MONASH University

MONASH BUSINESS SCHOOL

ETC3550/ETC5550 Applied forecasting

Ch12. Some practical issues

OTexts.org/fpp3/

Outline

Models for different frequencies

Models for annual data

- ETS, ARIMA, Dynamic regression

Models for different frequencies

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 different frequencies

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 different frequencies

Models for weekly data

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

Models for different frequencies

Models for weekly data

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

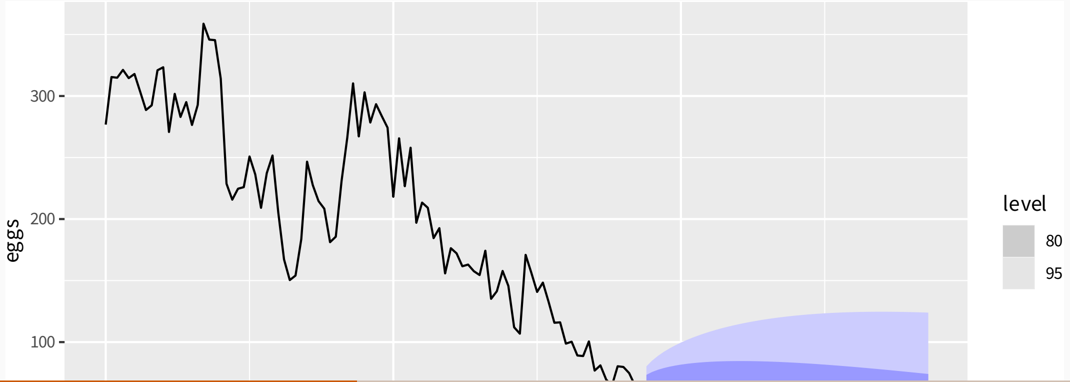
Models for daily, hourly and other sub-daily data

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

Outline

Positive forecasts

```
recent_prices <- prices |> filter(!is.na(eggs))
recent_prices |>
  model(ETS(log(eggs) ~ error("A") + trend("A") + season("N"))) |>
  forecast(h = 50) |>
  autoplot(recent_prices)
```



Outline

Forecast combinations

Clemen (1989)

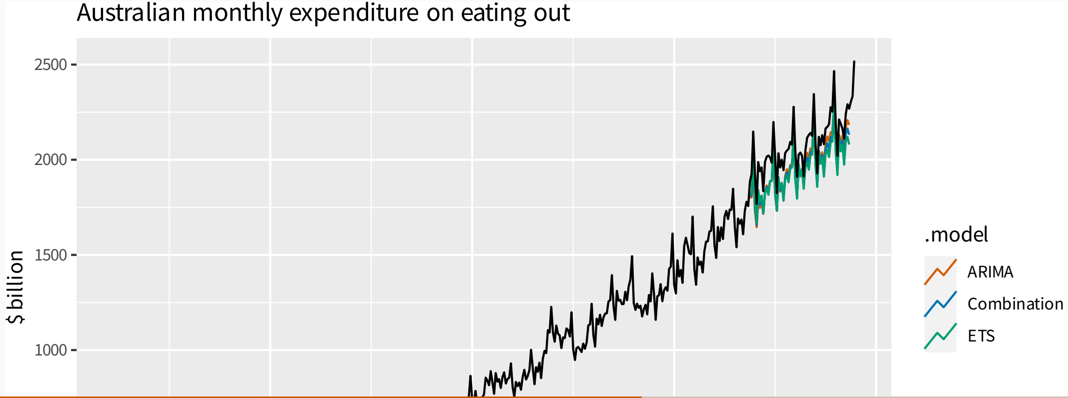
"The results have been virtually unanimous: combining multiple forecasts leads to increased forecast accuracy. …In many cases one can make dramatic performance improvements by simply averaging the forecasts."

Forecast combinations

```r
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")
```

Forecast combinations

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



Forecast combinations

```r
fc |> accuracy(aus_cafe)
```

```
# A tibble: 3 x 10
  .model      .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
  <chr>       <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 ARIMA       Test   112.  122.  112.  5.44  5.44  1.80  1.50 0.510
2 Combination Test   120.  125.  120.  5.81  5.81  1.93  1.55 0.382
3 ETS         Test   128.  133.  128.  6.18  6.18  2.06  1.64 0.324
```

Outline

Missing values

Functions which can handle missing values

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

Models which cannot handle missing values

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

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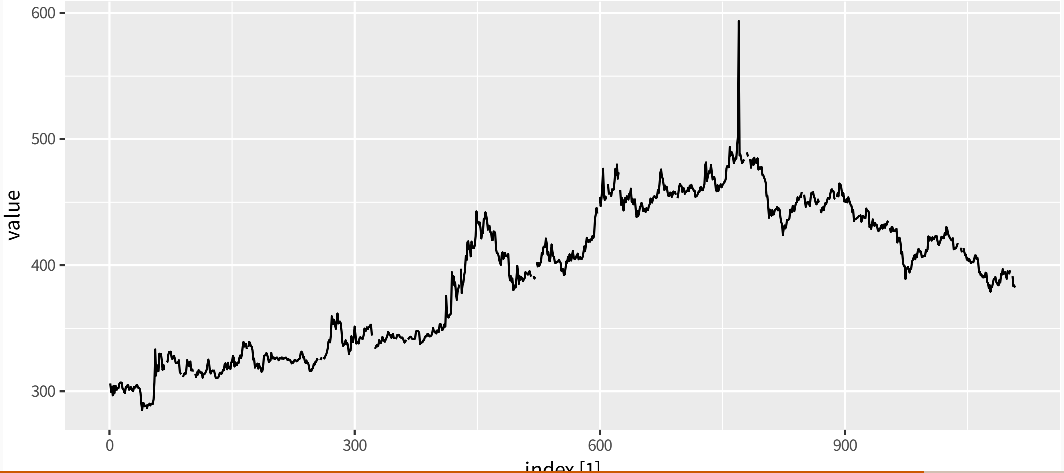
What to do?

1. Model section of data after last missing value

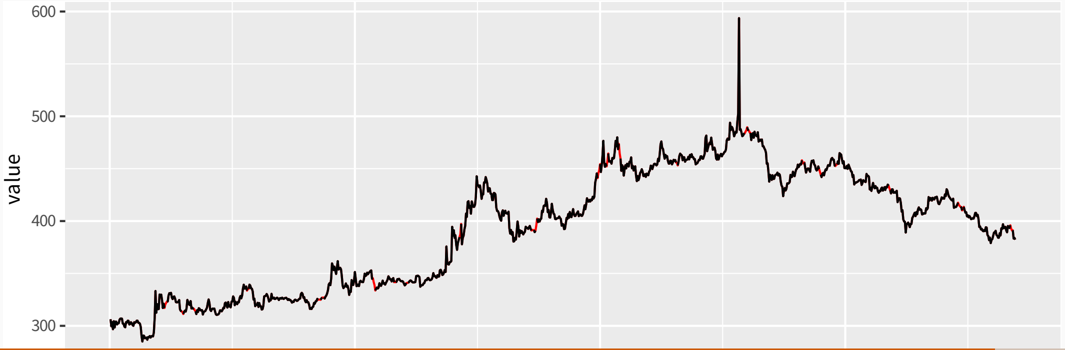
Missing values

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



Missing values

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



Outline

Outliers

```r
fit <- gold |>
  model(ARIMA(value))
augment(fit) |>
  mutate(stdres = .resid / sd(.resid, na.rm = TRUE)) |>
  filter(abs(stdres) > 10)
```

```
# A tsibble: 2 x 7 [1]
# Key:       .model [1]
  .model       index value .fitted .resid .innov stdres
  <chr>        <dbl> <dbl>   <dbl>  <dbl>  <dbl>  <dbl>
1 ARIMA(value)   770  594.    499.   94.7   94.7   16.4
2 ARIMA(value)   771  487.    562.  -74.8  -74.8  -12.9
```