“Chat Application Success Prediction”

PROJECT REPORT

Submitted for the course:
Data Mining Techniques (ITE2006)

GROUP 1

ARNAV BHUTANI 15BIT0044

SUNAYNA RAY 15BIT0225

DHANASHRI PATIL 15BIT0337

Slot: E1

Name of faculty: Prof. Thippa Reddy

(SCHOOL OF INFORMATION TECHNOLOGY)

VIT UNIVERSITY
(Estd. u/s 3 of UGC Act 1956)
VELLORE ▪ CHENNAI
www.vit.ac.in

April, 2017

ABSTRACT

This is the era of internet and mobile phones. Chat Applications are a major part of this digital revolution. Thus there is a large pool of customers for using such applications. Subsequently, there is a large pool of developers (and apps) too. Hence we find that any developer would like to predict the success rate of his application and abide by the rules that define the same. We have used WEKA tool for classification and association rule mining on an indigenously created dataset.

CONTENTS

1. INTRODUCTION

This is the era of internet and mobile phones. Chat Applications are a major part of this digital revolution. Gone are the days of typing elaborate emails (or even letters) for communicating with people far off. With this background, chat applications have proven to be of immense success.

Thus there is a large pool of customers for using such applications. Subsequently, there is a large pool of developers (and apps) too. Hence we find that any developer would like to predict the success rate of his application and abide by the rules that define the same.

1.1. PROBLEM STATEMENT

Due to the presence of numerous chat applications, the success of one's applications becomes critical. The demand is huge, but so is the supply. Any developer would wish to predict how successful his application will be and tailor its specifications accordingly. There are numerous apps on the Play Store, hence we have a high amount of data that can be mined to get the required knowledge.

1.2. DETAILED LITERARY SURVEY

Till date many research papers and projects have used Decision Trees as their method of classification. They can be used to predict GPA based on previous courses and to evaluate most important courses in their study plan [1]. They can also be used for Human Protein Function. Drug discoverers can easily use the model for predicting functions of proteins that are responsible for various diseases in human body [2].A credit card fraud detection problem for the resolution of reducing the bank's risk using decision tree algorithm has been proposed [3]. With the historical profile patterns, make use of credit card fraud detection models to equal the transaction information to predict the probability of being fraudulent for a new transaction. It offers a scientific basis for the authorization mechanisms. To predict movie profitability a study using historical data on over 100 films produced in the United States (including their genre, opening month, duration, budget, etc. Decision trees are models commonly used in the field of artificial intelligence as decision support tools. The results show that the resulting model forecasts whether or not a movie will be profitable with an accuracy of over 70%, and this model can be used as a decision support tool for film producers [4]. Several efficiency recommendation system use decision trees. Decision tree classifiers like C4.5 and C5.0 algorithms have the merits of high accuracy, high classifying speed, strong learning ability and simple construction. In this paper, the decision-tree-based recommendation system framework is proposed. It uses efficient classification algorithm combined with collaborative recommendation approach for book recommendation. This hybrid book recommendation system combines advantages of both decision tree classifier and collaborative filtering. The results of C4.5 and C5.0 decision tree classifiers are compared and book recommendations are given to user by using efficient C5.0 decision tree classifier [5].

RESEARCH PAPERS:

1. Predicting Students Final GPA Using Decision Trees: A Case Study by Mashael A. Al-Barrak and Muna Al-Razgan

2. Human Protein Function Prediction using Decision Tree Induction By Manpreet Singh, Parminder Kaur Wadhwa and Parvinder Singh Sandhu

3. Credit Card Fraud Detection Using Decision Tree Induction Algorithm by Snehal Patil, Harshada Somavanshi, Jyoti Gaikwad, Amruta Deshmane, and RinkuBadgujar

4. Using Decision Trees to Characterize and Predict Movie Profitability on the US Market by María C. Burgos, María L. Campanario, Juan A. Lara, David Lizcano

5. Efficient Recommendation System Using Decision Tree Classifier and Collaborative Filtering by Sayali D. Jadhav1, H. P. Channe 2

2. THE DATASET

The dataset initially:

ARFF-Viewer - C:\Users\W

File Edit View

appbasic.arff *

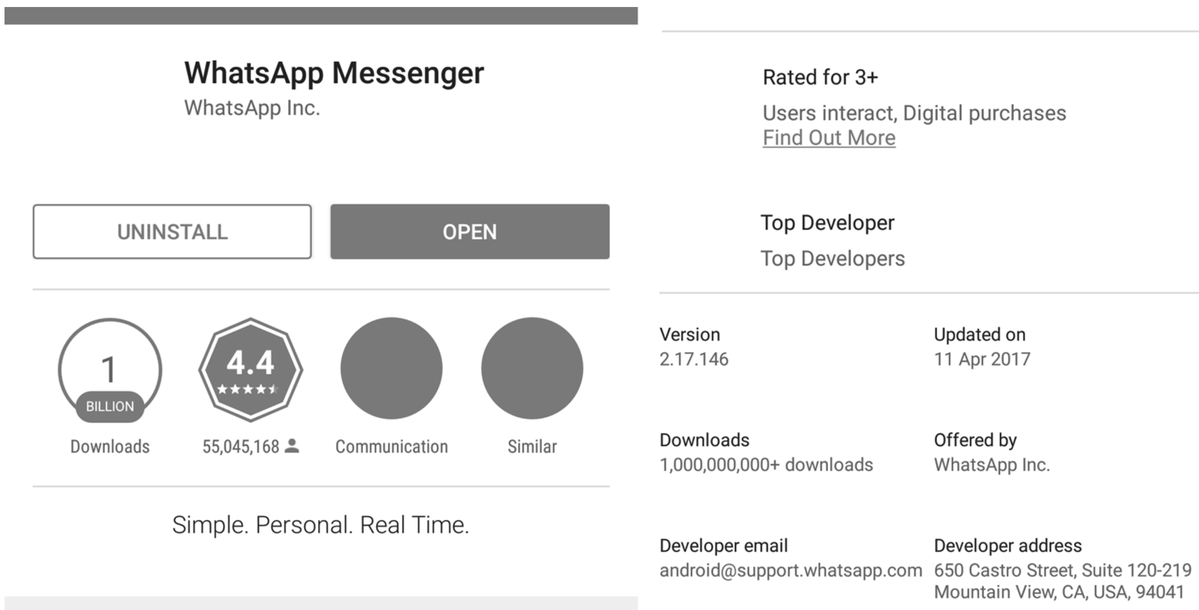
Relation: Databasic

No.	1: Sr.No Numeric	2: Name Nominal	3: Age Nominal	4: Top Developer Nominal	5: Ads Nominal	6: Size (MB) String	7: Rating Numeric	8: 5 Stars Nominal	9: Downloads (M) String
5	21.0	Live ...	12	No	No	20.55	4.7		1
6	22.0	Meet4U	18+	Yes	Yes	8.03	4.1		1
7	24.0	Asian...	18+	No	No	15.3	4.0		1
8	30.0	4 Chat	18+	No	Yes	2.56	4.2		1
9		DISA		no	no	25.67	4.2	.1+	1
10		Maaii		no	no	47.92	4.4	70k	1
11		Voxer		yes	no	19.67	4.3	.15+	1
12		Soma...		no	yes	20.06	4.4	.3+	1
13		Singl...		yes	no	23.29	4.6	88k+	1
14		VMS v...		no	yes	13.75	4.1	4k+	1
15		SliQ-...		no	no	10.84	4.2	5k+	1
16		Chat...	3+	No	No	14.85	4.1	15k	1
17		Primo	12+	No	Yes	35.83	4.1	24k	1
18		TalkU	3+	No	Yes	29	4.4	54k	1
19		Wire-...	3+	No	No	17	4.1	13k	1
20		Vona...	3+	No	No	20.74	4.1	17k	1
21		Chea...	3+	No	No	19.77	4.0	21k	1
22		trueC...	3+	No	No	9.78	4.0	4k	1
23		Near...	12+	No	Yes	5.14	3.9	11k	1
24		fiesta ...	12+	No	Yes	32.41	4.2	66k	1
25		mood...	3+	No	No	18.27	4.5	25k	1
26		MyDa...	12+	No	Yes	12.42	4.1	5k	1
27		Talk2	3+	No	Yes	14.85	3.9	19k	1
28	2.0	Glynk	12+	No	No	8.31	4.5		0.1
29	3.0	Stran...	18+	No	Yes	2.14	3.3		0.1
30	19.0	Girls ...	12+	No	Yes	3.22	3.9		0.1
31	20.0	India...	12+	No	Yes	4.32	3.7		0.1
32		imes...		no	yes	7	4.2	5k+	0.1
33		ChatOn		no	yes	598kb	3.9	1301	0.1
34		Just s...		no	no	20.47	4.3	2k+	0.1
35		Meec...		no	no	1.95	4.4	3k+	0.1
36		MeeM...		no	no	30.52	4.4	357only	0.1
37	4.0	Jaumo	18+	Yes	Yes	14.37	4.4		10
38	5.0	Hi	18+	Yes	Yes	6.86	4.2		10
39	8.0	Insta...	12+	No	Yes	16.88	4.4		10
40	9.0	Moco	18+	Yes	Yes	3.69	4.2		10
41	11.0	MeetMe	18+	Yes	Yes	28.59	4.2		10
42	18.0	Skout	18+	Yes	Yes	18.76	4.2		10

This dataset has missing values since some of us maintained the columns of Sr. No and number of 5 star ratings and some of us didn't. Also the age value is available for few apps and unavailable for few.

2.1. COLLECTION OF DATA

We have collected the following information for 132 apps from Play store: Name, Minimum age, Top developer or not, Ads are allowed or not, Size, Rating, Number of 5 stars and number of downloads.



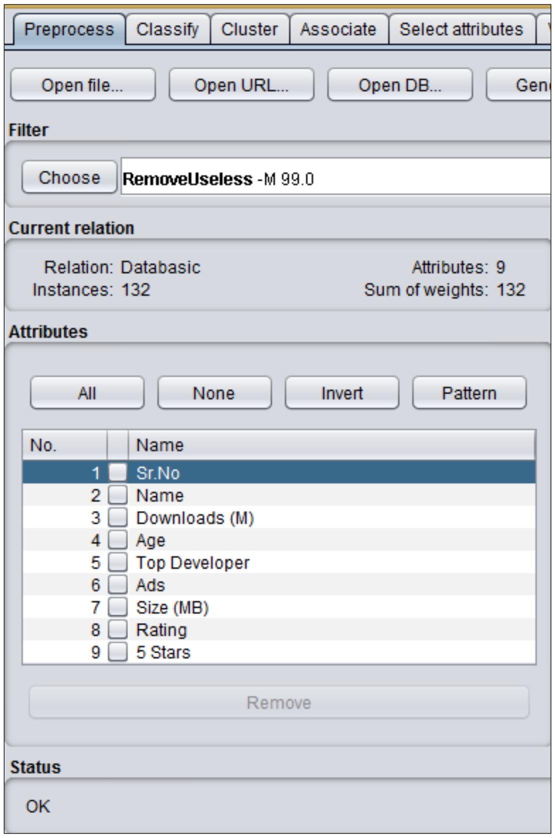
This dataset has missing values since some of us maintained the columns of Sr. No and number of 5 star ratings and some of us didn't. Also the age value was available for few apps and unavailable for few.

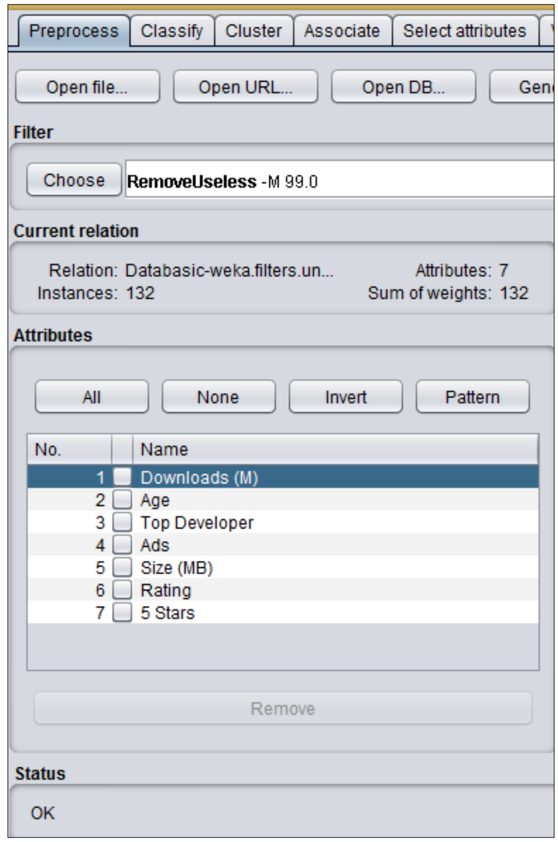
2.2. DATA PREPROCESSING

The collected data cannot be mined. It has too many missing values, useless attributes and possible outliers due to human error in noting down the values.

Hence the following cleaning process was done:

1. RemoveUseless: Remove useless attribute: Name and serial number. These have different value for each tuple.

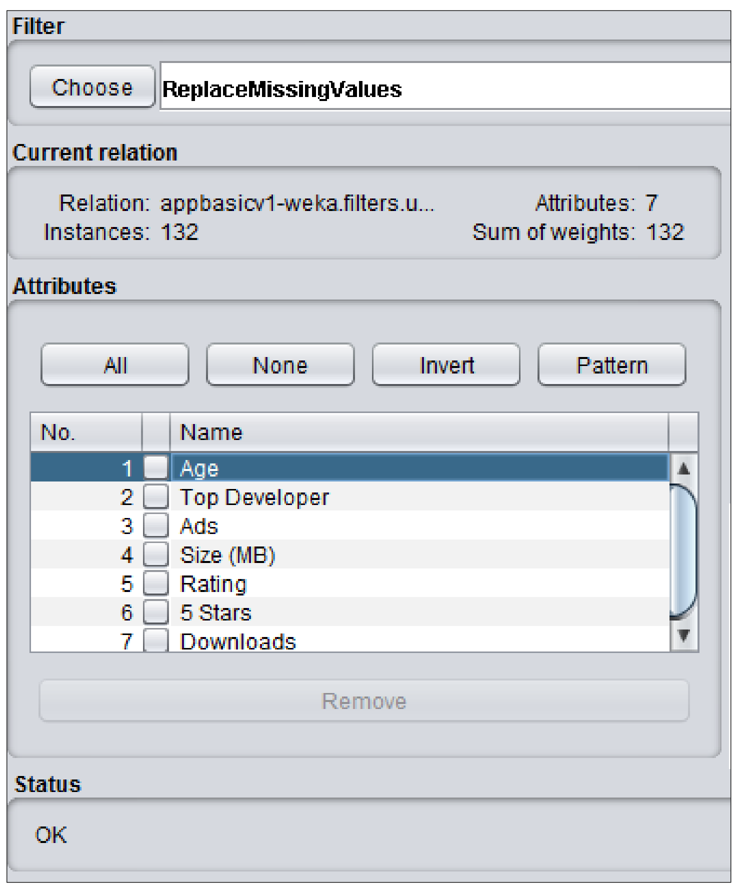




2. Fill in missing data:

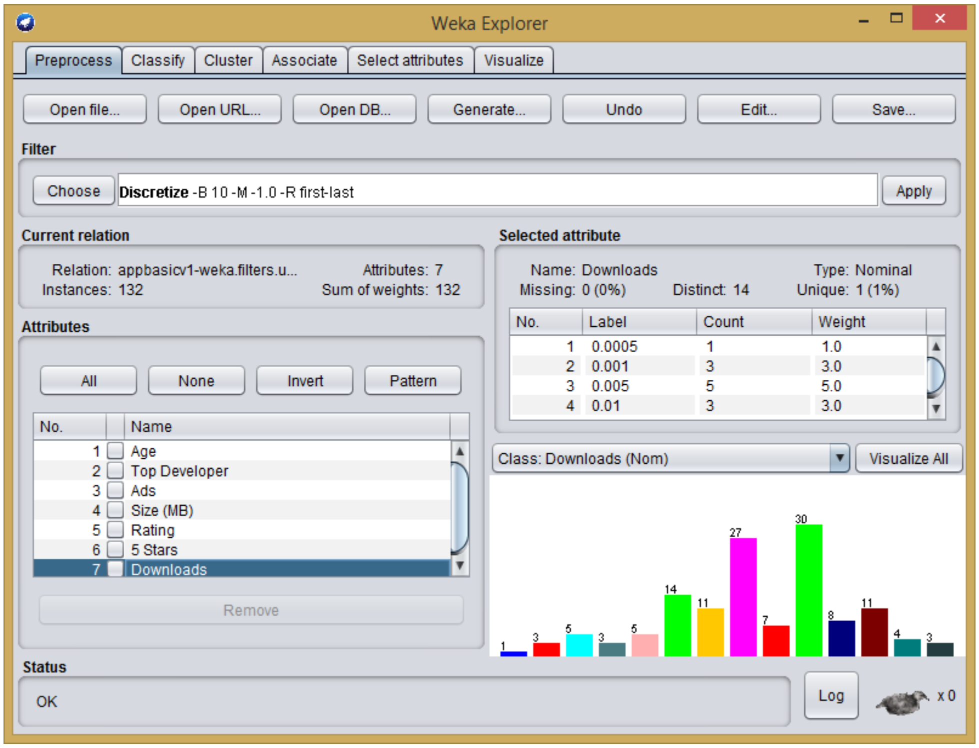
a. Few apps did not have age specification:
Default: 18+

b. Few of us noted down no. of 5 star ratings, few didn't: fill missing values with mean value



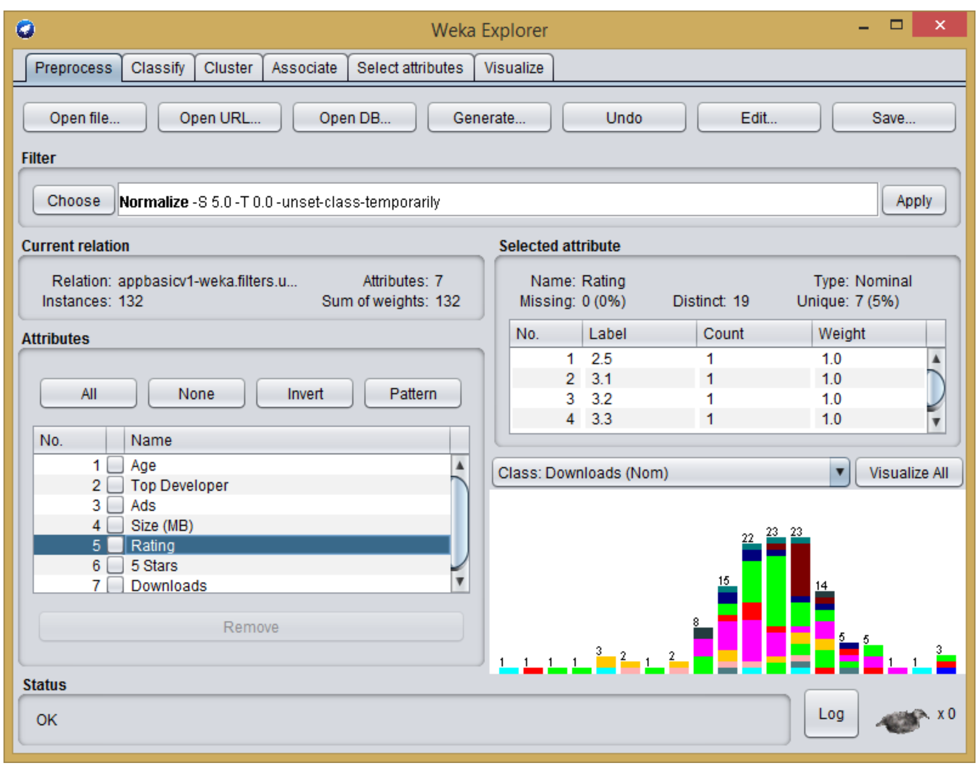
3. Discretisation:

Convert Numeric value of Downloads attribute to nominal.

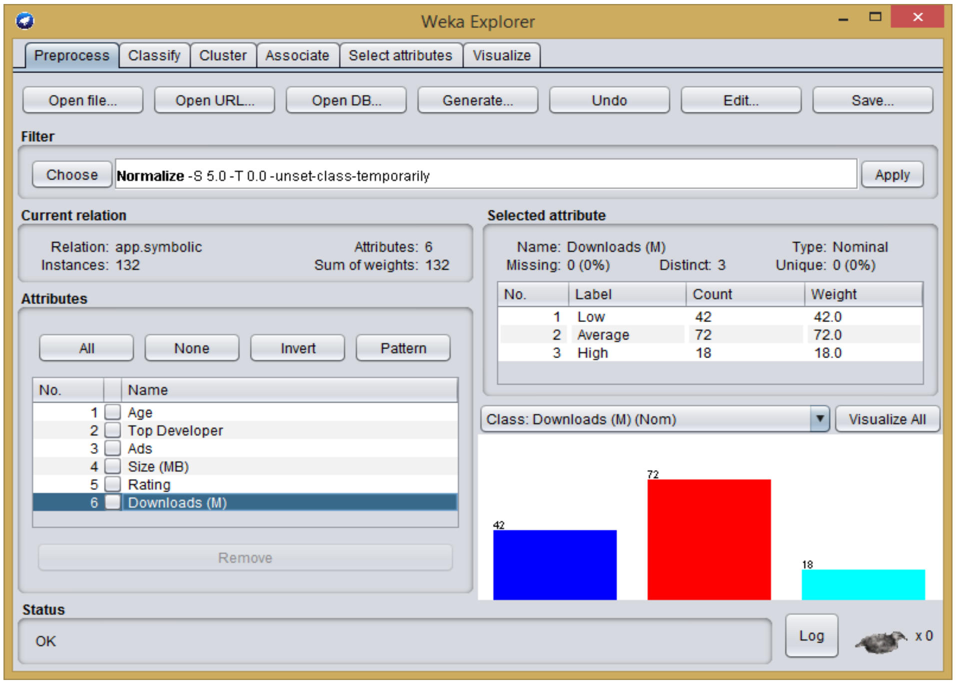


4. Normalise

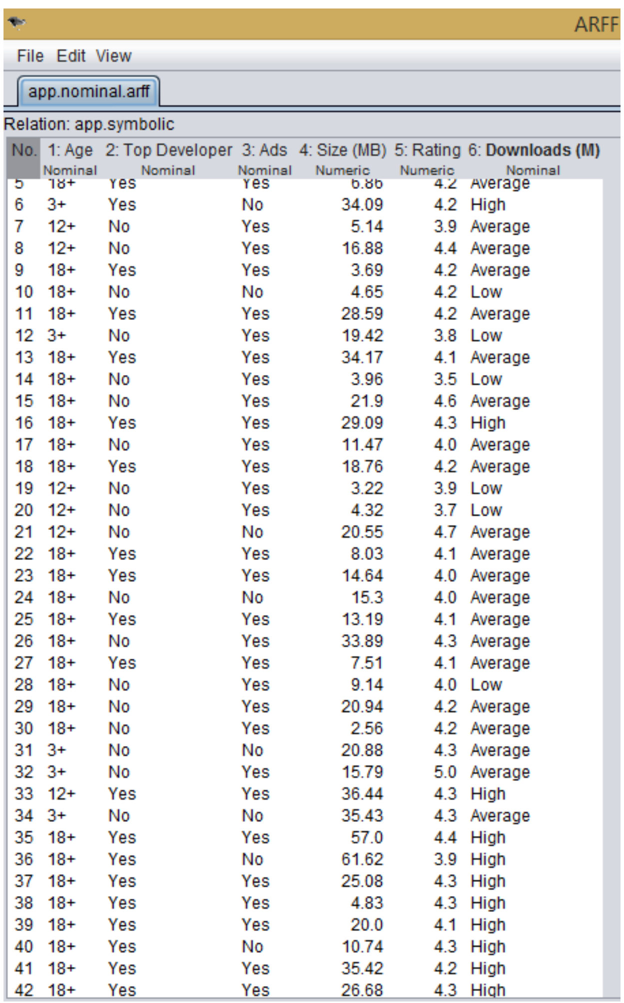
Normalize all attributes except class attribute since that is discretised. This is so that Apriori algorithm can be used.



5. Merge infrequent nominal values in class attribute



Thus the final dataset was:


ARFF

File Edit View

app.nominal.arff

Relation: app.symbolic

No.	1: Age (Nominal)	2: Top Developer (Nominal)	3: Ads (Nominal)	4: Size (MB) (Numeric)	5: Rating (Numeric)	6: Downloads (M) (Nominal)
5	18+	Yes	Yes	6.86	4.2	Average
6	3+	Yes	No	34.09	4.2	High
7	12+	No	Yes	5.14	3.9	Average
8	12+	No	Yes	16.88	4.4	Average
9	18+	Yes	Yes	3.69	4.2	Average
10	18+	No	No	4.65	4.2	Low
11	18+	Yes	Yes	28.59	4.2	Average
12	3+	No	Yes	19.42	3.8	Low
13	18+	Yes	Yes	34.17	4.1	Average
14	18+	No	Yes	3.96	3.5	Low
15	18+	No	Yes	21.9	4.6	Average
16	18+	Yes	Yes	29.09	4.3	High
17	18+	No	Yes	11.47	4.0	Average
18	18+	Yes	Yes	18.76	4.2	Average
19	12+	No	Yes	3.22	3.9	Low
20	12+	No	Yes	4.32	3.7	Low
21	12+	No	No	20.55	4.7	Average
22	18+	Yes	Yes	8.03	4.1	Average
23	18+	Yes	Yes	14.64	4.0	Average
24	18+	No	No	15.3	4.0	Average
25	18+	Yes	Yes	13.19	4.1	Average
26	18+	No	Yes	33.89	4.3	Average
27	18+	Yes	Yes	7.51	4.1	Average
28	18+	No	Yes	9.14	4.0	Low
29	18+	No	Yes	20.94	4.2	Average
30	18+	No	Yes	2.56	4.2	Average
31	3+	No	No	20.88	4.3	Average
32	3+	No	Yes	15.79	5.0	Average
33	12+	Yes	Yes	36.44	4.3	High
34	3+	No	No	35.43	4.3	Average
35	18+	Yes	Yes	57.0	4.4	High
36	18+	Yes	No	61.62	3.9	High
37	18+	Yes	Yes	25.08	4.3	High
38	18+	Yes	Yes	4.83	4.3	High
39	18+	Yes	Yes	20.0	4.1	High
40	18+	Yes	No	10.74	4.3	High
41	18+	Yes	Yes	35.42	4.2	High
42	18+	Yes	Yes	26.68	4.3	High

3. DATA MINING METHODOLOGY

3.1. TOOL USED

Weka:

Weka contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to these functions.

Advantages:

- Free availability under the GNU General Public License.
- Portability, since it is fully implemented in the Java programming language and thus runs on almost any modern computing platform.
- A comprehensive collection of data preprocessing and modeling techniques.
- Ease of use due to its graphical user interfaces.

3.2. ALGORITHM USED

Decision Tree

A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm.A decision tree is a flowchart-like structure in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules. They are simple to understand and interpret. People are able to understand decision tree models after a brief explanation. They have value even with little hard data. Important insights can be generated based on experts describing a situation (its alternatives, probabilities, and costs) and their preferences for outcomes. They allow the addition of new possible scenarios. Decision trees help determine worst, best and expected values for different scenarios. They can be combined with other decision techniques.

Applications

- Application of a range of machine learning methods to problems in agriculture and horticulture.
- Use of decision trees for filtering noise from Hubble Space Telescope images in Astronomy. Decision trees have helped in star-galaxy classification, determining galaxy counts and discovering quasars in the Second Palomar Sky Survey.
- They are used in biomedical engineering Use of decision trees for identifying features to be used in implantable devices.
- Decision trees have been recently used to non-destructively test welding quality, for semiconductor manufacturing, for increasing productivity , for material procurement method selection , to accelerate rotogravure printing , for process optimization in electrochemical machining , to schedule printed circuit board assembly lines , to uncover flaws in a Boeing manufacturing process and for quality control. For a recent review of the use of machine learning (decision trees and other techniques) in scheduling.
- Medical research and practice have long been important areas of application for decision tree techniques. Recent uses of automatic induction of decision trees can be found in diagnosis, cardiology, psychiatry, gastroenterology, for detecting micro calcifications in mammography, to analyse Sudden Infant Death (SID) syndrome and for diagnosing thyroid disorders.
- **Power systems:** Power system security assessmentand power stability prediction are two areas in power systems maintenance for which decision trees were used.

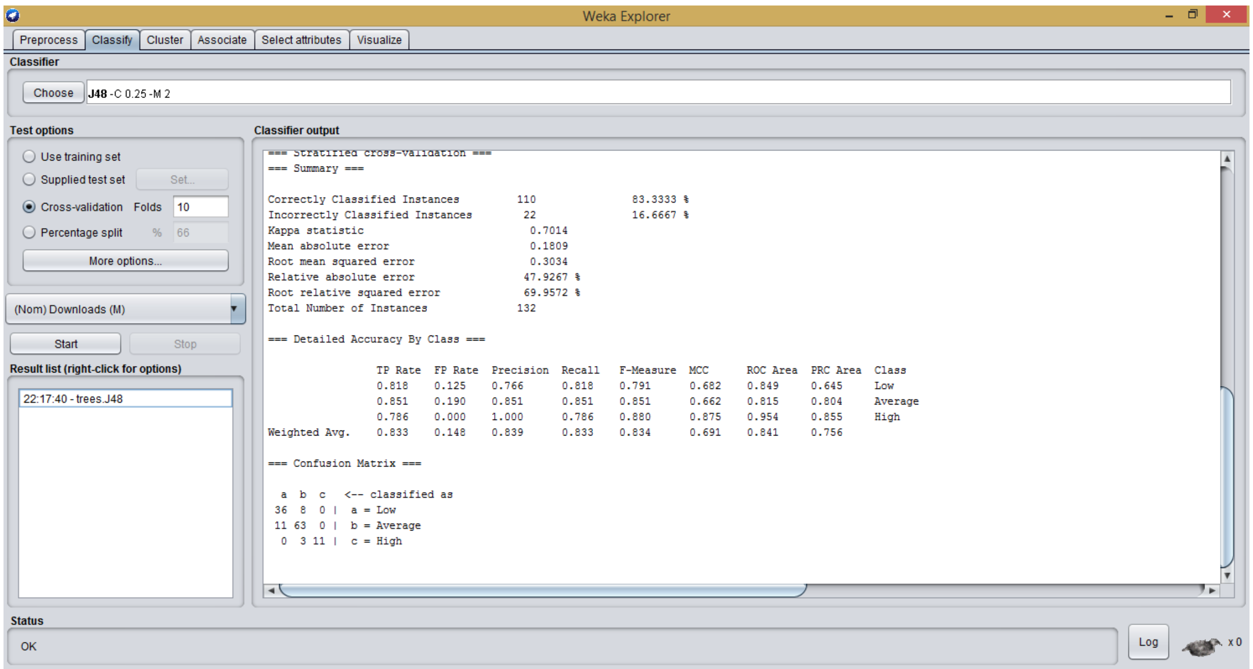
Apriori Algorithm

Apriori is an algorithm for frequent item set mining and association rule learning over transactional databases. It proceeds by identifying the frequent individual items in the database and extending them to larger and larger item sets as long as those item sets appear sufficiently often in the database. The frequent item sets determined by Apriori can be used to determine association rules which highlight general trends in the database: this has applications in domains such as market basket analysis.

Apriori uses a "bottom up" approach, where frequent subsets are extended one item at a time (a step known as *candidate generation*), and groups of candidates are tested against the data. The algorithm terminates when no further successful extensions are found.Apriori uses breadth-first search and a Hash tree structure to count candidate item sets efficiently. It generates candidate item sets of length k from item sets of length k-1. Then it prunes the candidates which have an infrequent sub pattern

4. CLASSIFICATION

A) Decision Tree algorithm (J48) with 10 fold cross validation was used and the following was the result:



=== Run information ===
Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: app.symbolic-weka.filters.unsupervised.attribute.StringToNominal-R4-weka.filters.unsupervised.attribute.StringToNominal-R4-weka.filters.unsupervised.attribute.NumericToNominal-R4-weka.filters.unsupervised.attribute.Discretize-B10-M-1.0-Rfirst-last
Instances: 132
Attributes: 6
    Age
    Top Developer
    Ads
    Size (MB)
    Rating
    Downloads (M)
Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree

Top Developer = Yes
| Ads = Yes: Average (33.0/3.0)
| Ads = No: High (11.0)
Top Developer = No

| Ads = Yes: Low (47.0/11.0)
| Ads = No: Average (41.0/8.0)
Number of Leaves : 4
Size of the tree : 7
Time taken to build model: 0.02 seconds
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	110	83.3333 %
Incorrectly Classified Instances	22	16.6667 %
Kappa statistic	0.7014	
Mean absolute error	0.1809	
Root mean squared error	0.3034	
Relative absolute error	47.9267 %	
Root relative squared error	69.9572 %	
Total Number of Instances	132	

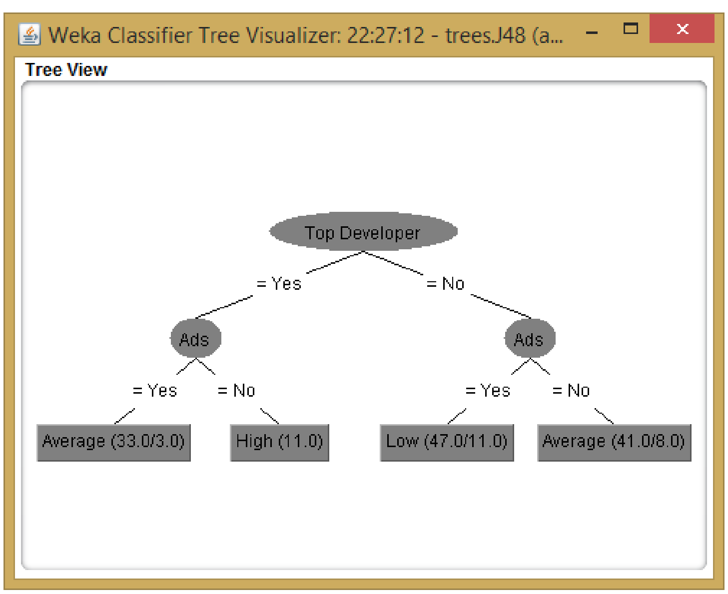
=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.818	0.125	0.766	0.818	0.791	0.682	0.849	0.645	Low
	0.851	0.190	0.851	0.851	0.851	0.662	0.815	0.804	Average
	0.786	0.000	1.000	0.786	0.880	0.875	0.954	0.855	High
Weighted Avg.	0.833	0.148	0.839	0.833	0.834	0.691	0.841	0.756	

=== Confusion Matrix ===

a	b	c	<-- classified as
36	8	0	| a = Low
11	63	0	| b = Average
0	3	11	| c = High

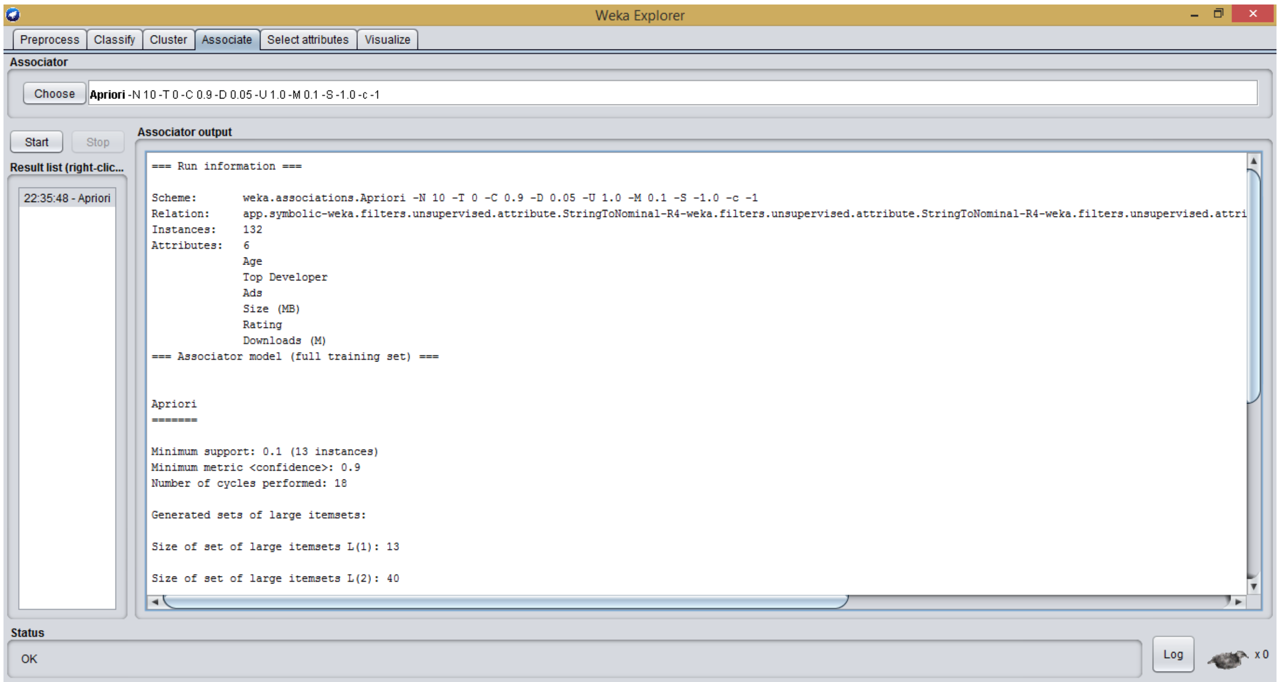
Tree:



5. ASSOCIATION RULE MINING

B) Apriori algorithm

This was to find useful association rules. The following was the result:



=== Run information ===

Scheme: weka.associations.Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1

Relation: app.symbolic-weka.filters.unsupervised.attribute.StringToNominal-R4-weka.filters.unsupervised.attribute.StringToNominal-R4-weka.filters.unsupervised.attribute.NumericToNominal-R4-weka.filters.unsupervised.attribute.Discretize-B10-M-1.0-Rfirst-last

Instances: 132

Attributes: 6

Age
Top Developer
Ads
Size (MB)
Rating
Downloads (M)

=== Associator model (full training set) ===

Apriori

=======

Minimum support: 0.1 (13 instances)

Minimum metric <confidence>: 0.9
Number of cycles performed: 18
Generated sets of large itemsets:
Size of set of large itemsets L(1): 3
Size of set of large itemsets L(2): 40
Size of set of large itemsets L(3): 34
Size of set of large itemsets L(4): 9
Size of set of large itemsets L(5): 1

Best rules found:

1. Downloads (M)=Low 44 ==> **Top Developer=No**
44 <conf:(1)> lift:(1.5) lev:(0.11) [14] conv:(14.67)

2. Ads=Yes Downloads (M)=Low 36 ==> **Top Developer=No**
36 <conf:(1)> lift:(1.5) lev:(0.09) [12] conv:(12)

3. Ads=No Downloads (M)=Average 33 ==> **Top Developer=No**
33 <conf:(1)> lift:(1.5) lev:(0.08) [11] conv:(11)

4. Top Developer=Yes Downloads (M)=Average 30 ==> **Ads=Yes**
30 <conf:(1)> lift:(1.65) lev:(0.09) [11] conv:(11.82)

5. Age=18+ Top Developer=Yes Downloads (M)=Average 23 ==> **Ads=Yes**
23 <conf:(1)> lift:(1.65) lev:(0.07) [9] conv:(9.06)

6. Age=18+ Downloads (M)=Low 19 ==> **Top Developer=No**
19 <conf:(1)> lift:(1.5) lev:(0.05) [6] conv:(6.33)

7. Top Developer=Yes Rating='(4-4.25]' Downloads (M)=Average 17 ==> **Ads=Yes**
17 <conf:(1)> lift:(1.65) lev:(0.05) [6] conv:(6.7)

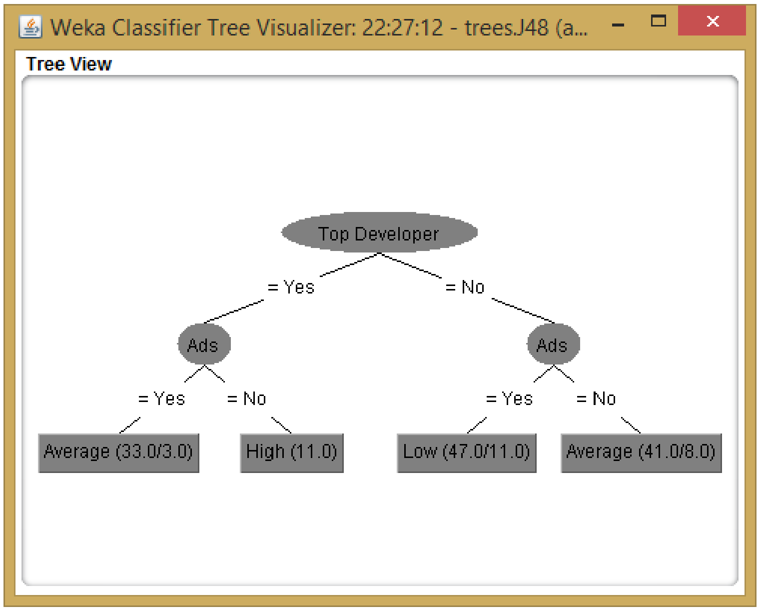
8. Top Developer=Yes Ads=Yes Rating='(4-4.25]' 17 ==> **Downloads (M)=Average**
17 <conf:(1)> lift:(1.78) lev:(0.06) [7] conv:(7.47)

9. Age=18+ Ads=Yes Downloads (M)=Low 16 ==> **Top Developer=No**
16 <conf:(1)> lift:(1.5) lev:(0.04) [5] conv:(5.33)

10. Downloads (M)=High 14 ==> **Top Developer=Yes**
14 <conf:(1)> lift:(3) lev:(0.07) [9] conv:(9.33)

6. CONCLUSION

By mining the collected data successfully we can conclude upon the decision tree which can help determine the success of an app.



We also find an important association rule: Developer=Yes Ads=Yes Rating='(4-4.25]' 17 ==> Downloads (M)=Average.

7. FUTURE SCOPE

Application developers can in future use the concluded results to ensure that their developed application is successful. Furthermore, more relevant data can be collected on this topic and more accurate results can be found on the same.

8. REFERENCES

We have referred to the following materials:

1. J. Han and M. Kamber , Data Mining: Concepts and Techniques , Third Edition, Morgan Kaufman,2011.

2. I. H. Witten and E. Frank, Data Mining: Practical Machine Learning Tools and Techniques, Third Edi t ion, Morgan Kaufmann, 2011.

3. G. K. Gupta, Introduction to Data Mining with Case Studies, Easter Economy Edition, Prentice Hall of India, 2014.

4. Alex Berson and Stephen J. Smith, Data Warehousing, Data Mining & OLAP, Tata McGraw Hill Edition, 2007.

5. WEKA MOOC you-tube tutorials by Ian Witten and E. Frank

6. WEKA MOOC online course by Ian Witten and E. Frank

7. Google