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LINEAR REGRESSION MODEL IN CONTEXT OF MOBILE APPLICATIONS USAGE

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Abstract
The popularity of mobile applications has resulted in an ever-increasing number of programmes being installed on smartphones. Whether or whether it is possible to predict which app a user will open is the subject of this study. The ability to forecast what apps will be needed in the future can aid in pre-loading the required apps into memory or in floating the relevant apps to the home screen to speed up launch times. We analysed a wide range of contextual information from the MDC dataset, including the user's profile, time and location, and the most recent App they utilised. The findings of our investigation can be divided into three categories. First and foremost, contextual information may be utilised to better understand how a user interacts with an app and to make more accurate predictions about how that app will be used in the future. A large part of the forecasting accuracy for the MDC dataset comes from the correlation between the sequentially used applications. The linear model is better than the Bayesian model because it can take into account all of the relevant information and provide more precise predictions than the latter. Predictions about app usage based on contextual information such as time, location and user profile and the most recently used app have been offered as a consequence of our research. For app usage prediction, we studied the topic of context awareness, and one of the things we observed was that context can significantly affect a user's app usage behaviour. We can deduce some patterns about how mobile app users interact with the software by examining contextual data. Personal mobile systems that employ contextual information to dynamically offer information, such as Apps to be used, to the user and improve the user-mobile phone interaction experience are suggested by this work. A personal mobile device is an example of this type of system.

INTRODUCTION

When it comes to the retail industry, there is a discussion about whether or not mobile applications have a more prominent standing than a mobile website or web app. Both the web app and the mobile website face competition from the mobile app. There have been more than 700,000 modifications of the mobile app since its inception in 2008, which are compatible with a variety of operating system platforms. "A sort of software that allows the user to do a given activity on various portable digital devices, such as smartphones and tablets," is how mobile applications are defined (or "app" for short). It is defined as "an IT software artefact that is specifically built for mobile operating systems deployed on handheld devices, such as smartphones or tablet computers" by the author of this article. This definition can be found in the source.

The two definitions illustrate that mobile applications cannot be used without a smartphone. Every one of these capabilities may be found in an online market-available mobile app, which can be downloaded by the user's own free will and then used to rate and review the app.

As of 2015, global app revenue was $8.3 billion dollars, and it is predicted that mobile apps would bring in 189 billion dollars in revenue by 2020. The success of mobile apps benefits everyone involved: app developers, mobile device manufacturers, and internet service providers. There is a steady increase in the number of customers utilizing mobile apps. Many people consider mobile app development one of the fastest-growing technological industries on Earth because of its numerous advantages and potential for growth. Mobile apps were identified to be a promising area of study by researchers combining the Theory of Planned Behavior with the Technology Acceptance Model and the Uses and Gratitude Theory. As a result of this study's findings, they advocated using their instrument as a substitute for mobile app evaluation. More symbol representations on the phone display may make it harder for users to find and open the desired programme. Creating an intelligent launcher could be possible if an on- board service correctly predicts which programme the user will use next. To make it easier for users to find commonly used programmes, this launcher places their icons at the very top of the screen. Pre-loading a programme into RAM can also be done using the launcher's configuration options for speedier execution. Predicting how an application will be utilised is our primary goal. Given the user's present location and other contextual cues, it is possible to predict which app they will use the most. The programmes a person uses when out to dinner with friends may be considerably different from those used while at work, however. Consequently, we decided to answer any further questions that came our way. To begin, what aspects of the surrounding environment are crucial to the app's ability to predict? How can we, secondly, distinguish and describe the many context-specific data sources? We also need to figure out a way to make predictions about how an app will be utilised by combining the various context sources. This analysis relied on data from the MDC dataset. We began by deleting any unnecessary information from the raw data. In the next step, we anticipated the next App to be released based on the time, location, profile of the user and the previously used App. A method for extracting the user's significant locations from WLANs detected by the phones was proposed as a consequence. Both a linear and a Bayesian model, which take into account context in various ways, were presented in order to make a forecast. For this purpose, the forecast is compared to a benchmark using the outcomes of two separate models and input from multiple contexts. According to the findings of this study, contextual information can be used to learn about and forecast app usage behaviour.

Since its inception, the smart app business has grown tremendously. Google's Market has 1.3 million apps, whereas Apple's iTunes Store offers 1.2 million apps, according to a 2014 Statista analysis. According to various research, the average smartphone has more than 40 apps installed.

Other mobile devices, like cellphones, have limited battery life. Increased consumption necessitates more effective optimization methods. The amount of time it takes for a software to load is a significant consideration. Apps may take a few seconds to load when the screen is on.

Some applications, such as games, take longer to load than the norm. Storing programmes in memory makes it faster to look for and load them. Because of its large memory footprint, this strategy is difficult to implement. Because of this, learning processes can build a library of pre-installed applications. In order to anticipate how an app will be used, various methods and frameworks have been developed. Some of these studies looked at how likely it was for users to switch between different Apps based on the order in which they launched them. A separate field of inquiry is focusing on personalized app recommendations.

Several studies have employed clustering approaches to categorise app usage based on context. Context data may be collected via human-centered activities such as jogging or walking, or from sensor-based activities like SMS and phone calls, for example. Some researchers have used time series models to investigate this topic. Learning Automata (LA), a classic reinforcement learning method, is still widely used today for a variety of reasons. Literature has presented a variety of different models of learning automata (LA). All of these works rely on information gleaned from the usage history of the apps in question. Sensor data from a smartphone's sensors can be correlated with the success or failure of a mobile app.

As time goes on, these algorithms learn more about how users interact with apps and utilise them over time, and they use this information to predict how apps will be launched in the future. To the best of our knowledge, the majority of existing solutions rely on an offline method and do not require a mobile device for learning. For this reason, cloud- based data classification systems are able to solve offline classification issues. Because of this trait, there is an added weight of network dependency, privacy, and response time. According to some, cellphones can't run complex algorithms due of their small size. On the other hand, a different group of algorithms relies on data from sensors. The utilization of several sensors provides a higher level of precision than simply focusing on App usage. If the algorithm is not designed to be resource efficient, it will have an impact on battery life. Many people find the usage of sophisticated categorization algorithms on mobile devices objectionable.

We use machine learning-based approaches since they are both resource-efficient and mobile-friendly. As long as the number of operations isn't too high, computational complexity is modest and practically linear with sample size. As a result, its response speed and throughput are well- suited to mobile platforms. Even better, we've developed an algorithm that learns from previous app launches and changes itself on a regular basis. Thus, our strategy avoids the danger of a shift in perspective.

People's performance expectations are based on how certain they are that using a new system would increase their job performance. When people believe that new technology has the potential to enhance their quality of life, it is more likely that they will use it. Information on performance expectations was derived from various sources, including theories about how people embrace new technologies (such as the innovation diffusion theory) and motivation models (such as PC usage models) (social cognition theory). The degree to which a user feels that a mobile app is more beneficial and enhances their experience is directly related to the degree to which they continue to use it. "The ease with which the system can be used" is a measure of effort expectation. According to researchers, it is built on three existing models. In light of the study's findings and the ease with which it can be utilised. The usefulness of the app and how long it is used will be influenced by how well it is received by its users. The main objectives of this study are:

- To predict the mobile app usage by using historical data.
- To apply regression analysis for predicting the usage of mobile application data and contextual usage
- To evaluate and compare the proposed model on the basis of performance metrics.

I. LITERATURE REVIEW

(Olaleye et al., 2018) The UTAUT, trust, and enjoyment components of the technology acceptance model are all part of this study. Use SPSS and general linear regression to analyse the link between mobile app technology, trust, and the end result variable. " Customers are more inclined to use apps with trust, privacy assurance, learning, and relaxing features. Technology adoption and trade have never seen anything quite like this. Age, gender, and marital status all had an impact on the frequency with which people used mobile retail apps, as was discovered in this study. As a result, management issues are addressed and an app solution is provided in this article.

Prykhodko et al. (in preparation for 2020) The planning phase of mobile application development is evaluated using a nonlinear multiple regression model, its confidence intervals, outlier detection, and multivariate normalising transformation. Linear regression and nonlinear regression are compared to models that use univariate transformations like the decimal logarithm or Box–Cox–Jenson transformations. Predictions made by this model are more accurate than those made by other regression models.

It's important to note that While full-fledged laptops still have their place in the professional world and on vacation, mobile technologies like smartphones and tablet PCs are already widespread. Thus, mobile applications were born, allowing users to access information from anywhere, at any time, on any device. Enhancing the mobile user experience is a major focus of machine learning. This is a collection of methods that allow robots to learn in the same way that humans learn. In supervised learning, the process is more closely monitored by providing labelled training examples, similar to those provided by human instructors to help students. In unsupervised learning, the process is less closely monitored. An effective app design strategy is one that incorporates guided examples that capture the unique human requirements and reasoning of each individual user. If you're an Android user, you'll appreciate this article's thorough examination of some useful methods for learning and their implementation in mobile apps. Detailed descriptions and examples of Android apps that use classification and regression techniques are provided. There are many unanswered questions about the apps and how they may be improved, and the author discusses these issues in detail. Mobile computing, human-computer interface (HCI), data mining and machine learning researchers and developers are likely to profit from this study.

As of 2022, (Tian et al.) The long-term viability of a mobile app is directly related to the level of user involvement. The amount of time a user spends on a page may indicate how interested they are in the content. The subject of how to adequately measure user interest in mobile applications is still an unanswered one. As an example, how much time do people spend using mobile apps, for example, during certain times of day? Mobile operating systems and publishers can benefit from asking these kinds of questions in order to improve advertising and service placement. First, the authors perform empirical research to assess the role that user attributes, temporal contexts, and long-term contexts play in enhancing population-level forecasts of app stay duration. A mobile advertising company gathered all of the app usage data needed to conduct a thorough examination. More than 12,000 anonymous users and more than 1.3 million log events are included in this collection. A new mobile app engagement prediction challenge has been developed as a result of the findings. As far as I'm aware, it's impossible to anticipate how long a user will stay in a particular app. In this joint prediction problem, the author provides many solutions and demonstrates that this model can greatly outperform current baselines. To better serve their clients, mobile app developers can use the information from this study.

Seven MLGs in Lagos were evaluated using cross-sectional data, according to a study (Balogun et al., 2020). The study surveyed 518 primary care physicians about their experiences with providing mother and child health services using mobile devices. Regression models like logistic and multivariable descriptors were used to analyse the data. By primary care practitioners utilising internet-enabled smart phones (ß=1.20, CI=0.61-1.79) MHealth (ß=1.20, CI=0.61-
1.79) was better understood. Mobile health champions have a positive attitude toward smartphones (ß=1.00, 95 percent CI=0.12-1.89) and an internet-enabled phone. Primary care doctors who were more familiar with mHealth in the context of maternal and child health used it 1.32 times as often as those who were not. Those with positive mHealth views boosted their use of mobile technology for mother and child health care by 1.15 times. Research suggests primary care clinicians' understanding and attitudes about mHealth may influence their use of mHealth to deliver care for mothers and children. Maternal and child health care need smartphones to increase awareness, attitudes, and use of mHealth.

The authors (Dey and Mockus, 2018) claim that (Paraphrase) Linear regression, Bayesian network, and Random Forest models are used to explain the interrelationships and give a release quality score that is sufficiently stable in terms of changes in software use. It was determined that the number of new users and the program's release date were the most important variables, not the frequency of use or the number of difficulties. Additionally, the number of crashes went up 1.3-fold as the number of new users increased. The average number of crashes per user, regardless of how the product is used, was found to be a predictor of how well a software version operates. These results are important because they can be used to evaluate software release quality and inspire additional research into this field, which we believe is the case.

Researchers have found that people's web browsing behaviours vary depending on the device they use to access the internet (Makan and Kutar, 2014) (Makan and Kutar, 2014). The data was gathered through a diary research and in-person interviews. According to the study's findings, next-generation users' online activities are restricted by their smartphones, the most often used devices in this generation. After conducting an interview, usability and convenience were found to be equally significant. According to some of the research, mobile apps on smartphones and tablets may be a viable alternative to more traditional methods of accessing the web.

In 2014, (Reuver, 2014) In user studies of mobile telecommunications, which are virtually entirely focused with service acceptability, little attention has been paid to data network preferences. The majority of smartphone users choose to use WiFi over cellular networks. In addition, the author examines the influence of various apps on data use. WiFi utilisation is now bigger than cellular network use in absolute terms. Participants in cellular networks have a wide range of usage, ranging from 0% to 100% of their entire traffic. There is no noticeable difference between Apple and Android users. Regardless of the data plan size, the amount of cellular data consumed was the same. Use of cell phones is driven mostly by chat, social networking, and web browsing apps. Despite the fact that video apps are increasingly popular, traditional capacity crunch arguments don't stand up. Log data on programme usage is better than self-reported utilisation levels. Cellular and WiFi network operators who want to control how much data is used should take note of these findings. A significant amount of data flow cannot be defined by application utilisation levels, and so preferences for data usage cannot be very adequately articulated.

(Sumter & Vandenbosch, 2019) To better understand how young people use and why they use dating apps, researchers looked at both demographic and personality-based criteria (e.g., gender and sexual orientation). Tinder was the most popular dating app among the people surveyed, with about half of them using it on a regular basis. People who don't use online dating services are more likely to be straight and less likely to be sexually adventurous than those who use them. People who have a high level of sexual permissiveness and self-esteem are more likely than others to use dating apps to meet someone for a romantic relationship or just to have a little fun. This study reveals that mobile dating consumers are motivated and engaged by their unique identities. Despite this, further research is needed into the impact of sexual orientation on mobile dating

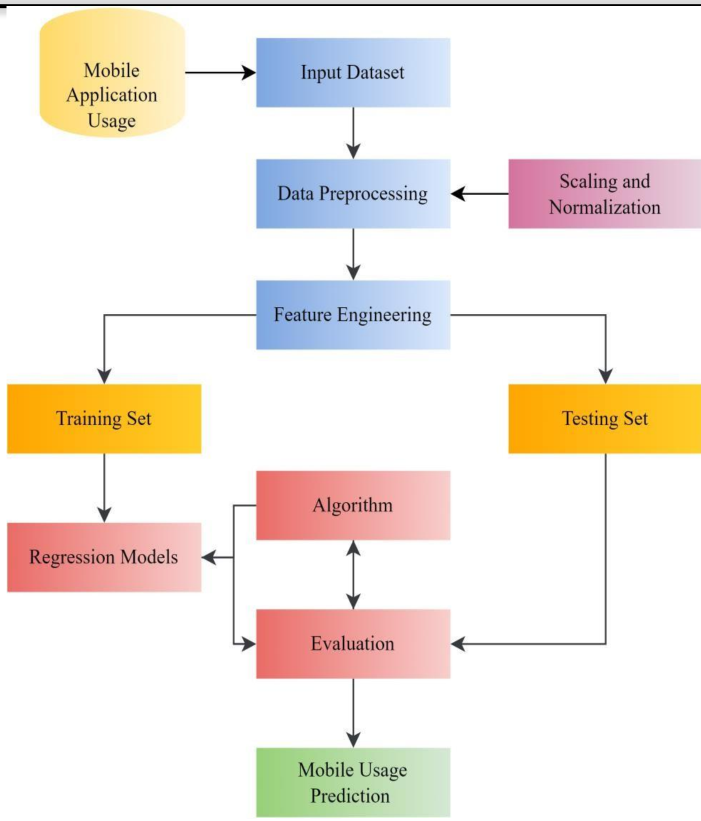
(Lai Kit and colleagues, 2014) For this study, surveys were given out to 300 students from Malaysia's largest private institution in Perak state, who were all active smartphone users. Linear regression tests are run on the collected data. A behavioural intention to use mobile apps is influenced by a number of variables (such as Habit and Habit), but the behavioural intention to use mobile apps is not influenced by SI, FC, or PV, according to our findings in this study. A new study will help mobile app marketing, engagement, and advertising managers better predict what the future holds.

Research by R. Ali, et al. It was the purpose of this study to analyse how mobile apps in the banking sector were rated by customers in order to improve app development. The 50 richest banks in the United States, according to the Federal Deposit Insurance Corporation, were all featured on this list (FDIC). The sample's iTunes Store app ratings were acquired by the author in 2012, 2016, and 2018. Using linear regression and Generalized Estimating Equations (GEEs), the data was analysed (GEE). To better serve their customers, banks could leverage the findings of this study. Managers can use the results to improve their mobile app development strategies in addition to assessing them. Banks can save money, time, and effort by using this approach from the beginning of the project to the end.

(Barbaro and colleagues, 2019) Mobile app developers face stiff competition despite the industry's rapid rise. Read on to learn why. A mobile app's success will be determined by its ability to keep users engaged as active service users and/or content contributors. It's possible that users of mobile applications will stop using them at any point due to the success of competing apps or a reduction in the services they offer. Consumers who have lost interest in an app can be re-engaged through the use of intervention strategies developed by app developers (e.g., sending push notifications with new contents). It is the goal of this study to show that it is possible to accurately predict when mobile app users would become disengaged. An app-engagement modelling and prediction framework has been built and tested as a result of these findings. Cox proportional hazards, negative binomial, random forest, and boosted-tree models are included in the proposed framework. An agglomerative hierarchy-based clumping model a year's worth of garbage recycling app data is used to test the suggested system. As a result, improved clustering models help all numerical models accurately classify their users.Boosted-tree and random forest methods produce the most accurate and resilient predictions.
For more information, see Tuckerman (2014). The data was used to train three alternative models to predict the success of mobile apps, including one based on a naive Bayes text classifier for app descriptions and another employing a generalised linear model to determine if an app is successful or not. In spite of this, exciting discoveries about the ecosystem, such as the current trend in photo-sharing apps, can be elucidated even if the model performance is not suitable to allow their use in driving investments in new applications
Roy (2017, p. 3) Smartphones have led to an increase in the use of mobile apps. TAM-expanded research looks at how consumers adopt mobile applications, as well as whether or whether such adoption leads to continuing use or switching intents. Two surveys in India were done in 2012, and extensive TAM was explored using factor analysis and structural equation modelling. The most important findings reveal that the majority of predictor characteristics have a significant impact on how useful and usable applications are assessed to be. Use behaviour and subsequent app switching intents are heavily influenced by behavioural intention. (Prassas and colleagues, 2001) Given the current forecasts for Internet sales growth, retailing over the Internet presents a number of challenges. Despite the convenience of shopping online, buyers still place a high value on product quality. Online retailers are expecting fierce competition in the years to come, and personalization is considered as the competitive advantage that will determine the winners. Recommender systems can help with personalization and reduce client information overload. No one is surprised that e-commerce sites have been employing them for a long time now. In this article, the author focuses on the specific traits and requirements of recommender systems used in e- commerce. It is also added to address the problems that underlying approaches face when executed in isolation." Before discussing an innovative European Commission- funded research project on internet commerce, the author takes a look at how the answer provided in this situation may be implemented.

II. PROPOSED METHDOOLOGY

Mobile machine learning architectures require a basic understanding of several fundamental concepts. The initial phase is the extraction of features. In data mining, the process of obtaining useful information from a dataset is called. The machine-learning algorithm creates an evaluation formula for a new piece of data once a feature set has been collected. When a model is trained, it is based on the extraction and classification of data. Prediction involves feeding our model with new data and evaluating how well our trained model is in predicting the expected results.



Raw Data Processing

Figure III-1 Proposed Flow Work malfunctions or even a faulty reading of the data. Before any statistical analysis can be carried out, it must be You have the raw data. There were a number of processes utilised to complete the data purification, including eliminating duplicates and null values. This technique is used in data mining to turn an unstructured dataset into a more comprehensible format. Real-world data is frequently missing, inconsistent, or incomplete for a variety of reasons. When classifications aren't evenly distributed, it's difficult to build accurate prediction models. Categorization machine learning algorithms typically have the same number of instances in each class. Several changes have been made to resampling techniques as a result of the findings of this investigation. Under sampling can be avoided by eliminating items from each cluster and obtaining the bulk of the class records. As an alternative to employing precise clones of minority class data, a larger range of synthetic samples can be generated by using over sampling. Using random oversampling, a subset of the original dataset is randomly selected for training purposes while maintaining the same proportions as the original dataset. The practise of "random Undersampling" can be used to lower the size of the training dataset by randomly picking examples from the majority class. A balanced and consistent dataset is essential for data mining research. There may be anomalies or outliers in a dataset. Every time you look at the data, you're bound to find an outlier. In this study, the outliers could be due to a variety of causes: human error, equipment removed from the data. The results of any information outliner can have an impact on the analysis and subsequent treatment if they are incomplete or incorrect.

A. Feature Engineering

Use only relevant data and remove noise from data to reduce the input variable to model the properties of a machine learning model are determined by the type of problem it is trying to solve. This study used the Pearson correlation. In order to determine whether two numerical variables have a linear relationship, the Pearson's correlation coefficient is employed.

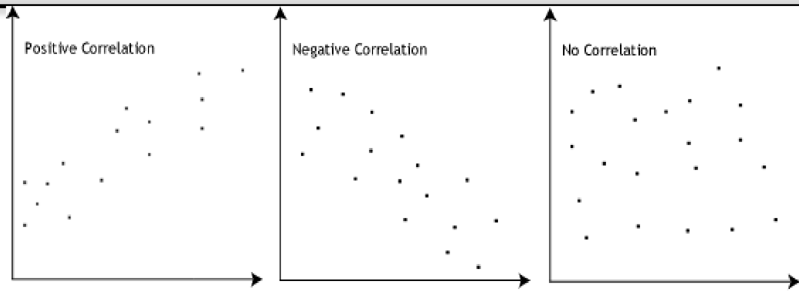


Figure III-2 Pearson Product Moment Correlation

The Pearson correlation can be used to gauge the strength of a linear connection between two variables. When it is set to
-1, it means there is no correlation at all; when it is set to 0, there is none; and when it is set to +1, there is a complete positive correlation.

B. Regression Algorithms

1) Dickey-Fuller test for stationarity

It is possible to determine if a time series is stationary using the Augmented Dickey Fuller test (ADF Test). This is one of the most commonly used statistical methods for determining whether or not a series is stationary.
One of the methods for determining stationarity is the Dickey-Fuller test. Using the Dickey-Fuller test, we may determine that the time series in question is not stationary but rather time-dependent. Because of this, we might conclude that the time series does not appear to have a distinct trend. Test results can be used to evaluate how significant they are by using their p-value. The null hypothesis, which asserts that the population is stationary, can be rejected if the p-value is less than 5% or 1%. According to our statistical analysis, we can't rule out the null hypothesis if the p-value is more than 5% or 10%.
Because the p-value is greater than 0.05 and the data are non-stationary with a unit root, the null hypothesis (H0) cannot be ruled out.
A unit root is required to rule out the null hypothesis (H0) as a viable alternative (p-value less than 0.5).
Using our p-value of 0.00027 percent, we can rule out the null hypothesis and conclude that our time series is stable and does not show any trend. Using a 1% significance level, the probability of rejecting the null hypothesis is -3.47 percent, which indicates that a significance level of less than 1% is possible. As a result, the likelihood of rejecting the hypothesis incorrectly is quite low.

2) Auto regression (AR)

It is a time series model that displays the relationship between the current value of a variable and its past values. By integrating the most recent prior values and using them as input data for an AR model, it attempts to forecast the future value of the series. Finally, the goal is to improve the model's ability to accurately forecast the results of experiments.
Next steps can be modelled as linear functions of previous observations using an auto regression (AR) approach.
Users can add seasonal dummies and time trends to the original software, as well as enter exogenous variables. As compared to AR, AutoReg's model is regarded to be immutable. As a result, a detailed specification, including the lag length, is required. It is impossible for the AR API to support this change in form. AutoReg models can have their lag durations set using the AR pick order function.

3) Moving Average (MA)

Technical analysts use moving average charts, or MA charts, to track changes in the price of a certain security. As a result, it plots the average price over a given period of time, with the moving average commonly superimposed onto a chart that includes candles or bars. In this method of forecasting, the next steps in the projected time series are predicted through the use of a mean process based on past observations.

4) SARIMA

By combining the acronyms SARIMA and ARIMA, the seasonal time series data analysis technique known as SARIMA has been developed. Other names include seasonal ARIMA. A single step separates autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA). Seasonal changes have an impact on a wide range of time series data.

5) **Holt Winters Simple Exponential Smoothing**

For the challenge of projecting "typical" values in today's and tomorrow's reality, Holt-Winters uses exponential smoothing to encode a huge number of historical values. If you want to make a time series appear smoother, you can use an exponentially weighted moving average (EWMA)."

C. Model Evaluation Parameters

RMSE and MAE have been used to evaluate the current study's performance. Using the following formula, you'll get the answer:

1) **Mean Absolute Error**

A time series classifiers mean absolute error is the average value of its erroneously forecasted data:

$$mea = \sum_{i=1}^{n} abs \frac{yi - \hat{f}(xi)}{n} \ldots (1)$$

2) **Mean Square Error**

The square root of the square of all the target values, minus the square of all the incorrectly predicted values by the classifier, is:

$$mse = \sum_{i=0}^{n} \frac{(\mathrm{wt(xi)})-yi)^2}{\mathrm{n}} \ldots (2)$$

III. RESULTS

A. Time series analysis and forecast

This study provides a platform for testing out time series analysis and forecasting. In addition to trend and seasonality analysis, each of the several components will provide a clear outlook for the near future. For the next week, we'll be using real-world data regarding how many people are using a mobile app at the same time on an hourly basis. Plot the total number of users over time in its original form, and you're done.

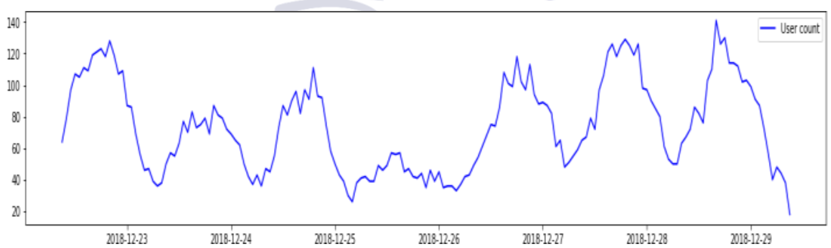


Figure IV-1 the original time series of user counts

B. Time Series Stationary Analysis

Stationary time series refers to a circumstance in which the features of the time series, such as its mean and variance do not vary during the period of the investigation. An established trend is one that has a consistent mean and variance over time. We've run a few tests to see if a time series' stationarity can be determined. Plotting the moving average and the moving variance across time is an easy-to- understand strategy that is also quite visual in nature.

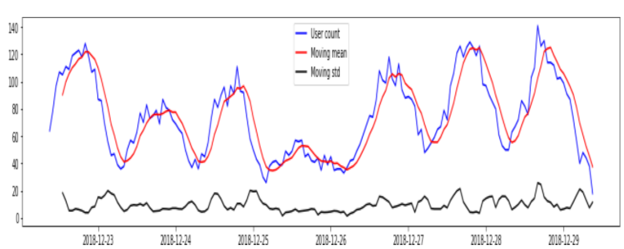


Figure IV-2 Time Series Stationary Analysis

C. **Dickey-Fuller test for stationarity**

If a time series is stationary, the Augmented Dickey Fuller (ADF) test, commonly known as the ADF Test, is used to determine this. It is one of the most often used statistical tests for assessing whether or not a series is stationary.

The Dickey-Fuller test is another method for determining stationarity. An H0 is established via the Dickey-Fuller test, which shows there is no relationship between the time series under consideration and any other time series. Defeating the null hypothesis suggests that the time series is not progressing in any particular direction. The test's p-value is used to deduce the meaning of the results. The null hypothesis, which claims that the population is stationary, can be rejected if the p-value is less than 5% or 1%. P- values larger than 5% or 10% suggest that we cannot reject the null hypothesis (non-stationary).

It is impossible to reject the null hypothesis (H0) since the p-value is greater than 0.05; the data are non-stationary and have a unit root.

H0 cannot be true, because the data are stationary and do not have a unit root, if p-value is less than 0.05

It is possible to reject the null hypothesis because our time series has a p-value of 0.00027 percent, allowing us to conclude that it is stable and does not exhibit any trend. It's conceivable to reject the null hypothesis with a significance level of less than 1 percent, based on the probability of -3.47 percent. This means that the probability of wrongly rejecting the hypothesis is quite low.

Make a time series immobile by transforming it from non- stationary to stationary.

As was said previously, there are two components that cause a time series to be non-stationary. These components are as follows:

A general upward or downward movement in the mean across time, such as an incremental rise or fall in the average number of users over time

Seasonality refers to fluctuations in the mean that occur at a predictable interval, such as a higher mean at the beginning of the day and a lower mean after business hours.

The goal is to determine whether or not a time series exhibits trends and seasonality, then apply the knowledge gained about trend and seasonality to the process of converting the time series into a stationary time series. The next step is to make a forecast using the stationary time series, after which you will once more use the trend in addition to the seasonal variations in order to obtain the final projection.

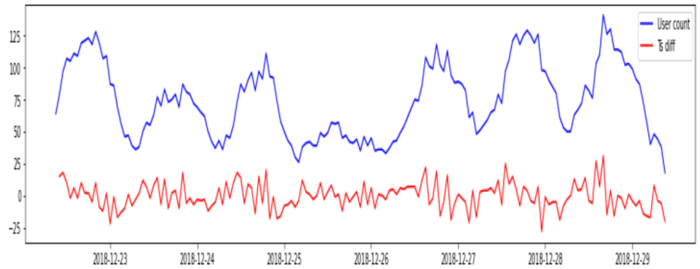


Figure IV-3 Difference

A decomposing step models each of the trend, seasonality, and residuals on their own.

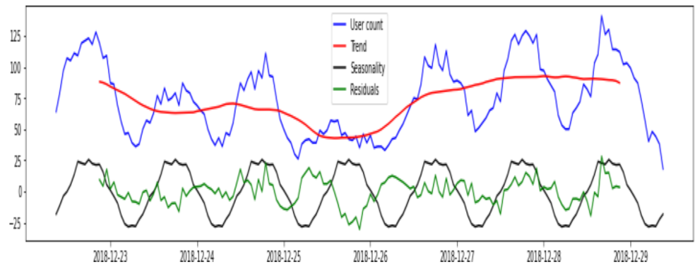


Figure IV-4 Decomposition

D. Forecasting a time series

As a result of our effective eradication of seasonality and trend components, we are now in a position to begin generating predictions about the time series into the future. Since each time series is made up of a variety components, for example:

- Trend
- Seasonality
- Residuals

E. Prediction with Auto regression (AR)

Autoregressive models are time-series models that explain how past values of a variable influence its current value. It is an attempt to predict the future value of the series by integrating the most recent prior values and utilizing them as input data for the AR model. Ultimately, the goal is to increase the model's accuracy in making predictions.

Observations made earlier in time are used to model the subsequent step in a sequence using the auto regression (AR) method.

An additional feature of AutoReg is the ability to input exogenous variables, include time trends, and use seasonal dummies. This API differs from AR in that the model is believed to be a one-time thing. As a result, when building the model, the whole specification, including the lag length, must be provided. In its current form, the AR API is unable to accommodate this change. The AR choose order function can be used to select lag lengths for AutoReg models.

AutoReg uses only conditional MLE for parameter estimations (OLS). Use SARIMAX as an estimation tool when estimating ARX and related models with full MLE and the Kalman Filter

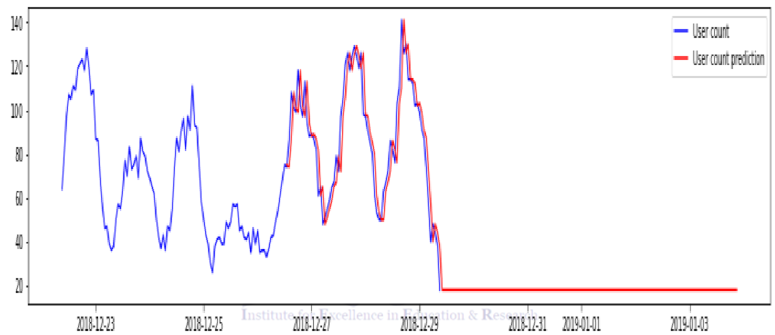


Figure IV-5 Prediction using AR Model

F. Moving Average (MA)

One of the tools that technical analysts use to keep tabs on price fluctuations is a moving average chart, often known as an MA chart. The moving average is commonly placed on a chart that utilizes candlesticks or bars to represent average prices over a certain period of time. This method of forecasting uses a mean process based on previous observations to model the upcoming steps in the anticipated time series.

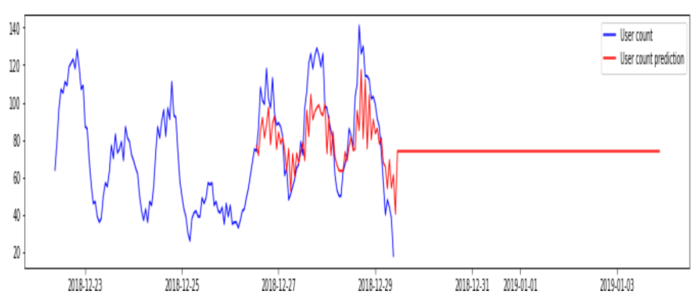


Figure IV-6 Moving Average

G. **SARIMA**

SARIMA (Seasonal Autoregressive Integrated Moving Average) utilizes ARIMA's seasonal component to cope with time series data that is seasonal in nature. In the lexicon, it's known as ARIMA (Seasonal). There is a one- step difference

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between an autoregressive integrated moving average (ARIMA) and a seasonal autoregressive integrated moving average (SARIMA). Seasonal impacts can affect a wide range of time series data.

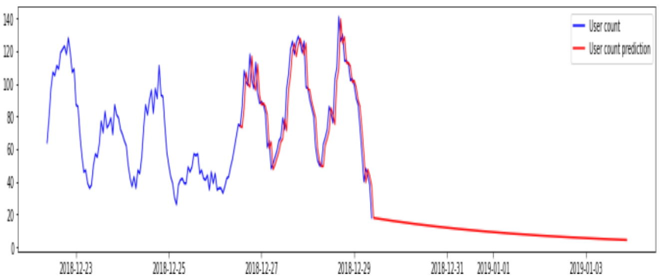

Figure IV-7 SARIMA

H. Holt Winters Simple Exponential Smoothing

Exponential smoothing is used in the Holt-Winters technique to encode a large number of past values, which are then applied to the problem of predicting "typical" values for the present and the future. If you want to make a time series appear smoother, you can use an exponentially weighted moving average (EWMA)."

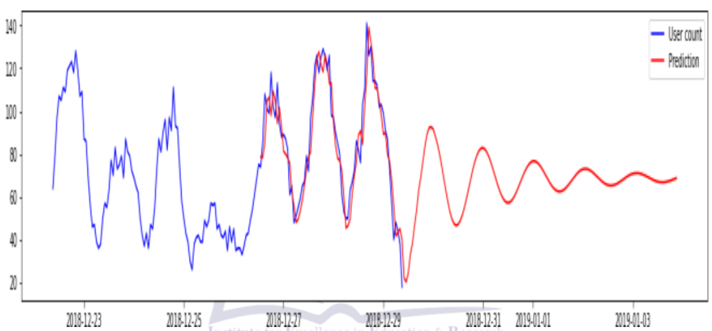

Figure IV-8 Holt Winters Simple Exponential Smoothing

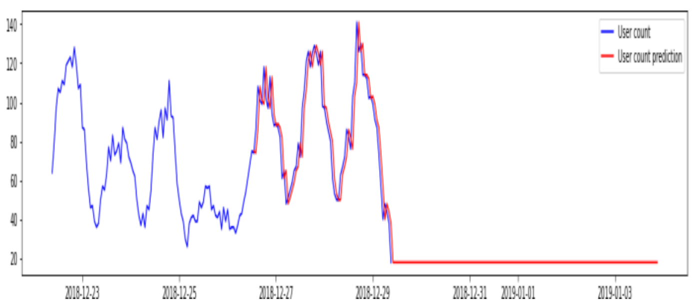

Figure IV-9 Holt Winters Triple Exponential Smoothing

IV. CONCLUSIONS

When there aren't many outrigger levels, shear pressures in the core wall take on a pattern similar to shear in a moment frame column, with larger-than-usual, reverse- direction shears concentrated at panel zones (outrigger levels). However, core wall panels are not a perfect parallel to column webs because they generally feature perforations in the form of lines for doorways. The capacity of a "panel zone" may be constrained by the shear stiffness and strength of connection beams at apertures. Several methods have been implemented in building designs to accommodate for this issue. It may be possible to construct a coupling beam that is a story taller (or deeper) to withstand the greater wall shear force if apertures can be deleted at one or more stories at the outrigger level. Wherever the size and placement of a gap allows, the strut and tie method can be used. For compression struts, this means having enough area at strut/tie intersections for force-transfer nodes, and for tension ties, it means having enough bands of continuous reinforcement or embedded tension members. Panel zone forces can be addressed by an embedded complete steel truss if outrigger connections and load routes are based on embedded steel members. Similarly to the other methods, this one necessitates suitable geometry. Two major considerations during core-and-outrigger building construction are the prevention of differential shortening and the impact on the total timetable. Due to differential axial shortening effects, as discussed in section 2.6, the construction sequence of an outrigger system cannot be considered to be "means and methods" distinct from the design. This is true regardless of the structural systems and materials chosen by the designer. But the order in which you build can help minimise them. Because of the differential post-top-out axial shortening of core and columns, additional forces in the outrigger system can be reduced, but not eliminated, by delaying the final outrigger connections joining core and columns until after topping out. The design process needs to account for these forces. If these extra forces could be kept to a minimum, the outrigger's ability to resist lateral forces would be preserved to a greater extent. A system that allows the outriggers' connections to be adjusted in the future is needed for this purpose. Multiple such systems have been proposed, and some have even found their way into brand-new skyscrapers.

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