Domain-Aware Augmentations for Unsupervised Online General Continual Learning

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Problem Setting

- **K** tasks: \( \{T_1, \ldots, T_K\} \) with **K** datasets \( \{D_1, \ldots, D_K\} \)
- \( D_k = \{X_k\} \), unlabeled data
- Only one pass over the data is allowed
- Task change is unknown

![Online Continual Learning Diagram](image)

**Considered Augmentations**
- CutMix
- Domain-Aware CutMix:

\[
 x_a = M \odot x_i + (1 - M) \odot x_d
\]

with \( M \) a binary mask constructed according to \( B = (r_x, r_y, r_w, r_h) \), defined with \( r_a = W \sqrt{1 - \lambda}, r_h = H \sqrt{1 - \lambda} \).

\( \lambda \sim U(0.5, 1) \) such that the augmented image \( x_a \) has a minimum amount of information coming from \( x_i \)

**Memory-based methods**
- Memory based approaches are state-of-the-art in OCL.

**Description of the approach**

**Overview**
- Many-view batch \( B_f \)
- Contrastive Training
- Considered Augmentations

**Datasets & Baselines**
- CIFAR100, CIFAR10. Tiny ImageNet: 110 000 64x64 images; 200 classes.

**Baselines**

**Results**

<table>
<thead>
<tr>
<th>Method</th>
<th>CIFAR10</th>
<th>CIFAR100</th>
<th>Tiny ImageNet</th>
</tr>
</thead>
<tbody>
<tr>
<td>ER</td>
<td>41.46 ± 3.41</td>
<td>52.93 ± 4.39</td>
<td>31.37 ± 0.69</td>
</tr>
<tr>
<td>SCR</td>
<td>49.16 ± 3.02</td>
<td>60.28 ± 1.21</td>
<td>37.79 ± 0.95</td>
</tr>
<tr>
<td>GSA</td>
<td>52.03 ± 2.14</td>
<td>61.30 ± 2.35</td>
<td>38.77 ± 1.07</td>
</tr>
<tr>
<td>STAM</td>
<td>30.64 ± 0.8</td>
<td>8.39 ± 0.4</td>
<td>-</td>
</tr>
<tr>
<td>SimSiam-ER</td>
<td>27.73 ± 1.18</td>
<td>30.59 ± 1.21</td>
<td>6.91 ± 0.37</td>
</tr>
<tr>
<td>BYOL-ER</td>
<td>29.43 ± 0.55</td>
<td>29.30 ± 1.01</td>
<td>9.39 ± 0.52</td>
</tr>
<tr>
<td>SimCLR-ER</td>
<td>43.20 ± 2.30</td>
<td>48.81 ± 0.78</td>
<td>21.2 ± 0.9</td>
</tr>
<tr>
<td>Ours (7,1,0,0)</td>
<td>45.68 ± 2.33</td>
<td>52.89 ± 0.57</td>
<td>27.27 ± 0.13</td>
</tr>
<tr>
<td>Ours (4,1,1,1)</td>
<td>48.09 ± 1.22</td>
<td>56.02 ± 1.34</td>
<td>29.02 ± 0.77</td>
</tr>
</tbody>
</table>

**Table. Final Average Accuracy (%)**

**Conclusions**
- Domain Aware Augmentations outperform standard augmentation strategies;
- Close performances to supervised baselines when memory size is small;
- Optimizing memory usage is key to improving memory-based approach in Online Continual Learning.