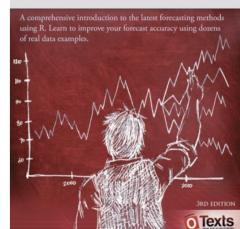
5. The forecaster's toolbox

5.7 Forecasting with decompositionOTexts.org/fpp3/

Rob J Hyndman George Athanasopoulos

FORECASTING PRINCIPLES AND PRACTICE



Forecasting and decomposition

$$y_t = \hat{S}_t + \hat{A}_t$$

- \blacksquare \hat{A}_t is seasonally adjusted component
- \hat{S}_t is seasonal component.
- Forecast \hat{S}_t using SNAIVE.
- Forecast \hat{A}_t using non-seasonal time series method.
- Combine forecasts of \hat{S}_t and \hat{A}_t to get forecasts of original data.

"" 0 1000 C. . D. L. . . T.

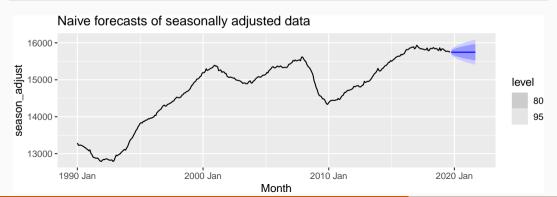
```
us_retail_employment <- us_employment |>
  filter(year(Month) >= 1990, Title == "Retail Trade") |>
  select(-Series_ID)
us_retail_employment
```

```
## # A tsibble: 357 x 3 [1M]
##
        Month Title
                           Employed
                              <dbl>
##
        <mth> <chr>
   1 1990 Jan Retail Trade
##
                             13256.
##
   2 1990 Feb Retail Trade
                             12966.
   3 1990 Mar Retail Trade
##
                             12938.
   4 1990 Apr Retail Trade
                             13012.
##
##
   5 1990 May Retail Trade
                             13108.
   6 1990 Jun Retail Trade
                             13183.
##
   7 1990 Jul Retail Trade
##
                             13170.
##
   8 1990 Aug Retail Trade
                             13160.
```

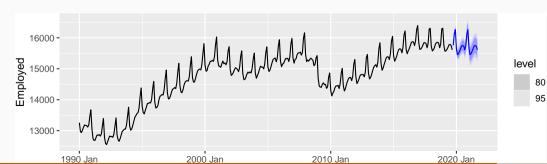
```
dcmp <- us_retail_employment |>
  model(STL(Employed)) |>
  components() |>
  select(-.model)
dcmp
```

```
## # A tsibble: 357 x 6 [1M]
##
       Month Employed trend season_year remainder season_adjust
##
       <mth>
             <dbl> <dbl>
                              <dbl>
                                         <dbl>
                                                     <dbl>
##
   1 1990 Jan 13256. 13288. -33.0
                                         0.836
                                                     13289.
##
   2 1990 Feb
             12966. 13269. -258.
                                       -44.6
                                                     13224.
   3 1990 Mar
                              -290.
                                       -22.1
                                                     13228.
##
             12938. 13250.
   4 1990 Apr
             13012. 13231. -220.
                                       1.05
                                                     13232.
##
   5 1990 May
##
             13108. 13211.
                              -114.
                                        11.3
                                                     13223.
   6 1990 Jun
             13183. 13192. -24.3
                                        15.5
                                                     13207.
##
##
   7 1990 Jul
              13170. 13172.
                              -23.2
                                        21.6
                                                     13193.
## 9 1000 Aug
              12160 12151
                                -0 52
                                        17 0
                                                     12160
```

```
dcmp |>
  model(NAIVE(season_adjust)) |>
  forecast() |>
  autoplot(dcmp) +
  labs(title = "Naive forecasts of seasonally adjusted data")
```



```
us_retail_employment |>
  model(stlf = decomposition_model(
    STL(Employed ~ trend(window = 7), robust = TRUE),
    NAIVE(season_adjust)
)) |>
  forecast() |>
  autoplot(us_retail_employment)
```



Decomposition models

decomposition_model() creates a decomposition model

- You must provide a method for forecasting the season_adjust series.
- A seasonal naive method is used by default for the seasonal components.
- The variances from both the seasonally adjusted and seasonal forecasts are combined.