Belly Rubb Analysis Report

Executive Summary

Belly Rubb is a small ghost kitchen in Los Angeles known for its expertly slow-cooked ribs and steak sandwiches, complemented with unique house-made sauces. Since its inception just over a year ago, Belly Rubb has experienced a 139% increase in gross sales. There remain certain areas of uncertainty in their business model however, including the ability to predict sales, number of transactions, and therefore profits. Their transaction data, collected through their POS system Square, was used to forecast their Average Order Value (AOV). This proved insufficient due to the limited amount of data available. Therefore we will need to explore other features to forecast and predict.

Introduction

Belly Rubb is a new business in Los Angeles, having begun its operations at the end of 2023. Since then it has experienced tremendous growth, yet there remains significant variability in its daily transaction, order values, and repeat customers. The data collected through their POS system Square contains much data, including card brand, customer information, and all transactional information. By utilizing the rich amount of features collected, a predictive forecasting model would both be able to help formulate a business plan, as well as understand customer patterns.

In order to explore these features and relationships between them, an in-depth analysis was conducted on the transaction data. The analysis followed the standard data science pipeline with (1) data wrangling and cleaning to prepare the data for exploration, (2) exploratory analysis, (3) feature generation and extraction, (4) preprocessing for modeling, and (5) applying a forecasting model.

Problem Statement

What are the predictions for 2025 for the Average Order Value based on orders in 2024?

Data Overview

Data Collection

The data used for this analysis was collected from the Square website and downloaded in a .csv format. It contains the transactional information for each transaction, including the amount, form of payment, customer information, etc.

Other datasets were also collected from the POS, including detailed customer information, information about menu items, and information about orders separated by menu items. These datasets will be utilized in future analyses.

Feature Overview

A detailed list of features, their datatypes, example data points, and additional notes about them can be found in the data-dictionary.md file found in the docs folder.

Data Cleaning

In order to prepare the data for analysis and modeling, inconsistencies and missing values were appropriately addressed. A streamlined pipeline was created to abstract the process for future datasets. The pipeline addresses common data cleaning issues utilizing a JSON file which stores the appropriate information.

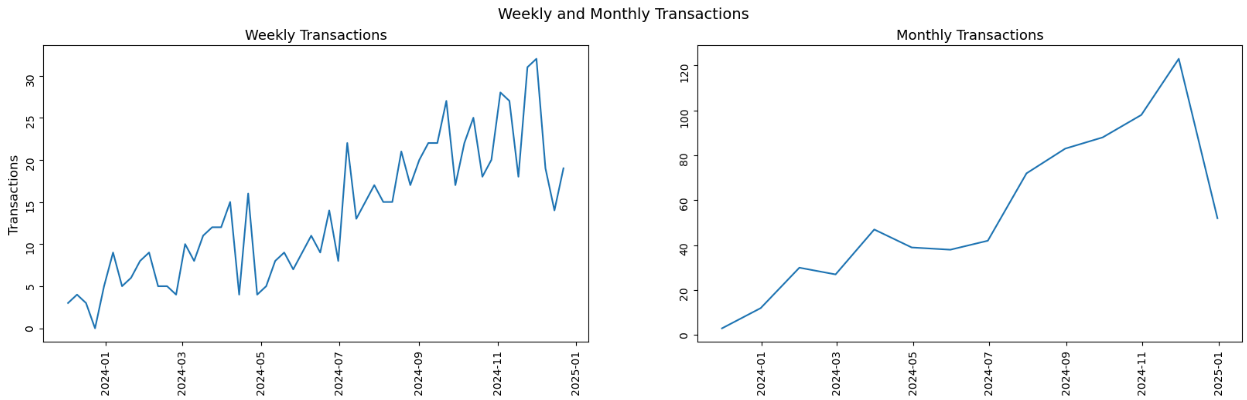
Most notable data cleaning steps in this pipeline include dropping columns or rows with more than 82% data missing, applying the correct data types to features, and auto correcting incorrectly inputted or mispelled entries. These steps ensure consistency in the data resulting in a more informative exploration and model.

Missingness was analyzed as well to determine missingness types. The most common missingness type was Missing Not At Random. Deeper analyses of these missing values revealed that they were dependent on factors such as tender type used, credit card brand used, and portal through which they ordered. Due to this, no imputation was applied to the data in order to not introduce incorrect data.

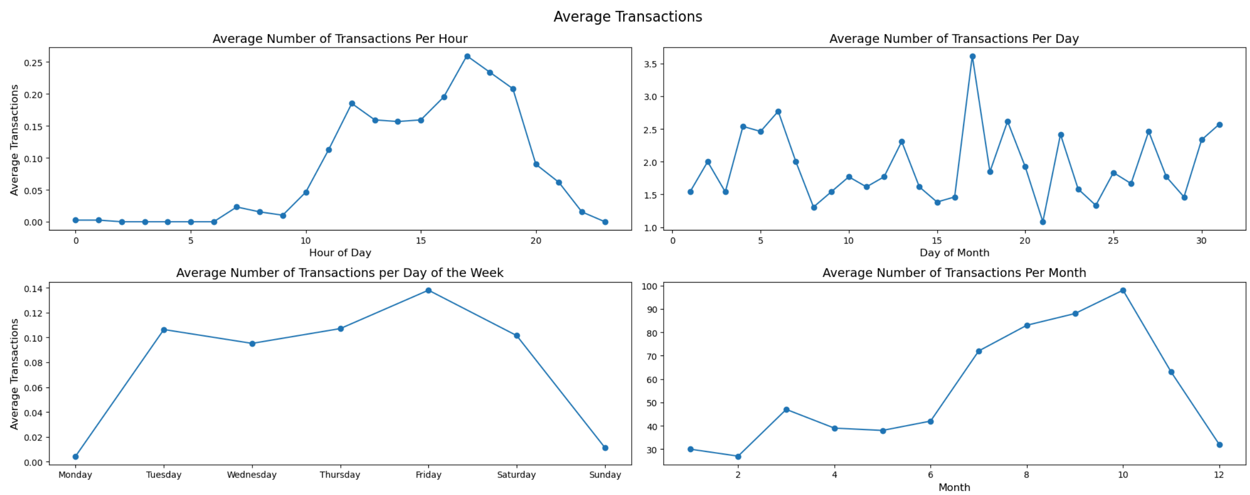
Exploratory Data Analysis Findings

Number of Transactions

Initial plots of the number of transactions appeared to show some seasonality on a weekly frequency, while the monthly showed an upwards trend until November. This prompted a deeper analysis of average transaction counts at different frequencies.

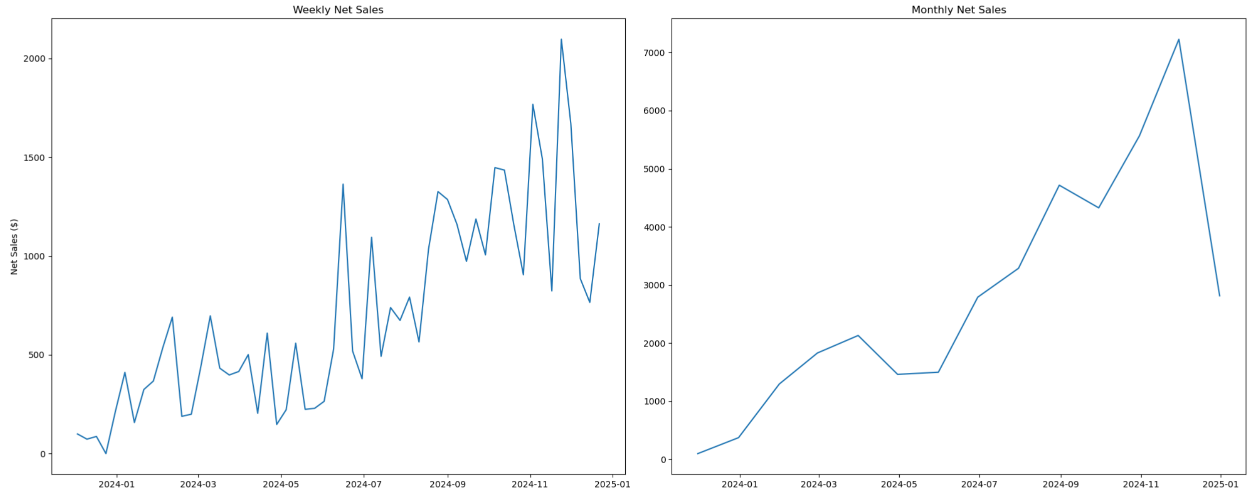


Trends exposed through this analysis follow predictable patterns. For example, more transactions take place during the lunch hour between 12-1, and around 5 for dinner time. More orders are placed close to the end of the week, particularly on Fridays. A slightly discernible pattern reveals itself on a monthly basis, but that can be related to the weekly trend.

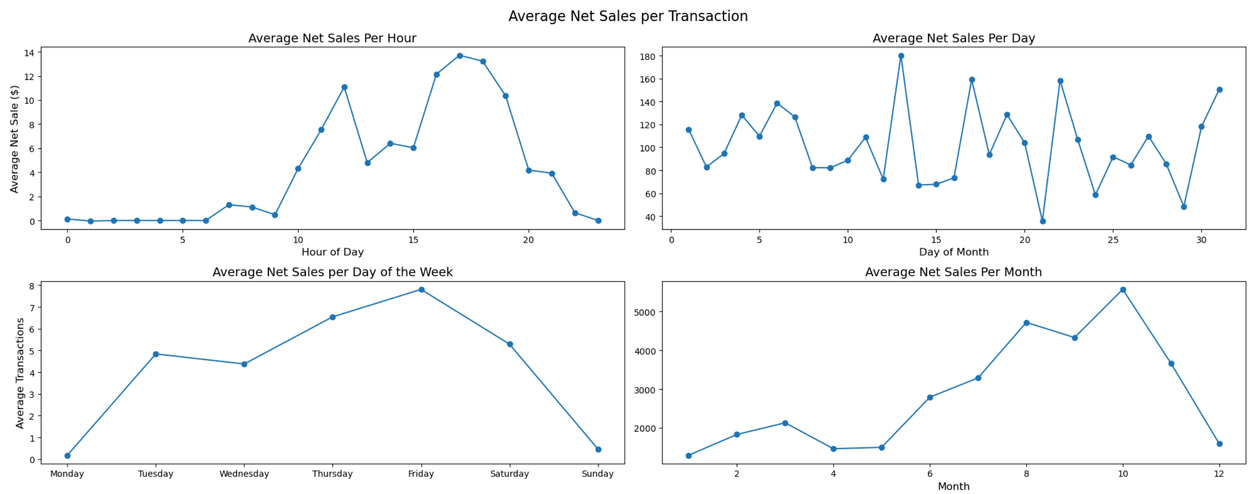


Net Sales

Along with the number of transactions, net or gross sales are required in order to calculate the AOV.

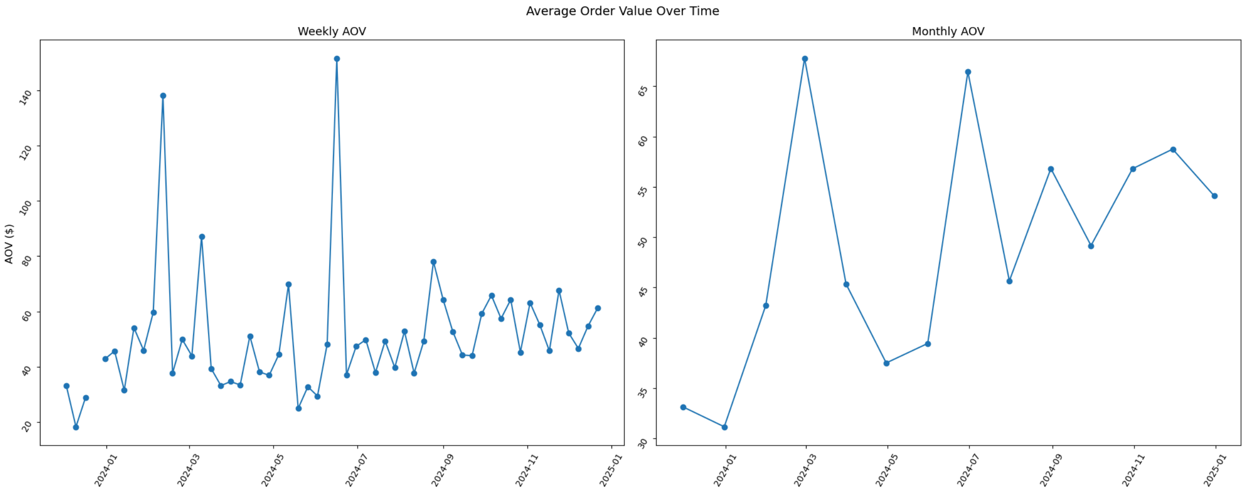


The trends seen here correlated strongly with the number of transactions.

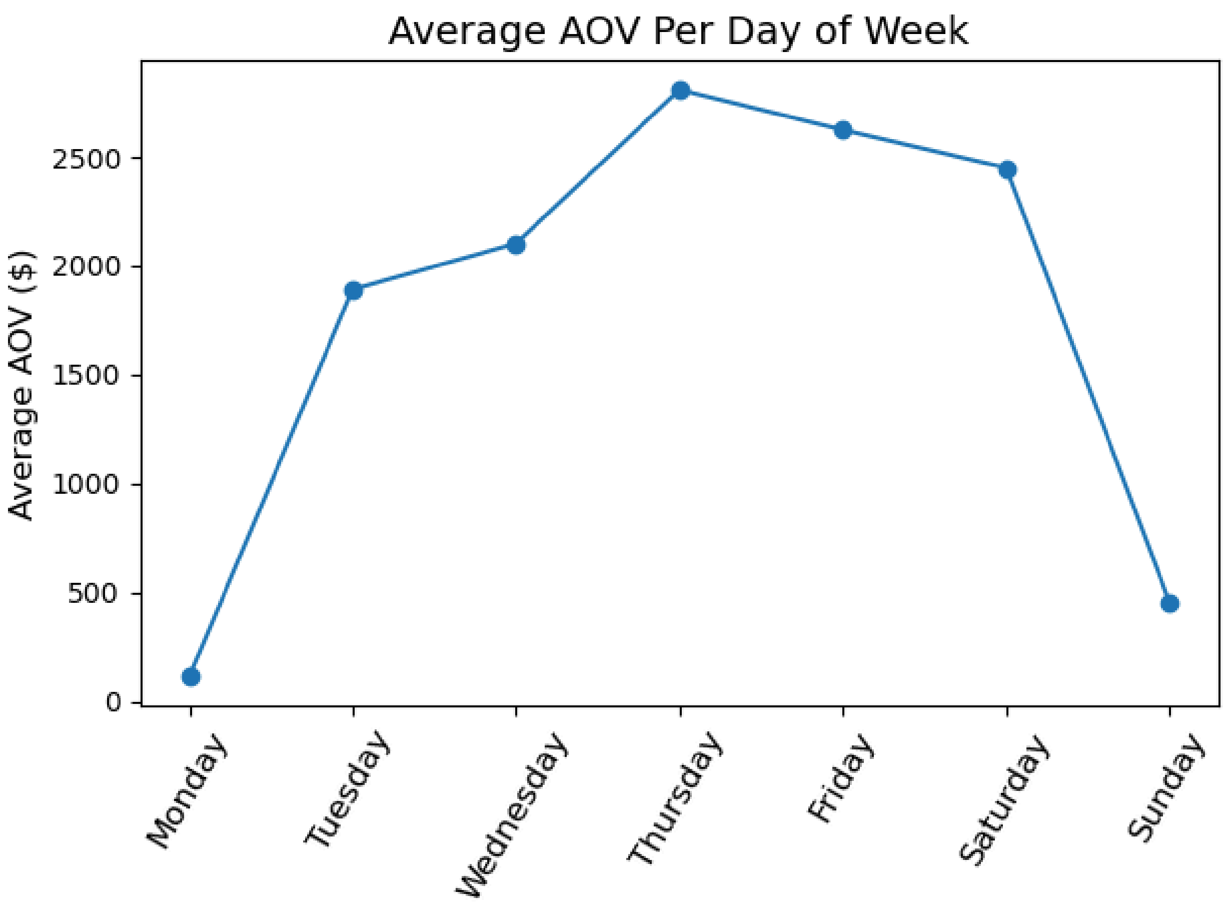


Average Order Value (AOV)

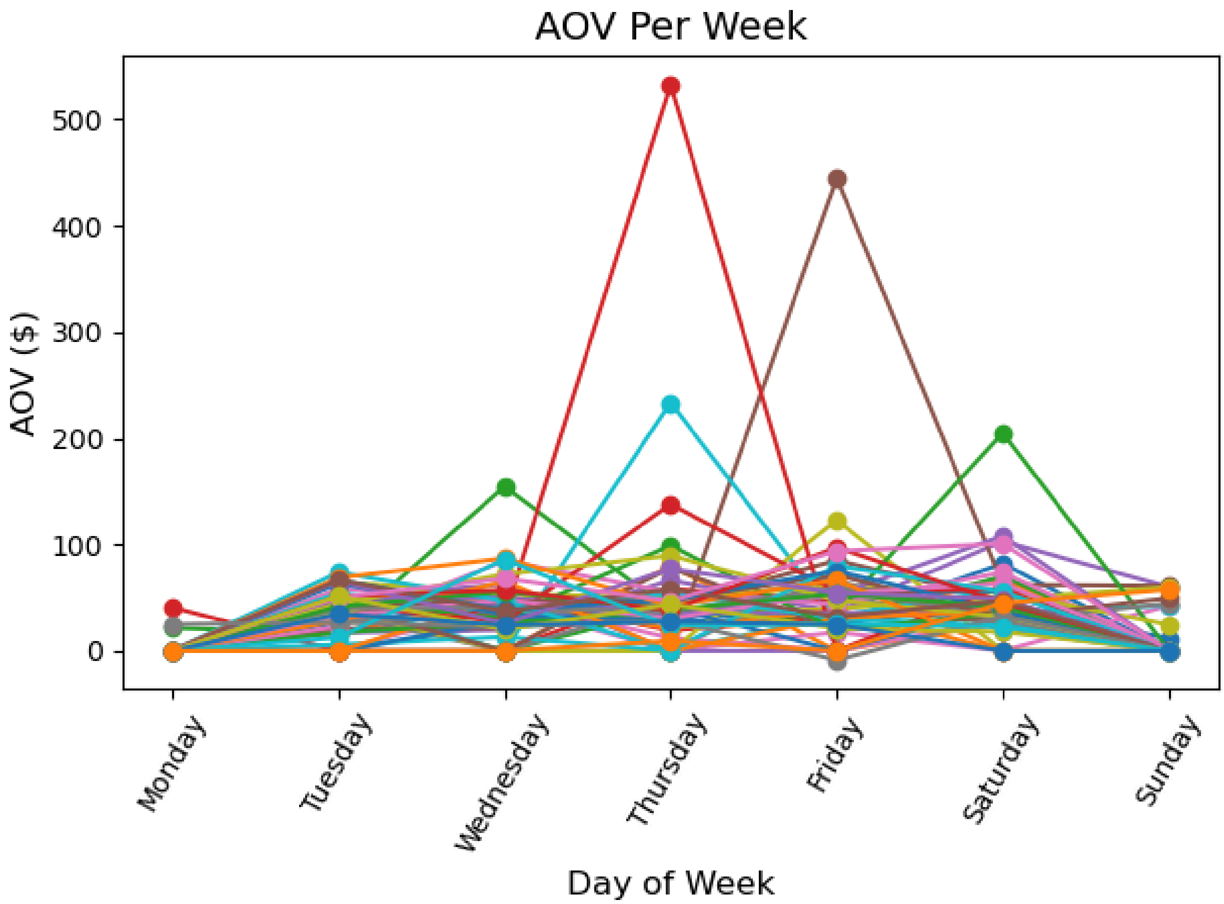
Calculating AOV allows the business owner to determine how much the customer is spending on average on each order. There are two spikes in AOV, but otherwise it seems to be following a slow upwards trend.



What stood out from analyzing AOV trends was that while the number of transactions and net sales are highest on Fridays, the highest average AOV per day of the week occurs on Thursdays.

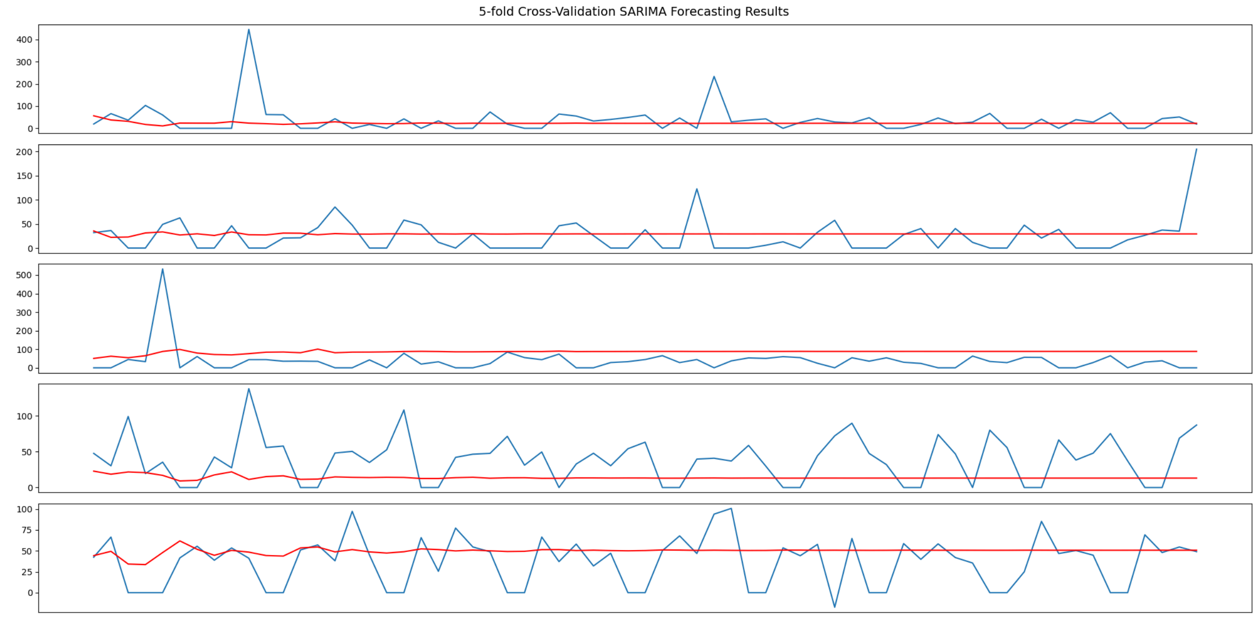


There also appears to be more variability in AOV from Thursday-Saturday. It does not suggest strong seasonality, but there is some as verified by a seasonal decomposition.

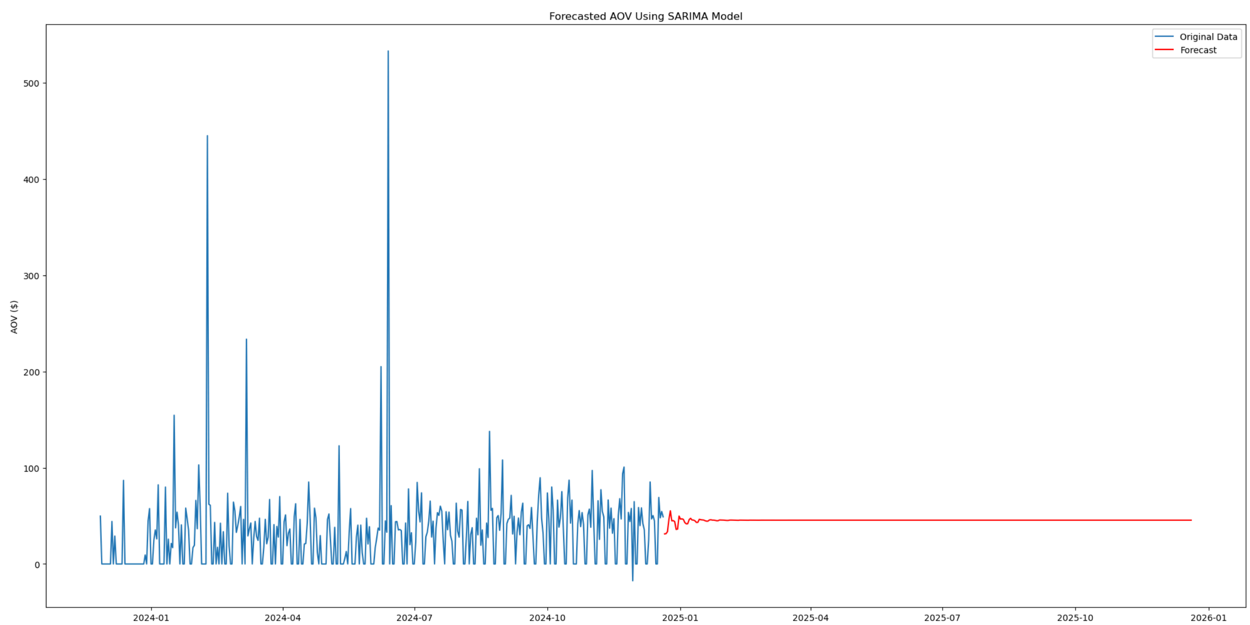


Modeling and Findings

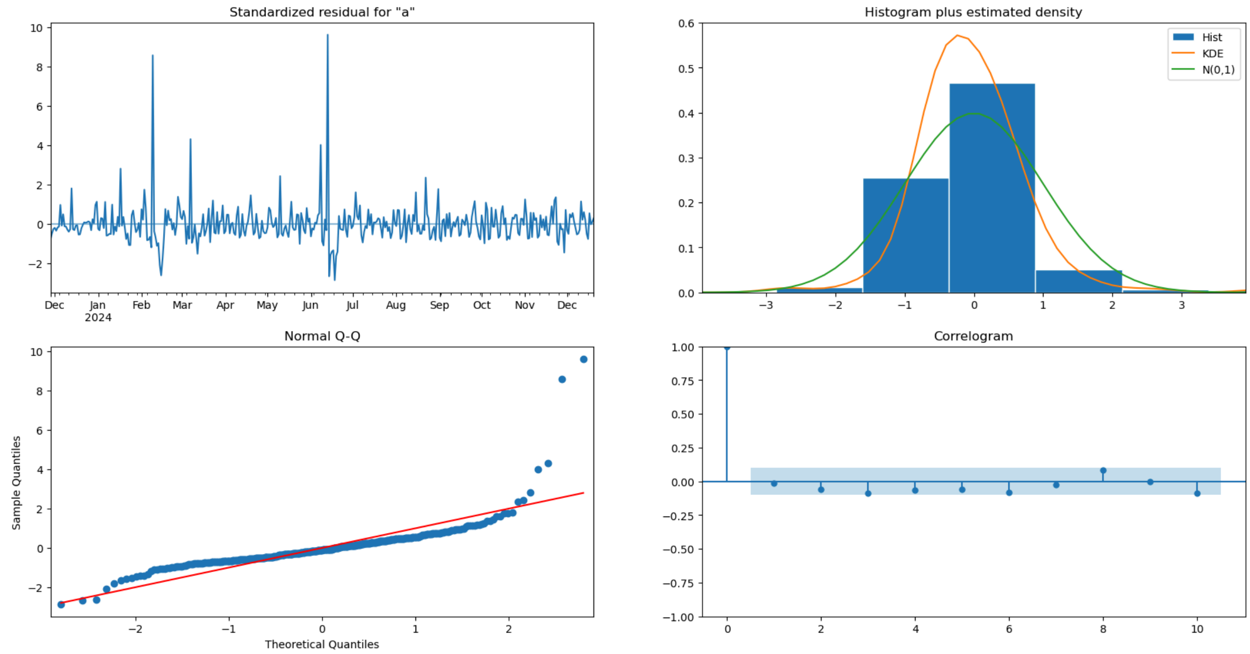
Originally, a model was going to be fit to weekly AOV. However, because of the limited data we were forced into using daily data. The risk behind this decision is that the model will fit much of the noise, which can and did lead to an unstable model. The following plots show the results of a five-fold cross-validation which temporally split the data into a training and test set. Using an automated grid search an optimal SARIMA model was found with an average RSME of $30.



Unfortunately, as shown above, the model did not fit better than using the mean or median to forecast. The following is the forecast it predicted for 2025.



Diagnostic plots of this model also highlight its poor performance.



While the standardized residual does look like noise, and the correlogram does not exhibit much correlation, the residuals are not normally distributed as displayed by the q-q graph. An alternate model with manually inputted seasonal order variables did not perform better.

Recommendations

More data needs to be collected in order to provide a better forecast of AOV. This is simply caused by the short duration the kitchen has been open. Instead of trying to optimize for AOV, it may be more critical to understand how to increase the number of transactions on a daily basis in order to keep trends moving upwards. Once enough data is collected, particularly following promotional campaigns, a better forecast model can be designed.