Maintaining Performance with Less Data

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Abstract—We propose a novel method for training a neural network for image classification to reduce input data dynamically, in order to reduce the costs of training a neural network model. As Deep Learning tasks become more popular, their computational complexity increases, leading to more intricate algorithms and models which have longer runtimes and require more input data. The result is a greater cost on time, hardware, and environmental resources. By using data reduction techniques, we reduce the amount of work performed, and therefore the environmental impact of AI techniques, and with dynamic data reduction we show that accuracy may be maintained while reducing runtime by up to 50%, and reducing carbon emission proportionally.

Index Terms—Data Reduction, Data Augmentation, Data Step, Data Increment, Data Cut

I. INTRODUCTION

When creating a deep learning solution, there are two main factors that determine its success: first, the model used, and second, the data used to train with. The model, often a Neural Network, may be programmed, optimised, and experimented with to reach an acceptable performance, but the data used to train it is argued to be the determining factor [1]. If inappropriate data is used to train and test a model, the model will perform poorly when deployed in real-world situations and can be regarded as a bottleneck to the system’s performance [2]. As such, consideration must be given to ensure not only an appropriate quantity of data is available, but also data of suitable quality [2]. It has been shown that increasing the data available to a model improves average accuracy [3]. Because of this, when creating new models for different tasks, researchers and data scientists alike will give as much data as possible to train the model, wherever possible, without considering if it is truly necessary. This direction is moving rapidly to a state that is environmentally unsustainable and technically unachievable for those outside of big tech companies [4].

In this paper, we analyze three novel methods to dynamically allocate the data used to train a neural network model, for Image Classification tasks.

The article is organized as follows: In Section II we review related methods to reduce and increase the data used for training, as well as existing methods to use dynamically changing training data. In Section III we describe the methods and environments used for our experimentation, in Section IV we describe the experiments techniques used in our investigation of dynamic data use. In Section V we discuss the results of the experimentation, and conclude our work in Section VI.

II. PREVIOUS WORK

A. Increasing data use

It is well established that a Deep Learning model will have increased performance if provided with more training data. Acquiring additional data may be achieved by manually gathering data, a process commonly performed either as an individual or part of a group/company, by using freely available data licenced as open-source, or via methods such as crowdfunding [2] [4]. Alternatively, data augmentation may be used. Data augmentation is a powerful technique that increases the amount of data available to a model [5]. Instead of collecting more data samples, currently existing data samples may be modified to give new, unique datapoints for training. This is preferable over manual data collection, as annotated data is relatively scarce and can be difficult to obtain, as well as requiring expert knowledge in order to label and validate the data [2] [5]. Table I shows the current State of the Art models for image classification across six datasets. Each model uses some form of data augmentation to artificially increase the amount and variety of data available for training, which gives the model the improved accuracy that puts the model at the top of their leaderboard.

B. Reducing data use

While it is popular to use methods of increasing data, there are uses for data reduction techniques. Such practises are uncommon, as basic linear random data exclusion causes an exponential decrease in system performance [4]. Not only is the average accuracy decreased, but the standard deviation of accuracy increases, showing that the training outputs are inconsistent and difficult to verify [14]. Contrary to this, some uses of data reduction techniques give an increase to a Neural Network model’s performance. In fields where labelled data is sparse, for example medical imaging, the data often suffers from class imbalance. In such cases, undersampling techniques may be employed to reduce the amount of data of the majority class, alleviating the effects of class imbalance [15]. Less success is to be gained with random exclusion, but methods such as Cluster Centroids [16] and Tomek Links [17] select the most appropriate data to remove; they are
TABLE I: Top performing Image Classification models and their data augmentation methods

| Dataset          | No training images | Model                        | Top Accuracy | Extra data/Augmentation used                  |
|------------------|--------------------|------------------------------|--------------|-----------------------------------------------|
| MNIST            | 60,000             | Homogeneous ensemble with Simple CNN [7] | 99.91%       | Random rotation/translation                   |
| CIFAR-10         | 50,000             | ViT-H/14 [8]                 | 99.50%       | Random horizontal flip, square crop           |
| CIFAR-100        | 50,000             | EffNet-L2 (SAM) [9]          | 96.08%       | Horizontal flip, padding, random crop, AutoAugment [10] |
| SmallNorb        | 24,300             | Efficient-CapsNet [17]       | 98.77%       | Downsampling, random 32x32 crop, random brightness |
| FlowerNet-102    | 1,020              | CCT-14/7x2 [12]             | 99.72%       | RandAugment [5], AutoAugment [10]             |
| iNaturalist 2018 | 675,170            | Homogeneous ensemble with MetaFormer [13] | 88.70%       | RandAugment [5], AutoAugment [10]             |

often used with oversampling techniques to give an increase in model performance [18]. Undersampling is a technique used primarily to resolve class imbalance and is therefore unsuitable for uniformly balanced datasets. However, for balanced datasets, methods exist for identifying the ‘usefulness’ of data, which allows less useful data to be removed from training. Dimensionality reduction with algorithms such as Uniform Manifold Approximation Projection (UMAP) [19] allows a dataset to be observable in as little as 2 or 3 dimensions. By applying the UMAP algorithm to a dataset, the centroid of each class (where all its datapoints revolve) can be calculated, and data may then be removed based on its distance from its centroid [20]. Surprisingly, by removing data closest to its class’s centroid, accuracy is increased, despite fewer training evaluations being performed [20].

C. Variable data use

Varying data usage is the process of using different data throughout training. It is a novel concept; the convention is that a model is trained with the same data over multiple iterations, to allow the model’s weights and biases to converge to a stable state. It would seem contradictory to add a change to a system that would disturb this convergence; however, there are cases where its use has improved performance, discussed below.

Real-time or online augmentation creates unique data each epoch. Compared to offline augmentation, where the data is augmented once (before the model is run), online augmentation performs augmentation before each epoch during training [21]. Augmentation is commonly used to combat issues such as overfitting and shortage of data [22], but for datasets with well-balanced data it is also used to achieve higher levels of generalisability [23]. Transfer learning is used to improve a model from one domain by transferring information from a related domain [24]. It may also be used to transfer knowledge within the same domain, to reinforce the model when new data becomes available [25].

Foremost, transfer learning is a technique used to reduce the amount of work needed to train a model [25]: a model may be trained with one set of data, and the outputs recorded; then, when more data is made available, training can recommence, but with the previous outputs used as a starting point. This means that the model need not be retrained with the original data each time more data is added. In a way, this is varying data usage; throughout the course of training, different data is used. The unique property of transfer learning is that when a model is introduced to new training data, the old training data is not also used. This can often cause catastrophic forgetting [26]. There has been no investigation of using less data at the start of training, and increasing data as training progresses. Unlike Transfer Learning, we have all the data needed at the start of training, but we choose to withhold some of it as training is performed. This is to show the effect of varying data use in a controlled manner.

The experiments described in this paper investigate some extreme cases of reducing data use at earlier stages, and show the effect of this on model performance. Our contributions are as follows:

- Three novel methods of dynamically introducing data to a model are described, which each reduce the amount of evaluations performed:
  - Data Step
  - Data Increment
  - Data Cut
- Testing on three datasets is shown, demonstrating the effect of these new methods on network accuracy and runtime.
- Evidence is given that these methods may be used to replicate the resources required for training while maintaining or improving on the performance of the training output with a runtime reduction of over 50%.

III. METHODS

Traditionally, a deep learning task has three stages: Data Collection [2], Data Processing [27] [28], and the training of the Network Model. These steps are most often performed sequentially, but are sometimes somewhat interlinked; for example, the Data Collection may be real-time image or text capture, or the model may use Online Augmentation, where data is augmented differently each training loop. Figure 1 shows the data flow of an Image Classification model with Online Augmentation. After each training loop, the model returns to the Augmentation stage. Figure 2 shows the model structure proposed in this paper, with a data selection stage. This allows the model to select data dynamically, at each loop of training. This in turn enables the various data reduction techniques described further in this paper.
This paper introduces and investigates three sets of experiments where, each epoch, data is selected for training during the data selection stage. The result is a model that does not use all data for each epoch. These methods are:

- Data Step
- Data Increment
- Data Cut

A. Datasets

Three datasets were used for experimentation: the handwritten digits dataset MNIST [29], CIFAR10 [30], and the model toy dataset smallNORB [31]. Table II shows the properties of each dataset.

Multiple variations of experiments were performed, to observe the effect of varying amounts of data reduction on model performance. As such, datasets with small image sizes are ideal, as they required less time to train.

| Dataset    | # Training images | # Test images | Image size (pixels) | # Colour channels |
|------------|-------------------|---------------|---------------------|-------------------|
| MNIST      | 60,000            | 10,000        | 28x28               | 1                 |
| CIFAR-10   | 50,000            | 10,000        | 32x32               | 3                 |
| smallNorb  | 24,300            | 24,300        | 96x96               | 1                 |

B. Hardware

Multiple hardware were used to perform training, to make the most of resources available for this research. Training for each dataset was carried out on only one machine, to ensure metrics were consistent across a single dataset. The average CO2 emission for each GPU is also given, which is used for emission reduction calculations [32]. For training on MNIST:

- CPU: AMD Ryzen 9 3950X 16-Core
- GPU: nVidia GeForce RTX 2070 32GB
- RAM: 64GB
- CO2 emission per hour: 0.066kg

For training on CIFAR-10:

- CPU: Intel i7 10700
- GPU: RTX 4000
- RAM: 64GB
- CO2 emission per hour: 0.0922kg

For training on smallNorb:

- CPU: AMD Ryzen 9 3950X 16-Core
- GPU: nVidia GeForce RTX 2070 32GB
- RAM: 64GB
- CO2 emission per hour: 0.066kg

C. Performance Metrics

These experiments are to observe the effect of reducing data used each epoch of training. To quantify this, the results of the experiments show the total number of evaluations performed; each evaluation is a single image used for training. The runtime of each experiment is also recorded. The successfullness of the model is quantified with the top1 accuracy achieved. The runtime and accuracy for each experiment is directly compared with the baseline for each dataset, to show the increase or decrease in performance in accuracy and runtime. As the model is otherwise unchanged when run with data reduction techniques, the CO2 reduction of each experiment is directly correlated to the runtime. Therefore, CO2 reduction is equal to the runtime reduction.

D. Network Architecture

The model used for testing is a Convolutional Neural Network with a Simple Monolithic Architecture. It uses 9 Convolutional Layers, and a Primary and Secondary Capsule layer. The Capsule layer uses Homogeneous Vector Capsules, which replace the fully connected layer. The model is based on [23], which shows relatively high performance despite its few network layers. Tests were run for 300 epochs with a batch size of 120. Optimisation was performed using the Adam optimiser with an initial learning rate of 0.999, with an exponential decay rate of 0.005 per epoch. These values provide consistent initial settings across all experiments for all datasets.

The datapoints to exclude for each of the methods were selected at random. The experiments were performed to gather an understanding of the effect of the novel dynamic data reduction methods with the simplest method of data exclusion, namely random data exclusion.

IV. EXPERIMENTATION

A. Benchmark

Table III shows the benchmark runtime and accuracy for MNIST, CIFAR-10 and smallNorb. These results will be
used to compare the data reduction experiments, to show the reduction in runtime and effect on performance. The number of total image evaluations is the number of training images evaluated multiplied by the number of training epochs.

B. Data Step

The simplest method of dynamically selecting data is to ‘step up’ the data usage at a given point during training. A fraction of the dataset is used for a given number of training loops, after which, the full dataset is used for training. This splits the training process into two sections; Section one (S1), which uses less data, and Section two (S2), which uses the full dataset. Below are definitions for the two sections:

- The number of epochs run in section 1: $S_{E1}^E$
- The amount of data used in section 1: $S_{D1}^D$
- The number of epochs run in section 2: $S_{E2}^E$
- The amount of data used in section 2: $S_{D2}^D$

With these definitions we can derive the formula for the total number of evaluations performed:

$$n_{total \, evaluations} = S_{D1}^D \cdot S_{E1}^E + S_{D2}^D \cdot S_{E2}^E$$

This data split causes a ‘step up’ in data usage, and model will only train with a fraction of the data for some time. Figure 3, Figure 4 and Figure 5 show how this split is applied between these sections. The hypothesis is that due to less data being processed in section S1, there will be a reduction in runtime. After the step, the full dataset is used; this is to ensure that all features are made available at some point in training, although not at every epoch. This is to aid the reduction of overfitting, which is common when too little data is used. Experimentation for the Data Step method is split into three parts, with three experiments each.

1) Starting with 25% of the dataset: Three experiments were performed, and each experiment is comprised of two sections. Each section corresponds to the amount of data used in a single epoch. Epochs in in $S_{E1}^E$ use $S_{D1}^D$, and epochs in $S_{E2}^E$ use the full dataset. Each of the experiments switch between these Sections at a different epoch, shown in Table IV. The values of $S_{D}^D$ vary between datasets as they each have a different amount of training images.

### TABLE IV: Part 1 Initial data and epoch distribution

| Experiment | $S_{D1}^D$ | $S_{D2}^D$ | $S_{E1}^E$ | $S_{E2}^E$ |
|------------|------------|------------|------------|------------|
| E1         | 25%        | 100%       | 25%        | 75%        |
| E2         | 25%        | 100%       | 50%        | 50%        |
| E3         | 25%        | 100%       | 75%        | 25%        |

Figure 3 shows graphs of the data use, for the MNIST dataset with 60,000 training images. The total area under the line represents the total number of evaluations.
This first phase of experiments sees the largest decrease in evaluations performed compared to each benchmark. In particular, experiment E3 has the largest decrease out of all the Data Step experiments. As such, if it is assumed that modifying number of evaluations performed would affect the outputs of the program, then these experiments would differ the most from the benchmarks. The results of this first phase of experiments have shown that when fewer evaluations are performed, runtime is reduced. This was expected. More importantly is the effect this has the accuracy:

- With the MNIST dataset, there has been a slight increase in average and best accuracy: E1, E2 and E3 show an average accuracy increase of 0.01%, 0.024% and 0.008% respectively.
- For the CIFAR-10 dataset, there is a much more noticeable decrease in accuracies. E1, E2 and E3 show average accuracy decrease of 0.507%, 1.141% and 2.346% respectively.
- For the smallNorb dataset, there is also a decrease in accuracy: E1, E2 and E3 show average accuracy decrease of 0.043%, 0.425% and 0.962% respectively.

Based on previous research on reducing data used for training, the results on CIFAR-10 and smallNorb datasets is perhaps to be expected. It is curious that the MNIST shows an increase in performance, albeit a slight one. What is interesting still is that for both MNIST and smallNorb datasets, the standard deviation of their accuracies is greater than their benchmarks, but for CIFAR-10 the standard deviation is lower. There seems to be no pattern, and all three datasets show unique characteristics.

2) Starting with 50% of the dataset: The next three experiments under the Data Step method follow the same form as in part one, but the initial data $S_1^D$ is 50% of the full dataset. This is shown in Table VI and Figure II shows graphs that demonstrate this with the MNIST dataset. This set of experiments is to observe the effect of a different amount of data reduction Experimental results are shown in Table VII.

The results of this second phase of experiments mirrors those of the previous phase of experiments. We observe that with fewer evaluations performed, runtime is reduced; though as more evaluations are performed compared to the previous phase, the runtime is decreased less. The accuracies show the following patterns:

- With the MNIST dataset, there is a slight increase in average and best accuracy for all but one experiments: E4 shows an average accuracy increase of 0.014%, while E5 and E6 show average accuracy decrease of 0.002% and 0.006% respectively.
- For the CIFAR-10 dataset, there is still a decrease in accuracies across all experiments, but not as steep a decline as in the previous experiments. E4, E5 and E6 show average accuracy decrease of 0.457%, 0.779% and 1.103% respectively.
- For the smallNorb dataset, there is also an accuracy decrease, but less extreme than in the previous phase. E4, E5 and E6 show average accuracy decrease of 0.056%, 0.520% and 0.084% respectively. The average accuracy of experiment E5 is also much higher than the others, and also has a higher standard deviation, which shows that the metrics are less stable.

The expectation is that as these experiments use more data than the last set, the accuracies should be improved. However, experiments E5 and E6 for MNIST and E5 for smallNorb show worse accuracies. This may show that dynamic data reduction in this particular way hinders the accuracy of the model, for these particular datasets.

3) Starting with 75% of the dataset: The last lot of three experiments were performed, also with two sections each. Epochs in $S_1^D$ use $S_1^D$, and epochs in $S_2^D$ use the full dataset $S_2^D$. In the same manner as the previous two lots of experiments, each of the experiments switch between these sections at a different epoch, shown in Table VIII.

![Table V: Data Step part 1 experimental results](image)

| Test type | # Image Evaluations | Runtime (hours) | Test Accuracy | Percentage difference |
|-----------|---------------------|----------------|---------------|-----------------------|
|           |                     |                | Best          | Average              | Standard deviation |
| MNIST     | Benchmark           | 18,000,000     | 02:01         | 99.719%              | 99.701%            | 1.10E-04          |
|           | E1                  | 14,678,880     | 01:43         | 99.739%              | 99.711%            | 2.79E-04          | -15.148%         | 0.020%         | 0.010%         |
|           | E2                  | 11,312,880     | 01:22         | **99.749%**          | **99.725%**        | **1.82E-04**      | -32.627%         | **0.030%**      | **0.024%**     |
|           | E3                  | 7,946,880      | 00:58         | **99.749%**          | **99.709%**        | **2.35E-04**      | **-51.742%**     | **0.030%**      | **0.008%**     |
| CIFAR-10  | Benchmark           | 14,976,000     | 02:54         | 88.825%              | 88.689%            | 9.59E-04          |
|           | E1                  | 12,214,320     | 02:25         | 86.675%              | 88.239%            | 2.78E-03          | -16.467%         | -0.170%         | **-0.507%**    |
|           | E2                  | 9,415,320      | 01:54         | 87.801%              | 87.677%            | **1.49E-03**      | -34.293%         | **-1.153%**     | **-1.141%**    |
|           | E3                  | 6,616,320      | 01:22         | 86.878%              | 86.608%            | 2.55E-03          | **-52.555%**     | **-2.193%**     | **-2.346%**    |
| smallNORB | Benchmark           | 7,272,000      | 01:27         | 93.152%              | 92.984%            | 1.35E-03          |
|           | E1                  | 5,931,120      | 01:15         | **93.172%**          | **92.944%**        | **2.22E-03**      | **-13.922%**     | **0.022%**      | **-0.043%**    |
|           | E2                  | 4,572,120      | 01:04         | 93.003%              | 92.588%            | 3.70E-03          | -26.674%         | -0.159%         | -0.425%        |
|           | E3                  | 3,213,120      | 00:51         | 92.628%              | 92.089%            | 4.59E-03          | **-41.191%**     | **-0.562%**     | **-0.962%**    |

| Experiment | $S_1^D$ | $S_2^D$ | $S_1^E$ | $S_2^E$ | $S_3^E$ |
|------------|---------|---------|---------|---------|---------|
| E1         | 50%     | 100%    | 25%     | 75%     |
| E2         | 50%     | 100%    | 50%     | 50%     |
| E3         | 50%     | 100%    | 75%     | 25%     |

![Table VI: Part 2 Initial data and epoch distribution](image)

![Table VII: Data Step part 2 experimental results](image)
TABLE VII: Data Step part 2 experimentation results

| Test type | # Image Evaluations | Runtime (hours) | Test Accuracy | Standard deviation | Percentage difference |
|-----------|---------------------|-----------------|---------------|--------------------|-----------------------|
|           | Best                | Average         | Best          | Average            | Best                  | Average              |
|           | accuracy            | runtime         | accuracy      | runtime            | accuracy              | runtime              |

**MNIST**

- **Benchmark** 18,000,000 02:01 99.719% 99.701% 1.10E-04
- **E4** 15,788,880 01:53 99.759% 99.715% 2.52E-04 -6.638% 0.040% 0.014%
- **E5** 13,547,880 01:39 99.719% 99.699% 1.59E-04 -18.038% -0.407% -0.457%
- **E6** 11,306,880 01:24 99.729% 99.695% 2.98E-04 -30.597% 0.010% 0.006%

**CIFAR-10**

- **Benchmark** 14,976,000 02:54 88.825% 88.689% 9.59E-04
- **E4** 13,137,840 02:35 88.464% 88.283% 1.78E-03 -10.458% -0.407% -0.457%
- **E5** 11,274,840 02:14 88.434% 87.998% 3.01E-03 -22.581% -0.441% -0.779%
- **E6** 9,411,840 01:55 88.243% 87.711% 3.00E-03 -33.831% 0.010% -1.103%

**smallNORB**

- **Benchmark** 7,272,000 01:27 93.152% 92.984% 1.35E-03
- **E4** 6,384,000 01:20 93.564% 92.978% 4.45E-03 -8.475% 0.443% -0.065%
- **E5** 5,484,000 01:11 93.263% 92.500% 6.19E-03 -18.317% 0.120% -0.520%
- **E6** 4,584,000 01:04 93.544% 92.905% 4.39E-03 -26.675% 0.421% -0.084%

Fig. 4: Data Step Experiments starting with 50% data.
(a) Step at 25% through training, (b) Step at 50% through training, (c) Step at 75% through training.

S shows graphs that demonstrate this. The aim of these experiments is to observe the effect of a smaller data reduction than in previous tests. Table IX shows the results of the experimentation.

TABLE VIII: Part 3 Initial data and epoch distribution

| Experiment | S₁D | S₁E | S₂D | S₂E |
|------------|-----|-----|-----|-----|
| E1         | 75% | 100%| 25% | 75% |
| E2         | 75% | 100%| 50% | 50% |
| E3         | 75% | 100%| 75% | 25% |
accuracy decrease of 0.062% and 0.250% respectively. There is an increase in performance with experiment E7; this is the only experiment on the smallNorb dataset to have an increase in performance. The average accuracies of experiments E8 and E9 are decreased, which shows how much of an effect such a slight difference in number of evaluations performed has on the model.

This final phase of testing uses the least data reduction, and as such, the decrease in both runtime and average accuracy is the smallest. The following patterns are observed:

- With the MNIST dataset there is an increase in accuracy for all experiments: E7, E8 and E9 show an average accuracy increase of 0.018%, 0.016% and 0.012% respectively. Experiment E7 shows a decrease in standard deviation of accuracies, compared to the benchmark.
- With the CIFAR-10 dataset, the results follow the same patterns as with the results of the last groups of experiments - the accuracy decrease directly correlates to the reduction in data used, although this correlation is non-linear. E7, E8 and E9 show an average accuracy decrease of 0.072%, 0.324% and 0.507% respectively.
- With the smallNorb dataset, E7 shows an average accuracy increase of 0.081%, and E8 and E9 show an average
TABLE IX: Data Step part 3 experimentation results

| Test type | # Image Evaluations | Runtime (hours) | Test Accuracy | Standard deviation | Percentage difference |
|-----------|---------------------|-----------------|---------------|--------------------|-----------------------|
|           |                     |                 | Best          | Average            | Runtime               | Best         | Average       |
| MNIST     |                     |                 |               |                    |                       |             |               |
| Benchmark | 18,000,000          | 02:01           | 99.719%       | 99.701%            | 1.10E-04              | -5.412%     | 0.010%        | 0.018%        |
| E7        | 16,898,880          | 01:55           | 99.729%       | 99.719%            | 1.00E-04              | -5.713%     | 0.010%        | 0.016%        |
| E8        | 15,782,880          | 01:54           | 99.729%       | 99.717%            | 1.31E-04              | -11.948%    | 0.010%        | 0.012%        |
| E9        | 14,666,880          | 01:47           | 99.729%       | 99.713%            | 1.52E-04              | -11.948%    | 0.010%        | 0.012%        |
| CIFAR-10  |                     |                 |               |                    |                       |             |               |
| Benchmark | 14,976,000          | 02:54           | 88.825%       | 88.689%            | 9.59E-04              | -4.027%     | -0.170%       | -0.072%       |
| E7        | 14,061,360          | 02:47           | 88.675%       | 88.625%            | 5.59E-04              | -9.888%     | -0.192%       | -0.324%       |
| E8        | 13,134,360          | 02:36           | 88.655%       | 88.402%            | 2.98E-03              | -9.528%     | 0.461%        | -0.062%       |
| E9        | 12,207,360          | 02:25           | 88.353%       | 88.239%            | 3.85E-03              | -13.423%    | 0.159%        | -0.250%       |

C. Data Increment

Like the methods described in the Step section, the incrementing method uses a fraction of the data at the start of training. At a previously defined interval, more of the data is added incrementally, causing multiple smaller steps in data usage throughout the training. As such, the number of sections present is equal to the number of increments.

Adding the data this way will decrease the time spent training for the earlier epochs, while ensuring that all training data is eventually used. Figure 6 shows example data usage graphs with varying increment intervals. Table X shows the results of the experimentation.

Using the data increment method causes much less data to be used throughout training. The most extreme case of this is with steps of 0.33%, where roughly half of the evaluations are performed. This makes the data increment method a more extreme data reduction method than the data step method. For each dataset, the observations are as follows:

- For the MNIST dataset, average accuracy is maintained with 33% and 25% increments, but is never improved upon the baseline. For both of these cases, runtime is shortened by at least 30%.
- For the CIFAR-10 dataset, all average accuracies are worse by at least 1%. Like MNIST, runtime is shortened by a minimum of 30%.
- For the smallNorb dataset, as the dataset has much fewer training images, both the runtime and accuracy reduction are not as large as with other datasets. For all experiments, average accuracy is reduced by less than 1%, while runtime is reduced by between 20% to 40%.

Based on these results, the data increment method seems to have a more detrimental effect on network performance. It is also worth noting that the standard deviation of average accuracies are worse than the benchmark across all experiments, meaning the networks are less reliable at getting consistent results.

D. Data Cut

The data cut method splits a dataset into multiple cuts of equal size. Each cut is then used for an equal number of training epochs. The more splits a deck is cut into, the less data is present in each split. As such, the more splits there are, the fewer evaluations will be performed. Figure 7 shows
### TABLE X: Data Increment experimentation results

| Test type | # Image Evaluations | Runtime (hours) | Test Accuracy | Standard deviation | Percentage difference | Average Accuracy |
|-----------|---------------------|-----------------|---------------|--------------------|-----------------------|-----------------|
|           |                     |                 | Best          | Average            | Runtime              | Best            |
|           |                     |                 | Test          | Standard            |                      | Average         |
|           |                     |                 | Accuracy      | deviation           |                      |                 |
| MNIST     | 18,000,000          | 02:01           | 99.719%       | 99.701%            | 1.10E-04             | 0.020%          |
| 33%       | 11,992,080          | 01:23           | 99.739%       | 99.703%            | 2.89E-04             | -31.790%        |
| 25%       | 11,241,120          | 01:20           | 99.719%       | 99.699%            | 1.42E-04             | -34.210%        |
| 10%       | 9,903,720           | 01:09           | 99.709%       | 99.687%            | 2.50E-04             | -42.630%        |
| 5%        | 9,456,720           | 01:07           | 99.729%       | 99.701%            | 1.93E-04             | -44.820%        |
| 1%        | 9,099,120           | 01:08           | 99.709%       | 99.677%            | 2.18E-04             | -44.090%        |
| 0.33%     | 9,041,880           | 01:04           | 99.719%       | 99.695%            | 1.96E-04             | -47.310%        |
| CIFAR-10  | 14,976,000          | 02:54           | 88.825%       | 88.689%            | 9.59E-04             | -1.090%         |
| 33%       | 9,981,360           | 02:00           | 88.153%       | 87.723%            | 2.69E-03             | -30.920%        |
| 25%       | 9,361,560           | 01:52           | 87.771%       | 87.582%            | 2.18E-03             | -35.130%        |
| 10%       | 8,253,000           | 01:42           | 87.550%       | 87.317%            | 1.52E-03             | -41.380%        |
| 5%        | 7,877,520           | 01:36           | 87.490%       | 87.275%            | 1.92E-03             | -44.530%        |
| 1%        | 7,581,360           | 01:33           | 87.599%       | 87.106%            | 1.25E-03             | -46.370%        |
| 0.33%     | 7,531,560           | 01:33           | 87.560%       | 87.225%            | 2.06E-03             | -46.560%        |
| smallNORB | 7,272,000           | 01:27           | 93.152%       | 92.984%            | 1.35E-03             | -0.540%         |
| 33%       | 4,840,200           | 01:07           | 92.954%       | 92.482%            | 3.61E-03             | -23.040%        |
| 25%       | 4,536,240           | 01:03           | 92.628%       | 92.463%            | 2.21E-03             | -28.180%        |
| 10%       | 3,990,840           | 01:02           | 92.788%       | 92.373%            | 3.51E-03             | -32.850%        |
| 5%        | 3,821,040           | 00:59           | 92.735%       | 92.291%            | 3.45E-03             | -32.180%        |
| 1%        | 3,676,560           | 00:57           | 92.562%       | 92.115%            | 4.91E-03             | -34.520%        |
| 0.33%     | 3,651,600           | 00:56           | 92.525%       | 92.248%            | 2.39E-03             | -35.700%        |

This approach is similar to Transfer Learning techniques, in which a network that has already been trained on some data is introduced to a new set of training data. The new input data contains the same classes as it had already been trained with, so the network does not need to adapt to new classes. However, while previous methods in this paper introduced new training data to accompany previously used data, this method does not include the previously used data when new data is introduced - it continues training on only new data. Normally, when introducing new data via transfer learning, a fresh network is deployed, and given the weights and biases of previously trained networks. The Data Cut method aims to give the network different data at different times, while preserving the state of the network throughout a single training cycle. Table XI shows the results of the experimentation.

Of the three experimental methods described in this paper, the Data Cut method cuts the number of evaluations performed down the most. It becomes apparent quickly that the more splits are used, the more the accuracy is degraded. Results on the MNIST dataset show that by cutting the dataset into two splits, we almost cut the runtime in half while maintaining the benchmark accuracy. With 24 splits, there is a large drop in performance. This shows a ‘cut-off point’, where too few evaluations are performed, and the model doesn’t have enough iterations to allow the weights and biases to converge, causing more classifications to fail. Figure 8 shows the percentage difference in runtime and accuracy of the CIFAR-10 dataset, compared to its benchmark. The results of this dataset show the biggest percentage differences. The graph shows that by introducing more data splits, the runtime decreases non-linearly.
TABLE XI: Data Cut experimentation results

| Test type | # Image Evaluations | Runtime (hours) | Best Test Accuracy | Standard deviation | Percentage difference |
|-----------|---------------------|-----------------|-------------------|--------------------|-----------------------|
|           |                     |                 | Average           |                     |                      |
|           |                     |                 | Best Accuracy      |                    |                      |
|           |                     |                 | Average           |                    |                      |
|           |                     |                 | Best Accuracy      |                     |                      |
|           |                     |                 | Runtime           | Best Accuracy       | Average Accuracy      |
| MNIST     |                     |                 |                   |                    |                      |
| Benchmark | 18,000,000          | 02:01           | 99.719%           | 99.701%            | 1.10E-04              |
| 2 Splits  | 9,000,000           | 01:07           | 99.719%           | 99.699%            | 1.23E-04 -44.272%    |
| 3 Splits  | 5,976,000           | 00:44           | 99.697%           | 99.655%            | 1.68E-04 -63.331%    |
| 6 Splits  | 2,988,000           | 00:25           | 99.659%           | 99.596%            | 4.10E-04 -78.800%    |
| 9 Splits  | 1,980,000           | 00:19           | 99.598%           | 99.526%            | 6.82E-04 -84.016%    |
| 12 Splits | 1,476,000           | 00:16           | 99.508%           | 99.337%            | 1.41E-03 -86.604%    |
| 15 Splits | 1,188,000           | 00:14           | 99.367%           | 99.102%            | 2.85E-03 -88.074%    |
| 18 Splits | 972,000             | 00:13           | 99.297%           | 98.855%            | 3.86E-03 -89.124%    |
| 21 Splits | 828,000             | 00:12           | 99.237%           | 97.476%            | 7.33E-03 -90.501%    |
| 24 Splits | 720,000             | 00:11           | 96.365%           | 95.645%            | -90.501% -3.363% -4.068% |
| CIFAR-10  |                     |                 |                   |                    |                      |
| Benchmark | 14,976,000          | 02:54           | 88.825%           | 88.689%            | 9.59E-04 -2.306% -2.436% |
| 2 Piles   | 7,488,000           | 01:33           | 86.777%           | 86.528%            | 1.54E-03 -46.518% -2.306% -2.436% |
| 3 Splits  | 4,968,000           | 01:04           | 85.492%           | 85.143%            | 3.20E-03 -62.692% -3.753% -3.998% |
| 6 Splits  | 2,484,000           | 00:37           | 82.269%           | 81.984%            | 3.27E-03 -78.491% -7.381% -7.560% |
| 9 Splits  | 1,656,000           | 00:28           | 80.110%           | 79.673%            | 6.68E-03 -83.690% -9.811% -10.166% |
| 12 Splits | 1,224,000           | 00:23           | 77.791%           | 77.072%            | 6.68E-03 -86.431% -12.422% -13.098% |
| 15 Splits | 972,000             | 00:20           | 75.552%           | 72.888%            | 3.27E-03 -88.971% -18.447% -22.125% |
| 18 Splits | 828,000             | 00:19           | 72.440%           | 69.066%            | 1.94E-02 -89.880% -23.748% -25.548% |
| 21 Splits | 684,000             | 00:17           | 67.731%           | 66.030%            | -90.880% -27.348% -25.548% |
| 24 Splits | 612,000             | 00:16           | 64.518%           | 60.600%            | 4.62E-02 -90.370% -27.365% -31.671% |
| smallNORB |                     |                 |                   |                    |                      |
| Benchmark | 7,272,000           | 01:27           | 93.152%           | 92.984%            | 1.35E-03 -32.490% -0.049% -0.257% |
| 2 Splits  | 3,636,000           | 00:59           | 93.106%           | 92.744%            | 3.37E-03 -32.490% -0.049% -0.257% |
| 3 Splits  | 2,412,000           | 00:31           | 92.880%           | 92.616%            | 2.36E-03 -41.598% -0.292% -0.396% |
| 6 Splits  | 1,188,000           | 00:42           | 92.946%           | 92.104%            | 5.30E-03 -52.148% -0.221% -0.946% |
| 9 Splits  | 792,000             | 00:38           | 91.840%           | 91.408%            | 9.39E-03 -55.659% -1.408% -1.694% |
| 12 Splits | 576,000             | 00:36           | 90.924%           | 90.012%            | 7.59E-03 -58.625% -2.392% -3.195% |
| 15 Splits | 468,000             | 00:36           | 89.975%           | 87.791%            | 2.33E-02 -58.774% -3.410% -5.584% |
| 18 Splits | 396,000             | 00:36           | 88.461%           | 87.139%            | 1.05E-02 -58.445% -5.035% -6.286% |
| 21 Splits | 324,000             | 00:36           | 86.865%           | 80.511%            | 8.85E-02 -58.097% -6.749% -13.414% |
| 24 Splits | 288,000             | 00:37           | 86.894%           | 80.776%            | 7.48E-02 -57.390% -6.718% -13.128% |

Fig. 8: Runtime reduction and accuracy loss with Data Cut method, on CIFAR-10 dataset

while the accuracy decreases more steadily. Therefore, the most appropriate number of data splits must be chosen to benefit the most from this dataset reduction technique.

V. DISCUSSION

The runtime of the experiment correlates directly with the total number of evaluations performed. This is as expected, as the fewer evaluations are performed, the fewer calculations are performed by the neural network.

For the Data Step method, the most notable results are those of the MNIST dataset, and E7, E8 and E9 of smallNorb, as they show an increase in accuracy despite the fewer evaluations performed. A future research direction would be to investigate why there is a performance increase in these cases, and how the detrimental effect on stability may be rectified. Also, further research into why CIFAR-10 does not show any increase could be explored.

As with the Data Step method, the Data Increment method shows that reducing the number of evaluations performed decreases the runtime. However, despite both methods performing the same fundamental task of data reduction, they produce different results for roughly the same number of evaluations performed. For example, comparing experiments E2 of the data step method and data increments of 25%, we can observe the accuracies when roughly the same number of evaluations are performed.

The number of evaluations for the two experiments are:
- E2 for MNIST dataset uses 11,312,880 evaluations, data increments of 25% use 11,241,120 evaluations, a difference of 0.634%.
- E2 for CIFAR-10 dataset uses 9,415,320 evaluations, data increments of 25% use 9,361,560 evaluations, a difference of 0.634%.
However, despite the marginal difference in number of evaluations performed, the difference in accuracy between these two experiments are:

- E2 for MNIST dataset gives an accuracy increase of 0.024%, data increments of 25% give an accuracy difference of 0%.
- E2 for CIFAR-10 dataset gives an accuracy decrease of 1.141%, data increments of 25% give an accuracy decrease of 1.250%.
- E2 for smallNorb dataset gives an accuracy decrease of 0.425%, data increments of 25% give an accuracy difference of 0.560%.

For all cases, the data increment method shows worse accuracy. While it is true that the data increment method has fewer evaluations performed, the difference in data (less than 1% for all datasets) amounts to less than 3 epochs of training. This amount is negligible as the top accuracy of a model settles at much earlier epochs. The results of the experimentation show that decreasing the number of evaluations with the Increment method has a more detrimental effect on the accuracy of the model.

Finally, the data cut method shows the largest reduction in evaluations performed. Below is a comparison between experiments data increment of 0.33% and data cut with 2 splits:

- Data Increment for MNIST dataset uses 9,041,880 evaluations, data cut with 2 splits use 9,000,000 evaluations, a difference of 0.463%.
- Data Increment for CIFAR-10 dataset uses 7,531,560 evaluations, data cut with 2 splits use 7,488,800 evaluations, a difference of 0.578%.
- Data Increment for smallNorb dataset uses 3,651,600 evaluations, data cut with 2 splits use 3,636,000 evaluations, a difference of 0.427%.

Comparing the accuracies between these two experiments, we observe:

- Data Increment for MNIST gives an accuracy decrease of 0.01%, data cut with 2 splits gives an accuracy decrease of 0.02%.
- Data Increment for CIFAR-10 gives an accuracy decrease of 1.65%, data cut with 2 splits gives an accuracy decrease of 2.436%.
- Data Increment for smallNorb gives an accuracy decrease of 0.79%, data cut with 2 splits gives an accuracy decrease of 0.257%.

Accuracy for all observed data cut experiments are worse than those of the data increment method. We can conclude that, as the data increment method is inferior to the data step method, the data cut method is least effective at maintaining accuracy. However, if the need is to reduce the runtime by as much as possible without hindering accuracy too greatly, a data cut of 9 splits appears to be the best compromise between runtime and accuracy.

VI. CONCLUSION

The results of this paper have shown that, contrary to the norm, reducing the data used for training has in some cases improved the performance of the model. It proves that not all data may be necessary for training, and in fact some data may hinder it.

The approaches used are somewhat brutish, excluding data randomly without consideration of the value of the data points removed. Other works cited have shown algorithmic approaches to select which data to remove to enhance performance, which is a next step for varying data usage. Still, having shown that even random exclusion has improved results, it would seem that varying data use is to be explored in further detail.

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