Classification and Feature Selection with Human Performance Data

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Scene Classification Framework



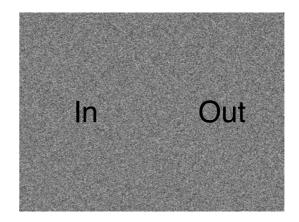
Related Work

- * Large amount of training data [Hays '07, Torralba '08]
- Learning from a few examples [Miller '00, Fei-Fei '06)]
- Semi-supervised Learning [Li '09, Fergus '09]
- Active Learning [Collins '08, Vijayanarasimhan '10]
- * Our approach: priors based on human performance

Psychophysics-based "labelings"

- * Images briefly seen by subjects may not be categorized perfectly.
- Categorization errors result from limited available features.
- Instead of "hard" labels, use categorization errors ("soft" labels).
- Benefits:
 - better generalizing classifiers
 - infer features employed by human vision

Ultra-Rapid Categorization

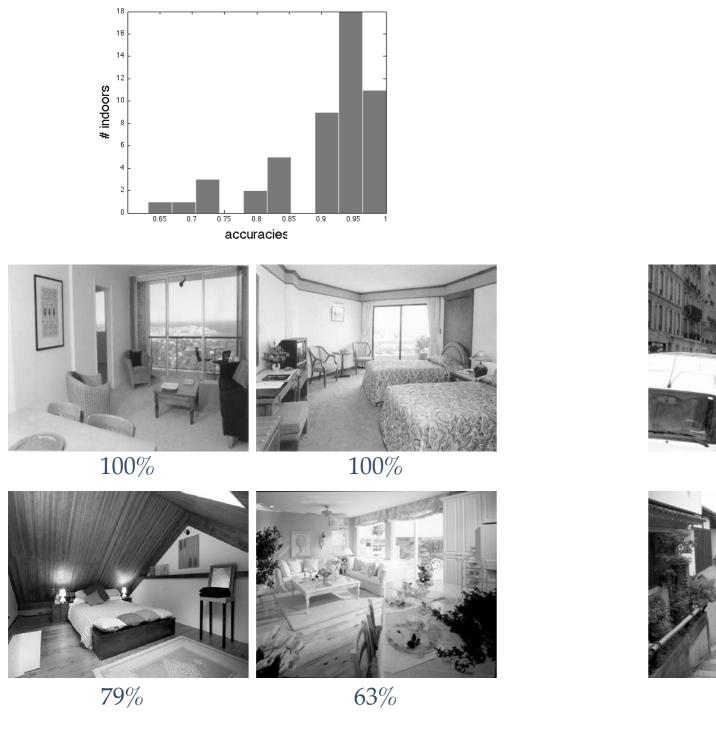


choice screen



fixation dot 1sec photo for 16ms

Example Accuracies





100%

16 14

outdoors

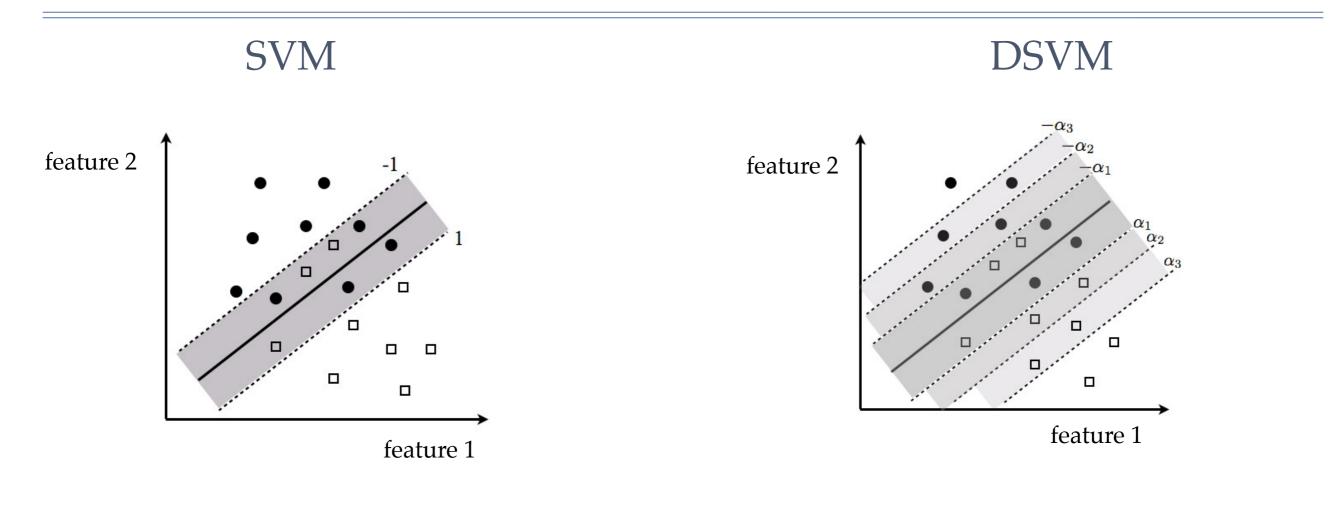
100%



74%

68%

Formulation



$$\min ||\mathbf{w}||_p + C \sum_i \xi_i$$

s.t. $y_i (\mathbf{x_i} \cdot \mathbf{w} + b) \geq 1 - \xi_i$
 $\xi_i \geq 0, \quad i = 1, \dots n$

$$\min ||\mathbf{w}||_1 + C \sum_i \xi_i$$

s.t. $y_i (\mathbf{x_i} \cdot \mathbf{w} + b) \geq \alpha_i - \xi_i$
 $\xi_i \geq 0, \quad i = 1, \dots n$

Non-linear SVM

$$\min \qquad \begin{aligned} \|\mathbf{w}\|_1 + C\sum_i \xi_i \\ \text{s.t.} \quad y_i \left(\sum_{j \neq i} y_j \ k(\mathbf{x_i}, \mathbf{x_j}) \ w_j + b\right) & \geq \alpha_i - \xi_i \\ \xi_i & \geq 0, \quad i = 1, \dots n \end{aligned}$$

Define kernel parameters with least squares fitting:

$$\min \sum_{i,j} [k(\mathbf{x_i}, \mathbf{x_j}) - r(\mathbf{x_i}, \mathbf{x_j})]^2$$

Kernel:
$$k(\mathbf{x_i}, \mathbf{x_j}) = \sum_{l=0}^{m} \beta_l h(\mathbf{x_i}, \mathbf{x_j})^l$$

Perceptual correlation:
$$r(\mathbf{x_i}, \mathbf{x_j}) = \begin{cases} 1 - |A(i) - A(j)|, & \text{if } y_i = y_j \\ |A(i) - A(j)|, & \text{if } y_i \neq y_j \end{cases}$$

Experimental Evaluation

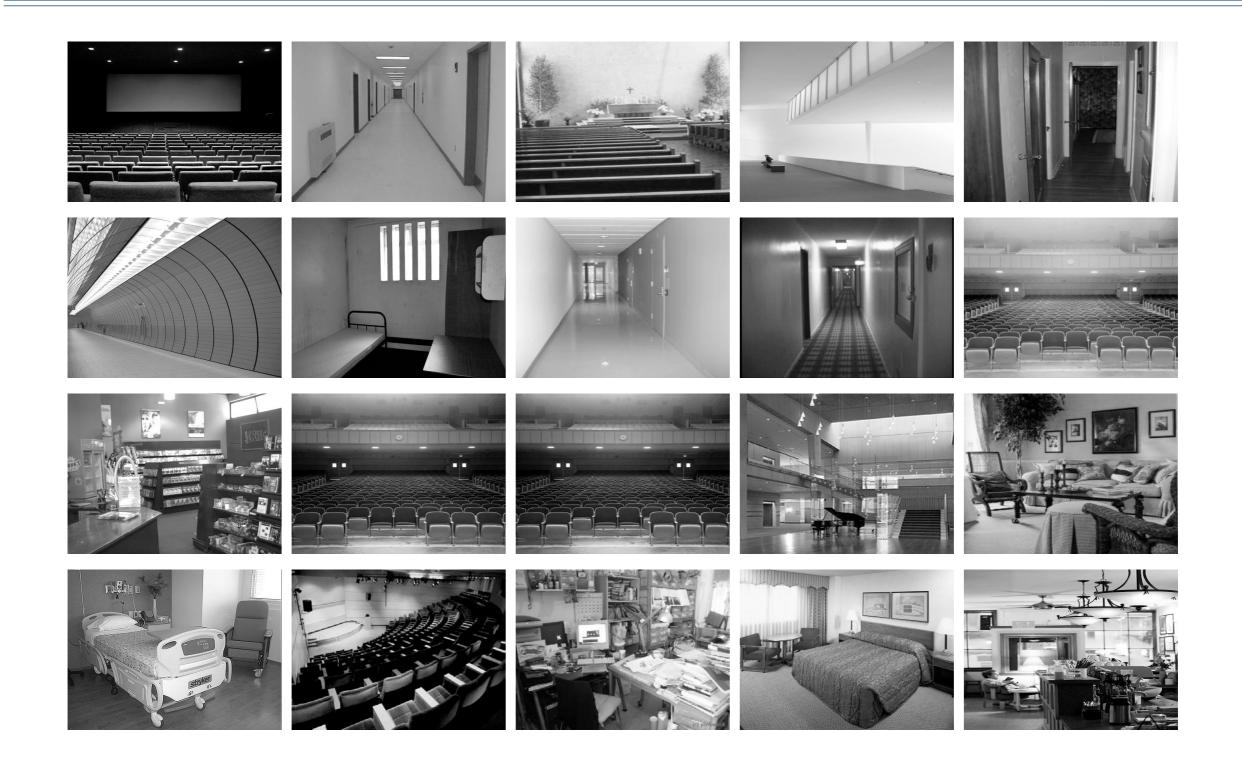
training:50 (indoors)50 (outdoors)testing:1,000 (indoors)1,000 (outdoors)

		SVM (%)		DSVM (%)	
	# dim	indoors	outdoors	indoors	outdoors
gist	512	56.5	78.7	+5.6	+0.9
tiny images	3072	56.0	67.1	+4.2	-0.6
sparse SIFT	2000	74.9	62.8	+0.5	+0.3
textons	10752	69.3	86.2	-1.0	+0.9

Indoors correctly classified by SVM only



Indoors correctly classified by DSVM only



Support Vectors

