Unlocking Sales Trend: Exploring Seasonality in NIB Data

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Abstract

This project analyzes NIB's revenue data from 2016 to 2024. The analysis aims to uncover seasonal patterns within the revenue streams, considering various Lines of Business (LOB) and Sub-Lines of Business (Sub-LoB) that represent different product lines.Through this analysis, we identify key seasonal trends and revenue fluctuations, providing insights into the factors influencing the performance of each segment. These findings offer valuable guidance for strategic decision-making and potential optimization of the organization's operations.

Introduction

National Industries for the Blind (NIB) is a nonprofit organization that creates employment opportunities for people who are blind by offering a wide range of products, including textiles, military resale items, and office supplies. Accurate sales forecasting is critical for managing these diverse product lines and optimizing inventory across various Lines of Business (LoB).

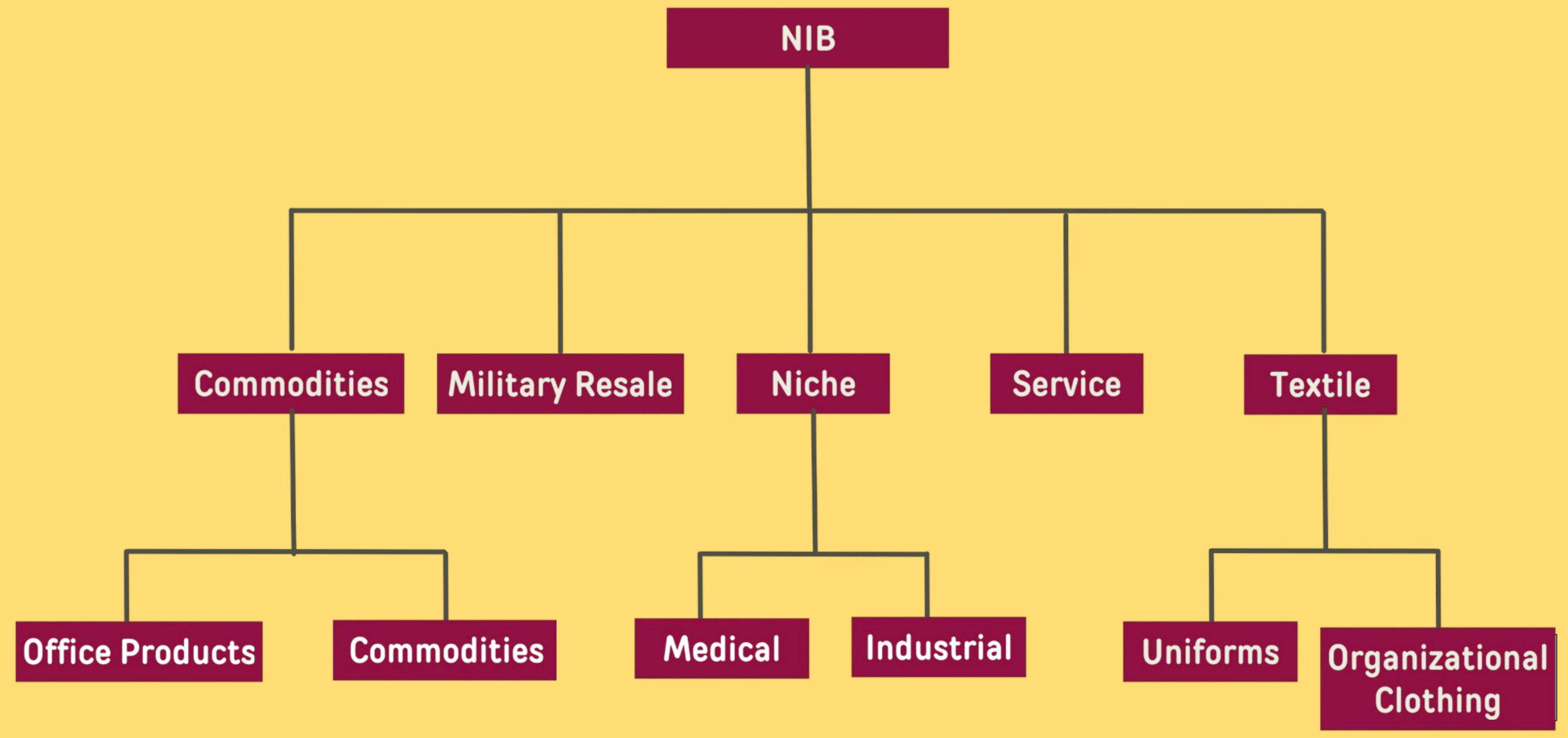
This study analyzes NIB's sales data to detect and quantify seasonality, aiming to improve forecast accuracy. Advanced time series techniques, such as seasonal trend decomposition (STL), Autocorrelation Functions (ACF), and the Ljung-Box test, were used to identify seasonal patterns and distinguish them from long-term trends and noise.

Data preprocessing involved aggregating sales, filtering negative values, and adjusting for quarter variations. Through STL decomposition, we isolated trends, seasonality, and residuals, providing clearer insights. The Augmented Dickey-Fuller (ADF) test was used to assess stationarity, which is critical for models like ARIMA and SARIMA. Our findings revealed varied seasonal patterns across business lines, offering insights to enhance NIB's forecasting models and supply chain strategies.

Figure 1. Military Product in NIB

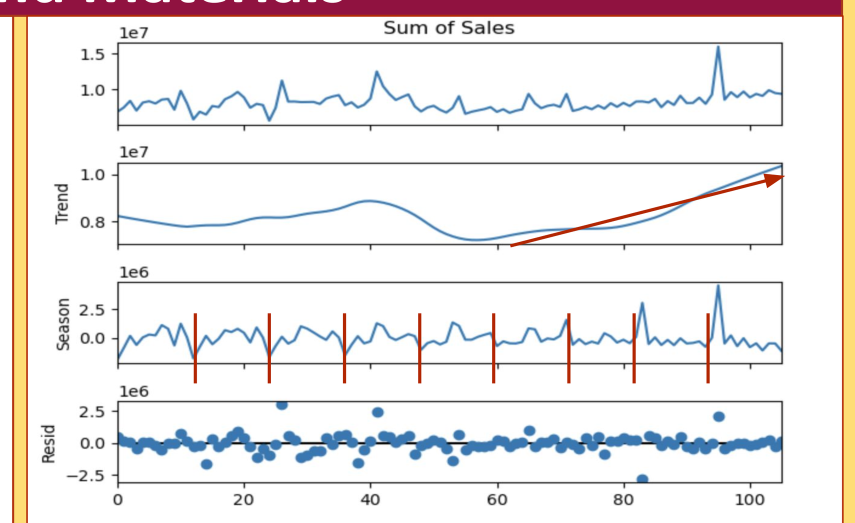
Figure 2. Medical Product Manufacturing Process

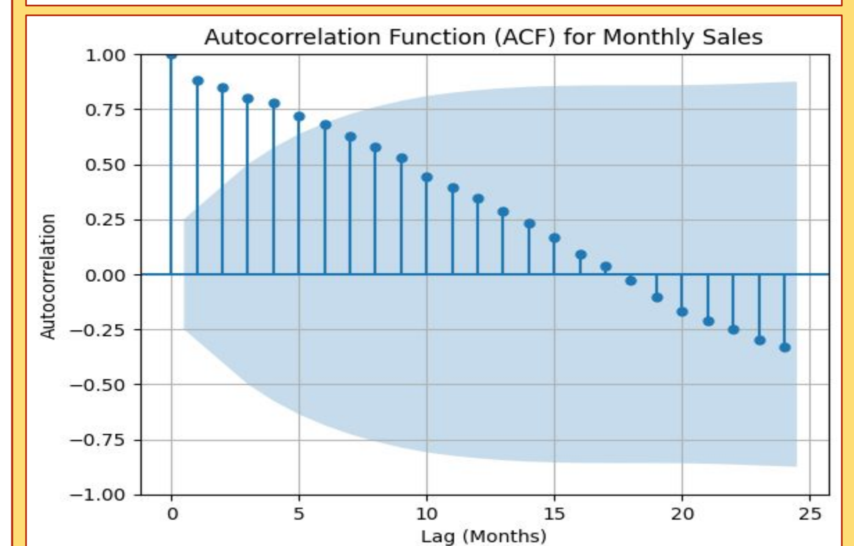
Year	Inflation rate	Final Rates
2015	0.00%	74.70
2016	1.30%	75.69
2017	2.10%	77.31
2018	2.40%	79.21
2019	1.80%	80.66
2020	1.20%	81.64
2021	4.70%	85.67
2022	8.00%	93.12
2023	4.00%	97.00
2024	3.00%	100.00

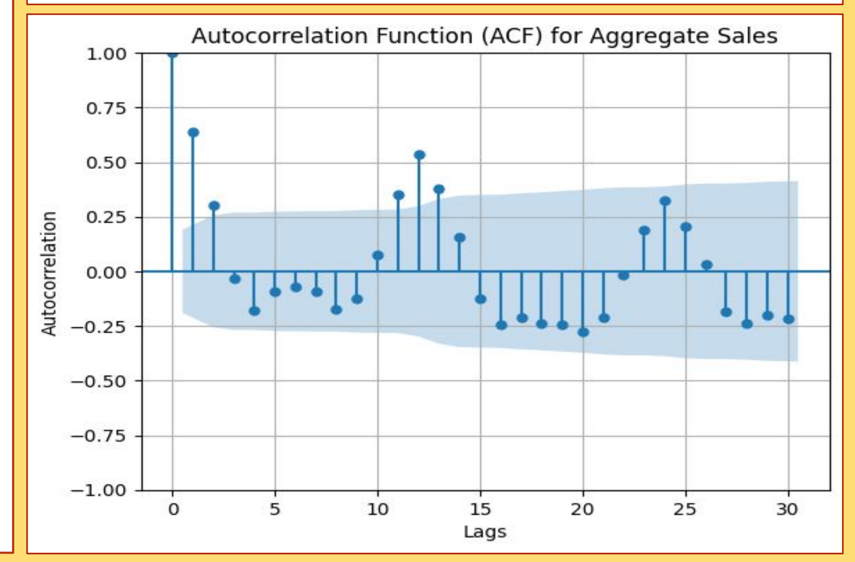


Methods and Materials

- **Seasonal-Trend decomposition using LOESS (STL):** This technique was applied to break down the time series into trend, seasonal, and residual components. STL is a robust as it handles non-stationary seasonality and allows flexibility in detecting seasonal changes.
- **Autocorrelation Function (ACF):** ACF was used to quantify the degree of correlation between observations at different time lags, helping identify seasonal patterns. The slow decrease in ACF plots and repeated peaks indicate potential seasonality.
- **Ljung-Box Test:** This statistical test was applied to validate the presence of autocorrelation at seasonal lags, providing further evidence of seasonal cycles.
- **Augmented Dickey-Fuller (ADF) Test:** The ADF test assessed the stationarity of the time series. Stationarity is a key assumption for many forecasting models, such as ARIMA and SARIMA, and is crucial for producing reliable forecasts.







Sub-Lines of Business	STL Decomposition	Autocorrelation Function	Ljung-Box Test	ADF Test
Office Products (Commodities)	Weak	**Strong**	**Strong**	Weak
JanSan (Commodities)	Weak	Weak	**Strong**	Weak
Military Resale	Weak	Weak	Weak	Weak
Medical (Niche)	**Strong**	Weak	**Strong**	Weak
Industrial (Niche)	**Strong**	Weak	**Strong**	Weak
Uniforms (Textiles)	**Strong**	Weak	**Strong**	Weak
Organizational Clothing (Textiles)	Weak	Weak	**Strong**	Weak
Services	**Strong**	**Strong**	**Strong**	Weak

Our Forward Approach

Our analysis revealed that, except for the Military product line—where all methods consistently indicated the absence of clear seasonal patterns—the other product lines exhibited mixed results. Depending on the method applied, some lines demonstrated seasonality while others did not, highlighting variability in the seasonal trends across different product lines.

Using traditional forecasting techniques

1. **Fit ARIMA and SARIMA Models**: Build both models using the historical sales data from 2016 - 2023 (divided into train and test dataset)
2. **Compare Forecasts with Actual Sales**
3. **Calculate Forecasting Errors**: Compute the error metrics such as **Mean Absolute Error (MAE)**, **Root Mean Squared Error (RMSE)**, or **Mean Absolute Percentage Error (MAPE)** to quantify the accuracy of the forecasts.
4. **Make Forecasts**: Use the fitted models to forecast sales for 2024 - 2025

Using Machine Learning techniques : We will be using **Convolutional Neural Networks (CNN)** because they excel at extracting local patterns or features from data by sliding a filter over the input. In time series data, CNNs can detect patterns such as trends, seasonality, or sudden spikes by analyzing a sliding window of time steps.

1. **Reshape the Data**: Prepare the time series data in sequences (windows of previous time steps) for the CNN to process.
2. **Build a 1D CNN Model**: Build a CNN using **Conv1D** layers to capture temporal patterns.
3. **Train the Model**: Train the CNN on your time series data.
4. **Forecast Future Sales**: Use the CNN to forecast future sales.
5. **Evaluate the Model**: Compare the forecast with actual sales data to compute error metrics.

Contact

References