Combining Multiple Kernels for Efficient Image Classification

Behjat Siddiquie, Shiv N. Vitaladevuni and Larry S. Davis

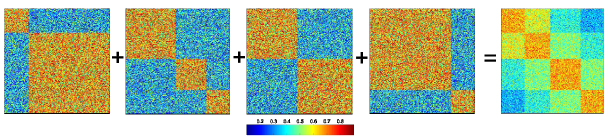
Method

➢ Image Classification:

- Kernel based methods (SVMs) have proved very successful
- Hard problems require multiple heterogeneous features
  - Compute a kernel for each feature channel
- MKL proposed to systematically combine multiple kernels
- Classification Efficiency
  - Need to compute the kernel distance to every Support Vector for all feature channels
  - Virtually every training sample ends up being a Support Vector

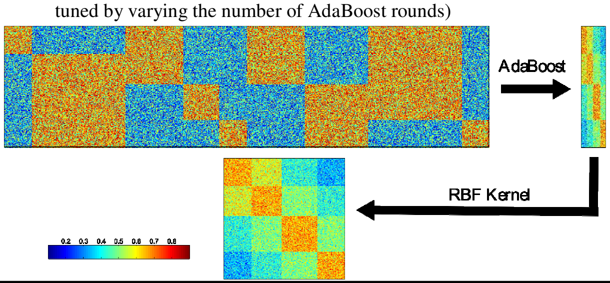
➢ Multiple Kernel Learning (EMKL):

- Learns a weighted linear combination of the kernels
  - Iterative optimization framework for learning the kernel weights as well as the SVM classification parameters simultaneously
  - [Rakotomamonjy et al. ICML07]
- Composite kernel is a mercer kernel
- Effective for combining information from different feature channels



➢ Boosted Kernel Learning (BKSVM):

- An efficient alternative to MKL
- Use AdaBoost for selecting discriminative feature-sample pairs
- Reduced dimensional feature vector obtained
  - Elements of vector represent kernel distance to the selected training samples in the corresponding feature space
  - Kernel learned from the feature vector
- Efficiency during test phase
  - Compute kernel distances of the test sample to only the selected feature-sample pairs
  - Efficiency is a function of the number of pairs selected (can be tuned by varying the number of AdaBoost rounds)



Experiments

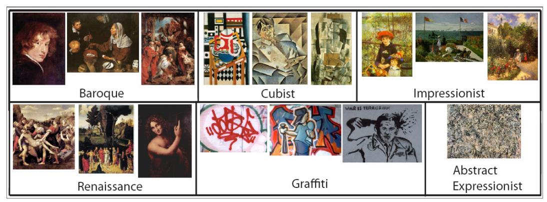
➢ UCI datasets:

- Standard Machine Learning benchmark
- Gaussian and Polynomial kernels used as the base kernels
- Two orders of magnitude reduction in complexity

Dataset			BK-SVM		EMKL	
name	size	kernels	accuracy	kernel computations	accuracy	kernel computations
Liver	345	91	66.2 ± 4.7	40	65.0 ± 2.3	1607 ± 324
Ionosphere	351	442	92.1 ± 3.6	40	92.3 ± 1.4	1496 ± 266
Pima	768	117	73.7 ± 6.4	60	75.8 ± 1.6	3123 ± 526
Sonar	208	793	76.3 ± 4.9	20	78.6 ± 4.2	2538 ± 351

➢ Painting dataset:

- 498 paintings, 6 different classes of painting styles
- Abstract nature of styles and high variability of paintings make this a challenging problem



➢ Features:

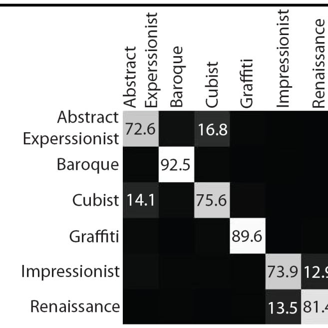
- Texture
  - Captures characteristics of the brushwork
  - MR8 filter bank [Varma & Zisserman ECCV02]
- HOG (histograms of gradients)
  - Captures local shape
  - Compute features on a densely on a grid as well as sparsely on edges
- Color
  - Color histograms (RGB) from local patches
- Saliency
  - Edge Continuity to identify salient curves
  - HOG features extracted from patches centered on salient curves

➢ Pyramid Match Kernel:

- A set of features vectors are extracted from each feature channel
- Pyramid Match Kernel [Grauman & Darrell ICCV05]
  - Feature space is subdivided into bins in a Pyramidal manner
  - Approximate the correspondence between the feature sets by a weighted intersection kernel computed over these pyramidal bins
- Kernels corresponding to each feature channel are obtained
- BKSVM and EMKL learn a combination of these kernels for classification

➢ Classification Results:

- Number of feature-sample pairs selected is 1/5th of the total



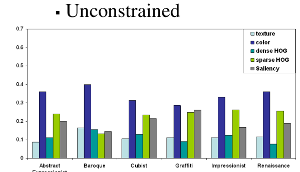
➢ Feature Combination:

- Individual features help in distinguishing certain classes
- Complement each other when combined

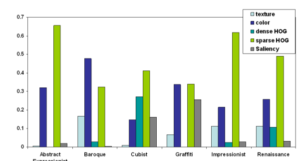
Feature	Accuracy
texture	73.5 ± 1.1
color	70.6 ± 1.1
dense HOG	69.3 ± 1.2
sparse HOG	69.0 ± 1.0
Saliency	62.2 ± 0.7
Combined EMKL	82.4 ± 0.9
Combined Our Method	81.3 ± 0.6

➢ Feature Selection:

- EMKL:
  - Intuitive weights assigned to the kernels
  - Sparsity constraint
- BKSVM:
  - Unconstrained



BKSVM



EMKL

➢ Efficiency:

- Performance/Accuracy tradeoff:
  - 10-fold increase in efficiency with a 2% drop in performance
  - 100-fold increase in efficiency with a 7% drop in performance
- Similar results with individual kernels