Connecting Content to Community in Social Media

Via image content, user tags and user communication

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The Problem

Given an image, how do we recommend the relevant communities that would enable social interaction and enhance its “reachability” to other users?
Community contributed social media...

Stormy Weather over the Manhattan Bridge...

Media-sharing

Concept-sharing (tagging)

Communication (commenting)
Nature and Colors
Travel
Pleasure
Long Exposure
New York City
Canon 350D
Portraiture Photography
Why is this problem challenging?

An empirical observation...
Simple keyword search returns too many groups!
“Most relevant”

“Most recent activity”

“Group size”

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Quality of content?
Community practices?
Richness of communication?
I want to find the *right* set of communities for my photos... help!
Approach
System Overview

Flickr Dataset

Feature Extraction

(a) Image Content Features  (b) Tag Features  (c) Communication Features

Model Learning

(d) Group Representation as bag-of-features  (e) Learning latent space of group features

'Folding-in' Technique

G1 G2  G1 G2  G1 G2

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Feature Extraction

\[ \vec{f}_i = \begin{bmatrix} \alpha_1 \vec{C}_i, & \alpha_2 \vec{T}_i, & \alpha_3 \vec{O}_i \end{bmatrix} \]

- **Image content features** –
  - color histogram, color moment, GLCM, phase symmetry, radial symmetry, phase congruency, SIFT, \( C_i \in \mathbb{R}_{+}^{1 \times m} \)

- **User tagging history features** –
  - frequency distribution of user tags in the past, \( T_i \in \mathbb{R}_{+}^{1 \times n} \)

- **User communication features** –
  - frequency of comments by the user on various groups, \( O_i \in \mathbb{R}_{+}^{1 \times p} \)
Image-group association often depends upon latent intent of the user – based on content, her prior tagging activity or communication...

\[ \vec{f}_i = \begin{bmatrix} \alpha_1 \vec{C}_i, \alpha_2 \vec{T}_i, \alpha_3 \vec{O}_i \end{bmatrix} \]

latent state, \( z_i \)  

group, \( G_j \)

\[ Y_j = \frac{1}{|G_j|} \sum_{i \in G_j} f_i \]

Probability of recommending group \( G_j \) to image \( i \):

\[
P(G_j | i) \propto P(G_j, i)
\]

\[
P(G_j, i) = \sum_{z} P(z).P(i | z).P(G_j | z)
\]

\[
\propto \sum_{z} P(z | i).P(G_j | z)
\]

Model learning

Folding-in technique

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Model Learning –
maximize the expectation of the feature space $F_m$ of the groups $G_j$

$$E\text{-step: } P(z | F_m, G_j) = \frac{P(z).P(F_m | z).P(G_j | z)}{\sum_{z'} P(z').P(F_m | z').P(G_j | z')}.$$  

$$M\text{-step: } P(G_j | z) \propto \sum_m Y_{m,j} \cdot P(z | F_m, G_j),$$  

$$P(F_m | z) \propto \sum_j Y_{m,j} \cdot P(z | F_m, G_j),$$  

$$P(z) \propto \sum_m \sum_j Y_{m,j} \cdot P(z | F_m, G_j).$$

Folding-in Technique –
for a new image $i$, maximize the expectation of the feature space $F_m$ given the latent state $z$

$$E\text{-step: } P(z | i, F_m) \propto P(F_m | z).P(z | i).$$  

$$M\text{-step: } P(z | i) \propto \sum_m Z_{m,i} \cdot P(z | i, F_m),$$
Experimental Results
Flickr Dataset

- Seed crawling from images ranked by Flickr’s proprietary “interestingness” criterion.
- 15,689 images
- 925 groups
- Upload time period from March 21, 2008 to August 20, 2008

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<table>
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<tr>
<td>Mean number of tags per photo</td>
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<tr>
<td>Mean number of groups per photo</td>
<td>3</td>
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<tr>
<td>Mean number of comments per photo</td>
<td>14</td>
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</tbody>
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Evaluation of Recommendations

Experimental Setup:

- 80% training (12,551 images), 20% testing (3,138 images)
- Metrics are computed at $k=1, 3, 10$
- Three recommendation analysis scenarios:
  - Image-based
  - User-based
  - Group-based
Evaluation of Recommendations

User-Based Analysis

Precision

Recall

F1 measure

Group-Based Analysis

Precision

Recall

F1 measure

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Evaluation of Feature Categories

Significant improvement in recall over tag only features

Significant improvement in precision over communication only features

Feature Category Evaluation

- Image Content features
- Tag features
- Communication features
- All features

- Precision
- Recall
- F1-measure
Conclusions
Problem:
How do we connect shared media to relevant communities?

Approach:
Characterize relationship of images to communities via content, tags and communication

Results:
Meaningful recommendations of communities
Questions? Suggestions?

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Thanks!
Related Work

- **Collective learning**
  - Recommendation of books, movies; Schein, Popescul, Ungar et al 2002.
  - Dynamic evolution of the properties of the items not considered.

- **Social media group and tag recommendation**
  - No consideration of social interaction.

- **User behavior in social media groups**
  - Negoescu & Gatica-Perez 2008.
  - Connection between media content and group behavior not explicit.