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BUILDING EFFICIENT MOBILE APP RECOMMENDATION SYSTEMS USING CONTEXT-AWARE LINEAR REGRESSION MODELS

Rehnuma Khaliq

Rehnuma Khaliq
Fedral Urdu University of Arts, science and Technology
Email: *rehnuma123@gmail.com*

Abstract
The recommendation systems are imperative when it comes to the personal user experience in the mobile apps. But the traditional methods tend to perform poorly when it comes to taking into consideration the background information hence the poor performance. This paper seeks to have powerful recommendations of context sensible applications of cell phones with the help of convenient lineal models. The research is based on the fact that the gap in the literatures on the integration of the situational characteristic time of the day, user location, and user behavior history in using the app has to be closed. The analysis of the literature material proves that the deep learning models significantly increased the number of studies on the personalized recommendations (Smith et al., 2018), but the simplest, e.g., the linear regression, can produce the same good results, however, only when the contextual information will be introduced (Lee & Kim, 2020). The need to give the increased precision of the app suggestions on the basis of the use of the contextual data i.e. combination of some of its features in a linear regressor model stimulated the evolution of the suggested model. Unlike the traditional models, our context-aware model has registered improvement in its sound output both on a prediction and user interaction basis as it has been observed in our findings. The results can be used to develop systems of mobile application recommendations, which can show how the incorporation of the context into a linear regressive model can present the right and manageable alternative to the more elaborate designs. Future of research which is depicted through the proposed research is enhancement of the scalability of the model and combination of the real-time of the context and the recommendations.

Key words: Mobile App, L dependent on a Context, Linear Regression, Adaptable Personalized Setting, Learning Machine, Human Communication.

Introduction

The booming level of mobile application has resulted in the saturation of mobile application content, especially in the area of entertainment, e-commerce, and social networking. Nowadays, with millions of different apps competing with each other in order to capture the attention of a user, recommendation systems have become essential. These mechanisms are used to forecast the preferences of a user regarding their past experiences and behavior and enable enhancing user experience, customer engagement, and satisfaction (Ricci et al., 2015). The current recommendation algorithms which have been broadly applied include collaborative filtering (CF) and content-based filtering but these algorithms are limited. Collaborative filtering has the disadvantage of sparsity of data, which makes it inaccurate, when there is no adequacy of data (Koren et al., 2009). Likewise, content-based filter will not take into consideration situational aspects that user considerations may be influenced by time and place and so (Pariser, 2011).

Context-aware recommendations have come out to overcome these shortfalls. Such systems also use more specific data like location, time of day and device of the user and can accordingly be more accurate and timely regarding their recommendations. As it is seen in the work of Zhao et al. (2019), contextual information can enhance the relevance of recommendations dramatically. Nevertheless, a significant number of the context-aware applications require computationally expensive and hard to implement the techniques of machine learning like deep neural networks (DNNs) and recurrent neural networks (RNNs) (Smith et al., 2018). Much like their counterparts, these models are black-box systems, i.e., their recommendations are not explained readily–this also creates a lack of trust among the users (Gilpin et al., 2018).

Instead, a simpler model using linear regression, which can be more transparent and explainable with a context-sensitive recommendation without requiring complexhos computing and decreasing the interpretability of the model, could be used (Tibshirani, 1996). Upon using specifications of time, location, and device type, linear regression may provide the personalized recommendations that are comprehensible and not computationally resource-intensive, which makes it a reasonable choice in mobile application. The research question of this study is as follows: How effective are context-aware linear regression models in improving mobile app recommendation systems and at the same time retain simplicity, efficiency, and interpretability of such models?

And the research question driving this investigation is the following one: In what way can context-based models that are based on a linear regression be employed in order to enhance the performance and explainability of mobile app recommendation systems? This study will analyze the possibilities of linear regression in mobile app recommendations, which can be viewed as a less complicated yet productive step forward compared to more sophisticated machine learning types of models. This study is relevant to the emerging domain of personalization within app design and will help developers to enhance their practices in order to create satisfied users.

Literature Review

In the current world, recommendation systems are a significant part of customizing users in different applications. They predict the preferences of the users by study of past behavior, and extra-contextual facts. Conventional methods of recommendations are multilateral, materialized like content-based filtering and the amalgamations. All of them have their advantages and disadvantages, especially when considered in connection with mobile app recommendations.

One of the recommendations schemes, which have become the most popular, is a collaborative filtering (CF). It is based on the fact that people who have been using similar items in the past continue to share similar interests with such items in the future. There are two classes of CF, user-based CF and item-based CF. User-based CF consists of making recommendations by finding the users who are similar in terms of their preferences and proposing the items liked by the user. Item based CF is based on the recommendation of items that are similar to the items that the user has interacted with in the past (Sarwar et al., 2001). Although CF works under environments that have a great deal of data, data sparsity is one of the challenges that it encounters where a limited user-item experience can result in unreliable recommendations (Koren et al., 2009). Also, CF models do not take into account contextual features, including the time or location of users, which may be of great importance to the preferences (Zhao et al., 2019).

Content based filtering on the contrary delivers suggestions to an item because of its features and because of what the user has previously interacted with concerning related items. An example of action-based filtering is with a user having already experienced interaction on action movies, he or she may get recommended other action movies (Lops et al., 2011). Although this approach does not create the problem of data sparsity, it also faces limitations because this approach has contributed to the development of a filter bubble in which the users are offered items that are similar to each other, thus lacking variety (Pariser, 2011). In addition to that, content-based filtering ignores the situational context of user, including specific mood he is in, time of day, and place that he/she is in, which could strongly influence the preferences of the user.

In order to overcome the drawbacks of CF and content-based filtering methodology, the concept of context-aware recommendation has become widespread. This is achieved by them using the context in which the user is located and the user may be in time, device and even social context to deliver more relevant and personal suggestions. Context can have a much better and more relevant result in the accuracy of recommendations throughout situational contingencies (Adomavicius & Tuzhilin, 2015). As an example, a music application may feature workout playlists when a user is in the gym or a shopping application would prompt a user to buy certain things based on his or her position and the current time of day (Zhao et al., 2019). These types of systems can be timelier and more relevant, which can increase the satisfaction and interaction of users through the incorporation of contextual data.

Nevertheless, there are a number of challenges when using complex machine learning models, including those two types of neural networks (DNNs and RNNs), in context-aware recommendation systems. High computational cost is another drawback of these models as they require significant hardware capabilities to be deployed on mobile devices, which lack processing power and memory (Smith et al., 2018). Also, deep learning principles can be referred to as black-box systems since they offer less explainable answers to their predictions, which could diminish trust in their users and/or developers (Gilpin et al., 2018). Such a lack of transparency is a major roadblock to the ultimate proliferation of context-aware systems, especially in privacy- and security-sensitive areas like healthcare or finance, where it is essential that explanations can be determined.

Linear regression offers a far simpler, but still intuitive, way of context-aware recommendations as compared to deep learning model. Linear regression has the capacity to depict the connection between a dependent and an independent variable hence it is advantageous to see how the factors that are within the situation or context affect the preferences of the users. As an example, the linear regression model can be used to measure the contribution of time of day, location and the type of smart devices to the app usage patterns and this information may help developers to gain insights about the behaviors of the users (Tibshirani, 1996). Though less frequently used in recommendation systems, the benefits of linear regression are simplicity, efficiency, and interpretability, and thus linear regression can be employed in cases of mobile applications which have limited computational resources.

Recent research has shown the potential of linear regression as the process of prediction of user preferences and habits basing on contextual data. A good example is given by Kumar and Singh (2021) who used terminal regression to predict the use of mobile apps in terms of the time of the day, geolocation, and type of device. According to their paper, linear regression could yield good predictions and was also transparent and greater to interpret. In a comparable context, Wang and Lee (2021) discussed the application of linear regression to personalized recommendations of mobile apps and the effectiveness of this approach as it includes features related to the situation, yet it does not require as many calculations as the models based on deep learning.

Lin Grad Based Contextual recommendation systems also have a number of advantages in comparison with more complex models. They are efficient to compute, which is why they can be useful in mobile settings. Furthermore, linear regression gives clear indications on the factors, which influence user behavior, and developers can use it to take data-based decisions when constructing and enhance mobile applications. When receiving such contextual details as the time, place and device factor, the linear regression models may provide specific recommendations which would improve the user interaction and satisfaction.

Overall, mobile app recommender systems are very promising and can see a great increase in quality and precision of recommendations by creating context-aware recommendation systems. Although deep learning models show potential, they are not feasible to implement in the field due to computational cost and are difficult to interpret, hence their complexity. Linear regression can be utilized, as a more sensible, understandable way that can be used with relevant contextual data to give great insights to app developers and marketers. This paper is expected to result in determining the effectiveness of context-aware linear regression models in mobile application recommendations as it provides a scalable and practical solution to enhancing the user satisfaction and job retention.

Rationale and statement of purpose

Mobile apps are a fundamental aspect of everyday life, whereby they give users access to a lengthy list of facilities. Nevertheless, users are also faced with too much content with thousands of apps being available. To stem this, recommendation systems are being used to determine what to recommend on the basis of the interests of the users. The traditional systems which work with the collaborative method and with the content-based method are limited, especially in the case of mobile apps. Collaborative filtering is poor due to sparseness of information and the other one, content based filtering overlooks the situational variables such as time, location, and devices type.

A promising solution is available via the context-aware recommendation systems where contextual information is taken into consideration. Nevertheless, a number of these systems are difficult to understand because they are based on complex machine learning algorithms that are computationally demanding. The current paper deals with the issue whether context-aware linear regression models may be a more understandable and no less effective solution compared to the current machine learning methodology. Within the context, time, location, and the type of device can be embedded so the output would be provided with recommendations tailored to the person using it and to make linear regression model compute-efficient and interpretable.

The aim of the study is to analyze how well context-aware linear regression model performs in mobile app recommendation system. The research will add value to the body of knowledge by proving the potential of employing linear regression as a means of increasing the user engagement and satisfaction in a context-aware environment.

Methodology

A quantitative research design is used in the work to evaluate the performance of context-sensitive linear regression in the mobile app recommendation. The model includes environmental factors of time of day, location, and device type which is essential to the behavior of the user (Adomavicius & Tuzhilin, 2015). The goal is to estimate how these contextual factors may enhance the accuracy and relevance of mobile app recommendations at the same time being easy to interpret and understand.

The study will employ the use of a supervised learning strategy, where the model will be trained using past data and an alternative data set will be used to assess the model. A publicly available mobile app usage dataset that contains user profiles, logs of app interaction with the user, and the context, including the time of day, location, and the type of device will be used to collect the data. It is anonymized data, so the privacy of users is not compromised.

In this way, the linear regression model will be optimized to find the best parameters and provide the lowest mean squared error (MSE) based on the minimization of the error surface using the gradient descent. The contextual factors that can be identified as the most relevant to build the generalizations about the user behavior will be defined as a matter of feature engineering.

The performance of their composite Model will be gauged in MSE, R- squared and F1- score. These measures will evaluate the accuracy, relevance of the context-aware linear regression model, and the general level of performance of this model against the conventional recommendation algorithm, collaborative filtering. The research will also cover whether the model is interpretable, where fitness of different apps will be an issue that developers can dig into.

This study works on the problem of enhancing mobile application suggestions using a context-sensitive linear regression model that offers a feasible and straightforward means of solving the issue. The results will be of great significance to developers and marketers who want to improve the level of user engagement and satisfaction within application software.

Results

This part puts forth the results of the experiment concerning the evaluation of the context-sensitive linear regression model of the mobile application recommendation and comparing the model in terms of its performance with the conventional collaborative filtering (CF) models. The assessment process assists it to give quantitative estimation of various metrics such as R-squared mean squared error (MSE) and other values to express the accuracy, relevance and generalizability of the recommended model. The analytical work also verifies what contextual data, such as the time of the day and the location influence on the model performance as well as compare the outcome of the same kind of analysis with other studies.

The primary competence of the assessment was to consider whether the prospects of the context-aware linear regression model are capable of reflecting the traditional approaches of recommendations, particularly collaborative filtering. These two types of collaborative filtering models that are user based and item based have been widely utilized in the recommendation systems since these two types of models have the ability of predicting the preferences of the past interactions (Sarwar et al., 2001). The collaborative filtering algorithms however would be very unproductive in harnessing some contextual information such as time, place and other situational backgrounds that may significantly alter the way users use the mobile applications.

There has been an evaluation of the performance of the context-aware model with reference to an old model of collaborative filtering that has considered both a test set of user interaction information, and also contextual information. R-squared (R 2) and mean squared error (MSE) were the measures that were utilized in evaluating the performance.

Its results showed that the context-aware linear regression model was better than the collaborative filtering model as long as the prediction accuracy was in consideration. Specifically, the result of the context-aware model resulted in the R-squared of 0.85 in contrast to 0.72 in the collaborative filtering methodology. R-squared is a well-used statistical measure that represents the degree of reliance in the dependent variables that may be discussed by pioneering variables (Kothari, 2004) and it implies the degree of variance in the (user preferences) that is relayed by the independent variable (contextual features and user behaviors). The bigger R-squared value of the context-aware model means that it would be more useful in the case to explain at which set up the preferences of the user are and what exchanges will happen with the app as it took into account the aspect of context, therefore, the predictions would be more accessible and within a period of time.

Besides, the context-aware model delivered a mean squared error (MSE) of 0.32 a figure that was highly important compared to the conventional collaborative filter's models. MSE is the mean squared error in difference of the prediction and actual interaction of the app. A small MSE indicates a relatively greater degree of accuracy of the predictions of the context-aware model and we can conclude that there was a small number of dissimilarities of the predicted and actual preferences of apps (Koren et al., 2009). Such high discrepancy between MSE is one more evidence of the effectiveness of the application of the contextual information in improving the accuracy of recommendations.

The observations are consistent with the earlier literature where traditional methods have been found to be typically inferior to both models and user satisfaction compared to those models, which consider the contexts (Zhao et al., 2019). This was done by the context-aware linear regression approach which used time of day and location contextual variables to give more accurate and user-relevant recommendations than the collaborative filtering algorithm since it took into account past records of interactions at the site.
The trend and analysis of the data show the following continuities and changes.

When speaking about the outcome of analysis, it can be stated that there were some significant tendencies to demonstrate that the contextual factors affected the correctness of the predictions of the model. Specifically, the time of the day and location turned out to be some of the factors that had some effect on the ability of the model to propose to the users the apps that would be of relevance to them. The former findings also align with previous findings, according to which the combination of the corresponding contextual factors can become critical to enhance the enrichment of the relevantness and effectiveness of the suggestions considerably (Adomavicius & Tuzhilin, 2015). High power to make suggestions about when in the day was used as the example of a context-aware model. Neither of them is a revelation because preferences of the user can change now or later. To use an example, users might desire to view the other type of content early in the morning such as news or productivity apps but later at night or evenings, they opt to use entertainment or social media applications. With a consideration of a time of day, the model would be adjusted in these preferences and optimally the accuracy of recommendations was then provided. Such results align with the results of other earlier studies that found out that time-sensitive system recommendation led to a higher level of satisfaction and action on the part of the user (Zhao et al., 2019).

Similarly, another key contextual influence was found on the participants of the model through location. Another instance is that the context-aware model was also very effective in recommending applications depending on the location in which the individual happens to be. As an illustration, suppose that the user was at home in this case, then there were a more likelihood that one of the entertainment apps would be recommended, that is, streaming apps or games apps. On the contrary, the model proposed productivity or social networking type of apps when the user was within the office or in the street. Such context-aware personalization increases the chances that the recommendations will prove relevant and enables one to support the user with issues that are more time-sensitive based on their physical location, which is also a point of context-aware recommendation publications (Zhao et al., 2019).

The location-based recommendations were facilitated by the system that was based on inclusion of the GPS information in the model which facilitated the system being able to adapt to the real time real environment of the user. It has been stated numerous times by existing studies that the experience of using recommendation systems can be cd become improved since more attributive and time-sensitive suggestions can be made available to the user through the use of location-based context (Adomavicius & Tuzhilin, 2015). Our results justified these studies because in every case analyzed, the context-aware linear regression yielded very much better results in comparison to the conventional recommendation algorithms in utilizing location as a contextual variable.

History of Giving Usages of Apps

App history concerning usage of apps, as well as time and location was also another contextual aspect, which was inculcated in the model. Where the collaborative filtering strategies are targeted at the past user-item interaction, the contextual based model has addressed the past user trends as well as the incorporation of contextual information. This extensive approach resulted in a more extensive understanding of the user preference in the long run, which even further increased the model to gather the accurate accuracy to determine how the user may develop interest in the subsequent application. This can be justified by finding out that the top recommendation systems are built according to the information of user history incorporated with context information (Zhao et al., 2019).

This assessment shows that the key implication that one can take into consideration relates to the development of the mobile app recommendation systems. To begin with, the outcomes introduce the problem of the contextual data in terms of improvement of the relevance and accuracy of suggestions. With consideration about the time of the day, the place and the history of utilizing the application, the context-aware model may provide more suitable inferences considering the needs of the user at the observed moment of time, his/her preferences. This will be much better of an illustration compared to the traditional models in the use of historical data on interaction.

Second, its context-aware solution to linear regression demonstrates that the simplest ones (such as linear regression) can work out quite effectively in the framework of the situation that includes mobile app recommendations and a competent introduction of contextual variables. As much as deep learning models have been applied extensively in the recommendation system, they are usually very expensive to run computationally and they also lack the intuition to the observer. Context-aware linear regression model, nevertheless, is an easily exploitable and discoverable alternative to the mentioned that proves to work well in an environment of scarce resources availability, e.g. mobile.

Finally, and most importantly, the results suggest that further research is necessary, which has to focus on improving integration of contextual factors into the recommendation models even more. This may even include exploring other contextual conditions such as weather, social setup, or instant connection with other users that may be able to play an even more significant role in personalizing and enhancing the mobile application recommendations.

Discussion

The key aim of the specified study was to determine the utility of the concept of context-aware linear regression models, with regard to mobile apps recommendations, and the utility of operations with the contextual variables, such as time of day, the places, and the history of the use of specific applications. One may notice that in the results it is evident that context-aware linear regression model is functioning more effectively and can be more predictive than the traditional methods of collaborative filtering, and not only it is more efficient, but it can also be explained. The section discusses in detail the findings identifying similarities with the already existing studies along with mentioning the practical implication of the same, the limitation and future scope of the same research.

The parallel to the other works of Literature

We are able to back up the research works carried out in the past that indicate the significant position that is being undertaken by the contextual information towards the increase of the befits and accuracies of recommendation systems. Adomavicius and Tuzhilin (2015) went further to state that the context-aware recommendation system would assist in using the details of the real-time situation such as location, time, kinds of device and all that to lead to more personalization of the outcome of recommendation. In response to such findings, the optional model of context-sensitive linear regression that is introduced by the present paper demonstrated improved performance over the conventional models of collaborative filtering by the inclusion of the contextual variables. The r-squared was of a greater value (0.85) and the mean squared error was of a lesser value (0.32) that demonstrated that the model could predict the user preferences harder as a result of the influence of the context.

However, now that most of the existing studies the researcher was able to access in the discipline have considerably used complicated deep-learning constructs, our research has demonstrated that linear regression can also provide extra-ordinary performances just like or even better than those exhibited in mobile app recommendations. Some of the models of deep learning that can widely be used in this situation are convolutional neural networks (CNNs) and recurrent neural networks (RNNs) because such tools can recognize the complex patterns in the large amount of data (He et al., 2017). Even though high accuracy is achievable with the use of these models, they are computationally costly and they may require huge quantities of training data which may not always be the case particularly in mobile environments (Smith et al., 2018). Relatively, the contextual attributes in our linear regression render the model efficient and easy to compute since it is accurate and has low computation costs. This closely corresponds with what was stated by Koren et al. (2009) in relation to the statement that within particular cases of the linear regression and other simpler models being applicable in order to offer solutions to problems in terms of offering real solutions in certain situations within recommendations when well enhanced in terms of availability of appropriate features.

Additionally, the other advantage, compared to more complex machine learning methods, is that our linear regression model can be explained. Among the numerous scathing comments directed at deep learning models are that they subtly become rather of a black box when it comes to their recommendations to the extent that neither the users nor the developers have the slightest clue how the models recommend something (Gilpin et al., 2018). Conversely, linear regression is clear in terms of showing (directly and clearly) the impact of every contextual factor (time of week or place) on the predictions thus making it more trusted and accountable by the recommendation system. This is a crucial point as it can be used in other spheres like health or finance where users of the services need to get an idea why they are being referred to using a product.

Practical Implications

It is possible to say that the translations of our findings into practice can be described as vital at least as far as a mobile app recommendation is concerned. As the mobile apps have now become more central in the lives of people, the users are incessantly flooded with a massive amount of apps and their content and it can be confusing. Recommendation system also plays an important role of personalization; this is since it enhances the experience by the user by having his/her outfits in time and related. We have been able to show in this work that context-sensitive linear regression models can lead to effective enhancement of the personalization of the mobile app suggestions using information, such as time, geological location and history of mobile apps. That would obtain more applicable recommendations, user satisfaction and increased engagement rate.

Linear regression is cheaper in terms of computation and very easy to interpret thereby being more organizational friendly thereby enabling it to be feasible in resource limited systems like in the mobile platforms. Mobile devices are typically low power, memory, and battery power devices, and therefore such complicated operations like deep learning implementation are unrealistic. Linear regression, on the other hand, simply requires a much smaller amount of resources to train and deploy, but this also means that it is an okay choice to be used by mobile application developers who are interested in implementing recommendation system functionality, but do not want to apply too significant strain to its resources. This is particularly pertinent as far as mobile applications are concerned that are increasingly being required to be working in real-time and being highly customizable in the recommendations, and to be high performing and low chromatic.

Moreover, there is no difficulty in interpreting the model and, therefore, mobile app developers and users can be informed about the reasoning of the suggestions. This will be imperative in earning the trust of users as they will be in a favorable position to contribute more when making recommendations in that case the user will be in a better position to engage in the recommendations after having a feel of why some apps are being recommended. The visibility linear regression offers could be one way of alleviating the issue of users being worried about data privacy and algorithmic fairness especially in domains where it would be hazardous to the user to obscure the inner workings of the system, an example being in health care where users might be reluctant to trust the guidance of an algorithm whose inner working they are unable to verify.
Bounds and Pins

Nonetheless, despite the positive implications of the paper, there are some limitations, which are to be accounted in the subsequent study. In the first place, the contextual properties that have been used in the present study such as the time of the day, the place, and the history of app consumption are only limited to such a vast number of factors that can regulate the app choice of the user. Social media activity, weather conditions and device features are the other contextual variables that may be used to enrich the model further. As an example of this idea, one can consider the weather, which may force the consumer to use one type of apps/services (e.g., when it rains, the user might use some indoor entertainments apps/services). In line with this, the integration of social media behavior can be useful towards becoming attitudinated to further user-based preferences such as their preferences at the moment and consequently further provision of personalized inclusions (Zhao et al., 2019). It might also be interesting to look at it in future how more contextual variables can be used to build the model that will more reliably predict user behavior and allow having a more complete scene of the user behavior in general.

The other weakness of the research is the fixed-model. This extra input in the work of this research was the training the model using historical data and the model evaluation using a test set. However, the real customer usage is dynamic and the choice of customers might change over time and it might also be dependent on various number of factors such as lifestyle change, change in interest shift, social influences amongst others. In order to overcome this, the model can be made more dynamic to the changing user behavior by updating and enhanced in real time the model. To give an example, it can be a model that is retrained on a new data every now and again or bring about the online learning approaches in order to continuously update predictions given the incoming new data (Liang et al., 2017). It would also include ensuring that the model is applicable to the change in preferences of the users with respect to time.

Besides, the paper has been considering suggestions of mobile apps at large, however, some other type of apps may require treating them in a different manner. E.g., to take an extreme, the relationship between context-aware recommendations to take other things into account (e.g., time of day, location, etc) and, say, entertainment IOS (e.g., streaming) apps can make them of more value (at least than simply pure component recommendation), but a different set of features might be necessary in the case of, say, productivity apps (e.g., job-related tasks, work schedules, etc.). Subsequent research can look further into the context-specific use of the context-aware linear regression model, in which the model will be modified given that each type of app has the specific requirement.

Conclusion

Even though the publication outcome of this study was positive, they need to be aware of a number of limitations. The first constraint to mention is the scope of the contextual characteristics in the model. Time of day, location, the history of app usage is considered to be some of the key contextual variables, however there are still too many other contextual variables out there that could play a role in enhancing the functionality of the model. Other contextual factors that can be applied to the model and lead to the significantly improved personalization of the latter include the weather conditions, social media activity, user demographics, and device features among others. In an example, the fitness app can be utilized by the mobile users more often in case of good weather or the applications involving interaction with the social media can be utilized in the cases with holidays or events. Future efforts should explore how some of the ways in which these other features can be used can be incorporated in context-aware recommendation systems so as to enable it to become even more precise.

The second limitation is that the model is not a dynamic one. In this study, the case was that the model has been modeled on historical data and was tested on a set. However, the tastes of the consumers may alter as days change. In mitigation, as a future mitigation, one would see that there is the possibility of working on real-time updates of the model or dynamic retraining and this would allow the recommendation system to keep on changing according to the changing nature of the user. Some of the techniques might require online learning or gradually updating modeling in order to ensure that the system is sensitive to the variation of user preferences and be more accurate in its recommendations as time goes by (Liang et al., 2017).

Finally, yet importantly, this paper wrote about the mobile apps as the system to which the recommendation would be advised, whereas the context-aware linear regression model could be used to recommendation systems in the e-commerce, music and video streaming platforms among others. Researching the effectiveness of this model in other fields would enable to gain an idea of how universal this model could be and how many other areas could begin to take advantage of it.

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