Square Volume Forecasting Report

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Abstract

The significance of forecasting cannot be understated for any business, more so for Square's support and planning unit. This report focuses on the Square Forecasting Analysis, aimed at ensuring optimal staffing and service quality by making accurate predictions of customer call volume and handle time. Through such forecasting, Square aspires to maintain its commitment to timely and effective customer support.

1. Project Objective and Scope

The primary objective of this analysis report is to utilize the provided dataset to generate accurate forecasts that support Square's operational and staffing decisions. Specifically, this study seeks to:

1. Produce a monthly volume prediction for the next 18 months
2. Produce a weekly volume prediction for the next 12 weeks
3. Predict what handle-time we should expect for the next year

To ensure the utmost clarity and applicability of the findings, this report will also incorporate a well-defined rationale behind each forecast, along with key insights derived from the data analysis.

2. Background

The dataset offers a structured record of interactions and contact handling times for the 'Priority Customer Service' group at Square from March 14, 2021, to August 10, 2023. Specifically, it tracks the number of contacts received and the average handle time (AHT) of those contacts for each half-hour window throughout multiple days.

Variable Specifications:

Date: The specific day when the contacts were received. The sequence is continuous, devoid of missing intervals.
Skill ID: Appears to be an identifier for a particular service skill or capability. In this dataset, a singular Skill ID, 12345, is consistently observed.

Group Name: Specifies the customer service group handling the contacts. Only one unique classification, 'Priority Customer Service', is evident throughout the dataset.
Time: Indicates a half-hour window on the specified date. Consistently ranging from 00:00:00 to 23:30:00.
Contacts Received: States the volume of customer interactions or inquiries received during that half-hour window.
AHT of Handled Contacts: represents the average time it took to address or resolve each received contact.

3. Components

3.1 Trend

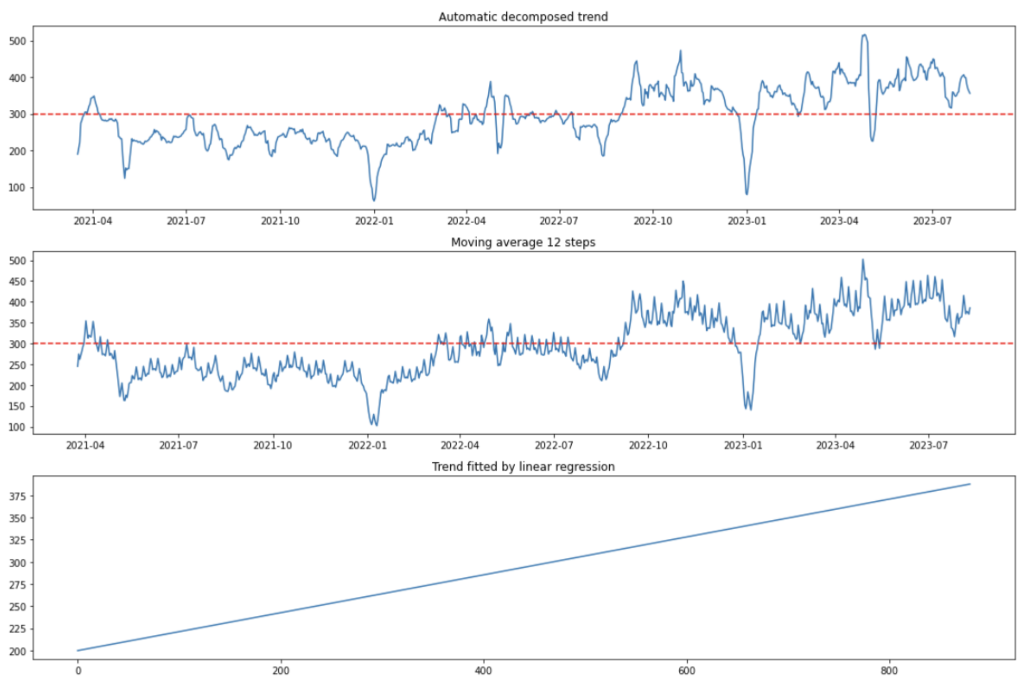


Figure 1 Automatic Decomposed Trend of Customer Received Volume

A trend is observed when there is an increasing or decreasing slope observed in the time series. It is crucial to note that while a trend may persist over an extended timeframe, its direction may not remain invariant throughout.

As depicted in Figure 1, we employed methods such as Automatic Decomposition, Moving Averages, and Linear Regression to discern underlying trends in the data. The results from both Automatic Decomposition and Moving Average models affirm the presence of a pronounced trend in our series. Over an extended period, our dataset indicates a systematic increase in our daily Contacts Received volume, with recent data points gravitating around an average of 350.

We could also try to split our series into smaller ones to identify subtrends with the mentioned methods.

3.2 Seasonality

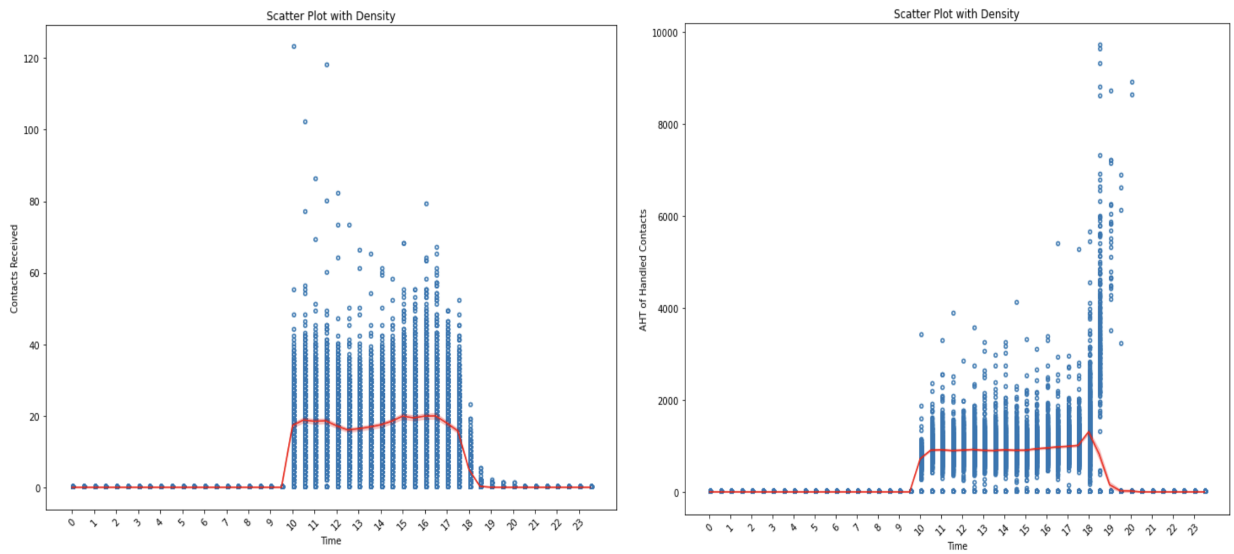


Figure 2 Hourly Distribution of Contacts Received and AHT

Seasonal fluctuations are evident when consistent and recurring patterns emerge over specific intervals, attributable to seasonal determinants. Such patterns can be a consequence of annual cycles, monthly variations, weekly trends, or diurnal rhythms. Examining daily volume distributions is pivotal for deciphering customer dynamics. From Figure 2, the Hourly Distribution of Contacts Received depicts that the majority of the processing times are clustered between 10:00 and 18:00. Notably, there are distinct peaks observed during the morning and afternoon intervals, complemented by noticeable troughs around the lunchtime period.

From the Hourly Distribution of AHT, we observed that the AHT is getting longer while the contact received volume is decreasing around 18:00. Based on this behavior, there are some operation actions that may cause this behavior:

1. End-of-Day Complex Queries: By the evening, customers who could not find answers during regular business hours may resort to calling the support center. These queries might be more complex, requiring longer handling time.
2. Fatigue: If agents have been working throughout the day, by evening, fatigue might set in, leading to reduced efficiency and longer handle times.
3. System or Technical Issues: Sometimes, there might be technical issues with the tools or systems the agents use, especially if maintenance or backups are scheduled during these times.
4. Training Needs: If newer or less experienced agents are scheduled during this time, they might take longer to resolve queries, hence increasing the AHT.

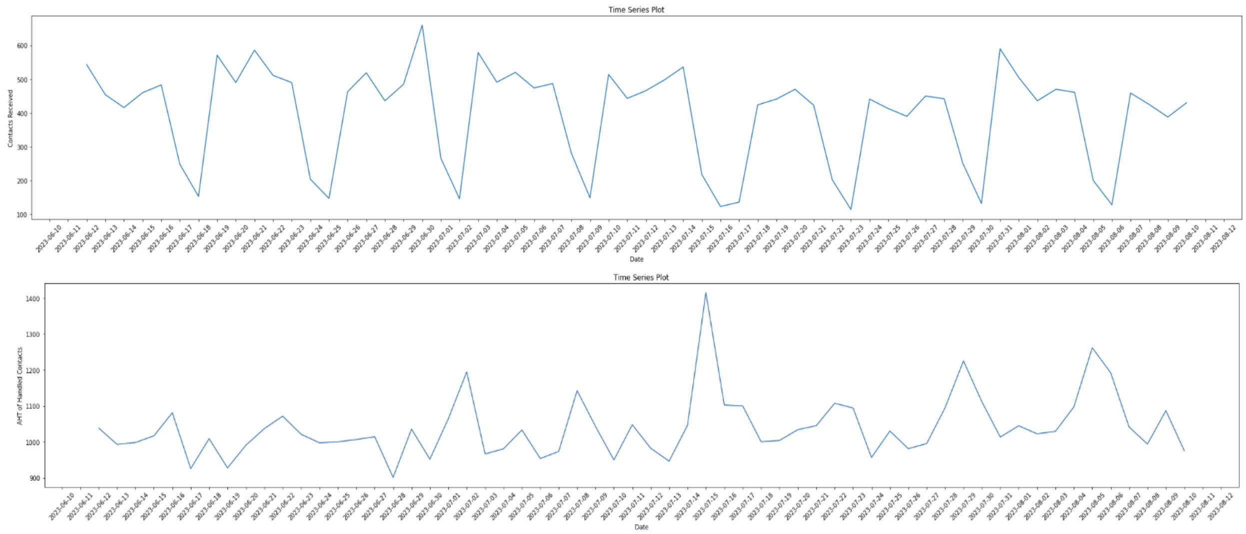


Figure 3 Contacts Received and AHT of The most recent 60 days

The above graph shows the Contacts Received volume and AHT of The most recent 60 days. From the Contacts Received Graph, we can see a clear weekly trend, approximately 4 spikes every month.

For the AHT of The most recent 60 days, it can be observed that the Handle time also declines during the weekends, with Friday seeing a peak in processing time.

Furthermore, isolating the most recent 60 days of data for observation, we notice from Figure 4 that the numbers of received contacts significantly decrease on Saturdays and Sundays, approximately 166 and 106 respectively. Meanwhile, the counts from Monday to Friday remain relatively stable, fluctuating around 350.

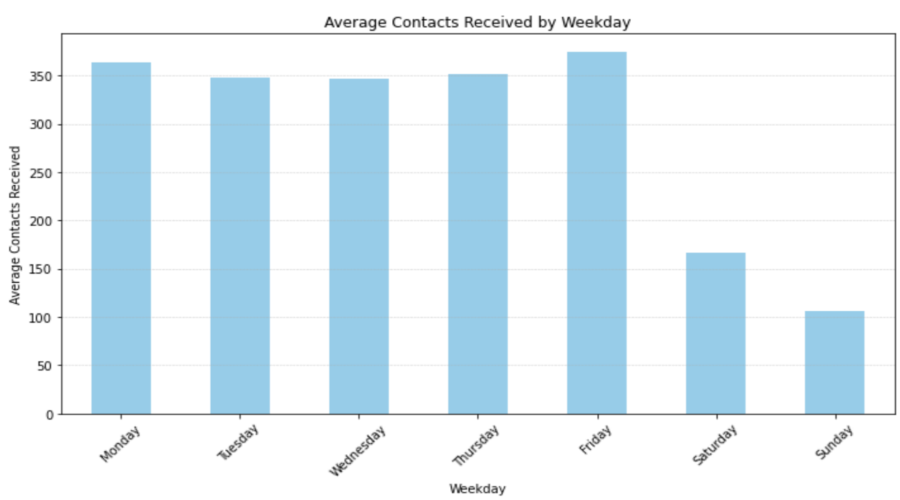


Figure 4 Average Contacts Received by Weekday

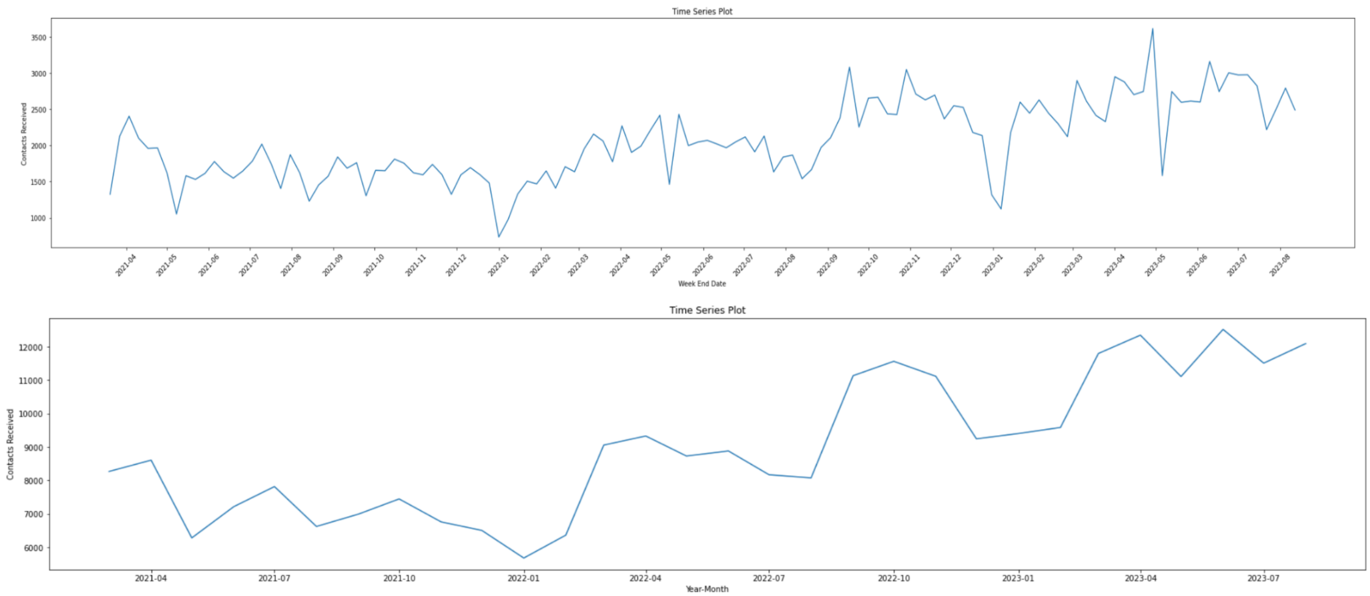


Figure 5 Weekly and Monthly Contacts Received Volume

When we take a look at the Weekly and Monthly Contacts Received Volume. we can deduce that the contacts have been gradually increasing. The trough was observed in December and January, after which there was a gradual rise. By April, the trend stabilized, and then an increase commenced again in August, continuing until November.

3.3 Noise

Our time series data may also contain a noise component. We identify the presence of white noise when the measurements are independent, identically distributed, and have a mean of zero. This implies that all our measurements maintain consistent variance and exhibit no correlation with any other values in the series.

If our time series exhibits white noise characteristics, it indicates that this component of the series is random and unpredictable, then our next step of modeling should be to produce errors that closely resemble this white noise.

We shall observe the noise for our series by checking the series histogram, correlation plots, standard deviation histogram, and means over time.

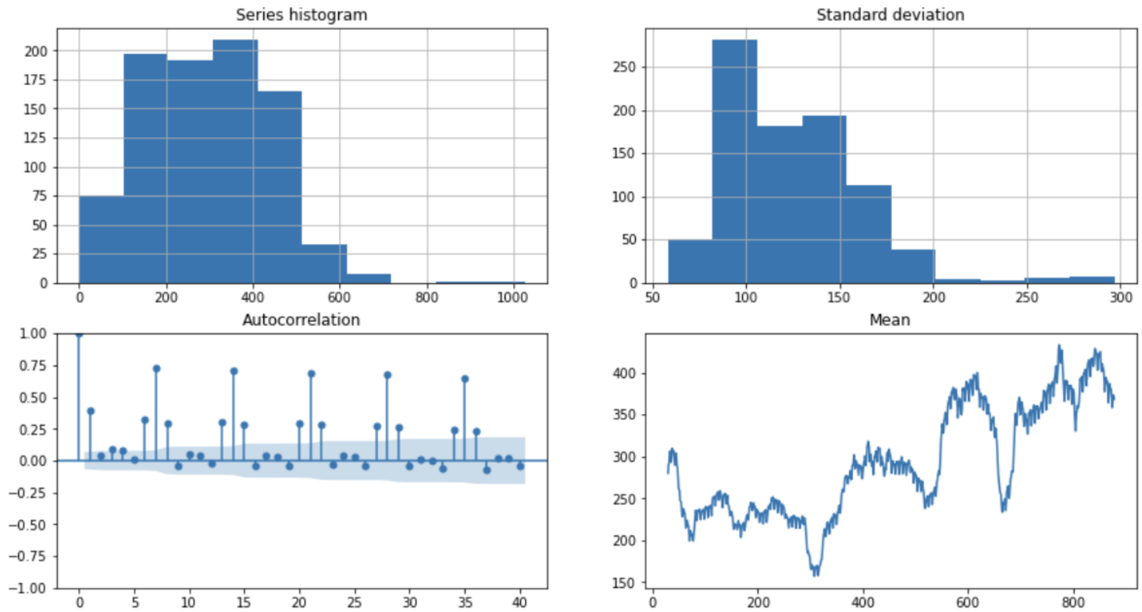


Figure 5 Weekly and Monthly Contacts Received Volume

From Figure 5, we shall see our histogram of time series data does not exhibit constant standard deviation, deviating from a Gaussian (normal) distribution. The standard deviation is centered around the mean, indicating the presence of a minor component of white noise that cannot be decoupled from the original series. Additionally, there's a high correlation with temporally adjacent data points, but this correlation diminishes with temporally distant measurements. Then, both the mean and standard deviation exhibit consistent behavior throughout the observed period. Therefore, based on our analysis, the time series contains components of white noise. Let’s take a closer look at Autocorrelation plots.

3.5 Stationarity

3.5.1 Autocorrelation and Partial Autocorrelation Plots

Stationarity is a crucial feature of time series data. A time series is considered stationary if it maintains a consistent mean and variance over time. Many models primarily operate with stationary data because it simplifies the modeling process. Autocorrelation plots illustrate the correlation of values at time t with subsequent time values. For a stationary series, autocorrelation values tend to diminish rapidly over time.

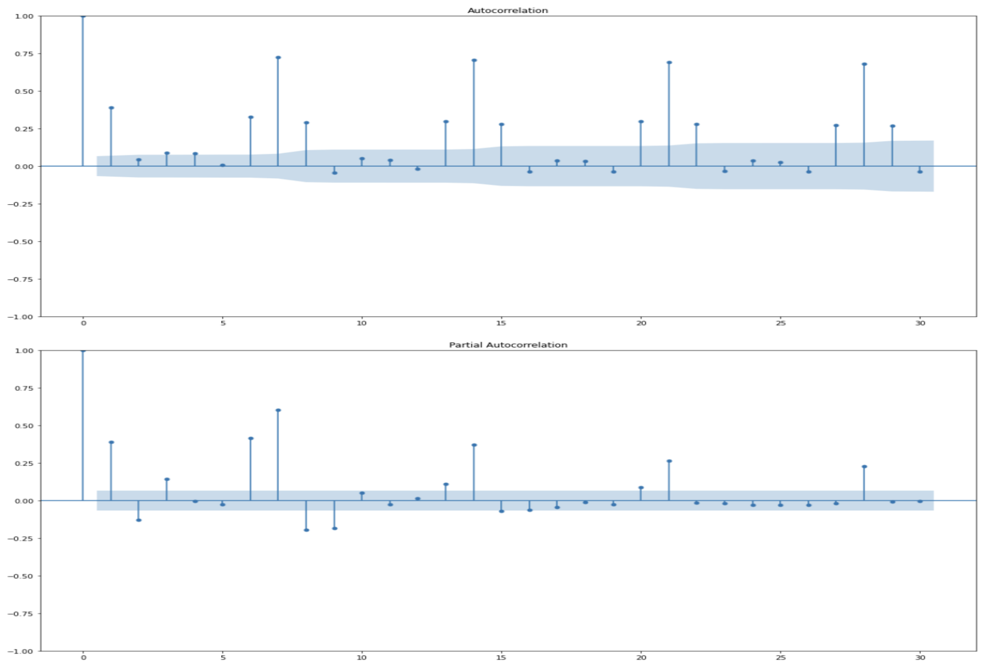


Figure 6 Autocorrelation and Partial autocorrelation plots

From Figure 6 presented, we observe that there are significant autocorrelations at lagged time points, suggesting the potential presence of seasonality or long-term trends in the data. Also, as the time lag t increases, the autocorrelation values do not exhibit rapid decay.

In conclusion, both observations indicate that information persists over time intervals, suggesting that the time series might be non-stationary.

Moreover, we could also check the stationary by conducting the Augmented Dickey-Fuller Hypothesis test.

3.5.2 Dickey-Fuller Hypothesis test

The Augmented Dickey-Fuller test is a type of statistical test called a unit root test. The intuition behind a unit root test is that it determines how strongly a time series is defined by a trend.

The null hypothesis of the test is the time series possesses a unit root, which indicates non-stationarity. Alternately, the alternate hypothesis (rejecting the null hypothesis) is that the time series is stationary. The P-value is evaluated based on the 0.05 threshold, if the p-value > 0.05 then, we shall Fail to reject the null hypothesis, and vice versa.

After conducting the test, we observed a p-value of 0.279978, which is greater than 0.05. Therefore, we fail to reject the null hypothesis (H0), the data has a unit root and is non-stationary. In conclusion, the error in our model is relatively significant, and further optimization is required.

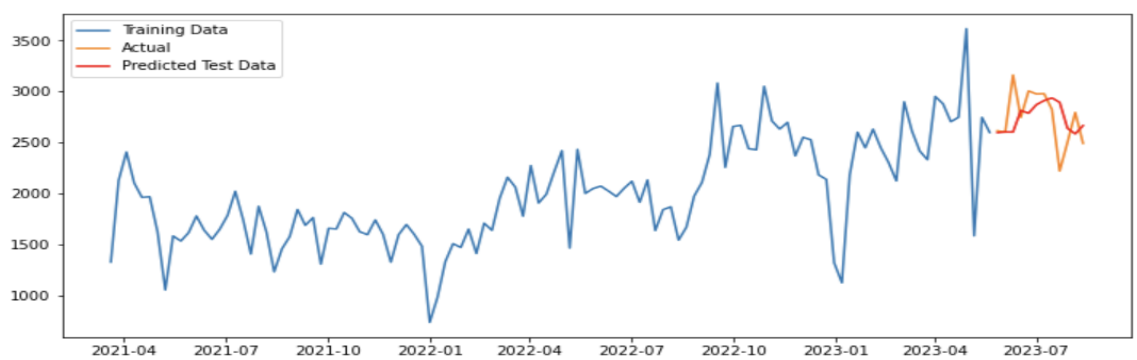
Based on our result, in this project, we will use the AUTO-ARIMA method, it will internally try different levels of differencing to identify the best model. Thus, we don't have to manually make the series stationary before feeding it to auto-arima.

4. Prediction

For our model selection, I decided to conduct both ARIMA and SARIMA on monthly volume prediction and weekly volume prediction. We will use AUTO-ARIMA for time-saving and to optimize our parameter selection. However, while Auto ARIMA provides several advantages, it's essential to recognize that it's not a silver bullet, sometimes we need to make some adjustments by hand in order to forecast the right values.

4.1 Weekly volume forecasting (next 12 weeks)

4.1.1 ARIMA



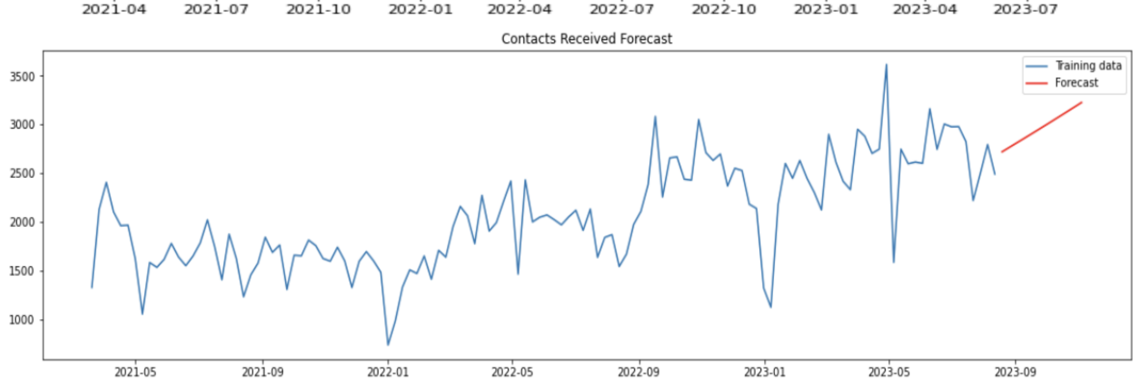


Figure 7 ARIMA result for Weekly volume forecasting without Adj.

As we can see from Figure 7, the ARIMA result after the optimal parameter by the auto-arima method is considered a bad performance based on our series, since there are no cyclic patterns showing in further weeks, it will be hard for us to conduct further workload and workforce forecasting and creating flexible weekly staffing plan.

In order to get a better performance, we shall make adjustments based on our model.

The underlying idea for this adjustment method involves analyzing historical data to identify analogous cycles.

More specifically, we first observe whether there is a regular trend or cycle in the historical data. Then we shall extract periods corresponding to the same week predict range or month from the previous year or previous cycle.

After performing forecasting on this extracted range, comparisons are made against the actual historical values. Discrepancies observed between the forecasted and actual historical values are then used to adjust our initial forecast for the future. This ensures that our forecasted data conforms to observed seasonality patterns. A more detailed approach will be shown in the Jupiter notebook.

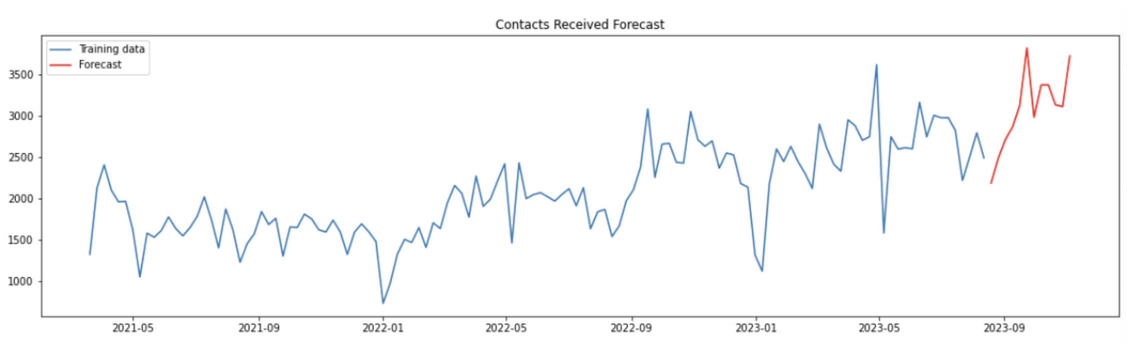


Figure 8 ARIMA result for Weekly volume forecasting with Adj.

Following the modification, as depicted in Figure 8, the time series exhibits improved statistical properties. We will proceed to evaluate the SARIMA model to ascertain potential optimizations in predictive performance.

4.1.2 SARIMA

The Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) serve as primary metrics in assessing the efficacy of our time series models, with lower values indicating superior performance. In our analysis, the SARIMA model outperformed the standard ARIMA model in terms of both MAE (182.305 versus 195.74) and MAPE (0.06997 versus 0.0737) on the test set. This superiority can be attributed to the pronounced and consistent seasonal components present in our time series data, be they monthly or yearly patterns. The SARIMA model, by design, excels in capturing such seasonality, whereas a conventional ARIMA model might find it challenging to deliver precise forecasts under these conditions.

***TASK 1**

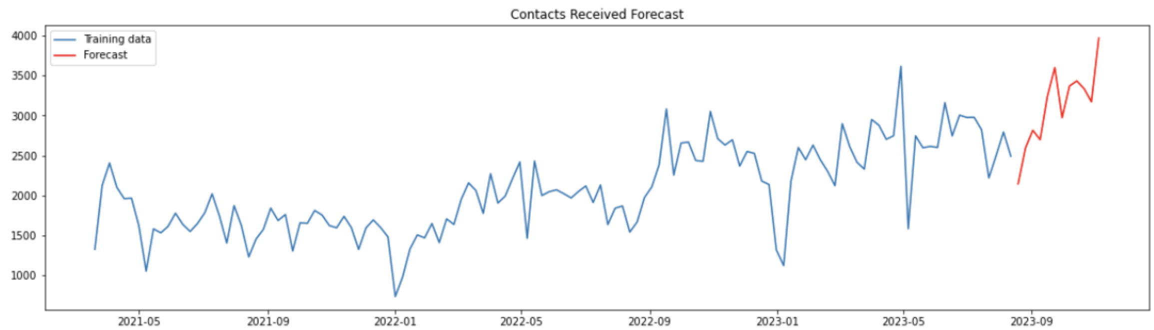


Figure 9 SARIMA result for Weekly volume forecasting with Adj.

After conducting the SARIMA model and adjustment, I decided to use this result as our best performance for Weekly received volume forecasting. Forecast results will show in both Jupiter Notebook and Google Sheets.

***TASK 2**

4.2 Best Monthly Volume Forecasting (next 18 months)

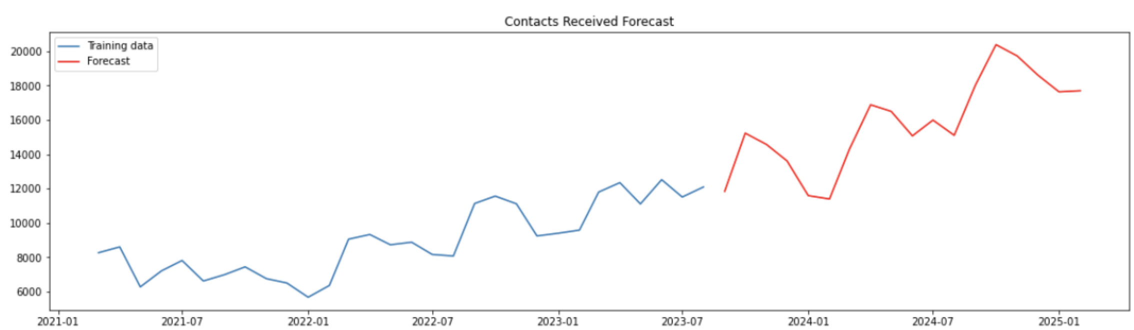


Figure 10 SARIMA result for Monthly volume forecasting with Adj.

4.3 Best Monthly AHT forecasting (next year/ 16 months)

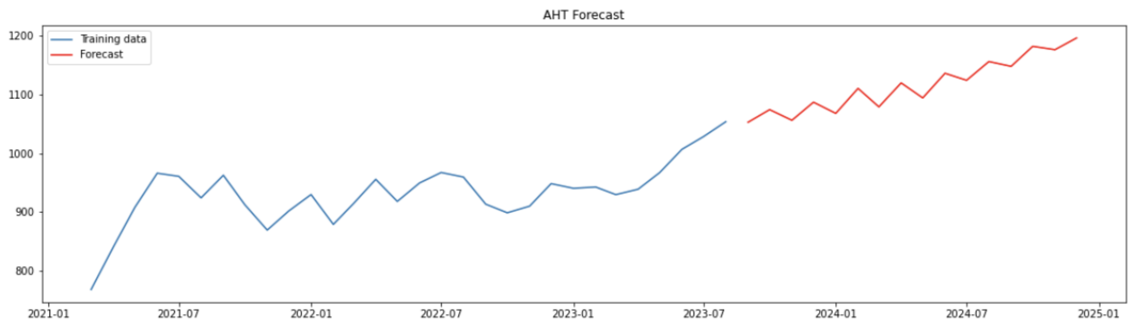


Figure 11 ARIMA result for Monthly volume forecasting with Adj.

***TASK 3**

4.4 Monthly HT forecasting (next year /16 months)

Based on the result of monthly AHT and Contacts received volume forecasting, we could simply predict the Handled Time for next year by multiplying the forecasting results of Contacts received and AHT. Figure 12 show the forecasting of HT result for next year or the next 16 months.

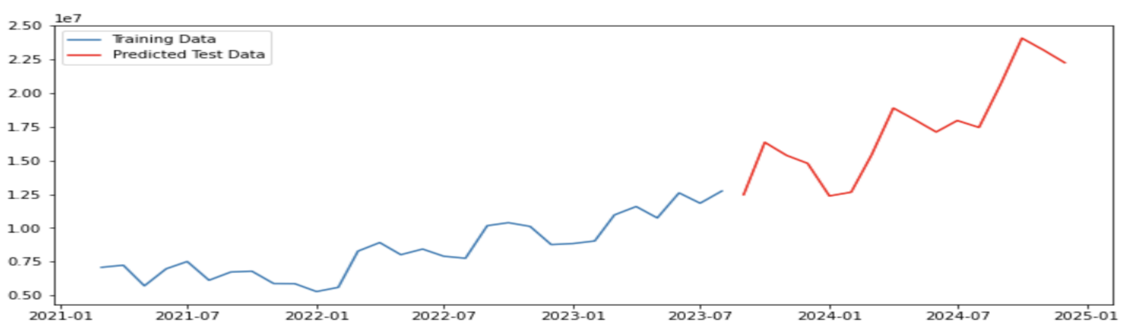


Figure 12 Forecast result for Monthly HT

5. Conclusion

Firstly, from Figures 9 and 10, we observe that while there are fluctuations in the forecasted received volume, the overarching trend demonstrates an upward trajectory. By the end of 2023, the projected weekly received volume is anticipated to reach approximately 4,000. This upward trend signifies an increasing workload and staff demand, necessitating adjustments in our workforce planning to prevent exacerbating staffing gaps and potential service shortfalls.

Furthermore, this surge in volume indicates the company's business expansion, with a consequent rise in customer service requirements. It's pertinent to note, considering historical patterns, that these volume surges may be seasonally influenced, potentially due to peak consumption periods.

Secondly, referencing Figures 12 and 10, we discern a correlation between an increase in monthly received volume and the time operators allocate to address customer inquiries. For example, as received volume increases, operators will spend more time handling customer requests. This observation suggests that as received volume augments, it will proportionally impact the Average Handle Time (AHT) in subsequent periods due to their strong correlation.

Lastly, our forecasted AHT presents an escalating trend in the coming months. This could hint at diminishing operator efficiency or the complications introduced by rising received volumes. As the business expands, it is plausible to anticipate the influx of more intricate customer requests.