Experiments

- Few shot learning benchmarks: outperforms other unsupervised algorithms and alternates for best with CACTUs-MAML [2].
- Massive reduction of required labeled data: 25000 to 25 for Omiglot (5,5) for 95.43% vs 98.83 vs MAML.

Works on video classification as well:
- Test on all samples of each class by looking at just one example for train
- Use frame selection to create augmented video
  - C3D architecture
  - Sample a sequence of length 16 from each video
- Kinetics for meta-learning and UCF101 for test

Works on unbalanced datasets (CelebA used for face recognition)

Motivation
- Meta learning (learning to learn) algorithms facilitate few-shot learning
- Model-agnostic meta-learning (MAML) [1]
  - Meta-learning phase: learn from tasks $T_1 \ldots T_n$
  - Target learning phase: few-shot learning on $T_{n+1}$
- The good:
  - Model-agnostic: no requirement for the network structure
  - Very little labeled data needed at the target phase
- The bad:
  - A lot of labeled data needed at the meta-learning phase
  - Tasks $T_1 \ldots T_n$ need to be drawn from the same distribution as the target - we need good knowledge of the target domain

Our Idea
- Keep the general flow of MAML but use unlabeled data for meta-learning!

References:

Unsupervised Meta-learning for Few-Shot Image Classification

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Unsupervised Meta-learning with Tasks constructed by Random sampling and Augmentation (UMTRA)

- On video: use frame selection to create augmented video
  - C3D architecture
  - Sample a sequence of length 16 from each video
  - Kinetics for meta-learning and UCF101 for test

Translation + Zeroing Pixels

Start with an unlabeled data set D of samples
- We assume a large number of classes C present, but we don’t know the class of each sample
- Generate synthetic one shot training tasks $T_1 \ldots T_n$
- Random selection of samples with artificial labels
- The large number of classes ensures high likelihood that classes are different
- Create validation data by augmentation $x \rightarrow (Ax)$
  - Augmentation type varies by domain, the objective is to maintain class membership of the augmented data
- Augmentation on image type data (Omiglot | MiniImageNet)

Translation + Zeroing Pixels

Algorithm 1: Unsupervised Meta-learning with Tasks constructed by Random sampling and Augmentation (UMTRA)

<table>
<thead>
<tr>
<th>Algorithm (N, K)</th>
<th>OmniGlot</th>
<th>Mini-ImageNet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clustering</td>
<td>(5,5)</td>
<td>(25)</td>
</tr>
<tr>
<td>(5,5)</td>
<td>(5,10)</td>
<td>(5,20)</td>
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<tr>
<td>Training from scratch</td>
<td>N/A</td>
<td>52.50</td>
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<tr>
<td>N_c nearest neighbors</td>
<td>BAGAN</td>
<td>49.57</td>
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<td>Linear classifier</td>
<td>BAGAN</td>
<td>48.28</td>
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<td>MLP with dropout</td>
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<td>48.54</td>
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<tr>
<td>cluster matching</td>
<td>CACTUS-MAML</td>
<td>43.96</td>
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<tr>
<td>CACTUS-ProtoNets</td>
<td>BAGAN</td>
<td>58.13</td>
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<tr>
<td>N_c nearest neighbors</td>
<td>ACAI</td>
<td>54.74</td>
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<tr>
<td>Linear classifier</td>
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<td>61.08</td>
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<td>MLP with dropout</td>
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<tr>
<td>cluster matching</td>
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<tr>
<td>UMTRA (ours)</td>
<td>BAGAN</td>
<td>83.90</td>
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<tr>
<td>MAML (Supervised)</td>
<td>BAGAN</td>
<td>94.48</td>
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<tr>
<td>Prototex (Supervised)</td>
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<td>98.35</td>
</tr>
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