Exercise Sheet Deep Learning

Part2: Generative Models
Summer 22

This sheet includes a theoretical part and a practical assignment on the second part of the lecture Deep Learning (2_GAN). Both parts give 20 points maximum each. Please hand in solutions as a pdf in groups of at most three persons via LernraumPlus.

name1:

name2:

name3:

PARTI – THEORY: For the following, you might answer only YES/NO (or abstain), or you can add short arguments (at most two lines per question). If you are not sure, it is better to abstain.

1. The following generative models rely on the specific objective, ...

yes **no** Variational autoencoders aim for an maximization of the likelihood of data generated by the discriminator

yes **no** GANs minimize the discrimination loss and generation probability of observed data

yes **no** Flow models minimize the data log likelihood

yes **no** Diffusion models directly optimize the data likelihood

2. For variational autoencoders, the following is true:

yes **no** The encoder part maps a data points to a distribution in the latent space, represented by mean and variance.

yes **no** The cost function of a VAE is the reconstruction error enhanced by a regularization part based on KL divergence.

yes **no** The reparametrization trick of VAEs enables backpropagation training, since then sampling is restricted to a neuron without adjustable parameters.

yes **no** VAEs can be used together with convolutions or resnet architectures

3. The following holds for GANs and its variants:

yes no Wasserstein GAN directly optimizes the difference of distributions, using a variation the JS distance of distributions.

yes no Distance measures for distributions are smooth, such that WGAN is very robust.

yes no WGAN CT and WGAN aim for a Lipschitz continuous discriminator.

yes no Conditional GANs use specific labels for conditioning the latent space output

4. The following tasks can be addressed with generative models:

yes no Cycle GAN for domain adaptation.

yes no Image manipulation by arithmetics in GANs latent space

yes no BigGAN provides a text generation module

yes no Diffusion models are part of text to image geneators

5. The following is true:

yes no Flow-based methods can be used with U-net architectures.

yes no In the equilibrium of GANs, the discriminator reaches 100% accuracy.

yes no Diffusion maps train a mapping which maps inputs to Gaussian noise

yes no InfoGAN imposed structural elements on the latent space

PARTII – PRACTICE: You can use code and models which are publicly available, please clearly reference such sources. It might be a good idea to start with the examples given in the practical part of the lecture (available at `https://jgoepfert.pages.ub.uni-bielefeld.de/talk-deep-learning`). Please give a link to your code, and please describe the experiments and results of your approach in a pdf which is well structured (e.g. modeling/training parameters/training/results/interpretation, use itemize, keywords are fine) and enables reproducability as well as easy access to your main results. Please use at most one page for both practical parts together including graphs and images.

1. Take the Fashion MNIST data set and train a variational autoencoder (VAE) on these data. Provide some insight in how good the data are represented, e.g. by reporting the reconstruction error and displaying typical results of generated images.

2. Investigate the latent space of the VAE: display how data are represented by means of a nonlinear dimensionality reduction (such as UMAP or tSNE) and investigate whether there are clusters corresponding to the classes. Investigate how generated data look like if one moves within the latent space from one point to another one from a different class on a straight line.