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FORECASTING PRINCIPLES AND PRACTICE



9. ARIMA models

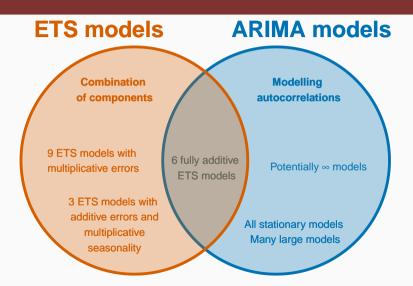
9.10 ARIMA vs ETS

OTexts.org/fpp3/

ARIMA vs ETS

- Myth that ARIMA models are more general than exponential smoothing.
- Linear exponential smoothing models all special cases of ARIMA models.
- Non-linear exponential smoothing models have no equivalent ARIMA counterparts.
- Many ARIMA models have no exponential smoothing counterparts.
- ETS models all non-stationary. Models with seasonality or non-damped trend (or both) have two unit roots; all other models have one unit root.

ARIMA vs ETS



Equivalences

ETS model	ARIMA model	Parameters
ETS(A,N,N)	ARIMA(0,1,1)	$\theta_1 = \alpha - 1$
ETS(A,A,N)	ARIMA(0,2,2)	θ_1 = α + β $-$ 2
		θ_{2} = 1 $-\alpha$
$ETS(A,A_d,N)$	ARIMA(1,1,2)	$\phi_1 = \phi$
		θ_{1} = α + $\phi\beta$ $-$ 1 $ \phi$
		θ_2 = (1 $-\alpha$) ϕ
ETS(A,N,A)	$ARIMA(0,0,m)(0,1,0)_m$	
ETS(A,A,A)	$ARIMA(0,1,m+1)(0,1,0)_m$	
$ETS(A,A_d,A)$	$ARIMA(1,0,m+1)(0,1,0)_m$	

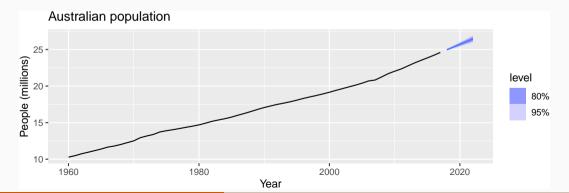
Example: Australian population

```
aus_economy <- global_economy |>
 filter(Code == "AUS") |>
 mutate(Population = Population / 1e6)
aus_economy |>
 slice(-n()) |>
  stretch tsibble(.init = 10) |>
 model(ets = ETS(Population), arima = ARIMA(Population)) |>
 forecast(h = 1) |>
 accuracy(aus economy) |>
  select(.model, ME:RMSSE)
## # A tibble: 2 x 8
##
    model ME RMSE MAE MPE MAPE MASERMSSE
## <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <
```

1 arima 0.0420 0.194 0.0789 0.277 0.509 0.317 0.746 ## 2 ets 0.0202 0.0774 0.0543 0.112 0.327 0.218 0.298

Example: Australian population

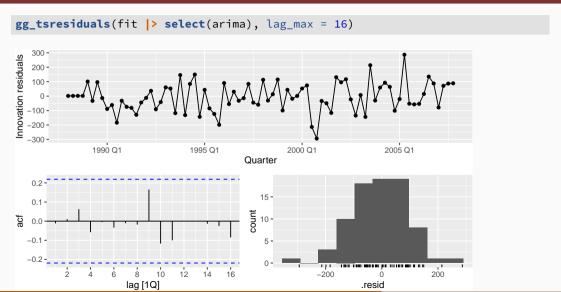
```
aus_economy |>
model(ETS(Population)) |>
forecast(h = "5 years") |>
autoplot(aus_economy) +
labs(title = "Australian population", y = "People (millions)")
```

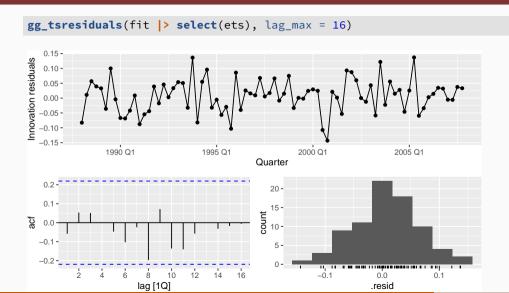


```
cement <- aus_production |>
    select(Cement) |>
    filter_index("1988 Q1" ~ .)
train <- cement |> filter_index(. ~ "2007 Q4")
fit <- train |>
    model(
        arima = ARIMA(Cement),
        ets = ETS(Cement)
)
```

```
fit |>
 select(arima) |>
  report()
## Series: Cement
## Model: ARIMA(1,0,1)(2,1,1)[4] w/ drift
##
## Coefficients:
                  mal sar1 sar2
##
           ar1
                                       smal constant
        0.8886 - 0.237 \ 0.081 - 0.234 - 0.898
                                                5.39
##
## s.e. 0.0842 0.133 0.157 0.139
                                      0.178
                                                1.48
##
## sigma^2 estimated as 11456: log likelihood=-464
## ATC=941 ATCc=943
                     BIC=957
```

```
fit |>
  select(ets) |>
  report()
## Series: Cement
## Model: ETS(M,N,M)
##
     Smoothing parameters:
   alpha = 0.753
##
##
    gamma = 1e-04
##
##
   Initial states:
   l[0] s[0] s[-1] s[-2] s[-3]
##
    1695 1.03 1.05 1.01 0.912
##
##
##
     sigma^2: 0.0034
##
    AIC AICC BIC
##
  1104 1106 1121
```





```
fit |>
  select(arima) |>
  augment() |>
  features(.innov, ljung_box, lag = 16, dof = 6)

## # A tibble: 1 x 3
```

```
## .model lb_stat lb_pvalue
## <chr> <dbl> <dbl>
## 1 arima 6.37 0.783
```

.model lb_stat lb_pvalue ## <chr> <dbl> <dbl> ## 1 ets 10.0 0.865

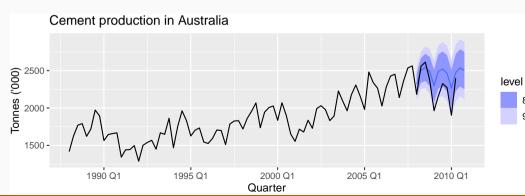
##

```
fit |>
  select(ets) |>
  augment() |>
  features(.innov, ljung_box, lag = 16)
## # A tibble: 1 x 3
```

```
fit |>
  forecast(h = "2 years 6 months") |>
  accuracy(cement) |>
  select(-ME, -MPE, -ACF1)
```

```
## # A tibble: 2 x 7
## .model .type RMSE MAE MAPE MASE RMSSE
## <chr> <chr> <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> 1.27 1.26
## 2 ets Test 222. 191. 8.85 1.30 1.29
```

```
fit |>
  select(arima) |>
  forecast(h = "3 years") |>
  autoplot(cement) +
  labs(title = "Cement production in Australia", y = "Tonnes ('000)")
```



80% 95%