D590_Final_Project_Part_2

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2023-04-02

1 - Analysis of AAPL

1.0 - Analysis Setup

Set up File name

```
file = "Data/AAPL_2023-03-26.csv"
```

Read the .CSV and select Date and Closing Price

```
Stock_information <- read.csv(file)

selected_stock_information <- Stock_information %>%
  select(c('Date','Close')) %>%
  mutate(row_value = row_number(),
         Date = as.Date(Date,origin="2022-01-01"))
```

Collect Stock/ETF Ticker to be displayed on future visualizations to remove confusion

```
file_name = substring(file,6,9)
```

First set

```
selected_stock_information_tsibble <- as_tsibble(selected_stock_information, index = row_value)
```

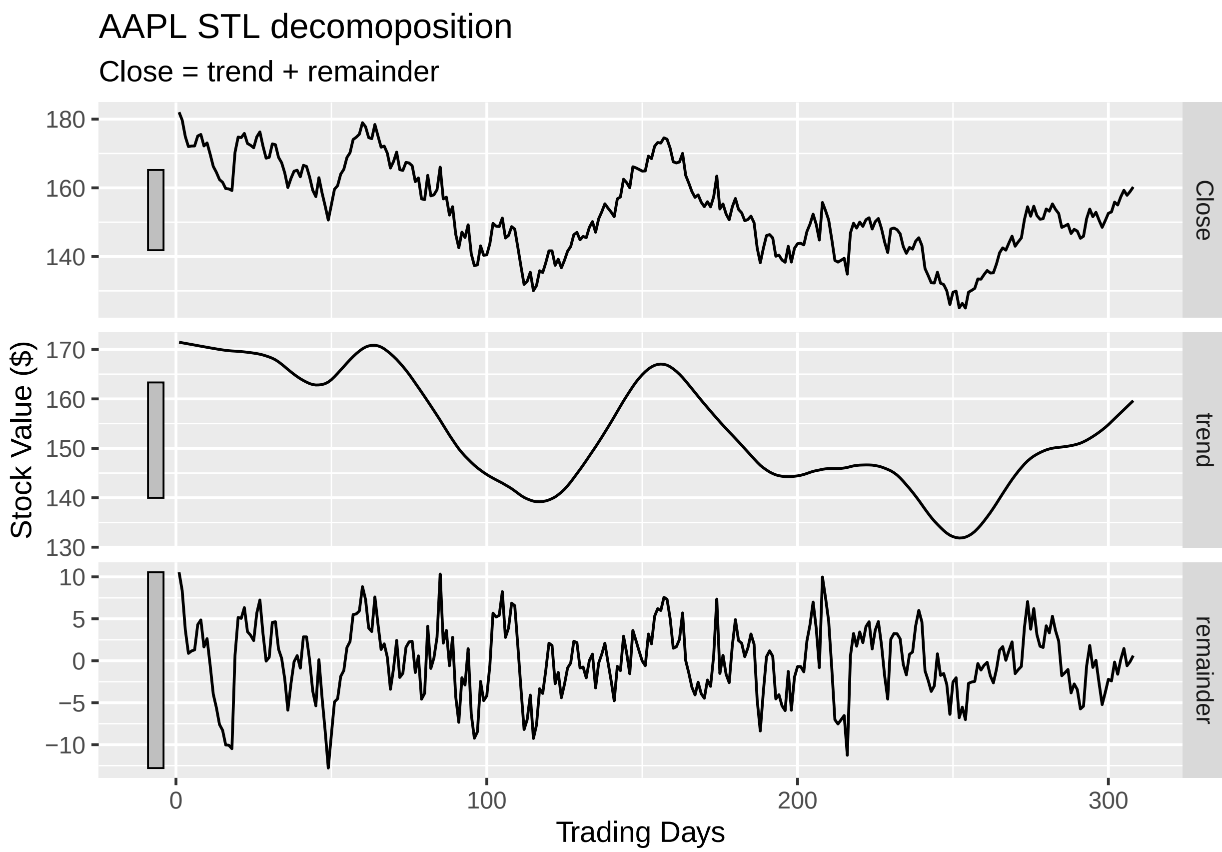
Set up for Monthly; second set. This could be useful in the future.

```
selected_stock_information_monthly <- yearmonth(selected_stock_information$`Date`, format = "%Y-%m-%d")
selected_stock_information$`Date` <- selected_stock_information_monthly
selected_stock_information_montly_tsibble <- as_tsibble(selected_stock_information, index = row_value)
```

```
selected_stock_information_montly_aggregated_tsibble <- selected_stock_information_montly_tsibble %>%
  aggregate(Close ~ Date, sum) %>%
  mutate(row_value = row_number()) %>%
  as_tsibble(index = row_value)
```

1.1 - Decomposition

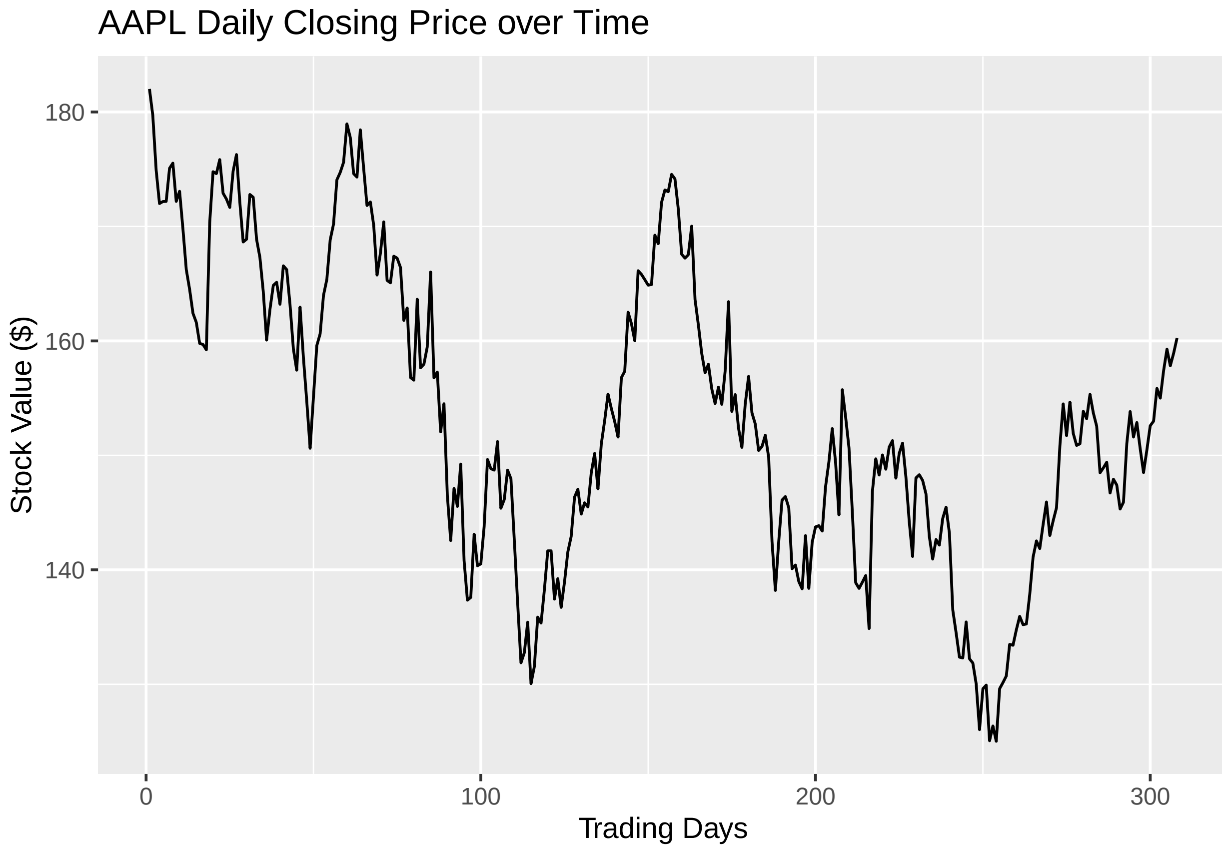
```
dcmp <- selected_stock_information_tsibble |>
  model(stl = STL(Close))

components(dcmp) |> autoplot() +
  labs(title = paste(file_name, "STL decomoposition"),
       y = "Stock Value ($)",
       x = "Trading Days")
```



1.2 - Time Series Visualization

```
autoplot(selected_stock_information_tsibble) +
  labs(y = "Stock Value ($)",
       title = paste(file_name,"Daily Closing Price over Time"),
       x = "Trading Days")
```

```
## Plot variable not specified, automatically selected `.vars = Close`
```

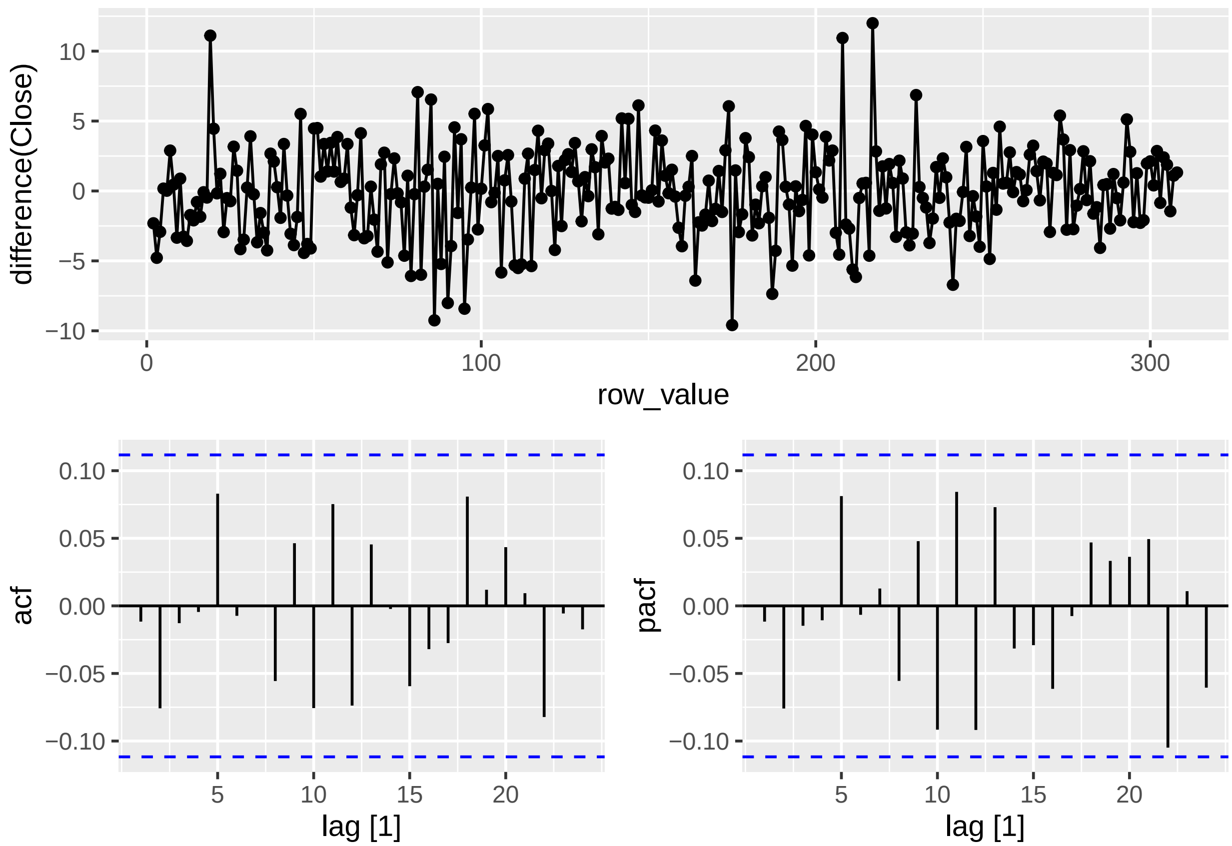


create residual, ACF, PACF plots

```
selected_stock_information_tsibble |>
  gg_tsdisplay(difference(Close), plot_type='partial')
```

```
## Warning: Removed 1 row containing missing values (`geom_line()`).
```

```
## Warning: Removed 1 rows containing missing values (`geom_point()`).
```



Residuals, ACF, and PACF suggest the series is similar to white noise.

1.3 - Description of the Time Series:

INPUT SOMETHING

1.4 - TS Models (transformations)

Checking if the data is stationary. If kpss_stat > kpss_pvalue, then we reject null hypothesis and claim the data is non-stationary. Differencing will be required.

```
selected_stock_information_tsibble |>
  features(Close, unitroot_kpss)
```

```
## # A tibble: 1 x 2
##   kpss_stat kpss_pvalue
##       <dbl>       <dbl>
## 1      2.13        0.01
```

Output is the number of differences make the data stationary

```
selected_stock_information_tsibble |>
  features(Close, unitroot_ndiffs)
```

```
## # A tibble: 1 x 1
##   ndiffs
##    <int>
## 1      1
```

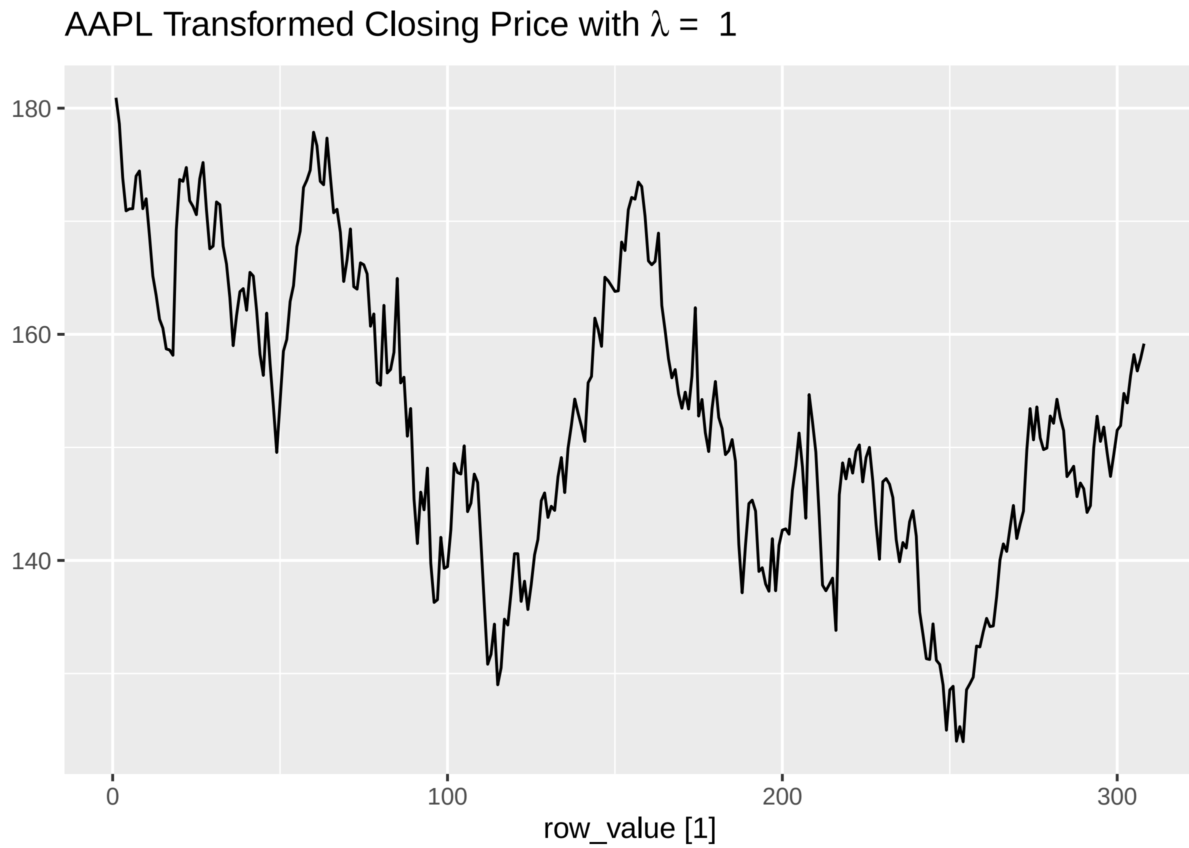
The difference

```
selected_stock_information_tsibble |>
  mutate(diff_close = difference(Close)) |>
  features(diff_close, unitroot_kpss)
```

```
## # A tibble: 1 x 2
##   kpss_stat kpss_pvalue
##       <dbl>       <dbl>
## 1     0.150         0.1
```

Using Box-Cox Transformation does not change the shape of the Closing Price with a lambda value of 1.

```
lambda <- selected_stock_information_tsibble |>
  features(Close, features = guerrero) |>
  pull(lambda_guerrero)
selected_stock_information_tsibble |>
  autoplot(box_cox(Close, lambda)) +
  labs(y = "",
       title = latex2exp::TeX(paste(file_name,
         "Transformed Closing Price with $\\lambda$ = ",
         round(lambda,2))))
```



First modeling approach will be to generate a few ARIMA orders and compare results.

```
selected_stock_fit <- selected_stock_information_tsibble |>
  model(arima010 = ARIMA(Close ~ pdq(0,1,0)),
        arima110 = ARIMA(Close ~ pdq(1,1,0)),
        arima011 = ARIMA(Close ~ pdq(0,1,1)),
        arima111 = ARIMA(Close ~ pdq(1,1,1)),
        search = ARIMA(Close, stepwise=FALSE))

print(selected_stock_fit$search)
```

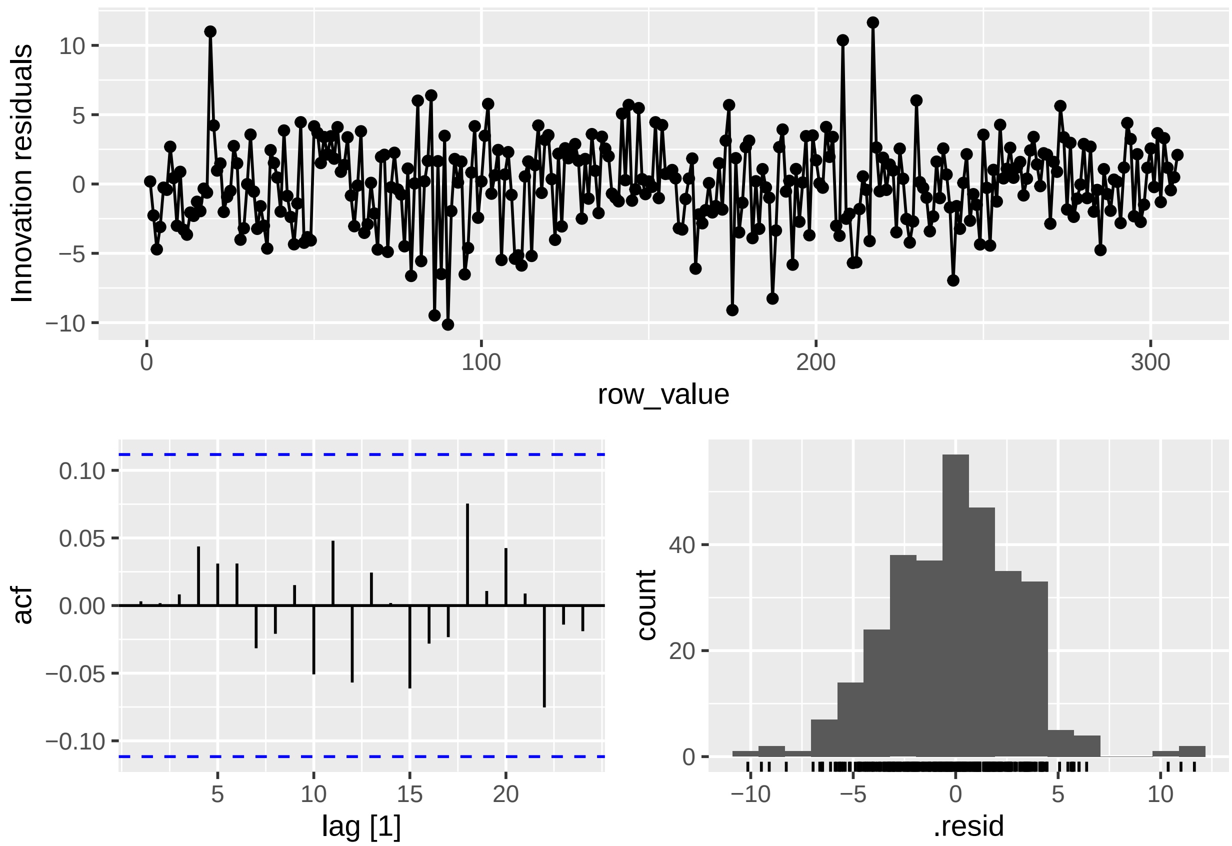
```
## <lst_mdl[1]>
## [1] <ARIMA(4,1,1)>
```

```
glance(selected_stock_fit) |> arrange(AICc) |> select(.model:BIC)
```

```
## # A tibble: 5 x 6
##   .model   sigma2 log_lik   AIC  AICc   BIC
##   <chr>     <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 search     10.2   -790. 1592. 1592. 1614.
## 2 arima010   10.4   -796. 1593. 1593. 1597.
## 3 arima011   10.5   -796. 1595. 1595. 1603.
## 4 arima110   10.5   -796. 1595. 1595. 1603.
## 5 arima111   10.5   -795. 1597. 1597. 1608.
```

Show the residuals using the 'search' ARIMA

```
selected_stock_fit |>
  select(search) |>
  gg_tsresiduals()
```



Portmanteau test shows a large P-value, suggesting the residuals are simliar to white noise

```
augment(selected_stock_fit) |>
  filter(.model=='search') |>
  features(.innov, ljung_box, lag = 10, dof = 3)
```

```
## # A tibble: 1 x 3
##   .model lb_stat lb_pvalue
##   <chr>    <dbl>     <dbl>
## 1 search    2.59     0.920
```

Second approach, creating a Train set and a Test set with stepwise ARIMA and Prophet models

```
length_df = nrow(selected_stock_information_tsibble)
Train_number = round(length_df * 0.98, 0)



Train <- selected_stock_information_tsibble %>%
```

```
  filter(row_value <= Train_number) %>%
  mutate(Date = as.Date(Date,origin="2022-01-01")) %>%
  as_tsibble(index=Date) %>%
  fill_gaps()
Test <- selected_stock_information_tsibble[Train_number:length_df,]
```

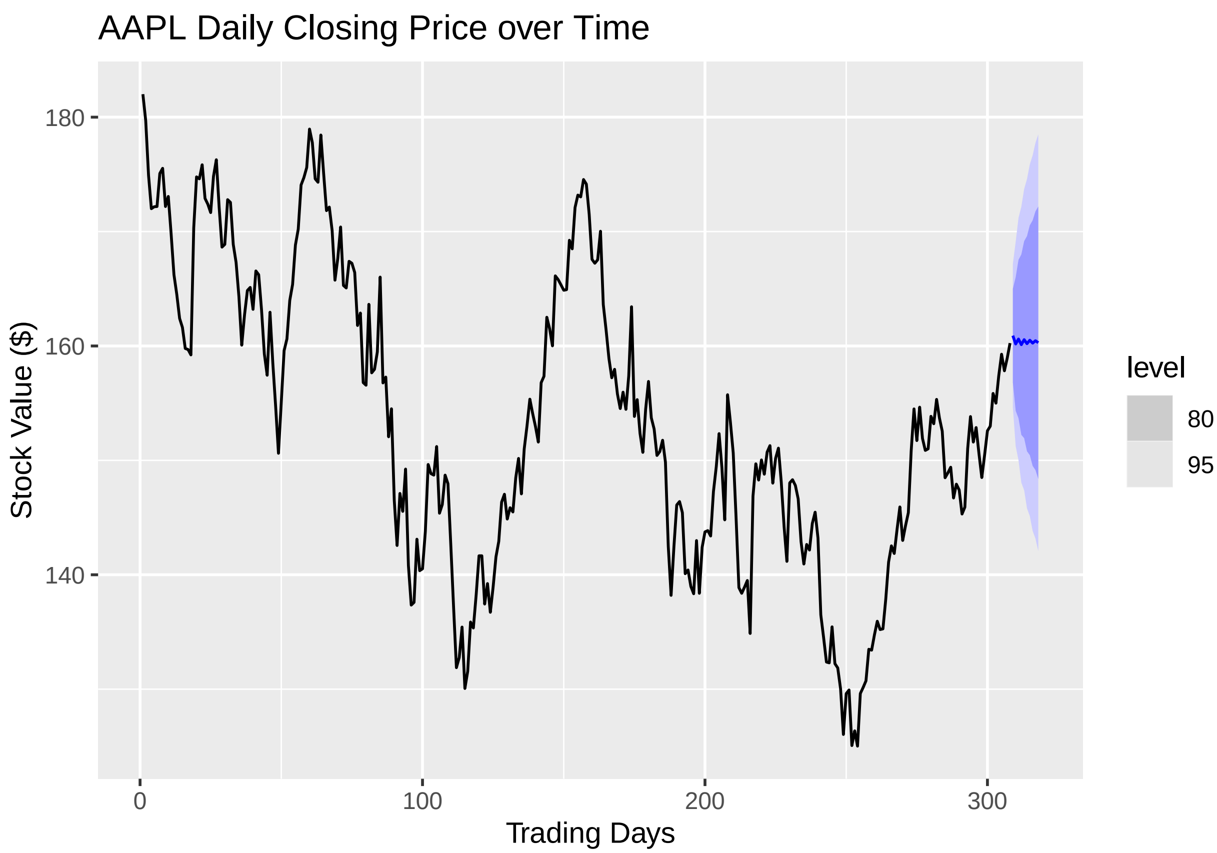
Period is set to twelve for the months, and order = 1 since data is non-seasonal

```
selected_stock_information_tsibble_fit <- Train |>
  model(
    arima = ARIMA(Close),
    prophet = prophet(Close ~ season(period = 12, order = 1,
                                     type = "additive"))
  )
```

1.5 - Predictions

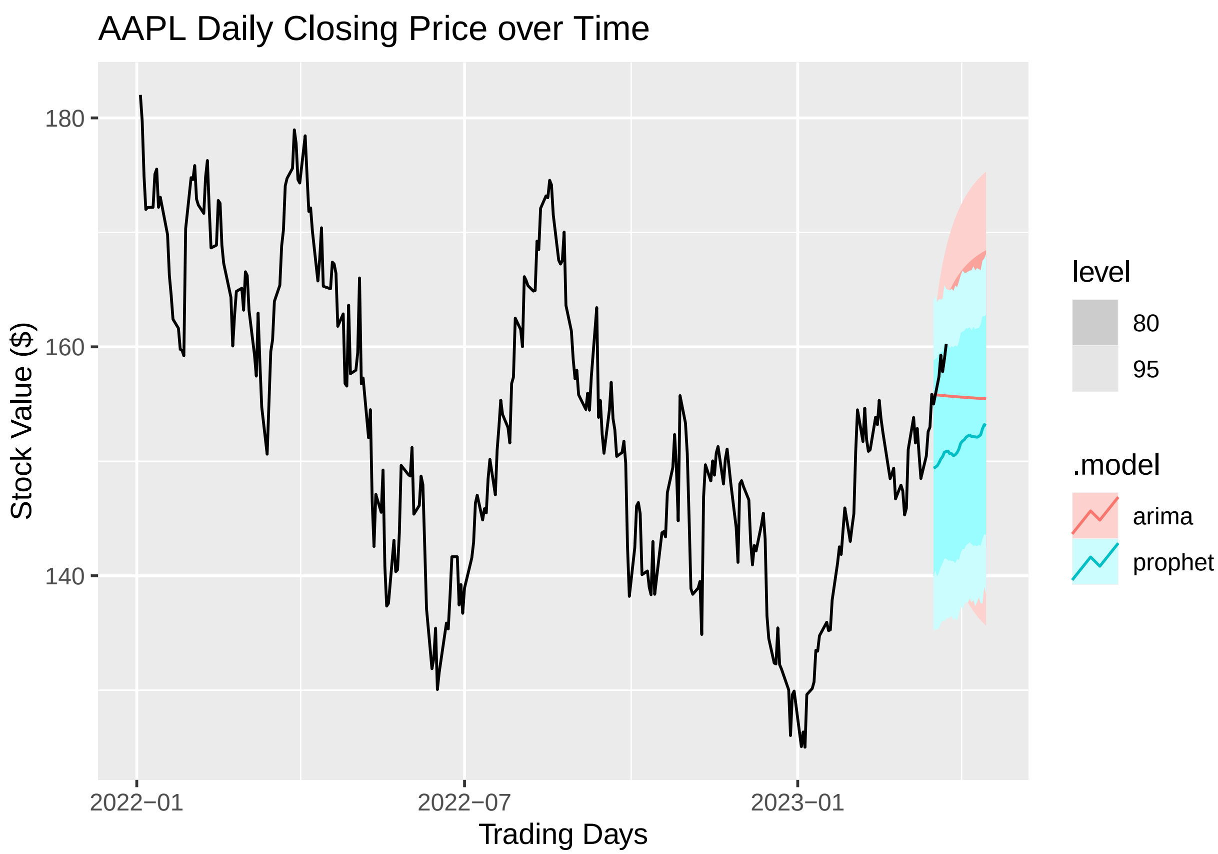
First Prediction - uses selected ARIMA

```
selected_stock_fit |>
  forecast(h=10) |>
  filter(.model=='search') |>
  autoplot(selected_stock_information_tsibble)  +
  labs(y = "Stock Value ($)",
       title = paste(file_name, "Daily Closing Price over Time"),
       x = "Trading Days")
```



Second Prediction set - Prophet + stepwise ARIMA

```
selected_stock_information_tsibble_fit_fc <- selected_stock_information_tsibble_fit |> forecast(h = 30)
selected_stock_information_tsibble_fit_fc |> autoplot(selected_stock_information_tsibble %>% as_tsibble
  labs(y = "Stock Value ($)",
       title = paste(file_name, "Daily Closing Price over Time"),
       x = "Trading Days")
```


AAPL Daily Closing Price over Time
Stock Value ($)
180
160
140
2022−01
2022−07
2023−01
Trading Days
level
80
95
.model
arima
prophet

2 - Analysis of MSFT

2.0 - Analysis Setup

Set up File name

```
file = "Data/MSFT_2023-03-26.csv"
```

Read the .CSV and select Date and Closing Price

```
Stock_information <- read.csv(file)

selected_stock_information <- Stock_information %>%
  select(c('Date','Close')) %>%
  mutate(row_value = row_number(),
         Date = as.Date(Date,origin="2022-01-01"))
```

Collect Stock/ETF Ticker to be displayed on future visualizations to remove confusion

```
file_name = substring(file,6,9)
```

First set

```
selected_stock_information_tsibble <- as_tsibble(selected_stock_information, index = row_value)
```

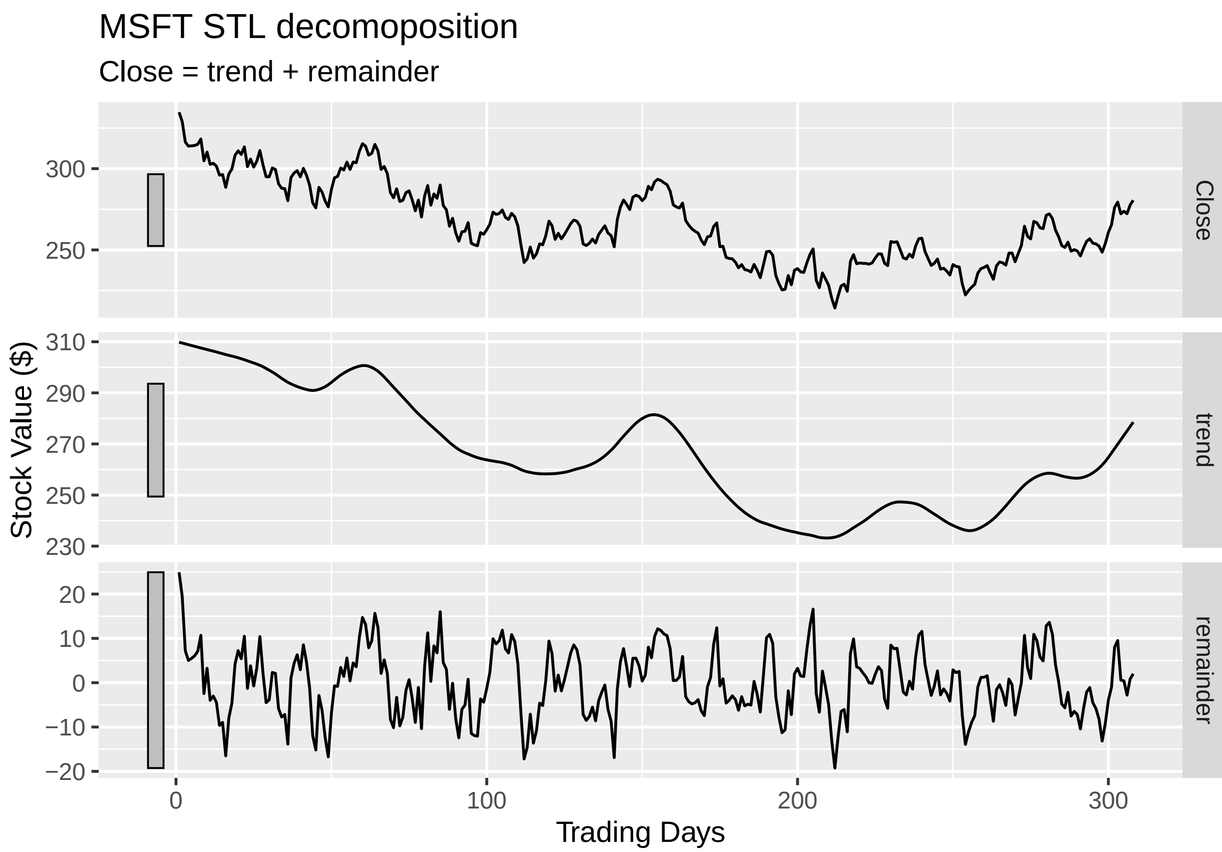
Set up for Monthly; second set. This could be useful in the future.

```
selected_stock_information_monthly <- yearmonth(selected_stock_information$`Date`, format = "%Y-%m-%d")
selected_stock_information$`Date` <- selected_stock_information_monthly
selected_stock_information_montly_tsibble <- as_tsibble(selected_stock_information, index = row_value)
```

```
selected_stock_information_montly_aggregated_tsibble <- selected_stock_information_montly_tsibble %>%
  aggregate(Close ~ Date, sum) %>%
  mutate(row_value = row_number()) %>%
  as_tsibble(index = row_value)
```

2.1 - Decomposition

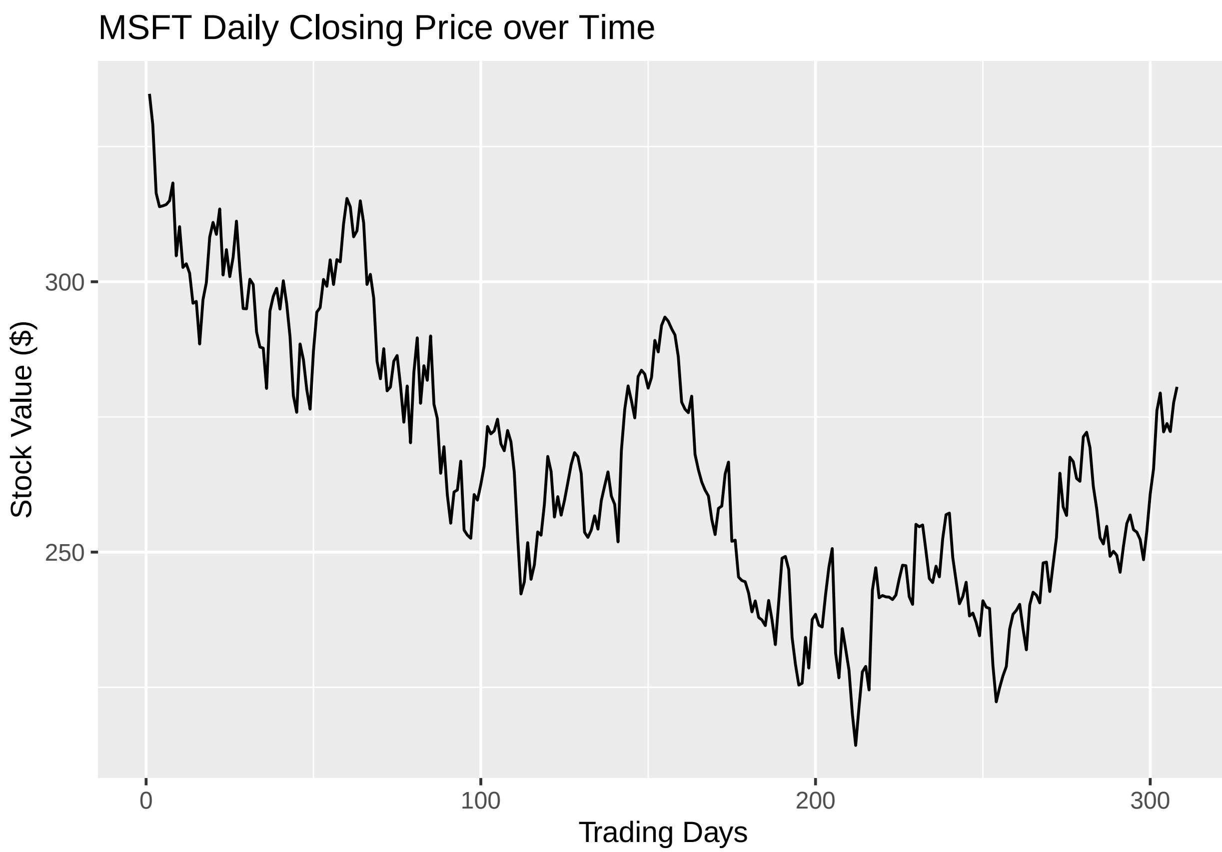
```
dcmp <- selected_stock_information_tsibble |>
  model(stl = STL(Close))

components(dcmp) |> autoplot() +
  labs(title = paste(file_name, "STL decomoposition"),
       y = "Stock Value ($)",
       x = "Trading Days")
```



2.2 - Time Series Visualization

```
autoplot(selected_stock_information_tsibble) +
  labs(y = "Stock Value ($)",
       title = paste(file_name,"Daily Closing Price over Time"),
       x = "Trading Days")
```

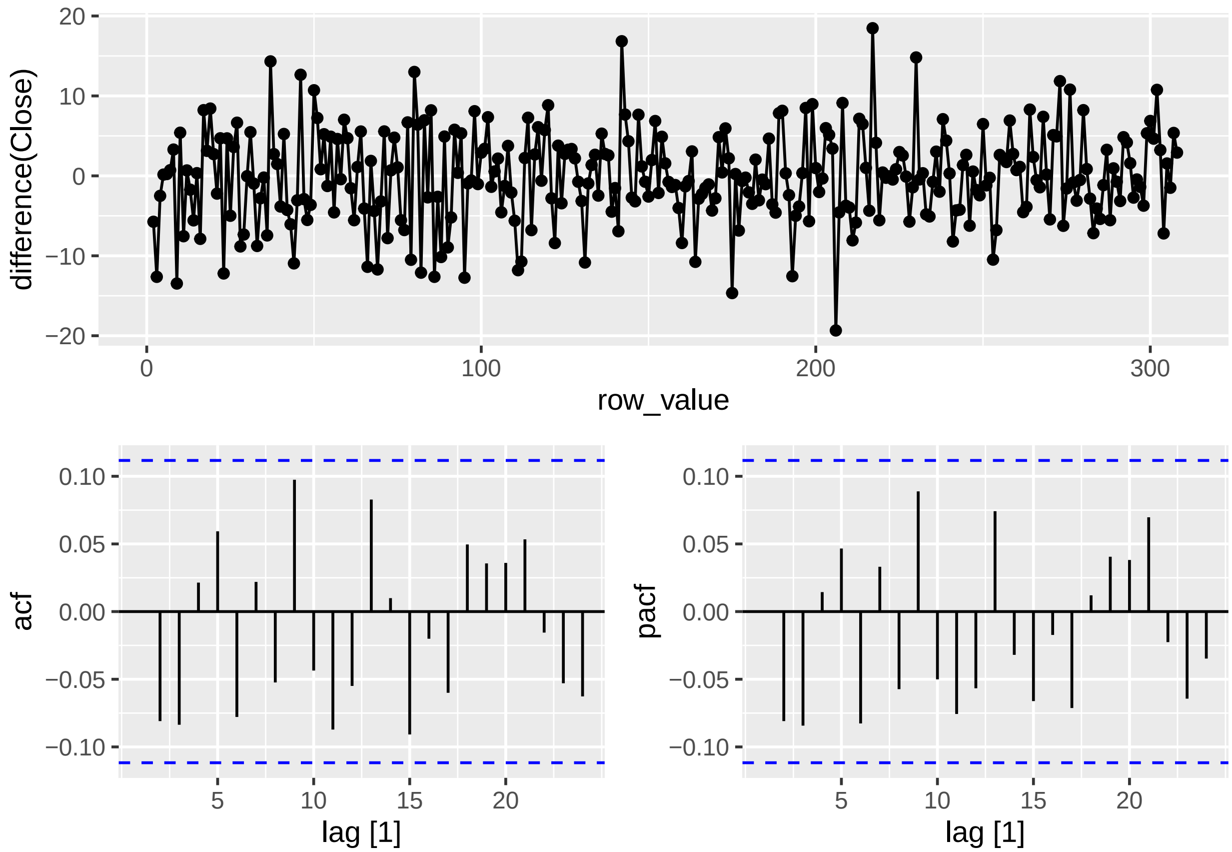
```
## Plot variable not specified, automatically selected `.vars = Close`
```



create residual, ACF, PACF plots

```
selected_stock_information_tsibble |>
  gg_tsdisplay(difference(Close), plot_type='partial')
```

```
## Warning: Removed 1 row containing missing values (`geom_line()`).
## Warning: Removed 1 rows containing missing values (`geom_point()`).
```



Residuals, ACF, and PACF suggest the series is similar to white noise.

2.3 - Description of the Time Series:

INPUT SOMETHING

2.4 - TS Models (transformations)

Checking if the data is stationary. If kpss_stat > kpss_pvalue, then we reject null hypothesis and claim the data is non-stationary. Differencing will be required.

```
selected_stock_information_tsibble |>
  features(Close, unitroot_kpss)
```

```
## # A tibble: 1 x 2
##   kpss_stat kpss_pvalue
##       <dbl>       <dbl>
## 1      3.37        0.01
```

Output is the number of differences make the data stationary

```
selected_stock_information_tsibble |>
  features(Close, unitroot_ndiffs)
```

```
## # A tibble: 1 x 1
##   ndiffs
##    <int>
## 1      1
```

The difference

```
selected_stock_information_tsibble |>
  mutate(diff_close = difference(Close)) |>
  features(diff_close, unitroot_kpss)
```

```
## # A tibble: 1 x 2
##   kpss_stat kpss_pvalue
##       <dbl>       <dbl>
## 1     0.238         0.1
```

Using Box-Cox Transformation does not change the shape of the Closing Price with a lambda value of 1.

```
lambda <- selected_stock_information_tsibble |>
  features(Close, features = guerrero) |>
  pull(lambda_guerrero)
selected_stock_information_tsibble |>
  autoplot(box_cox(Close, lambda)) +
  labs(y = "",
       title = latex2exp::TeX(paste(file_name,
         "Transformed Closing Price with $\\lambda$ = ",
         round(lambda,2))))
```

First modeling approach will be to generate a few ARIMA orders and compare results.

```
selected_stock_fit <- selected_stock_information_tsibble |>
  model(arima010 = ARIMA(Close ~ pdq(0,1,0)),
        arima110 = ARIMA(Close ~ pdq(1,1,0)),
        arima011 = ARIMA(Close ~ pdq(0,1,1)),
        arima111 = ARIMA(Close ~ pdq(1,1,1)),
        search = ARIMA(Close, stepwise=FALSE))

print(selected_stock_fit$search)
```

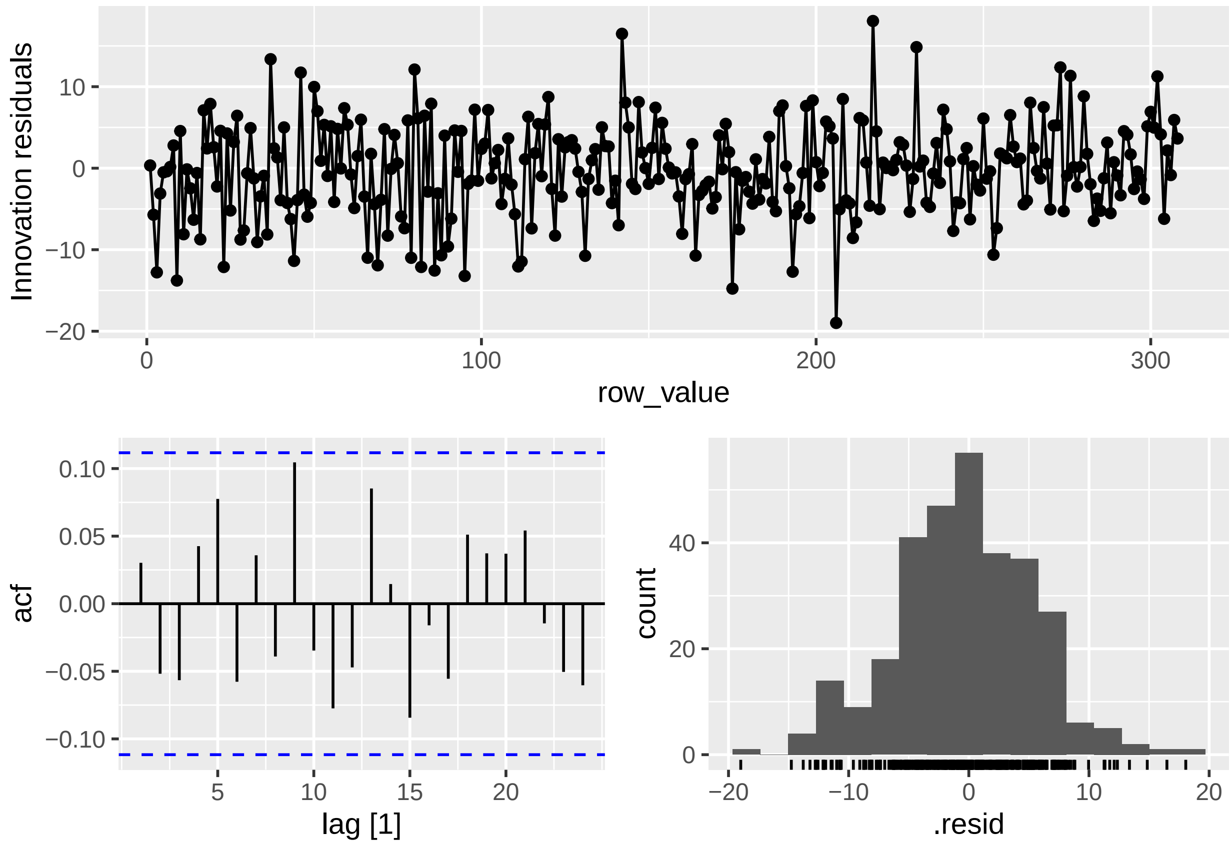
```
## <lst_mdl[1]>
## [1] <ARIMA(1,1,1)>
```

```
glance(selected_stock_fit) |> arrange(AICc) |> select(.model:BIC)
```

```
## # A tibble: 5 x 6
##   .model   sigma2 log_lik   AIC  AICc   BIC
##   <chr>     <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 arima010   33.1   -973. 1948. 1948. 1952.
## 2 arima111   33.1   -972. 1950. 1950. 1961.
## 3 search     33.1   -972. 1950. 1950. 1961.
## 4 arima011   33.2   -973. 1950. 1950. 1957.
## 5 arima110   33.2   -973. 1950. 1950. 1957.
```

Show the residuals using the 'search' ARIMA

```
selected_stock_fit |>
  select(search) |>
  gg_tsresiduals()
```



Portmanteau test shows a large P-value, suggesting the residuals are simliar to white noise

```
augment(selected_stock_fit) |>
  filter(.model=='search') |>
  features(.innov, ljung_box, lag = 10, dof = 3)
```

```
## # A tibble: 1 x 3
##   .model lb_stat lb_pvalue
##   <chr>    <dbl>     <dbl>
## 1 search    10.4     0.166
```

Second approach, creating a Train set and a Test set with stepwise ARIMA and Prophet models

```
length_df = nrow(selected_stock_information_tsibble)
Train_number = round(length_df * 0.98, 0)


Train <- selected_stock_information_tsibble %>%
```

```
  filter(row_value <= Train_number) %>%
  mutate(Date = as.Date(Date,origin="2022-01-01")) %>%
  as_tsibble(index=Date) %>%
  fill_gaps()
Test <- selected_stock_information_tsibble[Train_number:length_df,]
```

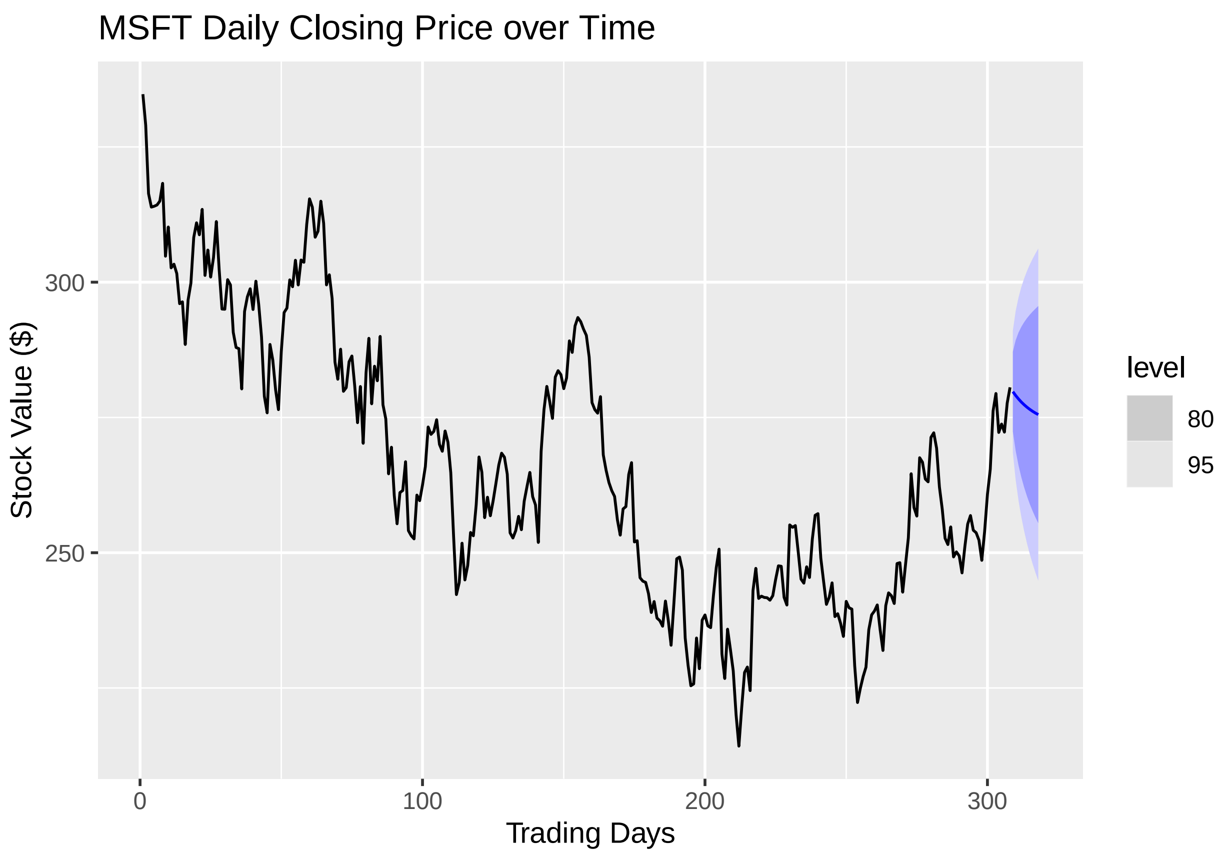
Period is set to twelve for the months, and order = 1 since data is non-seasonal

```
selected_stock_information_tsibble_fit <- Train |>
  model(
    arima = ARIMA(Close),
    prophet = prophet(Close ~ season(period = 12, order = 1,
                                     type = "additive"))
  )
```

2.5 - Predictions

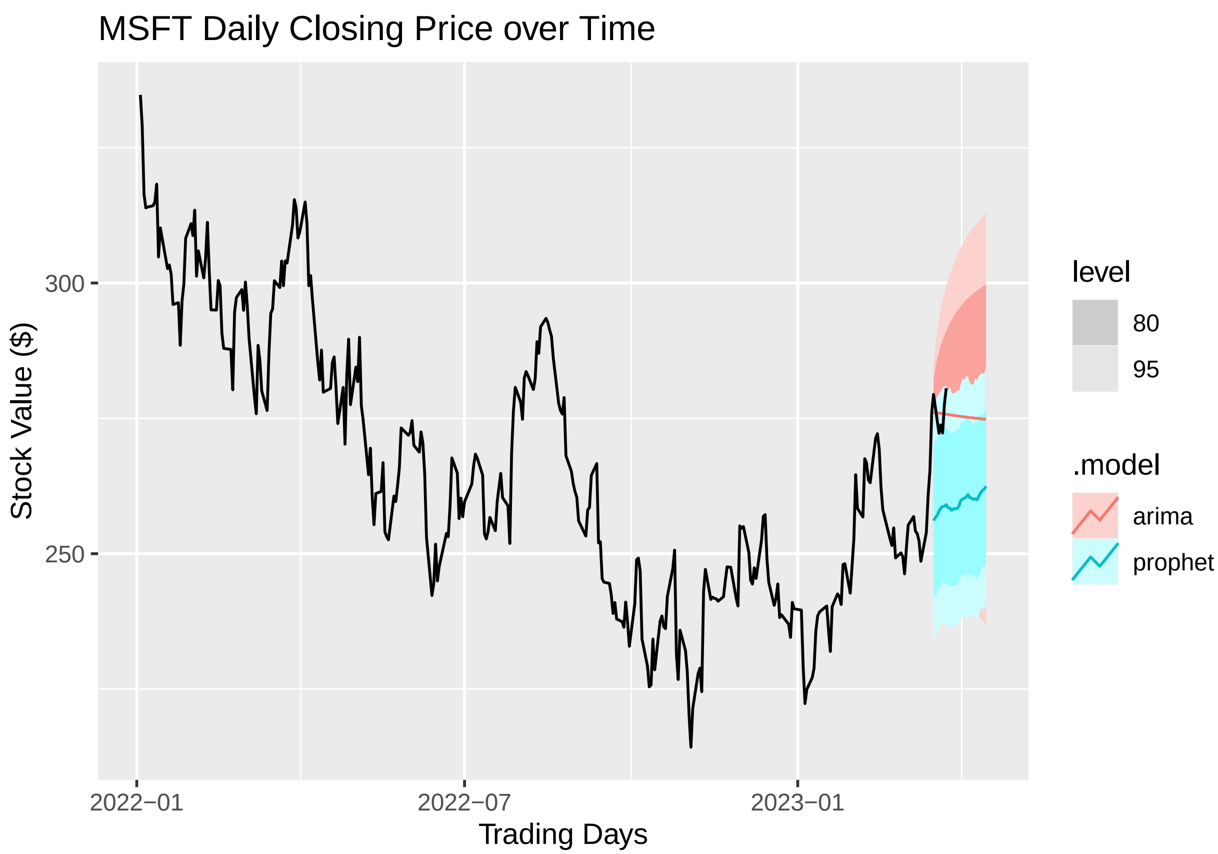
First Prediction - uses selected ARIMA

```
selected_stock_fit |>
  forecast(h=10) |>
  filter(.model=='search') |>
  autoplot(selected_stock_information_tsibble)  +
  labs(y = "Stock Value ($)",
       title = paste(file_name, "Daily Closing Price over Time"),
       x = "Trading Days")
```



Second Prediction set - Prophet + stepwise ARIMA

```
selected_stock_information_tsibble_fit_fc <- selected_stock_information_tsibble_fit |> forecast(h = 30)
selected_stock_information_tsibble_fit_fc |> autoplot(selected_stock_information_tsibble %>% as_tsibble
  labs(y = "Stock Value ($)",
       title = paste(file_name, "Daily Closing Price over Time"),
       x = "Trading Days")
```


MSFT Daily Closing Price over Time
Stock Value ($)
300
250
2022−01
2022−07
2023−01
Trading Days
level
80
95
.model
arima
prophet

3 - Analysis of TSLA

3.0 - Analysis Setup

Set up File name

```
file = "Data/TSLA_2023-03-26.csv"
```

Read the .CSV and select Date and Closing Price

```
Stock_information <- read.csv(file)

selected_stock_information <- Stock_information %>%
  select(c('Date','Close')) %>%
  mutate(row_value = row_number(),
         Date = as.Date(Date,origin="2022-01-01"))
```

Collect Stock/ETF Ticker to be displayed on future visualizations to remove confusion

```
file_name = substring(file,6,9)
```

First set

```
selected_stock_information_tsibble <- as_tsibble(selected_stock_information, index = row_value)
```

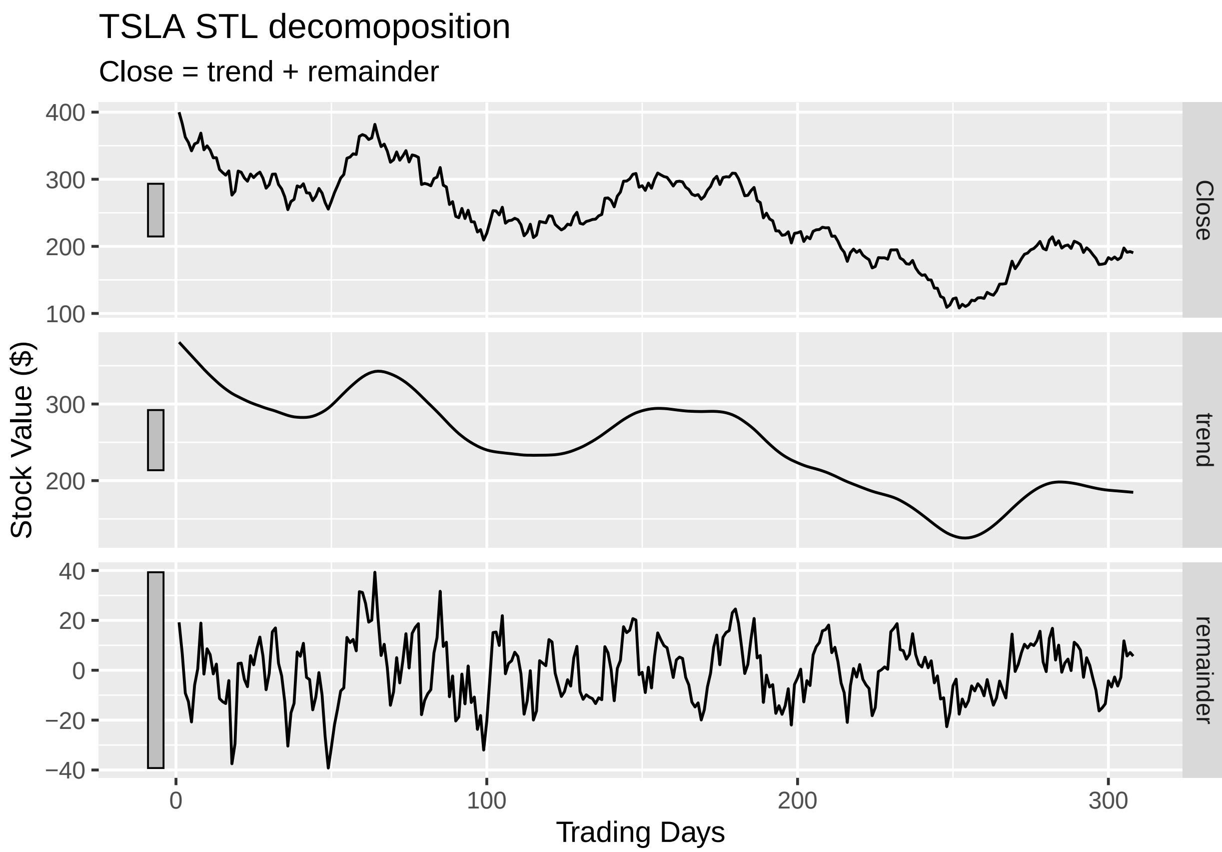
Set up for Monthly; second set. This could be useful in the future.

```
selected_stock_information_monthly <- yearmonth(selected_stock_information$`Date`, format = "%Y-%m-%d")
selected_stock_information$`Date` <- selected_stock_information_monthly
selected_stock_information_montly_tsibble <- as_tsibble(selected_stock_information, index = row_value)
```

```
selected_stock_information_montly_aggregated_tsibble <- selected_stock_information_montly_tsibble %>%
  aggregate(Close ~ Date, sum) %>%
  mutate(row_value = row_number()) %>%
  as_tsibble(index = row_value)
```

3.1 - Decomposition

```
dcmp <- selected_stock_information_tsibble |>
  model(stl = STL(Close))

components(dcmp) |> autoplot() +
  labs(title = paste(file_name, "STL decomoposition"),
       y = "Stock Value ($)",
       x = "Trading Days")
```



3.2 - Time Series Visualization

```
autoplot(selected_stock_information_tsibble) +
  labs(y = "Stock Value ($)",
       title = paste(file_name,"Daily Closing Price over Time"),
       x = "Trading Days")
```

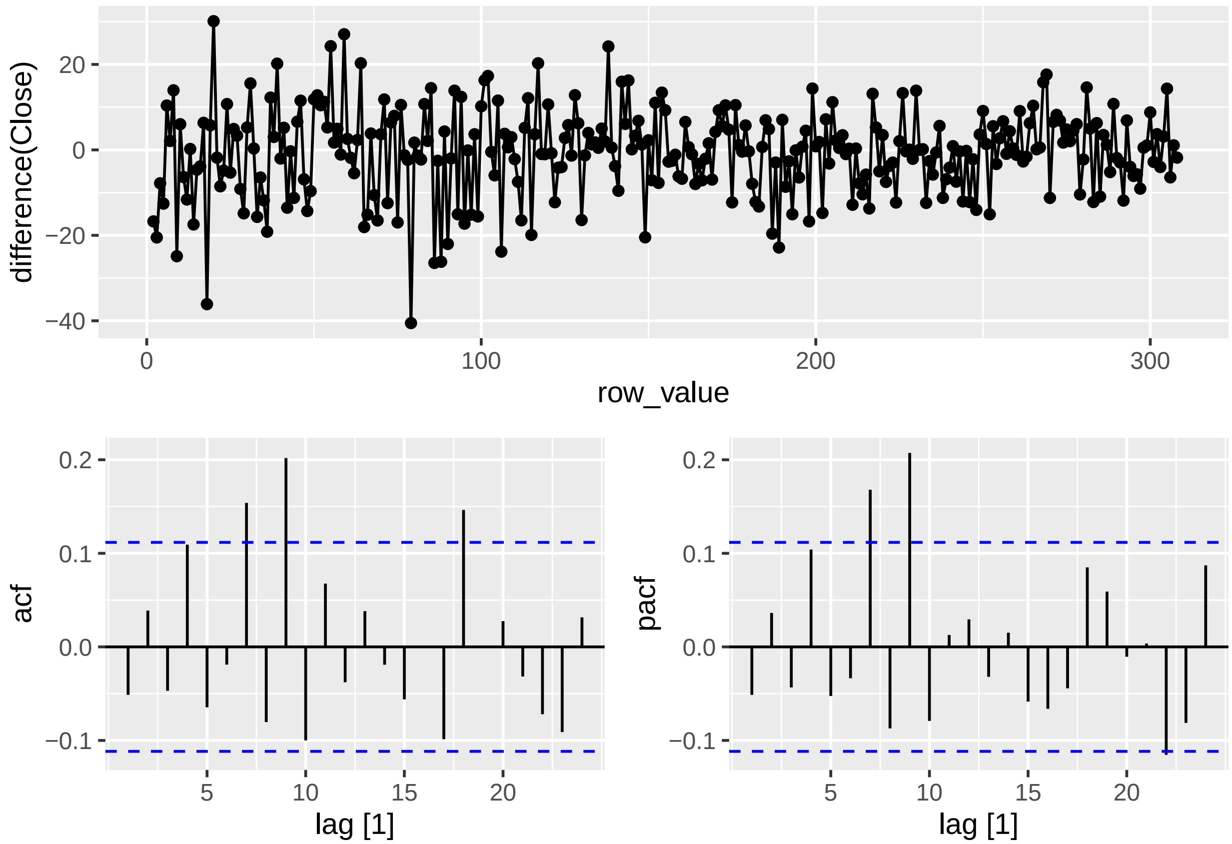
```
## Plot variable not specified, automatically selected `.vars = Close`
```

create residual, ACF, PACF plots

```
selected_stock_information_tsibble |>
  gg_tsdisplay(difference(Close), plot_type='partial')
```

```
## Warning: Removed 1 row containing missing values (`geom_line()`).
```

```
## Warning: Removed 1 rows containing missing values (`geom_point()`).
```



Residuals, ACF, and PACF suggest the series is similar to white noise.

3.3 - Description of the Time Series:

INPUT SOMETHING

3.4 - TS Models (transformations)

Checking if the data is stationary. If kpss_stat > kpss_pvalue, then we reject null hypothesis and claim the data is non-stationary. Differencing will be required.

```
selected_stock_information_tsibble |>
  features(Close, unitroot_kpss)
```

```
## # A tibble: 1 x 2
##   kpss_stat kpss_pvalue
##       <dbl>       <dbl>
## 1      3.58        0.01
```

Output is the number of differences make the data stationary

```
selected_stock_information_tsibble |>
  features(Close, unitroot_ndiffs)
```

```
## # A tibble: 1 x 1
##   ndiffs
##    <int>
## 1      1
```

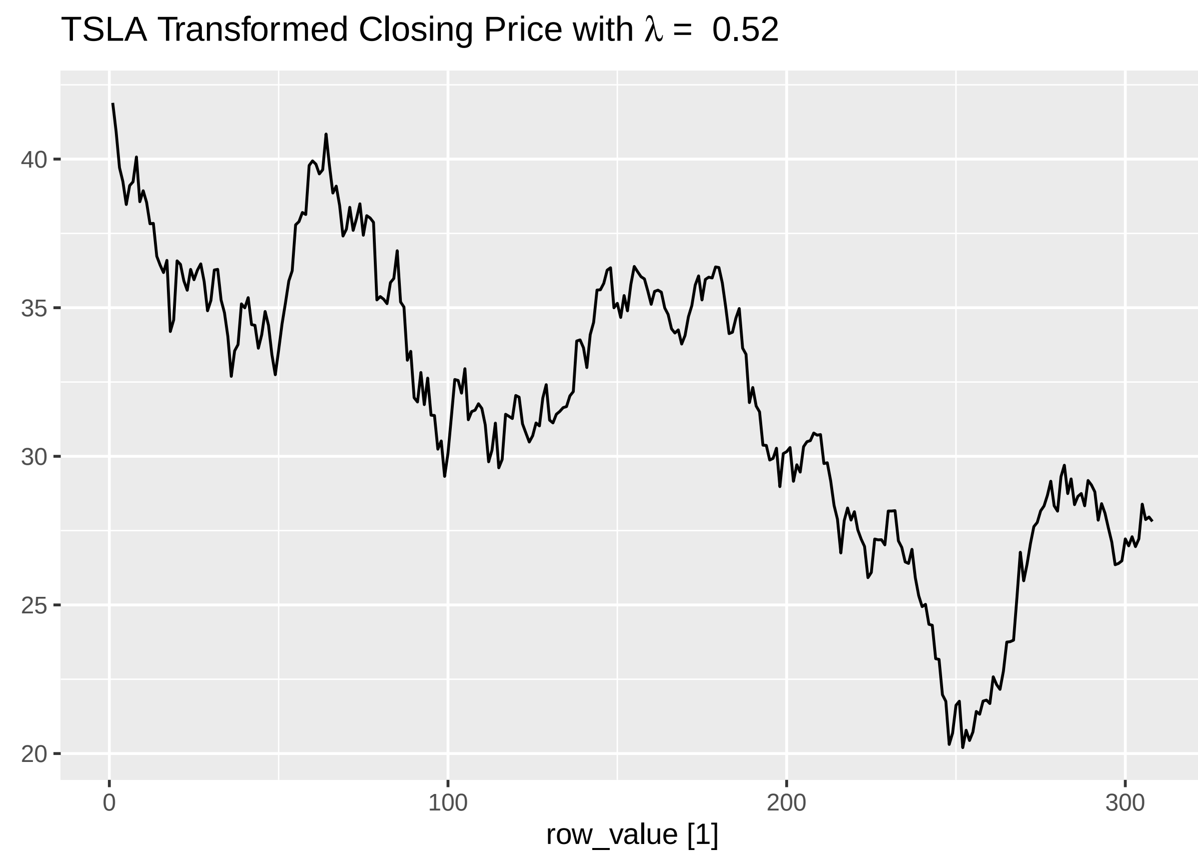
The difference

```
selected_stock_information_tsibble |>
  mutate(diff_close = difference(Close)) |>
  features(diff_close, unitroot_kpss)
```

```
## # A tibble: 1 x 2
##   kpss_stat kpss_pvalue
##       <dbl>       <dbl>
## 1     0.127         0.1
```

Using Box-Cox Transformation does not change the shape of the Closing Price with a lambda value of 1.

```
lambda <- selected_stock_information_tsibble |>
  features(Close, features = guerrero) |>
  pull(lambda_guerrero)
selected_stock_information_tsibble |>
  autoplot(box_cox(Close, lambda)) +
  labs(y = "",
       title = latex2exp::TeX(paste(file_name,
         "Transformed Closing Price with $\\lambda$ = ",
         round(lambda,2))))
```



First modeling approach will be to generate a few ARIMA orders and compare results.

```
selected_stock_fit <- selected_stock_information_tsibble |>
  model(arima010 = ARIMA(Close ~ pdq(0,1,0)),
        arima110 = ARIMA(Close ~ pdq(1,1,0)),
        arima011 = ARIMA(Close ~ pdq(0,1,1)),
        arima111 = ARIMA(Close ~ pdq(1,1,1)),
        search = ARIMA(Close, stepwise=FALSE))

print(selected_stock_fit$search)
```

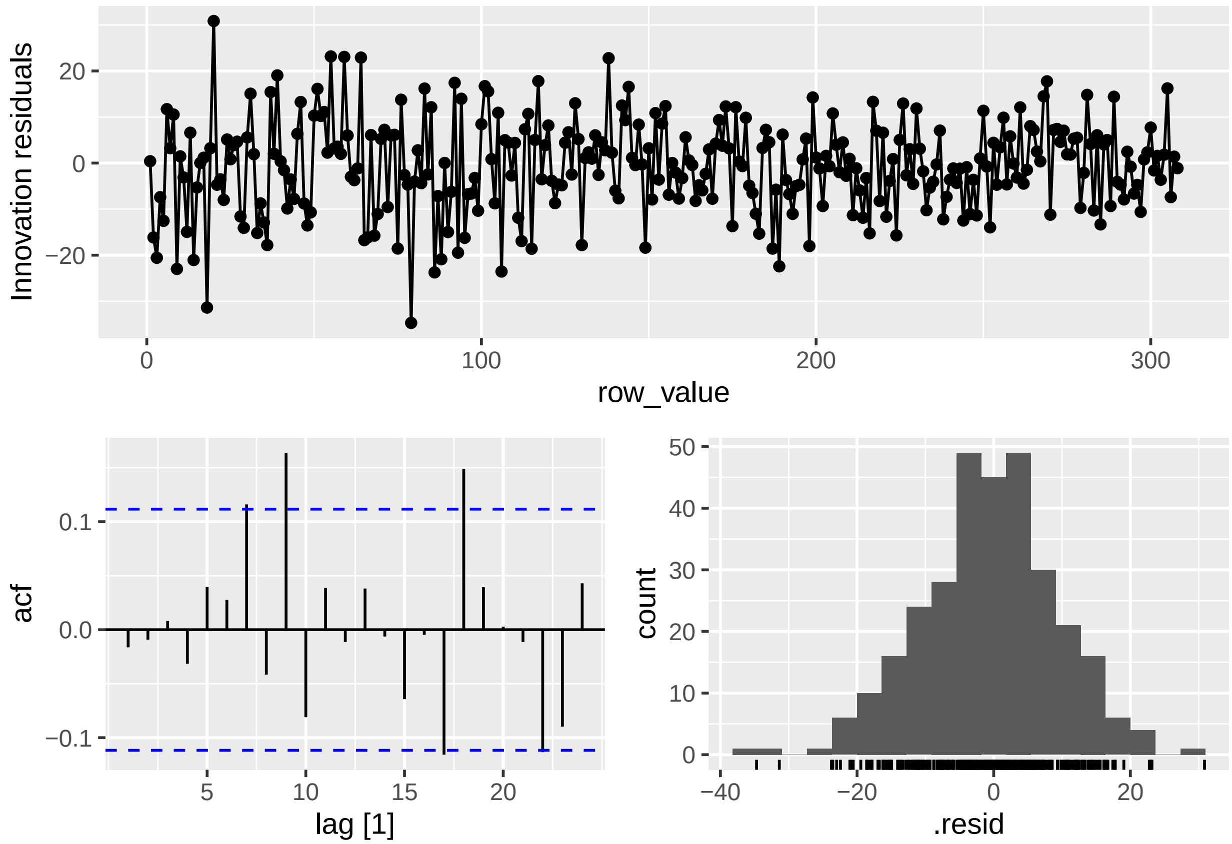
```
## <lst_mdl[1]>
## [1] <ARIMA(0,1,5)>
```

```
glance(selected_stock_fit) |> arrange(AICc) |> select(.model:BIC)
```

```
## # A tibble: 5 x 6
##   .model   sigma2 log_lik   AIC  AICc   BIC
##   <chr>     <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 search     102.  -1143. 2297. 2298. 2320.
## 2 arima010   105.  -1150. 2301. 2301. 2305.
## 3 arima110   105.  -1149. 2302. 2302. 2310.
## 4 arima011   105.  -1149. 2302. 2302. 2310.
## 5 arima111   105.  -1149. 2305. 2305. 2316.
```

Show the residuals using the 'search' ARIMA

```
selected_stock_fit |>
  select(search) |>
  gg_tsresiduals()
```



Portmanteau test shows a large P-value, suggesting the residuals are simliar to white noise

```
augment(selected_stock_fit) |>
  filter(.model=='search') |>
  features(.innov, ljung_box, lag = 10, dof = 3)
```

```
## # A tibble: 1 x 3
##   .model lb_stat lb_pvalue
##   <chr>    <dbl>     <dbl>
## 1 search    16.7    0.0197
```

Second approach, creating a Train set and a Test set with stepwise ARIMA and Prophet models

```
length_df = nrow(selected_stock_information_tsibble)
Train_number = round(length_df * 0.98, 0)


Train <- selected_stock_information_tsibble %>%
```

```r
  filter(row_value <= Train_number) %>%
  mutate(Date = as.Date(Date,origin="2022-01-01")) %>%
  as_tsibble(index=Date) %>%
  fill_gaps()
Test <- selected_stock_information_tsibble[Train_number:length_df,]
```

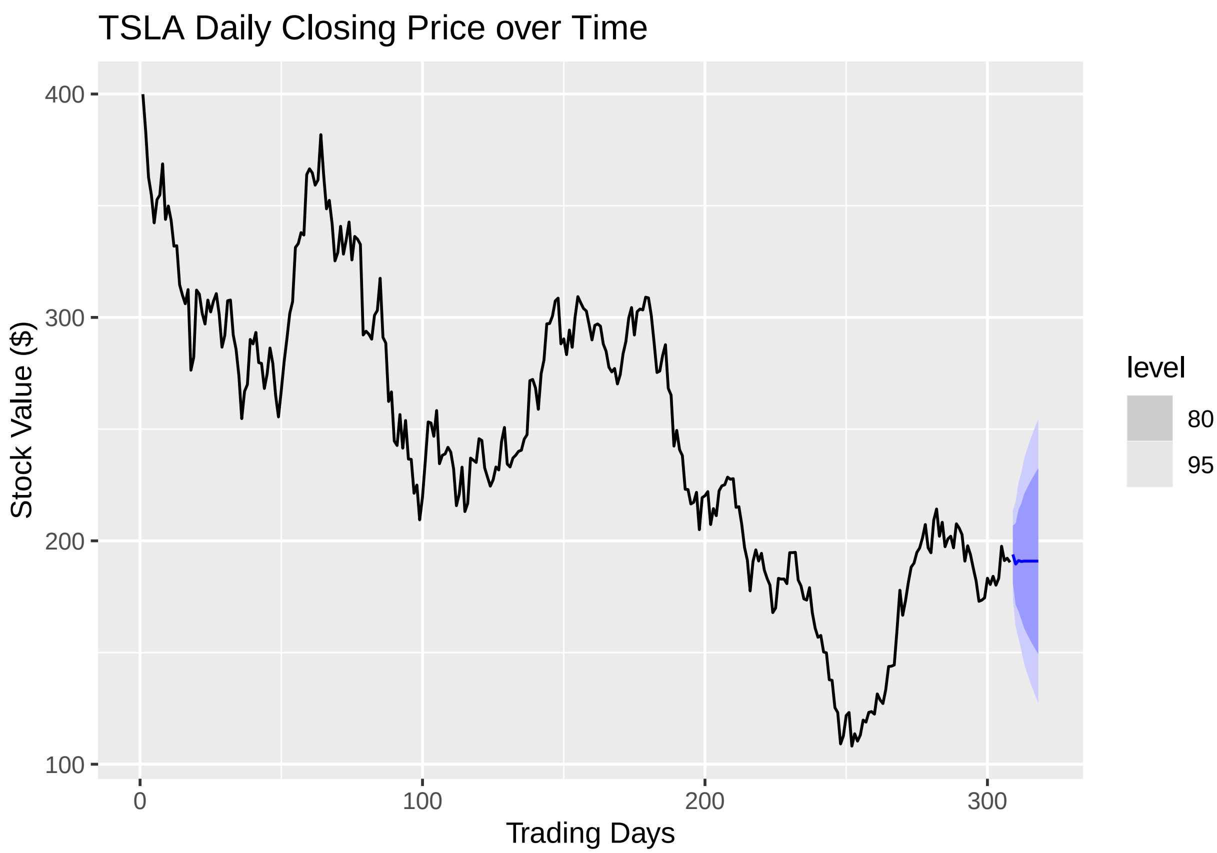
Period is set to twelve for the months, and order = 1 since data is non-seasonal

```r
selected_stock_information_tsibble_fit <- Train |>
  model(
    arima = ARIMA(Close),
    prophet = prophet(Close ~ season(period = 12, order = 1,
                                     type = "additive"))
  )
```

3.5 - Predictions

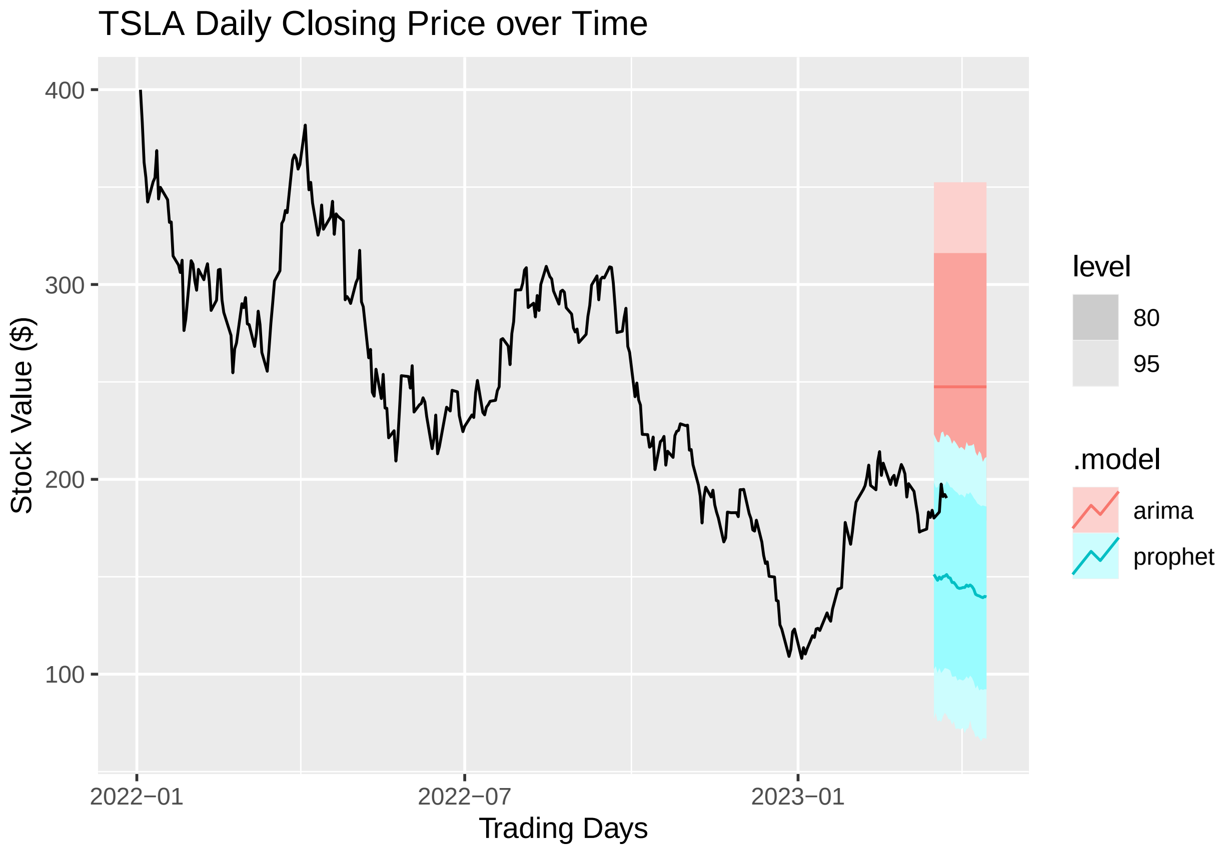
First Prediction - uses selected ARIMA

```
selected_stock_fit |>
  forecast(h=10) |>
  filter(.model=='search') |>
  autoplot(selected_stock_information_tsibble)  +
  labs(y = "Stock Value ($)",
       title = paste(file_name, "Daily Closing Price over Time"),
       x = "Trading Days")
```



Second Prediction set - Prophet + stepwise ARIMA

```
selected_stock_information_tsibble_fit_fc <- selected_stock_information_tsibble_fit |> forecast(h = 30)
selected_stock_information_tsibble_fit_fc |> autoplot(selected_stock_information_tsibble %>% as_tsibble
  labs(y = "Stock Value ($)",
       title = paste(file_name, "Daily Closing Price over Time"),
       x = "Trading Days")
```



4 - Conclusions

Each of the stocks appears to be best modeled by random walk models, either with or without drift. This aligns with conventional wisdom of stock prices following a random walk pattern, although the timeframe selected (Jan 1, 2022 through Mar 24, 2023) features a downwards drift for many cases.

Including a different timeframe, or different stocks, may result in random walks without drift or random walks with upwards drift providing a better model fit for stock prices.

Team contributions (pending…)

Brian: Completed rough draft of the Part 2 submission.

Mohan: Generated Github repo and place Datasets. Picked option 1.

Brendan: Formatted Part 2 document, provided model descriptions and rough draft bug fixes.