Inductive Regularized Learning of Kernel Functions

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Kernel Learning

- Goal: Learn appropriate kernel function for a given task
  - Supervision should be flexible
    - Labels
    - Pair-wise distance constraints
    - Relative distance constraints
  - Generalization to new points with good error bounds
- Existing approaches:
  - Parametric approaches: Multiple Kernel Learning ($\kappa(x, y) = \sum_i \mu_i \kappa_i(x, y)$), Gaussian Kernel Learning ($\kappa(x, y) = exp(-\|x - y\|^2/\sigma)$
  - Non-parametric approaches: mostly limited to Transductive settings

Our Approach

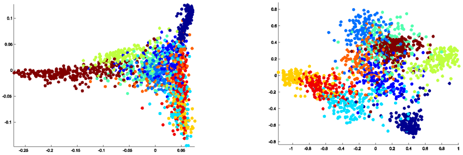
- Define a kernel *matrix* learning framework
  - $K = \Phi^T \Phi$, $K \in \mathbb{R}^{n \times n}$
  - Learn a new kernel matrix K_W:

$$\min_{K_W \succeq 0} f(K^{-1/2} K_W K^{-1/2})$$
$$\text{s.t. } g_i(K_W) \leq b_i, \; 1 \leq i \leq m.$$

  - f: $\mathbb{R}^{n \times n} \to \mathbb{R}$. *regularizer*, g_i: *constraints*.
  - Problem: how to compute K_W for points outside $[\mathbf{x}_1, \mathbf{x}_2 \ldots, \mathbf{x}_n]$.
- Show that the learned kernel matrix parameterizes a general kernel *function*
  - Learns linear transformation kernel $\kappa_W(\mathbf{x}, \mathbf{y}) = \mathbf{x}^T W \mathbf{y}$ for *spectral* regularizer f
  - Known to have good generalization bounds
- Use the learned kernel *function* to compute kernel value for unseen points

Results

- Special Cases:
  - Kernelizes most existing convex formulations for Mahalanobis metric learning
  - Provides efficient method for inductive semi-supervised kernel dimensionality reduction
- Empirical Results:
  - UCI datasets: efficiently learns kernel for k-NN classification
  - USPS digits: maps digits dataset to 2-dimensions, better than baseline Kernel-PCA



(a) KPCA (b) Our Method

- For more details: T55