Object Recognition I

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ECE/CSE 576

Low- to High-Level

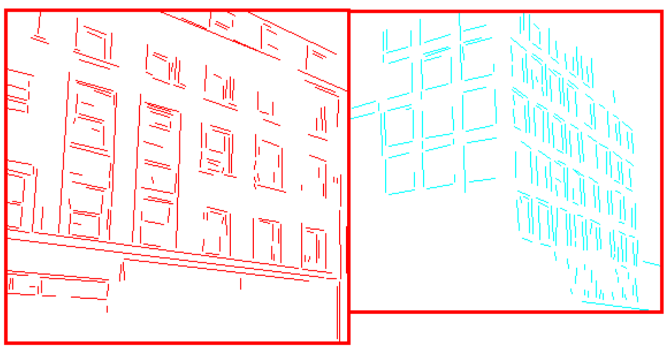
low-level

edge image

mid-level

consistent line clusters

high-level



Building Recognition

High-Level Computer Vision

- Detection of classes of objects (faces, motorbikes, trees, cheetahs) in images
- Recognition of specific objects such as George Bush or machine part #45732
- Classification of images or parts of images for medical or scientific applications
- Recognition of events in surveillance videos
- Measurement of distances for robotics

High-level vision uses techniques from AI

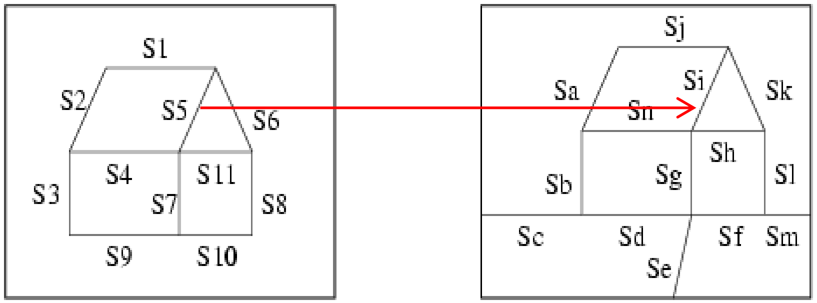
- Graph-Matching: A*, Constraint Satisfaction, Branch and Bound Search, Simulated Annealing
- Learning Methodologies: Decision Trees, Neural Nets, SVMs, EM Classifier
- Probabilistic Reasoning, Belief Propagation, Graphical Models

Graph Matching for Object Recognition

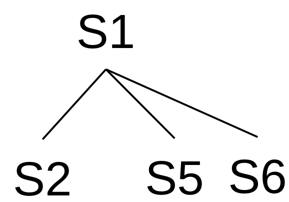
- For each specific object, we have a geometric model.
- The geometric model leads to a symbolic model in terms of image features and their spatial relationships.
- An image is represented by all of its features and their spatial relationships.
- This leads to a graph matching problem.

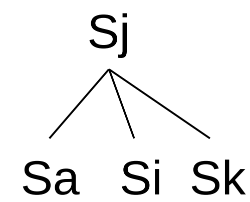
House Example

2D model   2D image   Graph G1   Graph G2



P   **Image 1**   **L**   **Image 2**





$P = \{S1, S2, S3, S4, S5, S6, S7, S8, S9, S10, S11\}.$

$L = \{Sa, Sb, Sc, Sd, Se, Sf, Sg, Sh, Si, Sj, Sk, Sl, Sm\}.$

Find a mapping f from P to L that satisfies
(x,y) ε G1 => (f(x),f(y)) ε G2

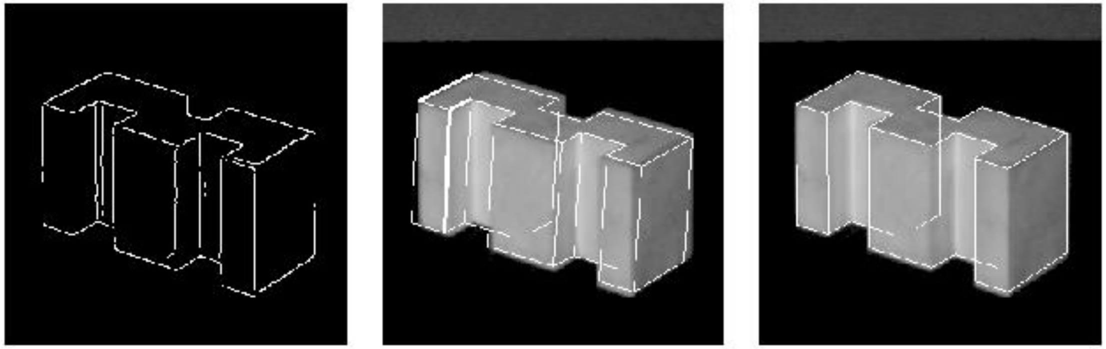
f(S1)=Sj   f(S4)=Sn   f(S7)=Sg   f(S10)=Sf
f(S2)=Sa   f(S5)=Si   f(S8) = Sl   f(S11)=Sh
f(S3)=Sb   f(S6)=Sk   f(S9)=Sd

But this is too simplistic

- The model specifies all the features of the object that may appear in the image.
- Some of them don’t appear at all, due to occlusion or failures at low or mid level.
- Some of them are broken and not recognized.
- Some of them are distorted.
- Relationships don’t all hold.

TRIBORS: view class matching of polyhedral objects

edges from image model overlayed improved location



- A view-class is a typical 2D view of a 3D object.

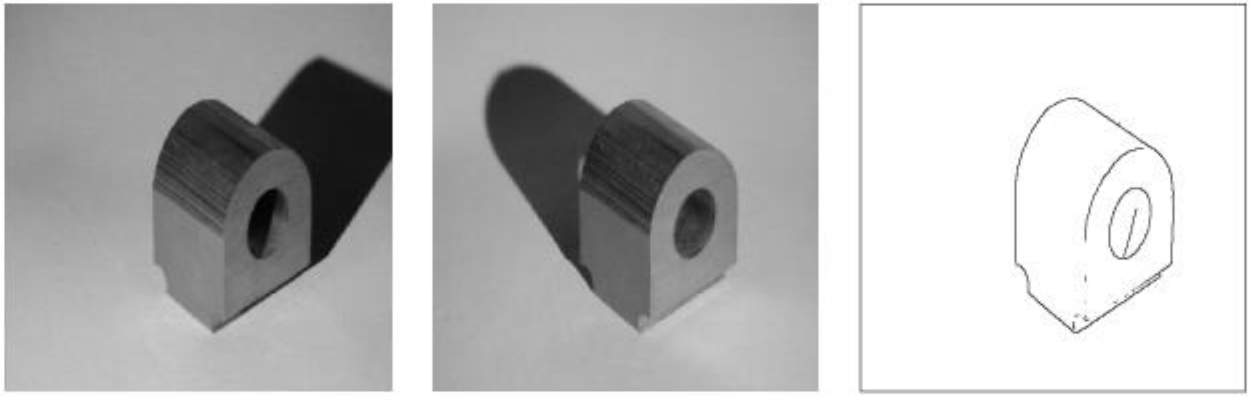
- Each object had 4-5 view classes (hand selected).

- The representation of a view class for matching included:
  - triplets of line segments visible in that class
  - the probability of detectability of each triplet

The first version of this program used iterative-deepening A* search.
STILL TOO MUCH OF A TOY PROBLEM.

RIO: Relational Indexing for Object Recognition

- RIO worked with more complex parts that could have
  - planar surfaces
  - cylindrical surfaces
  - threads



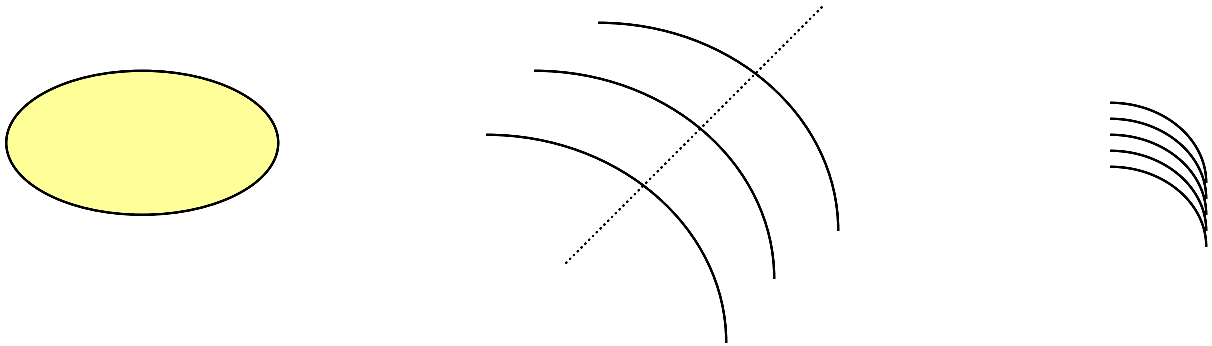
Object Representation in RIO

- 3D objects are represented by a 3D mesh and set of 2D view classes.

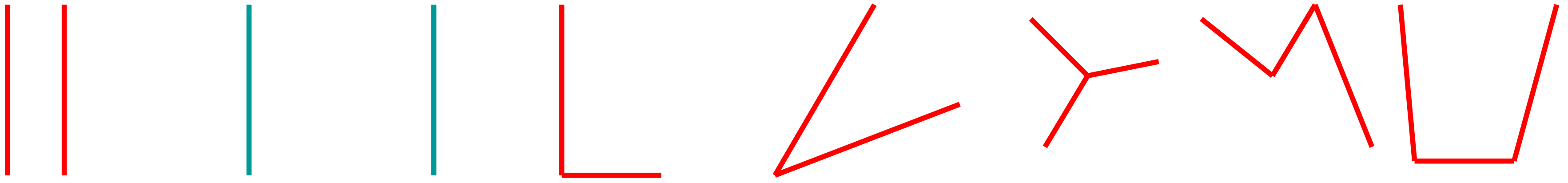
- Each view class is represented by an attributed graph whose nodes are features and whose attributed edges are relationships.

- For purposes of indexing, attributed graphs are stored as sets of 2-graphs, graphs with 2 nodes and 2 relationships.

RIO Features



ellipses coaxials coaxials-multi

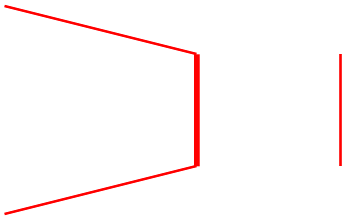


parallel lines close and far

junctions L V

triples Y Z U

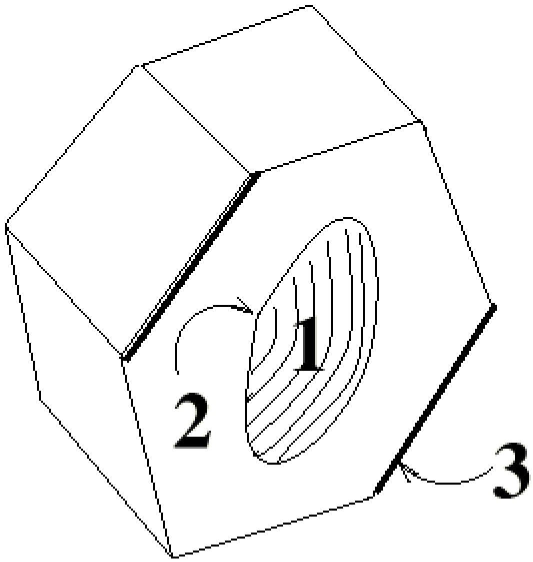
RIO Relationships



- share one arc
- share one line
- share two lines
- coaxial
- close at extremal points
- bounding box encloses / enclosed by

Hexnut Object

MODEL-VIEW



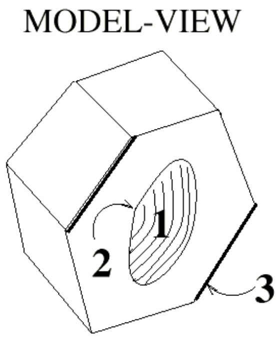
RELATIONS:
a: encloses
b: coaxial

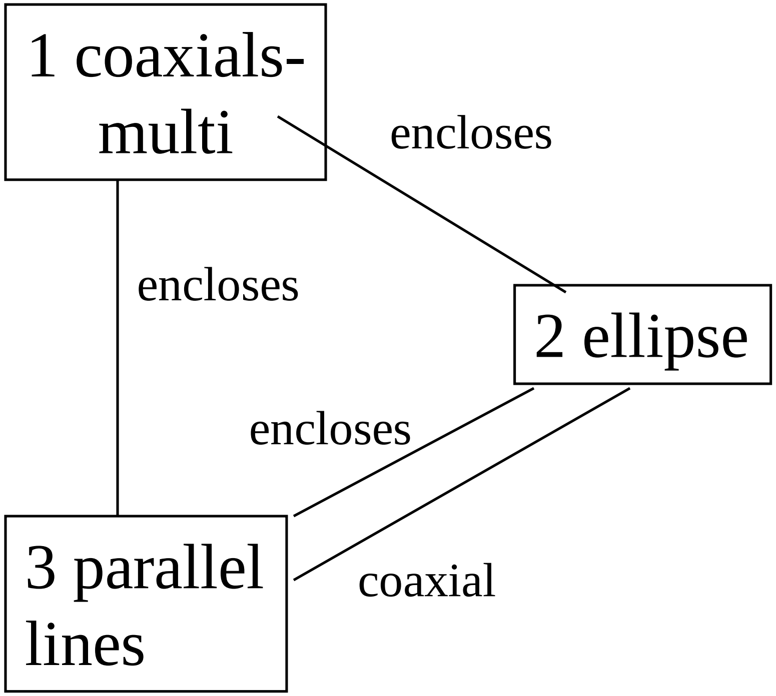
FEATURES:
1: coaxials-multi
2: ellipse
3: parallel lines

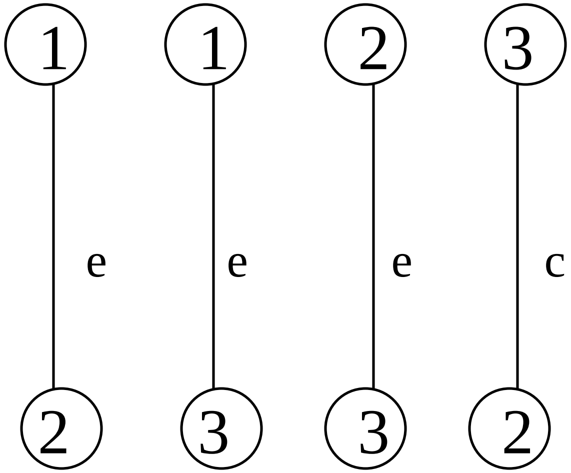
How are 1, 2, and 3 related?

What other features and relationships can you find?

Graph and 2-Graph Representations







RDF!

Relational Indexing for Recognition

Preprocessing (off-line) Phase

for each model view Mi in the database

- encode each 2-graph of Mi to produce an index
- store Mi and associated information in the indexed bin of a hash table H

Matching (on-line) phase

1. Construct a relational (2-graph) description D for the scene

2. For each 2-graph G of D

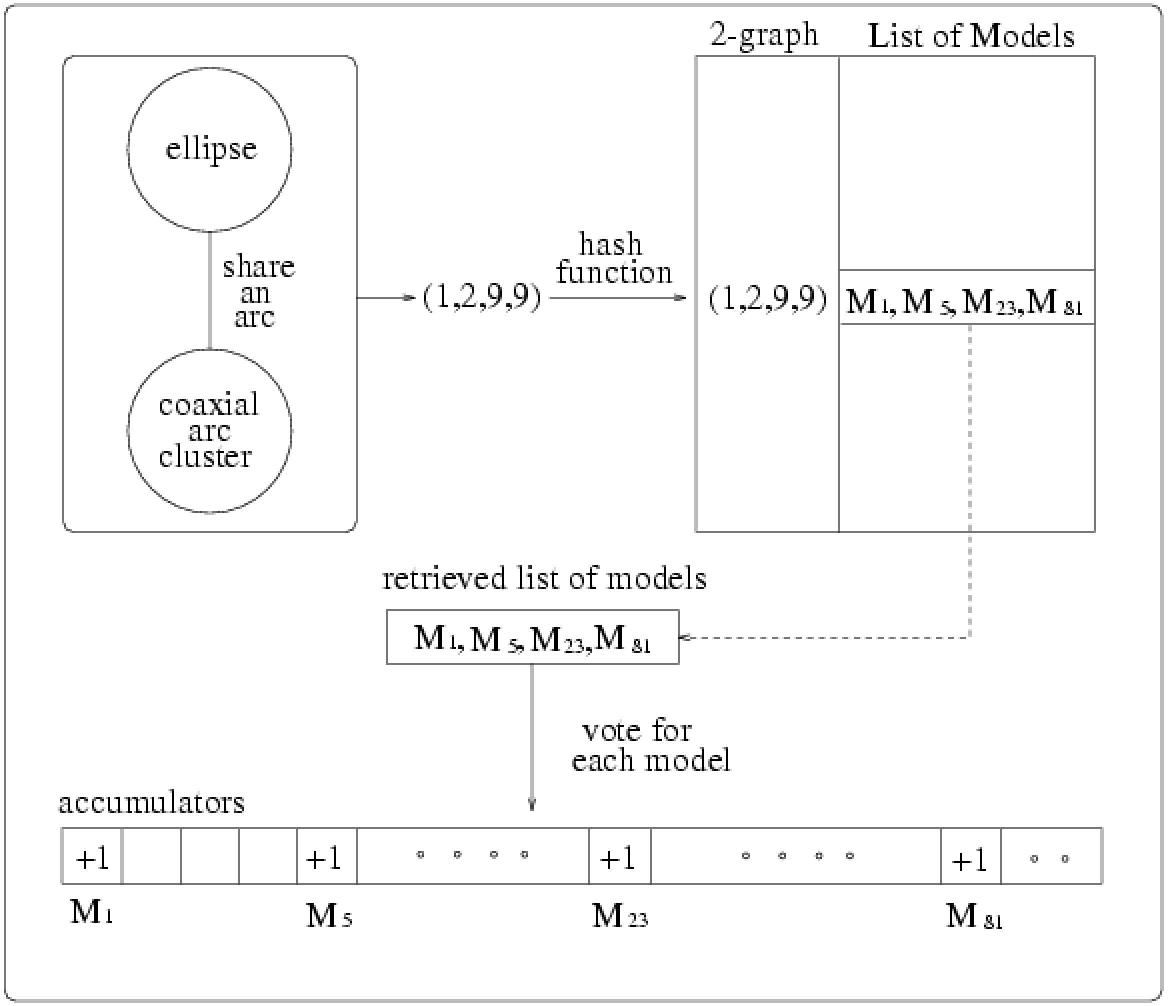
    - encode it, producing an index to access the hash table H

    - cast a vote for each Mi in the associated bin

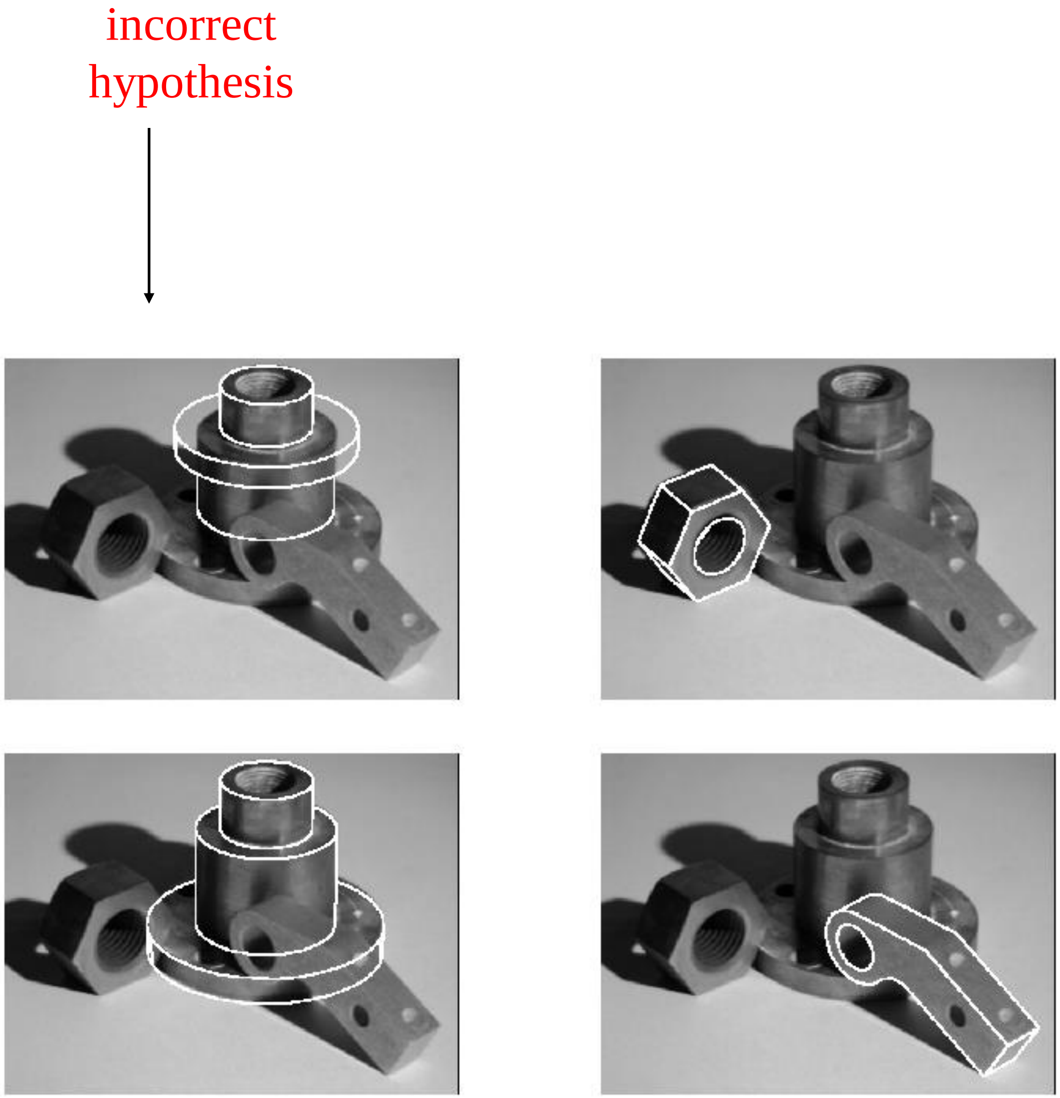
3. Select the Mi's with high votes as possible hypotheses

4. Verify or disprove via alignment, using the 3D meshes

The Voting Process



RIO Verifications



1. The matched features of the hypothesized object are used to determine its **pose**.

2. The **3D mesh** of the object is used to project all its features onto the image.

3. A **verification procedure** checks how well the object features line up with edges on the image.

But those models were hand-created, not learned; Use of classifiers is big in computer vision today.

- 2 Examples:
  - Rowley's Face Detection using neural nets
  - Yi's image classification using EM

Object Detection:
Rowley's Face Finder

1. convert to gray scale
2. normalize for lighting
3. histogram equalization
4. apply neural net(s)
   trained on 16K images

What data is fed to
the classifier?

32 x 32 windows in
a pyramid structure

Preprocessing

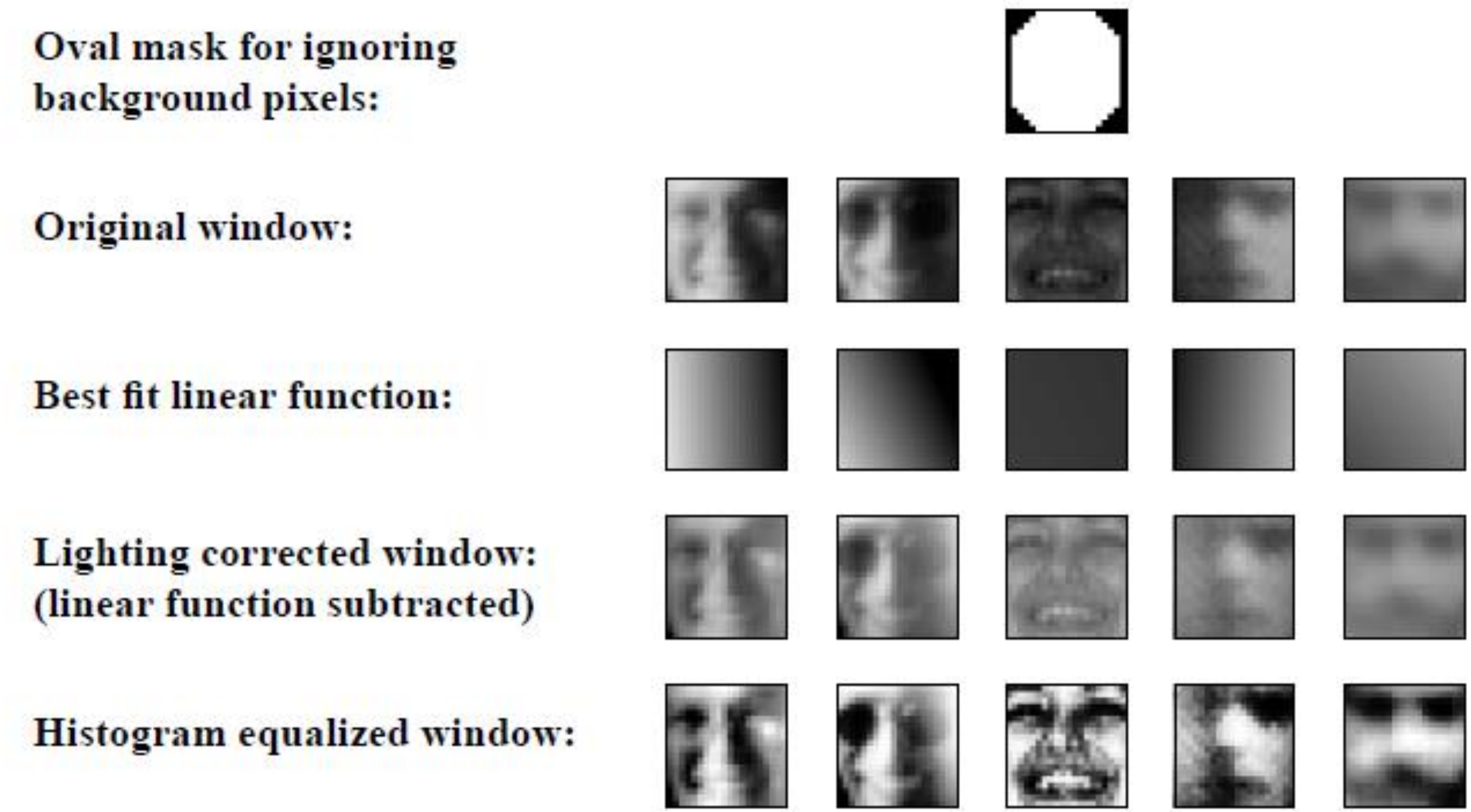
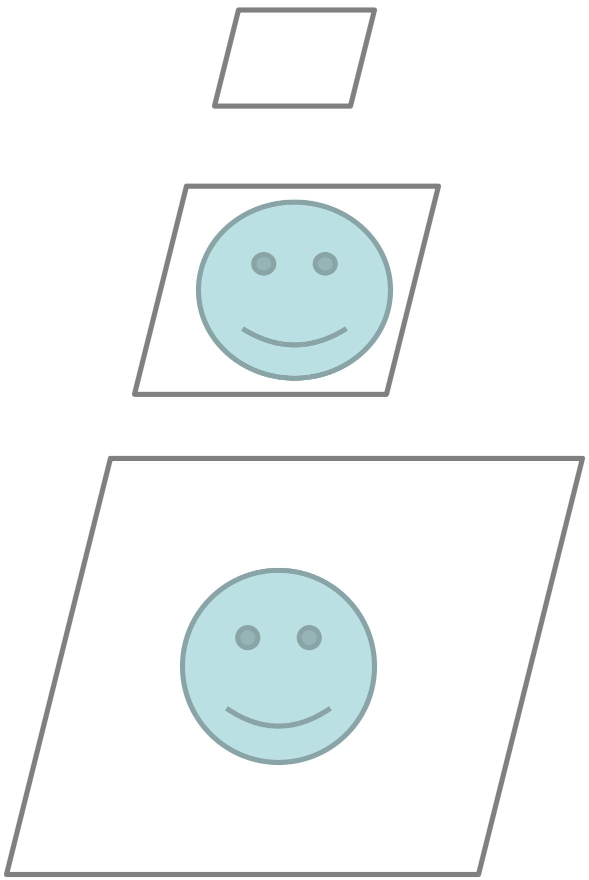


Image Pyramid Idea



even lower resolution (1/16 of original)

lower resolution image (1/4 of original)

original image (full size)

Training the Neural Network

Positive Face Examples

- Nearly 1051 face examples collected from face databases at CMU, Harvard, and WWW
- Faces of various sizes, positions, orientations, intensities
- Eyes, tip of nose, corners and center of mouth labeled manually and used to normalize each face to the same scale, orientation, and position

Result: set of 20 X 20 face training samples

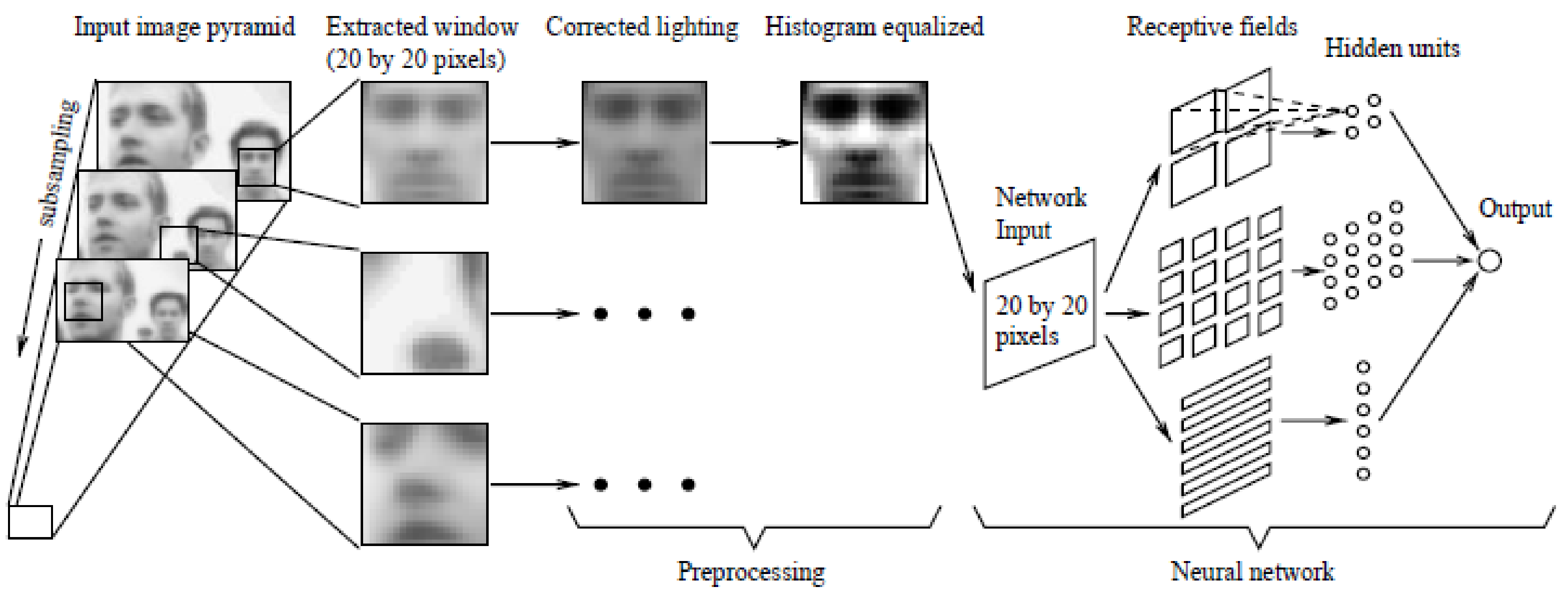
Training the Neural Network

Negative Face Examples

- Generate 1000 random nonface images and apply the preprocessing
- Train a neural network on these plus the face images
- Run the system on real scenes that contain no faces
- Collect the false positives
- Randomly select 250 of these and apply preprocessing
- Label them as negative and add to the training set

Overall Algorithm

Rowley, Baluja, and Kanade: Neural Network-Based Face Detection (PAMI, January 1998) 17



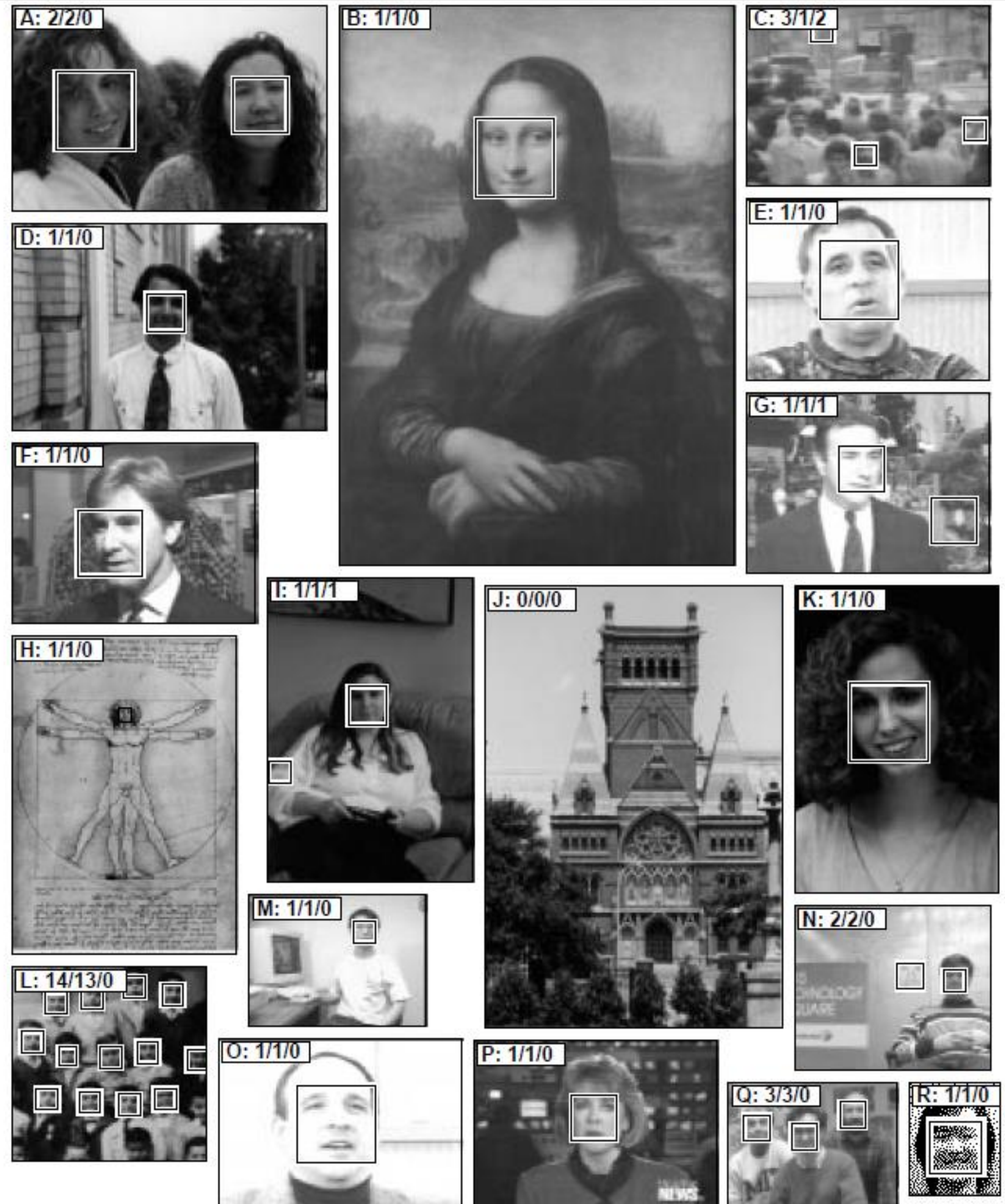
More Pictures

Even More

And More

Accuracy: detected 80-90% on different image sets with an “acceptable number” of false positives

Fast Version: 2-4 seconds per image (in 1998)



EM Classifier Approach
Object Class Recognition using Images of Abstract Regions

Yi Li, Jeff A. Bilmes, and Linda G. Shapiro
Department of Computer Science and Engineering
Department of Electrical Engineering
University of Washington

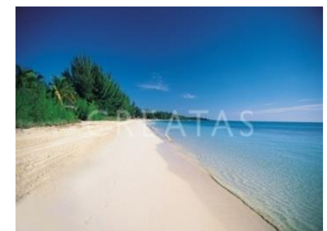
Problem Statement

Given: Some images and their corresponding descriptions

{trees, grass, cherry trees}

{cheetah, trunk}

{mountains, sky}



{beach, sky, trees, water}

•••

To solve: What object classes are present in new images

?

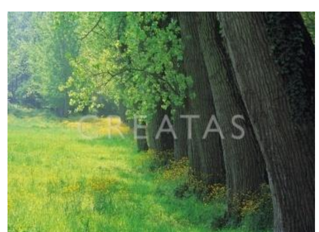


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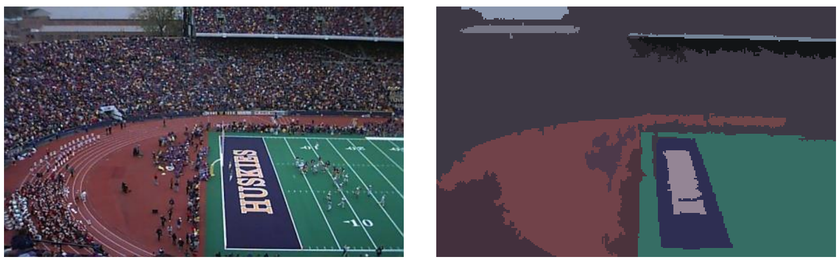
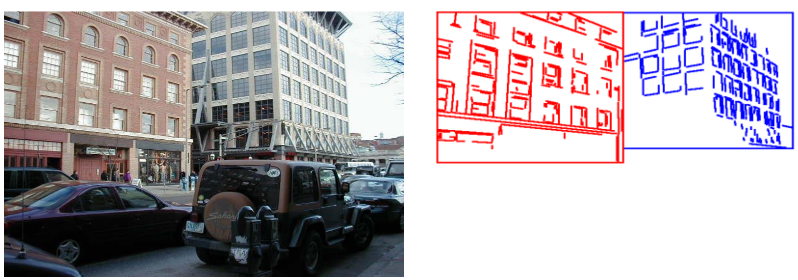
Image Features for Object Recognition

- Color

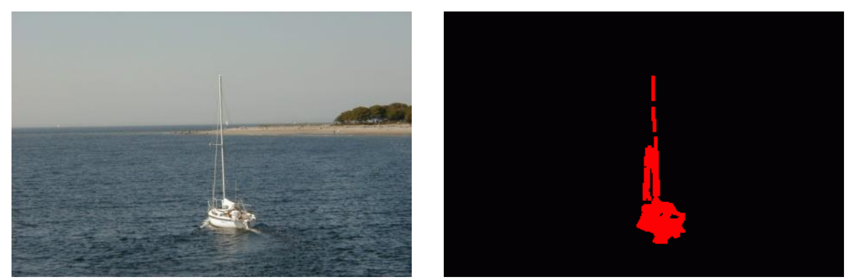


- Texture

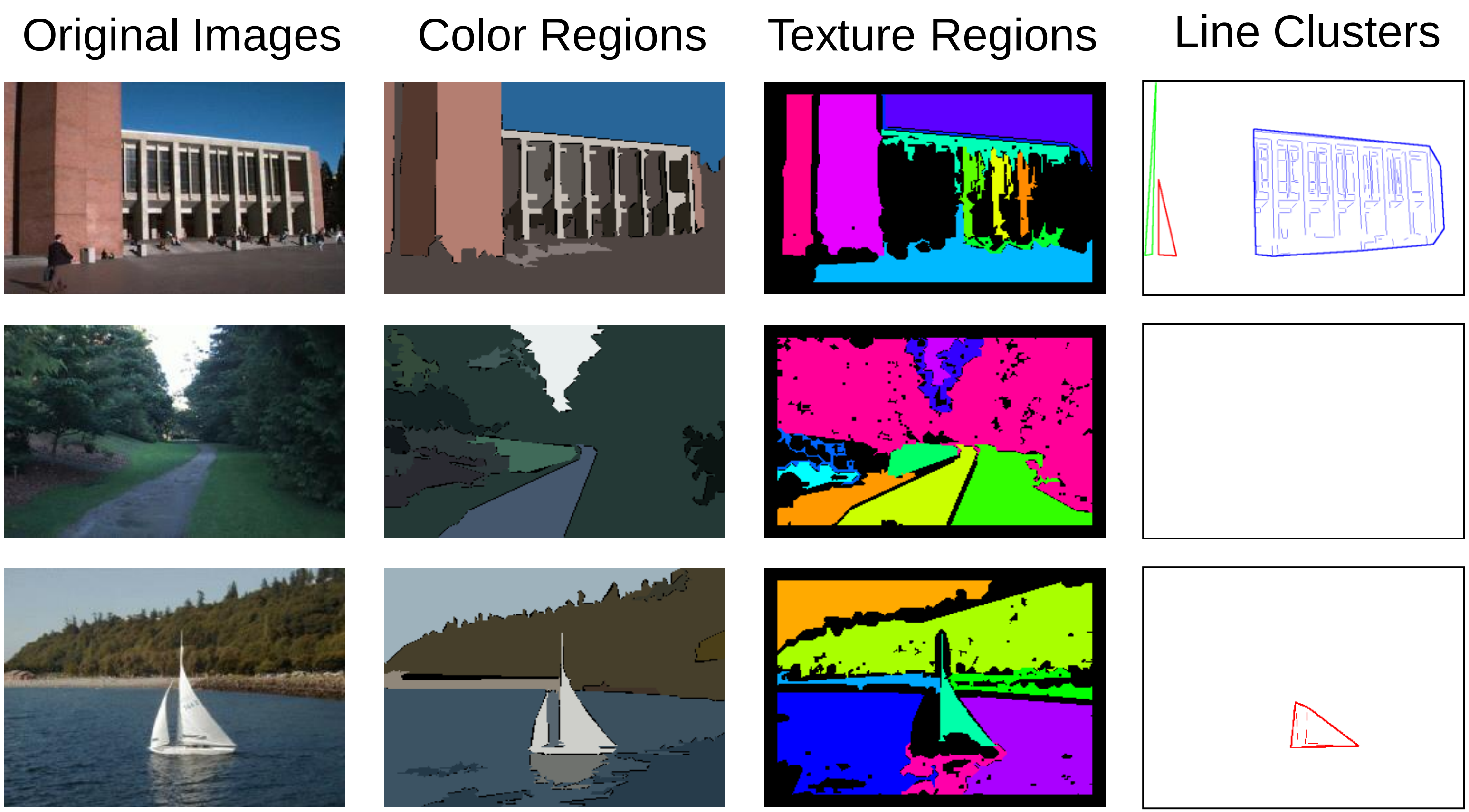
- Structure



- Context



Abstract Regions



Abstract Regions

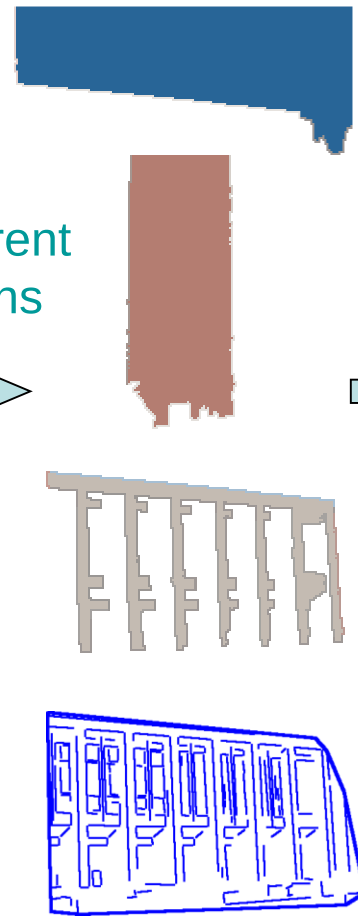
Multiple segmentations whose regions are not labeled;
a list of labels is provided for each training image.

image

labels

{sky, building}

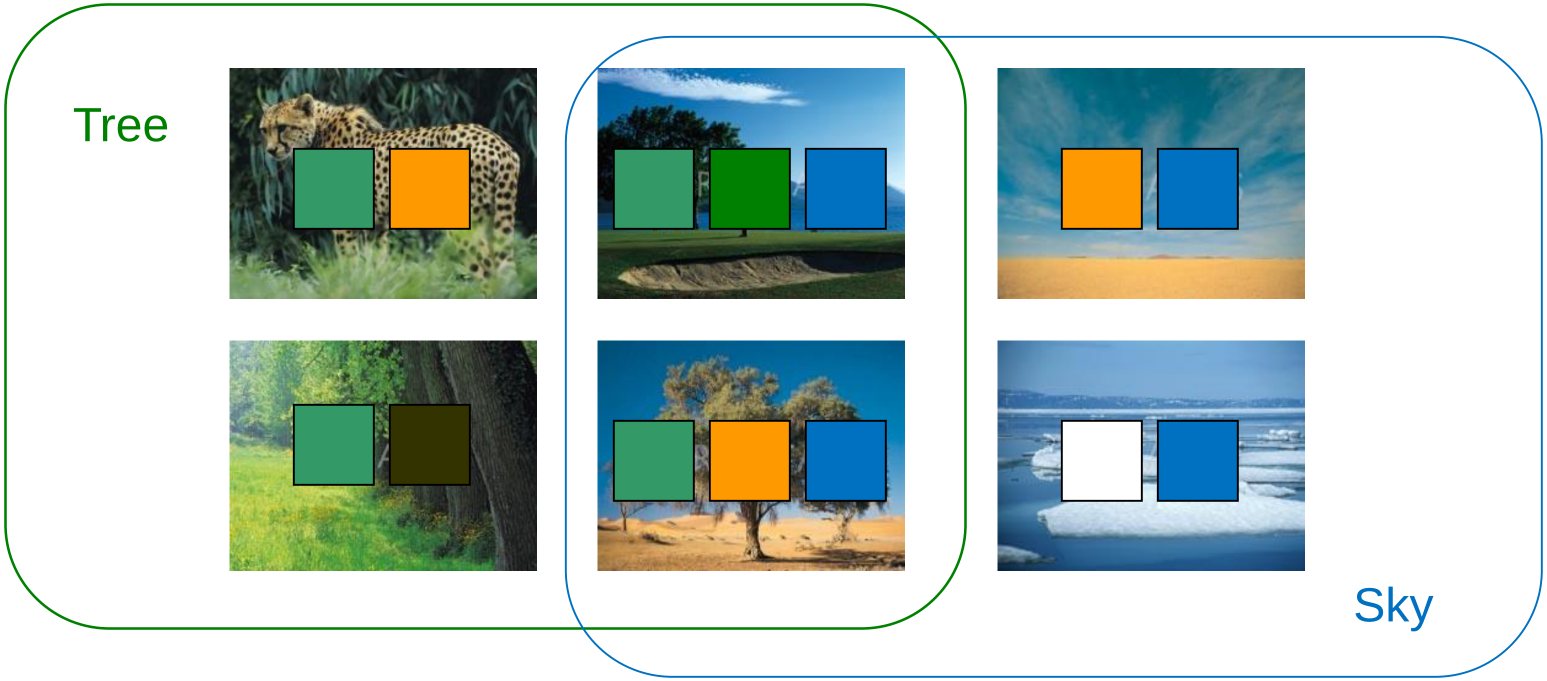
various different
segmentations



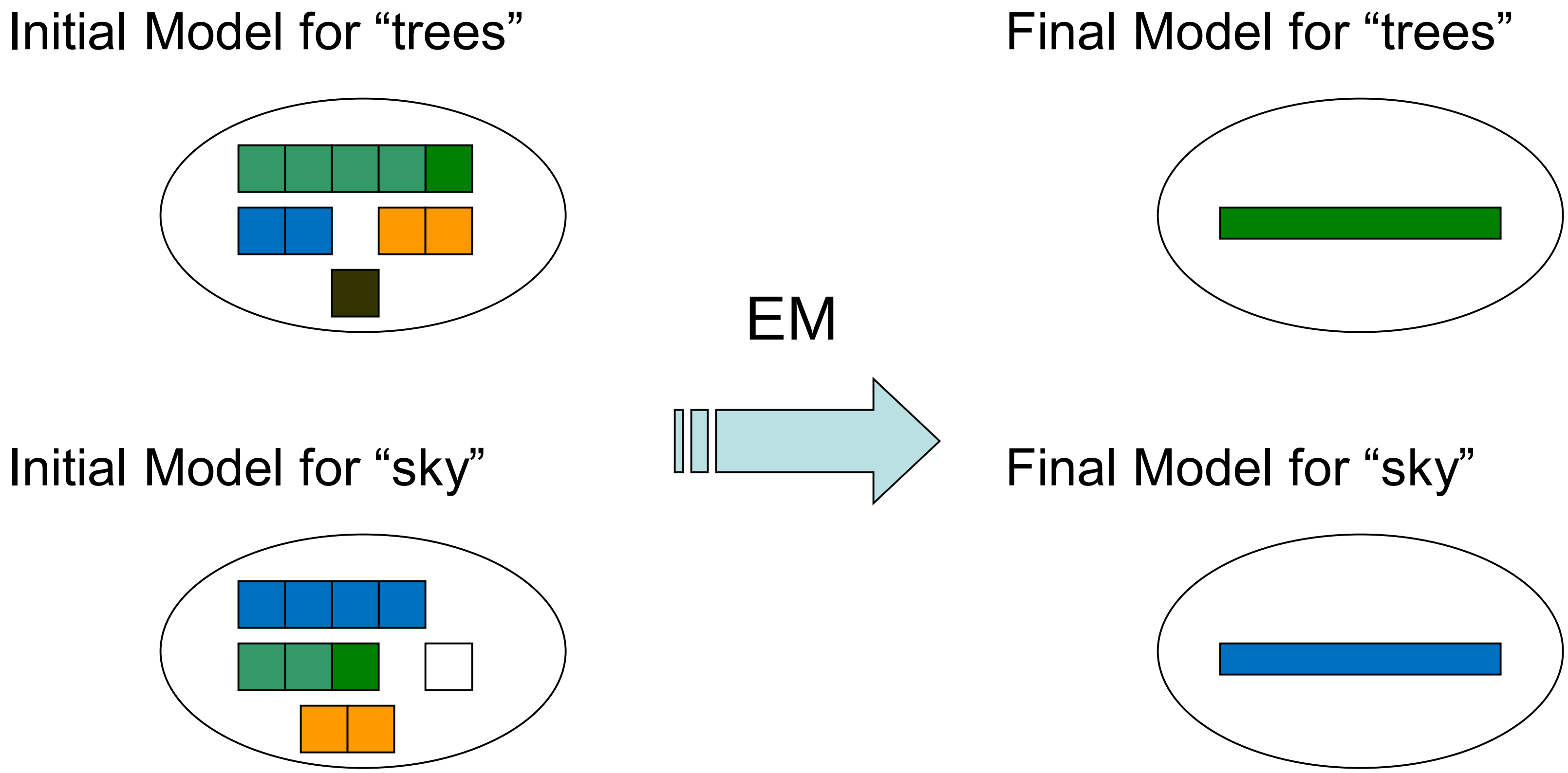
region
attributes
from several
different
types of
regions

Model Initial Estimation

- Estimate the initial model of an object using all the region features from all images that contain the object



EM Classifier: the Idea

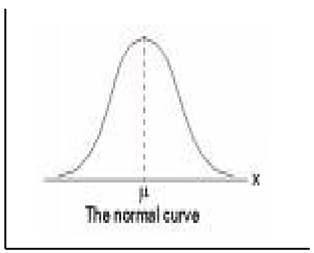


EM Algorithm

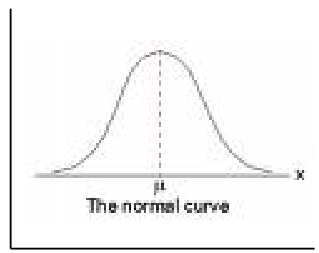
- Start with K clusters, each represented by a probability distribution
- Assuming a Gaussian or Normal distribution, each cluster is represented by its mean and variance (or covariance matrix) and has a weight.
- Go through the training data and soft-assign it to each cluster. Do this by computing the probability that each training vector belongs to each cluster.
- Using the results of the soft assignment, recompute the parameters of each cluster.
- Perform the last 2 steps iteratively.

1-D EM with Gaussian Distributions

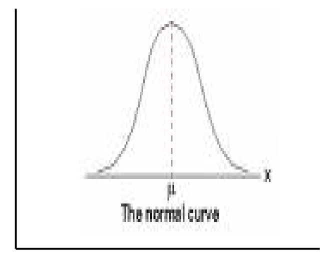
- Each cluster C_j is represented by a Gaussian distribution $N(\mu_j , \sigma_j)$.
- Initialization: For each cluster C_j initialize its mean μ_j , variance σ_j, and weight α_j.



$N(\mu_1 , \sigma_1)$
$\alpha_1 = P(C_1)$



$N(\mu_2 , \sigma_2)$
$\alpha_2 = P(C_2)$



$N(\mu_3 , \sigma_3)$
$\alpha_3 = P(C_3)$

- With no other knowledge, use random means and variances and equal weights.

Standard EM to EM Classifier

- That's the standard EM algorithm.
- For n-dimensional data, the variance becomes a co-variance matrix, which changes the formulas slightly.
- But we used an EM variant to produce a classifier.
- The next slide indicates the differences between what we used and the standard.

EM Classifier

1. Fixed Gaussian components (one Gaussian per object class) and fixed weights corresponding to the frequencies of the corresponding objects in the training data.

2. Customized initialization uses only the training images that contain a particular object class to initialize its Gaussian.

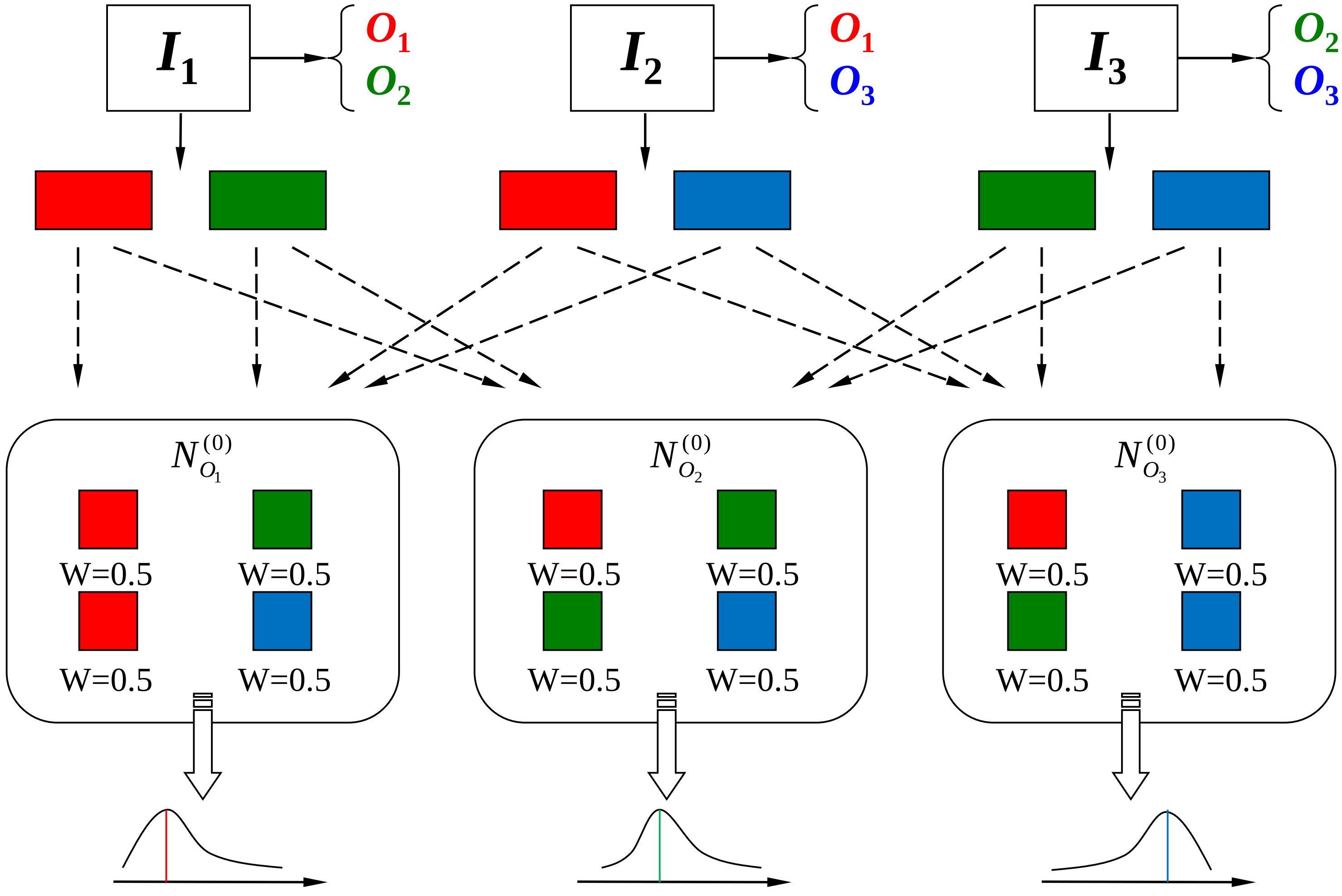
3. Controlled expectation step ensures that a feature vector only contributes to the Gaussian components representing objects present in its training image.

4. Extra background component absorbs noise.

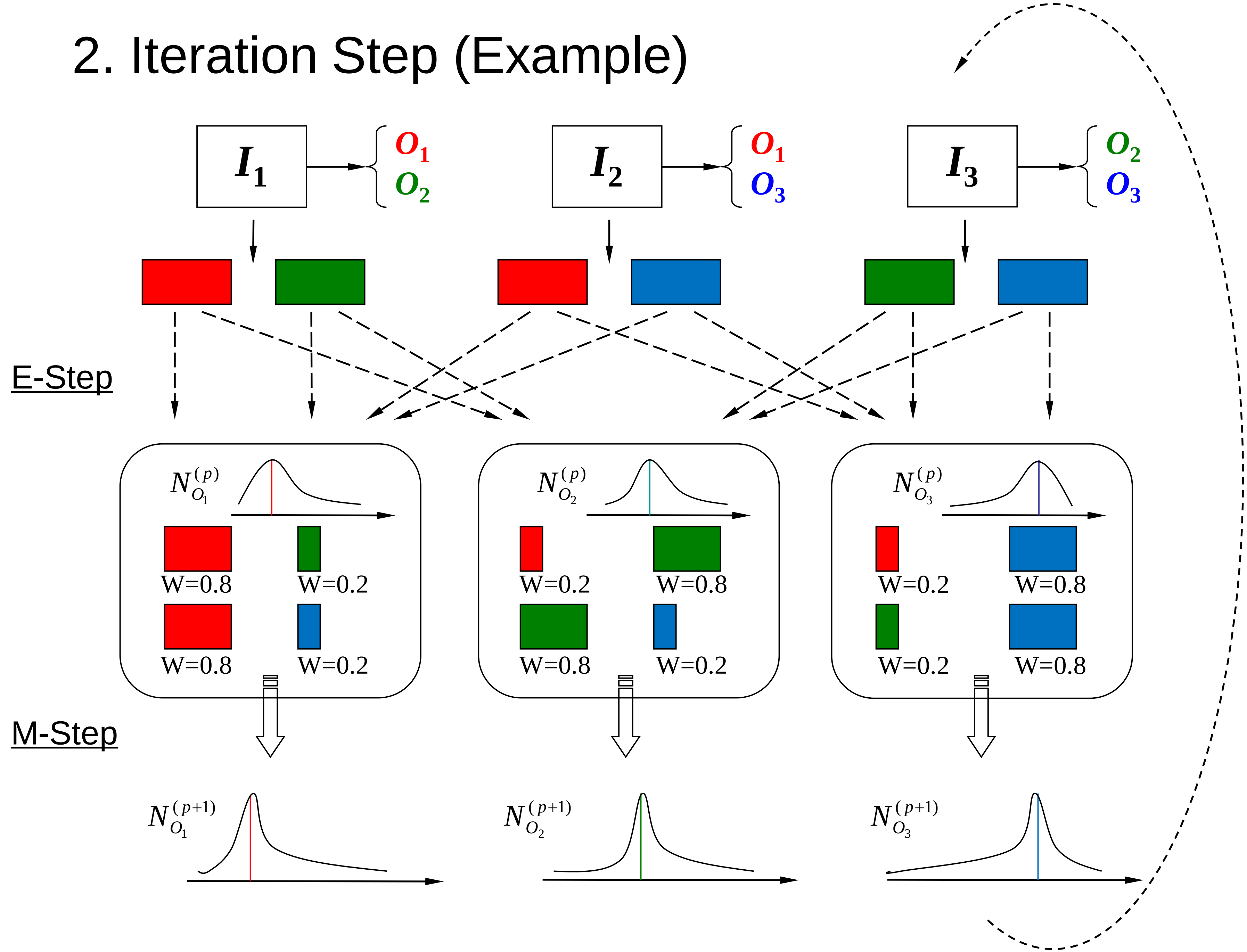
Gaussian for trees	Gaussian for buildings	Gaussian for sky	Gaussian for background

1. Initialization Step (Example)

Image & description



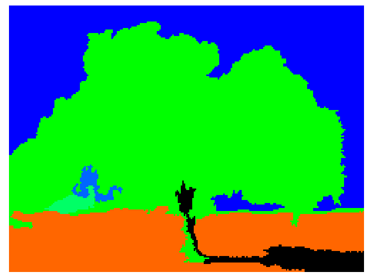
2. Iteration Step (Example)



Recognition

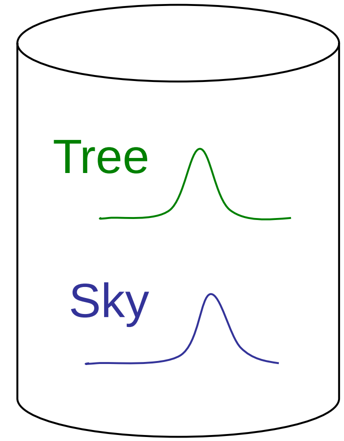
Test Image

Color Regions



compare

Object Model Database



How do you decide if a particular object is in an image?

To calculate $p(tree \mid image)$

$$p(tree \mid image) = f\left(\begin{matrix} p(\ tree \mid \quad) \\ p(\ tree \mid \quad) \\ p(\ tree \mid \quad) \\ p(\ tree \mid \quad) \end{matrix}\right)$$




f is a function that combines probabilities from all the color regions in the image.

e.g. max or mean

Combining different types of abstract regions: First Try

- Treat the different types of regions independently and combine at the time of classification.

1. $P(object| a_1, a_2,..,a_n) = P(object|a_1)*..*P(object|a_n)$

2. Form intersections of the different types of regions, creating smaller regions that have both color and texture properties for classification.

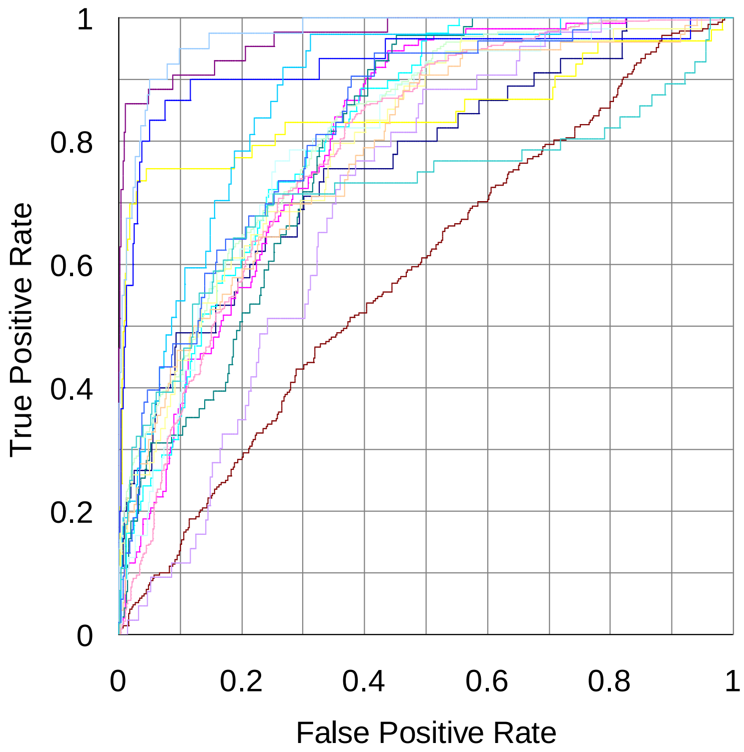
Experiments (on 860 images)

- 18 keywords: mountains (30), orangutan (37), track (40), tree trunk (43), football field (43), beach (45), prairie grass (53), cherry tree (53), snow (54), zebra (56), polar bear (56), lion (71), water (76), chimpanzee (79), cheetah (112), sky (259), grass (272), tree (361).

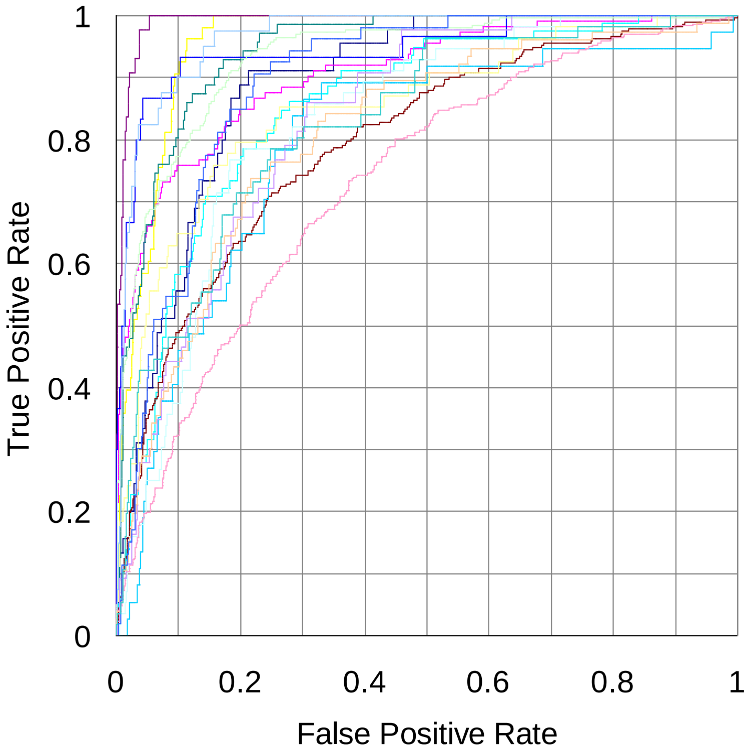
- A set of cross-validation experiments (80% as training set and the other 20% as test set)

- The poorest results are on object classes "tree," "grass," and "water," each of which has a high variance; a single Gaussian model is insufficient.

ROC Charts:
True Positive vs. False Positive



Independent Treatment of
Color and Texture



Using Intersections of
Color and Texture Regions

Sample Retrieval Results

cheetah

Sample Results (Cont.)

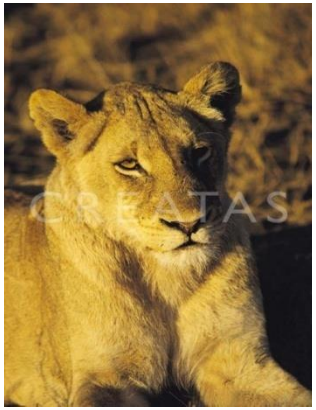
grass

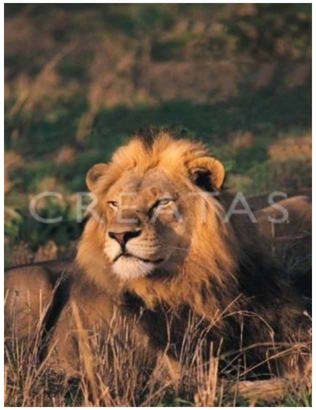
Sample Results (Cont.)

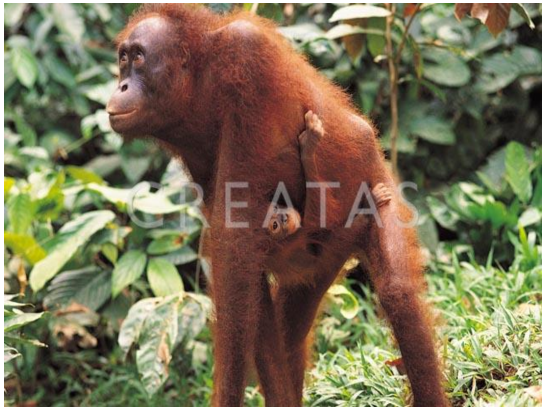
cherry tree

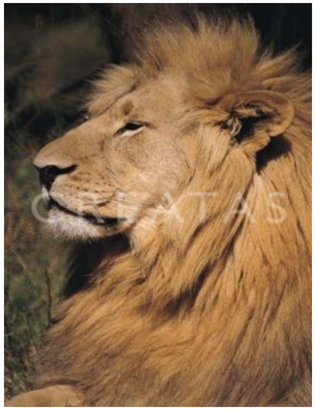
Sample Results (Cont.)

lion









Summary

- Designed a set of abstract region features: color, texture, structure, . . .
- Developed a new semi-supervised EM-like algorithm to recognize object classes in color photographic images of outdoor scenes; tested on 860 images.
- Compared two different methods of combining different types of abstract regions. The intersection method had a higher performance

Weakness of the EM Classifier Approach

- It did not generalize well to multiple features

- It assumed that object classes could be modeled as Gaussians

Second Approach

Two Stages: Clustering and Classifying

A Generative Discriminative Learning Algorithm for Image Classification

Yi Li, Linda Shapiro, Jeff Bilmes

ICCV 2005

A Better Approach to Combining Different Feature Types

Phase 1: JUST CLUSTERING in features space

- Treat each type of abstract region separately

- For abstract region type ***a*** and for object class ***o***, use the EM algorithm to construct clusters that are multivariate Gaussians over the features for type ***a*** regions.

Consider only abstract region type color (c) and object class object (o)

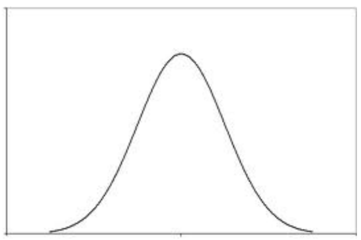
- At the end of Phase 1, we can compute the distribution of color feature vectors in an image containing object *o*.

$$P(X^c|o) = \sum_{m=1}^{M^c} w_m^c \cdot N(X^c; \mu_m^c, \Sigma_m^c)$$

- M^c is the number of components (clusters).
- The w's are the weights (α's) of the components.
- The μ's and Σ's are the parameters of the components.
- $N(X^c, \mu^c_m, \Sigma^c_m)$ specifies the probabilty that X^c belongs to a particular normal distribution.

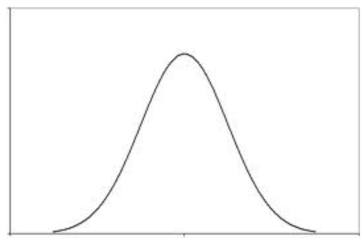
Color Components for Class o

$$P(X^c|o) = \sum_{m=1}^{M^c} w_m^c \cdot N(X^c; \mu_m^c, \Sigma_m^c)$$



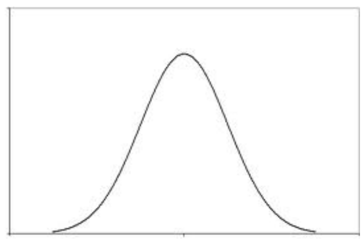
component 1

μ_1, Σ_1, w_1



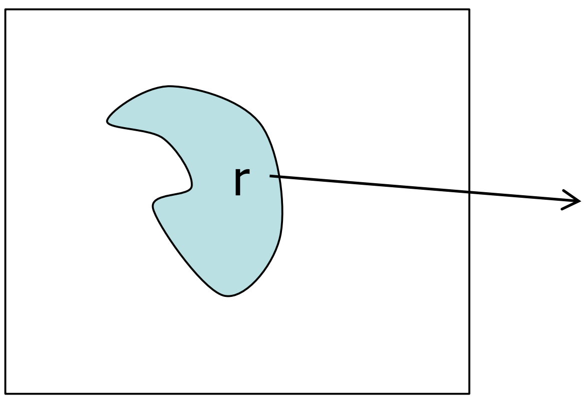
component 2

μ_2, Σ_2, w_2



component M^c

μ_M, Σ_M, w_M



color feature vector

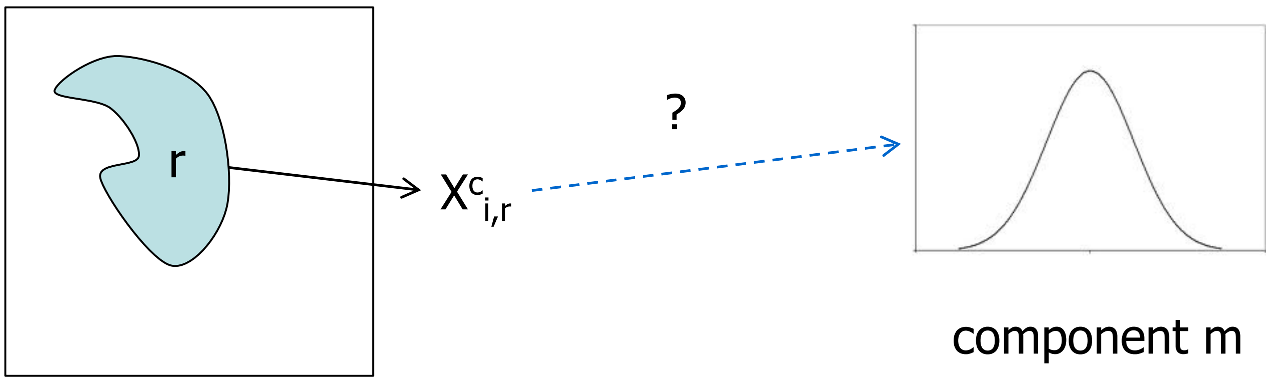
X^c for region r

Now we can determine which components are likely to be present in an image.

- The probability that the feature vector X from color region r of image I_i comes from component m is given by:

$$P(X^c_{i,r}, m^c) = w^c_m \cdot N(X^c_{i,r}, \mu^c_m, \Sigma^c_m)$$

$$f_{\mathbf{x}}(x_1, \ldots, x_k) = \frac{1}{(2\pi)^{k/2}|\boldsymbol{\Sigma}|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right)$$

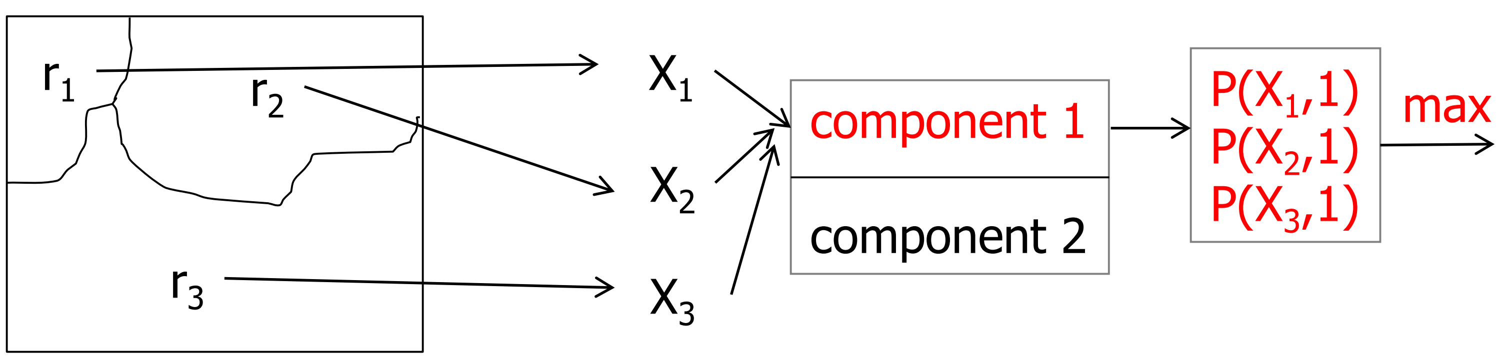


And determine the probability that the whole image is related to component m as a function of the feature vectors of all its regions.

- Then the probability that image I_i has a region that comes from component m is

$$P(I_i, m^c) = f(\{P(X_{i,r}^c, m^c) | r = 1, 2, \ldots\})$$

- where f is an aggregate function such as mean or max



Aggregate Scores for Color

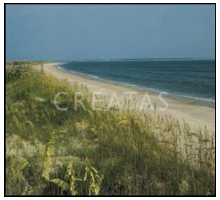
Components

1	2	3	4	5	6	7	8

beach

.93	.16	.94	.24	.10	.99	.32	.00

beach



.66	.80	.00	.72	.19	.01	.22	.02

not beach

.43	.03	.00	.00	.00	.00	.15	.00

We now use positive and negative training images, calculate for each the probabilities of regions of each component, and form a training matrix.

$$
\begin{array}{l}
\text{Positive Examples} \\
\\
\\
\text{Negative Examples}
\end{array}
\begin{bmatrix}
I1 & P(I1, 1) & P(I1, 2) & \ldots & P(I1, M) \\
I2 & P(I2, 1) & P(I2, 2) & \ldots & P(I2, M) \\
 & & & & \\
In & P(In, 1) & P(In, 2) & \ldots & P(In, M)
\end{bmatrix}
$$

Phase 2 Learning

- Let C_i be row i of the training matrix.

- Each such row is a feature vector for the color features of regions of image I_i that relates them to the Phase 1 components.

- Now we can use a second-stage classifier (ie. neural net) to learn $P(o|I_i)$ for each object class o and image I_i.

Multiple Feature Case

- We calculate separate Gaussian mixture models for each different features type:

- Color: C_i
- Texture: T_i
- Structure: S_i

- and any more features we have (motion).

Now we concatenate the matrix rows from the different region types to obtain a multi-feature-type training matrix and train a neural net classifier to classify images.

$$\begin{array}{ccccc} \textit{color} & \textit{texture} & \textit{structure} & & \textit{everything} \\ \begin{pmatrix} C_1^+ \\ C_2^+ \\ . \\ . \\ C_1^- \\ C_2^- \\ . \\ . \end{pmatrix} & \begin{pmatrix} T_1^+ \\ T_2^+ \\ . \\ . \\ T_1^- \\ T_2^- \\ . \\ . \end{pmatrix} & \begin{pmatrix} S_1^+ \\ S_2^+ \\ . \\ . \\ S_1^- \\ S_2^- \\ . \\ . \end{pmatrix} & \longrightarrow & \begin{pmatrix} C_1^+ & T_1^+ & S_1^+ \\ C_2^+ & T_2^+ & S_2^+ \\ . & . & . \\ . & . & . \\ C_1^- & T_1^- & S_1^- \\ C_2^- & T_2^- & S_2^- \\ . & . & . \\ . & . & . \end{pmatrix} \end{array}$$

ICPR04 Data Set with General Labels

	EM-variant with single Gaussian per object	EM-variant extension to mixture models	Gen/Dis with Classical EM clustering	Gen/Dis with EM-variant extension
African animal	71.8%	85.7%	89.2%	90.5%
arctic	80.0%	79.8%	90.0%	85.1%
beach	88.0%	90.8%	89.6%	91.1%
grass	76.9%	69.6%	75.4%	77.8%
mountain	94.0%	96.6%	97.5%	93.5%
primate	74.7%	86.9%	91.1%	90.9%
sky	91.9%	84.9%	93.0%	93.1%
stadium	95.2%	98.9%	99.9%	100.0%
tree	70.7%	79.0%	87.4%	88.2%
water	82.9%	82.3%	83.1%	82.4%
MEAN	**82.6%**	**85.4%**	**89.6%**	**89.3%**

Comparison to ALIP: the Benchmark Image Set

- Test database used in SIMPLIcity paper and ALIP paper.

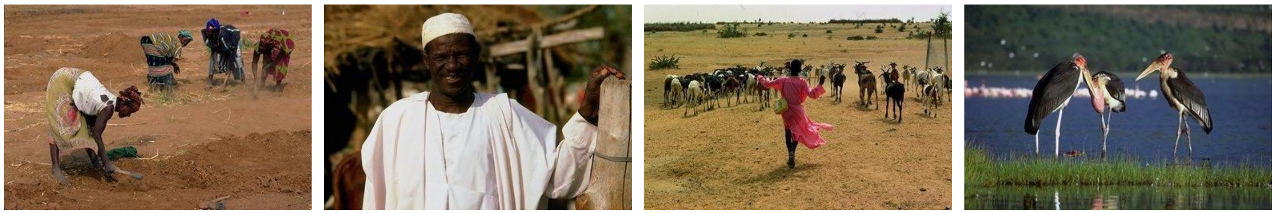
- 10 classes (*African people*, *beach*, *buildings*, *buses*, *dinosaurs*, *elephants*, *flowers*, *food*, *horses*, *mountains*). 100 images each.

Comparison to ALIP: the Benchmark Image Set

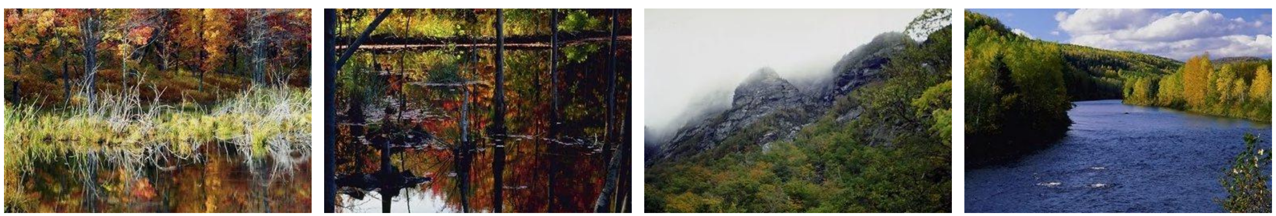
	ALIP	cs	ts	st	ts+st	cs+st	cs+ts	cs+ts+st
African	52	69	23	26	35	79	72	74
beach	32	44	38	39	51	48	59	64
buildings	64	43	40	41	67	70	70	78
buses	46	60	72	92	86	85	84	95
dinosaurs	100	88	70	37	86	89	94	93
elephants	40	53	8	27	38	64	64	69
flowers	90	85	52	33	78	87	86	91
food	68	63	49	41	66	77	84	85
horses	60	94	41	50	64	92	93	89
mountains	84	43	33	26	43	63	55	65
MEAN	**63.6**	**64.2**	**42.6**	**41.2**	**61.4**	**75.4**	**76.1**	**80.3**

Comparison to ALIP: the 60K Image Set

0. Africa, people, landscape, animal



1. autumn, tree, landscape, lake



2. Bhutan, Asia, people, landscape, church

Comparison to ALIP: the 60K Image Set

3. California, sea, beach, ocean, flower




4. Canada, sea, boat, house, flower, ocean




5. Canada, west, mountain, landscape, cloud, snow, lake




Comparison to ALIP: the 60K Image Set

Number of top-ranked categories required	1	2	3	4	5
ALIP	11.88	17.06	20.76	23.24	26.05
Gen/Dis	11.56	17.65	21.99	25.06	27.75

The table shows the percentage of test images whose true categories were included in the top-ranked categories.

Groundtruth Data Set

- UW Ground truth database (1224 images)
- 31 elementary object categories: *river* (30), *beach* (31), *bridge* (33), *track* (35), *pole* (38), *football field* (41), *frozen lake* (42), *lantern* (42), *husky stadium* (44), *hill* (49), *cherry tree* (54), *car* (60), *boat* (67), *stone* (70), *ground* (81), *flower* (85), *lake* (86), *sidewalk* (88), *street* (96), *snow* (98), *cloud* (119), *rock* (122), *house* (175), *bush* (178), *mountain* (231), *water* (290), *building* (316), *grass* (322), *people* (344), *tree* (589), *sky* (659)
- 20 high-level concepts: *Asian city , Australia, Barcelona, campus, Cannon Beach, Columbia Gorge, European city, Geneva, Green Lake, Greenland, Indonesia, indoor, Iran, Italy, Japan, park, San Juans, spring flowers, Swiss mountains, and Yellowstone*.

beach, sky, tree, water

people, street, tree

building, grass, people, sidewalk, sky, tree

building, bush, sky, tree, water

flower, house, people, pole, sidewalk, sky

flower, grass, house, pole, sky, street, tree

building, flower, sky, tree, water

boat, rock, sky, tree, water

building, car, people, tree

car, people, sky

boat, house, water

building

Groundtruth Data Set: ROC Scores

street	60.4	*tree*	80.8	*stone*	87.1	*columbia gorge*	94.5
people	68.0	*bush*	81.0	*hill*	87.4	*green lake*	94.9
rock	73.5	*flower*	81.1	*mountain*	88.3	*italy*	95.1
sky	74.1	*iran*	82.2	*beach*	89.0	*swiss moutains*	95.7
ground	74.3	*bridge*	82.7	*snow*	92.0	*sanjuans*	96.5
river	74.7	*car*	82.9	*lake*	92.8	*cherry tree*	96.9
grass	74.9	*pole*	83.3	*frozen lake*	92.8	*indoor*	97.0
building	75.4	*yellowstone*	83.7	*japan*	92.9	*greenland*	98.7
cloud	75.4	*water*	83.9	*campus*	92.9	*cannon beach*	99.2
boat	76.8	*indonesia*	84.3	*barcelona*	92.9	*track*	99.6
lantern	78.1	*sidewalk*	85.7	*geneva*	93.3	*football field*	99.8
australia	79.7	*asian city*	86.7	*park*	94.0	*husky stadium*	100.0
house	80.1	*european city*	87.0	*spring flowers*	94.4		

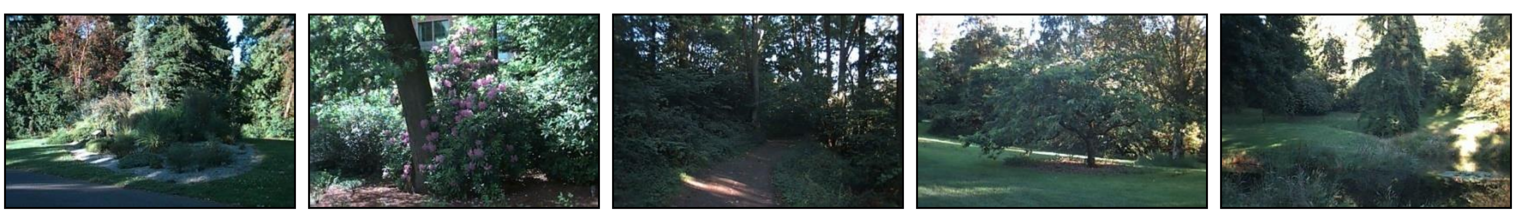
Groundtruth Data Set: Top Results

Asian city

Cannon beach

Italy

park



Groundtruth Data Set: Top Results

sky

spring flowers

tree

water

Groundtruth Data Set: Annotation Samples

tree(97.3), **bush**(91.6), **spring flowers**(90.3), **flower**(84.4), park(84.3), **sidewalk**(67.5), **grass**(52.5), **pole**(34.1)

sky(99.8), **Columbia gorge**(98.8), lantern(94.2), **street**(89.2), house(85.8), bridge(80.8), car(80.5), hill(78.3), boat(73.1), pole(72.3), **water**(64.3), mountain(63.8), **building**(9.5)

sky(95.1), **Iran**(89.3), house(88.6), **building**(80.1), boat(71.7), bridge(67.0), **water**(13.5), **tree**(7.7)

Italy(99.9), grass(98.5), **sky**(93.8), rock(88.8), **boat**(80.1), **water**(77.1), Iran(64.2), stone(63.9), bridge(59.6), **European**(56.3), sidewalk(51.1), **house**(5.3)

Comments

- The generative/discriminative approach, using EM clustering to produce feature vectors, followed by a neural net classifier, was much more powerful.
- It is strongly related to the bag-of-words approach.
- Instead of histograms of words, it is using vectors of responses to Gaussians as feature vectors.