Shifted Compression Framework: Generalizations and Improvements

Abstract

Communication is one of the key bottlenecks in the distributed training of large-scale machine learning models, and lossy compression of exchanged information, such as stochastic gradients or models, is one of the most effective instruments to alleviate this issue. Among the most studied compression techniques is the class of unbiased compression operators with variance bounded by a multiple of the square norm of the vector we wish to compress. By design, this variance may remain high, and only diminishes if the input vector approaches zero. However, unless the model being trained is overparameterized, there is no a-priori reason for the vectors we wish to compress to approach zero during the iterations of classical methods such as distributed compressed SGD, which has adverse effects on the convergence speed. Due to this issue, several more elaborate and seemingly very different algorithms have been proposed recently, with the goal of circumventing this issue. These methods are based on the idea of compressing the *difference* between the vector we would normally wish to compress and some auxiliary vector that changes throughout the iterative process. In this work we take a step back, and develop a unified framework for studying such methods, both conceptually and theoretically. Our framework incorporates methods compressing both gradients and models, using unbiased and biased compressors, and sheds light on the construction of the auxiliary vectors. Furthermore, our general framework can lead to the improvement of several existing algorithms, and can produce new algorithms. Finally, we performed several numerical experiments to illustrate and support our theoretical findings.

1 INTRODUCTION

We consider the distributed optimization problem

$$\min_{x\in\mathbb{R}^d} \left[f(x) := \frac{1}{n}\sum_{i=1}^{n} f_i(x) \right], \qquad (\star)$$

where n is the number of workers/clients and $f_i : \mathbb{R}^d \to \mathbb{R}$ is a smooth function representing the loss of the model parametrized by $x \in \mathbb{R}^d$ for data stored on node i. This formulation has become very popular in recent years due to the increasing need for training large-scale machine learning models (Goyal et al., 2018).

Communication bottleneck. Compute nodes have to exchange information in a distributed learning process. The size of the sent messages (usually gradients or model updates) can be very large, which creates a significant bottleneck (Luo et al., 2018; Peng et al., 2019; Sapio et al., 2021) to the whole training procedure. One of the main practical solutions to this problem is lossy *communication compression* (Seide et al., 2014; Konečný et al., 2016; Alistarh et al., 2017). It suggests applying a (possibly randomized) mapping $\mathcal{C}$ to a vector/matrix/tensor x before it is transmitted in order to produce a less accurate estimate $\mathcal{C}(x) : \mathbb{R}^d \to \mathbb{R}^d$ and thus save bits sent per every communication round.

Compression operators. The topic of gradient compression in distributed learning has been studied extensively over the last years from both practical (Xu et al., 2020) and theoretical (Beznosikov et al., 2020; Safaryan et al., 2021c; Albasyoni et al., 2020) approaches. Compression operators are typically divided into two large groups: *unbiased* and *biased* ones. The first group includes methods based on some sort of rounding or *quantization*: Random Dithering (Goodall, 1951; Roberts, 1962), Ternary quantization (Wen et al., 2017), Natural (Horváth et al., 2019a), and Integer (Mishchenko et al., 2021) compression. Another popular example is random *sparsification* – `Rand-K` (Wangni et al., 2018; Stich et al., 2018; Konečný and Richtárik, 2018), which preserves only a subset of the original vector coordi-

Submitted to the 38th Conference on Uncertainty in Artificial Intelligence (UAI 2022). **To be used for reviewing only**.

Table 1: Overview of results for methods obtained as special cases of our general framework DCGD-SHIFT (Alg. 1). Iteration complexities are presented in $\tilde{\mathcal{O}}$-notation to omit $\log 1/\varepsilon$ factors and for the simplified case $\omega_i \equiv \omega, \delta_i \equiv \delta, L_i \equiv L$, $p_i \equiv p$. More refined statements are in theorems with links in the last column. Complexities for DCGD-SHIFT and GDCI are shown in the interpolation regimes: $\nabla f_i(x^\star) = 0 = x^\star - \gamma \nabla f_i(x^\star)$.

Instance of DCGD-SHIFT	**Shift**	**Previous**	**Our result**	**Theorem**
DCGD-FIXED (this work)	(6)	–	$\kappa\left(1+\frac{\omega}{n}\right)$	1
DCGD-STAR (this work)	(8)	–	$\kappa\left(1+\frac{\omega}{n}(1-\delta)\right)$	2
DIANA (Mishchenko et al., 2019)	(10)	$\max\left\{\kappa\left(1+\frac{\omega}{n}\right), \omega\right\}$	$\max\left\{\kappa\left(1+\frac{\omega}{n}(1-\delta)\right), \omega(1-\delta)\right\}$	3
Rand-DIANA (this work)	(12)	–	$\max\left\{\kappa\left(1+\frac{\omega}{n}(1-\delta)\right), \frac{1}{p}\right\}$	4
GDCI (Khaled and Richtárik, 2019)	(13)	$\kappa^2\left(1+\frac{\omega}{n}\right)$	$\kappa\left(1+\frac{\omega}{n}\right)$	5

nates. These two approaches can also be combined (Basu et al., 2019) for even more aggressive compression. There are also many other approaches based on low-rank approximation (Vogels et al., 2020; Wang et al., 2018; Safaryan et al., 2021b), vector quantization (Gandikota et al., 2021), etc. The second group of biased compressors mainly includes greedy sparsification – `Top-K` (Alistarh et al., 2018; Stich et al., 2018) and various sign-based quantization methods (Seide et al., 2014; Bernstein et al., 2018; Safaryan and Richtárik, 2021). For a more complete review of compression operators, one can refer to the surveys (Xu et al., 2020) and (Beznosikov et al., 2020; Safaryan et al., 2021c).

Optimization algorithms. Compression operators on their own are not sufficient for building a distributed learning system because they always go along with optimization algorithms. One of the first theoretically analyzed methods is Distributed Compressed Gradient Descent (DCGD) (Khirirat et al., 2018) which considered arbitrary unbiased compressors. The issue with DCGD is that it was proven to converge linearly only to a neighborhood of the optimal point with constant step-size. DIANA (Mishchenko et al., 2019) fixed this problem by compressing specially designed gradient differences. Later DIANA was combined with variance reduction (Horváth et al., 2019b), accelerated (Li et al., 2020) in Nesterov's sense (Nesterov, 1983) and by using smoothness matrices (Safaryan et al., 2021a) with a properly designed sparsification technique.

On the other side are methods working with biased compressors, which require the use of the error-feedback (EF) mechanism (Seide et al., 2014; Alistarh et al., 2018; Stich and Karimireddy, 2020). Such algorithms were often considered to be better in practice due to the smaller variance of biased updates (Beznosikov et al., 2020). However, it was recently demonstrated that biased compressors can be incorporated into specially designed unbiased operators, and show superior to error-feedback results (Horváth and Richtárik, 2021). In addition, error-feedback was recently combined with the DIANA trick (Gorbunov et al., 2020b), which led to the first linearly converging method with EF.

Compressed iterates. Most of the existing literature (including all methods described above) focuses on compression of the gradients, while in applications like Federated Learning (McMahan et al., 2017; Konečný et al., 2016; by: Peter Kairouz and McMahan, 2021), it is vital to reduce the size of the broadcasted model parameters (Reisizadeh et al., 2020). This demand gives rise to optimization algorithms with compressed iterates. The first attempt to analyze such methods was done by Khaled and Richtárik (2019) for Gradient Descent with Compressed iterates (GDCI) in a single node set up. Later GDCI was combined with variance-reduction for noise introduced by compression and generalized to a much more general setting of distributed fixed point methods (Chraibi et al., 2019).

Summary of contributions. The obtained results are summarized in Table 1, with the improvements over previous works highlighted. The main contributions include:

1. Generalizations of existing methods. We introduce the concept of a *Shifted Compressor*, which generalizes a common definition of compression operators used in distributed learning. This technique allows to study various strategies for updating the shifts using both biased and unbiased compressors, to recover and improve such previously known methods as DCGD and DIANA. Additionally, as a byproduct, a new algorithm is obtained: DCGD-STAR, which achieves linear convergence to the exact solution if we know the local gradients at the optimum.

2. Improved rates. The notion of a shifted compressor allows us to revisit existing analysis of distributed methods with *compressed iterates* and improve guarantees in both cases: with and without variance-reduction. Obtained results indicate that algorithms with model compression can have

the same complexity as compressed gradient methods.

3. New algorithm. We present a novel distributed algorithm with compression, called Randomized DIANA, with linear convergence rate to the exact optimum. It has a significantly *simpler analysis* than the original DIANA method. Via examination of its experimental performance we highlight the cases when it can outperform DIANA in practice.

2 GENERAL FRAMEWORK

In this section we introduce compression operators and the framework of shifted compressors.

2.1 STANDARD COMPRESSION

At first recall some basic definitions.

Definition 1 (General contractive compressor)**.** *A (possibly) randomized mapping $\mathcal{C} : \mathbb{R}^d \to \mathbb{R}^d$ is a* **compression operator** *($\mathcal{C} \in \mathbb{B}(\delta)$ for brevity) if for some $\delta \in (0, 1]$ and $\forall x \in \mathbb{R}^d$*

$$\mathbf{E}\,\|\mathcal{C}(x) - x\|^2 \leq (1-\delta)\|x\|^2,$$

where the expectation is taken w.r.t. (possible) randomness of operator $\mathcal{C}$.

One of the most known operators from this class is *greedy sparsification* ($\texttt{Top-K}$ for $K \in \{1, \ldots, d\}$):

$$\mathcal{C}_{\texttt{Top-K}}(x) := \sum_{i=d-K+1}^{d} x_{(i)} e_{(i)},$$

where coordinates are ordered by their magnitudes so that $|x_{(1)}| \leq |x_{(2)}| \leq \cdots \leq |x_{(d)}|$, and $e_1, \ldots, e_d \in \mathbb{R}^d$ are the standard unit basis vectors. This compressor belongs to $\mathbb{B}\left(d/K\right)$.

Definition 2 (Unbiased compressor)**.** *A randomized mapping $\mathcal{Q} : \mathbb{R}^d \to \mathbb{R}^d$ is an* **unbiased compression operator** *($\mathcal{Q} \in \mathbb{U}(\omega)$ for brevity) if for some $\omega \geq 0$ and $\forall x \in \mathbb{R}^d$*

$$\begin{aligned} &(a)\, \mathbf{E}\,\mathcal{Q}(x) = x, && \textit{(Unbiasedness)} \\ &(b)\, \mathbf{E}\,\|\mathcal{Q}(x) - x\|^2 \leq \omega\|x\|^2 && \textit{(Bounded variance)} \end{aligned}$$

The last inequality implies that

$$\mathbf{E}\,\|\mathcal{Q}(x)\|^2 \leq (1+\omega)\|x\|^2. \tag{1}$$

A notable example from this class is the *random sparsification* ($\texttt{Rand-K}$ for $K \in \{1, \ldots, d\}$) operator:

$$\mathcal{Q}_{\texttt{Rand-K}}(x) := \frac{d}{K} \sum_{i \in S} x_i e_i, \tag{2}$$

where S is a random subset of $[d] := \{1, \ldots, d\}$ sampled from the uniform distribution on the all subsets of $[d]$ with cardinality K. $\texttt{Rand-K}$ belongs to $\mathbb{U}\left(d/K - 1\right)$.

Notice that property (a) from Definition 2 is "uniform" across all vectors x, while property (b) is not. Namely, vector $x = 0$ is treated *in a special way* because $\mathbf{E}\,\|\mathcal{Q}(0) - 0\|^2 = 0$, which means that the compressed zero vector has *zero variance*. In other words, zero is mapped to itself with probability 1.

2.2 COMPRESSION WITH SHIFT

We can generalize the class of unbiased compressors $\mathbb{U}(\omega)$ to a class of operators with other (not only 0) "special" vectors. Specifically, this class allows for **shifts** away from the origin, which is formalized in the following definition.

Definition 3 (Shifted compressor)**.** *A randomized mapping $\mathcal{Q}_h : \mathbb{R}^d \to \mathbb{R}^d$ is a* ***shifted compression operator*** *($\mathcal{Q}_h \in \mathbb{U}(\omega; h)$ in short) if exists $\omega \geq 0$ such that $\forall x \in \mathbb{R}^d$*

$$\begin{aligned} &(a)\, \mathbf{E}\,\mathcal{Q}_h(x) = x \\ &(b)\, \mathbf{E}\,\|\mathcal{Q}_h(x) - x\|^2 \leq \omega\|x - h\|^2. \end{aligned}$$

Vector $h \in \mathbb{R}^d$ is called a ***shift****. Note that class of unbiased compressors $\mathbb{U}(\omega)$ is equivalent to $\mathbb{U}(\omega; 0)$.*

The next lemma shows that shifts add up and all shifted compression operators $\mathcal{Q}_h \in \mathbb{U}(\omega; h)$ arise by a shift of some operator $\mathcal{Q}_0$ from $\mathbb{U}(\omega; 0)$.

Lemma 1 (Shifting a shifted compressor)**.** *Let $\mathcal{Q}_h \in \mathbb{U}(\omega; h)$ and $v \in \mathbb{R}^d$. Then the (possibly) randomized mapping $\mathcal{Q}$ defined by*

$$\mathcal{Q}(x) := v + \mathcal{Q}_h(x - v)$$

satisfies $\mathcal{Q} \in \mathbb{U}(\omega; h + v)$.

The shifted compressor concept allows us to construct a shifted compressed **gradient estimator** $\mathcal{Q}_h \in \mathbb{U}(\omega; h)$ given by

$$g_h(x) = \mathcal{Q}_h\left(\nabla f(x)\right) = h + \mathcal{Q}(\nabla f(x) - h), \tag{3}$$

which is the main focus of this work. In particular, we are going to study different mechanisms for choosing this shift vector throughout the optimization process.

Note: Estimator (3) is clearly unbiased, as soon as operator $\mathcal{Q}$ satisfies $\mathbf{E}\,\mathcal{Q}(x) = x$.

Estimator (3) uses operator $\mathcal{Q}$ from class of unbiased compressors $\mathbb{U}(\omega)$, which are usually easier to analyse but have higher empirical variance than their biased counterparts (Beznosikov et al., 2020). In an attempt to kill two birds

with one stone, we can incorporate the (possibly) biased compressor $\mathcal{C} \in \mathbb{B}(\delta)$ into h using a similar shift trick:

$$h = s + \mathcal{C}(\nabla f(x) - s), \tag{4}$$

as $g_h(x)$ allows for virtually any shift vector. This leads to the following estimator[1]

$$\boxed{\begin{aligned} g_h(x) &= h + \mathcal{Q}\left(\nabla f(x) - h\right) \\ &= s + \mathcal{C}(\nabla f(x) - s) \\ &\quad + \mathcal{Q}\left(\nabla f(x) - s - \mathcal{C}(\nabla f(x) - s)\right). \end{aligned}} \tag{5}$$

2.3 THE META-ALGORITHM

Now we are ready to present the general distributed optimization algorithm for solving ($\star$) employing shifted gradient estimators

$$g_h(x) = \frac{1}{n}\sum_{i=1}^{n} g_{h_i}(x) = \frac{1}{n}\sum_{i=1}^{n}\left[h_i + \mathcal{Q}_i\left(\nabla f_i(x) - h_i\right)\right].$$

Algorithm 1 Distributed Compressed Gradient Descent with Shift (DCGD-SHIFT)

Parameters: learning rate $\gamma > 0$; unbiased compressors $\mathcal{Q}_1, \ldots, \mathcal{Q}_n$; initial iterate $x^0 \in \mathbb{R}^d$, initial local shifts $h_1^0, \ldots, h_n^0 \in \mathbb{R}^d$ (stored on the n nodes)
Initialize: $h^0 = \frac{1}{n}\sum_{i=1}^{n} h_i^0$ (stored on the master)
for $k = 0, 1, 2 \ldots$ **do**
  Broadcast x^k to all workers
  for $i = 1, \ldots n$ **do** in parallel
    Compute local gradient: $\nabla f_i(x^k)$
    Compress: $m_i^k = \mathcal{Q}_i(\nabla f_i(x^k) - h_i^k)$
    Update the local shift: h_i^{k+1}
    Send m_i^k and/or (maybe) h_i^{k+1} to the master
  end for
  Aggregate received messages: $m^k = \frac{1}{n}\sum_{i=1}^{n} m_i^k$
  Compute global estimator: $g^k = h^k + m^k$
  Take Gradient Descent step: $x^{k+1} = x^k - \gamma g^k$
  Update aggregated shift: $h^{k+1} = \frac{1}{n}\sum_{i=1}^{n} h_i^{k+1}$
end for

In Algorithm 1, each worker $i = 1, \ldots, n$ queries the gradient oracle $\nabla f_i(x^k)$ in iteration k. Then, a compression operator is applied to the difference between the local gradient and shift, and the result is sent to the master (and also possibly the new shift). The shift is updated on both the server and workers. After receiving the messages m_i^k a global gradient estimator is formed on the server, and a gradient step is performed.

[1]The resulting estimator is related to induced compressor (Horváth and Richtárik, 2021) $\mathcal{Q}_{ind}(x) = \mathcal{C}(x) + \mathcal{Q}\left(x - \mathcal{C}(x)\right)$, which belongs to the $\mathbb{U}(\omega(1-\delta))$ class for $\mathcal{C} \in \mathbb{B}(\delta)$ and $\mathcal{Q} \in \mathbb{U}(\omega)$.

Note that this method is not fully defined because it requires a description of the mechanism for updating the shifts h_i^{k+1} (highlighted in red) throughout the iteration process on both workers and master. In the next section, we illustrate how the shifts can be chosen and updated.

3 CHOOSING THE SHIFTS

First, in Table 2, we show the generality of our approach by presenting some of the existing and new distributed methods that fall into our framework of DCGD-SHIFT with shift updates of the form (4).

The following assumptions are needed to analyze convergence and compare with previous results.

Assumption 1 (Strong convexity). *Function $f : \mathbb{R}^d \to \mathbb{R}$ is μ-strongly convex if*

$$f(x) \geq f(y) + \langle \nabla f(y), x - y\rangle + \frac{\mu}{2}\|x - y\|^2, \ \forall x, y \in \mathbb{R}^d.$$

If $\mu = 0$, then the function is convex.

Assumption 2 (Smoothness). *Function $f : \mathbb{R}^d \to \mathbb{R}$ is L-smooth if*

$$f(x) \leq f(y) + \langle \nabla f(y), x - y\rangle + \frac{L}{2}\|x - y\|^2, \ \forall x, y \in \mathbb{R}^d.$$

Now, we can provide a general convergence guarantee for Algorithm 1 with fixed shifts

$$h_i^k \equiv h_i. \tag{6}$$

Theorem 1 (DCGD with `fixed` SHIFT). *Assume each f_i is convex and L_i-smooth, and f is L-smooth and μ-strongly convex. Let $\mathcal{Q}_i \in \mathbb{U}(\omega_i)$ - independent unbiased compression operators. If the step-size satisfies*

$$\gamma \leq \frac{1}{L + 2\max_i\left(L_i\omega_i/n\right)}.$$

Then the iterates of Algorithm 1 with fixed shifts $h_i^k \equiv h_i$ satisfy

$$\begin{aligned} \mathbf{E}\left\|x^k - x^\star\right\|^2 &\leq (1-\gamma\mu)^k\|x^0 - x^\star\|^2 \\ &\quad + \frac{2\gamma}{\mu}\frac{1}{n}\sum_{i=1}^{n}\frac{\omega_i}{n}\left\|\nabla f_i(x^\star) - h_i\right\|^2. \end{aligned} \tag{7}$$

This theorem establishes a linear convergence rate up to a certain oscillation radius, controlled by the average distance of shift vectors h_i to the optimal local gradients $\nabla f_i(x^\star)$ multiplied by the step-size γ. This means that in the interpolation/**overparameterized regime** ($\nabla f_i(x^\star) = 0$ for all i) method reaches **exact solution** with zero shifts $h_i^0 = 0$.

In the following subsections, we study how the shifts can be formed to guarantee linear convergence to the exact optimum. We start by introducing practically useless, but theoretically insightful DCGD-STAR, and then move onto implementable algorithms that learn the optimal shifts.

Table 2: List of existing and new algorithms that fit our general framework. **VR** – variance reduced method. $\mathcal{O}/\mathcal{I}$ – zero/identity operator, $\mathcal{B}_{p_i}$ – Bernoulli[2] compressor. DGD refers to Distributed Gradient Descent.

			Shift $h_i^{k+1} = s_i^k + \mathcal{C}_i\left(\nabla f_i(x^k) - s_i^k\right)$	
Method	**Reference**	**VR?**	s_i^k	$\mathcal{C}_i$
DCGD	(Khirirat et al., 2018)	✗	0	$\mathcal{O}$
DCGD-SHIFT	(this work)	✗	s_i^0	$\mathcal{O}$
DGD		✓	0	$\mathcal{I}$
DCGD-STAR	(this work)	✓	$\nabla f_i(x^\star)$	any $\mathcal{C}_i \in \mathbb{B}(\delta)$
DIANA	(Mishchenko et al., 2019)	✓	h_i^k	$\alpha\mathcal{Q}_i,\ \mathcal{Q}_i \in \mathbb{U}(\omega_i)$
RAND-DIANA	(this work)	✓	h_i^k	$\mathcal{B}_{p_i}$
GDCI	(Chraibi et al., 2019)	✗	x^k/γ	$\mathcal{O}$

3.1 OPTIMAL SHIFTS

Assume, for the sake of argument, that we know the values $\nabla f_i(x^\star)$ for every $i \in [n]$. Then, we can construct optimally shifted compressed shift updates sequence using the form (4)

$$h_i^{k+1} = \nabla f_i(x^\star) + \mathcal{C}_i(\nabla f_i(x^k) - \nabla f_i(x^\star)). \tag{8}$$

This is enough to fully characterize the Algorithm 1 and obtain the following convergence guarantee:

Theorem 2 (DCGD-STAR)**.** *Assume each f_i is convex and L_i-smooth, and f is L-smooth and μ-strongly convex. Let $\mathcal{Q}_i \in \mathbb{U}(\omega_i), \mathcal{C}_i \in \mathbb{U}(\delta_i)$ - independent compression operators. If the step-size satisfies*

$$\gamma \leq \frac{1}{L + \max_i\left(L_i\omega_i(1-\delta_i)/n\right)}, \tag{9}$$

then the iterates of DCGD *with* ***optimally shifted compressed shift*** *update* (8) *satisfy*

$$\mathbf{E}\left\|x^k - x^\star\right\|^2 \leq (1-\gamma\mu)^k\|x^0 - x^\star\|^2.$$

This is the first presented algorithm with linear convergence to the exact solution for the general *not-overparameterized case*. Notice that for zero-identity operators $\mathcal{C}_i \equiv 0$ we obtain the simplest optimal shift $h_i = \nabla f_i(x^\star)$ and the term δ_i in (9) should be interpreted as zero.

The issue with the described method is that, in general, we do not know the values $h_i^\star := \nabla f_i(x^\star)$ (unless the problem is overparametrized), which makes it impractical.

[2] $\mathcal{B}_p(x) := \begin{cases} x & \text{with probability } p \\ 0 & \text{with probability } 1-p \end{cases}$

3.2 LEARNING THE OPTIMAL SHIFTS

We need to design the sequences $\{h_1^k\}_{k\geq 0}, \ldots, \{h_n^k\}_{k\geq 0}$ in such a way that they all converge to the optimal shifts:

$$h_i^k \to \nabla f_i(x^\star) \quad \text{as} \quad k \to \infty.$$

However, at the same time, we do not want to send uncompressed vectors from workers to the master. So, the challenge is not only learning the shifts, but doing so in a communication-efficient way. We present two different solutions to this problem in this work.

3.2.1 DIANA-like Trick

Our first approach is based on the celebrated DIANA (Mishchenko et al., 2019; Horváth et al., 2019b) algorithm:

$$\begin{aligned} h_i^{k+1} = h_i^k + \alpha\big[&\mathcal{C}_i(\nabla f_i(x^k) - h_i^k) \\ &+ \mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k - \mathcal{C}_i(\nabla f_i(x^k) - h_i^k)\right)\big], \end{aligned} \tag{10}$$

where α is a suitably chosen step-size. For $\mathcal{C}_i \equiv 0$, it takes the simplified form

$$h_i^{k+1} = h_i^k + \alpha\mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k\right). \tag{11}$$

This recursion resolves both of the raised issues earlier. Firstly, this sequence of h_i^k indeed converges to the optimal shifts $\nabla f_i(x^\star)$, which is formalized in the Theorem 3 presented later. Moreover, the shift on the master

$h^{k+1} = \frac{1}{n}\sum_{i=1}^n h_i^{k+1}$ is updated this way

$$
\begin{aligned}
h^{k+1} &= \frac{1}{n}\sum_{i=1}^n \Big\{ h_i^k + \alpha\big[\mathcal{C}_i(\nabla f_i(x^k) - h_i^k) \\
&\qquad + \mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k - \mathcal{C}_i(\nabla f_i(x^k) - h_i^k)\right)\big]\Big\} \\
&= \frac{1}{n}\sum_{i=1}^n h_i^k + \alpha\frac{1}{n}\sum_{i=1}^n \{c_i^k + m_i^k\} \\
&= h^k + \alpha\left(c^k + m^k\right),
\end{aligned}
$$

which only requires aggregation of the compressed vectors $c_i^k := \mathcal{C}_i(\nabla f_i(x^k) - h_i^k)$ and $m_i^k := \mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k - c_i^k\right)$ from the workers. In the case of update (11), it is not even needed to send anything in addition to the messages m_i^k required by default in Algorithm 1.

Furthermore, simplified recursion (11) can be interpreted as one step of Compressed Gradient Descent (CGD) with step-size α applied to such optimization problem:

$$
\max_{h_i\in\mathbb{R}^d}\left[\phi_i^k\left(h_i\right) := -\frac{1}{2}\left\|h_i - \nabla f_i(x^k)\right\|^2\right],
$$

which is in fact a 1-smooth and 1-strongly concave function. In this way, h_i^{k+1} keeps track of the latest local gradient and produces a better estimate than the previous shift h_i^k offered.

Now we present the convergence result for the Algorithm 1 with described shift learning procedure.

Theorem 3 (Generalized DIANA)**.** *Assume each f_i is convex and L_i-smooth, and f is μ-strongly convex. Let $\mathcal{Q}_i \in \mathbb{U}(\omega_i), \mathcal{C}_i \in \mathbb{U}(\delta_i)$ - independent compression operators. If the step-sizes for all i satisfy*

$$
\begin{aligned}
\alpha &\le \frac{1}{1+\omega_i(1-\delta_i)}, \\
\gamma &\le \frac{1}{\frac{2}{n}\max_i\left(\omega_i L_i\right) + (1+\alpha M)L_{\max}},
\end{aligned}
$$

where $L_{\max} := \max_i L_i, M > 2/(n\alpha)$ and δ_i should be interpreted as zero for $\mathcal{C}_i \equiv 0$, then the iterates of DCGD *with the* DIANA*-like shift update (10) satisfy*

$$
\mathbf{E}\,V^k \le \max\left\{(1-\gamma\mu)^k, \left(1-\alpha+\frac{2\omega}{nM}\right)^k\right\} V^0,
$$

where the Lyapunov function V^k is defined by

$$
V^k := \left\|x^k - x^\star\right\|^2 + M\gamma^2\cdot\frac{1}{n}\sum_{i=1}^n \omega_i\left\|h_i^k - \nabla f_i(x^\star)\right\|^2.
$$

Our result represents an improvement over the original DIANA in several ways. Firstly, it uses much more general shift updates involving $\mathcal{C}_i$, which allow biased operators to be used for learning the optimal shifts. Secondly, one can use different compressors $\mathcal{Q}_i$, which can be particularly beneficial when different workers have various bandwidths/connection speeds to the master. Thus, the slower processors can compress more, and therefore use operators with higher ω_i. At the same, time the opposite makes sense for "faster" workers.

3.2.2 Randomized DIANA (Rand-DIANA)

Recalling the original issue stated in Section 3.2 that we are dealing with:

design sequences $\{h_i^k\}_{k\ge 0}$ such that $h_i^k \to \nabla f_i(x^\star)$

The simplest possible solution would be just to set h_i^k to $\nabla f_i(x^k)$ because if $x^k \to x^\star$ in the optimization process, then $\nabla f_i(x^k)$ converges to the optimal local shift. However, this approach is not efficient, as workers have to transfer full (uncompressed) vectors $h_i^k = \nabla f_i(x^k)$. Our alternative to the DIANA solution is to update a reference point w_i^k for calculating the shift $h_i^k = \nabla f_i(w_i^k)$ infrequently (with a small probability $p_i \in (0,1]$), so that it needs to be communicated very rarely:

$$
\begin{aligned}
h_i^k &= \nabla f_i(w_i^k) \\
w_i^{k+1} &= \begin{cases} x^k & \text{with probability } p_i \\ w_i^k & \text{with probability } 1-p_i \end{cases}
\end{aligned}
\tag{12}
$$

This method has a remarkably simpler analysis than DIANA, but can solve the original problem of eliminating the variance introduced by gradient compression. Next, we state the convergence result for DCGD with shifts updated in a `randomized` fashion (12). We give it a Randomized-DIANA name (Rand-DIANA in short) to acknowledge the original method (Mishchenko et al., 2019) to first solve this problem.

Theorem 4 (Rand-DIANA)**.** *Assume that f_i are convex, L_i-smooth for all i and f is μ-convex. If the stepsize satisfies*

$$
\gamma \le \frac{1}{\left(1+\frac{2\omega}{n}\right)L_{\max} + M\max_i(p_i L_i)},
$$

where $M > \frac{2\omega}{np_m}$ and $p_m := \min_i p_i$. Then, the iterates of DCGD *with* Randomized-DIANA *shift update (12) satisfy*

$$
\mathbf{E}\,V^k \le \max\left\{(1-\gamma\mu)^k, \left(1-p_m+\frac{2\omega}{nM}\right)^k\right\} V^0,
$$

where the Lyapunov function V^k is defined by

$$
V^k := \left\|x^k - x^\star\right\|^2 + M\gamma^2\cdot\frac{1}{n}\sum_{i=1}^n\left\|h_i^k - \nabla f_i(x^\star)\right\|^2.
$$

Though appropriate choice of the parameters $M = \frac{4\omega}{np_m}$ and $p_i \equiv p = \frac{1}{\omega+1}$ for every i, we can basically obtain the same iteration complexity as the original DIANA (Horváth et al., 2019b)

$$
\max\left\{\frac{1}{\gamma\mu}, \frac{1}{p_m - \frac{2\omega}{nM}}\right\} = \max\left\{\frac{L_{\max}}{\mu}\left(1+\frac{\omega}{n}\right), \omega+1\right\}
$$

3.3 COMPRESSING THE ITERATES

In this section, we discuss how the shifted compression framework can be applied and leads to improved results for the case where the iterates themselves need to be compressed.

Let $\mathcal{Q} \in \mathbb{U}(\omega)$. Consider the following shifted by vector x/γ compressor

$$\hat{\mathcal{Q}}(z) := \frac{x}{\gamma} + \mathcal{Q}\left(z - \frac{x}{\gamma}\right),$$

which clearly belongs to the class $\mathbb{U}(\omega; x/\gamma)$. Based on the fact that for $\gamma \neq 0$ compressor $\bar{\mathcal{Q}}(z) := -\frac{1}{\gamma} \cdot \mathcal{Q}(-\gamma z) \in \mathbb{U}(\omega)$ we can transform $\hat{\mathcal{Q}}$ to operator

$$\tilde{\mathcal{Q}}(z) := \frac{x}{\gamma} + \bar{\mathcal{Q}}\left(z - \frac{x}{\gamma}\right) = \frac{1}{\gamma}\left[x - \mathcal{Q}(x - \gamma z)\right],$$

which also belongs to $\mathbb{U}(\omega; x/\gamma)$ and is helpful for analysing algorithms with compressed iterates.

Distributed Gradient Descent with Compressed Iterates (GDCI) was first analyzed by Khaled and Richtárik (2019) for single node and, in short, was relaxed and formulated in a convenient form by Chraibi et al. (2019):

$$x^{k+1} = (1-\eta)x^k + \eta\mathcal{Q}\left(x^k - \gamma\nabla f(x^k)\right). \qquad \text{(GDCI)}$$

This algorithm can be reformulated using the previously described shifted compressor $\tilde{\mathcal{Q}} \in \mathbb{U}(\omega; x^k/\gamma)$

$$\begin{aligned} x^{k+1} &= x^k - (\eta\gamma)\frac{1}{\gamma}\left[x^k - \mathcal{Q}\left(x^k - \gamma\nabla f(x^k)\right)\right] \\ &= x^k - (\eta\gamma)\tilde{\mathcal{Q}}^k(\nabla f(x^k)), \end{aligned}$$

which for the distributed case takes the form

$$x^{k+1} = (1-\eta)x^k + \eta\frac{1}{n}\sum_{i=1}^{n}\mathcal{Q}_i\left(x^k - \gamma\nabla f_i(x^k)\right). \quad (13)$$

The essence of this method is compression of the local workers' iterates $\mathcal{Q}_i\left(x^k - \gamma\nabla f_i(x^k)\right)$, their aggregation on the master and convex combination with the previous model. Established linear convergence up to a neighborhood introduced due to variance of compression operator (similarly to DCGD with fixed shifts Theorem 1 is presented next.

Theorem 5 (GDCI). *Assume each f_i is convex and L_i-smooth, and f is L-smooth and μ-strongly convex. Let $\mathcal{Q}_i \in \mathbb{U}(\omega)$ - independent compression operators. If the step-sizes satisfy*

$$\eta \leq \left[\frac{L}{\mu} + \frac{2\omega}{n}\left(\frac{L_{\max}}{\mu} - 1\right)\right]^{-1}, \gamma \leq \frac{1 + 2\eta\omega/n}{\eta\left(L + 2L_{\max}\omega/n\right)},$$

then the iterates of the Distributed GDCI *(13) satisfy*

$$\begin{aligned} \mathbf{E}\left\|x^k - x^\star\right\|^2 &\leq (1-\eta)^k\|x^0 - x^\star\|^2 \\ &\quad + \eta\frac{2\omega}{n}\frac{1}{n}\sum_{i=1}^{n}\|x^\star - \gamma\nabla f_i(x^\star)\|^2. \end{aligned} \quad (14)$$

In the interpolation regime ($\nabla f_i(x^\star) = 0 = x^\star - \gamma\nabla f_i(x^\star)$ for every i) this result matches the complexity of DCGD with fixed shifts (7)

$$\tilde{\mathcal{O}}\left(\kappa\left(1 + \omega/n\right)\right)$$

and improves over the original rate of GDCI from (Chraibi et al., 2019) analyzed for fixed point problems and specialized for gradient mappings:

$$\tilde{\mathcal{O}}\left(\kappa\max\left\{1, \kappa\omega/n\right\}\right) \lesssim \tilde{\mathcal{O}}\left(\kappa^2\omega/n\right).$$

Due to space limitations, the results for **Distributed Variance-Reduced Gradient Descent with Compressed Iterates** (VR-GDCI), which eliminates the neighborhood in (14), along with detailed proofs of all stated theorems are presented in the Supplementary Material.

4 EXPERIMENTS

In this section, we present some of the obtained experimental results. The rest (including real-world data and other models) is available in Section C of the Supplementary Material. We focus on well-controlled settings which satisfy the assumptions in our work, so as to provide evidence that our theory translates into observable predictions.

Consider a classical ridge-regression optimization problem

$$\min_{x\in\mathbb{R}^d}\left[f(x) := \frac{1}{2}\|\mathbf{A}x - y\|^2 + \frac{\lambda}{2}\|x\|^2\right],$$

where $\lambda = 1/m$ and $\mathbf{A} \in \mathbb{R}^{m\times d}, y \in \mathbb{R}^m$ are generated using Scikit-learn library (Pedregosa et al., 2011) method sklearn.datasets.make_regression with default parameters for $m = 100, d = 80$. Obtained data is uniformly at random distributed evenly among 10 workers. To compare selected algorithms, we evaluate the logarithm of a relative argument error $\log\left(\|x^k - x^\star\|^2/\|x^0 - x^\star\|^2\right)$ on vertical axis, while for horizontal one we calculate number of communicated bits needed to reach certain error tolerance ε. The starting point $x^0 \in \mathbb{R}^d$ entries are sampled from the normal distribution $\mathcal{N}(0, 10)$.

In our simulations we thoroughly examine the method Rand-DIANA, which is presented for the first time. Extensive studies of the methods with compressed iterates can be found in the works by Khaled and Richtárik (2019); Chraibi et al. (2019).

4.1 RANDOMIZED-DIANA VS DIANA

In the first set of experiments we compare Rand-DIANA and DIANA with different compressors $\mathcal{Q}_i$ ($\mathcal{C}_i \equiv 0$) and varied operators' parameters. Obtained results are summarized in Figure 1. Designation $q := k/d$ is used for the share of non-zeroed coordinates of `Random sparsification`

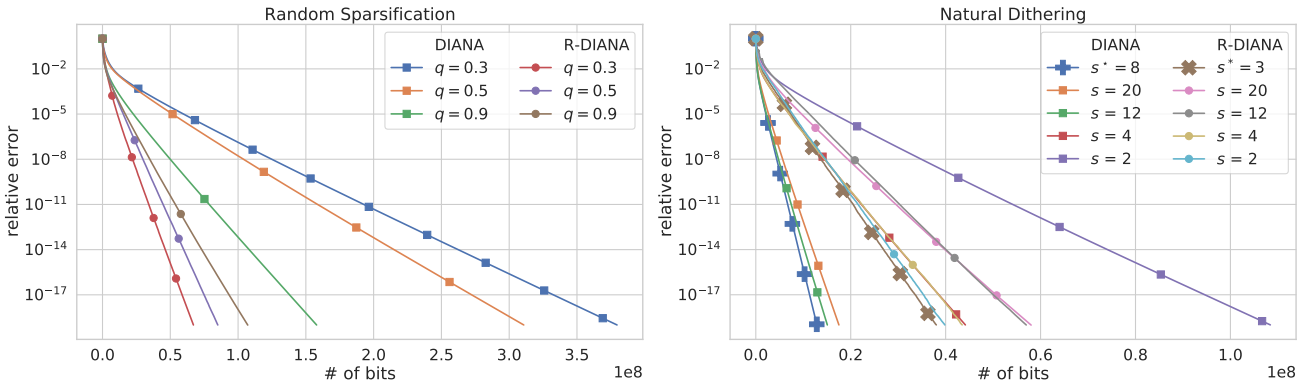

Figure 1: Comparison of DIANA and Randomized-DIANA. **Left plot**: methods equipped with `Rand-K` for different q values. **Right plot**: selected results of a grid search for the `ND` parameter s over $\{2, \ldots, 20\}$.

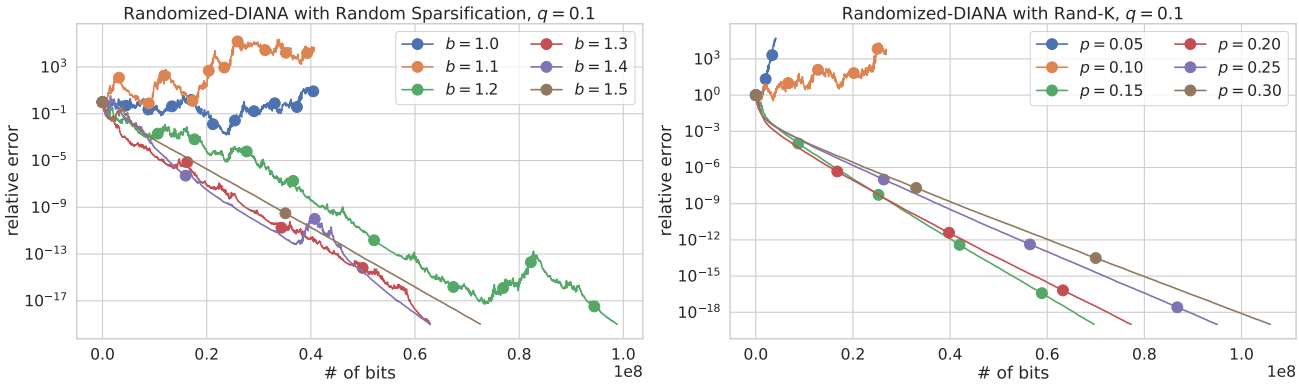

Figure 2: Study of Rand-DIANA stability and performance with varying parameters b and p.

(`Rand-K`) operator and s corresponds to number of levels for `Natural Dithering` (`ND`) (Horváth et al., 2019a) compressor. Parameter p of Rand-DIANA was chosen as $1/(\omega + 1)$ for every run.

Left plot in Figure 1 clearly shows that Rand-DIANA performs better than original DIANA for every value of `Rand-K` compressor parameter. It is worth noting that DIANA performs better with higher q, while for Rand-DIANA the opposite holds.

From the right plot in Figure 1 one can find that DIANA with `ND` can be superior to Rand-DIANA for optimized parameter $s^\star$. Nevertheless, for very aggressive compression (e.g., $s = 2$) Rand-DIANA is highly preferable.

In the next experimental setup, we closer investigate the behavior of Rand-DIANA with respect to it's parameters.

4.2 RANDOMIZED-DIANA STUDY

According to the formulation of Theorem 4 constant M has to be chosen strictly greater than $M' := 2\omega/(np)$. In the left plot of Figure 2 we show that for smaller values of M (set to $M' \cdot b$) the method becomes less stable and can even diverge. But too big M (for $b = 1.5$) can lead to overall (stable) slowdown. We conclude that the condition imposed by theoretical analysis is indeed critical.

The right plot in Figure 2 examines how parameter p affects the convergence in high compression regime ($q = 0.1$). The conclusion is that for smaller p method converges faster, and after certain threshold it can diverge. So, there is a similar to the previous study of M trade-off.

We do not conduct additional experiments to show the effect of combining unbiased compressors with biased ones. The reason for this is that the benefits of such an approach have already been clearly demonstrated by Horváth and Richtárik (2021) for distributed training of deep neural networks.

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Supplementary Material

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A BASIC FACTS

Bregman Divergence associated with a continuously-differentiable, strictly convex function $f : \mathbb{R}^d \to \mathbb{R}^d$ is defined as

$$D_f(x, y) \coloneqq f(x) - f(y) - \langle \nabla f(y), x - y \rangle.$$

Bregman Divergence and Strong Convexity Inequality:

$$\langle \nabla f(x) - \nabla f(y), x - y \rangle \geq D_f(x, y) + \frac{\mu}{2} \|x - y\|^2. \tag{15}$$

Bregman Divergence and L-smoothness Inequality:

$$\|\nabla f(x) - \nabla f(y)\|^2 \leq 2L D_f(x, y). \tag{16}$$

Basic Inequalities. For all vectors $a, b \in \mathbb{R}^d$ and random vector $X \in \mathbb{R}^d$:

$$\|a + b\|^2 \leq 2\|a\|^2 + 2\|b\|^2, \tag{17}$$

$$2\langle a, b \rangle = \|a\|^2 + \|b\|^2 - \|a - b\|^2, \tag{18}$$

$$\mathbf{E}\, \|X - a\|^2 = \mathbf{E}\, \|X - \mathbf{E}\, X\|^2 + \|\, \mathbf{E}\, X - a\|^2. \tag{19}$$

B PROOFS

For brevity, we can use notation $\mathbf{E}\, \|x\|^2$ instead of $\mathbf{E}\left[\|x\|^2\right]$.

B.1 SHIFTED COMPRESSION

B.1.1 Proof of Lemma 1

Proof. For the proof, we need to show unbiasedness and (shifted) bounded variance property for operator $\mathcal{Q} \coloneqq v + \mathcal{Q}_h(x - v)$ with $\mathcal{Q}_h \in \mathbb{U}(\omega; h)$.
(a) Unbiasdeness:

$$\mathbf{E}\, \mathcal{Q}(x) = \mathbf{E}\left[v + \mathcal{Q}_h(x - v)\right] = v + \mathbf{E}\, \mathcal{Q}_h(x - v) = v + (x - v) = x.$$

(b) Variance:

$$\begin{aligned}
\mathbf{E}\, \|\mathcal{Q}(x) - x\|^2 &= \mathbf{E}\, \|v + \mathcal{Q}_h(x - v) - x\|^2 \\
&= \mathbf{E}\, \|\mathcal{Q}_h(x - v) - (x - v)\|^2 \\
&\leq \omega\, \|x - (v + h)\|^2,
\end{aligned}$$

where the last inequality is due to the Shifted Compressor Definition 3. □

B.1.2 Compression of the Iterates

Lemma 2. *Let $\mathcal{Q} \in \mathbb{U}(\omega)$, then for*

$$\hat{\mathcal{Q}}(z) \coloneqq -t \cdot \mathcal{Q}\left(-\frac{z}{t}\right), \qquad t \neq 0, \tag{20}$$

we have $\hat{\mathcal{Q}}(z) \in \mathbb{U}(\omega)$.

Proof. We consequentially show the unbiasedness (1) and bounded variance (2) properties according to Definition 2

$$1)\, \mathbf{E}\, \hat{\mathcal{Q}}(z) = -t \cdot \mathbf{E}\, \mathcal{Q}\left(-\frac{z}{t}\right) = -t \cdot \left(-\frac{z}{t}\right) = z;$$
$$2)\, \mathbf{E}\left\|\hat{\mathcal{Q}}(z)\right\|^2 = \mathbf{E}\left\|-t \cdot \mathcal{Q}\left(-\frac{z}{t}\right)\right\|^2 = t^2\, \mathbf{E}\left\|\mathcal{Q}\left(-\frac{z}{t}\right)\right\|^2 \leq t^2(\omega+1)\left\|-\frac{z}{t}\right\|^2 = (\omega+1)\|z\|^2.$$

□

Now we prove that shifted compressor $\tilde{\mathcal{Q}}(z) \coloneqq \frac{1}{\gamma}\left[x - \mathcal{Q}(x - \gamma z)\right]$, obtained from (20) by procedure described in Section 3.3, belongs to class $\mathbb{U}\left(\omega; x/\gamma\right)$ for $\mathcal{Q} \in \mathbb{U}(\omega)$.

Proof. 1) **Unbiasedness** follows from $\mathbf{E}\, \mathcal{Q}(x) = x$.

2) Computation of the **variance**:

$$\begin{aligned}
\mathbf{E}\left\|\tilde{\mathcal{Q}}(z)\right\|^2 &= \mathbf{E}\left\|\frac{1}{\gamma}\left[x - \mathcal{Q}(x - \gamma z)\right]\right\|^2 \\
&= \frac{1}{\gamma^2}\, \mathbf{E}\left\|x - \mathcal{Q}(x - \gamma z)\right\|^2 \\
&= \frac{1}{\gamma^2}\, \mathbf{E}\left\|x - \gamma z - \mathcal{Q}(x - \gamma z) + \gamma z\right\|^2 \\
&= \frac{1}{\gamma^2}\left[\mathbf{E}\left\|x - \gamma z - \mathcal{Q}(x - \gamma z)\right\|^2 + \|\gamma z\|^2\right] \\
&\overset{2}{\leq} \frac{1}{\gamma^2}\left[\omega\left\|x - \gamma z\right\|^2 + \|\gamma z\|^2\right] \\
&= \omega\left\|\frac{x}{\gamma} - z\right\|^2 + \|z\|^2,
\end{aligned}$$

which implies

$$\mathbf{E}\left\|\tilde{\mathcal{Q}}(z) - z\right\|^2 \leq \omega\left\|z - \frac{x}{\gamma}\right\|^2.$$

□

B.1.3 Induced Compressor

Definition 4 (Induced Compression Operator (Horváth and Richtárik, 2021))**.** *For $\mathcal{C} \in \mathbb{B}(\delta)$, choose $\mathcal{Q} \in \mathbb{U}(\omega)$ and define the induced compressor via*

$$\mathcal{C}_{\text{ind}}(x) \coloneqq \mathcal{C}(x) + \mathcal{Q}(x - \mathcal{C}(x)). \tag{21}$$

Lemma 3. *The induced operator satisfies $\mathcal{C}_{\text{ind}} \in \mathbb{U}(\tilde{\omega})$ for*

$$\tilde{\omega} = \omega(1 - \delta) \tag{22}$$

Proof.

$$\begin{aligned}
\mathbf{E}\left\|\mathcal{C}_{\text{ind}}(x) - x\right\|^2 &\overset{(21)}{=} \mathbf{E}\left\|\mathcal{Q}(x - \mathcal{C}(x)) - (x - \mathcal{C}(x))\right\|^2 \\
&\overset{2}{\leq} \omega\, \mathbf{E}\left\|x - \mathcal{C}(x)\right\|^2 \\
&\overset{1}{\leq} \omega(1 - \delta)\|x\|^2 \\
&= \tilde{\omega}\|x\|^2
\end{aligned}$$

□

B.2 PROOF OF THEOREM 1 (DCGD-SHIFT)

According to Algorithm 1, the gradient estimator always has the following form

$$g_h(x) = \frac{1}{n}\sum_{i=1}^n g_{h_i}(x) = \frac{1}{n}\sum_{i=1}^n \left[h_i + \mathcal{Q}_i\left(\nabla f_i(x) - h_i\right)\right]. \tag{23}$$

Obvious unbiasedness (as $\mathcal{Q}_i \in \mathbb{U}(\omega_i)$) of this estimator for any h_i will be used in all further proofs.

Decomposition due to (19)

$$\mathbf{E}\left\|g_h(x^k) - \nabla f(x^\star)\right\|^2 = \mathbf{E}\left\|g_h(x^k) - \nabla f(x^k)\right\|^2 + \left\|\nabla f(x^k) - \nabla f(x^\star)\right\|^2. \tag{24}$$

Next we upper-bound the first term from (24).

Expectation conditional on x^k and $h = (h_1, \ldots, h_n)$ for brevity

$$\begin{aligned}
\mathbf{E}\left\|g_h(x^k) - \nabla f(x^k)\right\|^2 &= \mathbf{E}\left\|g_h(x^k) - \nabla f(x^k)\right\|^2 \\
&\overset{(23)}{=} \mathbf{E}\left\|\frac{1}{n}\sum_{i=1}^n \underbrace{\mathcal{Q}_i\left(\nabla f_i(x^k) - h_i\right) + h_i - \nabla f_i(x^k)}_{b_i^k}\right\|^2 \\
&= \frac{1}{n^2}\mathbf{E}\left[\sum_{i=1}^n \|b_i^k\|^2 + \sum_{i\neq j}\langle b_i^k, b_j^k\rangle\right] \\
&= \frac{1}{n^2}\sum_{i=1}^n \mathbf{E}\,\|b_i^k\|^2 + \frac{1}{n^2}\sum_{i\neq j}\underbrace{\langle \mathbf{E}\, b_i^k, \mathbf{E}\, b_j^k\rangle}_{=0\ (\mathbf{E}\,\mathcal{Q}_i(x)=x)} \\
&= \frac{1}{n^2}\sum_{i=1}^n \mathbf{E}\,\|\mathcal{Q}_i\left(\nabla f_i(x^k) - h_i\right) + h_i - \nabla f_i(x^k)\|^2 \\
&\overset{2}{\leq} \frac{1}{n^2}\sum_{i=1}^n \omega_i\|\nabla f_i(x^k) - h_i\|^2 \\
&= \frac{1}{n^2}\sum_{i=1}^n \omega_i\|\nabla f_i(x^k) - \nabla f_i(x^\star) - (h_i - \nabla f_i(x^\star))\|^2 \\
&\overset{(17)}{\leq} \frac{2}{n^2}\sum_{i=1}^n \omega_i\left[\left\|\nabla f_i(x^k) - \nabla f_i(x^\star)\right\|^2 + \|h_i - \nabla f_i(x^\star)\|^2\right] \\
&\overset{(16)}{\leq} \frac{2}{n^2}\sum_{i=1}^n \omega_i \cdot 2L_i D_{f_i}(x^k, x^\star) + \frac{2}{n^2}\sum_{i=1}^n \omega_i\,\|h_i - \nabla f_i(x^\star)\|^2 \\
&\leq \frac{4}{n}\max\left(\omega_i L_i\right)\frac{1}{n}\sum_{i=1}^n D_{f_i}(x^k, x^\star) + \frac{2}{n^2}\sum_{i=1}^n \omega_i\,\|h_i - \nabla f_i(x^\star)\|^2 \\
&\leq \frac{4}{n}\max\left(\omega_i L_i\right) D_f(x^k, x^\star) + \frac{2}{n^2}\sum_{i=1}^n \omega_i\,\|h_i - \nabla f_i(x^\star)\|^2.
\end{aligned}$$

Combined with (24) we obtain

$$\mathbf{E}\left[\left\|g_h(x^k) - \nabla f(x^\star)\right\|^2 \mid x^k, h\right] \leq 2\left[\frac{2}{n}\max\left(\omega_i L_i\right) + L\right] D_f(x^k, x^\star) + \frac{2}{n^2}\sum_{i=1}^n \omega_i\,\|h_i - \nabla f_i(x^\star)\|^2$$

Now from Gorbunov et al. (2020a, Theorem 4.1), we get statement of Theorem 3.

B.3 PROOF OF THEOREM 2 (DCGD-STAR)

Distributed Compressed Gradient Descent with optimal Shift is determined by the update

$$h_i^k = \nabla f_i(x^\star) + \mathcal{C}_i(\nabla f_i(x^k) - \nabla f_i(x^\star)).$$

Proof. At first, we compute the **variance of the estimator**.

Expectation conditional on x^k and $h^k = (h_1^k, \dots, h_n^k)$ for brevity

$$\begin{aligned}
\mathbf{Var}[g^k] &= \mathbf{E}\left\|g^k - \mathbf{E}\left[g^k\right]\right\|^2 \\
&= \mathbf{E}\left\|\frac{1}{n}\sum_{i=1}^n \mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k\right) + h_i^k - \nabla f(x^k)\right\|^2 \\
&= \mathbf{E}\left\|\frac{1}{n}\sum_{i=1}^n \left[\mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k\right) + h_i^k - \nabla f_i(x^k)\right]\right\|^2 \\
&= \frac{1}{n^2}\sum_{i=1}^n \mathbf{E}\left\|\mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k\right) + h_i^k - \nabla f_i(x^k)\right\|^2 \\
&\overset{2}{\leq} \frac{1}{n^2}\sum_{i=1}^n \omega_i\, \mathbf{E}\left\|\nabla f_i(x^k) - h_i^k\right\|^2 \\
&= \frac{1}{n^2}\sum_{i=1}^n \omega_i\, \mathbf{E}\left\|\nabla f_i(x^k) - h_i^\star - \mathcal{C}_i\left(\nabla f_i(x^k) - h_i^\star\right)\right\|^2 \\
&\overset{1}{\leq} \frac{1}{n^2}\sum_{i=1}^n \omega_i(1-\delta_i)\|\nabla f_i(x^k) - \nabla f_i(x^\star)\|^2 \\
&\overset{(16)}{\leq} \frac{1}{n^2}\sum_{i=1}^n \omega_i(1-\delta_i)\cdot 2L_i D_{f_i}(x^k, x^\star) \\
&\leq \frac{2}{n}\max\{\omega_i(1-\delta_i)L_i\}\frac{1}{n}\sum_{i=1}^n D_{f_i}(x^k, x^\star) \\
&\leq \frac{2}{n}\max\{\omega_i(1-\delta_i)L_i\} D_f(x^k, x^\star).
\end{aligned} \tag{25}$$

Now we can move to the **convergence proof**. Expectation conditional on x^k and h^k:

$$\begin{aligned}
\mathbf{E}\left\|r^{k+1}\right\|^2 &= \mathbf{E}\left\|x^{k+1} - x^\star\right\|^2 \\
&= \mathbf{E}\left\|x^k - \gamma g^k - (x^\star - \gamma\nabla f(x^\star))\right\|^2 \\
&= \mathbf{E}\left\|x^k - x^\star - \gamma(g^k - \nabla f(x^\star))\right\|^2 \\
&= \|r^k\|^2 - 2\gamma\langle x^k - x^\star, \mathbf{E}\, g^k - \nabla f(x^\star)\rangle + \gamma^2\,\mathbf{E}\left\|g^k - \nabla f(x^\star)\right\|^2 \\
&= \|r^k\|^2 - 2\gamma\langle x^k - x^\star, \nabla f(x^k) - \nabla f(x^\star)\rangle \\
&\qquad + \gamma^2\left[\mathbf{E}\left\|g^k - \nabla f(x^k)\right\|^2 + \left\|\nabla f(x^k) - \nabla f(x^\star)\right\|^2\right] \\
&\overset{(15)}{\leq} \|r^k\|^2 - 2\gamma\left[D_f(x^k, x^\star) + \frac{\mu}{2}\|x^k - x^\star\|^2\right] \\
&\qquad + \gamma^2\left[\mathbf{Var}[g^k] + \left\|\nabla f(x^k) - \nabla f(x^\star)\right\|^2\right] \\
&\overset{(25)}{\leq} (1-\gamma\mu)\|r^k\|^2 - 2\gamma D_f(x^k, x^\star) \\
&\qquad + \gamma^2\left[\frac{2}{n}\max\{\omega_i(1-\delta_i)L_i\}D_f(x^k, x^\star) + 2LD_f(x^k, x^\star)\right] \\
&= (1-\gamma\mu)\|r^k\|^2 - 2\gamma\left[1 - \gamma\left(L + \max\{L_i\omega_i(1-\delta_i)/n\}\right)\right] D_f(x^k, x^\star)
\end{aligned}$$

$$\leq (1-\gamma\mu)\|r^k\|^2, \tag{26}$$

where the last inequality is due to the step-size choice

$$\gamma \leq \frac{1}{L + \max_i \left(L_i\omega_i(1-\delta_i)/n\right)}.$$

Therefore,

$$\begin{aligned}
\mathbf{E}\,\|x^{k+1} - x^\star\|^2 &= \mathbf{E}\left[\mathbf{E}\left[\|x^{k+1} - x^\star\|^2 \mid x^k, h^k\right]\right] \\
&\overset{(26)}{\leq} (1-\gamma\mu)\,\mathbf{E}\,\|x^k - x^\star\|^2 \\
&\leq (1-\gamma\mu)^{k+1}\|x^0 - x^\star\|^2,
\end{aligned}$$

which concludes the proof. □

B.4 PROOF OF THEOREM 3 (DIANA-LIKE)

DIANA-like shift update has the following form

$$h_i^{k+1} = h_i^k + \alpha\left[\mathcal{C}_i(\nabla f_i(x^k) - h_i^k) + \mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k - \mathcal{C}_i(\nabla f_i(x^k) - h_i^k)\right)\right].$$

which is in fact equivalent to the standard DIANA shift update with induced compressor $\mathcal{Q}_i^{\text{ind}} \in \mathbb{U}\left(\omega_i(1-\delta_i)\right)$ defined before (4):

$$h_i^{k+1} = h_i^k + \alpha\mathcal{Q}_i^{\text{ind}}\left(\nabla f_i(x^k) - h_i^k\right),$$

The proof of Theorem 3 is mainly a generalization of the original DIANA analysis. Our approach is based on (Gorbunov et al., 2020a, Theorem 4.1), which requires the following Lemma (referred as Assumption 4.1 in (Gorbunov et al., 2020a)).

Lemma 4. *Assume that functions f_i are convex and L_i-smooth for all i, and $\mathcal{Q}_i \in \mathbb{U}(\omega_i), \mathcal{C}_i \in \mathbb{B}(\delta_i)$. Let $h = (h_1, h_2, \ldots, h_n) \in \mathbb{R}^d \times \mathbb{R}^d \ldots \times \mathbb{R}^d = \mathbb{R}^{nd}$ and define $\sigma : \mathbb{R}^{nd} \to [0, \infty)$ and σ^k by*

$$\sigma(h) = \frac{1}{n}\sum_{i=1}^n \omega_i\,\|h_i - \nabla f_i(x^\star)\|^2, \qquad \sigma^k := \sigma(h^k) = \frac{1}{n}\sum_{i=1}^n \omega_i\,\left\|h_i^k - \nabla f_i(x^\star)\right\|^2.$$

Then for all iterations of DCGD *with* DIANA*-like shift update, we have*

$$\begin{aligned}
\mathbf{E}\left[g^k \mid x^k, h^k\right] &= \nabla f(x^k), \\
\mathbf{E}\left[\left\|g^k - \nabla f(x^\star)\right\|^2 \mid x^k, h^k\right] &\leq 2\left(2\max_i(L_i\omega_i/n) + L_{\max}\right)D_f(x^k, x^\star) + \frac{2}{n}\sigma^k, \\
\mathbf{E}\left[\sigma^{k+1} \mid x^k, h^k\right] &\leq (1-\alpha)\sigma^k + 2\alpha\max_i(L_i\omega_i)D_f(x^k, x^\star).
\end{aligned}$$

Proof. The lemma consists of three statements.
1) Unbiasedness of the shifted gradient estimator was already shown in B.2.

2) Expected smoothness:

$$
\begin{aligned}
G^k &:= \mathbf{E}\left[\left\|g^k - \nabla f(x^\star)\right\|^2 \mid x^k, h^k\right] \\
&\overset{(19)}{=} \mathbf{E}\left[\|g^k - \nabla f(x^k)\|^2 \mid x^k, h^k\right] + \left\|\nabla f(x^k) - \nabla f(x^\star)\right\|^2 \\
&\overset{(16)}{\leq} \mathbf{E}\left[\|g^k - \nabla f(x^k)\|^2 \mid x^k, h^k\right] + 2LD_f(x^k, x^\star) \\
&\overset{(23)}{=} \mathbf{E}\left[\left\|\frac{1}{n}\sum_{i=1}^n \left(h_i^k + \mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k\right) - \nabla f_i(x^k)\right)\right\|^2 \mid x^k, h^k\right] + 2LD_f(x^k, x^\star) \\
&\leq \frac{1}{n^2}\sum_{i=1}^n \mathbf{E}\left[\left\|\mathcal{Q}_i\left(\nabla f_i(x^k) - h_i^k\right) - \left(\nabla f_i(x^k) - h_i^k\right)\right\|^2 \mid x^k, h^k\right] + 2LD_f(x^k, x^\star) \\
&\overset{2}{\leq} \frac{1}{n^2}\sum_{i=1}^n \omega_i \left\|\nabla f_i(x^k) - h_i^k)\right\|^2 + 2LD_f(x^k, x^\star) \\
&\overset{(17)}{\leq} \frac{1}{n^2}\sum_{i=1}^n \omega_i \left[2\left\|\nabla f_i(x^k) - \nabla f_i(x^\star))\right\|^2 + 2\left\|\nabla f_i(x^\star) - h_i^k)\right\|^2\right] + 2LD_f(x^k, x^\star) \\
&\overset{(16)}{\leq} 2\frac{2}{n}\max(\omega_i L_i)\frac{1}{n}\sum_{i=1}^n D_{f_i}(x^k, x^\star) + \frac{2}{n}\frac{1}{n}\sum_{i=1}^n \omega_i \left\|\nabla f_i(x^\star) - h_i^k)\right\|^2 + 2LD_f(x^k, x^\star) \\
&\leq 2\left[\frac{2}{n}\max(\omega_i L_i) + L_{\max}\right] D_f(x^k, x^\star) + \frac{2}{n}\sigma^k.
\end{aligned}
$$

3) Sigma-k recursion: Denote $m_i^k := \mathcal{Q}_i^{\text{ind}}\left(\nabla f_i(x^k) - h_i^k\right)$.

$$
\begin{aligned}
\mathbf{E}\left[\sigma^{k+1} \mid x^k, h^k\right] &= \mathbf{E}\left[\frac{1}{n}\sum_{i=1}^n \omega_i \left\|h_i^{k+1} - \nabla f_i(x^\star)\right\|^2 \mid x^k, h^k\right] \\
&= \mathbf{E}\left[\frac{1}{n}\sum_{i=1}^n \omega_i \left\|h_i^k + \alpha m_i^k - h_i^\star\right\|^2 \mid x^k, h^k\right] \\
&= \frac{1}{n}\sum_{i=1}^n \omega_i \left(\left\|h_i^k - h_i^\star\right\|^2 + 2\alpha\left\langle \mathbf{E}\, m_i^k, h_i^k - h_i^\star\right\rangle + \alpha^2\, \mathbf{E}\left[\left\|m_i^k\right\|^2 \mid x^k, h^k\right]\right) \\
&= \sigma^k + \frac{1}{n}\sum_{i=1}^n \omega_i \left(2\alpha\left\langle \nabla f_i(x^k) - h_i^k, h_i^k - h_i^\star\right\rangle + \alpha^2\, \mathbf{E}\left[\left\|m_i^k\right\|^2 \mid x^k, h^k\right]\right) \\
&\overset{(1,22)}{\leq} \sigma^k + \frac{1}{n}\sum_{i=1}^n \omega_i \left(2\alpha\left\langle \nabla f_i(x^k) - h_i^k, h_i^k - h_i^\star\right\rangle + \alpha^2\left(1 + \omega_i(1-\delta_i)\right)\left\|\nabla f_i(x^k) - h_i^k\right\|^2\right) \\
&\overset{(*)}{\leq} \sigma^k + \frac{1}{n}\sum_{i=1}^n \omega_i\alpha \left(2\left\langle \nabla f_i(x^k) - h_i^k, h_i^k - h_i^\star\right\rangle + \left\|\nabla f_i(x^k) - h_i^k\right\|^2\right) \\
&\overset{(18)}{=} \sigma^k + \frac{1}{n}\sum_{i=1}^n \alpha\omega_i \left(\left\|\nabla f_i(x^k) - h_i^\star\right\|^2 - \left\|h_i^k - h_i^\star\right\|^2\right) \\
&= \sigma^k + \frac{1}{n}\sum_{i=1}^n \alpha\omega_i \left\|\nabla f_i(x^k) - h_i^\star\right\|^2 - \alpha\sigma^k \\
&\overset{(16)}{\leq} (1-\alpha)\sigma^k + \frac{1}{n}\sum_{i=1}^n \alpha\omega_i \cdot 2L_i D_{f_i}(x^k, x^\star) \\
&\leq (1-\alpha)\sigma^k + 2\alpha\max_i(L_i\omega_i) D_f(x^k, x^\star),
\end{aligned}
$$

where $(*)$ follows from condition on the step-size $\alpha \leq \frac{1}{1+\omega_i(1-\delta_i)}$ (for every i). □

Now by direct application of (Gorbunov et al., 2020a, Theorem 4.1) we get statement of Theorem 3.

B.5 PROOF OF THEOREM 4 (RANDOMIZED-DIANA)

In short Rand-DIANA is defined by the shift update

$$h_i^k = \nabla f_i(w_i^k)$$
$$w_i^{k+1} = \begin{cases} x^k & \text{with probability } p_i \\ w_i^k & \text{with probability } 1 - p_i \end{cases}$$

which is similar to gradient estimator structure of Loopless-SVRG (Kovalev et al., 2020).

The proof of Theorem 4 is also based on (Gorbunov et al., 2020a, Theorem 4.1), which requires a modified version of Lemma 4.

Lemma 5. *Assume that functions f_i are convex and L_i-smooth for all i, and $\mathcal{Q}_i \in \mathbb{U}(\omega)$ for all i. Let $h = (h_1, h_2, \ldots, h_n) \in \mathbb{R}^d \times \mathbb{R}^d \ldots \times \mathbb{R}^d = \mathbb{R}^{nd}$ and define $\sigma : \mathbb{R}^{nd} \to [0, \infty)$ and σ^k by*

$$\sigma(h) = \frac{1}{n}\sum_{i=1}^n \|h_i - \nabla f_i(x^\star)\|^2 \quad \sigma^k := \sigma(h^k) = \frac{1}{n}\sum_{i=1}^n \left\|h_i^k - \nabla f_i(x^\star)\right\|^2.$$

Then for all iterations of Rand-DIANA *we have*

$$\mathbf{E}\left[g^k \mid x^k, h^k\right] = \nabla f(x^k),$$
$$\mathbf{E}\left[\left\|g^k - \nabla f(x^\star)\right\|^2 \mid x^k, h^k\right] \le 2\left(\frac{2\omega}{n} + 1\right) L_{\max} D_f(x^k, x^\star) + \frac{2\omega}{n}\sigma^k,$$
$$\mathbf{E}\left[\sigma^{k+1} \mid x^k, h^k\right] \le 2\max_i(p_i L_i) D_f(x^k, x^\star) + (1 - \min_i p_i)\sigma^k.$$

Proof. **1) Unbiasedness** of the shifted gradient estimator was already shown in B.2.

2) Expected smoothness: Exactly the same as in Lemma 4 with simplified σ^k (without ω_i) and $\omega_i \equiv \omega$.

3) Sigma-k recursion:

$$\begin{aligned}
\mathbf{E}\left[\sigma^{k+1} \mid x^k, h^k\right] &= \frac{1}{n}\sum_{i=1}^n \mathbf{E}\left[\|h_i^{k+1} - h_i^\star\|^2 \mid x^k, h^k\right] \\
&= \mathbf{E}\left[\frac{1}{n}\sum_{i=1}^n \|\nabla f_i(w_i^{k+1}) - \nabla f_i(x^\star)\|^2 \mid x^k, h^k\right] \\
&= \frac{1}{n}\sum_{i=1}^n \left[p_i\|\nabla f_i(x^k) - \nabla f_i(x^\star)\|^2 + (1-p_i)\|\nabla f(w_i^k) - \nabla f_i(x^\star)\|^2\right] \\
&\le \frac{1}{n}\sum_{i=1}^n p_i \cdot 2L_i D_{f_i}(x_k, x^\star) + \max_i(1-p_i)\frac{1}{n}\sum_{i=1}^n \|\nabla f(w_i^k) - \nabla f_i(x^\star)\|^2 \\
&\le 2\max_i(p_i L_i) D_f(x_k, x^\star) + (1 - \min_i p_i)\sigma^k
\end{aligned}$$

Applying Theorem 4.1 from Gorbunov et al. (2020a) we get statement of Theorem 4. □

B.6 PROOF OF THEOREM 5 (GDCI)

This and Subsection B.7 rely on lemma from Subsection B.1.2.

Distributed Gradient Descent with Compressed Iterates (GDCI) has the form

$$x^{k+1} = x^k - (\eta\gamma)\frac{1}{\gamma}\left[x^k - \frac{1}{n}\sum_{i=1}^n \mathcal{Q}_i\left(x^k - \gamma\nabla f_i(x^k)\right)\right] = x^k - (\eta\gamma)\tilde{\mathcal{Q}}^k(\nabla f(x^k)).$$

where shifted compressor $\tilde{\mathcal{Q}}^k(\nabla f(x^k))$ belongs to class $\mathbb{U}\left(\omega;\, x^k/\gamma\right)$ for $\mathcal{Q}_i \in \mathbb{U}(\omega)$

Convergence analysis for the non-regularized case ($\nabla f(x^\star) = 0$).

Proof. Expectation conditional on x^k:

$$\begin{aligned}
\mathbf{E}\left\|r^{k+1}\right\|^2 &:= \mathbf{E}\left\|x^{k+1} - x^\star\right\|^2 \\
&\overset{(13)}{=} \mathbf{E}\left\|x^k - \eta\gamma\tilde{\mathcal{Q}}^k(\nabla f(x^k)) - x^\star\right\|^2 \\
&= \mathbf{E}\left\|x^k - \eta\gamma\tilde{\mathcal{Q}}^k(\nabla f(x^k)) - (x^\star - \eta\gamma\nabla f(x^\star))\right\|^2 \\
&= \left\|r^k\right\|^2 + (\eta\gamma)^2\,\mathbf{E}\left\|\tilde{\mathcal{Q}}^k(\nabla f(x^k)) - \nabla f(x^\star)\right\|^2 - 2\eta\gamma\langle x^k - x^\star, \nabla f(x^k) - \nabla f(x^\star)\rangle \\
&\overset{(19)}{=} \left\|r^k\right\|^2 + (\eta\gamma)^2\left[\mathbf{E}\left\|\tilde{\mathcal{Q}}^k(\nabla f(x^k)) - \nabla f(x^k)\right\|^2 + \left\|\nabla f(x^k) - \nabla f(x^\star)\right\|^2\right] \\
&\quad - 2\eta\gamma\langle x^k - x^\star, \nabla f(x^k) - \nabla f(x^\star)\rangle.
\end{aligned} \tag{27}$$

Next we upper-bound the variance of $\tilde{\mathcal{Q}}^k(\nabla f(x^k))$

$$\begin{aligned}
\mathbf{E}\left\|\tilde{\mathcal{Q}}^k(\nabla f(x^k)) - \nabla f(x^k)\right\|^2 &= \mathbf{E}\left\|\frac{1}{\gamma}\left[x^k - \frac{1}{n}\sum_{i=1}^n \mathcal{Q}_i\left(x^k - \gamma\nabla f_i(x^k)\right)\right] - \frac{1}{n}\sum_{i=1}^n \nabla f_i(x^k)\right\|^2 \\
&= \mathbf{E}\left\|\frac{1}{n^2}\sum_{i=1}^n\left(\nabla f_i(x^k) - \frac{1}{\gamma}\left[x^k - \mathcal{Q}_i\left(x^k - \gamma\nabla f_i(x^k)\right)\right]\right)\right\|^2 \\
[\text{independence of } \mathcal{Q}_i] &\le \frac{1}{n^2}\sum_{i=1}^n \mathbf{E}\left\|\nabla f_i(x^k) - \frac{1}{\gamma}\left[x^k - \mathcal{Q}_i\left(x^k - \gamma\nabla f_i(x^k)\right)\right]\right\|^2 \\
&\overset{2}{\le} \frac{1}{n^2}\sum_{i=1}^n \omega\left\|\nabla f_i(x^k) - \frac{1}{\gamma}x^k\right\|^2 \\
&= \frac{1}{n^2}\sum_{i=1}^n \frac{\omega}{\gamma^2}\left\|x^k - \gamma\nabla f_i(x^k)\right\|^2 \\
&= \frac{\omega}{n^2\gamma^2}\sum_{i=1}^n \left\|x^k - \gamma\nabla f_i(x^k) \pm (x^\star - \gamma\nabla f_i(x^\star))\right\|^2 \\
&\overset{(17)}{\le} \frac{\omega}{n^2\gamma^2}\sum_{i=1}^n 2\left[\left\|x^k - \gamma\nabla f_i(x^k) - (x^\star - \gamma\nabla f_i(x^\star))\right\|^2 + \left\|x^\star - \gamma\nabla f_i(x^\star)\right\|^2\right] \\
&= \frac{2\omega}{n^2\gamma^2}\sum_{i=1}^n\Big[\left\|x^k - x^\star\right\|^2 - 2\gamma\langle x^k - x^\star, \nabla f_i(x^k) - \nabla f_i(x^\star)\rangle \\
&\qquad + \gamma^2\left\|\nabla f_i(x^k) - \nabla f_i(x^\star)\right\|^2 + \left\|x^\star - \gamma\nabla f_i(x^\star)\right\|^2\Big] \\
&\overset{(16,15)}{\le} \frac{2\omega}{n^2\gamma^2}\sum_{i=1}^n\Big[\left\|r^k\right\|^2 - 2\gamma\left(D_{f_i}(x^k, x^\star) + \frac{\mu}{2}\left\|x^k - x^\star\right\|^2\right) \\
&\quad + \gamma^2 2L_i D_{f_i}(x^k, x^\star) + \left\|x^\star - \gamma\nabla f_i(x^\star)\right\|^2\Big]
\end{aligned}$$

$$
\begin{aligned}
&= \frac{2\omega}{n^2\gamma^2}\sum_{i=1}^n \left[(1-\gamma\mu)\left\|r^k\right\|^2 - 2\gamma\left(1-\gamma L_i\right) D_{f_i}(x^k,x^\star) + \|x^\star - \gamma\nabla f_i(x^\star)\|^2\right] \\
&\leq \frac{2\omega}{n\gamma^2}(1-\gamma\mu)\left\|r^k\right\|^2 + \frac{2\omega}{n^2\gamma^2}\sum_{i=1}^n \|x^\star - \gamma\nabla f_i(x^\star)\|^2 \\
&\quad - \frac{2\omega}{n\gamma^2}\cdot 2\gamma\left(1-\gamma L_{\max}\right) D_f(x^k,x^\star).
\end{aligned}
$$

Combining it with (27) and using notation $\mathcal{T}_i(x) := x - \gamma\nabla f_i(x)$ we get

$$
\begin{aligned}
\mathbf{E}\left\|r^{k+1}\right\|^2 &\leq \|r^k\|^2 - 2\eta\gamma\langle x^k - x^\star, \nabla f(x^k) - \nabla f(x^\star)\rangle + (\eta\gamma)^2\left\|\nabla f(x^k) - \nabla f(x^\star)\right\|^2 \\
&\quad + \frac{2\omega\eta^2}{n}\left[(1-\gamma\mu)\left\|r^k\right\|^2 - 2\gamma\left(1-\gamma L_{\max}\right) D_f(x^k,x^\star) + \frac{1}{n}\sum_{i=1}^n \|\mathcal{T}_i(x^\star)\|^2\right] \\
&\overset{(16,15)}{\leq} \|r^k\|^2 - 2\eta\gamma\left[D_f(x^k,x^\star) + \frac{\mu}{2}\|x^k - x^\star\|^2\right] + (\eta\gamma)^2\cdot 2LD_f(x^k,x^\star) \\
&\quad + \frac{2\omega\eta^2}{n}\left[(1-\gamma\mu)\left\|r^k\right\|^2 - 2\gamma\left(1-\gamma L_{\max}\right) D_f(x^k,x^\star) + \frac{1}{n}\sum_{i=1}^n \|\mathcal{T}_i(x^\star)\|^2\right] \\
&= \left[1 - \eta\gamma\mu + \frac{2\omega\eta^2}{n}(1-\gamma\mu)\right]\|r^k\|^2 + \frac{2\omega\eta^2}{n}\frac{1}{n}\sum_{i=1}^n \|\mathcal{T}_i(x^\star)\|^2 \\
&\quad - 2\eta\gamma\left[1 - \eta\gamma L + \frac{2\omega\eta}{n}\left(1-\gamma L_{\max}\right)\right] D_f(x^k,x^\star),
\end{aligned}
$$

which after choosing the step-size

$$
\gamma \leq \frac{1 + 2\eta\omega/n}{\eta\left(L + 2L_{\max}\omega/n\right)}
$$

and after optimizing over γ and η (to maximize contraction term before $\|r^k\|^2$) leads to

$$
\mathbf{E}\left[\|x^{k+1} - x^\star\|^2 \mid x^k\right] \leq (1-\eta)\|r^k\|^2 + \frac{2\omega\eta^2}{n}\frac{1}{n}\sum_{i=1}^n \|\mathcal{T}_i(x^\star)\|^2,
$$

for

$$
\eta \leq \left[\frac{L}{\mu} + \frac{2\omega}{n}\left(\frac{L_{\max}}{\mu} - 1\right)\right]^{-1},
$$

And after unrolling the recursion and standard simplifications we obtain the desired result

$$
\mathbf{E}\|x^k - x^\star\|^2 \leq (1-\eta)^k\left\|x^0 - x^\star\right\|^2 + \frac{2\omega\eta}{n}\frac{1}{n}\sum_{i=1}^n \|x^\star - \gamma\nabla f_i(x^\star)\|^2.
$$

□

B.7 VARIANCE-REDUCED GRADIENT DESCENT WITH COMPRESSED ITERATES (VR-GDCI)

In this section we describe the method first introduced by Chraibi et al. (2019) and show its improved analysis.

Algorithm 2 Distributed Variance-Reduced Gradient Descent with Compressed Iterates (VR-GDCI)

Parameters: learning rates $\alpha, \gamma, \eta > 0$; compressors $\mathcal{Q}_i \in \mathbb{U}(\omega)$, initial iterate $x^0 \in \mathbb{R}^d$, initial local shifts $h_1^0, \ldots, h_n^0 \in \mathbb{R}^d$ (stored on the n nodes)
Initialize: $h^0 = \frac{1}{n}\sum_{i=1}^n h_i^0$ (stored on the master)
for $k = 0, 1, 2 \ldots$ **do**
  Broadcast x^k to all workers
  for $i = 1, \ldots n$ **do** in parallel
    Compress shifted local model $\delta_i^{k+1} = \mathcal{Q}_i\left(x^k - \gamma \nabla f_i(x^k) - h_i^k\right)$
    Update the local shift: $h_i^{k+1} = h_i^k + \alpha \delta_i^{k+1}$
    Send message δ_i^{k+1} to the master
  end for
  Aggregate received messages: $\delta^{k+1} = \frac{1}{n}\sum_{i=1}^n \delta_i^{k+1}$
  Update aggregated shift: $h^{k+1} = h^k + \alpha \delta^{k+1}$
  Compute $\Delta^{k+1} = \delta^{k+1} + h^k$
  Take "model" step: $x^{k+1} = (1-\eta)x^k + \eta \Delta^{k+1}$
end for

We can rewrite VR-GDCI (Algorithm 2) in the following equivalent way

$$\delta^{k+1} = \frac{1}{n}\sum_{i=1}^n \delta_i^{k+1} = \frac{1}{n}\sum_{i=1}^n \mathcal{Q}_i\left(\mathcal{T}_i(x^k) - h_i^k\right),$$
$$h^{k+1} = h^k + \alpha \delta^k,$$

which leads to such update rule

$$\begin{aligned} x^{k+1} &= x^k - \eta\left(x^k - h^k - \delta^k\right) \\ &= x^k - (\eta\gamma)\frac{1}{\gamma}\left(x^k - h^k - \frac{1}{n}\sum_{i=1}^n \mathcal{Q}_i\left(x^k - h_i^k - \gamma \nabla f_i(x^k)\right)\right) \\ &= x^k - (\eta\gamma)\tilde{\mathcal{Q}}^k(\nabla f(x^k)). \end{aligned}$$

Theorem 6. *Let Ψ^k be the following Lyapunov function:*

$$\Psi^k := \|x^k - x^\star\|^2 + \frac{4\eta^2\omega}{\alpha n}\sigma^k, \qquad \sigma^k := \frac{1}{n}\sum_{i=1}^n \left\|h_i^k - \mathcal{T}_i(x^\star)\right\|^2$$

Suppose that f is L-smooth and μ-strongly convex. Choose the stepsizes α, η, γ such that

$$\alpha \le \frac{1}{\omega+1}, \qquad \eta = \left[\frac{L}{\mu} + \frac{6\omega}{n}\left(\frac{L_{\max}}{\mu} - 1\right)\right]^{-1}, \qquad \gamma \le \frac{1 + 6\omega\eta/n}{\eta(L + 6L_{\max}\omega/n)}.$$

Then the iterates defined by Algorithm 2 satisfy

$$\mathbf{E}\,\Psi^k \le \left(1 - \min\left\{\frac{\alpha}{2}, \eta\right\}\right)^k \|x^0 - x^\star\|^2 \Psi^0.$$

Proof. Beginning of the analysis is exactly the same as in the previous section (27).
Expectation conditional on x^k and h^k

$$\begin{aligned} \mathbf{E}\,\|r^{k+1}\|^2 := \mathbf{E}\,\|x^{k+1} - x^\star\|^2 &= \|r^k\|^2 - 2\eta\gamma\langle x^k - x^\star, \nabla f(x^k) - \nabla f(x^\star)\rangle \\ &+ (\eta\gamma)^2\Big[\mathbf{E}\underbrace{\left\|\tilde{\mathcal{Q}}^k(\nabla f(x^k)) - \nabla f(x^k)\right\|^2}_{\tau^k} + \left\|\nabla f(x^k) - \nabla f(x^\star)\right\|^2\Big]. \end{aligned} \tag{28}$$

Let $\mathcal{T}_i(x) := x - \gamma \nabla f_i(x)$. For term τ^k we employ similar upper bound using the fact that $\tilde{\mathcal{Q}}_i^k \in \mathbb{U}(\omega; \left(x^k - h_i^k\right)/\gamma)$

$$
\begin{aligned}
\mathbf{E}\left[\left\|\tilde{\mathcal{Q}}^k(\nabla f(x^k)) - \nabla f(x^k)\right\|^2 \mid x^k, h^k\right] &\leq \frac{\omega}{n^2}\sum_{i=1}^n \left\|\nabla f_i(x^k) - \left(x^k - h_i^k\right)/\gamma\right\|^2 \\
&= \frac{\omega}{n^2}\frac{1}{\gamma^2}\sum_{i=1}^n \left\|x^k - h_i^k - \gamma\nabla f_i(x^k) \pm \mathcal{T}_i(x^\star)\right\|^2 \\
&\overset{(17)}{\leq} \frac{2\omega}{n^2\gamma^2}\sum_{i=1}^n \left\|\mathcal{T}_i(x^k) - \mathcal{T}_i(x^\star)\right\|^2 \\
&\quad + \frac{2\omega}{\gamma^2 n}\underbrace{\frac{1}{n}\sum_{i=1}^n \left\|h_i^k - \mathcal{T}_i(x^\star)\right\|^2}_{\sigma^k}.
\end{aligned}
\tag{29}
$$

Next we upper-bound the σ^{k+1} term (expectation conditional on x^k and h^k):

$$
\begin{aligned}
\mathbf{E}\,\sigma^{k+1} &= \frac{1}{n}\sum_{i=1}^n \mathbf{E}\left\|h_i^{k+1} - \mathcal{T}_i(x^\star)\right\|^2 \\
&= \frac{1}{n}\sum_{i=1}^n \mathbf{E}\left\|h_i^k + \alpha\mathcal{Q}_i\left(\mathcal{T}_i(x^k) - h_i^k\right) - (x^\star - \gamma\nabla f_i(x^\star))\right\|^2 \\
&= \frac{1}{n}\sum_{i=1}^n \left[\|h_i^k - \mathcal{T}_i(x^\star)\|^2 + \alpha^2\,\mathbf{E}\left\|\mathcal{Q}_i\left(\mathcal{T}_i(x^k) - h_i^k\right)\right\|^2 + 2\alpha\langle h_i^k - \mathcal{T}_i(x^\star), \mathcal{T}_i(x^k) - h_i^k\rangle\right] \\
&\overset{2}{\leq} \sigma^k + \frac{1}{n}\sum_{i=1}^n \left[\alpha^2(\omega+1)\left\|\mathcal{T}_i(x^k) - h_i^k\right\|^2 - 2\alpha\langle h_i^k - \mathcal{T}_i(x^\star), h_i^k - \mathcal{T}_i(x^k)\rangle\right] \\
&\overset{(*)}{\leq} \sigma^k + \frac{1}{n}\sum_{i=1}^n \left[\alpha\left\|\mathcal{T}_i(x^k) - h_i^k\right\|^2 - 2\alpha\langle h_i^k - \mathcal{T}_i(x^\star), h_i^k - \mathcal{T}_i(x^k)\rangle\right] \\
&\overset{(18)}{=} \sigma^k + \frac{1}{n}\sum_{i=1}^n \alpha\left[\left\|\mathcal{T}_i(x^k) - \mathcal{T}_i(x^\star)\right\|^2 - \left\|h_i^k - \mathcal{T}_i(x^\star)\right\|^2\right] \\
&= (1-\alpha)\sigma^k + \alpha\frac{1}{n}\sum_{i=1}^n \left\|\mathcal{T}_i(x^k) - \mathcal{T}_i(x^\star)\right\|^2,
\end{aligned}
$$

where $(*)$ follows from $\alpha \leq 1/(\omega+1)$.

Simplification of the second term (same as first term in (29))

$$
\begin{aligned}
\frac{1}{n}\sum_{i=1}^n \left\|\mathcal{T}_i(x^k) - \mathcal{T}_i(x^\star)\right\|^2 &= \frac{1}{n}\sum_{i=1}^n \left\|x^k - \gamma\nabla f_i(x^k) - (x^\star - \gamma\nabla f_i(x^\star))\right\|^2 \\
&= \frac{1}{n}\sum_{i=1}^n \Big[\left\|x^k - x^\star\right\|^2 + \gamma^2\left\|\nabla f_i(x^k) - \nabla f_i(x^\star)\right\|^2 \\
&\qquad - 2\gamma\langle x^k - x^\star, \nabla f_i(x^k) - \nabla f_i(x^\star)\rangle\Big] \\
&\overset{(16,15)}{\leq} \left\|r^k\right\|^2 + \frac{1}{n}\sum_{i=1}^n \left[\gamma^2 2L_i D_{f_i}(x^k, x^\star) - 2\gamma\left(D_{f_i}(x^k, x^\star) + \frac{\mu}{2}\|x^k - x^\star\|^2\right)\right] \\
&= (1-\gamma\mu)\left\|r^k\right\|^2 - 2\gamma\cdot\frac{1}{n}\sum_{i=1}^n (1-\gamma L_i)\,D_{f_i}(x^k, x^\star) \\
&\leq (1-\gamma\mu)\left\|x^k - x^\star\right\|^2 - 2\gamma\cdot(1-\gamma L_{\max})\,D_f(x^k, x^\star).
\end{aligned}
\tag{30}
$$

Combining the obtained bounds for $\|r^{k+1}\|^2$ and σ^{k+1} we get the Lyapunov function (expectation conditional on x^k, h^k):

$$
\begin{aligned}
\mathbf{E}\,\Psi^{k+1} &:= \mathbf{E}\left\|x^{k+1} - x^\star\right\|^2 + \frac{4\eta^2\omega}{\alpha n}\,\mathbf{E}\,\sigma^{k+1} \\
&\leq \|r^k\|^2 - 2\eta\gamma\langle x^k - x^\star, \nabla f(x^k) - \nabla f(x^\star)\rangle + (\eta\gamma)^2\left\|\nabla f(x^k) - \nabla f(x^\star)\right\|^2 \\
&\quad + (\eta\gamma)^2\left[\frac{2\omega}{n^2\gamma^2}\sum_{i=1}^n\left\|\mathcal{T}_i(x^k) - \mathcal{T}_i(x^\star)\right\|^2 + \frac{2\omega}{\gamma^2 n}\sigma^k\right] \\
&\quad + \frac{4\eta^2\omega}{\alpha n}\left[(1-\alpha)\sigma^k + \alpha\frac{1}{n}\sum_{i=1}^n\left\|\mathcal{T}_i(x^k) - \mathcal{T}_i(x^\star)\right\|^2\right] \\
&\overset{(15,16)}{\leq} (1-\eta\gamma\mu)\|r^k\|^2 - 2\eta\gamma\left(1 - L\eta\gamma\right)D_f(x^k, x^\star) \\
&\quad + \frac{4\eta^2\omega}{\alpha n}\left(1 - \frac{\alpha}{2}\right)\sigma^k + \frac{6\omega\eta^2}{\alpha n}\frac{1}{n}\sum_{i=1}^n\left\|\mathcal{T}_i(x^k) - \mathcal{T}_i(x^\star)\right\|^2 \\
&\overset{(30)}{\leq} \left[1 - \mu\eta\gamma + \frac{6\omega\eta^2}{n}\left(1 - \gamma\mu\right)\right]\|r^k\|^2 + \frac{4\eta^2\omega}{\alpha n}\left(1 - \frac{\alpha}{2}\right)\sigma^k \\
&\quad - 2\eta\gamma\left[1 - L\eta\gamma + \frac{6\eta\omega}{n}\left(1 - \gamma L_{\max}\right)\right]D_f(x^k, x^\star) \\
&\overset{(*)}{\leq} \left[1 - \mu\eta\gamma + \frac{6\omega\eta^2}{n}\left(1 - \gamma\mu\right)\right]\|r^k\|^2 + \frac{4\eta^2\omega}{\alpha n}\left(1 - \frac{\alpha}{2}\right)\sigma^k \\
&\leq (1-\eta)\,\|x^k - x^\star\|^2 + \frac{4\eta^2\omega}{\alpha n}\left(1 - \frac{\alpha}{2}\right)\sigma^k,
\end{aligned}
$$

where $(*)$ follows from condition on γ

$$
\gamma \leq \frac{1 + \frac{6\omega}{n}\eta}{\eta\left(L + \frac{6\omega}{n}L_{\max}\right)},
$$

and for

$$
\eta = \mu\left[L + \frac{6\omega}{n}\left(L_{\max} - \mu\right)\right]^{-1}.
$$

The last inequality was obtained via minimization of the term $\left[1 - \mu\eta\gamma + \frac{6\omega\eta^2}{n}\left(1 - \gamma\mu\right)\right]$ w.r.t. γ, η and using contraction inequality constraint. Using the definition of the Lyapunov function we obtain

$$
\mathbf{E}\left[\Psi^{k+1} \mid x^k, h^k\right] \leq \left(1 - \min\left\{\eta, \frac{\alpha}{2}\right\}\right)\|x^k - x^\star\|^2\Psi^k,
$$

which by unrolling the recursion and taking full expectation leads to the statement of the Theorem 6. □

Obtained theorem gives rise to the following iteration complexity result

$$
\max\left\{2(\omega+1), \frac{L}{\mu} + \frac{6\omega}{n}\left(\frac{L_{\max}}{\mu} - 1\right)\right\}\log 1/\varepsilon,
$$

which after simplification ($L_i \equiv L$) is equivalent to complexity of DIANA up to numerical constants

$$
\max\left\{2(\omega+1), \left(1 + 6\frac{\omega}{n}\right)\kappa\right\}\log 1/\varepsilon,
$$

and improves over the original rate of VR-GDCI from (Chraibi et al., 2019) analyzed for fixed point problems and specialized for gradient mappings:

$$
2\max\left\{\omega + 1, \kappa\min\left(1, 12\frac{\omega}{n}\kappa\right)\right\}\log 1/\varepsilon.
$$

C ADDITIONAL EXPERIMENTS

Here we supplement the Section 4 with further experimental details and results.

All simulations are performed on a machine with 24 Intel(R) Xeon(R) Gold 6246 CPU @ 3.30 GHz.

Rand-DIANA stability. In this section we show complementary stability results of Rand-DIANA plotted in Figure 2 for different values of `Rand-K` parameter q.

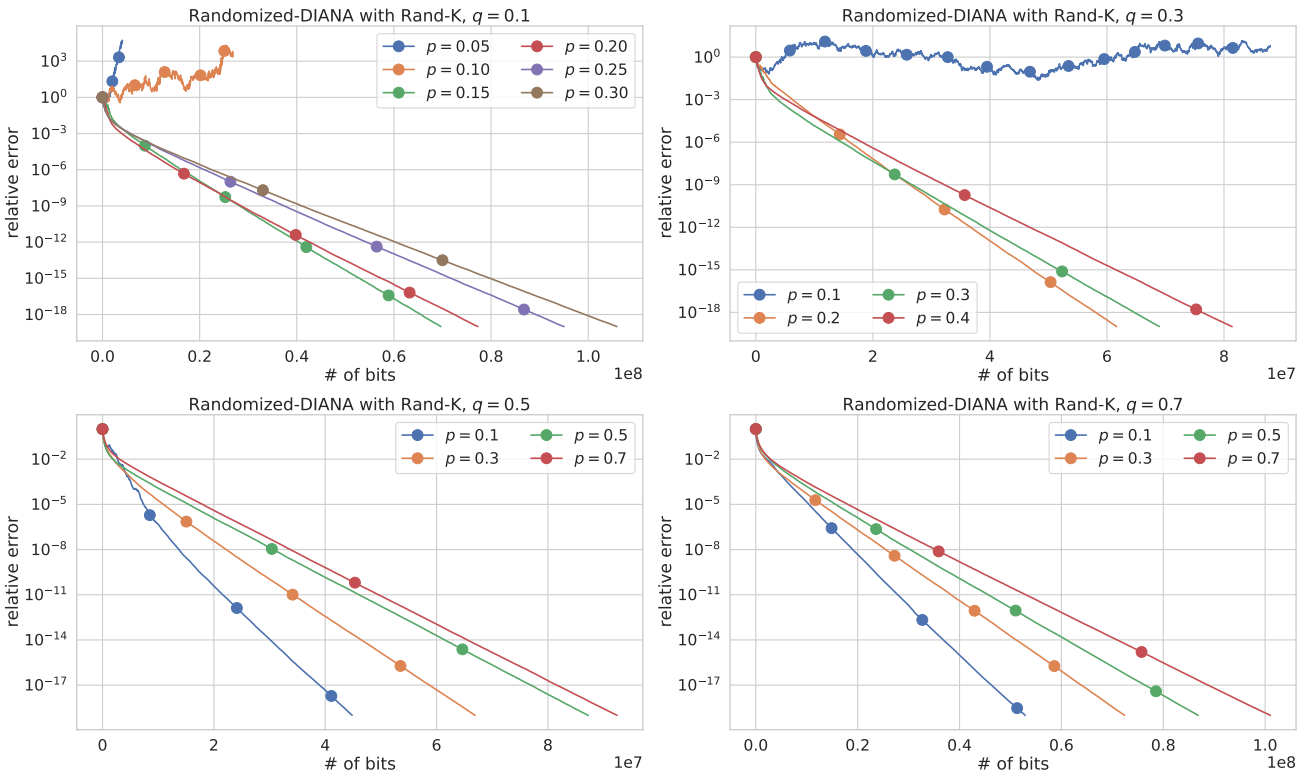

Figure 3: Performance of Rand-DIANA with `Rand-K` sparsification operator for different values of p.

Rand-DIANA vs DIANA on Logistic Regression. Consider an ℓ_2-regularized logistic regression optimization problem with *w2a* dataset from the LibSVM repository (Chang and Lin, 2011).

$$f_i(x) := \frac{1}{m}\sum_{l=1}^{m} \log\left(1 + \exp\left(-\mathbf{A}_{i,l}^{\top} x \cdot b_{i,l}\right)\right) + \frac{\lambda}{2}\|x\|^2,$$

where λ is set to guarantee that the condition number of the loss function f equals to 100. $\mathbf{A}_{i,l} \in \mathbb{R}^d, b_{i,l} \in \{-1, 1\}$ are the feature and label of l-th data point on the i-th worker. The "optimum" $x^\star$ is obtained by running AGD (Accelerated Gradient Descent) with the whole data using one cpu core until $\|\nabla f(x)\|^2 \leq 10^{-32}$.

Conclusions are basically the same as the ones for Ridge Regression problem presented in Section 4.1. Although DIANA performs slightly better with `Rand-K` compressor for $q = 0.9$.

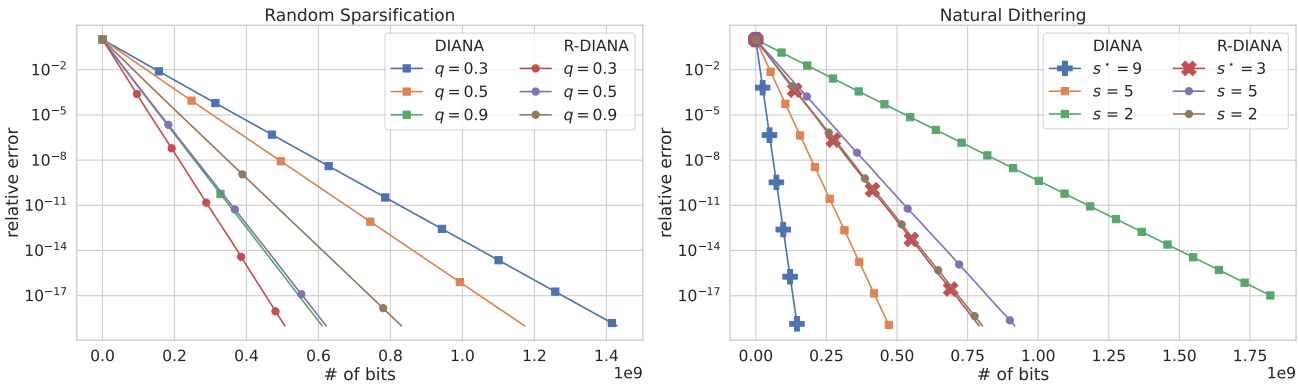

Figure 4: Comparison of DIANA and Randomized-DIANA. **Left plot**: methods equipped with `Rand-K` for different q values. **Right plot**: selected results of grid search for `Natural Dithering` parameter s over $\{2, \ldots, 20\}$.