**THE DEVELOPMENT OF THE PREDICTIVE MODEL TO FORECAST RETAIL STORE SALES DURING PEAK AND OFF-PEAK PERIODS**

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**RESEARCH LITERATURE REVIEW**

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MONTH, YEAR MAY 2020

**RESEARCH LITERATURE REVIEW**

**CHAPTER 2: LITERATURE REVIEW**

Predictive analytics incorporates a variety of statistical techniques from modelling, machine learning and data mining that analyse current and historical data in order to determine patterns; predict about future outcome and trends. Predictive analytics does not tell what will happen in the future, it forecasts what might happen in the future with an acceptable level of reliability. It helps to identify potential risks and opportunities for a company. This also helps to better understand customers, products, partners and market. Often the unknown event of interest is in the future (Ranjana, 2019).

Sales forecasting is the process of using a company’s sales records over the past years to predict the short-term or long-term sales performance of that company in the future. This is one of the pillars of proper financial planning. As with any prediction-related process, risk and uncertainty are unavoidable in sales forecasting too. Sales forecasting helps businesses to manufacture sufficient products by estimating customer demand in advance. Hence, businesses must make sales forecasting to improve customer experience and reduce complaints. Also, they can drive sales by processing just-in-time orders efficiently. In order to reach a high achievement in sales forecasting/ prediction, it is wise and highly recommended to always look back in what has been done in the previous studies and researches and examine the steps involved in sales forecasting. Again sales forecasting and predicting analytics have a crucial impart on the success and performance of companies. Companies faces several challenges regarding accurate forecasts. For instance, they have to place their production plans before exact knowledge about future demands is available (Thoben, 2015). Sales forecasting allows companies to spot potential issues or risks and design appropriate corrective actions to mitigate them (Deloitte, 2018). Classification of data is very important in decision making. Clustering techniques are very useful in discovering distribution patterns and clustering algorithms employ a distance metric based similarity measures (Tsai, et al., 2002)

Predictive analytics is a group of methods that uses statistical and other experimental techniques to predict future events, based on past occurrences. This can be useful for demand forecasting, defect detection, maximizing equipment value, preventive maintenance, optimize marketing strategies, retain customer and connected aftermarket service in industry (Ranjana, 2019). In contrast to the application of predictive analytics to sales forecasting, a lot more literature and applications can be found in the area of advertising, including target marketing and recommender systems, finance and risk analytics (Miller, 2014).

In addition to manufacturing sufficient products, businesses also need to monitor and manage inventory proactively. Often enterprises fail to monitor and manage inventory efficiently due to lack of information regarding future demand for a product. Insufficient inventory management further makes many businesses to have overstock and stock-out situations. Sales forecasting helps businesses to avoid overstock and stock-out situations by predicting demand for a product accurately and managing inventory proactively. (bluepiit.com, n.d.)

Generally two major categories of forecasting techniques have to be distinguished here: quantitative and qualitative methods. Traditional forecasting is accomplished by quantitative, statistical methods like time series and regression models, which are most commonly used techniques for prediction of sales data according to literature (Makridakis, et al., 1998).

In various areas of research it is believed that the model obtained using neural networks is better compared to other ways of modelling. (Lapedes & Farber, 1987) Published an article where they trained the network to generate a time series using a specific equation and they obtained agreeable results which provided accurate forecasting.

(Thiesing & Vornberger, 1997) discussed sales forecasting using neural networks trained with back-propagation algorithm that were applied to predict the future values of time series that consisted of the weekly demand on items in a supermarket. The influencing indicators of prices advertising campaigns and holidays were taken into consideration. The design and implementation of a neural network forecasting system was described and developed as a prototype for the headquarters of a German supermarket company to support the management in the process of determining the expected sale figures. The performance of the networks was evaluated by comparing them to two prediction techniques used in the supermarket. The comparison showed that neural networks outperformed the conventional techniques with regard to the prediction quality. Initially the exploratory analysis and partial autocorrelation functions were used to analyse the time series sales data to verify the existence of seasonal components, non-stationary and the randomness in data. The number of intermediate layers for the back-propagation model was determined by trial and error approach. Error analysis of the time series were carried out for accurate forecasting.

A number of researchers have developed nonlinear forecasting models for predicting stocks or sales, (Chiu, et al., 2008) used improved BPN/Cauchy machine and genetic algorithms to build an efficient neural network and to forecast Taiwanese electronic stock indexes. Authors after comparing the back-propagation procedure to other traditional methodologies, found that the back-propagation procedure is one of the most appropriate procedures for forecasting, especially for nonlinear data. Back-propagation updated the weights in each perception to justify the real results as matching or approaching the desired result.

Another common forecasting method is the regression technique, which focuses on the correlations between sales and all the explanatory, outside factors discussed above. Regression models investigate how sales will develop if the exogenous factors change, for example if a marketing action such as a sales promotion program is carried out. According to (Mentzer & Moon, 2005), regression models consequently provide a broad environmental perspective for forecasting sales. Regression models needed huge data sets including past history on each factor and sales volume and therefore were most useful when time horizon is more than six months (Brannon, 2010).

According to (Sayli, et al., 2016), in order to be competent enough and to generate higher revenue, business organizations are constantly in search of a better model or technique for data mining and maintenance of critical data. Business industry faces severe challenges to identify an accurate data mining technique and effective predication strategy (Maingi, n.d.). Sales data analysis faces lot of issues and major aspects of sales functions are identification of product attribute, price fixation, net sales realization and launch of new product. Various prediction methods, sales forecasting strategies and Expectation Maximization (EM) algorithm are discussed (Sastry, et al., 2013).

Data mining is the discovery of structures and patterns in large and complex sets (David & Adams, 2015). Classification of data is very important in decision making. Clustering techniques are very useful in discovering distribution patterns and clustering algorithms employ a distance metric based similarity measures (Tsai, et al., 2002). In an appropriate data mining techniques information from a bulky data set can be transformed into a reasonable format and can be done by using supervised and unsupervised learning (Kaur & Mann, 2013). With an appropriate sales prediction technique, effective business decision making can be done. As suggested by (Korelev & Ruegg, 2015), the prediction error can be reduced with the implementation of XGBoost and additional support of SigOpt Bayesian Optimization method.

Authors in (Jain, et al., 2015) performed sales forecasting for stores using different data mining techniques. The task involved predicting the sales on any given day at any store, in order to familiarize themselves with the task they have studied previously.

According to (Lassen & Vatrapu, 2014), social media can play a crucial role in prediction of sales of this model. While mentions on social media are the rate of attention that a product receives, Google trends may represent the interest that potential customers have for the product. Research have shown that search activities can represent buying intention and even predict consumer behaviour and sales of both lower and higher involvements purchases (Choi & Varian, 2012).

There has been previous research that explored the relevance of social media to predict sales (Asur & Huberman, 2010). The study predicted box office sales remarkably accurate by including many variables such as sentiments and the frequency of tweets into their prediction model. Various other predictive study has followed the approached by (Asur & Huberman, 2010). A study based on this method by (Lassen & Vatrapu, 2014) predicted quarterly iPhone sales by analysing the sentiments of tweets and using a seasonal weighting of tweets to calculate the given quarter’s proportion of the last calendar year.

(Massaro, et al., 2018) Compared data mining model performance of sales predictive algorithms based on RapidMiner Workflows. Authors processed RapidMiner workflows dataset originated from different data files, and containing information about the sales over three years of a large chain of retail stores. Authors subsequently constructed a deep learning model performing a predictive algorithm suitable for sales forecasting. The model was based on artificial neural network (ANN) algorithm to learn the model starting from sales historical data and pre-processing the data. The best built model used a multilayer neural network together with an “optimized operator” to automatically find the best parameter setting of the implemented algorithm. In order to prove the best performing predictive model, other machine learning algorithms were tested. The performance comparison was performed between support vector machine (SVM), k-Nearest Neighbor (k-NN), Gradient Boosted Trees, Decision Trees, and Deep Learning algorithms. The comparison of the degree of correlation between real and predicted values, the average absolute error and the relative average error proved that ANN exhibited the best performance. The Gradient Boosted Trees approach represented an alternative approach having the second best performance. The study was deployed within the framework of an industry project oriented on the integration of high performance data mining models to predict sales using enterprise resource planning (ERP) and customer relationship management (CRM) tools.

An improved demand forecasting model using learning approach and proposed decision integration strategy for supply chain had been developed by (Kilimci, et al., 2019), since demand forecasting is one of the main issues of supply chains. The research aimed to optimize stocks, reduce costs, increase sales, profit, and customer loyalty. Historical data was analysed to improve demand forecasting by using various methods like machine learning techniques, time series analysis and interpretation of the historical data by using different forecasting methods which included time series analysis techniques, support vector regression algorithm, and deep learning models. The other novelty of the authors work was the adaption of boosting ensemble strategy to demand forecasting system by implementing a novel decision integration model. The developed system was applied and tested on real life data obtained from SOK Market in turkey which operates as a fast-growing company with 6700 stores, 1500 products, and 23 distribution centres. After a wide range of comparative and extensive experiments demonstrated that the proposed demand forecasting system exhibits noteworthy results compared to the state-of-art studies. But unlike the state-of-art-studies, inclusion of support vector regression, deep learning models, and a novel integration strategy to the proposed forecasting system ensures significant accuracy improvement.

In the study referenced in (Pavlyshenko, 2018)**,** the author used store sales historical data from “Rossman Store Sales” Kaggle competition (Anon., 2018). The calculations were conducted in Python environment using the main packages pandas, sklearn, numpy, keras, matplotlib, seaborn. Jupiter Notebook was used for analysis. They first conducted the descriptive analytics, which is the study of sales distributions, data visualization with different pair plots. The supervised machine-learning approach was considered using sales historical time series and for categorical features, one-hot encoding was applied when one categorical variable was replaced by n binary variables, whereas n is the amount of unique values of categorical variables. In the forecast, bias on validation set may be observed which is a constant (stable) under or over-valuation of sales when the forecast is going to be higher or lower with respect to real values. The accuracy on the validation set was considered an important indicator for choosing an optimal number of iterations of machine-learning algorithms. The results showed that staking techniques can greatly improve the performance of predictive models for sales time series forecasting.

According to (Pavlyshenko, 2018) the effect of machine-learning generalization consists in the fact that a regression algorithm captures the patterns which exists in the whole set of stores or products. In case of short time period more precise results can be received. The effect of machine-learning generalization enables the making of predictions in case of very small number historical sales data, which was important in a new product or store launched. Expert correction can be made by multiplying the prediction by a time dependent coefficient to take into account the transitory processes, e.g., the process of the product cannibalization when new products substitute other products.

Authors ( (Wolpert, 1992); (Rokach, 2018); (Dietterich, 2000); (Rokach, 2005)) -considered the stacking techniques for building ensemble of predictive models. In that approach, the results of predictions on the validation set were treated as input regression for the next level models. Authors considered a linear model or another type of a machine-learning algorithm, e.g., Random Forest or Neural Network. On the first level, (Pavlyshenko, 2018) used many single models, most were based on XGBoost machine-learning algorithm (Chen & Guestrin , 2016). For the second stacking level, the author used two models from Python scikit-learn package: Extra Tree model and linear model, as well as Neural Network model. The results from the second level were summed up with weights on the third level. A lot of new features were constructed but the most important of them were based on aggregation target variable and its lags with grouping by different factors.

Retaining the customers is the major challenge for organizations. (Mohanty & Ranjana, 2018) Mentioned that they did not have any analytics related to customer behaviour earlier. Organizations were normally facing challenges in building perfect model and they did not have any perfect method to achieve optimized marketing strategies. In their research, authors explained how they use predictive analytics using Big Data Analytics tools and Python.

The has been substantial research work done by (Rokach, 2005; Rokach, 2005; Simmons, et al., 2010; Dorr & Denton, 2009; Gavrilov, et al., 2000; Kharratzadeh & Coates M, 2012) in predicting the stock prices of the companies based on the analysis of content from the online media such as news items, web blogs, twitter feeds. For example, (Gavrilov, et al., 2000) applied data mining techniques on the stock information from various companies by clustering them according to their Standard and Poor (S&P) 500 index, whereas the content from the weblogs was used by (Kharratzadeh & Coates M, 2012) to identify the underlying relationships between the companies to make predictions about the evolution of stock prices. (Asur & Huberman, 2010) Showed that social media feeds can be used as effective indicators of the real-world performance. In their work, authors used analysis of hourly rate of tweets about movies, their re-tweets and sentiment polarity to accurately forecast the box-office movies revenue. The prediction of movie revenues based on the social media measured from twitter outperformed the leading marker based predictions of the Hollywood Stock Exchange. (Penpece & Elma, 2014) Predicted sales revenue using Artificial Neural Network (ANN) in grocery retailing industry in Turkey. Since forecasting sales quantity and sales revenue is very vital for a company to take action for the next period for sustainable completion, it is especially important for growing industries like grocery retailing industry that are evolving rapidly. ANN models were used because of their capabilities of pattern recognition and machine learning. ANN method was used to forecast the sales revenue of upcoming period. According to results there were high similarities between forecasted and actual data. Forecasted results of their study were bigger or smaller than the actual data for only 10%. Because of that high accuracy, companies at grocery retailing industry in Turkey can use ANN as a forecasting model.

(Aye, et al., 2013) Forecasted aggregate retail sales, the case of South Africa to improve portfolio investors’ ability to predict movements in the stock prices of the retailing chains. Authors used data from 1970:01 – 2012:05, with 1987:01 – 2012:05 as the out-of-sample period. They deviated from the uniform symmetric quadratic loss function typically used in forecast evaluation excises. Hence, authors considered loss functions that overweight forecast error in booms and recessions to check whether a specific model that appears to be a good choice on average is also preferable in times of economic stress. Authors used weighted version of the Diebold-Mariano tests to evaluate the different forecasts. Results showed that focussing on the single model alone their performances differ greatly across forecast horizons and for different weighting schemes. However, the combination forecasts models in general produced better forecasts and are largely unaffected by business cycles and time horizons.

Manufactures need to sell their products. Demand is often seasonal or cyclical. In such cases as these, knowing how external factors such as prices, weather, the consumer price index and prime rate could affect your customer’s sales demand can help in resource allocation in manufacturing. Predictive analytics take historical sales data and applies forms of regression to predict future sales based upon past sales. Good predictive models find additional factors that influenced sales in the past and apply those factors to forecasted sales models. In our study we have reviewed that (Maita, 2019) Have done Sales prediction using Clustering & ML (ARIMA & Holt’s Winter Approach). The author used the sales transaction dataset from UCI ML depository. The dataset contained weekly purchased quantities of 800 products over a year 52 weeks. The cluster partitioning methods were considered helpful in minimizing total intra-cluster variation (Known as total within-cluster variation or total within-cluster sum of square).In preparation to build the predictive model, the author performed product segmentation using clustering. Clusters of items were identified based on their similarities and a common forecast was then computed for each cluster item. There were three popular methods for determining the optimal clusters; those were Elbow method, Silhouette method and Gap statistic. The study has predicted an average of less than 1.5 transaction per week for items in low demand and maximum average of 24 transactions per week for highly demanded items.

(Omar, et al., 2016) Researchers used Hybrid Neural Network Model for sales forecasting based on ARIMA (Autoregressive Integrated Moving Average) and search popularity of Article titles. Authors saw that the publishing industries usually pick attractive titles and headlines for their stories to increase sales, since popular article titles and headlines can attract readers to buy magazines. Authors’ information retrieval techniques were adopted to extract words from article titles. The popularity measures of article titles were then analysed using the search indexes obtained from Google search engine. Back Propagation Neural Networks (BPNNs) was successfully used to develop models for sales forecasting. Novel hybrid neural network model was proposed for sales forecasting based on the prediction results of time series forecasting and popularity of article titles, the proposed model uses the historical sales data, popularity of article titles, and the result of a time series. Authors used ARIMA forecasting method to learn prediction techniques. The experimental result showed that the proposed forecasting method outperformed conventional techniques which did not consider the popularity of title words.

(Aberg & Dahlen, 2017) Predicted sales in a food store department using ML in order to improve business operations and profitability. The study aimed to compare three ML methods for sales prediction in the food industry: Multilayer Perception (MLP), Support Vector Machine (SVM), and Radial Basis Function Network (RBFN). After these methods were compared due to their prediction accuracy on the daily sales, the performance of the models was determined by using the performance measures: Mean Average Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The end results showed that the SVM performed lower error measures than the other two methods. The difference between the methods was determined by the repeated measure analysis of variation (rANOVA).

Finding of optimal parameter settings for each model were down prioritized due to the time constraints of the study. Lack of deeper knowledge in how to find optimal parameter settings can be seen as a strong limitations of the study of (Aberg & Dahlen, 2017). Deep understanding of what features that affects the sales would result in a more accurate prediction. The results of a statistical comparison between ML methods might not be very informative without sufficient amount of data.

(Reznek, et al., 2017) Performed predictive analytics in an automated sales and marketing platform. The techniques introduced in the authors’ study empower sales leaders and sales representatives to forecast sales with confidence. The content included a series of slides that included information regarding a product or service pitched by the sales representative to the viewer (e.g., a prospective customer) and the content can be can be shared via a browser-based screen sharing technology that uses scripting computer languages codes to detect instances of viewer activity. The objective activity of viewer interactions with the content was generated by the scripting computer language codes and automatically uploaded to an analytics platform via one or more application programming interfaces (APIs). The analytics platform applied predictive modelling techniques to the objective activity data in order to measure the actual engagement of the viewer with the content shared by the sales representative. Prediction on whether future deals are likely to close using the historical data set of past deals was done in analytics platform. Authors discovered that automated collection of objective activity data by the analytics platform enables accurate prediction of sales performance by the sales representative and eliminates subjective human bias from the sales activity data used to forecast sales.

Sales forecasting can be done using different data mining and machine learning techniques where predicting sales on any given day at any store can be carried out, the detailed analysis and procedures were shown by (Jain, et al., 2015). The tasks involved in predicting the sales on any given day at any store, in order to familiarize ourselves with the task we have studied or reviewed previously. It seems clear that predictive analytics have had a positive impact on businesses since the early days. It is also clear that the impact will increase exponentially as data, models, methods and machine learning continue to improve based on maturity, high degree of accuracy, and decision making. The demand for predictive analytics will sweep across the industry and take the business to new heights. The market leaders continue to put forth their effort to transform data and apply analytics with increasing sophistication. A brief description has been given on how to develop predictive models in an industry using two of the existing algorithms (i.e. Time Series and Logistic regression algorithms) in Python. More predictive models can be developed based on the business scenarios by using different tools like tableau, Python and etc. The output of these predictive models can be compared with the real time data i.e. streaming from outside world into Big Data space or batch data. Organizations can use the tools like Apache Kafka and Strom for streaming process and can use any of the tools in Hadoop echo system for batch processing.

In our case study, we considered different machine-learning approaches for the time series. The method used by (Pavlyshenko, 2018) and author’s team using machine-learning predictive model is very much similar to the one we will be using for the completion of our research for retail sale forecasting. We will be using retail data analytics to accurately predict future sales. We focused on finding complicated patterns in the sales dynamics, using supervised machine – learning methods. Some of the most popular are tree-based ML algorithms (James, et al., 2013), e.g., Random Forest (Breiman, 2001), Gradient Boosting Machine (Friedman, 2001) and (Friedman, 2002).

The use of regression approaches for sales forecasting can often give better results than time series methods. ARIMA and ANN models have achieved successes in both linear and nonlinear domains (Zhang, 2003). One of the main assumptions of regression methods is that the patterns in historical data will be repeated in the future. Using staking makes it possible to take into account the differences in the results for multiple models with different sets of parameters and improve accuracy on the validation and on the out-of-sample data sets.

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