MONASH University

MONASH BUSINESS SCHOOL

Tidy Forecasting in R

tsibble

Fable

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Outline

forecast package

Pre 2003	Private functions used for consulting projec
July/August 2003	**ets** and **thetaf** added
August 2006	v1.0 available on CRAN
May 2007	**auto.arima** added
May 2010	**arfima** added
Feb/March 2011	**tslm**, **stlf**, **naive**, **snaive** added
August 2011	v3.0. Box Cox transformations added
December 2011	**tbats** added
April 2012	Package moved to github
November 2012	v4.0. **nnetar** added
June 2013	Major speed-up of **ets**
February 2016	v7.0. Added ggplot2 graphics
February 2017	v8.0. Added **checkresiduals**, **tsCV** and **%>%**
April 2018	v8.3. Added **mstl**

fable package

A replacement for the forecast package.

Why change?

- Integrating with tidyverse packages
- Designed for forecasting many related time series
- Consistency of interface using formulas
- Distribution forecasting rather than point + interval
- Flexible transformations
- Sub-daily data and multiple seasonal data handled more easily
- Simpler interface for forecast reconciliation

Outline

Formula model specification

```
?ets
```

ets {forecast} R Documentation

Exponential smoothing state space model

Description

Returns ets model applied to y.

Usage

```
ets(y, model = "ZZZ", damped = NULL, alpha = NULL, beta = NULL,
  gamma = NULL, phi = NULL, additive.only = FALSE, lambda = NULL,
  biasadj = FALSE, lower = c(rep(1e-04, 3), 0.8), upper = c(rep(0.9999,
  3), 0.98), opt.crit = c("lik", "amse", "mse", "sigma", "mae"), nmse = 3,
  bounds = c("both", "usual", "admissible"), ic = c("aicc", "aic", "bic"),
  restrict = TRUE, allow.multiplicative.trend = FALSE,
  use.initial.values = FALSE, na.action = c("na.contiguous", "na.interp",
  "na.fail"), ...)
```

Formula model specification

```
?auto.arima
```

auto.arima {forecast} R Documentation

Fit best ARIMA model to univariate time series

Description

Returns best ARIMA model according to either AIC, AICc or BIC value. The function conducts a search over possible model within the order constraints provided.

Usage

```
auto.arima(y, d = NA, D = NA, max.p = 5, max.q = 5, max.P = 2,
  max.Q = 2, max.order = 5, max.d = 2, max.D = 1, start.p = 2,
  start.q = 2, start.P = 1, start.Q = 1, stationary = FALSE,
  seasonal = TRUE, ic = c("aicc", "aic", "bic"), stepwise = TRUE,
  trace = FALSE, approximation = (length(x) > 150 | frequency(x) > 12),
  truncate = NULL, xreg = NULL, test = c("kpss", "adf", "pp"),
  seasonal.test = c("seas", "ocsb", "hegy", "ch"), allowdrift = TRUE,
  allowmean = TRUE, lambda = NULL, biasadj = FALSE, parallel = FALSE,
  num.cores = 2, x = y, ...)
```

Formula model specification

To simplify model building, we use a model formula. This should be more familiar to those who have done regression modelling.

```
t(y) ~ {model specification}
```

LHS: Response

- Defines the response variable from the data
- Specification of transformations (which are automatically back-transformed)

RHS: Specials

- Model specific special functions
- Exogenous regressors (if supported by model)

Outline

Example: Australian eating-out expenditure

```
fpp2::auscafe
```

```
##          Jan   Feb   Mar   Apr   May   Jun   Jul   Aug   Sep
## 1982                   0.342 0.342 0.329 0.339 0.332 0.342
## 1983 0.369 0.348 0.366 0.351 0.360 0.347 0.364 0.376 0.378
## 1984 0.389 0.377 0.398 0.383 0.414 0.382 0.393 0.409 0.395
## 1985 0.426 0.392 0.416 0.420 0.446 0.407 0.449 0.466 0.455
## 1986 0.504 0.453 0.480 0.497 0.531 0.485 0.526 0.538 0.537
## 1987 0.572 0.525 0.544 0.558 0.565 0.542 0.599 0.584 0.593
## 1988 0.605 0.586 0.625 0.612 0.630 0.635 0.659 0.656 0.660
## 1989 0.733 0.661 0.713 0.694 0.710 0.722 0.741 0.746 0.767
## 1990 0.858 0.764 0.840 0.805 0.809 0.799 0.815 0.828 0.812
## 1991 0.862 0.771 0.813 0.797 0.821 0.801 0.829 0.854 0.882
## 1992 0.938 0.862 0.936 0.932 0.929 0.869 0.891 0.875 0.914
## 1993 0.918 0.838 0.870 0.862 0.852 0.828 0.882 0.867 0.905
## 1994 0.985 0.902 1.015 0.939 0.941 0.935 1.013 1.018 1.041
## 1995 1.076 0.982 1.099 1.068 1.083 1.045 1.094 1.110 1.126
## 1996 1.213 1.128 1.180 1.169 1.146 1.109 1.138 1.146 1.105
## 1997 1.180 1.060 1.148 1.141 1.170 1.113 1.165 1.173 1.154
## 1998 1.186 1.050 1.141 1.107 1.144 1.088 1.162 1.145 1.149
## 1999 1.244 1.124 1.245 1.236 1.271 1.208 1.219 1.234 1.261
```

Example: Australian eating-out expenditure

```r
library(tsibble)
cafe <- as_tsibble(fpp2::auscafe)
cafe
```

```
## # A tsibble: 426 x 2 [1MONTH]
##         index value
##         <mth> <dbl>
##  1 1982 Apr 0.342
##  2 1982 May 0.342
##  3 1982 Jun 0.329
##  4 1982 Jul 0.338
##  5 1982 Aug 0.332
##  6 1982 Sep 0.342
##  7 1982 Oct 0.358
##  8 1982 Nov 0.375
##  9 1982 Dec 0.433
## 10 1983 Jan 0.369
## # ... with 416 more rows
```

Example: Australian eating-out expenditure

```r
library(fable)
cafe %>% ARIMA(log(value))
```

```
## # A mable: 1 model [1MONTH]
##   data                       model
##   <list>                     <model>
## 1 <tsibble [426 x 2]> ARIMA(2,1,1)(2,1,2)[12]
```

Example: Australian eating-out expenditure

```
cafe %>% ARIMA(log(value)) %>% summary()
```

```
## Series: log(value)
## ARIMA(2,1,1)(2,1,2)[12]
##
## Coefficients:
##          ar1     ar2    ma1   sar1    sar2   sma1   sma2
##       -0.925  -0.318  0.588  0.724  -0.213  -1.44  0.557
## s.e.   0.182   0.060  0.189  0.174   0.074   0.17  0.149
##
## sigma^2 estimated as 0.000554:  log likelihood=959
## AIC=-1903   AICc=-1903   BIC=-1871
##
## Training set error measures:
##                    ME   RMSE    MAE     MPE MAPE  MASE
## Training set -0.00106 0.0371 0.0267 -0.0506 1.78 0.256
##                 ACF1
## Training set -0.0184
```

Example: Australian eating-out expenditure

```r
cafe %>% ARIMA(log(value)) %>% forecast()
```

```
## # A fable: 1 forecast [1MONTH]
##   data                   model                        forecast
##   <list>                 <model>                      <fc>
## 1 <tsibble [426 x 2]> ARIMA(2,1,1)(2,1,2)[12] ~t(N) [h=24
```

Example: Australian eating-out expenditure

```r
cafe %>% ARIMA(log(value)) %>% forecast() %>%
  summary()
```

```
## # A tsibble: 24 x 4 [1MONTH]
##        index  mean              80%              95%
##        <mth> <dbl>           <hilo>           <hilo>
##  1 2017 Oct  3.81 [3.70, 3.93]80 [3.64, 3.99]95
##  2 2017 Nov  3.79 [3.65, 3.93]80 [3.58, 4.00]95
##  3 2017 Dec  4.17 [3.99, 4.34]80 [3.91, 4.43]95
##  4 2018 Jan  3.73 [3.55, 3.90]80 [3.46, 4.00]95
##  5 2018 Feb  3.40 [3.22, 3.57]80 [3.14, 3.67]95
##  6 2018 Mar  3.77 [3.56, 3.99]80 [3.46, 4.10]95
##  7 2018 Apr  3.70 [3.48, 3.93]80 [3.37, 4.05]95
##  8 2018 May  3.76 [3.52, 4.00]80 [3.40, 4.13]95
##  9 2018 Jun  3.66 [3.41, 3.90]80 [3.29, 4.04]95
## 10 2018 Jul  3.88 [3.61, 4.15]80 [3.48, 4.31]95
## # ... with 14 more rows
```

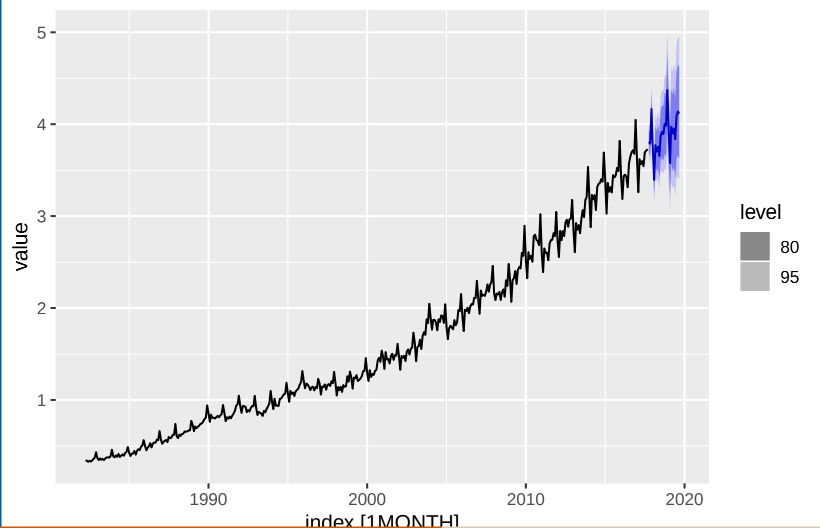
Example: Australian eating-out expenditure

```r
cafe %>% ARIMA(log(value)) %>% forecast() %>%
  summary(level=90)
```

```
## # A tsibble: 24 x 3 [1MONTH]
##       index  mean           90%
##       <mth> <dbl>        <hilo>
##  1 2017 Oct  3.81 [3.66, 3.96]90
##  2 2017 Nov  3.79 [3.62, 3.97]90
##  3 2017 Dec  4.17 [3.95, 4.39]90
##  4 2018 Jan  3.73 [3.50, 3.96]90
##  5 2018 Feb  3.40 [3.18, 3.62]90
##  6 2018 Mar  3.77 [3.51, 4.05]90
##  7 2018 Apr  3.70 [3.42, 3.99]90
##  8 2018 May  3.76 [3.46, 4.07]90
##  9 2018 Jun  3.66 [3.35, 3.98]90
## 10 2018 Jul  3.88 [3.54, 4.24]90
## # ... with 14 more rows
```

Example: Australian eating-out expenditure

```r
cafe %>% ARIMA(log(value)) %>% forecast() %>% autoplot()
```



Outline

Example: Half-hourly electricity demand

```
elecdemand
```

```
## # A tsibble: 17,520 x 4 [30MINUTE]
##    index               Demand Temperature WorkDay
##    <dttm>               <dbl>       <dbl>   <dbl>
##  1 2014-01-01 00:00:00   3.91        18.2       0
##  2 2014-01-01 00:30:00   3.67        17.9       0
##  3 2014-01-01 01:00:00   3.50        17.6       0
##  4 2014-01-01 01:30:00   3.34        16.8       0
##  5 2014-01-01 02:00:00   3.20        16.3       0
##  6 2014-01-01 02:30:00   3.10        16.6       0
##  7 2014-01-01 03:00:00   3.04        16.6       0
##  8 2014-01-01 03:30:00   3.01        16.7       0
##  9 2014-01-01 04:00:00   3.02        16.2       0
## 10 2014-01-01 04:30:00   3.03        16.6       0
```

Example: Half-hourly electricity demand

```r
fit2 <- ARIMA(elecdemand,
  Demand ~ Temperature + I(Temperature^2) + WorkDay)
summary(fit2)
```

```
## Series: Demand
## Regression with ARIMA(1,1,0)(2,0,2)[2] errors
##
## Coefficients:
##         ar1    sar1   sar2    sma1    sma2  Temperature
##       0.853  -0.181  0.523  -0.066  -0.792       -0.009
## s.e.  0.005   0.015  0.012   0.012   0.011        0.002
##       I(Temperature^2)  WorkDay
##                      0    0.016
## s.e.                 0    0.006
##
## sigma^2 estimated as 0.00846:  log likelihood=16949
## AIC=-33881   AICc=-33881   BIC=-33811
##
## Training set error measures:
##                    ME  RMSE    MAE     MPE MAPE  MASE  ACF1
## Training set 6.51e-06 0.092 0.0634 0.00633 1.39 0.292 0.103
```

Outline

Example: Australian prison population

```
fpp2::prisonLF
```

```
## # A tibble: 1,536 x 5
##    state gender legal     t          count
##    <fct> <fct>  <fct>     <date>     <dbl>
##  1 ACT   Female Remanded 2005-03-01     2
##  2 ACT   Female Remanded 2005-06-01     4
##  3 ACT   Female Remanded 2005-09-01     1
##  4 ACT   Female Remanded 2005-12-01     4
##  5 ACT   Female Remanded 2006-03-01     4
##  6 ACT   Female Remanded 2006-06-01     6
##  7 ACT   Female Remanded 2006-09-01     9
##  8 ACT   Female Remanded 2006-12-01     6
##  9 ACT   Female Remanded 2007-03-01     4
## 10 ACT   Female Remanded 2007-06-01     4
## # ... with 1,526 more rows
```

Example: Australian prison population

```r
prison <- fpp2::prisonLF %>%
  mutate(qtr=yearquarter(t)) %>%
  select(-t) %>%
  as_tsibble(index=qtr, key=id(state,gender,legal))
prison
```

```
## # A tsibble: 1,536 x 5 [1QUARTER]
## # Key:       state, gender, legal [32]
##    state gender legal    count     qtr
##    <fct> <fct>  <fct>    <dbl>   <qtr>
##  1 ACT   Female Remanded     2 2005 Q1
##  2 ACT   Female Remanded     4 2005 Q2
##  3 ACT   Female Remanded     1 2005 Q3
##  4 ACT   Female Remanded     4 2005 Q4
##  5 ACT   Female Remanded     4 2006 Q1
##  6 ACT   Female Remanded     6 2006 Q2
```

Example: Australian prison population

```r
prison %>% ETS(count)
```

```
## # A mable: 32 models [1QUARTER]
## # Key:     state, gender, legal [32]
##    state gender legal      data                 model
##    <fct> <fct>  <fct>      <list>               <model>
##  1 ACT   Female Remanded   <tsibble [48 x 2]> ETS(M,A,N)
##  2 ACT   Female Sentenced <tsibble [48 x 2]> ETS(A,A,N)
##  3 ACT   Male   Remanded   <tsibble [48 x 2]> ETS(M,N,N)
##  4 ACT   Male   Sentenced <tsibble [48 x 2]> ETS(A,N,N)
##  5 NSW   Female Remanded   <tsibble [48 x 2]> ETS(M,N,M)
##  6 NSW   Female Sentenced <tsibble [48 x 2]> ETS(M,N,M)
##  7 NSW   Male   Remanded   <tsibble [48 x 2]> ETS(M,A,A)
##  8 NSW   Male   Sentenced <tsibble [48 x 2]> ETS(M,A,A)
##  9 NT    Female Remanded   <tsibble [48 x 2]> ETS(M,N,N)
## 10 NT    Female Sentenced <tsibble [48 x 2]> ETS(M,A,A)
## # ... with 22 more rows
```

Example: Australian prison population

```r
prison %>% ETS(count) %>% forecast()
```

```
## # A fable: 32 forecasts [1QUARTER]
## # Key:     state, gender, legal [32]
##    state gender legal      data              model      forecast
##    <fct> <fct>  <fct>      <list>            <model>    <fc>
##  1 ACT   Female Remanded   <tsibble [48~ ETS(M,A,N) ~N [h=8]
##  2 ACT   Female Sentenced <tsibble [48~ ETS(A,A,N) ~N [h=8]
##  3 ACT   Male   Remanded   <tsibble [48~ ETS(M,N,N) ~N [h=8]
##  4 ACT   Male   Sentenced <tsibble [48~ ETS(A,N,N) ~N [h=8]
##  5 NSW   Female Remanded   <tsibble [48~ ETS(M,N,M) ~N [h=8]
##  6 NSW   Female Sentenced <tsibble [48~ ETS(M,N,M) ~N [h=8]
##  7 NSW   Male   Remanded   <tsibble [48~ ETS(M,A,A) ~N [h=8]
##  8 NSW   Male   Sentenced <tsibble [48~ ETS(M,A,A) ~N [h=8]
##  9 NT    Female Remanded   <tsibble [48~ ETS(M,N,N) ~N [h=8]
## 10 NT    Female Sentenced <tsibble [48~ ETS(M,A,A) ~N [h=8]
## # ... with 22 more rows
```


Aggregation and reconciliation not yet implemented.

Outline

Equivalent methods: forecast $\longrightarrow$ fable

```
auto.arima ⟶ ARIMA
ets        ⟶ ETS
tslm/lm    ⟶ LM
tbats      ⟶ TBATS
nnetar     ⟶ NNAR
stlm       ⟶ STL %>%
              modelcomponents(
                ETS(seasadj),SNAIVE(season))
```

- All functions have a formula interface with automatic modelling if no formula provided.
- All functions produce `mable` class objects.

Equivalent methods: forecast ⟶ fable

```
naive    ⟶ NAIVE %>% forecast
snaive   ⟶ SNAIVE %>% forecast
thetaf   ⟶ THETA %>% forecast
stlf     ⟶ STL %>%
             modelcomponents(
              ETS(seasadj),SNAIVE(season)) %>%
             forecast
hw       ⟶ HW %>% forecast
holt     ⟶ HOLT %>% forecast
ses      ⟶ SES %>% forecast
splinef  ⟶ SPLINE %>% forecast
croston  ⟶ CROSTON %>% forecast
```

- `forecast` produces `fable` class objects

Outline

Extending fable

fable simplifies the times-series model development process

Tools to easily create new fable models

- Easily create specials for model formulae
- Focus on model estimation and forecasts

Automatically supported fable functionality

- Transformations and back-transformations (with bias adjustments)
- Plotting tools
- Accuracy measures and evaluation
- Model combinations (hierarchies & ensembles)

Outline

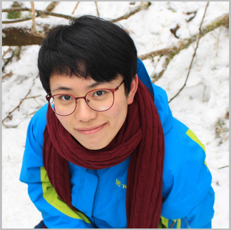
More information

tsibble

Fable

```r
devtools::install_github("tidyverts/tsibble")
devtools::install_github("tidyverts/fable")
```

Di Cook


Earo Wang


Mitchell O'Hara-Wild

Follow our progress

- `tidyverts.org`
- `robjhyndman.com/hyndsight`