## Asymptotic Properties of Suffix Trees

Analysis of height and feasible path length
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## Plan of the Talk

1. Suffix Trees: Construction
2. Depth of Insertion in a Suffix Tree
3. Height and Shortest Feasible Path in a Suffix Tree
4. Proof Techniques

## Definitions

- $\Sigma$ is a finite alphabet, $|\Sigma|=V$
- $\left\{X_{k}\right\}_{k=1}^{\infty}$ is a stationary ergodic sequence of symbols generated from $\Sigma$
- $X_{m}^{n}=\left(X_{m}, \ldots, X_{n}\right)$ for $m<n$ is a partial sequence


## The Problem: Construction

Consider a digital tree built in the following way:
Step 0. At the beginning, the tree consists of its root only.
Step 1. Consider a tree $\mathcal{T}_{n}$ built for the partial sequence $X_{1}^{n}=\left(X_{1}, \ldots, X_{n}\right)$.

Step 2. Set current vertex to root.
Step 3. Starting with $j=n+1$, we either
(A) move by the edge marked by $X_{j}$ from the current vertex if it exists thus changing the current vertex and increase $j$ by 1 , or
(B) construct a new edge marked with symbol $X_{j}$ from the current vertex to a new vertex marked with our suffix $X_{n+1}^{\infty}$ and proceed to Step 1 with $n$ increased by 1 otherwise

## Example

Tree with 4 inserted suffixes.


## Example

Fifth suffix insertion.


## The Problem: Questions

- What is the typical height of $\mathcal{T}_{n}$ ?
- What is the typical difference $j-n$ when Step 3 is finished?
- What is the typical minimal possible difference $j-n$ at the end of Step 3 for the tree $\mathcal{T}_{n}$ ?

Note that $j-n$ is the number of case (A) occurences during a single Step 3 .

## More Definitions

- $\Sigma$ is a finite alphabet, $|\Sigma|=V$
- $\left\{X_{k}\right\}_{k=1}^{\infty}$ is a stationary ergodic sequence of symbols generated from $\Sigma$
- $X_{m}^{n}=\left(X_{m}, \ldots, X_{n}\right)$ for $m<n$ is a partial sequence
- $P\left(X_{1}^{n}\right)=\operatorname{Pr}\left\{X_{k}=x_{k}, 1 \leqslant k \leqslant n, x_{k} \in \Sigma\right\}$ is $n$th order probability distribution
- $h=\lim _{n \rightarrow \infty} \frac{E\left\{-\log P\left(X_{1}^{n}\right)\right\}}{n}$ is the entropy of $\left\{X_{k}\right\}$

It is known that $h \leqslant \log V$.

## Parameter $L_{n}$

- $L_{n}$ is the smallest integer $L>0$ such that $X_{m}^{m+L-1} \neq X_{n+1}^{n+L}$ for all $1 \leqslant m \leqslant n$.


## Example:

Let $X_{1}^{10}=(0,1,0,1,1,0,1,1,1,0)$.
Here $L_{1}=1, L_{2}=3, L_{3}=2$, and $L_{4}=5$ since $X_{5}^{8}=X_{2}^{5}=(1,0,1,1)$ and therefore $L_{4}>4$ :

$$
(0, \underbrace{1,0,1,1}, 0,1,1,1,0) \text {. }
$$

## Mixing Condition

Let $F_{m}^{n}$ be a $\sigma$-field generated by $\left\{X_{k}\right\}_{k=m}^{n}$ for $m \leqslant n$.
$\left\{X_{k}\right\}$ satisfies the mixing condition $\Longleftrightarrow$ there exist constants
$0<c_{1} \leqslant c_{2}$ and an integer $d$ such that for all $A \in F_{-\infty}^{m}, B \in F_{m+d}^{\infty}$ and $-\infty \leqslant m \leqslant m+d \leqslant n$ the following condition is true: $c_{1} \operatorname{Pr}\{A\} \operatorname{Pr}\{B\} \leqslant \operatorname{Pr}\{A B\} \leqslant c_{2} \operatorname{Pr}\{A\} \operatorname{Pr}\{B\}$.

## Strong $\alpha$-Mixing Condition

Let $\alpha$ be a function of $d$ such that $\alpha(d) \underset{d \rightarrow \infty}{ } 0$.
$\left\{X_{k}\right\}$ satisfies the strong $\alpha$-mixing condition $\Longleftrightarrow$ for all $A \in F_{-\infty}^{m}, B \in F_{m+d}^{\infty}$ and $-\infty \leqslant m \leqslant m+d \leqslant n$ the following condition is true:

$$
(1-\alpha(d)) \operatorname{Pr}\{A\} \operatorname{Pr}\{B\} \leqslant \operatorname{Pr}\{A B\} \leqslant(1+\alpha(d)) \operatorname{Pr}\{A\} \operatorname{Pr}\{B\}
$$

## Parameters $h_{1}$ and $h_{2}$

$$
\begin{gathered}
h_{1}=\lim _{n \rightarrow \infty} \frac{\max \left\{\log P^{-1}\left(X_{1}^{n}\right), P\left(X_{1}^{n}\right)>0\right\}}{n}=\lim _{n \rightarrow \infty} \frac{\log \left(1 / \min \left\{P\left(X_{1}^{n}\right), P\left(X_{1}^{n}\right)>0\right\}\right)}{n} \\
h_{2}=\lim _{n \rightarrow \infty} \frac{\log \left(E\left\{P\left(X_{1}^{n}\right)\right\}\right)^{-1}}{2 n}=\lim _{n \rightarrow \infty} \frac{\log \left(\sum_{\left.X_{1}^{n} P^{2}\left(X_{1}^{n}\right)\right)^{-1}}^{2 n}\right.}{}
\end{gathered}
$$

The relationship with entropy $h$ is as follows:

$$
0 \leqslant h_{2} \leqslant h \leqslant h_{1}
$$

## Example: Bernoulli Model

Assume that symbols $X_{i}$ are generated indepenently, and $i$ th symbol is generated according to the probability $p_{i}$.
Thus, $h=\sum_{i=1}^{V} p_{i} \log \left(p_{i}^{-1}\right), h_{1}=\log \left(1 / p_{\min }\right)$ and $h_{2}=2 \log (1 / P)$
where $p_{\text {min }}=\min _{1 \leqslant i \leqslant V}\left\{p_{i}\right\}$ is the probability
of least probable symbol occurence
and $P=\sum_{i=1}^{V} p_{i}^{2}$ can be interpreted as a probability of a match between any two symbols.

## Theorem 1

Consider stationary ergodic sequence $\left\{X_{k}\right\}_{k=-\infty}^{\infty}$.

- Assume strong $\alpha$-mixing condition
- Let $h_{1}<\infty$ and $h_{2}>0$
- (*) $\exists \rho: 0<\rho<1, \exists \beta$ such that $\alpha(d)=O\left(d^{\beta} \rho^{d}\right)$ for $d \rightarrow \infty$

Then
(1) $\liminf _{n \rightarrow \infty} \frac{L_{n}}{\log n}=\frac{1}{h_{1}}$ (a.s.),
(2) $\limsup _{n \rightarrow \infty} \frac{L_{n}}{\log n}=\frac{1}{h_{2}}$ (a.s.).

## Is the Condition (*) Restrictive?

- In Bernoulli model, $\alpha(d)=0$ because of independence of $X_{k}$.
- If the sequence $\left\{X_{k}\right\}$ is Markovian, $\alpha(d)$ decays exponentially fast
- In general, statement (1) of Theorem 1 does not hold without the $(*)$ condition


## Depth in a Suffix Tree <br> Let $\left\{X_{k}\right\}_{k=1}^{\infty}$ be a sequence of symbols from $\Sigma$. <br> Let $\mathcal{T}_{n}$ be a suffix tree constructed from the first $n$ suffixes of $\left\{X_{k}\right\}$.

- $m$ th depth $L_{n}(m)$ is the depth of the $i$ th suffix in $\mathcal{T}_{n}$; note that $L_{n}=L_{n+1}(n+1)$
- Average depth $D_{n}$ is the depth of a randomly selected suffix, that is, $D_{n}=\frac{1}{n} \sum_{m=1}^{n} L_{n}(m)$


## Height and Shortest Feasible Path

- Height $H_{n}$ is the length of the longest path in $\mathcal{T}_{n} ; H_{n}=\max _{1 \leqslant m \leqslant n}\left\{L_{n}(m)\right\}$.
- Available node is a node which does not belong to $\mathcal{T}_{n}$ but its predecessor does, that is, a node that could be inserted in $\mathcal{T}_{n+1}$ at the next insertion.
- Shortest feasible path $s_{n}$ is the length of the shortest path from the root to an available node.


## Self-alignment

Let the suffix tree $\mathcal{T}_{n}$ be built from the suffixes $S_{1}, \ldots, S_{n}$. Self-alignment $C_{i, j}$ is the length of the longest common prefix of $S_{i}$ and $S_{j}$.
Relation to other suffix tree parameters:

- $L_{n}(m)=\max _{1 \leqslant k \leqslant n, k \neq m}\left\{C_{k, m}\right\}+1$
- $H_{n}=\max _{1 \leqslant i<j \leqslant n}\left\{C_{i, j}\right\}+1$
- $L_{n}=\max _{1 \leqslant m \leqslant n}\left\{C_{m, n+1}\right\}+1$


## Example



$$
\begin{aligned}
& S_{1}=0101101110 \\
& S_{2}=101101110 \\
& S_{3}=01101110 \\
& S_{4}=1101110
\end{aligned}
$$

$$
\text { Let } X_{1}^{10}=(0,1,0,1,1,0,1,1,1,0)
$$

Consider suffix tree $\mathcal{T}_{4}$ built from first 4 suffixes.

$$
\begin{gathered}
L_{4}(1)=3, L_{4}(2)=2, L_{4}(3)=3, L_{4}(4)=2 \\
H_{4}=3, s_{4}=2
\end{gathered}
$$

$$
\text { But } L_{4}=L_{5}(5)=5
$$

## Example



But $L_{4}=L_{5}(5)=5$.
$H_{5}=5$, and $s_{5}=2=s_{4}$.

## Theorem 2

Consider stationary ergodic sequence $\left\{X_{k}\right\}_{k=1}^{\infty}$.

- Assume strong $\alpha$-mixing condition
- Let $h_{1}<\infty$ and $h_{2}>0$

Then
(1) $\lim _{n \rightarrow \infty} \frac{s_{n}}{\log n}=\frac{1}{h_{1}}$ (a.s.) when ( $*$ ) holds,
(2) $\lim _{n \rightarrow \infty} \frac{H_{n}}{\log n}=\frac{1}{h_{2}}$ (a.s.) when $\alpha(d)$ satisfies the following: $\sum_{d=0}^{\infty} \alpha^{2}(d)<\infty$.

## Proof of Theorem 1 by Theorem 2

(1):

$$
\begin{aligned}
& \limsup _{n \rightarrow \infty} \frac{L_{n}}{\log n} \leqslant \lim _{n \rightarrow \infty} \frac{H_{n}}{\log n} \text { (a.s.): } \\
& \text { by definition: } L_{n} \leqslant H_{n} .
\end{aligned}
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\limsup _{n \rightarrow \infty} \frac{L_{n}}{\log n} \geqslant \lim _{n \rightarrow \infty} \frac{H_{n}}{\log n} \text { (a.s.): }
$$

Note that $H_{n}$ is a non-decreasing sequence;
$L_{n}=H_{n}$ a.s. when $H_{n+1}>H_{n}$, and that occurs infinitely often since
$H_{n} \rightarrow \infty$ and $\left\{X_{k}\right\}$ is an ergodic sequence, so

$$
\operatorname{Pr}\left\{L_{n}=H_{n} \quad \text { i.o. }\right\}=1
$$

and there exists a subsequence $n_{k} \rightarrow \infty$ such that $L_{n_{k}}=H_{n_{k}}$.

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and there exists a subsequence $n_{k} \rightarrow \infty$ such that $L_{n_{k}}=H_{n_{k}}$.
(2) can be proved in a similar way:
$s_{n}$ is a non-decreasing sequence also.

## Techniques: String-Ruler Approach

- Summary: The correlation between different substrings is measured using another string $\omega$ called a string-ruler.
- Example:

How to find the longest common prefix of two independent strings $\left\{X_{k}(1)\right\}_{k=1}^{\infty}$ and $\left\{X_{k}(2)\right\}_{k=1}^{\infty}$ ?
Let its length be $C_{1,2}$.
$C_{1,2} \geqslant k \Longleftrightarrow \exists \omega$ of length $k: X_{1}^{k}(1)=\omega=X_{1}^{k}(2)$.
We then construct a set $\mathcal{W}_{k}=\left\{\omega \in \Sigma^{k}:|\omega|=k\right\}$ and estimate the probabilities $P\left(\omega_{k}\right)=P\left(X_{m+1}^{m+k}=\omega_{k}\right)$ for a fixed position $m$ in our sequence $\left\{X_{k}\right\}$.

## Techniques: Second Moment Method

- Summary: Second Moment Method by Chung and Erdös: For a sequence of events $A_{i}$ we have

$$
\operatorname{Pr}\left\{\bigcup_{i=1}^{n} A_{i}\right\} \geqslant \frac{\left(\sum_{i=1}^{n} \operatorname{Pr}\left\{A_{i}\right\}\right)^{2}}{\sum_{i=1}^{n} \operatorname{Pr}\left\{A_{i}\right\}+\sum_{i \neq j} \operatorname{Pr}\left\{A_{i} \cap A_{j}\right\}} .
$$

- Application:

$$
\text { We then set } A_{i, j}=\left\{C_{i, j} \geqslant k\right\} \text {. }
$$

## Techniques: Second Moment Method

- Reasoning:

Markov's Inequality:

$$
\operatorname{Pr}\{X \geqslant t\} \leqslant \frac{E\{X\}}{t}
$$

Chebyshev's Inequality:

$$
\operatorname{Pr}\{|X-E\{X\}| \geqslant t\} \leqslant \frac{\operatorname{Var}\{X\}}{t^{2}}
$$

- Trivial Results:

First Moment Method:
For integer-valued nonnegative random variable $X$ $\operatorname{Pr}\{X>0\} \leqslant E\{X\}$.
Second Moment Method (Chebyshev):

$$
\operatorname{Pr}\{X=0\} \leqslant \frac{\operatorname{Var}\{X\}}{(E\{X\})^{2}}
$$

## References

1. Wojciech Szpankowski, Asymptotic properties of data compression and suffix trees, IEEE Transactions on Information Theory 39 (1993), no. 5, pp. 1647-1659.
2. Wojciech Szpankowski, Average case analysis of algorithms on sequences; available online as http://www.cs.purdue.edu/homes/spa/book.html.
