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Comparison Various Analytical Approaches to Find The Most Efficient and Effective Method for Peak Hour Identification

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***Abstract*— The Peak hour sales identification is essential to manage staff, inventory, and service capacity in coffee shop operations. This study compares an exploratory heatmap with two forecasting models, linear regression and Seasonal ARIMA (SARIMA) using six months of hourly transaction data from a coffee shop (1 March–17 August 2024) . The heatmap offers rapid visual recognition of high traffic periods but provides no predictive capability. For prediction, this study trained a linear regression and a SARIMA specification tuned by standard diagnostics; model performance was assessed on a held out set using MAE, RMSE, and MAPE. Linear regression yielded RMSE = 6.68, MAE = 5.40, and MAPE = 138.06%, indicating inadequate fit for intraday demand dynamics. In contrast, SARIMA achieved RMSE = 0.828, MAE = 0.557, and MAPE = 40.34%, substantially reducing error by explicitly modeling autocorrelation and recurrent seasonal cycles. The results show that seasonality aware time series modeling delivers actionable, interpretable forecasts for near term operational planning (such as staffing and product preparation). Overall, the proposed pipeline, heatmap for rapid situational awareness plus SARIMA for prediction, constitutes a practical baseline for peak hour identification in small scale retail.**

***Index Terms*— Peak hour identification; retail demand forecasting; coffee shop; SARIMA; linear regression; MAE; RMSE; MAPE.**

I. Introduction

The food and beverage service industry, particularly coffee shop, faces persistent challenges in balancing operational costs with service quality, especially in the allocation of labor and the management of inventories. One of critical factor for operational efficiency and revenue optimization is the identification and management of peak hours. The capacity to understand and accurately predict peak hours has become increasingly critical for business sustainability and growth, allow to minimize operational costs while maximizing service quality and revenue generation [1]. Peak hour identification enables coffee shop managers to optimize core operational aspects including staff scheduling, inventory management, and resource allocation [2]. The temporal demand fluctuations (customer traffic) form a distinct patterns which influenced by time of day, day of week, seasonality, and external events. Understaffing during peak periods produces longer wait times, diminished service quality, and lost sales opportunities. Overstaffing during off peak periods leads to unnecessary labor expense. In same conditions, understocking during peak periods leads to stockouts and customer dissatisfaction, while overstocking increases waste and holding costs [3].

Traditional statistics driven forecasting (likes regression analysis and autoregressive integrated moving average (ARIMA)), has been widely employ in retail and hospitality sectors to predict demand patterns [4]. Linear regression models offer simplicity and interpretability which making them attractive for businesses forecasting solutions. However, the effectiveness of these models in capturing complex temporal patterns, seasonality, and trend components remains an open subject of ongoing research. Seasonal Autoregressive Integrated Moving Average (SARIMA) models have become well known as effective forecasting tools in applications where data has strong seasonal patterns. SARIMA enhance the capabilities of traditional ARIMA by augmenting seasonal differencing and seasonal autoregressive with moving average components, enabling more accurate predictions of periodic fluctuations in demand [4]. Although previous methods are widely applied, comparative studies that focus on identifying peak hours demand is limited. Most existing literature focuses on daily or weekly demand aggregation, whereas decision making at the hourly level requires models sensitive to intraday fluctuations [5].

This research aims to address previous gap by comparing the performance of two forecasting methods, linear regression and SARIMA for peak hour identification using transactional data from a local coffee shop. By utilizing advanced data analytics

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techniques, this study streamline the analysis process, reducing the time and effort required to identify the peak hours as critical periods. Our research will focus on comparing various analytical approaches to find the most efficient and effective method for peak hour identification, ultimately enhancing operational efficiency and maximizing sales potential. The performance of each model is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

The remaind of this paper is organized as follows : Section 2 describes the methodology, including data collection, model specifications, and performance evaluation metrics. Section 3 shows the results of the comparative analysis between linear regression and SARIMA models. Section 4 explain and discuss the interpreted of the results and limitations of the study. Section 5 concludes with key insights and directions for future research.

II. Methods

A. Dataset Description

The dataset used in this research represents historical transaction data collected from a coffee shop over 6 months (from 1 March 2024 until 17 August 2024), containing six attributes such as date, datetime, cash_type, card, money and coffe_name. The data downloaded from Kaggle.com : https://www.kaggle.com/code/shivangi124/coffee-sales-analysis. Each observation corresponds to a defined hourly interval, enabling the analysis of temporal sales fluctuations and identification of recurring peak patterns. Data preprocessing steps included normalization to ensure model stability and prevent bias in performance evaluation.

Our research adopts a quantitative, comparative research design to evaluate two analytical techniques : Linear Regression and Seasonal Autoregressive Integrated Moving Average (SARIMA) for identifying and predicting peak hours in coffee shop operations. The objective is to determine which approach provides higher accuracy and operational interpretability in forecasting customer traffic patterns and sales volume.

B. Heatmap

Heatmap is the most general method to do some analytical data by visualizing the dataset. The algorithm to construct a heatmap for identifying peak sales hours and days from coffee sales data is illustrate in Figure 1. The first step to create the heatmap from data is loading the dataset using library Pandas in python. The library loads the CSV into a data frame which simplifies both data manipulation and analysis.

Convert the column datetime to a datetime format. The conversion to datetime enables to extract specific time related features like the day of the week and the hour of the day. Extract features the day of the week and hour from the datetime column. These two features will be used to analyze sales patterns over different times.

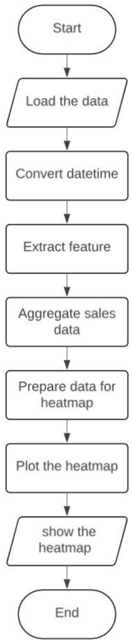

Fig. 1. Algorithm to construct the heatmap

The next step is performing cross classification by day and hour and sum the corresponding sales counts. Aggregate involves grouping the data and summing the sales counts to prepare for visualization.

Prepare the data for the heatmap by using group by to aggregate sales and unstack to format the data.

The last step is plot the heatmap using seaborn. Set appropriate labels and titles to clearly communicate the information. The heatmap will visually represent sales intensity, helping to identify peak sales periods at a glance. Aggregate the sales data by counting the number of sales for each combination of day and hour. This step involves grouping the data and summing the sales counts to prepare for visualization.

C. Linear Regression

Linear regression is the most intuitive and interpretable forecasting models for identifying relationships between dependent and independent variables [6]. In the context of coffee shop demand forecasting, the dependent variable Y_t represents hourly sales, while the independent variables X_t include hour of day and day of week. The linear regression equation is expressed as :

$$Y_t = \beta_0 + \beta_1 X_{1t} + \cdots + \beta_n X_{nt} + \epsilon_t \quad (1)$$

where β_0 denotes the intercept, β_i represents coefficients estimating each predictor contribution, and ϵ_t is the error term [7].

The algorithm to predict peak sales hours and days from coffee sales data using linear regression is illustrate in Figure 2. The pipeline first loads the dataset using pandas and represented as a data frame. The next step converts the datetime attribute into a machine interpretable datetime feature. Extract relevant features from the datetime column. Derive the day of the week and the hour of the day to provide key inputs for the regression model to identify peak sales periods.

Prepare the data by aggregating sales counts for each combination of day and hour, grouping the data and summing sales counts to create a target variable for the regression model. Split the dataset into training and testing sets. The data splitting is fundamental for obtaining reliable performance metrics and ensuring that it generalizes well to unseen data.

The next step in pipeline is building the Linear Regression model and training the model using the training dataset. The built model will learn the relationship between the features and the target variable. In the final step, the trained model is deployed to forecast future sales and identify peak periods. The prediction result need to be analyzed to gain insights when peak sales are likely to occur that can inform business decisions and strategies.

D. SARIMA (Seasonal Autoregressive Integrated Moving Average)

SARIMA is a statistical time series approach extending ARIMA to model data exhibiting both non stationary and seasonal periodic behavior. It is particularly effective for hourly and daily sales data with predictable cyclical patterns [8]. The general form of a SARIMA model is represented as :

$$SARIMA(p,d,q)(P,D,Q)_s \quad (2)$$

where p, d, and q denote the non seasonal autoregressive, difference, and moving average orders. P, D, and Q represent seasonal counterparts. s is the seasonal periodicity [9]. The SARIMA model equation can be expressed as :

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Y_t = \Theta_Q(B^s)\theta_q(B)\epsilon_t \quad (3)$$

where B is the backshift operator, ϵ_t is a white noise error term, and the parameters $(p,d,q)(P,D,Q)$ are determined using autocorrelation (ACF) and partial autocorrelation (PACF) plots [9].

The algorithm to predict peak sales hours and days from coffee sales data using SARIMA illustrate in Figure 3. The pipeline start by parsing the transaction timestamps data. Round each time down to the hour and count how many transactions occur in each hour. Filling any missing hours with zeros so the series is continuous. Split the hourly data series into a training portion (older data) and a testing portion (the most recent period), and build simple features that capture daily and weekly rhythms. Fit a SARIMA model on the training data using those rhythm features, generate predictions for the test window, and check how close they are to the real counts while also plotting train, test, and predictions. The next, forecast the next 14 days hour by hour and save these results (including an uncertainty range) to a file. Finally, compute average transactions for every day of week and hour combination, pick the highest hour for each day as its peak.

The primary advantage of SARIMA lies in its

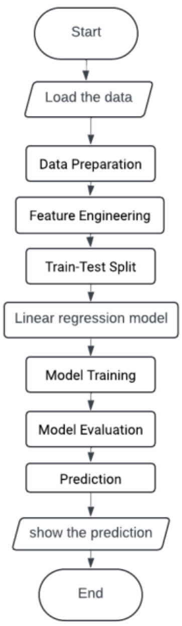

Fig. 2. Linear regression algorithm to predict the peak hours

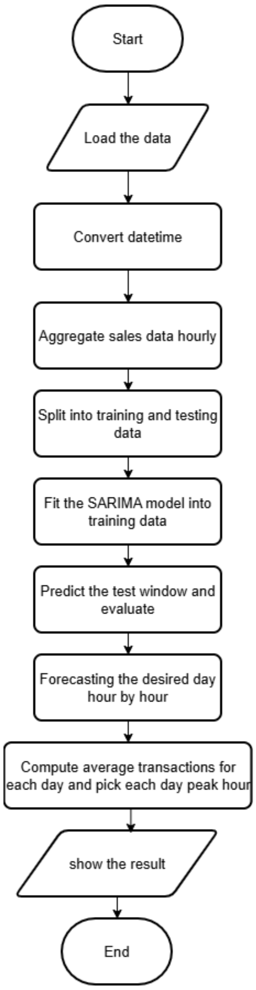

Fig. 3. SARIMA algorithm to predict the peak hours

robustness for univariate seasonal data, producing reliable short term forecasts of hourly demand. Its interpretability in decomposing trend, seasonality, and noise components further supports managerial decisions such as staff scheduling and product preparation during high traffic hours [10].

E. Performance Evaluation Metrics

Both Linear Regression and SARIMA models were evaluated using three quantitative performance metrics to ensure objective comparison :

- Root Mean Square Error (RMSE)

RMSE penalizes larger deviations, emphasizing major forecasting errors. The RMSE equation can be expressed as :

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \quad (4)$$

- Mean Absolute Error (MAE)

MAE measures average absolute deviation, offering interpretability for decision makers. The MAE equation can be expressed as :

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Y_t - \hat{Y}_t| \quad (5)$$

- Mean Absolute Percentage Error (MAPE)

MAPE provides a scale independent measurement of forecasting precision, ideal for business performance evaluation. The MAPE equation can be expressed as :

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \quad (6)$$

Combining these metrics provides a multidimensional understanding of the model's forecasting performance, balancing sensitivity to outliers (RMSE), interpretability (MAE), and scalability (MAPE).

III. Results

A. Heatmap

The heatmap presented in Figure 4 illustrates the distribution of peak sales hours across different days of the week. Heatmap derived from the transaction of coffee shop dataset. Using heatmap visualization enabling a clear identification of periods with heightened sales activity which crucial for optimizing operational strategies in a coffee shop. The heatmap will use color gradient to represent sales volume. The darker shades indicating higher sales. By examining the color intensity across the grid, we can discern the peak hours for each day. The heatmap shown in Figure 4 illustrates the distribution of peak sales hours across the days of the week, obtained from analysis of the coffee shop transactions dataset. The heatmap visualization enables precise identification of peak sales periods which is essential for optimizing coffee shop operations. The color gradient on heatmap represent sales volume. The darker shades indicating higher sales. Examination of intensity patterns across the grid reveals the peak hours for each day.

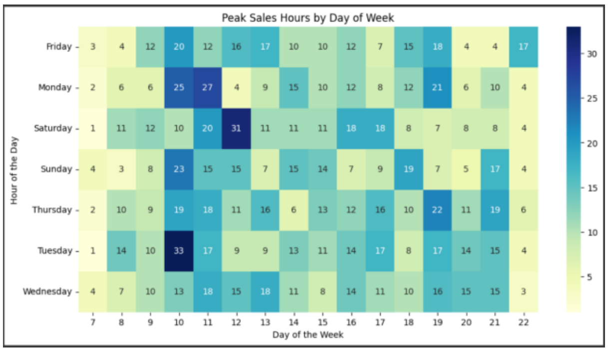

Fig. 4. Heatmap to show the peak hours

The darkest heatmap cell corresponds to Tuesday at 10:00 AM, indicating as the foremost peak with the highest level of sales activity. Additional observations include :

- Monday, between 10:00 AM and 11:00 AM.
- Saturday, at 11:00 AM.
- Thursday, at 5:00 PM.
- Friday, at 10:00 AM and 19:00
- Sunday, at 10:00 AM and 18:00

The heatmap can be an effective tools for visualizing patterns of complex datas. Understanding the pattern can help to make decision making regarding managing coffee shop operations.

B. Linear Regression

The performance of the linear regression model on the test dataset is summarized as follows RMSE : 6.68, MAE : 5.4, and MAPE : 138.06.

The results indicate substantial forecasting errors across all evaluation dimensions. The RMSE value of 6.68 suggests that the model's predictions deviate from actual sales values by approximately 6.68 units. This metric is particularly sensitive to large outliers due to the squaring of residuals. The MAE of 5.4 provides a more interpretable measure, indicating an average absolute deviation of 5.4 units between predicted and observed values. MAE is less influenced by extreme errors compared to RMSE and offers a clearer representation of typical prediction accuracy.

Particularly concerning is the MAPE of 138.06%. The values indicate performance that is decisively outside acceptable forecasting limits. MAPE values above 50% are generally considered indicative of poor model performance in retail forecasting contexts [11][12]. The extremely high value of MAPE indicates a poor model fit, suggesting that the linear regression model fails to adequately represent the temporal structure and seasonal dynamics characteristic of coffee shop sales data. The limitation is consistent with prior research, which demonstrates that linear models often fail to adequately model nonlinear relationships and complex seasonality in time series data [13].

There are many factors that can affect the poor performance of the linear regression. First, the model has false assumptions regarding the linear relationship between predictor and sales volume, whereas the sales data is actually complex and nonlinear. Second, linear regression model do not calculate the autocorrelation which is the fundamental characteristic of time series data. Third, the model is not capable of capturing multiple seasonal patterns which is the characterisation of coffee shop operations such as hourly cycles within days, weekly patterns and monthly variations.

C. SARIMA

In contrast to the linear regression model, the performance of the SARIMA model shows higher forecasting accuracy in all evaluation metrics: RMSE: 0.828, MAE: 0.557, MAPE: 40.34%.

The RMSE 0.82 explain that SARIMA's model is capable to model the temporal dependencies and seasonal patterns. Besides that, the value that is less than 1 means that the typical prediction error is less than one unit of sales, in other words, this model presents a highly accurate forecast for operational planning purposes. The value of MAE is 0.56, showing that on average, the model's predictions deviate only approximately 0.56 units from actual sales values. In this level, accuracy is valuable for the coffee shop manager to make decisions about scheduling staff, inventory preparation and resource allocation during different hours of the day

The MAPE is 40.34%. This value exceeds the ideal threshold of 10-20% for the accurate forecasts, but still in acceptable range for retail forecasting applications where variety of demand is high. There are conditions like extreme fluctuations in sales during special events, holidays or unexpected conditions that are difficult for any statistical model to predict without external contextual information [11].

D. Comparative Analysis of Model Performance

Table 1 shows performance comparison for both models, linear regression and SARIMA. The result highlight the high accuracy achieved by SARIMA. The comparative analysis reveals that SARIMA surpassing the linear regression consistently in all three evaluation metric. These finding align with existing literature that demonstrate the superiority of time series models incorporating seasonal components for forecasting retail and hospitality demand [14].

There are several factors that can affect this substantial performance gap between two models. SARIMA can models the seasonal pattern through seasonal autoregressive and moving average component. This characteristic enable the SARIMA to capture recurring hourly, daily, and weekly cycles as characterize coffee shop traffic. Contrary, linear regression can only approximate seasonality through dummy variables and not fully capture the complex temporal dynamics.

Table 1. Comparative Performance Metrics: Linear Regression vs. SARIMA

Metric	**Linear Regression**	**SARIMA**
RMSE	6.68	0.83
MAE	5.40	0.56
MAPE	138.06	40.34

Another factor is SARIMA taking into account for autocorrelation in time series data, recognizing that sales at one time point are influenced by sales at previous time points [14]. We know that temporal dependency is fundamental to peak hour identification, as customer traffic patterns exhibit strong inertia and predictable transitions between low and high demand periods.

The last factor is SARIMA's differencing component enables it to handle non-stationary data by removing trends and stabilizing the mean, making the model more robust to gradual shifts in sales patterns over time. Linear regression assumes that the data is stationary, which means that it may not work well when there are trends in the data.

IV. DISCUSSION

A heatmap can help to find peak hours in coffee shop, but it also has some constraints. The heatmap is a great way to see sales data and find peak hours, but it should be used with other analytical tools to get a better understanding of what is causing sales trends. This combined approach can help coffee shops come up with better ways to run their businesses.

The aim of this study is to compare the performance of Linear Regression and SARIMA models for peak hour identification in coffee shop data. The results demonstrate that SARIMA surpasses Linear Regression in all of three evaluation metrics. These findings have both theoretical and practical implications for demand forecasting in retail, especially for small to medium sized coffee shop operations which aiming to enhance resource allocation and operational efficiency. These findings have both theoretical and practical implications for demand forecasting in retail, especially for small to medium sized coffee shop operations which aiming to enhance resource allocation and operational efficiency.

The better performance of SARIMA is due to the fact that its fundamental design principles fit well with the way time series data works. Coffee shop sales have three important characteristic that SARIMA is designed to capture : temporal autocorrelation, non stationarity, and seasonal periodicity.

Temporal autocorrelation is the statistical relationship between observations was taken at different times. In coffee shop, sales always happen at certain times of the day and so on, because of how customers act and how the business run. For example, a busy morning rush at 8 AM often lasts until 9 AM as queues form and service continues. SARIMA's autoregressive component enabling the model to "learn" how past values influence current. Linear regression, on the other hand, treats each observation as independent, goes against the fundamental idea of independence and caused standard errors to biassed and inefficient estimates.

Seasonal periodicity of SARIMA is the most important benefit for coffee shop operations. Coffee shops have many seasonal patterns which nested inside each other. For example : there are hourly cycles (morning peak, lunch rush, afternoon slump), daily cycles (weekdays, weekends), and possibly monthly or yearly cycles (seasonal beverage preferences etc). SARIMA's seasonal parts include seasonal autoregressive, differencing, and moving average terms. These terms explicitly model these patterns that happen over and over. This part of the architecture helps SARIMA see that sales patterns happen over and over again. This architecture uses past seasonal patterns to predict future peaks accurately.

Linear regression can use dummy variables (like hour of day) to get an idea of seasonality, but this method has limitations. It treats each seasonal period as separate which means it can not capture the smooth transitions and momentum effects that happen between periods that are next to each other. The second limitation is it can not model interactions between more than one seasonal pattern without making the model much more complicated and possibly overfitting. The last, dummy variable methods assume that seasonal effects stay the same over the whole time period, while SARIMA lets seasonal patterns change slowly over time.

This study examine the theoretical fundamental, practical impact, constraints, and prospective developments from the comparison of Linear Regression and SARIMA in determining peak hours at coffee shops. But for it to work, successful implementation require attention to the quality of the data, keeping the good model, and making it easy for users to access. Using SARIMA based forecasting to make decisions for coffee shop is a great way to use data to improve operations. The results help to describe what is forecasting methods for other retail and service industries that have similar patterns of demand over time and operational problems.

V. CONCLUSIONS

This study was conducted a comprehensive comparative analysis of Linear Regression and SARIMA models for identifying peak hours in coffee shop operations using hourly sales data. The empirical results provide an unambiguous interpretation. The SARIMA's model performed a high accuration in all of the evaluation metrics for forecasting. The performance of SARIMA model is : RMSE = 0.828, MAE = 0.557, and MAPE = 40.34%. The three evaluation metrics show that SARIMA's basic architecture have better performance at modelling time series data that has temporal autocorrelation, non stationarity, and seasonal periodicity. Linear Regression which is famous with its simplicity and interpretability, failed to accurately represent the intricate temporal dynamics of coffee shop demand patterns, producing forecasts with unacceptably high error rates that would render them unreliable for operational decision-making. This research was addressed a gap in the current literature. There has been a lot of research on demand forecasting in retail and restaurant contexts, but not much research has been done on comparing basic statistical methods for finding peak hours in coffee shops. The future research should systematically compare SARIMA against advanced alternatives such as SARIMAX models incorporating exogenous variables, LSTM neural networks, Random Forests, and ensemble approaches combining multiple methods to get the better model in peak hour identification.

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