

# Initial models for time series

#Read Data and Basic Plots

*#Load packages*

library(readr)

library(fpp3) *#this imports a few things including dplyr, tidyr,ggplot2, and more*

## -- Attaching packages ----- fpp3 0.4.0 --

```
## v tibble      3.1.2      v tsibble      1.0.1
## v dplyr       1.0.7      v tsibbledata 0.3.0
## v tidyr       1.1.3      v feasts      0.2.2
## v lubridate   1.7.10     v fable       0.3.1
## v ggplot2     3.3.4
```

## -- Conflicts ----- fpp3\_conflicts --

```
## x lubridate::date()      masks base::date()
## x dplyr::filter()       masks stats::filter()
## x tsibble::intersect()   masks base::intersect()
## x tsibble::interval()   masks lubridate::interval()
## x dplyr::lag()           masks stats::lag()
## x tsibble::setdiff()     masks base::setdiff()
## x tsibble::union()      masks base::union()
```

library(tsibble)

library(forecast)

## Registered S3 method overwritten by 'quantmod':

## method from

## as.zoo.data.frame zoo

*#read in cvs as dataframe and convert to time series*

*#key = c(Mode,ORegionDAT, DRegionDAT) since these 4 categories each have one observation at each time*

df <- readr::read\_csv(file = "data\_shipping\_and\_weather\_joined\_cleaned.csv") %>% mutate(yw = yearweek(y

## Warning: Missing column names filled in: 'X1' [1]

##

## -- Column specification -----

## cols(

## X1 = col\_double(),

## Mode = col\_character(),

## ORegionDAT = col\_character(),

## DRegionDAT = col\_character(),

## yw = col\_character(),

## sanitized\_cost = col\_double(),

## prcp = col\_double(),

## tavg = col\_double(),

## tmax = col\_double(),

## tmin = col\_double()

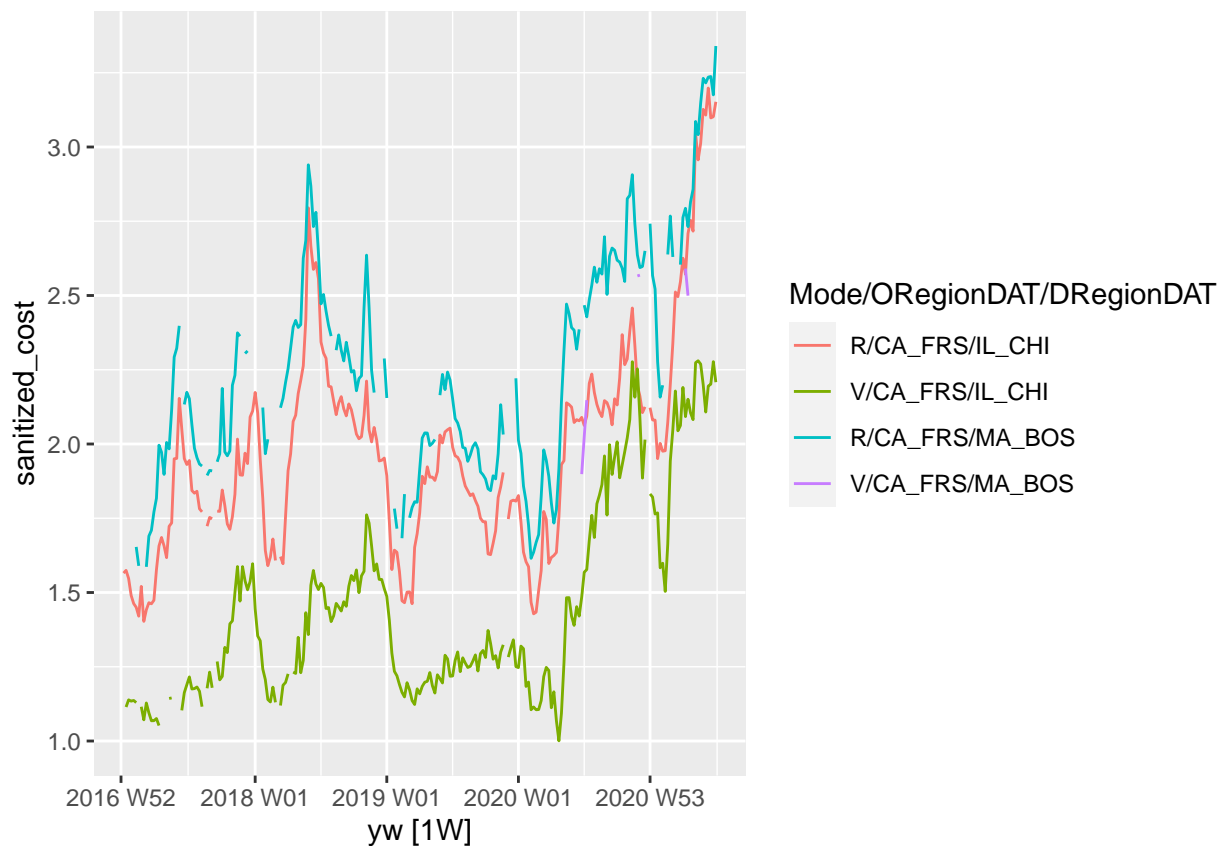
## )

```
head(df)
```

```
## # A tsibble: 6 x 10 [1W]
## # Key:      Mode, ORegionDAT, DRegionDAT [1]
##       X1 Mode ORegionDAT DRegionDAT      yw sanitized_cost  prcp  tavg  tmax
##   <dbl> <chr> <chr>      <chr>      <week>      <dbl>  <dbl> <dbl> <dbl>
## 1     1  R    CA_FRS    IL_CHI    2017 W01      1.57  0.309  49.4  56.9
## 2     2  R    CA_FRS    IL_CHI    2017 W02      1.57  0.357  49.9  53.1
## 3     3  R    CA_FRS    IL_CHI    2017 W03      1.55  0.238  47.7  54.9
## 4     4  R    CA_FRS    IL_CHI    2017 W04      1.49  0.0781 44.7  55.9
## 5     5  R    CA_FRS    IL_CHI    2017 W05      1.46  0.115  53.4  63.9
## 6     6  R    CA_FRS    IL_CHI    2017 W06      1.45  0.176   57   61.9
## # ... with 1 more variable: tmin <dbl>
```

```
autoplot(df, sanitized_cost)
```

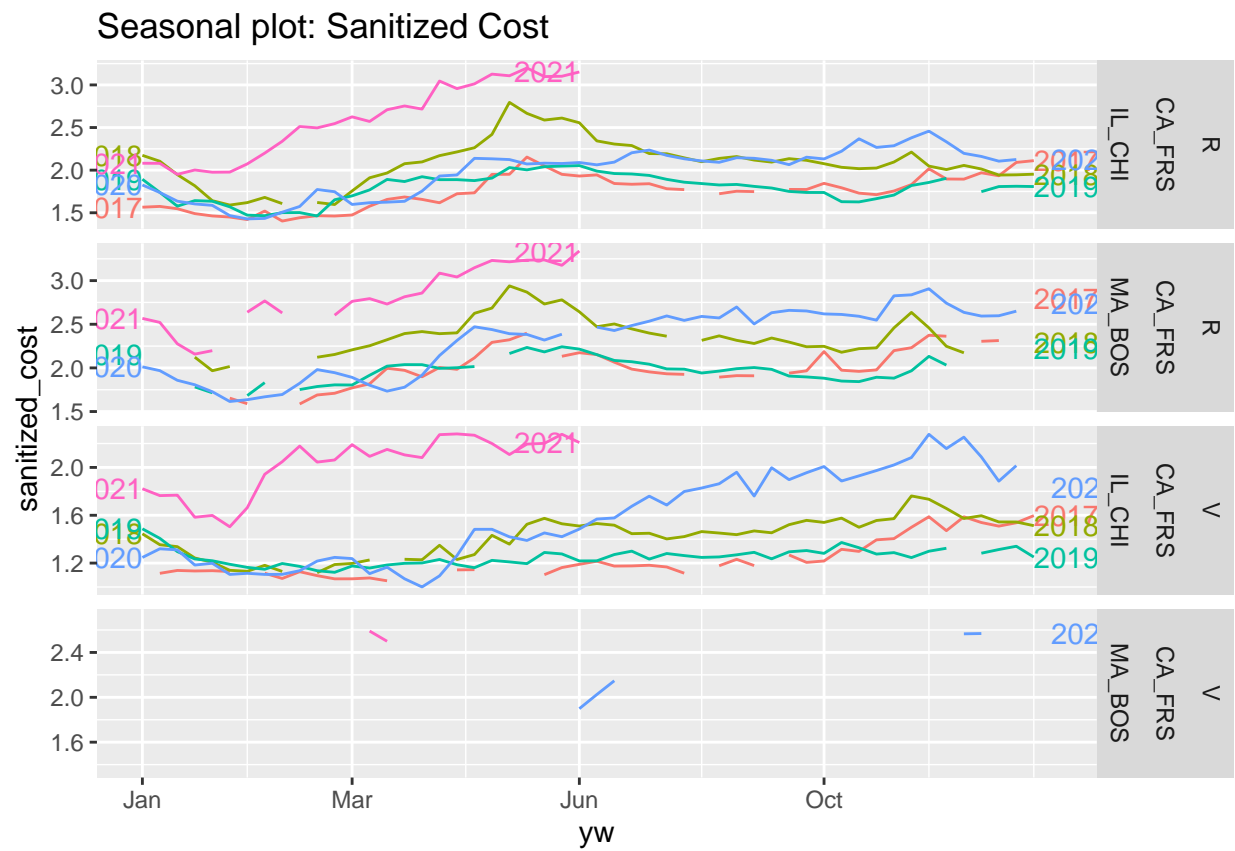
```
## Warning: Removed 41 row(s) containing missing values (geom_path).
```



```
#seasonal plot for cost
gg_season(df, y = sanitized_cost, labels = "both") +
  labs(title = "Seasonal plot: Sanitized Cost")
```

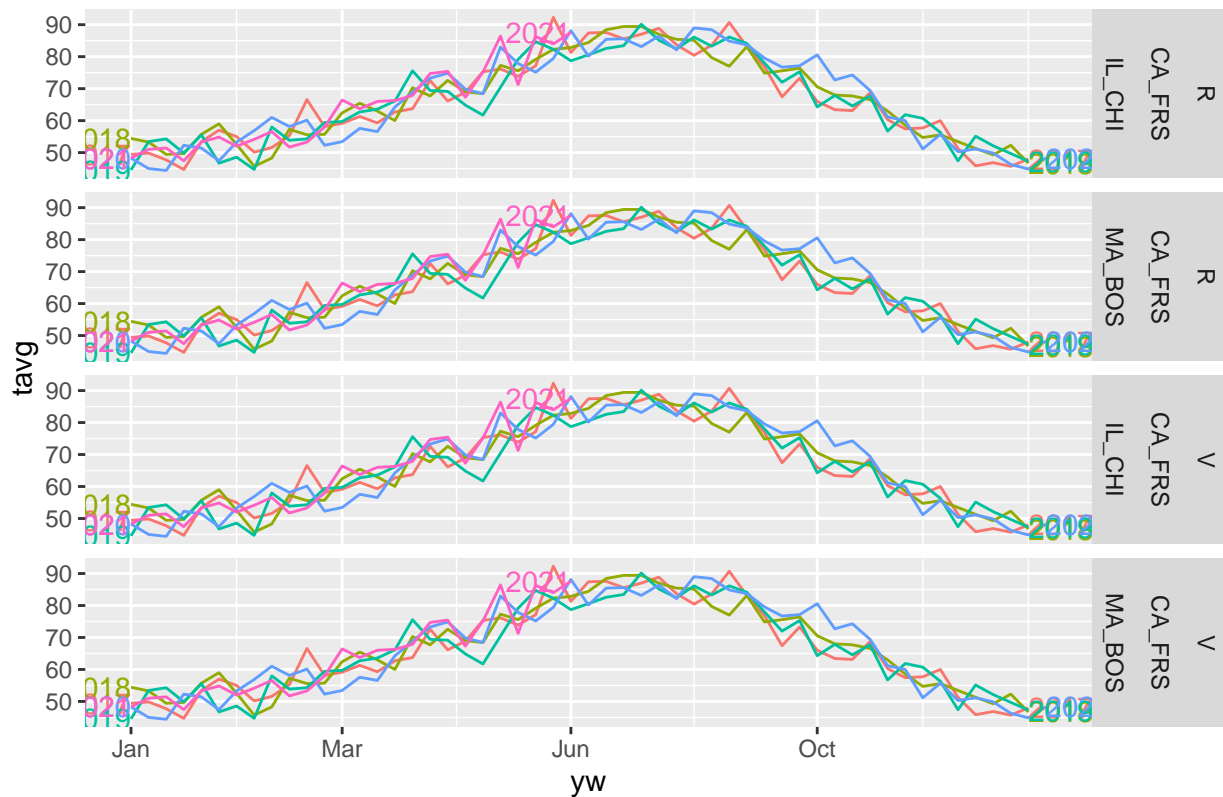
```
## Warning: Removed 39 row(s) containing missing values (geom_path).
```

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



```
# seasonal plot for temperature
gg_season(df, y = tavg, labels = "both") +
  labs(title = "Seasonal plot: Average daily temperature")
```

Seasonal plot: Average daily temperature



#Looking at Basic Models

Let's follow this article with our data set

```
is.ts(df)
```

```
## [1] FALSE
```

```
##Avg, Naive, SNaive (seasonal naive(!))
```

mean = the forecasts of all future values are equal to the average (or “mean”) of the historical data

naive = the forecasts for every horizon correspond to the last observed value

Seasonal Naive = we set each forecast to be equal to the last observed value from the same season of the year

```
snaive(
  df,
  h = 2 * frequency(x),
  level = c(80, 95),
  fan = FALSE,
  lambda = NULL,
  biasadj = FALSE,
  ...,
  x = y
)
```

```
#Look at just refridgerated trucks with dest IL_CHI
df_R_IL <- df %>%
  filter(df$Mode == "R", df$DRegionDAT == "IL_CHI")
```

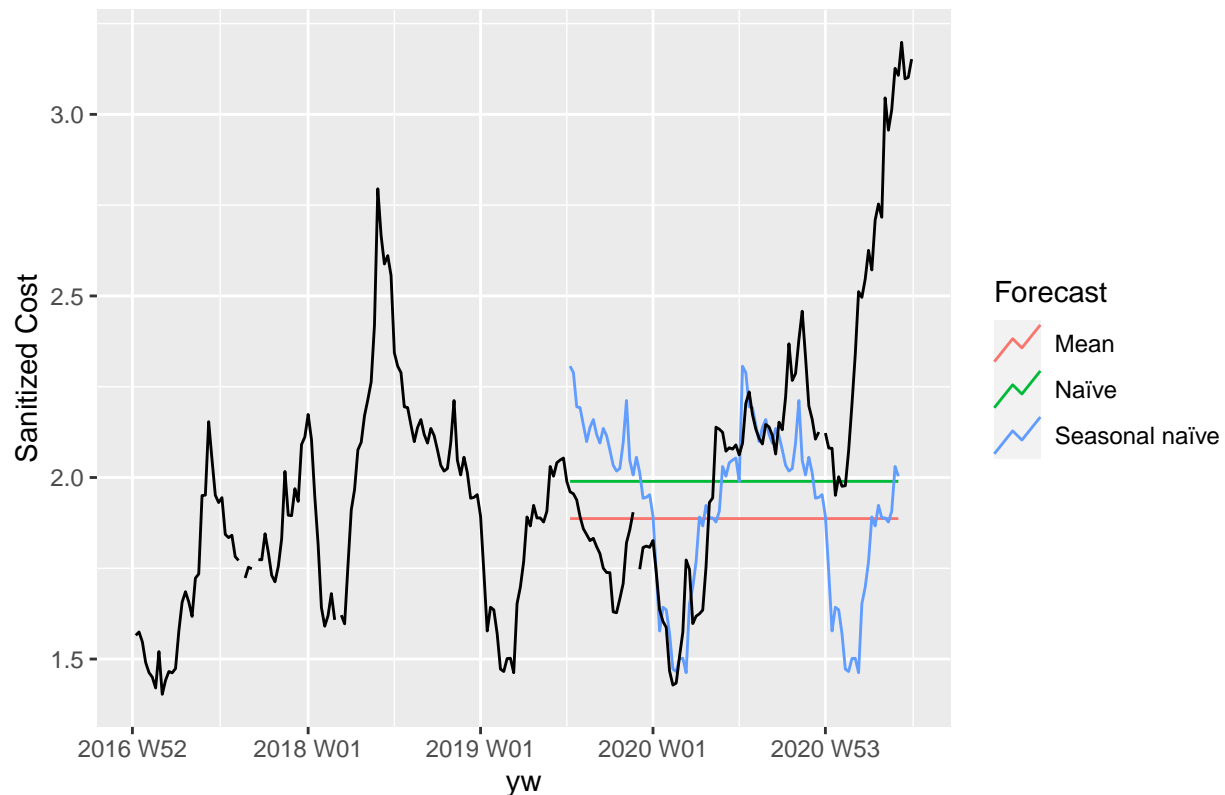
```
# Set training data from 2017 W01 to 2019 W27
train_R_IL <- df_R_IL %>%
  filter_index("2017 W01" ~ "2019 W27")
```

```
# Fit the models
cost_fit <- train_R_IL %>%
  model(
    Mean = MEAN(sanitized_cost),
    `Naïve` = NAIVE(sanitized_cost),
    `Seasonal naïve` = SNAIVE(sanitized_cost)
  )
```

```
# Generate forecasts for 54 weeks
cost_fc <- cost_fit %>% forecast(h = 100)
```

```
# Plot forecasts against actual values
cost_fc %>%
  autoplot(df_R_IL, level = NULL) +
  labs(
    y = "Sanitized Cost",
    title = "Forecasts for weekly cost Refridgerated to Chicago"
  ) +
  guides(colour = guide_legend(title = "Forecast"))
```

## Forecasts for weekly cost Refridrated to Chicago



*#mean = the forecasts of all future values are equal to the average (or "mean") of the historical data*

*#naïve = the forecasts for every horizon correspond to the last observed value*

*#Seasonal Naïve = we set each forecast to be equal to the last observed value from the same season of t*

*# Set training data from 2017 W01 to 2019 W27*

```
train <- df %>%
  filter_index("2017 W01" ~ "2019 W27")
```

*# Fit the models*

```
cost_fit <- train %>%
  model(
    Mean = MEAN(sanitized_cost),
    `Naïve` = NAIVE(sanitized_cost),
    `Seasonal naïve` = SNAIVE(sanitized_cost)
  )
```

*# Generate forecasts for 54 weeks*

```
cost_fc <- cost_fit %>% forecast(h = 100)
```

*# Plot forecasts against actual values*

```
cost_fc %>%
  autoplot(df, level = NULL) +
  labs(
```

```

y = "Sanitized Cost",
title = "Forecasts for weekly cost"
)+
guides(colour = guide_legend(title = "Forecast"))

```

## Warning: Removed 126 row(s) containing missing values (geom\_path).

## Warning: Removed 41 row(s) containing missing values (geom\_path).

