A Flatter Loss for Bias Mitigation in Cross-dataset Facial Age Estimation

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Abstract—Existing studies in facial age estimation have mostly focused on intra-database protocols that assume training and test images captured under similar conditions. However, this is rarely valid in practical applications, where training and test sets usually have different characteristics. In this paper, we advocate a cross-dataset protocol for age estimation benchmarking. In order to improve the cross-dataset age estimation performance, we mitigate the inherent bias caused by the learning algorithm itself. To this end, we propose a novel loss function that is more effective for neural network training. The relative smoothness of the proposed loss function is its advantage with regards to the optimisation process performed by stochastic gradient descent. Its lower gradient, compared with existing loss functions, facilitates the discovery of and convergence to a better optimum, and consequently a better generalisation. The cross-dataset experimental results demonstrate the superiority of the proposed method over the state-of-the-art algorithms in terms of accuracy and generalisation capability.

I. INTRODUCTION

With the emergence of Deep Neural Networks (DNN), age estimation systems have now shown much more promising performance. However, most existing DNN-based studies focus on intra-dataset evaluation protocols, which assume that all the images used in the training and evaluation stages are captured under similar conditions. In practical scenarios, we are interested in cross-dataset age estimation, where the test and training sets have different distributions and characteristics. A comparative illustration of the cross-dataset and intra-dataset concepts is shown in Fig. 1. Compared with the intra-dataset evaluation, the accuracy of an age estimation algorithm is significantly degraded for the cross-dataset evaluation. A more subtle aspect of the age estimation problem requires the trained model to accurately estimate the age of a face image under cross-dataset scenarios. However, this aspect of cross-dataset evaluation has not been well investigated by the community.

There are many factors, such as gene, gender, ethnicity, illumination conditions, image quality, makeup, lifestyle, cosmetic surgery, etc., which may confound the training process [1]. Since a neural network efficiently learns data distribution, a network is likely to learn the influence of these confounding factors and bias present in the data instead of actual discriminative cues. In this situation, the model performs best with data being similar to that used to train the model itself, not that collected in unseen conditions. This motivates us to design models with better generalisation capability.

One way to address the generalisation power is to ensure there exist roughly the same number of samples from each factor during the training stage. This may involve heavy data augmentation [2] and/or collecting images for significantly underrepresented or removing some images from the more dominant factors to re-establish a balance. However, this can prove to be a challenge as many of the ageing datasets are not annotated with these factors. On the other hand, it is a cumbersome task to account for all possible factors when curating large-scale datasets or using data augmentation techniques. Moreover, ageing data is relatively scarce and expensive to generate. The cross dataset testing could also be formulated as a domain adaptation problem [2]. In this approach, one needs a prior knowledge or a subset of images from the new domain so that a mapping between the original domain and the target domain can be determined. However, in many scenarios, such an approach leads to the generalisation of the trained model in a few domains. It may not be appropriate for the age estimation problem. It is important that the age estimation system performs well on any input image from any domain. On the other hand, it is an expensive task to account for all possible domains. Beside that, there exists another limitation with domain adaptation approaches. At the test stage, there is no knowledge about the domain which the tested subject falls into and it needs a discriminator to determine which model (original model or domain-shifted model) should be used to estimate the subject’s age.

These limitations call for designing alternative schemes to exhibit good generalisation properties. They provide the motivation to develop a learning framework that can render
an age estimation solution which is more domain invariant than existing methods. The design of machine learning systems involves the optimisation of a loss function. The choice of a loss function impacts on the systemic bias of the trained system. On the other hand, ageing datasets usually contain inadequate and unbalanced training data which introduces a dataset bias into the model. These two kinds of biases confute each other with the consequence that training on a deficient training set with an inappropriate loss function may result in the trained system having a severe bias, leading to a poor performance in unseen scenarios. Diversifying data is certainly one step to alleviate the dataset bias, as it would allow for more globalised inputs. But no amount of data diversification will guarantee good generalisation performance of the model, if the training process itself exhibits inherent (systemic) bias.

In order to improve the generalisation performance, we need to mitigate the dataset bias together with the systemic bias. In this study, we only consider the systematic bias and mitigate it by proposing a novel loss function. The relative flatness of the proposed loss function limits the systemic bias of the learnt model and improves the generalisation capability of the trained model in unseen (cross-dataset) scenarios. Its lower gradient facilitates the discovery of and convergence to a better optimum, and consequently a better generalisation. We stress that developing a useful machine learning model, which is robust to both, the systemic and dataset biases, is left as a future work. Finally, we introduce a novel subject-exclusive cross-dataset evaluation protocol. The proposed loss function is evaluated and compared with state-of-the-art methods on several challenging benchmarks under the proposed cross-dataset protocol. The experiments demonstrate that the proposed loss function achieves state-of-the-art results on this protocol.

II. RELATED WORK

With the success of novel machine learning methods, and specifically deep learning, in wide variety of fields [2]–[8], [16], [25], the research focus has shifted towards learning discriminative features by training a deep neural network end-to-end on a labelled dataset [10]. In the age estimation area, these end-to-end approaches can be categorised into four major groups, namely regression, ranking, classification and label distribution based methods. Regression-based algorithms [22], [25] make the problem definition intuitive by treating age labels as real and continuous values. Classification-based methods [15], [27], [29], [33], [42] cast age estimation as a multi-class classification problem. To consider the ordinal relationship among age labels, ranking-based methods [12], [13], [40] and label distribution learning-based methods [17]–[19], [24], [15], [16] have been proposed. The former employ the latter make use of the correlation among adjacent ages by adopting the concept of label distribution. These two formulations are at the core of many methods in the literature. A recent study [18] proves that the ranking and label distribution learning based algorithms have a linear relationship and so their age estimation performance are near to each other. However, the label distribution learning based methods are more stable during training. In the existing label distribution learning based methods, the KL divergence is widely employed as the loss function to measure the similarity between the estimated age distribution and ground-truth [18], [24]. Most these studies adopt the intra-dataset evaluation to show the performance of the proposed methods. Different from the exiting work, we propose a novel loss function and evaluate our system under the cross-dataset setting which is more challenging.

III. THE PROPOSED METHOD

In this section, we first analyse the limitations of the widely-used loss functions in the DNN-based age estimation algorithms. Then we present a new Distribution Cognisant (DC) loss and discuss the characteristics of the proposed DC loss.

A. Problem Formulation

Let \( S = \{ (x_n, y_n), n = 1, \ldots, N \} \) denote a set of training samples, where \( x_n \) represents the \( n \)-th training image and \( y_n \in [1, L] \) is the corresponding age label. The aim of an age estimation algorithm is to find a mapping function from the image space to the age label space. To this end, a typical method is the one-hot strategy in which a binary vector \( s = [s_1, \ldots, s_L]^T \in \mathbb{R}^L \) is assigned to the age label. If a face image belongs to the \( i \)-th age label, the \( i \)-th element in \( s \), i.e. \( s_i \) equals 1, otherwise \( s_i = 0 \). This kind of label encoding models the age estimation problem as a multi-class classification problem.

There is a strong visual semantic correlation among the face images of nearby ages, e.g., a person at age 30, 31 and 32 may have very similar facial features that are difficult to distinguish. By formulating the age estimation problem as a classification problem, this semantic correlation is ignored, leading to an inconsistency during DNN training. Therefore, a network trained with the one-hot age labels has difficulty to separate visually similar face samples that have different age labels. This inconsistency is even evident from the training loss curve of the classification formulation (cf. Fig. 7b DEX, in red colour). This problem has been partially addressed by using label distribution concept [19], in which a set of degrees \( q = [q_1, \ldots, q_L]^T \in \mathbb{R}^L \) is assigned to each label \( y \), where \( q_i \in [0, 1] \) and \( \sum_{i=1}^{L} q_i = 1 \). Each \( q_i \) can be considered as the probability that a face sample \( x \) is associated with the age label \( i \). Fig. 2 shows an instance at age 25 and its corresponding label distribution.

Now, the goal is to learn the mapping function that projects a face image to its corresponding label distribution \( q \). In this paper, we follow the distribution learning approach and, similar to [17], [19], a Gaussian distribution, centred at \( y \) with a standard deviation \( \sigma \), is considered for each label, where the shape (width) of the distribution at each age is controlled by \( \sigma \). We consider a constant value of \( \sigma = 2 \) at all ages.


B. Existing Loss Functions

The main goal of a learning algorithm is to minimise the distance between the estimated and ground-truth labels. The Cross Entropy (CE) loss function and Kullback–Leibler (KL) divergence have been widely used for training a DNN-based age estimation system with one-hot labels and label distributions, respectively. In this section, we theoretically analyse these loss functions and pinpoint their limitations in DNN-based age estimation.

CE loss: The CE loss is the most popular loss function for training a DNN with one-hot encoded age labels [33]. This loss assumes that the classes are independent. Consequently, the network ignores the label correlations, which are very informative for the age estimation problem. To alleviate this issue, Pan et al. [29] propose to use CE loss jointly with the mean and variance (MV) terms by considering the semantic correlation among age labels. The CE-MV loss is defined as:

\[
L_{CE-MV}(p, y) = -\log p_i + \lambda_1 (\mu_i - y)^2 + \lambda_2 \sigma_i^2,
\]

where \(\lambda_1\) and \(\lambda_2\) are regularisation parameters, \(\mu_i\) and \(\sigma_i^2\) are the mean and the variance of the estimated distribution \(p\). The second term (mean) penalises the difference between the mean of the estimated label distribution, \(\mu_i\), and the ground-truth age label \(y\). The third term (variance) minimises the standard deviation of the estimated age distribution, \(\sigma_i^2\). The general issue associated with the CE-MV loss is its instability due to the regularisation terms that are very sensitive to outliers in network training. An outlier leads to a large error with very large gradients. So, the convergence of the network training with the CE-MV loss is problematic.

KL loss: The KL divergence is a popular loss function for network training when age labels are encoded as label distributions [17], [20]. The KL loss is defined as:

\[
L_{KL}(p, q) = \sum_i q_i \log(q_i/p_i),
\]

where \(p\) and \(q\) are the estimated and ground-truth distributions. The lower the loss value, the better \(p\) matches \(q\). If two distributions perfectly match, \(L_{KL}(p, q) = 0\); otherwise, it takes positive values between 0 and \(\infty\).

One crucial issue of the KL loss is its asymmetric nature, i.e., \(L_{KL}(p, q) \neq L_{KL}(q, p)\). If \(q_i\) is greater than \(p_i\), the ratio \(r_i = q_i/p_i\) produces positive values. On the other hand, if \(q_i\) is smaller than \(p_i\), it leads to negative values for the ratio. As depicted in Fig. 3, this makes the matching process performs non-uniformly over the age range. For instance, points A and B in Fig. 3 have equal distance between two distributions, but the values of \(r_i\) are different. Thus, the contribution to the total error is more significant when \(q_i\) is greater than \(p_i\). That means the point A contributes more to the total error than the point B. After the minimisation of the distance via KL loss, a better fit of \(p_i\) to \(q_i\) is expected where \(q_i\) is greater than \(p_i\).

Another issue of the KL loss is the update rule of network parameters in back-propagation. With the chain rule, the derivative of the KL loss with respect to \(z\) can be obtained:

\[
\frac{\partial L_{KL}}{\partial z_i} = \frac{p_i - q_i}{q_i},
\]

where \(q_i\) is greater than \(p_i\). That is clear that the update of network parameters depends on the difference of the corresponding target bins, i.e., \(p_i - q_i\), irrespective of the contribution of the other bins. Ignoring the contribution of the other bins in network update renders the optimisation less robust.

C. Distribution Cognisant (DC) Loss

Consider a network with parameters \(\theta\). Its output for an input image \(x\) is \(z = f^{\theta}(x)\). Assume the last layer of the network is followed by a softmax layer. Therefore, the vector \(z\) is collapsed into a probability distribution form \(p\) where \(p_i = \exp(z_i)/\sum_k \exp(z_k)\) denotes the probability that sample \(x\) belongs to class \(i\). We define the proposed DC Loss as:

\[
L_{DC} = \log(1 - \alpha(1 - \sum_{k=1}^b \sqrt{p_k q_k}))/\log(1 - \alpha)
\]

where \(\alpha\) is the loss parameter satisfying \(0 < \alpha < 1\). Here, we should note that our DC loss approaches the Matusita’s divergence [11] when \(\alpha \to 0\). As will be discussed later, the best performance is achieved when \(\alpha\) gets a very small value near to 0. Instead, one can use the Matusita’s divergence formula as the loss function.

Compared with the exiting loss functions, the DC loss function avoids the problems discussed in Sec. III-B and has the advantage of being a more robust measure of difference of
two distributions. Our choice of the DC loss for age estimation is motivated by its desirable properties as follows.

I. Our DC loss is symmetric and bounded in the interval $[0, 1]$ for any value of $\alpha$. Due to these properties, as shown in Fig. 5, the behaviour of the matching process is uniform over the whole age range.

II. Our DC loss avoids the singularity problem that occurs when comparing points of distributions when $p_i$ is a non-zero value and $q_i \to 0$.

III. Based on the chain rule, the derivative of our DC loss with respect to $z$ is $\frac{\partial L_{DC}}{\partial z_i} = K(\sqrt{p_i q_i} - p_i \sum_{k=1}^L \sqrt{p_k q_k})/(1 - \alpha((1 - \sum_{k=1}^L \sqrt{p_k q_k}))$, where $K = \alpha \log e/2 \log(1 - \alpha)$. As can be seen, the update rule of the network parameters depends on all the entries of $p$. This is more robust than the KL loss function, where the update rule depends only on the difference of the corresponding target bins, i.e., $p_i - q_i$.

D. Mitigation of Bias

The relatively good performance of our loss function in unseenscenarios owes to its ability to limit the systemic bias of the learnt solution by a careful choice of the loss function properties. In fact, our loss function provides more appropriate control over the search space and thus obtains a closer model to the one that would work perfectly on any test set. In the following, we derive a theoretical analysis on the generalisation performance of deep neural networks. Here, we make use of a novel result due to the recent theoretical efforts on analysing the generalisation error [34], [39] to show the enhanced prospects of improved generalisation for a model trained with the proposed loss function.

In this paper, the goal is to learn a model $f^0 : X \to \mathcal{Q}$, described by parameters $\theta \in \mathcal{H}$, between the input space $X$ and its corresponding output space $\mathcal{Q}$. A common setting of such a learning algorithm is defined as

$$\arg\min_{\theta \in \mathcal{H}} \mathbb{E}_{s \sim D}[\ell(f^0(s))],$$

where it seeks a model $f^0$ over some hypothesis space $\mathcal{F}$ that minimises the true (expected) risk $R_{\mathcal{D}}(f^0) \equiv \mathbb{E}_{s \sim D}[\ell(f^0(s))]$ with respect to sample $s = (x, q) \in \mathcal{X} \times \mathcal{Q}$, drawn according to an unknown distribution $D$. $\ell : \mathcal{Q} \times \mathcal{Q} \to \mathbb{R}^+$ is the loss function which measures the accuracy of a hypothesis $f^0$ based on the discrepancy between the predicted and real outputs.

Since the distribution $D$ is unknown, the minimisation problem cannot be solved directly. Instead, the true risk $R_{\mathcal{D}}(f^0)$ is estimated with the empirical risk over a training set. Consider a finite set of $N$ training samples $S = \{s_n, n = 1, 2, \ldots, N\}$, where $s_n = (x_n, q_n)$, i.i.d. sampled according to an unknown distribution $D$. The empirical risk is then defined as $R_{\mathcal{D}}(f^0) \equiv \frac{1}{N} \sum_{n=1}^N \ell(f^0; s_n)$. Given a training set $S$, the generalisation error of the output model $f^0$, trained using the learning algorithm $\mathcal{A}$ on $S$, is the difference between the empirical and true risk, i.e., $E(S) = R_{\mathcal{D}}(f^0) - R_{\mathcal{D}}(f^0)$. Recently, Seong et al. [34] proved that the generalisation error can be upper-bounded as a function related directly to the smoothness of the loss function with respect to changes on the loss surface. Based on this, they present a new result which uncovers the relation between robustness and generalisation of the learning algorithm, being suitable for analysing the performance of neural networks with respect to the employed loss function. This assertion is stated as follows: If the loss surface is smoother, then it is more likely the model output by the learning algorithm to generalise better.

The main significance of this theoretical result, motivating our work, is that by choosing the loss function carefully, we can achieve a tighter bound on the generalisation error. To illustrate the favourable properties of our loss function, consider one ground-truth distribution labelling the age of 50 years old. By randomly shifting the ground-truth distribution and adding a uniform noise to the shifted distributions, we generate 1000 distributions. We consider these distributions as simulating the estimated output label distribution of DNN after the softmax layer. Fig. 4 shows the gradient of the proposed and KL loss functions for the 1000 samples with respect to $i$-th output of the last FC layer i.e. $\frac{\partial L}{\partial z_i}$. As can be seen, the magnitude of gradient of our loss function is always smaller than that of the KL divergence. This shows that a tighter bound for the robustness will be obtained by the model trained by our loss function, compared with that learned by the KL divergence. As a result, its lower gradient, compared to that of the KL loss function, facilitates the discovery of and convergence to a better optimum, and consequently a better generalisation.
IV. SUBJECT-EXCLUSIVE CROSS-DATASET EVALUATION PROTOCOL

The existing approaches to age estimation commonly follow intra-dataset evaluation protocols, where the training and test sets come from the same dataset. For instance, in the random splitting protocol, 80% images of a dataset are randomly selected for training and the rest is used for evaluation. If all images in the dataset were captured under the same shooting situations, the trained model might be biased to the target dataset and provide unreliable information about its performance in unseen scenarios. This is the case with MORPH [32] and FG-NET [30] datasets which are widely used in the age estimation literature. In many real-world scenarios, the test and training sets have different distributions and characteristics. Therefore, adopting the intra-dataset evaluation protocols does not provide meaningful information for a fair evaluation on the generalisation performance of an age estimation algorithm.

In this paper, we introduce a novel age estimation evaluation protocol, called subject-exclusive cross-dataset evaluation protocol, which provides more meaningful information for evaluating an age estimation algorithm. The main constraint in this protocol is: the trained model should be completely blind to the characteristics and shooting conditions of the target dataset. It means no image from the target dataset should be used for training the network. In addition, there should be no overlap of the sets of subjects in the training and target datasets. Note that this is different from the intra-dataset protocols, such as random splitting and subject-exclusive protocols [29], where the test images are selected from the same dataset. Under the proposed conditions, the generalisation capability of the trained model can be evaluated more reliably. To the best of our knowledge, we are the first to benchmark the performance of various age estimation systems under the subject-exclusive cross-dataset protocol.

V. EXPERIMENTAL RESULTS

We implement the proposed DC loss using Matlab powered by MatConvNet [38]. We use two evaluation metrics, Mean Absolute Error (MAE) and Cumulative Score (CS) [22], for benchmarking the performance of an algorithm. The MAE is calculated by averaging the error over the test data as \[ \frac{1}{K} \sum_{k=1}^{K} |y_k - \hat{y}_k|, \] where \(K\) is the total number of test images. The estimation accuracy is also given by the CS measure which is calculated as \[ \frac{K_{\hat{y}}}{K} \times 100\%, \] where \(K_{\hat{y}}\) is the number of the images whose \(|y_k - \hat{y}_k| < 1\). In this paper, \(I\) is set as 5.

The pre-trained VGG model [31] is used as the backbone to the proposed age estimator. The batch size, momentum and weight decay are set to 80, 0.9 and 0.0005. The learning rate decreases exponentially (with the exponential growth – 1) for 30 epochs in total from 0.001 to 0.000001. Random flipping, cropping and colour jittering are employed as data augmentation techniques during network training. All the images are aligned by using 5 facial landmarks detected by MTCNN [43]. Each face image is resized to \(256 \times 256\) after alignment. At the inference step, the predicted age is obtained by taking the most probable value in the estimated age distribution \(\mathbf{p}\), as \(\hat{y} = \text{argmax}_i p_i\).

A. The Training and Test Datasets

The well-known IMDB-WIKI dataset, introduced by Rothe et al. [33], is one of the largest age datasets, including 523,051 images, with age labels ranging from 0 to 100. However, there are many images with wrong labels in this dataset which are inappropriate for training age estimation systems. Recently, a cleaned version of the IMDB-WIKI dataset was introduced by Zhang et al. [42]. Commencing with this version, we cleaned the dataset more carefully in a semi-supervised approach and removed the following images from the dataset: 1) The multi-person images, since there is one age label for each image. 2) The images which the face detector has a confidence score lower than a certain threshold for the detected face. Then, we checked the remaining images one by one and removed all the low-quality images and also images with wrong labels. This results in a cleaned dataset with 155,764 images.

In addition, we collected a new in-the-wild set of 23,876 facial images of people with ages over 70 years old and younger than 20 years old. These images were crawled from Internet by searching the years as keywords on the Google Images. A human annotator got involved to further clean this small dataset carefully by checking each image separately. We mixed the cleaned IMDB-WIKI dataset with the two other existing facial datasets, namely AgeDB and UTKFace [39] and also our crawled collections to create a new large-scale dataset, called Balanced-Age (BAG) dataset, including 200,123 images. In contrast to the existing age datasets, the BAG dataset is more balanced across different ages. The distribution of different databases are shown in Fig. [5]. In contrast to the existing aging databases, the BAG database is not only large scale but also more balanced across different ages. For instance, there are over 20K images with age labels over 70 years-old or younger than 20 years-old. Looking at the Fig. [5] FACES database may look a bit more balanced but it has only 2052 samples. Moreover, the ages between 0 and 19 and 80 and 100 are not present at all.

The performance of our system is evaluated on five benchmarking datasets: MORPH Album II [32], FG-NET [30], FACES [14], SC-FACE [21] and our newly created BAG dataset. Fig. [6] shows some exemplar images of each database. MORPH dataset is a collection of 55,134 images from different races in the age range from 16 to 77 years old. FG-NET dataset contains 1,002 images in the age range from 0 to 69 years old. The FG-NET dataset is challenging due to the large variation in pose, expression and lighting conditions. FACES dataset has 2052 images with different expressions in the age range from 19 to 80 years old. SC-FACE dataset contains 4160 images with different quality and head pose in the age range from 21 to 75 years old.

\[1\] The AgeDB [28] and UTkFace [44] datasets are collections of 16,488 and 21,374 facial images, respectively.

\[2\] Our BAG database and trained models are available in https://github.com/Alien84/Cross-Database-Age-Estimation/
We separate this dataset into two small datasets, namely ROT and SC-FACE-SUR datasets. SC-FACE-ROT subset contains high quality images with different head pose. SC-FACE-SUR subset contains images captured using one high resolution, one infrared camera and five surveillance cameras with different qualities at different distances.

B. Cross-dataset Evaluation

The performance is compared with the well-known classification based age estimation method proposed by Rothe et al. [13], where the labels are one-hot encoded and CE is used as the loss function for training the network. We also evaluate the performance of the DNN by adopting the KL divergence as the loss function, as done in [17]. The results are also compared with three further state-of-the-algorithms, i.e. CE-MV [29], AEn [37] and DDL-v2 [18]. CE-MV and AEn are the enhanced versions of the CE-based loss function and DDL-v2 is the improved version of KL-based loss function. For a fair comparison, we implemented all these approaches and trained the models on our BAG dataset with the same network architecture and settings, including pre-processing steps and data augmentation techniques. Additionally, the performance of the proposed scheme is compared with the best available commercial API, i.e. Microsoft.

Table I reports the results on the evaluation datasets. We can see that the age estimation accuracy of the KL loss function is higher than that of CE loss function. This indicates that utilising label distribution is helpful to improve the age estimation performance. Consequently, it can be inferred from Table I that adopting the proposed loss function for the network training leads to the significantly higher prediction accuracy than that achieved by the other loss functions. It is evident that the proposed method has a good generalisation ability in the cross-dataset testing which deals with unseen scenarios. It should be again emphasised that the competing methods, i.e. CE-MV, uses the regularisation terms jointly with the CE and KL loss functions, respectively. Due to the different scales of these regularisation terms, training the network is sensitive to the choice of these regularisation parameters. As a positive point, our proposed loss function is free from any regularisation hyper-parameter and effectively alleviates this issue, delivering superior performance in age prediction.

The performance comparison on the FACES dataset is noteworthy. Our method cannot outperform DDL-v2 in the presence of facial expressions. However, the performance is very close to DDL-v2 which is the best among existing age estimation algorithms. On the other hand, the performance of our method is significantly better than state-of-the-arts on the SC-FACE-ROT dataset, which has faces with different head poses. More interestingly, the performance of our age estimation is less sensitive to the image quality than the state-of-the-art methods, when comparing the results on the SC-FACE-SUR dataset.

C. Discussions

1) Cross-dataset vs. intra-dataset settings: Here, we should emphasise that the performance of age estimation systems under the intra-dataset protocols is much higher than the performance under the cross-dataset protocol. For instance, the state-of-the-art approaches [18], [29] and the proposed DC loss achieve the MAE around 2 years for the intra-dataset evaluation (random-splitting protocol) on the MORPH dataset. However, Table I shows that we could get the MAE around 4.63 years old for the cross-dataset evaluation on the MORPH dataset. Thus, achieving a high age estimation accuracy in the intra-dataset evaluation does not guarantee a good performance under cross-dataset scenarios. This confirms that the intra-dataset evaluation protocols cannot truly assess the generalisation performance of age estimation systems. Obviously, unseen situations lead to a performance degradation of these estimation methods due to the uncontrolled environment which is manifest in changes in lighting, variations in the pose of the subject and in expression of the face, etc. However, our method still provides the lowest MAEs and CS scores among these approaches for both cross-dataset and intra-dataset scenarios.

2) Sensitivity to Hyper-parameters: The only hyperparameter in our proposed loss function is the parameter $\alpha$. We evaluate the influence of the parameter $\alpha$ on age estimation. We change the value of $\alpha$ in the range (0, 1) and train the VGG model on a subset of 50K images from the BAG dataset. MAE of the trained model for each value of $\alpha$ on the FG-NET dataset is shown in Fig. 7a. Our analysis shows that the performance of age estimation is not sensitive to $\alpha$ when $\alpha$ is less than 0.2 and the performance degrades when using large values of $\alpha$.

3) Over-fitting Analysis: In order to illustrate the learning behaviour of the proposed method, the VGG model is trained using different approaches on a subset of 50K images from BAG and evaluated on the validation dataset. 90% images of this dataset are randomly selected for training and the rest is used for validation. Fig. 7b plots the loss function evolution computed on the validation set for different approaches. Since

![Histogram of Datasets](https://www.microsoft.com/cognitive-services/en-us/face-api/)
Fig. 6. Sample images from the BAG and evaluation databases.

### TABLE I

| Method       | FG-NET MAE CS (%) | MORPH MAE CS (%) | FACES MAE CS (%) | SC-FACE-ROT MAE CS (%) | SC-FACE-SUR MAE CS (%) | Average MAE CS (%) |
|--------------|-------------------|------------------|------------------|------------------------|------------------------|--------------------|
| Human [23]   | 4.70 69.5         | 6.30 51.0        | NA NA            | NA NA                  | NA NA                  | 5.50 60.25        |
| Microsoft    | 6.20 53.80        | 5.59 46.00       | 6.07 53.59       | 5.44 66.76             | 5.10 64.88            |
| CE [33]      | 3.20 82.14        | 5.50 60.34       | 5.13 63.12       | 5.25 63.93             | 4.96 66.01            |
| AGEn [37]    | 3.15 82.98        | 5.40 60.95       | 5.54 59.98       | 5.25 65.71             | 5.46 68.53            |
| KL [17]      | 3.08 83.83        | 5.27 62.43       | 5.72 66.76       | 5.46 65.71             | 4.90 71.27            |
| CE-MV [29]   | 3.07 83.23        | 5.22 61.31       | 5.62 69.88       | 5.13 69.98             | 5.48 69.75            |
| DLDL-v2 [18] | 3.06 82.83        | 4.95 64.95       | 4.39 71.00       | 4.90 71.27             | 4.50 70.95            |
| DC [ours]    | 2.93 84.43        | 4.63 66.03       | 4.47 69.88       | 4.72 71.19             | 4.78 71.75            | 4.30 72.65         |

Fig. 7. Ablation study: (a) the influence of $\alpha$ on age estimation accuracy; (b) validation curves (loss scores vs. epoch) of different approaches.

the loss values have different scales, we normalise the loss values to the range [0, 1]. The plots indicate the over-fitting problem is more severe for the CE and KL loss functions. The proposed approach significantly alleviates the over-fitting problems of other learning methods.

VI. CONCLUSION

In this work, we addressed the cross-dataset age estimation problem which is more demanding in practice. To take the inter-class relationships into account among age labels, we modelled the age estimation problem as a distribution learning problem by assigning a Gaussian label distribution to each face sample. For this purpose, we proposed a novel loss function and embedded it into a DNN architecture. Despite the existing loss functions, relative flatness of the proposed loss function limits the systemic bias of the learnt solution and improves the generalisation capability of the trained model in unseen (cross-dataset) scenarios. An extensive cross-dataset evaluation confirms the superiority of the proposed approach.

ACKNOWLEDGMENT

This work was supported in part by the EPSRC Programme Grant (FACER2VM) EP/N007743/1 and the EPSRC/dstl/MURI project EP/R018456/1.

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