## 1 Useful versions of the Ahlswede-Winter Inequality

Theorem 1 Let $Y$ be a random, symmetric, positive semi-definite $d \times d$ matrix such that $\mathrm{E}[Y]=I$. Suppose $\|Y\| \leq R$ for some fixed scalar $R \geq 1$. Let $Y_{1}, \ldots, Y_{k}$ be independent copies of $Y$ (i.e., independently sampled matrices with the same distribution as $Y$ ). For any $\epsilon \in(0,1)$, we have

$$
\operatorname{Pr}\left[(1-\epsilon) I \preceq \frac{1}{k} \sum_{i=1}^{k} Y_{i} \preceq(1+\epsilon) I\right] \geq 1-2 d \cdot \exp \left(-\epsilon^{2} k / 4 R\right)
$$

This event is equivalent to the sample average $\frac{1}{k} \sum_{i=1}^{k} Y_{i}$ having minimum eigenvalue at least $1-\epsilon$ and maximum eigenvalue at most $1+\epsilon$.

Proof: We apply the Ahlswede-Winter inequality with $X_{i}=\left(Y_{i}-\mathrm{E}\left[Y_{i}\right]\right) / R$. Note that $\mathrm{E}\left[X_{i}\right]=0$, $\left\|X_{i}\right\| \leq 1$, and

$$
\begin{aligned}
\mathrm{E}\left[X_{i}^{2}\right] & =\frac{1}{R^{2}} \mathrm{E}\left[\left(Y_{i}-\mathrm{E}\left[Y_{i}\right]\right)^{2}\right] \\
& =\frac{1}{R^{2}}\left(\mathrm{E}\left[Y_{i}^{2}\right]-2 \mathrm{E}\left[Y_{i}\right]^{2}+\mathrm{E}\left[Y_{i}\right]^{2}\right) \\
& \preceq \frac{1}{R^{2}} \mathrm{E}\left[Y_{i}^{2}\right] \quad\left(\text { since } \mathrm{E}\left[Y_{i}\right]^{2} \succeq 0\right) \\
& \preceq \frac{1}{R^{2}} \mathrm{E}\left[\left\|Y_{i}\right\| \cdot Y_{i}\right] \\
& \preceq \frac{R}{R^{2}} \mathrm{E}\left[Y_{i}\right]
\end{aligned}
$$

Finally, since $0 \preceq \mathrm{E}\left[Y_{i}\right] \preceq I$, we get

$$
\begin{equation*}
\lambda_{\max }\left(\mathrm{E}\left[X_{i}^{2}\right]\right) \leq 1 / R \tag{1}
\end{equation*}
$$

Now we use Claim 15 from the Notes on Symmetric Matrices, together with the inequalities

$$
\begin{aligned}
1+x & \leq e^{x} \quad \forall x \in \mathbb{R} \\
e^{x} & \leq 1+x+x^{2} \quad \forall x \in[-1,1] .
\end{aligned}
$$

Since $\left\|X_{i}\right\| \leq 1$, for any $\lambda \in[0,1]$, we have $e^{\lambda X_{i}} \preceq I+\lambda X_{i}+\lambda^{2} X_{i}^{2}$, and so

$$
\mathrm{E}\left[e^{\lambda X_{i}}\right] \preceq \mathrm{E}\left[I+\lambda X_{i}+\lambda^{2} X_{i}^{2}\right] \preceq I+\lambda^{2} \mathrm{E}\left[X_{i}^{2}\right] \preceq e^{\lambda^{2} \mathrm{E}\left[X_{i}^{2}\right]}
$$

Thus by (1) we have

$$
\left\|\mathrm{E}\left[e^{\lambda X_{i}}\right]\right\| \leq\left\|e^{\lambda^{2} \mathrm{E}\left[X_{i}^{2}\right]}\right\| \leq e^{\lambda^{2} / R}
$$

The same analysis also shows that $\left\|\mathrm{E}\left[e^{-\lambda X_{i}}\right]\right\| \leq e^{\lambda^{2} / R}$. Substituting these two bounds into the basic Ahlswede-Winter inequality from the previous lecture, we obtain

$$
\operatorname{Pr}\left[\left\|\sum_{i=1}^{k} \frac{1}{R}\left(Y_{i}-\mathrm{E}\left[Y_{i}\right]\right)\right\|>t\right] \leq 2 d \cdot e^{-\lambda t} \prod_{i=1}^{k} e^{\lambda^{2} / R}=2 d \cdot \exp \left(-\lambda t+k \lambda^{2} / R\right)
$$

Substituting $t=k \epsilon / R$ and $\lambda=\epsilon / 2$ we get

$$
\operatorname{Pr}\left[\left\|\frac{1}{R} \sum_{i=1}^{k} Y_{i}-\frac{k}{R} \mathrm{E}\left[Y_{i}\right]\right\|>\frac{k \epsilon}{R}\right] \leq 2 d \cdot \exp \left(-k \epsilon^{2} / 4 R\right)
$$

Multiplying by $R / k$ and using the fact that $\mathrm{E}\left[Y_{i}\right]=I$, we have bounded the probability that any eigenvalue of the sample average matrix $\sum_{i=1}^{k} Y_{i} / k$ is less than $1-\epsilon$ or greater than $1+\epsilon$.

Corollary 2 Let $Z$ be a random, symmetric, positive semi-definite $d \times d$ matrix. Define $U:=\mathrm{E}[Z]$ and suppose $Z \preceq R \cdot U$ for some scalar $R \geq 1$. Let $Z_{1}, \ldots, Z_{k}$ be independent copies of $Z$. For any $\epsilon \in(0,1)$, we have

$$
\operatorname{Pr}\left[(1-\epsilon) U \preceq \frac{1}{k} \sum_{i=1}^{k} Z_{i} \preceq(1+\epsilon) U\right] \geq 1-2 d \cdot \exp \left(-\epsilon^{2} k / 4 R\right)
$$

Proof: Let $U^{+/ 2}:=\left(U^{+}\right)^{1 / 2}$ denote the square root of the pseudoinverse of $U$. Let $I_{\mathrm{im} U}$ denote the orthogonal projection on the image of $U$. Define the random, positive semi-definite matrices

$$
Y:=U^{+/ 2} \cdot Z \cdot U^{+/ 2} \quad \text { and } \quad Y_{i}:=U^{+/ 2} \cdot Z_{i} \cdot U^{+/ 2}
$$

Because $Z_{i} \succeq 0$ and $U=\mathrm{E}\left[\sum_{i} Z_{i}\right]$, we have $\operatorname{im}\left(Z_{i}\right) \subseteq \operatorname{im}(U)$. So Claim 16 in Notes on Symmetric Matrices implies

$$
(1-\epsilon) U \preceq \frac{1}{k} \sum_{i=1}^{k} Z_{i} \preceq(1+\epsilon) U \quad \Longleftrightarrow \quad(1-\epsilon) I_{\mathrm{im} U} \preceq \frac{1}{k} \sum_{i=1}^{k} Y_{i} \preceq(1+\epsilon) I_{\mathrm{im} U}
$$

We would like to use Theorem 1 to obtain our desired bound. We just need to check that the hypotheses of the theorem are satisfied. By Fact 6 from the Notes on Symmetric Matrices, we have

$$
Y=U^{+/ 2} \cdot Z \cdot U^{+/ 2} \preceq U^{+/ 2} \cdot(R \cdot U) \cdot U^{+/ 2}=R \cdot I_{\mathrm{im} U}
$$

showing that $\|Y\| \leq R$. Next,

$$
\mathrm{E}[Y]=U^{+/ 2} \cdot \mathrm{E}[Z] \cdot U^{+/ 2}=U^{+/ 2} \cdot U \cdot U^{+/ 2}=I_{\mathrm{im} U}
$$

So the hypotheses of Theorem 1 are almost satisfied, with the small issue that $\mathrm{E}[Y]$ is not actually the identity, but merely the identity on the image of $U$. But, one may check that the proof of Theorem 1 still goes through as long as every eigenvalue of $\mathrm{E}[Y]$ is either 0 or 1 , i.e., $\mathrm{E}[Y]$ is an orthogonal projection matrix. The details are left as an exercise.

