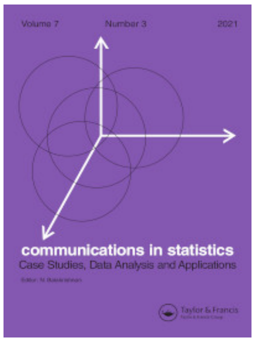

Communications in Statistics: Case Studies, Data Analysis and Applications

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ucas20

Accuracy of automatic forecasting methods for univariate time series data: A case study predicting the results of the 2018 Swedish general election using decades-long data series

Andreas Karlsson Rosenblad

To cite this article: Andreas Karlsson Rosenblad (2021) Accuracy of automatic forecasting methods for univariate time series data: A case study predicting the results of the 2018 Swedish general election using decades-long data series, Communications in Statistics: Case Studies, Data Analysis and Applications, 7:3, 475-493, DOI: 10.1080/23737484.2021.1964407

To link to this article: https://doi.org/10.1080/23737484.2021.1964407

COMMUNICATIONS IN STATISTICS: CASE STUDIES, DATA ANALYSIS AND APPLICATIONS
2021, VOL. 7, NO. 3, 475–493
https://doi.org/10.1080/23737484.2021.1964407

Accuracy of automatic forecasting methods for univariate time series data: A case study predicting the results of the 2018 Swedish general election using decades-long data series

Andreas Karlsson Rosenblad[a,b]

[a]Department of Statistics, Stockholm University, Stockholm, Sweden; [b]Department of Medical Sciences, Uppsala University, Uppsala, Sweden

ABSTRACT

This study compared the accuracy of automatic time series forecasting methods in predicting the results of the 2018 Swedish general election using data from the Party Preference Survey opinion poll collected during the years 1984–2018. The general exponential smoothing state space (ETS) model performed best, outperforming even the exit poll collected at the time of the election, while the complex seasonal autoregressive integrated moving average (ARIMA) model was beaten by the simple exponential smoothing method. Holt's linear trend method performed worse than even the naïve method. The results of this study show the usefulness of easily applied automatic forecasting methods.

ARTICLE HISTORY
Received June 2020
Accepted August 2021

KEYWORDS
ARIMA models; electoral studies; exponential smoothing; model comparison; state space models

1. Introduction

Selecting the best model for forecasting a univariate time series has traditionally been a complicated, arduous, time-consuming, and subjective task, requiring expert knowledge and manual tweaking of models. Subjective assessments of trends, seasonal variation and other patterns of the time series at hand will often result in selecting a model that is acceptable but not necessarily optimal in an objective sense. The availability of modern well-performing automatic forecasting methods for univariate time series data, without the need of human supervision and intervention, has made this task more easy, efficient, fast, and objective, with the selected model being optimal based on the applied criteria. Available implementations of automatic time series forecasting are, for example, the ESM procedure in SAS (SAS Institute 2020, chap. 15) applying exponential smoothing (ES) models and the R package "forecast" (Hyndman et al. 2019) applying exponential smoothing state space (ETS) as well as autoregressive integrated

CONTACT Andreas Karlsson Rosenblad andreas.rosenblad@medsci.uu.se Department of Medical Sciences, Uppsala University, SE - 751 85 Uppsala, Sweden

Supplemental data for this article can be accessed on the publisher's website.

moving average (ARIMA) models. The wide availability, efficiency, and ease-of-use of these procedures make them attractive for use in practical day-to-day forecasting work, especially for those without time or knowledge to apply more advanced forecasting methods.

The automatically estimated ETS and ARIMA models have also been shown to perform well in comparisons with other forecasting methods. When applied to a set of 111 empirical time series from the NN3 competition (Crone, Hibon, and Nikolopoulos 2011), both methods thus outperformed more complex methods such as generalized regression neural networks (GRNNs), *k*-nearest neighbours (KNN) regression, and multilayer perceptron (MLP) methods (Martínez et al. 2019). In another comparison of recurrent neural network (RNN) models applied to datasets from previous forecasting competitions such as the M4 competition (Makridakis, Spiliotis, and Assimakopoulos 2018) and the Tourism competition (Athanasopoulos et al. 2011), the automatically estimated ETS and ARIMA models were used as benchmarks, due to these being strong and well-established state-of-the-art forecasting techniques. Both methods were found to overall perform very well compared to a plethora of RNN models; in particular, the automatically estimated ARIMA models outperformed all other methods when applied to 48,000 time series from the M4 competition, while the automatically estimated ETS models came out on top when applied to 366 time series from the Tourism competition (Hewamalage, Bergmeir, and Bandara 2021).

Predictions of election results are always of great interest in a democracy, with opinion polls of voting intentions being the main tool used for constructing these predictions. While the actual election results of a political party give a univariate time series describing the outcome of the predictions, there are thus also usually a time series of predictions from opinion polls available. In Sweden, general elections to its unicameral national parliament, *Riksdagen*, is held in September every fourth year. The latest (at the time of writing) election was held on September 9, 2018, resulting in eight parties getting seats in the parliament. Since 1984, Statistics Sweden, the Swedish national statistics agency, has collected data for the Party Preference Survey (PPS; *Partisympatiundersökningen*, PSU) opinion poll on voting intentions for Swedish general elections twice a year, in May and November. This survey is the largest opinion poll in Sweden, aiming to present "election results if an election were to be held today" (Statistics Sweden 2019a).

Given the long time series of data available from the PPS, with repeated collection at the same period of time each year, it is of interest to study how well these data work in predicting election results in Sweden. Moreover, with the ease-of-use, efficiency, and attractiveness for use in practical day-to-day forecasting work of automatic time series forecasting methods, as well as the strong performance of these methods in the previous evaluations, it is of interest to evaluate the accuracy of these methods in predicting election results.

Considering the irregularities of opinion polls time series data, the ETS and ARIMA models should be well suited for forecasting this kind of data. Against this background, the aim of the present case study was to evaluate the accuracy of automatic time series forecasting methods in predicting the results of Swedish general elections using data from the PPS, focusing on the general election of September 9, 2018. In addition to this, we also wanted to compare the accuracy of these time series based forecasts with the accuracy of the exit poll's prediction of the outcome of the election.

The remaining parts of this article are organized as follows: Sec. 2 gives an overview of the available data material and the setting in which it was collected. Sec. 3 gives details of the studied forecasting methods as well as the methods used for evaluating the forecasting accuracy of these methods, while Sec. 4 presents the results of this evaluation. Sec. 5 concludes the main text with a discussion of the study's findings in relation to the aim of the study. Computer code for automatic time series forecasting used in the present study is given in Appendix A.

2. Material and setting

This section gives the necessary background details about the Swedish political system and the collection of data for the PPS and the exit poll.

2.1. The Swedish political system

The Swedish parliament, *Riksdagen*, has 349 seats, with simultaneous elections for all seats taking place in September every fourth year since 1994. Prior to this year, elections took place every third year. The members of *Riksdagen* are elected through a party-list proportional representation system with a 4% national electoral threshold. In the election of September 9, 2018, eight parties took seats in the parliament: The Social Democratic Party (social democracy), the Moderate Party (liberal conservatism), the Sweden Democrats (national conservative immigration scepticism), the Centre Party (agrarian neo-liberalism), the Left Party (post-communistic socialism), the Liberal Party (social liberalism), the Green Party (green politics), and the Christian Democrats (social conservatism). Of these parties, the Green Party has, with the exception of the years 1991–1994, been represented in the Swedish parliament since 1988, while the Christian Democrats and the Sweden Democrats have been represented in the parliament since 1991 and 2010, respectively. The remaining five parties have all been represented in the Swedish parliament continuously since the unicameral legislature was introduced in 1971. The results of the Swedish general election held on September 9, 2018, is given in Table 1.

Table 1. Results of the PPS in May 2018, with 95% confidence intervals (CIs), together with the exit poll and actual results (eligible votes) of the Swedish general election held on September 9, 2018

Party	PPS May 2018 % (95% CI)	Exit poll %	Votes *n*	Votes %	Seats *n*
Social Democratic Party	28.3 (27.5–29.1)	26.2	1,830,386	28.3	100
Moderate Party	22.6 (21.8–23.4)	17.8	1,284,698	19.8	70
Sweden Democrats	18.5 (17.7–19.3)	19.2	1,135,627	17.5	62
Centre Party	8.7 (8.2–9.2)	8.9	557,500	8.6	31
Left Party	7.4 (6.9–7.9)	9.0	518,454	8.0	28
Liberal Party	4.4 (4.0–4.8)	5.5	355,546	5.5	20
Green Party	4.3 (3.9–4.7)	4.2	285,899	4.4	16
Christian Democrats	2.9 (2.6–3.2)	7.4	409,478	6.3	22
Other parties	2.9 (2.5–3.3)	1.8	99,137	1.5	–
Total	100	100	6,476,725	100	349

Source: Statistics Sweden (2019b), Sveriges Television (2018), and Valmyndigheten (2018).

2.2. The PPS

The PPS is collected using a random sample of about 9000 Swedish citizens, with voting intentions measured with the question "Which party would you vote for if there was an election to the *Riksdag* any of the next few days?" (Statistics Sweden 2018, p. 12). Information about party voted for in the last election to the *Riksdag* is used as auxiliary information when estimating voting intentions (Statistics Sweden 2018). The PPS has been collected by Statistics Sweden since November 1972, usually twice a year (May and November), but for some years also at the third time point (February). There is, however, a break in the time series, since no data were collected from November 1981 to November 1983. Thus, since data are available twice a year for the same months only from 1984, it was decided that only data collected in May and November each year, starting at May 1984 and ending at May 2018, should be analyzed in the present study.

Of the eight parties included in the PPS, data are available for the Social Democratic Party, Moderate Party, Centre Party, Left Party, and Liberal Party from May 1984 (i.e., a length of 69 data points), while data for the Green Party are available from November 1988 (60 data points), for the Christian Democrats from May 1991 (55 data points), and for the Sweden Democrats from November 2010 (16 data points). At each time point, the percentage of voting intentions for each party is given, accompanied with a 95% confidence interval (CI), both measured with a precision of one decimal. All data are publicly available at Statistic Sweden's website (Statistics Sweden 2019b). Further details about the PPS are given by (Statistics Sweden 2019a).

The results of the PPS poll from May 2018, the last poll before the Swedish general election took place on September 9, 2018, are given in Table 1, together with 95% CIs. Time series plots of the results of all included PPS polls from May 1984 to May 2018 are given in Tables 1 and 2 for the four parties with the highest and lowest support, respectively, in the PPS from May 2018. A data set with results from the included PPS polls can be accessed on the publisher's website as Supplemental data file ME0201B1.RData.

Table 2. Overview of all possible exponential smoothing state space (ETS) models.

Error component	Trend component	Seasonal component		
		None	Additive	Multiplicative
Additive	None	A, N, N	A, N, A	A, N, M
	Additive	A, A, N	A, A, A	A, A, M
	Additive damped	A, A_d, N	A, A_d, A	A, A_d, M
	Multiplicative	A, M, N	A, M, A	A, M, M
	Multiplicative damped	A, M_d, N	A, M_d, A	A, M_d, M
Multiplicative	None	M, N, N	M, N, A	M, N, M
	Additive	M, A, N	M, A, A	M, A, M
	Additive damped	M, A_d, N	M, A_d, A	M, A_d, M
	Multiplicative	M, M, N	M, M, A	M, M, M
	Multiplicative damped	M, M_d, N	M, M_d, A	M, M_d, M

2.3. Exit poll

Exit polls for Swedish general elections have been performed since 1991 by Sveriges Television (SVT), the national Swedish public service television broadcaster. The exit poll for the 2018 general election was performed during the preelection period September 3 to September 8, 2018, for 50 early voting polling stations and during the election day September 9, 2018, for 100 ordinary polling stations. In total, 11,808 questionnaires were collected, of which 3774 (32.0%) were obtained from early voting polling stations and 8034 (68.0%) from ordinary polling stations (Sveriges Television 2018). The results of the exit poll is given in Table 1.

3. Methods

This section introduces the notation that will be used in the remaining parts of the paper, discusses the time series methods that will be evaluated, and presents the evaluation criteria used in the study. Much of the material in this section is adapted from Hyndman et al. (2008), Hyndman and Khandakar (2008), and Hyndman and Athanasopoulos (2018).

The irregularities observed in the time series plots in Figures 1 and 2 confirm that a natural choice of time series methods to focus on are ES and ARIMA models. This is also the models that the most popular automatic forecasting algorithms are based on Hyndman and Khandakar (2008). In addition, automatic forecasting algorithms for ES and ARIMA models are freely available in the popular R package “forecast” (Hyndman et al. 2019), described in detail by Hyndman and Khandakar (2008). All statistical analyses in the present study were performed in R 3.5.2 using version 8.9 of the “forecast” package.

3.1. Notation

The time series considered in this paper may be viewed as consisting of three components: a trend (T) part giving the direction of the series, a seasonal (S)

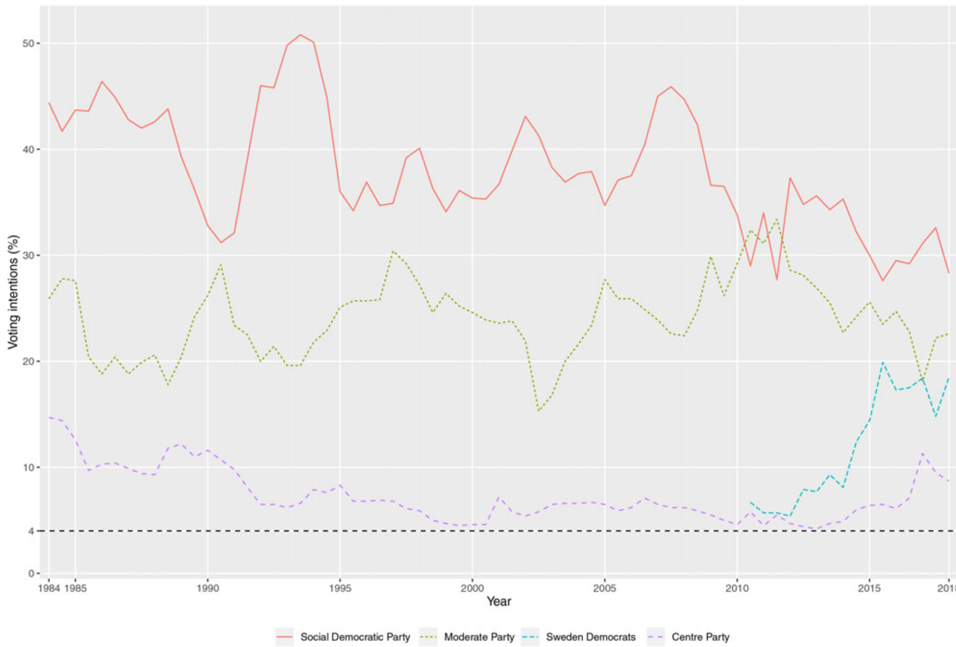

Figure 1. Time series plot of the results of all included PPS polls from May 1984 to May 2018 for the four parties with the highest support in the PPS from May 2018. Source: Statistics Sweden (2019b).

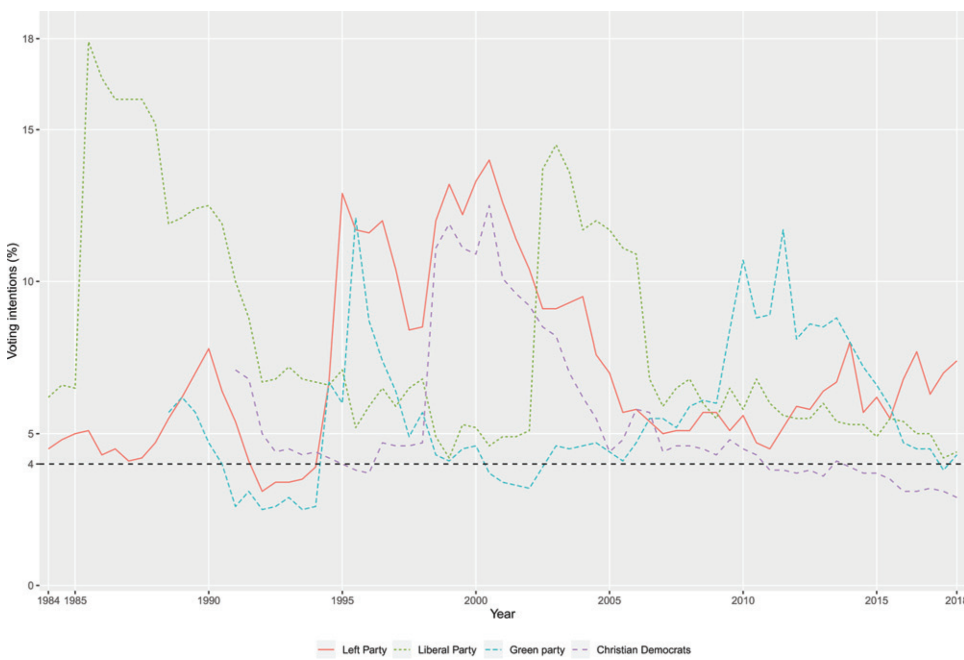

Figure 2. Time series plot of the results of all included PPS polls from May 1984 to May 2018 for the four parties with the lowest support in the PPS from May 2018. Source: Statistics Sweden (2019b).

part representing a pattern of periodicity of the series, and an error (E) part giving the random component of the series. With $f(E, T, S)$ denoting a function of these three components, a univariate time series y may thus be written as follows:

$$y = f(E, T, S) \tag{1}$$

Setting $f(E, T, S) = T + S + E$ thus gives a purely additive model, while $f(E, T, S) = T \times S \times E$ results in a purely multiplicative model. In our case the length of the periodicity is two, since the PPS was collected twice a year.

For a univariate time series y consisting of τ data points, let y_t denote the observed value of the series at time $t = 1, 2, ..., \tau$, with the one-step forecasted value of y_t being denoted $\hat{y}_t$. In general, with h denoting the number of forecasting steps, let $\hat{y}_{t+h|t}$ denote the forecasted value for observation y_{t+h} made at time t (i.e., $\hat{y}_t = \hat{y}_{t+1|t}$). The forecast error e_{t+h}, defined as the difference between the observed and forecasted values of the times series y at time $t + h$, is given by

$$e_{t+h} = y_{t+h} - \hat{y}_{t+h|t} \tag{2}$$

Moreover, for n separate time series y_i consisting of τ_i data points, let $y_{i,t}$ denote the observed value of series i at time $t = 1, 2, ..., \tau_i$, with the one-step forecasted value of $y_{i,t}$ being denoted $\hat{y}_{i,t}$. In general, the forecasted value for observation $y_{i,t+h}$ made at time t will be denoted $\hat{y}_{i,\,t+h|t}$. The forecast error $e_{i,t+h}$, that is, the difference between the observed and forecasted values of the times series y_i at time $t + h$, is then given by

$$e_{i,t+h} = y_{i,t+h} - \hat{y}_{i,\,t+h|t} \tag{3}$$

3.2. Evaluation criteria

We are interested in the accuracy of the different time series analysis methods in predicting the outcome of the Swedish general election of September 9, 2018, taking into account all observed PPS data for each political party i up to the last PPS poll before the election, which was conducted in May 2018. We consider this as a one-step forecast, that is, $h = 1$ in (3). With the time τ_i when the forecast was made being May 2018, we thus wanted to predict $\hat{y}_{i,\,\text{Sep. 9, 2018}|\text{May 2018}}$ and evaluate the accuracy of this forecast against the observed value $y_{i,\,\text{Sep. 9, 2018}}$ based on the forecast error

$$e_{i,\,\text{Sep. 9, 2018}} = y_{i,\,\text{Sep. 9, 2018}} - \hat{y}_{i,\,\text{Sep. 9, 2018}|\text{May 2018}} \tag{4}$$

The forecasting accuracies of the examined time series analysis methods were then evaluated using the mean absolute error (MAE)

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \left| e_{i,\,\text{Sep. 9, 2018}} \right| \tag{5}$$

with $n = 8$ parties being included in the present study. Since the voting intentions reported by the PPS are only given with one decimal, the values of $y_{i,\text{Sep. 9, 2018}}$ and $\hat{y}_{i,\text{Sep. 9, 2018}|\text{May 2018}}$ were rounded to one decimal before calculating $e_{i,\text{Sep. 9, 2018}}$. As a benchmark criteria, to be deemed a useful forecasting method, it was required that a method performed better in terms of MAE than the naïve method, that is, when the forecasted value for the next time period is simply the same value as the one observed for the current period,

$$\hat{y}_{t+h|t} = y_t \tag{6}$$

3.3. Exponential smoothing state space (ETS) models

Exponential smoothing (ES) is a class of forecasting methods based on the idea that a forecasted value $\hat{y}_{t+h|t}$ should be the result of a weighted combination of past observations $y_t, y_{t-1}, y_{t-2}, \ldots$, where more recent observations are given more weight than older observations. The weights are decreasing exponentially as the observations get older, thus giving rise to the name *ES* (Hyndman et al. 2008, p. 5) Many different ES methods can be shown to be special cases of a more general *exponential smoothing state space* models framework.

For the purpose of producing point forecasts $\hat{y}_{t+h|t}$, the ES forecasting methods differ only in their handling of the trend (T) and seasonal (S) components of a time series. The trend component may be classified as being additive (A), additive damped (A_d), multiplicative (M), multiplicative damped (M_d), or none (N) if there is no trend, while the seasonal component may be classified as additive (A), multiplicative (M), or none (N). This thus results in 15 different ES forecasting methods. However, for constructing prediction intervals (PIs), one also has to take account of the error (E) component, which in turn may be additive (A) or multiplicative (M). Each exponential smoothing state space model may thus be described by defining the error, trend, and seasonal (E,T,S) components of the model, and exponential smoothing state space models are thus also known as ETS models. We will use the notation ETS $(\cdot,\cdot,\cdot)$ to describe a specific ETS model, with the dots replaced by N, A, A_d, M, or M_d, representing the error, trend, and seasonal components of the model. An overview of all 30 possible ETS models is given in Table 2.

In general, we expect that the seasonal part of the PPS time series data (i.e., if the PPS poll was collected in May or November of a specific year) should only have a minor influence on the observed voting intentions, implying that the trend component T should play the major part in producing the point forecasts $\hat{y}_{t+h|t}$. The trend component consists of a combination of a level term ℓ, a growth or slope term b, and a damping parameter ϕ, with the latter taking values between 0 and 1. With T_h denoting the trend forecasted for h steps ahead, the five different types of trends are as follows:

$$\begin{aligned}
\text{None } (N): &\quad T_h = \ell \\
\text{Additive } (A): &\quad T_h = \ell + bh \\
\text{Additive damped } (A_d): &\quad T_h = \ell + \left(\phi + \phi^2 + \cdots + \phi^h\right) b \\
\text{Multiplicative } (M): &\quad T_h = \ell b^h \\
\text{Multiplicative damped } (M_d): &\quad T_h = \ell b^{\left(\phi + \phi^2 + \cdots + \phi^h\right)}
\end{aligned}$$

Let ℓ_t, b_t, and s_t denote the level, slope, and seasonal components, respectively, of a series at time t, with accompanying smoothing parameters (all taking values between 0 and 1) α, β^*, and γ. Different combinations of ℓ_t, b_t, and s_t, weighted by the smoothing parameters α, β^*, and γ, give the 15 different ES forecasting methods. Formulas for recursive calculations of ℓ_t, b_t, and s_t for these 15 methods, as well as calculations of the point forecasts $\hat{y}_{t+h|t}$, are given by Hyndman and Khandakar (2008). With ε_t denoting the error of a series at time t and m denoting the length of the periodicity or seasonality (thus, $m = 2$ for the present study of PPS data), let $\mathbf{x}_t$ denote the state vector

$$\mathbf{x}_t = \left(\ell_t, b_t, s_t, s_{t-1}, \ldots, s_{t-m+1}\right)' \tag{7}$$

and set $\beta = \alpha\beta^*$. All 30 possible ETS models given in Table 2 may then be written as *state space models* using the state space equations

$$y_t = w\left(\mathbf{x}_{t-1}\right) + r\left(\mathbf{x}_{t-1}\right)\varepsilon_t \tag{8}$$

$$\mathbf{x}_t = v\left(\mathbf{x}_{t-1}\right) + g\left(\mathbf{x}_{t-1}\right)\varepsilon_t \tag{9}$$

where it is assumed that ε_t is Gaussian white noise with expected value $\mathrm{E}\left(\varepsilon_t\right) = 0$ and variance $\mathrm{Var}\left(\varepsilon_t\right) = \sigma^2$. With $\mu_t = w\left(\mathbf{x}_{t-1}\right)$, we have the following results for the models with additive and multiplicative errors, respectively:

$$\begin{aligned}
\text{Additive error:} &\quad r\left(\mathbf{x}_{t-1}\right) = 1 \Rightarrow y_t = \mu_t + \varepsilon_t \\
\text{Multiplicative error:} &\quad r\left(\mathbf{x}_{t-1}\right) = \mu_t \Rightarrow y_t = \mu_t\left(1 + \varepsilon_t\right)
\end{aligned}$$

The state space equations for all 30 possible ETS models in Table 2, based on Equations (8) and (9), are given by Hyndman et al. (2008). Two special cases are described in the following.

3.4. *Simple exponential smoothing (SES) method:* ETS(*A*, *N*, *N*)

The earliest attempt at using ES methods was Brown's SES method, which only includes a level term ℓ_t with an accompanying smoothing parameter α. For the SES method, the level ℓ_t and forecasted value $\hat{y}_{t+h|t}$ are given by

$$\ell_t = \alpha y_t + (1 - \alpha)\,\ell_{t-1} \tag{10}$$

$$\hat{y}_{t+h|t} = \ell_t \tag{11}$$

respectively. Assuming additive errors, this may be described in the ETS framework as an ETS(A, N, N) model. Using Equations (8) and (9), with $\mathbf{x}_t = (\ell_t)$, it may thus be expressed in state space form as

$$y_t = \mathbf{x}_{t-1} + \varepsilon_t \tag{12}$$
$$\mathbf{x}_t = \mathbf{x}_{t-1} + \alpha\varepsilon_t \tag{13}$$

3.5. Holt's linear trend (HLT) method: ETS(A, A, N)

An extension of the SES method, which in addition to the level term ℓ_t also includes a separate slope term b_t with accompanying smoothing parameter β^*, is Holt's linear trend (HLT) method (Holt 2004). For the HLT method, the level ℓ_t, slope b_t, and forecasted value $\hat{y}_{t+h|t}$ are given by

$$\ell_t = \alpha y_t + (1 - \alpha)(\ell_{t-1} + b_{t-1}) \tag{14}$$
$$b_t = \beta^* (\ell_t - \ell_{t-1}) + \left(1 - \beta^*\right) b_{t-1} \tag{15}$$
$$\hat{y}_{t+h|t} = \ell_t + hb_t \tag{16}$$

respectively. Assuming additive errors, this may be described in the ETS framework as an ETS(A, A, N) model. Using Equations (8) and (9) with $\mathbf{x}_t = (\ell_t, b_t)'$, it may be expressed in state space form as

$$y_t = \begin{bmatrix} 1 & 1 \end{bmatrix} \mathbf{x}_{t-1} + \varepsilon_t \tag{17}$$
$$\mathbf{x}_t = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \mathbf{x}_{t-1} + \begin{bmatrix} \alpha \\ \beta \end{bmatrix} \varepsilon_t \tag{18}$$

3.6. ARIMA models

ARIMA models, also known as Box-Jenkins models, are based on the idea that a time series can be modeled as a mixture of autoregressive (AR) and moving average (MA) processes. The AR(p) component describes how the current value y_t of the series depends on the p previous (lagged) values $y_{t-1}, y_{t-2}, ..., y_{t-p}$ of the series, while the MA(q) component models the influence of the present and q past error terms $\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, ..., \varepsilon_{t-q}$ on the current value y_t. The integrated, I(d), part of the model, finally, describes how many times d the series has to be differenced to achieve stationarity. With ε_t assumed to be a Gaussian white noise error term with expected value $\mathrm{E}(\varepsilon_t) = 0$ and variance $\mathrm{Var}(\varepsilon_t) = \sigma^2$, $\Phi(z)$ and $\Theta(z)$ denoting polynomials of orders p and q, respectively, with no roots for $|z| < 1$, B denoting the backshift operator

$$B^d y_t = y_{t-d} \tag{19}$$

and c being a constant, a non-seasonal ARIMA $\left(p, d, q\right)$ model is given by

$$\Phi(B)(1 - B)^d y_t = c + \Theta(B)\varepsilon_t \tag{20}$$

using the parameterization

$$\Phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p \tag{21}$$

$$\Theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q \tag{22}$$

Further, for a time series with a seasonality of length m, with $\Phi^*(z)$ and $\Theta^*(z)$ denoting seasonal polynomials of orders P and Q, respectively, again with no roots for $|z| < 1$, and D denoting the number of times the series has to be seasonally differenced, a general seasonal ARIMA $(p, d, q)(P, D, Q)_m$ model is given by

$$\Phi^*(B^m)\,\Phi(B)\,(1 - B^m)^D (1 - B)^d y_t = c + \Theta^*(B^m)\,\Theta(B)\,\varepsilon_t \tag{23}$$

using the parameterization

$$\Phi^*(B^m) = 1 - \phi_1^* B^m - \cdots - \phi_P^* B^{Pm} \tag{24}$$

$$\Theta^*(B^m) = 1 + \theta_1^* B^m + \cdots + \theta_Q^* B^{Qm} \tag{25}$$

3.7. Estimation and model selection

The general ETS model is estimated using the `ets()` function in the ’forecast’ package. This is a fully automated procedure, which estimates the starting values $\mathbf{x}_0$ as well as the values of the parameters α, β, γ, and ϕ for all 30 possible ETS models from Equations (8) and (9) using optimization of a log-likelihood function, and then selects the best of these 30 models based on their in-sample fits, using the penalized likelihood given by the corrected Akaike information criterion (AICc). For the ARIMA model, the main task is to identify the most appropriate order of the model for each party, that is, the values of the order parameters p, d, q, P, D, and Q. This is performed using the `auto.arima()` function in the “forecast” package, which is a fully automated procedure that works by first determining the number of seasonal differences D and ordinary differences d (in that order) needed to make the time series stationary, and then estimating all possible ARIMA $(p, d, q)(P, D, Q)_m$ models for the selected values of d and D, subject to constraints on the maximum values of the order parameters p, q, P, and Q, after which the best performing model is selected according to the AICc values of the different models. For the present study, we used the default maximum values of 5 for the order parameters p and q, 2 for P and Q, 2 for d, and 1 for D, but changed the function’s default maximum value of $p + q + P + Q$ from 5 to 14. Details about the ETS and ARIMA estimation procedures are given by Hyndman and Khandakar (2008), Hyndman and Athanasopoulos (2018), and Hyndman et al. (2019).

After selecting the most appropriate ETS and ARIMA models for each party, the predictions of the results of the 2018 general election, with accompanying 95% PIs, were calculated as the one-step forecasts for these models using the `forecast()` function in the “forecast” package. In addition to the general

ETS model, point predictions and 95% PIs for the two special cases SES and HLT were also calculated using the `ses()` and `holt()` functions, respectively, which are simply wrapper functions for `forecast(ets())`.

Contrary to ARIMA models, ETS models are non-stationary and does not assume homoscedasticity (Hyndman and Khandakar 2008). The ETS, SES, and HLT methods were thus all applied to the raw (untransformed) PPS data, while the ARIMA models used PPS data that had been automatically transformed using the Box–Cox formula

$$f_\lambda\left(y_t\right) = \begin{cases} \frac{y_t^\lambda - 1}{\lambda}, & \lambda \neq 0 \\ \log\left(y_t\right), & \lambda = 0 \end{cases} \tag{26}$$

where the transformation parameter λ was selected using the method of Guerrero (1993). Mean forecasts were produced using adjusted back-transformation. R codes for model estimation and forecasting used in the present study are given in Appendix A.

4. Results

The predicted values $\hat{y}_{i,\,\text{Sep. 9, 2018}|\text{May 2018}}$ of the results of the 2018 Swedish general election using the SES, HLT, ETS, and ARIMA methods are given in Tables 3, 4, 5, and 6, respectively, together with 95% PIs and forecast errors $e_{i,\,\text{Sep. 9, 2018}}$. Table 7 provides an overview of the results by giving the absolute errors $\left|e_{i,\,\text{Sep. 9, 2018}}\right|$ and MAEs for these four methods, together with the corresponding values for the naïve method and the exit poll.

Table 3. Forecasts of the results of the 2018 Swedish general election using SES, with 95% PIs.

Party	α	Forecast (95% PI)	Forecast error
Social Democratic Party	0.9999	28.3 (21.9–34.7)	0.0
Moderate Party	0.9712	22.6 (17.5–27.7)	−2.8
Sweden Democrats	0.8562	18.0 (12.9–23.2)	−0.5
Centre Party	0.9968	8.7 (6.6–10.8)	−0.1
Left Party	0.9999	7.4 (4.9–9.9)	0.6
Liberal Party	0.9999	4.4 (0.5–8.3)	1.1
Green Party	0.8071	4.2 (1.4–7.0)	0.2
Christian Democrats	0.9999	2.9 (0.7–5.1)	3.4

Table 4. Forecasts of the results of the 2018 Swedish general election using Holt's linear trend (HLT) method, with 95% PIs.

Party	α	β	Forecast (95% PI)	Forecast error
Social Democratic Party	0.9999	0.0001	28.1 (21.6–34.6)	0.2
Moderate Party	0.9704	0.0001	22.5 (17.4–27.7)	−2.7
Sweden Democrats	0.7055	0.0001	19.0 (13.8–24.1)	−1.5
Centre Party	0.9999	0.0001	8.6 (6.5–10.7)	0.0
Left Party	0.9999	0.0001	7.4 (4.8–9.9)	0.6
Liberal Party	0.9994	0.0001	4.4 (0.4–8.4)	1.1
Green Party	0.8116	0.0001	4.2 (1.4–7.0)	0.2
Christian Democrats	0.9999	0.0042	2.8 (0.6–5.0)	3.5

Table 5. Forecasts of the results of the 2018 Swedish general election using exponential smoothing state space (ETS) models, with 95% PIs.

Party	Model	α	Forecast (95% PI)	Forecast error
Social Democratic Party	A, N, N	0.9999	28.3 (21.9–34.7)	0.0
Moderate Party	A, N, N	0.9713	22.6 (17.5–27.7)	−2.8
Sweden Democrats	M, N, N	0.8390	18.0 (9.3–26.7)	−0.5
Centre Party	M, N, N	0.9999	8.7 (6.1–11.3)	−0.1
Left Party[a]	M, M_d, N	0.9999	7.7 (5.0–10.3)	0.3
Liberal Party	A, N, N	0.9999	4.4 (0.5–8.3)	1.1
Green Party	A, N, N	0.8071	4.2 (1.4–7.0)	0.2
Christian Democrats[b]	M, N, M	0.9955	3.1 (1.9–4.3)	3.2

Note: A, additive; d, damped; M, multiplicative; N, none.
[a] $\beta = 0.5459, \phi = 0.8$.
[b] $\gamma = 0.0045$.

Table 6. Forecasts of the results of the 2018 Swedish general election using ARIMA models for Box-Cox λ-transformed data, with 95% PIs.

Party	Model	λ	Forecast (95% PI)	Forecast error
Social Democratic Party[a]	$(0,1,0)\ (2,0,2)_2$	1.18	28.7 (22.3–34.9)	−0.4
Moderate Party[b]	$(1,0,0)$	−0.40	23.1 (18.8–28.4)	−3.3
Sweden Democrats[c]	$(0,1,0)\ (1,0,0)_2$	−0.29	17.3 (11.1–26.8)	0.2
Centre Party	$(0,1,0)$	−0.32	8.8 (6.6–11.8)	−0.2
Left Party[d]	$(1,1,1)\ (2,0,2)_2$	−0.64	7.9 (5.8–11.1)	0.1
Liberal Party	$(0,1,0)$	−0.25	4.5 (3.1–6.4)	1.0
Green Party[e]	$(0,1,0)\ (1,0,1)_2$	−0.15	4.6 (3.1–6.8)	−0.2
Christian Democrats[f]	$(0,1,0)\ (0,0,2)_2$	−1.00	2.9 (2.5–3.4)	3.4

Note: $c = 0$ for all except the Moderate Party.
[a] $\phi_1^* = 0.50, \phi_2^* = -0.93, \theta_1^* = -0.38, \theta_2^* = 0.81$.
[b] $c = 0.48, \phi_1 = 0.73$.
[c] $\phi_1^* = 0.44$.
[d] $\phi_1 = -0.33, \theta_1 = 0.56, \phi_1^* = 0.37, \phi_2^* = -0.88, \theta_1^* = -0.11, \theta_2^* = 0.95$.
[e] $\phi_1^* = -0.62, \theta_1^* = 0.95$. [f] $\theta_1^* = -0.15, \theta_2^* = 0.39$.

Table 7. Absolute and mean absolute errors of forecasts of the results of the 2018 Swedish general election for different forecasting methods as well as for the exit poll, together with the length of each time series.

	Absolute forecast error						
Party	Naïve	ETS	SES	HLT	ARIMA	Exit poll	Length
Social Democratic Party	**0.0**	**0.0**	**0.0**	0.2	0.4	2.1	69
Moderate Party	2.8	2.8	2.8	**2.7**	3.3	2.0	69
Sweden Democrats	1.0	0.5	0.5	1.5	**0.2**	1.7	16
Centre Party	0.1	0.1	0.1	**0.0**	0.2	0.3	69
Left Party	0.6	0.3	0.6	0.6	**0.1**	1.0	69
Liberal Party	1.1	1.1	1.1	1.1	**1.0**	0.0	69
Green Party	**0.1**	0.2	0.2	0.2	0.2	0.2	60
Christian Democrats	3.4	**3.2**	3.4	3.5	3.4	1.1	55
Mean absolute error	1.1375	**1.025**	1.0875	1.225	1.1	1.05	

Note: ARIMA, autoregressive integrated moving average model; ETS, exponential smoothing state space model; HLT, Holt's linear trend method; SES, simple exponential smoothing method.
The lowest absolute forecast error for each party is given in **bold**.

Notably, for the SES method (Table 3), the smoothing parameter α was close to one for all parties except the Sweden Democrats and the Green Party, thus giving almost completely unsmoothed series, with $\hat{y}_t \approx y_t$. In fact, the predicted values $\hat{y}_{i,\,\text{Sep. 9, 2018}|\text{May 2018}}$ were for all these parties just the value of the PPS in

May 2018. Moreover, comparing the SES method with the general ETS model (Table 5), all parties except the Left Party and the Christian Democrats had ETS $(\cdot, N, N)$ models, thus giving the same point predictions as for the SES method. The latter two parties were also the ones for which the general ETS model produced better forecasts than the SES method, with forecast errors of 0.3 and 3.2 percentage points, compared to 0.6 and 3.4 percentage points, respectively. Overall, ETS also had the lowest MAE value of all the examined forecasting methods, followed by SES (Table 7). With MAE values of 1.025 for ETS and 1.0875 for SES, both were also performing better than the benchmark naïve method, with an MAE value of 1.1375. Notably, ETS was even performing better than the exit poll, with the latter having an MAE of 1.05.

Maybe surprisingly, the HLT method (Table 4), although being a more general method than SES, was performing bad for this data set. Even though it managed to produce slightly better forecasts than the other methods for the Moderate and Centre Parties, with an MAE of 1.225, it was beaten even by the naïve method (Table 7).

The ARIMA method (Table 6) produced a mixture of quite easy and quite complex models. While the time series for the Moderate Party was modeled as an AR(1) series, and the Centre and Liberal Parties were modeled as I(1) series, the remaining parties were all modeled with some kind of seasonal parameters, with the most complex model being the $(1, 1, 1)\ (2, 0, 2)_2$ model of the Left Party. In addition, all series had to undergo some kind of Box–Cox transformation, with λ values ranging from -1.00 for the Christian Democrats to 1.18 for the Social Democratic Party. However, despite the additional complexity of ARIMA models compared to ETS models, this did not pay out in terms of performance. Although it produced somewhat better forecasts than the other methods for the Sweden Democrats, the Left Party, and the Liberal Party, and overall performed better than the benchmark naïve method, with an MAE of 1.1 it was beaten even by the simple SES method (Table 7).

Overall the results of the Christian Democrats proved to be the hardest to predict, with all forecasts underestimating the true election result. Thus, while the results for all other parties were inside the 95% PIs for all forecasting methods, the results of the Christian Democrats were outside the 95% PIs for all forecasting methods. Even the best performing forecasting method, the general ETS model, had a forecast error of 3.2 percentage points for this party. The predictions for the Moderate Party also showed large deviations, with the best performing forecasting method, the HLT method, having a forecast error of 2.7 percentage points. Contrary to the Christian Democrats, however, all forecasts were overestimating the true election results for the Moderate Party.

The results for the Social Democratic, Centre, and Green Parties were the easiest to predict, which should come as no surprise, since the differences between the observed voting intentions from the PPS collected in May 2018 and the actual election results were small, between -0.1 and 0.1 percentage points, for these parties. Notably, however, although the values for the Social Democratic Party were exactly the same for the PPS and election data, giving a forecast error of 0.0 for the naïve, ETS, and SES methods, the ARIMA method failed considerably in this case, with a forecast error of −0.4. Another notable discrepancy between the results of the ARIMA method and those of the other forecasting methods was that the ARIMA method was the only one that underestimated the results for the Sweden Democrats, with a forecast error of 0.2, compared to values between −1.5 and −0.5 for the other methods.

Overall, from Table 7, it is notable that the ETS method, although having the lowest MAE of all the examined forecasting methods, had the lowest absolute forecast error for only two of the eight parties, and in one of these cases shared with the naïve and SES methods. As a comparison, the HLT method, which overall performed worse than even the naïve method, had the lowest absolute forecast error for two parties, and the ARIMA method, although performing worse than both the ETS and SES methods, had the lowest absolute forecast error for three parties. Thus, the strength of the ETS method lies in its overall good performance in different situations and for time series with different characteristics, although in specific cases it can be beaten by other methods.

5. Discussion

In evaluating the accuracy of automatic time series forecasting methods in predicting the results of the Swedish general election on September 9, 2018, using data from the PPS collected twice a year up to May 2018, we focused on automatically estimated ETS and ARIMA models, which are strong, efficient, and well-established state-of-the-art forecasting techniques for univarate time seris data well-suited for irregular time series such as opinion polls data. In the present study, especially the general ETS model was found to perform well, beating even the exit poll collected at the time of the election. Notably, the simplest special case of ETS models, the SES model, performed remarkably well, with an MAE only slightly larger than for the general ETS model. It even outperformed the complex seasonal ARIMA model with Box-Cox transformed data.

It should be noted that the present study used a short forecasting horizon of only one step ahead, and it is unclear have well the evaluated methods would have worked for longer forecasting horizons. Previous studies have however shown that both methods have worked well even for longer forecasting horizons, such as the 18-step-ahead forecasts for the M4 competition and 24-steps-ahead forecasts for the Tourism competition discussed by Hewamalage, Bergmeir, and Bandara (2021). Moreover, since opinion polls data are by design bounded between 0% and 100%, meaning that longer time trends are rarely observed, ETS and ARIMA models, which are not dependent on longer time trends to work well, may be well-suited even for forecasts several steps ahead when applied to this kind of data.

In the present case study, the elections results of two parties, the Moderate Party and the Christian Democrats, were found to be hard to predict, with absolute forecast errors as high as 2.7 and 3.2 percentage points, respectively, even for the best performing forecasting methods. One reason for this may be that these two parties were the ones that had changed their party leader since the prior election in 2014, with the election of September 9, 2018, thus being the acid test of the new party leaders. The latter may have been reflected in the election results of these two parties, with the Moderate Party underperforming and the Christian Democrats overperforming compared to what could have been expected from the observed PPS data. It should be noted that while the Green Party had also changed one of its two spokespersons since the prior election in 2014, their election results did not deviate much from what could be expected from the observed PPS data. This may, however, not be surprising, since with the Green Party having a two-person leadership, the influence of a person change should, arguably, be smaller in such a setting. Further research should examine if the postulated influence of party leader changes on the ability of forecasting methods to correctly predict the outcome of Swedish general elections may be observed for prior and future elections. Moreover, it should be noted that the last observed PPS data used for predicting the results of the general election in September 2018 were collected in May 2018, that is, before the most intensive part of the election campaign, when most cases of changing voting intentions should be expected to occur. Arguably, this made it harder for the forecasting methods to correctly predict the outcome of the general election, thus contributing to explain the failure of the examined forecasting methods to predict the election results for the Moderate Party and the Christian Democrats.

As a final caution, it should be noted that a limitation of a case study such as this is the small sample size, including only eight time series, with several of these having few observations. The shortest time series thus had a lenght of only 16 data points, while the longest time series had a length of 69 data points (Table 7). This also meant that it was not feasible to perform any formal statistical tests regarding if the observed differences in performance of the applied techniques were statistically significant.

5.1. Conclusion

The present case study showed that the automatic forecasting methods applied to PPS data, especially the general ETS model, overall performed well in forecasting the results of the Swedish general election on September 9, 2018. This shows the usefulness of these easily applied methods, accessible in freely available statistical software, for irregular data such as those in the present study, but also the ability of the PPS data to correctly measure voting intentions.

Further research should examine if the observed results hold also for prior and future Swedish general elections.

Acknowledgments

The author is thankful to Mariana Ehn and Jackie Casey for checking the language of the paper.

Disclosure statement

The author declares that there is no conflict of interest.

Code availability

R code used in the present study is given in Appendix A.

ORCID

Andreas Karlsson Rosenblad http://orcid.org/0000-0003-3691-8326

References

Athanasopoulos, G., R. J. Hyndman, H. Song, and D. C. Wu. 2011. "The Tourism Forecasting Competition." *International Journal of Forecasting*, 27(3):822–44.

Crone, S. F., M. Hibon, and K. Nikolopoulos. 2011. "Advances in Forecasting With Neural Networks? Empirical Evidence From the NN3 Competition on Time Series Prediction." *International Journal of Forecasting*, 27(3):635–660.

Guerrero, V. M. 1993. "Time-Series Analysis Supported by Power Transformations." *Journal of Forecasting*, 12(1):37–48.

Hewamalage, H., C. Bergmeir, and K. Bandara. 2021. "Recurrent Neural Networks for Time Series Forecasting: Current Status and Future Directions." *International Journal of Forecasting*, 37(1):388–427.

Holt, C. C. 2004. "Forecasting Seasonals and Trends by Exponentially Weighted Moving Averages." *International Journal of Forecasting*, 20:5–10.

Hyndman, R. J., G. Athanasopoulos. 2018. *Forecasting: Principles and Practice*. 2nd ed. Melbourne: OTexts.

Hyndman, R. J., G. Athanasopoulos, C. Bergmeir, G. Caceres, L. Chhay, M. O'Hara-Wild, F. Petropoulos, S. Razbash, E. Wang, and F. Yasmeen. 2019. *Forecast: Forecasting Functions for Time Series and Linear Models*. R package version 8.9.

Hyndman, R. J., Y. Khandakar. 2008. "Automatic Time Series Forecasting: The Forecast Package for R." *Journal of Statistical Software*, 27(3):1–22.

Hyndman, R. J., A. B. Koehler, J. Keith Ord, and R. D. Snyder. 2008. *Forecasting With Exponential Smoothing: The State Space Approach*. Springer.

Makridakis, S., E. Spiliotis, and V. Assimakopoulos. 2018. "The M4 Competition: Results, Findings, Conclusion and Way Forward." *International Journal of Forecasting*, 34(4):802–808.

Martínez, F., F. Charte, A. J. Rivera, and M. P. Frías. 2019. "Automatic Time Series Forecasting With GRNN: A Comparison With Other Models." In *Advances in Computational Intelligence*, edited by I. Rojas, G. Joya, and A. Catala. Cham: Springer International Publishing, pp. 198–209.

SAS Institute. 2020. *SAS/ETS 15.2 User's Guide*. Cary, NC: SAS Institute.

Statistics Sweden. 2018. *The Party Preference Survey in May 2018*. Stockholm: Statistics Sweden.

Statistics Sweden. 2019a. *Party Preference Survey (PSU)*. Stockholm: Statistics Sweden.
Statistics Sweden. 2019b. *Statistikdatabasen: Valresultat om det varit val idag (PSU)*. Stockholm: Statistics Sweden.
Sveriges Television. 2018. *SVT:s Vallokalsundersökning Riksdagsvalet 2018*. Stockholm: Sveriges Television.
Valmyndigheten. 2018. *Fördelning av mandat i riksdagen och fastställande av vilka kandidater som har valts till ledamöter och ersättare*. Number: 200 378253-18/98236. Stockholm: Valmyndigheten.

Appendix A. R code for automatic modeling and forecasting

```
library(forecast) # Loading R package 'forecast'

# Automatic estimation of a general ETS model
out.ets <- ets(data, restrict = FALSE,
    allow.multiplicative.trend = TRUE)

# One-step forecasting of the ETS model
forecast(out.ets, h = 1)

# Automatic estimation and one-step forecasting of SES model
ses(data, h = 1)

# Automatic estimation and one-step forecasting of HLT model
holt(data, h = 1)

# Automatic estimation of a general seasonal ARIMA model with
# Box-Cox transformation
out.arima <- auto.arima(data, stepwise = FALSE, approximation =
   FALSE, lambda = "auto", biasadj = TRUE, max.order = 14)

# One-step forecasting of the ARIMA model
forecast(out.arima, h = 1)
```