STAT481/581: Introduction to Time Series Analysis

Some practical forecasting issues

OTexts.org/fpp3/

Outline

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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

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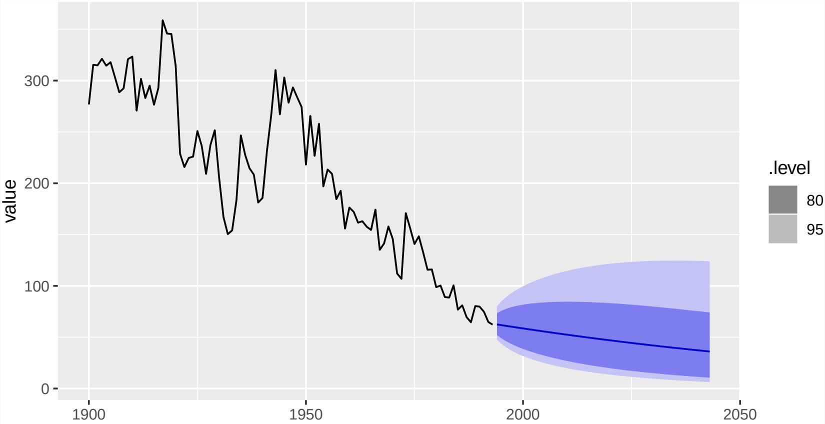
Positive forecasts

```
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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Forecast combinations

Clemen (1989)

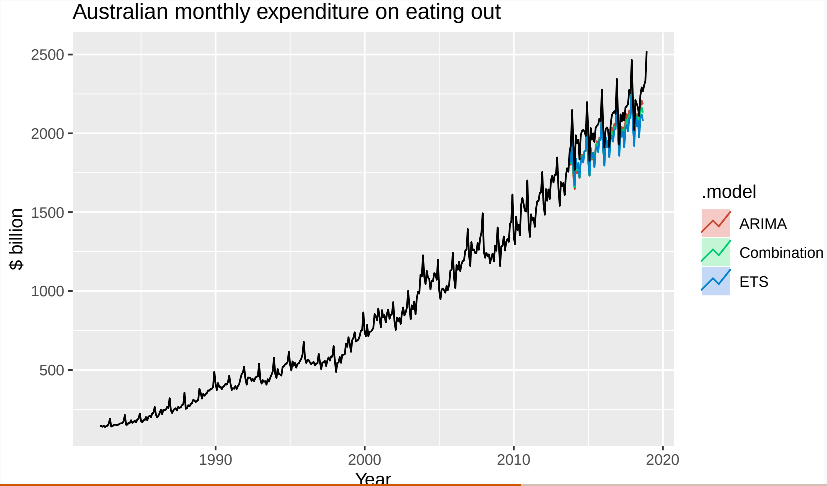
"The results have been virtually unanimous: combining multiple forecasts leads to increased forecast accuracy. . . . In many cases one can make dramatic performance improvements by simply averaging the forecasts."

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

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

```
## # A tibble: 3 x 9
##   .model      .type    ME  RMSE   MAE   MPE  MAPE  MASE  ACF1
##   <chr>       <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 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 ETS         Test   128.  133.  128.  6.18  6.18  2.06 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.
2. Estimate missing values with `interpolate()`.

Missing values

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

Missing values

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

Outline

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