Noise Resistant Graph Ranking for Improved Web Image Search
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http://www.ee.columbia.edu/ln/dvmm/

Graph Ranker = Personalized PageRank or Manifold Rank
Spectral filter outputs the denoised label vector \( \tilde{\mathbf{y}} \). Then the graph ranker (on a graph \( G(X, E) \)) gives the final ranking score vector \( \mathbf{f} \).

Goal
- Propose a novel ranking framework that can handle query samples with noisy relevance labels.
- Apply to web image search re-ranking. The original highest ranked images are treated as pseudo queries, which are filtered (denoised) and used to re-rank a much larger result set.

Framework

Spectral Filter = Progressive Sparse Eigenbase Fitting
- The multi-region assumption is that the true positive samples in the noisy query set \( \mathbf{y}_q \) reside in multiple high-density regions (clusters).
- Find these regions from the low-frequency spectrum of the graph Laplacian of a k-NN graph built on the working set (up to 1k) containing the images to be re-ranked. Each smooth eigenvector discloses a high-density region.
- Compute \( m \) lowest eigenvalues \( \lambda = \text{diag}(\lambda_1, \ldots, \lambda_m) \) and corresponding eigenvectors \( \mathbf{U} = [\mathbf{u}_1, \ldots, \mathbf{u}_m] \in \mathbb{R}^{n \times m} (m < n) \). Given the noisy label vector \( \mathbf{y}_q \) and previous \( q \) query samples, we formulate a sparse optimization problem Sparse Eigenbase Fitting to filter out the outliers:

\[
\min_{\mathbf{y}_q, \mathbf{w}_q} f(\mathbf{y}_q, \mathbf{w}_q) = \| \mathbf{U}_a \mathbf{y}_q - \mathbf{y}_q \|^2 + \gamma \mathbf{w}_q \cdot \mathbf{w}_q
\]

- Progressive fitting via alternating between \( \mathbf{a} \) and \( \mathbf{y}_q \) (\( j = 0,1,2,\ldots \)):

\[
\mathbf{a}^{j+1} = \text{argmin}_{\mathbf{a}} f(\mathbf{a}, \mathbf{y}_q), \quad \text{Projected Gradient Descent}
\]

\[
\mathbf{y}_q^{j+1} = \text{round}(\mathbf{U}_a\mathbf{a}^{j+1}), \quad \text{Rounding}
\]

- L1 norm

Results on Fergus dataset: ranking precision at 0.15 recall of 7 object categories: airplane, cars (rear), face, guitar, leopard, motorbike, and wrist watch using top-50 ranked images as pseudo queries.

Google top-50
- LabelFilt (sparse eigenbases)
- SpecFilter (sparse eigenbases)

Fergus airplane: top-50 images from Google.
SF improves query set precision from 0.5 to 1. SF+MR improves re-ranking precision of MR from 0.39 to 0.80 at 0.15 recall.

INRIA dataset: mean average precision (MAP) of ranking over 353 text queries with visual query sets of different sizes.

Google top-50
- LabelFilt (sparse eigenbases)
- SpecFilter (sparse eigenbases)

Fergus cars_rear: top-50 images from Google.
SF improves query set precision from 0.48 to 1. SF+MR improves re-ranking precision of MR from 0.53 to 1 at 0.15 recall.

LogReg (t+v) 0.6730
- PPR (v) 0.6931
- MR (v) 0.6980
- SF+MR (v) 0.7275

- SF improves query set precision from 0.5 to 1.
- SF+MR improves re-ranking precision of MR from 0.39 to 0.80 at 0.15 recall.