



Time-Series Techniques for Prediction Sales in Cashback Websites

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Abstract - Forecasting sales using time-series data has been an area of active research. In recent years, a significant amount of research effort went into forecasting sales in e-commerce platforms. The mechanisms of cashback are the main attractions for both advertisers and publishers. This B2C transaction enables the cashback website's publishers to earn a commission, and from that, they offer a percentage back to the consumers/end users in the form of cashback (aka rewards). This paper proposes a model that leverages an existing time-series technique seasonal persistence for forecasting sales in cashback websites. This paper contribution is to select different time-series models like Arima, XGBoost, Fbprophet, and applied them on three popular European-based cashback websites Cashback Korting, Nucash, iPay, to forecast their sales. The results confirm that XGBoost performs comparatively better than the other selected models as it produces reasonably low error rates (e.g., the Mean absolute percentage error (MAPE) rate in XGBoost remains between 7 to 14). The evaluation results demonstrate that our proposed model produces reasonably low error rates (e.g., the MAPE rate of our model is under 1) and also requires less expertise and dimensions of data to forecast sales, which may further help in making effective business decisions and offer exciting propositions to drive the business forward.

Keywords: Cashback, business intelligence, data mining, forecasting historical data, websites

INTRODUCTION

Data Science draws knowledge from several other disciplines as it's an interdisciplinary field. This field uses sources like scientific methods, processes & algorithms to fetch data in various forms. Besides having its connection with the roots of Data Mining, this new concept is often used interchangeably with earlier concepts i.e. business analytics, business intelligence, statistics & predictive modeling. When it comes to forecast businesses based on the past performances and data collection, Data Science helps a lot by providing such techniques to gain insight and drive business planning efficiently. The proposed research will also utilize & exploit the best possible techniques of Data Science to predict the sales associated with cash back business. For this, we will study the existing forecasting models, by keeping our directions focused on cash back site's standard flow. We will be using the machine's learning approaches like time-series forecasting to predict future's sale taking into account popular parameters like trends, seasonal changes, cash back percentage & past transactions.

The Need for Forecasting

Good forecasts are vital in many areas of scientific, industrial, commercial and economic activity (Chatfield 2000). Nowadays every brand, company, product, government, local authorities, websites, processes generating & collecting a lot of data. The data was mostly unmanaged data. This data in turn is used for making money, saving lives, conducting decision making and forecasting future aspects. According to Smart Insight (Allen 2017) in each minute of 2017 there were more than 29 million whatsapp messages sent, 3.3 million face book posts added, more than 3.8 million queries searched on Google, and more than 500 hours of new YouTube videos were uploaded. Imagine, the amount of data being

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iKSP Journal of Computer Science and Engineering (2021) 1(1): 49-63

posted daily, monthly and annually? This significant amount of data will increase even higher in rate over the years. Looking forward to such a situation, this has already increased the need to build the effective solutions for collection, managing and analyzing the data. Bigger IT industries i.e Facebook, Google and IBM has already started investing time & money to build and enhance the forecasting model like Facebook prophet as cited by Taylor and Letham (2017), IBM SPSS Forecasting (IBM 2012) and Google keyword planner forecasting as forecasting plays a vital role in decision making. Nowadays, data collection has become easy, since fields like IoT, social networks are available which are capable of storing TB of data/second. The real issue which industry is facing right now is to convert this data into something valuable after processing. Hence, proposing forecasting and AI models to find patterns, trends & seasonal changes is the next thing to get started. The proposed research will be exploiting the use of forecasting in cash back/affiliate business.

What is Cash back?

So the question which comes first in our mind is: what is a cash back site? Before proceeding further, let's discuss a term called "Affiliate marketing/Link". Affiliate marketing consists of four key roles- the merchant, the network, the publisher aka affiliate, the customer. It's a kind of performance-based-marketing where business rewards one or multiple affiliates for each customer/sale brought by the publisher using their own marketing efforts. According to one research (Consulting Feb 03, 2016) Affiliate Marketing accounts for 7.5% of total digital spend among retailers. Same study revealed that US based Affiliate Marketing Spending would reach 6.82 billion by 2020. Now cash back site is a reward based site, which pays its members a defined percentage of amounts, after the customer has successfully bought goods or services via its affiliate link. In turns, cash back site receive commissions from the retailer. The reward can be of several types to maintain the customer's loyalty. According to Altinkemer and Ozelik (2007) Loyalty is a crucial part of today's business because retaining a customer is generally less expensive than attracting a new one. These rewards are a clever way for companies to attract new customers and to retain those they have already cultivated. This is the sole strategy which has increased the size of cashback sites, both in terms of users and business considerably over the last decade (María et al. 2016). Big names of cashback industries are Quidco, Topcashback, Lyoness, Swagbucks and Orangebuddies. All the cashback websites work on the principle of Affiliate Marketing. They bring in customers for the e-com giants and in turn get commissioned. The cash back websites use a major part of the commission they get as cash back and the remaining portion as their profit. Cash back is the process of making the relationship between Core Customer and organization stable & healthy.

Why Forecasting is vital for Cash back

Cash back processes and techniques are not only being used in the E-commerce sector, but also banking sector and due to the enormity of such techniques and its global impact forecasting of such solutions is necessary like any other field to find out the latest trends, advertiser, best percentage and impact of seasonal changes. Although several forecasting models are available for standard E-commerce (B2C), those don't cover the parameters & set of variables which are necessary while forecasting sales in cash back business. In the proposed study, we will mainly put our focus on parameters like transactional history, competitor cash back and retailer's cash back percentage. We will also focus on generalizing our model so that it can be able to run on any cash back based businesses.

Problem Statement

In time series past data used to predict future sales. In particular, use cash back percentage, competitor's data, past transactions, trends and seasonal changes to forecast sale per retailer. Further demonstrate how forecasting models help in making decisions and improve business. Problem is to find accurate patterns & algorithms for effective sale forecasting of Cash back business. This problem can be solved by time series forecasting models and techniques.

LITERATURE REVIEW

Literature on the topic of cash back is vast and has been used by several researchers in the past decade. Researches focused on best optimizing the cash back rates have also been conducted and the results were shared by (Agrawal et al. 2010). In order to determine the optimal rates, they have used historical data i.e. sales, previous cash and price information to determine optimal rates. Further in this field, research conducted by (Ho et al. 2012) revealed that under which conditions a merchant can take advantage or benefit from its opponent existing in the same cashback market. There has also been a lot of research conducted on the sale and demand forecasting along with price optimizations, but those were specific to the normal ecommerce model. People like (Ferreira et al. 2015) used machine learning algorithms to forecast such attributes, during their research they took one example of the online retailer shop and provided a generic algorithm for other retailers on how they can set the price for the new product to get more sales. (Jain et al. 2015) also

developed and proposed a new predictor titled XGBoost predictor. The Extreme Gradient Boosting algorithm was meant to predict those sales which are likely to happen in the near future. According to their findings, they said their algorithm predicted well as compared to traditional approaches i.e. linear regressions. XGBoost also keeps the previous data like public holidays, season, accessibility, location and promotion to predict effectively. It is also concluded in several literature that it's difficult to forecast those products which were never sold, since no history is available which one can use as the starting point for prediction. This was and is the rising issue where the historical data is not present for the successful planning of the online inventory. Several literature were developed to address this issue, one of the solutions proposed by (Jha et al. 2015) is to find the similarity between the products, because there is a possibility that the new product has never been sold at all, and no history is found against that particular item. So by grouping similar items and then doing forecasting so that historical data can be combined used to forecast the products having similar attributes. To get the similarity, authors used the semantic approach, which compares items' description, titles, colors and brands. Literature also covers forecasting using neural networks, for example (Bakir et al. 2018) used LSTM (Long Short-Term Memory) neural network to forecast phone prices in European markets. It is also stated by (Gao et al. 2014) that the traditional approaches like neural networks have weakened in terms of speed, so they proposed an algorithm ELM (extreme learning machine) which covers both speed and accuracy while forecasting the sales on a large scale. Literature belonging to forecasting also covers time series which is a very active research topic now a day, time series is actually defined as the sequence of numerical data points in successive order. Whereas forecasting in time series is to predict the future values based on previously observed values. Now literature includes a lot of methods and models proposed in time to conduct prediction in time series data. Now there is extensive literature also exists on which models is best fit and in which situation or condition i.e (Khandelwal et al. 2015; Ul Haq et al., 2020; Bhatti, Z. et al., 2018) used Hybrid ARIMA (Autoregressive Integrated Moving Average) and ANN (Artificial Neural Network) models based on DWT (Discrete Wavelet Transform) decomposition to improve the precision in time series forecasting. There was also working done where authors used two different models and each level to improve the prediction, for example (Suhartono et al. 2015) introduces two level ARIMAX and regression models for forecasting in time series data. At the end they concluded their two level model predicted well as compared to ARIMA and Neural Networks model. Literature also covers the findings made on aggregate sales. By forecasting the aggregate sales in a particular region may benefit investors to predict the movement in the stock market. Aye et al., (2015) forecast the aggregate seasonal sales in South Africa with the help of 26 forecasting models covering both linear and nonlinear. This study contributed a lot in literature by observing 509 observations of monthly sales data from 1970 to 2012.

Fashion industry is also one of the biggest industries nowadays and with the great number of competitors and business strategies out there, forecasting plays an important role in this particular industry to efficiently manage the supply chain process. A reasonable amount of literature is available already, Erhard and Bug (2016) tried to cover all the obstacles the fashion industry is facing while forecasting along with the limitations in the previous methods/models used by the researchers. Similarly, forecasting is done in food industry as well as revealed by Arunraj and Ahrens (2015) Since ecommerce is an umbrella field and cash back business is one of its type, a lot of work had already been done in e commerce especially B2B type to forecast in order to improve the sales and manage inventory effectively. But unfortunately due to different parameters involved in cash back business i.e. social network impact between the customers as mentioned by (Ballestar et al. 2016) so this research supposed to follow the standard procedures to forecast but by keeping the cash back related parameters in mind. The reason why the literature is less in this field are the challenges like less historical data is available as compared to normal ecommerce sites, lesser correlation, continuous price changes, affiliate network changes and commission changes (Abro et al., 2020). We hope our research will play a vital role to develop the literature associated with the cash back forecasting.

METHODOLOGY

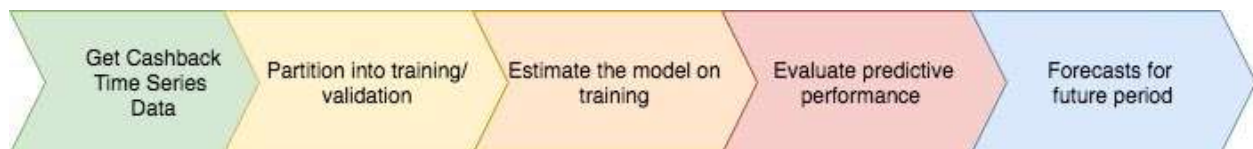


Figure 1: Steps in our Methodology

Detailed steps involved in the methodology we followed is shown in the above Figure1. We divided our methodology into two steps.

1. Initial data ready for prediction
2. Forecasting and findings

For forecasting in any domain, it is mandatory to set up the data first to reach the highest possible level of prediction. Since if the data is not configured or filtered in a well-mannered way, the end result would be difficult to analyze and may not reveal the valuable outcomes.

As far as first step is concerned, prior to setting up the data, we used historical data of the sale's commission from well reputed three European based cash back sites. In our research work, we referred to those as site-1, site-2 and site-3. The historical data was providing an insight of daily sales commissions between the periods starting from Jan, 2016 to Dec, 2018. As far as tools for the analysis are concerned, we used Python environment and Jupyter Notebook.

We then applied the cleansing process, where we filtered and removed the unwanted/missing data to achieve meaningful results, such as we removed the unwanted information like compensations, loyalty rewards, signups reward, promotions and campaigns related data. Since, the data provided by the sites had a lot of other information which was not required during the experiment along with some missing information, so we filtered it from our base collection of the data. Out of 100% data we collected we used 70% of the data as training data and 30% of the data as testing data. After processing and applying prediction models we compared our findings with the remaining 30% of the data we collected to ensure that our forecasting went well. It is also necessary to convert the collected data to a stationary data. In order to check for stationarity in data we ran a Dickey Fuller test on our collected data to ensure that data is stationary and prediction ready. We got the p value < 0.05 , against all three samples' site; hence the data was stamped as stationary. This whole process of data collection, data filtration, removal of unwanted data, categorizing into training and testing data, and lastly conversion into stationary data is a prerequisite of conducting actual prediction on the top of data. At the end, we got the data having daily sales commissions only to whom we were ready to process for the forecasting and analysis purposes. As shown in Figure 1.1, we got the week day sales information; we observed from all sites that sales were high on Monday in the past 3 years, while the Saturdays have few sales compared to other week days. The reason might be the campaigns launching on Monday since the past 3 years. Similarly Figure 1.2 and 1.3 showing the week day sales information against site-2 and site-3 respectively. The pattern seems to be similar as far as all sample sites are concerned.

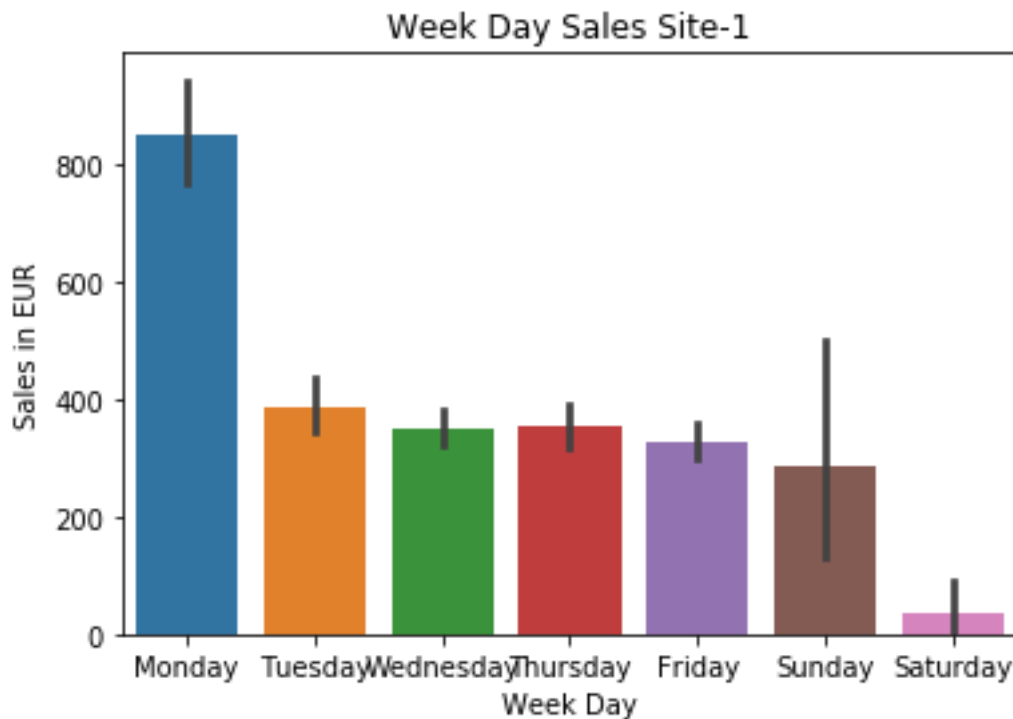


Figure 1.1: Three-year week day sale for site-1

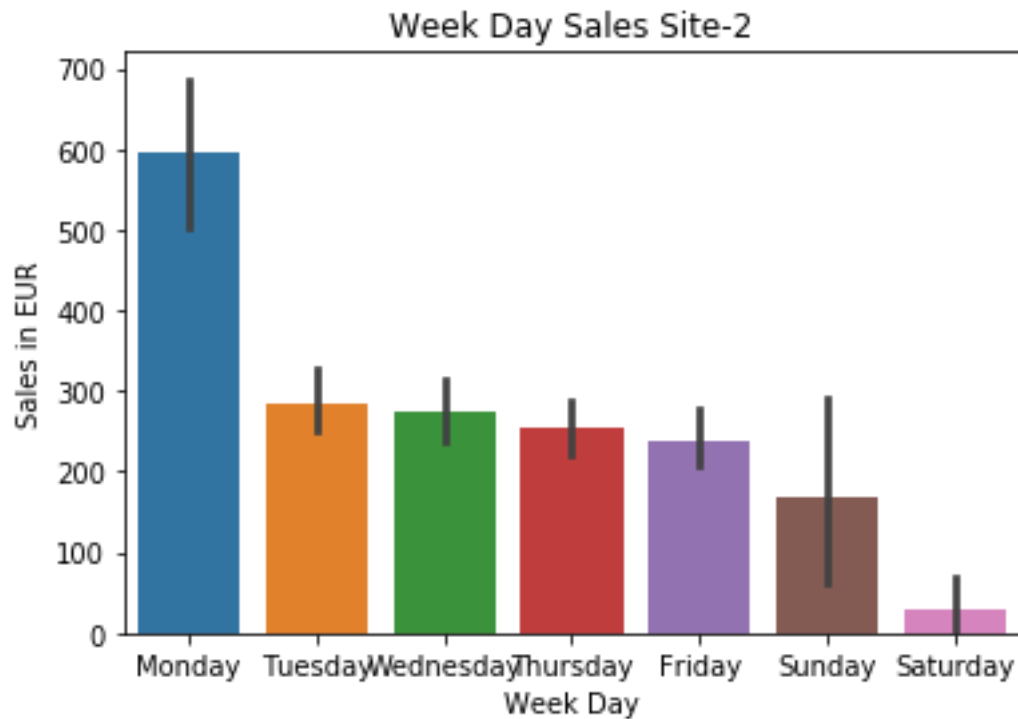


Figure 1.2: Three-year week day sale for site-2

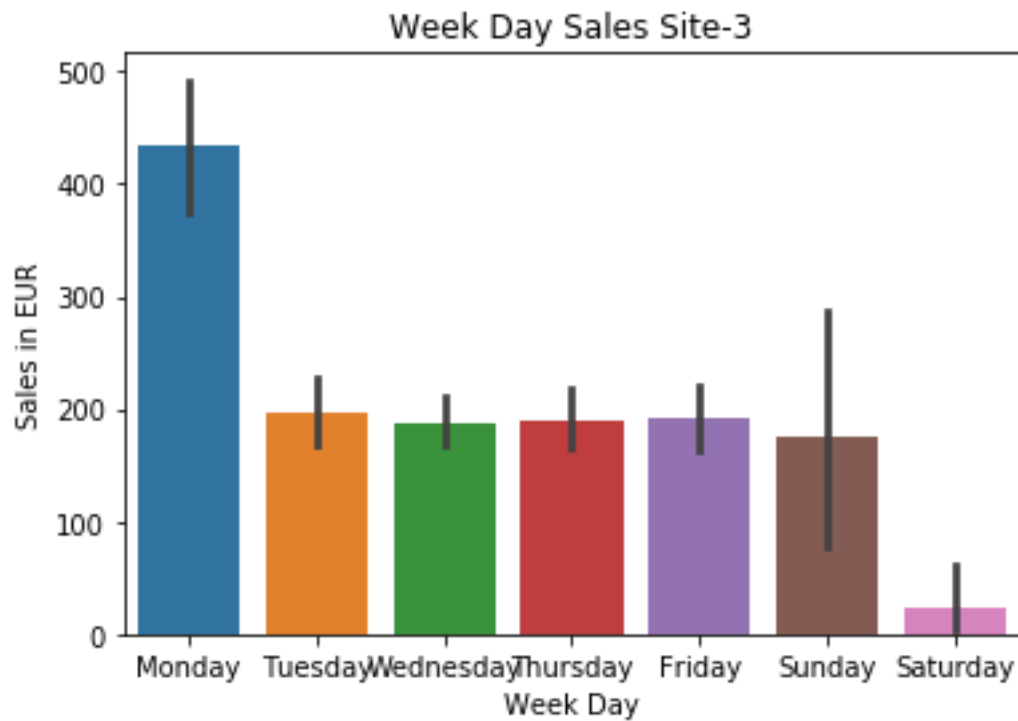


Figure 1.3: Three-year week day sale for site-3

We further checked the Month Days Sales against each sample site. The term “Month Days Sales” means the sales conducted on a particular date of the month on each year against each site.

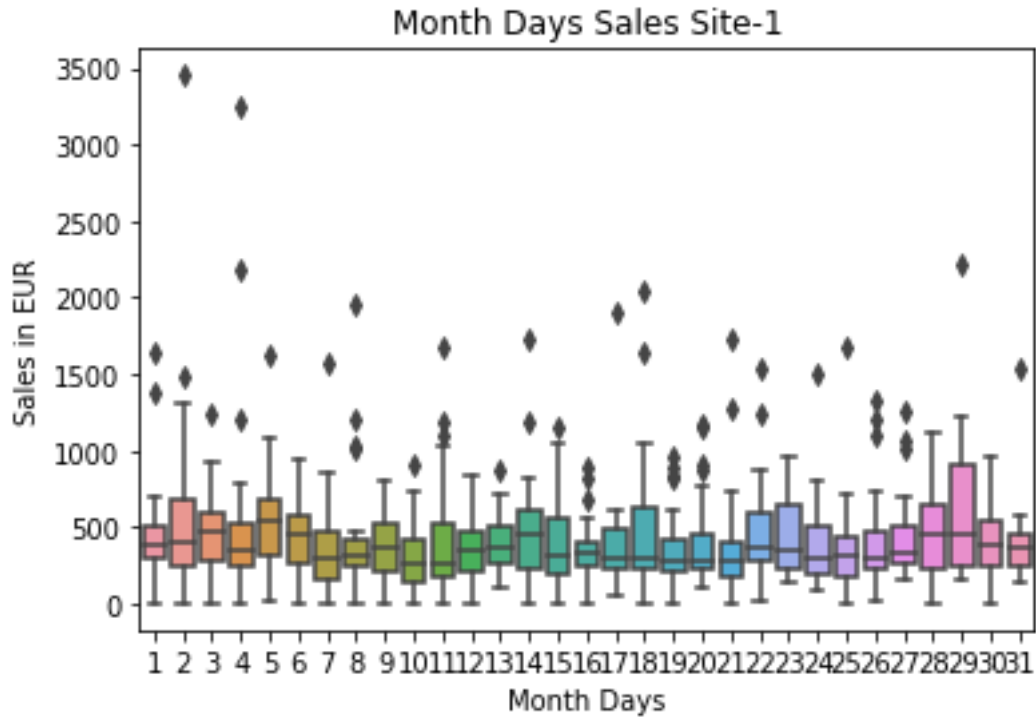


Figure 2.1: Three-year month-day sale for site-1

From Figure 2.1, we observed the sales were high on the first few days of each month. The reason could be people getting their salaries in the first week of each month. Similar pattern can be observed in case of Figure 2.2 and 2.3, the sales were less in the middle and last week of each month. Another reason could be the strategy of the owners to run a campaign on the first few days of each month.

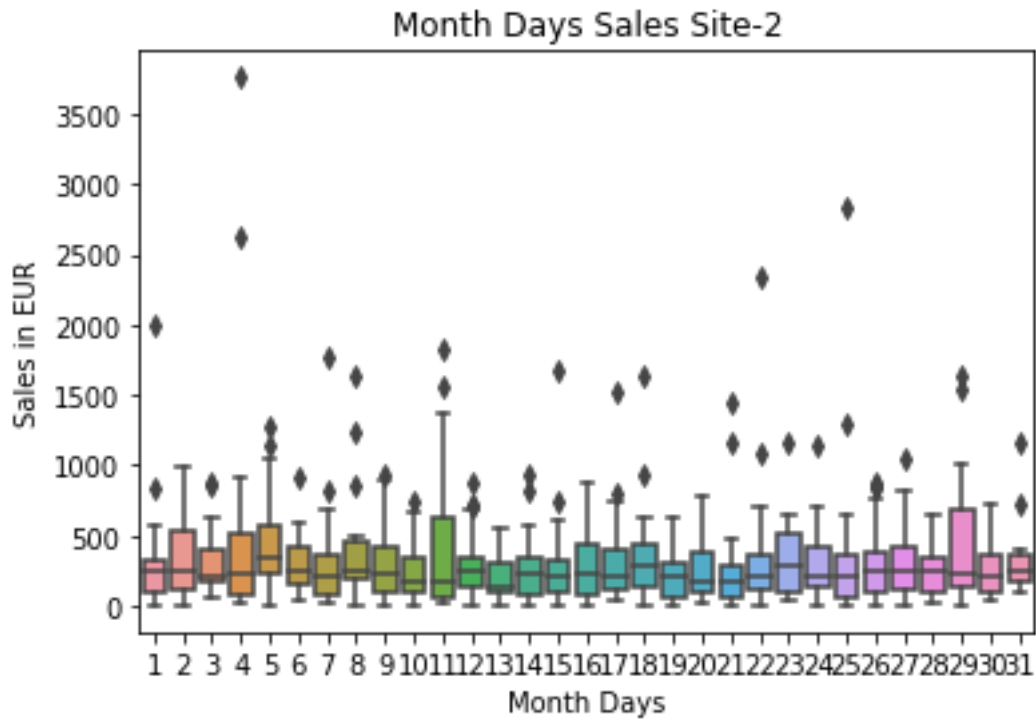


Figure 2.2: Three-year month-day sale for site-2

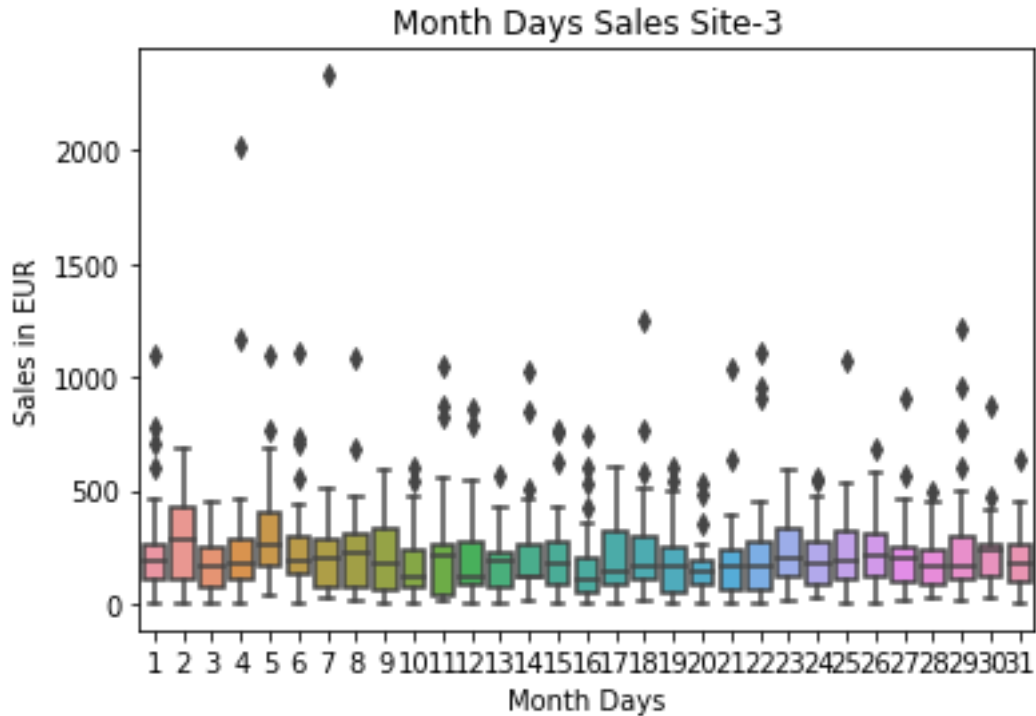


Figure 2.3: Three-year month-day sale for site-3

We then tried to observe the monthly sale pattern from each of the sites and after analysis it was found that sales were high from Nov-Dec as shown in Figure 3.1. Also it was observed that starting of each year has good sales, while the middle of the year has fewer sales compared to other months.

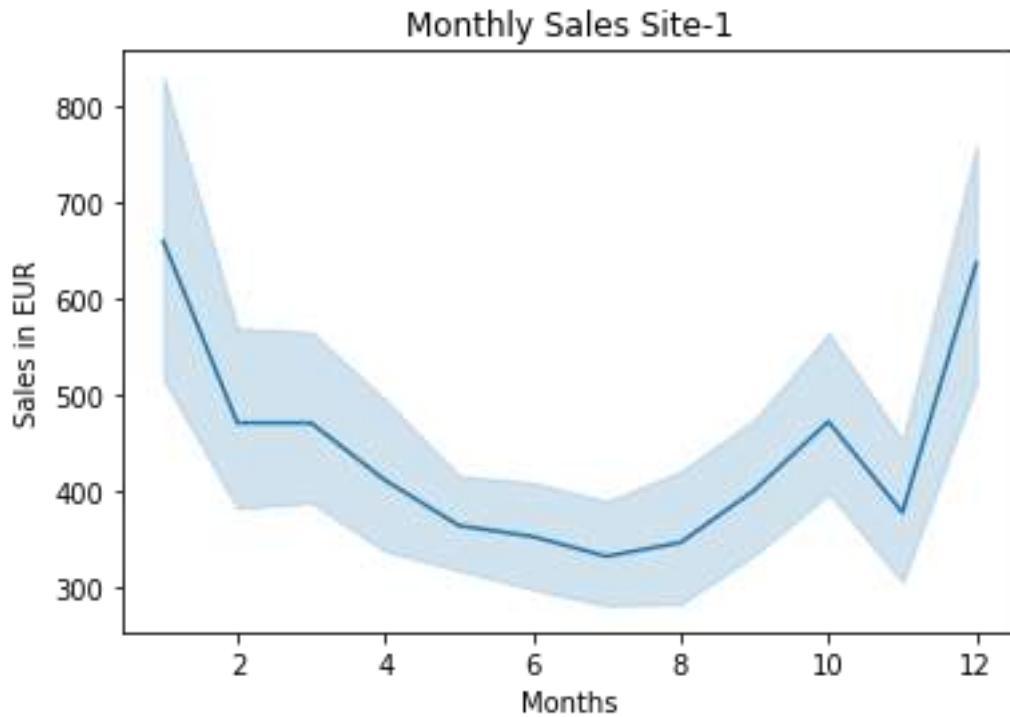


Figure 3.1: Three-year each month sale for site-1

The reason might be the Christmas holidays in December till the New Year. Further events i.e. Black Friday used to appear in November. The same pattern was observed against site-2 and site-3 in Figure 3.2 and 3.3.

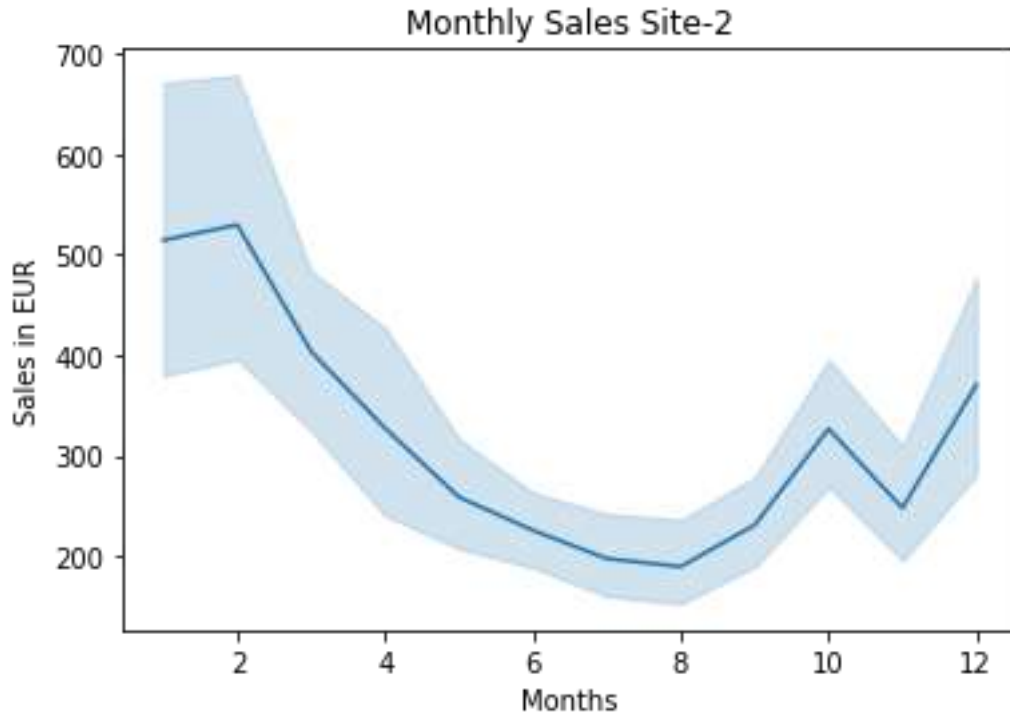


Figure 3.2: Three-year each month sale for site-2

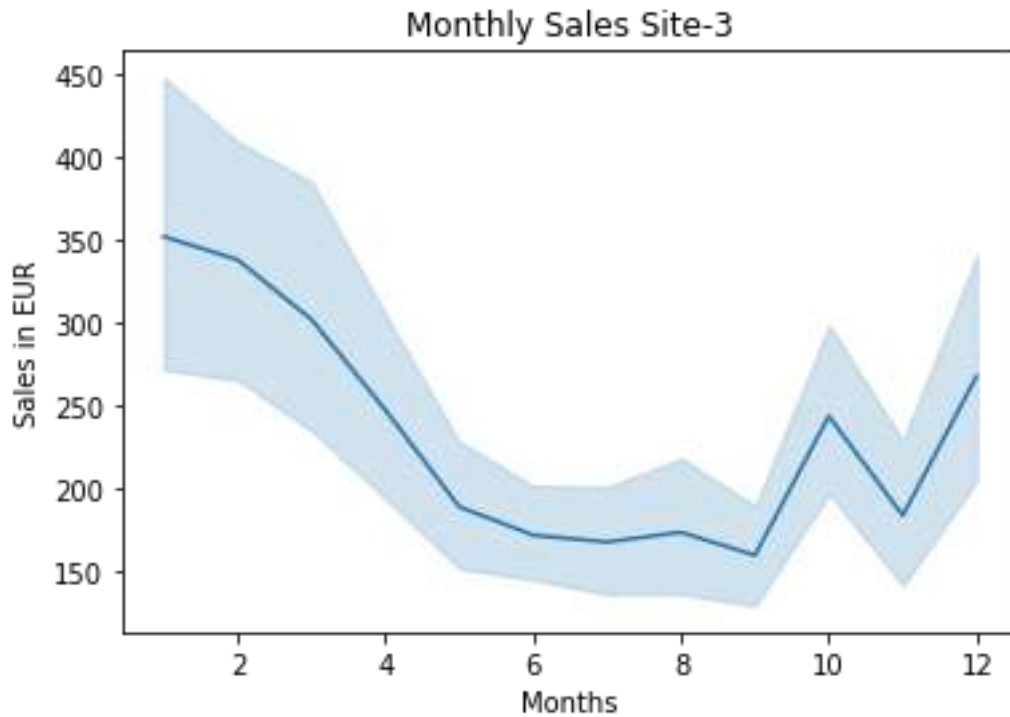


Figure 3.3: Three-year each month sale for site-3

Due to the complex nature and structure of cash back sites, there have been more challenges available for predictors to predict the sales. Literature also has few examples where forecasting was conducted against a cash back business. One reason might be that there are challenges involved in it, which makes forecasting quite tough as compared to standard ecommerce- online web shop based forecasting. Unlike standard e-commerce, that covers attributes like pricing, inventory, sales, discounts, and known competitors etc are all under controlled environment to make predictions, cash back prediction requires a lot of historical data including challenges like frequent changes in the amount of networks, commission tiers, product pricing, less promo information, competitors data and less information to find correlation among data.

Considering these challenges and to overcome those, we have to find a general pattern which can work well for cash back sites forecasting. In this study we mainly focused on what could be the possible generic patterns out there that can work well for sales commission forecasting when we have limited historical data with minimum data correlation.

During our experiment we used well sophisticated time series models and traced their performance. The models we used while analyzing were Naive, Moving average, Average forecast, Drift forecast, linear regression, Arima, Fb Prophet, Xgboost and Seasonal persistence techniques.

To check the selected model's accuracy against all three sample sites, we used the popular Metrics i.e. RMSE, MAE and MAPE. We used RMSE (root-mean-square error) to find out the difference between the testing data and values observed after prediction. The formula for the calculation is shown in Figure 4.1.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{j=1}^n (y_j - \hat{y}_j)^2}$$

Figure 4.1: Formula to calculate Root Mean Square Error

We then used MAE (Mean Absolute Error) shown in Figure 4.2 to calculate the average magnitude of the errors while prediction.

$$\text{MAE} = \frac{1}{n} \sum_{j=1}^n |y_j - \hat{y}_j|$$

Figure 4.2: Formula to calculate Mean Absolute Error

We then used MAPE (Mean absolute percentage error) to calculate the percentage accuracy of the models used for prediction. The formula to calculate the MAPE is shown in Figure 4.3

$$\text{MAPE} = \frac{\sum \frac{|A-F|}{A} \times 100}{N}$$

Figure 4.3: Formula to calculate Mean absolute percentage error

The resultant we got after applying all those metrics against each model we used is shown in the table 1.1

Table 1.1: Prediction model's accuracy found per site

Model	Sites	RMSE	MAE	MAPE
Naive	site-1	340.79	264.83	34.90
	site-2	244.81	182.06	31.57
	site-3	287.28	258.54	30.86
Avg Forecast	site-1	331.68	229.79	27.46
	site-2	253.99	178.69	25.34
	site-3	193.93	128.80	12.99
Drift Forecast	site-1	577.01	431.39	14.33
	site-2	704.57	571.94	24.84
	site-3	247.40	191.13	13.67
LinearRegression	site-1	352.56	228.20	21.73
	site-2	374.85	296.61	8.10

Arima	site-3	254.05	192.22	6.56
	site-1	332.24	246.14	31.70
	site-2	254.99	204.10	37.81
Moving Avg	site-3	191.21	151.11	20.76
	site-1	338.04	224.56	24.79
	site-2	276.22	195.98	20.28
Fb Prophet	site-3	207.96	141.11	11.00
	site-1	233.36	150.96	13.93
	site-2	198.42	136.17	22.17
Xgboost	site-3	140.23	91.53	10.04
	site-1	250.60	158.22	12.54
	site-2	200.60	136.35	7.65
	site-3	149.21	94.42	7.08

As shown from Figure 5.1, Xgboost and FBprophet performed very well as compared to the other models we tested, since they were able to capture patterns closer to the actual forecasting. XGboost performed well in feature extraction while FBprophet captured seasonality. But there is still more room for improvement for both models, so by adding parameters like holidays, campaign/promo data, weekly and monthly seasonality we may improve score a little bit more because residual data seems to have less correlation left, so this means that there is either no or little room for improvements.

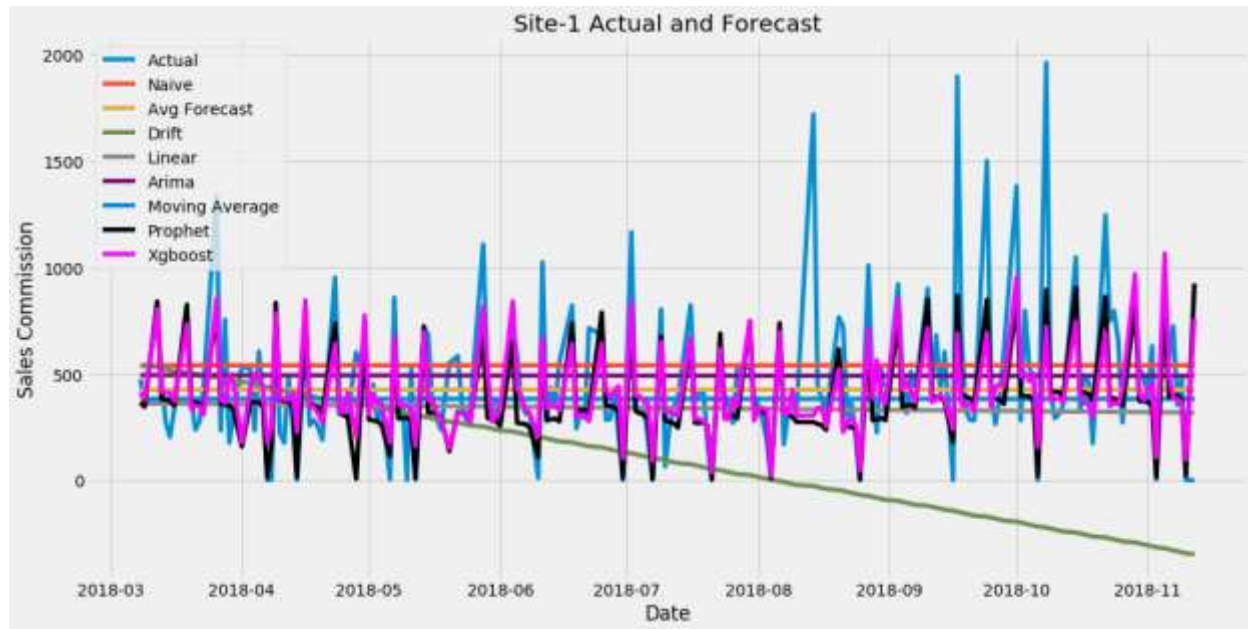


Figure 5.1: Actual Vs Forecast sale data for site-1

Figure 5.2 & Figure 5.3 displaying the case of site-2 and site-3 respectively, we can again observe that the aforementioned two models are performing well and capturing the forecasting closer to the original sale data.

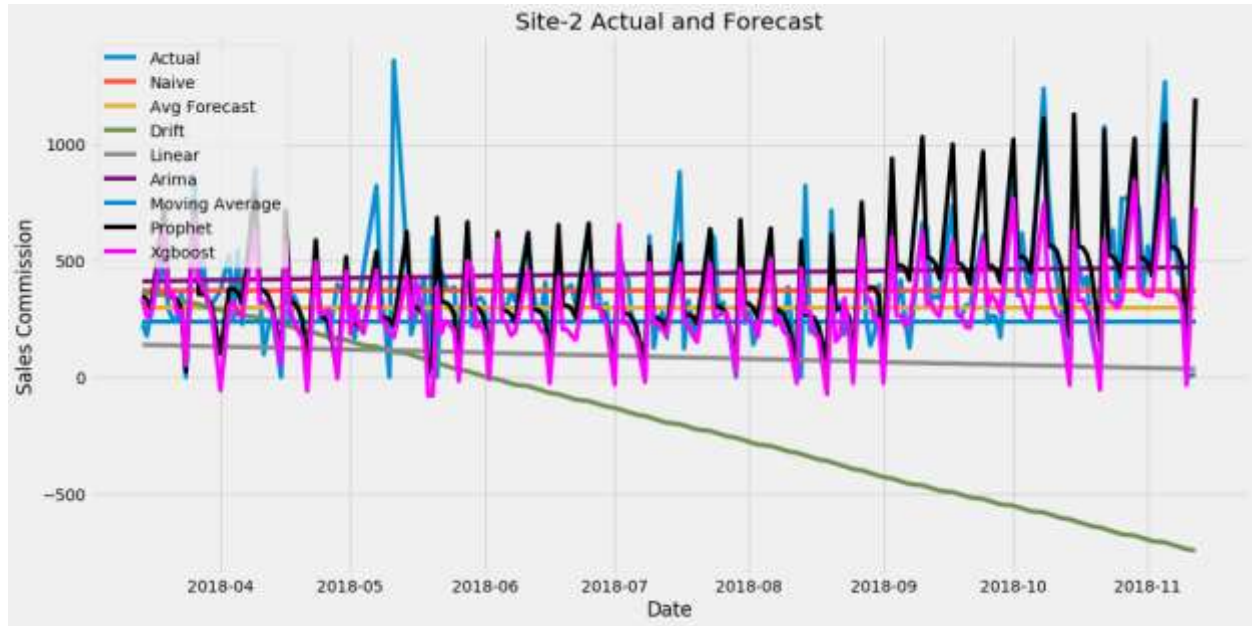


Figure 5.2: Actual Vs Forecast sale data for site-2

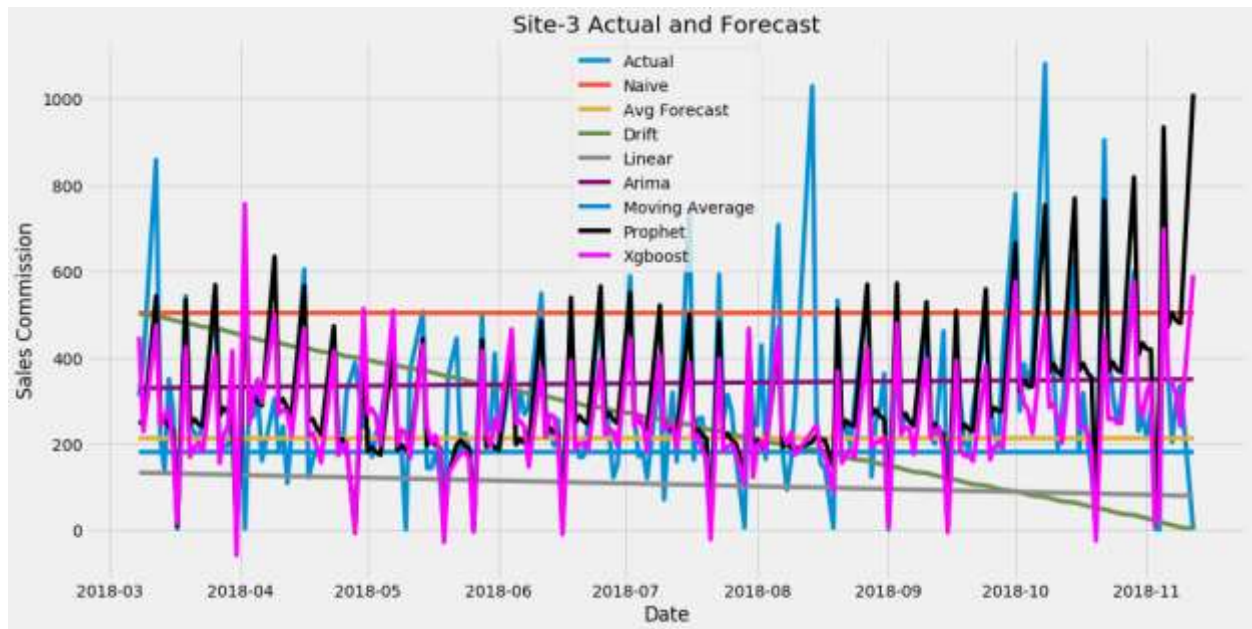


Figure 5.3: Actual Vs Forecast sale data for site-3

Proceeding in the experiment further, we tried another technique besides the previous models we used, that technique called “seasonal persistence”. Seasonal persistence assumes that the observations will stay the same as of the previous year observation. By adding different sets of seasonal components, one can predict the next sales using this naive approach.

The results we got after applying the seasonal persistence were even closer then what we got against XGboost and FBProphet. We checked this new technique was performing well in all types of sales i.e. daily sales, weekly sales and monthly sales as shown in Figure 6.1, Figure 6.2 and Figure 6.3. Although seasonal persistence is used for benchmarking purposes, here we noticed that it performed very well when we had less dimensions and less correlations were available. We still have much correlation left in residual so we can improve the model even more. So by checking Ljung-box test we found there is still a lot of correlation among residuals, although the model provided good accuracy, but still hold the fact that it can be improved even more.

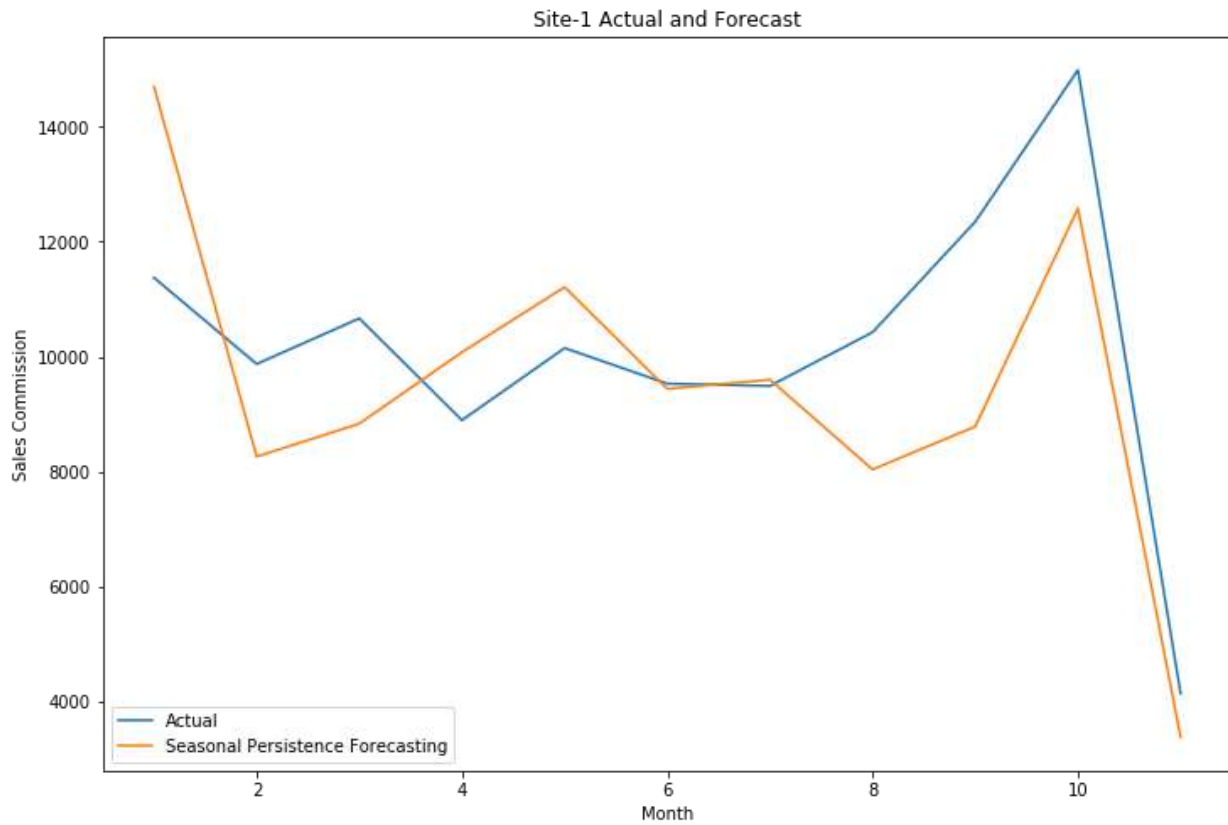


Figure 6.1: Actual Vs Forecast sale data using seasonal persistence technique for site-1

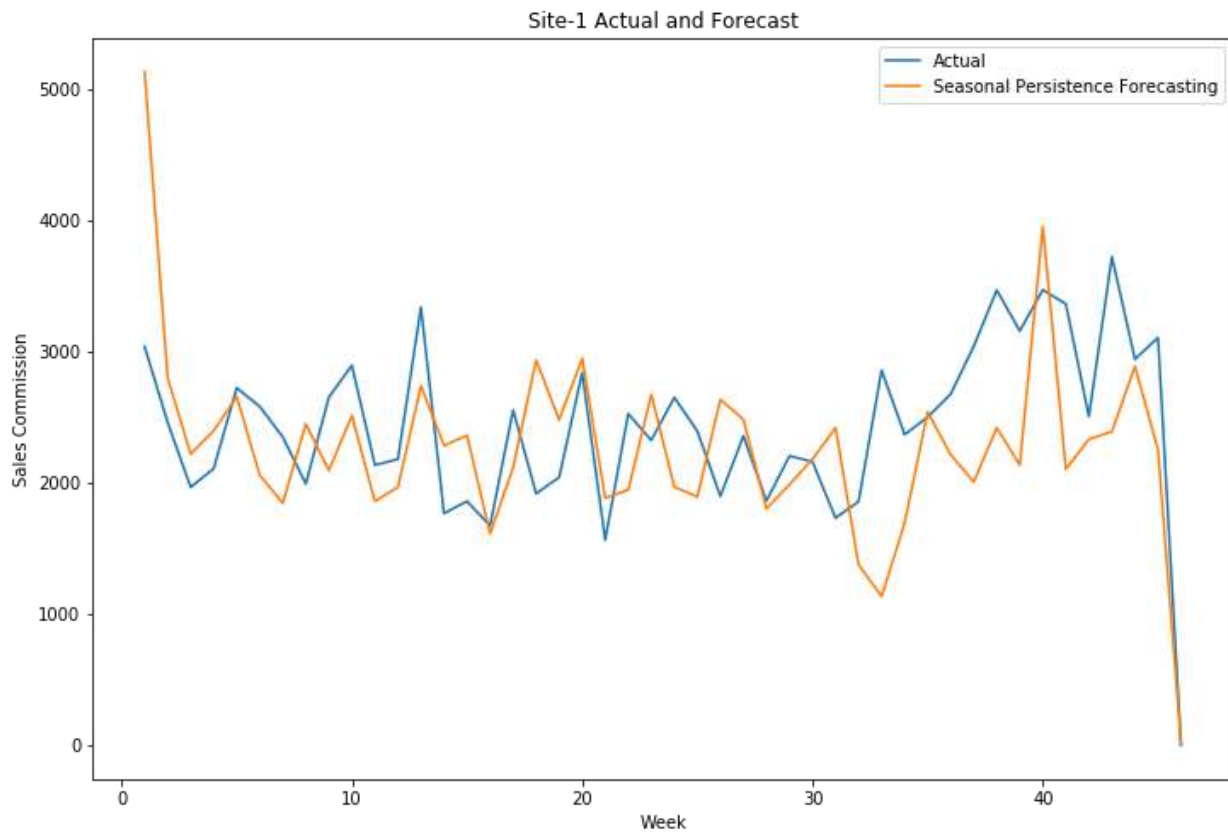


Figure 6.2: Actual Vs Forecast sale data using seasonal persistence technique for site-2

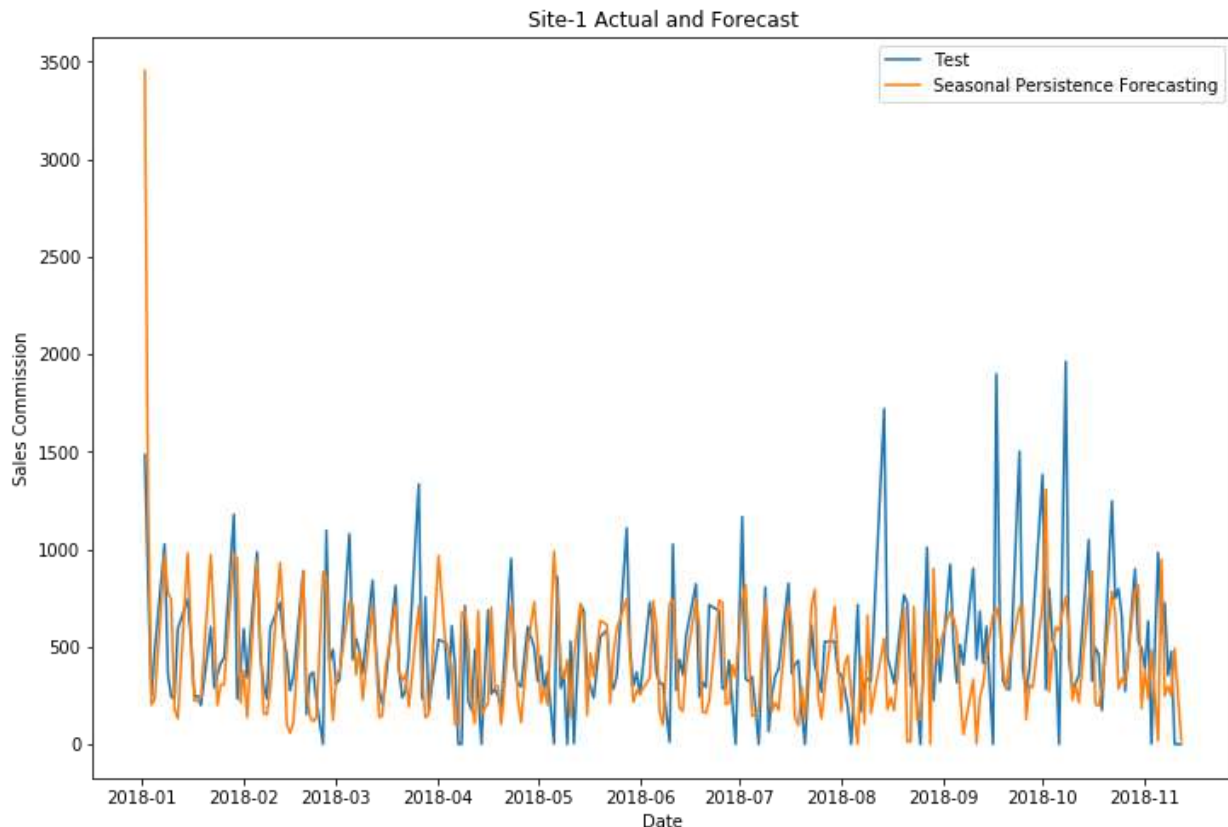


Figure 6.3: Actual Vs Forecast sale data using seasonal persistence technique for site-3

While closely inspecting residuals we find out that model under cast on Monday and overcast on Weekends. If we fine tune weekday sales, the model will perform even better. Few suggestions are

1. Adding yearly growth rate factor - biased value
2. Checking the previous year same week day

We further noticed that December to March sales were high and this approach already captured this.

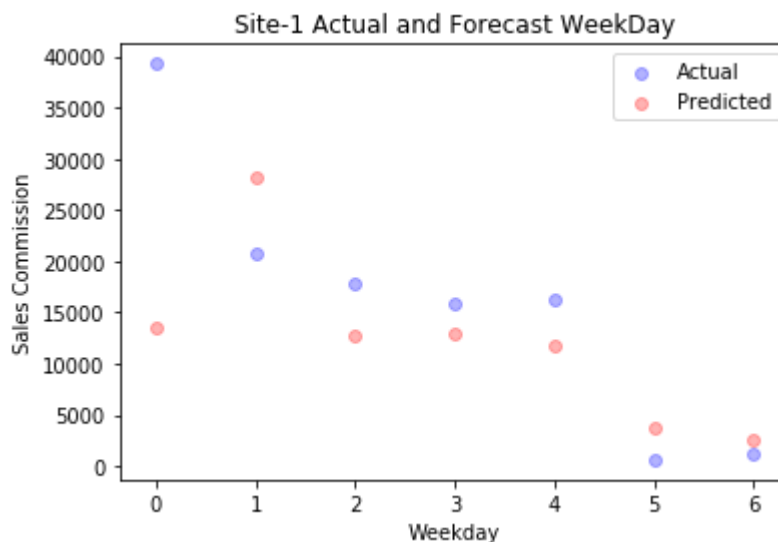


Figure 7.1: Actual Vs Forecast Week Day Sale data using seasonal persistence technique

Based on these facts we can improve model score, which already captures sales patterns nicely compared to other approaches. Also since results from the Ljung-Box test revealed that residual p value was < 0.05 So this tells us seasonal persistence still has much room for improvements, as quite a correlation is left as shown in the Figure 7.2 & 7.3 below.

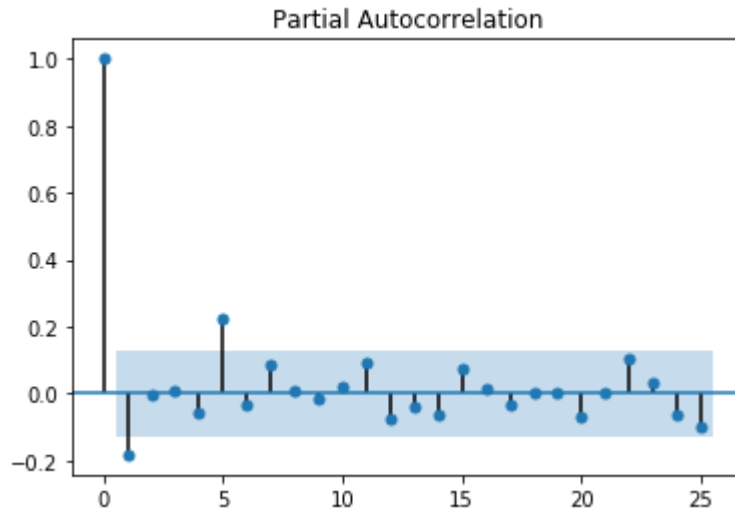


Figure 7.2: Partial Autocorrelation

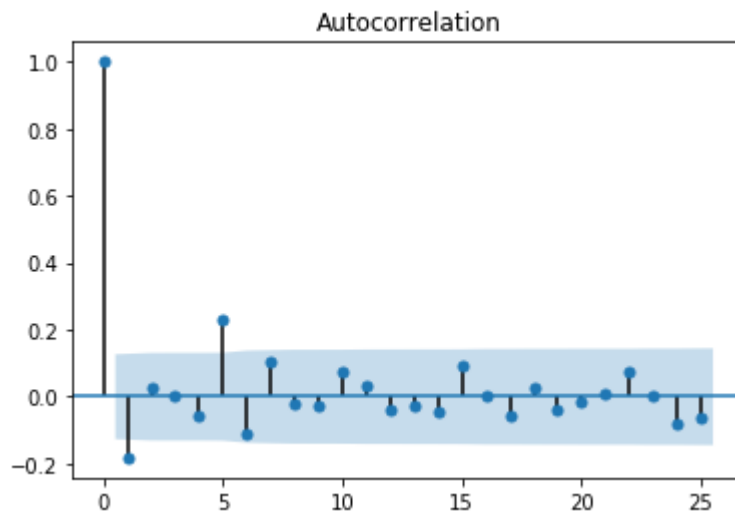


Figure 7.3: Autocorrelation

These patterns we found in all sites and scores of seasonal persistence models are RMSPE under 0.10 and MAPE under 1. Other sophisticated models don't have much room for improvement as well.

Problem is we have less historical data, we don't have other parameters like Promotion records, Stores Types, Categories sales, Competitor data also affiliate data change frequently, new stores, commission tiers and competitors add frequently so it is difficult to correlate with these stats and fine tune more sophisticated models. In our experiment we found when we have less data to correlate, data change frequently and many attributes which can affect sales simple seasonal persistence forecast work better. Also, we found before moving to more complex model we should test with simple benchmark models sometime it perform better than complex models.

Usually cashback site owners don't have a huge budget to invest on forecasting models. Through our research it will benefit medium and small level cashback site owners. With this simple technique they can apply good effective models which can increase overall revenue; they are able to set cash back ratios more freely as they will know what they will earn in the future.

CONCLUSIONS

This paper contribution is to choose different time-series models like Arima, XGBoost, Fbprophet, and applied them on three popular European-based cashback websites. The results confirm that XGBoost performs comparatively better than the other selected models as it produces reasonably low error rates (e.g., the Mean absolute percentage error (MAPE) rate in XGBoost remains between 7 to 14). After going through all of these, we concluded that one of the simplest yet effective approaches called "seasonal persistence" stood first among the rest of the models and provided great results while forecasting (e.g., the MAPE rate of our model is under 1) and also requires less expertise and dimensions of data

to forecast sales, which may further help in making effective business decisions and offer exciting opportunities to boost the business forward. We also proved that it is better to use a seasonal persistence approach as a first-cut model before investing on other models, since its simple, effective and low budget technique to predict sales.

Future Work

It is our prediction that the future of the proposed study will be even more interesting since the existing fields like machine learning, neural networks and deep learning models will provide more room for improvement in the work associated with the sales forecasting for cash back. As far as our study is concerned, there is still need to know how we can improve seasonal persistence models for cash back domains as it requires fewer budgets and affects to implement. Future work also covers the highlighting of other cash back forecasting problem industries/researchers facing ,so that more improvements can be made in earlier stages to boost and welcome more candidates to work on this particular domain having better options than before to improve precision.

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