Optimal Tag Sets for Automatic Image Annotation

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Image Annotation: Given an un-annotated test image and a training set of annotated images select tags that reflect the content of the test image.
Overview/Motivation

- Popular field of research:
  - Annotation as machine translation [Duygulu et al. ’02]
  - Continuous Relevance Model (CRM) [Lavrenko et al. ’03]
  - Label diffusion over a similarity graph [Liu et al. ’09]
  - Supervised multiclass labeling [Carneiro et al. ’07]

- Limiting assumptions across a broad class of models:
  - Gaussian kernel: Standard workhorse of many models. But is it necessarily the most accurate default kernel?
  - Tags independent: Leads to incohesive and contradictory tags e.g. \{tropical, blizzard, supernova\}.

- BS-CRM: principled framework for solving both limitations in a generative model of image annotation.
Outline

- Continuous Relevance Model (CRM)
- Capturing Feature Covariance with Minkowski Kernels
- Capturing Keyword Correlation through Beam Search
- Experiments
- Discussion
Continuous Relevance Model [Lavrenko et al. 2003]

- Statistical generative model for automatic image annotation.

- Estimates joint distribution of visterms and tags [De Finetti’31]:

\[ P(w, f) = \sum_{J \in T} P(J) \prod_{j=1}^{n} P(w_j|J) \prod_{i=1}^{m} P(\vec{f}_i|J) \]

  - \( P(J) \): Uniform prior
  - \( P(\vec{f}_i|J) \): Gaussian non-parametric kernel density estimate
  - \( P(w_i|J) \): Dirichlet prior for word smoothing

- Estimate marginal probability distribution over individual tags:

\[ P(w|f) = \frac{P(w, f)}{\sum_{w} P(w, f)} \]

- Top e.g. 5 words used as annotation of image.
Capturing Feature Covariance with Minkowski Kernels

Gaussian kernel

Minkowski kernel with $p = 0.75$

$$P(\vec{f}_i|J) = \frac{1}{n} \sum_{j=1}^{n} c_{p} \exp \left\{ -\frac{|\vec{f}_i - \vec{f}_j|^p}{\beta} \right\}$$
Sensing subtle changes
Minkowski kernel much more sensitive to subtle feature changes. Known to be an important facet of human vision [Howarth’05].

Conjunction of features
Minkowski kernel mimicks logical AND of variations in feature values whilst Gaussian kernel is closer to a logical OR.
Capturing Keyword Correlation with Beam Search

- CRM computes a set to set mapping of tags to visterms $P(w, f)$
- Add measure to penalize frequent words $I(w)$.

$$I(w) = P(w|f) \cdot \log \frac{P(w|f)}{P_0(w)}$$

- $P(w|f)$: Dependence model between a tag set and image features.
- $P_0(w)$: Background model that treats every tag as an isolated event.

- Goal: Find optimal tag set maximizing $S_k^* = \arg\max_{S_k \subset \mathcal{V}} I(S_k)$

- Optimisation over universe of all possible tag sets: use efficient approximation via Beam Search.
Capturing Keyword Correlation with Beam Search
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Capturing Keyword Correlation with Beam Search

Top 5 tags used as annotation of test image:

- Valley: 0.20
- Sand: 0.18
- People: 0.15
- Mountain: 0.14
- Beach: 0.09

- Canyon: 0.07
- Sky: 0.05
- Rocks: 0.03

Tree, Water, Mountain, Sky, River

Valley, Sand, Canyon

Valley, Canyon, Rocks, Sky

Canyon, Valley, Sand Rocks

People, Sand, Beach, Water, Sky
Capturing Keyword Correlation with Beam Search

Top 5 tags used as annotation of test image:

<table>
<thead>
<tr>
<th>Keyword</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valley</td>
<td>0.20</td>
</tr>
<tr>
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<td>0.18</td>
</tr>
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</tr>
<tr>
<td>River</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Ground truth: \{Valley, Sand, Canyon, Rocks\}

CRM: \{Valley, Sand, People, Mountain, Beach\}

Valley, Sand, Canyon

Valley, Canyon, Rocks, Sky

Canyon, Valley, Sand Rocks

Tree, Water, Mountain, Sky, River

People, Sand, Beach, Water, Sky
Capturing Keyword Correlation with Beam Search

Initialise beam with top $B=5$ words from CRM:
- Beach
- Mountain
- People
- Sand
- Valley
Capturing Keyword Correlation with Beam Search

- Beach
- Mountain
- People
- Sand
- Valley
Capturing Keyword Correlation with Beam Search

- Beach → Water
- Mountain
- People → Beach
- Sand
- Valley → Sand
Capturing Keyword Correlation with Beam Search
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Capturing Keyword Correlation with Beam Search
Capturing Keyword Correlation with Beam Search
Ground truth: \{Valley, Sand, Canyon, Rocks\}
Setup of Experiments - Data

- Corel 5K:
  - 5000 images: landscape, animals, cities
  - Vocabulary of 260 words
Setup of Experiments - Data

- IAPR TC-12:
  - 20,000 images: touristic photos, sports
  - Vocabulary of 291 words
  - Annotations extracted from descriptive text (nouns)
University of Washington (UW):
- 1109 images: natural scenes, sports
- Vocabulary of 158 words
- Manually removed function words and morphological variants
Colour and texture based features:

- Region colour average, standard deviation, skewness
- Gabor mean orientated energy in 30 degree increments

Model parameters optimized on a held out validation set:

1. Grid search over the $\beta$ and $\mu$ for standard CRM model.
2. Hold $\beta$ and $\mu$ constant: optimize $B$ for varying beam widths.
3. Hold $\beta$, $\mu$ and $B$ constant: optimize $p$ for Minkowski density.

Evaluation metrics (for fixed annotation length):

- Mean per word Recall
- Mean per word Precision
- F1 Measure
- Number of words with Recall $> 0$
Setup of Experiments - Optimisation

![Graph showing F1 score vs Minkowski Kernel P Value]
Setup of Experiments - Evaluation

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>P</th>
<th>F1</th>
<th>N^+</th>
</tr>
</thead>
<tbody>
<tr>
<td>COREL</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRM (p=2)</td>
<td>19</td>
<td>16</td>
<td>17</td>
<td>106</td>
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<tr>
<td>Zhou et al.</td>
<td>20</td>
<td>19</td>
<td>19</td>
<td>...</td>
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<tr>
<td>Liu et al.</td>
<td>24</td>
<td>19</td>
<td>21</td>
<td>125</td>
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<tr>
<td>CRM (p=0.75)</td>
<td>25</td>
<td>21</td>
<td>23</td>
<td>119</td>
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<tr>
<td>Wang et al.</td>
<td>23</td>
<td>23</td>
<td>23</td>
<td>123</td>
</tr>
<tr>
<td>BS-CRM (p=0.75)</td>
<td>27</td>
<td>22</td>
<td>24</td>
<td>130</td>
</tr>
</tbody>
</table>

- **Corel 5k:**
  - CRM (p=2) vs CRM (p=0.75): 35\% increase in F1
  - T-test: \( p \leq 0.00004 \)
  - CRM (p=2) vs BS-CRM (p=0.75): 41\% increase in F1
  - T-test: \( p \leq 0.00001 \)
Setup of Experiments - Evaluation

<table>
<thead>
<tr>
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<th>N+</th>
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<tr>
<td><strong>UW</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRM (p=0.70)</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>86</td>
</tr>
<tr>
<td>BS-CRM (p=0.70)</td>
<td>46</td>
<td>42</td>
<td>44</td>
<td>106</td>
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<td>23</td>
<td>19</td>
<td>202</td>
</tr>
<tr>
<td>BS-CRM (p=0.70)</td>
<td>22</td>
<td>24</td>
<td>23</td>
<td>250</td>
</tr>
</tbody>
</table>

- **UW:**
  - CRM (p=0.70) vs BS-CRM (p=0.70): 22% increase in F1
  - T-test: \( p \leq 0.001 \)

- **IAPR TC-12:**
  - CRM (p=0.70) vs BS-CRM (p=0.70): 19% increase in F1
  - T-test: \( p \leq 2 \times 10^{-9} \)
Summary & Conclusions

Contributions

- BS-CRM: a considerably more powerful model of image annotation:
  - *Minkowski kernel* to model the covariance of image features.
  - *Beam search* to select the optimal mutually correlated tag set.
- Consistent performance gains on standard evaluation datasets.
- Much greater recall of the more rarer words in the vocabulary.
- Ideas could be used to improve the performance of other models.

Future Work

- Datasets with larger number of average tags per image: more correlations for set based model.
- Dynamically adapt model parameters, beam width B, μ and β.
Thank you for listening