

# Fair Latent Deep Generative Models (FLDGM) for Syntax-agnostic and Fair Synthetic Data Generation

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## Abstract

Deep Generative Models (DGMs) for generating synthetic data with properties such as quality, diversity, fidelity, and privacy is an important research topic. Fairness is one particular aspect that has not received the attention it deserves. One difficulty is training DGMs with an in-process fairness objective, which can disturb the global convergence characteristics. To address this, we propose Fair Latent Deep Generative Models (FLDGMs) as enablers for more flexible and stable training of fair DGMs, by first learning a syntax-agnostic, model-agnostic fair latent representation (low dimensional) of the data. This separates the fairness optimization and data generation processes thereby boosting stability and optimization performance. Moreover, data generation in the low dimensional space enhances the accessibility of models by reducing computational demands. We conduct extensive experiments on image and tabular domains using Generative Adversarial Networks (GANs) and Diffusion Models (DMs) and compare them to the state-of-the-art in terms of fairness and utility. Our proposed FLDGMs achieve superior performance in generating high-quality, high-fidelity, and high-diversity fair synthetic data compared to the state-of-the-art fair generative models.

## Our Contributions

- We propose a novel formulation of a fair latent generative framework common for both GANs and Diffusion models.
- In contrast to previous works [1, 2] which generate both fair and accurate synthetic data simultaneously, our proposed approach does not require a delicate weighting factor of generation quality and fairness penalty.
- We introduce the concept of syntax-agnostic, model-agnostic fair latent vectors and show how this can be fine-tuned across various generative architectures (different GAN versions and DM) with less computational overhead.

## Fair Latent Deep Generative Models (FLDGM)

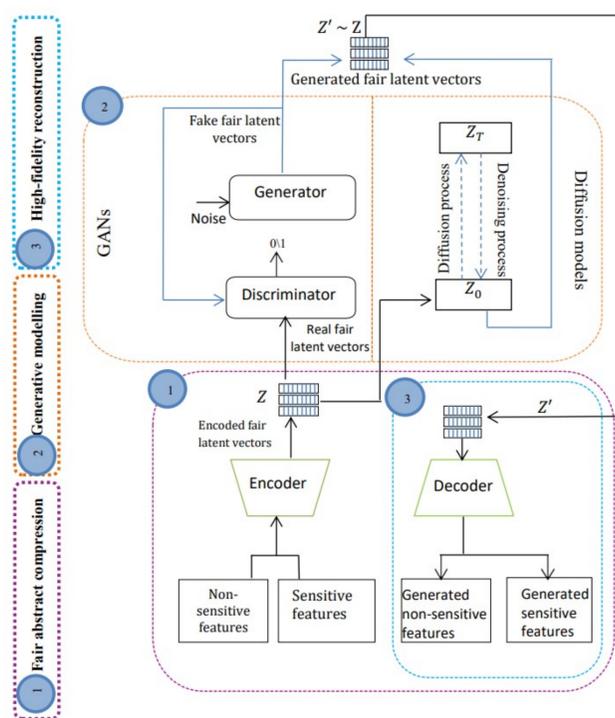


Figure 1 : The FLDGM method: high level diagram

## Results

We have the following variants: FLD-WGAN-GP, FLD-LSGAN, and FLD-DM each with Fairness Through Unawareness (FTU) [3] and Demographic Parity (DP). Figure 2 and 3 shows the generated samples by FLDGM using sensitive attributes. For Color MNIST, we use visualization results as given in fig 4. PCA & t-SNE plots of latent space of the original and synthetic data is shown in fig 5.

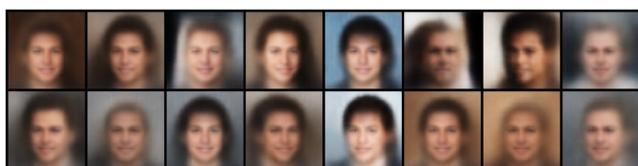


Figure 2: 'Female' as the sensitive sub-group



Figure 3: 'Male' as the sensitive sub-group

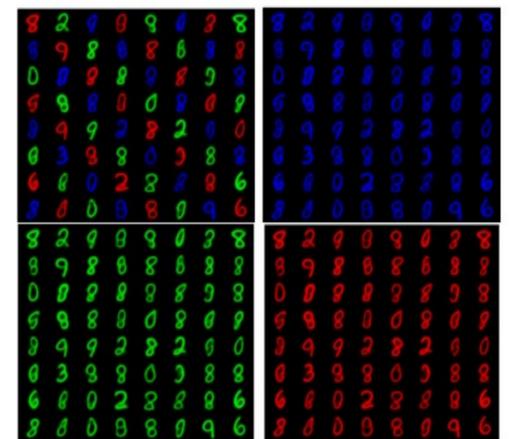


Figure 4: Visualization analysis on Color MNIST

## PCA and t-SNE Analysis

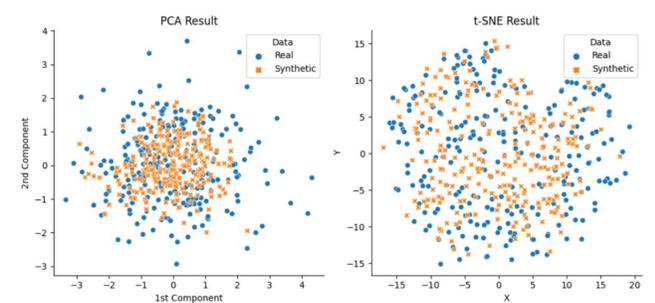


Figure 5 : PCA (left) and t-SNE (right) plot of FLD-WGAN-GP

## Conclusion

Fair Latent Deep Generative Models (FLDGM) are proposed for syntax-agnostic, model-agnostic, and fair synthetic data generation using Diffusion models and Generative Adversarial Networks on image and tabular data. Based on our experimental analysis and evaluation, we did demonstrate favourable results in terms of quality, fidelity, diversity, generalization, and fairness compared to state-of-the-art schemes across a wide range of proposed models in the absence of task-specific architectures.

## Future Direction

Extend this framework for de-biasing hate speech detection and replace the biased contents in the tweets or speech with another, that could be generated by any underlying Natural Language Generation (NLG) methods.

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## References

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Poster

