Predicting Useful Neighborhoods for Lazy Local Learning

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Lazy Local Learning

Our Idea

Learn the properties of a "good neighborhood" using a large-scale multi-label classification framework to enhance local learning.

- determine distribution of neighborhood composition size
- maintain bias towards local neighbors while not strictly adhering to the ranking

Similarity-Based (prior work)
"which images are most similar to the test image?"

Distribution-Based (ours)
"which set of images would jointly train a good classifier for the test image?"

Key Idea: learn about neighborhoods instead of just neighbors

Our Idea

Predicting Useful Neighborhoods

Phase 1: Generate Training Neighborhoods (offline)
- empirically determine "ground truth" neighborhoods
- weighted and balanced sampling of candidate neighborhoods (K x S candidates)
- select the best point-neighborhood pairs (x, y) based on prediction confidences

<table>
<thead>
<tr>
<th>Test Point</th>
<th>y_1</th>
<th>y_2</th>
<th>y_3</th>
<th>y_4</th>
<th>y_5</th>
<th>...</th>
<th>y_S</th>
</tr>
</thead>
<tbody>
<tr>
<td>x_1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td></td>
<td>0</td>
</tr>
<tr>
<td>x_2</td>
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<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>...</td>
<td>0</td>
</tr>
<tr>
<td>x_3</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>x_4</td>
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<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
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Neighborhood Indicator Vectors (y)

Note: y_i indicates all M training points

Phase 2: Neighborhood Mapping with Compressed Sensing (offline)
- we cast our learning task as a large-scale multi-label classification problem
- learn a prediction function that jointly estimates all useful neighbors
- offline stages require only hours compared to days for the naive approach

Phase 3: Infer Best Neighborhoods (online)
- infer real-valued indicator vector (\hat{y}_i) for each test point
- form candidate neighborhoods using top K inferred points
- determine best neighborhood based on normalized decision values

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<th>y_5</th>
<th>...</th>
<th>y_S</th>
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<tbody>
<tr>
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Experimental Results

SUN Attributes Dataset: 14,340 images, 707 classes, 8 attributes

Top-5 Neighbors: Local baseline captures global similarity but not class distribution. We capture informative samples specific to the neighborhood.

Observation: We outperform all baselines on all attributes by a sizeable margin (~25%), esp. on ones with fewer positive samples.

aPascal Dataset: 6,440 images, 20 classes, 6 attributes

Observation: We outperform all Local baselines but lag behind Global in some cases due to better spatial alignment and lower visual diversity.

Conclusion
- novel lazy local learning approach that predicts the best neighborhood
- enhances learning over large + unbalanced datasets
- outperforms traditional local approaches on 2 challenging datasets