

Kumari_Herath_T00655616

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```
library(tsibble)
```

```
##
## Attaching package: 'tsibble'

## The following objects are masked from 'package:base':
##
## intersect, setdiff, union
```

```
library(fpp3)
```

```
## -- Attaching packages ----- fpp3 0.5 --
```

```
## v tibble      3.2.1      v tsibbledata 0.4.1
## v dplyr       1.1.3      v feasts      0.3.1
## v tidyr       1.3.0      v fable       0.3.3
## v lubridate   1.9.2      v fabletools  0.3.4
## v ggplot2     3.4.4
```

```
## Warning: package 'ggplot2' was built under R version 4.3.2
```

```
## Warning: package 'fabletools' was built under R version 4.3.2
```

```
## -- Conflicts ----- fpp3_conflicts --
```

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

```
library(ggplot2)
library(fable)
library(forecast)
```

```
## Warning: package 'forecast' was built under R version 4.3.2
```

```

## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo

library(tidyr)
library(quantmod)

## Warning: package 'quantmod' was built under R version 4.3.2

## Loading required package: xts

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following object is masked from 'package:tsibble':
##
##   index

## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric

##
## ##### Warning from 'xts' package #####
## #
## # The dplyr lag() function breaks how base R's lag() function is supposed to #
## # work, which breaks lag(my_xts). Calls to lag(my_xts) that you type or #
## # source() into this session won't work correctly. #
## #
## # Use stats::lag() to make sure you're not using dplyr::lag(), or you can add #
## # conflictRules('dplyr', exclude = 'lag') to your .Rprofile to stop #
## # dplyr from breaking base R's lag() function. #
## #
## # Code in packages is not affected. It's protected by R's namespace mechanism #
## # Set 'options(xts.warn_dplyr_breaks_lag = FALSE)' to suppress this warning. #
## #
## #####
##
##
## Attaching package: 'xts'

## The following objects are masked from 'package:dplyr':
##
##   first, last

## Loading required package: TTR

```

```
library(fable.prophet)
```

```
## Warning: package 'fable.prophet' was built under R version 4.3.2
```

```
## Loading required package: Rcpp
```

```
library(prophet)
```

```
## Warning: package 'prophet' was built under R version 4.3.2
```

```
## Loading required package: rlang
```

```
##
```

```
## Attaching package: 'prophet'
```

```
## The following object is masked from 'package:fable.prophet':
```

```
##
```

```
## prophet
```

```
library(fabletools)
```

```
# Download data from yahoo Finance!
```

```
start.date = '2020-10-01' # starting date of stock
```

```
end.date = '2023-11-29' # ending date of stock
```

```
# Download the selected stocks from Yahoo finance using `quantmod` package
```

```
getSymbols("DJI", src = "yahoo", from = start.date, to = end.date, auto.assign = TRUE)
```

```
## [1] "DJI"
```

```
# Get close price
```

```
Close = DJI$DJI.Close
```

```
head(Close)
```

```
## DJI.Close
```

```
## 2020-10-01 27816.90
```

```
## 2020-10-02 27682.81
```

```
## 2020-10-05 28148.64
```

```
## 2020-10-06 27772.76
```

```
## 2020-10-07 28303.46
```

```
## 2020-10-08 28425.51
```

```
# Create date variable
```

```
DJI <- zoo::fortify.zoo(DJI)
```

```
DJI <- DJI %>% rename(c("Date" = "Index", "Close" = "DJI.Close"))
```

```
# create a tsibble
```

```
DJI<- as_tsibble(DJI, index = Date)
```

```
# Reindex by taking care of missing values
```

```
DJI <- DJI |>
mutate(day = row_number()) |>
update_tsibble(index = day, regular = TRUE)
```

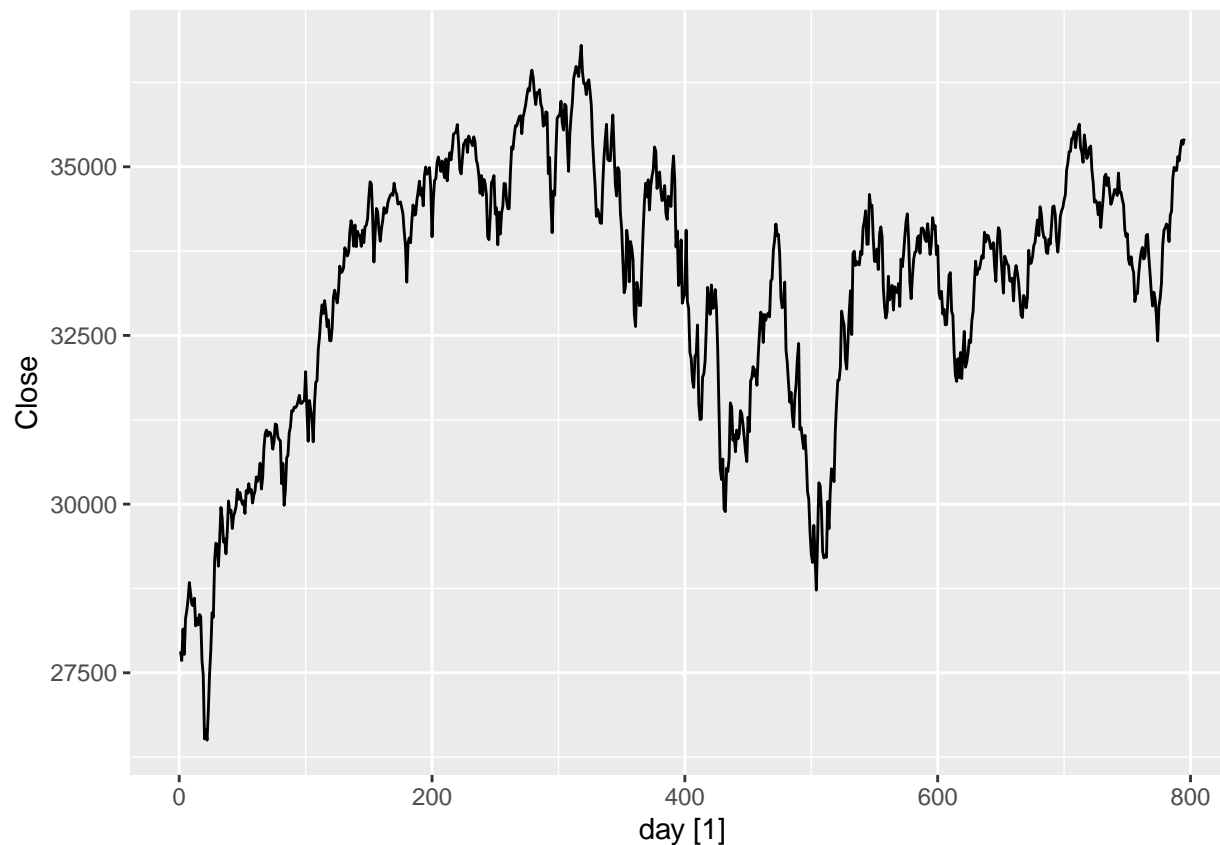
DJI

```
## # A tsibble: 795 x 8 [1]
##   Date      DJI.Open DJI.High DJI.Low  Close DJI.Volume DJI.Adjusted  day
##   <date>      <dbl>   <dbl>   <dbl>   <dbl>   <dbl>      <dbl> <int>
## 1 2020-10-01  27941.  28041.  27669.  27817.  373450000  27817.      1
## 2 2020-10-02  27536.  27861.  27383.  27683.  392770000  27683.      2
## 3 2020-10-05  27825.  28163.  27825.  28149.  318210000  28149.      3
## 4 2020-10-06  28214.  28354.  27728.  27773.  435030000  27773.      4
## 5 2020-10-07  27971.  28370.  27971.  28303.  328750000  28303.      5
## 6 2020-10-08  28349.  28459.  28266.  28426.  314750000  28426.      6
## 7 2020-10-09  28534.  28676.  28441.  28587.  324050000  28587.      7
## 8 2020-10-12  28671.  28958.  28660.  28838.  493680000  28838.      8
## 9 2020-10-13  28765.  28809.  28604.  28680.  526110000  28680.      9
## 10 2020-10-14 28731.  28793.  28462.  28514  370800000  28514     10
## # i 785 more rows
```

```
#Create train and test sets for GOOG
DJI_train <- DJI |> filter(yearmonth(Date) <= yearmonth("2023 Sept"))
DJI_test <- DJI |> filter(yearmonth(Date) > yearmonth("2023 Oct"))
```

```
# Make the data stationary
return.DJI = diff(log(Close ))
return.DJI <- na.omit(return.DJI)

DJI |> autoplot(Close)
```



```
summary(DJI)
```

```
##      Date      DJI.Open      DJI.High      DJI.Low
## Min.   :2020-10-01  Min.   :26481  Min.   :26639  Min.   :26144
## 1st Qu.:2021-07-17  1st Qu.:32162  1st Qu.:32406  1st Qu.:31874
## Median :2022-04-29  Median :33733  Median :33897  Median :33520
## Mean   :2022-04-30  Mean   :33229  Mean   :33423  Mean   :33029
## 3rd Qu.:2023-02-13  3rd Qu.:34584  3rd Qu.:34782  3rd Qu.:34438
## Max.   :2023-11-28  Max.   :36723  Max.   :36953  Max.   :36636
##      Close      DJI.Volume      DJI.Adjusted      day
## Min.   :26502  Min.   :117040000  Min.   :26502  Min.   : 1.0
## 1st Qu.:32158  1st Qu.:291555000  1st Qu.:32158  1st Qu.:199.5
## Median :33731  Median :328910000  Median :33731  Median :398.0
## Mean   :33234  Mean   :344528616  Mean   :33234  Mean   :398.0
## 3rd Qu.:34582  3rd Qu.:381760000  3rd Qu.:34582  3rd Qu.:596.5
## Max.   :36800  Max.   :811890000  Max.   :36800  Max.   :795.0
```

```
# Fit the models
```

```
# Fit Benchmark model
```

```
Benchmark_fit <- DJI_train |>
  model( NAIVE(Close),
        MEAN(Close),
        RW(Close ~ drift())
  )
```

```

# Fit ARIMA model
arima_fit <- DJI_train |>
  model(ARIMA(Close))

# Fit NN model
NN_fit <- DJI_train |>
  model(NNETAR(sqrt(Close)))

report(Benchmark_fit)

```

```

## Warning in report.mdl_df(Benchmark_fit): Model reporting is only supported for
## individual models, so a glance will be shown. To see the report for a specific
## model, use 'select()' and 'filter()' to identify a single model.

```

```

## # A tibble: 3 x 2
##   .model          sigma2
##   <chr>          <dbl>
## 1 NAIVE(Close)    100810.
## 2 MEAN(Close)    3951772.
## 3 RW(Close ~ drift()) 100810.

```

```

report(arima_fit)

```

```

## Series: Close
## Model: ARIMA(0,1,0)
##
## sigma^2 estimated as 100734: log likelihood=-5405.83
## AIC=10813.65 AICc=10813.66 BIC=10818.28

```

```

report(NN_fit)

```

```

## Series: Close
## Model: NNAR(1,1)
## Transformation: sqrt(Close)
##
## Average of 20 networks, each of which is
## a 1-1-1 network with 4 weights
## options were - linear output units
##
## sigma^2 estimated as 0.7629

```

```

#Get best fit ARIMA Model
arima_fit <- DJI_train |>
model(
  arima010 = ARIMA(Close ~ 1 + pdq(0, 1, 0)),
  arima011 = ARIMA(Close ~ 1 + pdq(0, 1, 1)),
  arima012 = ARIMA(Close ~ 1 + pdq(0, 1, 2)),
  arima013 = ARIMA(Close ~ 1 + pdq(0, 1, 3)),
  arima110 = ARIMA(Close ~ 1 + pdq(1, 1, 0)),
  arima111 = ARIMA(Close ~ 1 + pdq(1, 1, 1)),

```

```

arima112 = ARIMA(Close ~ 1 + pdq(1, 1, 2)),
arima113 = ARIMA(Close ~ 1 + pdq(1, 1, 3)),
arima210 = ARIMA(Close ~ 1 + pdq(2, 1, 0)),
arima211 = ARIMA(Close ~ 1 + pdq(2, 1, 1)),
arima212 = ARIMA(Close ~ 1 + pdq(2, 1, 2)),
arima213 = ARIMA(Close ~ 1 + pdq(2, 1, 3)),
arima310 = ARIMA(Close ~ 1 + pdq(3, 1, 0)),
arima311 = ARIMA(Close ~ 1 + pdq(3, 1, 1)),
arima312 = ARIMA(Close ~ 1 + pdq(3, 1, 2)),
arima313 = ARIMA(Close ~ 1 + pdq(3, 1, 3))
)

```

```

## Warning in wrap_arima(y, order = c(p, d, q), seasonal = list(order = c(P, :
## possible convergence problem: optim gave code = 1

```

```

## Warning in sqrt(diag(best$var.coef)): NaNs produced

```

```

## Warning in sqrt(diag(best$var.coef)): NaNs produced

```

```

arima_fit|>
  glance() |>
  arrange(AICc) |>
  select(.model, AICc)

```

```

## # A tibble: 16 x 2
##   .model      AICc
##   <chr>      <dbl>
## 1 arima010 10815.
## 2 arima111 10816.
## 3 arima011 10817.
## 4 arima110 10817.
## 5 arima212 10818.
## 6 arima211 10818.
## 7 arima210 10819.
## 8 arima012 10819.
## 9 arima213 10820.
## 10 arima013 10820.
## 11 arima310 10820.
## 12 arima113 10820.
## 13 arima112 10820.
## 14 arima313 10820.
## 15 arima311 10822.
## 16 arima312 10824.

```

```

best_arima_fit <- DJI_train|>
model(ARIMA(Close ~ 1 + pdq(0, 1, 0)))

best_arima_fit |> report()

```

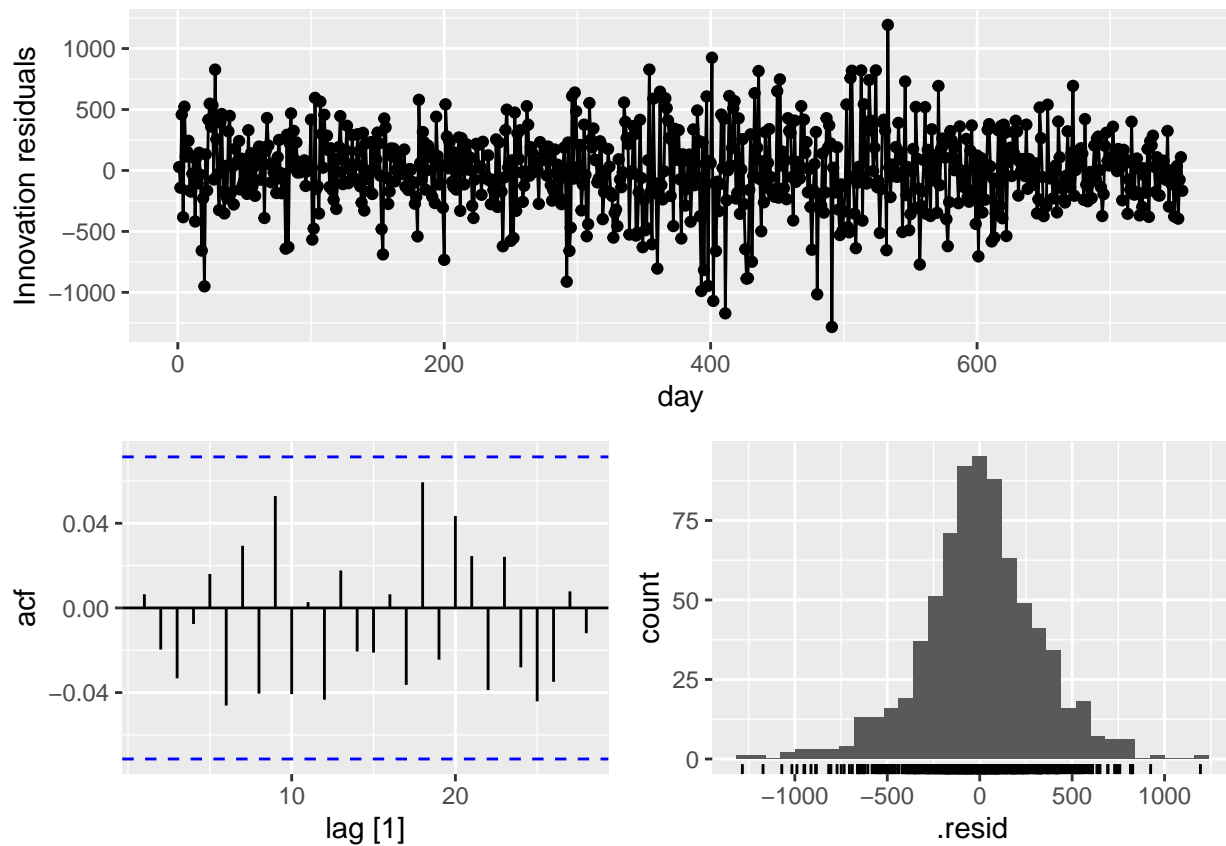
```

## Series: Close
## Model: ARIMA(0,1,0) w/ drift

```

```
##
## Coefficients:
##      constant
##      7.5572
## s.e.    11.5629
##
## sigma^2 estimated as 100811:  log likelihood=-5405.61
## AIC=10815.23   AICc=10815.24   BIC=10824.48
```

```
# get the residuals for arima model
best_arima_fit |> gg_tsresiduals()
```



```
augment(best_arima_fit) |> features(.innov, ljung_box, dof = 1, lag = 10)
```

```
## # A tibble: 1 x 3
##   .model          lb_stat lb_pvalue
##   <chr>          <dbl>   <dbl>
## 1 ARIMA(Close ~ 1 + pdq(0, 1, 0))  8.34    0.500
```

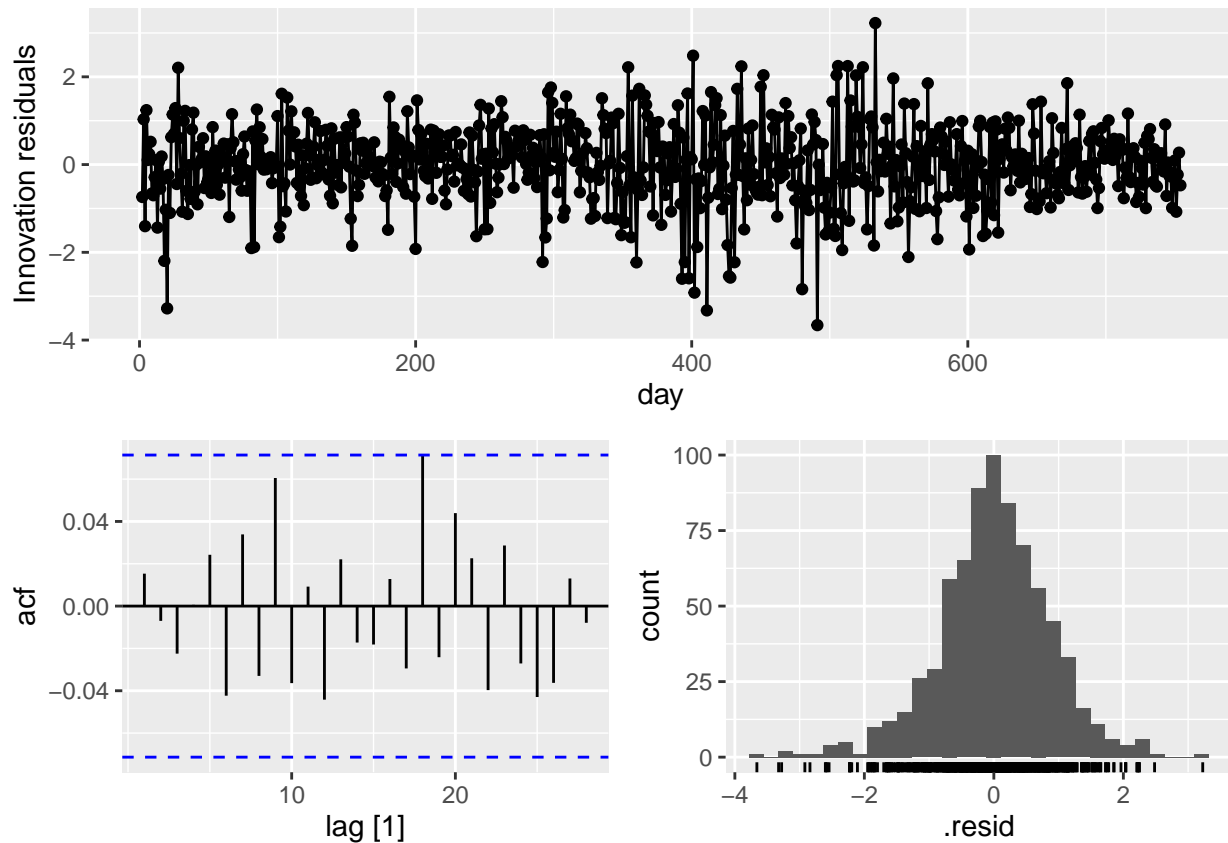
```
# get the residuals for NN model
NN_fit |> gg_tsresiduals()
```

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

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



```
## Warning: Removed 1 rows containing non-finite values ('stat_bin()').
```



```
augment(NN_fit) %>% features(.resid, lbjung_box, lag=10, dof=0)
```

```
## # A tibble: 1 x 3
##   .model          lb_stat lb_pvalue
##   <chr>          <dbl>   <dbl>
## 1 NNETAR(sqrt(Close))  7.67    0.661
```

```
# For ARIMA model:
# ACF function shows that the residuals are white noise.
# The residual follows a normal distribution.
```

```
# For NN model:
# ACF function shows that the residuals are white noise.
# The residual follows a normal distribution.
```

```
accuracy <- Benchmark_fit |>
  forecast(h = 2) |>
  accuracy(DJI)
```

```
accuracy
```

```
## # A tibble: 3 x 10
```

```
##   .model                .type      ME  RMSE   MAE      MPE  MAPE  MASE  RMSSE  ACF1
##   <chr>                 <chr> <dbl> <dbl> <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 MEAN(Close)          Test    20.7  216.  215.   0.0582 0.648 0.903 0.682 -0.5
## 2 NAIVE(Close)         Test   -290.  361.  290.  -0.876 0.876 1.21  1.14 -0.5
## 3 RW(Close ~ drift()) Test   -301.  372.  301.  -0.910 0.910 1.26  1.17 -0.5
```

```
accuracy_NN_fit <- NN_fit |>
  forecast(h = 40 ,times = 10) |>
  accuracy(DJI)
```

```
accuracy_NN_fit
```

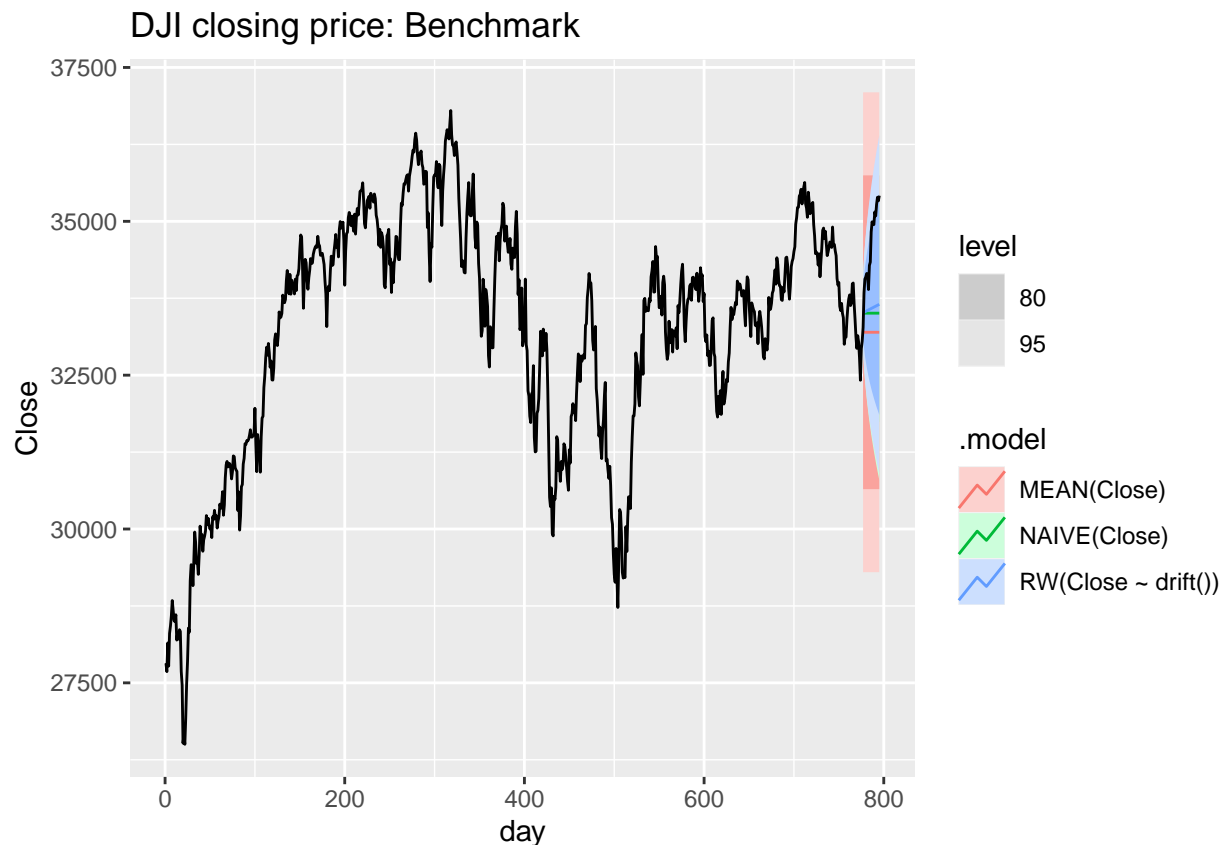
```
## # A tibble: 1 x 10
##   .model                .type      ME  RMSE   MAE      MPE  MAPE  MASE  RMSSE  ACF1
##   <chr>                 <chr> <dbl> <dbl> <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 NNETAR(sqrt(Close)) Test   -132.  714.  572.  -0.437 1.69  2.40  2.25 0.884
```

#The MEAN method has the smallest RMSE value among these models.

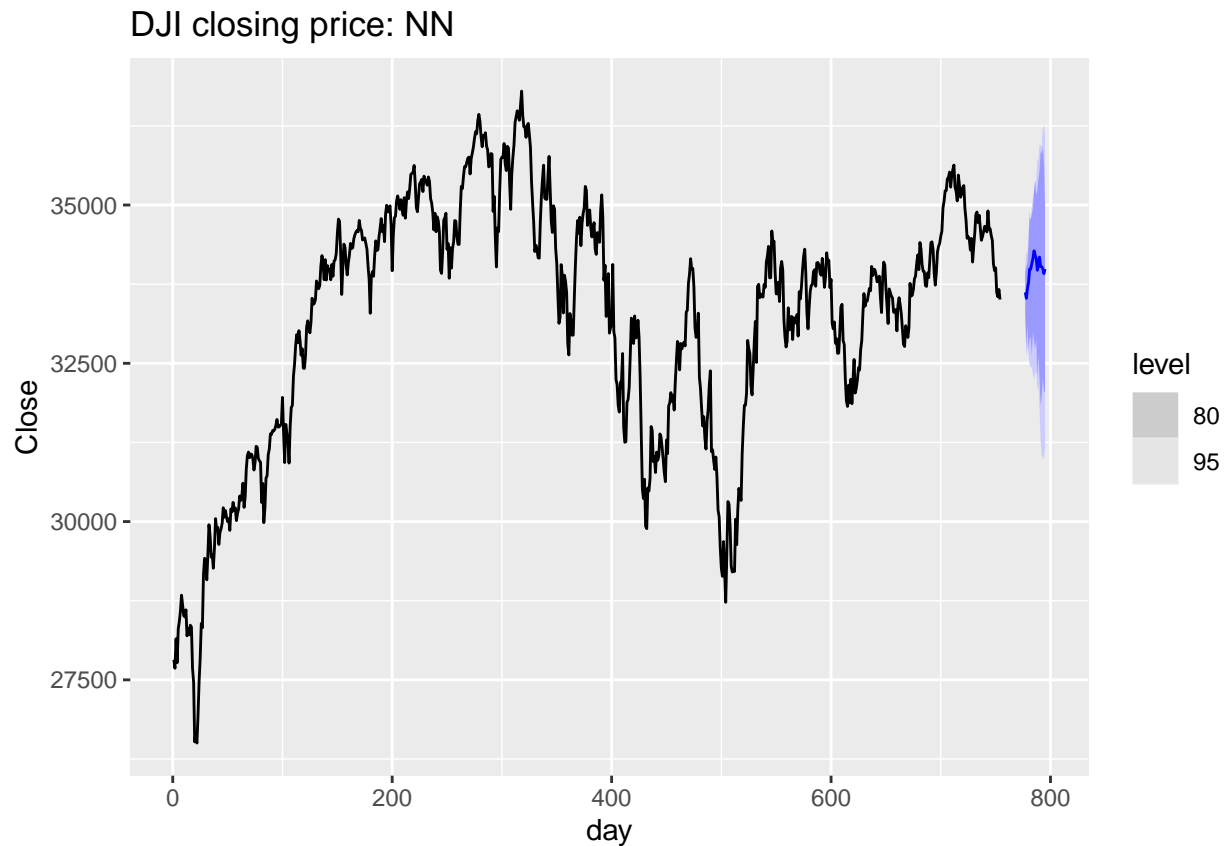
perform forecast on test set

For Benchmark model

```
Benchmark_fit |>
  forecast(DJI_test) |>
  autoplot(DJI)+
  labs(title="DJI closing price: Benchmark")
```



```
# For NN model
NN_fit |>
  forecast(DJI_test, times= 10) |>
  autoplot(DJI_train) +
  labs(title="DJI closing price: NN")
```



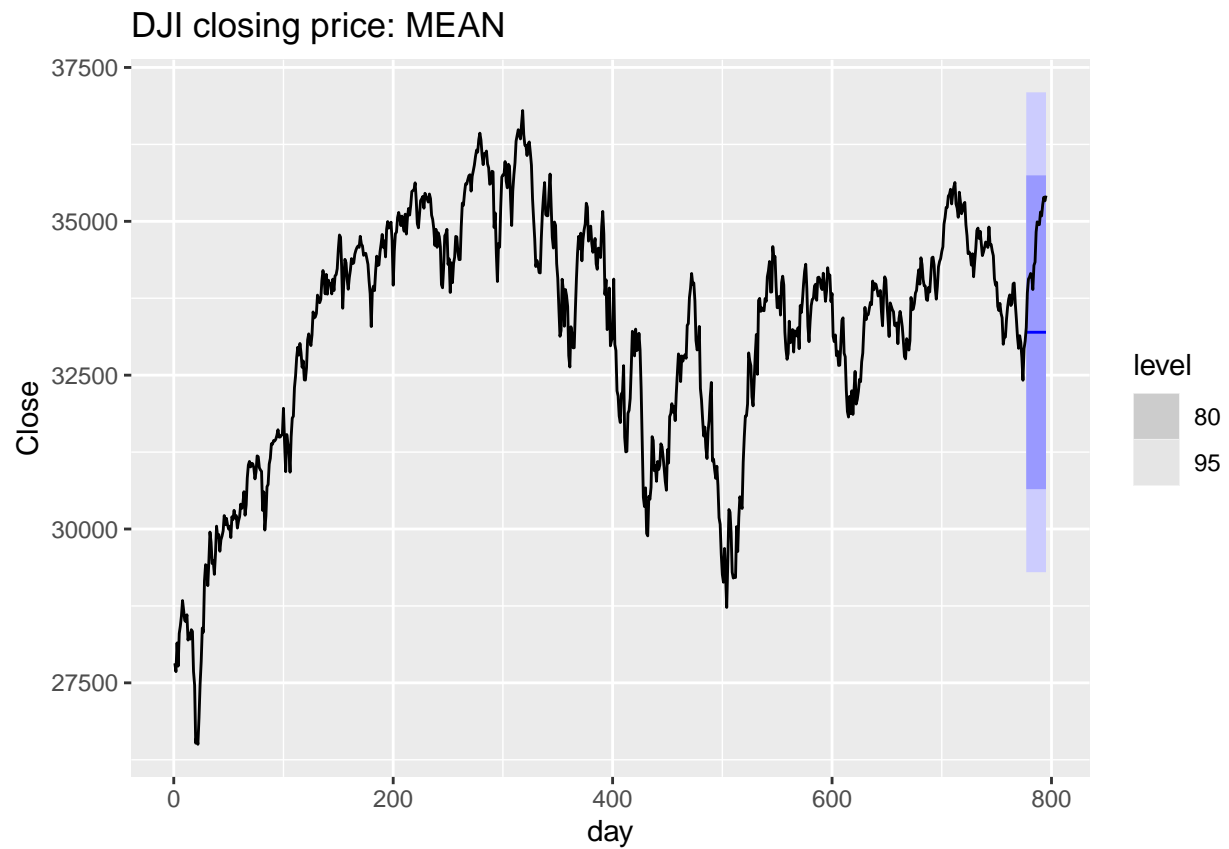
*# I did not do a forecast for ARIMA model since the best ARIMA model is (0,1,0).
Therefore, I ruled out ARIMA model.*

```
# forecast the models seperately for better visualization
mean_fit_model <- DJI_train |>
  model(MEAN(Close))

naive_fit_model <- DJI_train |>
  model(NAIVE(Close))

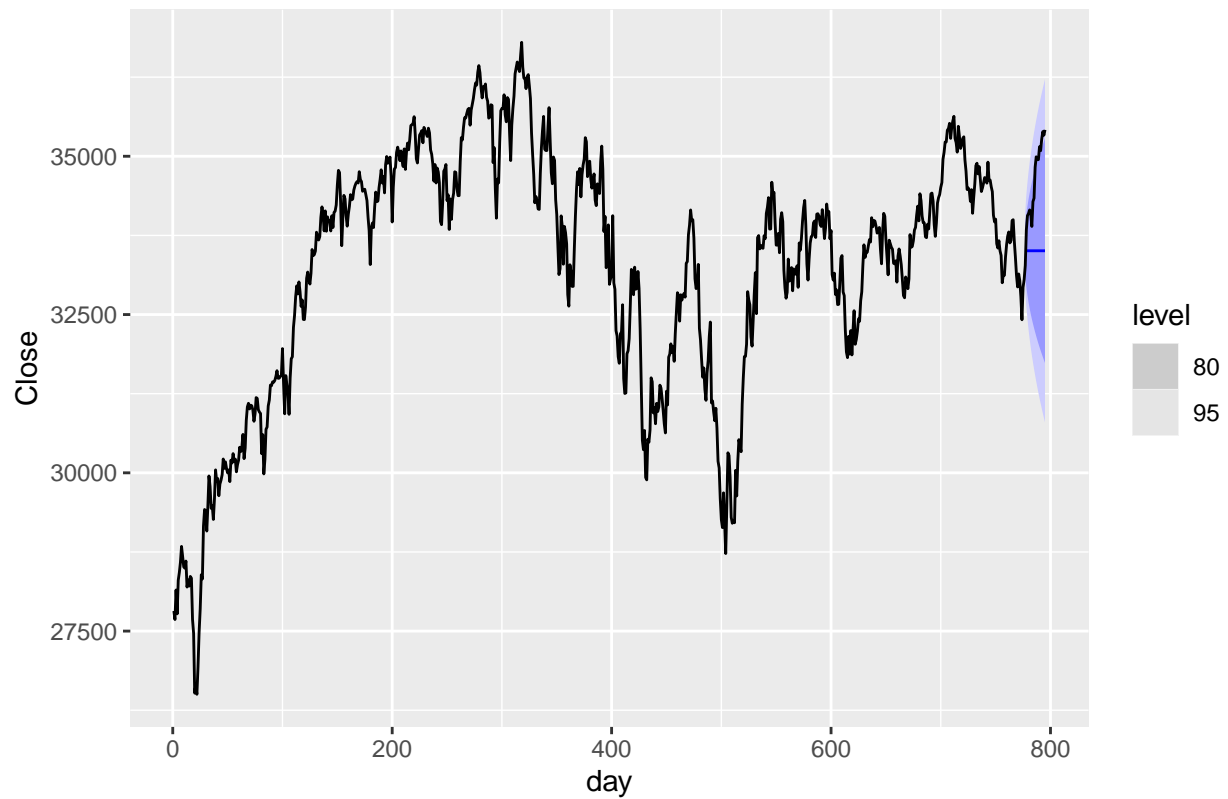
drift_fit_model <- DJI_train |>
  model(RW(Close ~ drift()))

mean_fit_model |>
  forecast(DJI_test) |>
  autoplot(DJI) +
  labs(title="DJI closing price: MEAN")
```



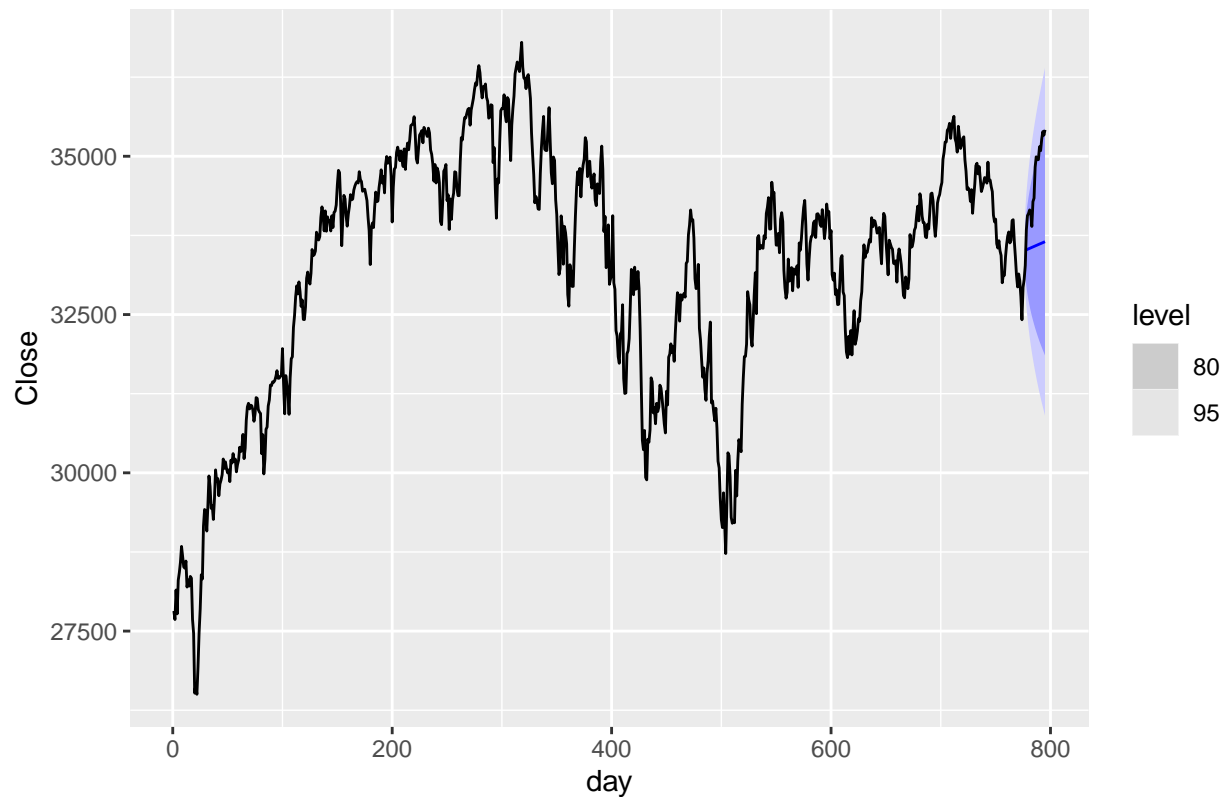
```
naive_fit_model |>  
  forecast(DJI_test) |>  
  autoplot(DJI) +  
  labs(title="DJI closing price: NAIVE")
```

DJI closing price: NAIVE



```
drift_fit_model |>  
  forecast(DJI_test) |>  
  autoplot(DJI) +  
  labs(title="DJI closing price: DRIFT")
```

DJI closing price: DRIFT



*# Even though MEAN model has the smallest RMSE, the certainty of the forecast is less than other method.
Therefore, I choose NAIVE model as the best model among these model and it has the second smallest RM.
and NAIVE RMSE is not very larger than MEAN RMSE.*

cross validation

```
DJI_CV <- DJI|>
  stretch_tsibble(.init = 300, .step = 1) |>
  relocate(Date, .id)
head(DJI_CV)
```

```
## # A tsibble: 6 x 9 [1]
## # Key:       .id [1]
##   Date       .id DJI.Open DJI.High DJI.Low Close DJI.Volume DJI.Adjusted
##   <date>     <int>   <dbl>   <dbl>   <dbl> <dbl>       <dbl>       <dbl>
## 1 2020-10-01     1  27941.  28041.  27669. 27817.   373450000    27817.
## 2 2020-10-02     1  27536.  27861.  27383. 27683.   392770000    27683.
## 3 2020-10-05     1  27825.  28163.  27825. 28149.   318210000    28149.
## 4 2020-10-06     1  28214.  28354.  27728. 27773.   435030000    27773.
## 5 2020-10-07     1  27971.  28370.  27971. 28303.   328750000    28303.
## 6 2020-10-08     1  28349.  28459.  28266. 28426.   314750000    28426.
## # i 1 more variable: day <int>
```

```
accuracy_NAIVE <- naive_fit_model |>
  forecast(h = 40) |>
  accuracy(DJI)
```

```
accuracy_NAIVE
```

```
## # A tibble: 1 x 10
##   .model      .type    ME  RMSE   MAE   MPE  MAPE  MASE  RMSSE  ACF1
##   <chr>      <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 NAIVE(Close) Test   368.  875.  688.  1.03  2.01  2.89  2.76  0.909
```