Nonparametric statistical inference for the context tree of a stationary ergodic process

Sandro Gallo

Statistics Department
Federal University of São Carlos, Brazil
e-mail: sandro.gallo@ufscar.br

and

Florencia Leonardi†

Institute of Mathematics and Statistics
University of São Paulo, Brazil
e-mail: florencia@usp.br

Abstract: We consider the problem of estimating the context tree of a stationary ergodic process with finite alphabet without imposing additional conditions on the process. As a starting point we introduce a Hamming metric in the space of irreducible context trees and we use the properties of the weak topology in the space of ergodic stationary processes to prove that if the Hamming metric is unbounded, there exist no consistent estimators for the context tree. Even in the bounded case we show that there exist no two-sided confidence bounds. However we prove that one-sided inference is possible in this general setting and we construct a consistent estimator that is a lower bound for the context tree of the process with an explicit formula for the coverage probability. We develop an efficient algorithm to compute the lower bound and we apply the method to test a linguistic hypothesis about the context tree of codified written texts in European Portuguese.

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1. Introduction

In this work we address the issue of whether or not there exist consistent estimators (and confidence bounds) for the context tree of a discrete time stationary ergodic process with finite alphabet. In words, the context tree of a stochastic process is a set of finite strings or left-infinite sequences that determines the portion of the past the process has to look at in order to decide the distribution of its next symbol. For example, an i.i.d. process has the empty string as context tree since it has no dependence on the past. A $k$-steps Markov chain has a context tree containing at least one string of length $k$, and a non-Markovian chain (sometimes coined infinite memory process) has a context tree having at least one left-infinite sequence.

Finite context trees were introduced by Rissanen (1983) as an efficient tool for data compression. The corresponding processes were originally called Variable Length Markov Chains (VLMC) and its estimation was first addressed in Bühlmann and Wyner (1999). Recently, they have received increasing attention in the applied statistics literature, being used in a wide range of problems from different areas (Bejerano and Yona, 2001; Dalevi, Dubhashi and Hermansson, 2006; Busch et al., 2009; Galves et al., 2012, for instance). Its success in real word applications seems to stem from its parsimony (including memory only where data needs) and its capacity to capture structural dependencies in the data. The counterpart of the model, when compared to finite step Markov models for instance, is that estimation is a much complicated task. When he introduced the model, Rissanen (1983) also provided an algorithm for recovering the context tree out of a given sample. Since then, a large part of the related statistical literature has focussed on consistent estimation of the context tree in the finite and infinite memory case, an incomplete list includes Bühlmann and Wyner (1999); Galves and Leonardi (2008); Collet, Galves and Leonardi (2008); Csiszár and Talata (2006); Garivier and Leonardi (2011).

Most of the above cited works make some assumptions on the processes, such as lower bounding the transition probabilities or imposing mixing conditions, additionally to stationarity and ergodicity. In the present paper we refer to our statistical inference problem as nonparametric because we make no further assumptions concerning the distribution of the process, else than stationarity and ergodicity. In this nonparametric setting, Csiszár and Talata (2006) proved the consistency of the Bayesian Information Criterion (BIC) when the context trees are truncated to a given finite length (the truncation being necessary only for infinite context trees). Interestingly, nothing has been done concerning confidence bounds as far as we know.

Given a sample of a stationary ergodic process, it is natural to wonder whether this process has a finite or infinite context tree. This cannot be consistently decided in this general class (Bailey, 1976; Morvai and Weiss, 2005). That is, there exists no two-valued function of the sample which, as the sample size increases, stabilizes to the value “yes” for every process having a finite context tree and “no” for every process having an infinite context tree. Thus, the existence of a universal consistent estimator for this functional relies on assumptions
that cannot be checked empirically. This situation has its counterpart in non-parametric statistics for i.i.d observations. For instance, Fraiman and Meloche (1999) observed that it is impossible to decide, out of a random sample, whether or not the underlying distribution has a finite number of modes. Assuming a priori that the number of modes is finite, they can be consistently estimated.

In the present work the space of irreducible context trees with finite alphabet is equipped with the Hamming distance. Using only topological arguments we prove that if this metric in the space of trees is unbounded, there exists no consistent estimator of the context tree in the class of stationary ergodic processes. In the bounded metric case, we construct an estimator that is consistent and also a nonparametric lower bound with an explicit coverage probability, based on results by Donoho (1988) and Garivier and Leonardi (2011). We also prove that it is not possible to obtain nonparametric upper bounds even in the smaller class of processes having finite context trees. To our knowledge, this is the first work considering the problem of construction of nonparametric confidence bounds for context trees.

Notation, definitions and main results are given in the next section. In Section 3 we show how to compute the lower confidence bound and we present a practical application, testing a linguistic hypothesis about the memory of stressed and non-stressed syllables in European Portuguese written texts. The proofs of the results are given in Section 4.

2. Definitions and results

In this section we present the main definitions and theoretical results of this paper. We begin by describing the notion of irreducible tree and we introduce a Hamming distance in the set of all irreducible trees over a finite alphabet. Then we proceed by defining the context tree of a stationary ergodic process and by establishing some topological properties of the set of all stationary ergodic probability measures with respect to the weak topology. The last part of the section is dedicated to the statements of the main results of the paper.

2.1. Metric tree space

Let $A$ be a finite set called alphabet. For any $m \leq n$, we denote by $a^n_m$ the string $a_m \ldots a_n$ of symbols in $A$ with length $n - m + 1$. This notation is also valid for $m = -\infty$ in which case we obtain a left-infinite sequence $a^n_{-\infty}$. If $m > n$ we let $a^n_m$ denote the empty string $\lambda$. The length of a string $w$ will be denoted by $|w|$. For any $j \in \{0, 1, \ldots\}$, we let $A^j$ denote the set of strings in $A$ having length $j$, in particular $A^0 = \{\lambda\}$. We also let $A^* = \cup_{j \geq 0} A^j$ denote the set of all finite strings on $A$ and we denote by $A^\infty$ the set of all left-infinite sequences $a^n_{-\infty}$ with symbols in $A$.

We will need to concatenate strings; for instance, if $v \in A^i$ and $w \in A^j$ are strings of length $i$ and $j$ respectively, then $vw$ denotes the string of length $i + j$ obtained by putting the symbols in $w$ after the ones in $v$. We also extend
Fig 1. Graphical representation of the trees $\tau_1 = \{00, 010, 110, 1\}$ and $\tau_2 = \{10^i : i = 0, 1, \ldots \} \cup \{0^\infty\}$. In both cases, the contexts corresponds to the sequences obtained by concatenating the symbols from the leaves to the root of the trees. In the case of $\tau_2$ we only show the strings of length at most 3.
at level $k$, defined by the set of its nodes
\[ \tilde{\tau}_k = \{ v \in \tilde{\tau} : |v| \leq k \}. \]

Finally, $\mathcal{T}$ is equipped with the Hamming distance defined by
\[ d_\phi(\tau, \tau') = \sum_{v \in A^*} \phi(v) |1_{\{v \in \tau\}} - 1_{\{v \in \tau'\}}|, \tag{2.1} \]
where $\phi: A^* \to \mathbb{R}^+$. In the summable case $\sum_{v \in A^*} \phi(v) < +\infty$ we have that $(\mathcal{T}, d_\phi)$ is a bounded metric space.

### 2.2. Context tree of a stationary ergodic process

Let \( \{X_i : i \in \mathbb{Z}\} \) be a stationary and ergodic process assuming values in the alphabet $A$. We denote by $P(a^n_m)$ the stationary probability of the string $a^n_m$, that is
\[ P(a^n_m) = \text{Prob}(X^n_m = a_m^n). \]

If $s \in A^*$ is such that $P(s) > 0$ we write
\[ P(a|s) = \text{Prob}(X_0 = a | X_{-|s|} = s), \]
with the convention that if $s = \lambda$ then $P(a|s) = \text{Prob}(X_0 = a)$.

A process as above is said to have law, or measure, $P$.

**Definition 2.1.** We say that the string $s \in A^*$ is a context for a process with measure $P$ if it satisfies
1. $P(s) > 0$ or $s = \lambda$.
2. For all $a \in A$ and all $w \in A^*$ such that $s$ is suffix of $w$
   \[ \text{Prob}(X_0 = a | X_{-|w|}^{-1} = w) = P(a|s). \tag{2.2} \]
3. No proper suffix of $s$ satisfies 2.

An infinite context is a left-infinite sequence $x_{-1}^{-1}$ such that its finite suffixes $x_{-n}^{-1}$, $n = 1, 2, \ldots$ have positive probability but none of them is a context.

By this definition, the set of contexts of a process with measure $P$ is an irreducible tree, it will be denoted by $\tau_P$.

**Example 2.2.** Consider the stationary Markov chain of order 3 over the alphabet $A = \{0, 1\}$ defined by the transition probabilities
\[
\begin{array}{c|cc}
  w & P(0|w) & P(1|w) \\
  \hline
  ab1 & 0.2 & 0.8 \\
  a00 & 0.5 & 0.5 \\
  010 & 0.3 & 0.7 \\
  110 & 0.7 & 0.3 \\
\end{array}
\]
where \( a, b \in A \) are arbitrary. This is an example of what is called a *Variable Length Markov Chain* (VLMC). By Definition 2.1, the only contexts of this process are the strings 1, 00, 010 and 110. The context tree \( \tau_P \) is the tree \( \tau_1 \) represented in Fig. 1.

**Example 2.3.** Suppose that the process \( \{X_i: i \in \mathbb{Z}\} \) takes values in \( \{0, 1\} \), and in order to decide the probability distribution of the next symbol based on the past realization, we only need to know the distance to the last occurrence of a 1. Then, for any \( k \geq 0 \), any \( i \geq 1 \) and any \( v, w \in A \)

\[
P(1|v10^k) = P(1|w10^k).
\]

According to Definition 2.1, the strings \( 10^k, k \geq 0 \), as well as the semi-infinite sequence \( 0^\infty \) are context of this process. Therefore, the context tree \( \tau_P \) is \( \tau_2 \) shown in Fig. 1.

### 2.3. The weak topology in the space of stationary ergodic processes

Let \( \Sigma \) be the \( \sigma \)-algebra on \( \Omega = A^{\mathbb{Z}} \) obtained as the product of the discrete \( \sigma \)-algebras on \( A \). Let \( \mathcal{P} \) denote the set of all stationary ergodic probability measures over \( (\Omega, \Sigma) \).

Define the following distance in \( \mathcal{P} \)

\[
D(P, Q) = \sum_{k \in \mathbb{N}} 2^{-k} |P - Q|_k,
\]

where

\[
|P - Q|_k = \sum_{a_1^k \in A^k} |P(a_1^k) - Q(a_1^k)|
\]

is the \( k \)-th order variational distance. This distance is known in the literature as the *weak distance*, and the topology induced by it is known as the *weak topology* (Shields, 1996, Section I.9).

We now state a basic lemma about the topological properties of the space \( \mathcal{P} \) with respect to the weak topology.

**Lemma 2.4.** The space \( (\mathcal{P}, D) \) is a Baire space.

### 2.4. Consistent estimation and confidence bounds

As mentioned in the Introduction, in this paper we are interested in the estimation of properties of the context tree \( \tau_P \) from samples \( X_1, \ldots, X_n \) of size \( n \) of the corresponding stationary and ergodic process \( P \). Up to now this problem has been reduced to the consistent identification of the set of contexts (in the finite case) or of a truncated version of the context tree (in the infinite case). The latter corresponds to a special case of our distance \( d_\phi \); for instance when the interest is in estimating contexts of length at most \( k \) we can consider \( \phi(v) = 0 \).
for all $|v| > k$. In the sequel we define the notion of consistency of a sequence of estimators in a general setting.

Let $F : \mathcal{P} \rightarrow \mathcal{F}$ be a functional with values in some metric space $(\mathcal{F}, d)$.

**Definition 2.5.** We say that $F$ is consistently estimable on $\mathcal{P}$ (in probability) if there exists a sequence $\{F_n\}_{n \in \mathbb{N}}$ of statistics, with $F_n : A^n \rightarrow \mathcal{F}$, such that for all $P \in \mathcal{P}$

$$d(F_n(X_1, \ldots, X_n), F(P)) \xrightarrow{P} 0.$$  

In this case we say that $\{F_n\}_{n \in \mathbb{N}}$ is a consistent estimator for $F$ on $\mathcal{P}$. We say that $F$ is strongly consistently estimable on $\mathcal{P}$ if the convergence takes place almost surely with respect to the probability measure $P$, and in this case we say that $\{F_n\}_{n \in \mathbb{N}}$ is a strongly consistent estimator for $F$ on $\mathcal{P}$.

The following result establishes a necessary condition for the existence of consistent estimators of a bounded real functional defined on $\mathcal{P}$.

**Proposition 2.6.** Assume $F : \mathcal{P} \rightarrow \mathbb{R}$ is bounded (that is there exists $R \in \mathbb{R}$ such that $|F(P)| \leq R$ for all $P \in \mathcal{P}$). If $F$ is consistently estimable on $\mathcal{P}$ then $F$ must be continuous on a dense subset of $\mathcal{P}$.

In this paper we are concerned with the functional $T : \mathcal{P} \rightarrow \mathcal{T}$ that assigns to any measure $P \in \mathcal{P}$ its associated context tree $\tau_P \in \mathcal{T}$. The first question we address here is if it is possible to decide, out from a finite sample, if the sum of the function $\phi$ over the nodes of the context tree is finite or not.

**Theorem 2.7.** If $\sum_{v \in A^*} \phi(v) = +\infty$ then the functional

$$L(P) = 1\{\sum_{v \in \tau_P} \phi(v) < +\infty\}$$

is not consistently estimable on $\mathcal{P}$.

This result states, in particular, that the functional that attributes the value 1 if the measure is Markovian, and 0 otherwise, is not consistently estimable when $\phi$ is not summable. This is a known result; see Morvai and Weiss (2005) and references therein. However, our proof is completely different from theirs and it is mainly based on topological properties of $\mathcal{P}$.

Our main result about consistent estimation for the context tree on $\mathcal{P}$ is given in the following theorem.

**Theorem 2.8.** $T$ is consistently estimable on $\mathcal{P}$ if and only if $\sum_{v \in A^*} \phi(v)$ is finite.

The only if part of this theorem is a direct consequence of Theorem 2.7. The if part is proved constructively later, because the estimator $\{T_n^c\}_{n \in \mathbb{N}}$ defined by (2.3) below will be proved to be consistent when $\phi$ is summable.

As mentioned before, the present work is also concerned with the obotention of confidence bounds for the context tree of a stationary and ergodic process. We use the following general definition of upper and lower confidence bounds, taken from Donoho (1988). Suppose $\mathcal{F}$ is equipped with a partial order $<$ with supremum and infimum.
Definition 2.9. Given \( n \geq 1 \), a statistic \( U_n : A^n \to \mathcal{F} \) is called a non-trivial upper confidence bound for \( F \) on \( \mathcal{P} \) with coverage probability at least \( 1 - \alpha \) if

\[
\sup_{\mathcal{P}} P(U_n < \sup_{P' \in \mathcal{P}} F(P')) = 1
\]

and

\[
\inf_{\mathcal{P}} P(F(P) \leq U_n) \geq 1 - \alpha.
\]

Analogously we say that \( L_n \) is a non-trivial lower confidence bound for \( F \) on \( \mathcal{P} \) with coverage probability at least \( 1 - \alpha \) if

\[
\sup_{\mathcal{P}} P(\inf_{P' \in \mathcal{P}} F(P') < L_n) = 1
\]

and

\[
\inf_{\mathcal{P}} P(L_n \leq F(P)) \geq 1 - \alpha.
\]

Our first theorem concerning confidence bounds is a negative result stating that the functional \( T \) does not admit a non-trivial upper confidence bound neither on \( \mathcal{P} \) nor in the class of stationary ergodic measures with finite context tree.

**Theorem 2.10.** If \( U_n \) is an upper bound that satisfies \( \sup_{\mathcal{P}} P(U_n \prec \tau^\infty) = 1 \) then the coverage probability \( \inf_{\mathcal{P}} P(\tau_P \preceq U_n) = 0 \). This is also satisfied even in the smaller class \( \mathcal{P}_f \subset \mathcal{P} \) of stationary ergodic measures having finite context tree.

The functional \( T \) does however admit non-trivial lower confidence bounds on \( \mathcal{P} \). In what follows, we construct a sequence of statistics which will be proved to be a non-trivial lower confidence bound and a consistent estimator of \( T \) on \( \mathcal{P} \), when \( \sum_{v \in A^*} \phi(v) < +\infty \).

We will first define a discrepancy measure between a sample \( X_1, \ldots, X_n \) and a measure \( Q \in \mathcal{P} \). To do so, we need to introduce some more notation and definitions. Given a string \( w \), denote by \( N_n(w) \) the number of occurrences of \( w \) in the sample \( X_1, \ldots, X_n \); that is

\[
N_n(w) = \begin{cases} 
\sum_{i=0}^{n-|w|} 1\{X_{i+1}^{|w|} = w\} & n \geq |w| \\
0 & n < |w|.
\end{cases}
\]

If \( N_{n-1}(w) > 0 \), we define for any \( a \in A \) the estimated transition probability

\[
\hat{p}_n(a|w) := \frac{N_n(wa)}{N_{n-1}(w)}.
\]

Denote also by \( C_{n-1}(w) \) the set of children of \( w \) that appear in the sample \( X_1, \ldots, X_{n-1} \) at least once, that is

\[
C_{n-1}(w) = \{bw : b \in A \text{ and } N_{n-1}(bw) > 0\}.
\]
and by $S_{n-1}$ the set of all such strings $w$; that is

$$S_{n-1} = \{ w \in A^*: N_{n-1}(w) > 0 \}.$$ 

Finally, for any context tree $\tau$, let

$$\tau^* := \{ u \in A^*: u \notin \hat{\tau} \}.$$ 

Now, we can define our discrepancy measure as a function $d_n: A^n \times P \rightarrow \mathbb{R}$

$$d_n(X^n, Q) := \max_{w \in S_{n-1} \cap \tau^*} \left\{ N_{n-1}(w) \max_{a \in A} |\hat{p}_n(a|w) - Q(a|w)| \right\}$$

if $S_{n-1} \cap \tau^*_Q \neq \emptyset$. If $S_{n-1} \cap \tau^*_Q = \emptyset$ we define $d_n(X^n, Q) = 0$.

We are now ready to introduce the lower bound for the functional $T$. Given a constant $c > 0$, for any $n \in \mathbb{N}$ let $T^c_n: A^n \rightarrow C$ be defined by

$$T^c_n(X^n) = \inf \left\{ \tau_Q: d_n(X^n, Q) \leq c \log(n) \right\},$$

where the infimum is taken with respect to the order $\prec$ between trees, and the logarithm is taken in base 2. Note that the set in (2.3) is not empty and since the tree $\tau_{\text{root}}$ is the smallest element of $C$ with respect to $\prec$, this infimum always exists. In Section 3 we show how to practically compute $T^c_n(X^n)$.

We now state the main result of this paper.

**Theorem 2.11.** Given $0 < \alpha < 1$ and $n > 2$, for any $c$ satisfying

$$c \leq \frac{n - 1}{2|A| \log(n)}$$

we have that the statistic $T^c_n$ is a non-trivial lower confidence bound for $T$ on $P$, with nonparametric coverage probability of at least $1 - \alpha$. Moreover, if $\sum_{v \in A^*} \phi(v) < \infty$, for any $c > 2(|A| - 1)$ the sequence $\{T^c_n\}_{n \in \mathbb{N}}$ is a consistent estimator of $T$ on $P$ and if $c > 3(|A| - 1)$ then $\{T^c_n\}_{n \in \mathbb{N}}$ is strongly consistent.

3. Computation and application of the lower confidence bound

In this section we show how to compute the confidence bound (2.3) and we present a practical application of Theorem 2.11 to linguistic data.

3.1. Tree lower bound algorithm

Let $X_1, \ldots, X_n$ be a given sample and let $c > 0$ be a fixed constant. To compute the tree $T^c_n(X^n)$, we will identify its nodes, i.e. the set $T^c_n(X^n)$. By definition, we know that $w \in T^c_n(X^n)$ if and only if every process $Q$ satisfying $d_n(X^n, Q) \leq c \log(n)$ has context tree with $w$ as a node. The next proposition gives a simple criteria to check whether or not we have to include a string $w$ in the set $T^c_n(X^n)$.
Tree lower bound (TLB) algorithm

1. Initialise with $T^c_n(X^n_1) \leftarrow \{\lambda\}$ and $S \leftarrow \{\lambda\}$.
2. While $S \neq \emptyset$, pick any $w \in S$ and do:
   (a) Remove $w$ from $S$;
   (b) For any $a \in A$ compute the values $l_n(w,a)$ and $u_n(w,a)$ (see (3.1) and (3.2)).
   (c) If for some $a \in A$, $u_n(w,a) < l_n(w,a)$ or if
      \[ 1 \notin \sum_{a \in A} l_n(w,a) : \sum_{a \in A} u_n(w,a) \]
      then add $C_{n-1}(w)$ to $T^c_n(X^n_1)$ and to $S$.

Fig 2. Algorithmic steps to compute the lower bound in (2.3).

It relies on two quantities, $l_n(w,a)$ and $u_n(w,a)$, which are defined for any $w$ with $C_{n-1}(w) \neq \emptyset$ and any $a \in A$ by

\[ l_n(w,a) = \max_{s \in A^* : sw \in S_{n-1}} \left\{ \hat{p}(a|sw) - \frac{c \log(n)}{N_{n-1}(sw)} \right\} \]  \hspace{1cm} (3.1)
\[ u_n(w,a) = \min_{s \in A^* : sw \in S_{n-1}} \left\{ \hat{p}(a|sw) + \frac{c \log(n)}{N_{n-1}(sw)} \right\}. \]  \hspace{1cm} (3.2)

**Proposition 3.1.** Let $w$ such that $C_{n-1}(w) \neq \emptyset$. Then there exists a process $Q$ satisfying $d_n(X^n_1, Q) \leq c \log(n)$ and having $w$ as a context if and only if the following conditions hold

\[ \begin{align*}
1. \text{For any } a \in A, \quad & l_n(w,a) \leq u_n(w,a). \\
2. \sum_{a \in A} l_n(w,a) \leq 1 \leq \sum_{a \in A} u_n(w,a). 
\end{align*} \]

We now give a simple algorithm (see Fig 2) to construct the estimated tree. Let us explain how it works. Since every context tree has the root $\lambda$ as node, then $\lambda \in T^c_n(X^n_1)$, and we can initialize the algorithm with $\lambda$. We then proceed iteratively as follows, until we exhaust the set $S_{n-1}$.

Suppose that a string $w$ has been included in $T^c_n(X^n_1)$. If $C_{n-1}(w) \neq \emptyset$ and at least one of the conditions of Proposition 3.1 is not satisfied for $w$, this means that there do not exist processes $Q$ satisfying $d_n(X^n_1, Q) \leq c \log(n)$ and having $w$ as a context. In other words, all processes such that $d_n(X^n_1, Q) \leq c \log(n)$ have $w$ as a proper suffix of their contexts. Thus the set $C_{n-1}(w)$ must belong to $T^c_n(X^n_1)$. On the other hand, if both conditions of Proposition 3.1 are satisfied for $w$, then there exists at least one process $Q$ such that $d_n(X^n_1, Q) \leq c \log(n)$ and having $w$ as a context. In this case $w$ must be a context of $T^c_n(X^n_1)$ and we do not need to continue checking its descendants $sw \in S_{n-1}$, with $s \in A^*$. 

3.2. One-sided test of hypotheses for context trees

In this subsection we present an application of the lower confidence bound introduced in (2.3) to test a hypothesis about the context tree of codified texts written in European Portuguese. This dataset was first analyzed in Galves et al. (2012) where a method to estimate a context tree was proposed and then applied to solve a linguistic conjecture about the rhythmic distinction between European and Brazilian Portuguese. The written texts were codified into the alphabet $A = \{0, 1, 2, 3, 4\}$ taking into account the stressed syllables and the boundaries of words; see Galves et al. (2012) for details about the codification and information on how to obtain the publicly available dataset. The European Portuguese context tree obtained in the cited work is the one shown in Fig. 3(a).

A recent analysis of the same dataset with similar results can be found in Belloni and Oliveira (2015).

An interesting difference between the two languages (with a corresponding linguistic interpretation, see Galves et al. (2012)), observed from the codified data, was the ramification of the string “2” into the set of contexts “02,” “12,” “32” and “42” that appears in the European Portuguese context tree in Fig. 3(a) (in the Brazilian Portuguese context tree this ramification did not occur and the string “2” was identified as a context). A natural idea is then to test if there is enough evidence in the data supporting that the European Portuguese context tree ramifies from the sequence “2” or not.

It is well known that tests of hypotheses can be constructed using confidence bounds. Let $\tau_0$ be a tree and suppose we want to test the hypotheses

$$H_0 : \tau_P \preceq \tau_0 \text{ vs. } H_1 : \tau_P \npreceq \tau_0.$$ 

Given $n$ and $\alpha$, consider the test that rejects $H_0$ if and only if $T_n^\alpha (X^n_1) \in R = \{ \tau \in T : \tau \npreceq \tau_0 \}$, with $c = (|A| - 1)(\log((|A| - 1)/\alpha)/\log(n) + 2)$. By Theorem 2.11 we have that

$$\sup_{P : \tau_P \preceq \tau_0} P(T_n^\alpha (X^n_1) \npreceq \tau_0) \leq \sup_{P \in P} P(T_n^\alpha (X^n_1) \npreceq \tau_P) \leq \alpha.$$ 

Thus, the test defined by the rejection region $R$ has significance level $\alpha$ for the hypotheses $H_0 : \tau_P \preceq \tau_0$ vs. $H_1 : \tau_P \npreceq \tau_0$.

In our application the null hypothesis is defined by a tree $\tau_0$ having the string “2” as a context. Since we impose no further condition, we let 2 be the unique finite context of $\tau_0$, that is

$$\tau_0 = \{2\} \cup \{wa : w \in \tau^\infty, a \in A, a \neq 2\}.$$ 

This tree is represented in Fig. 3(b). We set the significance level $\alpha = 0.05$, and as our sample size is $n = 107,761$ we have $c = 9,513$.

The estimated tree with the TLB algorithm of Fig 2 is given in Fig. 3(c). We see that $T_n^\alpha (X^n_1)$ belongs to the rejection region $R$ therefore we reject the null
Fig 3. On top we show the European Portuguese context tree over the alphabet $A = \{0, 1, 2, 3, 4\}$ estimated from a corpus of codified written texts. On the middle we show the tree $\tau_0$ used for the definition of the test of hypothesis. The triangles with $\tau^{\infty}$ written inside represent infinite complete trees that ramify from symbols 0, 1, 3 and 4. In other words, $\tau_0$ has a unique finite context, which is 2. The bottom tree corresponds to the lower bound $T_{\alpha}^{c}(X^n)$ computed on the same sample as the tree on top, with $\alpha = 0.05$ and $c = 9,513$.

hypothesis at the significance level $\alpha = 0.05$, confirming in this way the results of Galves et al. (2012) about the ramification of sequence "2" in the European Portuguese context tree.

The algorithm described in Fig. 2 was coded in the R language and is available upon request.
4. Proofs

Proof of Lemma 2.4. With respect to the weak topology, the set of all stationary probability measures over \((\Omega, \mathcal{F})\) is a compact Hausdorff space (Shields, 1996) and the subspace \(\mathcal{P}\) of all stationary and ergodic probability measures over \((\Omega, \mathcal{F})\) is a \(G_δ\) set (Parthasarathy, 1961, Theorem 2.1). Therefore, \(\mathcal{P}\) is a Baire space with the induced topology.

Proof of Proposition 2.6. The proof uses the same arguments of Lemma 1.1 in Fraiman and Meloche (1999). The difference is that here we do not have independent random variables and the space \(\mathcal{P}\) is not a complete metric space with respect to \(D\). But the same result can be obtained in our setting, as we show in the sequel. Recall that in the conditions of the proposition, there exists \(R \in \mathbb{R}\) such that \(|F(P)| \leq R\) for all \(P \in \mathcal{P}\), and assume that \(\{F_n\}_{n \in \mathbb{N}}\) is a consistent estimator for \(F\). Define

\[ F'_n = F_n 1 \{ |F_n| \leq R \} + \text{sg}(F_n) R 1 \{ |F_n| > R \}, \]

where \(\text{sg}\) is the sign of \(F_n\). It is not hard to show that \(\{F'_n\}_{n \in \mathbb{N}}\) is also a consistent estimator for \(F\), for details see (Fraiman and Meloche, 1999, Lemma 1.1). As for any \(n \in \mathbb{N}\) the function \(F'_n\) is bounded by \(R\) we have that the convergence in probability to \(F(P)\) implies convergence in mean. Therefore we have that

\[ \phi_n(P) := \mathbb{E}_P(F'_n) \to F(P) \]

as \(n \to \infty\). Moreover,

\[ |\phi_n(P) - \phi_n(Q)| = \left| \sum_{x^n_1 \in A^n} F'_n(x^n_1) P(x^n_1) - \sum_{x^n_1 \in A^n} F'_n(x^n_1) Q(x^n_1) \right| \]
\[ \leq \sum_{x^n_1 \in A^n} \left| F'_n(x^n_1) \right| \left| P(x^n_1) - Q(x^n_1) \right| \]
\[ \leq R 2^n D(P, Q). \]

Therefore, for each \(n\), \(\phi_n\) is uniformly continuous with respect to the weak topology (induced by \(D\)) on \(\mathcal{P}\). Then, by Lemma 2.4 and the Baire’s Category Theorem, the function \(F\) must be continuous on a dense subset of \(\mathcal{P}\).

To continue we need two basic lemmas that constitute the core of all our negative results.

Lemma 4.1. Any measure \(P \in \mathcal{P}\) can be approximated with respect to \(D\) by a sequence of measures \(\{P_n\}_{n \in \mathbb{N}}\) in \(\mathcal{P}\) each of which have as context tree a given tree \(\tau\), with \(\tau_P \leq \tau\). In particular, \(\tau\) can be infinite.

Proof. We proceed in two steps, first we define a sequence of Markov measures \(\{P^{[k]}\}_{k \in \mathbb{N}}\) converging to \(P\) and then for any \(k \in \mathbb{N}\), we construct a sequence of stationary ergodic measures \(\{P_{i[k]}\}_{i \in \mathbb{N}}\) each of which have context tree \(\tau\) and that converges to \(P^{[k]}\). The conclusion of the proof then follows by a diagonal
argument, since convergence in $D$ (or in the weak topology) corresponds to convergence of the measure of cylinders (Shields, 1996, Section I.9).

For any $k \in \mathbb{N}$, let $P^{[k]}$ be the $k$-steps canonical Markov approximation of $P$, which is a Markov chain of order $k$ with transition probabilities

$$P^{[k]}(a|a_{-k}^{-1}) := P(a|a_{-k}^{-1}), \quad a \in A, \ a_{-k}^{-1} \in A^k. \quad (4.1)$$

An important observation is that $\tau_{P^{[k]}} \leq \tau_P$, since for any semi-infinite sequence $a_{-\infty}^{-1} \in A^{\infty}$ the length of the context of $P^{[k]}$ along $a_{-\infty}^{-1}$ is at most the length of the context of $P$. Moreover, it is well known that the sequence $\{P^{[k]})_{k \in \mathbb{N}}$ converges weakly to $P$ (see Rudolph and Schwarz (1977) for instance), then the first step is proven.

To continue, let us introduce the continuity rate of a process $\tilde{P}$ along a given past $a_{-l}^{-1}$, which is the non-increasing sequence $\{\beta_l^{\tilde{P}}(a_{-\infty})\}_{l \in \mathbb{N}}$ defined as

$$\beta_l^{\tilde{P}}(a_{-\infty}) := \sup_{a_{-\infty}^{-1}, b_{-\infty}^{-1}, c_{-\infty}^{-1}} |\tilde{P}(a|b_{-\infty}^{-1}a_{-l}^{-1}) - \tilde{P}(a|c_{-\infty}^{-1}a_{-l}^{-1})|, \quad l \geq 1.$$  

Observe that $\beta_l^{\tilde{P}}(a_{-\infty}) > 0$ means $a_{-l}^{-1} \in \tau_{\tilde{P}}$ and therefore $\beta_l^{\tilde{P}}(a_{-l}^{-1}) > 0$ for all $l \geq 0$ means that the infinite sequence $a_{-\infty}^{-1} \in \tau_{\tilde{P}}$. Let $\tilde{P}$ be a measure in $\mathcal{P}$ satisfying the following three conditions:

(i) $\inf_{a_{-\infty}^{-1}} \{\tilde{P}(a|a_{-\infty}^{-1})\} > 0$.

(ii) For any $a_{-\infty}^{-1} \in A^{\infty}$ and any $l \in \mathbb{N}$, $\beta_l^{\tilde{P}}(a_{-\infty}) > 0$.

(iii) $\sum_{l \in \mathbb{N}} \sup_{a_{-\infty}^{-1}} \beta_l^{\tilde{P}}(a_{-\infty}) < \infty$.

If it is not clear to the reader that such a measure $\tilde{P} \in \mathcal{P}$ can always be selected, let us mention as an example the observable chain in a Hidden Markov Model, which under simple assumptions satisfy conditions (i)-(iii) above, see for instance Collet and Leonardi (2014).

Now consider any context tree $\tau$ such that $\tau_P \leq \tau$. For all $i \in \mathbb{N}$ define the kernel

$$P_i^{[k]}(a|a_{-\infty}^{-1}) = (1 - 1/i) P^{[k]}(a|a_{-k}^{-1}) + 1/i \tilde{P}(a|a_{-l}^{-1}), \quad a \in A, \ a_{-l}^{-1} \in \tau.$$

We have $\inf_{a_{-\infty}^{-1}} \{P_i^{[k]}(a|a_{-\infty}^{-1})\} \geq 1/i \inf_{a_{-\infty}^{-1}} \{\tilde{P}(a|a_{-\infty}^{-1})\} > 0$ for any $i \in \mathbb{N}$. Thus, this kernel satisfies (i) and let us show that it also satisfies property (iii). For any $a_{-\infty}^{-1}$ with $a_{-l}^{-1} \in \tau$ we have

$$|P_i^{[k]}(a|b_{-\infty}^{-1}a_{-l}^{-1}) - P_i^{[k]}(a|c_{-\infty}^{-1}a_{-l}^{-1})| = 1/i |\tilde{P}(a|b_{-\infty}^{-1}a_{-l}^{-1}) - \tilde{P}(a|c_{-\infty}^{-1}a_{-l}^{-1})|$$

for all $r < l$ or $|P_i^{[k]}(a|b_{-\infty}^{-1}a_{-l}^{-1}) - P_i^{[k]}(a|c_{-\infty}^{-1}a_{-l}^{-1})| = 0$ if $r \geq l$, for all $a \in A$ and all $b_{-\infty}^{-1}, c_{-\infty}^{-1} \in A^{\infty}$. Conditions (i) and (iii) ensure that there exists a unique stationary ergodic measure having kernel $P_i^{[k]}$, see for instance Bressaud, Fernández and Galves (1999); Fernández and Galves (2002).
By the above observations, the contexts of $P_i^{[k]}$ are exactly the sequences in $\tau$, since $\tau_{P_i^{[k]}} \leq \tau_P \leq \tau$. Now, since $\{P_i^{[k]}\}_{i \in \mathbb{N}}$ converges uniformly to $P^{[k]}$ as $i \to \infty$ we also have $\{P_k^{[k]}\}_{k \in \mathbb{N}}$ converging in $D$ to $P$ as $k$ diverges. \hfill \square

**Lemma 4.2.** Any measure $P \in \mathcal{P}$ can be approximated with respect to $D$ by a sequence of measures $\{P_n\}_{n \in \mathbb{N}}$ in $\mathcal{P}$ each of which have a finite context tree.

**Proof.** We prove this lemma using a similar two-steps argument as in the previous one. First, we use the same sequence of canonical Markov approximations $\{P_i^{[k]}\}_{i \in \mathbb{N}}$ defined in (4.1) to approximate $P$. Second, as we do not know whether these Markov measures are ergodic or not, we construct, for any $k \geq 1$, a sequence $\{P_i^{[k]}\}_{i \in \mathbb{N}}$ of ergodic Markov measures converging to $P^{[k]}$ when $i \to \infty$. The conclusion of the proof also follows from a diagonal argument.

The construction of $P_i^{[k]}$ is also carried as in the previous lemma, by specifying the kernel of transition probabilities

$$P_i^{[k]}(a|a_i^{-1}) = (1 - 1/i) P_i^{[k]}(a|a_i^{-1}) + \frac{1}{i|A|}, \quad a \in A, \quad a_i^{-1} \in A^\infty.$$ 

It is easy to see that this definition leads to a Markovian (i.e. with finite context tree) ergodic measure, and that the sequence $\{P_i^{[k]}\}_{i \in \mathbb{N}}$ converges to $P^{[k]}$ when $i \to \infty$. As before we have that $\{P_k^{[k]}\}_{k \in \mathbb{N}}$ converges to $P$ when $k \to \infty$ and this concludes the proof. \hfill \square

We are now ready to prove Theorem 2.7.

**Proof of Theorem 2.7.** Assume that $\sum_{v \in A^\infty} \phi(v) = +\infty$. Then Lemmas 4.1 and 4.2 imply that any $P \in \mathcal{P}$ having $L(P) = 0$ (respectively $L(P) = 1$) is limit in $D$ of a sequence of measures $\{P_n\}_{n \in \mathbb{N}}$ in $\mathcal{P}$ satisfying $L(P_n) = 1$ (respectively $L(P_n) = 0$) for all $n \in \mathbb{N}$. In other words, the functional $L$ is discontinuous (with respect to the $D$-distance) at any point of $\mathcal{P}$. Together with Proposition 2.6, this proves that $L$ is not consistently estimable on $\mathcal{P}$ when $\sum_{v \in A^\infty} \phi(v) = +\infty$. \hfill \square

**Proof of Theorem 2.8.** As we already mentioned, the proof of the if part of the theorem follows from Theorem 2.11 which states that $\{T_n\}_{n \in \mathbb{N}}$ is actually a consistent estimator of $\tau_P$. It remains to prove the only if part. Assume $\sum_{v \in A^\infty} \phi(v) = +\infty$ and suppose there exists $\{T_n\}_{n \in \mathbb{N}}$, a consistent estimator of $T$ on $\mathcal{P}$. Define $L_n : A^n \to \{0, 1\}$ by $L_n(a^n_1) = 1 \{\sum_{v \in T_n(a^n_1)} \phi(v) < +\infty\}$. We will prove that $\{L_n\}_{n \in \mathbb{N}}$ is a consistent estimator of $L$, which is a contradiction with Theorem 2.7, concluding the proof of the theorem.

Fix $P \in \mathcal{P}$. As \{T_n\}_{n \in \mathbb{N}} is consistent we have that for any $\epsilon > 0$

$$\lim_{n \to \infty} P(d_\phi(T_n(X^n_1), \tau_P) \leq \epsilon) = 1.$$ 

We will prove that for any $\epsilon > 0$ the ball of center $\tau_P$ and radius $\epsilon$ contains only trees where $L$ is constant and equal to $L(\tau_P)$. By the definition of $d_\phi$, see (2.1), for $\tau' \in T$,

$$d_\phi(\tau_P, \tau') = \sum_{v \in \tau'_P} \phi(v) + \sum_{v \in \tau_P} \phi(v) - 2 \sum_{v \in \tau_P \cap \tau'} \phi(v).$$
Then if $d_{\phi}(\tau, \tau') < \epsilon$ we have $L(\tau) = 1$ if and only if $L(\tau') = 1$. Therefore
\[
\lim_{n \to \infty} P(L_n(X^n_1) = L(P)) \geq \lim_{n \to \infty} P(d_{\phi}(T_n(X^n_1), \tau_P) \leq \epsilon) = 1
\]
which proves that $L$ is consistently estimable on $P$. But by Theorem 2.7, $L$ is not consistently estimable on $P$, which is a contradiction. 

\textbf{Proof of Theorem 2.10.} Suppose $U_n$ satisfies
\[
\sup_{P \in \mathcal{P}} P(U_n \prec \tau^\infty) = 1.
\]
Given $\delta > 0$ choose a measure $P_\delta \in \mathcal{P}_f$ such that
\[
P_\delta(U_n \prec \tau^\infty) \geq 1 - \frac{\delta}{3}.
\]
This can always be done because the set $\mathcal{P}_f$ is dense in $\mathcal{P}$ (see Lemma 4.2). Let $\{\tau_k\}_{k \in \mathbb{N}}$ be an increasing sequence of finite trees and denote by $V_k$ the event
\[
V_k = \{\tau_k \prec U_n\}.
\]
We have $V_k \supset V_{k+1}$ for all $k \geq 1$ and $\cap_{k \geq 1} V_k = \{U_n = \tau^\infty\}$. Therefore
\[
\lim_{k \to \infty} P_\delta(V_k) = P_\delta(U_n = \tau^\infty) \leq \frac{1}{3}\delta.
\]
Now let $k^*$ be such that
\[
P_\delta(V_{k^*}) < \frac{2}{3}\delta,
\]
and denote by $\tau$ the finite tree given by $\bar{\tau} = \bar{\tau}_{k^*} \cup \bar{\tau}_{P_\delta}$. We have
\[
P_\delta(\tau \not\prec U_n) \geq P_\delta(\tau_{k^*} \not\prec U_n) \geq 1 - \frac{2}{3}\delta.
\]
By Lemma 4.1, there exists a measure $Q_\delta \in \mathcal{P}_f$ with $\tau_{Q_\delta} = \tau$ such that
\[
D(P_\delta, Q_\delta) < 2^{-n}\delta.
\]
Moreover we have
\[
P_\delta(\tau \not\prec U_n) - Q_\delta(\tau \not\prec U_n)
\leq \sum_{x^n_1 \in A^n} 1_{\{\tau \not\prec U_n(x^n_1)\}} P_\delta(x^n_1) - \sum_{x^n_1 \in A^n} 1_{\{\tau \not\prec U_n(x^n_1)\}} Q_\delta(x^n_1)
\leq \sum_{x^n_1 \in A^n} 1_{\{\tau \not\prec U_n(x^n_1)\}} |P_\delta(x^n_1) - Q_\delta(x^n_1)|
\leq 2^n D(P_\delta, Q_\delta) < \frac{\delta}{3}.
\]
Therefore

\[ Q_\delta(\tau \not\in U_n) > P_\delta(\tau \not\in U_n) - \frac{\delta}{3} \geq 1 - \delta. \]

As \( \delta \) is arbitrary we have just proved that

\[ \inf_{Q \in \mathcal{P}} Q(\tau \leq U_n) = \inf_{Q \in \mathcal{P}} f_Q(\tau \leq U_n) = 0. \]

In order to prove Theorem 2.11 we will need the following lemma.

**Lemma 4.3.** Given \( P \in \mathcal{P} \), let \( X_1, \ldots, X_n \) be a sample of size \( n \) with law \( P \). Then for any constant \( c > 0 \) we have

\[ P\left( d_n(X^n_1, P) \leq c \log(n) \right) \geq 1 - \frac{|A| - 1}{n^{c/(|A|-1)} - 1}. \]

**Proof.** First note that if \( S_{n-1} \cap \tau_P^* = \emptyset \) then the assertion of the lemma is trivial because in this case \( d_n(X^n_1, P) = 0 \) and then

\[ P\left( d_n(X^n_1, P) \leq c \log(n) \right) = 1. \]

Now suppose \( S_{n-1} \cap \tau_P^* \neq \emptyset \) and let \( w \in S_{n-1} \cap \tau_P^* \). We recall the reader that all the logarithms are taken in base 2. This is not a restriction, as if the base is \( r > 1 \) we can replace \( c \) by \( c/\log_2(r) \) and the result holds as well. First note that we can write

\[ \max_{a \in A} |\hat{p}_n(a|w) - p(a|w)| = \sum_{p(a|w) > \hat{p}_n(a|w)} (p(a|w) - \hat{p}_n(a|w)). \]

For a proof of this equivalence see for instance (Levin, Peres and Wilmer, 2009, Proposition 4.2 and Remark 4.3). Therefore we have that the event

\[ B_n(w) = \{ N_{n-1}(w) \max_{a \in A} |\hat{p}_n(a|w) - p(a|w)| > c \log(n) \} \]

is included in the event

\[ E_n(w) = \bigcup_{a \in A} E_n(w, a) \] (4.3)

where

\[ E_n(w, a) = \left\{ (N_{n-1}(w)p(a|w) - N_n(wa))1\{p(a|w) > \hat{p}_n(a|w)\} > \frac{c \log(n)}{|A| - 1} \right\}. \]

Observe that the union (4.3) has at most \( |A| - 1 \) non empty sets. Now define the random variables\[ W_n(w, a) = 2^{N_{n-1}(w) \log(1+p(a|w)) - N_n(wa)} \quad n \geq |w|. \]

Then, by the inequality \( p(a|w) \leq \log_2(1 + p(a|w)) \) valid in the interval \((0, 1]\) we have that for \( a \in A \) such that \( p(a|w) > \hat{p}_n(a|w) \), the event \( E_n(w, a) \) is included in the event

\[ F_n(w, a) = \left\{ W_n(w, a) > n^{c/(|A|-1)} \right\}. \] (4.4)
As in Garivier and Leonardi (2011, Proposition A.1), we will show that when \( w \in \tau_P \), the sequence \( \{W_n(w,a)\}_{n \in \mathbb{N}} \) is a martingale with respect to the filtration \( \{\sigma(X_1, \ldots, X_{n-1})\}_{n \in \mathbb{N}} \). In fact, note that by the definition of \( N_n(\cdot) \) we have that

\[
\mathbb{E}(2(N_{n+1}(wa) - N_n(wa)) | X_1, \ldots, X_n) = \mathbb{E}(21(X_{n+1}^n = wa) | X_1, \ldots, X_n)
\]

\[
= 21(X_{n+1}^n = wa) \log(1 + p(a|w))
\]

which implies that \( \mathbb{E}(W_{n+1}(w,a) | X_1, \ldots, X_n) = W_n(w,a) \). Thus \( \mathbb{E}(W_n(w,a)) = \mathbb{E}(W_1(w,a)) = 1 \) and therefore, by Markov’s inequality and a union bound we have that

\[
P(E_n(w)) \leq (|A| - 1) \sup_{a \in A} P(E_n(w,a)) \leq \frac{|A| - 1}{n^{c/(|A| - 1)}}.
\]

One more union bound over \( S_{n-1} \cap \tau_P \) yields

\[
P\left( d_n(X^n_1, P) > c \log n \right) = P\left( \bigcup_{w \in S_{n-1} \cap \tau_P} B_n(w) \right)
\]

\[
\leq n^2 \sup_{w \in S_{n-1} \cap \tau_P} \{ P(E_n(w)) \}
\]

\[
\leq \frac{|A| - 1}{n^{c/(|A| - 1) - 2}}. \quad \Box
\]

**Proof of Theorem 2.11.** Observe that for any \( P \in \mathcal{P} \) the event \( \{d_n(X^n_1, P) \leq c \log(n)\} \) implies \( \{T^n_\pi(X^n_1) \leq \tau_P\} \). Therefore, by Lemma 4.3 and the condition on \( c \) we have

\[
P(T^n_\pi(X^n_1) \leq \tau_P) \geq P(d_n(X^n_1, P) \leq c \log(n))
\]

\[
\geq 1 - (|A| - 1)/n^{c/(|A| - 1) - 2}
\]

\[
\geq 1 - \alpha.
\]

To prove that \( T^n_\pi(X^n_1) \) is not trivial we have to prove that

\[
\sup_{P \in \mathcal{P}} P(\tau_{\text{root}} < T^n_\pi(X^n_1)) = 1. \quad (4.5)
\]

For that consider the transition matrix \( Q^\epsilon \) on \( A = \{1, \ldots, k\} \) defined by

\[
Q^\epsilon(i, i) = 1 - Q^\epsilon(i, i+1) = \epsilon, \quad \text{for } i = 1, \ldots, k-1, \text{ and}
\]

\[
Q^\epsilon(k, k) = 1 - Q^\epsilon(k, 1) = \epsilon.
\]

The parameter \( \epsilon \) will be chosen adequately later. Observe that if \( \epsilon > 0 \) there exists a unique stationary ergodic Markov chain \( P \) specified by \( Q^\epsilon \). It is also easy to see, by symmetry, that \( P(i) = 1/k \) for any \( i = 1, \ldots, k \). Now for any \( n \geq 3 \) denote by \( \mathcal{M}_n \) the set of strings \( x^n_1 \in A^n \) such that \( x_{i+1} = x_i + 1 \) for \( i = 1, \ldots, n - 1 \). Observe that there are exactly \( k \) such strings, independently
of $n$, each beginning in a different symbol of $A$. Moreover, each of these strings have equal measure

$$P(x^n_1) = \frac{1}{k}(1 - \epsilon)^{n-1}.$$  

On the other hand, thanks to Proposition 3.1 and the TLB algorithm in Fig. 2, the $k$ trees $\{T^n_c(x^n_1) : x^n_1 \in \mathcal{M}_n\}$ will be different from $\tau_{\text{root}}$, because if $c \leq (n - 1)/2|A| \log(n)$, as $N_{n-1}(x_1) \geq N_{n-1}(x_2) \geq \lceil \frac{n-1}{|A|} \rceil$ we will have

$$u_n(x_2, x_2) \leq \hat{\rho}_n(x_2|x_2) + \frac{c \log(n)}{N_{n-1}(x_2)} < 1/2.$$  

and

$$l_n(x_1, x_2) \geq \hat{\rho}_n(x_2|x_1) - \frac{c \log(n)}{N_{n-1}(x_1)} > 1/2.$$  

In other words,

$$P(\tau_{\text{root}} < T^n_c(X^n_1)) \geq P(X^n_1 \in \mathcal{M}_n) = k \times \frac{1}{k}(1 - \epsilon)^{n-1}.$$  

To conclude, observe that for any $\delta > 0$, we can take $\epsilon = 1 - (1 - \delta)^{1/(n-1)}$, and we get

$$P(\tau_{\text{root}} < T^n_c(X^n_1)) \geq 1 - \delta$$  

proving that (4.5) holds.

Now we will prove the consistency of the estimator $\{T^n_c(X^n_1)\}_{n \in \mathbb{N}}$ for any $c > 2(|A| - 1)$, by showing that for any $P \in \mathcal{P}$ and any $\epsilon > 0$ the event $d_\phi(T^n_c(X^n_1) \geq \tau_P) \leq \epsilon$ occurs with probability converging to 1 as $n \to \infty$. To begin, notice that by Lemma 4.3 we have that

$$P(d_n(X^n_1, P) \leq c \log n) \geq 1 - \frac{|A| - 1}{n^\delta} \quad \text{for all } n \geq 1,$$

where $\delta = c/(|A| - 1) - 2 > 0$. This implies, by the definition of $T^n_c(X^n_1)$, that

$$P(T^n_c(X^n_1) \geq \tau_P) \geq 1 - \frac{|A| - 1}{n^\delta} \quad \text{for all } n \geq 1.$$  

(4.6)

Now, recall that in the conditions of the theorem $\sum_{v \in \tau_P} \phi(v) < \infty$, and take $k \in \mathbb{N}$ such that

$$\sum_{u \in \tau_P : |u| > k} \phi(u) < \epsilon.$$  

(4.7)

Thus we have with probability at least $1 - (|A| - 1)/n^\delta$ that

$$d_\phi(T^n_c(X^n_1), \tau_P) \leq \sum_{u \in \tau_P \setminus T^n_c(X^n_1)} \phi(u) + \sum_{u \in \tau_P : |u| > k} \phi(u) \leq \sum_{u \in \tau_P \setminus T^n_c(X^n_1)} \phi(u) + \epsilon.$$  

(4.8)
Therefore it is enough to prove that \( \bar{\tau}_P|_k \setminus \bar{T}_n^c(X^n_t) = \emptyset \) with probability converging to 1 as \( n \to \infty \), or what is stronger, with probability equal to 1 for \( n \) sufficiently large, a fact that we refer to as to occur \textit{eventually almost surely} or e.a.s. for short. To prove this last assertion, for any \( v \in \bar{\tau}_P|_k \) we will show that the set \( \{ Q : d_n(X^n_t, Q) \leq c \log n \} \) is included in the set \( \{ Q : v \in \bar{\tau}_Q \} \) e.a.s. As the set \( \bar{\tau}_P|_k \) is finite we will have \( \{ Q : d_n(X^n_t, Q) \leq c \log n \} \subset \{ Q : \tau_Q \supset \tau_P|_k \} \) e.a.s. and therefore \( T_n^c(X^n_t) \supset \tau_P|_k \) e.a.s., which in turns implies that \( \bar{\tau}_P|_k \setminus \bar{T}_n^c(X^n_t) = \emptyset \) e.a.s. So, let \( v \in \bar{\tau}_P|_k, v = v'_1 \), and denote by \( v' \) its largest proper suffix, that is \( v' = v'_2 \). It can be shown that we can always find a symbol \( b \in A \) and another finite string \( w \in A^* \) such that the following conditions hold

(i) \( P(a|v_1 w v') \neq P(a|b w v') \) for some \( a \in A \) and

(ii) \( v \) is a suffix (proper or not) of \( v_1 w v' \).

If \( v \) is a context for \( P \), i.e if \( v \in \tau_P \cap \bar{\tau}_P|_k \) then it is enough to take \( w = \lambda \) and \( b \neq v_1 \) satisfying (i) (such \( b \) must always exist because \( v \) is a context). In this case we have \( v = v_1 w v' \) and (ii) is also satisfied. On the other hand, if \( v \) is not a context then it is an internal node of \( \tau_P \) and we must have some \( w = w' v_1 \), with \( w' \in A^* \), and \( b \in A \) such that (i)-(ii) are satisfied. If not, this would imply that for any \( u \in A^* \) \( P(\cdot | u v) = P(\cdot | v) \), contradicting the fact that \( v \) is a proper suffix of a context. Using the triangle inequality we have, for any \( Q \in \mathcal{P} \), that

\[
|Q(a|v_1 w v') - Q(a|b w v')| \geq |P(a|v_1 w v') - P(a|b w v')| - |P(a|v_1 w v') - \hat{P}_n(a|v_1 w v')| - |\hat{P}_n(a|v_1 w v') - Q(a|v_1 w v')| - |Q(a|b w v') - \hat{P}_n(a|b w v')| - |\hat{P}_n(a|b w v') - P(a|b w v')|.
\] (4.9)

Now, by ergodicity we have that \( P \)-almost surely, for any finite sequence \( s \in A^* \)

\[
\frac{N_n(s)}{n} - P(s) \to 0
\] (4.10)

when \( n \to \infty \), which in turns implies that for any \( s \in A^* \)

\[
|\hat{P}_n(a|s) - P(a|s)| \to 0.
\] (4.11)

In particular by (4.10), for any finite sequence \( s \in A^* \) we will have \( N_n(s) \geq n P(s)/2 \) e.a.s. This fact, together with (4.11) and the inequality (4.9) implies that for a sufficiently large \( n \), any measure \( Q \) such that \( d_n(X^n_t, Q) \leq c \log n \) will satisfy

\[
|Q(a|v_1 w v') - Q(a|b w v')| > 0
\] (4.12)

and thus \( v \in \bar{\tau}_Q \). Therefore \( \{ Q : d_n(X^n_t, Q) \leq c \log n \} \subset \{ Q : v \in \bar{\tau}_Q \} \) and \( \bar{\tau}_P|_k \setminus \bar{T}_n^c(X^n_t) = \emptyset \) e.a.s., as required, showing that

\[
P(d_n(\bar{T}_n^c(X^n_t), \tau_P) \leq \epsilon) \to 1 \quad \text{when } n \to \infty.
\]

To finish the proof we only emphasize that if \( c > 3(|A| - 1) \) then \( \delta > 1 \) and therefore the bound in (4.6) is summable. This fact together with the Borel-Cantelli lemma implies that \( \bar{T}_n^c(X^n_t) \leq \tau \) e.a.s. Therefore, as the other inclusion
The main contribution of this work is the introduction of a lower confidence bound for the context tree in the class of stationary ergodic probability measures over $A^2$, with $A$ a finite alphabet. We derive an explicit formula for the
coverage probability of this confidence bound and we show the almost sure convergence of this estimator with respect to the Hamming distance $d_\phi$, when $\phi$ is summable. To our knowledge, this is the first lower confidence bound for context trees and it is also the first strong consistent estimator that do not restrict the length of the estimated contexts, as for example does the BIC context tree estimator in Csiszár and Talata (2006) that only allows candidate contexts of length $o(\log n)$. Using only topological arguments we also prove that if $\phi$ is not summable then there exists no consistent estimator of the context tree in the class of stationary and ergodic processes. This is not the case in the class of processes having finite context trees because in this case the BIC estimator is strongly consistent. On the other hand we also prove that it is not possible to obtain nonparametric upper confidence bounds even in the smaller class of processes having finite context trees, because any process can be approximated in $D$ by stationary ergodic processes having arbitrary large context trees, as shown in Lemma 4.1. We also show in this work a practical application of the lower confidence bound to test a hypothesis involving the presence of finite contexts in codified written texts of European Portuguese. We support at the confidence level of 95% the results obtained in Galves et al. (2012) for this dataset, where only point estimation of the context tree was addressed.

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