Data Exploration

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Introduction

In this part of this study, for initial modeling and analysis, I will be looking at the total number of thefts from January 2001 - March 11, 2023 that were reported. Note that due to the large size of the original dataset (nearly 8 million rows), the raw data is not included in this repository. The raw data can be accessed here.

Data Overview

For this partition of the data, there are two variables: year/month and the number of thefts reported in each month. The full dataset has more variables, which are described below. Each row in the full dataset represents an individual crime that was reported.

Variables

ID	Unique identifier for the record.
Case number	Chicago id for the case number
Date	Date when the incident occurred, this is sometimes a best estimate.
Block	The partially redacted address where the incident occurred.
IUCR	The Illinois Unifrom Crime Reporting Code.
Primary Type	The primary description of the IUCR code.
Description	The secondary description of the IUCR code.
Location description	The primary description of the location where the incident occurred.
Arrest	Whether or not the incident resulted in an arrest.
Domestic	Whether or not the incident was a domestic incident.
Beat	Indicates the beat where the incident occurred.
District	The police district where the incident occurred.
Ward	The city council district where the incident occurred.
Community Area	The community area where the incident occurred.
FBI Code	FBI Code crime classification.
X Coordinate	The X coordinate location where the incident occurred.
Y coordinate	The Y coordinate where the incident occurred.
Year	Year the incident occurred.
Updated on	Date and time the record was last updated.
Latitude	The latitude where the incident occurred.
Longitude	The longitude where the incident occurred.
Location	The location of the incident.

```
chicago_crime <- read.csv("data/thefts_by_month.csv")
chicago_crime <- chicago_crime %>%
  select(-X) %>%
  rename(NumThefts = sum.Count.) %>%
  drop_na(month)
head(chicago_crime)
```

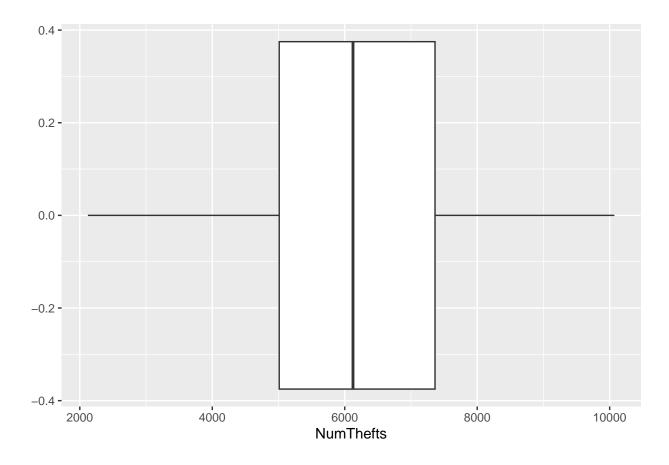
```
## year month NumThefts
## 1 2022 10
                    5224
## 2 2015
           2
                    3228
          10
## 3 2019
                    5390
## 4 2001 1
                    7867
## 5 2017
                    4493
            3
## 6 2008
             8
                    8501
chicago_crime_monthly <- chicago_crime %>%
mutate(month = month.name[month]) %>%
 mutate(Month = str_c(year, month, sep = " ")) %>%
 select(Month, NumThefts) %>%
 mutate(Month = yearmonth(Month)) %>%
 filter(year(Month) < 2023) %>%
 as_tsibble(index = Month)
head(chicago_crime_monthly)
## # A tsibble: 6 x 2 [1M]
       Month NumThefts
##
##
       <mth>
                <int>
## 1 2001 Jan
                  7867
## 2 2001 Feb
                  6669
## 3 2001 Mar
                 7765
## 4 2001 Apr
                7686
## 5 2001 May
                  8420
## 6 2001 Jun
                  8612
```

Data Analysis

Number of Thefts Over Time

Boxplot

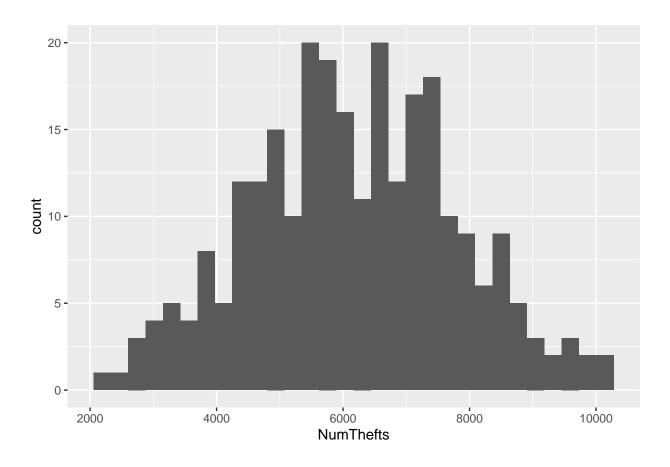
```
ggplot(chicago_crime_monthly, aes(x = NumThefts)) + geom_boxplot()
```



Histogram

```
ggplot(chicago_crime_monthly, aes(x = NumThefts)) + geom_histogram()
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.



Distribution Table

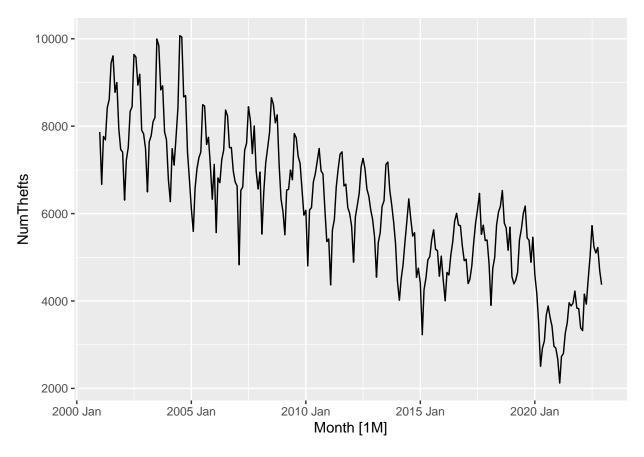
summary(chicago_crime_monthly\$NumThefts)

Min. 1st Qu. Median Mean 3rd Qu. Max. ## 2122 5011 6124 6161 7363 10071

Number of Thefts Reported in Chicago By Month

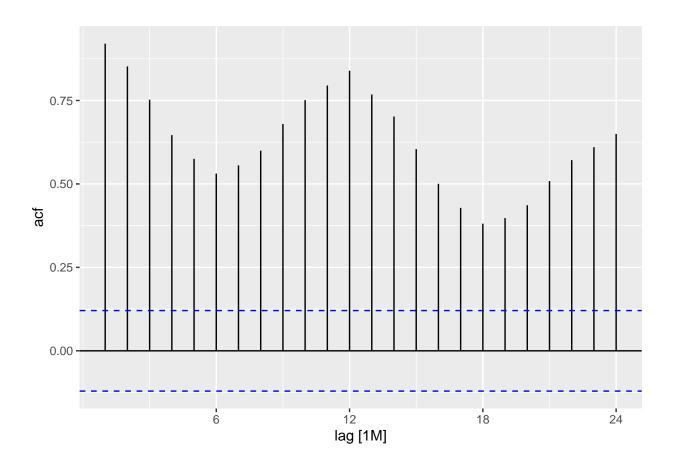
Due to the long time frame of the dataset, it's hard to see exactly where the seasonal pattern is occurring, but there does appear to be a seasonal pattern. There appears to be a general decreasing trend. Initially, I had included the raw data from 2023 as well, but there is a steep drop in March 2023 due to the smaller number of days there, so that is not included here.

chicago_crime_monthly %>%
 autoplot(NumThefts)



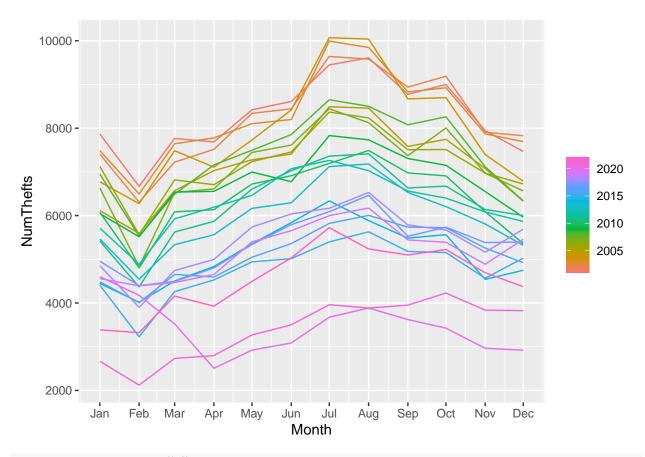
There is really strong positive autocorrelation throughout the monthly data, however it appears to follow a pattern of peaking, sharp decrease, then peaking.

```
chicago_crime_monthly %>%
  ACF(NumThefts) %>%
  autoplot()
```

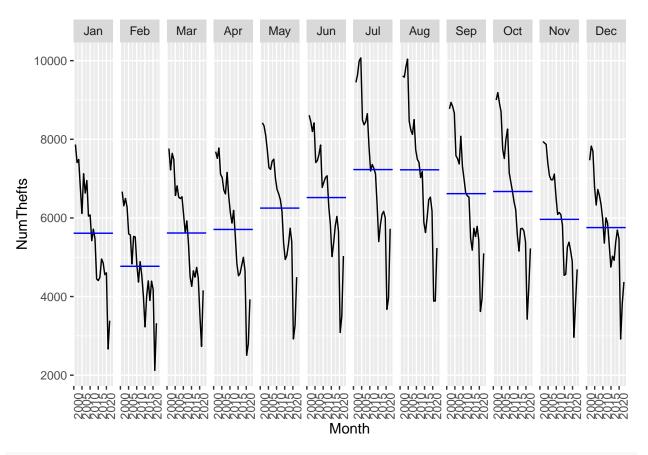


Number of Thefts By Year

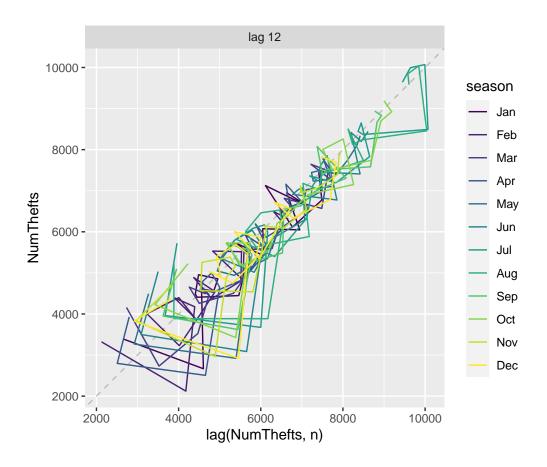
chicago_crime_monthly %>%
 gg_season(NumThefts)



chicago_crime_monthly %>%
 gg_subseries(NumThefts)



chicago_crime_monthly %>%
 gg_lag(NumThefts, lags = 12)



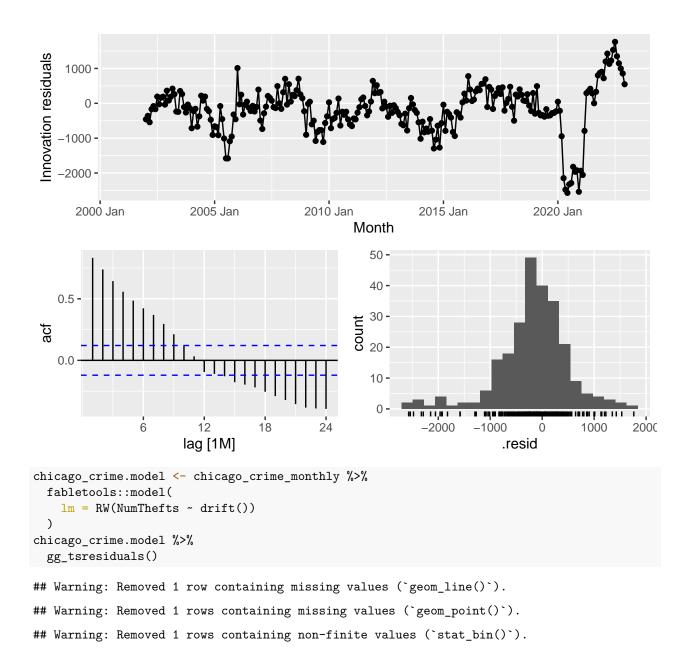
Models

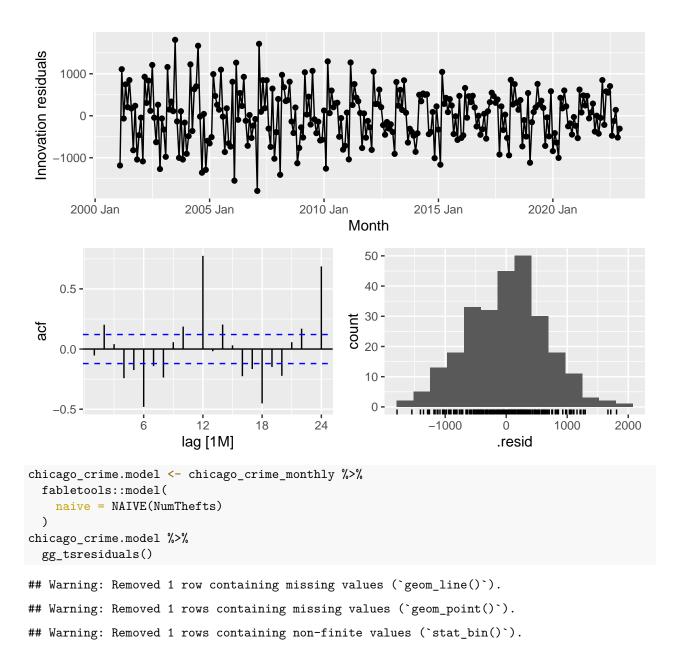
```
chicago_crime.model <- chicago_crime_monthly %>%
  fabletools::model(
    snaive = SNAIVE(NumThefts)
)
chicago_crime.model %>%
  gg_tsresiduals()

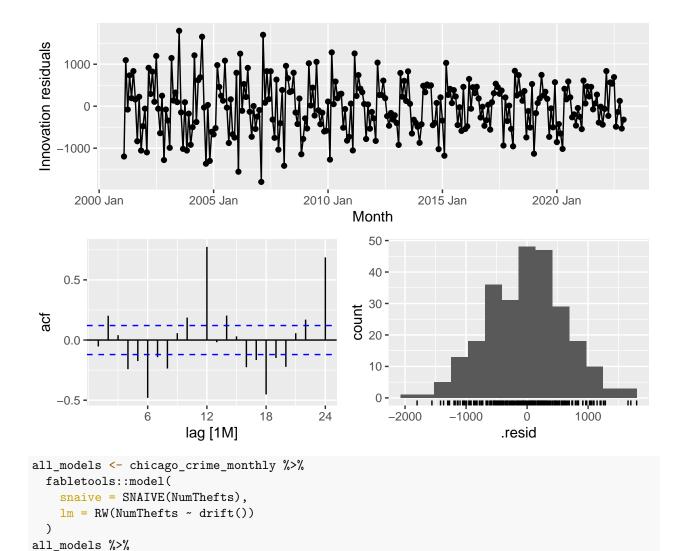
## Warning: Removed 12 rows containing missing values (`geom_line()`).

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

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

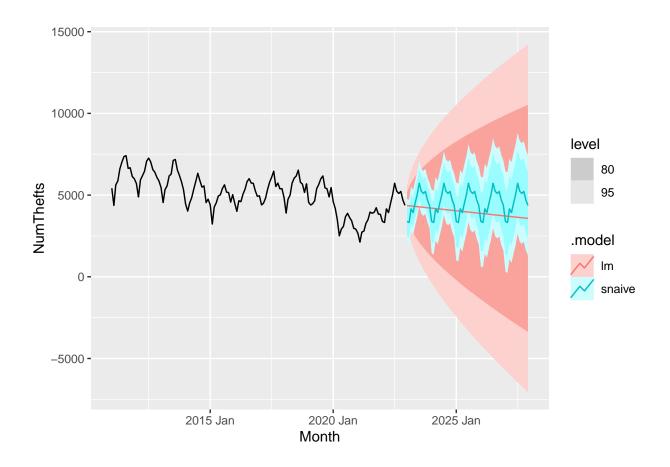






forecast(h = "5 years") %>%

autoplot(filter(chicago_crime_monthly, year(Month) > 2010))

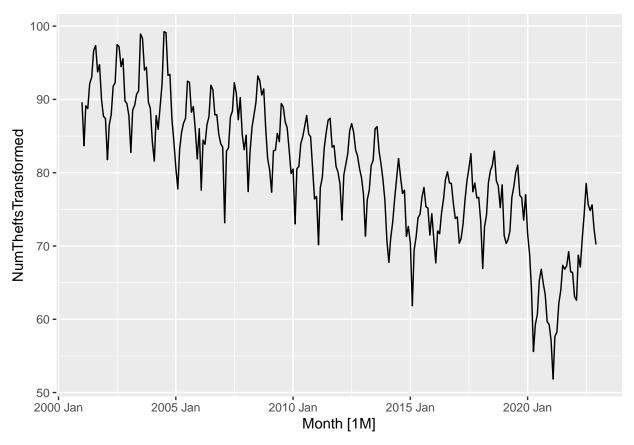


Transforming the Data

```
lambda <- chicago_crime_monthly |>
  features(NumThefts, features = guerrero) |>
  pull(lambda_guerrero)
lambda

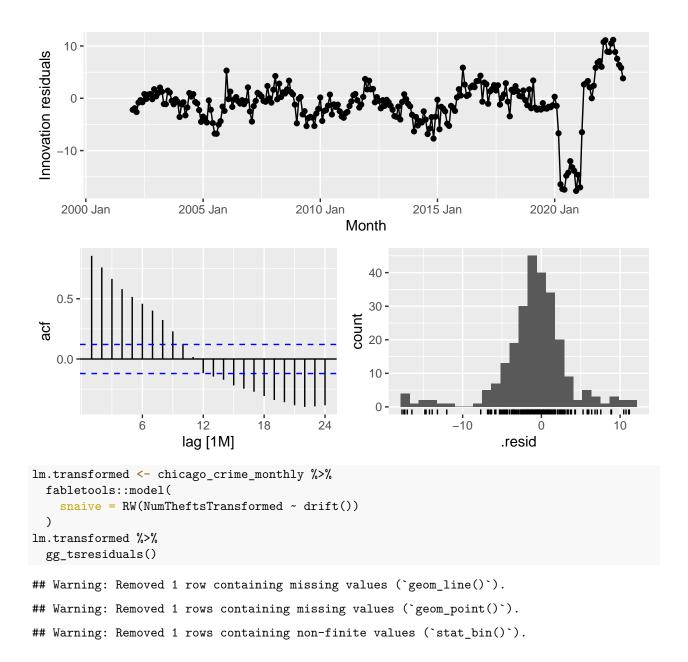
## [1] 0.4028242

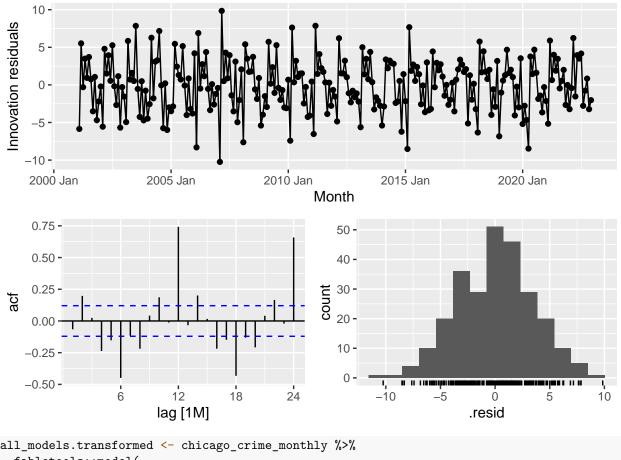
chicago_crime_monthly <- chicago_crime_monthly %>%
  mutate(NumTheftsTransformed = box_cox(NumThefts, lambda))
chicago_crime_monthly %>%
  autoplot(NumTheftsTransformed)
```



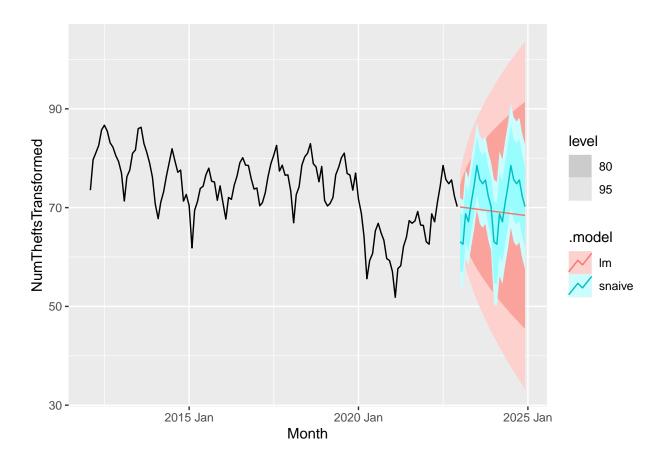
```
snaive.transformed <- chicago_crime_monthly %>%
  fabletools::model(
    snaive = SNAIVE(NumTheftsTransformed)
)
snaive.transformed %>%
  gg_tsresiduals()
```

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





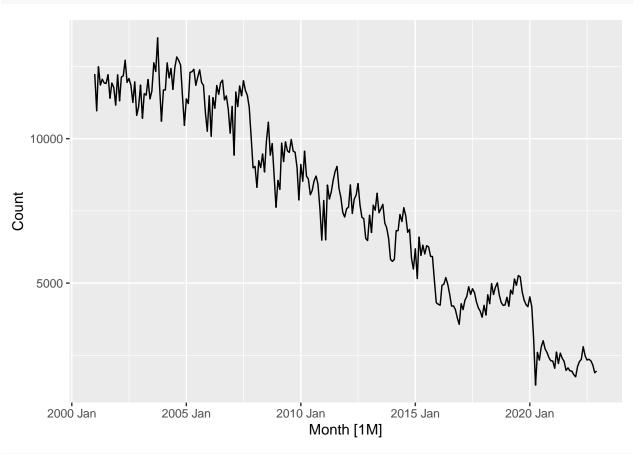
```
all_models.transformed <- chicago_crime_monthly %>%
  fabletools::model(
    snaive = SNAIVE(NumTheftsTransformed),
    lm = RW(NumTheftsTransformed ~ drift())
)
all_models.transformed %>%
  forecast(h = "2 years") %>%
  autoplot(filter(chicago_crime_monthly, Month > yearmonth("Jan 2012")))
```



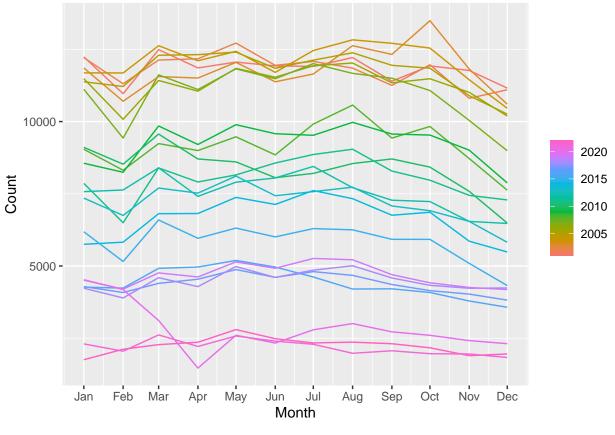
Arrests Over Time

```
arrests = read.csv("data/arrests_by_month.csv")
arrests <- arrests %>%
  select(-X) %>%
  rename(Count = sum.Count.) %>%
  drop_na(month)
head(arrests)
##
     Arrest year month Count
## 1 false 2012
                     1 18749
      true 2019
## 2
                     3 4761
## 3 false 2005
                     2 20774
## 4
      true 2014
                     9 6757
## 5
      true 2015
                     5 6313
## 6 false 2009
                     9 24304
arrests_ts <- arrests %>%
mutate(month = month.name[month]) %>%
 mutate(Month = str_c(year, month, sep = " ")) %>%
  mutate(Month = yearmonth(Month)) %>%
  filter(year(Month) < 2023) %>%
  select(-c(year, month)) %>%
  filter(Arrest == "true") %>%
  as_tsibble(key = Arrest, index = Month)
head(arrests_ts)
```

arrests_ts %>%
 autoplot(Count)



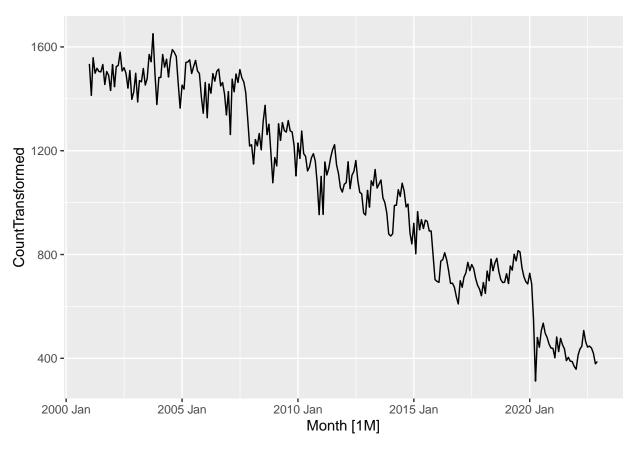
arrests_ts %>%
 gg_season(Count)



```
lambda <- arrests_ts |>
  features(Count, features = guerrero) |>
  pull(lambda_guerrero)
lambda
```

[1] 0.7487626

```
arrests_ts <- arrests_ts %>%
  mutate(CountTransformed = box_cox(Count, lambda))
arrests_ts %>%
  autoplot(CountTransformed)
```

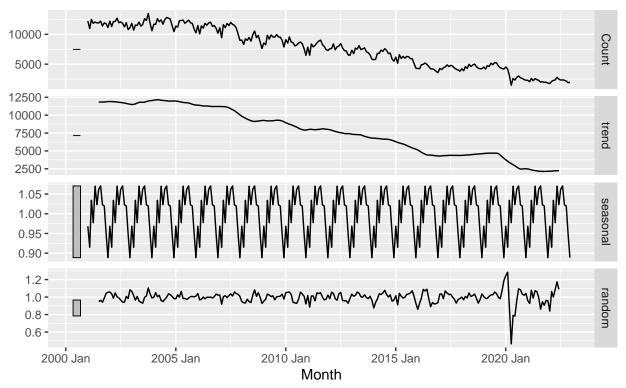


```
arrests_ts %>%
  model(
    classical_decomposition(Count, type = "multiplicative")
) %>%
  components() %>%
  autoplot()
```

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

Classical decomposition

Count = trend * seasonal * random



```
arrests_ts %>%
  model(
    RW(Count ~ drift()),
    SNAIVE(Count)
) %>%
  forecast(h = "5 years") %>%
  autoplot(arrests_ts)
```

