MOON: A Mixed Objective Optimization Network for the Recognition of Facial Attributes

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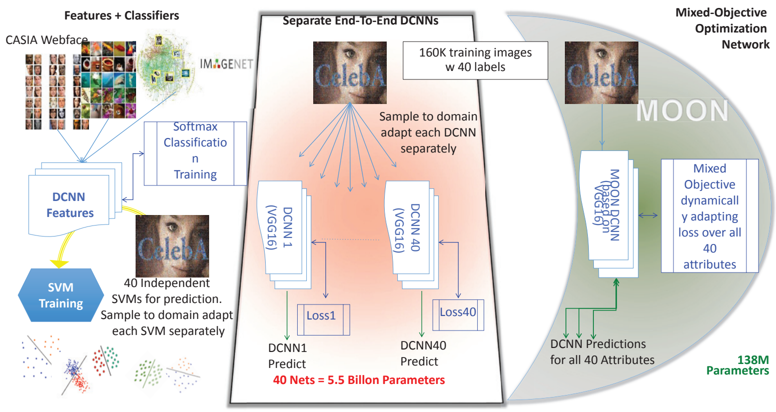
Overview

- Facial attributes have implicit latent correlations – which are naturally learnt through a multi-label approach.
- Due to demographic correlations, it is difficult to obtain a balanced multi-label facial attribute training set; thus a multi-label classifier trained for one demographic might perform poorly on another due to training set biases.
  - **CelebA**, for example, contains images of celebrities where **Young** is over-represented and anti-correlated attributes like **Bald** and **Gray Hair** are under-represented.



Our Approach

- Idea: Backpropagate multi-label Euclidean loss, weighting frequency discrepancy between source distribution S_i and target distribution T_i.
- Given binary labels $\{+1, -1\}$, let S_i^+ and S_i^- be the number of occurrences in the source distribution and T_i^+ and T_i^- be the number of occurrences in the target distribution.
- The domain adaptive weights for each class then become:

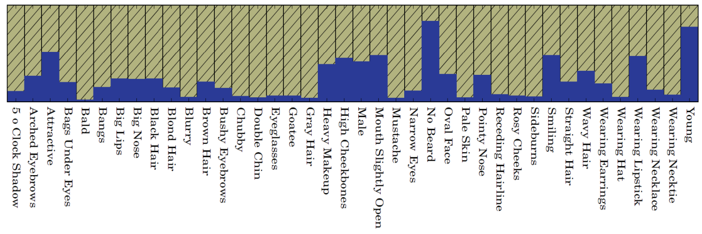
$$P(i|+1) = \begin{cases} 1 & \text{if } T_i^+ > S_i^+ \\ \frac{S_i^- T_i^+}{S_i^+ T_i^-} & \text{otherwise} \end{cases} \text{ and } P(i|-1) = \begin{cases} 1 & \text{if } T_i^- > S_i^- \\ \frac{S_i^+ T_i^-}{S_i^- T_i^+} & \text{otherwise.} \end{cases}$$

- The **mixed-objective Euclidean loss function** across an N-sample data tensor $\boldsymbol{X}$ with $N \times M$ label matrix $\boldsymbol{Y}$ and classification output $f(\cdot)$ is then:

$$L(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{j=1}^{N} \sum_{i=1}^{M} P(i|\boldsymbol{Y}_{ji}) \left\| f_i(\boldsymbol{X}_j) - \boldsymbol{Y}_{ji} \right\|^2 .$$

- Using the CelebA training partition, we trained a VGG-16 base architecture, replacing the final layer with our mixed-objective loss function.

Label Bias of the CelebA Dataset

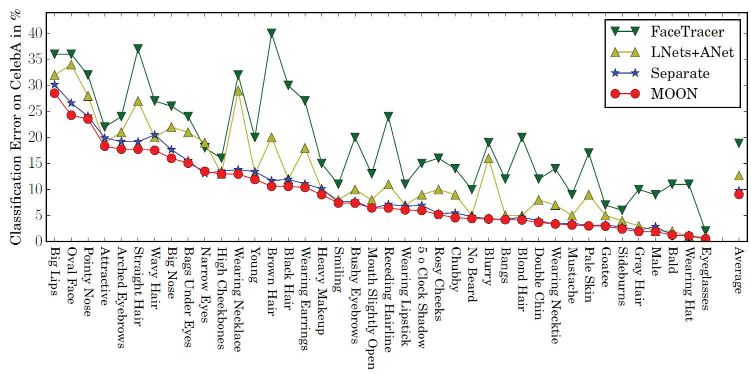


Approaches to the Balancing Problem

- **Features + Classifiers (FaceTracer, LNets+ANet):** Derive a feature space from non-attribute face data with attribute classifiers trained in that feature space.
  - \+ Easy to balance. Requires less training data.
  - \- Assumes that attribute related features will be implicitly embedded in the feature space with no explicit guidance.
- **Separate End-To-End DCNNs (Separate):** Train one network per attribute label; hope that the network learns correlations between attributes without explicitly optimizing to that end.
  - \+ More accurate.
  - \- Leads to a huge representation. Requires more data.
- **Mixed-Objective Optimization Network (MOON):** Combine the objectives of multi-label optimization with re-balancing under a domain-adaptive **mixed objective function.**
  - \+ Most accurate. Allows for a compact, domain-adaptive, multi-label representation.
  - \- Requires a new approach to balancing (this work).

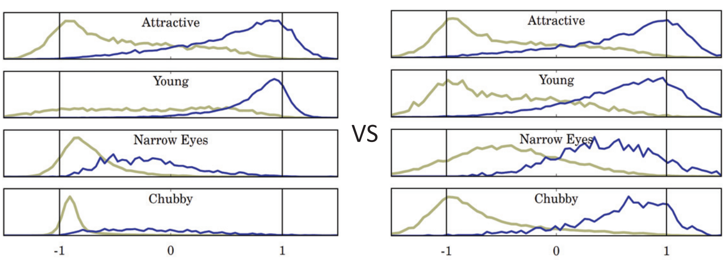
Evaluation: CelebA Dataset Un-Balanced

- For evaluation on the same dataset, we assume that $S_i \cong T_i$.
- MOON advances the state of the art over the Features+Classifiers approach with a relative reduction in classification error of 28.7%.
- Our approach also outperforms separate end-to-end networks of the same topology.



Re-Balanced CelebA: CelebAB

- Re-balancing the classifier to a uniform target distribution yields a shift in output scores distributions.



- Underperforms the unbalanced classifier on the unbalanced CelebA evaluation protocol but still advances the state of the art.
- Outperforms the unbalanced classifier when adapting the classification error measure to the target domain, i.e.:

$$E_i^B(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{j=1}^{N_{test}} \begin{cases} \dfrac{e_i(X_j, Y_{ji}) T_i^+}{N_i^+} & \text{if } Y_{ji} = +1 \\ \dfrac{e_i(X_j, Y_{ji}) T_i^+}{N_i^-} & \text{if } Y_{ji} = -1. \end{cases}$$

- Rebalancing yields superior attribute-based verification rates on the LFW dataset.