tidyverts & prophet

Lecture 12

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Tidy time series

`ts` objects

In base R, time series are usually encoded using the `ts` S3 class,

```r
co2
```

```
      Jan    Feb    Mar    Apr    May    Jun
1959 315.42 316.31 316.50 317.56 318.13 318.00
1960 316.27 316.81 317.42 318.87 319.87 319.43
1961 316.73 317.54 318.38 319.31 320.42 319.61
1962 317.78 318.40 319.53 320.42 320.85 320.45
1963 318.58 318.92 319.70 321.22 322.08 321.31
1964 319.41 320.07 320.74 321.40 322.06 321.73
1965 319.27 320.28 320.73 321.97 322.00 321.71
1966 320.46 321.43 322.23 323.54 323.91 323.59
1967 322.17 322.34 322.88 324.25 324.83 323.93
1968 322.40 322.99 323.73 324.86 325.40 325.20
1969 323.83 324.26 325.47 326.50 327.21 326.54
1970 324.89 325.82 326.77 327.97 327.91 327.50
1971 326.01 326.51 327.01 327.62 328.76 328.40
1972 326.60 327.47 327.58 329.56 329.90 328.92
1973 328.37 329.40 330.14 331.33 332.31 331.90
```

```r
typeof(co2)
```

```
[1] "double"
```

```r
class(co2)
```

```
[1] "ts"
```

```r
attributes(co2)
```

```
$tsp
[1] 1959.000 1997.917   12.000

$class
[1] "ts"
```

tidyverts

This is an effort headed by Rob Hyndman (of forecast fame) and others to provide a consistent tidy data based framework for working with time series data and models.

Core packages:

- `tsibble` - temporal data frames and related tools
- `fable` - tidy forecasting (modelling)
- `feasts` - feature extraction and statistics
- `tsibbledata` - sample tsibble data sets

tsibble

A tsibble is a tibble with additional infrastructure for encoding temporal data - specifcially a tsibble is a tidy data frame with an *index* and *key* where

- the *index* is the variable that descibes the inherent ordering of the data (from past to present)
- and the *key* is one or more variables that define the unit of observation over time
- each observation should be uniquely identified by the *index* and *key*

global_economy

```r
tsibbledata::global_economy
```

```
# A tsibble: 15,150 x 9 [1Y]
# Key:       Country [263]
   Country Code   Year    GDP Growth   CPI Imports
   <fct>   <fct> <dbl>  <dbl>  <dbl> <dbl>   <dbl>
 1 Afghan… AFG    1960 5.38e8     NA    NA    7.02
 2 Afghan… AFG    1961 5.49e8     NA    NA    8.10
 3 Afghan… AFG    1962 5.47e8     NA    NA    9.35
 4 Afghan… AFG    1963 7.51e8     NA    NA   16.9
 5 Afghan… AFG    1964 8.00e8     NA    NA   18.1
 6 Afghan… AFG    1965 1.01e9     NA    NA   21.4
 7 Afghan… AFG    1966 1.40e9     NA    NA   18.6
 8 Afghan… AFG    1967 1.67e9     NA    NA   14.2
```

vic_elec

```
tsibbledata::vic_elec
```

```
# A tsibble: 52,608 x 5 [30m]
#   <Australia/Melbourne>
   Time                Demand Tempera…¹ Date
   <dttm>               <dbl>     <dbl> <date>
 1 2012-01-01 00:00:00  4383.      21.4 2012-01-01
 2 2012-01-01 00:30:00  4263.      21.0 2012-01-01
 3 2012-01-01 01:00:00  4049.      20.7 2012-01-01
 4 2012-01-01 01:30:00  3878.      20.6 2012-01-01
 5 2012-01-01 02:00:00  4036.      20.4 2012-01-01
 6 2012-01-01 02:30:00  3866.      20.2 2012-01-01
 7 2012-01-01 03:00:00  3694.      20.1 2012-01-01
 8 2012-01-01 03:30:00  3562.      19.6 2012-01-01
```

aus_retail

```
tsibbledata::aus_retail
```

```
# A tsibble: 64,532 x 5 [1M]
# Key:       State, Industry [152]
   State            Indus…¹ Serie…²    Month Turno…³
   <chr>            <chr>   <chr>      <mth>   <dbl>
 1 Australian Ca… Cafes,… A33498… 1982 Apr      4.4
 2 Australian Ca… Cafes,… A33498… 1982 May      3.4
 3 Australian Ca… Cafes,… A33498… 1982 Jun      3.6
 4 Australian Ca… Cafes,… A33498… 1982 Jul      4
 5 Australian Ca… Cafes,… A33498… 1982 Aug      3.6
 6 Australian Ca… Cafes,… A33498… 1982 Sep      4.2
 7 Australian Ca… Cafes,… A33498… 1982 Oct      4.8
 8 Australian Ca… Cafes,… A33498… 1982 Nov      5.4
```

as_tsibble()

Existing ts objects can be converted to a tsibble easily,

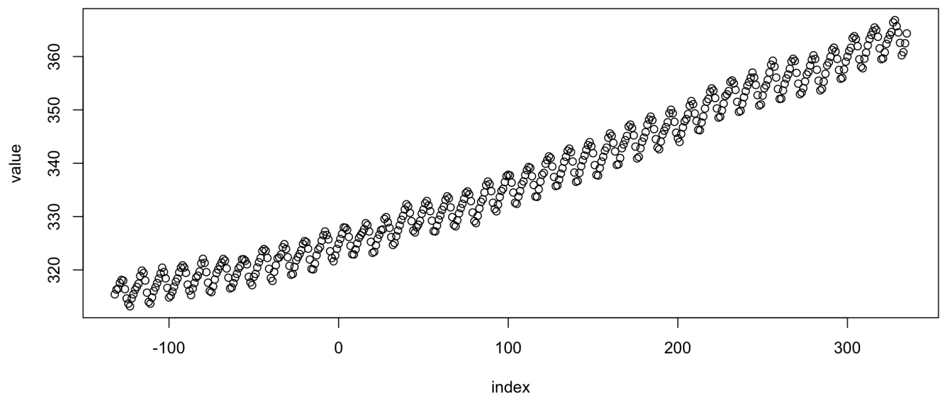
```r
tsibble::as_tsibble(co2)
```

```
# A tsibble: 468 x 2 [1M]
      index value
      <mth> <dbl>
 1 1959 Jan  315.
 2 1959 Feb  316.
 3 1959 Mar  316.
 4 1959 Apr  318.
 5 1959 May  318.
 6 1959 Jun  318
 7 1959 Jul  316.
 8 1959 Aug  315.
 9 1959 Sep  314.
```

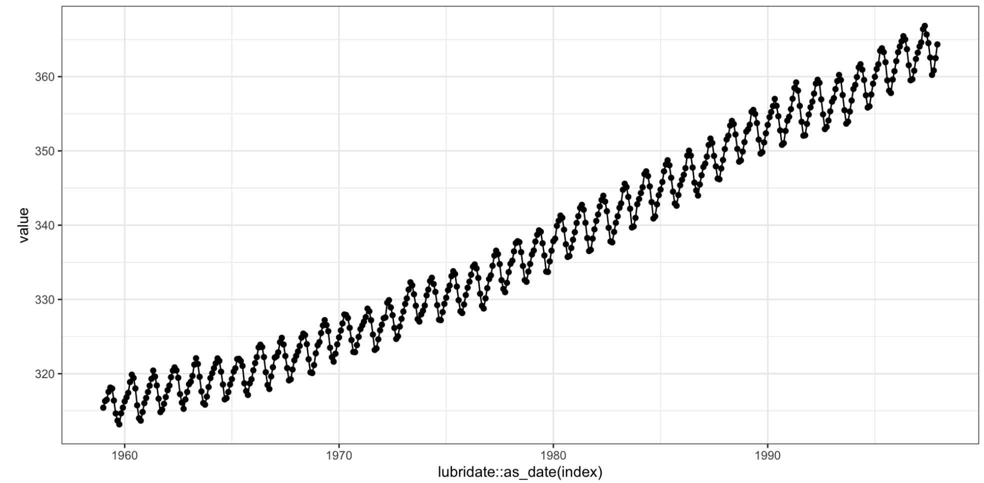
plotting tsibbles

As the tsibble is basically just a tibble which is basically just a data frame both base and ggplot plotting methods will work.

```r
tsibble::as_tsibble(co2) %>%
  plot()
```

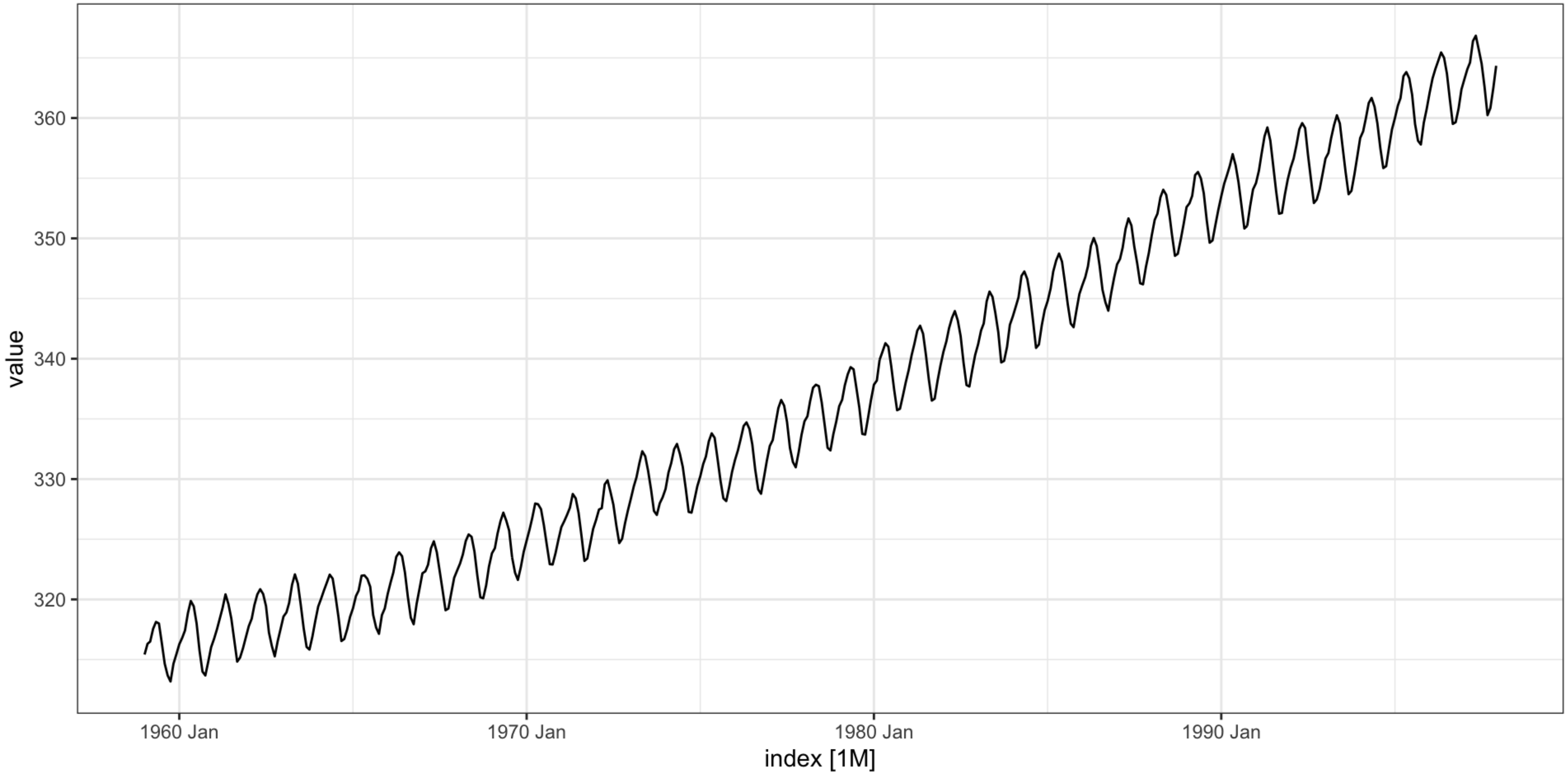



```r
tsibble::as_tsibble(co2) %>%
  ggplot(aes(x=lubridate::as_date(index),y=va
    geom_point() +
    geom_line()
```



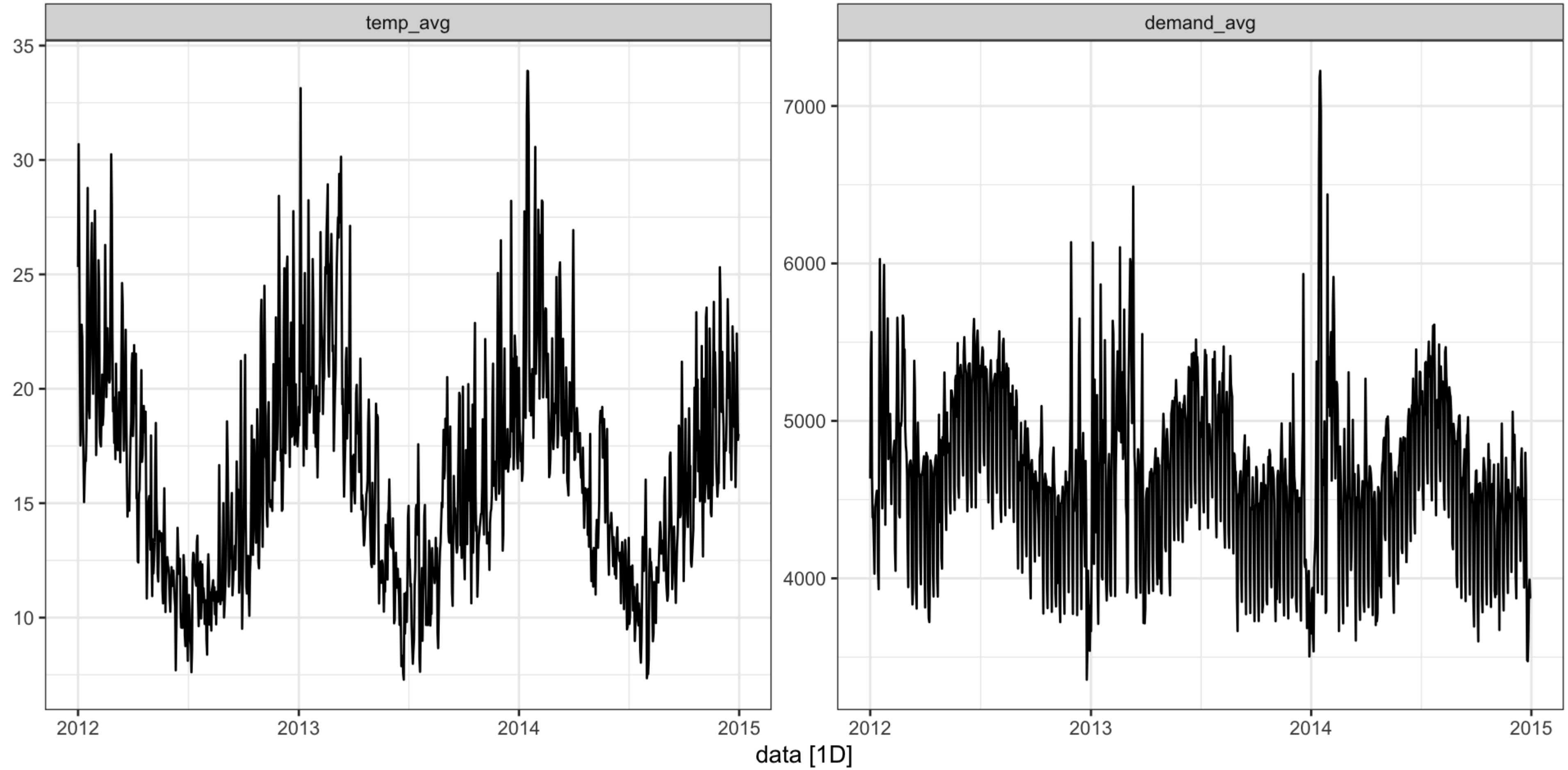
autoplot

```r
library(fabletools) # needed to support autoplot
tsibble::as_tsibble(co2) %>%
  autoplot(.vars = vars(value))
```



Multiple variables

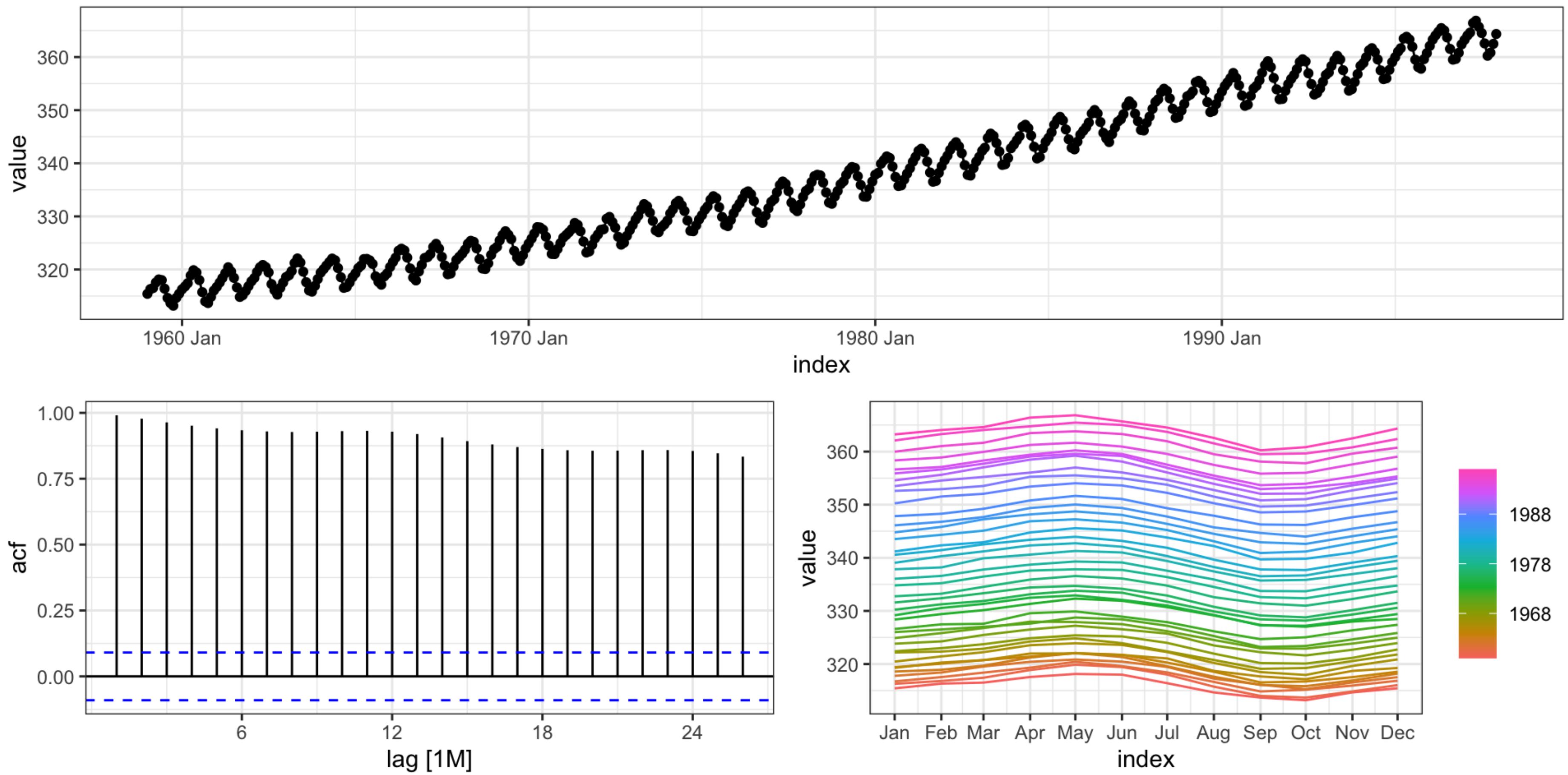
```
tsibbledata::vic_elec %>%
  tsibble::index_by(data = ~ lubridate::as_date(.)) %>%
  summarize(
    demand_avg = mean(Demand, na.rm=TRUE),
    temp_avg = mean(Temperature, na.rm=TRUE)
  ) %>%
  autoplot(.vars = vars(temp_avg, demand_avg))
```


temp_avg
demand_avg
35
30
25
20
15
10
7000
6000
5000
4000
2012
2013
2014
2015
data [1D]

ggtsdisplay() replacement

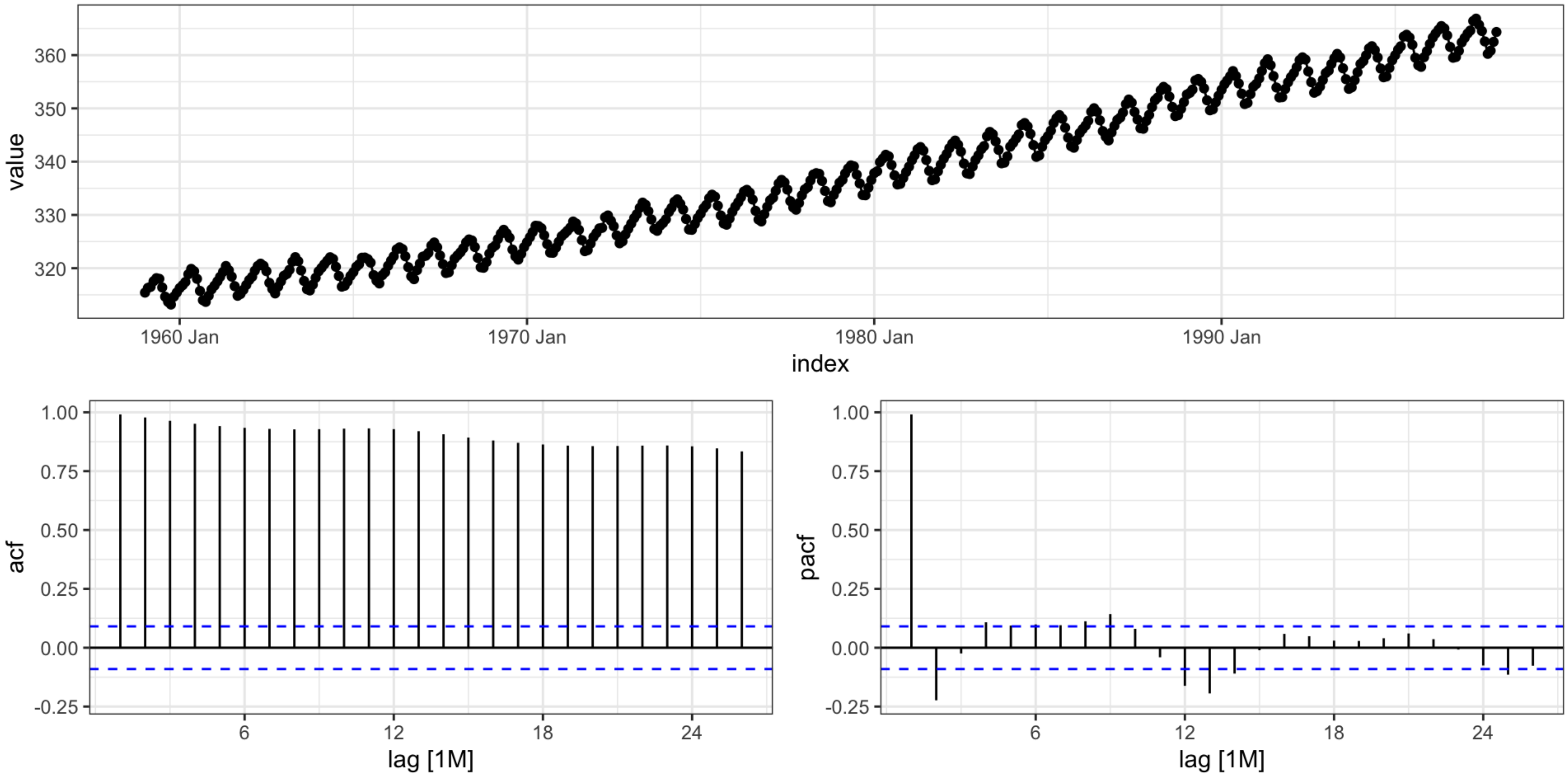
The equivalent to this plot is provided by `feasts`,

```
tsibble::as_tsibble(co2) %>%
  feasts::gg_tsdisplay(y = value)
```



ggtsdisplay() - pACT

```
tsibble::as_tsibble(co2) %>%
  feasts::gg_tsdisplay(y = value, plot_type = "partial")
```



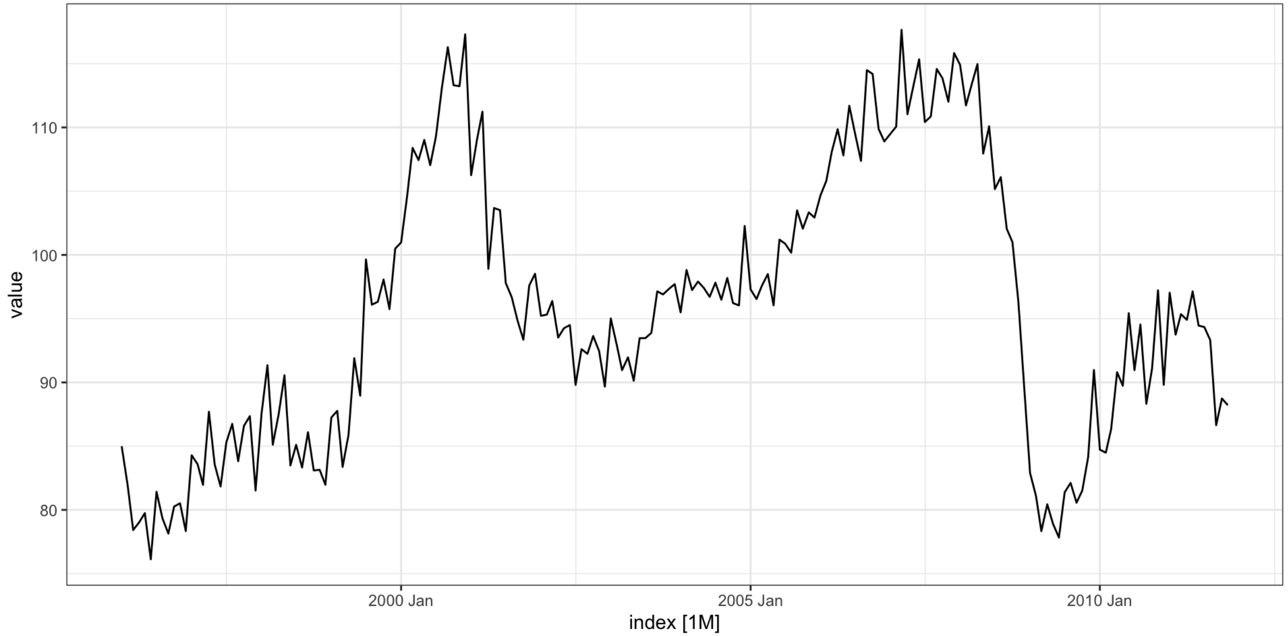
Modeling with fable

elec_sales

```r
( elec_sales = as_tsibble(
  elec_sales
) )
```

```
# A tsibble: 191 x 2 [1M]
      index value
      <mth> <dbl>
 1 1996 Jan  85.0
 2 1996 Feb  81.9
 3 1996 Mar  78.4
 4 1996 Apr  79.0
 5 1996 May  79.7
 6 1996 Jun  76.1
 7 1996 Jul  81.4
 8 1996 Aug  79.3
 9 1996 Sep  78.1
10 1996 Oct  80.3
# … with 181 more rows
```

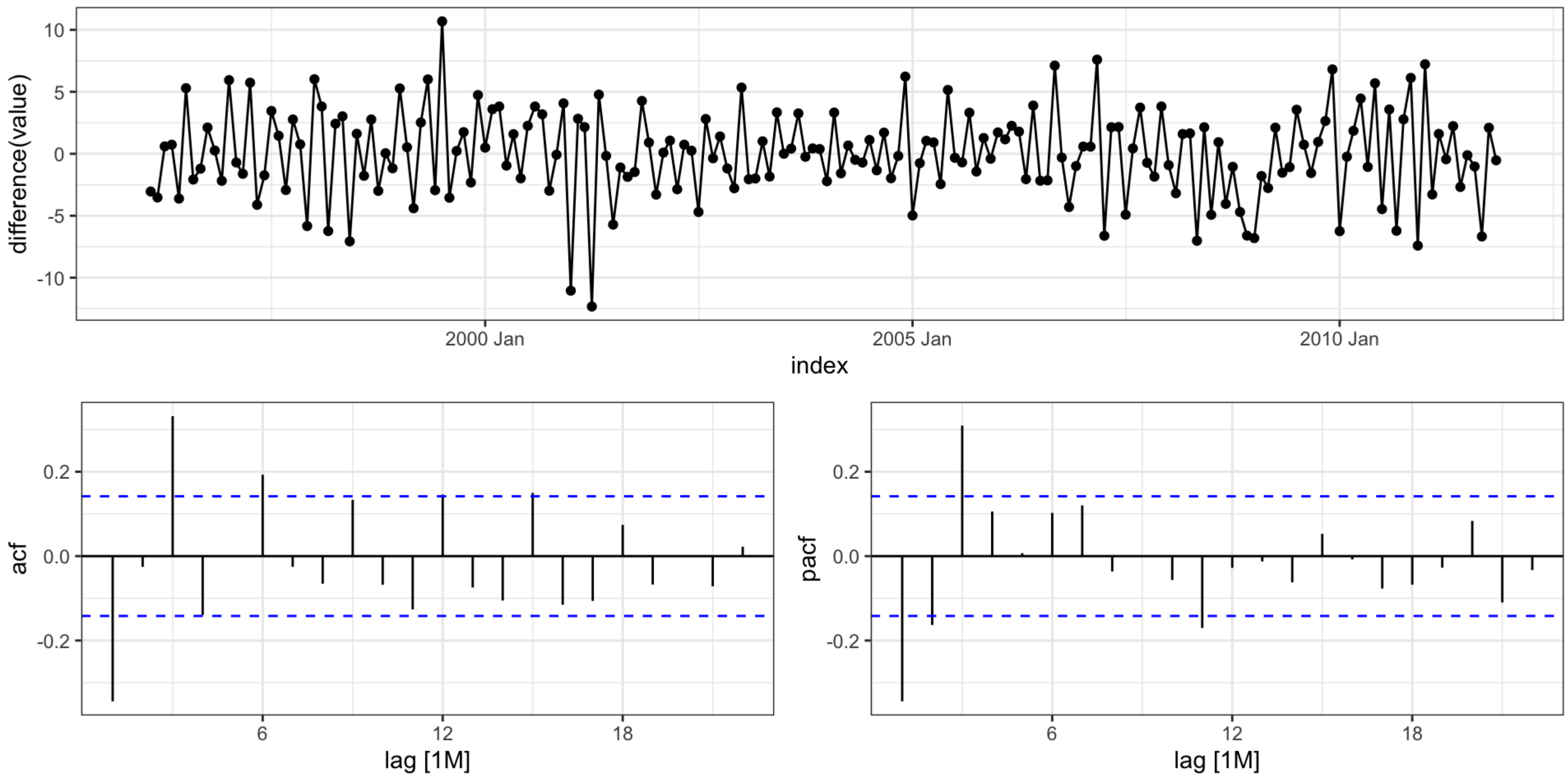
```r
elec_sales %>%
  autoplot(value)
```



These data were also fit in Lecture 11

Differencing

```r
elec_sales %>%
  feasts::gg_tsdisplay(difference(value), plot_type="partial")
```



Modeling

To fit a model with fable we use the `model()` function along with a specific function for the model we are trying to fit (`ARIMA()` here).

As with the rest of tidyverts - `fable` using a tidy approach for modeling which means that the model results are stored in a tibble (called a mable for model table).

```r
library(fable)
( m = elec_sales %>%
    model(
      ARIMA(value ~ pdq(3,1,0))
    )
)
```

```
# A mable: 1 x 1
  `ARIMA(value ~ pdq(3, 1, 0))`
                        <model>
1                <ARIMA(3,1,0)>
```

Model summary

```r
m %>%
  report()
```

```
Series: value
Model: ARIMA(3,1,0)

Coefficients:
          ar1      ar2     ar3
      -0.3488  -0.0386  0.3139
s.e.   0.0690   0.0736  0.0694

sigma^2 estimated as 9.853:  log likelihood=-485.67
AIC=979.33   AICc=979.55   BIC=992.32
```

Model details (broom + yardstick)

```r
m %>% glance()
```

```
# A tibble: 1 × 8
  .model                       sigma2 log_lik   AIC  AICc   BIC ar_roots   ma_roots
  <chr>                         <dbl>   <dbl> <dbl> <dbl> <dbl> <list>     <list>
1 ARIMA(value ~ pdq(3, 1, 0))   9.85   -486.  979.  980.  992. <cpl [3]> <cpl [0]>
```

```r
m %>% accuracy()
```

```
# A tibble: 1 × 10
  .model                       .type        ME  RMSE   MAE     MPE  MAPE  MASE RMSSE    ACF1
  <chr>                        <chr>     <dbl> <dbl> <dbl>   <dbl> <dbl> <dbl> <dbl>   <dbl>
1 ARIMA(value ~ pdq(3, 1, 0)) Training 0.0117  3.11  2.43 -0.0435  2.56 0.296 0.281 -0.0346
```

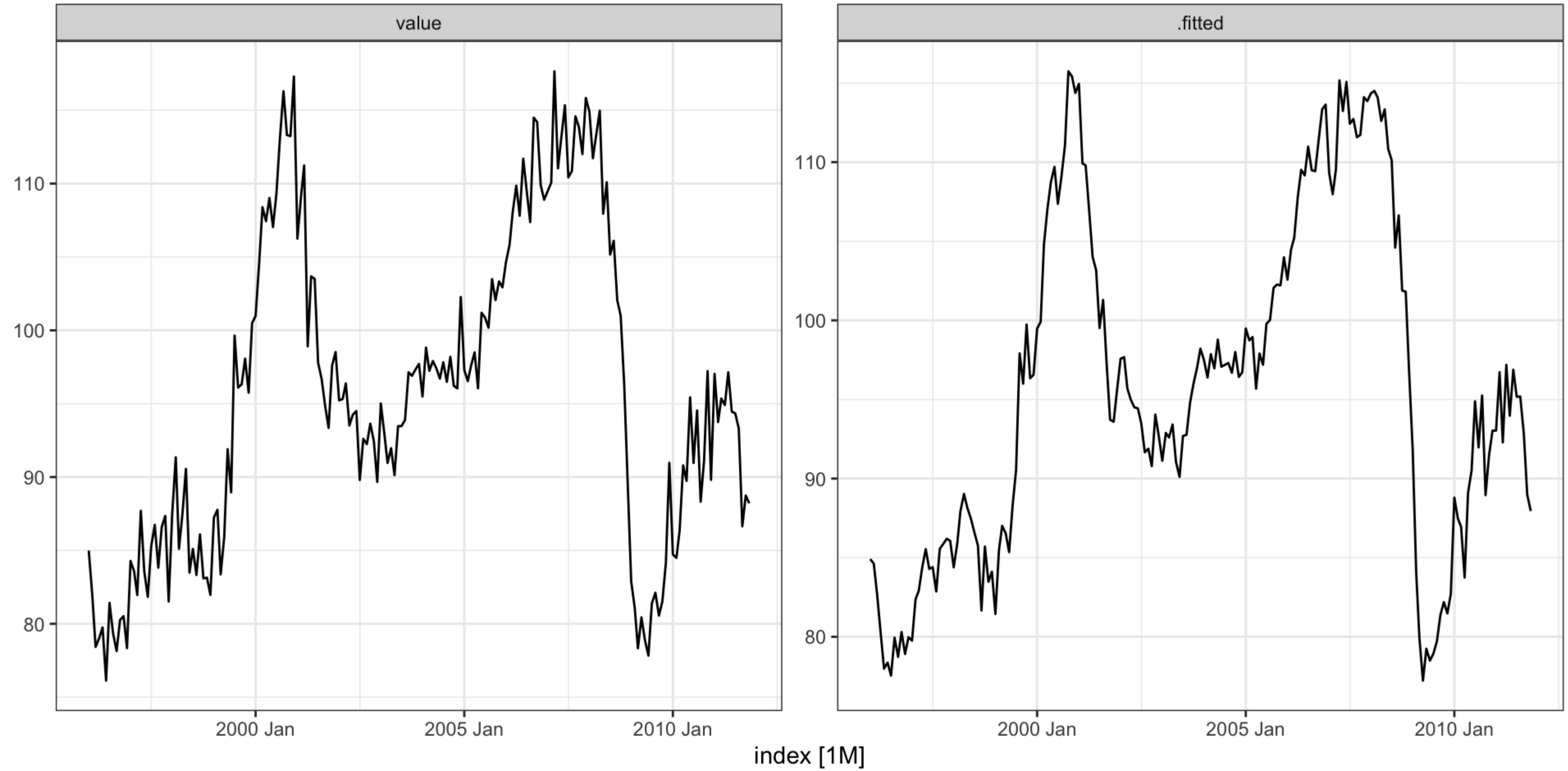
```r
m %>% augment()
```

```
# A tsibble: 191 x 6 [1M]
# Key:       .model [1]
   .model                         index value .fitted  .resid  .innov
   <chr>                          <mth> <dbl>   <dbl>   <dbl>   <dbl>
 1 ARIMA(value ~ pdq(3, 1, 0)) 1996 Jan  85.0    84.9  0.0850  0.0850
 2 ARIMA(value ~ pdq(3, 1, 0)) 1996 Feb  81.9    84.6 -2.68   -2.68
 3 ARIMA(value ~ pdq(3, 1, 0)) 1996 Mar  78.4    82.7 -4.28   -4.28
 4 ARIMA(value ~ pdq(3, 1, 0)) 1996 Apr  79.0    80.3 -1.25   -1.25
 5 ARIMA(value ~ pdq(3, 1, 0)) 1996 May  79.7    78.0  1.76    1.76
 6 ARIMA(value ~ pdq(3, 1, 0)) 1996 Jun  76.1    78.4 -2.24   -2.24
 7 ARIMA(value ~ pdq(3, 1, 0)) 1996 Jul  81.4    77.5  3.87    3.87
```

```
 8 ARIMA(value ~ pdq(3, 1, 0)) 1996 Aug  79.3    79.9 -0.599  -0.599
 9 ARIMA(value ~ pdq(3, 1, 0)) 1996 Sep  78.1    78.7 -0.588  -0.588
10 ARIMA(value ~ pdq(3, 1, 0)) 1996 Oct  80.3    80.3 -0.0448 -0.0448
# … with 181 more rows
```

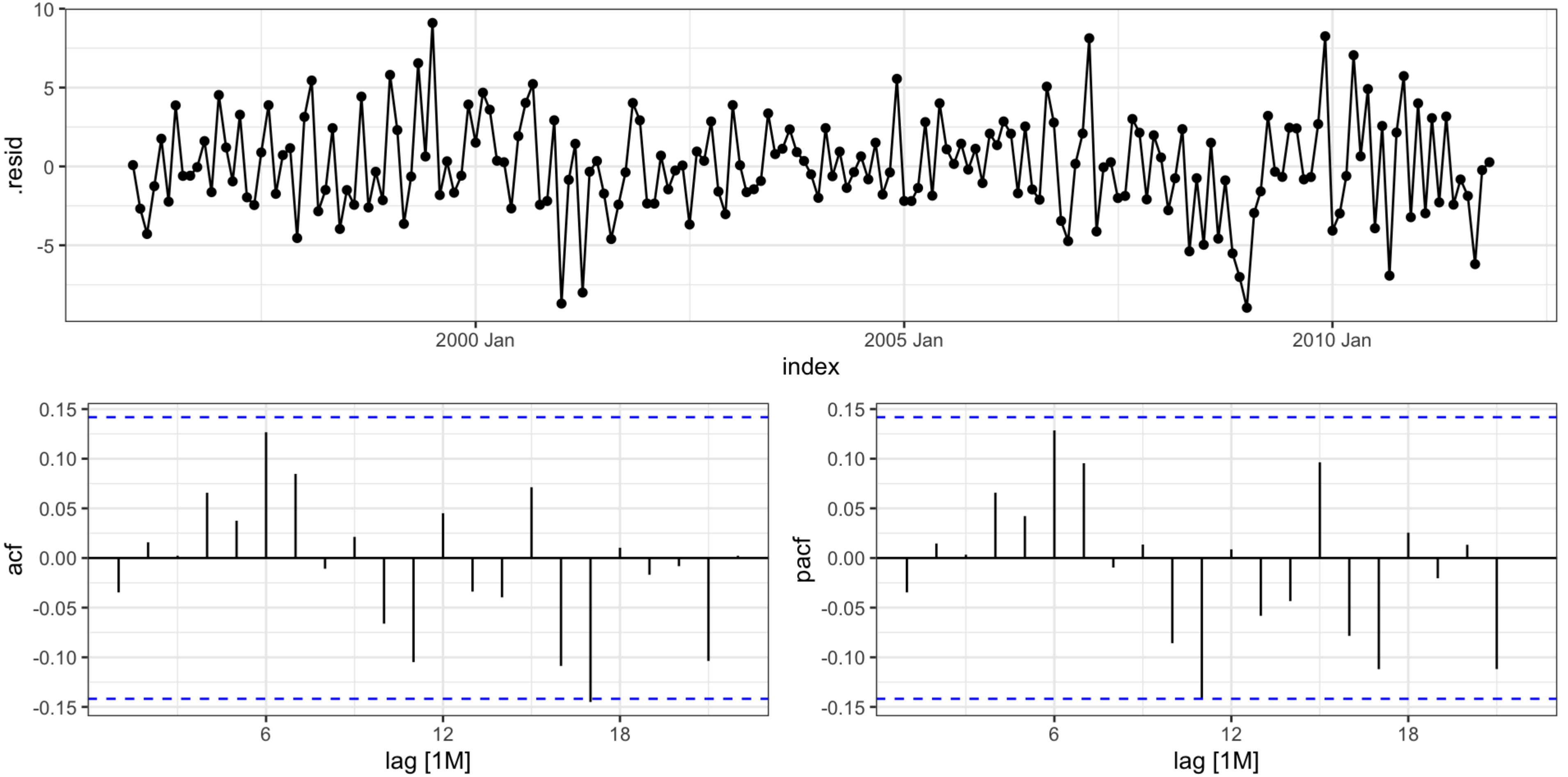
Observed vs predicted

```
m %>%
  augment() %>%
  autoplot(vars(value, .fitted))
```



Residuals

```
m %>%
  augment() %>%
  feasts::gg_tsdisplay(.resid, plot_type="partial")
```



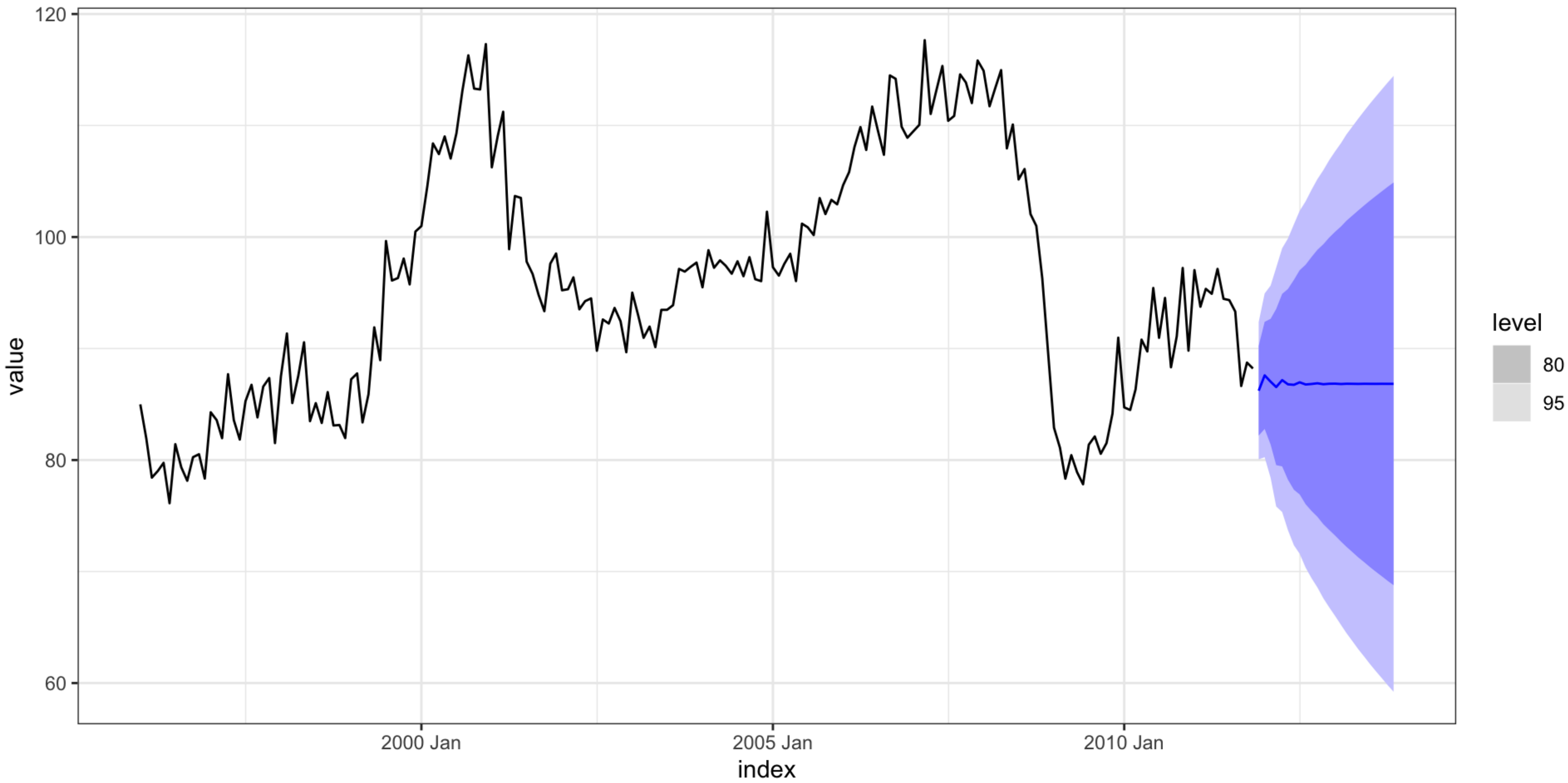
Forecasting

```
m %>%
  forecast()
```

```
# A fable: 24 x 4 [1M]
# Key:     .model [1]
  .model                          index    value .mean
  <chr>                           <mth>   <dist> <dbl>
1 ARIMA(value ~ pdq(3, 1, 0)) 2011 Dec N(86, 9.9)  86.2
2 ARIMA(value ~ pdq(3, 1, 0)) 2012 Jan  N(88, 14)  87.6
3 ARIMA(value ~ pdq(3, 1, 0)) 2012 Feb  N(87, 19)  87.0
4 ARIMA(value ~ pdq(3, 1, 0)) 2012 Mar  N(87, 30)  86.5
5 ARIMA(value ~ pdq(3, 1, 0)) 2012 Apr  N(87, 36)  87.2
6 ARIMA(value ~ pdq(3, 1, 0)) 2012 May  N(87, 44)  86.8
7 ARIMA(value ~ pdq(3, 1, 0)) 2012 Jun  N(87, 54)  86.7
8 ARIMA(value ~ pdq(3, 1, 0)) 2012 Jul  N(87, 62)  87.0
```

Forecasting - autoplot

```r
m %>%
  forecast() %>%
  autoplot(elec_sales)
```



Comparing models

The `fable` `model()` function also has the ability to fit multiple models at the same time which then makes comparison more straight forward.

```
( mm = elec_sales %>%
    model(
      arima310 = ARIMA(value ~ pdq(3,1,0)),
      arima013 = ARIMA(value ~ pdq(0,1,3)),
      autoarima = ARIMA(value),
      autoarima_bf = ARIMA(value, stepwise = FALSE)
    )
)
```

```
# A mable: 1 x 4
       arima310        arima013      autoarima   autoarima_bf
        <model>         <model>        <model>        <model>
1 <ARIMA(3,1,0)> <ARIMA(0,1,3)> <ARIMA(3,1,1)> <ARIMA(1,1,5)>
```

broom + multiple models

```r
mm %>% glance() %>% arrange(AICc)
```

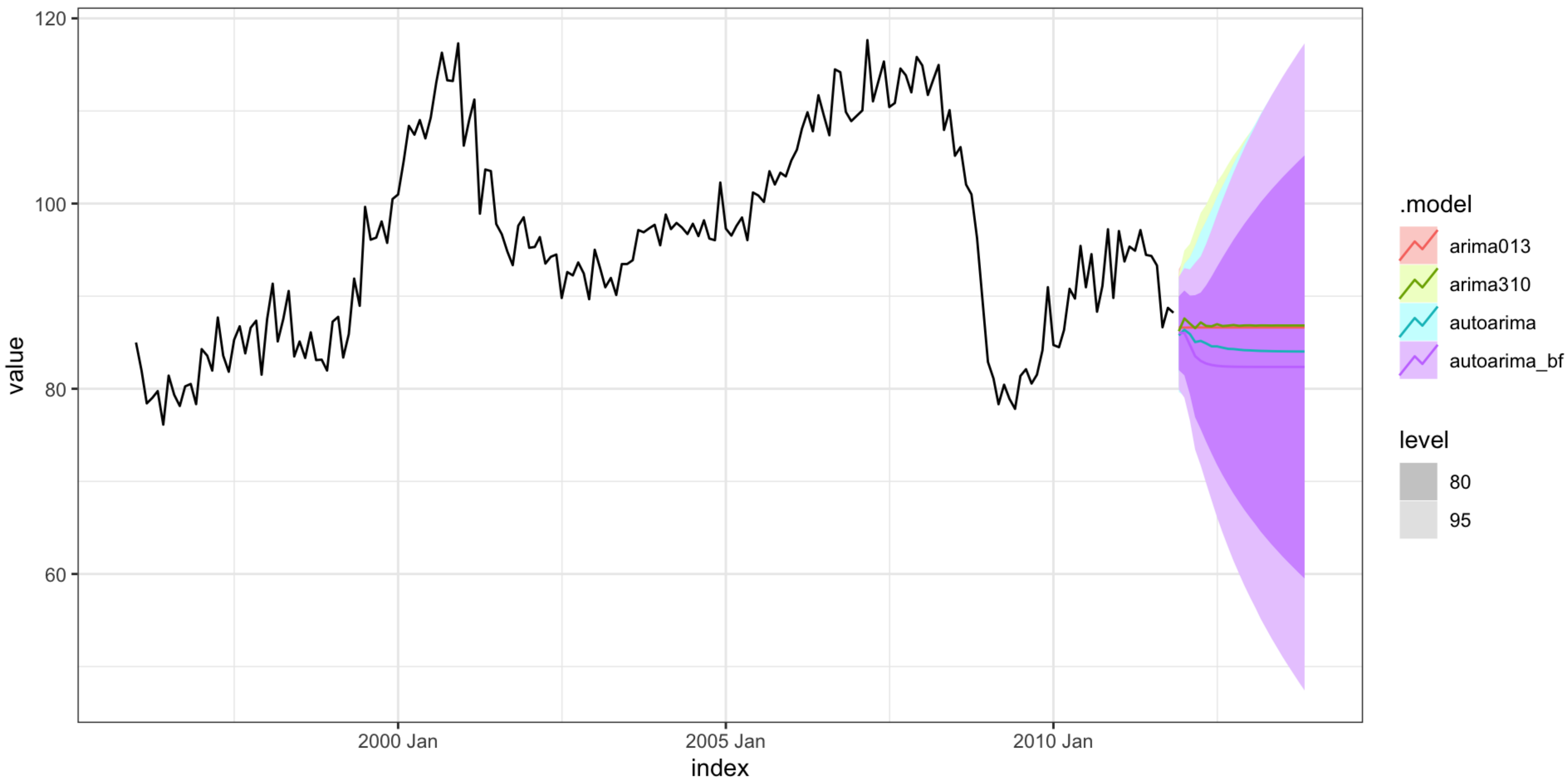
```
# A tibble: 4 × 8
  .model       sigma2 log_lik   AIC  AICc   BIC ar_roots   ma_roots  
  <chr>         <dbl>   <dbl> <dbl> <dbl> <dbl> <list>     <list>    
1 autoarima      9.74   -484.  978.  978.  994. <cpl [3]> <cpl [1]>
2 autoarima_bf   9.63   -482.  978.  979. 1001. <cpl [1]> <cpl [5]>
3 arima310       9.85   -486.  979.  980.  992. <cpl [3]> <cpl [0]>
4 arima013      10.2    -489.  986.  987.  999. <cpl [0]> <cpl [3]>
```

```r
mm %>% accuracy() %>% arrange(RMSE)
```

```
# A tibble: 4 × 10
  .model       .type          ME  RMSE   MAE     MPE  MAPE  MASE RMSSE     ACF1
  <chr>        <chr>       <dbl> <dbl> <dbl>   <dbl> <dbl> <dbl> <dbl>    <dbl>
1 autoarima_bf Training -0.00719  3.05  2.41 -0.0458  2.55 0.294 0.275  0.00916
2 autoarima    Training -0.00123  3.08  2.39 -0.0429  2.52 0.291 0.278  0.00893
3 arima310     Training  0.0117   3.11  2.43 -0.0435  2.56 0.296 0.281 -0.0346 
4 arima013     Training  0.0105   3.17  2.40 -0.0486  2.53 0.292 0.286 -0.0210 
```

Forecasting - autoplot

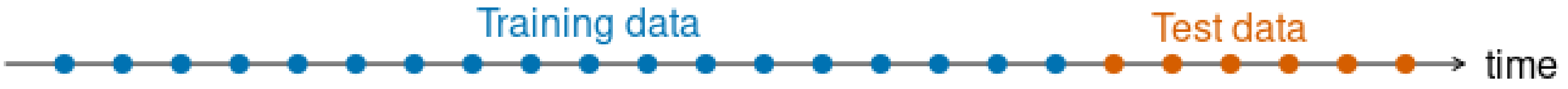
```
mm %>%
  forecast() %>%
  autoplot(elec_sales)
```



Cross validation

Test train split

The general approach is to keep the data ordered and split the first `prop`% into the training data and the remained as testing data.




```r
elec_sales_split = rsample::initial_time_split(elec_sales, prop=0.9)
```

```r
rsample::training(elec_sales_split)
```

```
# A tsibble: 171 x 2 [1M]
      index value
      <mth> <dbl>
 1 1996 Jan  85.0
 2 1996 Feb  81.9
 3 1996 Mar  78.4
 4 1996 Apr  79.0
 5 1996 May  79.7
 6 1996 Jun  76.1
 7 1996 Jul  81.4
 8 1996 Aug  79.3
 9 1996 Sep  78.1
10 1996 Oct  80.3
# … with 161 more rows
```

```r
rsample::testing(elec_sales_split)
```

```
# A tsibble: 20 x 2 [1M]
      index value
      <mth> <dbl>
 1 2010 Apr  90.8
 2 2010 May  89.7
 3 2010 Jun  95.4
 4 2010 Jul  91.0
 5 2010 Aug  94.5
 6 2010 Sep  88.3
 7 2010 Oct  91.1
 8 2010 Nov  97.2
 9 2010 Dec  89.8
10 2011 Jan  97.0
11 2011 Feb  93.7
12 2011 Mar  95.4
13 2011 Apr  94.9
```

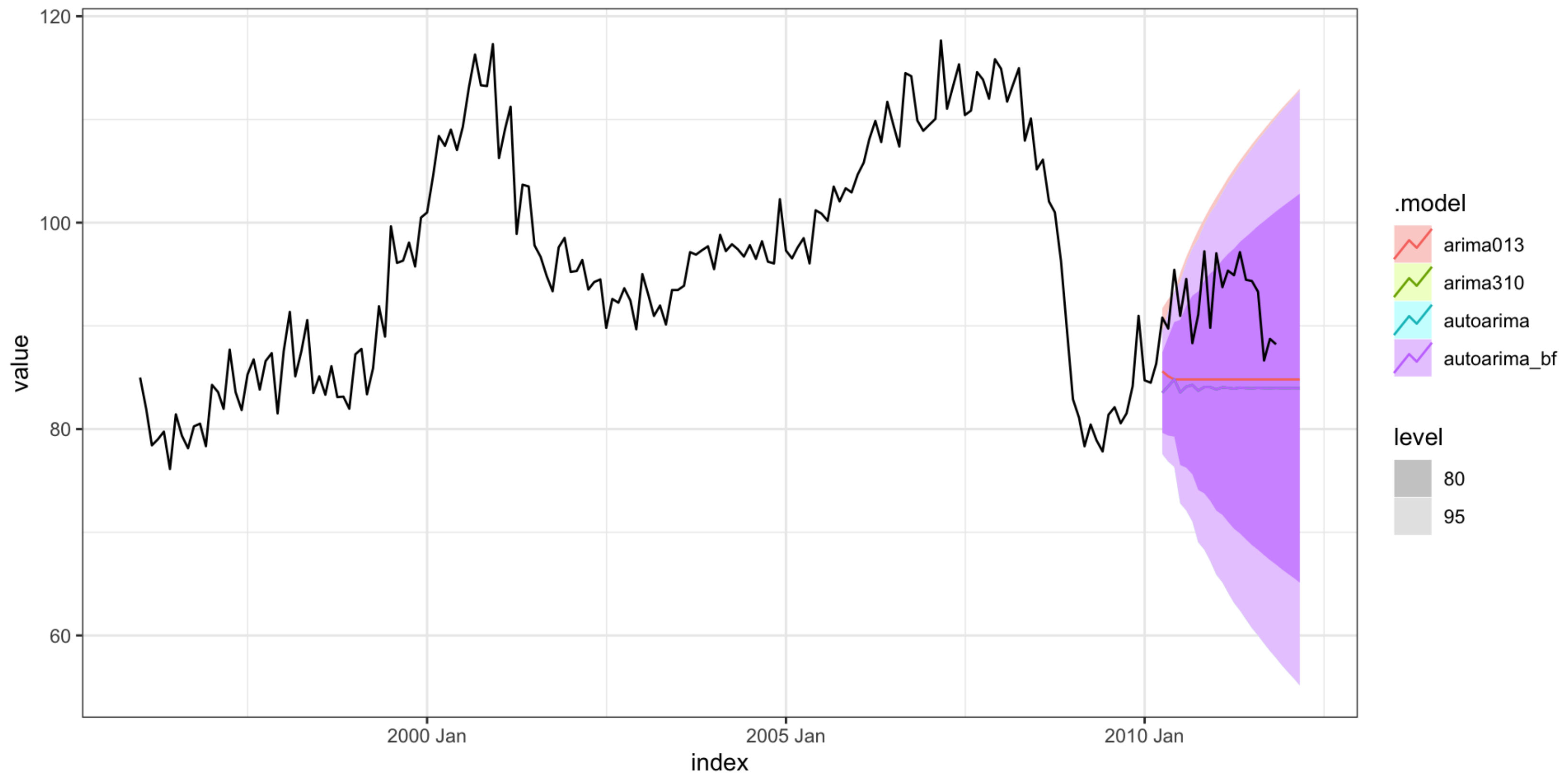
Model fit (training)

```r
( mm = rsample::training(elec_sales_split) %>%
    model(
      arima310 = ARIMA(value ~ pdq(3,1,0)),
      arima013 = ARIMA(value ~ pdq(0,1,3)),
      autoarima = ARIMA(value),
      autoarima_bf = ARIMA(value, stepwise = FALSE)
    )
)
```

```
# A mable: 1 x 4
       arima310       arima013      autoarima   autoarima_bf
        <model>        <model>        <model>        <model>
1 <ARIMA(3,1,0)> <ARIMA(0,1,3)> <ARIMA(3,1,0)> <ARIMA(3,1,0)>
```

Forecasting

```r
mm %>%
  forecast() %>%
  autoplot(
    elec_sales
  )
```



Accuracy

Out-of-sample:

```r
mm %>%
  forecast() %>%
  accuracy(elec_sales)
```

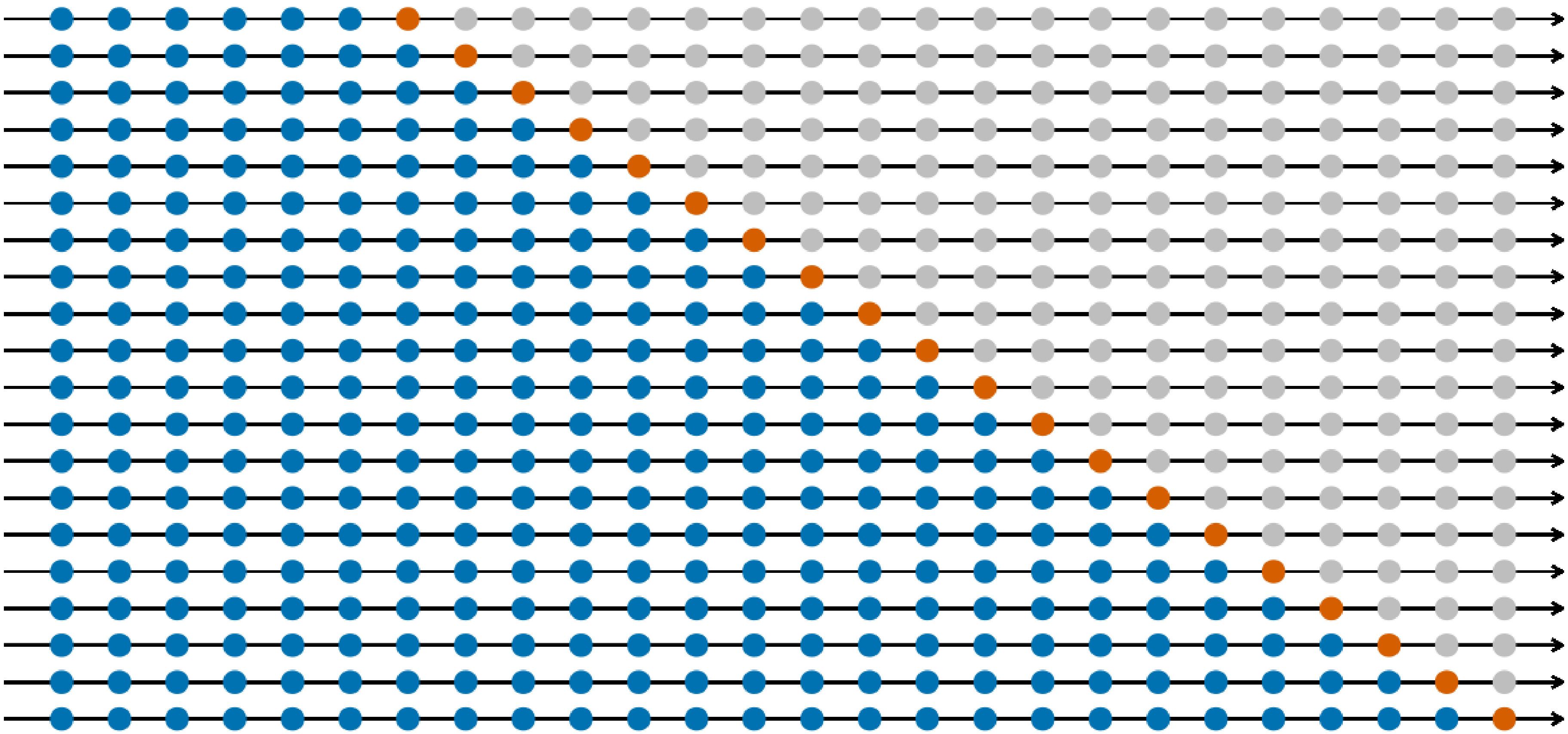
```
# A tibble: 4 × 10
  .model       .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
  <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 arima013     Test   7.73  8.39  7.73  8.24  8.24 0.935 0.742 0.148
2 arima310     Test   8.60  9.17  8.60  9.18  9.18 1.04  0.811 0.162
3 autoarima    Test   8.60  9.17  8.60  9.18  9.18 1.04  0.811 0.162
4 autoarima_bf Test   8.60  9.17  8.60  9.18  9.18 1.04  0.811 0.162
```

Within-sample:

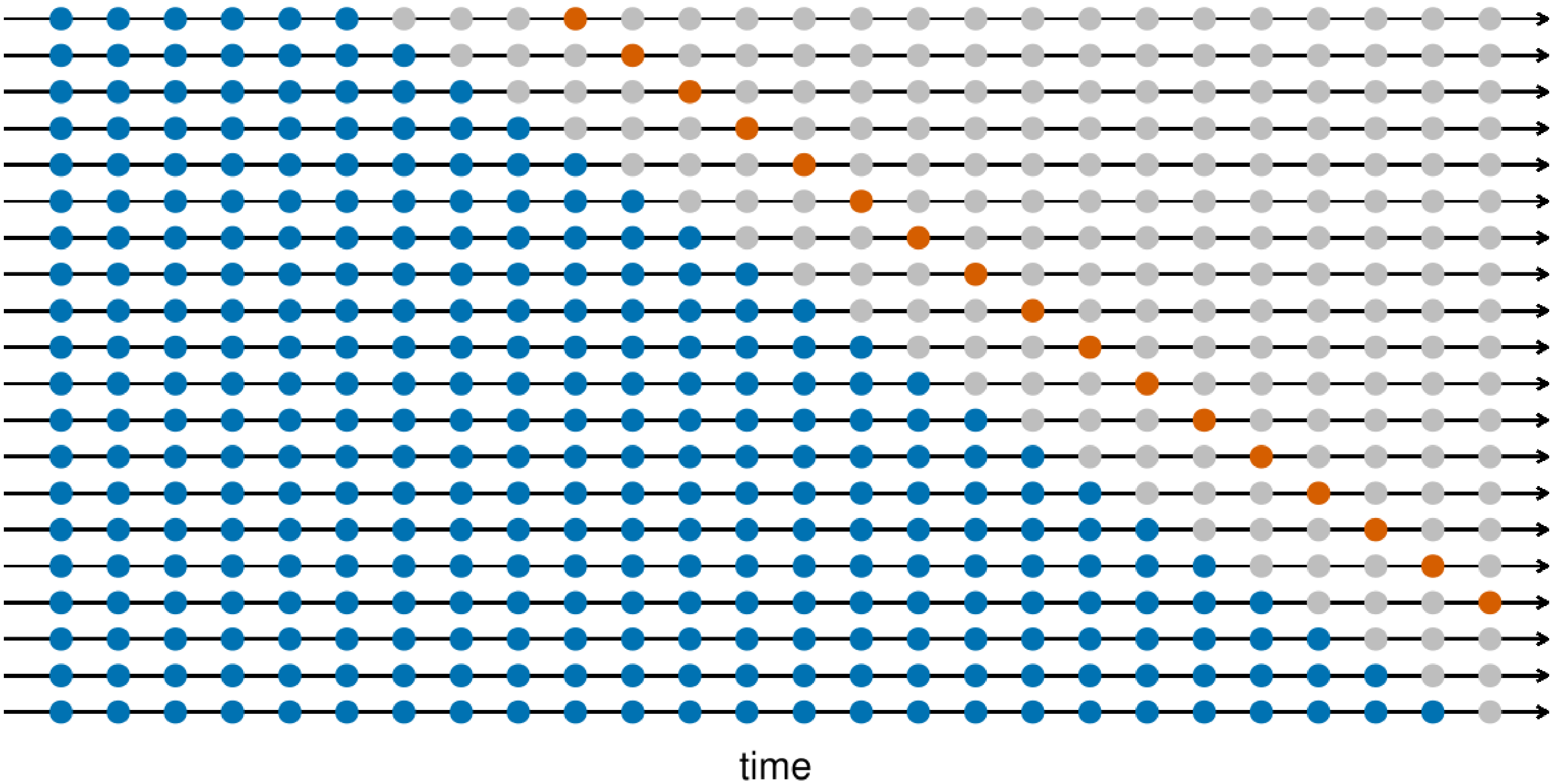
```r
mm %>%
  accuracy()
```

```
# A tibble: 4 × 10
  .model       .type           ME  RMSE   MAE     MPE  MAPE  MASE RMSSE    ACF1
  <chr>        <chr>        <dbl> <dbl> <dbl>   <dbl> <dbl> <dbl> <dbl>   <dbl>
1 arima310     Training -0.00435   3.00  2.31 -0.0535  2.42 0.279 0.265 -0.0317
2 arima013     Training -0.000151  3.08  2.32 -0.0541  2.44 0.281 0.272 -0.0318
3 autoarima    Training -0.00435   3.00  2.31 -0.0535  2.42 0.279 0.265 -0.0317
4 autoarima_bf Training -0.00435   3.00  2.31 -0.0535  2.42 0.279 0.265 -0.0317
```

Rolling forecasting origin



From Hyndman FPP3 - Chp 5.10



From Hyndman FPP3 - Chp 5.10

Prophet

Prophet model

Prophet uses a modeling framework that looks a lot like traditional GAM approaches. Specifically the time series is modeled as

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

where

- $g(t)$ is a piecewise linear trend component
- $s(t)$ is a seasonal component based on Fourier terms with specified period(s) and order
- $h(t)$ are holiday effects (specific dummy coded variables for important dates / times)
- ϵ_t white noise error

Implementation

Prophet is implemented in its own R package and Python packages (`prophet`) which provide all of the basic functionality.

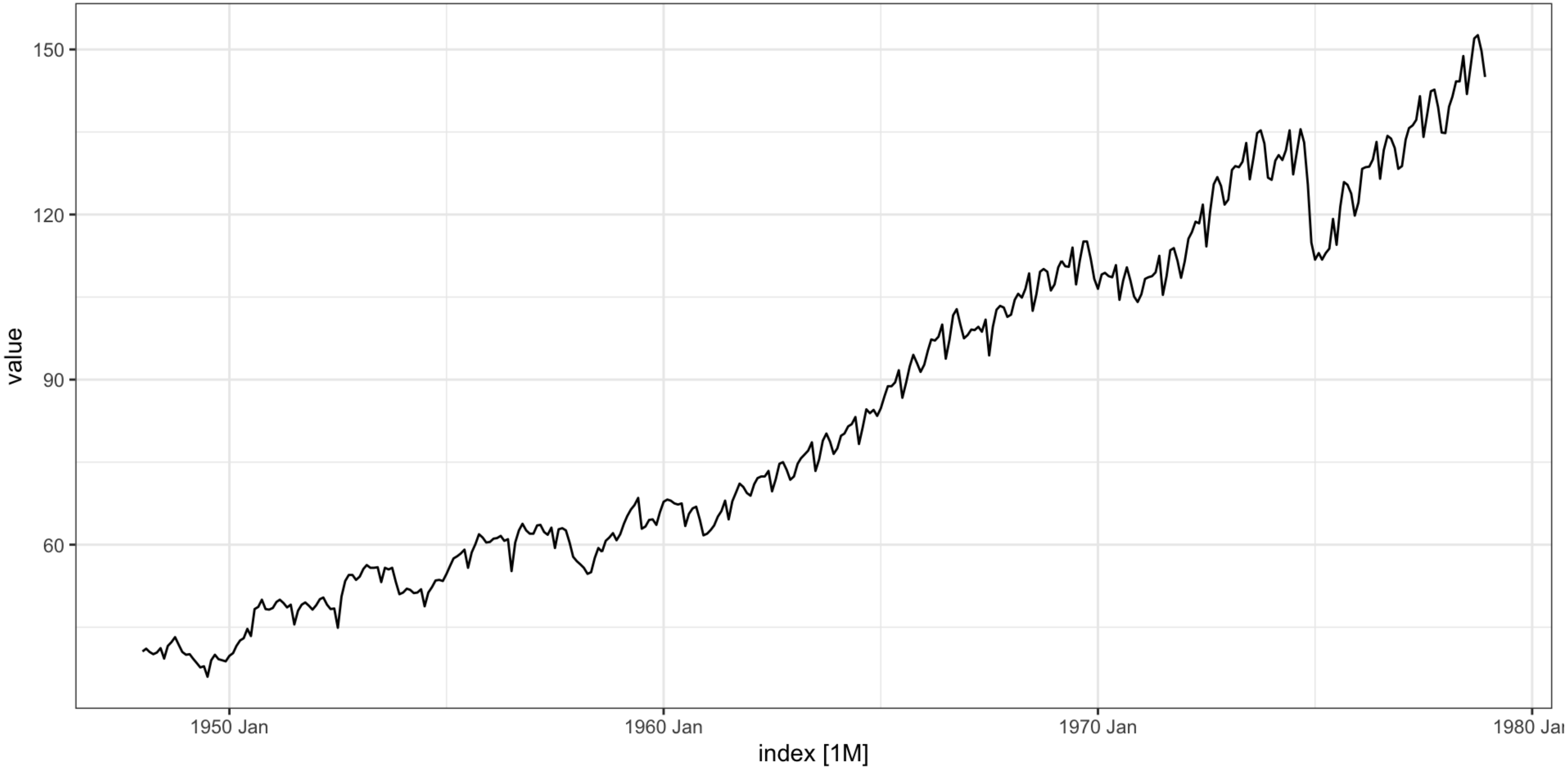
The model fitting is done using a Bayesain approach with the specific implementation using Stan.

Other frameworks like `fable` (or `modeltime`) provide higher level interfaces to this package.

`prodn` from `astsa`

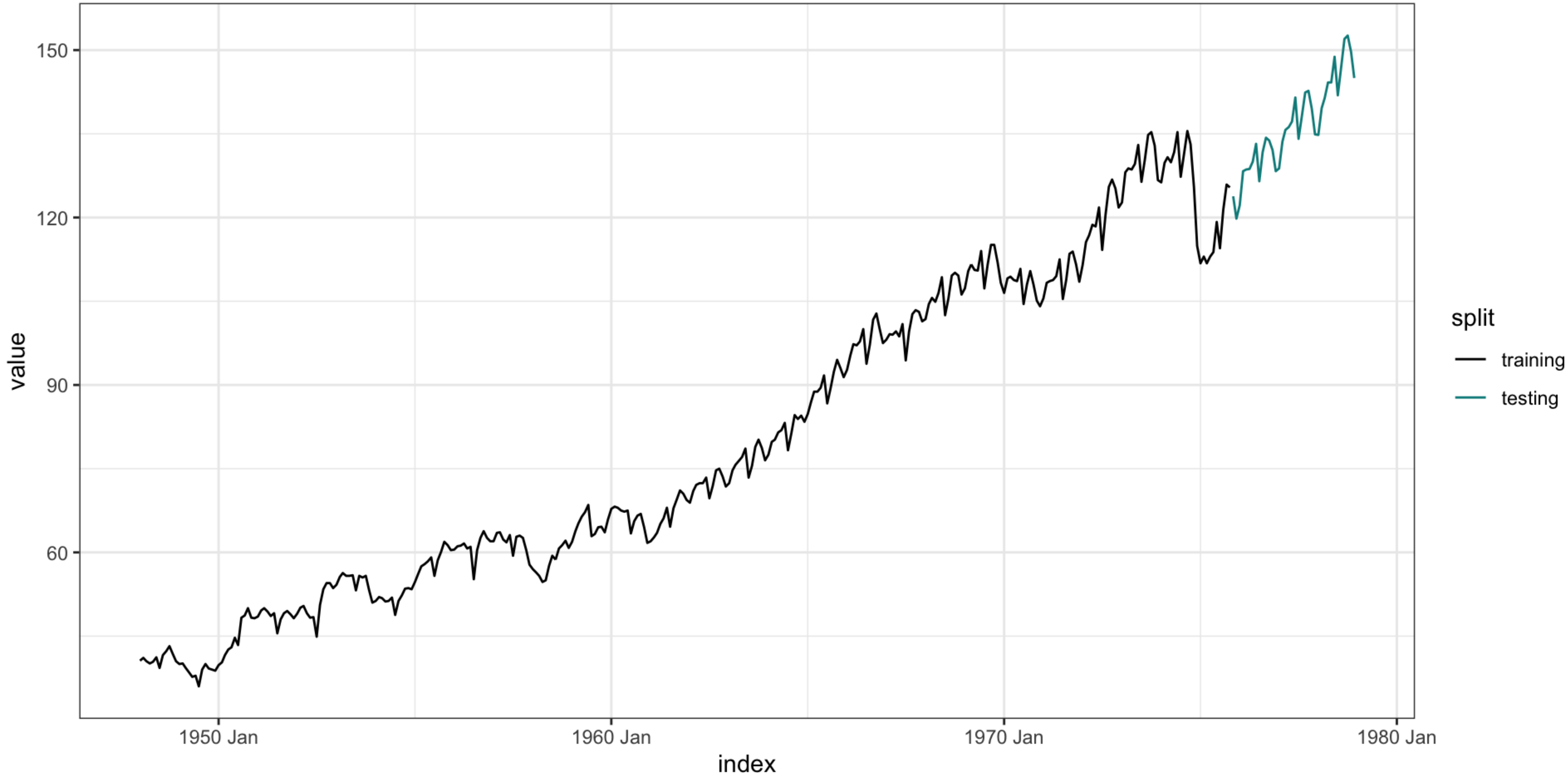
Monthly Federal Reserve Board Production Index (1948-1978)

```r
prodn = tsibble::as_tsibble(astsa::prodn)
autoplot(prodn, value)
```



Test train split

```
prodn_split = rsample::initial_time_split(prodn, prop=0.90)
```



Models

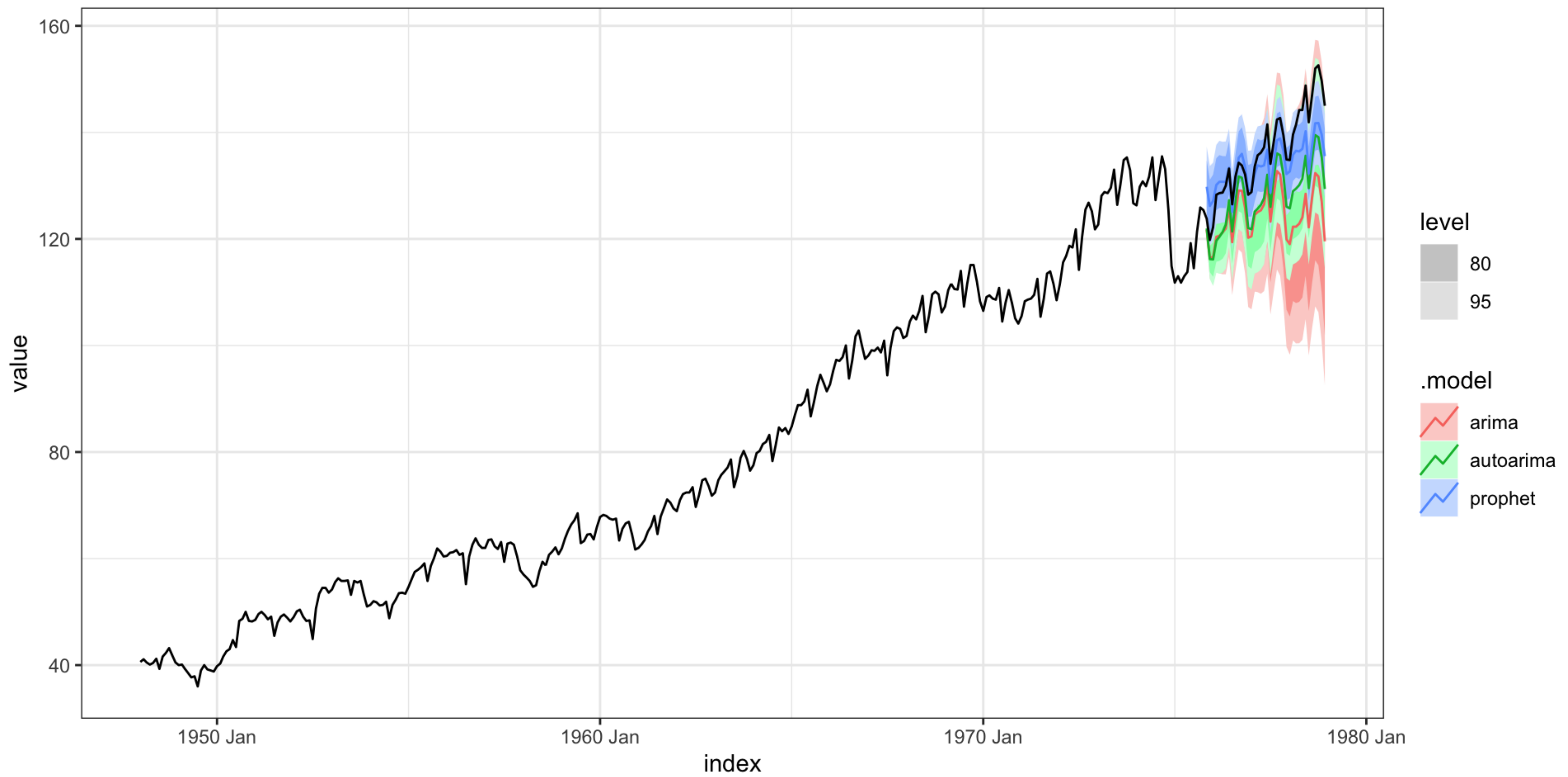
```
library(fable.prophet)

( prodn_fit = rsample::training(prodn_split) %>%
    model(
      arima = ARIMA(value ~ pdq(1,1,0) + PDQ(0,1,3)),
      autoarima = ARIMA(value),
      prophet = prophet(value ~ season(period=12, type = "multiplicative'
    )
)
```

```
# A mable: 1 x 3
                      arima                                  autoarima   prophet
                    <model>                                    <model>   <model>
1 <ARIMA(1,1,0)(0,1,3)[12]> <ARIMA(2,0,1)(0,1,1)[12] w/ drift> <prophet>
```

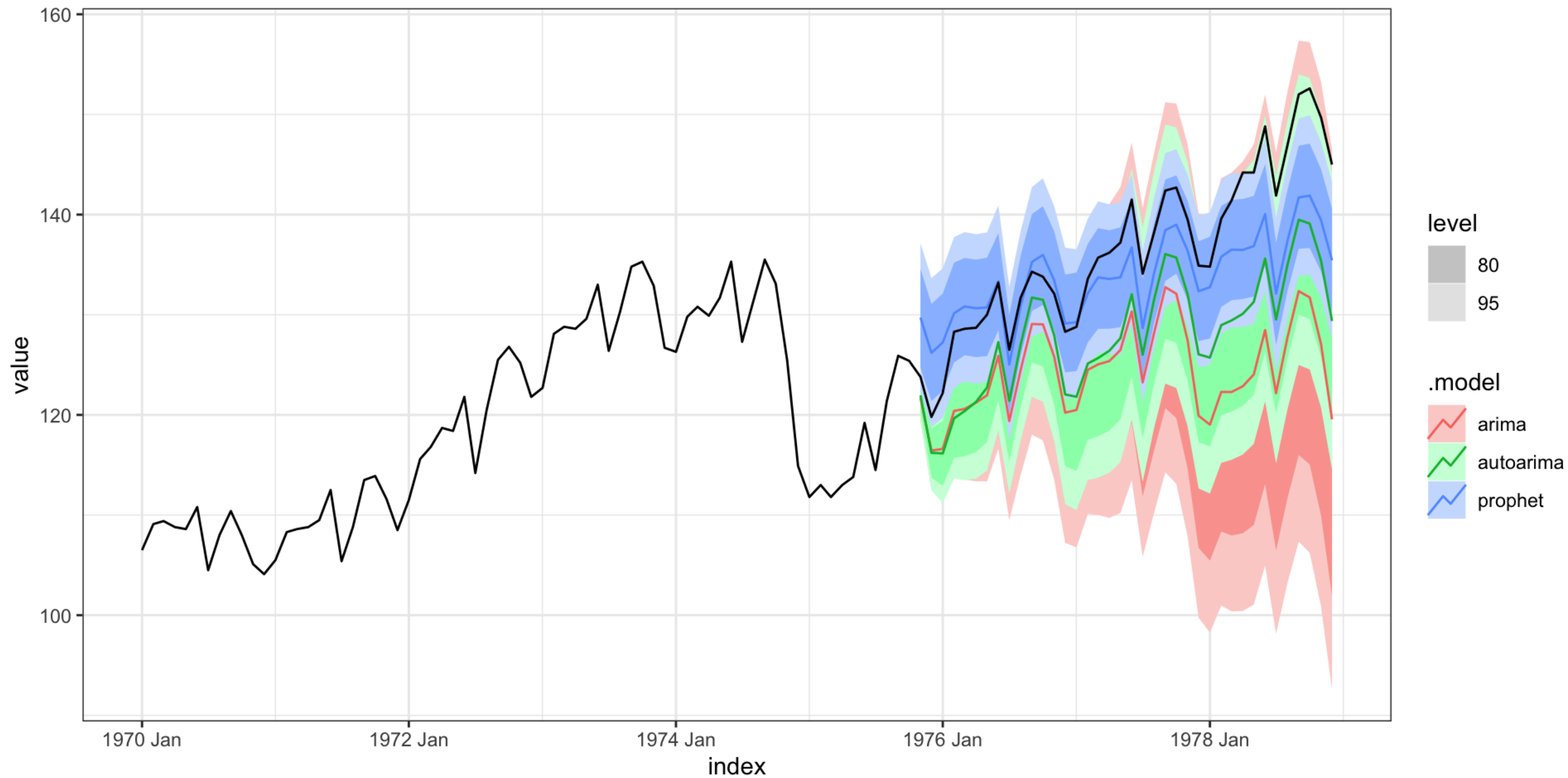
Forecast

```
prodn_fc = forecast(prodn_fit, h=38)
prodn_fc %>%
  autoplot(prodn)
```



Forecast - zoom

```r
prodn_fc = forecast(prodn_fit, h=38)
prodn_fc %>%
  autoplot(
    prodn %>% filter(index >= make_yearmonth(1970L, 1L))
  )
```



Accuracy

Out-of-sample:

```
prodn_fit %>%
  forecast() %>%
  accuracy(prodn)
```

```
# A tibble: 3 × 10
  .model    .type    ME  RMSE   MAE    MPE  MAPE  MASE RMSSE  ACF1
  <chr>     <chr> <dbl> <dbl> <dbl>  <dbl> <dbl> <dbl> <dbl> <dbl>
1 arima     Test  7.93   8.29  7.93 5.95    5.95 1.56  1.34  0.755
2 autoarima Test  6.52   6.93  6.52 4.91    4.91 1.28  1.12  0.759
3 prophet   Test  0.145  3.22  2.65 0.0162  2.01 0.522 0.521 0.833
```

Within-sample:

```
prodn_fit %>%
  accuracy()
```

```
# A tibble: 3 × 10
  .model    .type           ME  RMSE   MAE     MPE  MAPE  MASE RMSSE     ACF1
  <chr>     <chr>        <dbl> <dbl> <dbl>   <dbl> <dbl> <dbl> <dbl>    <dbl>
1 arima     Training -0.00242   1.14 0.821  0.0129  1.11 0.162 0.185 -0.0348
2 autoarima Training  0.000504  1.17 0.831 -0.0402  1.11 0.164 0.189  0.00432
3 prophet   Training  0.000883  3.83 2.87  -0.234   3.70 0.565 0.620  0.950
```

Components

```r
prodn_fit %>%
  select(prophet) %>%
  components() %>%
  autoplot()
```