

# Analysis of Association Rule for Heart Disease Prediction from Large Datasets

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**ABSTRACT:** Cardiovascular disease is a major threat to half of the world population. The term heart disease is related to all the diverse diseases affecting the heart. The healthcare industry generates huge amounts of data that are too difficult to be analyzed by traditional methods. Hence computer assisted methods are necessary to make correct decisions. Heart disease is a term that assigns to a large number of medical conditions related to heart. These medical conditions describe the abnormal health conditions that directly influence the heart and all its parts. The main issue about mining association rules in a medical data is the large number of rules that are discovered, most of which are irrelevant. A rule-based decision support system (DSS) is presented for the diagnosis of coronary vascular disease (CVD). Such number of rules makes the search slow. However, not all of the generated rules are interesting, and some rules may be ignored. In medical terms, association rules relate disease data measures the patient risk factors and the occurrence of the disease. Association rules are compared to predictive rules mined with decision trees, a well-known machine learning technique. In this paper, we propose a new system to find the strength of association among the attributes of a given data set. The proposed system has several advantages since it is automatically generated. It provides CVD diagnosis based on ease and none invasively acquired features.

**KEYWORDS:** Data mining; Decision Tree; Association Rule Mining; Machine Learning Technique

## I. INTRODUCTION

Data mining is the process of finding previously unknown patterns and trends in databases and using that information to build predictive models. In healthcare, data mining is becoming increasingly popular, if not increasingly essential. Healthcare industry today generates large amounts of complex data about patients, hospital resources, disease diagnosis, electronic patient records, medical devices, etc. The large amount of data is a key resource to be processed and analyzed for knowledge extraction that enables support for cost-savings and decision making. Data mining provides a set of tools and techniques that can be applied to this processed data to discover hidden patterns and also provides healthcare professionals an additional source of knowledge for making.

Recent studies have documented poor population health outcomes in coal mining areas. These findings include higher chronic cardiovascular disease (CVD) mortality rates and higher rates of self-reported CVD [13]. The risk for CVD is influenced by environmental, genetic, demographic, and health services variables. Risk behaviors, in turn, are related to lower socioeconomic status (SES); low SES persons are more likely to smoke, consume poor quality diets, and engage in sedentary lifestyles. Coal mining areas are characterized by lower SES relative to non-mining areas, suggestive of higher CVD risk. Environmental agents that contribute to CVD include arsenic, cadmium and other metals, non-specific particulate matter (PM), and polycyclic aromatic Hydrocarbons (PAHs).

We also refer to Computer-aided diagnosis methodologies as stated [15] in the literature; in this case, the data obtained by some of the aforesaid methods or other sources (i.e., laboratory examinations, demographic and/or History data, etc.) are evaluated from a computer-based application, leading to a CVD diagnosis. These methodologies can be divided into various categories, based on the type of data they use for subject characterization: 1) methods that employ the resting or exercise ECG of the patient, extracting features from it, such as the ST segment [17], [16], the QT interval, the T wave amplitude, the R wave, and the heart rate variability (HRV); 2) methods using medical images such as SPECT; 3)

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methods based on heart sounds associated with coronary occlusions[18] ; 4) methods based on arterio-scillography[19]; 5) methods based on Doppler ultrasound signals[20] ; 6) methods employing demographic, history, and laboratory data (subject's data) ; and 7) methods combining more than one type of data such as ECG, scintigraphy, and subject's data.

## II. RELATED WORK

This section introduces association rules, terminology and some related work on rare association rules.

### A. ASSOCIATION RULES:

Formally, association rules are defined as follows: Let  $me = \{i_1, i_2 \dots i_n\}$  be a set of items,  $D$  is a set of transactions, where each transaction  $T$  is a set of items such that  $T \subseteq I$ . Each transaction is associated with a unique identifier  $TID$ . An action  $T$  is said to contain  $X$ , a set of items in  $I$ , if  $X \subseteq T$ . An association rule is an

The implication of the form " $X \rightarrow Y$ ", where  $X \subseteq I$ ; why  $I$ , and  $X \cap Y = \Phi$ . The rule  $X \rightarrow Y$  has *supported* in the Transaction set  $D$  if  $s\%$  of the transactions in  $D$  contains  $X \cup Y$ . In other words, the support of the rule is the probability that  $X$  and  $Y$  hold together among all the possible presented cases. It is said that the rule  $X \rightarrow Y$  holds in the transaction set  $D$  with *confidence*  $c$ . If  $c\%$  of transactions in  $D$  that contain  $X$  also contain  $Y$ . In other words, the confidence of the rule is the conditional probability that the consequent  $Y$  is true under the condition of the antecedent  $X$ . The problem of discovering all association rules from a set of transactions  $D$  consists of generating the rules that have a *supportive* and *confidence* greater than are given thresholds. These rules are called *strong rules*, and the framework is known as the support-confidence framework for association rule mining.

### B. TRANSFORMING MEDICAL DATA SET:

A medical dataset with numeric and categorical attributes must be transformed to binary dimensions, in order to use association rules. Numeric attributes are binned into intervals and each interval is mapped to an item. Categorical attributes are transformed by mapping each categorical value to one item. Our first constraint is the negation of an attribute, which makes the search more exhaustive. If an attribute has negatively then additional items are created corresponding to each negated categorical value or each negated interval. Missing values are assigned to additional items, but they are not used. In short, each transaction is a set of items and each item corresponds to the presence or absence of one categorical value or one numeric interval.

Markos G. Tsipouras et.al proposed as in prediction of heart attack describes two demographic features were recorded: the age and sex of the patient. From the subject's history, the family history of CAD (FH), smoking history (smoke), history of diabetes mellitus (DM), and hypertension (HT) or hyperlipidemia were used. Family history of CAD was defined as the presence of CAD in the father or brother aged  $<55$  years or mother or sister aged  $<65$  years. Current and ex-smokers were defined as having smoked the last cigarette less than a week and less than a year before the CA, respectively. Diabetes mellitus was defined as a fasting blood glucose concentration (FBGC)  $\geq 126$  mg/dl or antihyperglycemic drug treatment, hypertension as systolic blood pressure (SBP)  $>140$  mm Hg, and/or diastolic blood pressure (DBP)  $>90$  mm Hg or use of antihypertensive agents, and hyperlipidemia as fasting total cholesterol  $>220$  mg/deal or use of lipid-lowering agents (statins or fibrates). Other clinical data were also recorded; body mass index (BMI), calculated as weight (kg) divided by the square of height (square meter), waist perimeter measured in centimeter, resting heart rate (HR), measured in beats per minute (b/min), resting SBP and DBP measured in mmHg. The laboratory investigations also incorporated were creatinine (Cr), glucose (Glu), total cholesterol (Tchol), high-density lipoprotein (HDL), and triglycerides (TRG) measured in milligrams per deciliter (mg/DL). All the aforementioned features are considered to be traditional cardiovascular risk factors widely used to assess the risk of CAD. In addition, carotid-femoral pulse wave velocity (PWVcf) and augmentation index (AIx) expressed in meter per second, and percentage, respectively, were also used as noninvasively indices of arterial stiffness.

In the association rules we generate the rules such as  $Rule_i = (at_1 op V1) \wedge (at_2 op V2) \wedge \dots \wedge (at_m op Vm)$ , where  $(at, V_j)$  is an attribute and its threshold-values pair and  $op$  is a comparison operator can be  $(=, !=, >, <, \leq, \geq)$ .

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## III. PROPOSED METHODOLOGY AND DISCUSSION

We propose the AA (I) Attribute Association, which is an extension to OA which finds the association among the attributes [4] of a dataset. A patient having a disease that can be always a combination of symptoms such as fever, may come with stress or due to change in climate. The other patient may have a fever with cold and cough. Our interest is to find the strength between the symptoms or diseases how frequently they are associated. In our future study, we would like to extend this to the heart attack and find the strength between co-morbid attributes influencing the patient towards CVD. Let  $I = \{\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_m\}$  be an attribute set.

Further, we calculate frequencies of various attributes in the dataset which has more association among the attributes and analyze the results.

### **ALGORITHM: DAST (Defining Association Strength)**

**Input:** TD-transaction Database, MS-Minimum Support, MC-Minimum Confidence, MA-Minimum Association

**Output:** Strong Association datasets

**Method:**

Step 1.  $C_1$  = Candidate 1-itemsets

Step 2.  $L_1$  = frequent 1-itemsets

Step 3. for ( $K=2$ ;  $L_{K-1} \neq \emptyset$ ;  $K++$ )

Step 4. {

Step 5.  $CK = L_{K-1} \bowtie L_{K-1}$

Step 6. for each  $c \in CK$

Step 7. If any subset of  $c \notin L_{K-1}$

Step 8. Then  $CK = CK - \{c\}$

Step 9. for each  $c \in CK$

Step 10. {

Step 11. If support ( $c$ )  $\geq M_s$  then  $L_k = L_k \cup \{c\}$

Step 13. }

Step 14. for each  $c \in L_k$

Step 15. {

Step 16. If  $A(c) \geq M_a$

Step 17. {

Step 18. for each  $c = (x \cup y)$  //  $x$  contains any number of items but  $y$  contains only one item //

Step 19. If confidence ( $x \rightarrow y$ )  $\geq M_c$

Step 20. Then  $SAR = SAR \cup \{x \rightarrow y\}$

Step 21. }

Step 22. }

Step 23. }

## IV. EXPERIMENTAL RESULTS

We calculate frequencies of various attributes in the dataset which has more association among the attributes and analyze the results. The experiment result is derived depends on age and sex centralized category.

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Table 1. For Age

|       |       | Frequency | Percent | Valid Percent | Cumulative Percent |
|-------|-------|-----------|---------|---------------|--------------------|
| Valid | 25-35 | 7         | 2.3     | 2.3           | 2.3                |
|       | 35-45 | 57        | 18.6    | 18.6          | 20.9               |
|       | 45-55 | 89        | 29.0    | 29.0          | 49.9               |
|       | 55-65 | 121       | 39.4    | 39.4          | 89.3               |
|       | 65-75 | 31        | 10.0    | 10.0          | 99.3               |
|       | >75   | 2         | 0.7     | 0.7           | 100.0              |
|       | Total | 307       | 100.0   | 100.0         |                    |

The above table shows that the CVD risk between the grouped persons which they belongs to different age groups for the test analysis. The frequencies are measured based on the parameters required.

Table 2. For Sex

|       |        | Frequency | Percent | Valid Percent | Cumulative Percent |
|-------|--------|-----------|---------|---------------|--------------------|
| Valid | Male   | 98        | 32.0    | 32.0          | 32.0               |
|       | Female | 209       | 68.0    | 68.0          | 100.0              |
|       | Total  | 307       | 100.0   | 100.0         |                    |

The above table show that the CVD risk is more in male gender that are in the age range between 55 & 65. Similar measures are applied to calculate the statistics of each attribute frequency and we can apply this for prediction of heart attack.

## V. CONCLUSION

In this paper, we proposed a new measure that finds the association among the various attributes in a dataset. Our method generates valid association rules by taking a probability measure. We conducted experiments on synthetic and real data sets. We have applied the measure to both frequent and infrequent items set to the dataset. Surprisingly, we found that the infrequent itemset is also having the association among the attributes. This type of association is possible in the case of diseases. In our future work we wish to conduct experiments on large real time health datasets to predict the diseases like heart attack and compare the performance of our algorithm with other related algorithms.

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