

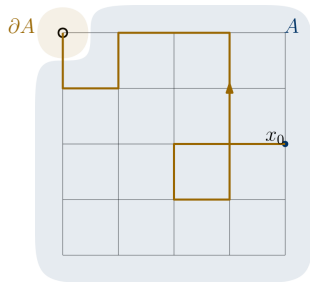
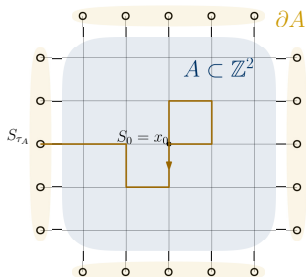
Loop-Erased Random Walks

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Markov Chains on Finite Sets

- Let $A, \partial A$ be disjoint finite vertex sets and denote $\bar{A} = A \cup \partial A$. We may also use $A, \partial A, \bar{A}$ to denote their complete graphs.
- A Markov chain S from x_0 to ∂A is given by the measure \mathbf{P}^{x_0} with transition probabilities $(p(x, y))_{x, y \in \bar{A}}$.
- It is stopped at ∂A by setting $p(x, y) = \delta_{xy}$ for $x, y \in \partial A$.
- Its path is given by $S[0, \tau_A] = [S_0, \dots, S_{\tau_A}]$, where $\tau_A = \inf \{j \geq 0; S_j \notin A\}$ is the exit time of A .
- Simple random walk: a Markov chain with transition probabilities $p(x, y) = 1/d_A(x)$, the degree of x in A .



Markov Chain as Measure on Path Space

- Given a directed edge $\vec{e} = [x, y]$, define weight $p(\vec{e}) = p(x, y)$.
- We can concatenate directed edges $\vec{e} = [x, y]$, $\vec{f} = [y, z]$ to form a path $\vec{e} \oplus \vec{f} = [x, y, z]$.
- For a path $\omega = [x_0, \dots, x_n] = \vec{e}_1 \oplus \dots \oplus \vec{e}_n$, $p(\omega) = \prod_{j=1}^n p(\vec{e}_j)$.
- This induces a measure p on sets of paths, e.g. we can write $p(\mathcal{K}_A(x, y))$, where $\mathcal{K}_A(x, y)$ denotes the set of paths from x to y in A .
- Let $\omega = [x_0, \dots, x_n] \in \mathcal{K}_A(x_0, x_n)$. By the Markov property, we can write

$$\mathbf{P}^{x_0} \{S[0, n] = \omega\} = \mathbf{P}^{x_0} \{S_0 = x_0, \dots, S_n = x_n\} = p(\omega).$$

Let $\mathcal{W}_A(x, y)$ denote the set of SAWs from x to y in A .

Definition (Loop-erasure)

We define a deterministic procedure called (chronological) loop-erasure

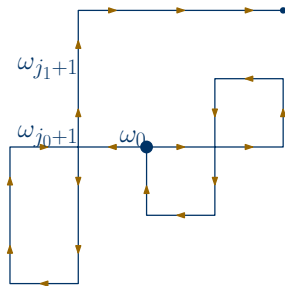
$$\text{LE} : \omega \in \mathcal{K}_A(x, y) \mapsto \eta \in \mathcal{W}_A(x, y).$$

It is given by the following:

- 1 Let $\omega = [\omega_0, \dots, \omega_n] \in \mathcal{K}_A(x, y)$, $j_0 = \sup \{k; \omega_k = \omega_0\}$, and $\eta_0 = \omega_0 = \omega_{j_0}$.
- 2 If $j_i < n$, set $j_{i+1} = \sup \{k; \omega_k = \omega_{j_i}\}$, and $\eta_{j_{i+1}} = \omega_{j_{i+1}} (= \omega_{j_i})$.
Recursively apply this procedure until $j_m = n$.
- 3 Set $\text{LE}(\omega) = \eta = [\eta_0, \dots, \eta_m]$.

Definition (Loop-erasure)

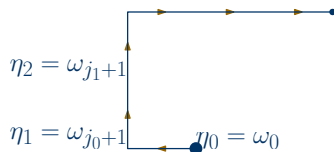
- 1 Let $\omega = [\omega_0, \dots, \omega_n] \in \mathcal{K}_A(x, y)$, $j_0 = \sup \{k; \omega_k = \omega_0\}$, and $\eta_0 = \omega_0 = \omega_{j_0}$.
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$$j_0 = 8, j_1 = 15, j_2 = 16$$

Definition (Loop-erasure)

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What is the probability that η is the loop-erasure of the path of a Markov chain. That is, what is $p(\text{LE}^{-1}(\eta))$?

Theorem

Let $\eta = [x_0, \dots, x_m, x_{m+1}]$, where $x_{m+1} \in \partial A$.

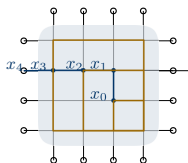
$$p(\text{LE}^{-1}(\eta)) = p(\eta) \prod_{j=0}^m p(\mathcal{K}_{A_j}(x_j, x_{j+1})), \text{ where } A_j = A \setminus \{x_0, \dots, x_{j-1}\}.$$

The product is a measure of all possible combinations of loops erased. We write

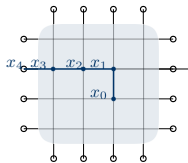
$$F_\eta(A) = \prod_{j=0}^m p(\mathcal{K}_{A_j}(x_j, x_{j+1})).$$

Loop-Erasure

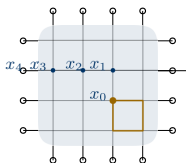
$$\omega = \ell_0 \oplus [x_0, x_1] \oplus \ell_1 \oplus [x_1, x_2] \oplus \ell_2 \oplus [x_2, x_3] \oplus \ell_3 \oplus [x_3, x_4]$$



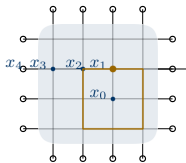
Whole path ω



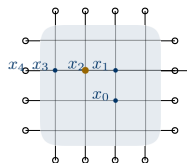
Loop-erasure η



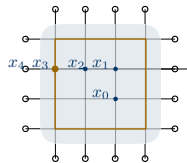
Loop ℓ_0 at x_0



Loop ℓ_1 at x_1



Loop ℓ_2 at x_2



Loop ℓ_3 at x_3

Proof (sketch).

Given some path $\omega \in LE^{-1}(\eta)$, we have the unique decomposition

$$\omega = \ell_0 \oplus [x_0, x_1] \oplus \ell_1 \oplus [x_1, x_2] \oplus \cdots \oplus [x_{m-1}, x_m] \oplus \ell_m \oplus [x_m, x_{m+1}],$$

where $\ell_j \in \mathcal{K}_{A_j}(x_j, x_j)$. From this, we obtain $p(\omega) = p(\eta)p(\ell_0) \dots p(\ell_m)$. Summing over all possible choices of the loops ℓ_0, \dots, ℓ_m , we arrive at

$$p(LE^{-1}(\eta)) = p(\eta) \prod_{j=0}^m p(\mathcal{K}_{A_j}(x_j, x_j)).$$

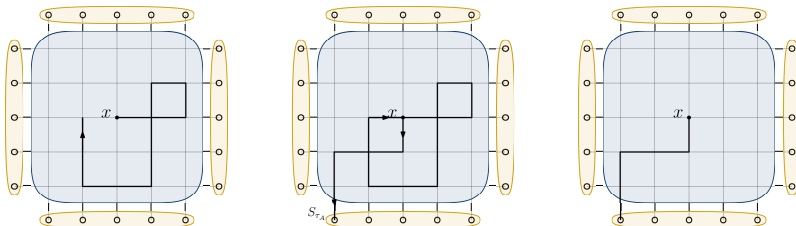


LERW in Finite Sets

Definition

The LERW from x to ∂A in A is the path $LE(S[0, \tau_A])$, given by the probability measure

$$\hat{p}_A(\eta) = \mathbf{P}^x \{LE(S[0, \tau_A]) = \eta\} = \mathbf{P}^x \{S[0, \tau_A] \in LE^{-1}(\eta)\}.$$

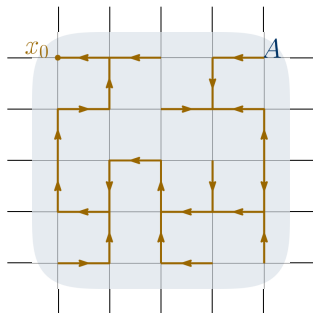


Proposition

$$\hat{p}_A(\eta) = p(\eta)F_\eta(A).$$

Spanning Trees

- A tree T of A is a collection of edges which contains no loops (cycles) and the restriction of the graph A to T is connected.
- The tree T is a spanning tree of A if every vertex in A is incident on some edge in T .
- Given a root x_0 , $(T; x_0)$ is a rooted tree for which we can define an orientation of T , where each edge points toward x_0 .



Uniform Spanning Tree

We define the weight of T with respect to x_0 by

$$p(T; x_0) = \prod_{e \in T} p(\vec{e}),$$

where \vec{e} is a directed edge with the orientation given by the tree.

Definition (uniform spanning tree)

The uniform spanning tree (UST) on A is random spanning tree with the probability measure μ_A on the set \mathfrak{T} of spanning trees of A given by

$$\mu_A(T) = \frac{p(T; x_0)}{\sum_{T \in \mathfrak{T}} p(T; x_0)}.$$

This is the uniform distribution on \mathfrak{T} if p is given by the simple random walk on A .

Wilson's Algorithm

Wilson's algorithm builds a random spanning tree from LERW.

Definition (Wilson's algorithm)

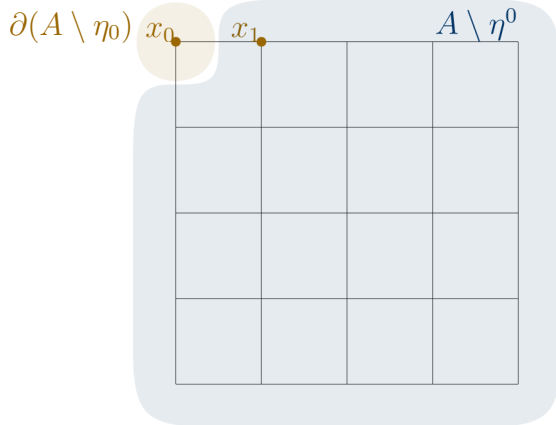
Let $A, \mathbf{P}, x_0 \in A$. Initialise $\mathcal{T}_0 = \emptyset, \eta_0 = [x_0]$.

- 1 Run a LERW in $A_0 = A \setminus \eta^0$ from x_1 to $\partial A_0 = x_0$ to get a path η^1 . Add η^1 to the tree by defining $\mathcal{T}_1 = \mathcal{T}_0 \cup \eta^1$ and $A_1 = A_0 \setminus \mathcal{T}_1$.
- 2 Recursively, if A_k is empty, then we have a spanning tree $\mathcal{T} \stackrel{\text{def}}{=} \mathcal{T}_k$. STOP.
- 3 Otherwise, let j denote the smallest index with $x_j \notin A_k$. Run a LERW η in A_k from x_j to \mathcal{T}_k . Add η to the tree \mathcal{T}_k to form $\mathcal{T}_{k+1} \stackrel{\text{def}}{=} \mathcal{T}_k \cup \eta$ and let $A_{k+1} = A_k \setminus \mathcal{T}_{k+1}$, i.e. the vertices that are not yet connected to the tree.

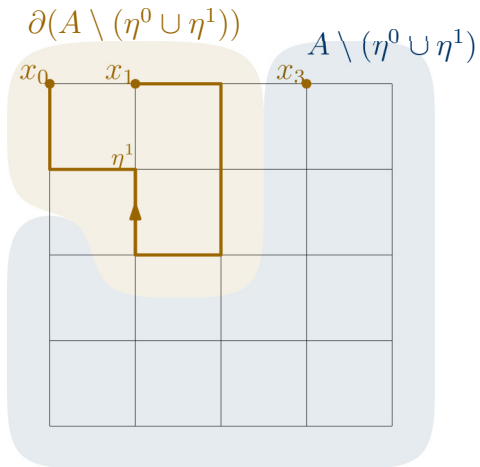
Theorem

Wilson's Algorithm generates spanning trees in the same distribution as the uniform spanning tree.

Wilson's Algorithm

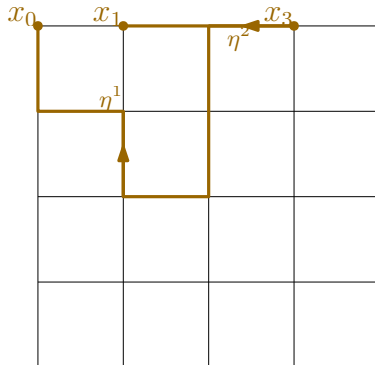


Wilson's Algorithm



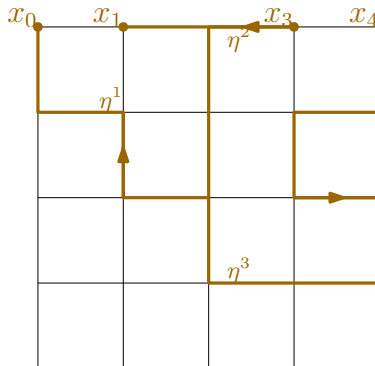
$$p(\eta^1)F_{\eta^1}(A \setminus \eta^0)$$

Wilson's Algorithm



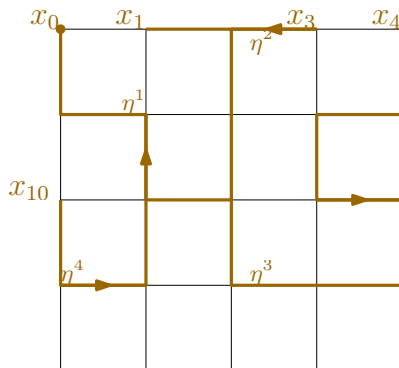
$$p(\eta^1)F_{\eta^1}(A \setminus \eta^0)p(\eta^2)F_{\eta^2}(A \setminus (\eta^0 \cup \eta^1))$$

Wilson's Algorithm



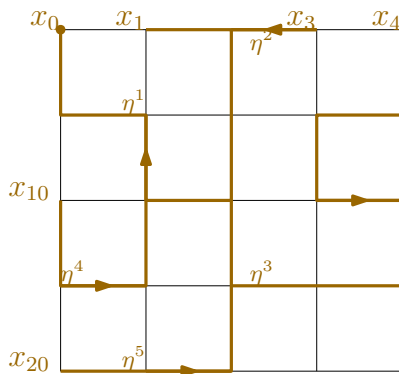
$$p(\eta^1)F_{\eta^1}(A \setminus \eta^0)p(\eta^2)F_{\eta^2}(A \setminus (\eta^0 \cup \eta^1))p(\eta^3)F_{\eta^3}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2))$$

Wilson's Algorithm



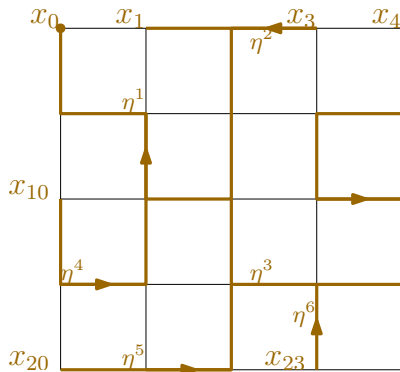
$$p(\eta^1)F_{\eta^1}(A \setminus \eta^0)p(\eta^2)F_{\eta^2}(A \setminus (\eta^0 \cup \eta^1))p(\eta^3)F_{\eta^3}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2))p(\eta^4)F_{\eta^4}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2 \cup \eta^3))$$

Wilson's Algorithm



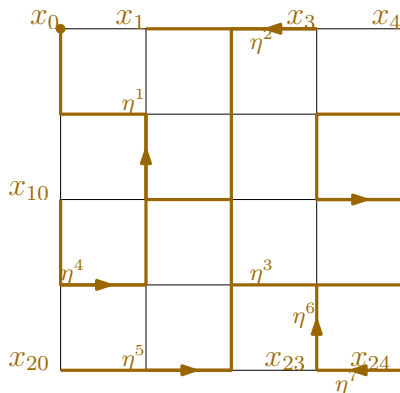
$$p(\eta^1)F_{\eta^1}(A \setminus \eta^0)p(\eta^2)F_{\eta^2}(A \setminus (\eta^0 \cup \eta^1))p(\eta^3)F_{\eta^3}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2))p(\eta^4)F_{\eta^4}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2 \cup \eta^3))p(\eta^5)F_{\eta^5}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2 \cup \eta^3 \cup \eta^4))$$

Wilson's Algorithm



$$\begin{aligned}
 & p(\eta^1)F_{\eta^1}(A \setminus \eta^0)p(\eta^2)F_{\eta^2}(A \setminus (\eta^0 \cup \eta^1))p(\eta^3)F_{\eta^3}(A \setminus (\eta^0 \cup \eta^1 \cup \\
 & \eta^2))p(\eta^4)F_{\eta^4}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2 \cup \eta^3))p(\eta^5)F_{\eta^5}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2 \cup \eta^3 \cup \\
 & \eta^4))p(\eta^6)F_{\eta^6}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2 \cup \eta^3 \cup \eta^4 \cup \eta^5))
 \end{aligned}$$

Wilson's Algorithm



$$\begin{aligned}
 & p(\eta^1)F_{\eta^1}(A \setminus \eta^0)p(\eta^2)F_{\eta^2}(A \setminus (\eta^0 \cup \eta^1))p(\eta^3)F_{\eta^3}(A \setminus (\eta^0 \cup \eta^1 \cup \\
 & \eta^2))p(\eta^4)F_{\eta^4}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2 \cup \eta^3))p(\eta^5)F_{\eta^5}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2 \cup \eta^3 \cup \\
 & \eta^4))p(\eta^6)F_{\eta^6}(A \setminus (\eta^0 \cup \eta^1 \cup \eta^2 \cup \eta^3 \cup \eta^4 \cup \eta^5))p(\eta^7)F_{\eta^7}(A \setminus (\eta^0 \cup \eta^1 \cup \\
 & \eta^2 \cup \eta^3 \cup \eta^4 \cup \eta^5 \cup \eta^6))
 \end{aligned}$$

Wilson's Algorithm Generates UST

Proof (sketch).

The probability that T is chosen is

$$p(\eta^1)F_{\eta^1}(A)p(\eta^2)F_{\eta^2}(A \setminus (\eta^0 \cup \eta^1)) \cdots p(\eta^k)F_{\eta^k}(A \setminus (\eta^1 \cup \cdots \cup \eta^{k-1})).$$

Note that vertex sets, $A = \eta^1 \cup \cdots \cup \eta^{k-1} \cup \eta^k$. Hence, the above is equal to $p(T; x_0)F_A(A)$. Therefore, the probability that T is chosen is

$$\frac{p(T; x_0)F_A(A)}{\sum_{T \in \mathfrak{T}} p(T; x_0)F_A(A)} = \frac{p(T; x_0)}{\sum_{T \in \mathfrak{T}} p(T; x_0)}.$$



Not in this presentation

- This presentation was very combinatorial, only includes LERW on finite graphs.
- We can define LERW as $\text{LE}(S[0, \infty))$ for transient Markov chains on infinite graphs, e.g. simple random walk on \mathbb{Z}^d for $d \geq 3$.
- LERW can only be defined for some recurrent Markov chains: $\text{LE}(S[0, \infty))$ is not well-defined since

$$\sup \{k; \omega_k = \omega_0\}$$

does not exist.