Summary of Feature Transfer Learning for Face Recognition with Under-Represented Data and Practical Full Resolution Learned Lossless Image Compression

*Deep Learning Assignement

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I. Summary of Feature Transfer Learning for Face Recognition with Under-Represented Data

Face recognition is successful in deep learning. It requires a large data to improve its results. Insufficient data set leads to biased classifier in conventionally trained deep networks. There is a large set of data that is Under Represented. Only few samples are available for each class. Simply discarding Under Represented classes will cause insufficient training data.The inherently uneven sampling leads to bias in the weight norm distribution across regular and UR classes. UR classes at a higher frequency alleviates the problem, but still leads to biased decision boundaries due to insufficient intraclass variance in UR classes.This paper proposes a novel feature transfer approach for deep face recognition training which explores the imbalance issue with UR classes. By applying the proposed feature transfer approach, we en-rich the feature space of the UR classes, while retaining identity. A center-based feature transfer algorithm is used to enrich the distribution of UR classes, leading to diversity without sacrificing volume. It also leads to an effective disentanglement of identity and nonidentity representations. New samples of UR classes are generated at feature space, by transferring the linear combination of the principal components of variance that are estimated from regular classes to the UR classes. Feature transfer addresses the issue of imbalanced training data. Using the transferred data directly for training is suboptimal as the transfer might skew the class distributions. Thus a two-stage alternative training scheme is adapted to achieve a less biased classifier and retain discriminative power of the feature representation. A simple but effective metric regularization to enhance performance for both our method and baselines is proposed which is also applicable to other recognition tasks. To study the empirical properties of our method, a UR datasets was constructed by limiting the number of samples for various proportions of classes and evaluate and the hold-out test set. We observe that our FTL consistently improves upon baseline method that does not specifically handle UR classes. Feature transfer module was visualised through smooth feature interpolation. It showed that for our feature representation, identity is preserved while non-identity aspects were successfully disentangled and transferred to the target subject. Extensive ablation experiments demonstrated the effectiveness of our FTL framework. Most recent success in deep face recognition works on novel losses or regularizations, which aim at improving model generalization. In contrast, this method focuses on enlarging intra-class variance of UR classes by transferring knowledge from regular classes. At first glance, our goal of diversifying features seems to contradict with the general premise of face recognition frameworks, i.e., pursuing compact features. In fact, this enlarge the intra-class variance of UR classes at a lower level feature space, which is rich-feature layer. The subsequent filtering layers will learn a more discriminative representation. m-L2reg-ularization was proposed which demonstrates consistent advantages which can potentially boost performance across different recognition tasks. The disentangled nature of the augmented featurespace is visualized through smooth interpolations. Experiments consistently show that our method can learn better presentations to improve the performance on regular,UR,and unseen classes.

II. Summary of Practical Full Resolution Learned Lossless Image Compression

The goal of lossless image compression is to represent an image signal with the smallest possible number of bits without loss of any information, thereby speeding up transmission and minimizing storage requirements. This paper proposed the first practical learned lossless image compression system, L3C, and show that it outperforms the popular engineered codecs, PNG, WebP and JPEG2000. In this system is based on a hierarchy of fully parallel learned feature extractors and predictors which are trained jointly for the compression task. The role of the feature extractors is to build an auxiliary hierarchical feature representation which helps the predictors to model both the image and the auxiliary features themselves. To encode an image x, it is fed through the S feature extractors E (s) and predictors D (s) . Then predictions of the probability distributions p is obtained for both x and the auxiliary features z (s) , in parallel in a single forward pass. These predictions are then used with an adaptive arithmetic encoder to obtain a compressed bitstream of both x and the auxiliary features. Types of lossless compression: Arithmetic coding: It is an entropy encoding technique, in which the frequently seen symbols are encoded with fewer bits than lesser seen symbols. It has some advantages over well-known techniques such as Huffman coding. Adaptive arithmetic coding Cross Entropy Fully parallel hierarchical probabilistic model with auxiliary feature representations was evaluated. In this L3C model outperforms PNG, JPEG2000 and WebP on all datasets. It was observed that it significantly outperformed the RGB Shared and RGB baselines which rely on predefined heuristic feature representations, showing that learning the representations is crucial. Additionally, it was observed that using PixelCNN-based methods for losslessly compressing full resolution images takes two to five orders of magnitude longer than L3C.