$$
\begin{aligned}
& \text { CSC2414: Discrepancy Theory in Computer Science } \\
& \text { Lecture } 8 \text { - November } 16,2015 \\
& \text { Aleksandar Nikolov } \\
& \text { Scribe: Assimakis Kattis } 2015 \\
& \hline
\end{aligned}
$$

## $\gamma_{2}$ and herdisc: the Lower Bound

Last lecture: Recall that for $A \in \mathbb{R}^{m \times n}$, we defined the following norms:
$\underline{\gamma_{2} \text { norm: }}$

$$
\gamma_{2}(A)=\min \{r(U) \cdot c(V): U V=A\}
$$

Norms of Rows: For $a_{i *}$ the $i$-th row of $A$ :

$$
r(A)=\max _{i=1}^{\max }\left\|a_{i *}\right\|_{2}
$$

Norms of Columns: For $a_{* i}$ the $i$-th column of $A$ :

$$
c(A)=\max _{i=1}^{n}\left\|a_{* i}\right\|_{2}
$$

Theorem 1 (Larsen). For all $A \in \mathbb{R}^{m \times n}$ :

$$
\operatorname{herdisc}(A)=\gamma_{2}(A) \cdot O(\sqrt{\log m})
$$

This lecture: We show the following result:
Theorem 2. For all $A \in \mathbb{R}^{m \times n}$ :

$$
\operatorname{herdisc}(A)=\gamma_{2}(A) \cdot \Omega\left(\frac{1}{\log \operatorname{rank} A}\right)
$$

We have previously shown that the determinant lower bound, given by:
where $A_{S, T}$ the subset of $A$ indexed by $S$ and $T$, satisfies:

$$
\operatorname{herdisc}(A) \geq \frac{1}{2} \operatorname{detlb}(A) .
$$

Thus, it suffices to show that:

Theorem 3 ([MNT14]). For all $A \in \mathbb{R}^{m \times n}$ :

$$
\begin{gathered}
\gamma_{2}(A) \geq \operatorname{detlb}(A) \\
\operatorname{detlb}(A)=\gamma_{2}(A) \cdot \Omega\left(\frac{1}{\log \operatorname{rank} A}\right)
\end{gathered}
$$

Dual Characterization of $\gamma_{2}$ : We have shown that the following vector program has $\gamma_{2}(A)$ as its optimum:

$$
\begin{array}{ll}
\operatorname{minimize} & t \\
\text { subject to } & \left\langle u_{i}, v_{j}\right\rangle=A_{i j} \\
& \left\langle u_{i}, u_{i}\right\rangle \leq t \\
& \left\langle v_{j}, v_{j}\right\rangle \leq t \\
& u_{i}, v_{j} \in \mathbb{R}^{m+n} \\
\text { where } & (i, j) \in[m] \times[n],
\end{array}
$$

This exhibits strong duality, meaning that it is equal to its dual (maximization) problem, which is shown below:

$$
\begin{array}{ll}
\operatorname{maximize} & \|B\|_{t r} \\
\text { subject to } & B_{i j}=p_{i} q_{j} A_{i j} \\
& \sum_{i=1}^{m} p_{i}^{2}=\sum_{j=1}^{n} q_{j}^{2}=1 \\
& p_{i}, q_{j} \geq 0 \\
\text { where } & (i, j) \in[m] \times[n]
\end{array}
$$

where $\|B\|_{t r}$ is the trace or nuclear norm, which is equal to the sum of its singular values:

$$
\|B\|_{t r}=\sum_{i=1}^{\min (m, n)} \sigma_{i} .
$$

Claim. $\gamma_{2}(A) \geq \operatorname{detlb}(A)$
Proof. Pick optimal $S, T$ with $S \subseteq[m], T \subseteq[n]$ and $|S|=|T|=k$ for which $\left|\operatorname{det} A_{S, T}\right|^{1 / k}=$ detlb $(A)$. Suffices to show that:

$$
\gamma_{2}(A) \geq\left|\operatorname{det} A_{S, T}\right|^{1 / k}
$$

For the dual maximization problem for $\gamma_{2}$, define the following:

$$
p_{i}= \begin{cases}1 / \sqrt{k} & i \in S \\ 0 & \text { otherwise }\end{cases}
$$

$$
q_{j}= \begin{cases}1 / \sqrt{k} & j \in T \\ 0 & \text { otherwise }\end{cases}
$$

Since the above are orthogonal, we can reorder the corresponding matrix $B=p_{i} q_{j} A_{i j}$ :

$$
B^{\prime}=\left[\begin{array}{cc}
\frac{1}{k} A_{S, T} & 0 \\
0 & 0
\end{array}\right]
$$

from which we get that:

$$
\|B\|_{t r}=\left\|B^{\prime}\right\|_{t r}=\frac{1}{k}\left\|A_{S, T}\right\|_{t r}
$$

By the AM-GM inequality and since $\gamma_{2}(A)$ is the maximum possible value for $\|B\|_{t r}$, this implies:

$$
\gamma_{2}(A) \geq \frac{1}{k}\left\|A_{S, T}\right\|_{t r} \geq\left|\operatorname{det} A_{S, T}\right|^{1 / k}
$$

Bucketing Lemma: For all $\sigma \in \mathbb{R}_{+}^{r}, \exists R \in[r]$ for which:

$$
\begin{gathered}
\sum_{i \in R} \sigma_{i} \geq \frac{1}{2 \log 2 r} \sum_{i=1}^{r} \sigma_{i} \\
\forall i, j \in R, \sigma_{i} \leq 2 \sigma_{j}
\end{gathered}
$$

Proof. Without loss of generality, assume that $\sum_{i=1}^{r} \sigma_{i}=1$. Then define the following sets, where $1 \leq k \leq\lceil\log 2 r\rceil$ :

$$
\begin{gathered}
R_{k}=\left\{i:(1 / 2)^{k-1} \geq \sigma_{i} \geq(1 / 2)^{k}\right\} \\
R_{\infty}=\left\{i: \sigma_{i} \leq(1 / 2 r)\right\}
\end{gathered}
$$

The main motivation behind this construction is that we can ignore $R_{\infty}$, and the rest will follow by averaging. Note also that all $R_{k}$ satisfy the second property.

Since $\left|R_{\infty}\right|<r$, we have that:

$$
\begin{gathered}
\sum_{i \in R_{\infty}} \sigma_{i}<\left|R_{\infty}\right| \cdot \frac{1}{2 r}<\frac{1}{2} \\
\log 2 r \\
\sum_{k=1}^{\log } \sum_{i \in R_{k}} \sigma_{i}=1-\sum_{i \in R_{\infty}} \sigma_{i}>1 / 2
\end{gathered}
$$

This means that as we have $\log 2 r$ terms, we get:

$$
\log 2 r \cdot \min _{k} \sum_{i \in R_{k}} \sigma_{i}>1 / 2
$$

Thus, $\exists R_{l}$ for which:

$$
\sum_{i \in R_{l}} \sigma_{i} \geq \frac{1}{2 \log 2 r}
$$

We can immediately see that for such a set $R$, we have:
Corollary 4. For $R$ satisfying the conditions of the Bucketing Lemma:

$$
\frac{1}{|R|} \sum_{i \in R} \sigma_{i} \leq 2\left(\prod_{i \in R} \sigma_{i}\right)^{1 /|R|}
$$

Proof.

$$
\frac{1}{|R|} \sum_{i \in R} \sigma_{i}=\max _{i \in R} \sigma_{i} \leq 2 \min _{i \in R} \sigma_{i} \leq 2\left(\prod_{i \in R} \sigma_{i}\right)^{1 /|R|}
$$

## Claim 5.

$$
\operatorname{detlb}(A)=\gamma_{2}(A) \cdot \Omega\left(\frac{1}{\log \operatorname{rank} A}\right)
$$

Proof. Take a feasible solution $(B, p, q)$ to the dual maximization problem for $\gamma_{2}(A)$. This implies that $\gamma_{2}(A)=\|B\|_{\text {tr }}$.
Now, let the singular value decomposition (SVD) of $B$ be $B=U \Sigma V^{T}$. Here, $r=\operatorname{rank} B, U \in \mathbb{R}^{m \times r}$, $V \in \mathbb{R}^{n \times r}, U^{T} U=I$ and $\Sigma$ a diagonal matrix with the singular values of $B$ on the diagonal.

Pick $R \in[n]$ with $|R|=k$ to be a subset of singular values that satisfies the conditions of the Bucketing lemma. If we define $C:=U_{R}^{T} B$, where $U_{R}$ the subset of $U$ indexed by $R$, then the singular values of $C$ are $\left\{\sigma_{i}\right\}_{i \in R}$. This means that:

$$
\begin{equation*}
\left|\operatorname{det} C C^{T}\right|^{\frac{1}{2 k}}=\left|\prod_{i \in R} \sigma_{i}\right|^{\frac{1}{k}} \geq \frac{1}{2 k} \sum_{i \in R} \sigma_{i} \geq \frac{1}{4 k \log 2 r} \sum_{i=1}^{r} \sigma_{i}=\frac{1}{4 k \log 2 r}\|B\|_{t r} \tag{1}
\end{equation*}
$$

Cauchy-Binet Formula: For $X, Y \in \mathbb{R}^{m \times n}$ :

$$
\operatorname{det} X Y^{T}=\sum_{\substack{S \subseteq[n] \\|S|=m}} \operatorname{det} X_{S} \operatorname{det} Y_{S}
$$

If we define $P \in \mathbb{R}^{m \times m}$ and $Q \in \mathbb{R}^{n \times n}$ as the diagonal matrices with $p_{i}$ and $q_{j}$ as the diagonal entries respectively, then we have $B=P A Q$. Similarly, $C=U_{R}^{T} B=U_{R}^{T} P A Q$.
Define $D:=U_{R}^{T} P A$ so that $C=D Q$. By applying Cauchy-Binet to $C \in \mathbb{R}^{k \times n}$ we get:

$$
\begin{aligned}
\operatorname{det}\left(C C^{T}\right)=\sum_{\substack{S \subseteq[n] \\
|S|=k}} \operatorname{det} C_{S} \operatorname{det} C_{S}=\sum_{\substack{S \subseteq[n] \\
|S|=k}}\left(\operatorname{det} C_{S}\right)^{2}=\sum_{\substack{S \subseteq[n] \\
|S|=k}}\left(\operatorname{det} D_{S} Q_{S}\right)^{2} \\
\quad=\sum_{\substack{S \subseteq[n] \\
|S|=k}}\left(\operatorname{det} D_{S}\right)^{2}\left(\prod_{j \in S} q_{j}^{2}\right) \leq\left(\max _{\substack{S \subseteq[n] \\
|S|=k}}\left(\operatorname{det} D_{S}\right)^{2}\right)\left(\sum_{\substack{S \subseteq[n] \\
|S|=k}} \prod_{j \in S} q_{j}^{2}\right)
\end{aligned}
$$

which follows by Hölder.
By picking distinct $j$ from each of the $k$ sums, we will get each $j k$ ! times. Therefore, this implies:

$$
\sum_{\substack{S \subseteq[n] \\|S|=k}} \prod_{j \in S} q_{j}^{2} \leq \frac{1}{k!}\left(\sum_{j=1}^{n} q_{j}^{2}\right)^{k}=\frac{1}{k!}
$$

Thus, $\exists S \subseteq[n]$ such that:

$$
\left(\operatorname{det} D_{S}\right)^{1 / k} \geq(k!)^{1 / 2 k} \cdot\left(\operatorname{det} C C^{T}\right)^{1 / 2 k}
$$

or equivalently:

$$
\max _{\substack{S \subseteq[n] \\|S|=k}}\left|\operatorname{det} D_{S}\right|^{1 / k} \geq(k!)^{1 / 2 k} \cdot\left(\operatorname{det} C C^{T}\right)^{1 / 2 k}
$$

which by Stirling means:

$$
(k!)^{1 / 2 k} \cdot\left(\operatorname{det} C C^{T}\right)^{1 / 2 k} \geq \sqrt{\frac{k}{e}}\left(\operatorname{det} C C^{T}\right)^{1 / 2 k}=\Omega(\sqrt{k})\left(\operatorname{det} C C^{T}\right)^{1 / 2 k}
$$

Thus, by applying equation (1) here this implies:

$$
\begin{equation*}
\left(\operatorname{det} D_{S}\right)^{1 / k} \geq \frac{\|B\|_{t r}}{4 e \sqrt{k} \log 2 r} \tag{2}
\end{equation*}
$$

Consider the orthonormal matrix $W \in \mathbb{R}^{m \times m}$ for which the first $k$ columns are equal to the columns of $U_{R}$. Such a matrix always exists since we can complete the orthonormal basis for $\mathbb{R}^{m}$ starting with the column vectors of $U_{R}$. The $m-k$ new vectors we get can be used to define the rest of the columns of $W$.

Define $E_{S}:=P A_{S} \in \mathbb{R}^{m \times k}$, meaning that $D_{S}=U_{R}^{T} E_{S}$. It can be shown that:

$$
\begin{gathered}
\operatorname{det}\left(E_{S}^{T} E_{S}\right)=\operatorname{det}\left(\left(E_{S}^{T} W\right)\left(W^{T} E_{S}\right)\right)=\operatorname{det}\left(\left(E_{S}^{T} W\right)\left(E_{S}^{T} W\right)^{T}\right) \\
=\sum_{\substack{T \subseteq[n] \\
|T|=k}} \operatorname{det}\left(\left(E_{S}^{T} W\right)_{T}\right)^{2}=\sum_{\substack{T \subseteq[n] \\
|T|=k}} \operatorname{det}\left(E_{S}^{T} W_{T}\right)^{2} \geq \operatorname{det}\left(E_{S}^{T} U_{R}\right)^{2}=\operatorname{det}\left(U_{R}^{T} E_{S}\right)^{2} \\
\therefore \operatorname{det}\left(E_{S}^{T} E_{S}\right) \geq \operatorname{det}\left(D_{S}\right)^{2}
\end{gathered}
$$

Now, we can apply the exact same analysis as in (2), but this time to $D_{S}^{T}=\left(A_{S}\right)^{T} P$ instead of $C$. This means that $\exists T \in[m]$ for which:

$$
\max _{\substack{T \subseteq[m] \\|\bar{T}|=k}}\left(\operatorname{det} A_{S, T}\right)^{1 / k} \geq(k!)^{1 / 2 k} \cdot \operatorname{det}\left(A_{S}^{T} P^{2} A_{S}\right)^{1 / 2 k}=(k!)^{1 / 2 k} \cdot \operatorname{det}\left(E_{S}^{T} E_{S}\right)^{1 / 2 k}
$$

Putting all of this together and applying Stirling just like before, we get that:

$$
\max _{\substack{S \subseteq[n] \\ T \subseteq[m] \\|S|=|T|=k}}\left|\operatorname{det} A_{S, T}\right|^{1 / k} \geq \frac{\|B\|_{t r}}{4 e \log (2 r)}
$$

By maximizing over all $k$, this yields the desired result.

## References

[MNT14] J. Matousek, A. Nikolov, and K. Talwar. Factorization Norms and Hereditary Discrepancy. ArXiv e-prints, August 2014.

