Can Deep Neural Networks Match the Related Objects?: A Survey on ImageNet-trained Classification Models

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Abstract
Deep neural networks (DNNs) have shown the state-of-the-art level of performances in wide range of complicated tasks. In recent years, the studies have been actively conducted to analyze the black box characteristics of DNNs and to grasp the learning behaviours, tendency, and limitations of DNNs. In this paper, we investigate the limitation of DNNs in image classification task and verify it with the method inspired by cognitive psychology. Through analyzing the failure cases of ImageNet classification task, we hypothesize that the DNNs do not sufficiently learn to associate related classes of objects. To verify how DNNs understand the relatedness between object classes, we conducted experiments on the image database provided in cognitive psychology. We applied the ImageNet-trained DNNs to the database consisting of pairs of related and unrelated object images to compare the feature similarities and determine whether the pairs match each other. In the experiments, we observed that the DNNs show limited performance in determining relatedness between object classes. In addition, the DNNs present somewhat improved performance in discovering relatedness based on similarity, but they perform weaker in discovering relatedness based on association. Through these experiments, a novel analysis of learning behaviour of DNNs is provided and the limitation which needs to be overcome is suggested.

Introduction
In a recent decade, deep neural networks (DNNs) have achieved remarkable performances in a wide range of complicated tasks in image recognition, speech processing, health care, robotics, and gaming (LeCun, Bengio, and Hinton 2015). Especially, in image recognition, the DNNs have shown outstanding performances for image classification and object detection in ImageNet database (Russakovsky et al. 2015), and have opened the era of deep learning in the field of computer vision.

One of the interesting characteristics of DNNs is that it is difficult to intuitively grasp the principle and internal structure of learning, which is so-called black box characteristic. This black box characteristic causes can cause a number of problems in several tasks. For instance, when analyzing medical images, it is very important not only to improve the accuracy of the diagnosis, but also to provide a detailed explanation that the physician and the patient can understand the basis of the diagnosis. In addition, when DNNs do not achieve satisfactory performance for a given task, one cannot figure out which part of DNNs the limitation comes from because the internal structure is not known. The fact that one should heavily rely on fine-tuning parameters and models to improve the performance of DNNs, can be also considered as the limitation caused by the black box characteristic of DNNs.

To address these limitations, various researches have been currently suggested to discover the internal structure of the DNN black boxes. Many of them have visualized the features learned in DNNs to provide intuition of learning behaviour of DNNs (Higgins et al. 2016; Karpathy, Johnson, and Li 2015; Li et al. 2015; Raposo et al. 2017; Yosinski et al. 2015; Zeiler and Fergus 2013). In addition, the studies on the weaknesses of DNN learning have been investigated through the degradation of its performance in certain images (Nguyen, Yosinski, and Clune 2014; Hosseini and Poovendran 2017). By reversing the information about the internal structure of DNNs obtained by the above analy-
Table 1: Examples of the ImageNet classification failure cases in which the predicted classes and the ground truth class are similar. It is difficult to conclude that the CNN performs incorrectly because these images are classified as the classes semantically similar to the ground truths. However, the rankings of the ground truths in the predicted probabilities are relatively low despite the semantic similarities between the classes. This can be understood as evidence that the current CNN training does not fully take into account the semantic similarities between classes.

| Images | Top-5 predicted classes (Predicted probabilities) | Ground truth classes (Predicted probabilities, ranks in the predicted classes) |
|--------|--------------------------------------------------|---------------------------------------------------------------------------|
| ![Image](image1.png) | desk (23.5%) desktop_computer (9.8%) library (7.5%) monitor (3.1%) | notebook (1.5%, 11th) |
| ![Image](image2.png) | palace (65.9%) triumphant_arch (5.8%) fountain (4.4%) pedestal (3.4%) monastery (3.3%) | castle (0.19%, 18th) |
| ![Image](image3.png) | tow_truck (9.5%) garbage_truck (9.2%) tank (7.9%) jeep (7.5%) trailer_truck (3.6%) | moving_van (0.85%, 22nd) |

In this paper, we investigated the weakness of DNN learning through a cognitive psychology method. A recent study visually evaluated the failure cases of the ImageNet classification results to analyze how the DNNs fail to recognize certain images (Lee, Agarwal, and Kim 2017). In addition, one recent research studied the shape bias in DNN learning through cognitive psychology-inspired approaches (Ritter et al. 2017). Inspired by both of these studies, we conducted experiments in which we constructed the hypothesis about the weakness of DNN learning from observing the ImageNet failure cases, and verified it with the cognitive psychology approach. We hypothesized that the DNNs are successful in learning by distinguishing objects of different classes in highly sophisticated units, but fail in relating the objects of similar classes with each other. To verify our hypothesis, we used DNNs on the database including the pairs of related/unrelated object images provided from the cognitive psychology, to evaluate and analyze how well DNNs determine the relatedness between these object images.

Our results are summarized as follows. First, the DNNs are not successful in learning the relatedness of similar classes in general. Second, the performance of relatedness matching is generally proportional to the ImageNet classification performance. Third, there are two types of relatedness between object images: One is relatedness based on similarity in which two objects share similar characteristics, and the other is relatedness based on association in which two objects usually interact each other. Fourth, it is analyzed that the DNNs can grasp the relatedness based on similarity but not the relatedness based on association. Through these experiments, we not only investigated the limitations of DNN learning, but also obtained the insight on the principle of relatedness between objects.

**Motivation from ImageNet Failure Cases**

We first hypothesized the weakness of DNN learning by observing the failure cases of ImageNet classification. Lee et al. applied the ensemble model of ResNet-based convolutional neural networks (CNNs) to train ImageNet and performed visual inspection on 400 failure images sampled from the validation set (Lee, Agarwal, and Kim 2017). They then categorized the images into five categories, and one of them is so-called *similar class* group, which accounts for about 15% of the failure cases. In the images of this similar class group, the top-1 predicted class and the ground truth class have similar or almost the same meaning. In fact, these cases can not be regarded as a 100% failure because the DNNs predict semantically correctly for these cases. Thus, Lee et al. suggested to improve the evaluation method of ImageNet and put these failure cases into the successful cases.

However, it is noteworthy that the ground truth class is not shown in the top-5 predicted classes, although the ground truth and the top-1 predicted class are similar. Of course, in many cases in the similar class group, the ground truth class is ranked in the top 6th or top 7th in the predicted probability list. However, there are the cases in which ground truth class in ranked below the top 10th in the predicted probability list, as shown in Table 1. In the middle image, the probability of castle is measured to be 0.19% while the probability of palace is 65.9%. It inevitably raises the question of how extreme DNNs treat castle and palace differently. According to
the common knowledge, it is thought that the classes of similar objects should have similar probabilities, but it seems that the learning behaviour of DNNs shown in these ImageNet failure cases is not been significantly affected by our intuition. Therefore, we hypothesized that the DNNs do not sufficiently learn the relatedness between the similar object classes, and conducted the experiments to verify it.

**Experiments**

To evaluate how DNNs grasp the relatedness between the similar classes, we suggest the experiment summarized in Fig. 2. As experimental data, we used the Pool Of Pairs Of Related Objects (POPORO) database [Kovalenko, Chaumon, and Busch 2012] from cognitive psychology researches. The POPORO database consists of 400 pairs of images and each pair consists of 3 images, as shown in Fig. 3. The pair consists of an object image, an image of an object which is ‘related’ to the object, and an image of an object which is ‘unrelated’ to the object. The basic experiments were performed by showing three image sequentially and letting users to rate the relatedness with the object on two non-object images. In our experiments, the similarities between the object image and related/unrelated images were determined using DNNs, and the image with high similarity was matched to the object, to evaluate the matching performance of DNNs.

Our experimental framework consists of three steps. First, the features of three images are extracted using the ImageNet-trained DNN models. Two state-of-the-art CNN models, ResNet (He et al. 2015) and DenseNet (Huang, Liu, and Weinberger 2016), were used as DNN models. In order to observe the tendency in performance according to the internal parameter changes, six ResNet models and eight DenseNet models with different number of layers and channels were used, as summarized in Table 1. We used open source implementations for ResNet[1] and DenseNet[2] to extract the features from the last layer of DNNs. Second, the similarities between the object feature and related/unrelated features were calculated using cosine similarity [Ritter et al. 2017]. Using these cosine similarities, finally, the non-object image with higher similarity with the object was selected as matched image. In the experiments, we evaluated the matching performances as an error rate for whether the matched image determined by DNNs is the ‘related’ image.

**Results**

Fig. 4 shows the distribution of cosine similarities of DNN features and the user ratings provided by the database [Kovalenko, Chaumon, and Busch 2012] for all pairs of (object, related) and (object, unrelated). In user ratings, a significant difference was observed between the related (red) and unrelated classes (blue). On the other hand, the cosine similarities are found to have no meaningful difference between the related and unrelated classes. As a result, the ratio of the correct matches (o) to the incorrect matches (x) is almost 5:5.

[1] https://github.com/facebook/fb.resnet.torch
[2] https://github.com/liuzhuang13/DenseNet

![Figure 2: A framework for matching images of POPORO database with semantic relatedness using ImageNet-trained CNN models.](image2)

![Figure 3: Example images of POPORO database. For each object image, one ‘related’ image and one ‘unrelated’ image are provided. The labeling of related/unrelated was performed based on the user ratings of semantic relatedness.](image3)
Figure 4: A distribution of cosine similarities of CNN features for each pair of POPORO images. The x-axis represents the average of the user ratings used in the relatedness labeling for the POPORO database. The points with the related/unrelated ground truth labels are shown in red/blue, respectively. The points for which the matching results by similarity comparison are correct/incorrect, are indicated by o/x, respectively. In the graph, we can see that the related and unrelated pairs have a large difference between user ratings, but their cosine similarities are distributed in almost same range without a tendency. The cosine similarities are calculated from the features extracted from the ResNet-200, which shows the best matching results, and the cosine similarities computed with other CNN models show almost the same distributions.

In (a) and (d), the bag and the other bag, and the backpack and the backrest, were matched well because the class and the shape of the bags were clearly identifiable. However, if the class information is not enough clear for object or non-object and the two have large shape similarity such as (c), or if the two classes share no image similarity and the relatedness should be defined based on the association property between two, DNN matching showed incorrect results. Through the cosine similarity distribution, it can be observed that the DNNs does not show a meaningful behaviour in determining the relatedness between the two classes. Especially, as shown in Fig. 5, the cosine similarity distribution shows the same tendency for all the DNN models applied to the experiments, so all DNN models have a similarity distribution similar to Fig. 4.

With the cosine similarities computed from 400 related pairs and 400 unrelated pairs, we first predicted the relatedness for each data by changing the threshold for the cosine similarity. The receiver-operator characteristic (ROC) curves and their area-under-curve (AUC) values are shown in Fig. 5 and Table 2. As mentioned above, because the ratio of the correct matches to the incorrect matches was nearly 5:5, the ROC curves appeared almost diagonal. Inside the DNN models, the ResNet-200 which has the most layers outperformed other ResNet models, and the most fine-tuned DenseNet-cosine-264 with \( k = 48 \) outperformed other DenseNet models. From all models, the ResNet-200 showed the best matching performance with an AUC of 0.611.

Table 2 shows the matching error rates of the matching results obtained comparing the cosine similarities of the related pair and unrelated par for each data, according to the suggested experiments. These error rates also vary slightly within the DNN models at approximately 40%, and the tendency is similar to the tendency of ROC curves and AUC values in the above threshold-based prediction. Interestingly, the tendency of the matching performance is similar to that of the top-1 error performance from ImageNet classification. This is shown more clearly in Fig. 6 as a bar graph. In Fig. 6 it can be observed that the classification error, matching error, and AUC error increase and decrease with the almost same tendency according to the DNN models. However, there is a little difference that the ResNet tends to outperform the DenseNet models in matching performance for the same level of ImageNet performance. As a result, the ResNet-200 model achieved the best matching performance with matching error rate of 38.75%.

Figs. 7 & 8 illustrate the example images from the correct matches and incorrect matches by ResNet-200 model, respectively, where the difference between the two cosine similarities is large. In the ‘best’ cases, the similarity with the related is much larger than that with the unrelated, where it
can be seen that the object and the related have similar class as well as similar shape. On the other hand, in the ‘worst’ cases, the similarity with the unrelated is much larger than that with the related, where it can be observed that the object and the related have low class similarity while the unrelated has a very similar shape with the object, so the DNNs match them incorrectly.

Figs. 9 & 10 show the example images from the correct matches and incorrect matches by ResNet-200 model, respectively, where the difference between the two cosine similarities is small. In the ‘good luck’ cases where the related was fortunately correctly matched, the unrelated has more similar shape with the object, but the related also has a similar class with the object so the DNNs match them correctly. In the ‘bad luck’ cases where the related was unfortunately incorrectly matched, the cases show similar trend with the ‘good luck’ cases, but the object class is ambiguous or probably not identified in the ImageNet database, so the DNNs consider the shape similarity only and match them incorrectly.

**Discussion**

Our proposed experiments and their analyses provide a number of unique insights about the weakness of DNN learning. First, the DNNs are not fully aware of the relatedness between similar classes. This is due to the fact that the most of the image recognition tasks such as ImageNet are set up to classify and distinguish the given classes independently without considering their semantic similarity, rather than the limitation of the DNN model itself. Thus, it is not unnatural...
Figure 6: A bar graph for different CNN model performances shown in Table 2. To observe the tendency of errors, the AUC of the matching results is converted to the AUC error as 1–AUC to be plotted in the graph. It can be observed that the matching performances show a significant correlation with the ImageNet performances.

Figure 7: The ‘best’ cases of the correct matching results in which the difference of cosine similarity between the related and unrelated is large. The cases where the object and the related object are visually highly similar are mainly included.

Figure 8: The ‘worst’ cases of the incorrect matching results in which the difference of cosine similarity between the related and unrelated is large in negative direction. The cases where the object and the related object are semantically related rather than visually, and the unrelated object is more visually similar to the object than the related one, are mainly included.

Second, the performance of relatedness matching is generally proportional to the ImageNet classification performance. This interesting observation suggests that the DNNs, which currently are trained on the semantically similar
classes independently, is somewhat learning some degree of relatedness between the classes. We can also conversely argue that the learning of relatedness between the classes can be helpful for the learning of existing class-independent image recognition tasks such as ImageNet classification.

Third, there are two types of relatedness between the classes: One is relatedness based on similarity in which two classes share similar characteristics in shape and hierarchy, and the other is relatedness based on association in which two classes usually interact each other. Consider a monkey, a panda bear, and a banana. If one is told to match the related two, some will match the monkey and the panda bear, because the monkey and the panda bear are both animals and like to hang on trees. However, some may match the monkey and the banana, because the monkey loves the banana (although this is not a fact). The former matching is determining the relatedness based on similarity with similar hierarchy or shape between two objects or classes. The latter matching is then determining the relatedness based on association with interaction between two different objects or classes.

Finally, it was analyzed that the DNNs can grasp the relatedness based on similarity well, but hardly captures the relatedness based on association. This can be confirmed by observing the ‘best’ and ‘worst’ cases in Figs. 6 & 7. In the ‘best’ cases, the DNNs correctly matched all the related ones which show relatedness based on similarity. In the ‘worst’ cases, the DNNs failed to match the related ones which show relatedness based on association. This also can explain the reasons why DNNs showing better performance in ImageNet also show better matching performance. If the DNN does not capture the proper relatedness based on similarity from the semantically similar classes, this causes the degradation in ImageNet classification performance as shown in our ImageNet failure cases. Thus, it can be analyzed that as the DNNs have been improved to achieve better ImageNet performance, they unintentionally learn the relatedness based on similarity between the semantically similar classes. Therefore, it is expected that it will be a direction to improve the performance of DNNs in existing image recognition tasks, as well as the next step of cognitive machine learning, to enable learning of relatedness based on association.

Conclusion

In this paper, we investigated the weakness of DNN learning, by hypothesizing the lack of learning of relatedness through the ImageNet failure cases, and verifying it by using the cognitive psychology database. Our analysis provided not only performance of DNNs in determining relatedness, but also the insight of how the current DNNs recognize the concept of relatedness and how to enhance it. To improve the DNN learning that can determine relatedness based on association remains as future works.
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