**Summary**

- Socially curated contents reveal underlying contexts
- Develop a novel method for discovering image contexts

**Motivations**

- Image understanding only from image contents is too difficult
- High performance comparable with humans seems extremely difficult to achieve, especially when dealing with contexts that are often difficult to verbalize.

**Social curation as corpora**

- One of the most emerging social curation platforms in the world focused on images.
- “Social scrapbooks”: Image contents are manually collected, selected and maintained, so that users can easily and quickly find images they want.

**Our key insights**

**Typical user behaviors**
- Pin a web image on one’s own board
- “Repin”: Create a new link to an existing pin to one’s own board
- Repeat 1-2.
- Many images pinned on a single board.
- Re-organize boards, so that users can easily and quickly find images they want.

**Key ideas**

A pair of boards sharing lots of image contents often share specific context.

**The problem to be solved**

1. Finding clusters sharing lots of images with each other.
   (The main contribution of this paper)
2. Extracting topics and image features that correspond to every cluster.

**Experiments and discussions**

**Dataset verification**: Does a board cluster share a similar context?

- To validate our hypothesis (every board in a cluster share a similar context), and the utility as a corpus of context-aware image classification and retrieval.
- 200K images (150K for training), 10 classes determined by the board name.
  - Architecture, fashion, cupcakes, animals, chocolate, flowers, blue, sea, Christmas and green.
- Features for image classification
  - User info. (192 dim): If user_j pinned image_i → The j-th element=1, otherwise 0.
  - Board info. (963 dim): If image_i was pinned on board_j → The l-th element=1.
- Cluster info. (1570 dim): M-th element = # times image_i was pinned to a board contained in cluster m.

<table>
<thead>
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<th>Linear regression</th>
<th>kNN</th>
<th>Large regression</th>
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<tr>
<td>k = 1</td>
<td>87.60</td>
<td>85.46</td>
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<tr>
<td>k = 5</td>
<td>98.94</td>
<td>97.36</td>
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<tr>
<td>k = 10</td>
<td>97.36</td>
<td>97.13</td>
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- Cluster features marked performance comparable to board features
- Clusters discovered by our method appropriately captured image contexts.

**Evaluating the effectiveness of our dictionary learning**

- Cluster info is used as side information for dictionary learning.
- 12.5K images (5K for training, 5K for test, randomly selected), 10 classes.
- Image features = GIST [Oliva+ IJCV2001]
- Methods to be evaluated:
  - ORI (raw GIST), Graph Reg. (graph-regularized regression [Mahajan+ ACMMM110]), PCA, LFDA (compressed GIST with PCA/LFDA), Prop. (proposed method).

<table>
<thead>
<tr>
<th>m</th>
<th>ORI</th>
<th>Graph Reg.</th>
<th>PCA</th>
<th>LFDA</th>
<th>Prop.</th>
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<td>960</td>
<td>900</td>
<td>10</td>
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<tr>
<td>Linear reg.</td>
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<td>39.4</td>
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<td>45.6</td>
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- Socially-generated side information can be used to improve the performance of image classification and retrieval.

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