Algorithm 1 Modification of Newton's method

Initialize: Choose starting iterate $w^0 \in \mathbb{R}^d$, probability p and $x^0 = w^0$

for $k = 0, 1, 2, \dots do$

$$x^{k+1} = \left[\frac{1}{n} \sum_{i=1}^{n} \nabla^2 f_i(w^k)\right]^{-1} \left[\frac{1}{n} \sum_{i=1}^{n} \nabla^2 f_i(w^k) w^k - \nabla f_i(w^k)\right]$$

$$w^{k+1} = \begin{cases} x^{k+1}, & \text{with probability } p \\ w^k, & \text{with probability } 1 - p \end{cases}$$

end for

Lemma 1. Let $\varphi : \mathbb{R}^d \to \mathbb{R}$ has H-Lipschitz Hessian, i. e. $\|\nabla^2 \varphi(x) - \nabla^2 \varphi(x)\| \le H\|x - y\|$. Then φ admits for any $x, y \in \mathbb{R}^d$ following estimate

$$\left\|\nabla\varphi(x) - \nabla\varphi(y) - \nabla^2\varphi(y)(x - y)\right\| \le \frac{H}{2}\|x - y\|^2. \tag{1}$$

Proof. Indeed,

$$\|\nabla \varphi(x) - \nabla \varphi(y) - \nabla^{2} \varphi(y)(x - y)\| = \left\| \int_{0}^{1} \left[\nabla^{2} \varphi(x + \tau(y - x)) - \nabla^{2} \varphi(x) \right] (y - x) d\tau \right\|$$

$$\leq H \|x - y\|^{2} \int_{0}^{1} \tau d\tau = \frac{H}{2} \|x - y\|^{2}.$$

Lemma 2. Let f_i i be μ -strongly convex and have H-Lipschitz Hessian for all i = 1, ..., n and consider the following Lyapunov function:

$$\mathcal{W}^k \stackrel{\text{def}}{=} \|w^k - x^*\|^2. \tag{2}$$

Then the iterates of Algorithm 1 satisfy

$$||x^{k+1} - x^*|| \le \frac{H}{2\mu} \mathcal{W}^k.$$
 (3)

Proof. Letting $H^k = \frac{1}{n} \sum_{i=1}^n \nabla^2 f_i(w^k)$, we have

$$x^{k+1} = (H^k)^{-1} \left[\frac{1}{n} \sum_{i=1}^n \nabla^2 f_i(w^k) w^k - \frac{1}{n} \sum_{i=1}^n \nabla f_i(w^k) \right].$$
 (4)

Subtracting $x^* = (H^k)^{-1} H^k x^*$ from both sides, and using the fact that $\sum_{i=1}^n \nabla f_i(x^*) = 0$, this further leads to

$$x^{k+1} - x^* = (H^k)^{-1} \left[\frac{1}{n} \sum_{i=1}^n \nabla^2 f_i(w^k) \left(w^k - x^* \right) - \frac{1}{n} \sum_{i=1}^n \left(\nabla f_i(w^k) - \nabla f_i(x^*) \right) \right]. \tag{5}$$

Next, note that since f_i is μ -strongly convex, we have $\nabla^2 f_i(w^k) \succeq \mu I$ for all i. It implies that $H^k \succeq \mu I$, which in turns gives

$$\left\| H^k \right\|^{-1} \le \frac{1}{\mu}.\tag{6}$$

It gives us following inequality

$$\|x^{k+1} - x^*\| \stackrel{(5)}{\leq} \| (H^k)^{-1} \| \| \frac{1}{n} \sum_{i=1}^n \left[\nabla^2 f_i(w^k) \left(w^k - x^* \right) - \left(\nabla f_i(w^k) - \nabla f_i(x^*) \right) \right] \|$$

$$\stackrel{(6)}{\leq} \frac{1}{\mu} \| \frac{1}{n} \sum_{i=1}^n \left[\nabla^2 f_i(w^k) \left(w^k - x^* \right) - \left(\nabla f_i(w^k) - \nabla f_i(x^*) \right) \right] \|$$

$$\leq \frac{1}{n\mu} \sum_{i=1}^n \| \nabla^2 f_i(w^k) \left(w^k - x^* \right) - \left(\nabla f_i(w^k) - \nabla f_i(x^*) \right) \|$$

$$\stackrel{(1)}{\leq} \frac{1}{n\mu} \sum_{i=1}^n \frac{H}{2} \| w^k - x^* \|^2 = \frac{H}{2\mu} \| w^k - x^* \|^2 \leq \beta \| w^k - x^* \|^2.$$

Lemma 3. Assume that each f_i is μ -strongly convex and has H-Lipschitz Hessian. If $||w^0 - x^*|| \le \frac{\mu}{H}$, then for all k

$$\mathcal{W}^k \le \frac{\mu^2}{H^2}.\tag{7}$$

Proof. For k=0 it follows from the assumption of the lemma. Assume that the statement of the lemma is true for $k \geq 0$, let's prove for k+1. If $w^{k+1} = w^k$ with probability 1-p, then $\mathcal{W}^{k+1} = \mathcal{W}^k$ and the inequality (7) holds by induction assumption for \mathcal{W}^k . If $w^{k+1} = x^{k+1}$ with probability p, then

$$\mathcal{W}^{k+1} = \left\| x^{k+1} - x^* \right\|^2 \stackrel{(3)}{\leq} \left(\frac{H}{2\mu} \right)^2 \left(\mathcal{W}^k \right)^2 \stackrel{(7)}{\leq} \left(\frac{H\mu^2}{2\mu H^2} \right)^2 \leq \frac{\mu^2}{H^2}. \tag{8}$$

Lemma 4. The random iterates of Algorithm 1 satusfy the identity

$$\mathbb{E}_k \left[\mathcal{W}^{k+1} \right] \stackrel{\text{def}}{=} \mathbb{E} \left[\mathcal{W}^{k+1} \mid x^k \right] = p \mathbb{E}_k \left[\left\| x^{k+1} - x^* \right\|^2 \right] + (1-p) \mathcal{W}^k. \tag{9}$$

Proof. Obviously.

Theorem 1. Assume that every f_i is μ -strongly convex and has H-Lipschitz Hessian. Then for random iterates of Algorithm 1 we have the recursion

$$\mathbb{E}_k \left[\mathcal{W}^{k+1} \right] \le \left(1 - p + p \left(\frac{H}{2\mu} \right)^2 \mathcal{W}^k \right) \mathcal{W}^k. \tag{10}$$

Furthemore, if $||w^0 - x^*|| \le \frac{\mu}{H}$, then

$$\mathbb{E}_k \left[\mathcal{W}^{k+1} \right] \le \left(1 - \frac{3p}{4} \right) \mathcal{W}^k. \tag{11}$$

Proof. Using lemmas (2), (3) and (4), we obtain

$$\mathbb{E}_{k} \left[\mathcal{W}^{k+1} \right] \stackrel{(9)}{=} p \mathbb{E}_{k} \left[\left\| x^{k+1} - x^{*} \right\|^{2} \right] + (1-p) \mathcal{W}^{k} \stackrel{(3)}{\leq} p \left(\frac{H}{2\mu} \mathcal{W}^{k} \right)^{2} + (1-p) \mathcal{W}^{k}$$

$$= \left(1 - p + p \left(\frac{H}{2\mu} \right)^{2} \mathcal{W}^{k} \right) \mathcal{W}^{k} \stackrel{(7)}{\leq} \left(1 - \frac{3p}{4} \right) \mathcal{W}^{k}.$$