Generating images with Generative Adversial Networks

Képgenerálás Generatív Versengő Hálózatokkal

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Abstract

Képek generálása az egyik újszerű alkalmazása a neurális paradigmának. A gépi tanulás ezen része az ún. felügyelet nélküli tanuláshoz tartozik, ez az az eset, ahol bemeneteinkhez nem tartoznak elvárt kimenetek, ezek alapján kell valamilyen eloszlást megtanulnunk vagy klaszterekbe csoportosítani a tanítómintáinkat. Jelen esetben a tanítóminták halmazát a Google Open Image Dataset-ből szereztük, jelen esetben kutyákat generáltunk. Természetesen ennek valós alkalmazásai is lehetnek, például emberek „öregítése", vagy különböző filterek létrehozása, esetleg a jövőben lehetséges lehet akár a ruhapróbálás otthonról. A képgenerálást generatív versengő hálózatokkal valósítottuk meg, ebben az esetben egy két szereplős játék folyik le egy generátorhálózat és egy diszkriminátorhálózat között. A generátor megpróbál olyan képeket generálni, amelyek átverik a diszkriminátor hálót, a diszkriminátor pedig megpróbálja megkülönböztetni a valódi és a generált mintákat egymástól, így a diszkriminátoron keresztül tanul a generátor, ami problémát jelenthet[7]. A dolgozatunkban kitérünk a hálózat tanítása során felmerülő esetleges problémákra, illetve azok megoldásaira.

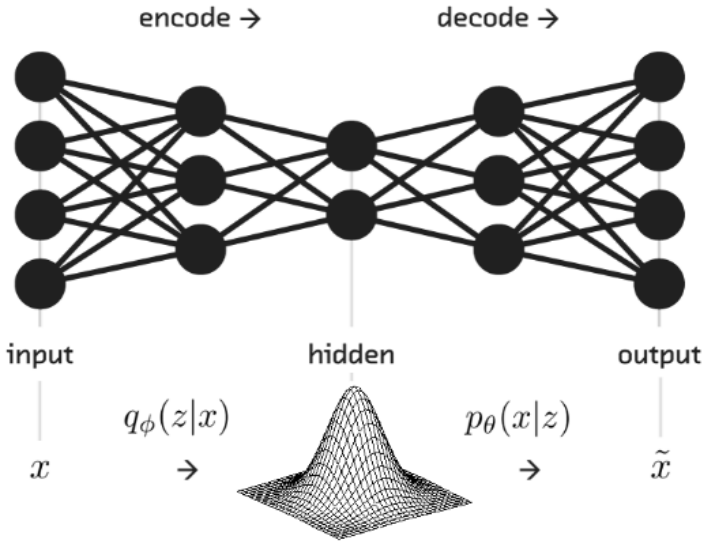
Genereting images is one of the newest applications of the neural paradigm. This part of machine learning is called unsupervised learning, which means that there are no expected values linked tot he inputs, only the inputs itself. This way we can learn the distribution function or cluster the data. In this case we obtained our data from the Google Open Image Dataset, with the aim of generating dogs. Of course, there are several actual applications of generating images, for example „aging" the person on a picture or creating different filters and perhaps in the future trying on clothes from your apartment might be an opportunity. We solved the problem with Generative Adversial Networks (GAN). A GAN is basically a two-player game. The generator network tries to generate pictures that deceive the discriminator network, meanwhile the discriminator network tries to guess whether the picture came from the generator or from the real world. This way the generator network is trained through the discriminator network, which might cause some trouble[7]. In our study, we tried to cover the problems of training a GAN, and suggest solutions to the problems.

Introduction

Neural networks and deep learning(DL) is one of the most researched areas of artificial intelligence(AI). This has come so far that if we see an article in the news which mentions AI, we are 99% accurate if we say that the device uses some sort of deep learning algorithms. One of the most shocking interactions with AI today might be when we look at a picture and we wouldn't even think that it was made by a machine, but it turns out to be made by one. This is where unsupervised learning comes to the table. The job of the network is to learn some of the features of the target we want to create pictures of. For example a human has two eyes, one nose and two ears (well, most of the cases), so it has to be represented somehow by the network. Different networks use different methods to represent a higher level knowledge of the object.

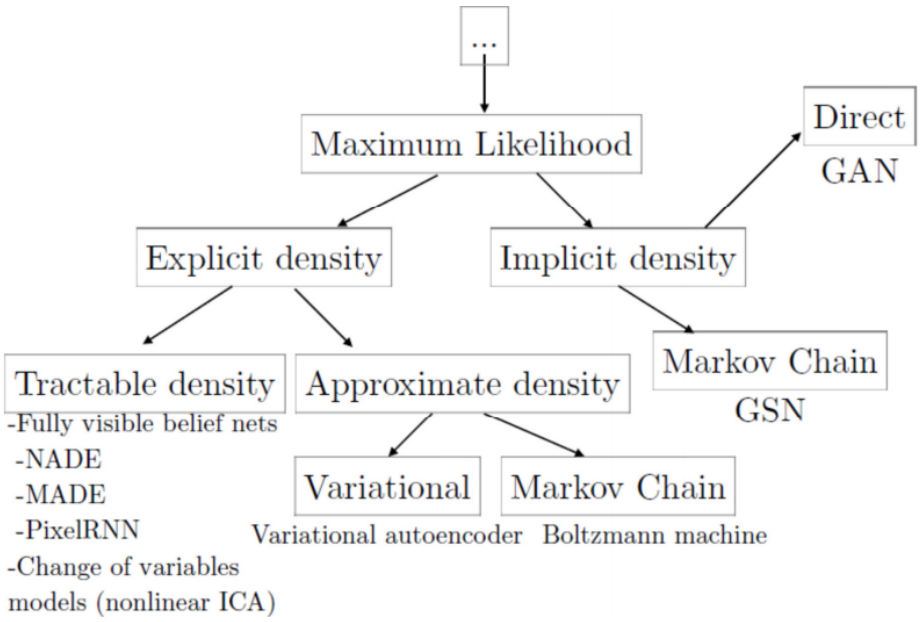
Related Work

Since neural networks and computer vision is one of the most researched areas, there are several solutions tot he problem of image generation. One of the first approaches are Autoencoders[1]. The points of the encoder part is to transfer the input pictures to a latent dimension, that represent a higher level knowledge, this could interpreted as compressing the data. After the encoding, the decoder part of the network decodes encoded input vector. This way if we generate latent vectors with unimodal density functions and we feed it into the decoder network, the output is a desired picture.



1 Visualization of an Autoencoder network[5]

Altough there are several ways of learning density functions - shown in picture 2 -, we decided to use GANs.[7] We created both of the networks in keras, with dense layers and then tried to optimize the hyperparameters so that we get perfectly cute, yet not real dogs.



2 Methods used to generate pictures[4]

Our Work:

Our work had one purpose and one purpose only, which is to generate perfectly real dog pictures using GAN.

Preparing the data:

We gathered our data from the Google Open Image Dataset and we used all the dog pictures to train our network. Using 10% validation split. We used data augmentation techniques too[9].

Training and optimizing:

The training at the beginning was not so well, but it would have been a miracle if it was okay at first. The loss of the generator was so big and the loss of the discriminator was so small. The discriminator overlearned. The problem was that, the neural network was so shallow. Then we tried make deeper neural network, which was a good choice. If the discriminator was too deep, we had vanishing gradients problem[10]. At first the activation was Leaky ReLu, then we tried the normal ReLu and the normal ReLu was better. Without a convolutional layer it was not good because it had lost its essence the consecutive pixels. We thought that the discriminator don not need so much layer, but it need. After that the

generator overlearned, so we had to use higher learning rate, which resulted in better learning. We used glorot nominationat[11] the initializer.

Evaluation:

Testing:

We asked some of our friends to tell if a picture was from the real world or is it generated by the network. We showed them pictures from the training data and from our generated dataset. The 3 pictures below got different realness percentages:

Insert PICTURES + %s

Conclusion

Spectral normalization[8] could be tried in the future to stabilize the training of the discriminator. A persisting challenge in the training of GANs is the performance control of the discriminator. In high dimensional spaces, the density ratio estimation by the discriminator is often inaccurate and unstable during the training, and generator networks fail to learn the structure of the target distribution.

References

[1] [1]http://proceedings.mlr.press/v27/baldi12a/baldi12a.pdf

[2] https://arxiv.org/pdf/1511.06434.pdf

[3] https://arxiv.org/pdf/1411.1784.pdf

[4] http://www.iangoodfellow.com/slides/2016-12-9-gans.pdf

[5]https://blog.fastforwardlabs.com/2016/08/22/under-the-hood-of-the-variational-autoencoder-in.html

[6] https://lanpartis.github.io/deep%20learning/2018/03/12/tricks-of-gans.html

[7] https://arxiv.org/pdf/1406.2661.pdf

[8] https://arxiv.org/pdf/1802.05957.pdf

[9] https://arxiv.org/pdf/1711.04340.pdf

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[10] https://arxiv.org/pdf/1804.00140.pdf

[11] http://proceedings.mlr.press/v9/glorot10a/glorot10a.pdf?fbclid=IwAR014jWVeGNHDbSL-tqIqGKC_QF5RzXpcA-mOfGt4-rera9mD-ceIlIEuuk