

ETC3550 Applied forecasting for business and economics

Ch12. Some practical forecasting issues

OTexts.org/fpp3/

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

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Models for annual data

■ ETS, ARIMA, Dynamic regression

Models for annual data

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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

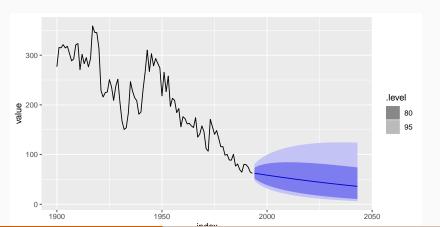
Models for daily, hourly and other sub-daily data

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

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Positive forecasts

```
eggs <- as_tsibble(fma::eggs)
eggs %>%
  model(ETS(log(value) ~ error("A") + trend("A") + season("N"))) %>%
  forecast(h=50) %>%
  autoplot(eggs)
```



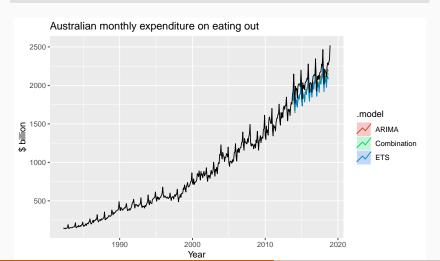
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Clemen (1989)

"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."

```
aus_cafe <- aus_retail %>%
  filter(Industry == "Cafes, restaurants and catering services") %>%
  summarise(Turnover = sum(Turnover))
fc <- aus cafe %>%
  filter(Month <= yearmonth("2013 Sep")) %>%
  model(
    ETS = ETS(Turnover),
   ARIMA = ARIMA(Turnover)
  ) %>%
  mutate(
    Combination = (ETS + ARIMA)/2
  ) %>%
  forecast(h = "5 years")
```

```
fc %>% autoplot(aus_cafe, level = NULL) +
labs(x = "Year", y = "$ billion",
    title = "Australian monthly expenditure on eating out")
```



```
fc %>% accuracy(aus_cafe)
```

A tibble: 3 x 9

```
##
     .model
                  .type
                           ME
                                RMSE
                                       MAE
                                              MPE
                                                   MAPE
                                                         MASE
                                                                ACF1
                  <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <
##
     <chr>
  1 ARIMA
                  Test
                         112.
                                122.
                                      112.
                                             5.44
                                                   5.44
                                                         1.80 0.510
##
   2 Combination Test
                         120.
                                125.
                                      120.
                                             5.81
                                                   5.81
                                                         1.93 0.382
## 3 FTS
                         128.
                               133.
                                      128.
                                            6.18
                                                   6.18 2.06 0.324
                  Test
```

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Functions which can handle missing values

- ARIMA()
- TSLM()
- NNETAR()
- VAR()
- FASSTER()

Models which cannot handle missing values

- ETS()
- STL()
- TBATS()

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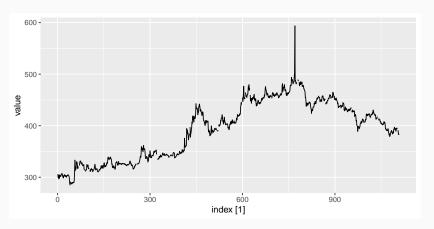
Models which cannot handle missing values

- ETS()
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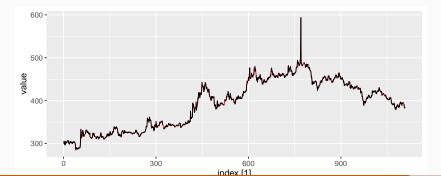
What to do?

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

```
gold <- as_tsibble(forecast::gold)
gold %>% autoplot(value)
```



```
gold_complete <- gold %>%
  model(ARIMA(value)) %>%
  interpolate(gold)
gold_complete %>%
  autoplot(value, colour = "red") +
  autolayer(gold, value)
```



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Outliers

```
fit <- gold %>%
 model(ARIMA(value))
augment(fit) %>%
 mutate(stdres = .resid/sd(.resid, na.rm=TRUE)) %>%
 filter(abs(stdres) > 10)
## # A tsibble: 2 x 6 [1]
             .model [1]
## # Key:
              index value .fitted .resid stdres
    .model
##
## <chr>
              ## 1 ARIMA(value) 770 594. 499. 94.7 16.4
## 2 ARIMA(value) 771 487. 562. -74.8 -12.9
```