### Cost Statistics And Income Urban Household Year 2015 In Iran

### Hanie Jalili

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First chapter: Introduction of data and its preparation

### Introduction

The plan to collect statistics on the expenditure and income of urban households in the country has been started since 1347 by the Statistics Center of Iran. Since 1353, in addition to the cost, the income of urban households has also been included in this census, and it has been implemented every year in the country except for the years 1355, 1357, and 1360. Every year with the necessary reviews and compliance with the standards advice Internationally, the changes needed in line with the evolution of the preparation and implementation of the plan are applied by the relevant experts.

## **Target**

The aim of this project is to find the best predictive model to predict the income category of urban households using the data of the household income and expenditure plan in the year 1400, which was prepared by the Iranian Statistics Center.

The budget and planning organization of the country can use this model and according to the situation subsistence people and with the aim of increasing their welfare and income level, plan the next year's budget and consider facilities for people who are in low income percentiles. For example, if the pension has a great impact on the percentage of people's income, you can focus on it.

### Questionnaire data and information

Questionnaire of expenditure and income plan of urban households includes the following sections:

- Social characteristics of family members
- The details of the place of residence and facilities and the main necessities of life
- costs of Food and non-food households
- Household incomes

### Definition of variables

City code	C.SH
variable defining	Variable name

The gender of the head of the household	JENS.S
Age of the head of the household	SEN.S
Is the head of the household literate or not?	SAVAD.S
Educational qualification of the head of the household	M.T.S
The activity status of the head of the household	V.F.S
How to occupy a residential house	N.T.M
Number of rooms available	T.0
The basement level of the residence	S.Z
Major building materials for the residence	M.O.B
personal car	HERE
motorcycle	МО
Bike	DO
set voice	ZABT
Color TV	TV
All kinds of subsidies and tablets	PC
Cellular phone	TEL.H
vacuum cleaner	JAROO.B
washing machine	M. LEBAS
Sewing Machine	CHARKH.KH
Fan	PUNK
dishwasher	M. ENVELOPE
Oven	M. ENVELOPE  OJAGH.GAZ
Oven	OJAGH.GAZ
Oven  Variable defining  Household food and drink expenses in the last	OJAGH.GAZ  Variable name
Oven  variable defining  Household food and drink expenses in the last month  The cost of household communication in the last	OJAGH.GAZ  Variable name  H. KHORAKI. NOOSHIDANI
Oven  Variable defining  Household food and drink expenses in the last month  The cost of household communication in the last month	OJAGH.GAZ  Variable name  H. KHORAKI. NOOSHIDANI  H.ERTEBATAT
Oven  Variable defining  Household food and drink expenses in the last month  The cost of household communication in the last month  Household health expenses in the last month  Household transportation expenses in the last	OJAGH.GAZ  Variable name  H. KHORAKI. NOOSHIDANI  H.ERTEBATAT  H.BEHDASHT
Oven  Variable defining  Household food and drink expenses in the last month  The cost of household communication in the last month  Household health expenses in the last month  Household transportation expenses in the last month  The cost of miscellaneous goods or services of	OJAGH.GAZ  Variable name  H. KHORAKI. NOOSHIDANI  H.ERTEBATAT  H.BEHDASHT  H.HAMLONAGHL
Oven  Variable defining  Household food and drink expenses in the last month  The cost of household communication in the last month  Household health expenses in the last month  Household transportation expenses in the last month  The cost of miscellaneous goods or services of the household in the last month  Housing expenses - water, fuel, lighting, etc. in	OJAGH.GAZ  Variable name  H. KHORAKI. NOOSHIDANI  H.ERTEBATAT  H.BEHDASHT  H.HAMLONAGHL  H. KALA. MOT
Oven  Variable defining  Household food and drink expenses in the last month  The cost of household communication in the last month  Household health expenses in the last month  Household transportation expenses in the last month  The cost of miscellaneous goods or services of the household in the last month  Housing expenses - water, fuel, lighting, etc. in the last month  Costs of furniture and household appliances and	OJAGH.GAZ  Variable name  H. KHORAKI. NOOSHIDANI  H.ERTEBATAT  H.BEHDASHT  H.HAMLONAGHL  H. KALA. MOT  H. MASKAN
Oven  Variable defining  Household food and drink expenses in the last month  The cost of household communication in the last month  Household health expenses in the last month  Household transportation expenses in the last month  The cost of miscellaneous goods or services of the household in the last month  Housing expenses - water, fuel, lighting, etc. in the last month  Costs of furniture and household appliances and their usual maintenance in the last month	OJAGH.GAZ  Variable name  H. KHORAKI. NOOSHIDANI  H.ERTEBATAT  H.BEHDASHT  H.HAMLONAGHL  H. KALA. MOT  H. MASKAN  H.MOBLEMAN

variable defining	Variable name
Total continuous and non-continuous gross	
incomes of the last 12 months of employed	M.DARAMAD.NAKH
members of the household before deductions	
Wages and salaries for the past 12 months	HOOGHOOGH.MOSTAMAR
Discontinuous benefits of the last 12 months	GH. MOSTAMAR
Total net income from sales	M.DARAMAD.KH.F
Gross receipts from sales	DARYAFTI.NAKH.F
Income from renting business premises, gardens,	
land,real estate Home, business rights, movable	DARAMAD.M.KH.1
and immovable property, etc. in the last 12	
months	
Proceeds Saving Fixed deposit, shares, insurance	DARAMAD.M.KH.2
and the like in the last 12 months	DARAMAD.IVI.RI I.2
RightsRetirement In the last 12 months	DARAMAD.M.KH.3
Scholarship in the last 12 months	DARAMAD.M.KH.4
Monthly net income	DARAMAD. KHALES

- \* **Appendix 1:** for data analysis because the time frameOne Month It is considered that we divide the variables of household durable goods purchase cost in the last 12 months and household investment cost in the last 12 months into 12.
- \* **Appendix 2:**According to the purpose and necessity of this project, we created a monthly net income variable using the following formula.

(continuous wages and salaries for the past 12 months (after deductions) + non-continuous benefits for the past 12 months (after deductions) + income from renting business premises, gardens, land,real estate Home, business rights, movable and immovable property and the like in the last 12 months + income from saving fixed deposits, shares, insurance and the like in the last 12 months + salaryRetirement in the

last 12 months + scholarships in the last 12 months + total net income from sales) divided by 12

Then, using code, we converted it to a binary variable. (If the total monthly income was more than the 90th percentile, 1 and otherwise 0)

# Defining the meanings of variables

#### • Urban locations:

In this plan, urban points are defined as all the points that had a municipality at the time of the general census of 2011.

## • Household (typical resident):

A household consists of several people who live together in a fixed residence And they spend money with each other and usually eat together eat. A person who lives alone is also considered a household.

#### Households:

The head of the household is one of the members of the household who is known as this in the household.

#### • Literate:

Any family member aged 6 years or older who can read simple texts in Farsi or any other language to writeWhether he has an official educational certificate or not, he is considered literate.

### • Studying:

Every family member aged 6 years and older who is studying according to the official educational programs of the country is considered to be studying.

#### • Student:

People aged 10 years and more who are employed, unemployed, looking for work and havelncome Those who were not without work, and were engaged in studies in the 7 days before the day of the census, are considered as students.

#### • work:

Work is any intellectual or physical activity for the purpose of earningIncome (cash and non-cash) and its purpose is to produce goods or provide services. Therefore, activities such as sports (except professionally), housekeeping, education, etc. are not considered work, because these activities are for the purpose of earning.Income It is not done.

### • My job status:

- Employer: is someone who employs at least one wage earner to perform his work activities.
- Independent worker: He is a person who, within seven days before the visitagent
   A statistician, a salaried person should not be employed and himself also Do not
   take wages and salaries.

- Get wages and salaries in the public sector: He is a person who works in the
  public sector and receives wages and salaries (cash and non-cash) for the work
  he does.
- 4. Get wages and salaries of the cooperative sector: He is a person who is active in the cooperative sector and receives wages and salaries (cash and non-cash) for the work he does.
- Receive wages and salaries, private sector: is someone who receives wages and salaries (cash and non-cash) for individuals or Institute Personalities of work May Kind.
- 6. Unpaid family worker: An unpaid family worker is a person who works for a member of his family with whom he has a family relationship, and for this reason, he does not receive wages or salary.

### How to occupy the residence of the family:

- 1. Ownership of the land and nobles: It is the way of occupying the place of residence where the family is the owner of the land and its building.
- 2. Ownership of nobles: It is the way of occupying a place of residence where the household is only the owner of its building.
- 3. Leasing: It is the way of occupying a residence that is rented.
- 4. Mortgage: The method of occupying a place of residence is that the household has deposited money in the form of a good loan with the owner for its temporary possession.

- 5. Against service: It is the way of occupying a place of residence that is placed at the disposal of the household in exchange for doing the work of one or more members of the household.
- 6. Free: It is the way of occupying a place of residence that the household does not pay for its use and does not do anything.
- 7. Other: It is the way of occupying the place of residence that the household has in a way other than the above five modes.

#### room:

In a normal residential unit, it means a room, an enclosed space, etcYou have a roof It has an area of at least four square meters and a height of two meters. Except for tents, capers, slums and the like as The room is used by the family, even if fourSquare meters. Even if it does not have an area, the room is considered.

#### • Income:

Income is all the funds and the value of the goods that are against the work done or the capital used or through other sources (rights retirement, transferable incomes and the like) have been assigned to the household at the desired statistical time.

 Net income from public wages and salaries: the income of all members of the household in the public sector, includingReceipts Continuous and discontinuous Boolean and non-monetary They are after deduction of taxes and retirement.

- Net income from wages and salaries of the cooperative: The income of all
  members of the household in the cooperative sector includes their monetary and
  non-monetary receipts after deduction of taxes and retirement.
- 3. Net income from private wages and salaries: the income of all members of the household who are wage earners and salary earners in the private sector, which includes wages and salaries and continuous and non-continuous monetary and non-monetary benefits after deduction of taxes and retirement.
- 4. Net income from agricultural self-employment: the income of people from the household who work in the agricultural sector as an employer or self-employed, after deducting employment expenses. Income It is considered as one of the free agricultural jobs.
- 5. Net income from freelance jobs non-agricultural: The income of people from the household who are employed as self-employed or self-employed in non-agricultural jobs, after deducting employment expenses, as Income Net refers to non-agricultural jobs.
- 6. Miscellaneous income: all the funds and the value of the goods that the household received from a way other than the employment of its members, such as the rental of movable and immovable property. Transported, Rights Retirement and the like are considered miscellaneous incomes.

#### • cost:

The monetary value of goods or services provided by the household for the consumption of members or gifts to others is called cost. The goods or services

provided can be provided to the household through purchase, home production, against service, from the place of purchase and free of charge (from organizations), which is calculated in monetary form and is included in the cost.

- Gross cost: Gross cost is the value of the product without deducting second-hand sales of the same product.
- 2. Net cost: When the value of sold second-hand goods is subtracted from the value of similar goods purchased in the statistical period, the remainder will be the net cost of the household in the relevant item.

## Actions taken to clean up data

In the food and beverage cost variable, we had 28 missing data. We used the
distribution of the values of this variable to find the appropriate method. The
variable distribution of food and beverage costs is not symmetrical and has a
skewed state. Therefore, the best method is the middle of the data; Therefore,
we replaced the missing data with the median of the data.

# Define categorical variables

Note: Changes have been made in the categories of M.T.S and M.O.B variables.

variable	NO	Yes
HERE	0	1
МО	0	1
DO	0	1
PC	0	1
TEL.H	0	1

M. LEBAS	0	1
M. ENVELOPE	0	1
ZABT	0	1
TV	0	1
OJAGH.GAZ	0	1
JAROO.B	0	1
CHARKH.KH	0	1
PUNK	0	1

m.t.s	Name
0	Literary
1	Ebtedai
2	Guide
3	Fashion balance
	Diploma.Pishdaneshgah
4	i
5	Foghe. Diploma
6	Licence
7	Foghe.lisans.Dr.herfei
8	Dr. specialist
	Savad.amuzi.gheyre.as
9	mi

variable	NO	Yes
SAVAD.S	2	1
jens.s	Name	
1	man	
2	woman	

n.t.	
m	Name
1	Melki. arse. ayan
2	Melki. ayan

3	Ejare
4	Rahn
	Darbarabare.
5	khedmat
"	
6	Raygan

v.f.s	Name
1	Shaghel
2	Use it
3	Daramad.Bedunekar
4	Mohasel
5	Khanedar
6	Sayer

m.o.b	Name
	Tamam.chub/Khesht.g
0	el
1	Ajor.ahan
2	Ajor.chub
3	Block.simani
4	ok.ajor
6	Khesht.chub
8	Sayer

# Number of data

Туре	Number of data
Training*	1500
Validation	300
Test	121

\*Important note: After classifying the response variable (net monthly income) into the

mentioned categories, we find that category 1 is rare in this data. That is, the number

of response variables = 1 in this data is very small compared to the total number of

data. That is why it is necessary to use oversampling methods. For this, we use the

combination of oversampling and undersampling methods, and from the 1500 data

that we considered for training the model, we generate 10000 data with an almost

equal number of categories zero and one, and from now on these data will be the

training data of the model, we say. In fact, we train the model with these data and

validate with the validation data on which we did not do any oversampling or

undersampling.

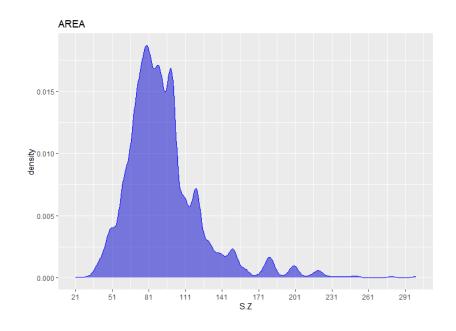
The second chapter: data visualization

- univariate

s.z variable diagram (land area)

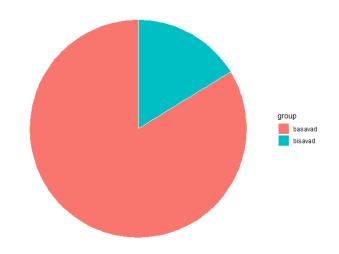
Most people live in houses between 51 and 100 meters.

12



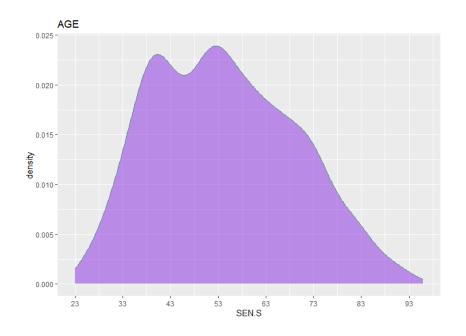
# savad.s variable graph

Many people participating in this survey are literate.



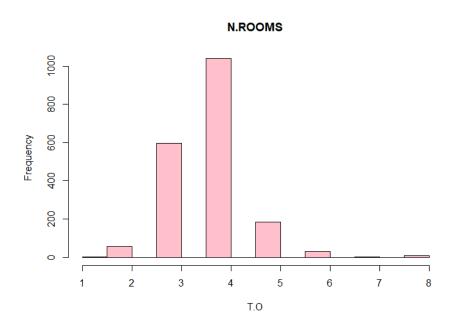
# graph of sen.s variable (supervisor's age)

At the age of 3843 years old And we have the largest number of supervisors aged 49 to 58.



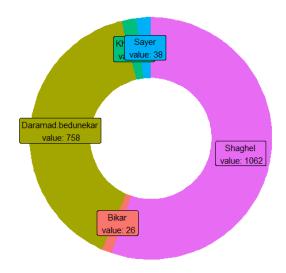
# Variable graph t.o (number of rooms)

The highest number is related to houses with 4 or 3 rooms.



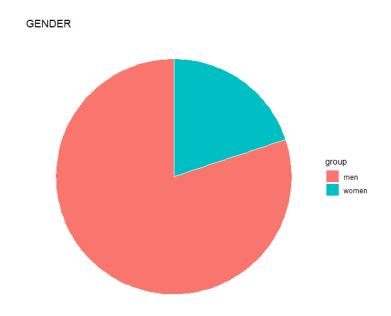
# v.f.s variable chart (current status of supervisor)

Most supervisors are employed or have income without work.



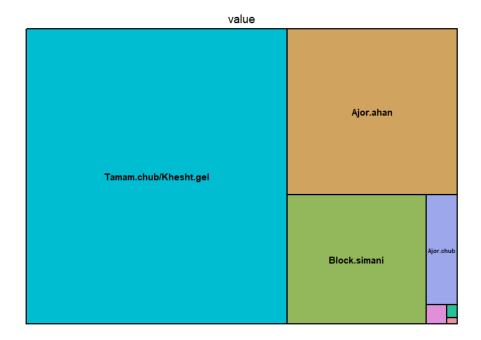
Jens.s variable graph (supervisor gender)

Most of the supervisors are men.



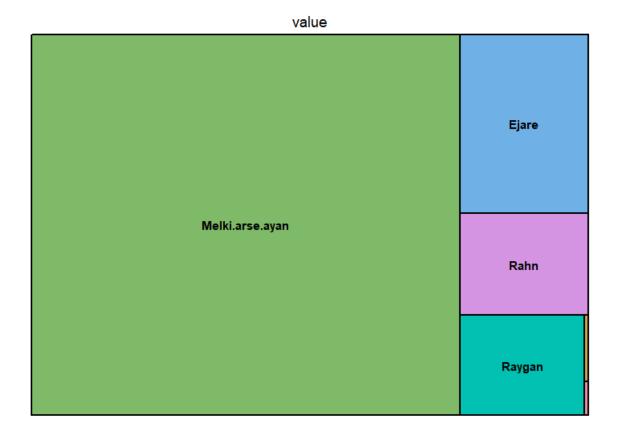
m.o.b variable diagram (major building materials)

Wood, clay and mud, brick and iron are the main building materials.



n.t.m variable diagram (how to occupy the house)

Most of the ways of occupying the house are related to rent and real estate.



variable diagram m.t.s (supervisor's educational qualification)

As we have seen before, many supervisors were literate and according to this graph, it can be seen that most of them have studied up to elementary, pre-university and middle school levels.

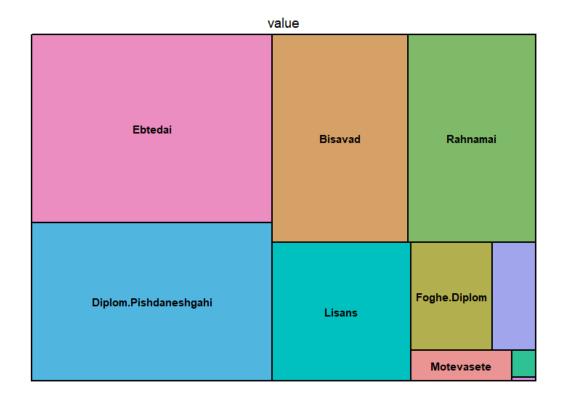
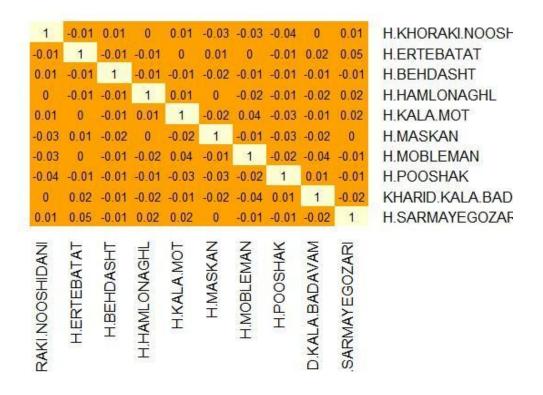
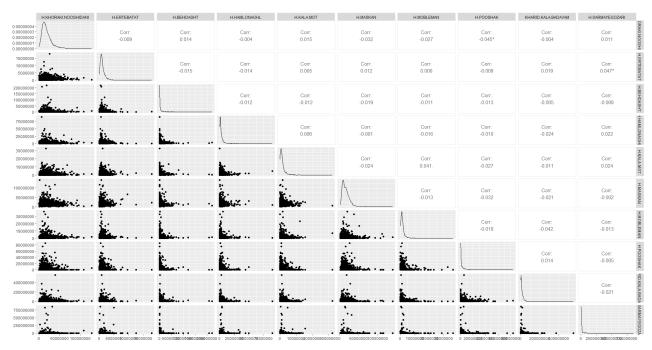


Diagram of cost variables (cost of food, clothing, furniture, etc.)

In this graph, you can see and compare the correlation between different costs. For example, the highest correlation is related to communication cost and investment cost. The cost of furniture and the cost of miscellaneous goods are also highly correlated. Also, the cost of clothing and the cost of food have a high correlation with each other, which is considered an obvious issue because food and clothing are among the basic needs that people pay for.



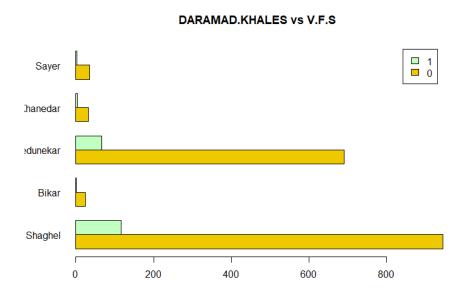


#### Two variables

(In the cost graphs for various goods against net income, to understand and increase the readability of the graph, we drew the logarithm of costs against net income.)

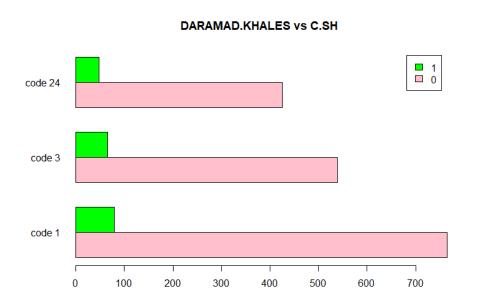
# A graph of the current position of the supervisor against the net income

It is obvious that the job status of supervisors has a high impact on their net income.



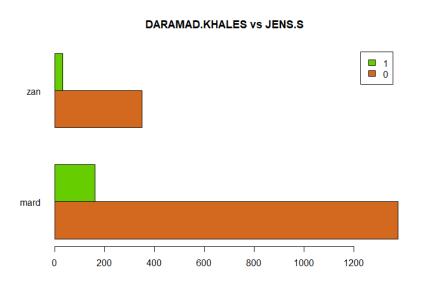
# Chart of county code against net income

People's net income is highly related to where they live.



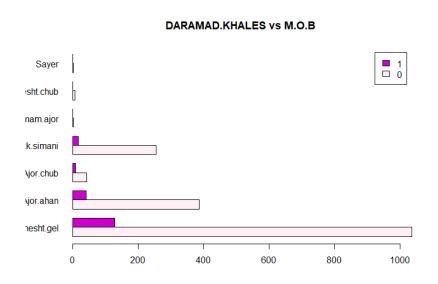
# Graph of Gender vs. Net Income

The gender of supervisors is an influencing factor in their net income.



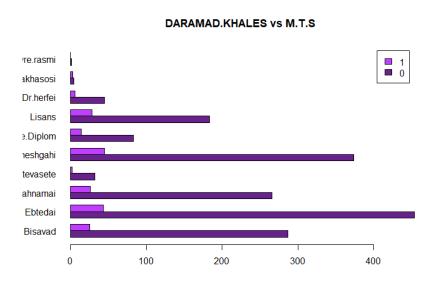
## Chart of major building materials against net income

Cement, brick and wood, iron, clay and mud are building materials that have a great impact on people's net income.



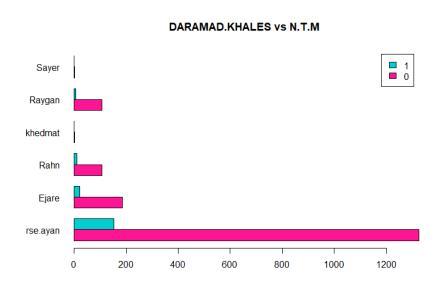
## Chart of Superintendent's Education Degree vs. Net Income

Obviously, the supervisor's degree has a great impact on their net income.

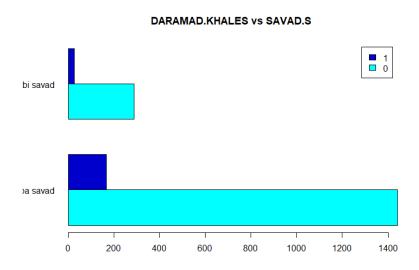


## Chart of how to occupy the house against the net income

Among other factors that affect people's net income, we can mention the way of occupying the house.

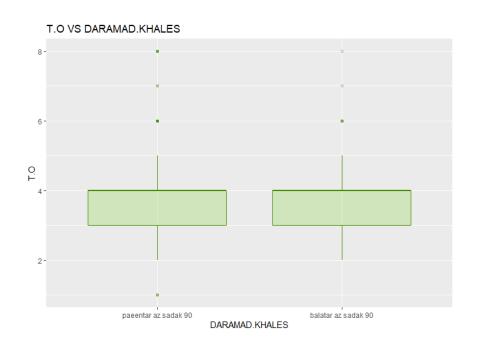


# Superintendent's Literacy vs. Net Income Chart

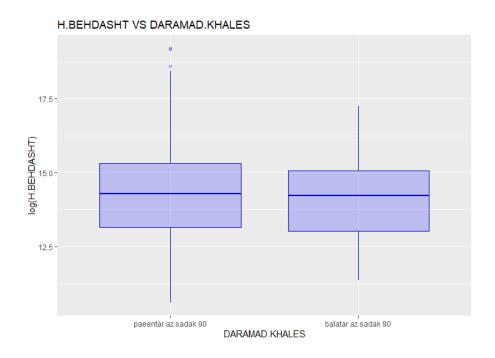


# Graph of number of rooms against net income

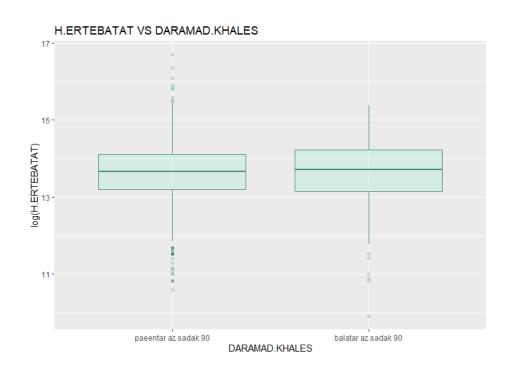
The median of the two graphs and their distribution are the same. That is, the number of rooms does not have much effect on people's net income.



### Health Cost vs. Net Income Chart



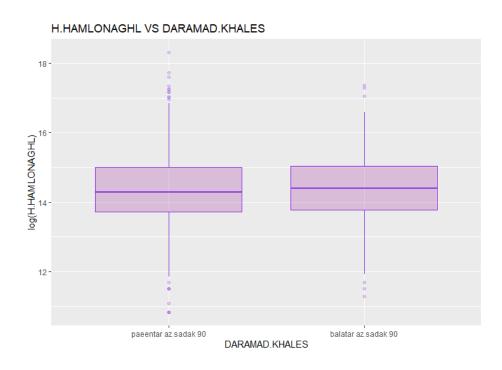
# Communication cost versus net income graph



In the health cost graph, the distribution of two box plots and their median are different from each other. That is, this variable affects the net income. The cost of communication is the same.

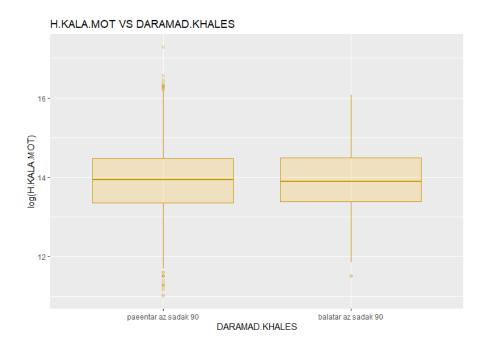
### Graph of shipping cost vs. net income

In addition to the effectiveness of this variable, it can be said that people who have an income above the 90th percentile spend more on transportation.



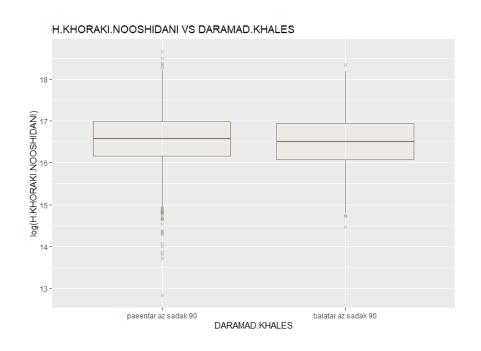
# A graph of the cost of miscellaneous goods against net income

It is interesting to note that people with income less than the 90th percentile spend more on miscellaneous goods than other people.



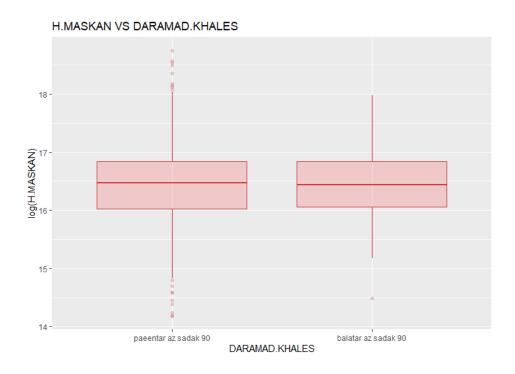
# Chart of food and beverage expenses against net income

The median in both parts of the box plot is higher than the median in the rest of the plots. It means that people spend more on food than other consumer items and this is obvious.



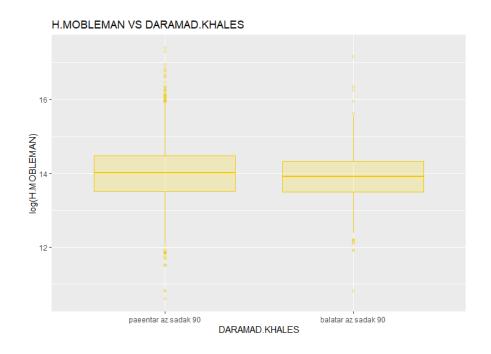
## Housing cost vs net income chart

The cost of housing affects the net income of all people in different economic percentiles.



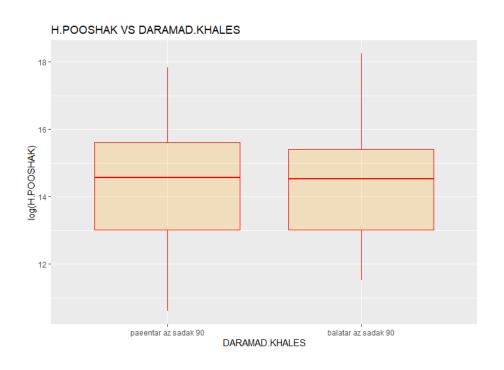
### Furniture cost vs. net income chart

Spending on furniture by people with incomes below the 90th percentile is more dispersed. It can also be concluded that they spend more on furniture than people with income above the 90th percentile.



## Clothing cost vs. net income chart

maximum People with income above the 90th percentile spend more to buy clothes than people with income below the 90th percentile, and their minimum spending for clothes is also higher. This means that these people pay more for clothes.



### Investment cost versus net income graph

The middle of the two box plots have a drastic change with each other. This shows that people with incomes above the 90th percentile spend much more on investments than people with lower incomes. Outlier values are significant for people with incomes below the 90th percentile.

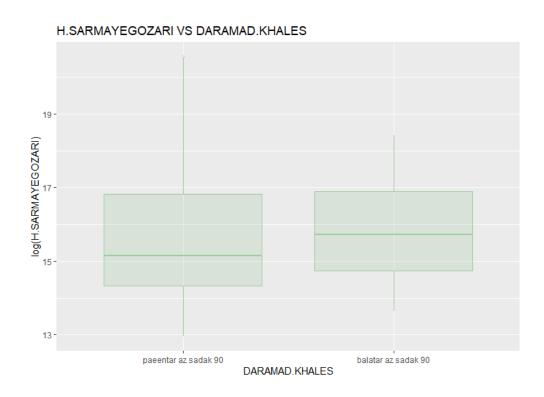
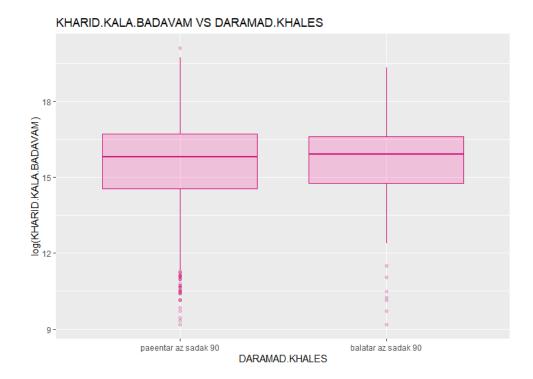


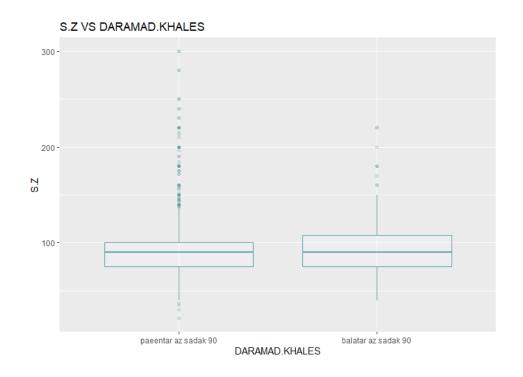
Chart of cost of purchasing durable goods against net income

It is clear that the cost of buying durable goods affects people's income.

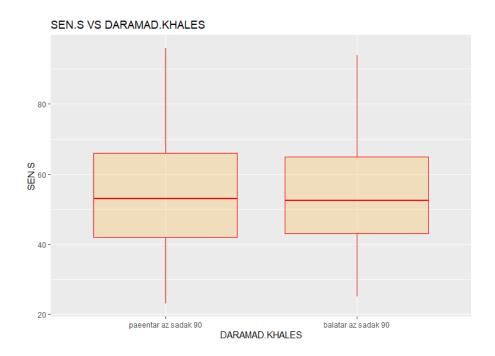


### Plot of land area versus net income

The area of land for people with income above 90th percentile has more dispersion.



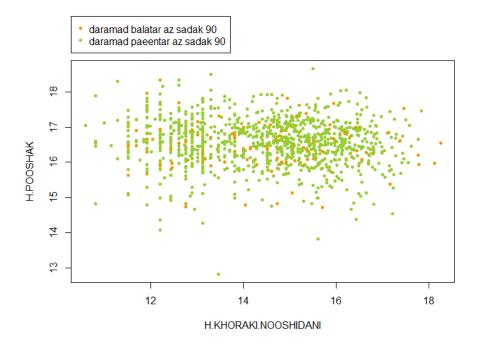
# Chart of Supervisor's Age vs. Net Income



### - Multivariate

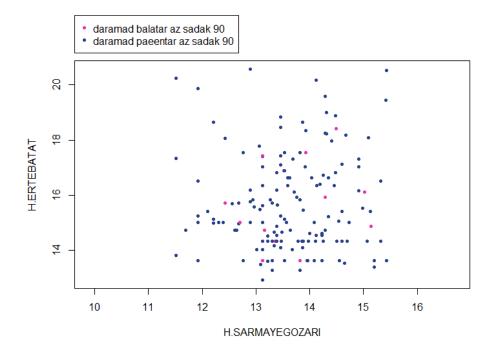
Chart of clothing expenses and food expenses against net income

The high correlation between the cost of clothing and food and the large number of people with income below the 90th percentile is the information obtained from this graph.

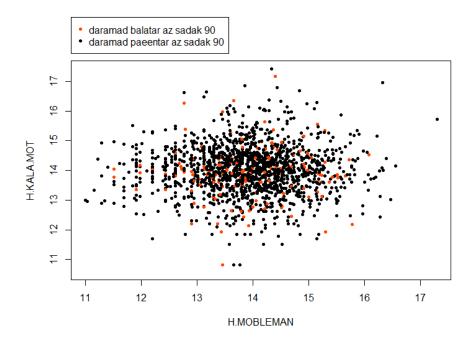


Graph of communication cost and investment cost against net income

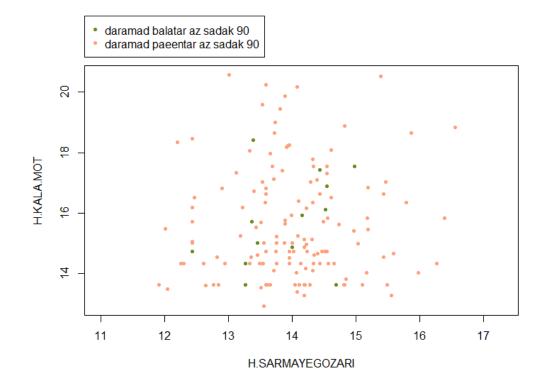
As it is clear from this graph, these two variables do not have a high correlation with each other.



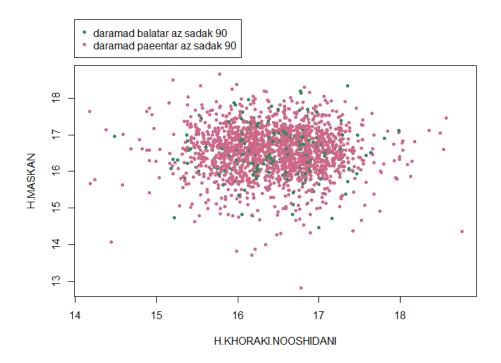
# Chart of the cost of miscellaneous goods and the cost of furniture against net income



# Chart of cost of miscellaneous goods and investment cost against net income



# Graph of housing cost and food cost against net income



The third chapter: Implementation of the logistic regression model

Firstonce We apply the logistic regression model to the training data on which we did not perform oversampling:

Reference Prediction 0 1 0 263 35 1 1 0

Accuracy: 0.8796

95% CI: (0.8372, 0.9142)

No Information Rate : 0.8829 P-Value [Acc > NIR] : 0.6145

Kappa: -0.0065

Mcnemar's Test P-Value : 3.798e-08

Sensitivity: 0.9962
Specificity: 0.0000
Pos Pred Value: 0.8826
Neg Pred Value: 0.0000
Prevalence: 0.8829
Detection Rate: 0.8796

Detection Prevalence: 0.9967
Balanced Accuracy: 0.4981

'Positive' Class : 0

The accuracy of the model is high, but the specification factor is very low, which is not our desired case. (That is, the values of net income, which in reality are equal to 1, are mistakenly predicted to be equal to 0 in this model, which is wrong.)

Now we apply the model to the training data on which we performed oversampling. As it is known, the accuracy is reduced, but the values of the characterization and sensitivity factors are acceptable values. (that is, the values of net income that are equal to 1 in reality (income above the 90th percentile), are also predicted to be approximately equal to 1 in this model, as well as the values of net income that are

actually equal to 0 (income below the 90th percentile), in this The model was also predicted to be almost equal to 0.)

```
Reference
Prediction 0 1
        0 154 19
        1 110 16
              Accuracy: 0.5686
                95% CI: (0.5103, 0.6254)
   No Information Rate: 0.8829
   P-Value [Acc > NIR] : 1
                 Kappa : 0.019
Mcnemar's Test P-Value : 2.299e-15
           Sensitivity: 0.5833
           Specificity: 0.4571
        Pos Pred Value : 0.8902
        Neg Pred Value: 0.1270
            Prevalence: 0.8829
        Detection Rate: 0.5151
  Detection Prevalence: 0.5786
     Balanced Accuracy: 0.5202
       'Positive' Class : 0
```

To achieve higher accuracy, we use different methods of forward, backward, or both, and we observe that the forward and both methods do not have higher accuracy, and only the backward method has higher accuracy.

### Reference Prediction 0 1 0 158 19 1 106 16

Accuracy : 0.5819

95% CI: (0.5238, 0.6385)

No Information Rate: 0.8829

P-Value [Acc > NIR] : 1

Kappa : 0.0268

Mcnemar's Test P-Value: 1.448e-14

Sensitivity: 0.5985 Specificity: 0.4571

### The variables that influence this model are:

```
Call: glm(formula = DARAMAD.KHALES ~ C.SH + JENS.S + SEN.S + M.T.S +
    V.F.S + N.T.M + S.Z + M.O.B + MO + DO + ZABT + TV + PC +
    OJAGH.GAZ + JAROO.B + M.LEBAS + CHARKH.KH + PANKE + H.KHORAKI.NOOSHIDAN:
    H.ERTEBATAT + H.BEHDASHT + H.HAMLONAGHL + H.MASKAN + H.MOBLEMAN +
    H.POOSHAK + KHARID.KALA.BADAVAM + H.SARMAYEGOZARI, family = "binomial",
    data = data.rose)
```

#### Coefficients:

Coefficients:		
(Intercept)	C.SH3	C.SH24
-2.864e-01	4.857e-01	4.784e-01
JENS.S2	SEN.S	M.T.S1
-1.408e-01	2.665e-02	3.478e-01
M.T.S2	M.T.S3	M.T.S4
2.848e-01	-4.184e-01	5.538e-01
M.T.S5	M.T.S6	M.T.S7
1.039e+00	1.017e+00	1.440e+00
M.T.S8	M.T.S9	V.F.S2
2.884e+00	-1.436e+01	-1.146e+00
V.F.S3	V.F.S5	V.F.S6
-2.818e-01	5.142e-01	-2.583e-01
N.T.M3	N.T.M4	N.T.M5
3.000e-01	1.926e-01	-1.502e+01
N.T.M6	N.T.M7	S.Z
-4.426e-01	-1.408e+01	-4.120e-03
M.O.B1	M.O.B2	M.O.B3
-2.117e-02	5.691e-01	-5.537e-01
M.O.B6	M.O.B8	MO1
-1.417e+01	-1.447e+01	4.573e-01
DO1	ZABT1	TV1
-1.093e+00	6.019e-01	-3.340e-01
PC1	OJAGH.GAZ1	JAROO.B1
-1.610e-01	-1.349e+00	2.348e-01
M.LEBAS1	CHARKH.KH1	PANKE1
-3.690e-01	2.752e-01	4.467e-01
H.KHORAKI.NOOSHIDANI	H.ERTEBATAT	H.BEHDASHT
2.675e-09	8.252e-08	-1.689e-08
H.HAMLONAGHL	H.MASKAN	H.MOBLEMAN
2.643e-08	-1.015e-08	-2.784e-08
H.POOSHAK	KHARID.KALA.BADAVAM	H.SARMAYEGOZARI
1.349e-08	-2.747e-09	-4.988e-09

## Check more fit:

By applying the model to the training data, it can be seen that no overfitting has been done in this model.

Accuracy of the model on the training data:

#### Confusion Matrix and Statistics

Reference Prediction 0 1 0 3153 1703 1 1894 3250

Accuracy: 0.6403

95% CI: (0.6308, 0.6497)

No Information Rate : 0.5047 P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.2808

Mcnemar's Test P-Value : 0.001535

Sensitivity: 0.6247 Specificity: 0.6562

### Accuracy of the model on validation data:

Reference Prediction 0 1 0 158 19 1 106 16

Accuracy: 0.5819

95% CI: (0.5238, 0.6385)

No Information Rate : 0.8829

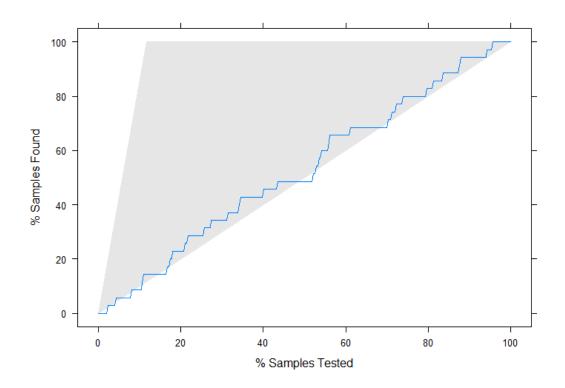
P-Value [Acc > NIR] : 1

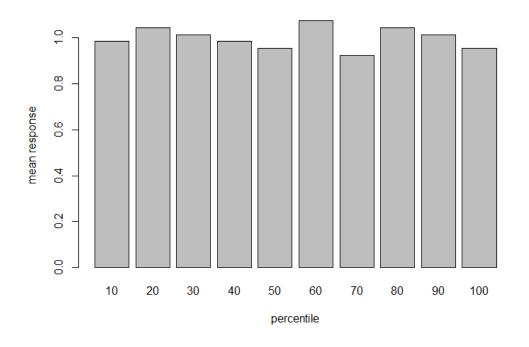
Kappa : 0.0268

Mcnemar's Test P-Value: 1.448e-14

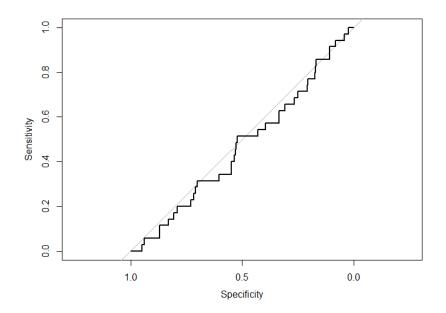
Sensitivity: 0.5985 Specificity: 0.4571

The lifting chart, the percentile lifting chart and the roc chart for the logistic regression model with regression removal show the acceptability of the model.



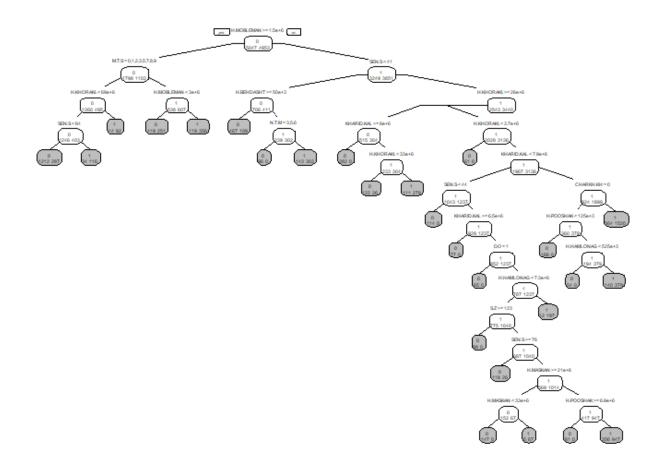


# > auc(r) Area under the curve: 0.4663



# Chapter 4: Implementation of the decision tree model

To select the decision tree model, we tried random forest, boosted tree and single tree models; Both the random forest and the enhanced tree had high accuracy, but their sensitivity and specificity indices did not have acceptable values. So we ran the single tree model as the final decision tree model on the data:



One of the above single tree decision rules is as follows:

H.MOBLEMAN >= 1492500 and M.T.S = 0,1,2,3,5,7,8,9 and H. KHORAKI. NOOSHIDANI<
6.8856e+07 daramad. khales = 1 (above the 90th percentile)

The accuracy of the single tree model and the roc curve are as follows:

#### Confusion Matrix and Statistics

#### Reference Prediction 0 0 182 25 1 83 10

Accuracy : 0.64 95% CI : (0.5828, 0.6944)

No Information Rate : 0.8833

P-Value [Acc > NIR] : 1

Kappa : -0.016

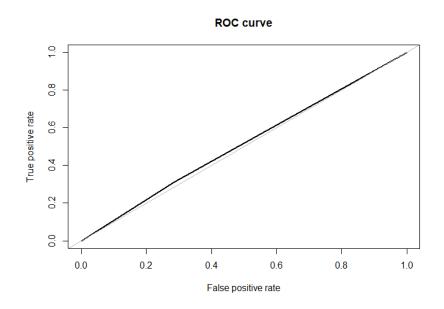
Mcnemar's Test P-Value: 4.139e-08

Sensitivity: 0.6868 Specificity: 0.2857 Pos Pred Value : 0.8792 Neg Pred Value: 0.1075 Prevalence: 0.8833 Detection Rate: 0.6067

Detection Prevalence: 0.6900 Balanced Accuracy: 0.4863

'Positive' Class : 0

# Area under the curve (AUC): 0.514



#### Check more fit:

By applying the model to the training data, it can be seen that no overfitting has been done in this model.

Accuracy of the model on the training data:

```
Confusion Matrix and Statistics
         Reference
Prediction 0
        0 3549 699
        1 1498 4254
              Accuracy : 0.7803
                95% CI: (0.7721, 0.7884)
   No Information Rate: 0.5047
    P-Value [Acc > NIR] : < 2.2e-16
                 Kappa : 0.5612
Mcnemar's Test P-Value : < 2.2e-16
           Sensitivity: 0.7032
           Specificity: 0.8589
        Pos Pred Value: 0.8355
        Neg Pred Value: 0.7396
            Prevalence: 0.5047
        Detection Rate: 0.3549
  Detection Prevalence: 0.4248
     Balanced Accuracy: 0.7810
       'Positive' Class : 0
```

# Chapter 5: Implementation of the KNN model

Before implementing the KNN model, because this model is based on distance calculation, the data must be pre-processed. That is, they must be numerical and also the normalization process must be done on them so that the output obtained from the model can be relied upon.

For this purpose, we first converted the classified variables into binary variables (dummy variable) and then normalized all the variables and finally applied the model to the data.

(Note: we applied the knn model only to the community of variables that were significant in the single tree model and logistic regression.)

```
k accuracy
1
    1 0.8166667
2
    2 0.8166667
3
    3 0.8100000
    4 0.8100000
4
5
    5 0.8033333
    6 0.8033333
7
    7 0.7866667
8
    8 0.7866667
    9 0.7533333
10 10 0.7533333
11 11 0.7466667
12 12 0.7466667
13 13 0.7266667
14 14 0.7266667
```

According to the table above and considering the valuesIndicator sensitivity and specificity, it seems that k=14 is suitable for all three factors of accuracy, sensitivity and specificity.

Reference Prediction 0 1 0 210 27 1 55 8

Accuracy: 0.7267

95% CI : (0.6725, 0.7763)

No Information Rate : 0.8833 P-Value [Acc > NIR] : 1.000000

Kappa : 0.0156

Mcnemar's Test P-Value: 0.002867

Sensitivity: 0.7925 Specificity: 0.2286 Pos Pred Value: 0.8861 Neg Pred Value: 0.1270 Prevalence: 0.8833

Detection Rate : 0.7000 Detection Prevalence : 0.7900

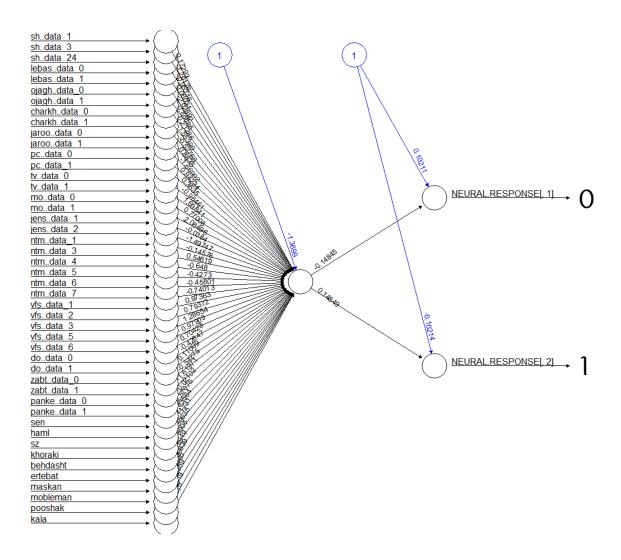
Balanced Accuracy : 0.5105

'Positive' Class: 0

# Chapter 6: Implementation of the neural network model

The output of the neural network model with a hidden layer is as follows:

(Note: We applied the neural network model only to the community of variables that were significant in the single tree model and logistic regression.)



### Check more fit:

By applying the model to the training data, it can be seen that no overfitting has been done in this model.

Accuracy of the model on the training data:

#### Reference

Prediction 0 1 0 2307 2083 1 2740 2870

Accuracy: 0.5177

95% CI: (0.5079, 0.5275)

No Information Rate : 0.5047 P-Value [Acc > NIR] : 0.004793

Kappa : 0.0365

Mcnemar's Test P-Value : < 2.2e-16

Sensitivity: 0.4571 Specificity: 0.5794 Pos Pred Value: 0.5255 Neg Pred Value: 0.5116 Prevalence: 0.5047

Detection Rate: 0.2307
Detection Prevalence: 0.4390
Balanced Accuracy: 0.5183

'Positive' Class : 0

# Accuracy of the model on validation data:

Reference Prediction 0 1 0 124 16

1 141 19

Accuracy: 0.4767

95% CI: (0.419, 0.5348)

No Information Rate : 0.8833

P-Value [Acc > NIR] : 1

Kappa: 0.0042

Mcnemar's Test P-Value : <2e-16

Sensitivity: 0.4679 Specificity: 0.5429 Pos Pred Value: 0.8857

Neg Pred Value : 0.1188 Prevalence : 0.8833

Detection Rate: 0.4133

Detection Prevalence: 0.4667 Balanced Accuracy: 0.5054

'Positive' Class: 0

The seventh chapter: summary and conclusion about the final model

Considering that our problem is classification, the factors of accuracy, sensitivity and specification are effective in choosing the final model.

precision	Model	
0.58	Logistic regression with regression elimination	
0.64	Single decision tree	
0.72	Knn	
0.47	neural network	
allergy	Model	
0.59	Logistic regression with regression elimination	
0.68	Single decision tree	
0.79	Knn	
0.46	neural network	
specification	Model	
0.45	Logistic regression with regression elimination	
0.28	Single decision tree	
0.22	Knn	
0.54	neural network	

According to these indicators, Can concluded that the logistic regression model is the best model for this problem.