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A COMPARATIVE STUDY ON EFFECT OF TIME SERIES MODELLING AND MACHINE LEARNING APPROACH TO PREDICT ADVERTISEMENT AIRING TIME INVENTORIES

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Abstract

Although there are emerging streams to deliver the promotional messages to customers such as social media marketing and email marketing, television advertisements have the dominating power over them. The local and global television companies make their revenue basically by publishing these commercials or advertisements to the end user during the TV programs. Moreover, some of these local television operators borrow foreign channels and broadcast them locally. Hence, these local TV operators should have the information on program schedules of these foreign channels in advance to prepare their advertisement inventories which need to be sold to customers. However, the local TV operators usually receive the program schedule from global TV channels very close to the actual schedule date. Thus, they do not have adequate time to sell their advertisement airing time to their customers. The proposed approach of this study has addressed and achieved this problem by utilizing time series modelling and machine learning approaches such as SARIMAX, SVR, RFR, GBR and LSTM. The experimental results show that both time series and machine learning models can be used interchangeably to forecast the next seven days of advertisement airing time/ ad inventory in one hour time resolution for given TV channels with a significant level of accuracy. Furthermore, the LSTM model has shown better accuracies for five test samples with mean deviation of 89 seconds.

Keywords: TV Advertising, Time Series Modelling, Supervised Machine Learning, Ad Inventory Prediction

INTRODUCTION

Television (TV) advertisements play a vital role in promoting products, brand images and services in a highly competitive market over the past few decades despite the newly introduced media. The largest share of the revenue of global and local TV channels is still generated by these commercials (Panaggio et al., 2016). Therefore, TV channels are now focusing and researching on giving more air time for the advertisements which helps to promote any brand or product by bringing in a huge income to the TV company. However, predicting the allocated airing time for TV commercials is difficult with no prior information about the airing time or a proper TV programme schedule (Panaggio et al., 2016). It will be more difficult due to the daily changes in TV programme schedule that leads to dynamic total advertisement airing time [2,3]. This is a major problem for most of the free to air local TV channels who purchase foriegn TV channels for the telecasting purpose (Yang et al., 2021) as their main income is generated from the paid advertisements overlay on their platforms. Generally, these international TV channels issue their TV programme schedules 1 to 2 days in advance. It would definitely be a challenging task for TV operators to collect and schedule advertisements within this short period of time since they have to render the original advertisements and overlay them which were received from the channel distributors. This can be resolved with an advertisement replacement system where foreign TV commercials are replaced by local ones automatically in real time. However, accurate advertisement inventory is critical for the replacement system to operate effectively, so the sales and marketing teams are incapable of knowing in advance how many advertisement slots are available for sale in each channel during each hour of a given day. Moreover, the advertising companies are hesitant to advertise their products or goods in such a TV channel with no prior information about the available airing time slots (Perlich et al., 2014).

This research is carried out for the purpose of predicting advertisement airing time slots with one hour time resolution for next seven days. The term advertisement airing time refers to the time duration which is available to broadcast TV commercials in a given period of time. For example, suppose the model/s predict 360 seconds (s) from 8:00 AM to 9:00 AM next Monday. Then the time resolution is one hour and there would be 360 seconds from 8 to 9 AM to broadcast TV commercials on next Monday. Thus, the TV operator has the information of ad inventories in advance for the next 7 days. Hence, ad inventories can be sold to the potential customers and finalize the optimum time slot schedule for TV commercials.

The remainder of this paper is organized as follows. In section 2, we discuss related work with available literature. The proposed approach to address the said problem is discussed in detail under section 3. The experimental results and discussion is available in section 4. Conclusions are given in section 5.

LITERATURE REVIEW

Researchers and experts have developed and implemented several algorithms using distinct methodologies to predict and optimize the scheduling of advertisements as per the need of broadcasting companies. However, predicting advertisement airing time during a short notified period with no prior information is crucial and has given little consideration thus, researchers are still working on it.

Panaggio et al. (2016) have investigated advertisement airing time in linear television to find a prediction model and an optimized schedule for advertisements by comparing various methods for estimating the number of impressions using simulated past program viewership data. They have also proposed an optimal advertisement schedule using integer programming. Malthouse et al. (2018) has discussed the rise of the programmatic TV models by proposing a model as a recommendation for the future of the TV commercials in terms of distribution, ad inventory and data which is abbreviated as DAD. Bollaparagda & Mallik (2007) have presented an optimized solution to manage on-air TV ad inventory and suggested that the performance uncertainty can be occured in TV schedule and revenue of the market according to the introduced model. Furthermore, they have proposed a qualitative methodology to uplift the market activities of the TV broadcasting companies. Another research has been carried out to give a solution for an Italian TV broadcaster by managing the TV program schedule in several mathematical formulations to maximize the revenue of the broadcaster by accepting and scheduling commercials on TV breaks (Guerriero et al., 2016). The researchers have tested the introduced model with real data and have found that it performs well with a very small increase in the computational time. Another algorithm has been developed (Bai & Xie, 2006) to accept and schedule advertisements simultaneously on broadcast television by maximizing the revenue generated by the advertisements and to find a new optimized TV schedule for the broadcasting company. They have proposed three algorithms to perform an integer programming model and the finding guaranteed that the model is effective. A slightly different model was proposed by Kimms & Muller-Bungart (2007) in their study to identify which requested orders to be accepted or rejected when managing the requests simultaneously using a mathematical model with five algorithms. They have concluded that the future orders can be predicted with sufficient accuracy and suggested that a stochastic model would be more appropriate for the study due to the dynamic behavior of placing requests. Turrin et al. (2014) have investigated time-based TV programs to provide recommendations to viewers and found that it is strongly influenced by dynamic daily- basis time context of the TV schedule and the channel preference of the viewers.

According to the available literature, we were unable to find a similar research or system implementation which directly addresses the research problem of this study. Thus, experiment on time series modelling and machine learning approaches to forecast ad inventories with a predefined time resolution (i.e one hour, two hour etc.) is advantageous.

METHODS

The goal of this study is to accurately predict the ad inventories in one hour time resolution for next seven days. In order to accomplish the said goal, data cleaning, feature engineering, model selection and validation need to be performed along with time series modelling and machine learning approaches.

DATASET

The dataset is composed of ad inventory data from the year 2016 to mid of 2018 for each TV channel. Further, almost all the time series components can also be observed since the data set has ad inventory data for almost 2 and half years. Hence, this data set is fair enough to use as a baseline dataset in order to conduct experiments to evaluate the suitability of time series modelling and machine learning approaches in this domain. Moreover, as shown in Table 1 the data set contains three fields. The field 'End Time' corresponds to the advertisement ending time whereas the other two fields 'Start Frame Number' and 'End Frame Number' represent the starting frame and ending frame number of the advertisement respectively.

Table 1: Instances of raw data of a Channel

Start Frame Number	End Frame Number	End Time
142307	142343	00:15:13
142319	142352	00:15:45
142454	143147	00:15:48

Source: Compiled by the author

As per the specification of the ad replacement system, one frame is equal to 40 milliseconds (ms). Hence, the ad airing time can be calculated by multiplying the difference of the end and start frame numbers by 40. The calculated ad inventory is formulated hourly based as illustrated in Table 2 since the objective of the study is to predict the ad inventories hourly. The data set has mainly 2 fields as follows;

- date_time : hourly based date time
- ad_duration : total ad airing time during given hour (in seconds)

Table 2: Instances of processed data of a Channel with total ad airing time in seconds

date_time	ad_duration
2016-01-01 00:00:00	809.00
2016-01-01 01:00:00	182.00
2016-01-01 02:00:00	231.00

Source: Compiled by the author

FEATURE ENGINEERING

Preliminary analysis was done to inspect the behavior of the data set before applying any model to forecast the ad airing time as it will be helpful to explore any precedent patterns of the data. Hourly, weekly, monthly and quarterly basis mean advertisement durations (in seconds) were plotted as the first step for this purpose which illustrated as in Figure. 1, 2, 3 and 4 respectively.

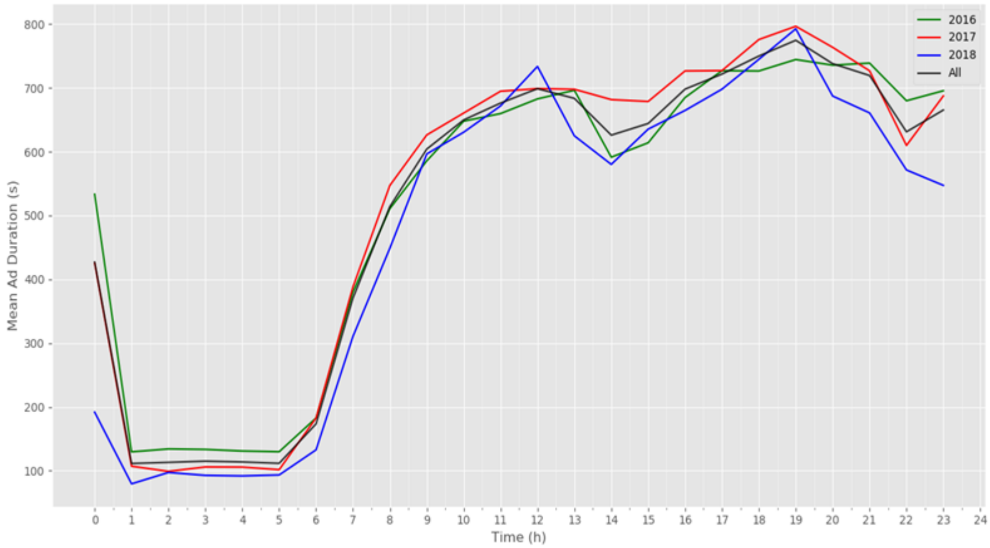

Figure 1. Mean ad duration per hour for the years 2016 - 2018.
Source: Compiled by the author

Figure. 1 depicts mean ad duration for a 24 hour window for the period from 2016 - 2018. It shows that the mean ad duration was as low as 100 s during 01:00 am to 05:00 am while it has gradually increased afterwards recording its second highest peak around 700 s between 10:00 - 12:00 pm. After a sudden drop between 01:00 pm to 02:00 pm, it has again started rising up to 800 s by recording its peak at 07:00 pm.

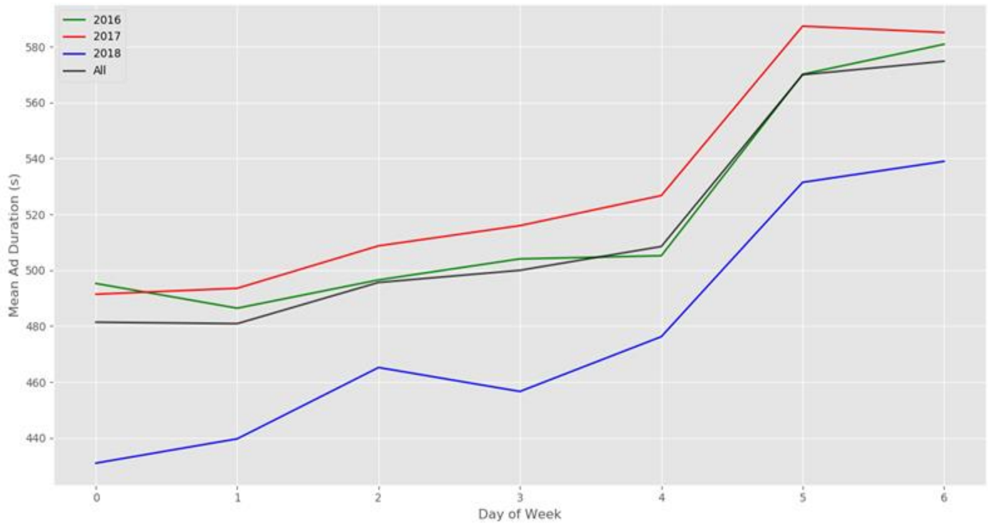

Figure 2. Mean ad duration per day (of week) for the years 2016 - 2018.
Source: Compiled by the author

It shows that the mean ad duration per day was gradually increasing from Monday to Sunday (from 0 to 6 respectively) whereas the highest value was recorded for either Saturday or Sunday for all the considered years in Figure. 2.

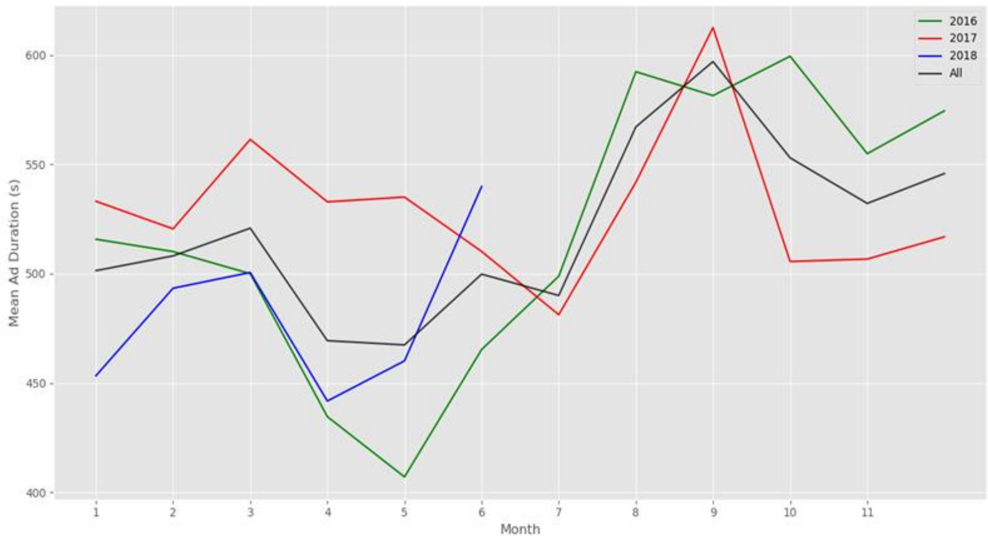

Figure 3. Mean ad duration per month for the years 2016 - 2018.
Source: Compiled by the Author

Figure. 3 illustrates the mean ad duration per month with the recorded peak values in September and October for 2017 and 2016 respectively. The lowest mean ad duration was recorded in May for 2016 whereas it is June for 2017.

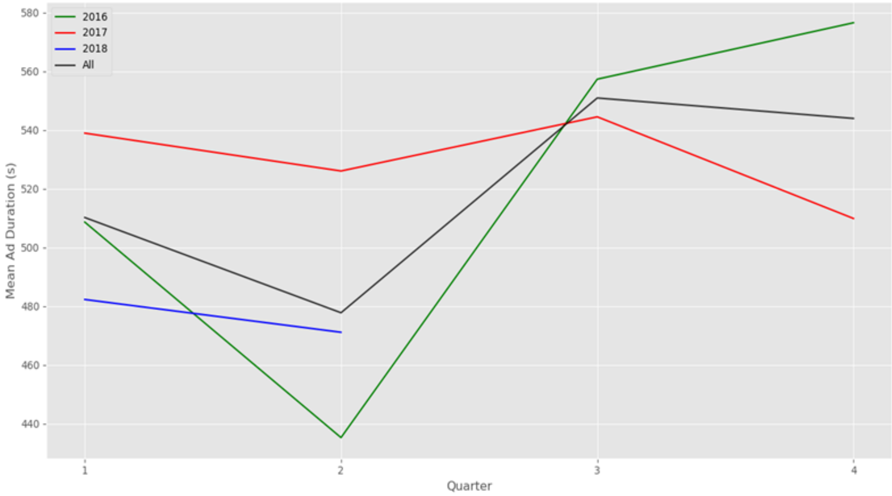

Figure 4. Mean ad duration per quarter for the years 2016 - 2018.
Source: Compiled by the author

According to Figure 4, it can be seen that the highest mean ad duration is recorded for the 3rd quarter over the period of 2016 - 2018 whereas it is almost the same for the 4th quarter as well. However, the lowest is for the 2nd quarter over the period. The highest gap for the mean ad duration is recorded for 2016 with almost 130 seconds mean ad duration jump from 2nd quarter to 3rd. This gap is minimum for the year 2017 which is lowest as 30 seconds. Figure. 1- 4 clearly demonstrates some seasonality patterns in mean ad duration per hour, day of the week, month and quarter.

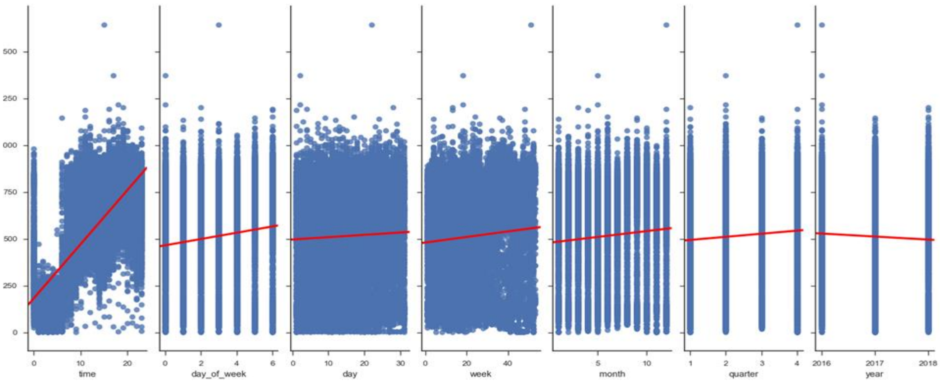

Figure 5. Mean ad duration against time, day of the week, day, week, month quarter and year.
Source: Compiled by the author

According to Figure. 5, it guarantees that mean ad duration is highly responsive for any changes in time in the day with a strong upward looking line whereas all the other variables remain approximately horizontal showing a very weak relationship with ad duration.

FEATURE SELECTION AND MODELS EVALUATION

The authors have decided to apply various methodologies of the field of machine learning and time series analysis to find an optimum solution for the said problem. Applying machine learning techniques as an ensemble method, it enables better predictive performance as multiple learning algorithms than it could be obtained from any of the learning algorithms alone (Dietterich, 2000). The main principle behind ensemble methods is that a group of weak learners can perform together to form a strong learner by giving more effective predictive power. Thus, Random Forest Regressor (RFR) and Gradient Boosting Regressor (GBR) have been experimented as ensemble learners in this study. Moreover, Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors (SARIMAX), Support Vector Regression (SVR) and Long-Short Term Memory (LSTM) were applied on the extracted data after performing respective feature engineering to forecast the hourly basis ad airing time for the purpose of managing ad inventory system for television operators and identifying the best model for future predictions.

SARIMAX

As the first model, the SARIMAX model was considered since the variable is based on a time series data and two data sets were formed from raw data as training and testing for this purpose. Before training the SARIMAX model, the stationarity has been checked by applying Rolling Window method and Dickey Fuller test to forecast the future ad airing inventories.

First, two data sets have been created for the training and testing purposes to apply the time series model. Then, the presence of the stationarity of the mean ad duration has been checked by applying both the rolling window graph and the Dickey Fuller test (ADF) (Paparoditis & Politis, 2016; Mushtaq, 2011; Zivot & Wang, 2006). The null hypothesis is; time series is not stationary whereas alternative hypothesis is time series is stationary based on the p-value. if the p-value < 0.05 the null hypothesis can be rejected. According to the ADF test result (Test statistics: -2.49517214 and p-value: 0.1166534) it is found that the data does not follow the stationarity behavior by giving statistically not significant results for the p-value. Moreover, the rolling window as illustrated in Figure.6 verifies that ADF test results are correct.

Figure 6: Rolling mean and standard deviation for Ad duration with window 24.
Source: Compiled by the author

The automatic decomposition method has been used to identify any underlying patterns of the data since it provides a beneficial model summary for the time series data and for better understanding the problem by splitting it into several components such as trend and seasonality along with the accounted noise (Dagum, 2013; Sen & Chaudhuri, 2016).

Figure 7. Decomposition of ad duration data over the period 2016 - 2018.
Source: Compiled by the author

Figure 7 shows that seasonality occurs when certain patterns are not consistent and appear periodically with trend, seasonality and residual components. Since ARIMA is a forecasting method for univariate time series data with trend and without seasonal components (Cools et al., 2009), it cannot be applied for the data set as the data involves seasonality. Therefore, the SARIMAX model has been used as it performs as SARIMAX with the modeling of exogenous variables to predict the future hourly basis ad airing inventory (Cools et al., 2009). For SARIMAX, the initial parameters were identified using the Autocorrelation Function (ACF) to determine the order (q) of Moving Average (MA) process and Partial Autocorrelation Function (PACF) to identify the order (p) of Autoregressive (AR) process as shown in Figure 8 below.

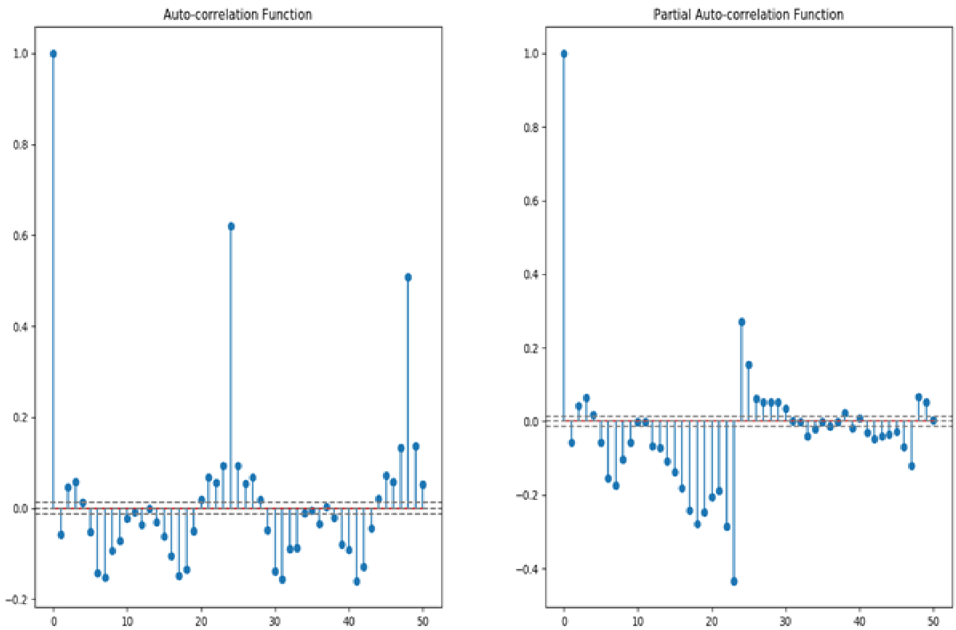

Figure 8. ACF and PACF graphs.
Source: Compiled by the author

The p and q parameters were identified according to PACF and ACF respectively with differencing at lag 1 (i.e d=1). Hence, the initial parameters were set as 1,1,1, and 24 for p,q,d and s respectively for SARIMAX. However, Auto ARIMA (SARIMAX) used to perform the hyperparameter tuning process so that best fit values can be identified for parameters. The best fit values were p=0, q=1, d=1 and s=24.

SVR, RFR AND GBR

SVR; one of the supervised learning algorithms which is used for regression analysis, has been applied as the second method since time series predictions can be performed by this method (Deng et al., 2005) and difficulties can be reduced by using linear functions in the high-dimensional feature space (Lu et al., 2009). Furthermore, RFR is applied as the third model due to its capability of determining the importance of the feature, much quicker and simpler to build with high efficiency. As the fourth model, GBR is considered as the benchmark results have shown that this method is better than RFR in terms of predictive accuracy and flexibility although it takes longer time to run and is computationally expensive (Wang et al., 2017). The data has been fed to SVR, RFR and GBR models as a set of features to apply and identify the performance of each model based on the selected features. Moreover, one hot encoding is used on categorical features prior to feed to the models. 8 features have been created for this purpose as follows;

month: month (1 to 12)
week: week (1 to 53)
day: day (1 to 31)
day_of_week: week day (0 to 6)
time: time (0 to 23)
shift_one_week: shifted value of the ad_duration
shift_two_week: shifted value of the ad_duration
shift_four_week: shifted value of the ad_duration

The finalized parameters for each algorithm have been identified by grid search cv for parameter tuning.

LSTM

Finally, the LSTM model (Gers et al., 2002) was used to create features with the help of an hourly basis 14 day sliding window. This method was used to predict the ad airing time due to the ability of its processing and predicting time series data sets with given time lags of unknown duration by feeding data to the model with automatic feature extraction ability (Bouktif et al., 2018). Moreover, it is trained and tested for checking and comparing the accuracy and the performance of the model over the other methods.

Despite the drawbacks of each method listed above, all have been tested and modeled to find the better fit with low Mean Absolute Error (MAE) to guarantee high accuracy to predict the ad airing time of the TV operator for the purpose of handling their ad inventory in an efficient manner. One advantage of using MAE to identify the best performing model is its non-sensitivity property to the outliers (Bouktif et al., 2018; Brassington, 2017) and most importantly it is good to apply this method if the purpose of the model is prediction. It measures the prediction capability of the model by indicating the absolute fit of the model providing how close the observed data points are to the predicted values of the model (Najafi & Salam, 2016).

$$MAE = \sum_{i=1}^{N} |\widehat{y_i} - y_i|/N$$

where,

$$\widehat{y_i} = predicted\ value$$
$$y_i = observed\ value$$
$$N\ is\ the\ number\ of\ observations$$

RESULTS & DISCUSSION

The results section mainly focuses on investigating and predicting the mean ad duration with five models which have been described in the methodology section. The MAE of the fitted SARIMAX model has been confirmed as 129.35 respectively. The SARIMAX model is trained to forecast the ad duration along with the actual ad duration data as in Figure. 9 below.

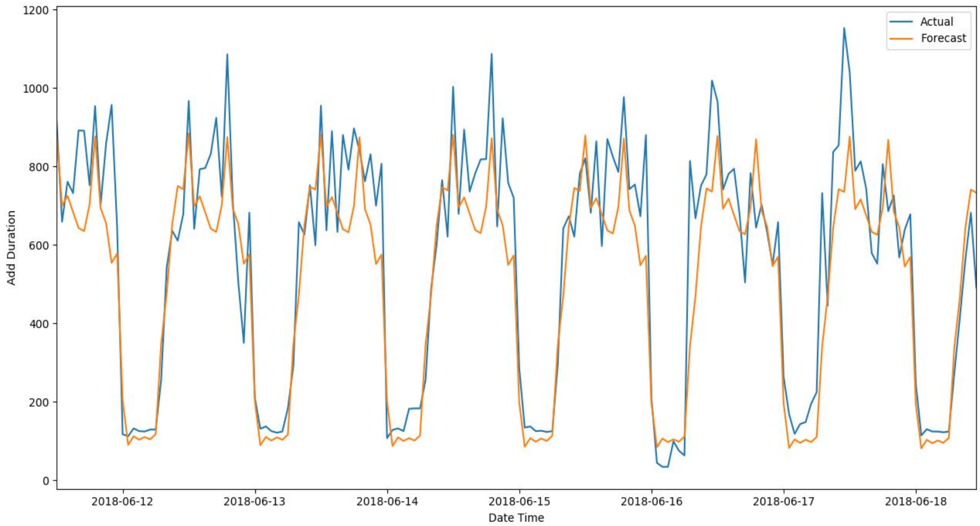

Figure 9. The forecasted SARIMAX model for ad duration with actual data.
Source: Compiled by Author

Figure 9 shows a fine matching between the actual and forecasted data for the ad duration for 7 days while guaranteeing a nearly perfect fit model. However, some mismatches can be seen in the peaks and troughs between the two data sets as displayed in Figure 9. Table 3 illustrates the finalized set of parameters of RFR, GBR and SVR algorithms according to the performance of grid search cv for parameter tuning.

Table 3: Finalized tuning parameters for SVR, RFR and GBR and models.

Model	Tuning Parameters
SVR	*C=5.0, cache_size=100, coef0=1.0, degree=4, epsilon=0.2, gamma='auto', kernel='rbf', max_iter=-1, shrinking=True, tol=0.1, verbose=False*
RFR	*n_estimators=25,random_state=42,max_depth=5,min_samples_split=20*
GBR	*n_estimators=25,random_state=42,max_depth=15,min_samples_split=20 ,learning_rate=0.3*

Source: Compiled by the author

To make a comparison between the three models to select the best performed, MAE values were used for both training and testing data sets. In the LSTM model, the ad duration was checked by shifting within a 14 day sliding window with respect to hourly basis and the correlation coefficients were calculated to plot the correlation heat map as in Figure 10.

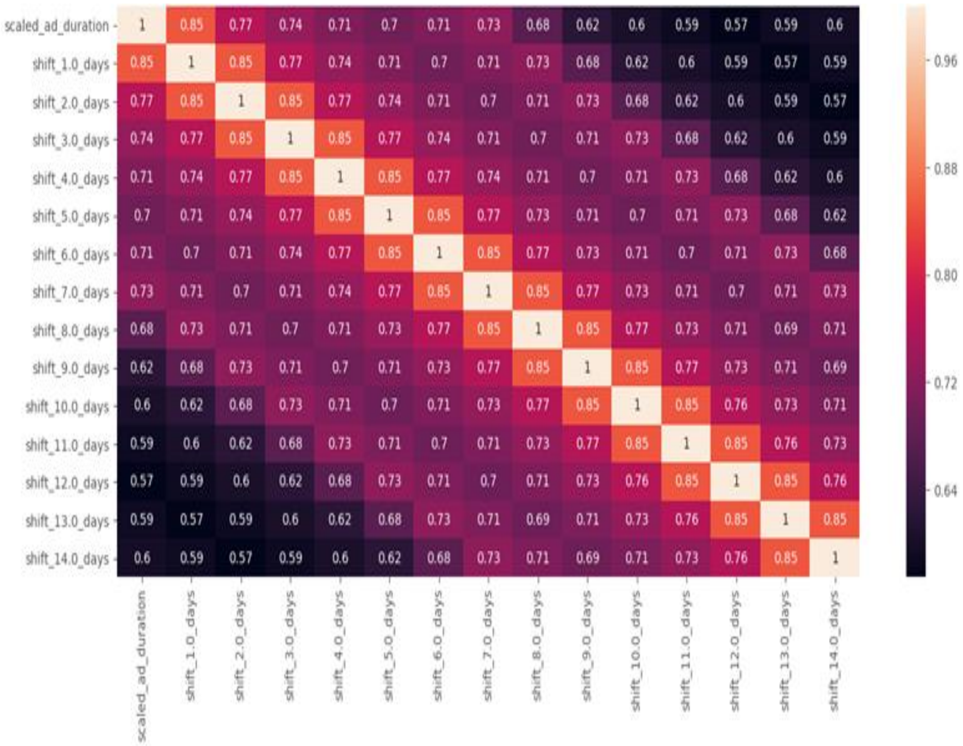

Figure 10. Correlation heat map for LSTM model with 14 day shifted window.
Source: Compiled by the author

According to Figure 10, stronger correlation coefficient can be seen between the smaller time shifts whereas it reduces to some moderate values between more than 8 day shifts and upper levels. MAE for LSTM model was calculated along with well tallied actual and forecasted ad duration for a period of 28 days as in Figure 11.

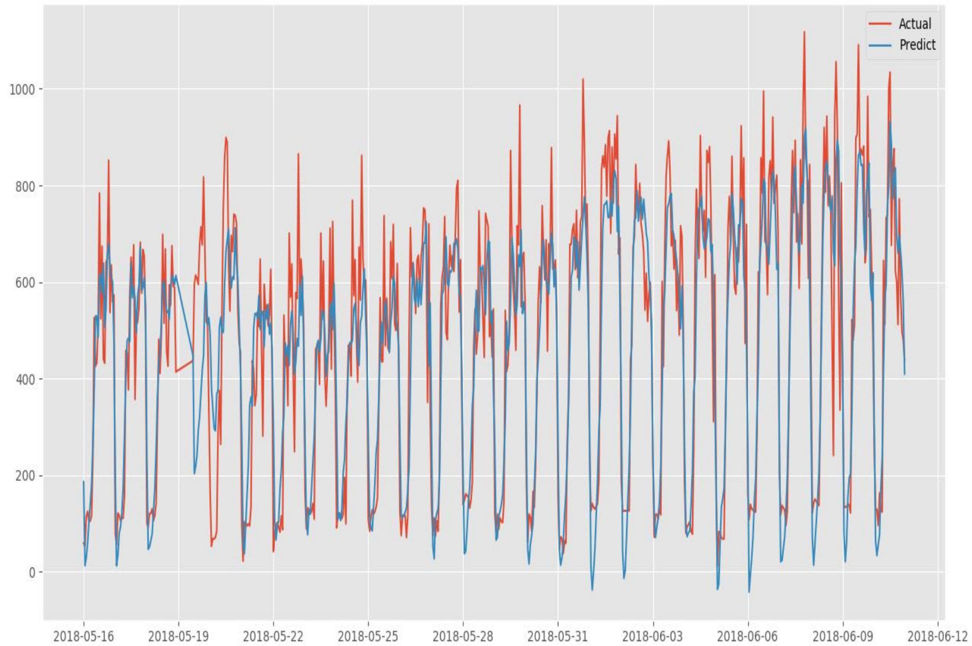

Figure 11. The forecasted LSTM model for ad duration with actual data.
Source: Compiled by the author

According to monthly and quarterly mean ad duration variation, it clearly indicates that several samples should have to be taken to calculate the MAE in different algorithms with unbiased drawn samples to cover a period of one year. Therefore, 5 random samples have been considered as in Table 4 and the MAE values were calculated accordingly to the chosen 5 algorithms.

Table 4: MAE values of 5 test samples for each model.

Model	Test Sample1	Test Sample2	Test Sample3	Test Sample4	Test Sample5	Mean	STD
SVR	145.78	148.91	139.87	136.45	168.23	147.85	11.08
GBR	112.07	107.02	103.75	89.47	128.12	108.08	12.52
RFR	105.28	98.36	99.12	87.42	125.09	103.05	12.42

LSTM	98.45	82.51	80.61	75.84	108.44	89.17	12.27
SARI MAX	109.86	103.21	97.22	83.56	129.35	104.64	15.09

Source: Compiled by Author

As illustrated in Table 4 GBR and the SVR obtained higher MAE values whereas the results are quite lower for RFR and SARIMAX models comparatively. However, the LSTM model performed well by recording lowest MAE values for all the 5 test samples. The experiment results further verified the inheritance nature of the LSTM to cope with sequence data. Moreover, the time series modelling with SARIMAX also shows the capacity to grab time series components in an underline data set. However, SVR and GBR are not smart enough to accumulate better prediction accuracies though RFR was able to compete with LSTM and SARIMAX model to some extent. The RFR has the ability to make a more accurate prediction even though it may receive weak predictors. RFR uses ensemble learning methods to formulate stronger predictors with weak predictors so that model prediction accuracy can be enhanced.

CONCLUSION

The experimental results show the applicability of the time series modelling and machine learning approaches in the domain of advertisement inventory prediction. Both approaches have shown significant capabilities to predict the ad inventories for next seven days with an one hour time resolution. The LSTM model is the best fitted model against the experiment results with 14 days sliding window but SARIMAX and RFR also perform well when comparing the mean and standard deviation of the testing samples. On the other hand the results imply that in different time windows, the efficiency/ accuracy of the models vary. Thus, the best fit model can be identified with the lowest MAE values in a given time window. Hence, the proposed approach is quite reasonable and acceptable in the real world advertisement replacement systems. Moreover, this proposed approach is flexible enough to add more potential machine learning models to the pipeline with a lesser effort to enhance the performance.

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