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 2

Background Research

In this chapter, we begin with presenting the necessary background to understand the supervised learning and data reduction methods, as well as, other ideas required to understand our research method. We we start with the structure of CNN and the training procedure. We then discuss the modern subset selection methods 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 BlinkML [7] 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 [4], 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 Supervised Learning with CNN

CNN based supervised learning is a kind of machine learning task which learns the mapping between input visual data and output based on a set of well-labelled training samples. The visual data can be images, videos or even 3D models [9]. The CNN itself can be considered as a set of chained operations with trainable parameters. These parameters define the actual input-out mapping. For this reason, we use the symbol $f(x|\theta)$ to represent the output predicted by the CNN which takes the input x with a particular parameter set θ. Figure 2.1 gives a basic CNN structure which is designed to classify images as cats or dogs. It contains two convolutional (Conv) layers, one max pooling layer and one fully connected (FC) layer. The FC layer is actually a multi-class logistic regression model which maps the outputs of the max pooling layer to the class scores. From this perspective, we can divide the CNN structure into two parts: feature extraction part and logistic regression part. The feature extraction part performs as a blackbox which transforms the input images to points in a lower-dimensional, linearly separable space.

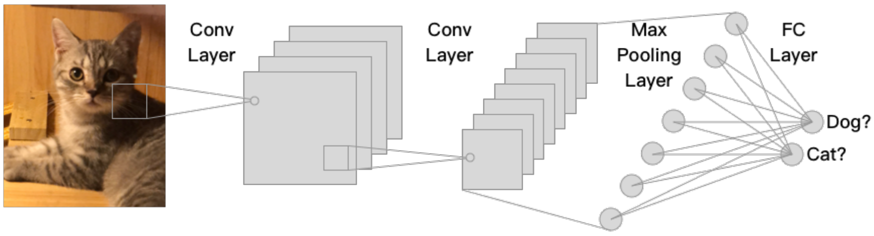

Figure 2.1: A basic CNN structure to classify images between cats and dogs. The outputs of the penultimate layer are extracted lower-dimensional features of the input images. These features should be linearly separable to achieve a high classification accuracy

If we use the symbol y to represent the ground truth of the input sample x, use $L(f(x|\theta),y)$ to represent the loss function which measures the difference between the predicted output and the ground truth label, then the training process is to find the parameter set θ^* which minimise the average loss of the whole training set as fellows:

$$\theta^* = arg_\theta \ min \ \frac{1}{N}\sum_{i=1}^{N} L(f(x_i|\theta),y_i) \tag{2.1}$$

where the symbol N stands for the number of samples in the training set. This turns the training process into an optimisation problem. Different from machine learning algorithms like logistic regression and support vector machine, the equation 2.1 is non-convex thus cannot be solved analytically [1, p. 304]. A number of techniques have been developed to solve the problem with the requirement that the loss function $L(.,.)$ is continuous. The basic one to train on large dataset is called stochastic gradient descent (SGD) which updates the parameters with the partial derivatives of a randomly selected sample. At each step, the new parameter is calculated with

$$\theta_{t+1} = \theta_t - \eta \frac{\partial L(f(x|\theta),y)}{\partial \theta_t} \tag{2.2}$$

and η is the step size whose typical value is between 0.1 to 0.001. A simple variant of SGD is mini-batch gradient descent which divides the training set into disjoint subsets and averages the gradients within the subset before updating the parameters:

$$\theta_{t+1} = \theta_t - \eta \frac{1}{M} \sum_{i=1}^{M} \frac{\partial L(f(x_i|\theta), y_i)}{\partial \theta_t} \tag{2.3}$$

where M is the batch size of the subset. For CNN, batch size M is often smaller than the training set size N because it takes too much memory to fit the whole dataset. Usually we use 128 or 256 as the batch size.

2.2 Importance Sampling

Since the mini-batch gradient method trains the network with a subset of samples at each step, how to select the samples becomes a problem in the deep learning literature. Instead of uniform sampling, importance sampling method ranks the sampling with the scores and selects a mini-batch based on different criteria. According to [2], we can divide the importance sampling methods into two categories: **current hypothesis method** and **targer hypothesis method**. Current hypothesis method measures the importance based on the parameter set θ_t at step t while targer hypothesis method is based on the final parameter set θ^*.

2.2.1 Current Hypothesis Method

2.2.2 Target Hypothesis Method

2.3 Data Reduction Algorithms

2.4 Trade-off Framework

2.5 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) [8], Enhanced Global Density-based Instance Selection (EGDIS) [6], and Curriculum Learning (CL) [2]. 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 the 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 [3] and incremental training [5]. We also describe the model fitting procedure of the SVM-baseline.

3.1 Image Feature Extraction

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Conclusion and Future Work

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