25 Years of CNNs: Can We Compare to Human Abstraction Capabilities?

catchy title

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Abstract. We try to determine the progress made by convolutional neural networks over the past 25 years in classifying images into abstract classes. For this purpose we compare the performance of LeNet to that of GoogLeNet at classifying randomly generated images which are differentiated by an abstract property (e.g., one class contains two objects of the same size, the other class two objects of different sizes). Our results show that there is still work to do in order to solve vision problems humans are able to solve without much difficulty.

problem

methods

results

Keywords: Convolutional neural networks · Abstract classes · Abstract reasoning

1 Introduction

context

Deep learning methods have gained interest from the machine learning and computer vision research communities over the past several years because these methods provide exceptional performance for a vast majority of classification tasks. An important example of deep learning methods are Convolutional Neural Networks (CNNs) — first introduced in 1989 by LeCun *et al.* [1] — which have become popular for object classification. CNNs were more widely used after the deep CNN from Krizhevsky *et al.* [2] outperformed state-of-the-art methods by a wide margin in the “ImageNet Large Scale Visual Recognition Competition” of 2012.

Convolutional neural networks consist of multiple layers of nodes, also called neurons. One important layer type is the convolutional layer, from which the networks obtain their name. In a convolutional layer, the responses of the nodes depend on the convolution of a region of the input image with a kernel. Additional layers introduce non-linearities, rectification, pooling, etc. The goal of training a CNN lies in optimizing the network weights (including the kernels used for convolution) using image-label pairs to best reconstruct the correct label, given an image. During testing, the network is confronted with novel images and expected to generate the correct label. The network is trained by gradient descent which is calculated by backpropagation of labeling errors. The general idea of CNNs is to automatically learn the features needed to distinguish classes

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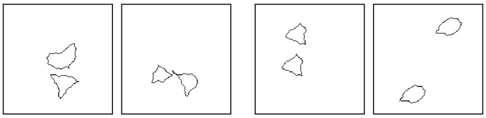
and generate increasingly abstract features as the information is transferred to higher layers.

Since CNNs are very popular at the moment and are being perceived — in parts of the computer vision community — as achieving human-like performance, we wanted to test their applicability on visual tasks slightly outside the mainstream which are still trivially solved by humans.

2 Materials and Methods

2.1 The Dataset

We use the framework presented by Fleuret *et al.* [3] to generate our dataset consisting of 23 different problems which are briefly summarized as follows: Each problem consists of two classes of images. Images of the first class exhibit some abstract property which is not present in images of the second class and vice versa. Figure 1 shows examples of the two classes for problem one. Both classes contain two random objects. In the first class the objects are different, while in the second they are identical. The goal is to assign the correct class to previously unseen images. These problems are reminiscent of the Bongard problems presented by Bongard [4] and further popularized by Hofstadter [5].



(a) Class 1 (b) Class 2

Fig. 1. Example images for Problem 1

For each class of each problem we generate 20000 training images. We also generate an additional 10000 images per class and problem as a testing set. The size of the generated images varies depending on the used CNN. We chose images of 64×64 pixels for LeNet, and 224×224 pixels for GoogLeNet.

2.2 Learning Framework

For training the CNNs, we used Caffe by Jia *et al.* [6]. More specifically, we used the implementations of LeNet and GoogLeNet provided with Caffe. Only slight adaptations were made to some hyperparameters. See the appendix for concrete values. In addition, we used ADAM by Kingma & Ba [7] as the solver method instead of stochastic gradient descent and changed the last fully connected layer to only contain two neurons representing our two classes.

3 Experimental Evaluation

Since we want to know how much progress has been made between the first CNNs and a state-of-the-art model, we compare the performance of LeNet by LeCun *et al.* [1] from 1989 to GoogLeNet by Szegedy *et al.* [8] from 2014. We chose GoogLeNet as the modern CNN since it is a very popular architecture and it performed best in a number of categories in ILSVRC14. LeNet was chosen since it is the oldest widely known CNN.

We train one instance of LeNet and GoogLeNet for each problem using 20000 training images per class. The trained networks are then evaluated on a testing set containing 10000 previously unseen images per class for the same problem. The reported accuracy of the network is the proportion of correctly classified images to the number of all tested images. For three problems (3, 11, 13) from Fleuret *et al.* [3] we could not generate images of the correct size. Since we do not think it will influence the overall conclusion, we excluded those problems from our evaluation.

4 Results

Table 1 gives an overview of the achieved accuracy of both tested network architectures, the method presented by Fleuret *et al.* [3], and human test subjects. In addition, the table gives a short description of the properties which are used to differentiate the two classes.

At first glance, CNNs do not seem to have made much progress over the last 25 years with the types of problems we tested, and even compare very unfavorably to the boosting method presented by Fleuret *et al.* [3]. The average accuracy of GoogLeNet even decreased slightly compared to LeNet.

Upon closer inspection, there seem to be two groups of problems: Ones which require the comparison of shapes and ones that do not. If we only consider problems which do not, the two CNNs perform very well. LeNet has an average accuracy of 0.95 and GoogLeNet achieves practically perfect accuracy. Both also compare very favorably to the method presented by Fleuret *et al.* [3] which achieves a mean accuracy of 0.86 on this subset of problems. We will discuss those two subsets of problems in the following sections in more detail.

interpretation

4.1 Problems Not Involving Comparisons

Problems 2, 4, 9, 10, 12, 14, 18, and 23 can be differentiated by the relative positioning or grouping of the shapes. The shapes themselves are not relevant to the classification except for problems 9 and 12, where the size of some of the shapes play a roll in the classification. Apparently, those problems can be solved by detecting local and global features alone. Hence CNNs work well on those problems.

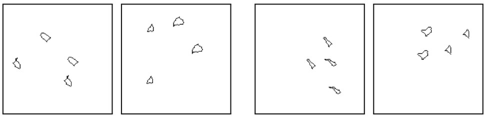
Table 1. Accuracy comparison of presented methods. The two groupings consist of problems which either need shape comparison to be solved or not. Accuracy of LeNet and GoogLeNet are experimentally determined in this paper. Fleuret are results from the best performing system proposed by Fleuret *et al.* [3] (Boosting with feature group 3). The human results are estimated accuracies of participants also tested by Fleuret *et al.* [3] and reinterpreted for this paper.

Problem	LeNet	GoogLeNet	Fleuret	Human	Difference between classes
1	0.57	0.50	0.98	0.98	Compare
5	0.54	0.50	0.87	0.90	Compare & grouping
6	0.76	0.86	0.76	0.70	Compare & grouping
7	0.53	0.50	0.76	0.90	Compare & grouping
8	0.94	0.91	0.90	1.00	Compare & relative position
15	0.52	0.50	1.00	0.95	Compare
16	0.98	0.50	1.00	0.78	Compare
17	0.75	0.95	0.67	0.78	Compare & relative position
19	0.51	0.50	0.61	0.98	Compare
20	0.55	0.50	0.70	0.98	Compare
21	0.51	0.51	0.50	0.83	Compare
22	0.59	0.50	0.97	1.00	Compare
2	1.00	1.00	0.98	1.00	Relative position
4	0.98	1.00	0.93	1.00	Relative position
9	0.93	1.00	0.68	0.93	Size & relative position
10	0.99	1.00	0.94	0.98	Relative position
12	0.97	1.00	0.84	0.95	Size & relative position
14	0.90	1.00	0.73	0.98	Alignment
18	0.99	0.99	0.99	0.93	Grouping
23	0.87	1.00	0.75	1.00	Relative position
Average	0.77	0.76	0.83	0.93	

4.2 Problems Involving Comparisons

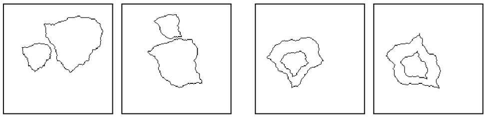
Problems 1, 5, 6, 7, 8, 15, 17, 19, 20, 21, and 22 involve comparing shapes in one way or another. To solve these problems, an agent has to be able to decide whether two shapes are similar or not at one stage of the classification process; e.g., in problem 1 (Fig. 1) the two classes only differ by whether the two presented shapes are identical or not. Except for problems 6, 8, 16, and 17, LeNet as well as GoogLeNet do not achieve accuracies significantly above chance.

Problems 6, 8, and 17 seem to be solvable by the tested CNNs although they in theory also require the comparison of shapes. *Problem 6* (Fig. 2) presents two pairs of identical shapes and the two classes are separated by whether the distances between each pair is the same or not. *Problem 8* (Fig. 3) presents two



(a) Class 1 (b) Class 2

Fig. 2. Example images for Problem 6



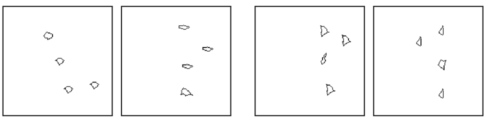
(a) Class 1 (b) Class 2

Fig. 3. Example images for Problem 8

shapes of differing size. One class always contains a small shape inside a bigger version of the same shape. The other class either has a smaller shape inside a different, bigger shape or two identical shapes which are not nested. *Problem 17* (Fig. 4) presents four shapes, of which three are identical. The two classes are separated by whether the distance between the identical shapes are all the same or not.

In theory, an agent has to be able to compare shapes to solve problems 6, 8, and 17; otherwise the additional information, like relative position, does not matter. We had the suspicion that the generation process for these problems imparts some unwanted pattern to the images which the CNNs can use to separate the classes thus avoiding the need to compare shapes. If this is the case, we can expect the same accuracy even if images of both classes contain identical shapes. Theoretically this should mean that those modified problems are not solvable. Training and testing the CNNs with those modified problems gives us similar results (Table 2) to the original problems, which indicates that the CNNs are exploiting some unintended pattern in the data and comparing the shapes does not contribute to the classification.

Problem 16 (Fig. 5) requires the agent to decide whether shapes on the right side are identical copies of the shapes on the left, or whether they are vertically mirrored. Surprisingly, LeNet solves this problem almost perfectly, with an

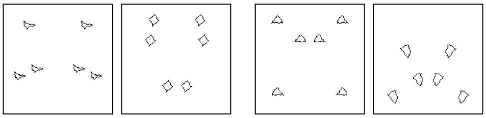


(a) Class 1 (b) Class 2

Fig. 4. Example images for Problem 17

Table 2. Results for problems 6, 8, and 17 when all images only contain identical shapes.

Problem	LeNet	GoogLeNet	Difference between classes
6	0.75	0.85	Compare and grouping
8	0.95	0.90	Compare and relative position
17	0.77	0.93	Compare and relative position



(a) Class 1 (b) Class 2

Fig. 5. Example images for Problem 16

accuracy of 0.98, while GoogLeNet cannot solve it at all, with an accuracy of 0.5. We suspected this to be an artifact and that generating the images with a relatively small size of 64×64 pixels for LeNet adds some unwanted pattern to the images which the network can exploit. Since GoogLeNet uses images with a size of 224×224 pixels it would not profit from this. To test this hypothesis, we trained LeNet using images with a size of 128×128 pixels, and, as expected, the accuracy dropped to 0.5.

4.3 Human Performance

Fleuret *et al.* [3] presented experiments to determine the performance of humans on the same dataset we use for our experiments. Each participant was tested on all problems. For each of the problems, an example which is randomly chosen from one of the two classes is presented and the participant has to indicate whether it is from class one or two. After choosing a class, the correct answer is revealed and the next example is shown. All previously seen images are kept on the screen with their correct class. What is recorded in the experiment is the number of examples the person has to see until he or she consistently chooses the correct class. It is also recorded if a test subject can not solve a problem at all.

Unfortunately, the mode of testing is sufficiently different from the way machine learning solutions are evaluated that a direct quantitative comparison is difficult. To get some accuracy values we can compare other methods to we define accuracy of humans as follows. We assume a person which was able to solve a problem to have an accuracy of 1.0 and one which was not of 0.5. We can then calculate an expected accuracy of the whole group of test subjects with

$$a = \frac{p_a + \frac{p_n}{2}}{n} \tag{1}$$

where a is the accuracy, p_a is the number of participants who were able to solve this problem, p_n being the number of participants who were not able to solve the problem and n being the number of all participants. The accuracies reported in Table 1 were calculated from the original data reported by Fleuret *et al.* [3] using Eq. 1.

5 Discussion

at a higher level than the details discussed above

Each parag

Looking at the results of our experiments one can come to very different conclusions. Simply looking at the overall performance looks very disappointing. The over 25 year old LeNet is better than the current GoogLeNet, although only marginally. A closer inspection reveals that there is a problem class which neither of the CNNs is capable of solving at all; namely problems which require the comparison of shapes. We showed that the few problems in this class which the CNNs can learn are actually learned because of some unexpected side effects of image generation. We conclude that CNNs have an inherent problem when it comes to comparative features. It should be noted that neither humans nor the boosting method employed by [3] show this big performance gap between the two subsets. The mean accuracy of the boosting method is 0.81 for problems with shape comparison versus 0.86 for problems without. The human test subjects show a mean accuracy of 0.90 and 0.97 for the two subsets respectively.

If we accept that CNNs are generally not capable of solving problems containing shape comparison, the results look a lot better. Not only do both networks perform very well on the other problems, but GoogLeNet achieves, for all intents and purposes, perfect accuracy. It even outperforms the human test subjects. Obviously, the CNNs need a much larger training set to achieve those accuracies. Where human subjects usually need below 20 images and often only require 2 images to correctly learn the class and achieve perfect accuracy, GoogLeNet generally needs about 4000 images to achieve an accuracy ≥ 0.99 (problem 2: 400 images, problem 4: 4000, 9: 4000, 10: 4000, 12: 40000, 14: 40000, 18: 4000, 23: 4000). Of course, humans have a lot of prior knowledge, so the results are hard to compare. An interesting difference between machine learning algorithms and humans is the fact that an algorithm can have an accuracy of e.g. 80 % on these abstract problems, but human subjects generally either understand what separates the two classes and achieve an accuracy of 100 %, or do not understand it and have an accuracy close to pure chance. This suggests that the underlying principles of classification are probably very different.

Further, our experiments show how difficult it can be to evaluate CNNs on abstract problems. One has to be extremely careful to guarantee that the network is actually solving the problem one wants to test and does not use some additional superficial pattern. In our case it would have appeared as if CNNs can in fact compare shapes because they were able to solve problems 6, 8, and 17 quite successfully. Only close scrutiny revealed that the networks were in fact exploiting patterns which were a side effect of the dataset generation.

We think it will be useful to further investigate the performance of deep learning methods on more abstract problems than are usually considered since it can reveal a lot about the shortcomings and strengths of specific methods and might inform further advances of the methods. We further hypothesize that if the shape comparison problem of CNNs can be solved they would presumably also perform better on more common tasks.

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Appendix

details a reader might want to know, in particular to reproduce these results, b

- Parameters used for LeNet: iterations = 25000, base learning rate = 0.001, weight decay = 0.00005, solver = ADAM, $\beta_1 = 0.9$, $\beta_1 = 0.999$, $\epsilon = 10^{-8}$.
- Parameters used for GoogLeNet: iterations = 25000, base learning rate = 0.001, average loss = 100, weight decay = 0.002, solver = ADAM, $\beta_1 = 0.9$, $\beta_1 = 0.999$, $\epsilon = 10^{-8}$.

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automatically generated

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