TECHNISCHE UNIVERSITÄT DRESDEN

MASTER THESIS

Forecasting univariate stock indices with parametric models and neural networks: A comparison

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**TECHNISCHE
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Abstract

Faculty of Business and Economics

Chair of Quantitative Methods, esp. Econometrics

Master thesis

**Forecasting univariate stock indices with parametric models and neural networks: A
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by Niklas PAULIG

The purpose of this article is to conduct a Monte-Carlo simulation study that compares the
efficiency, accuracy and empirical computation time of three different estimators in terms of
selecting copulae and estimating their parameters. I will compare two moment-based esti-
mators, the inverse of Kendall's Tau and Blomqvist's Beta, to the classic canonical maximum
likelihood estimator. I find that, in terms of estimating parameters for a given copula, the
moment-based estimators are inferior to maximum likelihood, especially for small sample
sizes. For selecting copulae from a set of data, however, all three estimators are equally
accurate while the moment-based ones are at least 16 times faster computationally.

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List of Abbreviations

i.i.d idependent and **i**dentically **d**istributed
CDF **C**umulative **D**istribution Function

1 Introduction

The aim of this thesis is to survey the accuracy and practicability of different univariate forecasting methods for different stock indices around the world. The methods used in this study are split into two groups based on their inner workings. The first group encompasses models with a well-established statistical foundation i.e. Exponential state-space and ARIMA(p,d,q) models, while the latter focuses on artificial neural networks (ANNs) which can be considered non-parametric as they do not need statistical assumptions before estimation but rather derive a structure directly from the underlying data.

The models are configured to provide a seven-day-ahead forecast which will be compared using scale invariant error metrics. The models with statistical foundation will also be compared among themselves using maximum entropy estimators or their derivatives.

The present thesis will be structured as follows. The first chapter reviews the history and literature of all here considered models. The second chapter gives an in depth explanation of those models and points out their utility in terms of univariate time-series forecasting. The third chapter presents the data to be analyzed and applies the models to the data. The fourth chapter discusses the results and concludes.

1.1   History of time series forecasting and literature review

The forecasting of serially structured data, i.e. data that has a temporal component ordering it from past to present, has challenged researchers ever since the first mathematical models for describing such data have evolved.

Exponential Smoothing models

More than 60 years ago, the family of exponential smoothing models emerged from the works of Brown (1962), Holt (1957) and Winters (1960), although they did not have profound statistical foundations but much rather were seen as ad-hoc techniques for extrapolating serially dependent data. Those models received not much attention among statisticians until the mid 1980s, when Gardner Jr (1985) (later revised as part two (see Gardner Jr (2006))) published a comprehensive review and classification of all known-to-date exponential smoothing models. In the same year Snyder (1985) laid the foundation for describing exponential smoothing models as innovation state space models and gave way for most of the recent developments in this field. Today, state-space models are the state of the art for modeling exponential smoothing, especially since Hyndman et al. (2002) and Taylor (2003)

designed automatic state space frameworks for nearly all smoothing models (following their own taxonomy), which are now also natively implemented into various statistical software packages.

Although not very complex, exponential smoothing models are widely adapted in industry and commerce for inventory control or sales forecasting. Until today surprisingly accurate forecasts can be generated with such models (Chatfield et al., 2001) and even out-perform more advanced models such as ARIMA (Hyndman, 2001).

ARIMA models

Inspired by the concept of a deterministic world, Yule (1927) was the first to develop the idea that time series can be seen as realizations of stochastic processes. This simple, yet novel approach laid the foundation for ample research efforts, developing many of the standard tools for time series analysis known today. After the subsequent description of autoregressive (AR) and moving average (MA) models, Box and Jenkins (1976) consolidated and integrated the existing knowledge and formulated a three stage approach for the identification, estimation and verification of time series. This approach, the *Box-Jenkins-approach*, is used until today in various applications.

It gave way for an abundance of studies successfully implementing their procedure (at least in parts) in different fields of investigation such as forecasting of the federal funds rate (Hein and Spudeck, 1988), monthly electricity consumption (Harris and Liu, 1993) or stock price prediction of the NYSE and NSE (Ariyo, Adewumi, and Ayo, 2014) which is closely related to this study's goal.

Artificial neural networks

Neural networks have a history that dates back nearly as long as that of the above mentioned methodologies, starting with Rosenblatt (1957) and his *Perceptron* as a first associative memory, based on the concept of neurons working in the human brain and Hu and Root (1964) using neural networks specifically for forecasting purposes. The practical utility, however, remained low in the early days as the number of solvable problems using such nets were limited due to lacking computational power and mathematical restraints.

In the subsequent decades, neural networks received only limited research attention until Rumelhart, Hinton, and Williams (1985) simplified training of networks by introducing the back-propagation algorithm to tackle complex learning problems with multi-layer-perceptrons (MLPs). This publication revived interest in the field and gave way for several advances, such as the proof that MLPs are able to approximate any measurable function arbitrarily well (Hornik, Stinchcombe, and White, 1989), the first commercial use of neural networks for handwritten zip-code recognition (LeCun et al., 1989), the emergence of convolutional neural networks (LeCun, Bengio, et al., 1995) or the invention of long-short-term memory cells (LSTM) by Hochreiter and Schmidhuber (1997) to circumvent learning problems of recurrent neural networks (RNNs).

Despite new research advancements, neural networks remained hard to train and work with, shifting away research efforts to related models such as Support Vector Machines or Random Forests (see Boser, Guyon, and Vapnik (1992) or Ho (1995)).

The era of deep learning began with the work of Hinton, Osindero, and Teh (2006), who showed that proper weight initialization made it possible to train networks with many hidden layers (deep networks), by pre-training every layer separately at first. These advancements lead to efficient weight intitializers that did not need the layers to be pre-trained (Glorot and Bengio, 2010). The same authors also highlighted the impact of activation functions on the capabilities of neural networks, leading to new research resulting in the well known rectified linear unit (ReLU) activation function and its derivatives (Jarrett et al. (2009) and Nair and Hinton (2010)).

The insights from the last decades, paired with an stark increase in available data and computational power, led to remarkable results in multiple fields of research, for example the forecasting of retail demand (Wen et al. (2017), Salinas et al. (2020)), traffic (Laptev et al. (2017), Li et al. (2017)) or energy (Dimoulkas, Mazidi, and Herre (2019)).

Despite the multitude of positive feedback, there are still doubts whether artificial neural networks are being oversold. There are several papers documenting ANNs being outperformed by basic random walks (see Conejo et al. (2005), or Tkacz (2001)).

2 Model description

2.1 Exponential smoothing

2.1.1 Model description

Developed independently by Robert G. Brown and Charles C. Holt in the early 1950s to develop a tracking model for fire-control information and forecasting spare parts, exponential smoothing methods quickly became a useful technique for extrapolating serial data.

In this thesis the notation and taxonomy implemented by Gardner Jr (2006), Hyndman et al. (2002) and Taylor (2003) is used. This thesis uses three different models presented below. The following notation is used:

Symbol	Definition
α	Smoothing parameter for the level of the series.
γ	Smoothing parameter for the trend.
m	Number of periods in the forecast.
ϕ	Autoregressive or damping parameter.
S_t	Smoothed level of the series, computed after X_t is observed.
X_t	Observed value of the time series in period t.
T_t	Smoothed additive trend at the end of period t.
$\hat{X}_t(m)$	Forecast for m periods ahead from origin t.
e_t	One-step-ahead forecast error, $e_t = X_t - \hat{X}_{t-1}$.
	$e_t(m)$ should be used for other forecast origins.

TABLE 2.1: Notation used to describe exponential smoothing models (same as in Gardner Jr (2006))

No trend, no seasonality

This type is the simple exponential smoothing method by Brown (1962). Following Gardner Jr (2006) there will be two separate equations for each model, one using the recursive form and the other being the error correction form.

Given a series $\{X_t\}$ with $t = \{1, \ldots, T\}$, the simple exponential smoothing model in recursive form is given by

$$
\begin{aligned}
S_t &= \alpha X_t + (1-\alpha)S_{t-1} \\
\hat{X}_t(m) &= S_t
\end{aligned}
\tag{2.1}
$$

while the error correction form is given by

$$
\begin{aligned}
S_t &= S_{t-1} + \alpha e_t \\
\hat{X}_t(m) &= S_t.
\end{aligned}
\tag{2.2}
$$

Additive trend, no seasonality

The model with additive trend is that of Holt (1957) (Holt's linear method), adding a trend term to the estimated parameter one time step prior in 2.1, resulting in a linear trend. The recursive form is given by

$$
\begin{aligned}
S_t &= \alpha X_t + (1-\alpha)\left(S_{t-1} + T_{t-1}\right) \\
T_t &= \gamma\left(S_t - S_{t-1}\right) + (1-\gamma)T_{t-1} \\
\hat{X}_t(m) &= S_t + mT_t
\end{aligned}
\tag{2.3}
$$

and the error correction form by

$$
\begin{aligned}
S_t &= S_{t-1} + T_{t-1} + \alpha e_t \\
T_t &= T_{t-1} + \alpha\gamma e_t \\
\hat{X}_t(m) &= S_t + mT_t.
\end{aligned}
\tag{2.4}
$$

Damped-additive trend, no seasonality

In order to allow the trend to decay over time, Gardner Jr and McKenzie (1989) used a dampening factor, reducing the trend influence over the course of the forecast horizon m. The recursive form is given by

$$
\begin{aligned}
S_t &= S_{t-1} + \phi T_{t-1} + \alpha e_t \\
T_t &= \phi T_{t-1} + \alpha\gamma e_t \\
\hat{X}_t(m) &= S_t + \sum_{i=1}^{m}\phi^i T_t
\end{aligned}
\tag{2.5}
$$

and the error correction form by

$$
\begin{aligned}
S_t &= S_{t-1}R_{t-1} + \alpha e_t \\
R_t &= R_{t-1} + \alpha\gamma e_t / S_{t-1} \\
\hat{X}_t(m) &= S_t R_t^m.
\end{aligned}
\tag{2.6}
$$

For all above equations it is assumed for $\alpha, \gamma \in [0,1]$ otherwise observations would gain influence the further they are away from the forecast. This becomes evident once we look at the expanded form of 2.1. We substitute the expression of S_{t-1} back into itself and thus arrive at the geometric progression

$$S_t = \alpha X_t + (1 - \alpha) S_{t-1}$$
$$= \alpha X_t + \alpha (1 - \alpha) X_{t-1} + (1 - \alpha)^2 S_{t-2}$$
$$= \alpha \left[X_t + (1 - \alpha) X_{t-1} + (1 - \alpha)^2 X_{t-2} + (1 - \alpha)^3 X_{t-3} + \cdots + (1 - \alpha)^{t-1} X_1 \right] + (1 - \alpha)^t X_0.$$

These expressions can be defined analogously for 2.3 and 2.5. For ϕ, different values can be used to give the trend convex, linear or even concave shape.

2.1.2 Model selection

Selecting an appropriate model can be done in several different ways, of which a few will be presented here. Depending on the number of time series to forecast either aggregate or individual model selection can be used. Fildes (2001) comes to the conclusion that in aggregate selection, the damped-additive trend model is hard to beat, although individual selection does yield better results sometimes. The "individual selection of exponential smoothing methods, [however], is best described as inconclusive." (Gardner Jr, 2006, p. 28).

On the one hand there are selection criteria based on time-series characteristics, as described for example in Shah (1997) or Meade (2000), which led to promising results when applied to time series that were generated using one of the processes to identify, but when applied to other series the results were less convincing. On the other hand there are expert-systems that generate rules based on experience made from earlier forecasting procedures (see for example Collopy and Armstrong (1992) or Flores and Pearce (2000)).

The model selection used in this study will be based on information criteria, as they are easy to derive and readily available. The results in selecting the appropriate model, however, are not convincing either. Comparing the studies of Gardner Jr and McKenzie (1985) and Hyndman et al. (2002), one can find that only for a forecast horizon of two and 15, the AIC as an information criterion selected more accurate models rather than the aggregate choice of a damped-additive trend model. For this reason this study also fits a damped-additive trend model to the data regardless of the decision based on information criteria. Nevertheless does the choice of an information criterion as a model selector provide an easily accessible procedure as this study estimates parameters via state-space maximum likelihood, from which arbitrary information criteria can be derived handily. The choice and description of information criteria used in this study will be discussed in more detail in section SECCCTIONN!!!!!

2.1.3 The state-space model

In order to estimate the parameters for the above described models, this study uses an "innovations", single-source of error (SSOE) state-space model. The model framework is that

of Ord, Koehler, and Snyder (1997), which was expanded by Hyndman et al. (2002). The basic state space framework can be described by the following equations:

$$y_t = w(\mathbf{X}_{t-1}) + r(\mathbf{X}_{t-1})\varepsilon_t \tag{2.7a}$$

$$\mathbf{x}_t = f(\mathbf{X}_{t-1}) + g(\mathbf{X}_{t-1})\varepsilon_t \tag{2.7b}$$

with y_t being the observation at time t, $\mathbf{X}_t$ the state vector containing unobserved components that describe the level, trend and seasonality of the series and w, r, f, g are continuous functions with $w, r : \mathbb{R}^p \to \mathbb{R}$ and $f, g : \mathbb{R} \to \mathbb{R}$. $\{\varepsilon_t\}$ is a Gaussian white noise process with variance σ^2. Equation 2.7a is called the *measurement equation* as it measures the relationship between the unobserved states $\mathbf{X}_{t-1}$ and the observation y_t. Equation 2.7b is called *transition equation*, describing the evolution of the states over time.

All of the equations from 2.1 to 2.5 can be translated into state-space terminology. To ensure that this thesis is self-contained I will present the equations in their state-space equations below, however they are exactly taken from Hyndman et al. (2002), which discusses them in great detail. The models in this study use additive trends, such that $r(\mathbf{X}_{t-1}) = 1$ and if we define the one-step forecast made in period $t-1$ as $\mu_t = F_{(t-1)+1} = w(\mathbf{X}_{t-1})$. Further defining $e_t = r(X_{t-1})\varepsilon_t$ we can rewrite $Y_t = \mu_t + e_t$ which is equal to $Y_t = \mu_t + \varepsilon_t$ for additive errors. Suppose that l_t is the level of our series at time t, b_t is the slope of the series at time t and α, γ, ϕ are constants, Brown's method from 2.1 becomes

$$\begin{aligned} \mu_t &= l_{t-1} \\ l_t &= l_{t-1} + \alpha\varepsilon_t. \end{aligned} \tag{2.8}$$

Holt's linear trend method becomes

$$\begin{aligned} \mu_t &= l_{t-1} + b_{t-1} \\ l_t &= l_{t-1} + b_{t-1} + \alpha\varepsilon_t \\ b_t &= b_{t-1} + \alpha\gamma\varepsilon_t, \end{aligned} \tag{2.9}$$

and Gardener's damped additive trend becomes

$$\begin{aligned} \mu_t &= l_{t-1} + b_{t-1} \\ l_t &= l_{t-1} + b_{t-1} + \alpha\varepsilon_t \\ b_t &= \phi b_{t-1} + \alpha\gamma\varepsilon_t. \end{aligned} \tag{2.10}$$

2.1.4 Parameter estimation and initial values

As we assumed the error term $\{\varepsilon_t\}$ to be Gaussian noise, the likelihood function will also be a Gaussian likelihood. In essence, the joint density of the series is the weighted product of the densities of the individual innovations:

$$p\left(\boldsymbol{y} \mid \boldsymbol{\theta}, \boldsymbol{x}_0, \sigma^2\right) = \prod_{t=1}^{n} p\left(\varepsilon_t\right) / \left|r\left(\boldsymbol{x}_{t-1}\right)\right|, \tag{2.11}$$

with $\boldsymbol{X}_0$ being the seed states or initial values. This given, the Gaussian likelihood can be described as

$$\mathcal{L}\left(\boldsymbol{\theta}, \boldsymbol{X}_0, \sigma^2 \mid \boldsymbol{y}\right) = \left(2\pi\sigma^2\right)^{-n/2} \left|\prod_{t=1}^{n} r\left(\boldsymbol{X}_{t-1}\right)\right|^{-1} \exp\left(-\frac{1}{2}\sum_{t=1}^{n} \varepsilon_t^2 / \sigma^2\right), \tag{2.12}$$

and the log likelihood is given as

$$\log \mathcal{L} = -\frac{n}{2}\log\left(2\pi\sigma^2\right) - \sum_{t=1}^{n} \log\left|r\left(\boldsymbol{X}_{t-1}\right)\right| - \frac{1}{2}\sum_{t=1}^{n} \varepsilon_t^2 / \sigma^2. \tag{2.13}$$

If we now set the partial derivative with respect to σ^2 to zero, we can calculate the maximum likelihood estimate of the variance as

$$\hat{\sigma}^2 = n^{-1} \sum_{t=1}^{n} \varepsilon_t^2. \tag{2.14}$$

This allows us to write the likelihood from 2.12 without dependency from the variance as

$$\mathcal{L}\left(\boldsymbol{\theta}, \boldsymbol{X}_0 \mid \boldsymbol{y}\right) = \left(2\pi\hat{\sigma}^2\right)^{-n/2} \left|\prod_{t=1}^{n} r\left(\boldsymbol{x}_{t-1}\right)\right|^{-1}. \tag{2.15}$$

Recapitulating from above we know that for additive models $r(\boldsymbol{X}_{t-1}) = 1$, and thus by taking the twice the negative logarithm we arrive at

$$\begin{aligned}\mathcal{L}^*\left(\boldsymbol{\theta}, \boldsymbol{X}_0\right) &= n\log\left(2\pi\right) + n\log\left(\hat{\sigma}^2\right) \\ &= n\log\left(2\pi\right) + n\log\left(\sum_{t=1}^{n} \varepsilon_t^2\right).\end{aligned} \tag{2.16}$$

To arrive at maximum likelihood estimates for the parameters this study minimizes 2.16.

One last step prior to fitting the model, the initial values for $\boldsymbol{X}_0$ must be set. Here we use $\alpha = \gamma = 0.5$ and $\phi = 0.9$, while for the level l_0 of the series we compute a linear trend of the first ten observations and use the intercept as a starting value. For the initial trend b_0 coefficient we use the slope of the before computed trend.

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Declaration of Authorship

I, Niklas PAULIG, declare that this thesis titled, "Forecasting univariate stock indices with parametric models and neural networks: A comparison" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.

- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.

- Where I have consulted the published work of others, this is always clearly attributed.

- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.

- I have acknowledged all main sources of help.

- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

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Date:

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