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A Multi Layer Perceptron Classifier for Content-based Recommender System

K.R.Sekar, Makkena Sai Kumar, Mogadampalli Jayanth, N.Sivaramakrishan, G.Sathiamoorthy

Abstract: ***For the past one and half year decades, recommended system is playing a vital role and providing the outline and peripheral information to the mobile customers. The objective of the work is to recommend good quality mobiles for the requirement of the customers with all required amenities. Multilayer perceptron neural network classifier is the methodology deployed and employed for the recommendations. The result outcome will always be very precise and has got a high precision of accuracy because of the above said methodology. Reliability and the accuracy are the prominent factors to the non-functional activity and the customers to buy the trusted mobiles from the shopping cart. Ordinal values will taken into account for the evaluation of ten top mobiles. The real characterization can be gauged through the recommendation given by the customers in the respective portals. Customers' sentiments and the values of their comments are the features used to gauge the commodity values. Overall in the research work recommendations are classified into supervised leanings. Non minor can easily get the most favorite mobile with existing money affordable by them to buy the mobile commodity.***

Index Terms*: *Multilayer perceptron, Reliability, Accuracy, Recommender System and Sentiment analysis

I. INTRODUCTION

With the escalation of technology, more and more mobile phones are introduced to the market through popular distribution channels. So there is uncertainty in the customers regarding the selection of mobile phones. E-commerce carts such as Flipkart, Amazon where users can search, buy, and sell different mobile phones with a few clicks. Use of Sentimental analysis in micro blogging sites to know user viewpoint SoftMax based algorithm is used to identify the user nature efficiently. Complete understanding on user interested over the product[1].These platforms also allow users to share their opinion about the products in the text reviews, ratings where they can express their satisfaction on specific mobile phone or request a new feature. Recent empirical studies showed that e-commerce reviews include feedback/opinion such as user requirements, bug reports, and documentation of user experiences with mobile phones. Product reviews are not only useful to the buyers for their purchasing decision but also extremely helpful for mobile companies and competitors. In understanding the emotions behind the user comments and to extract the reason behind it Polaris a system for analyzing and predicting users sentimental trajectories. Through trajectory and sentimental analysis users can obtain insight of the issue at a glance through other user comments [2]. The user opinions can be better grasped with analysis on user's ratings which helps the company and customers to get a good understanding of required features for opting a smartphone from wide range of variants in today mobile industry. To analyze the drawbacks in the software quality through user reviews QinU prediction, polarity classification and QinU scoring is the steps used in measuring the software reviews. QinUF automates software QinU measurement , therefore users could compare and acquire software [3]. To increase the quality of the online products by reviewing the customer suggestions Jont sentiment-topic model is used to extract the topics and associated sentiments in review texts. It helps business analytics operations by focusing on more relevant aspects that ultimately drive sales [4].Analyzing the viewpoints and sentiments of the users in the Twitter Cuckoo search method is used to find the optimum cluster heads from the sentimental contents of Twitter dataset. To know the latest trending topic on the internet by analyzing the user comments [5]. The information in the ratings and reviews represents "voice of the users" and is helpful to drive the development efforts and improve forthcoming release playing a key role in the revenue generation for the developers. So, in this paper we have applied a technique to get analysis and trend of various smart phones

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K.R.Sekar , School of Computing, SASTRA Deemed University, India
Makkena Sai Kumar, School of Computing, SASTRA Deemed University, India
Mogadampalli Jayanth, School of Computing, SASTRA Deemed University, India
N.Sivaramakrishan, School of Computing, SASTRA Deemed University, India
G.Sathiamoorthy, School of Humanities and Science, SASTRA Deemed University, India

II. RELATED WORKS

To increase the quality of the online products by reviewing the customer suggestions Joint sentiment-topic model is used to extract the topics and associated sentiments in review texts. It helps business analytics operations by focusing on more relevant aspects that ultimately drive sales [4].Analyzing the viewpoints and sentiments of the users in the Twitter Cuckoo search method is used to find the optimum cluster heads from the sentimental contents of Twitter dataset. To know the latest trending topic on the internet by analyzing the user comments [5].

In reducing the error rate of video clips by incorporating contextual information from other utterances of the same clip. Hierarchical fusion with context modeling is used which fuses the modalities two in two and only then fusing all three modalities. Reduce in the error rate in the video clip to almost 10%. [6].To classify the opinions of the social media users expressed in the form of texts Corpora and lexicon based approaches are combined and lexicons are generated from the text. We can get a better understanding of the specific language and culture of twitter users and sentiment orientation of words in different contexts [7].Sentiment and emotional analysis in visualization of medical records of patient and identifying the type of disease and solution. Various sentiments and emotional analysis methodologies can be used to analyze the problem. Identifying the problem and cure for the disease from the complete reports of patient [8].Analysis of stock market indicators such as sensex and nifty has been done to predict the price of stock. Text mining and natural language programming are used to identify user emotions. Understanding in the ups and downs in stock market so that investors can invest [9].In analyzing peoples sentiments,opinions ,attitudes, and emotions on any topic products and services. Many methods like CRC, soft max algorithm etc., can be used to analyze. To know the higher preferences by many people on different products and services and hence, we can improve the quality of them [10].

III. APPLIED METHODOLOGY

The training set is taken from the website repository and the user sentiments above the top mobiles as arranged in a semantic so that to apply the methodology of multilayer perceptron neural network for classification. Here five attributes were employed as Excellent, Good, Bad, Satisfactory and Poor. The cardinal values will be distributed and normalized for manipulation purpose. Well reduced entropy training set were taken for increasing the accuracy of the Table 1.

Table 1.Training Set

Mobiles	Ex	Gd	Bt	Sa	Pr
One plus 6	710	160	40	20	70
redmi note 5 pro	734	169	38	13	44
Moto G6	505	250	95	44	103
Nokia 6	511	219	98	45	125
Honor 9	590	240	73	26	69
Samsung Galaxy J8	667	208	56	16	52
Sony Xperia R1+	523	218	102	42	112
Asus Zenfone Max Pro M1	592	247	65	23	70
Xiaomi M1	647	213	58	21	60
Vivo V9	670	201	54	19	53
Oppo F7	668	213	53	17	47
Lenovo Vibe K5 Note	525	257	94	36	85
Total	7342	2595	826	322	890

Legends 1: Ex-Excelelnt, Gd- Good, Bt-Better,
Sa-Satisfactory, Pr-Poor

Table 2. Normalized Distribution with Class

Mobiles	Ex	Gd	Bt	Sa	Pr	Total	Percentile	Class
One plus 6	0.1	0.062	0.048	0.062	0.079	0.348	62.929	Satisfactory
Redmi note 5 pro	0.1	0.065	0.046	0.040	0.049	0.301	54.420	Poor
Moto G6	0.1	0.096	0.115	0.137	0.116	0.533	96.334	Excellent
Nokia 6	0.1	0.084	0.119	0.140	0.140	0.553	100.000	Excellent
Honor 9	0.1	0.092	0.088	0.081	0.078	0.419	75.793	Good
Samsung Galaxy J8	0.1	0.080	0.068	0.050	0.058	0.347	62.761	Satisfactory
Sony Xperia R1+	0.1	0.084	0.123	0.130	0.126	0.535	96.704	Excellent
Asus Zenfone Max Pro M1	0.1	0.095	0.079	0.071	0.079	0.405	73.229	Good
Xiaomi M1	0.1	0.082	0.070	0.065	0.067	0.373	67.438	Satisfactory
Vivo V9	0.1	0.077	0.065	0.059	0.060	0.352	63.723	Satisfactory
Oppo F7	0.1	0.082	0.064	0.053	0.053	0.343	61.998	Satisfactory
Lenovo Vibe K5 Note	0.1	0.099	0.114	0.112	0.096	0.492	88.995	Excellent

A. Multilayer Perceptron Classification

In the multi layered perceptron, the sigmoid value will be changed for the learning purpose of the method.The threshold value is also calculated for archiving the optimum results to the earliest. Fourteen iteration has been made to fix the supervised learning.

Sigmoid Node 0, Threshold -2.44485970442835
Input Weight Input Weight

Node 4 0.12958139720214812	Node 5 -1.1422160166580497
Node 6 4.56637673678924	Node 7 -2.2763532664012085
Node 8 -0.062093580933367476	Node 9 0.3980041177295846
Node 10 -1.2615547165661463	Node 11 -0.17329600251594873
Node 12 -0.1057989963003019	Node 13 1.9842661064117113
Node 14 -0.6183795760407365	

Sigmoid Node 1, Threshold 0.04639598154257539
Inputs Weights
Inputs Weights

Node 4 -1.4419436240829677	Node 5 -0.8188760405570852
Node 6 -2.7335357001358296	Node 7 -1.509456199093708
Node 8 1.2709319333975884	Node 9 -1.7972230851355298
Node 10 -0.6908276590922425	Node 11 0.8283783474222036
Node 12 1.2915896739981905	Node 13 -1.9253120895991624
Node 14 -0.8587009634857665	

Sigmoid Node 2 , Threshold -0.9074099331619964
Inputs Weights Inputs Weights

Node 4 -0.02593891599515197	Node 5 1.5937985364497507
Node 6 -0.6821439567288093	Node 7 0.8531581845392925
Node 8 -1.7004698062671921	Node 9 -0.300155944961549
Node 10 1.612139763620821	Node 11 -3.1606313540279394
Node 12 -1.5232126272729911	Node 13 0.6262978208497636
Node 14 1.2002403031879278	S

Sigmoid Node 13, Threshold 0.09901086972676722
Inputs Weights Inputs Weights
Inputs Weights

Attrib Mobile Name =One plus 6 0.5132108098395418	Attrib Mobile Name =redmi note 5 pro -1.6751979318890753	Attrib Mobile Name =Moto G6 0.09035631018036568
Attrib Mobile Name =Nokia 6 0.014258614858313097	Attrib Mobile Name =Honor 9 -1.5845926120153964	Attrib Mobile Name =Samsung Galaxy J8 0.6220674564976144
Attrib Mobile Name =Sony Xperia R1+ 0.0775260194893871	Attrib Mobile Name =Asus Zenfone Max Pro M1 -1.459075104210365	Attrib Mobile Name =Xiaomi M1 0.5175668692714619
Attrib Mobile Name =Vivo V9 0.5672645639031679	Attrib Mobile Name =Oppo F7 0.59450200097762	Attrib Mobile Name =Lenovo Vibe K5 Note 0.23740010702225156
Attrib Excellent -0.01573238506029203	Attrib Good -0.37519371172199534	Attrib Satisfactory 0.25307917984841155
Attrib Bad 0.38326180139639143	Attrib Worst 0.2016363429708939	Attrib Total 0.20669122922049185
Attrib Percentile 0.28312946519372634		

Sigmoid Node 14, Threshold -0.010551016840935578
Inputs Weights Inputs Weights
Inputs Weights

Attrib Mobile Name =One plus 6 0.10487507277235857	Attrib Mobile Name =redmi note 5 pro 0.0811541225482057	Attrib Mobile Name =Moto G6 0.36882692455936533
Attrib Mobile Name =Nokia 6 0.2818463303664641	Attrib Mobile Name =Honor 9 -0.7629082526068011	Attrib Mobile Name =Samsung Galaxy J8 0.08921070071965556
Attrib Mobile Name =Sony Xperia R1+ 0.3030201652452199	Attrib Mobile Name =Asus Zenfone Max Pro M1 -0.59878270138972	Attrib Mobile Name =Xiaomi M1 -0.00790209730759472
Attrib Mobile Name =Vivo V9 0.08973761683034183	Attrib Mobile Name =Oppo F7 0.0919686734881061	Attrib Mobile Name =Lenovo Vibe K5 Note 0.6150062208721987
Attrib Excellent -0.3203345067046024	Attrib Good -0.11269247583794008	Attrib Satisfactory 0.5530582913247528
Attrib Bad 0.6367322676507922	Attrib Worst 0.49981652076374883	Attrib Total 0.5581695704173387
Attrib Percentile 0.552067856530608		

Test Data

Mobile Name	Excellent	Good	Satisfactory	Bad	Worst	Total	Percentile
Honor 9	0.08	0.092	0.088	0.081	0.078	0.419	75.793

Input	Node 0
Class Poor	Input
Node 1	Class Excellent
Input	Node 2
Class Good	Input
Node 3	
Predicted Class : Good	**(Correctly Classified)**

Time taken to build model: 0.17 seconds, Time taken to test model on training data: 3 seconds

Correctly Classified Instances 12 100 %	Incorrectly Classified Instances 0 0 %
Kappa statistic 1	Mean absolute error 0.0224
Root mean squared error 0.0311	Relative absolute error 6.405 %
Root relative squared error 7.5168 %	Total Number of Instances 12
Ignored Class Unknown Instances 1	

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Satisfactory
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Poor
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Excellent
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Good

Wighted Avg. 1.000 0.000 1.000 1.000 1.000 1.000 1.000 1.000

Confusion Matrix

a b c d <-- classified as	5 0 0 0 | a = Satisfactory
0 1 0 0 | b = Poor	0 0 4 0 | c = Excellent
0 0 0 2 | d = Good	

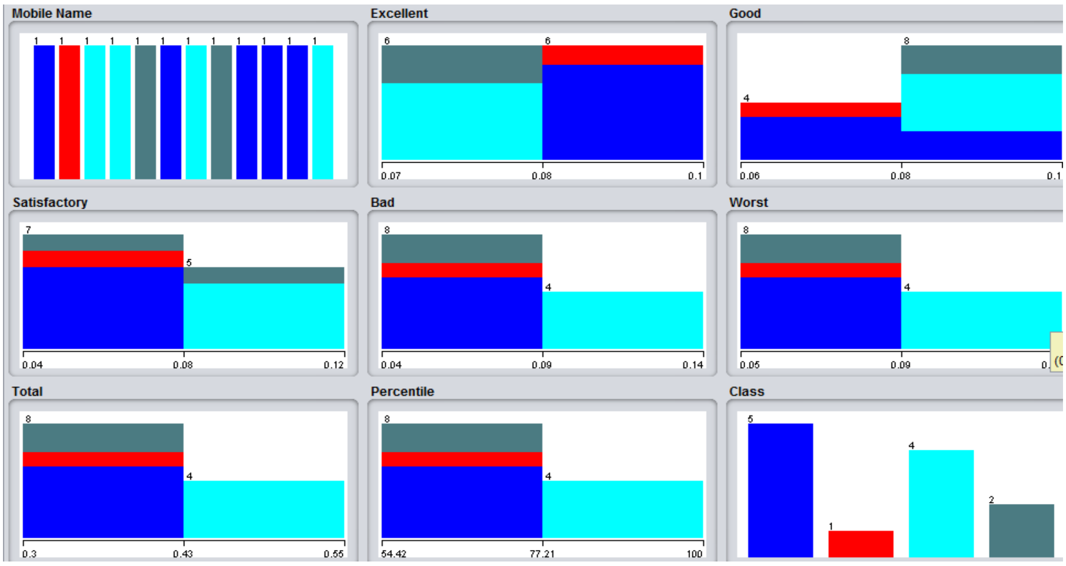

Fig 1.Cost/Benefit Analysis Curve

IV. RESULTS AND DISCUSSIONS

The normalized Table2 helps us to find the supervised value for the class were it found through statistical methodology. In the semantic of Table 2 each and mobile has got its own attributes with significance. The customer satisfaction is the first and the foremost factor for this work. Their sentiments were taken into the account for the research recommender system. Multilayer perceptron neural network was employed and the iteration methods were exhibits with sigmoid value. For every sigmoid value threshold has been found. In this small range of sample training set, 14 iteration have been made to get the results. The obtained results shows the correct predictions made and the outcome results are good for the incoming patterns. The well trained dataset and the confusion matrix also provides and proves the supervised learning is perfect. The test data or pattern taken from the same semantic of Table2 for the testing purpose. Our model builds within 17 seconds. The cost and benefits ratio was calculate and depicted as Fig1. The Root mean squared error, Mean absolute error, Relative absolute error and Root relative squared errors were identified for correct predictions.

V. CONCLUSION

In this research work top mobiles are gagged through the customer sentiments and their superstitious. Here this methodology of mining is meant for non mining persons. The Semantic collected from the Google sites and other repository and arranged to the good order for the predictions. The ordinal and nominal values were converted into cardinal values for real time predictions. Multilayer perceptron will classify the pattern in high rate of predicting the results in optimum level. Sigmoid value and the thresholds brings the iterations to converge the lot rather at the earliest. The confusion matrix remains the research no to deviate the process at any instance. Taking large sample of training set and the set data will provide greater accuracy to the work. Still huge and brilliant methodology are awaiting for the researchers to do the wonder in the months to come.

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