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A Machine Learning Based Model for Forecasting Mobile App Ratings

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Abstract:

New software must be developed in accordance with preexisting implementation standards. When it comes to software sales and customer acceptability, marketplace app development has been a challenge. App stores provide information such as the total number of downloads, comments, and ratings for each app. It is possible to infer a pattern of app success from the challenges faced by these industries and the ways they analyze problems. The goal was to use this situation to build two inference engines using Random Forest and Support Vector Machine methods, investigate which features are most strongly correlated with app ratings, and compute and evaluate regression metrics using data from the Google Play Store. Applications for the Google Play Store, Rating Prediction, and Machine Learning are among the terms that are often used.

. INTRODUCTION

Machine learning methods are the only ones that can fix many of our issues. A lot of information on machine learning models and architectures is presented here. Many different fields have found applications for machine learning, and the field shows promise for further development in many areas. In the future, predictions supported by machine learning are likely to be increasingly prevalent. Meanwhile, it will enhance its unsupervised learning skills; there is a wealth of data available, and it would be redundant to list it all. In order to distinguish between highlights with high semantic significance and those with lower importance, it is anticipated that brain system topologies would get more unexpected. Furthermore, we may take use of deep learning's benefits and enhanced flexibility to finish more tasks.

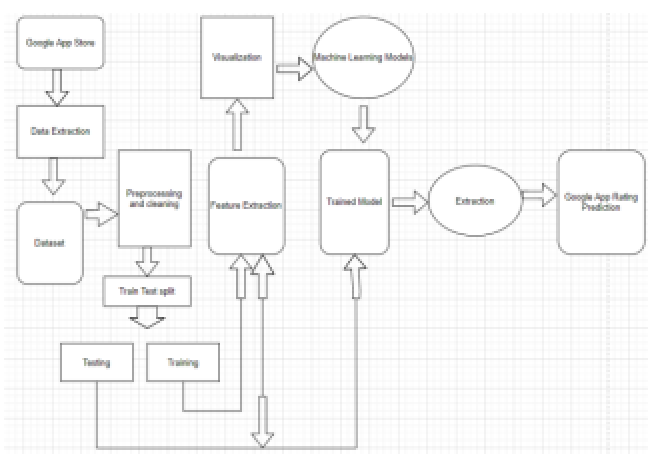

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Figure 1: Building Design Opinion mining is one approach

that combines computational linguistics, text analysis, and natural language processing to discover and identify subjective data. This branch of text mining involves working on algorithms to find and extract people's ideas and thoughts from text. Every day, people's choices are heavily influenced by their own ideas and values. The influence of smartphones on our daily lives, both at work and at home, is growing. Medical, fitness, beauty, monitoring, and sports-related apps are now available for smartphones and other mobile devices. [1] In March 2019, the Google Play store has around 2.6 million applications, as seen in Figure 1A. Many people will have the opportunity to provide input on these applications by rating and reviewing them. The present annual app download rate is 205.4 billion, according to Figure 1B, and it is expected to reach 352.9 billion by 2021. User reviews and numerical ratings are the most important aspects for other users [2]. Research shows that numerical ratings and reviews from users significantly affect the overall adoption of mobile apps [3]. Research shows that you may expect to pay 20-99% more for a product with 5 stars compared to a 4-star one. App users and developers alike may reap the benefits of shared reviews, ratings, and bug reporting [4]. Seeing the extremes of the polarity in user evaluations is essential to all of the solutions to these challenges [6, 7]. There are three ways to characterize polarity and subjectivity: positively, negatively, or neutrally. These methods have a flaw in that they ignore the problem of mathematically out of sync ratings in favor of user evaluations, which do not reflect actual app ratings. We found that there is often inconsistency between the numerical ratings and user reviews that show up on the product page.

LITERATURE REVIEW

2.1.1 An empirical research on user feedback in the Appstore [4]: App shops, such as Apple's App Store and Google Play, allow users to rank and review software that they have downloaded. Both app developers and end users have been drawn to these platforms, which have grown in popularity over the last few years. No one knows for sure how these changes will affect requirements engineering processes just yet. This research examined data from over one million reviews found in the Apple AppStore. Timely and relevant user input, along with the impact of feedback material on the community at large, needed to be observed. The majority of comments are left in the first few days after a release, but after that, they quickly level out. The majority of the time, reviewers look at things like user experiences, issues, and feature requests. Offensiveness spans the gamut in terms of practicality and originality. More good reviews lead to higher ratings, and the same holds true for the amount of downloads. Criticism and other negative aspects of a scenario tend to get more attention than the situation's context and the user's experience. Both software engineering and requirements engineering stand to benefit greatly from our research.
2.2.2 Sentiment analysis of social media comments made by Thai consumers [5]: Sentiment analysis, sometimes called opinion mining, has grown in significance in recent years because to the proliferation of Thai online customer evaluations on various platforms. This approach examines how individuals feel, think, and feel about things. It is possible to differentiate between positive and negative data using a range of keywords using a "bag of words" approach for opinion mining. Language assessments in Europe are ideal for these methods due of their geographical dispersion. When it comes to feedback from Thai consumers, these techniques that depend on a mishmash of words fail. The Thai text is just a string of characters without any breaks between them, thus these methods won't work. Up till now, there is a dearth of literature on the topic of Thai consumer sentiment analysis.
2.3 To find features in mobile applications, an algorithm is utilized that is based on user reviews: A lot of what happens in App Store Optimization depends on the store ranking and user feedback on Google Play. User reviews and the average rating are good indicators of an app's quality. Since the star rating is only a mathematical expression, we do not believe it to be a reliable indicator of customer happiness. We can't get a whole picture of people's feelings about the app from just one number on a scale from one to five. Consequently, we support an alternative approach to assessing app features via user input, which we think yields a more precise app rating. For both assessment and popular aspect mining, reviewers' remarks were combed through. We started by searching the Google Play Store for reviews across different product categories. Using sentiment analysis, we determined how much each evaluation agreed or disagreed. A polarity strength rating was assigned to each assessment. To arrive at the final score, we used the average of all reviewers' ratings. Following that, we contrasted the user-generated star ratings with the preexisting star ratings. It was discovered that the existing ratings were far higher than the total review scores. Using the app's category as a basis, machine learning was used to ascertain the most popular features. Based on user input, we developed app features and determined their popularity. Learn which features are most sought after by app users and why they score so high by consulting these rankings. In the meanwhile, app developers may figure out which features aren't getting much use and work to make them better.

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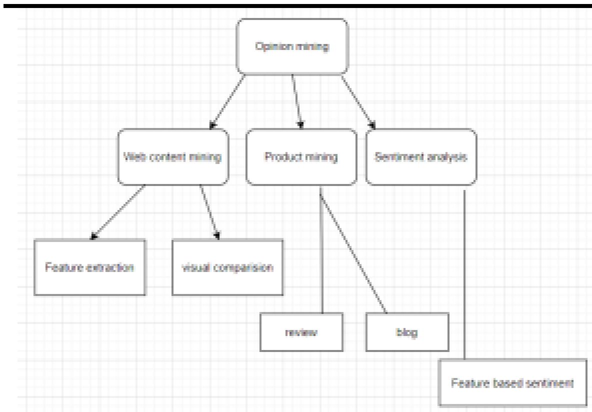
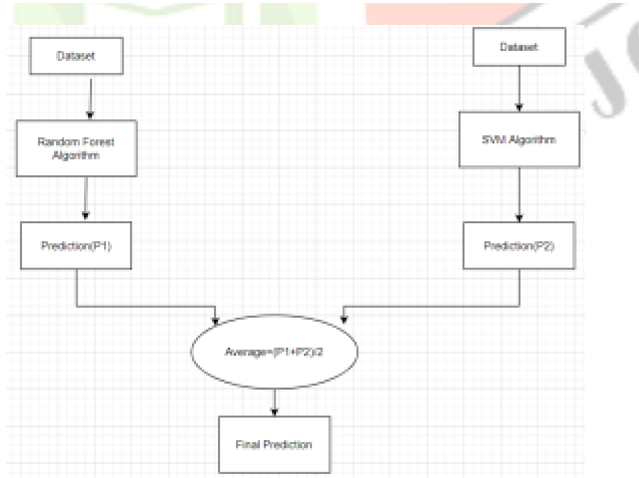
2.4 In order to find out whether top-rated free hybrid Android/iOS applications keep their ratings and reviews: The main goal of these hybrid development tools is to create an app that users perceive as being same across all platforms. Star ratings and user reviews used to be the go-to criteria for consumers when selecting which apps to download. We investigate whether developers may get cross-platform consistency in star ratings and user reviews by using a hybrid app development framework, considering the significance of these metrics. The 68 applications that were part of this analysis were "hybrid apps," meaning they could be found on both the Google Play and the Apple App Store. A total of 33 out of the 68 hybrid applications that were evaluated showed inconsistent star ratings. 2.5 Mining user sentiment and online shopping opinions (8 points): An increasing number of individuals are sharing their thoughts and feelings on current events and other topics of public interest on social media. When deciding, this data might be useful. Using social media, companies and individuals may find out what other people think about a subject before making a choice. [9] Global companies are realizing that e-commerce is about more than just making sales; it's also about improving operational efficiency to take on the other major players in the industry, according to a study. A user's perspective on a given issue may be shaped by their topic selection, the impact of their peers, and the details provided in their profile.



IMPLEMENTATION

This project utilizes the Random Forest and Support Vector Machine algorithms to improve upon the present app rating criteria in terms of accuracy and performance. Among the many machine learning algorithms available, Random Forest is by far the most popular choice for both classification and regression. Being a supported machine learning method, Support Vector Machine may be used to both classification and regression tasks.



It would be impossible to exaggerate the significance of mobile applications to modern customers, according to this analysis and forecast. Evidence suggests that the proliferation of mobile app ads has a major effect on state-of-the-art innovation. the eleventh However, with an ever-increasing demand for mobile applications comes an equal and opposite supply of mobile app designers, leading to nothing short of a meteoric surge in the worldwide mobile app industry's profitability. It is crucial for a designer to know that he is heading in the correct way while competing with global competitors. If the application designers want to keep this money and their existing place in the market, they may need to figure out how to keep their current position. There have been claims that the Google Play Store has more downloads than any other software distribution channel. The amount of downloads is more than twice that of the Apple App Store, but the income generated is much less. In order to narrow our analysis to the Play Store, we scraped data using this method. Thanks to advancements in cellular technology, mobile apps have become an integral part of our everyday lives. [12] It is challenging for us to stay up with the facts and understand everything about the applications, even when new ones are introduced every day. As of September 2011, the verifiable number of applications on Android1market exceeded one million. About 0.675,000 apps for Android are available in the Google Play Store at this very moment. Customers are given a broad choice of alternatives due to the enormous number of applications. We think that online application questionnaires have an effect on paid applications. Reading all of the reviews and comments on literature might be overwhelming for a prospective buyer. Since application developers can't rely on broad assessments to determine how to enhance the program's performance, perusing the many written remarks would be a great help. Artificial Intelligence (AI) in the Form of Machine Learning: AI allows automated systems to learn and evolve without human intervention. The goal of automated learning is to give computers the ability to learn from their own data and make judgments independently.

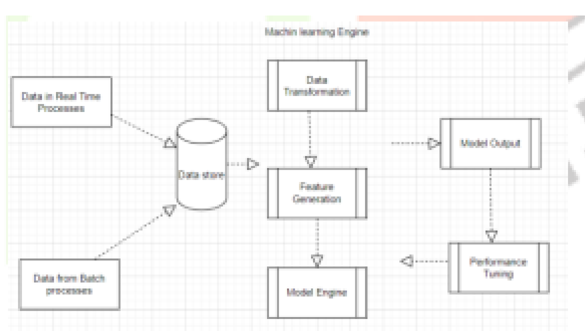


Fig.4: Machine Learning Architecture

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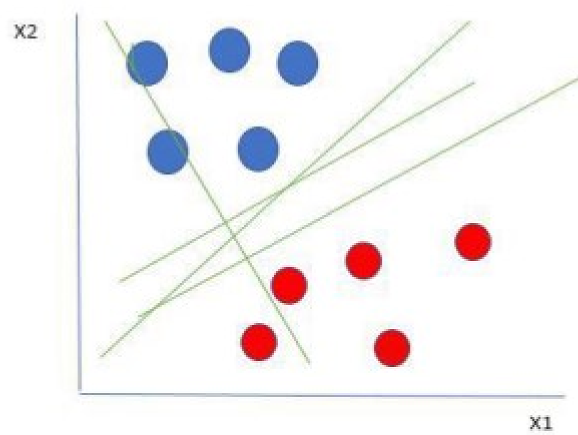
The term "supervised learning" is used to describe the process of teaching a computer to learn from a dataset or other information. In order to produce the correct output from the given input, sustained learning analyses the supplied data (models) [13]. During training, unsupervised learning does not rely on any real-time data or input. There can't be any instruction since there isn't a teacher. This time around, we'll just let the algorithm figure out what to do on its own. The main task of the computer, in the absence of any training or guidance, is to identify similarities and patterns in the incoming information. A semi-supervised machine learning system uses both supervised and unsupervised approaches due to the fact that it is only partly monitored. Traditional supervised machine learning techniques are used to a "labeled" dataset in order to train an algorithm.

METHODOLOGY

When it comes to classification and regression, supervised machine learning algorithms like Support Vector Machine (SVM) come in handy. We can also use it for regression situations, but classification is where it really shines. Finding a hyperplane in an N-dimensional space that distinguishes the data points is the goal of the SVM method. The hyperplane's size is proportional to the number of features. The hyperplane becomes a simple line when there are only two input characteristics. With three characteristics as input, the hyperplane flattens down into a two-dimensional plane. Once you go beyond three characteristics, it becomes tough to picture. Here we have a single dependent variable, represented by a blue or red circle, and two independent variables, x1 and x2.



Multiple lines divide our data points into red and blue circles, or perform classification, as seen in the picture above. In this case, our hyperplane is a line as we are only examining two input characteristics, x1 and x2. Consequently, how can we choose the optimal line, or hyperplane, to divide up our data?

The SVM Kernel component:

The support vector machine (SVM) kernel may be used to turn a not-divisible issue into a separable one by operating on a low-dimensional input space and transforming it into a higher-dimensional space. Its main use is to separation issues that are not linear. To put it simply, the kernel performs a number of complicated data transformations before determining how to partition the data according to the specified labels or outputs. Benefits of Support Vector Machineing: Useful in situations with several dimension • A subset of training points termed support vectors is used in the decision function, making it memory-efficient. • Decision functions may be customized using different kernel functions, and custom kernels are also an option. Many SVM Types: SVM comes in two varieties: Linear Support Vector Machines (SVM): When dealing with datasets that can be easily divided into two groups using just a single straight line, we say that the dataset is linearly separable, and when looking for a classifier, we call it a Linear SVM classifier. If a dataset cannot be categorized using a straight line, it is said to be non-linear data, and the classifier used is called a Non-Linear SVM classifier. Non-Linear SVM is used for non-linearly separated

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data. Decodable Woodland: It is possible that Random Forest is a supervised learning method used in machine learning. Every ML task involving classification or regression makes use of it. The idea behind it is ensemble learning, which involves combining several classifiers to improve a model's performance and tackle difficult problems. In light of the term, "Random Forest could be a classifier that contains a variety of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." The random forest uses the forecasts of all the decision trees to determine the final output, rather than relying on just one. Accuracy and the avoidance of overfitting are both improved by increasing the forest's tree density.

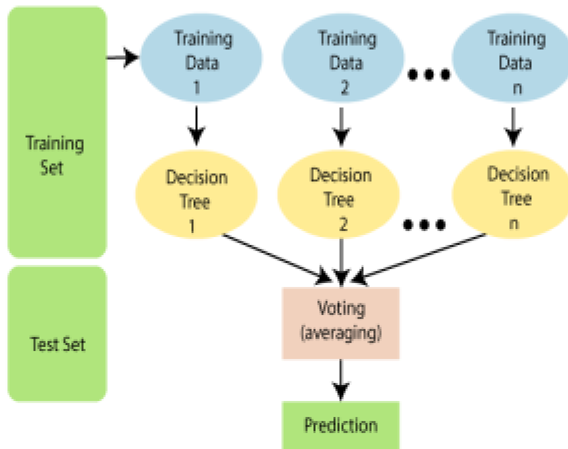

Fig.6: Random Forest model

EXPERIMENTAL RESULTS

To provide a trustworthy dataset, preprocessing is necessary to remove duplicates and null values. Using the train-test split function, the dataset is divided into two parts: one for training and one for testing. In order to build machine learning models, a training dataset is required. Vector regression and random forest regression are made possible by machine learning models in this technique. Predictions may be generated by training models on the test data set. Conclusions are drawn from the two machine learning methods to arrive at the final prediction.

MODULE 8: PREDICTION ON DATA FEATURES

[35]:
```
apps_in_test_set = apps_in_test_set.reshape(-1, 1)
avg = avg.reshape(-1, 1)
y_test = y_test.reshape(-1, 1)
average = np.concatenate([apps_in_test_set, avg,y_test], axis = 1)
average = pd.DataFrame(average, columns = ['App Name', 'Predicted Rating','Actual Rating'])
average
```

[35]:

	App Name	Predicted Rating	Actual Rating
0	Tattoo Photo Editor- Photo Tattoos, Tattoo Maker	4.0	4.1
1	Handsent 6 ThanksGiving Skin	3.6	4.3
2	Monkey Sounds	4.4	3.8
3	HealthSpective	3.9	1.7
4	Craft King	3.6	4.2
...	...	...	...
119995	Massage Guide: Learn Relaxing Massages	3.8	2.8
119996	Kamus Obat Terbaru (Lengkap & Praktis)	3.8	4.4
119997	Interprétation des rêves - Signification	4.3	4.2
119998	Loco Craft: 3 Creative Maps	4.0	4.1
119999	Save Status to Gallery And Was tickers Text	4.0	4.1

120000 rows × 3 columns

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Random Forest Regression:

Mean absolute error: 0.540935

Mean squared error: 0.518304

Root mean squared error: 0.719936

Support Vector Regression:

Mean absolute error: 0.551403

Mean squared error: 0.597192

Root mean squared error: 0.772781

Combined Model:

Mean absolute error: 0.520076

Mean squared error: 0.488790

Root mean squared error: 0.699135

. CONCLUSION

We ran our hypothesis through all of these algorithms and procedures, and we got to the conclusion that it is right. Predicting app ratings is therefore feasible, but it requires extensive preprocessing prior to beginning the classification and regression procedures. App development businesses stand to gain a great deal from the data acquired by applications in the Google Play Store. This data will be useful for developers as they strive to dominate the Android market. Size, Type, Price, Content Rating, and Genre are the five factors that determine an app's success or failure on the Google Play Store in terms of having over 100,000 downloads. 7. THE AIM FOR THE FUTURE From user reviews, we can only glean polarity and subjectiveness. Due to the massive growth of review-based data, predictions are especially crucial. Due of the qualitative nature of user evaluations and the mostly quantitative nature of ratings, this is a difficult but ultimately gratifying procedure. Furthermore, it's possible that better customer ratings attract an unfair number of new users, distorting Google's numerical rating system. Thus, the purpose of this research was to determine if ensemble classifiers could be used to forecast numerical ratings for applications in the Google Play store by analyzing user reviews. Multiple ensemble classifiers were evaluated using the Google App store evaluations. In the future, numerical ratings will be predicted using deep learning technology.

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