Lecture 16: February 28
Lecturer: Naveen Garg
Scribe: Akshay Kumar Pansari

Note: $E^{A} T_{E} X$ template courtesy of UC Berkeley EECS dept.
Disclaimer: These notes have not been subjected to the usual scrutiny reserved for formal publications. They may be distributed outside this class only with the permission of the Instructor.

### 16.1 Red-Blue Matching Problem : When Unique Matching Exist

This was introduced in the previous class.
Problem Statement: Given a graph $G=(U, V, E)$ with each $e \in E$ is either red or blue, does there exist a perfect matching with exactly k red edges?

Consider the $\mathrm{n} \times \mathrm{n}$ matrix A, whose entries are given as

$$
A(i, j)= \begin{cases}y, & (i, j) \in \mathrm{E} \text { and is red } \\ 1, & (i, j) \in \mathrm{E} \text { and is blue } \\ 0, & \text { otherwise }\end{cases}
$$

Assume that there exist a unique red-blue perfect matching.

$$
\operatorname{det}(A)=p(y)=\sum_{n=0}^{n} a_{i} y^{i}
$$

Let us define $p(y)$ the determinant of $A$ as a function of $y$. Then the $p(y)$ will be a polynomial with degree atmost n . Observe that the Graph $G$ will have a unique perfect matching with exactly k red edges if and only if $\mathrm{p}(\mathrm{y})$ has a term of the form $\pm y^{k}$.
We will use Lagrangian interpolation to find the polynomial $\mathrm{p}(\mathrm{y})$. We will need $\mathrm{n}+1$ points say $\left(y_{0}, y_{1}, \cdots, y_{n}\right)$ to find all the coefficients of $\mathrm{p}(\mathrm{y})$. We will find the value of $\mathrm{p}(\mathrm{y})$ at these $\mathrm{n}+1$ points $p\left(y_{0}\right), p\left(y_{1}\right), \ldots, p\left(y_{n}\right)$ by computing the determinant of A at $y=y_{i}$ for each i. Then we can easily find if there is a perfect matching with k red edges by observing the coefficient of $y^{k}$.

### 16.2 Red-Blue Matching Problem : More than one Perfect Matching Exist

In the previous section we saw the Red-Blue Matching Problem. One assumption that we took was that there is a unique Red-Blue perfect matching with k red edges. In this section, we will prove show that graph $G$ will contain a unique minimum weight perfect matching with Probability more than 0.5 .

### 16.2.1 Isolation Lemma

Assign every edge $e \in E$ in the Graph G has a weight $w_{e}$ from the set $S=\{1,2,3, \cdots, 2 m\}$ picked at random and independent of other edge.

We can show that

$$
\begin{equation*}
\mathrm{P}(\text { there exist a unique minimum weight perfect matching }) \geq \frac{1}{2} \tag{16.1}
\end{equation*}
$$

This is known as "isolation lemma" which was proved for sets by Mulmuley, Vazirani, and Vazirani in 1987. Proof:
Definition 1: We will call an edge $e$ confused if $\exists$ two minimum weight matchings $M_{1}, M_{2}$ such that $e \in M_{1}$ and $e \notin M_{2}$.

If no edge is confused then G has a unique minimum weight matching since $M_{1}$ will be equal to $M_{2}$. For a given edge $e$,

$$
\begin{equation*}
\mathrm{P}(e \text { is confused }) \leq \frac{1}{2 m} \tag{16.2}
\end{equation*}
$$

To prove 16.1 we need to prove 16.2 first. The proof of 16.2 is as follows:

Let us arbitrarily choose an edge $e$. We choose weights for all the edges in E randomly except this particular edge $e$. We define $M_{1}$ to be the minimum weight Perfect Matching in graph G without the edge $e$ and $M_{2}$ be a minimum weight Perfect Matching without the vertices of edge $e=(u, v)$ where $u \in U$ and $v \in V$. By addition of edge e to $M_{2}$, we get a perfect matching of n edges. Let $W_{1}$ and $W_{2}$ be the respective weights of the matching.

Note that we have constructed $M_{1}$ and $M_{2}$ in such a way that $M_{1}$ contain n edges whereas $M_{2}$ contain n-1 edges so that we can add the edge $e$ to $M_{2}$ to make it a minimum weight perfect matching.

Case 1. If $W_{2} \geq W_{1}$, then e is never confused so $M_{1}$ and $M_{2}$ can't be a minimum weight matchings.
Case 2. If $W_{2}<W_{1}$, then if the weight of e is $W_{1}-W_{2}$ then we will get e to be confused.
Since we are picking weights randomly and independent of other edges from the set $S=\{1,2, \cdots, 2 m\}$ so

$$
\mathrm{P}(e \text { is confused }) \leq \frac{1}{2 m}
$$

Here we have proved 16.2.

$$
\begin{equation*}
\mathrm{P}(\text { some edge is confused }) \leq \frac{m}{2 m} \leq \frac{1}{2} \tag{16.3}
\end{equation*}
$$

which is equivalent of saying
$\mathrm{P}($ min weight perfect matching is not unique $) \leq \frac{1}{2} \Rightarrow \mathrm{P}\left(\right.$ min weight perfect matching is unique $\geq \frac{1}{2}$
Here we have proved 16.1.
In 16.3 we have used Union Bound which states that the probability that at least one of the events happens is no greater than the sum of the probabilities of the individual events.

### 16.2.2 Red-Blue Matching when the matching is not unique

Given edges $e \in E$ with weights $w_{e}$ chosen uniformly from set $S=\{1,2,3, \cdots, 2 m\}$. We define matrix $A$ as

$$
A(i, j)=\left\{\begin{array}{cl}
2^{w_{e}} y, & (i, j) \in \mathrm{E} \text { and is red } \\
2^{w_{e}}, & (i, j) \in \mathrm{E} \text { and is blue } \\
0, & \text { otherwise }
\end{array}\right.
$$

Every red-blue perfect matching $M$ with k red edges contributes

$$
\pm y^{k} 2^{\sum_{e} w_{e}}= \pm y^{k} 2^{w(M)} \quad \text { to } \operatorname{det}(\mathrm{A})
$$

where $\sum_{e} w_{e}=w(M)$ where $\mathrm{w}(\mathrm{M})$ is the sum of the weight of the edges of the perfect matching and

$$
\operatorname{det}(A)=p(y)=\sum_{n=0}^{n} a_{i} y^{i}
$$

If G contains a red blue matching, then $a_{k}$, the coefficient of $y^{k}$ is non-zero with Probability $\geq \frac{1}{2}$
This can be proved using isolation lemma. We can see that the

$$
\text { coefficient of } y^{k}= \pm 2^{w\left(M_{1}\right)} \pm 2^{w\left(M_{2}\right)} \pm \cdots \pm 2^{w\left(M_{t}\right)}
$$

where $\pm w\left(M_{1}\right)$ is the sum of the minimum weight perfect matching edges and $\pm w\left(M_{t}\right)$ is the sum of the perfect matching edges weights other than the minimum weight.
Taking $2^{w\left(M_{1}\right)}$ out as common we get:

$$
\text { coefficient of } y_{k}=2^{w\left(M_{1}\right)}\left( \pm 1 \pm 2^{w\left(M_{2}\right)-w\left(M_{1}\right)} \pm \cdots \pm 2^{w\left(M_{t}\right)-w\left(M_{1}\right)}\right)
$$

Note that the coloured term in the above expression will always be even and hence the coefficient of $y_{k}$ will always be odd if the minimum weight perfect matching is unique (as we will have either +1 or -1 . This will ensure that the coefficient of $y_{k}$ will be odd). As shown above in 16.1 that this probability is $\geq \frac{1}{2}$.
If the minimum weight perfect matching is not unique then $\pm 1$ terms will cancel each other.
We can repeat this multiple times to be sure that the graph $G$ has red-blue matching or not.
Also note that no deterministic polynomial time algorithm exist for this red-blue matching problem and only randomised algorithm exist. Hence, there is active research going on in this field.

### 16.2.3 Bipartite Graph Matching vs Red-Blue Matching

In Bipartite Matching we picked $x_{i, j}$ from the field $\mathbb{F}$ randomly and with Probability $\geq 1-\frac{1}{n^{2}}$ we have $\operatorname{det}(\mathrm{A}) \neq 0$, iff G has a perfect matching.
In Red Blue Matching we picked $w_{i, j}$ from the set $\mathrm{S}=\{1,2,3, \cdots, 2 m\}$ randomly and independently. With Probability $\geq \frac{1}{2}$ we can say that the minimum weight perfect matching is unique and coefficient of $y^{k} \neq 0$

Homework: Using the ideas for existence of red-blue perfect matching, give an algorithm to find the red-blue perfect matching if it exists like we did for Bipartite Matching.

### 16.2.4 Bipartite Graph Matching using Polynomial Number of Processors

Definition 2: Parallel Random Access Machine (PRAM) : Multiple processors are connected in parallel with a single shared memory unit. In this, n number of processors can perform independent operations on n number of data in a particular unit of time.

Definition 3: In complexity theory, the class NC (for "Nick's Class") is the set of decision problems decidable in polylogarithmic time on a parallel computer with a polynomial number of processors. In other words, a problem is in NC if there exist constants c and k such that it can be solved in time $O\left(\log ^{c} n\right)$ using $O\left(n^{k}\right)$ parallel processors.

Bipartite Graph Matching can be parallelised because this require only finding the determinant of a matrix and this can be done efficiently if we have large number (but polynomial) of parallel processors.

- Matrix multiplication can be done in $N C^{1}\left(N C^{k}=O\left(\log ^{k}(n)\right)\right)$. Here n denotes size of the matrix $n \times n$.
- Also note that Addition of n numbers can be done in $N C^{1}$ time and we will require n parallel processor to do it.
- Determinant can be computed in $N C^{2}$ time.
- Hence Bipartite Matching can be solved in $R N C^{2}$ time where RNC stands for randomised NC. This is because we need to compute determinants only.

Note: This section 16.2.4 was discussed in the class in brief.

