Use of CART and Logistic Regression Analysis to Identify Key Determinants of Pregnancy Wastage

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DECLARATION

This project is my original work and has not been presented for a degree in any other University.

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ABSTRACT

This master research project compares the performance of Classification and Regression Trees (CART) and Logistic Regression in studying determinants of pregnancy wastage using pregnancy information from a population-based sample survey, The Kenya Demographic and Health Survey 2008/2009.The project report also describes in detail the fundamental principles of tree construction, splitting algorithms and pruning procedures. It also briefly introduces the logistic regression and then shows the comparisons of the analysis results from the two statistical methods using Receiver Operating Curve, Variable Importance and Hosmer-LemeshowModel Goodness of Fit Tests. Logistic regression performed slightly better than CART using AUC with both agreeing on age of the woman as the most important determinant of pregnancy wastage. CART found that the age of the woman, highest level of educational attainment, age at first birth, Type of place of residence being either ourban or rural and birth order to be the most important determinants of pregnancy wastage. Logistic regression analysis found out that Age of the woman, marriage to first birth interval, usage of anti-malarial during pregnancy, type of place of residence and usage of iron supplementation during pregnancy to be the most important determinants. The Hosmer-Lemeshow Goodness of Fit Test showed that CART didn’t fit the well the data while the Hosmer-Lemeshow Goodness of Fit Test for logistic regression showed that did fit the data well.The lack of close fit for the data could be explained by the nature of data and this needs further investigation comparing fits both population based data and obstetric data. However, CART results could be used for selection of key variables to be used in logistic regression analysis. When applied prudently, both CART and logistic regression are suitable for the analysis of the determinants of pregnancy wastage.

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DEDICATION

I dedicate this master's degree research project to my beloved wife, SusanVataKisamwa for her unwavering support and encouragement all through. I specifically acknowledge the time you spend at the HMIS department of The National Spinal Injury Hospital at Hurligham, Nairobi, as you went through dusty patient files as we unsuccessfully tried to assemble a dataset for the Masters Research Project. I appreciate all the sacrifice you made in many ways. May God, The Holy One Of Israel, Jehovah God, Bless You. Thank You Always.

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ABBREVIATIONS

CART	Classification and Regression Tree
ROC	Receive Operating Characteristic
AUC	Area Under Curve

CHAPTER ONE: INTRODUCTION

1.1 Background

Pregnancy is a female state that is produced due to the implantation of the fertilised ovum in the uterine endometrium and ultimately gives rise to a foetus; and pregnancy wastage is the loss of product of conception normally or therapeutically (Jeffcoate, 1975). Pregnancy wastage is one of the adverse birth outcomes among others including preterm births and low birth weights.Adverse birth outcomes are far more frequent in the developing world because of the many unplanned pregnancies, pregnancy and birth complications whose repercussions are generally unfavorable both for the mother and the baby. They remain significant contributors to perinatal mortality and developmental disabilities globally. Abu-Saad and Fraser, (2010) concluded that adverse birth outcomes carry lifelong consequences for development, life quality and health care costs.

Pregnancy wastage can be classified as intra-uterine foetal death, abortion and menstrual regulation (Jeffcoate 1195, and Shaw, Scoutter and Stanton 2003.

Every year about eight million women suffer from pregnancy related complications and over half a million die(Atikur et al) . About 99% of them are in developing countries (WHO, 2004).

Generally pregnancy wastage into one of the four categories: miscarriages, stillbirth, birth loss and medically based termination.

It is estimated that more than 3.3 million babies are stillborn every year. Worldwide 1.2 million stillbirths occur during labour (intrapartum) according to The Lancet. Before labour (antepartum) stillbirths account for more than half of stillbirths (1.4 million). The five big causes of stillbirth are childbirth complications, maternal infections in pregnancy, maternal disorders, especially hypertension and diabetes, fetal growth restriction and congenital abnormalies. The priority programme investments include family planning, care at birth, antenatal care with hypertension and advanced antenatal care.In 2005 WHO gave a global estimate of 3.3 million stillbirth deaths.

In Kenya a study on poor pregnancy outcomes by Magadi2006 among adolescents in South Nyanza region of Kenya found significant associations between socio-economic and demographic characteristics with pregnancy outcomes with place being rural or urban and the level of education attainment being strongly associated with adverse pregnancy outcomes.

The purpose of this study is to determine risk factors associated with the pregnancy wastage as an adverse birth outcome, the normal pregnancy wastage which is not therapeutic.

1.2 Statement of the Hypothesis and Research Questions

Based on 2008/09 KDHS, there were 6,079 pregnacies reported in Kenya out of which 1,370 ended preterm resulting in pregnancy wastage. The question is what are the major risk factors determining the occurence of pregnancy wastage?.

1.2.1 Hypotheses

- To determine if maternal age at first pregnancy is a determinant of pregrancy wastage.
- To establish whether a woman's household wealth index is a determinant of pregnancy wastage.
- To examine whether the place of residence is a determinant of pregnancy wastage.
- To compare CART and Logistic Regression Analysis model performancesfor identifying key determinants of pregnancy wastage.

1.2.2 Research Questions

- Is maternal age at first pregnacy a risk factor in pregnancy wastage?
- Is Woman's household wealth index a risk factor for pregnancy wastage?
- Is the place of residence a risk factor for pregnancy wastage?

1.3 Significant of the Study

Risk factors for pregnancy wastage have not been studied extensively in Kenya. One documented study was done poor pregnancy outcomes among adolescents in South Nyanza region of Kenya(Magadi, 2006).

Pregnancy outcome is influenced by hereditary and environmental factors including those which affect stature in early life, current health and nutritional status, inter-pregnancy interval, maternal age, genitourinary or general diseases in women and socioeconomic and educational status.

This study found that adolescents living in rural areas, not enrolled in school or with low educational attainment had higher proportion of experiencing pregnancy wastage compared to their counterparts who were living in urban areas, had higher educational attainment or enrolled in school at the time of index pregnancy among other associations. Overall the patterns of associations between socio-economic and demographic characteristics with pregnancy outcomes observed in the bivariate and multivariate analyses conform to what is expected but the issue is that these associations are not statistically significant possibly due to the relatively small number of cases analysed and hence insufficient power to detect statistical significance.

Also the study only covered a region and such there is no study to at national level to look at the trends of pregnancy wastage or the issues which aggravate the situation.

This study will use two classification techniques, one parametric-discriminant function analysis and the other non-parametric-classification and regression trees in order to provide a non-subjective risk analysis of pregnancy wastage.

1.4 Justifications Of the Study

The findings of the study shall also enable program developers and implementers to know profiles of women with enormous need for reproductive health services at population level, including treatment of reproductive tract infections and malaria prevention so as to check on adverse birth outcomes which may not be captured at health facility level because program data may not The risk factors for pregnancy wastage in Kenya have therefore not been studied extensively and there is no national study that has been done to establish socio-demographic and health risk factors for pregnancy wastage using population based data. As such therefore, there is need to have information the effect of various socio-demographic and health factors on the risk of pregnancy outcome in Kenyaconcerned with family planning services to trace areas of need and advise people on the need to check high-risk pregnancies and unsafe abortions so as to reduce the number of adverse pregnancy outcomes.

1.5 Definitions

Miscarriages

Any pregnancy that ends unintentionally before the foetus is viable.

Preterm births

A Preterm birth is defined as birth of less than 37 weeks' gestation pregnancy.

Still births

WHO promotes the definition of stillbirth or late fetal death as death occurring at least 28 weeks of gestation or at least 1000g birth weight(3). This means its babies born within the last trimester of pregnancy.

Pregnancy Wastage

Pregnancy is a female that is produced due to implantation of the fertilized ovum in the uterine endometrium and ultimately giving rise to a foetus. Pregnancy wastage is the loss of product of conception normally or therapeutically (Jeffcoate, 1975). Pregnancy wastage in this case means stillbirths, abortions and miscarriages.

1.6 Scope, Limitations and Assumptions

The study will utilise the 2008-09 Kenya Demographic and Health Survey (KDHS 2008/09) which is a nationally representative sample survey of 8,444 women aged 15 to 49 and men aged 15 to 54 selected from 400 sample points(clusters) throughout Kenya. It is designed to provide data to monitor the population and health situation.

The survey utilised a two-stage sample based on the 1999 Population and Housing Census and was designed to produce separate estimates for key indicators for each of the eight provinces in Kenya. Data collection took place over a three month period from 13th November 2008 to late February 2009.

Obstetric data is not available for this study, however, the population based approach gives a real picture of what is happening country wide. Furthermore, the KDHS data is statistically representative of the country as opposed to specific facility data which may be biased based on the profile of the people coming for service based on the geographical and spatial distribution, socio-economic and other factors, human and natural.

The authorization to use the dataset was sought from both MEASURE DHS and The Kenya National Data Archive (KeNADA).

CHAPTER TWO:LITERATURE REVIEW

2.1Introduction

This chapter reviews various literatures on factors associated with pregnancy wastage. It especially points socio-economic, demographic and health factors found out to determine occurrence of pregnancy wastage. It will also do a review of literature on the methods for studies done on methods Presentation of conceptual framework and operational framework will follow, and then hypotheses and definition of key variables will be discussed. Reviews of this literature will cite what is already known about pregnancy wastage as well as spell out the gaps from different studies.

2.2 Pregnancy Wastage

Sidhu and Sidhu(1) examined pregnancy wastage and found that the poor living conditions contributed to higher pregnancy wastage in the scheduled caste women of Punjab. They could not attribute the very high rate if pregnancy wastage to a particular cause but envisaged that illiteracy, lower socio-economic status and non-availability of medical care may be contributing factors. They did note an increasing rate of foetal deaths with increasing age just as was observed by other investigators including Yerushalmy et al. 1956, Potter et al. 1965 and Nortman, 1974.

Atikur et al (2) studying the velocity and elasticity of pregnancy wastage and caesarian deliveries in Bangladesh on the contrary found out that pregnancy wastage decreases over ages where caesarian delivery increases. In looking at the two, they found out that increased age increase the risk of caesarian delivery but decrease the risk of pregnancy wastage. They however did agree that in the extreme age groups, pregnancy wastages are observed substantially larger.

Prakash et al (3) using data from the third wave of National Family Health Survey (NFHS, 2005-2006) for India to examine the effects of early marriage on the reproductive health status of women and on the well-being of their children found that early marriage had detrimental effects on the reproductive health status of women so that women who married at an early age were exposed to frequent childbearing, unplanned motherhood and abortions. Also in relation to marriage, Sureender et al (4) in their analysis of the the same data for Tamil Nadu, 1992 revealed that women marrying their close relatives had low age at marriage and experienced a higher percent of pregnancy wastage and child loss(first child) as compared to those women marrying their distant relatives or nonrelatives.

In a longitudinal study for the period 1988-92, Agarwal et al (5) looking at the relationship between pregnancy wastage and maternal under-nutrition and other socio-demographic factors in rural Indian women found no differences in abortion and stillbirth rates during the study years. However an increase in haemoglobin showed consistent reduction in abortion ratios. Stillbirths showed significant relationship with maternal weight and height. In this study, risk factors for increased perinatal mortality (stillbirths and neonatal deaths in the first week) were illiteracy, birth interval, previous stillbirth, previous preterm, untrained birth attendant and birth weight.

In Kenya a study on poor pregnancy outcomes by Magadi (2006) among adolescents in South Nyanza region of Kenya found significant associations between socio-economic and demographic characteristics with pregnancy outcomes with place being rural or urban and the level of education attainment being strongly associated with adverse pregnancy outcomes. A similar study among the adolescents in Bangladesh by Rahman*et al* 2010 on adolescent pregnancy compilation and wastage found out that young adolescents aged under 20 years were observed to have highest proportions of delivery complications and pregnancy wastage.

A study done in Cameroon using 2004 CDHS on spousal violence on potentially preventable single and recurrent spontaneous fetal loss found out that spousal violence increases the likelihood of single or repeated fetal loss. A large proportion of the risk for recurrent fetal mortality is attributable to spousal violence, and therefore is potentially preventable. The findings found out that Cameroonian women exposed to spousal violence are 50% more likely to experience single or repeated episodes of spontaneous fetal loss. Intimate partner violence within the household among women was associated with a third of reported fetal mortality in women.

A prospective study of 84 pregnant women done by Sundari (1993) looking at the effect of socio-demographic factors found out that the highest proportion of negative outcomes was to women who were pregnant for the first time with 12 percent of all pregnancies ending up wastage. In this study, it was found out that negative pregnancy outcome is lower for lower parities. However, in the same study, it was found out that the history of difficult and complicated deliveries were ages 20-24 and over 35 years suffered the highest proportion of negative outcome. On the contrary, in a study done by Ibrahim on a community-based prospective study of 6275 women studying the occurrence of stillbirths, it was found out that the correlation of the outcome of the last pregnancy with that of the current pregnancy was highly significant.

Data collected from 750 women of the reproductive ages (15-49) in the rural Rajshahi district of Bangladesh by Mahfuzar et al in a purposive sample found out that increased age increases the risk of pregnancy wastage. The pregnancy wastage in the age group 25-29 was lower among the women, followed by the age-group 40-44 which was the highest. The proportion of pregnancy wastage to live births was high in the age group 15-19.

According to Priyali and Umesh, various studies document the relationships between lowered zinc concentrations during pregnancy and low birth weight so that there is a threshold for serum zinc concentration below which adverse pregnancy outcome increases significantly.

Ibrahim et al in a community-based prospective study on stillbirths found out that the outcome of last pregnancy with that of the current pregnancy was highly significant.

Nadia et al(2009).

2.3 Statistical Analysis Methods Review and Pregnancy Wastage

In review of statistical analysis methods review for pregnancy wastage, Amina et al (2009) using Cameroon DHS, studied single and recurrent fetal loss as the dependent variable with physical, sexual and emotional as independent variable with individual level of analysis used Chi-square test to measure the differences in maternal and socio-demographic characteristics between the 2 groups(violence and no violence). Logistic regression model was used to generate adjusted odds ratio and 95% C.Is. Generalised estimating equation to account for intraclass correlation.

Rahman et al (2010) studied reproductive complications leading to pregnancy wastage using Micro level survey of 400 adolescents (10-19) and indepth interview with 37 adolescents who had experienced pregnancy wastage. Micro level survey of 400 adolescents (10-19) and in-depth interview with 37 adolescents who had experienced pregnancy wastage. Logistic regression was used to estimate the relative risks of the predictors of higher proportions of women suffer pregnancy problems especially in cases of early conception.

Ibrahim et al used Linear Logistic regression were fitted to calculate odds ratios of Outcome of last pregnancy with that of the current pregnancy. Stratification was used based on the mid wife.MahfuzarRahman used Logistic regression model to study pregnancy wastage using Data collected from 750 women of reproductive ages (15-49) in the rural Rajshahi district, Bangladesh.

Using 2001 Census data for Madya Pradesh, India, Diamond-Smith et al studying fetal losses and maternal deaths using Monte Carlo Sensitivity analysis to assess the plausibility of the estimates of Fetal losses and maternal deaths.

Monica Magadi (2004) used Bivariate and multinomial regression analysis to study pregnancy outcome including pregnancy wastage, premature live birth and full time live births.

Z proportion test, Relative Risk and Multiple Regression were performed on a Follow up study betweenJanuary 1988 to December 1992 by Agarwalet al to study pregnancy wastage.

2.4 Summary of Literature review

These studies provide some evidence that a relationship exists between pregnancy wastage and various factors including poor living conditions, lower socio-economic status, non-availability of medical care, extreme ages, early marriage and maternal under nutrition. Other factors including maternal under nutrition, birth interval, spousal violence and parity are also associated with higher incidences of pregnancy wastage.

Various methods have also been used to study pregnancy wastage including logistic regression, generalised estimating equation, linear logistic regression, bivariate and multinomial regression and various other methods.

An investigation is needed to establish in depth the risk profiles of pregnancy wastage in the Kenyan situation.

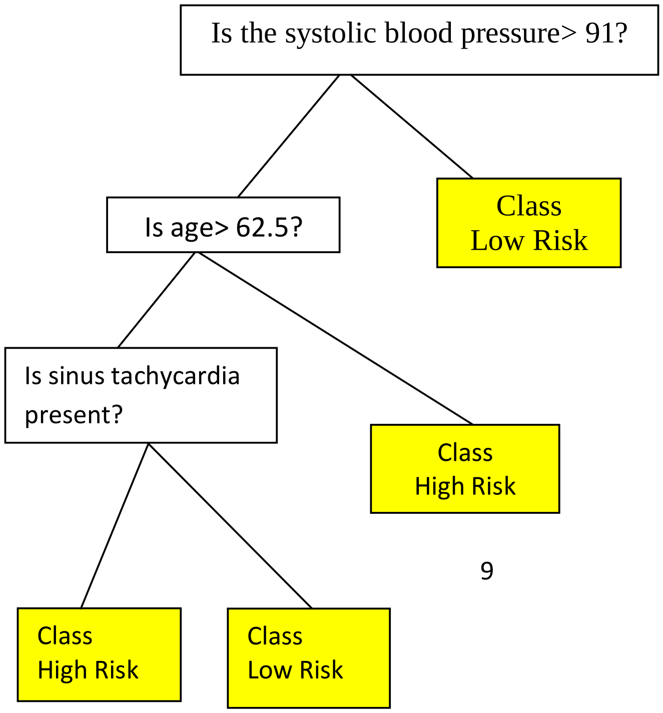
CHAPTER THREE: METHODS

3.1 CART Model

Classification and Regression Tree is a type of decision tree introduced by Leo Breiman et al in 1984. In mathematical terms, a decision tree is defined as a directed, acyclic and connected graph having one distinguishable vertex called a root node. The tree structure consists of nodes and branches connecting these nodes. If a node has branches leading to other nodes, it is called a parent node, and the nodes to which these branches lead to are called children of this node. The terminal nodes are called leaves.

As indicated CART methodology was developed in 80s by Breiman, Freidman, Olshen, Stone in their paper “classification and Regression Trees” (1984). For building decision trees, CART use so- called learning sample- a set of historical data with pre- assigned classes for all observations. For example, learning sample for credit scoring system would be fundamental information about previous borrows (variables) matched with actual payoff results (classes).

Decision trees are represented by a set of questions which splits the learning sample into smaller and smaller parts. CART asks only yes/no questions. A possible question could be: “Is age greater than 50?” or “is sex male?” CART algorithm will search for all possible variables and all possible values in order to find the best split-the question that splits the data into two parts with maximum homogeneity. The process is then repeated for each of the resulting data fragments. Here is an example of simple classification tree, used by San Diego Medical Center for classification of their patients to different levels of risk:



Classification Tree

The characteristic feature of CART is that the tree constructed by CART algorithm is strictly binary. The decision tree is constructed recursively where an attribute is selected at first to be placed at the root of the node to make one branch for each possible value. This splits up the example set into subsets, one for every value of the attribute (Witten, Frank; 2000). The cases from the training set are recursively portioned into subsets with similar values of the target variable and the tree is built through the thorough search of all available variables and all possible divisions for each decision node and the selection of the optimal divisions according to a given criterion.

The basic principle of the tree model is to partition space spanned by the input variables to maximise a score of class purity and that the majority of the points in each cell of the partition belong to one class. They are mappings of observations to conclusions (target values). Each inner node responds to a variable; an arc to a child represents a possible value of that variable. A leaf represents the predicted value of target variable given the values of the variables represented by the path from the root (T. Menzies, Y. Hu; 2003).

Splitting Criterion

The splitting criterions have always the following form. The case is moved to the left child if the condition is met, and goes to the right child if otherwise.

For continuous variables, the condition is defined as “explanatory variable $x_j \leq C$”. For nominal variables, the condition expresses the fact the variables takes on specific values.

The splitting criterion measures the decrease in the distribution of the target variable between the root node and the first subsequent node and between each pair of subsequent nodes. The splitting criterion has two objectives: to determine the best split for each input variable and to choose the best split among a multitude of possible splits from input variables. For classification trees, there are two common splitting criterions, which are Gini index and entropy reduction.

Gini Index (Total Leaf Impurity)

Gini index is a measure of purity. If the target values are the same within the node then the Gini index is one. The best split is selected by the largest Gini index. The Gini index can be calculated as follows:

$$\text{Gini index} = E_G(m) = \sum_{leaves} P_{leaves} \left(\sum_{i}^{classes} p_i^2 \right)$$

- E_G (m) is the Gini index at node m.
- p_i is the proportion of each target class in the ith node.
- p_{leaves}= number of individuals in the leaf node/total number of individuals in node *m*. (Matiganon, 2007)

Entropy reduction

Entropy reduction is a measure of variability in categorical data. If the target values are the same within the node then the entropy is zero. Thus, the best split is selected by smallest entropy reduction. The Entropy reduction is defined as:

Entropy reduction= E_E(m)

$$= -1 \cdot \sum_{leaves} \left(p_{leaves} \left(\sum_{i}^{classes} pi \cdot \log_2 \, pi \right) \right)$$

- p_i is the proportion of each target class in corresponding node *m*. (Matignon, 2007).

Construction of maximum tree

Let t_p be a parent node and t_i, t_r – respectively left and tight child nodes of parent nodet_p. Consider the learning sample with variable matrix X with M number of variables x_j and N observations. Let class vector Y consist of N observations with total amount of K classes.

Classification tree is built in accordance with splitting rule-the rule that performs the splitting of learning sample into smaller parts. Each time data have to be divided into two parts with maximum homogeneity:

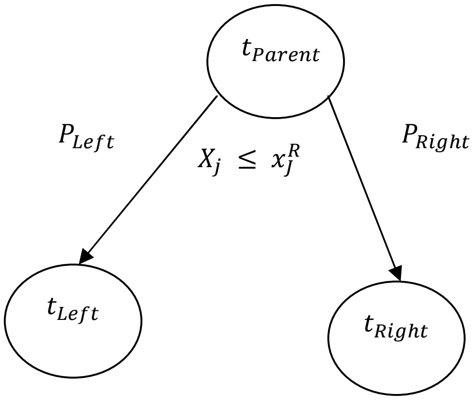


Figure 2.1: Splitting algorithm of CART

where$t_p, t_{I,} t_r -$ parent, left and right nodes; $x_j - variable\, j$; $x_j^R -$ best splitting value of variable x_j.

Maximum homogeneity of child nodes is defined by so-called impurity function i (t). Since the impurity of parent node t_p is constant for any of the possible splits $x_j \leq x_{J,}^R\, j = 1, \dots \dots \dots., m,$ the maximum homogeneity of left and right child nodes will be equivalent to the maximization of change of impurity function $\Delta\, i(t)$:

$$\Delta i(t) = i(t_p) - E\{i(t_{c)}\}$$

wheret_c −left and right child nodes of the parent node t_p. Assuming that the P_1, P_r- probabilities of right and left nodes, we get:

$$\Delta i(t) = i\big(t_p\big) - P_1 i(t_1) - P_1 i(t_r)$$

Therefore, at each node CART solves the following maximization problem:

$$\arg\max\big[i(t_p) - P_1 i(t_1) - P_r i\ (t_r)\big]$$

Equation 2.1 implies that CART will search through all possible values of all variables in matrix X for the best split question $x_j < x_j^R$ which will maximize the change of impurity measure$\Delta i(t)$.

The next important question is how to define the impurity function I (t). In theory there are several impurity functions, but only two of them are widely used in practice: Gini splitting rule and Twoing splitting rule.

Gini splitting rule

Gini splitting rule (or Gini index) is most broadly used rule. It uses the following impurity function I (t):

$$i(t) = \sum_{k\#1} P\left(\frac{k}{t}\right) p\ (l/t)$$

wherek,l,I,……….,k,-index of the class; p (k/t)-conditional probability of class k provided we are in node t.

Applying the Gini impurity function 2.2 to maximization problem 2.1 we will get the following change of impurity measure $\Delta i(t)$:

$$\Delta \mathrm{i(t)} = -\sum_{k=1}^{k} \mathrm{P}^2\left(\frac{\mathrm{K}}{\mathrm{t_p}}\right) + \mathrm{P_1}\sum_{\mathrm{K}=1}^{\mathrm{K}} \mathrm{P}^2\ (\frac{\mathrm{K}}{\mathrm{t_1}} + \mathrm{P_r}\sum_{\mathrm{K}=1}^{\mathrm{K}} \mathrm{P}^2\ (\frac{\mathrm{k}}{\mathrm{t_r}})$$

Therefore, Gini algorithm will solve the following problem:

arg max

$$x_j \leq\ x_j^R, \qquad j = 1, \dots .m \left[-\sum_{\mathrm{K}=1}^{\mathrm{K}} \mathrm{P}^2(\mathrm{k/t_p}) + \mathrm{P_1}\sum_{\mathrm{K}=1}^{\mathrm{K}} \mathrm{P}^2\left(\frac{\mathrm{K}}{\mathrm{t_l}}\right) + \mathrm{P_r}\sum_{\mathrm{K}=1}^{\mathrm{K}} \mathrm{P}^2(\mathrm{K/t_r}\right]$$

Gini algorithm will search in learning sample for the largest class and isolate it from the rest of the data. Ginni works well for noisy data.

3.2Regression tree

Regression trees do not have classes. Instead there are response vector Y which represents the response values for each observation in variable matrix X. Since regression trees do not have pre-assigned classes, classification splitting rules like Gini 2.3 or Twoing 2.4 cannot be applied.

Splitting in regression trees is made in accordance with squared residuals minimization algorithm which implies that expected sum variances for two resulting nodes should be minimized.

$$\text{arg min } [P_l var(Y_l] + P_r Var(Y_r)$$

$$x_j \leq x_j^R, j = 1, \dots \dots m(P_l \; Var \; (Y_l) + P_r \; Var \; (Y_r \;)\}$$

whereVar$(Y_l), Var(Y_r) -$ response vectors for corresponding left and right child nodes; $x_j \leq \; x_j^R, j = 1, \dots \dots \dots . . m, -$ optimal splitting question which satisfies the condition 2.5

Squared residuals minimization algorithm is identical to Gini splitting rule. Gini impurity function 2.2 simple to interpret through variances notation. If we assign to objects of class k the value, 1, and value 0 to objects of other classes, then sample variance of these values would be equal to p (k/t)(t) (1-p(k/t). Summarizing by number of classes k, we will get the following impurity measure I (t):

$$i(t) = 1 - \sum_{k=1}^{k} p^2 \, (\frac{k}{t})$$

Up to this point so-called maximum tree was constructed which means that splitting was made up to the last observations in learning sample. Maximum tree may turn out to be very big, especially in the case of regression trees, when each response value may result in a separate node.

Recursive partitioning

Up to this point the classification problem has been used to define and motivate our formulae. However, the partitioning procedure is quite general and can be extended by specifying 5 "ingredients".

- A splitting criterion, which is used to decide which variable, gives the best split. For classification this was either the Gini or log –likelihood function. In the anova method the splitting criteria are $SS_T - (SS_L + SS_R)$, where $SS_T = \sum(y_i - y)^2$the sum of squares for the node is, and SS_r, SS_l are the sums of squares for the right and left son, respectively. This is equivalent to choosing the split to maximize the between-groups sum-of-squares in a simple analysis of variance. This rule is identical to the regression option for tree.
- A summary statistics or vector, which is used to describe a node. The first element of the vector is considered to be fitted value. For the anova method this is the mean of the node; for classification the response is the predicted class followed by the vector of class probabilities.
- The error of a node. This will be the variance of y for anova, and the predicted loss for classification.
- The prediction error for a new observation, assigned to the node. For anova this is $(Y_{new} - y)$.
- Any necessary initialization.

The anova method leads to regression trees; its is the default method if y a simple numeric vector, i.e, not a factor, matrix, or survival object.

Notation

The partitioning method can be applied to many different kinds of data. We will start by looking at the classification problem, which is one of the more instructive cases (but also has the most complex equations). The sample population consists of n observations from C classes. A given model will break these observations into k terminal groups; to each of these groups is assigned a predicted class (this will be the response variable). In an actual application, most parameters will be estimated from the data, such estimates are given by ≈ formulae.

$\pi_i\ i = 1,2 \dots\dots\dots..C$ Prior probabilities of each class.

$L(i,j)$ i=1,2,….C Loss matrix for incorrectly classifying an I as a j. L 9i,i)=0

A Some node of the tree.

Note that A represents both a set of individuals in the sample data, and, via the tree that produced it, a classification rule for future data.

r(x) True class of an observation x, where x is the vector of predictor variables.

$r(A)$ The class assigned to A, if A were to be taken as a final node.

n_i, n_ANumber of observations in the sample that are class I, number of obs in node A.

ni_ANumber of observations in the sample that are class i and node A.

$P\ (A)$Probability of A (for future observations).

=$\sum_{i=}^{C} 1\, \pi_i\, P\{x\ \varepsilon\ A \frac{}{r}(x) = i\}$

$\approx\ \sum_{i}^{C} = 1\, \pi_i\, n_i A/n_i$

R (A) Risk of A

=$\sum_{i}^{C} = 1\ P(i)A\ L\left(i, r\ (A)\right)$

where r 9A) is chosen to minimize this risk.

R (T) Risk of a model (or tree) T

$$= \sum_{j}^{k} = 1\ P\left(A_j\right) R\ (A_j)$$

where$A_j$are the terminal nodes of the tree.

If L (i,j)= 1 for all I # j, and we set the prior probabilities II equal to the observed class frequencies in the sample then p (i/A) =$n_{i\ A/nA}$ and R (T) is the proportion misclassified.

Building the tree

Splitting criteria

If we split a node A into two sons A_L and $A_r$into two sons), we will have.

$$P(A_l)R\ (A_L) +\ P(A_R)\ R(A_R)\ \leq P(A)R\ (A)$$

(this is proven in (1). Using this, one obvious way to build a tree is to choose that split which maximizes Δ R, the decrease in risk. There are defects with this, however, as the following example shows.

Suppose losses are equal and that the data is 80% class I's and that some trial split results in A_L being 54% class 1's and A_R being 100% class 1's. Class 1's versus class 0's are the outcome variable in this example. Since the minimum risk prediction for both the left and right son is r $(A_l) = r\ (A_R) = 1,$ this split will have $\Delta_R = 0$, yet scientifically this is a very informative division of the sample. In real data with such a majority, the first few splits very often can do no better than this.

A more serious defect with maximizing ΔR is that the risk reduction is essentially linear. If there were two competing splits, one separating the data into groups of 85% and 50% purity respectively, and the other into 70%-70%, we would usually prefer the former, if for no other reason than because it better sets things up for the next splits.

One way around both of these problems is to use look ahead rules; but these are computationally very expensive. Instead rpart uses one of several measurers of impurity, of diversity, of a node. Let f be some impurity function and define the impurity of a node A as.

$$1(A) = \sum_{i=1}^{C} f\ (P_i\, A)$$

where$P_i A$ is the proportion of those in A that belong to class I for future samples. Since we would like I (A)=0 when A is pure, f must be concave with f (0)=f (1)= 0.

Two candidates for f are the information index f (p) =-p log (p) and the Gini index f (p)=p (1-p). We then use that split with maximal impurity reduction.

$$\Delta I = P(A)I\ (A) - p\ (A_L) - p\ (A_R)I\ (A_R)$$

The two impurity functions are plotted in figure (2), with the second plot scaled so that the maximum for both measurers is at 1. For the two class problem the measurers differ only slightly, and will nearly always choose the same split point.

Another convex criteria not quite of the above class is towing for which

1 (A)=min (f (PC_1)+ f (PC_2)

where$C_{1,}C_2$ is some partition of the C classes into two disjoint sets. If C=2 twoing is equivalent to the usual impurity index for f. surprisingly, towing can be calculated almost as efficiently as the usual impurity index. One potential advantage of towing.

is that the output may give the user additional insight concerning the structure of the data. It can be viewed as the partition of C into two super classes which are in some sense the most dissimilar for those observations in A. For certain problems there may be a natural ordering of the response categories (e.g. level of education), in which case ordered towing can be naturally defined, by restricting C_1 to be an interval (1,2,…..k) of classes. Twoing is not part of rpart.

Incorporating losses

One salutatory aspect of the risk reduction criteria not found in the impurity measurers is inclusion of the loss function. Two different ways of extending the impurity criteria to also include losses are implemented in CART, the generalized Gini index and altered priors. The rpart software implements only the altered priors method.

Generalized Gini index

The Gini index has the following interesting interpretation. Suppose an object is selected at random from one of C classes according to the probabilities ($P_{1,}P_{2,}\dots.PC$ and is randomly assigned to a class using the same distribution. The probability of misclaffification is.

$\sum_i \sum_{j\#i} P_i\, P_j = \sum_i \sum_j P_i P_j - \sum_i P_i^2 = \sum_i 1 - P_i^2$ =Gini index for p

Let L (I,j) be the loss of assigning class j to an object which actually belongs to class i. The expected cost of misclassification is $\sum\sum L(i,j)P_iP_j$.This suggests defining a generalized Gini index of impurity by.

$$G(P) = ({}^{1}\!/_{2})\sum\sum L(i,j)P_iP_j$$

In particular, for two-class problems, G in effect ignores the loss matrix.

3.2.2 Altered priors

Remember the definition of R (A)

$$R\ (A) = \sum_{i=1}^{C} P_i\, A\, L\ (i, r\ (A)$$

$$\sum_{i=L}^{C} \pi_i\ L\big(i, r\ (A)\big)(ni_A/n_{i\ A}/n_i)(n/\eta\mathrm{A})$$

Assume there exists π and L be such that

$$\pi_i L\ (i,j) = \pi_i\ L\ (i,j)\forall_i\, j\ \varepsilon\ C$$

Then R (A) is unchanged under the new losses and priors. If L is proportional to the zero-one loss matrix then the priors π should be used in the splitting criteria. This is possible only if L is of the form.

$$L(i,j) = \begin{pmatrix} L_i & i\#j \\ 0 & i{=}j \end{pmatrix}$$

in which case.

This is always possible when C=2, and hence altered priors are exact for the two class problem. For arbitrary loss matrix of dimension C>2, rpart uses the above formula with $L_i \sum_j L\ ?\ (i,j)$.

A second justification for altered priors is this. An impurity index $I(A) = \sum f\ (P_i)$ has its maximum at $P_1 = P_2 = \cdots . = P_c = \frac{1}{C}. If$ a problem had, for instance, a misclassification loss for class 1 which was twice the loss for a class 2 or 3 observation, one would wish 1 (A) to have its maximum at $P_1 = {}^{1}\!/_{5}\,, P_2 = P_3 = {}^{2}\!/_{5}$, since this is the worst possible set of proportions on which to decide a node's class.

The altered priors technique does exactly this, by shifting the P_i

To final notes

When altered priors are used, they affect only the choice of split. The ordinary losses and priors are used to compute the risk of the node. The altered priors simply help the impurity rule choose splits that are likely to be "good" in terms of the risk.

The argument for altered priors is valid for both the gini and information splitting rules.

Pruning the tree

We have built a complete tree, possibly quite large and/or complex, and must now decide how much of that model to retain. In forward stepwise regression, for in-stance, this issue is addressed sequentially and no additional variables are added when the F-test for the remaining variables fails to achieve some level a.

Let $T_1, T_2, \dots \dots \dots T_k$ be the terminal nodes of a tree T. Define

$|T| = number\ of\ terminal\ nodes$

$$risk\ of\ T = R\ (T) = \sum_{i}^{k} =_l\ P(T_i)R\ (T_i)$$

In comparison to regression, $|T|$ is analogous to the model degrees of freedom and R (T) to the residual sum of squares.

Now let a be some number between 0 and ∞ which measures the 'cost' of adding another variable to the model; a will be called a complexity parameter. Let R (T_0) be the risk for the zero split tree. Define.

$$R_a(T) = R(T) + a|T|$$

to be the cost for the tree, and define T_a to be that sub-tree of the full model which has minimal cost. Obviously T_0 =the full model and T_∞ =the model with no splits at all. The following results are shown in $|1|$.

1. If T_1 and T_2 are subtrees of T with $R_a(T_1) = R_a(T_2)$, then either T_1 is a subtree of T_2 or T_2 is a subtree of T_i;hence either $|T_1| < |T_2|\ or\ |T_2| < |T_1|$.
2. If $a > \beta$ then either $T_a = T_\beta\ or\ T_a$ is a strict subtreeof T_β.
3. Given some set of numbers $a_1, a_2, \dots \dots \dots \dots \dots . a_{m;}$ both $T_a, \dots \dots \dots \dots T_{am}\ and\ R\ (T_{a,}) .., R(T_{am})$ can be computed efficiently.

Using the first result, we can uniquely define T_a as the smallest tree T for which $R_a(T)$ is minimized.

2 implies that all possible values of a can be grouped into m intervals, m ≤ (T)

$I_1 = [0, a_1]$

$1_2 = (a_1, a_2)$

.
.
.

$I_m = (a_m - 1, \infty)$

where all $a\varepsilon I_i$ share the same minimizing subtree

Cross-validation

The procedure of cross validation is based on optimal proportion between the complexity of the tree and misclassification error. With the increase in size of the tree, misclassification error is decreasing and in case of maximum tree, misclassification error is equal to 0. But on the other hand, complex decision trees poorly perform on independent data. Performance of decision tree on independent data is called true predictive power of the tree. Therefore, the primary task-is to find the optimal proportion between the tree complexity and misclassification error. This task is achieved through cost-complexity function:

$$R_a(T) = R\ (T) +\ a(T) - \frac{min}{T}$$

where R (T)-misclassification error of the tree T; a (T)-complexity measure which depends on T-total sum of terminal nodes in the tree a-parameter is found through the sequence of in-sample testing when a part of learning sample is used to build the tree, the other part of the data is taken as a testing sample. The process repeated several times for randomly selected learning and testing samples.

Although cross- validation does not require adjustment of any parameters, this process is time consuming since the sequence of trees is constructed because the testing and learning sample are chosen randomly, the final tree may differ from time to time.

Cross- validation is used to choose a best value for a by the following steps:

1. Fit the full model on the data set

computer$1_1, 1_2, \ldots\ldots\ldots, 1_m$

set$\beta_1 = 0$

$\beta_2 = \sqrt{a_1 a_2}$

$\beta_{\exists=\sqrt{a_2 a_3}}$

.
.
.

$\beta_m - 1 = \sqrt{a_m - 2a_m} - 1$

$\beta_m = \infty$

each$\beta_i$is a ‘typical value’ for its L_i

2. Divide the data set into s groups $G_1, G_{2,\ldots\ldots\ldots}G_s$ each of size s/n. and for each group separately:

- Fit a full model on the data set ‘everyone except $G_{i,}$ and determine $T_{\beta 1}, T_{\beta 2}, \ldots .T\beta_m$ for this reduced data set.
- Compute the predicted class for each observation in G_i, under each of the models
- from this compute the risk for each subject.

3. Sum over the G_i to get an estimate of risk for each β_j. For that β (complexity parameter) with smallest risk compute T_β for the full data set, this is chosen as the best trimmed tree.

In actual practice, we may use instead the I-SE rule. A plot of β versus risk often has an initial sharp drop followed by a relatively flat plateau and then a slow rise. The choice of β among those models on the plateau can be essentially random. To avoid this, both an estimate of the risk within one standard error of the achieved minimum is marked as being equivalent to the minimum (i.e considered to be part of the flat plateau). The simplest model, among all those “tied” on the plateau, is chosen.

In the usual definition of cross-validation we would have taken s=n above, i.e. each of the G_i would contain exactly one observation, but for moderate n this is computationally prohibitive. A value of s=10 has been found to be sufficient.

3.3 Logistic Regression

Logistic regression is used in this study to show whether an event will occur or not using a set of independent variables. Furthermore, it will be used to explain the percent of variance in the dependent variable which is explained by a specific predictor variable. This will be explained in terms of odds ratio. The logistic equation may be written as follows;

An explanation of logistic regression begins with an explanation of thelogisticfunction, which always takes on values between zero and one:

$$f(t) = \frac{e^t}{e^t + 1} = \frac{1}{1 + e^{-t}},$$

and viewing *t* as a linear function of an explanatoryvariable$x$, we have

$$\pi(x) - \frac{e^{(\beta_0 + \beta_1 x)}}{e^{(\beta_0 + \beta_1 x)} + 1} - \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}.$$

Where $\pi(x)$ is the probability that the response y = 1

$\beta_0$is the equation constant and

$\beta_1$is the coefficient of the predictor X_1

The advantage of a logistic regression model is that the independent variables don't have to be normally distributed. Secondly, it does not assume a linear relationship between the independent and dependent variables. However logistic regression is sensitive to high correlations among the predictor variables. This is referred to as multicollinearity. Pallant (2005) recommends that multicollinearity problems should be checked before logistic regression analysis. Furthermore, SPSS package can perform collinearity diagnostics. This can pick up problems with multicollinearity that may not be evident in a correlation matrix (Pallant 2005).

CHAPTER FOUR: RESULTS AND DISCUSSIONS

Risk Factors for Pregnancy Wastage

This chapter presents the results of the analysis on the major factors contributing to pregnancy wastage using both the CART and Logistic Regression to profile and explain the determinants ofpregnancy wastage .

4.1. Bivariate Analysis

Bivariate analysis shows that mother's educational attainment, household wealth index, age at first marriage, the nature of place of residence whether urban or rural, current age of the woman and marriage to the first birth interval as factors showing significant association with pregnancy wastage.

4.2. Classification and Regression tree

The CART methodology is used to find significant risk factors by applying recursive partitioning the data into smaller and smaller strata in order to improve the fit as best as possible. They partition the sample space into a set of rectangles and fit the model in each one. The optimal split is found over all variables at all split points. This in essence split the populations into meaningful subgroups which allow the identification of groups of interest.

CART analysis constructs a set of decision rules that identify homogenous groups of the response variable as a function of a set of explanatory variables.

For gaining understanding on the influence of different variables on pregnancy wastage, CART was employed to determine variable importance. Fourteen possible risk factors were considered as predictor (independent variables) and pregnancy wastage considered as predictive (dependent) variable, the one whose occurrence is influenced by the risk factors tested. The response variable is categorical

The CART derived clusters to help identify which variables can best explain pregnancy wastage in Kenya on population based data. Maternal education, maternal work status, household wealth index, birth order, age at first birth, the nature of the place of residence whether urban or rural, whether the woman was given iron or not during pregnancy,number of antenatal visits,timing of antenatal visits, age at first marriage, Age at first birth, marriage to first birth interval and use of malarial drugs during pregnancy including Chloroquine, Fansidar or any other malarial drug were used in the CART model for the analysis.

The most important risk factors for pregnancy wastage from the analysis are the mother's age, mother's educational attainment, mothers age at first birth, the nature of place of residence whether urban or rural , birth order and marriage to first birth interval with a prediction with average prediction success of 60.55% with an overall correct rate of 62.21% as shown in table 4.2.3. Table 4.2.2 below shows the variable importance. Fifty three trees with different complexities and error values using CART based on the splitting criteria are reflected in Table 4.2.1. These variables where used as splitters to spilt the data recursively.

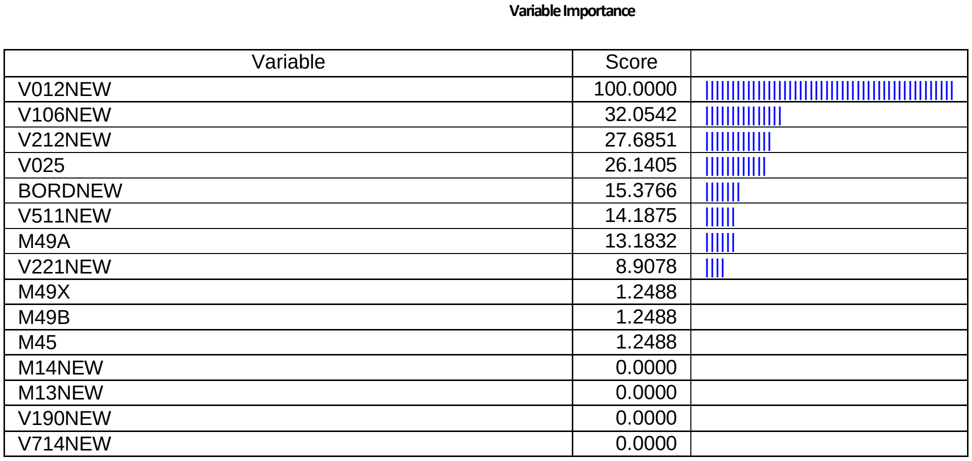
Figure 4.2.1 shows the splitters used to generate the CART optimal tree (Figure 4.2.2) based on the lowest cross-validated relative error. The tree selected for deriving decision rules is shown in Figure 4.2.3 along with relative cost.

Table 4.2.1. Details of trees generated using CART along with relative error complexities

Tree	Terminal	Cross-Validated	Resubstitution	Complexity
Number	Nodes	Relative Cost	Relative Cost	
1	1018	0.69476 ± 0.00887	0.47558	0
2	866	0.68866 ± 0.00885	0.47668	0.00001
3	794	0.68363 ± 0.00883	0.47886	0.00002
4	683	0.68331 ± 0.00884	0.48467	0.00003
5	618	0.68094 ± 0.00883	0.48938	0.00004
6	561	0.67773 ± 0.00881	0.49481	0.00005
7	514	0.67741 ± 0.00881	0.50015	0.00006
8	485	0.67724 ± 0.00881	0.50403	0.00007
9	440	0.67534 ± 0.00880	0.51105	0.00008
10	395	0.67713 ± 0.00881	0.51895	0.00009
11	352	0.67441 ± 0.00880	0.52774	0.00011
12	329	0.67565 ± 0.00880	0.53286	0.00012
13	291	0.67184 ± 0.00879	0.54181	0.00013
14	257	0.67463 ± 0.00878	0.55089	0.00014
15	249	0.67026 ± 0.00876	0.55323	0.00015
16	234	0.66656 ± 0.00874	0.55797	0.00016
17	208	0.66541 ± 0.00871	0.56664	0.00017
18	187	0.66552 ± 0.00872	0.57418	0.00019
19**	175	0.66528 ± 0.00870	0.57886	0.0002
20	166	0.66740 ± 0.00872	0.5827	0.00022
21	150	0.66794 ± 0.00870	0.58993	0.00023
22	140	0.66857 ± 0.00867	0.59466	0.00024
23	137	0.66914 ± 0.00867	0.59618	0.00026
24	132	0.67217 ± 0.00869	0.59901	0.00029
25	130	0.67300 ± 0.00870	0.60024	0.00031
26	128	0.67401 ± 0.00873	0.60155	0.00034
27	127	0.67544 ± 0.00876	0.60224	0.00035
28	125	0.67498 ± 0.00876	0.60368	0.00037
29	117	0.67561 ± 0.00874	0.60969	0.00038
30	115	0.68117 ± 0.00874	0.61126	0.0004
31	112	0.68141 ± 0.00873	0.61369	0.00041
32	111	0.68866 ± 0.00876	0.61455	0.00044
33	110	0.68984 ± 0.00878	0.61543	0.00045
34	107	0.69697 ± 0.00881	0.61823	0.00047
35	96	0.69846 ± 0.00882	0.62891	0.00049
36	91	0.70018 ± 0.00883	0.63386	0.0005
37	88	0.70044 ± 0.00886	0.63695	0.00052
38	81	0.69863 ± 0.00885	0.64471	0.00056
39	79	0.70473 ± 0.00887	0.64707	0.0006
40	71	0.71072 ± 0.00889	0.65677	0.00061
41	70	0.71575 ± 0.00896	0.65803	0.00064
42	66	0.71709 ± 0.00899	0.66362	0.00071
43	63	0.72161 ± 0.00901	0.66794	0.00073
44	44	0.72769 ± 0.00902	0.69758	0.00079
45	43	0.73284 ± 0.00905	0.69916	0.0008

46	31	0.73891 ± 0.00905	0.71985	0.00087
47	16	0.76462 ± 0.00897	0.74672	0.0009
48	13	0.77793 ± 0.00909	0.7555	0.00147
49	11	0.78241 ± 0.00915	0.76206	0.00165
50	7	0.78894 ± 0.00925	0.77749	0.00194
51	3	0.82517 ± 0.00933	0.81506	0.00471
52	2	0.82528 ± 0.00886	0.82528	0.00512
53	1	1.00000 ± 1.18721E-009	1	0.08737

Table 4.2.2Variable importance of determinants of pregnancy wastage.

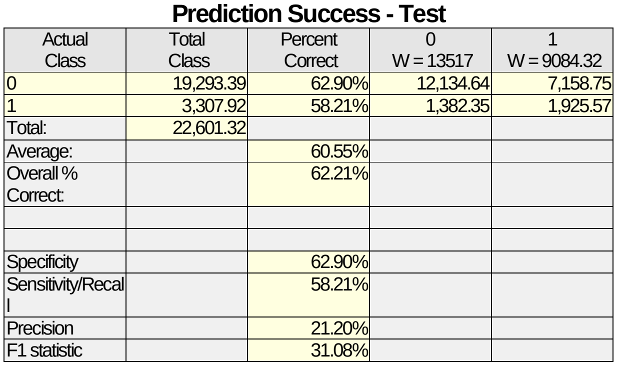


Variable Importance

Variable	Score	
V012NEW	100.0000	||||||||||||||||||||||||||||||||||||||||||||||||
V106NEW	32.0542	|||||||||||||||
V212NEW	27.6851	|||||||||||||
V025	26.1405	||||||||||||
BORDNEW	15.3766	|||||||
V511NEW	14.1875	||||||
M49A	13.1832	||||||
V221NEW	8.9078	||||
M49X	1.2488	
M49B	1.2488	
M45	1.2488	
M14NEW	0.0000	
M13NEW	0.0000	
V190NEW	0.0000	
V714NEW	0.0000	

To calculate the variable importance score, the CART algorithm looks at the improvement attributable to each variable in its role as a surrogate to the primary split. These values for the respective improvements are summed over each node and are scaled relative to the best performing variable in the dataset. The variable with the highest sum of improvements thus scores the highest score 100, and all the other variables have lower scores ranging downwards towards zero as shown in the table above.

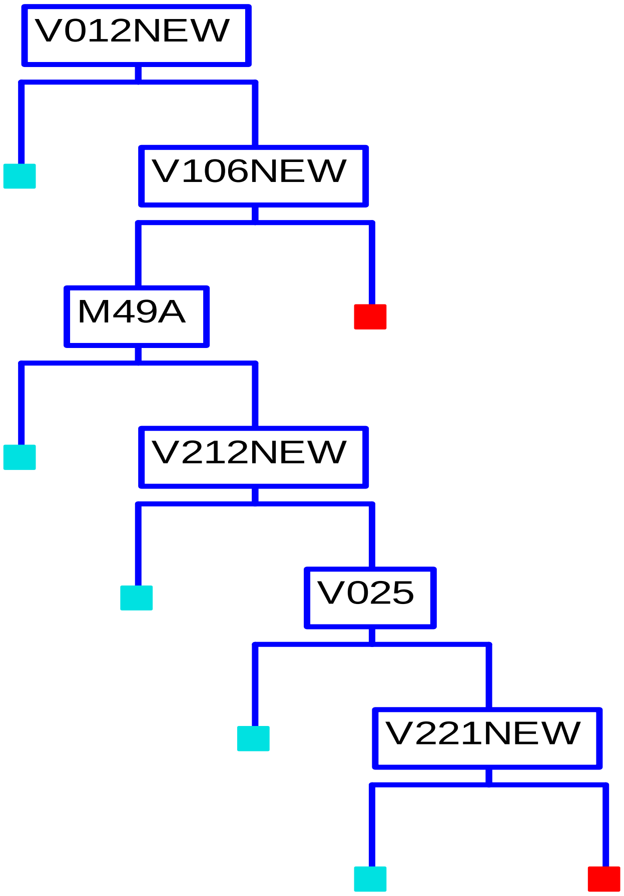
Table 4.2.3 Prediction Success



Prediction Success - Test

Actual Class	Total Class	Percent Correct	0 W = 13517	1 W = 9084.32
0	19,293.39	62.90%	12,134.64	7,158.75
1	3,307.92	58.21%	1,382.35	1,925.57
Total:	22,601.32			
Average:		60.55%		
Overall % Correct:		62.21%		
Specificity		62.90%		
Sensitivity/Recal l		58.21%		
Precision		21.20%		
F1 statistic		31.08%		

Figure 4.2.1Splitters for the tree generated using CART.



The high value split variables always go to the right, low value goes to the left.

Figure 4.2.2Classification tree for Pregnancy Wastage

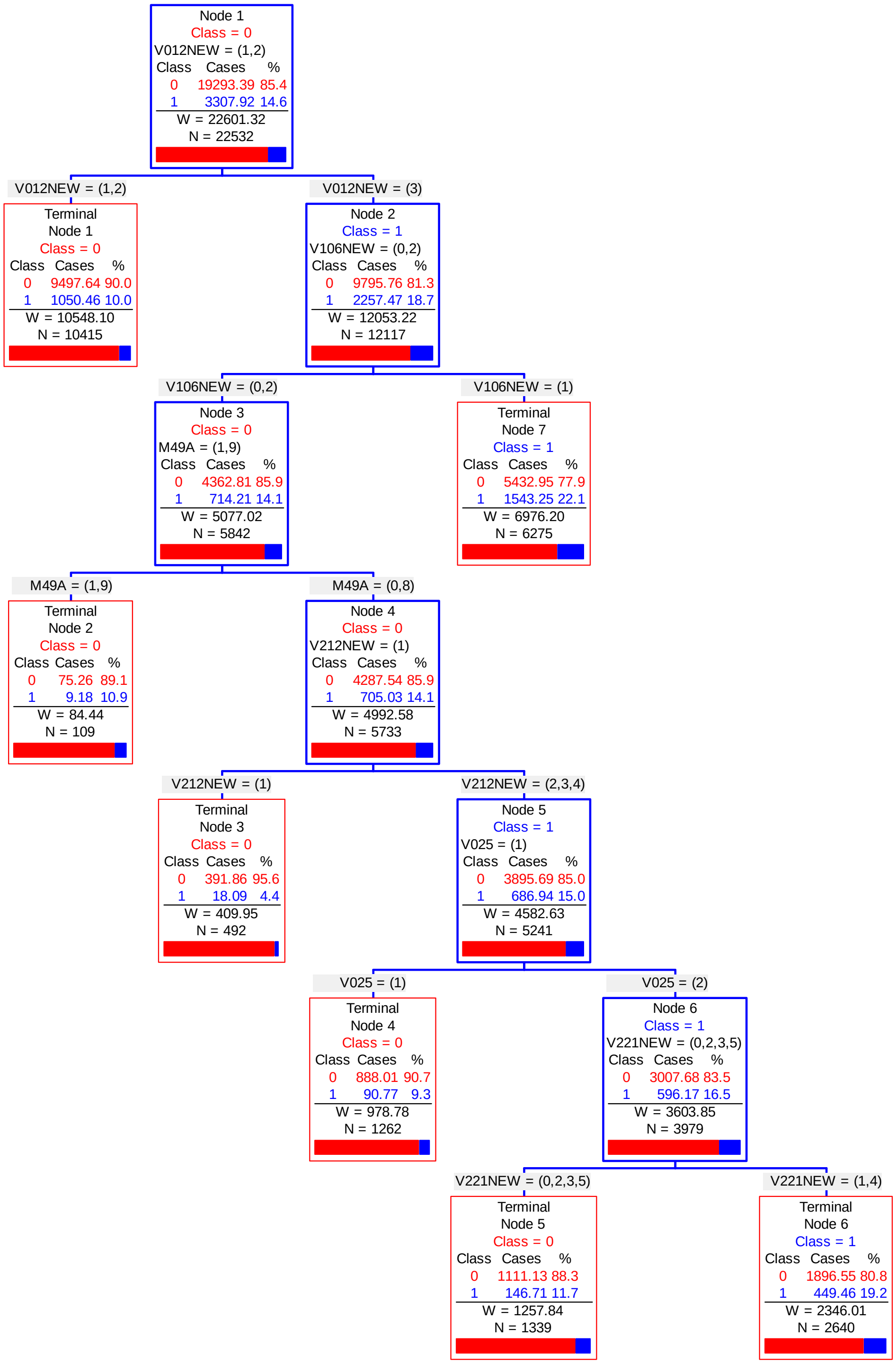
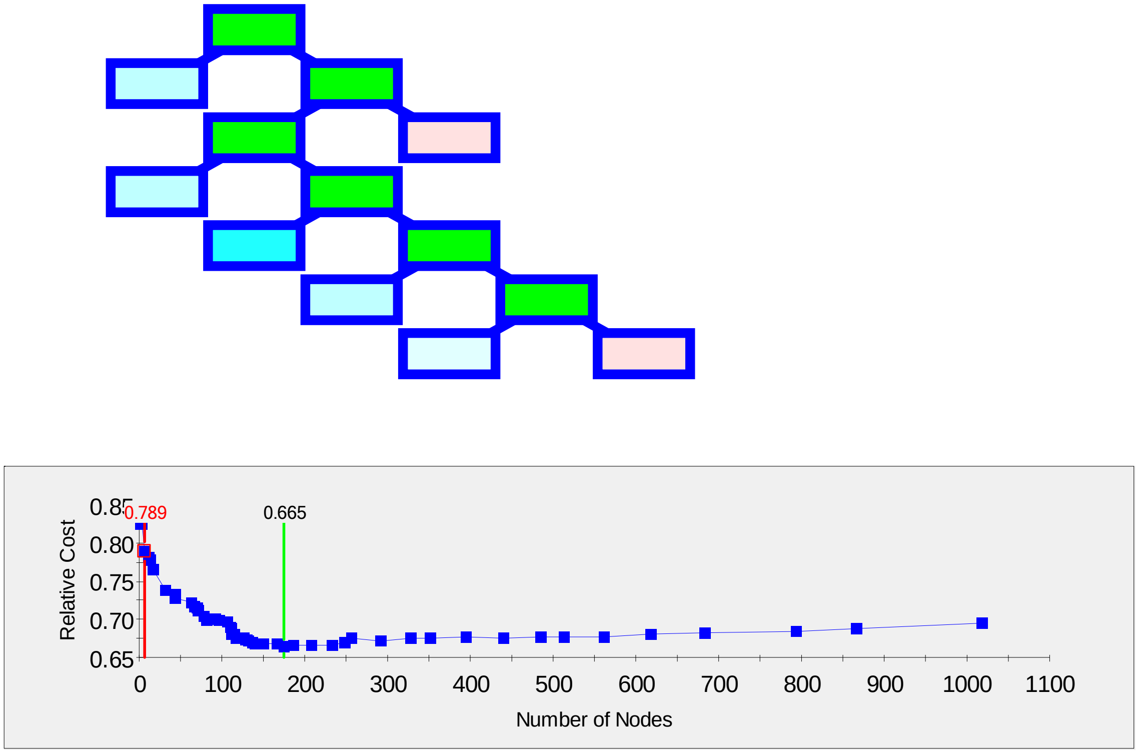


Figure 4.2.3Thetree sequence of lowest complexity which yielded 7 nodes with the cross validation error rate



The CART doesn’t fit the data very well because the relative cost is very high as shown above.

4.3 Logistic Regression

Usinglogistic regression. The same number of factors required were used to test their influence on pregnancy wastage.Table 4.3.1 shows the relative importance/relevance of the variables to pregnancy wastage in decreasing order (based on value of the z, the higher the z, the higher the relevance of the variable).

Table 4.3.1 Variable importance in multivariable logistic regression

Risk Factor	**Odds Ratio**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**
Age	1.065908	0.0162074	4.2	0	1.03461 - 1.098152
Marriage to 1st birth interval	1.154148	0.0499918	3.31	0.001	1.06021 - 1.25641
Took other drug for Malaria	1.651662	0.3862566	2.15	0.032	1.044383 - 2.612056
Place of residence - Urban/Rural	1.269734	0.2126851	1.43	0.154	.9143941 - 1.763162
Iron tablets/Syrup during pregnancy	1.090229	0.068895	1.37	0.172	.9632247 - 1.233979
Age at first birth	1.032773	0.0255224	1.3	0.192	.9839426 - 1.084028
Timing of first antenatal visit	1.007722	0.0063795	1.22	0.224	.995296 - 1.020304
Wealth Index	1.062593	0.0572546	1.13	0.26	.956098 - 1.180949
Antenatal visits for pregancy	1.000322	0.0040246	0.08	0.936	.992465 - 1.008241
Mother’s working status	0.9941402	0.0848496	-0.07	0.945	.8410035 - 1.175161
Birth Order	0.9934445	0.0442516	-0.15	0.883	.9103911 - 1.084075
Highest educational level	0.9263823	0.0841678	-0.84	0.4	.7752703 - 1.106948
Took fansidar during pregnancy	0.8908719	0.1015907	-1.01	0.311	.7124401 - 1.113992
Took chloroquine for malaria	0.6625726	0.1714748	-1.59	0.112	.398971 - 1.100337
Age at first marriage	0.9200581	0.0198984	-3.85	0	.881873 - .9598965

From this, it shows it shows that the relative importance of factors for pregnancy wastage are the age of the woman, marriage to first birth interval, anti-malarial drug usage during pregnancy, type of place of residence, usage of iron supplementation during pregnancy, age at first birth, timing of first ante-natal visit, household wealth index, ante-natal visits for pregnancy, working status of the mother, birth order, highest educational attainment of the mother, usage of fansidar or chloroquine for malaria during pregnancy and lastly the age at first marriage in that order.

Table 4.3.2. Results of Multivariate Logistic Regression

Variable	Levels	Odds Ratio	Linearized Std. Err.	t	P>|t|	[95% Conf. Interval]	
Highest Educational Level	No education	0.852353	0.1766125	-0.77	0.441	.5671292	1.281023
	Primary	0.787333	0.2047538	-0.92	0.358	.4721578	1.312892
Currently Working	No	0.843393	0.1586171	-0.91	0.366	.5826837	1.220751
Wealth Index	Middle	0.917795	0.1859998	-0.42	0.672	.6161558	1.367102
	Highest	1.006131	0.2022944	0.03	0.976	.6775848	1.493982
Birth order	2 to 3	1.055562	0.2541275	0.22	0.822	.6575087	1.694596
	> 4	1.008084	0.2995363	0.03	0.978	.5620401	1.808115
Age at first Birth	11 to 14	1.173486	0.3117018	0.6	0.547	.6960802	1.978322
	15-24	1.00774	0.4078315	0.02	0.985	.454744	2.233211
	35+	0.753782	1.335683	-0.16	0.873	.023127	24.56814
Age at first marriage	11 to 14	1.082811	0.2392909	0.36	0.719	.701204	1.672096
	15-24	0.789768	0.2648966	-0.7	0.482	.4083993	1.527263
	35+	2.206343	2.899372	0.6	0.547	.166544	29.22921
Place of residence	Rural	1.365983	0.3322349	1.28	0.201	.8467485	2.203618
Antenatal visits for pregnancy	4 and above	0.876008	0.1596188	-0.73	0.468	.6122285	1.253437
Use of other drug for malaria	m49x	2.451994	0.6979032	3.15	0.002	1.401105	4.291097
Chloroquine use during pregnancy	m49b	0.372047	0.1232539	-2.98	0.003	.1939576	.7136576
Fansidar use during pregnancy	m49a	1.079495	0.1491623	0.55	0.58	.8226742	1.416491
Iron use during pregnancy	m45	1.051042	0.1034121	0.51	0.613	.8661694	1.275374
Timing of 1st Antenatal Check	4 to 6	0.690992	0.1447347	-1.76	0.078	.4577316	1.043121
	6 to 8	0.723473	0.2397971	-0.98	0.329	.3770401	1.388215
Age	25 to 34	1.728685	0.3892827	2.43	0.016	1.110251	2.691599
	35+	3.49599	1.060411	4.13	0	1.925559	6.347219
Marriage to first birth interval	6 to 10	0.655335	0.2326104	-1.19	0.235	.3261103	1.316927
	11 to 15	1.245112	0.3950709	0.69	0.49	.6672083	2.323569
	16 to 20	1.336205	0.5127981	0.76	0.451	.6282927	2.841739
	21 & Above	1.430901	0.4449803	1.15	0.25	.7763509	2.637311

In the logistic regression increased incidence of pregnancy wastage was associated with the type of the place of residence whether urban or rural, non-usage of anti malarial drug during pregnancy, failure to use iron supplements during pregnancy, all aspects of the age of the woman, marriage to first birth interval and birth order. The other factors favour the reduction of the pregnancy wastage including education, household's wealth index and antenatal visits.

Having more than four antenatal visits greatly reduces the odds of pregnancy wastage by 13%. An increase in educational attainment is associated with a reduction in pregnancy wastage. There is notable reduction in pregnancy wastage from secondary(21.3% reduction) compared to primary (14.8%). The timing of antenatal visits is also an important factor in pregnancy wastage. Having ante-natal visits earlier in the pregnancy period reduces the likelihood of pregnancy wastage. The women who had ante-natal visits earlier in pregnancy(4-6 months) had a 30.9 reduction in the likelihood as opposed to those who attended later (6-8 months) who had a 27.7% reduction.

The maternal work status is also associated with pregnancy wastage in that being working status reduces pregnancy wastage by 16%. The increase in household wealth indexreduces pregnancy wastage. Being middle class reduces the pregnancy wastage by 8.3%. By contrast, being in the highest wealth index increases the likelihood of pregnancy wastage by 0.6%. This is a paradox which may need further investigation.

Increase in birth order is associated with decrease in pregnancy wastage. Women with 2 to 3 children are more likely to experience pregnancy wastage than those with more than four children at 5.5% and 0.8% respectively.

Age at first birth is also an important factor for pregnancy wastage. With increasing age at first birth, there is increased pregnancy wastage. Women in the 11-14 age category have 8% increased chance, 15-24 have 21.1% increased chance and the 35+ category have 121% increase in pregnancy wastage. Being in the 24-35 years old category is associated with 72.8% increase in pregnancy wastage while being 35+ years old increase pregnancy wastage by 250%.

The nature of the place of residence is also associated with pregnancy wastage. Being in rural residency increases the likelihood of pregnancy wastage by 36.6%. Looking at the antenatal visits, women who have had more than 4 antenatal visits have had their pregnancy wastage incidence reduced by 13%.

No usage of any anti-malarial drug increase the risk of pregnancy wastage by 95.8%. Usage of any anti-malarial drug decrease the pregnancy wastage by 23.5%, while the usage of chloroquine is associated with 99.6% reduction in pregnancy wastage and usage of fansidar reduce pregnancy by a 25.8%. When considering Iron supplementation during pregnancy, non-usage of Iron supplementation during pregnancy increase the likelihood of experiencing pregnancy wastage by 5.1%.

Shorter marriage to first birth interval is also associated with decrease in pregnancy wastage. The 6-11 years interval reduces the wastage by 34.5%. Any interval beyond this increases pregnancy wastage with 11-15 interval associated with 24.5% increase, 33.6% increase associated with 16-20 interval and 21+ years associated with a 43.1% increase.

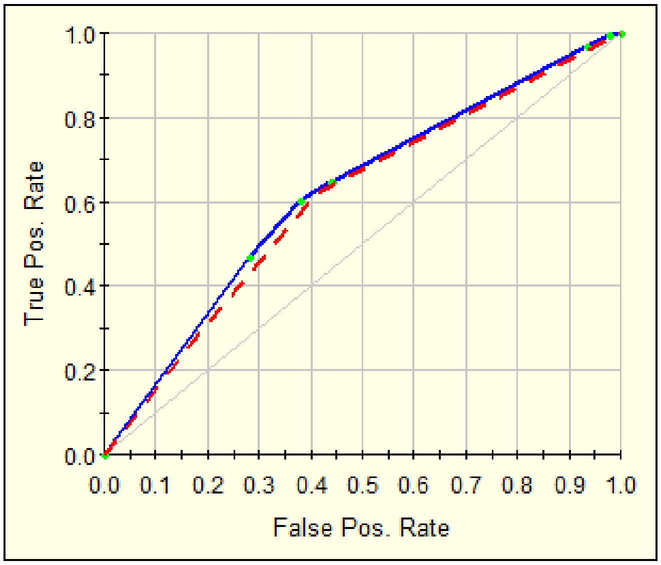
4.4CART and Logistic Regression

The results of logistic regression analysis and CART analysis show different dichotomies in the factors associated with pregnancy wastage as shown in Table 4.3.1. However both CART and logistic regression agree on Age of the mother as the most important factor for pregnancy wastage. When comparing the two models we use ROC and Hosmer-Lemeshow tests. Plotting pairs of sensitivities and specificities on a scatter plot provides a ROC (Receiver Operating Characteristic) curve. The area under this curve (AUC of ROC) provides and overall fit of the model.

4.4.1 Receiver Operating Characteristic Analysis

In CART the AUC is 0.62003 while the logistic regression the AUC is .6548. The area under ROC curve is a measure how well a method can separate instances of different classes.

Figure 4.4.1CART Navigator 1 (7 Nodes) - Summary Results - Gains Chart - ROC, Sample: Full sample, Target class: 1



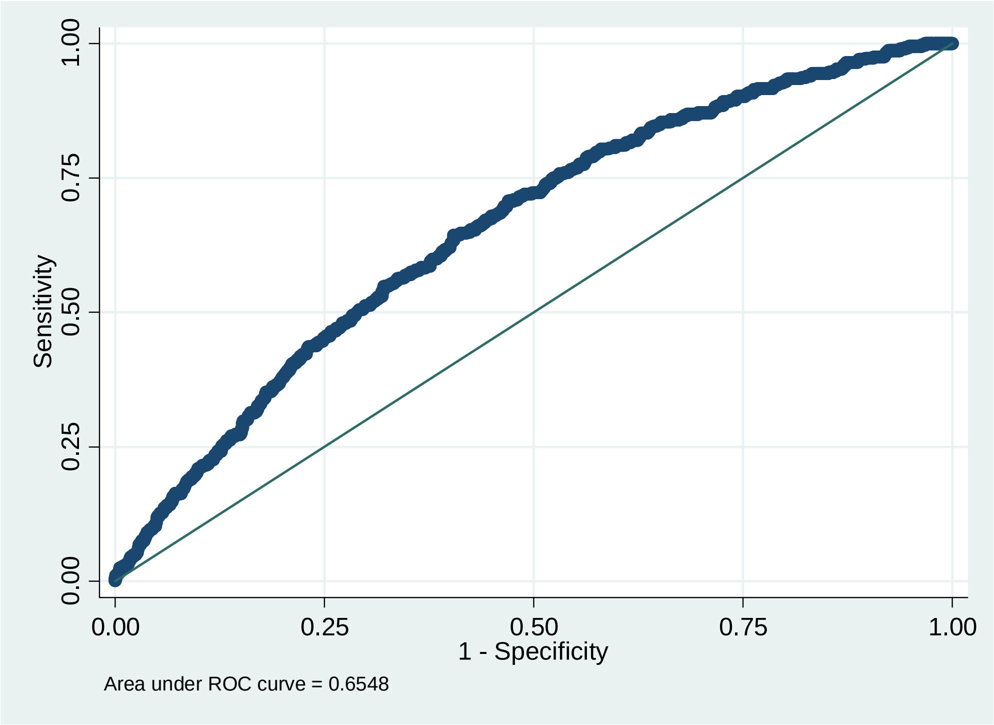


Figure 4.4.2. ROC curve for Logistic Regression

According to Perlich et al if you rank the test instances by the scores given by the model, the better the ranking the larger the AUR. A randomly shuffled ranking will give a AUR of (near) 0.5. A perfect ranking (perfectly separates the classes into two groups) gives a AUR of 1. Therefore the maximum AUR achieved by any method (max AUR) can be considered an estimation of the fundamental separating signal from noise estimated with respect to the modelling method available(Perlich, Provost and Simonoff, 2003). Therefore logistic regression performed slightly better than CART in risk factor analysis for pregnancy wastage.

Table 4.4.1 Comparison of CART and logistic regression variable importance

	CART	Logistic Regression	
Variable	Score	Variable	z
Age	100	Age	4.2
Highest Education Level	32.054	Marriage to 1st birth interval	3.31
Age at first birth	27.69	Took other drug for Malaria	2.15
Type of place of residence - Rural/Urban	26.14	Place of residence - Urban/Rural	1.43
Birth order	15.376	Iron tablets/Syrup during pregnancy	1.37
Age at marriage	14.188	Age at first birth	1.3
Took fansidar during pregnancy	13.183	Timing of first antenatal visit	1.22
Marriage to first birth interval	8.908	Wealth Index	1.13
Took other drug for malaria during pregnancy	1.249	Antenatal visits for pregancy	0.08
Took chloroquine for malaria during pregnancy	1.249	Mother’s working status	-0.07
Iron tablets/Syrup during pregnancy	1.249	Birth Order	-0.15
Antenatal visits for pregnancy	0	Highest educational level	-0.84
Timing of first antenatal check	0	Took fansidar during pregnancy	-1.01
Household Wealth Index	0	Took chloroquine for malaria	-1.59
Working status of the mother	0	Age at first marriage	-3.85

4.4.2. Hosmer-LemeshowAnalysis

Table 4.2.2 Logistic RegressionHosmer-Lemeshow Model Goodness of Fit Test

Group	ProbObs	_1 Exp	_1 Obs	_0 Exp_	0 Total
1 0.0528	12	14.7	327	324.3	339
2 0.0675	21	20.4	317	317.6	338
3 0.0795	22	24.9	317	314.1	339
4 0.0912	27	28.7	311	309.3	338
5 0.1063	34	33.3	304	304.7	338
6 0.1231	48	39	293	302	341
7 0.1392	42	44.1	294	291.9	336
8 0.1587	52	50.5	287	288.5	339
9 0.1966	64	59.4	274	278.6	338
10 0.620	6 74	80.9	264	257.1	338

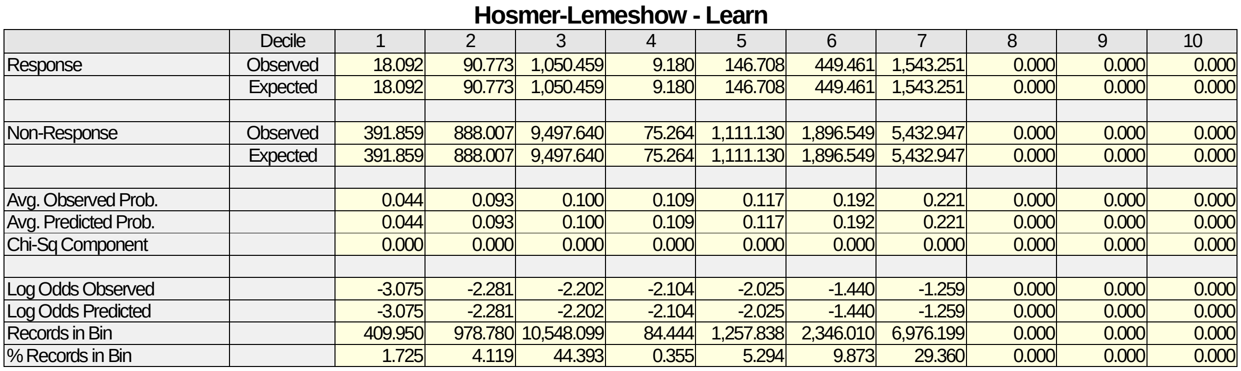
Number of observations = 3384

Number of groups = 10

Prob>chi2 = 0.7845

The chi-square goodness of fit is not significant and as such the logistic model has adequate fit.

Table 4.4.3 CART Hosmer-Lemeshow



Hosmer-Lemeshow - Learn

	Decile	1	2	3	4	5	6	7	8	9	10
Response	Observed	18.092	90.773	1,050.459	9.180	146.708	449.461	1,543.251	0.000	0.000	0.000
	Expected	18.092	90.773	1,050.459	9.180	146.708	449.461	1,543.251	0.000	0.000	0.000
Non-Response	Observed	391.859	888.007	9,497.640	75.264	1,111.130	1,896.549	5,432.947	0.000	0.000	0.000
	Expected	391.859	888.007	9,497.640	75.264	1,111.130	1,896.549	5,432.947	0.000	0.000	0.000
Avg. Observed Prob.		0.044	0.093	0.100	0.109	0.117	0.192	0.221	0.000	0.000	0.000
Avg. Predicted Prob.		0.044	0.093	0.100	0.109	0.117	0.192	0.221	0.000	0.000	0.000
Chi-Sq Component		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log Odds Observed		-3.075	-2.281	-2.202	-2.104	-2.025	-1.440	-1.259	0.000	0.000	0.000
Log Odds Predicted		-3.075	-2.281	-2.202	-2.104	-2.025	-1.440	-1.259	0.000	0.000	0.000
Records in Bin		409.950	978.780	10,548.099	84.444	1,257.838	2,346.010	6,976.199	0.000	0.000	0.000
% Records in Bin		1.725	4.119	44.393	0.355	5.294	9.873	29.360	0.000	0.000	0.000

The total chi-square for CART Hosmer-Lemeshow is 6.7912e012 with HL stastic p-vale of 1. Comparing both CART and logistic regression is still a better fit for the model.

CHAPTER FIVE:CONCLUSION

According to CART the five most important factors for pregnancy wastage are age of the woman, highest level of educational attainment, age at first birth, place of residence being either urban or rural, birth order, age at first marriage, usage of Fansidar during pregnancy for malaria prevention and marriage to first birth interval. According to logistic regression the most important factors are age of the woman, marriage to first birth interval, use of anti-malarial drug pregnancy, the type of place of residence being either urban or rural and use of iron supplementation during pregnancy. Both methods agree on the fact that Age of the Woman is the most important risk factor for pregnancy wastage.

In calculating ROC areas of logistic regression models, this may not be a problem since many threshold values can be used to derive many sensitivity-specificity pairs. This may be a problem for classification trees in which the number of sensitivity – specificity pair is limited by the number of leaves in the tree. With fewer points on the ROC curve, underestimation of the actual area and thus the performance may be accentuated for classification trees.

Tsien et al comparing classification tree and logistic regression to study myocardial infarction states difficulties in choosing the attributes and levels for inclusion in the model or exclusion from the model. While there are differences in the chronology of variables, it is suggested that the use of CART is to select attributes for logistic regression models. Another could be to decide breakpoint values for continuous variables should dichotomous values be required. Logistic model was found to be a better fit.Another study by Vanichbuncha using Cox regression, Continuation Ratio Model, Logistic Regression, ANN and Decision trees found out that logistic regression and the continuation ratio model showed the highest AUCs or accuracy.

More and biological studies are harnessing CART methodologies owing to its simplicity and ability to handle missing variables (Banerjee et al, 2008). The data used for this study is population-based. However in most of the cases CART is used with facility-based or epidemiological data. It is recommended that this study could be repeated with obstetric data from facility or clinical investigation to see how CART will perform. Many studies have used CART in medical research and it is therefore an important tool for use in clinical decision making and identifying pathways of disease epidemiology.It is important to have known the factors which discriminate women at risk of pregnancy wastage.

From a methodological view, the approach of using CART and then Logistic regression helps in reduction of dimensions of many risk factors for use in regression modelling to look at fewer factors for specific medical question under investigation. This is particularly important when using large data sets which in practice can be a challenge to the classical analyses by becoming problematic due to the sizes of the datasets. Therefore the aggregations produced after recursive partitioning by CART produces a smaller number of variables which can easily be investigated in a classical model. Using CART the problem of missing values effect is also reduced and the whole two-tier analysis for a single research question also improves confidence in the final results.

It is recommended that the same study could be repeated to compare the goodness of fits and variable importance using both population-based data and obstetric data. This could explain further why the current results show disparity.

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