SSDL: Self-Supervised Domain Learning for Improved Face Recognition
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Problem Statement

Face recognition in unconstrained environments is challenging due to variations in illumination, quality of sensing, motion blur and etc. An individual's face appearance can vary drastically under different conditions creating a gap between train (source) and varying test (target) data. To this end, we propose a self-supervised domain learning (SSDL) scheme that trains on triplets mined from unlabelled data.

Challenges:
1. How to generate reliable triplets from unlabelled data?
2. How to address data scarcity in network training?

Performance Evaluation

| System            | YTC (%) | System            | YTF (%) |
|-------------------|---------|-------------------|---------|
| MMDML             | 78.5    | DeepFace-single   | 91.40   |
| DRM-PWV           | 72.55   | Sohn et al. (UDA) | 95.38   |
| Fast FR           | 72.1    | FaceNet           | 95.12   |
| GJRNPa            | 81.3    | NAN               | 95.72   |
| ClusterFace       | 91.06   | TBE-CNN           | 94.96   |
| Baseline          | 88.43   | Baseline          | 93.92   |
| SSDL cycle 1      | 94.75   | SSDL cycle 1      | 95.01   |
| SSDL cycle 2      | 94.75   | SSDL cycle 2      | 95.66   |

JBJ-A verification (TAR)

| System                              | FAR=0.001 | FAR=0.01 | FAR=0.1  |
|-------------------------------------|-----------|----------|----------|
| DCNNmanual-metric (*)               | -         | 78.7     | 94.7     |
| DCNN-fusion (*)                     | -         | 83.8     | 97.8     |
| NAN                                 | 88.1      | 94.1     | 97.8     |
| Template                            | 83.6      | 93.9     | 97.9     |
| Triplet Emb (BTAS16) (*)            | 81.3      | 91       | 96.4     |
| Contrastive                         | 63.91     | 84.01    | 95.31    |
| Sohn et al. (UDA)                   | 64.9      | 86.4     | 97.0     |
| ClusterFace                         | 86.60     | 94.23    | 98.30    |
| Baseline                            | 63.84     | 84.82    | 96.24    |
| SSDL cycle 1                        | 77.98     | 92.09    | 97.83    |
| SSDL cycle 2                        | 88.77     | 94.73    | 98.11    |

Table: System evaluation on benchmarks

| System               | V2-V1 | V3-V1 | V3-V2 | V1-V2 | V1-V3 | V2-V3 |
|----------------------|-------|-------|-------|-------|-------|-------|
| Baseline             | 91.07 | 87.49 | 84.79 | 91.84 | 82.27 | 79.44 |
| SSDL cycle 1         | 90.14 | 92.31 | 94.44 | 87.48 | 87.0  | 91.06 |
| SSDL cycle 2         | 96.41 | 96.01 | 95.82 | 93.07 | 95.17 |

Discussion

- SSDL adapts to domain data in all four benchmarks.
- SSDL cycle 2 achieves better adaptation than SSDL cycle 1.
- SSDL achieves highly competitive results compared to state-of-the-art outperforming systems that perform supervised fine-tuning on benchmark specific train data.

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Figure: Image sources: Train data: VGGFace2 train database, Test data: YTF benchmark (top), IJB-A benchmark (middle) and YTC benchmark (bottom).

SSDL cycle
- Hierarchical clustering algorithm to group unlabelled domain data into identity clusters
- Select the critical training samples through strict margins to avoid overfitting.
- Once trained repeat SSDL cycle for better clustering result and more informative triplets.