

# 미세먼지량 예측 모형

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2020 10 25

```
library(tidyverse)
```

```
## -- Attaching packages ----- tidyverse 1.3.0 --
```

```
## √ ggplot2 3.3.2      √ purrr  0.3.4
## √ tibble  3.0.3      √ dplyr  1.0.2
## √ tidyr   1.1.2      √ stringr 1.4.0
## √ readr   1.3.1      √ forcats 0.5.0
```

```
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(tsibble)
library(fpp3)
```

```
## -- Attaching packages ----- fpp3 0.3 --
```

```
## √ lubridate 1.7.9      √ feasts 0.1.5
## √ tsibbledata 0.2.0    √ fable  0.2.1
```

```
## -- Conflicts ----- fpp3_conflicts --
## x lubridate::date()    masks base::date()
## x dplyr::filter()      masks stats::filter()
## x lubridate::interval() masks tsibble::interval()
## x dplyr::lag()         masks stats::lag()
```

```
setwd('C:/Users/JIHYUN/Desktop/수업/통계학특강/2차과제')
```

## 8개 도시 월별 미세먼지 측정량

## 데이터 전처리

- tot는 제거

```
pm10w <- readr::read_csv('PM10w.csv') %>%
  select(-tot)
```

```
## Parsed with column specification:
## cols(
##   yymm = col_character(),
##   tot = col_double(),
##   seoul = col_double(),
##   busan = col_double(),
##   daegu = col_double(),
##   incheon = col_double(),
##   gwangju = col_double(),
##   daejeon = col_double(),
##   ulsan = col_double(),
##   sejong = col_double()
## )
```

```
head(pm10w)
```

```
## # A tibble: 6 x 9
##   yymm      seoul busan daegu incheon gwangju daejeon ulsan sejong
##   <chr>    <dbl> <dbl> <dbl>   <dbl>   <dbl>   <dbl> <dbl>   <dbl>
## 1 2010. 01      59    47    56      64     46     48    46     NA
## 2 2010. 02      50    44    49      54     39     39    44     NA
## 3 2010. 03      61    64    69      67     65     52    60     NA
## 4 2010. 04      49    50    47      55     42     41    47     NA
## 5 2010. 05      56    56    55      62     62     52    54     NA
## 6 2010. 06      51    46    47      57     39     40    50     NA
```

## 결측확인

```
colSums(is.na(pm10w))
```

```
##   yymm      seoul      busan      daegu incheon gwangju daejeon      ulsan      sejong
##      0          0          0          0          0          0          0          0          72
```

```
pm10w$sejong[is.na(pm10w$sejong)]
```

```
## [1] NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA
## [26] NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA
## [51] NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA
```

## WDF를 LDF로 변환

```
pm10w <- pivot_longer(pm10w,
  col = c(-yymm,seoul,busan,inccheon,
    gwangju,daejeon,ulsan,sejong),
  names_to = 'city',
  values_to = 'y')
pm10w
```

```
## # A tibble: 984 x 3
##   yymm      city      y
##   <chr>   <chr>  <dbl>
## 1 2010. 01 seoul    59
## 2 2010. 01 busan    47
## 3 2010. 01 daegu    56
## 4 2010. 01 inccheon 64
## 5 2010. 01 gwangju  46
## 6 2010. 01 daejeon  48
## 7 2010. 01 ulsan    46
## 8 2010. 01 sejong   NA
## 9 2010. 02 seoul    50
## 10 2010. 02 busan   44
## # ... with 974 more rows
```

## tisbble로 변환

- yymm칼럼의 데이터형을 시간형태로 변환

```
pm10w <- pm10w %>%
  mutate(yymm = yearmonth(yymm)) %>%
  as_tibble(key=city,index= yymm)
pm10w
```

```
## # A tsibble: 984 x 3 [1M]
## # Key:      city [8]
##   yymm city      y
##   <mth> <chr> <dbl>
## 1 2010 1 busan    47
## 2 2010 2 busan    44
## 3 2010 3 busan    64
## 4 2010 4 busan    50
## 5 2010 5 busan    56
## 6 2010 6 busan    46
## 7 2010 7 busan    41
## 8 2010 8 busan    42
## 9 2010 9 busan    38
## 10 2010 10 busan   41
## # ... with 974 more rows
```

## 데이터 탐색

# 기초 통계량

- na.rm=T -> 결측 대체하고 계산

## 연별 미세먼지 평균

```
pm10w %>%  
  index_by(Year=year(yymm))%>%  
  summarize(n=n(),my=mean(y, na.rm= T))
```

```
## # A tibble: 11 x 3 [1Y]  
##   Year      n    my  
##   <dbl> <int> <dbl>  
## 1  2010     96  48.6  
## 2  2011     96  47.5  
## 3  2012     96  42.4  
## 4  2013     96  45.5  
## 5  2014     96  45.2  
## 6  2015     96  45.7  
## 7  2016     96  44.7  
## 8  2017     96  43.8  
## 9  2018     96  40.9  
## 10 2019     96  40.5  
## 11 2020     24  38.1
```

## 분기별 미세먼지 평균

```
pm10w %>%  
  index_by(Quarter=quarter(yymm))%>%  
  summarize(n=n(),my=mean(y, na.rm= T))
```

```
## # A tibble: 4 x 3 [1]  
##   Quarter      n    my  
##   <int> <int> <dbl>  
## 1      1    264  51.7  
## 2      2    240  49.8  
## 3      3    240  31.5  
## 4      4    240  43.1
```

## 월별 미세먼지 평균

```
pm10w %>%  
  index_by(Month=month(yymm))%>%  
  summarize(n=n(),my=mean(y, na.rm= T))
```

```
## # A tibble: 12 x 3 [1]
##   Month     n    my
##   <dbl> <int> <dbl>
## 1     1     88 49.9
## 2     2     88 50.3
## 3     3     88 54.9
## 4     4     80 52.0
## 5     5     80 55.8
## 6     6     80 41.6
## 7     7     80 32.8
## 8     8     80 30.6
## 9     9     80 31.0
## 10    10     80 37.1
## 11    11     80 47.2
## 12    12     80 45.1
```

## 도시별 연평균 미세먼지 측정량

```
yyfd <- pm10w %>%
  index_by(Year=year(yymm))%>%
  group_by(city)%>%
  summarize(n=n(),my=mean(y, na.rm= T))
yyfd
```

```
## # A tibble: 88 x 4 [1Y]
## # Key:       city [8]
##   city   Year     n    my
##   <chr> <dbl> <int> <dbl>
## 1 busan  2010     12 48.7
## 2 busan  2011     12 47.6
## 3 busan  2012     12 43.4
## 4 busan  2013     12 48.5
## 5 busan  2014     12 48.4
## 6 busan  2015     12 45.1
## 7 busan  2016     12 43.8
## 8 busan  2017     12 43.8
## 9 busan  2018     12 41.6
## 10 busan 2019     12 36.9
## # ... with 78 more rows
```

## 도시별 월평균 미세먼지 측정량

```
mmfd <- pm10w %>%
  index_by(Month=month(yymm))%>%
  group_by(city)%>%
  summarize(n=n(),my=mean(y, na.rm= T))
mmfd
```

```
## # A tibble: 96 x 4 [1]
## # Key:      city [8]
##   city Month     n   my
##   <chr> <dbl> <int> <dbl>
## 1 busan     1    11  45.9
## 2 busan     2    11  47.6
## 3 busan     3    11  52.1
## 4 busan     4    10  52.6
## 5 busan     5    10  58.1
## 6 busan     6    10  44
## 7 busan     7    10  38.3
## 8 busan     8    10  35.5
## 9 busan     9    10  33.2
## 10 busan    10    10  37.4
## # ... with 86 more rows
```

## 도시별 분기별 미세먼지 측정량

```
qqfd <- pm10w %>%
  index_by(quarter=quarter(yymm))%>%
  group_by(city)%>%
  summarize(n=n(),my=mean(y, na.rm= T))
qqfd
```

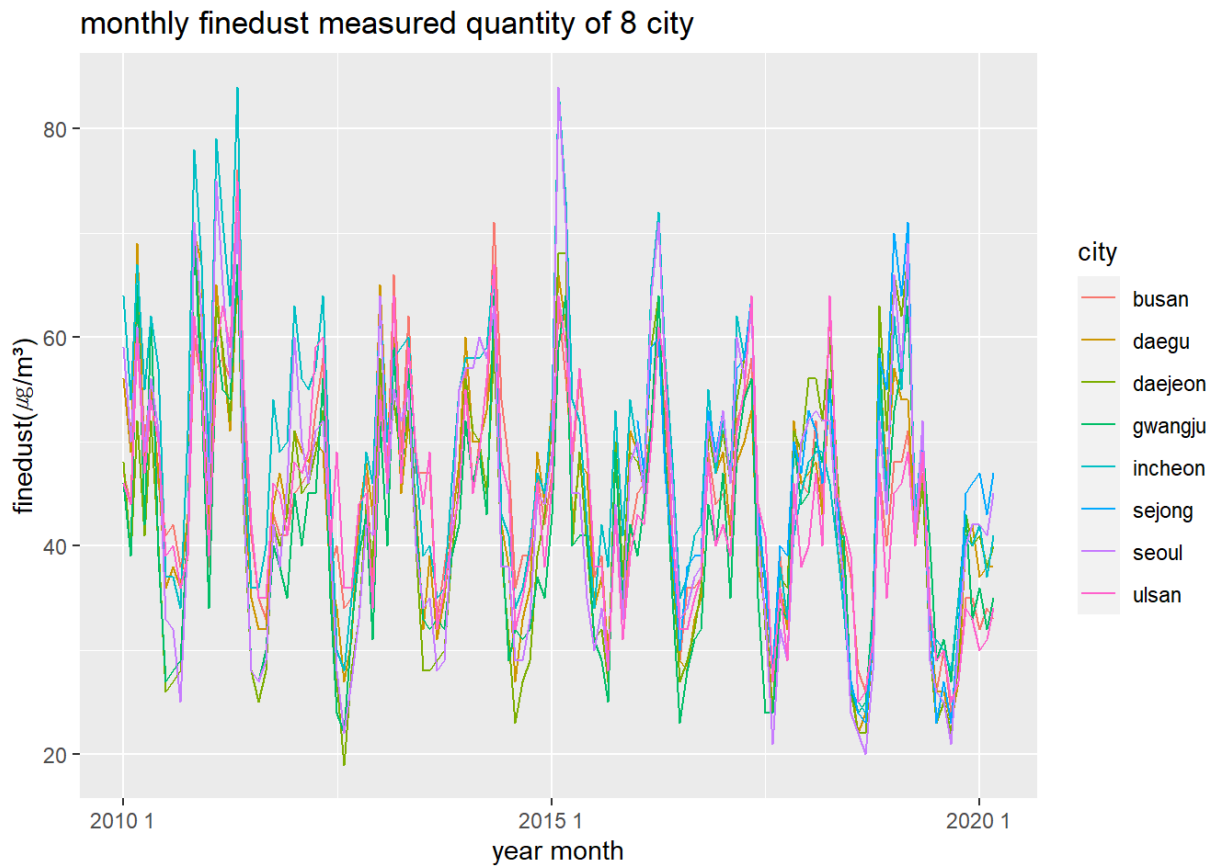
```
## # A tibble: 32 x 4 [1]
## # Key:      city [8]
##   city   quarter     n   my
##   <chr>    <int> <int> <dbl>
## 1 busan         1    33  48.5
## 2 busan         2    30  51.6
## 3 busan         3    30  35.7
## 4 busan         4    30  41.8
## 5 daegu         1    33  51.6
## 6 daegu         2    30  47.3
## 7 daegu         3    30  31.1
## 8 daegu         4    30  44.7
## 9 daejeon        1    33  52.4
## 10 daejeon        2    30  47.4
## # ... with 22 more rows
```

## 시계열 그림

- 추세가 없고 등분산이지만 계절성이 있어 비정상 시계열로 보인다.

```
pm10w %>%
  autoplot(y) +
  ylab("finedust( $\mu\text{g}/\text{m}^3$ )") +
  labs(title="monthly finedust measured quantity of 8 city")+
  xlab("year month")
```

```
## Warning: Removed 72 row(s) containing missing values (geom_path).
```

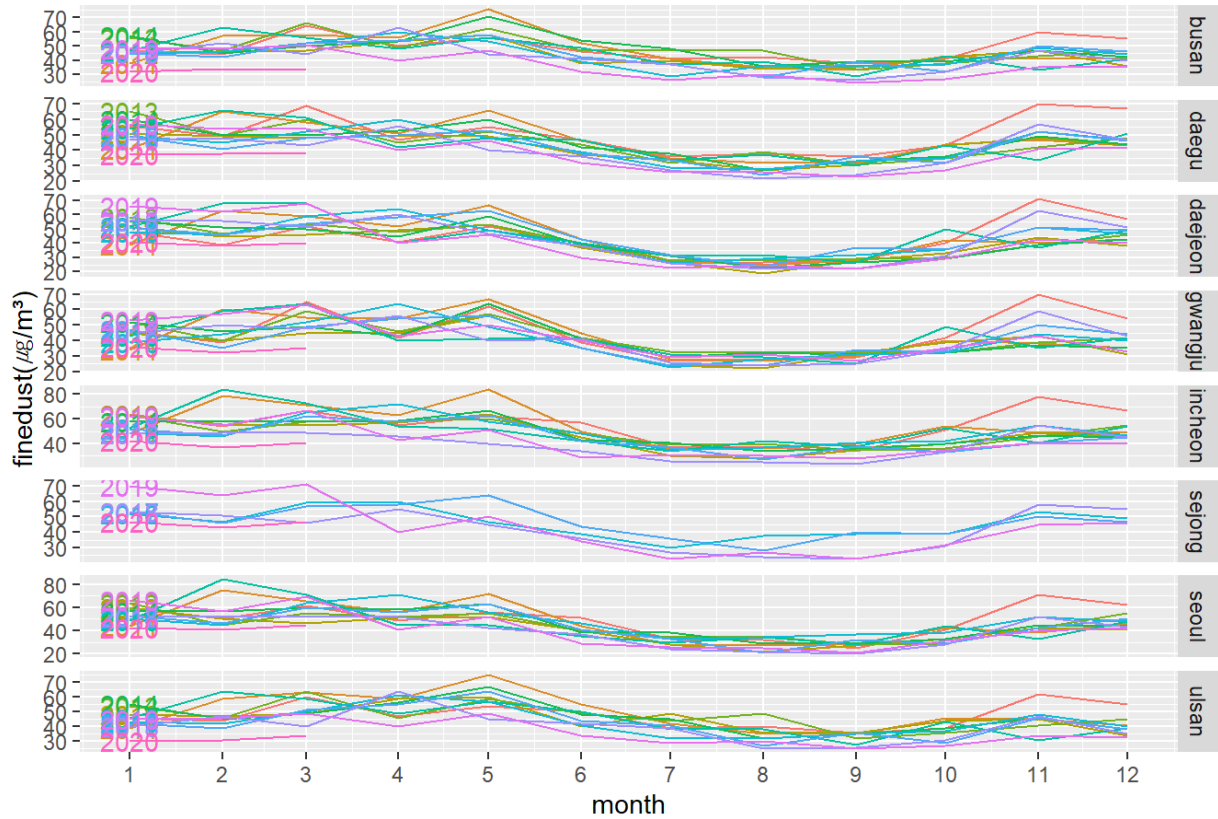


## 계절성 그림 (gg\_series, gg\_subseries)

```
pm10w %>% gg_season(y, labels = "left")+  
  ylab("finedust( $\mu\text{g}/\text{m}^3$ )")+  
  xlab("month")+  
  ggtitle("Seasonal plot : finedust measured quantity of 8 city")
```

```
## Warning: Removed 6 rows containing missing values (geom_text).
```

Seasonal plot : finedust measured quantity of 8 city



pm10w %>%

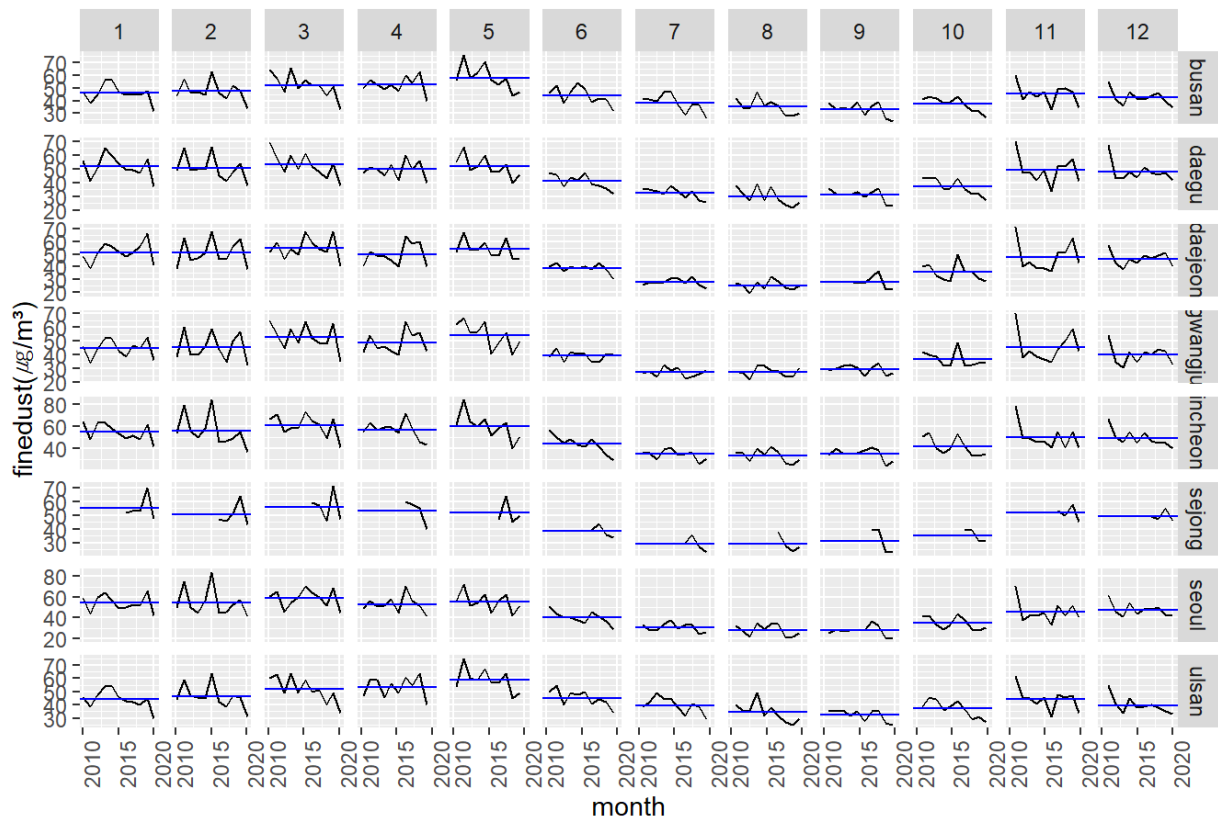
gg\_subseries(y) +

ylab("finedust( $\mu\text{g}/\text{m}^3$ )") +

xlab("month")+

ggtitle("Seasonal subseries plot : finedust measured quantity of 8 city")

Seasonal subseries plot : finedust measured quantity of 8 city





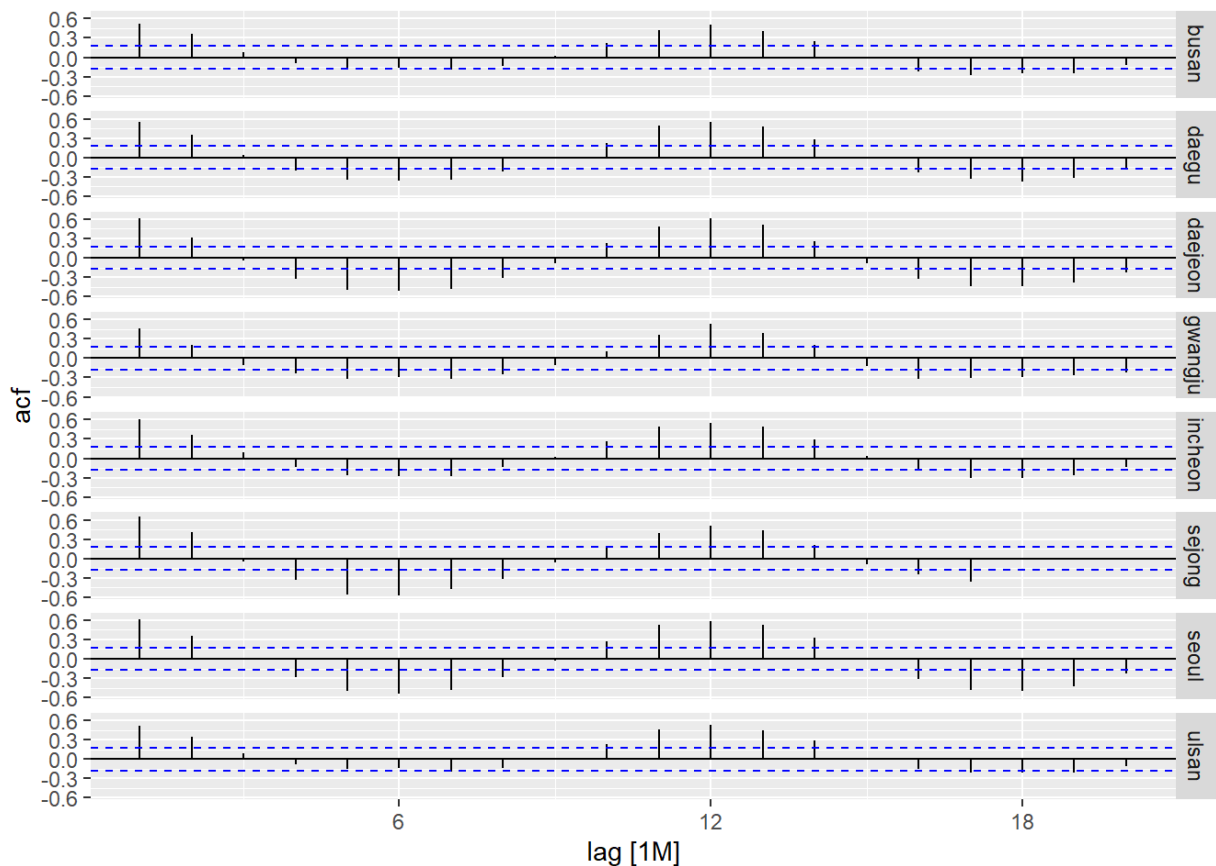
# ACF의 특징 기술

- 계절성이있는 비정상 시계열의 acf모양인 scalloped pattern을 보인다.

```
pm10w %>% ACF(y, lag_max=12)
```

```
## # A tibble: 96 x 3 [1M]
## # Key:      city [8]
##   city    lag    acf
##   <chr> <lag>  <dbl>
## 1 busan   1M  0.517
## 2 busan   2M  0.369
## 3 busan   3M  0.0834
## 4 busan   4M -0.0903
## 5 busan   5M -0.170
## 6 busan   6M -0.169
## 7 busan   7M -0.197
## 8 busan   8M -0.128
## 9 busan   9M  0.0274
## 10 busan  10M  0.220
## # ... with 86 more rows
```

```
autoplot(ACF(pm10w,y,type='cor'))
```



## Ljung-Box 검정

- p-value가  $\alpha = 0.05$ 보다 작으므로  $H_0 = \rho_1 = \dots = \rho_{12} = 0$ 를 기각한다. 따라서 y를 백색잡음으로 보기 어렵다.

```
pm10w %>% features(y, ljung_box, lag=12, dof=0)
```

```
## # A tibble: 8 x 3
##   city    lb_stat lb_pvalue
##   <chr>    <dbl>    <dbl>
## 1 busan     134.         0
## 2 daegu     195.         0
## 3 daejeon   275.         0
## 4 gwangju   149.         0
## 5 incheon   184.         0
## 6 sejong    127.         0
## 7 seoul     281.         0
## 8 ulsan     139.         0
```

## 서울 미세먼지

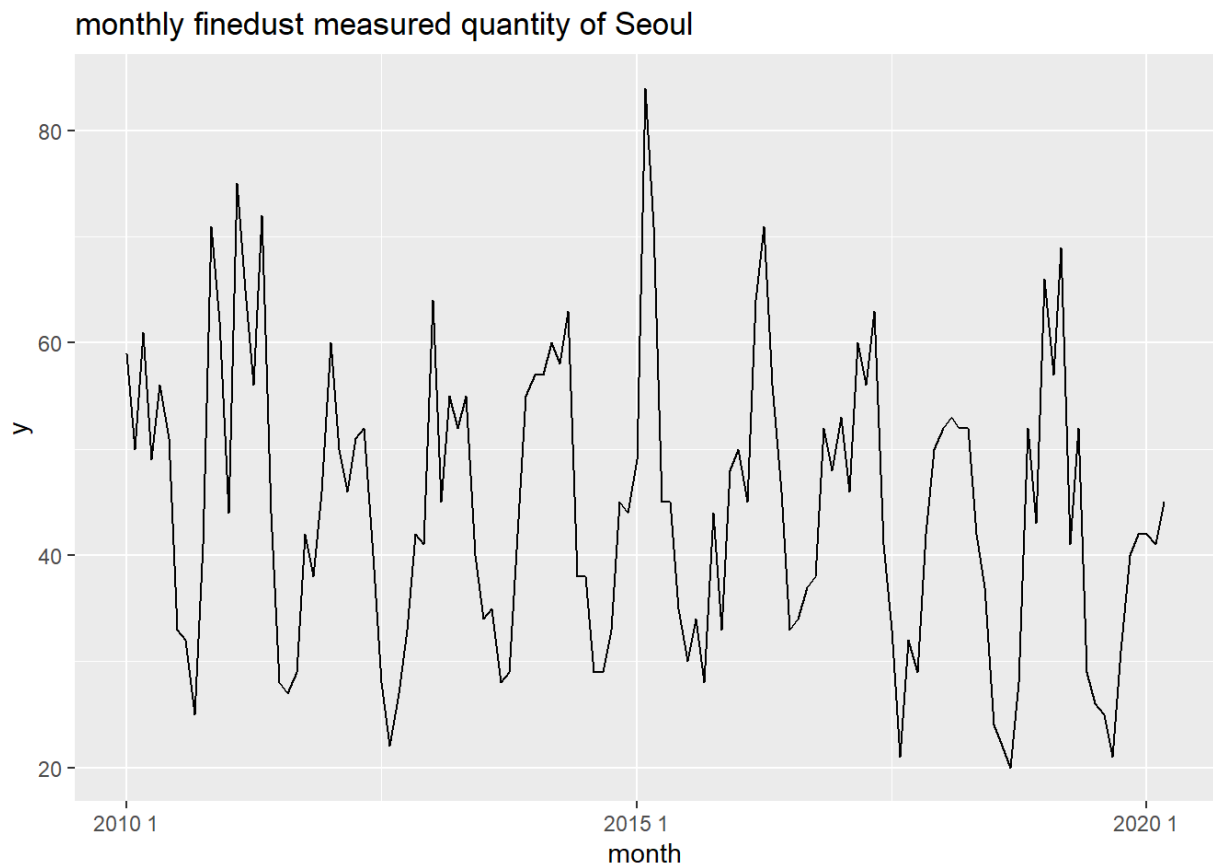
```
pm10s <- pm10w %>%
  filter(city=='seoul') %>%
  select(-city)
pm10s
```

```
## # A tsibble: 123 x 2 [1M]
##   yymm      y
##   <mth> <dbl>
## 1 2010 1    59
## 2 2010 2    50
## 3 2010 3    61
## 4 2010 4    49
## 5 2010 5    56
## 6 2010 6    51
## 7 2010 7    33
## 8 2010 8    32
## 9 2010 9    25
## 10 2010 10   41
## # ... with 113 more rows
```

## 시계열 그림

```
autoplot(pm10s)+
  labs(title="monthly finedust measured quantity of Seoul")+
  xlab("month")
```

```
## Plot variable not specified, automatically selected `vars = y`
```

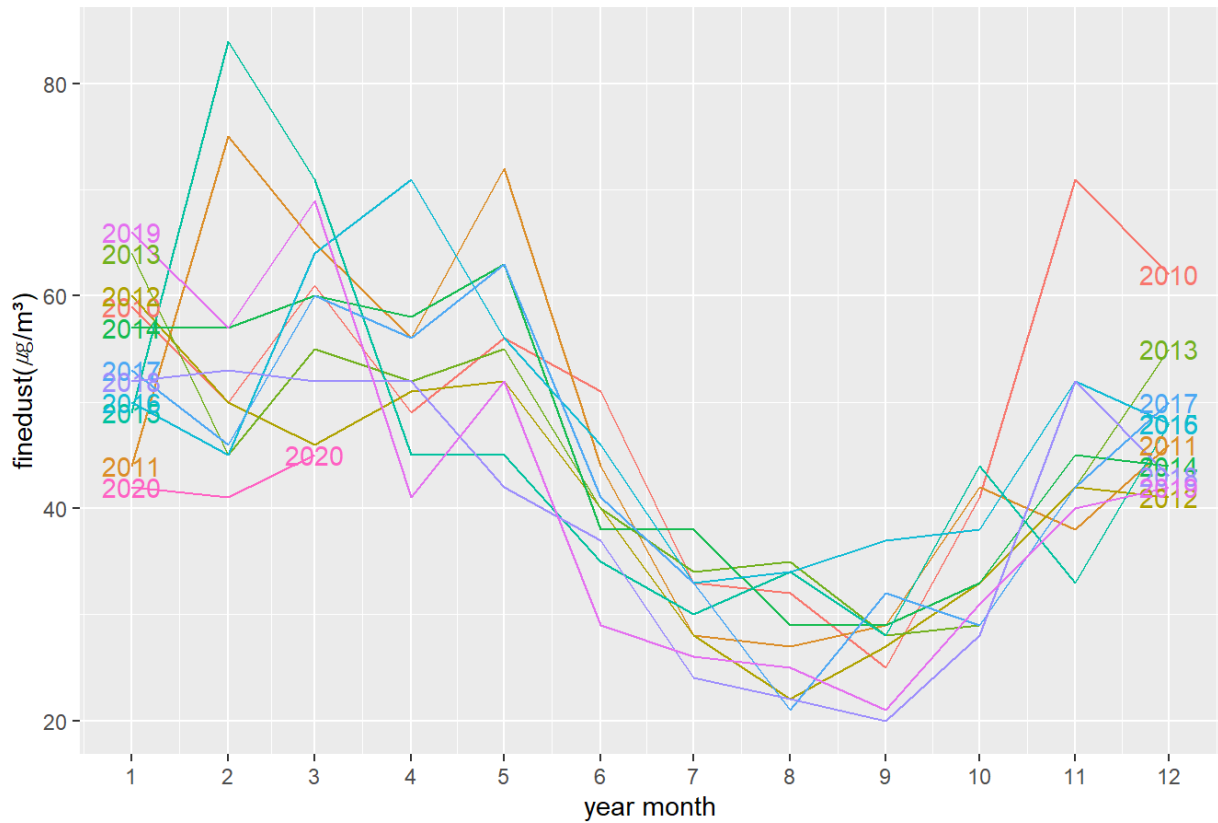


## 계절성 검토

- 서울의 미세먼지 측정량은 2월~5월, 10월~12월에 증가하고, 7~9월에 감소하는 계절성을 보인다.

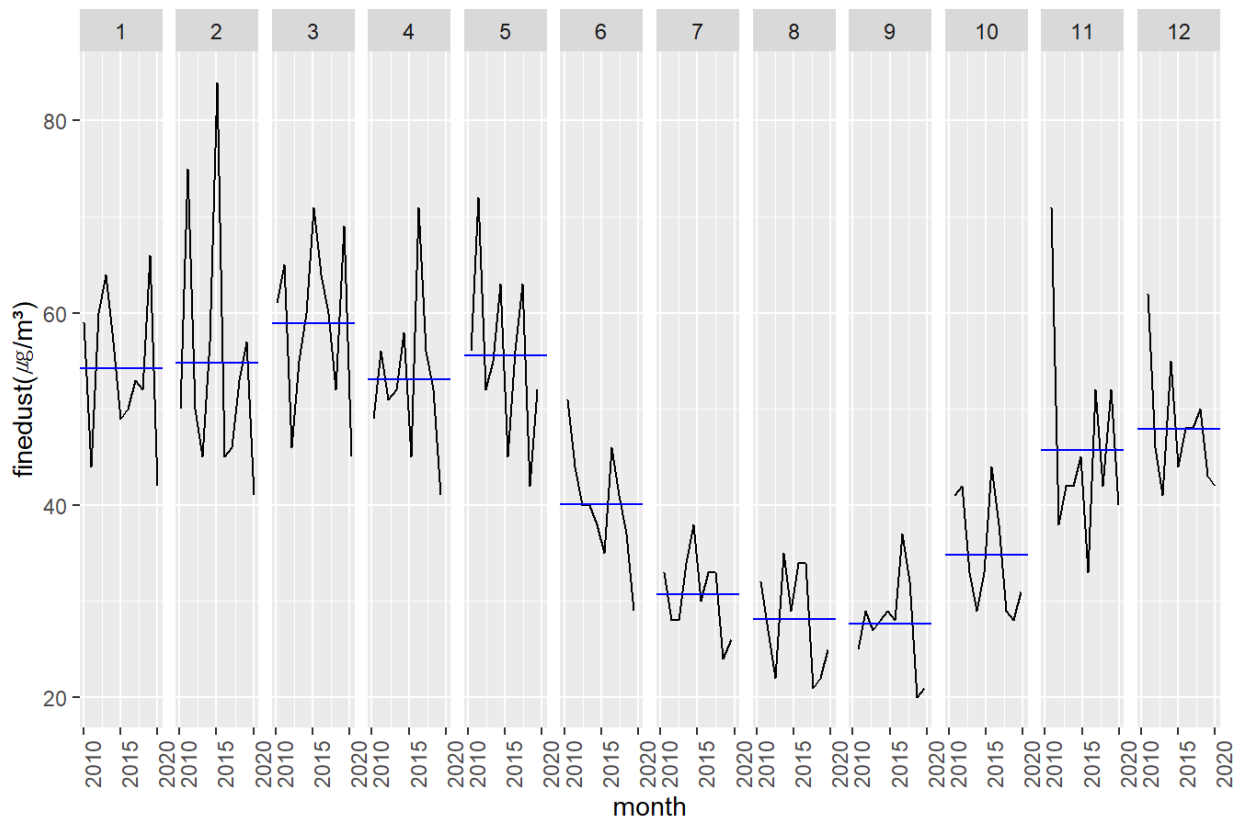
```
pm10s %>% gg_season(y, labels = "both")+  
  ylab("finedust( $\mu\text{g}/\text{m}^3$ )")+  
  xlab("year month")+  
  ggtitle("Seasonal plot : finedust measured quantity of seoul")
```

Seasonal plot : finedust measured quantity of seoul



```
pm10s %>%
  gg_subseries(y) +
  ylab("finedust( $\mu\text{g}/\text{m}^3$ )") +
  xlab("month")+
  ggtitle("Seasonal subseries plot : findust measured quantity of seoul")
```

Seasonal subseries plot : findust measured quantity of seoul



# 시계열 그림, 계절성 검토. 추세여부, 등분산성 등을 설명하시오

- 서울의 미세먼지 측정량은 2월~5월, 10월~12월에 증가하고, 7~9월에 감소하는 계절성을 보인다.
- 추세는 존재하지않는 것으로 보이며 등분산성을 가지는 것으로 보인다.

## 자료 분할

- TRN(적합용): 2010.1~2017.12 월별 미세먼지 측정량
- TST(검정용): 2018.1~2019.12 월별 미세먼지 측정량

```
TRN <- filter_index(pm10s, ~'2017 12')
TST <- filter_index(pm10s, '2018 1'~'2020 1')
```

## TRN를 X11, SEATS, STL로 분해하고 설명하시오

### x11 decomposition

- 분해결과 미세먼지 측정량은 몇년도든 간 3월에 가장 높다.
- 뚜렷한 계절성을 갖고, 등분산이며 결정적 추세는 존재하지않는 것으로 보인다.

```
library(seasonal)
```

```
## Warning: package 'seasonal' was built under R version 4.0.3
```

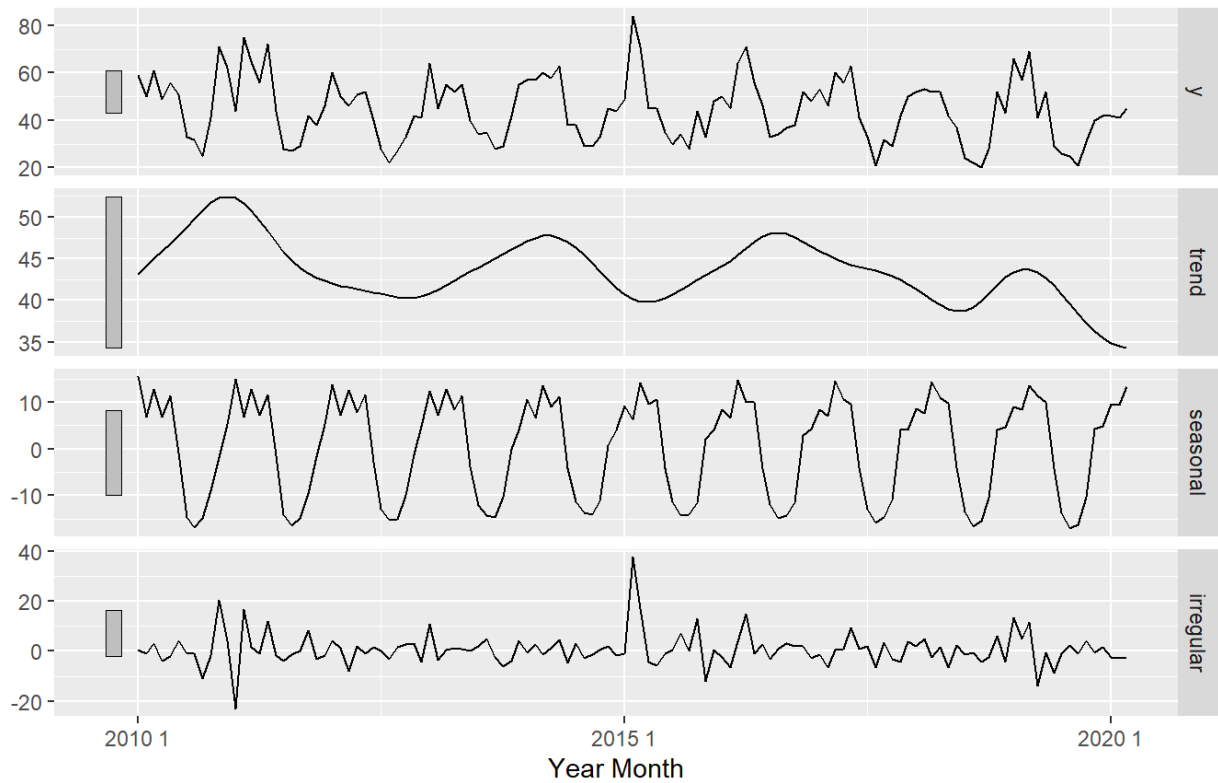
```
##
## Attaching package: 'seasonal'
```

```
## The following object is masked from 'package:tibble':
##
## view
```

```
x11_dcmp <- pm10s %>%
  model(x11 = feasts::X11(y, type = "additive")) %>%
  components()
autoplot(x11_dcmp) + xlab("Year Month") +
  ggtitle("Additive X11 decomposition of finedust measured quantity in the Seoul")
```

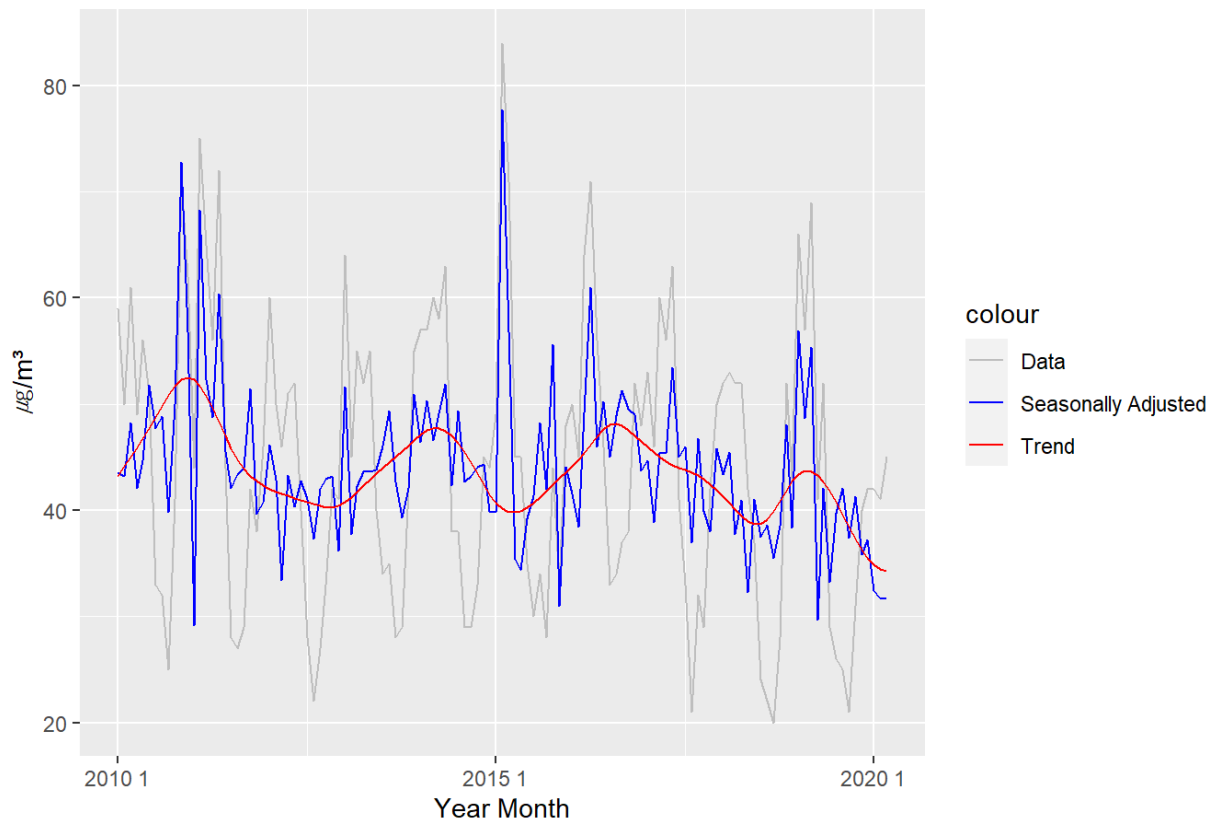
## Additive X11 decomposition of finedust measured quantity in the Seoul

$y = \text{trend} + \text{seasonal} + \text{irregular}$

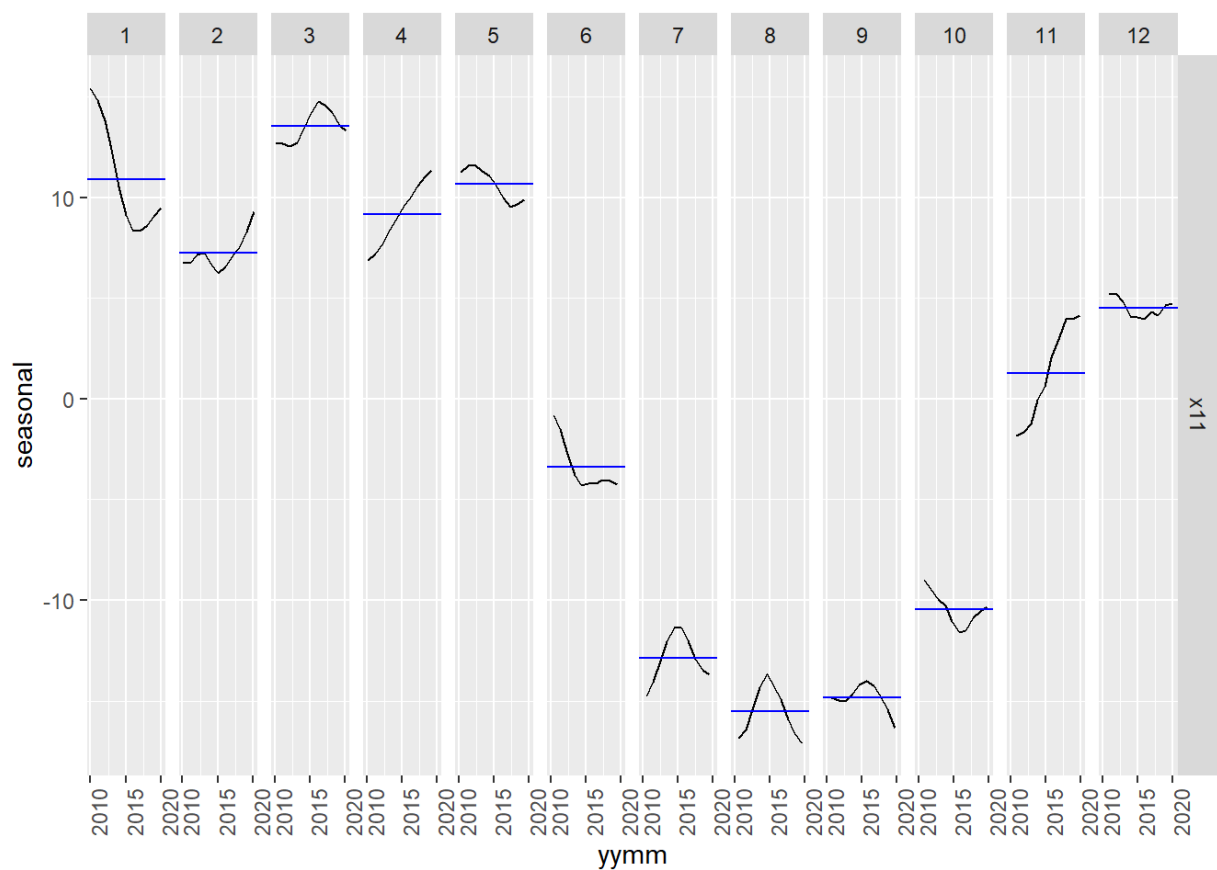


```
x11_dcmp %>%
  ggplot(aes(x = yymm)) +
  geom_line(aes(y = y, colour = "Data")) +
  geom_line(aes(y = season_adjust, colour = "Seasonally Adjusted")) +
  geom_line(aes(y = trend, colour = "Trend")) +
  xlab("Year Month") + ylab("μg/m³ ") +
  ggtitle("finedust measured quantity in the Seoul") +
  scale_colour_manual(values=c("gray","blue","red"),
    breaks=c("Data", "Seasonally Adjusted", "Trend"))
```

finedust measured quantity in the Seoul



```
x11_dcmp %>%
  gg_subseries(seasonal)
```



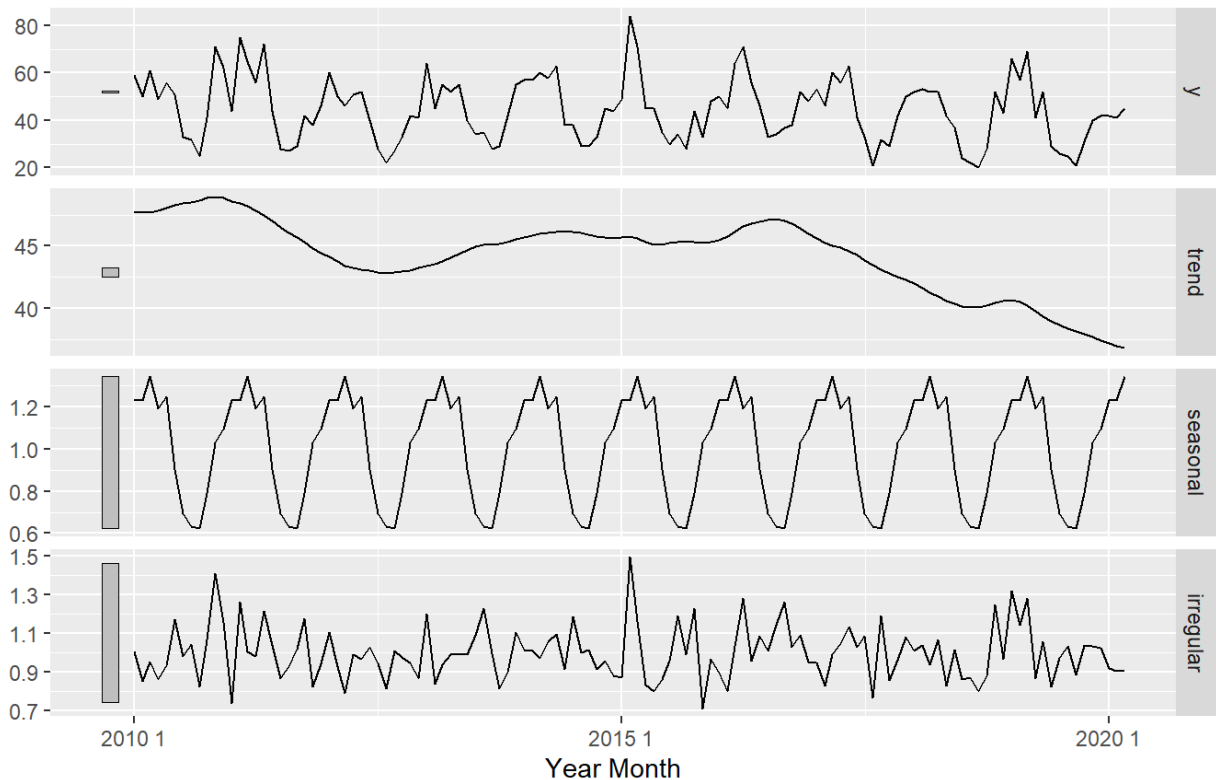
SEATS decomposition

- 분해결과 서울시 미세먼지 측정량은 감소하는 추세이며 등분산이고 뚜렷한 계절성을 가지는 것으로 보인다.

```
seats_dcmp <- pm10s %>%
  model(seats = feasts::SEATS(y)) %>%
  components()
autoplot(seats_dcmp)+ xlab("Year Month") +
  ggtitle("Additive X11 decomposition of finedust measured quantity in the Seoul")
```

### Additive X11 decomposition of finedust measured quantity in the Seoul

$y = \text{trend} * \text{seasonal} * \text{irregular}$



## STL decomposition

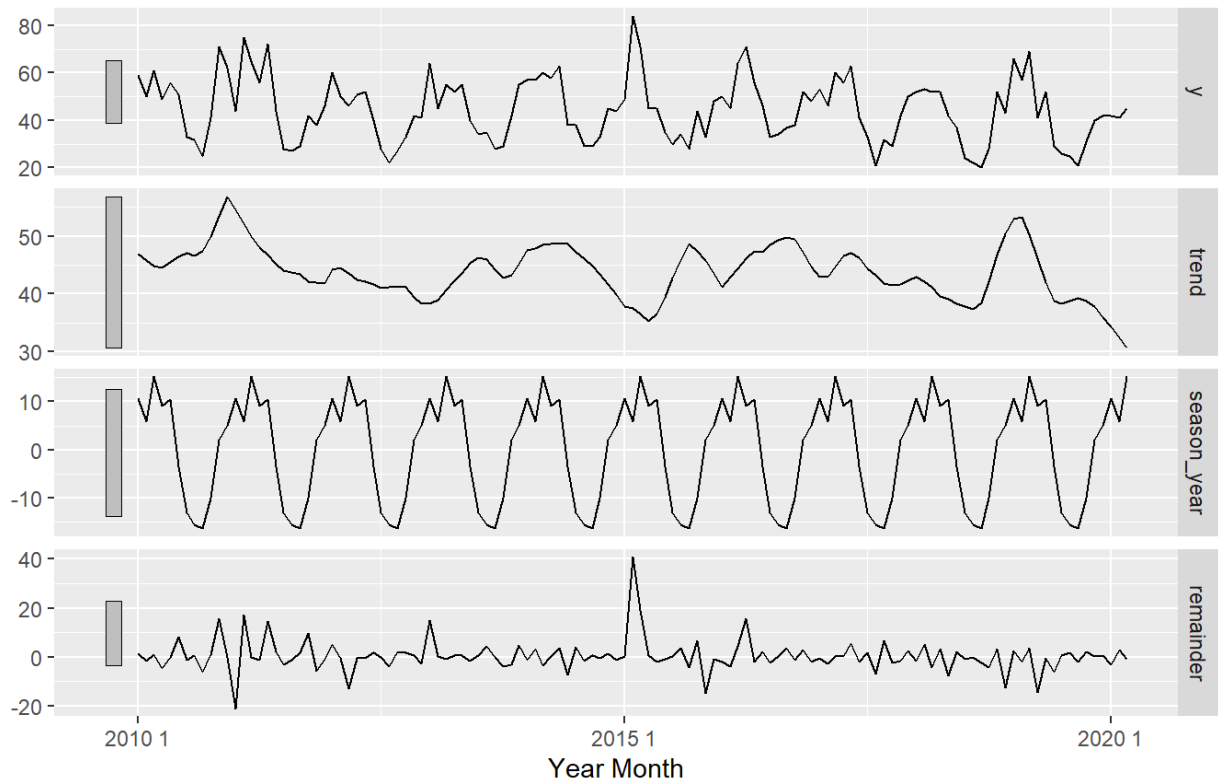
- 분해결과 결정적 추세는 존재하지 않으며 등분산이며 뚜렷한 계절성을 가지는 것으로 보인다.

```
pm10s %>%
  model(STL(y ~ trend(window=7) + season(window='periodic'),
    robust = TRUE)) %>%
  components() %>%
  autoplot()+ xlab("Year Month") +
  ggtitle("Additive X11 decomposition of finedust measured quantity in the Seoul")
```



## Additive X11 decomposition of finedust measured quantity in the Seoul

$y = \text{trend} + \text{season\_year} + \text{remainder}$



## 단순예측법 실행

### MBL 생성

```
MS <- model(TRN,
  mn = MEAN(y),
  rw = NAIVE(y),
  rwd = RW(y~drift()),
  srw = SNAIVE(y))
```

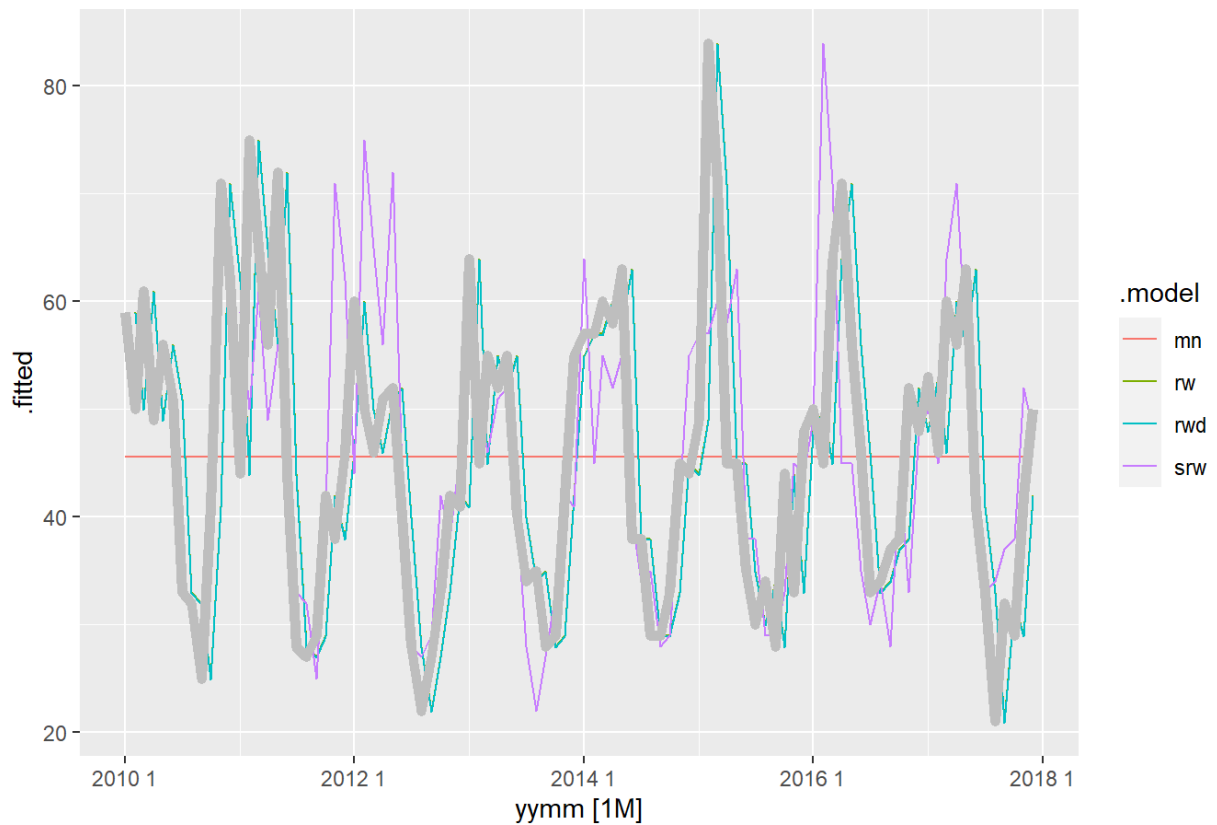
MS

```
## # A mable: 1 x 4
##      mn      rw      rwd      srw
##   <model> <model>   <model> <model>
## 1  <MEAN> <NAIVE> <RW w/ drift> <SNAIVE>
```

```
AS <- augment(MS)
autoplot(AS, .fitted)+
  autolayer(AS,y,color='gray',size=2)+
  ggtitle('TRN: augment(MS)$fitted')
```

```
## Warning: Removed 14 row(s) containing missing values (geom_path).
```

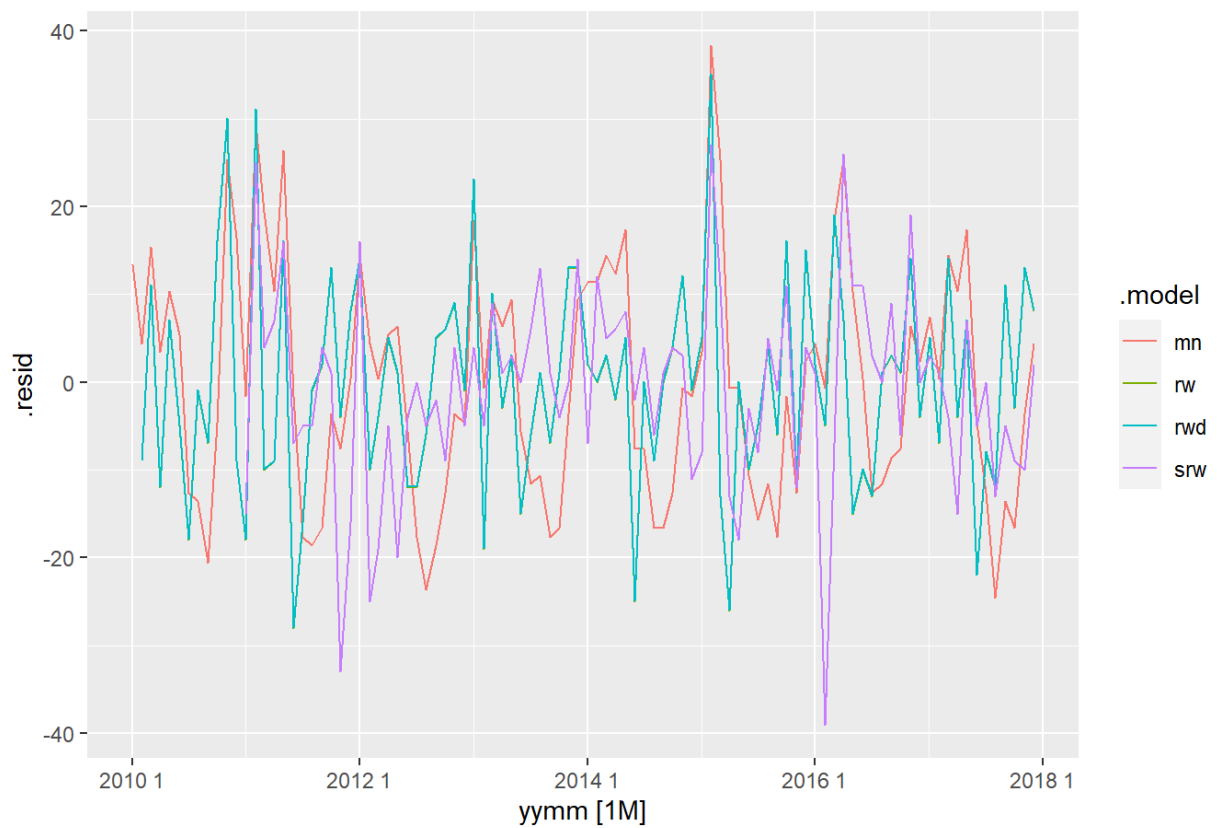
TRN: augment(MS)\$fitted



```
autoplot(AS,.resid)+
  ggtitle('TRN: augment(MS)$resid')
```

## Warning: Removed 14 row(s) containing missing values (geom\_path).

TRN: augment(MS)\$resid



```
features(AS,.resid,ljung_box, lag=4, dof=0)
```

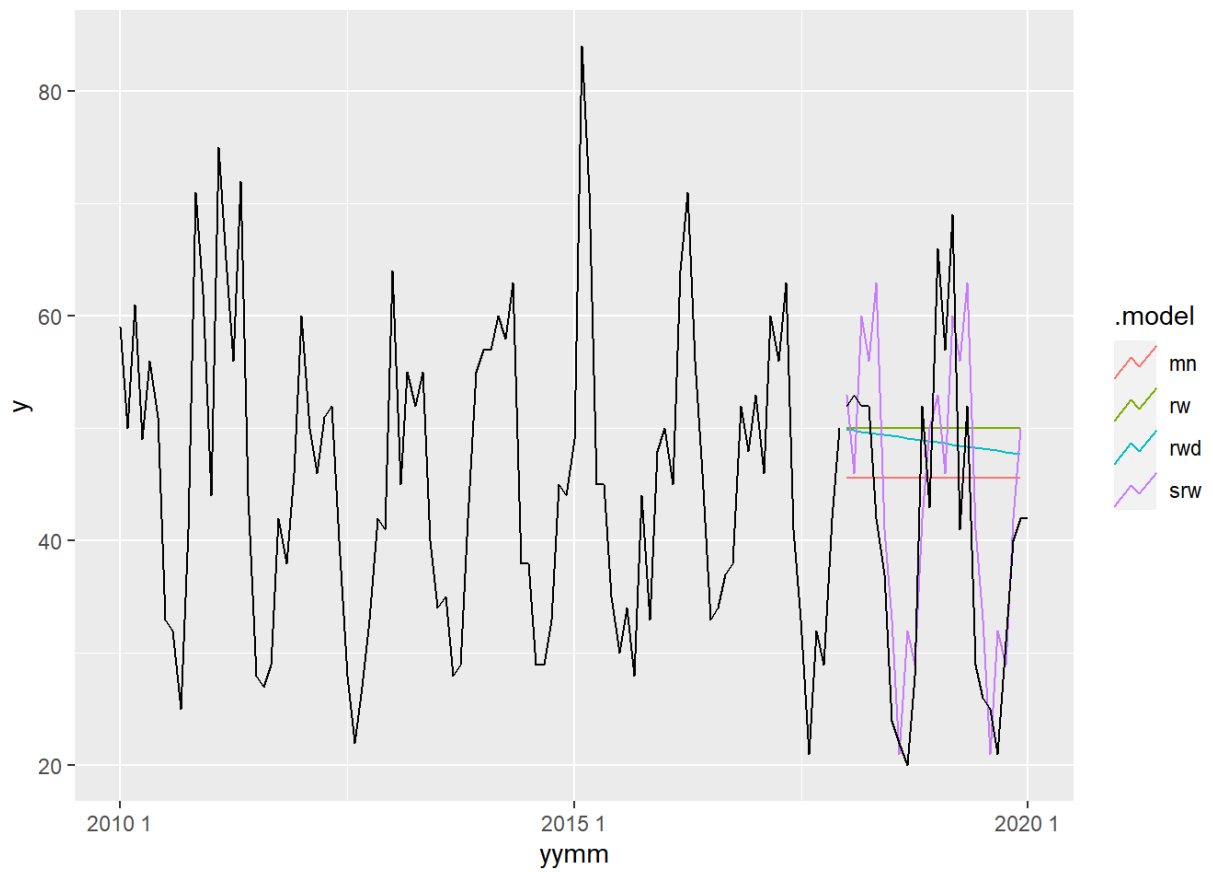
```
## # A tibble: 4 x 3
##   .model lb_stat lb_pvalue
##   <chr>   <dbl>   <dbl>
## 1 mn      51.6  1.65e-10
## 2 rw      4.64  3.27e- 1
## 3 rwd      4.64  3.27e- 1
## 4 srw      2.84  5.85e- 1
```

## FBL생성

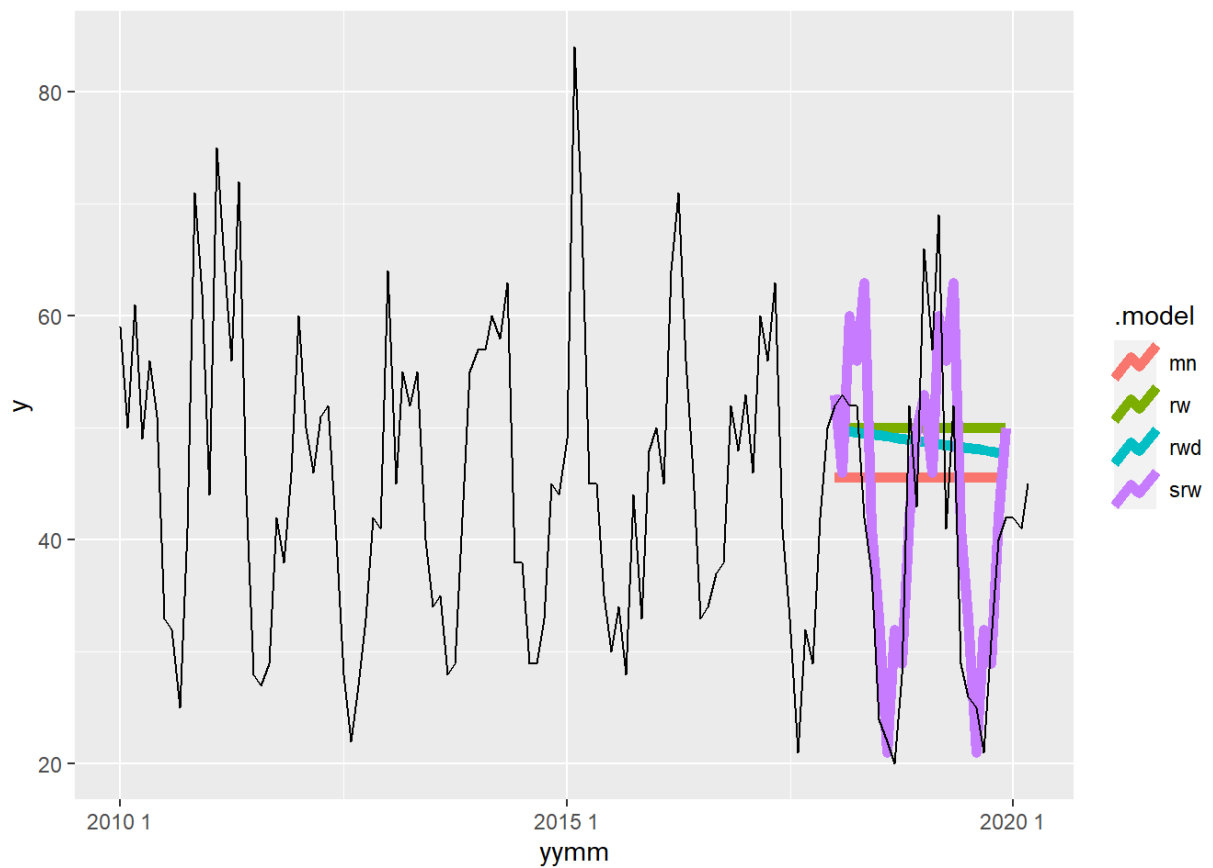
```
FS <- forecast(MS, data=pm10s)
FS
```

```
## # A fable: 96 x 4 [1M]
## # Key:   .model [4]
##   .model   yymm          y .mean
##   <chr>   <mtm>   <dist> <dbl>
## 1 mn      2018 1 N(46, 181) 45.6
## 2 mn      2018 2 N(46, 181) 45.6
## 3 mn      2018 3 N(46, 181) 45.6
## 4 mn      2018 4 N(46, 181) 45.6
## 5 mn      2018 5 N(46, 181) 45.6
## 6 mn      2018 6 N(46, 181) 45.6
## 7 mn      2018 7 N(46, 181) 45.6
## 8 mn      2018 8 N(46, 181) 45.6
## 9 mn      2018 9 N(46, 181) 45.6
## 10 mn     2018 10 N(46, 181) 45.6
## # ... with 86 more rows
```

```
autoplot(FS,TRN, level=NULL)+
  autolayer(TST,y)
```



```
autoplot(FS,pm10s,level=NULL,size=2)
```



## 성능 평가

TRN에 대한 성능평가

- TRN에서의 성능은 rwd의 RMSE,MAE,MAPE가 각각 06916,9.445097,21.17628로 rwd 모델이 가장 우수한 것으로 나타났다.

```
as.data.frame(accuracy(MS))
```

```
##      .model      .type      ME      RMSE      MAE      MPE      MAPE      MASE
## 1      mn Training -2.368688e-15 13.30051 10.882161 -9.328597 26.79283 1.291104
## 2      rw Training -9.473684e-02 12.06954  9.442105 -3.504211 21.19058 1.120250
## 3      rwd Training -1.498984e-16 12.06916  9.445097 -3.276447 21.17628 1.120605
## 4      srw Training -7.619048e-01 11.44552  8.428571 -4.414184 18.61234 1.000000
##           ACF1
## 1 0.58671564
## 2 -0.12066405
## 3 -0.12066405
## 4 0.06814661
```

## TST에 대한 성능평가

- TST에서의 성능은 SRW의 RMSE,MAE,MAPE가 각각 9.313968, 7.916667,21.54606로 가장 우수한것으로 나타났다.

```
as.data.frame(accuracy(FS, data=pm10s))
```

```
##      .model .type      ME      RMSE      MAE      MPE      MAPE      MASE
## 1      mn  Test -4.947917 15.009578 12.820312 -28.32122 41.66175 1.5210540
## 2      rw  Test -9.333333 16.968107 13.916667 -40.65811 48.07065 1.6511299
## 3      rwd Test -8.149123 16.225114 13.364035 -37.18026 45.69019 1.5855635
## 4      srw Test -3.166667  9.313968  7.916667 -12.25656 21.54606 0.9392655
##           ACF1
## 1 0.6312537
## 2 0.6312537
## 3 0.6260702
## 4 0.0960204
```

## 최종모형 -SNAIVE

- TST에서 성능이 가장 좋은 snaive모델을 최종모형으로 선택

```
MSRW <- model(TRN,
              srw = SNAIVE(y))
MSRW
```

```
## # A mable: 1 x 1
##      srw
##      <model>
## 1 <SNAIVE>
```

```
ASRW <- augment(MSRW)
ASRW
```

```
## # A tibble: 96 x 6 [1M]
## # Key:      .model [1]
##   .model    yymm      y .fitted .resid .innov
##   <chr>    <mth> <dbl>   <dbl> <dbl> <dbl>
## 1 srw     2010 1     59     NA     NA     NA
## 2 srw     2010 2     50     NA     NA     NA
## 3 srw     2010 3     61     NA     NA     NA
## 4 srw     2010 4     49     NA     NA     NA
## 5 srw     2010 5     56     NA     NA     NA
## 6 srw     2010 6     51     NA     NA     NA
## 7 srw     2010 7     33     NA     NA     NA
## 8 srw     2010 8     32     NA     NA     NA
## 9 srw     2010 9     25     NA     NA     NA
## 10 srw    2010 10    41     NA     NA     NA
## # ... with 86 more rows
```

## 예측값 생성

```
FSRW <- forecast(MSRW, data=pm10s)
```

## 모형평가

- TRN평가

```
accuracy(MSRW)
```

```
## # A tibble: 1 x 9
##   .model .type      ME  RMSE  MAE  MPE  MAPE  MASE  ACF1
##   <chr> <chr>    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 srw   Training -0.762  11.4  8.43 -4.41  18.6    1 0.0681
```

- TST평가

```
accuracy(FSRW, pm10s)
```

```
## # A tibble: 1 x 9
##   .model .type      ME  RMSE  MAE  MPE  MAPE  MASE  ACF1
##   <chr> <chr>    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 srw   Test    -3.17  9.31  7.92 -12.3  21.5  0.939 0.0960
```

## 잔차 검토

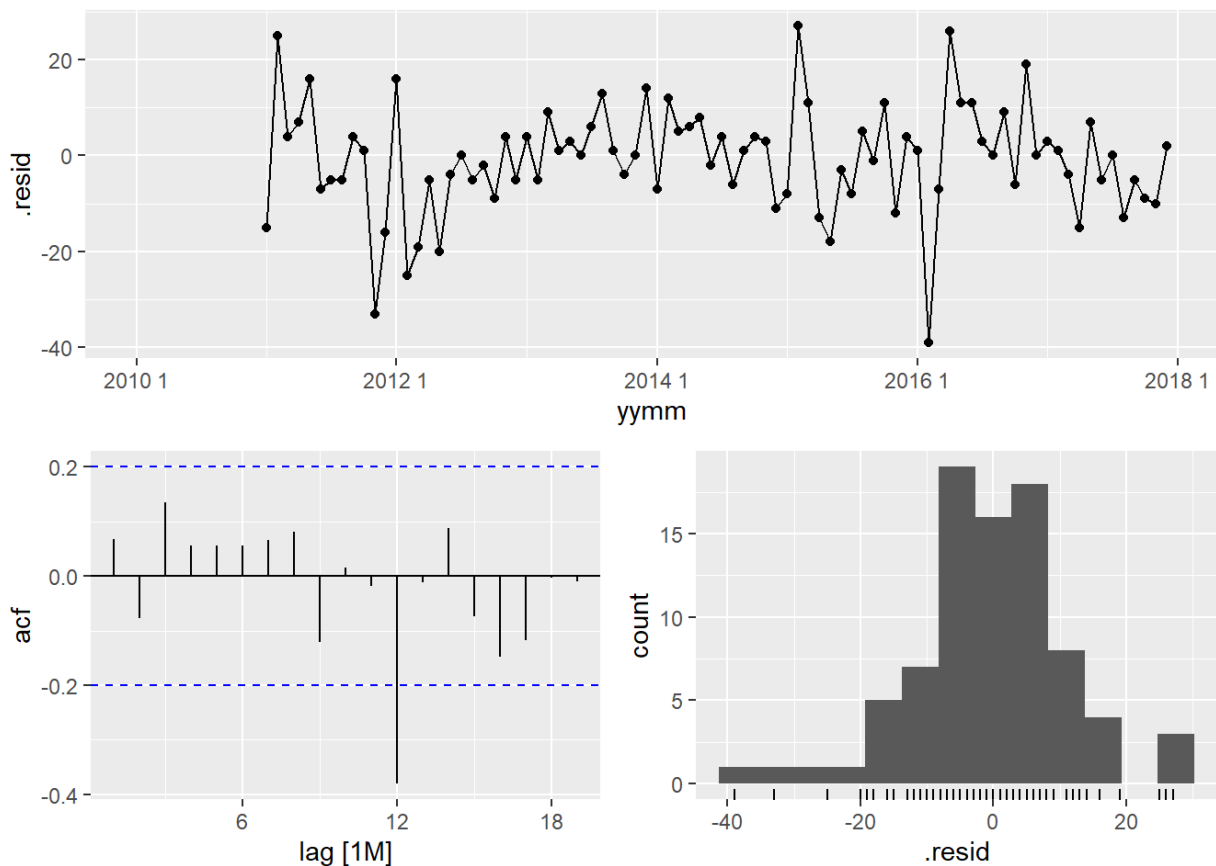
- 잔차는 등분산에 가깝고, 잔차의 ACF에서 잔차의 자기상관이 없고, 정규분포를 따르는 것으로 보인다.

```
MSRW %>%
  gg_tsresiduals()
```

```
## Warning: Removed 12 row(s) containing missing values (geom_path).
```

```
## Warning: Removed 12 rows containing missing values (geom_point).
```

```
## Warning: Removed 12 rows containing non-finite values (stat_bin).
```



### 잔차의 백색잡음 검정

- p-value가  $\alpha = 0.05$ 보다 크다. 따라서  $H_0 = \rho_1 = \dots = \rho_{12} = 0$ 를 기각할 수 없다.

```
features(ASRW,.resid, lbjung_box, lag=12,dof=0)
```

```
## # A tibble: 1 x 3
##   .model lb_stat lb_pvalue
##   <chr>   <dbl>   <dbl>
## 1 srw     20.5    0.0589
```