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SPOT (Sales Production based On Time-Series): A Comprehensive Approach to Sales Forecasting using Contextually-tailored Time Series Analysis

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Abstract— **Unit sales in retail chain stores exhibit a significant degree of variance, affected by seasonality and special events. Individual products and categories also display a considerable difference in sales based on the geography of individual stores. In various businesses, a myriad of products is moved each day, and accurately predicted knowledge of sales facilitates the planning of logistics, warehousing, and procurement, besides other executive decision-making processes. Software developed for this purpose are undergoing continuous improvements. SPOT (Sales Production based On Time-Series) is an application to produce sales forecasts for customized input parameters – such as an individual store, state in which store is located, a particular product, category/sub-category of products, which will prove to be immensely useful for decision-making processes across a variety of concerned business units. SPOT delivers the results in the form of graphical summarization of selected data, along with its time-series forecasts. More incisive sales predictions can be exported as a tabular numeric file. For the purpose of demonstrating the entire process, data from Walmart was considered; however, this can be extended to any related application fields as well.**

Keywords— Time-Series, LSTM., LightGBM, Sales, Forecast, Walmart

I. Introduction

The primary purpose of the discipline of forecasting is to provide accurate forecasts that contribute to the success of actions. Another vital purpose is to give exact estimates of the uncertainty inherent in all projections, as well as guidance on how to cope with the risks that ensue. The previous practices are no longer efficient[1]. This research objective is to enhance forecasting accuracy and uncertainty estimates as much as feasible, to avoid costly mistakes, and to apply best forecasting practices to businesses. The purpose is to increase the use of forecasting in commercial enterprises, to promote the development of better strategies to meet forecasting needs, demonstrating cost reduction and promoting sustainability. A dynamic application-based forecaster would minimize unsold food wastage and the ecological footprints left by enterprises.

With the great deluge of information in recent decades, businesses can no longer consider basing their decisions on data as an optional aspect. Different methods are being implemented for predicting different aspects related to business and sales [2]–[4]. The knowledge of past behaviour is a reasonable predictor of future behaviour, and copious amounts of detailed past data allow for more reliable predictions of future behaviour [5], [6]. Thus, a scientific tool that uses Time Series Analysis methods to provide the user with predictions on selected parameters will prove to be indispensable in corporate and logistical decision-making [7], [8]. Accurate predictions can be made readily available based on the users' concerned parameters [9].

Creating forecasts is generally a fixed-input undertaking. The predictions are static, and considerations for associated conditions should be known equally by the analyst generating the forecast and the user putting them to use [10]. Allowing the user to embody both functions will serve as the key feature of this application [11]. The end-user gets to benefit from the optionality of customizing the input conditions based on which forecasts are made. This dramatically expands the scope for the definition of the end-user, and within the realm of corporate Walmart, this application can serve as a universal tool [12]. Different developed techniques are in practice towards that goal [13], [14]. Especially, from the perspective of logistics, warehousing, store-management, and operational granularities, sales forecasting is of utmost importance [15].

We are primarily reliant on the LightGBM [16] algorithm for producing the predictions, implemented on the User Interface (UI) created by an application written in R-Shiny, which lets us build interactive web applications and dynamic dashboards entirely with R code.

The key contributions of the work are summed up as follows:

- A thorough method of predicting sales utilizing specialized time series analysis.
- Implementation of algorithm for forecasting sales.
- User Interface (UI) created by R shiny application.
- Creating dynamic dashboards and interactive web apps with R code.

There are five sections in the paper's structure. The theoretical foundation of the work is described in section two. The third section expands on the main idea and talks about the strategy. The results of employing customized time series analysis for sales forecasting are shown in section four. Section five concludes by summarizing the work and its effects.

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II. THEORETICAL BACKGROUND

Leveraging previous information to guide decision-making is the foundation of predictive analysis as seen in Fig. 1. The fact that the future result is wholly unknown at the time of the task and can only be anticipated through a comprehensive examination and evidence-based priors is an essential distinction in forecasting. Time is a crucial aspect that must be considered in all models to forecast overall trajectory of the capital sector.

A time-series analysis implies a connection between several data streams.

$$a(t) = b(t)\beta + \varepsilon\,(t) \qquad (1)$$

Equation one [17], [18] is an example of a regression model where $a\,(t) = \{a; t = 0, \pm 1, \pm 2, \dots\dots\}$ can be considered as a sequence with the combination of unobservable white noise sequence $\varepsilon\,(t) = \{\varepsilon_t\}$ and observable signal sequence $b\,(t) = \{b_t\}$ of similar and independent distributed random variables. It can also be expressed as shown in equation two.

$$\sum_{i=0}^{m} \alpha_i a(t-i) = \sum_{i=0}^{n} \beta_i b(t-i) + \sum_{i=0}^{p} \vartheta_i \varepsilon(t-i) \quad (2)$$

Even though any of the sums in equation 2 [17], [18] might be infinite, the sequence coefficients only need to be dependent on a small set of variables for the model to work. A more generalized model can be represented by equation 3 [17], [18].

$$a(t) = \sum_{i=1}^{m} \phi_i a(t-i) + \sum_{i=0}^{n} \beta_i b(t-i) + \sum_{i=0}^{p} \vartheta_i \varepsilon(t-i) \quad (3)$$

Gradient-boosted decision trees are a machine learning method for improving a model's prediction power over subsequent learning phases. In order to reduce the loss function, the decision tree iterates by changing the coefficients, weights, or biases assigned to each input variable that is used to forecast the target value. The difference between the expected and actual target values is measured by the loss function. The incremental adjustments performed at each stage of the process are known as the gradient, and boosting is a technique for speeding the increase in predicted accuracy to an adequate optimal value. A gradient boosting system called LightGBM makes use of tree-based learning techniques. Due to its distributed and efficient architecture, it has benefits including increased accuracy, lower memory use, support for parallel, distributed, and GPU learning, and the capacity to handle massive amounts of data [16].

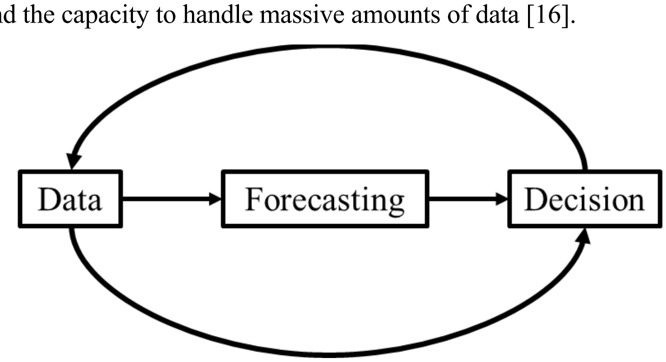


Fig. 1. A typical forecasting cycle

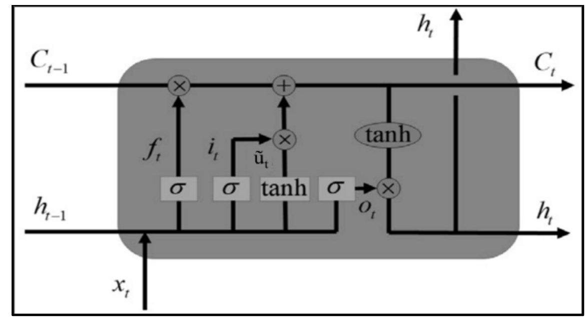


Fig. 2. LSTM graphical representation [21]

LightGBM is a gradient boosting framework built on decision trees that improves model performance while using less memory. In order to address the constraints of the histogram-based approach, which is largely employed in all GBDT (Gradient Boosting Decision Tree) frameworks, it employs two creative methods: gradient-based one side sampling and exclusive feature bundling (EFB). Together, they enable the model to function well and provide it an advantage over competing GBDT frameworks [19].

An enhanced recurrent neural network (RNN), or sequential network, called a long short-term memory network (LSTM), permits information to endure. It is capable of resolving the RNN's vanishing gradient issue. RNNs are utilized for permanent memory. Three different gate types are introduced by the LSTM: input gates, output gates, and forget gates. The forget gate stops the current h vector from being updated to the specified RNN unit while the input gate combines the input and updates the h vector [20]. Fig. 2 illustrates the process.

An LSTM unit's functioning may be summed up as follows [21]:

$$i_t = \sigma_g\,(W_i \,.\, x_t + U_i \,.\, h_{t-1} + b_i) \qquad (4)$$
$$f_t = \sigma_g\,(W_f \,.\, x_t + U_f \,.\, h_{t-1} + b_f) \qquad (5)$$
$$\tilde{u}_t = \tanh\,(W_u \,.\, x_t + U_u \,.\, h_{t-1} + b_u) \qquad (6)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{u}_t \qquad (7)$$
$$o_t = \sigma_g\,(W_o \,.\, x_t + U_o \,.\, h_{t-1} + b_o) \qquad (8)$$
$$h_t = o_t \odot \tanh\,(c_t) \qquad (9)$$

Here, the activation functions are $\sigma_g(x) = \frac{1}{(1+e^{-x})}$ and $\tanh x = \frac{e^x - e^{-x}}{(e^x + e^{-x})}$, W_i and U_i are weight parameters, b_i is bias and Θ indicates the pointwise multiplication [21].

Both long-term seasonality, like an annual pattern, and short-term seasonality, like weekly patterns, may be captured by the LSTM. It is able to prioritize the effect patterns from various event types. It can accept inputs of various lengths. LSTM is extremely reliable for creating broad forecasting models. LSTM's capacity to capture non-linear interactions for forecasting is improved by the many gates within of it. Sales is typically affected nonlinearly by causal variables. The LSTM may learn the nonlinear connection for predicting when these parameters are included as an input variable. However, compared to other recurrent neural networks, the LSTM takes more processing. The primary factor is that it contains more characteristics that are utilized to anticipate demand/sales [22].

In the context of the study done in this paper, the characteristics and qualities of LSTM and LightGBM guarantee a reasonably positive conclusion.

III. APPROACH

As discussed in section II, the application of LSTM and LightGBM for predicting sales forecast will ensure a good outcome for the stakeholders to visualize. The implementation approach can be summarized by Fig. 3.

Regarding dataset for further analysis, Walmart is chosen for its' vast data resource and accessibility. The data is fed to Time Series data processing as seen in Fig. 3. The combination of LSTM and LightGBM help to get satisfactory results, more of which has been discussed in section IV.

The visualizations of sales forecast might be useful to anybody interested in trade. The first step in using the program is selecting search filters depending on specific needs. The stakeholders have options like picking a location, a specific retailer in that area, a category, and a sub category of products. Additionally, they have a choice in visualizing techniques. Some of the options for visualization that are available to the stakeholders include net sales trend, sales forecasting, specific sales prediction by category, aggregated sales over a specified time period, product sales trend for a category or store, and comparison of sales for various time zones (months, weeks, days).

The methodological approach for sales forecasting with tailored time series analysis may be outlined with subsections for software architecture and software functionality.

A. *Software Architecture*

The M-competitions are organized by Spyros Makridakis to evaluate and compare different forecasting methods on real-world problems. The first competition took place in 1982, with 1001 time series, followed by a competition circa every decade up to the M4 in 2018 with 100 000 times series, and the use of Machine Learning algorithm which performed poorly compared to statistical methods or hybrid using both statistical and ML.

The 5th edition of the M-competitions took place for four months, from March 3rd to June 30th, 2020. The data are provided by Walmart and consist of 3049 items from 3 categories and seven departments across ten stores in 3 different states, resulting in 30490 hierarchical time series provided by Walmart, with 1941 days of history (refer Fig. 4).

We use the M5 dataset to train our model [16]. It uses hierarchical sales data, starting at the item level and aggregating to that of departments, product categories, and stores in three geographical areas of the U.S.: California, Texas, and Wisconsin.

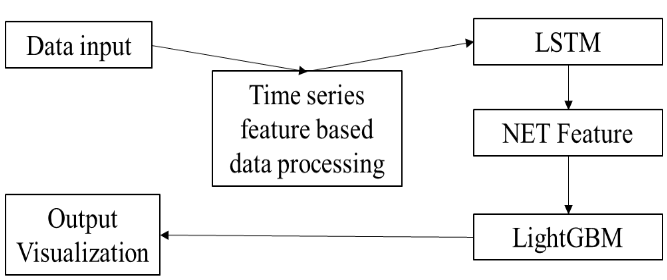


Fig. 3. Model structure for sales forecasting

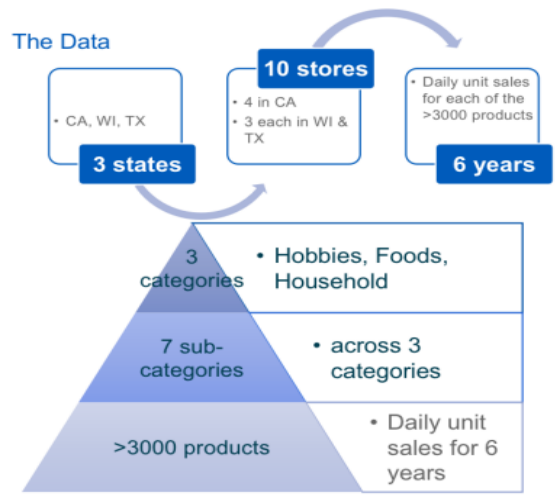


Fig. 4. Structure of the dataset

Besides the time series data, it also includes explanatory variables such as price, promotions, day of the week, and special events (e.g., Super Bowl, Valentine's Day, Easter) that affect sales which are used to improve forecasting accuracy.

B. *Software Functionalities*

The tool offers the function to display visualizations on different aspects of the selected data, which can be filtered via parameters selected as an input, using the Shiny app in R.

The ability to select sub-features for which relevant parameters can be viewed is a major functionality (Fig 5) that makes quick and in-depth analysis possible for looking at the smaller pictures. For example, our dataset contains sales data from Walmart stores across 3 U.S. states: C.A., WI, and TX. Individual states can be selected at the U.I. to monitor and analyze the difference in predicted sales between stores from different states. From more than 3000 different listed items, forecasted sales can be isolated for specific items. The individual products can also be clubbed into 3 product categories across seven sub-categories, using which the behaviour of different categories can be separated in analysis. This should be the main U.S.P. of this enterprise, as selectively knowing the forecast of

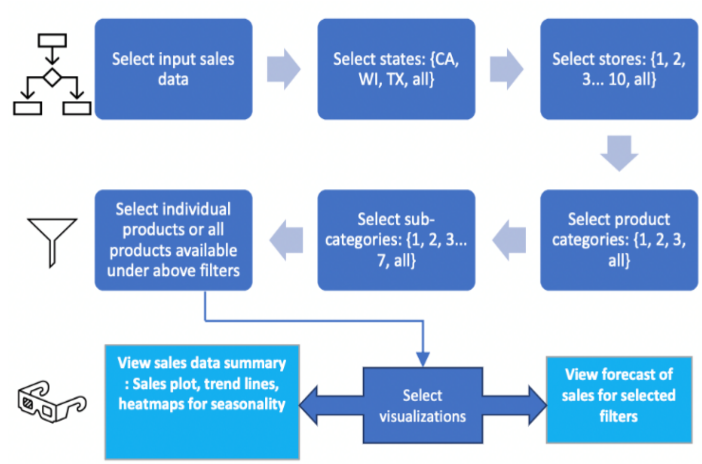


Fig. 5. Tool functionality at U.I. level to visualize sales data and forecasted sales based on selected parameters

sales for individual products at selected stores is far more useful than an overall measurement. Store-level sales performance can also be isolated by selecting the stores from the given list of 10 stores across the three states.

To make the tool generalizable, the user has the option to provide any input file with the data in the specified format. Time series and machine learning algorithms are then implemented for the prediction of sales for the subsequent time period. The final visualizations can be seen for the sales data we are using to create the forecasts based on the selected filters. Alternatively, the visualizations can be displayed for the forecasted sales using time series analysis.

IV. Result and Discussion

This section focuses on the results and offers descriptive examples that illustrate each step of the procedure.

The tool is an application built on Shiny to provide functionalities to the user in terms of selectivity on the inputs to be considered for analysis.

1. The user is free to select any combination of the ten available stores for analysis (Figs. 5, 6). They can select all the stores from only one state (E.g. TX), or they can mix and match multiple stores across different states (E.g. CA_1, TX_1, WI_2).

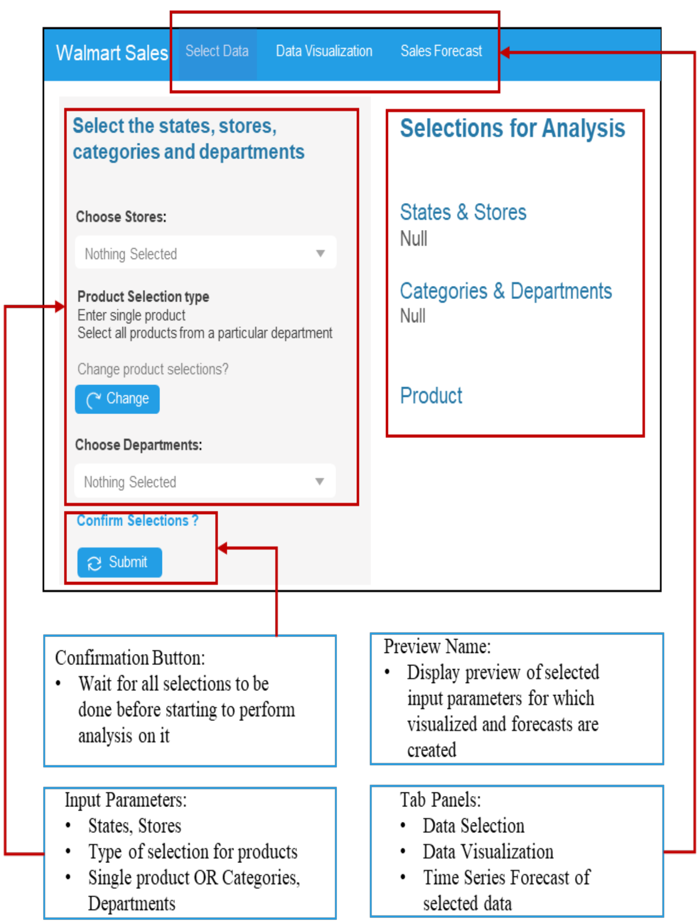


Fig. 6. Home Pane: Data Selection

The user can then select the products that they need analysis for in two different ways:

a. Whether analysis and predictions are to be made for a single product across single or multiple stores, in this scenario, the categories and departments cannot be specified as they are intrinsic to the product selected.

Examples :

- Product_0421 from all the stores in California.
- Product_2055 from the selected stores across all three states {CA_2, TX_1, TX_2, WI_3}

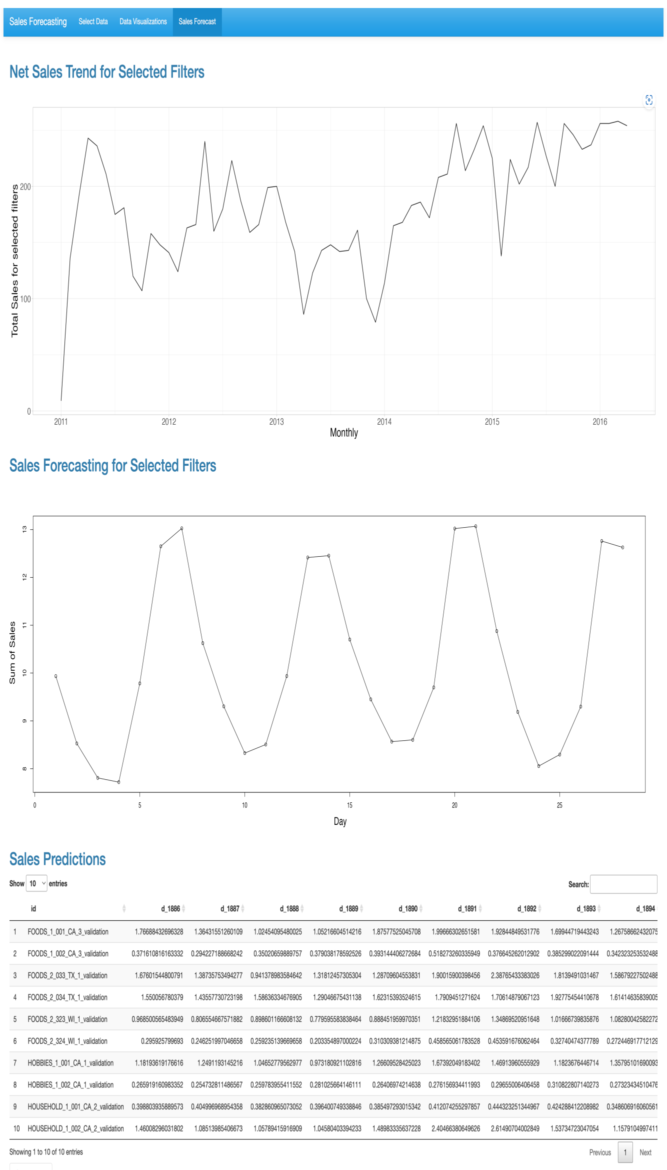
Fig. 7. Comparative sales visualizations for all products, stores, states, categories, departments.

b. Or whether the analysis and forecasts are to be made for all the products within a selected one/many of 3 categories or one/many of 7 departments (sub-categories).

Examples:

- All products/departments under the category {Household}.
- The products that come under the departments {Foods_2, Hobbies_2, Household_1}

2. Additionally, the app allows for the optionality to view the analysis of selected parameters (States, Stores, Categories, Departments, Products), and holistically visualize the nature of this data created from the selected inputs (refer Fig. 7). This allows for the user to get an overview or an understanding of the nature of past sales parameterized by their desired input criteria.



	id	d_1886	d_1887	d_1888	d_1889	d_1890	d_1891	d_1892	d_1893	d_1894
1	FOODS_1_001_CA_3_validation	1.76688432696328	1.36431551260109	1.02454095480025	1.05216604514216	1.87577525045708	1.99666302651581	1.92844849531776	1.69944719443243	1.26758662432075
2	FOODS_1_002_CA_3_validation	0.371610816163332	0.294227188668242	0.35020659889757	0.379038178592526	0.393144406272684	0.518273260335949	0.376645262012902	0.385299022091444	0.342323253532488
3	FOODS_2_033_TX_1_validation	1.67601544800791	1.38735753494277	0.941378983584642	1.31812457305304	1.28709604553831	1.90015900398456	2.38765433383026	1.8139491031467	1.58679227502488
4	FOODS_2_034_TX_1_validation	1.550056780379	1.43557730723198	1.58636334676905	1.29046675431138	1.62315393524615	1.7909451271624	1.70614879067123	1.92775454410678	1.61414635839005
5	FOODS_2_323_WI_1_validation	0.968500565483949	0.806554667571882	0.898601166608132	0.779595583838464	0.888451959970351	1.21832951884106	1.34869520951648	1.01666739835876	1.08280042582272
6	FOODS_2_324_WI_1_validation	0.295925799693	0.246251997046658	0.259235139669658	0.203354897000224	0.310309381214875	0.458565061783528	0.453591676062464	0.32740474377789	0.272446917712129
7	HOBBIES_1_001_CA_1_validation	1.18193619176616	1.2491193145216	1.04652779562977	0.973180921102816	1.26609528425023	1.67392049183402	1.46913960555929	1.1823676446714	1.35795101690093
8	HOBBIES_1_002_CA_1_validation	0.265919160983352	0.254732811486567	0.259783955411552	0.281025664146111	0.26406974214638	0.276156934411993	0.29655006406458	0.310822807140273	0.27323434510476
9	HOUSEHOLD_1_001_CA_2_validation	0.398803935889573	0.404996968954358	0.382860965073052	0.396400749338846	0.385497293015342	0.412074255297857	0.444323251344967	0.424288412208982	0.348606916060561
10	HOUSEHOLD_1_002_CA_2_validation	1.46008296031802	1.08513985406673	1.05789415916909	1.04580403394233	1.48983335637228	2.40466380649626	2.61490704002849	1.53734723047054	1.1579104997411

Fig. 8. Sales forecasts for all departments and categories for the store CA_1.

3. Finally, the app houses the results from the time series analysis performed on the input criteria under the "Sales Forecast" tab (refer Fig. 8). Predictions on sales for the selected products/departments/categories/stores/states are available here. The predictions are updated by and are only relevant for the selected inputs. The user is free to form an opinion and make business decisions based on these forecasts that concern relevant selections. This R-Shiny application integrates data visualization and sales forecasting and provides a flexible selection of data parameters, acting as a comprehensive sales analysis software for different business-related applications. In addition to Company owners, executives, and board of directors being the most direct stakeholders, there are also secondary stakeholders for whom this tool will be of immense value, such as employees and managers in logistics, warehouse administrators, retail outlet stockers, investors, and stockholders.

The tool has the potential to impact its' stakeholders to a high extent. Some of them are elaborated below.

Impact on an employee: Based on the prediction result, product sales of all stores can be monitored and forecasted. Users will be prepared for the increase in workload, shift in trends, and emergent patterns in sales. By looking at forecast data, business managers and employees have the flexibility to allocate their time, resources, and energy based on relevant planning, thereby improving efficiency, and profits, while adding to sustainability. Current trends, shifts in seasonality, etc., can be monitored as well.

Impact on shareholders: A predictability in sales can allow for a direct relation to be made with the predictability of profits. Being a strong indicator of the company's growth, this can allow for the predictability of business performance as a publicly listed company and the value of its shares. This ability is of great value to shareholders.

Impact on executives and investors: Performance predictability will attract more investors. Executives can make strategic and operational decisions on behalf of the company if the future of its sales can always be accurately predicted.

One feature that could be incorporated in the future is commodity price forecasting. This function mainly serves consumers who want to spend at Walmart or any other related platform at a low price. The main functions include finding products with lower prices and good sales among similar products and recommending products that are more likely to reduce prices or increase sales in the future. Meeting consumers' demand for high-quality and low-cost products, this aspect of the app will be consumer-oriented rather than the currently existing business purpose utility.

This feature requires price data for various items of different institutions (e.g., Walmart) in each region in the form of time series. The model should be roughly the same as the previous sales number prediction and can be selected between SVM, L.S.T.M., and A.R.I.M.A. The advantage of using SVM is that sales data can be used as a variable to help forecast. L.S.T.M. and A.R.I.M.A. models can better grasp the cyclical changes in prices and notify purchasers of future changes in prices on their preferred products.

V. Conclusion

The U.S.P. of the app is that it performs data analysis and time series forecasts on the unique combination of input data relevant to the user. The functionalities of the app/tool, from a user's perspective, can be summarized in the following: -

- The ability to mix and match stores across multiple states for granularity and uniqueness of business requirements.
- The ability to select a single product or all products from mixed-and-matched product categories and departments.
- The ability to visualize the performance of selected products, stores, etc., in terms of sales in the past.
- The ability to produce time-series forecasts on sales for the required business criteria.

The app can serve as a go-to tool for store managers who need usable estimates of future sales to order and stock goods appropriately. Approximately $1 trillion worth of food produced for human consumption is wasted annually across the world [23]. This accounts for about a third of all food production. The United States is one of the largest consumers, and Walmart being the world's largest corporation in terms of revenue and goods sold, contributes to much of it. There are many other organizations where this concept can be implemented. This application enables sustainability by minimizing wastage, providing the corporation with the means to minimize the wastage of unsold goods.

Appendix

Nr	Code metadata description	
C1	Current code version	*v1.0*
C2	Permanent link to code/repository used for this code version	*https://github.com/asjotawar/WalmartSalesForcasting_RShiny*
C3	Code versioning system used	*none*
C4	Software code languages, tools and services used	*R, R-Shiny, R-Studio*
C5	If available, link to developer documentation/manual	*https://shiny.rstudio.com/*

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