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COMPARATIVE CHARACTERISTICS OF THE ABILITY OF CONVOLUTIONAL NEURAL NETWORKS TO THE CONCEPT OF TRANSFER LEARNING

The object of research is the ability to combine a previously trained model of a deep neural network of direct propagation with user data when used in problems of determining the class of one object in the image. That is, the processes of transfer learning in convolutional neural networks in classification problems are considered. The conducted researches are based on application of a method of comparison of theoretical and practical results received at training of convolutional neural networks. The main objective of this research is to conduct two different learning processes. Traditional training during which in each epoch of training there is an adjustment of values of all weights of each layer of a network. After that there is a process of training of a neural network on a sample of the data presented by images. The second process is learning using transfer learning methods, when initializing a pretrained network, the weights of all its layers are «frozen» except for the last fully connected layer. This layer will be replaced by a new one with the number of outputs, which should be equal to the number of classes in the sample. After that, to initialize its parameters by the random values distributed according to the normal law. Then conduct training of such convolutional neural network on the set sample. When the training was conducted, the results were compared. In conclusion, learning from convolutional neural networks using transfer learning techniques can be applied to a variety of classification tasks, ranging from numbers to space objects (stars and quasars). The amount of computer resources spent on research is also quite important. Because not all model of a convolutional neural network can be fully taught without powerful computer systems and a large number of images in the training sample.

Keywords: *neural networks, transfer learning, convolutional neural networks, computer resources.*

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1. Introduction

The concept of transfer learning is to transfer knowledge gained in one or more initial tasks and use them to improve learning in the current task. As a result, it has become possible to retrain an artificial neural network trained in a single sample of data to perform tasks on a new data set, which significantly speeds up the learning process of the network.

Much research is currently underway into transfer learning. For example, work is being done to transfer knowledge between texts and images [1], knowledge is being transferred from unallocated data [2], and so on. Thus, for the task of recognizing diabetic retinopathy, some participants used transfer training [3, 4]. It is worth noting that there are already many different architectures of artificial neural networks that perform well image classification tasks. So when solving problems on new data it is easier and more efficient to choose one of the existing neural networks don't building it from scratch.

Therefore, it is important to investigate the ability of the existing variant of the architecture of the convolutional neural network to transfer learning, as it consists in using the existing neural network, trained in a particular task. In the new data sample, this network is no longer fully trained, but only the last few layers, assuming that when running each image from this sample to these layers, the network has identified features that carry all the necessary information about the image.

Thus, *the object of research* is the processes of transfer learning in convolutional neural networks. *The aim of this paper* is to investigate the ability of convolutional neural networks to transfer between different tasks of classification of tagged images.

2. Research methodology

In the classification problem, the neural network is better, the more accurately it classifies the object that is fed to it for the first time. Classic fully connected neural networks are not suitable for this task due to the large number of connections between neurons and a different architecture must be chosen. One of the most effective architectures to solve this problem is convolutional neural networks (CNN).

CNN is a specialized type of neural network for data processing that has a network topology. This paper considers the following architectures of wrapped neural networks:

– AlexNet;
– VGG;
– ResNet;
– DenseNet with different number of layers.

AlexNet is a network that includes convolutional layers (Fig. 1). It is a combination of convolutional layers, subsampling operations and only the last three layers are fully connected. Moreover, the size of the core of the convolution operation is first taken large and reduced in the process of passing through the network. The subsampling operation takes place after each convolution, increasing the density of uncorrelated areas.

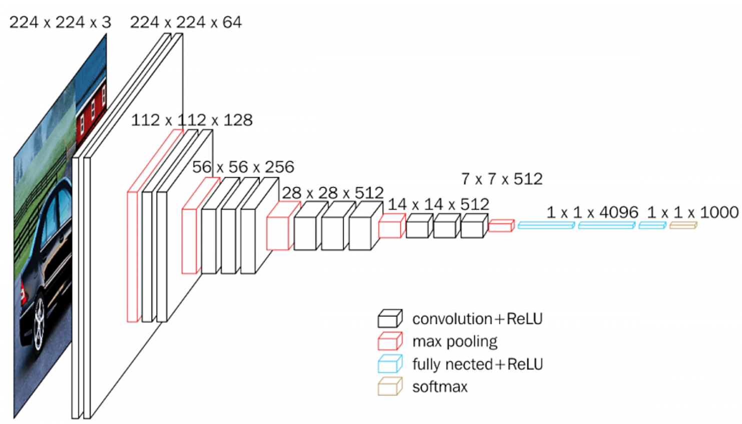

Fig. 2. Structure of VGG-16 [7]

As a result, after passing through the network, get the class to which the input image belongs. It takes a lot of examples and time to learn to find the right weights iteratively.

Neural networks VGG are deeper than AlexNet – and consist of 11–19 layers [6]. It should be noted that the size of the cores of the convolution operation is preferably equal to 3×3 or 1×1, in contrast to the previous network, which has a positive effect on the total number of parameters. For example, in packages with 3×3 and 7×7 cores, the receptive fields are the same, but the number of parameters is smaller. Accordingly, learning such a model requires less memory. The architecture of VGG-16 is presented in Fig. 2.

According to the data from [8] on the image set ImageNet VGG-13 gives an error of 10.75 %, VGG-16 – 9.62 %, and VGG-19 – 9.12 %. From this let's conclude that the deeper the network, the more effective it will be, but in practice it turned out that this is not the case: the quality of the model reached a certain limit, and then began to decline.

The authors of ResNet were able to find such a topology that as the depth of the network increases, its effectiveness does not decrease. The architecture of the ResNet network [9] consists of layers, which, in turn, consist of such blocks. The last two layers are the subsampling layer and the fully connected layer.

To improve the information flow between the layers, the authors of [10] proposed a slightly different scheme from ResNet: they introduced direct connections from any layer in all the following. Due to such a density of connections in the network, it got its name. The number of feature maps on the transition layers has also been reduced. This network has the same feature as ResNet: increasing the depth improves the accuracy of the model. Compared to ResNet, DenseNet was more effective.

This paper considers the use of transfer training in solving classification problems on the following well-known data sets:

1. MNIST. Database representing handwritten numbers [11].
2. Fashion-MNIST. Image base, which is an image of clothing.
3. CIFAR-10. Database of marked color images.
4. CIFAR-100. The data set is similar to the previous one with the only difference that this set has 100 classes.
5. LabelMe. An open dynamic dataset created at the Massachusetts Institute of Technology Artificial Intelligence Laboratory.
6. SDSS17. Classification of a set of stars and quasars from galaxy the DR17.
7. Vegetable Image Dataset. A total of 21000 images from 15 classes are used where each class contains 1400 images of size 224×224 and in *.jpg format. The dataset split 70 % for training, 15 % for validation, and 15 % for testing purpose.
8. Caltech101. Is a voluminous database of images intended for development and testing of image recognition and machine vision methods [12].

The purpose of transfer learning is to improve the quality of learning in the current (target) task, using the knowledge gained earlier from the original task. Thus, knowledge transfer can have a positive impact on the following learning indicators:

– initial performance achievable in the current task by selecting the initial parameters of the model, using a priori information (knowledge transferred);
– the time it takes to fully study the current task, taking into account the transmitted data;
– the final level of productivity achievable in the current task.

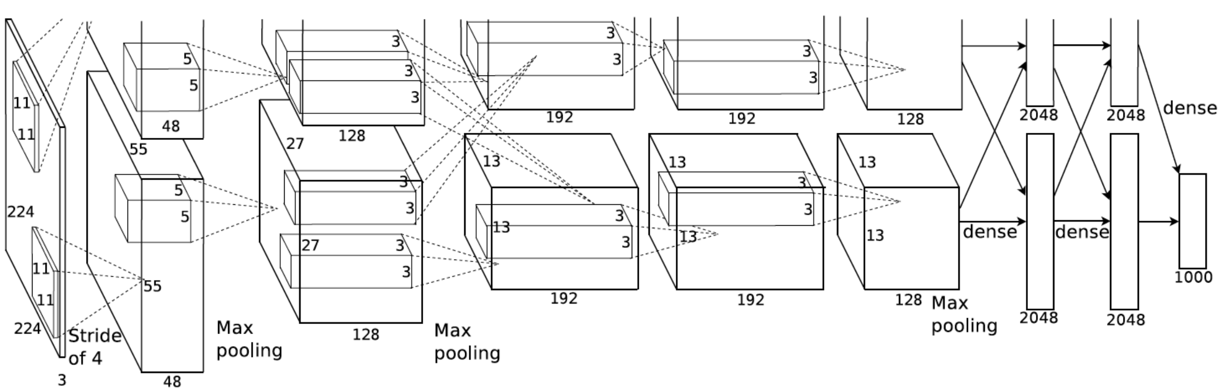

Fig. 1. Structure of AlexNet [5]

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There are cases when the original task is not closely related to the current task or this relationship is not fully taken into account when using the method of knowledge transfer. Then productivity can both remain at the same level and decrease. This phenomenon is called negative transfer. Thus, one of the tasks of researchers in the field of transfer learning is to get a positive result when transferring knowledge between similar tasks and eliminate the negative result between unrelated tasks.

This article considers the application of transfer learning to image classification tasks, where learning takes place on a sample of data consisting of «object – label» pairs. To conduct the study, it is proposed to teach networks in two ways, without the use of transfer training and with its use.

In the process of learning CNN without the use of transfer learning in each epoch of learning, there is an adjustment of the values of all weights of each layer of the network, there is a standard learning process of the neural network on a sample of data represented by images.

Learning CNN using transfer learning can be done in two ways [8]:

1) fine-tuning of the network: instead of arbitrary initialization of the network take the weight of pre-trained on a large sample of the network. The learning process not only retrains the classifier for the new data set, but also fine-tunes the weights of the network by reverse propagating the error;

2) when initializing a pre-trained network, the freezes of all layers are «frozen», except for the last fully connected layer. This layer is replaced by a new one with random weights, and only it learns.

Thus, the research technique is to load the previously trained convolutional neural networks discussed earlier.

The following algorithm is offered:
- download training and test samples of images;
- download a pre-trained model of CNN;
- to record («freeze») the parameters of all layers of the convolutional block of the neural network;
- in the classifier block, replace the last fully connected layer with a new one with the number of outputs equal to the number of classes in the sample, initialize its parameters with random values distributed according to the normal law;
- to train such a wrapped neural network on a given sample.

As a result, it will be concluded to which classification methods may be applicable and whether they can be applied in the general case.

3. Research results and discussion

Table 1 shows the accuracy of the classification of some CNN after regular training. The criterion for stopping in the learning process is the number of epochs of learning. The average learning time of networks is about 5 hours. That is, the limitations are the number of training epochs, the process of negative transfer and the computing power of the server, because the power of the server depends on the training time.

In Table 2 shows the accuracy of image classification of pre-trained neural networks after training using transfer training methods. The criterion for stopping in the learning process is the number of epochs of learning. This learning process took from 5 minutes to 3 hours (for neural networks with a very large number of layers). It is worth noting that these figures may be higher, but this requires a different criterion of stopping, and also requires more time and more powerful computer resources.

Analyzing the results shown in Tables 1, 2, it is possible to say that the use of transfer learning methods in the learning process can be applied to different classification tasks. The results of image classification from test samples are quite high in both training options. The disadvantage of the study is that it took place on basic training sets, in the future you should use your own specialized data sets.

As a result of this study, there has been a reduction in efforts to re-collect data for intelligent system training. That will reduce the cost of its development and minimize the risks of «restructuring» the system, and as a consequence, reduce the cost of its maintenance. Therefore, the minimization of economic and time needs for the development of intelligent systems is obtained.

Table 1

Accuracy of CNN classification of images from the test sample after classical training

Architecture CNN	MNIST	CIFAR-10	CIFAR-100	Fashion MNIST	LabelMe	SDSS17	Vegetable Image Dataset	Caltech 101
AlexNet	0.9453	0.9369	0.6473	0.8109	0.9297	0.9504	0.8492	0.9425
VGG-16	0.9719	0.9186	0.6023	0.7615	0.9521	0.7917	0.8049	0.9513
VGG-19	0.9643	0.9152	0.6217	0.7634	0.9504	0.8695	0.7885	0.9457

Table 2

Accuracy of classification of CNN images from test sample after training by means of transfer learning

Architecture CNN	MNIST	CIFAR-10	CIFAR-100	Fashion MNIST	LabelMe	SDSS17	Vegetable Image Dataset	Caltech 101
AlexNet	0.9465	0.8391	0.6138	0.8619	0.9013	0.9124	0.9215	0.9425
VGG-16	0.9303	0.8398	0.6253	0.8650	0.9538	0.8237	0.8214	0.9605
VGG-19	0.9204	0.8515	0.6321	0.8632	0.9535	0.9287	0.7893	0.9786
ResNet 50	0.9221	0.8183	0.6181	0.8469	0.9409	0.9632	0.8450	0.9962
ResNet 101	0.9156	0.8031	0.5913	0.8485	0.9379	0.9636	0.8446	0.9837
ResNet 152	0.9169	0.8034	0.5894	0.8503	0.9512	0.9479	0.8427	0.9936
DenseNet 121	0.9379	0.8263	0.6119	0.8513	0.9612	0.9697	0.8106	0.9701
DenseNet 161	0.9458	0.8841	0.6719	0.8734	0.9639	0.9818	0.8803	0.9916

4. Conclusions

This paper discusses the concept of transfer learning in relation to image classification tasks that differ in subject area and image parameters, and provides a brief overview of several convolutional neural network architectures. A study was conducted to conduct two different learning processes (traditional learning and learning using transfer learning methods) on several samples of images and to compare the obtained indicators.

Based on the results, it can be concluded that CNN training using transfer training methods can be applied to different classification tasks, and training was more effective with much less time. Also be noted that the most effective networks for transfer training were ResNet and DenseNet, whose average accuracy was 86.19 and 89.91 %, respectively. In the future, it is recommended to use these two architectures to transfer learning. The amount of computer resources spent on research is also quite important, as not every model of CNN can be fully trained without powerful processors. Transfer training allows to partially solve this problem, as in the process of such training changes the parameters of not all, but only a few layers.

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