
Supplementary Material: $O(\log T)$ Projections for Stochastic Optimization of Smooth and Strongly Convex Functions

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A. Proof of Lemma 1

We need the following lemma that characterizes the property of the extra gradient descent

Lemma 8 Let ω be a smooth function on \mathcal{E} . Let \mathcal{Z} be a convex compact set in Euclidean space \mathcal{E} with inner product $\langle \cdot, \cdot \rangle$, let $\|\cdot\|$ be a norm on \mathcal{E} and $\|\cdot\|$ be its dual norm, and let $\omega: \mathcal{Z} \rightarrow \mathbb{R}$ be a α -strongly convex function with respect to $\|\cdot\|$. The Bregman distance associated with ω for points $\mathbf{z}, \mathbf{w} \in \mathcal{Z}$ is defined as

$$B_\omega(\mathbf{z}, \mathbf{w}) = \omega(\mathbf{z}) - \omega(\mathbf{w}) - \langle \mathbf{z} - \mathbf{w}, \nabla \omega(\mathbf{w}) \rangle.$$

Let \mathcal{U} be a convex and closed subset of \mathcal{Z} , and let $\mathbf{z} \in \mathcal{Z}$, let $\xi, \eta \in \mathcal{E}$, and let $\gamma > 0$. Consider the points

$$\begin{aligned} \mathbf{w} &= \arg \min_{\mathbf{y} \in \mathcal{U}} \{ \langle \gamma \xi - \nabla \omega(\mathbf{z}), \mathbf{y} \rangle + \omega(\mathbf{y}) \}, \\ \mathbf{z}_+ &= \arg \min_{\mathbf{y} \in \mathcal{U}} \{ \langle \gamma \eta - \nabla \omega(\mathbf{z}), \mathbf{y} \rangle + \omega(\mathbf{y}) \}. \end{aligned}$$

Then for all $\mathbf{z} \in \mathcal{U}$ one has

$$\langle \mathbf{w} - \mathbf{z}, \gamma \eta \rangle \leq B_\omega(\mathbf{z}, \mathbf{z}) - B_\omega(\mathbf{z}, \mathbf{z}_+) + \frac{\gamma^2}{\alpha} \|\eta - \xi\|^2 - \frac{\alpha}{2} (\|\mathbf{w} - \mathbf{z}\|^2 + \|\mathbf{z}_+ - \mathbf{w}\|^2).$$

Proof of Lemma 1. We first state the inner loop in Algorithm 1 below

for $t = 1$ to M do

 Compute the average gradient at \mathbf{w}_t^k over B^k calls to the gradient oracle

$$\mathbf{g}_t^k = \frac{1}{B^k} \sum_{i=1}^{B^k} \mathbf{g}(\mathbf{w}_t^k, i)$$

 update

$$\mathbf{z}_t^k = \mathbf{P}_{\mathcal{D}}(\mathbf{w}_t^k - \eta \mathbf{g}_t^k)$$

 Compute the average gradient at \mathbf{z}_t^k over B^k calls to the gradient oracle

$$\mathbf{f}_t^k = \frac{1}{B^k} \sum_{i=1}^{B^k} \mathbf{g}(\mathbf{z}_t^k, i)$$

update

$$\mathbf{w}_{t+1}^k = \mathbf{P}_{\mathcal{D}}(\mathbf{w}_t^k - \eta \mathbf{f}_t^k)$$

end for

to simplify the notation we define

$$\mathbf{g}_t^k = \nabla F(\mathbf{w}_t^k) \text{ and } \mathbf{f}_t^k = \nabla F(\mathbf{z}_t^k).$$

Let the two norms $\|\cdot\|$ and $\|\cdot\|_{\ell_2}$ in Lemma be the vector ℓ_2 norm. Each iteration in the inner loop satisfies the conditions in Lemma by doing the assignments below

$$\mathcal{U} = \mathcal{Z} = \mathcal{E} \leftarrow \mathcal{D}, \omega_{\mathbf{z}} \leftarrow -\|\mathbf{z}\|^2, \alpha \leftarrow \cdot, \gamma \leftarrow \eta, \mathbf{z} \leftarrow \mathbf{w}_t^k, \boldsymbol{\xi} \leftarrow \mathbf{g}_t^k, \boldsymbol{\eta} \leftarrow \mathbf{f}_t^k, \mathbf{w} \leftarrow \mathbf{z}_t^k, \mathbf{z}_{t+1}^k \leftarrow \mathbf{P}_{\mathcal{D}}(\mathbf{z}_t^k - \eta \boldsymbol{\eta}).$$

Following Lemma we have

$$\begin{aligned} & \langle \mathbf{z}_t^k - \mathbf{w}, \eta \mathbf{f}_t^k \rangle \\ \leq & \frac{\|\mathbf{w}_t^k - \mathbf{w}\|^2}{2} - \frac{\|\mathbf{w}_{t+1}^k - \mathbf{w}\|^2}{2} + \eta^2 \|\mathbf{g}_t^k - \mathbf{f}_t^k\|^2 - \|\mathbf{w}_t^k - \mathbf{z}_t^k\|^2 \\ \leq & \frac{\|\mathbf{w}_t^k - \mathbf{w}\|^2}{2} - \frac{\|\mathbf{w}_{t+1}^k - \mathbf{w}\|^2}{2} + \eta^2 (\|\mathbf{g}_t^k - \mathbf{g}_t^k\|^2 + \|\mathbf{f}_t^k - \mathbf{f}_t^k\|^2 + \|\mathbf{g}_t^k - \mathbf{f}_t^k\|^2) - \|\mathbf{w}_t^k - \mathbf{z}_t^k\|^2 \\ \leq & \frac{\|\mathbf{w}_t^k - \mathbf{w}\|^2}{2} - \frac{\|\mathbf{w}_{t+1}^k - \mathbf{w}\|^2}{2} + \eta^2 (\|\mathbf{g}_t^k - \mathbf{g}_t^k\|^2 + \|\mathbf{f}_t^k - \mathbf{f}_t^k\|^2) + \eta^2 \|\mathbf{g}_t^k - \mathbf{f}_t^k\|^2 - \|\mathbf{w}_t^k - \mathbf{z}_t^k\|^2 \\ \leq & \frac{\|\mathbf{w}_t^k - \mathbf{w}\|^2}{2} - \frac{\|\mathbf{w}_{t+1}^k - \mathbf{w}\|^2}{2} + \eta^2 (\|\mathbf{g}_t^k - \mathbf{g}_t^k\|^2 + \|\mathbf{f}_t^k - \mathbf{f}_t^k\|^2) + \eta^2 L^2 \|\mathbf{w}_t^k - \mathbf{z}_t^k\|^2 - \|\mathbf{w}_t^k - \mathbf{z}_t^k\|^2 \\ \leq & \frac{\|\mathbf{w}_t^k - \mathbf{w}\|^2}{2} - \frac{\|\mathbf{w}_{t+1}^k - \mathbf{w}\|^2}{2} + \eta^2 (\|\mathbf{g}_t^k - \mathbf{g}_t^k\|^2 + \|\mathbf{f}_t^k - \mathbf{f}_t^k\|^2), \end{aligned}$$

where due to the Lipschitz property of the subgradients we have the smoothness

$$\|\mathbf{g}_t^k - \mathbf{f}_t^k\| \leq L \|\mathbf{w}_t^k - \mathbf{z}_t^k\|.$$

Dividing both sides by M and following Jensen's inequality we have

$$\begin{aligned}
 & F\left(\frac{1}{M}\sum_{t=1}^M \mathbf{z}_t^k\right) - F\mathbf{w} \\
 & \leq \frac{1}{M}\sum_{t=1}^M F\mathbf{z}_t^k - F\mathbf{w} \\
 & \leq \frac{\|\mathbf{w}_1^k - \mathbf{w}\|^2}{M\eta} \dashv \frac{\eta}{M}\left(\sum_{t=1}^M \|\mathbf{g}_t^k - \mathbf{g}_t^k\|^2 \dashv \sum_{t=1}^M \|\mathbf{f}_t^k - \mathbf{f}_t^k\|^2\right) \dashv \frac{1}{M}\sum_{t=1}^M \langle \mathbf{f}_t^k - \mathbf{f}_t^k, \mathbf{z}_t^k - \mathbf{w} \rangle - \frac{\lambda}{M}\sum_{t=1}^M \|\mathbf{z}_t^k - \mathbf{w}\|^2.
 \end{aligned}$$

which gives the first inequality in Lemma

Let $\mathbb{E}_{k-1}[\cdot]$ denote the expectation conditioned on all the randomness up to epoch $k-1$ and $\mathbb{E}_k^{t-1}[\cdot]$ denote the expectation conditioned on all the randomness up to the $t-1$ th iteration in the k th epoch. Using the conditional expectation of Lemma we have

$$\begin{aligned}
 & \mathbb{E}_{k-1}\left[F\left(\frac{1}{M}\sum_{t=1}^M \mathbf{z}_t^k\right)\right] - F\mathbf{w} \\
 & \leq \frac{\|\mathbf{w}_1^k - \mathbf{w}\|^2}{M\eta} \dashv \frac{\eta}{M}\left(\sum_{t=1}^M \mathbb{E}_{k-1}[\|\mathbf{g}_t^k - \mathbf{g}_t^k\|^2] \dashv \sum_{t=1}^M \mathbb{E}_{k-1}[\|\mathbf{f}_t^k - \mathbf{f}_t^k\|^2]\right) \dashv \frac{1}{M}\sum_{t=1}^M \mathbb{E}_{k-1}[\langle \mathbf{f}_t^k - \mathbf{f}_t^k, \mathbf{z}_t^k - \mathbf{w} \rangle],
 \end{aligned}$$

where we drop the last term since it is negative. To bound $\mathbb{E}_{k-1}[\|\mathbf{g}_t^k - \mathbf{g}_t^k\|^2]$ we have

$$\begin{aligned}
 & \mathbb{E}_{k-1}[\|\mathbf{g}_t^k - \mathbf{g}_t^k\|^2] = \mathbb{E}_{k-1}\left[\left\|\frac{1}{B^k}\sum_{i=1}^{B^k} \mathbf{g}\mathbf{w}_{t,i}^k - \mathbf{g}_t^k\right\|^2\right] = \mathbb{E}_{k-1}\left[\left\|\frac{1}{B^k}\sum_{i=1}^{B^k} (\mathbf{g}\mathbf{w}_{t,i}^k - \mathbf{g}_t^k)\right\|^2\right] \\
 & = \frac{1}{B^{k-2}}\left(\sum_{i=1}^{B^k} \mathbb{E}_{k-1}[\|\mathbf{g}\mathbf{w}_{t,i}^k - \mathbf{g}_t^k\|^2] \dashv \mathbb{E}_{k-1}\left[\sum_{i=j} \langle \mathbb{E}_k^{t-1}[\mathbf{g}\mathbf{w}_{t,i}^k - \mathbf{g}_t^k], \mathbb{E}_k^{t-1}[\mathbf{g}\mathbf{w}_{t,j}^k - \mathbf{g}_t^k] \rangle\right]\right) \\
 & = \frac{1}{B^{k-2}}\left(\sum_{i=1}^{B^k} \mathbb{E}_{k-1}[\|\mathbf{g}\mathbf{w}_{t,i}^k - \mathbf{g}_t^k\|^2]\right) \leq \frac{G^2}{B^k},
 \end{aligned}$$

where we use the facts $\mathbf{g}\mathbf{w}_{t,i}^k$ and $\mathbf{g}\mathbf{w}_{t,j}^k$ are independent when $i \neq j$ and

$$\mathbb{E}_k^{t-1}[\mathbf{g}\mathbf{w}_{t,i}^k - \mathbf{g}_t^k] = \mathbf{0}, \quad \mathbb{E}_k^{t-1}[\|\mathbf{g}\mathbf{w}_{t,i}^k - \mathbf{g}_t^k\|^2] \leq \mathbb{E}_k^{t-1}[\|\mathbf{g}\mathbf{w}_{t,i}^k\|^2] \leq G^2, \quad \forall i = 1, \dots, B^k.$$

Therefore we also have

$$\mathbb{E}_{k-1}[\|\mathbf{f}_t^k - \mathbf{f}_t^k\|^2] \leq \frac{G^2}{B^k}.$$

Notice that \mathbf{f}_t^k is an unbiased estimate of \mathbf{f}_t^k thus

$$\mathbb{E}_{k-1}[\langle \mathbf{f}_t^k - \mathbf{f}_t^k, \mathbf{z}_t^k - \mathbf{w} \rangle] = \mathbb{E}_{k-1}[\langle \mathbb{E}_k^{t-1}[\mathbf{f}_t^k - \mathbf{f}_t^k], \mathbf{z}_t^k - \mathbf{w} \rangle] = 0.$$

Substituting

(1)

(2)

(3)

(4)

(5)

(6)

(7)

(8)

(9)

(10)

(11)

(12)

(13)

(14)

into (1) we get the second inequality in Lemma. \square

B. Proof of Lemma

Recall that $\mathbf{g}_t^k = \frac{1}{B^k}\sum_{i=1}^{B^k} \mathbf{g}\mathbf{w}_{t,i}^k$ thus

$$\|\mathbf{g}_t^k - \mathbf{g}_t^k\| = \left\|\frac{1}{B^k}\sum_{i=1}^{B^k} \mathbf{g}\mathbf{w}_{t,i}^k - \mathbf{g}_t^k\right\|.$$

Since $\|\mathbf{g}_{t,i}^k\| \leq G$ and $\mathbb{E} \mathbf{g}_{t,i}^k = \mathbf{g}_t^k$ we have with a probability at least $1 - \delta$

$$\|\mathbf{g}_t^k -$$

C.2. $A > \eta G^2 / \lambda B^k$

Similar to the above proof on event E_1 we bound

$$|Z_t^k| \leq \|\mathbf{f}_t^k - \mathbf{f}_t^k\| \|z_t^k - \mathbf{w}\| \leq \frac{\theta}{\theta} \|\mathbf{f}_t^k - \mathbf{f}_t^k\|^2 + \frac{\theta}{\theta} \|z_t^k - \mathbf{w}\|^2 \leq \frac{C^2}{\theta} + \frac{\theta A}{\theta},$$

where θ can be any nonnegative real number. Denote the sum of conditional variances by

$$\frac{2}{M} \sum_{t=1}^M \mathbb{E}_k^{t-1} [Z_t^k{}^2] \leq C^2 \sum_{t=1}^M \|z_t - \mathbf{w}\|^2 \leq C^2 A,$$

where $\mathbb{E}_k^{t-1} \cdot$ denote the expectation conditioned on all the randomness up to the $(t-1)$ th iteration in the k th epoch.

Notice that A in the upper bound for $|Z_t^k|$ and $\frac{2}{M}$ is a random variable thus we cannot directly apply Hoeffding's inequality to address this challenge. We make use of the peeling technique described in [Bartlett et al.](#) and have

$$\begin{aligned} & \Pr \left(\sum_{t=1}^M Z_t^k \geq \sqrt{C^2 A \tau} - \left(\frac{C^2}{\theta} + \frac{\theta A}{\theta} \right) \tau \right) \\ & \Pr \left(\sum_{t=1}^M Z_t^k \geq \sqrt{C^2 A \tau} - \left(\frac{C^2}{\theta} + \frac{\theta A}{\theta} \right) \tau, \frac{\eta G^2}{\lambda B^k} < A \leq \frac{M G^2}{\lambda^2} \right) \\ & \Pr \left(\sum_{t=1}^M Z_t^k \geq \sqrt{C^2 A \tau} - \left(\frac{C^2}{\theta} + \frac{\theta A}{\theta} \right) \tau, \max_t |Z_t^k| \leq \frac{C^2}{\theta} + \frac{\theta A}{\theta}, \frac{2}{M} \leq C^2 A, \frac{\eta G^2}{\lambda B^k} < A \leq \frac{M G^2}{\lambda^2} \right) \\ & \leq \sum_{i=1}^n \Pr \left(\sum_{t=1}^M Z_t^k \geq \sqrt{C^2 A \tau} - \left(\frac{C^2}{\theta} + \frac{\theta A}{\theta} \right) \tau, \max_t |Z_t^k| \leq \frac{C^2}{\theta} + \frac{\theta A}{\theta}, \frac{2}{M} \leq C^2 A, \frac{\eta G^2}{\lambda B^k} < A \leq \frac{\eta G^2}{\lambda B^k} \right) \\ & \leq \sum_{i=1}^n \Pr \left(\sum_{t=1}^M Z_t^k \geq \sqrt{\left(C^2 \frac{\eta G^2}{\lambda B^k} \right)^{i-1}} \tau - \left(\frac{C^2}{\theta} + \frac{\theta \eta G^2}{\lambda B^k} \right)^{i-1} \tau, \max_t |Z_t^k| \leq \frac{C^2}{\theta} + \frac{\theta \eta G^2}{\lambda B^k}, \frac{2}{M} \leq C^2 \frac{\eta G^2}{\lambda B^k} \right) \\ & \leq \sum_{i=1}^n \Pr \left(\sum_{t=1}^M Z_t^k \geq \sqrt{\left(C^2 \frac{\eta G^2}{\lambda B^k} \right)^i} \tau - \left(\frac{C^2}{\theta} + \frac{\theta \eta G^2}{\lambda B^k} \right)^i \tau, \max_t |Z_t^k| \leq \frac{C^2}{\theta} + \frac{\theta \eta G^2}{\lambda B^k}, \frac{2}{M} \leq C^2 \frac{\eta G^2}{\lambda B^k} \right) \\ & \leq n e^{-\tau}, \end{aligned}$$

where

$$n = \left\lceil \log_2 \frac{M B^k}{\eta \lambda} \right\rceil,$$

and the last step follows the Bernstein's inequality for martingales in [Hoeffding](#).

$$\begin{aligned} \theta &= \frac{\lambda}{\tau}, \\ \tau &= \log \frac{n}{\delta}, \end{aligned}$$

with a probability at least $1 - \delta/2$ we have

$$\begin{aligned} & \sum_{t=1}^M Z_t^k \\ & \leq \sqrt{C^2 A \tau} - \left(\frac{C^2}{\theta} + \frac{\theta A}{\theta} \right) \tau + \sqrt{C^2 A \tau} - \frac{C^2}{\lambda} \tau^2 + \frac{\lambda A}{\lambda} \\ & \leq \frac{C^2}{\lambda} \tau + \frac{\lambda A}{\lambda} - \frac{C^2}{\lambda} \tau^2 + \frac{\lambda A}{\lambda} - \frac{C^2}{\lambda} \left(\log \frac{n}{\delta} - \log^2 \frac{n}{\delta} \right) + \frac{\lambda A}{\lambda}. \end{aligned}$$

Complete the proof by combining [\(1\)](#) and [\(2\)](#).

D. Proof of Lemma 7

As follows the logic used in the proof of Lemma 6.

It is straightforward to check that

$$B^k \leq \alpha \eta \lambda^{k-1} = \frac{\alpha \eta G^2}{V_k}.$$

Then $k \leq k_1$ with a probability at least $1 - \delta^{1/2}$ we have

$$F(\mathbf{w}_1^{k+1}) - F(\mathbf{w}^*) \stackrel{(1)}{\leq} \frac{G^2}{\lambda} = \frac{G^2}{\lambda^{1/2}} = V_1.$$

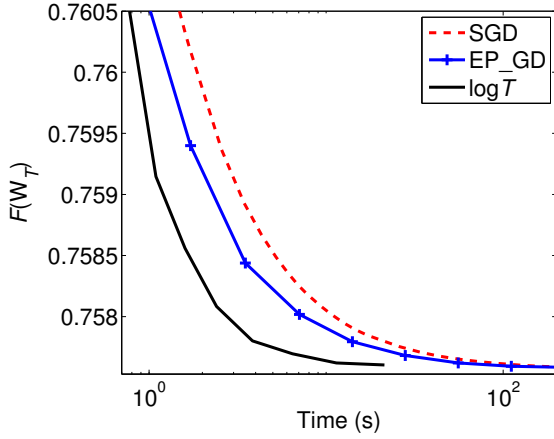
Assume that with a probability at least $1 - \delta^{k-1}$ $k \leq V_k$ for some $k \geq k_1$. We now prove the case for $k > k_1$. Notice that N defined in (10) is larger than n defined in (10). From Lemma 6 with a probability at least $1 - \delta$ we have

$$\begin{aligned} & F(\mathbf{w}_1^{k+1}) - F(\mathbf{w}^*) \\ & \leq \frac{\|\mathbf{w}_1^k - \mathbf{w}^*\|^2}{M\eta} \leq \frac{G^2 \eta}{B^k} \log^2 \frac{M}{\delta} \leq \frac{G^2}{\lambda B^k M} \left[\log^2 \frac{M}{\delta} \left(\log \frac{N}{\delta} - \log^2 \frac{N}{\delta} \right) \right] \\ & \leq \frac{1}{\alpha} \log^2 \frac{M}{\delta} \leq \frac{1}{\alpha} \left[\log^2 \frac{M}{\delta} \left(\log \frac{N}{\delta} - \log^2 \frac{N}{\delta} \right) \right] \frac{V_k}{V_k}. \end{aligned}$$

Using the definition of α in (10) with a probability at least $1 - \delta^k$ we have

$$k_{k+1} \leq -V_k \leq -V_k \leq -V_k \leq -V_k \leq V_{k+1}.$$

E. More Results for the Regularized Distance Metric Learning



(a) Mushrooms

