CHENNAI MATHEMATICAL INSTITUTE

Masters Thesis

Random Spanning Trees

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Declaration of Authorship

I, Bhishmaraj S, declare that this thesis titled, "Random Spanning Trees" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
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- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
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Abstract

Faculty Name Computer Science at CMI

Master of Science

Random Spanning Trees

by Bhishmaraj S

The Thesis Abstract is written here (and usually kept to just this page). The page is kept centered vertically so can expand into the blank space above the title too. . . . I see

Acknowledgements

The acknowledgments and the people to thank go here, don't forget to include your project advisor. . .

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LAH List Abbreviations HereWSF What (it) Stands For

1 Introduction

2 Background

- 2.1 Markov Chains
- 2.1.1 Fundamental theorem of Markov chain
- 2.1.2 Markov chain tree theorem
- 2.2 Results from Spectral Graph Theory
- 2.2.1 Kirchoff Matrix Tree Theorem
- 2.2.2 Some properties of Laplacian
- 2.3 Electric Networks

3 Random Walk Approach

- 3.1 Aldous, Broder
- 3.2 Wilson

4 Matrix Approach

4.1 Colbourn, Day, Nel

4.2 Harvey, Xu

4.2.1 Techniques used

Naive chain rule algorithm

```
Input: G = (V, E) and L_G^+
Output: Set of edges corresponding to a random spanning tree

1 for e = (u, v) \in E do

2 R_e^{\text{eff}} = (\chi_u - \chi_v)^T L_G^+ (\chi_u - \chi_v);
3 if (X \sim Bernoulli(R_e^{\text{eff}})) = 1 then

4 | Add edge e to the spanning tree;

5 | G = G/e;

6 else

7 | G = G \setminus e;

8 end

9 | Update L_G^+;

10 end
```

Algorithm 1: Sampling uniform spanning tree using chain rule

4.2.2 Facts used

Fact 1 (Woodbury matrix identity). Let $M \in \mathbb{M}_{n \times n}$, $U \in \mathbb{M}_{n \times k}$, $V \in \mathbb{M}_{n \times k}$. Suppose M is non-singular then $M+UV^T$ is non-singular $\iff I+V^TM^{-1}U$ is non-singular. If $M+UV^T$ is non-singular, then

$$(M + UV^T)^{-1} = M^{-1} - \left(M^{-1} \cdot U \cdot (I + V^T M^{-1} U)^{-1} \cdot V^T \cdot M^{-1}\right)$$

Proof. TODO

Fact 2. For any $L \in \mathbb{M}_{n \times n}$ with ker(L) = span(1), we have $LL^+ = I - \frac{1 \cdot 1^T}{n}$ and $P := I - \frac{1 \cdot 1^T}{n}$ is called the **projection matrix**.

Fact 3 (Sub-matrices). For all the results below, S denotes a index set and S^c denotes it's complement.

- 1. For any $A, B \in \mathbb{M}_{n \times n}, (A + B)_{S,S} = A_{S,S} + B_{S,S}$
- 2. If $C = D \cdot E \cdot F$ then $C_{S,S} = D_{S,*} \cdot E \cdot F_{*,S}$
- 3. For $A \in \mathbb{M}_{m \times n}$, $B \in \mathbb{M}_{n \times l}$, If $A_{S^c,S^c} = 0$ or $B_{S^c,S^c} = 0$ then $(AB)_{S,S} = A_{S,S} \cdot B_{S,S}$

- 4. For any matrix C where $C = D \cdot E \cdot F$. If $D_{*,S^c} = 0$ and $F_{S^c,*} = 0$, then $C = D_{*,S} \cdot E_{S,S} \cdot F_{S,*}$
- 5. $D = \begin{bmatrix} M & 0 \\ 0 & 0 \end{bmatrix}$, and $E = \begin{bmatrix} A & B \\ X & Y \end{bmatrix}$ where $M, A \in \mathbb{M}_{n \times n}$ and If (MA I) is invertible Then.

$$(DE - I)^{-1} = \begin{bmatrix} (MA - I)^{-1} & (MA - I)^{-1} \cdot M \cdot B \\ 0 & -I \end{bmatrix}$$

Proof. $(DE-I)^{-1}$ can be computed using Shur's Complement(Wikipedia contributors, 2020) .

Suppse $N = \begin{bmatrix} P & Q \\ R & S \end{bmatrix}$ and Shur's complement of block S and P is

$$N/S := P - QS^{-1}R$$
 $N/P := S - RP^{-1}Q$

Then

$$N^{-1} = \begin{bmatrix} P^{-1} + (P^{-1}Q(N/P)^{-1}RP^{-1}) & -(P^{-1}Q(N/P)^{-1}) \\ -((N/P)^{-1}RP^{-1}) & (N/P)^{-1} \end{bmatrix}$$

In our case $N = \begin{bmatrix} MA - I & MB \\ 0 & -I \end{bmatrix}$ and (N/P) = -I. From this it follows that

$$N^{-1} = (DE - I)^{-1} = \begin{bmatrix} (MA - I)^{-1} & (MA - I)^{-1} \cdot M \cdot B \\ 0 & -I \end{bmatrix}$$

Fact 4. Let $A, B \in \mathbb{M}_{n \times n}$ with B being symmetric PSD. Suppose x is an eigenvector of AB corresponding to eigenvalue λ . Then $\sqrt{B}x$ is an eigenvector of $\sqrt{B}A\sqrt{B}$ corresponding to eigenvalue λ

Fact 5 (Laplacian and graph connectivity). Let G be a graph with n vertices. Suppose $(\lambda_1, \lambda_2 \cdots \lambda_n)$ be the eigenvalues corresponding to the eigenvectors $(v_1, v_2 \cdots v_n)$ of the Laplacian of G denoted as L_G . L_G is symmetric PSD with $\lambda_1 = 0$ and $v_1 = 1$. The following properties relate the eigenvalues of L_G with the connectivity of G:

- 1. $\lambda_2 > 0 \iff G \text{ is connected}$
- 2. G is disconnected $\iff \exists z \text{ with } z^T \mathbf{1} = 0 \text{ and } z^T L_G z = 0$

The above is true for L_G^+ also

Definition 1 (χ_u) . χ_u is a vector of size |V|

$$\chi_u(i) = \begin{cases} 1, & if \ i = u \\ 0, & otherwise \end{cases}$$

Definition 2 (Uniform random spanning tree). Let \hat{T} be the random variable denoting a uniformly random spanning tree, then $\mathbb{P}(\hat{T} = T) = \frac{1}{|\mathcal{T}|}$, where \mathcal{T} is the set of all spanning trees of G.

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Fact 6. Given a graph G = (V, E) with laplacian L_G , the effective resistance of an edge $e = \{u, v\} \in E$ is

$$R_e^{eff} = (\chi_u - \chi_v)^T L_G^+ (\chi_u - \chi_v)$$

Then for any $e \in E$ we have

$$\mathbb{P}(e \in \hat{T}) = R_e^{eff}$$

4.2.3 Recursive Algorithm with lazy updates

Deletion

Lemma 1 (Formulas in **Theorem 1** are well defined). Let G = (V, E) be a connected graph and $D \subseteq E$ then

$$(I - L_D L_G^+)$$
 is invertible $\iff G \setminus D$ is connected

Proof. First let's show that If $(I - L_D L_G^+)$ is singular then $G \setminus D$ is disconnected

• Since $(I - L_D L_G^+)$ is singular $\exists x \neq 0$ s.t. $(I - L_D L_G^+)x = 0$

$$\implies L_D L_G^+ x = x \tag{4.1}$$

$$\implies 1 \in eigenvalues(L_D L_G^+)$$
 (4.2)

$$\implies 1 \in eigenvalues((L_G - L_{G \setminus D})L_G^+)$$
 (4.3)

- Let $x \perp 1$ be an eigenvector of $(L_G L_{G \setminus D})L_G^+$ with eigenvalue 1.
- By Fact 4, $y = \frac{\sqrt{L_G^+ x}}{\|\sqrt{L_G^+ x}\|}$ is an eigenvector of $\sqrt{L_G^+ (L_G L_{G \setminus D})} \sqrt{L_G^+}$

$$= y^{T} \cdot \sqrt{L_{G}^{+}} (L_{G} - L_{G \setminus D}) \sqrt{L_{G}^{+}} \cdot y = 1$$
(4.4)

$$= y^{T} \sqrt{L_{G}^{+}} L_{G} \sqrt{L_{G}^{+}} y = (HOW) y^{T} L_{G}^{+} L_{G} y = y^{T} P y$$
(4.5)

$$= y^T \left(I - \frac{\mathbf{1}^T \mathbf{1}}{n} \right) y = y^T y - \left(\frac{y^T \mathbf{1}^T \mathbf{1} y}{n} \right) = (HOW) y^T y = 1 \tag{4.6}$$

• : $y^T \sqrt{L_G^+} L_{G \setminus D} \sqrt{L_G^+} y = 0$ now if we consider $z = \sqrt{L_G^+} y$ and show that $z^T \mathbf{1} = 0$ then we can use **Fact 5** to complete the proof

$$y^T \sqrt{L_G^+} \mathbf{1} = x^T \sqrt{L_G^+} \sqrt{L_G^+} \mathbf{1} = 0 \text{(HOW is 1 in kernel of } L_G^+$$
 (4.7)

$$G \setminus D$$
 is disconnected (4.8)

Now to prove the converse, If $G \setminus D$ is disconnected then $I - L_D L_G^+$ is singular

• If $G \setminus D$ is disconnected then $\exists y \perp 1, ||y|| = 1$ we have

1.
$$y^T \cdot \sqrt{L_G^+} \cdot L_{G \setminus D} \cdot \sqrt{L_G^+} \cdot y = 0(HOW)$$

2.
$$y^T \cdot \sqrt{L_G^+} \cdot L_G \cdot \sqrt{L_G^+} \cdot y = y^T y = 1$$

• From (1) and (2) we get $y^T \sqrt{L_G^+} (L_G - L_{G \setminus D}) \sqrt{L_G^+} y = 1$

$$\implies y^T \cdot \sqrt{L_G^+} \cdot L_D \cdot \sqrt{L_G^+} \cdot y = 1 \tag{4.9}$$

$$\implies 1 \in \text{eigenvalues}(L_D L_G^+)(HOW)$$
 (4.10)

$$\implies (I - L_D L_G^+) \text{ is singular}$$
 (4.11)

Theorem 1 (Update identity for Deletion). Let G = (V, E) be a connected graph and $D \subseteq E$. If $G \setminus D$ is connected then

$$(L_G - L_D)^+ = L_G^+ - (L_G^+ \cdot (L_D L_G^+ - I)^{-1} \cdot L_D \cdot L_G^+)$$

Proof. If R.H.S is indeed true then it should satisfy the property of $LL^+ = P$

$$(L_{G} - L_{D}) \cdot (L_{G} - L_{D})^{+}$$

$$(L_{G} - L_{D}) \cdot \left(L_{G}^{+} - \left(L_{G}^{+} \cdot (L_{D}L_{G}^{+} - I)^{-1} \cdot L_{D} \cdot L_{G}^{+}\right)\right)$$

$$\left[P - L_{D}L_{G}^{+}\right] - \left[(L_{G}L_{G}^{+} - L_{D}L_{G}^{+}) \cdot (L_{D}L_{G}^{+} - I)^{-1} \cdot L_{D} \cdot L_{G}^{+}\right]$$

$$\left[P - L_{D}L_{G}^{+}\right] + \left[\left((L_{D}L_{G}^{+} - I) + \frac{\mathbf{1}\mathbf{1}^{T}}{n}\right) \cdot \left((L_{D}L_{G}^{+} - I)^{-1} \cdot L_{D} \cdot L_{G}^{+}\right)\right]$$

$$\left[P - L_{D}L_{G}^{+}\right] + \left[(L_{D}L_{G}^{+}) + \left(\frac{\mathbf{1}\mathbf{1}^{T}}{n} \cdot (L_{D}L_{G}^{+} - I)^{-1} \cdot L_{D} \cdot L_{G}^{+}\right)\right]$$

We can see that $-\mathbf{1}^T (L_D L_G^+ - I) = -\mathbf{1}^T L_D L_G^+ + (I\mathbf{1})^T = 0 + \mathbf{1}^T = \mathbf{1}^T$. Hence $\mathbf{1}^T (L_D L_G^+ - I)^{-1} = -\mathbf{1}^T$. And also $\mathbf{1}^T L_D = 0$. Hence,

$$P - L_D L_G^+ + L_D L_G^+ + \mathbf{1}^T L_D L_G^+ = P$$

Definition 3 (Submatrix).

Corollary 1 (Improved **Theorem 1** for submatrix). Let G = (V, E) be a connected graph and $D \subseteq G$. For $S \subseteq V$ define E[S] as $(S \times S) \cap E$. Suppose $E_D \subseteq E[S]$ and $G \setminus D$ is connected then

$$(L_G - L_D)_{S,S}^+ = (L_G^+)_{S,S} - \left((L_G^+)_{S,S} \cdot ((L_D)_{S,S} \ (L_G^+)_{S,S} - I)^{-1} \cdot (L_D)_{S,S} \cdot (L_G^+)_{S,S} \right)$$

Proof. From **Theorem 1** we know that $(L_G - L_D)^+ = L_G^+ - \left(L_G^+ \cdot (L_D L_G^+ - I)^{-1} \cdot L_D \cdot L_G^+\right)$. If we apply **Fact 3.1** to $(L_G - L_D)^+$ we get

$$(L_G^+)_{S,S} - \left(L_G^+ \cdot (L_D L_G^+ - I)^{-1} \cdot L_D \cdot L_G^+\right)_{S,S}$$

Applying Fact 3.3 we get (HOW)

$$(L_G^+)_{S,S} - ((L_G^+)_{S,S} \cdot (L_D L_G^+ - I)_{S,S}^{-1} \cdot (L_D)_{S,S} \cdot (L_G^+)_{S,S})$$

Now applying Fact 3.5 to $(L_D L_G^+ - I)_{S,S}^{-1}$

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Fact 3.5 states that If $D = \begin{bmatrix} M & 0 \\ 0 & 0 \end{bmatrix}$, and $E = \begin{bmatrix} A & B \\ X & Y \end{bmatrix}$ where $M, A \in \mathbb{M}_{n \times n}$ and If (MA - I) is invertible Then,

$$(DE - I)^{-1} = \begin{bmatrix} (MA - I)^{-1} & (MA - I)^{-1} \cdot M \cdot B \\ 0 & -I \end{bmatrix}$$

Here we have $L_D=\begin{bmatrix} (L_D)_{S,S} & 0\\ 0 & 0 \end{bmatrix}$, (HOW can it always be this way) and $L_G=\begin{bmatrix} (L_G)_{S,S} & (L_G)_{S,S^c}\\ (L_G)_{S^c,S} & (L_G)_{S^c,S^c} \end{bmatrix}$

$$\therefore (L_D L_G - I)^{-1} = \begin{bmatrix} ((L_D)_{S,S} (L_G)_{S,S} - I)^{-1} & (L_D)_{S,S} (L_G)_{S,S^c} \\ 0 & -I \end{bmatrix}$$

Hence we get the required result

$$(L_G - L_D)_{S,S}^+ = (L_G^+)_{S,S} - \left((L_G^+)_{S,S} \cdot ((L_D)_{S,S} \ (L_G^+)_{S,S} \ - \ I)^{-1} \cdot (L_D)_{S,S} \cdot (L_G^+)_{S,S} \right)$$

Contraction

Definition 4 (Incidence Matrix). Let G = (V, E), given an edge $e = u, v \in E$ the incidence vector of e is defined as $v_e = (\chi_u - \chi_v)$. Given a set of edges $D = \{e_1, e_2 \cdots e_m\} \subseteq E$, the incidence matrix of D is defined as $B_D = [v_{e_1} | v_{e_2} \cdots | v_{e_m}]$

Definition 5 (G+ke). G+ke is the weighted graph obtained by increasing e's weight by k

Lemma 2 (Formulas in **Theorem 2** are well defined). Let G = (V, E) be a connected graph. Given $F \subseteq E$ with |F| = r and let B_F be the incidence matrix of F.

$$B_F^T L_G^+ B_F$$
 is invertible \iff F is a forest

Proof. For any $x \in \mathbb{R}^r$, $x \neq 0$, let $y = B_F x$. We first prove the following claim

Claim 1. The incidence matrix of a acyclic graph has full column rank

Therefore $y \neq 0$

Lemma 3 (Formulas in **Theorem 2** are well defined). Let G = (V, E) be a connected graph. Given $F \subseteq E$ and let B_F be the incidence matrix of F. For any k > 0,

If F is a forest then
$$\left(\frac{I}{k} + B_F^T L_G^+ B_F\right)$$
 is invertible for any $k > 0$

Theorem 2 (Contraction update formula for finite k). Let G = (V, E) be a connected graph. Given $F \subseteq E$ and let B_F be the incidence matrix of F. For any k > 0,

$$(L_G + k L_F)^+ = L_G^+ - \left(L_G^+ \cdot B_F \cdot (\frac{I}{k} + B_F^T L_G^+ B_F)^{-1} \cdot B_F^T \cdot L_G^+\right)$$

Proof. TODO

Corollary 2 (Improves **Theorem 2** for sub-matrices). Let G = (V, E) be a connected graph. Given $F \subseteq E$ and let B_F be the incidence matrix of F. Suppose $F \subseteq E[S]$, where $S \subseteq V$. For any k > 0,

$$(L_G + k \ L_F)_{S,S}^+ = (L_G^+)_{S,S} - \left((L_G^+)_{S,S} \ (B_F)_{S,*} \ (\frac{I}{k} + (B_F^T)_{S,*} \ (L_G^+)_{S,S} \ (B_F)_{S,*} \right)^{-1} \ (B_F^T)_{S,*} \ (L_G^+)_{S,S}$$

Proof. TODO

Theorem 3 (Extends **Theorem 2** to $k \to \infty$ case). For a forest $F_1 \subseteq E$, let G(k) = G + k F_1 as defined in **Definition 3**. Let $F_2 \subseteq E$ be disjoint from F_1 such that $F_1 \cup F_2$ is a forest. Let B_{F_2} be the incidence matrix of F_2 . For k > 0 define $N = \lim_{k \to \infty} L_{G(k)}^+$

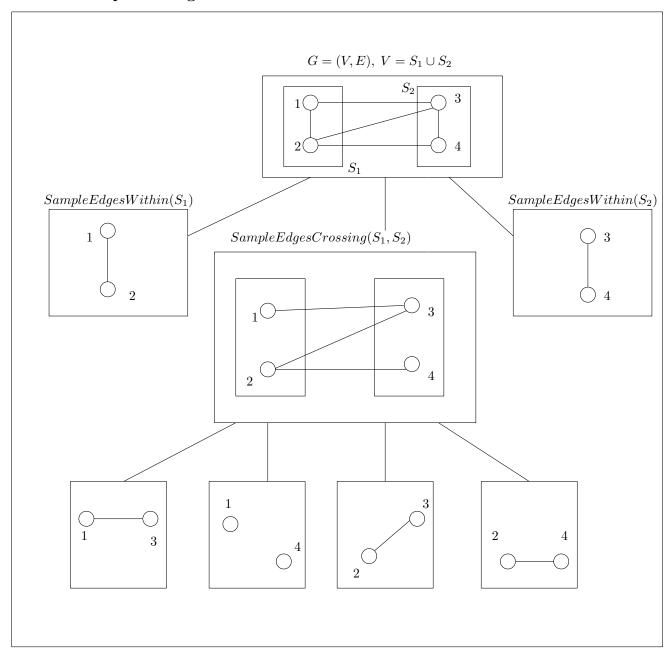
$$\lim_{k \to \infty} L_{G(k)+kF_2}^+ = N - \left(N \cdot B_{F_2} \cdot (B_{F_2}^T \ N \ B_{F_2}) \cdot B_{F_2}^T \cdot N \right)$$

Also
$$ker\left(\lim_{k\to\infty}L^+_{G(k)+kF_2}\right) = span\left(B_{F_1\cup F_2}\cup \mathbf{1}\right)$$

Proof. TODO

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4.2.4 The updated algorithm



5 Laplacian Paradigm

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6 Conclusion

Bibliography

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