

# Real-Time Computerized Annotation of Pictures

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# How Visible Are Web Images?

Keukenhof photos



# ALIPR: Automatic Linguistic Indexing for Pictures - Real Time



plant, flower,  
landscape,  
people, tulip



tree, plant,  
people,  
water, garden

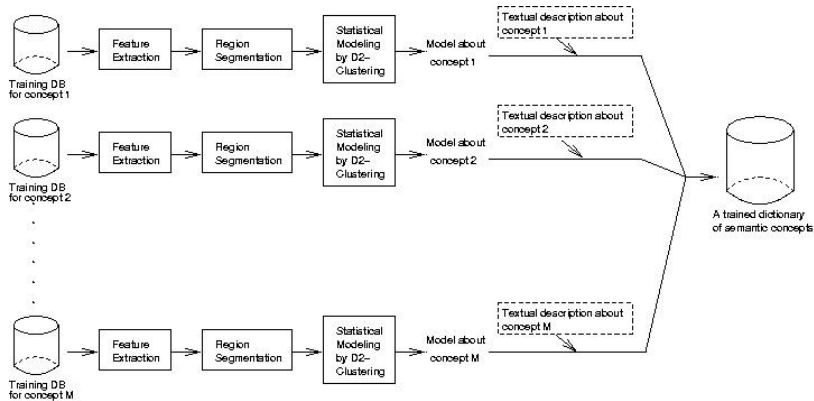


flower,  
plant,lake,  
rural,  
building

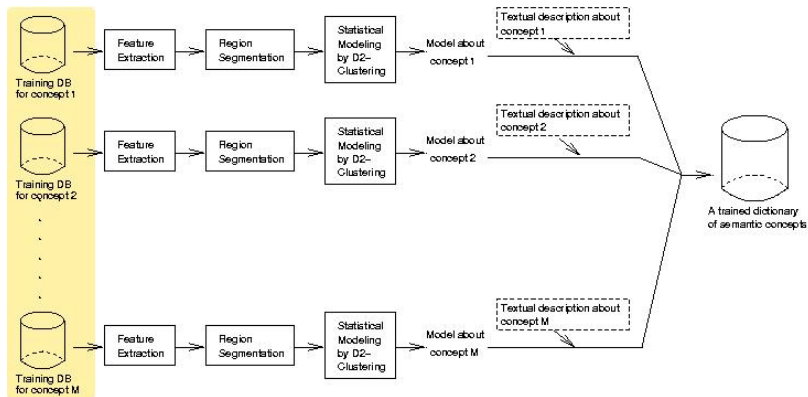


animal,  
people,  
wild-life, dog,  
landscape

# Architecture for Training

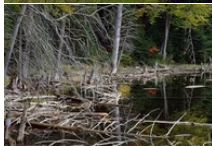


## Image “Knowledge Base”

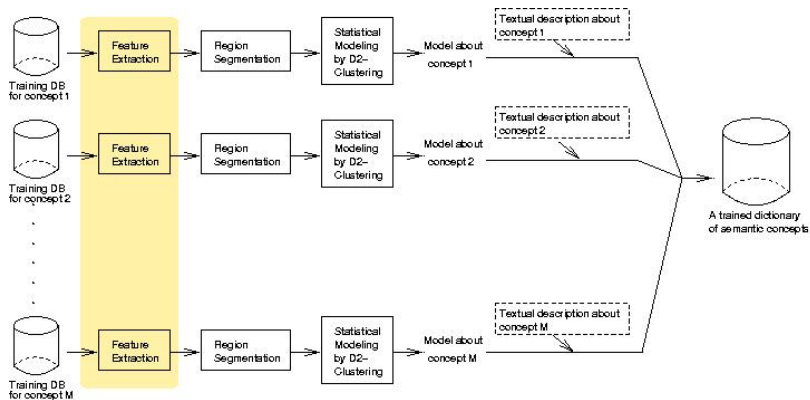


# Six Hundred Semantic Categories

- ▶ Corel image database
  - ▶ 80 images per category.
  - ▶ Each category is described by several words: ‘‘autumn, tree, landscape, lake’’.
  - ▶ A total of 332 distinct words.

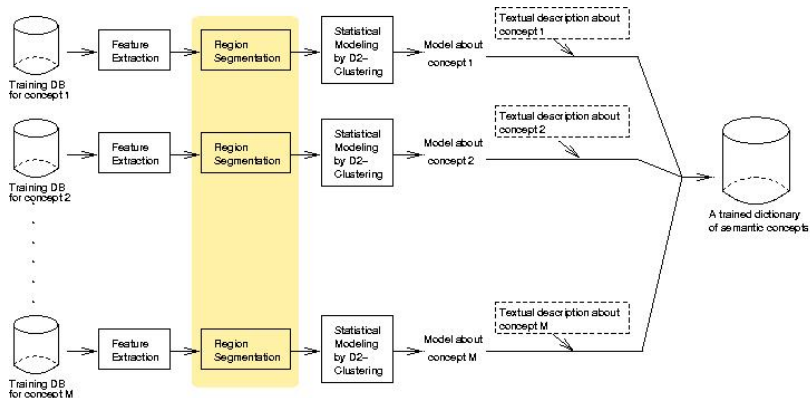


## Feature Extraction



- ▶ Color components: LUV
- ▶ Texture features: wavelet coefficients

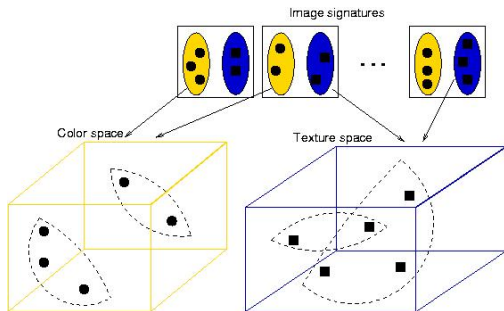
# Region Segmentation and Signature Formulation



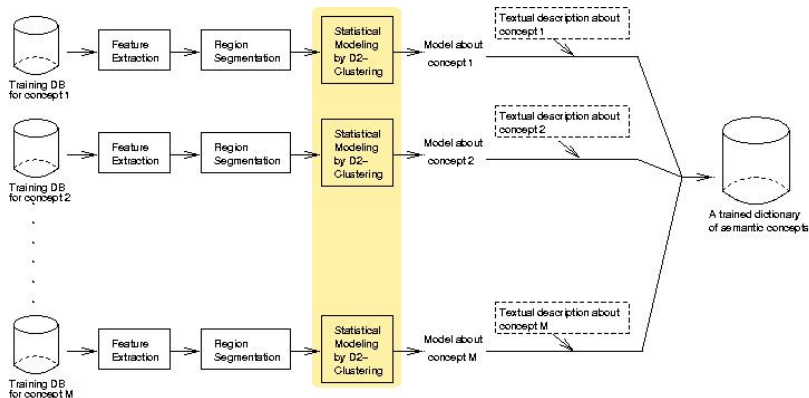


# Region Segmentation and Signature Formulation

- ▶ An image signature resides in  $\Omega = \Omega_1 \times \Omega_2$ .
- ▶ Color distribution:  $\beta_{i,1} \in \Omega_1$ .
- ▶ Texture distribution:  $\beta_{i,2} \in \Omega_2$ .
- ▶  $\beta_{i,j} = \{(v_{i,j}^{(1)}, p_{i,j}^{(1)}), \dots, (v_{i,j}^{(m_{i,j})}, p_{i,j}^{(m_{i,j})})\}$ .

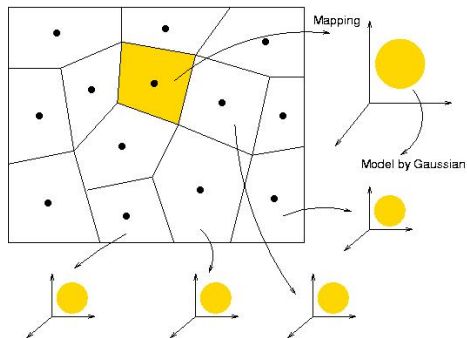


# Profiling Image Concepts via Mixture Models

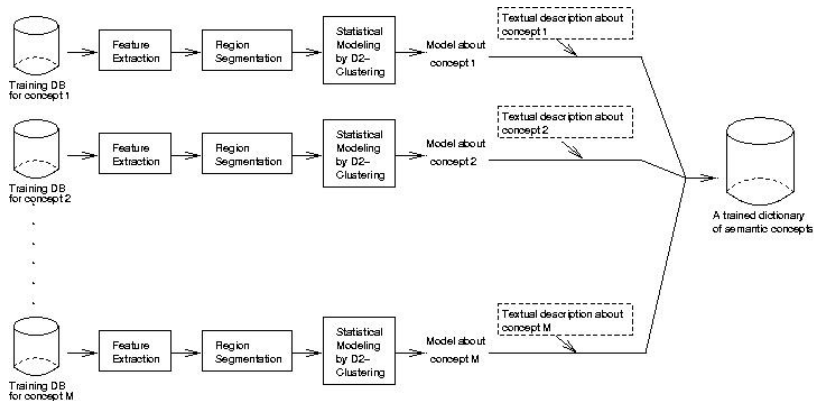


# Mixture Modeling via Local Mapping

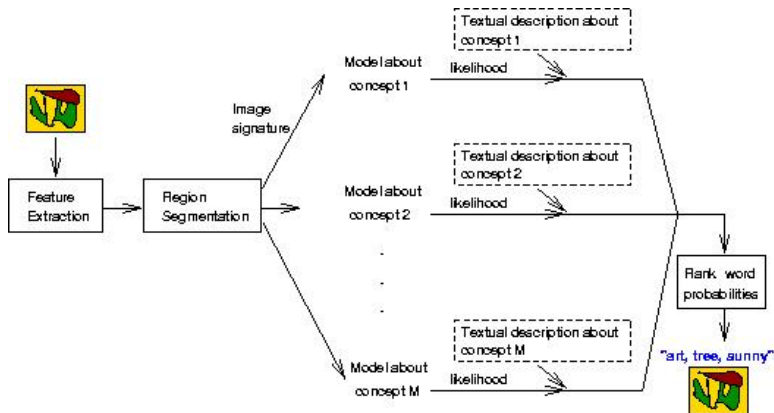
- ▶ Mixture modeling for space  $\Omega$ 
  - ▶ Carve  $\Omega$  into cells by clustering.
  - ▶ Map each cell to an Euclidean space, preserving pairwise distances.
  - ▶ Model the mapped points by Gaussian.
  
- ▶ Images: a grid of feature vectors
  - ▶ Gaussian mixture
  - ▶ 2-D HMM



# Architecture for Training



## Architecture for Annotation



## Word Probabilities

- ▶ Total word list:  
 $\mathcal{W} = \{w_1, w_2, \dots, w_K\}$ .
- ▶ Semantic categories containing word  $w_i$ :  $\mathcal{C}(w_i)$ .
- ▶ Model of category  $m$ :  $\mathcal{M}_m$ ,  
 $m = 1, \dots, M$ .
- ▶ Prior on categories:  $\rho_m$  (set uniform).

### Category prob. given signature $\beta$

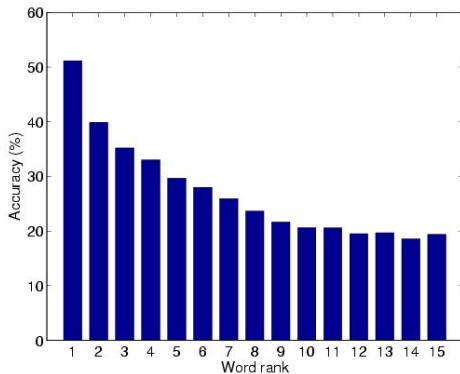
$$p_m(\beta) = \frac{\rho_m f(\beta | \mathcal{M}_m)}{\sum_{l=1}^M \rho_l f(\beta | \mathcal{M}_l)}$$

### Word probability

$$q(\beta, w_i) = \sum_{m: m \in \mathcal{C}(w_i)} p_m(\beta) .$$

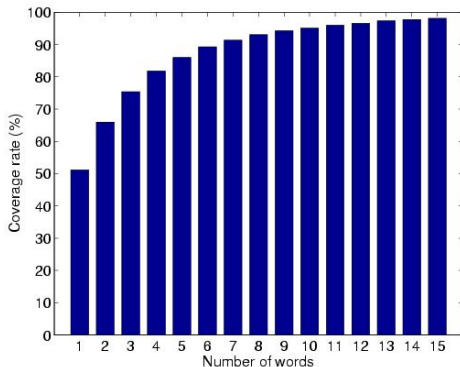
## Human Evaluation on flickr.com Images

- ▶ Manual evaluation on 5,411 flickr.com images.
- ▶ Accuracy of the first word: 51.17%.



## Human Evaluation on flickr.com Images

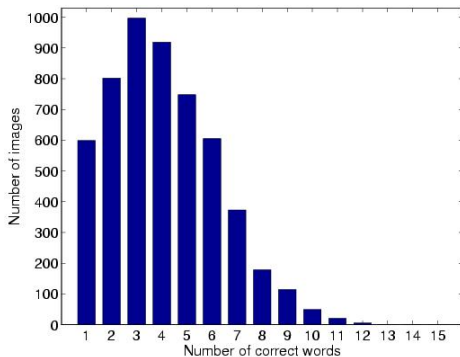
- ▶ Coverage rate: percentage of images correctly annotated by at least one word.
- ▶ Top 4 words: > 80%.
- ▶ Top 7 words: 91.37%.
- ▶ Top 15 words: 98.13%.





# Human Evaluation on flickr.com Images

- ▶ Annotate using top 15 words.
- ▶ # correct: 4.1 on average



# Speed

- ▶ Training:
  - ▶ 109 seconds on ave.
  - ▶ 80 images per category
  - ▶ 2.4 GHz AMD processor
- ▶ Annotation:
  - ▶ 1.4 seconds on ave. for example images
  - ▶ 3.0 GHz Intel processor
  - ▶ Convert from JPEG to raw format; extract image signature; find annotation words.

## Conclusions

### System

- ▶ The ALIPR system: real-time automatic annotation of pictures
- ▶ Human evaluation on web images

### Learning methodology

- ▶ D2-clustering
  - ▶ Generalized k-means to bags of weighted vectors
- ▶ Mixture modeling via mapping to conjectural space

- ▶ Human evaluation on 5,400+ Web images has demonstrated promising results.
- ▶ Future work: bridge with retrieval, incremental learning, improve modeling, Web applications ...
- ▶ **ALIPR your pictures: <http://alipr.com>**



### ALIPR Computerized Annotation

Please help us to train ALIPR. Check those correctly annotated words.

- indoor   
  animal   
  food   
  drawing   
  fruit  
 art   
  man-made   
  flower   
  dog   
  pet  
 ancestor   
  drink   
  antique   
  dinosaur   
  poster

Any tags missing by ALIPR? (Add tags here – separate with ',')

submit