A NOVEL THREE-STAGE Training
STRATEGY FOR LONG-TAILED
CLASSIFICATION

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Abstract
The long-tailed distribution datasets poses great challenges for deep learning based classification models on how to handle the class imbalance problem. Existing solutions usually involve class-balacing strategies or transfer learning from head- to tail-classes or use two-stages learning strategy to re-train the classifier. However, the existing methods are difficult to solve the low quality problem when images are obtained by SAR. To address this problem, we establish a novel three-stages training strategy, which has excellent results for processing SAR image datasets with long-tailed distribution. Specifically, we divide training procedure into three stages. The first stage is to use all kinds of images for rough-training, so as to get the rough-training model with rich content. The second stage is to make the rough model learn the feature expression by using the residual dataset with the class 0 removed. The third stage is to fine tune the model using class-balanced datasets with all 10 classes (including the overall model fine tuning and classifier re-optimization). Through this new training strategy, we only use the information of SAR image dataset and the network model with very small parameters to achieve the top 1 accuracy of 22.34 in development phase.

1 Contribution details
1.1 Three-stage training method
We propose a novel three-stage training procedure by decoupling the information-rich head-class data and the rest-classes data and transferring model’s expression ability from parts classes dataset to all classes dataset: we use the complete dataset for rough training, then we use rest-classes to train model, and after that we use class-balanced datasets to fine tune the whole model and classifier individually.
Figure 1: An illustration of the proposed three-stage training method.

1.2 References

We choose Shake-shake32[1] as our backbone, which proves to have great performance when facing over-fitting datasets. The inspiration for our approach comes from OLTR[2] and LDAM[3].

References

[1] Gastaldi, Xavier. "Shake-Shake regularization of 3-branch residual networks." In International Conference on Learning Representations (ICLR) Workshop, 2017.

[2] Ziwei Liu, Zhongqi Miao, Xiaohang Zhan, Jiayun Wang, Boqing Gong, and Stella X Yu. Large-scale long-tailed recognition in an open world. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 2537–2546, 2019.

[3] Kaidi Cao, Colin Wei, Adrien Gaidon, Nikos Arechiga, and Tengyu Ma. Learning imbalanced datasets with label-distribution-aware margin loss. In Advances in Neural Information Processing Systems, 2019.
2 Global Method Description

2.1 Complexity
We can get quite good results only by modifying the training strategy of the model. The method is easy to implement.

2.2 Pre-trained model
Our model is trained from scratch, which means we don’t use any pre-trained model which is obtained from a vast dataset such as Imageset.

2.3 Additional data
No additional data is used in our method. The only dataset involved is the provided NTIRE training and validation data.

2.4 Training description
Our training procedure contains three stages. The first stage is to use the whole dataset to train a rough model. The reason of using all images is that network model can always be more general when observing more data. Besides, as we use SGDM as our optimizer, the momentum of SGD will drive the model to an area that are more smooth to class 0 because of the long-tailed distribution. Therefore, the next stage will not move model to go far away from the good area for class 0. The second stage is to use class-0-removed dataset to train a model having prominent feature expression ability about class 1-9 targets. By discarding class-0 images, the distribution of rest data are more balanced, thus resolving the most troublesome difficulty caused by Long-tailed images. Due to the stage 1, this model still memorizes some information of class 0. Besides, because class-0 images account for more than 80% of the dataset, the class 1-9 dataset is quite small that makes training faster a lot. The third stage is to use a class-balanced dataset which contains the same number of 10 categories of images to fine tune model. In this stage, we establish a sub-dataset containing of 50000 images (5000 per class) by random selecting and image augmentation. First, we train the model 20 epochs to transfer the 9-classes model to a 10-classes model. Second, we train another 10 epochs by freezing backbone parameters and only adjusting the classifier. After this two sub-stages, our final model are obtained with good classification accuracy on all 10 categories validation dataset.

As shows above, figure 2(a) demonstrates that after the first stage, model is moved to an area that is flat for class-0 images’ feature while it is hard to discriminate images labeled 0-9. Figure 2(b) shows after the second stage, our model can capture semantic features of the images labeled 1-9, thus easy to distinguish them. Besides, model still remembers some class-0 information. From figure 2(c) we can get a final model which can classify all 10 classes images well.
2.5 Test description

Our test procedure is clear and simple. We just input an image into the model and get corresponding result. We try our best to use less tricks to reflect the performance of the model itself more realistically. The only trick we use is test time augmentation (TTA) while we set the number of images generated by one image to 3.

2.6 Advantages

Our method can achieve better performance than any other two-stage method which means using instance-balanced dataset to train a feature extractor and class-balance dataset to fine tune a classifier. Because when just using long-tailed dataset to train, the model will be continuously driven in a class-0 direction because of momentum, thus hindering networks feature expression ability. Our method use long-tailed dataset just to get a rough model and then use dataset without class-0 to train the rough model. By Decoupling class-0 and other classes images, we alleviate the problem two-stage method are confronted. Specifically, our method achieves 22.34% top-1 accuracy while the best two-stage method only achieves 21.09%.

Another edge our model possess is that our backbone is lightweight. The inference time of our shake-shake-26 2x32d(S-S-I) model is only 0.0146 s, while ResNet-50 is 0.0225 s. Our model’s size is only 11.2 Mb while ResNet-50 is 70 Mb. In conclusion, our model is light and fast enough.

2.7 Novelty degree

Our three-stage training procedure is put forward first time. Our method is motivated by both two-stage method and transfer learning method. We explore further and combine these two ways together and re-design the training procedure elaborately. Instead transferring head- to tail-classes, our solution are more likely to transferring tail- to head-classes.
3 Competition particularities

There are three particularities of the deployed solution:

- A novel three-stage training strategy is proposed
- No ensemble is used, so the inference time is very short
- The model we used is a light weight deep neural network, and the parameters of the model is only 12M.

4 Ensembles and fusion strategies

Our goal is to propose a solution that is light weight and fast, but ensembles consist of more than one model and multiply the inference time. Consequently, no ensemble and fusion strategy is used in our solution.

5 Technical details

- The method is implemented on the PyTorch framework on an NVIDIA 2080Ti GPU and Xeon(R) CPUs E5-2630 v4 @ 2.20GHz.

- We developed three-strategy training strategy for long-tailed SAR image datasets. After three-strategy training, the model can overcome long-tailed distribution. In the validation phase, we use TTA (Test Time Augmentation) to get a better result.

- In the test phase, the time required for predicting one image is around 0.01s. In the first train stage, we trained model from scratch in SAR image datasets, totally 20 epoch and 2 hours. In the second train stage, we trained model in SAR image datasets without 0 class with first stage pretrained model weights, totally 100 epoch and 14 hours. The third train stage, is to fine tune model in class-balanced datasets with all 20 classes and spend very little time.

- We evaluate our model on SAR image test datasets, we have counted the probability of 10 categories and founded that our model can achieve an approximate uniform distribution. The three-stages training strategy we proposed is very easy to transfer to other long-tailed datasets. It is easy to deploy it for other sets of downscaling operators.

- We develop shake-shake-26 2x32d(S-S-I) model as base model[1], which is a ResNet style model with 3-branch and replace the standard summation of parallel branches with a stochastic affine combination. This model can help overfit problem and get a higher performance. Importantly, our method is compute- and memory-efficient, can overcome long-tail distribution problem.
6 Other details

- As we know, NTIRE (New Trends in Image Restoration and Enhancement) workshop is focus on low-level vision tasks, so is very puzzled to see a classification task in NTIRE.

- We expect more image restoration challenges in real world scene, such as burst image super-resolution, burst image denoising, etc.