Abstract

Deep metric learning is a technique used in a variety of discriminative tasks to achieve zero-shot, one-shot or few-shot learning. When applied, the system learns an embedding space where a non-parametric approach, such as K-nearest neighbor (KNN), can be used to discriminate features during test time. This work focuses on investigating to what extent feature information contained within this embedding space can be used to carry out sub-discrimination in the feature space. The study shows that within a discrimination embedding, the information on the salient attributes needed to solve the problem of sub-discrimination is saved within the embedding and that this inherent information can be used to carry out sub-discriminative tasks. To demonstrate this, an embedding designed initially to discriminate faces is used to differentiate several attributes such as gender, age and skin tone, without any additional training. The study is split into two study cases: intra class discrimination where all the embeddings took into consideration are from the same identity; and extra class discrimination where the embeddings represent different identities. After the study, it is shown that it is possible to infer common attributes to different identities. The system can also perform extra class sub-discrimination with
a high accuracy rate, notably 99.3%, 99.3% and 94.1% for gender, skin tone, and age, respectively. Intra class tests show more mixed results with more nuanced attributes like emotions not being reliably classified, while more distinct attributes such as thick-framed glasses and beards, achieving 97.2% and 95.8% accuracy, respectively.

Keywords: Machine learning, Unsupervised learning, Deep metric learning, Zero-shot learning, One-shot learning, N-shot learning.

1. Introduction

The field of machine learning has seen enormous growth in numerous application spaces due to the ability of machine learning models to out-perform traditional approaches. The success of deep learning in areas such as computer vision, natural language processing and speech recognition, has been principally due to the ability to leverage large amounts of data to develop models capable of meaningful representation. However, accessing large high-quality datasets is not always possible and the lack of such datasets can present a significant barrier to developing machine learning models. With this in mind, methods aimed at solving the problems associated with limited data availability have emerged, namely few-shot learning, one-shot learning and zero-shot learning. These methods of learning are commonly utilized in computer vision tasks, where employing an object categorization model still gives appropriate results even with zero, one or few training samples. These methods may use generative [1, 2] or discriminative models [3, 4, 5, 6] to achieve their goal. This work studies one of the most common discriminative approaches where a model generates a vector in a low dimensional space with the help of a similarity metric.

In order to achieve high accuracy in the discrimination task, the system creates a structure within the embedding space. This structure exhibits an intrinsic coherence which can be measured using a distance metric. An example of this intrinsic coherence can be seen in the dimensionality reduction technique developed in [7]. Here, the authors demonstrate a mapping test of horizontally
translated Modified National Institute of Standards and Technology (MNIST) digits to a 2D output manifold. The manifold exhibits clustering with respect to the translations despite the system not being trained to do so. This clustering can be viewed as a result of the intrinsic coherence produced when the system learns a representation of the input data.

The objective of this study is to determine whether the same intrinsic coherence applies to facial recognition embeddings. In addition, this work investigates whether this property can perform sub-discrimination on intra and extra class attributes by applying a form of Zero-shot learning (ZSL). The results of this study show that this intrinsic coherence is generally present in embeddings created by discriminative models and can be used to discriminate additional attributes contained in the input samples without any additional training and information.

This work provides an experimental study that uses embeddings created by a state-of-the-art model trained for face recognition to show how the intrinsic coherence of these embeddings can be used to discriminate a range of additional attributes. The attributes are split into extra and intra class. Extra class attributes are defined as distinguishable facial features between different identities such as age, gender and skin tone. Intra class attributes are distinguishable within a single identity, namely the presence of beards and glasses and the expression of different moods and emotions happy, angry, sad and neutral. The goal of this experimental study is to provide insight into the additional information contained within the embedding created for facial recognition. The main contributions of the study are:

- An insight into the presence and the hierarchy of attribute representation within embeddings created for facial recognition;

- A demonstration of the ability to use additional information to perform sub-discrimination on intra and extra class attributes using a form of zero-shot learning;

- A method to extract the additional information contained within the em-
beddings using a lightweight framework in order to accelerate the sub-discrimination process.

The rest of the paper is organized as follows: Section 2 provides background material and discussions on related work, such as N-shot learning and deep metric learning. Section 3 describes the experimental set-up for performing discriminative studies of embeddings from high accuracy models. Section 4 details the results and an evaluation of the study. Section 5 describes the application of the results to perform reliable sub-discrimination on unseen images. Finally, Section 6 discusses future work and Section 7 provides a conclusion.

2. Background

Recently, machine learning algorithms have contributed greatly to the development of object recognition tasks using convolutional neural networks (CNNs) [9, 10, 11]. The availability of large scale data volumes in recent times has led to image classification models that can recognize objects and generalize the image features at scale. However, in difficult classification settings where the number of classes is large, several constraints must be addressed to successfully implement effective image classification. Some of these constraints include an increasing number of object classes can increase the number of weights in a CNN, this consequently increases the model size which can inhibit the deployment of these large models on some devices. Class imbalance is another constraint which arises when there is a shortage of images per object class in the training set, this can lead to poorer accuracy in testing for the underrepresented classes. It is also often required to design image classification models which are adaptive to changes in certain ecosystems in which a new unseen class can be presented, thus requiring the retraining of the model to accommodate the new class.

A combination of deep learning and metric learning collectively known as deep metric learning (DML) [12] has been viewed as a way to alleviate the above constraints resulting in the development of robust, efficient object recognition.
models. The brief history between the unification of deep learning and distance metric learning is discussed below.

2.1. Distance Metric Learning

Distance metric learning has been established as a key branch of machine learning, comprehensive surveys of the area can be found here [13, 14]. The goal of metric learning is to provide a distance metric by analysing data. This new distance metric must possess the ability to measure the similarity between samples effectively [15]. The Mahalanobis distance metric is a commonly used distance metric in this regard. This metric has the property that, given a linear transformation from the original space to the low dimensional embedding space, the Euclidean distance in the transformed space is equal to the Mahalanobis distance in original space. When given two samples \( x_i \) and \( x_j \) and a linear transformation \( W \) that puts a sample \( x_i \) in the embedding space, it is possible to compute the Euclidean distance in that embedding space, see Equation 1:

\[
\begin{align*}
    d(x_i, x_j) &= \|Wx_i - Wx_j\| \\
    &= \sqrt{((x_i - x_j)WW(x_i - x_j))} \\
    &= \sqrt{((x_i - x_j)M(x_i - x_j))}
\end{align*}
\]

The last expression can be seen as the Mahalanobis distance in the domain of \( x_i \), where \( M \) is a symmetric semi-definite matrix and can represent a covariance. When working with linear metric learning the Mahalanobis distance metric is favourable as it allows convex optimization formulations and a robustness to over-fitting [16]. However, its representation capabilities over data are limited as most data, in reality, consist of non-linear features and the Mahalanobis distance is only effective for linearly separable data. In order to overcome this problem, kernel tricks [17] can be applied. Kernel tricks refer to a method which converts non-linear classification to linear classification. Kernel methods represent the data only through a set of pairwise similarity comparisons between the original data observations with the original coordinates in the lower dimensional space. This is in contrast to explicitly applying the transformations and representing the data by these transformed coordinates in the higher dimensional feature space.
space. These kernel tricks have a negative effect against over-fitting although, through the use of deep learning, these negative effects on over-fitting can be resolved.

2.2. Deep Metric Learning

Instead of using kernel tricks, the deep metric learning approach uses the non-linear activation functions of neural networks to solve the problem of non-linearity. Deep metric learning approaches have achieved exceptional results on various tasks ranging from face verification and recognition to three-dimensional (3D) modelling, a broad review of these studies can be seen in [13]. Specifically, with regards to image recognition it can be seen that on a number of hard fine-grained datasets [18] [19] [20] [21] where the examples are difficult to distinguish e.g. images of objects from the same class, deep metric learning classification can eclipse the state-of-the-art [22].

A deep metric learning system has three main components [23]: informative input sampling, network model and a metric loss function.

2.2.1. Informative Input Samples

In order to train a metric model, training pairs of similar/dissimilar samples are required. The correct choice of informative training samples is imperative to the model’s ability to generalize its representation to unseen data. It has been shown that some ‘easy’ samples do not benefit the training process while using hard negative samples can improve the training process significantly, [24] [25].

2.2.2. Network Model

Most traditional deep learning models can be applied to deep metric learning, and the choice of one model over other models relies deeply on the nature of the problem. However, all network architectures share a similarity in that they are based on the common weight sharing Siamese network architecture [26].

2.2.3. Metric Loss Function

Loss functions must have the ability to measure the similarity or differences

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1 Easy samples refer to samples which differ greatly from one another (cats and dogs). Hard negative samples refer to samples which are harder to differentiate (dogs and wolves).
between samples within the discrimination. Following the metric learning objective, these loss functions are minimized to allow objects of the same class to be close to one another and objects of different classes to be further apart. A popular used distance between samples in the embedding space is the L2 distance, other distances such as the cosine distance and L1 distance are also commonly used. There are a variety of mostly equivalent loss functions used for training, two commonly used loss functions are: contrastive divergence [7] and triplet loss [27]. For a review on a variety of loss functions see [23].

In summary, DML proposes to train a CNN based non-linear feature encoder that embeds the extracted features that are semantically similar, close to one another and maps dissimilar features further away from each other using an appropriate distance metric. Together with a discriminative classification algorithm such as KNN [28], the object recognition task can be performed using extracted image features without being conditioned about the number of classes. These features are also generalized enough for distinguishing new unseen classes. These properties of DML make it an ideal candidate for the solution of the zero-shot, one-shot, and few-shot learning problems, where a model is required to learn a new task from a small amount of new data and in some cases, to recognize a new class through the observation of unseen examples of that new class.

Aforementioned, non-parametric approaches such as KNN are commonly used to achieve class discrimination [27, 29, 30]. In most of the approaches such as [27, 30] there is an assumption that the category distribution is unimodal in the embedding space. Recently new approaches consider multi-modal mixtures, as can be seen in [22, 24]. This multi-modal behaviour illustrates that a hierarchical coherence is created within the embedding space. The purpose of this work is to study this embedding space in order to examine the hierarchical coherence within the embedding structure and use it to infer new discrimination abilities. Additionally, this inherent coherence makes metric learning an ideal method used to solve the problem of N-shot learning, where a model must learn
3. Experimental Study

In order to examine the inherent coherence within the embeddings created by DML models, this study uses embeddings created for facial recognition and applies clustering to demonstrate a hierarchy of representation within the embeddings and to perform sub-discrimination tasks.

3.1. Deep Metric Learning Model

The model chosen for the experiment is the dlib face recognition ResNet model v1 contained in the Dlib library [31]. This model was selected as it represents a state-of-the-art facial recognition model achieving an accuracy of 99.38% on the standard labeled faces in the Wild face recognition dataset [32]. The dlib face recognition ResNet model v1 is a CNN based on the ResNet 29 architecture [33]. The creator of the model trained it using approximately 3 million faces and 7485 individual identities, any overlap with the Labeled Faces in the Wild (LFW) dataset was avoided. The work of King [31] specifies that the datasets used to train the network include the Face Scrub dataset [34], the VGG dataset [6], and images sourced from the Internet. The model performs facial recognition by mapping images of faces to a 128-dimensional space where images of the same identity are mapped near to each other and images of different identities are mapped far apart in the new embedding space. King [31] states that the network training started with randomly initialized weights and used a metric loss function that tries to project all identities into non-overlapping clusters of distance threshold radius 0.6. When using a distance threshold of 0.6, the model received its highest accuracy of 99.38% on the standard LFW face recognition benchmark.

The facial recognition task can be achieved by applying a discriminative classification algorithm such as KNN onto the embeddings without being conditioned about the number of classes, or in our case the number of identities. Consequently, it is possible to perform facial recognition using only one example, achieving one-shot learning. For example, if you have 10 images of 10 different
identities, it is possible to classify the identity of a new unseen image of one of the 10 known identities. This can be achieved by using the KNN algorithm with the value of $k = 1$, which will assign the new unseen image to the class (or identity) of its single nearest neighbour. This is known as a one-shot learning solution as you only require one training sample of an identity to successfully classify an unseen image of that same identity. In contrast to using a discriminative classification algorithm for the discrimination task, feature sub-discrimination is achieved by applying an unsupervised machine learning algorithm such as K-Means to cluster the embeddings. K-Means will cluster the embeddings based on salient intra and extra class attributes should an inherent coherence exist within the structure of these facial recognition embeddings. Subsequently, it is shown that it is possible to successfully classify a person’s gender, skin tone and general age category through no additional retraining of the model. The ability to recognize objects or features in an image without any labeled training data to aid the classification task is known as zero-shot learning. As King’s model was explicitly trained to map similar identities close to one another and map dissimilar ones far apart, through this study’s adoption of the K-Means algorithm, it is possible to interpret the output in such a way that is possible to identify new class attributes that the model was not explicitly trained to classify. King’s model classifies identities, whereas this study’s interpretation of the output classifies intra and extra class attributes.

3.2. Experimental Procedure

To examine the inherent coherence a number of tests were undertaken to determine if embeddings generated by the model would cluster images based on specific attributes without any additional training of the model. For these tests, datasets with specific class attributes were manually created before investigating how accurately the K-Means algorithm can cluster the resulting embeddings based on attribute discrimination. The attributes used within the experiments are categorised as extra class and intra class. Extra class attributes are facial features which are distinguishable between different identities namely gender, skin tone and age. Intra class attributes are noted as facial features which are
distinguishable between one unique identity namely emotions, the presence and absence of beards, and the presence and absence of glasses. The images used for the test datasets were selected from the facial expressions dataset available from the Muxspace GitHub repository \[35\]. The facial expressions dataset consists of 13,718 unprocessed images and was chosen due to its diversity in terms of gender, age, and ethnicity. It also displays variety in terms of emotions for unique identities, which makes it suitable for some intra class tests. To perform intra class attribute testing it is imperative that each dataset contains only one unique identity. However, for some intra class tests, the facial expressions dataset did not contain enough images of the same identity with certain attributes. For example, as this dataset was created for facial expression diversity it was very difficult to find images of the same identity with/without beards. Therefore, images were manually sourced from the internet to create the required datasets for tests in which the attributes of beards and glasses were examined.

Images used for the extra class tests were manually chosen from the facial expressions dataset, examples of the images used in these tests can be seen in Figure 1.

Images for the test datasets are manually chosen based on the desired attribute for discrimination. For example, in a test where gender is investigated, the test dataset would contain 100 images of which 50 are male and 50 are female. Each image is manually labeled based on their respective gender.

Each image within the dataset is then passed through the model to create an embedding. The model applies the following steps prior to the creation of the embedding representation. The frontal face detector is used to detect the face within the image and place a bounding box around it. This verifies that a face is present and that the image does not contain more than one face. The landmarks for the detected face are then identified using the shape predictor 68 face landmarks model \[31\], these landmarks are used to precisely localize the face. The images and their respective landmarks are then passed to the dlib face recognition ResNet model v1 which converts the images into their respective 128-dimensional embeddings.
Once the embeddings have been created, clustering is performed on the embeddings using Scikit-learns K-Means algorithm [36], this experimental process can be seen in Figure 2. Dlibs chinese whispers [31] clustering algorithm was the original clustering algorithm of choice. However, this algorithm did not perform well and was substituted for the K-Means algorithm. Several tests were carried out to compare initialization of the K-Means algorithm using random seeds against manual seeds. The random seeds provided more consistent results therefore the rest of the tests were carried out using random seed initialization. As this form of K-Means initialization can create slightly different clusters on occasion, each dataset was run through the algorithm five times as most if not all clustering possibilities could be captured in five test runs, thus providing a reliable average classification accuracy.

When the data is clustered, output labels are generated by K-Means which are then compared with the manually created labels to assess the performance of the clustering through the use of confusion matrices.

4. Evaluation

4.1. Extra Class

A set of experiments were undertaken to examine the presence of extra class attributes representing gender, skin tone and age. K-Means was initialized with
random seeds and two clusters for each test. While it is appreciative that these attributes exist on a continuum, to understand how the representation within the embedding is structured the attributes are classified in a binary fashion. Therefore, dichotomic clusters are used as gender is classified as male/female, skin tone as dark/pale and age as young/old.

The sample sizes for each test were 100 images and the average accuracy for each test were 99.3%, 99.3% and 94.1% for gender, skin tone and age, respectively, these results can been in Table 1. It is evident from the high clustering accuracies achieved above, that the extra class discriminative properties of gender, skin tone and age are represented within the embeddings.

Before these results were achieved a restriction emerged in that every time the K-Means algorithm was run with two clusters the images would always cluster based on skin tone. Therefore, to examine the attributes of gender and age it was compulsory that all images in the dataset contained only one
Figure 3: Examples of images sourced from the internet that were used to examine the presence of beards, glasses and emotions as intra class discriminative properties.

skin tone. This requirement demonstrates that a hierarchical coherence exists between features within the embedding structure. To explore this condition further a new dataset of 200 images was created and manually labeled, ensuring an equal representation of attributes within the dataset. In the first part of this experiment, K-Means was initialized with two clusters, this would determine which attribute held prominence above the other two. This process was repeated for K-Means initialized with four clusters and then eight clusters. The results of these experiments can be seen in Table 1. When using two clusters, the data was classified based on skin tone, such that one cluster contained pale-skinned people and the other contained dark-skinned people. When four clusters were used, gender was taken into consideration and the resulting clusters contained, dark-skinned males, dark-skinned females, pale-skinned males and pale-skinned females. Finally, when eight clusters were used, each image was classified based on the skin tone, gender and age of the person in the image. For example, one cluster would contain old dark-skinned males and another would contain young dark-skinned males. These results indicate that a hierarchical coherence exists between features within the embedding structure and that the features representing the extra class attributes rank in order of skin tone, gender and
Table 1: Results of the 2nd extra class test where the inherent hierarchical coherence between features in the embedding structure is examined. Outcomes indicate the ability to correctly identify a person’s gender, age and skin tone with high classification accuracy (shown in bold). It is also evident that a hierarchical coherence exists between features in the embedding structure and that the features representing the extra class attributes rank in order of skin tone, gender and age, respectively.

| No. Clusters | Cluster Content | Test 1 | Test 2 | Test 3 | Test 4 | Test 5 | Average Accuracy |
|--------------|----------------|--------|--------|--------|--------|--------|------------------|
| 2            | Dark Skin      | 99.0%  | 99.0%  | 99.0%  | 99.0%  | 99.0%  | 99.0%            |
|              | Pale Skin      | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0%           |
| 4            | Dark Skin      | 99.0%  | 99.0%  | 99.0%  | 99.0%  | 99.0%  | 99.0%            |
|              | Pale Skin      | 100.0% | 99.0%  | 99.0%  | 100.0% | 99.0%  | 99.4%            |
|              | Male           | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0%           |
|              | Female         | 99.0%  | 99.0%  | 99.0%  | 99.0%  | 99.0%  | 99.0%            |
| 8            | Male           | 99.0%  | 100.0% | 99.0%  | 99.0%  | 100.0% | 99.4%            |
|              | Female         | 99.0%  | 99.0%  | 99.0%  | 97.0%  | 99.0%  | 98.6%            |
|              | Dark Skin      | 99.0%  | 99.0%  | 98.0%  | 99.0%  | 98.0%  | 98.6%            |
|              | Pale Skin      | 99.0%  | 99.0%  | 99.0%  | 99.0%  | 99.0%  | 99.0%            |
|              | Young          | 94.0%  | 90.0%  | 91.0%  | 93.0%  | 87.0%  | 91.0%            |
|              | Old            | 88.0%  | 79.0%  | 89.0%  | 80.0%  | 80.0%  | 83.2%            |

The results from the two extra class discrimination experiments above support the hypothesis that embeddings generated for one purpose i.e. facial recognition, can be used for another purpose, namely in the identification of the sub-discriminatory extra class attributes such as gender, skin tone and general age category by utilizing an unsupervised machine learning algorithm, such as K-Means, to perform zero-shot learning. These results also highlight an inherent hierarchical coherence that exists between different features in the embedding structure and that the features representing the extra class attributes rank in order of skin tone, gender and age, respectively.

In the next section of this paper, the presence of the intra class attributes of beards, glasses and emotions within the embedding structure are experimentally evaluated, along with the possibility that the features representing the intra class
attributes behave in the same manner as the extra class results indicate.

4.2. Intra Class

As discussed in Section 3.2, the facial expressions dataset was compatible with the intra class experiments as it contained 3–10 images for each unique identity and showed significant variety in terms of emotions for each unique person. The initial intra class test mirrored the initial extra class test, in that the possible presence of these intra class discriminative properties was examined. Firstly, the emotions happy, angry, sad, and neutral were investigated. These four emotions are chosen as they are represented well in terms of image quantity in the facial expressions dataset. However, although these emotions were represented the best they were not represented perfectly, resulting in a shortage of images for some identities, which produced a disparate attribute ratio split. For each attribute combination three individual tests were run, where each individual test represents a unique identity. The results of the initial experiment can be seen in Table 2. The results achieved in the completion of this experiment indicate that the method described is not sufficiently accurate to discriminate these intra class attributes. To this end, a deeper exploration of these discriminative properties is required.

In the remainder of this section, the presence of beards and glasses are experimentally evaluated as intra class discriminative properties within the embeddings. None of the datasets used in prior experiments contained enough images of the same identity with/without beards/glasses, therefore, images were manually sourced from the Internet, examples of these images can be seen in Figure 3.

The presence of beards, thin-framed glasses and thick-framed glasses were all examined using three separate datasets per discriminative property. All datasets contained 10 images with a 50:50 attribute ratio split, the average accuracies across all tests were 95.8%, 97.2% and 75.3% for beards, thick-framed glasses, and thin-framed glasses, respectively; these results are shown in Table 2. These results suggest that beards and some types of glasses which lie more prominent on the face (thick-framed glasses and sunglasses) can be classified as intra class
Table 2: Results of the initial Intra Class test, where the presence of the attribute emotions are examined. Each emotion is tested three times against every other emotion. Each test contains one unique identity (9 unique identities in total). Table is read as follows; Happy vs Neutral, Angry vs Neutral, Sad vs Neutral etc.

| Emotion | Neutral | Happy  | Angry  | Sad  |
|---------|---------|--------|--------|------|
|         | Sample Size | Accuracy | Sample Size | Accuracy | Sample Size | Accuracy | Sample Size | Accuracy |
| Happy   | Test 1    | 8       | 75.0%   | 10     | 70.0%   | 9        | 70.0%     |
|         | Test 2    | 10      | 44.0%   | 7      | 41.0%   | 10       | 58.0%     |
|         | Test 3    | 4       | 100.0%  | x      | x       | 10       | 72.0%     |
| Happy   | Test 1    | 10      | 54.0%   | 10     | 70.0%   | x        | x         |
|         | Test 2    | 10      | 50.0%   | 7      | 41.0%   | x        | x         |
|         | Test 3    | 10      | 76.0%   | 10     | 72.0%   | x        | x         |
| Angry   | Test 1    | 8       | 55.5%   | 9      | 70.0%   | x        | x         |
|         | Test 2    | 5       | 73.3%   | 10     | 58.0%   | x        | x         |
|         | Test 3    | 8       | 75.0%   | 10     | 44.0%   | 10       | 58.0%     |

discriminative properties, the results of these experiments can be seen in Table 3.

4.3. Summary of Intra and Extra class tests

In summary, from initial inspection some extra class discriminative properties have been identified to exist within embeddings, results also indicate that these properties adhere to a hierarchical coherence that exists within the embedding structure. For example, in the initial extra class experiments, when using dichotomic clusters, if a dataset contained more than one skin tone the resulting clusters would always consist of dark or pale-skinned people, therefore when testing for a different attribute datasets of a single skin tone were required. In addition, a couple of intra class discriminative properties were identified however, it is apparent that further techniques are required to increase the performance of these properties.

Most importantly, the initial hypothesis of this study remains valid as the ability to use existing features present in the structure of facial recognition embeddings to perform sub-discrimination tasks through the use of zero-shot learning has been successfully identified and demonstrated.

5. Application of Results

While the results of this study suggest that the application of intra class discriminative properties appears limited, a large avenue appears prevalent for
Table 3: Results of the $2^{nd}$ intra Class where the presence of the attributes; beards, glasses and thick-framed glasses are examined. Results indicate that the attributes of beards and thick-framed glasses are represented within the embedding structure.

| Attribute          | No Beard                  | No Glasses                 | No Thick Framed Glasses   |
|--------------------|---------------------------|----------------------------|----------------------------|
| Sample Size | Accuracy | Sample Size | Accuracy | Sample Size | Accuracy |
| Test 1 10 100.0%  x x x | x x | Test 2 10 87.5%  x x x x | x x | Test 3 10 100.0%  x x | x x |
| Beard              |                         |                             |                            |
| Test 1 x x 10 48.0%  x x | x | Test 2 x x 10 88.0%  x x | x | Test 3 x x 10 90.0%  x x | x |
| Glasses             |                         |                             |                            |
| Test 1 x x 10 100.0%  x | x | Test 2 x x 10 100.0%  x | x | Test 3 x x 10 91.6%  x | x |
| Thick Framed Glasses |                         |                             |                            |

The application of extra class discriminative properties. One possible avenue includes training one of the many existing unsupervised learning algorithms to cluster data based on skin tone, gender and age. This can be accomplished by saving the resultant cluster centroids and clustering unseen data by taking the Euclidean distance of each unseen embedding and classifying its discriminative properties based on which cluster centroid it lies closest to. To highlight the possibility of this application a dataset of 1000 unique identities was manually created from the CelebA dataset [37]. The dataset used for this experiment consisted of:

- 125 young pale-skinned males;
- 125 young dark-skinned males;
- 125 young pale-skinned females;
- 125 young dark-skinned females;
- 125 old pale-skinned males;
- 125 old pale-skinned females;
- 125 old dark-skinned males;
- 125 old dark-skinned females.
This dataset was broken down into 70% train data and 30% test data, a validation set was not used as we are training an unsupervised learning algorithm. In adherence with previous extra class experiments, K-Means initialized with random seeds was chosen as the unsupervised learning algorithm. The training data was processed through K-Means several times using two clusters initially, then four clusters and finally eight clusters. The cluster centroids for each cluster are generated by the K-Means algorithm and saved. The centroids that produced the highest attribute accuracies in training are chosen to cluster the test data. Classification is achieved by classifying embeddings based on the cluster centroid they lie closest to. The results of this experiment can be seen in Figure 4 denoted as 'K-Means Train' and 'K-Means Test'.

The results from this experiment indicate the possibility of using means generated by an unsupervised learning algorithm to cluster unseen embeddings based on extra class discriminative properties. This yields an advantage in terms of computation speed for the sub-discrimination task. In contrast to comparing a new unseen embedding to each known identity it is more computa-
tionally efficient to instead, compare a new embedding to each cluster centroid. This reduction in comparisons, especially with larger sample sizes, can greatly increase computation speed while maintaining high performance on the sub-discrimination task as shown by the high attribute accuracies achieved for this experiment.

In the final stage of this experimental study, the substantial drop in accuracy for the dark skin attribute between the train and test sets in the prior experiment is examined. A different unsupervised algorithm was trained and tested on the same datasets to investigate whether K-Means was accurate enough. The algorithm used for this experiment was the MoG. The method used to initialize the weights, the means and the precision was left as K-Means, which is the default initial parameter option for the MoG algorithm.

Figure 4 shows the train and test accuracies for both MoG and K-Means. The results show both algorithms are capable of accurately identifying extra class discriminative properties. MoG does increase the accuracy of the dark skin attribute however, it does not perform as well as K-Means with respect to the pale skin attribute. Although both algorithms display good performance, it is not yet apparent which algorithm yields the best performance. A path for future work in the area is to examine the behaviour of several unsupervised algorithms to determine which has the best performance in terms of feature classification and the zero-shot learning task.

The decrease in accuracy for the dark skin attribute can be seen as a consequence of the content of the test and training datasets. Additionally as a result of the limitation of the experiment whereby this study attempts to perform binary classification on continuous attributes. For the chosen dataset dark skin people are defined as being of dark or mixed skin tone, as shown in Figure 5. It is noted that 19% of the images representing the dark class in the training set were of mixed skin tone, while 32% of the images representing the black class in the test set were of mixed skin tone. This indicates that because of the low percentage of mixed skin tone images in the training set, the model is less likely to correctly classify mixed skin tone data in the test dataset, therefore, provid-
Figure 5: The various skin tones and their respective class labels. As skin tone is defined as being a binary representation in this study, the dark skin tone class consists of both mixed and dark skin tone shades.

6. Future Work

Although there are many areas in which future work can be conducted, the area of most relevance resides in the application of the knowledge and techniques demonstrated in this experimental study upon embeddings generated for a diverse collection of tasks.

Embeddings created for any purpose may contain inherent information which could be then used to perform sub-discriminative tasks through zero-shot learning. Speech recognition is one of many possible areas in which these principles can be applied. For example, spectrograms of voices can be represented as embeddings and through the use of an unsupervised learning algorithm it may be
possible to accurately identify disparate speakers.

7. Conclusion

In this paper, the sub-discriminative properties of embeddings which were created for the application of facial recognition were experimentally evaluated. Results confirm that the inherent information contained within these embeddings hold the ability to perform sub-discriminative tasks through the use of a zero-shot learning method. The study is split into two cases, extra class sub-discrimination and intra class sub-discrimination. Extra class sub-discrimination can be achieved with high accuracy notably with an attribute accuracy of 99.3%, 99.3% and 94.1% for skin tone, gender and age respectively. In addition, the intra class attributes of beards and thick-framed glasses yielded an attribute accuracy of 95.8% and 97.2% respectively. The main findings of this experimental study are summarized below:

- It is possible to perform extra class sub-discriminative tasks with a high degree of accuracy by performing a form of zero-shot learning, namely through the use of unsupervised learning algorithms. The discovery of inherent information within embeddings designed for the purpose of facial recognition, confirm the ability to perform extra class sub-discrimination namely for the attributes gender, skin tone and age;

- The results from the intra class sub-discrimination experiments highlight the need for additional techniques to help increase the ability to extract/identify these intra class attributes with higher accuracies, an N-shot or few-shot learning approach may substantially increase the attribute accuracy;

- The most common approaches follow DML for training and a discriminative class posterior is computed at test time, usually a non-parametric approach such as KNN is commonly used. As aforementioned, most of the approaches have an assumption of the category distribution being uni-modal in the embedding space. But new approaches consider multi-modal mixtures as being more representative. Results from this study
agree with the latter, as it is demonstrated that the embedding space has a multi-modal mixture shape given that, up to some extent, the more clusters used the better results achieved.

- Finally, the possibility of training unsupervised algorithms to perform extra class sub-discrimination at extremely high accuracies by saving cluster centroids created during training is demonstrated.

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