INTERNATIONAL RESEARCH JOURNAL IN ADVANCED ENGINEERING AND TECHNOLOGY (IRJAET) E - ISSN: 2454-4752 P - ISSN : 2454-4744
VOL 3 ISSUE 2 (2017) PAGES 2141 - 2146
RECEIVED : 28-03-17. PUBLISHED: 22-04-17.

April 22, 2017

ENHANCED ARCHITECTURE DESIGN FOR THREE TIER ARCHITECTURE USING MICO BLOGGING

[1]Suganya L, [2]Arun J,

[1]PG Scholar, Department of Information Technology, Maharaja Engineering College, Avinashi.

[2]Assistant Professor, Department of Information Technology, Maharaja Engineering College, Avinashi.

ABSTRACT

Initially and as usual the user can sign up in the social network. While signing up in the social network, the user need provide all the personal and educational information for the user profile. After creating the social network account, the users may search for new friends and they may chat with the friends, the advanced micro blogging information considers only the public data and public chats. A micro data array will be created for the user. The micro array consists of the entire user's most important information only. Automatically the micro array details will send and search through the E-Commerce application. Here the artificial neural network will works as a third party agent and the agent will retrieves all the recommended products, as micro blogging information. A panel will be design in the social network for displaying the recommended product details. All the displayed products will be more relevant to the user's profile. The generated micro blogging information contains an alphanumerical characters like (A34#ULKNELRL*!). The micro blogging information has been generated using Artificial Neural Network (ANN) and Advanced text categorization. This micro blogging information will reduce the time of data retrieval from social network to ecommerce application. The same architecture has been enhanced for new channels, here three news channels taken for the consideration. And this is the third tier among the two tiers. As mentioned above the same micro blogging information generated for news channels also. Here the only the relevant news for the user will be displayed, so that they can quickly go through the news updates. In added with search options also provided for other news information like, user can search the news area wise, city wise and state wise. All the information will be shown in a single window.

1. RELATED WORKS

The store radically changes based on customer interests, showing programming titles to a software engineer and baby toys to a new mother. The click-through and conversion rates two important measures of Web-based and email advertising effectiveness vastly exceed those of untargeted content such as banner advertisements and top-seller lists. E-commerce recommendation algorithms often operate in a challenging environment [1]. With the increasing popularity of online e-commerce services, more and more people buy products online. As such, a large volume of online reviews have been constantly generated by users. Since review data contain rich information about users' feedback and opinions towards products they purchased, mining online reviews has attracted much interest (Hu and Liu 2004) which could be subsequently used for product sales prediction (Liu et al. 2007). Nevertheless, we argue that online reviews sometimes also contain implicit user demographic information which could be leveraged for product recommendation [2].

Distributed representations of words in a vector space help learning algorithms to achieve better performance in natural language processing tasks by grouping similar words. One of the earliest use of word representations dates back to 1986 due to Rumelhart, Hinton, and Williams. This idea has since been applied to statistical language modelling with considerable success. The follow up work includes applications to automatic speech recognition and machine translation, and a wide range of NLP tasks [3]. While this growth has provided users with a myriad of unique and useful apps, the sheer number of choices also makes it more difficult for users to find apps that are relevant to their interests. Historically, recommender systems have been introduced to alleviate this type of information overload by helping users find relevant items (i.e., apps) [4].

2. METHODOLOGY

Micro blogs data, e.g., fb, reviews, news comments, and social media comments, has gained considerable attention in recent years due to its popularity and rich contents. Nowadays, micro blogs applications span a wide spectrum of interests, including detecting and analyzing events, user analysis for geo-targeted ads and political elections, and critical applications like discovering health issues and rescue services. Consequently, major research efforts are spent to analyze and manage micro blogs data to support different applications. In this method, we give a 1.5 hours overview about micro blogs data analysis, management, and systems. The method gives a comprehensive review for research efforts that are trying to analyze micro blogs contents to build on them new functionality and use cases. In addition, the tutorial reviews existing research that proposes core data management components to support micro blogs queries at scale. Finally, the method reviews system-level issues and on-going work on supporting micro blogs data through the rising big data systems. Through its different parts, the tutorial highlights the challenges and opportunities in micro blogs data research. Micro blogs data, e.g., tweets, reviews, news comments, and social media comments, has become very popular in recent years. Every day, over billion users post more than four billions micro blogs on Facebook and Twitter. Such tremendous amounts of user-generated data have rich contents, e.g., news, updates on on-going events, reviews, and discussions in politics, products, and many others. The richness of micro blogs data has motivated researchers and developers worldwide to take advantage of micro blogs to support a wide variety of practical applications, including social media analysis, discovering health-related issues, real-time news delivery, rescue services, and geo-targeted advertising. The distinguished nature of micro blogs data, that includes large data sizes and high velocity, has motivated researchers to develop new techniques for data management and analysis on micro blogs.

3. ARTIFICIAL NEURAL NETWORK

In artificial intelligence or machine learning, a training set consists of an input vector and an answer vector, and is used together with a supervised learning method to train a knowledge database (e.g. a neural net or a naive Bayes classifier) used by an AI machine. Validation sets can be used for regularization by early stopping: stop training when the error on the validation set increases, as this is a sign of over fitting to the training set. This simple procedure is complicated in practice by the fact that the validation error may fluctuate during training, producing multiple local minima. This complication has led to the creation of many ad-hoc rules for deciding when over fitting has truly begun. In statistical modelling, a training set is used to fit a model that can be used to predict a "response value" from one or more "predictors." The fitting can include both variable selection and parameter estimation. Statistical models used for prediction are often called regression models, of which linear regression and logistic regression are two examples. In these fields, a major emphasis is placed on avoiding over fitting, so as to achieve the best possible performance on an independent **test set** that follows the same probability distribution as the training set.

These can be defined as:

- Training set: A set of examples used for learning that is to fit the parameters [i.e., weights] of the classifier.
- Validation set: A set of examples used to tune the hyper parameters [i.e., architecture, not weights] of a classifier, for example to choose the number of hidden units in a neural network.
- Test set: A set of examples used only to assess the performance [generalization] of a fully-specified classifier.

4. ALGORITHM

Initialization:

Let S1: Server 1 (Social Network), S2: Server 2 (Ecommerce Application) S3: Server 3 (News Channels)

Profile information – P1, P2, P3......Pn

Product and Information : Pr1(a,b,cd), Pr2(a,b,c,d),Pr3(a,b,c,d).....PrN(a,b,c,d)

News Information N1,N2,N3

Users X, X1, X2, X3.....Xn

Let Communication for ANN is Artificial Neural Network. And Micro blog as MB.

Working Model

Step 1: Start Process

Step 2: S3 displays N1, N2 and N3;

Step 3: S2 shows and updates P1, P2, P3......Pn;

Step 4: S1 having P1, P2, P3......Pn;

Step 5: while loading local host. Add(rd[0].ToString().ToUpper());

Step 6: S1 will be merged with S2 with the condition of access Pr1(a,b,cd), Pr2(a,b,c,d), Pr3(a,b,c,d) .....PrN(a,b,c,d)

Step 7: After loading rd[0], next initialization is rd[1] connection S1 to S3

INTERNATIONAL RESEARCH JOURNAL IN ADVANCED ENGINEERING AND TECHNOLOGY (IRJAET) E - ISSN: 2454-4752 P - ISSN : 2454-4744
VOL 3 ISSUE 2 (2017) PAGES 2141 - 2146
RECEIVED : 28-03-17. PUBLISHED: 22-04-17.

April 22, 2017

Step 8: Now via Local host S1→ S2 →S3; creates an artificial neural network through local host Add(rd[0][1][2]);

Step 9: MD trigger out using P1, P2, P3......Pn for the given information as the profile information; Eg: (AXRti67%*^*Fg)

Step 10: MB pass through P1, P2, P3......Pn merge with Pr1(a,b,cd), Pr2(a,b,c,d),Pr3(a,b,c,d).....PrN(a,b,c,d) for X, X1, X2, X3.....Xn.

Step 11: Lopped formation will done for the above process

Step 12: User X, X1, X2, X3.....Xn = Session [user] for Step 10 and Step 11.

Step 13: Merge recommended product by P1(Pr1(a,b,cd)),P2(Pr2(a,b,c,d)),P3(Pr3(a,b,c,d)) up to all recommendations.

Step 14 : Repeat process for S1 to S3 and User X, X1, X2, X3.....Xn = Session [user] N1,N2,N3;

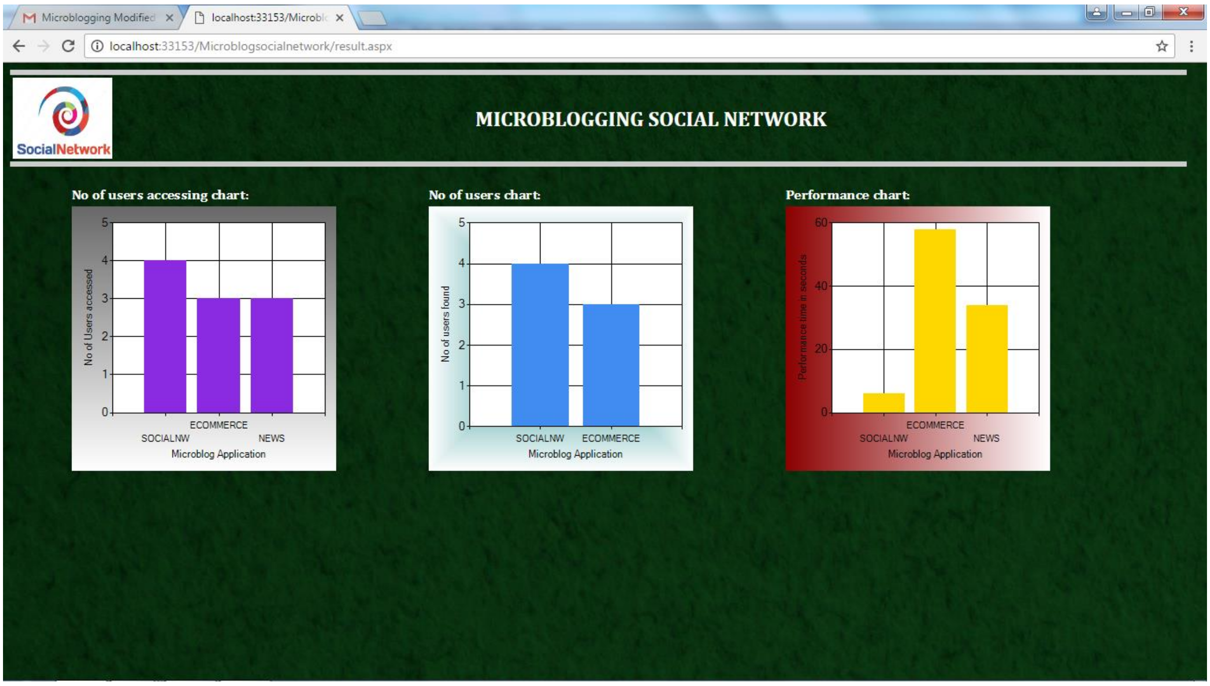
Step 15 : Display P1(Pr1(a,b,cd)),P2(Pr2(a,b,c,d)),P3(Pr3(a,b,c,d)) and X, X1, X2, X3.....Xn = Session [user] N1,N2,N3 in S1 as the head node

Step 15: Repeat Process for X, X1, X2, X3.....Xn

Step 16 : Now S1 = S2+S3;

Step 17: Stop the process.

5. RESULT AND DISCUSSION



The above shows are various diagrams from the architecture and various results obtained during the time of execution.

Result 1:

It shows the times of access of three networks. Mostly in this result the social network shows the major impact. Most of the users will interact with the social networks to obtain more information from other two networks.

Result 2:

It shows available users in the social network and ecommerce application. This shows the impact of the available users in social network and ecommerce application.

Result 3:

It shows the time of execution, in seconds. The processing time will be calculates according to the CPU and Ram process. The output shown in seconds, and social network takes less time in execution than ecommerce and news networks.

CONCLUSION

Thus this project has been executed successfully and the output has been verified. All obtained outputs are according to committed in abstract. Initially more problems occurred during the architecture creation. As mentioned above here three tier architecture has been implemented successfully. All three networks are working perfectly in the architecture. And these networks will works on independent process too. These features will make this project more successful and efficient. The micro blog creates an internal data transfer for efficient data retrieval from the three networks. Displaying name and news will be change according to the user profile information. All the displaying news and products are more relevant to the users. As mentioned in the abstract, now the 89 % of the internet users may use the 60% of the ecommerce application. This makes more sales in the ecommerce application. And also according the news concept, 89 % of the social network users will view all the news. This makes all the network users are raised to 89 % among the internet users. More information can be viewed in a single screen in less mobile data. These features makes this project more successful.

REFERENCE

[1] Amazon.com recommendations: Item-to-item collaborative filtering. G. Linden, B. Smith, and J. York, “Amazon.com recommendations: Item-to-item collaborative filtering,” IEEE Internet Comput.,vol. 7, no. 1, pp. 76–80, Jan./Feb. 2003.

[2] Improving Latent Factor Models via Personalized Feature Projection for One Class Recommendation. Y. Seroussi, F. Bohnert, and I. Zukerman, “Personalized rating prediction for new users using latent factor models,” in Proc. 22nd ACM Conf. Hypertext Hypermedia, 2011, pp. 47–56

[3] Distributed representations of words and phrases and their compositionality. T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality," in Proc. Adv. Neural Inf. Process. Syst., 2013, pp. 3111–3119.

[4] Addressing Cold-Start in App Recommendation: Latent User Models Constructed from Twitter Followers. J. Lin, K. Sugiyama, M. Kan, and T. Chua, "Addressing cold-start in app recommendation: Latent user models constructed from twitter followers," in Proc. 36th Annu. Int. ACM SIGIR Conf. Res.Develop. Inf. Retrieval, 2013, pp. 283–292

[5] L. Breiman, J. Friedman, R. Olshen, and C. Stone,Classification and Regression Trees. Monterey, CA, USA: Wadsworth & Brooks, 1984.

[6] L. Breiman, "Random forests,"Mach. Learn., vol. 45, no. 1, pp. 5–32, Oct. 2001.

[7] K. Zhou, S. Yang, and H. Zha, "Functional matrix factorizations for Cold-start recommendation," in Proc. 34th Int. ACM SIGIR. Conf. Res. Develop. Inf. Retrieval, 2011, pp. 315–324.

[8] T. Chen, H. Li, Q. Yang, and Y. Yu, "General functional matrix fac-torization using gradient boosting," inProc. Int. Conf. Mach. Learn., 2013, pp. 436–444.

[9] T. Chen, W. Zhang, Q. Lu, K. Chen, Z. Zheng, and Y. Yu, "SVDFeature: A toolkit for feature-based collaborative filtering," J. Mach. Learn. Res., vol. 13, pp. 3619–3622, 2012.

[19] S. Rendle, "Factorization machines with libFM," ACM Trans. Intell. Syst. Technol., vol. 3, no. 3, May 2012.

[10] S. Rendle, "Social network and Click-through prediction with fac-torization machines," inProc. KDDCup Workshop, 2012.

[11] B. Xiao and I. Benbasat, "E-commerce product recommendation. agents: Use, characteristics, and impact," MIS Quart., vol. 31, pp. 137–209, 2007.

[12] L. Hong, A. S. Doumith, and B. D. Davison, "Co-factorization. machines: Modeling user interests and predicting individual deci-sions in twitter," inProc. 6th ACM Int. Conf. Web Search Data Min-ing, 2013 pp. 557–566.

[13] H. Ma, T. C. Zhou, M. R. Lyu, and I. King, "Improving recom-mender systems by incorporating social contextual information," ACM Trans. Inf. Syst., vol. 29, no. 2, 2011.

[24] Y. Zhang, G. Lai, M. Zhang, Y. Zhang, Y. Liu, and S. Ma, "Explicit. factor models for explainable recommendation based on Phrase-level sentiment analysis," in Proc. 37th Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 2014, pp. 83–92.

[25] M. Zhang, J. Tang, X. Zhang, and X. Xue, "Addressing cold start in, recommender systems: A Semi-supervised Co-training algo-rithm," in Proc. 37th Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 2014, pp. 73–82