Adjusting Active Basis Model by Regularized Logistic Regression

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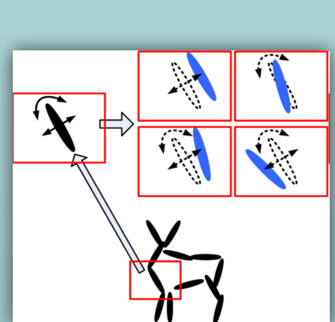
Abstract

Active basis model is a generative model seeking a common wavelet sparse coding of images from the same object category, where the images share the same set of selected wavelet elements, which are allowed to perturb their locations and orientations to account for shape deformations. This work applies discriminative methods to adjust λ's of selected basis elements, including logistic regression, SVM and AdaBoost. Results on supervised learning show that discriminative post-processing on active basis model improves its classification performance in terms of testing AUC. Among the three methods the L2-regularized logistic regression is the most natural one and performs the best.

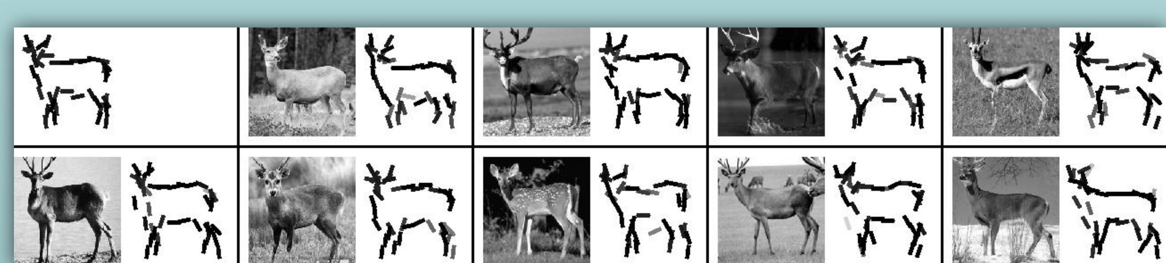
Introduction

➢ Active Basis – Generative Model

- a common template for a set of images: $\mathbf{B} = (B_i, i = 1, \ldots, n)$
- perturbed to match each image. $I_m = \sum_{i=1}^{n} c_{m,i} B_{m,i} + U_m$ where $B_{m,i} \approx B_i, i = 1, 2, \ldots, n$



Basis perturbation

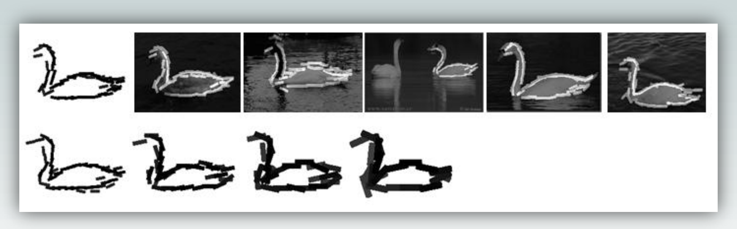


A set of images share an active basis

➢ Unsupervised Learning

- Unknown categories:

- Unknown locations and scales:



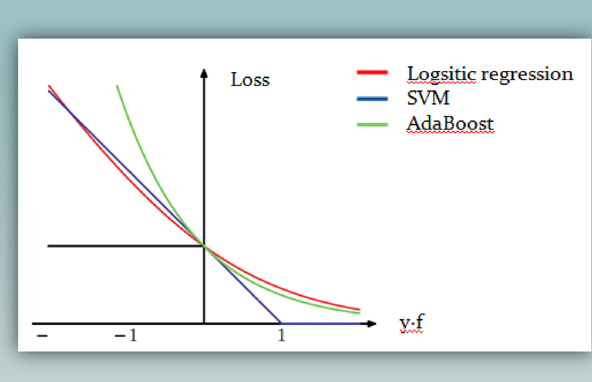
Hidden variables

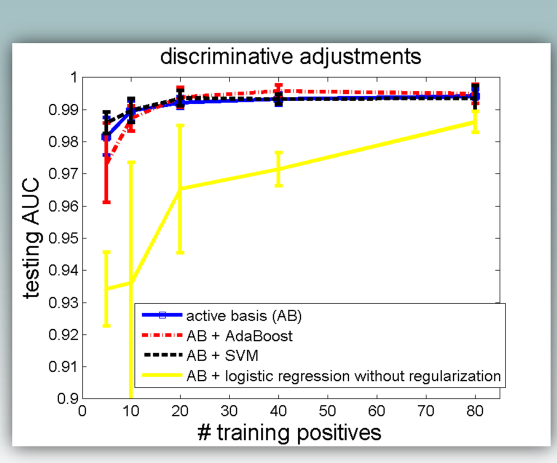
Methods

➢ Discriminative Adjustment

Adjust λ's of the template $\mathbf{B} = (B_i : i = 1, \ldots, n)$ by:

- L2-regularized logistic regression:
  - Model: $P(y = \pm 1) = \dfrac{1}{1 + \exp(-y(b + \boldsymbol{\lambda}^T \mathbf{x}))}$
  - Loss function: $\dfrac{1}{2}\boldsymbol{\lambda}^T \boldsymbol{\lambda} + C \sum_{i=1}^{N+P} \log(1 + e^{-y_i(\boldsymbol{\lambda}^T \mathbf{x}_i + b)})$
- SVM and AdaBoost:



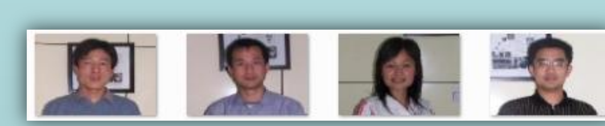


Over-fitting without regularization.

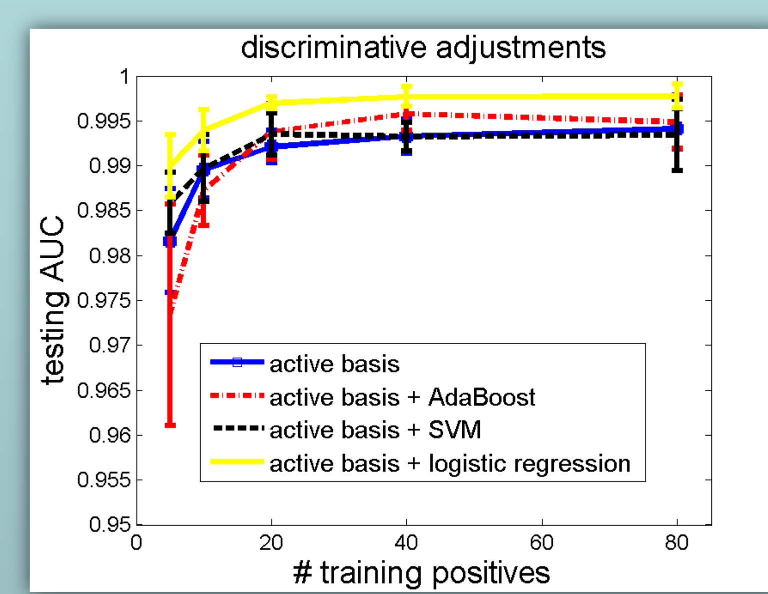
Results

➢ Classification Experiment

- Template size = 80. Tuning parameter = 0.01.
- Head_shoulder data: training negatives 160, testing negatives 471.

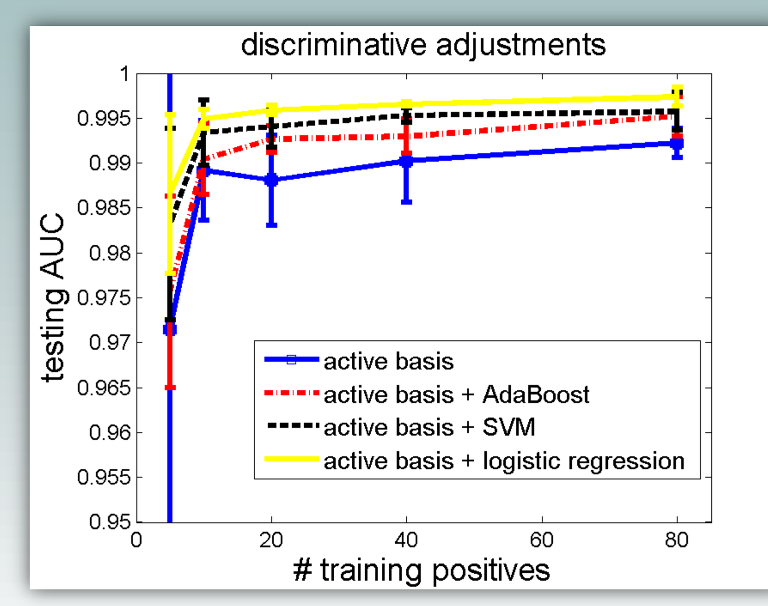


Intel Core i5 CPU, RAM 4GB, 64bit windows		
# pos	Learning time (s)	LR time (s)
5	0.338	0.010
10	0.688	0.015
20	1.444	0.015
40	2.619	0.014
80	5.572	0.013



- Guitar data: training negatives 160, testing negatives 855.

Intel Core i5 CPU, RAM 4GB, 64bit windows		
# pos	Learning time (s)	LR time (s)
5	0.478	0.011
10	0.852	0.014
20	1.749	0.015
40	2.643	0.015
80	5.827	0.014

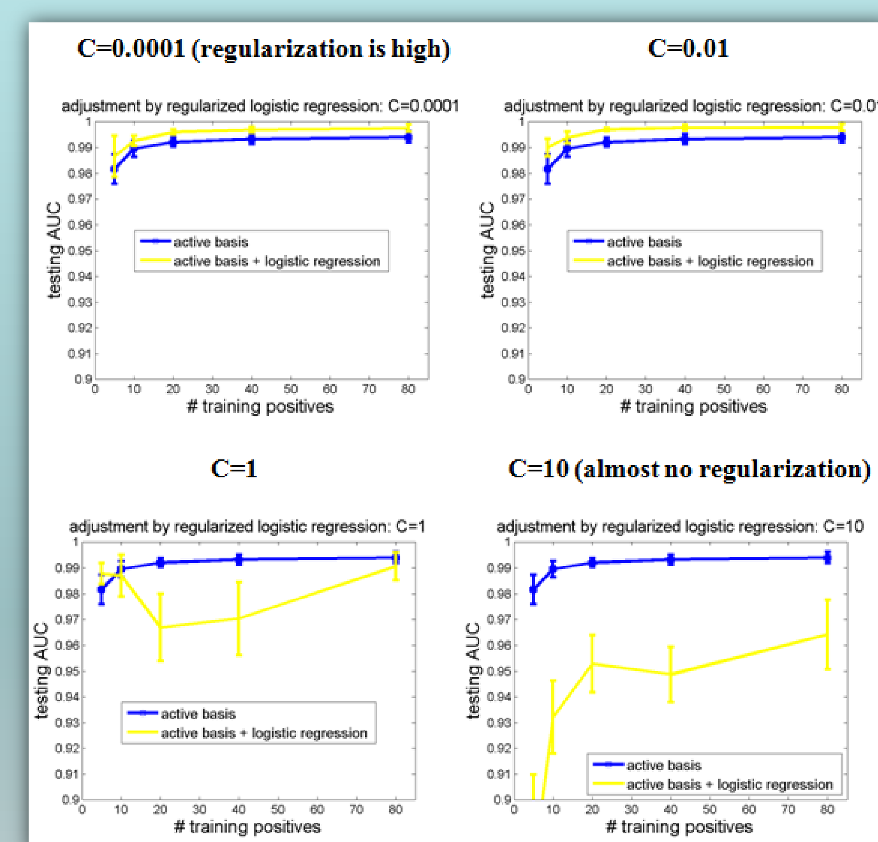


Discussion

➢ Tuning Parameter

Small tuning parameters

- imply high regularization
- guarantee high performances



➢ Future Work

Extend to unsupervised learning – adjust mixture model

- Generative learning by active basis
- Discriminative adjustment on feature weights

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