Comparison of Performance of Multiple Data Augmentation Methods such as CutMix, mixUp in a Limited Environment

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Abstract

With the recent development of deep learning technology, deep learning models are being applied to solve problems faced in various industries. However, creating a good model requires a sufficient number of refined data and high-performance computing resources, which is another challenge that model designers need to consider and solve. Usually, data augmentation is used to solve these problems, which is an attempt to solve the problem of data shortage by transforming existing data in a situation where there is a lack of data required for model training. This article compares the performance of models learned with various data augmentation methods such as CutMix, mixUp in a limited environment to see which data augmentation methods show excellent performance.

1. Introduction

There are various methods of data augmentation, including cutMix and mixUp, which have recently been evaluated as producing good results. CutMix is a method of increasing generalization and localization performance by allowing the model to see and learn less distinct parts and overall areas of the image, and mixUp is a method of randomly selecting two sample data from multiple learning data to create new learning data. CutMix and mixUp are relatively up-to-date data augmentation methods, and this experiment also used techniques such as random flip, random crop, and random contrast, which are classical data augmentation methods.

2. Experiments

2.1. Experimental Settings

For comparison of data augmentation methods, ResNet-50 was used as the backbone model in this experiment, and the 'stanford dogs' dataset, which is basically provided by Tensorflow-dataset, was used as the dataset. Also the circumstances that require data augmentation presuppose that we have no choice but to train the model in a limited environment as well as a small number of data. Therefore, in this experiment, several conditions were constrained to artificially set this situation. As a setting for a limited environment, the GPU used to learn the model is RTX 3070 16GB, and a total of 15 Epochs were set with a batch size of 16.

2.2. Main Results

Figures 1 and 2 graphically show the model's prediction accuracy for validation data as learning progresses when CutMix, mixUp, and classical data augmentation methods are applied. In Figure 2, aug1 represents random flip and random crop, and aug2 represents the accuracy of predicting the validation data of the model to which random contrast, random hue, and random brightness are applied. In addition, Table 1 shows the loss

Methods	**train loss**	**train accuracy**	**val loss**	**val accuracy**
Cutmix	1.7094	0.8062	1.2801	0.6854
mixUp	1.8322	0.8447	1.2879	0.6792
aug1	0.0092	0.9992	0.9507	0.7620
aug2	0.0077	0.9994	1.2144	0.6994

Table 1: Performance evaluation table of models according to each data augmentation method

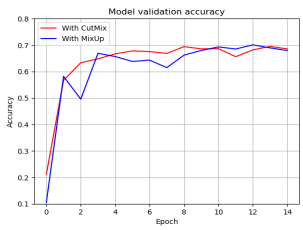

Figure 1: Validation Data Prediction Accuracy of Learning Progress in a Model with CutMix and Mixup

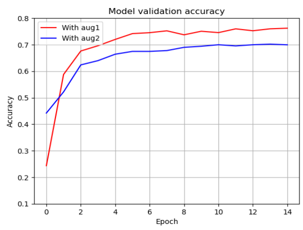

Figure 2: Validation Data Prediction Accuracy of Learning Progress in a Model with classic Methods

and accuracy of learning and validation data of models when applying each data augmentation method.

3. Summary and conclusions

As Figures 1 and 2 and Table 1 show, in a limited environment, classical data augmentation seems to help the model learn more than state-of-the-art data augmentation methods such as CutMix and mixUp. This is because modern data augmentation methods such as CutMix and mixUp use more computer resources to transform data than conventional data augmentation methods, and it only works after sufficient learning, so the classical method is more suitable for model learning with a small number of Epoch and limited computing environments.

References

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