

# **DS745: Project One**

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## Introduction

In forecasting, for my project, I will apply the Autoregressive Integrated Moving Average (ARIMA) to five years of GameStop (GME) stock to inform whether I should sell my holdings now or wait until a better time. So, let's embark on this stocky endeavor.

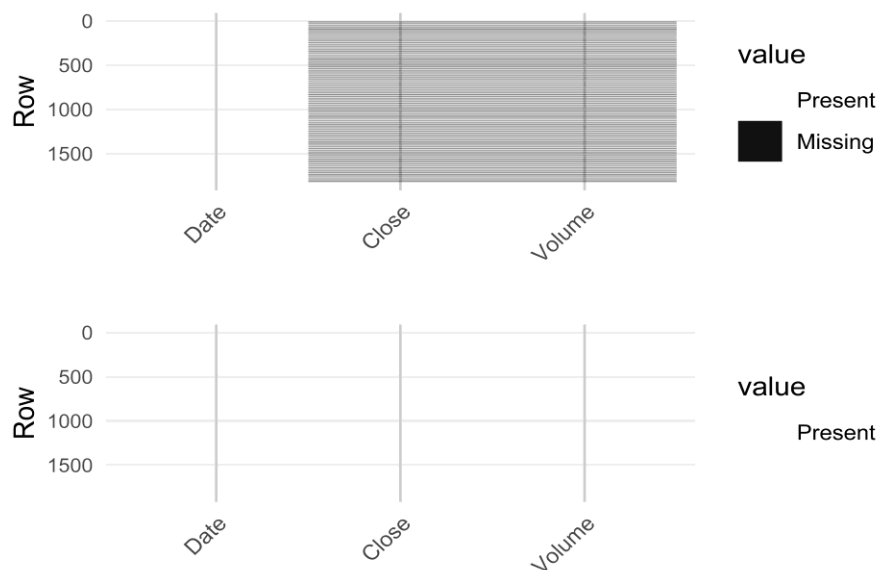
## Data Preparation

Although the GME stock data (Yahoo! Finance 2023) is relatively tidy and simple in column structure and size, there are nuances to it ("GameStop (GME) - Stock Split History" n.d.):

1. **Date** - Stock exchange dates do not include all calendar dates by default.
2. **Close** - The stock price per day at the closing time, with stock splits accounted for.
3. **Volume** - The volume of the stock bought or sold daily, with stock splits accounted for.

The **Close** and **Volume** have missing dates on Saturdays and Sundays because stock markets close on weekends. Therefore, I imputed **Close** by filling it down as the price remains fixed over the weekend. Whereas **Volume** is typically at 0 during the offline periods when no

Figure 1: Missingness before and after imputing

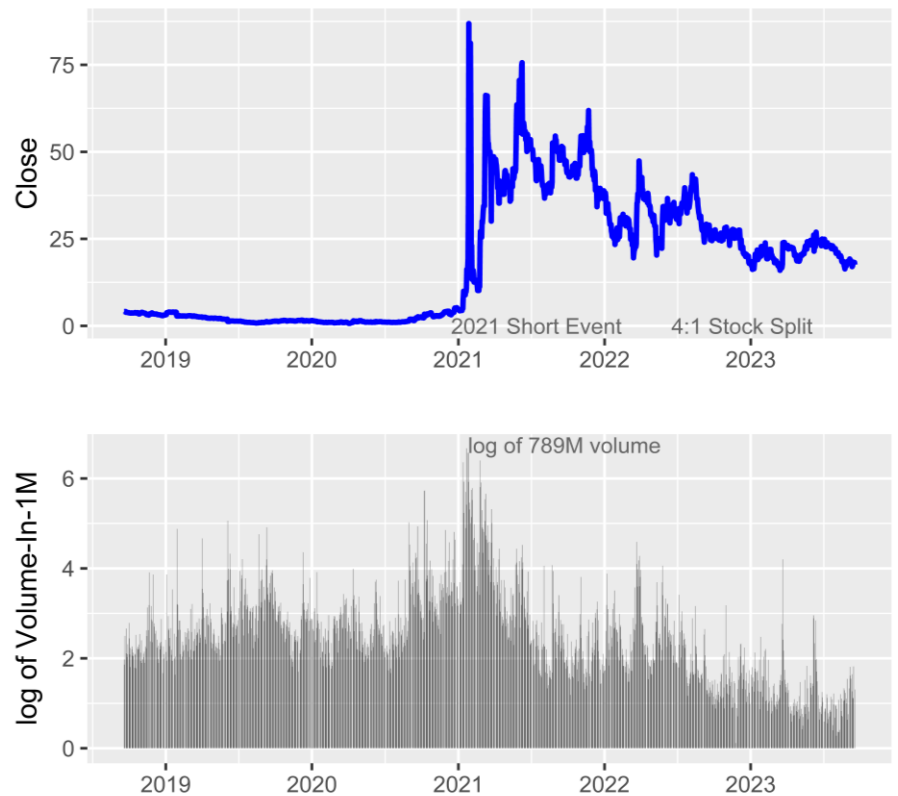


one can trade at the stock markets, I imputed NAs to 0. Figure 1 is the before and after heatmap of missingness (Woodward 2023).

Next, let's visualize the Close and Volume time series in Figure 2:

Figure 2 illustrates the extreme price surge in early 2021, which is challenging for prediction models. Also, in 2022, GameStop underwent a stock split, quadrupling its supply (“GameStop (GME) - Stock Split History” n.d.). Despite adjustments, this event may complicate the model, causing disruptions in ‘Close’ and ‘Volume’ data.

Figure 2: GME stock (with stock splits)



## Forecasting with ARIMA

In ARIMA forecasting and variable accounting, I included the time series of closing prices (e.g., Close), Volume, and post-transformed volume. The hypothesis behind this was that volume correlates directly to closing prices.

## Hyperparameter tuning/seasonality/customer lifetime value

With **customer lifetime value**, I needed to learn more before applying it to data in the project; likewise, applying it in this project did not seem relevant and cohesive, so I decided not to.

However, **tuning hyperparameters** and considering **seasonality** seemed appropriate, given the scope. Therefore, to accomplish both, I used `auto.arima` from R's *forecast* library and varied my forecasting ARIMA models between four scenarios: (1) ARIMA; (2) ARIMA with coerced seasonality (Pierre and Kolassa 2016); (3) #2 with exogenous variable of volume; (4) #2 with exogenous variable of volume transformed.

As a result of tuning, I found the best ARIMA model for GME forecasting (Figure 3):

Figure 3 shows that AIC values

fall within the 8000s range.

While there are subtle

distinctions between coerced

and non-coerced seasonality,

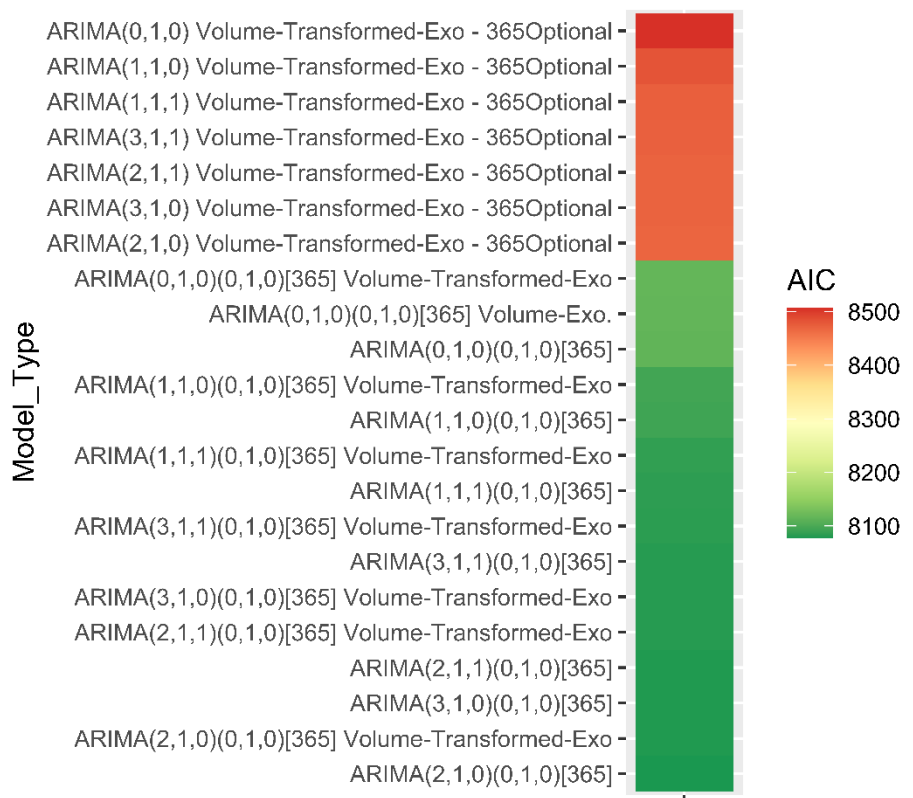
there is generally minor

variability among various

autoregressions and exogenous

variables.

Figure 3: GME ARIMA models



## Model-fitting and Conclusions

Due to the high AIC value (e.g., 8000s), our model may not accurately capture the intricate behavior of GME stock. As a result, we should approach its forecasts cautiously.

Figure 4 shows some interesting information about the forecasting model and expected prices in the future:

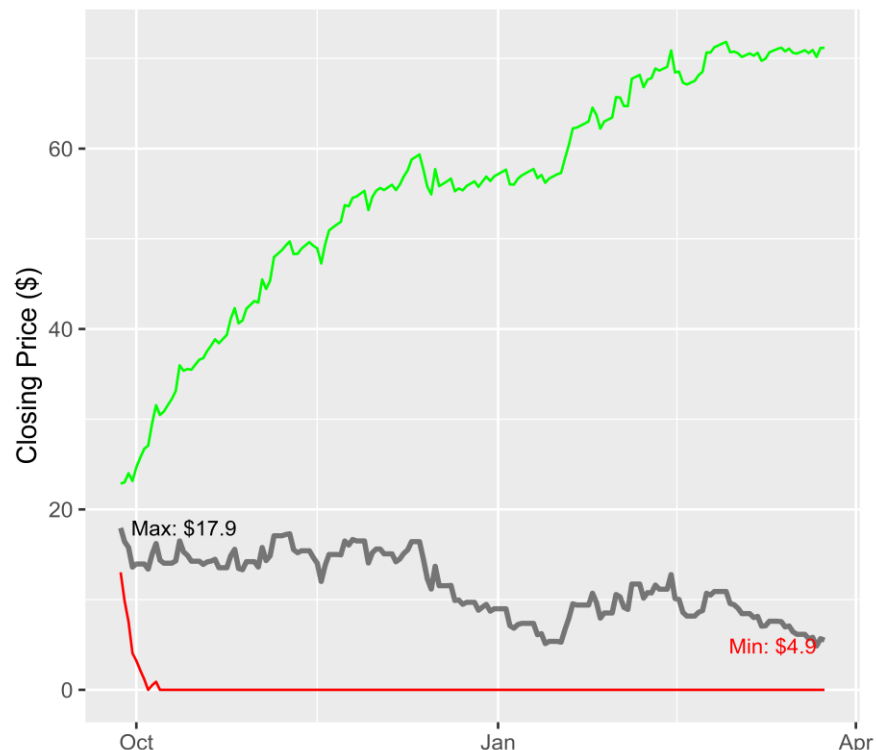
- The maximum Close price predicted is \$17.90 right now, and the minimum is \$4.90 at the end of the forecast horizon of 6 months. This indicates a pessimistic forecast that the price is just rolling downhill.
- Concurrently, the 80% prediction interval

(Hyndman and Khandakar

2008) on the lower end broached the negative realm, so I had to cut it off at 0; this adds to a pessimistic tale—conversely, the upper bound paints a maximum of around \$70 per share, which seems unlikely.

The prediction model suggests that selling now is a **reasonable choice**. However, if the model isn't reliable and I sell just before the stock gains significantly, I may miss out on potential profits. Forecasting volatile stocks is tricky!

Figure 4: GME ARIMA(2,1,0)(0,1,0)[365] forecasting



## References

“GameStop (GME) - Stock Split History.” n.d. CompaniesMarketCap.com. n.d.

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