A Resizable Mini-batch Gradient Descent based on a Randomized Weighted Majority

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Abstract

Determining the appropriate batch size for mini-batch gradient descent is always time consuming as it often relies on grid search. This paper considers a resizable mini-batch gradient descent (RMGD) algorithm-inspired by the randomized weighted majority algorithm-for achieving best performance in grid search by selecting an appropriate batch size at each epoch with a probability defined as a function of its previous success/failure and the validation error. This probability encourages exploration of different batch size and then later exploitation of batch size with history of success. At each epoch, the RMGD samples a batch size from its probability distribution, then uses the selected batch size for mini-batch gradient descent. After obtaining the validation error at each epoch, the probability distribution is updated to incorporate the effectiveness of the sampled batch size. The RMGD essentially assists the learning process to explore the possible domain of the batch size and exploit successful batch size. Experimental results show that the RMGD achieves better performance than grid search.

1. Introduction

Gradient descent (GD) is a common algorithm in minimizing the expected loss. It takes iterative steps proportional to the negative gradient (or approximate gradient) of the loss function at each iteration. It is based on the observation that if the multi-variable loss functions \( f(w) \) is differentiable at a point \( w \), then \( f(w) \) decreases fastest in the direction of the negative gradient of \( f \) at \( w \), i.e., \(-\nabla f(w)\). Even when \( f \) is not differentiable, any subgradient of \( f \) can be used for GD. The model parameters are updated iteratively in GD as follows:

\[
    w_{t+1} = w_t - \eta_t g_t, \quad g_t \in \partial f(w_t) \tag{1}
\]

where \( w_t, \ g_t, \) and \( \eta_t \) are the model parameters, (sub)gradients of \( f \), and learning rate at time \( t \) respectively. For small enough \( \eta_t \), \( f(w_t) \geq f(w_{t+1}) \) and ultimately the sequence of \( w_t \) will move down toward a local minimum. For a convex loss function, GD is guaranteed to converge to a global minimum with an appropriate learning rate.

There are various issues to consider in gradient-based optimization. First, GD can be extremely slow and impractical for large dataset: gradients of all the data have to be evaluated for each iteration. With larger data size, the convergence rate, the computational cost and memory become critical, and special care is required to minimize these factors. Second, for non-convex function which is often encountered in deep learning, GD can get stuck in a local minimum without the hope of escaping. Third, stochastic gradient descent (SGD), which is based on the gradient of a single training sample, has large gradient variance, and it requires a large number of iterations. This ultimately translates to slow convergence. Mini-batch gradient descent (MGD), which is based on the gradient over a small batch of training data, trades off between the robustness of SGD and the stability of GD. There are three advantages for using MGD over GD and SGD: 1) The batching allows both the efficiency of memory usage and implementations; 2) The model update frequency is higher than GD which allows for a more robust convergence avoiding local minimum; 3) MGD requires less iteration per epoch and provides a more stable update than SGD. For these reason, MGD has been a popular algorithm for learning. However, selecting an appropriate batch size is difficult. Various studies suggest that there is a close link between performance and batch size used in MGD [3, 9, 12].

There are various guidelines for selecting a batch size but have not been completely practical [2]. Grid search is a popular method but it comes at the expense of search time. There are a small number of adaptive MGD algorithms to
replace grid search [1, 4, 5, 6]. These algorithms increase the batch size gradually according to their own criterion. However, these algorithms are only applicable for convex function and can not be applied to deep learning. For non-convex optimization, it is difficult to determine the optimal batch size for best performance.

This paper considers a resizable mini-batch gradient descent (RMGD) algorithm based on the randomized weighted majority for achieving best performance in grid search by selecting an appropriate batch size at each epoch with a probability defined as a function of its previous success/failure and the validation error. At each epoch, RMGD samples a batch size from its probability distribution, then uses the selected batch size for mini-batch gradient descent. After obtaining the validation error at each epoch, the probability distribution is updated to incorporate the effectiveness of the sampled batch size. The benefit of RMGD is that it avoids the need for cumbersome grid search to achieve best performance. The detailed algorithm and mechanism of RMGD are described in Section 3, and experiment results are presented in Section 4.

2. Related works

There are only a few published results on the topic of batch size. In [12], it was empirically shown that SGD converged faster than GD on a large speech recognition database. In [3], it was determined that the range of learning rate resulting in low test errors was considerably getting smaller as the batch size increased on convolutional neural networks (CNN). Also, it was observed that small batch size yielded the best test error, while large batch size could not yield comparable low error rate. In [9], it was observed that larger batch size are more liable to converge to a sharp local minimum thus leading to poor generalization. In [7], it was found that the learning rate and the batch size controlled the trade-off between the depth and width of the minima in MGD.

A small number of adaptive MGD algorithms have been proposed. In [4], a relatively small batch size is chosen at the start, then the algorithm chooses a larger batch size when the optimization step does not produce improvement in the target objective function. In [6], the algorithm uses relatively few samples to approximate the gradient, and gradually increase the number of measurements. In [1, 5], similar increasing batch size algorithms is introduced with just different criterion for batch size and growing step. In [10], it was observed that increasing the batch size is more effective than decaying the learning rate for reducing the number of iterations. In [8], a batch size is determined by using a hidden Markov model which seems too complex to be used for large data.

3. Resizable Mini-batch Gradient Descent based on Randomized Weighted Majority

The overall framework of the RMGD algorithm is shown in Figure 1. The RMGD consists of three components: selector, updater, and terminator. The selector samples a batch size based on certain selection probability. The updater updates the model parameters, states of the batch sizes, and unnormalized probabilities of the batch sizes based on the validation error. The terminator stops training based on the terminal condition.

Selector samples a batch size $b_k \in \mathcal{B} = \{b_j\}_{j=1}^K$ with probability of $\tilde{\pi}_k / \sum_j \tilde{\pi}_j$ at epoch $\tau$. Here the $k$th batch size $b_k$ in the $\mathcal{B}$ is associated with unnormalized probability $\tilde{\pi}_k$. When $\tau = 0$, $\tilde{\pi}_1^0 = \cdots = \tilde{\pi}_K^0 = e^\alpha$ where $\alpha$ is a...
positive constant. Let the batch size at epoch \( \tau \) be \( m_\tau \in \mathcal{B} \).

**Updater** updates the model parameters \( w \), state of selected batch size \( s^k \), and unnormalized probability \( \hat{\pi}^k \). When \( \tau = 0 \), \( s^1_1 = \cdots = s^K_1 = 0 \) and \( \varepsilon^\text{min}_1 = 1 \) for classification where \( \varepsilon^\text{min}_\tau \) is the minimal validation error until epoch \( \tau \). For each epoch, MGD iterates \( T = \lceil m/m_\tau \rceil \) times where \( m \) is the total number of training samples. After \( T \) iterations at epoch \( \tau \), the model parameter \( w_{\tau,t+1} \) is updated as follows:

\[
 w_{\tau,t+1} = w_{\tau,t} - \eta_t g_t, \quad g_t \in \partial f(w_{\tau,t})
\]

(2)

where \( w_{\tau,t+1} \), \( \eta_t \), \( g_t \), and \( f(w_{\tau,t}) \) are the model parameters after \( t \) iterations at epoch \( \tau \), learning rate at epoch \( \tau \), (sub)gradients of \( f \), and training loss with respect to \( w_{\tau,t} \) respectively. After \( T \) iterations at epoch \( \tau \), the updater obtains validation error \( \varepsilon(w_{\tau,T+1}) \), then conditionally updates \( \varepsilon^\text{min}_T \) and \( s^k_T+1 \). When \( \varepsilon(w_{\tau,T+1}) < \varepsilon^\text{min}_T \), then \( \varepsilon^\text{min}_T = \varepsilon(w_{\tau,T+1}) \) and \( s^k_T+1 = 0 \); otherwise, \( s^k_T+1 = s_T + 1 \). The unnormalized probability \( \hat{\pi}^k_{\tau+1} \) is unconditionally updated as follows:

\[
 \hat{\pi}^k_{\tau+1} = e^{\alpha \varepsilon^\text{min}_T - \beta s^k_T+1}
\]

(3)

where \( \beta \) is a positive constant.

**Terminator** stops the training when the following condition is met. For epoch \( \tau \), the terminator compares the minimal state of the batch size \( s^\text{min}_{\tau+1} \) with the termination threshold \( C \in \mathbb{N} \). Thus, when \( s^\text{min}_{\tau+1} \geq C \), then the training is stopped.

1\([x]\) is the least integer that is greater than or equal to \( x \)

### 4. Experiments

This section describes the dataset, model settings, and various experimental results. Experimental results
comparing the performance of the RMGD with that of the MGD are presented.

### 4.1. Dataset

**MNIST** is a dataset of handwritten digits that is commonly used for image classification. Each sample is a black and white image and $28 \times 28$ in size. The MNIST is split into three parts: 55,000 samples for training, 5,000 samples for validation, and 10,000 samples for test.

**CIFAR10** consists of 60,000 $32 \times 32$ color images in 10 classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck), with 6,000 images per class. The CIFAR10 is split into three parts: 45,000 samples for training, 5,000 samples for validation, and 10,000 samples for test.

### 4.2. Settings

In the experiments, simple convolutional neural networks (CNN) and ‘All-CNN-C’ [11] are used. For MNIST, the simple model consists of two convolution layers with $5 \times 5$ filter and $1 \times 1$ stride, two max pooling layers with $2 \times 2$ kernel and $2 \times 2$ stride, single fully-connected layer, and softmax classifier. For CIFAR10, the simple model consists of two convolution layers with $5 \times 5$ filter and $1 \times 1$ stride, two max pooling layers with $3 \times 3$ kernel and $2 \times 2$ stride, two fully-connected layers, and softmax classifier. The ‘All-CNN-C’ is used for CIFAR10 only. Description of the network is provided in Table 1. For simple CNNs, AdamOptimizer is used as optimizer, $\eta = 10^{-4}$, and $B = \{16, 32, 64, 128, 256\}$. For ‘All-CNN-C’, MomentumOptimizer with fixed momentum of 0.9 is used as optimizer. The learning rate $\eta^k$ is adapted for each batch size ($\eta^k = 0.05 * b_k/256$ where $b_k$ is the batch size) and decayed by a schedule $S = [200, 250, 300]$ in which $\eta^k$ is multiplied by a fixed multiplier of 0.1 after 200, 250, and 300 epochs respectively. The model is trained for a total of 350 epochs. Dropout is applied to the input image as well as after each convolution layer with stride 2. The dropout probabilities are 20% for dropping out inputs and 50% otherwise. The model is regularized with weight decay $\lambda = 0.001$, and $B = \{16, 32, 64, 128, 256\}$ for all experiments, rectified linear unit (ReLU) is used as activation function, $\alpha = 1$, and $\beta = 1$.

### 4.3. Results

Image classification was performed using the MNIST dataset to compare the performances between the MGD and
the RMGD. The experiments were repeated 100 times for each algorithm and the results were analyzed for significance. Figure 3 shows the test accuracy for each algorithm. The left figure represents the mean test accuracy with standard error. The number in parenthesis next to RMGD represents the threshold for termination. Among the MGD algorithms, small batch size lead to higher performance than large batch size and batch size 16 achieved the best performance. The t-test was performed to validate the significance of the experimental results and p-values of t-test are presented in Table 2. The p-values of RMGD (C=3), RMGD (C=5), and RMGD (C=7) versus all MGD were much less than 0.001. The right figure represents the histogram of test accuracies for each algorithm.

Almost test accuracies of RMGD (C=3), RMGD (C=5), and RMGD (C=7) were distributed in higher accuracy region than the others. Table 3 presents iterations and relative time for training, mean, maximum, and minimum of test accuracies for each algorithm. The MGD (total) is the total iterations and the total relative time for grid search. For RMGD, there was trade-off between the performance and the computation time. The RMGD (C=1) achieved best performance of MGD much faster than best performing MGD-about 2.8 times faster than MGD (16) and 6.3 times faster than grid search in terms of iterations. This is about 2.1

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**Table 2. P-values by t-test for test accuracy of the experiments with MNIST dataset.**

| Algorithms         | MGD (16) | MGD (32) | MGD (64) | MGD (128) | MGD (256) | MGD (512) | RMGD (C=1) | RMGD (C=3) | RMGD (C=5) | RMGD (C=7) |
|--------------------|----------|----------|----------|-----------|-----------|-----------|------------|------------|------------|------------|
| MGD (16)           |          |          |          |           |           |           |            |            |            |            |
| MGD (32)           | -        | 0.480    | 0.002    | <0.001    | <0.001    | 0.789     | <0.001     | <0.001     | <0.001     | <0.001     |
| MGD (64)           | 0.480    | -        | 0.011    | <0.001    | <0.001    | 0.709     | <0.001     | <0.001     | <0.001     | <0.001     |
| MGD (128)          | 0.002    | 0.011    | -        | 0.018     | <0.001    | 0.009     | <0.001     | <0.001     | <0.001     | <0.001     |
| MGD (256)          | <0.001   | <0.001   | 0.018    | -         | <0.001    | <0.001    | <0.001     | <0.001     | <0.001     | <0.001     |
| MGD (512)          | <0.001   | <0.001   | <0.001   | <0.001    | <0.001    | <0.001    | <0.001     | <0.001     | <0.001     | <0.001     |
| RMGD (C=1)         | 0.789    | 0.709    | 0.009    | <0.001    | <0.001    | <0.001    | <0.001     | <0.001     | <0.001     | <0.001     |
| RMGD (C=3)         | <0.001   | <0.001   | <0.001   | <0.001    | <0.001    | <0.001    | <0.001     | <0.001     | <0.001     | <0.001     |
| RMGD (C=5)         | <0.001   | <0.001   | <0.001   | <0.001    | <0.001    | <0.001    | <0.001     | <0.001     | <0.001     | <0.001     |
| RMGD (C=7)         | <0.001   | <0.001   | <0.001   | <0.001    | <0.001    | <0.001    | <0.001     | <0.001     | <0.001     | <0.001     |

**Table 3. Iterations and relative time for training, and test accuracy of the experiments with MNIST dataset.**

| Algorithms | Iterations | Relative time (sec) | Test accuracy (%) |
|------------|------------|---------------------|-------------------|
|            | Mean ± SD  | Max                 | Min               |
| MGD (16)   | 63,844 ± 14,559 | 195.17 ± 54.82      | 99.241 ± 0.073    |
| MGD (32)   | 36,563 ± 9,505   | 147.88 ± 38.89      | 99.234 ± 0.066    |
| MGD (64)   | 20,287 ± 4,494   | 88.87 ± 19.54       | 99.208 ± 0.077    |
| MGD (128)  | 11,778 ± 3,143   | 69.52 ± 18.54       | 99.182 ± 0.078    |
| MGD (256)  | 6,942 ± 1,629    | 63.74 ± 14.77       | 99.131 ± 0.087    |
| MGD (512)  | 4,131 ± 801      | 64.69 ± 12.49       | 99.072 ± 0.086    |
| MGD (total)| 143,545         | 629.87              | 99.260 ± 0.058    |
| RMGD (C=1)| 22,885 ± 5,173   | 92.38 ± 18.48       | 99.238 ± 0.084    |
| RMGD (C=3)| 40,165 ± 6,394   | 162.30 ± 24.13      | 99.301 ± 0.071    |
| RMGD (C=5)| 56,288 ± 8,428   | 235.77 ± 31.35      | 99.319 ± 0.066    |
| RMGD (C=7)| 72,197 ± 9,472   | 303.89 ± 35.10      | 99.334 ± 0.063    |

**Figure 4. The correlation between the total epochs for training and the test accuracy of RMGD (C=5) experiments. The red line represents trendline.**
Figure 5. The normalized probabilities, states, and selected batch size for RMGD (C=5). The white dot is selected batch size at epoch. (top) The results of the best performing case. (bottom) The results of the worst performing case.

Figure 6. The states of the batch sizes.
times faster than MGD (16) and 6.8 times faster than grid search in terms of relative time. The RMGD (C=3) outperformed all MGD and was trained faster than best performing MGD -about 1.6 times faster than MGD (16) and 3.6 times faster than grid search in terms of iterations. This is about 1.2 times faster than MGD (16) and 3.9 times faster than grid search in terms of relative time. The RMGD (C=7) slightly outperformed RMGD (C=3) and RMGD (C=5), but it was not significant rather required more time for training. One can ask whether the learning with longer epochs yields high performance. However, Figure 5 shows that there is no correlation between the performance and the total epochs for training.

Figure 5 shows the normalized probabilities, the states of batch sizes and the selected batch size with respect to epoch during training for RMGD (C=5). The white dot represents the batch size selected at each epoch. The top figure represents the best performing case and the bottom figure represents the worst case. In the early stages, various batch sizes were selected in both cases (exploration). In the later stages, the successful batch size, 256 in this case, was selected more often at epochs from 46 to 56 in the best case (exploitation); however, no such exploitation occurred in the worst case. This phenomenon appears due to the randomness of parameters initialization and mini-batch sampling during training. No exploitation means there is no successful batch size. This probabilities and states map can be an additional measure of whether the learning has been successful. Figure 6 shows the states of six cases. In the results, any batch size can be a successful batch size in the later stages without any particular order. The RMGD is more effective for such situation than the MGD or directional adaptive MGD such as gradually increasing batch size algorithm.

The CIFAR10 dataset was, also, used to compare the performance. The first experiment, which used simple CNNs, were repeated 10 times for each algorithm in both cases with or without batch normalization (BN). In this experiment, early stopping condition for MGD was loosen to avoid lack of training, actually the performance of longer training did not exceed that of early stopped model. The termination thresholds for RMGD were loosen too. Fig-

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**Table 4. Iterations and relative time for training, and test accuracy for CIFAR10. Each experiment was repeated 10 times without batch normalization.**

| Algorithms | Iterations | Relative time (sec) | Test accuracy (%) |
|------------|------------|---------------------|-------------------|
|            |            |                     | Mean ± SD         | Max     | Min     |
| MGD (16)   | 133,899 ± 29,855 | 543.12 ± 131.26 | 75.969 ± 0.367 | 76.720  | 75.520  |
| MGD (32)   | 80,480 ± 12,327 | 435.90 ± 74.09   | 75.637 ± 0.587 | 76.330  | 74.390  |
| MGD (64)   | 49,280 ± 6,297  | 345.98 ± 43.76   | 75.753 ± 0.375 | 76.320  | 74.970  |
| MGD (128)  | 30,237 ± 4,417  | 330.79 ± 48.90   | 75.302 ± 0.443 | 76.080  | 74.590  |
| MGD (256)  | 18,779 ± 1,854  | 350.53 ± 34.89   | 75.014 ± 0.328 | 75.560  | 74.460  |
| MGD (512)  | 13,596 ± 2,180  | 467.54 ± 72.54   | 74.514 ± 0.760 | 75.830  | 73.020  |
| MGD (total)| 326,271       | 2,473.66         | 76.425 ± 0.485 | 76.970  | 75.190  |
| RMGD (C=3) | 49,345 ± 3,874  | 361.39 ± 30.99   | 76.425 ± 0.485 | 76.970  | 75.190  |
| RMGD (C=5) | 58,423 ± 5,376  | 441.73 ± 39.47   | 76.444 ± 0.354 | 77.030  | 75.850  |
| RMGD (C=7) | 73,082 ± 4,624  | 551.27 ± 36.41   | 76.547 ± 0.213 | 76.980  | 76.300  |
| RMGD (C=10)| 87,821 ± 3,726  | 779.51 ± 420.11  | 76.369 ± 0.563 | 76.940  | 74.860  |

**Table 5. Iterations and relative time for training, and test accuracy for CIFAR10. Each experiment was repeated 10 times with batch normalization.**

| Algorithms | Iterations | Relative time (sec) | Test accuracy (%) |
|------------|------------|---------------------|-------------------|
|            |            |                     | Mean ± SD         | Max     | Min     |
| MGD (16)   | 126,585 ± 24,780 | 611.25 ± 125.40 | 75.726 ± 0.307 | 76.130  | 75.060  |
| MGD (32)   | 80,340 ± 14,669 | 538.40 ± 99.06    | 75.646 ± 0.667 | 76.650  | 74.070  |
| MGD (64)   | 37,875 ± 6,256  | 415.30 ± 68.55    | 75.726 ± 0.283 | 76.130  | 75.320  |
| MGD (128)  | 25,731 ± 3,289  | 526.55 ± 68.02    | 75.430 ± 0.251 | 75.890  | 75.060  |
| MGD (256)  | 16,438 ± 1,579  | 643.14 ± 62.98    | 75.071 ± 0.350 | 75.410  | 74.430  |
| MGD (512)  | 9,398 ± 839    | 688.69 ± 61.53    | 74.071 ± 0.388 | 74.490  | 73.400  |
| MGD (total)| 296,367       | 3,423.33          | 76.344 ± 0.214 | 76.690  | 75.920  |
| RMGD (C=3) | 41,387 ± 3,717  | 472.46 ± 28.42    | 76.385 ± 0.214 | 76.690  | 75.920  |
| RMGD (C=5) | 51,378 ± 4,389  | 618.62 ± 45.10    | 76.291 ± 0.632 | 76.880  | 74.580  |
| RMGD (C=7) | 63,497 ± 5,573  | 781.50 ± 59.70    | 75.928 ± 0.597 | 76.610  | 74.700  |
| RMGD (C=10)| 80,267 ± 4,294  | 975.57 ± 50.52    | 76.022 ± 0.845 | 77.120  | 74.760  |
Figure 7. The results of test accuracy and relative time in both cases with and without batch normalization for the CIFAR10 dataset. (left) The mean test accuracy of 10 times repeated experiments for each algorithm. The error bar is standard error. (right) The mean relative time of 10 times repeated experiments for each algorithm.

Figure 8. The results of test accuracy and relative time for the ‘All-CNN-C’. (left) The mean test accuracy of 25 times repeated experiments for each algorithm. The error bar is standard error. (right) The mean relative time of 25 times repeated experiments for each algorithm.

The second experiment, which used ‘All-CNN-C’, were repeated 25 times for each algorithm. In this experiment, all images are whitened and contrast normalized before being input to the network. Figure 8 shows the test accuracy and relative time for training. The RMGD outperformed all MGD significantly. The detailed results of iterations, relative time and test accuracy are presented in Table 6. The RMGD was a little bit slower than single best performing MGD -about 0.76 times slower than MGD (256) in terms of relative time, however, it was much faster than grid search -about 4.9 times faster. In addition, the difference of the performance for each batch size is not significant, thus, it is not guaranteed that the batch size 256 is optimal. Therefore, this results, also, show the effectiveness of the RMGD.

Conclusion

Selecting batch size affects the model quality and training efficiency, and it leads the difficulty of determining the appropriate batch size when performing mini-batch gradient descent. Determining the appropriate batch size is always time consuming as it often relies on grid
Table 6. Iterations and relative time for training, and test accuracy for CIFAR10 with ‘All-CNN-C’. Each experiment was repeated 25 times.

| Algorithms      | Iterations | Relative time (sec) | Test accuracy (%) |
|-----------------|------------|---------------------|-------------------|
|                 |            | Mean ± SD           | Max               | Min               |
| MGD (16)        | 1,072,050  | 10,085.26 ± 216.48  | 87.778 ± 0.207    | 88.290            | 87.480            |
| MGD (32)        | 536,200    | 7,643.93 ± 459.95   | 87.851 ± 0.160    | 88.250            | 87.630            |
| MGD (64)        | 268,100    | 6,160.16 ± 68.54    | 87.853 ± 0.202    | 88.330            | 87.450            |
| MGD (128)       | 134,050    | 5,675.15 ± 181.80   | 87.873 ± 0.234    | 88.210            | 87.090            |
| MGD (256)       | 67,200     | 5,466.79 ± 402.20   | 87.897 ± 0.293    | 88.260            | 87.170            |
| MGD (total)     | 2,077,600  | 35,031.29           |                   |                   |                   |
| RMGD            | 430,251 ± 19,715 | 7,191.77 ± 444.20 | **88.009 ± 0.185** | **88.360** | **87.700** |

search. This paper considers a resizable mini-batch gradient descent (RMGD) algorithm based on a randomized weighted majority for achieving best performance in grid search by selecting an appropriate batch size at each epoch with a probability defined as a function of its previous success/failure and the validation error. This probability encourages exploration of different batch size and then later exploitation batch size with history of success. The RMGD essentially assists the learning process to explore the possible domain of the batch size and exploit successful batch size. The benefit of RMGD is that it avoids the need for cumbersome grid search to achieve best performance. Experimental results show that the RMGD achieves performance better than the best performing single batch size. Furthermore, it attains this performance in a shorter amount of time than that of the best performing. The RMGD can be used widely in various field of machine learning.

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