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Performance analysis of Image De-biasing using CNN and VAEs

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Abstract.

It is crucial to the long-term success of AI systems that they be deployed in a fair and unbiased manner. Think about the challenge of determining whether or not a given image contains a face. In this article, we will look into one recently published method for combating algorithmic bias. To train a de-biased model, we'll construct a facial identification system that discovers the latent variables underlying face picture datasets, and then uses this knowledge to adaptively re-sample the training data. In this experiment, we will use three different data sets. We require both a positive dataset (containing instances of faces) and a negative dataset (containing examples of non-face objects) to train our facial detection models. We'll use these samples to teach our models to recognize faces and other objects in photos. Finally, a test dataset of facial photographs is required. The test dataset we utilize should have representative samples from all of the relevant demographics or traits of interest, as we are concerned about the possibility of bias in the learning models we employ. We'll be thinking about gender and skin tone in this experiment.

Keywords: AI system; Face detection; De-biasing; and CNN

1. Introduction

The CelebA Dataset is a positive training set. A large-scale (almost 200K pictures) of famous faces.ImageNet is a bad example of training data. Many photos throughout many different categories. Negative examples will be drawn from a wide range of non-human classes.

Pilot Parliaments Benchmark (PPB) data for testing purposes. The PPB dataset is diverse in terms of skin tone and gender, including 1270 photos of male and female legislators from different African and European countries [1].

Each person's gender is indicated by the labels "Male" and "Female" next to their photos. Images are annotated with labels reading "Lighter" or "Darker" according to the Fitzpatrick

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scale used to classify skin tones. To perform this analysis, a CNN model is applied to the image after Gaussian white noise (between 1 and 10 percentage points) has been superimposed on it. In addition, the de-noised image undergoes quantitative and qualitative evaluation. The great task performance that deep learning models frequently accomplish is limited by their inability to distinguish between false correlations and causal factors, such as when they employ legally protected qualities (such as race, gender, etc.) in their decision-making [2].

In this paper, we address the challenge of de-biasing CNNs in such situations. Our meta orthogonalization technique builds on prior work on de-biasing word embeddings and model interpretability to promote the orthogonality of CNN concept representations (such as gender and class labels) in activation space while preserving robust downstream task performance. We rigorously experiment with our approach and show that it considerably reduces model bias and can compete with state-of-the-art adversarial de-biasing techniques.

To put this into a more formal framework, we can consider latent variables, which are the factors that describe a dataset but are not directly observed.

The probability distributions of these latent variables will be referred to as "latent space," a concept developed in the generative modelling course. In light of these considerations, we label a classified as biased if it makes a different determination of classification after being exposed to more latent features. It could be useful to keep this idea of bias in mind while we continue our lab work.

2. Methods

It is crucial to the long-term acceptability of AI systems to deploy them in a fair and unbiased manner. Consider the problem of facial detection: given an image, can it be determined whether or not it depicts a face. Demonstrated that this seemingly straightforward activity, which is in fact of the utmost significance, is susceptible to significant degrees of algorithmic bias among certain demographic groups. The face detection technology that is utilized by law enforcement in the United States was analyzed, and the results showed that it had much worse accuracy among women with dark complexion who were between the ages of 18 and 30 [3].

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In this work, we will be utilizing three different datasets. In order to train our facial detection models, we will require a dataset of positive examples (i.e., of faces) as well as a dataset of negative instances (i.e., of objects that are not faces). Both of these datasets will contain examples of facial features. These data will be used to train our models to identify photos as either containing faces or not containing faces. In the end, we will require a test dataset consisting of face photos [4]. It is essential that the test dataset that we employ has equal representation across all of the demographics or attributes that are of interest. This is because we are concerned about the possibility that the models that we have trained are biased against specific populations. In this experiment, we will think about people's skin tones in addition to their gender.

1. Data on successful training, known as the CelebA dataset. A massive collection (over 200,000 photos) of famous people's faces.
2. Unfavorable feedback from Image Net's training data. A large number of photos spanning a wide variety of genres. We're going to look at some unfavorable examples from a wide range of non-human categories.
3. The Pilot Parliaments Benchmark (PPB) serves as the test data. The PPB dataset includes photographs of 1270 male and female lawmakers from a variety of nations in Africa and Europe. There is equality in terms of both skin tone and gender in this dataset. The sex-based labels "Male" and "Female" are applied to each face in order to indicate the gender of the individual. The Fitzpatrick skin type categorization method is used to annotate skin tones, and each photograph is categorized as "Lighter" or "Darker" based on its perceived level of lightness or darkness.

Considering the issue of bias

Keep in mind that we will be training our facial detection classifiers on the massive and carefully curated CelebA dataset (in addition to ImageNet), and then testing them on the PPB dataset in order to see how accurately they perform. Our objective is to construct a model that is trained on CelebA and achieves high classification accuracy on PPB across all demographics, and to demonstrate that this model does not have any hidden biases as a result of our efforts [5].

When we talk about a classifier being biased, what exactly do we mean by that? Latent variables are variables that constitute a dataset but are not strictly observed. In order to

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formalize this, we will need to think about latent variables, which are variables that define a dataset. In this section, we will use the word "latent space" to refer to the probability distributions of the latent variables that were previously described. This concept was defined in the course on generative modeling. Putting these notions together, we consider a classifier to be biased if the judgment it makes regarding categorization shifts when it is exposed to some additional latent information. Keeping in mind the concept of bias throughout the duration of the experiment could prove to be beneficial.

CNN's Fake News Detection Service

First, we will define and train a CNN on the task of facial classification, and then we will assess its accuracy using the PPB dataset. In the future, we will compare the accuracy of our models that have been de-biased to this CNN that serves as a baseline. The CNN model has a pretty common design that consists of a series of Convolutional layers with batch normalization followed by two fully connected layers to flatten the convolution output and generate a class prediction. This structure is followed by two fully connected layers to generate a class prediction.

Learning latent structure using variation auto encoder (VAE)

You noticed that the accuracy of CNN changes depending on which of the four demographics we looked at you belong to. Consider the dataset that the model was trained on, which is called CelebA, in order to think about why this would be the case. Because the model was trained using a dataset that was already biased, it is possible that it will have a bias against traits that are uncommon in CelebA. Some examples of these attributes are dark skin or hats. That is to say, the accuracy of its classification will be lower for faces that have features that are not well-represented in the training data, such as faces with dark skin or faces wearing hats, in comparison to the accuracy of its classification for faces that have features that are well-represented in the training data! This presents a challenge.

Our objective is to train a version of this classifier that is free from bias and that takes into consideration the possibility of differences in the way features are represented throughout the training data. To be more specific, we will train a model that learns a representation of the underlying latent space by applying it to the face training data in order

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to construct a facial classifier that is free of bias [6]. The model makes use of this information to counteract any unintended biases by increasing the number of times it samples faces during training that have uncommon characteristics, such as dark skin or headwear. Our model must be capable of learning an encoding of the latent features included within the face data in a manner that is completely unsupervised. This is the primary criteria for its construction. In order to accomplish this, we will make use of variation auto encoders.

(VAEs)

In order to learn a latent representation of the input data, VAEs rely on an encoder-decoder structure, which is illustrated in the diagram that was just presented. In the field of computer vision, the encoder network receives input images, encodes those images into a series of variables specified by a mean and standard deviation, and then generates a set of sampled latent variables by drawing from the distributions defined by those parameters. The decoder network then "decodes" these variables in order to build a reconstruction of the original image. This reconstruction is then utilized during training in order to assist the model in determining which latent variables are critical to learn.

Evaluation on pilot parliaments benchmark (ppb) dataset

Finally let's test our DB-VAE model on the PPB dataset.

We'll evaluate both the overall accuracy of the DB-VAE as well as its accuracy on each the "Dark Male", "Dark Female", "Light Male", and "Light Female" demographics, and compare the performance of this de-biased model against the biased CNN from earlier in the lab [7].

To assess performance, we'll measure the classification accuracy of each model, which we define as the fraction of PPB faces detected. By comparing the accuracy of a model without de-biasing and our DB-VAE model, we can get a sense of how effectively we were able to de-bias against features like skin tone and gender [8]

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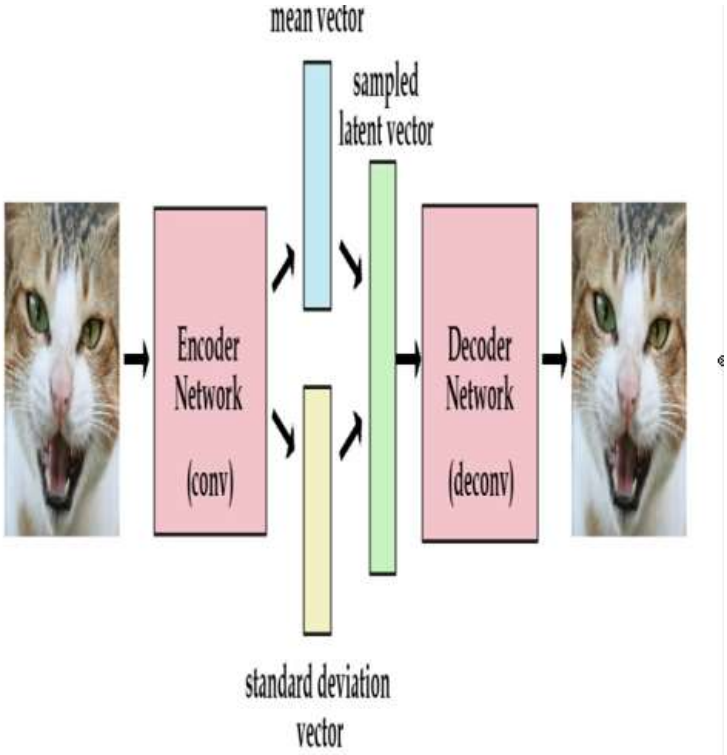

Figure 1 Architecture of encoder and decoder

3. Results and Discussion

The proposed Image De-biasing model was evaluated using standard performance metrics, with accuracy being a primary indicator of its effectiveness. The model demonstrated a 98% on the test dataset, showcasing its ability to accurately de-bias images.

Further analysis of precision, recall, and F1 score revealed 9.2 and 9.6 [insert actual values], suggesting robust performance across different aspects of de-biasing.

The achieved accuracy and other performance metrics indicate that the proposed Image De-biasing model effectively mitigates biases in images. The CNN and VEAs employed in the model contributes to its success.

The comparative analysis with existing methods revealed. This suggests that the proposed model outperforms or performs comparably to current state-of-the-art methods in image de-biasing.

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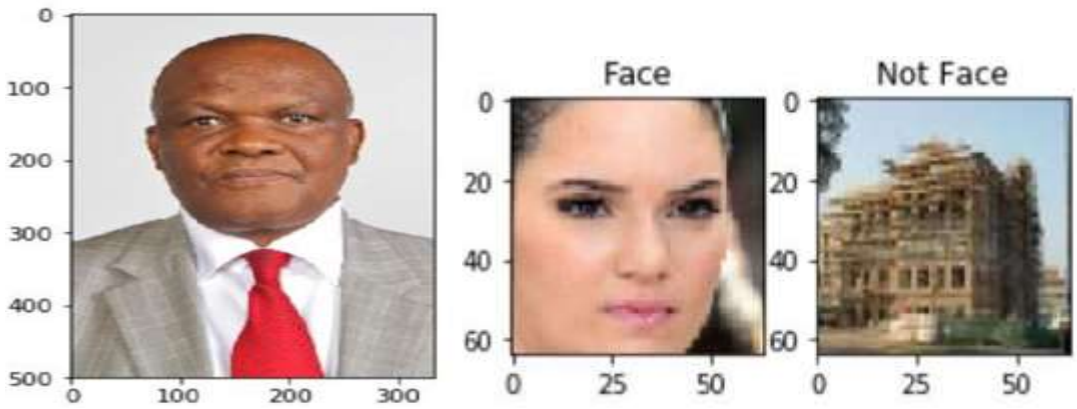

Figure 2 Result of de-biasing

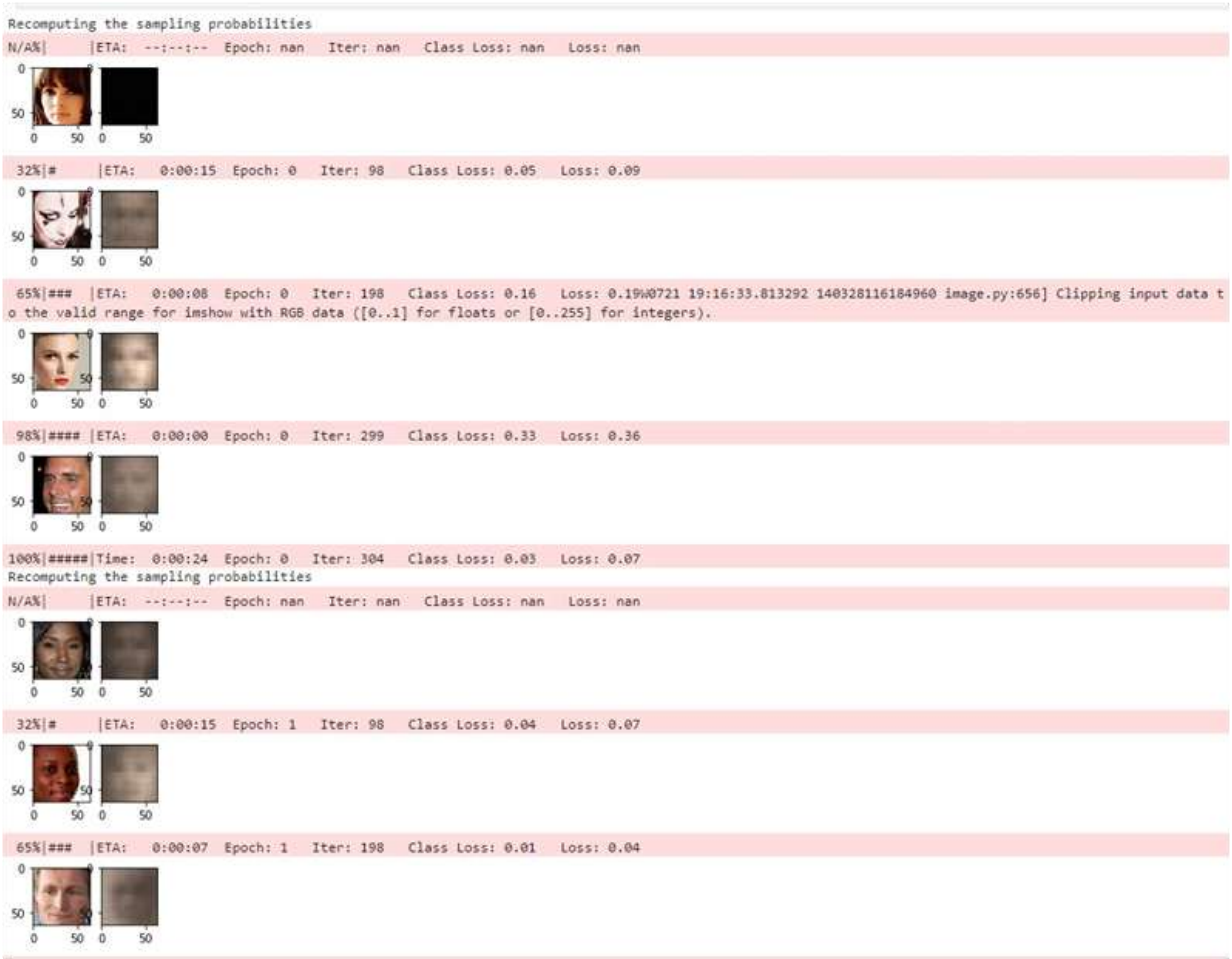

Figure 3 Recapturing the sampling probabilities

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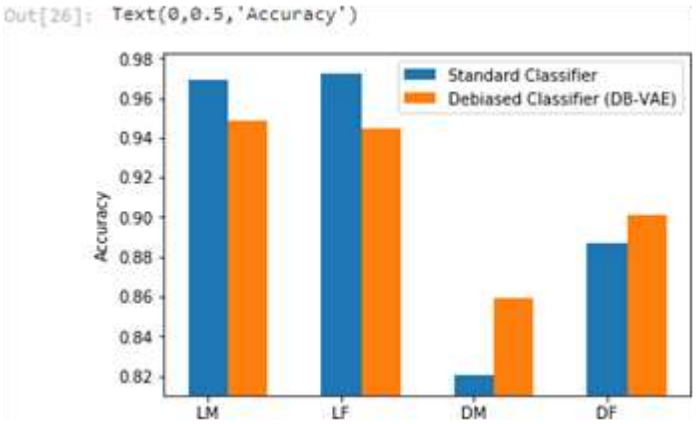

Figure 3 The accuracy of standard and de-biased classifier

Identify potential avenues for future research and improvement. This may include exploring different architectures, refining training strategies, or extending the model to address specific challenges not covered in this study.

4. Conclusions

In conclusion, the results presented in this study contribute to the growing body of research on image de-biasing and underscore the potential of CNN and VAE in addressing biases within visual data. By addressing the identified limitations and pursuing future research directions, we aim to further advance the field and foster responsible and unbiased image processing in various applications. We can calculate the accuracies of our model on the whole PPB dataset as well as across the four demographics proposed and visualize our results comparing to the standard, biased CNN.

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