Adult face predicting machine

Theory and test report on an AI model predicting an adult face based on the image of a baby face

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August 28, 2024 - September 12, 2024

Abstract

Text.

1 Introduction

Introduction to the topic at hand; and explain, why it is to be solved using deep learning models.

2 Theoretical foundation

2.1 Background

Give some background on the topic at hand, and by what tools it is to be solved.

2.2 Neural networks

Introduce neural networks as the basic building block of any deep learning model.

2.2.1 Single layer perceptron

Explain theory on single layer perceptron.

2.2.2 Multi layer perceptron

Explain theory on multi layer perceptrons.

2.2.3 Loss function

Explain, why a loss function is needed for an SLP or MLP.

2.2.4 Training process

Explain how one goes about training a deep learning model.

2.3 Convolutional neural networks

Exlain the working principle of convolutional neural networks and why they are effective at machine vision tasks.

2.4 Generative models

Explain, what generative models in deep learning are. Mention the three basic generative models; GAN's, VAE's and flows. Explain, why GAN's are to be used for the task at hand and why the other models are not suitable for the task.

2.4.1 Generative adversarial networks (GAN)

Generative adversarial networks function as sketched in fig. 1. A generative adversarial network consists of a generator and a discriminator. The generator is basically a function $\bar{\boldsymbol{x}} = \boldsymbol{G}_{\boldsymbol{\phi}}(\boldsymbol{z})$, where $\bar{\boldsymbol{x}}$ is the output of the generator, $\boldsymbol{\phi}$ are the weights associated to the neural network implementing the generator function and $\boldsymbol{z}$ is a latent variable, which is chosen to follow a standard normal distribution, i.e. $\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z}) = \mathcal{N}(0,1)^d$ with $d \in \mathbb{N}$ again the dimensionality of the latent space. The purpose of the generator is to generate fake data $\bar{\boldsymbol{x}}$ based on samples $\boldsymbol{z}$ of the latent probability density $p_{\boldsymbol{z}}(\boldsymbol{z})$. The discriminator however takes an input $\boldsymbol{x}$, such as the output of the generator, and outputs a value 0 or 1, where 0 stands for "input is fake" and 1 represents the situation "input is real". The task of the discriminator is therefore to decide, if an input $\boldsymbol{x}$ is fake or real.

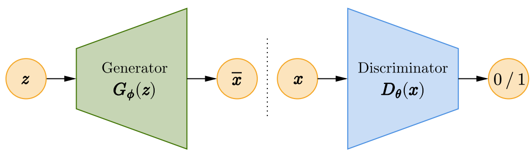

Figure 1: Working principle of a generative adversarial network (GAN). Figure inspired by [Weng, 2018].

A generative adversarial network is trained in such a way, that the generator learns how to generate the best possible real-looking data $\bar{\boldsymbol{x}}$, whereas the discriminator learns as good as possible to distinguish between real data contained in the training set $\hat{\mathbf{x}}$ and fake data $\bar{\boldsymbol{x}}$ generated by the generator. Herein lies the adversarity of the model; the generator and the discriminator are actually competing against each other; the generator learns how to create the best possible fake data, whereas the discriminator learns, how to best distinguish between real and fake data - in this way, both the generator and the discriminator are optimized for their respective task. The loss function for training therefore has to be defined accordingly in a game-theoretical manner, where both the discriminator and the generator try to optimize their outcomes. Once trained, one can just use the generator to create fake data $\bar{\boldsymbol{x}} = \boldsymbol{G}_{\boldsymbol{\phi}}(\boldsymbol{z})$ from samples $\boldsymbol{z}$ of $p_{\boldsymbol{z}}(\boldsymbol{z})$ at will.

2.4.2 Conditional generative adversarial networks (cGAN)

Explain theory on cGAN's.

3 Methods

3.1 GAN on the MNIST dataset

Explain methods for a GAN on the MNIST dataset.

3.2 GAN on faces dataset

Explain methods for a GAN on a faces dataset.

3.3 cGAN on MNIST dataset

Explain methods for cGAN's on the MNIST dataset.

3.4 cGAN (Pix2Pix) on baby face photo dataset)

Explain methods for cGAN's on the baby face photo dataset.

4 Results

4.1 GAN on the MNIST dataset

Explain results for a GAN on the MNIST dataset.

4.2 GAN on faces dataset

Explain results for a GAN on a faces dataset.

4.3 cGAN on MNIST dataset

Explain results for cGAN's on the MNIST dataset.

4.4 cGAN (Pix2Pix) on baby face photo dataset)

Explain results for cGAN's on the baby face photo dataset.

5 Discussion

5.1 GAN on the MNIST dataset

Discuss results for a GAN on the MNIST dataset.

5.2 GAN on faces dataset

Discuss results for a GAN on a faces dataset.

5.3 cGAN on MNIST dataset

Discuss results for cGAN's on the MNIST dataset.

5.4 cGAN (Pix2Pix) on baby face photo dataset)

Discuss results for cGAN's on the baby face photo dataset.

6 Conclusions

Draw general conclusions from the conducted experiments and their outcomes.

A Appendix 1

Elucidate on possible appendices.

References

[Goodfellow et al., 2014] Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2014). Generative adversarial networks.

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