# Access to scientific information

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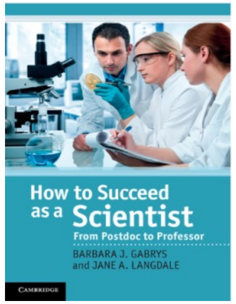
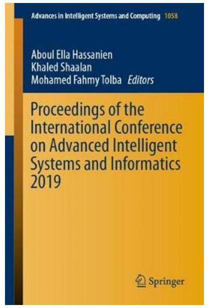
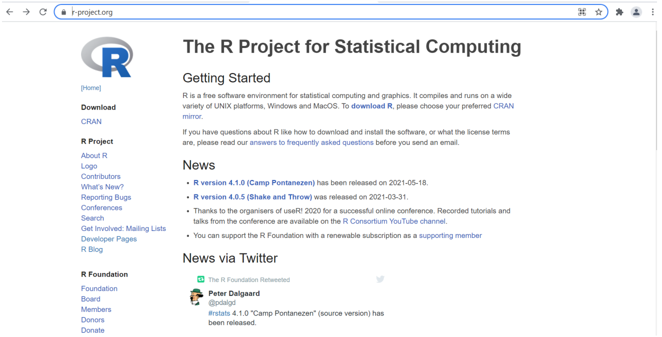
# SCIENTIFIC INFORMATION SOURCES




Books



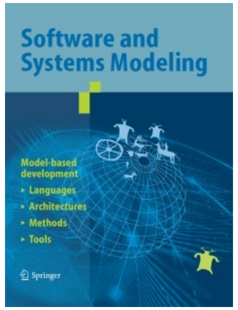

Conference proceedings



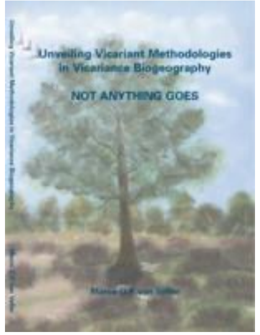


Preprints

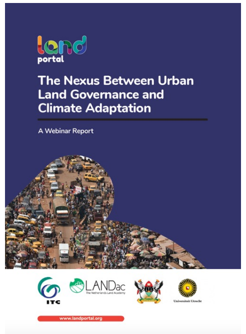
Websites



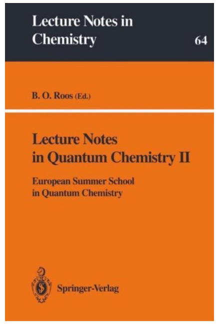

Journals




Theses




Reports




Lecture notes

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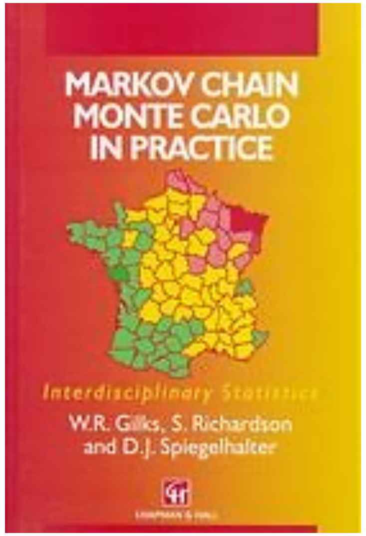
# BOOK

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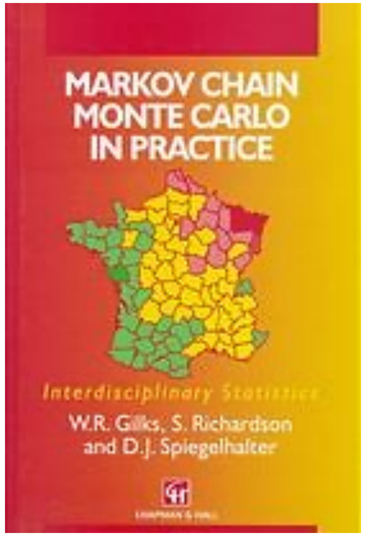


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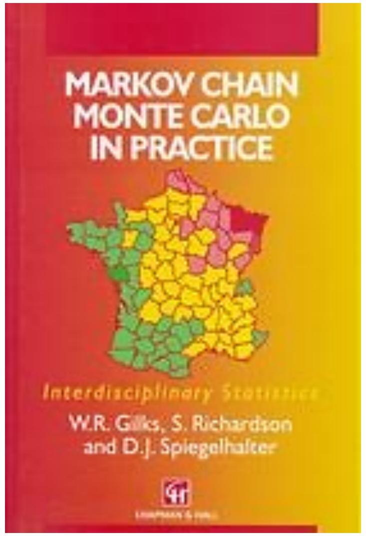


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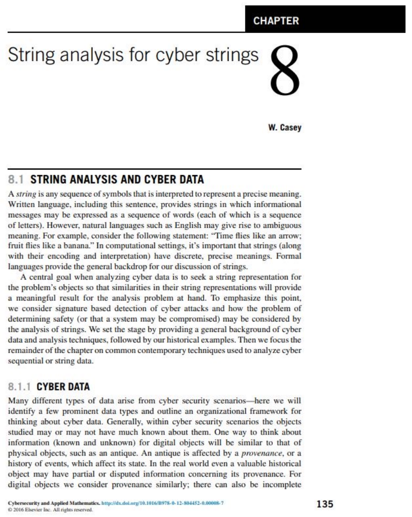
CHAPTER

String analysis for cyber strings 8

W. Casey

## 8.1 STRING ANALYSIS AND CYBER DATA

A *string* is any sequence of symbols that is interpreted to represent a precise meaning. Written language, including this sentence, provides strings in which informational messages may be expressed as a sequence of words (each of which is a sequence of letters). However, natural languages such as English may give rise to ambiguous meaning. For example, consider the following statement: "Time flies like an arrow; fruit flies like a banana." In computational settings, it's important that strings (along with their encoding and interpretation) have discrete, precise meanings. Formal languages provide the general backdrop for our discussion of strings.

A central goal when analyzing cyber data is to seek a string representation for the problem's objects so that similarities in their string representations will provide a meaningful result for the analysis problem at hand. To emphasize this point, we consider signature based detection of cyber attacks and how the problem of determining safety (or that a system may be compromised) may be considered by the analysis of strings. We set the stage by providing a general background of cyber data and analysis techniques, followed by our historical examples. Then we focus the remainder of the chapter on common contemporary techniques used to analyze cyber sequential or string data.

### 8.1.1 CYBER DATA

Many different types of data arise from cyber security scenarios—here we will identify a few prominent data types and outline an organizational framework for thinking about cyber data. Generally, within cyber security scenarios the objects studied may or may not have much known about them. One way to think about information (known and unknown) for digital objects will be similar to that of physical objects, such as an antique. An antique is affected by a *provenance*, or a history of events, which affect its state. In the real world even a valuable historical object may have partial or disputed information concerning its provenance. For digital objects we consider provenance similarly; there can also be incomplete

Cybersecurity and Applied Mathematics. http://dx.doi.org/10.1016/B978-0-12-804452-0.00008-7



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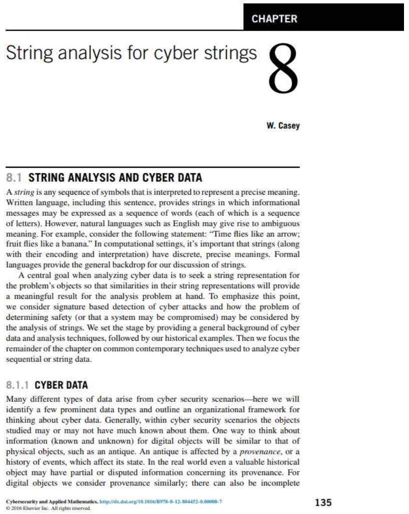

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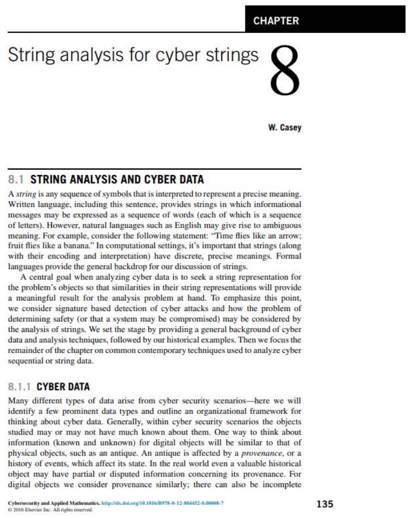
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# JOURNAL ARTICLE


Neural Computing and Applications (2020) 32:9621–9647
https://doi.org/10.1007/s00521-019-04474-5

ORIGINAL ARTICLE

## A novel error-output recurrent neural network model for time series forecasting

Waddah Waheeb[1] · Rozaida Ghazali[1]

Received: 6 October 2018 / Accepted: 29 August 2019 / Published online: 9 September 2019


**Abstract**
It is a well-known fact that improving forecasting accuracy is an important yet often challenging issue. Extensive research has been conducted using neural networks (NNs) to improve their forecasting accuracy. In general, the inputs to NNs are the auto-regressive (i.e. lagged variables) of one or more time series. In addition, either network outputs or network errors have been used as extra inputs to NNs. In this paper, however, we propose a novel recurrent neural network forecasting model which is called the ridge polynomial neural network with error-output feedbacks (RPNN-EOF). RPNN-EOF has two main types of inputs: auto-regressive and moving-average inputs. The former is represented by the lagged variables of a time series, while the latter is represented by feeding back network error to the input layer. In addition, network output is fed back to the input layer. The proposed recurrent model has the ability to produce more accurate forecasts due to the advantages of learning temporal dependence and the direct modelling of the moving-average component. A comparative analysis of RPNN-EOF with five neural network models was completed using ten time series. Simulation results have shown that RPNN-EOF is the most accurate model among all the compared models with the time series used. This shows that employing auto-regressive and moving-average inputs together helps to produce more accurate forecasts.

**Keywords** Recurrent neural network · Error-output feedbacks · Moving-average · NARMA · Ridge polynomial neural network · Forecasting · Nonlinear time series

### 1 Introduction

Time series is a sequence of observations observed sequentially over time [10]. Examples of time series data are the daily exchange rate, monthly sales, and annual runoff. Forecasting time series data are important because of the role of forecasting in helping to make effective and efficient planning [45].

In the field of forecasting, numerous models have been employed for time series forecasting such as adaptive neuro-fuzzy inference system, support vector regression, and neural networks [66, 76, 82]. Neural networks (NNs) have been extensively applied for time series forecasting. A search conducted in September 2018 using Scopus database for publications with "neural network" and "forecast" terms led to the retrieval of around 10,850 results, with a peak in 2017, the year with most papers issued (with 892 in total). That means NNs are still attracting much interest among scholars to deal with forecasting problems. The reasons for the interest to employ NNs are due to their capability of handling nonlinear functional dependencies, and they are data-driven models with few prior assumptions about underlying models [61, 87]. Furthermore, NNs are universal function approximators; therefore, they can approximate any continuous function with an arbitrary degree of accuracy [61, 87].

The well-known multilayer perceptron (MLP) neural network is a universal function approximator [20]. However, the number of hidden layers and units must be sufficient to deal with the given problem, deciding how many hidden units directly affect the performance of MLP. An MLP of size below the sufficiency usually fails to

Rozaida Ghazali
rozaida@uthm.edu.my

Waddah Waheeb
waddah.waheeb@gmail.com

[1] Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, Batu Pahat, Johor, Malaysia

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† Hospital Group Twente, Hengelo, The Netherlands
§ Faculty of Medicine, University of Duisburg-Essen, Essen, Germany
Email: <t.q.e.nguyen,d.theodorakopoulos>@student.utwente.nl, <s.pathak,m.vankeulen,c.seifert>@utwente.nl, <j.geerdink,o.vijlbrief>@zgt.nl
‡ Authors contributed equally to this work.

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† *Hospital Group Twente, Hengelo, The Netherlands*
§ *Faculty of Medicine, University of Duisburg-Essen, Essen, Germany*
*Email: <t.q.e.nguyen,d.theodorakopoulos>@student.utwente.nl, <s.pathak,m.vankeulen,c.seifert>@utwente.nl, <j.geerdink,o.vijlbrief>@zgt.nl*
‡ *Authors contributed equally to this work.*

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| conference papers | Bibliographic databases, Institutional repositories, Publisher digital libraries |
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