
Breaking Locality Accelerates Block Gauss-Seidel

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Abstract

Recent work by Nesterov and Stich (2016) showed that momentum can be used to accelerate the rate of convergence for block Gauss-Seidel in the setting where a fixed partitioning of the coordinates is chosen ahead of time. We show that this setting is too restrictive, constructing instances where breaking locality by running non-accelerated Gauss-Seidel with randomly sampled coordinates substantially outperforms accelerated Gauss-Seidel with any fixed partitioning. Motivated by this finding, we analyze the accelerated block Gauss-Seidel algorithm in the random coordinate sampling setting. Our analysis captures the benefit of acceleration with a new data-dependent parameter which is well behaved when the matrix sub-blocks are well-conditioned. Empirically, we show that accelerated Gauss-Seidel with random coordinate sampling provides speedups for large scale machine learning tasks when compared to non-accelerated Gauss-Seidel and the classical conjugate-gradient algorithm.

1. Introduction

The randomized Gauss-Seidel method is a commonly used iterative algorithm to compute the solution of an $n \times n$ linear system $Ax = b$ by updating a single coordinate at a time in a randomized order. While this approach is known to converge linearly to the true solution when A is positive definite (see e.g. (Leventhal & Lewis, 2010)), in practice it is often more efficient to update a small block of coordinates at a time due to the effects of cache locality.

In extending randomized Gauss-Seidel to the block setting, a natural question that arises is how one should sample the next block. At one extreme a *fixed partition* of the coordi-

nates is chosen ahead of time. The algorithm is restricted to randomly selecting blocks from this fixed partitioning, thus favoring data locality. At the other extreme we break locality by sampling a new set of *random coordinates* to form a block at every iteration.

Theoretically, the fixed partition case is well understood both for Gauss-Seidel (Qu et al., 2015; Gower & Richtárik, 2015) and its Nesterov accelerated variant (Nesterov & Stich, 2016). More specifically, at most $O(\mu_{\text{part}}^{-1} \log(1/\varepsilon))$ iterations of Gauss-Seidel are sufficient to reach a solution with at most ε error, where μ_{part} is a quantity which measures how well the A matrix is preconditioned by the block diagonal matrix containing the sub-blocks corresponding to the fixed partitioning. When acceleration is used, Nesterov and Stich (2016) show that the rate improves to $O\left(\sqrt{\frac{n}{p} \mu_{\text{part}}^{-1}} \log(1/\varepsilon)\right)$, where p is the partition size.

For the random coordinate selection model, the existing literature is less complete. While it is known (Qu et al., 2015; Gower & Richtárik, 2015) that the iteration complexity with random coordinate section is $O(\mu_{\text{rand}}^{-1} \log(1/\varepsilon))$ for an ε error solution, μ_{rand} is another instance dependent quantity which is not directly comparable to μ_{part} . Hence it is not obvious how much better, if at all, one expects random coordinate selection to perform compared to fixed partitioning.

Our first contribution in this paper is to show that, when compared to the random coordinate selection model, the fixed partition model can perform very poorly in terms of iteration complexity to reach a pre-specified error. Specifically, we present a family of instances (similar to the matrices recently studied by Lee and Wright (2016)) where *non-accelerated* Gauss-Seidel with random coordinate selection performs *arbitrarily* faster than both non-accelerated and even accelerated Gauss-Seidel, using *any* fixed partition. Our result thus shows the importance of the sampling strategy and that acceleration cannot make up for a poor choice of sampling distribution.

This finding motivates us to further study the benefits of acceleration under the random coordinate selection model. Interestingly, the benefits are more nuanced under this model. We show that acceleration improves the rate from $O(\mu_{\text{rand}}^{-1} \log(1/\varepsilon))$ to $O\left(\sqrt{\nu \mu_{\text{rand}}^{-1}} \log(1/\varepsilon)\right)$, where ν is

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a new instance dependent quantity that satisfies $\nu \leq \mu_{\text{rand}}^{-1}$. We derive a bound on ν which suggests that if the sub-blocks of A are all well conditioned, then acceleration can provide substantial speedups. We note that this is merely a sufficient condition, and our experiments suggest that our bound is conservative.

In the process of deriving our results, we also develop a general proof framework for randomized accelerated methods based on Wilson et al. (2016) which avoids the use of estimate sequences in favor of an explicit Lyapunov function. Using our proof framework we are able to recover recent results (Nesterov & Stich, 2016; Allen-Zhu et al., 2016) on accelerated coordinate descent. Furthermore, our proof framework allows us to immediately transfer our results on Gauss-Seidel over to the randomized accelerated Kaczmarz algorithm, extending a recent result by Liu and Wright (2016) on updating a single constraint at a time to the block case.

Finally, we empirically demonstrate that despite its theoretical nuances, accelerated Gauss-Seidel using random coordinate selection can provide significant speedups in practical applications over Gauss-Seidel with fixed partition sampling, as well as the classical conjugate-gradient (CG) algorithm. As an example, for a kernel ridge regression (KRR) task in machine learning on the augmented CIFAR-10 dataset ($n = 250,000$), acceleration with random coordinate sampling performs up to $1.5\times$ faster than acceleration with a fixed partitioning to reach an error tolerance of 10^{-2} , with the gap substantially widening for smaller error tolerances. Furthermore, it performs over $3.5\times$ faster than conjugate-gradient on the same task.

2. Background

We assume that we are given an $n \times n$ matrix A which is positive definite, and an n dimensional response vector b . We also fix an integer p which denotes a block size. Under the assumption of A being positive definite, the function $f(x) = \frac{1}{2}x^\top Ax - x^\top b$ is strongly convex and smooth. Recent analysis of Gauss-Seidel (Gower & Richtárik, 2015) proceeds by noting the connection between Gauss-Seidel and (block) coordinate descent on f . This is the point of view we will take in this paper.

2.1. Existing rates for randomized block Gauss-Seidel

We first describe the sketching framework of (Qu et al., 2015; Gower & Richtárik, 2015) and show how it yields rates on Gauss-Seidel when blocks are chosen via a fixed partition or randomly at every iteration. While we will only focus on the special case when the sketch matrix represents column sampling, the sketching framework allows us to provide a unified analysis of both cases.

To be more precise, let \mathcal{D} be a distribution over $\mathbb{R}^{n \times p}$, and let $S_k \sim \mathcal{D}$ be drawn iid from \mathcal{D} . If we perform block coordinate descent by minimizing f along the range of S_k , then the randomized block Gauss-Seidel update is given by

$$x_{k+1} = x_k - S_k(S_k^\top AS_k)^\dagger S_k^\top (Ax_k - b). \quad (1)$$

Column sampling. Every index set $J \subseteq [n]$ with $|J| = p$ induces a sketching matrix $S(J) = (e_{J(1)}, \dots, e_{J(p)})$ where e_i denotes the i -th standard basis vector in \mathbb{R}^n , and $J(1), \dots, J(p)$ is any ordering of the elements of J . By equipping different probability measures on $2^{[n]}$, one can easily describe fixed partition sampling as well as random coordinate sampling (and many other sampling schemes). The former puts uniform mass on the index sets $J_1, \dots, J_{n/p}$, whereas the latter puts uniform mass on all $\binom{n}{p}$ index sets of size p . Furthermore, in the sketching framework there is no limitation to use a uniform distribution, nor is there any limitation to use a fixed p for every iteration. For this paper, however, we will restrict our attention to these cases.

Existing rates. Under the assumptions stated above, (Qu et al., 2015; Gower & Richtárik, 2015) show that for every $k \geq 0$, the sequence (1) satisfies

$$\mathbb{E}[\|x_k - x_*\|_A] \leq (1 - \mu)^{k/2} \|x_0 - x_*\|_A, \quad (2)$$

where $\mu = \lambda_{\min}(\mathbb{E}[P_{A^{1/2}S}])$. The expectation in (2) is taken with respect to the randomness of S_0, S_1, \dots , and the expectation in the definition of μ is taken with respect to $S \sim \mathcal{D}$. Under both fixed partitioning and random coordinate selection, $\mu > 0$ is guaranteed (see e.g. (Gower & Richtárik, 2015), Lemma 4.3). Thus, (1) achieves a linear rate of convergence to the true solution, with the rate governed by the μ quantity shown above.

We now specialize (2) to fixed partitioning and random coordinate sampling, and provide some intuition for why we expect the latter to outperform the former in terms of iteration complexity. We first consider the case when the sampling distribution corresponds to fixed partitioning. Assume for notational convenience that the fixed partitioning corresponds to placing the first p coordinates in the first partition J_1 , the next p coordinates in the second partition J_2 , and so on. Here, $\mu = \mu_{\text{part}}$ corresponds to a measure of how close the product of A with the inverse of the block diagonal is to the identity matrix, defined as

$$\mu_{\text{part}} = \frac{p}{n} \lambda_{\min} \left(A \cdot \text{blkdiag} \left(A_{J_1}^{-1}, \dots, A_{J_{n/p}}^{-1} \right) \right). \quad (3)$$

Above, A_{J_i} denotes the $p \times p$ matrix corresponding to the sub-matrix of A indexed by the i -th partition. A loose lower bound on μ_{part} is

$$\mu_{\text{part}} \geq \frac{p}{n} \frac{\lambda_{\min}(A)}{\max_{1 \leq i \leq n/p} \lambda_{\max}(A_{J_i})}. \quad (4)$$

On the other hand, in the random coordinate case, Qu et al. (2015) derive a lower bound on $\mu = \mu_{\text{rand}}$ as

$$\mu_{\text{rand}} \geq \frac{p}{n} \left(\beta + (1 - \beta) \frac{\max_{1 \leq i \leq n} A_{ii}}{\lambda_{\min}(A)} \right)^{-1}, \quad (5)$$

where $\beta = (p - 1)/(n - 1)$. Using the lower bounds (4) and (5), we can upper bound the iteration complexity of fixed partition Gauss-Seidel N_{part} by $O\left(\frac{n}{p} \frac{\max_{1 \leq i \leq n/p} \lambda_{\max}(A_{J_i})}{\lambda_{\min}(A)} \log(1/\varepsilon)\right)$ and random coordinate Gauss-Seidel N_{rand} as $O\left(\frac{n}{p} \frac{\max_{1 \leq i \leq n} A_{ii}}{\lambda_{\min}(A)} \log(1/\varepsilon)\right)$. Comparing the bound on N_{part} to the bound on N_{rand} , it is not unreasonable to expect that random coordinate sampling has better iteration complexity than fixed partition sampling in certain cases. In Section 3, we verify this by constructing instances A such that fixed partition Gauss-Seidel takes arbitrarily more iterations to reach a pre-specified error tolerance compared with random coordinate Gauss-Seidel.

2.2. Accelerated rates for fixed partition Gauss-Seidel

Based on the interpretation of Gauss-Seidel as block coordinate descent on the function f , we can use Theorem 1 of Nesterov and Stich (2016) to recover a procedure and a rate for accelerating (1) in the fixed partition case; the specific details are discussed in Section A.4.3 of the appendix. We will refer to this procedure as ACDM.

The convergence guarantee of the ACDM procedure is that for all $k \geq 0$,

$$\mathbb{E}[\|x_k - x_*\|_A] \leq O\left(\left(1 - \sqrt{\frac{p}{n} \mu_{\text{part}}}\right)^{k/2} D_0\right). \quad (6)$$

Above, $D_0 = \|x_0 - x_*\|_A$ and μ_{part} is the same quantity defined in (3). Comparing (6) to the non-accelerated Gauss-Seidel rate given in (2), we see that acceleration improves the iteration complexity to reach a solution with ε error from $O(\mu_{\text{part}}^{-1} \log(1/\varepsilon))$ to $O\left(\sqrt{\frac{n}{p} \mu_{\text{part}}^{-1}} \log(1/\varepsilon)\right)$, as discussed in Section 1.

3. Results

We now present the main results of the paper. All proofs are deferred to the appendix.

3.1. Fixed partition vs random coordinate sampling

Our first result is to construct instances where Gauss-Seidel with fixed partition sampling runs arbitrarily slower than random coordinate sampling, even if acceleration is used.

Consider the particular family of $n \times n$ positive definite matrices \mathcal{A} given by $\mathcal{A} = \{A_{\alpha,\beta} : \alpha > 0, \alpha + \beta > 0\}$

with $A_{\alpha,\beta}$ defined as $A_{\alpha,\beta} = \alpha I + \frac{\beta}{n} \mathbf{1}_n \mathbf{1}_n^\top$. The family \mathcal{A} exhibits a crucial property that $\Pi^\top A_{\alpha,\beta} \Pi = A_{\alpha,\beta}$ for every $n \times n$ permutation matrix Π . Lee and Wright (2016) recently exploited this invariance to illustrate the behavior of cyclic versus randomized permutations in coordinate descent.

We explore the behavior of Gauss-Seidel as the matrices $A_{\alpha,\beta}$ become ill-conditioned. To do this, we consider a particular parameterization which holds the minimum eigenvalue equal to one and sends the maximum eigenvalue to infinity via the sub-family $\{A_{1,\beta}\}_{\beta > 0}$. Our first proposition characterizes the behavior of Gauss-Seidel with fixed partitions on this sub-family.

Proposition 3.1. *Fix $\beta > 0$ and positive integers n, p, k such that $n = pk$. Let $\{J_i\}_{i=1}^k$ be any partition of $\{1, \dots, n\}$ with $|J_i| = p$, and denote $S_i \in \mathbb{R}^{n \times p}$ as the column selector for partition J_i . Suppose $S \in \mathbb{R}^{n \times p}$ takes on value S_i with probability $1/k$. For every $A_{1,\beta} \in \mathcal{A}$ we have that*

$$\mu_{\text{part}} = \frac{p}{n + \beta p}. \quad (7)$$

Next, we perform a similar calculation under the random column sampling model.

Proposition 3.2. *Fix $\beta > 0$ and integers n, p such that $1 < p < n$. Suppose each column of $S \in \mathbb{R}^{n \times p}$ is chosen uniformly at random from $\{e_1, \dots, e_n\}$ without replacement. For every $A_{1,\beta} \in \mathcal{A}$ we have that*

$$\mu_{\text{rand}} = \frac{p}{n + \beta p} + \frac{(p-1)\beta p}{(n-1)(n + \beta p)}. \quad (8)$$

The differences between (7) and (8) are striking. Let us assume that β is much larger than n . Then, we have that $\mu_{\text{part}} \approx 1/\beta$ for (7), whereas $\mu_{\text{rand}} \approx \frac{p-1}{n-1}$ for (8). That is, μ_{part} can be made arbitrarily smaller than μ_{rand} as β grows.

Our next proposition states that the rate of Gauss-Seidel from (2) is tight order-wise in that for any instance there always exists a starting point which saturates the bound.

Proposition 3.3. *Let A be an $n \times n$ positive definite matrix, and let S be a random matrix such that $\mu = \lambda_{\min}(\mathbb{E}[P_{A^{1/2}S}]) > 0$. Let x_* denote the solution to $Ax = b$. There exists a starting point $x_0 \in \mathbb{R}^n$ such that the sequence (1) satisfies for all $k \geq 0$,*

$$\mathbb{E}[\|x_k - x_*\|_A] \geq (1 - \mu)^k \|x_0 - x_*\|_A. \quad (9)$$

From (2) we see that Gauss-Seidel using random coordinates computes a solution x_k satisfying $\mathbb{E}[\|x_k - x_*\|_{A_{1,\beta}}] \leq \varepsilon$ in at most $k = O\left(\frac{n}{p} \log(1/\varepsilon)\right)$ iterations. On the other hand, Proposition 3.3 states that for any fixed partition, there exists an input x_0 such that $k = \Omega(\beta \log(1/\varepsilon))$

iterations are required to reach the same ε error tolerance. Furthermore, the situation does not improve even if use ACDM from (Nesterov & Stich, 2016). Proposition 3.6, which we describe later, implies that for any fixed partition there exists an input x_0 such that $k = \Omega\left(\sqrt{\frac{n}{p}}\beta \log(1/\varepsilon)\right)$ iterations are required for ACDM to reach ε error. Hence as $\beta \rightarrow \infty$, the gap between random coordinate and fixed partitioning can be made arbitrarily large. These findings are numerically verified in Section 5.1.

3.2. A Lyapunov analysis of accelerated Gauss-Seidel and Kaczmarz

Motivated by our findings, our goal is to understand the behavior of accelerated Gauss-Seidel under random coordinate sampling. In order to do this, we establish a general framework from which the behavior of accelerated Gauss-Seidel with random coordinate sampling follows immediately, along with rates for accelerated randomized Kaczmarz (Liu & Wright, 2016) and the accelerated coordinate descent methods of (Nesterov & Stich, 2016) and (Allen-Zhu et al., 2016).

For conciseness, we describe a simpler version of our framework which is still able to capture both the Gauss-Seidel and Kaczmarz results, deferring the general version to Section A.3 of the appendix. Our general result requires a bit more notation, but follows the same line of reasoning.

Let H be a random $n \times n$ positive semi-definite matrix. Put $G = \mathbb{E}[H]$, and suppose that G exists and is positive definite. Furthermore, let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be strongly convex and smooth, and let μ denote the strong convexity constant of f w.r.t. the $\|\cdot\|_{G^{-1}}$ norm.

Consider the following sequence $\{(x_k, y_k, z_k)\}_{k \geq 0}$ defined by the recurrence

$$x_{k+1} = \frac{1}{1+\tau}y_k + \frac{\tau}{1+\tau}z_k, \quad (10a)$$

$$y_{k+1} = x_{k+1} - H_k \nabla f(x_{k+1}), \quad (10b)$$

$$z_{k+1} = z_k + \tau(x_{k+1} - z_k) - \frac{\tau}{\mu}H_k \nabla f(x_{k+1}), \quad (10c)$$

where H_0, H_1, \dots are independent realizations of H and τ is a parameter to be chosen. Following (Wilson et al., 2016), we construct a candidate Lyapunov function V_k for the sequence (10) defined as

$$V_k = f(y_k) - f_* + \frac{\mu}{2}\|z_k - x_*\|_{G^{-1}}^2. \quad (11)$$

The following theorem demonstrates that V_k is indeed a Lyapunov function for (x_k, y_k, z_k) .

Theorem 3.4. *Let f, G, H be as defined above. Suppose further that f has 1-Lipschitz gradients w.r.t. the $\|\cdot\|_{G^{-1}}$*

norm, and for every fixed $x \in \mathbb{R}^n$,

$$f(\Phi(x; H)) \leq f(x) - \frac{1}{2}\|\nabla f(x)\|_H^2, \quad (12)$$

holds for a.e. H , where $\Phi(x; H) = x - H\nabla f(x)$. Set τ in (10) as $\tau = \sqrt{\mu/\nu}$, with

$$\nu = \lambda_{\max}\left(\mathbb{E}\left[(G^{-1/2}HG^{-1/2})^2\right]\right).$$

Then for every $k \geq 0$, we have

$$\mathbb{E}[V_k] \leq (1-\tau)^k V_0.$$

We now proceed to specialize Theorem 3.4 to both the Gauss-Seidel and Kaczmarz settings.

3.2.1. ACCELERATED GAUSS-SEIDEL

Let $S \in \mathbb{R}^{n \times p}$ denote a random sketching matrix. As suggested in Section 2, we set $f(x) = \frac{1}{2}x^T Ax - x^T b$ and put $H = S(S^T AS)^\dagger S^T$. Note that $G = \mathbb{E}[S(S^T AS)^\dagger S^T]$ is positive definite iff $\lambda_{\min}(\mathbb{E}[P_{A^{1/2}S}]) > 0$, and is hence satisfied for both fixed partition and random coordinate sampling (c.f. Section 2). Next, the fact that f is 1-Lipschitz w.r.t. the $\|\cdot\|_{G^{-1}}$ norm and the condition (12) are standard calculations detailed in Section A.3.1. All the hypotheses of Theorem 3.4 are thus satisfied, and the conclusion is Theorem 3.5, which characterizes the rate of convergence for accelerated Gauss-Seidel (Algorithm 1).

Algorithm 1 Accelerated randomized block Gauss-Seidel.

Require: $A \in \mathbb{R}^{n \times n}$, $A \succ 0$, $b \in \mathbb{R}^n$, sketching matrices $\{S_k\}_{k=0}^{T-1} \subseteq \mathbb{R}^{n \times p}$, $x_0 \in \mathbb{R}^n$, $\mu \in (0, 1)$, $\nu \geq 1$.

- 1: Set $\tau = \sqrt{\mu/\nu}$.
 - 2: Set $y_0 = z_0 = x_0$.
 - 3: **for** $k = 0, \dots, T-1$ **do**
 - 4: $x_{k+1} = \frac{1}{1+\tau}y_k + \frac{\tau}{1+\tau}z_k$.
 - 5: $H_k = S_k(S_k^T AS_k)^\dagger S_k^T$.
 - 6: $y_{k+1} = x_{k+1} - H_k(Ax_{k+1} - b)$.
 - 7: $z_{k+1} = z_k + \tau(x_{k+1} - z_k) - \frac{\tau}{\mu}H_k(Ax_{k+1} - b)$.
 - 8: **end for**
 - 9: **Return** y_T .
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Theorem 3.5. *Let A be an $n \times n$ positive definite matrix and $b \in \mathbb{R}^n$. Let $x_* \in \mathbb{R}^n$ denote the unique vector satisfying $Ax_* = b$. Suppose each S_k , $k = 0, 1, 2, \dots$ is an independent copy of a random matrix $S \in \mathbb{R}^{n \times p}$. Put $\mu = \lambda_{\min}(\mathbb{E}[P_{A^{1/2}S}])$, and suppose the distribution of S satisfies $\mu > 0$. Invoke Algorithm 1 with μ and ν , where*

$$\nu = \lambda_{\max}\left(\mathbb{E}\left[(G^{-1/2}HG^{-1/2})^2\right]\right), \quad (13)$$

with $H = S(S^T AS)^\dagger S^T$ and $G = \mathbb{E}[H]$. Then with $\tau = \sqrt{\mu/\nu}$, for all $k \geq 0$,

$$\mathbb{E}[\|y_k - x_*\|_A] \leq \sqrt{2}(1-\tau)^{k/2}\|x_0 - x_*\|_A. \quad (14)$$

Note that in the setting of Theorem 3.5, by the definition of ν and μ , it is always the case that $\nu \leq 1/\mu$. Therefore, the iteration complexity of acceleration (Algorithm 1) is at least as good as the iteration complexity without acceleration (Equation 1).

We conclude our discussion of Gauss-Seidel by describing the analogue of Proposition 3.3 for Algorithm 1, which shows that our analysis in Theorem 3.5 is tight order-wise. The following proposition applies to ACDM as well; Section A.4.2 of the appendix shows how ACDM can be viewed as a special case of Algorithm 1.

Proposition 3.6. *Under the setting of Theorem 3.5, there exists starting positions $y_0, z_0 \in \mathbb{R}^n$ such that the iterates $\{(y_k, z_k)\}_{k \geq 0}$ produced by Algorithm 1 satisfy*

$$\mathbb{E}[\|y_k - x_*\|_A + \|z_k - x_*\|_A] \geq (1 - \tau)^k \|y_0 - x_*\|_A.$$

3.2.2. ACCELERATED KACZMARZ

The argument for Theorem 3.5 can be slightly modified to yield a result for randomized accelerated Kaczmarz in the sketching framework, for the case of a consistent overdetermined linear system.

Specifically, suppose we are given an $m \times n$ matrix A which has full column rank, and $b \in \mathcal{R}(A)$. Our goal is to recover the unique x_* satisfying $Ax_* = b$. To do this, we apply a similar line of reasoning as (Lee & Sidford, 2013). We set $f(x) = \frac{1}{2}\|x - x_*\|_2^2$ and $H = P_{A^\top S}$, where S again is our random sketching matrix. At first, it appears our choice of f is problematic since we do not have access to f and ∇f , but a quick calculation shows that $H\nabla f(x) = (S^\top A)^\dagger S^\top (Ax - b)$. Hence, with $r_k = Ax_k - b$, the sequence (10) simplifies to

$$x_{k+1} = \frac{1}{1 + \tau} y_k + \frac{\tau}{1 + \tau} z_k, \quad (15a)$$

$$y_{k+1} = x_{k+1} - (S_k^\top A)^\dagger S_k^\top r_{k+1}, \quad (15b)$$

$$z_{k+1} = z_k + \tau(x_{k+1} - z_k) - \frac{\tau}{\mu} (S_k^\top A)^\dagger S_k^\top r_{k+1}. \quad (15c)$$

The remainder of the argument (Section A.5) proceeds nearly identically, and the conclusion is the following theorem.

Theorem 3.7. *Let A be an $m \times n$ matrix with full column rank, and $b = Ax_*$. Suppose each S_k , $k = 0, 1, 2, \dots$ is an independent copy of a random sketching matrix $S \in \mathbb{R}^{m \times p}$. Put $H = P_{A^\top S}$ and $G = \mathbb{E}[H]$. The sequence (15) with $\mu = \lambda_{\min}(\mathbb{E}[P_{A^\top S}])$, $\nu = \lambda_{\max}(\mathbb{E}[(G^{-1/2} H G^{-1/2})^2])$, and $\tau = \sqrt{\mu/\nu}$ satisfies for all $k \geq 0$,*

$$\mathbb{E}[\|y_k - x_*\|_2] \leq \sqrt{2}(1 - \tau)^{k/2} \|x_0 - x_*\|_2. \quad (16)$$

Specialized to the setting of (Liu & Wright, 2016) where each row of A has unit norm and is sampled uniformly

at every iteration, it can be shown (see Section A.5.1) that $\nu \leq m$ and $\mu = \frac{1}{m} \lambda_{\min}(A^\top A)$. Hence, Theorem 3.7 states that the iteration complexity to reach ε error is $O\left(\frac{m}{\sqrt{\lambda_{\min}(A^\top A)}} \log(1/\varepsilon)\right)$, which matches Theorem 5.1 of (Liu & Wright, 2016) order-wise. On the other hand, Theorem 3.7 applies more generally for any sketching matrix.

3.3. Specializing accelerated Gauss-Seidel to random coordinate sampling

We now instantiate Theorem 3.5 to random coordinate sampling. The μ quantity which appears in Theorem 3.5 is identical to the quantity appearing in the rate (2) of non-accelerated Gauss-Seidel. That is, the iteration complexity to reach tolerance ε is $O\left(\sqrt{\nu \mu_{\text{rand}}^{-1}} \log(1/\varepsilon)\right)$, and the only new term here is ν . In order to provide a more intuitive interpretation of the ν quantity, we present an upper bound on ν in terms of an effective block condition number defined as follows. Given an index set $J \subseteq [n]$, define the effective block condition number of a matrix A as $\kappa_{\text{eff},J}(A) = \frac{\max_{i \in J} A_{ii}}{\lambda_{\min}(A_J)}$. Note that $\kappa_{\text{eff},J}(A) \leq \kappa(A_J)$ always. The following lemma gives upper and lower bounds on the ν quantity.

Lemma 3.8. *Let A be an $n \times n$ positive definite matrix and let p satisfy $1 < p < n$. We have that*

$$\frac{n}{p} \leq \nu \leq \frac{n}{p} \left(\frac{p-1}{n-1} + \left(1 - \frac{p-1}{n-1}\right) \kappa_{\text{eff},p}(A) \right),$$

where $\kappa_{\text{eff},p}(A) = \max_{J \subseteq [n], |J|=p} \kappa_{\text{eff},J}(A)$, ν is defined in (13), and the distribution of S corresponds to uniformly selecting p coordinates without replacement.

Lemma 3.8 states that if the $p \times p$ sub-blocks of A are well-conditioned as defined by the effective block condition number $\kappa_{\text{eff},J}(A)$, then the speed-up of accelerated Gauss-Seidel with random coordinate selection over its non-accelerate counterpart parallels the case of fixed partitioning sampling (i.e. the rate described in (6) versus the rate in (2)). This is a reasonable condition, since very ill-conditioned sub-blocks will lead to numerical instabilities in solving the sub-problems when implementing Gauss-Seidel. On the other hand, we note that Lemma 3.8 provides merely a sufficient condition for speed-ups from acceleration, and is conservative. Our numerical experiments in Section A.7.2 suggest that in many cases the ν parameter behaves closer to the lower bound n/p than Lemma 3.8 suggests. We leave a more thorough theoretical analysis of this parameter to future work.

With Lemma 3.8 in place, we can combine Theorem 3.5 with (5) to derive the following upper bound on the iteration complexity of accelerated Gauss-Seidel with random

coordinates as

$$N_{\text{rand,acc}} \leq O\left(\frac{n}{p} \sqrt{\frac{\max_{1 \leq i \leq n} A_{ii}}{\lambda_{\min}(A)} \kappa_{\text{eff},p}(A) \log(1/\varepsilon)}\right).$$

Illustrative example. We conclude our results by illustrating our bounds on a simple example. Consider the subfamily $\{A_\delta\}_{\delta > 0} \subseteq \mathcal{A}$, with

$$A_\delta = A_{n+\delta, -n}, \quad \delta > 0. \quad (17)$$

A simple calculation yields that $\kappa_{\text{eff},p}(A_\delta) = \frac{n-1+\delta}{n-p+\delta}$, and hence Lemma 3.8 states that $\nu(A_\delta) \leq \frac{n}{p} \left(1 + \frac{p-1}{n-1}\right)$. Furthermore, by a similar calculation to Proposition 3.2, $\mu_{\text{rand}} = \frac{p\delta}{n(n-p+\delta)}$. Assuming for simplicity that $p = o(n)$ and $\delta \in (0, 1)$, Theorem 3.5 states that at most $O\left(\frac{n^{3/2}}{p\sqrt{\delta}} \log(1/\varepsilon)\right)$ iterations are sufficient for an ε -accurate solution. On the other hand, without acceleration (2) states that $O\left(\frac{n^2}{p\delta} \log(1/\varepsilon)\right)$ iterations are sufficient and Proposition 3.3 shows there exists a starting position for which it is necessary. Hence, as either n grows large or δ tends to zero, the benefits of acceleration become more pronounced.

4. Related Work

We split the related work into two broad categories of interest: (a) work related to coordinate descent (CD) methods on convex functions and (b) randomized solvers designed for solving consistent linear systems. See (Kelley, 1995) for classical background on numerical methods for solving linear systems. For a more recent survey on coordinate descent methods in optimization, see (Wright, 2015).

When A is positive definite, Gauss-Seidel can be interpreted as an instance of coordinate descent on a strongly convex quadratic function. We therefore review related work on both non-accelerated and accelerated coordinate descent, focusing on the randomized setting instead of the more classical cyclic order or Gauss-Southwell rule for selecting the next coordinate. See (Tseng & Yun, 2009) for a discussion on non-random selection rules.

Nesterov’s original paper (Nesterov, 2012) first considered randomized CD on convex functions, assuming a partitioning of coordinates fixed ahead of time. The analysis included both non-accelerated and accelerated variants for convex functions. This work sparked a resurgence of interest in CD methods for large scale data analysis. Most relevant to our paper are extensions to the block setting (Richtárik & Takáč, 2014), to handling arbitrary sampling distributions (Qu & Richtárik, 2014a;b; Fountoulakis & Tappenden, 2016), and second order updates for quadratic functions (Qu et al., 2016).

For accelerated CD, Lee and Sidford (2013) generalize the analysis of Nesterov (2012). While the analysis of (Lee &

Sidford, 2013) was limited to selecting a single coordinate at a time, several follow on works (Qu & Richtárik, 2014a; Lin et al., 2014; Lu & Xiao, 2015; Fercoq & Richtárik, 2015) generalize to block and non-smooth settings. More recently, both Allen-Zhu et al. (2016) and Nesterov and Stich (2016) independently improve the results of (Lee & Sidford, 2013) by using a different non-uniform sampling distribution. One of the most notable aspects of the analysis in (Allen-Zhu et al., 2016) is a departure from the (probabilistic) estimate sequence framework of Nesterov (see (Nesterov, 2004) for background on estimate sequences). Instead, the authors of (Allen-Zhu et al., 2016) construct a valid Lyapunov function for coordinate descent, although they do not explicitly mention this. In our work, we make this Lyapunov point of view explicit. The constants we choose in our acceleration updates arise from a particular discretization and Lyapunov function outlined from Wilson et al. (2016). Using this framework makes our proof particularly transparent, and allows us to recover results for strongly convex functions from (Allen-Zhu et al., 2016) and (Nesterov & Stich, 2016) as a special case.

From the numerical analysis side, we focus on the literature for solving consistent systems. Both the Gauss-Seidel and Kaczmarz algorithm are considered classical. Strohmer and Vershynin (2009) were the first to prove a linear rate of convergence for randomized Kaczmarz, and Leventhal and Lewis (2010) provide a similar kind of analysis for randomized Gauss-Seidel. Both (Strohmer & Vershynin, 2009) and (Leventhal & Lewis, 2010) were in the single constraint/coordinate setting. The block setting was later analyzed by Needell and Tropp (2014). More recently, Gower and Richtárik (2015) provide a unified analysis for both randomized block Gauss-Seidel and Kaczmarz in the sketching framework, which we adopt in this paper. Finally, Liu and Wright (2016) provide an accelerated analysis of randomized Kaczmarz once again in the single constraint setting and we extend this to the block setting.

5. Experiments

In this section we experimentally validate our theoretical results on how our accelerated algorithms can improve convergence rates. Our experiments use a combination of synthetic matrices and matrices from large scale machine learning tasks.

Setup. We run all our experiments on a 4 socket Intel Xeon CPU E7-8870 machine with 18 cores per socket and 1TB of DRAM. We implement all our algorithms in Python using `numpy`, and use the Intel MKL library with 72 OpenMP threads for numerical operations. We report errors as relative errors, i.e. $\|x_k - x_*\|_A^2 / \|x_*\|_A^2$. Finally, we use the best values of μ and ν found by tuning each experiment.

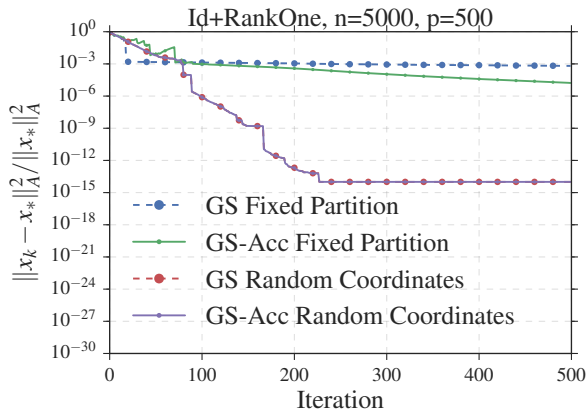


Figure 1. Experiments comparing fixed partitions versus random coordinate sampling for the example from Section 3.1 with $n = 5000$ coordinates, block size $p = 500$.

5.1. Fixed partitioning vs random coordinate sampling

Our first set of experiments numerically verify the separation between fixed partitioning sampling versus random coordinate sampling.

Figure 1 shows the progress per iteration on solving $A_{1,\beta}x = b$, with the $A_{1,\beta}$ defined in Section 3.1. Here we set $n = 5000$, $p = 500$, $\beta = 1000$, and $b \sim N(0, I)$. Figure 1 verifies our analytical findings in Section 3.1, that the fixed partition scheme is substantially worse than uniform sampling on this instance. It also shows that in this case, acceleration provides little benefit in the case of random coordinate sampling. This is because both μ and $1/\nu$ are order-wise p/n , and hence the rate for accelerated and non-accelerated coordinate descent coincide. However we note that this only applies for matrices where μ is as large as it can be (i.e. p/n), that is instances for which Gauss-Seidel is already converging at the optimal rate (see (Gower & Richtárik, 2015), Lemma 4.2).

5.2. Kernel ridge regression

We next evaluate how fixed partitioning and random coordinate sampling affects the performance of Gauss-Seidel on large scale machine learning tasks. To do this we use the popular image classification datasets CIFAR-10. The task we evaluate is kernel ridge regression (KRR) with a Gaussian kernel. Specifically, given a labeled dataset $\{(x_i, y_i)\}_{i=1}^n$, we solve the linear system $(K + \lambda I)\alpha = Y$ with $K_{ij} = \exp(-\gamma \|x_i - x_j\|_2^2)$, where $\lambda, \gamma > 0$ are tunable parameters. The key property of kernel ridge regression is that the kernel matrix K is always positive semi-definite, and hence Algorithm 1 applies.

For the CIFAR-10 dataset, we augment the dataset¹ to in-

¹Similar to <https://github.com/akrizhevsky/cuda-convnet2>.

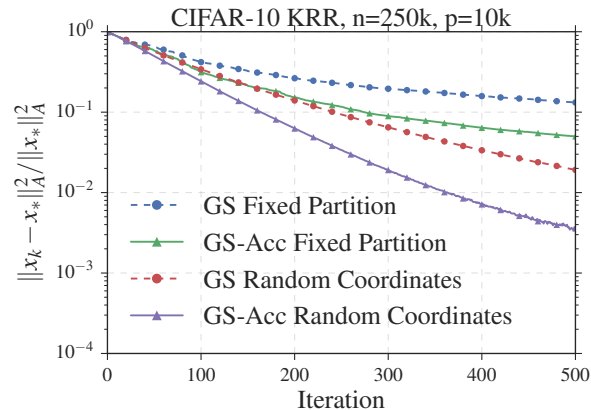


Figure 2. Experiments comparing fixed partitions versus uniform random sampling for CIFAR-10 augmented matrix while running kernel ridge regression. CIFAR-10 augmented matrix has $n = 250000$ coordinates and we set block size to $p = 10000$.

clude five reflections, translations per-image and then apply standard pre-processing steps used in image classification (Coates & Ng, 2012; Sparks et al., 2017). We finally apply a Gaussian kernel on our pre-processed images and the resulting kernel matrix has $n = 250000$ coordinates. We also include experiments on a smaller MNIST kernel matrix ($n = 60000$) in Section A.7.

Results from running 500 iterations of random coordinate sampling and fixed partitioning algorithms are shown in Figure 2. Comparing convergence across iterations, similar to previous section, we see that un-accelerated Gauss-Seidel with random coordinate sampling is better than accelerated Gauss-Seidel with fixed partitioning. However we also see that using acceleration with random sampling can further improve the convergence rates, especially to achieve errors of 10^{-3} or lower.

We also compare the convergence with respect to running time in Figure 3. Fixed partitioning has better performance in practice random access is expensive in multi-core systems. Furthermore, the partitions can be computed once and cached across iterations. However, we see that this speedup in implementation comes at a substantial cost in terms of convergence rate. For example in the case of CIFAR-10, using fixed partitions leads to an error of 1.2×10^{-2} after around 7000 seconds. In comparison we see that random coordinate sampling achieves a similar error in around 4500 seconds and is thus $1.5\times$ faster. We also note that this speedup increases for lower error tolerances.

5.3. Comparing Gauss-Seidel to Conjugate-Gradient

We also compared Gauss-Seidel with random coordinate sampling to the classical conjugate-gradient (CG) algorithm. CG is an important baseline to compare with, as

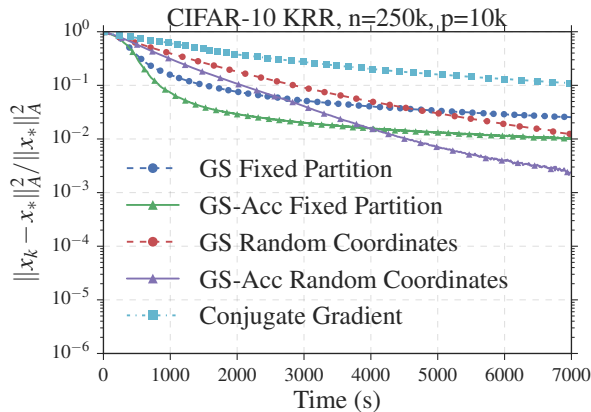


Figure 3. Experiments comparing conjugate gradient with accelerated and un-accelerated Gauss-Seidel methods for CIFAR-10 augmented matrix while running kernel ridge regression. CIFAR-10 augmented matrix has $n = 250000$ coordinates and we set block size to $p = 10000$.

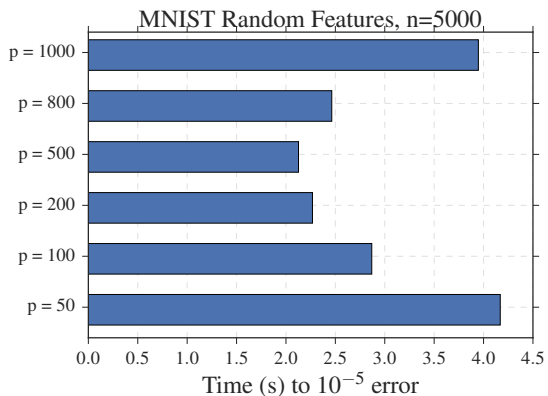


Figure 4. The effect of block size on the accelerated Gauss-Seidel method. For the MNIST dataset (pre-processed using random features) we see that block size of $p = 500$ works best.

it is the de-facto standard iterative algorithm for solving linear systems in the numerical analysis community. The results of our experiment are shown in Figure 3. We note that Gauss-Seidel both with and without acceleration outperform CG. As an example, we note that to reach error 10^{-1} on CIFAR-10, CG takes roughly 7000 seconds, compared to less than 2000 seconds for accelerated Gauss-Seidel, which is a $3.5\times$ improvement.

To understand this performance difference, we recall that our matrices A are fully dense, and hence each iteration of CG takes $O(n^2)$. On the other hand, each iteration of both non-accelerated and accelerated Gauss-Seidel takes $O(np^2 + p^3)$. Hence, as long as $p = O(n^{2/3})$, the time per iteration of Gauss-Seidel is order-wise no worse than CG. In terms of iteration complexity, standard results state that CG takes at most $O(\sqrt{\kappa} \log(1/\varepsilon))$ iterations to reach an ε error solution, where κ denotes the condition num-

ber of A . On the other hand, Gauss-Seidel takes at most $O(\frac{n}{p} \kappa_{\text{eff}} \log(1/\varepsilon))$, where $\kappa_{\text{eff}} = \frac{\max_{1 \leq i \leq n} A_{ii}}{\lambda_{\min}(A)}$. In the case of any (normalized) kernel matrix associated with a translation-invariant kernel such as the Gaussian kernel, we have $\max_{1 \leq i \leq n} A_{ii} = 1$, and hence generally speaking κ_{eff} is much lower than κ .

5.4. Effect of block size

We next analyze the importance of the block size p for the accelerated Gauss-Seidel method. As the values of μ and ν change for each setting of p , we use a smaller MNIST matrix for this experiment. We apply a random feature transformation (Rahimi & Recht, 2007) to generate an $n \times d$ matrix F with $d = 5000$ features. We then use $A = F^T F$ and $b = F^T Y$ as inputs to the algorithm. Figure 4 shows the wall clock time to converge to 10^{-5} error as we vary the block size from $p = 50$ to $p = 1000$.

Increasing the block-size improves the amount of progress that is made per iteration but the time taken per iteration increases as $O(p^3)$ (Line 5, Algorithm 1). However, using efficient BLAS-3 primitives usually affords a speedup from systems techniques like cache blocking. We see the effects of this in Figure 4 where using $p = 500$ performs better than using $p = 50$. We also see that these benefits reduce for much larger block sizes and thus $p = 1000$ is slower.

6. Conclusion

In this paper, we extended the accelerated block Gauss-Seidel algorithm beyond fixed partition sampling. Our analysis introduced a new data-dependent parameter ν which governs the speed-up of acceleration under more general sampling schemes. Specializing our theory to random coordinate sampling, we derived an upper bound on ν which shows that well conditioned blocks are a sufficient condition to ensure speedup. Experimentally, we showed that block Gauss-Seidel with random coordinate sampling is readily accelerated beyond what our bound suggests.

The most obvious question remains to derive a sharper bound on the ν constant from Theorem 3.5. Another interesting question is whether or not the iteration complexity of random coordinate sampling is always bounded above by the iteration complexity with fixed coordinate sampling.

In the future, we also plan to study a practical implementation of accelerated Gauss-Seidel in a distributed setting, in the style of Tu et al. (2016). The main challenges here are in determining how to sample coordinates efficiently without significant communication overheads, and to efficiently estimate the μ and ν parameters. We plan to explore if other sampling schemes such as shuffling the coordinates at the end of every epoch (Recht & Ré, 2013) can be used.

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Supplementary Material

A.1. Preliminaries

Notation. The notation is standard. $[n] = \{1, 2, \dots, n\}$ refers to the set of integers from 1 to n , and $2^{[n]}$ refers to the set of all subsets of $[n]$. We let $\mathbf{1}_n \in \mathbb{R}^n$ denote the vector of all ones. Given a square matrix M with real eigenvalues, we let $\lambda_{\max}(M)$ (resp. $\lambda_{\min}(M)$) denote the maximum (resp. minimum) eigenvalue of M . For two symmetric matrices M, N , the notation $M \succcurlyeq N$ (resp. $M \succ N$) means that the matrix $M - N$ is positive semi-definite (resp. positive definite). Every such $M \succ 0$ defines a real inner product space via the inner product $\langle x, y \rangle_M = x^\top M y$. We refer to its induced norm as $\|x\|_M = \sqrt{\langle x, x \rangle_M}$. The standard Euclidean inner product and norm will be denoted as $\langle \cdot, \cdot \rangle$ and $\|\cdot\|_2$, respectively. For an arbitrary matrix M , we let M^\dagger denote its Moore-Penrose pseudo-inverse and P_M the orthogonal projector onto the range of M , which we denote as $\mathcal{R}(M)$. When $M \succcurlyeq 0$, we let $M^{1/2}$ denote its unique Hermitian square root. Finally, for a square $n \times n$ matrix M , $\text{diag}(M)$ is the $n \times n$ diagonal matrix which contains the diagonal elements of M .

Partitions on $[n]$. In what follows, unless stated otherwise, whenever we discuss a partition of $[n]$ we assume that the partition is given by $\bigcup_{i=1}^{n/p} J_i$, where

$$J_1 = \{1, 2, \dots, p\}, \quad J_2 = \{p+1, p+2, \dots, 2p\}, \quad \dots$$

This is without loss of generality because for any arbitrary equal sized partition of $[n]$, there exists a permutation matrix Π such that all our results apply by the change of variables $A \leftarrow \Pi^\top A \Pi$ and $b \leftarrow \Pi^\top b$.

A.2. Proofs for Separation Results (Section 3.1)

A.2.1. Expectation calculations (Propositions 3.1 and 3.2)

Recall the family of $n \times n$ positive definite matrices \mathcal{A} defined in (17) as

$$A_{\alpha, \beta} = \alpha I + \frac{\beta}{n} \mathbf{1}_n \mathbf{1}_n^\top, \quad \alpha > 0, \alpha + \beta > 0. \quad (18)$$

We first gather some elementary formulas. By the matrix inversion lemma,

$$A_{\alpha, \beta}^{-1} = \left(\alpha I + \frac{\beta}{n} \mathbf{1}_n \mathbf{1}_n^\top \right)^{-1} = \alpha^{-1} I - \frac{\beta/n}{\alpha(\alpha + \beta)} \mathbf{1}_n \mathbf{1}_n^\top. \quad (19)$$

Furthermore, let $S \in \mathbb{R}^{n \times p}$ be any column selector matrix with no duplicate columns. We have again by the matrix inversion lemma

$$(S^\top A_{\alpha, \beta} S)^{-1} = \left(\alpha I + \frac{\beta}{n} \mathbf{1}_p \mathbf{1}_p^\top \right)^{-1} = \alpha^{-1} I - \frac{\beta/n}{\alpha(\alpha + \beta p/n)} \mathbf{1}_p \mathbf{1}_p^\top. \quad (20)$$

The fact that the right hand side is independent of S is the key property which makes our calculations possible. Indeed, we have that

$$S(S^\top A_{\alpha, \beta} S)^{-1} S^\top = \alpha^{-1} S S^\top - \frac{\beta/n}{\alpha(\alpha + \beta p/n)} S \mathbf{1}_p \mathbf{1}_p^\top S^\top. \quad (21)$$

With these formulas in hand, our next proposition gathers calculations for the case when S represents uniformly choosing p columns without replacement.

Proposition A.2.1. Consider the family of $n \times n$ positive definite matrices $\{A_{\alpha,\beta}\}$ from (18). Fix any integer p such that $1 < p < n$. Let $S \in \mathbb{R}^{n \times p}$ denote a random column selector matrix where each column of S is chosen uniformly at random without replacement from $\{e_1, \dots, e_n\}$. For any $A_{\alpha,\beta}$,

$$\mathbb{E}[S(S^\top A_{\alpha,\beta} S)^{-1} S^\top A_{\alpha,\beta}] = p \frac{(n-1)\alpha + (p-1)\beta}{(n-1)(n\alpha + p\beta)} I + \frac{(n-p)p\beta}{n(n-1)(n\alpha + p\beta)} \mathbf{1}_n \mathbf{1}_n^\top, \quad (22)$$

$$\begin{aligned} \mathbb{E}[S(S^\top A_{\alpha,\beta} S)^{-1} S^\top G_{\alpha,\beta}^{-1} S(S^\top A_{\alpha,\beta} S)^{-1} S^\top] &= \left(\frac{1}{\alpha} - \frac{(n-p)^2\beta}{(n-1)((n-1)\alpha + (p-1)\beta)(n\alpha + p\beta)} \right) I \\ &+ \frac{(p-1)\beta(n\alpha(1-2n) + np(\alpha - \beta) + p\beta)}{(n-1)n\alpha((n-1)\alpha + (p-1)\beta)(n\alpha + p\beta)} \mathbf{1}_n \mathbf{1}_n^\top. \end{aligned} \quad (23)$$

Above, $G_{\alpha,\beta} = \mathbb{E}[S(S^\top A_{\alpha,\beta} S)^{-1} S^\top]$.

Proof. First, we have the following elementary expectation calculations,

$$\mathbb{E}[SS^\top] = \frac{p}{n} I, \quad (24)$$

$$\mathbb{E}[S \mathbf{1}_p \mathbf{1}_p^\top S^\top] = \frac{p}{n} \left(1 - \frac{p-1}{n-1} \right) I + \frac{p}{n} \left(\frac{p-1}{n-1} \right) \mathbf{1}_n \mathbf{1}_n^\top, \quad (25)$$

$$\mathbb{E}[SS^\top \mathbf{1}_n \mathbf{1}_n^\top S^\top] = \mathbb{E}[S \mathbf{1}_p \mathbf{1}_n^\top S^\top] = \mathbb{E}[SS^\top \mathbf{1}_n \mathbf{1}_n^\top S^\top] = \mathbb{E}[S \mathbf{1}_p \mathbf{1}_p^\top S^\top], \quad (26)$$

$$\mathbb{E}[S \mathbf{1}_p \mathbf{1}_p^\top S^\top \mathbf{1}_n \mathbf{1}_n^\top S \mathbf{1}_p \mathbf{1}_p^\top S^\top] = \frac{p^3}{n} \left(1 - \frac{p-1}{n-1} \right) I + \frac{p^3}{n} \left(\frac{p-1}{n-1} \right) \mathbf{1}_n \mathbf{1}_n^\top. \quad (27)$$

To compute $G_{\alpha,\beta}$, we simply plug (24) and (25) into (21). After simplification,

$$G_{\alpha,\beta} = \mathbb{E}[S(S^\top A_{\alpha,\beta} S)^{-1} S^\top] = \frac{p}{\alpha n} \left(1 - \frac{\beta/n}{\alpha + \beta p/n} \left(1 - \frac{p-1}{n-1} \right) \right) I - \frac{p}{n} \frac{p-1}{n-1} \frac{\beta/n}{\alpha(\alpha + \beta p/n)} \mathbf{1}_n \mathbf{1}_n^\top.$$

From this formula for $G_{\alpha,\beta}$, (22) follows immediately.

Our next goal is to compute $\mathbb{E}[S(S^\top A_{\alpha,\beta} S)^{-1} S^\top G_{\alpha,\beta}^{-1} S(S^\top A_{\alpha,\beta} S)^{-1} S^\top]$. To do this, we first invert $G_{\alpha,\beta}$. Applying the matrix inversion lemma, we can write down a formula for the inverse of $G_{\alpha,\beta}$,

$$G_{\alpha,\beta}^{-1} = \underbrace{\frac{(n-1)\alpha(n\alpha + p\beta)}{(n-1)p\alpha + (p-1)p\beta}}_{\gamma} I + \underbrace{\frac{(p-1)\beta(n\alpha + p\beta)}{np((n-1)\alpha + (p-1)\beta)}}_{\eta} \mathbf{1}_n \mathbf{1}_n^\top. \quad (28)$$

Next, we note for any r, q , using the properties that $S^\top S = I$, $\mathbf{1}_n^\top S \mathbf{1}_p = p$, and $\mathbf{1}_p^\top \mathbf{1}_p = p$, we have that

$$\begin{aligned} &(rSS^\top + qS \mathbf{1}_p \mathbf{1}_p^\top S^\top)(\gamma I + \eta \mathbf{1}_n \mathbf{1}_n^\top)(rSS^\top + qS \mathbf{1}_p \mathbf{1}_p^\top S^\top) \\ &= \gamma r^2 SS^\top + 2r\gamma q S \mathbf{1}_p \mathbf{1}_p^\top S^\top + \eta r^2 SS^\top \mathbf{1}_n \mathbf{1}_n^\top SS^\top \\ &\quad + pr\eta q (SS^\top \mathbf{1}_n \mathbf{1}_p^\top S^\top + S \mathbf{1}_p \mathbf{1}_n^\top SS^\top) + pq^2 \gamma S \mathbf{1}_p \mathbf{1}_p^\top S^\top \\ &\quad + \eta q^2 S \mathbf{1}_p \mathbf{1}_p^\top S^\top \mathbf{1}_n \mathbf{1}_n^\top S \mathbf{1}_p \mathbf{1}_p^\top S^\top. \end{aligned}$$

Taking expectations of both sides of the above equation and using the formulas in (24), (25), (26), and (27),

$$\begin{aligned} &\mathbb{E}[(rSS^\top + qS \mathbf{1}_p \mathbf{1}_p^\top S^\top)(\gamma I + \eta \mathbf{1}_n \mathbf{1}_n^\top)(rSS^\top + qS \mathbf{1}_p \mathbf{1}_p^\top S^\top)] \\ &= \frac{p(p(n-p)q^2 + 2(n-p)qr + (n-1)r^2)\gamma + p(n-p)(pq+r)^2\eta}{n(n-1)} I \\ &\quad + \frac{p(p-1)(q(pq+2r)\gamma + (pq+r)^2\eta)}{n(n-1)} \mathbf{1}_n \mathbf{1}_n^\top. \end{aligned}$$

We now set $r = \alpha^{-1}$, $q = -\frac{\beta/n}{\alpha(\alpha + \beta p/n)}$, and γ, η from (28) to reach the desired formula for (23). \square

Proposition 3.2 follows immediately from Proposition A.2.1 by plugging in $\alpha = 1$ into (22). We next consider how (21) behaves under a fixed partition of $\{1, \dots, n\}$. Recall our assumption on partitions: $n = pk$ for some integer $k \geq 1$, and we sequentially partition $\{1, \dots, n\}$ into k partitions of size p , i.e. $J_1 = \{1, \dots, p\}$, $J_2 = \{p+1, \dots, 2p\}$, and so on. Define $S_1, \dots, S_k \in \mathbb{R}^{n \times p}$ such that S_i is the column selector matrix for the partition J_i , and S uniformly chooses S_i with probability $1/k$.

Proposition A.2.2. *Consider the family of $n \times n$ positive definite matrices $\{A_{\alpha, \beta}\}$ from (18), and let n , p , and S be described as in the preceding paragraph. We have that*

$$\mathbb{E}[S(S^\top A_{\alpha, \beta} S)^{-1} S^\top A_{\alpha, \beta}] = \frac{p}{n} I + \frac{p\beta}{n^2\alpha + np\beta} \mathbf{1}_n \mathbf{1}_n^\top - \frac{p\beta}{n^2\alpha + np\beta} \text{blkdiag}(\underbrace{\mathbf{1}_p \mathbf{1}_p^\top, \dots, \mathbf{1}_p \mathbf{1}_p^\top}_{k \text{ times}}). \quad (29)$$

Proof. Once again, the expectation calculations are

$$\mathbb{E}[SS^\top] = \frac{p}{n} I, \quad \mathbb{E}[S \mathbf{1}_p \mathbf{1}_p^\top S^\top] = \frac{p}{n} \text{blkdiag}(\underbrace{\mathbf{1}_p \mathbf{1}_p^\top, \dots, \mathbf{1}_p \mathbf{1}_p^\top}_{k \text{ times}}).$$

Therefore,

$$\mathbb{E}[S(S^\top A_{\alpha, \beta} S)^{-1} S^\top] = \frac{p}{\alpha n} I - \frac{p}{n} \frac{\beta/n}{\alpha(\alpha + \beta p/n)} \text{blkdiag}(\mathbf{1}_p \mathbf{1}_p^\top, \dots, \mathbf{1}_p \mathbf{1}_p^\top).$$

Furthermore,

$$\text{blkdiag}(\mathbf{1}_p \mathbf{1}_p^\top, \dots, \mathbf{1}_p \mathbf{1}_p^\top) \mathbf{1}_n \mathbf{1}_n^\top = \mathbf{1}_n \mathbf{1}_n^\top \text{blkdiag}(\mathbf{1}_p \mathbf{1}_p^\top, \dots, \mathbf{1}_p \mathbf{1}_p^\top) = p \mathbf{1}_n \mathbf{1}_n^\top,$$

Hence, the formula for $\mathbb{E}[S(S^\top A_{\alpha, \beta} S)^{-1} S^\top A_{\alpha, \beta}]$ follows. \square

We now make the following observation. Let Q_1, \dots, Q_k be any partition of $\{1, \dots, n\}$ into k partitions of size p . Let $\mathbb{E}_{S \sim Q_i}$ denote expectation with respect to S uniformly chosen as column selectors among Q_1, \dots, Q_k , and let $\mathbb{E}_{S \sim J_i}$ denote expectation with respect to the S in the setting of Proposition A.2.2. It is not hard to see there exists a permutation matrix Π such that

$$\Pi^\top \mathbb{E}_{S \sim Q_i} [S(S^\top A_{\alpha, \beta} S)^{-1} S^\top] \Pi = \mathbb{E}_{S \sim J_i} [S(S^\top A_{\alpha, \beta} S)^{-1} S^\top].$$

Using this permutation matrix Π ,

$$\begin{aligned} \lambda_{\min}(\mathbb{E}_{S \sim Q_i} [P_{A_{\alpha, \beta} S}^{1/2}]) &= \lambda_{\min}(\mathbb{E}_{S \sim Q_i} [S(S^\top A_{\alpha, \beta} S)^{-1} S^\top] A_{\alpha, \beta}) \\ &= \lambda_{\min}(\mathbb{E}_{S \sim Q_i} [S(S^\top A_{\alpha, \beta} S)^{-1} S^\top] \Pi A_{\alpha, \beta} \Pi^\top) \\ &= \lambda_{\min}(\Pi^\top \mathbb{E}_{S \sim Q_i} [S(S^\top A_{\alpha, \beta} S)^{-1} S^\top] \Pi A_{\alpha, \beta}) \\ &= \lambda_{\min}(\mathbb{E}_{S \sim J_i} [S(S^\top A_{\alpha, \beta} S)^{-1} S^\top] A_{\alpha, \beta}) \\ &= \lambda_{\min}(\mathbb{E}_{S \sim J_i} [P_{A_{\alpha, \beta} S}^{1/2}]). \end{aligned}$$

Above, the second equality holds because $A_{\alpha, \beta}$ is invariant under a similarity transform by any permutation matrix. Therefore, Proposition A.2.2 yields the μ_{part} value for every partition Q_1, \dots, Q_k . The claim of Proposition 3.1 now follows by substituting $\alpha = 1$ into (29).

A.2.2. Proof of Proposition 3.3

Define $e_k = x_k - x_*$, $H_k = S_k(S_k^\top A S_k)^\dagger S_k^\top$ and $G = \mathbb{E}[H_k]$. From the update rule (1),

$$e_{k+1} = (I - H_k A) e_k \implies A^{1/2} e_{k+1} = (I - A^{1/2} H_k A^{1/2}) A^{1/2} e_k.$$

Taking and iterating expectations,

$$\mathbb{E}[A^{1/2} e_{k+1}] = (I - A^{1/2} G A^{1/2}) \mathbb{E}[A^{1/2} e_k].$$

Unrolling this recursion yields for all $k \geq 0$,

$$\mathbb{E}[A^{1/2}e_k] = (I - A^{1/2}GA^{1/2})^k A^{1/2}e_0.$$

Choose $A^{1/2}e_0 = v$, where v is an eigenvector of $I - A^{1/2}GA^{1/2}$ with eigenvalue $\lambda_{\max}(I - A^{1/2}GA^{1/2}) = 1 - \lambda_{\min}(GA) = 1 - \mu$. Now by Jensen's inequality,

$$\mathbb{E}[\|e_k\|_A] = \mathbb{E}[\|A^{1/2}e_k\|_2] \geq \|\mathbb{E}[A^{1/2}e_k]\|_2 = (1 - \mu)^k \|e_0\|_A.$$

This establishes the claim.

A.3. Proofs for Convergence Results (Section 3.2)

We now state our main structural result for accelerated coordinate descent. Let \mathbb{P} be a probability measure on $\Omega = \mathcal{S}^{n \times n} \times \mathbb{R}_+ \times \mathbb{R}_+$, with $\mathcal{S}^{n \times n}$ denoting $n \times n$ positive semi-definite matrices and \mathbb{R}_+ denoting positive reals. Write $\omega \in \Omega$ as the tuple $\omega = (H, \Gamma, \gamma)$, and let \mathbb{E} denote expectation with respect to \mathbb{P} . Suppose that $G = \mathbb{E}[\frac{1}{\gamma}H]$ exists and is positive definite.

Now suppose that $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is a differentiable and strongly convex function, and put $f_* = \min_x f(x)$, with x_* attaining the minimum value. Suppose that f is both μ -strongly convex and has L -Lipschitz gradients with respect to the G^{-1} norm. This means that for all $x, y \in \mathbb{R}^n$, we have

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2} \|y - x\|_{G^{-1}}^2, \quad (30a)$$

$$f(y) \leq f(x) + \langle \nabla f(x), y - x \rangle + \frac{L}{2} \|y - x\|_{G^{-1}}^2. \quad (30b)$$

We now define a random sequence as follows. Let $\omega_0 = (H_0, \Gamma_0, \gamma_0), \omega_1 = (H_1, \Gamma_1, \gamma_1), \dots$ be independent realizations from \mathbb{P} . Starting from $y_0 = z_0 = x_0$ with x_0 fixed, consider the sequence $\{(x_k, y_k, z_k)\}_{k \geq 0}$ defined by the recurrence

$$\tau(x_{k+1} - z_k) = y_k - x_{k+1}, \quad (31a)$$

$$y_{k+1} = x_{k+1} - \frac{1}{\Gamma_k} H_k \nabla f(x_{k+1}), \quad (31b)$$

$$z_{k+1} - z_k = \tau \left(x_{k+1} - z_k - \frac{1}{\mu \gamma_k} H_k \nabla f(x_{k+1}) \right). \quad (31c)$$

It is easily verified that $(x, y, z) = (x_*, x_*, x_*)$ is a fixed point of the aforementioned dynamical system. Our goal for now is to describe conditions on f , μ , and τ such that the sequence of updates (31a), (31b), and (31c) converges to this fixed point. As described in Wilson et al. (2016), our main strategy for proving convergence will be to introduce the following Lyapunov function

$$V_k = f(y_k) - f_* + \frac{\mu}{2} \|z_k - x_*\|_{G^{-1}}^2, \quad (32)$$

and show that V_k decreases along every trajectory. We let \mathbb{E}_k denote the expectation conditioned on $\mathcal{F}_k = \sigma(\omega_0, \omega_1, \dots, \omega_{k-1})$. Observe that x_{k+1} is \mathcal{F}_k -measurable, a fact we will use repeatedly throughout our calculations. With the preceding definitions in place, we state and prove our main structural theorem.

Theorem A.3.1. (Generalization of Theorem 3.4.) *Let f and G be as defined above, with f satisfying μ -strongly convexity and L -Lipschitz gradients with respect to the $\|\cdot\|_{G^{-1}}$ norm, as defined in (30a) and (30b). Suppose that for all fixed $x \in \mathbb{R}^n$, we have that the following holds for almost every $\omega \in \Omega$,*

$$f(\Phi(x; \omega)) \leq f(x) - \frac{1}{2\Gamma} \|\nabla f(x)\|_H^2, \quad \Phi(x; \omega) = x - \frac{1}{\Gamma} H \nabla f(x). \quad (33)$$

Furthermore, suppose that $\nu > 0$ satisfies

$$\mathbb{E} \left[\frac{1}{\gamma^2} H G^{-1} H \right] \preceq \nu \mathbb{E} \left[\frac{1}{\gamma^2} H \right]. \quad (34)$$

Then as long as we set $\tau > 0$ such that τ satisfies for almost every $\omega \in \Omega$,

$$\tau \leq \frac{\gamma}{\sqrt{\Gamma}} \sqrt{\frac{\mu}{\nu}}, \quad \tau \leq \sqrt{\frac{\mu}{L}}, \quad (35)$$

we have that V_k defined in (32) satisfies for all $k \geq 0$,

$$\mathbb{E}_k[V_{k+1}] \leq (1 - \tau)V_k. \quad (36)$$

Proof. First, recall the following two point equality valid for any vectors $a, b, c \in V$ in a real inner product space V ,

$$\|a - b\|_V^2 - \|c - b\|_V^2 = \|a - c\|_V^2 + 2\langle a - c, c - b \rangle_V. \quad (37)$$

Now we can proceed with our analysis,

$$\begin{aligned} V_{k+1} - V_k &\stackrel{(37)}{=} f(y_{k+1}) - f(y_k) - \mu \langle z_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} + \frac{\mu}{2} \|z_{k+1} - z_k\|_{G^{-1}}^2 \\ &= f(y_{k+1}) - f(x_{k+1}) + f(x_{k+1}) - f(y_k) - \mu \langle z_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} + \frac{\mu}{2} \|z_{k+1} - z_k\|_{G^{-1}}^2 \\ &\stackrel{(30a)}{\leq} f(y_{k+1}) - f(x_{k+1}) + \langle \nabla f(x_{k+1}), x_{k+1} - y_k \rangle - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 \\ &\quad - \mu \langle z_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} + \frac{\mu}{2} \|z_{k+1} - z_k\|_{G^{-1}}^2 \end{aligned} \quad (38a)$$

$$\begin{aligned} &\stackrel{(31c)}{=} f(y_{k+1}) - f(x_{k+1}) + \langle \nabla f(x_{k+1}), x_{k+1} - y_k \rangle - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 \\ &\quad + \tau \langle \frac{1}{\gamma_k} H_k \nabla f(x_{k+1}) - \mu(x_{k+1} - z_k), x_* - z_k \rangle_{G^{-1}} + \frac{\mu}{2} \|z_{k+1} - z_k\|_{G^{-1}}^2 \end{aligned} \quad (38b)$$

$$\begin{aligned} &= f(y_{k+1}) - f(x_{k+1}) + \langle \nabla f(x_{k+1}), x_{k+1} - y_k \rangle - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 \\ &\quad + \tau \langle \frac{1}{\gamma_k} H_k \nabla f(x_{k+1}), x_* - x_{k+1} \rangle_{G^{-1}} + \tau \langle \frac{1}{\gamma_k} H_k \nabla f(x_{k+1}), x_{k+1} - z_k \rangle_{G^{-1}} \\ &\quad - \tau \mu \langle x_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} + \frac{\mu}{2} \|z_{k+1} - z_k\|_{G^{-1}}^2 \\ &\stackrel{(31c)}{=} f(y_{k+1}) - f(x_{k+1}) + \langle \nabla f(x_{k+1}), x_{k+1} - y_k \rangle - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 \\ &\quad + \tau \langle \frac{1}{\gamma_k} H_k \nabla f(x_{k+1}), x_* - x_{k+1} \rangle_{G^{-1}} + \tau \langle \frac{1}{\gamma_k} H_k \nabla f(x_{k+1}), x_{k+1} - z_k \rangle_{G^{-1}} \\ &\quad - \tau \mu \langle x_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} + \frac{\mu}{2} \|\tau(x_{k+1} - z_k)\|_{G^{-1}}^2 + \frac{\tau^2}{2\mu\gamma_k^2} \|H_k \nabla f(x_{k+1})\|_{G^{-1}}^2 \\ &\quad - \tau \langle x_{k+1} - z_k, \tau \frac{1}{\gamma_k} H_k \nabla f(x_{k+1}) \rangle_{G^{-1}} \end{aligned} \quad (38c)$$

$$\begin{aligned} &\stackrel{(33)}{\leq} -\frac{1}{2\Gamma_k} \|\nabla f(x_{k+1})\|_{H_k}^2 + \langle \nabla f(x_{k+1}), x_{k+1} - y_k \rangle - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 \\ &\quad + \tau \langle \frac{1}{\gamma_k} H_k \nabla f(x_{k+1}), x_* - x_{k+1} \rangle_{G^{-1}} + \tau \langle \frac{1}{\gamma_k} H_k \nabla f(x_{k+1}), x_{k+1} - z_k \rangle_{G^{-1}} \\ &\quad - \tau \mu \langle x_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} + \frac{\mu}{2} \|\tau(x_{k+1} - z_k)\|_{G^{-1}}^2 + \frac{\tau^2}{2\mu\gamma_k^2} \|H_k \nabla f(x_{k+1})\|_{G^{-1}}^2 \\ &\quad - \tau \langle x_{k+1} - z_k, \tau \frac{1}{\gamma_k} H_k \nabla f(x_{k+1}) \rangle_{G^{-1}}. \end{aligned} \quad (38d)$$

Above, (38a) follows from μ -strong convexity, (38b) and (38c) both use the definition of the update sequence given in (31), and (38d) follows using the gradient inequality assumption (33). Now letting $x \in \mathbb{R}^n$ be fixed, we observe that

$$\begin{aligned} \mathbb{E} \left[\frac{\tau^2}{2\mu\gamma^2} \nabla f(x)^\top H G^{-1} H \nabla f(x) - \frac{1}{2\Gamma} \|\nabla f(x)\|_H^2 \right] &\stackrel{(34)}{\leq} \mathbb{E} \left[\left(\frac{\tau^2 \nu}{2\mu\gamma^2} - \frac{1}{2\Gamma} \right) \|\nabla f(x)\|_H^2 \right] \\ &\stackrel{(35)}{\leq} 0. \end{aligned} \quad (39)$$

The first inequality uses the assumption on ν , and the second inequality uses the requirement that $\tau \leq \frac{\gamma}{\sqrt{\Gamma}} \sqrt{\frac{\mu}{\nu}}$. Now taking expectations with respect to \mathbb{E}_k ,

$$\begin{aligned}
 \mathbb{E}_k[V_{k+1}] - V_k &\leq \mathbb{E}_k \left[\frac{\tau^2}{2\mu\gamma_k^2} \nabla f(x_{k+1})^\top H_k G^{-1} H_k \nabla f(x_{k+1}) - \frac{1}{2\Gamma_k} \|\nabla f(x_{k+1})\|_{H_k}^2 \right] \\
 &\quad + \langle \nabla f(x_{k+1}), x_{k+1} - y_k \rangle - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 \\
 &\quad + \tau \langle \nabla f(x_{k+1}), x_* - x_{k+1} \rangle + \tau \langle \nabla f(x_{k+1}), x_{k+1} - z_k \rangle - \tau \mu \langle x_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} \\
 &\quad + \frac{\mu}{2} \|\tau(x_{k+1} - z_k)\|_{G^{-1}}^2 - \tau \langle x_{k+1} - z_k, \tau \nabla f(x_{k+1}) \rangle \\
 &\stackrel{(39)}{\leq} \langle \nabla f(x_{k+1}), x_{k+1} - y_k \rangle - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 + \tau \langle \nabla f(x_{k+1}), x_* - x_{k+1} \rangle \\
 &\quad + \tau \langle \nabla f(x_{k+1}), x_{k+1} - z_k \rangle - \tau \mu \langle x_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} \\
 &\quad + \frac{\mu}{2} \|\tau(x_{k+1} - z_k)\|_{G^{-1}}^2 - \tau \langle x_{k+1} - z_k, \tau \nabla f(x_{k+1}) \rangle \\
 &\stackrel{(30a)}{\leq} -\tau \left(f(x_{k+1}) - f_* + \frac{\mu}{2} \|x_{k+1} - x_*\|_{G^{-1}}^2 \right) + \langle \nabla f(x_{k+1}), x_{k+1} - y_k \rangle - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 \\
 &\quad + \tau \langle \nabla f(x_{k+1}), x_{k+1} - z_k \rangle - \tau \mu \langle x_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} \\
 &\quad + \frac{\mu}{2} \|\tau(x_{k+1} - z_k)\|_{G^{-1}}^2 - \tau \langle x_{k+1} - z_k, \tau \nabla f(x_{k+1}) \rangle \tag{40a} \\
 &\stackrel{(31a)}{=} -\tau \left(f(x_{k+1}) - f_* + \frac{\mu}{2} \|x_{k+1} - x_*\|_{G^{-1}}^2 \right) - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 - \tau \mu \langle x_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} \\
 &\quad + \frac{\mu}{2} \|\tau(x_{k+1} - z_k)\|_{G^{-1}}^2 - \tau \langle y_k - x_{k+1}, \nabla f(x_{k+1}) \rangle \tag{40b} \\
 &\stackrel{(30b)}{\leq} -\tau \left(f(x_{k+1}) - f_* + \frac{\mu}{2} \|x_{k+1} - x_*\|_{G^{-1}}^2 \right) - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 - \tau \mu \langle x_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} \\
 &\quad + \frac{\mu}{2} \|\tau(x_{k+1} - z_k)\|_{G^{-1}}^2 + \tau(f(x_{k+1}) - f(y_k)) + \frac{\tau L}{2} \|y_k - x_{k+1}\|_{G^{-1}}^2 \tag{40c} \\
 &\stackrel{(37)}{=} -\tau \left(f(x_{k+1}) - f_* + \frac{\mu}{2} \|x_{k+1} - z_k\|_{G^{-1}}^2 + \frac{\mu}{2} \|z_k - x_*\|_{G^{-1}}^2 + \mu \langle x_{k+1} - z_k, z_k - x_* \rangle_{G^{-1}} \right) \\
 &\quad - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 - \tau \mu \langle x_{k+1} - z_k, x_* - z_k \rangle_{G^{-1}} \\
 &\quad + \frac{\mu}{2} \|\tau(x_{k+1} - z_k)\|_{G^{-1}}^2 + \tau(f(x_{k+1}) - f(y_k)) + \frac{\tau L}{2} \|y_k - x_{k+1}\|_{G^{-1}}^2 \tag{40d} \\
 &\stackrel{(32)}{=} -\tau V_k - \frac{\mu}{2} \|x_{k+1} - y_k\|_{G^{-1}}^2 - \frac{\tau \mu}{2} \|x_{k+1} - z_k\|_{G^{-1}}^2 + \frac{\mu}{2} \|\tau(x_{k+1} - z_k)\|_{G^{-1}}^2 + \frac{\tau L}{2} \|y_k - x_{k+1}\|_{G^{-1}}^2 \\
 &\stackrel{(31a)}{=} -\tau V_k + \left(\frac{\tau L}{2} - \frac{\mu}{2\tau} \right) \|y_k - x_{k+1}\|_{G^{-1}}^2 \tag{40e} \\
 &\stackrel{(35)}{\leq} -\tau V_k .
 \end{aligned}$$

Above, (40a) follows from μ -strong convexity, (40b) and (40e) both use the definition of the sequence (31), (40c) follows from L -Lipschitz gradients, (40d) uses the two-point inequality (37), and the last inequality follows from the assumption of $\tau \leq \sqrt{\frac{\mu}{L}}$. The claim (36) now follows by re-arrangement. \square

A.3.1. Proof of Theorem 3.5

Next, we describe how to recover Theorem 3.5 from Theorem A.3.1. We do this by applying Theorem A.3.1 to the function $f(x) = \frac{1}{2}x^\top Ax - x^\top b$.

The first step in applying Theorem A.3.1 is to construct a probability measure on $\mathcal{S}^{n \times n} \times \mathbb{R}_+ \times \mathbb{R}_+$ for which the randomness of the updates is drawn from. We already have a distribution on $\mathcal{S}^{n \times n}$ from setting of Theorem 3.5 via the random matrix H . We trivially augment this distribution by considering the random variable $(H, 1, 1) \in \Omega$. By setting $\Gamma = \gamma = 1$, the sequence (31a), (31b), (31c) reduces to that of Algorithm 1. Furthermore, the requirement on the ν parameter from (34) simplifies to the requirement listed in (13). This holds by the following equivalences which are valid since conjugation by

G (which is assumed to be positive definite) preserves the semi-definite ordering,

$$\begin{aligned}
 \lambda_{\max} \left(\mathbb{E} \left[(G^{-1/2} H G^{-1/2})^2 \right] \right) \leq \nu &\iff \mathbb{E} \left[(G^{-1/2} H G^{-1/2})^2 \right] \preceq \nu I \\
 &\iff \mathbb{E} \left[G^{-1/2} H G^{-1} H G^{-1/2} \right] \preceq \nu I \\
 &\iff \mathbb{E} \left[H G^{-1} H \right] \preceq \nu G.
 \end{aligned} \tag{41}$$

It remains to check the gradient inequality (33) and compute the strong convexity and Lipschitz parameters. These computations fall directly from the calculations made in Theorem 1 of (Qu et al., 2015), but we replicate them here for completeness.

To check the gradient inequality (33), because f is a quadratic function, its second order Taylor expansion is exact. Hence for almost every $\omega \in \Omega$,

$$\begin{aligned}
 f(\Phi(x; \omega)) &= f(x) - \langle \nabla f(x), H \nabla f(x) \rangle + \frac{1}{2} \nabla f(x)^\top H A H \nabla f(x) \\
 &= f(x) - \langle \nabla f(x), H \nabla f(x) \rangle + \frac{1}{2} \nabla f(x)^\top S (S^\top A S)^\dagger S^\top A S (S^\top A S)^\dagger S^\top \nabla f(x) \\
 &= f(x) - \langle \nabla f(x), H \nabla f(x) \rangle + \frac{1}{2} \nabla f(x)^\top S (S^\top A S)^\dagger S^\top \nabla f(x) \\
 &= f(x) - \frac{1}{2} \nabla f(x)^\top H \nabla f(x).
 \end{aligned}$$

Hence the inequality (33) holds with equality.

We next compute the strong convexity and Lipschitz gradient parameters. We first show that f is $\lambda_{\min}(\mathbb{E}[P_{A^{1/2}S}])$ -strongly convex with respect to the $\|\cdot\|_{G^{-1}}$ norm. This follows since for any $x, y \in \mathbb{R}^n$, using the assumption that G is positive definite,

$$\begin{aligned}
 f(y) &= f(x) + \langle \nabla f(x), y - x \rangle + \frac{1}{2} (y - x)^\top A (y - x) \\
 &= f(x) + \langle \nabla f(x), y - x \rangle + \frac{1}{2} (y - x)^\top G^{-1/2} G^{1/2} A G^{1/2} G^{-1/2} (y - x) \\
 &\geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\lambda_{\min}(A^{1/2} G A^{1/2})}{2} \|y - x\|_{G^{-1}}^2.
 \end{aligned}$$

The strong convexity bound now follows since

$$A^{1/2} G A^{1/2} = A^{1/2} \mathbb{E}[H] A^{1/2} = \mathbb{E}[A^{1/2} S (S^\top A S)^\dagger S^\top A^{1/2}] = \mathbb{E}[P_{A^{1/2}S}].$$

An nearly identical argument shows that f is $\lambda_{\max}(\mathbb{E}[P_{A^{1/2}S}])$ -strongly convex with respect to the $\|\cdot\|_{G^{-1}}$ norm. Since the eigenvalues of projector matrices are bounded by 1, we have that f is 1-Lipschitz with respect to the $\|\cdot\|_{G^{-1}}$ norm. This calculation shows that the requirement on τ from (35) simplifies to $\tau \leq \sqrt{\frac{\mu}{\nu}}$, since $L = 1$ and $\nu \geq 1$ by Proposition A.6.1 which we state and prove later.

At this point, Theorem A.3.1 yields that $\mathbb{E}[V_k] \leq (1 - \tau)^k V_0$. To recover the final claim (14), recall that $f(y_k) - f_* = \frac{1}{2} \|y_k - x_*\|_A^2$. Furthermore, $\mu G^{-1} \preceq A$, since

$$\begin{aligned}
 \mu \leq \lambda_{\min}(A^{1/2} G A^{1/2}) &\iff \mu \leq \lambda_{\min}(G^{1/2} A G^{1/2}) \\
 &\iff \mu I \preceq G^{1/2} A G^{1/2} \\
 &\iff \mu G^{-1} \preceq A.
 \end{aligned}$$

Hence, we can upper bound V_0 as follows

$$\begin{aligned}
 V_0 &= f(y_0) - f_* + \frac{\mu}{2} \|z_0 - x_*\|_{G^{-1}}^2 = \frac{1}{2} \|y_0 - x_*\|_A^2 + \frac{\mu}{2} \|z_0 - x_*\|_{G^{-1}}^2 \\
 &\leq \frac{1}{2} \|y_0 - x_*\|_A^2 + \frac{1}{2} \|z_0 - x_*\|_A^2 = \|x_0 - x_*\|_A^2.
 \end{aligned}$$

On the other hand, we have that $\frac{1}{2}\|y_k - x_*\|_A^2 \leq V_k$. Putting the inequalities together,

$$\frac{1}{\sqrt{2}}\mathbb{E}[\|y_k - x_*\|_A] \leq \sqrt{\mathbb{E}\left[\frac{1}{2}\|y_k - x_*\|_A^2\right]} \leq \sqrt{\mathbb{E}[V_k]} \leq \sqrt{(1-\tau)^k V_0} \leq (1-\tau)^{k/2}\|x_0 - x_*\|_A^2,$$

where the first inequality holds by Jensen's inequality. The claimed inequality (14) now follows.

A.3.2. Proof of Proposition 3.6

We first state and prove an elementary linear algebra fact which we will use below in our calculations.

Proposition A.3.2. *Let A, B, C, D be $n \times n$ diagonal matrices, and define $M = \begin{bmatrix} A & B \\ C & D \end{bmatrix}$. The eigenvalues of M are given by the union of the eigenvalues of the 2×2 matrices*

$$\begin{bmatrix} A_i & B_i \\ C_i & D_i \end{bmatrix}, \quad i = 1, \dots, n,$$

where A_i, B_i, C_i, D_i denote the i -th diagonal entry of A, B, C, D respectively.

Proof. For every $s \in \mathbb{C}$ we have that the matrices $-C$ and $sI - D$ are diagonal and hence commute. Applying the corresponding formula for a block matrix determinant under this assumption,

$$\begin{aligned} 0 &= \det \begin{bmatrix} sI - A & -B \\ -C & sI - D \end{bmatrix} = \det((sI - A)(sI - D) - BC) \\ &= \prod_{i=1}^n ((s - A_i)(s - D_i) - B_i C_i) = \prod_{i=1}^n \det \begin{bmatrix} s - A_i & -B_i \\ -C_i & s - D_i \end{bmatrix}. \end{aligned}$$

□

Now we proceed with the proof of Proposition 3.6. Define $e_k = \begin{bmatrix} y_k - x_* \\ z_k - x_* \end{bmatrix}$. It is easy to see from the definition of Algorithm 1 that $\{e_k\}$ satisfies the recurrence

$$e_{k+1} = \frac{1}{1+\tau} \begin{bmatrix} I - H_k A & \tau(I - H_k A) \\ \tau(I - \frac{1}{\mu} H_k A) & I - \frac{\tau^2}{\mu} H_k A \end{bmatrix} e_k.$$

Hence,

$$\begin{aligned} &\begin{bmatrix} A^{1/2} & 0 \\ 0 & \mu^{1/2} G^{-1/2} \end{bmatrix} e_{k+1} \\ &= \frac{1}{1+\tau} \begin{bmatrix} A^{1/2} & 0 \\ 0 & \mu^{1/2} G^{-1/2} \end{bmatrix} \begin{bmatrix} I - H_k A & \tau(I - H_k A) \\ \tau(I - \frac{1}{\mu} H_k A) & I - \frac{\tau^2}{\mu} H_k A \end{bmatrix} e_k \\ &= \frac{1}{1+\tau} \begin{bmatrix} A^{1/2} - A^{1/2} H_k A & \tau(A^{1/2} - A^{1/2} H_k A) \\ \mu^{1/2} \tau G^{-1/2} (I - \frac{1}{\mu} H_k A) & \mu^{1/2} G^{-1/2} (I - \frac{\tau^2}{\mu} H_k A) \end{bmatrix} e_k \\ &= \frac{1}{1+\tau} \begin{bmatrix} I - A^{1/2} H_k A^{1/2} & \mu^{-1/2} \tau (A^{1/2} - A^{1/2} H_k A) G^{1/2} \\ \mu^{1/2} \tau G^{-1/2} (I - \frac{1}{\mu} H_k A) A^{-1/2} & G^{-1/2} (I - \frac{\tau^2}{\mu} H_k A) G^{1/2} \end{bmatrix} \begin{bmatrix} A^{1/2} & 0 \\ 0 & \mu^{1/2} G^{-1/2} \end{bmatrix} e_k. \end{aligned}$$

Define $P = \begin{bmatrix} A & 0 \\ 0 & \mu G^{-1} \end{bmatrix}$. By taking and iterating expectations,

$$\mathbb{E}[P^{1/2} e_{k+1}] = \frac{1}{1+\tau} \begin{bmatrix} I - A^{1/2} G A^{1/2} & \mu^{-1/2} \tau (A^{1/2} G^{1/2} - A^{1/2} G A G^{1/2}) \\ \mu^{1/2} \tau (G^{-1/2} A^{-1/2} - \frac{1}{\mu} G^{1/2} A^{1/2}) & I - \frac{\tau^2}{\mu} G^{1/2} A G^{1/2} \end{bmatrix} \mathbb{E}[P^{1/2} e_k].$$

Denote the matrix $Q = A^{1/2}G^{1/2}$. Unrolling the recurrence above yields that

$$\mathbb{E}[P^{1/2}e_k] = R^k P^{1/2}e_0, \quad R = \frac{1}{1+\tau} \begin{bmatrix} I - QQ^\top & \mu^{-1/2}\tau(Q - QQ^\top Q) \\ \mu^{1/2}\tau(Q^{-1} - \frac{1}{\mu}Q^\top) & I - \frac{\tau^2}{\mu}Q^\top Q \end{bmatrix}.$$

Write the SVD of Q as $Q = U\Sigma V^\top$. Both U and V are $n \times n$ orthonormal matrices. It is easy to see that R^k is given by

$$R^k = \frac{1}{(1+\tau)^k} \begin{bmatrix} U & 0 \\ 0 & V \end{bmatrix} \begin{bmatrix} I - \Sigma^2 & \mu^{-1/2}\tau(\Sigma - \Sigma^3) \\ \mu^{1/2}\tau(\Sigma^{-1} - \frac{1}{\mu}\Sigma) & I - \frac{\tau^2}{\mu}\Sigma^2 \end{bmatrix}^k \begin{bmatrix} U^\top & 0 \\ 0 & V^\top \end{bmatrix}. \quad (42)$$

Suppose we choose $P^{1/2}e_0$ to be a right singular vector of R^k corresponding to the maximum singular value $\sigma_{\max}(R^k)$. Then we have that

$$\mathbb{E}[\|P^{1/2}e_k\|_2] \geq \|\mathbb{E}[P^{1/2}e_k]\|_2 = \|R^k P^{1/2}e_0\|_2 = \sigma_{\max}(R^k) \|P^{1/2}e_0\|_2 \geq \rho(R^k) \|P^{1/2}e_0\|_2,$$

where $\rho(\cdot)$ denotes the spectral radius. The first inequality is Jensen's inequality, and the second inequality uses the fact that the spectral radius is bounded above by any matrix norm. The eigenvalues of R^k are the k -th power of the eigenvalues of R which, using the similarity transform (42) along with Proposition A.3.2, are given by the eigenvalues of the 2×2 matrices R_i defined as

$$R_i = \frac{1}{1+\tau} \begin{bmatrix} 1 - \sigma_i^2 & \mu^{-1/2}\tau(\sigma_i - \sigma_i^3) \\ \mu^{1/2}\tau(\sigma_i^{-1} - \frac{1}{\mu}\sigma_i) & 1 - \frac{\tau^2}{\mu}\sigma_i^2 \end{bmatrix}, \quad \sigma_i = \Sigma_{ii}, \quad i = 1, \dots, n.$$

On the other hand, since the entries in Σ are given by the eigenvalues of $A^{1/2}G^{1/2}G^{1/2}A^{1/2} = \mathbb{E}[P_{A^{1/2}S}]$, there exists an i such that $\sigma_i = \sqrt{\mu}$. This R_i is upper triangular, and hence its eigenvalues can be read off the diagonal. This shows that $\frac{1-\tau^2}{1+\tau} = 1 - \tau$ is an eigenvalue of R , and hence $(1 - \tau)^k$ is an eigenvalue of R^k . But this means that $(1 - \tau)^k \leq \rho(R^k)$. Hence, we have shown that

$$\mathbb{E}[\|P^{1/2}e_k\|_2] \geq (1 - \tau)^k \|P^{1/2}e_0\|_2.$$

The desired claim now follows from

$$\begin{aligned} \|P^{1/2}e_k\|_2 &= \sqrt{\|y_k - x_*\|_A^2 + \mu\|z_k - x_*\|_{G^{-1}}^2} \\ &\leq \sqrt{\|y_k - x_*\|_A^2 + \|z_k - x_*\|_A^2} \leq \|y_k - x_*\|_A + \|z_k - x_*\|_A, \end{aligned}$$

where the first inequality holds since $\mu G^{-1} \preceq A$ and the second inequality holds since $\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$ for non-negative a, b .

A.4. Recovering the ACDM Result from Nesterov and Stich (2016)

We next show how to recover Theorem 1 of Nesterov and Stich (2016) using Theorem A.3.1, in the case of $\alpha = 1$. A nearly identical argument can also be used to recover the result of Allen-Zhu et al. (2016) under the strongly convex setting in the case of $\beta = 0$. Our argument proceeds in two steps. First, we prove a convergence result for a simplified accelerated coordinate descent method which we introduce in Algorithm 2. Then, we describe how a minor tweak to ACDM shows the equivalence between ACDM and Algorithm 2.

Before we proceed, we first describe the setting of Theorem 1. Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a twice differentiable strongly convex function with Lipschitz gradients. Let J_1, \dots, J_m denote a partition of $\{1, \dots, n\}$ into m partitions. Without loss of generality, we can assume that the partitions are in order, i.e. $J_1 = \{1, \dots, n_1\}$, $J_2 = \{n_1 + 1, \dots, n_2\}$, and so on. This is without loss of generality since we can always consider the function $g(x) = f(\Pi x)$ for a suitable permutation matrix Π . Let B_1, \dots, B_m be fixed positive definite matrices such that $B_i \in \mathbb{R}^{|J_i| \times |J_i|}$. Set $H_i = S_i B_i^{-1} S_i^\top$, where $S_i \in \mathbb{R}^{n \times |J_i|}$ is the column selector matrix associated to partition J_i , and define $L_i = \sup_{x \in \mathbb{R}^n} \lambda_{\max}(B_i^{-1/2} S_i^\top \nabla^2 f(x) S_i B_i^{-1/2})$ for $i = 1, \dots, m$. Furthermore, define $p_i = \frac{\sqrt{L_i}}{\sum_{j=1}^m \sqrt{L_j}}$.

Algorithm 2 Accelerated randomized coordinate descent.

Require: $\mu > 0$, partition $\{J_i\}_{i=1}^m$, positive definite $\{B_i\}_{i=1}^m$, Lipschitz constants $\{L_i\}_{i=1}^m$, $x_0 \in \mathbb{R}^n$.

- 1: Set $\tau = \frac{\sqrt{\mu}}{\sum_{i=1}^m \sqrt{L_i}}$.
 - 2: Set $H_i = S_i B_i^{-1} S_i^\top$ for $i = 1, \dots, m$. // S_i denotes the column selector for partition J_i .
 - 3: Set $p_i = \frac{\sqrt{L_i}}{\sum_{j=1}^m \sqrt{L_j}}$ for $i = 1, \dots, m$.
 - 4: Set $y_0 = z_0 = x_0$.
 - 5: **for** $k = 0, \dots, T - 1$ **do**
 - 6: $i_k \leftarrow$ random sample from $\{1, \dots, m\}$ with $\mathbb{P}(i_k = i) = p_i$.
 - 7: $x_{k+1} = \frac{1}{1+\tau} y_k + \frac{\tau}{1+\tau} z_k$.
 - 8: $y_{k+1} = x_{k+1} - \frac{1}{L_{i_k}} H_{i_k} \nabla f(x_{k+1})$.
 - 9: $z_{k+1} = z_k + \tau(x_{k+1} - z_k) - \frac{\tau}{\mu p_{i_k}} H_{i_k} \nabla f(x_{k+1})$.
 - 10: **end for**
 - 11: **Return** y_T .
-

A.4.1. Proof of convergence of a simplified accelerated coordinate descent method

Now consider the following accelerated randomized coordinate descent algorithm in Algorithm 2.

Theorem A.3.1 is readily applied to Algorithm 2 to give a convergence guarantee which matches the bound of Theorem 1 of Nesterov and Stich. We sketch the argument below.

Algorithm 2 instantiates (31) with the definitions above and particular choices $\Gamma_k = L_{i_k}$ and $\gamma_k = p_{i_k}$. We will specify the choice of μ at a later point. To see that this setting is valid, we construct a discrete probability measure on $\mathcal{S}^{n \times n} \times \mathbb{R}_+ \times \mathbb{R}_+$ by setting $\omega_i = (H_i, L_i, p_i)$ and $\mathbb{P}(\omega = \omega_i) = p_i$ for $i = 1, \dots, m$. Hence, in the context of Theorem A.3.1, $G = \mathbb{E}[\frac{1}{\gamma} H] = \sum_{i=1}^m p_i H_i = \text{blkdiag}(B_1^{-1}, B_2^{-1}, \dots, B_m^{-1})$. We first verify the gradient inequality (33). For every fixed $x \in \mathbb{R}^n$, for every $i = 1, \dots, m$ there exists a $c_i \in \mathbb{R}^n$ such that

$$\begin{aligned}
 f(\Phi(x; \omega_i)) &= f(x) - \frac{1}{L_i} \langle \nabla f(x), H_i \nabla f(x) \rangle + \frac{1}{2L_i^2} \nabla f(x)^\top H_i \nabla^2 f(c_i) H_i \nabla f(x) \\
 &= f(x) - \frac{1}{L_i} \langle \nabla f(x), H_i \nabla f(x) \rangle + \frac{1}{2L_i^2} \nabla f(x)^\top S_i B_i^{-1/2} B_i^{-1/2} S_i^\top \nabla^2 f(c_i) S_i B_i^{-1/2} B_i^{-1/2} S_i^\top \nabla f(x) \\
 &\leq f(x) - \frac{1}{L_i} \langle \nabla f(x), H_i \nabla f(x) \rangle + \frac{1}{2L_i} \nabla f(x)^\top S_i B_i^{-1} S_i^\top \nabla f(x) \\
 &= f(x) - \frac{1}{2L_i} \|\nabla f(x)\|_{H_i}^2.
 \end{aligned}$$

We next compute the ν constant defined in (34). We do this by checking the sufficient condition that $H_i G^{-1} H_i \preceq \nu H_i$ for $i = 1, \dots, m$. Doing so yields that $\nu = 1$, since

$$H_i G^{-1} H_i = S_i B_i^{-1} S_i^\top \text{blkdiag}(B_1, B_2, \dots, B_m) S_i B_i^{-1} S_i^\top = S_i B_i^{-1} B_i B_i^{-1} S_i^\top = S_i B_i^{-1} S_i^\top = H_i.$$

To complete the argument, we set μ as the strong convexity constant and L as the Lipschitz gradient constant of f with respect to the $\|\cdot\|_{G^{-1}}$ norm. It is straightforward to check that

$$\mu = \inf_{x \in \mathbb{R}^n} \lambda_{\max}(G^{1/2} \nabla^2 f(x) G^{1/2}), \quad L = \sup_{x \in \mathbb{R}^n} \lambda_{\max}(G^{1/2} \nabla^2 f(x) G^{1/2}).$$

We now argue that $\sqrt{L} \leq \sum_{i=1}^m \sqrt{L_i}$. Let $x \in \mathbb{R}^n$ achieve the supremum in the definition of L (if no such x exists, then

let x be arbitrarily close and take limits). Then,

$$\begin{aligned}
 L &= \lambda_{\max}(G^{1/2}\nabla^2 f(x)G^{1/2}) = \lambda_{\max}((\nabla^2 f(x))^{1/2}G(\nabla^2 f(x))^{1/2}) \\
 &= \lambda_{\max}\left((\nabla^2 f(x))^{1/2}\left(\sum_{i=1}^m S_i B_i^{-1} S_i^\top\right)(\nabla^2 f(x))^{1/2}\right) \\
 &\stackrel{(a)}{\leq} \sum_{i=1}^m \lambda_{\max}((\nabla^2 f(x))^{1/2} S_i B_i^{-1} S_i^\top (\nabla^2 f(x))^{1/2}) \\
 &\stackrel{(b)}{=} \sum_{i=1}^m \lambda_{\max}(S_i S_i^\top \nabla^2 f(x) S_i S_i^\top S_i B_i^{-1} S_i^\top) \\
 &\stackrel{(c)}{=} \sum_{i=1}^m \lambda_{\max}(B_i^{-1/2} S_i^\top \nabla^2 f(x) S_i B_i^{-1/2}) \leq \sum_{i=1}^m L_i.
 \end{aligned}$$

Above, (a) follows by the triangle inequality, (b) follows by the fact that $S_i^\top S_i = I$, and (c) follows since $\lambda_{\max}(S_i M S_i^\top) = \lambda_{\max}(M)$ for any $p \times p$ symmetric matrix M . Using the fact that $\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$ for any non-negative a, b , the inequality $\sqrt{L} \leq \sum_{i=1}^m \sqrt{L_i}$ immediately follows. To conclude the proof, it remains to calculate the requirement on τ via (35). Since $\frac{\gamma_i}{\sqrt{\Gamma_i}} = \frac{p_i}{\sqrt{L_i}} = \frac{1}{\sum_{i=1}^m \sqrt{L_i}}$, we have that $\frac{\gamma_i}{\sqrt{\Gamma_i}} \leq \frac{1}{\sqrt{L}}$, and hence the requirement is that $\tau \leq \frac{\sqrt{\mu}}{\sum_{i=1}^m \sqrt{L_i}}$.

A.4.2. Relating Algorithm 2 to ACDM

For completeness, we replicate the description of the ACDM algorithm from Nesterov and Stich in Algorithm 3. We make one minor tweak in the initialization of the A_k, B_k sequence which greatly simplifies the exposition of what follows.

Algorithm 3 ACDM from Nesterov and Stich (Nesterov & Stich, 2016), $\alpha = 1, \beta = 1/2$ case.

Require: $\mu > 0$, partition $\{J_i\}_{i=1}^m$, positive definite $\{B_i\}_{i=1}^m$, Lipschitz constants $\{L_i\}_{i=1}^m$, $x_0 \in \mathbb{R}^n$.

- 1: Set $H_i = S_i B_i^{-1} S_i^\top$ for $i = 1, \dots, m$. // S_i denotes the column selector for partition J_i .
 - 2: Set $p_i = \frac{\sqrt{L_i}}{\sum_{j=1}^m \sqrt{L_j}}$ for $i = 1, \dots, m$.
 - 3: Set $A_0 = 1, B_0 = \mu$. // Modified from $A_0 = 0, B_0 = 1$.
 - 4: Set $S_{1/2} = \sum_{i=1}^m \sqrt{L_i}$.
 - 5: Set $y_0 = z_0 = x_0$.
 - 6: **for** $k = 0, \dots, T - 1$ **do**
 - 7: $i_k \leftarrow$ random sample from $\{1, \dots, m\}$ with $\mathbb{P}(i_k = i) = p_i$.
 - 8: $a_{k+1} \leftarrow$ positive solution to $a_{k+1}^2 S_{1/2}^2 = (A_k + a_{k+1})(B_k + \mu a_{k+1})$.
 - 9: $A_{k+1} = A_k + a_{k+1}, B_{k+1} = B_k + \mu a_{k+1}$.
 - 10: $\alpha_k = \frac{a_{k+1}}{A_{k+1}}, \beta_k = \mu \frac{a_{k+1}}{B_{k+1}}$.
 - 11: $y_k = \frac{(1-\alpha_k)x_k + \alpha_k(1-\beta_k)z_k}{1-\alpha_k\beta_k}$.
 - 12: $x_{k+1} = y_k - \frac{1}{L_{i_k}} H_{i_k} \nabla f(y_k)$.
 - 13: $z_{k+1} = (1-\beta_k)z_k + \beta_k y_k - \frac{a_{k+1}}{B_{k+1} p_{i_k}} H_{i_k} \nabla f(y_k)$.
 - 14: **end for**
 - 15: **Return** x_T .
-

We first write the sequence produced by Algorithm 3 as

$$y_k = \frac{(1-\alpha_k)x_k + \alpha_k(1-\beta_k)z_k}{1-\alpha_k\beta_k}, \quad (43a)$$

$$x_{k+1} = y_k - \frac{1}{L_{i_k}} H_{i_k} \nabla f(y_k), \quad (43b)$$

$$z_{k+1} - z_k = \beta_k \left(y_k - z_k - \frac{a_{k+1}}{B_{k+1} p_{i_k} \beta_k} H_{i_k} \nabla f(y_k) \right). \quad (43c)$$

Since $\beta_k B_{k+1} = \mu a_{k+1}$, the z_{k+1} update simplifies to

$$z_{k+1} - z_k = \beta_k \left(y_k - z_k - \frac{1}{\mu p_{i_k}} H_{i_k} \nabla f(y_k) \right).$$

A simple calculation shows that

$$(1 - \alpha_k \beta_k) y_k = (1 - \alpha_k) x_k + \alpha_k (1 - \beta_k) z_k,$$

from which we conclude that

$$\frac{\alpha_k (1 - \beta_k)}{1 - \alpha_k} (y_k - z_k) = x_k - y_k. \quad (44)$$

Observe that

$$A_{k+1} = \sum_{i=1}^{k+1} a_i + A_0, \quad B_{k+1} = \mu \sum_{i=1}^{k+1} a_i + B_0.$$

Hence as long as $\mu A_0 = B_0$ (which is satisfied by our modification), we have that $\mu A_{k+1} = B_{k+1}$ for all $k \geq 0$. With this identity, we have that $\alpha_k = \beta_k$ for all $k \geq 0$. Therefore, (44) simplifies to

$$\beta_k (y_k - z_k) = x_k - y_k.$$

We now calculate the value of β_k . At every iteration, we have that

$$a_{k+1}^2 S_{1/2}^2 = A_{k+1} B_{k+1} = \frac{1}{\mu} B_{k+1}^2 \implies \frac{a_{k+1}}{B_{k+1}} = \frac{1}{\sqrt{\mu} S_{1/2}}.$$

By the definition of β_k ,

$$\beta_k = \mu \frac{a_{k+1}}{B_{k+1}} = \frac{\sqrt{\mu}}{S_{1/2}} = \frac{\sqrt{\mu}}{\sum_{i=1}^m \sqrt{L_i}} = \tau.$$

Combining these identities, we have shown that (43a), (43b), and (43c) simplifies to

$$y_k = \frac{1}{1 + \tau} x_k + \frac{\tau}{1 + \tau} z_k, \quad (45a)$$

$$x_{k+1} = y_k - \frac{1}{L_{i_k}} H_{i_k} \nabla f(y_k), \quad (45b)$$

$$z_{k+1} - z_k = \tau \left(y_k - z_k - \frac{1}{\mu p_{i_k}} H_{i_k} \nabla f(y_k) \right). \quad (45c)$$

This sequence directly coincides with the sequence generated by Algorithm 2 after a simple relabeling.

A.4.3. Accelerated Gauss-Seidel for fixed partitions from ACDM

We now describe Algorithm 4, which is the specialization of ACDM (Algorithm 3) to accelerated Gauss-Seidel in the fixed partition setting.

As mentioned previously, we set the function $f(x) = \frac{1}{2} x^\top A x - x^\top b$. Given a partition $\{J_i\}_{i=1}^{n/p}$, we let $B_i = S_i^\top A S_i$, where $S_i \in \mathbb{R}^{n \times p}$ is the column selector matrix associated to the partition J_i . With this setting, we have that $L_1 = L_2 = \dots = L_{n/p} = 1$, and hence we have $p_i = p/n$ for all i (i.e. the sampling distribution is uniform over all partitions). We now need to compute the strong convexity constant μ . With the simplifying assumption that the partitions are ordered, μ is simply the strong convexity constant with respect to the norm induced by the matrix $\text{blkdiag}(B_1, B_2, \dots, B_{n/p})$. Hence, using the definition of μ_{part} from (3), we have that $\mu = \frac{n}{p} \mu_{\text{part}}$. Algorithm 4 now follows from plugging our particular choices of f and the constants into Algorithm 3.

Algorithm 4 Accelerated randomized block Gauss-Seidel for fixed partitions (Nesterov & Stich, 2016).

Require: $A \in \mathbb{R}^{n \times n}$, $A \succ 0$, $b \in \mathbb{R}^n$, $x_0 \in \mathbb{R}^n$, block size p , μ_{part} defined in (3).

- 1: Set $A_0 = 0, B_0 = 1$.
 - 2: Set $\sigma = \frac{n}{p} \mu_{\text{part}}$.
 - 3: Set $y_0 = z_0 = x_0$.
 - 4: **for** $k = 0, \dots, T - 1$ **do**
 - 5: $i_k \leftarrow$ uniform from $\{1, 2, \dots, n/p\}$.
 - 6: $S_k \leftarrow$ column selector associated with partition J_{i_k} .
 - 7: $a_{k+1} \leftarrow$ positive solution to $a_{k+1}^2 (n/p)^2 = (A_k + a_{k+1})(B_k + \sigma a_{k+1})$.
 - 8: $A_{k+1} = A_k + a_{k+1}, B_{k+1} = B_k + \sigma a_{k+1}$.
 - 9: $\alpha_k = \frac{a_{k+1}}{A_{k+1}}, \beta_k = \sigma \frac{a_{k+1}}{B_{k+1}}$.
 - 10: $y_k = \frac{(1-\alpha_k)x_k + \alpha_k(1-\beta_k)z_k}{1-\alpha_k\beta_k}$.
 - 11: $x_{k+1} = y_k - S_k(S_k^T A S_k)^{-1} S_k^T (A y_k - b)$.
 - 12: $z_{k+1} = (1 - \beta_k)z_k + \beta_k y_k - \frac{n a_{k+1}}{p B_{k+1}} S_k(S_k^T A S_k)^{-1} S_k^T (A y_k - b)$.
 - 13: **end for**
 - 14: Return x_T .
-

A.5. A Result for Randomized Block Kaczmarz

We now use Theorem A.3.1 to derive a result similar to Theorem 3.5 for the randomized accelerated Kaczmarz algorithm. In this setting, we let $A \in \mathbb{R}^{m \times n}$, $m \geq n$ be a matrix with full column rank, and $b \in \mathbb{R}^m$ such that $b \in \mathcal{R}(A)$. That is, there exists a unique $x_* \in \mathbb{R}^n$ such that $Ax_* = b$. We note that this section generalizes the result of (Liu & Wright, 2016) to the block case (although the proof strategy is quite different).

We first describe the randomized accelerated block Kaczmarz algorithm in Algorithm 5. Our main convergence result concerning Algorithm 5 is presented in Theorem A.5.1.

Algorithm 5 Accelerated randomized block Kaczmarz.

Require: $A \in \mathbb{R}^{m \times n}$, A full column rank, $b \in \mathcal{R}(A)$, sketching matrices $\{S_k\}_{k=0}^{T-1} \subseteq \mathbb{R}^{m \times p}$, $x_0 \in \mathbb{R}^n$, $\mu \in (0, 1)$, $\nu \geq 1$.

- 1: Set $\tau = \sqrt{\mu/\nu}$.
 - 2: Set $y_0 = z_0 = x_0$.
 - 3: **for** $k = 0, \dots, T - 1$ **do**
 - 4: $x_{k+1} = \frac{1}{1+\tau} y_k + \frac{\tau}{1+\tau} z_k$.
 - 5: $y_{k+1} = x_{k+1} - (S_k^T A)^\dagger S_k^T (A x_{k+1} - b)$.
 - 6: $z_{k+1} = z_k + \tau(x_{k+1} - z_k) - \frac{\tau}{\mu} (S_k^T A)^\dagger S_k^T (A x_{k+1} - b)$.
 - 7: **end for**
 - 8: Return y_T .
-

Theorem A.5.1. (Theorem 3.7 restated.) Let A be an $m \times n$ matrix with full column rank, and $b \in \mathcal{R}(A)$. Let $x_* \in \mathbb{R}^n$ denote the unique vector satisfying $Ax_* = b$. Suppose each S_k , $k = 0, 1, 2, \dots$ is an independent copy of a random sketching matrix $S \in \mathbb{R}^{m \times p}$. Let $\mu = \lambda_{\min}(\mathbb{E}[P_{A^T S}])$. Suppose the distribution of S satisfies $\mu > 0$. Invoke Algorithm 5 with μ and ν , where ν is defined as

$$\nu = \lambda_{\max} \left(\mathbb{E} \left[(G^{-1/2} H G^{-1/2})^2 \right] \right), \quad G = \mathbb{E}[H], \quad H = P_{A^T S}. \quad (46)$$

Then for all $k \geq 0$ we have

$$\mathbb{E}[\|y_k - x_*\|_2] \leq \sqrt{2} \left(1 - \sqrt{\frac{\mu}{\nu}} \right)^{k/2} \|x_0 - x_*\|_2. \quad (47)$$

Proof. The proof is very similar to that of Theorem 3.5, so we only sketch the main argument. The key idea is to use the correspondence between randomized Kaczmarz and coordinate descent (see e.g. Section 5.2 of (Lee & Sidford, 2013)). To do this, we apply Theorem A.3.1 to $f(x) = \frac{1}{2} \|x - x_*\|_2^2$. As in the proof of Theorem 3.5, we construct a probability

measure on $\mathcal{S}^{n \times n} \times \mathbb{R}_+ \times \mathbb{R}_+$ from the given random matrix H by considering the random variable $(H, 1, 1)$. To see that the sequence (31a), (31b), and (31c) induces the same update sequence as Algorithm 5, the crucial step is to notice that

$$\begin{aligned} H_k \nabla f(x_{k+1}) &= P_{A^\top S_k} \nabla f(x_{k+1}) = A^\top S_k (S_k^\top A A^\top S_k)^\dagger S_k^\top A (x_{k+1} - x_*) \\ &= A^\top S_k (S_k^\top A A^\top S_k)^\dagger S_k^\top (A x_{k+1} - b) = (S_k^\top A)^\dagger S_k^\top (A x_{k+1} - b). \end{aligned}$$

Next, the fact that f is $\lambda_{\min}(\mathbb{E}[P_{A^\top S}])$ -strongly convex and 1-Lipschitz with respect to the $\|\cdot\|_{G^{-1}}$ norm, where $G = \mathbb{E}[P_{A^\top S}]$, follows immediately by a nearly identical argument used in the proof of Theorem 3.5. It remains to check the gradient inequality (33). Let $x \in \mathbb{R}^n$ be fixed. Then using the fact that f is quadratic, for almost every $\omega \in \Omega$,

$$\begin{aligned} f(\Phi(x; \omega)) &= f(x) - \langle \nabla f(x), H(x - x_*) \rangle + \frac{1}{2} \|H(x - x_*)\|_2^2 \\ &= f(x) - \langle x - x_*, P_{A^\top S}(x - x_*) \rangle + \frac{1}{2} \|P_{A^\top S}(x - x_*)\|_2^2 \\ &= f(x) - \frac{1}{2} \langle x - x_*, P_{A^\top S}(x - x_*) \rangle. \end{aligned}$$

Hence the gradient inequality (33) holds with equality. \square

A.5.1. Computing ν and μ in the setting of (Liu & Wright, 2016)

We first state a proposition which will be useful in our analysis of ν .

Proposition A.5.2. *Let $M_1, \dots, M_s \subseteq \mathbb{R}^n$ denote subspaces of \mathbb{R}^n such that $M_1 + \dots + M_s = \mathbb{R}^n$. Then we have*

$$\sum_{i=1}^s P_{M_i} \left(\sum_{i=1}^s P_{M_i} \right)^{-1} P_{M_i} \preceq \sum_{i=1}^s P_{M_i}.$$

Proof. We will prove that for every $1 \leq i \leq s$,

$$P_{M_i} \left(\sum_{i=1}^s P_{M_i} \right)^{-1} P_{M_i} \preceq P_{M_i}, \quad (48)$$

from which the claim immediately follows. By Schur complements, (48) holds iff

$$\begin{aligned} 0 &\preceq \begin{bmatrix} P_{M_i} & P_{M_i} \\ P_{M_i} & \sum_{i=1}^s P_{M_i} \end{bmatrix} = \begin{bmatrix} P_{M_i} & P_{M_i} \\ P_{M_i} & P_{M_i} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & \sum_{j \neq i}^s P_{M_j} \end{bmatrix} \\ &= \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \otimes P_{M_i} + \begin{bmatrix} 0 & 0 \\ 0 & \sum_{j \neq i}^s P_{M_j} \end{bmatrix}. \end{aligned}$$

Since the eigenvalues of a Kronecker product are given by the Cartesian product of the individual eigenvalues, (48) holds. \square

Now we can estimate the ν and μ values. Let $a_i \in \mathbb{R}^n$ denote each row of A , with $\|a_i\|_2 = 1$ for all $i = 1, \dots, m$. In this setting, $H = P_{a_i} = a_i a_i^\top$ with probability $1/m$. Hence, $G = \mathbb{E}[H] = \sum_{i=1}^m \frac{1}{m} a_i a_i^\top = \frac{1}{m} A^\top A$. Furthermore,

$$\begin{aligned} \mathbb{E}[H G^{-1} H] &= \sum_{i=1}^m a_i a_i^\top m (A^\top A)^{-1} a_i a_i^\top \frac{1}{m} \\ &= \sum_{i=1}^m a_i a_i^\top (A^\top A)^{-1} a_i a_i^\top \\ &\stackrel{(a)}{\preceq} \sum_{i=1}^m a_i a_i^\top = A^\top A = mG, \end{aligned}$$

where (a) follows from Proposition A.5.2. Hence, $\nu \neq m$. On the other hand,

$$\mu = \lambda_{\min}(\mathbb{E}[P_{A^\top S}]) = \lambda_{\min}(G) = \frac{1}{m} \lambda_{\min}(A^\top A).$$

A.6. Proofs for Random Coordinate Sampling (Section 3.3)

Our primary goal in this section is to provide a proof of Lemma 3.8. Along the way, we prove a few other results which are of independent interest. We first provide a proof of the lower bound claim in Lemma 3.8.

Proposition A.6.1. *Let A be an $n \times n$ matrix and let $S \in \mathbb{R}^{n \times p}$ be a random matrix. Put $G = \mathbb{E}[P_{A^{1/2}S}]$ and suppose that G is positive definite. Let $\nu > 0$ be any positive number such that*

$$\mathbb{E}[P_{A^{1/2}S}G^{-1}P_{A^{1/2}S}] \preceq \nu G, \quad G = \mathbb{E}[P_{A^{1/2}S}]. \quad (49)$$

Then $\nu \geq n/p$.

Proof. Since trace commutes with expectation and respects the positive semi-definite ordering, taking trace of both sides of (49) yields that

$$\begin{aligned} n &= \mathbf{Tr}(GG^{-1}) = \mathbf{Tr}(\mathbb{E}[P_{A^{1/2}S}G^{-1}]) = \mathbb{E}[\mathbf{Tr}(P_{A^{1/2}S}G^{-1})] = \mathbb{E}[\mathbf{Tr}(P_{A^{1/2}S}G^{-1}P_{A^{1/2}S})] \\ &= \mathbf{Tr}(\mathbb{E}[P_{A^{1/2}S}G^{-1}P_{A^{1/2}S}]) \stackrel{(49)}{\leq} \nu \mathbf{Tr}(\mathbb{E}[P_{A^{1/2}S}]) \\ &= \nu \mathbb{E}[\mathbf{Tr}(P_{A^{1/2}S})] = \nu \mathbb{E}[\text{rank}(A^{1/2}S)] \leq \nu p. \end{aligned}$$

□

Next, the upper bound relies on the following lemma, which generalizes Lemma 2 of (Qu et al., 2016).

Lemma A.6.2. *Let M be a random matrix. We have that*

$$\mathbb{E}[P_M] \succeq \mathbb{E}[M](\mathbb{E}[M^T M])^\dagger \mathbb{E}[M^T]. \quad (50)$$

Proof. Our proof follows the strategy in the proof of Theorem 3.2 from (Zhang, 2005). First, write $P_B = B(B^T B)^\dagger B^T$. Since $\mathcal{R}(B^T) = \mathcal{R}(B^T B)$, we have by generalized Schur complements (see e.g. Theorem 1.20 from (Zhang, 2005)) and the fact that expectation preserves the semi-definite order,

$$\begin{bmatrix} B^T B & B^T \\ B & P_B \end{bmatrix} \succeq 0 \implies \begin{bmatrix} \mathbb{E}[B^T B] & \mathbb{E}[B^T] \\ \mathbb{E}[B] & \mathbb{E}[P_B] \end{bmatrix} \succeq 0.$$

To finish the proof, we need to argue that $\mathcal{R}(\mathbb{E}[B^T]) \subseteq \mathcal{R}(\mathbb{E}[B^T B])$, which would allow us to apply the generalized Schur complement again to the right hand side. Fix a $z \in \mathcal{R}(\mathbb{E}[B^T])$; we can write $z = \mathbb{E}[B^T]y$ for some y . Now let $q \in \text{Kern}(\mathbb{E}[B^T B])$. We have that $\mathbb{E}[B^T B]q = 0$, which implies $0 = q^T \mathbb{E}[B^T B]q = \mathbb{E}[\|Bq\|_2^2]$. Therefore, $Bq = 0$ a.s. But this means that $z^T q = \mathbb{E}[y^T Bq] = 0$. Hence, $z \in \text{Kern}(\mathbb{E}[B^T B])^\perp = \mathcal{R}(\mathbb{E}[B^T B])$. Now applying the generalized Schur complement one more time yields the claim. □

We are now in a position to prove the upper bound of Lemma 3.8. We apply Lemma A.6.2 to $M = A^{1/2}SS^T A^{1/2}$ to conclude, using the fact that $\mathcal{R}(M) = \mathcal{R}(MM^T)$, that

$$\mathbb{E}[P_{A^{1/2}S}] = \mathbb{E}[P_{A^{1/2}SS^T A^{1/2}}] \succeq \mathbb{E}[A^{1/2}SS^T A^{1/2}](\mathbb{E}[A^{1/2}SS^T ASS^T A^{1/2}])^\dagger \mathbb{E}[A^{1/2}SS^T A^{1/2}]. \quad (51)$$

Elementary calculations now yield that for any fixed symmetric matrix $A \in \mathbb{R}^{n \times n}$,

$$\mathbb{E}[SS^T] = \frac{p}{n}I, \quad \mathbb{E}[SS^T ASS^T] = \frac{p}{n} \left(\frac{p-1}{n-1}A + \left(1 - \frac{p-1}{n-1}\right) \text{diag}(A) \right). \quad (52)$$

Hence plugging (52) into (51),

$$\mathbb{E}[P_{A^{1/2}S}] \succeq \frac{p}{n} \left(\frac{p-1}{n-1}I + \left(1 - \frac{p-1}{n-1}\right) A^{-1/2} \text{diag}(A) A^{-1/2} \right)^{-1}. \quad (53)$$

We note that the lower bound (5) for μ_{rand} presented in Section 2 follows immediately from (53).

We next manipulate (13) in order to use (53). Recall that $G = \mathbb{E}[H]$ and $H = S(S^\top AS)^\dagger S^\top$. From (41), we have

$$\lambda_{\max} \left(\mathbb{E} \left[(G^{-1/2} H G^{-1/2})^2 \right] \right) \leq \nu \iff \mathbb{E} [H G^{-1} H] \preceq \nu G .$$

Next, a simple computation yields

$$\mathbb{E}[H G^{-1} H] = \mathbb{E}[S(S^\top AS)^{-1} S^\top G^{-1} S(S^\top AS)^{-1} S^\top] = A^{-1/2} \mathbb{E}[P_{A^{1/2}S} (\mathbb{E}[P_{A^{1/2}S}])^{-1} P_{A^{1/2}S}] A^{-1/2} .$$

Again, since conjugation by $A^{1/2}$ preserves semi-definite ordering, we have that

$$\mathbb{E}[H G^{-1} H] \preceq \nu G \iff \mathbb{E}[P_{A^{1/2}S} (\mathbb{E}[P_{A^{1/2}S}])^{-1} P_{A^{1/2}S}] \preceq \nu \mathbb{E}[P_{A^{1/2}S}] .$$

Using the fact that for positive definite matrices X, Y we have $X \preceq Y$ iff $Y^{-1} \preceq X^{-1}$, (53) is equivalent to

$$(\mathbb{E}[P_{A^{1/2}S}])^{-1} \preceq \frac{n}{p} \left(\frac{p-1}{n-1} I + \left(1 - \frac{p-1}{n-1} \right) A^{-1/2} \text{diag}(A) A^{-1/2} \right) .$$

Conjugating both sides by $P_{A^{1/2}S}$ and taking expectations,

$$\mathbb{E}[P_{A^{1/2}S} (\mathbb{E}[P_{A^{1/2}S}])^{-1} P_{A^{1/2}S}] \preceq \frac{n}{p} \left(\frac{p-1}{n-1} \mathbb{E}[P_{A^{1/2}S}] + \left(1 - \frac{p-1}{n-1} \right) \mathbb{E}[P_{A^{1/2}S} A^{-1/2} \text{diag}(A) A^{-1/2} P_{A^{1/2}S}] \right) . \quad (54)$$

Next, letting $J \subseteq 2^{[n]}$ denote the index set associated to S , for every S we have

$$\begin{aligned} & P_{A^{1/2}S} A^{-1/2} \text{diag}(A) A^{-1/2} P_{A^{1/2}S} \\ &= A^{1/2} S (S^\top AS)^{-1} S^\top A^{1/2} A^{-1/2} \text{diag}(A) A^{-1/2} A^{1/2} S (S^\top AS)^{-1} S^\top A^{1/2} \\ &= A^{1/2} S (S^\top AS)^{-1/2} (S^\top AS)^{-1/2} (S^\top \text{diag}(A) S) (S^\top AS)^{-1/2} (S^\top AS)^{-1/2} S^\top A^{1/2} \\ &\preceq \lambda_{\max}((S^\top \text{diag}(A) S) (S^\top AS)^{-1}) A^{1/2} S (S^\top AS)^{-1} S^\top A^{1/2} \\ &\preceq \frac{\max_{i \in J} A_{ii}}{\lambda_{\min}(A_J)} P_{A^{1/2}S} \\ &\preceq \max_{J \in 2^{[n]}: |J|=p} \kappa_{\text{eff}, J}(A) P_{A^{1/2}S} . \end{aligned}$$

Plugging this calculation back into (54) yields the desired upper bound of Lemma 3.8.

A.7. More Experiments

A.7.1. Kernel ridge regression on smaller datasets

In addition to using the large CIFAR-10 augmented dataset, we also tested our algorithms on the smaller MNIST² dataset. To generate a kernel matrix, we applied the Gaussian kernel on the raw MNIST pixels to generate a matrix K with $n = 60000$ rows and columns.

Results from running 500 iterations of random coordinate sampling and fixed partitioning algorithms are shown in Figure 5. We plot the convergence rates both across time and across iterations. Comparing convergence across iterations we see that random coordinate sampling is essential to achieve errors of 10^{-4} or lower. In terms of running time, similar to the CIFAR-10 experiment, we see that the benefits in fixed partitioning of accessing coordinates faster comes at a cost in terms of convergence rate, especially to achieve errors of 10^{-4} or lower.

A.7.2. Computing the μ and ν constants

In our last experiment, we explicitly compute the μ and ν constants from Theorem 3.5 for a few 16×16 positive definite matrices constructed as follows.

²<http://yann.lecun.com/exdb/mnist/>

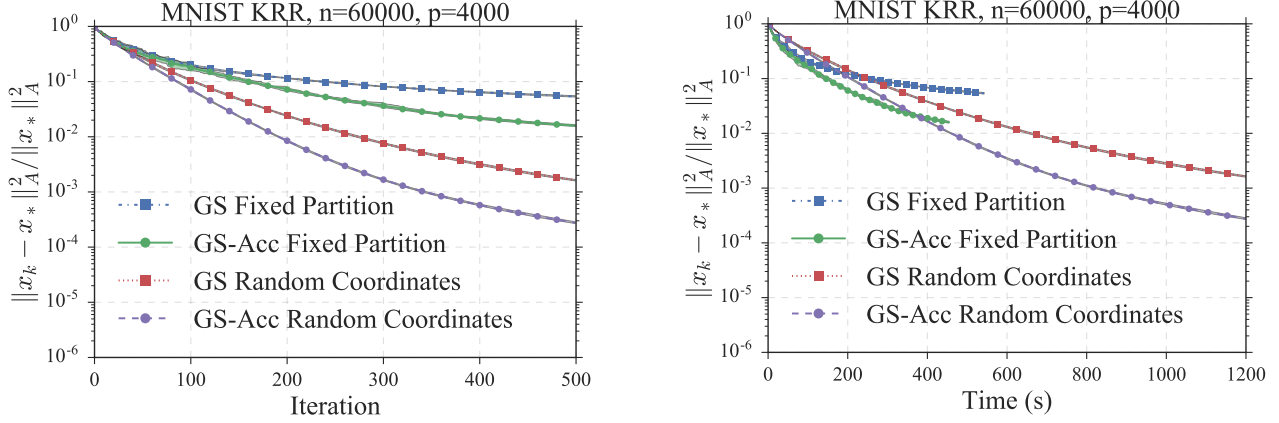


Figure 5. Experiments comparing fixed partitions versus uniform random sampling for MNIST while running kernel ridge regression. MNIST has $n = 60000$ coordinates and we set block size to $p = 4000$.

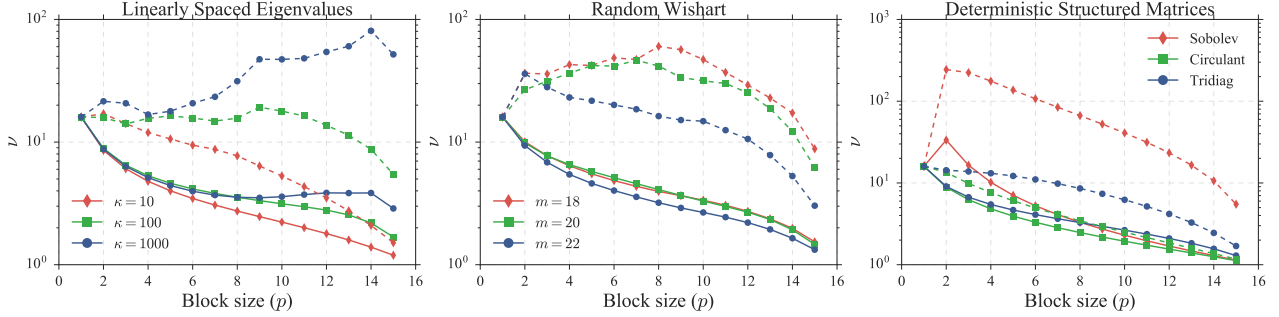


Figure 6. Comparison of the computed ν constant (solid lines) and ν bound from Theorem 3.5 (dotted lines) on random matrices with linearly spaced eigenvalues and random Wishart matrices.

Linearly spaced eigenvalues. We first draw Q uniformly at random from $n \times n$ orthogonal matrices. We then construct $A_i = Q\Sigma_i Q^T$ for $i = 1, 2, 3$, where Σ_1 is $\text{diag}(\text{linspace}(1, 10, 16))$, Σ_2 is $\text{diag}(\text{linspace}(1, 100, 16))$, and Σ_3 is $\text{diag}(\text{linspace}(1, 1000, 16))$.

Random Wishart. We first draw B_i with iid $N(0, 1)$ entries, where $B_i \in \mathbb{R}^{m_i \times 16}$ with $m_1 = 18$, $m_2 = 20$, and $m_3 = 22$. We then set $A_i = B_i^T B_i$.

Sobolev kernel. We form the matrix $A_{ij} = \min(i, j)$ with $1 \leq i, j \leq n$. This corresponds to the gram matrix for the set of points $x_1, \dots, x_n \in \mathbb{R}$ with $x_i = i$ under the Sobolev kernel $\min(x, y)$.

Circulant matrix. We let A be a 16×16 instance of the family of circulant matrices $A_n = F_n \text{diag}(c_n) F_n^*$ where F_n is the $n \times n$ unitary DFT matrix and $c_n = (1, 1/2, \dots, 1/(n/2 + 1), \dots, 1/2, 1)$. By construction this yields a real valued circulant matrix which is positive definite.

Tridiagonal matrix. We let A be a tridiagonal matrix with the diagonal value equal to one, and the off diagonal value equal to $(\delta - a)/(2 \cos(\pi n/(n + 1)))$ for $\delta = 1/10$. The matrix has a minimum eigenvalue of δ .

Figure 6 shows the results of our computation for the linearly spaced eigenvalues ensemble, the random Wishart ensemble and the other deterministic structured matrices. Alongside with the actual ν values, we plot the bound given for each instance by Lemma 3.8. From the figures we see that our bound is quite close to the computed value of ν for circulant matrices and for random matrices with linearly spaced eigenvalues with small κ . We plan to extend our analysis to derive a tighter bound in the future.

Supplementary References

Zhang, Fuzhen. *The Schur Complement and its Applications*, volume 4 of *Numerical Methods and Algorithms*. Springer, 2005.