Evaluating data reduction techniques for supervised training

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Abstract

Training deep neural networks can be resources-consuming. The budget required is increasing with the size of the dataset. During the past few decades, many research is dedicated to developing training procedures to accelerate the convergence speed of deep learning. However, we still need the whole dataset to train the network and paying for a large dataset may not pay back well if we can use a smaller subset to achieve an acceptable performance. To solve this issue, we first adapted and evaluated three methods, Patterns by Ordered Projections (POP), Enhanced Global Density-based Instance Selection (EGDIS), and Curriculum Learning (CL), to reduce the size of two image datasets, CIFAR10 and CIFAR100, for the classification task. Based on the analysis, we present our two contributions: the Weighted Curriculum Learning (WCL) and a trade-off framework. The WCL outperforms POP and EGDIS in terms of both classification accuracy and time complexity. It achieves comparable performance compared with CL while keeping a portion of hard examples. The trade-off framework selects a subset of samples according to the acceptable relative accuracy and the dataset. In addition, the framework is also extended to predict the number of samples needed to achieve a particular accuracy with a given subset.

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Chapter 1

Introduction

1.1 Motivation

1.2 Research Goal

1.3 Significance

1.4 Beneficiaries

Chapter 2

Background Research

In this chapter, we begin with presenting the necessary background to understand the deep convolutional neural network (deep CNN) and data reduction methods, as well as, other ideas required to understand our research method. In the next section we we start with the structure of CNN and the gradient descent training procedure. We then discuss the modern research outputs that can speed up the training procedure and outline their deficiencies. Next, we review the data reduction literature and present a CNN data reduction framework - use the network pre-trained on ImageNet to extract low-dimensional features and run the data reduction methods on extracted features. Furthermore, we cover the existing trade-off framework in the context of maximum-likelihood estimation machine learning algorithms and explain why it is not suitable for deep neural network. Finally, we present TAPAS [3], which is an accuracy predictor for deep neural network without training and has several properties that make it useful to build our trade-off framework.

2.1 Deep Convolutional Neural Network

2.2 Data Reduction Algorithms

2.3 Trade-off Framework

2.4 Accuracy Predictor

Chapter 3

Adapted Data Reduction Methods

In this chapter, we begin by presenting the pre-processing feature extraction process for image dataset. Next we adapt three methods overviewed in Chapter 2 to reduce the size of image dataset, called the Patterns by Ordered Projections (POP) [6], Enhanced Global Density-based Instance Selection (EGDIS) [5], and Curriculum Learning (CL) [1]. Then we propose our weighted data reduction method, called Weighted Curriculum Learning (WCL), based on CL scores and the EGDIS selected boundary instances. We also illustrate the selection patterns with three generated blob datasets, which correspond to 2-dimensional special case of extracted image feature space. After that, our work is focused on the comprehensive evaluation of the methods. We describe image augmentation algorithms and the details of the DenseNet architecture [2] and incremental training [4]. We also describe the model fitting procedure of the SVM-baseline.

3.1 Image Feature Extraction

3.2 Patterns by Ordered Projections

3.3 Enhanced Global Density-based Instance Selection

3.4 Curriculum Learning

3.5 Weighted Curriculum Learning

3.6 Evaluation Designs

Chapter 4

Data Reduction Evaluations

4.1 Time Complexity

4.2 Classification Accuracy

Chapter 5

Trade-off Framework

5.1 Subset Selection Framework

Chapter 6

Trade-off Evaluation

6.1 Relative Accuracy Precision

Chapter 7

Conclusion and Future Work

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