A New Learning Algorithm of Naive Bayesian Classification

by

Md. Shamsul Huda

প্রকৌশল বিশ্ববিদ্যালয়
98033
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লাইব্রেরী, ঢাকা
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Board of Examiners

CM Rahman

Dr. Chowdhury Mofizur Rahman — Chairman and Supervisor
Professor
Department of Computer Science and Engineering
Bangladesh University of Engineering and Technology
BUET, Dhaka-1000, Bangladesh

M. M. Islam 9.06.03

Dr. Md. Monirul Islam — Member
Assistant Professor
Department of Computer Science and Engineering
Bangladesh University of Engineering and Technology
BUET, Dhaka-1000, Bangladesh

Dr. Md. Abul Kashem Mia — Member (Ex-officio)
Associate Professor and Head
Department of Computer Science and Engineering
Bangladesh University of Engineering and Technology
BUET, Dhaka-1000, Bangladesh

Md. Haider Ali.

Dr. Md. Haider Ali — Member (External)
Associate Professor
Computer Science Department
University of Dhaka
Bangladesh.

Declaration

This is to certify that the work presented in this thesis is the outcome of the investigation carried out by the candidate under the supervision of Prof. Dr. Chowdhury Mofizur Rahman in the Department of Computer Science and Engineering, Bangladesh University of Engineering and Technology, Dhaka. It is also declared that neither of this thesis nor any part thereof has been submitted or is being concurrently submitted anywhere else for the award of any degree or diploma.

Signature of
Supervisor

Signature of
Author

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Abstract

Naive Bayes (NB) is one of the most efficient and effective learning algorithms for machine learning and data mining tasks due to its linear computational and memory complexities and easier implementation technique. The main focus of NB is the simplification of Bayes Optimal Classifier. A common problem in Bayes Optimal Classifier is the direct estimation of class-conditional probability distribution (CPD) from a given training data set with high dimensional feature space while finding the *maximum a posteriori* probability (MAP) hypothesis for a given example whose prediction is not specified. Estimation of CPD from a given training data set with high dimensional feature space requires that every possible combination of attribute values must be available in training data which is usually not found in real life learning domains. NB uses some approximations to eliminate this problem by using the simplifying assumption that attribute values are conditionally independent given the class values. If all the attributes are truly independent, NB makes the same prediction as Bayes Optimal Classifier and NB is said to be working perfectly. But this independence assumption is almost always violated in practice and as a result classification accuracy of NB degrades in a large number of learning domains. In this thesis, we propose a new learning algorithm of Naive Bayesian classification to alleviate the independence assumption problem in NB, thereby, improving the performance of NB and sustaining its optimality to all learning domains which makes it universal. In our algorithm, a measure of attribute dependence is considered for each attribute. Attribute dependence of each attribute on other attributes is estimated from training data set with the help of dependency equation. Most interdependent attributes are selected based on their dependency and by applying a leave-one-out cross validation on training data set. A subset of examples is chosen using these attributes with their values in a test example. A local NB is applied on this subset to classify the test example. The algorithm has been tested on a wide range of natural and artificial learning domains taken from UCI machine learning repository. Experimental result shows that the new algorithm obtains a lower error rate than that of NB classifier, BSEJ and LBR. In some domains its error rate is lower than that of modern decision tree learning algorithm C4.5, LAZYDT also.

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Chapter One

Introduction

In section 1.1 of this chapter we spell out the classification and associated problems and their applications in real life problems. Section 1.2 explains the weakness of Naive Bayesian classification and its suitability in very restricted learning problems. Section 1.3 surveys the related works attempted to alleviate the problems of Naive Bayesian classifier. Section 1.4 briefly mentions the objective of this thesis and the organization of the thesis is discussed in section 1.5.

1.1 Classification and its Applications

Classification is a task of selecting a hypothesis from a set of alternatives that best fits a set of observations. In a classification task, one is given an object having some set of attributes and is expected to correctly classify the object into one of several predefined categories. The attribute values of the incoming objects vary, and one hopes that the classification can be done based on the actual values of these attributes. In a supervised learning scenario, the classifier is provided with a set of training examples prior to performing the real classification task. Each training example consists of an object to be classified, as well as the correct category to which it should be assigned. Thus, during learning phase the classifier analyzes the training examples and builds a model to store any knowledge which is learned about the problem space. This model is later applied to help the classifier perform the real classification task.

Classification is an automatic and intelligent technique of machine learning which is widely used in many practical applications of the fields like data mining, information retrieval, image processing, bioinformatics, stock prediction, medical diagnosis, weather forecasting etc. These applications typically involve finding inherent pattern, extracting hidden information in massive data, predicting unknown data, discovering appropriate decision for new situations.

A large number of machine learning applications concern recognizing diseases and predicting the development of diseases. In these studies patient's records are collected and used in a classification technique to learn a model that can recognize a disease or predicts its development. Medical diagnosis is known to be subjective and depends not only on the available data but also on the experience of the physician, his intuition and biases, and even on the psycho-physiological condition of the physician. Several studies have shown that the diagnosis of one patient can differ significantly if the patient is examined by different physicians or even by the same physician at different time (different day of the week or different hour of the day). Machine learning technology is well suited for the induction of diagnostic and prognostic rules and solving of small and specialized diagnostic and prognostic problems. Data about correct diagnoses/prognoses is often made available from archives of specialized hospitals and clinics, where the number of stored cases grows daily. Past records of the patients with known correct diagnosis are used in classification algorithm to train the classifier and medical diagnostic knowledge can be automatically derived from the description of cases solved in the past by the derived classifier. This classifier can then be used either to assist the physician when diagnosing new patients in order to improve the diagnostic speed, accuracy and/or reliability, or to train the students or physicians non-specialists to diagnose the patients in some special diagnostic problem. Automatically derived diagnostic knowledge may assist physicians to make the diagnostic process more objective and more reliable and in many studies, it is seen that classifier outperform the diagnostic accuracy of physicians specialists when physicians have available exactly the same information as the input of the learning algorithm.

Biological data are flooding in an enormous rate and causing the current databases to expand at an exponential rate due to the new and efficient experimental techniques in analyzing genomes and proteins sequences. Conventional algorithms are becoming unable to handle the large, rapidly expanding amount of data and to address the real world problems due to the complexity of biological systems and lack of fundamental theory at molecular level. Machine learning approaches as well as classification algorithms are becoming one of the favorite techniques in bioinformatics because programs based on these approaches can learn automatically from the available data and produces useful hypotheses.

In an information retrieval system, classification technique is used to classify a document into groups on the basis of common content or common characters. Classification of text is the primary requirement in these systems.

In a decision support weather forecasting system weather observing and forecasting operations is greatly assisted with the immediate assessment of metrological parameters when ground observations are not available. To this end, numerical weather prediction data and satellite data from various sensors and platforms are being used to develop automated algorithms to assist in operational weather assessment and forecasting. Supervised machine learning techniques as well as classification algorithms are used to develop associated classification and parameter estimation algorithms. These approaches are used to diagnose the sensible weather elements more accurately than numerical weather prediction or satellite methods alone.

1.2 Naive Bayesian Classification and its Problems

The Naive Bayes' (NB) Model [14, 15] is an efficient and well known method for performing supervised learning of classification problems. Primarily it tries to remove some problems of Bayesian learning, though Bayes' rule provides an optimal way to predict the class of an unknown example. But it requires that every possible combination of attribute values must be available in training data. Thus the application of Bayes' rule in machine learning is restricted by the inability to determine accurate values for class conditional probabilities. In standard machine learning applications class conditional probabilities must be estimated from training data. If there were sufficient randomly sampled examples of every possible combination of attribute values, such estimation would be straight-forward and acceptably reliable and accurate. However, most combinations are not represented in the training data. Hence, class conditional probabilities can not be calculated accurately while applying Bayesian learning. Naive Bayesian (NB) learning circumvents this problem by assuming that all attributes are independent. This assumption makes Naive Bayes simple and time efficient, gives it a linear time complexity dependent only of training data. Given n training examples over k attributes, the time required to learn a NB classifier is O(nk). The independence assumption makes NB also space efficient. Since, after discretization, NB builds up a frequency table in size of the product of the number of attributes, number of class values and the number of values per attribute. Many empirical comparisons between NB and modern decision tree algorithm such as C4.5 [20] show that NB predicts equally as well as C4.5. NB is robust to the domains with noise and irrelevant attributes. NB considers evidence from many attributes to classify examples. This is important when many attributes affect the classification. However, when the attribute independence assumption of NB is violated, which appears to be very common and realistic, the performance of Naive Bayesian classifier becomes very poor and classification accuracy degrades. In other words, the performance of NB classifier in this kind of domain can be further improved.

1.3 Literature Review

A number of approaches have been sought to alleviate the independence assumption problem of Naive Bayesian classifier. It includes NBTree [12], LBR [24], RBC [16], BSEJ [19] etc.

NBTree is a hybrid approach combining the Naive Bayesian classifier and Decision tree learning. It uses Bayesian tree method to split the instance space into sub-spaces and generate one Naïve Bayesian classifier in each sub-space. While splitting the training space into subspace it suffers from small disjuncts problem of tree learning [10]. NBTree frequently achieves higher accuracy than a Naïve Bayesian classifier or Decision tree learner but error rate increases due to the problem of small disjuncts.

LBR [24] (Lazy learning of Bayesian Rule) uses a lazy learning technique to learn a Bayesian rule. It retains all training example until classification time. Before classifying a test example, LBR generates a rule called Bayesian rule that is most appropriate to the test example. For a given training set and each test example, LBR starts from a special Bayesian rule whose antecedent is true. Its local naive Bayesian classifier in the consequent part is trained on the entire training set using all attributes. This Bayesian rule is identical to a conventional naive Bayesian classifier. LBR then uses an extensive search to grow an antecedent that matches the test example, with the aim of reducing the errors of its local naive Bayesian classifier. During the growth of the Bayesian rule each candidate Bayesian rule is evaluated by performing an N-fold cross validation estimation of its local naive Bayesian classifier on the local training set. At each step of the search, LBR tries to add, to the current Bayesian rule, each attribute that has not already been in the antecedent of the rule, so long as its value on the test example is not missing. The objective is to determine whether including a test on this attribute can significantly improve upon the classification accuracy. At the end of this step, the candidate attribute-value pair with lowest measure is added to the antecedent of the current Bayesian rule. All the current local training examples that satisfy this attribute-value pair form the local training set to the new Bayesian rule, while all other examples are discarded. This process is repeated until no candidate attribute-value pair can be found. This happens when further growing of the Bayesian rule would not significantly reduces error. Then the growth of Bayesian rule stops. Local naive Bayesian classifier of this Bayesian rule is used to classify the test case. LBR ignores attributes with missing value in the test case. It requires extensive computation while generating Bayesian rule for a test example. While applying LBR on a dataset of small size, it can not improve the performance of Naive Bayesian classifier. LBR is similar to LAZYDT [9] with respect to performing lazy learning of decision rule.

LAZYDT generates decision rule at classification time and a subset is chosen by this rule. Then a majority vote is applied in the subset to classify the test case. Consequent of a rule in LAZYDT is a single class that is used for classification whereas LBR uses a local Naive Bayesian classifier in the consequent of a rule.

RBC [16] alleviates the attribute inter-dependence problem of NB classification by identifying regions of the instance space in which the independence assumption holds. It recursively splits the instance space into sub-spaces using a tree structure. Each internal node of the tree is a naive Bayesian classifier that divides the local training examples at the node into clusters of which each corresponds to an instances sub-space of the (sub) space at the node. When a cluster consists of training examples from only one class the tree growing procedure halts. RBC performs well on artificial domain but did not prove superior to NB on a set of natural domains.

BSEJ [19] (Constructive Bayesian Classifier) uses constructive induction and attribute deletion to alleviate the attribute independence assumption problem of NB classifier. It uses an extensive search at each step to delete one attribute or to create one new attribute through joining two attributes (by generating the Cartesian product of two attributes). It starts from the set all original attributes and stops when neither join nor deletion can improve upon the accuracy of NB classifier estimated using N-CV on the training set. The NB classifier built on the current set of attributes including new attributes is returned as the final classifier. This requires enormous computational time in attribute deletion and addition.

1.4 Objective of the Thesis

Classification algorithms of Machine Learning Technology are comprehensively used in the fields like data mining, pattern recognition, image processing, bioinformatics etc. Research work is being continued to develop efficient classification algorithm and to boost up the performance of existing classification algorithms. The present research focuses the enhancement of the most well known optimal learning algorithm "Naive Bayesian (NB) classifier".

The objectives of the present research are as follows:

- Investigation and elimination of the problems of NB classification.
- Analysis of existing algorithms improving the performance of NB.
- To develop an efficient learning algorithm of NB classification and improve the performance of NB.
- To observe the effect of training data set size on the performance of the proposed learning algorithm.
- To make the learning algorithm applicable to small size as well as large size of dataset.

1.5 Thesis Organization

The remaining part of this thesis is organized in four chapters. Chapter 2 describes the problems of Bayes' theorem, evolution of Naive Bayesian classification. Some recently developed algorithms improving the performance of NB are also discussed in this chapter. Attribute dependence, proposed algorithm, flow chart, working procedure and description of the steps of proposed algorithm using example data sets of Soybean and Zoology domain are delineated in chapter 3. Chapter 4 illustrates detail description of experimental analysis for a wide range of natural and artificial learning domains including domain descriptions, attribute dependence and error rate chart for each domain. Conclusions of the obtained result are presented in Chapter 5.

Chapter Two

Bayesian Learning

Section 2.1 of this chapter explains Bayes' theorem and its application to classification problems. We illustrate the difficulties arising out in direct application of Bayes' theorem to classification problems. Section 2.2 explains how Naive Bayesian classification evolves from the original Bayes' theorem by adopting some simplifying assumption. Adoption of this simplifying assumption makes Naive Bayesian approach inapplicable to most of the real world problems. Some recent algorithms for alleviating the Naive Bayesian problem are discussed in section 2.3. Section 2.4 briefly explains our approach to solve the problems of Naive Bayesian classification.

2.1 Bayes' Theorem and its Problems

In many machine learning applications, we are often interested in determining the best prediction of a test example whose attribute's values are given but class value is not specified, given a set of training examples. In training examples both the attribute values and class values of each example are given. One way to specify what we mean by the best prediction of test example is to say that we demand the most probable prediction of the test example. Bayes theorem provides a direct method to calculate the most probable prediction of an unknown example. Let us assume that we are given a set of training examples which has attributes A_1 through A_k and an associated class C. Each attribute and class of each example in training data has a discrete value. We consider a test example whose class value is unknown but attributes A_1 through A_k have the values $a_1, \ldots, a_k$. Thus the test example can be described as $A_1 = a_1, A_2 = a_2, A_3 = a_3, \ldots\ldots, A_k = a_k$, $Class\ C = unknown$. The optimal prediction of the test example is class value c such that $P(C = c \mid A_1 = a_1 \wedge \ldots\ldots A_k = a_k)$ is maximum.

By Bayes' rule this probability equals.

$$\arg\max_{c_i \in C} \frac{P(A_1 = a_1 \wedge \ldots\ldots A_k = a_k \mid C = c_i)}{P(A_1 = a_1 \wedge \ldots\ldots A_k = a_k)} P(C = c_i)$$

(2.1)

$P(C=c_i)$ = Prior probability of class c_i

$P(A_1 = a_1 \wedge \ldots\ldots A_k = a_k)$ = Example Probability

$P(A_1 = a_1 \wedge \ldots\ldots A_k = a_k \mid C = c_i)$ = Class conditional probability

$c_i = i\ th$ value of class C

The prior probability of a class can be estimated from training data. The example probability is irrelevant for decision making since it is same for each class value c. Learning is therefore reduced to the problem of estimating the class conditional probability from training examples.

We know conditionalized version of product rule as:

$[P(A \wedge B \mid E) = P(A \mid B \wedge E) P(B \mid E)]$

Using this rule class-conditional probability can be written as:

$$P(A_1 = a_1 \mid A_2 = a_2 \wedge \ldots\ldots A_k = a_k \wedge C = c_i).\ P(A_2 = a_2 \wedge \ldots\ldots A_k = a_k \mid C = c_i)$$

Recursively the second factor can be written as:

$$P(A_2 = a_2 \mid A_3 = a_3 \wedge \ldots\ldots A_k = a_k \wedge C = c_i) \cdot P(A_3 = a_3 \wedge \ldots\ldots A_k = a_k \mid C = c_i)$$

In this way class conditional probabilities can be written in expanded from as:

$$\begin{aligned} P(A_1 = a_1 \wedge \ldots\ldots A_k = a_k \mid C = c_i) = {} & P(A_1 = a_1 \mid A_2 = a_2 \wedge \ldots\ldots A_k = a_k \wedge C = c_i) \\ & \times P(A_2 = a_2 \mid A_3 = a_3 \wedge \ldots\ldots A_k = a_k \wedge C = c_i) \\ & \times P(A_3 = a_3 \mid A_4 = a_4 \wedge \ldots\ldots A_k = a_k \wedge C = c_i) \\ & \times P(A_4 = a_4 \wedge \ldots\ldots A_k = a_k \mid C = c_i) \end{aligned}$$

(2.2)

and so on.

All factors in equation (2.2) must be calculated from training examples. From equation (2.2) it is seen that Bayes' rule requires that every possible combination of attribute values must be available while calculating class conditional probabilities. In practical training data set, all possible combination of attribute values are not easily found since large number of examples is not available in training data set. Therefore calculation of class-conditional probabilities contains error. Hence classification accuracy goes down in Bayesian learning. This problem is alleviated partially in Naive Bayes'.

2.2 From Bayes to Naive Bayes'

One highly practical Bayesian learning method is the Naive Bayes learner, often called the *Naive Bayesian classifier.* The naive Bayes classifier is based on the simplifying assumption that the attributes are conditionally independent given the class value of each example in the training data set. Suppose we assume for each attribute A_i that its outcome is independent of the outcome of all other attributes A_j, given c, then first factor at the right hand side of equation (2.2) can be written as:

$$P\left(A_1 = a_1 \mid A_2 = a_2 \wedge ......A_k = a_k \wedge C = c_i\right) = P\left(A_1 = a_1 \mid C = c_i\right).$$

Similarly second factor at the right hand side of equation (2.2) can be written as:

$$P\left(A_2 = a_2 \mid A_3 = a_3 \wedge ......A_k = a_k \wedge C = c_i\right) = P\left(A_2 = a_2 \mid C = c_i\right)$$

The third factor will be:

$$P\left(A_3 = a_3 \mid A_4 = a_4 \wedge ......A_k = a_k \wedge C = c_i\right) = P\left(A_3 = a_3 \mid C = c_i\right)$$

For A_4 through A_k similar expressions follow.

Thus class conditional probabilities transforms as:

$$P\left(A_1 = a_1 \wedge ......A_k = a_k \mid C = c_i\right)$$

$$= P\left(A_1 = a_1 \mid C = c_i\right) P\left(A_2 = a_2 \mid C = c_i\right) ......P\left(A_k = a_k \mid C = c_i\right)$$

By assuming i = 1.....k and attributes are mutually independent within each class, class-conditional probabilities transforms as:

$$P\left(A_1 = a_1 \wedge ...... A_k = a_k \mid C = c_i\right) = \prod_{i=1}^{k} P\left(A_i = a_i \mid C = c_i\right)$$

If we put this value in equation (2.1) and discard the example probability as it is same for all class values, equation (2.1) transforms as follows:

$$\equiv \operatorname{argmax}_{class\ value\ c_i \in C} P\left(C = c_i\right) \prod_{i=1}^{k} P\left(A_i = a_i \mid C = c_i\right) \qquad (2.3)$$

This equation is known as Naive Bayesian equation. Independence assumption makes Bayesian learning easier in Naive Bayes' and classification accuracy in NB increases more than that of Bayesian learning in many domains. But a large number of domains violate this assumption of NB and classification accuracy degrades.

2.3 Recently Improved Algorithms

A number of algorithms have been developed to remove the independence assumption problem of Naive Bayesian classifier. One of them is LBR [25] which uses a lazy learning technique to classify an unknown example. It retains all training example until classification time. It requires extensive computation while classifying a test example. While applying LBR on a dataset of small size, it can not improve the performance of Naive Bayesian classifier. A recent improvement in LBR has been made which is known as "A heuristic Lazy Bayesian rule algorithm" [25]. In this improvement, LBR is compared with tree augmented Bayesian classifier and a new heuristic LBR classifier is formed by combining the elements of the two. It reduces the computational overhead of previous version but prediction accuracy remains same. Another improved implementation of BSEJ [19] is BSE [24]. BSE is selective naive Bayesian classifier similar to BSEJ except that each step of greedy search, BSE only considers deleting one existing attribute whereas BSEJ considers both deletion of existing attribute and creation of new attribute from two nominal attributes. Cartesian product attribute formed from two nominal attributes is a nominal attribute whose value set is the Cartesian product of the value sets of the nominal attributes. For example, two nominal attributes A and B has the value sets $\{a_1, a_2, a_3\}$ and $\{b_1, b_2\}$ respectively. The Cartesian product attribute formed from A and B has the value set $\{a_1b_1, a_1b_2, a_2b_1, a_2b_2, a_3b_1, a_3b_2\}$. BSE reduces the computational overhead of BSEJ but accuracy is kept unchanged.

2.4 Our Approach

In our algorithm, to alleviate the attribute independence assumption problem of Naive Bayesian classifier we consider a measure of attribute dependence for each attribute in the training examples. The dependence of each attribute on other attributes is calculated using dependency equation described in the next chapter. Attributes are ordered according to its dependencies in descending order. Most inter dependent attributes are selected using leave-one-out procedure. These attributes with their values found in a test example are used to select a subset of examples from the training examples. A local Naive Bayesian classification is applied on this subset of examples to classify the test example.

Chapter Three

Proposed Algorithm

In this chapter, we describe a new algorithm to alleviate the independence assumption problem in Naive Bayesian classification. The steps of the proposed algorithm, flow chart and pseudocode of the algorithm, attribute dependency, dependency equation and the procedure for selecting the final rule from the calculated error rate are described in detail in Section 3.1. Section 3.2 gives a detail delineation of proposed algorithm using two popular datasets Soybean and Zoology domains.

3.1 Operational Description of Proposed Algorithm

We propose a new algorithm which mitigates the independence assumption problem in Naive Bayesian (NB) classification and makes it applicable to various natural and artificial domains. The algorithm is applicable to domains of both small and large dataset size. In this algorithm a test example is classified by choosing a subset of examples from the training data and applying a local NB on the subset. The subset is chosen with a selection criteria based on most interdependent attributes and their values in the test example. The main steps of the algorithm and the working procedure are as follows. Fig 3.1 gives the flow diagram and Fig 3.2 gives the pseudocode of the algorithm.

Step 1: We take a data set as initial training data T_i of total "m" examples and "L" attributes.

Step 2: We find the distinct values of each attribute from the training data. An attribute of an example in training data has a specified value. This value may be repeated in other examples of the training data. But we consider only the distinct values for a particular attribute in all training examples. If the example has no specified value for a particular attribute, we consider it as a missing value and in our algorithm it is taken as a new type [11] of value for that attribute.

Step 3: In this algorithm we mitigate the independence assumption problem in Naive Bayesian classification. For this purpose, we find attribute's dependency on each other. Hence, we compute a measure of attribute dependency of each attribute on other attributes from training examples by the help attribute dependency equation (3.1). We describe attribute dependency and dependency equation later in this chapter.

Step 4: At this step, attributes are ordered based on their dependency in descending. This helps us to choose the highest dependency attribute first. This ordered attribute set is denoted as A_D.

Step 5: From the ordered attributes set A_D, "A_L", the highest dependent attribute is selected. An example T_E is chosen from initial training data T_i. Attribute A_L with its value in one training example is taken as iteration rule "R".

Step 6: N-fold cross validation process is started. At each step of cross validation the value of the highest dependent attribute is the value of the corresponding attribute of the example currently under classification in present step of cross validation based on rule "R".

Step 7: We choose a subset "S_T" of examples from (T_i - T_E) examples.

Step 8: A local Naive Bayesian classification is applied on the subset "S_T". We choose only the attributes for local NB that are not used in iteration rule "R". All class conditional probabilities and prior probability of each class value are computed based on the subset of examples "S_T". According to Naive Bayesian theorem [2.2] described in chapter two, the example T_E is classified.

Step 9: If all the examples of training data T_i are classified, calculate the error rate other wise we go to step 6.

Step 10: If all "L" attributes of training data T_i is encountered in the iteration rule "R" then we find the final rule which has the lowest error rate other wise we go to step 5. In step 5, next available highest dependent attribute with its value in one example is and-ed with its previous rule and the execution continues with step 6.

Step 11: For any test example, the attributes in the final rule with their values in the test example are used to choose a subset of examples from the training data. Then a local NB is applied on this subset. All class conditional probabilities and prior probability of each class value in the subset are computed. Only the attributes that are not included in the final rule are used in local NB. The test example is classified using the Naive Bayesian equation [2.2] using the already calculated probabilities.

In our algorithm, we encounter the attribute dependency to select most interdependent attribute while generating the iteration rule. At each step, error rate is calculated to find the best rule. The attribute dependence and the process of selecting the final rule from error rate of cross validations are narrated in detail in the next sub sections.

3.1.1 Attribute Dependence

The dependence of an attribute A_M on other attribute A_i can be defined as [2]:

$$\frac{\sum i \sum j_i P\left(A_i = V_{ij_i}\right) \sum jM \left[P\left(A_M = V_{Mj_M} \mid A_i = V_{ij_i}\right)^2 - P\left(A_M = V_{Mj_M}\right)^2 \right]}{\left| \left\{ i \mid A_i \neq A_M \right\} \right|} \tag{3.1}$$

Attribute A_M is independent of all other attributes, A_i, if equation (3.1) equals to zero. It is possible only when,

$$\left[P\left(A_M = V_{Mj_M} \mid A_i = V_{ij_i}\right)^2 - P\left(A_M = V_{Mj_M}\right)^2 \right] = 0$$

$(A_i = V_{ij_i})$ = j th value of attribute A_i

$P\left(A_M = V_{Mj_M}\right)$ = Prior probability of the jth value V_{Mj_M} of attribute A_M

$P\left(A_M = V_{Mj_M} \mid A_i = V_{ij_i}\right)$ = Conditional probability of $(A_M = V_{Mj_M})$ given that $A_i = V_{ij_i}$

$P\left(A_i = V_{ij_i}\right)$ = Prior probability of the jth value V_{ij_i} of attribute A_i

From training data set we calculate the aforesaid probability terms and putting these values in equation 3.1 we can calculate the attribute dependency of each attribute of the training examples.

3.1.2 Selection of Final Rule from the Error Rate

To quantify the concept of true error rate, we make the following definitions which are essentially the same as those in [3]. Let an example be x = (t, y), where t stands for the features of the example and y is the true classification of the example. Suppose a learning algorithm constructs prediction rule $\eta(t, X)$ from training set X.

Let $\eta_i = \eta(t_i, X)$ be the prediction on example xi and let $Q(y_i, \eta_i)$ be the error of the learned rule on that example.

We define Q as:

$$Q(y_i,\eta_i)=0 \quad if \quad \eta_i = y_i$$
$$=1 \quad if \quad \eta_i \neq y_i \qquad (3.2)$$

We then define true error rate (Err) as the probability of incorrectly classifying a randomly selected example $X_0=(T_0,Y_0)$, that is the expectation:-

$$Err = E_F\ Q(Y_0,\eta(T_0\ ,Y_0)) \qquad (3.3)$$

Here *"F"* is the distribution of training examples and "E_F" is the probability of selected example. Cross validation estimates error by reserving part of the training set for testing the learned theory. In general, v-fold cross validation(randomly) splits the training set into v equalized subsets, trains on (v-1) of them and tests on one of them. Each subset is used once as the test set (i.e., left out of the original training set). A common choice for v is the size of the original training set. Since each subset contains one element, this is called 'leave-one-out' (n=1) cross validation. We define 'leave-one-out' cross validation estimate of error as:

$$Err(cv)= {}^{1}\!/_{n} \sum_{1}^{n} Q(y_i\ ,\eta(t_i\ ,X_{(i)}\ ) \qquad (3.4)$$

Where X(i) is the training set with xi removed and $\eta(t_i,X_{(i)})$ is the rule learned from X(i). At first iteration, learned rule is:

η_{i1} = *Attribute with highest dependency with its value in one of the example*. Err(cv) is calculated at each iteration. At next iteration second highest dependency attribute is and-ed with η_{i1} and Err (cv) is calculated again.

Now, learned rule is:

$\eta_{i2}=\eta_{i1}\wedge$ *Attribute with second highest dependency with its value in one of the example*

This process continues until all attributes encountered once.

The final learned rule will be all attributes and-ed with their values in one training example: $\eta_{in}=\eta_{i1}\wedge\eta_{i2}\wedge\eta_{i3}\wedge...$

which produces minimum error rate (i.e., which gives a minimum value for Err(cv)). This rule is used to classify any unknown instance I, I$\notin$X.

The flow chart is as follows:

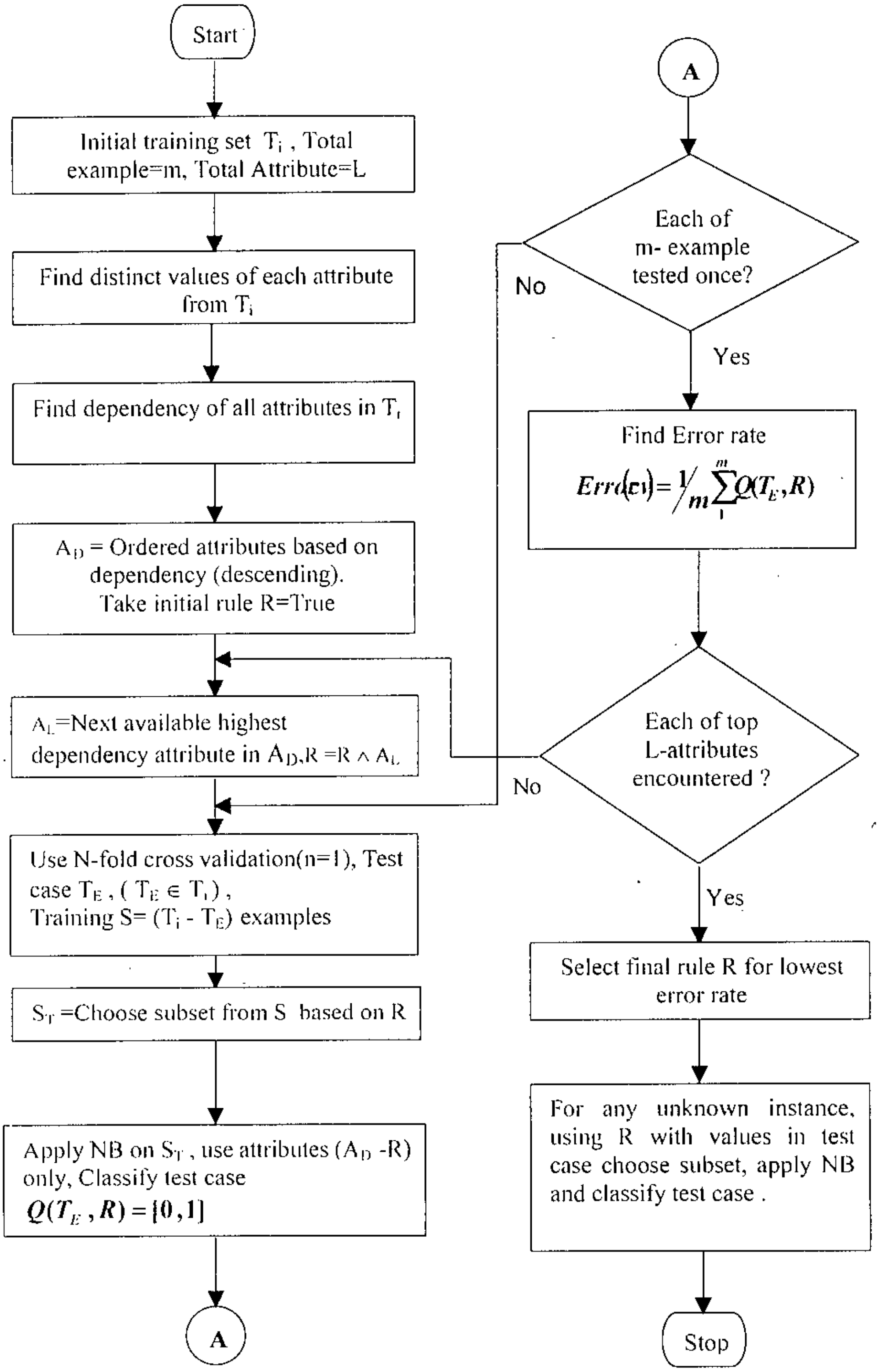

Figure 3.1: Flow chart of proposed algorithm.

The pseudocode of the algorithm is as follows:

NBDependency($T_{training}$, $E_{example}$)

Input:

$T_{training}$: A set of training examples having a total of L attributes and m examples with attribute values and class values are known.

$E_{example}$: A test example whose attribute values are given but class value is unknown.

Output:

A predicted class for the test example $E_{example}$.

```
For each attribute in T_training Do
{
    Find distinct values of the attribute.
}

For each attribute in T_training Do
{
    Use distinct values of the attribute.
    Use all examples in T_training
    Find dependency of each attribute using dependency equation.
}// put sorted attributes in array A_D[ ].
A_D[L] : = Sorted attributes on dependency in descending.
R : =True                        //Initial iteration Rule
ErrorOfEachIteration [ L ] : = Φ  // a set of error at each iteration, initial value
                                    null.
For p : = 0 to L Do // For each attribute generate an iteration rule R.
{
    A : = A_D[ p ]             // Next available highest dependency
                                  attribute.
    R : =R ∧ A                 // Attributes of each iteration Rule.
    E_tested [ m ] : = Φ       // Initial set of tested example is null.
```

```
For k := 0 to m-1   Do    // For Each test example in T_training classify
                            each test example.
                            //Apply Leave-One-Out cross Validation
                            on T_training.
    {
        e := One example from T_training
        If e ∉ E_tested then I := e          // Choose test case
        S := T_training – I                  // Training set
        C := True     // Selection criteria , initial value = True

        For q := 0 to p Do // Make selection criteria taking all
                              attributes in R for each test
                              instance I.
            {
                C := C ∧ A with its value in I
            }
        T_subset := A set of examples from S that satisfies the
                    condition "C"

        For j := p+1 to L Do
        // Take attributes for (NB) that are not in "C"
            {
                AttributesForNB [ j - (p +1) ] := A_D[ j ]
            }
        Apply NB on T_subset and classify I , use attributes that
        are in AttributesForNB [ j ] only.
        E_tested [ k ] := I

        // find error rate
        If "I" is correctly classified Then
            {
                Y := 0
            }
```

```
                    Else
                        {
                            Y : = 1
                        }
                    TotalError : = TotalError + Y
            }
        ErrorOfEachIteration [ p ] : = (1/m) * TotalError *100
        // Error rate in percent
        }
    FinalRule := Select rule R having lowest error rate in ErrorOfEachIteration[L].
    Choose a subset from T_training by using attributes in FinalRule with their values
    in E_example
    Apply NB on this subset, use attributes not in FinalRule, classify E_example.
    End.
```

Figure 3.2: Pseudocode of proposed Algorithm.

3.2 Detailed Working Procedure

The new algorithm is explained using two popular dataset Soybean and Zoology domains

3.2.1 Applying Proposed Algorithm on Soybean Dataset

The main classification task is to find the diseases categories of a Soybean plant from a given set of attribute values. The data set is widely used in many classification algorithms in the past [7, 24]. The data set has a total number of instances 683. The missing values in the attributes are denoted by "?". Attributes are : (1. date, 2. plant-stand, 3. precip, 4. temp, 5. hail, 6. crop-hist, 7. area-damaged, 8. severity, 9. seed-tmt, 10. germination, 11. plant-growth, 12. leaves, 13. leafspots-halo, 14. leafspots-marg, 15. leafspot-size, 16. leaf-shread, 17. leaf-malf, 18. leaf-mild, 19. stem, 20. lodging, 21. stem-cankers, 22. canker-lesion, 23. fruiting-bodies, 24. external decay, 25. mycelium, 26. int-discolor,

27. sclerotia, 28. fruit-pods, 29. fruit spots, 30. seed, 31. mold-growth, 32. seed-discolor, 33. seed-size, 34. shriveling, 35. roots, 36.Class).

Step-1: First we find distinct values of attributes of the domain from training set. These values are given in the following table. Here header row of the table gives the name of the attributes. Attribute name "A1" means this is the first attribute in the attribute information list described at early paragraph in this chapter whose actual name is "Date". Renaming the attribute in this way does not affect the rest of the procedure. Next rows in the table are the distinct values of their attribute in the corresponding column. Missing attribute values are denoted by "?".

Table 3.1: Distinct values of attributes of Soybean domain. Total of 35 attributes exist in the domain. Some attributes have missing value in the examples. This is denoted by "?". This means a particular example has no value for this attribute.

A1	A2	A3	A4	A5	A6	A7	A8	A9
?	?	?	?	?	?	?	?	?
april	lt-normal	gt-norm	gt-norm	no	diff-lst-year	low-areas	minor	fungicide
august	normal	lt-norm	lt-norm	yes	same-lst-sev-yrs	scattered	pot-severe	none
july		norm	norm		same-lst-two-yrs	upper-areas	severe	other
june					same-lst-yr	whole-field		
may								
october								
september								

Continuation of Table 3.1

A10	A11	A12	A13	A14	A15	A16	A17	A18	A19
80-89	?	abnorm	?	?	?	?	?	?	?
90-100	abnorm	norm	absent	Dna	dna	absent	absent	absent	abnorm
?	norm		no-yellow-halos	no-w-s-marg	gt-1/8	present	present	lower-surf	norm
lt-80			yellow-halos	w-s-marg	lt-1/8			upper-surf	

Continuation of Table 3.1

A20	A21	A22	A23	A24	A25	A26	A27	A28
?	?	?	?	?	?	?	?	?
no	above-sec-ndc	brown	absent	absent	absent	black	absent	diseased
yes	above-soil	dk-brown-blk	present	Firm-and-dry	present	brown	present	dna
	Absent	dna		watery		none		few-present
	below-soil	tan						norm

Continuation of Table 3.1

A29	A30	A31	A32	A33	A34	A35	Class
?	?	?	?	?	?	?	2-4-d-injury
absent	abnorm	absent	absent	lt-norm	absent	galls-cysts	alternarialeaf-spot
brown-w/blk-specks	norm	present	present	norm	present	norm	Anthracnose
colored						rotted	bacterial-blight
dna							bacterial-pustule
							brown-spot
							brown-stem-rot
							charcoal-rot
							cyst-nematode
							diaporthe-pod-&-stem-blight
							diaporthe-stem-canker
							downy-mildew
							frog-eye-leaf-spot
							herbicide-injury
							Phyllosticta-leaf-spot
							phytophthora-rot
							powdery-mildew
							purple-seed-stain
							rhizoctonia-root-rot

Step-2: Now we find the attribute's dependencies from the distinct values of attributes and training examples using dependency equation. The attribute's dependencies are given in the following table:

Table 3.2: First column of the table gives the abbreviated name of the attribute in the training data. Middle column gives the dependency of each attribute. All of the 35 attributes' dependencies are given in this table.

Attribute Name	Dependency	Attribute Sl No(0-35)
A29	0.17411481477680107	28
A34	0.16655758587323488	33
A20	0.16401849410315217	19
A32	0.1576619031391632	31
A23	0.1569907694989127	22
A33	0.15110309842271025	32
A5	0.14784659182398138	4
A28	0.14765412809728	27
A14	0.144042511013062	13
A18	0.14200400939156918	17
A30	0.14102965218211927	29
A8	0.14087462579066126	7
A13	0.1356451968968302	12
A35	0.13481602313402816	34
A15	0.13448928296769305	14
A9	0.12866330569656903	8
A31	0.1250136954522472	30
A17	0.12250635559331303	16
A16	0.11836843806578816	15
A22	0.11706404499400117	21
A11	0.11627402988184009	10
A10	0.11082311042285567	9
A21	0.10183103940935141	20
Class	0.09506869181147803	35
A19	0.0917037946433417	18
A2	0.07673799037532297	1
A24	0.0660153731569228	23
A3	0.05974218290098993	2
A26	0.05455056319917149	25
A27	0.04840329545949396	26
A25	0.0451979618506194	24
A4	0.04482361659593675	3
A7	0.04047682579518786	6
A1	0.020209091031211456	0
A12	0.018752830150328265	11
A6	0.012983205058785969	5

Step-3: The dependencies calculated are ordered in descending. A graphical presentation of ordered values are given in the following figure for convenience. Attribute dependency is plotted against the attributes.

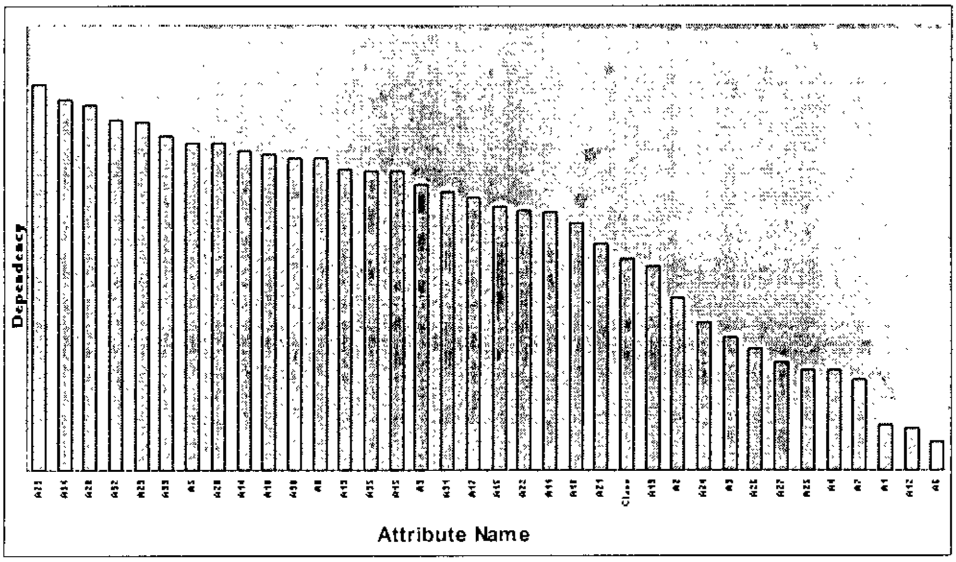

Figure 3.3: Here horizontal axis denotes the attribute's name and vertical axis denotes the attributes dependencies.

We see in the chart that "A29" has the highest dependency.

Step-4: In this step we successively choose the next available highest dependency attribute and it is And-ed with its previous iteration rule and a leave-one-cross validation is applied in each iteration to find the best rule having lowest error rate. The detail procedure and some intermediate calculation (Class conditional probabilities, prior probability of the class etc.) of local NB classifier at each iteration are given in the following:

First iteration(A29).

From attribute dependency chart we see that attribute "A29" has the highest dependency. Hence first iteration contains only attribute "A29". We apply Leave-One-Out cross validation here and classify 683 examples.

Example-1: Classifying a test example from one of the 683 examples in Leave-One-Out cross validation procedure for first iteration:

Table 3.3: This gives a description of an example taken from the training data. First column of the table gives the abbreviated name of the attribute. Second column gives the corresponding values of each attribute in the example.

Attribute Name	Attribute values in the example
a1	july
a2	normal
a3	lt-norm
a4	norm
a5	yes
a6	same-lst-yr
a7	upper-areas
a8	pot-severe
a9	none
a10	90-100
a11	abnorm
a12	abnorm
a13	absent
a14	dna
a15	dna
a16	absent
a17	absent
a18	absent
a19	abnorm
a20	yes
a21	absent
a22	tan
a23	absent
a24	absent
a25	absent
a26	black

Continuation of Table 3.3:

Attribute Name	Attribute values in the example
a27	present
a28	norm
a29	dna
a30	norm
a31	absent
a32	absent
a33	norm
a34	absent
a35	norm

We take the values of attribute "A29" in this example and make a selection criteria: a29 ='dna'; and choose a subset based on this selection criteria from 682 examples excluding this example (Note that total example in training set = 683). The total number of examples that satisfies this selection criteria is 99. Thus total number of training examples for local NB is 99.

Selection criteria for subset: a29 = 'dna'

Subset Total Example: 99.0

Total class categories in this subset: 5

We apply a local Naïve Bayes' on this subset of 99 examples. Attributes for local Naïve Bayes' with their values in test example (Exclude subset generating attribute "A29", include all other attributes) are as follows:

Table 3.4: **Local NB attributes of example-1:** This gives a description of attributes for local NB of example-1. First column of the table gives the abbreviated name of the attribute. Second column gives the corresponding values of each attribute in the example.

Attribute Name	Attribute values in the test example
a1	July
a2	Normal
a3	lt-norm
a4	norm
a5	Yes

Continuation of Table 3.4:

Attribute Name	**Attribute values in the test example**
a6	same-lst-yr
a7	upper-areas
a8	pot-severe
a9	none
a10	90-100
a11	abnorm
a12	abnorm
a13	absent
a14	Dna
a15	Dna
a16	absent
a17	absent
a18	absent
a19	abnorm
a20	Yes
a21	absent
a22	Tan
a23	absent
a24	absent
a25	absent
a26	black
a27	present
a28	norm
a30	norm
a31	absent
a32	absent
a33	norm
a34	absent
a35	norm

The name of the classes in the subset are as follows:(brown-stem-rot, charcoal-rot, diaporthe-stem-canker, phytophthora-rot, rhizoctonia-root-rot)

We calculate the class conditional probabilities for class value "brown-stem-rot". These are as follows:

Class conditional probabilities for class value = brown-stem-rot

P(a1=july | brown-stem-rot): 0.24286856838176485
P(a2=normal | brown-stem-rot): 0.45614502799253537
P(a3=lt-norm | brown-stem-rot): 0.5097307384697414
P(a4=norm | brown-stem-rot): 0.36790189282857905
P(a5=yes | brown-stem-rot): 0.5578512396694215
P(a6=same-lst-yr | brown-stem-rot): 0.11276992801919489
P(a7=upper-areas | brown-stem-rot): 0.29192215409224204
P(a8=pot-severe | brown-stem-rot): 0.6336976806185017
P(a9=none | brown-stem-rot): 0.4950679818715009
P(a10=90-100 | brown-stem-rot): 0.3400426552919221
P(a11=abnorm | brown-stem-rot): 0.9390829112236736
P(a12=abnorm | brown-stem-rot): 0.5351906158357771
P(a13=absent | brown-stem-rot): 0.5293255131964809
P(a14=dna | brown-stem-rot): 0.5293255131964809
P(a15=dna | brown-stem-rot): 0.5293255131964809
P(a16=absent | brown-stem-rot): 0.9738736336976805
P(a17=absent | brown-stem-rot): 0.9828045854438816
P(a18=absent | brown-stem-rot): 0.9802719274860037
P(a19=abnorm | brown-stem-rot): 0.9584110903758998
P(a20=yes | brown-stem-rot): 0.2509997334044255
P(a21=absent | brown-stem-rot): 0.9594774726739536
P(a22=tan | brown-stem-rot): 0.9176219674753399
P(a23=absent | brown-stem-rot): 0.9720074646760863
P(a24=absent | brown-stem-rot): 0.9752066115702479
P(a25=absent | brown-stem-rot): 0.9941348973607038
P(a26=black | brown-stem-rot): 0.002532657957877899
P(a27=present | brown-stem-rot): 0.002532657957877899
P(a28=norm | brown-stem-rot): 0.9632098107171421
P(a30=norm | brown-stem-rot): 0.9724073580378565
P(a31=absent | brown-stem-rot): 0.9788056518261796
P(a32=absent | brown-stem-rot): 0.9773393761663556
P(a33=norm | brown-stem-rot): 0.9798720341242335
P(a34=absent | brown-stem-rot): 0.9808051186350306
P(a35=norm | brown-stem-rot): 0.9824046920821115

Now we calculate class absolute probability.
Base rate of the class: P(brown-stem-rot): 0.20202020202020202

Class Name-brown-stem-rot, [(Product of all Class conditional Probability)*Base rate of the class]: 6.227878140110804E-13

Again, we calculate the class conditional probabilities for class value "charcoal-rot". These are as follows:

Class conditional probabilities for class value = charcoal-rot

P(a1=july | charcoal-rot): 0.11157659544756318
P(a2=normal | charcoal-rot): 0.9540566959921799
P(a3=lt-norm | charcoal-rot): 0.9149560117302052
P(a4=norm | charcoal-rot): 0.24256388772517803
P(a5=yes | charcoal-rot): 0.4415584415584 4154
P(a6=same-lst-yr | charcoal-rot): 0.21337801982963273
P(a7=upper-areas | charcoal-rot): 0.44868035190615835
P(a8=pot-severe | charcoal-rot): 0.9495880463622399
P(a9=none | charcoal-rot): 0.4710236000558581
P(a10=90-100 | charcoal-rot): 0.26099706744868034
P(a11=abnorm | charcoal-rot): 0.9361820974724201
P(a12=abnorm | charcoal-rot): 0.989247311827957
P(a13=absent | charcoal-rot): 0.935483870967742
P(a14=dna | charcoal-rot): 0.935483870967742
P(a15=dna | charcoal-rot): 0.935483870967742
P(a16=absent | charcoal-rot): 0.9726295210166178
P(a17=absent | charcoal-rot): 0.9819857561793046
P(a18=absent | charcoal-rot): 0.9793324954615277
P(a19=abnorm | charcoal-rot): 0.9564306661080855
P(a20=yes | charcoal-rot): 0.8343806730903505
P(a21=absent | charcoal-rot): 0.9575478285155704
P(a22=tan | charcoal-rot): 0.9136992040217846
P(a23=absent | charcoal-rot): 0.9706744868035191
P(a24=absent | charcoal-rot): 0.974025974025974
P(a25=absent | charcoal-rot): 0.9938556067588326
P(a26=black | charcoal-rot): 0.9074151654796816
P(a27=present | charcoal-rot): 0.9074151654796816
P(a28=norm | charcoal-rot): 0.961457896941768
P(a30=norm | charcoal-rot): 0.9710934227063259
P(a31=absent | charcoal-rot): 0.9777963971512359
P(a32=absent | charcoal-rot): 0.976260298840944
P(a33=norm | charcoal-rot): 0.9789135595587208
P(a34=absent | charcoal-rot): 0.9798910766652702
P(a35=norm | charcoal-rot): 0.9815668202764977

Base rate of the class: P(charcoal-rot): 0.1919191919191919

Class Name-charcoal-rot, [(Product of all Class conditional Probability) * Base rate of the class]: 7.193591316202711E-6

Class conditional probabilities for class value = diaporthe-stem-canker

P(a1=july | diaporthe-stem-canker): 0.24286856838176485
P(a2=normal | diaporthe-stem-canker): 0.9561450279925353
P(a3=lt-norm | diaporthe-stem-canker): 0.009730738469741403
P(a4=norm | diaporthe-stem-canker): 0.9588109837376699
P(a5=yes | diaporthe-stem-canker): 0.9214876033057852
P(a6=same-lst-yr | diaporthe-stem-canker): 0.29458810983737665

P(a7=upper-areas | diaporthe-stem-canker): 0.019194881364969343
P(a8=pot-severe | diaporthe-stem-canker): 0.6791522260730471
P(a9=none | diaporthe-stem-canker): 0.5405225273260463
P(a10=90-100 | diaporthe-stem-canker): 0.15822447347374033
P(a11=abnorm | diaporthe-stem-canker): 0.9390829112236736
P(a12=abnorm | diaporthe-stem-canker): 0.9897360703812317
P(a13=absent | diaporthe-stem-canker): 0.93841642228739
P(a14=dna | diaporthe-stem-canker): 0.93841642228739
P(a15=dna | diaporthe-stem-canker): 0.93841642228739
P(a16=absent | diaporthe-stem-canker): 0.9738736336976805
P(a17=absent | diaporthe-stem-canker): 0.9828045854438816
P(a18=absent | diaporthe-stem-canker): 0.9802719274860037
P(a19=abnorm | diaporthe-stem-canker): 0.9584110903758998
P(a20=yes | diaporthe-stem-canker): 0.70554518794988
P(a21=absent | diaporthe-stem-canker): 0.05038656358304452
P(a22=tan | diaporthe-stem-canker): 0.008531058384430818
P(a23=absent | diaporthe-stem-canker): 0.0629165555851773
P(a24=absent | diaporthe-stem-canker): 0.06611570247933884
P(a25=absent | diaporthe-stem-canker): 0.9941348973607038
P(a26=black | diaporthe-stem-canker): 0.002532657957877899
P(a27=present | diaporthe-stem-canker): 0.002532657957877899
P(a28=norm | diaporthe-stem-canker): 0.9632098107171421
P(a30=norm | diaporthe-stem-canker): 0.9724073580378565
P(a31=absent | diaporthe-stem-canker): 0.9788056518261796
P(a32=absent | diaporthe-stem-canker): 0.9773393761663556
P(a33=norm | diaporthe-stem-canker): 0.9798720341242335
P(a34=absent | diaporthe-stem-canker): 0.9808051186350306
P(a35=norm | diaporthe-stem-canker): 0.9824046920821115

Base rate of the class: P(diaporthe-stem-canker): 0.20202020202020202

Class Name-diaporthe-stem-canker, [(Product of all Class conditional Probability) * Base rate of the class]: 6.22666765708598E-19

Class conditional probabilities for class value = phytophthora-rot
P(a1=july | phytophthora-rot): 0.15195947747267394
P(a2=normal | phytophthora-rot): 0.04705411890162623
P(a3=lt-norm | phytophthora-rot): 0.009730738469741403
P(a4=norm | phytophthora-rot): 0.5497200746467609
P(a5=yes | phytophthora-rot): 0.6942148760330579
P(a6=same-lst-yr | phytophthora-rot): 0.29458810983737665
P(a7=upper-areas | phytophthora-rot): 0.019194881364969343
P(a8=pot-severe | phytophthora-rot): 0.36097040789122903
P(a9=none | phytophthora-rot): 0.4950679818715009
P(a10=90-100 | phytophthora-rot): 0.3400426552919221
P(a11=abnorm | phytophthora-rot): 0.9390829112236736
P(a12=abnorm | phytophthora-rot): 0.9897360703812317
P(a13=absent | phytophthora-rot): 0.93841642228739
P(a14=dna | phytophthora-rot): 0.93841642228739
P(a15=dna | phytophthora-rot): 0.93841642228739
P(a16=absent | phytophthora-rot): 0.9738736336976805
P(a17=absent | phytophthora-rot): 0.9828045854438816
P(a18=absent | phytophthora-rot): 0.9802719274860037
P(a19=abnorm | phytophthora-rot): 0.9584110903758998

P(a20=yes | phytophthora-rot): 0.8873633697680618
P(a21=absent | phytophthora-rot): 0.05038656358304452
P(a22=tan | phytophthora-rot): 0.008531058384430818
P(a23=absent | phytophthora-rot): 0.9720074646760863
P(a24=absent | phytophthora-rot): 0.7024793388429752
P(a25=absent | phytophthora-rot): 0.9941348973607038
P(a26=black | phytophthora-rot): 0.002532657957877899
P(a27=present | phytophthora-rot): 0.002532657957877899
P(a28=norm | phytophthora-rot): 0.05411890162623301
P(a30=norm | phytophthora-rot): 0.9724073580378565
P(a31=absent | phytophthora-rot): 0.9788056518261796
P(a32=absent | phytophthora-rot): 0.9773393761663556
P(a33=norm | phytophthora-rot): 0.9798720341242335
P(a34=absent | phytophthora-rot): 0.9808051186350306
P(a35=norm | phytophthora-rot): 0.9824046920821115

Base rate of the class: P(phytophthora-rot): 0.20202020202020202

Class Name- phytophthora-rot, [(Product of all Class conditional Probability)*Base rate of the class]: 1.0049689552270597E-19

Class conditional probabilities for class value = rhizoctonia-root-rot
P(a1=july | rhizoctonia-root-rot): 0.061050386563583046
P(a2=normal | rhizoctonia-root-rot): 0.13796320981071714
P(a3=lt-norm | rhizoctonia-root-rot): 0.009730738469741403
P(a4=norm | rhizoctonia-root-rot): 0.04972007464676086
P(a5=yes | rhizoctonia-root-rot): 0.8760330578512397
P(a6=same-lst-yr | rhizoctonia-root-rot): 0.24913356438283124
P(a7=upper-areas | rhizoctonia-root-rot): 0.019194881364969343
P(a8=pot-severe | rhizoctonia-root-rot): 0.45187949880031997
P(a9=none | rhizoctonia-root-rot): 0.7677952545987736
P(a10=90-100 | rhizoctonia-root-rot): 0.021860837110103972
P(a11=abnorm | rhizoctonia-root-rot): 0.9390829112236736
P(a12=abnorm | rhizoctonia-root-rot): 0.12609970674486803
P(a13=absent | rhizoctonia-root-rot): 0.93841642228739
P(a14=dna | rhizoctonia-root-rot): 0.93841642228739
P(a15=dna | rhizoctonia-root-rot): 0.93841642228739
P(a16=absent | rhizoctonia-root-rot): 0.9738736336976805
P(a17=absent | rhizoctonia-root-rot): 0.9828045854438816
P(a18=absent | rhizoctonia-root-rot): 0.9802719274860037
P(a19=abnorm | rhizoctonia-root-rot): 0.9584110903758998
P(a20=yes | rhizoctonia-root-rot): 0.8873633697680618
P(a21=absent | rhizoctonia-root-rot): 0.05038656358304452
P(a22=tan | rhizoctonia-root-rot): 0.008531058384430818
P(a23=absent | rhizoctonia-root-rot): 0.9720074646760863
P(a24=absent | rhizoctonia-root-rot): 0.06611570247933884
P(a25=absent | rhizoctonia-root-rot): 0.7214076246334311
P(a26=black | rhizoctonia-root-rot): 0.002532657957877899
P(a27=present | rhizoctonia-root-rot): 0.002532657957877899
P(a28=norm | rhizoctonia-root-rot): 0.05411890162623301
P(a30=norm | rhizoctonia-root-rot): 0.9724073580378565
P(a31=absent | rhizoctonia-root-rot): 0.9788056518261796
P(a32=absent | rhizoctonia-root-rot): 0.9773393761663556
P(a33=norm | rhizoctonia-root-rot): 0.9798720341242335

P(a34=absent | rhizoctonia-root-rot): 0.9808051186350306
P(a35=norm | rhizoctonia-root-rot): 0.936950146627566

Base rate of the class: P(rhizoctonia-root-rot): 0.20202020202020202

Class Name- rhizoctonia-root-rot, [(Product of all Class conditional Probability)*Base rate of the class]: 1.1835998866976362E-23

We know, Naive Bayesian classification gives the class value of test example as the following equation:

$$\equiv \operatorname{argmax}_{class\ value\ c_i \in C} P(C = c_i) \prod_{j=1}^{k} P(A_i = a_i \mid C = c_i)$$

While calculating class conditional probabilities we used m-estimation (m=2) technique [3].The class value of the test example will be the highest value among the values of [(Product of all Class conditional Probability)*Base rate of the class] calculated for each class value.

These calculated values are summarized in the following table:

Table 3.5: Class probabilities of example-1: Table shows the product of all class conditional Probability and base rate of each class value in the subset for local NB.

Class Name		[(Product of all Class conditional Probability)*Base rate of the class]
1.	charcoal-rot	7.193591316202711E-6
2.	brown-stem-rot	6.227878140110804E-13
3.	diaporthe-stem-canker	6.22666765708598E-19
4.	phytophthora-rot	1.0049689552270597E-19
5.	rhizoctonia-root-rot	1.1835998866976362E-23

Class value "charcoal-rot" has the highest value for [(Product of all Class conditional Probability)*Base rate of the class]. At this iteration, we say, the class for this test example is "charcoal-rot" and we classify this example as **"charcoal-rot".**

Example-2: Classifying another test example in Leave-One-Out cross validation for first iteration:

Table 3.6: **Example-2:** This gives a description of an example taken from the training data. First column of the table gives the abbreviated name of the attribute. Second column gives the corresponding values of each attribute in the example.

Attribute Name	Attribute values in the example
a1	august
a2	lt-normal
a3	gt-norm
a4	gt-norm
a5	no
a6	same-lst-yr
a7	low-areas
a8	pot-severe
a9	none
a10	90-100
a11	norm
a12	abnorm
a13	absent
a14	dna
a15	dna
a16	absent
a17	absent
a18	absent
a19	abnorm
a20	no
a21	above-sec-nde
a22	dk-brown-blk
a23	Present
a24	firm-and-dry
a25	Absent
a26	None
a27	Absent
a28	Diseased
a29	brown-w/blk-specks
a30	Abnorm
a31	Present
a32	Absent
a33	lt-norm

Continuation of Table 3.6:

Attribute Name	Attribute values in the example
a34	Absent
a35	Norm

Selection criteria for subset generation: a29 = 'brown-w/blk-specks'

Choose subset from 682 examples excluding this example (Total example in training set: 683)

Total examples in the subset: 56.0

Total class categories in this subset: 4

We apply a local Naïve Bayes' on this subset of 56 examples.

Attributes for local Naïve Bayes' with their values in test example (Exclude subset generating attributes include all other attributes):

Table 3.7: **Local NB attributes for Example-2:** This gives a description of attributes for local NB of example-2. First column of the table gives the abbreviated name of the attribute. Second column gives the corresponding values of each attribute in the example.

Attribute Name	Attribute values in the example
a1	August
a2	lt-normal
a3	gt-norm
a4	gt-norm
a5	No
a6	same-lst-yr
a7	low-areas
a8	pot-severe
a9	None
a10	90-100
a11	Norm
a12	Abnorm
a13	Absent
a14	Dna
a15	Dna

Continuation of Table 3.7:

Attribute Name	Attribute values in the example
a16	Absent
a17	Absent
a18	Absent
a19	Abnorm
a20	No
a21	above-sec-nde
a22	dk-brown-blk
a23	Present
a24	firm-and-dry
a25	Absent
a26	None
a27	Absent
a28	Diseased
a30	Abnorm
a31	Present
a32	Absent
a33	lt-norm
a34	Absent
a35	Norm

The class names in the subset are: (anthracnose, brown-spot, diaporthe-pod-&-stem-blight, rog-eye-leaf-spot).

We calculate the class conditional probabilities for class value "anthracnose". These are as follows:

Class conditional probabilities for class value = anthracnose
P(a1=august | anthracnose): 0.1636213249116475
P(a2=lt-normal | anthracnose): 0.5604180765471087
P(a3=gt-norm | anthracnose): 0.9831566283179186
P(a4=gt-norm | anthracnose): 0.24565756823821341
P(a5=no | anthracnose): 0.24024362734040156
P(a6=same-lst-yr | anthracnose): 0.2943830363185202
P(a7=low-areas | anthracnose): 0.29904504098052487
P(a8=pot-severe | anthracnose): 0.7164448454771035
P(a9=none | anthracnose): 0.48439732310700057
P(a10=90-100 | anthracnose): 0.32002406195954586
P(a11=norm | anthracnose): 0.8023159636062862
P(a12=abnorm | anthracnose): 0.3788254755996691
P(a13=absent | anthracnose): 0.9652605459057072
P(a14=dna | anthracnose): 0.9652605459057072
P(a15=dna | anthracnose): 0.9652605459057072
P(a16=absent | anthracnose): 0.9852620497781788
P(a17=absent | anthracnose): 0.990300022558087
P(a18=absent | anthracnose): 0.9888713437100534

P(a19=abnorm | anthracnose): 0.9765395894428152
P(a20=no | anthracnose): 0.1056470411309121
P(a21=above-sec-nde | anthracnose): 0.9630047371982855
P(a22=dk-brown-blk | anthracnose): 0.8081058726220016
P(a23=present | anthracnose): 0.7513346868185579
P(a24=firm-and-dry | anthracnose): 0.3434092788931498
P(a25=absent | anthracnose): 0.9966914805624483
P(a26=none | anthracnose): 0.9923302503947665
P(a27=absent | anthracnose): 0.9956387698323181
P(a28=diseased | anthracnose): 0.9584179261598617
P(a30=abnorm | anthracnose): 0.5470336115497405
P(a31=present | anthracnose): 0.5177832919768404
P(a32=absent | anthracnose): 0.884652981427175
P(a33=lt-norm | anthracnose): 0.46589969170614337
P(a34=absent | anthracnose): 0.5019926310248891
P(a35=norm | anthracnose): 0.9900744416873448

Base rate of the class: P(anthracnose): 0.6607142857142857

Class Name-anthracnose, [(Product of all Class conditional Probability)*Base rate of the class]: 1.0282986214162714E-8

Class conditional probabilities for class value = brown-spot

P(a1=august | brown-spot): 0.3453079178885631
P(a2=lt-normal | brown-spot): 0.4640762463343109
P(a3=gt-norm | brown-spot): 0.5857771260997067
P(a4=gt-norm | brown-spot): 0.3951612903225806
P(a5=no | brown-spot): 0.342375366568915
P(a6=same-lst-yr | brown-spot): 0.6202346041055719
P(a7=low-areas | brown-spot): 0.41568914956011727
P(a8=pot-severe | brown-spot): 0.48533724340175954
P(a9=none | brown-spot): 0.22287390029325513
P(a10=90-100 | brown-spot): 0.12023460410557185
P(a11=norm | brown-spot): 0.8225806451612903
P(a12=abnorm | brown-spot): 0.9435483870967742
P(a13=absent | brown-spot): 0.16129032258064516
P(a14=dna | brown-spot): 0.16129032258064516
P(a15=dna | brown-spot): 0.16129032258064516
P(a16=absent | brown-spot): 0.8563049853372434
P(a17=absent | brown-spot): 0.905425219941349
P(a18=absent | brown-spot): 0.8914956011730205
P(a19=abnorm | brown-spot): 0.7712609970674487
P(a20=no | brown-spot): 0.030058651026392963
P(a21=above-sec-nde | brown-spot): 0.6392961876832844
P(a22=dk-brown-blk | brown-spot): 0.12903225806451613
P(a23=present | brown-spot): 0.3255131964809384
P(a24=firm-and-dry | brown-spot): 0.09824046920821114
P(a25=absent | brown-spot): 0.967741935483871
P(a26=none | brown-spot): 0.9252199413489737
P(a27=absent | brown-spot): 0.9574780058651027
P(a28=diseased | brown-spot): 0.594574780058651
P(a30=abnorm | brown-spot): 0.08357771260997067
P(a31=present | brown-spot): 0.04838709677419355

P(a32=absent | brown-spot): 0.875366568914956
P(a33=lt-norm | brown-spot): 0.04252199413489736
P(a34=absent | brown-spot): 0.8944281524926686
P(a35=norm | brown-spot): 0.9032258064516129

Base rate of the class: P(brown-spot): 0.03571428571428571

Class Name-brown-spot, [(Product of all Class conditional Probability)*Base rate of the class]: 1.297799389031491E-17

Class conditional probabilities for class value = diaporthe-pod-&-stem-blight

P(a1=august | diaporthe-pod-&-stem-blight): 0.022425392444367778
P(a2=lt-normal | diaporthe-pod-&-stem-blight): 0.1680179403139555
P(a3=gt-norm | diaporthe-pod-&-stem-blight): 0.8437122649646368
P(a4=gt-norm | diaporthe-pod-&-stem-blight): 0.9165085388994307
P(a5=no | diaporthe-pod-&-stem-blight): 0.02173538036915646
P(a6=same-lst-yr | diaporthe-pod-&-stem-blight): 0.2047610833189581
P(a7=low-areas | diaporthe-pod-&-stem-blight): 0.038985682249439366
P(a8=pot-severe | diaporthe-pod-&-stem-blight): 0.055373469035708126
P(a9=none | diaporthe-pod-&-stem-blight): 0.05244091771606003
P(a10=90-100 | diaporthe-pod-&-stem-blight): 0.3224081421424875
P(a11=norm | diaporthe-pod-&-stem-blight): 0.9582542694497154
P(a12=abnorm | diaporthe-pod-&-stem-blight): 0.10436432637571158
P(a13=absent | diaporthe-pod-&-stem-blight): 0.03795066413662239
P(a14=dna | diaporthe-pod-&-stem-blight): 0.03795066413662239
P(a15=dna | diaporthe-pod-&-stem-blight): 0.03795066413662239
P(a16=absent | diaporthe-pod-&-stem-blight): 0.08383646713817493
P(a17=absent | diaporthe-pod-&-stem-blight): 0.09539416939796445
P(a18=absent | diaporthe-pod-&-stem-blight): 0.09211661204071071
P(a19=abnorm | diaporthe-pod-&-stem-blight): 0.9461790581335173
P(a20=no | diaporthe-pod-&-stem-blight): 0.007072623770915991
P(a21=above-sec-nde | diaporthe-pod-&-stem-blight): 0.03277557357253752
P(a22=dk-brown-blk | diaporthe-pod-&-stem-blight): 0.030360531309297913
P(a23=present | diaporthe-pod-&-stem-blight): 0.9001207521113162
P(a24=firm-and-dry | diaporthe-pod-&-stem-blight): 0.02311540451957909
P(a25=absent | diaporthe-pod-&-stem-blight): 0.9924098671726755
P(a26=none | diaporthe-pod-&-stem-blight): 0.9824046920821115
P(a27=absent | diaporthe-pod-&-stem-blight): 0.9899948249094359
P(a28=diseased | diaporthe-pod-&-stem-blight): 0.9046058306020355
P(a30=abnorm | diaporthe-pod-&-stem-blight): 0.725547697084699
P(a31=present | diaporthe-pod-&-stem-blight): 0.8937381404174572
P(a32=absent | diaporthe-pod-&-stem-blight): 0.08832154562704847
P(a33=lt-norm | diaporthe-pod-&-stem-blight): 0.8923581162670347
P(a34=absent | diaporthe-pod-&-stem-blight): 0.09280662411592203
P(a35=norm | diaporthe-pod-&-stem-blight): 0.09487666034155597

Base rate of the class: P(diaporthe-pod-&-stem-blight): 0.26785714285714285

Class Name-diaporthe-pod-&-stem-blight, [(Product of all Class conditional Probability)*Base rate of the class]: 2.779210691887117E-29

Class conditional probabilities for class value = frog-eye-leaf-spot

P(a1=august | frog-eye-leaf-spot): 0.09530791788856305
P(a2=lt-normal | frog-eye-leaf-spot): 0.21407624633431085
P(a3=gt-norm | frog-eye-leaf-spot): 0.3357771260997067
P(a4=gt-norm | frog-eye-leaf-spot): 0.6451612903225806
P(a5=no | frog-eye-leaf-spot): 0.09237536656891496
P(a6=same-lst-yr | frog-eye-leaf-spot): 0.12023460410557185
P(a7=low-areas | frog-eye-leaf-spot): 0.1656891495601173
P(a8=pot-severe | frog-eye-leaf-spot): 0.23533724340175954
P(a9=none | frog-eye-leaf-spot): 0.47287390029325516
P(a10=90-100 | frog-eye-leaf-spot): 0.6202346041055719
P(a11=norm | frog-eye-leaf-spot): 0.8225806451612903
P(a12=abnorm | frog-eye-leaf-spot): 0.9435483870967742
P(a13=absent | frog-eye-leaf-spot): 0.16129032258064516
P(a14=dna | frog-eye-leaf-spot): 0.16129032258064516
P(a15=dna | frog-eye-leaf-spot): 0.16129032258064516
P(a16=absent | frog-eye-leaf-spot): 0.8563049853372434
P(a17=absent | frog-eye-leaf-spot): 0.905425219941349
P(a18=absent | frog-eye-leaf-spot): 0.8914956011730205
P(a19=abnorm | frog-eye-leaf-spot): 0.7712609970674487
P(a20=no | frog-eye-leaf-spot): 0.030058651026392963
P(a21=above-sec-nde | frog-eye-leaf-spot): 0.6392961876832844
P(a22=dk-brown-blk | frog-eye-leaf-spot): 0.6290322580645161
P(a23=present | frog-eye-leaf-spot): 0.5755131964809385
P(a24=firm-and-dry | frog-eye-leaf-spot): 0.34824046920821117
P(a25=absent | frog-eye-leaf-spot): 0.967741935483871
P(a26=none | frog-eye-leaf-spot): 0.9252199413489737
P(a27=absent | frog-eye-leaf-spot): 0.9574780058651027
P(a28=diseased | frog-eye-leaf-spot): 0.594574780058651
P(a30=abnorm | frog-eye-leaf-spot): 0.5835777126099707
P(a31=present | frog-eye-leaf-spot): 0.04838709677419355
P(a32=absent | frog-eye-leaf-spot): 0.625366568914956
P(a33=lt-norm | frog-eye-leaf-spot): 0.2925219941348974
P(a34=absent | frog-eye-leaf-spot): 0.6444281524926686
P(a35=norm | frog-eye-leaf-spot): 0.9032258064516129

Base rate of the class: P(frog-eye-leaf-spot): 0.03571428571428571

Class Name-frog-eye-leaf-spot, [(Product of all Class conditional Probability)*Base rate of the class]: 1.2924416993490396E-16

According to NB the class value of the test example will be the highest value among the values of [(Product of all Class conditional Probability)*Base rate of the class] calculated for each class value. These values are in the following table:

Table 3.8: **Class probabilities for example-2:** Table shows the product of all class conditional Probability and base rate of each class value in the subset for local NB.

Class Name	[(Product of all Class conditional Probability)*Base rate of the class]
1. anthracnose	1.0282986214162714E-8
2. frog-eye-leaf-spot	1.2924416993490396E-16
3. brown-spot	1.297799389031491E-17
4. diaporthe-pod-&-stem-blight	2.779210691887117E-29

Class value "anthracnose" has the highest value for [(Product of all Class conditional Probability)*Base rate of the class]. At this iteration, we say, the class for this test example is "anthracnose" and we classify this example as **"anthracnose".**

In this way we classify all of 683 examples of the training set for first iteration and we calculate the error rate for first iteration according to the equation (5). The error rate in first iteration is 6.73%.

Second iteration(A29,A34).

Classifying Example-1 described in table 3.3:

In second iteration next available highest dependency attribute is "A34". We take attribute "A34" and it is And-ed with first iteration attribute "A29". Now selection criterion contains these two attributes only. We again apply leave-one-out cross validation for second iteration rule.

While classifying the first example given above, for this leave-one-out procedure,

the selection criteria for first example is : A29 = 'dna' and A34 = 'absent', because it has value for these two attribute as follows:

Table 3.9: Attribute and its value in example-1 (Table 3.3) used for selection criteria:

Attribute Name	Attribute values
a29	Dna
a34	Absent

We choose subset of examples from 682 examples (Total examples: 683-First examples) based on this selection criteria. Then local NB is applied on this subset. In local NB only attributes (A1-A28 and A30-A33, A35) are considered. We calculate the class conditional probabilities for NB and classify the first example.

These are as follows:

Subset Total Examples: 99.0
Total class categories in subset: 5
Subset examples and class categories remains same for second iteration, but attributes for local NB become one less than that of first iteration.

Class conditional probabilities for class value = brown-stem-rot
P(a1=july | brown-stem-rot): 0.24286856838176485
P(a2=normal | brown-stem-rot): 0.45614502799253537
P(a3=lt-norm | brown-stem-rot): 0.5097307384697414
P(a4=norm | brown-stem-rot): 0.36790189282857905
P(a5=yes | brown-stem-rot): 0.5578512396694215
P(a6=same-lst-yr | brown-stem-rot): 0.11276992801919489
P(a7=upper-areas | brown-stem-rot): 0.29192215409224204
P(a8=pot-severe | brown-stem-rot): 0.6336976806185017
P(a9=none | brown-stem-rot): 0.4950679818715009
P(a10=90-100 | brown-stem-rot): 0.3400426552919221
P(a11=abnorm | brown-stem-rot): 0.9390829112236736
P(a12=abnorm | brown-stem-rot): 0.5351906158357771
P(a13=absent | brown-stem-rot): 0.5293255131964809
P(a14=dna | brown-stem-rot): 0.5293255131964809
P(a15=dna | brown-stem-rot): 0.5293255131964809
P(a16=absent | brown-stem-rot): 0.9738736336976805
P(a17=absent | brown-stem-rot): 0.9828045854438816
P(a18=absent | brown-stem-rot): 0.9802719274860037
P(a19=abnorm | brown-stem-rot): 0.9584110903758998
P(a20=yes | brown-stem-rot): 0.2509997334044255
P(a21=absent | brown-stem-rot): 0.9594774726739536
P(a22=tan | brown-stem-rot): 0.9176219674753399
P(a23=absent | brown-stem-rot): 0.9720074646760863
P(a24=absent | brown-stem-rot): 0.9752066115702479
P(a25=absent | brown-stem-rot): 0.9941348973607038
P(a26=black | brown-stem-rot): 0.002532657957877899
P(a27=present | brown-stem-rot): 0.002532657957877899
P(a28=norm | brown-stem-rot): 0.9632098107171421
P(a30=norm | brown-stem-rot): 0.9724073580378565
P(a31=absent | brown-stem-rot): 0.9788056518261796
P(a32=absent | brown-stem-rot): 0.9773393761663556
P(a33=norm | brown-stem-rot): 0.9798720341242335
P(a35=norm | brown-stem-rot): 0.9824046920821115

P(brown-stem-rot): 0.20202020202020202

Class Name: brown-stem-rot, [(Product of all Class conditional Probability)*Base rate of the class]: 6.3497610501646I8E-13

Class conditional probabilities for class value = charcoal-rot
P(a1=july | charcoal-rot): 0.11157659544756318
P(a2=normal | charcoal-rot): 0.9540566959921799
P(a3=lt-norm | charcoal-rot): 0.9149560117302052
P(a4=norm | charcoal-rot): 0.24256388772517803
P(a5=yes | charcoal-rot): 0.44155844155844154
P(a6=same-lst-yr | charcoal-rot): 0.21337801982963273
P(a7=upper-areas | charcoal-rot): 0.44868035190615835
P(a8=pot-severe | charcoal-rot): 0.9495880463622399
P(a9=none | charcoal-rot): 0.4710236000558581
P(a10=90-100 | charcoal-rot): 0.26099706744868034
P(a11=abnorm | charcoal-rot): 0.9361820974724201
P(a12=abnorm | charcoal-rot): 0.989247311827957
P(a13=absent | charcoal-rot): 0.935483870967742
P(a14=dna | charcoal-rot): 0.935483870967742
P(a15=dna | charcoal-rot): 0.935483870967742
P(a16=absent | charcoal-rot): 0.9726295210166178
P(a17=absent | charcoal-rot): 0.9819857561793046
P(a18=absent | charcoal-rot): 0.9793324954615277
P(a19=abnorm | charcoal-rot): 0.9564306661080855
P(a20=yes | charcoal-rot): 0.8343806730903505
P(a21=absent | charcoal-rot): 0.9575478285155704
P(a22=tan | charcoal-rot): 0.9136992040217846
P(a23=absent | charcoal-rot): 0.9706744868035191
P(a24=absent | charcoal-rot): 0.974025974025974
P(a25=absent | charcoal-rot): 0.9938556067588326
P(a26=black | charcoal-rot): 0.9074151654796816
P(a27=present | charcoal-rot): 0.9074151654796816
P(a28=norm | charcoal-rot): 0.961457896941768
P(a30=norm | charcoal-rot): 0.9710934227063259
P(a31=absent | charcoal-rot): 0.9777963971512359
P(a32=absent | charcoal-rot): 0.976260298840944
P(a33=norm | charcoal-rot): 0.9789135595587208
P(a35=norm | charcoal-rot): 0.9815668202764977
P(charcoal-rot): 0.1919191919191919

Class Name: charcoal-rot, [(Product of all Class conditional Probability)*Base rate of the class]: 7.341215250866129E-6

Class conditional probabilities for class value = diaporthe-stem-canker
P(a1=july | diaporthe-stem-canker): 0.24286856838176485
P(a2=normal | diaporthe-stem-canker): 0.9561450279925353
P(a3=lt-norm | diaporthe-stem-canker): 0.009730738469741403
P(a4=norm | diaporthe-stem-canker): 0.9588109837376699
P(a5=yes | diaporthe-stem-canker): 0.9214876033057852
P(a6=same-lst-yr | diaporthe-stem-canker): 0.29458810983737665
P(a7=upper-areas | diaporthe-stem-canker): 0.019194881364969343
P(a8=pot-severe | diaporthe-stem-canker): 0.6791522260730471
P(a9=none | diaporthe-stem-canker): 0.5405225273260463
P(a10=90-100 | diaporthe-stem-canker): 0.15822447347374033
P(a11=abnorm | diaporthe-stem-canker): 0.9390829112236736
P(a12=abnorm | diaporthe-stem-canker): 0.9897360703812317

P(a13=absent | diaporthe-stem-canker): 0.93841642228739
P(a14=dna | diaporthe-stem-canker): 0.93841642228739
P(a15=dna | diaporthe-stem-canker): 0.93841642228739
P(a16=absent | diaporthe-stem-canker): 0.9738736336976805
P(a17=absent | diaporthe-stem-canker): 0.9828045854438816
P(a18=absent | diaporthe-stem-canker): 0.9802719274860037
P(a19=abnorm | diaporthe-stem-canker): 0.9584110903758998
P(a20=yes | diaporthe-stem-canker): 0.70554518794988
P(a21=absent | diaporthe-stem-canker): 0.05038656358304452
P(a22=tan | diaporthe-stem-canker): 0.008531058384430818
P(a23=absent | diaporthe-stem-canker): 0.0629165555851773
P(a24=absent | diaporthe-stem-canker): 0.06611570247933884
P(a25=absent | diaporthe-stem-canker): 0.9941348973607038
P(a26=black | diaporthe-stem-canker): 0.002532657957877899
P(a27=present | diaporthe-stem-canker): 0.002532657957877899
P(a28=norm | diaporthe-stem-canker): 0.9632098107171421
P(a30=norm | diaporthe-stem-canker): 0.9724073580378565
P(a31=absent | diaporthe-stem-canker): 0.9788056518261796
P(a32=absent | diaporthe-stem-canker): 0.9773393761663556
P(a33=norm | diaporthe-stem-canker): 0.9798720341242335
P(a35=norm | diaporthe-stem-canker): 0.9824046920821115
P(diaporthe-stem-canker): 0.20202020202020202

Class Name: diaporthe-stem-canker, [(Product of all Class conditional Probability)*Base rate of the class]: 6.348526877338818E-19

Class conditional probabilities for class value = phytophthora-rot

P(a1=july | phytophthora-rot): 0.15195947747267394
P(a2=normal | phytophthora-rot): 0.04705411890162623
P(a3=lt-norm | phytophthora-rot): 0.009730738469741403
P(a4=norm | phytophthora-rot): 0.5497200746467609
P(a5=yes | phytophthora-rot): 0.6942148760330579
P(a6=same-lst-yr | phytophthora-rot): 0.29458810983737665
P(a7=upper-areas | phytophthora-rot): 0.019194881364969343
P(a8=pot-severe | phytophthora-rot): 0.36097040789122903
P(a9=none | phytophthora-rot): 0.4950679818715009
P(a10=90-100 | phytophthora-rot): 0.3400426552919221
P(a11=abnorm | phytophthora-rot): 0.9390829112236736
P(a12=abnorm | phytophthora-rot): 0.9897360703812317
P(a13=absent | phytophthora-rot): 0.93841642228739
P(a14=dna | phytophthora-rot): 0.93841642228739
P(a15=dna | phytophthora-rot): 0.93841642228739
P(a16=absent | phytophthora-rot): 0.9738736336976805
P(a17=absent | phytophthora-rot): 0.9828045854438816
P(a18=absent | phytophthora-rot): 0.9802719274860037
P(a19=abnorm | phytophthora-rot): 0.9584110903758998
P(a20=yes | phytophthora-rot): 0.8873633697680618
P(a21=absent | phytophthora-rot): 0.05038656358304452
P(a22=tan | phytophthora-rot): 0.008531058384430818
P(a23=absent | phytophthora-rot): 0.9720074646760863
P(a24=absent | phytophthora-rot): 0.7024793388429752
P(a25=absent | phytophthora-rot): 0.9941348973607038
P(a26=black | phytophthora-rot): 0.002532657957877899
P(a27=present | phytophthora-rot): 0.002532657957877899

P(a28=norm | phytophthora-rot): 0.0541189016262330l
P(a30=norm | phytophthora-rot): 0.9724073580378565
P(a31=absent | phytophthora-rot): 0.9788056518261796
P(a32=absent | phytophthora-rot): 0.9773393761663556
P(a33=norm | phytophthora-rot): 0.9798720341242335
P(a35=norm | phytophthora-rot): 0.982404692082l115
P(phytophthora-rot): 0.20202020202020202

Class Name: phytophthora-rot, [(Product of all Class conditional Probability)*Base rate of the class]: 1.0246367358131833E-19

Class conditional probabilities for class value = rhizoctonia-root-rot
P(a1=july | rhizoctonia-root-rot): 0.061050386563583046
P(a2=normal | rhizoctonia-root-rot): 0.13796320981071714
P(a3=lt-norm | rhizoctonia-root-rot): 0.009730738469741403
P(a4=norm | rhizoctonia-root-rot): 0.04972007464676086
P(a5=yes | rhizoctonia-root-rot): 0.8760330578512397
P(a6=same-lst-yr | rhizoctonia-root-rot): 0.24913356438283124
P(a7=upper-areas | rhizoctonia-root-rot): 0.019194881364969343
P(a8=pot-severe | rhizoctonia-root-rot): 0.45187949880031997
P(a9=none | rhizoctonia-root-rot): 0.7677952545987736
P(a10=90-100 | rhizoctonia-root-rot): 0.021860837110103972
P(a11=abnorm | rhizoctonia-root-rot): 0.9390829112236736
P(a12=abnorm | rhizoctonia-root-rot): 0.12609970674486803
P(a13=absent | rhizoctonia-root-rot): 0.93841642228739
P(a14=dna | rhizoctonia-root-rot): 0.93841642228739
P(a15=dna | rhizoctonia-root-rot): 0.93841642228739
P(a16=absent | rhizoctonia-root-rot): 0.9738736336976805
P(a17=absent | rhizoctonia-root-rot): 0.9828045854438816
P(a18=absent | rhizoctonia-root-rot): 0.9802719274860037
P(a19=abnorm | rhizoctonia-root-rot): 0.9584110903758998
P(a20=yes | rhizoctonia-root-rot): 0.8873633697680618
P(a21=absent | rhizoctonia-root-rot): 0.05038656358304452
P(a22=tan | rhizoctonia-root-rot): 0.008531058384430818
P(a23=absent | rhizoctonia-root-rot): 0.9720074646760863
P(a24=absent | rhizoctonia-root-rot): 0.06611570247933884
P(a25=absent | rhizoctonia-root-rot): 0.7214076246334311
P(a26=black | rhizoctonia-root-rot): 0.002532657957877899
P(a27=present | rhizoctonia-root-rot): 0.002532657957877899
P(a28=norm | rhizoctonia-root-rot): 0.05411890162623301
P(a30=norm | rhizoctonia-root-rot): 0.9724073580378565
P(a31=absent | rhizoctonia-root-rot): 0.9788056518261796
P(a32=absent | rhizoctonia-root-rot): 0.9773393761663556
P(a33=norm | rhizoctonia-root-rot): 0.9798720341242335
P(a35=norm | rhizoctonia-root-rot): 0.936950146627566
P(rhizoctonia-root-rot): 0.20202020202020202

Class Name: rhizoctonia-root-rot, [(Product of all Class conditional Probability)*Base rate of the class]: 1.2067635702644288E-23

In second iteration, Example-1 is classified as "**charcoal-rot**".

Classifying Example-2 described in Table 3.6:

While classifying the second example given above, for this leave-one-out procedure, **the selection criteria for second example is:** A29 = 'brown-w/blk-specks' and A34 = 'absent' .

Note that the second example has the attribute values:

Table 3.10: Attribute and its value in example-2 (Table 3.6) used for selection criteria:

Attribute Name	Attribute values
a29	brown-w/blk-specks
a34	absent

We choose subset of examples from 682 (Total examples: 683-Second example) based on this criteria. A local NB is applied on this subset. In local NB only attributes (A1-A28 and A30-A33, A35) are considered. The calculation for local NB is as follows.

Subset Total Examples: 21.0

Total class càtegories in subset: 3

Class conditional probabilities for class value = anthracnose

P(a1=august | anthracnose): 0.2690615835777126
P(a2=lt-normal | anthracnose): 0.5928152492668622
P(a3=gt-norm | anthracnose): 0.9671554252199414
P(a4=gt-norm | anthracnose): 0.42903225806451617
P(a5=no | anthracnose): 0.41847507331378303
P(a6=same-lst-yr | anthracnose): 0.37404692082111435
P(a7=low-areas | anthracnose): 0.38313782991202344
P(a8=pot-severe | anthracnose): 0.597067448680352
P(a9=none | anthracnose): 0.44457478005865103
P(a10=90-100 | anthracnose): 0.27404692082111437
P(a11=norm | anthracnose): 0.6645161290322581
P(a12=abnorm | anthracnose): 0.5887096774193549
P(a13=absent | anthracnose): 0.932258064516129
P(a14=dna | anthracnose): 0.932258064516129
P(a15=dna | anthracnose): 0.932258064516129
P(a16=absent | anthracnose): 0.9712609970674487
P(a17=absent | anthracnose): 0.9810850439882698
P(a18=absent | anthracnose): 0.9782991202346041
P(a19=abnorm | anthracnose): 0.9542521994134897
P(a20=no | anthracnose): 0.2060117302052786
P(a21=above-sec-nde | anthracnose): 0.9278592375366569
P(a22=dk-brown-blk | anthracnose): 0.7758064516129032
P(a23=present | anthracnose): 0.6651026392961877

P(a24=firm-and-dry | anthracnose): 0.5196480938416422
P(a25=absent | anthracnose): 0.9935483870967742
P(a26=none | anthracnose): 0.9850439882697948
P(a27=absent | anthracnose): 0.9914956011730205
P(a28=diseased | anthracnose): 0.9189149560117302
P(a30=abnorm | anthracnose): 0.11671554252199415
P(a31=present | anthracnose): 0.10967741935483871
P(a32=absent | anthracnose): 0.8750733137829912
P(a33=lt-norm | anthracnose): 0.00850439882697947
P(a35=norm | anthracnose): 0.9806451612903226
P(anthracnose): 0.8571428571428571

Class Name: anthracnose, [(Product of all Class conditional Probability)*Base rate of the class]: 2.9794012706457844E-10

Class conditional probabilities for class value = brown-spot
P(a1=august | brown-spot): 0.3453079178885631
P(a2=lt-normal | brown-spot): 0.4640762463343109
P(a3=gt-norm | brown-spot): 0.5857771260997067
P(a4=gt-norm | brown-spot): 0.3951612903225806
P(a5=no | brown-spot): 0.342375366568915
P(a6=same-lst-yr | brown-spot): 0.6202346041055719
P(a7=low-areas | brown-spot): 0.41568914956011727
P(a8=pot-severe | brown-spot): 0.48533724340175954
P(a9=none | brown-spot): 0.22287390029325513
P(a10=90-100 | brown-spot): 0.12023460410557185
P(a11=norm | brown-spot): 0.8225806451612903
P(a12=abnorm | brown-spot): 0.9435483870967742
P(a13=absent | brown-spot): 0.16129032258064516
P(a14=dna | brown-spot): 0.16129032258064516
P(a15=dna | brown-spot): 0.16129032258064516
P(a16=absent | brown-spot): 0.8563049853372434
P(a17=absent | brown-spot): 0.905425219941349
P(a18=absent | brown-spot): 0.8914956011730205
P(a19=abnorm | brown-spot): 0.7712609970674487
P(a20=no | brown-spot): 0.030058651026392963
P(a21=above-sec-nde | brown-spot): 0.6392961876832844
P(a22=dk-brown-blk | brown-spot): 0.12903225806451613
P(a23=present | brown-spot): 0.3255131964809384
P(a24=firm-and-dry | brown-spot): 0.09824046920821114
P(a25=absent | brown-spot): 0.967741935483871
P(a26=none | brown-spot): 0.9252199413489737
P(a27=absent | brown-spot): 0.9574780058651027
P(a28=diseased | brown-spot): 0.594574780058651
P(a30=abnorm | brown-spot): 0.08357771260997067
P(a31=present | brown-spot): 0.04838709677419355
P(a32=absent | brown-spot): 0.875366568914956
P(a33=lt-norm | brown-spot): 0.04252199413489736
P(a35=norm | brown-spot): 0.9032258064516129
P(brown-spot): 0.09523809523809523

Class Name: brown-spot, [(Product of all Class conditional Probability)*Base rate of the class]: 3.86928604729826E-17

Class conditional probabilities for class value = frog-eye-leaf-spot
P(a1=august | frog-eye-leaf-spot): 0.1270772238514174
P(a2=lt-normal | frog-eye-leaf-spot): 0.2854349951124145
P(a3=gt-norm | frog-eye-leaf-spot): 0.447702834799609
P(a4=gt-norm | frog-eye-leaf-spot): 0.5268817204301075
P(a5=no | frog-eye-leaf-spot): 0.12316715542521994
P(a6=same-lst-yr | frog-eye-leaf-spot): 0.1603128054740958
P(a7=low-areas | frog-eye-leaf-spot): 0.2209188660801564
P(a8=pot-severe | frog-eye-leaf-spot): 0.31378299120234604
P(a9=none | frog-eye-leaf-spot): 0.6304985337243402
P(a10=90-100 | frog-eye-leaf-spot): 0.49364613880742914
P(a11=norm | frog-eye-leaf-spot): 0.7634408602150538
P(a12=abnorm | frog-eye-leaf-spot): 0.924731182795699 ·
P(a13=absent | frog-eye-leaf-spot): 0.21505376344086022
P(a14=dna | frog-eye-leaf-spot): 0.21505376344086022
P(a15=dna | frog-eye-leaf-spot): 0.21505376344086022
P(a16=absent | frog-eye-leaf-spot): 0.8084066471163245
P(a17=absent | frog-eye-leaf-spot): 0.8739002932551319
P(a18=absent | frog-eye-leaf-spot): 0.8553274682306939
P(a19=abnorm | frog-eye-leaf-spot): 0.6950146627565982
P(a20=no | frog-eye-leaf-spot): 0.04007820136852395
P(a21=above-sec-nde | frog-eye-leaf-spot): 0.5190615835777126
P(a22=dk-brown-blk | frog-eye-leaf-spot): 0.5053763440860215
P(a23=present | frog-eye-leaf-spot): 0.4340175953079179
P(a24=firm-and-dry | frog-eye-leaf-spot): 0.46432062561094817
P(a25=absent | frog-eye-leaf-spot): 0.956989247311828
P(a26=none | frog-eye-leaf-spot): 0.9002932551319649
P(a27=absent | frog-eye-leaf-spot): 0.9433040078201369
P(a28=diseased | frog-eye-leaf-spot): 0.45943304007820135
P(a30=abnorm | frog-eye-leaf-spot): 0.4447702834799609
P(a31=present | frog-eye-leaf-spot): 0.06451612903225806
P(a32=absent | frog-eye-leaf-spot): 0.8338220918866079
P(a33=lt-norm | frog-eye-leaf-spot): 0.056695992179863146
P(a35=norm | frog-eye-leaf-spot): 0.8709677419354838
P(frog-eye-leaf-spot): 0.047619047619047616

Class Name: frog-eye-leaf-spot, [(Product of all Class conditional Probability)*Base rate of the class]: 4.784076844425185E-16

Thus the second example is classified as anthracnose.

In this procedure all 683 examples of second iteration are classified and the error rate is calculated according to the equation (3.4). The error rate for second iteration is 7.03 %.

Third iteration(A29,A34,A20).

In third iteration, the next available highest dependency attribute is "A20". This attribute is And-ed with the second iteration rule. Leave-One-out procedure is applied on 683 examples again for third iteration rule and error rate is calculated. This rule generation procedure continues until all attribute of training set is considered in the iteration rule. At each iteration of rule generation procedure error rate is calculated. The final rule is selected from all iteration's rules which has the lowest error rate. The test examples are classified according to this rule and a local Naïve Bayesian classifier. The error rate is plotted against the attributes in each iteration, the graph looks like the following:

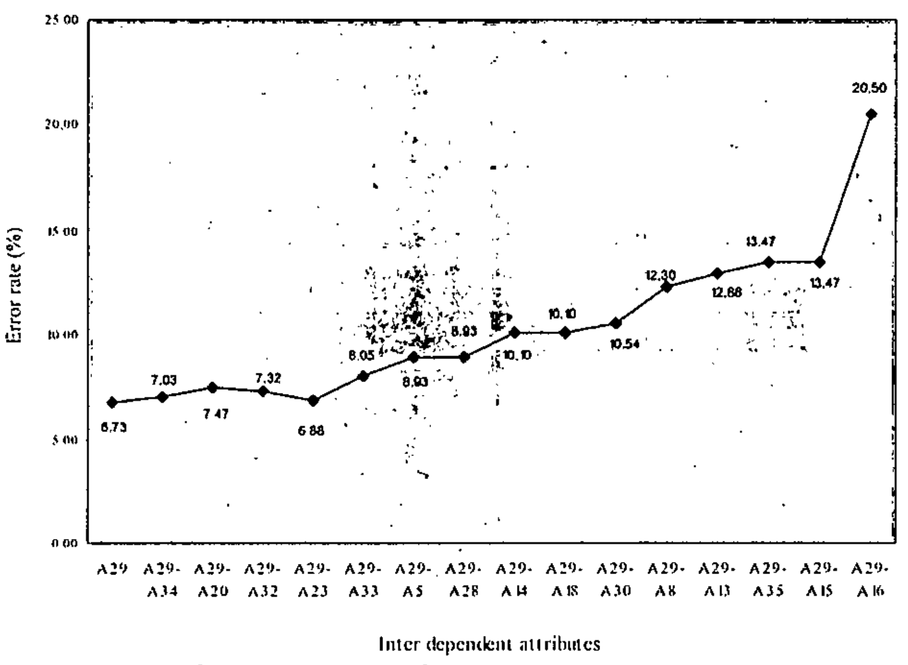

Figure 3.4: Error rate vs interdependent attributes, Horizontal axis gives the attributes name and the vertical axis gives the corresponding error rate.

From the chart it is seen that attribute "A29" has the lowest error rate among all iteration rule. Thus we find the best rule with lowest error rate. The attributes in the rule and its values in any example are used to classify the example.

3.2.2 Applying Proposed Algorithm on Zoology Dataset

For zoology dataset, the procedure for finding distinct values of attributes, attribute dependency, error rate of each iteration rule are same as described in section 3.3.1 and the results are given in chapter four, section 4.6. This domain has a total 101 instances in its training set. A full description of the classification of these 101 instances, calculation for class conditional probabilities in local NB, class absolute probabilities, and other calculation are given in the appendix.

Chapter Four

Experimental Study

Section 4.1 reveals a wide range of natural domains used in experimental study including the distinct values of attributes of each domain, attribute dependency, dependency chart, error rate chart of each domain. Section 4.2 gives the detail description of experimental result of House Vote dataset. In section 4.3, we state the detail analysis of experimental result of postoperative patient domain. Section 4.4 gives the description of Iris domain. Section 4.5 describes the experimental result for Tic-Tac-Toe domain. Section 4.6 explains the experimental result for Zoology domain. Section 4.7 discusses the comparison of proposed algorithm with other well known algorithms and gives a detail analysis for Soybean domain with ignoring missing values in attributes and comparison of ignoring missing values with considering missing values in the same domain. Some issues of Tic-Tac-Toe endgame domain are also explained in this section.

4.1 Domain Description

Experimental analysis is done on a wide range of natural domains. Data sets are taken from UCI machine learning repository. Cross validation method is used to test the performance the algorithm. The Table 4.1 gives a brief description of each domain.

Table 4.1: Description of the learning domains used in experimental study.

Domain Name	**Size**	**No of Classes**	**Numeric Attribute**	**Nominal Attribute**
House Vote1984	435	2	0	16
Soybean	683	19	0	35
Postoperative Patient	90	3	1	7
Zoology	101	7	1	16
Lymphography	148	4	3	15
Iris Plants	150	3	4	0
Tic-Tac-Toe Endgame	958	2	0	9

4.2 1984 US Congressional Voting Records Dataset

This data set includes votes for each of the U.S. House of Representatives Congressmen on the 16 key issues identified by the CQA (Congressional Quarterly Almanac, 98th Congress, 2nd session 1984, Volume XL: Congressional Quarterly Inc. Washington, D.C., 1985). It is used in many classification problems in the past [21, 24]. The CQA lists nine different types of votes: voted for, paired for, and announced for (these three simplified to yea), voted against, paired against, and announced against (these three simplified to nay), voted present, voted present to avoid conflict of interest, and did not vote or otherwise make a position known (these three simplified to an unknown disposition). The main problem is to find the categories of the Congressmen given that 16 key issues identified by the CQA. Total number of instances 435 (267 democrats, 168 republicans). Total number of attributes 16 + class name = 17 (all Boolean valued). These are given in the following. Missing Attribute Values: Denoted by "?". The attributes are (0:handicapped-infants, 1:water-project-cost-sharing, 2:adoption-of-the-budget-resolution, 3:physician-fee-freeze, 4:el-salvador-aid, 5:religious-groups-in-schools, 6:anti-satellite-test-ban, 7:aid-to-nicaraguan-contras, 8:mx-missile, immigration, 9:synfuels-corporation-cutback, 10:education-spending, 11:superfund-right-to-sue, 12:crime, 13:duty-free-exports, 14:export-administration-act-south-africa, 15:Class Name.).Class Distribution: (2 classes, 1. 45.2 percent are democrat, 2. 54.8 percent are republican).

Table 4.2: Distinct values of attributes of House vote data set. Total of 16 attributes exist in the domain. Some attributes have missing value in the examples. This is denoted by "?". This means a particular example has no value for this attribute.

A0	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	Class
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	Democrat
n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	Republican
y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	

Table 4.3: Attribute dependency table of House vote data set. First column of the table gives the abbreviated name of the attribute in the training data. Middle column gives the dependency of each attribute. All of the 16 attribute's dependencies are given in the table.

Attribute Name	Dependency	Attribute Sl No(0-16)
A4	0.17249619482437073	4
A3	0.16296937573274278	3
A7	0.1596495597698321	7
Class	0.14897293573268264	16
A8	0.1369207415643222	8
A2	0.13662775565645163	2
A6	0.1270902830081607	6
A11	0.12541166609534252	11
A13	0.12352366436665933	13
A12	0.11508408668833203	12
A5	0.09454851584131857	5
A14	0.09039489093145354	14
A0	0.05557356021572302 4	0
A15	0.026804360843675434	15
A10	0.018194798990602442	10
A1	0.012575740784865919	1
A9	0.005102697188242126	9

When Attribute dependency is plotted against attribute we get the graph:

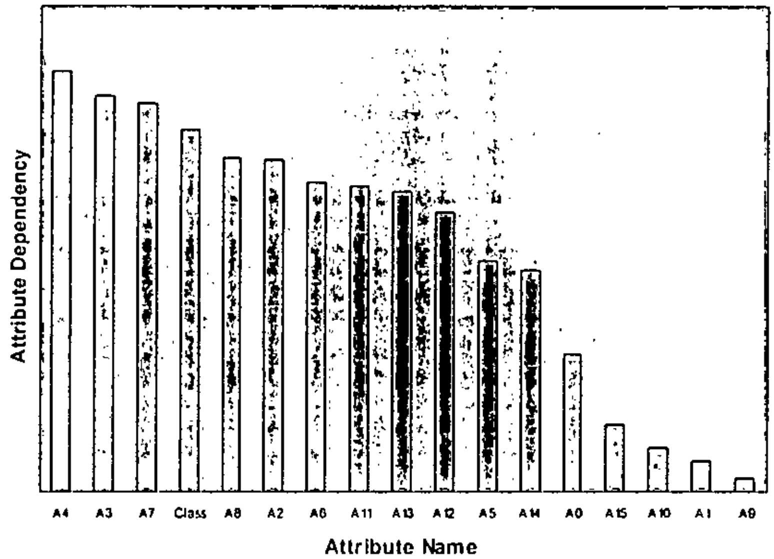

Figure 4.1: Attribute dependency chart for House vote data set. Horizontal axis denotes the attribute's name and vertical axis denotes the attributes dependencies.

Error rate is plotted against attribute set at each iteration. This is as follows:

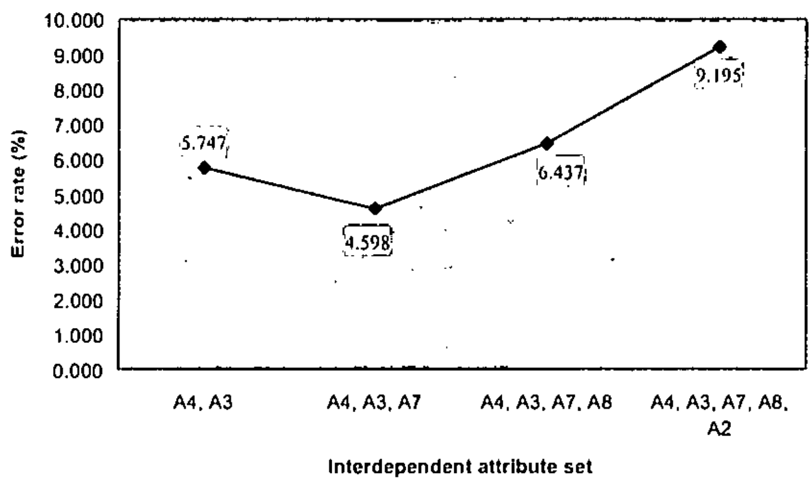

Figure 4.2: Error rate vs interdependent attribute set of House vote data set. Horizontal axis gives the attributes name and the vertical axis gives the corresponding error rate.

From the graph above, it is seen that final rule with lowest error rate contains the attributes:

4. el-salvador-aid: 2 (y,n)

3. physician-fee-freeze: 2 (y,n)

7. aid-to-nicaraguan-contras: 2 (y,n)

Error Rate: 4.59 %

4.3 Postoperative Patient Dataset

The classification task of this database is to determine where patients in a postoperative recovery area should be sent to next. Because hypothermia is a significant concern after surgery [23]. The data set is widely used in many classification problems in the past [23]. The attributes correspond roughly to body temperature measurements. The total number of instances is 90. The attributes are (

0: L-CORE-patient's internal temperature in C- [high (> 37), mid (>= 36 and <= 37), low (< 36)], 1: L-SURF -patient's surface temperature in C-[high (> 36.5), mid (>= 36.5 and <= 35), low (< 35)], 2: L-O2 -oxygen saturation in %-[excellent (>= 98), good (>= 90 and < 98),fair (>= 80 and < 90), poor (< 80)], 3:L-BP -last measurement of blood pressure-[high (> 130/90), mid (<= 130/90 and >= 90/70), low (< 90/70)], 4: SURF-STBL -stability of patient's surface temperature-[stable, mod-stable, unstable], 5: CORE-STBL-stability of patient's core temperature-[stable, mod-stable, unstable], 6: BP-STBL-stability of patient's blood pressure-[stable, mod-stable, unstable], 7: COMFORT -patient's perceived comfort at discharge, measured as an integer between 0 and 20), 8: decision ADM-DECS-discharge decision[I= patient sent to Intensive Care Unit), S=patient prepared to go home, A = patient sent to general hospital floor]. Attribute 8 has 3 missing values.

Class Distributions are I (2), S (24), A (64).

Table 4.4: Distinct values of attributes of Post operative patient data set. Total of 8 attributes exist in the domain. Attribute with serial no 7 has missing value in the examples. This is denoted by "?". This means a particular example has no value for this attribute.

A0	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**Decision**
high	high	excellent	high	stable	mod-stable	mod-stable	05	A
low	low	Good	low	unstable	stable	stable	07	I
mid	mid		mid		unstable	unstable	10	S
							15	
							?	

Table 4.5: Attribute dependency table of Post operative patient data set. First column of the table gives the abbreviated name of the attribute in the training data. Middle column gives the dependency of each attribute. All of the 8 attribute's dependencies are given in the table.

Attribute Name	**Dependency**	**Attribute Sl No(0-8)**
A6	0.015755493039959607	6
A1	0.012895888484226865	1
A2	0.011632866938200943	2
A0	0.010849464197221156	0
A4	0.009247226522661878	4
A3	0.009136369347329283	3
A7	0.008070034032456439	7
Decision	0.007263092298830586	8
A5	0.002839345223096981	5

Attributes are plotted against the dependency and the following graph is obtained.

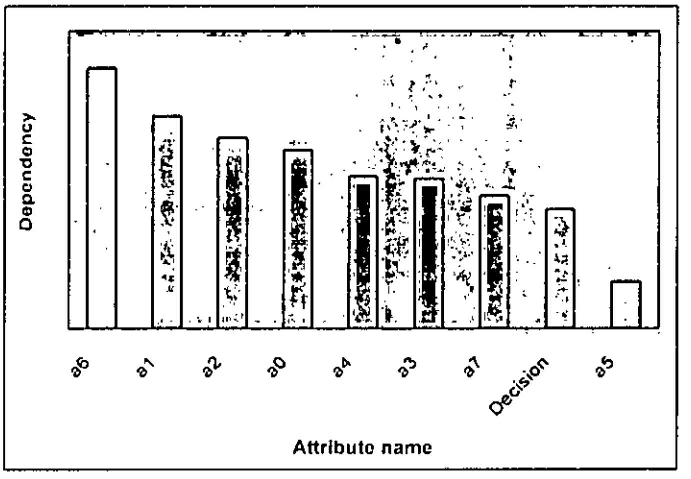

Figure 4.3: Attribute dependency chart for Post operative patient data set. Horizontal axis denotes the attribute's name and vertical axis denotes the attributes dependencies.

We plot the error rate against attribute set at each iteration. This graph is as follows:

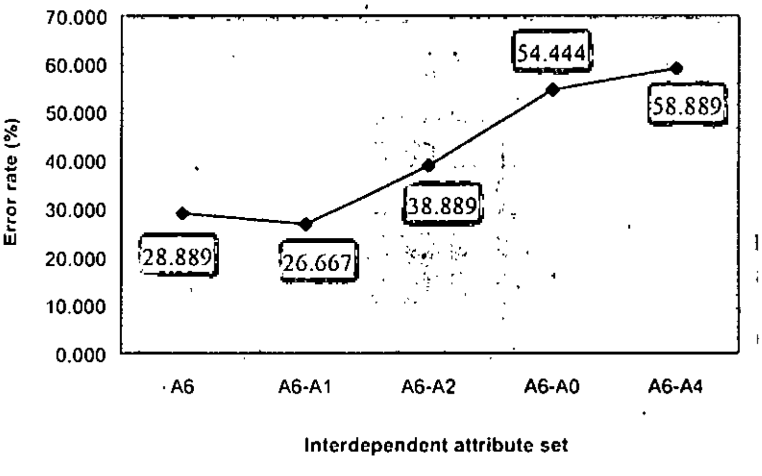

Figure 4.4: Error rate vs interdependent attribute set of post operative patient data set. Horizontal axis gives the attributes name and the vertical axis gives the corresponding error rate.

The graph shows that final iteration rule with lowest error rate contains the attributes:

6. BP-STBL (stability of patient's blood pressure) stable, mod-stable, unstable

1. L-SURF (patient's surface temperature in C): high (> 36.5), mid (>= 36.5 and <= 35), low (< 35)

Error Rate: 26.67%

4.4 Iris Plants Dataset

This is perhaps the best known database to be found in the pattern recognition literature. It is widely used in the past [5, 24] in classification and pattern recognition problems. Conceptual clustering system finds classes of the Iris plants from a set of given attributes. The data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant. One class is linearly separable from the other 2; the latter are not linearly separable from each other. Total number of Instances in data set is 150 (50 in each of three classes).Total number of attributes is 4 numeric, predictive attributes and the class. There is no missing value in the attributes. The attributes are (0. sepal length in cm, 1. sepal width in cm, 2. petal length in cm, 3. petal width in cm, 4. class[Iris Setosa, Iris Versicolour, Iris Virginica]).

Table 4.6: Distinct values of attributes of Iris plant data set. Total of 4 attributes exist in the domain.

A0	A1	A2	A3	Class
4.3	2.0	1.0	0.1	Iris-setosa
4.4	2.2	1.1	0.2	Iris-versic
4.5	2.3	1.2	0.3	Iris-virgin
4.6	2.4	1.3	0.4	
4.7	2.5	1.4	0.5	
4.8	2.6	1.5	0.6	
4.9	2.7	1.6	1.0	
5.0	2.8	1.7	1.1	
5.1	2.9	1.9	1.2	
5.2	3.0	3.0	1.3	
5.3	3.1	3.3	1.4	
5.4	3.2	3.5	1.5	
5.5	3.3	3.6	1.6	

Continuation of Table 4.6:

A0	A1	A2	A3	Class
5.6	3.4	3.7	1.7	
5.7	3.5	3.8	1.8	
5.8	3.6	3.9	1.9	
5.9	3.7	4.0	2.0	
6.0	3.8	4.1	2.1	
6.1	3.9	4.2	2.2	
6.2	4.0	4.3	2.3	
6.3	4.1	4.4	2.4	
6.4	4.2	4.5	2.5	
6.5	4.4	4.6		
6.6		4.7		
6.7		4.8		
6.8		4.9		
6.9		5.0		
7.0		5.1		
7.1		5.2		
7.2		5.3		
7.3		5.4		
7.4		5.5		
7.6		5.6		
7.7		5.7		
7.9		5.8		
		5.9		
		6.0		
		6.1		
		6.3		
		6.4		
		6.6		
		6.7		
		6.9		

Table 4.7: Attribute dependency table of Iris plant data set. First column of the table gives the abbreviated name of the attribute in the training data. Middle column gives the dependency of each attribute. All of the 4 attribute's dependencies are given in the table.

Attribute Name	**Dependency**	**Attribute Sl No(0-4)**
Class	0.43787840862840843	4
A3	0.2514892348392349	3
A1	0.18182307692307692	1
A2	0.17354088319088307	2
A0	0.1734857142857143	0

Attribute dependency chart for this domain:

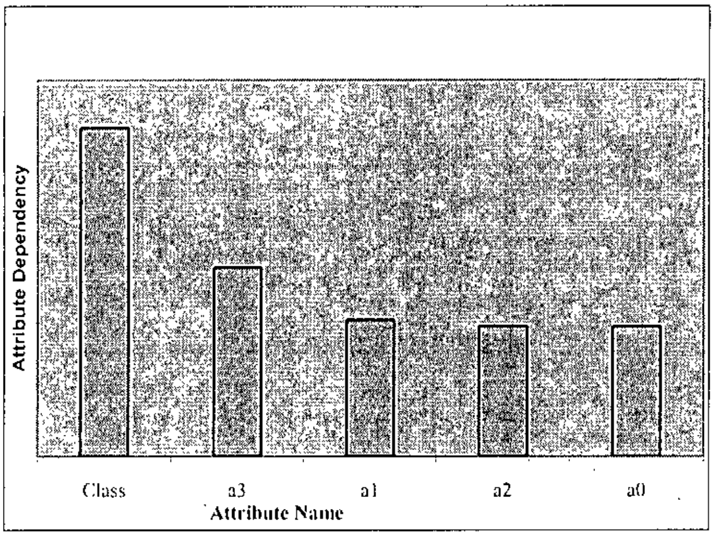

Figure 4.5: Attribute dependency chart for Iris plant data set. Horizontal axis denotes the attribute's name and vertical axis denotes the attributes dependencies.

Error rate is plotted against attribute set at each iteration. This is as follows:

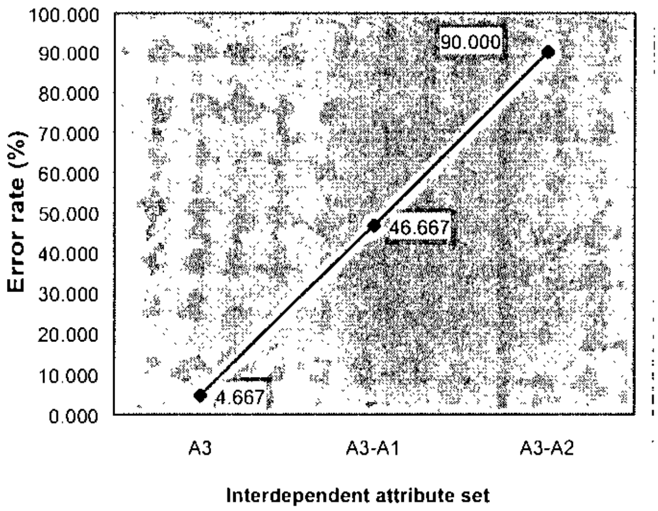

Figure 4.6: Error rate vs interdependent attribute set of Iris plant data set. Horizontal axis gives the attributes name and the vertical axis gives the corresponding error rate.

Final rule contains the attribute:

3. petal width in cm

Error Rate: 4.60%

4.5 Tic-Tac-Toe Endgame Dataset

This database encodes the complete set of possible board configurations at the end of tic-tac-toe games, where "x" is assumed to have played first. The target concept is "win for x" (i.e., true when "x" has one of 8 possible ways to create a "three-in-a-row"). The main problem is to find the target concept from a given set of attribute values. The data set is widely used in many classification problems in the past [17, 18]. Total number of instances is 958 (legal tic-tac-toe endgame boards). Number of Attributes: 9, each corresponding to one tic-tac-toe square. Attributes are (0. top-left-square, 1. top-middle-square, 2. top-right-square, 3. middle-left-square, 4. middle-middle-square, 5. middle-right-square, 6. bottom-left-square, 7. bottom-middle-square, 8. bottom-right-square, 9. Class). Attributes values (x = player x has taken, o = player o has taken, b =

blank). Missing attribute values are none. Class Distribution: about 65.3% are positive (i.e., wins for "x").

Table 4.8: Distinct values of attributes of Tic-Tac-Toe Endgame data set. Total of 9 attributes exist in the domain.

A0	A1	A2	A3	A4	A5	A6	A7	A8	Class
b	b	b	b	b	b	b	b	b	negative
o	o	o	o	o	o	o	o	o	positive
x	x	x	x	x	x	x	x	x	

Table 4.9: Attribute dependency table of Tic-Tac-Toe Endgame data set. First column of the table gives the abbreviated name of the attribute in the training data. Middle column gives the dependency of each attribute. All of the 9 attribute's dependencies are given in the table.

Attribute Name	Dependency	Attribute Sl No(0-9)
Class	0.01188628333831695	9
A7	0.01017926989682871	7
A5	0.01017926989682871	5
A1	0.01017926989682871	1
A3	0.01017926989682871	3
A4	0.01003035537556346	4
A0	0.00883726960208207	0
A2	0.00883726960208207	2
A6	0.00883726960208206	6
A8	0.00883726960208206	8

Attributes are plotted against dependency. The chart is as follows:

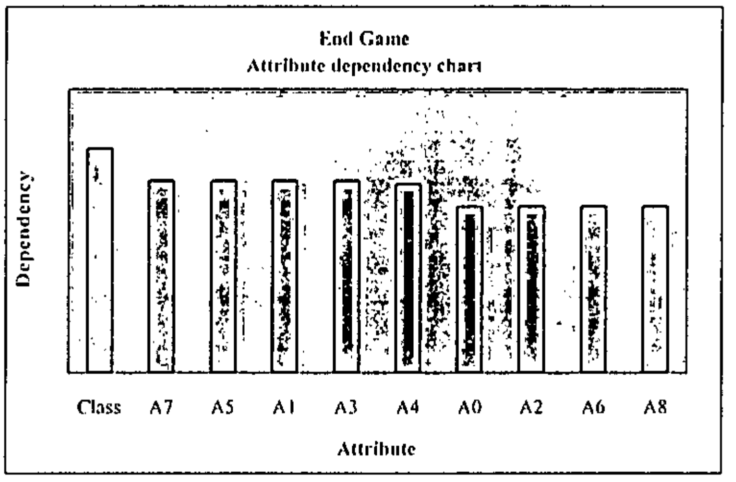

Figure 4.7: Attribute dependency chart for Tic-Tac-Toe Endgame data set. Horizontal axis denotes the attribute's name and vertical axis denotes the attributes dependencies.

The error rate is plotted against attribute set at each iteration. This is as follows:

98033

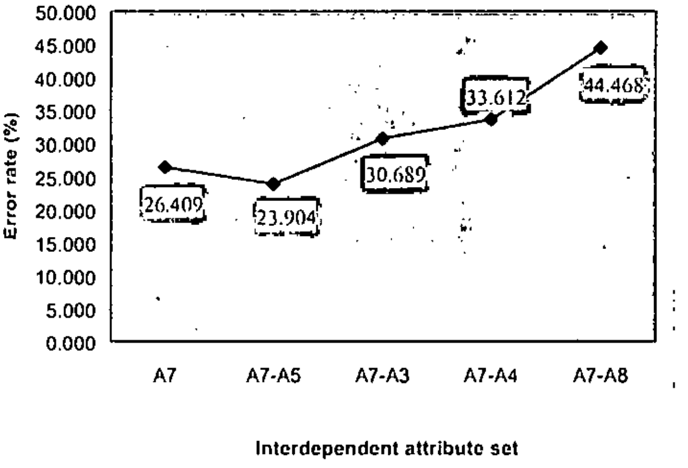

Figure 4.8: Error rate vs interdependent attribute set of Tic-Tac-Toe Endgame set. Horizontal axis gives the attributes name and the vertical axis gives the corresponding error rate.

Final rule with lowest error rate contains the attributes for this domain:

7. bottom-middle-square: {x,o,b}, 5. middle-right-square: {x,o,b}.

Error Rate: 23.90%

4.6 Zoology Dataset

A simple database containing 17 Boolean-valued attributes. The "type" attribute is the the class attribute. The data set is used in many classification algorithms in the past [24]. Animal groups are denoted by the "Type". The total number of instances is 101 and number of Attributes are 18 (animal name, 15 Boolean attributes, 2 numeric). The main classification problem is to find the name of the class of the animal given the attribute's value of that animal. There is no missing value in the attributes. Attributes are (0. animal name, 1. hair, 2. feathers, 3. eggs, 4. milk, 5. airborne, 6. aquatic, 7. predator, 8. toothed, 9. backbone, 10. breathes, 11. venomous, 12. fins, 13. legs, 14. tail, 15. domestic, 16. catsize, 17. type)

Table 4.10: Distinct values of attributes of Zoology data set. Total of 17 attributes exist in the domain.

		A0		
aardvark	dove	kiwi	piranha	slug
antelope	duck	ladybird	pitviper	sole
bass	elephant	lark	platypus	sparrow
bear	flamingo	leopard	polecat	squirrel
boar	flea	lion	pony	starfish
buffalo	frog	lobster	porpoise	stingray
calf	fruitbat	lynx	puma	swan
carp	giraffe	mink	pussycat	termite
catfish	girl	mole	raccoon	toad
cavy	gnat	mongoose	reindeer	tortoise
cheetah	goat	moth	rhea	tuatara
chicken	gorilla	newt	scorpion	tuna
chub	gull	octopus	seahorse	vampire
clam	haddock	opossum	seal	vole
crab	hamster	oryx	sealion	vulture
crayfish	hare	ostrich	seasnake	wallaby
crow	hawk	parakeet	seawasp	wasp
deer	herring	penguin	skimmer	wolf
dogfish	honeybee	pheasant	skua	worm
dolphin	housefly	pike	slowworm	wren

Continuation of Table 4.10: Distinct values of attributes of Zoology data set.

A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	Type
false	false	false	false	false	false	false	false	false	false	false	false	0	false	false	false	Amphibi-an
true	true	true	true	true	true	true	true	true	true	true	true	2	true	true	true	bird
												4				fish
												5				insect
												6				Invertebr-ate
												8				mammal
																reptile

Table 4.11: Attribute dependency table of Zoology data set. First column of the table gives the abbreviated name of the attribute in the training data. Middle column gives the dependency of each attribute. All of the 17 attribute's dependencies are given in the table.

Attribute Name	Dependency	Attribute Sl No(0-17)
Type	0.18098941362605506	17
A4	0.1628845285408043	4
A3	0.15219808741220325	3
A13	0.15024333619341945	13
A1	0.14355816725982407	1
A8	0.13931424836080453	8
A6	0.08766731352919219	6
A16	0.08463514317016013	16
A2	0.0807278857108441	2
A5	0.07841797653079857	5
A10	0.07747687891005263	10
A9	0.07290147146170568	9
A14	0.06700200980508142	14
A12	0.05907913797610531	12
A7	0.0507421376606038	7
A15	0.018001307433701468	15
A0	0.015550424229140674	0
A11	0.013023980011462485	11

Attribute's dependency is plotted against the attribute. This is as follows:

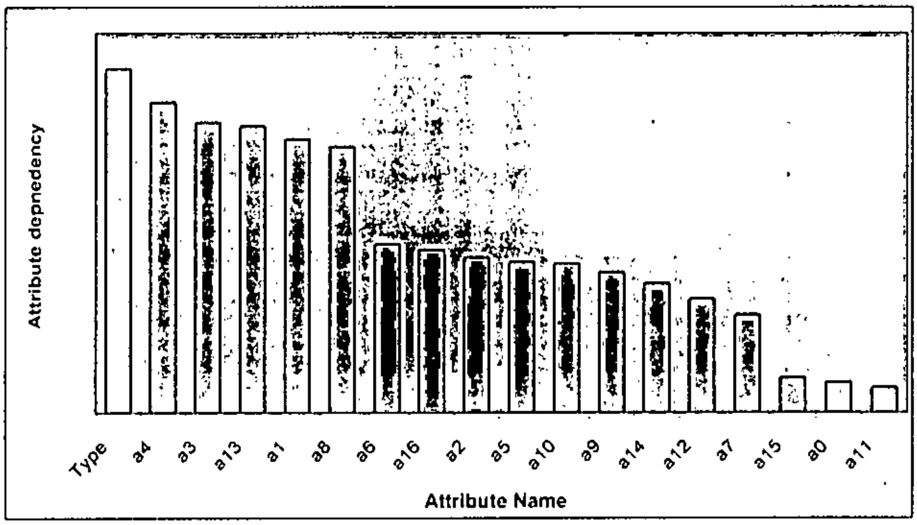

Figure 4.9: Attribute dependency chart for Zoology data set. Horizontal axis denotes the attribute's name and vertical axis denotes the attributes dependencies.

Error rate is plotted against attribute set at each iteration. This is as follows:

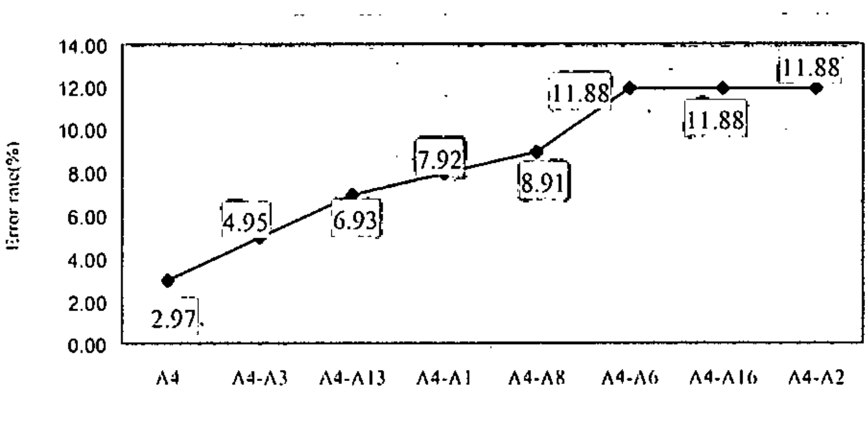

Figure 4.10: Error rate vs interdependent attribute set of Zoology data set. Horizontal axis gives the attributes and vertical axis gives the corresponding error rate.

From the graph it is seen that the final rule with lowest error rate contains the attributes: 4. milk {true, false}

Error Rate: 2.97%.

4.7 Experimental Result

Error rates(%) of Proposed algorithm and NB are given in the following table and the error rate is compared with some well known algorithm C4.5, LAZYDT, BSEJ, LBR. We obtain a lower rate than that of NB in each domain except Lymphography. In this domain NB has lower rate than that of other algorithms (C4.5, LAZYDT) and NB works perfectly in this domain.

Table 4.12: Comparison of error rate(%) of proposed algorithm with other algorithms.

Domain Name	NB	C4.5	LAZYDT	BSEJ	LBR	Proposed algorithm
House Vote 84	9.8	5.6	6.1	8.4	5.6	4.59
Soybean	9.2	8.5	10	8.2	5.9	6.7
Iris	6.3	5.7	6.3	6.0	6.3	4.6
Lymphography	16.1	21.9	19.5	18.2	16.1	16.1
Postoperative	33.9	30	37.8	33.9	33.9	26.67
Tic-Tac-Toe	30.6	13.7	4.5	21.8	13.5	23.9
Zoology	5.5	7.4	7	4.0	5.5	2.97

From the above table it is seen that LBR has lower error rate in Soybean and Tic-Tac-Toe domain than that of our algorithm. These two facts is clarified in the next sections. LBR ignores attribute with missing value. We consider missing values in attributes [11]. For this reason our algorithm has a slightly higher error rate in Soybean domain.

4.7.1 Analysis for Soybean Dataset

Soybean data set has many missing values in the attributes of training examples. Here we mean "missing values in an attribute for a particular example" is that the value for that attribute in a test example is unknown. In our algorithm, we consider the missing value as a new type of value [11] for that attribute. But LBR ignores the missing values. As a result we obtain a larger error rate for Soybean domain than that of LBR. On the other hand if we ignore the missing values in attributes like LBR we obtain a lower error rate than that of LBR for Soybean domain. Here is a statistics for attributes which have missing value in the examples in Soybean data set:

Table 4.13: Statistics for missing value in the attributes in the Soybean domain. Last column denotes the total number of example which has missing value in corresponding attribute in the training data.

Attribute Name	Attribute sl no	Total no. of examples containing missing value(?) in this attribute
A35	34	31
A34	33	106
A33	32	92
A32	31	106
A31	30	92
A30	29	92
A29	28	106
A28	27	84
A20	19	121
A23	22	106
A5	4	121
A14	13	84

If we ignore the missing values in attributes while calculating attribute dependency then we obtain the following dependencies for attributes in Soybean data set:

Table 4.14: Attribute dependency table of soybean data set ignoring the missing value in the attributes. First column of the table gives the abbreviated name of the attribute in the training data. Middle column gives the dependency of each attribute. All of the 35 attribute's dependencies are given in tbe table.

Attribute Name	Attribute dependency (Missing values ignored)	Attribute Sl No(0-34)
a35	0.1440850968859877	34
a34	0.14189621243796083	33
a33	0.14047519075425213	32
a32	0.12934624799682215	31
a28	0.127825196717452	27
a20	0.12715293961381277	19
a17	0.12452822484703598	16
a30	0.12326844419487978	29
a23	0.12248252354701832	22
a29	0.12099390398409152	28
a18	0.1204921614335488	17

Continuation of Table 4.14:

Attribute Name	Attribute dependency (Missing values ignored)	Attribute Sl No(0-34)
a14	0.12013675583313307	13
a31	0.11589063413130792	30
a13	0.11018616665510211	12
a15	0.10755711162389826	14
a11	0.10447436201494624	10
a21	0.1014562841765434	20
a5	0.0998357126076578	4
a16	0.09803623820549003	15
a22	0.08998810410746731	21
a19	0.0813243391962274	18
a8	0.08096674434500432	7
a9	0.06898133264845267	8
a24	0.06756796465582222	23
a27	0.0631803113206591	26
a25	0.06283638878529312	24
a2	0.06090928261166796	1
class	0.0602989908819818	class
a3	0.05981870604875205	2
a26	0.0590101374073419	25
a4	0.04347544363641335	3
a10	0.027685263940558993	9
a7	0.018313868463145033	6
a1	0.017289426840164362	0
a6	0.012193619407510523	5
a12	0.009218326484997876	11

We plot these attribute dependencies against attributes. This is as follows:

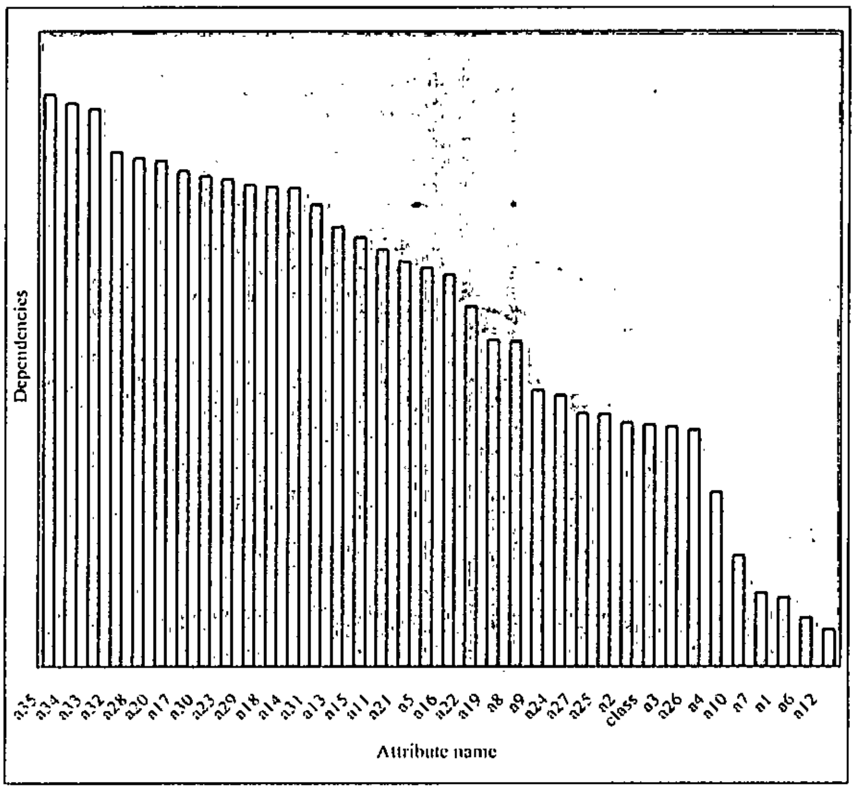

Figure 4.11: Attribute dependency chart for Śoybean data set with ignoring missing value. Horizontal axis denotes the attribute name and vertical axis denotes the attribute dependencies.

If we compare dependencies in both cases (missing values considered and missing values ignored) we see that there is a change in the order of dependencies among attributes. This is clarified in Table 4.15.

Table 4.15: Comparison of attribute's dependencies of soybean data set among the dependencies calculated ignoring the missing value and considering the missing value. First halves of the columns of the table denotes the dependencies calculated ignoring the missing value. Second halves of the columns of the table denotes the dependencies calculated considering. All of the 35 attribute's dependencies are given in the table.

Missing values ignored			**Missing values considered**		
Attribute Name	**Attribute dependency**	**Attr. Sl No 0-34**	**Attr. Name**	**Attribute dependency**	**Sl no**
a35	0.1440850968859877	34	a29	0.17411481477680107	28
a34	0.14189621243796083	33	a34	0.16655758587323488	33
a33	0.14047519075425213	32	a20	0.16401849410315217	19
a32	0.12934624799682215	31	a32	0.1576619031391632	31
a28	0.127825196717452	27	a23	0.1569907694989127	22
a20	0.12715293961381277	19	a33	0.15110309842271025	32
a17	0.12452822484703598	16	a5	0.14784659182398138	4
a30	0.12326844419487978	29	a28	0.14765412809728	27
a23	0.12248252354701832	22	a14	0.144042511013062	13
a29	0.12099390398409152	28	a18	0.14200400939156918	17
a18	0.1204921614335488	17	a30	0.14102965218211927	29
a14	0.12013675583313307	13	a8	0.14087462579066126	7
a31	0.11589063413130792	30	a13	0.1356451968968302	12
a13	0.11018616665510211	12	a35	0.13481602313402816	34
a15	0.10755711162389826	14	a15	0.13448928296769305	14
a11	0.10447436201494624	10	a9	0.12866330569656903	8
a21	0.1014562841765434	20	a31	0.1250136954522472	30
a5	0.0998357126076578	4	a17	0.12250635559331303	16
a16	0.09803623820549003	15	a16	0.11836843806578816	15
a22	0.08998810410746731	21	a22	0.11706404499400117	21
a19	0.0813243391962274	18	a11	0.11627402988184009	10
a8	0.08096674434500432	7	a10	0.11082311042285567	9
a9	0.06898133264845267	8	a21	0.10183103940935141	20
a24	0.06756796465582222	23	class	0.09506869181147803	35
a27	0.0631803113206591	26	a19	0.0917037946433417	18
a25	0.06283638878529312	24	a2	0.07673799037532297	1
a2	0.06090928261166796	1	a24	0.0660153731569228	23
Class	0.0602989908819818	class	a3	0.05974218290098993	2
a3	0.05981870604875205	2	a26	0.05455056319917149	25
a26	0.0590101374073419	25	a27	0.04840329545949396	26
a4	0.04347544363641335	3	a25	0.0451979618506194	24
a10	0.027685263940558993	9	a4	0.04482361659593675	3
a7	0.018313868463145033	6	a7	0.04047682579518786	6
a1	0.017289426840164362	0	a1	0.020209091031211456	0
a6	0.012193619407510523	5	a12	0.018752830150328265	11
a12	0.009218326484997876	11	a6	.012983205058785969	5

When we ignore the missing values the highest dependency attribute is "A35" and considering the missing values in attributes the highest dependency attribute becomes "A29". We apply leave-one-out method for new dependencies of attributes described in our algorithm and the error rate obtained at each iteration are given in the following table:

Table 4.16: Error rate obtained in Soybean data set ignoring the missing value.

Attributes at each iteration	Error rate(%)
A35	5.86
A35-A34	6.73
A35-A33	7.03
A35-A32	7.03
A35-A28	7.76
A35-A20	8.35
A35-A31	10.25
A35-A15	11.13

The error rate is plotted against the most interdependent attributes. The chart looks like as follows:

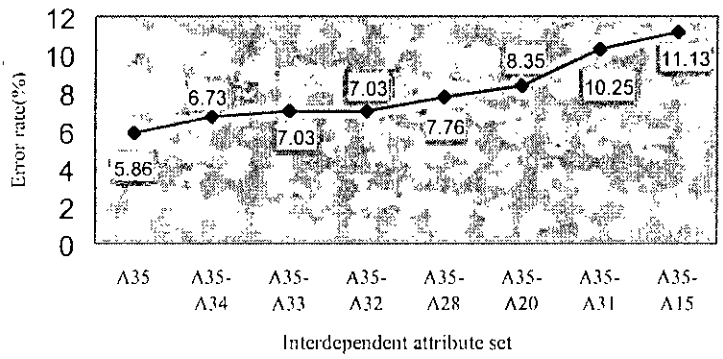

Figure 4.12: Error rate vs interdependent attribute set for Soybean data set with ignoring missing value, Horizontal axis gives the attributes name and vertical axis gives the corresponding error rate.

We see that attribute "A35" has the lowest error rate of 5.86% for soybean domain whereas LBR has an error rate of 5.9%. A detail analysis for Tic-Tac-Toe end game domain has been given in the next section.

4.7.2 Analysis for Tic-Tac-Toe Endgame Dataset

From the attribute dependency Table 4.9 it is seen that some attributes in this domain have equal dependency. Attributes in the domain can be divided into four groups according to their dependency. All attributes in a group have equal dependency. The four groups are as follows. Each attribute in a group is denoted by its serial-no mentioned in the attribute dependency table.

Table 4.17: Attribute groups having equal dependency and attribute dependency of each group for Tic-Tac-Toe Endgame data set.

Group Name	Order of dependency	Attributes serial no corresponds to table 4.9 in Chapter 4	Attribute dependency
Group-1	First highest dependency attributes	{1,3,5,7}	0.0101792698968287l
Group-2	Second highest dependency attributes	{4}	0.01003035537556346
Group-3	Third highest dependency attributes	{0,2}	0.00883726960208207
Group-4	Fourth highest dependency attributes	{6,8}	0.00883726960208206

We take exactly one attribute from each group and make a selection criteria by And operation of these four attributes with their values in one example of training set (total Example of the domain = 958) which is taken as a test example of a leave-one-out test. Then we choose subset of examples from 957 (958-test example, excluding the test example). A local NB is applied on this subset of examples and the test example is classified. Thus applying leave-one-out procedure we classify all examples of training set. Using equation (3.2) error rate is calculated for each leave-one-out test. The Table 4.18 gives error rate of some leave-one-out test.

Table 4.18: Attribute groups having equal dependency used in each iteration rule and their corresponding error rate for Tic-Tac-Toe Endgame data set. In Each iteration rule, only one attribute is taken from each group.

Iteration rule	Group-1 attributes	Group-2 attributes	Group-3 Attributes	Group-4 attributes	Error rate (%) of leave-one-out test
a)	1	4	0	6	13.57
b)	3	4	0	6	13.05
c)	5	4	2	6	20.04
d)	5	4	0	6	8.04
e)	7	4	0	6	13.57
f)	7	4	2	6	20.04

From the above table it is seen that final iteration rule d) has the lowest error rate (8.04%) having attributes with serial-no {5, 4, 0, 6}. This error rate is lower than that of NB, C4.5, LBR, BSEJ listed Table 4.12.

If more than one attribute is taken from each group and leave-one-out test is applied on the training examples, it is seen that error rate increases which is greater than that of previous error rate described in Table 4.18. For this later case obtained error is listed in the following table:

Table 4.19: Attribute groups having equal dependency used in each iteration rule and their corresponding error rate for Tic-Tac-Toe Endgame data set. In Each iteration rule, more than one attribute is taken from each group.

Iteration rule	Group-1 attributes	Group-2 attributes	Group-3 attributes	Group-4 attributes	Error rate of leave-one-out test
a)	3,5,7			6	30.38 %
b)	1,5,7	4		6	50.42 %
c)	1,3,5,7	4	0,2		63.88 %
d)	1,5,7	4	0,2	6	63.88 %
e)	1,5	4	2	6,8	34.44 %

We obtain a reasonable lower error rate for this domain, it shows a special characteristics of having more than one attribute with equal dependency.

Chapter Five

Conclusions

In this thesis, We propose an efficient classification algorithm of Naive Bayesian(NB) classification which can be used in many real life applications like medical diagnosis, weather forecasting, gene classification, text classification, stock prediction, prediction of credit-worthiness and other practical applications of machine learning technology for classification, pattern recognition, information retrieval tasks. The proposed algorithm improves the performance of NB in learning domains where attribute independence assumption of NB is violated and NB gives an error rate higher than that of some well known algorithms like decision tree learning C4.5, LAZYDT.

Compared with other existing algorithms improving the performance of NB, the superiority of our algorithm is that it introduces a measure of attribute dependence for each attribute in the training data. A set of most inter-dependent attributes is selected based on their dependency and by the use of leave-one-out cross validation on training data. In this way, the detrimental attribute inter-dependencies in training data for NB classification is factored out and independence assumption problem of NB is diminished. When a test example is to be classified most inter-dependent attributes with their values in the test example is used to select a subset of examples from training data. A local NB classifier is applied on this subset to classify the test example. Use of attribute dependence shrinks the search space to find a set of effective attributes for local NB classifier used to classify the test example.

The proposed algorithm has been compared experimentally with NB, LBR, BSEJ, LAZYDT, C4.5 etc. in a large number of artificial and natural learning domains. Experimental result shows that it improves the performance of NB in each domain and obtains a lower error rate than that of existing algorithms deployed in the enhancement of NB. Proposed algorithm considers missing values in attributes as a new type of value. For this reason, It has a slightly higher error rate in Soybean domain. If missing values in attributes are ignored performance is improved.

The proposed algorithm is applied on datasets of small size (e.g. Postoperative. Zoology, Iris) and it improves the performance of NB in these kind of learning domains. Existing algorithms (LBR) do not improve the performance of NB in domains with a small number of training examples.

Learning domains may have attributes with equal attribute dependency(e.g. Tic-Tac-Toe Endgame). This characteristics of domains may affect the performance of the algorithm. A suitable heuristic may be applied to eradicate this problem. Appropriate choice of attributes from each attribute dependency group and use of these attributes as most inter-dependent attributes in final rule selection procedure improves the performance of the algorithm in these domains. Investigation of appropriate extension of the technique for these type of domains remains an interesting direction for future research.

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Appendix

Zoology Dataset

Detail of the Leave-One-Out procedure for first iteration (A4):

Here we have introduced an additional identifier "slno" for simplification of leave-one-out procedure. This does not affect the whole procedure.

Instance 1 : a0=chicken a1=false a2=true a3=true a4=false a5=true a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=true a16=false

Selection criteria for subset generation A4='false' and slno!=1
Subset Total Examples: 59.0
Total class categories in subset: 6
P(a0=chicken | amphibian): 0.0
P(a1=false | amphibian): 0.8566666666666666
P(a2=true | amphibian): 0.06333333333333334
P(a3=true | amphibian): 0.86
P(a5=true | amphibian): 0.07666666666666667
P(a6=false | amphibian): 0.21333333333333335
P(a7=false | amphibian): 0.31333333333333335
P(a8=false | amphibian): 0.13
P(a9=true | amphibian): 0.94
P(a10=true | amphibian): 0.9299999999999999
P(a11=false | amphibian): 0.8066666666666666
P(a12=false | amphibian): 0.9433333333333334
P(a13=2 | amphibian): 0.08666666666666667
P(a14=true | amphibian): 0.41333333333333333
P(a15=true | amphibian): 0.04
P(a16=false | amphibian): 0.8533333333333333
P(amphibian): 0.06779661016949153
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.714222603521923E-9
P(a0=chicken | bird): 0.0
P(a1=false | bird): 0.9590476190476619
P(a2=true | bird): 0.9228571428571428
P(a3=true | bird): 0.96
P(a5=true | bird): 0.7361904761904762
P(a6=false | bird): 0.68
P(a7=false | bird): 0.518095238095238
P(a8=false | bird): 0.9419047619047619
P(a9=true | bird): 0.9828571428571429
P(a10=true | bird): 0.98
P(a11=false | bird): 0.9923809523809524
P(a12=false | bird): 0.9838095238095238
P(a13=2 | bird): 0.9295238095238095
P(a14=true | bird): 0.9752380952380952
P(a15=true | bird): 0.10666666666666666
P(a16=false | bird): 0.6723809523809524
P(bird): 0.3220338983050847
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.004086809464998421
P(a0=chicken | fish): 0.0
P(a1=false | fish): 0.9426666666666667
P(a2=true | fish): 0.025333333333333333
P(a3=true | fish): 0.9440000000000001
P(a5=true | fish): 0.030666666666666667
P(a6=false | fish): 0.08533333333333333
P(a7=false | fish): 0.3253333333333333

P(a8=false | fish): 0.052000000000000005
P(a9=true | fish): 0.976
P(a10=true | fish): 0.10533333333333333
P(a11=false | fish): 0.9226666666666667
P(a12=false | fish): 0.11066666666666666
P(a13=2 | fish): 0.034666666666666665
P(a14=true | fish): 0.9653333333333334
P(a15=true | fish): 0.08266666666666667
P(a16=false | fish): 0.6746666666666666
P(fish): 0.22033898305084745
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 4.308413571848901E-12
P(a0=chicken | insect): 0.0
P(a1=false | insect): 0.514
P(a2=true | insect): 0.038
P(a3=true | insect): 0.916
P(a5=true | insect): 0.646
P(a6=false | insect): 0.928
P(a7=false | insect): 0.7879999999999999
P(a8=false | insect): 0.878
P(a9=true | insect): 0.16399999999999998
P(a10=true | insect): 0.9580000000000001
P(a11=false | insect): 0.784
P(a12=false | insect): 0.966
P(a13=2 | insect): 0.052000000000000005
P(a14=true | insect): 0.148
P(a15=true | insect): 0.124
P(a16=false | insect): 0.912
P(insect): 0.13559322033898305
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.0419947264196475E-7
P(a0=chicken | invertebrate): 0.0
P(a1=false | invertebrate): 0.9283333333333333
P(a2=true | invertebrate): 0.03166666666666667
P(a3=true | invertebrate): 0.8466666666666667
P(a5=true | invertebrate): 0.03833333333333334
P(a6=false | invertebrate): 0.44
P(a7=false | invertebrate): 0.24
P(a8=false | invertebrate): 0.8983333333333334
P(a9=true | invertebrate): 0.13666666666666666
P(a10=true | invertebrate): 0.38166666666666667
P(a11=false | invertebrate): 0.82
P(a12=false | invertebrate): 0.9716666666666667
P(a13=2 | invertebrate): 0.043333333333333335
P(a14=true | invertebrate): 0.20666666666666667
P(a15=true | invertebrate): 0.02
P(a16=false | invertebrate): 0.8433333333333334
P(invertebrate): 0.1694915254237288
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 9.630404955470096E-11
P(a0=chicken | reptile): 0.0
P(a1=false | reptile): 0.8771428571428571
P(a2=true | reptile): 0.054285714285714284
P(a3=true | reptile): 0.7371428571428571
P(a5=true | reptile): 0.06571428571428571
P(a6=false | reptile): 0.7542857142857142
P(a7=false | reptile): 0.26857142857142857
P(a8=false | reptile): 0.2542857142857143
P(a9=true | reptile): 0.9485714285714286
P(a10=true | reptile): 0.7971428571428572
P(a11=false | reptile): 0.6914285714285714
P(a12=false | reptile): 0.9514285714285714
P(a13=2 | reptile): 0.07428571428571429
P(a14=true | reptile): 0.9257142857142857
P(a15=true | reptile): 0.03428571428571429
P(a16=false | reptile): 0.7314285714285714
P(reptile): 0.0847457627118644
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 8.637739234754138E-9
Instance sl no 1: class name bird

Instance 2 : a0=chub a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=2
Subset Total Examples: 59.0

Appendix

Total class categories in subset: 6
P(a0=chub | amphibian): 0.0
P(a1=false | amphibian): 0.8566666666666666
P(a2=false | amphibian): 0.9333333333333333
P(a3=true | amphibian): 0.86
P(a5=false | amphibian): 0.9199999999999999
P(a6=true | amphibian): 0.7833333333333333
P(a7=true | amphibian): 0.6833333333333333
P(a8=true | amphibian): 0.8666666666666666
P(a9=true | amphibian): 0.94
P(a10=false | amphibian): 0.06666666666666667
P(a11=false | amphibian): 0.8066666666666666
P(a12=true | amphibian): 0.05333333333333334
P(a13=0 | amphibian): 0.07333333333333333
P(a14=true | amphibian): 0.41333333333333333
P(a15=false | amphibian): 0.9566666666666666
P(a16=false | amphibian): 0.8533333333333333
P(amphibian): 0.06779661016949153
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.3273481643140987E-6
P(a0=chub | bird): 0.0
P(a1=false | bird): 0.9609090909090908
P(a2=false | bird): 0.07272727272727274
P(a3=true | bird): 0.9618181818181818
P(a5=false | bird): 0.2509090909090909
P(a6=true | bird): 0.3045454545454545
P(a7=true | bird): 0.4590909090909091
P(a8=true | bird): 0.05454545454545454
P(a9=true | bird): 0.9836363636363636
P(a10=false | bird): 0.018181818181818184
P(a11=false | bird): 0.9927272727272727
P(a12=true | bird): 0.014545454545454545
P(a13=0 | bird): 0.02
P(a14=true | bird): 0.9763636363636363
P(a15=false | bird): 0.8518181818181818
P(a16=false | bird): 0.6872727272727273
P(bird): 0.3389830508474576
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.2871320137552647E-10
P(a0=chub | fish): 0.0
P(a1=false | fish): 0.9385714285714285
P(a2=false | fish): 0.9714285714285714
P(a3=true | fish): 0.94
P(a5=false | fish): 0.9657142857142856
P(a6=true | fish): 0.9071428571428571
P(a7=true | fish): 0.65
P(a8=true | fish): 0.9428571428571428
P(a9=true | fish): 0.9742857142857142
P(a10=false | fish): 0.8857142857142857
P(a11=false | fish): 0.9171428571428571
P(a12=true | fish): 0.88
P(a13=0 | fish): 0.8885714285714286
P(a14=true | fish): 0.9628571428571429
P(a15=false | fish): 0.91
P(a16=false | fish): 0.6514285714285714
P(fish): 0.2033898305084746
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.03305833102626958
P(a0=chub | insect): 0.0
P(a1=false | insect): 0.514
P(a2=false | insect): 0.9600000000000001
P(a3=true | insect): 0.916
P(a5=false | insect): 0.352
P(a6=true | insect): 0.06999999999999999
P(a7=true | insect): 0.21000000000000002
P(a8=true | insect): 0.12
P(a9=true | insect): 0.16399999999999998
P(a10=false | insect): 0.04
P(a11=false | insect): 0.784
P(a12=true | insect): 0.032
P(a13=0 | insect): 0.044
P(a14=true | insect): 0.148
P(a15=false | insect): 0.8739999999999999
P(a16=false | insect): 0.912

P(insect): 0.13559322033898305
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.2508698939861324E-11
P(a0=chub | invertebrate): 0.0
P(a1=false | invertebrate): 0.9283333333333333
P(a2=false | invertebrate): 0.9666666666666667
P(a3=true | invertebrate): 0.8466666666666667
P(a5=false | invertebrate): 0.9600000000000001
P(a6=true | invertebrate): 0.5583333333333333
P(a7=true | invertebrate): 0.7583333333333333
P(a8=true | invertebrate): 0.09999999999999999
P(a9=true | invertebrate): 0.13666666666666666
P(a10=false | invertebrate): 0.6166666666666667
P(a11=false | invertebrate): 0.82
P(a12=true | invertebrate): 0.026666666666666667
P(a13=0 | invertebrate): 0.37
P(a14=true | invertebrate): 0.20666666666666667
P(a15=false | invertebrate): 0.9783333333333334
P(a16=false | invertebrate): 0.8433333333333334
P(invertebrate): 0.1694915254237288
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 6.08583271822701E-7
P(a0=chub | reptile): 0.0
P(a1=false | reptile): 0.8771428571428571
P(a2=false | reptile): 0.9428571428571428
P(a3=true | reptile): 0.7371428571428571
P(a5=false | reptile): 0.9314285714285715
P(a6=true | reptile): 0.24285714285714283
P(a7=true | reptile): 0.7285714285714285
P(a8=true | reptile): 0.7428571428571429
P(a9=true | reptile): 0.9485714285714286
P(a10=false | reptile): 0.2
P(a11=false | reptile): 0.6914285714285714
P(a12=true | reptile): 0.045714285714285714
P(a13=0 | reptile): 0.49142857142857144
P(a14=true | reptile): 0.9257142857142857
P(a15=false | reptile): 0.9628571428571429
P(a16=false | reptile): 0.7314285714285714
P(reptile): 0 0847457627118644
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.2151620520202515E-5
Instance sl no 2 : class name fish

Instance 3 : a0=clam a1=false a2=false a3=true a4=false a5=false a6=false a7=true a8=false a9=false a10=false a11=false a12=false a13=0 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=3
Subset Total Examples: 59.0
Total class categories in subset: 6
P(a0=clam | amphibian): 0 0
P(a1=false | amphibian): 0.8566666666666666
P(a2=false | amphibian): 0.9333333333333333
P(a3=true | amphibian): 0.86
P(a5=false | amphibian): 0.9199999999999999
P(a6=false | amphibian): 0.21333333333333335
P(a7=true | amphibian): 0.6833333333333333
P(a8=false | amphibian): 0.13
P(a9=false | amphibian): 0.056666666666666667
P(a10=false | amphibian): 0.06666666666666667
P(a11=false | amphibian): 0.8066666666666666
P(a12=false | amphibian): 0.9433333333333334
P(a13=0 | amphibian): 0.07333333333333333
P(a14=false | amphibian): 0.5833333333333334
P(a15=false | amphibian): 0.9566666666666666
P(a16=false | amphibian): 0.8533333333333333
P(amphibian): 0.06779661016949153
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 8.159637284716098E-8
P(a0=clam | bird): 0.0
P(a1=false | bird): 0 9609090909090908
P(a2=false | bird): 0.07272727272727274
P(a3=true | bird): 0.9618181818181818
P(a5=false | bird): 0.2509090909090909
P(a6=false | bird): 0.6945454545454546
P(a7=true | bird): 0.4590909090909091

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P(a8=false | bird): 0.9445454545454545
P(a9=false | bird): 0.015454545454545455
P(a10=false | bird): 0.018181818181818184
P(a11=false | bird): 0.9927272727272727
P(a12=false | bird): 0.9845454545454545
P(a13=0 | bird): 0.02
P(a14=false | bird): 0.022727272727272728
P(a15=false | bird): 0.8518181818181818
P(a16=false | bird): 0.6872727272727273
P(bird): 0.3389830508474576
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.258351012462104E-10
P(a0=clam | fish): 0.0
P(a1=false | fish): 0.9426666666666667
P(a2=false | fish): 0.9733333333333334
P(a3=true | fish): 0.9440000000000001
P(a5=false | fish): 0.968
P(a6=false | fish): 0.08533333333333333
P(a7=true | fish): 0.6733333333333333
P(a8=false | fish): 0.052000000000000005
P(a9=false | fish): 0.02266666666666667
P(a10=false | fish): 0.8933333333333333
P(a11=false | fish): 0.9226666666666667
P(a12=false | fish): 0.11066666666666666
P(a13=0 | fish): 0.896
P(a14=false | fish): 0.03333333333333333
P(a15=false | fish): 0.916
P(a16=false | fish): 0.6746666666666666
P(fish): 0.22033898305084745
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 2.1064198938449653E-8
P(a0=clam | insect): 0.0
P(a1=false | insect): 0.514
P(a2=false | insect): 0.9600000000000001
P(a3=true | insect): 0.916
P(a5=false | insect): 0.352
P(a6=false | insect): 0.928
P(a7=true | insect): 0.21000000000000002
P(a8=false | insect): 0.878
P(a9=false | insect): 0.8340000000000001
P(a10=false | insect): 0.04
P(a11=false | insect): 0.784
P(a12=false | insect): 0.966
P(a13=0 | insect): 0.044
P(a14=false | insect): 0.8500000000000001
P(a15=false | insect): 0.8739999999999999
P(a16=false | insect): 0.912
P(insect): 0.13559322033898305
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 2.780157215669152E-6
P(a0=clam | invertebrate): 0.0
P(a1=false | invertebrate): 0.9218181818181819
P(a2=false | invertebrate): 0.9636363636363637
P(a3=true | invertebrate): 0.8327272727272728
P(a5=false | invertebrate): 0.9563636363636364
P(a6=false | invertebrate): 0.38909090909090904
P(a7=true | invertebrate): 0.7363636363636363
P(a8=false | invertebrate): 0.8890909090909092
P(a9=false | invertebrate): 0.8490909090909091
P(a10=false | invertebrate): 0.5818181818181818
P(a11=false | invertebrate): 0.8036363636363636
P(a12=false | invertebrate): 0.9690909090909091
P(a13=0 | invertebrate): 0.3127272727272727
P(a14=false | invertebrate): 0.7727272727272727
P(a15=false | invertebrate): 0.9763636363636364
P(a16=false | invertebrate): 0.8290909090909091
P(invertebrate): 0.15254237288135594
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 0.0020688819220456138
P(a0=clam | reptile): 0.0
P(a1=false | reptile): 0.8771428571428571
P(a2=false | reptile): 0.9428571428571428
P(a3=true | reptile): 0.7371428571428571
P(a5=false | reptile): 0.9314285714285715
P(a6=false | reptile): 0.7542857142857142

P(a7=true | reptile): 0.7285714285714285
P(a8=false | reptile): 0.2542857142857143
P(a9=false | reptile): 0.04857142857142858
P(a10=false | reptile): 0.2
P(a11=false | reptile): 0.6914285714285714
P(a12=false | reptile): 0.9514285714285714
P(a13=0 | reptile): 0.49142857142857144
P(a14=false | reptile): 0.07142857142857142
P(a15=false | reptile): 0.9628571428571429
P(a16=false | reptile): 0.7314285714285714
P(reptile): 0.0847457627118644
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.0623458982644412E-6
Instance sl no 3: class name invertebrate

Instance 4 : a0=crab a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=false a9=false a10=false a11=false a12=false a13=4 a14=false a15=false a16=false

Selection criteria for subset generation A4='false' and slno!=4
Subset Total Examples: 59.0
Total class categories in subset: 6
P(a0=crab | amphibian): 0.0
P(a1=false | amphibian): 0.8566666666666666
P(a2=false | amphibian): 0.9333333333333333
P(a3=true | amphibian): 0.86
P(a5=false | amphibian): 0.9199999999999999
P(a6=true | amphibian): 0.7833333333333333
P(a7=true | amphibian): 0.6833333333333333
P(a8=false | amphibian): 0.13
P(a9=false | amphibian): 0.05666666666666667
P(a10=false | amphibian): 0.06666666666666667
P(a11=false | amphibian): 0.8066666666666666
P(a12=false | amphibian): 0.9433333333333334
P(a13=4 | amphibian): 0.7899999999999999
P(a14=false | amphibian): 0.5833333333333334
P(a15=false | amphibian): 0.9566666666666666
P(a16=false | amphibian): 0.8533333333333333
P(amphibian): 0.06779661016949153
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 3.227634933041641E-6
P(a0=crab | bird): 0.0
P(a1=false | bird): 0.9609090909090908
P(a2=false | bird): 0.07272727272727274
P(a3=true | bird): 0.9618181818181818
P(a5=false | bird): 0.2509090909090909
P(a6=true | bird): 0.3045454545454545
P(a7=true | bird): 0.4590909090909091
P(a8=false | bird): 0.9445454545454545
P(a9=false | bird): 0.015454545454545455
P(a10=false | bird): 0.018181818181818184
P(a11=false | bird): 0.9927272727272727
P(a12=false | bird): 0.9845454545454545
P(a13=4 | bird): 0.03363636363636364
P(a14=false | bird): 0.022727272727272728
P(a15=false | bird): 0.8518181818181818
P(a16=false | bird): 0.6872727272727273
P(bird): 0.3389830508474576
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 9.27966492114932E-11
P(a0=crab | fish): 0.0
P(a1=false | fish): 0.9426666666666667
P(a2=false | fish): 0.9733333333333334
P(a3=true | fish): 0.9440000000000001
P(a5=false | fish): 0.968
P(a6=true | fish): 0.9133333333333333
P(a7=true | fish): 0.6733333333333333
P(a8=false | fish): 0.05200000000000005
P(a9=false | fish): 0.02266666666666667
P(a10=false | fish): 0.8933333333333333
P(a11=false | fish): 0.9226666666666667
P(a12=false | fish): 0.11066666666666666
P(a13=4 | fish): 0.04933333333333333
P(a14=false | fish): 0.03333333333333333

P(a15=false | fish): 0.916
P(a16=false | fish): 0.6746666666666666
P(fish): 0.22033898305084745
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.2413321291271545E-8
P(a0=crab | insect): 0.0
P(a1=false | insect): 0.514
P(a2=false | insect): 0.9600000000000001
P(a3=true | insect): 0.916
P(a5=false | insect): 0.352
P(a6=true | insect): 0.06999999999999999
P(a7=true | insect): 0.21000000000000002
P(a8=false | insect): 0.878
P(a9=false | insect): 0.8340000000000001
P(a10=false | insect): 0.04
P(a11=false | insect): 0.784
P(a12=false | insect): 0.966
P(a13=4 | insect): 0.074
P(a14=false | insect): 0.8500000000000001
P(a15=false | insect): 0.8739999999999999
P(a16=false | insect): 0.912
P(insect): 0.13559322033898305
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.526943176226049E-7
P(a0=crab | invertebrate): 0.0
P(a1=false | invertebrate): 0.9218181818181819
P(a2=false | invertebrate): 0.9636363636363637
P(a3=true | invertebrate): 0.8327272727272728
P(a5=false | invertebrate): 0.9563636363636364
P(a6=true | invertebrate): 0.5181818181818182
P(a7=true | invertebrate): 0.7363636363636363
P(a8=false | invertebrate): 0.8890909090909092
P(a9=false | invertebrate): 0.8490909090909091
P(a10=false | invertebrate): 0.5818181818181818
P(a11=false | invertebrate): 0.8036363636363636
P(a12=false | invertebrate): 0.9690909090909091
P(a13=4 | invertebrate): 0.06727272727272728
P(a14=false | invertebrate): 0.7727272727272727
P(a15=false | invertebrate): 0.9763636363636364
P(a16=false | invertebrate): 0.8290909090909091
P(invertebrate): 0.15254237288135594
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 5.927070166260325E-4
P(a0=crab | reptile): 0.0
P(a1=false | reptile): 0.8771428571428571
P(a2=false | reptile): 0.9428571428571428
P(a3=true | reptile): 0.7371428571428571
P(a5=false | reptile): 0.9314285714285715
P(a6=true | reptile): 0.24285714285714283
P(a7=true | reptile): 0.7285714285714285
P(a8=false | reptile): 0.2542857142857143
P(a9=false | reptile): 0.04857142857142858
P(a10=false | reptile): 0.2
P(a11=false | reptile): 0.6914285714285714
P(a12=false | reptile): 0.9514285714285714
P(a13=4 | reptile): 0.3914285714285714
P(a14=false | reptile): 0.07142857142857142
P(a15=false | reptile): 0.9628571428571429
P(a16=false | reptile): 0.7314285714285714
P(reptile): 0.0847457627118644
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.7244137564502775E-7
Instance sl no 4: class name invertebrate

Instance 5 : a0=crayfish a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=false a9=false a10=false a11=false a12=false a13=6 a14=false a15=false a16=false

Selection criteria for subset generation A4='false' and slno!=5
Subset Total Examples: 59.0
Total class categories in subset: 6
P(a0=crayfish | amphibian): 0.0
P(a1=false | amphibian): 0.8566666666666666
P(a2=false | amphibian): 0.9333333333333333
P(a3=true | amphibian): 0.86

P(a5=false | amphibian): 0.9199999999999999
P(a6=true | amphibian): 0.7833333333333333
P(a7=true | amphibian): 0.6833333333333333
P(a8=false | amphibian): 0.13
P(a9=false | amphibian): 0.05666666666666667
P(a10=false | amphibian): 0.06666666666666667
P(a11=false | amphibian): 0.8066666666666666
P(a12=false | amphibian): 0.9433333333333334
P(a13=6 | amphibian): 0.03
P(a14=false | amphibian): 0.5833333333333334
P(a15=false | amphibian): 0.9566666666666666
P(a16=false | amphibian): 0.8533333333333333
P(amphibian): 0.06779661016949153
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.225684151787965E-7
P(a0=crayfish | bird): 0.0
P(a1=false | bird): 0.9609090909090908
P(a2=false | bird): 0.07272727272727274
P(a3=true | bird): 0.9618181818181818
P(a5=false | bird): 0.2509090909090909
P(a6=true | bird): 0.3045454545454545
P(a7=true | bird): 0.4590909090909091
P(a8=false | bird): 0.9445454545454545
P(a9=false | bird): 0.015454545454545455
P(a10=false | bird): 0.018181818181818184
P(a11=false | bird): 0.9927272727272727
P(a12=false | bird): 0.9845454545454545
P(a13=6 | bird): 0.008181818181818182
P(a14=false | bird): 0.022727272727272728
P(a15=false | bird): 0.8518181818181818
P(a16=false | bird): 0.6872727272727273
P(bird): 0.3389830508474576
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 2.257215791630915 6E-11
P(a0=crayfish | fish): 0.0
P(a1=false | fish): 0.9426666666666667
P(a2=false | fish): 0.9733333333333334
P(a3=true | fish): 0.9440000000000001
P(a5=false | fish): 0.968
P(a6=true | fish): 0.9133333333333333
P(a7=true | fish): 0.6733333333333333
P(a8=false | fish): 0.052000000000000005
P(a9=false | fish): 0.02266666666666667
P(a10=false | fish): 0.8933333333333333
P(a11=false | fish): 0.9226666666666667
P(a12=false | fish): 0.11066666666666666
P(a13=6 | fish): 0.012
P(a14=false | fish): 0.03333333333333333
P(a15=false | fish): 0.916
P(a16=false | fish): 0.6746666666666666
P(fish): 0.22033898305084745
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 3.0194565303092947E-9
P(a0=crayfish | insect): 0.0
P(a1=false | insect): 0.514
P(a2=false | insect): 0.9600000000000001
P(a3=true | insect): 0.916
P(a5=false | insect): 0.352
P(a6=true | insect): 0.06999999999999999
P(a7=true | insect): 0.21000000000000002
P(a8=false | insect): 0.878
P(a9=false | insect): 0.8340000000000001
P(a10=false | insect): 0.04
P(a11=false | insect): 0.784
P(a12=false | insect): 0.966
P(a13=6 | insect): 0.8180000000000001
P(a14=false | insect): 0.8500000000000001
P(a15=false | insect): 0.8739999999999999
P(a16=false | insect): 0.912
P(insect): 0.13559322033898305
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.898702051557985E-6
P(a0=crayfish | invertebrate): 0.0
P(a1=false | invertebrate): 0.9218181818181819
P(a2=false | invertebrate): 0.9636363636363637

P(a3=true | invertebrate): 0.8327272727272728
P(a5=false | invertebrate): 0.9563636363636364
P(a6=true | invertebrate): 0.5181818181818182
P(a7=true | invertebrate): 0.7363636363636363
P(a8=false | invertebrate): 0.8890909090909092
P(a9=false | invertebrate): 0.8490909090909091
P(a10=false | invertebrate): 0.5818181818181818
P(a11=false | invertebrate): 0.8036363636363636
P(a12=false | invertebrate): 0.9690909090909091
P(a13=6 | invertebrate): 0.10727272727272727
P(a14=false | invertebrate): 0.7727272727272727
P(a15=false | invertebrate): 0.9763636363636364
P(a16=false | invertebrate): 0.8290909090909091
P(invertebrate): 0.15254237288135594
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 9.451274048901598E-4
P(a0=crayfish | reptile): 0.0
P(a1=false | reptile): 0.8771428571428571
P(a2=false | reptile): 0.9428571428571428
P(a3=true | reptile): 0.7371428571428571
P(a5=false | reptile): 0.9314285714285715
P(a6=true | reptile): 0.24285714285714283
P(a7=true | reptile): 0.7285714285714285
P(a8=false | reptile): 0.2542857142857143
P(a9=false | reptile): 0.04857142857142858
P(a10=false | reptile): 0.2
P(a11=false | reptile): 0.6914285714285714
P(a12=false | reptile): 0.9514285714285714
P(a13=6 | reptile): 0.025714285714285714
P(a14=false | reptile): 0.07142857142857142
P(a15=false | reptile): 0.9628571428571429
P(a16=false | reptile): 0.7314285714285714
P(reptile): 0.0847457627118644
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.7897608619016426E-8
Instance sl no 5: class name invertebrate

Similarly we get for other examples as follows:

Instance 6 : a0=buffalo a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=6
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.09755589743311713
Instance sl no 6 class name mammal
Instance 7 : a0=calf a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=true a16=true
Selection criteria for subset generation A4='true' and slno!=7
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.0209337491824471 84
Instance sl no 7 class name mammal
Instance 8 : a0=carp a1=false a2=false a3=true a4=false a5=false a6=true a7=false a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=true a16=false
Selection criteria for subset generation A4='false' and slno!=8
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.544826598701969E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 2.6175415412500738E-11
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 2.655296794008853E-4
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.730679955765354E-11
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 3.9374427381156841E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.5950460169649664E-7
Instance sl no 8 class name fish
Instance 9 : a0=catfish a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=9
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.3273481643140987E-6
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.2871320137552647E-10
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.03305833102626958
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.2508698939861324E-11
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 6.085832718227011E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.2151620520202515E-5
Instance sl no 9 class name fish
Instance 10 : a0=cavy a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=false a15=true a16=false
Selection criteria for subset generation A4='true' and slno!=10
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 9.289132582864564E-4

Instance sl no 10 class name mammal
Instance 11 : a0=cheetah a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=11
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463
Instance sl no 11 class name mammal
Instance 12 : a0=aardvark a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=false a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=12
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.017702022584034256
Instance sl no 12 class name mammal
Instance 13 : a0=antelope a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=13
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.09755589743311713
Instance sl no 13 class name mammal
Instance 14 : a0=bass a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=14
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.3273481643140987E-6
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.2871320137552647E-10
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.03305833102626958
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.2508698939861324E-11
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 6.08583271822701E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.215162052020251 5E-5
Instance sl no 14 class name fish
Instance 15 : a0=bear a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=false a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=15
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.017702022584034256
Instance sl no 15 class name mammal
Instance 16 : a0=boar a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=16
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463
Instance sl no 16 class name mammal
Instance 17 : a0=crow a1=false a2=true a3=true a4=false a5=true a6=false a7=true a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=17
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 8.941160184238683E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.02707088691457766
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 9.880615167566098E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.9572592116327779E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.4885050390808624E-8
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 6.580532988817348E-7
Instance sl no 17 class name bird
Instance 18 : a0=deer a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=18
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.09755589743311713
Instance sl no 18 class name mammal
Instance 19 : a0=dogfish a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=19
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.229530119746338E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 5.839765617963701E-11
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.01399179361418866
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.0655132772237646E-12
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.1185423770654387E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 4.414455892104819E-6
Instance sl no 19 class name fish
Instance 20 : a0=dolphin a1=false a2=false a3=false a4=true a5=false a6=true a7=true a8=true a9=true a10=true a11=false a12=true a13=0 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=20
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 7.113254948545375E-6
Instance sl no 20 class name mammal
Instance 21 : a0=dove a1=false a2=true a3=true a4=false a5=true a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=true a16=false
Selection criteria for subset generation A4='false' and slno!=21
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.714222603521923E-9
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.004086809464998421

Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 4.308413571848901E-12
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.0419947264196475E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 9.630404955470096E-11
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 8.637739234754138E-9
Instance sl no 21 class name bird
Instance 22 : a0=duck a1=false a2=true a3=true a4=false a5=true a6=true a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=22
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.505413326751772E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.012919230175873795
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 5.109672088821155E-10
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 5.539943458213468E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 5.977812444660406E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 7.810228547333723E-8
Instance sl no 22 class name bird
Instance 23 : a0=elephant a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=23
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.0975558974331713
Instance sl no 23 class name mammal
Instance 24 : a0=flamingo a1=false a2=true a3=true a4=false a5=true a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=24
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 6.886465218119808E-9
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.013432378068948609
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 2.292652269852185E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 6.92562355127037E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 8.658324060014294E-10
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 8.812349783737936E-8
Instance sl no 24 class name bird
Instance 25 : a0=flea a1=false a2=false a3=true a4=false a5=false a6=false a7=false a8=false a9=false a10=true a11=false a12=false a13=6 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=25
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.1352015818854542E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 3.266691687272537E-9
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.607196288992625E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 0.002360675483556681
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 3.646466346746874E-4
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 8.167212290761162E-8
Instance sl no 25 class name insect
Instance 26 : a0=frog a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=26
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 4.071362387721417E-4
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.6728041632195033E-11
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.529800937930174E-9
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 4.5404458817720706E-10
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 3.4339130429951643E-8
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.770042470896956E-7
Instance sl no 26 class name amphibian
Instance 27 : a0=frog a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=true a11=true a12=false a13=4 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=27
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.4843508705234338E-5
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.0723103610381433E-13
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.2600961482950852E-10
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.2393564014020701E-10
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 7.468062918708995E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 7.826220842395635E-8
Instance sl no 27 class name amphibian
Instance 28 : a0=fruitbat a1=true a2=false a3=false a4=true a5=true a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='true' and slno!=28
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 2 1881759866914253E-4
Instance sl no 28 class name mammal
Instance 29 : a0=giraffe a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=29
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.0975558974331713
Instance sl no 29 class name mammal

Instance 30 : a0=girl a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=2 a14=false a15=true a16=true
Selection criteria for subset generation A4='true' and slno!=30
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 8.056754141517921E-4
Instance sl no 30 class name mammal
Instance 31 : a0=gnat a1=false a2=false a3=true a4=false a5=true a6=false a7=false a8=false a9=false a10=true a11=false a12=false a13=6 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=31
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.779334651571211 6E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 9.740895864584412E-9
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 5.091668684136416E-13
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 0.005114796881039475
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.4560542704023972E-5
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 5.762143640721064E-9
Instance sl no 31 class name insect
Instance 32 : a0=goat a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=true a16=true
Selection criteria for subset generation A4='true' and slno!=32
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.02093374918244718 4
Instance sl no 32 class name mammal
Instance 33 : a0=gorilla a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=2 a14=false a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=33
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.0032075714505845 47
Instance sl no 33 class name mammal
Instance 34 : a0=gull a1=false a2=true a3=true a4=false a5=true a6=true a7=true a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=34
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 3.283082255150141E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.010805606121365028
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.0575345921535589E-9
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.4763808708436907E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.8888226821670034E-8
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.1187322123086154E-7
Instance sl no 34 class name bird
Instance 35 : a0=haddock a1=false a2=false a3=true a4=false a5=false a6=true a7=false a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=35
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 6.086376948562207E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.513973101327975E-10
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.014095200481530328
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.219850226886225E-10
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.9260657393949222E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 4.479420897643281E-6
Instance sl no 35 class name fish
Instance 36 : a0=hamster a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=true a16=false
Selection criteria for subset generation A4='true' and slno!=36
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.005992334982546086
Instance sl no 36 class name mammal
Instance 37 : a0=hare a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=false
Selection criteria for subset generation A4='true' and slno!=37
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.027925605291589082
Instance sl no 37 class name mammal
Instance 38 : a0=hawk a1=false a2=true a3=true a4=false a5=true a6=false a7=true a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=38
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 8.941160184238683E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.02707088691457766
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 9.880615167566098E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.957259211632779E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.4885050390808624E-8
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 6.580532988817348E-7
Instance sl no 38 class name bird
Instance 39 : a0=herring a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=39
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.3273481643140987E-6
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.2871320137552647E-10
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.03305833102626958

Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.2508698939861324E-11
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 6.085832718227011E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.2151620520202515E-5
Instance sl no 39 class name fish
Instance 40 : a0=honeybee a1=true a2=false a3=true a4=false a5=true a6=false a7=false a8=false a9=false a10=true a11=true a12=false a13=6 a14=false a15=true a16=false
Selection criteria for subset generation A4='false' and slno!=40
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.8637337810988967E-11
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 4.2896714350562084E-13
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 2.2485043211695164E-16
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 2.4517619772050053E-5
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 4.8812772685143674E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.2411227949875206E-11
Instance sl no 40 class name insect
Instance 41 : a0=housefly a1=true a2=false a3=true a4=false a5=true a6=false a7=false a8=false a9=false a10=true a11=false a12=false a13=6 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=41
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.907862076497701E-9
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 3.870554648179235E-10
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 3.0247536737444055E-14
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 0.004744159425891686
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.0979224301059369E-6
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 7.883062961247058E-10
Instance sl no 41 class name insect
Instance 42 : a0=kiwi a1=false a2=true a3=true a4=false a5=false a6=false a7=true a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=42
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.072939222108642E-6
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.007914644815904983
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 3.118837657240428E-9
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.0664941834283874E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 3.727734358741639E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 9.327190236323719E-6
Instance sl no 42 class name bird
Instance 43 : a0=ladybird a1=false a2=false a3=true a4=false a5=true a6=false a7=true a8=false a9=false a10=true a11=false a12=false a13=6 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=43
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 3.880463867788216E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 8.281401366355433E-9
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.0538084776593815E-12
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 8.177727571429395E-4
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 4.600727034952 02E-5
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.563134711046672E-8
Instance sl no 43 class name insect
Instance 44 : a0=lark a1=false a2=true a3=true a4=false a5=true a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=44
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 4.099849060089932E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.03236607138797856
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 4.774000199774508E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 7.344382184602997E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 4.710873090717455E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.425765101760120 6E-7
Instance sl no 44 class name bird
Instance 45 : a0=leopard a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=45
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463
Instance sl no 45 class name mammal
Instance 46 : a0=lion a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=46
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463
Instance sl no 46 class name mammal
Instance 47 : a0=lobster a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=false a9=false a10=false a11=false a12=false a13=6 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=47
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.225684151787965E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 2.257215791630915 6E-11
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 3.019456530309294 7E-9
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.898702051557985E-6

Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 9.451274048901598E-4
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.7897608619016426E-8
Instance sl no 47 class name invertebrate
Instance 48 : a0=lynx a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=48
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463
Instance sl no 48 class name mammal
Instance 49 : a0=mink a1=true a2=false a3=false a4=true a5=false a6=true a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=49
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.01844973324729309
Instance sl no 49 class name mammal
Instance 50 : a0=mole a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=false
Selection criteria for subset generation A4='true' and slno!=50
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.0326883409398368
Instance sl no 50 class name mammal
Instance 51 : a0=mongoose a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=51
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463
Instance sl no 51 class name mammal
Instance 52 : a0=moth a1=true a2=false a3=true a4=false a5=true a6=false a7=false a8=false a9=false a10=true a11=false a12=false a13=6 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=52
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.907862076497701E-9
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 3.8705546481792355E-10
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 3.0247536737444055E-14
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 0.004744159425891686
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.0979224301059369E-6
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 7.883062961247058E-10
Instance sl no 52 class name insect
Instance 53 : a0=newt a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=53
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 0.0011814933987897443
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 7.905003353710083E-7
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 3.322727637184338E-5
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.952858767660389 7E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 5.378592218922952 5E-6
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 8.028912647988595E-4
Instance sl no 53 class name amphibian
Instance 54 : a0=octopus a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=false a9=false a10=false a11=false a12=false a13=8 a14=false a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=54
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.2875181652292754E-9
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.137896849690482E-12
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.6111724568844062E-10
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 8.98877172698673E-10
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 7.703926549673336E-5
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 7.224295145696731E-10
Instance sl no 54 class name invertebrate
Instance 55 : a0=opossum a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=false
Selection criteria for subset generation A4='true' and slno!=55
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.0326883409398368
Instance sl no 55 class name mammal
Instance 56 : a0=oryx a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=56
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.09755589743311713
Instance sl no 56 class name mammal
Instance 57 : a0=ostrich a1=false a2=true a3=true a4=false a5=false a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=57
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 8.263758261743769E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.003927189448360l365
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 7.236806730055158E-10
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.773714380877973E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 2.168345503725319 6E-8

Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.2490547954341595E-6
Instance sl no 57 class name bird
Instance 58 : a0=parakeet a1=false a2=true a3=true a4=false a5=true a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=true a16=false
Selection criteria for subset generation A4='false' and slno!=58
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.714222603521923E-9
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.004086809464998421
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 4.308413571848901E-12
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.0419947264196475E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 9.630404955470096E-11
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 8.637739234754138E-9
Instance sl no 58 class name bird
Instance 59 : a0=penguin a1=false a2=true a3=true a4=false a5=false a6=true a7=true a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=59
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 6.617462670537004E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.0013111156381717048
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.603094498011 2264E-8
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 7.585988288621648E-10
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 8.693972627455064E-8
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.090959973043013E-6
Instance sl no 59 class name bird
Instance 60 : a0=pheasant a1=false a2=true a3=true a4=false a5=true a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=60
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 4.099849060089932E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.03236607138797856
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 4.774000199774508E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 7.344382184602997E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 4.710873090717455E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.4257651017601206E-7
Instance sl no 60 class name bird
Instance 61 : a0=pike a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=61
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.229530119746338E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 5.839765617963701E-11
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.01399179361418866
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.0655132772237646E-12
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.1185423770654387E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 4.414455892104819E-6
Instance sl no 61 class name fish
Instance 62 : a0=piranha a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=62
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.3273481643140987E-6
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.2871320137552647E-10
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.03305833102626958
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.2508698939861324E-11
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 6.08583271822701E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.2151620520202515E-5
Instance sl no 62 class name fish
Instance 63 : a0=pitviper a1=false a2=false a3=true a4=false a5=false a6=false a7=true a8=true a9=true a10=true a11=true a12=false a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=63
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.1008600153176192E-5
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 6.871427497086249E-9
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 4.644302043670964E-6
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 8.505109341520895E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 2.352231902307226E-6
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 3.702073630540879E-4
Instance sl no 63 class name reptile
Instance 64 : a0=platypus a1=true a2=false a3=true a4=true a5=false a6=true a7=true a8=false a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=64
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 1.0428344616789723E-5
Instance sl no 64 class name mammal
Instance 65 : a0=polecat a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=65
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463

Instance sl no 65 class name mammal
Instance 66 : a0=pony a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=true a16=true
Selection criteria for subset generation A4='true' and slno!=66
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.020933749182447184
Instance sl no 66 class name mammal
Instance 67 : a0=porpoise a1=false a2=false a3=false a4=true a5=false a6=true a7=true a8=true a9=true a10=true a11=false a12=true a13=0 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=67
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 7.113254948545375E-6
Instance sl no 67 class name mammal
Instance 68 : a0=puma a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=68
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463
Instance sl no 68 class name mammal
Instance 69 : a0=pussycat a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=true a16=true
Selection criteria for subset generation A4='true' and slno!=69
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.02450401784597897
Instance sl no 69 class name mammal
Instance 70 : a0=raccoon a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=70
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463
Instance sl no 70 class name mammal
Instance 71 : a0=reindeer a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=true a16=true
Selection criteria for subset generation A4='true' and slno!=71
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.020933749182447184
Instance sl no 71 class name mammal
Instance 72 : a0=rhea a1=false a2=true a3=true a4=false a5=false a6=false a7=true a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=72
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.8022025996356096E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.0032846897040512174
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.497781720769613E-9
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.0056853045486986E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 6.851369473576529E-8
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 3.3883933280394755E-6
Instance sl no 72 class name bird
Instance 73 : a0=scorpion a1=false a2=false a3=false a4=false a5=false a6=false a7=true a8=false a9=false a10=true a11=true a12=false a13=8 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=73
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.3722386819797252E-9
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 3.2931266569776956E-12
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 5.105589351587615E-13
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.2876892544882556E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 6.897540216171643E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 4.9755232658313476E-8
Instance sl no 73 class name invertebrate
Instance 74 : a0=seahorse a1=false a2=false a3=true a4=false a5=false a6=true a7=false a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=74
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 6.086376948562207E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.513973101327975E-10
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.014095200481530328
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.219850226886225E-10
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.9260657393949222E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 4.479420897643281E-6
Instance sl no 74 class name fish
Instance 75 : a0=seal a1=true a2=false a3=false a4=true a5=false a6=true a7=true a8=true a9=true a10=true a11=false a12=true a13=0 a14=false a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=75
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 2.0013032511514483E-5
Instance sl no 75 class name mammal
Instance 76 : a0=sealion a1=true a2=false a3=false a4=true a5=false a6=true a7=true a8=true a9=true a10=true a11=false a12=true a13=2 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=76
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 3.449781524348467E-4
Instance sl no 76 class name mammal

Instance 77 : a0=seasnake a1=false a2=false a3=false a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=true a12=false a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=77
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 8.787694426898939E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 2.164238691425185E-12
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 2.4413461698092753E-5
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 2.3979649229942005E-11
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 8.639029117056573E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.0423518901583009E-6
Instance sl no 77 class name fish
Instance 78 : a0=seawasp a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=false a9=false a10=false a11=true a12=false a13=0 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=78
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 7.056969358779194E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 3.536947821643885E-13
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.857053033669935E-8
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 5.7242307203779086E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 3.553197744283736E-4
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.5123397108557308E-7
Instance sl no 78 class name invertebrate
Instance 79 : a0=skimmer a1=false a2=true a3=true a4=false a5=true a6=true a7=true a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=79
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 3.2830822551501 41E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.010805606121365028
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.0575345921535589E-9
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.4763808708436907E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.8888226821670034E-8
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.1187322123086154E-7
Instance sl no 79 class name bird
Instance 80 : a0=skua a1=false a2=true a3=true a4=false a5=true a6=true a7=true a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=80
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 3.283082255150141E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.010805606121365028
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.0575345921535589E-9
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.4763808708436907E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.8888226821670034E-8
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.1187322123086154E-7
Instance sl no 80 class name bird
Instance 81 : a0=slowworm a1=false a2=false a3=true a4=false a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=81
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 8.919440766787084E-5
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.0719426895454547E-6
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 5.638345638982996E-5
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.1158905251179346E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.0815870055468741E-5
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 0.001247014275550612
Instance sl no 81 class name reptile
Instance 82 : a0=slug a1=false a2=false a3=true a4=false a5=false a6=false a7=false a8=false a9=false a10=true a11=false a12=false a13=0 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=82
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 5.219381644608889E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 7.985246346666202E-9
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.2000398957811602E-9
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 2.498514050877982E-4
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 2.6860345077422455E-4
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.560845015567689E-6
Instance sl no 82 class name invertebrate
Instance 83 : a0=sole a1=false a2=false a3=true a4=false a5=false a6=true a7=false a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=83
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 6.086376948562207E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.513973101327975E-10
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.014095200481530328
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.2198502268862251E-10
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.9260657393949222E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 4.479420897643281E-6
Instance sl no 83 class name fish

Instance 84 : a0=sparrow a1=false a2=true a3=true a4=false a5=true a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=84
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 4.0998490600899321E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.032366071387978S6
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 4.774000199774508E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 7.344382184602997E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 4.710873090717455E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.4257651017601206E-7
Instance sl no 84 class name bird
Instance 85 : a0=squirrel a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='true' and slno!=85
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.00592306267082501
Instance sl no 85 class name mammal
Instance 86 : a0=starfish a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=false a9=false a10=false a11=false a12=false a13=5 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=86
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 4.085613839293217E-6
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 2.7588193008822303E-9
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 2.5162137752577457E-7
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 4.766139427332499E-6
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 0.008810509706603187
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 6.960181129617499E-7
Instance sl no 86 class name invertebrate
Instance 87 : a0=stingray a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=true a12=true a13=0 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=87
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 5.251372596096745E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 3.74343949869468E-13
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.5255849735096671E-4
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 8.367600016911806E-13
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 2.4326023241057305E-8
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.951846200228164E-6
Instance sl no 87 class name fish
Instance 88 : a0=swan a1=false a2=true a3=true a4=false a5=true a6=true a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=88
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.528623947278367E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.005361663514916461
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 2.453854382576I675E-10
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 5.2240694891048054E-9
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.0986888485245409E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.837309589461078E-8
Instance sl no 88 class name bird
Instance 89 : a0=termite a1=false a2=false a3=true a4=false a5=false a6=false a7=false a8=false a9=false a10=true a11=false a12=false a13=6 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=89
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.135201581885 4542E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 3.266691687272537E-9
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.607196288992625E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 0.002360675483556681
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 3.646466346746874E-4
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 8.167212290761162E-8
Instance sl no 89 class name insect
Instance 90 : a0=toad a1=false a2=false a3=true a4=false a5=false a6=true a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=90
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 5.665399907012722E-4
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 2.164376713361 6308E-8
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 5.543635082004395E-7
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 8.518741321039025E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 6.5206612508743344E-6
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.283701854608 23E-5
Instance sl no 90 class name amphibian
Instance 91 : a0=tortoise a1=false a2=false a3=true a4=false a5=false a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=91
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.1100870409905188E-5
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.6660280098148512E-5
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 3.956804651392507E-8

Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.3567037936l119E-6
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 2.2148727554246885E-6
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 7.3990542245391l4E-6
Instance sl no 91 class name bird
Instance 92 : a0=tuatara a1=false a2=false a3=true a4=false a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=92
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 9.608670280584266E-4
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 1.8028127051446279E-6
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 3.1044462595590897E-6
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 5.240361337698344E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 4.238651778494506E-6
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 8.892642784664199E-4
Instance sl no 92 class name amphibian
Instance 93 : a0=tuna a1=false a2=false a3=true a4=false a5=false a6=true a7=true a8=true a9=true a10=false a11=false a12=true a13=0 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=93
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 2.229530119746338E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 5.839765617963701E-11
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 0.013991793614l8866
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 3.0655132772237646E-12
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 1.1185423770654387E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 4.414455892104819E-6
Instance sl no 93 class name fish
Instance 94 : a0=vampire a1=true a2=false a3=false a4=true a5=true a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='true' and slno!=94
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 2.1881759866914253E-4
Instance sl no 94 class name mammal
Instance 95 : a0=vole a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=false
Selection criteria for subset generation A4='true' and slno!=95
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.027925605291589082
Instance sl no 95 class name mammal
Instance 96 : a0=vulture a1=false a2=true a3=true a4=false a5=true a6=false a7=true a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=true
Selection criteria for subset generation A4='false' and slno!=96
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 1.5018354996963413E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.011234801509874298
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 4.745038509325221E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 1.8456610986888045E-8
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 2.7357898939628497E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.390584249843802E-7
Instance sl no 96 class name bird
Instance 97 : a0=wallaby a1=true a2=false a3=false a4=true a5=false a6=false a7=false a8=true a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=97
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.020691751830316317
Instance sl no 97 class name mammal
Instance 98 : a0=wasp a1=true a2=false a3=true a4=false a5=true a6=false a7=false a8=false a9=false a10=true a11=true a12=false a13=6 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=98
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 6.849096626461527E-10
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 2.481124774473869E-12
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 2.4914878526507385E-15
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 7.906932376486142E-4
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 2.3877581305149444E-7
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 3.485486515923286E-10
Instance sl no 98 class name insect
Instance 99 : a0=wolf a1=true a2=false a3=false a4=true a5=false a6=false a7=true a8=true a9=true a10=true a11=false a12=false a13=4 a14=true a15=false a16=true
Selection criteria for subset generation A4='true' and slno!=99
Class Name: mammal, [(Product of all conditional Probability)*P(Class value)]: 0.11419413841482463
Instance sl no 99 class name mammal
Instance 100 : a0=worm a1=false a2=false a3=true a4=false a5=false a6=false a7=false a8=false a9=false a10=true a11=false a12=false a13=0 a14=false a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=100
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 5.219381644608889E-7
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 7.985246346666202E-9
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 1.2000398957811602E-9
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 2.498514050877982E-4

Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 2.6860345077422455E-4
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 1.560845015567689E-6
Instance sl no 100 class name invertebrate
Instance 101 : a0=wren a1=false a2=true a3=true a4=false a5=true a6=false a7=false a8=false a9=true a10=true a11=false a12=false a13=2 a14=true a15=false a16=false
Selection criteria for subset generation A4='false' and slno!=101
Class Name: amphibian, [(Product of all conditional Probability)*P(Class value)]: 4.099849060089932E-8
Class Name: bird, [(Product of all conditional Probability)*P(Class value)]: 0.03236607138797856
Class Name: fish, [(Product of all conditional Probability)*P(Class value)]: 4.774000199774508E-11
Class Name: insect, [(Product of all conditional Probability)*P(Class value)]: 7.344382184602997E-7
Class Name: invertebrate, [(Product of all conditional Probability)*P(Class value)]: 4.710873090717455E-9
Class Name: reptile, [(Product of all conditional Probability)*P(Class value)]: 2.425765101760120 6E-7
Instance sl no 101 class name bird
Error rate=2.97%

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