Nizhny Novgorod State University
Institute of Information Technologies, Mathematics and Mechanics
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Educational course
«Modern methods and technologies of deep learning in computer vision»

Lecture №7
Preparing synthetic data based on generative adversarial networks

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Content

1 Abstract

The goal of this lecture is to study the general scheme of constructing ***generative adversarial networks*** (GANs) and the algorithm of their training, to consider the classification of generative adversarial networks and their applications.

First, the concept of a generative model is introduced and the difference between generative and discriminative modelling in probabilistic terms is formulated [4]. Further, we consider the general scheme of constructing generative adversarial networks, it consists of two neural networks named generator and discriminator [1, 2]. Generator is a network which generates data samples. The goal of the generator is to study to "fool" a discriminator. Discriminator is a network which tries to distinguish real observations from generated samples. The goal of the discriminator is to study recognizing "lie" in the best way. The lecture provides the mathematical statement of the problem of training generative adversarial networks and the description of training algorithm.

Further, we consider the classification of generative adversarial networks [3].

- ***Fully Connected GANs*** [1, 2].
- ***Conditional GANs*** (CGAN) [6].
- ***Laplacian Pyramid of Adversarial Networks*** (LAPGAN) [7].
- ***Deep Convolutional GANs*** (DCGAN) [8].
- ***Generative Recurrent Adversarial Networks*** (GRAN) [9].
- ***Information Maximizing GANs*** (InfoGAN) [10].
- ***Bidirectional GANs*** (BiGAN) [11].

For each of the represented models, a general structure is given, the features of their training and testing are described. Generative adversarial networks are not limited to those listed in this classification. These models are widely used; various modifications are being developed based on these models. There are specialized generative adversarial networks that solve specific problems.

The lecture concludes with the selected applications of generative adversarial networks [3].

- ***Data augmentation*** [5] means generating of synthetic data similar to the data in some existing dataset, but containing various transformations. As a rule, data augmentation is required to extend train dataset.
- ***Image super-resolution*** [7] and ***generating high-resolution images*** based on the auxiliary information [12].
- ***Image inpainting*** [13] means removing unwanted objects in the image or restoring damaged fragments of old photos.
- ***Style transfer*** [14] means transferring the style of one image to others, for example, transferring the style of drawing pictures by a painter in a photo.

Generative adversarial networks are deep models that are widely used to generate synthetic data for solving various problems. The range of problems covers both entertainment and practically significant areas. The represented applications confirm this statement.

2 Literature

2.1 Books

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2.2 Further reading

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