Benchmarking Nonstationary Time Series Prediction*

Rebecca Pontes Salles[1],
Advisors: Eduardo Ogasawara[1], **Pedro González**[1]

[1]Federal Center for Technological Education of Rio de Janeiro (CEFET/RJ)

rebecca.salles@eic.cefet-rj.br, eogasawara@ieee.org

Abstract. *The prediction of time series has gained increasingly more attention among researchers since it is a crucial aspect of decision-making activities. Unfortunately, most time series prediction methods assume the property of stationarity, i.e., statistical properties do not change over time. In practice, it is the exception and not the rule in most real datasets. Several transformation methods were designed to treat nonstationarity in time series. In this context, nonstationary time series prediction is challenging since it demands knowledge of both data transformation and prediction methods. Since there are no silver bullets, it leads to exploring a large number of data transformation and prediction method combinations for building prediction setups. However, selecting a prediction setup that is appropriate to a particular time series and application is not a simple task. Benchmarking of different candidate combinations helps this selection. This work contributes by providing a review and experimental analysis of transformation methods and a systematic framework (TSPred) for benchmarking and selecting prediction setups for nonstationary time series. Suitable nonstationary time series transformation methods provided improvements of more than 30% in prediction accuracy for half of the evaluated time series. They improved the prediction by more than 95% for 10% of the time series. The features provided by TSPred are also shown to be competitive regarding prediction accuracy. Furthermore, the adoption of a validation phase during model training enables the selection of suitable transformation methods.*

1. Introduction

Prediction is knowingly a crucial aspect of decision-making activities. The future states of information about a problem can massively impact the success or failure of its solution. Notably, the prediction of time series is an object of interest of many researchers due to increasing importance and applications in science, business, and government [Han et al., 2011]. As a consequence, a great variety of time series prediction methods have been developed and can be found in the literature [Cheng et al., 2015]. Among them, the state-of-the-art is based on machine learning.

Most methods applied for time series prediction assume that the behavior of a time series presents a level of regularity over time. It is generally approached with the study of the concept of stationarity [Gujarati, 2002]. Suppose a time series violates any of the constraints imposed by a stationary process. In that case, it is considered a nonstationary time series. Nonstationarity manifests in many different ways. Generally, it implies that the time series mean or variance functions are non-constant and vary over time, *i.e.*, dependent on time. In practice, it is observed that the majority of real-world time series are

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nonstationary. Generally, any form of nonstationarity, if not adequately addressed, may lead to misleading statistical inferences and bad or unexpected prediction results. When observed the presence of nonstationarity in a time series, the state-of-the-art approaches search for ways to transform them into a stationary process. In these cases, the known time series prediction methods can be applied [Salles et al., 2019].

There exist several transformation methods in the literature for coping with nonstationarity in times series. Such methods can have different features depending on the implementation of the data properties they consider. They can address different kinds of nonstationarity, such as trends and seasonality. Choosing an adequate method for a particular time series application is not a simple task. The analysis of their features and expected advantages is crucial. However, not many authors focus on studying transformation methods for nonstationarity treatment [Yang and Zurbenko, 2010; Cheng et al., 2015].

Furthermore, there is a wide variety of models for time series prediction. Each one has different properties and complexities, and many of them are generated by state-of-the-art machine learning methods (MLM). Still, none of them is a silver bullet for the prediction of time series. Additionally, nonstationarity leads to the possibility of exploring different data transformation and model fitting methods for obtaining predictions. The number of modeling alternatives and combinations may become very high. Finding a transformation-model combination that solves a time series prediction problem is similar to solving an optimization problem. In this context, a benchmarking process provides a way of assessing the relative quality of predictions and selecting adequate transformation-model combinations for a particular time series application.

Benchmarking frameworks and tools for MLM performance assessment have been developed, as well as works to facilitate automatic time series prediction. Nonetheless, there are no works that propose and implement a systematic benchmarking framework that focuses on (i) time series prediction, (ii) addressing nonstationary properties, and (iii) comparing and selecting adequate transformation-MLM combinations. This gap aggravates the already intricate problem of selecting adequate transformation-model setups for a particular nonstationary time series prediction application. Moreover, there are no works that focus on the study of different ways to coerce a time series into stationarity and their effects on time series prediction.

1.1. Theoretical Contributions

This work targets the gaps as mentioned earlier and contributes by providing:

- A thorough review of nonstationary time series transformation methods and their features for time series prediction.
- A timeline of related works with the evolution of data transformation methods for nonstationary time series prediction grouped by their application domain.
- A systematic framework for nonstationary time series prediction that enables benchmarking data transformation methods and MLM.
- A benchmarking and experimental analysis of representative transformation methods for the time series prediction problem.
- A discussion on transformation methods whose adoption consistently provided accuracy improvements in time series prediction.

- Use case examples of the framework usability for benchmarking transformation methods and MLM modeling.

1.2. Research products

As a by-product of this dissertation, we also developed and published a the *TSPred* R-Package [Salles and Ogasawara, 2018] which implements the proposed systematic framework for nonstationary time series prediction. It is the first tool to seamlessly integrate a broad range of transformation methods [Salles et al., 2019] and state-of-the-art MLM prediction methods for addressing nonstationary time series. The framework encapsulated in *TSPred* was made available worldwide on The Comprehensive R Archive Network (CRAN). Currently, at version 5.1, it has been downloaded over $50,000$ times, having over $2,600$ downloads per month (by May 2021), being in the 69th percentile of impact compared to all research software on CRAN (according to depsy.org). These numbers keep increasing, which indicates the overall interest and demand for *TSPred*. Moreover, several papers (over 10) have been published as a consequence of this work. Among them, we mention the main and most directly related to this research:

- Main dissertation paper, entitled "Nonstationary time series transformation methods: An experimental review", published in the Knowledge-Based Systems journal (Qualis A1) [Salles et al., 2019]. Since its publication, it counts with 27 citations accumulated in the last two years.
- The features of the earliest versions of *TSPred* were presented in the paper "A Framework for Benchmarking Machine Learning Methods Using Linear Models for Univariate Time Series Prediction". It was published in the International Joint Conference on Neural Networks (IJCNN) (Qualis A1) [Salles et al., 2017]. It has accumulated 11 citations.
- One of the reviewed models for coping with nonstationarity in time series was applied for evaluating temporal aggregation for predicting the sea surface temperature of the Atlantic Ocean, which resulted in a publication in the Ecological Informatics journal (Qualis A2) with 10 citations [Salles et al., 2016].
- Best paper (category: short, vision, industry) presenting a novel model for nonstationary time series (Autoregressive Adaptive Integration Model (ARAI)) published in the proceedings of the XXXIV Brazilian Database Symposium (SBBD) (Qualis B2) [Ronald et al., 2019].
- Nonstationarity concepts and methods were applied in order to develop a novel framework (called *Harbinger*) for integration and analysis of event detection methods for time series. It was presented in a paper published in the XXXV Brazilian Database Symposium (SBBD) (Qualis B2) [Salles et al., 2020].
- The reviewed nonstationary preprocessing techniques and implemented framework were applied to estimate COVID-19 under-reporting in the Brazilian States through SARI in a paper published in the New Generation Computing journal (Qualis B1). It has received 6 citations in only two months since it is publicly available [Paixão et al., 2021].
- Analogously, *TSPred* was applied in the development of a paper on the use of data science to predict fertilizer consumption in Brazil published in the proceedings of the XIV Brazilian e-Science Workshop (Qualis B4) [Andrade et al., 2020].

2. Background Review and Developed Framework

Nonstationarity is pervasive in many real-world scenarios and poses challenges to time series prediction. As a consequence, several methods for statistical analysis of nonstationary time series have been developed. This research presents a discussion of some of the most researched time series transformation methods for handling nonstationarity. Focus is given to the state-of-the-art methods. To provide a better overview and for helping the discussion of their particular features, a general categorization of the reviewed transformation methods is introduced. Furthermore, the dissertation presents an overview of the research scenario by providing a timeline table of publications presenting some of the most researched methods for coping with nonstationarity grouped by their application domain.

This research proposes the encapsulation of the knowledge acquired by reviewing nonstationary time series transformation methods in a systematic benchmarking framework. The framework enables the application of this knowledge together with the predictive capabilities of the most commonly used MLM and linear models (LM). The framework provides means of benchmarking nonstationary time series predictions. The benchmarking results can be helpful either for indicating demands for prediction improvement or for selecting adequate transformation-model combinations.

It differs from the mainstream frameworks since it establishes a prediction process that seamlessly integrates nonstationary time series transformations with state-of-the-art machine learning methods. It is made available in the *TSPred* R-Package. It provides functions for defining and conducting time series prediction, including the tasks of data pre(post)processing, decomposition, modeling, prediction, and accuracy assessment. Besides, *TSPred* enables automatic parameterization and user-defined methods. These features significantly expand the applicability of the framework. The source code and documentation can be obtained from: https://CRAN.R-project.org/package=TSPred. The package is also freely available at GitHub, where one can find its code and wiki pages: https://github.com/RebeccaSalles/TSPred. The main functionality modules representing the concept and structure of the framework are depicted in Figure 1.

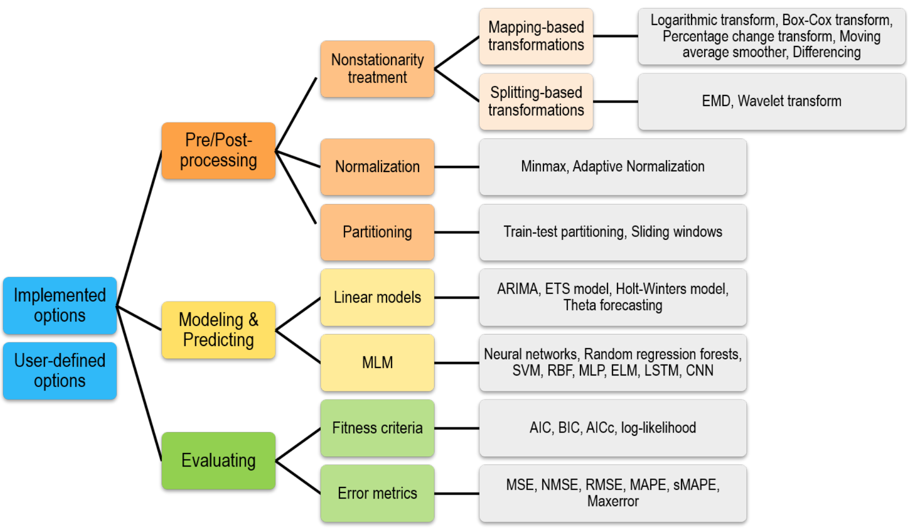

Figure 1. TSPred functionality modules and pre-implemented algorithms

3. Main Experimental Results

The developed framework was used for performing the benchmarking and experimental analysis of the reviewed transformation methods. The goal is to provide a practical perspective regarding their advantages and limitations to the time series prediction problem. Although it was possible to note a somewhat consistency in the results of the evaluated transformation methods, there was no uniquely best method across all datasets. Nonetheless, it was possible to observe better predictions when transformation methods based on differencing and moving average smoothing were applied (Figure 2(a)). Transformation methods that perform time series decomposition, which has been an object of increasing attention, were among the best methods. As expected, among the worst methods was the one where no data transformation is performed before prediction.

According to the experimental evaluation conducted, suitable nonstationary time series transformation methods provided improvements of more than 30% in prediction accuracy for approximately half (130/262) of the evaluated time series (Figure 2(b)). Accuracy improvements reached more than 95% for over 10% of the evaluated time series (Figure 2(c)). This observed outcome suggests the need to consider these transformation methods and compare them during time series prediction. Additionally, the adoption of a validation phase for exploring different transformation methods generally led to selecting one of the top five most appropriate for a particular time series (Figure 2(d)).

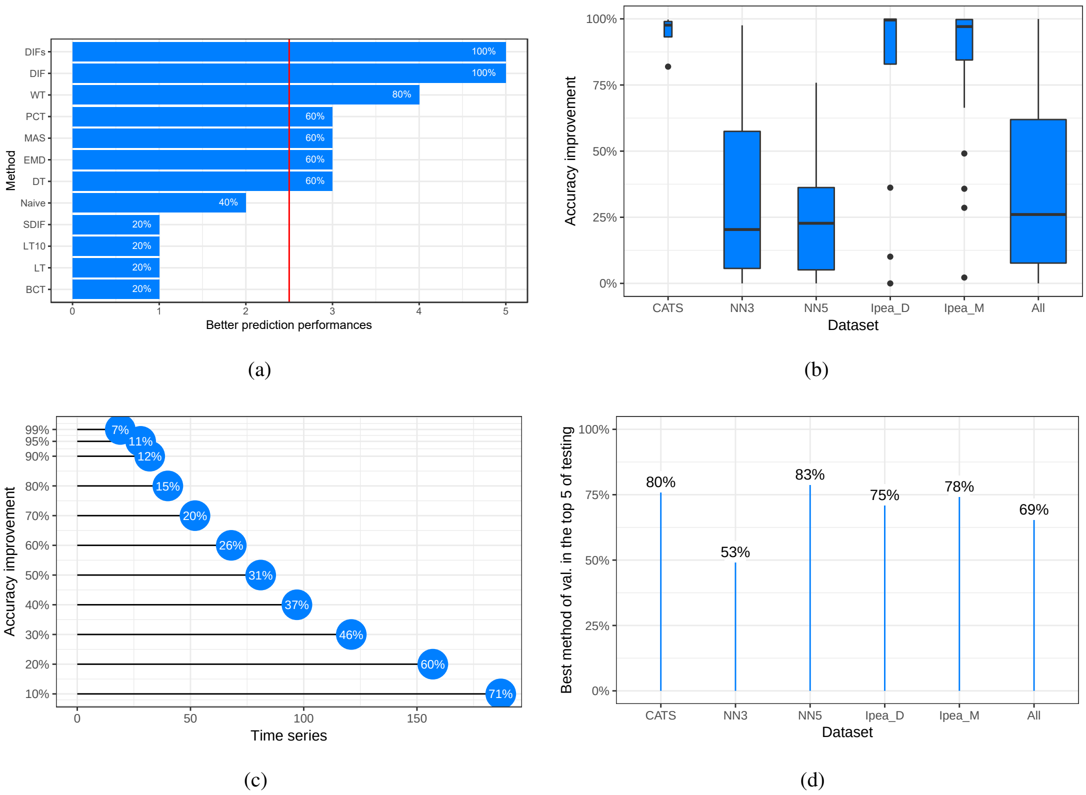

Figure 2. (a) the number of times (and percentage) the use of each method provided more accurate predictions among the five evaluated datasets; (b) the prediction accuracy improvements provided by the best method; (c) the number (and percentage) of time series for which at least a minimum percentage of prediction accuracy improvement was provided by their best method; (d) the (percentage) number of times the best method found during validation was also present in the top five ranked methods found during testing.

4. Conclusions

This work focus on the study of nonstationary time series prediction and the benchmarking of preprocessing and modeling options for time series applications. The main contribution is a systematic framework for benchmarking transformation methods and models for nonstationary time series prediction (*TSPred* R-package). It also includes a thorough review of nonstationary time series transformation methods. An overview of the effects of the evaluated methods regarding predictions and stationarity was produced based on experimental results. The nature and statistical properties of the time series were especially relevant to the results. Overall, more accurate predictions were observed when transformation methods were applied before predicting the time series of the selected datasets. The features provided by *TSPred* are also shown to be competitive regarding time series prediction accuracy. Additionally, results indicate that the use of a validation phase for exploring different transformation methods generally leads to selecting one of the most appropriate for obtaining accurate time series predictions. In this context, the potential of the developed framework for enabling the benchmarking of data transformation methods and prediction models for a particular nonstationary time series application was indicated.

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