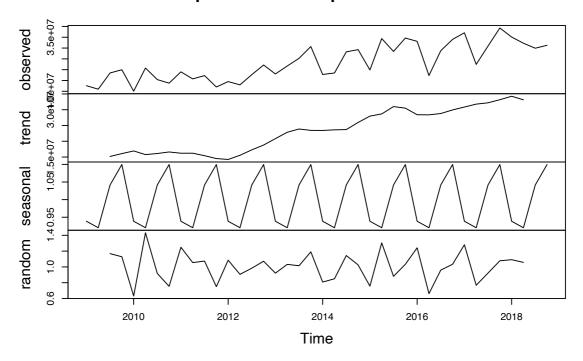
```
#Import dataset
BOROUGH <- readxl::read_excel("/Users/shimonyagrawal/Desktop/NYC Real Estate/BOROUGH.xlsx")
NEIGHBORHOOD <- readxl::read_excel("/Users/shimonyagrawal/Desktop/NYC Real Estate/NEIGHBORHOOD.xlsx")</pre>
BUILDING_CLASS <- readxl::read_excel("/Users/shimonyagrawal/Desktop/NYC Real Estate/BUILDING_CLASS.xlsx
NYC_HISTORICAL <- readxl::read_excel("/Users/shimonyagrawal/Desktop/NYC Real Estate/NYC_HISTORICAL.xlsx
#Install packages for analysis
tinytex::install_tinytex()
## Warning: Detected an existing tlmgr at /usr/local/bin/tlmgr. It seems TeX
## Live has been installed (check tinytex::tinytex_root()). You are recommended
## to uninstall it, although TinyTeX should work well alongside another LaTeX
## distribution if a LaTeX document is compiled through tinytex::latexmk().
## TinyTeX installed to /Users/shimonyagrawal/Library/TinyTeX
install.packages("readxl")
## The downloaded binary packages are in
## /var/folders/rj/t11km2gs693dyq4szgcrm4vr0000gn/T//Rtmp9bEnUj/downloaded_packages
install.packages("DBI")
##
## The downloaded binary packages are in
## /var/folders/rj/t11km2gs693dyq4szgcrm4vr0000gn/T//Rtmp9bEnUj/downloaded_packages
install.packages("odbc")
##
## The downloaded binary packages are in
## /var/folders/rj/t11km2gs693dyq4szgcrm4vr0000gn/T//Rtmp9bEnUj/downloaded_packages
install.packages("tidyverse")
##
## The downloaded binary packages are in
## /var/folders/rj/t11km2gs693dyq4szgcrm4vr0000gn/T//Rtmp9bEnUj/downloaded_packages
install.packages("lubridate")
##
## The downloaded binary packages are in
## /var/folders/rj/t11km2gs693dyq4szgcrm4vr0000gn/T//Rtmp9bEnUj/downloaded_packages
```

```
install.packages("GGally")
##
## The downloaded binary packages are in
## /var/folders/rj/t11km2gs693dyq4szgcrm4vr0000gn/T//Rtmp9bEnUj/downloaded_packages
install.packages("forecast")
##
## The downloaded binary packages are in
## /var/folders/rj/t11km2gs693dyq4szgcrm4vr0000gn/T//Rtmp9bEnUj/downloaded_packages
library(readxl)
library(DBI)
library(odbc)
library(tidyverse)
## -- Attaching packages ------ tidyver:
## v ggplot2 3.3.0
                    v purrr 0.3.4
## v tibble 3.0.1 v dplyr 0.8.5
## v tidyr 1.1.0 v stringr 1.4.0
## v readr 1.3.1 v forcats 0.5.0
## -- Conflicts -----
                                                                      ----- tidyverse_con:
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
library(lubridate)
##
## Attaching package: 'lubridate'
## The following objects are masked from 'package:dplyr':
##
      intersect, setdiff, union
## The following objects are masked from 'package:base':
##
      date, intersect, setdiff, union
library (GGally)
## Registered S3 method overwritten by 'GGally':
## method from
##
   +.gg ggplot2
## Attaching package: 'GGally'
```

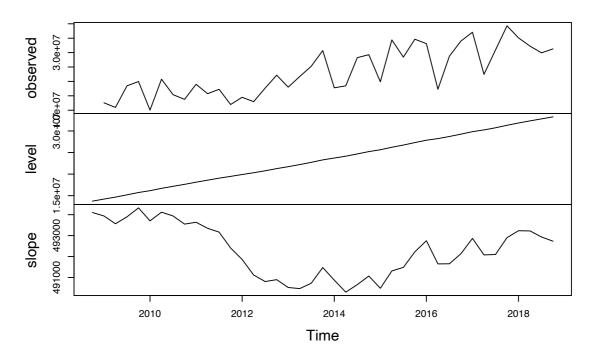
```
## The following object is masked from 'package:dplyr':
##
##
       nasa
library(forecast)
## Registered S3 method overwritten by 'quantmod':
   method
                      from
    as.zoo.data.frame zoo
#Predictive Statistics for Neighborhood Madison (149) to forecast sales for next 8 quarters
#create dataframe with required data and filter N/A or missing values
NYCdf <- NYC_HISTORICAL %>%
 left_join(NEIGHBORHOOD, by= "NEIGHBORHOOD_ID") %>%
  left_join(BUILDING_CLASS, by= c("BUILDING_CLASS_FINAL_ROLL"="BUILDING_CODE_ID")) %>%
  select (NEIGHBORHOOD_ID, NEIGHBORHOOD_NAME, SALE_DATE, SALE_PRICE, GROSS_SQUARE_FEET, RESIDENTIAL_UNI'
  filter(SALE_PRICE >0, TYPE == "RESIDENTIAL", GROSS_SQUARE_FEET > 0 ) %>%
  mutate(Year = year(SALE_DATE), Quarter = quarter(SALE_DATE)) %>%
  select(TYPE, SALE_PRICE, Quarter, Year, NEIGHBORHOOD_ID)
view(NYCdf)
#Time series analysis on the total dollar amount of residential real estate sales in Madison using sale.
forecast <- NYCdf %>%
  filter(NEIGHBORHOOD_ID == 149, SALE_PRICE > 0, Year > 2008) %>%
  mutate(t = as.numeric(Year)*4 + Quarter - 2009*4) %>%
  group_by(t) %>%
  summarise (TotalSales = sum(SALE_PRICE))
Timeseries_Madison <- ts(forecast$TotalSales, start = c(2009,1), frequency = 4)
ets_madison <- ets(Timeseries_Madison, model = "MAN")</pre>
Forecast_Madison <- forecast (ets_madison, 8)</pre>
decomposets <- decompose(Timeseries_Madison, type = "multiplicative")</pre>
plot(decomposets)
```

Decomposition of multiplicative time series



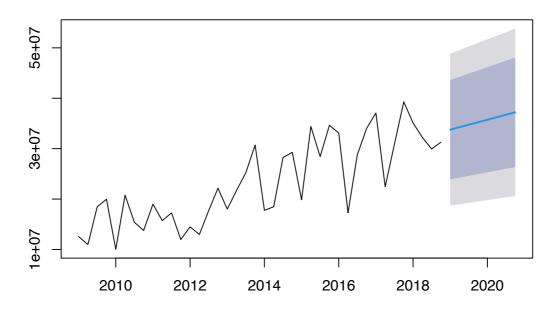
plot(ets_madison)

Decomposition by ETS(M,A,N) method



plot(Forecast_Madison)

Forecasts from ETS(M,A,N)



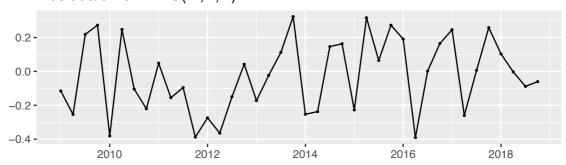
summary(Forecast_Madison)

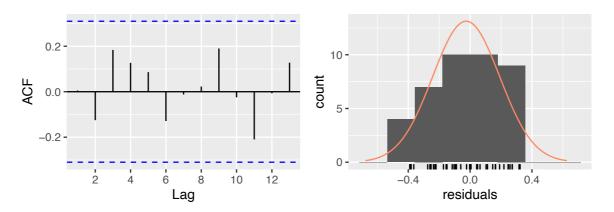
```
##
## Forecast method: ETS(M,A,N)
## Model Information:
## ETS(M,A,N)
##
## Call:
   ets(y = Timeseries_Madison, model = "MAN")
##
##
    Smoothing parameters:
##
      alpha = 0.011
##
      beta = 1e-04
##
##
    Initial states:
##
      1 = 13732187.4752
##
      b = 494103.341
##
##
     sigma: 0.2275
##
##
##
        AIC
                AICc
## 1390.764 1392.529 1399.208
## Error measures:
```

```
MPE
##
                      ME
                            RMSE
                                     MAE
                                                        MAPE
                                                                 MASE
                                                                             ACF1
## Training set -342565.5 5000256 4227643 -8.138045 21.20466 0.8195974 0.01219138
##
## Forecasts:
                            Lo 80
                                     Hi 80
                                              Lo 95
##
        Point Forecast
## 2019 Q1
                33765836 23921020 43610652 18709489 48822183
## 2019 Q2
                34258569 24269463 44247675 18981550 49535588
## 2019 Q3
                34751302 24617895 44884709 19253593 50249011
## 2019 Q4
                35244035 24966315 45521755 19525619 50962451
## 2020 Q1
                35736768 25314723 46158813 19797626 51675910
## 2020 Q2
                36229501 25663119 46795883 20069614 52389388
## 2020 Q3
                36722234 26011502 47432965 20341584 53102884
## 2020 Q4
                37214967 26359874 48070060 20613534 53816400
```

checkresiduals(Forecast_Madison)

Residuals from ETS(M,A,N)





```
##
## Ljung-Box test
##
## data: Residuals from ETS(M,A,N)
## Q* = 4.1936, df = 4, p-value = 0.3804
##
## Model df: 4. Total lags used: 8
```

```
#Use a multiple regression model to come up with another forecast for the next 8 quarters of sales. Inc
forecast <- cbind(forecast, c("Q1", "Q2", "Q3", "Q4"))</pre>
names(forecast)[3] <- "Quarter"</pre>
#regression including time
regression_time <- lm ( data=forecast, formula = TotalSales~t)</pre>
summary(regression_time)
##
## Call:
## lm(formula = TotalSales ~ t, data = forecast)
## Residuals:
##
                  Min
                                           1Q
                                                         Median
                                                                                        30
## -11459830 -3445107
                                                       -345006
                                                                          4020272
                                                                                                    7964821
##
## Coefficients:
##
                                Estimate Std. Error t value Pr(>|t|)
68332 8.390 3.54e-10 ***
## t.
                                   573281
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 4989000 on 38 degrees of freedom
## Multiple R-squared: 0.6494, Adjusted R-squared: 0.6402
## F-statistic: 70.39 on 1 and 38 DF, p-value: 3.537e-10
x \leftarrow \text{data.frame}(t=c(41,42,43,44,45,46,47,48), \text{ TotalSales} = c(0,0,0,0,0,0,0,0), \text{ Quarter} = c("Q1", "Q2", "Q1", "Q2", "Q2", "Q1", "Q2", "Q2", "Q3", "Q4", "Q4",
predict.lm(regression_time, x, interval = "confidence")
##
                      fit.
                                          lwr
## 1 35039921 31785454 38294389
## 2 35613202 32237517 38988888
## 3 36186483 32688309 39684657
## 4 36759764 33137961 40381567
## 5 37333045 33586585 41079506
## 6 37906326 34034279 41778373
## 7 38479607 34481133 42478082
## 8 39052888 34927222 43178554
#regression using time and seasonality
regression_timeseason <- lm(data = forecast, TotalSales~t+Quarter)</pre>
summary(regression_timeseason)
##
## Call:
## lm(formula = TotalSales ~ t + Quarter, data = forecast)
##
## Residuals:
##
             Min
                                        1Q Median
                                                                                3Q
## -9124795 -3815801 510591 3139841 10338911
```

```
##
## Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
##
561321
## t.
                                                     66565 8.433 6.01e-10 ***
## QuarterQ2 -1566033 2164134 -0.724 0.474
                           1211001 2167203 0.559
## QuarterQ3
                                                                                           0.580
                              3324139 2172309 1.530
## QuarterQ4
                                                                                          0.135
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
##
## Residual standard error: 4837000 on 35 degrees of freedom
## Multiple R-squared: 0.6964, Adjusted R-squared: 0.6617
## F-statistic: 20.07 on 4 and 35 DF, p-value: 1.147e-08
y \leftarrow \text{data.frame}(t=c(41,42,43,44,45,46,47,48), \text{TotalSales} = c(0,0,0,0,0,0,0), \text{Quarter} = c("Q1", "Q2", "Q2", "Q1", "Q2", "Q2", "Q1", "Q2", "Q2", "Q1", "Q2", "Q2
predict.lm(regression_timeseason, y, interval = "confidence")
                    fit
                                     lwr
## 1 34052463 29753575 38351351
## 2 33047750 28748863 37346638
## 3 36386105 32087218 40684993
## 4 39060565 34761677 43359453
## 5 36297746 31608758 40986734
## 6 35293034 30604046 39982022
## 7 38631389 33942401 43320377
## 8 41305848 36616860 45994836
# Use a multiple regression model to determine the sale of a given residential property in your neigh
#a.Sale Date
#b. Year built
#c.Building type (categorical)
#d. Gross Square Feet
#e.Number of Units
NYC.df1 <- NYC HISTORICAL %>%
   left_join(NEIGHBORHOOD, by= "NEIGHBORHOOD_ID") %>%
   left_join(BUILDING_CLASS, by= c("BUILDING_CLASS_FINAL_ROLL"="BUILDING_CODE_ID")) %>%
   select (NEIGHBORHOOD_ID, NEIGHBORHOOD_NAME, SALE_DATE, DESCRIPTION, YEAR_BUILT, ADDRESS, SALE_PRICE,GI
   filter(SALE_PRICE >0, TYPE == "RESIDENTIAL", GROSS_SQUARE_FEET > 0 ) %>%
   mutate (Year = year(SALE_DATE),Quarter = quarter(SALE_DATE))%>%
    select (BUILDING_CLASS_FINAL_ROLL, NEIGHBORHOOD_ID, TYPE,SALE_DATE, DESCRIPTION, ADDRESS, Year, YEAR_I
view(NYC.df1)
Madison_Regression <- NYC.df1 %>%
    filter (Year>2008, NEIGHBORHOOD_ID == 149) %>%
    select (SALE_DATE, YEAR_BUILT, SALE_PRICE, GROSS_SQUARE_FEET, BUILDING_CLASS_FINAL_ROLL, RESIDENTIAL_UNI'
{\tt Madison\_Model} \ {\tt <-lm(SALE\_PRICE\_{\tt <-lm}, \ data = Madison\_Regression)}
summary (Madison Model)
```

##

```
## Call:
## lm(formula = SALE_PRICE ~ ., data = Madison_Regression)
## Residuals:
##
      Min
                 1Q Median
                                   30
                                           Max
## -1308950 -106884 10921 117966 1929248
##
## Coefficients:
##
                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                              -5.624e+05 2.393e+05 -2.350 0.018938 *
## SALE DATE
                              1.458e-03 8.808e-05 16.552 < 2e-16 ***
## YEAR BUILT
                              -4.536e+02 1.024e+02 -4.429 1.03e-05 ***
## GROSS SQUARE FEET
                              2.284e+02 1.486e+01 15.374 < 2e-16 ***
## BUILDING_CLASS_FINAL_ROLLA2 -2.438e+04 8.905e+04 -0.274 0.784330
## BUILDING_CLASS_FINAL_ROLLA3 1.032e+06 1.671e+05 6.173 9.03e-10 ***
## BUILDING_CLASS_FINAL_ROLLA5 -2.133e+05 2.447e+04 -8.717 < 2e-16 ***
## BUILDING_CLASS_FINAL_ROLLA9 -1.258e+05 2.962e+04 -4.247 2.33e-05 ***
## BUILDING_CLASS_FINAL_ROLLB1 -1.377e+04 3.131e+04 -0.440 0.660029
## BUILDING_CLASS_FINAL_ROLLB2 1.298e+05 3.452e+04 3.761 0.000177 ***
                                                    3.499 0.000483 ***
## BUILDING_CLASS_FINAL_ROLLB3 1.191e+05 3.403e+04
## BUILDING_CLASS_FINAL_ROLLB9 -1.916e+04 7.760e+04 -0.247 0.804998
## BUILDING_CLASS_FINAL_ROLLCO 1.967e+05 5.325e+04
                                                     3.694 0.000230 ***
                                                    1.379 0.168244
## BUILDING_CLASS_FINAL_ROLLC2 4.052e+05 2.939e+05
## BUILDING_CLASS_FINAL_ROLLC3 4.155e+05 9.851e+04
                                                     4.218 2.64e-05 ***
## BUILDING_CLASS_FINAL_ROLLD1 1.815e+06 3.529e+05
                                                     5.143 3.14e-07 ***
## BUILDING_CLASS_FINAL_ROLLD3 -1.692e+06 2.793e+05 -6.058 1.82e-09 ***
## RESIDENTIAL_UNITS
                              -2.148e+05 2.311e+04 -9.293 < 2e-16 ***
## --
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
## Residual standard error: 278200 on 1255 degrees of freedom
## Multiple R-squared: 0.4827, Adjusted R-squared: 0.4757
## F-statistic: 68.87 on 17 and 1255 DF, p-value: < 2.2e-16
#Properties that are the biggest bargains and most expensive
Madison_Address <- NYC.df1 %>%
  filter (Year>2008, NEIGHBORHOOD_ID == 149) %>%
  select (ADDRESS, DESCRIPTION)
Madison_Regression["Residuals"] <- Madison_Model$residuals</pre>
Madison_Regression["Address"] <- Madison_Address$ADDRESS</pre>
Madison_Regression["Description"] <- Madison_Address$DESCRIPTION</pre>
```