Short-Term Restaurant Customer Flow Forecasting with ARIMA

1. Problem Statement

Customer flow in the catering industry shows significant time fluctuations, mainly affected by weekly seasonality, holidays, and short-term events. An effective forecast of future customer flow is beneficial for supporting restaurant decision-making, including optimizing work schedules and inventory arrangements, thereby improving operational efficiency and reducing resource waste.

Based on the Kaggle Recruit Restaurant Visitor Forecasting dataset, we construct a daily customer flow time series using data from a single restaurant. We select one popular restaurant and aim to forecast the number of customers over the next three weeks (21 days). This task belongs to a univariate time series forecasting problem. We apply ARIMA model and analyze its performance in a short-term forecasting scenario.

2. Dataset Introduction and Preprocessing

2.1 Single Store Data and Sample Size

Our dataset only keeps customer visit dates from 2016-01-02 to 2017-04-22 and the corresponding number of visits. After data collection and filtering, we obtained 478 consecutive daily observations, which are used as the input data for subsequent modeling and forecasting analysis.

2.2 Data Preprocessing and Time Series Construction

Data preprocessing includes unifying the date format, sorting records by date, and checking for duplicate or abnormal values. We then construct a daily time series indexed by date, ensuring that the data are continuous and that the time order is correct.

2.3 Time Settings and Model Inputs

With 478 daily observations, weekly seasonality is displayed by setting frequency = 7 in the ts() function. This setting only affects the representation of seasonal structure, while the data remain at daily granularity.
The ARIMA model uses a univariate customer visit sequence for modeling, while Prophet applies the ds and y format to fit trend and seasonality and generate forecasting results.

3. ARIMA Model Construction

3.1 Stationarity and Randomness Analysis

From the original restaurant time plot (Figure 1), we observe that the fluctuation range of the series increases over time, indicating clear heteroskedasticity. The series also shows a stable weekly cycle and short-term abnormal fluctuations. Overall, the original customer visit series is non-stationary.

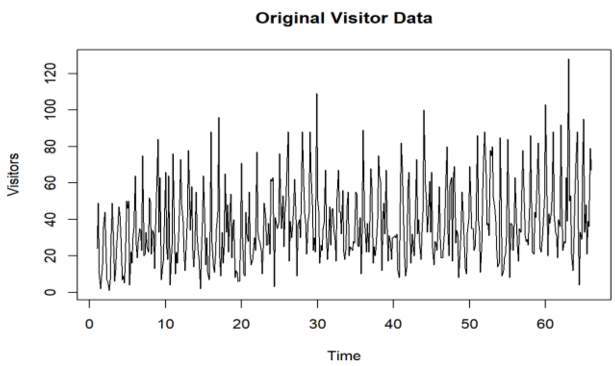

Figure 1. Time Series of Original Daily Restaurant Visitor Counts

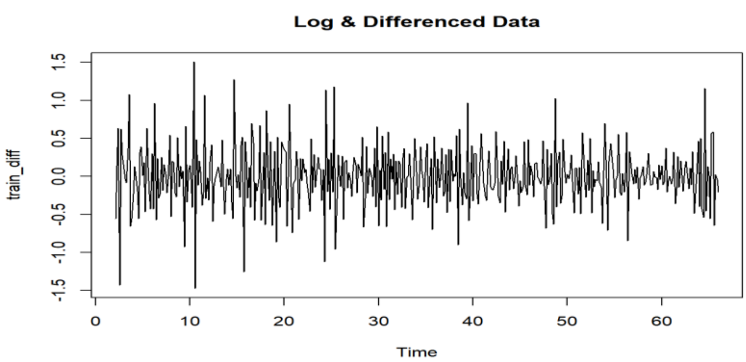

Figure 2. Time Series of Transformed Restaurant Visitor Counts

To mitigate heteroskedasticity, we first apply a base-10 logarithmic transformation to the series. Then, a first-order differencing is performed to remove the long-term trend. In addition, considering the evident weekly seasonality in customer visits, seasonal differencing with a lag of 7 is introduced. After these transformations and differencing steps, the fluctuation range converges visibly, and the time series structure becomes more stable (Figure 2).

Based on the transformed series, we conduct the Augmented Dickey–Fuller (ADF) test after logarithmic transformation, first-order differencing, and seasonal differencing. The test results show that the Dickey–Fuller statistic is −10.258 with a p-value smaller than 0.01, which strongly rejects the null hypothesis of a unit root. This indicates that the processed series satisfies the stationarity requirement and is suitable for subsequent ARIMA modeling.

3.2 Autocorrelation and Partial Autocorrelation Analysis and Initial Model Selection

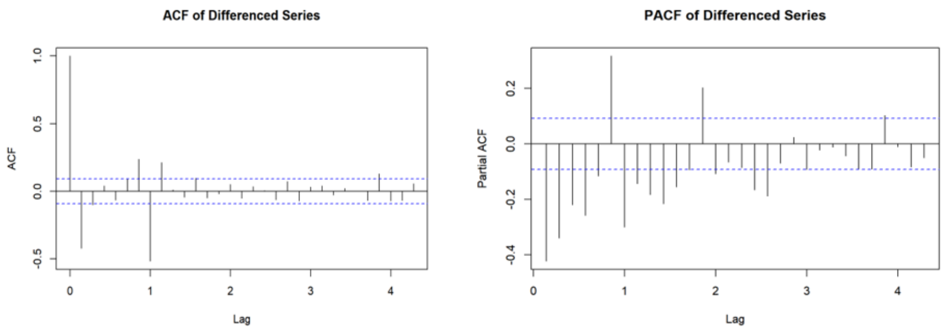

Figure 3. ACF and PACF Plots of the Processed Time Series

After obtaining a stationary series, we analyze its autocorrelation function (ACF) and partial autocorrelation function (PACF). The results are shown in Figure 3. The ACF exhibits a significant spike at lag 1 in the non-seasonal component, and clear correlation at the seasonal lag where s=7. This indicates that the series contains moving average structures in both the non-seasonal and seasonal components.

Based on the overall behavior of the ACF and PACF plots, this study selects ARIMA(0,1,1) × (0,1,1)[7] as the initial model. In this specification, the non-seasonal part applies first-order differencing and an MA(1) term, while the seasonal part uses first-order seasonal differencing with a period of 7 and a seasonal MA(1) term. This model will be further validated and adjusted based on information criteria and residual diagnostics in the subsequent analysis.

3.3 Model Fitting and Residual Diagnostics

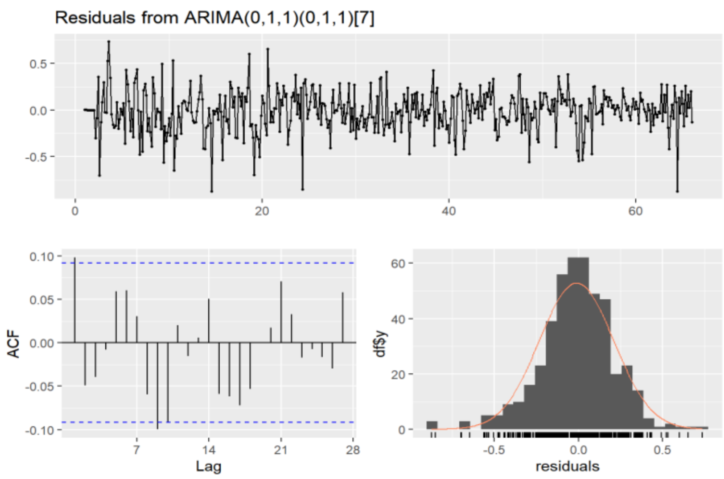

Figure 4 Residual Diagnostics of the Initial ARIMA Model

After selecting ARIMA(0,1,1) × (0,1,1) [7] as the initial model, we conduct residual diagnostics to evaluate model adequacy. The Ljung–Box test yields a p-value of 0.04025, which is smaller than 0.05, indicating that the residuals do not fully satisfy the white noise assumption and that some unmodeled structure remains in the series.

Further investigation of the residual ACF shows significant correlation at lag = 1, and periodic fluctuations are still observed at some seasonal lags (e.g., lag 14 and 21). This suggests that the model does not completely capture short-term dependence and multi-week seasonal patterns in the data. Based on these residual characteristics, we adjust the non-seasonal and seasonal orders of the model and evaluate alternative specifications using information criteria and residual diagnostics.

3.4 Model Selection and Final Model Determination

Table1 Comparison of Candidate SARIMA Models Based on AIC and ADF Test

model	df	AIC	ADF test
ARIMA(1,1,1)×(0,1,1)[7]	4	-49.9007	Passed
ARIMA(1,1,1)×(0,1,2)[7]	5	-48.3160	Passed
ARIMA(1,1,1)×(1,1,1)[7]	5	-48.3730	Passed
Auto model: ARIMA(0,1,2)×(2,0,0)[7]	5	-2.6159	Failed

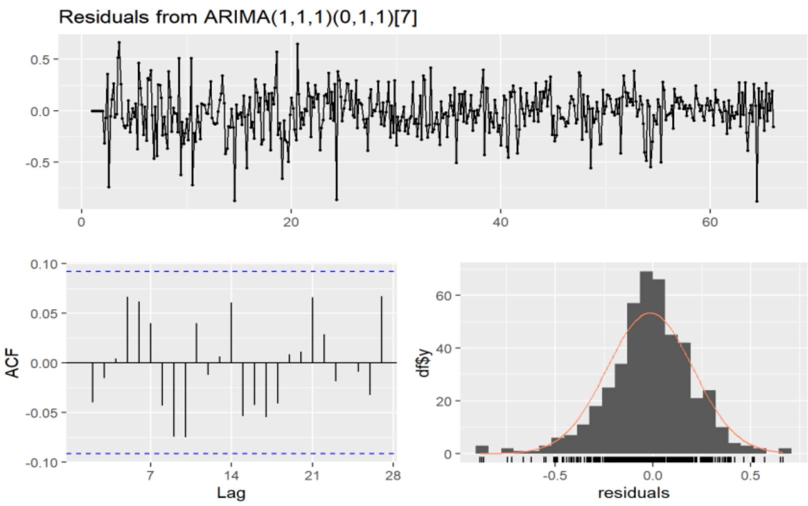

Figure 5 Residual Diagnostics of the Final ARIMA Model

Among multiple candidate models, we conduct a systematic comparison of different ARIMA specifications, as shown in Table 1. Considering the AIC values, stationarity test results, and model complexity together, ARIMA(1,1,1) × (0,1,1)[7] achieves the lowest AIC value (−49.9007) while maintaining a relatively low parameter dimension. In addition, the differenced series under this specification passes the ADF stationarity test.

Based on these results, the final model can be expressed as:

$$(1 - 0.1252B)(1 - B)(1 - B^7)Y_t = (1 - 0.9420B)(1 - 0.9323B^7)Z_t$$

3.4 Forecasting Results and Model Performance

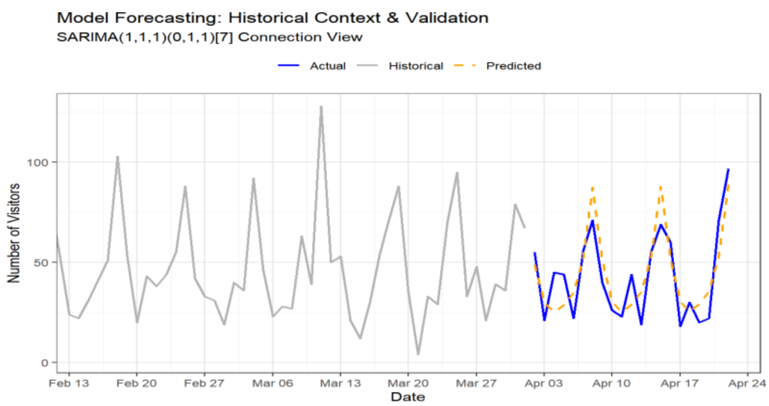

Figure 6. ARIMA Model Forecast of Restaurant Visitor Counts

Figure 6 presents the restaurant customer flow forecasting results based on the final SARIMA model. The predicted curve is generally consistent with the observed values in terms of overall trend. The model is able to effectively capture the regular pattern with a 7-day cycle, demonstrating its strength in short-term seasonal modeling.

Within the validation period, the model achieves an MAE of 10.82 and an RMSE of 12.15. The overall forecasting error remains at an acceptable level, indicating that the model has a certain degree of practicality for the customer volume forecasting task.

Table 2 Forecast Comparison Using ARIMA(1,1,1) × (0,1,1)[7]

Date	Actual_Visitors	Predicted_Visitors	Absolute_Error	Error_Rate
2017-4-2	55	49	5.98	10.87%
2017-4-3	21	30	8.86	42.19%
2017-4-4	45	25	20.02	44.49%
2017-4-5	44	29	15.19	34.52%
2017-4-6	22	35	12.93	58.77%
2017-4-7	56	52	3.64	6.50%
2017-4-8	71	87	16.38	23.07%
2017-4-9	40	51	11.05	27.62%
2017-4-10	26	30	4.24	16.31%
2017-4-11	23	25	2.2	9.57%
2017-4-12	44	29	14.94	33.95%
2017-4-13	19	35	16.23	85.42%
2017-4-14	55	53	2.2	4.00%
2017-4-15	69	88	19.12	27.71%
2017-4-16	60	51	8.52	14.20%
2017-4-17	18	30	12.5	69.44%
2017-4-18	30	25	4.59	15.30%
2017-4-19	20	29	9.3	46.50%
2017-4-20	22	36	13.53	61.50%
2017-4-21	71	53	17.75	25.00%
2017-4-22	97	89	8.13	8.38%

Further analysis shows that the model exhibits systematic bias around peak and trough points in the series. Specifically, it tends to underestimate customer volume during peak periods and overestimate customer volume during low-demand periods. This behavior mainly arises from the ARIMA model relying on historical linear time series structures for prediction. Its ability to capture exogenous shocks, such as holiday effects or unexpected events, is limited, which leads to smoothing effects and mean reversion characteristics in the forecasting results.

In addition, the RMSE is higher than the MAE, indicating that the overall forecasting error is mainly driven by a small number of abnormal fluctuations. This further confirms the model's limitation in predicting extreme time points. Overall, the ARIMA model is able to effectively capture the general trend and periodic structure of customer volume, making it suitable as a baseline forecasting model for short-term operational analysis. However, there remains room for improvement in forecasting accuracy on peak days or abnormal days, which could be achieved by incorporating exogenous variables or adopting more flexible models, such as Prophet.

Appendix A: Supplementary ARIMA Model Plots

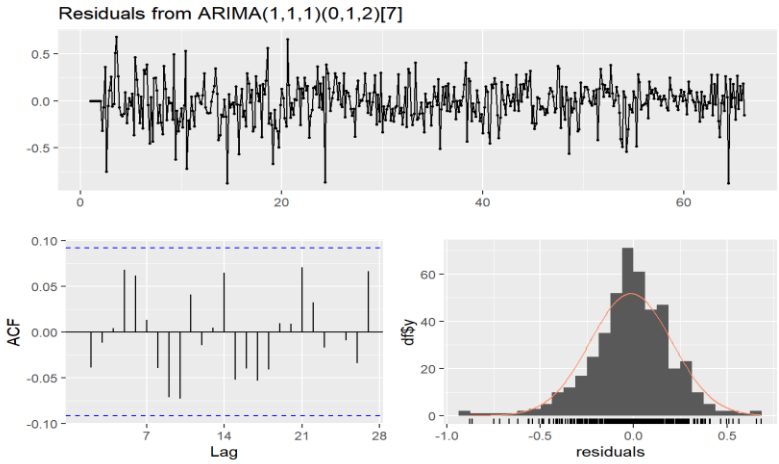

Figure A1. Residual Diagnostics for SARIMA(1,1,1)(0,1,2)[7]

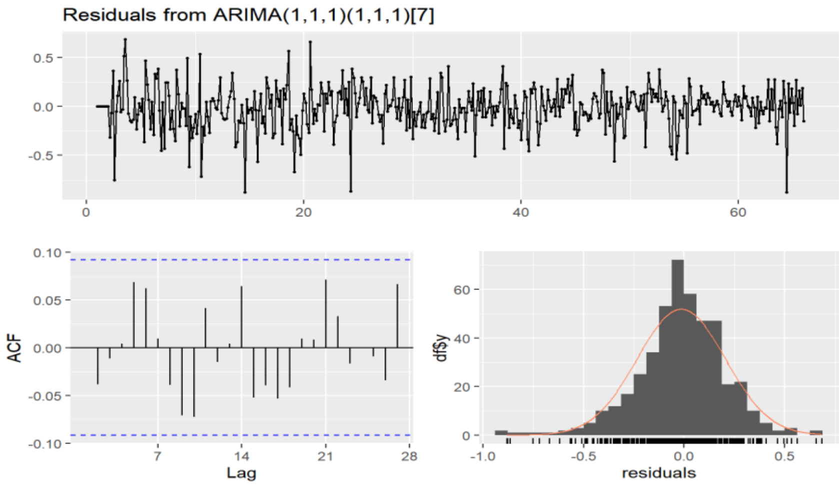

Figure A2. Residual Diagnostics for SARIMA(1,1,1)(1,1,1)[7]

Appendix B: ARIMAX Model Extension with Day-of-Week Dummy Variables

To further eliminate the remaining intra-week correlation structure in the residuals of the baseline SARIMA model, this study introduces day-of-week dummy variables as exogenous regressors and constructs an ARIMAX model. By encoding Monday through Sunday as dummy variables (with one category removed to avoid multicollinearity), the model is able to explicitly capture systematic differences in customer flow between weekdays and weekends.

After incorporating the exogenous variables, the seasonal differencing order is adjusted to D = 0 to avoid over-differencing. The Ljung–Box test p-value for the residuals increases to 0.3043, indicating that the residuals can be regarded as white noise, and the previously observed autocorrelation at certain lags (e.g., lag 9–10) is effectively mitigated. Meanwhile, the model's AIC decreases noticeably, and both training and validation error metrics (MAE and RMSE) improve compared with the baseline SARIMA model. These results suggest that explicitly modeling day-of-week effects helps enhance forecasting accuracy for customer flow during weekdays and weekends.

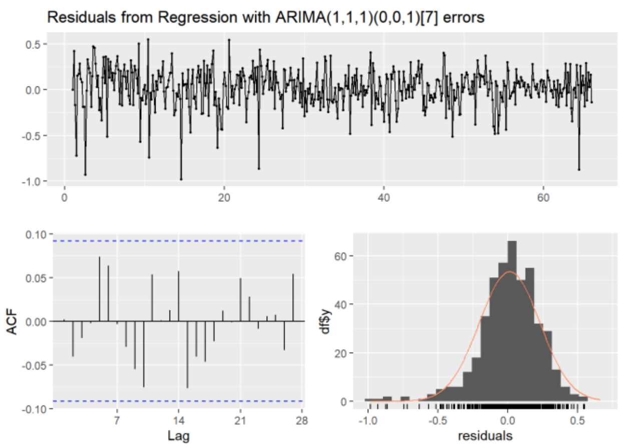

Figure B1. ARIMAX Residual Diagnostics with Dummies

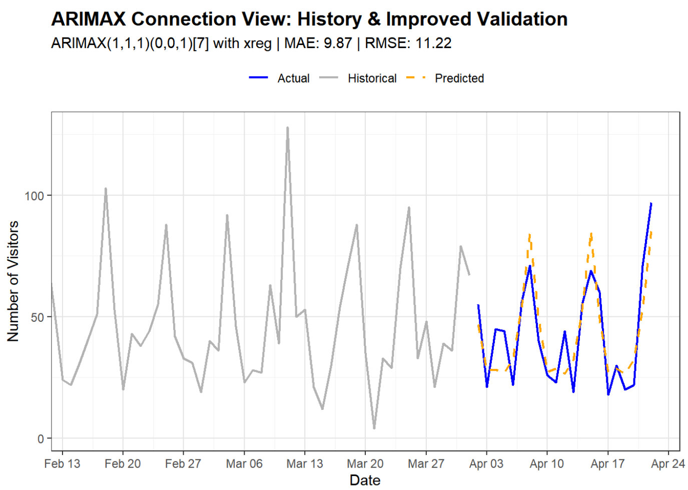

Figure B2. ARIMAX Forecast Results with Dummies