PageRank for Product Image Search

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CS685: Data Mining

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Image Search

Text on Pages

- Well-studied
- Human-recognizable objects
  - Faces
  - Highly textured objects
- Processing

Drawback

- Inconsistent results in terms of quality
Image Search

- Analyzing distribution of “Visual Similarities”
- Symbol “M” – Repetition in a large fraction of images
- Finding multiple visual themes and their relative strengths

Challenges

- Image Processing (crooked, rotated, non-standard color, etc.)
- Ranking
Image Processing – Content Based Image Ranking

- Object Category Model
- Homogeneous Object Category
- Limited Scale of Experiment

Solution

- Model *expected user behavior*
- Similarities as probabilistic visual hyperlinks
- Graph: *vertices* (images) & *edges* (visual hyperlinks)

Query: “nemo”
Google ? PageRank : ImageRank

<table>
<thead>
<tr>
<th>PageRank</th>
<th>ImageRank</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R = M^* R$</td>
<td>$IR = S^* IR$</td>
</tr>
<tr>
<td>$M^*$ - stochastic matrix</td>
<td>$S^*$ - normalized symmetrical adjacency matrix</td>
</tr>
</tbody>
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**Damping Effect:** $d > 0.8$

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<tr>
<td>$R = dM^* R + (1 - d)1/N$</td>
<td>$IR = dS^* IR + (1 - d)p$ where $p = [1/n](n \times 1)$</td>
</tr>
</tbody>
</table>

- Global Features versus Local Descriptors
- Scale Invariant Feature Transform (SIFT)
- Difference of Gaussian interest point detector
- Orientation Histogram feature representation

Search: “prius”
A Full Retrieval System

- Queries with homogeneous visual concepts
- “Mona-Lisa” and other comical variations
Search: “Mona Lisa”
A Full Retrieval System

- Queries with heterogeneous visual concepts

- “Apple” (computer and fruit), “Jaguar” (car and animal)

Search: “Monet Paintings”
Why Eigenvector Approach?

- Alternative: Select high degree nodes in the graph
- Fails to identify the different distinctive visual concepts

Search: “Monet Paintings”
Experimental Results

- Existing Google Search results
- Neglect Sparse Graphs
- Challenge – “quantify the quality of image search results”
- User preference influenced by personal biases
- Comparing the quality of a set of images is difficult

- Example: Five relevant but mediocre images *versus* five mixed with great and bad results

- Two evaluation strategies –
  - Minimizing Irrelevant Images
  - Click Study
Minimizing Irrelevant Images

- Identification of Irrelevant images with 150 volunteers revealed

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<thead>
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<th>ImageRank</th>
<th>Google</th>
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<tbody>
<tr>
<td>Among top 10 results</td>
<td>0.47</td>
<td>2.82</td>
</tr>
<tr>
<td>Among top 5 results</td>
<td>0.30</td>
<td>1.31</td>
</tr>
<tr>
<td>Among top 3 results</td>
<td>0.20</td>
<td>0.81</td>
</tr>
</tbody>
</table>

- Importance
  - Google Product Search
  - Mixed-Result-Type Search

- Overall Performance
  - ImageRank contains less irrelevant images than Google for 762 queries
  - In only 70 queries, Google performs better
  - In rest 202, both approaches tied

- Drawbacks
  - Inflated logo-score
  - Saved web-pages as images
Click Study

- User satisfaction not purely a function of relevance
- Diversity of images is an important factor
- **Experiment**: Applied ImageRank to Google’s top-1000 images for top 130 queries
- Images received 17.5% more clicks than those in *default ranking*
- Extremely severe bias that favors the default ordering
- Function of the position of image in Google Search result besides relevance and quality
Conclusion

- An effective method to infer a graph in which the images could be embedded
- Outperformed Google ranking on the vast majority of queries tried
- Extremely important is the ability to reduce the number of irrelevant images
- Human-coded information recaptured by
  - Query dependent approach
  - Reliance on the intelligence of crowds
- Customizability of the similarity function
Questions ???