

Social Scope: Enabling Information Discovery on Social Content Sites

Authors: S.A.Yahia(Yahoo Inc) , L.V. Lakshmanan (UBC), Cong Yu (Yahoo Inc)

Presenter : Tony Wu

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Overview


- ▶ Motivation
- ▶ Goals
- ▶ Architecture
- ▶ Social Content Graph Model
- ▶ Information Discovery Layer
- ▶ Collaborative Filtering Example
- ▶ Content Management Layer
- ▶ Information Representation Layer
- ▶ Conclusions

Motivation

- Integration of social and content sites has led to the emergence of **social content sites** and **social content graphs**
- Traditional IR system only return results that are semantically relevant, but **not socially relevant**

	general (e.g., things to do)	categorical (e.g., family)	specific
with locations	32.36%	22.52%	8.37%
w/o locations	21.38%	5.34%	

Table 1: Summary Statistics of 10 Million Y!Travel Queries.



Motivation - Example

- ▶ John has a day off from his conference in Toronto, he searches for “Toronto Attractions” on Y! Travel
- ▶ John has in the past visited a few “baseball fields” on Y! Travel and on Facebook he has many friends with interests in “baseball”
- ▶ Traditional IR systems would return all the generic popular attractions based on semantic relevance (e.g. CN Tower), but not baseball related (e.g. Rogers Center)
- ▶ Social-Scope solves this problem by incorporating social relevance its search results (e.g. consider John’s friends interests)



Goals

- ▶ Query results must be both semantically relevant and socially relevant
- ▶ Efficient content management
- ▶ Effective navigation of search results

Architecture

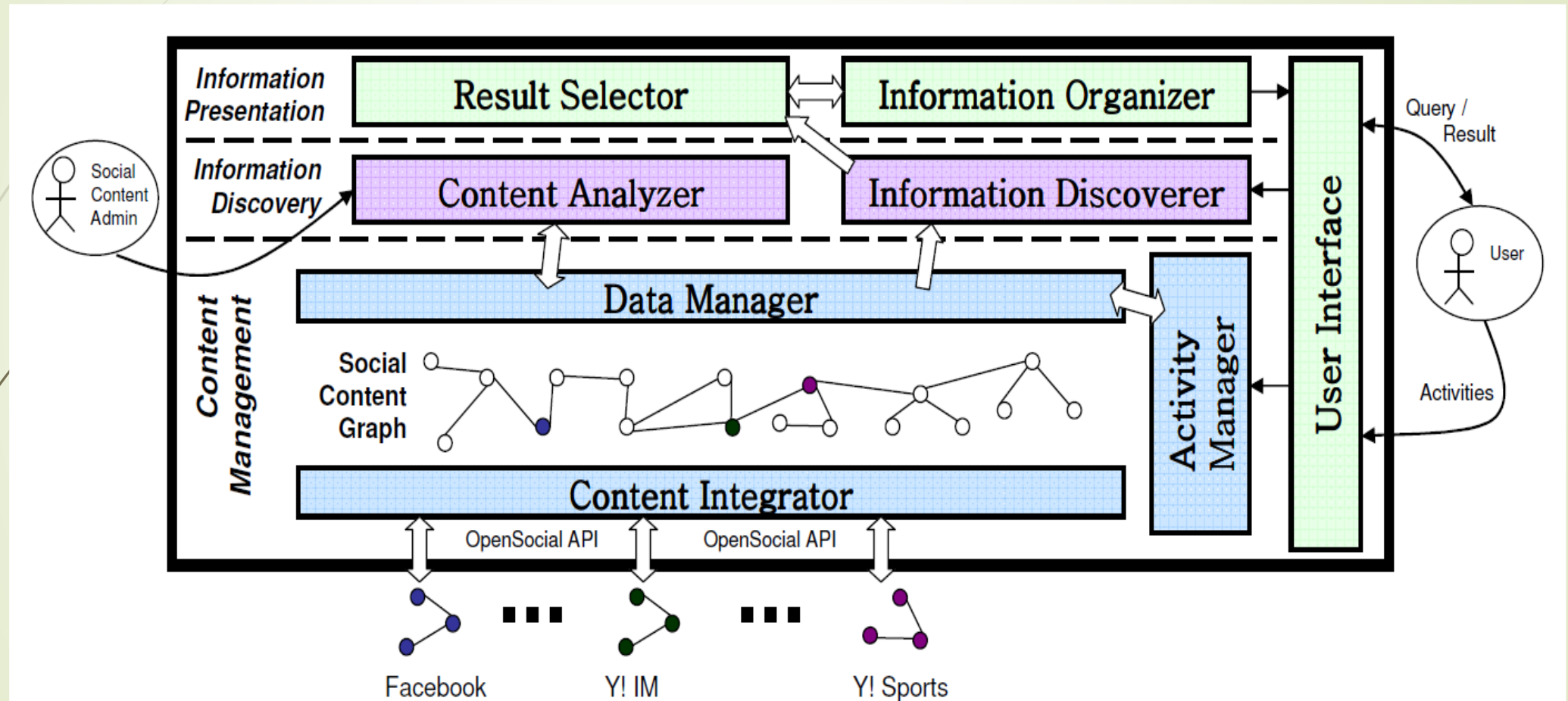


Figure 1: Architecture of SocialScope.

Social Content Graph Model

► Nodes:

- Represent users and entities like restaurants and attractions
- Each node has an ID and a set of attributes ('type' attribute is mandatory)
- E.g. $n_1 = \{id = 1; type = 'user, traveler'; name = 'John'\}$

► Links:

- Represents relationships between nodes (e.g. "visited")
- Can also used to represent user tags
- E.g. $L_{12}(n_1, n_2) = \{id = 12; type = 'act, tag'; date = '2008-8-2'; tags = 'Rockies baseball'\}$

Information Discovery Layer

- ▶ Unary Operators:
 - ▶ **Node Selection:** $\sigma_{\langle C, S \rangle}^N (G)$
 - ▶ **Link Selection:** $\sigma_{\langle C, S \rangle}^L (G)$
 - ▶ Outputs and a set of nodes (for NS) or links (for LS) that satisfies condition C, and their scores based on the scoring function S

- ▶ Basic Binary Operators (Set theoretic Operators):
 - ▶ **Union :** $G1 \cup G2$
 - ▶ **Intersection :** $G1 \cap G2$
 - ▶ **Difference :** $G1 / G2$
 - ▶ Applies to both links and nodes

Information Discovery Layer

- ▶ Advanced Binary Operators:
 - ▶ **Composition:** $G = G_1 \odot_{\langle \delta, F \rangle} G_2$
 - ▶ Creates new links between the nodes in G_1 and G_2 satisfying the directional condition δ
 - ▶ Directional constraints have values *src* or *tgt* (e.g. $\delta = (\text{src}, \text{tgt})$ means source node of G_1 matches target node of G_2)
 - ▶ F specifies the composition function of how the attributes of the new links should be determined based on the attributes of the input links
 - ▶ **Semi-Join:** $G_1 \bowtie_{\delta} G_2$
 - ▶ Produces a sub-graph of G_1 where the links of G_1 matches the links of G_2 based on the directional condition δ
 - ▶ e.g. $G_1 \bowtie_{(\text{tgt}, \text{src})} G_2$ produces a sub-graph of G_1 where the all links of the sub-graph have target nodes that matches the source nodes of G_2

Information Discovery Layer

➤ Aggregate Operators:

➤ **Node Aggregation:** $\gamma_{\langle C, d, att, A \rangle}^N(G)$

- Aggregates the links of the nodes based on aggregate function A satisfying condition C and directional parameter (src or tgt)
- The aggregation function produces a new node attribute att

➤ **Link Aggregation:** $\gamma_{\langle C, att, A \rangle}^L(G)$

- Replaces the set of links satisfying C and have the same source and target nodes where the new link has attribute att of which the value is determined by A

Collaborative Filtering Example

Problem :

Recommendation of travel destinations to John based on his social network

Solution:

1. $G_1 = \sigma_{type='visit'}^L (G \bowtie_{src,src} \sigma_{id=101}^N(G))$

► User John and places he has visited

2. $G'_1 = \gamma_{type='visit',src,vst,A}^N(G_1)$

► Set of destinations John has visited and stores in the vst att of node JOHN

3. $G_2 = \sigma_{type='visit'}^L (G \bowtie_{src,src} \sigma_{id \neq 101}^N(G))$

► Users other than John and the places they have visited

4. $G'_2 = \gamma_{type='visit',src,vst,A}^N(G_2)$

► Set of destinations that other users have visited and stores in the vst att of the nodes

Collaborative Filtering Example

Solution – Cont'd

5. $G_3 = G_1 \odot_{\langle \delta, F \rangle} G_2$

- ▶ $\delta = (tgt, tgt)$ and F is the composition function that computes the Jaccard similarity, which is stored in links produced from John to another user

6. $G_4 = \gamma_{\langle sim > 0.5, type, A' \rangle}^L(G_3)$

- ▶ Replaces score of the links with similarity > 0.5 with string “Match”

7. $G_5 = \sigma_{type='visit'}^L \left(G \bowtie_{tgt, src} \sigma_{type='destination'}^N(G) \right)$

- ▶ All destinations that users have visited

8. $G_6 = (G_4 \bowtie_{tgt, src} G_5) \odot_{\langle (tgt, src), sim_{sc}, F' \rangle} (G_5 \bowtie_{src, tgt} G_4)$

- ▶ For each of John's similarity network friends who has visited a destination, a new link is added from John to that destination. F' copies sim score from link of john to user to new link

9. $G_7 = \gamma_{C, score, AVERAGE}^L(G_3)$

- ▶ Replace set of links from John to destination node with attribute score, which is the average of the similarity score, score can be used to rank destinations

Content Management Layer

- ▶ Provides **efficient storage** of indexes to support keyword-based queries
- ▶ **Inverted list (IL)** is used to store the item scores for each (tag, user) pair, each entry of the list consists of the form $(i, \text{score}_k(i, u))$, $k = \text{tag}$, $l = \text{item}$ and $u = \text{user}$
- ▶ Score for each item is calculated by summing the item score across each IL of all (tag, user) pair
- ▶ **Problem:** Storing a list of scores for every (tag, user) pair can consumes a huge amount of storage since the number of items and users can be huge (requires 1 terabyte for a site with 100,000 users, million items and 1000 distinct tags!)

Content Management Layer

- ▶ Clustering will reduce the storage complexity of storing inverted list
- ▶ Score of the cluster will be calculated as follows:

$$\text{Score}_k(i, C) = \max_{u \in C} \text{score}_k(i, u)$$

- ▶ **Network-based Cluster:**

$$\frac{|\text{network}(u_1) \cap \text{network}(u_2)|}{|\text{network}(u_1) \cup \text{network}(u_2)|} \geq \theta$$

- ▶ **Behavior-based Cluster:**

$$\frac{|\text{items}(u_1) \cap \text{items}(u_2)|}{|\text{items}(u_1) \cup \text{items}(u_2)|} \geq \theta$$

Information Presentation Layer

- ▶ Results are grouped to allow users to navigate the results more effectively

- ▶ **Social Grouping:**

$$\frac{|taggers(i_1) \cap taggers(i_2)|}{|taggers(i_1) \cup taggers(i_2)|} \geq \theta$$

- ▶ Provides explanation to items to allow user realize **social provenance:**
 - ▶ Content-based strategy
 - ▶ Collaborative filtering strategy



Conclusions

- ▶ Social Scope is able to search for results not only semantically relevant, but also social relevant
- ▶ Information discovery layer is based on a set of graph processing operators to return socially relevant results from the social content graph
- ▶ Content Management layer leverages clustering to efficiently store inverted index for key-word based search
- ▶ Search results are grouped in the presentation layer based on social grouping and descriptions are attached to results to realize social provenance



Thank You!

Questions?