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.

Acknowledgements

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Finally, I would like to send my love to my fiancee Danni Li for her accompany during the past three years . I wouldn't have the chance to study full-time without her full support.

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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 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 [20] 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 [9], 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 [23]. The output score after the softmax operation can be considered as the probability for a given image belongs to each class, $P(class|image, network)$. 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 score 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.

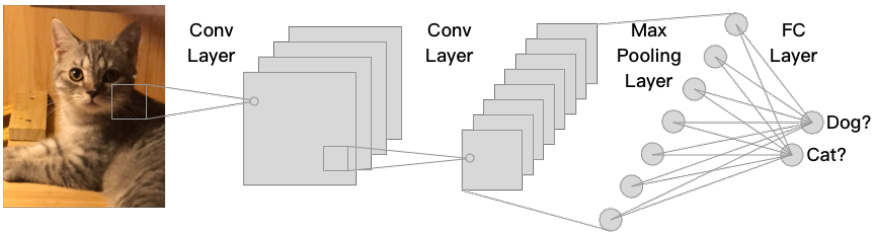


Figure 2.1: A basic CNN structure to classify images between cats and dogs. The outputs of the penultimate layer are extracted lower-dimensional features of the input images. These features should be linearly separable to achieve a high classification accuracy

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:

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

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 [7, 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 Mini-batch 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, many researchers proposed to rank the samples with importance score or classification difficulty and selects a mini-batch based on different criteria. According to [8], we can divide the sampling methods into two categories: **current hypothesis method** and **targer hypothesis method**. Current hypothesis method measures the samples 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

Different authors have proposed a variety of current hypothesis methods. Specifically, in self-paced learning [14, 15, 18], active bias learning [5], and hard example mining [22, 16], the scores are calculated based on the sample difficulty, which is proportional to the classification score of the true class, $f(x|\theta, y)$. For importance sampling methods, the scores are calculated based on the gradient norm for each sample, $|\frac{\partial L(f(x_i|\theta), y_i)}{\partial x_i}|$. We finish this section by briefly explaining the actual implementations of these approaches.

2.2.1.1 Difficulty Based Method

Self-paced learning method tends to select easy samples which have a high classification score by injecting a pace function into the optimisation target function 2.1:

$$\theta^* = \arg\min_{\theta, v} \sum_{i=1}^{N} v_i L(f(x_i|\theta), y_i) + \lambda \sum_{i=1}^{N} v_i \tag{2.4}$$

where v is the score calculated by the pace function. The pace function can be either a simple step function [14] or a more complicated dynamic function which changes with step t [15] as long as it can assign value 0 to samples. By minimising the target function 2.4, the method would zero out hard examples which have higher loss L thus keep only the easy samples. This makes the trained network more robust to outliers [18].

A potential problem of self-paced learning is that it would gradually increase the loss of hard examples [5]. The possible solution is to use the active bias learning method, which is designed to select the uncertain samples whose classification score vary near the decision threshold. Chang et al. proposed and evaluated many self-paced methods and the representative one is called SGD Sampled by Threshold Closeness (SGD-STC) [5]. It records the historical average classification probability $\bar{P}$ for each sample and the score is calculated with a equation that is proportional to $(1-\bar{P}) \times \bar{P}$. However, the problem is that we need extra space and computation to maintain the historical scores.

Hard example mining is yet another heuristic method aims at maximising the convergence speed by extending the self-paced learning method [22]. The algorithm proposed by [16] ranks the samples based on the latest computed classification score in descending order. At early training stages, the algorithm chooses easy samples just like self-paced learning. After a thorough exploitation process, the algorithm tends to select hard examples which have low classification scores.

2.2.1.2 Importance Based Method

Although published experiments in the cited resources above prove that difficulty based methods can surely speed up the training process and may achieve even higher accuracy, the lack of mathematical prove could lower the interests of researchers. In the contrary, importance based method raises from the profound mathematical demonstration [24] and is more reliable. Despite the elaborate derivation, the most important conclusion is that the optimal weight distribution is proportional to the per sample gradient norm.

The challenge is that computing the per sample gradient norm $|\frac{\partial L(f(x_i|\theta),y_i)}{\partial x_i}|$ is intractable. In the past few years, many researchers have adapted their approximate methods to speed up the process. The most convincing one is proposed by Katharopoulos et al. which derives an upper bound of the gradient norm [10],

$$|\frac{\partial L(f(x_i|\theta), y_i)}{\partial x_i}| \leq |h(x_i)| \tag{2.5}$$

that $h(x_i)$ is the upper bound function depends on the last layer pre-activation outputs and time step t. With this equation, we can compute the largest sample gradient after a single forward propagation.

The benefits of current hypothesis methods is that the sample importance varies with time step thus the chosen samples at each step can reflect the current capacity of the network. However, because evaluating the whole training set is time-consuming, we often select a subset uniformly first and then select the samples within the subset. This would affect the optimal theory performance.

2.2.2 Target Hypothesis Method

Compared with current hypothesis method, target hypothesis method selects instances based on the possible final performance of the network thus the weights of the samples are pre-defined and won't change during the training process [3]. For this reason, target hypothesis methods are more suitable to reduce the size of the dataset. To our knowledge, Curriculum Learning (CL) is the only method with these properties.

Similar with hard example mining, CL trains the network with easy samples first then adds more difficult samples into the dataset and gradually the subset would contain all the training samples. The main difference is that the difficulties of the samples are measured in advance, whether with a pre-trained network or with a linear classifier like SVM [8].

We use extracted features from NasNetLarge to train a simple two FC layer network. The output score is recored and used to select samples in descending order.

Algorithm 1: CL

Data: compressed 128-D feature vectors M

Input: number of samples to select m, classification score for each sample *scores*, number of classes n

Output: selected sample index by CL

```
selected_idx_list = [] ;
foreach class label L do
    scores = all sample scores with label L ;
    idx_list = sort_by_value(scores) ;
    selected_idx_list.append(idx_list[: floor(m/n)]) ;
end
return selected_idx_list ;
```

2.3 Data Reduction Algorithm

Data reduction algorithm becomes famous with the increasing of dataset size and compute time. The most common one is called Principal Components Analysis (PCA) which projects the features onto the most important few eigenvectors to capture the most variants. The famous example eigenface proves that PCA is efficient even with image dataset [11]. Apart from PCA, there are other methods such as dimensionality reduction methods which reduce the size of the sample features and instance selection methods that can reduce the number of samples in the training set. We discuss some typical implementations in the next subsections.

2.3.1 Dimensionality Reduction Methods

As discussed above, PCA is the most common method for both structured dataset and unstructured dataset. In the context of deep CNN, however, the term feature extraction is more famous as discussed in section 2.1. Kornblith et al. evaluated the extracted features with pre-trained networks on many vision datasets and the results show that the logistic regression accuracy is linearly related to the ImageNet classification accuracy [12].

2.3.2 Instance Selection Methods

Most instance selection methods are designed to reduce the size of structured dataset for machine learning algorithms like SVM and logistic regression with the assumption that we can recover the decision boundary with fewer samples. According to the thorough review [19], the instance selection methods can be divided in to two categories: wrapper and filter. Wrapper methods select the subset samples based on the classification results. Often misclassified samples will be selected because they can contribute to the accuracy of classifier like k-NN [2]. Filter methods tend to select samples near the decision boundary because these samples can help the classifier to recover the original shape [21]. Although the wrapper methods could achieve higher accuracy because they are classifier dependent, they tend to cost too much compute time because they need to evaluate the accuracy multiple times. From this perspective, filter methods are more suitable for deep learning.

The POP algorithm is designed to select inner samples by projecting the samples onto each feature dimension.

Algorithm 2: POP for continuous features

Data: compressed 128-D feature vectors M

Input: weakness threshold wt, equal tolerance et

Output: selected sample index by POP

$weakness = zeros(len(M))$;
foreach *feature dimension* $F_j = M[:,\ j]$ **do**
    $idx\_list = sort\_by\_value(F_j)$;
    $idx\_list = resort\_by\_label(F_j,\ et,\ idx\_list)$;
    foreach *idx in idx_list* **do**
        if *M[idx, j] is not border* **then**
            $weakness[idx] += 1$;
        end
    end
end
return $argwhere(weakness < wt)$;

EGDIS selects the boundary samples with the 3-NN algorithm and the samples at the densest area.

Algorithm 3: EGDIS

Data: compressed 128-D feature vectors M

Input: number of neighborhoods k

Output: selected sample index by EGDIS

```
boundary_idx = [] ;
densest_idx = [] ;
neighbour_distance_list, neighbour_index_list = kneighbours(M, k) ;
for i in range(len(neighbour_index_list)) do
    neighbour_index = neighbour_index_list[i, :] ;
    irrelevance_score = irrelevance(neighbour_index) ;
    if irrelevance_score is greater or equal to floor(k/2) then
        boundary_idx.append(k) ;
    else
        if density(M[i]) is larger than density(M[neighbour_index]) then
            densest_idx.append(i)
        end
    end
end
return union1d(boundary_idx, densest_idx) ;
```

2.4 Trade-off Framework

2.5 Accuracy Predictor

Chapter 3

Adapted Data Reduction Methods

In this chapter, we begin by presenting the experimental datasets, CIFAR10 and CIFAR100 along with the image feature extraction process. Next we adapt three methods overviewed in Chapter 2 to reduce the size of image dataset, called the Patterns by Ordered Projections (POP) [21], Enhanced Global Density-based Instance Selection (EGDIS) [17], and Curriculum Learning (CL) [8]. Then we propose our edited data reduction method, called Weighted Curriculum Learning (WCL), based on CL scores and Boundary Based Curriculum Learning (BBCL), based on the EGDIS selected boundary instances. After that, our work is focused on the comprehensive evaluation of the methods. We illustrate the data reduction geometry patterns with three generated datasets, blobs, moons and circles. We then describe the model fitting procedure of the logistic regression algorithm. Finally, we extend the reduction pipeline to deep learning method with the particular network, DenseNet121. Figure 3.1 gives the pipeline overview of this project.

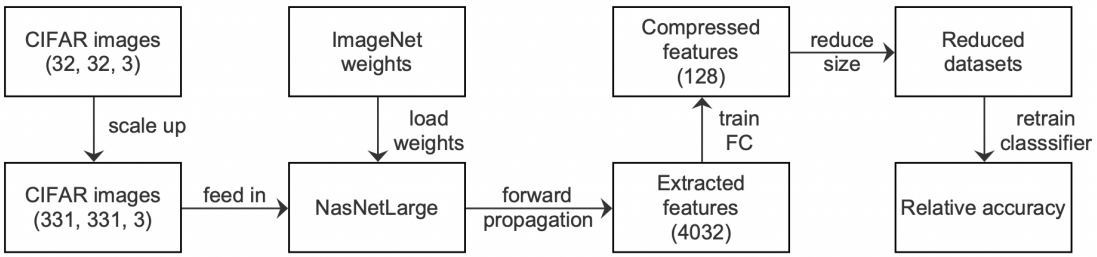


Figure 3.1: Overview of the data reduction pipeline.

3.1 Datasets and Image Feature Extraction

We choose to use CIFAR10 and CIFAR100 [13] as our experimental datasets which contain 6,000 and 600 tiny images of size 32×32 per class respectively. The advantage of CIFAR is that they are large in the number of images and small in the size of images. With CIFAR datasets, we could train the network faster thus explore the reduction rate for a wider scale within the required timetable. Another advantage is that CIFAR datasets can reflect the performance of data reduction algorithms for both simple dataset and hard dataset in term of classification accuracy. According to Kornblith et al. [12], the test set results indicate that CIFAR10 is very easy to classify and CIFAR100 is as difficult as other high resolution datasets such as the Describable Textures Dataset (DTD) [6], Food-101 [4]. These features could gain us thorough and representative evaluation results with limited compute resources.

After scaling up the image size to 331 and transforming the images into range 0 to 1 by dividing 255, we therefore performed the feature extraction task. The goal was to provide structural data for the data reduction algorithms to work with. We did this job with pre-trained NasNetLarge [25] because Kornblith et al. [12] have evaluated the quality of extracted features and the quality of extracted features is good enough. Their experiments show that the classification scores with simple logistic regression are very close to the state-of-art classification scores with CNN. In order to simplify the implementation, we chose to use the Keras implemented NasNetLarge network from TensorFlow Hub, which is designed to get feature vectors from images [1]. However, the original shape of the feature vector is 4032 and it would take longer time to run the reduction algorithms. To speed up the reduction process, we trained another network with two FC layers. The depth of the first FC layer is 128 and we took the outputs as compressed feature vectors. The test accuracy is also reported as the baseline performance. Figure 3.2 represents the network structure. We also trained a batch normalisation layer after the 128-D FC layer to limit the feature range. This ensured that the Euclidean distance between two vectors wouldn't be dominated by dimensions with wider range.

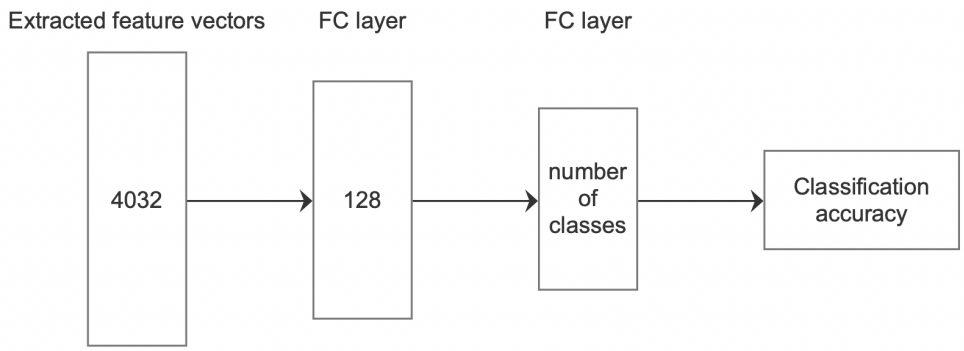


Figure 3.2: Network structure to compress the extracted feature vectors.

3.2 Difficulty Tuneable Algorithms

Before presenting the evaluation plans, it should be noted that the algorithms described in 2.2.1.2 are not perfect. POP and EGDIS are not deep learning based so the CNN may not work well with selected samples. Also, although CL is target hypothesis based algorithm, by keeping easy samples only may limit the performance that the network could achieve. Therefore, our first contribution is to modify these

3.2.1 Weighted Curriculum Learning

Instead of selecting the top N samples based on CL scores, we use the scores as the sample weights just like the importance based methods. In this way, not only the easy samples are selected, some hard examples are also selected. Because we only select the subset once, this behaviour should be able to achieve higher accuracy if the network is good enough. However, if the network is not capable of handling these hard examples, then the accuracy may decay.

Algorithm 4: WCL

Data: compressed 128-D feature vectors M

Input: number of samples to select m, classification score for each sample *scores*, number of classes n

Output: selected sample index by WCL

```
selected_idx_list = [] ;
foreach class label L do
    scores = all sample scores with label L ;
    scores = scores / sum(scores) ;
    idx_list = choose floor(m/n) samples based on scores ;
    selected_idx_list.append(idx_list)) ;
end
return selected_idx_list ;
```

3.2.2 Boundary Based Weighted Curriculum Learning

We also evaluated its EGDIS based variants which takes a propotion of EGDIS boundary samples so that we would have a higher chance selecting them. We keep class balance as a basic rule so we select 20%, 40% boundary samples if possible.

Algorithm 5: BWCL

Data: compressed 128-D feature vectors M

Input: number of samples to select m, classification score for each sample *scores*, number of classes n, EGDIS boundary sample index list $egdis\_boundary\_index$, percent of boundary to select p

Output: selected sample index by BWCL

```
selected_idx_list = [] ;
foreach class label L do
    scores = all non-EGDIS sample scores with label L ;
    egdis_boundary_index_L = all EGDIS boundary sample index with label L ;
    egdis_idx = choose floor(m/n × p) samples from egdis_boundary_index_L ;
    selected_idx_list.append(egdis_idx)) ;
    scores = scores / sum(scores) ;
    idx_list = choose floor(m/n× (1-p)) samples based on scores ;
    selected_idx_list.append(idx_list)) ;
end
return selected_idx_list ;
```

3.3 Evaluation Designs

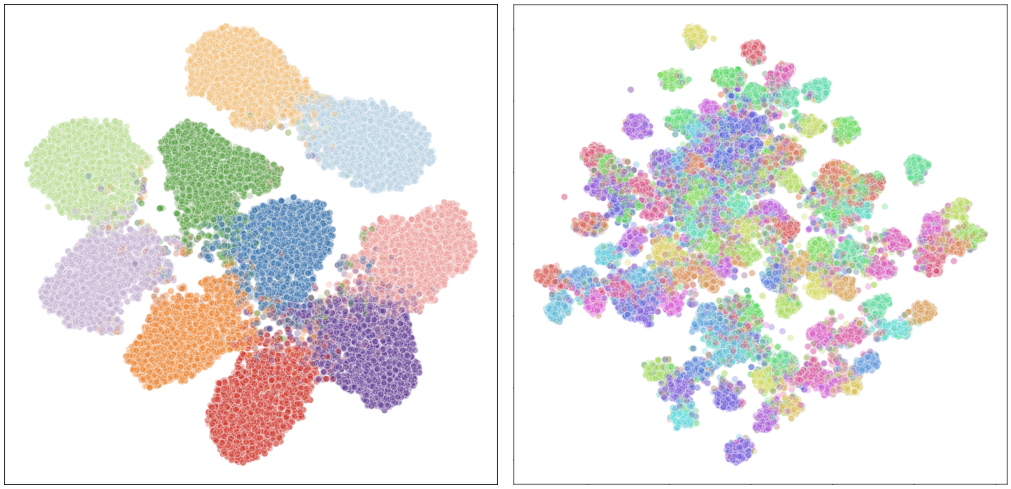
We have the following few experiments: 1. We use generated dataset to explore the intrinsic behaviour of these methods. 2. We use logistic regression to test all these methods. We also use the experiment results to decide how to select the subsets and the percentage range. 3. We select 3 subsets based on the test result of exp1, to run deep learning using incremental method. In total, we have experiment 9 network results on 5 datasets. We compare the experiment results and conclude the experiments.

Chapter 4

Data Reduction Evaluations

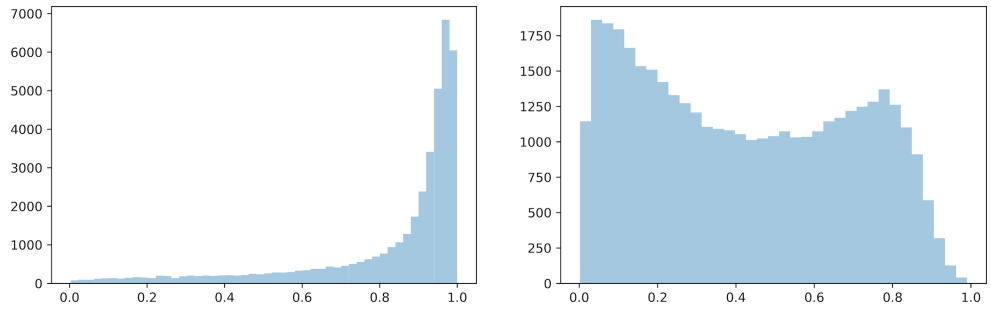
4.1 Experiment 1: Feature Extraction

In this section we extract the features for CIFAR10 and CIFAR100 with the method described in Section 3. With early stop method, the final test accuracy of CIFAR10 is 0.9241, for CIFAR100 the accuracy is 0.7266. The training history is shown in appendix.



(a) CIFAR10 (b) CIFAR100

Figure 4.1: Extracted features visualisation with t-SNE algorithm



(a) CIFAR10 (b) CIFAR100

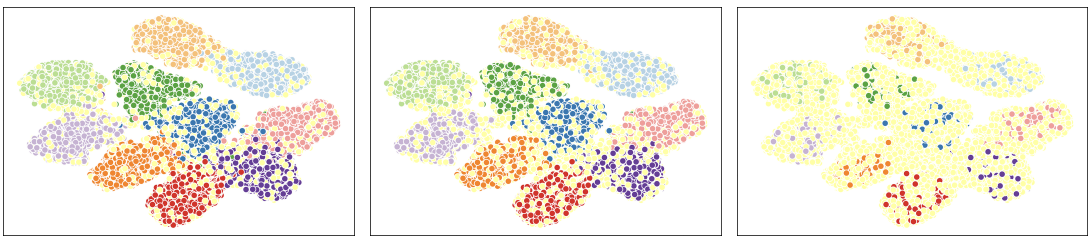
Figure 4.2: Score distribution

4.2 Experiment 2: Intrinsic Behaviour

In this section, we use CIFAR10 to show the intrinsic behaviour of each data reduction algorithm described in Section 3. First we visualise the compressed cifar10 training features with the t-SNE algorithm, which projects the features down to 2 dimensional and maintains the relative distance between samples.

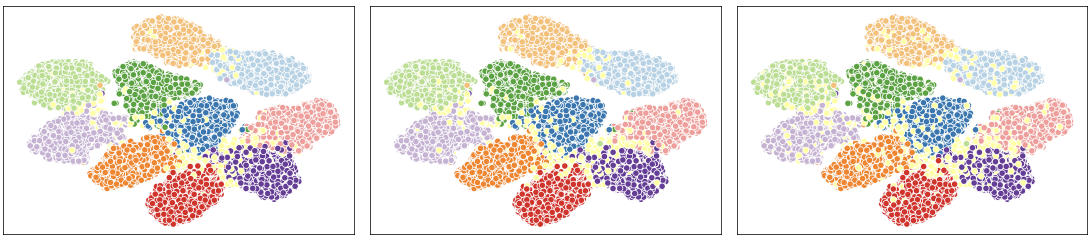
4.2.1 Tuneable Parameters and Sample Preference

For POP, we can tune the difference tolerance. For EGDIS, we can tune the k of the k-NN classifier. For CL, we can tune the number of samples selected. For WCL, we can tune the difficulty sample portion.



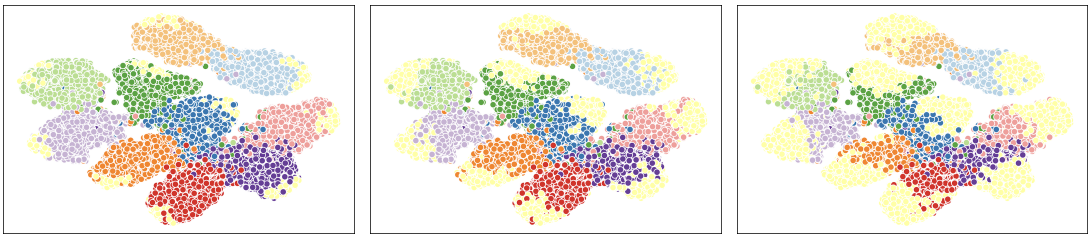
(a) T=1, 8701 samples (b) T=0.5, 14111 samples (c) T=0.1, 31966 samples

Figure 4.3: POP tune threshold



(a) k=7, 3313 samples (b) k=5, 4034 samples (c) k=3, 5966 samples

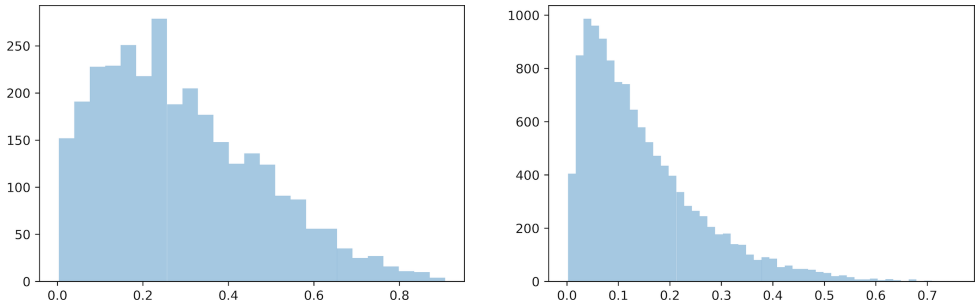
Figure 4.4: EGDIS tune kNN



(a) P=10%, 4000 samples (b) P=30%, 12000 samples (c) P=50%, 20000 samples

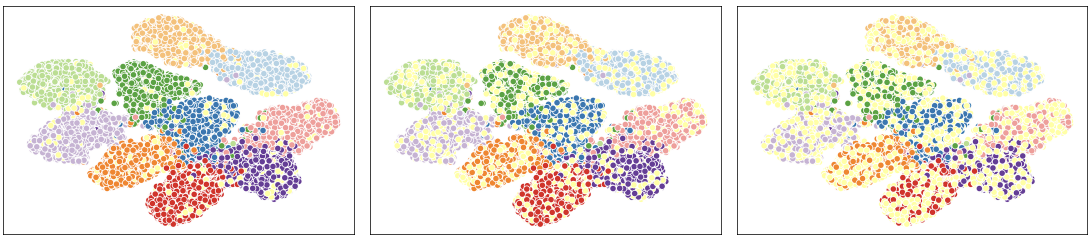
Figure 4.5: CL tune selection percentage

WCL which takes the sample within each class based on the sample score. Although most samples are selected from the high score region, there are some sample selected from the low score region. The problem is that for relatively easy dataset like CIFAR10, the behaviour is close to random selection because most samples have a score higher than 0.8. The score distribution is shown below.

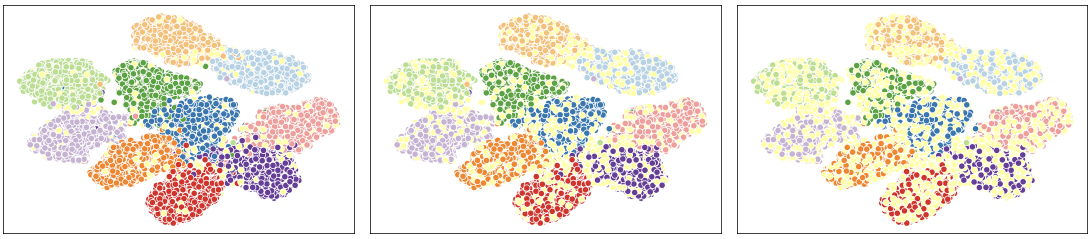


(a) CIFAR10 (b) CIFAR100

Figure 4.6: EGDIS boundary score distribution



(a) P=10%, 4000 samples (b) P=30%, 12000 samples (c) P=50%, 20000 samples



(d) P=10%, 4000 samples (e) P=30%, 12000 samples (f) P=50%, 20000 samples

Figure 4.7: WCL tune selection percentage. The first row we use weighted sampling method, the second row we use EGDIS based method.

In theory, POP tends to select pure boundary samples. EGDIS tends to select samples near two closing clusters and the samples from densest area, which could be anywhere actually. For CL, it tends to select samples far from the boundary, i.e the inner samples. WCL, would choose sample from both the closer cluster boundaries as well as the inner samples. The drawback of CL is that when all the samples are simple enough, with score larger than 0.9, they would tend to act like random selection.

4.3 Experiment 3: Logistic Regression

We choose 40 and 20 as the number of our extra synthesised datasets, with LR accuracy: 0.78925, 0.853. By fine-tuning the selected subsets, the test accuracy is: 0.8065, 0.8745.

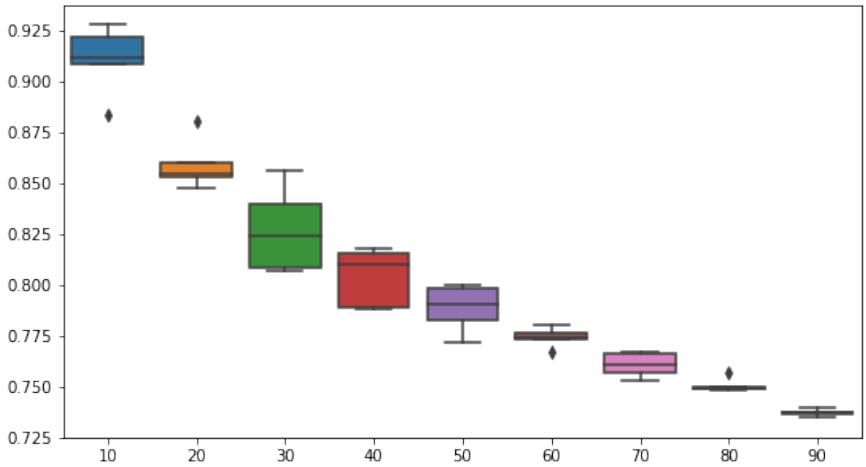
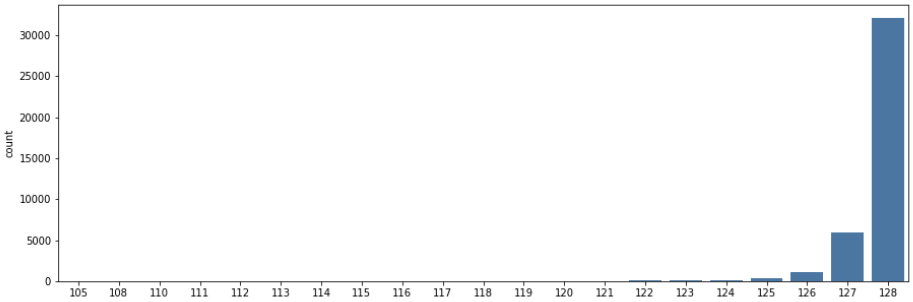
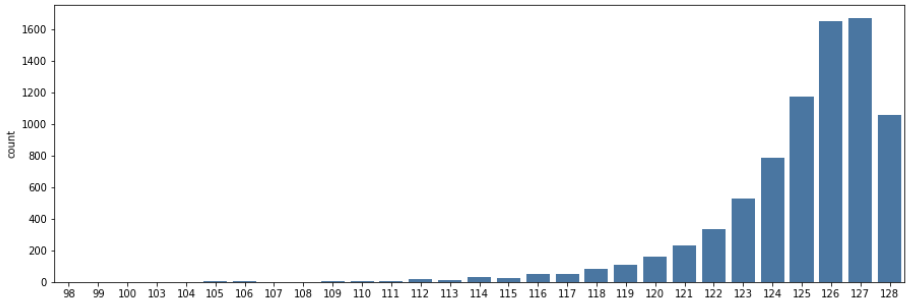


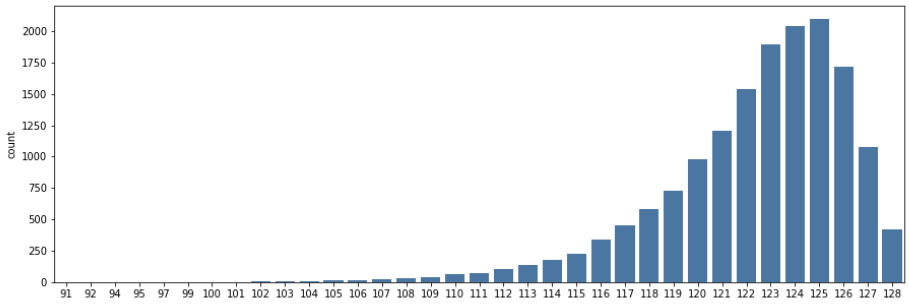
Figure 4.8: The test set accuracies of CIFAR100 subsets. Horizontal axis is the number of classes selected. Vertical axis is the accuracy score. For each selection, we randomly choose the classes for five times and report the accuracy with logistic regression model.



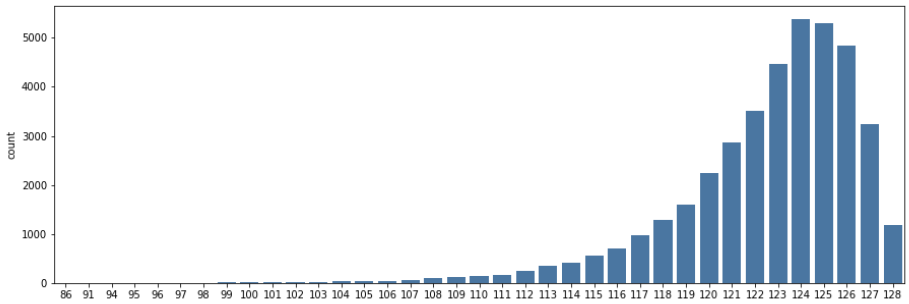
(a) CIFAR10, 40000 samples



(b) CIFAR20, 8028 samples



(c) CIFAR40, 16042 samples



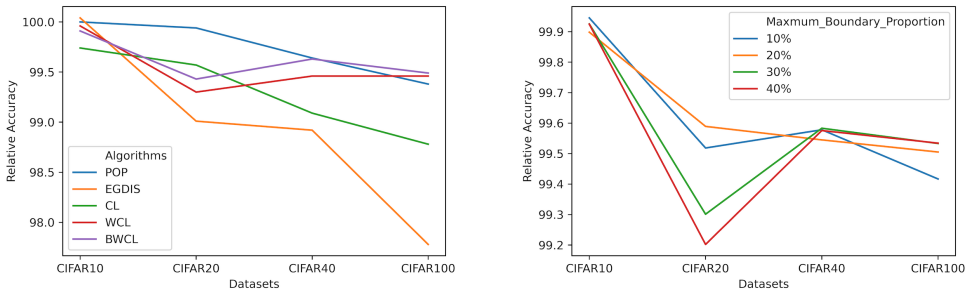
(d) CIFAR100, 40000 samples

Figure 4.9: POP with 4 datasets.

Even for POP with threshold 1, the number of pure inner is still low. Therefore, it is not good to choose samples with weakness ¡ 128. We fix the number and choose CIFAR samples. From our experiment, we found that the relative accuracy acquired from EGDIS is good enough. Therefore, we make POP to select the same amount of samples as EGDIS, by ranking POP samples based on weakness, to compare their performance.

Datasets	NONE	POP	EGDIS	CL	WCL	BWCL
CIFAR10	0.9258	0.9258	**0.9262**	0.9234	0.9254	0.9250
CIFAR20	0.8825	**0.8820**	0.8738	0.8787	0.8764	0.8775
CIFAR40	0.8159	**0.8130**	0.8071	0.8085	0.8115	0.8129
CIFAR100	0.7444	0.7398	0.7279	0.7353	0.7404	**0.7406**

Table 4.1: Logistic Regression test set accuracy by averaging 12 runs



(a) Relative Accuracy

(b) Relative Accuracy of BWCL by tuning maximum boundary proportion

Figure 4.10: Relative Accuracy of data reduction algorithms

However, this is not a solid conclusion because the quality of the extracted features are so good that the classes are classified easily. We show this effect by varying the proportion of samples selected with BWCL, 0.4.

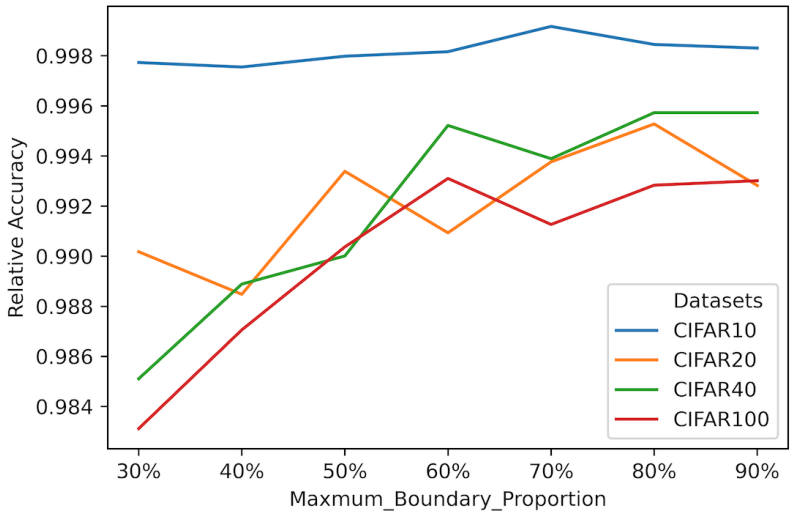


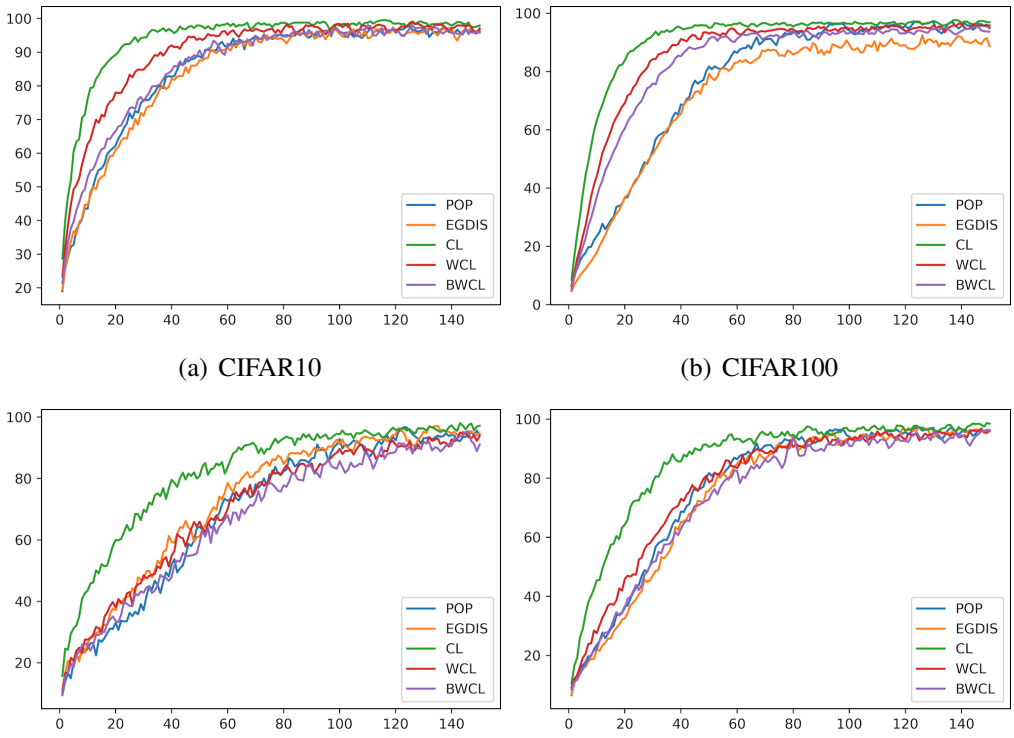
Figure 4.11: The test set accuracies of CIFAR100 subsets. Horizontal axis is the number of classes selected. Vertical axis is the accuracy score. For each selection, we randomly choose the classes for five times and report the accuracy with logistic regression model.

4.3.1 Experiment 4: Data Reduction for CNN

We train the network densenet101, three times, with learning rate 0.1 (150 epochs), 0.01 (100 epochs) and 0.001 (100 epochs)

Datasets	Retention Rate	NONE	POP	EGDIS	CL	WCL	BWCL
CIFAR10	14.915%	95.22	82.65	81.11	82.57	84.14	81.28
CIFAR20	16.67%	86.6	51.9	53.2	61.45	60.05	53.1
CIFAR40	21.09%	81.59	52.675	52.6	62.375	58.75	56.0
CIFAR100	31.48%	78.42	59.0	57.83	64.87	65.27	64.5

Table 4.2: 12312312



(a) CIFAR10 (b) CIFAR100

(c) CIFAR20 (d) CIFAR40

Figure 4.12: The training trend of four datasets by selecting the same amount of samples as EGDIS, of the first 150 epochs

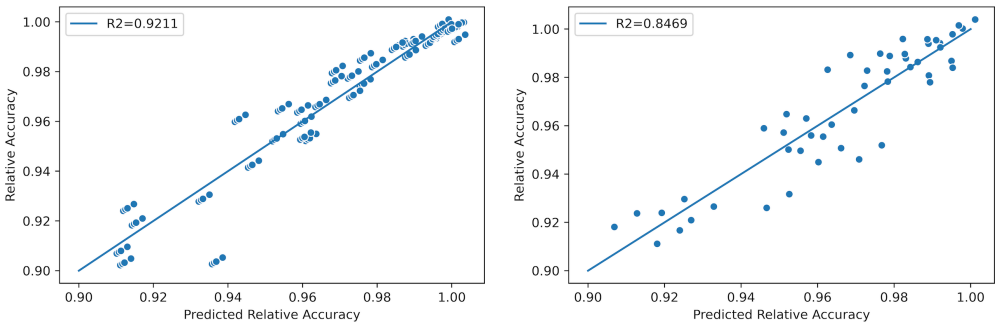
Chapter 5

Trade-off Framework

5.1 Subset Selection Framework

Chapter 6

Trade-off Evaluation



(a) CIFAR10 (b) CIFAR100

Figure 6.1: The training trend of four datasets by selecting the same amount of samples as EGDIS, of the first 150 epochs

Chapter 7

Conclusion and Future Work

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