A Note on Data Biases in Generative Models

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Figure 1: Model or Data Progress? Our method can render the same content projected onto different datasets with the same model, thereby questioning a popular conception on the effective progress of generative models.

"ML systems are biased when data is biased."
—Yann LeCun [1]

Awareness for Biases It is tempting to think that machines are less prone to unfairness and prejudice. However, machine learning (ML) approaches compute their outputs based on data. While biases can enter at any stage of the ML development pipeline [2], models are particularly receptive to mirror biases of the datasets they are trained on. Because the quality of training datasets play an important role in the quality of trained models, practitioners are typically well aware that predictions of ML systems do not necessarily reflect truths about the world but, first of all, truths about the data [3]. However, this knowledge can also be misused to conceal agendas behind a cloak of objectivity [4]. It is therefore increasingly important to raise awareness about the relationship between modern algorithms and the data that shape them. Besides the fact that art in general, and visual illustrations (e.g. images) of this interplay in particular are already a good tool to make this relationship accessible to a wider, non-specialist, audience, the value of interactive demonstrations that offer the possibility to analyze your own data cannot be underestimated [5]. Thus, we provide code for a web-based demonstration at https://git.io/JkoKp (see Fig. 3), which allows for an interactive exploration of the effects when models are trained on biased data.

Disentangling Dataset and Content Our goal is to demonstrate how the choice of a particular dataset affects the outcome of a generative model. We aim to project an image onto different datasets, i.e. visualize how this image looks in a data-biased model. Thus, we need to recover the generating factor which is independent of the dataset and hence free of data biases. This means that given an image \( x \), we have to find and disentangle: (i) \( y \), which specifies the dataset, and (ii) the data-unbiased content \( z \), such that both of them together fully describe the input \( x \). We interpret this task as a minimization of their mutual information \( I(z, y) \), and, following [6], minimize an upper bound on it where we model the distribution \( p(z|y) \) with a conditional INN \( \tau \) and use a standard normal prior \( q(z) \). An image \( x \) from dataset \( y \) is then projected onto a different dataset \( y^* \) by inferring its content \( z = \tau(x|y) \) and recombining it as \( x^* = \tau^{-1}(z|y^*) \). We follow [6] and use an autoencoder to obtain the data representation \( x \), which, once trained, allows for efficient training of the conditional INN.
On the Progress of Generative Models  
Bad intentions behind carefully curated datasets should be considered an exception that must not overshadow the potential of data driven systems. But even in good-spirited attempts to improve the performance of models, it must be understood that the training dataset is a confounding factor when assessing effectiveness of models. While previous works which introduced higher-quality datasets for generative modeling controlled for this factor [7, 8, 9], the perceived improvements in model quality is to a large extent influenced by qualitative results such as Fig. 13 from [10]. Our approach directly visualizes the effect of the dataset on a single model and thereby gives an impression to what extent samples from a fixed generative model can be improved by biasing it to datasets of different quality. The left part of Fig. 1 shows how the same latent code is interpreted in three different datasets corresponding to the datasets used in the three rightmost images of Fig. 13: From left-to-right, CelebA [11], CelebA-HQ [7] and FFHQ [8]. The transition from CelebA to CelebA-HQ shows a drastic improvement in resolution and high-frequency detail while maintaining person-identity well. These changes reflect the fact that CelebA-HQ uses a “high-quality” subset of upsampled CelebA images. Going from CelebA-HQ to FFHQ we observe a further increase in realism through more realistic and varied lighting and specular reflections. This might be due to the fact that for FFHQ high quality images were collected from the beginning. A similar discussion applies to the right of Fig. 1 which demonstrates even more drastic improvements when transitioning from the AnimalFaces [12] dataset to its corresponding high-quality version, AnimalFacesHQ [9].

On the Bias of Generative Models  
While the previous paragraph discussed the implicit conception of progress that arises when introducing new high-quality datasets alongside new models, our method can also be used as a probing tool for biases within different datasets. Recently, the publication of the PULSE model [13] led to controversial discussions about the role of data bias in ML [1, 14, 5], revealing the need for demonstrations of these data biases. Since our method can infer a content code \( z = \tau(x|y) \) from the data and then render it conditioned on the dataset of interest, we are able to project a given input onto a given training dataset. In Fig. 2 col. 3, and Fig. 4 we apply this method to project inputs from the FFHQ dataset onto the CelebA-HQ dataset. Fig. 11 shows sampled codes \( z \sim q(z) = N(z|0, 1) \) which are projected onto CelebA, CelebA-HQ and FFHQ. Besides the already discussed difference in image quality, biases between the datasets containing images of celebrities (CelebA, CelebA-HQ) and FFHQ, which contains a wider variety of face images become apparent. For the FFHQ \( \rightarrow \) CelebA(-HQ) direction, the most obvious differences include a loss of diversity in facial features such as hair style or skin appearance, a strong bias towards more make-up and less skin wrinkles and a decreased diversity of age. By demonstrating how societal biases of curated datasets are mapped into and replicated by ML models, awareness for the topic can be raised.

On Creative Applications  
The ability to visualize the same content viewed under differently biased datasets immediately enables applications in creative content creation by producing visual analogies between diverse datasets such as photographs, portraits and anime characters. We show examples in Fig. 2 col. 1, 2, Fig. 6. Thus, it can be stated that biases in data sets not only have disadvantages, but can also be used explicitly and consciously for creative content creation – although one should always keep in mind that "nothing good ever comes from face datasets" [15].
Ethical Implications

Biases in Machine Learning are a sensitive issue that should not be dismissed as being caused by the underlying data alone. Datasets are not the sole cause of societal bias in ML models [16]. Therefore, we give some additional remarks on our presented approach.

- We can compare dataset biases here since we first train an autoencoder on all relevant datasets combined, i.e. we create one big dataset containing all the sub-datasets and train a single autoencoder on it. While the combined dataset contains yet other biases, we can faithfully compare biases present within the different sub-datasets.
- We then train the cINNs through maximum likelihood learning. Compared to GANs, this approach does not suffer from data regions being ignored (so-called “mode-collapse”), but, by trying to cover all data regions, can suffer from estimating a “broader” distribution than the original one, i.e. assign too high density to regions between data points. This can result in a bias towards averaged data points, which, in the case of aligned face images, might be perceived as more attractive faces [17].
- We do not make a statement on how to generally investigate and solve societal biases of ML models. We do however provide a method to project images onto a given dataset by disentangling the effects of different datasets with respect to a generative model.
- Finally, since we use an autoencoder to obtain an efficient data representation, the reconstruction of an input image may not be accurate. This effect might be enhanced by our use of a patch-based discriminator, which boosts realism of the reconstructions but, to some extent, introduces GAN-related issues. Therefore, carefully balancing these different factors is important when using the proposed method.

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Figure 3: Screenshot of our interactive web-based demonstration at https://git.io/JkoKp.

Figure 4: FFHQ to CelebA-HQ Transfer.
Figure 5: Portrait-to-Image transfer (row 1, 2) and samples (row 3), all synthesized with the same model.

Figure 6: Image-to-Anime Transfer.

AnimalFacesHQ  AnimalFaces

Figure 7: Samples from our model, conditioned on AnimalFacesHQ (left) and the older AnimalFaces (right).
Figure 8: Samples from our model, conditioned on the CelebA, CelebA-HQ and FFHQ datasets (left to right).

Oil Portraits Photography

Figure 9: Samples from our model, conditioned on the Portrait dataset (left) and the FFHQ dataset (right).
Figure 10: Samples from our model, conditioned on the Anime dataset (left) and the FFHQ dataset (right).

Figure 11: Samples from our model, conditioned on the FFHQ dataset (left) and the CelebA-HQ dataset (right).
Figure 12: Samples from our model, conditioned on the concatenated FacesHQ dataset (consisting of CelebA-HQ and FFHQ) (left column) and the CelebA dataset (right column).

Figure 13: Reproduced from [10], where it was used to illustrate “4.5 years of GAN progress”. The three rightmost figures were obtained with three different models on three different datasets. In contrast, Fig. 1 shows samples from a single model on the same three datasets.