

# Analysis of the Variance Reduction in SVRG and a New Acceleration Method

## Abstract

Stochastic gradient descent (SGD) with variance reduction technique such as SVRG is efficient to train parameters of many machine learning models. Although many variants of SVRG have been proposed, the analysis of variance has not been thoroughly discussed. Besides, the variants of SVRG have to keep a snapshot of the full gradient in every epoch, which is computationally expensive. In this paper, we propose a general framework EUI to unify the existing variants of SVRG, and then provide a general and fine-grained analysis of the variance from a new perspective. Moreover, a new variant of SGD with the variance reduction technique named SAMPLEVR is proposed. SAMPLEVR replaces the full gradient computation with an estimation, thus decreasing gradient complexity significantly. Both the theoretical analysis and the empirical studies show that SAMPLEVR makes training loss converge faster than its counterparts significantly.

## Introduction

Many machine learning tasks such as classification and regression can be presented as solving the optimisation problem described by Equation 1.  $F(\omega)$  denotes the training loss or the loss function which is the sum of a finite number of functions, i.e.  $\nabla f_i(\omega)$  with  $i \in \{1, 2, \dots, n\}$ .  $\omega$  is the parameter of the machine learning model, and  $n$  represents the size of the training data.  $R(\omega)$  is the regulariser which is used to prevent overfitting.

$$\min F(\omega), \quad F(\omega) = \frac{1}{n} \sum_{i=1}^n f_i(\omega) + R(\omega) \quad (1)$$

Gradient descent (GD) is used to train the parameters for such underlying machine learning problems. Since GD computes a full gradient every iteration, it performs a large amount of gradient calculations. This would affect the performance significantly in the presence of a large amount of training data. The stochastic gradient descent (SGD) improves the time efficiency by using a stochastic gradient instead of the full gradient to train parameter. However, variance caused by the stochastic gradient usually impairs convergence of the training loss. Specifically, when the parameter is close to the optimum, it is increasingly difficult to

make a further progress due to the variance. Conventional studies show that a decaying learning rate can be used to decrease the variance. But the training loss converges slowly when the learning rate is small.

Recently, Johnson & Zhang improve SGD with the variance reduction technique named SVRG which uses a constant learning rate to train the parameter (Johnson and Zhang 2013). Based on the variance reduction technique adopted by SVRG, many variants of SVRG such as S2GD (Konečný and Richtárik 2013), mS2GD (Konečný et al. 2016), EMGD (Zhang, Mahdavi, and Jin 2013), SVR-GHT (Li et al. 2016), Prox-SVRG (Xiao and Zhang 2014), SVRG++ (Allen-Zhu and Yuan 2016), and Katyusha (Allen-Zhu 2016) have been proposed. However, the analysis of the variance, which is essential to understand and exploit the variance reduction technique, lacks enough discussion. Although Allen-Zhu & Hazan present an upper bound of the variance, it is obtained with many simplifications (Allen-Zhu and Hazan 2016). Moreover, those existing algorithms are organised by epochs. One epoch consists of some iterations. SVRG and its variants have to keep a snapshot of the full gradient for every epoch, leading to a large amount of gradient calculations. When the size of the training data is huge, the snapshot of the full gradient is extremely time-consuming. In short, it is meaningful to give a quantitative analysis of the variance in general settings so that the potential of the variance reduction technique can be exploited. Additionally, if the snapshot of the full gradient in an epoch can be avoided, SVRG and its variants will be accelerated a lot, which results in a better performance of the convergence.

As an important improvement of SVRG and its variants, we provide a thorough analysis about the variance from a new perspective. To present the analysis, we propose a general framework named EUI, and then perform the analysis under the framework. The update rule of the parameter in the variance reduction technique can be divided into three parts, including the variance source, the variance reducer and the progressive direction. The variance reducer is the real reason to reduce the variance. More specifically, we provide both lower and upper bounds of the variance, and then analyse improvement of the variance reduction in the existing variants of SVRG. Moreover, a new variant of SGD with the variance reduction technique denoted by SAMPLEVR is proposed, which replaces the snapshot of the full gradient

by using an unbiased estimation, and accelerates the convergence of the training loss. The contributions of the paper are outlined as follows:

- The variance caused by the stochastic gradient is analysed in a framework, EUI. Both lower and upper bounds of the variance are presented in general settings.
- A new variant of SGD with the variance reduction technique, i.e. SAMPLEVR is proposed, which achieves a linear convergence rate with low gradient complexity.
- Extensive evaluation tests show that SAMPLEVR outperforms other previous work significantly.

To keep the paper concise, a list of symbols used in the paper and the proofs are given in support materials. The paper is organised as follows. First, we review recent related work about SGD with the variance reduction technique. Second, we present the general framework, i.e. EUI, and then provide the analysis of the variance reduction under the framework. After that, we present a new reduced variance SGD, i.e. SAMPLEVR, and provide the theoretical analysis of both the performance of convergence and the gradient complexity. Furthermore, we demonstrate the extensive performance evaluations to verify the theoretical analysis. Finally, we conclude this paper.

### Related work

Various variants of SGD with the variance reduction technique have been proposed, including SAG (Schmidt, Roux, and Bach 2016), SAGA (Defazio, Bach, and Lacoste-Julien 2014), SDCA (Shalev-Shwartz 2016), and SVRG (Johnson and Zhang 2013) and its variants and so on. It is noting that SAG, SAGA and SDCA adopt different variance reduction techniques from SVRG and its variants. Although variance reduction techniques used in SAG, SAGA and SDCA are competitive with that of SVRG and its variants, this paper focuses on the variance reduction technique used in SVRG and its variants. To the best of our knowledge, the variants of SVRG includes S2GD (Konečný and Richtárik 2013), mS2GD (Konečný et al. 2016), EMGD (Zhang, Mahdavi, and Jin 2013), SVR-GHT (Li et al. 2016), Prox-SVRG (Xiao and Zhang 2014), SVRG++ (Allen-Zhu and Yuan 2016), and CHEAPSVRG (Shah et al. 2016).

Allen-Zhu & Hazan have presented an upper bound of the variance caused by the stochastic gradients when using the variance reduction technique (Allen-Zhu and Hazan 2016). Such upper bound of the variance is subject to many simplifications. Our analysis about the variance is a complement to that work, which is obtained in general settings, and does not require the simplifications assumed in that work. Shah et al. have proposed CHEAPSVRG which uses sampled instances to estimate the full gradient (Shah et al. 2016). The number of those sampled instances is a parameter which needs to be identified before running of CHEAPSVRG. Comparing with CHEAPSVRG, our proposed algorithm, i.e. SAMPLEVR does not need to tune extra parameters. Additionally, although both CHEAPSVRG and SAMPLEVR can achieve a linear convergence rate, the analysis of CHEAPSVRG is obtained with two extra strong assumptions, which are not

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### Algorithm 1 EUI: the general framework of reduced variance SGD

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**Require:**  $\omega_0 = \tilde{\omega}_0 = \mathbf{0}$ .  $\forall i_t \in \{1, 2, \dots, n\}$  where  $t$  is a non-negative integer.

- 1: **Epoch:** identify the sequence of epoch size  $\{m_0, m_1, \dots, m_S\} \leftarrow \mathcal{E}(s)$  with  $s \in \{0, 1, \dots, S\}$ ;
- 2: **for**  $s = 0, 1, 2, \dots, S - 1$  **do**
- 3:    $\omega_0 = \tilde{\omega}_s$ ;
- 4:    $g = \frac{1}{n} \sum_{i=1}^n \nabla f_i(\tilde{\omega}_s)$ ;
- 5:   **for**  $t = 0, \dots, m_s - 1$  **do**
- 6:     pick an instance  $\langle x_{i_t}, y_{i_t} \rangle$  randomly;
- 7:      $\gamma_t = \nabla f_{i_t}(\omega_{i_t}) - \nabla f_{i_t}(\tilde{\omega}_s) + g$ ;
- 8:     **Update:**  $\omega_{t+1} = \mathcal{U}(\eta, \omega_t, \gamma_t)$ ;
- 9:   **Identify:**  $\tilde{\omega}_{s+1} \leftarrow \mathcal{I}(\omega_j)$  with  $j \in \{0, 1, \dots, m_s\}$ ;
- return**  $\tilde{\omega}_S$ .

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required in SAMPLEVR. Furthermore, extensive empirical studies show that SAMPLEVR outperforms CHEAPSVRG significantly.

### EUI: the general framework of reduced variance SGD

#### Framework

As illustrated in Algorithm 1, we present a general framework named EUI which contains a loop of epochs. Every epoch consists of a number of iterations. The epoch size needs to be identified, as calculated by the function  $\mathcal{E}$ . After that, a snapshot of the full gradient is computed at the beginning of an epoch. During the training of the parameter in an epoch, EUI randomly picks an instance  $x_{i_t}$  from the training data first. The parameter is then trained by the update rule, as denoted by the function  $\mathcal{U}$ . At the end of an epoch, the global parameter  $\tilde{\omega}_s$  will be identified by the local parameter  $\omega_t$  with  $t \in \{0, 1, \dots, m_s\}$ , which is shown by the function  $\mathcal{I}$ .

Table 1 illustrates that SVRG and its variants can be unified by EUI when the functions, i.e.  $\mathcal{E}$ ,  $\mathcal{U}$ , and  $\mathcal{I}$  are implemented. For example, the function  $\mathcal{E}$  in SVRG is implemented by a constant, that is,  $m_s = m$  with  $s = \{0, 1, \dots, S - 1\}$ . The function  $\mathcal{U}$  in SVRG is implemented by the steepest descent, and the function  $\mathcal{I}$  is implemented by either any of the local parameters, i.e.  $\omega_j$  with  $j \in \{0, 1, \dots, m_s\}$  or  $\omega_{m_s}$ . Compared to SVRG, its variants implement those functions by using different strategies. Those strategies are explained with the analysis of the variance reduction in the following part.

#### The analysis of the variance

As illustrated in Table 1, the variants of SVRG usually adopt the same update rule of the parameter with SVRG. The update rule is shown by Equ. 3. We take SVRG as an example to present the analysis of the variance, and the improvement of variance reduction in other existing algorithms.

As illustrated in Equ. 3, the first item of  $\gamma_t$  is the stochastic gradient which is denoted by the ‘‘variance source’’. The sec-

Table 1: Variants of SVRG can be unified by the general framework EUI when the functions  $\mathcal{E}, \mathcal{U}$  and  $\mathcal{I}$  are implemented.

Name	Algorithms					
	SVRG	S2GD	EMGD	SVR-GHT	Prox-SVRG	SVRG++
$\mathcal{E}$	$m_s=m$	$P(m_s=t)=\frac{\phi(t)}{\sum_{t=1}^m \phi(t)}$ <sup>†</sup>	$m_s=m$	$m_s=m$	$m_s=m$	$m_s=2^s m$
$\mathcal{U}$	$\omega_t - \eta \gamma_t$	$\omega_t - \eta \gamma_t$	$\omega_t - \mathbb{B}_{\Delta_s}(\eta \gamma_t)$	$\mathcal{H}_\kappa(\omega_t - \eta \gamma_t)$	$\omega_t - \eta \gamma_t$ <sup>‡</sup>	$\omega_t - \eta \gamma_t$ <sup>‡</sup>
$\mathcal{I}$	randomly pick any of $\omega_j$ with $j \in \{0, 1, \dots, m_s-1\}$ $\omega_{m_s}$	$\omega_{m_s}$	$\frac{1}{m_s+1} \sum_{i=0}^{m_s} \omega_i$	$\omega_{m_s}$	$\frac{1}{m_s} \sum_{i=0}^{m_s-1} \omega_i$	$\frac{1}{m_s} \sum_{i=0}^{m_s-1} \omega_i$

<sup>†</sup>  $\phi(t)=(1-\tilde{\mu}\eta)^{m-t}$ .  $P(m_s=t)$  means the probability of  $m_s=t$ , which shows that a large epoch size is used with a high probability.

<sup>‡</sup> The update rules of Prox-SVRG and SVRG++ are presented in the setting of the differentiable optimisation objective.

ond item of  $\gamma_t$  is denoted by the ‘‘variance reducer’’ which is used to reduce the variance. The third item of  $\gamma_t$  is denoted by the ‘‘progressive direction’’ which makes sure that  $\gamma_t$  will not be too far away from the full gradient when updating parameter in an epoch. The update rule of the parameter in SGD and GD are denoted by  $\gamma_t^{\text{SGD}}$  and  $\gamma_t^{\text{GD}}$ , respectively. We refer the variance of SGD to the maximum, and the variance of GD to the minimum.

$$\gamma_t^{\text{SGD}} = \nabla f_{i_t}(\omega_{i_t}) - \frac{1}{n} \sum_{i=1}^n \nabla f_i(\tilde{\omega}) + \frac{1}{n} \sum_{i=1}^n \nabla f_i(\tilde{\omega}); \quad (2)$$

$$\gamma_t = \nabla f_{i_t}(\omega_{i_t}) - \nabla f_{i_t}(\tilde{\omega}) + \frac{1}{n} \sum_{i=1}^n \nabla f_i(\tilde{\omega}); \quad (3)$$

$$\gamma_t^{\text{GD}} = \nabla f_{i_t}(\omega_{i_t}) - \nabla f_{i_t}(\omega_{i_t}) + \frac{1}{n} \sum_{i=1}^n \nabla f_i(\tilde{\omega}); \quad (4)$$

It is obvious that the difference among the update rule of SGD, GD and SVRG is the variance reducer. SGD causes the maximal variance because its variance reducer is a constant which does not help to reduce the variance. GD does not lead to variance because that its variance reducer decreases all the variance caused by the variance source. The variance reducer in SVRG is a tradeoff between those of SGD and GD. It does not reduce all the variance like that of GD because that its input parameter, i.e.  $\tilde{\omega}$  becomes stale against  $\omega_t$  when  $\omega_t$  is updated during the iterations in the epoch. The variance due to the staleness will be accumulated with the iterative updates of the parameter  $\omega_t$ . Such the staleness of the parameter can be measured by the distance  $d_t$  with  $d_t = \|\omega_t - \tilde{\omega}\|^2$ .  $d_0 = \|\omega_0 - \tilde{\omega}\|^2 = 0$  holds according to the framework. If  $\gamma_t$  is  $p$ -dimensional, and can be denoted by  $\gamma_t = (a_{t1}, a_{t2}, \dots, a_{tp})$ , we obtain Theorem 1 as follows.

**Theorem 1.** *After  $t$  iterations in an epoch, the distance  $d_t$  holds that  $d_t = \eta^2 \sum_{j=1}^p \left( \sum_{i=1}^t a_{ij} \right)^2$ . Furthermore,  $d_t$  has an upper bound such that  $d_t \leq \eta^2 t^2 p \left( \frac{1}{tp} \sum_{i=1}^t \sum_{j=1}^p a_{ij}^2 \right)$ , and a lower bound such that  $d_t \geq \eta^2 t^2 p \left( \frac{1}{tp} \sum_{i=1}^t \sum_{j=1}^p a_{ij}^2 \right)^2$ .*

As demonstrated in Theorem 1, the distance becomes large with a large learning rate  $\eta$ , a high dimension  $p$ , and iterative updates of the parameter. Given a specific machine learning task, if a constant learning rate is adopted, the variance in an epoch is thus dominated by the epoch size  $m_s$  and the update gradient, i.e.  $\gamma_t$ . As illustrated in Table 1, the epoch size, i.e.  $m_s$  is designed as a constant in EMGD, SVR-GHT and Prox-SVRG, and an ascending variable for S2GD and SVRG++. Considering EMGD,  $\|\gamma_t\|^2 \leq \frac{\Delta_0}{2^{s-1}}$  holds and  $d_t \leq \eta^2 t^2 p \left( \frac{1}{tp} \sum_{i=0}^t \frac{\Delta_0}{2^{s-1}} \right) \leq \eta^2 t^2 \frac{\Delta_0}{2^{s-1}}$ , which is decreased with the number of epochs exponentially. The hard-thresholding mechanism in SVR-GHT keeps the  $\kappa$ -largest elements and sets others to be zero. Without loss of generality, suppose that the elements  $a_{tj}$  with  $j \in \{1, 2, \dots, \kappa\}$  is the  $\kappa$ -largest elements. Thus,  $d_t \leq \eta^2 t^2 p \left( \frac{1}{tp} \sum_{i=0}^t \sum_{j=1}^{\kappa} a_{ij}^2 \right) \leq \eta^2 t^2 p \left( \frac{1}{tp} \sum_{i=0}^t \sum_{j=1}^p a_{ij}^2 \right)$  holds, which is smaller than the variance in SVRG significantly. Considering S2GD, and taking the expectation of  $t$ , we obtain  $\mathbb{E}(t) = \frac{\phi(t)m}{\sum_{t=1}^m \phi(t)} \leq m$ . Thus, the expectation of the upper bound is smaller than that of SVRG. SVRG++ increases the epoch size exponentially, and thus the upper bound of the variance grows fast.

The variance in the current epoch will be passed to the next epoch via the identification of the parameter. SVRG provides two strategies to identify the parameter  $\tilde{\omega}_{s+1}$ . If  $\tilde{\omega}_{s+1}$  is identified randomly, the expectation of the variance is  $d \leq \frac{1}{m} \sum_{t=0}^{m-1} \left( \eta^2 t^2 p \left( \frac{1}{tp} \sum_{i=1}^t \sum_{j=1}^p a_{ij}^2 \right) \right)$ . If  $\tilde{\omega}_{s+1}$  is identified to be  $\omega_m$ , then the variance is  $d_m \leq \eta^2 m^2 p \left( \frac{1}{mp} \sum_{i=1}^m \sum_{j=1}^p a_{ij}^2 \right)$ . It is significant that the random strategy introduces less variance to the next epoch in expectation. S2GD and SVR-GHT uses  $\omega_{m_s}$  to identify the parameter, which is same with SVRG. Considering Prox-SVRG, the variance is  $d = \left\| \frac{1}{m} \sum_{t=0}^{m-1} (\tilde{\omega}_s - \omega_t) \right\|^2 \leq \frac{1}{m} \sum_{t=0}^{m-1} \left( \eta^2 t^2 p \left( \frac{1}{tp} \sum_{i=1}^t \sum_{j=1}^p a_{ij}^2 \right) \right)$ . Similarly, the

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**Algorithm 2** SAMPLEVR

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**Require:**  $\alpha = 0.01, g = \mathbf{0}$ , and  $\tilde{\omega}_0 = \mathbf{0}, \forall i_t \in \{1, 2, \dots, n\}$ .  
 $\epsilon$  is a positive real number.

- 1: **for**  $s = 0, 1, 2, \dots, S-1$  **do**
- 2:    $\omega_0 = \tilde{\omega}_s$ ;
- 3:   **for**  $t = 0, 1, \dots, m-1$  **do**
- 4:     pick an instance  $\langle x_{i_t}, y_{i_t} \rangle$  randomly;
- 5:      $\gamma_t = \nabla f_{i_t}(\omega_t) - \nabla f_{i_t}(\tilde{\omega}_s) + \dot{g}$ ;
- 6:      $\omega_{t+1} = \omega_t - \eta \gamma_t$ ;
- 7:    $\tilde{\omega}_{s+1}$  is identified by using any of  $\omega_i$  with  $i \in \{0, 2, \dots, m-1\}$  randomly;
- 8:    $k = -\frac{s \log \frac{\alpha}{2}}{\epsilon}$ ;
- 9:    $\dot{g} = \frac{1}{k} \sum_{j=1}^k \nabla f_{i_j}(\tilde{\omega}_{s+1})$ ;

**return**  $\tilde{\omega}_S$ .

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variance of SVRG++ is  $d = \|\tilde{\omega}_s - \frac{1}{2^s m} \sum_{t=0}^{2^s m-1} \omega_t\|^2 \leq \frac{1}{2^s m} \sum_{t=0}^{2^s m-1} \left( \eta^2 t^2 p \left( \frac{1}{tp} \sum_{i=1}^t \sum_{j=1}^p a_{ij}^2 \right) \right)$ . Thus, the variance of parameter of identification in Prox-SVRG is same with the randomly strategy of SVRG, but obtained in deterministic way, not in expectation. The variance of SVRG++ is significantly larger than SVRG. The variance of EMGD is  $d \leq \frac{1}{m+1} \sum_{t=0}^m \left( \eta^2 t^2 p \left( \frac{1}{tp} \sum_{i=1}^t \sum_{j=1}^p a_{ij}^2 \right) \right)$ , which is slightly smaller than Prox-SVRG and SVRG.

**SAMPLEVR: a new reduced variance SGD**

Although the variance reduction technique is effective for decreasing the variance caused by the stochastic gradient, it has to keep a snapshot of the full gradient every epoch. Unfortunately, the computation of the full gradient requires extensive gradient calculations which are extremely time-consuming. We design a new reduced variance SGD which uses an estimation of the full gradient to replace the real computation of it. As illustrated in Algorithm 2, the new variant of SGD with the variance reduction technique is denoted by SAMPLEVR. SAMPLEVR estimates the full gradient by using stochastic gradients which are computed by the training data. The mean of the stochastic gradients denoted by  $\dot{g}$  is used as the progressive direction for the next epoch. Since  $\mathbb{E}(\dot{g}) = \mathbb{E}\left(\frac{1}{k} \sum_{i=1}^k \nabla f_{i_t}(\tilde{\omega})\right) = \mathbb{E}\left(\frac{1}{n} \sum_{i=1}^n \nabla f_i(\tilde{\omega})\right) = \nabla F(\tilde{\omega})$  holds according to Equ. 5, the new update gradient, i.e.  $\dot{\gamma}_t$  is the same with  $\gamma_t$  in probability, that is,  $\mathbb{E}(\dot{\gamma}_t) = \mathbb{E}(\gamma_t) = \nabla F(\omega_t)$ .

$$\dot{\gamma}_t = \nabla f_{i_t}(\omega_t) - \nabla f_{i_t}(\tilde{\omega}) + \frac{1}{k} \sum_{j=1}^k \nabla f_{i_j}(\tilde{\omega}); \quad (5)$$

We illustrate Assumption 1 and Assumption 2 for analysis, which are basic and used in SVRG and its variants.

Although the estimation of the full gradient, i.e.  $\dot{g}$  is unbiased, the variance between  $\dot{g}$  and  $g$  impedes the convergence of the training loss, especially when the parameter gets close to the optimum. This problem is mitigated in SAMPLEVR by increasing the number of the sampled instances over epochs linearly. In specific, according to Assumption 1 and Assumption 2, every stochastic gradient  $\nabla f_i(\omega)$  with  $i \in \{1, 2, \dots, n\}$  is bounded by a positive constant denoted by  $C$ , that is,  $\|\nabla f_i(\omega)\| \leq C$ .

$$\mathbb{E}\left(\frac{1}{k} \sum_{i=1}^k \|\nabla f_i(\tilde{\omega}_{s+1})\|\right) = \frac{1}{n} \sum_{i=1}^n \|\nabla f_i(\tilde{\omega}_{s+1})\|. \text{ Suppose } \chi = \frac{1}{k} \sum_{i=1}^k \|\nabla f_i(\tilde{\omega}_{s+1})\| - \frac{1}{n} \sum_{i=1}^n \|\nabla f_i(\tilde{\omega}_{s+1})\|,$$

we obtain  $P(|\chi| \geq \rho) \leq 2e^{-\frac{2k\rho^2}{C^2}}$ , according to Hoeffding's inequality. Let  $\alpha = P(|\chi| \geq \rho) \leq 2e^{-\frac{2k\rho^2}{C^2}}$ . Such the probability represents the level of significance, i.e.  $\alpha$  for a confidence interval around the expectation of size  $2\rho$ . Let  $\epsilon = \frac{2\rho^2}{C^2}$ . If we require at least  $k$  instances to acquire  $(1-\alpha)$ -confidence interval  $[-\rho, \rho]$ ,  $k$  should satisfy

$$k \geq -C^2 \frac{\log \frac{\alpha}{2}}{2\rho^2} = -\frac{\log \frac{\alpha}{2}}{2\rho^2/C^2} = -\frac{\log \frac{\alpha}{2}}{\epsilon} \quad (6)$$

. Therefore,  $k$  is increased with the decrease of  $\epsilon$ , and thus the variance caused by the estimation is reduced. However,  $k$  is not trivial to be identified. On one hand, a large  $k$  leads to much computation cost to obtain the estimation of the full gradient. On the other hand, a small  $k$  causes much variance between the estimation and the full gradient. SAMPLEVR sets  $k$  by decreasing  $\chi$  linearly, which is a good tradeoff between the time efficiency and the variance. Extensive empirical studies have shown the advantage of this strategy.

**Assumption 1.** Each a function  $f_{i_t}$  with  $i_t \in \{1, 2, \dots, n\}$  in Equ. 1 is  $L$ -Lipshitz continuous, that is, for any two parameters  $\omega_i$  and  $\omega_j$ ,  $f_{i_t}(\omega_i) \leq f_{i_t}(\omega_j) + \nabla f_{i_t}(\omega_j)^T(\omega_i - \omega_j) + \frac{L}{2} \|\omega_i - \omega_j\|^2$ .

**Assumption 2.** The function  $F$  in Equ. 1 is  $\mu$ -strongly convex, that is, for any two parameters  $\omega_i$  and  $\omega_j$ ,  $F(\omega_i) \geq F(\omega_j) + \nabla F(\omega_j)^T(\omega_i - \omega_j) + \frac{\mu}{2} \|\omega_i - \omega_j\|^2$ .

**Theorem 2.** If  $\delta = \frac{\mu m \eta^2 (8Ln - 8Lk + 4Lnk) + nk}{\mu m n k \eta (1 - 2\eta L)} < 1$  with  $\sqrt{\frac{1}{2\mu m (4Ln - 4Lk + 3Lnk)}} < \eta < \frac{1}{4(4Ln - 4Lk + 3Lnk)} \sqrt{\frac{nk(2\mu m n k - 32Ln + 32Lk - 24Lnk)}{\mu m}}$  holds, SAMPLEVR makes the training loss converge as  $\mathbb{E}_t[F(\tilde{\omega}_{s+1}) - F(\omega_*)] \leq \delta \mathbb{E}_t[F(\tilde{\omega}_s) - F(\omega_*)]$ .

**Corollary 1.** Given  $m=15\frac{L}{\mu}$ ,  $k=n$ , and  $\eta=\frac{1}{8L}$ , we obtain  $\delta=\frac{31}{90}\approx\frac{1}{3}$ , and  $\mathbb{E}_t[F(\tilde{\omega}_{s+1}) - F(\omega_*)] \leq \delta^s \mathbb{E}_t[F(\tilde{\omega}_0) - F(\omega_*)]$ .

**Theorem 3.** SAMPLEVR requires at least  $\frac{\ln \zeta}{\ln \delta} m + \left(-\frac{\log \frac{\alpha}{2}}{2\epsilon} \left(\frac{\ln \zeta}{\ln \delta} + 1\right) \left(\frac{\ln \zeta}{\ln \delta}\right)\right)$  atomic gradient calculations with  $\delta = \frac{\mu m \eta^2 (8Ln - 8Lk + 4Lnk) + nk}{\mu m n k \eta (1 - 2\eta L)}$  to achieve  $\mathbb{E}_t[F(\tilde{\omega}_s) - F(\omega_*)] \leq \zeta \mathbb{E}_t[F(\omega_0) - F(\omega_*)]$ .



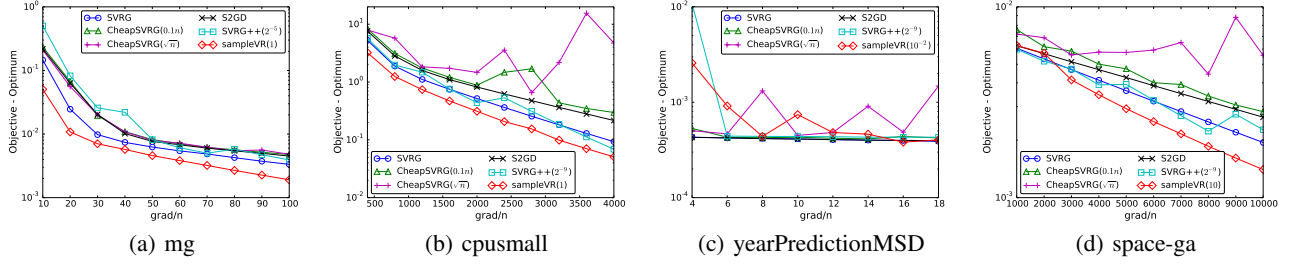


Figure 3: Generally, SAMPLEVR outperforms the other existing algorithms on the convergence of the training loss when conducting the ridge regression tasks.

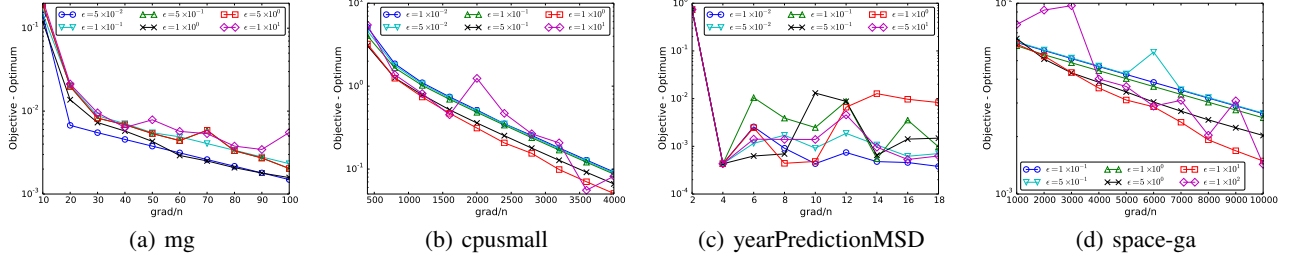


Figure 4: A large  $\epsilon$  leads to the fast convergence of the training loss for SAMPLEVR when conducting the ridge regression tasks. However, the performance of SAMPLEVR is impaired due to the increase of variance when  $\epsilon$  is set to be too large.

time. The value in the bracket of the legend of SVRG++ and SAMPLEVR represents the initial epoch size divided by the size of the training data, i.e.  $n$  and  $\epsilon$  according to Algorithm 2, respectively.

### $l_2$ -regularised logistic regression

As illustrated in Figure 1, we compare the performance of all the algorithms by conducting the  $l_2$ -regularised logistic regression tasks. It is obvious that our proposed algorithm, i.e. SAMPLEVR makes the training loss converge linearly, and outperforms other existing algorithms. The main reason is that SAMPLEVR replaces the computation of the full gradient with an estimation, thus getting rid of the time-consuming calculations of the gradient. Although the estimation of the full gradient is used in CHEAPSVRG, the number of sampled instances in CHEAPSVRG is determined as a constant such as  $\sqrt{n}$ , leading to much variance. Benefiting from the increase of the number of sampled instances, SAMPLEVR reduces the variance over epochs, and thus outperforms CHEAPSVRG. Additionally, the comparison of the performance of SAMPLEVR by varying  $\epsilon$  is shown in Figure 2. SAMPLEVR generally obtains a better performance with a larger  $\epsilon$ . It is because that the number of the required sampled instances becomes small with a large  $\epsilon$  according to Equ. 6, which leads to the acceleration of SAMPLEVR. However, as illustrated in Figure 2(a) and 2(d), if  $\epsilon$  is set to be too large, the performance will be impaired due to the variance between the full gradient and the estimation. In specific, a very large  $\epsilon$  means that the number of the sampled instances becomes extremely small, leading to much variance between the full gradient and the estimation, which

slows the convergence of the training loss.

### Ridge regression

As illustrated in Figure 3, we report the comparison of the performance by using all the algorithms to conduct ridge regression tasks. SAMPLEVR has a better performance for the datasets mg, cpusmall, and space-ga than the existing algorithms significantly. The main reason is that SAMPLEVR uses an unbiased estimation of the full gradient, instead of costing much time to compute it. Although SAMPLEVR does not outperform other algorithms for the dataset yearPredictionMSD at the beginning of the train process, its performance is comparable to the other algorithms, and finally shows the advantage over most of the existing algorithms. As illustrated in Figure 3(c), the variance of the training loss by using SAMPLEVR is decreased, which benefits from the increase of the sampled instances. As illustrated in Figure 4, the performance of SAMPLEVR has been compared by varying the value of  $\epsilon$ . It is significant that the variance becomes noticeable with the increase of  $\epsilon$ . It is because that a large  $\epsilon$  leads to few sampled instances according to Equ. 6, incurring much variance in the estimation of the full gradient. Moreover, as illustrated in Figure 4(a), 4(b) and 4(d), an extremely small  $\epsilon$  impairs the performance of SAMPLEVR. The reason is that a small  $\epsilon$  means that a large number of the instances are required to be sampled, thus incurring much calculations of gradients. A large amount of calculations of gradients cost much time, and thus makes the convergence of the loss function slow down.

## Conclusion

This paper first analyses the variance reduction technique from a new prospective in a general framework. Then, a new variant of SGD with the variance reduction technique, i.e. SAMPLEVR is proposed. The theoretical and empirical studies show the advantages of SAMPLEVR significantly.

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