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Improvement in order planning process through AI-based zonal sales prediction and analysis

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Abstract : The team at Pantaloons does sales prediction and order planning manually in an excel sheet. Through our project, we try to see how the prediction process can be improved and incorporate everything into a software that'll be based on machine learning, helping in getting an output that'll be much more accurate and relevant, with a significant drop in human input.

***IndexTerms* – order planning, forecast, machine learning, LSTM**

I. INTRODUCTION

Order planning is something that plays a major role in how a company will do. If the order quantity is way off from what is actually required, the company could suffer huge losses. An important aspect of order planning is sales forecasting that allows you to spot potential issues while there's still time to avoid or mitigate them. Discovering problems in the ordering plan now -versus at the end of the month or quarter- has a huge impact. Sales forecasts also come into play for a number of decisions, from hiring and resource management to goal setting and budgeting.

1.1 Need of the Project

The garment manufacturing industry faces many global challenges due to various factors including competition, increased production costs, less productivity/efficiency and labor attribution. So, there is a need to focus and concentrate on identifying the real issues, taking initiative in introducing contemporary tools suited to the company and the departments at hand, and empowering the technical and managerial staff by enhancing their knowledge and ability by creating conceptual awareness. Hence, the role of introducing a dynamic application for sales prediction and planning in general is very crucial in improvement of the organization's performance.

• This industry also requires upgradation. The manual process should be done with the ease of computer which reduces the processing time and increases the quality of work with fewer defects.
• The basic need of the project is to reduce the monthly order planning time, from days to within a few hours, without any difficulties.

In current scenario, there is no provision for automated logic-based prediction according to requirements, which can easily be done by using upcoming tools like machine learning and artificial intelligence.

1.2 Objectives

The project was undertaken to make sure that the order planning process improved as a whole, through tools leading to more accuracy and less time usage.

1.3 Sub-objectives

- Make the data more sensitive on the zonal level
- To convert manual work to automated work as much as possible
- Prevent losses due to over-buying or under-buying

II. REVIEW OF LITERATURE

2.1 Order Planning

Order planning is a fundamental part of fashion retail operations. It helps in balancing supply and demand, and relies heavily on accurate forecast of future demand. Any sort of prediction is affected largely by various parameters associated with sales. Hence, sales forecasting refers to predicting future demand (or sales), assuming that the factors which affected demand in the past and are affecting the present will still have an influence in the future. In the fashion retailing industry, forecasting itself can be treated as a "service" which represents the set of analytical tools that facilitate the companies to make the best decisions for predicting the future. Undoubtedly, a good forecasting service system can help to avoid understocking or overstocking in retail inventory planning. In order to successfully plan the future under a highly competitive environment, a company should adopt a consumer-demand driven "pull" operational strategy, which in turn puts more importance on forecasting. [1]
The fashion industry is a very fascinating sector for the sales forecasting. Indeed, the long time-to-market which contrasts with the short life cycle of products, makes the forecasting process very challenging. [2]

2.2 Methods of Sales Forecasting

There are various ways in with forecasting can be done, including the buzzword of the century- 'machine learning'. The most commonly used prediction methods are:

2.2.1 Statistical Tools (Traditional)

A lot of statistical methods can be and have been used for sales forecasting, which include linear regression, moving average, weighted average, exponential smoothing (used when a trend is present but not linear), exponential smoothing with trend, double exponential smoothing, etc.

These methods are not very well preferred now because AI is a new tool coming up, which is more sophisticated in its working and more accurate with its results. Also, traditional statistical tools aren't very inclusive on all parameters relevant to the process. [3] Lastly, it requires an expert knowledge of statistics on the whole so as to shortlist the most suitable method for given data, which is highly inconvenient. [1]

A study done in 2015 [4] showed the use of some basic statistical tools for sales prediction of 7 categories of clothing. The results were very inconsistent and did have a considerable deviation from the actual sales. So, even if traditional methods are to be used, one needs to know exactly which one to use, and even after that chances are that it wouldn't be applicable for all the relevant parameters of the process.

2.2.2 Artificial Intelligence-based Systems

As discussed above, there are a lot of areas where traditional statistical tools fall short and fail to give accurate results. To make up for these shortcomings and cut down on human time and efforts, various artificial intelligence methods are being used nowadays; the most popular ones being Neural Network (NN) and fuzzy logic. [5]

2.2.2.1 Artificial Neural Network (ANN)

Artificial neural network is an AI-based model that is inspired by the human nervous system, and how it processes information. It consists of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. [6] ANN models imitate the parallel processing capabilities of a human brain, using mathematical artificial neurons distributed in parallel layers. In contrast to traditional time series models, ANNs constitute a model-free and data-driven approach which entails two significant features: flexibility and generalizability. [7] ANNs comprise an input layer, one or more hidden layers, and one output layer, each of which contains the corresponding neurons. ANNs with a single hidden layer are generally preferred, as they are less liable to produce an overfitted model that fits well with in sample data, but performs poorly in terms of generalization to out-of-sample data [8]

Table 1: [9] Comparison of error observed by different models

Model	Validation Error	Out-of-sample Error
• ExtraTree	• 14.6%	• 13.9%
• ARIMA	• 13.8%	• 11.4%
• RandomForest	• 13.6%	• 11.9%
• Lasso	• 13.4%	• 11.5%
• Neural Network	• 13.6%	• 11.3%

Table 1: [9] shows that Neural networks overall have a better result when it comes to prediction of data

2.2.2.1.1 Recurrent Neural Networks (RNN)

RNNs are a special type of NNs that are suited to model sequences of variable lengths [8]. In addition to the standard input and output layer, RNNs contain special hidden layers that are composed of recurrently connected nodes. These hidden layers are commonly referred to as memory states, as they enable the networks to preserve the sequential information and persist the knowledge acquired from subsequent time steps. The past information is retained through a feedback loop topology, where as a part of the input of the current step, the RNN uses the output of the previous time step during the network training. In effect, this recurrent model enables the network to take the previous values into account. [10]

2.2.2.1.1.1 Long Short-term Memory (LSTM)

RNNs, and in particular Long Short-term Memory (LSTM) networks are naturally suited for modelling problems that demand capturing dependency in a sequential context, and are able to preserve knowledge as they progress through the subsequent time steps in the data. [10]

2.3 Advantages

There are various advantages that AI based systems have, and that is evident by their excessive use in every field. Some of these are:
- during turbulent economic times, ANNs generally provide superior forecasts over the traditional methods. ANNs provide significantly better forecasts when the parameters experience large fluctuations. [11]
- ANN may be useful in a situation where time series present a non-linear behavior and do not show an explicit statistic behavior (given that ANNs allow the approximation of almost all non-linear continuous function [12]

2.4 Challenging Parameters

A research paper [5] is specifically dedicated to the challenges faced in sales prediction in the clothing industry, and states that there are numerous attributes that have a direct effect on sales and in directly on sales forecasting. Some of them are as follows:
- New fashion cycles
- Short lifecycle
- Long prediction time
- Weather conditions
- Large number of products

What retailers have is large volumes of previous years' sales data and they use it to forecast future purchases using conventional techniques [13]. While these help in estimating demand at reasonable levels of confidence for existing/previously sold merchandise, they cannot be used for predicting demand for new merchandise. Since multiple parameters in design interact non-linearly to define the look or appeal of an item in fashion, past sales data in itself is not instructive in predicting demand for future designs. [14]

2.5 Market Scenarios/Applications

Table 2: [6] Application of machine learning in the garment industry

Yarn	Fabric	Garment
• Fibre identification • Structural image processing • Quality and property prediction	• Quality and property prediction • Defect identification • Consequence predictability	• Pattern/marker efficiency improvement • Seam performance analysis • Fit/wear trials • Sensory comfort analysis

Table 2: [6] shows the applications of machine learning, artificial neural network to be precise, in the garment industry. It shows how promising the scope of ANN is in this sector

III. RESEARCH METHODOLOGY

3.1 Primary Study

3.1.1. Study of existing order planning process

1) Season: This lists all 4 seasons of fashion for each year, which are- Spring (SP), Summer (SU), Autumn/Festive (FE) and Winter (WI).
2) No. of weeks: This row is for listing the no. of weeks of each month mentioned in the row below.
3) Sales LY: Like the name suggests, it lists the no. of items sold last year during the same month.
4) Sales CY: Like the name suggests, it lists the no. of items sold in the current year during month mentioned. This row has predictions which are decided by the manger by her gut feeling or instincts, based on the trends, plans and all the parameters mentioned in the sheet.
5) PI%: This is Performance Indicator % which showed the growth in sales for that month as compared to the closing stock.

$$\text{PI\%} = \frac{(\text{Sales CY/Closing stock of last month})}{\text{No. of weeks}}$$

6) Ideal stock: This showed the quantity that should be available in the store to satisfy the average weekly sales. Just to be on the safer side, it took the average of the predicted sales for the next 2 months, in case there were any jumps due to festivities.

$$\text{Ideal stock} = \frac{\text{Sum of Sales CY of next 2 months}}{\text{Sum of No. of weeks of next 2 months}}$$

7) Closing stock: Closing stock simply states the quantity of products left on the last day of that month. This also serves as the opening stock for the next month.

8) Adjustments: These ideally list the number of products that have been found unfit for sale due to some issue (legal or otherwise) and products that have been in the store for more than 2 years (4 seasons old).

(Note: Ideally these clothes are supposed to be scraped off from the stores, but the protocol is not really followed. The only time adjustments make a difference is when there is a legal issue/case involved, which could lead to serious consequences.)

9) Inwards: This is also predicted initially, and then replaced by actual inward figures as months pass. It helps in keeping a track of how much has been ordered and how much gets delivered every month.

10) Original order quantity: This is the final verdict passed by the manager. After looking at the sales prediction and trends, the manager analyses the data at hand to decide how much to order, or if to even place an order or not.

(Note: It is observed that an unusually large number of products were ordered during SS19, because the strategy of the planning team back then was different. The aim was to get as many products in as possible, so as to try and inculcate a push system towards consumers and satisfy demands for the growing rate of new stores coming up. Unfortunately, the strategy didn't work out very well and finally resulted in a huge stock left in warehouses. Because of this, the manger tried not to place any new orders in some months to make up for the backlog. Also, the strategy shifted to studying the data at hand and working accordingly, instead of taking a far-fetched leap.)

11) Projected: As and when the months pass and the predicted sales get replaced by actual figures, the predicted numbers are shifted on to this row. This is to keep a track of what the predictions for the month were.

12) Ach %: This relates the predictions from the row above with the actual sales of the month. The aim is to make this value reach as close to 100% as possible. The disparities in the values are a lot, and the variation of actual figures from projected numbers have gone up to more than 50%.

$$\text{Ach\%} = \frac{\text{Projected sales}}{\text{Sales CY}}$$

The manger takes care of order planning and has complete control over it. He/she makes sales predictions for coming months, solely based on mental calculations and 'gut instinct'. Out of the 12 fields, 4 (Sales LY, PI%, Ideal stock, Ach%) are calculated automatically based on the other 8 manually entered fields.

Overall, the whole order planning for 1 division (out of 4) takes a day's time, and the final order planning for all 4 divisions takes 3-4 days

3.2 Requirement Analysis

Biggest issue observed during internships was the roles and responsibilities of the manager of the planning department.

- A lot of time went behind just this one activity, while there were so many things for the manager to do.
- All of the mental calculations, trend analysis and data processing often led the manager to go to an empty meeting room to focus.
- Finally, 3/4th of the fields in 1 Excel sheet were left for manual entry, which when multiplied into 4 divisions with 3 products in each with 4 zones for all, would create a lot of data left for just the manager to fill up. All of this would is a cumbersome task for an individual, while providing a huge scope for human errors.

The project aims to create an application for sales prediction, that would do all of the calculations based on the input, through machine learning. Also, the final Excel for order planning could be designed in such a way that the majority of fields would be formulated, while leaving very few fields for manual entry.

This would help the manager to perform in a very efficient and quick manner, leaving very little scope for human input and error, so that they can concentrate in different areas and tasks

3.3 Data Collection

For the project to be successful, a lot of data would need to be collected. This would include:

3.3.1 Sales Report

- Tool Used: BOBI (Internet Explorer)
- Microsoft Excel Outcome: The report gives the number of sales in terms of quantity sold and Net Sales Value, for whatever time period specified.

3.3.2 Stock Report

- Tool Used: CUBE (Retail Planning share-folder)
- Microsoft Excel Outcome: The report gives details on the quantity of each article, be it intransit or at the warehouse. This report comes out every week.

3.3.3 Inwards Report

- Tool Used: SAP software
- Microsoft Excel Outcome: The report gives details on the quantity of inwards, for whatever time period is selected

3.3.4 Festival Mapping

Table 3: Festival mapping for the years 2018, 2019, 2020 & 2021

Sr. No.	Festival Name	Month for 2018	Month for 2019	Month for 2020	Month for 2021	Stores/Areas/Cities seeing a spike in sales			
						East	North	South	West
1	Pongal/Sakranti	January	January	January	January				
2	Gudi Padwa	March	April	March	April				
3	Poila Boisakh	April	April	April	April				
4	Onam	August	September	August					
5	Diwali	November	October	November					
6	Durga Puja	October	October	October					

- Tool Used: Manual entry
- Microsoft Excel Outcome: The table gives details on the festivals that see a spike in sales. Each festival may fall in a different month for a different year, so that needs to be mapped. Also, festivals affect zones differently, so whatever zone is affected by that particular festival is marked as green.

3.4 Data Processing

3.4.1 For the sales prediction application

Some parameters were shortlisted as relevant input for the application. These are:

1) Season
2) Year
3) Month
4) No. of weeks
5) Division
6) Product
7) EOSS (Y/N)
8) Zonal festive rating
9) Zonal store count
10) Sales

Out of these, all parameters excluding sales (number 10) are the same for all divisional products, so they can be made a part of one Excel sheet, and sales data can be part of another sheet.

3.4.1.1 Sales Input Sheet

Figure 1: Sales Input sheet for the application

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Division	JB	JB	JB	JB	JB	JB	JB	JB	JB	JB	JB	JB	JB
2	Product	AOP	AOP	AOP	AOP	AOP	AOP	AOP	AOP	AOP	AOP	AOP	AOP	AOP
3	Season	SP18	SP18	SP18	SU18	SU18	SU18	AW18	AW18	AW18	WI18	WI18	WI18	SP19
4	Year	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2019
5	Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan
6	E sales	1020	998	1568	2245	1987	1693	1815	1792	1915	1029	172	312	946
7	N sales	1036	600	1998	2122	2105	3369	2161	2328	672	336	191	399	1289
8	S sales	1567	978	1564	1995	2007	1304	1155	1466	836	1078	894	1354	2844
9	W sales	2400	1099	2062	4129	4256	2383	2392	2369	743	942	1383	3022	3244

3.4.1.1 Data Input Sheet

Figure 2: Data Input sheet for the application

C19

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Season	SP18	SP18	SP18	SU18	SU18	SU18	AW18	AW18	AW18	WI18	WI18	WI18	SP19
2	Year	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2019
3	Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan
4	Weeks	4.4	4.2	4.4	4.3	4.4	4.3	4.3	4.4	4.3	4.3	4.4	4.3	4.4
5	EOSS (Y/N)	Yes	No	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes
6	E festive rating	5	0	0	5	0	0	0	0	0	5	5	0	5
7	E store count	53	53	55	57	57	58	58	58	60	61	61	61	61
8	N festive rating	5	0	0	0	0	0	0	0	0	0	5	0	5
9	N store count	71	72	77	77	77	77	77	77	77	81	82	84	85
10	S festive rating	5	0	0	0	0	0	0	5	0	0	5	0	5
11	S store count	57	59	62	63	64	65	66	67	69	71	73	73	74
12	W festive rating	5	0	5	0	0	0	0	0	0	0	5	0	5
13	W store count	62	63	66	67	67	67	68	70	70	72	74	74	75

3.4.1 For the Excel-based Order Plan

The final order planning sheet on Excel can be much more descriptive and automated (formulated) as compared to the current format. The relevant parameters as follows:

(Note: Example given for the month of April)

- Sales LY= From input (LY)
- Sales CY= Predictions (because Jan-March will be input)
- PI%= (Sales CY of April/Closing stock of March)/No. of weeks of April
- Ideal stock= (Sum of sales CY of May and June/Sum of no. of weeks of May and June) * Weeks ideal forward cover
- Closing stock = Closing stock of March + Inwards of April - Sales CY of April - Adjustments of April
- Adjustments= Manual entry
- Inwards= Manual entry

- Weeks ideal forward cover= 16 (for all columns)
- Actual NWC= Closing stock of April/Sales CY of April) * No. of weeks
- Average weekly sales LY= Sales LY for April / No. of weeks in April
- Average weekly sales CY= Sales CY of April / No. of weeks in April
- Store count= from input (CY)
- Per store per week ROS= Avg. wk sales CY of April / Store count of April
- Original order quantity= Manual entry

With these 14 parameters, only 3 are left for manual entry while rest are formulated. This saves a lot of time and scope of error. Also, with the added details, it is much easier to decide about the final order quantity.

3.5 Design and Layout

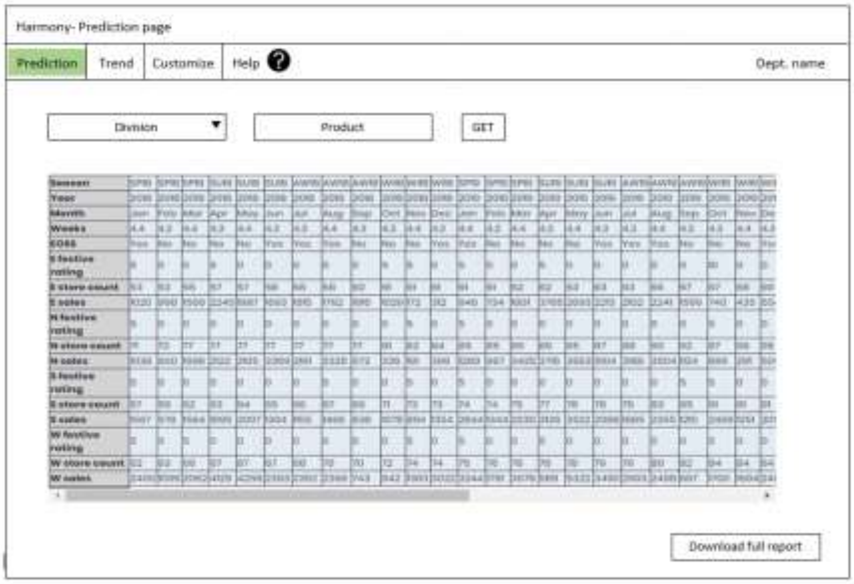
3.5.1 Application design

Apart from basic layout pages like Home and Help page, there are 3 other important sheets:

3.5.1.1 Prediction page

The main page of the application is the prediction page, that will show the sales prediction data zone-wise. The data is based on the input provided. Also, the categorization is on the Division>Product level, and can be changed to whatever data you want to filter out.

Figure 3: Prediction page for the application Harmony



3.5.1.2 Trends page (Welcome page)

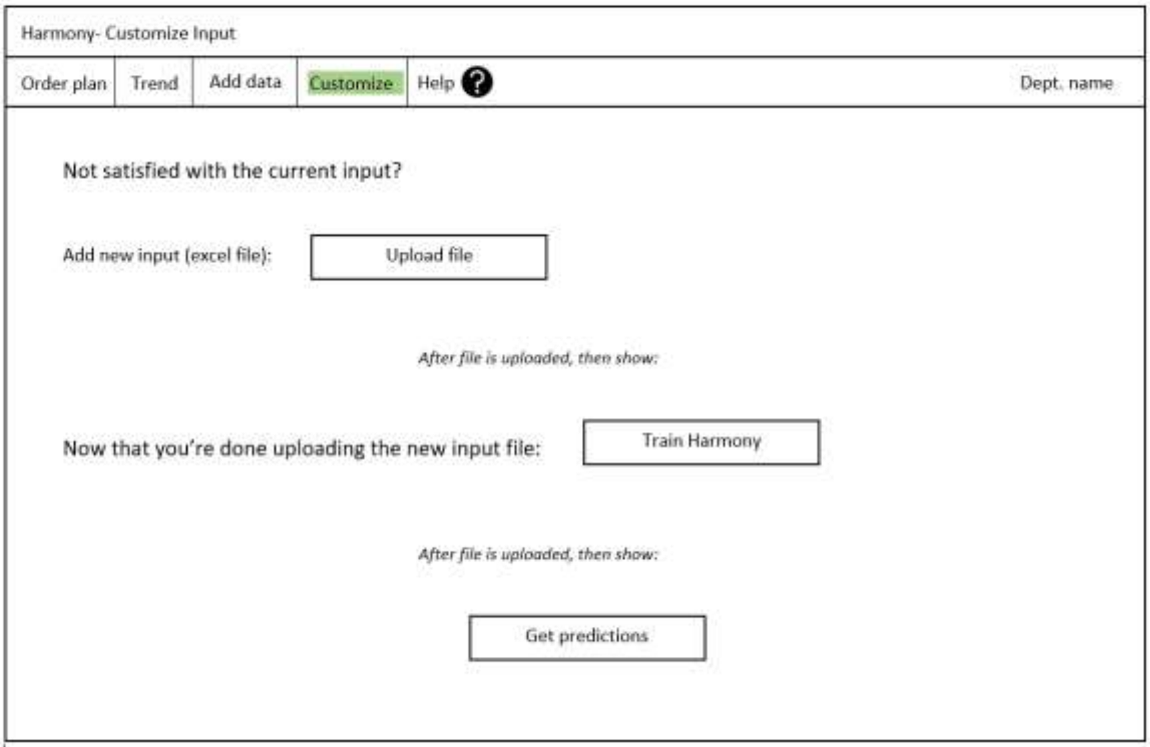
This page adds some extra features to this application and is the first page that logging in leads to. It shows a visual representation of sales for all divisions, according to the input and output present in the system. At a time, it shows all products present under any one division that is clicked on. The main purpose is to provide a quick summary of how well or unwell the divisions and products are doing. The format is quite easy to grasp and make inferences from. This could also prove to be very helpful in decision-making & future strategizing.

Figure 4: Welcome page (visual representation of sales trends) for the application Harmony

3.5.1.2 Customize Page

This page is important for providing an input or changing it for getting the desirable output. Without this page, it would make the application a mere one-sided one, that would show the same data all the time.

Figure 5: Customize input page for the application Harmony



3.5.2 Order Plan design

The new order plan would have some new fields to give a more elaborate idea of the monthly sales.

Out of the 13 fields here, only 3 are left for manual entry with everything else being formulated for ease. This would reduce human involvement to a great extent and lead to less errors too.

Figure 6: Order plan (on Excel)

EAST

		Season	FE19		WI19			SP20			SU20	
		No. of weeks	4.4	4.3	4.3	4.4	4.3	4.4	4.2	4.4	4.3	4.4
		Month	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
		Store Count	65	67	67	68	69	69	70	71	71	72
Div	Proc											
JB	AOP	Sales LY	1792	1915	1029	172	312	946	734	1801	3765	2693
JB	AOP	Sales CY	2241	1599	740	435	554	1080	953	1130		
JB	AOP	PI %	3%	2%	1%	1%	1%	1%	1%	1%	0%	0%
JB	AOP											
JB	AOP	Ideal stock	4352	2161	1819	3005	3782	3875	2078	0	0	0
JB	AOP											
JB	AOP	Closing stock	17225	15626	15520	17563	20686	19606	22327	23038	23038	23038
JB	AOP	Adjustments (Non Tradeable)	0	0	0	0	0	0	0	0	0	0
JB	AOP											
JB	AOP	Inwards actual/plan	0	0	634	2478	3677	0	3674	1841		
JB	AOP											
JB	AOP	Weeks Ideal forward cover	16	16	16	16	16	16	16	16	16	16
JB	AOP	Actual NWC	34	43	91	178	161	80	99	90	#DIV/0!	#DIV/0!
JB	AOP											
JB	AOP	Avg. wk sales LY	408	446	240	40	73	215	175	410	876	613
JB	AOP	Avg. wk sales CY	510	372	173	99	129	246	227	257	0	0
JB	AOP	Per Store Per Week ROS	8	6	3	2	2	4	4	4	0	0
JB	AOP											
JB	AOP	Original Order Qty	0	0	0	0	0	0	0	0	0	0

3.6 Implementation

3.6.1 Conceptual Awareness

First Step of Implementation was giving conceptual awareness to the manager and the executives in the planning team and to explain the importance of automation. Also, another main task was to explain topics like machine learning and algorithms that went into the making of the application.

3.6.2 Validation Testing

To check the effectiveness of predictions, data from SS18 till date was considered. 80% of the data (randomly chosen) was taken as input for training the model, and the rest 20% was kept aside for getting predictions.

IV. RESULTS AND DISCUSSION

4.1 Result of Validation Testing

Figure 7: Results obtained from validation testing

Month	Year	Division	Product	Sale	Prediction	Error %
Feb	2019	jg	pl	7.8	8.406212	7.771947
oct	2019	jg	sl	7.8	7.098456	8.994149
jun	2018	jg	sl	6.4	5.983769	6.503618
aug	2018	jg	pl	12.8	13.98956	9.293461
jul	2018	tb	aop	11.8	11.52265	2.350442
may	2019	jg	sl	6.4	6.310551	1.397645
oct	2018	jg	gt	28.7	25.97987	9.477812
oct	2019	jg	gt	33.4	30.17144	9.666358
mar	2019	jg	st	10.5	10.00397	4.724058
jan	2018	jb	gt	9.2	8.636799	6.121752
nov	2019	jg	pl	16.8	15.68097	6.660909
dec	2019	tg	sl	8.5	8.112144	4.563017
oct	2019	tb	st	23.6	23.06756	2.256117
nov	2018	jg	sl	4.4	4.823234	9.618946
dec	2019	tb	aop	6.3	6.547188	3.923624
sep	2019	jg	st	9.6	8.783327	8.507009
aug	2019	tb	gt	25.6	26.39329	3.098772

Maximum error obtained was 9.6% as compared to the maximum error from old sheet to be 44%, thus showing this method was much more reliable and accurate.

4.2 Time, manpower, effort study

4.2.1 Current Scenario

- The manager had to exclusively sit for seeing the report and analysing it to make predictions (if not to enter data first and then do all this).
- That would take over 1 hour for each divisional product (out of 14 in all).
- Predicting sales for 14 products by itself would take 2 working days, leave alone the order quantity planning bit.
- After predictions, the manager studied the data at hand (parameters like closing stock, festivals, etc.) and came up with the quantity they would like to buy for the future months in question.
- A lot of time went behind just this one activity, while there were so many things for the manager to do.
- All the mental calculations, trend analysis and data processing often led the manager to go to an empty meeting room to focus.

4.2.2 Proposed Scenario

- Given the new data with added parameters and divided on the zonal level, there would be 14*4= 56 products to be studied and predictions made for all of them. That would lead to madness and increase human errors by a huge margin. Hence, an application was designed to make all predictions based on the input fed.
- 2 working days for prediction has been reduced to less than an hour for everything (given the new database that has data from 2018 till now).
- The new order planning sheet on Excel too has a new layout, and added parameters that'll be relevant for deciding order quantities.
- Even though there are added tables, most of the fields are formulated, thus saving time and efforts going behind the activity. All of it could very easily be done within 2 hours (against the one day's time it takes on an average)
- Total time taken during proposed model is 3 hours against the 2 days it takes with the traditional methods.
- Lastly, the new process is automated and simplified to the extent that everything can be done by a planning executive and then the final order quantity could be given to the manager for checking.

4.3 Conclusion

Over the course of the internship, it was observed that human intervention with numerical data often led to a lot of errors and hence it is important to take help from contemporary, upcoming machine-related methods as much as possible. The same ideology was supported upon the completion of the project.

The application and Excel order plan were fully functional and was able to meet the set objective "... to make sure that the order planning process improved as a whole, through tools for better accuracy and less time usage" and sub-objectives mentioned. This system will give ease to the team in taking necessary decisions and scheduling the orders of all departments in a proper manner. This system will give a much better performance than any manual record entry/analysis system. Thus, the occurrence of human errors would be minimized to the maximum.

We need to deskill the operations where people are taking more time in making reports and instead of taking actions. There is a need of shifting of thought process and approach. Apart from learning tools and techniques, it was found that in today's world, it is more important to know the process.

4.4 Future Scope

- To bring order planning on the software as well, to eliminate the use of excel altogether) – this will help in bringing the whole process of ordering of core plus products on one platform
- To incorporate all other worlds into the software (Men's and women's- western and ethnic)
- To link the software with other platforms, so as to automatically pull data like sales and store count.

V. ACKNOWLEDGEMENT

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