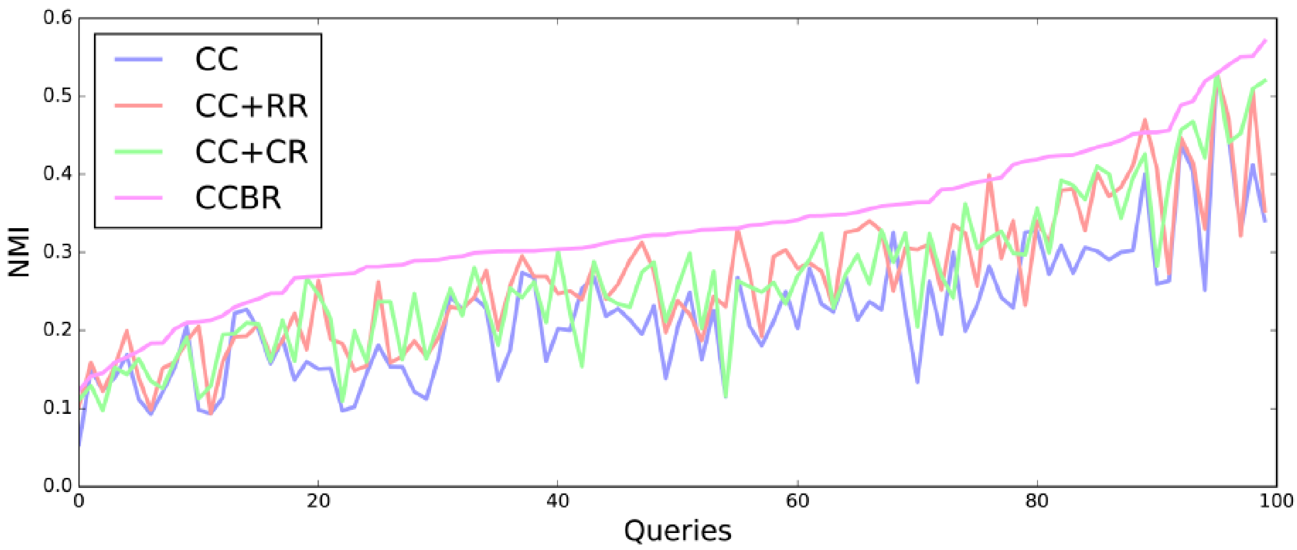
Twitter

Flickr

YouTube

Results of Hashtag Clustering

- **CC**: original Bregman Co-Clustering
- **CC+RR:** Co-Clustering with hashtag co-occuRrence Regularization
- **CC+CR**: Co-Clustering with intra-topic Correlation Regularization
- **CCBR**: Co-Clustering with Bilateral Regularization

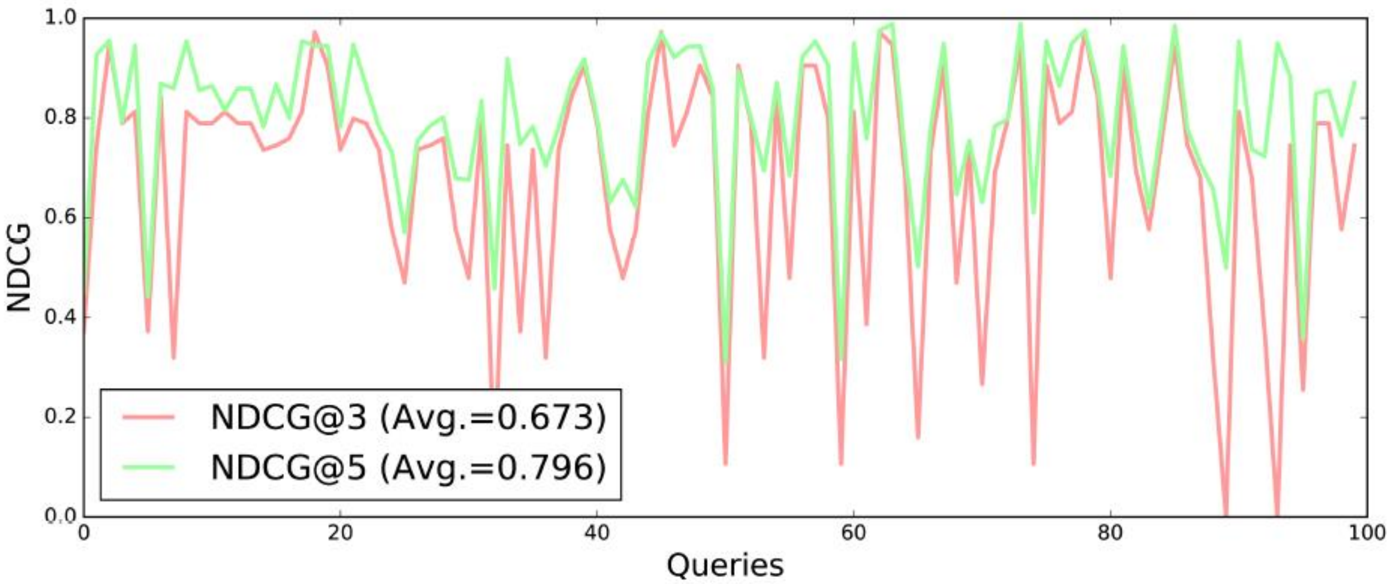


Negative Pearson correlations indicate that queries with larger #hashtag have a lower NMI

Method	CC	CC+CR	CC+RR	CCBR
NMI & #hashtag	-0.689	-0.633	-0.643	-0.526

Pearson correlation coefficient

Search Result Demonstration

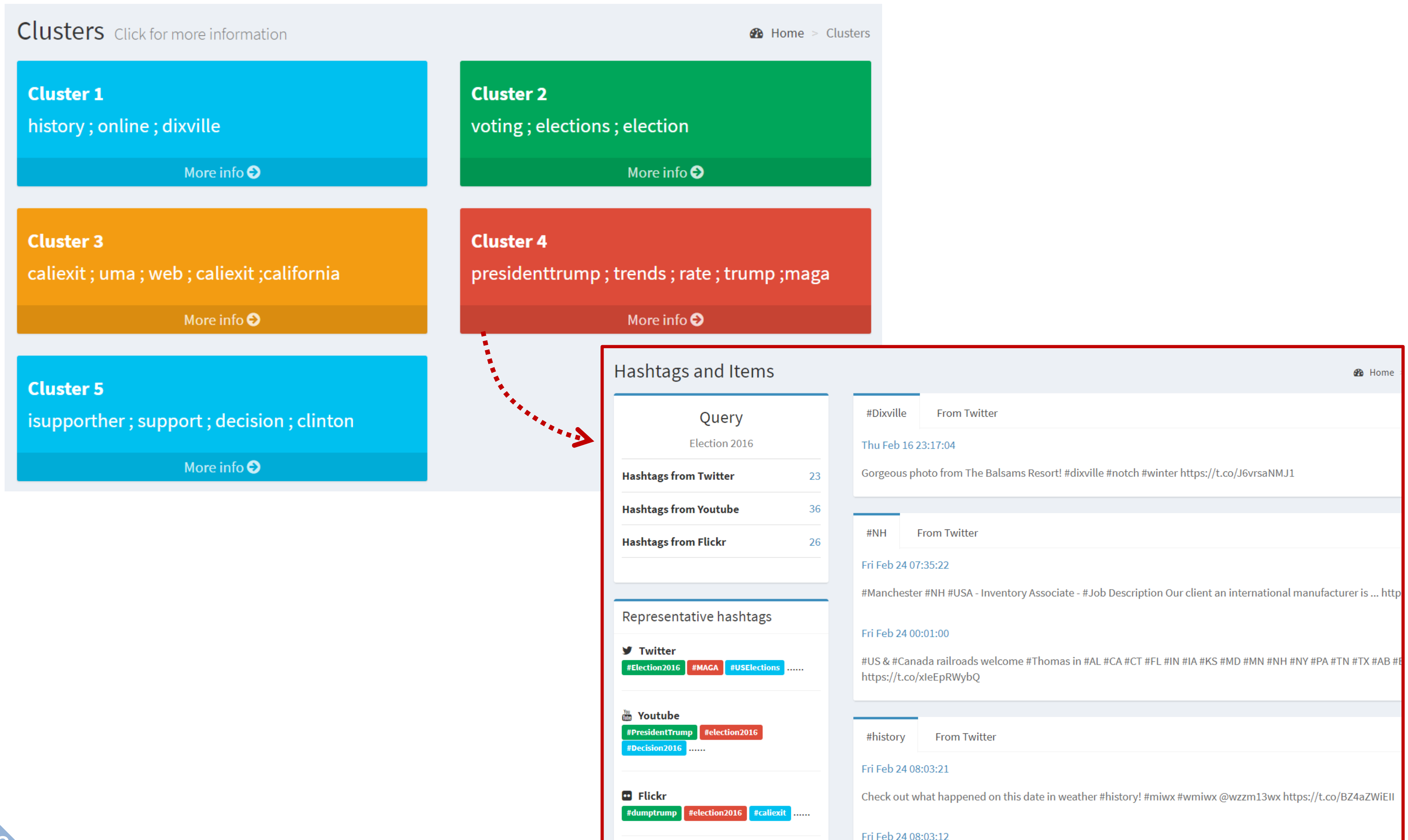


NDCG of hashtag cluster rank for different queries

- NDCG@5 = 79.6%: the cluster rank solution is reasonable and practical in real application.
  (most queries have a ground-truth of 5-9 clusters).
- When only examining the rank-1 cluster, the proposed rank method achieves performance with average NDCG@1=37%.

Demonstration: Cluster-Hashtag-Item Hierarchy

https://hashtagasbridge.github.io/Hashtag



Contribution and Limitation

Contribution:

- Discussed and analyzed the Cross-OSN hashtag usage;
- Positioned the problem of Cross-OSN immersive search, and introduced a preliminary hashtag-centric solution.

Limitation:

- **Time cost**: the first stage of cross-OSN topical representation learning prevents a practical solution.
- **Narrow focus on event queries**: remains unknown whether can apply to general queries.
- **Insufficient utilization of contextual data**, e.g., time (enable topic evolution), hyperlink (for better clustering).
- **Lack of exploiting representative OSN features**, e.g., Twitter list, Flickr group, YouTube channel, authoritative Users.

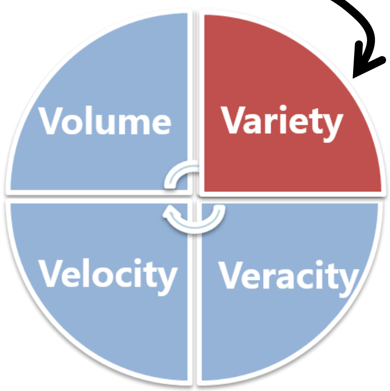
Outline

5

Discussion:
Cross-Modal ⇨ Cross-OSN

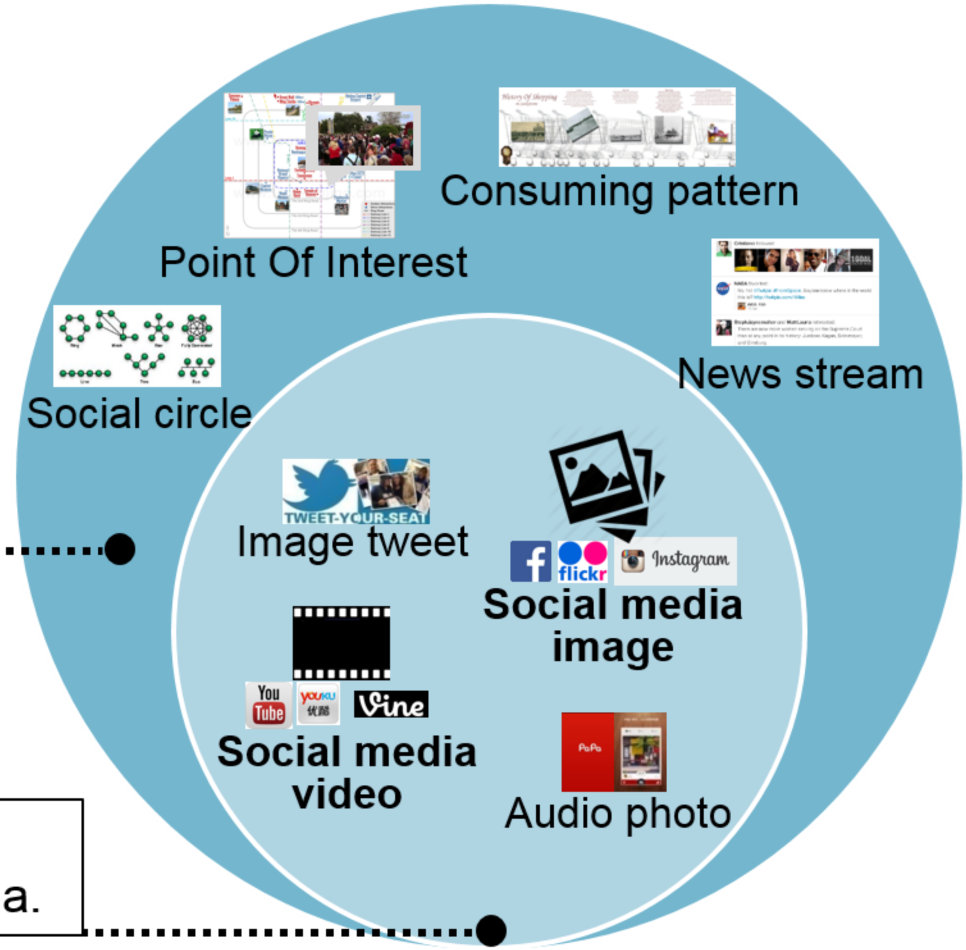
Social Multimedia: Special ➡ General

Multimedia:
Media of different **types** and **sources**



General Social Multimedia:
all types of individual and aggre-
-gated data on social media
(beyond modality, beyond object).

Special Social Multimedia:
multi-modal objects on social media.



General Social Multimedia Analysis

Web Multimedia

- **WEB1.0**
- Data is professionally edited.
- Core problem is media understanding.

Social Multimedia

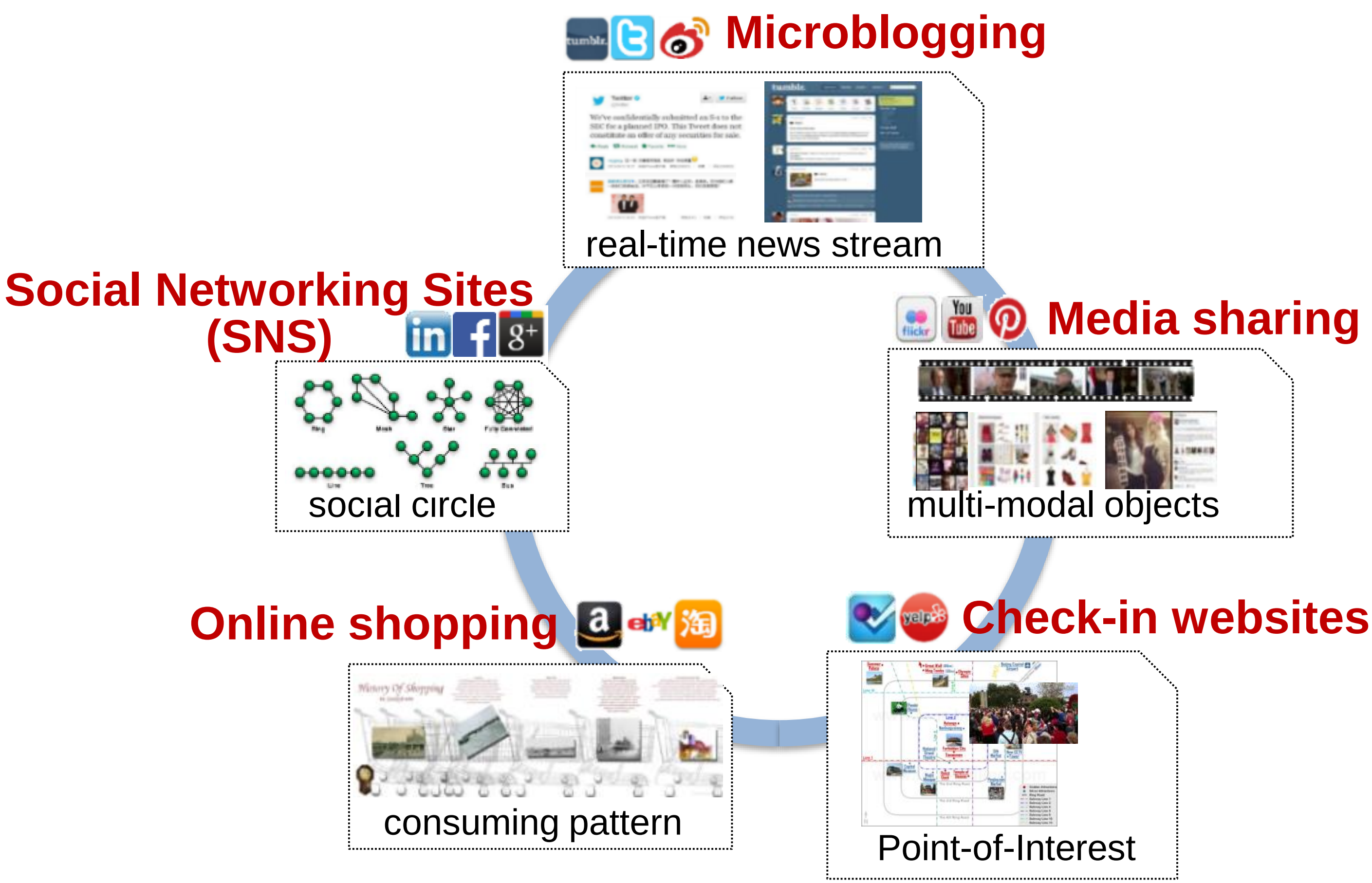
- Interaction is key.
- User contributes to data generation.
- User modeling is one basic problem.

General Social Multimedia

- **Media type**: beyond modalities.
- **Granularity**: beyond objects.
- **Association**: beyond semantic.

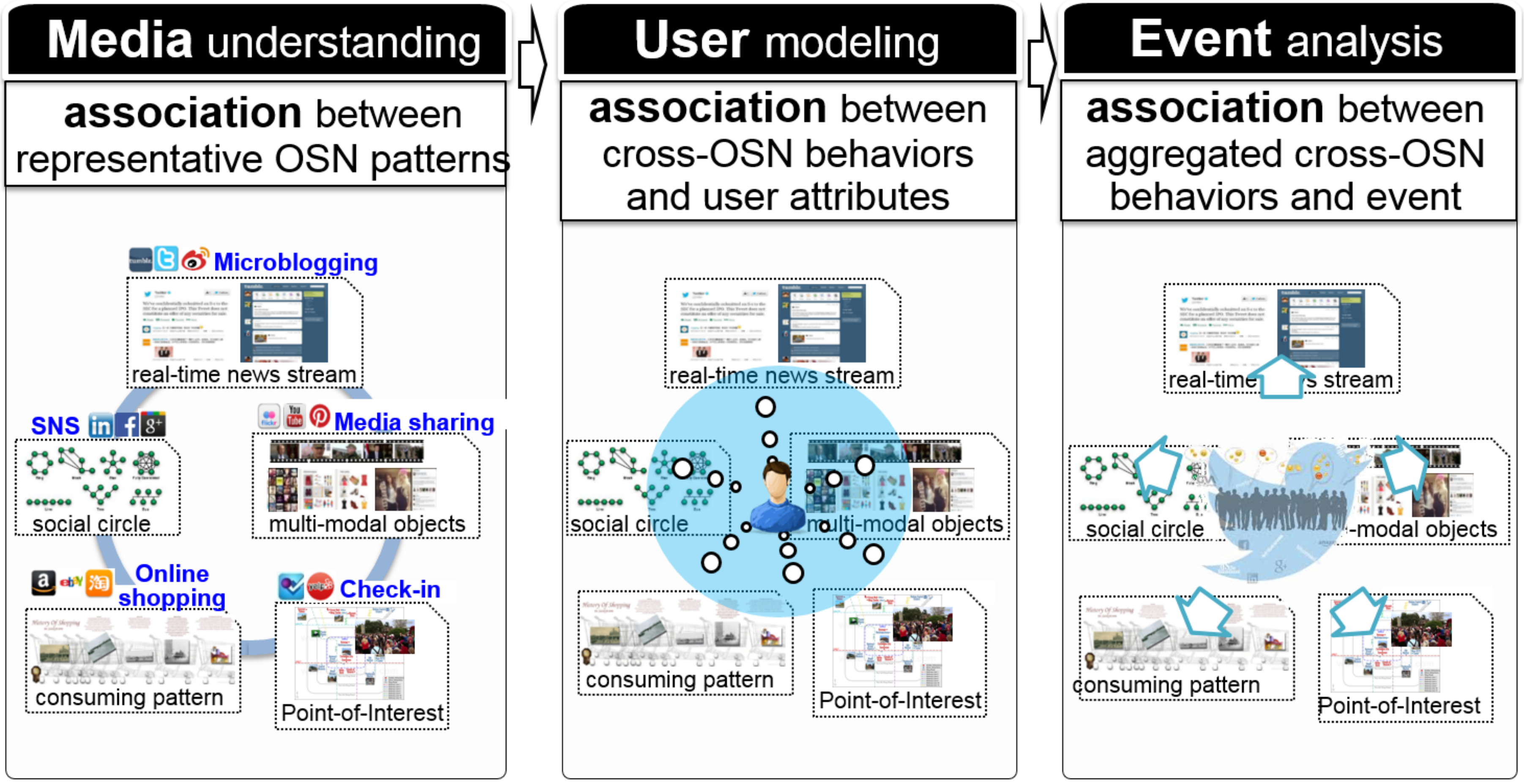
Cross-OSN: an Instantiation

Cross-OSN (Online Social Networks)



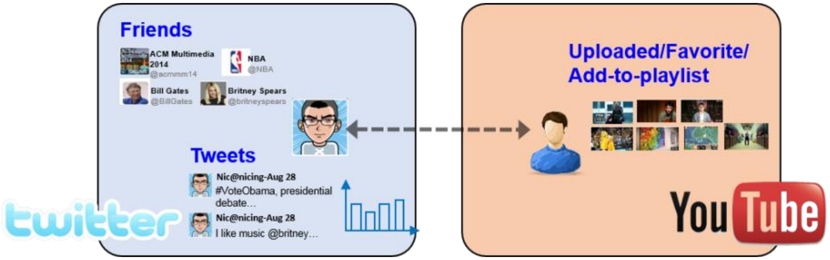
General Social Multimedia distributes among OSNs.
Cross-OSN provides both dataset & application scenarios.

Cross-OSN Data Mining

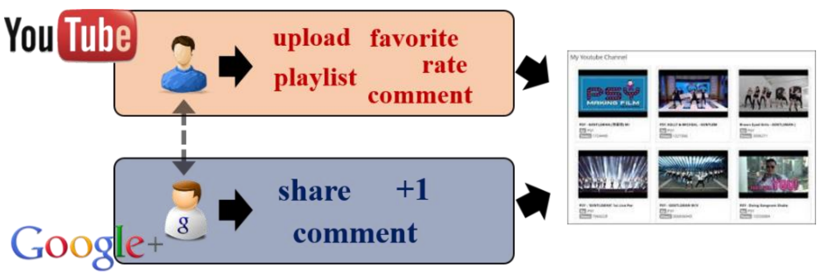


Jitao Sang, Changsheng Xu, Ramesh Jain.
Social Multimedia Mining: from Special to General. *ISM 2016*, Invited Paper.

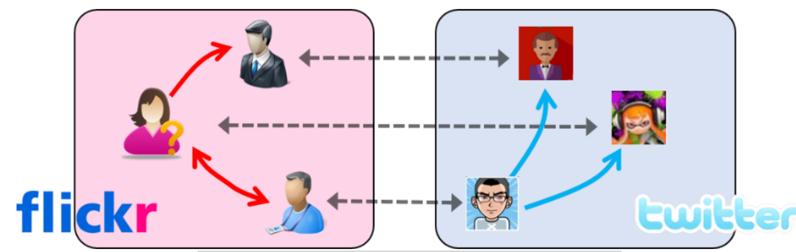
Cross-OSN Dataset (User-centric)



CrossOSN-U: Hetero



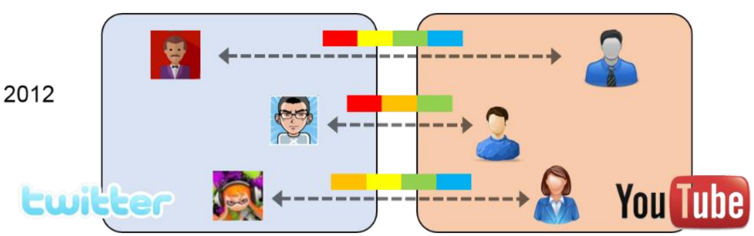
CrossOSN-U: Homo



CrossOSN-U: SN

Event List

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



CrossOSN-U: Event

Thank you!

Questions?