



Rob J Hyndman

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6. ETS models

OTexts.com/fpp/7/

Forecasting using R

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Outline

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- Holt-Winters' seasonal method https://tutorcs.com
 Taxonomy of exponential smoothing
- - WeChat: cstutorcs
- **Exponential smoothing state space models**

Simple exponential smoothing: no trend.

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■ Holt's method: linear trend.

https://tutorcs.com

holt(x, exponential=TRUE)

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■ Damped exponential trend method.

holt(x, damped=TRUE, exponential=TRUE)

Simple exponential smoothing: no trend.

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- WeChat: cstutorcs
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Assignment Project Exam Help Holt's method: linear trend.

```
halt (x)
Exponential frequency.com
  holt(x, exponential=TRUE)
```

- WeChat: cstutorcs

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Assignment Project Exam Help

Holt's method: linear trend.

```
holt(x)
Exponential (rend method.Com
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```

- Dawberthatretstutorcs
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Assignment Project Exam Help

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Outline

- Holt-Winters' seasonal method https://tutorcs.com
- 3 Taxonomy of exponential smoothing
 - WeChat: cstutorcs
- 4 Exponential smoothing state space models

Holt and Winters extended Holt's method to capture seasonality.

- Parameters: $0 \le \alpha \le 1$, $0 \le \beta^* \le 1$, 0 https://tutorcs.com seasonality.
 - WeChat: cstutorcs

Holt and Winters extended Holt's method to capture seasonality.

Assible smethin Project Example Ipone for trend, and one for seasonality.

- Parameters: $0 \le \alpha \le 1$, $0 \le \beta^* \le 1$, 0 https://tutores.com seasonality.
- Holt-Winters additive method
 - WeChat: cstutorcs

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 - Parameters: $0 \le \alpha \le 1$, $0 \le \beta^* \le$

Holt-Winters additive method

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$$b_t = \beta^* (\ell_t - \ell_{t-1}) + (1 - \beta^*) b_{t-1}$$

$$s_t = \gamma (v_t - \ell_{t-1} - b_{t-1}) + (1 - \gamma) s_{t-1}$$

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y_{t+} WeChat: cstutorcs

$$b_t = \beta^* (\ell_t - \ell_{t-1}) + (1 - \beta^*) b_{t-1}$$

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- Assible smoothin paguations—The for the level pone for trend, and one for seasonality.
 - Parameters: $0 \le \alpha \le 1$, $0 \le \beta^* \le$

Holt-Winters additive method

$$\hat{y}_{t+1} = \alpha(y_t - s_{t-m}) + (1 - \alpha)(\ell_{t-1} + b_{t-1})$$

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$$h_m^+ = \lfloor (h-1) \mod m \rfloor + 1$$

Holt-Winters multiplicative method

Holt-Winters multiplicative method ASSIGNMENT PROJECT EXAM Help $y_{t+h|t} = (\ell_t + hb_t)s_{t-m+h_m^+}$ $\ell_t = \alpha(y_t/s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$ $https://(\ell_t utoff stressed of the properties of the project of the project$

- WeChat: cstutorcs

 Most textbooks use $s_t = \gamma(y_t/\ell_t) + (1 \gamma)s_{t-m}$
- We optimize for α , β^* , γ , ℓ_0 , b_0 , s_0 , s_{-1} , ..., s_{1-m} .

Holt-Winters multiplicative method

Holt-Winters multiplicative method ASSIGNMENT PROJECT Exam Help $y_{t+h|t} = (\ell_t + hb_t)s_{t-m+h_m^+}$ $\ell_t = \alpha(y_t/s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$ $https://(\ell_t ut_{t-1} + b_{t-1}) + (1-\gamma)s_{t-m}$ $s_t = \gamma(y_t/(\ell_{t-1} + b_{t-1})) + (1-\gamma)s_{t-m}$

- WeChat: cstutorcs

 Most textbooks use $s_t = \gamma(y_t/\ell_t) + (1 \gamma)s_{t-m}$
- We optimize for α , β^* , γ , ℓ_0 , b_0 , s_0 , s_{-1} , ..., s_{1-m} .

Damped Holt-Winters method

Damped Holt-Winters multiplicative method
$$\hat{y}_{t+h|t} = [\ell_t + (1+\phi+\phi^2+\cdots+\phi^{h-1})b_t]s_{t-m+h_m^+}$$

$$\ell_t = \alpha(y_t/s_{t-m}) + (1-\alpha)(\ell_{t-1}+\phi b_{t-1})$$

$$\ell_t = \alpha(y_t/s_{t-m}) + (1-\alpha)(\ell_{t-1}+\phi b_{t-1})$$

$$s_t = \gamma[y_t/(\ell_{t-1}+\phi b_{t-1})] + (1-\gamma)s_{t-m}$$

WeChat: cstutorcs
 This is often the single most accurate forecasting method for seasonal data.

All these methods can be confusing!

- The ETS framework provides an ahttps://tutorcs.com/he best method.
- It WeChat: cstutorcs e problem of automatically forecasting pharmaceutical sales across thousands of products.

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Outline

- Holt-Winters' seasonal method https://tutorcs.com
 Taxonomy of exponential smoothing
- - wethods WeChat: cstutorcs
- **Exponential smoothing state space models**



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(N,N): Wimple exponential smoothing CSTUTOTCS



(N,N): Wimple exponential smoothing CS
(A,N): Hote's linear method



(N,N): Wimple exponential smoothing CS

(A,N): Hort's linear method

(A,A): Additive Holt-Winters' method



(N,N): Wimme exponential smoothing CS

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(A,M): Multiplicative Holt-Winters' method



(N,N): Warmer typonential smoothing CS
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(A_d,M): Damped multiplicative Holt-Winters' method



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(A,N): Holf's finear method

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(A,M): Multiplicative Holt-Winters' method

(A_d,M): Damped multiplicative Holt-Winters' method

There are 15 separate exponential smoothing methods.

R functions

- https://tutorcs.com
- WeChat: cstutorcs

R functions

- holt() implements methods (A,N), https://tutorcs.com
- hw() implements methods (A,A), (A_d,A), (WeChat: cstutorcs

R functions

- holt() implements methods (A,N), (Ad,N), (M,N), (Md,N)S.COM
- hw() implements methods (A,A), (A_d,A), (A,M), (A,M), (A,M), (A,M), (A,M).

Outline

Assignment Project Exam Help

- Holt-Winters' seasonal method https://tutorcs.com
- 3 Taxonomy of exponential smoothing

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4 Exponential smoothing state space models

Exponential smoothing

- Intil recently, there has been no stochastic modelling framework incorporating likelihood ASSIGNMENTE LICIOSECTATION HELD
 - Ord, Koehler & Snyder (JASA, 1997) and
 Hadran White Snyder and Grose (IJF, 2002) Phowed that all Es methods (including non-linear methods) are optimal forecasts from in Wechate estutores
 - Hyndman et al. (2008) provides a comprehensive and up-to-date survey of area.

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Hyndman et al. (2008) pro comprehensive and up-to-

The forecast package im space framework Example 1 P. S. Keehler 1 P. J. Keehler 1 P. J. Keehler 1 P. S. Keehler 1 P. S

Correcasting
With Exponential
Smoothing

The Space Approach

Springer

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 Hyndman et al. (2008) provides a
 - Hyndman et al. (2008) provides a comprehensive and up-to-date survey of area.
 - The **forecast** package implements the state space framework.



Gen WeChat: cstutorcs, Seasonal)



Geneval aptation ETS (Error Trend, Seasonal)



Geneval action: ETS(Error Trend, Seasonal)
Exponential Smoothing



Geneval action: Exponential Smoothing

ETS(A,N,N): Simple exponential smoothing with additive errors



Geneval action: Exponential Smoothing

ETS(A,A,N): Holt's linear method with additive errors



Geneval a Cation: ETS (Error Trend, Seasonal)
Exponential Smoothing

ETS(A,A,A): Additive Holt-Winters' method with additive errors



Genevi a Cation: EXECUTOR Trend, Seasonal)
Exponential Smoothing

ETS(M,A,M): Multiplicative Holt-Winters' method with multiplicative errors



Geneval a Cation: ETS (Error Trend, Seasonal)
Exponential Smoothing

ETS(A,A_d,N): Damped trend method with additive errors



Geneval action: EXECUTE Trend, Seasonal)
Exponential Smoothing

There are 30 separate models in the ETS framework

```
SES
\hat{y}_{t+1|t} = \ell_t
Assignment = Payo f(1Ct \alpha)\ell_t x_1 am Help
```

https://tutorcs.com

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SES

$$\hat{y}_{t+1|t} = \ell_t$$
Assignment = Paroj (1Ct α) i_t x_t x_t x_t x_t

If
$$\varepsilon_t = y_t - \hat{y}_{t-1|t}$$

$$\sim \frac{\text{Wethos}^2}{\text{ETS(A,N,N)}}$$

$$y_t = \psi + Chat:$$
 $\ell_t = \alpha y_t + Chat:$
 $\ell_{t-1} + \alpha \varepsilon_t$

SES

$$\hat{y}_{t+1|t} = \ell_t$$

$$ssignment = Poyo + cict \alpha P_t x_1 am Help$$

If
$$\varepsilon_t = y_t - \hat{y}_{t-1|t}$$
 If $\varepsilon_t = (y_t - \hat{y}_{t-1|t})/\hat{y}_{t-1|t}$ $\sim 10^{10} \text{ (0, } \sigma^2)$, then ETS(A,N,N) ETS(M,N,N)

ETS(A.N.N)

$$y_t = \psi + C_{t-\alpha}$$
 $\ell_t = \alpha y_t + C_{t-\alpha}$
 ℓ_{t-1}
 $\ell_{t-1} + \alpha \varepsilon_t$

$y_t = \psi_t + Chat: cstutorcs_{t=0}^{t-1}(1+\varepsilon_t)$ $\ell_t = \alpha y_t + (1-\alpha)\ell_{t-1}$ $=\ell_{t-1}(1+\alpha\varepsilon_t)$

SES

$$\hat{\mathbf{y}}_{t+1|t} = \ell_t$$
Assignment Povoj (1Ct α) ℓ_t x am Help

If
$$\varepsilon_t = y_t - \hat{y}_{t-1|t}$$
 If $\varepsilon_t = (y_t - \hat{y}_{t-1|t})/\hat{y}_{t-1|t}$ ~ 1000 ETS(A,N,N) ETS(M,N,N)

$$y_{t} = \begin{cases} y_{t} + Chat: \\ \ell_{t} = \alpha y_{t} + Chat: \\ \ell_{t-1} = \ell_{t-1} + \alpha \varepsilon_{t} \end{cases} cstu \begin{cases} y_{t} = \ell_{t-1}(1 + \varepsilon_{t}) \\ \ell_{t} = \alpha y_{t} + (1 - \alpha)\ell_{t-1} \\ = \ell_{t-1}(1 + \alpha \varepsilon_{t}) \end{cases}$$

All exponential smoothing methods can be written using analogous state space equations.

Assignment Project Exam Help

ETS(M,A,M)

https://tutorest.com
$$\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha \varepsilon_t)$$
We that:
$$CStutores$$

$$k_{t-m} = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$$

where $\beta = \alpha \beta^*$.

- Prediction intervals can be obtained by simulating many future sample paths.
 https://tutorcs.com/ https://tutorcs.com/ and the control of the con
- be obtained analytically as well.
- A WeChat: cstutorcs is give the same point forecasts.
- Estimation is handled via maximizing the likelihood of the data given the model.

All the methods can be written in this state

- Prediction intervals can be obtained by
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 For many models, the prediction intervals can be obtained analytically as well.
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 For many models, the prediction intervals can be obtained analytically as well.
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All the methods can be written in this state

- Prediction intervals can be obtained by simulating many future sample paths.
- simulating many future sample paths.

 For many models, the prediction intervals can be obtained analytically as well.
- Additive and multiplicative yersigns give the same point forecasts.
- Estimation is handled via maximizing the likelihood of the data given the model.

$$AIC = -2 \log(Likelihood) + 2p$$

where p is the number of estimated parameters in parameters in the highest the model. The model is the model in the model

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$$AIC = -2 \log(Likelihood) + 2p$$

Awhere p is the number of estimated parameters in paramete

Minimizing the AIC gives the best model for property. //tutorcs.com

AIC corrected (for small sample bias)

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Schwartz' Bayesian IC

 $BIC = AIC + p(\log(n) - 2)$

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Minimizing the AIC gives the best model for predictive://tutorcs.com

AIC corrected (for small sample bias)

WeChat: cstutorcs 2

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Schwartz' Bayesian IC

$$\mathsf{BIC} = \mathsf{AIC} + p(\log(n) - 2)$$

■ Value of AIC/AICc/BIC given in the R output.

Assignment Project Exam Help useful in comparison to AIC value for another model fitted, to same data set.

- model fitted to same data set. **https://tutorcs.com**values close to the minimum.
- WeChat: cstutorcs is not regarded as substantial model.
- AIC can be negative.

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- From Hyndman et al. (2008): Assignments Project Exampletp to the data. Estimate parameters and initial values using MLE torcs.com
 Select best method using AIC.

 - Produce forecasts using best method.
 WeChat: cstutorcs inderlying

- Assignment of the transproprieto to the data. Estimate parameters and initial values using MLE.

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 Select best method using AIC.**

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 ASSLED DECEMBER 1 (2008):

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Method performed very well in M3 competition.

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ILLDS.//LUTORCS.COM**

Select best method using AIC.

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Method performed very well in M3 competition.

```
fit <- ets(ausbeer)</pre>
Assignments Project Exam Help
 fcast2 <- forecast(fit2, h=20)</pre>
     https://tutorcs.com
   WeChat: cstutorcs
```

```
fit <- ets(ausbeer)</pre>
Assignments Projecto Exam Help
 fcast2 <- forecast(fit2, h=20)</pre>
ets(y, model ZZZ", damped=NULL; alpha=NULL.
    beta=NULL, gamma=NULL, phi=NULL.
    additive.only=FALSE,
lowevec Cochadi, 3C, Stattorcs
    upper=c(rep(0.9999,3),0.98),
    opt.crit=c("lik","amse","mse","sigma"), nmse=3,
    bounds=c("both", "usual", "admissible"),
    ic=c("aic","aicc","bic"), restrict=TRUE)
```

```
> fit
ETS(M,Md,M)
```

Assignment Project Exam Help beta = 0.0454 gamma = 0.1947 phi https://tutorcs.com

```
Initial states:

l = 263.8531
b = We Chat: cstutorcs
s = 1.1856 0.9109 0.8612 1.0423
sigma: 0.0356
```

AIC AICc BIC 2272.549 2273.444 2302.715

```
> fit2
ETS(A,A,A)
```

Assignment Project Exam Help beta = 0.0304

https://tutorcs.com

```
Initial states:
```

l = 255.6559

b = \$\sqrt{687}{\$c\$hat:3c\$stutorc\$

```
sigma: 15.9053
```

```
AIC AICc BIC 2312.768 2313.481 2339.583
```

Assignment Project ExamuHelp the AIC, AICc or BIC.

- https://tutorcs.com
- Produces_prediction intervals for every model
- EWeChat: cstutorcs sible (equivalent to invertible)
- Produces an object of class ets.

- Assignment Project Examulterp the AIC. AICc or BIC.
 - Cantandle Any combination of trend, seasonality and damping
 - Produces prediction intervals for every model
 - EWeChat: cstutorcs ssible

ets() function

- Assignment Project Examulalp
 the AIC, AICC or BIC.
 - Canthandle hay combination of trend, seasonality and damping
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- Assignment Project Examulting
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 - Envresthepatanesettlaterussible (equivalent to invertible)
 - Produces an object of class ets.

```
Assignment Project Exam Help residuals(), fitted(), simulate() ahttps://dutorcs.com
```

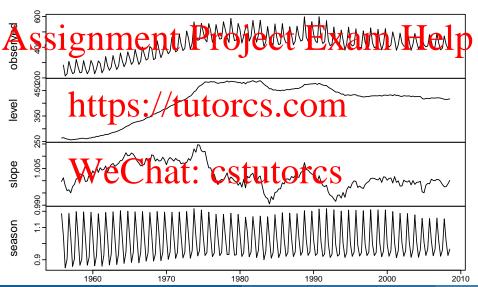
plot() function shows time plots of the or WeChat: estutores the the extracted components (level, growth and seasonal).

ets objects

Assignment Project Exam Help residuals(), fitted(), simulate() ahttps://dutorcs.com

plot() function shows time plots of the original seciety to be with the extracted components (level, growth and seasonal).

Plot(fit)
Decomposition by ETS(M,Md,M) method



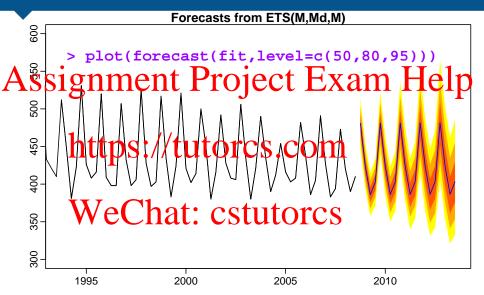
Goodness-of-fit

Assignment Project Exam Help ME RMSE MAE MPE MAPE MASE 0.17847 15.48781 11.77800 0.07204 2.81921 0.20705 https://tutorcs.com

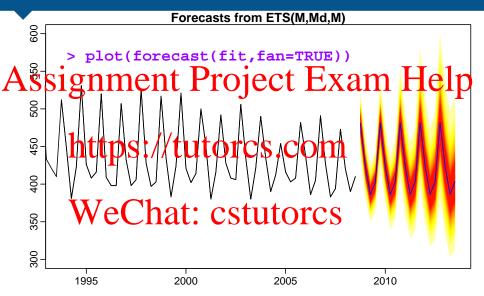
> accuracy(fit2)

ME RMSE MAE MPE MAPE MASE -0.1171 W 2 (52 h 2 t 18920 S t 198765 c 2 s 91255 0.21428

Forecast intervals



Forecast intervals



Assignment Project Exam Help

Unstable models

- ETS(M,M,A)
- Assignment Project Exam Help
 - ETS(A,A,M)
 - Etateps!!//tutorcs.com
 - ETS(A,M,N)

 - ETS(A,M,A)

 ets(A,M,A)

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 - ETS(A,Md,N)
 - ETS(A,M_d,A)
 - ETS(A,Md,M)

Unstable models

- ETS(M,M,A)
- ssignment Project Exam Help
 - ETS(A,A,M)
 - ETATOPS!! //tutores fine for short- to
 - ETS(A,M,N)

 - ETS(A,MA)

 ETS(A,MA)

 at: cstrictlyopeitive.
 - $ETS(A,M_d,N)$
 - $ETS(A,M_d,A)$
 - $ETS(A,M_d,M)$

- In practice, the models
- m-term forecasts provided the data are

Forecastability conditions

```
Assignmentamentale damped=NULL, alpha=NULL, Assignmentamentale damped=NULL, alpha=NULL, al
                                                   additive.only=FALSE,
                                                  httpS-ep(fulgercs, con
                                                   opt.crit=c("lik","amse","mse","sigma"),
                                                  nmWeChat: cstutorcs
bounds=c("both", "usual", "admissible"),
                                                   ic=c("aic","aicc","bic"), restrict=TRUE)
```

The magic forecast() function

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- ets object (or the output from many other time settps://tutorcs.com
- If you use forecast directly on data, it will select an ETS model automatically and then reWreChat: CStutorcs

The magic forecast() function

Assignment Project Exam Help forecast returns forecasts when applied to an

- ets object (or the output from many other time senet psde stutores.com
- If you use forecast directly on data, it will select an ETS model automatically and then return creatile. CSTUTOTCS