



# ETC3550: Applied forecasting for business and economics

Ch12. Some practical forecasting issues

OTexts.org/fpp2/

- 1 Models for different frequencies
- 2 Ensuring forecasts stay within limits
- **3** Forecast combinations
- 4 Missing values
- **5** Outliers

#### Models for annual data

■ ETS, ARIMA, Dynamic regression

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### Models for quarterly data

ETS, ARIMA/SARIMA, Dynamic regression,
 Dynamic harmonic regression, STL+ETS,
 STL+ARIMA

#### Models for annual data

■ ETS, ARIMA, Dynamic regression

## Models for quarterly data

ETS, ARIMA/SARIMA, Dynamic regression,
 Dynamic harmonic regression, STL+ETS,
 STL+ARIMA

#### Models for monthly data

ETS, ARIMA/SARIMA, Dynamic regression,
 Dynamic harmonic regression, STL+ETS,
 STL+ARIMA

#### Models for weekly data

 ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA, TBATS

#### Models for weekly data

 ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA, TBATS

### Models for daily, hourly and other sub-daily data

 ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA, TBATS

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## **Positive forecasts**

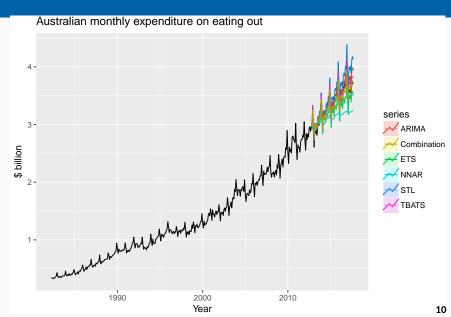
```
eggs %>%
  ets(model="AAN", damped=FALSE, lambda=0) %>%
  forecast(h=50, biasadj=TRUE) %>%
  autoplot()
   Forecasts from ETS(A,A,N)
                                                              level
200 -
                                                                 80
                                                                 95
 100 -
                       1950
                                         2000
                              Time
```

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#### **Clemen (1989)**

"The results have been virtually unanimous: combining multiple forecasts leads to increased forecast accuracy. ... In many cases one can make dramatic performance improvements by simply averaging the forecasts."

```
train <- window(auscafe, end=c(2012,9))
h <- length(auscafe) - length(train)</pre>
ETS <- forecast(ets(train), h=h)</pre>
ARIMA <- forecast(auto.arima(train, lambda=0, biasadj=TRUE),
  h=h)
STL <- stlf(train, lambda=0, h=h, biasadj=TRUE)</pre>
NNAR <- forecast(nnetar(train), h=h)</pre>
TBATS <- forecast(tbats(train, biasadj=TRUE), h=h)
Combination <- (ETS[["mean"]] + ARIMA[["mean"]] +</pre>
  STL[["mean"]] + NNAR[["mean"]] + TBATS[["mean"]])/5
autoplot(auscafe) +
  autolayer(ETS, series="ETS", PI=FALSE) +
  autolayer(ARIMA, series="ARIMA", PI=FALSE) +
  autolayer(STL, series="STL", PI=FALSE) +
  autolayer(NNAR, series="NNAR", PI=FALSE) +
  autolayer(TBATS, series="TBATS", PI=FALSE) +
  autolayer(Combination, series="Combination") +
  xlab("Year") + ylab("$ billion") +
  ggtitle("Australian monthly expenditure on eating out")
```



```
c(ETS = accuracy(ETS, auscafe)["Test set","RMSE"],
ARIMA = accuracy(ARIMA, auscafe)["Test set","RMSE"],
STL-ETS = accuracy(STL, auscafe)["Test set","RMSE"],
NNAR = accuracy(NNAR, auscafe)["Test set","RMSE"],
TBATS = accuracy(TBATS, auscafe)["Test set","RMSE"],
Combination =
    accuracy(Combination, auscafe)["Test set","RMSE"])
```

##	ETS	ARIMA	STL-ETS	NNAR
##	0.1370	0.1215	0.2145	0.3026
##	TBATS	Combination		
##	0.0941	0.0714		

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#### Functions which can handle missing values

- auto.arima(), Arima()
- tslm()
- nnetar()

#### Models which cannot handle missing values

- ets()
- stl()
- stlf()
- tbats()

#### Functions which can handle missing values

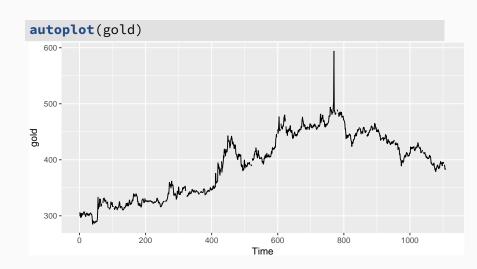
- auto.arima(), Arima()
- tslm()
- nnetar()

#### Models which cannot handle missing values

- ets()
- stl()
- stlf()
- tbats()

#### What to do?

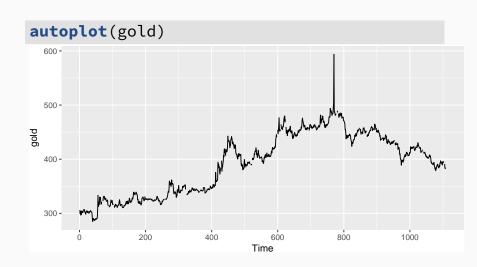
- Model section of data after last missing value.
- Estimate missing values with na.interp().



```
gold %>% na.interp() %>%
  autoplot(series="Interpolated") +
    autolayer(gold, series="Original") +
    scale_color_manual(
       values=c(Interpolated="red",Original="gray"))
600 -
500 -
                                                        series
                                                          Interpolated
                                                          Original
400 -
    m Muchan Manuel
300 -
                     400
                             600
                                     800
                                             1000
                                                               15
                           Time
```

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### **Outliers**



## **Outliers**

```
tsoutliers (gold)
```

```
## $index
## [1] 770
##
## $replacements
## [1] 495
```

#### **Outliers**

