EXPERIMENT REPORT

Student Name	Sareem Sandeed
Project Name	Part B: AT2 - Forecasting model using a time-series analysis algorithm
Date	10-October-2023
Deliverables	**Notebook**: sandeed_sareem_24622829_time_series_arima.ipynb **Best Model:** ARIMA **GitHub link:** https://github.com/ssandeed/adv_mla_at2

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1. EXPERIMENT BACKGROUND	
Provide information about the problem/project such as the scope, the overall objective, expectations. Lay down the goal of this experiment and what are the insights, answers you want to gain or level of performance you are expecting to reach.	
1.a. Business Objective	**Project Goal:** The goal of this project is to develop a forecast time series Machine Learning algorithm that accurately predicts the sales revenue for the next 7 days for all stores. **Usage of Results:** The results of this predictive model will be used to optimize inventory management, demand planning, pricing strategies, marketing efforts, and financial planning. **Impact of Accurate Results:** Accurate results from the predictive model will enable the business to make data-driven decisions, leading to improved profitability, efficient operations, and enhanced customer satisfaction. **Impact of Incorrect Results:** Incorrect results from the predictive model can lead to bad decision-making, ineffective pricing and marketing strategies, and potential customer dissatisfaction, ultimately affecting the business's success.
1.b. Hypothesis	**Hypothesis:** The hypothesis to forecast sales revenue for the next 7 days for the retail giant for a given date. **Question:** Can we accurately forecast the sales revenue for the next 7 days for a given day for the retail giant using a time series ML algorithm? **Reason:** It is worthwhile to consider this hypothesis because accurate sales revenue forecast for next upcoming week can significantly impact inventory management, demand planning, pricing, and marketing strategies, leading to improved operational efficiency and financial performance for the retail giant.

1.c. Experiment Objective	**Expected Outcome:** The expected outcome of the experiment is to successfully develop a forecasting model that accurately determines the sales revenue for the next 7 days for a given date. The primary evaluation metric for the model will be the Root Mean Squared Error (RMSE), with the goal of minimizing it. **Possible Scenarios:** 1. **Poor Model Performance:** The model's predictions have a high RMSE, indicating inaccurate sales revenue forecasts. In this scenario, further model refinement and feature engineering will be necessary to enhance its accuracy. 2. **Overfitting or Underfitting:** The model may exhibit signs of overfitting (performing well on the training data but poorly on new data) or underfitting (performing poorly on both training and new data). These scenarios would require adjustments to the model architecture and hyperparameters. 3. **Moderate Model Performance: T**he model performs reasonably well but may have a moderate RMSE. While not achieving the ideal accuracy, it still provides valuable insights for the business and can be considered a good starting point for further improvements.

2. EXPERIMENT DETAILS	
Elaborate on the approach taken for this experiment. List the different steps/techniques used and explain the rationale for choosing them.	
2.a. Data Preparation	The datasets didn't have major issues. There were three required datasets that needed to be joined to get relevant information like revenues, items prices, sales quantity, and date. • **calendar**: Dates with week id and date id • **items_weekly_sell_prices:** Unit sale price of each item • **sales_train:** Sales quantity on dates **The following steps were taken for data preparation:** 1. Checking the null values, duplicates in each of the datasets. 2. Checking data types of all columns. 3. Merging 3 datasets 4. Dropping columns that are not needed. 5. Finally have a table with date as index and corresponding aggregated revenue at national level 6. At last, data was split into train and validation data.
2.b. Feature Engineering	**In the final dataset before splitting at store level, following features were used for modelling:** • Date as index • aggregated revenue The ask of the project was to forecast next 7 days aggregated sales revenue for all stores. So, for using ARIMA algorithms, these features are required. Therefore, no feature engineering was required further.

2.c. Modelling	For the experiment, which aims to forecast sales revenue for the next 7 days for the retail giant, ARIMA time series forecasting models were considered and evaluated. **ARIMA (Auto Regressive Integrated Moving Average):** • **Why Chosen:** ARIMA is a classic and widely used time series forecasting model that can capture trends and seasonality in data. It is a suitable starting point for time series forecasting experiments. It runs fast and less computational. • **Hyperparameters Tuned:** Order parameters (p, d, q) were tuned. • **Values Tested:** Different combinations of p, d, and q were tested to find the best order for the ARIMA model. • **Rationale:** Tuning the ARIMA order is essential to capture the time series patterns effectively. The models selected for this experiment were chosen based on their suitability for time series forecasting, with each model having its unique strengths. Prophet and LSTM were computationally more intensive were taking a lot of time to train, therefore, ARIMA was considered over these.

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3. EXPERIMENT RESULTS	
Analyse in detail the results achieved from this experiment from a technical and business perspective. Not only report performance metrics results but also any interpretation on model features, incorrect results, risks identified.	
3.a. Technical Performance	The metric used for assessing model performance is the Root Mean Squared Error (RMSE) score. RMSE is in the same unit as the target variable, making it easy to interpret. This makes it more understandable to stakeholders. • RSME for train: 11651.05 • RSME for validation: 12426.31 • Mean of revenue in train: 92288.90 • Mean of revenue in validation: 114249.01 The RMSE values indicate the level of error in your ARIMA model's predictions. In this case, the RMSE for the training set (11651.05) is lower than the RMSE for the validation set (12426.31). This suggests that the model might be overfitting to some extent. Comparing RSME to mean revenue, it can forecast with good accuracy.
3.b. Business Impact	The experiment involved training a ARIMA time series model to predict sales revenue for next 7 days. The model achieved reasonable RSME on train and validation data. These scores indicate that the model can forecast revenue with good confidence. **Impact of Incorrect Results:** 1. Bad pricing decisions resulting from incorrect forecasting may lead to missed opportunities for profit during high-demand periods or unnecessary discounts during low-demand periods. 2. Misallocated marketing budgets based on inaccurate forecast can result in ineffective campaigns and missed chances to boost brand visibility and ROI. 3. Inaccurate sales forecast can disrupt financial planning, budgeting, and revenue target setting, potentially leading to financial instability.

	4. Inadequate stock levels due to inaccurate forecast can result in customer dissatisfaction, leading to lost sales and reduced loyalty. 5. Inaccurate forecast can damage the credibility of the business, especially when widely communicated to stakeholders, investors, or partners.
3.c. Encountered Issues	**Solved Issues:** **1. Big Datasets:** Handling large datasets can be computationally expensive and may lead to memory constraints during model training and evaluation **2. Datasets merging:** The data preparation required merging multiple datasets and handling them without the memory issue. **Unsolved Issues:** **1. Computational Resources:** Training complex models with extensive hyperparameter tuning can require substantial computational resources, which may be expensive or time-consuming if we have to consider other models like LSTM or Prophet. **2. Hyperparameter Tuning:** Tuning hyperparameters manually can be time-consuming and may not lead to optimal results. **Solutions or Workarounds:** 1. **Hyperparameter Tuning:** Perform hyperparameter tuning using techniques like grid search or random search. Optimize hyperparameters to achieve better model performance. 2. **Model Diversity:** Explore other models like LSTM or Prophet. **Issues for Future Experiments:** 1. **Model Evaluation:** While ARIMA was used successfully in this experiment, future experiments may explore other ensemble methods like LSTM or Prophet to determine if they offer improved performance. But must have to think with respect to computational capability. 2. **Domain Knowledge Integration:** Involve domain experts to validate model forecasting and provide insights on potentially overlooked factors. 3. **Overfitting:** Overfitting occurred in some cases, where the model performed well on the training data but poorly on validation or test data. In summary, while several issues have been addressed, hyperparameter tuning remains a gap, and other aspects such as model diversity and overfitting should be considered in future experiments to enhance the model's overall performance and reliability.

4. FUTURE EXPERIMENT	
Reflect on the experiment and highlight the key information/insights you gained from it that are valuable for the overall project objectives from a technical and business perspective.	
4.a. Key Learning	The experiment involving the ARIMA time series model for sales revenue forecasting has provided valuable insights and outcomes that can guide future experimentation. Here are the key takeaways and reflections: **New Insights Gained:** 1. **RMSE Metric Suitability:** The use of RMSE as the primary performance metric has proven to be effective for assessing model accuracy and comparing models consistently across different stores. This metric's interpretability makes it a valuable choice for stakeholders. 2. **Forecasting Accuracy:** The RMSE values, when compared to the mean revenue, indicate that the ARIMA model can provide reasonably accurate revenue forecasts. This suggests that the model has practical utility in making revenue predictions. 3. **Pricing Decisions:** Incorrect forecasting can result in suboptimal pricing decisions, leading to missed profit opportunities or unnecessary discounts. This underscores the importance of accurate forecasts for pricing strategies. 4. **Marketing Budget Allocation:** Misallocation of marketing budgets based on inaccurate forecasts can lead to ineffective campaigns and reduced return on investment. Accurate forecasts are critical for optimizing marketing efforts. 5. **Financial Planning:** Inaccurate sales forecasts can disrupt financial planning, budgeting, and revenue target setting, potentially causing financial instability or missed growth opportunities. 6. **Inventory Management:** Inadequate stock levels due to inaccurate forecasts can result in customer dissatisfaction and lost sales. On the other hand, overstocking can tie up capital and storage space. 7. **Credibility:** Inaccurate forecasts can damage the credibility of the business, especially when widely communicated to stakeholders, investors, or partners. Consistently reliable forecasts are essential for maintaining trust.
4.b. Suggestions / Recommendations	Based on the achieved results and the overall objective of the project, here are some potential next steps and experiments: **Hyperparameter Tuning (High Priority):** • **Expected Uplift:** Hyperparameter tuning can significantly enhance model performance by optimizing model parameters. • **Rank:** High priority. • **Recommendation:** Perform an exhaustive hyperparameter search using techniques like grid search, random search, or Bayesian optimization to fine-tune the model. Consider leveraging cloud resources to expedite this process. **Scaling for Larger Datasets (Medium Priority):** • **Expected Uplift:** Scaling the solution to handle even larger datasets can future proof the system. • **Rank:** Medium priority. • **Recommendation:** Explore distributed computing and big data frameworks but have to consider the trade-offs in terms of complexity and cost. **Feature Engineering (Low Priority):** • **Expected Uplift:** Carefully crafted features can enhance model performance by capturing more relevant information from the data.

	• **Rank:** Low priority. • **Recommendation:** Explore feature engineering techniques tailored to retail sales data, such as lag features, rolling statistics, and holiday/event indicators. **Deployment Steps for a Successful Solution:** If the experiment achieves the required outcome for the business, follow these steps to deploy the solution into production: **Model Evaluation:** Perform a final evaluation of the model's performance using an independent test dataset to ensure it meets the desired accuracy and reliability. **Scalability Assessment:** Verify that the model deployment can handle the anticipated workload and data volumes in a production environment. **Feedback Loop:** Establish a feedback loop to collect user feedback and monitor the model's accuracy and impact on business operations. **Business Integration:** Integrate the predictive model's outputs into key business processes, such as inventory management, pricing, marketing, and demand planning.