## Learning the Semantic Words and Pictures

Barnard *et al*. Presented by Michael S. Ryoo

### **Annotation Problem**

- We want to predict 'text' information, given an image.
- Primitive method:
  - Perform 'recognition' for each region.
  - Tiger in a sky?
- Joint probability!



## Input



Image processing\*



"This is a picture of the sun setting over the sea with waves in the foreground"

Language processing

Each blob is a large vector of features

sun sky waves sea

\* Thanks to Blobworld team [Carson, Belongie, Greenspan, Malik], N-cuts team [Shi, Tal, Malik]

#### Impossible

### Random Bits

#### Model for joint probability of text and blobs



Unlikely



Keywords: Shopping mall

Reasonable



Keywords: Sky water sun

### **Hierarchical model**

• Model for joint probability of text and blobs.

- Extension of Hofmann's model for text.
   Hofmann, 1998; Hofmann and Puzicha, 1998
  - Each node generates a (region, word) pair.
  - Following a path from the root to a leaf generates full image and full text.

### **Hierarchical model**



Lower level nodes emit more specific words and blobs (e.g. waves)

## **Probability Distribution**

### • Correlation considered model.

$$p(D|d) = \sum_{c} p(c) \prod_{(w,b) \in D} \left[ \sum_{l} p((w,b)|l,c) p(l|d) \right]$$



#### • Conditionally independent model.

$$p(D|d) = \sum_{c} p(c) \prod_{w \in W} \left[ \sum_{l} p(w|l,c) p(l|d) \right]^{\frac{N_W}{N_{w,d}}} \prod_{b \in B} \left[ \sum_{l} p(b|l,c) p(l|d) \right]^{\frac{N_b}{N_{b,d}}} \prod_{b \in B} \left[ \sum_{l} p(b|l,c) p(l|d) \right]^{\frac{N_b}{N_b}} \prod_{b \in B} \left[ \sum_{l} p(b|l,c) p(b|l,c) p(l|d) \right]^{\frac{N_b}{N_b}} \prod_{b \in B} \left[ \sum_{l} p(b|l,c) p(b|l,$$

Observations D = (W + B), document d, clusterc, and level l.

















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## Predicting words using model

- Annotation,  $P(w | b) \approx P(w, b)$
- Correlation considered model.

$$p(w \Leftrightarrow b) \approx \sum_{c} p(c) \sum_{l} p((w,b)|l,c) p(l|d).$$



### • Conditionally independent model.

$$p(w|b) \propto \sum_{c} p(c) \sum_{l} p(l) p(w|l,c) p(b|l,c).$$

### **Evaluation**

- Compared annotation done by their model and 'empirical' word distribution model.
  Annotate all region as common word (water?)
- Calculated Kullback-Leibler divergence.

$$E_{KL}^{(model)} = \sum_{w \in vocabulary} p(w) \log \frac{p(w)}{q(w|B)}. \qquad E_{KL}^{(model)} = -\frac{1}{K} \sum_{w \in observed} \log \frac{p(w)}{q(w|B)}$$

• Also constructed their own function.

 $-E_{NS}^{(model)} = r/n - w/(N-n)$ 

### **Corel Database**



392 CD's, each consisting of 100 annotated images.

# Experiments



## Experiments

Method	Training data	Held out data	Novel data
linear-I-0-doc-vert	0.301 (0.005)	0.174 (0.007)	0.081 (0.007)
binary-I-0-ave-vert	0.294 (0.006)	0.154 (0.006)	0.064 (0.008)
binary-I-0-doc-vert	0.325 (0.006)	0.160 (0.007)	0.065 (0.008)
binary-I-0-region-cluster	0.332 (0.006)	0.168 (0.007)	0.068 (0.008)
binary-I-0-region-only	0.234 (0.006)	0.160 (0.006)	0.062 (0.008)
binary-I-2-ave-vert	0.331 (0.006)	0.164 (0.008)	0.068 (0.007)
binary-I-2-doc-vert	0.322 (0.006)	0.170 (0.008)	0.074 (0.008)
binary-I-2-region-cluster	0.324 (0.006)	0.179 (0.008)	0.076 (0.008)
binary-I-2-region-only	0.228 (0.006)	0.163 (0.006)	0.068 (0.007)
linear-D-0-doc-vert	0.321 (0.005)	0.167 (0.006)	0.076 (0.008)
binary-D-0-ave-vert	0.284 (0.007)	0.151 (0.007)	0.061 (0.008)
binary-D-0-doc-vert	0.321 (0.007)	0.157 (0.007)	0.064 (0.008)
binary-D-0-region-cluster	0.330 (0.006)	0.166 (0.008)	0.067 (0.008)
binary-D-0-region-only	0.239 (0.006)	0.162 (0.007)	0.064 (0.007)
binary-D-2-ave-vert	0.312 (0.005)	0.162 (0.003)	0.066 (0.005)
binary-D-2-doc-vert	0.358 (0.005)	0.172 (0.003)	0.069 (0.005)
binary-D-2-region-cluster	0.360 (0.005)	0.179 (0.003)	0.072 (0.005)
binary-D-2-region-only	0.248 (0.005)	0.167 (0.003)	0.066 (0.005)
linear-C-0-region-only	0.240 (0.005)	0.124 (0.007)	0.046 (0.006)
binary-C-0-ave-vert	0.252 (0.006)	0.143 (0.007)	0.060 (0.008)
binary-C-0-doc-vert	0.281 (0.006)	0.148 (0.006)	0.054 (0.007)
binary-C-0-region-cluster	0.290 (0.006)	0.157 (0.007)	0.064 (0.007)
binary-C-0-region-only	0.233 (0.006)	0.163 (0.006)	0.071 (0.006)
discrete-translation	0.318 (0.005)	0.111 (0.007)	0.016 (0.008)
MoM-LDA	0.125 (0.005)	0.107 (0.005)	0.041 (0.007)





## **Searching Problem**

- Given query image or query sentences, find a document that best matches.
  - Google Images
  - Content-based Image Retrieval
- This paper mentions that annotated words can be matched with queries...
  - $-P(Q \mid d) vs P(d \mid Q)$
  - Need to consider prior probabilities.

### Conclusions

• Hierarchical model was proposed.

• Modeling image regions and words jointly.

• Annotation of image regions were done.



#### Keywords: rose flower plant leaves





#### Query on

### "Rose"

Example from Berkeley Blobworld system











#### Query on



Example from Berkeley Blobworld system















