Multi-Label Classification of Large Shape Collections via Graph-Based Semi-Supervised Learning

Qixing Huang       Hao Su       Leonidas Guibas
Geometric Computing Lab, Computer Science Department, Stanford University, USA

**Introduction**
- Larger and larger shape collections are becoming available while techniques to organize them still lack
- We study the problem of associating types and/or styles with shapes of a given category
- Our approach supports multiple labels per shape
- Our approach supports semi-supervised learning
- Experiments show that our approach are on par and sometimes better results than state-of-the-art supervised learning techniques using much more training data

**System Setup**

**Input:** shapes with *sparse* and *noisy* labels

**Output:** shapes with *complete*, *cleaned*, and *fine-grained* labels

---

**Approach**

**Goal:** align shapes so that they have the same orientation
- Pair Matching
- Candidate Trans.
- Trans. Selection
- Local Align.

* Assume input objects are up-right aligned, so we rotate shapes around the z-axis

* Joint transformation selection to enforce the consistency of rotations of each shape
* Further local alignment by fitting a free-form transformation

**Joint Distance Learning**

**Goal:** learn a distance metric for each class so that shapes from the same class clustered (pos pairs) and are separated from the other classes (neg pairs)

* Multiple Kernel Learning
* Large-margin framework
  - per class distance metric learning
  - capture spatial configuration by voxelizing the bounding cube
  - adaptively adjust unlabeled data
  - inducing structure regularity
  - persistency among neighboring viewpoints
  - sharing structure across classes by assuming a common latent space

**Graph Based Multi-Label Classification**

**Goal:** jointly extract the optimal shape set for each class

* Similarity graph construction
  - one similarity graph for each class
  - based upon the learned distance
* Per class shape set candidates extraction
  - based upon the similarity graphs
* Optimal shape set selection
  - a quadratic programming formulation

---

**Experiments**

**Shape Matching Result on Car dataset**

**Learned distance metrics for various label classes.**

**Order shapes by learned distance**

**Basic category classification results**

<table>
<thead>
<tr>
<th>Category</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aircraft</td>
<td>78.10%</td>
<td>78.10%</td>
<td>78.10%</td>
<td>78.10%</td>
</tr>
<tr>
<td>Chair</td>
<td>82.03%</td>
<td>82.03%</td>
<td>82.03%</td>
<td>82.03%</td>
</tr>
<tr>
<td>Car</td>
<td>84.13%</td>
<td>84.13%</td>
<td>84.13%</td>
<td>84.13%</td>
</tr>
<tr>
<td>Chair+Cars</td>
<td>87.07%</td>
<td>87.07%</td>
<td>87.07%</td>
<td>87.07%</td>
</tr>
<tr>
<td>Chair+Cars</td>
<td>87.07%</td>
<td>87.07%</td>
<td>87.07%</td>
<td>87.07%</td>
</tr>
</tbody>
</table>

**Fine-grained classification results**

<table>
<thead>
<tr>
<th>CarMaker</th>
<th>Harness</th>
<th>BMW</th>
<th>Dodge</th>
<th>Chevrolet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ford</td>
<td>80.00%</td>
<td>80.00%</td>
<td>80.00%</td>
<td>80.00%</td>
</tr>
<tr>
<td>Audi</td>
<td>70.00%</td>
<td>70.00%</td>
<td>70.00%</td>
<td>70.00%</td>
</tr>
<tr>
<td>Mercedes</td>
<td>60.00%</td>
<td>60.00%</td>
<td>60.00%</td>
<td>60.00%</td>
</tr>
<tr>
<td>Nissan</td>
<td>50.00%</td>
<td>50.00%</td>
<td>50.00%</td>
<td>50.00%</td>
</tr>
</tbody>
</table>

---

**Conclusion**

* Given a set of shapes with sparse and noisy labels, our approach outputs shapes with complete and clean
* Our approach is multi-label and semi-supervised, which uses labels more efficiently
* With the learned distance, we can better explore shapes