Question 1: VAE and GAN for Signature Generation*

*Comparative analysis of GANs and VAE for signature generation Task

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I. Introduction

This report describes the question 1 implementation of Variational Autoencoder (VAE) and Generative Adversarial Network (GAN) for generating signatures from a handwritten signatures dataset. The goal was to train both the VAE and GAN to reconstruct the signatures very close to the input signatures.

II. Methodology

A. Dataset

The dataset consists of 16 sheets having 12 rows each row belonging to one person having 5 columns , one for Id and the others having signatures. Here in this task, i had already extracted the signatures and stored them in the form such that one person had one folder so a total 192 folders each having 5 images one for id and the others for the images.

B. Preprocessing

- **Data Loading**: The `Sign_Data` class loads the dataset in an organized way. It reads the signature images, resizes them to 128x128 pixels, and converts them into binary which was an inspiration from MNIST dataset. Each signature is also labeled according to the individual it belongs to.
- **Noise Addition**: A Gaussian noise is added to the images to enhance the model's capability to generalize and prevent the discriminator from being biased. This is done by add noise method and it is conditioned such that the noise is a valid image pixel.
- **Transformations**: Since data is less so data augmentation is done using transformations such as random rotations, resized crops, normalization using torchvision's transform.

C. Model Architecture

1) *Variational Autoencoder (VAE) :*

- **Encoder**: The Encoder consists of several convolutional layers that downsamples the signature and extract meaningful latent representations. The encoder gives the latent mean and log variance.
- **Decoder**: The Decoder reconstructs the images from the latent space representation, using transposed convolutions to upscale the signature's feature maps to match the input.
- **Loss Function**: The VAE loss function comprises reconstruction loss (mean squared error) and Kullback-Leibler divergence.

2) *Generative Adversarial Network (GAN) :*

- **Generator**: The Generator takes a random noise and tries to create a valid signature.
- **Discriminator**: The Discriminator's goal is to find whether the image is fake or real.

D. Training

The training of both was done with 500 epochs at a time as shown in 1 and 2. The learning rate for VAE was 1e-5 and GAN's generator's was 0.0002 and discriminator's was 0.002 but i had to keep switching them to ensure learning.And in GAN the weights of both Generator and Discriminator were updated in alternate iterations.

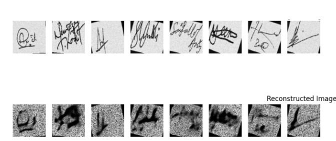

Fig. 1. VAE Training

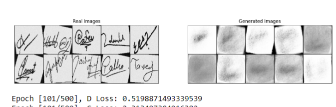

Fig. 2. GAN training

III. Results

A. VAE

:

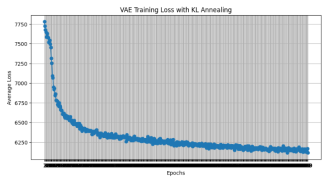

Fig. 3. VAE loss

- Loss: Epoch [401/500], Loss: 6163.5586, Beta: 1.00.
- The loss is high but the results were very good in comparision to GANs.
- Test results are as follows: Average Reconstruction Loss

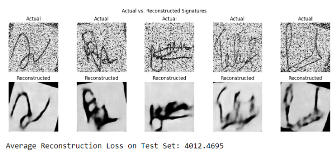

Fig. 4. VAE Results

on Test Set: 4012.4695.
- Another thing i did was to generate new images from VAE.

Fig. 5. VAE new signatures

B. GAN

- Loss : Epoch [401/500], D Loss: 0.76081782579422 Epoch [401/500], G Loss: 2.3190114498138428
- Training loss curves This was the initial loss of GAN

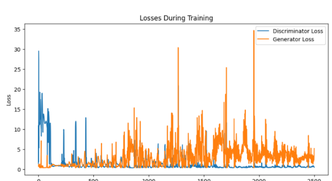

Fig. 6. GAN Loss

which has a lot of varying nature due to lack of convergence which is the main issue of GAN.
- Training results showed that the images had a relatively blurry shadow of the images.
- Average Generation Loss on Test Set: 7535.3822 which is higher than VAE and thus GAN had a bad performance than VAE.

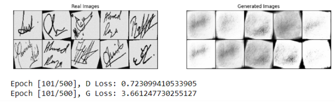

Fig. 7. GAN results during training

- For the training i had tried a variety of learning rates and changed the iterations of generator and discriminator's weight updation otherwise if they had been kept constant then the images would had overall turned darker only.

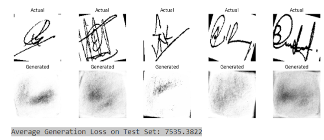

Fig. 8. GAN test results

- The new images i,e. unseen signatures were just like Test images generated by GAN.

IV. Discussion

- **Analysis of Coherence**: The VAE effectively understands the distribution of the signature images, thus it can generate realistic-looking signatures as compared to GAN. The GANs lack of convergence causes it to lag behinf VAE and produce blurry smoke like signatures and further training makes it more worse.
- **Model Improvements**: As training progresses, the model's ability to generate more realistic signatures improves. for VAE but not for GAN either it goes for white images or dark noisy versions. The VAE performance is better as Kullback-Leibler divergence term encourages better generalization. GANs need further optimization.
- **Challenges Encountered**: Key challenges included managing mode collapse and convergence in GAN training, ensuring stability between the generator and discriminator , and tuning hyperparameters such as learning rates.

Conclusion

The VAE performed better due to KL divergence and had no convergence issues and produced good results but GAN due to lack of convergence had a worse performance which could be made better with further optimization but the nondeterministic nature makes it hard to achieve better results. Maybe, the result was due to the lack of alignment of diversity in the dataset which had caused the GAN unable to understand the nature of distribution correctly.

Prompts

- Give me code for GAN and VAE.
- Give me code visualizing the results side by side during training.
- Code for reading and preprocessing the data correctly and binarizing it.
- Switch to cuda.

- How to make the GAN converge.
- Plot the results for this code.
- Give me report structure for this code.
- Code to generate new images.

REFERENCES

[1] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y. *Generative Adversarial Nets*. Advances in Neural Information Processing Systems, 2014, pp. 2672-2680.

[2] Kingma, D. P., Welling, M. *Auto-Encoding Variational Bayes*. arXiv preprint arXiv:1406.2661, 2014. Available at: https://arxiv.org/abs/1406.2661https://arxiv.org/abs/1406.2661