Few Shot Classification by Learning to Learn

Ravi Jain† Hideaki Yanagisawa‡ Hiroshi Watanabe

Graduate School of Fundamental Science and Engineering, Waseda University‡

Abstract: With advances in deep learning, computers have reached a stage to be able to classify images, after being shown abundant labeled instances. The task of classifying with only few examples still remains a challenge. Humans have the ability to accomplish this task, that is, we understand images, given only one, or few examples. The purpose of this research is to advance the ability of computers to be able to learn to generalize to unseen classes during training. In the current state, human annotation cost and scarcity of data make it difficult for deep neural networks to learn new concepts effectively, that is deep learning fails to generalize when little supervised information is given.

1 Introduction

The ability for computers to classify an image given only few examples is known as few shot classification. In this paper, we discuss the results of experiments carried out on few shot classification, as well as modifications to improve the accuracy on two datasets, CUB and moeimouto-faces from Tagged Anime Illustrations. We also see results of few shot regression experiments on sine wave.

2 Existing Research

One of few shot learning techniques is Model Agnostic Meta Learning (MAML), the aim is to learn a good model initialization, so that only within a few gradient update steps, novel classes can be learned. MAML is a gradient based meta learning algorithm that allows fast adaptation at test time. Another approach is Fast Context Adaptation via Meta Learning, (CAVIA) where model parameters are partitioned into context parameters, and shared parameters. Here, context parameters act as an additional input to the model, and are adapted on individual tasks, only these parameters are updated at test time. Few shot classification uses the terminology of K-shot N-way, where K instances are available from each of the N novel classes. We use two datasets for our classification experiments, moeimouto-faces from Tagged Anime Illustrations, and CUB. CUB is a standard dataset used for few shot classification, we use the evaluation protocol proposed by Hilliard et al. (2018) [2], for CUB, whereas for moeimouto-faces dataset, we split the dataset into 98 classes for training, 35, for validation, and 40 for testing.

For regression experiment, we use Sinusoidal wave as mentioned in CAVIA.

3 Experiments

We run our experiments using MAML approx, the results are displayed in the Table [1]. We modify the loss function to Label Smoothing Cross Entropy, and achieve better results, on CUB dataset. Here, we predict 1 - (epsilon) for the correct class and (epsilon) for other classes, where ‘i‘ is the correct class, N is the number of classes.

$$loss = (1 - \ epsilon) * cross\_entropy(i\ ) \\ + epsilon\ \sum cross\_entopy(j)/N$$

We compare the results with those mentioned in ‘A closer look at few-shot classification’ [1] using MAML approx for classification, and also display results obtained on moeimouto-faces dataset. On regression experiment with sine wave, AdaBound optimizer, gives better results as compared to Adam. For regression, we compare the results with those mentioned in ‘Fast context adaptation via Meta Learning’ [4] as shown in Table 2.

4 Tables and Figures

Table 1: Results of few shot experiments on CUB and mouimoto dataset with Conv-6 backbone, 5-Shot, 5-Way.

Dataset	Method	Test Accuracy	LabelSm oothing	Dropout
CUB	MAML approx.	78.04 +- 0.73	Yes	No

CUB	MAML approx.	78.95 +- 0.69	Yes	Yes
CUB	MAML	76.31 +- 0.74	No	No
Moeimouto-faces	MAML approx..	91.00 +- 0.58	Yes	No

Table 2: Results of few shot regression experiment on sine wave

Optimizer	Test Accuracy	Number of additional input parameters
AdaBound	0.1485 (+/-0.0342)	5
Adam	0.19(+/-0.02)	5

5 Conclusion

We find that with certain modifications to the loss function, optimizer, better results are obtained on few shot classification and regression. Further experiments would involve cross domain evaluation, that is training and validation on completely different datasets, along with further classification experiments using dynamic bound of learning rate. [3]

References

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AMS lab, Waseda University, Shillman Hall 401
3-14-9 Okubo, Shinjuku, Tokyo 169-0072 JAPAN
Tel: +81-3-5286-2509
E-mail: vainaijr114@akane.waseda.jp