

A Proof of Lemma 1

Proof. The proof follows a standard argument, which can be found in Bartlett and Mendelson [5, Theorem 8].

$$\begin{aligned}
L(\hat{\mathcal{W}}) - L(\mathcal{W}^*) &\leq \left(L(\hat{\mathcal{W}}) - \hat{L}(\hat{\mathcal{W}}) \right) + \left(\hat{L}(\hat{\mathcal{W}}) - \hat{L}(\mathcal{W}^*) \right) + \left(\hat{L}(\mathcal{W}^*) - L(\mathcal{W}^*) \right) \\
&\leq \sup_{\|\mathcal{W}\|_* \leq B_0} \left(L(\mathcal{W}) - \hat{L}(\mathcal{W}) \right) + \sqrt{\frac{\log(2/\delta)}{2\rho|S|m}} \quad (\text{w/ probability at least } 1 - \delta/2) \\
&\leq R(\ell \circ \mathcal{L}_{B_0}) + \left(c + \frac{1}{\sqrt{\rho}} \right) \sqrt{\frac{\log(2/\delta)}{2|S|m}} \quad (\text{w/ probability at least } 1 - \delta),
\end{aligned}$$

where

$$R(\ell \circ \mathcal{L}_{B_0}) := \mathbb{E} \sup_{\|\mathcal{W}\|_* \leq B_0} \frac{2}{|S|} \sum_{(p,q) \in S} \frac{1}{m_{pq}} \sum_{i=1}^{m_{pq}} \sigma_{ipq} \ell(\langle \mathbf{x}_{ipq}, \mathbf{w}_{pq} \rangle - y_{ipq}).$$

In the third line, we used McDiarmid's inequality and introduced Rademacher random variables $\sigma_{ipq} \in \{-1, +1\}$; the expectation is over both the Rademacher random variables and the training samples $(\mathbf{x}_{ipq}, y_{ipq})$. Using the fact that $c + 1/\sqrt{\rho} \leq c + 1 =: c'$, the last term can be upper bounded by the last term in the statement.

We further analyze the first term. Using the Lipschitz continuity of ℓ and the bound on $|y_{ipq}|$, we have

$$R(\ell \circ \mathcal{L}_{B_0}) \leq 2\Lambda \left(R(\mathcal{L}_{B_0}) + \frac{b \sqrt{\sum_{(p,q) \in S} m_{p,q}}}{|S|m} \right),$$

where

$$R(\mathcal{L}_B) = \frac{2}{|S|} \mathbb{E} \sup_{\|\mathcal{W}\|_* \leq B_0} \sum_{(p,q) \in S} \frac{1}{m_{pq}} \sum_{i=1}^{m_{pq}} \sigma_{ipq} \langle \mathbf{x}_{ipq}, \mathbf{w}_{pq} \rangle.$$

Finally, using the definition of \mathcal{D} and Hölder's inequality, we have

$$R(\mathcal{L}_{B_0}) \leq \frac{2B_0}{|S|} \mathbb{E} \|\mathcal{D}\|_{**},$$

which concludes the proof. \square

B Proof of Theorem 1

Proof of inequality (7): From Tomioka et al. [23, Lemma 1], we have

$$\|\mathcal{D}\|_{\text{overlap}^*} = \inf_{\mathcal{D}^{(1)} + \mathcal{D}^{(2)} + \mathcal{D}^{(3)} = \mathcal{D}} \max_k \|\mathcal{D}_{(k)}^{(k)}\|_{\text{op}},$$

where the infimum is over three tensors $\mathcal{D}^{(1)}$, $\mathcal{D}^{(2)}$, and $\mathcal{D}^{(3)}$ that sum to the original tensor \mathcal{D} , and $\|\cdot\|_{\text{op}}$ is the operator norm (maximal singular value). Since we can take any $\mathcal{D}^{(k)}$ to equal \mathcal{D} , the norm can be upper bounded as follows:

$$\|\mathcal{D}\|_{\text{overlap}^*} \leq \min_k \|\mathcal{D}_{(k)}\|_{\text{op}}.$$

Since the expectation of minimum over k can be upper bounded by the minimum of expectations, we have

$$\mathbb{E} \|\mathcal{D}\|_{\text{overlap}^*} \leq \mathbb{E} \min_k \|\mathcal{D}_{(k)}\|_{\text{op}} \leq \min_k \mathbb{E} \|\mathcal{D}_{(k)}\|_{\text{op}}.$$

Now we upper bound each expectation using Theorem 6.1 in Tropp [24, see also Remarks 6.3 and 6.5], which states that

$$\Pr \{ \|\mathcal{D}_{(k)}\|_{\text{op}} \geq t \} \leq \begin{cases} D_k \exp(-3t^2/8\sigma_k^2), & \text{for } t \leq \sigma_k^2/R_k, \\ D_k \exp(-3t/8R_k), & \text{for } t \geq \sigma_k^2/R_k, \end{cases} \quad (10)$$

and

$$\mathbb{E}\|\mathbf{D}_{(k)}\|_{\text{op}} \leq C(\sigma_k \sqrt{\log D_k} + R_k \log D_k), \quad (11)$$

where C is an absolute constant, and

$$\begin{aligned} \sigma_k^2 &:= \max \left(\left\| \sum_{(p,q) \in S} \sum_{i=1}^{m_{pq}} \mathbb{E} \left[\mathbf{Z}_{(k)}^{ipq} \left(\mathbf{Z}_{(k)}^{ipq} \right)^\top \right] \right\|_{\text{op}}, \left\| \sum_{(p,q) \in S} \sum_{i=1}^{m_{pq}} \mathbb{E} \left[\left(\mathbf{Z}_{(k)}^{ipq} \right)^\top \mathbf{Z}_{(k)}^{ipq} \right] \right\|_{\text{op}} \right), \\ R_k &\geq \left\| \mathbf{Z}_{(k)}^{ipq} \right\|_{\text{op}} \quad (\text{almost surely}). \end{aligned}$$

Due to our assumption $\|\mathbf{x}_{ipq}\| \leq R$, we can take $R_k = R/m$. Thus the remaining task is to compute σ_k^2 for $k = 1, 2, 3$.

First for $k = 1$, the unfolding $\mathbf{Z}_{(1)}^{ipq}$ is a $d \times PQ$ matrix that contains $\sigma_{ipq} \mathbf{x}_{ipq} / m_{pq}$ in the column specified by (p, q) . Therefore, using $m_{pq} \geq m$ and $\|\mathbf{C}_{pq}\| \leq \kappa/d$, we obtain

$$\sum_{i=1}^{m_{pq}} \mathbb{E} \left[\mathbf{Z}_{(1)}^{ipq} \left(\mathbf{Z}_{(1)}^{ipq} \right)^\top \right] = \frac{1}{m_{pq}} \mathbf{C}_{pq} \preceq \frac{\kappa}{md} \mathbf{I}_d,$$

from which we have

$$\left\| \sum_{(p,q) \in S} \sum_{i=1}^{m_{pq}} \mathbb{E} \left[\mathbf{Z}_{(1)}^{ipq} \left(\mathbf{Z}_{(1)}^{ipq} \right)^\top \right] \right\|_{\text{op}} \leq \frac{\kappa|S|}{md}. \quad (12)$$

Similarly, since the choice of (p, q) is uniform over $[P] \times [Q]$, we have

$$\sum_{i=1}^{m_{pq}} \mathbb{E} \left[\left(\mathbf{Z}_{(1)}^{ipq} \right)^\top \mathbf{Z}_{(1)}^{ipq} \right] = \frac{1}{PQ} \text{diag} \left(\frac{\text{Tr} \mathbf{C}_{pq}}{m_{pq}} \right) \preceq \frac{\kappa}{mPQ} \mathbf{I}_{PQ},$$

from which we have

$$\left\| \sum_{(p,q) \in S} \sum_{i=1}^{m_{pq}} \mathbb{E} \left[\left(\mathbf{Z}_{(1)}^{ipq} \right)^\top \mathbf{Z}_{(1)}^{ipq} \right] \right\|_{\text{op}} \leq \frac{\kappa|S|}{mPQ}. \quad (13)$$

Substituting inequalities (12) and (13) into (11), we have

$$\mathbb{E}\|\mathbf{D}_{(1)}\|_{\text{op}} \leq C \left(\sqrt{\frac{\kappa|S|}{mdPQ}} D_1 \log D_1 + \frac{R}{m} \log D_1 \right).$$

Following a similar line of argument, we have

$$\begin{aligned} \mathbb{E}\|\mathbf{D}_{(2)}\|_{\text{op}} &\leq C \left(\sqrt{\frac{\kappa|S|}{mdPQ}} D_2 \log D_2 + \frac{R}{m} \log D_2 \right), \\ \mathbb{E}\|\mathbf{D}_{(3)}\|_{\text{op}} &\leq C \left(\sqrt{\frac{\kappa|S|}{mdPQ}} D_3 \log D_3 + \frac{R}{m} \log D_3 \right). \end{aligned}$$

Taking the minimum over k and dividing by $|S|$, we obtain inequality (7). \square

Proof of inequality (8): From Tomioka et al. [21, Lemma 1], we know that

$$\|\mathcal{D}\|_{\text{latent}^*} = \max_k \|\mathbf{D}_{(k)}\|_{\text{op}}.$$

Combining inequality (10) with a union bound, we have

$$\Pr \left\{ \|\mathcal{D}\|_{\text{latent}^*} \geq t \right\} \leq 3(\max_k D_k) \max \left(\exp \left(-\frac{3t^2}{8 \max_k \sigma_k^2} \right), \exp \left(-\frac{3t}{8 \max_k R_k} \right) \right),$$

from which we have

$$\begin{aligned} \mathbb{E} \|\mathcal{D}\|_{\text{latent}^*} &\leq C \left(\max_k \sigma_k \sqrt{\log(\max_k D_k) + \log 3} + \max_k R_k (\log(\max_k D_k) + \log 3) \right) \\ &\leq C' \left(\max_k \sigma_k \sqrt{\log(\max_k D_k)} + \frac{R}{m} \log(\max_k D_k) \right). \end{aligned} \quad (14)$$

Here we used $R_k = R/m$ and the simplifying assumption that $\max_k D_k \geq 3$ in the second inequality. Finally, using $\sigma_k \leq \sqrt{\kappa|S|D_k/(mdPQ)}$ as in the proof of inequality (7), we obtain inequality (8).

Proof of inequality (9): Following the proof of [21, Lemma 1], we have

$$\|\mathcal{D}\|_{\text{scaled}^*} = \max_k \sqrt{n_k} \|\mathbf{D}_{(k)}\|_{\text{tr}},$$

where $n_1 = d$, $n_2 = P$, and $n_3 = Q$. Thus, replacing σ_k and R_k with $\sqrt{n_k}\sigma_k$ and $\sqrt{n_k}R/m$ in inequality (14), respectively, we have

$$\mathbb{E} \|\mathcal{D}\|_{\text{scaled}^*} \leq C' \left(\max_k (\sqrt{n_k}\sigma_k) \sqrt{\log(\max_k D_k)} + \frac{R \sqrt{\max_k n_k}}{m} \log(\max_k D_k) \right).$$

Finally, since $n_k D_k = n_k^2 + dPQ \leq 2dPQ$, we have

$$\sqrt{n_k}\sigma_k \leq \sqrt{\frac{\kappa |S| n_k D_k}{mdPQ}} \leq \sqrt{\frac{2\kappa |S|}{m}},$$

which gives inequality (9).

The last claim of the theorem is true, because $m|S| \geq R^2(\max_k n_k)(\log_k D_k)/\kappa$ implies

$$m|S| \geq \frac{R^2}{\kappa} \frac{dPQ}{n_k^2 + dPQ} n_k \log D_k = \frac{R^2}{\kappa} \frac{dPQ}{D_k} \log D_k,$$

which gives

$$\sqrt{\frac{\kappa}{m|S|dPQ}} D_k \log D_k \geq \frac{R}{m|S|} \log D_k.$$