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Let the SVD of  $C_t^>$  be  $C_t^> = U^> V^>$  where  $U \in \mathbb{R}^{d \times d}$ ;  $V \in \mathbb{R}^{d \times d}$ ;  $V \in \mathbb{R}^{d \times d}$ . According to Coollay 2, the probability is at least  $\frac{1}{2}$ , simultaneously for all  $t = 1; T$ ,

$$\begin{aligned} S_t^> S_t &= K_t - I_d = K_t^{1=2} X_t^{1=2} K_t^{1=2} - I_d \\ &= (1 + \frac{1}{2}) K_t - I_d = (1 + \frac{1}{2}) C_t^> C_t + I_d \\ &= U (1 + \frac{1}{2}) X_t^{1=2} + I_d U^> \end{aligned}$$

and

$$\begin{aligned} S_t^> S_t + I_d &= K_t - I_d + I_d \\ &= K_t^{1=2} X_t^{1=2} K_t^{1=2} - I_d + I_d \\ &= (1 - \frac{1}{2}) K_t - I_d + I_d \\ &= (1 - \frac{1}{2}) C_t^> C_t \end{aligned}$$

Then simultaneously for all  $t = 1; T$ , we have

$$(S_t^> S_t)^{1=2} \leq \frac{1}{1 + \frac{1}{2}} U (X_t^{1=2})^{1=2} U^> + \frac{1}{1 - \frac{1}{2}} U I_d U^> = \frac{1}{1 + \frac{1}{2}} X_t^{1=2} + \frac{1}{1 - \frac{1}{2}} I_d \quad (6)$$

and

$$\begin{aligned} (S_t^> S_t)^{1=2} &= (S_t^> S_t)^{1=2} + \frac{1}{1 - \frac{1}{2}} I_d - \frac{1}{1 - \frac{1}{2}} I_d \\ &= (S_t^> S_t) + I_d^{1=2} - \frac{1}{1 - \frac{1}{2}} I_d \\ &= \frac{1}{1 - \frac{1}{2}} X_t^{1=2} - \frac{1}{1 - \frac{1}{2}} I_d \end{aligned} \quad (7)$$

Then we consider bounding the term in the upper bound of Lemma 1. Let  $X_t$  denote  $S_t^> S_t$ . Simultaneously for all  $t = 1; T$ , we have

$$\begin{aligned} & B_{t+1} (D_{t+1}; t+1) - B_t (D_t; t+1) \\ &= \frac{1}{2} D_{t+1} (X_{t+1}^{1=2} - X_t^{1=2}) (D_{t+1})^E \\ &= \frac{1}{2} D_{t+1} \left( \frac{1}{1 + \frac{1}{2}} X_{t+1}^{1=2} - \frac{1}{1 + \frac{1}{2}} X_t^{1=2} \right) (D_{t+1})^E \\ &= \frac{1}{2} D_{t+1} \left( \frac{1}{1 - \frac{1}{2}} X_{t+1}^{1=2} - \frac{1}{1 - \frac{1}{2}} X_t^{1=2} \right) (D_{t+1})^E \\ &+ \frac{1}{2} D_{t+1} \left( \frac{1}{1 - \frac{1}{2}} I_d - \frac{1}{1 - \frac{1}{2}} I_d \right) (D_{t+1})^E \\ &= \frac{1}{2} D_{t+1} \left( \frac{1}{1 + \frac{1}{2}} X_{t+1}^{1=2} - \frac{1}{1 + \frac{1}{2}} X_t^{1=2} \right) (D_{t+1})^E \\ &+ \frac{1}{2} D_{t+1} \left( \frac{1}{1 - \frac{1}{2}} X_{t+1}^{1=2} - \frac{1}{1 - \frac{1}{2}} X_t^{1=2} \right) (D_{t+1})^E \\ &+ \frac{1}{2} k (D_{t+1}) k_2^2 \\ &+ \frac{1}{2} k (D_{t+1}) k_2^2 (X_{t+1}^{1=2} - X_t^{1=2}) \\ &+ \frac{1}{4} D_{t+1} (X_{t+1}^{1=2} + X_t^{1=2}) (D_{t+1})^E \\ &+ \frac{1}{2} k (D_{t+1}) k_2^2 \end{aligned}$$

we the simplification of (6), (7) and the last inequality has been proved in the proof of Theorem 1.

Then we can get

$$\begin{aligned}
 & \sum_{t=1}^{T-1} \mathbb{E} \left[ \frac{1}{2} \max_{\mathbf{x}_t} \mathbf{k}_t^T (\mathbf{X}_t^{-1/2}) \mathbf{k}_t + \frac{1}{2} \mathbf{k}_t^T (\mathbf{X}_t^{-1/2}) \mathbf{k}_t \right] \\
 & + \frac{1}{2} \max_{\mathbf{x}_T} \mathbf{k}_T^T (\mathbf{X}_T^{-1/2}) \mathbf{k}_T \\
 & + \frac{1}{4} \sum_{t=1}^{T-1} \mathbf{k}_t^T (\mathbf{X}_t^{-1/2}) \mathbf{k}_t \\
 & + \frac{1}{2} \sum_{t=1}^{T-1} \max_{\mathbf{x}_t} \mathbf{k}_t^T (\mathbf{X}_t^{-1/2}) \mathbf{k}_t
 \end{aligned} \tag{8}$$

Note that  $\mathbf{x}_1 = \mathbf{0}$ , then

$$\mathbf{B}_1(\mathbf{x}_1) = \frac{1}{2} \mathbf{D} + \frac{1}{2} (\mathbf{I}_d + \mathbf{X}_1^{-1/2}) \mathbf{E} \tag{9}$$

Before considering the upper bound of  $\sum_{t=1}^T \mathbf{k}_t^T (\mathbf{X}_t^{-1/2}) \mathbf{k}_t$ , we need to derive the upper bound of  $H_t^{-1}$ .

Let the SVD of  $\mathbf{S}_t^>$  be  $\mathbf{S}_t^> = \mathbf{U}_t \mathbf{V}_t^>$  where  $\mathbf{U}_t \in \mathbb{R}^{d \times d}$ ,  $\mathbf{V}_t \in \mathbb{R}^{d \times d}$ ,  $\mathbf{V}_t \in \mathbb{R}^{d \times d}$ . We also have, for all  $t = 1; T$ ,

$$\begin{aligned}
 \mathbf{H}_t &= \mathbf{I}_d + (\mathbf{S}_t^> \mathbf{S}_t)^{1/2} = \mathbf{U}_t (\mathbf{I}_d + (\mathbf{V}_t^> \mathbf{V}_t)^{1/2}) \mathbf{U}_t^> \\
 &= \mathbf{U}_t (\mathbf{I}_d + (\mathbf{V}_t^> \mathbf{V}_t)^{1/2}) \mathbf{U}_t^> = (\mathbf{I}_d + \mathbf{S}_t^> \mathbf{S}_t)^{1/2}
 \end{aligned}$$

denote  $\rho_i = \frac{\rho}{\rho + \lambda_i(\mathbf{S}_t^> \mathbf{S}_t)}$  for all  $i = 1; d$ .

Then according to Corollary 2, the probability is at least  $\frac{1}{2}$ , simultaneously for all  $t = 1; T$ ,

$$\begin{aligned}
 \mathbf{H}_t^{-1} &= (\mathbf{I}_d + \mathbf{S}_t^> \mathbf{S}_t)^{-1/2} = (\mathbf{K}_t^{1/2} \mathbf{I}_t \mathbf{K}_t^{1/2})^{-1/2} \\
 &= \frac{1}{\rho} (\mathbf{K}_t^{-1})^{1/2} = \frac{1}{\rho} (\mathbf{I}_d + \mathbf{X}_t)^{-1/2}.
 \end{aligned}$$

Then we can get

$$\begin{aligned}
 \mathbf{k}_t^T (\mathbf{X}_t^{-1/2}) \mathbf{k}_t &= \mathbf{g}_t^T \mathbf{H}_t^{-1} \mathbf{g}_t = \frac{1}{\rho} \mathbf{g}_t^T (\mathbf{I}_d + \mathbf{X}_t)^{-1/2} \mathbf{g}_t \\
 &= \frac{2 \|\mathbf{g}_t\| \|\mathbf{x}_t\|}{\rho} \mathbf{x}_t^T (\mathbf{X}_t^{-1/2}) \mathbf{x}_t :
 \end{aligned}$$

According to Lemma 2, we have

$$\begin{aligned} \sum_{t=1}^T \mathbb{E} \| \nabla f_t(x_t) \|^2 &\leq \frac{2}{\epsilon} \max_{t=1}^T \mathbb{E} \| \nabla f_t(x_t) \|^2 \sum_{t=1}^T \mathbb{E} \| \nabla f_t(x_t) \|^2 \\ &\leq \frac{4}{\epsilon} \max_{t=1}^T \mathbb{E} \| \nabla f_t(x_t) \|^2 \sum_{t=1}^T \mathbb{E} \| \nabla f_t(x_t) \|^2 \end{aligned} \quad (10)$$

We complete the proof by using (8), (9), and (10) into Lemma 1.

### A.6.1

Let  $C_t = U \Lambda V^T$  be the singular value decomposition of  $C_t$ . Notice that  $U \in \mathbb{R}^{d \times r}$ ;  $V \in \mathbb{R}^{d \times d}$ . According to Theorem 3, we have if  $\epsilon = \frac{r + \log(1/\delta)}{2}$ , then simultaneously  $\delta \times 2^r$ , the probability

$$(1 - \epsilon) \| Ux \|^2 \leq \| R_t Ux \|^2 \leq (1 + \epsilon) \| Ux \|^2$$

Let  $y \in \mathbb{R}^d$  be arbitrary, then  $C_t y = U \Lambda V^T y = Ux$  where  $x = V^T y \in \mathbb{R}^d$ .

Then we have

$$y^T S_t^> S_t y = y^T C_t^> R_t^> R_t C_t y = \| R_t Ux \|^2 \leq (1 + \epsilon) \| Ux \|^2 = (1 + \epsilon) y^T C_t^> C_t y$$

and

$$y^T S_t^< S_t y = y^T C_t^< R_t^< R_t C_t y = \| R_t Ux \|^2 \geq (1 - \epsilon) \| Ux \|^2 = (1 - \epsilon) y^T C_t^< C_t y$$

Then, we have  $(1 - \epsilon) C_t^< C_t \leq S_t^< S_t \leq (1 + \epsilon) C_t^< C_t$  with probability  $1 - \delta$ , provided  $\epsilon = \frac{r + \log(1/\delta)}{2}$ . Using the union bound, we have if  $\epsilon = \frac{r + \log(1/\delta)}{2}$ , the probability  $1 - \delta$  simultaneously for all  $t = 1, \dots, T$ ,

$$(1 - \epsilon) C_t^< C_t \leq S_t^< S_t \leq (1 + \epsilon) C_t^< C_t$$

### A.6.2

Let the SVD of  $C_t^>$  be  $C_t^> = U \Lambda V^T$  where  $U \in \mathbb{R}^{d \times d}$ ;  $\Lambda \in \mathbb{R}^{d \times d}$ ;  $V \in \mathbb{R}^{d \times d}$ . Then we have  $K_t = U(\Lambda + \epsilon I_d)^{-1} U^T$  and

$$\begin{aligned} f_t &= K_t^{-1/2} K_t K_t^{-1/2} = K_t^{-1/2} (\Lambda + C_t^> R_t^> R_t C_t) K_t^{-1/2} \\ &= U (\Lambda + \epsilon I_d)^{-1/2} (I_p + \epsilon I_p)^{-1/2} V^T R_t^> R_t V (\Lambda + \epsilon I_d)^{-1/2} U^T \\ &= U (\Lambda + \epsilon I_d)^{-1/2} (I_p + \epsilon I_p)^{-1/2} R R^T (\Lambda + \epsilon I_d)^{-1/2} U^T \end{aligned}$$

where  $R = V^T R_t^> \in \mathbb{R}^{d \times d}$  is a Gaussian random matrix and  $V$  is an orthogonal matrix and  $R$  is a Gaussian random matrix

Let  $c_1^2 = \frac{1}{1 + \frac{2}{t_1}}$  and  $s_1^2 = \frac{2}{1 + \frac{2}{t_1}}$ . Then according to Theorem 4, the probability is at least

$$(1 - c_1)I_d - t_1 - (1 + c_1)I_d$$

provided  $\frac{F_1 - t_1}{c_1^2(1 + \frac{2}{t_1})} \log \frac{2d}{c_1}$  is at least  $\frac{1}{2}$ . Using the union bound, complete the proof.