

Time Series Analysis & Forecasting Using R

9. Dynamic regression



Outline

- 1 Regression with ARIMA errors
- 2 Lab Session 18
- 3 Dynamic harmonic regression
- 4 Lab Session 19
- 5 Lagged predictors

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Regression with ARIMA errors

Regression models

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \varepsilon_t,$$

- y_t modeled as function of k explanatory variables
- In regression, we assume that ε_t is white noise.

Regression with ARIMA errors

Regression models

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RegARIMA model

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \eta_t,$$

$$\eta_t \sim \text{ARIMA}$$

- Residuals are from ARIMA model.
- Estimate model in one step using MLE
- Select model with lowest AICc value.

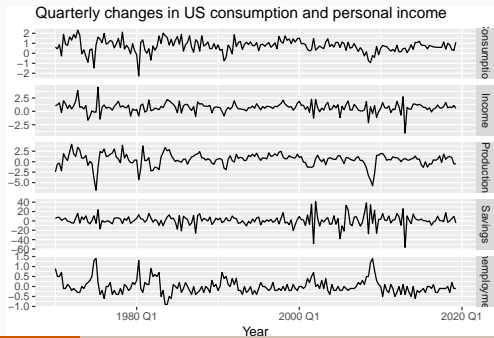
US personal consumption and income

us_change

```
## # A tsibble: 198 x 6 [1Q]
##   Quarter Consumption Income Production Savings Unemployment
##   <qtr>          <dbl>  <dbl>         <dbl>    <dbl>         <dbl>
## 1 1970 Q1         0.619   1.04         -2.45     5.30           0.9
## 2 1970 Q2         0.452   1.23         -0.551    7.79           0.5
## 3 1970 Q3         0.873   1.59         -0.359    7.40           0.5
## 4 1970 Q4        -0.272  -0.240        -2.19     1.17           0.700
## 5 1971 Q1         1.90    1.98          1.91     3.54          -0.100
## 6 1971 Q2         0.915   1.45          0.902    5.87          -0.100
## 7 1971 Q3         0.794   0.521         0.308   -0.406         0.100
## 8 1971 Q4         1.65    1.16          2.29    -1.49           0
## 9 1972 Q1         1.31    0.457         4.15    -4.29          -0.200
## 10 1972 Q2        1.89    1.03          1.89    -4.69          -0.100
## # ... with 188 more rows
```

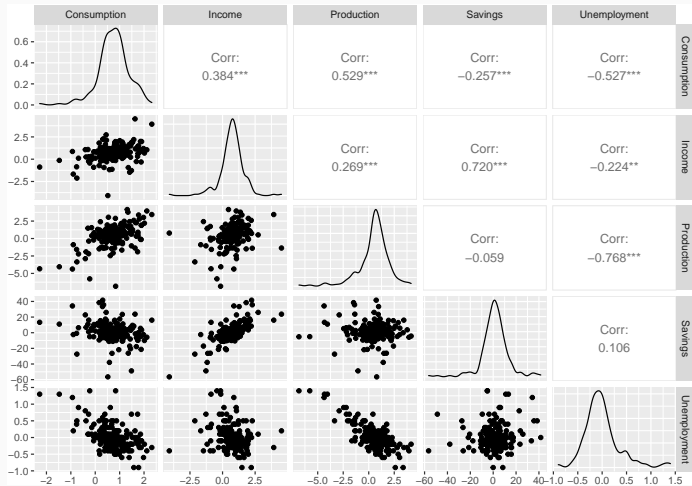
US personal consumption and income

```
us_change ▷  
  pivot_longer(-Quarter, names_to = "variable", values_to = "value") ▷  
  ggplot(aes(y = value, x = Quarter, group = variable)) +  
  geom_line() + facet_grid(variable ~ ., scales = "free_y") +  
  labs(x = "Year", y = "",  
       title = "Quarterly changes in US consumption and personal income")
```



US personal consumption and income

```
us_change > as_tibble() > select(-Quarter) > GGally::ggpairs()
```



US personal consumption and income

- No need for transformations or further differencing.
- Increase in income does not necessarily translate into instant increase in consumption (e.g., after the loss of a job, it may take a few months for expenses to be reduced to allow for the new circumstances). We will ignore this for now.

US personal consumption and income

```
fit <- us_change ▷  
  model(regarima = ARIMA(Consumption ~ Income + Production + Savings + Unemployment  
report(fit)
```

```
## Series: Consumption
```

```
## Model: LM w/ ARIMA(0,1,2) errors
```

```
##
```

```
## Coefficients:
```

##	ma1	ma2	Income	Production	Savings	Unemployment
##	-1.0882	0.1118	0.7472	0.0370	-0.0531	-0.2096
## s.e.	0.0692	0.0676	0.0403	0.0229	0.0029	0.0986

```
##
```

```
## sigma^2 estimated as 0.09588: log likelihood=-47.1
```

```
## AIC=108 AICc=109 BIC=131
```

US personal consumption and income

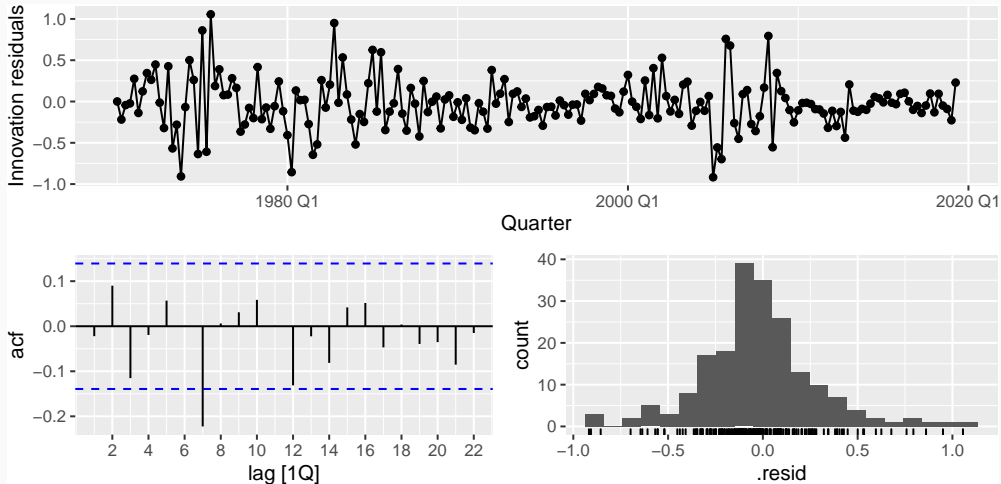
```
fit <- us_change ▷  
  model(regarima = ARIMA(Consumption ~ Income + Production + Savings + Unemployment  
report(fit)
```

```
## Series: Consumption  
## Model: LM w/ ARIMA(0,1,2) errors  
##  
## Coefficients:  
##           ma1      ma2  Income  Production  Savings  Unemployment  
##      -1.0882   0.1118   0.7472     0.0370   -0.0531     -0.2096  
## s.e.    0.0692   0.0676   0.0403     0.0229    0.0029     0.0986  
##  
## sigma^2 estimated as 0.09588:  log likelihood=-47.1  
## AIC=108   AICc=109   BIC=131
```

Write down the equations for the fitted model.

US personal consumption and income

```
gg_tsresiduals(fit)
```



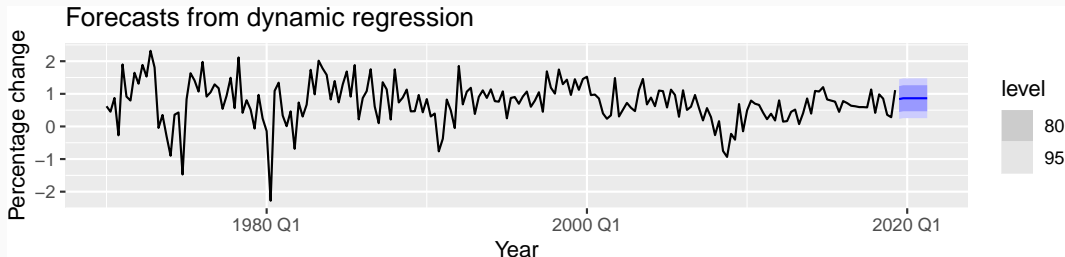
US personal consumption and income

```
augment(fit) ▷  
  features(.resid, ljung_box, dof = 6, lag = 12)
```

```
## # A tibble: 1 x 3  
##   .model    lb_stat lb_pvalue  
##   <chr>      <dbl>    <dbl>  
## 1 regarima    20.0    0.00274
```

US personal consumption and income

```
us_change_future <- new_data(us_change, 8) ▷  
  mutate(Income = tail(us_change$Income, 1),  
         Production = tail(us_change$Production, 1),  
         Savings = tail(us_change$Savings, 1),  
         Unemployment = tail(us_change$Unemployment, 1))  
forecast(fit, new_data = us_change_future) ▷  
  autoplot(us_change) +  
  labs(x = "Year", y = "Percentage change", title = "Forecasts from dynamic regress")
```



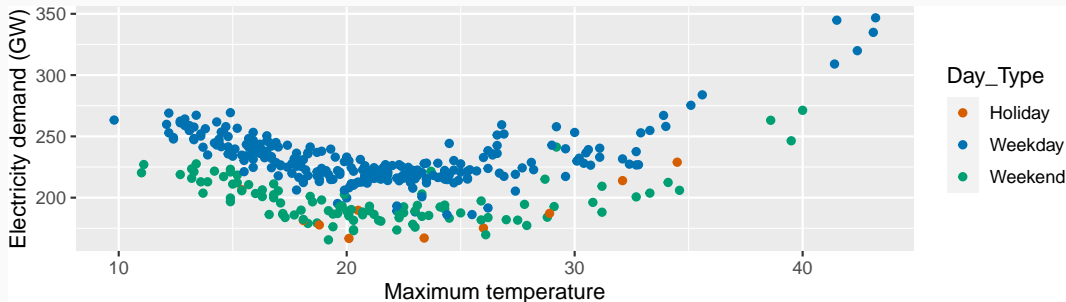
Forecasting

- To forecast a regression model with ARIMA errors, we need to forecast the regression part of the model and the ARIMA part of the model and combine the results.
- Some predictors are known into the future (e.g., time, dummies).
- Separate forecasting models may be needed for other predictors.
- Forecast intervals ignore the uncertainty in forecasting the predictors.

Daily electricity demand

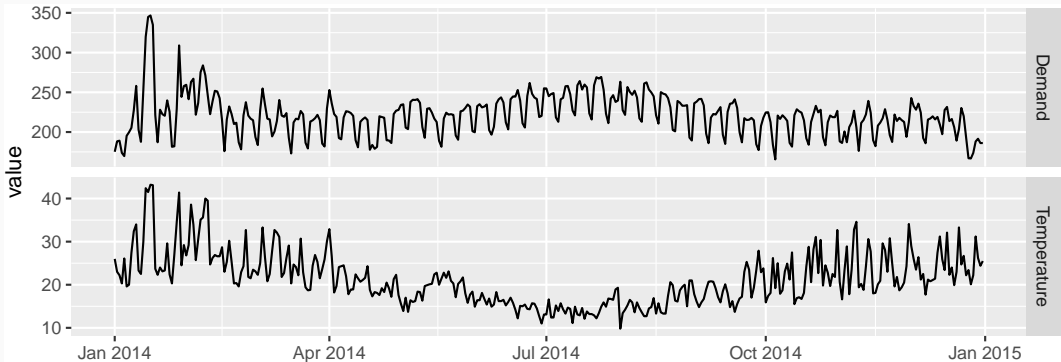
Model daily electricity demand as a function of temperature using quadratic regression with ARMA errors.

```
vic_elec_daily >  
  ggplot(aes(x = Temperature, y = Demand, colour = Day_Type)) +  
  geom_point() +  
  labs(x = "Maximum temperature", y = "Electricity demand (GW)")
```



Daily electricity demand

```
vic_elec_daily ▷  
  pivot_longer(c(Demand, Temperature)) ▷  
  ggplot(aes(x = Date, y = value)) +  
  geom_line() +  
  facet_grid(vars(name), scales = "free_y")
```



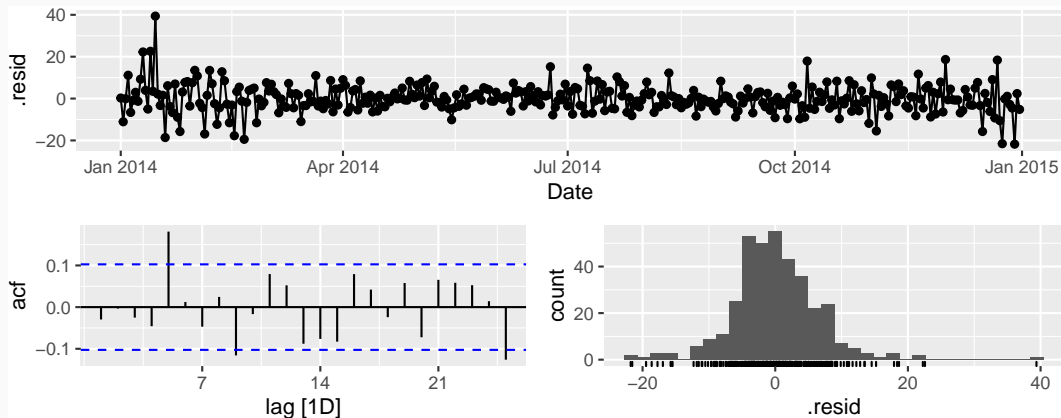
Daily electricity demand

```
fit <- vic_elec_daily >
  model(fit = ARIMA(Demand ~ Temperature + I(Temperature^2) +
    (Day_Type = "Weekday")))
report(fit)
```

```
## Series: Demand
## Model: LM w/ ARIMA(2,1,2)(2,0,0)[7] errors
##
## Coefficients:
##          ar1      ar2      ma1      ma2      sar1      sar2  Temperature
##        -0.1093  0.7226 -0.0182 -0.9381  0.1958  0.417      -7.614
## s.e.      0.0779  0.0739  0.0494  0.0493  0.0525  0.057      0.448
##      I(Temperature^2)  Day_Type = "Weekday"TRUE
##                0.1810                30.40
## s.e.                0.0085                1.33
##
## sigma^2 estimated as 44.91:  log likelihood=-1206
## AIC=2432   AICc=2433   BIC=2471
```

Daily electricity demand

```
augment(fit) ▷  
  gg_tsdisplay(.resid, plot_type = "histogram")
```



Daily electricity demand

```
augment(fit) ▷  
  features(.resid, ljung_box, dof = 9, lag = 14)
```

```
## # A tibble: 1 x 3  
##   .model lb_stat lb_pvalue  
##   <chr>    <dbl>    <dbl>  
## 1 fit      28.4 0.0000304
```

Daily electricity demand

```
# Forecast one day ahead
```

```
vic_next_day <- new_data(vic_elec_daily, 1) ▷  
  mutate(Temperature = 26, Day_Type = "Holiday")  
forecast(fit, vic_next_day)
```

```
## # A fable: 1 x 6 [1D]
```

```
## # Key:      .model [1]
```

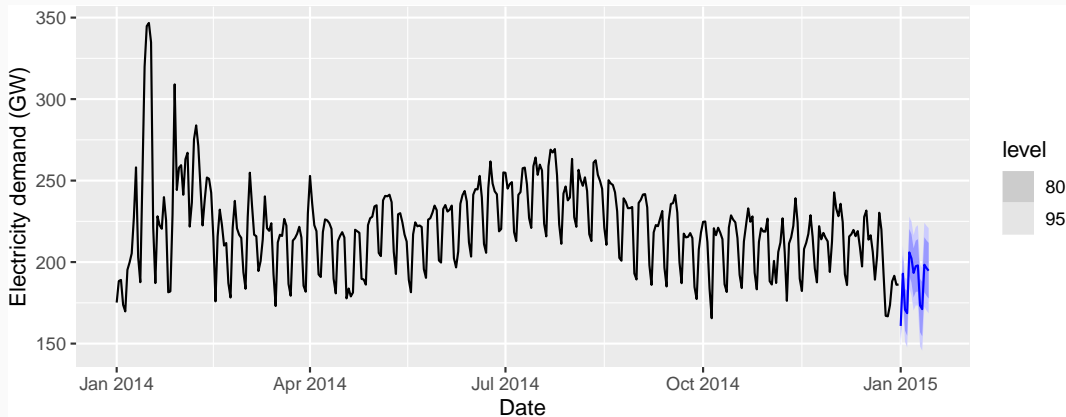
```
##   .model Date           Demand .mean Temperature Day_Type  
##   <chr>  <date>          <dist> <dbl>         <dbl> <chr>  
## 1 fit    2015-01-01 N(161, 45) 161.           26 Holiday
```

Daily electricity demand

```
vic_elec_future <- new_data(vic_elec_daily, 14) ▷  
  mutate(  
    Temperature = 26,  
    Holiday = c(TRUE, rep(FALSE, 13)),  
    Day_Type = case_when(  
      Holiday ~ "Holiday",  
      wday(Date) %in% 2:6 ~ "Weekday",  
      TRUE ~ "Weekend"  
    )  
  )
```

Daily electricity demand

```
forecast(fit, vic_elec_future) ▷  
  autoplot(vic_elec_daily) + labs(y = "Electricity demand (GW)")
```



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Lab Session 18

Repeat the daily electricity example, but instead of using a quadratic function of temperature, use a piecewise linear function with the “knot” around 20 degrees Celsius (use predictors Temperature & Temp2). How can you optimize the choice of knot?

```
vic_elec_daily <- vic_elec >
  filter(year(Time) == 2014) >
  index_by(Date = date(Time)) >
  summarise(Demand = sum(Demand) / 1e3,
            Temperature = max(Temperature),
            Holiday = any(Holiday)
  ) >
  mutate(Temp2 = I(pmax(Temperature - 20, 0)),
         Day_Type = case_when(
           Holiday ~ "Holiday",
           wday(Date) %in% 2:6 ~ "Weekday",
           TRUE ~ "Weekend"
         )
  )
```

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Dynamic harmonic regression

Combine Fourier terms with ARIMA errors

Advantages

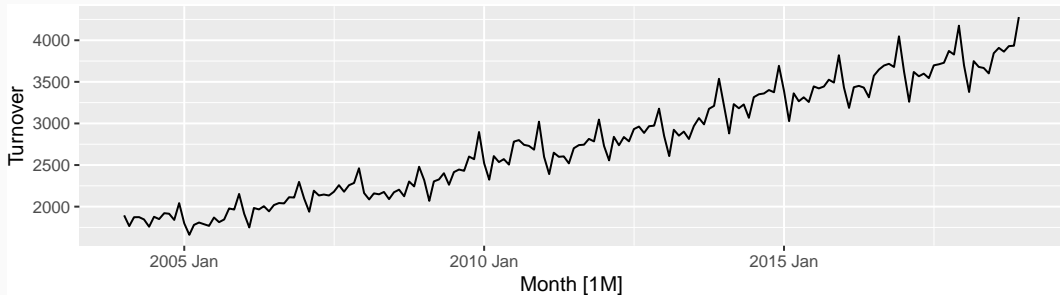
- it allows any length seasonality;
- for data with more than one seasonal period, you can include Fourier terms of different frequencies;
- the seasonal pattern is smooth for small values of K (but more wiggly seasonality can be handled by increasing K);
- the short-term dynamics are easily handled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

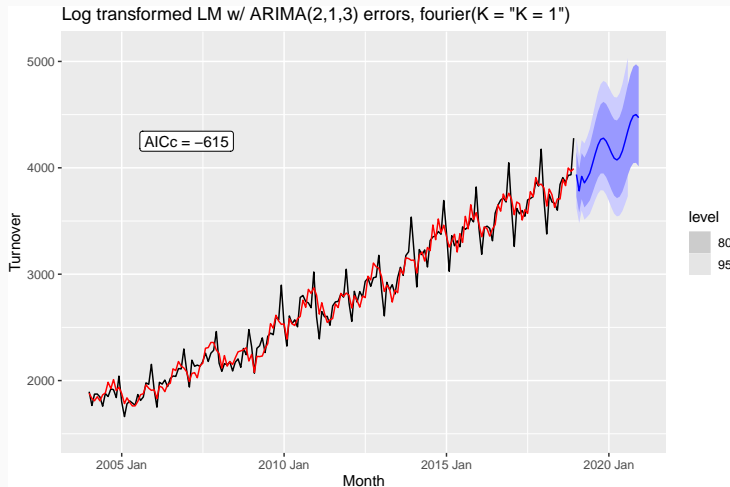


Eating-out expenditure

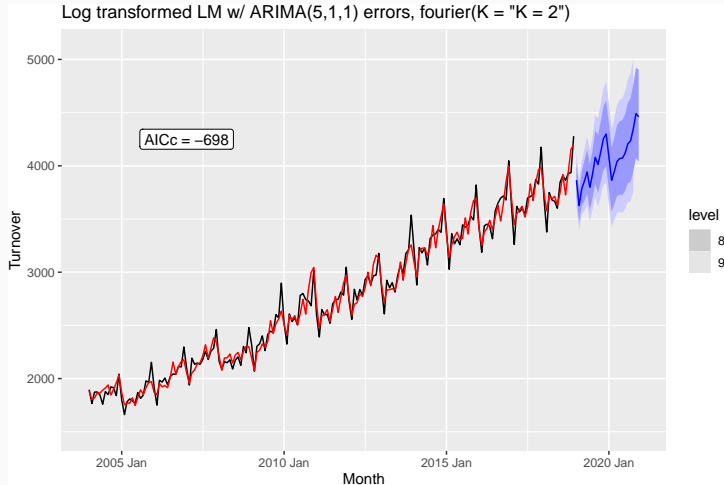
```
fit <- aus_cafe > model(  
  `K = 1` = ARIMA(log(Turnover) ~ fourier(K = 1) + PDQ(0, 0, 0)),  
  `K = 2` = ARIMA(log(Turnover) ~ fourier(K = 2) + PDQ(0, 0, 0)),  
  `K = 3` = ARIMA(log(Turnover) ~ fourier(K = 3) + PDQ(0, 0, 0)),  
  `K = 4` = ARIMA(log(Turnover) ~ fourier(K = 4) + PDQ(0, 0, 0)),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

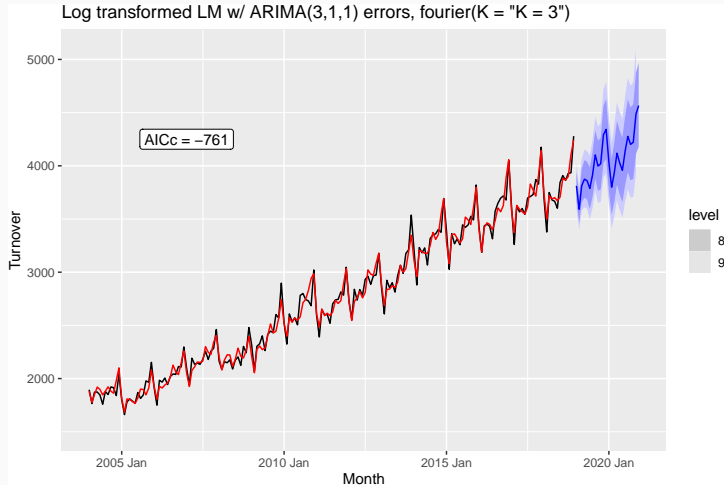
Eating-out expenditure



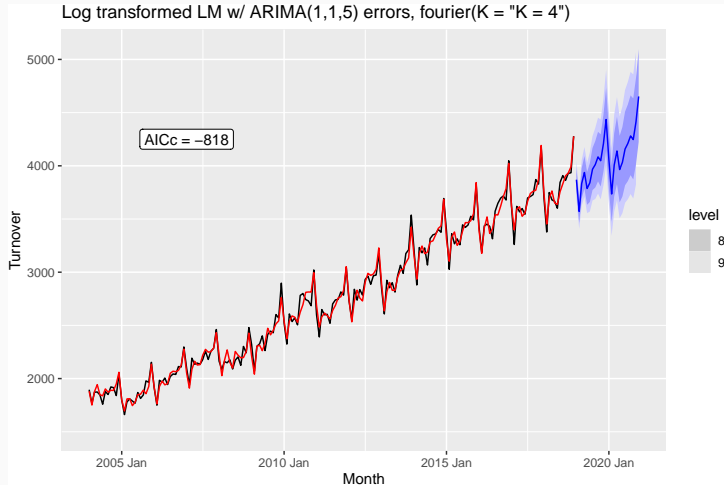
Eating-out expenditure



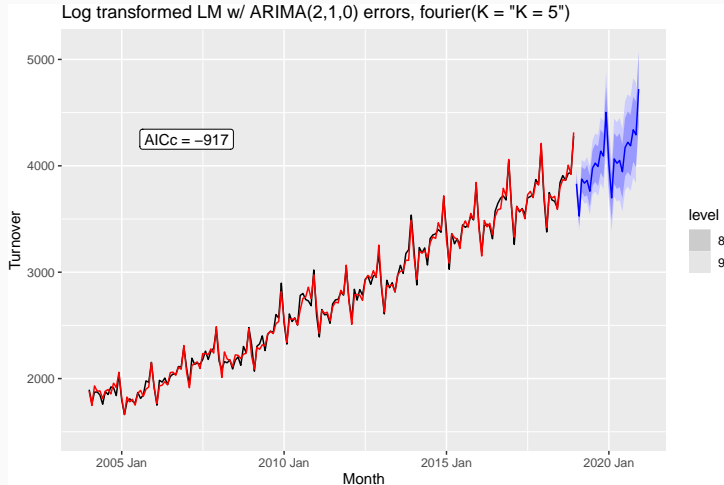
Eating-out expenditure



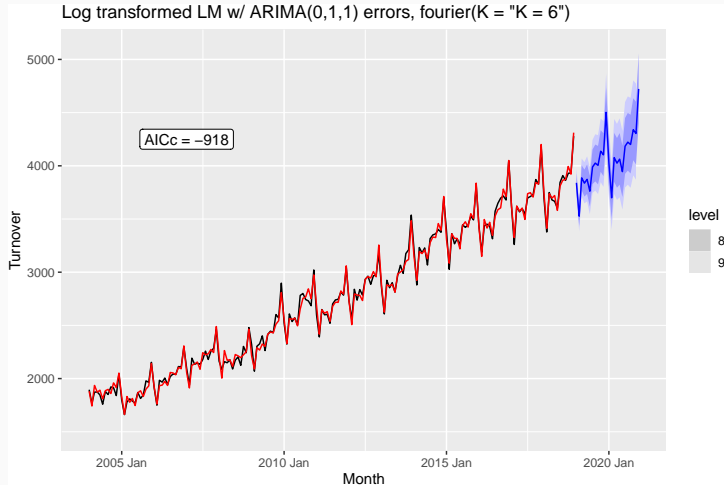
Eating-out expenditure



Eating-out expenditure



Eating-out expenditure



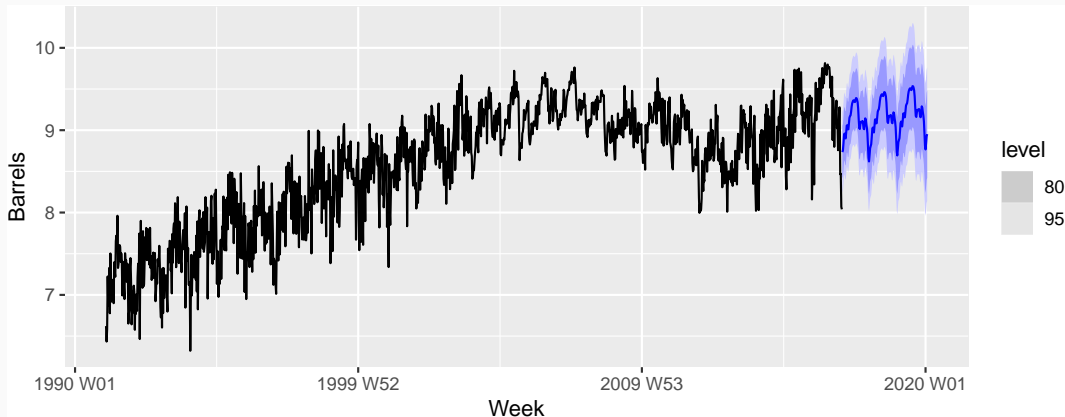
Example: weekly gasoline products

```
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  
##                   -0.0315          0.0009  
##                   0.0004          0.0004
```

Example: weekly gasoline products

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



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Lab Session 19

Repeat Lab Session 18 but using all available data, and handling the annual seasonality using Fourier terms.

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Lagged predictors

Sometimes a change in x_t does not affect y_t instantaneously

- $y_t = \text{sales}, x_t = \text{advertising}.$
- $y_t = \text{stream flow}, x_t = \text{rainfall}.$
- $y_t = \text{size of herd}, x_t = \text{breeding stock}.$

Lagged predictors

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- $y_t = \text{sales}, x_t = \text{advertising}.$
 - $y_t = \text{stream flow}, x_t = \text{rainfall}.$
 - $y_t = \text{size of herd}, x_t = \text{breeding stock}.$
-
- These are dynamic systems with input (x_t) and output (y_t).
 - x_t is often a leading indicator.
 - There can be multiple predictors.

Lagged predictors

The model include present and past values of predictor:

$x_t, x_{t-1}, x_{t-2}, \dots$

$$y_t = a + \nu_0 x_t + \nu_1 x_{t-1} + \dots + \nu_k x_{t-k} + \eta_t$$

where η_t is an ARIMA process.

Lagged predictors

The model include present and past values of predictor:

$x_t, x_{t-1}, x_{t-2}, \dots$

$$y_t = a + \nu_0 x_t + \nu_1 x_{t-1} + \dots + \nu_k x_{t-k} + \eta_t$$

where η_t is an ARIMA process.

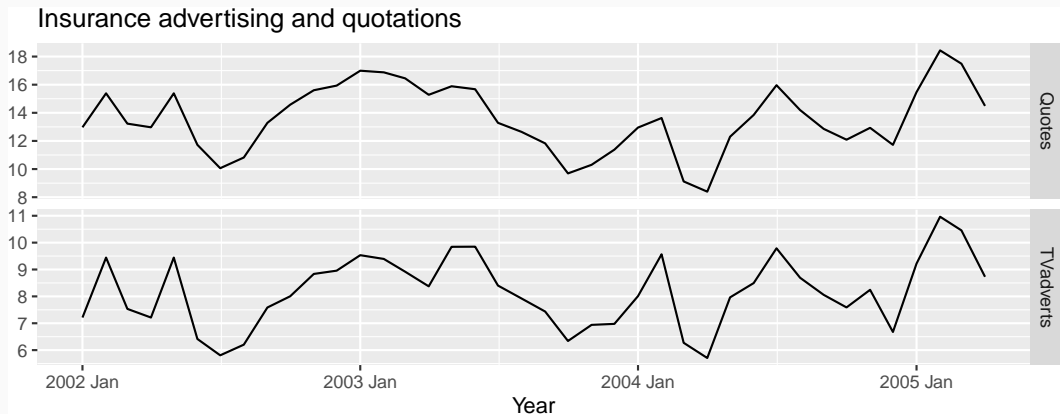
- x can influence y , but y is not allowed to influence x .

Example: Insurance quotes and TV adverts

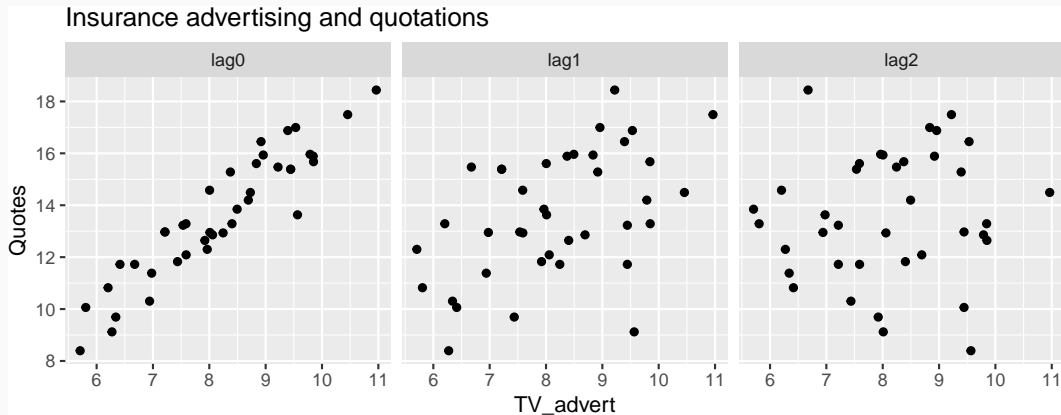
```
insurance
```

```
## # A tsibble: 40 x 3 [1M]
##       Month Quotes TVadverts
##       <mth>   <dbl>     <dbl>
## 1 2002 Jan    13.0      7.21
## 2 2002 Feb    15.4      9.44
## 3 2002 Mar    13.2      7.53
## 4 2002 Apr    13.0      7.21
## 5 2002 May    15.4      9.44
## 6 2002 Jun    11.7      6.42
## 7 2002 Jul    10.1      5.81
## 8 2002 Aug    10.8      6.20
## 9 2002 Sep    13.3      7.59
## 10 2002 Oct    14.6      8.00
```

Example: Insurance quotes and TV adverts



Example: Insurance quotes and TV adverts



Example: Insurance quotes and TV adverts

```
fit <- insurance ▷  
  # Restrict data so models use same fitting period  
  mutate(Quotes = c(NA, NA, NA, Quotes[4:40])) ▷  
  model(  
    ARIMA(Quotes ~ pdq(d = 0) + TVadverts),  
    ARIMA(Quotes ~ pdq(d = 0) + TVadverts +  
      lag(TVadverts)),  
    ARIMA(Quotes ~ pdq(d = 0) + TVadverts +  
      lag(TVadverts) +  
      lag(TVadverts, 2)),  
    ARIMA(Quotes ~ pdq(d = 0) + TVadverts +  
      lag(TVadverts) +  
      lag(TVadverts, 2) +  
      lag(TVadverts, 3))  
  )
```


Example: Insurance quotes and TV adverts

```
glance(fit)
```

Lag order	sigma2	log_lik	AIC	AICc	BIC
0	0.265	-28.3	66.6	68.3	75.0
1	0.209	-24.0	58.1	59.9	66.5
2	0.215	-24.0	60.0	62.6	70.2
3	0.206	-22.2	60.3	65.0	73.8

Example: Insurance quotes and TV adverts

```
# Re-fit to all data
fit <- insurance >
  model(ARIMA(Quotes ~ TVadverts + lag(TVadverts) + pdq(d = 0)))
report(fit)
```

```
## Series: Quotes
## Model: LM w/ ARIMA(1,0,2) errors
##
## Coefficients:
##          ar1      ma1      ma2 TVadverts lag(TVadverts) intercept
##          0.512  0.917  0.459    1.2527         0.1464         2.16
## s.e.    0.185  0.205  0.190    0.0588         0.0531         0.86
##
## sigma^2 estimated as 0.2166: log likelihood=-23.9
## AIC=61.9   AICc=65.4   BIC=73.7
```

Example: Insurance quotes and TV adverts

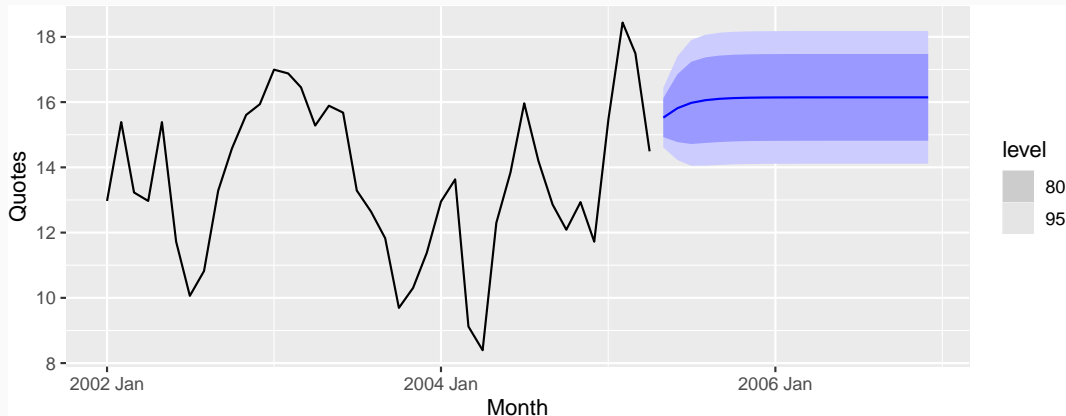
```
# Re-fit to all data
fit <- insurance >
  model(ARIMA(Quotes ~ TVadverts + lag(TVadverts) + pdq(d = 0)))
report(fit)
```

```
## Series: Quotes
## Model: LM w/ ARIMA(1,0,2) errors
##
## Coefficients:
##          ar1      ma1      ma2 TVadverts lag(TVadverts) intercept
##          0.512  0.917  0.459    1.2527          0.1464         2.16
## s.e.    0.185  0.205  0.190    0.0588          0.0531         0.86
##
## sigma^2 estimated as 0.2166: log likelihood=-23.9
## AIC=61.9   AICc=65.4   BIC=73.7
```

$$y_t = 2.16 + 1.25x_t + 0.15x_{t-1} + \eta_t,$$
$$\eta_t = 0.512\eta_{t-1} + \varepsilon_t + 0.92\varepsilon_{t-1} + 0.46\varepsilon_{t-2}.$$

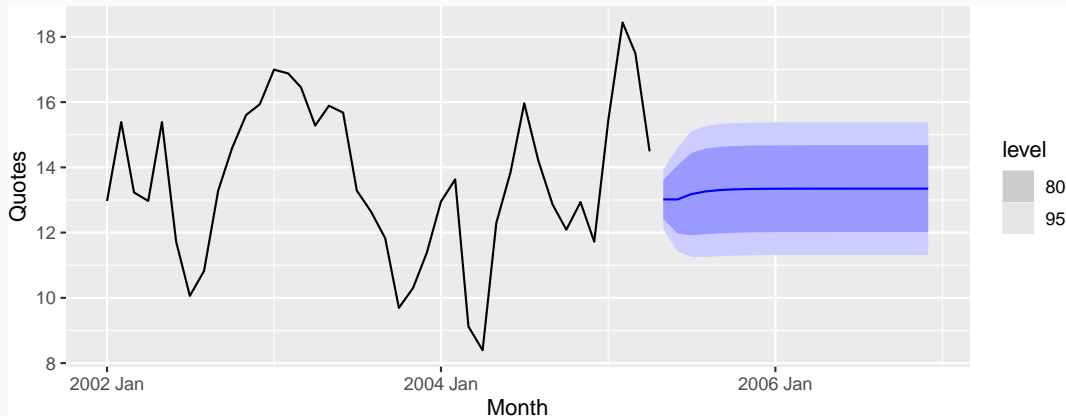
Example: Insurance quotes and TV adverts

```
advert_a <- new_data(insurance, 20) ▷  
  mutate(TVadverts = 10)  
forecast(fit, advert_a) ▷ autoplot(insurance)
```



Example: Insurance quotes and TV adverts

```
advert_b <- new_data(insurance, 20) ▷  
  mutate(TVadverts = 8)  
forecast(fit, advert_b) ▷ autoplot(insurance)
```



Example: Insurance quotes and TV adverts

```
advert_c <- new_data(insurance, 20) ▷  
  mutate(TVadverts = 6)  
forecast(fit, advert_c) ▷ autoplot(insurance)
```

