MONASH University

MONASH BUSINESS SCHOOL

ETF3231/5231: Business forecasting

Ch10. Dynamic Regression

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Outline

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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 $x_{1,t}, \ldots, x_{k,t}$.
- In regression, we assume that ε_t is WN.
- Now we want to allow ε_t to be autocorrelated.

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- In regression, we assume that ε_t is WN.
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Example: ARIMA(1,1,1) errors

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \eta_t,$$
$$(1 - \phi_1 B)(1 - B)\eta_t = (1 + \theta_1 B)\varepsilon_t,$$

where ε_t is white noise.

Residuals and errors

Example: η_t = ARIMA(1,1,1)

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- Be careful in distinguishing η_t from ε_t.
- Only the errors ε_t are assumed to be white noise.
- In ordinary regression, η_t is assumed to be white noise and so $\eta_t = \varepsilon_t$.

Estimation

If we minimize $\sum \eta_t^2$ (by using ordinary regression):

1. Estimated coefficients $\hat{\beta}_0, \dots, \hat{\beta}_k$ are no longer optimal as some information ignored;
2. Statistical tests associated with the model (e.g., t-tests on the coefficients) are incorrect.
3. *p*-values for coefficients usually too small (“spurious regression’ ’).
4. AIC of fitted models misleading.

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- Minimizing $\sum \varepsilon_t^2$ avoids these problems.
- Maximizing likelihood similar to minimizing $\sum \varepsilon_t^2$.

Stationarity

Regression with ARMA errors

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

where η_t is an ARMA process.

- All variables in the model must be stationary.
- If we estimate the model while any of these are non-stationary, the estimated coefficients can be incorrect.
- Difference variables until all stationary.
- If necessary, apply same differencing to all variables.

Stationarity

Model with ARIMA(1,1,1) errors

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Equivalent to model with ARIMA(1,0,1) errors

$$y'_t = \beta_1 x'_{1,t} + \cdots + \beta_k x'_{k,t} + \eta'_t,$$
$$(1 - \phi_1 B)\eta'_t = (1 + \theta_1 B)\varepsilon_t,$$

where $y'_t = y_t - y_{t-1}$, $x'_{t,i} = x_{t,i} - x_{t-1,i}$ and $\eta'_t = \eta_t - \eta_{t-1}$.

Regression with ARIMA errors

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Original data

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$$\text{where} \quad \phi(B)(1 - B)^d \eta_t = \theta(B)\varepsilon_t$$

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After differencing all variables

$$y'_t = \beta_1 x'_{1,t} + \cdots + \beta_k x'_{k,t} + \eta'_t.$$

where $\phi(B)\eta'_t = \theta(B)\varepsilon_t$,

$y'_t = (1-B)^d y_t, \quad x'_{i,t} = (1-B)^d x_{i,t}, \quad$ and $\eta'_t = (1-B)^d \eta_t$

Regression with ARIMA errors

- In R, we can specify an ARIMA(p, d, q) for the errors, and d levels of differencing will be applied to all variables ($y, x_{1,t}, \dots, x_{k,t}$) during estimation.
- Check that ε_t series looks like white noise.
- AICc can be calculated for final model.
- Repeat procedure for all subsets of predictors to be considered, and select model with lowest AICc value.

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.

Outline

Dynamic harmonic regression

Combine Fourier terms with ARIMA errors

Advantages

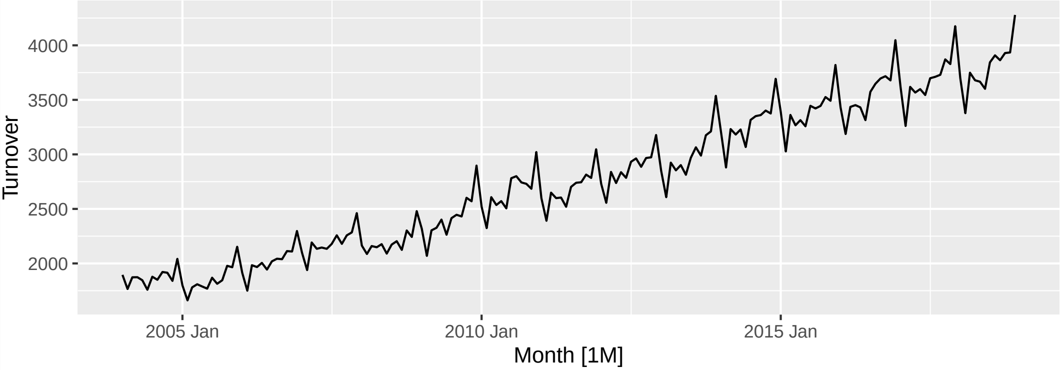
- it allows any length seasonality;
- for data with more than one seasonal period, you can include Fourier terms of different frequencies;
- the seasonal pattern is smooth for small values of K (but more wiggly seasonality can be handled by increasing K);
- the short-term dynamics are easily handled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

Disadvantages

- seasonality is assumed to be fixed

Eating-out expenditure

```r
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)
```



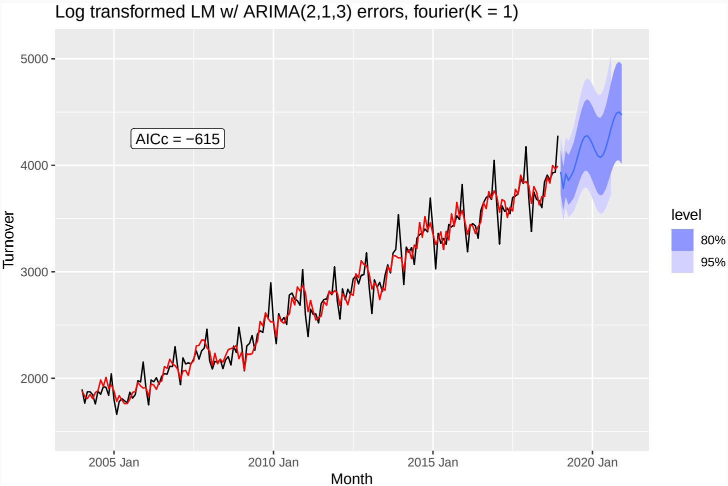
Eating-out expenditure

```r
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) %>% select(.model, sigma2, log_lik, AIC, AICc, BIC)
```

.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



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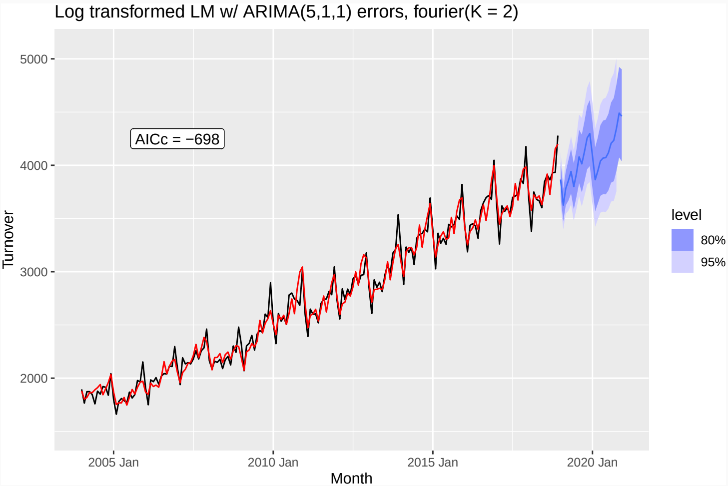

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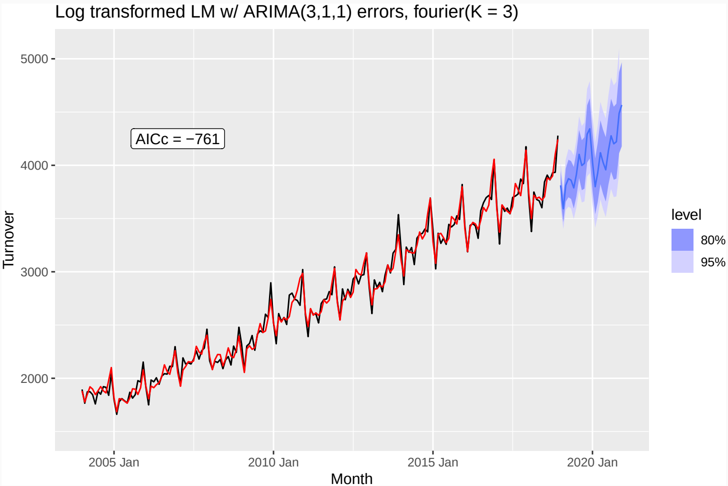

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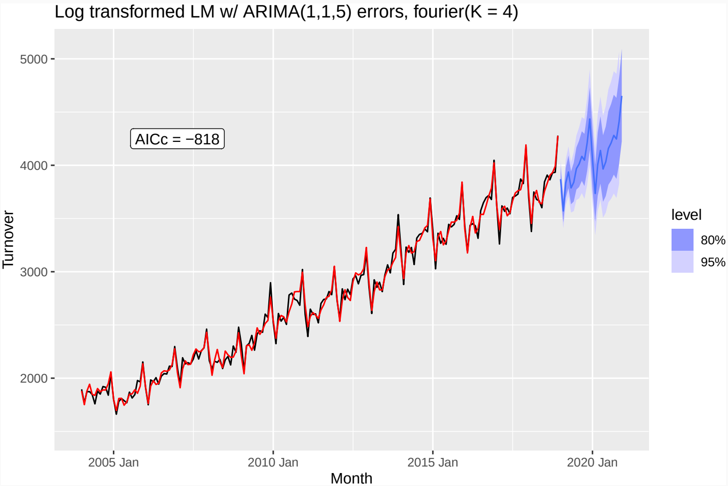

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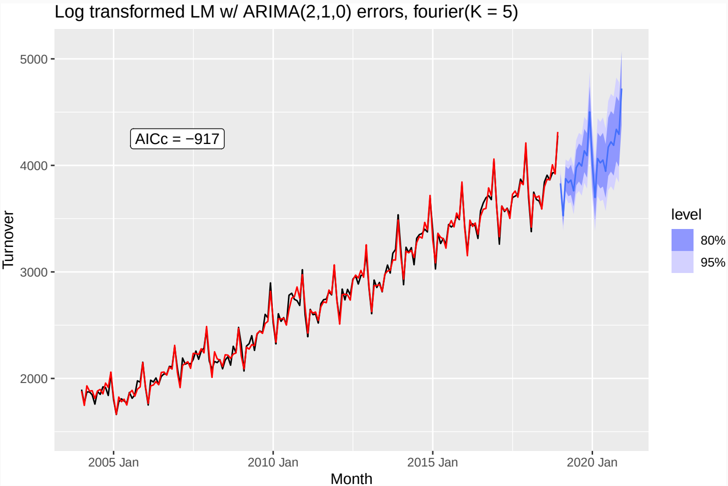

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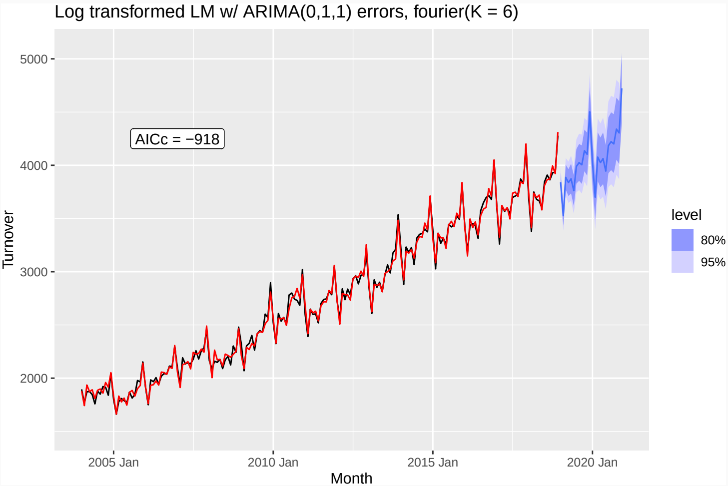

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Stochastic & deterministic trends

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where η_t is ARIMA process with $d = 1$.

Stochastic & deterministic trends

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Stochastic trend

$$y_t = \beta_0 + \beta_1 t + \eta_t$$

where η_t is ARIMA process with $d = 1$.

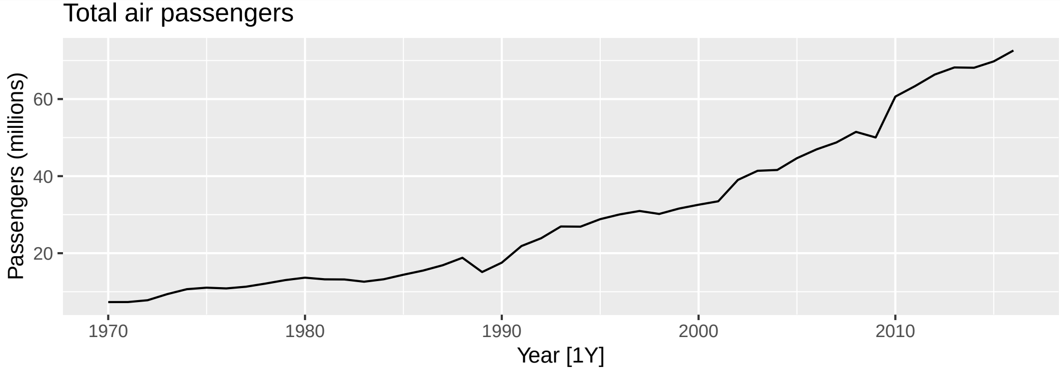
Difference both sides until η_t is stationary:

$$y'_t = \beta_1 + \eta'_t$$

where η'_t is ARMA process.

Air transport passengers Australia

```
aus_airpassengers %>%
  autoplot(Passengers) +
  labs(y = "Passengers (millions)",
       title = "Total air passengers")
```



Air transport passengers Australia

Deterministic trend

```
fit_deterministic <- aus_airpassengers %>%
  model(ARIMA(Passengers ~ 1 + trend() + pdq(d = 0)))
report(fit_deterministic)
```

```
## Series: Passengers
## Model: LM w/ ARIMA(1,0,0) errors
##
## Coefficients:
##          ar1  trend()  intercept
##       0.9564    1.415      0.901
## s.e.  0.0362    0.197      7.075
##
## sigma^2 estimated as 4.343:  log likelihood=-101
## AIC=210   AICc=211   BIC=217
```

Air transport passengers Australia

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```

$$y_t = 0.901 + 1.415t + \eta_t$$
$$\eta_t = 0.956\eta_{t-1} + \varepsilon_t$$
$$\varepsilon_t \sim \text{NID}(0, 4.343).$$

Air transport passengers Australia

Stochastic trend

```r
fit_stochastic <- aus_airpassengers %>%
  model(ARIMA(Passengers ~ 1 + pdq(d = 1)))
report(fit_stochastic)
```

```
## Series: Passengers
## Model: ARIMA(0,1,0) w/ drift
##
## Coefficients:
##       constant
##          1.419
## s.e.     0.301
##
## sigma^2 estimated as 4.271:  log likelihood=-98.2
## AIC=200   AICc=201   BIC=204
```

Air transport passengers Australia

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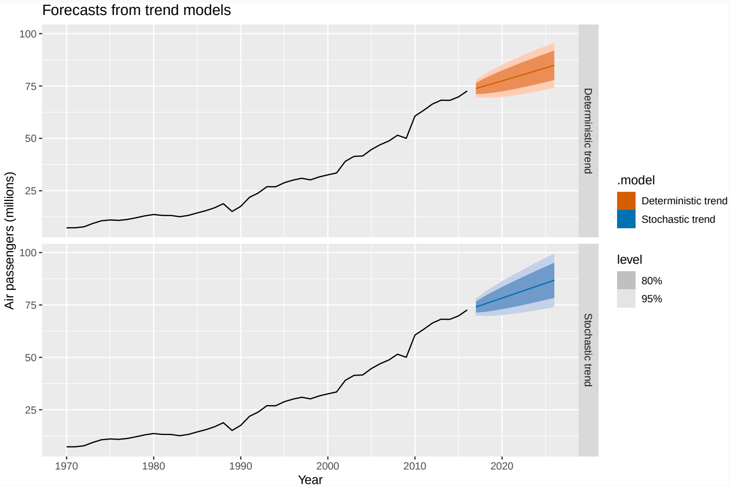
## s.e.     0.301
##
## sigma^2 estimated as 4.271:  log likelihood=-98.2
## AIC=200   AICc=201   BIC=204
```

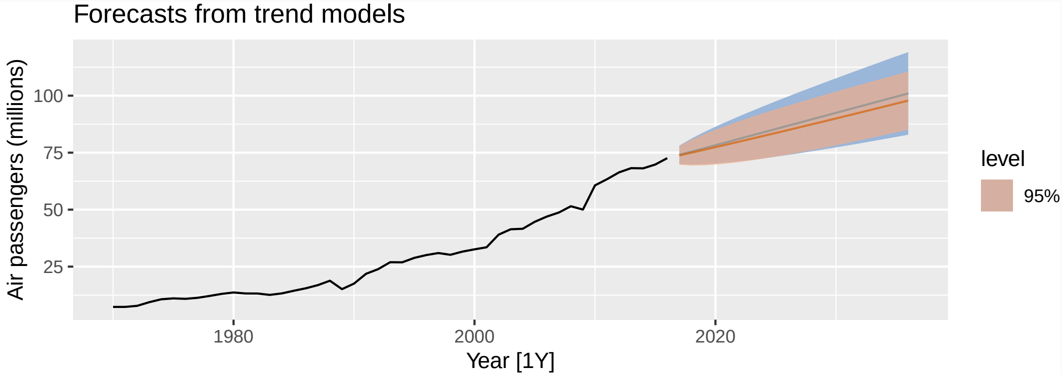
$$
\begin{aligned}
y_t - y_{t-1} &= 1.419 + \varepsilon_t, \\
y_t &= y_0 + 1.419t + \eta_t \\
\eta_t &= \eta_{t-1} + \varepsilon_t \\
\varepsilon_t &\sim \text{NID}(0, 4.271).
\end{aligned}
$$

Air transport passengers Australia



Air transport passengers Australia

```r
aus_airpassengers %>% autoplot(Passengers) +
  autolayer(fit_stochastic %>% forecast(h = 20), colour = "#0072B2", level = 95) +
  autolayer(fit_deterministic %>% forecast(h = 20), colour = "#D55E00", level = 95,
            alpha = 0.65) +
  labs(y = "Air passengers (millions)", title = "Forecasts from trend models")
```



Forecasting with trend

- Point forecasts are almost identical, but prediction intervals differ.
- Stochastic trends have much wider prediction intervals because the errors are non-stationary.
- Be careful of forecasting with deterministic trends too far ahead.