Research Paper: Modeling Children Ever Born and Ideal Number of Children by Classification Tree

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ABSTRACT

Background: Fertility is one of the important subjects in public health and demographic studies which affects population growth. The main objective of this paper was to introduce and apply a tree model to classify the ideal number of children and children ever born in the study of "Marriage and Fertility Attitudes of Married 15-49 Years Old Women in Semnan Province in Iran, 2012".

Methods: Classification trees are data mining methods designed for categorical dependent variables, with prediction error measured in terms of misclassification cost to determine the form of the relationship between the response and predictor variables in different field of studies.

Results: We applied the Classification and Regression Trees (CART) algorithm to present the merits of this algorithm to accurately classify the ideal number of children and children ever born of 405, 15-49-year-old married women in Semnan providence, Iran, according to some important predictor variables. Semnan is a province that is taking efficient steps toward development and modernization. Nowadays, it is considered as one of the developed provinces in Iran. In this province, changes in fertility attitudes and beliefs expected to be affected by modernization, industrialization, and urbanization.

Conclusion: As a result, the women's children ever born in the younger birth cohorts and the ideal number of children in the older birth cohorts are much more similar. Women's job status and age at first marriage are the two most important factors which have had significant effects on the desired and actual number of children in different birth cohorts.

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Introduction

There is a rich literature about fertility transition in Iran and how expansion in education, reduction in child mortality, urbanization, wide access to family planning services and importance of quality against quantity of children have contributed to the recent fertility decline in this country [1-4]. Decreasing trends of fertility even moving lower than replacement level, at which a population without migration exactly replaces itself from one generation to the next, in the most of countries all over the world is an important issue in public health and demographic researches. There are several determinants influencing fertility such as Children Ever Born (CEB) per woman which can influence infant, child and maternal mortality, obstetric and child health services, age structure of populations and etc [5].In addition, there is a measure of reproductive preference, IdealNumber of Children (INC), which its trends lie at the heart of family planning and population policy concerns. In particular, this information can identify populations with a demand for services and informs the interpretation of trends in contraceptive prevalence and fertility [6]. INC and CEB have become interested issues for many researchers who studied determinants influenced fertility behavior of Iranian families [1-4]. According to somesurveys, economic factors either at micro or macro levels, distribution of intra-household bargaining power, literacy, social norms of household size, and religion are determinants of fertility behavior of Iranian families [1, 4].

Education level as a major contributing factor in enhancement and inhibition of fertility was identified, using data of married adolescents in Bangladesh [7]. Researchers in North East India found that job and economic statuses of women among the other influential determinants considered in their study, had strong influence on fertility [8].

To analyze CEB, binary logistic model was used by dichotomizing collected data from 250 households with 15-49 year-old women of slum area in Bangladesh. Factors which had contributed significantly in CEB for large families were INC, educational level, average monthly income and expenditure, marriage age, and reproductive life span [9]. In a survey based on DHS data in developing countries in Asia and North Africa, results also showed that married women's INC ranges from 2 in Ukraine and India to 4 in Jordan and Pakistan. This range in Latin America and Caribbean is from 2.2 in Brazil to 3.7 in Guatemala [6].

Today, low fertility is one of the important issues which are considered by policy makers in public health and demography. Without determination of factors which affects fertility, suitable programs cannot be created. Therefore, we tried to examine factors affecting two important measures of fertility; namely, CEB and INC by classification tree in this article. When the number of covariates increases, using models such as logistic regression is not applicable for classification because many interactions should be added to the model and so the interpretation get complex. When there are many interactions in model, using classification tree is more applicable and the interpretation is easier than logistic regression. Up to our knowledge, there isn't any study which has applied classification tree to classify two important measures of fertility, including CEB and INC.

Methods

Different statistical methods such as factor analysis and multiple regression models were applied for analyzing influential factors on fertility [11]. However some methods such as data mining which is a computational process of discovering patterns in large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics, and database systems has not been used widely due to the lack of researchers' knowledge about the advantages of this method [12, 13].

Amongst data mining methods, decision tree has various advantages; model interprets simply, requires little data preparation, handles both numerical and categorical data, validates by statistical tests, performs well with large datasets. Decision tree can be described as a model that predicts the value of a target variable based on several input variables. It is a flow-chart-like structure, where each internal (non-leaf) node denotes a test on an attribute, each branch represents the outcome of a test, and each leaf (or terminal) node holds a class label. The top most nodes in a tree is the root node [14,15].

Two main types of decision tree, Classification tree and Regression tree are used in data mining. Classification tree is applied when the predicted outcome is categorical response and used widespread in many diverse fields such as medicine, social sciences, demography, business, and biology [16-21]. Regression tree is used when the predicted outcome is continuous value and the goal is approximating the regression function.

A number of methods and procedures are existed for extracting classification trees; Automatic Interaction Detection (AID), Theta AID (THAID),Chi-squared Automatic Interaction Detection (CHAID) and Classification and Regression Trees (CART) algorithm. The first three procedures generate multilevel splits and CART extracts binary splits. CART is a non-parametric statistical methodology developed for analyzing classification issues. If the dependent variable is categorical, CART algorithm produces a classification tree. When the dependent variable is continuous, it produces a regression tree. In both classification and regression trees, CART's major goal are to produce an accurate set of data classifiers by uncovering the predictive structure of the problem under consideration [22]. To produce classification trees of CEB and INC in this study, CART is used because it is distributional free algorithm, robust against the outliers and collinearities, can use both categorical and continuous variables, encounter missing data, detect interactions, and can be considered as an exploratory analysis [23].

CART methodology is done in three phases; Construction or building of maximum tree by some splitting rules such as Gini index (Gini is equal to sum of item selection probabilities time to incorrect classification probability)[22], Selection of right tree size is used to achieve optimum tree size by some Pruning methods, and Classification of new data

In this study, Children Ever Born (CEB) and Ideal Number of Children (INC) in survey of "Study Marriage and Fertility Attitudes of 15-49 Year-Old Married Women in Semnan, Iran; 2012" [10], were classified by CART algorithm based on some important influential factors. The data in this survey were obtained by a cross-sectional survey collected by a structural questionnaire. 405 samples from 2 cities and 6 villages of Semnan province, among 8 cities and 589 villages, were selected by random stratified sampling method. This sample included 15-49 year-old married women in private settled household. In this study, CEB, INC, age at first marriage, marriage type, educational level, job status, birth place, and birth cohort were collected [10]. Birth cohort is defined by a group of women who were born in the same period of time that were experienced similar historical events [24, 25].

Results

We consider 15-29 year-old women as those who were born in 1980s which were called 1980 birth cohort. By definition 1970 decade born women were 30-39 year-old (1970 birth cohort) and 1960 decade born women were 40-49 year-old (1960 birth cohort).The only continues predictor in this study was age at first marriage with mean equals to 20.57 and standard deviation equals to 3.15. Tables (1) and (2) show CEB and INC crossed by predicted variables for 15-49 year-old married women.

Table 1. Children Ever Born Crossed by Predicted Variables

Variables		Children Ever Born (Response Variable)					Test Statistic	P-value
Name	Value	0	1	2	3	Total		
Birth cohort	1960s	4.6	6.1	38.9	50.4	100	132.42*	<0.001
	1970s	6.9	9.7	66.9	16.6	100		
	1980s and more	23.3	49.6	27.1	0.0	100		
Job status	Unemployed	13.8	19.1	42.8	24.3	100	-0.077**	<0.939
	Employed	1.3	30.0	55.0	13.8	100		
Educational level	Under diploma	11.8	13.7	45.0	29.5	100	44.35*	<0.001
	Diploma and higher	10.4	36.6	45.5	7.5	100		
Marriage type	Non-familial marriage	9.2	24.2	45.8	20.8	100	-0.319**	0.750
	Familial marriage	14.5	17.0	44.2	24.2	100		
Birth place	Urban	12.5	24.6	42.8	20.1	100	-3.23**	0.001
	Rural	7.6	9.8	53.3	29.3	100		
Age at first marriage	18	6.9	8.5	43.1	41.5	100	58.44*	<0.001
	19-21	10.7	13.6	49.5	26.2	100		
	22-24	16.4	25.8	51.6	6.3	100		
	25	11.4	63.4	22.7	2.3	100		

*M^2(Mantel) statistic, **Mann-Whitney statistic

Table 2. Ideal Number of Children Crossed by Predicted Variables

Variables		Ideal Number of Children (Response Variable)					Test Statistic	P-value
Name	Value	0	1	2	3	Total		
Birth cohort	1960s	0.0	6.1	67.2	26.7	100	38.28*	<0.001
	1970s	4.8	11.0	72.4	11.7	100		
	1980s and more	8.5	16.3	71.3	3.9	100		
Job status	Unemployed	5.2	10.2	70.5	14.2	100	-0.16**	0.873
	Employed	1.3	15.0	70.0	13.8	100		
Educational level	Under diploma	3.0	12.2	69.0	15.9	100	2.64*	0.104
	Diploma and higher	7.5	9.0	73.1	10.4	100		
Marriage type	Non-familial marriage	4.2	11.3	73.3	11.3	100	-1.16**	0.245
	Familial marriage	4.8	10.9	66.1	18.2	100		
Birth place	Urban	4.8	11.2	72.3	11.8	100	-1.83**	0.067
	Rural	3.3	10.9	64.1	21.7	100		
Age at first marriage	18	3.8	10.8	66.9	18.5	100	7.03*	0.008
	19-21	1.0	5.8	73.8	19.4	100		
	22-24	8.6	15.6	68.8	7.0	100		
	25	2.3	11.4	77.3	9.1	100		

*M^2 (Mantel) statistic **Mann-Whitney statistic

According to the results of these Tables, for most of women, INC in all of the birth cohorts was 2 children and the same results were true for the other predictors. While, CEB of women in the first birth cohort was equal to 3 and more, second birth cohort was 2 children and third birth cohort was 1 child. The most of women with different job status, educational level, marriage type, birth place and age at first marriage had 2 children as their CEB except CEB of women with 25 years old and more that was one child.

Unemployed compared to employed women (24.3 against 13.8 percent), women with under diploma educational level compared to diploma and higher (29.5 against 7.5 percent), women with familial marriage compared to non-familial marriage (24.2 against 20.8 percent), women in rural area compared to urban area (29.3 against 20.1 percent) and women with 18 years old and less age at first marriage compared to the other ages (41.5 against 26.2, 6.3 and 2.3 percent) had 3 and more children. Unemployed compared to employed women (5.2 against 1.3 percent), women with educational level of diploma and higher compared to under diploma (7.5 against 3.0 percent), women with familial marriage compared to non-familial marriage (4.8 against 4.2 percent), women in urban area compared to rural area (4.8 against 3.3 percent) and women with 22-24 year-old age at first marriage compared to the other ages (8.6 against 3.8, 1.0 and 2.3 percent) were more intended to be childless.

According to the results of these Tables, except job status and marriage type, the other predictors had significant effects on CEB (p-value<0.01), while birth cohort and age at first marriage were just two significant factors on INC (p-value<0.01).

We fitted CART algorithm by Gini splitting rule with estimated and equal prior probabilities for both CEB and INC by applying Statistic a software version 7. According to the accuracy of the fitted classification trees, we chose models in Figures (1) and (2). Figure (1) presents the most accurate classification tree of CEB based on predicted variables of age at first marriage, marriage type, educational level, job status, birth place, and birth cohort. Figure (2) indicates the same results for INC. CART algorithm entered all of the predicted variables in these classification trees as nodes except birth place in Figure (1) (model 1) and marriage type in Figure (2) (model 2). Birth cohort has been placed in the root of the classification trees as the most influential variable on classifying CEB and INC.

Table (3) presents the misclassification matrix of models (1) and (2) which indicates the accuracy of two classification models.

Table 3. Misclassification Matrix for Classification Models (1) and (2)

Observed Category		Model (1) Predicted Category				Model (1) Total	Model (2) Predicted Category				Model (2) Total
		0	1	2	3		0	1	2	3	
0	Numbers	18	12	11	5	46	0	0	17	1	18
	Total Percentage	4.44	2.96	2.42	1.23	11.36	0	0	4.20	0.25	4.44
1	Numbers	12	49	1	24	86	0	0	41	4	45
	Total Percentage	2.96	12.10	5.93	0.25	21.23	0	0	10.12	0.99	11.11
2	Numbers	6	7	143	27	183	0	0	272	13	285
	Total percentage	1.48	1.73	35.31	6.67	45.19	0	0	67.16	3.21	70.37
3	Numbers	0	0	35	55	90	0	0	41	16	57
	Total Percentage	0	0	8.64	13.55	22.22	0	0	10.12	3.95	14.07
Total		36	68	213	88	405	0	0	371	34	405
Total Percentage		8.89	16.79	52.59	21.73	100	0	0	91.60	8.40	100

The shaded cells in Table (3) signify correct classification or accuracy of the classification trees on Figures (1) and (2). The accuracy of the classification trees for these two models can be calculated by Eq. (2) and Eq. (3).

$$Accuracy_{model\ (1)} = \frac{18+49+143+55}{405} = 0.65 \quad (2)$$

$$Accuracy_{model\ (2)} = \frac{0+0+272+16}{405} = 0.71 \quad (3)$$

Classification accuracies of models (1) and (2) were equal to 0.65 and 0.71 that meant CEB and INC of 65 and 71 percentages of women had been classified correctly (This value indicated that misclassifications of these two models were equal to 35 and 29 percent). Moreover, validity of classification models proposed by classification trees in Figures (1) and (2) was also confirmed by almost equal values of risk and standard error of classification trees for model (1) (risk values of 0.363 and 0.339 and standard errors of 0.024 and 0.025 for learning set and k-fold cross validity of training set, respectively) and model (2) (risk values of 0.289 and 0.289 and standard errors of 0.023 and 0.024 for learning set and k-fold cross validity of training set, respectively) which are calculated on training and learning data.

To fit CART algorithm to data sets, data were divided to two different groups of training and learning data and the model fits to these two groups. When the risk of these two data groups is close to each other, it confirms the validity of the fitted model [14, 26].

We can extract rules (1) to (5) from the classification tree of CEB in Figure (1):

1. CEB of women in the first birth cohort (1960s) whose age at first marriage was 19.5 years old and less was 3 and more though CEB of those women in this cohort whose age at first marriage was higher than 19.5 years old was 2.

2. CEB of women in the second birth cohort (1970s) whose age at first marriage was 15.5 years old and less was 3 and more. Educational level for women in this cohort whose age at first marriage was higher than 15.5 years old didn't play any specific rules in classifying CEB. Their CEB were 2 either they were under diploma or diploma and higher.

3. CEB of unemployed and employed women in the third birth cohort (1980s) whose age at first marriage was higher than 24.5 years old was 1.

4. CEB of employed women in the third birth cohort (1980s) whose age at first marriage was 24.5 years old and less was 2.

5. CEB of unemployed women in the third birth cohort (1980s) whose age at first marriage was 24.5 years old and less according to their marriage type was different. Those women with familial marriage were childless while CEB of those women with non-familial marriage was 1.

We can also extract rules (6) to (8) from the classification tree of INC in Figure (2):

6. INC of employed women in the first birth cohort (1960s) was 3 and more without effects of any other predictors. INC of unemployed women in this cohort regardless of educational level was 2.

7. INC of women in the second and third birth cohorts (1970s and 1980s) whose birth place were urban area was 2.

8. INC of women in the second and third birth cohorts (1970s and 1980s) whose birth place were rural area and their age at first marriage were 21.5 years old and less was 3 and more while INC of these women whose age at first marriage was higher than 21.5 years old was

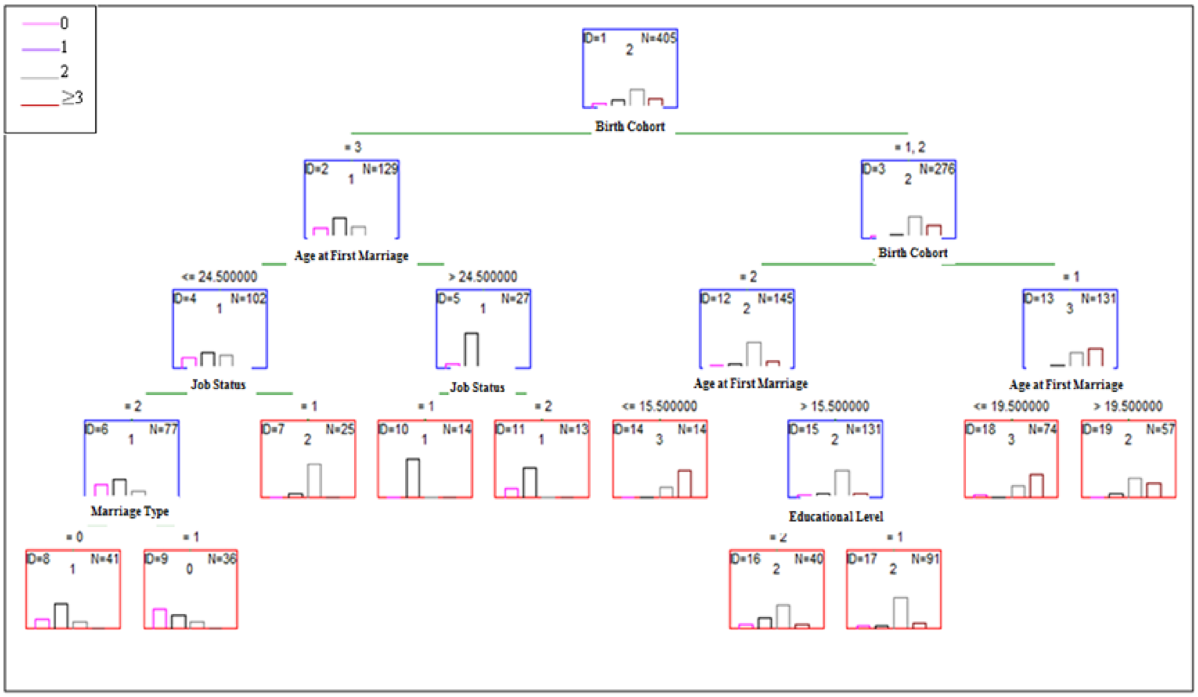

Figure 1. Classification Tree of CEB by Gini Splitting Rule and Estimated Prior Probabilities (Model 1)
Birth Cohort: 1960s=1, 1970s=2, 1980s=3; Job Status: Employed=1, Unemployed=2; Educational Level: Less than Diploma=1, Diploma and Higher=2; Marriage Type: Non-Familial=0, Familial=1; Birth Place: Urban=1, Rural=2.

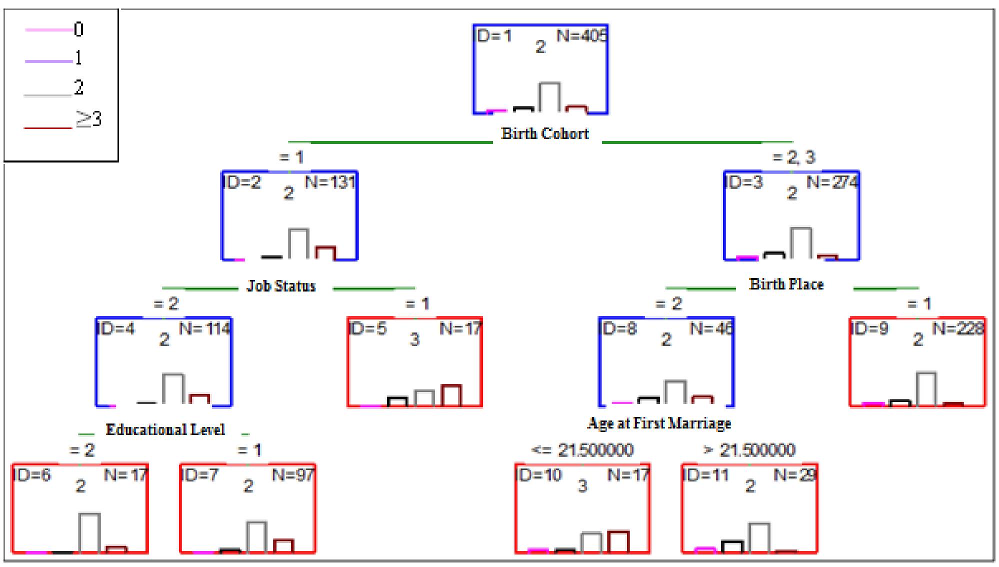

Figure 2. Classification Tree of INC by GiniSplitting Rule and Estimated Prior Probabilities (Model2)
Birth Cohort: 1960s=1, 1970s=2, 1980s=3; Job Status: Employed=1, Unemployed=2; Educational Level: Less than Diploma=1, Diploma and Higher=2; Marriage Type: Non-Familial=0, Familial=1; Birth Place: Urban=1, Rural=2.

Discussion

We considered Children Ever Born (CEB) and Ideal Number of Children (INC) in survey of "Study Marriage and Fertility Attitudes of Married 15-49 Year-Old Women in Semnan, Iran; 2012" and classified them by CART algorithm according to Gini splitting rule with estimated prior probabilities. We summarized the extracted results of CEB and INC classification trees as follows:

1. In CEB classification tree, the CART model had a specific classification for women in the first and second birth cohorts (1960s and 1970s) and another classification for women in the third birth cohort (1980s) which means similar behaviors by women in the first and second birth cohorts Than can be due to this fact that women in these two birth cohorts had finished or were in the last years of their reproductive life span and had delivered the number of children they wanted. In many studies, the same results were reported [7,8,10,27].

2. While in INC classification tree, women in the second and third birth cohorts had similar behaviors, the model had a specific classification for women in the second and third birth cohorts (1970s and 1980s) and another classification for women in the first birth cohort (1960s).

3. Job status had an important role in CEB and INC classification trees. In the third birth cohort, employed compared to unemployed women had more CEB.INC of employed compared to unemployed women in the first birth cohort was higher. Considering the results of Tables (1) and (2), we can conclude that job status does not have significant effect on CEB and INC. Therefore, if appropriate model is not selected for analyzing data, confusing results will be concluded. Effect of women's job status on CEB was also reported in surveys such as [7] and [11].

4. Age at first marriage had also key role in CEB and INC classification trees. INC of rural women in the second and third birth cohorts whose age at first marriage was 21.5 and less and CEB of employed women in the third birth cohort whose age at first marriage was 24.5 and less were more than women with higher ages at first marriage. Thus, it can be concluded that desired number of children can be achieved by preparing the condition for on time marriage. This result is similar to results of other studies [28]. Abbasi-Shavazi and Asgari-Nadushan mentioned that women who married in the higher ages compared to the others had less CEB and INC [28].

5. Marriage type did not have any significant effect on CEB according to the results of Table (1), while it could affect CEB of unemployed women in the third birth cohort (Figure 2).

6. INC of women in the second and third birth cohorts was 2 children regardless of any influential factors. So, we concluded that if the socio-economic condition for women in third birth cohort changes according to their needs, these women will have at least 2 children. This result has also been confirmed by other researches [28-30].

7. INC of women in different birth cohorts was 2 children so to make this comes true, some policies such as preparing the facility for decreasing marriage age and easier child bearing should be considered.

Conclusion

Classification and regression trees (CART) are useful in generating binary classification trees by splitting the subsets of the dataset using all predictor variables to create two child nodes repeatedly beginning with the entire dataset. The goal of CART is to produce subsets of the data that are as homogeneous as possible with respect to the target variable. Continuous, binary, and categorical variables can be used as response variables in CART.

Comparing extracted classification trees for CEB and INC showed that birth cohort, job status, and age at first marriage had effect on both CEB and INC, and birth cohort was the most important variable to classify CEB and INC. Marriage type only affected CEB and educational but not CEB and INC. As a result, policy makers are recommended to consider these variables in their program.

Ethical Considerations

Compliance with ethical guidelines

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Authors' contributions

Study design: Mahsa Saadati, Arezoo Bagheri; Data collection and analysis: Mahsa Saadati, Arezoo Bagheri, Hajiieh Bibi Razeghi Nasrabad; Manuscript preparation: Mahsa Saadati, Arezoo Bagheri.

Conflict of interest

The authors declared no conflict of interest.

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