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# FORECASTING

## PRINCIPLES AND PRACTICE

A comprehensive introduction to the latest forecasting methods using R. Learn to improve your forecast accuracy using dozens of real data examples.



3RD EDITION

 **OTexts**  
Oxford Texts in Finance and Probability

## 10. Dynamic regression models

### 10.5 Dynamic harmonic regression

[OTexts.org/fpp3/](http://OTexts.org/fpp3/)

# Dynamic harmonic regression

## Combine Fourier terms with ARIMA errors

### Advantages

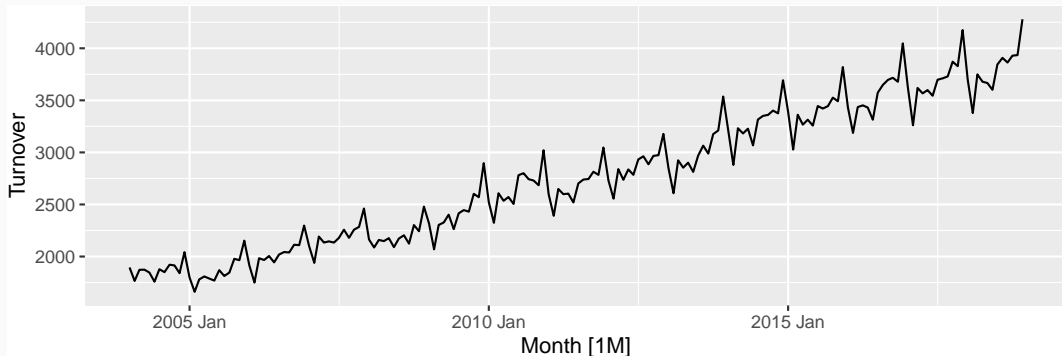
- it allows any length seasonality;
- for data with more than one seasonal period, you can include Fourier terms of different frequencies;
- the seasonal pattern is smooth for small values of  $K$  (but more wiggly seasonality can be handled by increasing  $K$ );
- the short-term dynamics are easily handled with a simple ARMA error.

### Disadvantages

- seasonality is assumed to be fixed

# Eating-out expenditure

```
aus_cafe <- aus_retail |>  
  filter(Industry == "Cafes, restaurants and takeaway food services",  
         year(Month) %in% 2004:2018) |>  
  summarise(Turnover = sum(Turnover))  
aus_cafe |> autoplot(Turnover)
```

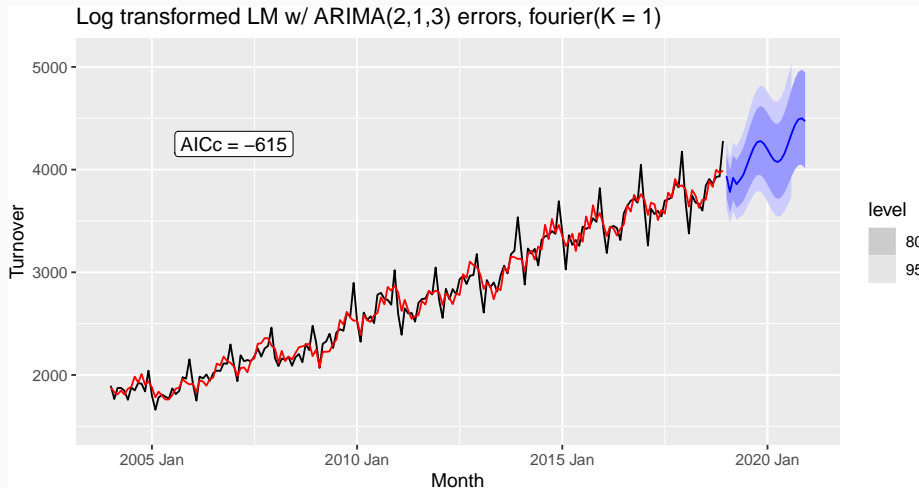


# Eating-out expenditure

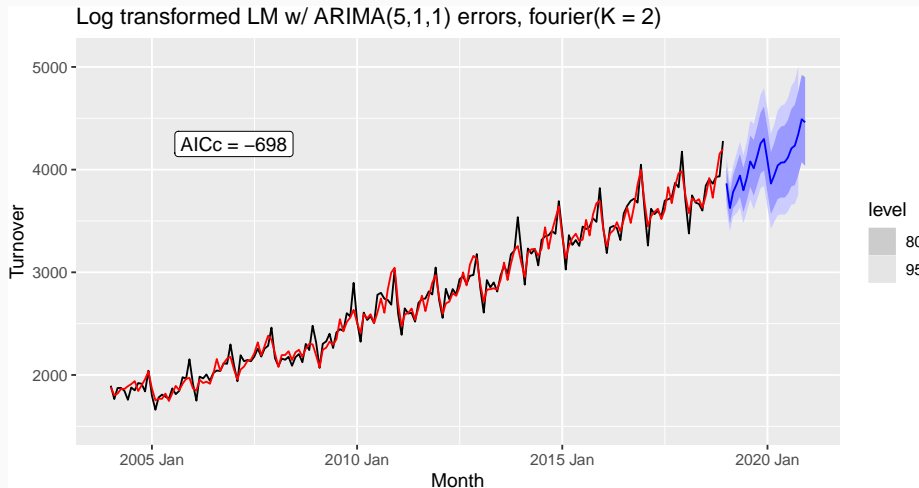
```
fit <- aus_cafe |> model(
  `K = 1` = ARIMA(log(Turnover) ~ fourier(K = 1) + PDQ(0, 0, 0)),
  `K = 2` = ARIMA(log(Turnover) ~ fourier(K = 2) + PDQ(0, 0, 0)),
  `K = 3` = ARIMA(log(Turnover) ~ fourier(K = 3) + PDQ(0, 0, 0)),
  `K = 4` = ARIMA(log(Turnover) ~ fourier(K = 4) + PDQ(0, 0, 0)),
  `K = 5` = ARIMA(log(Turnover) ~ fourier(K = 5) + PDQ(0, 0, 0)),
  `K = 6` = ARIMA(log(Turnover) ~ fourier(K = 6) + PDQ(0, 0, 0))
)
glance(fit)
```

.model	sigma2	log_lik	AIC	AICc	BIC
K = 1	0.002	317	-616	-615	-588
K = 2	0.001	362	-700	-698	-661
K = 3	0.001	394	-763	-761	-725
K = 4	0.001	427	-822	-818	-771
K = 5	0.000	474	-919	-917	-875
K = 6	0.000	474	-920	-918	-875

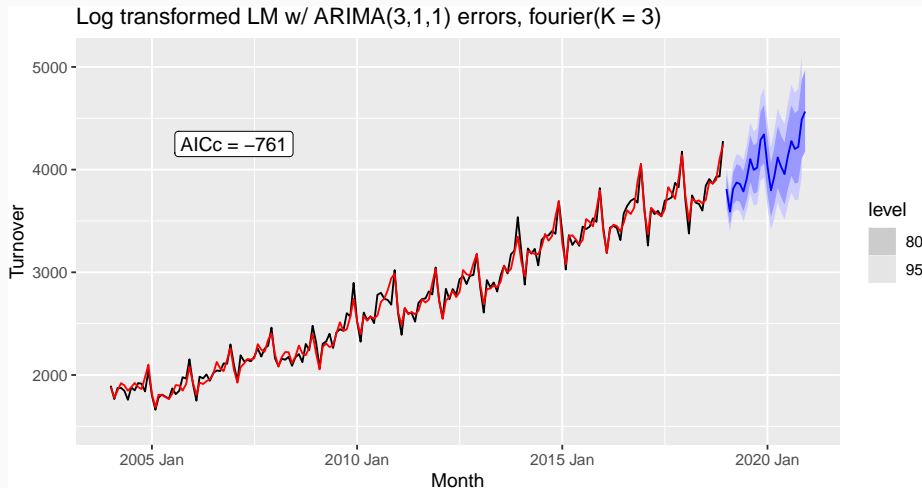
# Eating-out expenditure



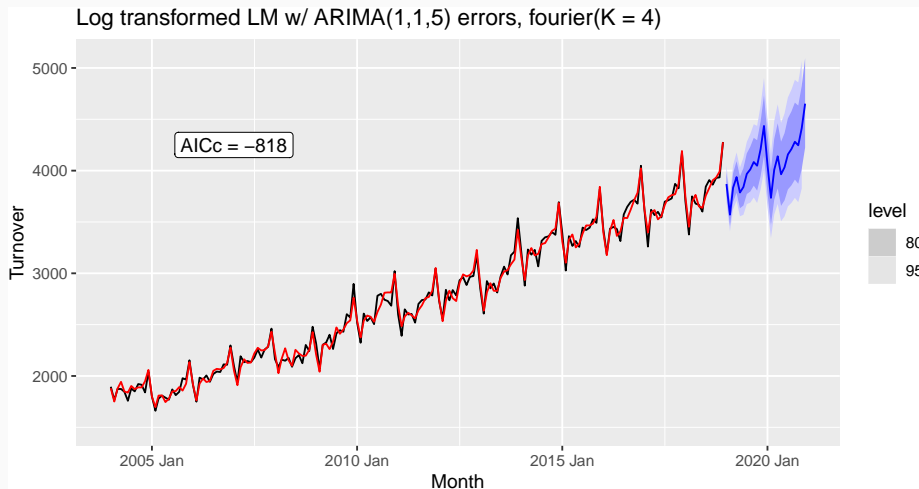
# Eating-out expenditure



# Eating-out expenditure

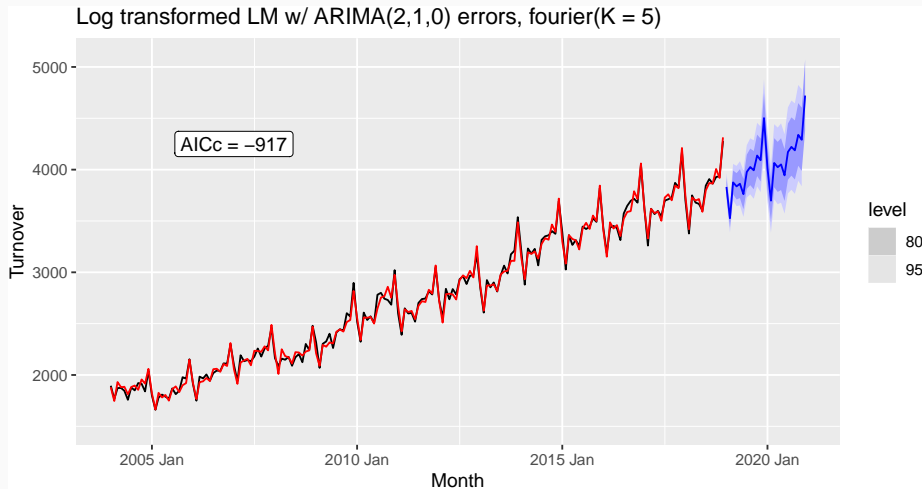


# Eating-out expenditure

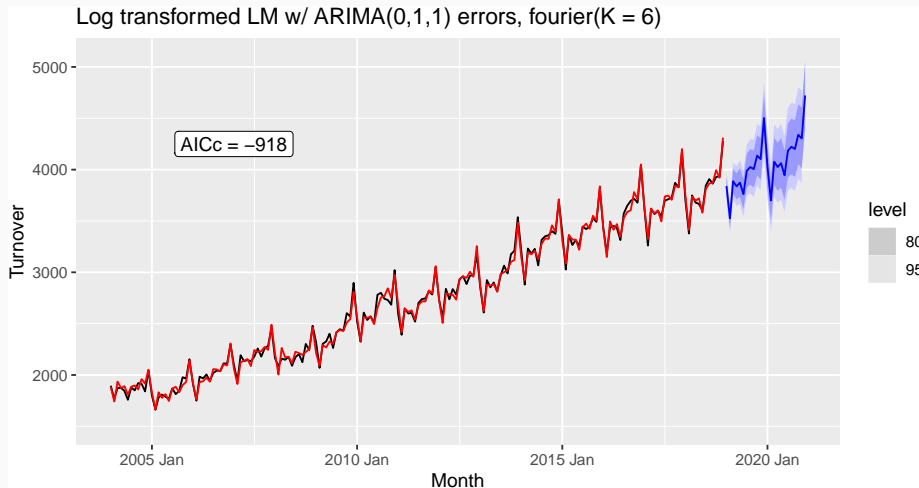




# Eating-out expenditure



# Eating-out expenditure



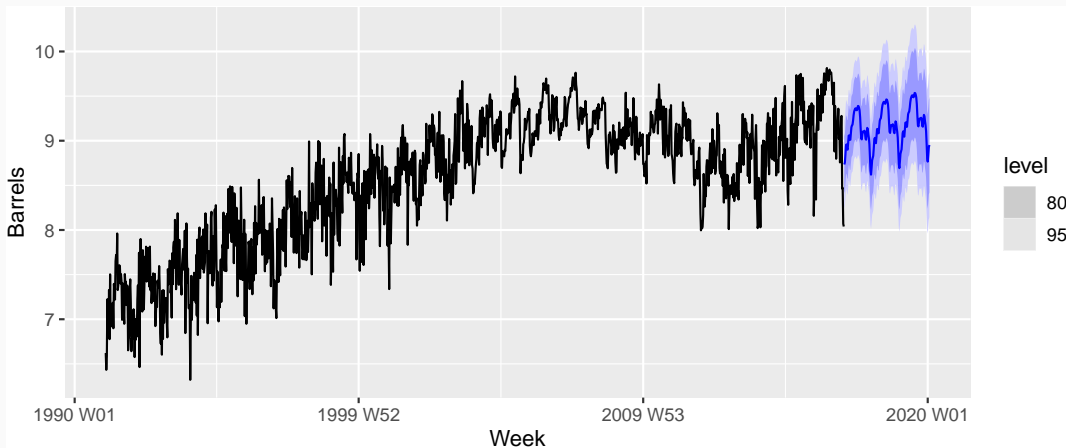
# Example: weekly gasoline products

```
fit <- us_gasoline |>
  model(ARIMA(Barrels ~ fourier(K = 13) + PDQ(0, 0, 0)))
report(fit)
```

```
## Series: Barrels
## Model: LM w/ ARIMA(0,1,1) errors
##
## Coefficients:
##          ma1  fourier(K = 13)C1_52  fourier(K = 13)S1_52
##        -0.8934             -0.1121             -0.2300
## s.e.    0.0132             0.0123             0.0122
##      fourier(K = 13)C2_52  fourier(K = 13)S2_52
##                0.0420             0.0317
## s.e.            0.0099             0.0099
##      fourier(K = 13)C3_52  fourier(K = 13)S3_52
##                0.0832             0.0346
## s.e.            0.0094             0.0094
##      fourier(K = 13)C4_52  fourier(K = 13)S4_52
##                0.0185             0.0398
## s.e.            0.0092             0.0092
##      fourier(K = 13)C5_52  fourier(K = 13)S5_52
```

# Example: weekly gasoline products

```
forecast(fit, h = "3 years") |>  
  autoplot(us_gasoline)
```



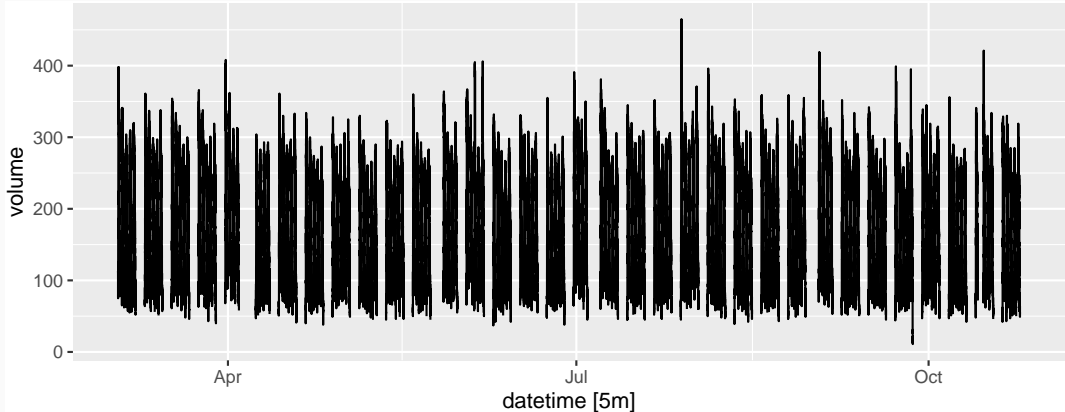
# 5-minute call centre volume

```
(calls <- readr::read_tsv("http://robjhyndman.com/data/callcenter.txt") |>
  rename(time = `...1`) |>
  pivot_longer(-time, names_to = "date", values_to = "volume") |>
  mutate(date = as.Date(date, format = "%d/%m/%Y"),
         datetime = as_datetime(date) + time) |>
  as_tsibble(index = datetime))
```

```
## # A tsibble: 27,716 x 4 [5m] <UTC>
##   time    date      volume datetime
##   <time> <date>      <dbl> <dtm>
## 1 07:00 2003-03-03    111 2003-03-03 07:00:00
## 2 07:05 2003-03-03    113 2003-03-03 07:05:00
## 3 07:10 2003-03-03     76 2003-03-03 07:10:00
## 4 07:15 2003-03-03     82 2003-03-03 07:15:00
## 5 07:20 2003-03-03     91 2003-03-03 07:20:00
## 6 07:25 2003-03-03     87 2003-03-03 07:25:00
## 7 07:30 2003-03-03     75 2003-03-03 07:30:00
## 8 07:35 2003-03-03     89 2003-03-03 07:35:00
```

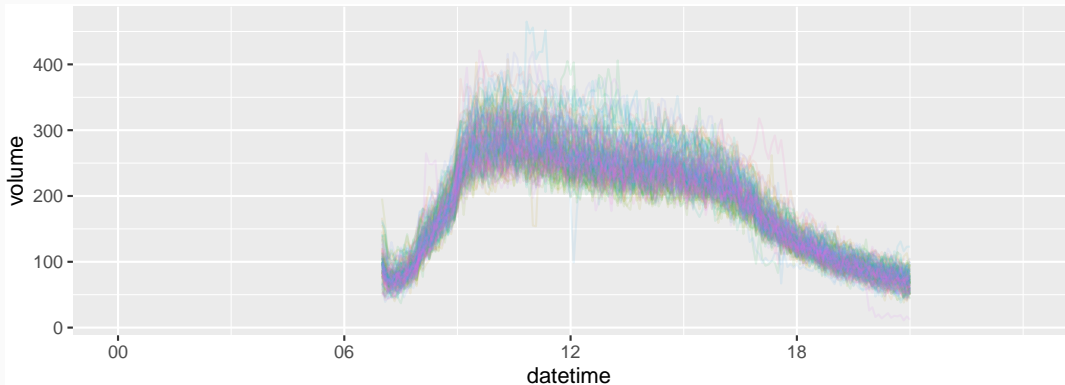
# 5-minute call centre volume

```
calls |>  
  fill_gaps() |>  
  autoplot(volume)
```



# 5-minute call centre volume

```
calls |>  
  fill_gaps() |>  
  gg_season(volume, period = "day", alpha = 0.1) +  
  guides(colour = FALSE)
```



# 5-minute call centre volume

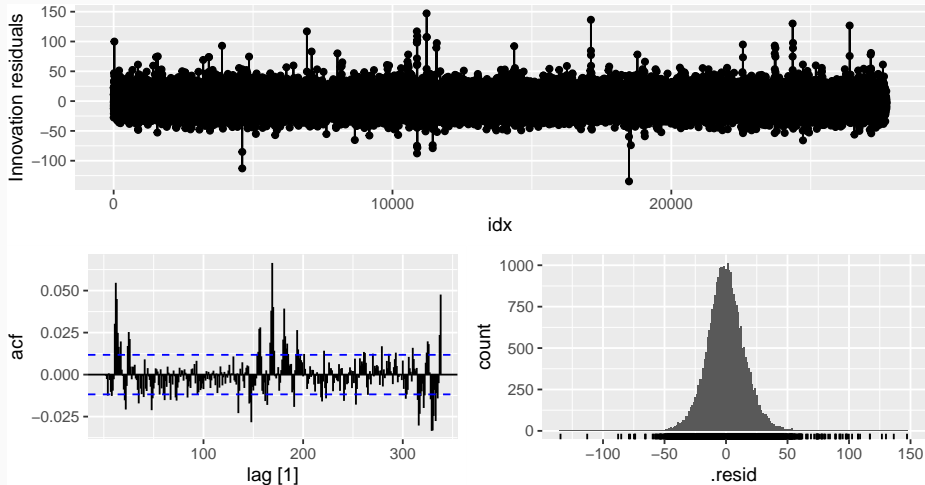
```
calls_mdl <- calls |>
  mutate(idx = row_number()) |>
  update_tsibble(index = idx)
fit <- calls_mdl |>
  model(ARIMA(volume ~ fourier(169, K = 10) + pdq(d = 0) + PDQ(0, 0, 0)))
report(fit)
```

```
## Series: volume
## Model: LM w/ ARIMA(1,0,3) errors
##
## Coefficients:
##          ar1          ma1          ma2          ma3  fourier(169, K = 10)C1_169
##          0.989   -0.7383   -0.0333   -0.0282                        -79.1
## s.e.        0.001    0.0061    0.0075    0.0060                        0.7
##          fourier(169, K = 10)S1_169  fourier(169, K = 10)C2_169
##                                55.298                        -32.361
## s.e.                                0.701                        0.378
##          fourier(169, K = 10)S2_169  fourier(169, K = 10)C3_169
##                                13.742                        -9.318
## s.e.                                0.379                        0.273
```



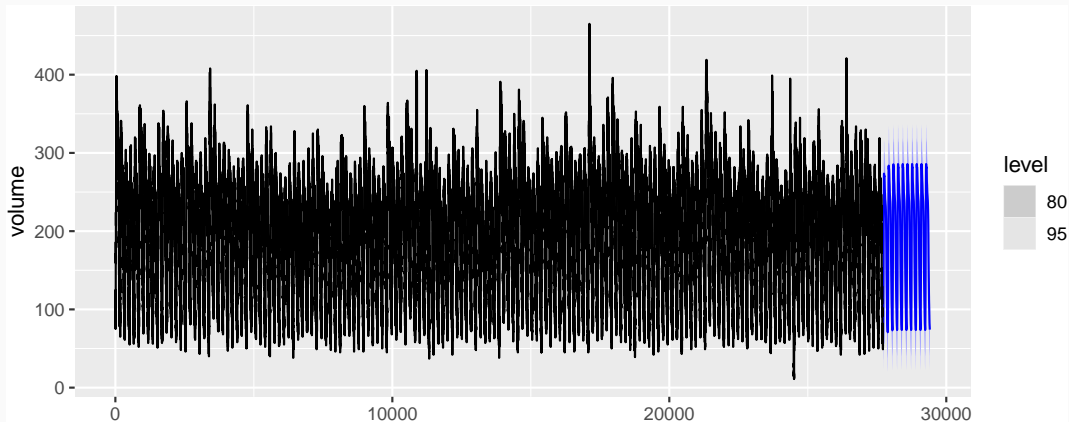
# 5-minute call centre volume

```
gg_tsresiduals(fit, lag = 338)
```



# 5-minute call centre volume

```
fit |>  
  forecast(h = 1690) |>  
  autoplot(calls_mdl)
```



# 5-minute call centre volume

```
fit |>  
  forecast(h = 1690) |>  
  autoplot(filter(calls_mdl, idx > 25000))
```

