

ETC3550

Applied forecasting for business and economics

Ch12. Some practical forecasting
issues

OTexts.org/fpp3/

Outline

- 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 different frequencies

Models for annual data

- ETS, ARIMA, Dynamic regression

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- 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

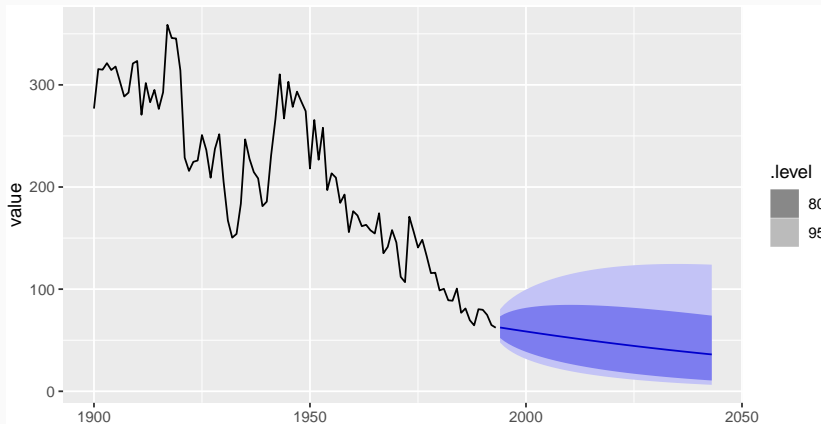
- ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA, TBATS

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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)

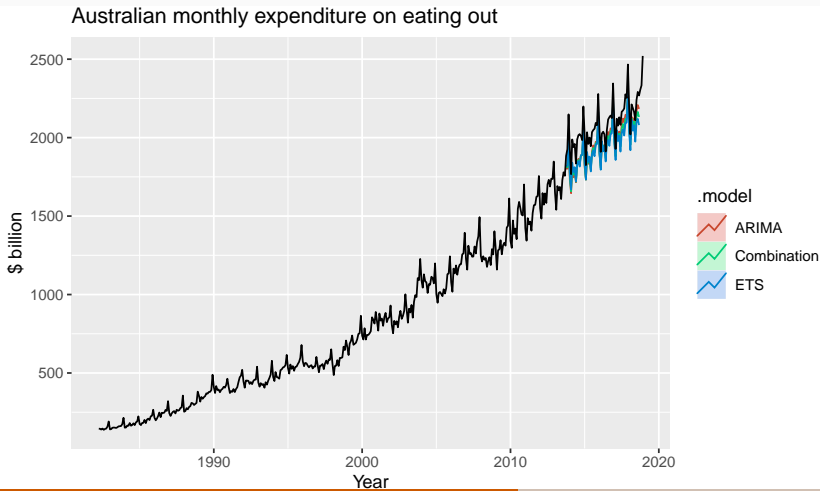
“The results have been virtually unanimous: combining multiple forecasts leads to increased forecast accuracy. ... In many cases one can make dramatic performance improvements by simply averaging the forecasts.”

Forecast combinations

```
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

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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

```
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]  
## # 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
```