Evaluation of Association Rules in Liver Disease Data using Analytical Hierarchy Process for Decision Making

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***Abstract*: In general, association rule mining techniques generate a pool of rule with low minimum support value. But, finding some best and potential rules from the pool of generated rules is a complex problem and nowadays it is also on demand. The proposed decision making process is based on analytic hierarchy process and gives potential rules related to liver disease which may play crucial role in decision making. For determining best rules from pool of generated rules some important measures such as support, confidence, length of rule and presence of high relevant features in a rule are considered. ILPD liver disease data is used for generating association rules and determining some of the best rules from pool of rule.**

***Index Terms*: Analytic Hierarchy Process,Decision Making, Liver disease data, Rule Evaluation**

I. INTRODUCTION

Data mining is the non-trivial process of finding hidden and useful knowledge from large collection of data. It can be applied successfully in various fields for extracting useful information[1-5]. Medical data are usually a rich source of knowledge. The large amount of medical data can be used to extract useful patterns and information using various data mining techniques. A large number of research papers are available related to the field of medical data mining. It is helpful for effective diagnosis and also for opting appropriate treatment mechanisms. A huge amount of medical data is generated by healthcare industry related to hospitals, medical treatments, pathology test, disease, treatment cost, medical claims and other similar data[6-9].

Association rule mining is a technique of data mining that define relationship between different unrelated frequent items in a database. It extract the rule in the form of A→ B, here A is known as the antecedent and B is known as the consequent of the rule. These rules provide the information regarding different correlations among terms in transaction data. There are a number of algorithms for association rule mining[1,2,3,10,11].

Analytic Hierarchy Process (AHP) is multiple criteria decision making tool proposed by Saaty. It is a powerfulclassical methodology for decision-making in order to determine the priorities amongmultiple criteria, comparing alternatives for each criteria and making decision on an overall ranking of the alternatives. The criteria can be either quantitative, qualitative or both. AHP process decompose the decision problem into a hierarchy. The top level of the hierarchy represents the overall goal of the decision problem, the intermediate levels represent the criteria and sub-criteria affect the decision, and the possible alternatives are represented by bottom level. The final output of the AHP process provide the best choice among different alternatives[12,13].

II. RELATED WORK

Identifying some best Association Rules using decision making process is on demand and researchers are using AHP and other decision-making approaches to find more important rules[14-25]. Some of related work is explored in Table 1.

III. RULE EVALUATION PROCESS

A. Factor (Criteria) Selection

In common Association Rules are generated using two measure (Criteria/factor) one is Support (S) and another is Confidence (C). Here we have used two more Measures (Criteria) to evaluate rules are Length of Rule (L) and Presence of highly relevant features (attribute) in a rule (P)[1-3].

Support (S): It indicates that how frequently the itemset appears in the database. It is the proportion of transactions in the database, which contains the itemset. For example, an itemset has a support of 20% of all transactions indicate itemset is present in 1 out of 5 transactions.

Confidence (C): It indicate how often the association has been found to be true. For example, for rule A→B the confidence is value of total number of transactions that contains {AB} divided by total number of transactions contain {A}.

Presence of highly relevant features in a rule (P): Suppose for a dataset A, B, C and D are items and their relevance order is D, C, B, and A, which can be obtained by Chi Squaremethod, Information Gain, Gini Index etc. If there are two rules R1: A→B and R2: C→D then P(R1) < P(R2) i.e. rule R2 having more relevant feature than the rule R1.

Length of Rule (L): Total number of Items(attributes) that form the rule is called length of rule. For example, for rule R1: A→B, the Length of rule L(R1)=2, similarly for rule R2: $A \wedge B \rightarrow C$, the Length of rule L(R2)=3.

So, any rule may get priority over the other based on these

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Table 1: Related work based of Decision Making Process

S.NO	AUTHOR & YEAR	AREA	PRINCIPLE TASK & TECHNIQUE	FINDING
1	Istrat, V., and N. Lalić, 2017[14]	Textile industry	Association rules mining	New interesting rules based on different parameters.
2	Xi. Jianfeng et. al., 2016[15]	Traffic accident analysis	Analytic Hierarchy Process (AHP) and Apriori Technique	The hierarchy of accident causing factors.
3.	Nadali, Ahmad, et. al., 2012[16]	Credit scoring	Association rule mining, AHP and SAW	Credit score of customers.
4.	Ait-Mlouk et. al., 2017[17]	Traffic accident analysis	Association rule and ELECTRE TRI (a multi-criteria sorting method)	Getting most interesting rules according to the decision makers' preferences.
5.	A.Haery et. al., 2008[18]	Supplier chain selection	Association rule mining.	Valuable patterns about supplier behaviour.
6.	Choi, Duke Hyunet. al. 2005 [19]	Business Analysis	Association rule mining	Identified new rules for business decision.
7.	Sagin, AyseNur et. al., 2018 [20]	Market Basket Analysis	Apriori and FP-Growth algorithms	A group of product with strong association
8.	Toloo, Mehdi, et. al., 2009[21]	Market Basket Analysis	Association rule mining, Integrated data envelopment analysis (DEA) model.	A set of most efficient association rule
9.	WachanaKhowfa et. al. 2017[22]	Supplier chain Selection (Cloud Service)	Association rule mining and AHP method.	Selection of best cloud service based on user's preference.
10.	Liu, Duen-Ren et. al., 2005[23]	Recommender system	AHP, Clustering and Association rule mining.	Recommendations of higher quality
11.	KhademolqoraniShakiba, 2016 [24]	Medical data analysis.	ANP model and association rule mining.	Generate interesting association rules useable and useful for medical diagnosis.
12.	Zhang, Zhen et. al., 2011 [25]	Market basket analysis.	Association rule mining and AHP method.	Evaluating the quality of association rules

defined criteria (factor) S, C, L, and P. For defining weightage or importance among criteria, the Saaty Rating Scale[12,13] is used which is a popular scale as given in figure 1.

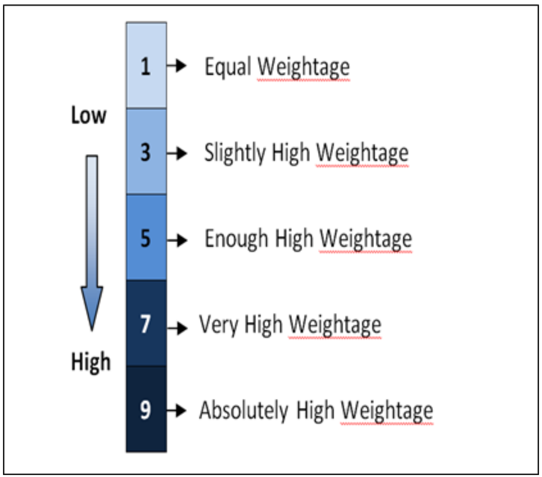

Fig. 1: Saaty Rating Scale

B. Calculation of Weightage for Criteria

The pairwise comparison among the criteria (factors) have been done using Saaty Rating scale [12,13] as given in Table 2. As stated in Table 2 cell CS is rated as 3 that means Confidence has slightly high weightage than support. The cell SC is reciprocal of cell CS. The normalized cell value is shown in Table 3.

Table 2: Overall Preference Matrix

	C	S	P	L
C	1	3	5	7
S	1/3	1	3	5
P	1/5	1/3	1	3
L	1/7	1/5	1/3	1

Table 3: Normalized Overall Preference Matrix

	C	S	P	L
C	0.59659	0.66177	0.53571	0.43750
S	0.19886	0.22059	0.32143	0.31250
P	0.11932	0.07353	0.10714	0.18750
L	0.08523	0.04412	0.03571	0.06250

The Relative Value Vector (RVV) that is an eignvector of weights of criteria is (0.55789, 0.26335, 0.12187, 0.05689, 1.00000). To check validity of RVV, the Consistency Ratio is calculated using Consistency Index (CI), RI and λ_{max}. Consistency Ratio (C.R) = CI/RI

Consistency Index (CI) = (λ_{max}-n)/n-1, where n is number of criteria &RI is the relative index value.

In this analysis the value of CI is found 0.05889 and RI is 0.9 for n=4 as given in index[12,13]. The value of CR is 0.06544 (<0.1) which is less than 0.1 i.e. means CR is consistent and RVV may be used for decision making.

C. Step of Rule Evaluation Process

Proposed Rule Evaluation Process consist the following steps for decision making[12,13]:
Step 1: Data Collection from source of data.
Step 2: Pre-process the Input Data (if required).
Step 3: Apply ARM algorithm to generate Association Rules.
Step 4: List the factors for Rule evaluation process.
Step 5: Establishing the hierarchy of factors based on Rating Scale.
Step 6: Getting the comparison matrix by pair-wise comparison among factors.
Step 7: Calculating the criteria-weight value.
Step 8: Calculating the consistency ratio based on consistency index and random index value.
Step 9: If consistency ratio is less than threshold value then use for assessment, otherwise go to step 6.
Step 10: Use criteria-weight value as RVV (Relative Value Vector) in decision-making process.
Step 11: List the novel rules which may play potential role in decision-making.
Step 12: Calculating the criteria-weight value for Rules with respect to each factor using Step-6 to Step-9.
Step 13: Established Option Performance Matrix (OPM) using criteria-weight value for set of rules with Respect to all factor.
Step 14: Find VFM (Value for Money Vector) by VFM= OPM * RVV (from Step 10).
Step 15: Use VFM as final rating of all rules with respect to all factors and analysis the rules.

IV. RESULTS AND ANALYSIS

Apriori algorithm[1-3] is implemented to generate association rules in ILPD datasets[26]. For this ILPD dataset is pre-processed and missing values are filled by average value of respective attributes. Feature selection is done using Chi Square Method and considered six attributes (feature) only as per their higher range. Data discretisation is conducted and each attribute is divided in three values Low, Normal and High as discussed in [8]. For generating rules from ILPD datasets minimum support value is used from 20% to 30% where at *min_supp*=20% generated rule are 50, at *min_supp*=25% rule are 31 and at *min_supp*=30%, 19 rules were generated. Further generated rules are huge in number and difficult to use them for decision-making purpose. For finding more weighted rules AHP method is applied on generated rules and chooses only 10 novel rules from total 100 rules[8], which is shown in Figure 2. Rule 18, 19, 48 and 49 chosen from support level 0.2 and denoted them as R1, R2, R3 and R4 respectively. Rule 21, 22, 26, 27 and 30 are chosen from support level 0.25 and denoted them as R5, R6, R7, R8 and R9 respectively, similarly rule 14 taken from support level 0.3 and labelled as R10.

The evaluation of rules is done based on four defined criteria (factors) C, S, L and P and their range value is shown in Table 4.

Table 4: Criteria Range Value

S. No.	Criteria (Factor)	Range(Value) of Criteria
1	C	90% to 99%
2	S	20% to 30%
3	P	DB, SGPT, SGOT, TB, ALP, & ALB (in decreasing order of rank as per Chi Square Test)
4	L	03 to 05

R1--18. Direct Bilirubin=DB_H Aspartate Aminotransferase =SGOT_H Albumin =ALB_L 116 ==> Total Bilirubin =TB_H 115 conf:(0.99), Supp(0.2)

R2--19. Direct Bilirubin=DB_H Alkaline Phosphotase=ALP_H Aspartate Aminotransferase =SGOT_H Albumin =ALB_L 105 ==> Total Bilirubin =TB_H 104 conf:(0.99), Supp(0.2)

R3--48. Direct Bilirubin=DB_H Alamine Aminotransferase =SGPT_N 105 ==> Alkaline Phosphotase=ALP_H 95 conf:(0.9), supp(0.2)

R4--49. Total Bilirubin =TB_H Direct Bilirubin=DB_H Aspartate Aminotransferase =SGOT_H Albumin =ALB_L 115 ==> Alkaline Phosphotase=ALP_H 104 conf:(0.9), Supp(0.2)

R5--21. Total Bilirubin =TB_H Aspartate Aminotransferase =SGOT_H Albumin =ALB_L 130 ==> Alkaline Phosphotase=ALP_H 119 conf:(0.92), supp(0.25)

R6--22. Total Bilirubin =TB_H Albumin =ALB_L 149 ==> Alkaline Phosphotase=ALP_H 136 conf:(0.91), Supp(0.25)

R7--26. Direct Bilirubin=DB_H Aspartate Aminotransferase =SGOT_H Albumin =ALB_L 116 ==> Alkaline Phosphotase=ALP_H 105 conf:(0.91)Supp(0.25)

R8--27. Total Bilirubin =TB_H Direct Bilirubin=DB_H Aspartate Aminotransferase =SGOT_H Albumin =ALB_L 115 ==> Alkaline Phosphotase=ALP_H 104 conf:(0.9), supp(0.25)

R9--30. Total Bilirubin =TB_H Direct Bilirubin=DB_H Albumin =ALB_L 131 ==> Alkaline Phosphotase=ALP_H 118 conf:(0.9), Supp(0.25)

R10--14. Total Bilirubin =TB_H Albumin =ALB_L 149 ==> Alkaline Phosphotase=ALP_H 136 conf:(0.91) , supp(0.3)

Fig. 2: Selected 10 rules for analysis purpose[8]

For factor P the rank order is calculated using Chi Square method and find the rank order in terms of features relevancy.

Table 5: Normalized Preference Matrix for rules with respect to Confidence

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
R1	0.26786	0.26786	0.19231	0.19231	0.32143	0.28846	0.28846	0.19231	0.19231	0.28846
R2	0.26786	0.26786	0.19231	0.19231	0.32143	0.28846	0.28846	0.19231	0.19231	0.28846
R3	0.05357	0.05357	0.03846	0.03846	0.03571	0.01923	0.01923	0.03846	0.03846	0.01923
R4	0.05357	0.05357	0.03846	0.03846	0.03571	0.01923	0.01923	0.03846	0.03846	0.01923
R5	0.08929	0.08929	0.11538	0.11538	0.10714	0.17308	0.17308	0.11538	0.11538	0.17308
R6	0.05357	0.05357	0.11538	0.11538	0.03571	0.05769	0.05769	0.11538	0.11538	0.05769
R7	0.05357	0.05357	0.11538	0.11538	0.03571	0.05769	0.05769	0.11538	0.11538	0.05769
R8	0.05357	0.05357	0.03846	0.03846	0.03571	0.01923	0.01923	0.03846	0.03846	0.01923
R9	0.05357	0.05357	0.03846	0.03846	0.03571	0.01923	0.01923	0.03846	0.03846	0.01923
R10	0.05357	0.05357	0.11538	0.11538	0.03571	0.05769	0.05769	0.11538	0.11538	0.05769

For finding Relative Value Vector(RVV) for rules with respect to each criteria, pairwise comparison among the rules is done on Saaty Rating Scale with respect to criteria. Table5 to Table 8 are showing Normalized Preference Matrix for rules with respect to Confidence, Support, Presence of relevant features and Length of rule respectively.

Table 6: Normalized Preference Matrix for rules with respect to Support

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
R1	0.04167	0.04167	0.04167	0.04167	0.03571	0.03571	0.03571	0.03571	0.03571	0.05769
R2	0.04167	0.04167	0.04167	0.04167	0.03571	0.03571	0.03571	0.03571	0.03571	0.05769
R3	0.04167	0.04167	0.04167	0.04167	0.03571	0.03571	0.03571	0.03571	0.03571	0.05769
R4	0.04167	0.04167	0.04167	0.04167	0.03571	0.03571	0.03571	0.03571	0.03571	0.05769
R5	0.12500	0.12500	0.12500	0.12500	0.10714	0.10714	0.10714	0.10714	0.10714	0.09615
R6	0.12500	0.12500	0.12500	0.12500	0.10714	0.10714	0.10714	0.10714	0.10714	0.09615
R7	0.12500	0.12500	0.12500	0.12500	0.10714	0.10714	0.10714	0.10714	0.10714	0.09615
R8	0.12500	0.12500	0.12500	0.12500	0.10714	0.10714	0.10714	0.10714	0.10714	0.09615
R9	0.12500	0.12500	0.12500	0.12500	0.10714	0.10714	0.10714	0.10714	0.10714	0.09615
R10	0.20833	0.20833	0.20833	0.20833	0.32143	0.32143	0.32143	0.32143	0.32143	0.28846

Table 7: Normalized Preference Matrix for rules with respect to Presence of relevant feature

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
R1	0.11029	0.08621	0.10417	0.08523	0.11250	0.13158	0.10274	0.10417	0.21429	0.13158
R2	0.11029	0.08621	0.06250	0.08523	0.11250	0.13158	0.10274	0.10417	0.07143	0.13158
R3	0.33088	0.43103	0.31250	0.42614	0.18750	0.13158	0.30822	0.31250	0.35714	0.13158
R4	0.11029	0.08621	0.06250	0.08523	0.11250	0.13158	0.10274	0.10417	0.07143	0.13158
R5	0.367	0.01724	0.06250	0.02841	0.03750	0.07895	0.03425	0.02083	0.02381	0.07895
R6	0.02206	0.01724	0.06250	0.01705	0.01250	0.02632	0.02055	0.02083	0.02381	0.02632
R7	0.11029	0.08621	0.10417	0.08523	0.11250	0.13158	0.10274	0.10417	0.07143	0.13158
R8	0.11029	0.08621	0.10417	0.08523	0.18750	0.13158	0.10274	0.10417	0.07143	0.13158
R9	0.03676	0.08621	0.06250	0.08523	0.11250	0.07895	0.10274	0.10417	0.07143	0.07895
R10	0.02206	0.01724	0.06250	0.01705	0.01250	0.02632	0.02055	0.02083	0.02381	0.02632

Table 8: Normalized Preference Matrix for rules with respect to Length of Rule

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
R1	0.0	0.06757	0.10000	0.06757	0.07143	0.10000	0.07143	0.06757	0.07143	0.10000
R2	0.21429	0.20270	0.16667	0.20270	0.21429	0.16667	0.21429	0.20270	0.21429	0.16667
R3	0.02381	0.04054	0.03333	0.04054	0.02381	0.03333	0.02381	0.04054	0.02381	0.03333
R4	0.21429	0.20270	0.16667	0.20270	0.21429	0.16667	0.21429	0.20270	0.21429	0.16667
R5	0.07143	0.06757	0.10000	0.06757	0.07143	0.10000	0.07143	0.06757	0.07143	0.10000
R6	0.02381	0.04054	0.03333	0.04054	0.02381	0.03333	0.02381	0.04054	0.02381	0.03333
R7	0.07143	0.06757	0.10000	0.06757	0.07143	0.10000	0.07143	0.06757	0.07143	0.10000
R8	0.21429	0.20270	0.16667	0.20270	0.21429	0.16667	0.21429	0.20270	0.21429	0.16667
R9	0.07143	0.06757	0.10000	0.06757	0.07143	0.10000	0.07143	0.06757	0.07143	0.10000
R10	0.02381	0.04054	0.03333	0.04054	0.02381	0.03333	0.02381	0.04054	0.02381	0.03333

The Relative Value Vector (RVV)with respect to Confidence is (0.249176, 0.249176, 0.03544,0.03544, 0.126648, 0.077747, 0.077747, 0.03544, 0.03544, 0.077747). With respect to Support the RVV is (0.040293, 0.040293, 0.040293, 0.040293, 0.113187, 0.113187, 0.113187, 0.113187, 0.113187, 0.272894). Similarly RVV with respect to Presence of relevant features is (0.118274, 0.099822, 0.292907, 0.099822, 0.04192, 0.024917, 0.103989, 0.111489, 0.081943,0.024917) and with respect to Length of rule the RVV is (0.078842, 0.196525, 0.031686, 0.196525, 0.078842, 0.031686, 0.078842, 0.196525, 0.078842, 0.031686). The consistency Ratio (CR) is calculated using λ_{max}, RI, and Consistency Index (CI) for validity of each RVV, which is shown in Table 9, where for each case CR is less than 0.1. RI value is taken 1.49 for n=10.

Table 9: Parameter value for RVV

For RVV with respect to	λ_{max}	CI	CR
C	10.77114	0.08568	0.05750
S	10.09621	0.01069	0.00717
P	10.58003	0.06445	0.04325
L	10.17544	0.01949	0.01308

As shown in Table 10, the rule R1 and R2 both exhibit the highest performance based on confidence. The rule R3 exhibit the best performance based on presence of relevant features. In similar way, we can find out the importance of other rules with respect to individual factor.

The Final Value for Money Vector (VMF) is (R1, R2, R3, R4, R5, R6, R7, R8, R9, R10)=(0.16850,0.17300, 0.06790, 0.05370, 0.11010, 0.07800, 0.09030, 0.07430, 0.06410, 0.12010) which is ranked rules and same is represented in figure 3.

Table 10: Option Performance Matrix

	C	S	P	L
R1	**0.249176**	0.040293	0.118274	0.078842
R2	**0.249176**	0.040293	0.099822	0.196525
R3	0.03544	0.040293	**0.292907**	0.031686
R4	0.03544	0.040293	0.099822	0.196525
R5	0.126648	0.113187	0.04192	0.078842
R6	0.077747	0.113187	0.024917	0.031686
R7	0.077747	0.113187	0.103989	0.078842
R8	0.03544	0.113187	0.111489	0.196525
R9	0.03544	0.113187	0.081943	0.078842
R10	0.077747	0.272894	0.024917	0.031686

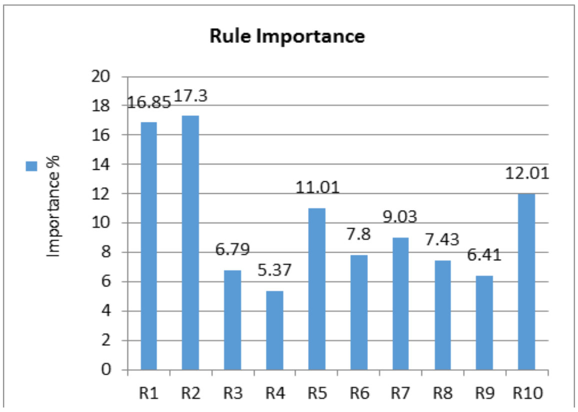

Fig. 3: Performance weightage of Rules

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As per result rule R2 is ranked as 17.3, which is highest over the other rules. It can be interpret as when Direct Bilirubin, Alkaline Phosphotase, Aspartate Aminotransferase, Total Bilirubin are high and Albumin is low, then 99% chance for liver disorder. Similarly R1 have ranked by 16.85 which is closer to R2 and it may interpret same as R2. But in both case Albumin is low which may indicate its importance in liver disorder.

V. CONCLUSION

In this work, AHP based rule evaluation method is proposed which works based of consistency in judgment among criteria and gives final Weight vector (importance) for rules generated by ARM technique. Further, rules are evaluated based on their weight values. In similar way importance of different rules with respect to individual criteria is evaluated based on Option Performance Matrix. It is observed that out of hundred rules only ten novel rules exhibit the importance for evaluation purpose and rule R2 scored the highest importance. And R1 scored the second highest importance and very close to R2. Both may be clubbed for recommendation purpose. In some situation where ranks of different rules are very close to each other, it is complex to prioritize the rules, in such situation fuzzy based evaluation process may play a better role in the analysis process.

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