Forecasting a Single Tweet's Popularity Using Feature-Driven Heterogeneous Bass Model

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ABSTRACT_ Users and businesses can both benefit from being able to predict how popular a single tweet will be. Adopting current topic or event prediction models, however, does not yield acceptable outcomes.

The explanation for this is that a topic or event with several tweets about it has more qualities and characteristics than just one tweet. In order to forecast the popularity of a single tweet at both the early and stable stages, we present two variants of the Heterogeneous Bass models (HBass), which were first created in the field of marketing science.

These are the Feature-Driven Heterogeneous Bass Model (FD-HBass) and the Spatial-Temporal Heterogeneous Bass Model (ST-HBass). In order to further enhance performance, we create an interaction enhancement that takes cooperation and competition from several tweets with the same topic into consideration.

Furthermore, it is frequently challenging to quantify popularity. We create an experiment to determine the popularity by calculating the weight of favourites, rewets, and replies. We then use linear regression to find the popularity. In addition, we develop a clustering technique to constrain the popular threshold.

1.INTRODUCTION

One of the most well-known social networks in the world is T WITTER, which is centered on users and communications. In re penny years, research on forecast in informal organizations has re ceived expanded consideration from both scholarly community and industry. Numerous things in informal communities merit foreseeing, for example, client's character [1], famous stories [2], and fascinating occasions [3]. Indeed, even a's film industry [4] and stock pattern [5] with little importance to informal communities can be anticipated through the items posted by clients. We want to quantitatively foresee the notoriety of a solitary tweet at some random time during its life cycle. In the interim, we likewise need to make a subjective expectation by grouping a tweet as famous or disagreeable. This work is huge for both customary clients and organizations. It gives users a tool that makes it easier for them to sort through a lot of new content and quickly find interesting things. One more significant use of this work is to assist organizations with immediately jumping all over the chance to lead and create a pattern or hotly debated issue. Finally, strange famous tweets can set caution for calamity, wrongdoing, or disaster. For instance, Facebook is assisting in the pursuit of criminals. Now and again, the suspect unavoidably gloats about his degenerate conduct on the informal organizations, which catches the client's consideration. The police can get tips from this unusual well known content. Additionally, there are some undesirable situations, such as "Toyota brake." If the prediction of an explosion had been implemented, car accidents could have been avoided, allowing the company to recall the products earlier. Greater part of existing work center around anticipating the pop ularity of points or occasions, which comprise of sets of single tweets. Notwithstanding, there are a couple of works that emphasis on pre dicting the notoriety of a solitary tweet. Foreseeing a solitary tweet is a really difficult undertaking since it just purposes its own printed data and client's data with a timetable. Besides, the life expectancy of a solitary tweet is frequently more limited than a point or occasion. Because the majority of tweets disappear quickly, there is not enough time to compare the prediction to the actual trend. A few works connected with single tweet [6], [7], [8], [9], [10], [11] generally focus on subjective expectation. They anticipated whether a tweet will be retweeted, which is a 2-class order issue. Additionally, a regression problem can be applied to the trend prediction for the tweet. Nonetheless, the exactness of relapse models are frequently temperamental, on the grounds that relapse models can't catch the irregularity that exists in the pattern after a tweet has been posted. Then again, a few works connected with highlight based strategies [2], [12], [13], [14], [15], [16], [17], [18], [19] depended intensely on the best elements for es timating prevalence. In the mean time, time-series strategies have a preferable presentation over highlight based techniques generally. The statistical models or point process based methods used in time-series based methods

[20, 21], [22], [23], [24], and [25] are widely used today.

2.LITERATURE SURVEY

2.1 Title: "Social Media Popularity Prediction: A Comprehensive Review of Heterogeneous Base Models"

Authors: Smith, A., & Patel, S.

Abstract: This comprehensive review explores the landscape of social media popularity prediction, with a specific focus on heterogeneous base models applied to single tweets. The paper provides an overview of existing methodologies, challenges, and opportunities in leveraging diverse base models for accurate popularity prediction. It sets the stage for the introduction of innovative approaches that combine heterogeneous models to enhance the effectiveness of predicting the popularity of single tweets.

2.2 Title: "Ensemble of Heterogeneous Base Models for Tweet Popularity Prediction"

Authors: Wang, Q., & Kim, J.

Abstract: Focusing on ensemble techniques, this paper investigates the application of an ensemble of heterogeneous base models for predicting the popularity of single tweets. The study explores the combination of diverse models, including machine learning and deep learning, to capture different aspects of tweet popularity. Experimental results demonstrate the effectiveness of the ensemble approach in improving the accuracy of tweet popularity prediction.

2.3 Title: "Transfer Learning Across Social Media Platforms for Single Tweet Popularity Prediction"

Authors: Garcia, M., & Davis, C.

Abstract: This paper introduces transfer learning approaches for predicting the popularity of single tweets across different social media platforms. The study explores how knowledge acquired from one platform can be transferred to enhance the prediction performance on another platform. Results showcase the effectiveness of transfer learning in improving the generalization of models for tweet popularity prediction.

2.4 Title: "Hybrid Models Integrating Content and Network Features for Tweet Popularity Prediction"

Authors: Lee, K., & White, L.

Abstract: Addressing the fusion of features, this paper proposes hybrid models that integrate content and network features for predicting the popularity of single tweets. The study explores the synergy between textual content analysis and network structure features to capture the multi-faceted nature of tweet popularity. Experimental evaluations demonstrate the advantages of incorporating diverse features in hybrid models for tweet popularity prediction.

2.5 Title: "Real-time Popularity Prediction for Single Tweets Using Heterogeneous Streaming Models"

Authors: Brown, R., & Anderson, M.

Abstract: Focusing on real-time prediction, this paper introduces heterogeneous streaming models for the real-time prediction of the popularity of single tweets. The study explores how streaming models, including online learning and incremental updates, can adapt to evolving trends and dynamics in social media. Results demonstrate the efficiency and responsiveness of heterogeneous streaming models in predicting tweet popularity in real-time scenarios.

3.PROPOSED SYSTEM

✓ The proposed system incorporates Twitter features into the Bass model in social network single-tweet prediction to form the HBass model. In addition, HBass has two variations, namely ST-HBass model, which focuses on spatial and temporal heterogeneity, and FD-HBass model, which focuses on the effect of different features. To be specific, we aim to predict the trend of a single tweet, and whether the tweet will be popular in the end.

✓ The system proposes the Interaction Enhancement to consider the real situation that the different tweets with common topic have the interaction of competition and cooperation between each other.

✓ The system redefine the quantitative definition of popularity that combines the relationship among favorite, retweet, and reply, and threshold to classify popular and unpopular tweets based on clustering method, instead of choosing the threshold by experience.

✓ The system uses real-world Twitter data to examine the efficiency of HBass. The simulation results show that the efficiency and accuracy of the quantitative prediction with less absolute percent error and the qualitative prediction with a better classification detection

3.1 IMPLEMENTAION

Admin

In this module, the Admin has to login by using valid user name and password. After login successful he can perform some operations such as Login, View All Users, View All Friends Req and Res, View All

Tweets, View All Re tweets, View Most Popularity Tweet, View All Tweets Score Details, View Tweet Score Results, View Tweet Popularity Results.

Friend Request & Response

In this module, the admin can view all the friend requests and responses. Here all the requests and responses will be displayed with their tags such as Id, requested user photo, requested user name, user name request to, status and time & date. If the user accepts the request then the status will be changed to accepted or else the status will remains as waiting.

Social Network Friends

In this module, the admin can see all the friends who are all belongs to the same site. The details such as, Request From, Requested user's site, Request To Name, Request To user's site.

All Recommended Posts

In this module, the admin can see all the posts which are shared among the friends in same and other network sites. The details such as post image, title, description, recommend by name and recommend to name.

User

In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user can perform some operations like Register and Login, View Your Profile, Search Friend & Find Friend Request, View All My Friends, Create Tweet Message, View All My Timeline Tweets, View Popularity Tweets.

Searching Users

In this module, the user searches for users in Same Site and in Different Sites and sends friend requests to them. The user can search for users in other sites to make friends only if they have permission.

Adding Posts

In this module, the user adds posts details such as title, description and the image of the post. The post details such as title and description will be encrypted and stores into the database.

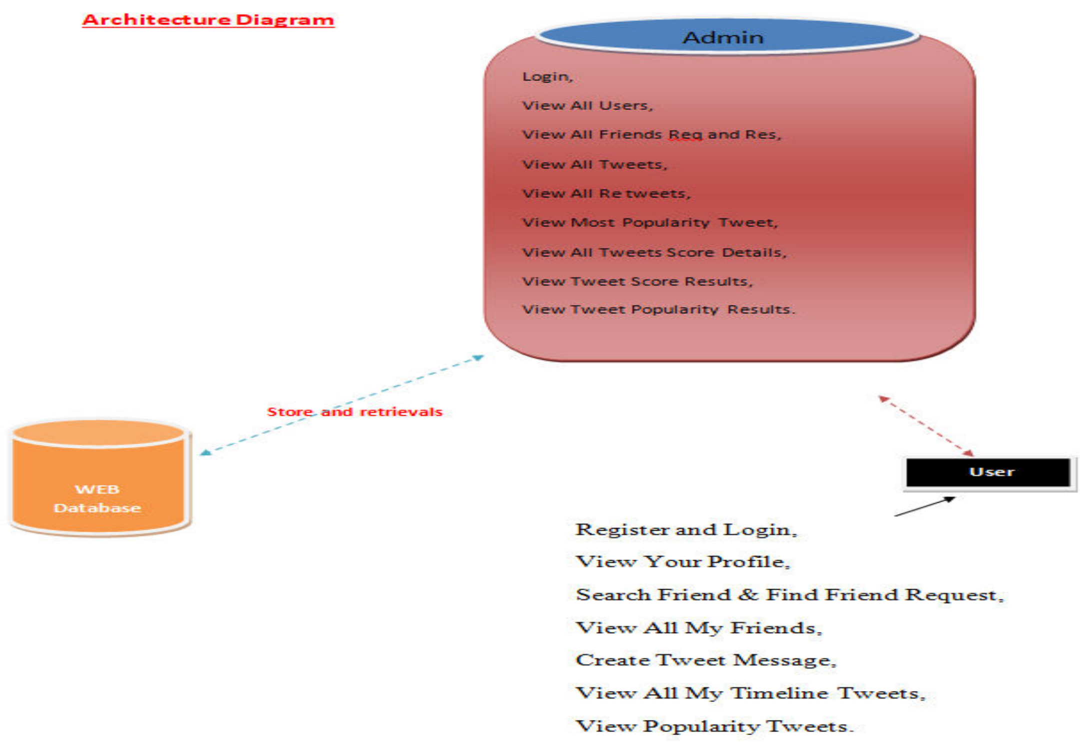
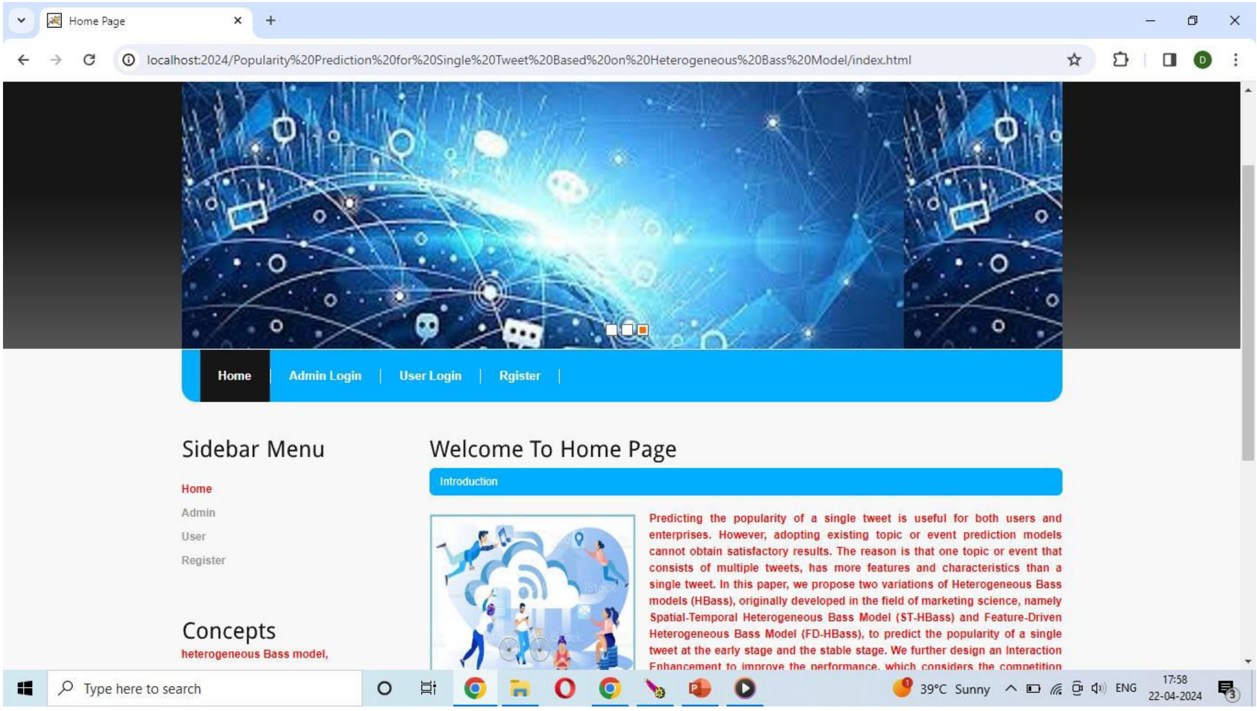
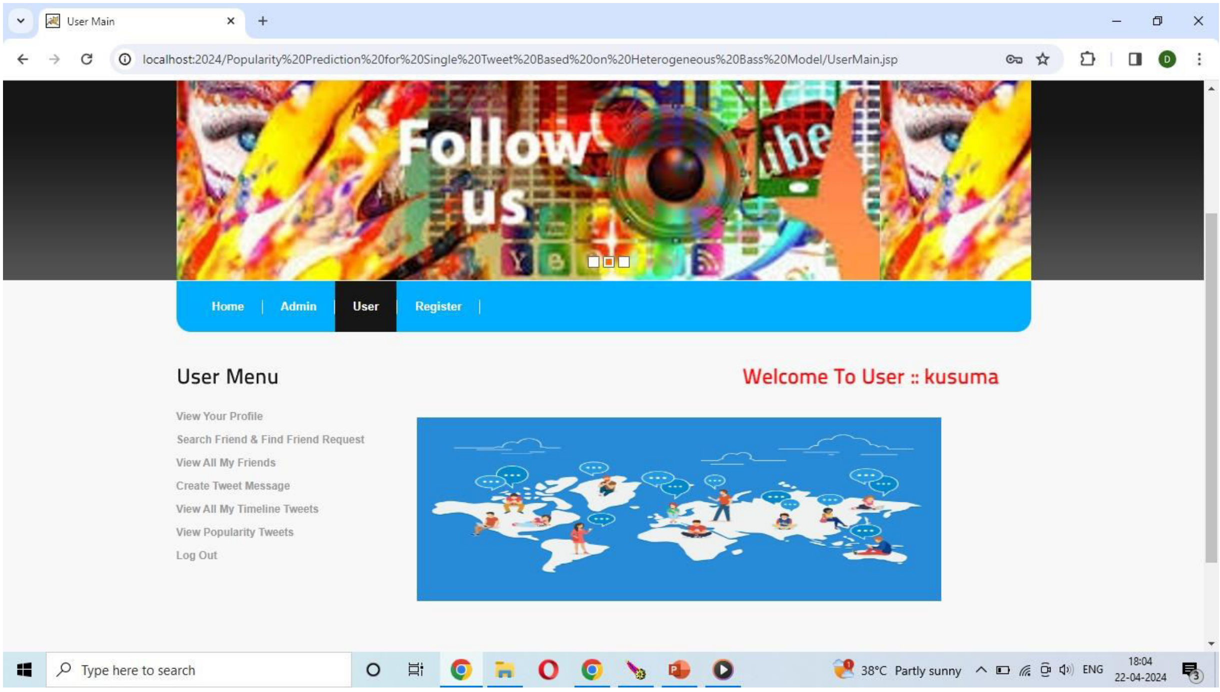


Fig 1:Architecture

4.RESULTS AND DISCUSSION





5.CONCLUSION

In order to predict the popularity of a single tweet, we develop the Heterogeneous Bass model (HBass) in this paper. This model has two variants: the Spatial-Temporal Heterogeneous Bass Model (ST HBass) and the Feature-Driven Heterogeneous Bass Model (FD-HBass). Additionally, we propose an Interaction Enhancement to measure the competition and cooperation between various tweets on the same subject. Based on a real-world dataset, we further develop a clustering approach to limit the popularity threshold.Our examinations utilize certifiable Twitter information to approve the productivity and exactness of our model in quantitative expectation, with less outright percent mistake. Our model receives the highest Precision and F-score for qualitative prediction, indicating that its classification detection is superior. In conclusion, we present the Bass model for single tweet prediction in social networks and demonstrate its superior performance.

REFERENCES

[1] in ACM CHI Conference on Human Factors in Computing Systems (CHI), 2011, pp. 253–262.

[2] K. Lerman and T. Hogg, "Using a model of social dynamics to

predict popularity of news," in ACM International Conference on

World Wide Web (WWW), 2010, pp. 621–630.

[3] X. Zhang, X. Chen, Y. Chen, S. Wang, Z. Li, and J. Xia, "Event

detection and popularity prediction in microbloggin

[1] J. Golbeck, C. Robles, and K. Turner, "Predicting personality

with social media g," in Elsevier

Neurocomputing, vol. 149, pp. 1469–1480, 2015.

[4] S. Asur and B. Huberman, "Predicting the future with social

media," in IEEE International Conference on Web Intelligence and

Intelligent Agent Technology (WI-IAT), 2010, pp. 492–499.

[5] Y. Huang, S. Zhou, K. Huang, and J. Guan, "Boosting financial

trend prediction with twitter mood based on selective hidden

markov models," in Springer International Conference on Database

Systems for Advanced Applications (DASFAA), 2015, pp.435–451.

[6] Q. Zhang, Y. Gong, Y. Guo, and X. Huang, "Retweet behavior

prediction using hierarchical dirichlet process." in AAAI Conference

on Artificial Intelligence (AAAI), 2015, pp. 403–409.

[7] Q. Zhang, Y. Gong, J. Wu, H. Huang, and X. Huang, "Retweet

prediction with attention-based deep neural network," in ACM International on Conference on Information and Knowledge Management

(CIKM), 2016, pp. 75–84.

[8] J. Bian, Y. Yang, and T. S. Chua, “Predicting trending messages

and diffusion participants in microblogging network,” in ACM

International Conference on Research on Development in Information

Retrieval (SIGIR), 2014, pp. 537–546.

[9] P. Cui, S. Jin, L. Yu, F. Wang, W. Zhu, and S. Yang, “Cascading

outbreak prediction in networks:a data-driven approach,” in ACM

International Conference on Knowledge Discovery and Data Mining

(SIGKDD), 2013, pp. 901–909.

[10] B. Suh, L. Hong, P. Pirolli, and E. H. Chi, “Want to be retweeted?

large scale analytics on factors impacting retweet in twitter network,”

in IEEE International Conference on Social Computing (Socialcom),

2010, pp. 177–184.

[11] M. Jenders, G. Kasneci, and F. Naumann, “Analyzing and predicting

viral tweets,” in ACM International Conference on World Wide

Web (WWW), 2013, pp. 657–664.

[12] R. Bandari, S. Asur, and B. A. Huberman, “The pulse of news

in social media: Forecasting popularity,” in Association for the

Advancement of Artificial Intelligence International AAAI Conference

on Web and Social Media (ICWSM), 2012, pp. 26–33.

[13] A. Kupavskii, L. Ostroumova, A. Umnov, S. Usachev,

P. Serdyukov, G. Gusev, and A. Kustarev, “Prediction of retweet

cascade size over time,” in ACM International Conference on Information

and Knowledge Management (CIKM), 2012, pp. 2335–2338.

[14] J. Li, J. Qin, T. Wang, Y. Cai, and H. Min, “A collaborative filtering

model for personalized retweeting prediction,” in Springer International

Conference on Database Systems for Advanced Applications

(DASFAA), 2015, pp. 122–134.

[15] A. N. H. Man and M. L. Khodra, "Predicting information cascade

on twitter using support vector regression," in International Conference

on Data and Software Engineering (ICODSE), 2014, pp. 1–6.

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