

A. proofs

A.1. proof of Lemma 1

Proof. For any t and $i \leq t$,

$$\begin{aligned}
 \lim_{\beta_1 \rightarrow 1} w_{i,t} &= \lim_{\beta_1 \rightarrow 1} \frac{(1 - \beta_1)\beta_1^{t-i}}{1 - \beta_1^t} \\
 &= \lim_{\beta_1 \rightarrow 1} \frac{1 - \beta_1}{1 - \beta_1^t} \lim_{\beta_1 \rightarrow 1} \beta_1^{t-i} \\
 &= \lim_{\beta_1 \rightarrow 1} \frac{1 - \beta_1}{1 - \beta_1^t} \\
 &= \lim_{\beta_1 \rightarrow 1} \frac{1}{t\beta_1^{t-1}} \\
 &= \frac{1}{t}.
 \end{aligned}$$

here, the second equality holds by the limit properties. The last second equality holds by L'Hôpital's rule. \square

A.2. proof of Proposition 1

Proof. from (11):

$$\begin{aligned}
 \sum_{i=1}^t w_{i,t} Q_i - \sum_{i=1}^{t-1} w_{i,t-1} Q_i &= \sum_{i=1}^{t-1} (w_{i,t} - w_{i,t-1}) Q_i + w_{t,t} Q_t \\
 &= \sum_{i=1}^{t-1} \left(\frac{(1 - \beta_1)\beta_1^{t-i}}{1 - \beta_1^t} - \frac{(1 - \beta_1)\beta_1^{t-1-i}}{1 - \beta_1^{t-1}} \right) Q_i + w_{t,t} Q_t \\
 &= \sum_{i=1}^{t-1} \left(\frac{\beta_1(1 - \beta_1^{t-1})}{1 - \beta_1^t} - 1 \right) w_{i,t-1} Q_i + w_{t,t} Q_t \\
 &= \frac{\beta_1 - 1}{1 - \beta_1^t} \sum_{i=1}^{t-1} w_{i,t-1} Q_i + w_{t,t} Q_t \\
 &= -w_{t,t} \sum_{i=1}^{t-1} w_{i,t-1} Q_i + w_{t,t} Q_t.
 \end{aligned}$$

Rearranging, we obtain

$$\begin{aligned}
 w_{t,t} Q_t &= \sum_{i=1}^t w_{i,t} Q_i - (1 - w_{t,t}) \sum_{i=1}^{t-1} w_{i,t-1} Q_i \\
 &= \text{diag} \left(\frac{d_t}{1 - \beta_1^t} \right) - (1 - w_{t,t}) \text{diag} \left(\frac{d_{t-1}}{1 - \beta_1^{t-1}} \right) \\
 &= \text{diag} \left(\frac{d_t - \beta_1 d_{t-1}}{1 - \beta_1^t} \right).
 \end{aligned}$$

Thus, $Q_t = \text{diag} \left(\frac{d_t - \beta_1 d_{t-1}}{1 - \beta_1^t} \right)$. \square

A.3. proof of Proposition 2

Proof. (13) can be rewritten as (apart from a constant)

$$\min_{\theta \in \Theta} \left\langle \sum_{i=1}^t w_{i,t} \left(g_i - \frac{\sigma_i}{1 - \beta_1} \theta_{i-1} \right), \theta \right\rangle + \frac{1}{2} \|\theta\|_{\text{diag} \left(\frac{d_t}{1 - \beta_1^t} \right)}^2. \quad (17)$$

Let $z_t = (1 - \beta_1^t) \sum_{i=1}^t w_{i,t} \left(g_i - \frac{\sigma_i}{1 - \beta_1} \theta_{i-1} \right)$. By (10), we have a simple recursive update rule:

$$\begin{aligned} z_t &= \beta_1 z_{t-1} + (1 - \beta_1) \left(g_t - \frac{\sigma_t}{1 - \beta_1} \theta_{t-1} \right) \\ &= \beta_1 z_{t-1} + (1 - \beta_1) g_t - \sigma_t \theta_{t-1}. \end{aligned}$$

Substituting z_t into (17), we have

$$\min_{\theta \in \Theta} \left\langle \frac{z_t}{1 - \beta_1^t}, \theta \right\rangle + \frac{1}{2} \|\theta\|_{\text{diag}\left(\frac{d_t}{1 - \beta_1^t}\right)}^2.$$

Rearranging, we obtain

$$\min_{\theta \in \Theta} \frac{1}{2} \|\theta + z_t/d_t\|_{\text{diag}\left(\frac{d_t}{1 - \beta_1^t}\right)}^2,$$

with optimal solution $\Pi_{\Theta}^{\text{diag}(d_t/(1 - \beta_1^t))}(-z_t/d_t)$. □

A.4. proof of Proposition 3

Proof. When $\beta_1 = 0$, we have $w_{t,t} = 1$ and $w_{i,t} = 0$ for all $i < t$. Thus, $\sigma_t = d_t$, and (13) reduces to:

$$\min_{\theta \in \Theta} \langle g_t, \theta \rangle + \frac{1}{2} \|\theta - \theta_{t-1}\|_{\text{diag}\left(\frac{1}{\eta_t} \left(\sqrt{\frac{v_t}{1 - \beta_2^t}} + \epsilon_t \mathbf{1} \right)\right)}^2,$$

We can rewrite above as

$$\min_{\theta \in \Theta} \frac{1}{2} \left\| \theta - \left(\theta_{t-1} - \frac{\eta_t}{\sqrt{\frac{v_t}{1 - \beta_2^t}} + \epsilon_t \mathbf{1}} g_t \right) \right\|_{\text{diag}\left(\frac{1}{\eta_t} \left(\sqrt{\frac{v_t}{1 - \beta_2^t}} + \epsilon_t \mathbf{1} \right)\right)}^2,$$

with optimal solution

$$\Pi_{\Theta}^{\text{diag}(d_t/(1 - \beta_1^t))} \left(\theta_{t-1} - \text{diag} \left(\frac{\eta_t}{\sqrt{\frac{v_t}{1 - \beta_2^t}} + \epsilon_t \mathbf{1}} \right) g_t \right). \quad (18)$$

analogous to (10) and Lemma 1,

$$\lim_{\beta_2 \rightarrow 1} \frac{v_t}{1 - \beta_2^t} = \lim_{\beta_2 \rightarrow 1} \sum_{i=1}^t \frac{(1 - \beta_2) \beta_2^{t-i}}{1 - \beta_2^t} g_i^2 = \frac{1}{t} \sum_{i=1}^t g_i^2. \quad (19)$$

Combining with $\eta_t = \eta/\sqrt{t}$ and $\epsilon_t = \epsilon/\sqrt{t}$, we obtain

$$\lim_{\beta_2 \rightarrow 1} \frac{\eta_t}{\sqrt{\frac{v_t}{1 - \beta_2^t}} + \epsilon_t \mathbf{1}} = \frac{\eta}{\sqrt{g_{1:t}^2} + \epsilon \mathbf{1}},$$

and (18) reduces to below

$$\Pi_{\Theta}^{\text{diag}((\sqrt{g_{1:t}^2} + \epsilon \mathbf{1})/\eta)} \left(\theta_{t-1} - \text{diag} \left(\frac{\eta}{\sqrt{g_{1:t}^2} + \epsilon \mathbf{1}} \right) g_t \right),$$

□

A.5. proof of Proposition 4

Proof. When $\beta_1 \rightarrow 1$, we have

$$\begin{aligned} \lim_{\beta_1 \rightarrow 1} \frac{\sigma_t}{1 - \beta_1} &= \lim_{\beta_1 \rightarrow 1} \left[\frac{d_t}{1 - \beta_1} - \frac{\beta_1 d_{t-1}}{1 - \beta_1} \right] \\ &= \lim_{\beta_1 \rightarrow 1} \left[\frac{1 - \beta_1^t \sqrt{\frac{v_t}{1 - \beta_2^t}} + \epsilon_t \mathbf{1}}{1 - \beta_1} \frac{1}{\eta_t} - \frac{\beta_1 (1 - \beta_1^{t-1}) \sqrt{\frac{v_{t-1}}{1 - \beta_2^{t-1}}}}{1 - \beta_1} \frac{1}{\eta_{t-1}} + \epsilon_{t-1} \mathbf{1} \right] \\ &= t \frac{\sqrt{\frac{v_t}{1 - \beta_2^t}} + \epsilon_t \mathbf{1}}{\eta_t} - (t-1) \frac{\sqrt{\frac{v_{t-1}}{1 - \beta_2^{t-1}}}}{\eta_{t-1}} + \epsilon_{t-1} \mathbf{1}. \end{aligned}$$

Substituting this into (13), we obtain

$$\min_{\theta \in \Theta} \sum_{i=1}^t \left(\langle g_i, \theta \rangle + \frac{1}{2} \|\theta - \theta_{i-1}\|_{\text{diag}(m_i)}^2 \right), \quad (20)$$

where $m_i = \frac{t}{\eta_t} \left(\sqrt{\frac{v_t}{1 - \beta_2^t}} + \epsilon_t \mathbf{1} \right) - \frac{t-1}{\eta_{t-1}} \left(\sqrt{\frac{v_{t-1}}{1 - \beta_2^{t-1}}} + \epsilon_{t-1} \mathbf{1} \right)$.

Combining with $\eta_t = \eta \sqrt{t}$, $\epsilon_t = \epsilon / \sqrt{t}$, and (19), we further obtain

$$\begin{aligned} \lim_{\beta_2 \rightarrow 1} m_i &= \lim_{\beta_2 \rightarrow 1} t \frac{\sqrt{\frac{v_t}{1 - \beta_2^t}} + \epsilon_t \mathbf{1}}{\eta_t} - (t-1) \frac{\sqrt{\frac{v_{t-1}}{1 - \beta_2^{t-1}}} + \epsilon_{t-1} \mathbf{1}}{\eta_{t-1}} = \frac{\sqrt{g_{1:t}^2} + \epsilon \mathbf{1}}{\eta} - \frac{\sqrt{g_{1:t-1}^2} + \epsilon \mathbf{1}}{\eta} \\ &= \frac{\sqrt{g_{1:t}^2} - \sqrt{g_{1:t-1}^2}}{\eta}. \end{aligned}$$

Substituting back into (20), we recover FTRL with adaptive learning rate. by using the equivalence theorem in (McMahan, 2011), we obtain $\theta_t \leftarrow \theta_{t-1} - \text{diag} \left(\frac{\eta}{\sqrt{g_{1:t}^2} + \epsilon \mathbf{1}} \right) g_t$. \square

A.6. proof of Theorem 1

Proof. Note that $w_{i,t} = \frac{\beta_1(1 - \beta_1^{t-1})}{1 - \beta_1^t} w_{i,t-1}$. with $\Theta = \mathbb{R}^d$, consider the first term in the objective of (17): with z_t defined in proposition 2

$$\begin{aligned} &\left\langle \sum_{i=1}^t w_{i,t} \left(g_i - \frac{\sigma_i}{1 - \beta_1} \theta_{i-1} \right), \theta \right\rangle \\ &= \frac{\beta_1(1 - \beta_1^{t-1})}{1 - \beta_1^t} \left\langle \sum_{i=1}^{t-1} w_{i,t-1} \left(g_i - \frac{\sigma_i}{1 - \beta_1} \theta_{i-1} \right), \theta \right\rangle + \left\langle w_{t,t} \left(g_t - \frac{\sigma_t}{1 - \beta_1} \theta_{t-1} \right), \theta \right\rangle \\ &= \frac{\beta_1}{1 - \beta_1^t} \langle z_{t-1}, \theta \rangle + \left\langle w_{t,t} \left(g_t - \frac{\sigma_t}{1 - \beta_1} \theta_{t-1} \right), \theta \right\rangle \\ &= -\frac{\beta_1}{1 - \beta_1^t} \langle d_{t-1} \theta_{t-1}, \theta \rangle + \frac{1 - \beta_1}{1 - \beta_1^t} \left\langle g_t - \frac{\sigma_t}{1 - \beta_1} \theta_{t-1}, \theta \right\rangle \\ &= \frac{1}{1 - \beta_1^t} \langle (1 - \beta_1) g_t - \theta_{t-1} (\sigma_t + \beta_1 d_{t-1}), \theta \rangle \\ &= \frac{1}{1 - \beta_1^t} \langle (1 - \beta_1) g_t - d_t \theta_{t-1}, \theta \rangle, \end{aligned}$$

where the second equality follows from the definition of z_t . The third equality holds since $\Theta = \mathbb{R}^d$ and therefore $\theta_t = -z_t/d_t$ by Proposition 2. Thus, combing this expression into (17), we obtain

$$\min_{\theta \in \mathbb{R}^d} \frac{1}{1 - \beta_1^t} \langle (1 - \beta_1) g_t - d_t \theta_{t-1}, \theta \rangle + \frac{1}{2} \|\theta\|_{\text{diag}(\frac{d_t}{1 - \beta_1^t})}^2,$$

With the definition of d_t , it can be seen that solving above problem (taking gradient w.r.t. θ and setting it to zero) leads to a gradient descent style update rule:

$$\theta_t \leftarrow \theta_{t-1} - \text{diag} \left(\frac{1 - \beta_1}{1 - \beta_1^t} \frac{\eta_t}{\left(\sqrt{\frac{v_t}{(1 - \beta_1^2)^t}} + \epsilon_t \mathbf{1} \right)} \right) g_t.$$

which concludes the proof. □

A.7. proof of Proposition 5

Proof. Note that (15) can be rewritten as

$$\begin{aligned} \min_{\theta \in \Theta} & \left(\left\langle \sum_{i=1}^t w_{i,t} g_i, \theta \right\rangle + \frac{1}{2} \|\theta - \theta_{t-1}\|_{\sum_{i=1}^t w_{i,t} \text{diag} \left(\frac{\sigma_i}{1 - \beta_1} \right)}^2 \right) \\ & = \min_{\theta \in \Theta} \left(\left\langle \sum_{i=1}^t w_{i,t} g_i, \theta \right\rangle + \frac{1}{2} \|\theta - \theta_{t-1}\|_{\text{diag} \left(\frac{d_t}{1 - \beta_1^t} \right)}^2 \right). \end{aligned}$$

Thus, with the definition of d_t , solving above problem, we obtain (16). □